Introduction, introspection, illustration

Pierre-Henri WUILLEMIN

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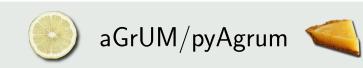
1 introduction

- short history
- components
- opensource project
- next

2 introspection : focus on 3 elementary Components

3 illustration

- The model (Liessman Eric Sturlaugson, Montana, 2014)
 - dynamic Bayesian Network
 - Chaîne de Markov à temps continu
 - CTBN
- Quick implementation of CTBNs using pyAgrum



(> 10 years) aGrUM's goals (as a tool for laboratory)

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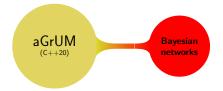
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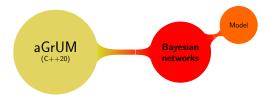
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- $\bullet \ \ \mbox{repository} : \ \mbox{svn} {\rightarrow} \ \mbox{local git} {\rightarrow} \ \mbox{local gitlab} {\rightarrow} \ \mbox{gitlab} \label{eq:gitlab}$
- Open Source : GPL then LGPL.

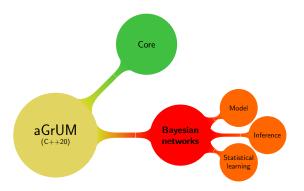


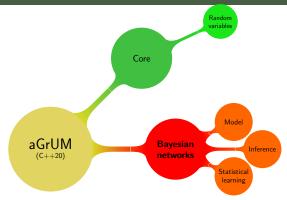


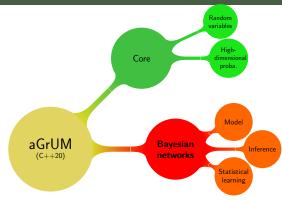


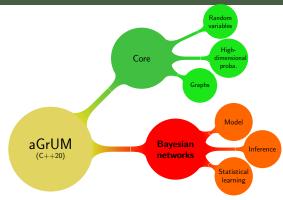


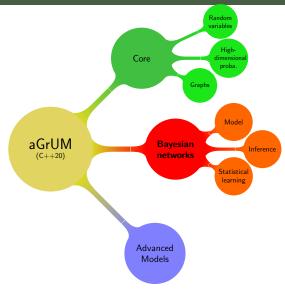


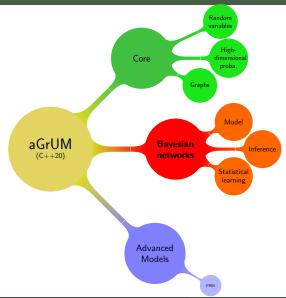


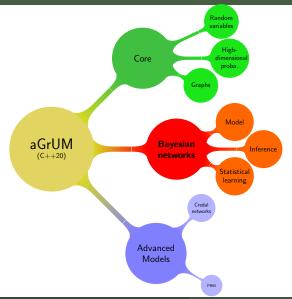


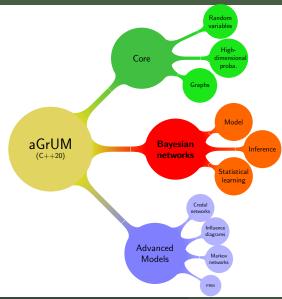


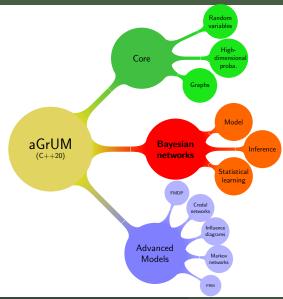


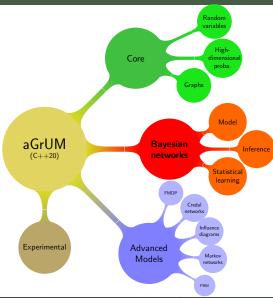


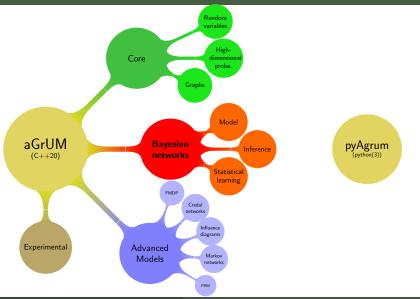


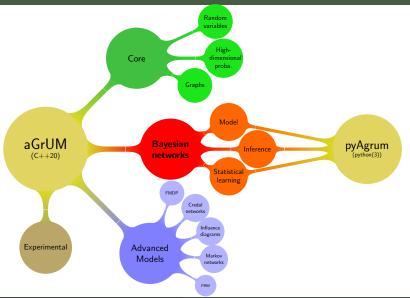


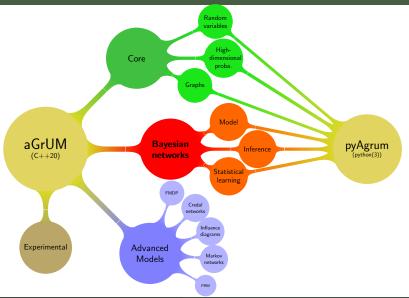




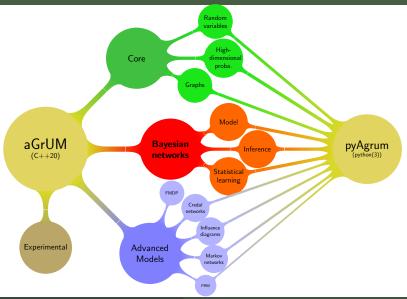


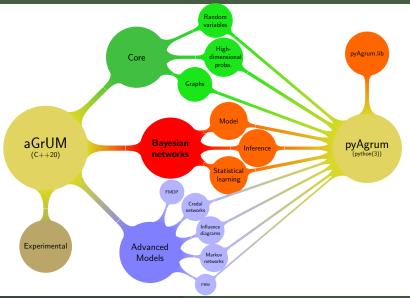


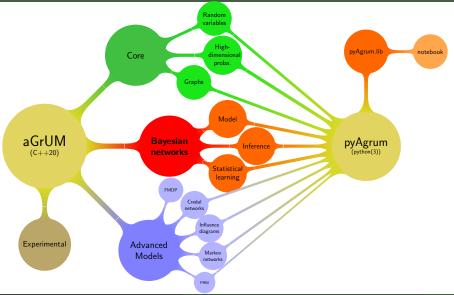


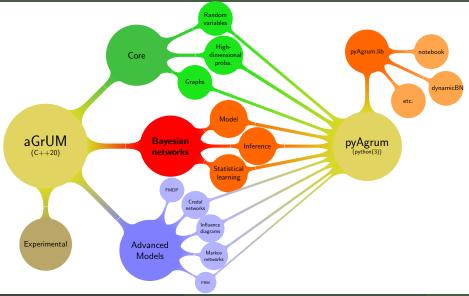


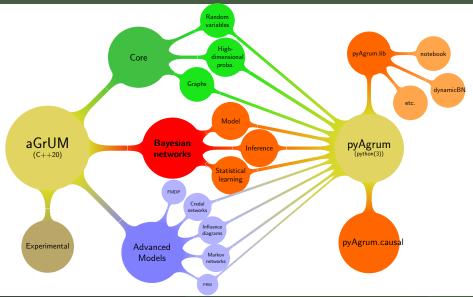
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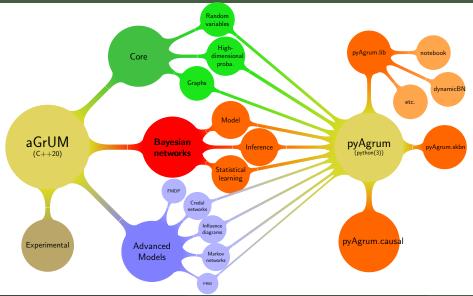














aGrUM/pyAgrum as OpenSource project



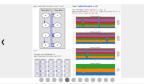
aGrUM/pyAgrum on the web



ovoj package 0.22.8 aGrum

aGrUM/pyAgrum

A GRaphical Universal Modeler (https://gitlab.com/agrumery/aGrUM)





aGrUM is a C++ library for graphical models. It is designed for easily building applications using graphical models such as Bayesian networks, influence diagrams,

decision trees, GAI networks or Markov decision processes.

aGrUM is written to provide the basic building blocks to perform the following tasks :

- designing graphical models,
- learning graphical models.
- elicitation of graphical models.
- Inference within graphical models.
- planification.

The probabilistic graphical models currently present in the library are the following:

- Bayesian networks (first and main target).
- Influence Diagrams.
- Markov networks.
- Credal networks.
- O3PRM (Probabilistic Relational Models).

pyAgrum

pvAgrum is a Python wrapper for the C++ aGrUM library (using SWIG interface generator). It provides a high-level interface to the part of aGrUM allowing to create, model, learn, use, calculate with and embed Bavesian Networks and other graphical models. Some specific (python and C++) codes are added in order to simplify and extend the aGrUM API.

Several topics have been added to pyAgrum (as pure python modules using pyAgrum) :

 Scikit-learn-compliant probabilistic classifiers based on Bayesian networks.

- Probabilistic causality (causal networks, do-calculus),
- dynamic Bayesian network,
- > tools for explainability in Bayesian networks.

See the tutorials as jupyter notebooks for more details.

Installation : here

Licence



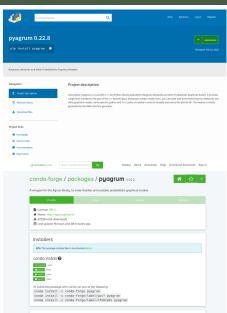
REPLY aGrUM/pyAgrum is released under the Gnu Lesser General Public License (LGPL v3.0), which means it can be freely copied and distributed, and costs nothing. Especially, aGrUM can be used and linked into both free software and proprietary software, provided that the code used under the LGPL is re-licensed under the LGPL (the other parts of the software are permitted have other you wish to integrate the aGrUM library into your product without being affected by the LGPL v.3, please contact

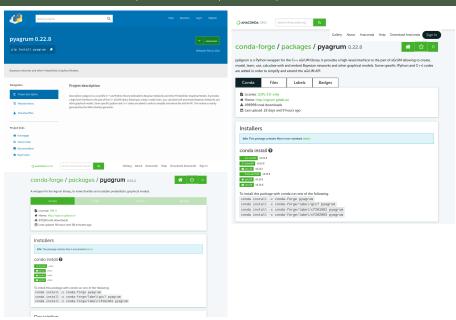
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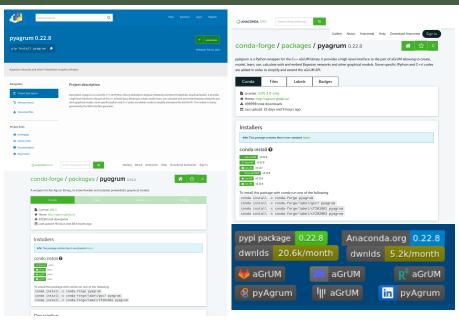
aGrUM/pyAgrum on gitlab.com

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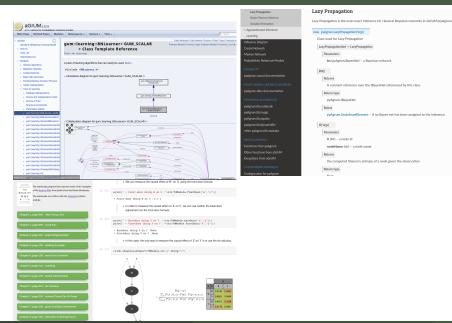


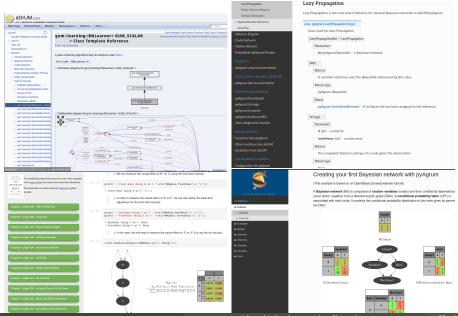




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Code quality in aGrUM/pyAgrum : tests

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Code quality in a GrUM/pyAgrum : continuous integration

CI on different platforms

Deployment (to be continued)

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• Visits (readthedocs, agrum.org, notebooks)

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Vues uniques

16 févr. 2022 - 17 mars 2022

5 835 % du total : 100,00 % (5 835)



16 févr. 2021 - 17 mars 2021

3079 % du total : 100,00 % (3079)



• Visits (readthedocs, agrum.org, notebooks)



• Téléchargements

Vues uniques

16 févr. 2022 - 17 mars 2022

5 835 % du total : 100,00 % (5 835)



16 févr. 2021 - 17 mars 2021

3079 % du total : 100,00 % (3079)



• Visits (readthedocs, agrum.org, notebooks)



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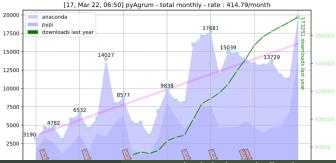


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Am

Téléchargements



Introduction, introspection, illustration

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communauty (?), consortium (?)

- Scientific orientation ?
 - models
 - algorithms
 - scientific committee
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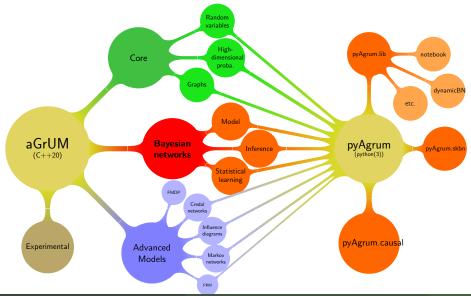
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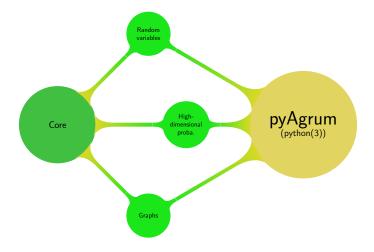
communauty (?), consortium (?)

- Scientific orientation ?
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- Development orientation ?
 - weaknesses, strengths
 - missing features
 - Ragrum, JSagrum
 - Steering committee
 - ?

Introspection : focus on 3 elementary components



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Representation of Discrete Variable

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Data structure : DiscreteVariable

goal : map a finite domain $[0, \dots, domainSize]$ on a list of labels.

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For a DiscreteVariable X that can take the values a, e, i, o, u, y, X is represented by an array :

index 0 1 2 3 4 5

label a e i o u y

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The kind of labels defines 4 different types of discrete variables :

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gum.LabelizedVariable	A{Red Green Blue}	Red Green Blue 0.2159 0.1766 0.6075	A Red 21.59% Green 17.66% Blue 60.75%
gum.RangeVariable	A[3,6]	A 5 6 0.1729 0.4902 0.1833 0.1536	$\begin{array}{c} A\\ \mu = 4.32; \ \sigma = 0.93\\ 3\\ 4\\ 49.02\%\\ 5\\ 5\\ 6\\ 15.36\%\\ \end{array}$
gum.DiscretizedVariable	A[-1,-0.5,0.5,1,10]	Image: Provide a state of the stat	$\mu = 1.15; \sigma = 2.45$ [-1:-0.5] [-0.5:0.5] [
gum.IntegerVariable	A{-14 5 6}	A -14 5 6 0.4087 0.0973 0.4940	$ \begin{array}{c} A \\ \mu = -2.27; \ \sigma = 9.76 \\ 14 \\ 5 \\ 9.73\% \\ 6 \\ 49.40\% \end{array} $

```
def aff(name,fastStx):
    bn=gum.fastBN(fastStx)
    return (f"<h2>(name)</h2>",
    f"<tt>{fastStx}</tt>",
    gnb.getPotential(bn.cpt(0)),
    gnb.getPosterior(bn.target=0,evs={}))
gnb.sideBySide(*aff("gum.LabelizedVariable","A{Red|Green|Blue}"),
    *aff("gum.RangeVariable","A[3,6]"),
    *aff("gum.IntegerVariable","A[-1,-0.5,0.5,1,10]"),
    *aff("gum.IntegerVariable","A{-14|5|6}"),
    ncols=4)
```



```
Introduction, introspection, illustration
```

A shared and simple API for all Discrete Variables

A shared and simple API for all Discrete Variables

```
def apiDiscreteVar(variable,value,position):
    print(f"{variable} : {value=}, {position=}")
    print(f" + {variable.domainSize()=}")
    print(f" + {variable[value]=}")
    print(f" + {variable.index(value)=}")
    print(f" + {variable.label(position)=}")
apiDiscreteVar(bn.variable("A"), "Green", 0)
apiDiscreteVar(bn.variable("B"), "5",0)
apiDiscreteVar(bn.variable("C")."0.75".0)
apiDiscreteVar(bn.variable("D")."5".0)
A:Labelized(<Red.Green.Blue>) : value='Green'. position=0
 + variable domainSize()=3
 + variable[value]=1
 + variable.index(value)=1
 + variable.label(position)='Red'
B:Range([3.6]) : value='5'. position=0
 + variable.domainSize()=4
 + variable[value]=2
 + variable.index(value)=2
 + variable.label(position)='3'
C:Discretized(<[-1:-0.5[,[-0.5:0.5[,[0.5:1[,[1:10]>) : value='0.75', position=0
 + variable.domainSize()=4
 + variable[value]=2
 + variable.index(value)=2
 + variable.label(position)='[-1;-0.5['
D:Integer(<-14.5.6>) : value='5'. position=0
 + variable.domainSize()=3
 + variable[value]=1
 + variable.index(value)=1
 + variable.label(position)='-14'
```

Data structure : Directed | Mixed | UnorientedGraph

goal : represent a list of Arc (a, b) and Edge $\{b, a\}$ between positive integers.

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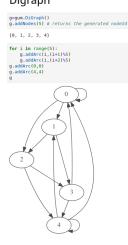
Several type of graphs :

- DiGraph
 - DAG (Directed Acyclic Graph)
- UndiGraph (and CliqueGraph)
- MixedGraph

• node : addNode, addNodeWithId(a), addNodes(nbr) , eraseNode(a)

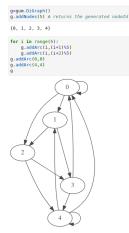
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- visualisation : toDot() (used by pyAgrum.lib.notebook for instance) Digraph



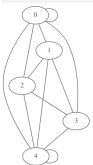
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Digraph



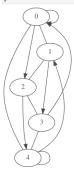
UndiGraph

g=gum.UndiGraph()
g.addNodes(5)
for i in range(5):
 g.addEdge(i,(i+1)%5)
 g.addEdge(i,(i+2)%5)
g.addEdge(0,0)
g.addEdge(4,4)
g



Mixed Graph

g=gum.MixedGraph()
g.addNodes(5)
for i in range(5):
 g.addEdge(i,(i+1)%5)
g.addArc(i,(i+2)%5)
g.addArc(0,0)
g.addEdge(4,4)



Representation of multi-dimensionnal arrays

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Implementing tensor algebra

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Implementing tensor alge	bra		
	f(,,) = g(,,) + h(,)		
[[[1. 2.] [3. 4.]] [[5. 6.] [7. 8.]]] g(,,)	[[1. 3.] [5. 7.]] h(,)	f(,,) = g(,,) + h(,)	

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$$f(a, b, c) = g(b, a, c) + h(b, c)$$

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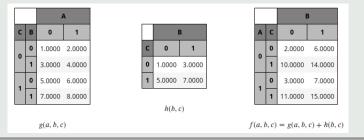
Representation of multi-dimensionnal arrays

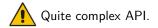
Data structure : Potential

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Quite complex API.

Creation and operations on Potential



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```
a=gum.LabelizedVariable("A","descr of A",2)
b=gum.LabelizedVariable("B","descr of B",2)
c=gum.LabelizedVariable("C","descr of C",2)
```

```
g=gum.Potential().add(b).add(a).add(c).fillWith([1,2,3,4,5,6,7,8])
h=gum.Potential().add(b).add(c).fillWith([1,3,5,7])
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f=g+h



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Methods on Potential



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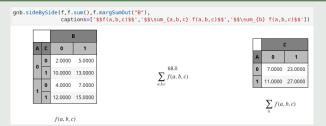
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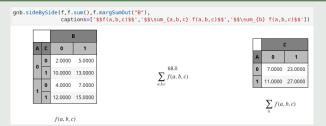
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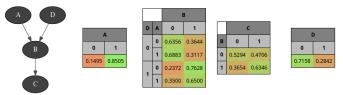
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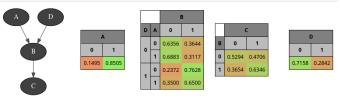
Potential for probabilities

Potential for probabilities

bn=gum.fastBN("A->B->C;D->B") gnb.sideBySide(bn,bn.cpt("A"),bn.cpt("B"),bn.cpt("C"),bn.cpt("D"))

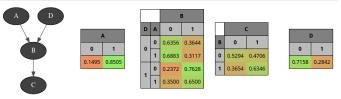


bn=gum.fastBN("A->B->C;D->B") gnb.sideBySide(bn,bn.cpt("A"),bn.cpt("B"),bn.cpt("C"),bn.cpt("D"))



P(A, B, C, D) = P(A) * P(D) * P(B|A, D) * P(C|B)

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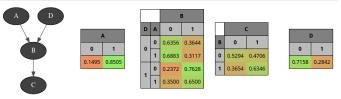


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pABCD=bn.cpt("A")*bn.cpt("B")*bn.cpt("C")*bn.cpt("D") pABCD

		D		
А	с	В	0	1
	0	0	0.0360	0.0053
0		1	0.0143	0.0118
	1	0	0.0320	0.0047
		1	0.0247	0.0206
	0	0	0.2218	0.0448
		1	0.0693	0.0574
Ľ	1	0	0.1972	0.0398
		1	0.1204	0.0997

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P(D|C)

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pABCD.margSumOut(["A","B"])/pABCD.margSumIn("C")

	с		
D	0	1	
0	0.7409	0.6943	
1	0.2591	0.3057	

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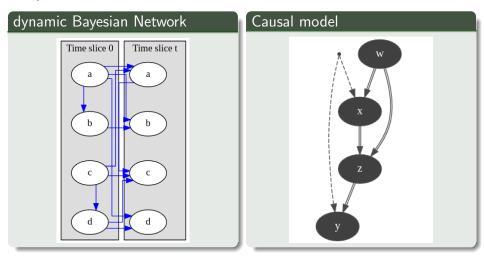
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Using these components to build new model in pyAgrum

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Two models exist only in pyAgrum and has been developped mainly from those components :



dBN (dynamic BN)

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a dynamic Bayesian network is a Bayesian network with wariables indexed by the time t and by $i : \mathbf{X}^{(t)} = X_1^{(t)}, \cdots, X_N^{(t)}$

dBN (dynamic BN)

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a dynamic Bayesian network is a Bayesian network with wariables indexed by the time t and by $i : \mathbf{X}^{(t)} = X_1^{(t)}, \cdots, X_N^{(t)}$ for which those properties hold :

• Markov property :

dBN (dynamic BN)

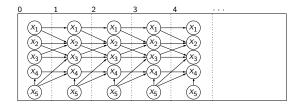
- Markov property : $P(\mathbf{X}^{(t)} | \mathbf{X}^{(0)}, \cdots, \mathbf{X}^{(t-1)}) = P(\mathbf{X}^{(t)} | \mathbf{X}^{(t-1)}),$
- Homogeneity :

dBN (dynamic BN)

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dBN (dynamic BN)

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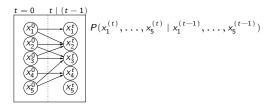
A dynamic Bayesian network is defined by

• initial distributions $(P(X^{(0)}))$,

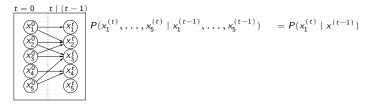
- initial distributions $(P(X^{(0)}),$
- the transition between the variables at time t-1 and the same variables at time t (*timeslices*).

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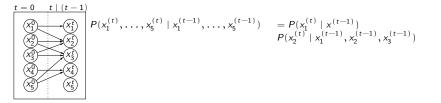
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$$\begin{array}{c|c} t = 0 & t \mid (t-1) \\ \hline (x_1^{(t)}, \dots, x_5^{(t)} \mid x_1^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_1^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_1^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_1^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_1^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots, x_5^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x_5^{(t-1)}, \dots, x_5^{(t-1)}) \\ \hline (x_2^{(t)}, \dots,$$

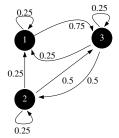
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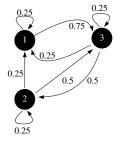
$$\begin{array}{c|c} t = 0 & t \mid (t-1) \\ \hline (x_1^{(1)}, \dots, x_5^{(t)} \mid x_1^{(t-1)}, \dots, x_5^{(t-1)}) & = P(x_1^{(t)} \mid x^{(t-1)}) \\ \hline (x_2^{(1)}, x_3^{(1)}, x_3^{(1)}) \\ \hline (x_3^{(1)}, x_4^{(1)}) \\ \hline (x_4^{(1)}, x_4^{(1)}) \\ \hline (x_5^{(1)}, x_4^{(1)}) \\ \hline (x_5^{(1)}, x_5^{(1)}) \\$$

A dynamic Bayesian network is defined by

- initial distributions $(P(X^{(0)}),$
- the transition between the variables at time t-1 and the same variables at time t (*timeslices*).

The representation a.k.a 2TBN (2 timeslices BN) allow the modelisation of a virtually infinite Bayesian network which is the unrolled model from time 0.



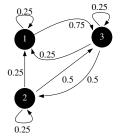


 $P(X^{n} \mid X^{n-1}) = \begin{pmatrix} 0.25 & 0 & 0.75 \\ 0.25 & 0.25 & 0.5 \\ 0.25 & 0.5 & 0.25 \end{pmatrix}$

Markov chain

- a discrete variable (X^n) (at time n).
- Parameters for this model :
 - Initial condition : $P(X^{O})$
 - transition probabilities : $P(X^n | X^{n-1})$

Equivalent dynamic Bayesian network :



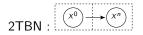
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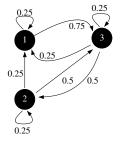
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Equivalent dynamic Bayesian network :

$$\mathsf{dBN}: \overset{(x^0)}{\longrightarrow} \overset{(x^1)}{\longrightarrow} \overset{(x^2)}{\longrightarrow} \overset{(x^3)}{\longrightarrow}$$





С

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$$\mathsf{IBN}: \overset{(x_0)}{\longrightarrow} \overset{(x_1)}{\longrightarrow} \overset{(x_2)}{\longrightarrow} \overset{(x_3)}{\longrightarrow} \overset{(x_3)}{\longrightarrow}$$

2TBN

Could we do the same with continuous time?

Dynamic processus dynamique verifying :

• a discrete variable

Dynamic processus dynamique verifying :

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$$\underbrace{0}_{X(0)} \underbrace{t_1}_{X(t_1)} \underbrace{t_2}_{X(t_2)} t_3 \cdots$$

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• Continuous time Markov property :

$$\forall s > r, \forall t > 0, P(X(s+t)|X(s)), X(r)) = P(X(s+t)|X(s)))$$

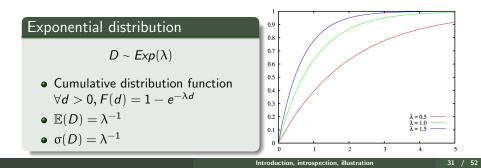
Dynamic processus dynamique verifying :

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A CTMC is a continuous stochastic process in which, for each state, the process will change state according to an exponential random variable and then move to a different state as specified by the probabilities of a stochastic matrix.

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 $X \sim \textit{Exp}(\lambda), Y \sim \textit{Exp}(\mu), X \perp\!\!\!\!\perp Y \Rightarrow \textit{min}(X,Y) \sim \textit{Exp}(\lambda + \mu)$

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 $(X_t \in x_1, \cdots, x_n)_{t \ge 0}$ CdMTC is defined by

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Continuous Time Markov Chain

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• <i>P</i> (<i>X</i> ₀)	1	/ -0.21	0.20	0.01 \
• $orall i,j\geq n,q_{i,j}$ tels que	$Q_X =$	0.05	-0.10	$\left(\begin{array}{c} 0.01 \\ 0.05 \\ -0.21 \end{array} \right)$
$\bullet \ q_{i,i} \in \mathbb{R}^-$		0.01	0.20	-0.21 <i>J</i>
$ \begin{array}{l} 2 \hspace{0.1in} \forall i \neq j, q_{i,j} \in \mathbb{R}^+ \\ \\ 3 \hspace{0.1in} \forall i, \sum_j q_{i,j} = 0 \end{array} \end{array} $	intensity matrix			

 $q_{i,j}$ is the parameter of the exponential distribution controlling the transition from state *i* to state *j* $-q_{i,j}$ is the parameter of the exponential distribution controlling a transition from state *i*.

- $(X_t \in x_1, \cdots, x_n)_{t \ge 0}$ CTMC :
 - $P(X_0)$
 - $Q_X = (q_{i,j})_{i \le n, j \le n}$ intensity matrix

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• Convergence of $P(X_t) = P(X_0)exp(Q_X t) \xrightarrow[t \to \infty]{} P^*$

CTBN

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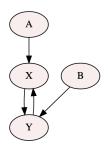
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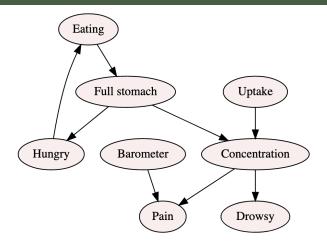
 Q_X is a CIM $\iff \forall < pa_X >, Q_{X| < pa_X >}$ intensity matrix.



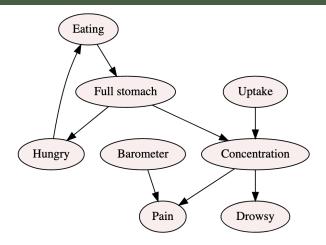
	A#j			
A#i	a0	a1		
a0	-1.0000	1.0000		
a1	2.0000	-2.0000		

			X#j		
Y	A	X#i	x0	x1	
у0 -	a0	x0	-1.0000	1.0000	
		x1	2.0000	-2.0000	
	a1	x0	-10.0000	10.0000	
		x1	20.0000	-20.0000	
y1 -	a0	x0	-5.0000	5.0000	
	au	x1	6.0000	-6.0000	
	a1	x0	-50.0000	50.0000	
		x1	60.0000	-60.0000	

CTBN - properties

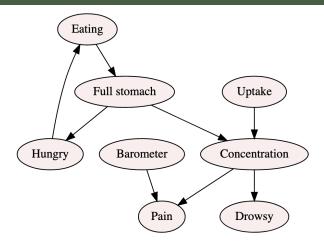


CTBN - properties

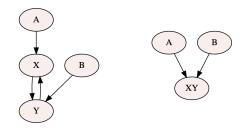


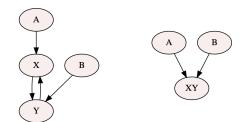
• Arc always temporal (which allows 'cycle') : $A \rightarrow B \iff P(B_{t+\delta_t} \mid A_t, \cdots) = \cdots$

CTBN - properties



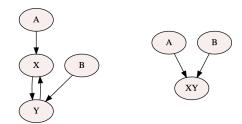
- Arc always temporal (which allows 'cycle') : $A \rightarrow B \iff P(B_{t+\delta_t} \mid A_t, \cdots) = \cdots$
- A Continuous-Time Bayseian network is a joint continuous-time Markov process.

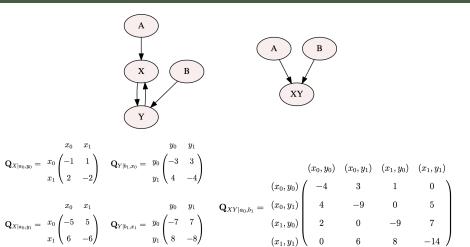




$$\mathbf{Q}_{X|a_0,y_0} = \begin{array}{ccc} x_0 & x_1 & y_0 & y_1 \\ \mathbf{Q}_{X|a_0,y_0} = & x_0 \begin{pmatrix} -1 & 1 \\ 2 & -2 \end{pmatrix} & \mathbf{Q}_{Y|b_1,x_0} = & y_0 \begin{pmatrix} -3 & 3 \\ 4 & -4 \end{pmatrix}$$

$$\mathbf{Q}_{X|a_0,y_1} = \begin{array}{ccc} x_0 & x_1 & y_0 & y_1 \\ -5 & 5 \\ x_1 \begin{pmatrix} -5 & 5 \\ 6 & -6 \end{pmatrix} & \mathbf{Q}_{Y|b_1,x_1} = \begin{array}{ccc} y_0 \begin{pmatrix} -7 & 7 \\ 8 & -8 \end{pmatrix} \end{array}$$





The amalgamation of all the CIMs of a CTBN produces the intensity matrix of the joint Markov process.

$$(X_{t+1}, D_t) = (argmin, min)_{X \in CTBN} Draw(Q_X)$$

CTBN Forward sampling

•
$$(X_{t+1}, D_t) = (\operatorname{argmin}, \operatorname{min})_{X \in CTBN} Draw(Q_X)$$

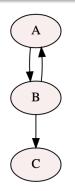
 $x_{t+1} = Draw(Q_X)$

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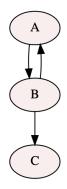
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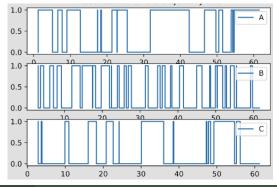


Forward sampling dans un CTBN

CTBN Forward sampling

- $(X_{t+1}, D_t) = (argmin, min)_{X \in CTBN} Draw(Q_X)$
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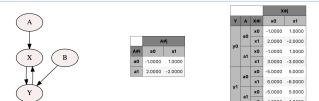
Implémentation (rapide)



Goal1 : way to define a CTBN

ctbn = Ctbn() ctbn.add(gum.LabelizedVariable("A", "A", ["a0", "a1"])) ctbn.add(gum.LabelizedVariable("B", "B", ["b0", "b1"])) ctbn.add(gum.LabelizedVariable("X", "X", ["x0", "x1"])) ctbn.add(gum.LabelizedVariable("Y", "Y", ["v0", "v1"])) ctbn.addArc("A", "X") ctbn.addArc("Y", "X") ctbn.addArc("B", "Y") ctbn.addArc("X", "Y") ctbn.CIM("A")[:] = [[-1, 1]. [2, -2]] ctbn.CIM("B")[:] = [[-3, 3], [2, -2]] ctbn.CIM("X")[{"A": "a0", "Y": "y0"}] = [[-1, 1], [2, -2]]ctbn.CIM("X")[{"A": "a1", "Y": "y0"}] = [[-1, 1], [3, -31] ctbn.CIM("X")[{"A": "a0", "Y": "y1"}] = [[-5, 5], [6, -61] ctbn.CIM("X")[{"A": "a1", "Y": "y1"}] = [[-5, 5], [4, -4]]ctbn.CIM("Y")[{"B": "b0", "X": "x0"}] = [[-2, 2]. [5. -51] ctbn.CIM("Y")[{"B": "b1", "X": "x0"}] = [[-3, 3], [4, -4]]ctbn.CIM("Y")[{"B": "b0", "X": "x1"}] = [[-3, 3], [5, -5]]ctbn.CIM("Y")[{"B": "b1", "X": "x1"}] = [[-7, 7], [8. -81]

gnb.sideBySide(ctbn,ctbn.CIM("A")._pot,ctbn.CIM("X")._pot)



Introduction, introspection, illustration

Goal2 : implement amalgamation

Goal2 : implement amalgamation

	in c m∗=ct	bn.(.names(CIM(x))):									
array		7., 0.,	1., 0.,	3., 0.,	0., 0.,	1., 0.],	0.,	0.,	0.,	2.,	0.,	0.,	
	[2., 0.,	-8., 0.,	0., 0., 0.,	3., 0.,	0., 0.],	1.,	0.,	0.,	0.,	2.,	0.,	
	[2., 0.,	0., 0.,	-7., 0.,	1., 0.,	0., 0.],	0.,	1.,	0.,	0.,	0.,	з.,	
	[0., 3.,	2., 0.,	2., 0.,	-8., 0.,	0., 0.],	0.,	0.,	1.,	0.,	0.,	0.,	
	[2., 0.,	0., 3.,	0., 0.,	0., 0.,	-9., 0.],	1.,	з.,	0.,	0.,	0.,	0.,	
	[0., 0.,	3., 0.,	0., 3.,	0., 0.,	2., - 0.],	11.,	0.,	3.,	0.,	0.,	0.,	
	[0., 0.,	0., 0.,	2., 0.,	0., 7.,	2., 0.],	0.,	-12.,	1.,	0.,	0.,	0.,	
	[0., 0.,	0., 0.,	0., 0.,	3., 0.,	0., 7.],	2.,	2.,	-14.,	0.,	0.,	0.,	
	[5., 0.,	0., 5.,	0., 0.,	0., 0.,	0., 0.],	0.,	0.,	0.,	-14.,	1.,	з.,	
		0., 3.,	5., 0.,	0., 5.,	0., 0.,	0., 0.],	0.,	0.,	0.,		-15.,	0.,	
		0., 1.,	0., 0.,	4., 0.,	0., 5.,	0., 0.],	0.,	0.,	0.,	2.,		-12.,	
	-1	0., 3.,	0., 0.,	0., 0.,	4., 0.,	0., 5.],	0.,	0.,	0.,	0.,	2.,	2.,	
			0., -15.,	0., 1.,	0., 3.,	5., 0.],	0.,	0.,	0.,	6.,	0.,	0.,	
	L	0.,	0.,	0.,	0.,	0.,	5.,	0.,	0.,	0.,	4.,	0.,	

3

Goal3 : implement the 2 'inference'

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ie=SimpleCtbnInference(ctbn) ie.makeInference() gnb.sideBySide(ie.posterior("A"),ie.posterior("B"),ie.posterior("Y"),ie.posterior("X"))



ie=ForwardSampleCtbnInference(ctbn) ie.makeInference() gnb.sideBySide(ie.posterior("A"),ie.posterior("B"),ie.posterior("Y"),ie.posterior("X"))

	4			в		Y		x
a0	a1		b0	b1	уO	y1	x0	
0.6651	0.3349	.9	0.396	0.6032	0.6081	0.3919	0.6060	0.

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CIM

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- Convergence
 - 'Exact' method (exp(IM))
 - Sampling (Forward Sampling)

CIM

CIM

CIM : wrapper de Potential



CIM : Amalgamation

Algorithm 2.2 Amalgamate two nodes of a CTBN. Amalgamate(X, Y)1: $\mathbf{Q}_{XY|\mathbf{Pa}(XY)} \leftarrow \emptyset$ 2: for each $\langle pa_{Y\setminus X} \rangle \in \mathbf{pa}_{X\setminus Y}$ and $\langle pa_{X\setminus Y} \rangle \in \mathbf{pa}_{Y\setminus X}$ $\mathbf{Q}^{XY} \leftarrow \mathbf{0}$ 3: for i, j = 1, ..., |X| and l, k = 1, ..., |Y|4: $\mathbf{Q}^X \leftarrow \mathbf{Q}_{X|\langle pa_X \setminus Y \rangle, x_i}$ 5: $\mathbf{Q}^Y \leftarrow \mathbf{Q}_{Y|\langle pa_{Y\setminus X}\rangle, y_k}$ 6: if $i = j \wedge k = l$ 7: $\begin{array}{c} q_{(i,j),(k,l)}^{XY} \leftarrow q_{i,j}^X + q_{k,l}^Y \\ \textbf{else if } i = j \land k \neq l \end{array}$ 8: 9: $\begin{array}{c} q_{(i,j),(k,l)}^{XY} \leftarrow q_{k,l}^{Y} \\ \textbf{else if } i \neq j \land k = l \end{array}$ 10: 11: $q^{XY}_{(i,j),(k,l)} \leftarrow q^X_{i,j}$ end if 12:13:end for 14: $\mathbf{Q}_{XY|\langle pa_{XY}\rangle} \leftarrow \mathbf{Q}^{XY}$ 15: $\mathbf{Q}_{XY|\mathbf{Pa}(XY)} \leftarrow \mathbf{Q}_{XY|\mathbf{Pa}(XY)} \cup \{\mathbf{Q}_{XY|\langle pa_{XY} \rangle}\}$ 16:17: end for 18: return $\mathbf{Q}_{XY|\mathbf{Pa}(XY)}$

CIM : Amalgamation

Algorithm 2.2 Amalgamate two nodes of a CTBN.
$\overline{Amalgamate(X,Y)}$
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2: for each $\langle pa_{Y\setminus X} \rangle \in \mathbf{pa}_{X\setminus Y}$ and $\langle pa_{X\setminus Y} \rangle \in \mathbf{pa}_{Y\setminus X}$
3: $\mathbf{Q}^{XY} \leftarrow 0$
4: for $i, j = 1,, X $ and $l, k = 1,, Y $
5: $\mathbf{Q}^{X} \leftarrow \mathbf{Q}_{X \langle pa_{X\setminus Y} \rangle, x_{i}}$
6: $\mathbf{Q}^Y \leftarrow \mathbf{Q}_{Y \langle pa_Y \setminus X \rangle, y_k}$
7: if $i = j \land k = l$
8: $q_{(i,j),(k,l)}^{XY} \leftarrow q_{i,j}^X + q_{k,l}^Y$
9: else if $i = j \land k \neq l$
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13: end if
14: end for O^{XY}
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17: end for
18: return $\mathbf{Q}_{XY \mathbf{Pa}(XY)}$

```
i = amal.instantiation()
iX = cimX.instantiation()
    iY.chgVal(v, iX[CIM.var_i(v.name())])
   if iX[CIM.var_i(v)] ≠ iX[CIM.var_j(v)]:
   if iY[CIM.var_i(v)] \neq iY[CIM.var_j(v)]:
```

- CIM : 210 lines
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CTBN

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- CIMs in a dictionnary.

```
self.graph = gum.DiGraph()
  self.id2var = {}
  self.name2id = {}
def add(self, var: gum.DiscreteVariable) → NodeId:
  n = NodeId(self.graph.addNode())
 self.id2var[n] = var
  self.name2id[var.name()] = n
  self.bn0.add(var)
 v_i.setName(CIM.var_i(var.name()))
 v_j = var.clone()
 v_j.setName(CIM.var_j(var.name()))
  self.cim[n] = CIM().add(v_j).add(v_i)
def addArc(self, val1: NameOrId, val2: NameOrId) → Tuple[NodeId, Node
  n1 = self._nameOrId(val1)
 n2 = self. nameOrId(val2)
  self.graph.addArc(n1, n2)
  self.cim[n2].add(self.id2var[n1])
```

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```
ctbn = Ctbn()
ctbn.add(gum.LabelizedVariable("A", "A", ["a0", "a1"]))
ctbn.add(gum.LabelizedVariable("B", "B", ["b0", "b1"]))
ctbn.add(gum.LabelizedVariable("X", "X", ["x0", "x1"]))
ctbn.add(gum.LabelizedVariable("Y", "Y", ["y0", "y1"]))
ctbn.addArc("A", "X")
ctbn.addArc("Y", "X")
ctbn.addArc("B", "Y")
ctbn.addArc("X", "Y")
ctbn.CTM("A")[:] = [[-1, 1].
                    [2. -21]
ctbn.CIM("B")[:] = [[-3, 3],
                     [2, -21]
ctbn.CIM("X")[{"A": "a0", "Y": "y0"}] = [[-1, 1],
ctbn.CIM("X")[{"A": "a1", "Y": "y0"}] = [[-1, 1],
ctbn.CIM("X")[{"A": "a0", "Y": "y1"}] = [[-5, 5],
                                          [6, -6]]
ctbn.CIM("X")[{"A": "a1", "Y": "v1"}] = [[-5, 5],
                                          [4, -4]]
ctbn.CIM("Y")[{"B": "b0", "X": "x0"}] = [[-2, 2],
                                          [5, -5]]
ctbn.CIM("Y")[{"B": "b1", "X": "x0"}] = [[-3, 3],
                                          [4. -4]]
ctbn.CIM("Y")[{"B": "b0", "X": "x1"}] = [[-3, 3],
                                          [5, -5]]
ctbn.CIM("Y")[{"B": "b1", "X": "x1"}] = [[-7, 7],
                                          [8, -8]]
```

gnb.sideBySide(ctbn,ctbn.CIM("A")._pot,ctbn.CIM("X")._pot)



Inférence simple

```
class SimpleCtbnInference(CtbnInference):
 def __init__(self, cim: Ctbn):
  def makeInference(self):
    for nod in self._model.nodes():
     g = g.amalgamate(self. model.CIM(nod))
    q.from_matrix(expm(5000 * q.to_matrix()))
    t0 = qum.Potential()
    for n in g.var names:
    self. joint = (t0 * g. pot).margSumOut(t0.var names)
  def posterior(self, name: str) → gum.Potential:
    return gum.Potential().add(self._model.variable(name)).fillWith(self._joint.margSumIn(vi), [vi])
```

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Forward Sampling

Forward Sampling

Algorithm 2.1 Forward sample CTBN.

 $ForwardSample(\mathcal{N})$ 1: for each $X \in \mathcal{N}$ choose X(0) by sampling from \mathcal{B} 2: 3: end for 4: $t \leftarrow 0, \sigma \leftarrow \emptyset$ 5: repeat until termination $Append(\sigma, \langle X, t \rangle)$ 6: for each $X \in \mathcal{N}$ 7: if $time(X) \neq null$ then continue end for 8: $\mathbf{A}_X \leftarrow \mathbf{A}_{X|\mathbf{Pa}(X)}$ 9: $i \leftarrow X(t)$ 10: $\Delta t \sim \text{Exponential}(a_{i,i})$ 11: $time(X) \leftarrow t + \Delta t$ 12: end for 13: $X' \leftarrow \operatorname{argmin}_{X \in \mathcal{N}} (time(X))$ 14: 15: $t \leftarrow time(X')$ 16: $X(t) \sim \text{Multinomial}(\mathbf{A}_{X'}, X(t))$ time(X') = null17: for each $Y \in \mathbf{Ch}(X')$ 18: time(Y) = null19: end for 20:21: end repeat 22: return σ

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Code based on the result of a student project (L2).

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 $\bullet\,$ model CTBN : compact representation of continuous-time Markov processes with a very large state space .

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goals reached !

- model CTBN : compact representation of continuous-time Markov processes with a very large state space .
- pyAgrum : toolbox for the implementation of new graphical models.

- aGrUM/pyAgrum still a lab/academic tool. We will not stop maintaining & developing !
- Many users imply many responsabilities
 - Interaction

gitlab issues, discord, gitter, linkedin, researchGate, what else?

Structuration

communauty (?), consortium (?)

- Scientific orientation ?
 - models
 - algorithms
 - scientific committee
 - ?
- Development orientation ?
 - weaknesses, strengths
 - missing features
 - Ragrum, JSagrum
 - Steering committee
 - ?