
Credici Documentation

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Credal Inference for Causal Inference

Credici is an open-source Java library for causal analysis. Inference is done using well-founded methods for inference on credal networks, which is done in a transparently to the user.

The main features of Credici are:

- Allows to easily define Structural Causal Networks (SCM).
- Causal inference: causal effects and counterfactuals.
- Inference is based in methods for inference in credal networks (exact and approximate).
- SCMs can me transformed in equivalent credal networks can be exported in UAI format.

INSTALLATION

Credici can be installed from maven. For further details, check the [Installation](#) section.

CITATION

For the theoretical results in which this tool is based, refer to the following publication.

```
@InProceedings{zaffalon2020structural,  
  author    = {Zaffalon, Marco and Antonucci, Alessandro and Caba\~{n}as, Rafael},  
  title     = {Structural Causal Models Are Credal Networks},  
  booktitle = {Proceedings of the tenth International Conference on Probabilistic_  
↪Graphical Models},  
  year      = {2020},  
  series    = {Proceedings of Machine Learning Research},  
  address   = {Aalborg, Denmark},  
  month     = {23--25 Sep},  
  publisher = {PMLR},  
}
```

2.1 Getting Started

2.1.1 30 seconds to Credici

As a short introduction to Credici, let us consider the following code snippet, in which an structural causal model is built from a discrete Bayesian network. A counterfactual query is performed using an approximate linear programming method.

```
package docs;  
  
import ch.idisia.credici.inference.CredalCausalApproxLP;  
import ch.idisia.credici.model.StructuralCausalModel;  
import ch.idisia.credici.model.builder.CausalBuilder;  
import ch.idisia.crema.IO;  
import ch.idisia.crema.factor.credal.linear.IntervalFactor;  
import ch.idisia.crema.model.graphical.specialized.BayesianNetwork;  
  
import java.io.IOException;  
  
public class StartingWithCredici {  
  public static void main(String[] args) throws IOException, InterruptedException {  
  
    // Load the empirical model  
    BayesianNetwork bnet = (BayesianNetwork) IO.read("models/simple-chain.uai");  
  
    // Build the causal model  
    StructuralCausalModel causalModel = CausalBuilder.of(bnet).build();  
  
  }  
}
```

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```
// Set up the inference engine
CredalCausalApproxLP inf = new CredalCausalApproxLP(causalModel, bnet.
↳getFactors());

// Run the query
IntervalFactor res = (IntervalFactor) inf.counterfactualQuery()
    .setTarget(2)
    .setIntervention(0,0)
    .setEvidence(2, 1)
    .run();

}
```

2.2 Requirements

2.2.1 System

Credici requires Java 11 or higher and maven (<https://maven.apache.org>). Tests have been done under Linux Ubuntu and macOS with openjdk 11 and 12.

2.2.2 Package Dependencies

Credici contains the dependencies shown below which are transparently managed with maven.

- org.apache.commons:commons-lang3:jar:3.4:compile
- ch.idsia:crema:jar:0.1.4-SNAPSHOT:compile
- org.eclipse.persistence:org.eclipse.persistence.moxy:jar:2.6.2:compile
- com.google.code.findbugs:jsr305:jar:3.0.2:compile
- commons-cli:commons-cli:jar:1.4:compile
- org.checkerframework:checker-qual:jar:2.10.0:compile
- org.junit.jupiter:junit-jupiter-api:jar:5.4.2:test
- org.jgrapht:jgrapht-core:jar:1.1.0:compile
- com.google.guava:listenablefuture:jar:9999.0-empty-to-avoid-conflict-with-guava:compile
- javax.xml.bind:jaxb-api:jar:2.3.1:compile
- org.apache.commons:commons-csv:jar:1.3:compile
- com.google.errorprone:error_prone_annotations:jar:2.3.4:compile
- org.opentest4j:opentest4j:jar:1.1.1:test
- com.google.guava:guava:jar:28.2-jre:compile
- org.glassfish:javax.json:jar:1.0.4:compile
- org.eclipse.persistence:org.eclipse.persistence.asm:jar:2.6.2:compile
- com.google.j2objc:j2objc-annotations:jar:1.3:compile

- net.sourceforge.csparsej:csparsej:jar:1.1.1:compile
- org.apache.commons:commons-math3:jar:3.6.1:compile
- colt:colt:jar:1.2.0:compile
- com.google.guava:failureaccess:jar:1.0.1:compile
- org.hamcrest:hamcrest-core:jar:1.3:compile
- log4j:log4j:jar:1.2.14:compile
- com.joptimizer:joptimizer:jar:3.5.1:compile
- net.sf.lpsolve:lp_solve:jar:5.5.2:compile
- junit:junit:jar:4.12:compile
- com.github.quickhull3d:quickhull3d:jar:1.0.0:compile
- javax.activation:javax.activation-api:jar:1.2.0:compile
- commons-logging:commons-logging:jar:1.2:compile
- concurrent:concurrent:jar:1.3.4:compile
- org.junit.platform:junit-platform-commons:jar:1.4.2:test
- org.junit.jupiter:junit-jupiter-params:jar:5.4.2:test
- javax.validation:validation-api:jar:1.1.0.Final:compile
- net.sf.trove4j:trove4j:jar:3.0.3:compile
- ch.javasoft.polco:polco:jar:4.7.1:compile
- org.eclipse.persistence:org.eclipse.persistence.core:jar:2.6.2:compile
- org.slf4j:slf4j-api:jar:1.7.7:compile
- org.springframework:spring-core:jar:2.5.6:compile
- org.apiguardian:apiguardian-api:jar:1.0.0:test

2.3 Installation

Credici can be easily included at any maven project. For this, add the following code in the pom.xml:

```
<repositories>
  <repository>
    <id>cremaRepo</id>
    <url>https://raw.githubusercontent.com/idsia/crema/mvn-repo/</url>
  </repository>
</repositories>

<dependencies>
  <dependency>
    <groupId>ch.idsia</groupId>
    <artifactId>credici</artifactId>
    <version>0.1.4</version>
    <scope>compile</scope>
  </dependency>
</dependencies>
```

2.4 Causal Model Definition

Here we will consider the different ways for defining a structural causal model (SCM) in Credici. This can be done by explicitly specifying all the nodes, arcs and factors in the model, or with the help of the class `CausalBuilder`.

2.4.1 Explicit Definition

The code snippet shown below shows how to explicitly define a SCM. For this, an object of class `StructuralCausalModel` is created. Then endogenous and exogenous variable are added to the model by indicating the cardinality. In case of the exogenous ones, the second input parameter should be set to `true`, which indicates the type of variable. Then the parents are set and finally the factors are specified, which are basically objects of class `BayesianFactor`.

```
StructuralCausalModel model = new StructuralCausalModel();

// define the variables (endogenous and exogenous)
int x1 = model.addVariable(2);
int x2 = model.addVariable(2);
int x3 = model.addVariable(2);
int x4 = model.addVariable(2);

int u1 = model.addVariable(2, true);
int u2 = model.addVariable(4, true);
int u3 = model.addVariable(4, true);
int u4 = model.addVariable(3, true);

// Define the structure
model.addParents(x1, u1);
model.addParents(x2, u2, x1);
model.addParents(x3, u3, x1);
model.addParents(x4, u4, x2, x3);

// define the CPTs of the exogenous variables
BayesianFactor pu1 = new BayesianFactor(model.getDomain(u1), new double[] { .4, .6 });
BayesianFactor pu2 = new BayesianFactor(model.getDomain(u2), new double[] { .07, .9, .
↪03, .0 });
BayesianFactor pu3 = new BayesianFactor(model.getDomain(u3), new double[] { .05, .0, .
↪85, .10 });
BayesianFactor pu4 = new BayesianFactor(model.getDomain(u4), new double[] { .05, .9, .
↪05 });

model.setFactor(u1, pu1);
model.setFactor(u2, pu2);
model.setFactor(u3, pu3);
model.setFactor(u4, pu4);

// Define the CPTs of endogenous variables as deterministic functions
BayesianFactor f1 = EquationBuilder.of(model).fromVector(x1, 0,1);
BayesianFactor f2 = EquationBuilder.of(model).fromVector(x2,0,0,1,1, 0,1,0,1);
BayesianFactor f3 = EquationBuilder.of(model).fromVector(x3,0,0,1,1, 0,1,0,1);
BayesianFactor f4 = EquationBuilder.of(model).fromVector(x4,0,1,1, 0,0,0, 0,0,0, 0,
↪1,1);

model.setFactor(x1, f1);
```

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```

model.setFactor(x2, f2);
model.setFactor(x3, f3);
model.setFactor(x4, f4);

model.printSummary();

```

2.4.2 Causal Builder

Additionally, Credici provides class `CausalBuilder` at `ch.idsia.credici.model.builder` for simplifying the code under some settings. We will assume that we have `BayesianNetwork` specifying the empirical information: empirical DAG and eventually empirical probabilities. For example:

```

BayesianNetwork bnet = new BayesianNetwork();
int y = bnet.addVariable(2);
int x = bnet.addVariable(2);

```

The following code shows 4 equivalent ways of building a SCM from such BN under the markovian setting.

```

// Markovian equationless from BN
StructuralCausalModel m1 = StructuralCausalModel.of(bnet);

// Markovian equationless from DAG and sizes
StructuralCausalModel m2 = StructuralCausalModel.of(bnet.getNetwork(), bnet.
↳getSizes(bnet.getVariables()));

// Markovian equationless from BN
StructuralCausalModel m3 = CausalBuilder.of(bnet).build();

// Markovian equationless from DAG and sizes
StructuralCausalModel m4 = CausalBuilder.of(bnet.getNetwork(), bnet.getSizes(bnet.
↳getVariables())) .build();

```

In the previous cases, factors associated to exogenous variables are empty. Instead, we could build it with some random factors:

```

// Markovian equationless with random P(U)
StructuralCausalModel m5 =
    CausalBuilder.of(bnet)
        .setFillRandomExogenousFactors(2)
        .build();

// Markovian with random P(U) and equations
StructuralCausalModel m6 =
    CausalBuilder.of(bnet)
        .setFillRandomExogenousFactors(2)
        .setFillRandomEquations(true)
        .build();

```

Instead of considering the default structural equation, these could be specified as follows.

```

// Markovian case specifying equations and with random exogenous factors

BayesianFactor eqy = EquationBuilder.fromVector(
    Strides.as(y, 2), Strides.as(u1, 2),

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```

        0,1
    );

    BayesianFactor eqx = EquationBuilder.fromVector(
        Strides.as(x,2), Strides.as(u2,4),
        0,1,1,0
    );

    BayesianFactor[] eqs = {eqy, eqx};

    StructuralCausalModel m9 = CausalBuilder.of(bnet)
        .setEquations(eqs)
        .setFillRandomExogenousFactors(3)
        .build();

```

The quasi-markovian case could be also considered by specifying the causal DAG, which should be consistent with the empirical one.

```

// Quasi Markovian specifying causal DAG with random factors
SparseDirectedAcyclicGraph dag2 = bnet.getNetwork().copy();
int u = dag2.addVariable();
dag2.addLink(u, y);
dag2.addLink(u, x);

StructuralCausalModel m8 =
    CausalBuilder.of(bnet)
        .setCausalDAG(dag2)
        .setExoVarSizes(new int[] {4})
        .setFillRandomEquations(true)
        .build();

```

2.5 Causal Inference

2.5.1 Credal Network Transformation

Any object of class `StructuralCausalModel` can be converted into an equivalent credal network using the methods `toVCredal` and `toHCredal` for a vertex and a constraints specification. The input is a collection of *BayesianFactors* which are the empirical distributions.

```

// convert the causal models into credal networks
SparseModel vc credal = causalModel.toVCredal(bnet.getFactors());
SparseModel hc credal = causalModel.toHCredal(bnet.getFactors());

```

2.5.2 Inference engine

First the exact and approximate inferences engines should be set up. For this create instances of classes `CredalCausalVE` and `CredalCausalApproxLP` as shown in the following code snippet.

```

// set up the exact inference engine
CredalCausalVE infExact = new CredalCausalVE(causalModel, bnet.getFactors());
// set up the approximate inference engine
CredalCausalApproxLP infApprox = new CredalCausalApproxLP(causalModel, bnet.
    ↪getFactors());

```

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Alternatively, engines can be instantiated from a credal network.

```
// set up the exact inference engine
CredalCausalVE infExact = new CredalCausalVE(vcredal);
// set up the approximate inference engine
CredalCausalAproxLP infApprox = new CredalCausalAproxLP(hcredal);
```

2.5.3 Causal Effects

Let us consider the causal effect of on a variable X_3 of a variable $X_1 = 1$, that is, $P(X_3|do(X_1 = 1))$. This can be calculated with the exact inference engine as follows.

```
// set up and run a causal query
VertexFactor resExact = (VertexFactor) infExact
    .causalQuery()
    .setTarget(x[3])
    .setIntervention(x[1], 1)
    .run();
```

Alternatively, for an approximate solution:

```
// set up and run a causal query
IntervalFactor resApprox = (IntervalFactor) infApprox
    .causalQuery()
    .setTarget(x[3])
    .setIntervention(x[1], 1)
    .run();
```

2.5.4 Conuterfactuals

Credici also allows counterfactual queries (in a twin graph) such as $P(X'_3|do(X'_1 = 1), X'_1 = 0)$. The exact computation of this query can be done as follows.

```
// exact inference
resExact = (VertexFactor) infExact
    .counterfactualQuery()
    .setTarget(x[3])
    .setIntervention(x[1], 1)
    .setEvidence(x[1], 0)
    .run();
```

On the other hand, using the approximate engine:

```
// set up and run a counterfactual query
resApprox = (IntervalFactor) infApprox
    .counterfactualQuery()
    .setTarget(x[3])
    .setIntervention(x[1], 1)
    .setEvidence(x[1], 0)
    .run();
```

2.6 Contact and Support



Credici has been developed at the Swiss AI Lab IDSIA (Istituto Dalle Molle di Studi sull'Intelligenza Artificiale). The members of the development and research team are:

- Rafael Cabañas (rcabanas@idsia.ch)
- Alessandro Antonucci (alessandro@idsia.ch)
- David Huber (david@idsia.ch)
- Marco Zaffalon (zaffalon@idsia.ch)

If you have any question, please use [Github issues](#).