FAST AND FURIOUS THINGS IN AGRUM/PYAGRUM

CHRISTOPHE GONZALES

LIS – AIX-MARSEILLE UNIVERSITÉ

Outline

Parallelization in Learning algorithms

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- Parallelization in Learning algorithms
- Parallelization in Inferences

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- Parallelization in Learning algorithms
- Parallelization in Inferences
- aGrUM's multithreading facility

BN structure learning : Greedy Hill Climbing

$\mathcal{G}_{best} \leftarrow$ initial graph (empty)
$sc_{best} \leftarrow \text{Score}(\mathcal{G}_{best})$

repeat
  found $\leftarrow$ false
  foreach $\mathcal{G}' \in$ *neighborhood of* $\mathcal{G}_{best}$ **do**
    $sc' \leftarrow \text{Score}(\mathcal{G}')$
    if $sc' > sc_{best}$ **then**
      $\mathcal{G}_{best} \leftarrow \mathcal{G}'$, $sc_{best} \leftarrow sc'$
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until *found* $=$ *false*;

return $\mathcal{G}_{best}$

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Parallelizing the scores

The BD score

$$\mathrm{Score}_{BD}(X_i|\mathbf{Pa}(X_i),\mathbf{D}) = \prod_{j=1}^{q_i} \frac{\Gamma(\alpha_{ij})}{\Gamma(N_{ij}+\alpha_{ij})} \prod_{k=1}^{r_i} \frac{\Gamma(N_{ijk}+\alpha_{ijk})}{\Gamma(\alpha_{ijk})}$$

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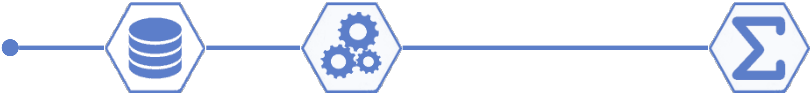

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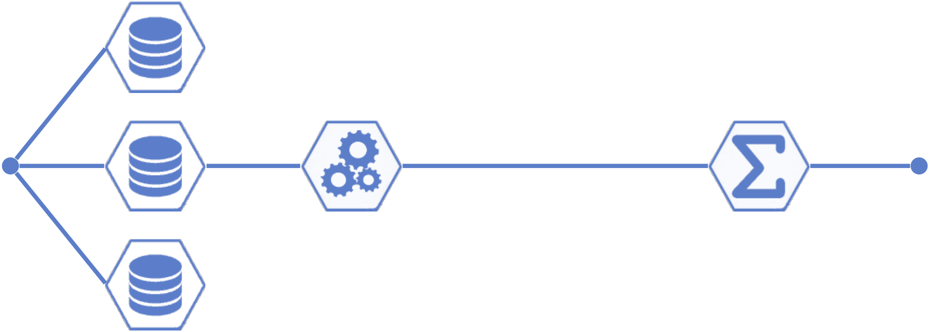

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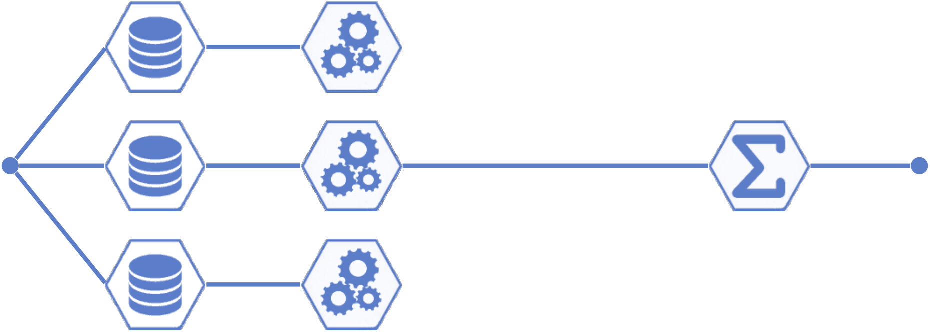

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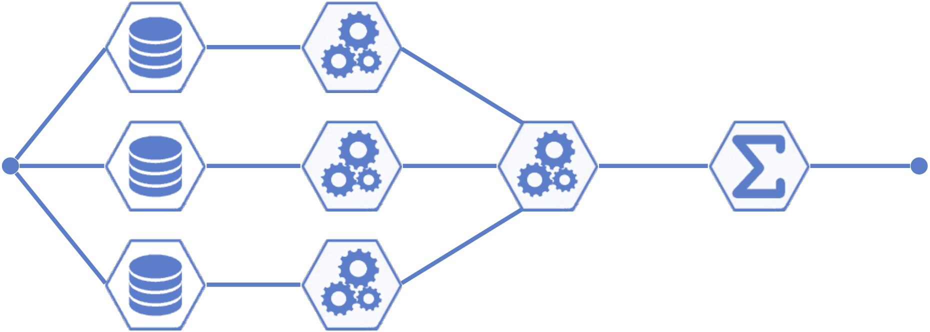
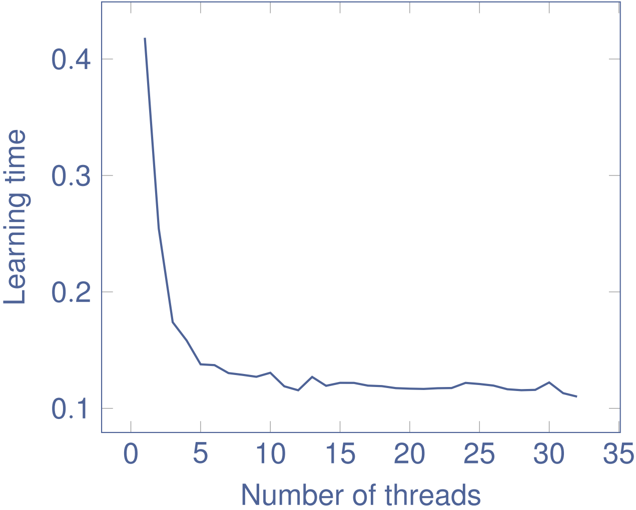


Alarm : learning structure with 10K records



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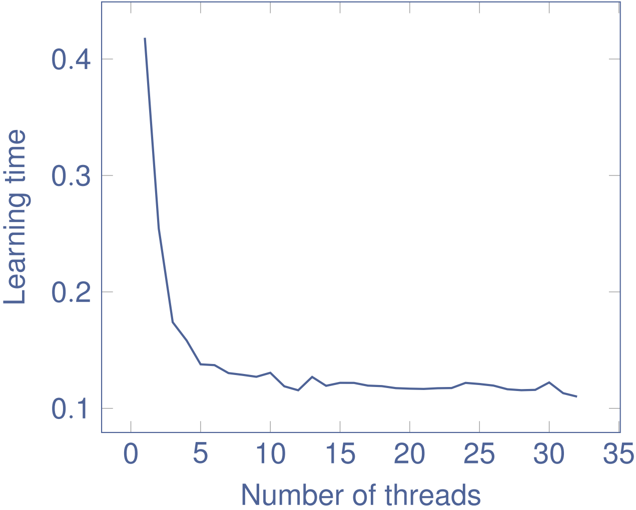
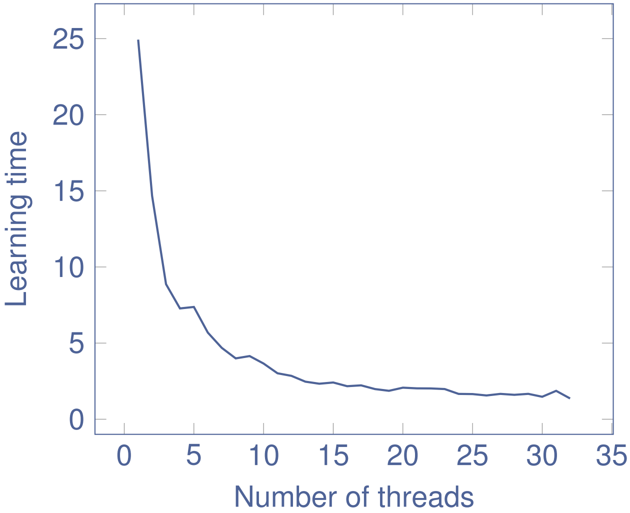


- **aGrUM's rule :** Number of records per thread ≥ 512

Alarm : learning structure with 200K records



Number of threads in pyAgrum : the rationale

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aGrUM's rules :

1. pyAgrum manages a « package-wide » number of threads

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2. Objects can override this number

pyAgrum's Package-wide API

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import pyAgrum as gum
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`gum.getMaxNumberOfThreads`	The number of processors of the computer
`gum.getNumberOfLogicalCores`	The number of processors
`gum.getNumberOfThreads`	The number of threads used by default by pyAgrum objects
`gum.setNumberOfThreads`	Sets the number of threads used by default

```python
import pyAgrum as gum

print("Nb procs =", gum.getMaxNumberOfThreads())
```

Using the pyAgrum-wide API – an example

```python
import pyAgrum as gum

print("Nb procs =", gum.getMaxNumberOfThreads())
```

```
Nb procs = 64
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print("Nb procs =", gum.getMaxNumberOfThreads())

# Default number of threads for all pyAgrum objects
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# Changing this default number
gum.setNumberOfThreads(10)
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Nb procs = 64
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Overriding the pyAgrum multithreading setting

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- **Object overriding methods :**

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`obj.getNumberOfThreads`	returns the current number of threads used by `obj`
`obj.setNumberOfThreads`	changes the number of threads used by `obj`
`obj.isGumNumberOfThreadsOverriden`	indicates whether `obj` uses its own number or that of pyAgrum

Using the object API – an example

```python
import pyAgrum as gum
learner = gum.BNLearner("data/alarm.csv")

print("pyAgrum threads =", gum.getNumberOfThreads())
print("Learner threads =", learner.getNumberOfThreads())
print("Learner override =",
      learner.isGumNumberOfThreadsOverriden())
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```
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```

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# changing the number of threads only for the learner
learner.setNumberOfThreads(10)
print("pyAgrum threads =", gum.getNumberOfThreads())
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# making the learner use the package-wide number again
learner.setNumberOfThreads(0) # 0 = package-wide
print("Learner threads =", learner.getNumberOfThreads(),
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Different situations :

- Performing just one learning :
  use pyAgrum number of threads

Toward an optimal choice of the number of threads

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  use 1 thread per BNlearner
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Different situations :

- Performing just one learning :
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- Performing a large amount of learning experiments :
  use 1 thread per BNlearner
  perform experiments in parallel
- Performing a small amount K of learnings :
  let nb processors $\approx A \times B$, with K multiple of A
  perform A experiments in parallel
  use B thread per BNlearner

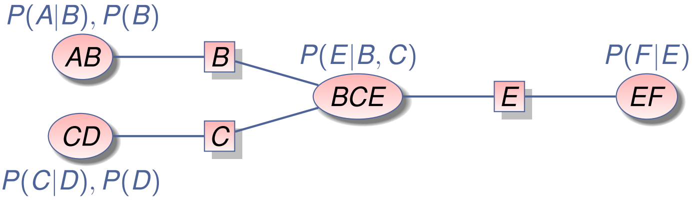
Next multithreading steps. . .

- Allow Databases to be column-wise instead of row-wise

  $\Longrightarrow$ improved cacheline use

Parallelization in Inferences

New exact inference architecture (1/2)



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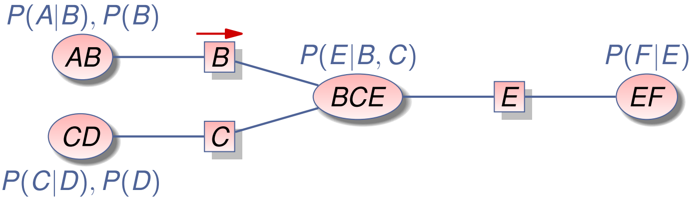

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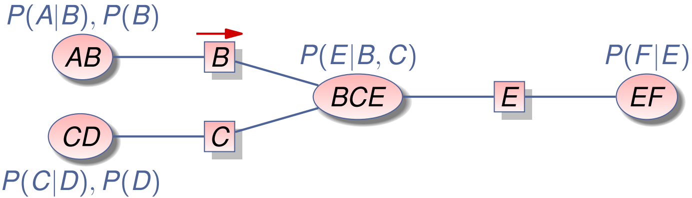

1. $P(A,B) = P(A|B) \times P(B)$

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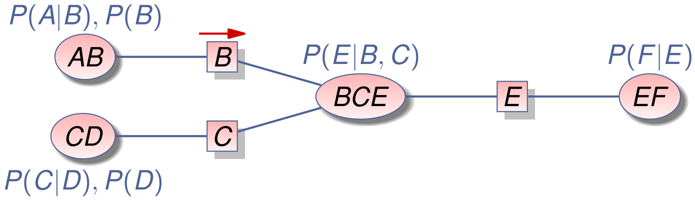

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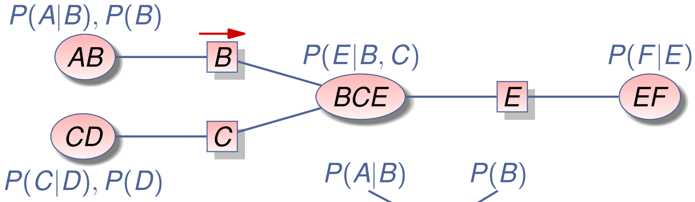

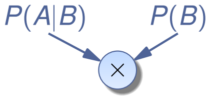

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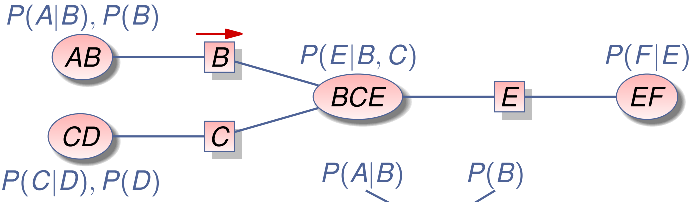

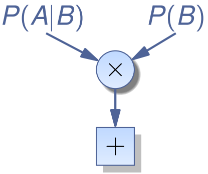

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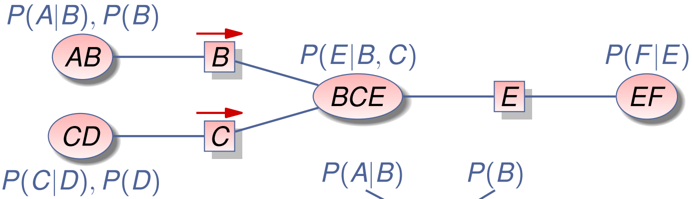

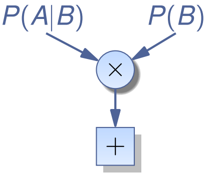

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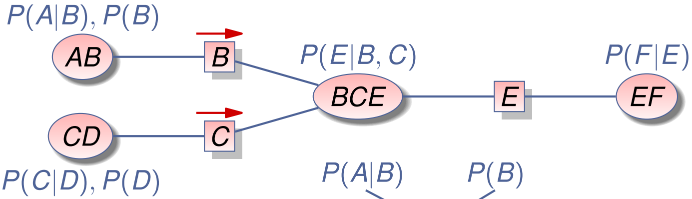

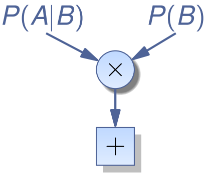

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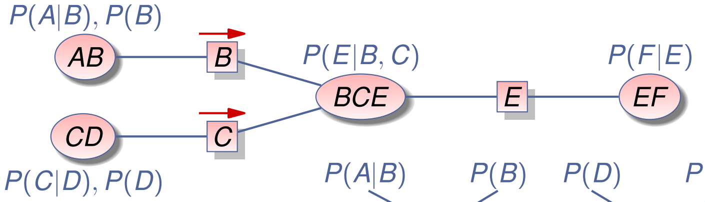

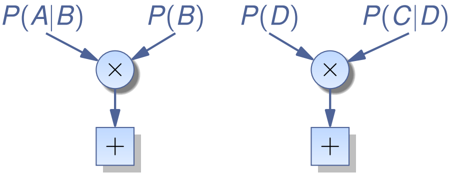

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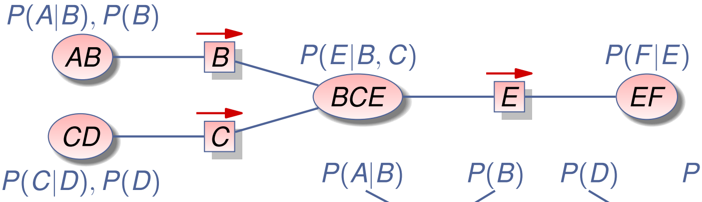

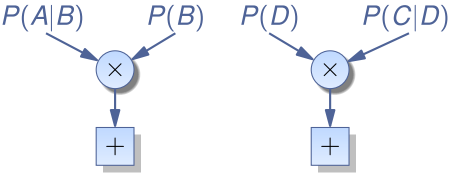

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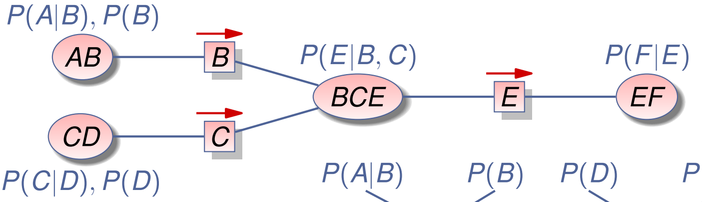

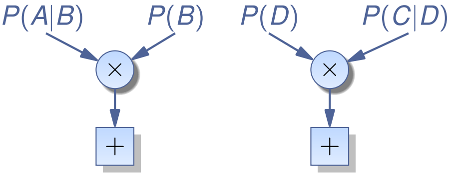

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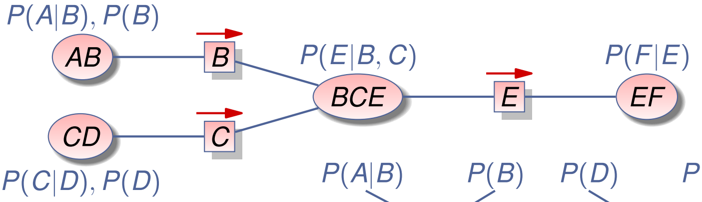

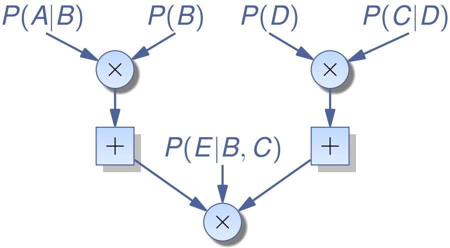

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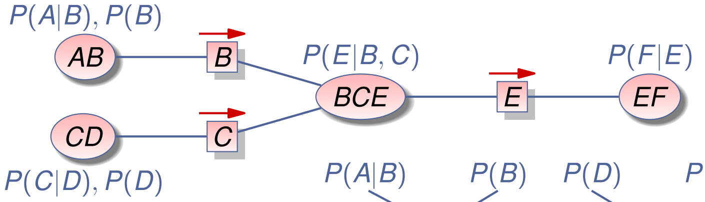

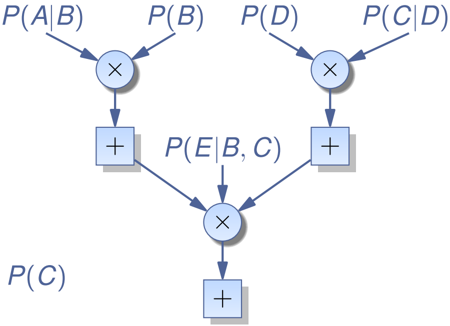

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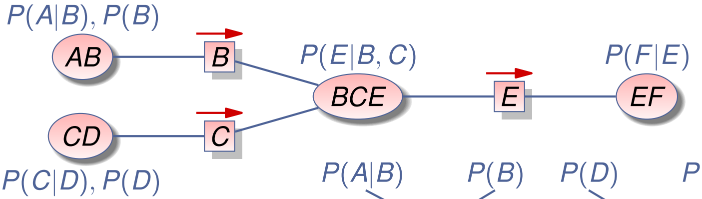

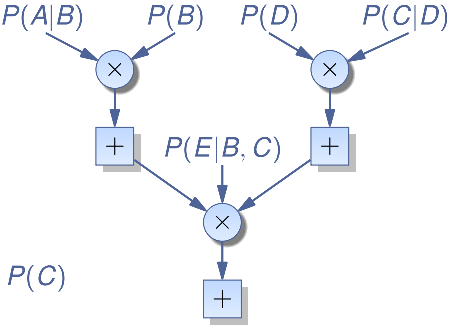

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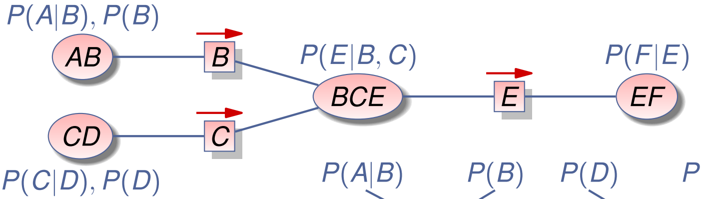

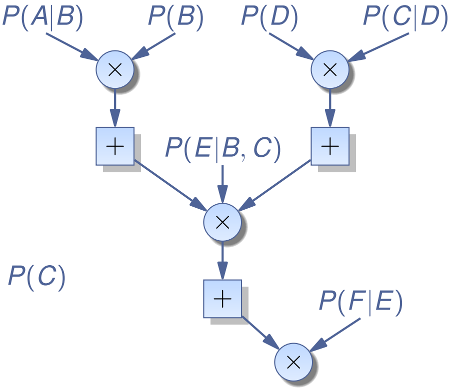

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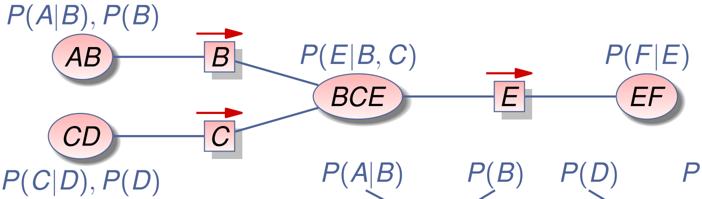

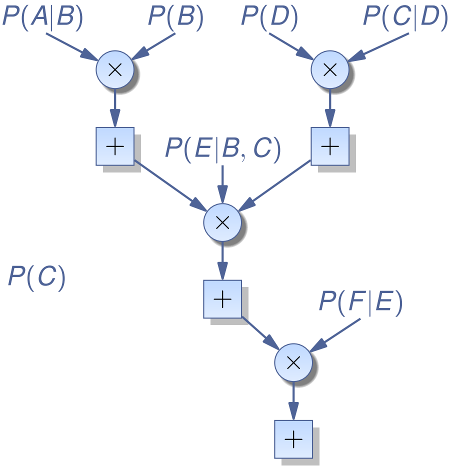

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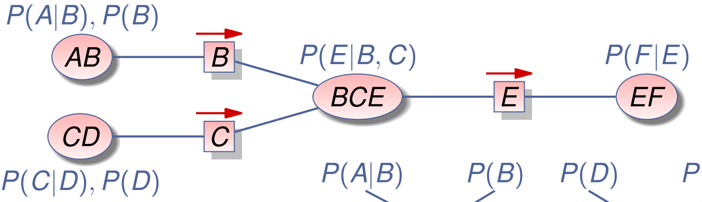

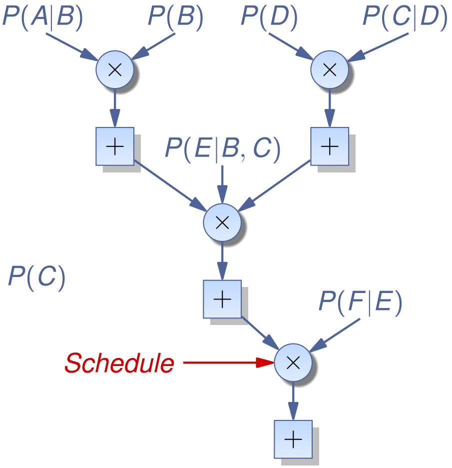

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- **Used by LazyPropagation and Shafer-Shenoy**
- **2 schedulers :**
  - Sequential scheduler
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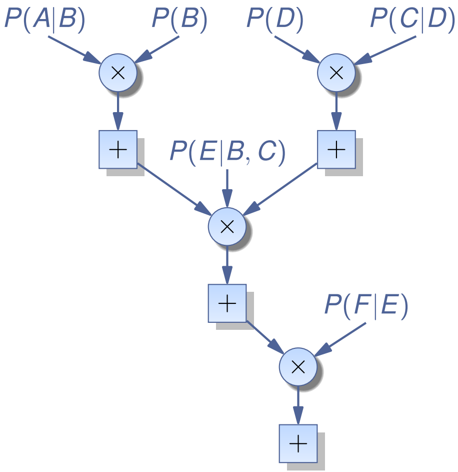
- **1 Rule :** Use the sequential scheduler if and only if :

  1 thread or nb elementary operations $< 10^6$

Parallel scheduler – an example



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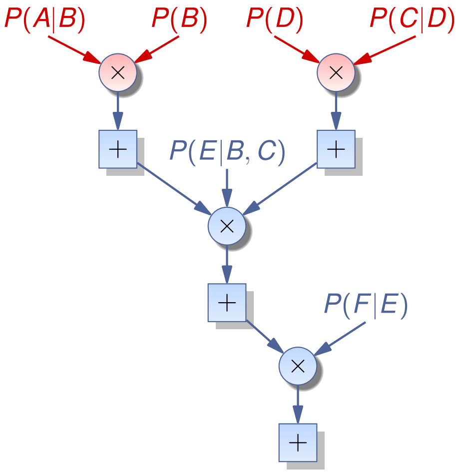

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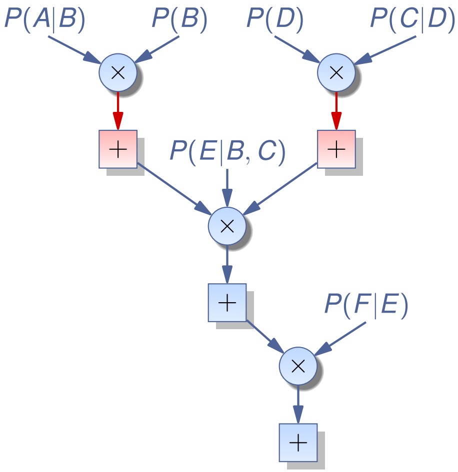

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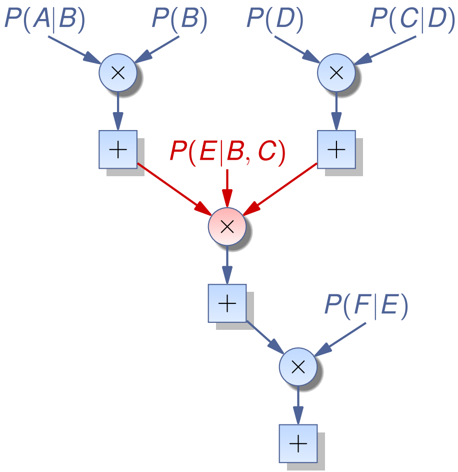

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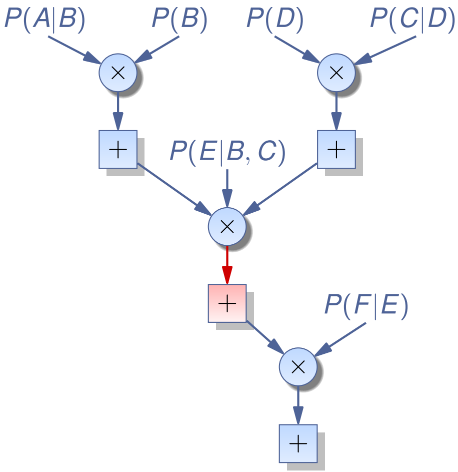

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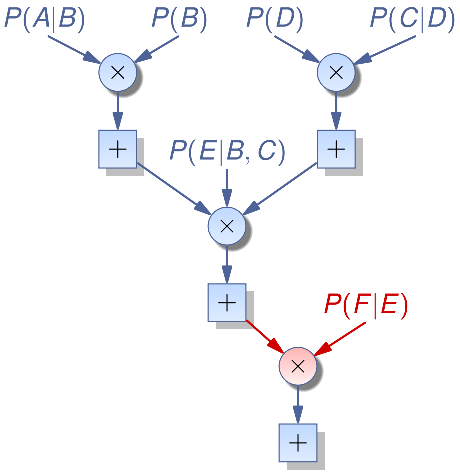

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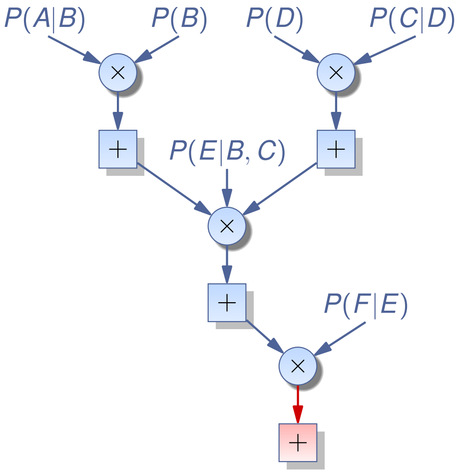
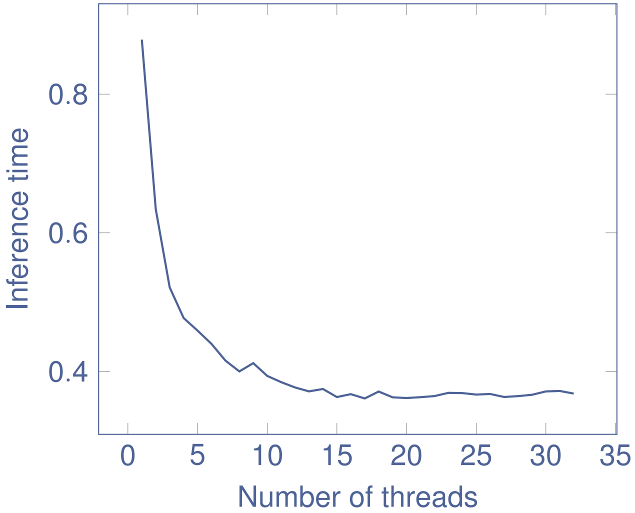


LazyPropagation's inferences on Munin4



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  - Explanation : clique sizes imbalanced

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  perform $K/4$ experiments in parallel
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- Multithreaded objects support both openMP and STL threads

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  - When one thread : no overhead

ThreadExecutors – an example

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auto func = [](const std::size_t this_thread,
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$\Longrightarrow$ Exceptions can be catched in Python !

ThreadExecutors – another example

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⟹ Functions can have as many parameters as wished

Only constraint : first 2 params : `this_thread` and `nb_threads`

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