Learning the Parameters of Probabilistic Logic Programs from Interpretations

DTAI
Declaratieve Talen en Artificiële Intelligentie

Bernd Gutmann

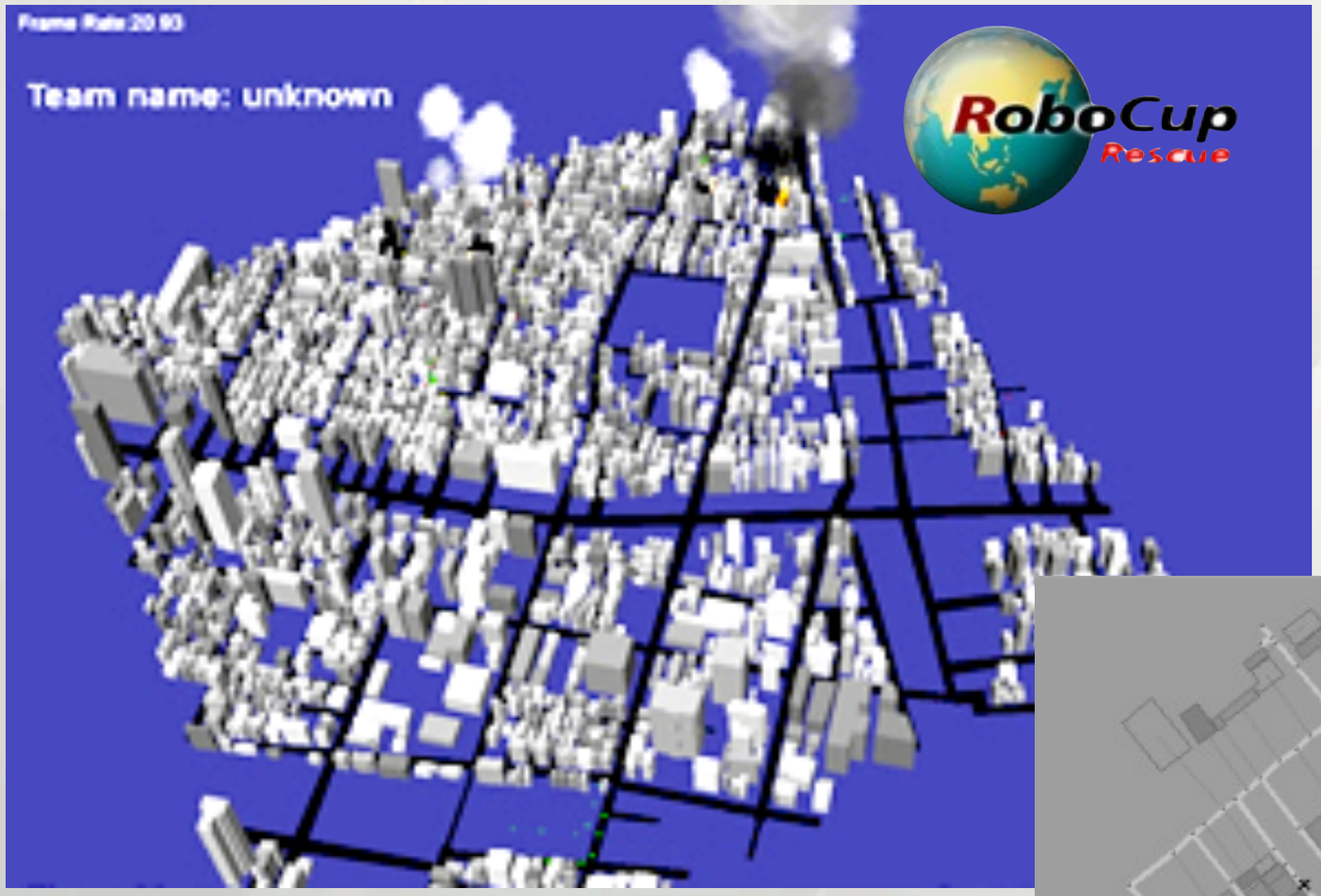
Ingo Thon

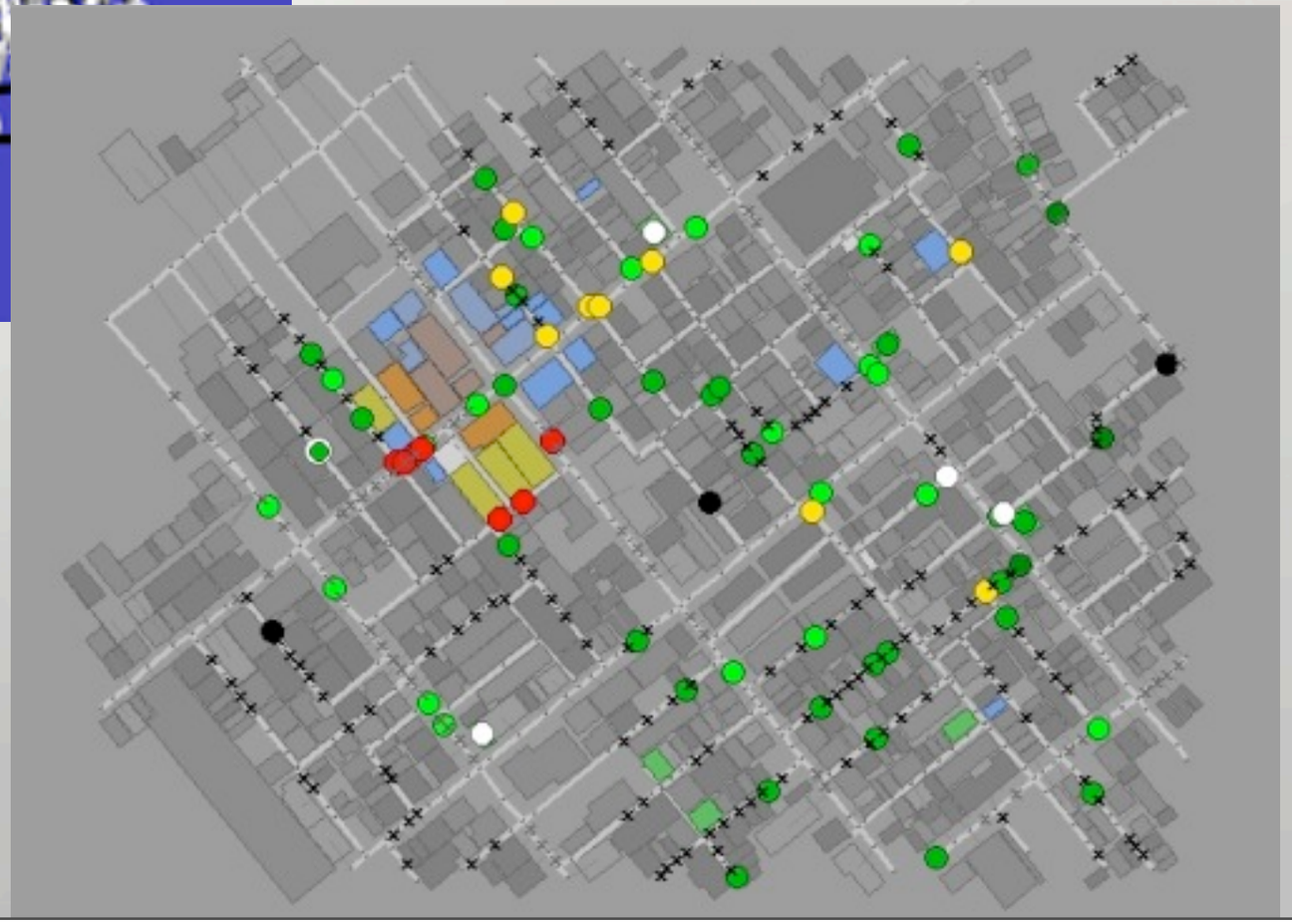
Luc De Raedt

Outline

- Motivation
- Background
- Contribution: LFI-Problog
- Experimental Results
- Conclusions

Consider you are ambulance dispatcher...





Probabilistic Programming

Programming Language:

Prolog

+

Random Variables:

probabilistic facts

$\models$

distribution over programs/return values:

distribution over queries

L. De Raedt et al., IJCAI 2007

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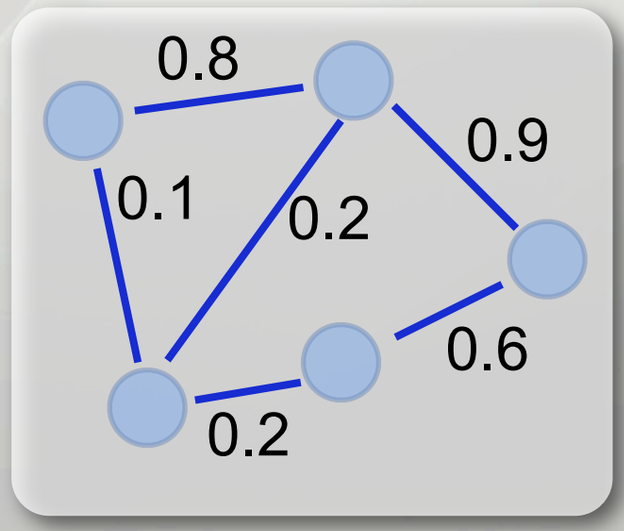

L. De Raedt et al., IJCAI 2007

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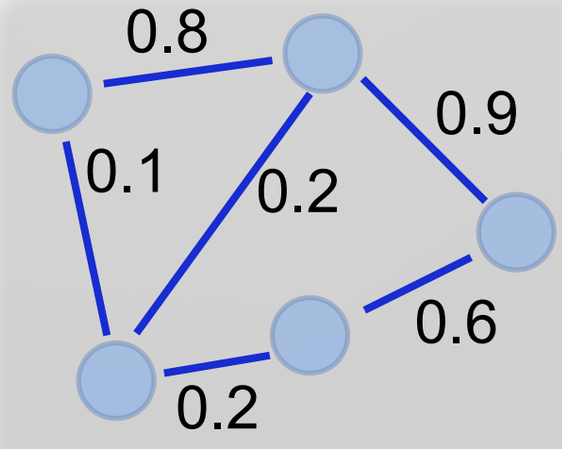

L. De Raedt et al., IJCAI 2007

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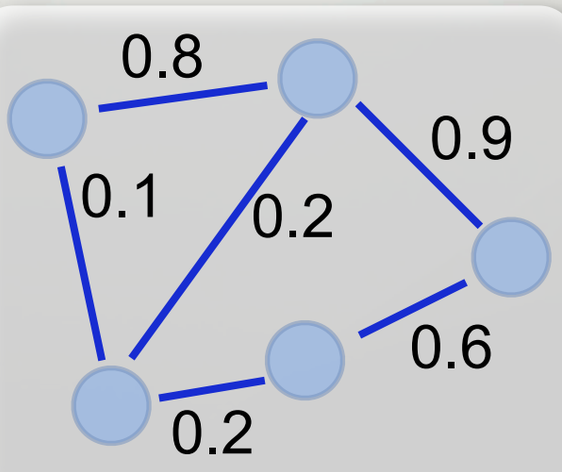

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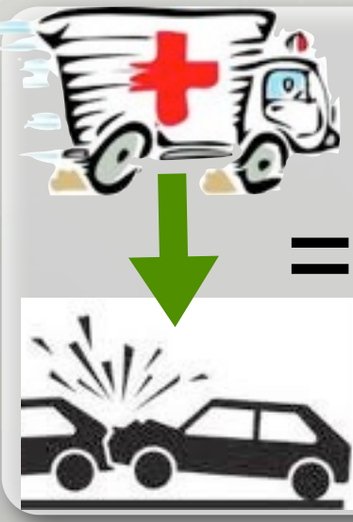

= 0.8

L. De Raedt et al., IJCAI 2007

Probabilistic Programming

Programming Language:

Prolog

+

Random Variables:

probabilistic facts

⊨

distribution over programs/return values:

distribution over queries

rule learner

+

soft evidence

0.2

⊨

probabilistic rule learner

L. De Raedt et al., IJCAI 2007

L. De Raedt et al., ILP 2009

Probabilistic Programming

Programming Language:

Prolog

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distribution over programs/return values:

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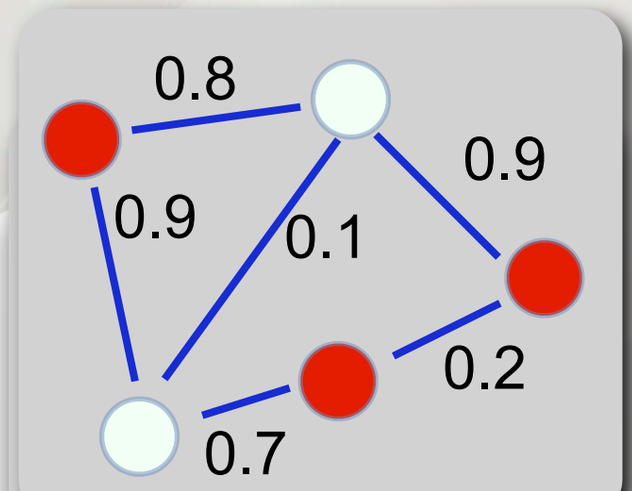
graph miner

+



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graph patterns

L. De Raedt et al., IJCAI 2007

L. De Raedt et al., ILP 2009

A. Kimmig et al., IJCAI 2009

Probabilistic Programming

Programming Language:

Prolog

lisp interpreter

+

Random Variables:

probabilistic facts

f() =
[0.4 :: true,
0.6 :: false]

0.7

0.2

+

⊨

distribution over programs/return values:

distribution over queries

probabilistic lisp

L. De Raedt et al., IJCAI 2007
L. De Raedt et al., ILP 2009

A. Kimmig et al., IJCAI 2009
to be published

Probabilistic Programming

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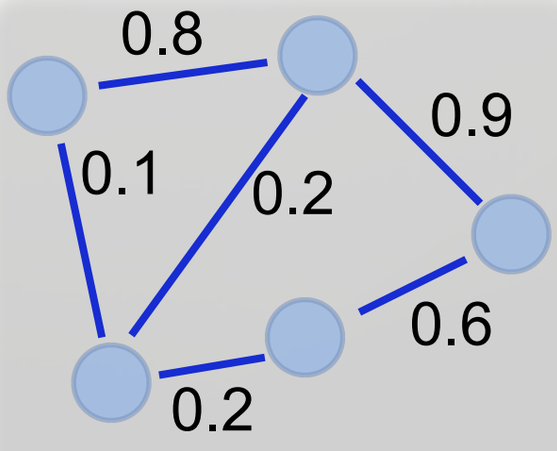

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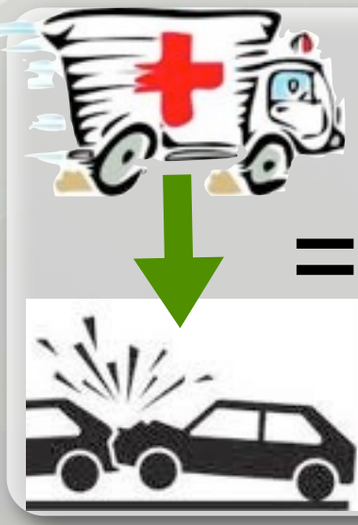

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Probabilistic Programming

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LEARN

⊨

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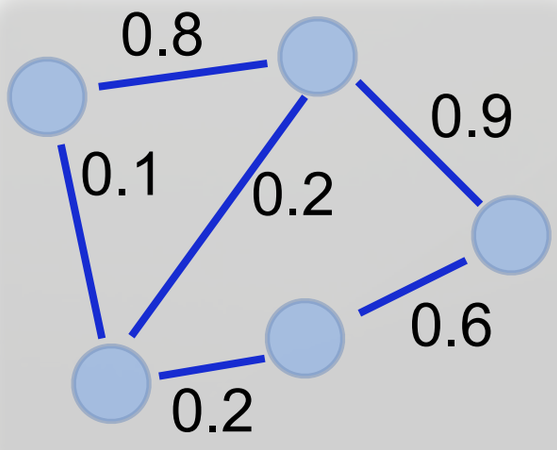
+



⊨

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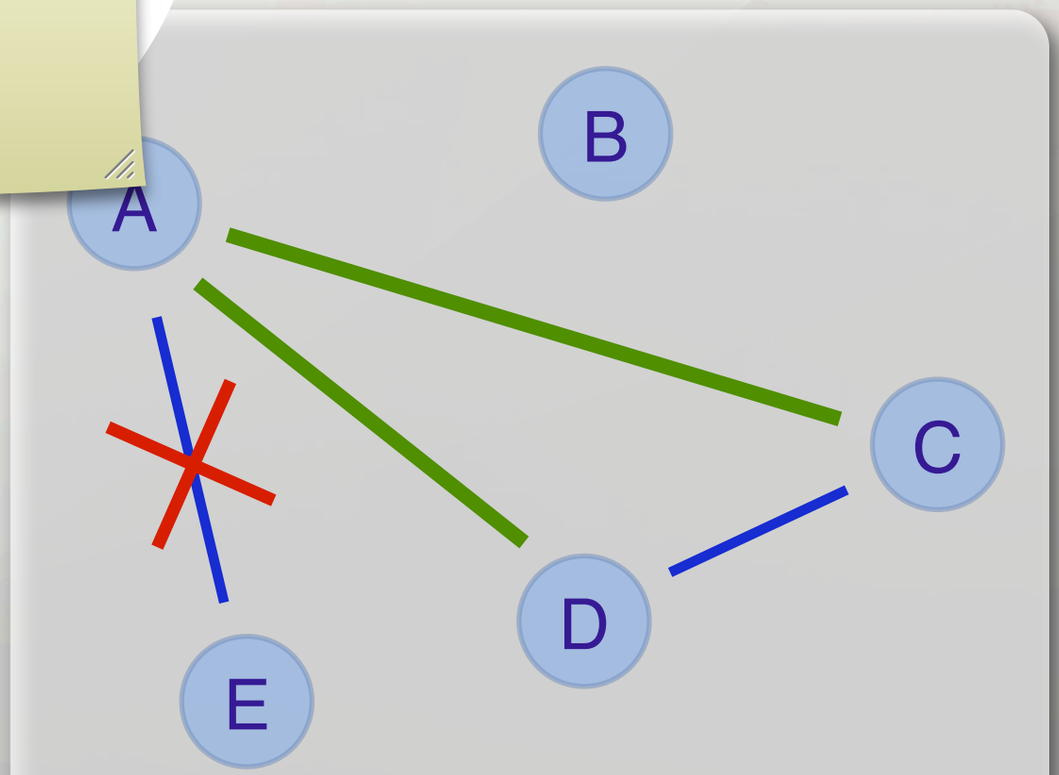
B. Gutmann et al. : ECML 2008

B. Gutmann et al. : ECML 2011!!!!

Training Example

Couldn't pass street from A to E managed to come road from D to C as well....

Work on smoth transition. Non-probabilistic case

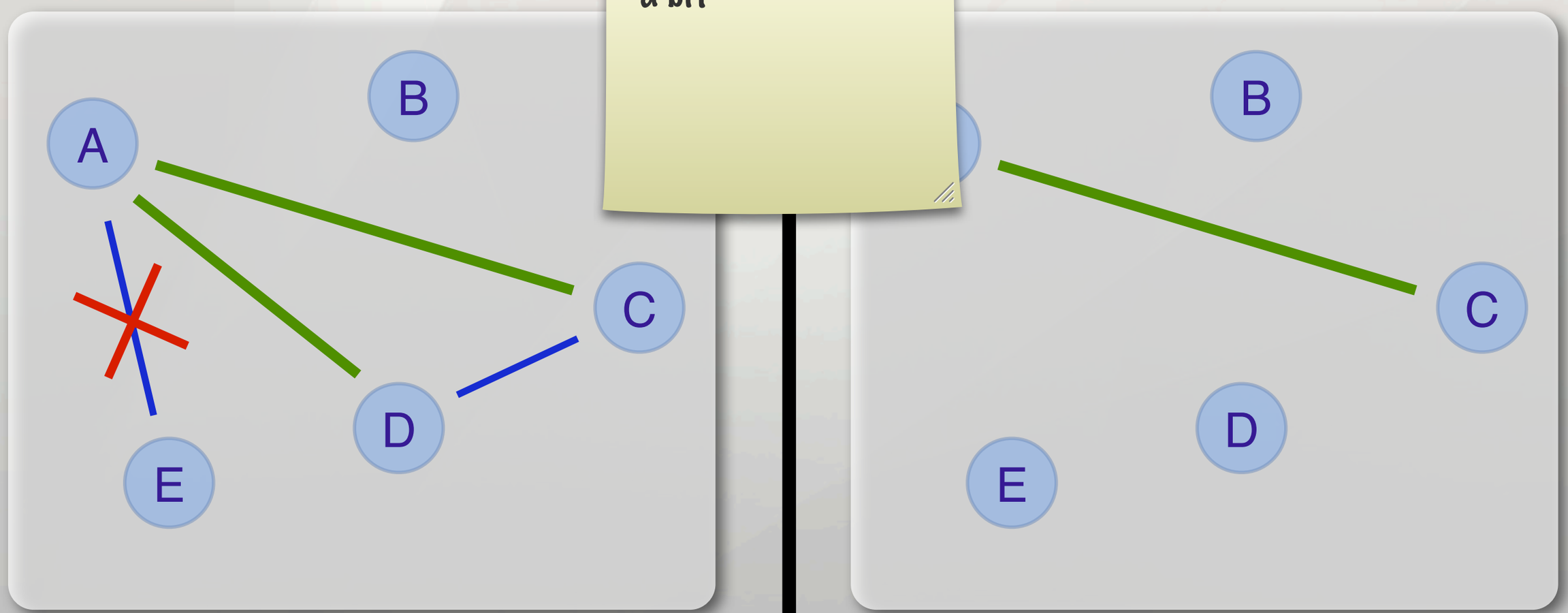


The ILP View on Learning

Learning from interpretations

Learning from entailment

Maybe elobarate a bit



B. Gutmann et al. : ECML 2011

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The ILP View on the Alphabet Soup

Learning from interpretations

Markov Logic

BLP

IBAL

PRM

KBMC

Learning from entailment

(Le)ProbLog

SLP

Prism

SDS

SDS: Sato's Distributions Semantics

KBMC: Knowledge Based Model Construction

The ILP View on the Alphabet Soup

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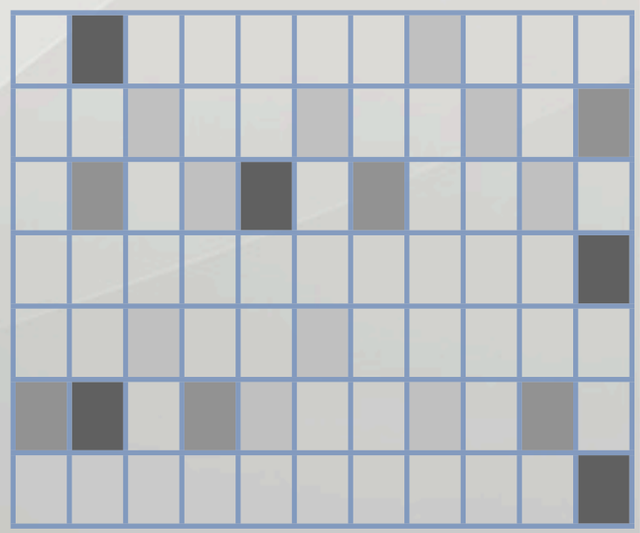
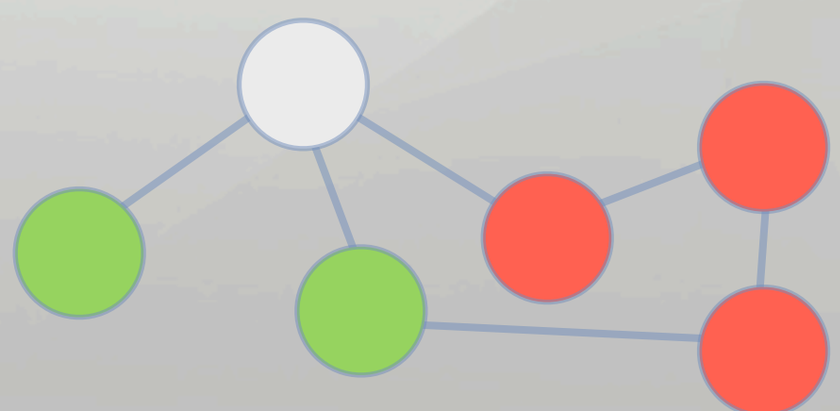
SDS: Sato's Distributions Semantics

KBMC: Knowledge Based Model Construction

Contribution of this Work

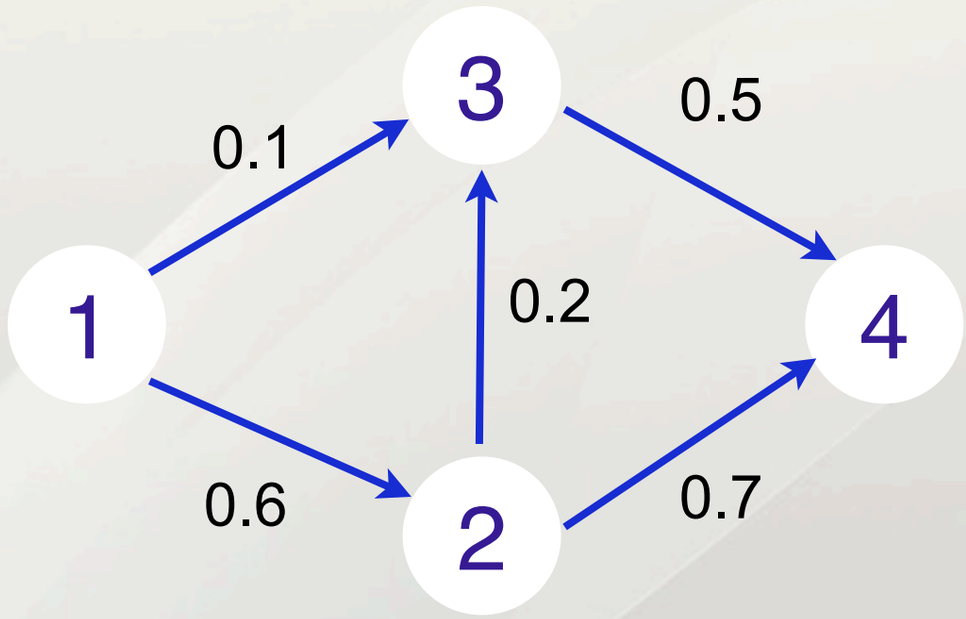
- LFI-ProbLog: First parameter learning approach from partial interpretations for probabilistic logic programming
- Generative setting
- Use (partial) interpretations as training data
- Setting applicable to wide variety of tasks
  - Collective classification
  - Clustering
  - Rule learning
  - Etc.





Toy Example

0.1 :: edge(1,3)
0.6 :: edge(1,2)
0.2 :: edge(2,3)
0.5 :: edge(3,4)
0.7 :: edge(2,4)

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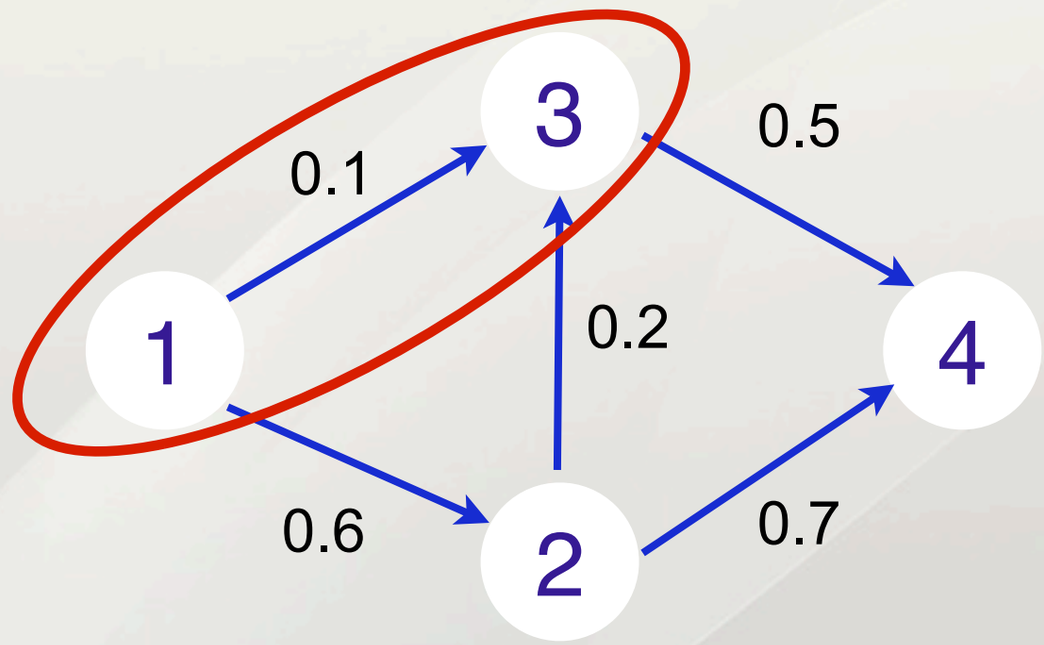


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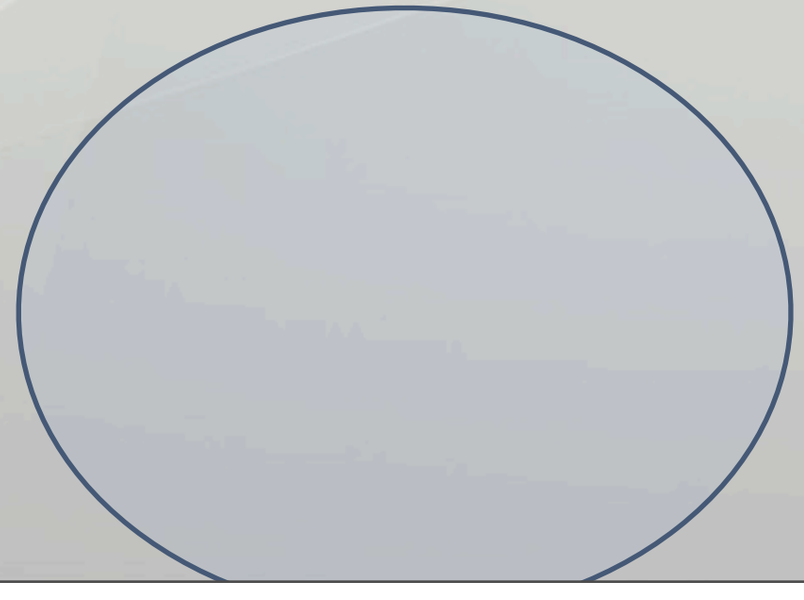

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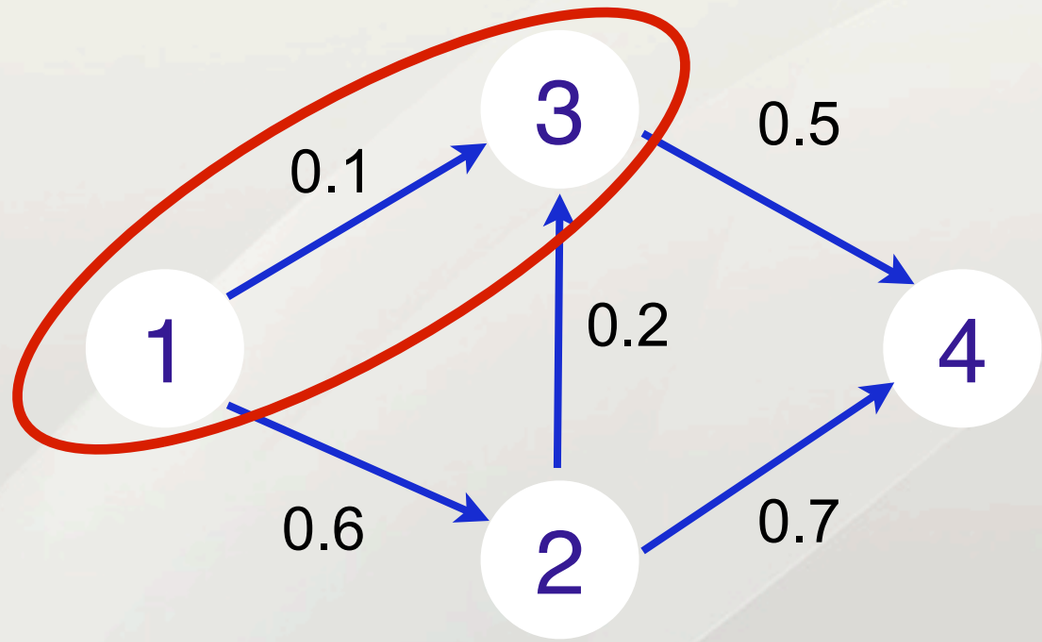


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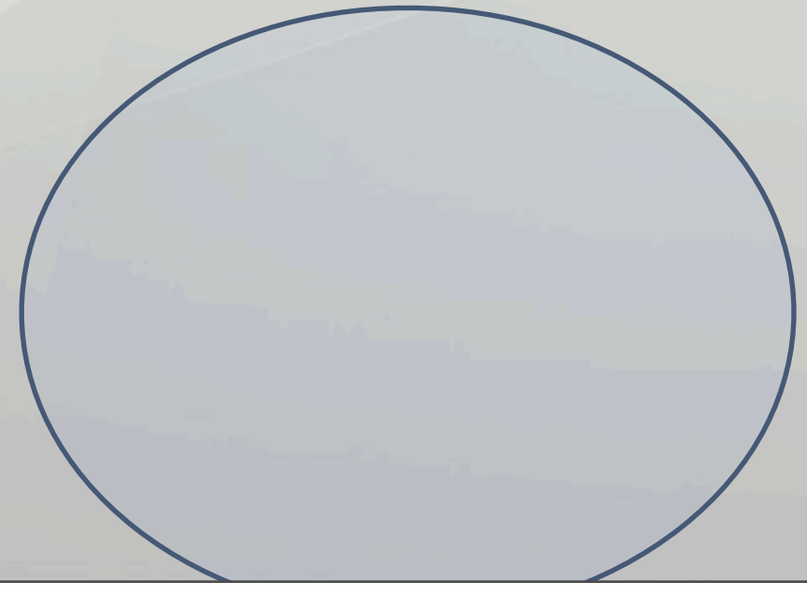

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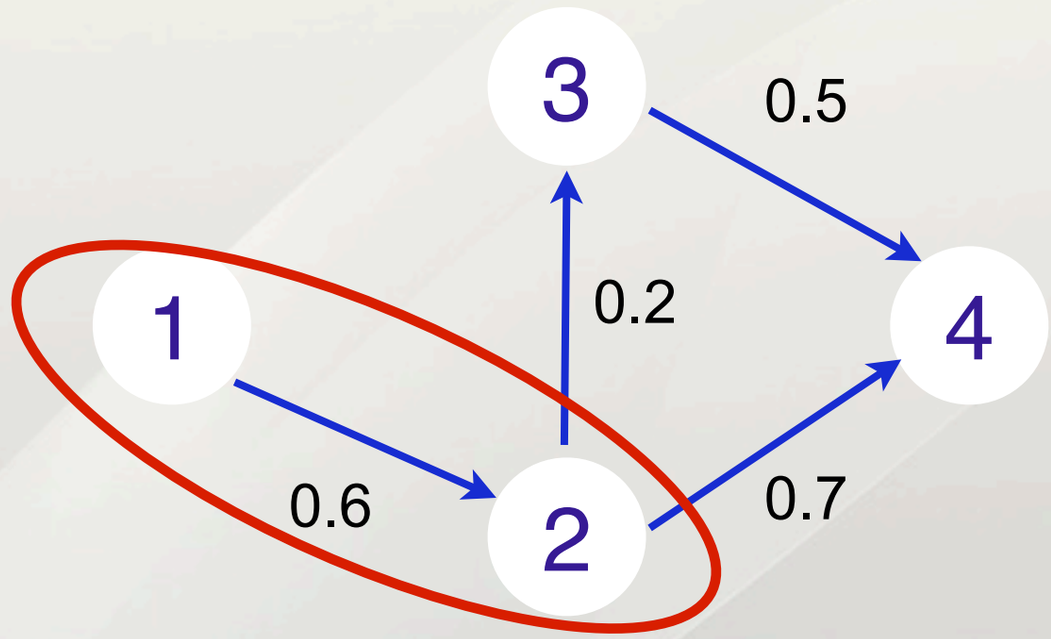


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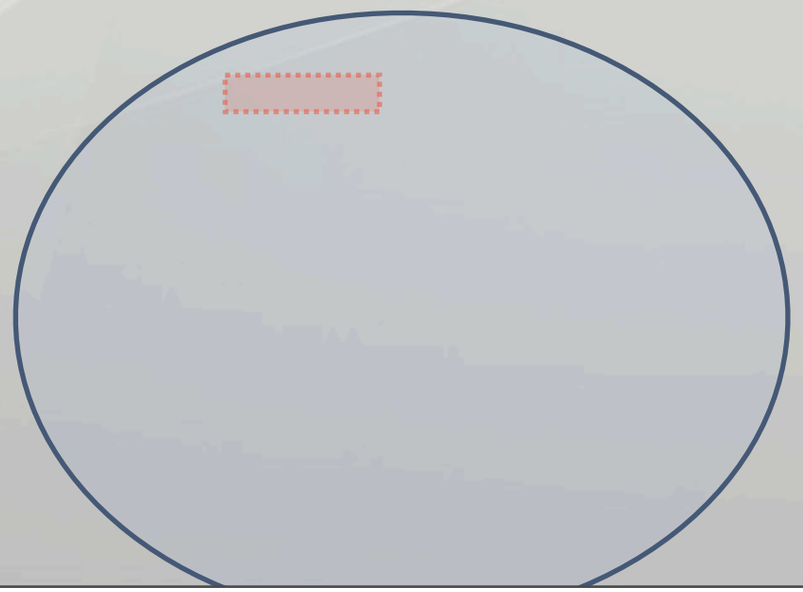

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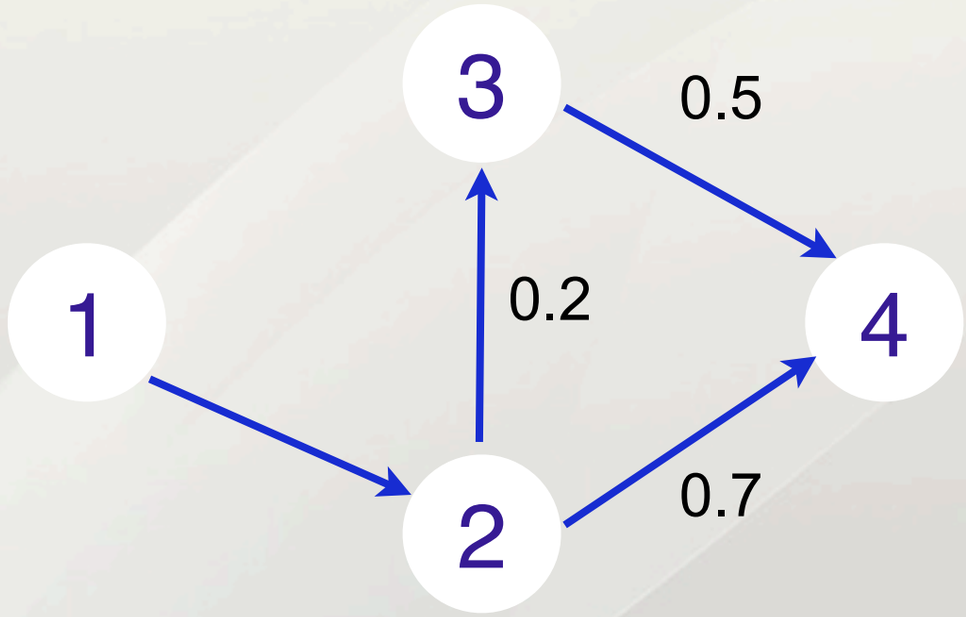


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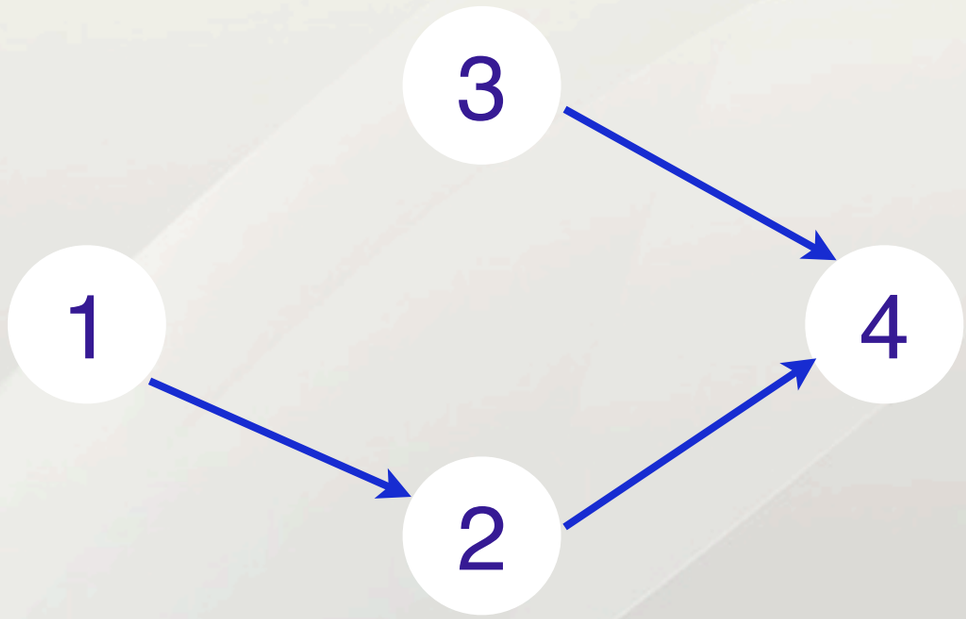


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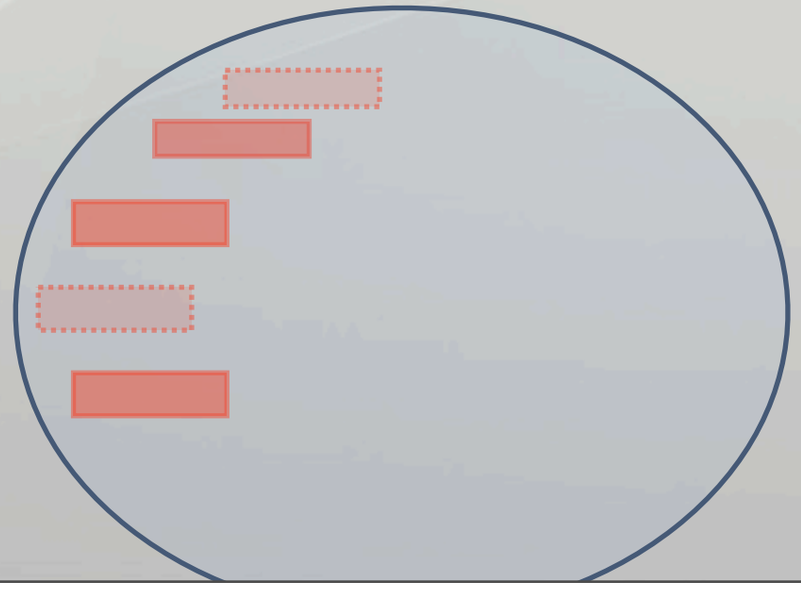

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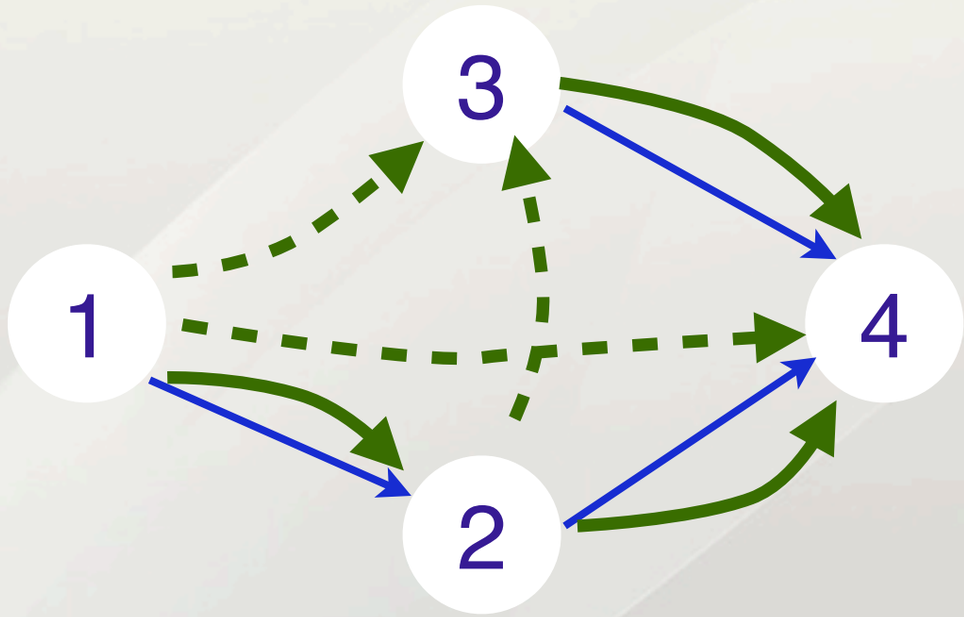


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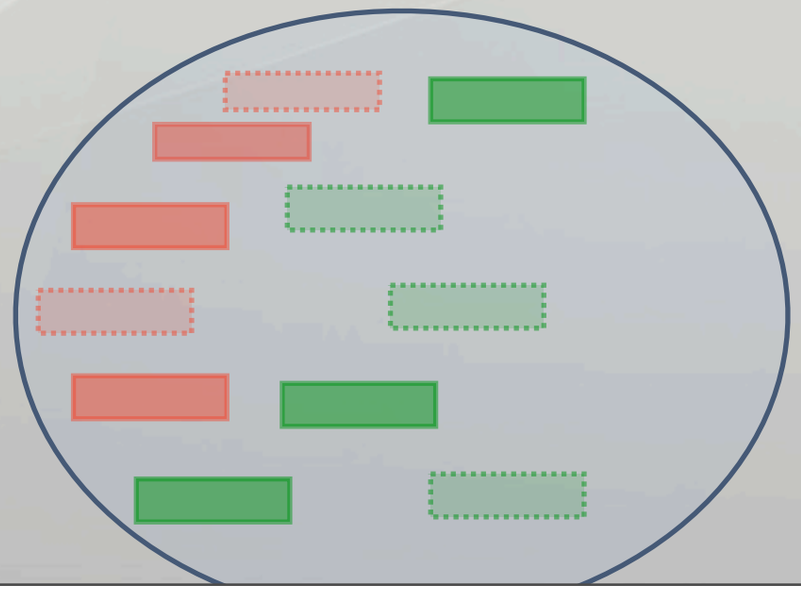

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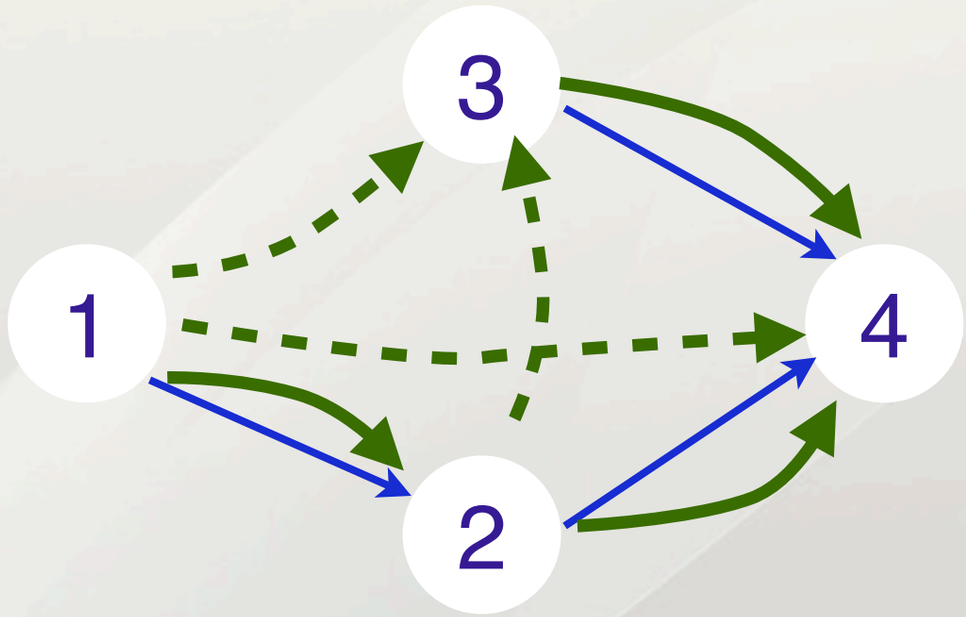


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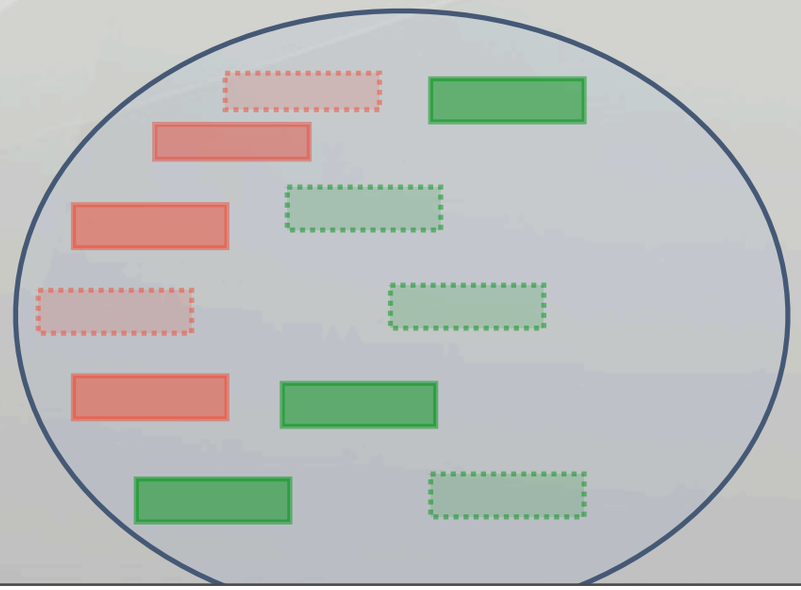

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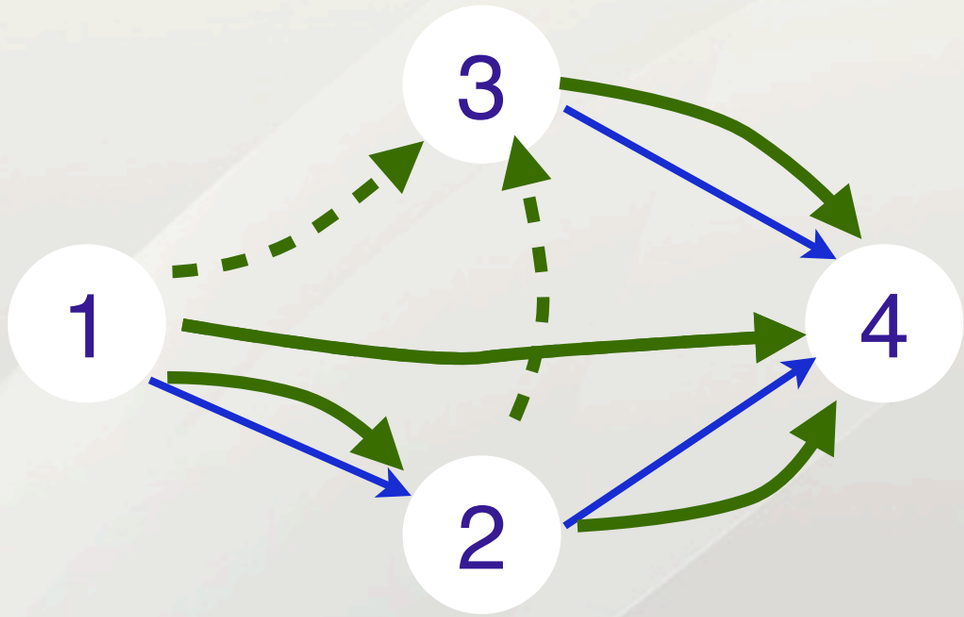


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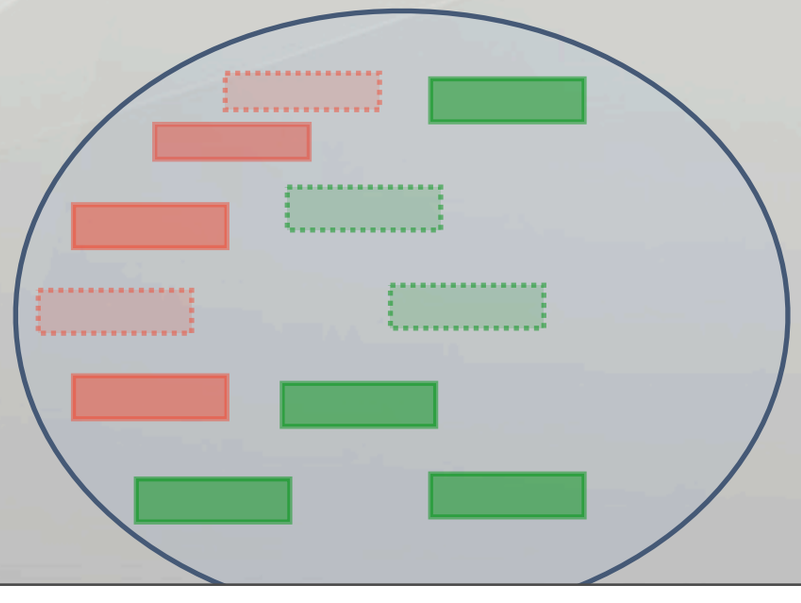
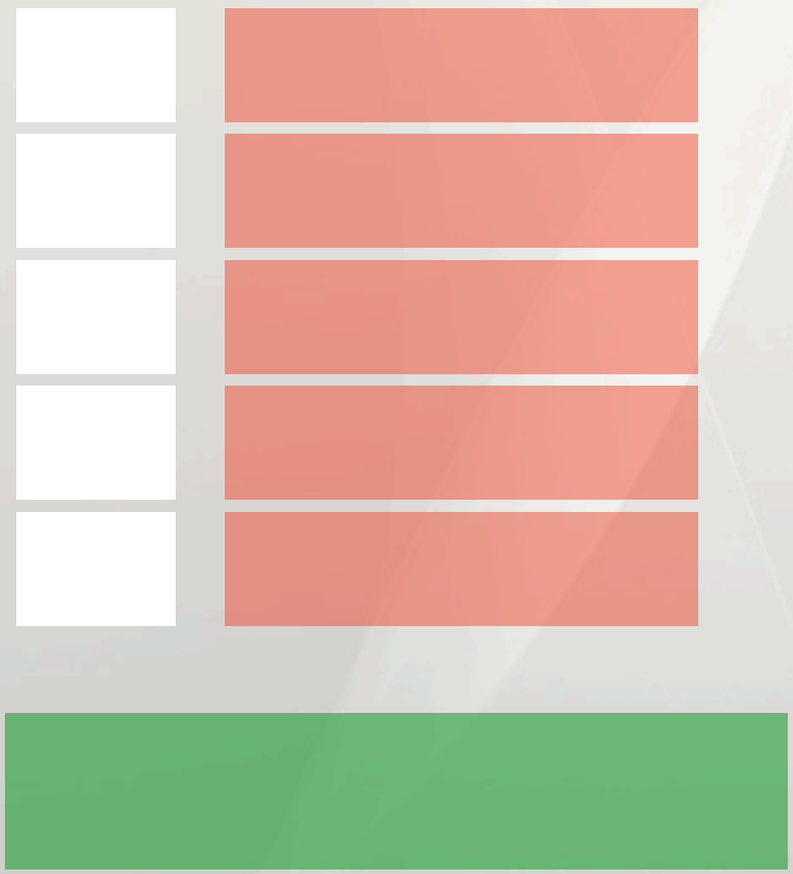


Sampling



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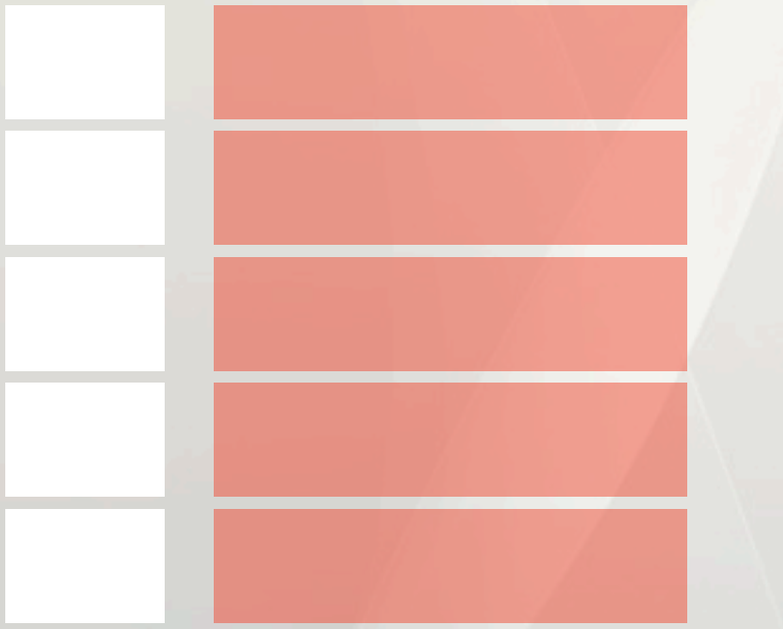

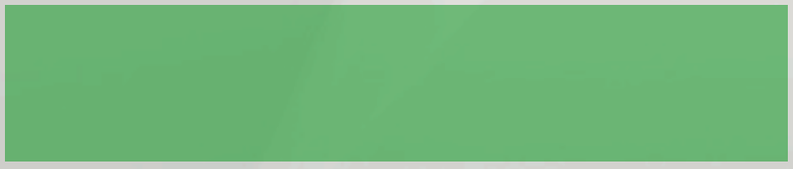

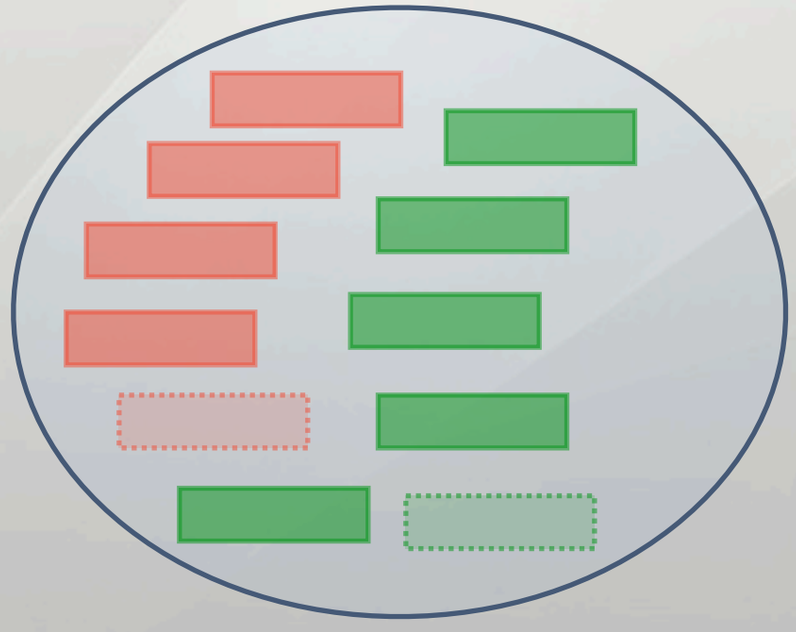

Sampling

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??

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??

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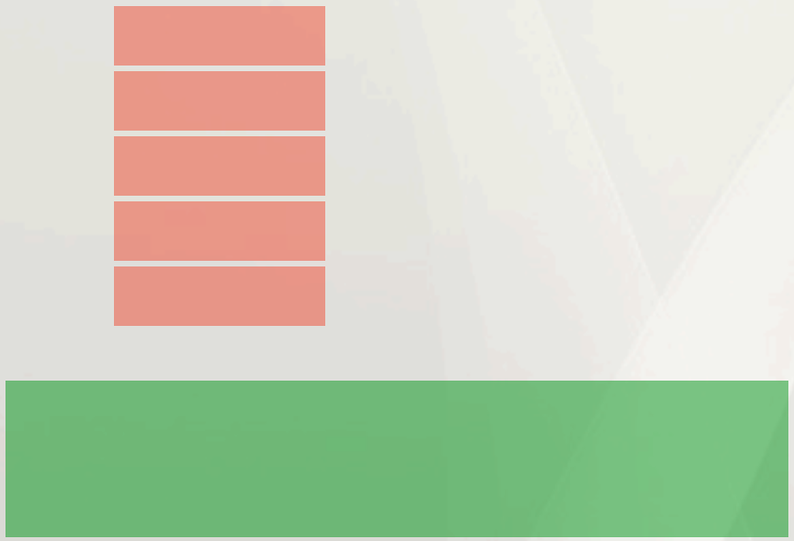
previous

next

Parameter Estimation



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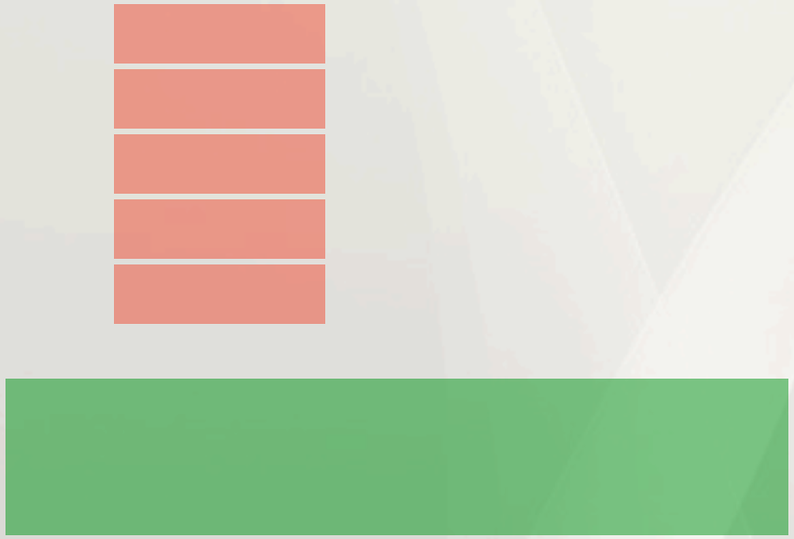
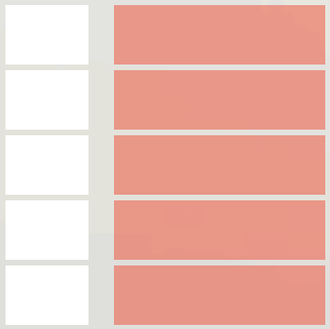
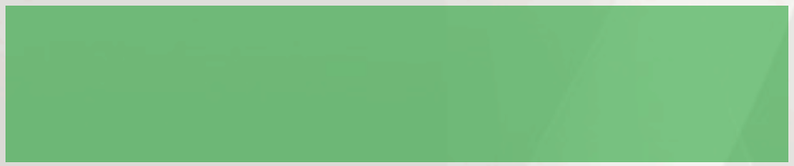
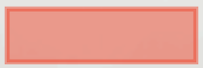


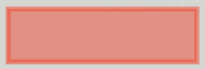
$$p(\textbf{fact}) = \frac{\text{count}(\textbf{fact} \text{ is true})}{\text{Number of observations}}$$

Parameter Estimation









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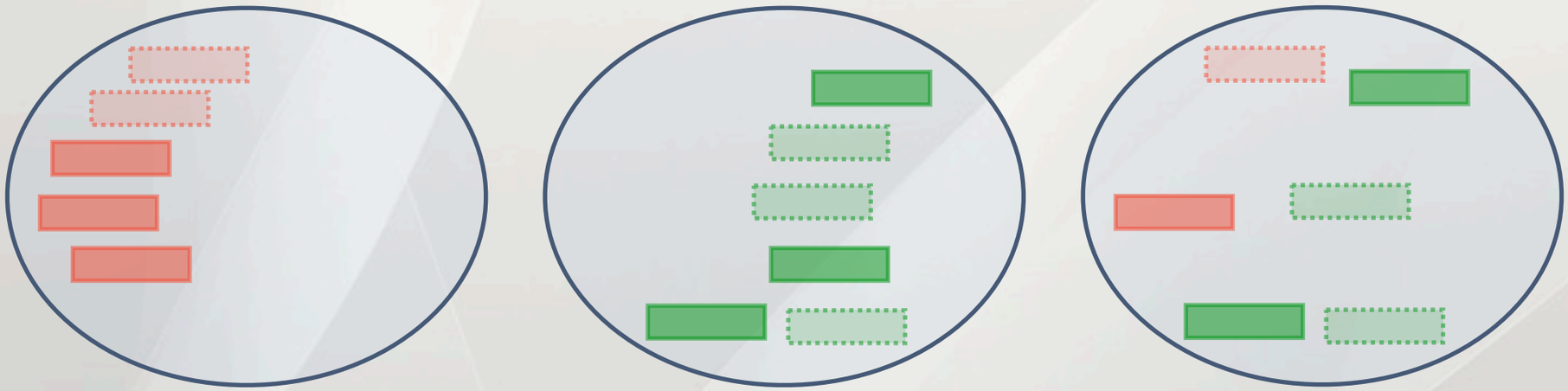
Missing Values

- Learning from **partial** interpretations



- Facts can be unobserved
- Soft-EM
- Use **expected_count** instead of **count**

LFI ProbLog

data examples

ProbLog program

CNF

diff with

abilistic

ectation
DD

e
probabilities

Wednesday 7 September 2011

LFI ProbLog

data examples

ProbLog
program

CNF

diff with

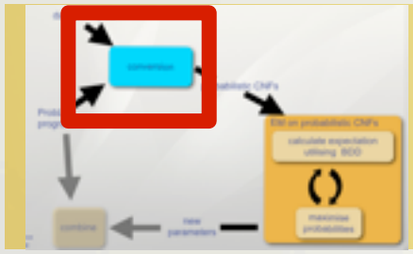
abilistic

ectation
DD

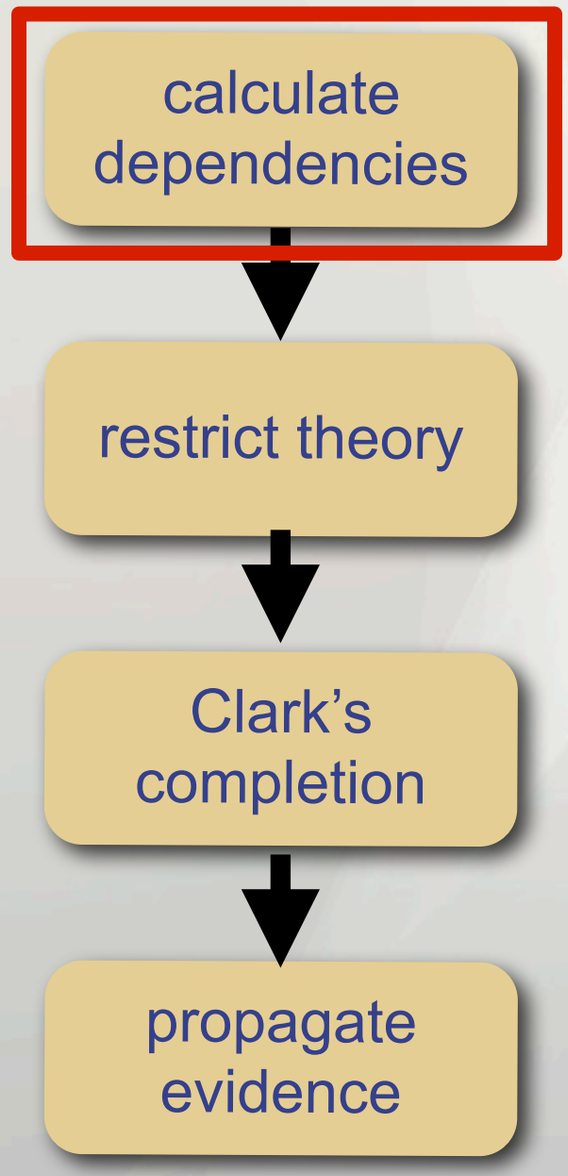
e
probabilities

Related Wo

- A. Darwich
- D. Fierens
- I. Thon et a



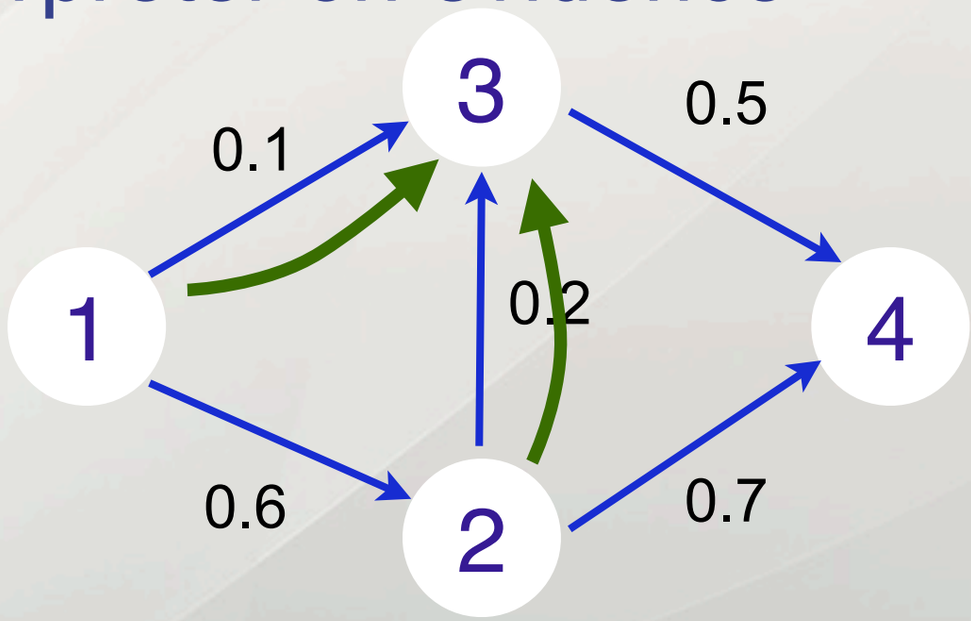
Conversion to Probabilistic CNF

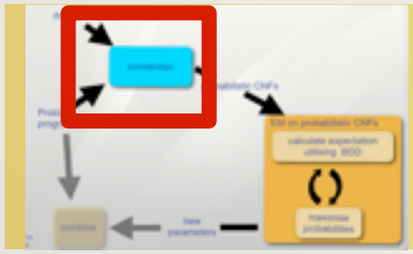


Goal: Find all relevant ground atoms

How: Run meta-interpreter on evidence

evidence:
{path(1,3) = true,
path(2,3) = true}





Conversion to Probabilistic CNF

calculate dependencies

restrict theory

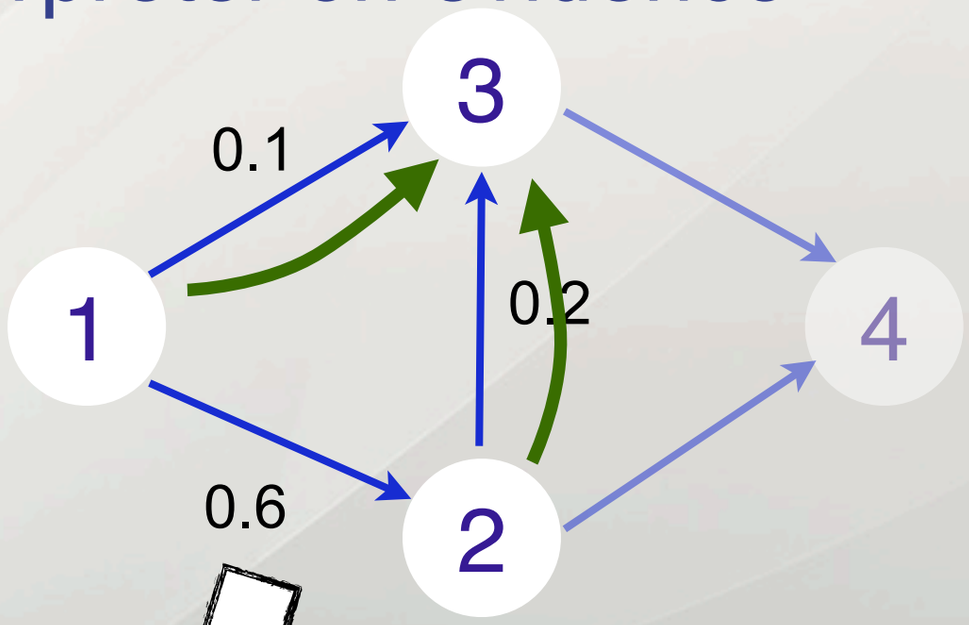
Clark's completion

propagate evidence

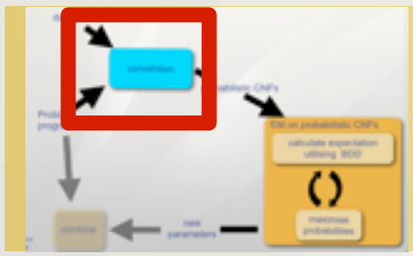
Goal: Find all relevant ground atoms

How: Run meta-interpreter on evidence

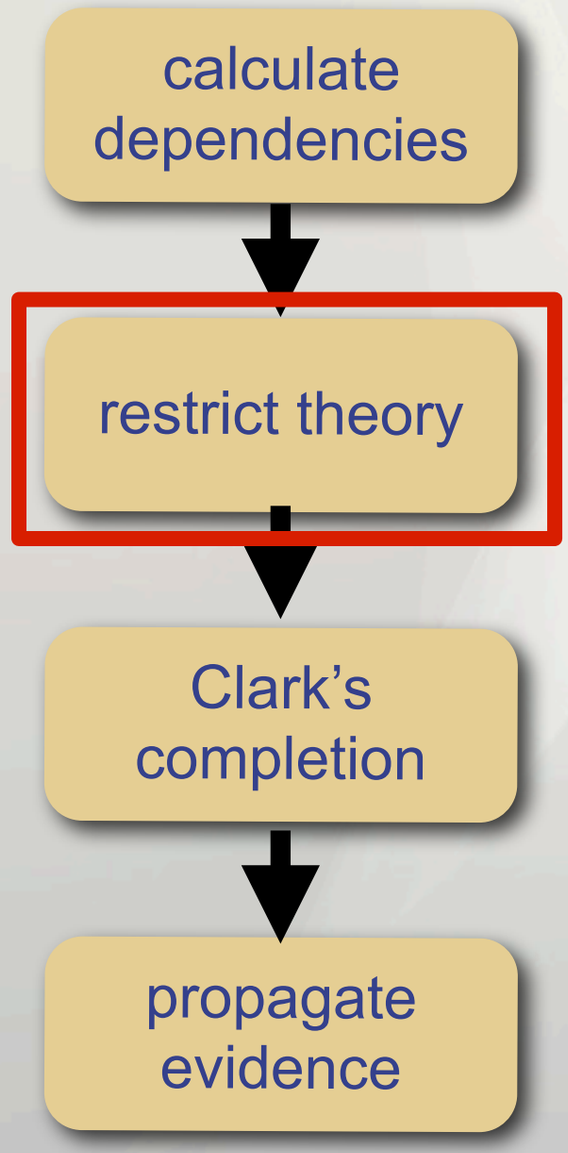
evidence:
{path(1,3) = true,
path(2,3) = true}



edge(1,2), edge(1,3), edge(2,3),
path(1,2),path(1,3), path(2,3),path(1,3)



Conversion to Probabilistic CNF

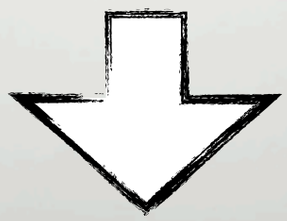


Goal: Finite ground program

How: Ground program using relevant fact

edge(1,2), edge(1,3), edge(2,3),
path(1,2), path(1,3), path(2,3), path(1,3)

path(A,B) :- edge(A,B).
path(A,B) :- edge(A,C),path(C,B).

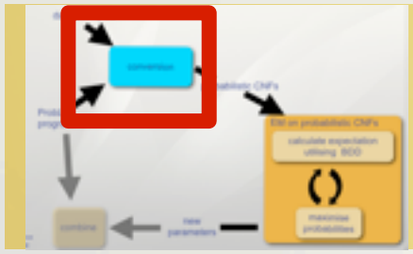


path(1,2) :- edge(1,2).

path(2,3) :- edge(2,3).

path(1,3) :- edge(1,3).

path(1,3) :- edge(1,2),path(2,3).



Conversion to Probabilistic CNF

calculate dependencies

restrict theory

Clark's completion

propagate evidence

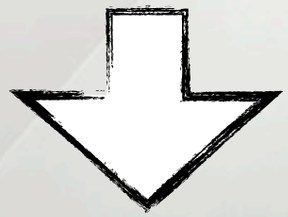
Goal: Propositional CNF

How: Clark's completion

path(1,2) :- edge(1,2). path(2,3) :- edge(2,3).

path(1,3) :- edge(1,3).

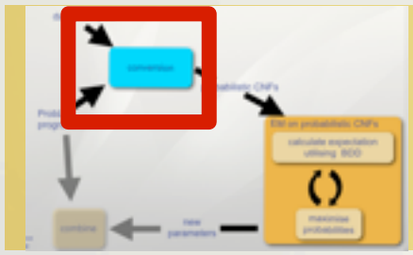
path(1,3) :- edge(1,2),path(2,3).



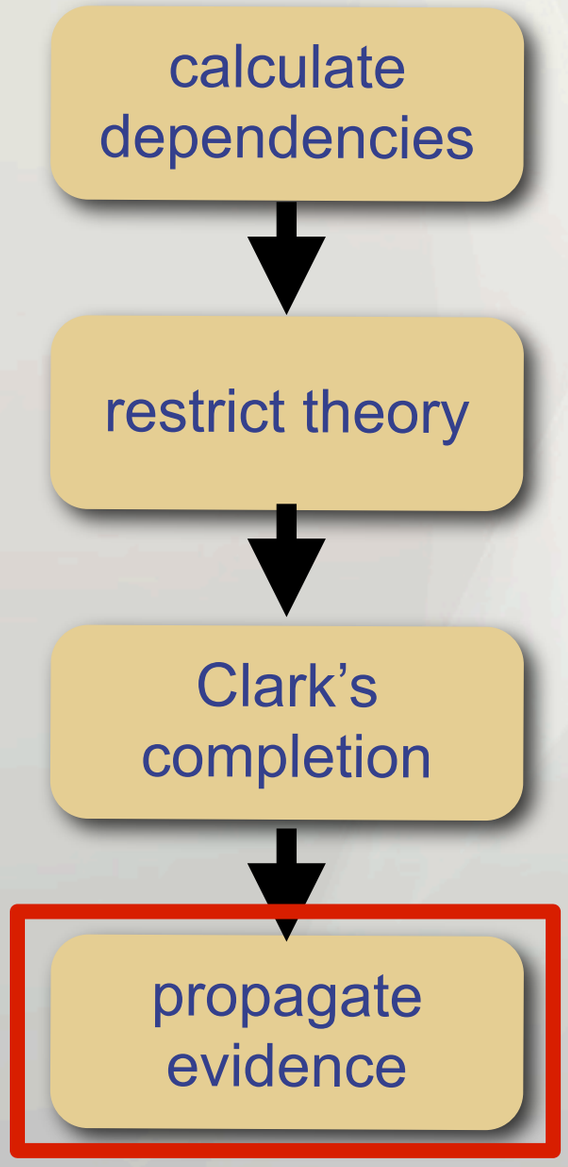
path(1,2) ⇔ edge(1,2)

∧ path(2,3) ⇔ edge(2,3)

∧ path(1,3) ⇔ (edge(1,3) ∨ (edge(1,2) ∧ path(2,3)))



Conversion to Probabilistic CNF



Goal: Simpler CNF

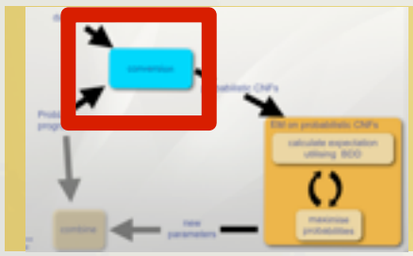
How: Unit propagation

I = {path(1,3) = true,
path(2,3) = true}

$$path(1,2) \Leftrightarrow edge(1,2)$$

$$\wedge\ path(2,3) \Leftrightarrow edge(2,3)$$

$$\wedge\ path(1,3) \Leftrightarrow (edge(1,3) \vee (edge(1,2) \wedge path(2,3)))$$



Conversion to Probabilistic CNF

calculate dependencies

restrict theory

Clark's completion

propagate evidence

Goal: Simpler CNF

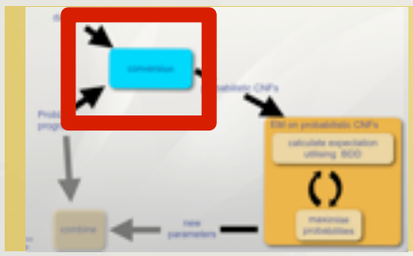
How: Unit propagation

I = {path(1,3) = true,
path(2,3) = true}

$$path(1,2) \Leftrightarrow edge(1,2)$$

$$\Lambda\ \cancel{path(2,3)}^{\text{true}} \Leftrightarrow edge(2,3)$$

$$\Lambda\ \cancel{path(1,3)}^{\text{true}} \Leftrightarrow (edge(1,3) \vee (edge(1,2) \wedge \cancel{path(2,3)}^{\text{true}}))$$



Conversion to Probabilistic CNF

calculate dependencies

restrict theory

Clark's completion

propagate evidence

Goal: Simpler CNF

How: Unit propagation

I = {path(1,3) = true,
path(2,3) = true}

path(1,2) ⇔ edge(1,2)

true

Λ path(2,3) ⇔ edge(2,3)

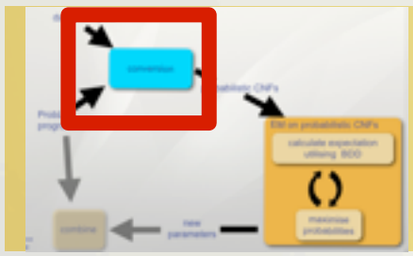
true

true

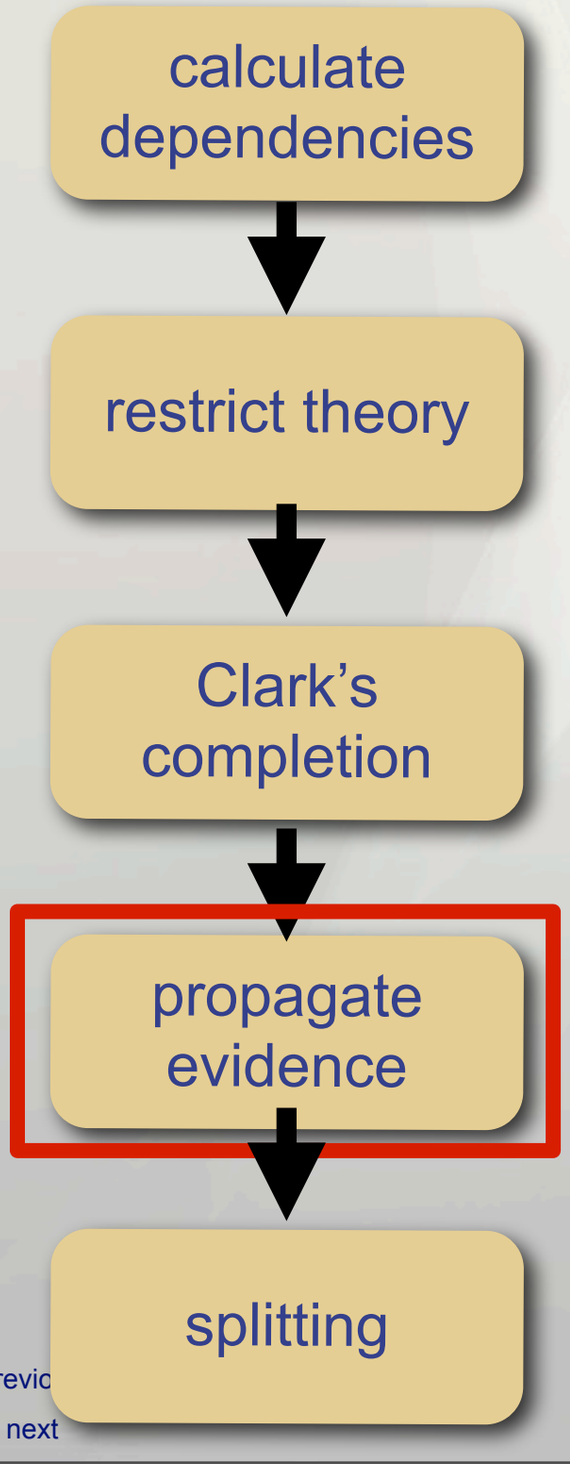
Λ path(1,3) ⇔ (edge(1,3) ∨ (edge(1,2) Λ path(2,3)))

true

propagated = { edge(2,3)= true)



Conversion to Probabilistic CNF



Goal: Simpler CNF

How: Unit propagation

I = {path(1,3) = true,
path(2,3) = true}

path(1,2) ⇔ edge(1,2)

true true

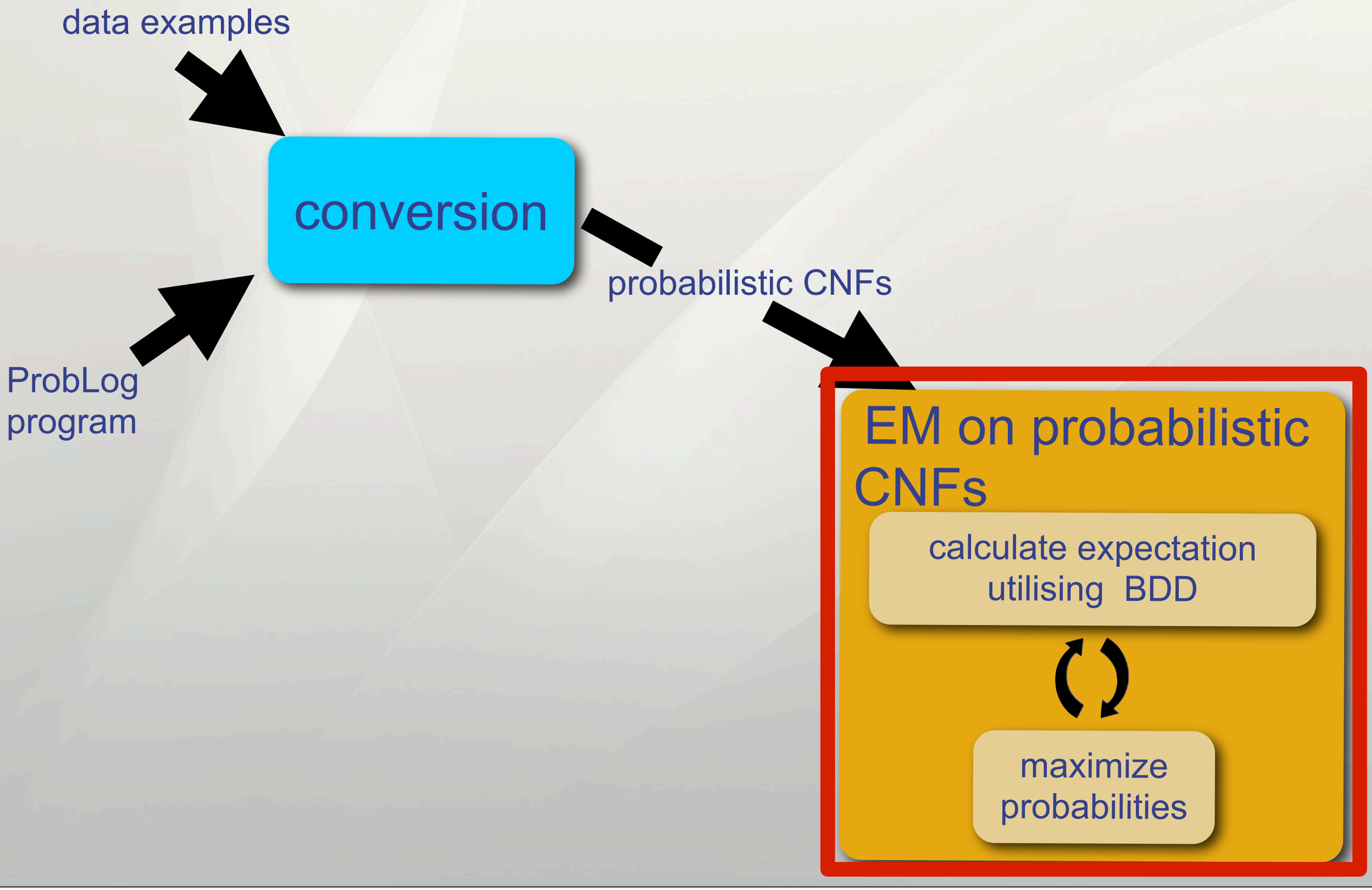
Λ path(2,3) ⇔ edge(2,3)

true true

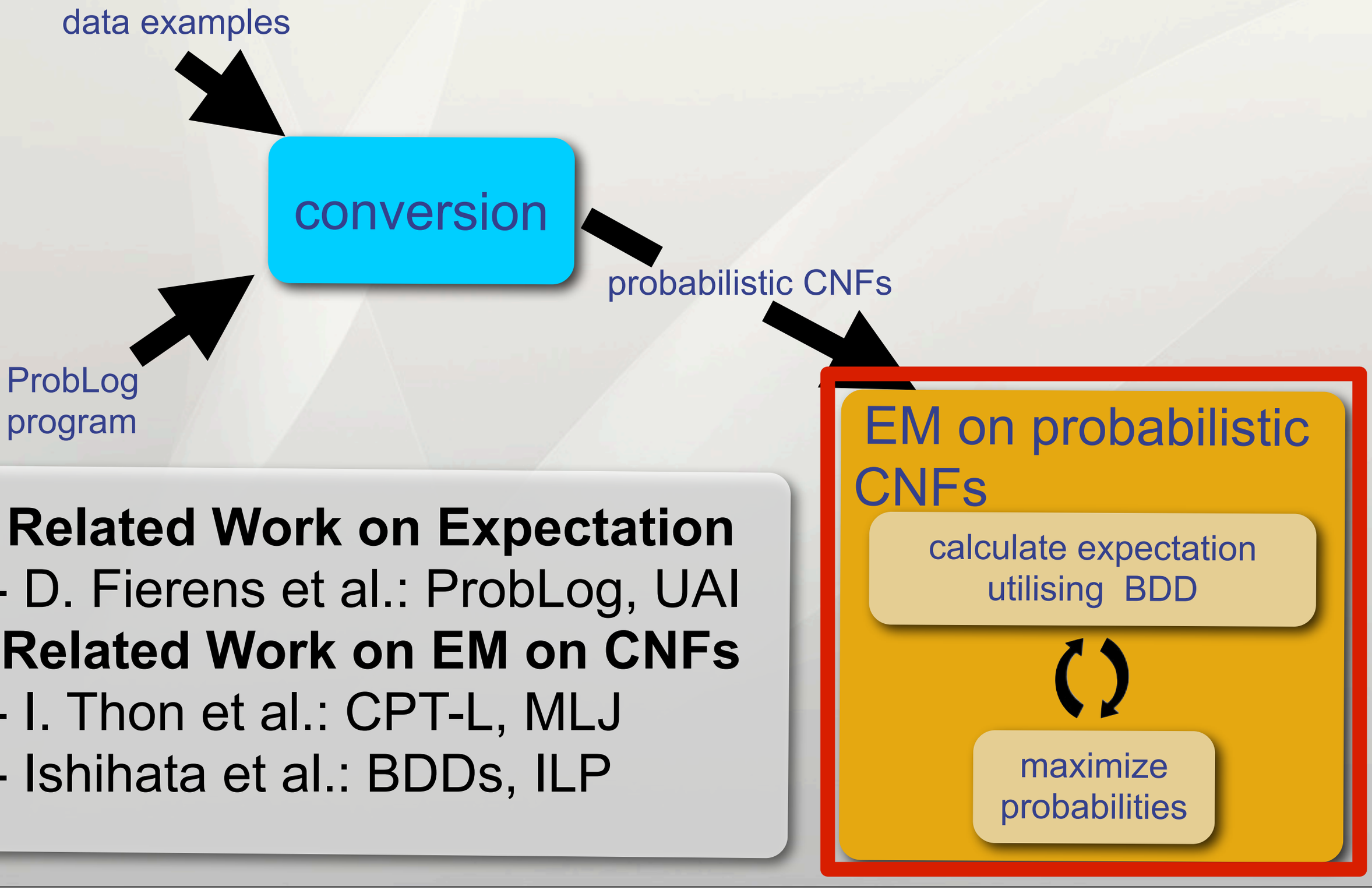
Λ path(1,3) ⇔ (edge(1,3) ∨ (edge(1,2) Λ path(2,3)))

propagated = { edge(2,3)= true)

LFI ProbLog


data examples
conversion
ProbLog program
probabilistic CNFs
EM on probabilistic CNFs
calculate expectation utilising BDD
maximize probabilities

LFI ProbLog

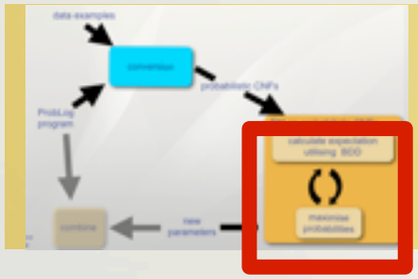


Related Work on Expectation

- D. Fierens et al.: ProbLog, UAI

Related Work on EM on CNFs

- I. Thon et al.: CPT-L, MLJ
- Ishihata et al.: BDDs, ILP



EM on CNFs

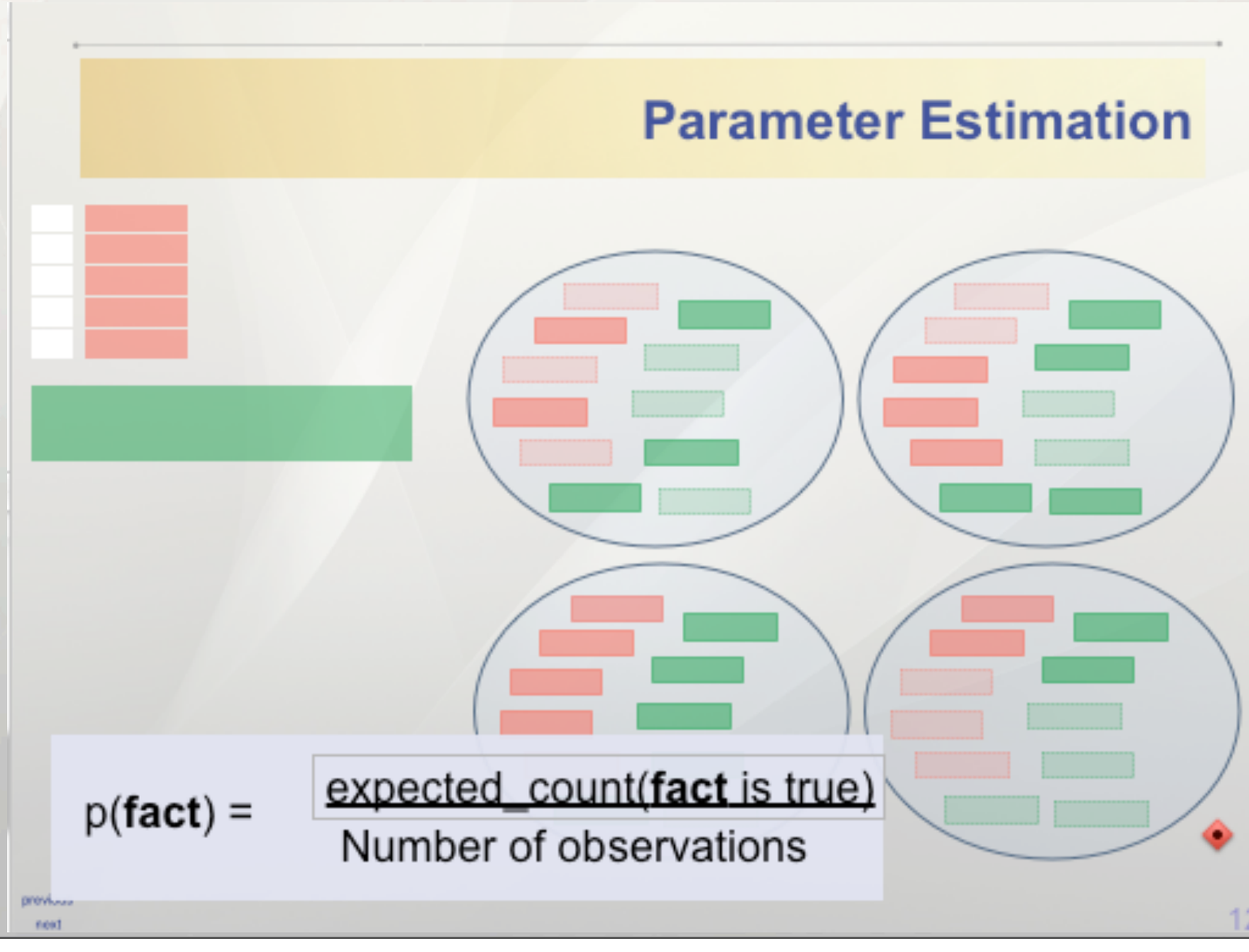
Goal: New parameters

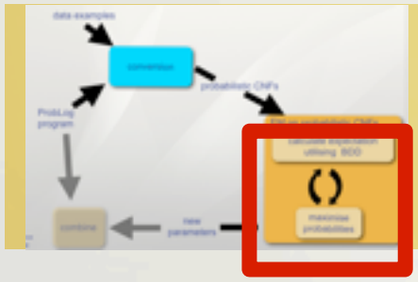
How: Counting expected counts

EM on probabilistic CNFs

calculate expectation utilising BDD

maximise probabilities





EM on CNFs

EM on probabilistic CNFs

calculate expectation utilising BDD

maximise probabilities

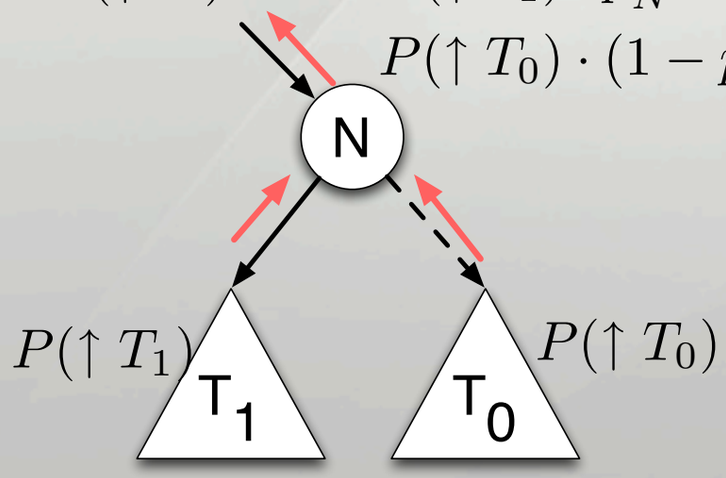
Goal: Marginalize over probabilistic facts

How: “Inside/outside” on BDDs

$$E[\delta^k_{m,n}|I_n] = \sum_{N \text{ represents } f_m} \frac{P(\downarrow N) \cdot p_N \cdot P(\uparrow h(N))}{P(BDD)}$$

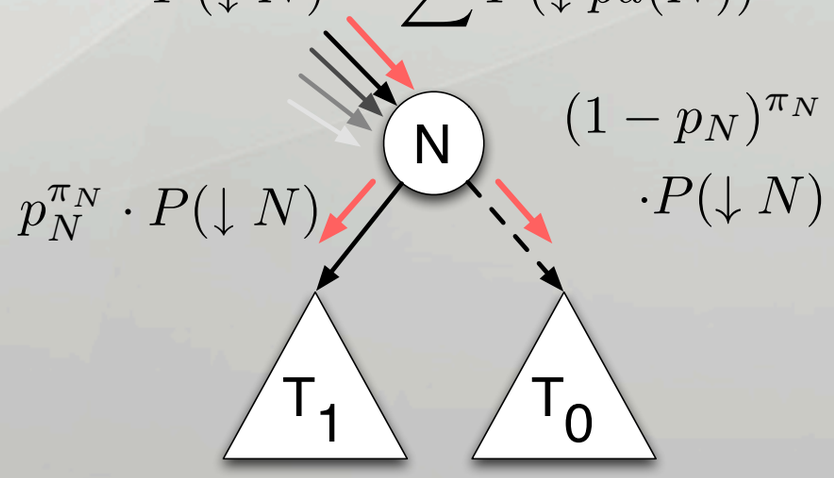
Upward Step

$$P(\uparrow N) = P(\uparrow T_1) \cdot p_N^{\pi_N} + P(\uparrow T_0) \cdot (1 - p_N)^{\pi_N}$$



Downward Step

$$P(\downarrow N) = \sum P(\downarrow pa(N))$$



Experimental Results

Real-world dataset: WebKB
Artificial dataset: Smoker

Q1: Is LFI-ProbLog competitive with existing state-of-the-art frameworks (like MLNs)?

Q2: Is LFI-ProbLog sensitive to the initial probabilities?

Q3: Is LFI-Problog able to recover the parameters of the original model with a reasonable amount of data?

Experimental Results

Real-world dataset: WebKB
Artificial dataset: Smoker

Q1: Is LFI-ProbLog competitive with existing state-of-the-art frameworks (like MLNs)?

YES

Q2: Is LFI-ProbLog sensitive to the initial probabilities?

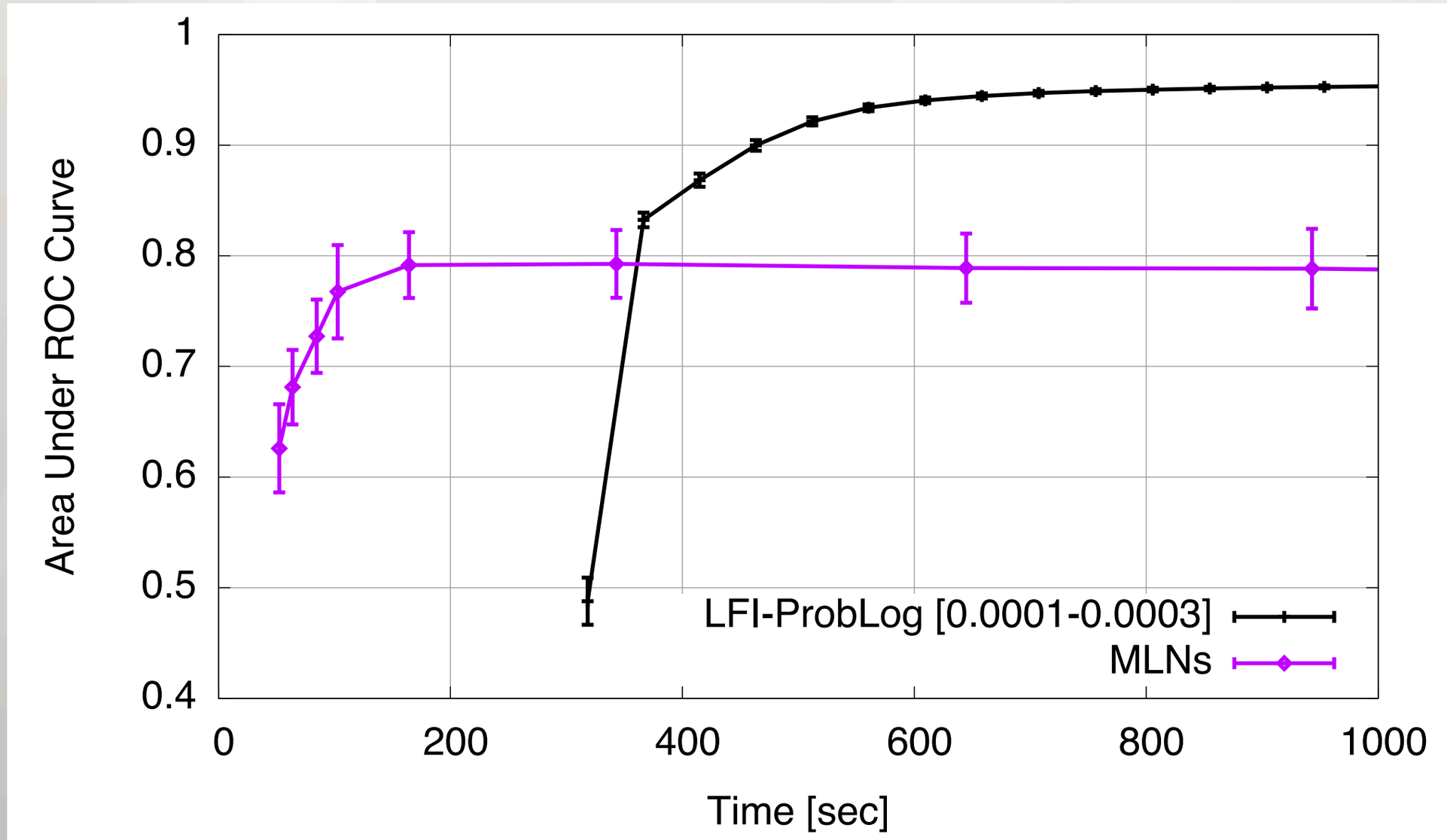
YES

Q3: Is LFI-Problog able to recover the parameters of the original model with a reasonable amount of data?

YES

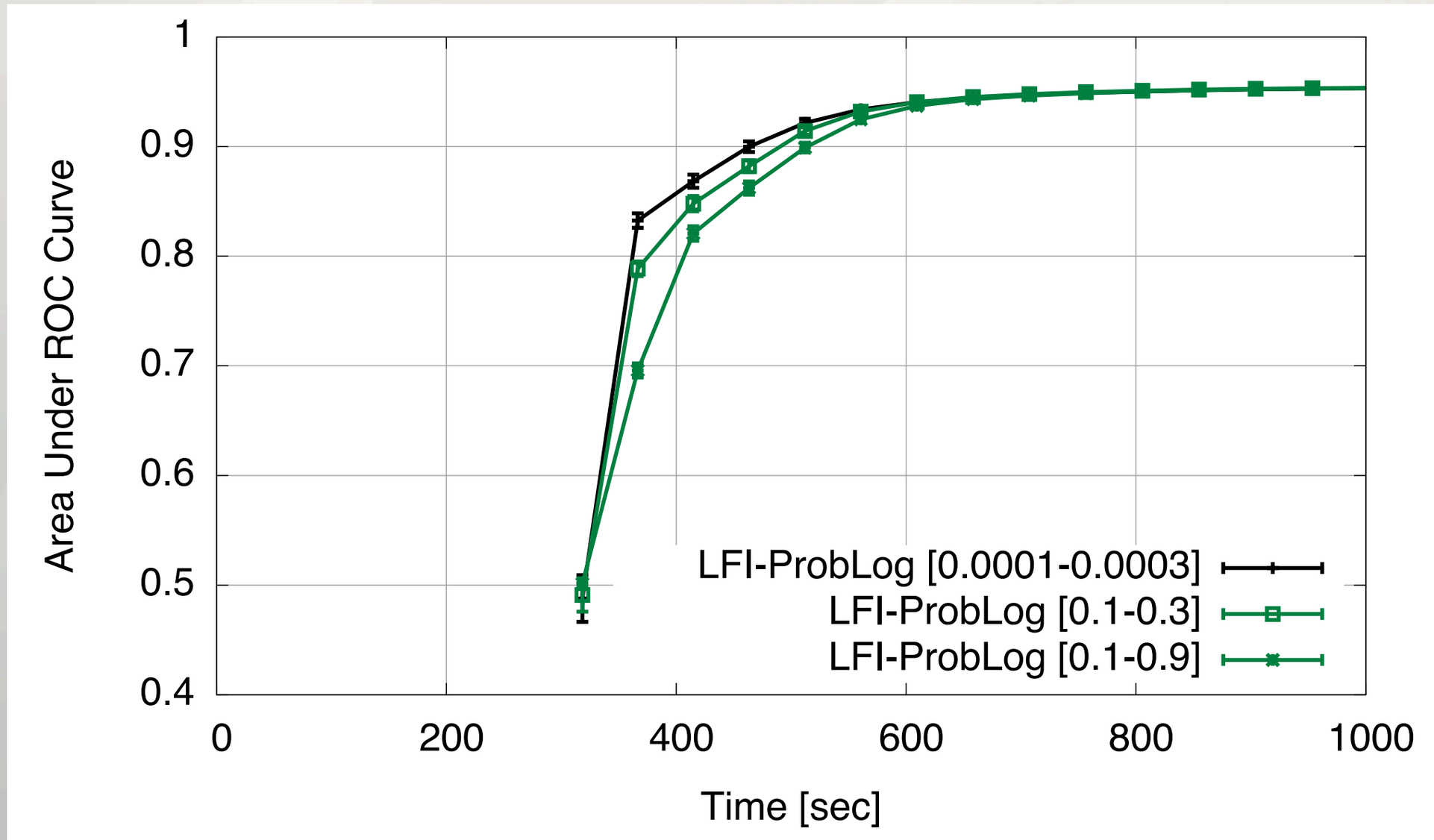
Experimental Results: WebKB

Q1: Is LFI-ProbLog competitive with existing state-of-the-art frameworks?



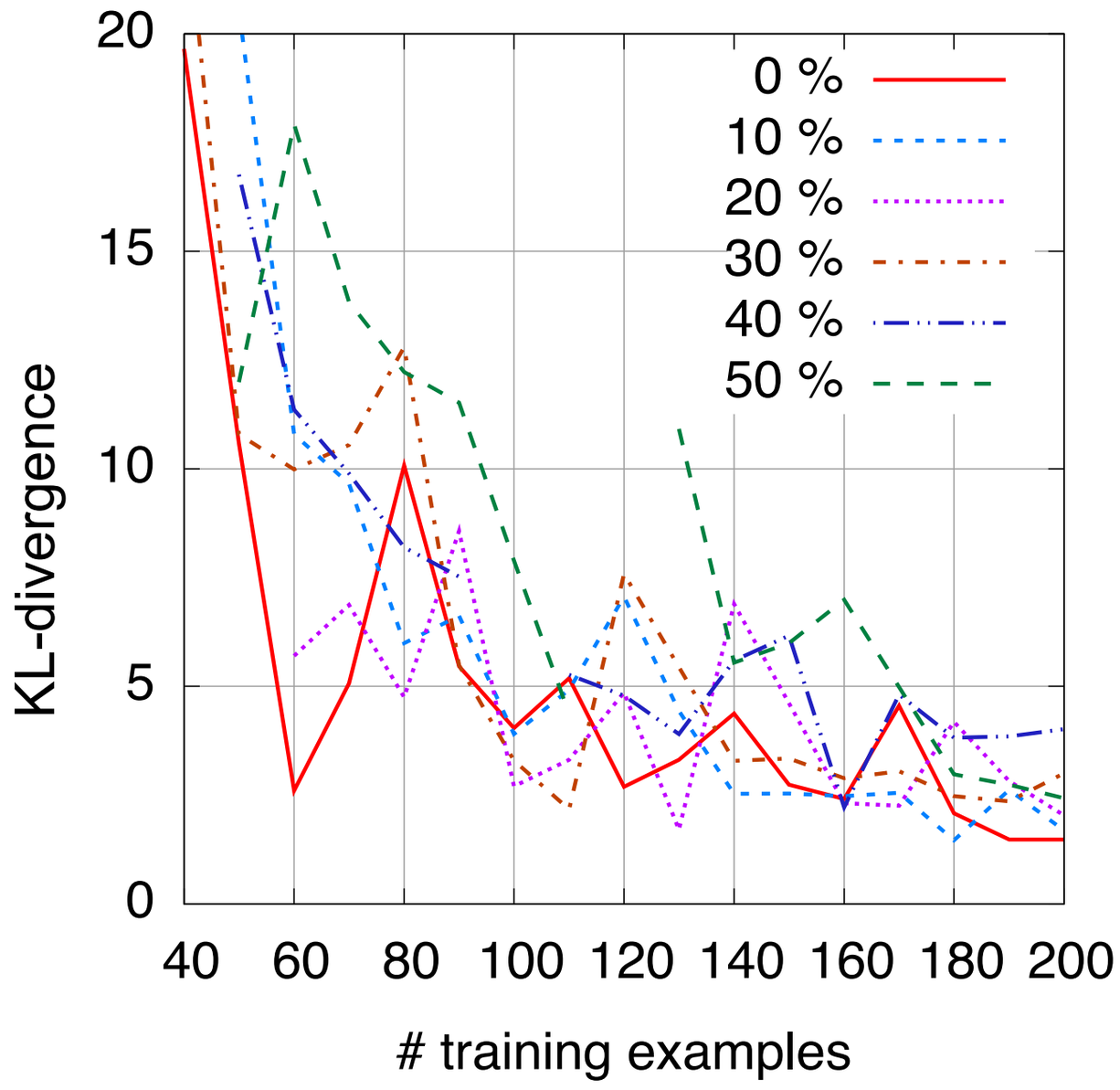
Experimental Results: WebKB

Q2: Is LFI-ProbLog insensitive to the initial probabilities?



Experimental Results: Smokers

Q3: Is LFI-Problog able to recover the parameters of the original model with a reasonable amount of data?



Goal t
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towa
data

Conclusions

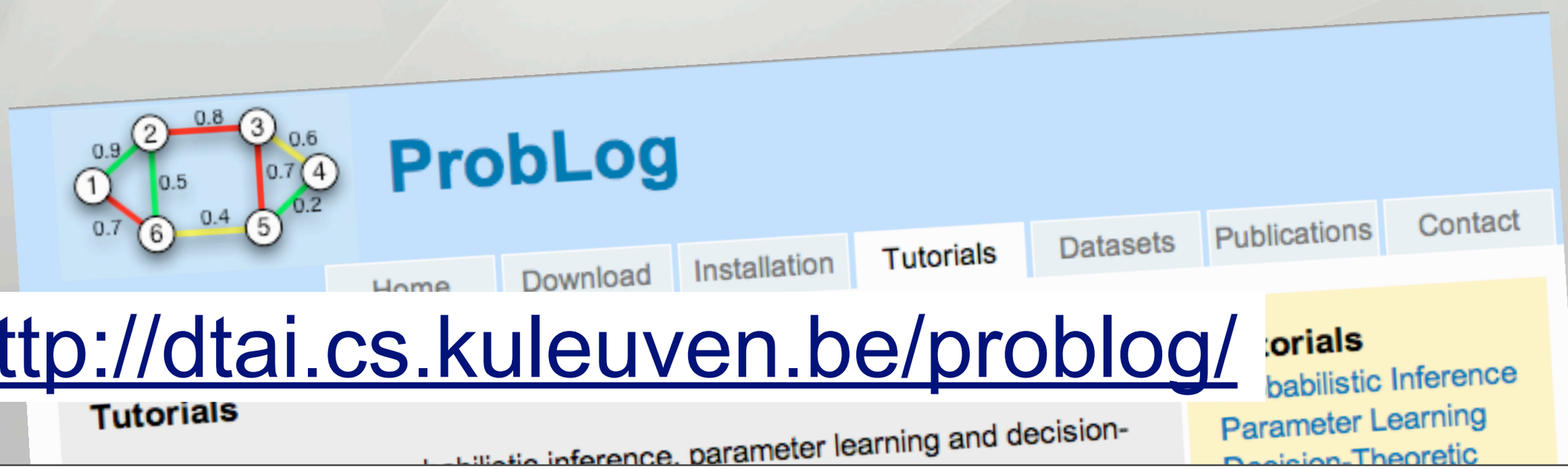
- Presented first algorithm for learning Probabilistic Logic Programs from interpretations
  - Learns in a generative setting
  - Handles missing/incomplete data

- Empirical results:
  - Accuracy competitive with other state of the art
  - Run time efficiency sufficient for real world tasks

- Publicly available implementation: Download and try it out!!
  - http://dtai.cs.kuleuven.be/problog/

Thank you

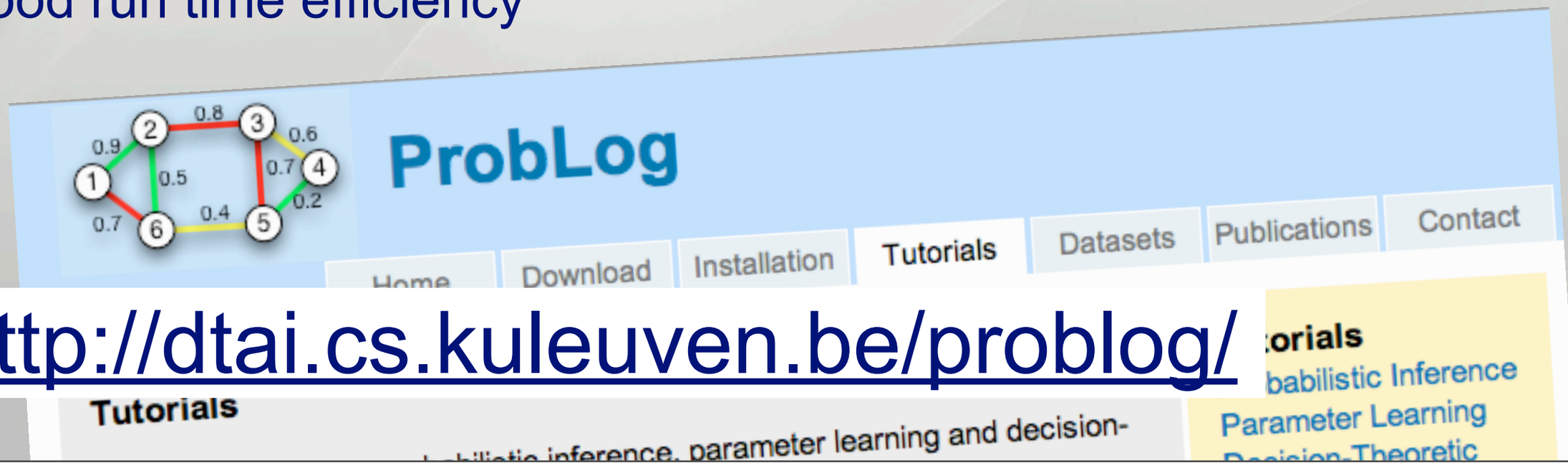
Questions?



http://dtai.cs.kuleuven.be/problog/

Conclusions

- Presented first ProbLog algorithm capable of learning from interpretation
  - Can learn in a generative setting
  - Can handle missing/incomplete data
- Strong empirical results
  - Accuracy competitive with other state of the art
  - Good run time efficiency

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