SMILE Wrappers

Programmer's Manual

Version 2.2.4.R1, Built on 4/27/2024
BayesFusion, LLC

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Introduction

1 Introduction

Welcome to SMILE Wrapper Programmer's Manual, Version 2.2.4.R1, Built on 4/27/2024.

For the most recent version of this manual, please visit https://support.bayesfusion.com/docs/.

To download the software described in this manual, go to http://download.bayesfusion.com.

SMILE is a C++ software library for performing Bayesian inference. In order to ensure that its functionality can be easily integrated into software written in other languages, BayesFusion, LLC, provides wrapper libraries for Java, Python, R and .NET. The names of these products are:

- jSMILE (Java and environments which can instantiate and use the JVM)
- PySMILE (Python 2.7 and 3.x)
- rSMILE (R 4.x)
- SMILE.NET (.NET)

Each wrapper includes SMILE, so you do not need to download SMILE or know how to use C++ SMILE in order to use the wrappers. We strive to ensure feature symmetry between the wrappers - features available in one wrapper are generally available in other wrappers.

We have also developed SMILE.COM, a wrapper exposing SMILE functionality through Windows' COM (Common Object Model). The target audience for SMILE.COM are Microsoft Excel users, although the library will work with any environment extensible through COM. This manual does not contain documentation for SMILE.COM.

If you are new to SMILE and would like to begin with an informal, tutorial-like introduction, please start with the Java, Python or .NET section of *Platforms and Wrappers* 14 (depending on the programming language you're going to use), followed by *Hello SMILE Wrapper!* 22 section. If you are an advanced user, please browse through the *Table of Contents* or search for the topic of your interest.

This manual refers to a good number of concepts that are assumed to be known to the reader, such as probability, utility, decision theory and decision analysis, Bayesian networks, influence diagrams, etc. Should you want to learn more about these, please refer to GeNIe manual. SMILE is GeNIe's Application Programmer's Interface (API) and practically every elementary operation performed with GeNIe translates to calls to SMILE methods. Being familiar with GeNIe may prove extremely useful in learning SMILE. Understanding some of SMILE's functionality may be easier when performed interactively in GeNIe. GeNIe manual, along with all other BayesFusion documentation, is available at https://support.bayesfusion.com/docs. Other resources, including introduction to probabilistic graphical models, are available at https://www.bayesfusion.com/resources/.

Yet another useful resource is available at https://repo.bayesfusion.com. The site is powered by BayesBox, our interactive model viewer/repository software. The repository contains more than 100 example Bayesian networks, hybrid Bayesian networks, dynamic Bayesian networks, and influence diagrams. BayesBox runs SMILE on the server side and calls into its API to calculate the posterior probabilities after evidence is modified in the web browser.

Licensing

2 Licensing

SMILE wrappers are commercial products that require a development license to use. There are two types of development licenses: Academic and Commercial. Academic license is free of charge for research and teaching use by those users affiliated with an academic institution. All other use requires a commercial license, available for purchase from BayesFusion, LLC.

Deployment of SMILE library or SMILE wrappers, i.e., embedding them into user programs, requires a deployment license. There are two types of deployment licenses: Server license, which allows a program linked with SMILE to be deployed on a computer server, and end-user program license, which allows distribution of user programs that include SMILE. Please contact BayesFusion, LLC, for details of the licenses and pricing.

The licensing system is implemented as a fragment of code which contains your license key and must be executed as first call into SMILE wrapper that your program uses. **This code is not included in the SMILE wrapper binary distribution**, it is personalized by BayesFusion, LLC, for you or your organization. The license keys are provided in a compressed .zip file, which contains Java, R, Python, C# and VB.NET code. 6-month academic and free 30-day evaluation licenses can be obtained directly at https://download.bayesfusion.com.

What's new in SMILE 2

3 What's new in SMILE 2

Major new features in SMILE 2 are:

- Support for metalog distributions in continuous nodes. There is no new API for metalog distributions, equation nodes can use `Metalog` and `MetalogA` functions in their equations. For details, see the metalog entry in the *Random Number Generators* 54 section.

- Discrete nodes with outcomes based on numeric intervals or point values. See the *Discrete nodes and numeric domains* 40 section for details.

Version 2.2 introduces new diagnostic algorithms for single-fault and multi-fault *diagnosis* 70.

Platforms and Wrappers

4 Platforms and Wrappers

In addition to ensuring feature parity between wrappers, we designed them to use similar names for the classes and methods. For example, all three wrappers contain the `Network` class. At the same time, wrappers honor the idioms of the specific languages they target:

- `Network` class in jSMILE has `addNode` method
- `Network` class in PySMILE has `add_node` method
- `Network` class in rSMILE has `addNode` method
- `Network` class in SMILE.NET has `AddNode` method

As you can see, the naming choices for the methods reflect the naming conventions of different programming languages.

The remainder of this chapter describes the platform-specific details related to the use of SMILE Wrappers.

4.1 Java and jSMILE

jSMILE is compatible with JDK 8 and newer. See the *Maven* [15] section below for information about using jSMILE in a Maven-based project, including the location of BayesFusion's Maven repository and POM integration with jSMILE's native library.

jSMILE contains two parts: the jar file and the native library, the latter is specific to your operating system. The jar file, named `jsmile-x.y.z.jar` where x.y.z is the version number, can be used as any Java jar.

The native library is used by the code in the jar file through Java Native Interface (JNI). The name of the native library file is platform-dependent:

- `jsmile.dll` on Windows
- `jsmile.so` on Linux
- `jsmile.jnilib` on macOS

In the static initializer of the smile.Wrapper class, jSMILE will attempt to load its native library. If the `jsmile.native.library` system property is set, jSMILE calls `System.load` method, which requires a complete path name of the native library (no relative paths are allowed), using the value of the property as the path name. Otherwise, the `System.loadLibrary` method is used. In such case, the native library must be located in one of the directories specified by the `java.library.path property`. Note that `java.library.path` cannot be set once JVM is running, but `jsmile.native.library` can be set with a call to `System.setProperty`.

Your license key should be pasted into the source code of your program.

The classes defined in jSMILE are located in `smile` and `smile.learning` packages. There are two types of classes:

- simple objects with public data members
- wrappers for C++ objects from SMILE library

The second group of classes, which includes `smile.Network`, is derived from `smile.Wrapper`. Each object instance of these classes has a related C++ object, which is deallocated by the Java object's finalizer or by a call to `Wrapper.Dispose` method. To ensure early deallocation of C++ object resources associated with your Java object, `Dispose` should be called as soon as the program doesn't need the object anymore. If `Dispose` is not called, the deallocation will happen in the finalizer during garbage collection.

4.1.1 Maven

If your Java project uses Maven, you can use BayesFusion's Maven repository to integrate jSMILE with your project. The repository URL is https://support.bayesfusion.com/maven-X, where X is either A for jSMILE Academic, or B for the commercial version of the library. The artifact id is `jsmile` and the group id is `com.bayesfusion`, regardless of the repository used.

In addition to the `jsmile` artifact, the repository contains three separate .zip artifacts for three platform-specific native libraries:

- `jsmile-native-win64` for 64-bit Windows
- `jsmile-native-linux64` for 64-bit Linux
- `jsmile-native-macos` for macOS

Please do not add the references to these artifacts in the <dependencies> section of the POM file. Instead, use the maven-dependency-plugin to integrate these with your Maven-based build process and ensure that the native library is extracted from the artifact's .zip file into the project directory during the compile phase. For projects that only run on one of the three supported native platforms, the artifact id specified in the plugin configuration can refer directly to one of three artifacts listed above. Another option is to use Maven's OS-based profile activation to select the appropriate native library. The POM file below uses this approach. Note that the CPU architecture is not tested against (we assume 64-bit environment for Windows and Linux). The location of the extracted library is arbitrarily set to ${project.basedir}. jSMILE version referenced in the POM is set to 2.2.0.

```
<project xmlns="http://maven.apache.org/POM/4.0.0"
  xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
  xsi:schemaLocation=
    "http://maven.apache.org/POM/4.0.0 https://maven.apache.org/xsd/maven-4.0.0.xsd">
  <modelVersion>4.0.0</modelVersion>
  <groupId>com.bayesfusion</groupId>
  <artifactId>test-maven-repo</artifactId>
  <version>0.0.1-SNAPSHOT</version>

  <repositories>
    <repository>
      <id>bayesfusion-repo</id>
         <name>BayesFusion Repository</name>
         <url>https://support.bayesfusion.com/maven-B</url>
    </repository>
  </repositories>

  <dependencies>
    <dependency>
      <groupId>com.bayesfusion</groupId>
      <artifactId>jsmile</artifactId>
      <version>2.2.0</version>
    </dependency>
  </dependencies>
```

```
<profiles>
  <profile>
    <id>MacNative</id>
    <activation>
      <os>
        <family>mac</family>
      </os>
    </activation>
    <properties>
      <nativeSuffix>macos</nativeSuffix>
    </properties>
  </profile>
  <profile>
    <id>WinNative</id>
    <activation>
      <os>
        <family>Windows</family>
      </os>
    </activation>
    <properties>
      <nativeSuffix>win64</nativeSuffix>
    </properties>
  </profile>
  <profile>
    <id>LinuxNative</id>
    <activation>
      <os>
        <family>Unix</family>
      </os>
    </activation>
    <properties>
      <nativeSuffix>linux64</nativeSuffix>
    </properties>
  </profile>
</profiles>

<build>
  <plugins>
    <plugin>
      <groupId>org.apache.maven.plugins</groupId>
      <artifactId>maven-dependency-plugin</artifactId>
      <executions>
        <execution>
          <id>resource-dependencies</id>
          <phase>compile</phase>
          <goals>
            <goal>unpack</goal>
          </goals>
          <configuration>
            <artifactItems>
              <artifactItem>
                <groupId>com.bayesfusion</groupId>
                <artifactId>jsmile-native-${nativeSuffix}</artifactId>
                <version>2.2.0</version>
```

```
                <type>zip</type>
                <overWrite>true</overWrite>
                <includes>*jsmile*</includes>
              </artifactItem>
            </artifactItems>
            <outputDirectory>${project.basedir}</outputDirectory>
          </configuration>
        </execution>
      </executions>
    </plugin>
  </plugins>
</build>

</project>
```

4.2 Python and PySMILE

To use PySMILE in your Python program, you just need to import the `pysmile` module:

```
import pysmile
```

Your license key can be pasted directly into your Python code, or imported:

```
import pysmile_license
```

PySMILE binaries are available for Python 2.7 and Python 3.x. PySMILE consists of a single dynamically loaded library. The library name is platform-dependent:

- `pysmile.pyd` on Windows
- `pysmile.so` on Linux and macOS

You can manually download PySMILE binaries from BayesFusion's software download website, or use pip (Python package manager) to automate the download. BayesFusion's software download website contains PySMILE binaries compatible with the single recent stable Python version, but our pip repository hosts builds for multiple Python releases.

To download using pip:

```
python -m pip install --no-cache-dir --index-url https://support.bayesfusion.com/pysmile-B/ pysmile
```

Replace **`pysmile-B`** with **`pysmile-A`** in the repository URL if you're using PySMILE academic. To force re-download of the pysmile module from the BayesFusion repository, add `--force-reinstall` to the command line.

Sonatype Nexus requires the pip repository URLs to end with `simple`. We maintain pip repository mirrors for users of Nexus at:

https://support.bayesfusion.com/python/pysmile-A/simple/
https://support.bayesfusion.com/python/pysmile-B/simple/

4.3 R and rSMILE

rSMILE is distributed as a compiled R package. rSMILE binaries are available for R 3.x.

To install rSMILE, use install.packages:

```
install.packages(<path-to-local-copy-of-rSMILE-package>)
```

Once the package is installed, use the library function to enable rSMILE functionality:

```
library(rSMILE)
```

Your license key can be pasted directly into your R code, or read from the license file:

```
source("License.R")
```

From December 2019 onwards, the licensing keys for R are generated in the format compatible with rSMILE and are ready to be used with rSMILE. If you obtained your SMILE licensing key before December 2019, your `License.R` file uses the syntax for jSMILE and rJava. To modify your licensing key, replace

```
.jnew("smile.License",paste(
```

with

```
rSMILE::License(paste(
```

Another required modification applies to the numeric part of the licensing key: replace `.jbyte` with `as.integer`. Please contact BayesFusion if you encounter any problems with the modification, or, if you're an academic user, generate new licensing key at our academic downloads site.

4.4 .NET and SMILE.NET

SMILE.NET, which is compatible with .NET framework 4.x, consists of a single mixed-mode assembly named `smilenet.dll`. To use the library, simply add `smilenet.dll` as a reference in your project.

We build SMILE.NET using C++/CLI compiler in Visual Studio 2013 to create a seamless package containing both native code (the C++ SMILE library) and .NET wrapper code. This compiler enforces the use of the dynamic C++ runtime library. This means that `smilenet.dll` has a runtime dependency on VS2013 C++ runtime. Your Windows system is likely to have this component already installed. However, if you are getting error messages referring to missing DLLs like `MSVCP120.DLL` or `MSVCR120.DLL`, you need to download and install the "Visual C++ Redistributable Package for Visual Studio 2013" from Microsoft's website.

Your license key should be pasted into the sources of your program. We provide the keys as C# and VB.NET code.

The classes defined in SMILE.NET are located in `Smile` and `Smile.Learning` namespaces. There are two types of classes:

- simple objects with public data members
- wrappers for C++ objects from SMILE library

The second group of classes, which includes `Smile.Network`, is derived from `Smile.WrappedObject` and also implements .NET's `IDisposable` interface. Each object instance of these classes has a related C++ object, which is deallocated by the .NET object's finalizer or its `IDisposable::Dispose` method. You can use C#'s `using`

statement to ensure deterministic finalization, otherwise the deallocation will be performed in the finalizer during garbage collection.

```
using (Network net = new Network())
{
    // use the net object in this scope
}
```

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Hello, SMILE Wrapper!

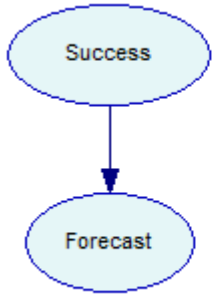
5 Hello, SMILE Wrapper!

In this section, we will show how SMILE can load and use a model created in GeNIe to perform useful work. We will use the model developed in the GeNIe on-line help (Section *Hello GeNIe!*). The model for this problem is available as one of the example networks (file `VentureBN.xdsl`). If you have GeNIe installed, you can copy the file into your working directory. The same file is also included in the zip file containing all source code for tutorials, available from http://support.bayesfusion.com/docs.

Alternatively, create a file named `VentureBN.xdsl` with any text editor by copying the content of the *VentureBN.xdsl* [22] section below.

5.1 Success/Forecast model

The model encodes information pertaining to a problem faced by a venture capitalist, who considers a risky investment in a startup company. A major source of uncertainty about her investment is the success of the company. She is aware of the fact that only around 20% of all start-up companies succeed. She can reduce this uncertainty somewhat by asking expert opinion. Her expert, however, is not perfect in his forecasts. Of all start-up companies that eventually succeed, he judges about 40% to be good prospects, 40% to be moderate prospects, and 20% to be poor prospects. Of all start-up companies that eventually fail, he judges about 10% to be good prospects, 30% to be moderate prospects, and 60% to be poor prospects.



Success	0.2
Failure	0.8

	Success	Failure
Good	0.4	0.1
Moderate	0.4	0.3
Poor	0.2	0.6

5.2 VentureBN.xdsl

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<smile version="1.0" id="VentureBN" numsamples="1000">
    <nodes>
        <cpt id="Success">
            <state id="Success" />
            <state id="Failure" />
            <probabilities>0.2 0.8</probabilities>
        </cpt>
        <cpt id="Forecast">
            <state id="Good" />
            <state id="Moderate" />
            <state id="Poor" />
            <parents>Success</parents>
            <probabilities>
                0.4 0.4 0.2 0.1 0.3 0.6
            </probabilities>
        </cpt>
```

```
    </nodes>
    <extensions>
        <genie version="1.0" app="GeNIe 2.1.1104.2"
            name="VentureBN"
            faultnameformat="nodestate">
            <node id="Success">
                <name>Success of the venture</name>
                <interior color="e5f6f7" />
                <outline color="0000bb" />
                <font color="000000" name="Arial" size="8" />
                <position>54 11 138 62</position>
            </node>
            <node id="Forecast">
                <name>Expert forecast</name>
                <interior color="e5f6f7" />
                <outline color="0000bb" />
                <font color="000000" name="Arial" size="8" />
                <position>63 105 130 155</position>
            </node>
        </genie>
    </extensions>
</smile>
```

5.3 The program

We will show how to load this model using SMILE, how to enter observations (evidence), how to perform inference, and how to retrieve the results of SMILE's calculations. Three complete source code versions (Java, Python, R, C#) are included below. Note that you'll need to use your SMILE license key. See the *Licensing* 10 section of this manual if you want to obtain your academic or trial license key. See *Platforms and Wrappers* 14 section for language-specific information on licensing.

Our network object - an instance of `Network` class - is declared as local variable. We proceed to read the XDSL file from disk:

```
Java:   net.readFile("VentureBN.xdsl");
Python: net.read_file("VentureBN.xdsl")
R:      net$readFile("VentureBN.xdsl")
C#:     net.ReadFile("VentureBN.xdsl");
```

We want to set the evidence on the *Forecast* node to *Moderate*. The wrappers can use node and outcome identifiers directly:

```
Java:   net.setEvidence("Forecast", "Moderate");
Python: net.set_evidence("Forecast", "Moderate")
R:      net$setEvidence("Forecast", "Moderate")
C#:     net.SetEvidence("Forecast", "Moderate");
```

Now we can update the network:

```
Java:   net.updateBeliefs();
Python: net.update_beliefs()
R:      net$updateBeliefs()
C#:     net.UpdateBeliefs();
```

After network update we can retrieve the posterior probabilities of the *Success* node:

```
Java:   double[] beliefs = net.getNodeValue("Success");
Python: beliefs = net.get_node_value("Success")
```

```
R:      beliefs <- net$getNodeValue("Success")
C#:     double[] beliefs = net.GetNodeValue("Success");
```

To print the probabilities, we simply iterate over the elements of the returned numeric array. Each probability printed to the console is preceeded by the identifier of the node outcome. If you compile and run the program, the output should be:

```
Success=0.25
Failure=0.75
```

"Success" and "Failure" are outcome identifiers of the *Success* node, which in Java are returned by the `Network.getOutcomeId` method. At this point you should easily derive the equivalent method names for Python, R and C# from Java method name.

Note that in case of any of method calls failing, the exception would be thrown. SMILE wrappers do not use error codes on failure.

We will build upon the simple network described in this chapter in the *Tutorials* [82] section of this manual.

5.3.1 Hello.java

```
import smile.*;

public class Hello {
    public static void main(String[] args) {
        System.out.println("Insert your licensing key below.");
        // new smile.License(...);

        Network net = new Network();
        net.readFile("VentureBN.xdsl");
        net.setEvidence("Forecast", "Moderate");
        net.updateBeliefs();
        double[] beliefs = net.getNodeValue("Success");
        for (int i = 0; i < beliefs.length; i ++) {
            System.out.println(net.getOutcomeId("Success", i) + " = " + beliefs[i]);
        }
    }
}
```

5.3.2 Hello.py

```
import pysmile

# pysmile_license is your license key
import pysmile_license

def hello_smile():
    net = pysmile.Network()
    net.read_file("VentureBN.xdsl");

    net.set_evidence("Forecast", "Moderate")
    net.update_beliefs()

    beliefs = net.get_node_value("Success")
    for i in range(0, len(beliefs)):
        print(net.get_outcome_id("Success", i) + "=" + str(beliefs[i]))
```

```
hello_smile()
```

5.3.3 Hello.R

```
library(rSMILE)

# License.R is your licensing key
source("License.R")

net <- Network()
net$readFile("VentureBN.xdsl")
net$setEvidence("Forecast", "Moderate")
net$updateBeliefs()
beliefs <- net$getNodeValue("Success")
for (i in 1:length(beliefs)) {
    cat(sprintf("%s = %f\n", net$getOutcomeId("Success", i-1L), beliefs[i]))
}
```

5.3.4 Hello.cs

```
using System;
using Smile;

namespace SmileNetTutorial
{
    class Hello
    {
        static void Main(string[] args)
        {
            Console.WriteLine("Insert your SMILE licensing key here.");
            // new Smile.License(...);

            Network net = new Network();
            net.ReadFile("VentureBN.xdsl");
            net.SetEvidence("Forecast", "Moderate");
            net.UpdateBeliefs();
            double[] beliefs = net.GetNodeValue("Success");
            for (int i = 0; i < beliefs.Length; i++)
            {
                Console.WriteLine("{0} = {1}", net.GetOutcomeId("Success", i), beliefs[i]);
            }
        }
    }
}
```

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Using SMILE Wrappers

6 Using SMILE Wrappers

6.1 Error handling

SMILE Wrappers throw exceptions when the underlying C++ SMILE calls fail. The exception types are:

```
Java:   smile.SMILEException
Python: pysmile.SMILEExcetpion
C#:     Smile.SmileException
```

6.2 Networks, nodes and arcs

The most important class defined by SMILE Wrappers is `Network`. The objects of this class act as containers for nodes and are responsible for node creation and destruction. Nodes and arcs are always created and destroyed by invoking the methods of the `Network` class. The access to existing nodes and arcs is always performed through the `Network` object where they live.

There are no classes representing nodes and arcs. The `Network` object works as a facade for the complex underlying data structure.

6.2.1 Network

To create a network, simply use a default constructor:

Java:

```
import smile.*;
...
Network net = new Network();
```

Python:

```
import pysmile
...
net = pysmile.Network()
```

R:

```
library(rSMILE)
...
net <- Network()
```

C#:

```
using Smile;
...
Network net = new Network();
```

See the *Platforms and Wrappers* 14 section for the platform-specific information about the lifetime of instances of `Network` class.

6.2.2 Nodes

Use the following methods to add and delete nodes:

Java:

```
Network.addNode
Network.deleteNode
```

Python:

```
Network.add_node
Network.delete_node
```

R:

```
Network$addNode
Network$deleteNode
```

C#:

```
Network.AddNode
Network.DeleteNode
```

When creating the node you need to specify its type.

Within the network, the nodes are uniquely identified by their handle. The node handle is a non-negative integer, which is preserved when network is copied. In addition to handles, each node has an unique (in the context of its containing network), persistent, textual identifier. This identifier is specified as an argument to `Network.addNode` method at node creation (it may be changed later). The identifiers in SMILE start are case-sensitive, start with a letter and contain letters, digits and underscores. Node's identifier can be converted to node handle with a call to `Network.getNode` method.

All methods of the `Network` class dealing with nodes can use either integer node handles or string identifiers to specify the nodes. However, the versions using identifiers will be internally performing O(N) string lookup (where N is the number of nodes in the network), while the versions using handlers are only using O(1) validity check.

The values of the handles are not guaranteed to be consecutive or start from any particular value. To iterate over nodes in the network, use `Network.getFirstNode` and `getNextNode`:

Java:

```
for (int h = net.getFirstNode(); h >= 0; h = net.getNextNode(h)) {
    // do something with net and node identified by h
}
```

Python:

```
h = net.get_first_node()
while (h >= 0):
    # do something with net and node identified by h
    h = net.get_next_node(h)
```

R:

```
for (h in net$getAllNodes()) {
    # do something with net and node identified by h
}
```

C#:

```
for (int h = net.GetFirstNode(); h >= 0; h = net.GetNextNode(h))
```

```
{
    // do something with net and node identified by h
}
```

Note the loop exit condition - we proceed only if the returned handle is greater than or equal to zero.

Here are the methods to obtain an array of all node handles, an array of all node identifiers or a number of nodes in the network:

Java:

```
Network.getAllNodes
Network.getAllNodeIds
Network.getNodeCount
```

Python:

```
Network.get_all_nodes
Network.get_all_node_ids
Network.get_node_count
```

R:

```
Network$getAllNodes
Network$getAllNodeIds
Network$getNodeCount
```

C#:

```
Network.GetAllNodes
Network.GetAllNodeIds
Network.NodeCount (read-only property)
```

Nodes may be marked as targets with `Network.setTarget` method. Target nodes are always guaranteed to be updated by the inference algorithm. Other nodes, i.e., nodes that are not designated as targets, may be updated or not, depending on the internals of the algorithm used, but are not guaranteed to be updated. Focusing inference on the target nodes can reduce time and memory required to complete the calculation. When no targets are specified, SMILE assumes that all nodes are of interest to the user.

6.2.3 Arcs

Here are the `Network` class methods to add and delete arcs between nodes:

Java:

```
Network.addArc
Network.deleteArc
```

Python:

```
Network.add_arc
Network.delete_arc
```

R:

```
Network$addArc
Network$deleteArc
```

C#:

```
Network.AddArc
```

```
Network.DeleteArc
```

The graph defined by nodes and arcs in a `Network` class instance a directed acyclic graph (DAG) at all times. An attempt to add an arc which would create a cycle in the graph will cause an exception.

To inspect the graph structure, you can use the following methods:

Java:

```
Network.getParents
Network.getParentIds
Network.getChildren
Network.getChildIds
```

Python:

```
Network.get_parents
Network.get_parent_ids
Network.get_children
Network.get_child_ids
```

R:

```
Network$getParents
Network$getParentIds
Network$getChildren
Network$getChildIds
```

C#:

```
Network.GetParents
Network.GetParentIds
Network.GetChildren
Network.GetChildIds
```

The methods with the "Ids" suffix return the arrays of string identifiers of the related nodes, otherwise the arrays of integer node handles are used.

6.3 Anatomy of a node

The different aspects of a node available through `Network` class methods are:

- node definition
- node value
- node evidence
- attributes which do not affect inference, but determine node's location, color, name, etc.

The definition of the node specifies how it interacts with other nodes in the network. The node definition is written as part of the network when the network is saved to a file or serialized as a string variable. For general chance node the definition consists of conditional probability table (CPT) and list of state names.

The value of the node contains the values (typically, the marginal probability distribution or the expected utilities) calculated for the node by the inference algorithm. Unlike the definition, the value is not written as part of the network.

6.3.1 Node definition

The definition of the node specifies how it interacts with other nodes in the network. The node definition is written as part of the network when the network is saved to a file or serialized.

Use the following methods to read or write the numeric part of node definition:

Java:

```
Network.setNodeDefinition
Network.getNodeDefinition
```

Python:

```
Network.set_node_definition
Network.get_node_definition
```

R:

```
Network$setNodeDefinition
Network$getNodeDefinition
```

C#:

```
Network.SetNodeDefinition
Network.GetNodeDefinition
```

The discrete nodes (including the general chance nodes) also have the list of outcomes as part of their definition. The outcomes are identified by string identifiers, which must be unique within the node and follow SMILE rules for identifier: are case-sensitive, start with a letter and contain letters, digits and underscores. Outcomes can be added, deleted or renamed.

6.3.2 Node value

The value of the node contains the values (typically, the marginal probability distribution or the expected utilities) calculated for the node by the inference algorithm. Unlike the definition, the value is not written as part of the network during I/O operations. In influence diagrams the node value is calculated for multiple sets of decisions. In such case, you also need to retrieve the indexing parents of node value to properly interpret the numbers. Note that value indexing parents are not the same as node parents. The value also stores its validity status; a flag set to true by the inference algorithm after it succesfully completes the calculations for the given node. You should not call any value-reading methods unless the value is valid.

Here are the methods related to node values:

Java:

```
Network.isValueValid
Network.getNodeValue
Network.getValueIndexingParents
Network.getValueIndexingParentIds
```

Python:

```
Network.is_value_valid
Network.get_node_value
```

```
Network.get_value_indexing_parents
Network.get_value_indexing_parent_ids
```

R:

```
Network$isValueValid
Network$getNodeValue
Network$getValueIndexingParents
Network$getValueIndexingParentIds
```

C#:

```
Network.IsValueValid
Network.getNodeValue
Network.getValueIndexingParents
Network.getValueIndexingParentIds
```

6.3.3 Node evidence

The output from the inference algorithms depends on the node definitions and the evidence set on nodes in the network. The evidence for discrete nodes is specified by outcome index or outcome identifier. For continuous, the evidence is a number, and related methods have 'cont' in their names (for example, `Network.get`**`Cont`**`Evidence`). In dynamic Bayesian networks (DBNs), evidence is specified for a specified time slice. The evidence methods for DBNs have 'temporal' in their names (for example, `Network.get`**`Temporal`**`Evidence`).

Nodes can become propagated evidence (implied by other evidence set in the network).

Special type of evidence for discrete nodes is virtual evidence, which is a probability distribution over the outcomes of the node.

The methods related to evidence include:

Java:

```
Network.isEvidence
Network.isPropagatedEvidence
Network.isRealEvidence
Network.clearEvidence
Network.getEvidence
Network.getEvidenceId
Network.setEvidence
Network.getContEvidence
Network.setContEvidence
Network.isVirtualEvidence
Network.getVirtualEvidence
Network.setVirtualEvidence
Network.isTemporalEvidence
Network.hasTemporalEvidence
Network.clearTemporalEvidence
Network.getTemporalEvidence
Network.getTemporalEvidenceId
Network.getTemporalVirtualEvidence
Network.setTemporalEvidence
Network.setTemporalVirtualEvidence
```

Python:

```
Network.is_evidence
Network.is_propagated_evidence
Network.is_real_evidence
Network.clear_evidence
Network.get_evidence
Network.get_evidence_id
Network.set_evidence
Network.get_cont_evidence
Network.set_cont_evidence
Network.is_virtual_evidence
Network.get_virtual_evidence
Network.set_virtual_evidence
Network.is_temporal_evidence
Network.has_temporal_evidence
Network.clear_temporal_evidence
Network.get_temporal_evidence
Network.get_temporal_evidence_id
Network.get_temporal_virtual_evidence
Network.set_temporal_evidence
Network.set_temporal_virtual_evidence
```

R:

```
Network$isEvidence
Network$isPropagatedEvidence
Network$isRealEvidence
Network$clearEvidence
Network$getEvidence
Network$getEvidenceId
Network$setEvidence
Network$getContEvidence
Network$setContEvidence
Network$isVirtualEvidence
Network$getVirtualEvidence
Network$setVirtualEvidence
Network$isTemporalEvidence
Network$hasTemporalEvidence
Network$clearTemporalEvidence
Network$getTemporalEvidence
Network$getTemporalEvidenceId
Network$getTemporalVirtualEvidence
Network$setTemporalEvidence
Network$setTemporalVirtualEvidence
```

C#:

```
Network.IsEvidence
Network.IsPropagatedEvidence
Network.IsRealEvidence
Network.ClearEvidence
Network.GetEvidence
Network.GetEvidenceId
Network.SetEvidence
Network.GetContEvidence
Network.SetContEvidence
```

```
Network.IsVirtualEvidence
Network.GetVirtualEvidence
Network.SetVirtualEvidence
Network.IsTemporalEvidence
Network.HasTemporalEvidence
Network.ClearTemporalEvidence
Network.GetTemporalEvidence
Network.GetTemporalEvidenceId
Network.GetTemporalVirtualEvidence
Network.SetTemporalEvidence
Network.SetTemporalVirtualEvidence
```

6.3.4 Other node attributes

Nodes have other attributes, which are not used by inference algorithms, but are required for graphical interpretation of the Bayesian network. Among these are: node name, description, position, color, etc. For brevity, the list below only includes the getter methods. The corresponding setters are also available.

Java:

```
Network.getNodeName
Network.getNodeDescription
Network.getNodePosition
Network.getNodeBgColor
Network.getNodeTextColor
Network.getNodeBorderColor
```

Python:

```
Network.get_node_name
Network.get_node_description
Network.get_node_position
Network.get_node_bgColor
Network.get_node_textColor
Network.get_node_borderColor
```

R:

```
Network$getNodeName
Network$getNodeDescription
Network$getNodePosition
Network$getNodeBgColor
Network$getNodeTextColor
Network$getNodeBorderColor
```

C#:

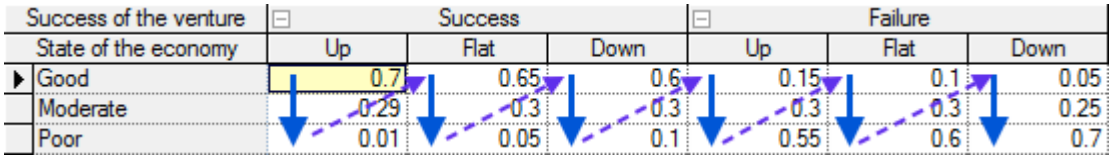
```
Network.GetNodeName
Network.GetNodeDescription
Network.GetNodePosition
Network.GetNodeBgColor
Network.GetNodeTextColor
Network.GetNodeBorderColor
```

6.4 Multidimensional arrays

Conditional probability table (CPT) describes the interaction between a node and its immediate predecessors. The number of dimensions and the total size of a conditional probability table are determined by the number of parents, the number of states of each of these parents, and the number of states of the child node. Essentially, there is a probability for every state of the child node for every combination of the states of the parents. Nodes that have no predecessors are specified by a prior probability distribution table, which specifies the prior probability of every state (outcome) of the node.

The conditional probability tables are stored as vectors of doubles that are a flattened version of multidimensional tables with as many dimensions as there are parents plus one for the node itself. The order of the coordinates reflects the order in which the arcs to the node were created. The most significant (leftmost) coordinate will represent the state of the first parent. The state of the node itself corresponds to the least significant (rightmost) coordinate.

The image below is an annotated screenshot of GeNIe's node properties window open for the *Forecast* node in the model created in Tutorial 1. *Forecast* has three outcomes and two parents: *Success of the venture* and *State of the economy*, with two and three outcomes, respectively. Therefore, the total size of the CPT is 2 x 3 x 3 = 18. The annotation arrows in the image (not part of the actual GeNIe window) show the ordering of the entries in the linear buffer used internally. The first (or rather, the zero-th, because all indexes in SMILE are zero-based) element, the one with the value of 0.7 and yellow background, represents *P(Forecast=Good | Success of the venture=Success & State of the economy=Up)*. It is followed by the probabilties for *Moderate* and *Poor* outcomes given the same parent configuration. The next parent configuration is *Success of the venture=Success* & *State of the economy=Flat*, and so on.



The node definition returned by `Network.getNodeDefinition` is a single-dimensional array. If your program needs to convert between linear and multidimensional coordinates, see *Tutorial 3*[99]. The code in this tutorial includes the conversion function.

Note that multidimensional arrays are not used exclusively for CPTs. Other uses include expected utility tables and marginal probability distributions.

6.5 Input and Output

SMILE supports two types of network I/O: string-based and file-based.

The native format for SMILE networks is XDSL. The format is XML-based and the definition schema is available at BayesFusion documentation website (http://support.bayesfusion.com/docs/). When writing network in this format to file, the `.xdsl` extension should be used.

XDSL is the only format supported by string I/O methods. File-based methods can read and write other formats. Depending on the feature parity between SMILE and the 3rd party software using other file types, some of the information may be lost.

Java:

```
Network.readFile
```

```
Network.writeFile
Network.readString
Network.writeString
```

Python:

```
Network.read_file
Network.write_file
Network.read_string
Network.write_string
```

R:

```
Network$readFile
Network$writeFile
Network$readString
Network$writeString
```

C#:

```
Network.ReadFile
Network.WriteFile
Network.ReadString
Network.WriteString
```

6.6 Inference

SMILE includes functions for several popular Bayesian network inference algorithms, including the clustering algorithm, and several approximate stochastic sampling algorithms. To run the inference , obtain the probability of evidence currently set in the network, or switch between various inference algorithm implementations, use the following methods:

Java:

```
Network.updateBeliefs
Network.probEvidence
Network.setBayesianAlgorithm
Network.getBayesianAlgorithm
Network.setInfluenceDiagramAlgorithm
Network.getInfluenceDiagramAlgorithm
```

Python:

```
Network.update_beliefs
Network.prob_evidence
Network.set_bayesian_algorithm
Network.get_bayesian_algorithm
Network.set_influence_diagram_algorithm
Network.get_influence_diagram_algorithm
```

R:

```
Network$updateBeliefs
Network$probEvidence
Network$setBayesianAlgorithm
Network$getBayesianAlgorithm
Network$setInfluenceDiagramAlgorithm
Network$getInfluenceDiagramAlgorithm
```

C#:

```
Network.UpdateBeliefs
Network.ProbEvidence
Network.BayesianAlgorithm (read/write property)
Network.InfluenceDiagramAlgorithm (read/write property)
```

The default algorithm for discrete Bayesian Networks is clustering over network preprocessed with relevance. The output of this algorithm is exact (as opposed to various sampling algorithms also available in the library).

The sampling inference algorithms can be controlled by setting the number of generated samples with the `Network.setSampleCount` method. Obviously, the more samples are generated, the more time it takes to complete the inference.

`Network.updateBeliefs` throws an exception with error code -42 if the temporary data structures required to complete the inference take too much memory. In such case, or if the inference takes too long, consider taking advantage of SMILE's relevance reasoning layer. Relevance reasoning runs as a preprocessing step, which can lessen the complexity of later stages of inference algorithms. Relevance reasoning takes the target node set into account, therefore, to reduce the workload you should reduce the number of nodes set as targets if possible. Note that by default all nodes are targets (this is the case when no nodes were marked as such). If your network has 1,000 nodes and you only need the probabilities of 20 nodes, by all means call `Network.setTarget` on them.

If changing the model to use *Noisy-MAX* [43] nodes is possible, then it's definitely worth trying. The inference can be performed very efficiently on the networks with Noisy-MAX nodes when Noisy-MAX decomposition is enabled. To enable it, call `Network.setNoisyDecompEnabled`. If enabled, the Noisy-MAX decomposition runs in the relevance layer and reduces the complexity of the subsequent phases of the inference algorithm. To further control the decomposition you can call `Network.setNoisyDecompLimit`, which controls the maximal number of parents in the temporary structures managed by SMILE during inference.

6.7 User properties

To integrate data specific to your application with SMILE, you can use SMILE's user properties. The user properties are arrays of key/value pairs available at the network and node level. The user properties are stored in the XDSL files. Property name (key) is unique for the set of properties defined for given node or for a network. It also follows the convention of SMILE identifiers: is case-sensitive, starts with a letter and contains letters, digits and underscores. The property is represented by an `UserProperty` object, which has `name` and `value` fields (both are strings).

Java:

```
Network.getUserProperties
Network.setUserProperties
Network.getNodeUserProperties
Network.setNodeUserProperties
```

Python:

```
Network.get_user_properties
Network.set_user_properties
Network.get_node_user_properties
Network.set_node_user_properties
```

R:

```
Network$getUserProperties
Network$setUserProperties
```

```
Network$getNodeUserProperties
Network$setNodeUserProperties
```

C#:

```
Network.GetUserProperties
Network.SetUserProperties
Network.GetNodeUserProperties
Network.SetNodeUserProperties
```

6.8 Submodels

For user interface purposes, like making complex network structure easier to understand and navigate, nodes can be placed in a submodel hierarchy. Each network contains at least one main submodel (which can't be deleted and is default submodel for new models to be placed in). Other submodels can be added and deleted. Submodels, except main submodel, have exactly one parent submodel, and can have multiple submodel children.

The assignment of nodes to submodels has no effect on inference.

Use the following methods to manage submodels:

Java:

```
Network.addSubmodel
Network.deleteSubmodel
Network.getSubmodelCount
Network.getSubmodel
Network.getMainSubmodel
Network.getMainSubmodelId
Network.getFirstSubmodel
Network.getNextSubmodel
Network.getSubmodelId
Network.setSubmodelId
Network.getSubmodelName
Network.setSubmodelName
Network.getSubmodelPosition
Network.setSubmodelPosition
Network.getSubmodelOfNode
Network.setSubmodelOfNode
Network.getSubmodelOfSubmodel
Network.setSubmodelOfSubmodel
```

Python:

```
Network.add_submodel
Network.delete_submodel
Network.get_submodel_count
Network.get_submodel
Network.get_main_submodel
Network.get_main_submodel_id
Network.get_first_submodel
Network.get_next_submodel
Network.get_submodel_id
Network.set_submodel_id
Network.get_submodel_name
```

```
Network.set_submodel_name
Network.get_submodel_Position
Network.set_submodel_Position
Network.get_submodel_of_node
Network.set_submodel_of_node
Network.get_submodel_of_submodel
Network.set_submodel_of_submodel
```

R:

```
Network$addSubmodel
Network$deleteSubmodel
Network$getSubmodelCount
Network$getSubmodel
Network$getMainSubmodel
Network$getMainSubmodelId
Network$getFirstSubmodel
Network$getNextSubmodel
Network$getSubmodelId
Network$setSubmodelId
Network$getSubmodelName
Network$setSubmodelName
Network$getSubmodelPosition
Network$setSubmodelPosition
Network$getSubmodelOfNode
Network$setSubmodelOfNode
Network$getSubmodelOfSubmodel
Network$setSubmodelOfSubmodel
```

C#:

```
Network.AddSubmodel
Network.DeleteSubmodel
Network.GetSubmodelCount
Network.GetSubmodel
Network.GetMainSubmodel
Network.GetMainSubmodelId
Network.GetFirstSubmodel
Network.GetNextSubmodel
Network.GetSubmodelId
Network.SetSubmodelId
Network.GetSubmodelName
Network.SetSubmodelName
Network.GetSubmodelPosition
Network.SetSubmodelPosition
Network.GetSubmodelOfNode
Network.SetSubmodelOfNode
Network.GetSubmodelOfSubmodel
Network.SetSubmodelOfSubmodel
```

6.9 Discrete nodes and numeric domains

By default, discrete nodes represent discrete random variables that have categorical outcomes described by outcome identifiers. In SMILE 2, it is possible to model discrete random variables that are numerical in nature. The outcomes of the node can be associated with adjacent numeric intervals with explicitly specified borders, or

with a set of discrete numeric values (one for each outcome). There are four possible outcome types for discrete nodes:

- identifiers (the default)
- identifiers and numeric intervals
- numeric intervals with no identifiers
- identifiers and numeric point values

6.9.1 Outcome intervals

Discrete nodes by default do not have any numeric information associated with their outcomes. To add outcome intervals, call `Network.setIntervals`:

Java:

```
net.setIntervals(nodeHandle, new double[] { 0, 2.78, 3.14, 77, Double.POSITIVE_INFINITY }, true);
```

Python:

```
net.set_intervals(nodeHandle, [ 0, 2.78, 3.14, 77, math.inf ], True)
```

R:

```
net$setIntervals(nodeHandle, c({ 0, 2.78, 3.14, 77, Inf }), TRUE)
```

C#:

```
net.setIntervals(nodeHandle, new double[] { 0, 2.78, 3.14, 77, Double.PositiveInfinity }, true);
```

The example above passes five numeric interval boundaries , and defines four intervals: 0 to 2.78, 2.78 to 3.14, 3.14 to 77, and 77 to infinity. Using negative infinity as first element in the intervals definition creates open first interval. The list of interval boundaries has to be sorted from lowest to highest. It is possible to specify a point interval by means of two identical numbers as its boundaries.

The second parameter in the `Network.setIntervals` call is set to **`true`** to indicate that existing outcome identifiers should be discarded. The use of outcome identifiers with outcome intervals is optional. If the identifiers were discarded, the outcome identifier array will have empty string for each outcome id.

It is possible to call the outcome modifying methods when node has intervals. After `Network.addOutcome` or `Network.insertOutcome` new interval will be created by splitting the existing interval at the appropriate index. `Network.deleteOutcome` will remove the interval at the specified index. At any time it is possible to call `Network.setIntervals` again with a new list of interval boundaries. In such case, the list of new interval boundaries may have different size than the existing list.

Other methods for working with intervals are `Network.hasIntervals`, `Network.getIntervals`, and `Network.removeIntervals`. The last function removes the interval boundaries from the node definition, and in case there were no outcome identifiers, creates the default set of identifiers. The number of outcomes does not change.

With intervals defined, it is possible to calculate the mean and standard deviation for the node given the marginal probability distribution over its outcomes. In calculating the moments of the distribution, SMILE treats it as a continuous distribution, assuming that it is uniform within each of the intervals. Open intervals are an exception; the distribution over these is assumed to be half-normal scaled to ensure the normal PDF height is equal to the neighboring closed interval's uniform distribution. To retrieve the mean or the standard deviation, call `Network.getNodeMean` or `Network.getNodeStdDev` respectively on the node value object.

Intervals allow for continuous evidence in discrete nodes. To set continuous evidence, call `Network.setContEvidence` The evidence will be stored and will be internally converted into an outcome index during inference in a discrete Bayesian network or an influence diagram. When discrete node with intervals has continuous evidence, and the child node is continuous, the exact value of continuous evidence in the parent will be used to evaluate the child during sampling.

6.9.2 Outcome point values

To define a discrete distribution over numeric node outcomes, use `Network.setNodePointValues`. The example below assumes that node has three outcomes:

Java:

```
net.setPointValues(nodeHandle, new double[] { 3.14, -2.78, 77 });
```

Python:

```
net.set_point_values(nodeHandle, [ 3.14, -2.78, 77 ])
```

R:

```
net$setPointValues(nodeHandle, c({ 3.14, -2.78, 77 }))
```

C#:

```
net.SetPointValues(nodeHandle, new double[] { 3.14, -2.78, 77 });
```

The three numeric values in will be associated with existing node outcomes. There is also no requirement for ordering point values. The identifiers of the outcomes will not be modified, as nodes with point values always require outcome identifiers.

Outcome modifying methods like `Network.addOutcome`, `Network.insertOutcome` or `Network.deleteOutcome` work normally when node has point values. New outcomes will have their point values initialized to zero. The point values can only be changed all at once with another `Network.setPointValues` call.

With point values defined, it is straightforward to calculate the mean and standard deviation for the marginal probability distribution over the outcomes of the node. To retrieve the mean or the standard deviation, call `Network.getNodeMean` or `Network.getNodeStdDev` respectively.

Point values do not allow for continuous evidence in the discrete nodes. Calling `Network.setContEvidence` will fail, even if the parameter is equal to one of the defined point values.

To remove point values, call `Network.removePointValues`. `Network.hasPointValues` returns true if node has point values defined.

6.10 Canonical nodes

Canonical probabilistic nodes, such as Noisy-MAX/OR, Noisy-MIN/AND, and Noisy-Adder gates, implemented by SMILE, are convenient knowledge engineering tools widely used in practical applications. In case of a general CPT binary node with *n* binary parents, the user has to specify *2^n* parameters, a number that is exponential in the number of parents. This number can quickly become prohibitive: when the number of parents *n* is equal to 10, we need 1,024 parameters, when it is equal to 20, the number of parameters is equal to 1,048,576, with each additional parent doubling it. A Noisy-OR model allow for specifying this interaction with only *n+1* parameters, one for each parent plus one more number. This comes down to 11 and 21 for *n* equal to 10 and 20 respectively.

Canonical models are not only great tools for knowledge engineering - they also lead to significant reduction in computation through the independences that they model implicitly. Using canonical gates makes thus model construction easier but also leads to models that are easier to solve.

To create canonical nodes, pass `Network.NodeType.NOISY_MAX` or `Network.NodeType.NOISY_ADDER` to `Network.addNode`. Each node type has its own specific attributes accessible through `Network` class methods, but otherwise works in exactly the same way as a CPT node (has at least two outcomes, can be used as a parent or a child wherever the CPT node can, etc).

6.10.1 Noisy-MAX

Noisy-MAX is a generalization of the popular canonical gate Noisy-OR and is capable of modeling interactions among variables with multiple states. If all the nodes in question are binary, a Noisy-MAX node reduces to a Noisy-OR node. The Noisy-MAX, as implemented in SMILE, includes an equivalent of negation. By DeMorgan's laws, the OR function (or its generalization, the MAX function) along with a negation, is capable of expressing any logical relationship, including the AND (and its generalization, MIN). This means that SMILE's Noisy-MAX can be used to model the Noisy-AND/MIN functions, as well as other logical relationships.

SMILE's inference algorithm contains special code path for networks with Noisy-MAX nodes, which can speed up computations significantly. See the *Inference* [37] section of this manual for details.

To create a Noisy-MAX node, use the `NOISY_MAX` type with `Network.addNode`:

Java:

```
net.addNode(Network.NodeType.NOISY_MAX, "node1");
```

Python:

```
net.add_node(pysmile.NodeType.NOISY_MAX, "node1")
```

R:

```
net$addNode(net$NodeType$NOISY_MAX, "node1")
```

C#:

```
net.AddNode(Network.NodeType.NoisyMax, "node1");
```

Noisy-MAX node has discrete outcomes (just like CPT nodes). Noisy-MAX specific attributes are:

- an array of conditionally independent (CI) probabilities, which can be set and retrieved by `Network.setNodeDefinition` and `getNodeDefinition`.
- for each of node's parents, an array of parent outcome strengths. Parent outcome strengths enable control of the order of states of the parent nodes, as they enter their relation with the child. A Noisy-MAX CI table always follows the order of strengths. Use `Network.setNoisyParentStrengths` and `getNoisyParentStrengths` to modify or read the parent strengths.

As an example, consider a binary Noisy-MAX node with two parents, each with three outcomes. The following snippet modifies the probabilities and outcome strengths for the second parent (with zero-based index 1).

Java:

```
double[] ci = net.getNodeDefiniton(h);
int BASE = 2 * 3;
ci[BASE]     = 0.1;
ci[BASE + 1] = 0.9;
ci[BASE + 2] = 0.3;
```

```
ci[BASE + 3] = 0.7;
net.setNodeDefiniton(h, ci);
net.setNoisyParentStrengths(h, 1, new int[] { 2, 0, 1 });
```

Python:

```
ci = net.get_node_definition(h)
BASE = 2 * 3
ci[BASE]     = 0.1
ci[BASE + 1] = 0.9
ci[BASE + 2] = 0.3
ci[BASE + 3] = 0.7
net.set_node_definition(h, ci)
net.set_noisy_parent_strengths(h, 1, [2, 0, 1])
```

R:

```
ci <- net$getNodeDefiniton(h)
BASE <- 2 * 3
ci[BASE + 1] <- 0.1
ci[BASE + 2] <- 0.9
ci[BASE + 3] <- 0.3
ci[BASE + 4] <- 0.7
net$setNodeDefiniton(h, ci)
net$setNoisyParentStrengths(h, 1, c(2L, 0L, 1L))
```

C#:

```
double[] ci = net.GetNodeDefinition(h);
int BASE = 2 * 3;
ci[BASE]     = 0.1;
ci[BASE + 1] = 0.9;
ci[BASE + 2] = 0.3;
ci[BASE + 3] = 0.7;
net.SetNoisyParentStrengths(h, 1, new int[] { 2, 0, 1 });
```

The value of `BASE` is calculated as a product of node outcome count and preceding parents' outcome counts (in this case, there is just one preceding parent with three outcomes). The probabilities for the parent are written into an array returned by `Network.getNodeDefiniton` and used in a `setNodeDefinition` call, because we just want to modify one parents' probabilities and leave other CI probabilities unchanged. The next step changes the order of parents' outcomes in relationship to the Noisy-MAX node with `Network.setParentOutcomeStrengths` call, the first column of probabilities for parent with index 1 (the one with 0.1 and 0.9) represents the probabilities for the parent outcome with index 2 (because 2 is the first element in the `strengths` array). Note that this does not modify the parent node in any way and the ordering is valid only in the context of this particular parent-child relationship. Assuming that we started with the default uniform probabilities in the table, our modifications yields the following Noisy-Max definition, as viewed in GeNIe:

Parent	p1			p2			LEAK
State	State0	State1	State2	State2	State0	State1	
State0	0.5	0.5	0	0.1	0.3	0	0.5
State1	0.5	0.5	1	0.9	0.7	1	0.5

The outcomes of both parent are *{State0, State1, State2}*. However, by using `setParentOutcomeStrenghts` for parent *p2*, its outcomes are seen by the Noisy-MAX child node as *{State2, State0, State1}*. Other Noisy-MAX nodes in the same network can set up their own parent outcome ordering if *p2* becomes their parent.

6.10.2 Noisy-Adder

Noisy-Adder nodes are not fully supported yet in the wrappers. Contact us if you need to use them; we can provide pre-release version of an SMILE wrapper compatible with your programming language and operating system.

6.11 Influence diagrams

Influence diagrams use two additional node types next to chance (CPT and canonical) and deterministic nodes:

- Decision nodes represent variables that are under control of the decision maker and model available decision alternatives, modeled explicitly as possible states of the decision node. They have no numerical parameters, only a discrete set of outcomes. Decision nodes can be children of decision and chance nodes. The node type identifier passed to `Network.addNode` is `Network.NodeType.DECISION`.

- Value nodes, i.e., a measure of desirability of the outcomes of the decision process. They are quantified by the utility of each of the possible combinations of outcomes of the parent nodes. Value nodes can be children of decision and chance nodes. Pass `Network.NodeType.UTILITY` to `Network.addNode` to create a value node.

- Multi-attribute utility (MAU) nodes, which combine value nodes to form a multi-attribute utility function. The function can be specified as a set of weights of a linear function (in such case, the node becomes an additive linear utility, ALU) or any expression that refers to identifiers of the value node parents. See the *Equations reference* [52] chapter for a list of available functions. MAU nodes can be children of decision, value, and other MAU nodes. If decision parents exist, the definition of the MAU node contains a separate set of weights or expressions for each combination of decision parents. Use `Network.NodeType.MAU` with `Network.addNode` to create a MAU node. By default, the MAU node is defined by weights. To use expressions, call `Network.setMauExpressions`.

As is the case with Bayesian networks, the values calculated by influence diagram inference algorithms are stored in node values and can be accessed through `Network.getNodeValue`. However, the interpretation of the numbers returned by `getNodeValue` is extended. The matrices are indexed by the set of nodes called indexing parents. These are are unobserved decision nodes that precede the current node or unobserved chance nodes that are predecessors of decision nodes and should have been observed before the decisions can be made. Call `Network.getIndexingParents` to retrieve indexing parent handles, or `Network.getIndexingParentIds` to get indexing parent identifiers. The set of outcomes of indexing parents is called a policy. After a successful inference in an influence diagram, node values are:

- for chance and deterministic nodes: posterior probabilities for each policy

- for decision nodes: expected utilities for all outcomes and for each policy

- for value and MAU nodes: expected utility for each policy

See *Tutorial 4* [108] for a simple influence diagram demo program.

6.12 Dynamic Bayesian networks

A Bayesian network is a snapshot of the system at a given time and is used to model systems that are in some kind of equilibrium state. Unfortunately, most systems in the world change over time and sometimes we are interested in how these systems evolve over time more than we are interested in their equilibrium states.

Whenever the focus of our reasoning is change of a system over time, we need a tool that is capable of modeling dynamic systems.

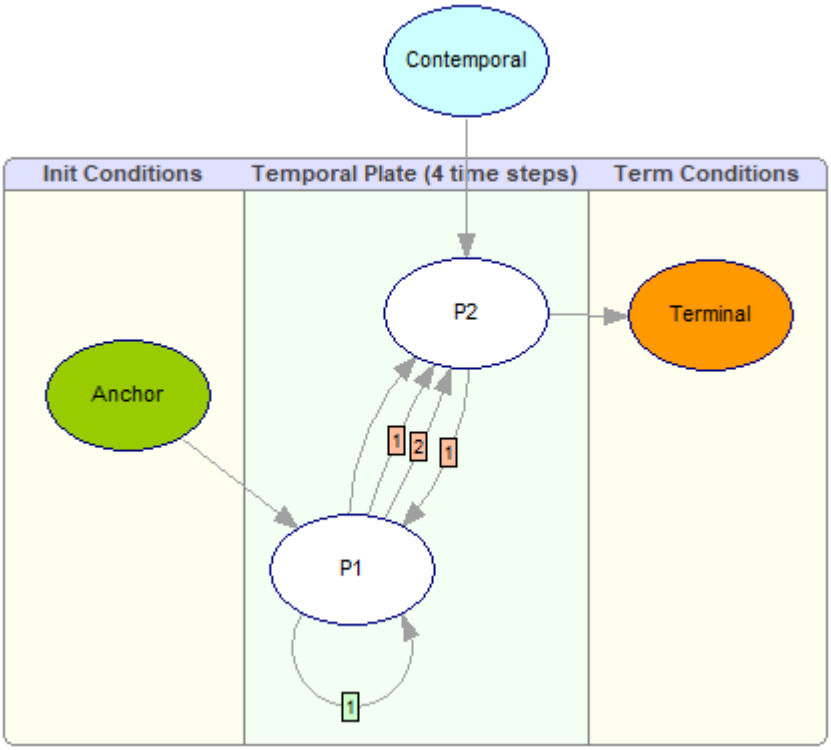
A dynamic Bayesian network (DBN) is a Bayesian network extended with additional mechanisms that are capable of modeling influences over time (Murphy, 2002). The temporal extension of BNs does not mean that the network structure or parameters changes dynamically, but that a dynamic system is modeled. In other words, the underlying process, modeled by a DBN, is stationary. A DBN is a model of a stochastic process.

The implementation of DBNs in SMILE allows for use both chance (CPT and canonical) and deterministic node types in dynamic models.

Tutorial 6 [122] contains a complete program demonstrating the use of DBNs.

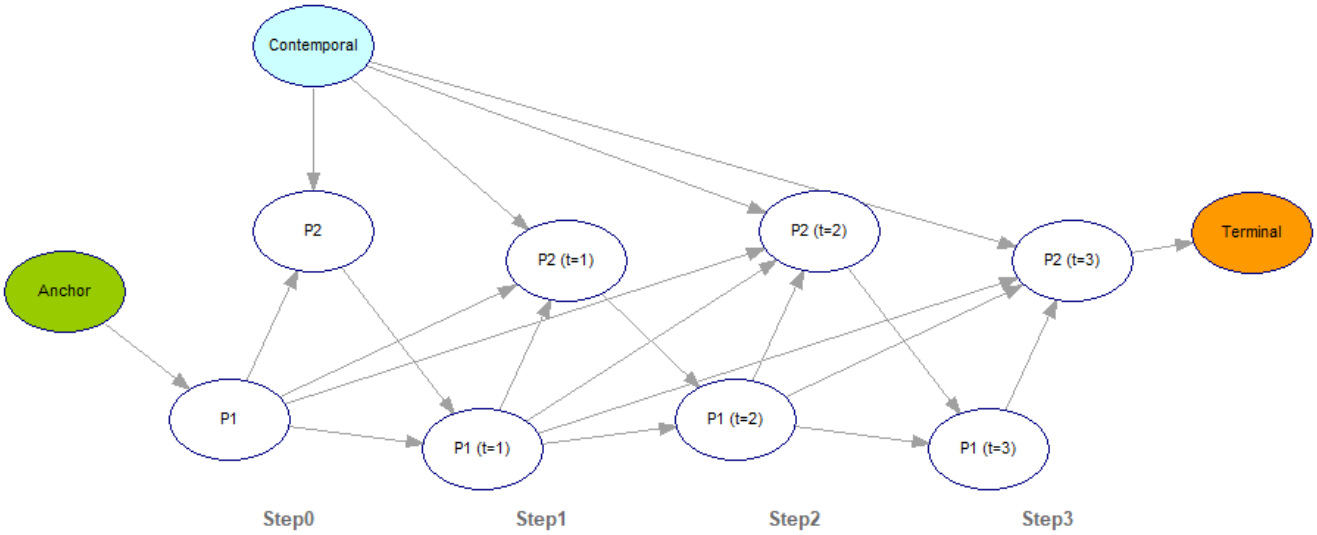
6.12.1 Unrolling

SMILE's inference algorithm for dynamic Bayesian networks converts DBNs (unrolls them over time) to temporary static networks and then solves these networks. Results of this inference are copied back into the node values in the original DBNs. The structure of the following DBN (in GeNIe format) does not represent any real system, it is created just for demonstration purposes.



Different colors of the nodes represent their location relative to the abstract "temporal plate." By default, the nodes in the network are set to be `Network.NodeTemporalType.CONTEMPORAL` and is located outside of the plate. By using `Network.setNodeTemporalType` you can change their temporal type assignment. In the example model above, the plate nodes (`Network.NodeTemporalType.PLATE`) are white, the anchor node (`Network.NodeTemporalType.ANCHOR`) is green, the terminal node (`Network.NodeTemporalType.TERMINAL`) is orange and the blue node is contemporal. For simplicity, we use only single anchor, terminal, and contemporal node. Note the presence of multiple arcs between two plate nodes and the arc linking *P1* with itself.

Some of the arcs between plate nodes have a tag with a number; these are *temporal arcs*, which are created by `Network.addTemporalArc`. The number on the tag is a *temporal order* of an arc. The arcs without the tag were added by `Network.addArc`. The result of unrolling the above DBN (this is performed automatically by the DBN inference algorithm; it is possible to create such network with `Network.unroll`) is the following:



To reduce the size of the unrolled network, we changed the number of time steps (slices) from the default value of 10 to 4 with a call to `Network.setSliceCount`. The colors of the original nodes were carried over to the unrolled model, which is extended by creating new copies of the plate nodes. The structure of this network shows how the temporal arcs are used to express the conditional dependency of plate nodes in time step i on the plate nodes in time step j, where $i > j$.

Consider the (temporal) arc between *P1* and *P2* with temporal order 2. It was copied twice to link *P1* with *P2 (t=2)*, and *P1 (t=1)* with *P2 (t=3)*. Note that there is no copy of this arc starting from *P1 (t=2)*, because its child would be in *t=2+2=4*, and (zero-based) time stops at 3 in our example. On the other hand, all three temporal arcs with temporal order 1 are copied three times. The relationship represented by an arc linking *P1* with itself in the DBN is clearly visible between *P1* and *P1 (t=1)*, *P1 (t=1)* and *P1 (t=2)* and *P1 (t=2)* and *P1 (t=3)*.

Note the difference between the arcs originating in *Contemporal* and *Anchor* nodes. The *Anchor* node has children only in the initial slice, while the *Contemporal* node is linked to all time slices. The *Terminal* node has parents only in the last slice.

To ensure that unrolled network remains a directed acyclic graph, the following arcs are forbidden in DBNs:

- from plate nodes to normal and anchor nodes
- from terminal nodes to non-terminal nodes

Unrolling is performed automatically during inference. For debug/explanatory purposes it is also possible to obtain an unrolled network by `Network.unroll`. The unrolled network created this way is an independent model, which means that changes made to the DBN after `unroll` call are not propagated into the unrolled network.

6.12.2 Temporal definitions

Consider node *P2* from the example in the previous section. It has four incoming arcs:

- normal arc from *Contemporal*
- normal arc from *P1*
- two temporal arcs from *P1* with temporal orders 1 and 2

However, in the unrolled network's slice for *t=0*, *P2* has only two incoming arcs. This is because there are no slices representing timepoints before *t=0*. *P2* in the slice for *t=1* has three incoming arcs, because it's now possible to link *P1* at *t=0* with *P2* at *t=1*. Finally, starting with slice for *t=2*, *P2* has four incoming arcs. The structure of the unrolled network requires *P2* to have separate CPTs for *t=0*, *t=1* and *t>=2*. Generally speaking, if a plate node has an incoming arc of order *x*, it will require *x+1* separate definitions. To get and set the temporal definitions, use `Network.getNodeTemporalDefinition` and `setNodeTemporalDefinition`.

All parents for the temporal definition with a specified temporal order can be retrieved by calling `Network.getUnrolledParents`. Note that `Network.getTemporalParents` called for the same temporal order returns only a subset of parents indexing this temporal definition. This is caused by unrolling: in the unrolled network node *P2* has four incoming arcs in slices for *t>=2*, but only two of these are actually arcs with temporal order 2.

6.12.3 Temporal evidence

To specify evidence for the plate nodes in the DBN, use `Network.setTemporalEvidence` and `setTemporalVirtualEvidence`. The code snippet below sets the temporal evidence in slices 5 and 7. Node represented by `evidenceNodeHandle` is assumed to have two outcomes.

Java:

```
net.setTemporalEvidence(evidenceNodeHandle, 5, 1);
net.setTemporalVirtualEvidence(evidenceNodeHandle, 7,
    new double[] { 0.4, 0.6 });
```

Python:

```
net.set_temporal_evidence(evidenceNodeHandle, 5, 1)
net.set_temporal_virtual_evidence(evidenceNodeHandle, 7, [0.4,0.6])
```

R:

```
net$setTemporalEvidence(evidenceNodeHandle, 5, 1)
net$setTemporalVirtualEvidence(evidenceNodeHandle, 7,
    c(0.4, 0.6))
```

C#:

```
net.SetTemporalEvidence(evidenceNodeHandle, 5, 1);
net.SetTemporalVirtualEvidence(evidenceNodeHandle, 7,
    new double[] { 0.4, 0.6 });
```

To retrieve the temporal evidence, use `Network.getTemporalEvidence` and `Network.getTemporalVirtualEvidence`.

Other useful methods are `Network.hasTemporalEvidence` and `isTemporalEvidence`, which check whether a node has any temporal evidence or temporal evidence in specified temporal order, respectively.

6.12.4 Temporal beliefs

For plate nodes in the DBN, the inference algorithm calculates the temporal beliefs, which are marginal posterior probability distributions as a function of time. Temporal beliefs are returned by `Network.getNodeValue`.

The dependency of the beliefs on time makes the temporal beliefs array larger. If a node has *X* outcomes and the slice count was set to *Y,* the matrix will have *X * Y* elements. The elements representing a single time slice are adjacent. Therefore, elements with indices *[0..X-1]* in the matrix are the beliefs for *t=0*, elements *[X..2*X-1]* are the beliefs for *t=1* and so on.

Only the plate nodes have the temporal beliefs. Other temporal node types have normal beliefs (the number of elements in the belief array is equal to their outcome count).

6.13 Continuous models

Graphical models, such as Bayesian networks, are not necessarily consisting of only discrete variables. They are, in fact, close relatives of systems of simultaneous structural equations. SMILE allows for constructing models consisting of equation nodes that are alternative, graphical representations of systems of simultaneous structural equations.

Tutorial 7[133] contains a complete program demonstrating the use of continuous models.

6.13.1 Equation-based nodes

To create an equation node, use `Network.NodeType.EQUATION` node type when creating a node with `Network.addNode`. The node equation will be initialized to *id=0*, where *id* is the node identifier passed to `addNode`. The code snippet below changes the default equation of the freshly created node (*x=0*) to an equation representing the standard Gaussian distribution: *x=Normal(0, 1)*.

Java:

```
int hx = net.addNode(Network.NodeType.EQUATION, "x");
net.setNodeEquation(hx, "x=Normal(0,1)");
```

Python:

```
hx = net.add_node(pysmile.NodeType.EQUATION, "x")
net.set_node_equation(hx, "x=Normal(0,1)")
```

R:

```
hx <- net$addNode(net$NodeType$EQUATION, "x")
net$setNodeEquation(hx, "x=Normal(0,1)")
```

C#:

```
int hx = net.AddNode(Network.NodeType.Equation, "x");
net.SetNodeEquation(hx, "x=Normal(0,1)");
```

SMILE defines many functions for use in node equations. The complete list of functions is available in the *Equations reference* [52] section. Among these functions, there are random generators, which generate a single sample based on the passed parameters. In the example above, the `Normal` is the name of SMILE's random generator function.

Node equations can reference other nodes by using their identifiers. Continuing with our code snippet:

Java:

```
int hy = net.addNode(Network.NodeType.EQUATION, "y");
net.setNodeEquation(hx, "y=2*x");
```

Python:

```
hy = net.add_node(pysmile.NodeType.EQUATION, "y")
net.set_node_equation(hy, "y=2*x")
```

R:

```
hy <- net$addNode(net$NodeType$EQUATION, "y");
net$setNodeEquation(hx, "y=2*x");
```

C#:

```
int hy = net.AddNode(Network.NodeType.Equation, "y");
net.SetNodeEquation(hx, "y=2*x");
```

Second node is added and its equation is set to *y=2*x*, where *x* is a reference to previously defined node. SMILE **adds an arc** between x and y automatically and it is not necessary to call `Network.addArc` before setting the equation referencing other nodes. Calling `addArc` will change the child node equation by adding a term representing the parent node as a last term on the right hand side of the child equation. Assuming network with equation nodes a, b, c and d and d's equation set to *d=Normal(a, 1)+Normal(b, 2)*, calling `AddArc` to with node handles of c and d would rewrite d's equation to *d=Normal(a, 1)+Normal(b, 2)+c*.

If an arc is removed, either by calling `Network.deleteArc` or `Network.deleteNode` on one of the parents, the node equation will be rewritten as sum of the remaining parents. This ensures that equations and arcs are always in sync. If node b would be removed with `deleteNode`, or an arc from b to d would be removed by `deleteArc`, d's equation would become *d=a+c*.

Node identifier changes are propagated into the equations. If the identifier of the first node from the code snippet above was changed from *x* to *x_prime*, the equation of node *y* would change to *y=2*x_prime*.

6.13.2 Continuous inference

To run the inference in continuous model, use `Network.updateBeliefs`; the same method which is used in discrete networks.

To set evidence in an equation node, use `Network.setContEvidence`. In the snippet below we are assuming that `evidenceNodeHandle` is the handle of the equation node.

Java:

```
net.setContEvidence(evidenceNodeHandle, 1.5);
```

Python:

```
net.set_cont_evidence(evidenceNodeHandle, 1.5)
```

R:

```
net$setContEvidence(evidenceNodeHandle, 1.5)
```

C#:

```
net.SetContEvidence(evidenceNodeHandle, 1.5);
```

To retrieve evidence from continuous node, use `Network.getContEvidence`.

The inference in continuous networks is based on stochastic sampling when there is no evidence in the network, or the evidence is specified only for nodes without parents. Otherwise, the inference is performed on a temporary discrete network, derived from the original continuous model. The definitions for the temporary discrete nodes are derived from the discretization intervals defined in each continuous node. In addition to `Network.setSampleCount`, stochastic sampling can be controlled at the network level by setting the discretization sample count with `Network.setDiscretizationSampleCount`. Large number of samples provides better approximation of the solution to the set of equations, which continuous network represents, but requires more time to complete.

Both types of inference algorithm use the lower and upper bounds defined for each equation node. To set the bounds, use `Network.setNodeEquationBounds` method. Stochastic sampling can reject a sample when its value falls outside of the bounds defined for the node. You can control this behavior by `Network.setOutlierRejectionEnabled`. By default, outlier rejection is disabled.

To set node's discretization intervals, use `Network.setNodeEquationDiscretization`. The method accepts an array of `DiscretizationInterval` objects intervals as its argument. Each interval is defined by its optional identifier (not used for inference) and an upper bound. The lower bound of the interval with index j is defined by upper interval of the interval with index j-1. The lower bound of the first interval is defined by the lower bound defined for the node with a `Network.setNodeEquationBounds` call.

Discretization intervals are used to obtain CPTs for the temporary discrete network. The CPTs are calculated by drawing a number of samples specified at the network level for each CPT column. The size of the discretized CPT is a product of the number of node intervals and parent node intervals. Note that this may lead to excessive memory use when the node has many parents.

The results of the inference in a continuous model can be either samples or discretized beliefs, depending on the inference algorithm:

- sampling algorithm outputs samples for each node. `Network.getNodeValue` will return an array of samples and `Network.getNodeSampleStats` returns an array with simple statistics for the sample set (mean, standard deviation, minimum and maximum. `Network.isValueDiscretized` returns false.
- discretizing algorithm outputs probability distribution over discretization intervals. `Network.getNodeValue` returns this distribution. `Network.isValueDiscretized` returns true.

6.14 Hybrid models

Hybrid models are networks with both discrete and continuous nodes. The arcs in a hybrid network can link all combinations of node types, so it is possible to add an arc from a continuous to a discrete node, and from a discrete to a continuous node. Iinference in hybrid models follows the rules defined for continuous nodes (sampling when there is no evidence in nodes with parents, discretization otherwise). Basically, hybrid models can be treated as continuous models with discrete nodes representing the specialized function, namely conditional probability table specified by an array of numbers.

Adding arcs from discrete to continuous nodes is performed by including discrete node identifier in the continuous node equation (as is the case for the continuous to continuous arcs). The following discussion assumes that reader is familiar with the functions from which the node equations are built, described in detail in the *Equations reference* [52] section of the reference part of this manual.

For example, assuming that a node *c* is continuous and a node *d* is discrete, the equation for *c* may look like this: *c=Normal(If(d=1, 1, -1), 5)*. When a sample for node *c* is evaluated, one of its inputs will be the value of its parent node *d*. Discrete node values are numbers drawn from the interval *[0 .. N-1]*, where *N* is the number of discrete node outcomes. Therefore, the example equation for *c* above says that c should be drawn from a normal distribution with standard deviation equal to 5, but with mean depending on the parent node *d*. If *d* is in its (zero-based) state with index 1, the mean will be 1 and -1 otherwise.

To improve the readability of the equation, the outcomes of the parent discrete nodes can also be represented as text literals. If *d* has three outcomes *High*, *Medium* and *Low*, then the equation from the preceding example could be rewritten as *c=Normal(If(d="Medium"), 1, -1), 5)*.

In addition to the function *If* or its counterpart, the ternary operator *?:*, the common functions to use with discrete nodes are *Switch* and *Choose*. For example, the equation for node *c* with three possible means of its normal distributions can look like this: *c=Normal(Switch(d, "High", 3.2, "Medium", 2.5, "Low", 1.4), 5)*. An alternative notation would be *c=Normal(Choose(d, 3.2, 2.5, 1.4), 5)*.

Important: SMILE will not modify the text literals representing the outcomes of discrete parent nodes if the outcome identifiers change. If the text literal cannot be associated with any parent node outcome, it's value is evaluated as -1 (minus one).

Generally speaking, discrete nodes can appear anywhere in the equation where numbers can be used: *c=log(1+d)* or *c=2^d*. This kind of equation does not use the text literals representing the discrete node outcomes (because there is no comparison involved in evaluation the equation).

To add an arc from a continuous to a discrete node, use `Network.addArc` (the method used in discrete models). In such case, the discretization intervals of the parent node are considered to be the equivalent of the outcomes of discrete parent.

Tutorial 8 [143] contains a complete program demonstrating the use of hybrid models.

6.15 Equations reference

The subsections of this chapter describe the notation used when specifying the definition for equation nodes and expression-based MAU nodes.

6.15.1 Operators

Arithmetic operators

+	addition, e.g., if x=3 and y=2, x+y produces 5
-	subtraction and unary minus, e.g., if x=3 and y=2, x-y produces 1 and -x produces -3
^	exponentiation (a^b means a^b), e.g., if x=3 and y=2, x^y produces 9

***** multiplication, e.g., if x=3 and y=2, x*y produces 6

/ division, e.g., if x=3 and y=2, x/y produces 1.5

Comparison operators

> greater than, e.g., if x=3 and y=2, x>y produces 1

< smaller than, e.g., if x=3 and y=2, x<y produces 0

>= greater or equal than, e.g., if x=3 and y=2, x>=y produces 1

<= smaller or equal than, e.g., if x=3 and y=2, x<=y produces 0

<> not equal, e.g., if x=3 and y=2, x<>y produces 1

= equal, e.g., if x=3 and y=2, x=y produces 0

Conditional selection operator

? : ternary conditional operator like in C, C++ or Java programming languages.

This operator is essentially a shortcut to the *If* function. For example, *a=b?5:3* is equivalent to *If(a=b, 5, 3)*.

Order of calculation, operator precedence, and parentheses

Expressions are evaluated from left to right, according to the precedence order specified below (1 denotes the highest precedence).

Precedence order	Operator
1	**-** (unary minus)
2	**^** (exponentiation)
3	***** and **/** (multiplicative operators)
4	**+** and **-** (additive operators)
5	**>**, **<**, **>=**, **<=**, **=** (comparison operators)
6	**?:** (conditional selection)

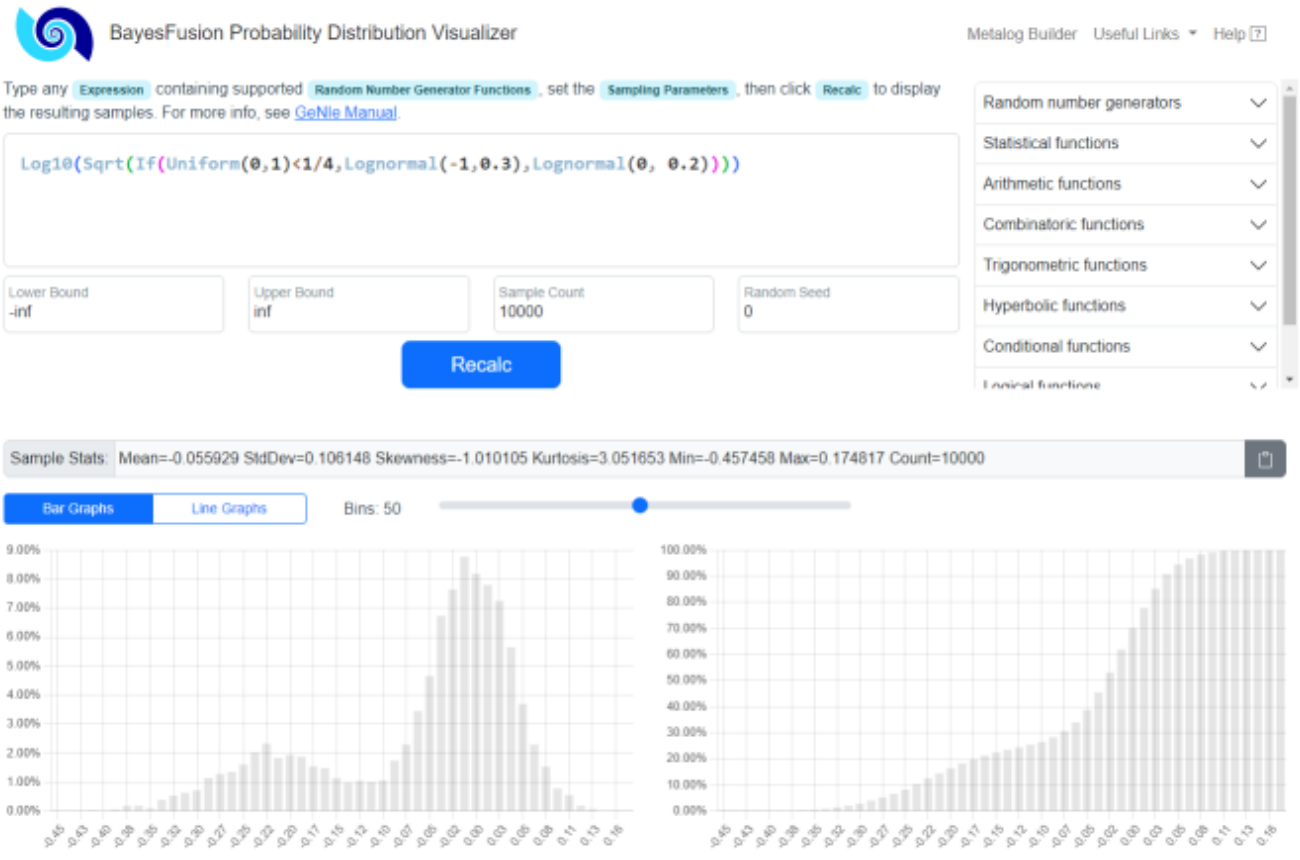
To change the order of calculation, enclose in parentheses those parts of the formula that should be calculated first. This can be done recursively, i.e., parentheses can be nested indefinitely. For example, if x=3 and y=2, 2*y+x/3-y+1 produces 4, 2*(y+x)/(3-y)+1 produces 11, and 2*((y+x)/(3-y)+1) produces 12.

6.15.2 Random Number Generators

Random number generators **each generate a single sample** from the distributions defined below. In most equations, they can be imagined as random noise that distorts the equation. Because the fundamental algorithm for inference in continuous and hybrid models is stochastic simulation, it is possible to visualize what probability distributions these single samples result in for each of the variables in the model.

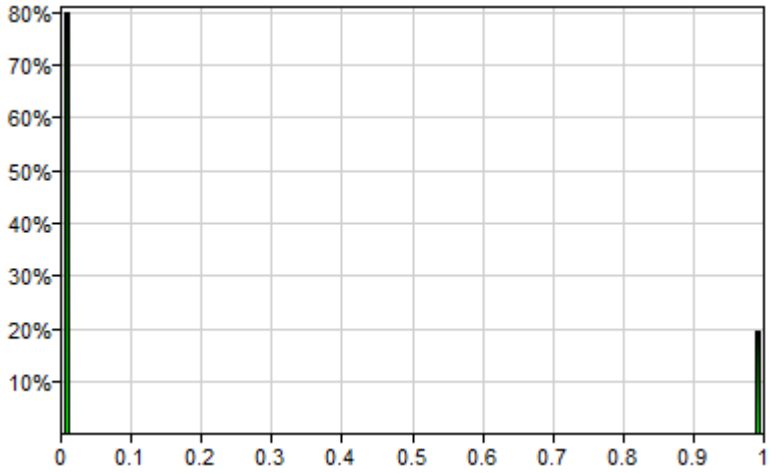
Caution: Probability distributions are not allowed in expression-based MAU nodes, as these are deterministic functions by definition.

Choosing the right probability distribution over continuous data is a skill that requires some statistical insight. When the distribution is transformed by an equation expression, the task is daunting even for an experienced decision analyst. GeNIe offers an interactive tool for visualizing expressions, the Distribution Visualizer, with probability distributions through Monte Carlo simulation. The same functionality is available online at https://prob.bayesfusion.com. The screenshot below shows the online visualizer with the probability distribution sampled from the expression *Log10(Sqrt(If(Uniform(0,1)<1/4,Lognormal(-1,0.3),Lognormal(0, 0.2))))*.



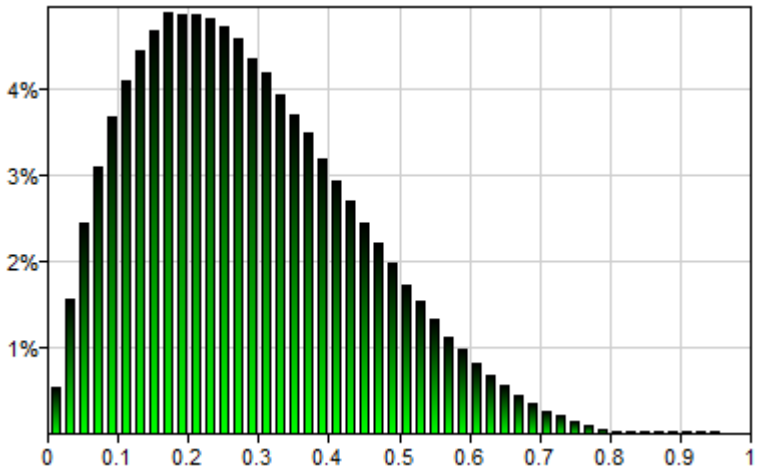
Bernoulli(p)

Bernoulli is a discrete distribution that generates 0 with probability 1-*p* and 1 with probability *p*. `Bernoulli(0.2)` will generate a single sample (0 or 1) from the following distribution, i.e., 1 with probability 0.2 and 0 with probability 0.8:



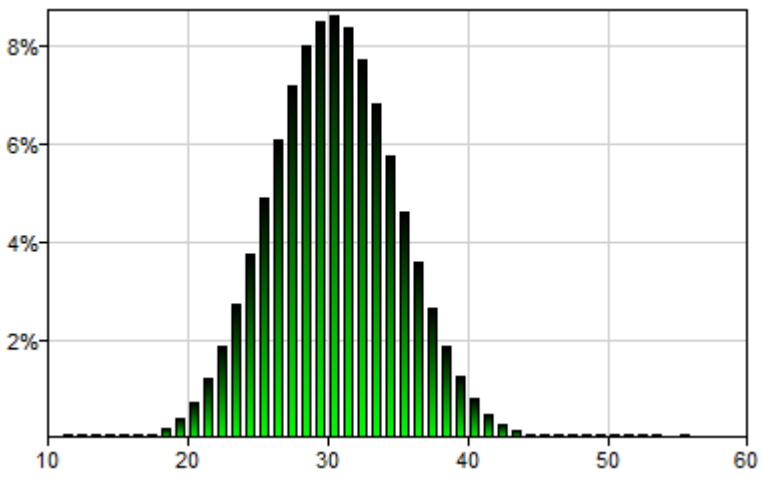
Beta(a,b)

The Beta distribution is a family of continuous probability distributions defined on the interval [0, 1] and parametrized by two positive shape parameters, *a* and *b* (typically denoted by α and β), that control the shape of the distribution. `Beta(2,5)` will generate a single sample from the following distribution:



Binomial(n,p)

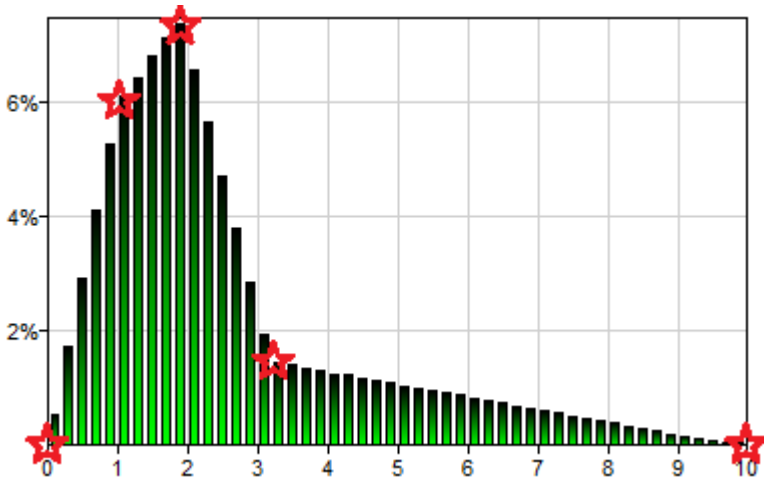
Binomial is a discrete probability distribution over the number of successes in a sequence of *n* independent trials, each of which yields a success with probability *p*. It will generate a single sample, which will be an integer number between 0 and *n*. A success/failure experiment is also called a Bernoulli trial. Hence, `Binomial(1,p)` is equivalent to `Bernoulli(p)`. `Binomial(100,0.3)` will generate a single sample from the following distribution:



CustomPDF(x1,x2,...y1,y2,...)

The `CustomPDF` distribution allows for specifying a non-parametric continuous probability distribution by means of a series of points on its probability density (PDF) function. Pairs (x_i,y_i) are coordinates of such points.

The total number of parameters of *`CustomPDF`* function should thus to be even. Please note that x coordinates should be listed in increasing order. The PDF function specified does not need to be normalized, i.e., the area under the curve does not need to add up to 1.0. For example, *`CustomPDF(0,1.02,1.9,3.2,10,0,4,5,1,0)`* generates a single sample from the following distribution:

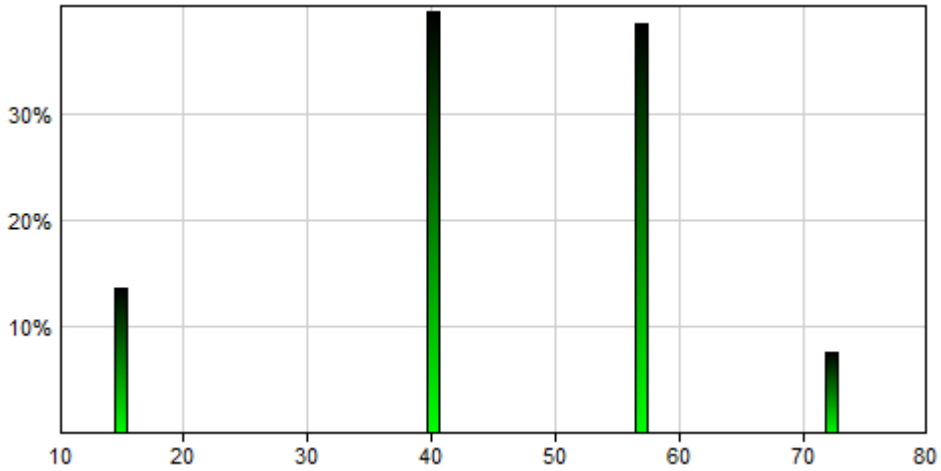


Stars on the plot mark the points defined by the *`CustomPDF`* arguments, i.e., (0, 0), (1.02, 4), (1.9, 5), (3.2, 1), and (10, 0).

Discrete(x1,x2,...,xn, p1,p2,...,pn)

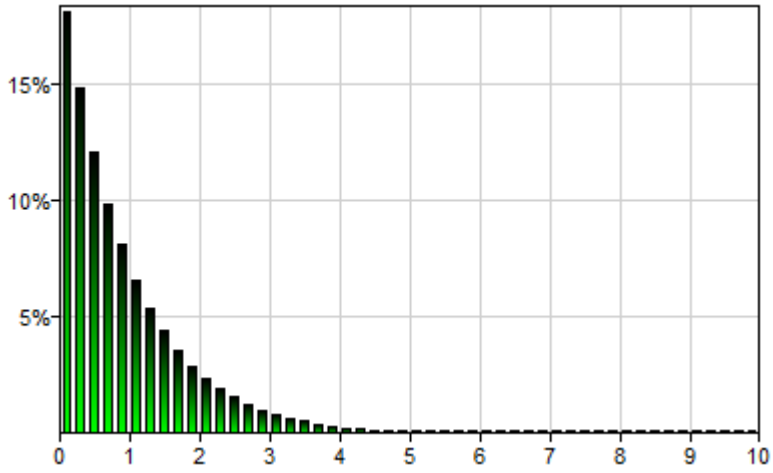
The Discrete distribution allows for specifying a discrete probability distribution over a collection of numerical values. It is one of the simplest random number generators, essentially replicating a discrete distribution and producing values x1, x2, ..., xn with probabilities p1, p2, ..., xn. This distribution is useful in simulating a discrete node using an equation node. The total number of parameters of *`Discrete()`* function should be even. Please note that x values should be listed in increasing order. Even though the p values should in theory add up to 1.0 and we advise that they do, GeNIe perform normalization, i.e., modifies them proportionally to add up to 1.0. For example, *`Discrete(15,40,57.5,72.5,0.137339,0.397711,0.387697,0.0772532)`* replicates the

definition of the variable Age in the HeparII model and generates a single sample from the following distribution:



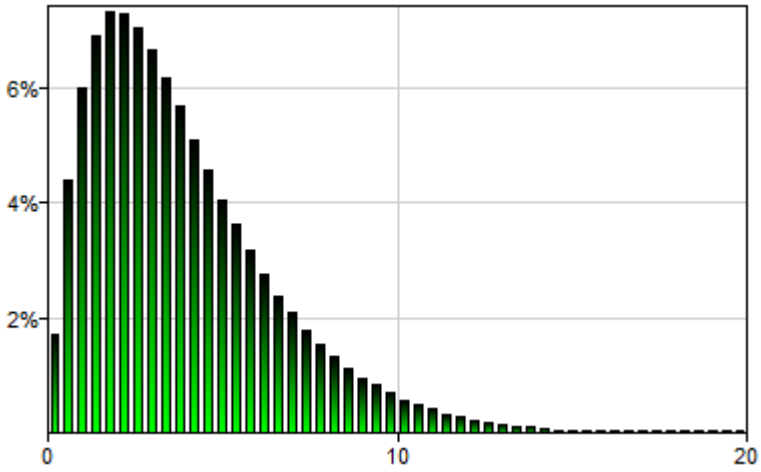
Exponential(lambda)

The exponential distribution is a continuous probability distribution that describes the time between events in a Poisson process, i.e., a process in which events occur continuously and independently at a constant average rate. Its only real-valued, positive parameter *lambda* (typically denoted by λ) determines the shape of the distribution. It is a special case of the Gamma distribution. `Exponential(lambda)` generates a single sample from the domain (0,∞). `Exponential(1)` will generate a single sample from the following distribution:



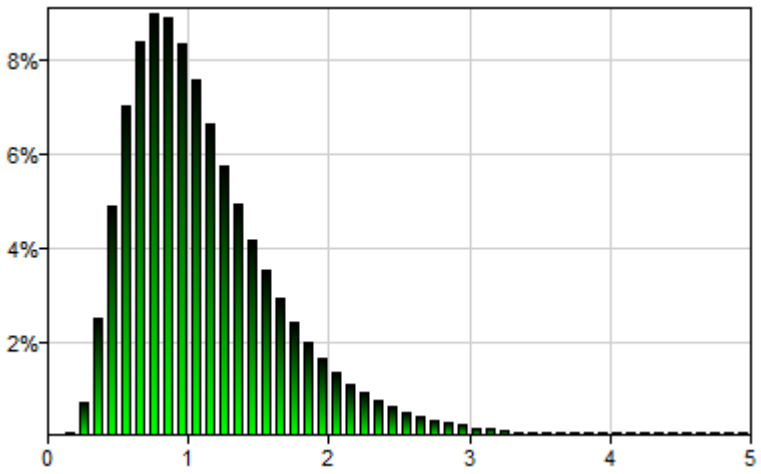
Gamma(shape,scale)

The Gamma distribution is a two-parameter family of continuous probability distributions. There are different parametrizations of the Gamma distribution in common use. SMILE parametrization follows one of the most popular parametrizations, with *shape* (often denoted by *k*) and *scale* (often denoted by θ) parameters, both positive real numbers. `Gamma(2.0,2.0)` will generate a single sample from the following distribution:



Lognormal(mu,sigma)

The lognormal distribution is a continuous probability distribution of a random variable, whose logarithm is normally distributed. Thus, if a random variable X is lognormally distributed, then a variable Y=Ln(X) has a normal distribution. Conversely, if Y has a normal distribution, then $X=e^Y$ has a lognormal distribution. A random variable which is lognormally distributed takes only positive values. *`Lognormal(0,0.5)`* will generate a single sample from the following distribution:

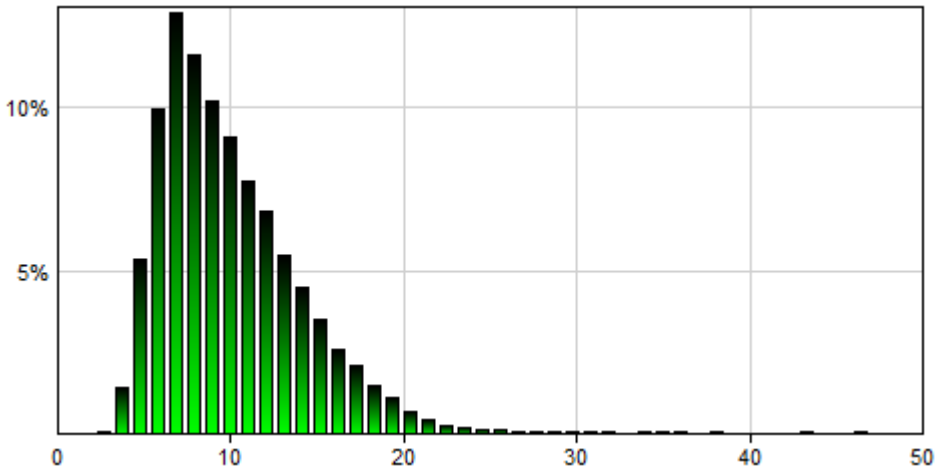


Metalog(lower,upper,k,x1,x2,...,y1,y2,...)

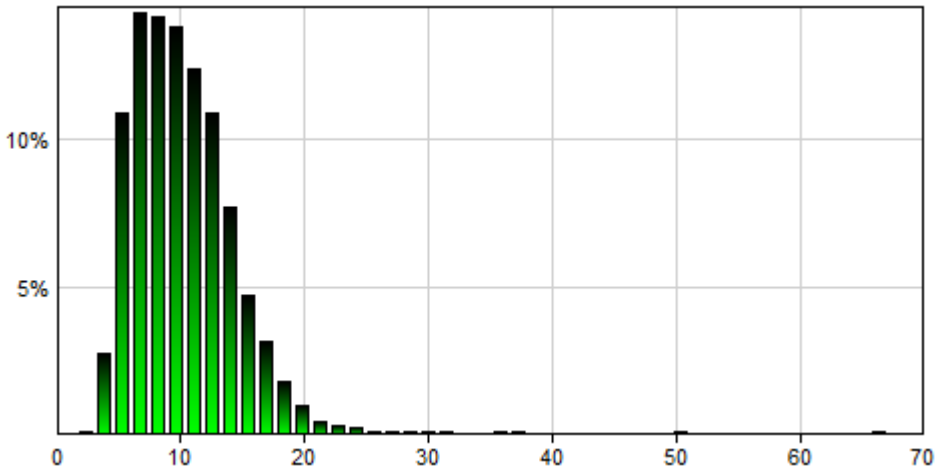
Metalog (also known as the Keelin) distribution is a very flexible distribution, capable of fitting many naturally occurring distributions. It can be specified by probability quantiles, which are values of the variable `xi` and their corresponding cumulative probabilities `yi`. Metalogs are able to represent distributions that are unbounded, semi-bounded, and bounded. lower and upper are the bounds of the distribution (*`-Inf()`* and *`Inf()`* denote lower and upper infinite bound respectively). *`k`* is a parameter of the metalog distribution, running from `2` to `n`, where `n` is the number of probability quantiles specified. Generally the higher the value of `k`, the more flexible the distribution but it is worth looking at the distributions generated for different values of `k` to find a compromise between complexity and goodness of fit. The choice of *`k`* is best performed interactively, looking at the family of metalog distributions generated from the probability quantiles. GeNIe contains a built-in tool, the Metalog Builder, which displays metalog PDF and CDF charts. This functionality is also available online at https://metalog.bayesfusion.com.

The examples below use identical bounds and probability quantiles with k equal 4, 6 and 8:

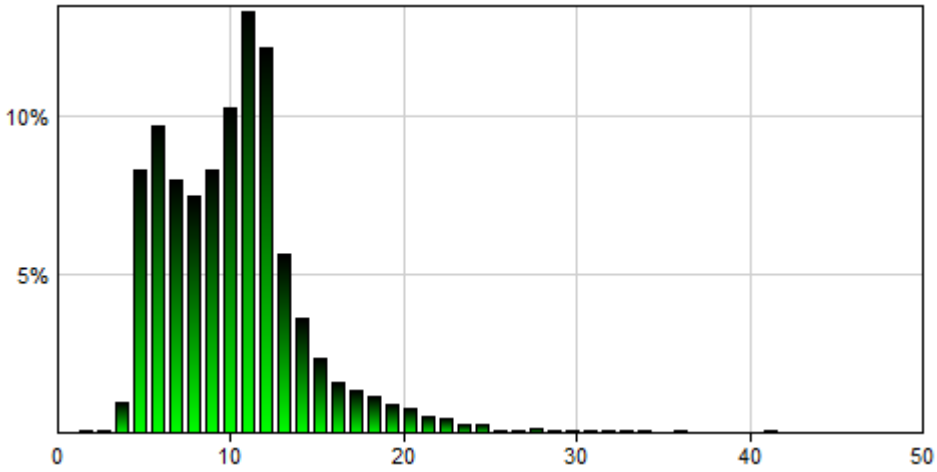
Metalog(0,Inf(),4,3,4,5,5,7,10,12,15,18,32,0.001,0.01,0.05,0.1,0.25,0.5,0.75,0.9,0.95,0.999) will generate a single sample from the following distribution:



Metalog(0,Inf(),6,3,4,5,5,7,10,12,15,18,32,0.001,0.01,0.05,0.1,0.25,0.5,0.75,0.9,0.95,0.999) will generate a single sample from the following distribution:



Metalog(0,Inf(),8,3,4,5,5,7,10,12,15,18,32,0.001,0.01,0.05,0.1,0.25,0.5,0.75,0.9,0.95,0.999) will generate a single sample from the following distribution:

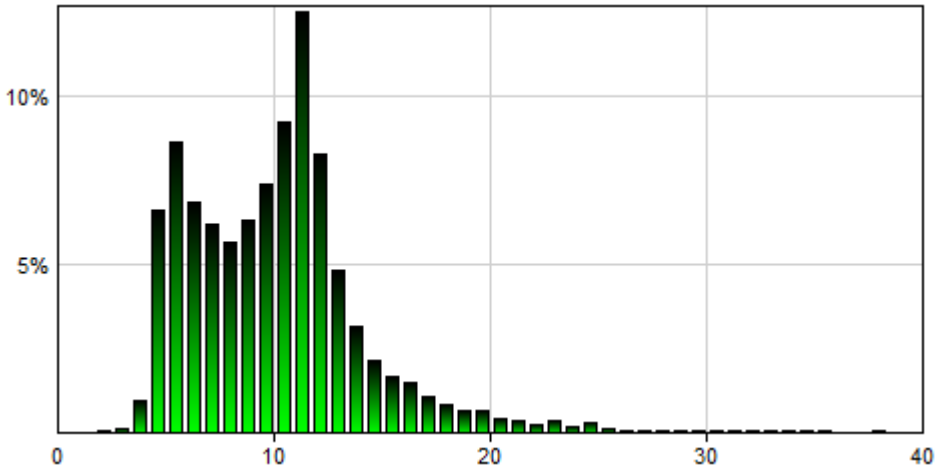


For more information about metalog distributions, please look at the comprehensive article on the topic on Wikipedia (https://en.wikipedia.org/wiki/Metalog_distribution), the Metalog Distribution web site created by Tom Keelin (http://metalogdistributions.com/) or the Metalog Distributions YouTube channel (https://www.youtube.com/channel/UCyHZ5neKhV1mSsedzDBoqyA).

MetalogA(lower,upper,a1,a2,...)

MetalogA function uses what one could call internal metalog coefficients (*ai* and, additionally, the *lower* and *upper* bound of the distribution) that, contrary to percentiles of the distribution used as parameters of *Metalog*, do not have easily interpretable meaning. One might expect that *MetalogA* is more efficient in sample generation, as it skips the whole process of deriving the distribution from which it subsequently generates a sample. However, SMILE has an efficient caching scheme that makes *Metalog* equally efficient in practice.

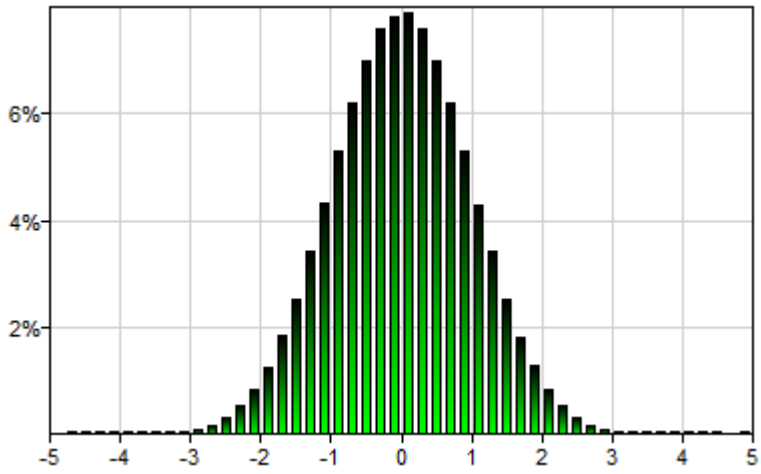
MetalogA(0,Inf(),2.30769,0.164148,-0.731388,0.343231,0.883249,-0.170727,1.40341,2.64853), which is equivalent to *Metalog(0,Inf(),8,3,4,5,5,7,10,12,15,18,32,0.001,0.01,0.05,0.1,0.25,0.5,0.75,0.9,0.95,0.999)*, will generate a single sample from the following distribution:



Please note that the number of ai parameters of *MetalogA* is the same as the *k* parameter in *Metalog*. Obtaining the parameters *ai* outside of tools like Metalog Builder is rather challenging.

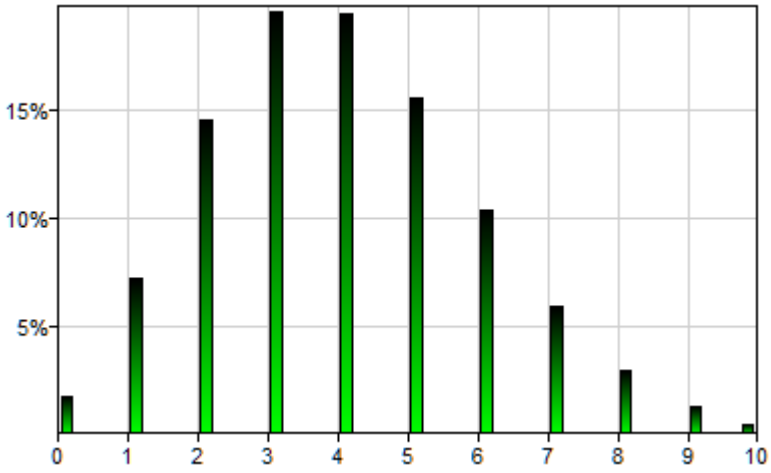
Normal(mu,sigma)

Normal (also known as Gaussian) distribution is the most commonly occurring continuous probability distribution. It is symmetric and defined over the real domain. Its two parameters, *mu* (mean, μ) and *sigma* (standard deviation, σ), control the position of its mode and its spread respectively. `Normal(0,1)` will generate a single sample from the following distribution:



Poisson(lambda)

Poisson distribution is a discrete probability distribution typically used to express the probability of a given number of events occurring in a fixed interval of time or space if these events occur with a known constant rate and independently of the time since the last event. Its only parameter, lambda, is the expected number of occurrences (which does not need to be integer). *Poisson(4)* will generate a single sample from the following distribution:

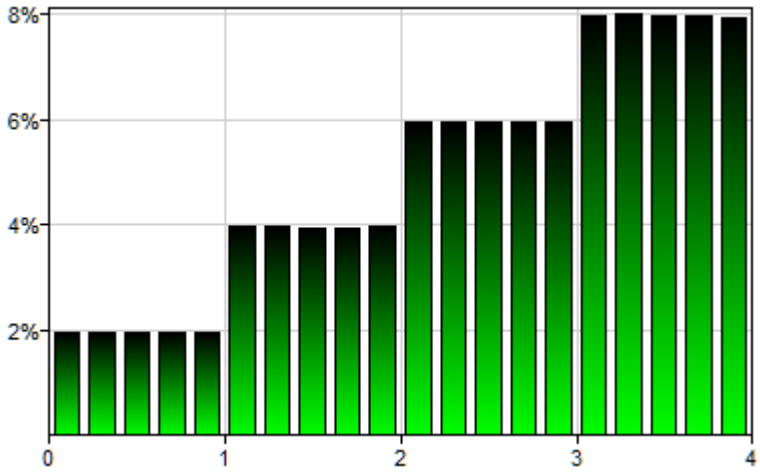


Steps(x1,x2,...y1,y2,...)

The *Steps* distribution allows for specifying a non-parametric continuous probability distribution by means of a series of steps on its probability density (PDF) function. It is similar to the *CustomPDF* function, although it does not specify the inflection points but rather intervals and the height of a step-wise probability distribution in

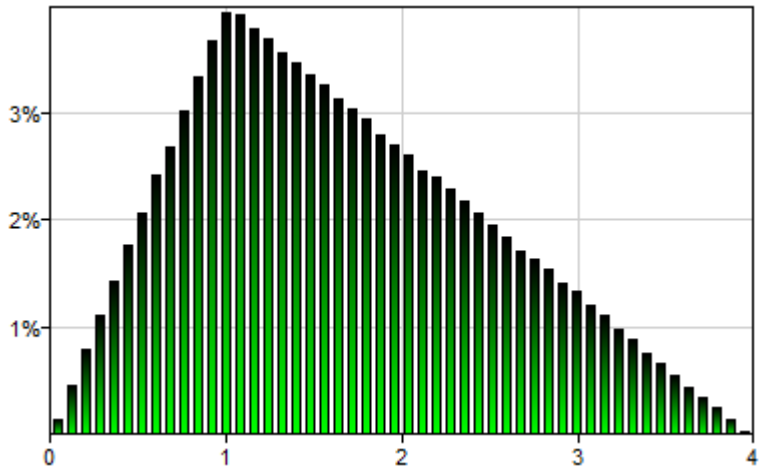
each of the intervals. Because the number of interval borders is always one more than the number of intervals between them, the total number of parameters of *Steps* function should be odd. Please note that x coordinates should be listed in increasing order. The PDF function specified does not need to be normalized, i.e., the area under the curve does not need to add up to 1.0.

Example: *Steps(0,1,2,3,4,1,2,3,4)* generates a single sample from the following distribution::



Triangular(min,mod,max)

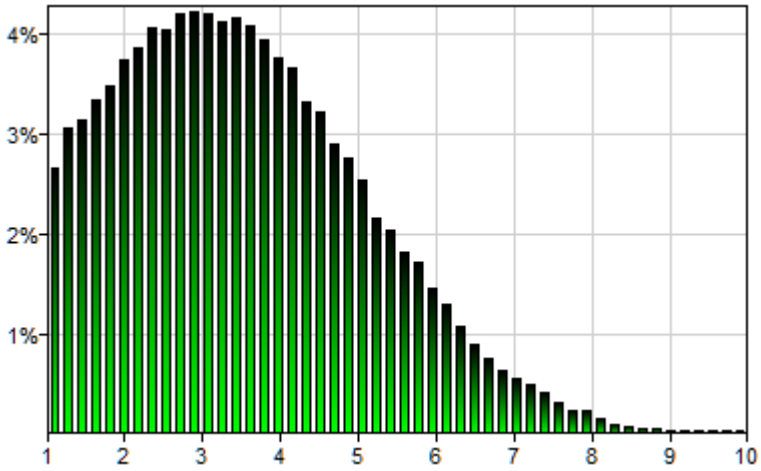
Triangular distribution is a continuous probability distribution with lower limit *min*, upper limit *max* and mode *mod*, where *min* ≤ *mod* ≤ *max*. `Triangular(0,1,3)` will generate a single sample from the following distribution:



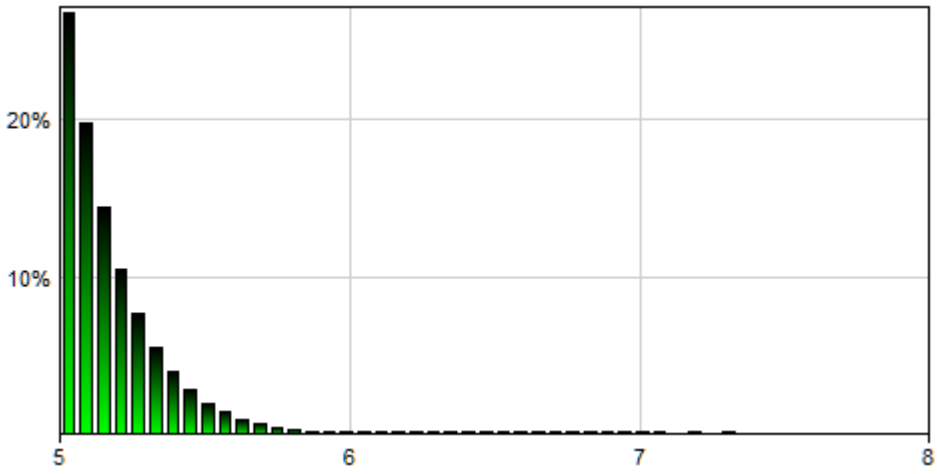
TruncNormal(mu,sigma,lower[,upper])

Truncated Normal distribution is essentially a Normal distribution that is truncated at the values lower and upper. This distribution is especially useful in situation when we want to limit physically impossible values in the model.

`TruncNormal(3,2,1)` will generate a single sample from the following distribution:

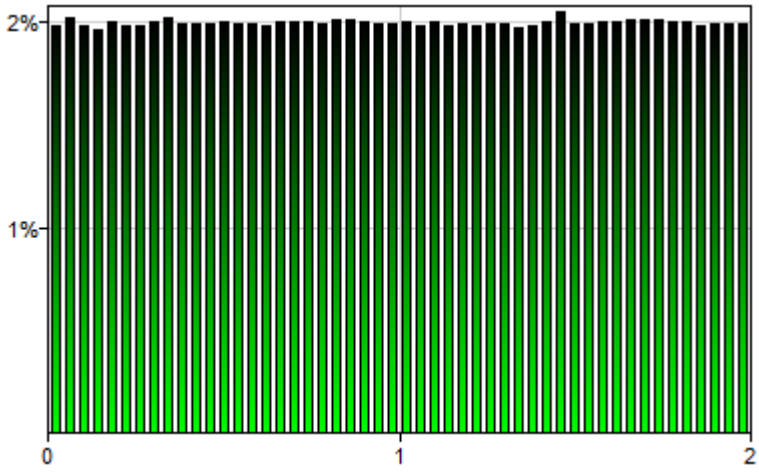


TruncNormal(0,1,5,10) will generate a single sample from the following distribution:



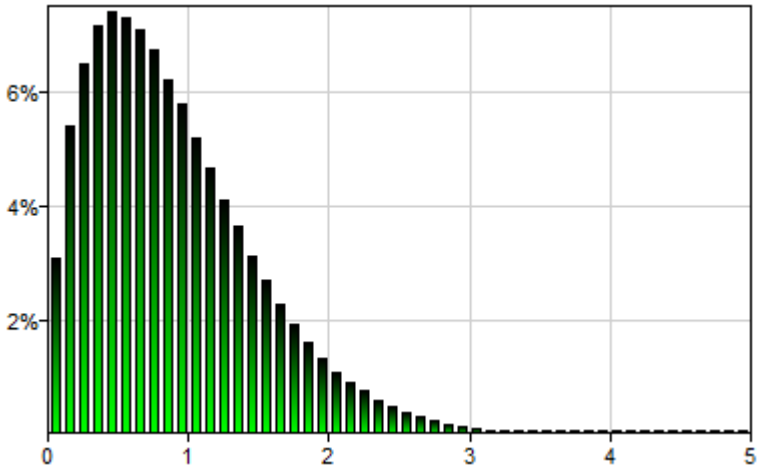
Uniform(a,b)

The continuous uniform distribution, also known as the rectangular distribution, is a family of probability distributions under which any two intervals of the same length are equally probable. It is defined two parameters, *a* and *b*, which are the minimum and the maximum values of the random variable. *Uniform(0,2)* will generate a single sample from the following distribution:



Weibull(lambda,k)

Weibull distribution is a continuous probability distribution named after a Swedish mathematician Waloddi Weibull, used in modeling such phenomena as particle size. It is characterized by two positive real parameters: the scale parameter *lambda* (λ) and the shape parameter *k*. `Weibull(1,1.5)` will generate a single sample from the following distribution:



6.15.3 Statistical Functions

Erf(x)

Returns error function ((also called the Gauss error function, inverse of the Normal PDF), e.g., Erf(1.0) =0.842701.

NormalPDF(x, mu, sigma)

Returns the value of PDF for the normal distribution given by mu and sigma at x.

NormalCDF(x, mu, sigma)

Returns the value of CDF for the normal distribution given by mu and sigma at x.

6.15.4 Arithmetic Functions

Abs(x)

Returns the absolute value of a number, e.g., `Abs(5.3)=Abs(-5.3)=5.3`.

Exp(x)

Returns *e* (Euler's number) raised to the power of *x*, e.g., `Exp(2.2)=`$e^{2.2}$`=9.02501`.

Gammaln(x)

Returns the natural logarithm of the Gamma function (Γ(*x*)), e.g., `Gammaln(2.2)=0.0969475`.

GCD(n,k)

Returns the greatest common integer divisor of its two integer arguments *n* and *k*, e.g., `GCD(15,25)=5.` When the arguments are not integers, their fractional part is ignored.

Inf()

Returns positive infinity. For negative infinity, please use `-Inf()`.

LCM(n,k)

Returns the least common integer multiple of its two integer arguments *n* and *k*, e.g., `LCM(15,25)=75.`When the arguments are not integers, their fractional part is ignored.

Ln(x)

Returns the natural logarithm of *x*, which has to be non-negative, e.g., `Ln(10)=2.30259`.

Log(x,b)

Returns the base *b* logarithm of *x*, which has to be non-negative, e.g., `Log(10,2)=3.32193`.

Log10(x)

Returns decimal logarithm of *x*, which has to be non-negative, e.g., `Log10(100)=2`.

Mod(x,y)

Returns the remainder of dividing x by y. This works for both integer and real arguments, e.g., `Mod(5,2)=1, Mod(9.2,3.7)=1.8`.

Pow10(x)

Returns 10 raised to the power of *x*, e.g., `Pow10(2)=10^2=100`.

Round(x)

Returns the integer that is nearest to x, e.g., `Round(2.2)=2, Round(3.5)=4`.

Sign(x)

Returns 1 if *x*>0, 0 when *x*=0, and -1 if *x*<0, e.g., `Sign(2.2)=1, Sign(0)=0, Sign(-3.5)=-1`.

Sqrt(x)

Returns the square root of *x*, which has to be non-negative, e.g., `Sqrt(2)=1.41421`.

SqrtPi(x)

Returns square root of π multiplied by *x*, which has to be non-negative, e.g. `SqrtPi(2)=Sqrt(Pi()*2) =2.50663.` This function is provided for the sake of compatibility with Microsoft Excel.

Sum(x1,x2,...)

Returns the sum of its arguments, e.g., `Sum(2.2, 3.5, 1.3)=7.0.` `Sum()` requires at least two arguments.

SumSq(x1,x2,...)

Returns the sum of squares of its arguments, e.g., `SumSq(2.2, 3.5, 1.3)=18.78.` `SumSq()` requires at least two arguments.

Trim(x,lo,hi)

Trims the value of the argument *x* to a value in the interval <*lo*, *hi*>. If *x*≤*lo*, the function returns *lo*, if *x*≥*hi*, the function returns *hi*, if *lo*<*x*<*hi*, the function returns *x*. The function is a shortcut to two nested conditional functions `If()` and is equivalent to `If(x<lo,lo,If(x>hi,hi,x))`. For example, `Trim(-0.5,0,1)=0, Trim(0.5,0,1)=0.5, Trim(1.5,0,1)=1`.

Truncate(x)

Returns the integer part of *x*, e.g., `Truncate(2.2)=2`.

6.15.5 Combinatoric Functions

Combin(n,k)

Returns the number of combinations of distinct k elements from among n elements, e.g., `Combin(10,2)`=45.

Fact(n)

Returns the factorial of *n*, e.g., `Fact(5)=5!=120.` `Fact` of a negative number returns 0.

FactDouble(n)

Returns the product of all even (when *n* is even) or all odd (when *n* is odd) numbers between 1 and *n*, e.g., `FactDouble(5)=15, FactDouble(6)=48.` `FactDouble` of a negative number returns 0.

Multinomial(n1,n2,...)

Factorial of sum of arguments, divided by the factorials of all arguments, e.g., `Multinomial(2,5,3) =Fact(2+5+3)/(Fact(2)*Fact(5)*Fact(3)=10!/(2!*5!*3!)=2520.` All arguments of `Multinomial` have to be positive.

6.15.6 Trigonometric Functions

Acos(x)

Returns arccosine (*arcus cosinus*) of *x*, e.g., `Acos(-1)=3.14159`.

Asin(x)

Returns arcsine (*arcus sinus*) of *x*, e.g., `Asin(1)=1.5708`.

Atan(x)

Returns arctangent (*arcus tangens*) of *x*, e.g., `Atan(1)=0.785398`.

Atan2(y,x)

Returns arctangent (*arcus tangens*) from *x* and *y* coordinates, e.g., `Atan2(1,1)=0.785398`.

Cos(x)

Returns cosine (*cosinus*) of *x*, e.g., `Cos(1)=0.540302`.

Pi()

Returns constant π, e.g., `Pi()=3.14159`.

Sin(x)

Returns sine (*sinus*) of *x*, e.g., `Sin(1)=0.841471`.

Tan(x)

Returns tangent (*tangens*) of *x*, e.g., `Tan(1)=1.55741`.

6.15.7 Hyperbolic Functions

Cosh(x)

Returns the hyperbolic cosine of *x*, e.g., `Cosh(1)=1.54308`.

Sinh(x)

Returns the hyperbolic sine of *x*, e.g., `Sinh(1)=1.1752`.

Tanh(x)

Returns the hyperbolic tangent of *x*, e.g., `Tanh(1)=0.761594`.

6.15.8 Logical/Conditional functions

And(b1,b2,...)

Returns the logical conjunction of the arguments, which are all interpreted as Boolean expressions. If any of the expressions evaluates to a zero, `And` returns 0. For example, `And(1=1,2,3)=1, And(1=2,2,3)=0`.

Choose(index,v0,v1,...,vn)

Returns v_i if *index* is equal to *i*. When *index* evaluates to a value smaller than 0 or larger than *n*-1, the function returns 0. Examples:

```
Choose(0,1,2,3,4,5)=1
Choose(4,1,2,3,4,5)=5
Choose(7,1,2,3,4,5)=0
```

If(cond,tval,fval)

If *cond* evaluates to non-zero return *tval*, *fval* otherwise, e.g., `If(1=2,3,4)=4, If(1,5,10)=5`.

Max(x1,x2,...)

Returns the largest of the arguments x_i. Examples:

```
Max(1,2,3,4,5)=5
Max(-3,2,0,2,1)=2
```

Min(x1,x2,...)

Returns the smallest of the arguments x_i. Examples:

```
Min(1,2,3,4,5)=1
Min(-3,2,0,2,1)=-3
```

Or(b1,b2,...)

Returns the logical disjunction of the arguments, which are all interpreted as Boolean expressions. If any of the expressions evaluates to a non-zero value, `Or` returns 1. For example, `Or(1=1,0,0)=1, Or(1=0,0,0)=0`.

Switch(x,a1,b1,a2,b2,...,[def])

If *x=a1*, return *b1*, if *x=a2*, return *b2*, when *x* is not equal to any of *a*s, return *def* (default value), which is an optional argument. When *x* is not equal to any of *a*s and no *def* is defined, return 0. Examples:

```
Switch(3,1,111,2,222,3,333,4,444,5,555,999)=333
Switch(8,1,111,2,222,3,333,4,444,5,555,999)=999
Switch(8,1,111,2,222,3,333,4,444,5,555)=0
```

Xor(b1,b2,...)

Returns logical exclusive OR of all arguments, which are all interpreted as Boolean expressions. `Xor` returns a 1 if the number of logical expressions that evaluate to non-zero is odd and a 0 otherwise.

Examples:

```
Xor(0,1,2,-3,0)=1
Xor(1,1,0,2,2)=0
Xor(-5,1,1,-2,2)=1
```

6.15.9 Custom Functions

It is possible to extend the available function set by calling `Network.setExtFunctions`. The functions are defined at the network level and stored within XDSL file. `setExtFunctions` requires an array of strings with the textual definition of functions. Each function definition has the following form:

```
function-name([parameter1[,parameter2...]]) = expression
```

For example, a function adding two numbers can be defined by the following string:

```
add(a,b)=a+b
```

Recursion is not allowed, but it is possible to use the preceding custom functions in the function expression, for example:

```
dbl(x)=x+x
quad(x)=2*dbl(x)
```

Reverse ordering of `dbl` and `quad` in the vector passed to `setExtFunctions` will result in a parser error for *`quad`*, because the *`dbl`* function is not defined when *`quad`* is parsed.

Each parameter specified on the LHS of the equal sign must be used in the function body on the RHS. The following is an incorrect custom function definition, because parameter `c` is not used:

```
myFunc(a,b,c)=sin(a)+cos(b)
```

Custom function can be defined as a constant. In such case the function has no parameters, but its definition and function calls in node equations still require parenthesis:

```
gEarth()=9.80665
```

Random number generators can be used in function definitions:

```
StdNormal()=Normal(0,1)
TwoStep(lo,hi)=Steps(lo,(lo+hi)/2,hi,1,2)
```

To retrieve the custom functions defined for the network, call `Network.getExtFunctions`. By default, there are no custom functions. Each call to `SetExtFunctions` sets up a complete set of custom functions. To add new functions to the existing set, call `getExtFunctions` first, then add new function definition to the output vector before calling `setExtFunctions`.

6.16 Diagnosis

Diagnosis is one of the most successful applications of Bayesian networks. The ability of probabilistic knowledge representation techniques to perform a mixture of both predictive and diagnostic inference makes it very suitable for diagnosis. Bayesian networks can perform fusion of observations such as patient (or equipment) history and risk factors with symptoms and test results.

A Bayesian network built with SMILE represents various components of a system, possible faulty behaviors produced by the system (symptoms), along with results of possible diagnostic tests. The model essentially captures how possible defects of the system (whether it is a natural system, such as human body, or a human-made device, such as a car, an airplane, or a copier) can manifest themselves by error messages, symptoms, and test results.

To work with diagnosis, some nodes in the network should be designated as diagnostic faults, and some other nodes should become diagnostic observations. It is also possible to provide observation costs. The output of SMILE diagnostic algorithms is two-fold: (1) the posterior marginal probability of diagnostic faults, and (2) ranking of possible observations from the most to the least informative from the point of view of the current diagnostic focus. Depending on the selected diagnostic algorithm, the ranking is based on one of the following measures:

- an information-theoretic measure known as cross-entropy and expresses, for each observation node X individually, the expected reduction in entropy of the probability distribution over the specified subset of fault states after observing X. Cross-entropy is a utility-free measure of value of information and it gives a good idea about the value of the observations for diagnosing the disorder in question.

- a distance between two vectors representing the probabilities of pursued faults. SMILE can use multiple distance definitions, including Euclidean, cosine or cityblock.

Tutorial 9 [153] uses a HeparII diagnostic model to show the diagnostic results for single- and multi-fault diagnosis.

6.16.1 Diagnostic roles

`Network.setNodeDiagType` allows for setting for each node one of three possible diagnostic roles:

- fault nodes, which require at least one fault state. During a diagnostic session, SMILE calculates the probabilities of the fault states after a change in the set of observations. To set a state of a diagnostic fault node to be a fault, use `Network.setFaultOutcome`.

- observation nodes, which can be instantiated (set to specified evidence) during a diagnostic session. Observations can have default outcomes, which are instantiated automatically when a diagnostic session begins. To set the default outcome, call `Network.setDefaultOutcome`. To mark that the observation node should be included in the ranked list of observations, use `Network.setRanked`. To make the observation mandatory, use `Network.setMandatory`. The diagnostic session will not rank observations until all mandatory observations have been instantiated.

- auxiliary nodes, which are neither observation nor a fault. The auxiliary role is a default when node is created.

When a network object is saved to a `.xdsl` file, the diagnostic roles of nodes are preserved.

6.16.2 Observation cost

Observing the value of a variable is often associated with a cost. For example, in order to observe the platelet count, one has to draw a blood sample and subject it to examination by professionals. Measuring the temperature of an air conditioner exhaust unit requires a technician's time. In order to perform an optimal diagnosis, one has to take into account the value of information along with the cost of obtaining it. For any diagnostic observation node, we can specify the cost of observing its value by calling the `Network.setNodeCost` method and read the cost by calling `Network.getNodeCost`.

The cost of performing a test can be expressed on some scale, like currency or time in minutes. It is also possible to specify negative number as cost. Negative cost indicate that tests so inexpensive that they should always be performed, for example checking the car model when diagnosing a car.

When observing the state of a node is independent of whether other nodes are observed or not, the cost is just a single number. Sometimes, however, the cost of observing a variable is not independent of observing other variables. For example, once a blood sample is drawn, performing additional tests on the sample is cheaper than performing these tests when no blood sample is available. The cost of measuring some parameter of a locomotive engine depends on whether the locomotive is in the shop or in the field. It may be much lower when the locomotive is in the shop. Taking off a locomotive cover may take a few hours but once it is removed, many tests become inexpensive. To represent such cases, use `Network.addCostArc`. This causes an observation cost arc to be added to the network. The observation cost arcs are not constrained by 'normal' arcs. When diagnostic observation has incoming cost arcs, its observation cost is a multi-dimensional matrix, just like conditional probability table, but with the last dimension size equal to one.

To remove a cost arc, call `Network.removeCostArc`. `Network.getCostParents/getCostParentIds` and `Network.getCostChildren/getCostChildrenIds` can be used to retrieve the information about cost parents and children.

6.16.3 Diagnostic session

With diagnostic attributes, such as node roles and (optionally) observation costs defined, we can start a diagnostic session in order to obtain a ranked observation list. The diagnostic session is represented by `DiagNetwork` object. Its constructor requires a reference to the `Network` object, where diagnostic information is defined. The session object provides an API to pursue faults, instantiate observations, and retrieve the statistics for observations. During the diagnostic session, your program should use the `DiagNetwork` instance to read information from the network.

Java:

```
DiagNetwork diagNet = new DiagNetwork(net);
```

Python:

```
diagnet = pysmile.DiagNetwork(net)
```

R:

```
diagNet <- DiagNetwork(net)
```

C#:

```
DiagNetwork diagNet = new DiagNetwork(net);
```

The diagnostic session instantiates the mandatory observation during its initialization. To obtain a ranking of uninstantiated observations, we need to calculate their diagnostic value, which is a dynamic measure, depending

on the already instantiated observations and the fault or faults selected as the focus of reasoning (these faults are called "pursued faults"). By default, the pursued fault is the one which is most likely.

From the diagnostic session point of view, the fault is a node/state pair (because one fault node can have more than one faulty state). The node/state pairs are referenced by their indices. Do not use fault node handles directly when setting the pursued fault. To convert the node handle/state pair to fault index, use `DiagNetwork.getFaultIndex`. To change the pursued fault, use `DiagNetwork.setPursuedFault`, or `setPursuedFaults` if more than one fault is to be pursued.

During the diagnostic session, the observation nodes can be set to evidence with calls to `DiagNetwork.instantiateObservation`**. Do not call `Network.setEvidence` directly during the diagnostic session**, as it will make the internal session state inconsistent. Instantiated observation can be reset to unobserved with `Network.releaseObservation`, which calls Network.clearEvidence internally.

After selecting the pursued faults and instantiating known observations, the application can call `DiagNetwork.update` to obtain the `DiagResults` object, which contains two arrays:

- `DiagResults.faults` contains an entry for each fault node in the network. Each entry includes the probability of the fault state in its `probability` member. The array is sorted by fault probability in the descending order.

- `DiagResults.observations` contains an entry for each uninstantiated observation node in the network. Each entry includes the diagnostic measure for the observation in its `measure` member, and the `infoGain` member contains effective measure combined with the observation cost. If there's no cost defined, `infoGain` is equal to `measure`. The array is sorted by the value of `infoGain` in the descending order.

The typical diagnostic program is interactive, starting with single pursued fault and no instantiated observations other than the ones with default value. The application user changes the pursued faults, and instantiates observations taking into account the diagnostic values of the observations displayed in the UI.

6.16.4 Distance and entropy-based measures

The diagnostic measures calculated for observations depend on the pursued fault set. The pursued faults define the focus of reasoning, and the changes in their probabilities are the inputs to the measure algorithms. To select the algorithm, use `DiagNetwork.setSingleFaultAlgorithm` and `setMultiFaultAlgorithm`. The output of the algorithm is a single number for each uninstantiated observation.

The available algorithms for single fault diagnosis are:

- Max probability change (default): for each observation, the maximum change is taken over the absolute values of the change in probability of the pursued fault. Note that this is a signed measure, meaning that some values may be negative (when the largest magnitude of fault probability change represents the probability decrease).

- Cross-entropy: the insight from the Max probability change is limited in the sense of not telling us a key piece of information how likely each of the changes happens. For example, a positive test result for cancer will make a huge change it the probability of cancer. However, the probability of seeing a positive test may be very small in a generally healthy person. So, effectively the expected amount of diagnostic information from performing this test is rather small. Cross-entropy is an information-theoretic measure that takes into account both the amount of information flowing from observing individual states of an observation variable and the probabilities of observing this states. A high cross-entropy indicates a high expected contribution of observing a variable to the probability of the pursued fault. Cross-entropy is unsigned.

- Normalized cross-entropy: the cross entropy divided by the current value of the entropy of the pursued fault node

For multi-fault diagnosis, the following algorithms are available:

- Max probability change (default): the value of the measure is the maximum change of probability over all pursued faults and outcomes of the observation. This is a signed measure.
- Euclidean distance, or L2 Norm: calculates the distance between two vectors in Euclidean space, where the vector coordinates are the probabilities of the pursued faults before and after the observation. The distance is normalized to ensure that a change from impossible (all coordinates are zero) to certain (all coordinates are ones) is equal to 1.0. For each observation, the selected value is the greatest distance over all observation outcomes. The larger the distance, the larger the impact of the observation.
- Cityblock distance: as above, but using cityblock metric
- Averaged L2 and cityblock distance
- Cosine distance, or cosine similarity: calculated between two fault probability vectors. Since vector coordinates are probabilities, and therefore non-negative, this measure will always produce non-negative values (despite general cosine similarity range between -1 and 1).
- A family of six entropy-based measures, which require calculation of the joint probability distribution over all pursued faults, which is computationally prohibitive, it is necessary to use approximations of the joint probability distribution. The approximations are based on two strong assumptions about dependencies among them: (1) complete independence (this is taken by the first group of approaches) and (2) complete dependence (this is taken by the second group of approaches). Each of the two extremes is divided into three groups: (1) At Least One, (2) Only One, and (3) All. These refer to different partitioning of the combinations of diseases in cross-entropy calculation.
- Two marginal probability-based measures, which are much faster than the independence/dependence-based joint probability distribution approaches but it is not as accurate because they make a stronger assumption about the joint probability distribution. Entropy calculations in this approach are based purely on the marginal probabilities of the pursued faults. The two algorithms that use the Marginal Probability Approach differ essentially in the function that they use to select the tests to perform. Both functions are scaled so that they return values between 0 and 1. Entropy/Marginal 1 uses a function without the support for maximum distance and its minimum is reached when all probabilities of the faults are equal to 0.5. Entropy/Marginal 2 uses a function that has support for maximum distance and is continuous in the domain [0,1].

The numeric identifiers of the algorithms are defined as follows:

Java:

`SingleFaultAlgorithmType` and `MultiFaultAlgorithmType` are static classes nested in `DiagNetwork`.

```
SingleFaultAlgorithmType.PROB_CHANGE
SingleFaultAlgorithmType.CROSSENTROPY
SingleFaultAlgorithmType.NORM_CROSSENTROPY
MultiFaultAlgorithmType.MAX_PROB_CHANGE
MultiFaultAlgorithmType.L2_NORMALIZED_DISTANCE
MultiFaultAlgorithmType.CITYBLOCK_DISTANCE
MultiFaultAlgorithmType.AVG_L2_CITY_DISTANCE
MultiFaultAlgorithmType.COSINE_DISTANCE
```

```
MultiFaultAlgorithmType.INDEPENDENCE_AT_LEAST_ONE
MultiFaultAlgorithmType.INDEPENDENCE_ONLY_ONE
MultiFaultAlgorithmType.INDEPENDENCE_ONLY_ALL
MultiFaultAlgorithmType.DEPENDENCE_AT_LEAST_ONE
MultiFaultAlgorithmType.DEPENDENCE_ONLY_ONE
MultiFaultAlgorithmType.DEPENDENCE_ONLY_ALL
MultiFaultAlgorithmType.MARGINAL_1
MultiFaultAlgorithmType.MARGINAL_2
```

Python:

`SingleFaultAlgorithmType` and `MultiFaultAlgorithmType` are `enums`.

```
SingleFaultAlgorithmType.PROB_CHANGE
SingleFaultAlgorithmType.CROSSENTROPY
SingleFaultAlgorithmType.NORM_CROSSENTROPY
MultiFaultAlgorithmType.MAX_PROB_CHANGE
MultiFaultAlgorithmType.L2_NORMALIZED_DISTANCE
MultiFaultAlgorithmType.CITYBLOCK_DISTANCE
MultiFaultAlgorithmType.AVG_L2_CITY_DISTANCE
MultiFaultAlgorithmType.COSINE_DISTANCE
MultiFaultAlgorithmType.INDEPENDENCE_AT_LEAST_ONE
MultiFaultAlgorithmType.INDEPENDENCE_ONLY_ONE
MultiFaultAlgorithmType.INDEPENDENCE_ONLY_ALL
MultiFaultAlgorithmType.DEPENDENCE_AT_LEAST_ONE
MultiFaultAlgorithmType.DEPENDENCE_ONLY_ONE
MultiFaultAlgorithmType.DEPENDENCE_ONLY_ALL
MultiFaultAlgorithmType.MARGINAL_1
MultiFaultAlgorithmType.MARGINAL_2
```

R:

```
SingleFaultAlgorithmType$PROB_CHANGE
SingleFaultAlgorithmType$CROSSENTROPY
SingleFaultAlgorithmType$NORM_CROSSENTROPY
MultiFaultAlgorithmType$MAX_PROB_CHANGE
MultiFaultAlgorithmType$L2_NORMALIZED_DISTANCE
MultiFaultAlgorithmType$CITYBLOCK_DISTANCE
MultiFaultAlgorithmType$AVG_L2_CITY_DISTANCE
MultiFaultAlgorithmType$COSINE_DISTANCE
MultiFaultAlgorithmType$INDEPENDENCE_AT_LEAST_ONE
MultiFaultAlgorithmType$INDEPENDENCE_ONLY_ONE
MultiFaultAlgorithmType$INDEPENDENCE_ONLY_ALL
MultiFaultAlgorithmType$DEPENDENCE_AT_LEAST_ONE
MultiFaultAlgorithmType$DEPENDENCE_ONLY_ONE
MultiFaultAlgorithmType$DEPENDENCE_ONLY_ALL
MultiFaultAlgorithmType$MARGINAL_1
MultiFaultAlgorithmType$MARGINAL_2
```

C#:

`SingleFaultAlgorithmType` and `MultiFaultAlgorithmType` are enum classes nested in `DiagNetwork`.

```
SingleFaultAlgorithmType.ProbChange
SingleFaultAlgorithmType.Crossentropy
```

```
SingleFaultAlgorithmType.NormCrossentropy
MultiFaultAlgorithmType.MaxProbChange
MultiFaultAlgorithmType.L2NormalizedDistance
MultiFaultAlgorithmType.CityblockDistance
MultiFaultAlgorithmType.AvgL2CityDistance
MultiFaultAlgorithmType.CosineDistance
MultiFaultAlgorithmType.IndependenceAtLeastOne
MultiFaultAlgorithmType.IndependenceOnlyOne
MultiFaultAlgorithmType.IndependenceOnlyAll
MultiFaultAlgorithmType.DependenceAtLeastOne
MultiFaultAlgorithmType.DependenceOnlyOne
MultiFaultAlgorithmType.DependenceOnlyAll
MultiFaultAlgorithmType.Marginal1
MultiFaultAlgorithmType.Marginal2
```

6.17 Learning

Learning in SMILE can perform two tasks:

- structure learning: create a new network from a dataset
- parameter learning: refine parameters (CPTs) in an existing network

SMILE also supports network validation, which is frequently used after learning to evaluate the results.

6.17.1 Learning network structure

The following classes can be used to learn `Network` from `DataSet`:

- `BayesianSearch`: Bayesian Search, a hill climbing procedure guided by scoring heuristic with random restarts
- `NaiveBayes`: Naive Bayes
- `TAN`: Tree Augmented Naive Bayes, semi-naive method based on the Bayesian Search approach
- `ABN`: Augmented Naive Bayes, another semi-naive method based on the Bayesian Search approach

In the simplest scenario, just create the object representing learning algorithm and call its `learn` method:

Java:

```
DataSet ds = new DataSet();
ds.readFile("mydatafile.txt");
BayesianSearch baySearch = new BayesianSearch();
Network net = baySearch.learn(ds);
```

Python:

```
ds = pysmile.learning.DataSet()
ds.read_file("mydatafile.txt")
baySearch = pysmile.learning.BayesianSearch()
```

```
net = baySearch.learn(ds)
```

R:

```
ds <- DataSet()
ds$readFile("mydatafile.txt")
baySearch <- BayesianSearch()
net <- baySearch$learn(ds)
```

C#:

```
DataSet ds = new DataSet();
ds.ReadFile("mydatafile.txt");
BayesianSearch baySearch = new BayesianSearch();
Network net = baySearch.Learn(ds);
```

Note that every variable in the dataset takes part in the learning process. After learning the structure, each of the algorithms listed above performs parameter learning with EM, so the output network has nodes with parameters based on the data.

The code example above used the default settings for Bayesian Search. To tweak the learning process, you can change some control options in the learning object before calling its `learn` method. The example below sets the number of iterations and maximum number of parents:

Java:

```
BayesianSearch baySearch = new BayesianSearch();
baySearch.setIterationCount(10);
baySearch.setMaxParents(4);
Network net = baySearch.learn(ds);
```

Python:

```
baySearch = pysmile.learning.BayesianSearch()
baySearch.set_iteration_count(10)
baySearch.set_max_parents(4)
net = baySearch.learn(ds)
```

R:

```
baySearch <- BayesianSearch()
baySearch$setIterationCount(10)
baySearch$setMaxParents(4)
net <- baySearch$learn(ds)
```

C#:

```
BayesianSearch baySearch = new BayesianSearch();
baySearch.IterationCount = 10;
baySearch.MaxParents = 4;
Network net = baySearch.Learn(ds);
```

For `NaiveBayes` and its semi-naive derivatives (`TAN` and `ABN`) it is required to specify a class variable identifier (a string value) with a call to `setClassVariableId` before invoking `learn`. This identifier has to match one of the columns in the `DataSet` objects passed to `learn`.

SMILE also contains the `PC` class, which implements the PC structure learning algorithm (algorithm name is an acronym derived from its inventors' names). This algorithm uses `DataSet` as data source, but instead of `Network` learns the `Pattern` object, which is a graph with directed and undirected edges, which is not guaranteed to be acyclic.

`BayesianSearch` and `PC` algorithms can use background knowledge, provided by the caller. The background knowledge influences the learned structure by:

- forcing arcs between specified variables
- forbidding arcs between specified variables
- ordering specified variables by temporal tiers: in the resulting structure, there will be no arcs from nodes in higher tiers to nodes in lower tiers

To specify the background knowledge, use `BayesianSearch.setBkKnowledge` or `PC.setBkKnowledge` methods.

Tutorial 10 [169] contains a program which performs structure learning using Bayesian Search, Tree Augmented Naive Bayes and PC.

6.17.2 Learning network parameters

To learn the parameters in the existing `Network` object, you can use the EM algorithm implemented in `EM` class. As with structure learning, the data comes in `DataSet` object. However, the network and the data must be matched to ensure that learning algorithm knows the relationship between the dataset variables and network nodes. If the variables and nodes have identical identifiers, you can use the `DataSet.matchNetwork` method:

Java:

```
DataSet ds = new DataSet();
Network net = new Network();
// load network and data here
DataMatch[] matching = ds.matchNetwork(net);
em = new EM();
em.learn(ds, net, matching);
```

Python:

```
ds = pysmile.learning.DataSet()
net = pysmile.Network()
# load network and data here
matching = ds.match_network(net)
em = pysmile.learning.EM()
em.learn(ds, net, matching)
```

R:

```
ds <- DataSet()
net <- Network()
# load network and data here
matching <- ds$matchNetwork(net)
em <- EM()
em$learn(ds, net, matching)
```

C#:

```
DataSet ds = new DataSet();
Network net = new Network();
// load network and data here
DataMatch[] matching = ds.MatchNetwork(net);
em = new EM();
em.Learn(ds, net, matching);
```

If your network and data cannot be automatically matched with `DataSet.matchNetwork`, you can build the array of `DataMatch` objects in your own code. `DataMatch` has `node` and `column` fields representing node handle and variable index, respectively. For each node/variable pair you need one element of the array.

The final section of *Tutorial 10* [169] is using EM parameter learning on a structure created by the PC algorithm.

6.17.3 Validation

To evaluate the predictive quality of your network you can use the `Validator` class.

The `Validator` constructor requires references to `DataSet` and `Network` objects to be specified. To properly match the network and data the constructor also requires the array of `DataMatch` objects (as did `EM.learn` method).

After the validator object is constructed, you need to specify which nodes in the network are considered class nodes by calling `Validator.addClassNode` method. Validation requires at least one class node.

For each record in the dataset during the validation, the variables matched to non-class nodes are used to set the evidence. The posterior probabilities are then calculated and for each class node the outcome with the highest probability is selected as a predicted outcome. The prediction is compared with an outcome in the dataset variable associated with the class node. The number of matches and calculated posteriors are used to obtain the accuracy, confusion matrix, ROC and calibration curves.

Validation can be either performed without parameter learning using `Validator.test` method, or with parameter learning using `Validator::kFold` and `leaveOneOut` methods. K-fold crossvalidation divides the dataset into K parts of equal size, trains the network on K-1 parts, and tests it on the last, Kth part. The process is repeated K times, with a different part of the data being selected for testing. Leave-one-out is an extreme case of K-fold, in which K is equal to the number of records in the data set.

The example below performs K-fold crossvalidation with 5 folds using one class node. The accuracy is obtained for the outcome with the index zero (that is, the first outcome of the node).

Java:

```
DataSet ds = new DataSet();
Network net = new Network();
// load network and data here
DataMatch[] matching = ds.matchNetwork();
Validator validator = new Validator(ds, net, matching);
int classNodehandle = net.getNode("someNodeId");
validator.addClassNode(classNodeHandle);
EM em = new EM();
// optionally tweak EM options here
validator.kFold(em, 5);
double acc = validator.getAccuracy(classNodeHandle, 0);
```

Python:

```
ds = pysmile.learning.DataSet()
net = pysmile.Network()
# load network and data here
matching = ds.match_network(net)
validator = pysmile.learning.Validator(ds, net, matching)
classNodehandle = net.getNode("someNodeId")
```

```
validator.addClassNode(classNodeHandle)
em = pysmile.learning.EM()
# optionally tweak EM options here
validator.k_fold(em, 5)
acc = validator.get_accuracy(classNodeHandle, 0)
```

R:

```
ds <- DataSet()
net <- Network()
# load network and data here
matching <- ds$matchNetwork()
validator <- Validator(ds, net, matching)
classNodehandle <- net$getNode("someNodeId")
validator$addClassNode(classNodeHandle)
em <- EM()
# optionally tweak EM options here
validator$kFold(em, 5)
acc <- validator$getAccuracy(classNodeHandle, 0)
```

C#:

```
DataSet ds = new DataSet();
Network net = new Network();
// load network and data here
DataMatch[] matching = ds.MatchNetwork();
Validator validator = new Validator(ds, net, matching);
int classNodehandle = net.GetNode("someNodeId");
validator.AddClassNode(classNodeHandle);
EM em = new EM();
// optionally tweak EM options here
validator.KFold(em, 5);
double acc = validator.GetAccuracy(classNodeHandle, 0);
```

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Tutorials

7 Tutorials

The complete, functionally equivalent source code for all the tutorials in Java, Python, R and C# is provided later in this chapter. The multi-line code snippets in the tutorial descriptions preceeding the source code are also given in Java, Python and C#. The inline examples in text paragraphs are using Java syntax (like `Network.updateBeliefs`) for brevity.

You can also download tutorial sources from our documentation site at https://support.bayesfusion.com/docs

7.1 Tutorial 1: Creating a Bayesian Network

Consider a slight twist on the problem described in the *Hello, SMILE Wrapper!* [22] section of this manual.

The twist will include adding an additional variable *State of the economy* (with the identifier *Economy*) with three outcomes (*Up*, *Flat*, and *Down*) modeling the developments in the economy. These developments are relevant to the decision, as they are impacting expert predictions. When the economy is heading *Up*, our expert makes more optimistic predictions, when it is heading *Down*, the expert makes more pessimistic predictions for the same venture. This is reflected by a directed arc from the node *State of the economy* to the node *Expert forecast*. *State of the economy* also impacts the probability of venture being successful, which we model by adding another arc.

We will show how to create this model and how to save it to disk. In subsequent tutorials, we will show how to enter observations (evidence), how to perform inference, and how to retrieve the calculation results.

We start by declaring our network variable. The three nodes in the network are subsequently created by calling a helper method `createCptNode`.

Java:

```
Network net = new Network();
int e = createCptNode(net,
    "Economy", "State of the economy",
    new String[] {"Up","Flat","Down"},
    160, 40);
int s = createCptNode(net,
    "Success", "Success of the venture",
    new String[] {"Success","Failure"},
    60, 40);
int f = createCptNode(net,
    "Forecast", "Expert forecast",
    new String[] {"Good","Moderate","Poor"},
    110, 140);
```

Python:

```
net = pysmile.Network()
e = self.create_cpt_node(net,
    "Economy", "State of the economy",
    ["Up","Flat","Down"],
    160, 40)
s = self.create_cpt_node(net,
    "Success", "Success of the venture",
    ["Success","Failure"],
    60, 40)
f = self.create_cpt_node(net,
    "Forecast", "Expert forecast",
    ["Good","Moderate","Poor"],
    110, 140)
```

C#:

```
Network net = new Network();
int e = CreateCptNode(net,
    "Economy", "State of the economy",
    new String[] { "Up", "Flat", "Down" },
    160, 40);
int s = CreateCptNode(net,
    "Success", "Success of the venture",
    new String[] { "Success", "Failure" },
    60, 40);
int f = CreateCptNode(net,
    "Forecast", "Expert forecast",
    new String[] { "Good", "Moderate", "Poor" },
    110, 140);
```

Before connecting the nodes with arcs, let's have a look at the createCptNode method.

Java:

```
private static int createCptNode(
        Network net, String id, String name,
        String[] outcomes, int xPos, int yPos) {
    int handle = net.addNode(Network.NodeType.CPT, id);
    net.setNodeName(handle, name);
    net.setNodePosition(handle, xPos, yPos, 85, 55);
    int initialOutcomeCount = net.getOutcomeCount(handle);
    for (int i = 0; i < initialOutcomeCount; i ++) {
        net.setOutcomeId(handle, i, outcomes[i]);
    }
    for (int i = initialOutcomeCount; i < outcomes.length; i ++) {
        net.addOutcome(handle, outcomes[i]);
    }
    return handle;
}
```

Python:

```
def create_cpt_node(self, net, id, name, outcomes, x_pos, y_pos):
    handle = net.add_node(pysmile.NodeType.CPT, id)
    net.set_node_name(handle, name)
    net.set_node_position(handle, x_pos, y_pos, 85, 55)
    initial_outcome_count = net.get_outcome_count(handle)
```

```
        for i in range(0, initial_outcome_count):
            net.set_outcome_id(handle, i, outcomes[i])
        for i in range(initial_outcome_count, len(outcomes)):
            net.add_outcome(handle, outcomes[i])
        return handle
```

C#:

```
    private static int CreateCptNode(
        Network net, String id, String name,
        String[] outcomes, int xPos, int yPos)
    {
        int handle = net.AddNode(Network.NodeType.Cpt, id);
        net.SetNodeName(handle, name);
        net.SetNodePosition(handle, xPos, yPos, 85, 55);
        int initialOutcomeCount = net.GetOutcomeCount(handle);
        for (int i = 0; i < initialOutcomeCount; i++)
        {
            net.SetOutcomeId(handle, i, outcomes[i]);
        }
        for (int i = initialOutcomeCount; i < outcomes.Length; i++)
        {
            net.AddOutcome(handle, outcomes[i]);
        }
        return handle;
    }
```

The function creates a CPT node with specified identifier, name, outcomes and position on the screen. CPT nodes are created with two outcomes named *State0* and *State1*. To change the number of node outcomes and rename them, we will use two loops - the first renames the default outcomes and the second adds new outcomes.

We can now add arcs linking the nodes. Note that we can use either node handles or node identifiers. In this simple program, we use both forms just to showcase this feature.

Java:

```
    net.addArc(e, s);
    net.addArc(s, f);
    net.addArc("Economy", "Forecast");
```

Python:

```
    net.add_arc(e, s)
    net.add_arc(s, f)
    net.add_arc("Economy", "Forecast")
```

C#:

```
    net.AddArc(e, s);
    net.AddArc(s, f);
    net.AddArc("Economy", "Forecast");
```

Next step is to initialize the conditional probability tables of the nodes. See the *Multidimensional arrays* [36] section in this manual for the description of the CPT memory layout. For each of three nodes we call the `Network.setNodeDefinition` method. Here's how we set the probabilities of the *Success* node - note that the comments for each probability show the combination of outcomes it is defined for.

Java:

```
    double[] successDef = new double[] {
        0.3, // P(Success=S|Economy=U)
```

```
        0.7, // P(Success=F|Economy=U)
        0.2, // P(Success=S|Economy=F)
        0.8, // P(Success=F|Economy=F)
        0.1, // P(Success=S|Economy=D)
        0.9  // P(Success=F|Economy=D)
    };
    net.setNodeDefinition(s, successDef);
```

Python:

```
    successDef = [
        0.3, # P(Success=S|Economy=U)
        0.7, # P(Success=F|Economy=U)
        0.2, # P(Success=S|Economy=F)
        0.8, # P(Success=F|Economy=F)
        0.1, # P(Success=S|Economy=D)
        0.9  # P(Success=F|Economy=D)
    ]
    net.set_node_definition(s, successDef)
```

C#:

```
    double[] successDef = new double[]
    {
        0.3, // P(Success=S|Economy=U)
        0.7, // P(Success=F|Economy=U)
        0.2, // P(Success=S|Economy=F)
        0.8, // P(Success=F|Economy=F)
        0.1, // P(Success=S|Economy=D)
        0.9  // P(Success=F|Economy=D)
    };
    net.SetNodeDefinition(s, successDef);
```

With CPTs initialized our network is complete. We write its contents to the tutorial1.xdsl file. Tutorial 2 will load this file and perform the inference. The split between tutorials is artificial, your program can use networks right after its creation without the need to write/read from the file system.

Java:

```
    net.writeFile("tutorial1.xdsl");
```

Python:

```
    net.write_file("tutorial1.xdsl");
```

C#:

```
    net.WriteFile("tutorial1.xdsl");
```

7.1.1 Tutorial1.java

```
package tutorials;

import smile.*;

// Tutorial1 creates a simple network with three nodes,
// then writes its content as XDSL file to disk.

public class Tutorial1 {
    public static void run() {
        System.out.println("Starting Tutorial1...");
```

```
Network net = new Network();

int e = createCptNode(net,
    "Economy", "State of the economy",
    new String[] {"Up","Flat","Down"},
    160, 40);

int s = createCptNode(net,
    "Success", "Success of the venture",
    new String[] {"Success","Failure"},
    60, 40);

int f = createCptNode(net,
    "Forecast", "Expert forecast",
    new String[] {"Good","Moderate","Poor"},
    110, 140);

net.addArc(e, s);
net.addArc(s, f);

// we can also use node identifiers when creating arcs
net.addArc("Economy", "Forecast");

double[] economyDef = {
    0.2, // P(Economy=U)
    0.7, // P(Economy=F)
    0.1  // P(Economy=D)
};
net.setNodeDefinition(e, economyDef);

double[] successDef = new double[] {
    0.3, // P(Success=S|Economy=U)
    0.7, // P(Success=F|Economy=U)
    0.2, // P(Success=S|Economy=F)
    0.8, // P(Success=F|Economy=F)
    0.1, // P(Success=S|Economy=D)
    0.9  // P(Success=F|Economy=D)
};
net.setNodeDefinition(s, successDef);

double[] forecastDef = new double[] {
    0.70, // P(Forecast=G|Success=S,Economy=U)
    0.29, // P(Forecast=M|Success=S,Economy=U)
    0.01, // P(Forecast=P|Success=S,Economy=U)

    0.65, // P(Forecast=G|Success=S,Economy=F)
    0.30, // P(Forecast=M|Success=S,Economy=F)
    0.05, // P(Forecast=P|Success=S,Economy=F)

    0.60, // P(Forecast=G|Success=S,Economy=D)
    0.30, // P(Forecast=M|Success=S,Economy=D)
    0.10, // P(Forecast=P|Success=S,Economy=D)

    0.15, // P(Forecast=G|Success=F,Economy=U)
    0.30, // P(Forecast=M|Success=F,Economy=U)
```

```
            0.55, // P(Forecast=P|Success=F,Economy=U)

            0.10, // P(Forecast=G|Success=F,Economy=F)
            0.30, // P(Forecast=M|Success=F,Economy=F)
            0.60, // P(Forecast=P|Success=F,Economy=F)

            0.05, // P(Forecast=G|Success=F,Economy=D)
            0.25, // P(Forecast=G|Success=F,Economy=D)
            0.70  // P(Forecast=G|Success=F,Economy=D)
        };
        net.setNodeDefinition(f, forecastDef);

        net.writeFile("tutorial1.xdsl");

        System.out.println("Tutorial1 complete: Network written to tutorial1.xdsl");
    }

    private static int createCptNode(
            Network net, String id, String name,
            String[] outcomes, int xPos, int yPos) {
        int handle = net.addNode(Network.NodeType.CPT, id);

        net.setNodeName(handle, name);
        net.setNodePosition(handle, xPos, yPos, 85, 55);

        int initialOutcomeCount = net.getOutcomeCount(handle);
        for (int i = 0; i < initialOutcomeCount; i ++) {
            net.setOutcomeId(handle, i, outcomes[i]);
        }

        for (int i = initialOutcomeCount; i < outcomes.length; i ++) {
            net.addOutcome(handle, outcomes[i]);
        }

        return handle;
    }
}
```

7.1.2 Tutorial1.py

```
import pysmile

# Tutorial1 creates a simple network with three nodes,
# then writes its content as XDSL file to disk.

class Tutorial1:
    def __init__(self):
        print("Starting Tutorial1...")
        net = pysmile.Network()

        e = self.create_cpt_node(net,
            "Economy", "State of the economy",
            ["Up","Flat","Down"],
            160, 40)
```

```
s = self.create_cpt_node(net,
    "Success", "Success of the venture",
    ["Success","Failure"],
    60, 40)

f = self.create_cpt_node(net,
    "Forecast", "Expert forecast",
    ["Good","Moderate","Poor"],
    110, 140)

net.add_arc(e, s)
net.add_arc(s, f)

# we can also use node identifiers when creating arcs
net.add_arc("Economy", "Forecast");

economyDef = [
    0.2, # P(Economy=U)
    0.7, # P(Economy=F)
    0.1  # P(Economy=D)
]
net.set_node_definition(e, economyDef)

successDef = [
    0.3, # P(Success=S|Economy=U)
    0.7, # P(Success=F|Economy=U)
    0.2, # P(Success=S|Economy=F)
    0.8, # P(Success=F|Economy=F)
    0.1, # P(Success=S|Economy=D)
    0.9  # P(Success=F|Economy=D)
]
net.set_node_definition(s, successDef)

forecastDef = [
    0.70, # P(Forecast=G|Success=S,Economy=U)
    0.29, # P(Forecast=M|Success=S,Economy=U)
    0.01, # P(Forecast=P|Success=S,Economy=U)

    0.65, # P(Forecast=G|Success=S,Economy=F)
    0.30, # P(Forecast=M|Success=S,Economy=F)
    0.05, # P(Forecast=P|Success=S,Economy=F)

    0.60, # P(Forecast=G|Success=S,Economy=D)
    0.30, # P(Forecast=M|Success=S,Economy=D)
    0.10, # P(Forecast=P|Success=S,Economy=D)

    0.15,  # P(Forecast=G|Success=F,Economy=U)
    0.30, # P(Forecast=M|Success=F,Economy=U)
    0.55, # P(Forecast=P|Success=F,Economy=U)

    0.10, # P(Forecast=G|Success=F,Economy=F)
    0.30, # P(Forecast=M|Success=F,Economy=F)
    0.60, # P(Forecast=P|Success=F,Economy=F)

    0.05, # P(Forecast=G|Success=F,Economy=D)
```

```
            0.25, # P(Forecast=G|Success=F,Economy=D)
            0.70  # P(Forecast=G|Success=F,Economy=D)
        ]
        net.set_node_definition(f, forecastDef)

        net.write_file("tutorial1.xdsl")

        print("Tutorial1 complete: Network written to tutorial1.xdsl")

    def create_cpt_node(self, net, id, name, outcomes, x_pos, y_pos):
        handle = net.add_node(pysmile.NodeType.CPT, id)

        net.set_node_name(handle, name)
        net.set_node_position(handle, x_pos, y_pos, 85, 55)

        initial_outcome_count = net.get_outcome_count(handle)

        for i in range(0, initial_outcome_count):
            net.set_outcome_id(handle, i, outcomes[i])

        for i in range(initial_outcome_count, len(outcomes)):
            net.add_outcome(handle, outcomes[i])

        return handle
```

7.1.3 Tutorial1.R

```
library(rSMILE)
source("License.R")

createCptNode = function(net, id, name, outcomes, xPos, yPos) {
    handle <- net$addNode(net$NodeType$CPT, id)

    net$setNodeName(handle, name)
    net$setNodePosition(handle, xPos, yPos, 85L, 55L)
    outcomesCount <- length(outcomes)
    initialOutcomeCount <- net$getOutcomeCount(handle)
    i <- 0
    for (outcome in outcomes[1:initialOutcomeCount]) {
        net$setOutcomeId(handle, i, outcome)
        i <- i + 1
    }

    if ((initialOutcomeCount + 1) <= outcomesCount) {
        for (outcome in outcomes[(initialOutcomeCount + 1):(outcomesCount)]) {
            net$addOutcome(handle, outcome)
        }
    }

    return(handle)
}

cat("Starting Tutorial1...\n")

net <- Network()
```

```
e <- createCptNode(net, "Economy", "State of the economy",
    c("Up", "Flat", "Down"), 160L, 40L)

s <- createCptNode(net, "Success", "Success of the venture",
    c("Success","Failure"), 60L, 40L)

f <- createCptNode(net, "Forecast", "Expert forecast",
    c("Good","Moderate","Poor"), 110L, 140L)

net$addArc(e, s)
net$addArc(s, f)

net$addArc("Economy", "Forecast")

economyDef <- c(0.2, # P(Economy=U)
                0.7, # P(Economy=F)
                0.1  # P(Economy=D)
               )
net$setNodeDefinition(e, economyDef)

successDef <- c(0.3, # P(Success=S|Economy=U)
                0.7, # P(Success=F|Economy=U)
                0.2, # P(Success=S|Economy=F)
                0.8, # P(Success=F|Economy=F)
                0.1, # P(Success=S|Economy=D)
                0.9  # P(Success=F|Economy=D)
               )
net$setNodeDefinition(s, successDef)

forecastDef <- c(0.70, # P(Forecast=G|Success=S,Economy=U)
                 0.29, # P(Forecast=M|Success=S,Economy=U)
                 0.01, # P(Forecast=P|Success=S,Economy=U)

                 0.65, # P(Forecast=G|Success=S,Economy=F)
                 0.30, # P(Forecast=M|Success=S,Economy=F)
                 0.05, # P(Forecast=P|Success=S,Economy=F)

                 0.60, # P(Forecast=G|Success=S,Economy=D)
                 0.30, # P(Forecast=M|Success=S,Economy=D)
                 0.10, # P(Forecast=P|Success=S,Economy=D)

                 0.15, # P(Forecast=G|Success=F,Economy=U)
                 0.30, # P(Forecast=M|Success=F,Economy=U)
                 0.55, # P(Forecast=P|Success=F,Economy=U)

                 0.10, # P(Forecast=G|Success=F,Economy=F)
                 0.30, # P(Forecast=M|Success=F,Economy=F)
                 0.60, # P(Forecast=P|Success=F,Economy=F)

                 0.05, # P(Forecast=G|Success=F,Economy=D)
                 0.25, # P(Forecast=G|Success=F,Economy=D)
                 0.70  # P(Forecast=G|Success=F,Economy=D)
                )
net$setNodeDefinition(f, forecastDef)
```

```
net$writeFile("tutorial1.xdsl")

cat("Tutorial1 complete: Network written to tutorial1.xdsl\n")
```

7.1.4 Tutorial1.cs

```
using System;
using Smile;

// Tutorial1 creates a simple network with three nodes,
// then writes its content as XDSL file to disk.

namespace SmileNetTutorial
{
    class Tutorial1
    {
        public static void Run()
        {
            Console.WriteLine("Starting Tutorial1...");
            Network net = new Network();

            int e = CreateCptNode(net,
                "Economy", "State of the economy",
                new String[] { "Up", "Flat", "Down" },
                160, 40);

            int s = CreateCptNode(net,
                "Success", "Success of the venture",
                new String[] { "Success", "Failure" },
                60, 40);

            int f = CreateCptNode(net,
                "Forecast", "Expert forecast",
                new String[] { "Good", "Moderate", "Poor" },
                110, 140);

            net.AddArc(e, s);
            net.AddArc(s, f);

            // we can also use node identifiers when creating arcs
            net.AddArc("Economy", "Forecast");

            double[] economyDef =
            {
                0.2, // P(Economy=U)
                0.7, // P(Economy=F)
                0.1  // P(Economy=D)
            };
            net.SetNodeDefinition(e, economyDef);

            double[] successDef = new double[]
            {
                0.3, // P(Success=S|Economy=U)
                0.7, // P(Success=F|Economy=U)
                0.2, // P(Success=S|Economy=F)
```

```
            0.8, // P(Success=F|Economy=F)
            0.1, // P(Success=S|Economy=D)
            0.9  // P(Success=F|Economy=D)
        };
        net.SetNodeDefinition(s, successDef);

        double[] forecastDef = new double[]
        {
            0.70, // P(Forecast=G|Success=S,Economy=U)
            0.29, // P(Forecast=M|Success=S,Economy=U)
            0.01, // P(Forecast=P|Success=S,Economy=U)

            0.65, // P(Forecast=G|Success=S,Economy=F)
            0.30, // P(Forecast=M|Success=S,Economy=F)
            0.05, // P(Forecast=P|Success=S,Economy=F)

            0.60, // P(Forecast=G|Success=S,Economy=D)
            0.30, // P(Forecast=M|Success=S,Economy=D)
            0.10, // P(Forecast=P|Success=S,Economy=D)

            0.15,  // P(Forecast=G|Success=F,Economy=U)
            0.30, // P(Forecast=M|Success=F,Economy=U)
            0.55, // P(Forecast=P|Success=F,Economy=U)

            0.10, // P(Forecast=G|Success=F,Economy=F)
            0.30, // P(Forecast=M|Success=F,Economy=F)
            0.60, // P(Forecast=P|Success=F,Economy=F)

            0.05, // P(Forecast=G|Success=F,Economy=D)
            0.25, // P(Forecast=G|Success=F,Economy=D)
            0.70  // P(Forecast=G|Success=F,Economy=D)
        };
        net.SetNodeDefinition(f, forecastDef);

        net.WriteFile("tutorial1.xdsl");

        Console.WriteLine("Tutorial1 complete: Network written to tutorial1.xdsl");
    }

    private static int CreateCptNode(
        Network net, String id, String name,
        String[] outcomes, int xPos, int yPos)
    {
        int handle = net.AddNode(Network.NodeType.Cpt, id);

        net.SetNodeName(handle, name);
        net.SetNodePosition(handle, xPos, yPos, 85, 55);

        int initialOutcomeCount = net.GetOutcomeCount(handle);
        for (int i = 0; i < initialOutcomeCount; i++)
        {
            net.SetOutcomeId(handle, i, outcomes[i]);
        }

        for (int i = initialOutcomeCount; i < outcomes.Length; i++)
```

```
            {
                net.AddOutcome(handle, outcomes[i]);
            }

            return handle;
        }
    }
}
```

7.2 Tutorial 2: Inference with a Bayesian Network

Tutorial 2 begins with the model we have previously created. We will perform multiple calls to Bayesian inference algorithm through the `Network.updateBeliefs`, starting with network without any evidence. After each `updateBeliefs` call the posterior probabilities of nodes will be displayed.

The model is loaded with the `Network.readFile`.

Java:

```
Java:
net.readFile("tutorial1.xdsl");
```

Python:

```
net.read_file("tutorial1.xdsl");
```

C#:

```
net.ReadFile("tutorial1.xdsl");
```

We update the probabilities and proceed to display them using the helper method `printAllPosteriors` defined in this tutorial.

Java:

```
printf("Posteriors with no evidence set:\n");
net.updateBeliefs();
printAllPosteriors(net);
```

Python:

```
print("Posteriors with no evidence set:")
net.update_beliefs()
self.print_all_posteriors(net)
```

C#:

```
Console.WriteLine("Posteriors with no evidence set:");
net.UpdateBeliefs();
PrintAllPosteriors(net);
```

`printAllPosteriors` displays posterior probabilities calculated by `updateBeliefs` for each node. To iterate over the nodes, `Network.getFirstNode` and `getNextNode` are used. In the body of the loop we call another helper function, `printPosteriors`.

Java:

```
for (int h = net.getFirstNode(); h >= 0; h = net.getNextNode(h)) {
    printPosteriors(net, h);
}
```

Python:

```
handle = net.get_first_node()
while (handle >= 0):
    self.print_posteriors(net, handle)
    handle = net.get_next_node(handle)
```

C#:

```
for (int h = net.GetFirstNode(); h >= 0; h = net.GetNextNode(h))
{
    PrintPosteriors(net, h);
}
```

`printPosteriors` checks if node has evidence set by calling `Network.isEvidence`; if this is the case the name of the evidence state is displayed. Please note that for demonstration purposes this tutorial calls `Network.getEvidence` to obtain an integer representing the index of the evidence state, then converts the integer index to outcome id with `Network.getOutcomeId`. The `Network.getEvidenceId` method combines these two actions into one call.

If node is does not have any evidence set, `printPosteriors` iterates over all states and displays the posterior probability of each.

Back in the main function of the tutorial, we repeatedly call `changeEvidenceAndUpdate` helper function to change evidence, update network and display posteriors. Note that we need to call different methods of the `Network` class to set evidence to the specified outcome (`setEvidence`) and remove the evidence (`clearEvidence`).

7.2.1 Tutorial2.java

```
package tutorials;

import smile.*;

// Tutorial2 loads the XDSL file created by Tutorial1,
// then performs the series of inference calls,
// changing evidence each time.

public class Tutorial2 {
    public static void run() {
        System.out.println("Starting Tutorial2...");
        Network net = new Network();

        // load the network created by Tutorial1
        net.readFile("tutorial1.xdsl");

        System.out.println("Posteriors with no evidence set:");
        net.updateBeliefs();
        printAllPosteriors(net);

        System.out.println("Setting Forecast=Good.");
        changeEvidenceAndUpdate(net, "Forecast", "Good");

        System.out.println("Adding Economy=Up.");
        changeEvidenceAndUpdate(net, "Economy", "Up");

        System.out.println("Changing Forecast to Poor, keeping Economy=Up.");
```

```
        changeEvidenceAndUpdate(net, "Forecast", "Poor");

        System.out.println("Removing evidence from Economy, keeping Forecast=Poor.");
        changeEvidenceAndUpdate(net, "Economy", null);

        System.out.println("Tutorial2 complete.");
    }

    private static void printPosteriors(Network net, int nodeHandle) {
        String nodeId = net.getNodeId(nodeHandle);
        if (net.isEvidence(nodeHandle)) {
            System.out.printf("%s has evidence set (%s)\n",
                nodeId,
                net.getOutcomeId(nodeHandle, net.getEvidence(nodeHandle)));
        } else {
            double[] posteriors = net.getNodeValue(nodeHandle);
            for (int i = 0; i < posteriors.length; i ++) {
                System.out.printf("P(%s=%s)=%f\n",
                    nodeId,
                    net.getOutcomeId(nodeHandle, i),
                    posteriors[i]);
            }
        }
    }

    private static void printAllPosteriors(Network net) {
        for (int h = net.getFirstNode(); h >= 0; h = net.getNextNode(h)) {
            printPosteriors(net, h);
        }
        System.out.println();
    }

    private static void changeEvidenceAndUpdate(
            Network net, String nodeId, String outcomeId) {
        if (outcomeId != null) {
            net.setEvidence(nodeId, outcomeId);
        } else {
            net.clearEvidence(nodeId);
        }

        net.updateBeliefs();
        printAllPosteriors(net);
    }
}
```

7.2.2 Tutorial2.py

```
import pysmile

# Tutorial2 loads the XDSL file created by Tutorial1,
# then performs the series of inference calls,
# changing evidence each time.

class Tutorial2:
    def __init__(self):
```

```
        print("Starting Tutorial2...")
        net = pysmile.Network()

        # load the network created by Tutorial1
        net.read_file("tutorial1.xdsl")

        print("Posteriors with no evidence set:")
        net.update_beliefs()
        self.print_all_posteriors(net)

        print("Setting Forecast=Good.")
        self.change_evidence_and_update(net, "Forecast", "Good")

        print("Adding Economy=Up.")
        self.change_evidence_and_update(net, "Economy", "Up")

        print("Changing Forecast to Poor, keeping Economy=Up.")
        self.change_evidence_and_update(net, "Forecast", "Poor")

        print("Removing evidence from Economy, keeping Forecast=Poor.")
        self.change_evidence_and_update(net, "Economy", None)

        print("Tutorial2 complete.")

    def print_posteriors(self, net, node_handle):
        node_id = net.get_node_id(node_handle)
        if net.is_evidence(node_handle):
            print(f"{node_id} has evidence set ({net.get_evidence_id(node_handle)})")
        else :
            posteriors = net.get_node_value(node_handle)
            for i in range(0, len(posteriors)):
                print(f"P({node_id}={net.get_outcome_id(node_handle, i)})={posteriors[i]}")

    def print_all_posteriors(self, net):
        for handle in net.get_all_nodes():
            self.print_posteriors(net, handle)

    def change_evidence_and_update(self, net, node_id, outcome_id):
        if outcome_id is not None:
            net.set_evidence(node_id, outcome_id)
        else:
            net.clear_evidence(node_id)
        net.update_beliefs()
        self.print_all_posteriors(net)
        print()
```

7.2.3 Tutorial2.R

```
library(rSMILE)
source("License.R")

printPosteriors = function(net, nodeHandle) {
    nodeId <- net$getNodeId(nodeHandle)
    if (net$isEvidence(nodeHandle)) {
        cat(sprintf("%s has evidence set (%s)\n",
```

```
            nodeId,
            net$getOutcomeId(nodeHandle, net$getEvidence(nodeHandle))))

    } else {
        posteriors <- net$getNodeValue(nodeHandle)
        for (i in 0:(length(posteriors)-1)) {
            cat(sprintf("P(%s=%s)=%f\n",
                nodeId, net$getOutcomeId(nodeHandle, i),posteriors[i+1]))
        }
    }
}

printAllPosteriors = function(net) {
    nodes <- net$getAllNodes()
    for (h in nodes) {
        printPosteriors(net, h)
    }
    cat("\n")
}

changeEvidenceAndUpdate = function(net, nodeId, outcomeId) {
    if (is.null(outcomeId)) {
        net$clearEvidence(nodeId)
    } else {
        net$setEvidence(nodeId, outcomeId)
    }
    net$updateBeliefs()
    printAllPosteriors(net)
}

cat("Starting Tutorial2...\n")
net <- Network()

# load the network created by Tutorial1
net$readFile("tutorial1.xdsl")

cat("Posteriors with no evidence set:\n")
net$updateBeliefs()
printAllPosteriors(net)

cat("Setting Forecast=Good.\n");
changeEvidenceAndUpdate(net, "Forecast", "Good");

cat("Adding Economy=Up.\n");
changeEvidenceAndUpdate(net, "Economy", "Up");

cat("Changing Forecast to Poor, keeping Economy=Up.\n");
changeEvidenceAndUpdate(net, "Forecast", "Poor");

cat("Removing evidence from Economy, keeping Forecast=Poor.\n");
changeEvidenceAndUpdate(net, "Economy", NULL);

cat("Tutorial2 complete.\n");
```

7.2.4 Tutorial2.cs

```
using System;
using Smile;

// Tutorial2 loads the XDSL file created by Tutorial1,
// then performs the series of inference calls,
// changing evidence each time.

namespace SmileNetTutorial
{
    class Tutorial2
    {
        public static void Run()
        {
            Console.WriteLine("Starting Tutorial2...");
            Network net = new Network();

            // load the network created by Tutorial1
            net.ReadFile("tutorial1.xdsl");

            Console.WriteLine("Posteriors with no evidence set:");
            net.UpdateBeliefs();
            PrintAllPosteriors(net);

            Console.WriteLine("Setting Forecast=Good.");
            ChangeEvidenceAndUpdate(net, "Forecast", "Good");

            Console.WriteLine("Adding Economy=Up.");
            ChangeEvidenceAndUpdate(net, "Economy", "Up");

            Console.WriteLine("Changing Forecast to Poor, keeping Economy=Up.");
            ChangeEvidenceAndUpdate(net, "Forecast", "Poor");

            Console.WriteLine("Removing evidence from Economy, keeping Forecast=Poor.");
            ChangeEvidenceAndUpdate(net, "Economy", null);

            Console.WriteLine("Tutorial2 complete.");
        }

        private static void PrintPosteriors(Network net, int nodeHandle)
        {
            String nodeId = net.GetNodeId(nodeHandle);
            if (net.IsEvidence(nodeHandle))
            {
                Console.WriteLine("{0} has evidence set ({1})",
                    nodeId,
                    net.GetOutcomeId(nodeHandle, net.GetEvidence(nodeHandle)));
            }
            else
            {
                double[] posteriors = net.GetNodeValue(nodeHandle);
                for (int i = 0; i < posteriors.Length; i++)
                {
                    Console.WriteLine("P({0}={1})={2}",
```

```
                        nodeId, net.GetOutcomeId(nodeHandle, i), posteriors[i]);
                }
            }
        }

        private static void PrintAllPosteriors(Network net)
        {
            for (int h = net.GetFirstNode(); h >= 0; h = net.GetNextNode(h))
            {
                PrintPosteriors(net, h);
            }
            Console.WriteLine();
        }

        private static void ChangeEvidenceAndUpdate(
            Network net, String nodeId, String outcomeId)
        {
            if (outcomeId != null)
            {
                net.SetEvidence(nodeId, outcomeId);
            }
            else
            {
                net.ClearEvidence(nodeId);
            }

            net.UpdateBeliefs();
            PrintAllPosteriors(net);
        }
    }
}
```

7.3 Tutorial 3: Exploring the contents of a model

This tutorial will not perform any calculations. Instead, we will display the information about the network structure (nodes and arcs) and parameters (in this case, conditional probability tables).

We load the network created by `Tutorial1` and for each node invoke the locally defined helper method `printNodeInfo`. This is where real work is done. The first displayed node attributes are identifier and name.

Java:

```
System.out.printf("Node id/name: %s/%s\n",
    net.getNodeId(nodeHandle),
    net.getNodeName(nodeHandle));
```

Python:

```
print("Node id/name: " + net.get_node_id(node_handle) + "/" +
    net.get_node_name(node_handle))
```

C#:

```
Console.WriteLine("Node id/name: {0}/{1}",
    net.GetNodeId(nodeHandle),
    net.GetNodeName(nodeHandle));
```

The identfiers of node's outcomes are next.

Java:

```
System.out.print("  Outcomes:");
for (String outcomeId: net.getOutcomeIds(nodeHandle)) {
    System.out.print(" " + outcomeId);
}
```

Python:

```
print("  Outcomes: " + " ".join(net.get_outcome_ids(node_handle)))
```

C#:

```
foreach (String outcomeId in net.GetOutcomeIds(nodeHandle))
{
    Console.Write(" " + outcomeId);
}
```

The parents of the node follow.

Java:

```
String[] parentIds = net.getParentIds(nodeHandle);
if (parentIds.length > 0) {
    System.out.print("  Parents:");
    for (String parentId: parentIds) {
        System.out.print(" " + parentId);
    }
    System.out.println();
}
```

Python:

```
parent_ids = net.get_parent_ids(node_handle)
if len(parent_ids) > 0:
    print("  Parents: " + " ".join(parent_ids))
```

C#:

```
String[] parentIds = net.GetParentIds(nodeHandle);
if (parentIds.Length > 0)
{
    Console.Write("  Parents:");
    foreach (String parentId in parentIds)
    {
        Console.Write(" " + parentId);
    }
    Console.WriteLine();
}
```

We proceed to display information about node's children. The code fragment is virtually identical to the iteration over parents. Note that while tutorial uses `Network.getParentIds` and `getChildIds` to obtain identifiers of related nodes, we could alternatively use the `Network.getParents` and `getChildren`, which return the node handles (integer numbers) instead of identifiers (strings).

Finally, the node probabilities are displayed by the `printCptMatrix` helper. We retrieve the single-dimensional array containing the probabilities with `Network.getNodeDefinition` and iterate over its elements, translating each index into a multi-dimensional coordinates of the elements within node's CPT. This conversion is performed in the helper method `indexToCoords`, which requires the information about the outcome counts of

the node and its parents in its `dimSizes` input parameter. The first part of printCptMatrix obtains the CPT and initializes dimSizes

Java:

```
double[] cpt = net.getNodeDefinition(nodeHandle);
int[] parents = net.getParents(nodeHandle);
int dimCount = 1 + parents.length;
int[] dimSizes = new int[dimCount];
for (int i = 0; i < dimCount - 1; i ++) {
    dimSizes[i] = net.getOutcomeCount(parents[i]);
}
dimSizes[dimSizes.length - 1] = net.getOutcomeCount(nodeHandle);
```

Python:

```
cpt = net.get_node_definition(node_handle)
parents = net.get_parents(node_handle)
dim_count = 1 + len(parents)
dim_sizes = [0] * dim_count
for i in range(0, dim_count - 1):
    dim_sizes[i] = net.get_outcome_count(parents[i])
dim_sizes[len(dim_sizes) - 1] = net.get_outcome_count(node_handle)
```

C#:

```
double[] cpt = net.GetNodeDefinition(nodeHandle);
int[] parents = net.GetParents(nodeHandle);
int dimCount = 1 + parents.Length;
int[] dimSizes = new int[dimCount];
for (int i = 0; i < dimCount - 1; i++)
{
    dimSizes[i] = net.GetOutcomeCount(parents[i]);
}
dimSizes[dimSizes.Length - 1] = net.GetOutcomeCount(nodeHandle);
```

The main loop in the printCptMatrix uses performs the iteration over the elements of the CPT. The `coords` integer array is filled by indexToCoords and used to print the textual information about the outcome of the node and parents for each element. Note that the node outcome is the rightmost entry in the `coords`. The parents' outcome indexes start from the left at index 0 in the `coords`. Part of the `Tutorial3` output for the node *Forecast* is show below. All lines starting with "P"(were printed by `printCptMatrix`.

```
Node: Expert forecast
 Outcomes: Good Moderate Poor
 Parents: Success Economy
 Definition type: CPT
   P(Good | Success=Success,Economy=Up)=0.7
   P(Moderate | Success=Success,Economy=Up)=0.29
   P(Poor | Success=Success,Economy=Up)=0.01
   P(Good | Success=Success,Economy=Flat)=0.65
   P(Moderate | Success=Success,Economy=Flat)=0.3
   P(Poor | Success=Success,Economy=Flat)=0.05
   P(Good | Success=Success,Economy=Down)=0.6
   P(Moderate | Success=Success,Economy=Down)=0.3
   P(Poor | Success=Success,Economy=Down)=0.1
   P(Good | Success=Failure,Economy=Up)=0.15
   P(Moderate | Success=Failure,Economy=Up)=0.3
   P(Poor | Success=Failure,Economy=Up)=0.55
```

```
P(Good | Success=Failure,Economy=Flat)=0.1
P(Moderate | Success=Failure,Economy=Flat)=0.3
P(Poor | Success=Failure,Economy=Flat)=0.6
P(Good | Success=Failure,Economy=Down)=0.05
P(Moderate | Success=Failure,Economy=Down)=0.25
P(Poor | Success=Failure,Economy=Down)=0.7
```

7.3.1 Tutorial3.java

```
package tutorials;

import smile.*;

// Tutorial3 loads the XDSL file and prints the information
// about the structure (nodes and arcs) and the parameters
// (conditional probabilities of the nodes) of the network.

public class Tutorial3 {
    public static void run() {
        System.out.println("Starting Tutorial3...");
        Network net = new Network();

        // load the network created by Tutorial1
        net.readFile("tutorial1.xdsl");

        for (int h = net.getFirstNode(); h >= 0; h = net.getNextNode(h)) {
            printNodeInfo(net, h);
        }

        System.out.println("Tutorial3 complete.");
    }

    private static void printNodeInfo(Network net, int nodeHandle) {
        System.out.printf("Node id/name: %s/%s\n",
            net.getNodeId(nodeHandle),
            net.getNodeName(nodeHandle));

        System.out.print("  Outcomes:");
        for (String outcomeId: net.getOutcomeIds(nodeHandle)) {
            System.out.print(" " + outcomeId);
        }
        System.out.println();

        String[] parentIds = net.getParentIds(nodeHandle);
        if (parentIds.length > 0) {
            System.out.print("  Parents:");
            for (String parentId: parentIds) {
                System.out.print(" " + parentId);
            }
            System.out.println();
        }

        String[] childIds = net.getChildIds(nodeHandle);
        if (childIds.length > 0) {
```

```
            System.out.print("  Children:");
            for (String childId: childIds) {
                System.out.print(" " + childId);
            }
            System.out.println();
        }

        printCptMatrix(net, nodeHandle);
    }

    private static void printCptMatrix(Network net, int nodeHandle) {
        double[] cpt = net.getNodeDefinition(nodeHandle);
        int[] parents = net.getParents(nodeHandle);
        int dimCount = 1 + parents.length;

        int[] dimSizes = new int[dimCount];
        for (int i = 0; i < dimCount - 1; i ++) {
            dimSizes[i] = net.getOutcomeCount(parents[i]);
        }
        dimSizes[dimSizes.length - 1] = net.getOutcomeCount(nodeHandle);

        int[] coords = new int[dimCount];
        for (int elemIdx = 0; elemIdx < cpt.length; elemIdx ++) {
            indexToCoords(elemIdx, dimSizes, coords);

            String outcome = net.getOutcomeId(nodeHandle, coords[dimCount - 1]);
            System.out.printf("    P(%s", outcome);

            if (dimCount > 1) {
                System.out.print(" | ");
                for (int parentIdx = 0; parentIdx < parents.length; parentIdx++)
                {
                    if (parentIdx > 0) System.out.print(",");
                    int parentHandle = parents[parentIdx];
                    System.out.printf("%s=%s",
                        net.getNodeId(parentHandle),
                        net.getOutcomeId(parentHandle, coords[parentIdx]));
                }
            }

            double prob = cpt[elemIdx];
            System.out.printf(")=%f\n", prob);
        }
    }

    private static void indexToCoords(int index, int[] dimSizes, int[] coords) {
        int prod = 1;
        for (int i = dimSizes.length - 1; i >= 0; i --) {
            coords[i] = (index / prod) % dimSizes[i];
            prod *= dimSizes[i];
        }
    }
}
```

7.3.2 Tutorial3.py

```
import pysmile

# Tutorial3 loads the XDSL file and prints the information
# about the structure (nodes and arcs) and the parameters
# (conditional probabilities of the nodes) of the network.

class Tutorial3:
    def __init__(self):
        print("Starting Tutorial3...")
        net = pysmile.Network()

        # load the network created by Tutorial1
        net.read_file("tutorial1.xdsl")
        for h in net.get_all_nodes():
            self.print_node_info(net, h)
        print("Tutorial3 complete.")

    def print_node_info(self, net, node_handle):
        print(f"Node id/name: {net.get_node_id(node_handle)}/{net.get_node_name(node_handle)}")
        print(f"  Outcomes: {' '.join(net.get_outcome_ids(node_handle))}")

        parent_ids = net.get_parent_ids(node_handle)
        if len(parent_ids) > 0:
            print(f"  Parents: {' '.join(parent_ids)}")
        child_ids = net.get_child_ids(node_handle)
        if len(child_ids) > 0:
            print(f"  Children: {' '.join(child_ids)}")

        self.print_cpt_matrix(net, node_handle)

    def print_cpt_matrix(self, net, node_handle):
        cpt = net.get_node_definition(node_handle)
        parents = net.get_parents(node_handle)
        dim_count = 1 + len(parents)

        dim_sizes = [0] * dim_count
        for i in range(0, dim_count - 1):
            dim_sizes[i] = net.get_outcome_count(parents[i])
        dim_sizes[len(dim_sizes) - 1] = net.get_outcome_count(node_handle)

        coords = [0] * dim_count
        for elem_idx in range(0, len(cpt)):
            self.index_to_coords(elem_idx, dim_sizes, coords)

            outcome = net.get_outcome_id(node_handle, coords[dim_count - 1])
            print(f"    P({outcome}", end="")

            if dim_count > 1:
                print(" | ", end="")
                for parent_idx in range(0, len(parents)):
                    if parent_idx > 0:
                        print(",", end="")
                    parent_handle = parents[parent_idx]
```

```
                    print(f"{net.get_node_id(parent_handle)}="
                        + f"{net.get_outcome_id(parent_handle, coords[parent_idx])}", end="")

            prob = cpt[elem_idx]
            print(f")={prob}")

    def index_to_coords(self, index, dim_sizes, coords):
        prod = 1
        for i in range(len(dim_sizes) - 1, -1, -1):
            coords[i] = int(index / prod) % dim_sizes[i]
            prod *= dim_sizes[i]
```

7.3.3 Tutorial3.R

```
library(rSMILE)
source("License.R")

# Tutorial3 loads the XDSL file and prints the information
# about the structure (nodes and arcs) and the parameters
# (conditional probabilities of the nodes) of the network.

indexToCoords = function(index, dimSizes) {
    prod <- 1L
    coords <- integer(length=length(dimSizes))
    for (i in length(dimSizes):1) {
        coords[i] <- floor(index / prod) %% dimSizes[[i]]
        prod <- prod * dimSizes[[i]]
    }
    return(coords)
}

printCptMatrix = function(net, nodeHandle) {
    cpt <- net$getNodeDefinition(nodeHandle)
    parents <- net$getParents(nodeHandle)
    dimCount <- 1 + length(parents)

    dimSizes <- sapply(parents, function(x) net$getOutcomeCount(x))
    dimSizes[length(dimSizes)+1] <- net$getOutcomeCount(nodeHandle)

    for (elemIdx in 0:(length(cpt)-1)) {
        coords <- indexToCoords(elemIdx, dimSizes)
        outcome <- net$getOutcomeId(nodeHandle, coords[dimCount])
        cat("    P(", outcome, sep="");
        if (dimCount > 1) {
            cat(" | ")
            parentIds <- sapply(parents, function(x) net$getNodeId(x))
            outcomeIds <- sapply(1:length(parents),
                function(x) net$getOutcomeId(parents[x], coords[x]))

            cat(paste(parentIds, outcomeIds, sep="=", collapse=","))
        }
        prob <- cpt[elemIdx + 1]
        cat(sprintf(")=%f\n", prob))
    }
}
```

```
printNodeInfo = function(net, nodeHandle) {
    cat(sprintf("Node id/name: %s/%s\n",
        net$getNodeId(nodeHandle),
        net$getNodeName(nodeHandle)))
    cat("  Outcomes: ")
    cat(paste(net$getOutcomeIds(nodeHandle), collapse=" "))
    cat("\n")

    parentIds <- net$getParentIds(nodeHandle)
    if (length(parentIds) > 0) {
        cat("  Parents: ")
        cat(paste(parentIds, collapse=" "))
        cat("\n")
    }

    childIds <- net$getChildIds(nodeHandle)
    if (length(childIds) > 0) {
        cat("  Children: ")
        cat(paste(childIds, collapse=" "))
        cat("\n")
    }

    printCptMatrix(net, nodeHandle)
}

cat("Starting Tutorial3...\n")
net <- Network()

# load the network created by Tutorial1
net$readFile("tutorial1.xdsl")

nodes <- net$getAllNodes()

for (h in nodes) {
    printNodeInfo(net, h)
}

cat("Tutorial3 complete.\n")
```

7.3.4 Tutorial3.cs

```
using System;
using Smile;

// Tutorial3 loads the XDSL file and prints the information
// about the structure (nodes and arcs) and the parameters
// (conditional probabilities of the nodes) of the network.

namespace SmileNetTutorial
{
    class Tutorial3
    {
        public static void Run()
        {
```

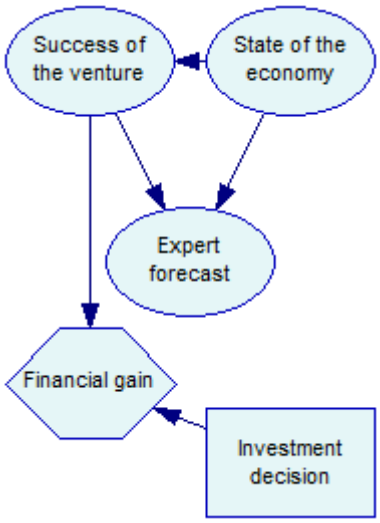
```
    Console.WriteLine("Starting Tutorial3...");
    Network net = new Network();

    // load the network created by Tutorial1
    net.ReadFile("tutorial1.xdsl");

    for (int h = net.GetFirstNode(); h >= 0; h = net.GetNextNode(h))
    {
        PrintNodeInfo(net, h);
    }

    Console.WriteLine("Tutorial3 complete.");
}

private static void PrintNodeInfo(Network net, int nodeHandle)
{
    Console.WriteLine("Node id/name: {0}/{1}",
        net.GetNodeId(nodeHandle),
        net.GetNodeName(nodeHandle));

    Console.Write("  Outcomes:");
    foreach (String outcomeId in net.GetOutcomeIds(nodeHandle))
    {
        Console.Write(" " + outcomeId);
    }
    Console.WriteLine();

    String[] parentIds = net.GetParentIds(nodeHandle);
    if (parentIds.Length > 0)
    {
        Console.Write("  Parents:");
        foreach (String parentId in parentIds)
        {
            Console.Write(" " + parentId);
        }
        Console.WriteLine();
    }

    String[] childIds = net.GetChildIds(nodeHandle);
    if (childIds.Length > 0)
    {
        Console.Write("  Children:");
        foreach (String childId in childIds)
        {
            Console.Write(" " + childId);
        }
        Console.WriteLine();
    }

    PrintCptMatrix(net, nodeHandle);
}

private static void PrintCptMatrix(Network net, int nodeHandle)
{
    double[] cpt = net.GetNodeDefinition(nodeHandle);
```

```
            int[] parents = net.GetParents(nodeHandle);
            int dimCount = 1 + parents.Length;

            int[] dimSizes = new int[dimCount];
            for (int i = 0; i < dimCount - 1; i++)
            {
                dimSizes[i] = net.GetOutcomeCount(parents[i]);
            }
            dimSizes[dimSizes.Length - 1] = net.GetOutcomeCount(nodeHandle);

            int[] coords = new int[dimCount];
            for (int elemIdx = 0; elemIdx < cpt.Length; elemIdx++)
            {
                IndexToCoords(elemIdx, dimSizes, coords);

                String outcome = net.GetOutcomeId(nodeHandle, coords[dimCount - 1]);
                Console.Write("    P({0}", outcome);

                if (dimCount > 1)
                {
                    Console.Write(" | ");
                    for (int pIdx = 0; pIdx < parents.Length; pIdx++)
                    {
                        if (pIdx > 0) Console.Write(",");
                        int parentHandle = parents[pIdx];
                        Console.Write("{0}={1}",
                            net.GetNodeId(parentHandle),
                            net.GetOutcomeId(parentHandle, coords[pIdx]));
                    }
                }

                double prob = cpt[elemIdx];
                Console.WriteLine(")={0}", prob);
            }
        }

        private static void IndexToCoords(
            int index, int[] dimSizes, int[] coords)
        {
            int prod = 1;
            for (int i = dimSizes.Length - 1; i >= 0; i--)
            {
                coords[i] = (index / prod) % dimSizes[i];
                prod *= dimSizes[i];
            }
        }
    }
}
```

7.4 Tutorial 4: Creating the Influence Diagram

We will further expand the model created in *Tutorial 1* [82] and turn it into an influence diagram. To this effect, we will add a decision node *Investment decision* and a utility node *Financial gain*. The decision will have two possible states: *Invest* and *DoNotInvest*, which will be the two decision options under consideration. Which

option is chosen will impact the financial gain and this will be reflected by a directed arc from *Investment decision* to *Financial gain*. Whether the venture succeeds of fails will also impact the financial gain and this will be also reflected by a directed arc from *Success of the venture* to *Financial gain*.



We will show how to create this model. In the subsequent tutorial, we will show how to enter observations (evidence), how to perform inference, and how to retrieve the utilities calculated for the *Financial gain* node.

The programs starts by reading the file, just like *Tutorial 2* [93] and *Tutorial 3* [99]. We convert the identfier of the node *Success* to node handle, which we will use later to create an arc between *Success* and *Gain*. Two new nodes will be created by calling a `createNode` helper function, which is slightly modified version of the `createCptNode` from *Tutorial 1* [82]. The difference is that we now want to create different types of nodes. Therefore, `createNode` has one additional input parameter, an integer which specifies the node type. Another difference is that `createNode` needs to be able to add utility nodes, which do not have outcomes. The function checks for the value of its outcomes input parameter and if it is `null`, the outcome initialization is skipped.

createNode is called to add two new nodes:

- a decision node *Investment* , with a `Network.NodeType.DECISION` type identifier
- an utility node Gain, with a `Network.NodeType.UTILITY` type identifier

With new nodes created we connect them to the rest of the model with `Network.addArc`. The only thing left is the initialization of the parameters for the *Gain* node (*Invest* is a decision node and decision nodes have no numeric parameters). *Gain* has two parents with two outcomes each and size of its definition is 2 x 2 x 1 = 4. The program therefore specifies four numbers for the utilities.

Java:

```
double[] gainDefinition = new double[] {
    10000, // Utility(Invest=I, Success=S)
    -5000, // Utility(Invest=I, Success=F)
    500,   // Utility(Invest=D, Success=S)
    500    // Utility(Invest=D, Success=F)
};
net.setNodeDefinition(g, gainDefinition);
```

Python:

```
gain_definition = [
```

```
        10000, # Utility(Invest=I, Success=S)
        -5000, # Utility(Invest=I, Success=F)
        500,   # Utility(Invest=D, Success=S)
        500    # Utility(Invest=D, Success=F)
    ]
    net.set_node_definition(g, gain_definition)
```

C#:

```
    double[] gainDefinition = new double[]
    {
        10000, // Utility(Invest=I, Success=S)
        -5000, // Utility(Invest=I, Success=F)
        500,   // Utility(Invest=D, Success=S)
        500    // Utility(Invest=D, Success=F)
    };
    net.SetNodeDefinition(g, gainDefinition);
```

The influence diagram is now complete, so we can write its contents to the file and exit the function. *Tutorial 5*[114] will load the file and perform the inference.

7.4.1 Tutorial4.java

```
package tutorials;

import smile.*;

// Tutorial4 loads the XDSL file file created by Tutorial1
// and adds decision and utility nodes, which transforms
// a Bayesian Network (BN) into an Influence Diagram (ID).

public class Tutorial4 {
    public static void run() {
        System.out.println("Starting Tutorial4...");
        Network net = new Network();

        net.readFile("tutorial1.xdsl");

        int s = net.getNode("Success");

        int i = createNode(net, Network.NodeType.DECISION,
                "Invest", "Investment decision",
                new String[]{ "Invest", "DoNotInvest" }, 160, 240);

        int g = createNode(net, Network.NodeType.UTILITY,
                "Gain", "Financial gain", null, 60, 200);

        net.addArc(i, g);
        net.addArc(s, g);

        double[] gainDefinition = new double[] {
            10000, // Utility(Invest=I, Success=S)
            -5000, // Utility(Invest=I, Success=F)
            500,   // Utility(Invest=D, Success=S)
            500    // Utility(Invest=D, Success=F)
        };
        net.setNodeDefinition(g, gainDefinition);
```

```
        net.writeFile("tutorial4.xdsl");

        System.out.println("Tutorial4 complete: Influence diagram written to tutorial4.xdsl.");
    }

    private static int createNode(
            Network net, int nodeType, String id, String name,
            String[] outcomes, int xPos, int yPos) {
        int handle = net.addNode(nodeType, id);

        net.setNodeName(handle, name);
        net.setNodePosition(handle, xPos, yPos, 85, 55);

        if (outcomes != null) {
            int initialOutcomeCount = net.getOutcomeCount(handle);
            for (int i = 0; i < initialOutcomeCount; i ++) {
                net.setOutcomeId(handle, i, outcomes[i]);
            }

            for (int i = initialOutcomeCount; i < outcomes.length; i ++) {
                net.addOutcome(handle, outcomes[i]);
            }
        }

        return handle;
    }
}
```

7.4.2 Tutorial4.py

```
import pysmile

# Tutorial4 loads the XDSL file file created by Tutorial1
# and adds decision and utility nodes, which transforms
# a Bayesian Network (BN) into an Influence Diagram (ID).

class Tutorial4:
    def __init__(self):
        print("Starting Tutorial4...")
        net = pysmile.Network()

        net.read_file("tutorial1.xdsl")

        s = net.get_node("Success")
        i = self.create_node(net, pysmile.NodeType.DECISION,
            "Invest", "Investment decision",
            ["Invest", "DoNotInvest"], 160, 240)

        g = self.create_node(net, pysmile.NodeType.UTILITY,
            "Gain", "Financial gain", None, 60, 200)

        net.add_arc(i, g)
        net.add_arc(s, g)
```

```
        gain_definition = [
            10000, # Utility(Invest=I, Success=S)
            -5000, # Utility(Invest=I, Success=F)
            500,   # Utility(Invest=D, Success=S)
            500    # Utility(Invest=D, Success=F)
        ]
        net.set_node_definition(g, gain_definition)

        net.write_file("tutorial4.xdsl")

        print("Tutorial4 complete: Influence diagram written to tutorial4.xdsl.")

    def create_node(self,
        net, node_type, id, name,
        outcomes, xPos, yPos):
        handle = net.add_node(node_type, id)

        net.set_node_name(handle, name)
        net.set_node_position(handle, xPos, yPos, 85, 55)

        if outcomes is not None:
            initial_outcome_count = net.get_outcome_count(handle)
            for i in range(0, initial_outcome_count):
                net.set_outcome_id(handle, i, outcomes[i])

            for i in range(initial_outcome_count, len(outcomes)):
                net.add_outcome(handle, outcomes[i])

        return handle
```

7.4.3 Tutorial4.R

```
library(rSMILE)
source("License.R")

# Tutorial4 loads the XDSL file file created by Tutorial1
# and adds decision and utility nodes, which transforms
# a Bayesian Network (BN) into an Influence Diagram (ID).

createNode = function(net, nodeType, id, name, outcomes, xPos, yPos) {
    handle <- net$addNode(nodeType, id)
    initialOutcomeCount <- net$getOutcomeCount(handle)
    count <- length(outcomes)
    net$setNodeName(handle, name)
    net$setNodePosition(handle, xPos, yPos, 85L, 55L)
    if (!is.null(outcomes)) {
        sapply(0:(initialOutcomeCount-1),
            function(x) net$setOutcomeId(handle, x, outcomes[x+1]))
        if (initialOutcomeCount < count) {
            sapply(initialOutcomeCount:(count-1),
                function(x) net$addOutcome(handle, outcomes[x+1]))
        }
    }

    return(handle)
```

```
}

cat("Starting Tutorial4...\n")
net <- Network()

net$readFile("tutorial1.xdsl")

s <- net$getNode("Success")

i <- createNode(net, net$NodeType$DECISION, "Invest", "Investment decision",
    c("Invest", "DoNotInvest"), 160L, 240L)

g <- createNode(net, net$NodeType$UTILITY, "Gain", "Financial Gain", NULL, 60, 200)

net$addArc(i, g)
net$addArc(s, g)

gainDefinition <- c(10000, # Utility(Invest=I, Success=S)
                    -5000, # Utility(Invest=I, Success=F)
                    500,   # Utility(Invest=D, Success=S)
                    500)   # Utility(Invest=D, Success=F)


net$setNodeDefinition(g, gainDefinition)

net$writeFile("tutorial4.xdsl")

cat("Tutorial4 complete: Influence diagram written to tutorial4.xdsl.\n")
```

7.4.4 Tutorial4.cs

```
using System;
using Smile;

// Tutorial4 loads the XDSL file file created by Tutorial1
// and adds decision and utility nodes, which transforms
// a Bayesian Network (BN) into an Influence Diagram (ID).

namespace SmileNetTutorial
{
    class Tutorial4
    {
        public static void Run()
        {
            Console.WriteLine("Starting Tutorial4...");
            Network net = new Network();

            net.ReadFile("tutorial1.xdsl");

            int s = net.GetNode("Success");

            int i = CreateNode(net, Network.NodeType.Decision,
                "Invest", "Investment decision",
                new String[] { "Invest", "DoNotInvest" }, 160, 240);
```

```
            int g = CreateNode(net, Network.NodeType.Utility,
                "Gain", "Financial gain", null, 60, 200);

            net.AddArc(i, g);
            net.AddArc(s, g);

            double[] gainDefinition = new double[]
            {
                10000, // Utility(Invest=I, Success=S)
                -5000, // Utility(Invest=I, Success=F)
                500,   // Utility(Invest=D, Success=S)
                500    // Utility(Invest=D, Success=F)
            };
            net.SetNodeDefinition(g, gainDefinition);

            net.WriteFile("tutorial4.xdsl");

            Console.WriteLine("Tutorial4 complete: ID written to tutorial4.xdsl.");
        }

        private static int CreateNode(
            Network net, Network.NodeType nodeType, String id, String name,
            String[] outcomes, int xPos, int yPos)
        {
            int handle = net.AddNode(nodeType, id);

            net.SetNodeName(handle, name);
            net.SetNodePosition(handle, xPos, yPos, 85, 55);

            if (outcomes != null)
            {
                int initialOutcomeCount = net.GetOutcomeCount(handle);
                for (int i = 0; i < initialOutcomeCount; i++)
                {
                    net.SetOutcomeId(handle, i, outcomes[i]);
                }

                for (int i = initialOutcomeCount; i < outcomes.Length; i++)
                {
                    net.AddOutcome(handle, outcomes[i]);
                }
            }

            return handle;
        }
    }
}
```

7.5 Tutorial 5: Inference in an Influence Diagram

This tutorial loads the influence diagram that we have created in *Tutorial 4* [108]. We will perform multiple inference calls and display calculated utilities.

With model loaded, we calculate the probabilities and utilities by calling `Network.updateBeliefs`. A helper function, `printFinancialGain`, is called to print out the utilities stored in the *Gain* node. `printFinancialGain` uses `Network.getNodeValue` to obtain the utilities. To properly interpret the utilities, we also need to call `Network.getValueIndexingParents`, which is an array containing the handles of decision nodes not set to evidence.

Java:

```
double[] expectedUtility = net.getNodeValue("Gain");
int[] utilParents = net.getValueIndexingParents("Gain");
printGainMatrix(net, expectedUtility, utilParents);
```

Python:

```
expected_utility = net.get_node_value("Gain")
util_parents = net.get_value_indexing_parents("Gain")
self.print_gain_matrix(net, expected_utility, util_parents)
```

C#:

```
double[] expectedUtility = net.GetNodeValue("Gain");
int[] utilParents = net.GetValueIndexingParents("Gain");
printGainMatrix(net, expectedUtility, utilParents);
```

`printGainMatrix` is a modification of `printCptMatrix` from *Tutorial 3* [99]. It iterates over the elements of an array and converts the linear index into multi-dimensional coordinates.

When we call `printGainMatrix` for the first time, the network has no evidence set. The utilities calculated without evidence suggest that we should not invest - here's what is printed on the screen:

```
Financial gain:
   Utility(Invest=Invest)=-1850
   Utility(Invest=DoNotInvest)=500
```

Next, we model the analyst's forecast to be good by calling local helper function `changeEvidenceAndUpdate`, which is based on the function with the same name from *Tutorial 2* [93].

Java:

```
changeEvidenceAndUpdate(net, "Forecast", "Good");
```

Python:

```
self.change_evidence_and_update(net, "Forecast", "Good")
```

C#:

```
ChangeEvidenceAndUpdate(net, "Forecast", "Good");
```

The expected gain changes, now the optimal decision is to invest:

```
Financial gain:
   Utility(Invest=Invest)=4455.78
   Utility(Invest=DoNotInvest)=500
```

Now we observe the state of the economy and conclude that it is growing - the program performs another `changeEvidenceAndUpdate` call . Growing economy makes our chances even better:

```
Financial gain:
   Utility(Invest=Invest)=5000
   Utility(Invest=DoNotInvest)=500
```

This concludes Tutorial 5.

7.5.1 Tutorial5.java

```
package tutorials;

import smile.*;

// Tutorial5 loads the XDSL file created by Tutorial4,
// then performs the series of inference calls,
// changing evidence each time.

public class Tutorial5 {
    public static void run() {
        System.out.println("Starting Tutorial5...");
        Network net = new Network();

        net.readFile("tutorial4.xdsl");

        System.out.println("No evidence set.");
        net.updateBeliefs();
        printFinancialGain(net);

        System.out.println("Setting Forecast=Good.");
        changeEvidenceAndUpdate(net, "Forecast", "Good");

        System.out.println("Adding Economy=Up");
        changeEvidenceAndUpdate(net, "Economy", "Up");

        System.out.println("Tutorial5 complete.");
    }

    static void changeEvidenceAndUpdate(
            Network net, String nodeId, String outcomeId) {
        if (outcomeId != null) {
            net.setEvidence(nodeId, outcomeId);
        } else {
            net.clearEvidence(nodeId);
        }

        net.updateBeliefs();
        printFinancialGain(net);
    }

    static void printFinancialGain(Network net) {
        double[] expectedUtility = net.getNodeValue("Gain");
        int[] utilParents = net.getValueIndexingParents("Gain");
        printGainMatrix(net, expectedUtility, utilParents);
    }

    static void printGainMatrix(Network net, double[] mtx, int[] parents) {
        int dimCount = 1 + parents.length;

        int[] dimSizes = new int[dimCount];
        for (int i = 0; i < dimCount - 1; i ++) {
            dimSizes[i] = net.getOutcomeCount(parents[i]);
        }
```

```
        dimSizes[dimSizes.length - 1] = 1;

        int[] coords = new int[dimCount];
        for (int elemIdx = 0; elemIdx < mtx.length; elemIdx ++) {
            indexToCoords(elemIdx, dimSizes, coords);

            System.out.print("    Utility(");

            if (dimCount > 1)
            {
                for (int parentIdx = 0; parentIdx < parents.length; parentIdx++)
                {
                    if (parentIdx > 0) System.out.print(",");
                    int parentHandle = parents[parentIdx];
                    System.out.printf("%s=%s",
                        net.getNodeId(parentHandle),
                        net.getOutcomeId(parentHandle, coords[parentIdx]));
                }
            }

            System.out.printf(")=%f\n", mtx[elemIdx]);
        }
        System.out.println();
    }

    static void indexToCoords(int index, int[] dimSizes, int[] coords) {
        int prod = 1;
        for (int i = dimSizes.length - 1; i >= 0; i --) {
            coords[i] = (index / prod) % dimSizes[i];
            prod *= dimSizes[i];
        }
    }
}
```

7.5.2 Tutorial5.py

```
import pysmile

# Tutorial5 loads the XDSL file created by Tutorial4,
# then performs the series of inference calls,
# changing evidence each time.

class Tutorial5:
    def __init__(self):
        print("Starting Tutorial5...")
        net = pysmile.Network()

        net.read_file("tutorial4.xdsl")

        print("No evidence set.")
        net.update_beliefs()
        self.print_financial_gain(net)

        print("Setting Forecast=Good.")
        self.change_evidence_and_update(net, "Forecast", "Good")
```

```
        print("Adding Economy=Up")
        self.change_evidence_and_update(net, "Economy", "Up")

        print("Tutorial5 complete.")

    def change_evidence_and_update(self, net, node_id, outcome_id):
        if outcome_id is not None:
            net.set_evidence(node_id, outcome_id)
        else:
            net.clear_evidence(node_id)

        net.update_beliefs()
        self.print_financial_gain(net)

    def print_financial_gain(self, net):
        expected_utility = net.get_node_value("Gain")
        util_parents = net.get_value_indexing_parents("Gain")
        self.print_gain_matrix(net, expected_utility, util_parents)

    def print_gain_matrix(self, net, mtx, parents):
        dim_count = 1 + len(parents)

        dim_sizes = [0] * dim_count
        for i in range(0, dim_count - 1):
            dim_sizes[i] = net.get_outcome_count(parents[i])
        dim_sizes[len(dim_sizes) - 1] = 1
        coords = [0] * dim_count
        for elem_idx in range(0, len(mtx)):
            self.index_to_coords(elem_idx, dim_sizes, coords)
            print("    Utility(", end="")
            if dim_count > 1:
                for parent_idx in range(0, len(parents)):
                    if parent_idx > 0:
                        print(",", end="")
                    parent_handle = parents[parent_idx]
                    print(f"{net.get_node_id(parent_handle)}="
                        + f"{net.get_outcome_id(parent_handle, coords[parent_idx])}", end="")
            print(f")={mtx[elem_idx]}")
        print()

    def index_to_coords(self, index, dim_sizes, coords):
        prod = 1
        for i in range(len(dim_sizes) - 1, -1, -1):
            coords[i] = int(index / prod) % dim_sizes[i]
            prod *= dim_sizes[i]
```

7.5.3 Tutorial5.R

```
library(rSMILE)
source("License.R")

# Tutorial5 loads the XDSL file created by Tutorial4,
# then performs the series of inference calls,
# changing evidence each time.
```

```
indexToCoords = function(index, dimSizes) {
    prod <- 1L
    coords <- integer(length=length(dimSizes))
    for (i in length(dimSizes):1) {
        coords[i] <- floor(index / prod) %% dimSizes[[i]]
        prod <- prod * dimSizes[[i]]
    }
    return(coords)
}

printGainMatrix = function(net, mtx, parents) {
    dimCount <- 1 + length(parents)

    dimSizes <- sapply(parents, function(x) net$getOutcomeCount(x))
    dimSizes[length(dimSizes)+1] <- 1

    for (elemIdx in 0:(length(mtx)-1)) {
        coords <- indexToCoords(elemIdx, dimSizes)
        cat("    Utility(");
        if (dimCount > 1) {
            parentIds <- sapply(parents, function(x) net$getNodeId(x))
            outcomeIds <- sapply(1:length(parents),
                function(x) net$getOutcomeId(parents[x], coords[x]))

            cat(paste(parentIds, outcomeIds, sep="=", collapse=","))
        }
        cat(sprintf(")=%f\n", mtx[elemIdx+1]))
    }
}

printFinancialGain = function(net) {
    expectedUtility <- net$getNodeValue("Gain")
    utilParents <- net$getValueIndexingParents("Gain")
    printGainMatrix(net, expectedUtility, utilParents)
}

changeEvidenceAndUpdate = function(net, nodeId, outcomeId) {
    if (!is.null(outcomeId)) {
        net$setEvidence(nodeId, outcomeId)
    } else {
        net$clearEvidence(nodeId)
    }
    net$updateBeliefs()
    printFinancialGain(net)
}

cat("Starting Tutorial5...\n")
net <- Network()

net$readFile("tutorial4.xdsl")

cat("No evidence set.\n")
net$updateBeliefs()
printFinancialGain(net)
```

```
cat("Setting Forecast=Good.\n")
changeEvidenceAndUpdate(net, "Forecast", "Good")

cat("Adding Economy=Up.\n")
changeEvidenceAndUpdate(net, "Economy", "Up")

cat("Tutorial5 complete.\n")
```

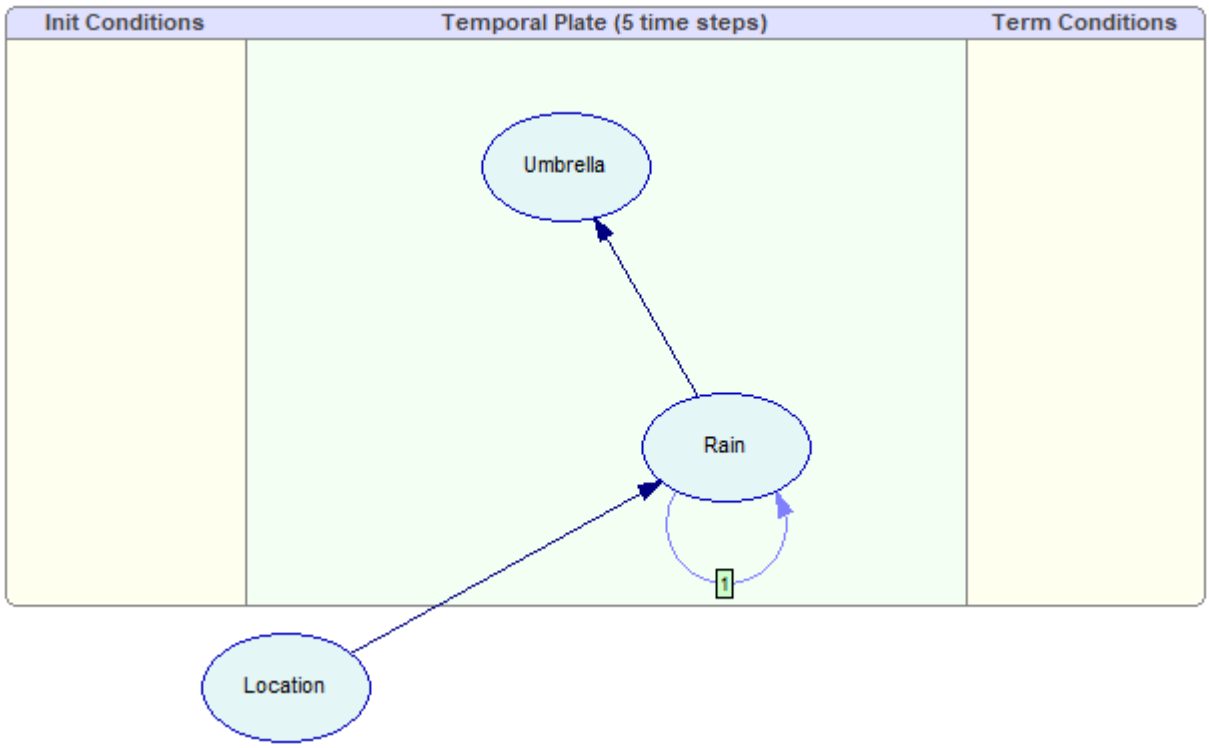
7.5.4 Tutorial5.cs

```
using System;
using Smile;

// Tutorial5 loads the XDSL file created by Tutorial4,
// then performs the series of inference calls,
// changing evidence each time.

namespace SmileNetTutorial
{
    class Tutorial5
    {
        public static void Run()
        {
            Console.WriteLine("Starting Tutorial5...");
            Network net = new Network();

            net.ReadFile("tutorial4.xdsl");

            Console.WriteLine("No evidence set.");
            net.UpdateBeliefs();
            PrintFinancialGain(net);

            Console.WriteLine("Setting Forecast=Good.");
            ChangeEvidenceAndUpdate(net, "Forecast", "Good");

            Console.WriteLine("Adding Economy=Up");
            ChangeEvidenceAndUpdate(net, "Economy", "Up");

            Console.WriteLine("Tutorial5 complete.");
        }

        static void ChangeEvidenceAndUpdate(Network net, String nodeId, String outcomeId)
        {
            if (outcomeId != null)
            {
                net.SetEvidence(nodeId, outcomeId);
            }
            else
            {
                net.ClearEvidence(nodeId);
            }
            net.UpdateBeliefs();
            PrintFinancialGain(net);
        }
```

```
        static void PrintFinancialGain(Network net)
        {
            double[] expectedUtility = net.GetNodeValue("Gain");
            int[] utilParents = net.GetValueIndexingParents("Gain");
            PrintGainMatrix(net, expectedUtility, utilParents);
        }

        static void PrintGainMatrix(Network net, double[] mtx, int[] parents)
        {
            int dimCount = 1 + parents.Length;

            int[] dimSizes = new int[dimCount];
            for (int i = 0; i < dimCount - 1; i++)
            {
                dimSizes[i] = net.GetOutcomeCount(parents[i]);
            }
            dimSizes[dimSizes.Length - 1] = 1;

            int[] coords = new int[dimCount];
            for (int elemIdx = 0; elemIdx < mtx.Length; elemIdx++)
            {
                IndexToCoords(elemIdx, dimSizes, coords);
                Console.Write("    Utility(");
                if (dimCount > 1)
                {
                    for (int pIdx = 0; pIdx < parents.Length; pIdx++)
                    {
                        if (pIdx > 0) Console.Write(",");
                        int parentHandle = parents[pIdx];
                        Console.Write("{0}={1}",
                            net.GetNodeId(parentHandle),
                            net.GetOutcomeId(parentHandle, coords[pIdx]));
                    }
                }
                Console.Write(")={0}\n", mtx[elemIdx]);
            }
            Console.WriteLine();
        }

        static void IndexToCoords(int index, int[] dimSizes, int[] coords)
        {
            int prod = 1;
            for (int i = dimSizes.Length - 1; i >= 0; i--)
            {
                coords[i] = (index / prod) % dimSizes[i];
                prod *= dimSizes[i];
            }
        }
    }
}
```

7.6 Tutorial 6: Dynamic model

Consider the following example, inspired by (Russell & Norvig, 1995), in which a security guard at some secret underground installation works on a shift of seven days and wants to know whether it is raining on the day of her return to the outside world. Her only access to the outside world occurs each morning when she sees the director coming in, with or without an umbrella. Furthermore, she knows that the government has two secret underground installations: one in Pittsburgh and one in the Sahara, but she does not know which one she is guarding. For each day *t*, the set of evidence contains a single variable $Umbrella_t$ (observation of an umbrella carried by the director) and the set of unobservable variables contains $Rain_t$ (a propositional variable with two states *true* and *false*, denoting whether it is raining) and *Location* (with two possible states: *Pittsburgh* and *Sahara*). The prior probability of rain depends on the geographical location and on whether it rained on the previous day. For simplicity, we do not use the initial and terminal condition nodes in this tutorial.



The model contains three discrete chance nodes (CPT), created with a call to `createCptNode` helper function, just like in nodes in *Tutorial 1* [82]. The *Rain* and *Umbrella* nodes are marked as belonging to the temporal plate by calling `Network.SetNodeTemporalType`:

Java:

```
net.setNodeTemporalType(rain, Network.NodeTemporalType.PLATE);
net.setNodeTemporalType(umb, Network.NodeTemporalType.PLATE);
```

Python:

```
net.set_node_temporal_type(rain, pysmile.NodeTemporalType.PLATE)
net.set_node_temporal_type(umb, pysmile.NodeTemporalType.PLATE)
```

C#:

```
net.SetNodeTemporalType(rain, Network.NodeTemporalType.Plate);
net.SetNodeTemporalType(umb, Network.NodeTemporalType.Plate);
```

Two of the three arcs in the model are created by `Network.addArc`. The temporal arc expressing the dependency of $Rain_t$ on $Rain_{t-1}$ is created by the `Network.addTemporalArc` method. Please note the temporal order of the arc passed as the 3rd parameter:

Java:

```
net.addArc(loc, rain);
net.addTemporalArc(rain, rain, 1);
net.addArc(rain, umb);
```

Python:

```
net.add_arc(loc, rain)
net.add_temporal_arc(rain, rain, 1)
net.add_arc(rain, umb)
```

C#:

```
net.AddArc(loc, rain);
net.AddTemporalArc(rain, rain, 1);
net.AddArc(rain, umb);
```

CPTs for the nodes are initialized with `Network.setNodeDefinition`, as in *Tutorial 1* [82]. However, the node Rain requires **two** CPTs, because it has an incoming temporal arc of order 1. The additional CPT is set by the call to Network.setNodeTemporalDefinition:

Java:

```
double[] rainDefTemporal = new double[] {
    0.7,   // P(Rain=true |Location=Pittsburgh,Rain[t-1]=true)
    0.3,   // P(Rain=false|Location=Pittsburgh,Rain[t-1]=true)
    0.3,   // P(Rain=true |Location=Pittsburgh,Rain[t-1]=false)
    0.7,   // P(Rain=false|Location=Pittsburgh,Rain[t-1]=false)
    0.001, // P(Rain=true |Location=Sahara,Rain[t-1]=true)
    0.999, // P(Rain=false|Location=Sahara,Rain[t-1]=true)
    0.01,  // P(Rain=true |Location=Sahara,Rain[t-1]=false)
    0.99  // P(Rain=false|Location=Sahara,Rain[t-1]=false)
};
net.setNodeTemporalDefinition(rain, 1, rainDefTemporal);
```

Python:

```
rain_def_temporal = [
    # probabilities go here
]
net.set_node_temporal_definition(rain, 1, rain_def_temporal)
```

C#:

```
double[] rainDefTemporal = new double[]
{
    // probabilities go here
};
net.SetNodeTemporalDefinition(rain, 1, rainDefTemporal);
```

Finally, we adjust the number of slices created during the network unrolling with a call to `Network.setSliceCount`. The network is complete. The program proceeds to the inference, first without any evidence in the network, then with two observations of the *Umbrella*, set in the time steps *t=1* and *t=3*:

Java:

```
net.setTemporalEvidence(umb, 1, 0);
```

```
net.setTemporalEvidence(umb, 3, 1);
```

Python:

```
net.set_temporal_evidence(umb, 1, 0)
net.set_temporal_evidence(umb, 3, 1
```

C#:

```
net.SetTemporalEvidence(umb, 1, 0);
net.SetTemporalEvidence(umb, 3, 1);
```

In dynamic Bayesian networks, the plate nodes have their beliefs calculated for each time slice. The number of elements in the node value matrix for these nodes is a product of outcome count and slice count. The helper function `updateAndShowTemporalResults` iterates over this matrix using two nested loops in order to print the results. Since the probabilities for the same slice are adjacent, the inner loop uses the product of the outcome count and slice index from the outer loop as a base index.

Java:

```
double[] v = net.getNodeValue(h);
for (int sliceIdx = 0; sliceIdx < sliceCount; sliceIdx++) {
    System.out.printf("\tt=%d:", sliceIdx);
    for (int i = 0; i < outcomeCount; i++) {
          System.out.printf(" %f", v[sliceIdx * outcomeCount + i]);
    }
    System.out.println();
}
```

Python:

```
v = net.get_node_value(h)
for slice_idx in range(0, slice_count):
    s = "\tt=" + str(slice_idx) + ":"
    for i in range(0, outcome_count):
        s = s + " " + str(v[slice_idx * outcome_count + i])
    print(s)
```

C#:

```
double[] v = net.GetNodeValue(h);
for (int sliceIdx = 0; sliceIdx < sliceCount; sliceIdx++)
{
    Console.Write("\tt={0}:", sliceIdx);
    for (int i = 0; i < outcomeCount; i++)
    {
                Console.Write(" {0}", v[sliceIdx * outcomeCount + i]);
    }
    Console.WriteLine();
}
```

7.6.1 Tutorial6.java

```
package tutorials;

import smile.*;

// Tutorial6 creates a dynamic Bayesian network (DBN),
// performs the inference, then saves the model to disk.
```

```
public class Tutorial6 {
    public static void run() {
        System.out.println("Starting Tutorial6...");
        Network net = new Network();

        int loc = createCptNode(
             net, "Location", "Location",
             new String[] { "Pittsburgh", "Sahara" },
             160, 360);

        int rain = createCptNode(
             net, "Rain", "Rain",
             new String[] { "true", "false" },
             380, 240);

        int umb = createCptNode(
             net, "Umbrella", "Umbrella",
             new String[] { "true", "false" },
             300, 100);

        net.setNodeTemporalType(rain, Network.NodeTemporalType.PLATE);
        net.setNodeTemporalType(umb, Network.NodeTemporalType.PLATE);

        net.addArc(loc, rain);
        net.addTemporalArc(rain, rain, 1);
        net.addArc(rain, umb);

        double[] rainDef = new double[] {
            0.7,  // P(Rain=true |Location=Pittsburgh)
            0.3,  // P(Rain=false|Location=Pittsburgh)
            0.01, // P(Rain=true |Location=Sahara)
            0.99  // P(Rain=false|Location=Sahara)
        };
        net.setNodeDefinition(rain, rainDef);

        double[] rainDefTemporal = new double[] {
            0.7,   // P(Rain=true |Location=Pittsburgh,Rain[t-1]=true)
            0.3,   // P(Rain=false|Location=Pittsburgh,Rain[t-1]=true)
            0.3,   // P(Rain=true |Location=Pittsburgh,Rain[t-1]=false)
            0.7,   // P(Rain=false|Location=Pittsburgh,Rain[t-1]=false)
            0.001, // P(Rain=true |Location=Sahara,Rain[t-1]=true)
            0.999, // P(Rain=false|Location=Sahara,Rain[t-1]=true)
            0.01,  // P(Rain=true |Location=Sahara,Rain[t-1]=false)
            0.99  // P(Rain=false|Location=Sahara,Rain[t-1]=false)
             };
        net.setNodeTemporalDefinition(rain, 1, rainDefTemporal);

        double[] umbDef = new double[] {
             0.9, // P(Umbrella=true |Rain=true)
            0.1, // P(Umbrella=false|Rain=true)
            0.2, // P(Umbrella=true |Rain=false)
            0.8  // P(Umbrella=false|Rain=false)
        };
        net.setNodeDefinition(umb, umbDef);
```

```
    net.setSliceCount(5);

    System.out.println("Performing update without evidence.");
    updateAndShowTemporalResults(net);

    System.out.println("Setting Umbrella[t=1] to true and Umbrella[t=3] to false.");
    net.setTemporalEvidence(umb, 1, 0);
    net.setTemporalEvidence(umb, 3, 1);
    updateAndShowTemporalResults(net);

    net.writeFile("tutorial6.xdsl");
    System.out.println("Tutorial6 complete: Network written to tutorial6.xdsl");
}

private static void updateAndShowTemporalResults(Network net) {
   net.updateBeliefs();
       int sliceCount = net.getSliceCount();
       for (int h = net.getFirstNode(); h >= 0; h = net.getNextNode(h)) {
          if (net.getNodeTemporalType(h) == Network.NodeTemporalType.PLATE) {
                 int outcomeCount = net.getOutcomeCount(h);
               System.out.printf(
                "Temporal beliefs for %s:\n", net.getNodeId(h));
               double[] v = net.getNodeValue(h);
                      for (int sliceIdx = 0; sliceIdx < sliceCount; sliceIdx++) {
                             System.out.printf("\tt=%d:", sliceIdx);
                             for (int i = 0; i < outcomeCount; i++) {
                                 System.out.printf(" %f", v[sliceIdx*outcomeCount+i]);
                             }
                             System.out.println();
                      }
           }
       }
       System.out.println();
}

private static int createCptNode(
        Network net, String id, String name,
        String[] outcomes, int xPos, int yPos) {
    int handle = net.addNode(Network.NodeType.CPT, id);

    net.setNodeName(handle, name);
    net.setNodePosition(handle, xPos, yPos, 85, 55);

    int initialOutcomeCount = net.getOutcomeCount(handle);
    for (int i = 0; i < initialOutcomeCount; i ++) {
        net.setOutcomeId(handle, i, outcomes[i]);
    }

    for (int i = initialOutcomeCount; i < outcomes.length; i ++) {
        net.addOutcome(handle, outcomes[i]);
    }

    return handle;
}
```

```
}
```

7.6.2 Tutorial6.py

```
import pysmile

# Tutorial6 creates a dynamic Bayesian network (DBN),
# performs the inference, then saves the model to disk.

class Tutorial6:
    def __init__(self):
        print("Starting Tutorial6...")
        net = pysmile.Network()
        loc = self.create_cpt_node(net,
              "Location", "Location",
              ["Pittsburgh", "Sahara"],
              160, 360)
        rain = self.create_cpt_node(net,
               "Rain", "Rain",
               ["true", "false"],
               380, 240)
        umb = self.create_cpt_node(net,
              "Umbrella", "Umbrella",
              ["true", "false"],
              300, 100)

        net.set_node_temporal_type(rain, pysmile.NodeTemporalType.PLATE)
        net.set_node_temporal_type(umb, pysmile.NodeTemporalType.PLATE)

        net.add_arc(loc, rain)
        net.add_temporal_arc(rain, rain, 1)
        net.add_arc(rain, umb)

        rain_def = [
            0.7,  # P(Rain=true |Location=Pittsburgh)
            0.3,  # P(Rain=false|Location=Pittsburgh)
            0.01, # P(Rain=true |Location=Sahara)
            0.99  # P(Rain=false|Location=Sahara)
        ]

        net.set_node_definition(rain, rain_def)

        rain_def_temporal = [
            0.7,   # P(Rain=true |Location=Pittsburgh,Rain[t-1]=true)
            0.3,   # P(Rain=false|Location=Pittsburgh,Rain[t-1]=true)
            0.3,   # P(Rain=true |Location=Pittsburgh,Rain[t-1]=false)
            0.7,   # P(Rain=false|Location=Pittsburgh,Rain[t-1]=false)
            0.001, # P(Rain=true |Location=Sahara,Rain[t-1]=true)
            0.999, # P(Rain=false|Location=Sahara,Rain[t-1]=true)
            0.01,  # P(Rain=true |Location=Sahara,Rain[t-1]=false)
            0.99   # P(Rain=false|Location=Sahara,Rain[t-1]=false)
        ]
        net.set_node_temporal_definition(rain, 1, rain_def_temporal)

        umb_def = [
```

```
            0.9, # P(Umbrella=true |Rain=true)
            0.1, # P(Umbrella=false|Rain=true)
            0.2, # P(Umbrella=true |Rain=false)
            0.8  # P(Umbrella=false|Rain=false)
        ]
        net.set_node_definition(umb, umb_def)

        net.set_slice_count(5)

        print("Performing update without evidence.")
        self.update_and_show_temporal_results(net)

        print("Setting Umbrella[t=1], to true and Umbrella[t=3] to false.")
        net.set_temporal_evidence(umb, 1, 0)
        net.set_temporal_evidence(umb, 3, 1)
        self.update_and_show_temporal_results(net)

        net.write_file("tutorial6.xdsl")
        print("Tutorial6 complete: Network written to tutorial6.xsdl")

    def update_and_show_temporal_results(self, net):
        net.update_beliefs()
        slice_count = net.get_slice_count()
        for h in net.get_all_nodes():
            if net.get_node_temporal_type(h) == pysmile.NodeTemporalType.PLATE:
                outcome_count = net.get_outcome_count(h)
                v = net.get_node_value(h)
                print(f"Temporal beliefs for {net.get_node_id(h)}:")
                for slice_idx in range(0, slice_count):
                    print(f"\tt={slice_idx}:", end="")
                    for i in range(0, outcome_count):
                        print(f" {v[slice_idx * outcome_count + i]}", end="")
                    print()

    def create_cpt_node(self, net, id, name, outcomes, x_pos, y_pos):
        handle = net.add_node(pysmile.NodeType.CPT, id)

        net.set_node_name(handle, name)
        net.set_node_position(handle, x_pos, y_pos, 85, 55)

        initial_outcome_count = net.get_outcome_count(handle)

        for i in range(0, initial_outcome_count):
            net.set_outcome_id(handle, i, outcomes[i])

        for i in range(initial_outcome_count, len(outcomes)):
            net.add_outcome(handle, outcomes[i])

        return handle
```

7.6.3 Tutorial6.R

```
library(rSMILE)
source("License.R")
```

```
# Tutorial6 creates a dynamic Bayesian network (DBN),
# performs the inference, then saves the model to disk.

createCptNode = function(net, id, name, outcomes, xPos, yPos) {
    handle <- net$addNode(net$NodeType$CPT, id)
    initialOutcomeCount <- net$getOutcomeCount(handle)
    count <- length(outcomes)
    net$setNodeName(handle, name)
    net$setNodePosition(handle, xPos, yPos, 85L, 55L)
    if (!is.null(outcomes)) {
        sapply(0:(initialOutcomeCount-1),
            function(x) net$setOutcomeId(handle, x, outcomes[x+1]))
        if (initialOutcomeCount < count) {
            sapply(initialOutcomeCount:(count-1),
                function(x) net$addOutcome(handle, outcomes[x+1]))
        }
    }

    return(handle)
}

updateAndShowTemporalResults = function(net) {
    net$updateBeliefs()
    sliceCount <- net$getSliceCount()
    handles <- net$getAllNodes()
    for (h in handles) {
        if (net$getNodeTemporalType(h) == net$NodeTemporalType$PLATE) {
            outcomeCount <- net$getOutcomeCount(h)
            cat(sprintf("Temporal beliefs for %s:\n", net$getNodeId(h)))
            v <- net$getNodeValue(h)
            for (sliceIdx in 0:(sliceCount-1)) {
                cat(sprintf("\tt=%d:", sliceIdx))
                for (i in 0:(outcomeCount-1)) {
                    cat(sprintf(" %f", v[(sliceIdx*outcomeCount+i)+1]))
                }
                cat("\n")
            }
        }
    }
    cat("\n")
}

cat("Starting Tutorial6...\n")
net <- Network()

loc <- createCptNode(net, "Location", "Location", c("Pittsburgh", "Sahara"), 160, 360)
rain <- createCptNode(net, "Rain", "Rain",c("true", "false"), 380, 240)
umb <- createCptNode(net, "Umbrella", "Umbrella", c("true", "false"), 300, 100)

net$setNodeTemporalType(rain, net$NodeTemporalType$PLATE)
net$setNodeTemporalType(umb, net$NodeTemporalType$PLATE)

net$addArc(loc, rain)
net$addTemporalArc(rain, rain, 1)
net$addArc(rain, umb)
```

```
rainDef <- c( 0.7,
              0.3,
              0.01,
              0.99 )

net$setNodeDefinition(rain, rainDef)

rainDefTemporal <- c( 0.7,
                      0.3,
                      0.3,
                      0.7,
                      0.001,
                      0.999,
                      0.01,
                      0.99 )

net$setNodeTemporalDefinition(rain, 1, rainDefTemporal)

umbDef <- c( 0.9,
             0.1,
             0.2,
             0.8 )

net$setNodeDefinition(umb, umbDef)

net$setSliceCount(5)

cat("Performing update without evidence.\n")
updateAndShowTemporalResults(net)

cat("Setting Umbrella[t=1] to true and Umbrella[t=3] to false.\n")
net$setTemporalEvidence(umb, 1, 0)
net$setTemporalEvidence(umb, 3, 1)
updateAndShowTemporalResults(net)

net$writeFile("tutorial6.xdsl")
cat("Tutorial6 complete: Network written to tutorial6.xdsl\n")
```

7.6.4 Tutorial6.cs

```
using System;
using Smile;

// Tutorial6 creates a dynamic Bayesian network (DBN),
// performs the inference, then saves the model to disk.

namespace SmileNetTutorial
{
    class Tutorial6
    {
        public static void Run()
        {
            Console.WriteLine("Starting Tutorial6...");
            Network net = new Network();
```

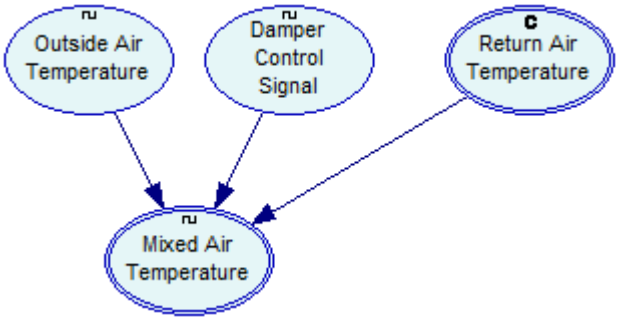
```
int loc = CreateCptNode(
    net, "Location", "Location",
    new String[] { "Pittsburgh", "Sahara" },
    160, 360);

int rain = CreateCptNode(
    net, "Rain", "Rain",
    new String[] { "true", "false" },
    380, 240);

int umb = CreateCptNode(
    net, "Umbrella", "Umbrella",
    new String[] { "true", "false" },
    300, 100);

net.SetNodeTemporalType(rain, Network.NodeTemporalType.Plate);
net.SetNodeTemporalType(umb, Network.NodeTemporalType.Plate);

net.AddArc(loc, rain);
net.AddTemporalArc(rain, rain, 1);
net.AddArc(rain, umb);

double[] rainDef = new double[]
{
    0.7,  // P(Rain=true |Location=Pittsburgh)
    0.3,  // P(Rain=false|Location=Pittsburgh)
    0.01, // P(Rain=true |Location=Sahara)
    0.99  // P(Rain=false|Location=Sahara)
};
net.SetNodeDefinition(rain, rainDef);

double[] rainDefTemporal = new double[]
{
    0.7,   // P(Rain=true |Location=Pittsburgh,Rain[t-1]=true)
    0.3,   // P(Rain=false|Location=Pittsburgh,Rain[t-1]=true)
    0.3,   // P(Rain=true |Location=Pittsburgh,Rain[t-1]=false)
    0.7,   // P(Rain=false|Location=Pittsburgh,Rain[t-1]=false)
    0.001, // P(Rain=true |Location=Sahara,Rain[t-1]=true)
    0.999, // P(Rain=false|Location=Sahara,Rain[t-1]=true)
    0.01,  // P(Rain=true |Location=Sahara,Rain[t-1]=false)
    0.99  // P(Rain=false|Location=Sahara,Rain[t-1]=false)
     };
net.SetNodeTemporalDefinition(rain, 1, rainDefTemporal);

double[] umbDef = new double[]
{
    0.9, // P(Umbrella=true |Rain=true)
    0.1, // P(Umbrella=false|Rain=true)
    0.2, // P(Umbrella=true |Rain=false)
    0.8  // P(Umbrella=false|Rain=false)
};
net.SetNodeDefinition(umb, umbDef);

net.SetSliceCount(5);
```

```
    Console.WriteLine("Performing update without evidence.");
    UpdateAndShowTemporalResults(net);

    Console.WriteLine("Setting Umbrella[t=1] to true and Umbrella[t=3] to false.");
    net.SetTemporalEvidence(umb, 1, 0);
    net.SetTemporalEvidence(umb, 3, 1);
    UpdateAndShowTemporalResults(net);

    net.WriteFile("tutorial6.xdsl");
    Console.WriteLine("Tutorial6 complete: Network written to tutorial6.xdsl");
}

private static void UpdateAndShowTemporalResults(Network net)
{
    net.UpdateBeliefs();
    int sliceCount = net.GetSliceCount();
    for (int h = net.GetFirstNode(); h >= 0; h = net.GetNextNode(h))
    {
        if (net.GetNodeTemporalType(h) == Network.NodeTemporalType.Plate)
        {
            int outcomeCount = net.GetOutcomeCount(h);
            Console.WriteLine("Temporal beliefs for {0}:", net.GetNodeId(h));
            double[] v = net.GetNodeValue(h);
            for (int sliceIdx = 0; sliceIdx < sliceCount; sliceIdx++)
            {
                Console.Write("\tt={0}:", sliceIdx);
                for (int i = 0; i < outcomeCount; i++)
                {
                    Console.Write(" {0}", v[sliceIdx * outcomeCount + i]);
                }
                Console.WriteLine();
            }
        }
    }
    Console.WriteLine();
}

private static int CreateCptNode(
    Network net, String id, String name,
    String[] outcomes, int xPos, int yPos)
{
    int handle = net.AddNode(Network.NodeType.Cpt, id);

    net.SetNodeName(handle, name);
    net.SetNodePosition(handle, xPos, yPos, 85, 55);

    int initialOutcomeCount = net.GetOutcomeCount(handle);
    for (int i = 0; i < initialOutcomeCount; i++)
    {
        net.SetOutcomeId(handle, i, outcomes[i]);
    }

    for (int i = initialOutcomeCount; i < outcomes.Length; i++)
    {
```

```
                net.AddOutcome(handle, outcomes[i]);
            }

            return handle;
        }
    }
}
```

7.7 Tutorial 7: Continuous model

The continuous Bayesian network used in this tutorial focuses on a fragment of a forced air heating and cooling system. In order to improve the system's efficiency, return air is mixed with the air that is drawn from outside. Temperature of the outside air depends on the weather and is specified by means of a Normal distribution. Return air temperature is constant and depends on the thermostat setting. Damper control signal determines the composition of the mixture.



Temperature of the mixture is calculated according to the following equation: *tma=toa*u_d+(tra-tra*u_d)*, where *tma* is mixed air temperature, *toa* is outside air temperature, *u_d* is the damper signal, and *tra* is return air temperature.

The nodes in this model are created by the helper function `createEquationNode`. It is a modified version of the `createCptNode` function used in the previous tutorials. The bold text marks the difference between two functions.

```
static int createEquationNode(
        Network net, String id, String name,
              String equation, double loBound, double hiBound,
              int xPos, int yPos) {
    int handle = net.addNode(Network.NodeType.EQUATION, id);
          net.setNodeName(handle, name);
          net.setNodeEquation(handle, equation);
          net.setNodeEquationBounds(handle, loBound, hiBound);

          net.setNodePosition(handle, xPos, yPos, 85, 55);

    return handle;
}
```

Instead of discrete outcomes, we specify the node equation and the bounds for the node value. Another helper function, `setUniformIntervals`, is used to define the discretization intervals. They will be used by the inference algorithm when the evidence is set for *Mixed Air Temperature* node (which has parents). The uniform intervals are chosen for simplicity here; in general case the choice of interval edges should be done based on the actual expected distribution of the node value (for example, in case of the Normal distribution, we might create narrow discretization intervals close to the mean.)

Note that while the model has three arcs, there are no calls to `Network.addArc` in this tutorial. The arcs are created implicitly by `Network.setNodeEquation` method (called by `createEquationNode` function).

The network is complete now and we can proceed to inference. Three inference calls are made, one without evidence and two with continuous evidence specified by calling `Network.setContEvidence`. Setting the *Outside Air Temperature* to 28.5 degrees (`toa` is the name of int variable holding the handle of the *Outside Air Temperature* node):

Java:

```
net.setContEvidence(toa, 28.5);
```

Python:

```
net.set_cont_evidence(toa, 28.5)
```

C#:

```
net.SetContEvidence(toa, 28.5);
```

The program uses `updateAndShowStats` helper function for inference. The helper calls `Network.updateBeliefs` and iterates over the nodes in the network and calls another helper, `showStats`, for each node. `showStats` first checks if the node has evidence set. If it does, the evidence value is printed, and the function returns. If node has no evidence, we need to check if its value comes from the sampling or discretized inference.

If discretization was used, `Network.isValueDiscretized` returns true. In such case, the array returned from `Network.getNodeValue` contains the probability distribution over node discretization intervals. To display human-readable information about the intervals and probabilities, `showStats` calls `Network.getNodeEquationDiscretization` and `getNodeEquationBounds`. Note that the program setup these node attributes in `createEquationNode`.

If node value was sampled, `Network.isValueDiscretized` returns false. `Network.getNodeValue` returns the array of sampled node values. After sampling, it's also possible to obtain sample statistics (mean, standard deviation, min and max values) with a call to `Network.getNodeSampleStats`.

At the end of the tutorial, the model is saved to disk. *Tutorial 8* [143] will expand it into a hybrid network by adding CPT nodes.

7.7.1 Tutorial7.java

```
package tutorials;

import smile.*;

// Tutorial7 creates a network with three equation-based nodes
// performs the inference, then saves the model to disk.

public class Tutorial7 {
    public static void run() {
        System.out.println("Starting Tutorial7...");
        Network net = new Network();

        net.setOutlierRejectionEnabled(true);

        createEquationNode(net,
```

```
        "tra", "Return Air Temperature",
        "tra=24", 23.9, 24.1,
        280, 100);

    createEquationNode(net,
        "u_d", "Damper Control Signal",
        "u_d = Bernoulli(0.539)*0.8 + 0.2", 0, 1,
        160, 100);

    int toa = createEquationNode(net,
        "toa", "Outside Air Temperature",
        "toa=Normal(11,15)", -10, 40,
        60, 100);

    // tra, toa and u_d are referenced in equation
    // arcs are created automatically
    int tma = createEquationNode(net,
        "tma", "Mixed Air Temperature",
        "tma=toa*u_d+(tra-tra*u_d)", 10, 30,
        110, 200);

    setUniformIntervals(net, toa, 5);
    setUniformIntervals(net, tma, 4);

    System.out.println("Results with no evidence:");
    updateAndShowStats(net);

    net.setContEvidence(toa, 28.5);
    System.out.println("Results with outside air temperature set to 28.5:");
    updateAndShowStats(net);

    net.clearEvidence(toa);
    System.out.println("Results with mixed air temperature set to 21:");
    net.setContEvidence(tma, 21.0);
    updateAndShowStats(net);

    net.writeFile("tutorial7.xdsl");
    System.out.println("Tutorial7 complete: Network written to tutorial7.xdsl");
}

static int createEquationNode(
         Network net, String id, String name,
       String equation, double loBound, double hiBound,
       int xPos, int yPos) {
         int handle = net.addNode(Network.NodeType.EQUATION, id);
  net.setNodeName(handle, name);
  net.setNodeEquation(handle, equation);
  net.setNodeEquationBounds(handle, loBound, hiBound);

  net.setNodePosition(handle, xPos, yPos, 85, 55);

         return handle;
}

static void showStats(Network net, int nodeHandle) {
```

```
            String nodeId = net.getNodeId(nodeHandle);

            if (net.isEvidence(nodeHandle)) {
                  double v = net.getContEvidence(nodeHandle);
                  System.out.printf("%s has evidence set (%g)\n", nodeId, v);
                  return;
            }

            if (net.isValueDiscretized(nodeHandle)) {
                  System.out.printf("%s is discretized.\n", nodeId);
                  DiscretizationInterval[] iv =
               net.getNodeEquationDiscretization(nodeHandle);
                  double[] bounds = net.getNodeEquationBounds(nodeHandle);
                  double[] discBeliefs = net.getNodeValue(nodeHandle);
                  double lo = bounds[0];
                for (int i = 0; i < discBeliefs.length; i++) {
                    double hi = iv[i].boundary;
                    System.out.printf(
                   "\tP(%s in %g..%g)=%g\n", nodeId, lo, hi, discBeliefs[i]);
                    lo = hi;
                }
            } else {
                  double[] stats = net.getNodeSampleStats(nodeHandle);
              System.out.printf("%s: mean=%g stddev=%g min=%g max=%g\n",
                  nodeId, stats[0], stats[1], stats[2], stats[3]);
            }
    }

    static void setUniformIntervals(Network net, int nodeHandle, int count) {
       double[] bounds = net.getNodeEquationBounds(nodeHandle);
       double lo = bounds[0];
       double hi = bounds[1];

       DiscretizationInterval[] iv = new DiscretizationInterval[count];
        for (int i = 0; i < count; i++) {
            iv[i] = new DiscretizationInterval(
                null, lo + (i + 1) * (hi - lo) / count);
        }

        net.setNodeEquationDiscretization(nodeHandle, iv);
    }

    static void updateAndShowStats(Network net) {
        net.updateBeliefs();
        for (int h = net.getFirstNode(); h >= 0; h = net.getNextNode(h))
        {
            showStats(net, h);
        }
        System.out.println();
    }
}
```

7.7.2 Tutorial7.py

```
import pysmile

# Tutorial7 creates a network with three equation-based nodes
# performs the inference, then saves the model to disk.

class Tutorial7:
    def __init__(self):
        print("Starting Tutorial7...")
        net = pysmile.Network()

        net.set_outlier_rejection_enabled(True)

        self.create_equation_node(net,
            "tra", "Return Air Temperature",
            "tra=24", 23.9, 24.1, 280, 100)

        self.create_equation_node(net,
            "u_d", "Damper Control Signal",
            "u_d=Bernoulli(0.539)*0.8+0.2", 0, 1, 160, 100)

        toa = self.create_equation_node(net,
            "toa", "Outside Air Temperature",
            "toa=Normal(11,15)", -10, 40, 60, 100)

        # tra, toa and u_d are referenced in equation
        # arcs are created automatically
        tma = self.create_equation_node(net,
            "tma", "Mixed Air Temperature",
            "tma=toa*u_d+(tra-tra*u_d)", 10, 30, 110, 200)

        self.set_uniform_intervals(net, toa, 5)
        self.set_uniform_intervals(net, tma, 4)

        print("Results with no evidence:")
        self.update_and_show_stats(net)

        net.set_cont_evidence(toa, 28.5)
        print("Results with outside air temperature set to 28.5:")
        self.update_and_show_stats(net)

        net.clear_evidence(toa)
        print("Results with mixed air temperature set to 21:")
        net.set_cont_evidence(tma, 21.0)
        self.update_and_show_stats(net)

        net.write_file("tutorial7.xdsl")
        print("Tutorial7 complete: Network written to tutorial7.xdsl")

    def create_equation_node(self, net, id, name, equation, lo_bound,
                             hi_bound, x_pos, y_pos):
        handle = net.add_node(pysmile.NodeType.EQUATION, id)
        net.set_node_name(handle, name)
        net.set_node_equation(handle, equation)
```

```
        net.set_node_equation_bounds(handle, lo_bound, hi_bound)

        net.set_node_position(handle, x_pos, y_pos, 85, 55)

        return handle

    def show_stats(self, net, node_handle):
        node_id = net.get_node_id(node_handle)

        if net.is_evidence(node_handle):
            v = net.get_cont_evidence(node_handle)
            print(f"{node_id} has evidence set: {v}")
            return

        if net.is_value_discretized(node_handle):
            print(f"{node_id} is discretized.")
            iv = net.get_node_equation_discretization(node_handle)
            bounds = net.get_node_equation_bounds(node_handle)
            disc_beliefs = net.get_node_value(node_handle)
            lo = bounds[0]
            for i in range(0, len(disc_beliefs)):
                hi = iv[i].boundary
                print(f"\tP({node_id} in {lo}..{hi})={disc_beliefs[i]}")
                lo = hi
        else:
            stats = net.get_node_sample_stats(node_handle)
            print(f"{node_id}: mean={stats[0]} stddev={stats[1]} min={stats[2]} max={stats[3]}")

    def set_uniform_intervals(self, net, node_handle, count):
        bounds = net.get_node_equation_bounds(node_handle)
        lo = bounds[0]
        hi = bounds[1]

        iv = [None] * count
        for i in range(0, count):
            iv[i] = pysmile.DiscretizationInterval("", lo + (i + 1) * (hi - lo)  / count)

        net.set_node_equation_discretization(node_handle, iv)

    def update_and_show_stats(self, net):
        net.update_beliefs()
        for h in net.get_all_nodes():
            self.show_stats(net, h)
        print()
```

7.7.3 Tutorial7.R

```
library(rSMILE)
source("License.R")

# Tutorial7 creates a network with three equation-based nodes
# performs the inference, then saves the model to disk.

createEquationNode = function(net, id, name, equation, loBound,
                              hiBound, xPos, yPos) {
```

```
    handle <- net$addNode(net$NodeType$EQUATION, id)
    net$setNodeName(handle, name)
    net$setNodeEquation(handle, equation)
    net$setNodeEquationBounds(handle, loBound, hiBound)
    net$setNodePosition(handle, xPos, yPos, 85, 55)

    return(handle)
}

showStats = function(net, nodeHandle) {
    nodeId <- net$getNodeId(nodeHandle)
    if (net$isEvidence(nodeHandle)) {
        v <- net$getContEvidence(nodeHandle)
        cat(sprintf("%s has evidence set (%g)\n", nodeId, v))
        return()
    }

    if (net$isValueDiscretized(nodeHandle)) {
        cat(sprintf("%s is discretized.\n", nodeId))
        iv <- net$getNodeEquationDiscretization(nodeHandle)
        bounds <- net$getNodeEquationBounds(nodeHandle)
        discBeliefs <- net$getNodeValue(nodeHandle)
        lo <- bounds[1]
        for(i in 0:(length(discBeliefs)-1)) {
            hi <- iv[[i+1]]$boundary
            cat(sprintf("\tP(%s in %g..%g)=%g\n",
                nodeId, lo, hi, discBeliefs[i+1]))
            lo <- hi
        }
    } else {
        stats <- net$getNodeSampleStats(nodeHandle)
        cat(sprintf("%s: mean=%g stddev=%g min=%g max=%g\n",
            nodeId, stats[1], stats[2], stats[3], stats[4]))
    }
}

setUniformIntervals = function(net, nodeHandle, count) {
    bounds <- net$getNodeEquationBounds(nodeHandle)
    lo <- bounds[1]
    hi <- bounds[2]

    iv <- lapply(rep("DiscretizationInterval", count), new)
    num <- 1
    for(i in iv) {
        i$id <- ""
        i$boundary <- lo + num * (hi - lo) / count
        num <- num + 1
    }
    net$setNodeEquationDiscretization(nodeHandle, iv)
}

updateAndShowStats = function(net) {
    net$updateBeliefs()
    nodes <- net$getAllNodes()
    for (h in nodes) {
```

```
        showStats(net, h)
    }
    cat("\n")
}

cat("Starting Tutorial7...\n")
net <- Network()

net$setOutlierRejectionEnabled(TRUE)

createEquationNode(net, "tra", "Return Air Temperature",
    "tra=24", 23.9, 24.1, 280, 100)

createEquationNode(net, "u_d", "Damper Control Signal",
    "u_d = Bernoulli(0.539)*0.8 + 0.2", 0, 1, 160, 100)

toa <- createEquationNode(net, "toa", "Outside Air Temperature",
    "toa=Normal(11,15)", -10, 40, 60, 100)

# tra, toa and u_d are referenced in equation
# arcs are created automatically
tma <- createEquationNode(net, "tma", "Mixed Air Temperature",
    "tma=toa*u_d+(tra-tra*u_d)", 10, 30, 110, 200)

setUniformIntervals(net, toa, 5)
setUniformIntervals(net, tma, 4)

cat("Results with no evidence:\n")
updateAndShowStats(net)

net$setContEvidence(toa, 28.5)
cat("Results with outside air temperature set to 28.5:\n")
updateAndShowStats(net)

net$clearEvidence(toa)
cat("Results with mixed air temperature set to 21:\n")
net$setContEvidence(tma, 21.0)
updateAndShowStats(net)

net$writeFile("tutorial7.xdsl")
cat("Tutorial7 complete: Network written to tutorial7.xdsl\n")
```

7.7.4 Tutorial7.cs

```
using System;
using Smile;

// Tutorial7 creates a network with three equation-based nodes
// performs the inference, then saves the model to disk.

namespace SmileNetTutorial
{
    class Tutorial7
    {
        public static void Run()
```

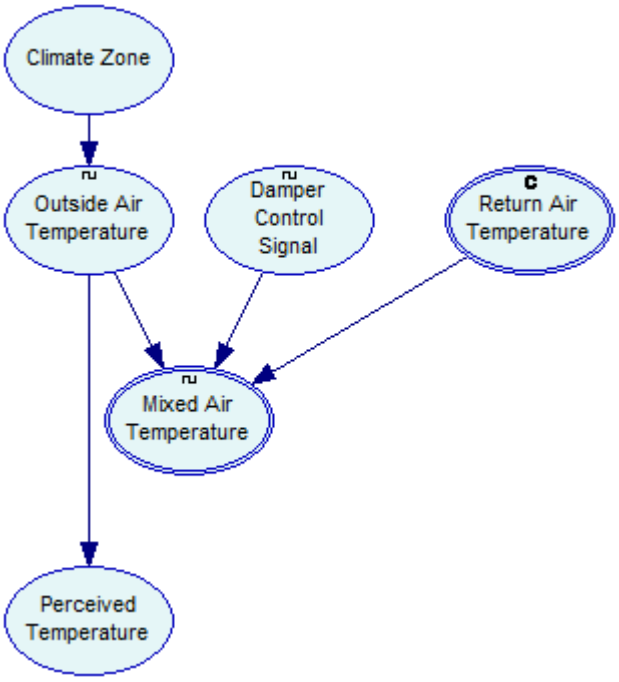
```
{
    Console.WriteLine("Starting Tutorial7...");
    Network net = new Network();

    net.OutlierRejectionEnabled = true;

    CreateEquationNode(net,
        "tra", "Return Air Temperature",
        "tra=24", 23.9, 24.1,
        280, 100);

    CreateEquationNode(net,
        "u_d", "Damper Control Signal",
        "u_d = Bernoulli(0.539)*0.8 + 0.2", 0, 1,
        160, 100);

    int toa = CreateEquationNode(net,
        "toa", "Outside Air Temperature",
        "toa=Normal(11,15)", -10, 40,
        60, 100);

    // tra, toa and u_d are referenced in equation
    // arcs are created automatically
    int tma = CreateEquationNode(net,
        "tma", "Mixed Air Temperature",
        "tma=toa*u_d+(tra-tra*u_d)", 10, 30,
        110, 200);

    SetUniformIntervals(net, toa, 5);
    SetUniformIntervals(net, tma, 4);

    Console.WriteLine("Results with no evidence:");
    UpdateAndShowStats(net);

    net.SetContEvidence(toa, 28.5);
    Console.WriteLine("Results with outside air temperature set to 28.5:");
    UpdateAndShowStats(net);

    net.ClearEvidence(toa);
    Console.WriteLine("Results with mixed air temperature set to 21:");
    net.SetContEvidence(tma, 21.0);
    UpdateAndShowStats(net);

    net.WriteFile("tutorial7.xdsl");
    Console.WriteLine("Tutorial7 complete: Network written to tutorial7.xdsl");
}

private static int CreateEquationNode(
    Network net, String id, String name,
    String equation, double loBound, double hiBound,
    int xPos, int yPos)
{
    int handle = net.AddNode(Network.NodeType.Equation, id);
    net.SetNodeName(handle, name);
    net.SetNodePosition(handle, xPos, yPos, 85, 55);
```

```
    net.SetNodeEquation(handle, equation);
    net.SetNodeEquationBounds(handle, loBound, hiBound);
    return handle;
}

private static void ShowStats(Network net, int nodeHandle)
{
    String nodeId = net.GetNodeId(nodeHandle);

    if (net.IsEvidence(nodeHandle))
    {
        double v = net.GetContEvidence(nodeHandle);
        Console.WriteLine("{0} has evidence set ({1})", nodeId, v);
        return;
    }

    if (net.IsValueDiscretized(nodeHandle))
    {
        Console.WriteLine("{0} is discretized.", nodeId);
        DiscretizationInterval[] iv = net.GetNodeEquationDiscretization(nodeHandle);
        double[] bounds = net.GetNodeEquationBounds(nodeHandle);
        double[] discBeliefs = net.GetNodeValue(nodeHandle);
        double lo = bounds[0];
        for (int i = 0; i < discBeliefs.Length; i++)
        {
            double hi = iv[i].Boundary;
            Console.WriteLine("\tP({0} in {1}..{2})={3}",
                nodeId, lo, hi, discBeliefs[i]);
            lo = hi;
        }
    }
    else
    {
        double[] stats = net.GetNodeSampleStats(nodeHandle);
        Console.WriteLine("{0}: mean={1} stddev={2} min={3} max={4}",
            nodeId, stats[0], stats[1], stats[2], stats[3]);
    }
}

private static void SetUniformIntervals(
    Network net, int nodeHandle, int count)
{
    double[] bounds = net.GetNodeEquationBounds(nodeHandle);
    double lo = bounds[0];
    double hi = bounds[1];

    DiscretizationInterval[] iv = new DiscretizationInterval[count];
    for (int i = 0; i < count; i++)
    {
        iv[i] = new DiscretizationInterval(null, lo + (i + 1) * (hi - lo) / count);
    }

    net.SetNodeEquationDiscretization(nodeHandle, iv);
}
```

```
        private static void UpdateAndShowStats(Network net)
        {
            net.UpdateBeliefs();
            for (int h = net.GetFirstNode(); h >= 0; h = net.GetNextNode(h))
            {
                ShowStats(net, h);
            }
            Console.WriteLine();
        }
    }
}
```

7.8 Tutorial 8: Hybrid model

We extend the model described in *Tutorial 7* [133] by adding two discrete nodes: *Climate Zone* and *Perceived Temperature*. *Climate Zone* refines the probability distribution of the outside air temperature and *Perceived Temperature* is an additional input originating from a subjective perception of the temperature, useful in case of a failure in the outside temperature sensor.



After loading the network created in the previous tutorial, the program adds two discrete nodes using the `CreateCptNode` helper function first seen in *Tutorial 1* [82]. The arc from *Climate Zone* (node identifier is *zone*) to *Outside Air Temperature* (node identifier is *toa*) is created by changing the equation of the latter:

Java:

```
net.setNodeEquation(toaHandle, "toa=If(zone=\"Desert\",Normal(22,5),Normal(11,10))");
```

Python:

```
net.set_node_equation("toa", 'toa=If(zone="Desert",Normal(22,5),Normal(11,10))')
```

C#:

```
net.SetNodeEquation(toaHandle, "toa=If(zone=\"Desert\",Normal(22,5),Normal(11,10))");
```

In the Java and C# code, we need to escape the double quote characters in order to use the text literal representing the *Desert* outcome of the parent. Python allows for single quotes to be used as string literal delimiter.

The new equation switches between two normal distribution based on the outcome of the parent. The equation could be also written in the following ways, all being functionally identical (assuming that *Climate Zone* has two outcomes, *Temperate* and *Desert*):

```
toa=zone="Desert" ? Normal(22,5) : Normal(11,10)
toa=zone="Temperate" ? Normal(11,10) : Normal(22,5)
toa=Switch(zone, "Desert",Normal(22,5),"Temperate",Normal(11,10))
toa=Choose(zone,Normal(11,10),Normal(22,5))
```

To create the arc from *Outside Air Temperature* to *Perceived Temperature* the program calls `Network.addArc`. The model loaded from disk had 5 discretization intervals already defined for *Outside Air Temperature*. With 5 possible discretized outcomes of its single parent and its own 3 outcomes, the CPT for *Perceived Temperature* has 3*5=15 entries. It is initialized by a call to Network.setNodeDefinition with an appropriately sized array as input. Note that for simplicity we do not change the default uniform distribution for the binary *Climate Zone* node.

The program performs inference for each of the *Climate Zone* outcomes set as evidence. The output displayed for the *Outside Air Temperature* node (*toa*) shows changing mean and standard deviation. Finally, the network is saved to disk. This concludes the tutorial.

7.8.1 Tutorial8.java

```
package tutorials;

import smile.*;

// Tutorial8 loads continuous model from the XDSL file written by Tutorial7,
// then adds discrete nodes to create a hybrid model. Inference is performed
// and model is saved to disk.

public class Tutorial8 {
    public static void run() {
        System.out.println("Starting Tutorial8...");
        Network net = new Network();

        net.readFile("tutorial7.xdsl");

        createCptNode(
             net, "zone", "Climate Zone",
             new String[] { "Temperate", "Desert" },
            60, 20);

        int toaHandle = net.getNode("toa");
        net.setNodeEquation(toaHandle, "toa=If(zone=\"Desert\",Normal(22,5),Normal(11,10))");

        int perceivedHandle = createCptNode(
             net, "perceived", "Perceived Temperature",
             new String[] { "Hot", "Warm", "Cold" },
            60, 300);
        net.addArc(toaHandle, perceivedHandle);
```

```
    double[] perceivedProbs = new double[] {
         0,    // P(perceived=Hot |toa in -10..0)
        0.02, // P(perceived=Warm|toa in -10..0)
        0.98, // P(perceived=Cold|toa in -10..0)
        0.05, // P(perceived=Hot |toa in 0..10)
        0.15, // P(perceived=Warm|toa in 0..10)
        0.80, // P(perceived=Cold|toa in 0..10)
        0.10, // P(perceived=Hot |toa in 10..20)
        0.80, // P(perceived=Warm|toa in 10..20)
        0.10, // P(perceived=Cold|toa in 10..20)
        0.80, // P(perceived=Hot |toa in 20..30)
        0.15, // P(perceived=Warm|toa in 20..30)
        0.05, // P(perceived=Cold|toa in 20..30)
        0.98, // P(perceived=Hot |toa in 30..40)
        0.02, // P(perceived=Warm|toa in 30..40)
        0     // P(perceived=Cold|toa in 30..40)
    };
    net.setNodeDefinition(perceivedHandle, perceivedProbs);

    net.setEvidence("zone", "Temperate");
    System.out.println("Results in temperate zone:");
    updateAndShowStats(net);

    net.setEvidence("zone", "Desert");
    System.out.println("Results in desert zone:\n");
    updateAndShowStats(net);

    net.writeFile("tutorial8.xdsl");
    System.out.println("Tutorial8 complete: Network written to tutorial8.xdsl");
}

static void showStats(Network net, int nodeHandle) {
         String nodeId = net.getNodeId(nodeHandle);

         if (net.isEvidence(nodeHandle)) {
                double v = net.getContEvidence(nodeHandle);
                System.out.printf("%s has evidence set (%g)\n", nodeId, v);
                return;
         }

         if (net.isValueDiscretized(nodeHandle)) {
                System.out.printf("%s is discretized.\n", nodeId);
                DiscretizationInterval[] iv =
            net.getNodeEquationDiscretization(nodeHandle);
                double[] bounds = net.getNodeEquationBounds(nodeHandle);
                double[] discBeliefs = net.getNodeValue(nodeHandle);
                double lo = bounds[0];
             for (int i = 0; i < discBeliefs.length; i++) {
                  double hi = iv[i].boundary;
                  System.out.printf(
                 "\tP(%s in %g..%g)=%g\n", nodeId, lo, hi, discBeliefs[i]);
                  lo = hi;
             }
         } else {
```

```
                double[] stats = net.getNodeSampleStats(nodeHandle);
              System.out.printf("%s: mean=%g stddev=%g min=%g max=%g\n",
                  nodeId, stats[0], stats[1], stats[2], stats[3]);
            }
    }

    static void updateAndShowStats(Network net) {
        net.updateBeliefs();
        for (int h = net.getFirstNode(); h >= 0; h = net.getNextNode(h))
        {
            if (net.getNodeType(h) == Network.NodeType.EQUATION) {
             showStats(net, h);
            }
        }
        System.out.println();
    }

    private static int createCptNode(
            Network net, String id, String name,
            String[] outcomes, int xPos, int yPos) {
        int handle = net.addNode(Network.NodeType.CPT, id);

        net.setNodeName(handle, name);
        net.setNodePosition(handle, xPos, yPos, 85, 55);

        int initialOutcomeCount = net.getOutcomeCount(handle);
        for (int i = 0; i < initialOutcomeCount; i ++) {
            net.setOutcomeId(handle, i, outcomes[i]);
        }

        for (int i = initialOutcomeCount; i < outcomes.length; i ++) {
            net.addOutcome(handle, outcomes[i]);
        }

        return handle;
    }
}
```

7.8.2 Tutorial8.py

```
import pysmile

# Tutorial8 loads continuous model from the XDSL file written by Tutorial7,
# then adds discrete nodes to create a hybrid model. Inference is performed
# and model is saved to disk.

class Tutorial8:
    def __init__(self):
        print("Starting Tutorial8...")
        net = pysmile.Network()

        net.read_file("tutorial7.xdsl")

        self.create_cpt_node(net,
            "zone", "Climate Zone",
```

```
            ["Temperate", "Desert" ],
            60, 20)
        toa_handle = net.get_node("toa")
        net.set_node_equation("toa", 'toa=If(zone="Desert",Normal(22,5),Normal(11,10))')

        perceived_handle = self.create_cpt_node(net,
            "perceived", "Perceived Temperature",
            ["Hot", "Warm", "Cold"],
            60, 300)

        net.add_arc(toa_handle, perceived_handle)

        perceived_probs = [
            0,    # P(perceived=Hot |toa in -10..0)
            0.02, # P(perceived=Warm|toa in -10..0)
            0.98, # P(perceived=Cold|toa in -10..0)
            0.05, # P(perceived=Hot |toa in 0..10)
            0.15, # P(perceived=Warm|toa in 0..10)
            0.80, # P(perceived=Cold|toa in 0..10)
            0.10, # P(perceived=Hot |toa in 10..20)
            0.80, # P(perceived=Warm|toa in 10..20)
            0.10, # P(perceived=Cold|toa in 10..20)
            0.80, # P(perceived=Hot |toa in 20..30)
            0.15, # P(perceived=Warm|toa in 20..30)
            0.05, # P(perceived=Cold|toa in 20..30)
            0.98, # P(perceived=Hot |toa in 30..40)
            0.02, # P(perceived=Warm|toa in 30..40)
            0     # P(perceived=Cold|toa in 30..40)
        ]

        net.set_node_definition(perceived_handle, perceived_probs)

        net.set_evidence("zone", "Temperate")
        print("Results in temperate zone:")
        self.update_and_show_stats(net)

        net.set_evidence("zone", "Desert")
        print("Results in desert zone:")
        self.update_and_show_stats(net)

        net.write_file("tutorial8.xdsl")
        print("Tutorial8 complete: Network written to tutorial8.xdsl")

    def show_stats(self, net, node_handle):
        node_id = net.get_node_id(node_handle)

        if net.is_evidence(node_handle):
            v = net.get_cont_evidence(node_handle)
            print(f"{node_id} has evidence set: {v}")
            return

        if net.is_value_discretized(node_handle):
            print(node_id + " is discretized.")
            iv = net.get_node_equation_discretization(node_handle)
            bounds = net.get_node_equation_bounds(node_handle)
```

```
            disc_beliefs = net.get_node_value(node_handle)
            lo = bounds[0]
            for i in range(0, len(disc_beliefs)):
                hi = iv[i].boundary
                print(f"\tP({node_id} in {lo}..{hi})={disc_beliefs[i]}")
                lo = hi
        else:
            stats = net.get_node_sample_stats(node_handle)
            print(f"{node_id}: mean={stats[0]} stddev={stats[1]} min={stats[2]} max={stats[3]}")

    def update_and_show_stats(self, net):
        net.update_beliefs()
        for h in net.get_all_nodes():
            if net.get_node_type(h) == pysmile.NodeType.EQUATION:
                self.show_stats(net, h)
        print()

    def create_cpt_node(self, net, id, name, outcomes, x_pos, y_pos):
        handle = net.add_node(pysmile.NodeType.CPT, id)

        net.set_node_name(handle, name)
        net.set_node_position(handle, x_pos, y_pos, 85, 55)

        initial_outcome_count = net.get_outcome_count(handle)

        for i in range(0, initial_outcome_count):
            net.set_outcome_id(handle, i, outcomes[i])

        for i in range(initial_outcome_count, len(outcomes)):
            net.add_outcome(handle, outcomes[i])

        return handle
```

7.8.3 Tutorial8.R

```
library(rSMILE)
source("License.R")

# Tutorial8 loads continuous model from the XDSL file written by Tutorial7,
# then adds discrete nodes to create a hybrid model. Inference is performed
# and model is saved to disk.

createCptNode = function(net, id, name, outcomes, xPos, yPos) {
    handle <- net$addNode(18, id)
    initialOutcomeCount <- net$getOutcomeCount(handle)
    count <- length(outcomes)
    net$setNodeName(handle, name)
    net$setNodePosition(handle, xPos, yPos, 85L, 55L)
    if (!is.null(outcomes)) {
        sapply(0:(initialOutcomeCount-1),
            function(x) net$setOutcomeId(handle, x, outcomes[x+1]))
        if (initialOutcomeCount < count) {
            sapply(initialOutcomeCount:(count-1),
                function(x) net$addOutcome(handle, outcomes[x+1]))
        }
```

```
    }

    return(handle)
}

showStats = function(net, nodeHandle) {
    nodeId <- net$getNodeId(nodeHandle)
    if (net$isEvidence(nodeHandle)) {
        v <- net$getContEvidence(nodeHandle)
        cat(sprintf("%s has evidence set (%g)\n", nodeId, v))
        return()
    }

    if (net$isValueDiscretized(nodeHandle)) {
        cat(sprintf("%s is discretized.\n", nodeId))
        iv <- net$getNodeEquationDiscretization(nodeHandle)
        bounds <- net$getNodeEquationBounds(nodeHandle)
        discBeliefs <- net$getNodeValue(nodeHandle)
        lo <- bounds[1]
        for(i in 0:(length(discBeliefs)-1)) {
            hi <- iv[[i+1]]$boundary
            cat(sprintf("\tP(%s in %g..%g)=%g\n",
                nodeId, lo, hi, discBeliefs[i+1]))
            lo <- hi
        }
    } else {
        stats <- net$getNodeSampleStats(nodeHandle)
        cat(sprintf("%s: mean=%g stddev=%g min=%g max=%g\n",
            nodeId, stats[1], stats[2], stats[3], stats[4]))
    }
}

updateAndShowStats = function(net) {
    net$updateBeliefs()
    nodes <- net$getAllNodes()
    for (h in nodes) {
        if(net$getNodeType(h) == net$NodeType$EQUATION) {
            showStats(net, h)
        }
    }
    cat("\n")
}

cat("Starting Tutorial8...\n")
net <- Network()

net$readFile("tutorial7.xdsl")

createCptNode(net, "zone", "Climate Zone", c("Temperate", "Desert"), 60, 20)

toaHandle <- net$getNode("toa")
net$setNodeEquation(toaHandle, "toa=If(zone=\"Desert\",Normal(22,5),Normal(11,10))")

perceivedHandle <- createCptNode(net, "perceived", "Perceived Temperature",
    c("Hot", "Warm", "Cold"), 60, 300)
```

```
net$addArc(toaHandle, perceivedHandle)

perceivedProbs = c( 0.00,
                    0.02,
                    0.98,
                    0.05,
                    0.15,
                    0.80,
                    0.10,
                    0.80,
                    0.10,
                    0.80,
                    0.15,
                    0.05,
                    0.98,
                    0.02,
                    0.00 )

net$setNodeDefinition(perceivedHandle, perceivedProbs)

net$setEvidence("zone", "Temperate")
cat("Results in temperate zone:\n")
updateAndShowStats(net)

net$setEvidence("zone", "Desert")
cat("Results in desert zone:\n")
updateAndShowStats(net)

net$writeFile("tutorial8.xdsl")

cat("Tutorial8 complete: Network written to tutorial8.xdsl\n")
```

7.8.4 Tutorial8.cs

```
using System;
using Smile;

// Tutorial8 loads continuous model from the XDSL file written by Tutorial7,
// then adds discrete nodes to create a hybrid model. Inference is performed
// and model is saved to disk.

namespace SmileNetTutorial
{
    class Tutorial8
    {
        public static void Run()
        {
            Console.WriteLine("Starting Tutorial8...");
            Network net = new Network();

            net.ReadFile("tutorial7.xdsl");

            CreateCptNode(
                net, "zone", "Climate Zone",
```

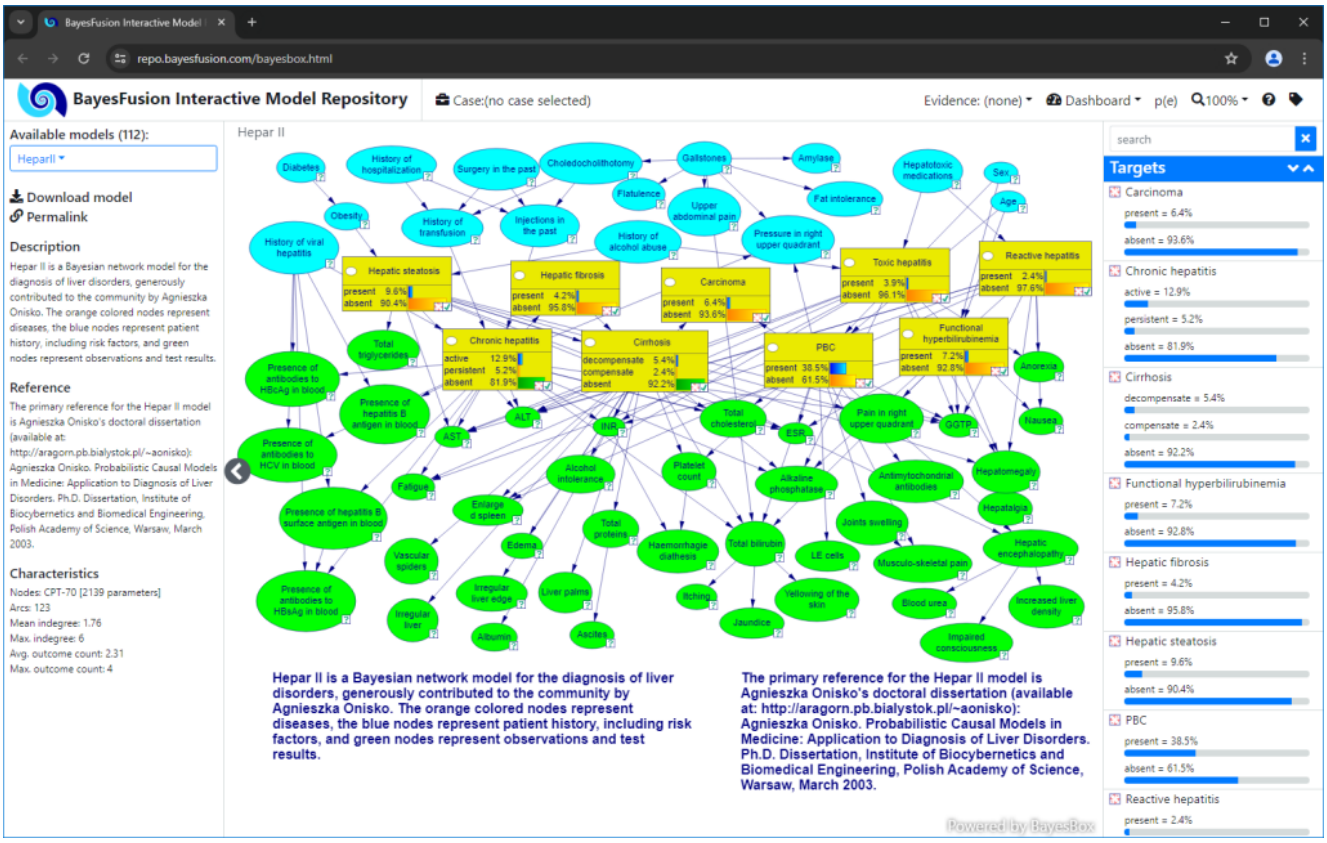
```
            new String[] { "Temperate", "Desert" },
            60, 20);

        int toaHandle = net.GetNode("toa");
        net.SetNodeEquation(toaHandle,
            "toa=If(zone=\"Desert\",Normal(22,5),Normal(11,10))");

        int perceivedHandle = CreateCptNode(
            net, "perceived", "Perceived Temperature",
            new String[] { "Hot", "Warm", "Cold" },
            60, 300);
        net.AddArc(toaHandle, perceivedHandle);

        double[] perceivedProbs = new double[] {
            0,    // P(perceived=Hot |toa in -10..0)
            0.02, // P(perceived=Warm|toa in -10..0)
            0.98, // P(perceived=Cold|toa in -10..0)
            0.05, // P(perceived=Hot |toa in 0..10)
            0.15, // P(perceived=Warm|toa in 0..10)
            0.80, // P(perceived=Cold|toa in 0..10)
            0.10, // P(perceived=Hot |toa in 10..20)
            0.80, // P(perceived=Warm|toa in 10..20)
            0.10, // P(perceived=Cold|toa in 10..20)
            0.80, // P(perceived=Hot |toa in 20..30)
            0.15, // P(perceived=Warm|toa in 20..30)
            0.05, // P(perceived=Cold|toa in 20..30)
            0.98, // P(perceived=Hot |toa in 30..40)
            0.02, // P(perceived=Warm|toa in 30..40)
            0     // P(perceived=Cold|toa in 30..40)
        };
        net.SetNodeDefinition(perceivedHandle, perceivedProbs);

        net.SetEvidence("zone", "Temperate");
        Console.WriteLine("Results in temperate zone:");
        UpdateAndShowStats(net);

        net.SetEvidence("zone", "Desert");
        Console.WriteLine("Results in desert zone:\n");
        UpdateAndShowStats(net);

        net.WriteFile("tutorial8.xdsl");
        Console.WriteLine("Tutorial8 complete: Network written to tutorial8.xdsl");
    }

    private static int CreateEquationNode(
        Network net, String id, String name,
        String equation, double loBound, double hiBound,
        int xPos, int yPos)
    {
        int handle = net.AddNode(Network.NodeType.Equation, id);
        net.SetNodeName(handle, name);
        net.SetNodePosition(handle, xPos, yPos, 85, 55);
        net.SetNodeEquation(handle, equation);
        net.SetNodeEquationBounds(handle, loBound, hiBound);
        return handle;
```

```
}

private static void ShowStats(Network net, int nodeHandle)
{
    String nodeId = net.GetNodeId(nodeHandle);

    if (net.IsEvidence(nodeHandle))
    {
        double v = net.GetContEvidence(nodeHandle);
        Console.WriteLine("{0} has evidence set ({1})", nodeId, v);
        return;
    }

    if (net.IsValueDiscretized(nodeHandle))
    {
        Console.WriteLine("{0} is discretized.", nodeId);
        DiscretizationInterval[] iv =
            net.GetNodeEquationDiscretization(nodeHandle);
        double[] bounds = net.GetNodeEquationBounds(nodeHandle);
        double[] discBeliefs = net.GetNodeValue(nodeHandle);
        double lo = bounds[0];
        for (int i = 0; i < discBeliefs.Length; i++)
        {
            double hi = iv[i].Boundary;
            Console.WriteLine("\tP({0} in {1}..{2})={3}",
                nodeId, lo, hi, discBeliefs[i]);
            lo = hi;
        }
    }
    else
    {
        double[] stats = net.GetNodeSampleStats(nodeHandle);
        Console.WriteLine("{0}: mean={1} stddev={2} min={3} max={4}",
            nodeId, stats[0], stats[1], stats[2], stats[3]);
    }
}

private static void UpdateAndShowStats(Network net)
{
    net.UpdateBeliefs();
    for (int h = net.GetFirstNode(); h >= 0; h = net.GetNextNode(h))
    {
        if (net.GetNodeType(h) == (int)Network.NodeType.Equation)
        {
            ShowStats(net, h);
        }
    }
    Console.WriteLine();
}

private static int CreateCptNode(
    Network net, String id, String name,
    String[] outcomes, int xPos, int yPos)
{
    int handle = net.AddNode(Network.NodeType.Cpt, id);
```

```
            net.SetNodeName(handle, name);
            net.SetNodePosition(handle, xPos, yPos, 85, 55);

            int initialOutcomeCount = net.GetOutcomeCount(handle);
            for (int i = 0; i < initialOutcomeCount; i++)
            {
                net.SetOutcomeId(handle, i, outcomes[i]);
            }

            for (int i = initialOutcomeCount; i < outcomes.Length; i++)
            {
                net.AddOutcome(handle, outcomes[i]);
            }

            return handle;
        }
    }
}
```

7.9 Tutorial 9: Diagnosis

The program in this section uses one of the example discrete networks distributed in GeNIe, which can be downloaded directly using the following link: https://support.bayesfusion.com/docs/Examples/Discrete%20Bayesian%20Networks/HeparII.xdsl. The model is also available in BayesFusion's online repository at https://repo.bayesfusion.com/network/permalink?net=Small+BNs%2FHeparII.xdsl.



HeparII.xdsl is a Bayesian network model for the diagnosis of liver disorders. It has diagnostic roles defined for its nodes. The model nodes were formatted to use yellow as a background for fault nodes, and green/blue for observation nodes. Note that while binary fault nodes have one fault state (*present*), there are also two fault nodes with three states. These nodes have two out of three states marked as faulty, like *active* and *persistent* in the case of *Chronic Hepatitis*.

Our program loads the network at startup and calls its helper function `printDiagTypes` to output the information about diagnostic roles. The first lines of the output look like this:

```
Node Id              Diagnostic Type               Fault Outcomes
alcoholism           NodeDiagType.OBSERVATION      n/a
vh_amn               NodeDiagType.OBSERVATION      n/a
hepatotoxic          NodeDiagType.OBSERVATION      n/a
THepatitis           NodeDiagType.FAULT            ['present']
hospital             NodeDiagType.OBSERVATION      n/a
surgery              NodeDiagType.OBSERVATION      n/a
gallstones           NodeDiagType.OBSERVATION      n/a
choledocholithotomy  NodeDiagType.OBSERVATION      n/a
injections           NodeDiagType.OBSERVATION      n/a
transfusion          NodeDiagType.OBSERVATION      n/a
ChHepatitis          NodeDiagType.FAULT            ['active', 'persistent']
sex                  NodeDiagType.OBSERVATION      n/a
...
```

The printDiagTypes function iterates over the nodes in the network. Its main loop calls `Network.getNodeDiagType` to determine the diagnostic role. If the node is a fault, its outcomes are also inspected using `Network.isFaultOutcome`.

Java:

```
int diagType = net.getNodeDiagType(nodeId);
List<String> faultOutcomes = new ArrayList<>();
if (diagType == Network.NodeDiagType.FAULT) {
    for (String outcomeId : net.getOutcomeIds(nodeId)) {
        if (net.isFaultOutcome(nodeId, outcomeId)) {
            faultOutcomes.add(outcomeId);
        }
    }
}
```

Python:

```
diag_type = net.get_node_diag_type(node_id)
fault_outcomes = []
if diag_type == pysmile.NodeDiagType.FAULT:
    for outcome_id in net.get_outcome_ids(node_id):
        if net.is_fault_outcome(node_id, outcome_id):
            fault_outcomes.append(outcome_id)
```

C#:

```
Network.NodeDiagType diagType = net.GetNodeDiagType(nodeId);
List<string> faultOutcomes = new List<string>();
if (diagType == Network.NodeDiagType.Fault)
{
    foreach (string outcomeId in net.GetOutcomeIds(nodeId))
    {
        if (net.IsFaultOutcome(nodeId, outcomeId))
        {
```

```
            faultOutcomes.Add(outcomeId);
        }
    }
}
```

We now proceed to the actual diagnosis: the `DiagNetwork` object is instantiated. In its constructor, the fault probabilities are calculated and the most likely fault is selected to be pursued. `DiagNetwork` uses zero-based integer indices to identify faults (node/node outcome pairs). The `printFaultIndices` helper function iterates over faults. It uses `DiagNetwork.getFaultCount`, `getFaultNodeId` and `getFaultOutcomeId` to emit the following output:

```
Diagnostic network has 11 faults (node/outcome pairs)
Fault Index  Fault Node Id        Fault Outcome Id
0            THepatitis           present
1            ChHepatitis          active
2            ChHepatitis          persistent
3            PBC                  present
4            fibrosis             present
5            Steatosis            present
6            Cirrhosis            decompensate
7            Cirrhosis            compensate
8            Hyperbilirubinemia   present
9            RHepatitis           present
10           carcinoma            present
```

We can read the index of the currently pursued fault with `DiagNetwork.getPursuedFault`. Initially, the most likely fault is at index 3, which represents the node *PBC* and its outcome *present*.

Java:

```
int pursuedFaultIdx = diag.getPursuedFault();
System.out.printf("The default (most likely) pursued fault is at index %d: %s=%s\n",
    pursuedFaultIdx, diag.getFaultNodeId(pursuedFaultIdx),
    diag.getFaultOutcomeId(pursuedFaultIdx));
```

Python:

```
pursued_fault_idx = diag.get_pursued_fault()
print(f"The default (most likely) pursued fault is at index {pursued_fault_idx}: "
    + f"{diag.get_fault_node_id(pursued_fault_idx)}"
    + f"={diag.get_fault_outcome_id(pursued_fault_idx)}")
```

C#:

```
int pursuedFaultIdx = diag.GetPursuedFault();
Console.WriteLine("The default (most likely) pursued fault is at index {0}: {1}={2}",
    pursuedFaultIdx,
    diag.GetFaultNodeId(pursuedFaultIdx), diag.GetFaultOutcomeId(pursuedFaultIdx));
```

The program performs the diagnostic update without any observations instantiated. `DiagNetwork.update` is called, and results are returned as a `DiagResults` object. The diagnostic results contain two arrays, one for faults, and another for observations. The arrays are sorted: faults are sorted by probability with most likely faults at the top, and observations are sorted by the magnitude of the information gain. Our `printDiagResults` iterates over the elements of these arrays. `printFaultInfo` and `printObservationInfo` are used to access the members of the `FaultInfo` and `ObservationInfo` objects, respectively. The first lines of the fault/observation output look like this:

```
Faults:
Node Id             Outcome Id          Probability             Is Pursued
PBC                 present             0.41341570632059377     Yes
```

```
ChHepatitis          active              0.1290048962276199       No
Steatosis            present             0.09585221239536176      No
carcinoma            present             0.0665709760500613       No
...
Observations:
Node Id              Measure                   Cost     InfoGain
ama                  0.5576308476489384        0.0      0.5576308476489384
cholesterol          0.4868445142223191        0.0      0.4868445142223191
ESR                  0.42960779128083926       0.0      0.42960779128083926
bilirubin            0.41580785350162774       0.0      0.41580785350162774
age                  -0.33803891617697684      0.0      -0.33803891617697684
skin                 0.3100428612068602        0.0      0.3100428612068602
...
```

The default diagnostic measure algorithm for single fault diagnosis uses the maximum magnitude of probability change in the pursued fault over all outcomes of the observation node. From the output, we can deduce that the *ama* node has an outcome that causes the probability *PBC=present* to increase by 0.55763. Note also that *age* infoGain is negative due to (signed) probability change used as a diagnostic measure algorithm. For brevity, the tutorial program does not use `ObservationInfo.outcomeGain` array, which contains per-outcome infoGain. From `outcomeGain`, we could determine which outcome of the *ama* node is responsible for the maximum change in *PBC*. Other members of `ObservationInfo` not displayed by this tutorial are `faultPosteriors` and `observationPriors`. The `faultPosteriors` array contains probabilities of pursued fault after instantiating each outcome of the observation. The `observationPriors` array contains prior probabilities for each observation outcome.

We will now instantiate (observe) some observation nodes. `DiagNetwork.instantiateObservation` calls `Network.setEvidence` internally, and updates `DiagNetwork`'s state. **Always call `DiagNetwork.instantiateObservation` when the diagnostic session is in progress**. Calling `Network.setEvidence` directly may lead to inconsistent results or errors. Our observations are:

- *jaundice=present*
- *nausea=absent*
- *obesity=present*

The code is straightforward:

Java:

```
diag.instantiateObservation("jaundice", "present");
diag.instantiateObservation("nausea", "absent");
diag.instantiateObservation("obesity", "present");
```

Python:

```
diag.instantiate_observation("jaundice", "present")
diag.instantiate_observation("nausea", "absent")
diag.instantiate_observation("obesity", "present")
```

C#:

```
diag.InstantiateObservation("jaundice", "present");
diag.InstantiateObservation("nausea", "absent");
diag.InstantiateObservation("obesity", "present");
```

After another call to `DiagNetwork.update` and `printDiagResults`, we get the following output:

```
Faults:
Node Id              Outcome Id          Probability              Is Pursued
```

```
PBC                 present             0.3716679804854865      Yes
Steatosis           present             0.20822898960092975     No
ChHepatitis         active              0.12911036437662063     No
Cirrhosis           decompensate        0.08774271003265043     No
...
Observations:
Node Id             Measure                 Cost    InfoGain
ama                 0.5940244757037065      0.0     0.5940244757037065
cholesterol         0.4557094807486714      0.0     0.4557094807486714
bilirubin           0.43194679397989816     0.0     0.43194679397989816
ESR                 0.41696920311719615     0.0     0.41696920311719615
age                 -0.3062170075414388     0.0     -0.3062170075414388
skin                0.2869860117172001      0.0     0.2869860117172001
...
```

With known *jaundice*, *nausea* and *obesity t*he fault probabilities and observation infoGains have changed, but the *ama* node is still our most useful observation.

The next step is to change the outcome of *obesity* to *absent* and retract the observation of *nausea*. We will also switch our pursued fault to *Hyperbilirubinemia=present*.

Java:

```
diag.releaseObservation("nausea");
diag.instantiateObservation("obesity", "absent");
int hyperbilirubinemiaIdx = diag.getFaultIndex("Hyperbilirubinemia", "present");
diag.setPursuedFault(hyperbilirubinemiaIdx);
```

Python:

```
diag.release_observation("nausea")
diag.instantiate_observation("obesity", "absent")
hyperbilirubinemia_idx = diag.get_fault_index("Hyperbilirubinemia", "present")
diag.set_pursued_fault(hyperbilirubinemia_idx)
```

C#:

```
diag.ReleaseObservation("nausea");
diag.InstantiateObservation("obesity", "absent");
int hyperbilirubinemiaIdx = diag.GetFaultIndex("Hyperbilirubinemia", "present");
diag.SetPursuedFault(hyperbilirubinemiaIdx);
```

Another `DiagNetwork.update` and `printDiagResults` calls produce this output:

```
Node Id             Outcome Id          Probability             Is Pursued
PBC                 present             0.3699731063429856      No
ChHepatitis         active              0.12884438248137664     No
Steatosis           present             0.08508721992530559     No
carcinoma           present             0.06083429718416463     No
ChHepatitis         persistent          0.05272028107403933     No
Hyperbilirubinemia  present             0.052337451916630945    Yes
...
Observations:
Node Id             Measure                 Cost    InfoGain
age                 0.2455407606076575      0.0     0.2455407606076575
hepatomegaly        0.04617967333309004     0.0     0.04617967333309004
bilirubin           0.042062826363683546    0.0     0.042062826363683546
ggtp                -0.03279259884194631    0.0     -0.03279259884194631
ESR                 -0.024267251569646417   0.0     -0.024267251569646417
ama                 -0.023463595723063817   0.0     -0.023463595723063817
```

```
...
```

We can immediately notice that the major factor determining the probability of *Hyperbilirubinemia=present* is *age*. Of course in the real-world scenario, we would know the age of the patient before starting the diagnosis.

Our final diagnosis with a single pursued fault will switch to a cross-entropy measure for infoGain. We do not change observations and the pursued faults remain the same.

Java:

```
diag.setSingleFaultAlgorithm(DiagNetwork.SingleFaultAlgorithmType.CROSSENTROPY);
```

Python:

```
diag.set_single_fault_algorithm(pysmile.SingleFaultAlgorithmType.CROSSENTROPY)
```

C#:

```
diag.SingleFaultAlgorithm = DiagNetwork.SingleFaultAlgorithmType.Crossentropy;
```

The output from `DiagNetwork.update` now has non-negative `infoGain` for all observations. Note that fault probabilities do not change when the diagnostic measure algorithm is changed, therefore the fragment of the tutorial output below omits the fault info.

```
Observations:
Node Id              Measure                 Cost     InfoGain
age                  0.05465458670852352     0.0      0.05465458670852352
hepatomegaly         0.01315927809591283     0.0      0.01315927809591283
ggtp                 0.010610204503726073    0.0      0.010610204503726073
bilirubin            0.006204569424644146    0.0      0.006204569424644146
sex                  0.0031695792371849163   0.0      0.0031695792371849163
pain_ruq             0.00263781234873367     0.0      0.00263781234873367
ESR                  0.0026302997853497323   0.0      0.0026302997853497323
ama                  0.0025319015011320833   0.0      0.0025319015011320833
hepatalgia           0.001572547559233084    0.0      0.001572547559233084
cholesterol          9.548883878895409E-4    0.0      9.548883878895409E-4
...
```

Without changing the observations, we now proceed to multi-fault diagnosis. We will keep *Hyperbilirubinemia=present* and add *Steatosis=present*. We know the fault index for the first fault already, but need to get the index for the second fault.

Java:

```
int steatosisIdx = diag.getFaultIndex("Steatosis", "present");
diag.setPursuedFaults(new int[]{steatosisIdx, hyperbilirubinemiaIdx});
```

Python:

```
steatosis_idx = diag.get_fault_index("Steatosis", "present")
diag.set_pursued_faults([steatosis_idx, hyperbilirubinemia_idx])
```

C#:

```
int steatosisIdx = diag.GetFaultIndex("Steatosis", "present");
diag.SetPursuedFaults(new int[] { steatosisIdx, hyperbilirubinemiaIdx });
```

After a `DiagNetwork.update` we will get identical fault probabilities (because observations did not change), but the infoGains will be different:

```
Observations:
Node Id              Measure                 Cost     InfoGain
triglycerides        0.32730161296292315     0.0      0.32730161296292315
```

```
age                 0.2455407606076575      0.0     0.2455407606076575
alcoholism          0.14812380191186358     0.0     0.14812380191186358
inr                 0.13221077172053503     0.0     0.13221077172053503
irregular_liver     0.11230469436997036     0.0     0.11230469436997036
spleen              0.09007368131876663     0.0     0.09007368131876663
spiders             0.06621496955185409     0.0     0.06621496955185409
palms               0.06617286150395034     0.0     0.06617286150395034
edge                0.058990744385672464    0.0     0.058990744385672464
ast                 -0.056481838925186656   0.0     -0.056481838925186656
alt                 -0.05257654040287       0.0     -0.05257654040287
platelet            0.05126314745980294     0.0     0.05126314745980294
...
```

The default measure algorithm for multi-fault diagnosis uses the maximum magnitude of probability change over all faults and all observation outcomes. Our last diagnosis will keep the observations, but the measure algorithm will be normalized Euclidean distance in the fault probability vector space.

Java:

```
diag.setMultiFaultAlgorithm(DiagNetwork.MultiFaultAlgorithmType.L2_NORMALIZED_DISTANCE);
```

Python:

```
diag.set_multi_fault_algorithm(pysmile.MultiFaultAlgorithmType.L2_NORMALIZED_DISTANCE)
```

C#:

```
diag.MultiFaultAlgorithm = DiagNetwork.MultiFaultAlgorithmType.L2NormalizedDistance;
```

Here's the observation output after DiagNetwork.update:

```
Observations:
Node Id             Measure                 Cost    InfoGain
age                 0.5131574568755791      0.0     0.5131574568755791
ast                 0.36613951542960194     0.0     0.36613951542960194
alt                 0.3263962662652687      0.0     0.3263962662652687
triglycerides       0.29763021106578275     0.0     0.29763021106578275
inr                 0.23813502209247214     0.0     0.23813502209247214
alcoholism          0.23215767497663264     0.0     0.23215767497663264
bilirubin           0.2217351591088665      0.0     0.2217351591088665
hepatomegaly        0.21201689659082573     0.0     0.21201689659082573
ggtp                0.20797749804060328     0.0     0.20797749804060328
cholesterol         0.20654898750297776     0.0     0.20654898750297776
irregular_liver     0.20400352015821183     0.0     0.20400352015821183
ESR                 0.19743075347810374     0.0     0.19743075347810374
spleen              0.18236843341781642     0.0     0.18236843341781642
albumin             0.18078914435171048     0.0     0.18078914435171048
...
```

This concludes tutorial 9.

7.9.1 Tutorial9.java

```
package tutorials;

import smile.*;

import java.util.ArrayList;
import java.util.List;
```

```
// Tutorial9 loads HeparII.xdsl file
// and runs multiple diagnostic algorithms
// Use the link below to download the HeparII.xdsl file:
// https://support.bayesfusion.com/docs/Examples/Discrete%20Bayesian%20Networks/HeparII.xdsl

public class Tutorial9 {
    public static void run() {
        System.out.println("Starting diagnosis example");
        Network net = new Network();
        net.readFile("HeparII.xdsl");
        System.out.println("Hepar model loaded");
        printDiagTypes(net);

        System.out.println("Creating diagnostic network object");
        DiagNetwork diag = new DiagNetwork(net);
        printFaultIndices(diag);

        int pursuedFaultIdx = diag.getPursuedFault();
        System.out.printf("The default (most likely) pursued fault is at index %d: %s=%s\n",
            pursuedFaultIdx, diag.getFaultNodeId(pursuedFaultIdx),
            diag.getFaultOutcomeId(pursuedFaultIdx));

        System.out.println("Running diagnosis with no instantiated observations");
        DiagResults diagResults = diag.update();
        printDiagResults(net, diagResults);

        System.out.println("Running diagnosis with three observations");
        diag.instantiateObservation("jaundice", "present");
        diag.instantiateObservation("nausea", "absent");
        diag.instantiateObservation("obesity", "present");
        diagResults = diag.update();
        printDiagResults(net, diagResults);

        System.out.println("Running diagnosis with two observations and "
            + "focusing on Hyperbilirubinemia");
        diag.releaseObservation("nausea");
        diag.instantiateObservation("obesity", "absent");
        int hyperbilirubinemiaIdx = diag.getFaultIndex("Hyperbilirubinemia", "present");
        diag.setPursuedFault(hyperbilirubinemiaIdx);
        diagResults = diag.update();
        printDiagResults(net, diagResults);

        System.out.println("Switching algorithm to cross-entropy, "
            + "observations and pursued fault unchanged");
        diag.setSingleFaultAlgorithm(DiagNetwork.SingleFaultAlgorithmType.CROSSENTROPY);
        diagResults = diag.update();
        printDiagResults(net, diagResults);

        System.out.println("Running diagnosis with two observations and "
            + "focusing on both Hyperbilirubinemia and Steatosis");
        int steatosisIdx = diag.getFaultIndex("Steatosis", "present");
        diag.setPursuedFaults(new int[]{steatosisIdx, hyperbilirubinemiaIdx});
        diagResults = diag.update();
        printDiagResults(net, diagResults);
```

```
        System.out.println("Swtiching algorithm to L2 distance, "
            + "observations and pursued faults unchanged");
        diag.setMultiFaultAlgorithm(DiagNetwork.MultiFaultAlgorithmType.L2_NORMALIZED_DISTANCE);
        diagResults = diag.update();
        printDiagResults(net, diagResults);

        System.out.println("Tutorial9 complete.");
    }

    public static void printDiagTypes(Network net) {
        System.out.printf("Network has %d nodes\n", net.getNodeCount());
        System.out.printf("%-20s %-30s %-30s\n",
            "Node Id", "Diagnostic Type", "Fault Outcomes");
        String[] nodeIds = net.getAllNodeIds();
        for (String nodeId : nodeIds) {
            int diagType = net.getNodeDiagType(nodeId);
            List<String> faultOutcomes = new ArrayList<>();
            if (diagType == Network.NodeDiagType.FAULT) {
                for (String outcomeId : net.getOutcomeIds(nodeId)) {
                    if (net.isFaultOutcome(nodeId, outcomeId)) {
                        faultOutcomes.add(outcomeId);
                    }
                }
            }
            System.out.printf("%-20s %-30s %-30s\n", nodeId, diagType,
                (faultOutcomes.size() != 0) ? String.join(", ", faultOutcomes) : "n/a");
        }
    }

    public static void printFaultIndices(DiagNetwork diag) {
        int faultCount = diag.getFaultCount();
        System.out.printf("Diagnostic network has %d faults (node/outcome pairs)\n",
            faultCount);
        System.out.printf("%-12s %-20s %-20s\n",
            "Fault Index", "Fault Node Id", "Fault Outcome Id");
        for (int fIdx = 0; fIdx < faultCount; fIdx++) {
            System.out.printf("%-12d %-20s %-20s\n",
                fIdx, diag.getFaultNodeId(fIdx), diag.getFaultOutcomeId(fIdx));
        }
    }

    public static void printFaultInfo(Network net, FaultInfo fault) {
        System.out.printf("%-20s %-20s %-24s %-8s\n",
            net.getNodeId(fault.node), net.getOutcomeId(fault.node, fault.outcome),
            fault.probability, fault.isPursued ? "Yes" : "No");
    }

    public static void printObservationInfo(Network net, ObservationInfo observation) {
        System.out.printf("%-20s %-24s %-8s %-20s\n",
            net.getNodeId(observation.node), observation.measure,
            observation.cost, observation.infoGain);
    }

    public static void printDiagResults(Network net, DiagResults diagResults) {
        System.out.println("Diag results start\n\nFaults:");
```

```
        System.out.printf("%-20s %-20s %-24s %-8s\n",
            "Node Id", "Outcome Id", "Probability", "Is Pursued");
        for (FaultInfo faultInfo : diagResults.faults) {
            printFaultInfo(net, faultInfo);
        }
        System.out.println("\nObservations:");
        System.out.printf("%-20s %-24s %-8s %-20s\n",
            "Node Id", "Measure", "Cost", "InfoGain");
        for (ObservationInfo observationInfo : diagResults.observations) {
            printObservationInfo(net, observationInfo);
        }
        System.out.println("\nDiag results end\n");
    }
}
```

7.9.2 Tutorial9.py

```
import pysmile

# Tutorial9 loads HeparII.xdsl file
# and runs multiple diagnostic algorithms
# Use the link below to download the HeparII.xdsl file:
# https://support.bayesfusion.com/docs/Examples/Discrete%20Bayesian%20Networks/HeparII.xdsl

class Tutorial9:
    def __init__(self):
        print("Starting tutorial 9...")
        net = pysmile.Network()
        net.read_file("HeparII.xdsl")
        print("Hepar model loaded")
        print_diag_types(net)

        print("Creating diagnostic network object")
        diag = pysmile.DiagNetwork(net)
        print_fault_indices(diag)

        pursued_fault_idx = diag.get_pursued_fault()
        print(f"The default (most likely) pursued fault is at index {pursued_fault_idx}: "
              + f"{diag.get_fault_node_id(pursued_fault_idx)}"
              + f"={diag.get_fault_outcome_id(pursued_fault_idx)}")

        print("Running diagnosis with no instantiated observations")
        diag_results = diag.update()
        print_diag_results(net, diag_results)

        print("Running diagnosis with three observations")
        diag.instantiate_observation("jaundice", "present")
        diag.instantiate_observation("nausea", "absent")
        diag.instantiate_observation("obesity", "present")
        diag_results = diag.update()
        print_diag_results(net, diag_results)

        print("Running diagnosis with two observations and focusing on Hyperbilirubinemia")
        diag.release_observation("nausea")
        diag.instantiate_observation("obesity", "absent")
```

```
        hyperbilirubinemia_idx = diag.get_fault_index("Hyperbilirubinemia", "present")
        diag.set_pursued_fault(hyperbilirubinemia_idx)
        diag_results = diag.update()
        print_diag_results(net, diag_results)

        print("Switching algorithm to cross-entropy, observations and pursued fault unchanged")
        diag.set_single_fault_algorithm(pysmile.SingleFaultAlgorithmType.CROSSENTROPY)
        diag_results = diag.update()
        print_diag_results(net, diag_results)

        print("Running diagnosis with two observations and "
            + "focusing on both Hyperbilirubinemia and Steatosis")
        steatosis_idx = diag.get_fault_index("Steatosis", "present")
        diag.set_pursued_faults([steatosis_idx, hyperbilirubinemia_idx])
        diag_results = diag.update()
        print_diag_results(net, diag_results)

        print("Swtiching algorithm to L2 distance, observations and pursued faults unchanged")
        diag.set_multi_fault_algorithm(pysmile.MultiFaultAlgorithmType.L2_NORMALIZED_DISTANCE)
        diag_results = diag.update()
        print_diag_results(net, diag_results)

        print("Tutorial 9 complete.")

def print_diag_types(net):
    print(f"Network has {net.get_node_count()} nodes")
    print("{:<20} {:<30} {:<30}".format("Node Id", "Diagnostic Type", "Fault Outcomes"))
    for node_id in net.get_all_node_ids():
        diag_type = net.get_node_diag_type(node_id)
        fault_outcomes = []
        if diag_type == pysmile.NodeDiagType.FAULT:
            for outcome_id in net.get_outcome_ids(node_id):
                if net.is_fault_outcome(node_id, outcome_id):
                    fault_outcomes.append(outcome_id)
        print("{:<20} {:<30} {:<30}".format(node_id, str(net.get_node_diag_type(node_id)),
            str(fault_outcomes) if diag_type == pysmile.NodeDiagType.FAULT else "n/a"))

def print_fault_indices(diag):
    fault_count = diag.get_fault_count()
    print(f"Diagnostic network has {fault_count} faults (node/outcome pairs)")
    print("{:<12} {:<20} {:<20}".format("Fault Index", "Fault Node Id", "Fault Outcome Id"))
    for fidx in range(fault_count):
        print("{:<12} {:<20} {:<20}".format(
            fidx, diag.get_fault_node_id(fidx), diag.get_fault_outcome_id(fidx)))

def print_fault_info(net, fault):
    print("{:<20} {:<20} {:<24} {:<8}".format(
        net.get_node_id(fault.node), net.get_outcome_id(fault.node, fault.outcome),
        fault.probability, "Yes" if fault.is_pursued else "No"))

def print_observation_info(net, observation):
    print("{:<20} {:<24} {:<8} {:<20}".format(net.get_node_id(observation.node),
        observation.measure, observation.cost, observation.info_gain))

def print_diag_results(net, diag_results):
```

```
    print("Diag results start\n\nFaults:")
    print("{:<20} {:<20} {:<24} {:<8}".format(
        "Node Id", "Outcome Id", "Probability", "Is Pursued"))
    for fault_info in diag_results.faults:
        print_fault_info(net, fault_info)
    print("\nObservations:")
    print("{:<20} {:<24} {:<8} {:<20}".format("Node Id", "Measure", "Cost", "InfoGain"))
    for observation_info in diag_results.observations:
        print_observation_info(net, observation_info)
    print("\nDiag results end\n")
```

7.9.3 Tutorial9.R

```
library(rSMILE)
source("License.R")

# Tutorial9 loads HeparII.xdsl file
# and runs multiple diagnostic algorithms
# Use the link below to download the HeparII.xdsl file:
# https://support.bayesfusion.com/docs/Examples/Discrete%20Bayesian%20Networks/HeparII.xdsl

printDiagTypes <- function(net) {
    cat(sprintf("Network has %d nodes\n", net$getNodeCount()))
    cat(sprintf("%-20s %-30s %-30s\n", "Node Id", "Diagnostic Type", "Fault Outcomes"))
    nodeIds <- net$getAllNodeIds()
    for (nodeId in nodeIds) {
        diagType <- net$getNodeDiagType(nodeId)
        faultOutcomes <- character()
        if (diagType == net$NodeDiagType$FAULT) {
            outcomeIds <- net$getOutcomeIds(nodeId)
            for (outcomeId in outcomeIds) {
                if (net$isFaultOutcome(nodeId, outcomeId)) {
                    faultOutcomes <- c(faultOutcomes, outcomeId)
                }
            }
        }
        cat(sprintf("%-20s %-30s %-30s\n",
            nodeId, as.character(net$getNodeDiagType(nodeId)),
            ifelse(diagType == net$NodeDiagType$FAULT,
                paste(faultOutcomes, collapse = ", "), "n/a")))
    }
}

printFaultIndices <- function(diag) {
    faultCount <- diag$getFaultCount()
    cat(sprintf("Diagnostic network has %d faults (node/outcome pairs)\n", faultCount))
    cat(sprintf("%-12s %-20s %-20s\n", "Fault Index", "Fault Node Id", "Fault Outcome Id"))
    for (fIdx in 0:(faultCount-1)) {
        cat(sprintf("%-12d %-20s %-20s\n", fIdx, diag
            $getFaultNodeId(fIdx), diag$getFaultOutcomeId(fIdx)))
    }
}

printFaultInfo <- function(net, fault) {
    cat(sprintf("%-20s %-20s %-24s %-8s\n",
```

```
        net$getNodeId(fault$node), net$getOutcomeId(fault$node, fault$outcome),
        fault$probability, ifelse(fault$isPursued, "Yes", "No")))
}

printObservationInfo <- function(net, observation) {
    cat(sprintf("%-20s %-24s %-8s %-20s\n", net$getNodeId(observation$node),
        observation$measure, observation$cost, observation$infoGain))
}

printDiagResults <- function(net, diagResults) {
    cat("\n-- Diag results start\n\nFaults:\n")
    cat(sprintf("%-20s %-20s %-24s %-8s\n",
        "Node Id", "Outcome Id", "Probability", "Is Pursued"))
    for (faultInfo in diagResults$faults) {
        printFaultInfo(net, faultInfo)
    }
    cat("\nObservations:\n")
    cat(sprintf("%-20s %-24s %-8s %-20s\n",
        "Node Id", "Measure", "Cost", "InfoGain"))
    for (observationInfo in diagResults$observations) {
        printObservationInfo(net, observationInfo)
    }
    cat("\nDiag results end\n")
}

cat("Starting Tutorial9\n")
net <- Network()
net$readFile("HeparII.xdsl")
cat("Hepar model loaded\n")
printDiagTypes(net)

cat("Creating diagnostic network object\n")
diag <- DiagNetwork(net)
printFaultIndices(diag)

pursuedFaultIdx <- diag$getPursuedFault()
cat(sprintf("The default (most likely) pursued fault is at index %d: %s=%s\n",
    pursuedFaultIdx,
    diag$getFaultNodeId(pursuedFaultIdx), diag$getFaultOutcomeId(pursuedFaultIdx)))

cat("Running diagnosis with no instantiated observations\n")
diagResults <- diag$update()
printDiagResults(net, diagResults)

cat("Running diagnosis with three observations\n")
diag$instantiateObservation("jaundice", "present")
diag$instantiateObservation("nausea", "absent")
diag$instantiateObservation("obesity", "present")
diagResults <- diag$update()
printDiagResults(net, diagResults)

cat("Running diagnosis with two observations and focusing on Hyperbilirubinemia\n")
diag$releaseObservation("nausea")
diag$instantiateObservation("obesity", "absent")
hyperbilirubinemiaIdx <- diag$getFaultIndex("Hyperbilirubinemia", "present")
```

```
diag$setPursuedFault(hyperbilirubinemiaIdx)
diagResults <- diag$update()
printDiagResults(net, diagResults)

cat("Switching algorithm to cross-entropy, observations and pursued fault unchanged")
diag$setSingleFaultAlgorithm(diag$SingleFaultAlgorithmType$CROSSENTROPY)
diagResults <- diag$update()
printDiagResults(net, diagResults)

cat("Running diagnosis with two observations",
    "and focusing on both Hyperbilirubinemia and Steatosis\n")
steatosisIdx <- diag$getFaultIndex("Steatosis", "present")
diag$setPursuedFaults(c(steatosisIdx, hyperbilirubinemiaIdx))
diagResults <- diag$update()
printDiagResults(net, diagResults)

cat("Swtiching algorithm to L2 distance, observations and pursued faults unchanged")
diag$setMultiFaultAlgorithm(diag$MultiFaultAlgorithmType$L2_NORMALIZED_DISTANCE)
diagResults <- diag$update()
printDiagResults(net, diagResults)

cat("Tutorial9 complete.\n")
```

7.9.4 Tutorial9.cs

```
using System;
using System.Collections.Generic;
using Smile;

// Tutorial9 loads HeparII.xdsl file
// and runs multiple diagnostic algorithms
// Use the link below to download the HeparII.xdsl file:
// https://support.bayesfusion.com/docs/Examples/Discrete%20Bayesian%20Networks/HeparII.xdsl

namespace SmileNetTutorial
{
    class Tutorial9
    {
        public static void Run()
        {
            Console.WriteLine(System.IO.Directory.GetCurrentDirectory());
            Console.WriteLine("Starting Tutorial9...");
            Network net = new Network();
            net.ReadFile("HeparII.xdsl");
            Console.WriteLine("Hepar model loaded");
            PrintDiagTypes(net);

            Console.WriteLine("Creating diagnostic network object");
            DiagNetwork diag = new DiagNetwork(net);
            PrintFaultIndices(diag);

            int pursuedFaultIdx = diag.GetPursuedFault();
            Console.WriteLine("The default (most likely) pursued fault is at index {0}: {1}={2}",
                pursuedFaultIdx,
                diag.GetFaultNodeId(pursuedFaultIdx), diag.GetFaultOutcomeId(pursuedFaultIdx));
```

```
    Console.WriteLine("Running diagnosis with no instantiated observations");
    DiagResults diagResults = diag.Update();
    PrintDiagResults(net, diagResults);

    Console.WriteLine("Running diagnosis with three observations");
    diag.InstantiateObservation("jaundice", "present");
    diag.InstantiateObservation("nausea", "absent");
    diag.InstantiateObservation("obesity", "present");
    diagResults = diag.Update();
    PrintDiagResults(net, diagResults);

    Console.WriteLine("Running diagnosis with two observations and "
        + "focusing on Hyperbilirubinemia");
    diag.ReleaseObservation("nausea");
    diag.InstantiateObservation("obesity", "absent");
    int hyperbilirubinemiaIdx = diag.GetFaultIndex("Hyperbilirubinemia", "present");
    diag.SetPursuedFault(hyperbilirubinemiaIdx);
    diagResults = diag.Update();
    PrintDiagResults(net, diagResults);

    Console.WriteLine("Switching algorithm to cross-entropy, "
        + "observations and pursued fault unchanged");
    diag.SingleFaultAlgorithm = DiagNetwork.SingleFaultAlgorithmType.Crossentropy;
    diagResults = diag.Update();
    PrintDiagResults(net, diagResults);

    Console.WriteLine("Running diagnosis with two observations and "
        + "focusing on both Hyperbilirubinemia and Steatosis");
    int steatosisIdx = diag.GetFaultIndex("Steatosis", "present");
    diag.SetPursuedFaults(new int[] { steatosisIdx, hyperbilirubinemiaIdx });
    diagResults = diag.Update();
    PrintDiagResults(net, diagResults);

    Console.WriteLine("Swtiching algorithm to L2 distance, "
        + "observations and pursued faults unchanged");
    diag.MultiFaultAlgorithm = DiagNetwork.MultiFaultAlgorithmType.L2NormalizedDistance;
    diagResults = diag.Update();
    PrintDiagResults(net, diagResults);

    Console.WriteLine("Tutorial9 complete.");
}

public static void PrintDiagTypes(Network net)
{
    Console.WriteLine("Network has {0} nodes", net.GetNodeCount());
    Console.WriteLine("{0,-20} {1,-30} {2,-30}",
        "Node Id", "Diagnostic Type", "Fault Outcomes");
    string[] nodeIds = net.GetAllNodeIds();
    foreach (string nodeId in nodeIds)
    {
        Network.NodeDiagType diagType = net.GetNodeDiagType(nodeId);
        List<string> faultOutcomes = new List<string>();
        if (diagType == Network.NodeDiagType.Fault)
        {
```

```
            foreach (string outcomeId in net.GetOutcomeIds(nodeId))
            {
                if (net.IsFaultOutcome(nodeId, outcomeId))
                {
                    faultOutcomes.Add(outcomeId);
                }
            }
        }
        Console.WriteLine("{0,-20} {1,-30} {2,-30}", nodeId, diagType,
            (faultOutcomes.Count != 0) ? string.Join(", ", faultOutcomes) : "n/a");
    }
}

public static void PrintFaultIndices(DiagNetwork diag)
{
    int faultCount = diag.FaultCount;
    Console.WriteLine("Diagnostic network has {0} faults (node/outcome pairs)",
        faultCount);
    Console.WriteLine("{0,-12} {1,-20} {2,-20}",
        "Fault Index", "Fault Node Id", "Fault Outcome Id");
    for (int fIdx = 0; fIdx < faultCount; fIdx++)
    {
        Console.WriteLine("{0,-12} {1,-20} {2,-20}", fIdx,
            diag.GetFaultNodeId(fIdx), diag.GetFaultOutcomeId(fIdx));
    }
}

public static void PrintFaultInfo(Network net, FaultInfo fault)
{
    Console.WriteLine("{0,-20} {1,-20} {2,-24} {3,-8}",
        net.GetNodeId(fault.Node), net.GetOutcomeId(fault.Node, fault.Outcome),
        fault.Probability, fault.IsPursued ? "Yes" : "No");
}

public static void PrintObservationInfo(Network net, ObservationInfo observation)
{
    Console.WriteLine("{0,-20} {1,-24} {2,-8} {3,-20}",
        net.GetNodeId(observation.Node), observation.Measure,
        observation.Cost, observation.InfoGain);
}

public static void PrintDiagResults(Network net, DiagResults diagResults)
{
    Console.WriteLine("Diag results start\n\nFaults:");
    Console.WriteLine("{0,-20} {1,-20} {2,-24} {3,-8}",
        "Node Id", "Outcome Id", "Probability", "Is Pursued");
    foreach (FaultInfo faultInfo in diagResults.Faults)
    {
        PrintFaultInfo(net, faultInfo);
    }
    Console.WriteLine("\nObservations:");
    Console.WriteLine("{0,-20} {1,-24} {2,-8} {3,-20}",
        "Node Id", "Measure", "Cost", "InfoGain");
    foreach (ObservationInfo observationInfo in diagResults.Observations)
    {
```

```
                PrintObservationInfo(net, observationInfo);
            }
            Console.WriteLine("\nDiag results end\n");
        }
    }
}
```

7.10 Tutorial 10: Structure learning

Suppose we have a file *Credit10K.csv* consisting of 10,000 records of customers collected at a bank. Each of these customers was measured on several variables, *Payment History*, *Work History*, *Reliability*, *Debit*, *Income*, *Ratio of Debts to Income*, *Assets*, *Worth*, *Profession*, *Future Income*, *Age* and *Credit Worthiness*. The file is too large to include in this manual, but it can be downloaded from https://support.bayesfusion.com/docs/Examples/Learning/Credit10K.csv. It is also included in the *Examples\Learning* directory of GeNIe installation. The first few records of the file (included among the example files with GeNIe distribution) look as follows in GeNIe:

	PaymentHistory	WorkHistory	Reliability	Debit	Income	RatioDebInc	Assets	Worth	Profession	FutureIncome	Age	CreditWorthiness
▶	Without_Reference	Unstable	Unreliable	a0_11100	s70001_more	Favorable	wealthy	High	Medium_income_profession	Promissing	a16_21	Negative
	Aceptable	Unjustified_no_work	Unreliable	a0_11100	s70001_more	Favorable	average	High	Medium_income_profession	Promissing	a66_up	Negative
	Aceptable	Unstable	Reliable	a25901_more	s30001_70000	Unfavorable	wealthy	High	Low_income_profession	Not_promissing	a16_21	Negative
	Excellent	Unstable	Reliable	a25901_more	s30001_70000	Unfavorable	average	Medium	Medium_income_profession	Not_promissing	a16_21	Negative
	Excellent	Unjustified_no_work	Unreliable	a11101_25900	s0_30000	Unfavorable	average	Low	Medium_income_profession	Not_promissing	a66_up	Negative
	Without_Reference	Stable	Reliable	a0_11100	s30001_70000	Favorable	average	High	Medium_income_profession	Promissing	a16_21	Positive
	NoAceptable	Stable	Unreliable	a0_11100	s70001_more	Favorable	wealthy	High	Medium_income_profession	Promissing	a66_up	Positive
	Excellent	Stable	Reliable	a0_11100	s70001_more	Favorable	wealthy	High	Low_income_profession	Promissing	a66_up	Positive
	Excellent	Stable	Reliable	a25901_more	s70001_more	Unfavorable	poor	High	Low_income_profession	Not_promissing	a16_21	Negative
	NoAceptable	Stable	Unreliable	a0_11100	s30001_70000	Favorable	average	Medium	Medium_income_profession	Promissing	a22_65	Positive
	Without_Reference	Justified_no_work	Reliable	a25901_more	s70001_more	Unfavorable	poor	High	Low_income_profession	Not_promissing	a16_21	Negative
	NoAceptable	Unstable	Unreliable	a25901_more	s30001_70000	Unfavorable	wealthy	High	Medium_income_profession	Promissing	a16_21	Negative
	NoAceptable	Justified_no_work	Unreliable	a25901_more	s30001_70000	Unfavorable	wealthy	High	High_income_profession	Promissing	a22_65	Negative
	Excellent	Stable	Reliable	a11101_25900	s0_30000	Unfavorable	average	Low	Medium_income_profession	Not_promissing	a16_21	Negative
	Aceptable	Stable	Unreliable	a25901_more	s0_30000	Unfavorable	wealthy	Medium	Medium_income_profession	Not_promissing	a66_up	Negative
	Without_Reference	Unjustified_no_work	Unreliable	a0_11100	s0_30000	Favorable	poor	Low	Low_income_profession	Not_promissing	a66_up	Positive
	Aceptable	Unstable	Reliable	a11101_25900	s30001_70000	Unfavorable	average	Medium	Low_income_profession	Not_promissing	a66_up	Negative
	Without_Reference	Unstable	Unreliable	a0_11100	s30001_70000	Unfavorable	average	High	Medium_income_profession	Promissing	a16_21	Negative

We want to learn the structure of the Bayesian network based on the data. Our program attempts to load the data file from disk, and prints the number of data set variables and records if loading was successful. For clarity, we omit the exception handling in the code snippets here. The tutorial programs include the exception handlers for each learning call.

Java:

```
DataSet ds = new DataSet();
ds.readFile("Credit10k.csv");
System.out.println(String.format(
    "Dataset has %d variables (columns) and %d records (rows)",
    ds.getVariableCount(), ds.getRecordCount()));
```

Python:

```
ds = pysmile.learning.DataSet()
ds.read_file("Credit10k.csv")
print(f"Dataset has {ds.get_variable_count()} variables (columns)
    and {ds.get_record_count()} records (rows)")
```

C#:

```
DataSet ds = new DataSet();
ds.ReadFile("Credit10k.csv");
Console.WriteLine(String.Format(
    "Dataset has {0} variables (columns) and {1} records (rows)",
```

```
      ds.VariableCount, ds.RecordCount));
```

The most general structure learning algorithm is Bayesian Search. It is a hill climbing procedure with random restarts, guided by log-likelihood scoring heuristic. Its search space is hyper-exponential, so for best results the algorithm can be fine-tuned with multiple with multiple options (details are available in the SMILE manual's *Reference* section). We set the number of iterations (random restarts) to 50, and fix the random number seed to ensure reproducible results. The `learn` method requires an input data set. The learning algorithm will perform 50 iterations, each starting with randomized structure, and compute a log-likelihood score for at the end of each iteration. The best structure will be copied into the output network, and parameter learning will be run internally. The output network will therefore be ready to use.

Java:

```
BayesianSearch bayesSearch = new BayesianSearch();
bayesSearch.setIterationCount(50);
bayesSearch.setRandSeed(9876543);
Network net1 = bayesSearch.learn(ds);
```

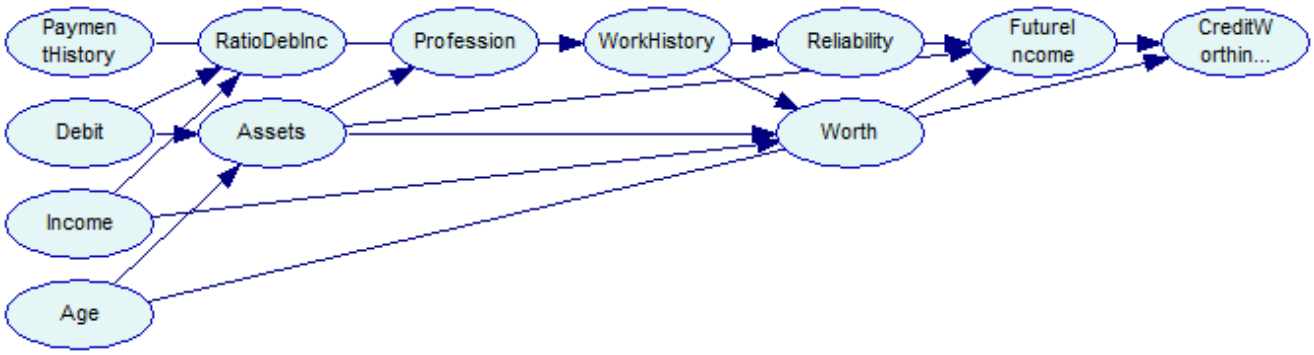
Python:

```
bayes_search = pysmile.learning.BayesianSearch()
bayes_search.set_iteration_count(50)
bayes_search.set_rand_seed(9876543)
net1 = bayes_search.learn(ds)
```

C#:

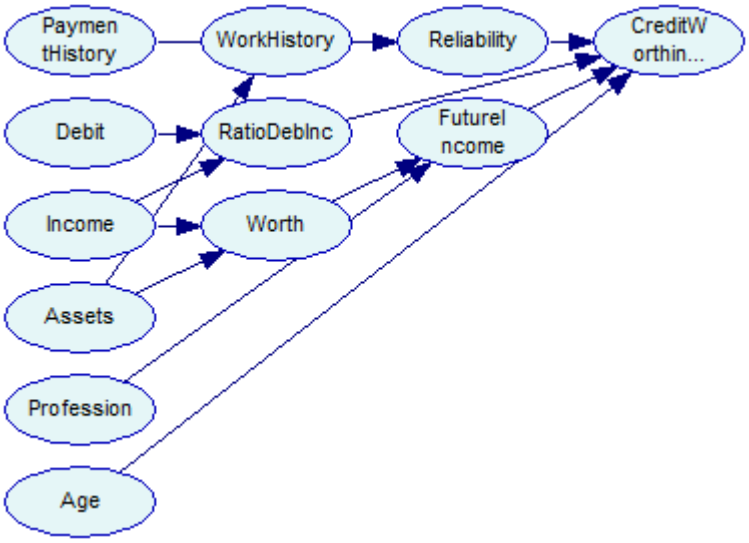
```
BayesianSearch bayesSearch = new BayesianSearch();
bayesSearch.IterationCount = 50;
bayesSearch.RandSeed = 9876543;
Network net1 = bayesSearch.Learn(ds);
```

The output network looks like this in GeNIe:



Please note that the nodes in the network learned in SMILE occupy the same screen position. The image below shows the network after the parent ordering layout has been applied. We plan to include simple layout as the last step of the learning in the upcoming release of SMILE.

The network is saved for reference in the *tutorial9-bs1.xdsl* file. We can obtain a different structure by changing the seed for the random number generator and calling `learn` again. The selected seed value is 3456789, and the output looks like this:



The tutorial saves this network to *tutorial9-bs2.xdsl* proceeds to third attempt at Bayesian Search, this time with background knowledge. We want to forbid the arc between *Age* and *CreditWorthiness*, and force an arc between *Age* and *Profession*. When specifying the background knowledge, we refer to the data set variables as their indices, so we need to convert the textual identifiers to indices first.

Java:

```
int idxAge = ds.findVariable("Age");
int idxProfession = ds.findVariable("Profession");
int idxCreditWorthiness = ds.findVariable("CreditWorthiness");
BkKnowledge backgroundKnowledge = new BkKnowledge();
backgroundKnowledge.matchData(ds);
backgroundKnowledge.addForbiddenArc(idxAge, idxCreditWorthiness);
backgroundKnowledge.addForcedArc(idxAge, idxProfession);
bayesSearch.setBkKnowledge(backgroundKnowledge);
Network net3 = bayesSearch.Learn(ds);
```

Python:

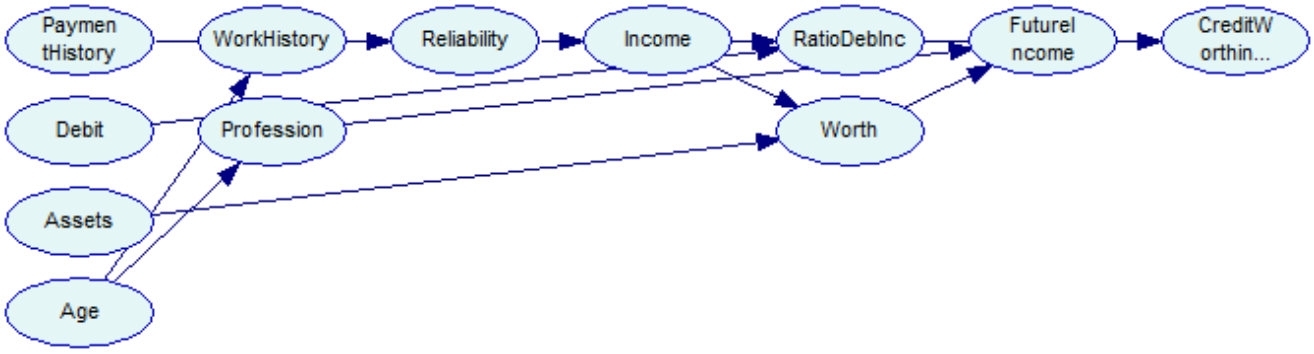
```
idx_age = ds.find_variable("Age")
idx_profession = ds.find_variable("Profession")
idx_credit_worthiness = ds.find_variable("CreditWorthiness")
background_knowledge = pysmile.learning.BkKnowledge()
background_knowledge.match_data(ds)
background_knowledge.add_forbidden_arc(idx_age, idx_credit_worthiness)
background_knowledge.add_forced_arc(idx_age, idx_profession)
 bayes_search.set_bk_knowledge(background_knowledge)
 net3 = bayes_search.learn(ds)
```

C#:

```
int idxAge = ds.FindVariable("Age");
int idxProfession = ds.FindVariable("Profession");
int idxCreditWorthiness = ds.FindVariable("CreditWorthiness");
BkKnowledge backgroundKnowledge = new BkKnowledge();
backgroundKnowledge.MatchData(ds);
backgroundKnowledge.AddForbiddenArc(idxAge, idxCreditWorthiness);
backgroundKnowledge.AddForcedArc(idxAge, idxProfession);
bayesSearch.BkKnowledge = backgroundKnowledge;
```

```
Network net3 = bayesSearch.Learn(ds);
```

The output network now looks as follows - please note the absence of an arc from *Age* to *CreditWorthiness* and the forced arc between *Age* and *Profession*. This network is saved to *tutorial9-bs3.xdsl*.



We now change our learning algorithm to Tree Augmented Naive Bayes (TAN). The TAN algorithm starts with a Naive Bayes structure (i.e., one in which the class variable is the only parent of all remaining, feature variables) and adds connections between the feature variables to account for possible dependence between them, conditional on the class variable. The algorithm imposes the limit of only one additional parent of every feature variable (additional to the class variable, which is a parent of every feature variable). We need to specify the class variable with its textual identifier. In this example *CreditWorthiness* is the class variable.

Java:

```
Network net4;
TAN tan = new TAN();
tan.setRandSeed(777999);
tan.setClassVariableId("CreditWorthiness");
net4 = tan.learn(ds);
```

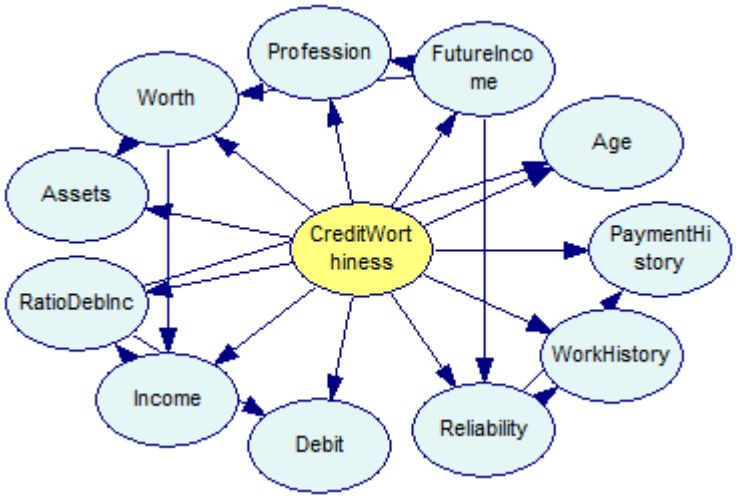
Python:

```
tan = pysmile.learning.TAN()
tan.set_rand_seed(777999)
tan.set_class_variable_id("CreditWorthiness")
net4 = tan.learn(ds)
```

C#:

```
Network net4;
TAN tan = new TAN();
tan.RandSeed = 777999;
tan.ClassVariableId = "CreditWorthiness";
net4 = tan.Learn(ds);
```

The program saves the network for reference in *tutorial9-tan.xdsl* file. The network looks as follows (the class node has yellow background):



Our final structure learning algorithm will be PC, which uses independences observed in data (established by means of classical independence tests) to infer the structure that has generated them. The output of the PC algorithm is a pattern, which is an adjacency matrix, and does not necessarily represent a directed acyclic graph (DAG). The pattern can be converted to network with the `makeNetwork` method, which enforces the DAG criterion on the pattern, and copies the variables and edges to the network.

Java:

```
PC pc = new PC();
Pattern pattern = pc.learn(ds);
Network net5 = pattern.makeNetwork(ds);
```

Python:

```
pc = pysmile.learning.PC()
pattern = pc.learn(ds)
net5 = pattern.make_network(ds)
```

C#:

```
PC pc = new PC();
Pattern pattern = pc.Learn(ds);
Network net5 = pattern.MakeNetwork(ds);
```

At this point our output network has nodes with outcomes based on the labels in the data set, but the probability distributions in node definitions are uniform over outcomes. To complete the learning process, we need to manually call a parameter learning procedure implemented in the `EM` class.

Java:

```
EM em = new EM();
DataMatch[] matching = ds.matchNetwork(net5);
em.setUniformizeParameters(false);
em.setRandomizeParameters(false);
em.setEqSampleSize(0);
em.learn(ds, net5, matching);
```

Python:

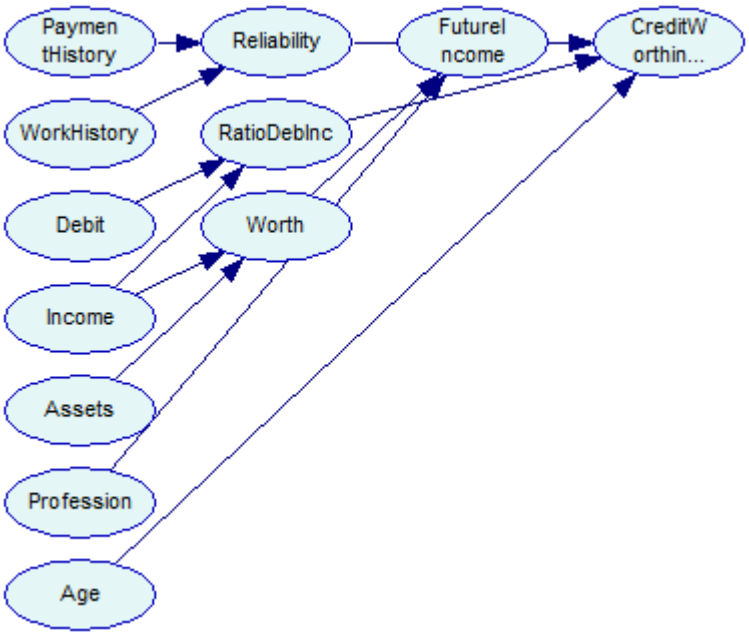
```
em = pysmile.learning.EM()
matching = ds.match_network(net5)
em.set_uniformize_parameters(False)
```

```
em.set_randomize_parameters(False)
em.set_eq_sample_size(0)
em.learn(ds, net5, matching)
```

C#:

```
EM em = new EM();
DataMatch[] matching = ds.MatchNetwork(net5);
em.UniformizeParameters = false;
em.RandomizeParameters = false;
em.EqSampleSize = 0;
em.Learn(ds, net5, matching);
```

Note the matchNetwork call, which populates the `matching` variable using identifiers of data set variables and network nodes. This information is subsequently used by `EM.learn` to associate data set variables with network node. The output network looks like as follows:



The network is saved for reference in the *tutorial9-pc-em.xdsl* file and Tutorial 9 finishes.

7.10.1 Tutorial10.java

```
package tutorials;

import smile.*;
import smile.learning.*;

// Tutorial9 loads Credit10k.csv file
// and runs multiple structure learning algorithms
// using the loaded dataset.
// Use the link below to download the Credit10k.csv file:
// https://support.bayesfusion.com/docs/Examples/Learning/Credit10K.csv

public class Tutorial10 {
    public static void run() {
        System.out.println("Starting Tutorial9...");
```

```
DataSet ds = new DataSet();
try
{
    ds.readFile("Credit10k.csv");
} catch (SMILEException ex)
{
    System.out.println("Dataset load failed");
    return;
}
System.out.printf("Dataset has %d variables (columns) and %d records (rows)\n",
    ds.getVariableCount(), ds.getRecordCount());
BayesianSearch bayesSearch = new BayesianSearch();
bayesSearch.setIterationCount(50);
bayesSearch.setRandSeed(9876543);
Network net1;
try
{
    net1 = bayesSearch.learn(ds);
} catch (SMILEException ex)
{
    System.out.println("Bayesian Search failed");
    return;
}
System.out.printf("1st Bayesian Search finished, structure score: %f\n",
    bayesSearch.getLastScore());
net1.writeFile("tutorial9-bs1.xdsl");

Network net2;
bayesSearch.setRandSeed(3456789);
try
{
    net2 = bayesSearch.learn(ds);
}
catch (SMILEException ex)
{
    System.out.println("Bayesian Search failed");
    return;
}
System.out.printf("2nd Bayesian Search finished, structure score: %f\n",
    bayesSearch.getLastScore());
net2.writeFile("tutorial9-bs2.xdsl");

int idxAge = ds.findVariable("Age");
int idxProfession = ds.findVariable("Profession");
int idxCreditWorthiness = ds.findVariable("CreditWorthiness");
if (idxAge < 0 || idxProfession < 0 || idxCreditWorthiness < 0)
{
    System.out.println("Can't find dataset variables for background knowledge");
    System.out.println("The loaded file may not be Credit10k.csv");
    return;
}

BkKnowledge backgroundKnowledge = new BkKnowledge();
     backgroundKnowledge.matchData(ds);
backgroundKnowledge.addForbiddenArc(idxAge, idxCreditWorthiness);
```

```
backgroundKnowledge.addForcedArc(idxAge, idxProfession);
bayesSearch.setBkKnowledge(backgroundKnowledge);
Network net3;
try
{
    net3 = bayesSearch.learn(ds);
}
catch (SMILEException ex)
{
    System.out.println("Bayesian Search failed");
    return;
}
System.out.printf("3rd Bayesian Search finished, structure score: %f\n",
    bayesSearch.getLastScore());
net3.writeFile("tutorial9-bs3.xdsl");

Network net4;
TAN tan = new TAN();
tan.setRandSeed(777999);
tan.setClassVariableId("CreditWorthiness");
try
{
    net4 = tan.learn(ds);
}
catch (SMILEException ex)
{
    System.out.println("TAN failed");
    return;
}
System.out.println("Tree-augmented Naive Bayes finished");
net4.writeFile("tutorial9-tan.xdsl");

PC pc = new PC();
Pattern pattern;
try
{
    pattern = pc.learn(ds);
} catch (SMILEException ex)
{
    System.out.println("PC failed");
    return;
}
Network net5 = pattern.makeNetwork(ds);
System.out.println("PC finished, proceeding to parameter learning");
net5.writeFile("tutorial9-pc.xdsl");
EM em = new EM();
DataMatch[] matching;
try
{
    matching = ds.matchNetwork(net5);
}
catch (SMILEException ex)
{
    System.out.println("Can't automatically match network with dataset");
    return;
```

```
        }
        em.setUniformizeParameters(false);
        em.setRandomizeParameters(false);
        em.setEqSampleSize(0);
        try
        {
            em.learn(ds, net5, matching);
        }
        catch (SMILEException ex)
        {
            System.out.println("EM failed");
            return;
        }
        System.out.println("EM finished");
        net5.writeFile("tutorial9-pc-em.xdsl");

        System.out.println("Tutorial10 complete");
    }
}
```

7.10.2 Tutorial10.py

```
import pysmile

# Tutorial10 loads Credit10k.csv file
# and runs multiple structure learning algorithms
# using the loaded dataset.
# Use the link below to download the Credit10k.csv file:
# https://support.bayesfusion.com/docs/Examples/Learning/Credit10K.csv

class Tutorial10:
    def __init__(self):
        print("Starting tutorial10...")
        ds = pysmile.learning.DataSet()
        try:
            ds.read_file("Credit10k.csv")
        except pysmile.SMILEException:
            print("Dataset load failed")
            return
        print(f"Dataset has {ds.get_variable_count()} variables (columns) "
            + f"and {ds.get_record_count()} records (rows)")
        bayes_search = pysmile.learning.BayesianSearch()
        bayes_search.set_iteration_count(50)
        bayes_search.set_rand_seed(9876543)
        try:
            net1 = bayes_search.learn(ds)
        except pysmile.SMILEException:
            print("Bayesian Search failed")
            return
        print(f"1st Bayesian Search finished, structure score: {bayes_search.get_last_score()}")
        net1.write_file("tutorial10-bs1.xdsl")

        bayes_search.set_rand_seed(3456789)
        try:
            net2 = bayes_search.learn(ds)
```

```
except pysmile.SMILEException:
    print("Bayesian Search failed")
    return
print(f"2nd Bayesian Search finished, structure score: {bayes_search.get_last_score()}")
net2.write_file("tutorial10-bs2.xdsl")

idx_age = ds.find_variable("Age")
idx_profession = ds.find_variable("Profession")
idx_credit_worthiness = ds.find_variable("CreditWorthiness")

if idx_age < 0 or idx_profession < 0 or idx_credit_worthiness < 0:
    print("Can't find dataset variables for background knowledge")
    print("The loaded file may not be Credit10k.csv")
    return
background_knowledge = pysmile.learning.BkKnowledge()
background_knowledge.match_data(ds)
background_knowledge.add_forbidden_arc(idx_age, idx_credit_worthiness)
background_knowledge.add_forced_arc(idx_age, idx_profession)

bayes_search.set_bk_knowledge(background_knowledge)
try:
    net3 = bayes_search.learn(ds)
except pysmile.SMILEException:
    print("Bayesian Search failed")
    return
print(f"3rd Bayesian Search finished, structure score: {bayes_search.get_last_score()}")
net3.write_file("tutorial10-bs3.xdsl")

tan = pysmile.learning.TAN()
tan.set_rand_seed(777999)
tan.set_class_variable_id("CreditWorthiness")
try:
    net4 = tan.learn(ds)
except pysmile.SMILEException:
    print("TAN failed")
    return
print("Tree-augmented Naive Bayes finished")
net4.write_file("tutorial10-tan.xdsl")

pc = pysmile.learning.PC()
try:
    pattern = pc.learn(ds)
except pysmile.SMILEException:
    print("PC failed")
    return
net5 = pattern.make_network(ds)
print("PC finished, proceeding to parameter learning")
net5.write_file("tutorial10-pc.xdsl")
em = pysmile.learning.EM()
try:
    matching = ds.match_network(net5)
except pysmile.SMILEException:
    print("Can't automatically match network with dataset")
    return
em.set_uniformize_parameters(False)
```

```
        em.set_randomize_parameters(False)
        em.set_eq_sample_size(0)
        try:
            em.learn(ds, net5, matching)
        except pysmile.SMILEException:
            print("EM failed")
            return
        print("EM finished")
        net5.write_file("tutorial10-pc-em.xdsl")

        print("Tutorial10 complete.")
```

7.10.3 Tutorial10.R

```
library(rSMILE)
source("License.R")

# Tutorial10 loads Credit10k.csv file
# and runs multiple structure learning algorithms
# using the loaded dataset.
# Use the link below to download the Credit10k.csv file:
# https://support.bayesfusion.com/docs/Examples/Learning/Credit10K.csv

cat("Starting Tutorial10...\n")
ds <- DataSet()

ds$readFile("Credit10k.csv")
cat(sprintf("Dataset has %d variables (columns) and %d records (rows)\n",
    ds$getVariableCount(), ds$getRecordCount()))
bayesSearch <- BayesianSearch()
bayesSearch$setIterationCount(50)
bayesSearch$setRandSeed(9876543)
net1 <- bayesSearch$learn(ds)
cat(sprintf("1st Bayesian Search finished, structure score: %f\n",
    bayesSearch$getLastScore()))
net1$writeFile("tutorial10-bs1.xdsl")

bayesSearch$setRandSeed(3456789)
net2 <- bayesSearch$learn(ds)
cat(sprintf("2nd Bayesian Search finished, structure score: %f\n",
    bayesSearch$getLastScore()))
net2$writeFile("tutorial10-bs2.xdsl")

idxAge <- ds$findVariable("Age")
idxProfession <- ds$findVariable("Profession")
idxCreditWorthiness <- ds$findVariable("CreditWorthiness")

backgroundKnowledge <- BkKnowledge()
backgroundKnowledge$matchData(ds)
backgroundKnowledge$addForbiddenArc(idxAge, idxCreditWorthiness)
backgroundKnowledge$addForcedArc(idxAge, idxProfession)

bayesSearch$setBkKnowledge(backgroundKnowledge)
net3 <- bayesSearch$learn(ds)
cat(sprintf("3rd Bayesian Search finished, structure score: %f\n",
```

```
    bayesSearch$getLastScore()))
net2$writeFile("tutorial10-bs3.xdsl")

tan <- TAN()
tan$setRandSeed(777999)
tan$setClassVariableId("CreditWorthiness")
net4 <- tan$learn(ds)
cat("Tree-augmented Naive Bayes finished")
net4$writeFile("tutorial10-tan.xdsl")

pc <- PC()
pattern <- pc$learn(ds)
net5 <- pattern$makeNetwork(ds)
cat("PC finished, proceeding to parameter learning\n")
net5$writeFile("tutorial10-pc.xdsl")
em <- EM()
matching <- ds$matchNetwork(net5)
em$setUniformizeParameters(FALSE)
em$setRandomizeParameters(FALSE)
em$setEqSampleSize(0)
em$learn(ds, net5, matching)
cat("EM finished\n")
net5$writeFile("tutorial10-pc-em.xdsl")

cat("Tutorial10 complete.\n")
```

7.10.4 Tutorial10.cs

```
using System;
using Smile;
using Smile.Learning;

// Tutorial10 loads Credit10k.csv file
// and runs multiple structure learning algorithms
// using the loaded dataset.
// Use the link below to download the Credit10k.csv file:
// https://support.bayesfusion.com/docs/Examples/Learning/Credit10K.csv

namespace SmileNetTutorial
{
    class Tutorial10
    {
        public static void Run()
        {
            Console.WriteLine("Starting Tutorial10...");
            DataSet ds = new DataSet();
            try
            {
                ds.ReadFile("Credit10k.csv");
            } catch (SmileException)
            {
                Console.WriteLine("Dataset load failed");
                return;
            }
            Console.WriteLine("Dataset has {0} variables (columns) and {1} records (rows)",
```

```
    ds.VariableCount, ds.RecordCount);
BayesianSearch bayesSearch = new BayesianSearch();
bayesSearch.IterationCount = 50;
bayesSearch.RandSeed = 9876543;
Network net1;
try
{
    net1 = bayesSearch.Learn(ds);
} catch (SmileException)
{
    Console.WriteLine("Bayesian Search failed");
    return;
}
Console.WriteLine("1st Bayesian Search finished, structure score: {0}",
    bayesSearch.LastScore);
net1.WriteFile("tutorial10-bs1.xdsl");

Network net2;
bayesSearch.RandSeed = 3456789;
try
{
    net2 = bayesSearch.Learn(ds);
}
catch (SmileException)
{
    Console.WriteLine("Bayesian Search failed");
    return;
}
Console.WriteLine("2nd Bayesian Search finished, structure score: {0}",
    bayesSearch.LastScore);
net2.WriteFile("tutorial10-bs2.xdsl");

int idxAge = ds.FindVariable("Age");
int idxProfession = ds.FindVariable("Profession");
int idxCreditWorthiness = ds.FindVariable("CreditWorthiness");
if (idxAge < 0 || idxProfession < 0 || idxCreditWorthiness < 0)
{
    Console.WriteLine("Can't find dataset variables for background knowledge");
    Console.WriteLine("The loaded file may not be Credit10k.csv");
    return;
}

BkKnowledge backgroundKnowledge = new BkKnowledge();
       backgroundKnowledge.MatchData(ds);
backgroundKnowledge.AddForbiddenArc(idxAge, idxCreditWorthiness);
backgroundKnowledge.AddForcedArc(idxAge, idxProfession);
bayesSearch.BkKnowledge = backgroundKnowledge;
Network net3;
try
{
    net3 = bayesSearch.Learn(ds);
}
catch (SmileException)
{
    Console.WriteLine("Bayesian Search failed");
```

```
    return;
}
Console.WriteLine("3rd Bayesian Search finished, structure score: {0}",
    bayesSearch.LastScore);
net3.WriteFile("tutorial10-bs3.xdsl");

Network net4;
TAN tan = new TAN();
tan.RandSeed = 777999;
tan.ClassVariableId = "CreditWorthiness";
try
{
    net4 = tan.Learn(ds);
}
catch (SmileException)
{
    Console.WriteLine("TAN failed");
    return;
}
Console.WriteLine("Tree-augmented Naive Bayes finished");
net4.WriteFile("tutorial10-tan.xdsl");

PC pc = new PC();
Pattern pattern;
try
{
    pattern = pc.Learn(ds);
} catch (SmileException)
{
    Console.WriteLine("PC failed");
    return;
}
Network net5 = pattern.MakeNetwork(ds);
Console.WriteLine("PC finished, proceeding to parameter learning");
net5.WriteFile("tutorial10-pc.xdsl");
EM em = new EM();
DataMatch[] matching;
try
{
    matching = ds.MatchNetwork(net5);
}
catch (SmileException)
{
    Console.WriteLine("Can't automatically match network with dataset");
    return;
}
em.UniformizeParameters = false;
em.RandomizeParameters = false;
em.EqSampleSize = 0;
try
{
    em.Learn(ds, net5, matching);
}
catch (SmileException)
{
```

```
                Console.WriteLine("EM failed");
                return;
            }
            Console.WriteLine("EM finished");
            net5.WriteFile("tutorial10-pc-em.xdsl");

            Console.WriteLine("Tutorial10 complete");
        }
    }
}
```

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Acknowledgments

8 Acknowledgments

SMILE internally uses portions of the following two software libraries: micro-ECC and Expat. PySMILE uses pybind11. These three libraries require an acknowledgment that we are reproducing below.

micro-ECC

Expat

pybind