Probabilistic Logic Programming and its Applications

Luc De Raedt
with many slides from Angelika Kimmig

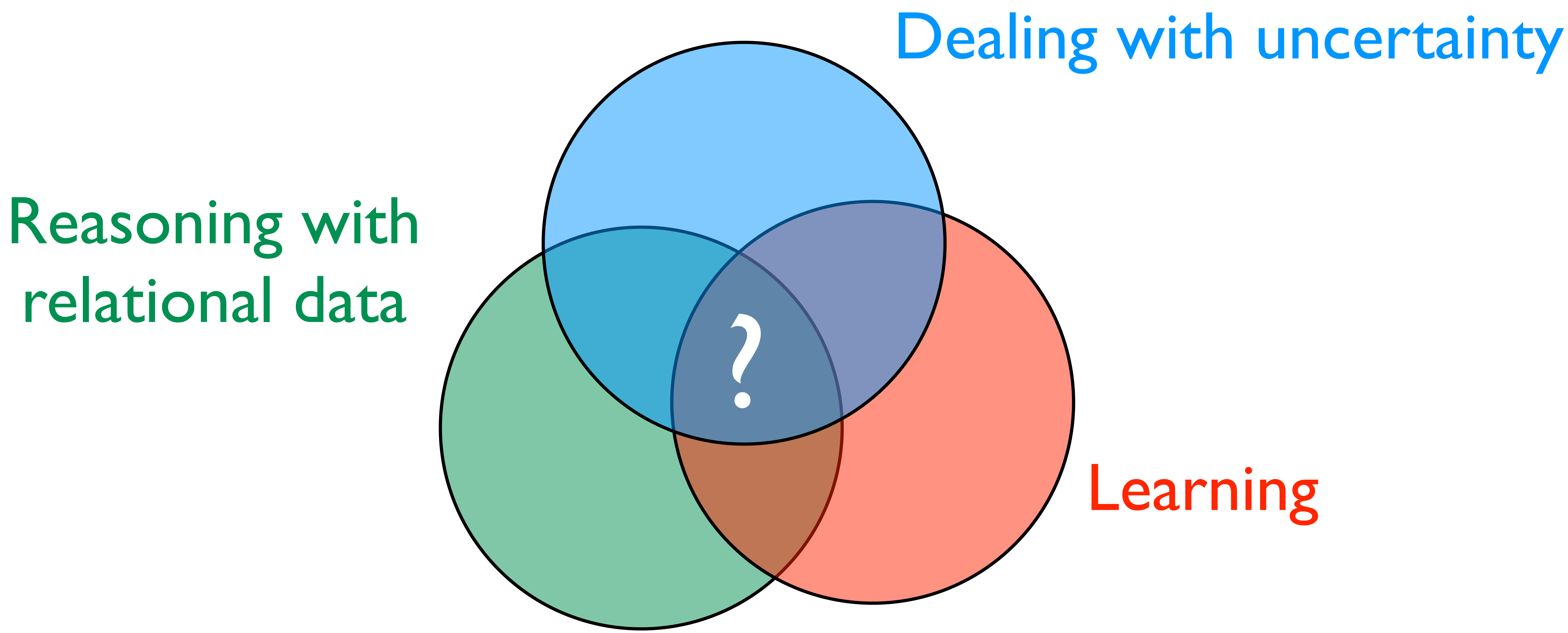
DTAI MACHINE LEARNING

KU LEUVEN

erc

The Turing, London, September 11, 2017

A key question in AI:

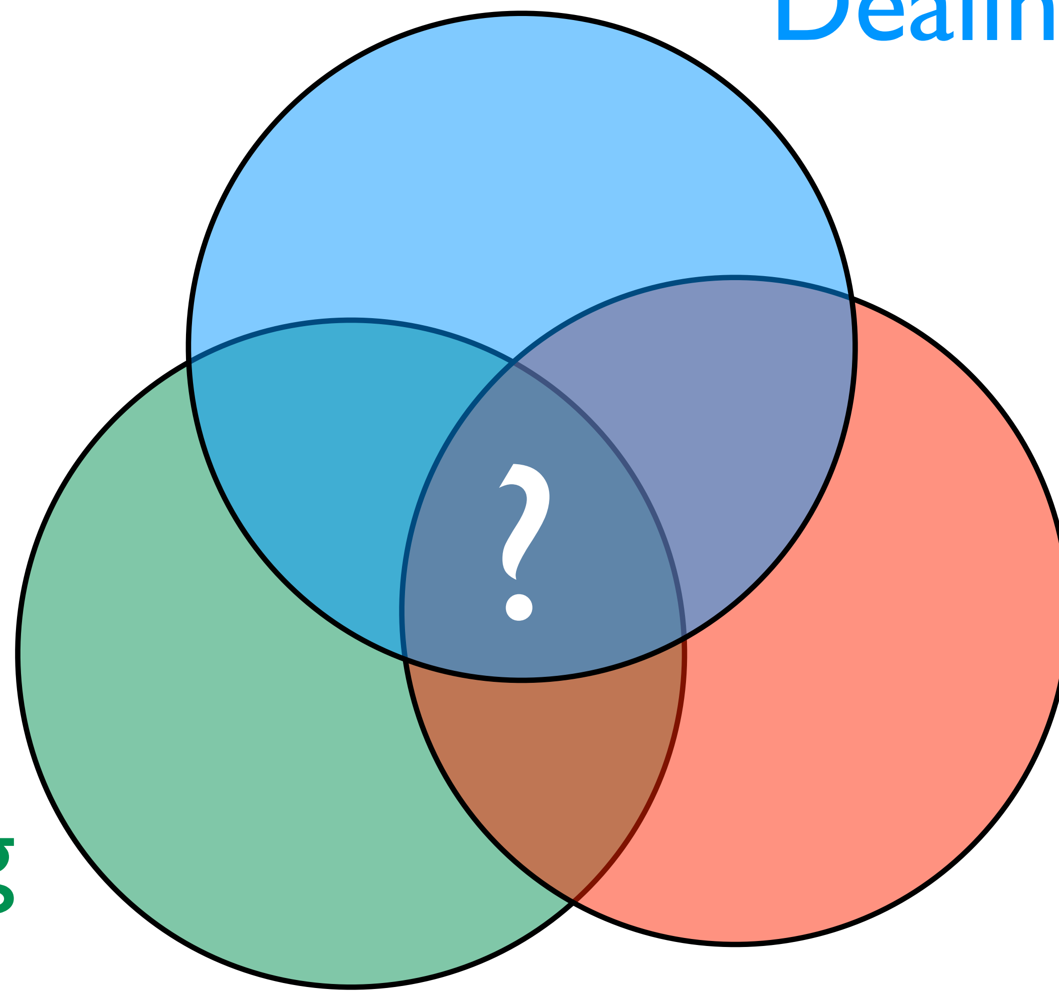


A key question in AI:

Dealing with uncertainty

Reasoning with relational data

- logic
- databases
- programming
- ...



Learning

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- probability theory
- graphical models
- ...

Reasoning with relational data

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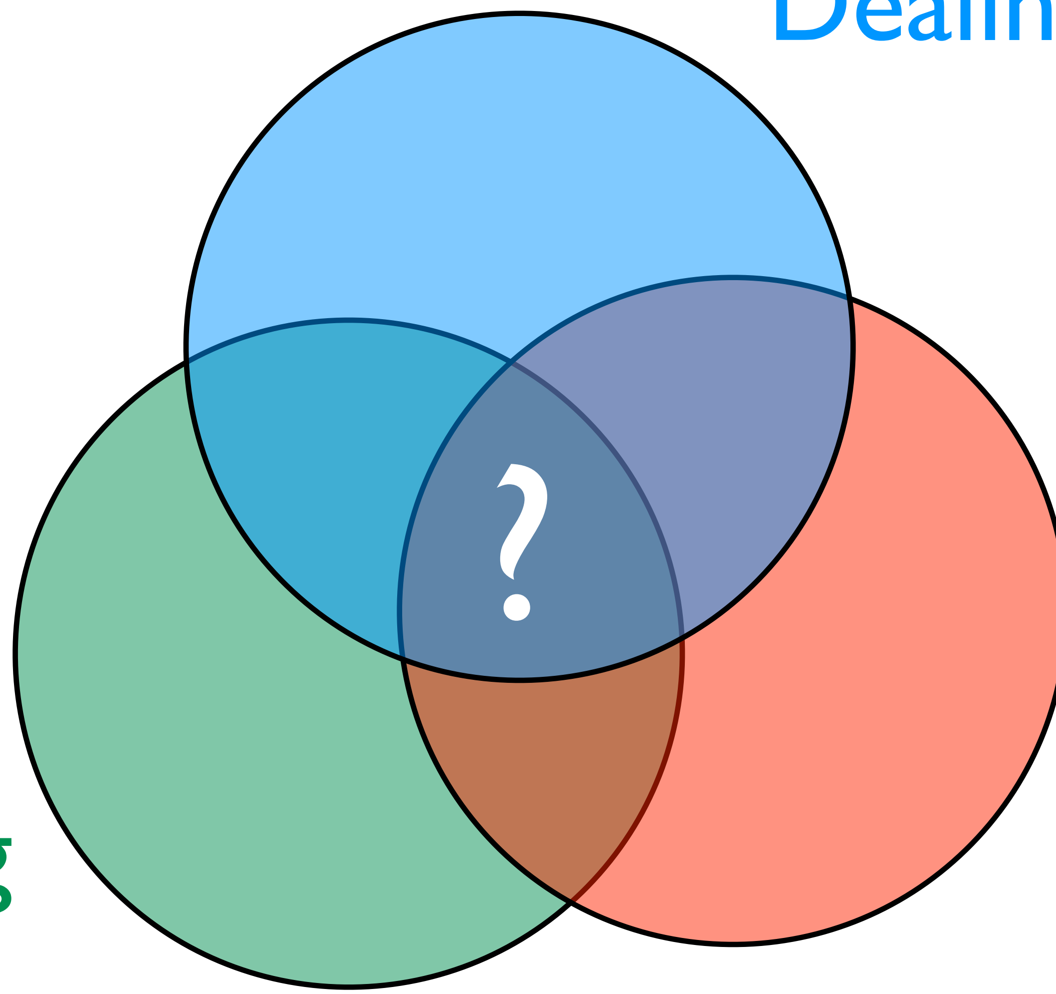

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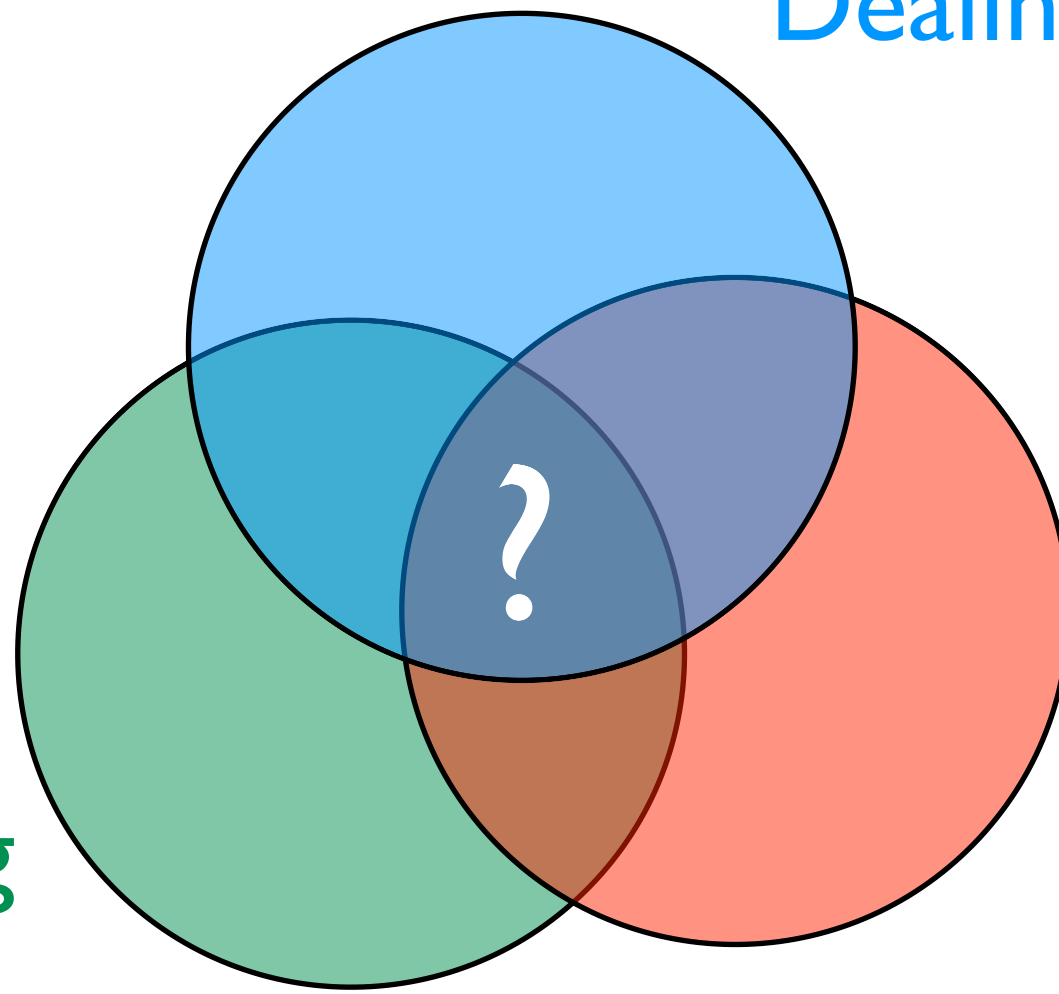

Learning

- parameters
- structure

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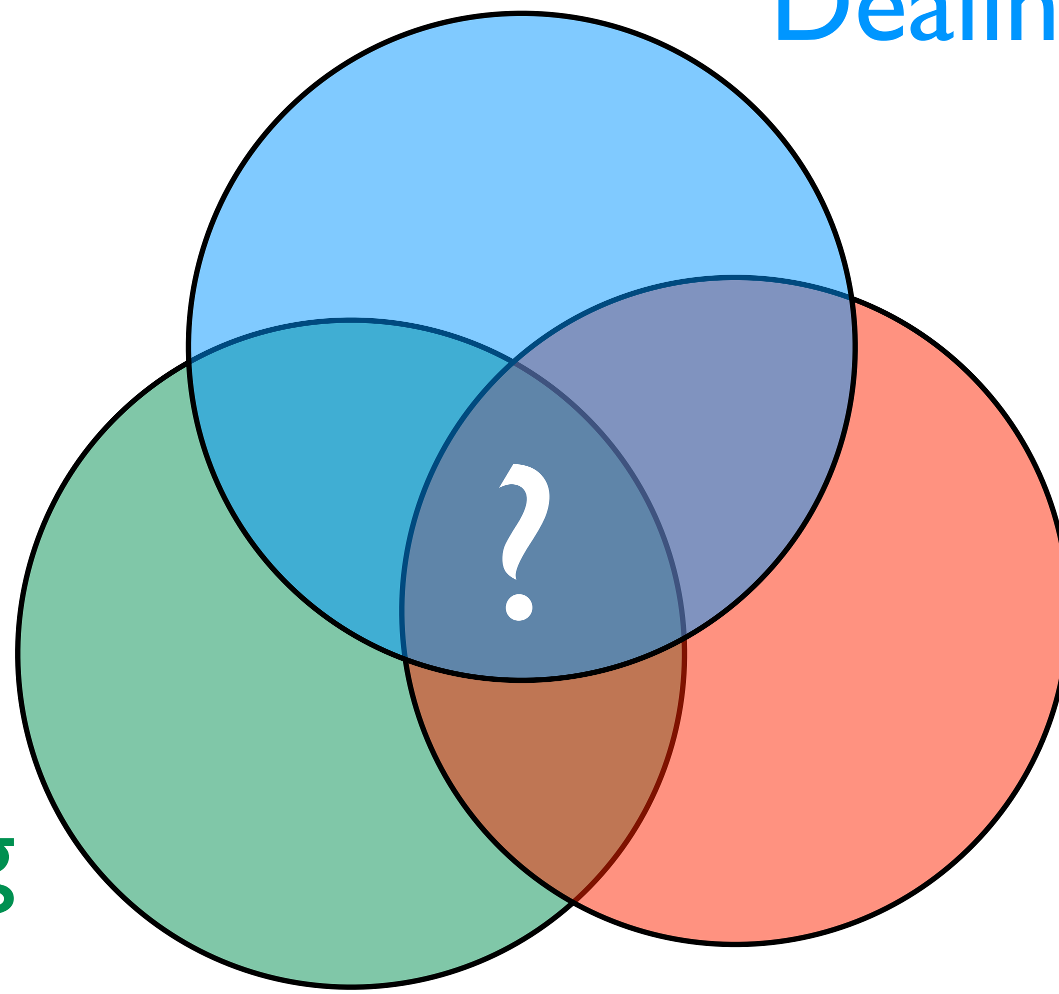


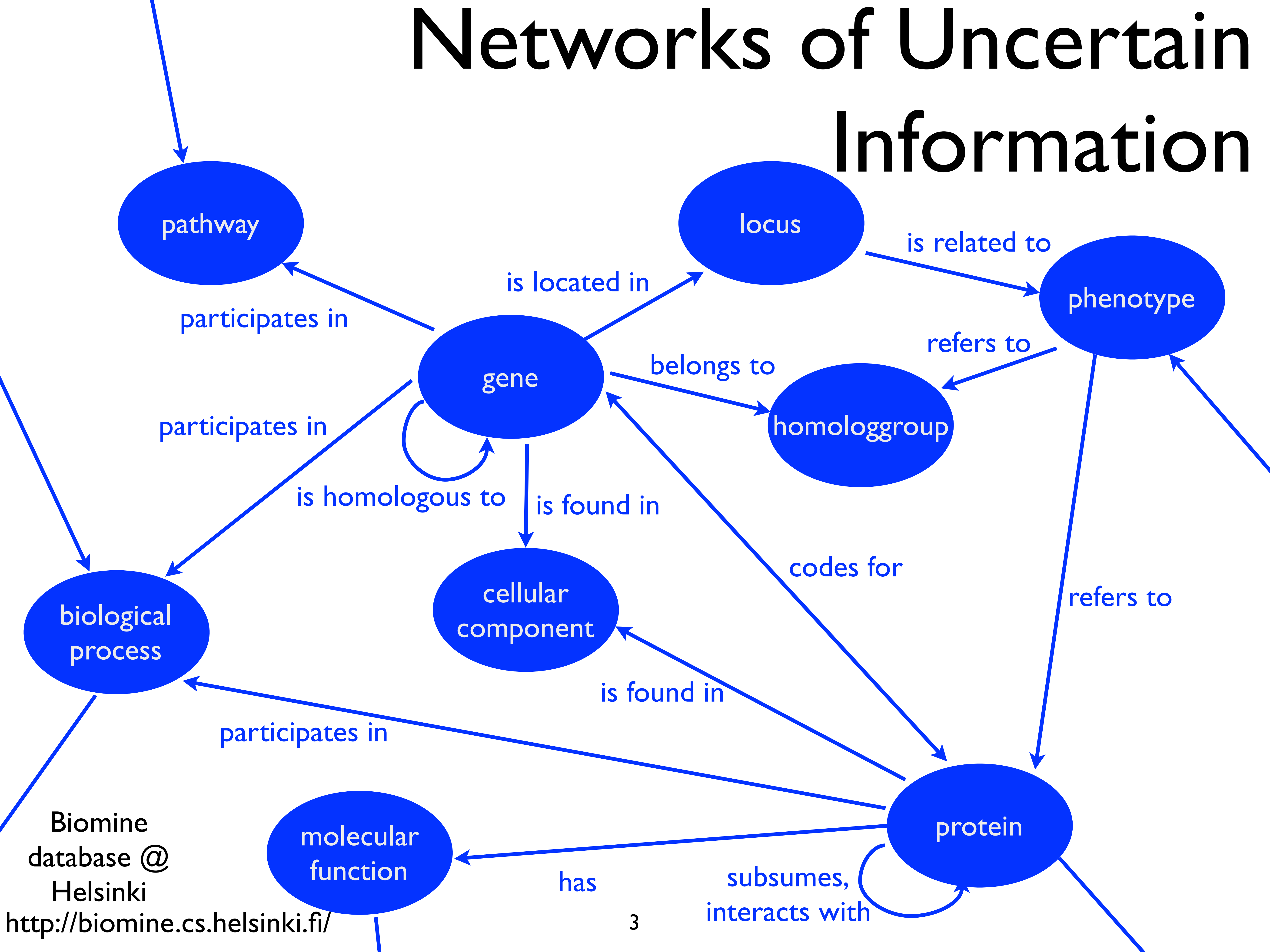
Reasoning with relational data
- logic
- databases
- programming
- ...

Dealing with uncertainty
- probability theory
- graphical models
- ...

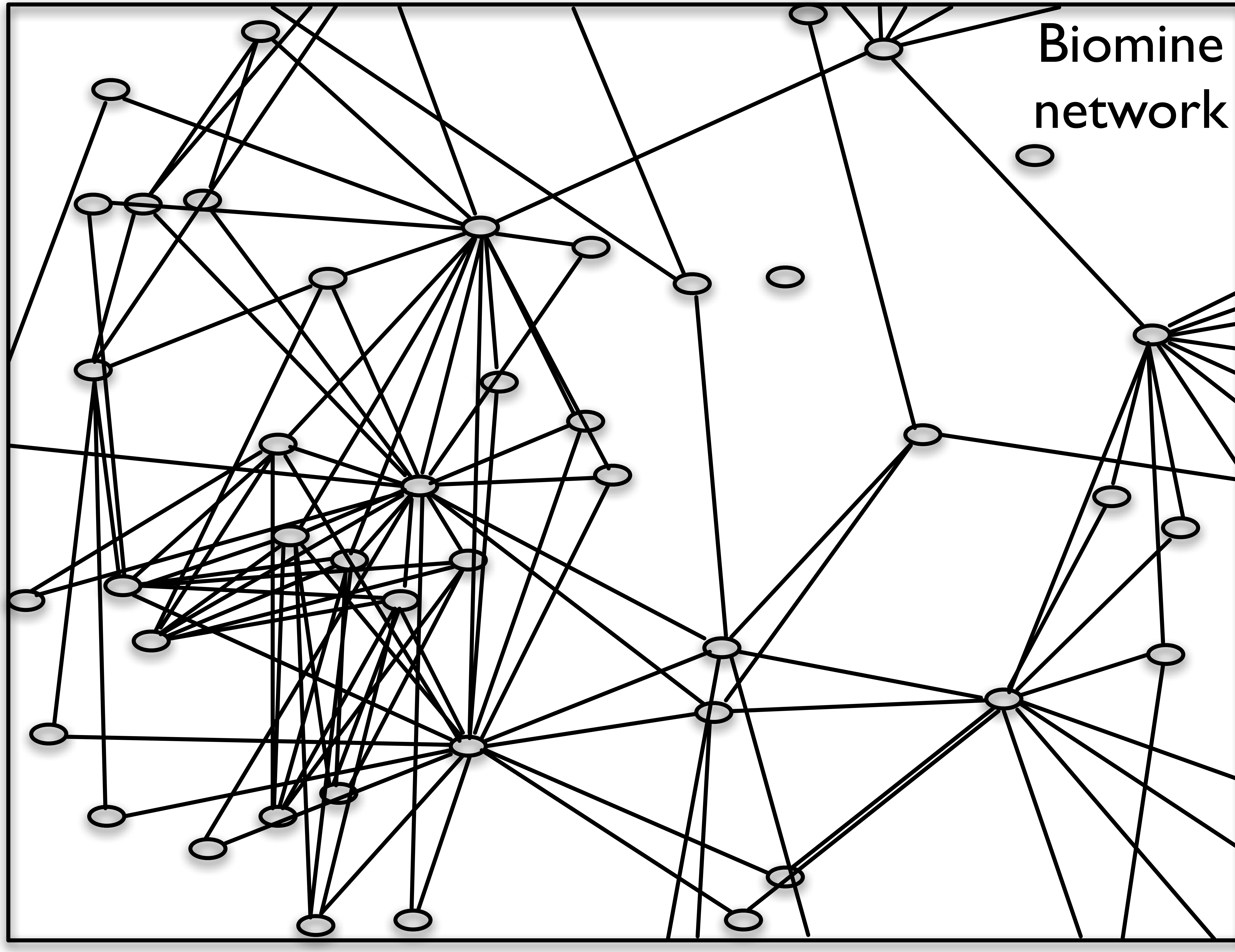
Learning
- parameters
- structure

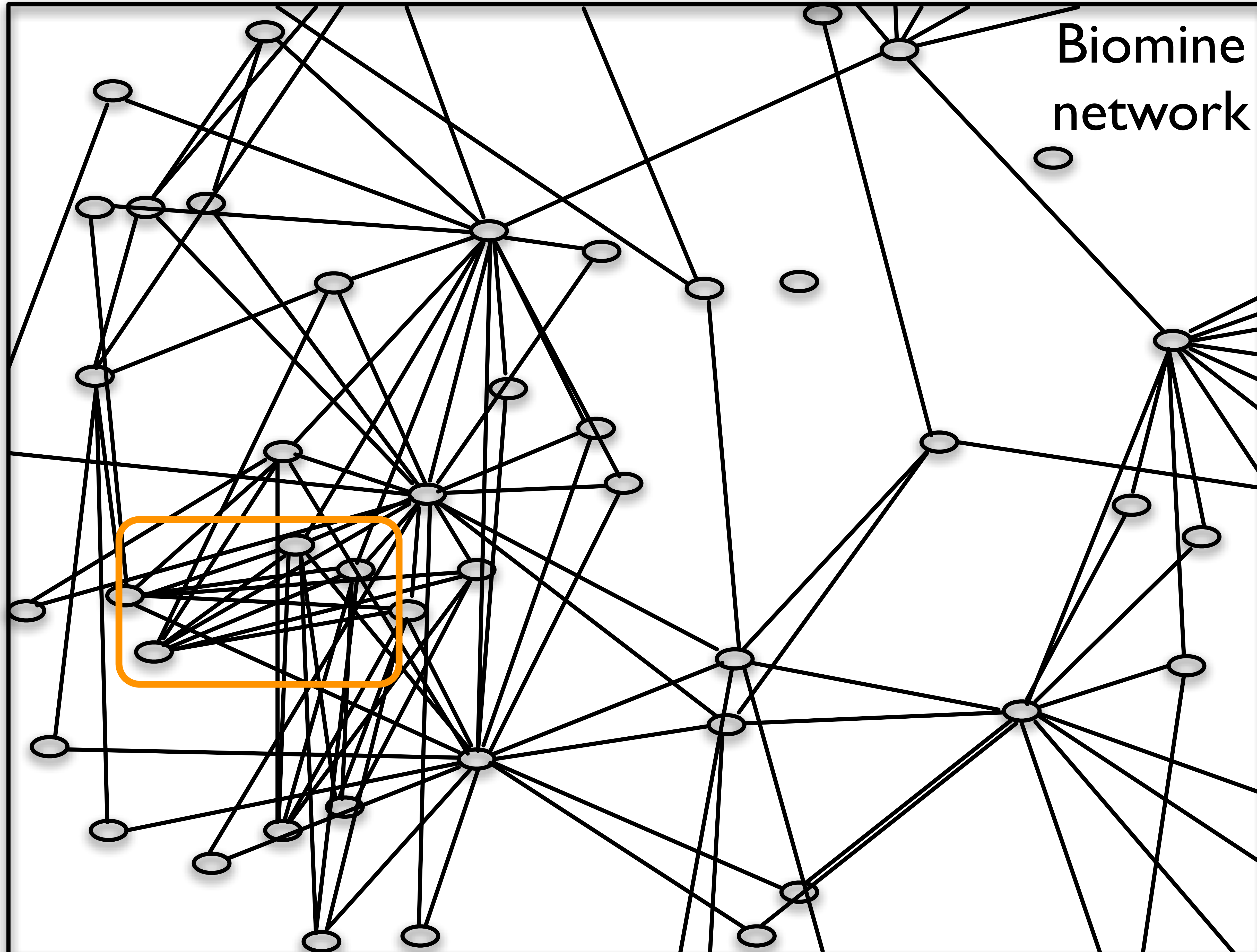
Statistical relational learning, probabilistic logic learning, probabilistic programming, ...

Networks of Uncertain Information



Biomine database @ Helsinki
http://biomine.cs.helsinki.fi/


Biomine
network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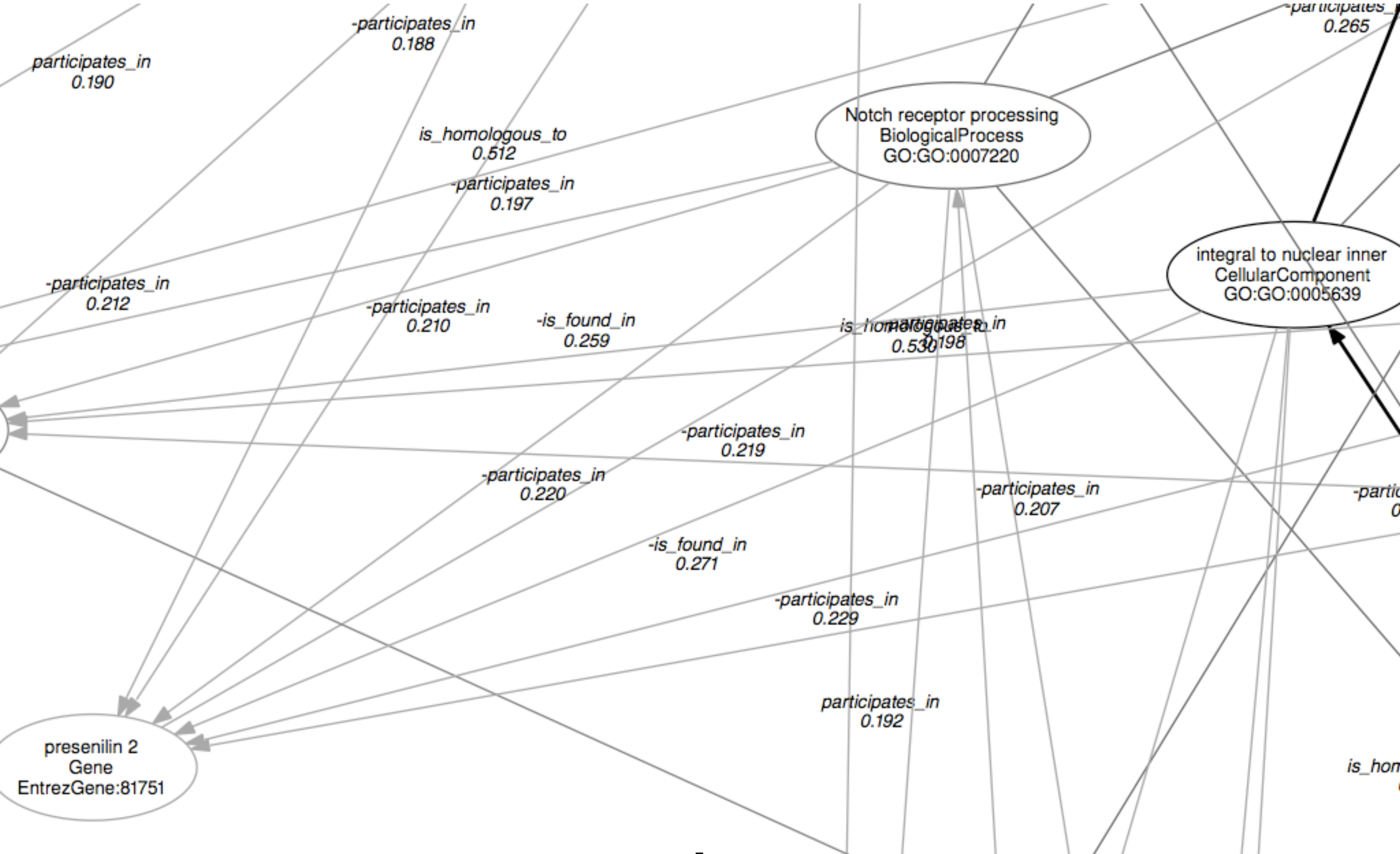
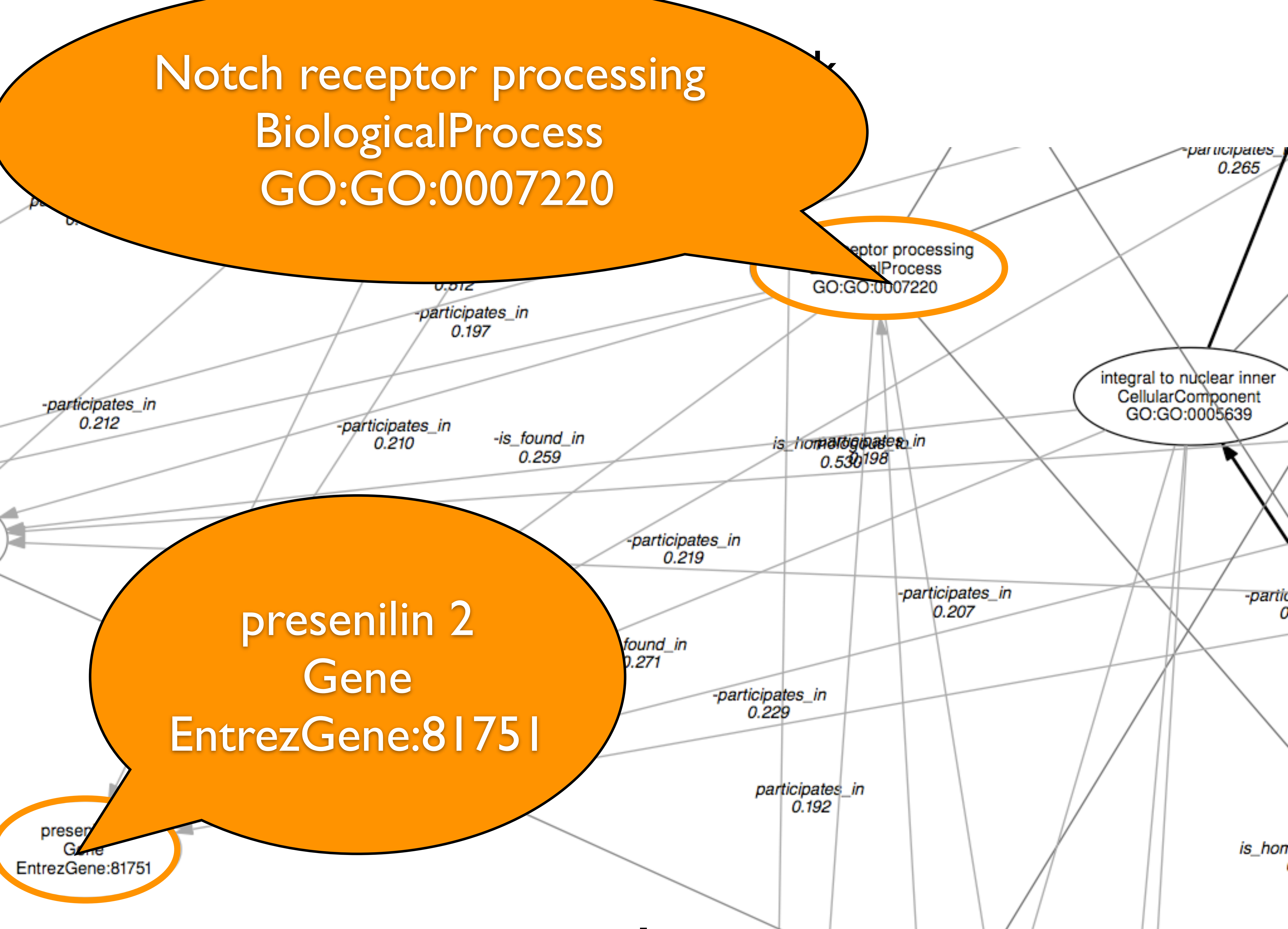
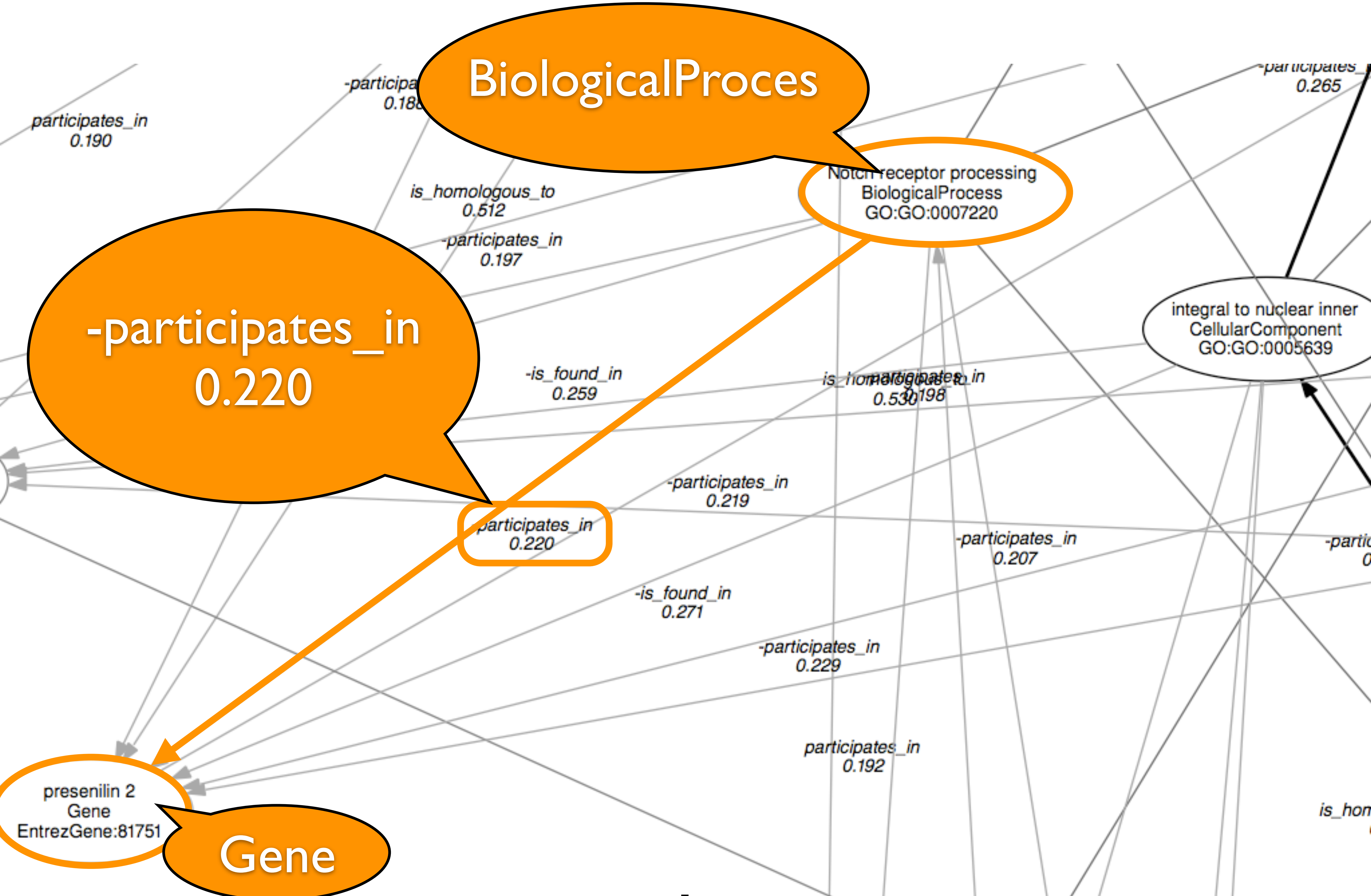
Biomine Network




Notch receptor processing
BiologicalProcess
GO:GO:0007220
presenilin 2
Gene
EntrezGene:81751
integral to nuclear inner
CellularComponent
GO:GO:0005639
-participates_in
0.197
-participates_in
0.212
-participates_in
0.210
-is_found_in
0.259
-participates_in
0.219
-participates_in
0.207
-participates_in
0.229
participates_in
0.192
0.265

Biomine Network



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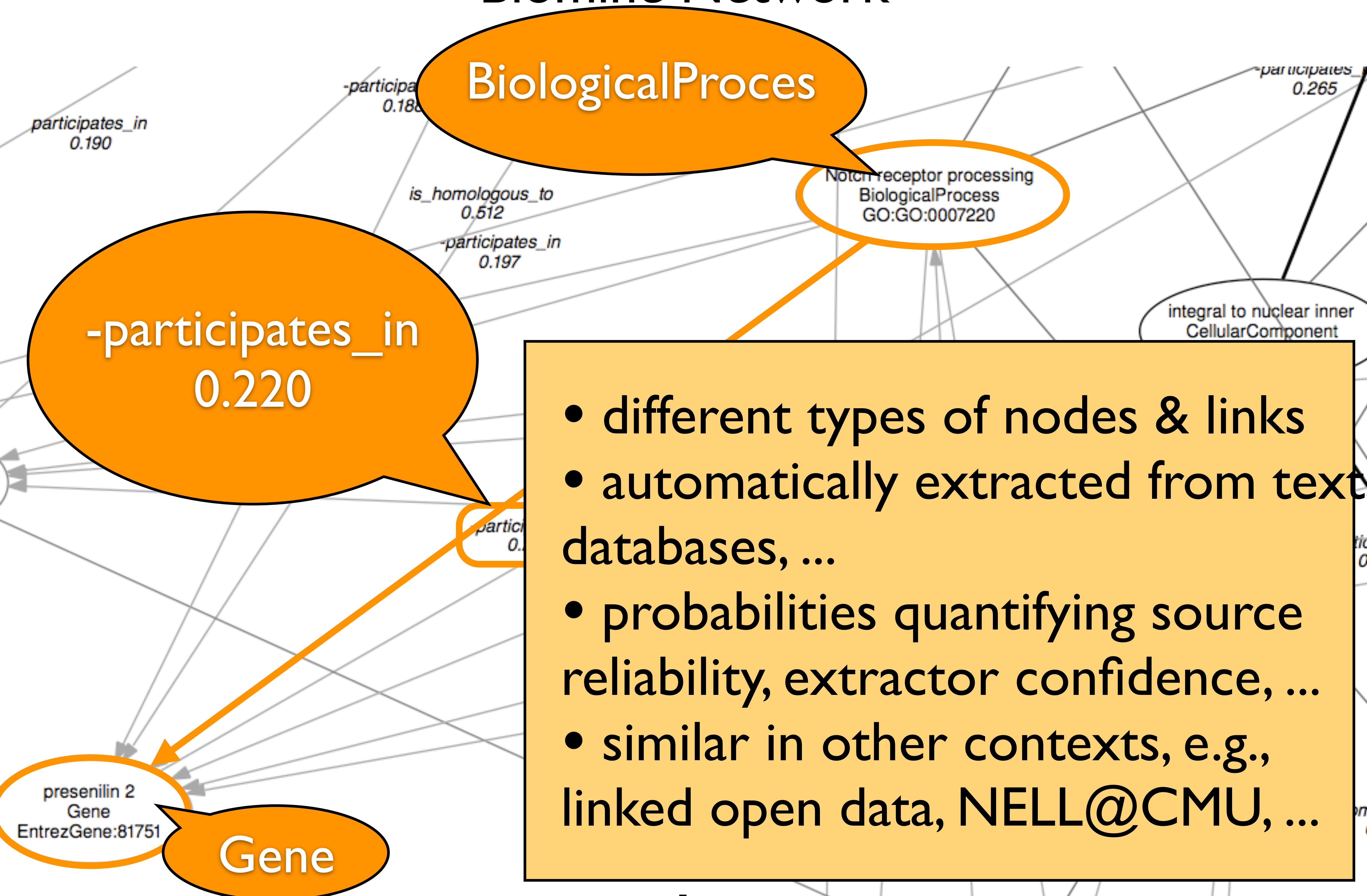

- different types of nodes & links
- automatically extracted from text, databases, ...
- probabilities quantifying source reliability, extractor confidence, ...
- similar in other contexts, e.g., linked open data, NELL@CMU, ...

Example: Information Extraction

Recently-Learned Facts twitter

Refresh

instance	iteration	date learned	confidence
kelly_andrews is a female	826	29-mar-2014	98.7
investment_next_year is an economic sector	829	10-apr-2014	95.3
shibenik is a geopolitical entity that is an organization	829	10-apr-2014	97.2
quality_web_design_work is a character trait	826	29-mar-2014	91.0
mercedes_benz_cls_by_carlsson is an automobile manufacturer	829	10-apr-2014	95.2
social_work is an academic program at the university rutgers_university	827	02-apr-2014	93.8
dante wrote the book the_divine_comedy	826	29-mar-2014	93.8
willie_aames was born in the city los_angeles	831	16-apr-2014	100.0
kitt_peak is a mountain in the state or province arizona	831	16-apr-2014	96.9
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NELL: http://rtw.ml.cmu.edu/rtw/

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instances for many different relations

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instances for many different relations

degree of certainty

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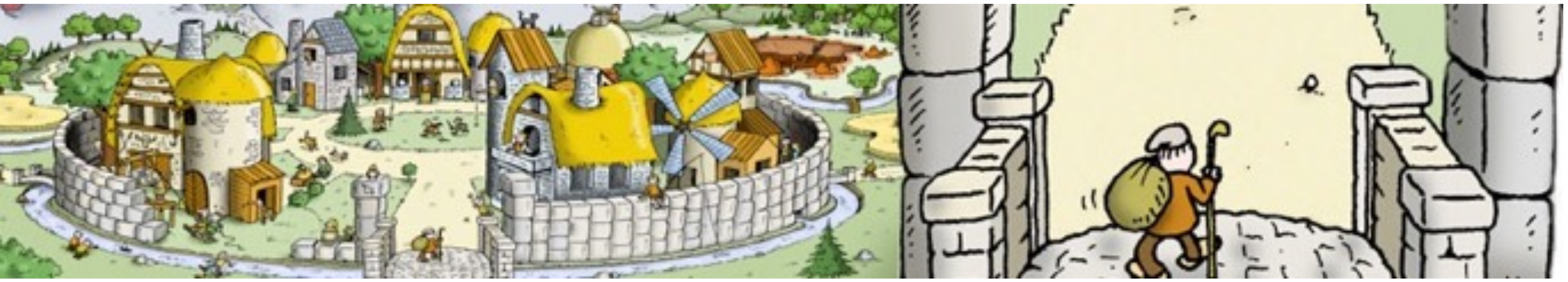
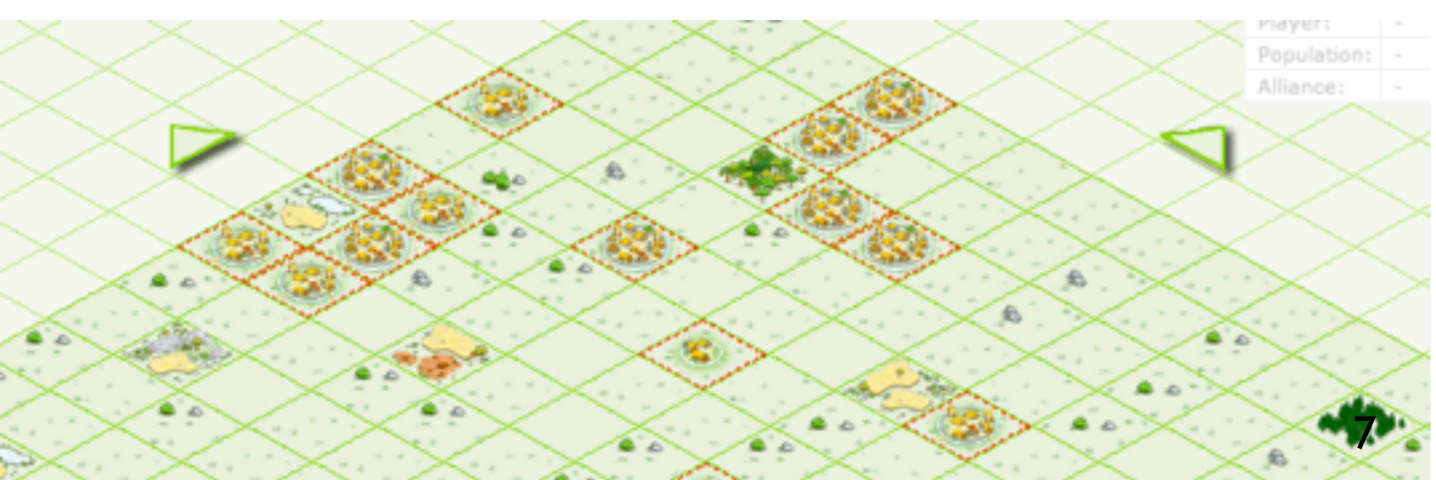
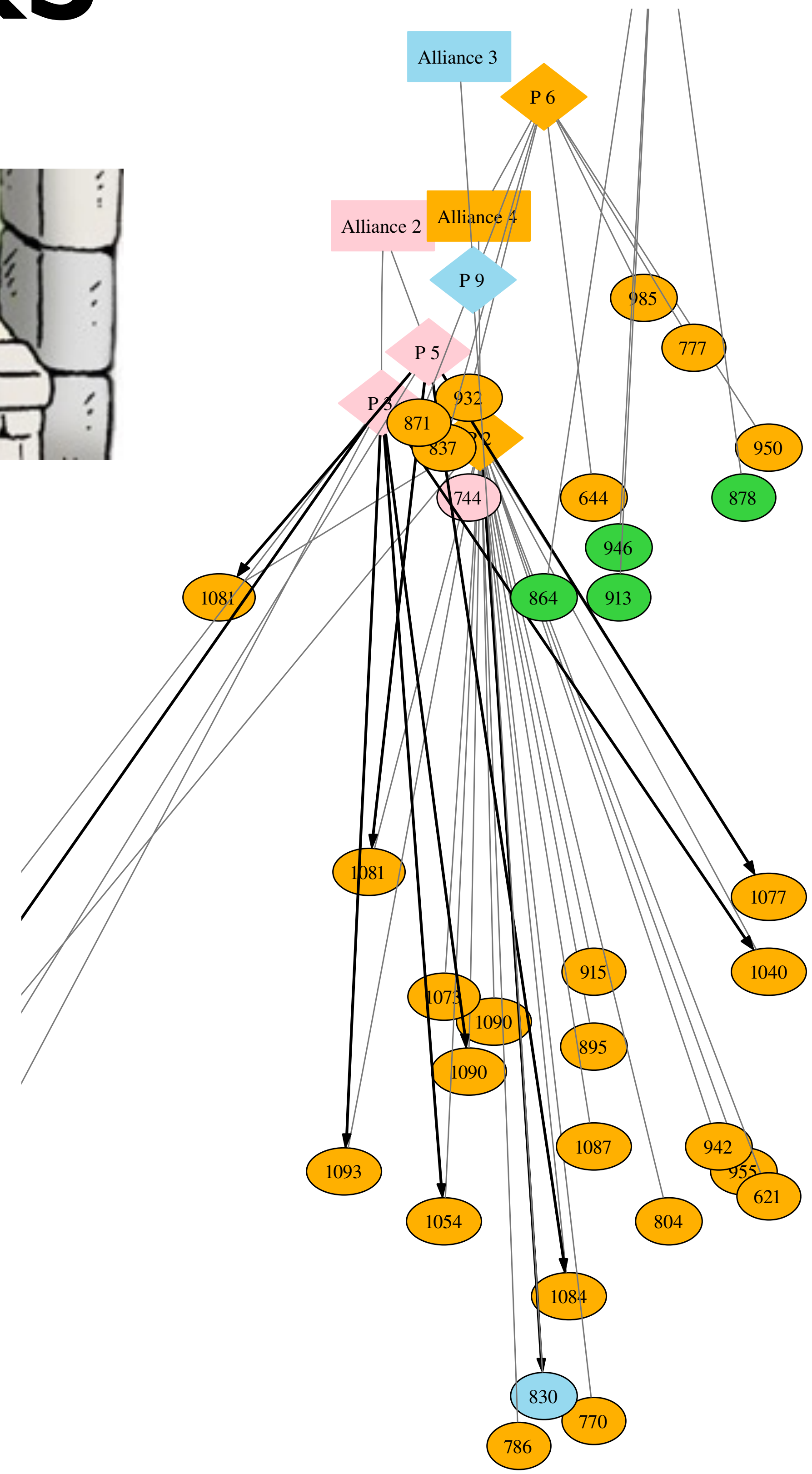
Dynamic networks



Travian: A massively multiplayer real-time strategy game

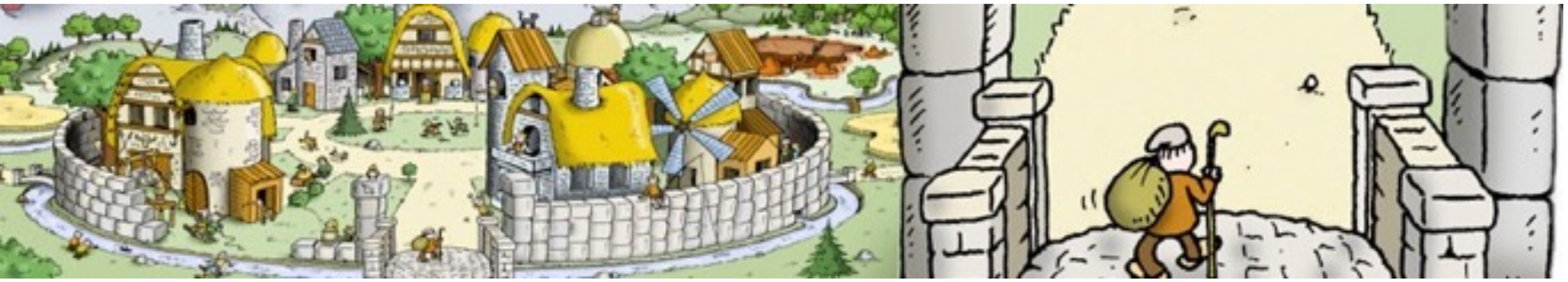
Can we build a model
of this world ?
Can we use it for playing
better ?





[Thon et al, MLJ 11]

Dynamic networks



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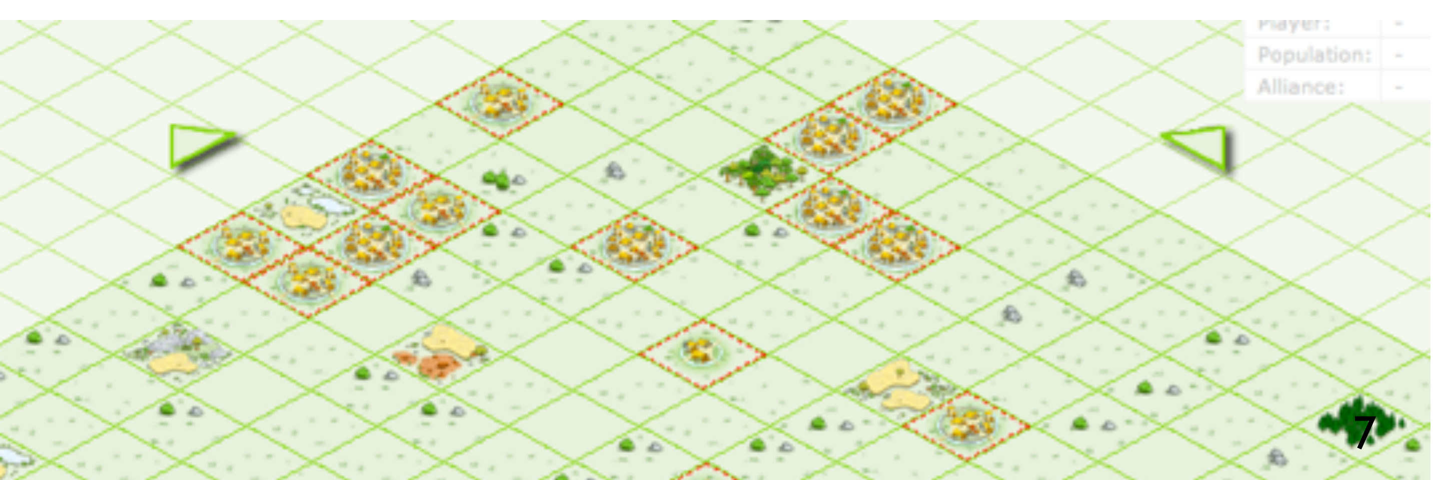
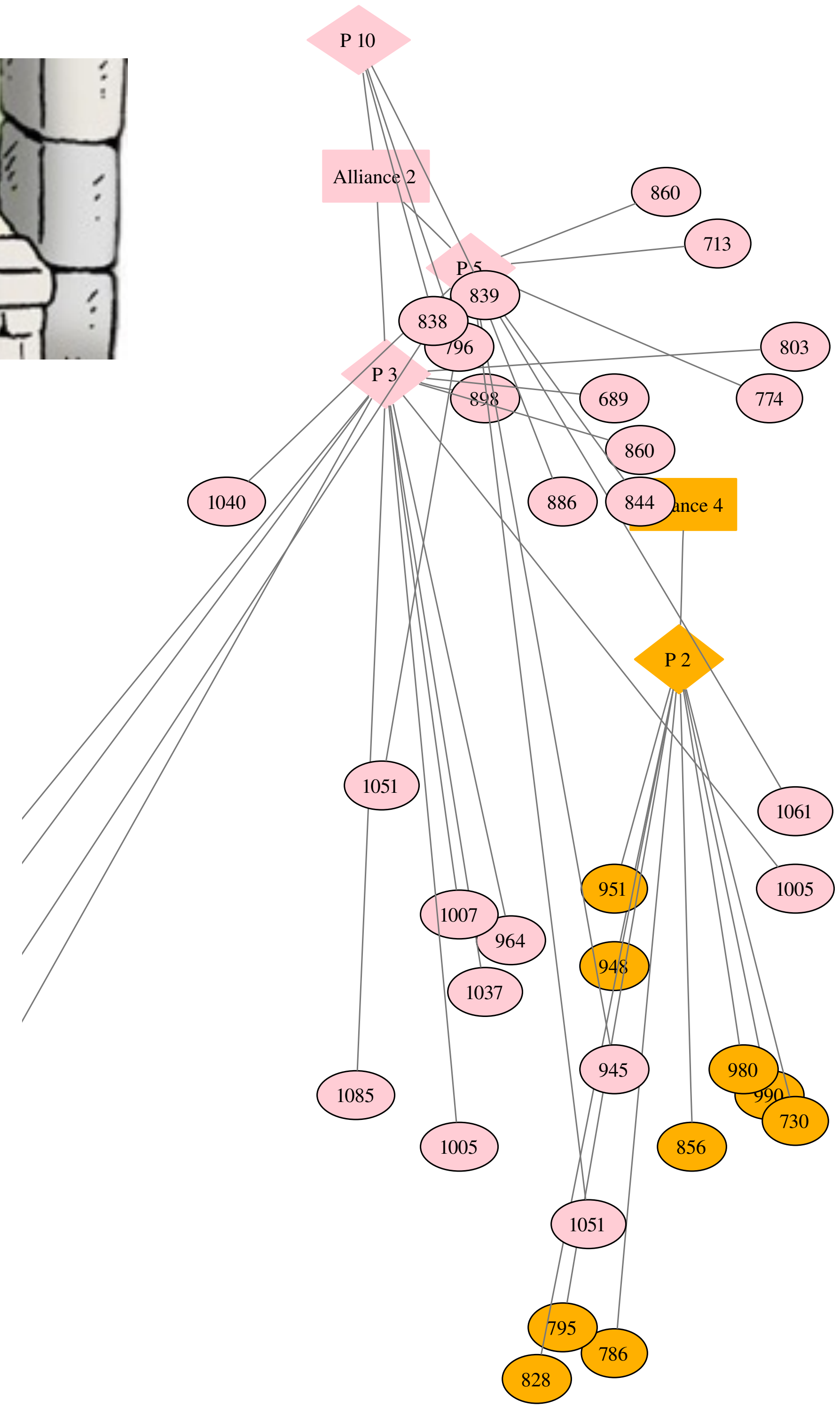




[Thon et al, MLJ 11]

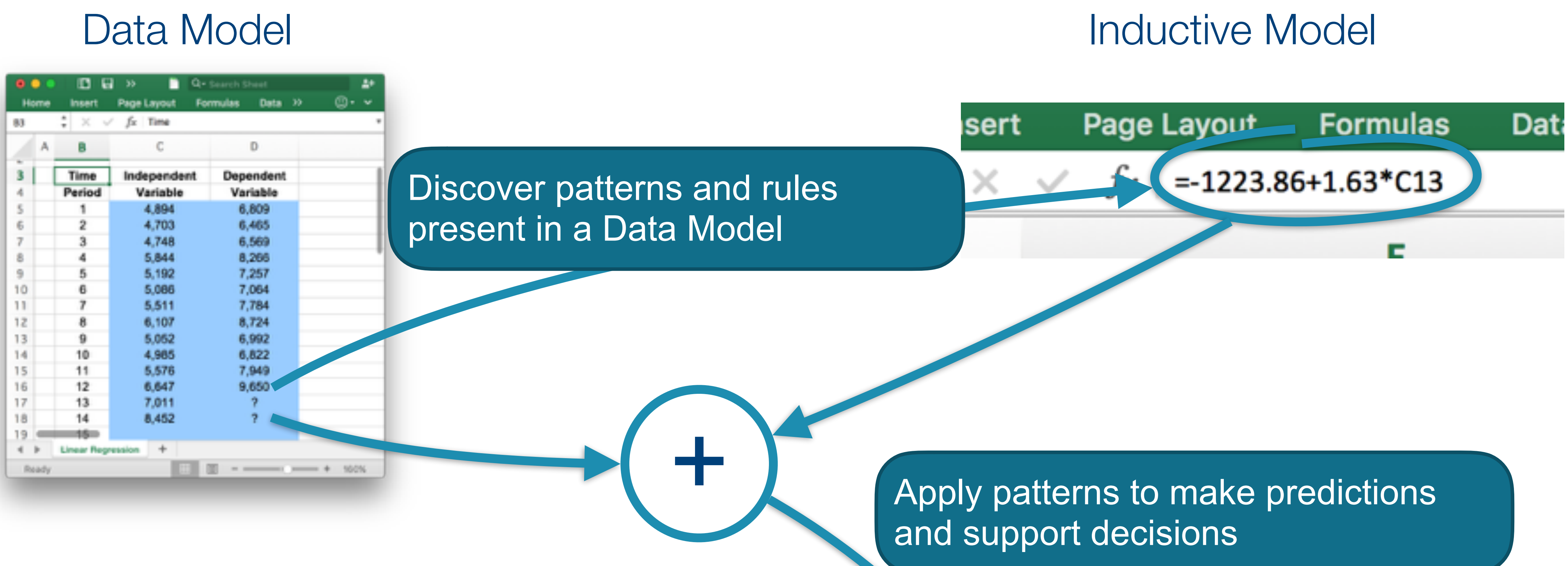
Answering Probability Questions

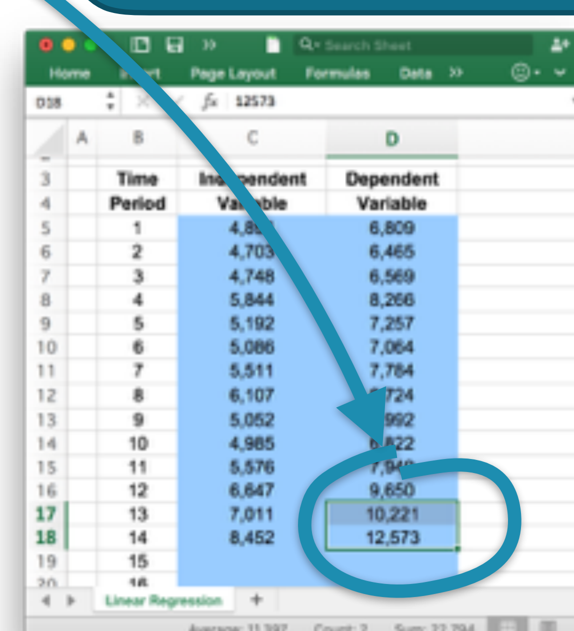
Mike has a bag of marbles with 4 white, 8 blue, and 6 red marbles. He pulls out one marble from the bag and it is red. What is the probability that the second marble he pulls out of the bag is white?

The answer is 0.235941.

[Dries et al., IJCAI 17]

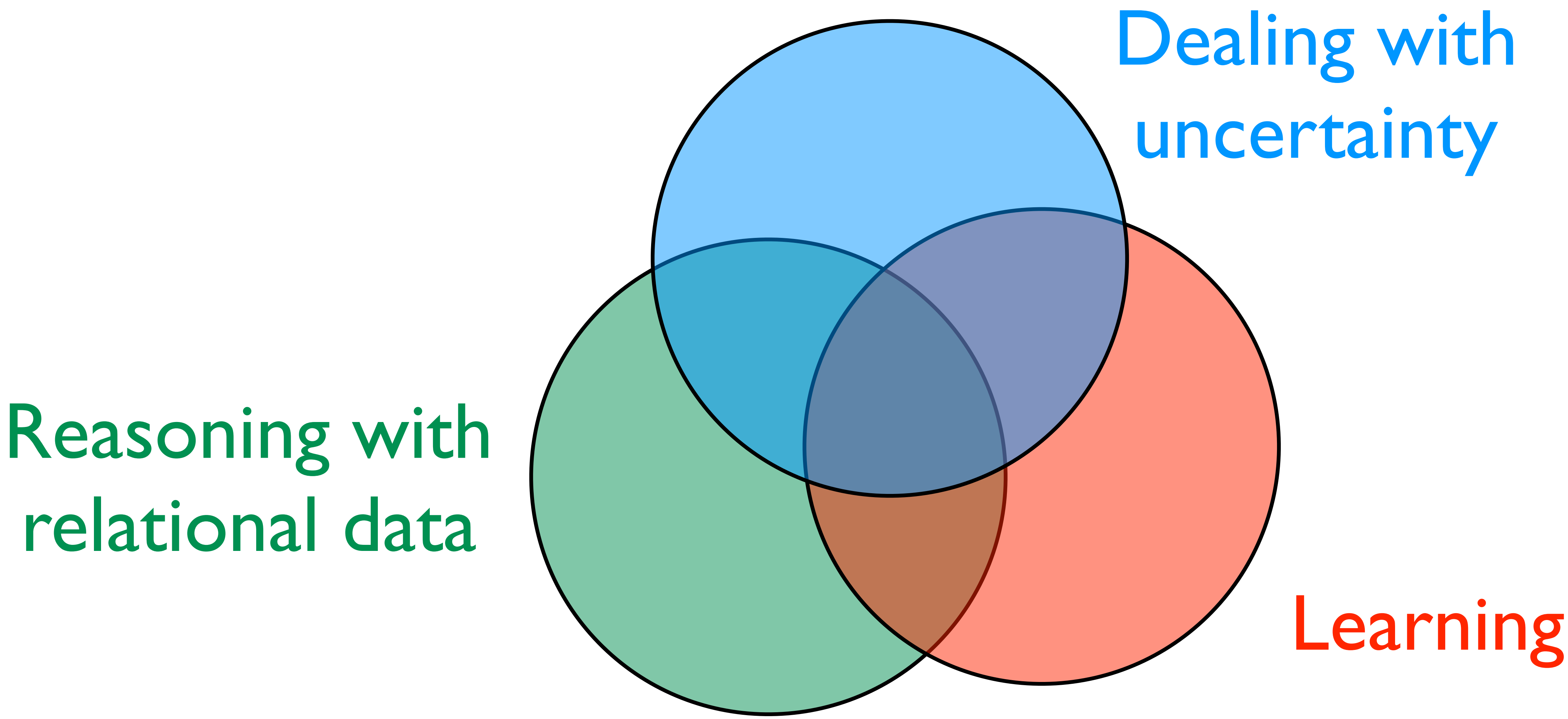
Synthesising inductive data models





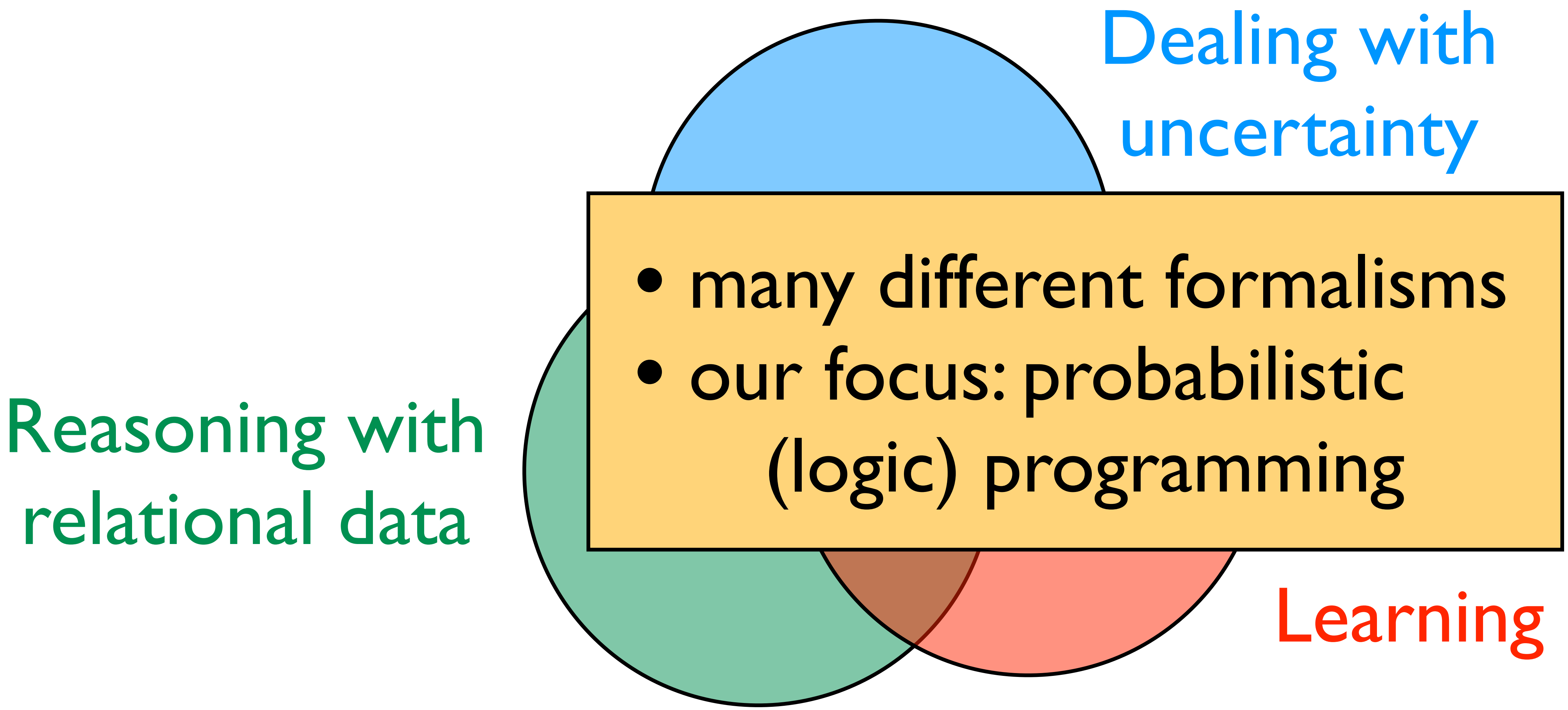
1. The synthesis system “learns the learning task”. It identifies the right learning tasks and learns appropriate Inductive Models
2. The system may need to restructure the data set before Inductive Models synthesis can start
3. A unifying IDM language for a set of core patterns and models will be developed — based on ProbLog

Common theme



Statistical relational learning, probabilistic logic learning, probabilistic programming, ...

Common theme



- many different formalisms
- our focus: probabilistic (logic) programming

Statistical relational learning, probabilistic logic learning, probabilistic programming, ...

The (Incomplete) SRL Alphabet Soup

[names in alphabetical order]

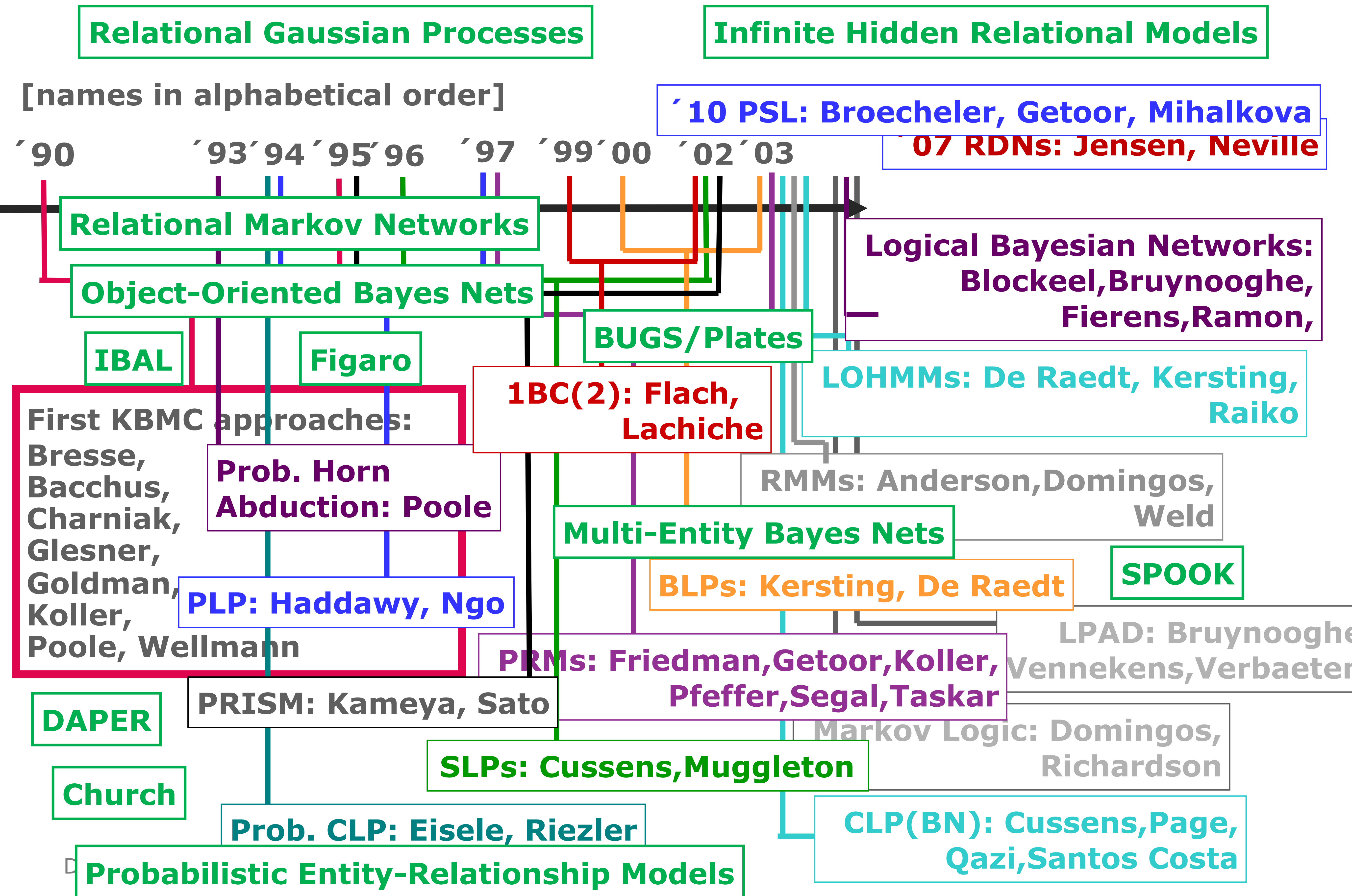
´99 ´03

The (Incomplete) SRL Alphabet Soup

[names in alphabetical order]

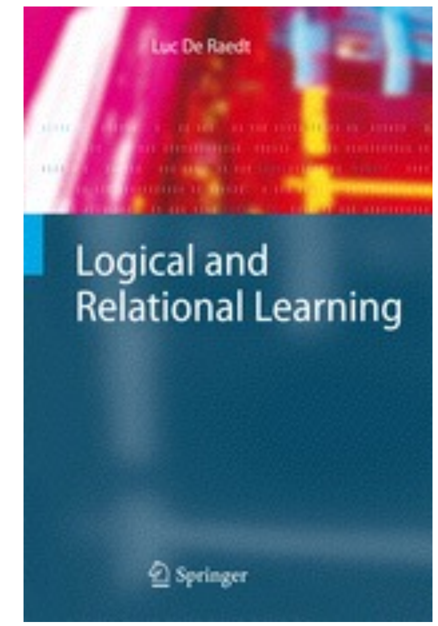
First KBMC approaches:
Bresse,
Bacchus,
Charniak,
Glesner,
Goldman,
Koller,
Poole, Wellmann

The (Incomplete) SRL Alphabet Soup

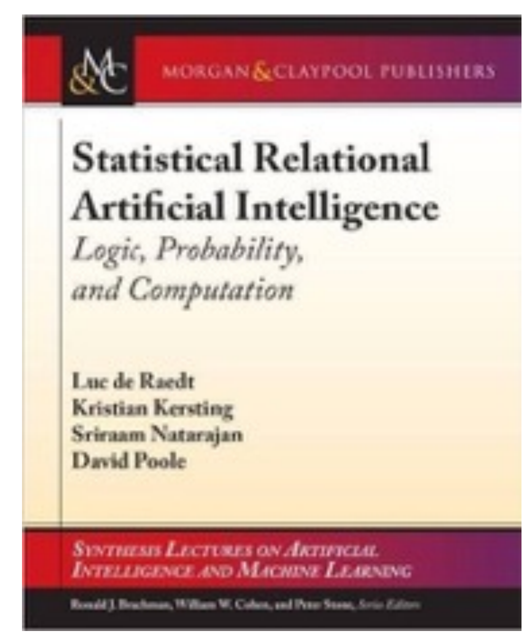


Many different angles

- Probabilistic programming
  - Logic programming and probabilistic databases
    - (ProbLog and DS as representatives)
  - Functional and imperative (Church as representatives)



- Statistical relational AI and learning
  - Markov Logic
  - Relational Bayesian Networks (and variants)



Probabilistic Logic Programs

- devised by Poole and Sato in the 90s.
- built on top of the *programming language* Prolog
- upgrade *directed* graphical models
  - combines the advantages / expressive power of programming languages (Turing equivalent) and graphical models
- Generalises probabilistic databases (Suciu et al.)
- Implementations include: PRISM, ICL, ProbLog, LPADs, CP-logic, Dyna, Pita, DC, …

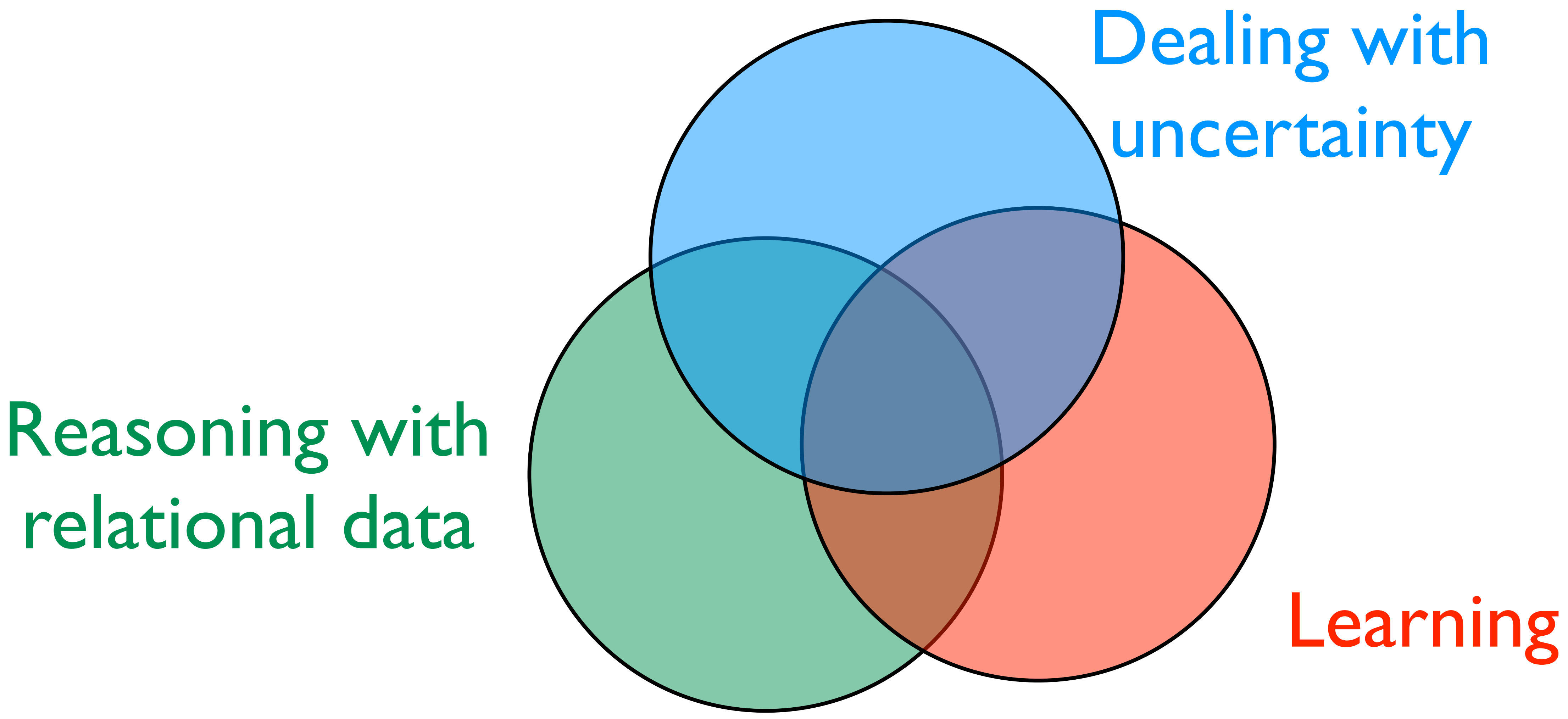
Roadmap

- Modeling
- Reasoning
- Learning
- Dynamics
- Decisions

Part 1 : Modeling

ProbLog

probabilistic Prolog



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

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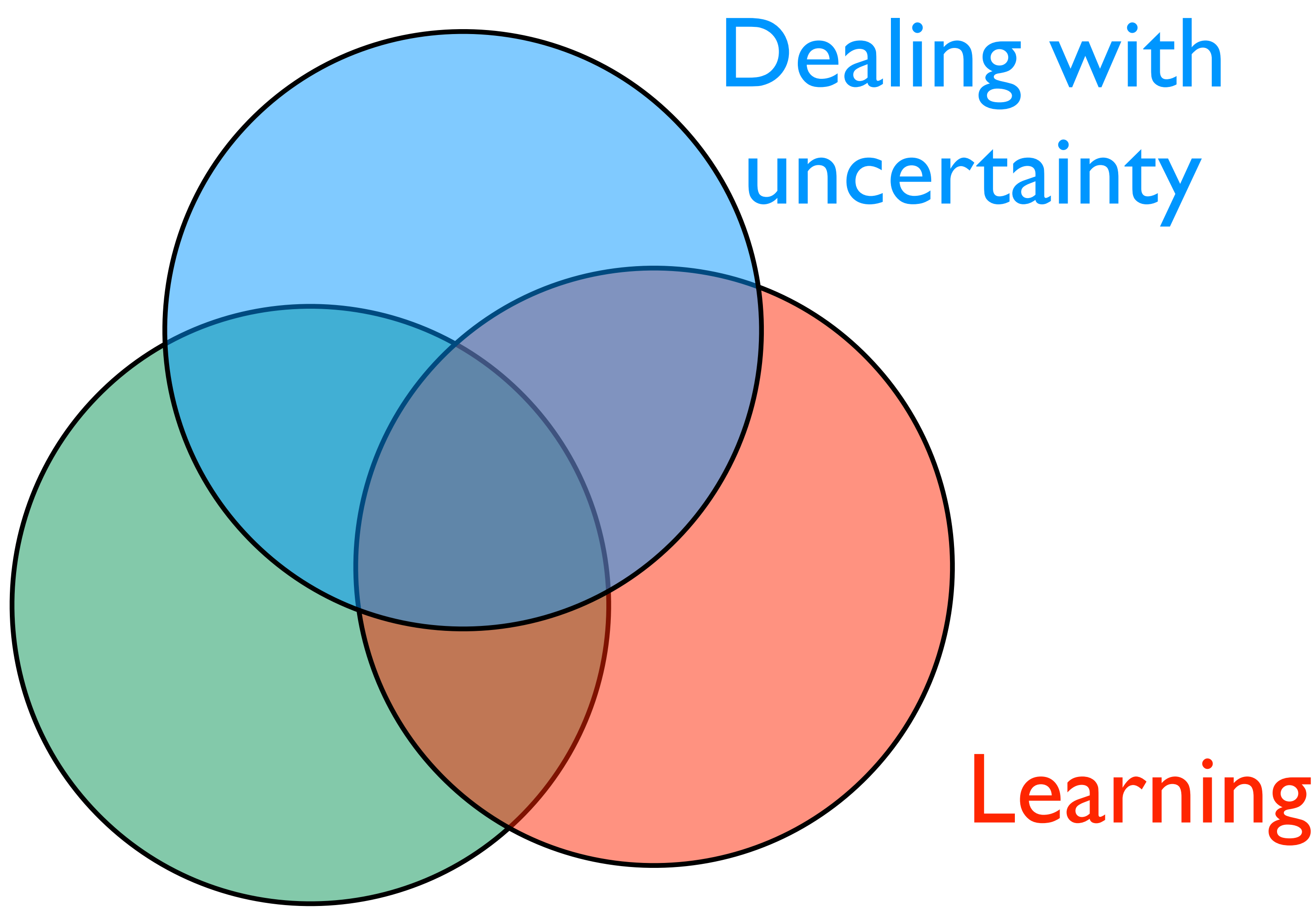


```
stress(ann).
influences(ann,bob).
influences(bob,carl).

smokes(X) :- stress(X).
smokes(X) :-
      influences(Y,X), smokes(Y).
```


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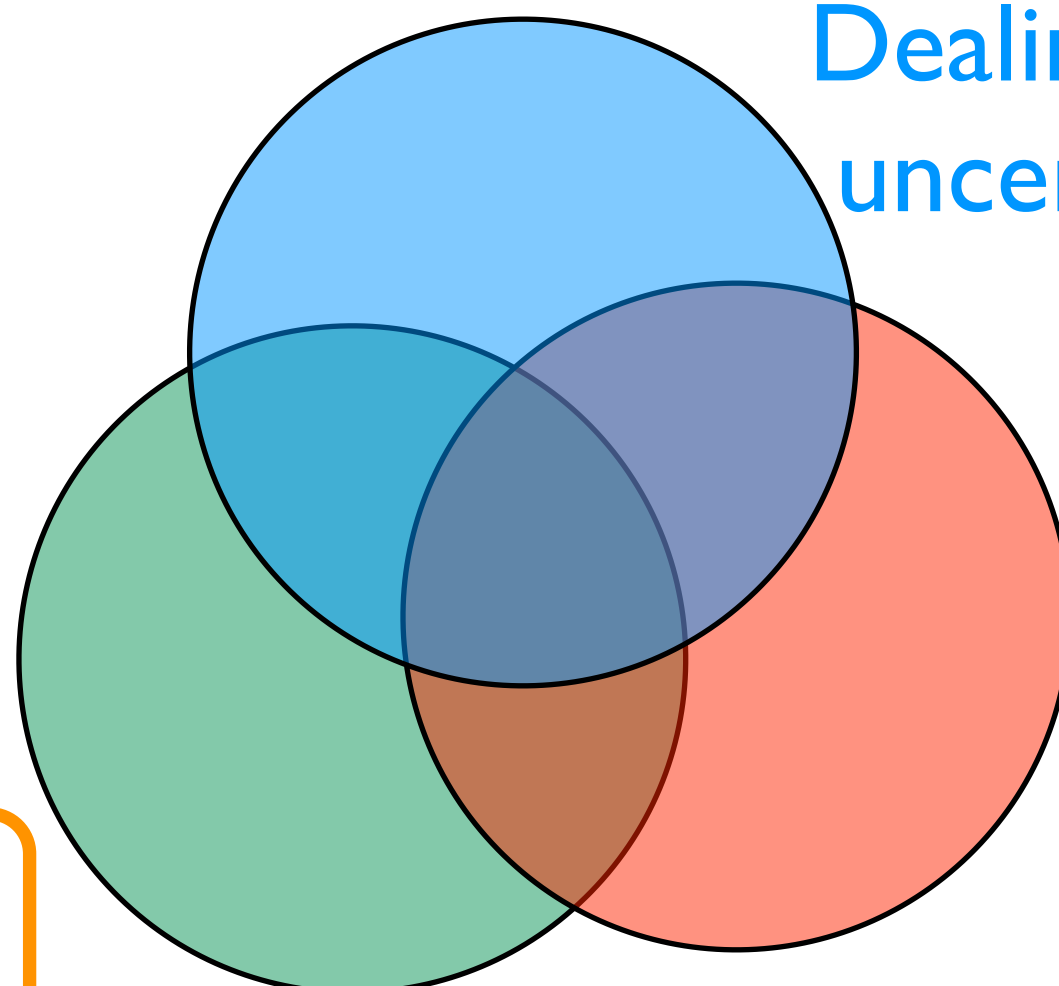
ProbLog

probabilistic Prolog

Dealing with uncertainty



Prolog / logic programming

Learning

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stress(ann).
influences(ann,bob).
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one world

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ProbLog

probabilistic Prolog

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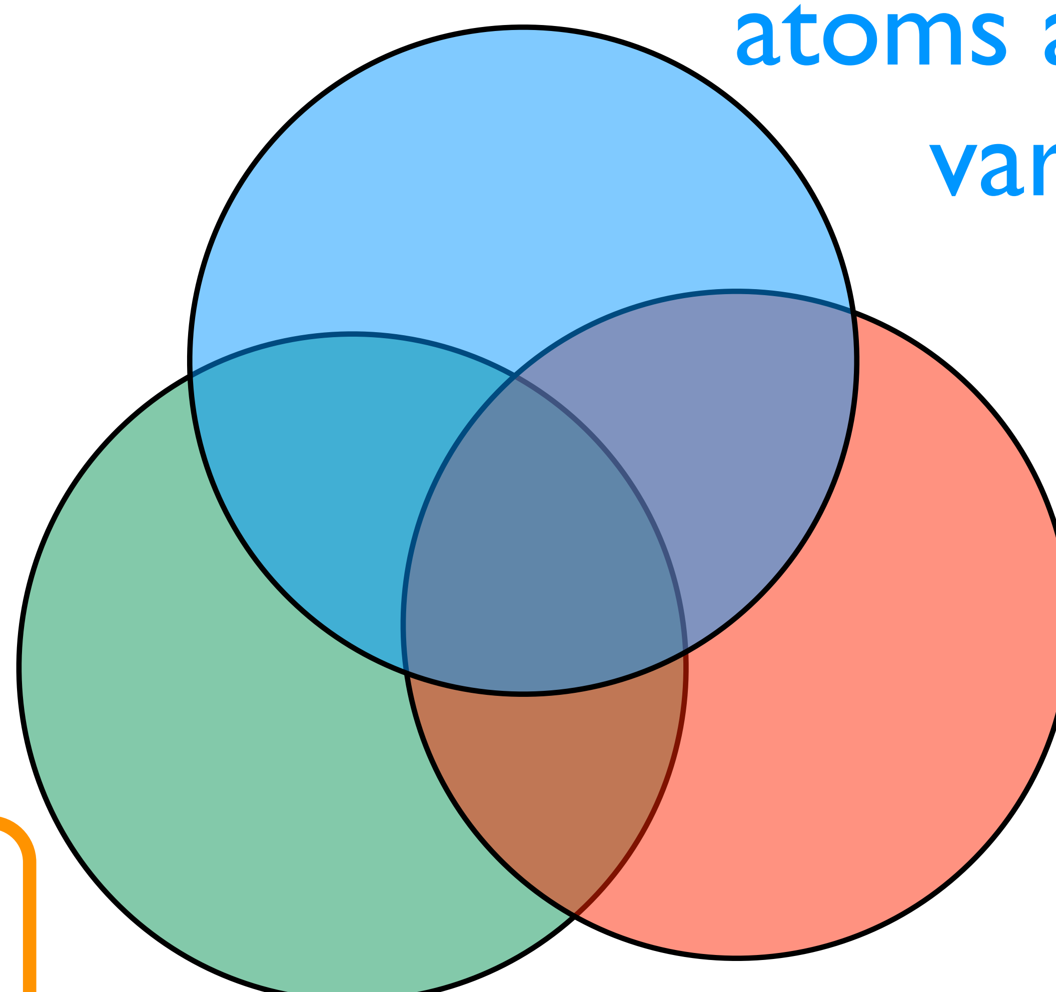
0.8::stress(ann).
0.6::influences(ann,bob).
0.2::influences(bob,carl).
```

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several possible worlds

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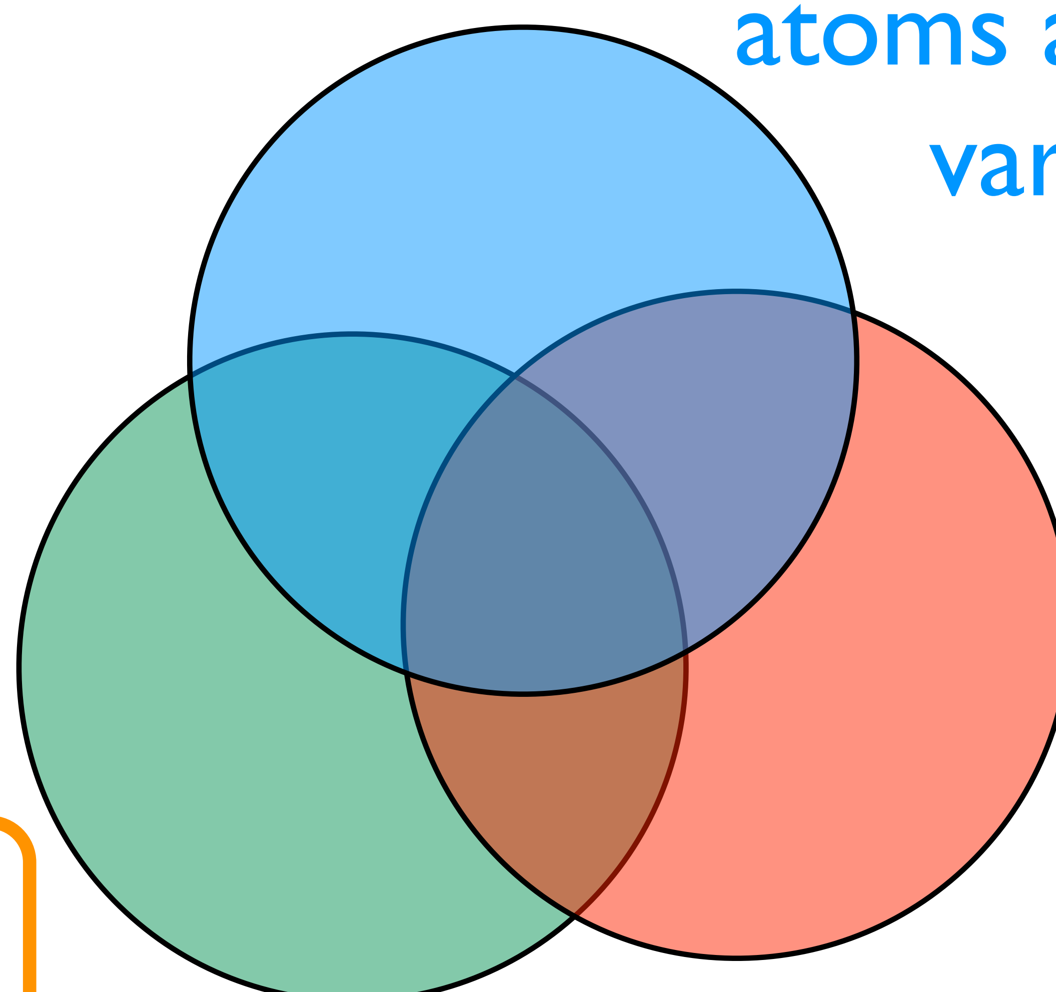
atoms as random variables



Prolog / logic programming

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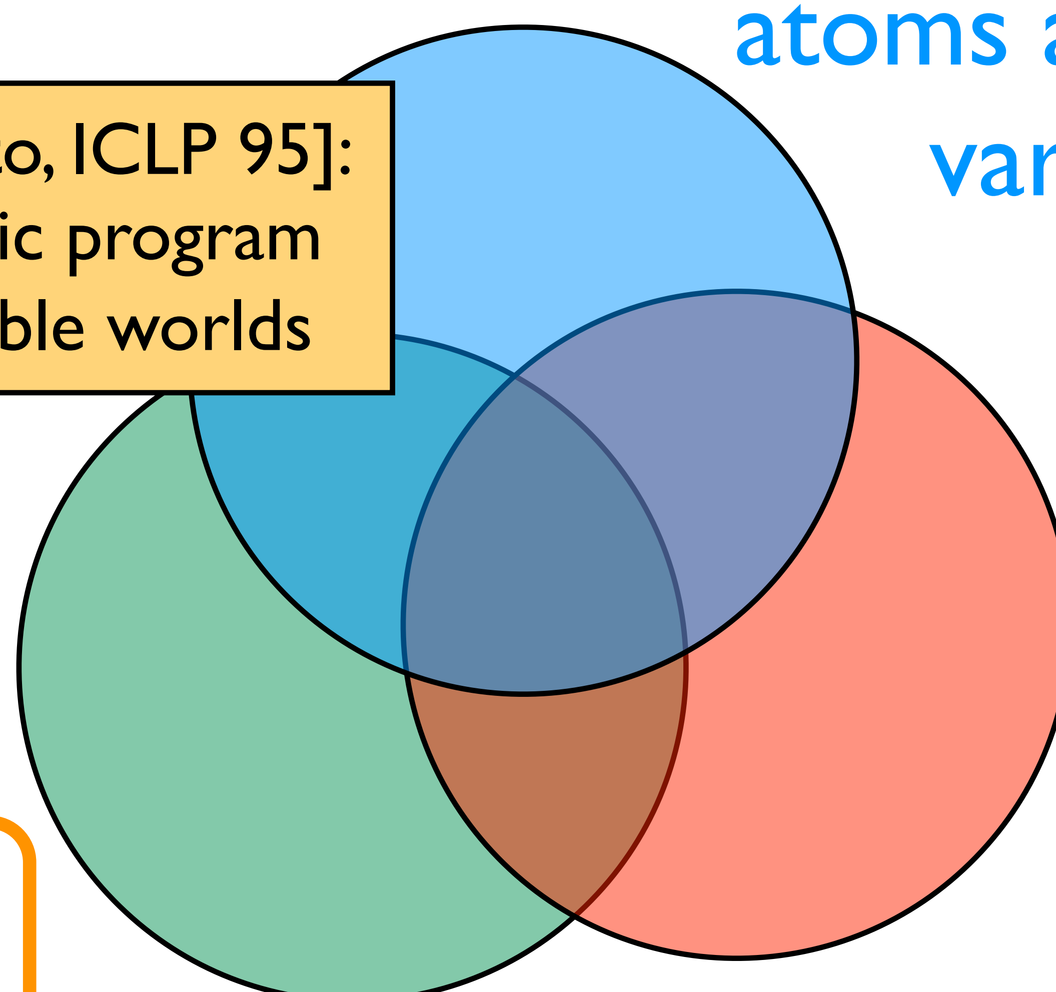
Distribution Semantics [Sato, ICLP 95]:
probabilistic choices + logic program
→ distribution over possible worlds



Prolog / logic programming

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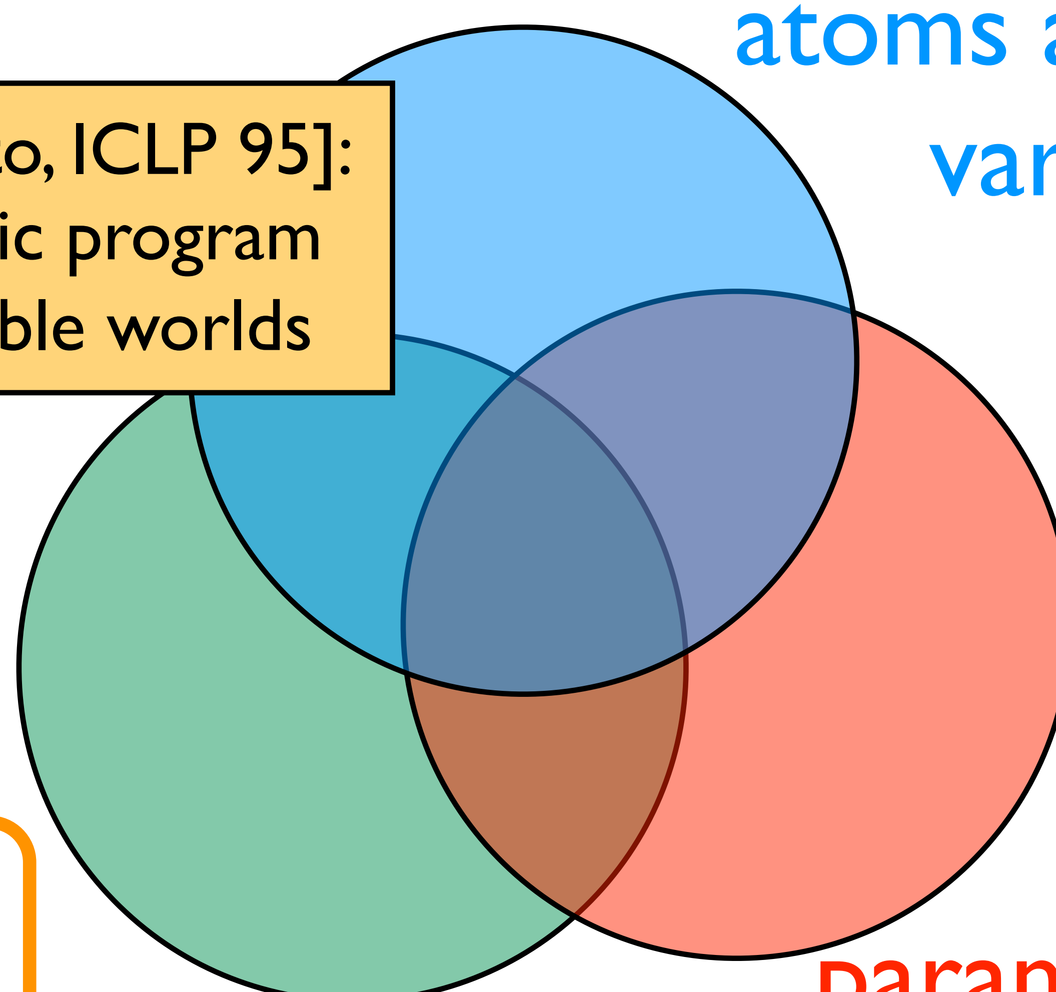

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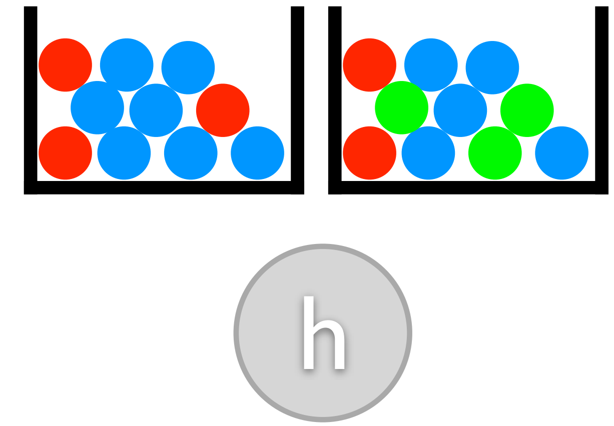
parameter learning, adapted relational learning techniques

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

ProbLog by example:

A bit of gambling



- toss (biased) coin & draw ball from each urn
- win if (heads and a red ball) or (two balls of same color)

ProbLog by example:

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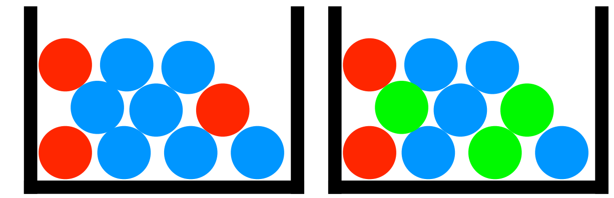

- toss (biased) coin & draw ball from each urn
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```
0.4 :: heads.
```

probabilistic fact: heads is true with probability 0.4 (and false with 0.6)

ProbLog by example:

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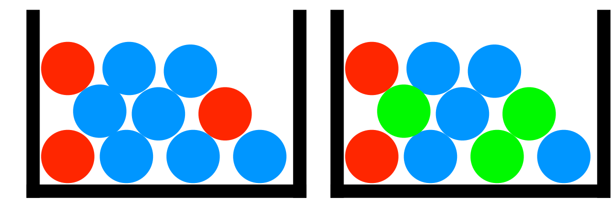

- toss (biased) coin & draw ball from each urn
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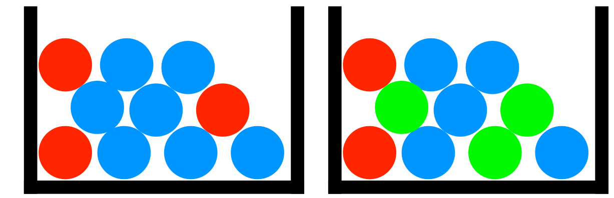
```
0.4 :: heads.
```

annotated disjunction: first ball is red with probability 0.3 and blue with 0.7

```
0.3 :: col(1,red); 0.7 :: col(1,blue).
```

ProbLog by example:

A bit of gambling



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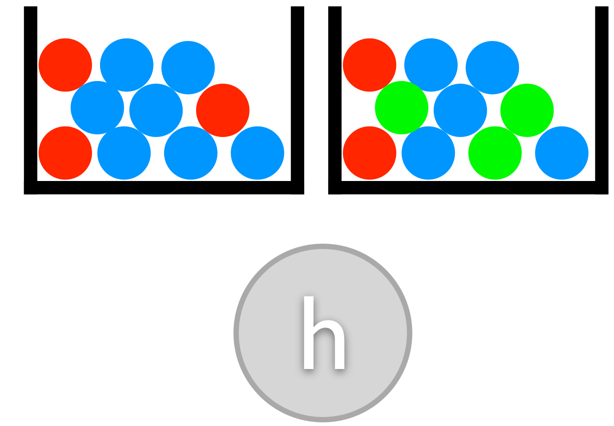
```

annotated disjunction: second ball is red with probability 0.2, green with 0.3, and blue with 0.5

ProbLog by example:

A bit of gambling



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win :- heads, col(_,red).
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logical rule encoding background knowledge

ProbLog by example:

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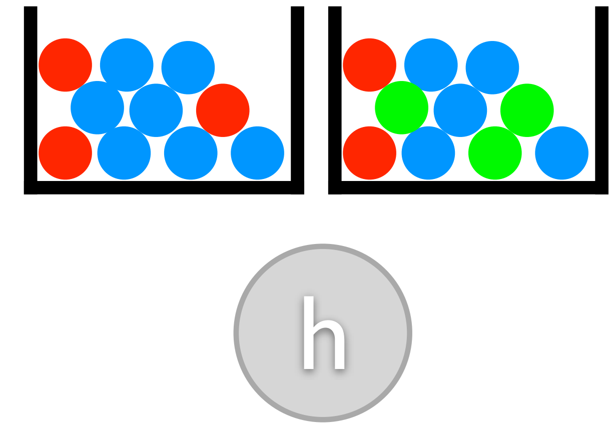

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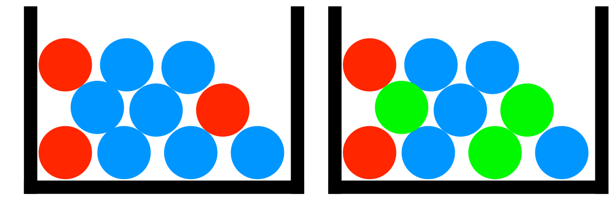
win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

logical rule encoding background knowledge

ProbLog by example:

A bit of gambling



- toss (biased) coin & draw ball from each urn
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probabilistic choices

```
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0.2 :: col(2,red); 0.3 :: col(2,green);
                   0.5 :: col(2,blue).
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```
win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

consequences

Questions

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

- Probability of **`win`**?
- Probability of **`win`** given **`col(2,green)`**?
- Most probable world where **`win`** is true?

Questions

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

marginal probability

- Probability of **`win`**?

query

- Probability of **`win`** given **`col(2,green)`**?
- Most probable world where **`win`** is true?

Questions

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

marginal probability

- Probability of **`win`**?

conditional probability

- Probability of **`win`** given `col(2,green)`?

evidence

- Most probable world where **`win`** is true?

Questions

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

marginal probability

- Probability of `win`?

conditional probability

- Probability of `win` given `col(2,green)`?

- Most probable world where `win` is true?

MPE inference

Possible Worlds

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

Possible Worlds

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
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win :- heads, col(_,red).
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```

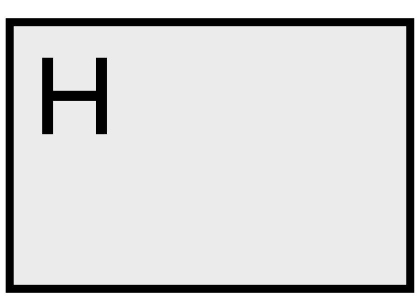
Possible Worlds

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

0.4



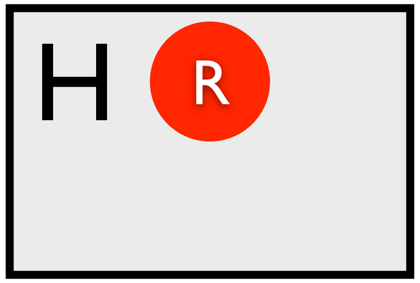
Possible Worlds

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

0.4 ×0.3



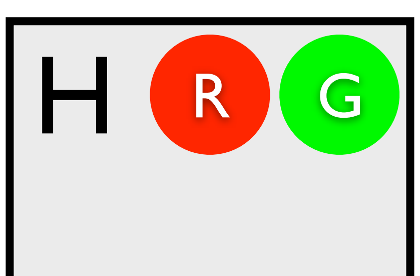
Possible Worlds

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

$0.4 \times 0.3 \times 0.3$



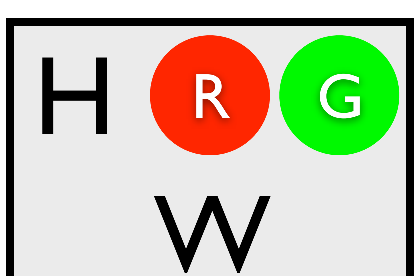
Possible Worlds

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

$0.4 \times 0.3 \times 0.3$



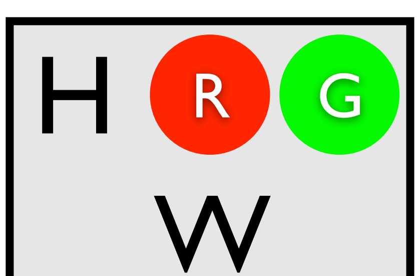
Possible Worlds

```
0.4 :: heads.

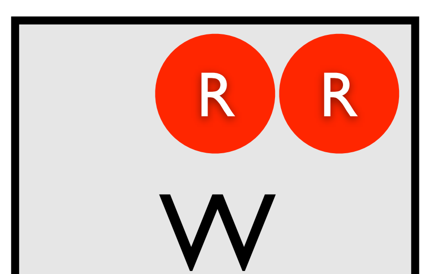
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

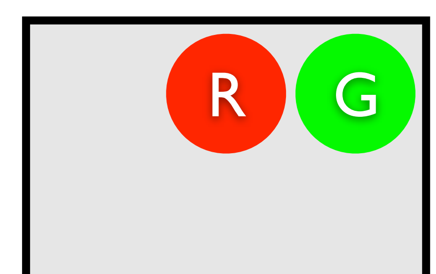
$0.4 \times 0.3 \times 0.3$



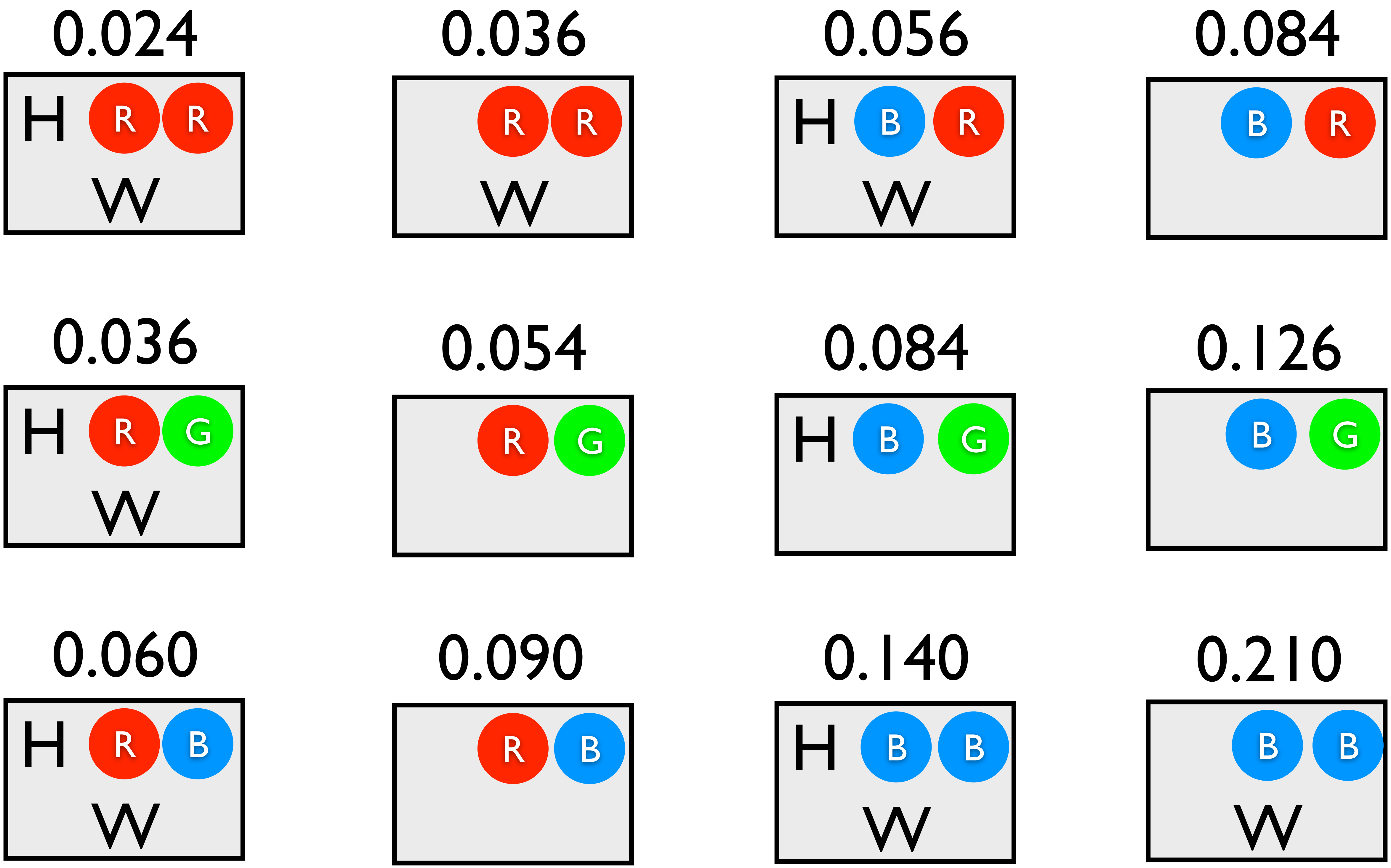
$(1-0.4) \times 0.3 \times 0.2$



$(1-0.4) \times 0.3 \times 0.3$

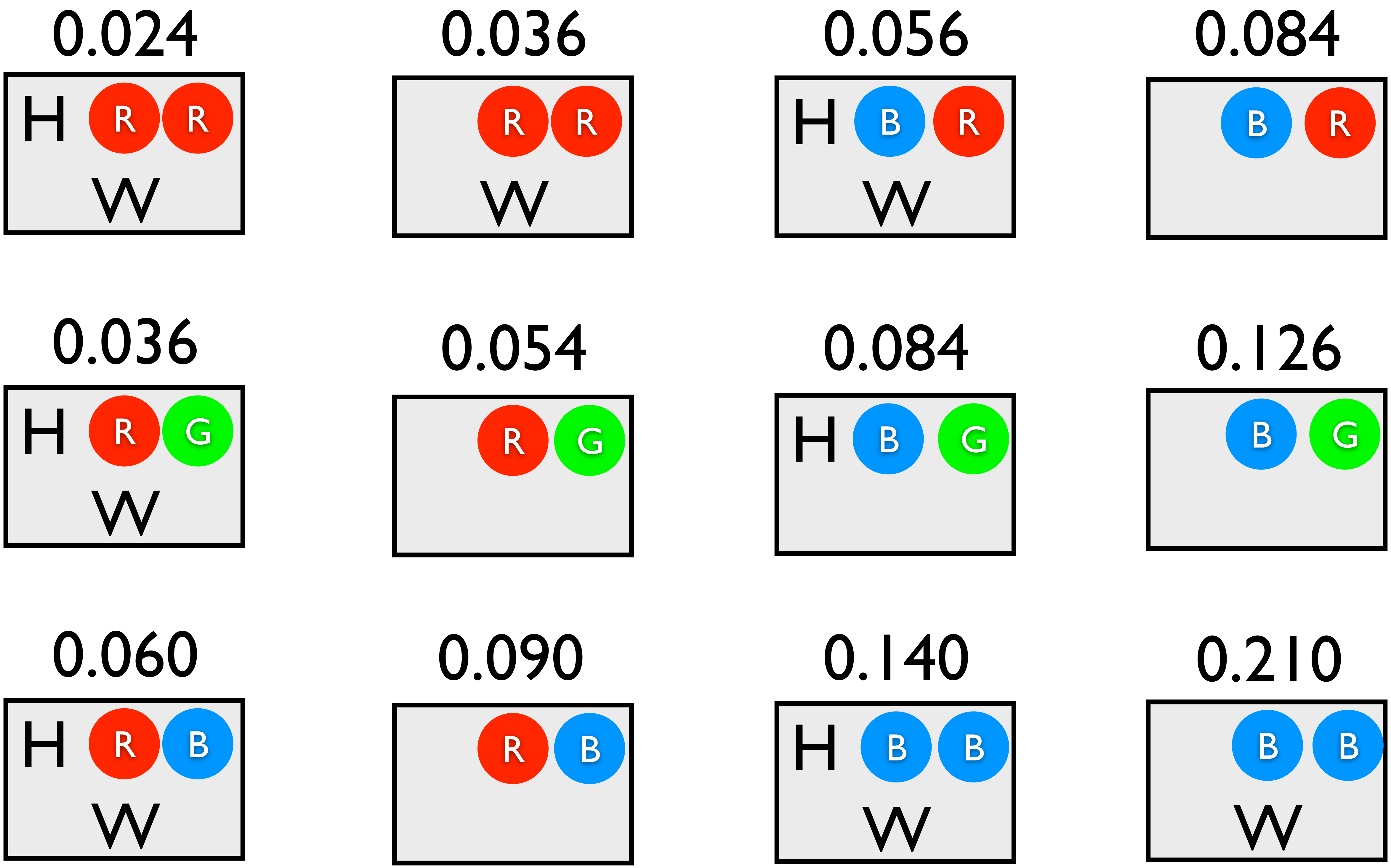


All Possible Worlds



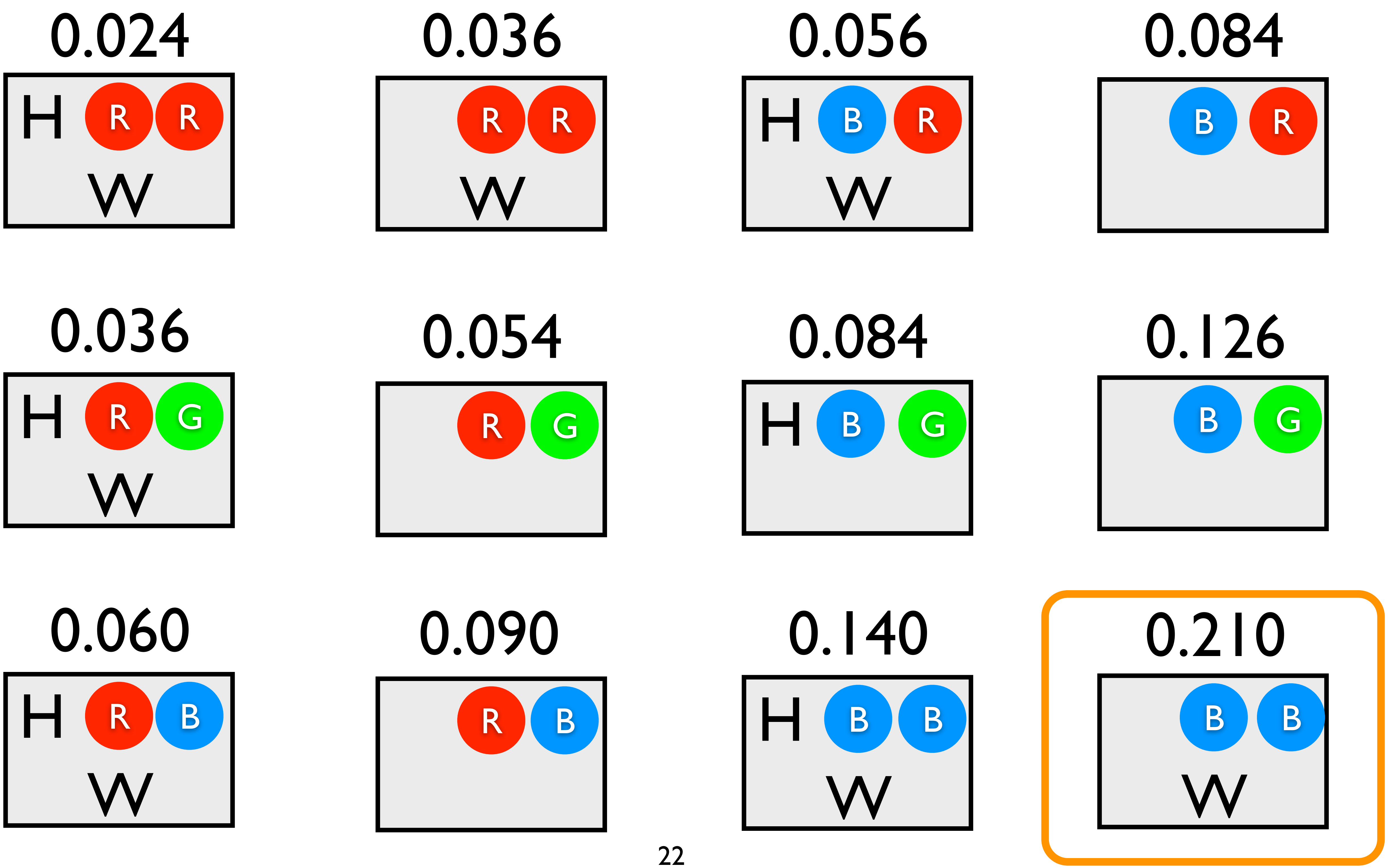
Most likely world where **`win`** is true?

MPE Inference



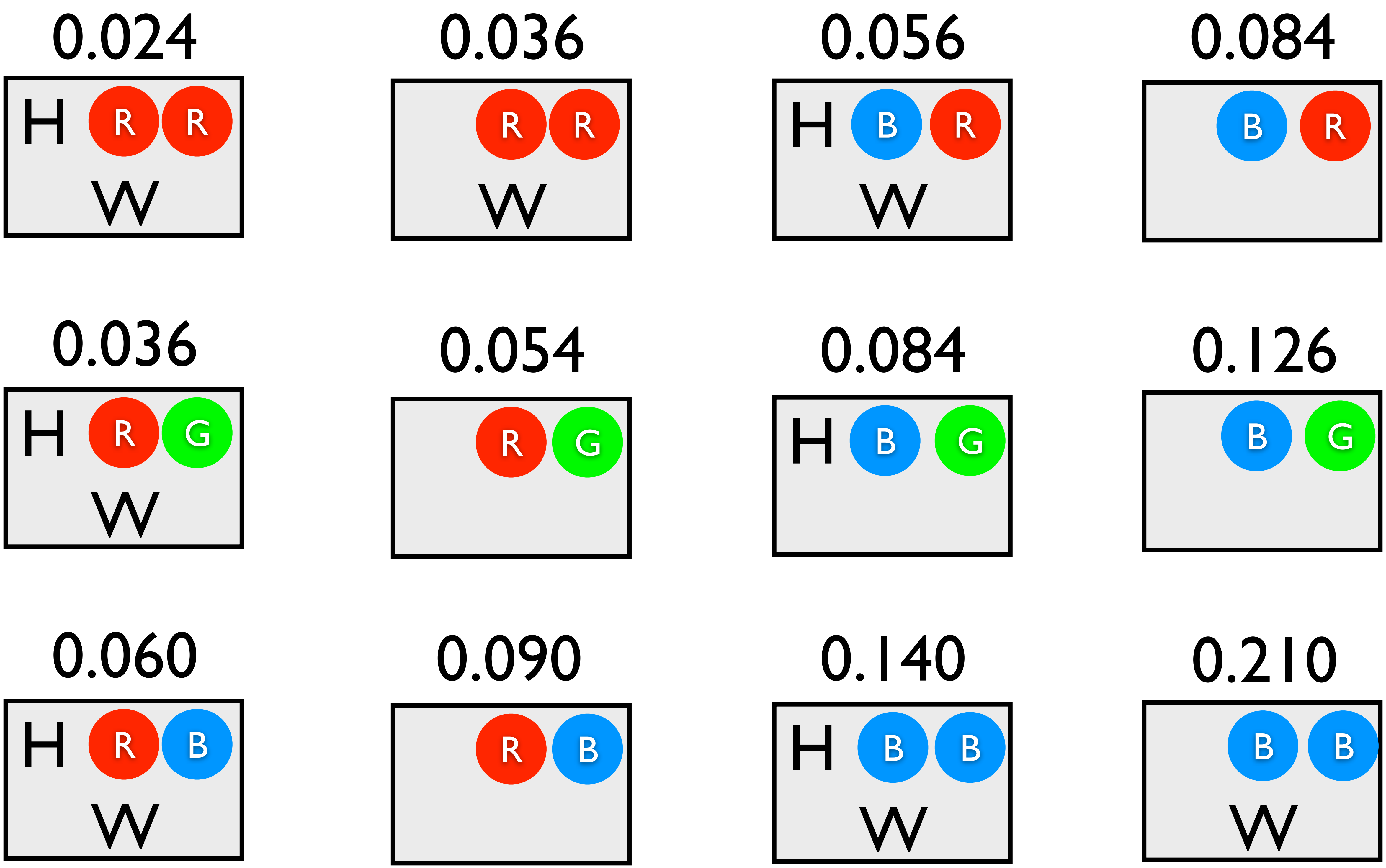
Most likely world where **win** is true?

MPE Inference



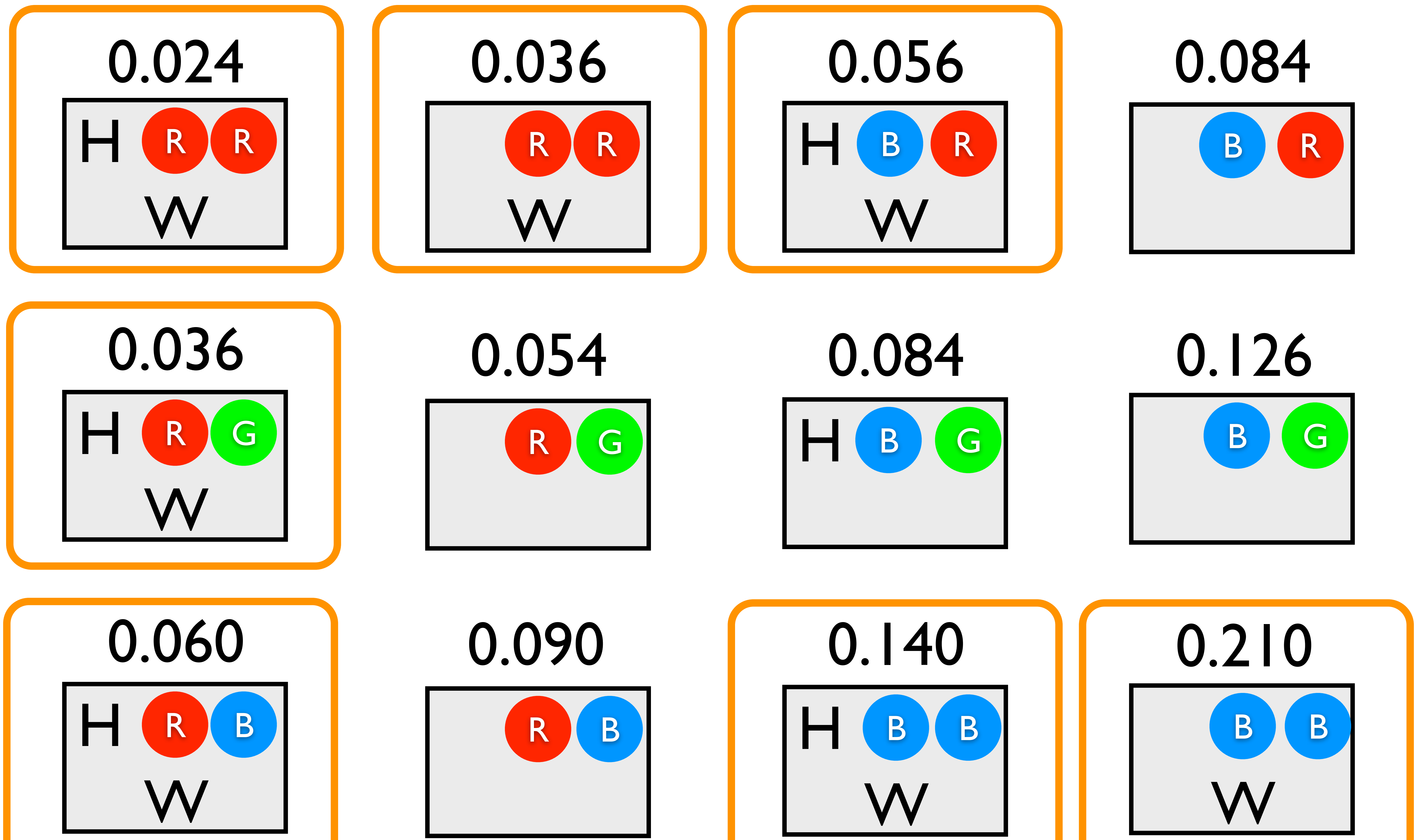
P(win)= ?

Marginal Probability



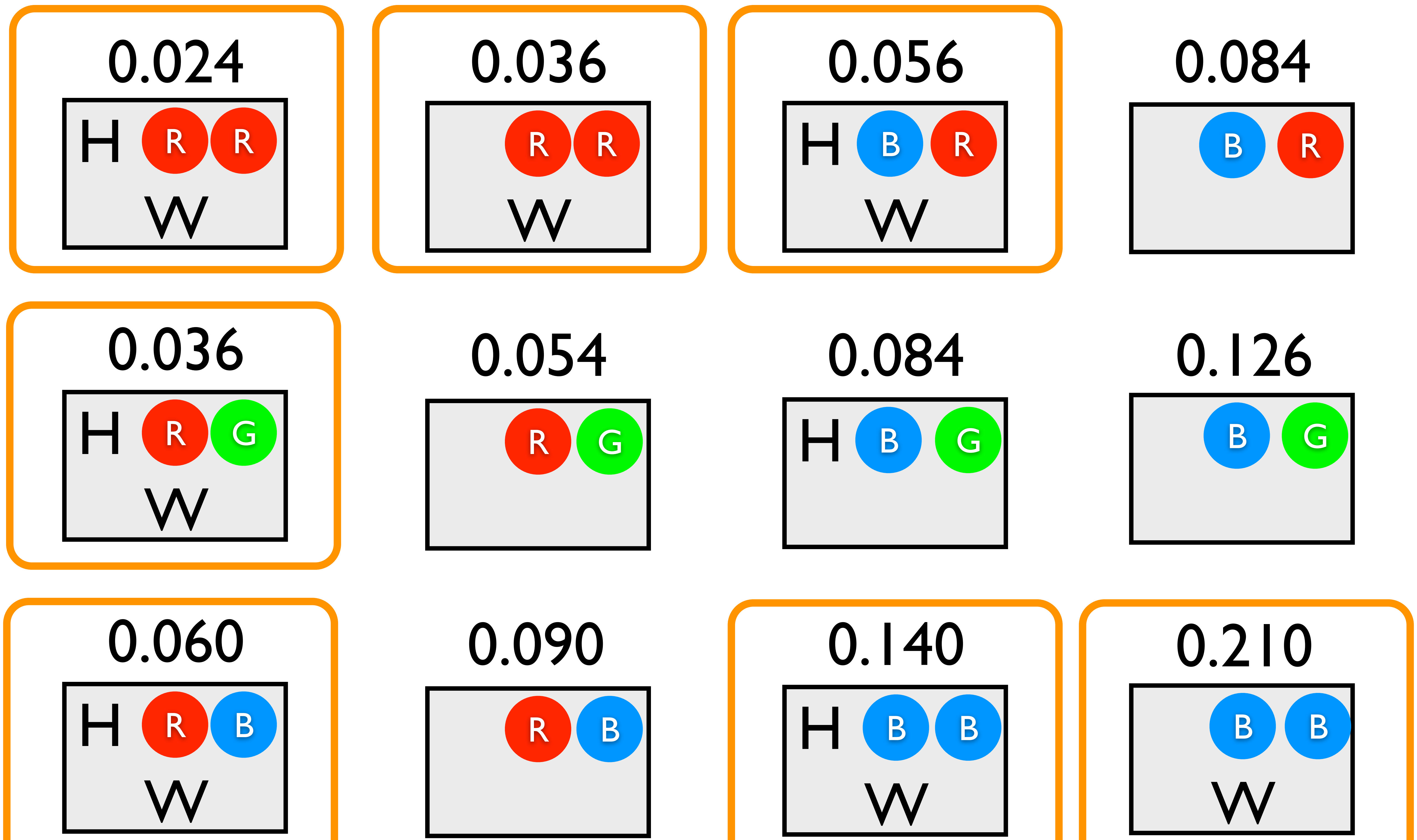
$P(\underline{win}) = \sum$

Marginal Probability



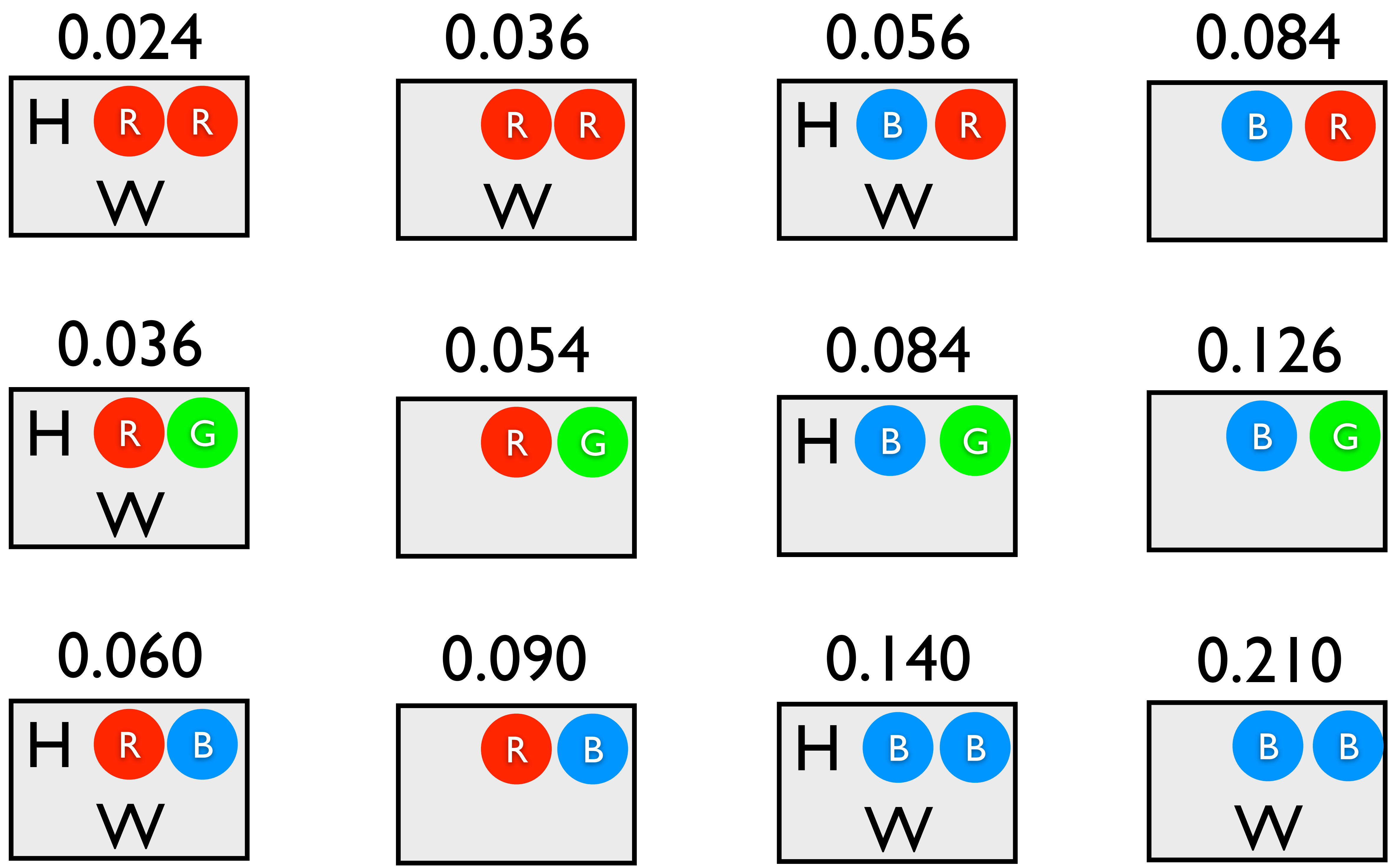
$P(\underline{win}) = \Sigma = 0.562$

Marginal Probability



P(win|col(2,green))= ?

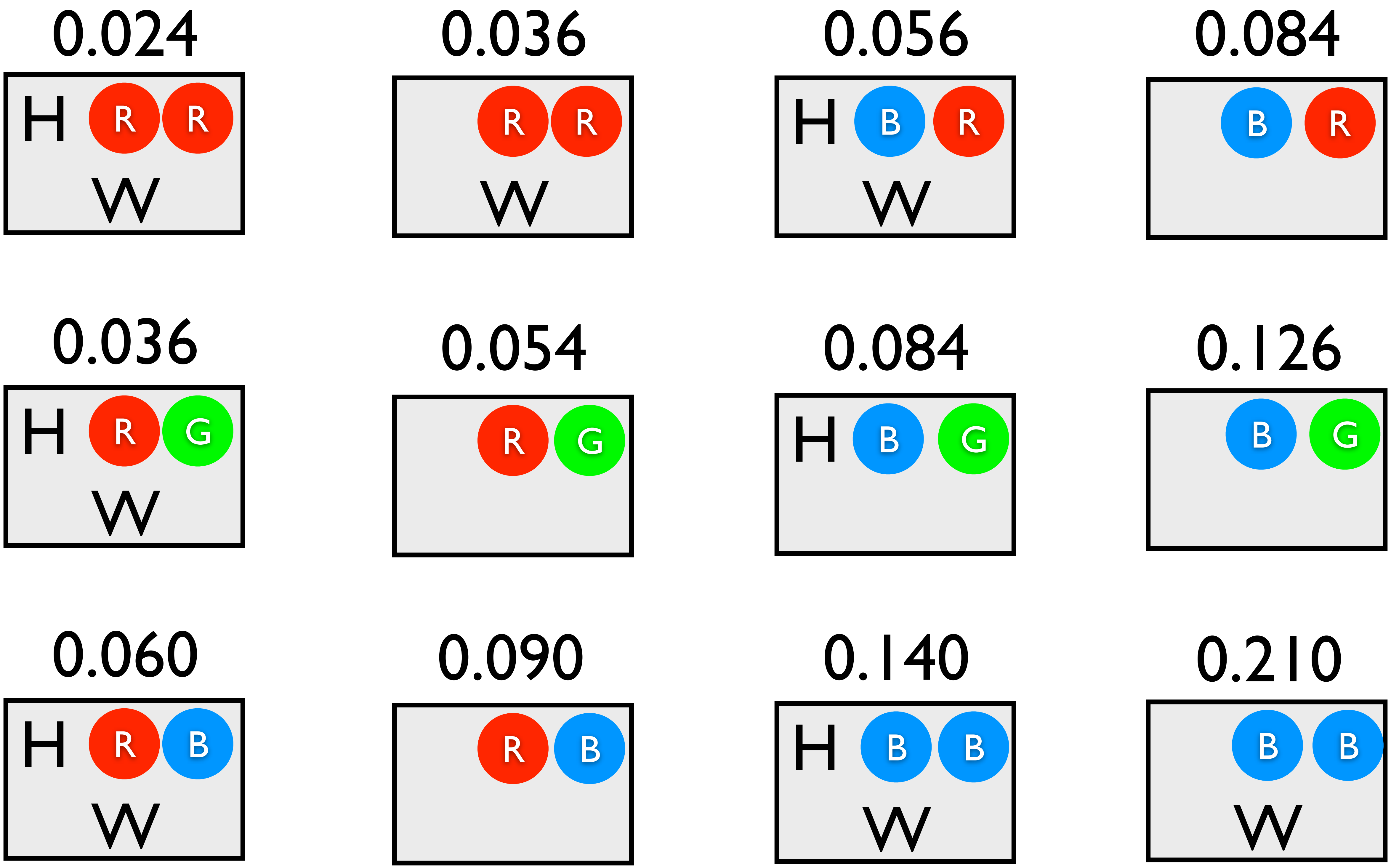
Conditional Probability



Conditional Probability

$$P(win|col(2,green)) = \Sigma/\Sigma$$

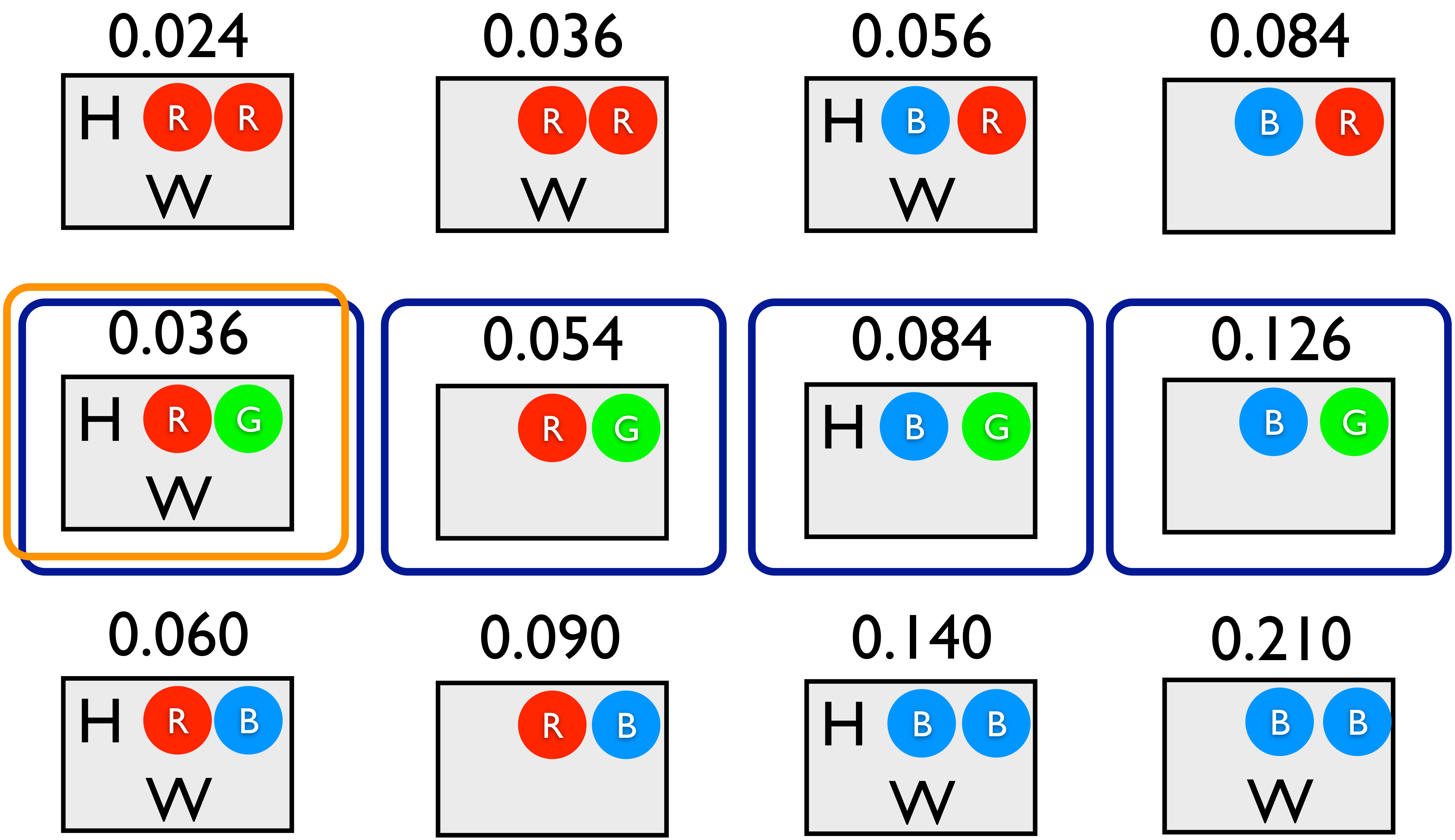
$$= P(win \wedge col(2,green))/P(col(2,green))$$



Conditional Probability

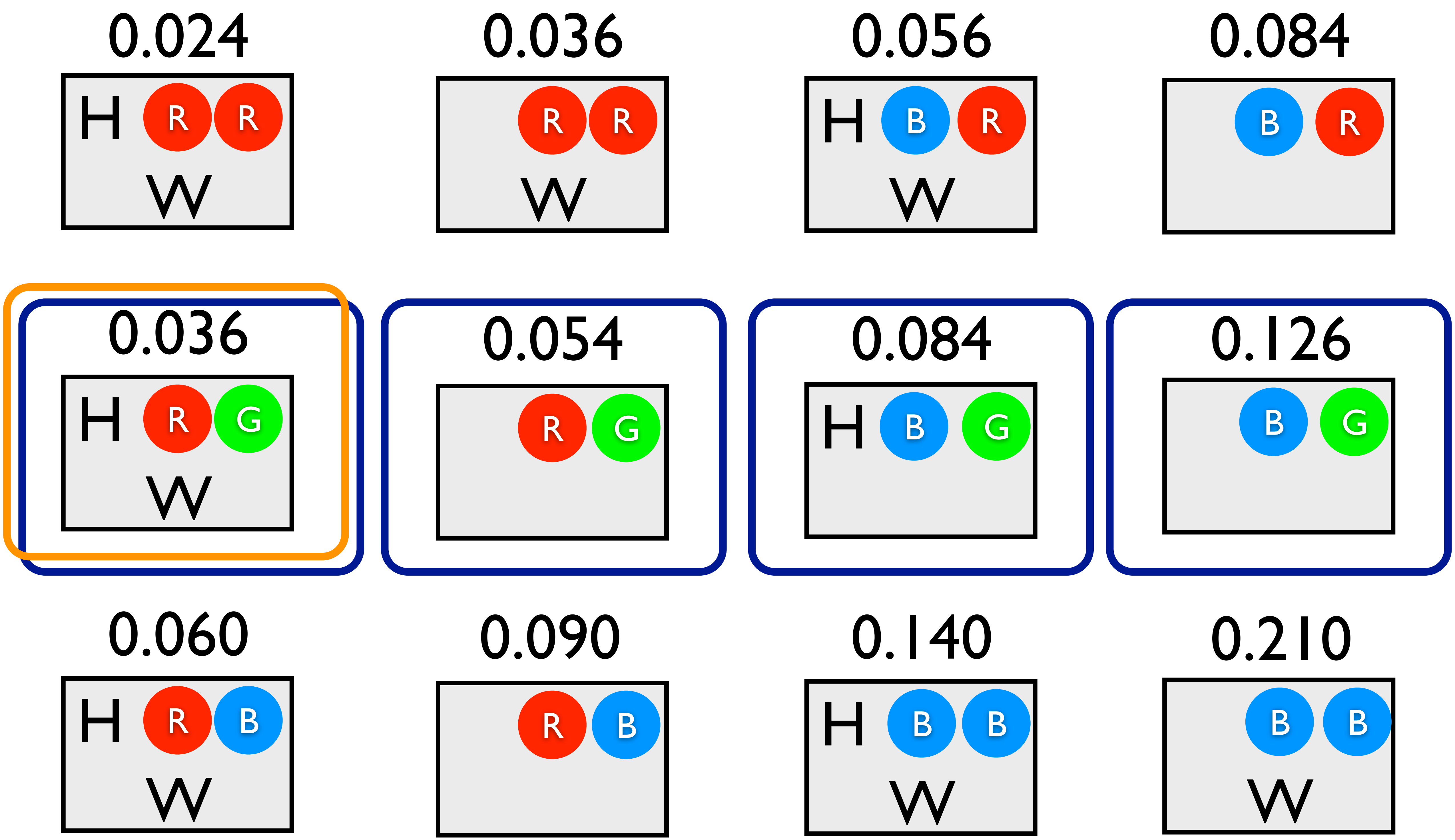
$P(win|col(2,green)) = \sum / \sum$

$= P(win \wedge col(2,green)) / P(col(2,green))$



$$P(win|col(2,green)) = \sum / \sum = 0.036/0.3 = 0.12$$

Conditional Probability



Distribution Semantics

(with probabilistic facts)

[Sato, ICLP 95]

query

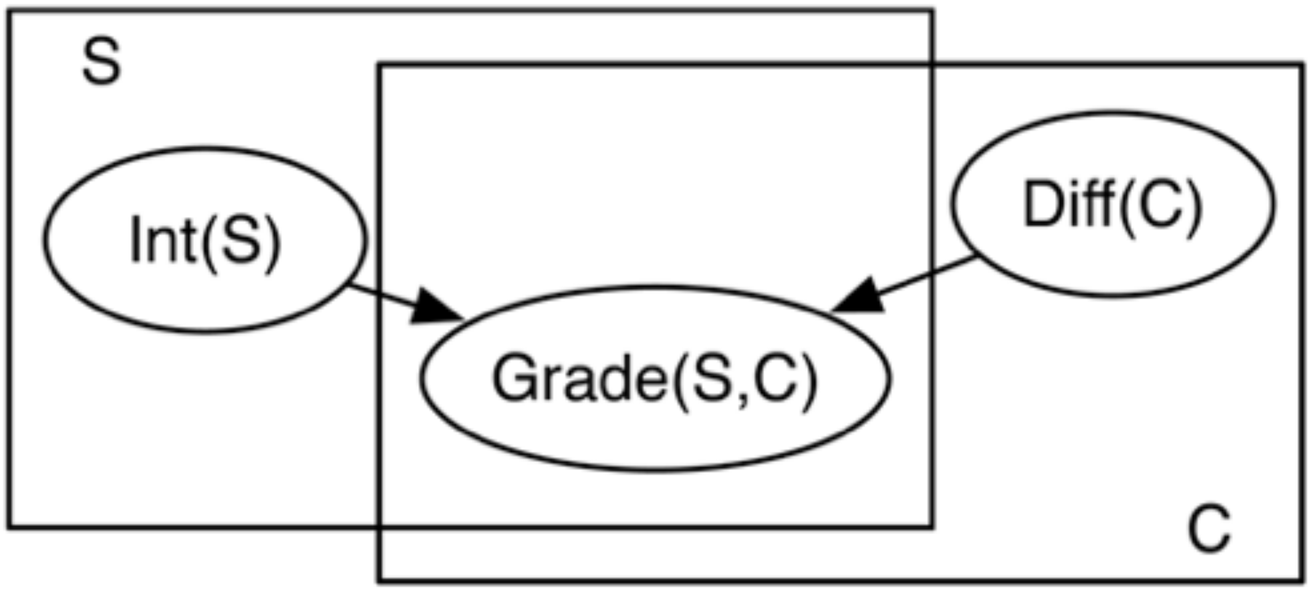
sum over possible worlds where Q is true

$$P(Q) = \sum_{F \cup R \models Q} \underbrace{\prod_{f \in F} p(f) \prod_{f \notin F} 1 - p(f)}_{\text{probability of possible world}}$$

subset of probabilistic facts

Prolog rules

Flexible and Compact Relational Model for Predicting Grades



"Program" Abstraction:

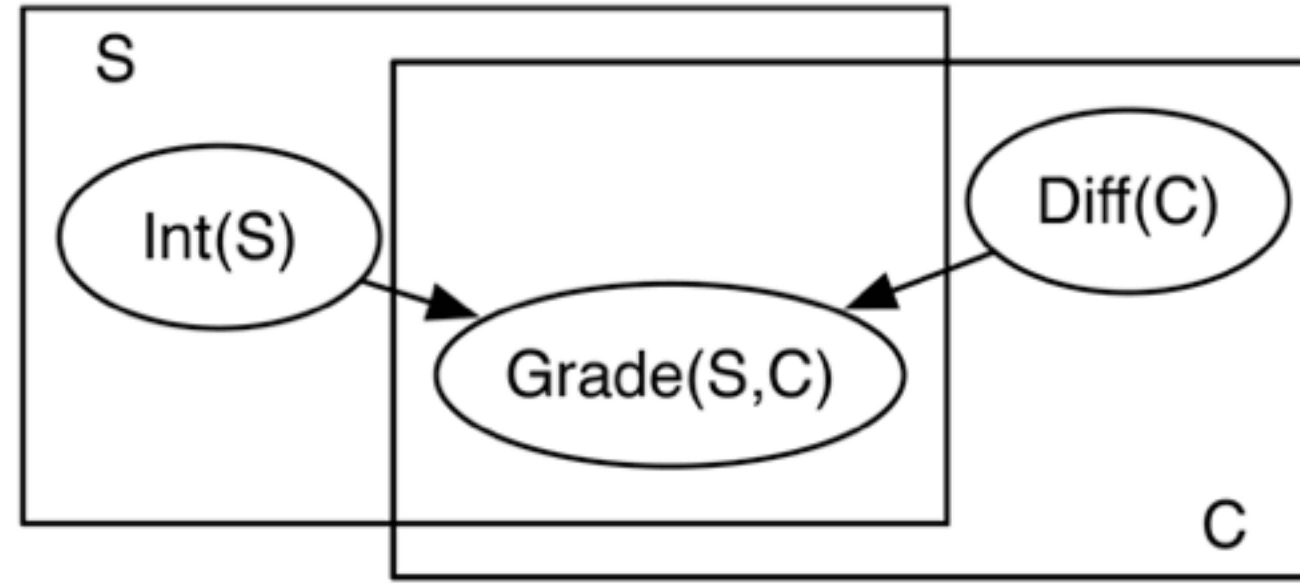
- S, C logical variable representing students, courses
- the set of individuals of a type is called a population
- Int(S), Grade(S, C), D(C) are parametrized random variables

Grounding:

- for every student s, there is a random variable Int(s)
- for every course c, there is a random variable Di(c)
- for every s, c pair there is a random variable Grade(s,c)
- all instances share the same structure and parameters

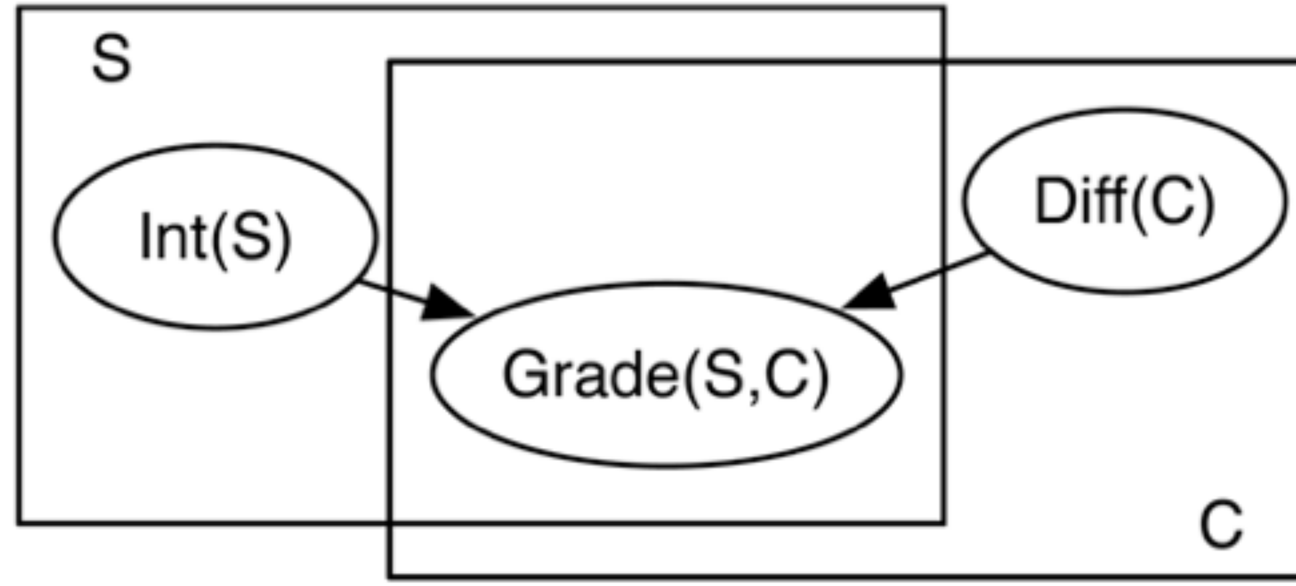
ProbLog by example:

Grading



ProbLog by example:

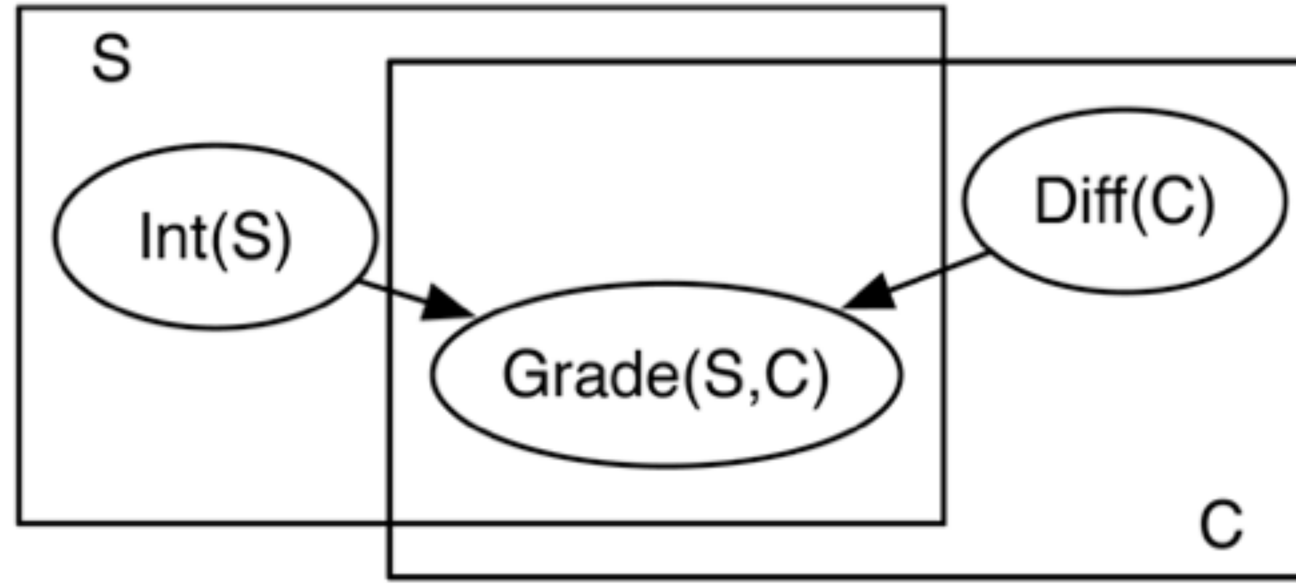
Grading




```
0.4 :: int(S) :- student(S).
```

ProbLog by example:

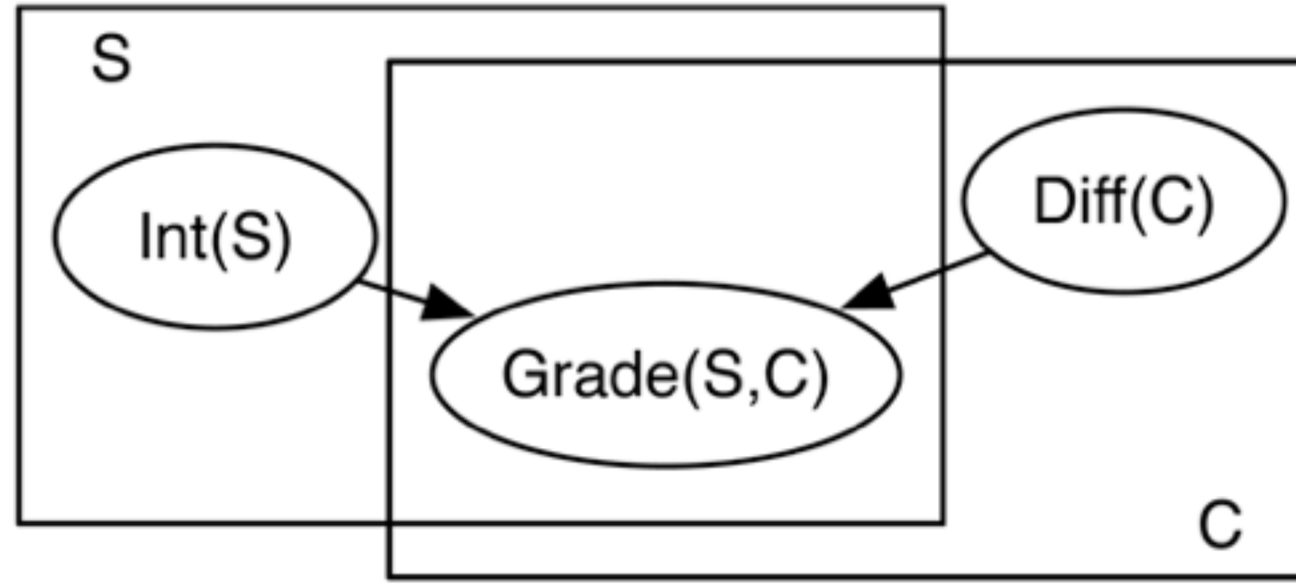
Grading




```
0.4 :: int(S) :- student(S).
0.5 :: diff(C):- course(C).
```

ProbLog by example:

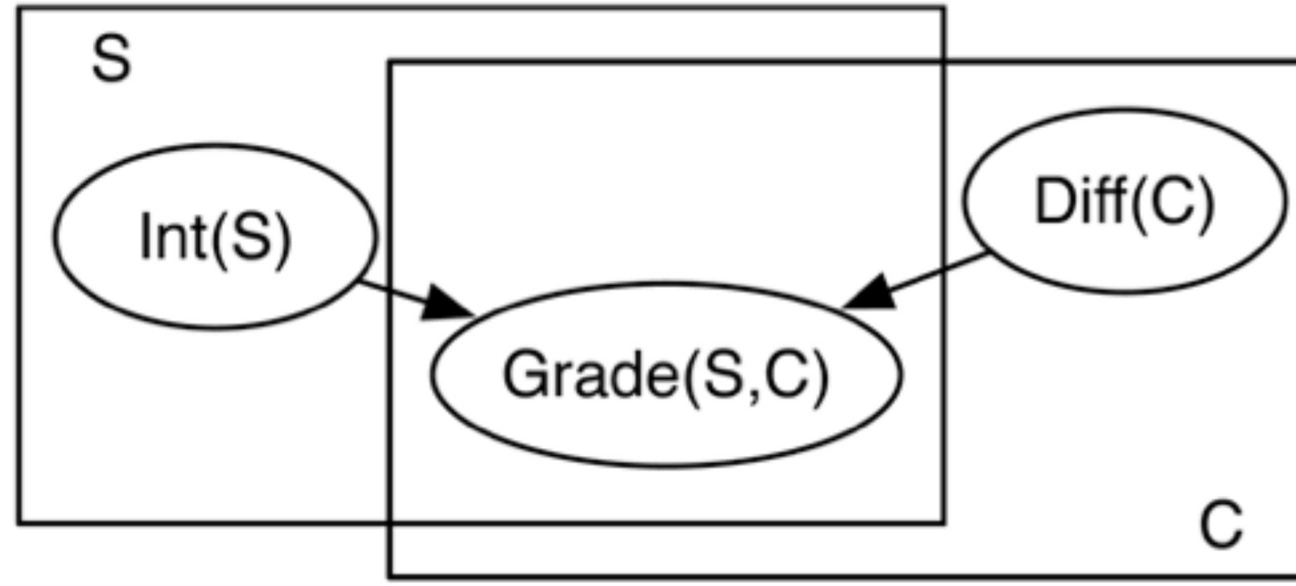
Grading




```
0.4 :: int(S) :- student(S).
0.5 :: diff(C):- course(C).
```

ProbLog by example:

Grading

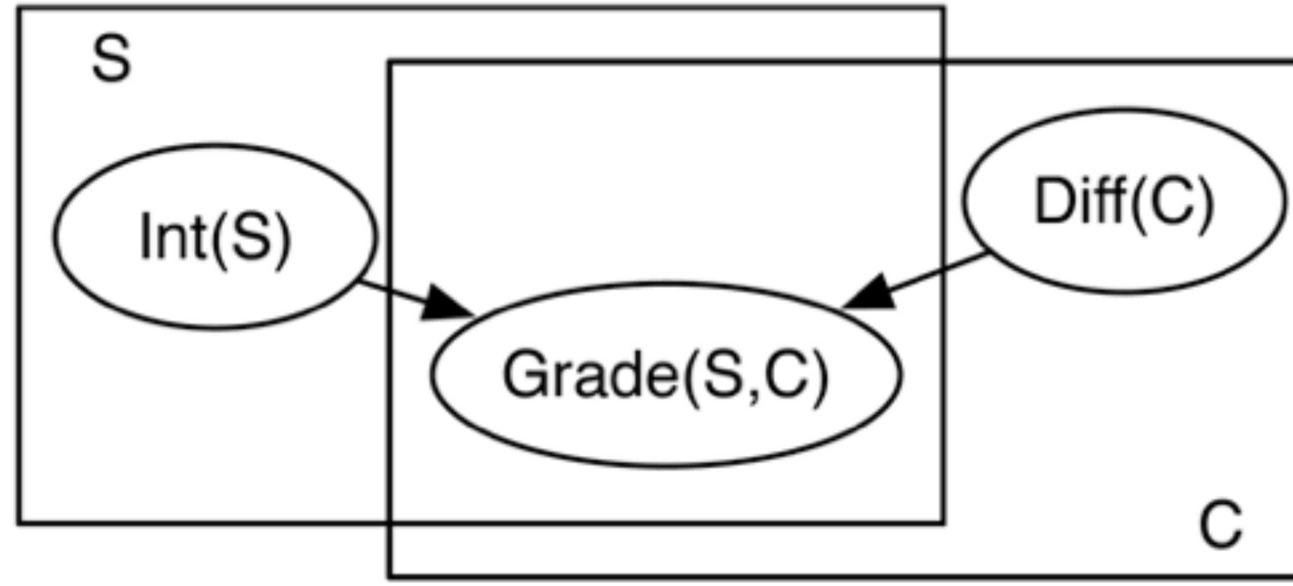



```
0.4 :: int(S) :- student(S).
0.5 :: diff(C):- course(C).

student(john). student(anna). student(bob).
```

ProbLog by example:

Grading

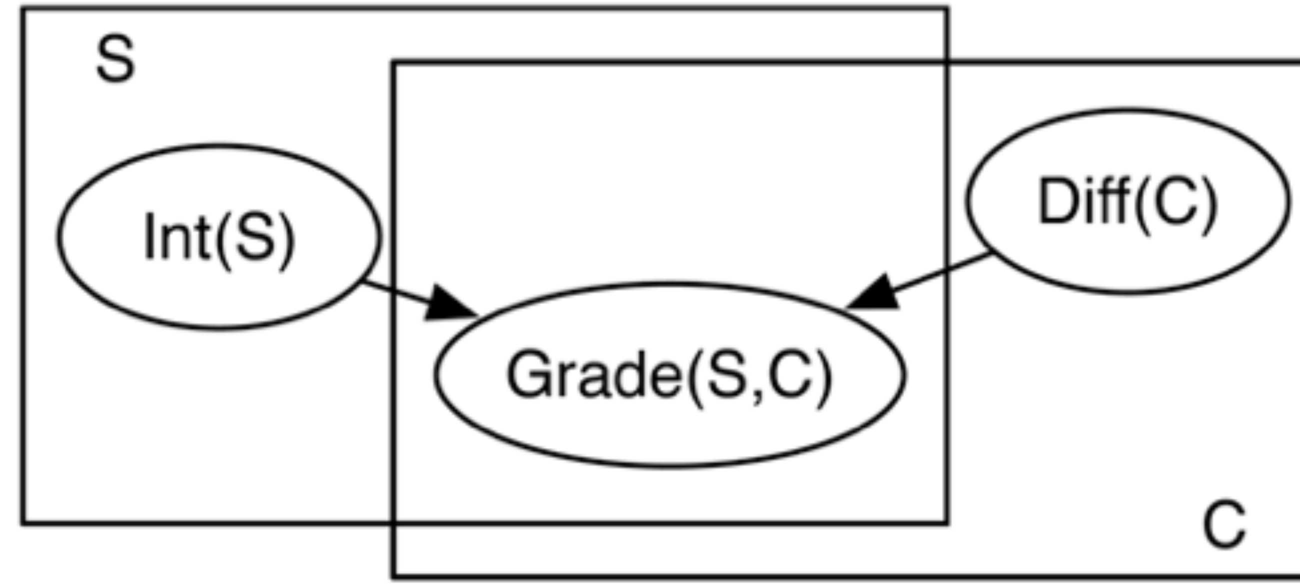



```
0.4 :: int(S) :- student(S).
0.5 :: diff(C):- course(C).

student(john). student(anna). student(bob).
course(ai).    course(ml).    course(cs).
```

ProbLog by example:

Grading

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ProbLog by example:

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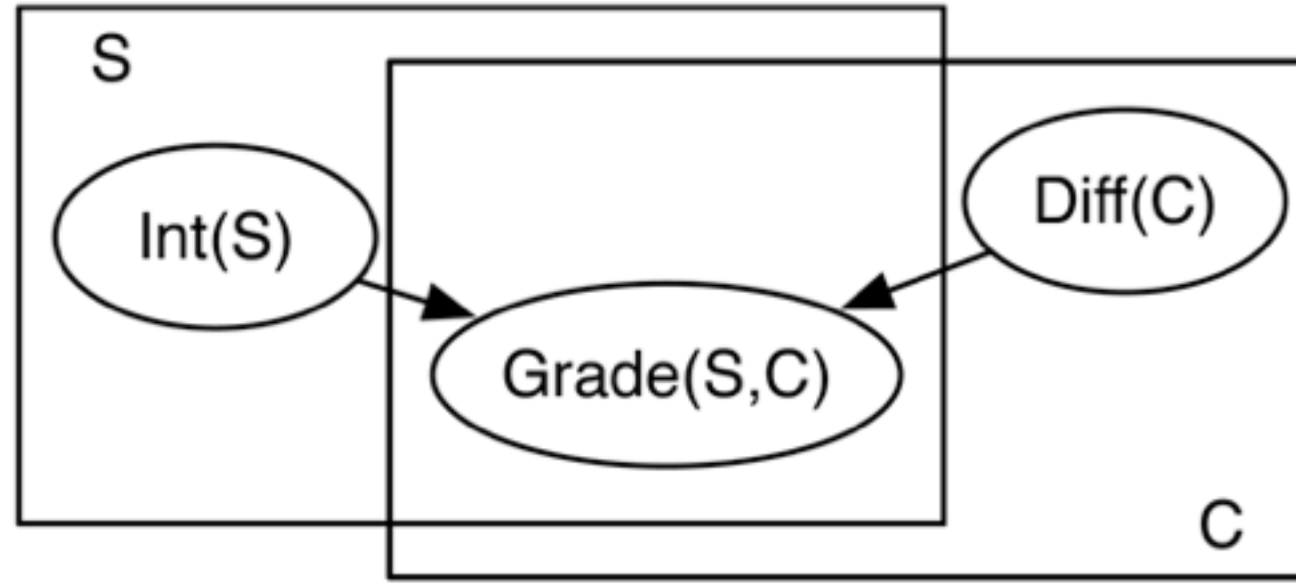


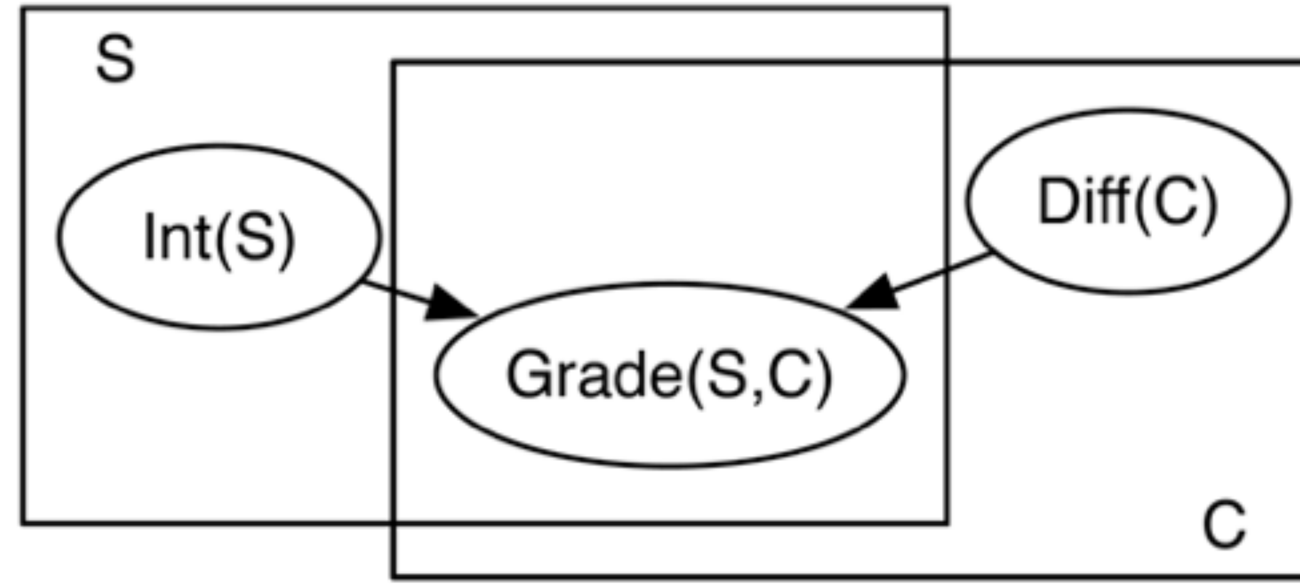

```
0.4 :: int(S) :- student(S).
0.5 :: diff(C):- course(C).

student(john). student(anna). student(bob).
course(ai).    course(ml).    course(cs).

gr(S,C,a) :- int(S), not diff(C).
```

ProbLog by example:

Grading

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0.4 :: int(S) :- student(S).
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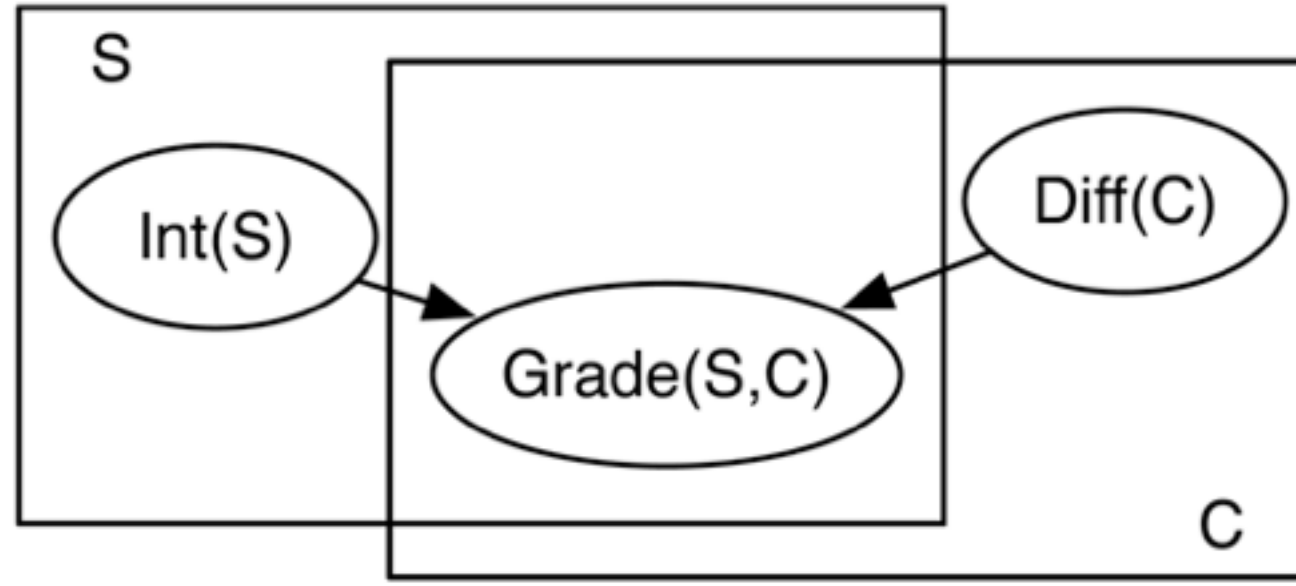
student(john). student(anna). student(bob).
course(ai).    course(ml).    course(cs).

gr(S,C,a) :- int(S), not diff(C).
0.3::gr(S,C,a); 0.5::gr(S,C,b);0.2::gr(S,C,c) :-
```

ProbLog by example:

Grading

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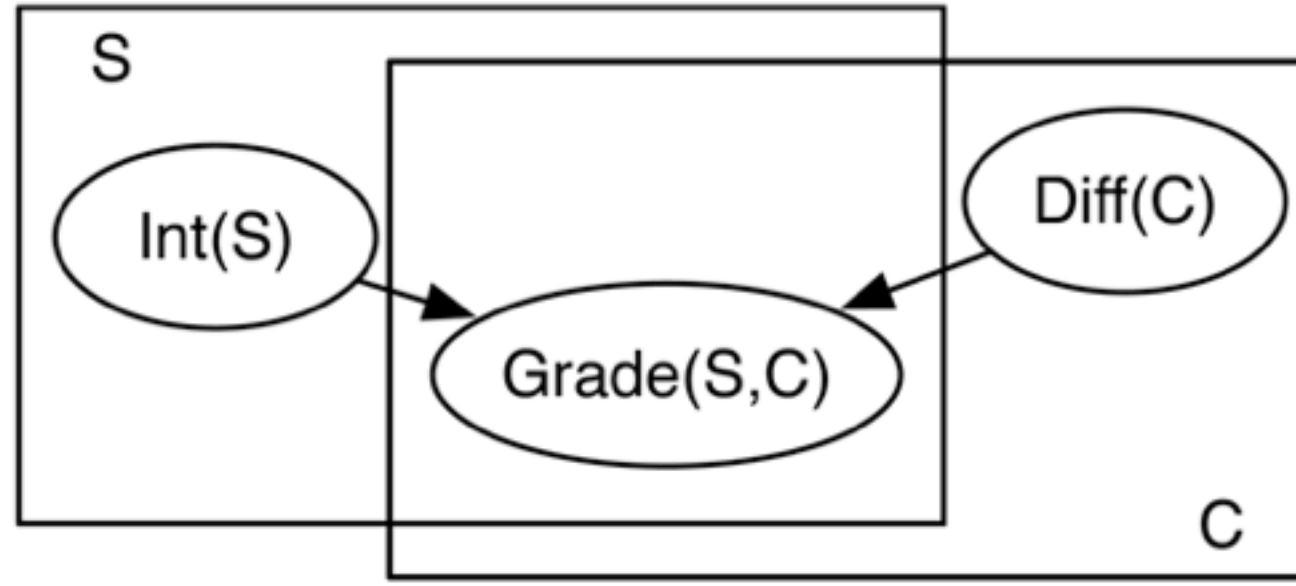
0.3::gr(S,C,a); 0.5::gr(S,C,b);0.2::gr(S,C,c) :-
          int(S), diff(C).
```

ProbLog by example:

Grading

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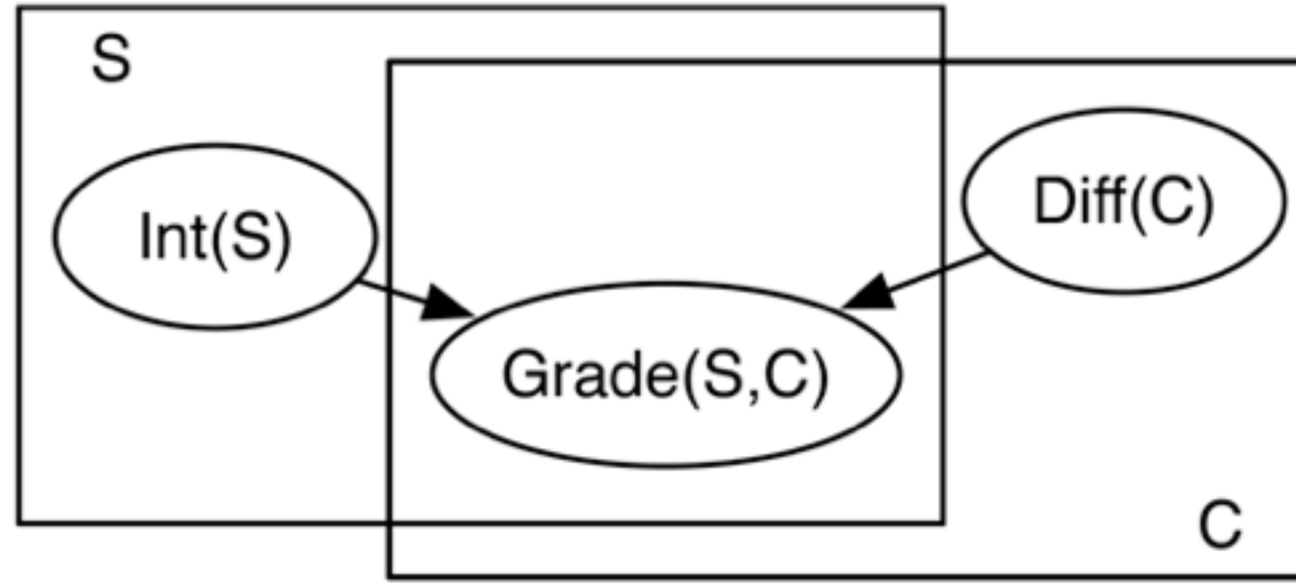
           int(S), diff(C).
0.1::gr(S,C,b); 0.2::gr(S,C,c); 0.2::gr(S,C,f) :-
```

ProbLog by example:

Grading

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0.5 :: diff(C):- course(C).

student(john). student(anna). student(bob).
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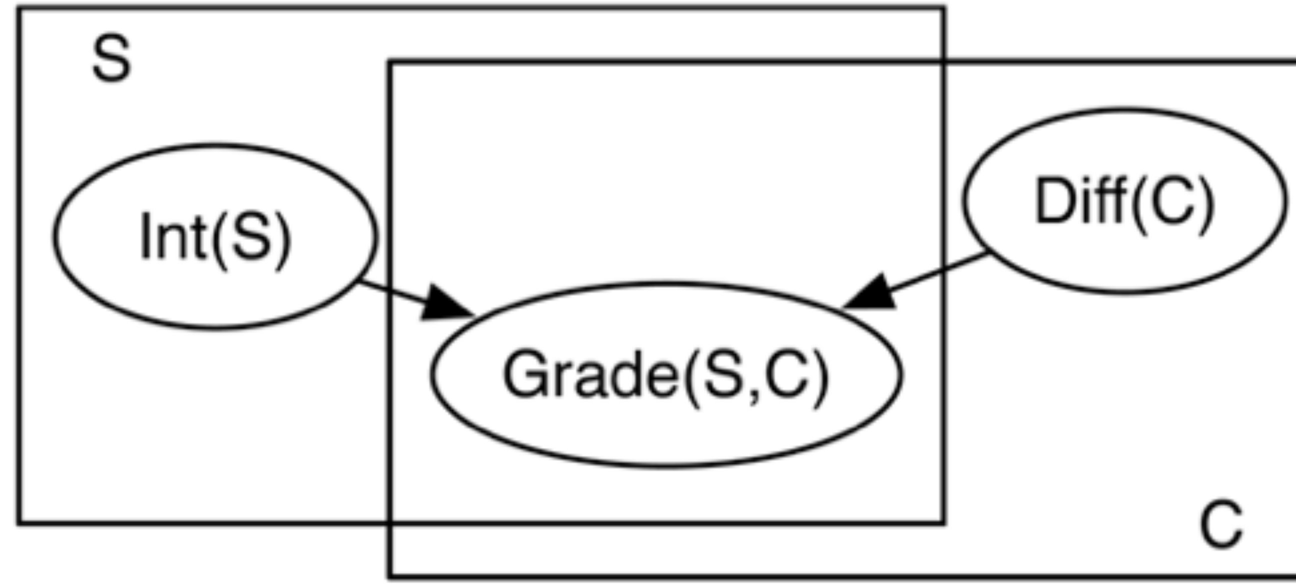
gr(S,C,a) :- int(S), not diff(C).
0.3::gr(S,C,a); 0.5::gr(S,C,b);0.2::gr(S,C,c) :-
           int(S), diff(C).
0.1::gr(S,C,b); 0.2::gr(S,C,c); 0.2::gr(S,C,f) :-
           student(S), course(C),
```

ProbLog by example:

Grading

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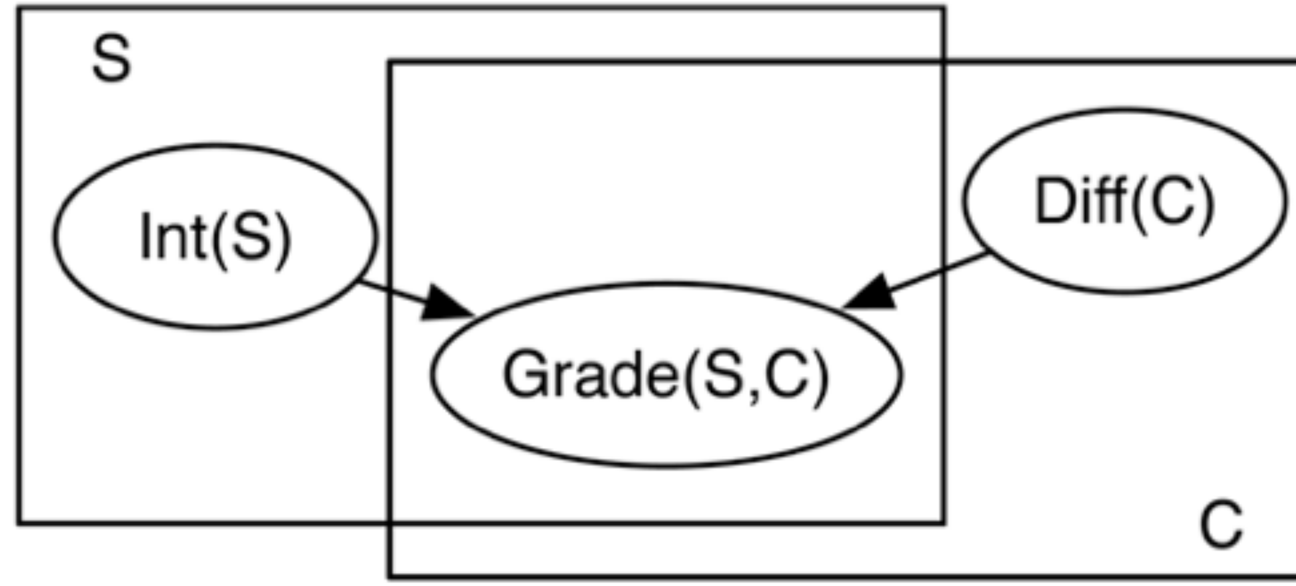
           int(S), diff(C).
0.1::gr(S,C,b); 0.2::gr(S,C,c); 0.2::gr(S,C,f) :-
           student(S), course(C),
           not int(S), not diff(C).
```

ProbLog by example:

Grading

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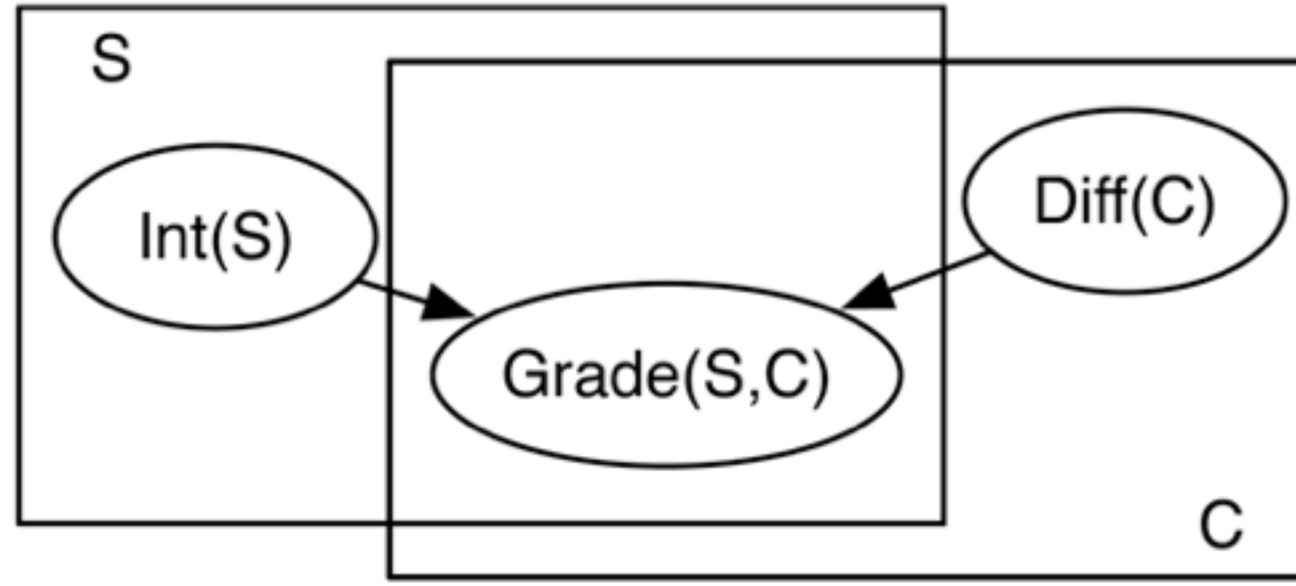
```

ProbLog by example:

Grading

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0.1::gr(S,C,b); 0.2::gr(S,C,c); 0.2::gr(S,C,f) :-
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           not int(S), not diff(C).
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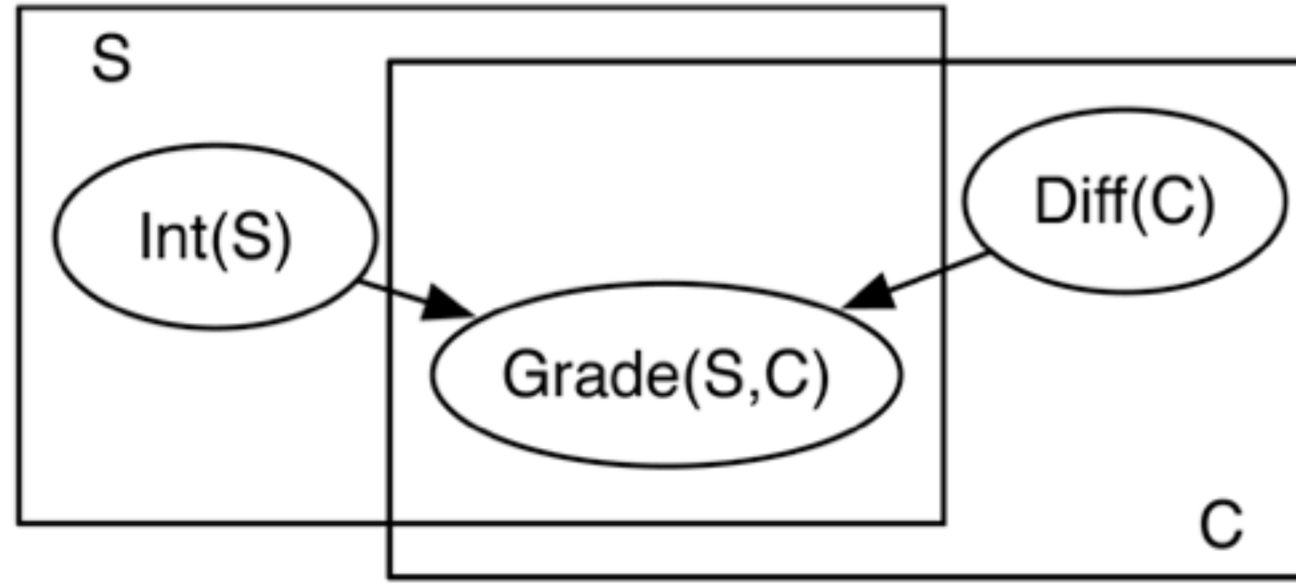
```

ProbLog by example:

Grading

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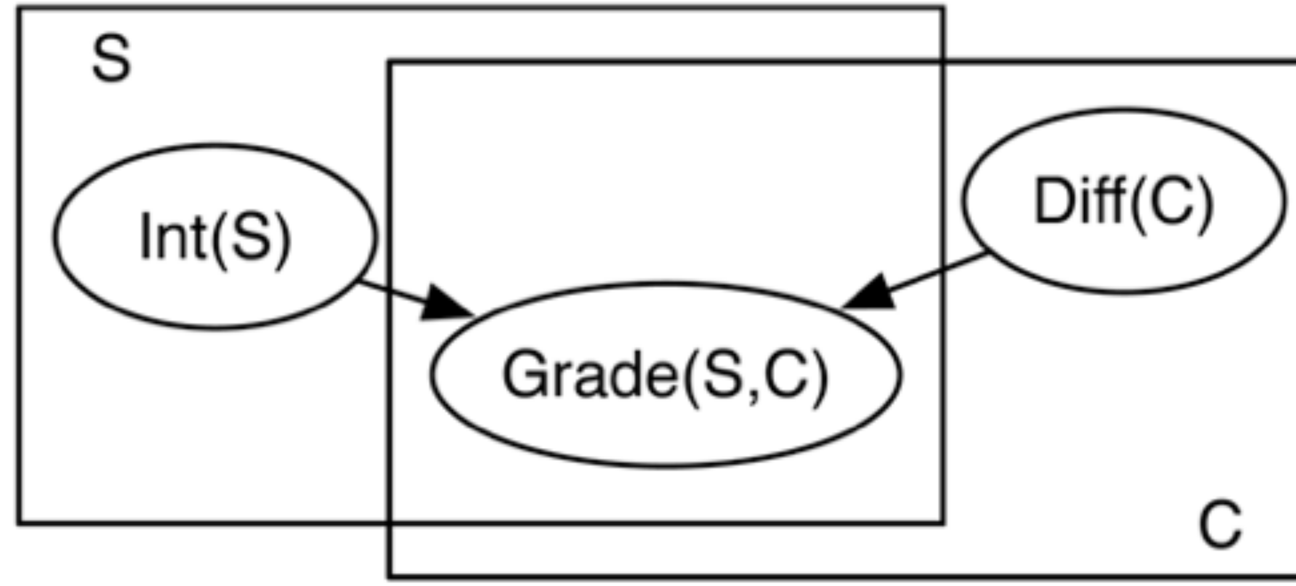
ProbLog by example:

Grading

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0.3::gr(S,C,c); 0.2::gr(S,C,f) :-
           not int(S), diff(C).
```

ProbLog by example: Grading

```
unsatisfactory(S) :- student(S), grade(S,C,f).

excellent(S) :- student(S), not grade(S,C,G), below(G,a).
excellent(S) :- student(S), grade(S,C,a).

0.4 :: int(S) :- student(S).
0.5 :: diff(C):- course(C).

student(john). student(anna). student(bob).
course(ai).    course(ml).    course(cs).

gr(S,C,a) :- int(S), not diff(C).
0.3::gr(S,C,a); 0.5::gr(S,C,b);0.2::gr(S,C,c) :-
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```

ProbLog by example:

Rain or sun?

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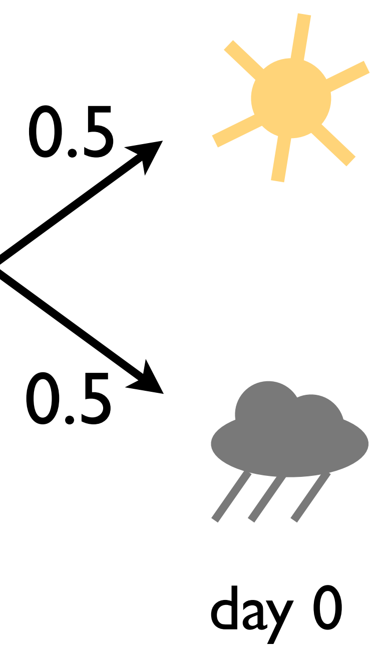
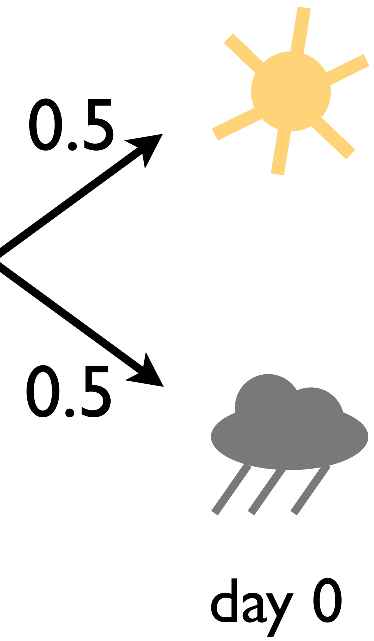


ProbLog by example:

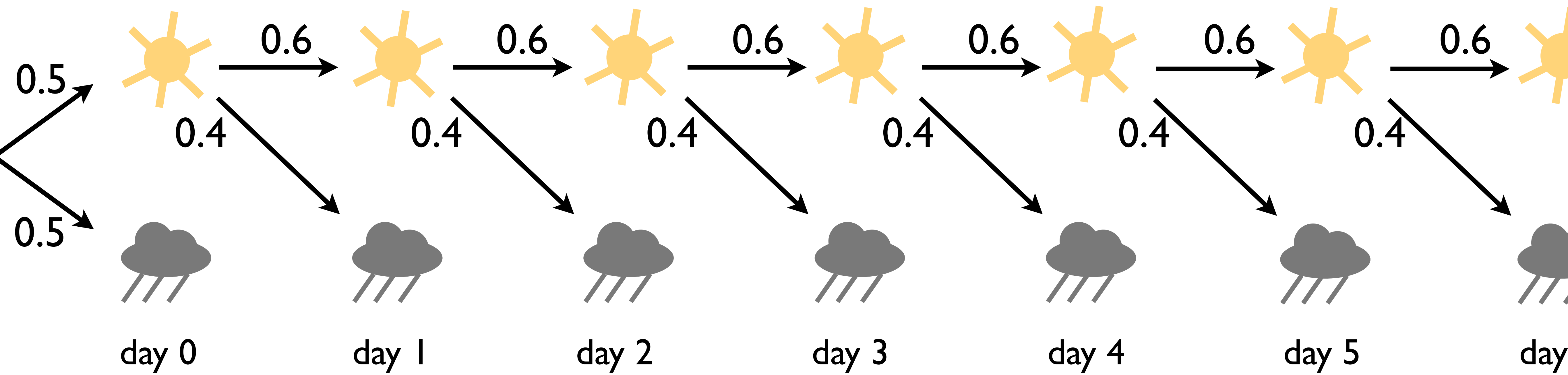
Rain or sun?




```
0.5::weather(sun,0) ; 0.5::weather(rain,0) <- true.
```

ProbLog by example:

Rain or sun?

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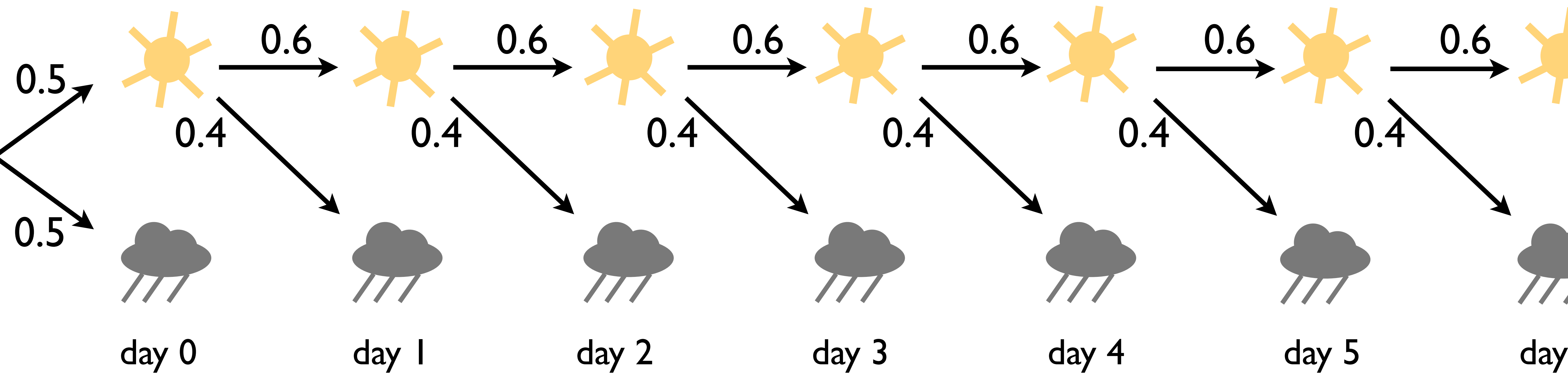


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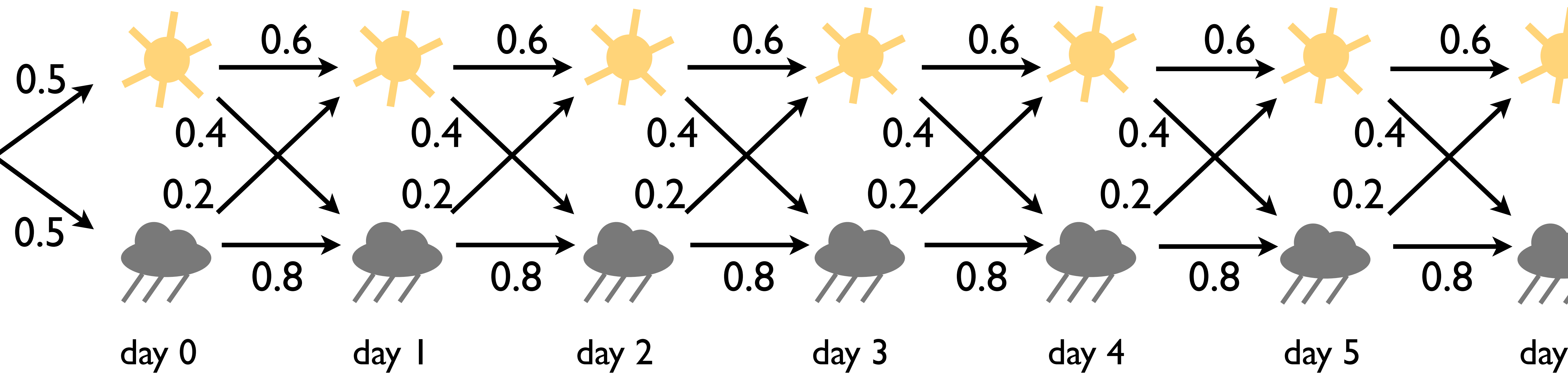


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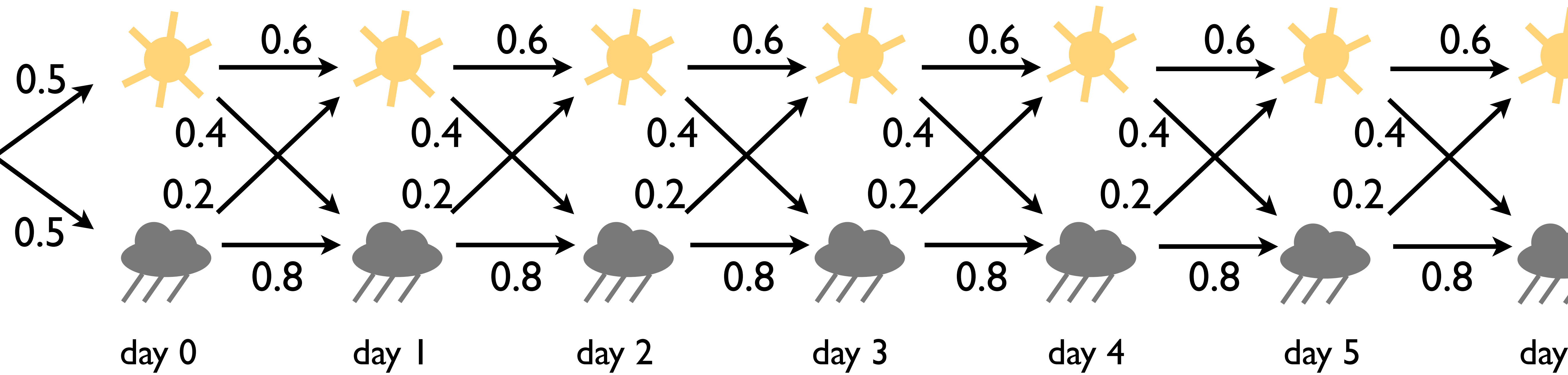
```

ProbLog by example:

Rain or sun?

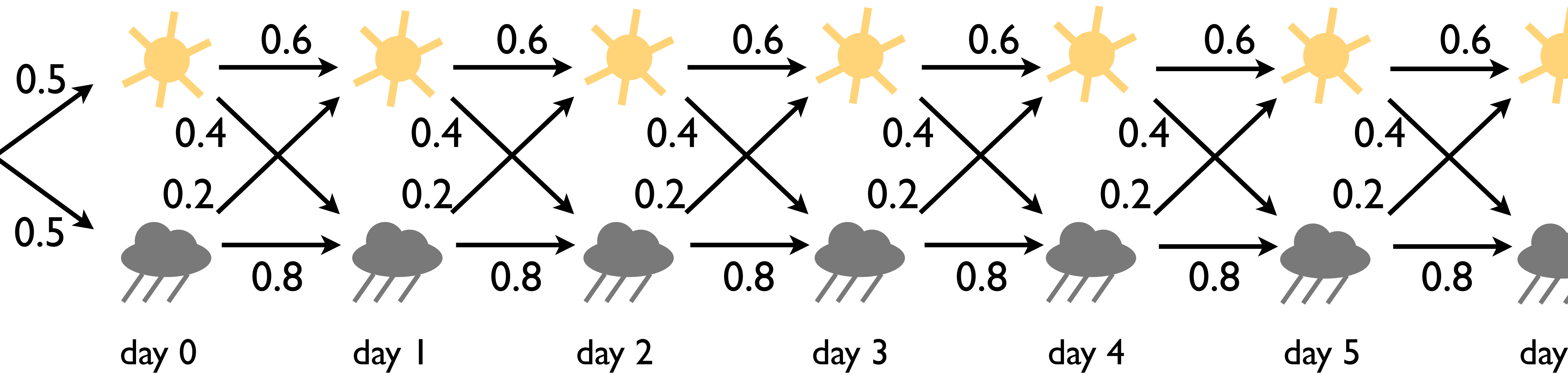



```
0.5::weather(sun,0) ; 0.5::weather(rain,0) <- true.

0.6::weather(sun,T) ; 0.4::weather(rain,T)
                <- T>0, Tprev is T-1, weather(sun,Tprev).
```

ProbLog by example:

Rain or sun?

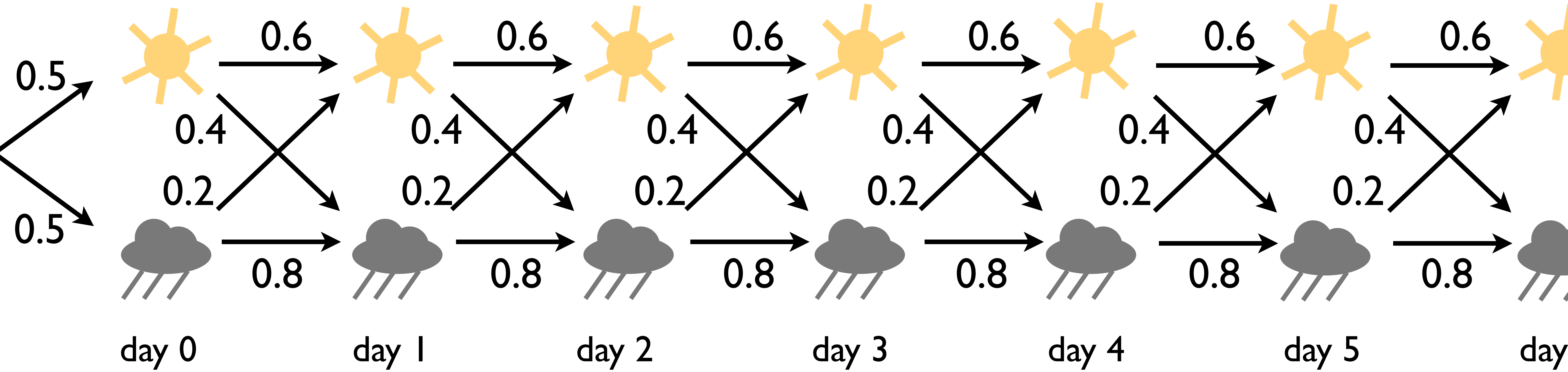



```
0.5::weather(sun,0) ; 0.5::weather(rain,0) <- true.

0.6::weather(sun,T) ; 0.4::weather(rain,T)
                <- T>0, Tprev is T-1, weather(sun,Tprev).
0.2::weather(sun,T) ; 0.8::weather(rain,T)
                <- T>0, Tprev is T-1, weather(rain,Tprev).
```

ProbLog by example:

Rain or sun?



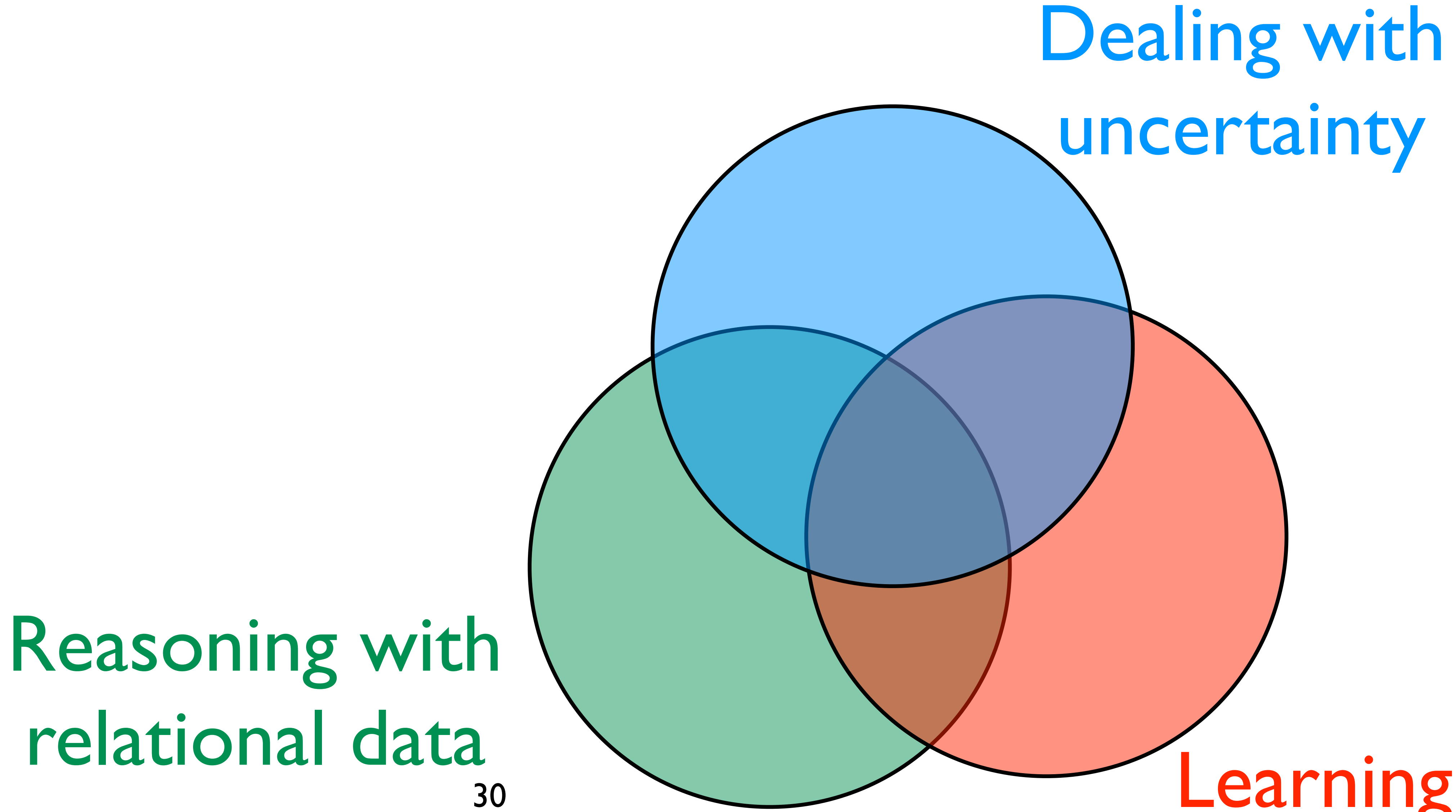

```
0.5::weather(sun,0) ; 0.5::weather(rain,0) <- true.

0.6::weather(sun,T) ; 0.4::weather(rain,T)
                  <- T>0, Tprev is T-1, weather(sun,Tprev).
0.2::weather(sun,T) ; 0.8::weather(rain,T)
                  <- T>0, Tprev is T-1, weather(rain,Tprev).
```

infinite possible worlds! BUT: finitely many partial worlds suffice to answer any given ground query

[Suciu et al 2011]

Probabilistic Databases



[Suciu et al 2011]

Probabilistic Databases

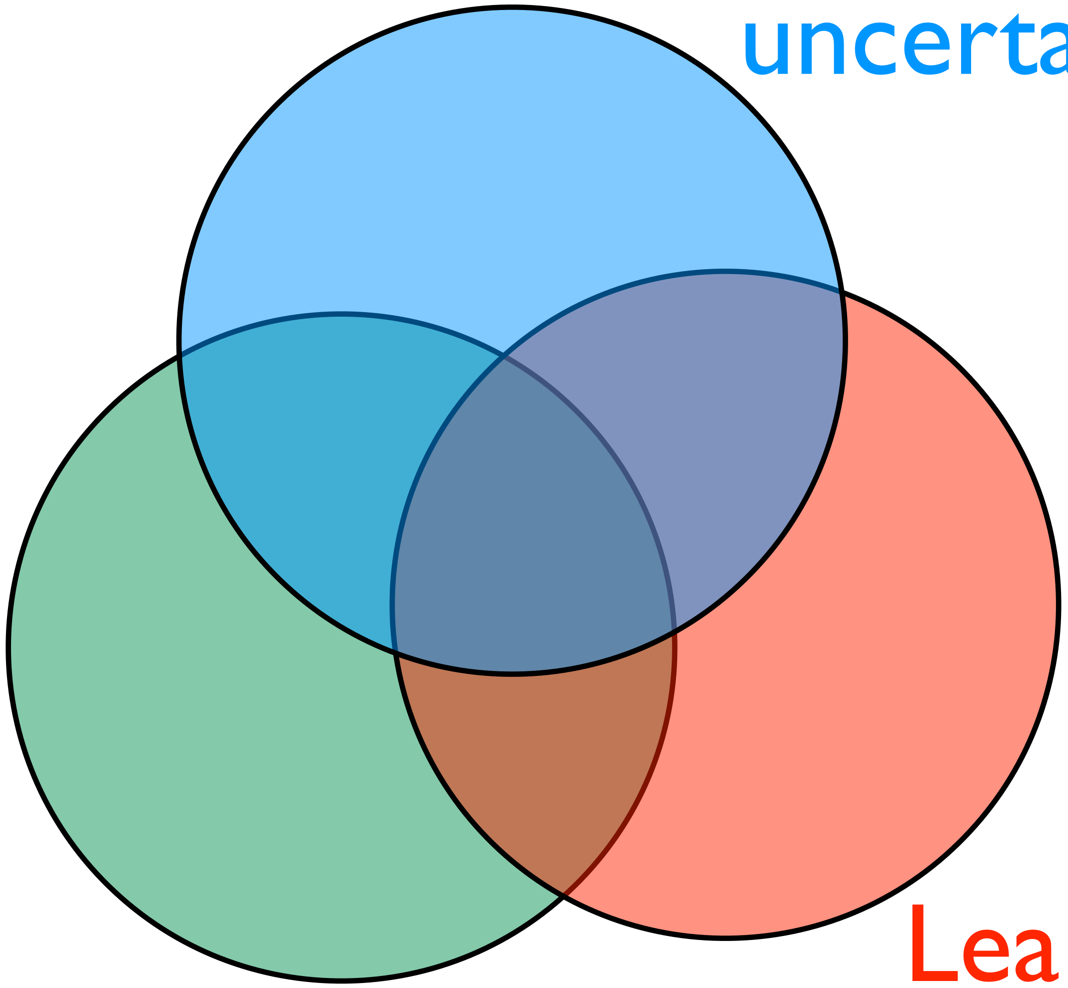
```
select x.person, y.country
from bornIn x, cityIn y
where x.city=y.city
```

cityIn

city	country
london	uk
york	uk
paris	usa

bornIn

person	city
ann	london
bob	york
eve	new york
tom	paris



[Suciu et al 2011]

Probabilistic Databases

```
select x.person, y.country
from bornIn x, cityIn y
where x.city=y.city
```

one world

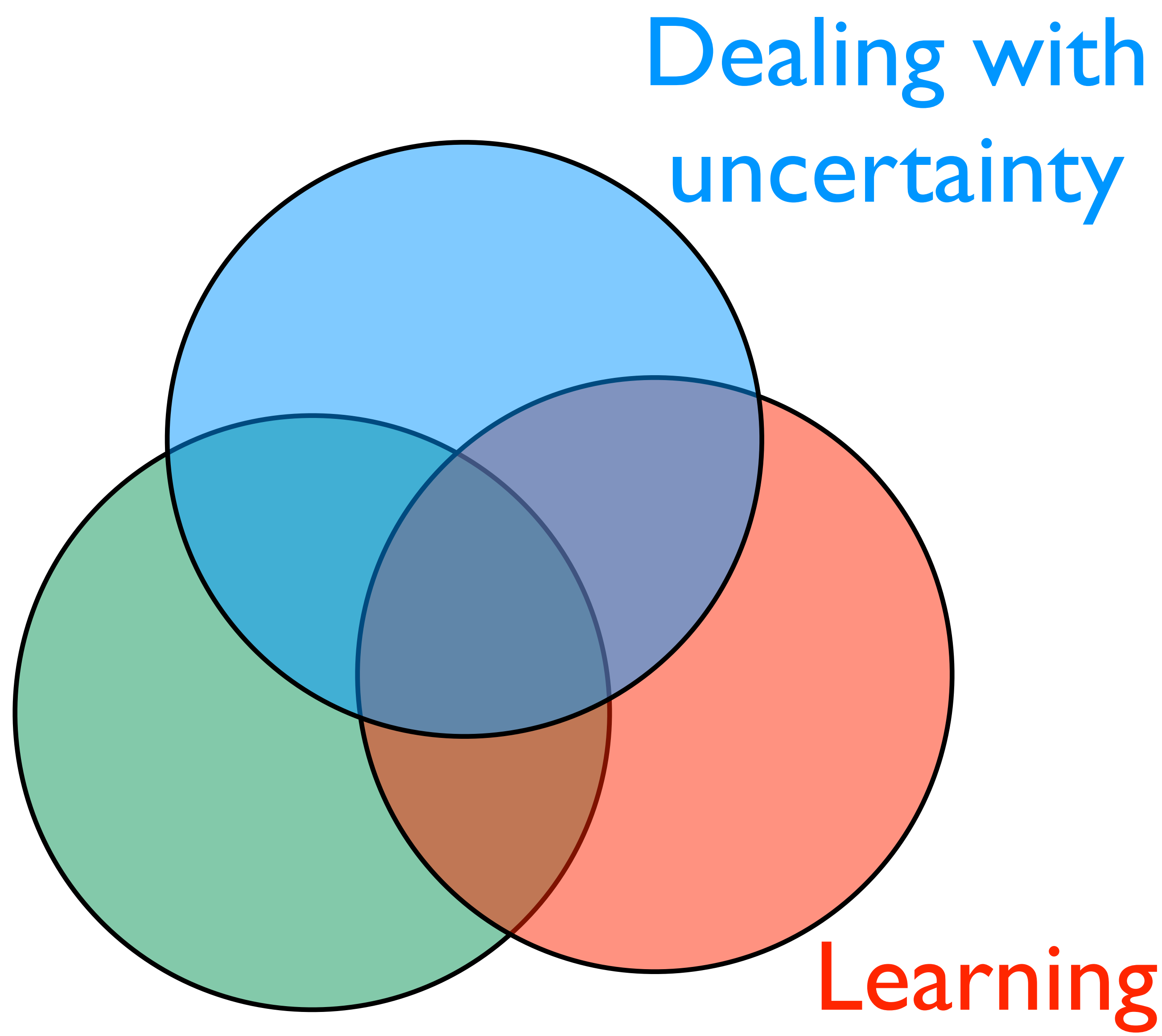
bornIn

person	city
ann	london
bob	york
eve	new york
tom	paris

cityIn

city	country
london	uk
york	uk
paris	usa

relational database



[Suciu et al 2011]

Probabilistic Databases

bornIn

person	city	P
ann	london	0,87
bob	york	0,95
eve	new york	0,9
tom	paris	0,56

cityIn

city	country	P
london	uk	0,99
york	uk	0,75
paris	usa	0,4

tuples as random variables

```
select x.person, y.country
from bornIn x, cityIn y
where x.city=y.city
```

one world

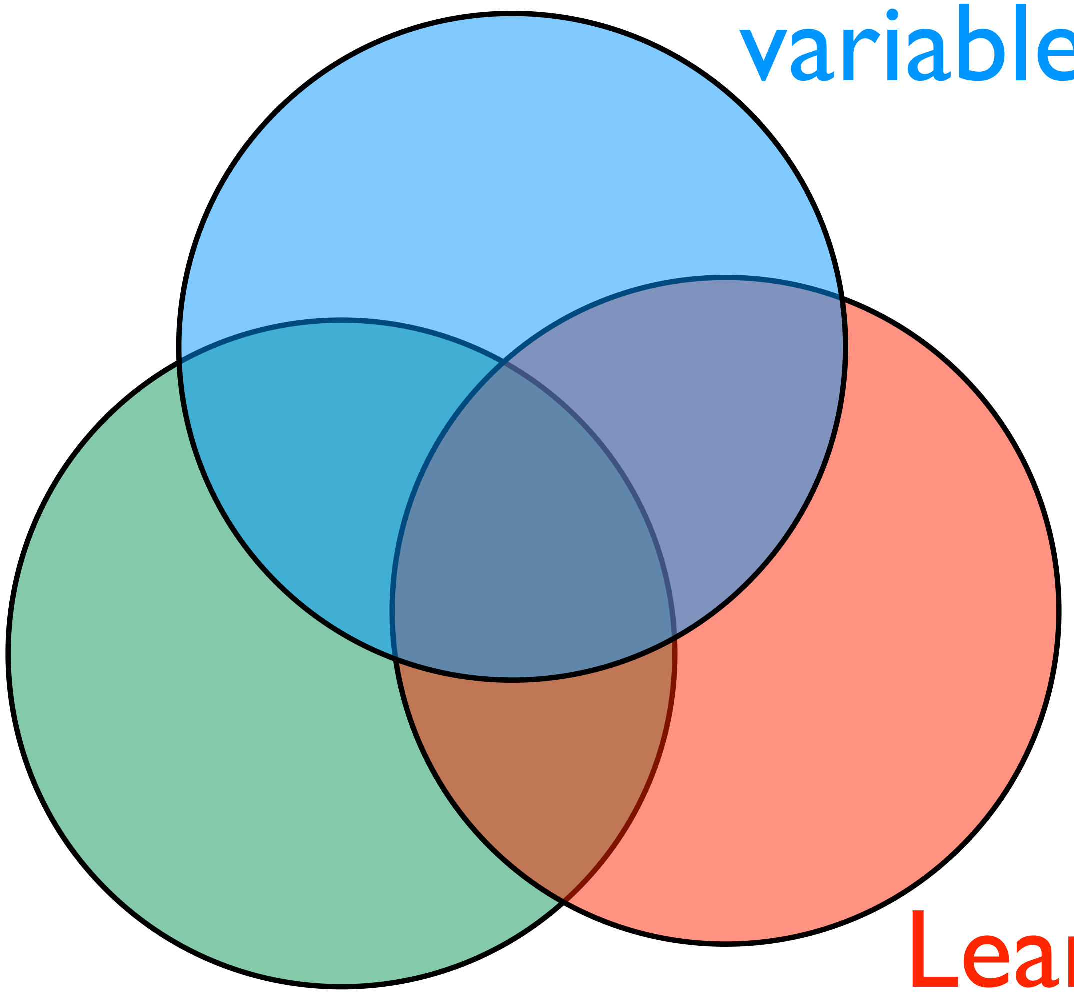
bornIn

person	city
ann	london
bob	york
eve	new york
tom	paris

cityIn

city	country
london	uk
york	uk
paris	usa

relational database



Learning

[Suciu et al 2011]

Probabilistic Databases

several possible worlds

bornIn

person	city	P
ann	london	0,87
bob	york	0,95
eve	new york	0,9
tom	paris	0,56

cityIn

city	country	P
london	uk	0,99
york	uk	0,75
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```
select x.person, y.country
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```

one world

bornIn

person	city
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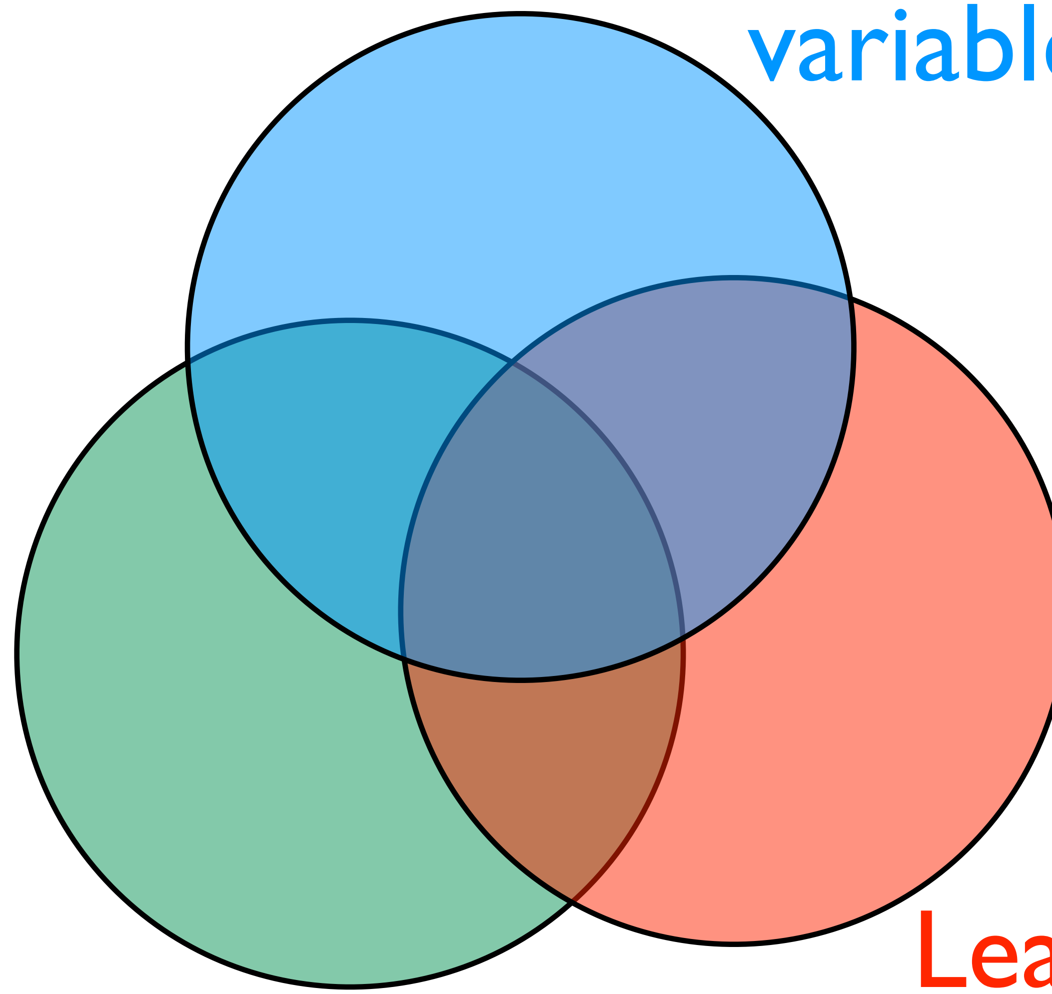
cityIn

city	country
london	uk
york	uk
paris	usa

relational database



Learning

[Suciu et al 2011]

Probabilistic Databases

several possible worlds

bornIn

person	city	P
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bob	york	0,95
		0,9
		0,56

cityIn

city	country	P
london	uk	0,99
york	uk	0,75
paris	usa	0,4

probabilistic tables + database queries
→ distribution over possible worlds

```
select
from bornIn x, cityIn y
where x.city=y.city
```

one world

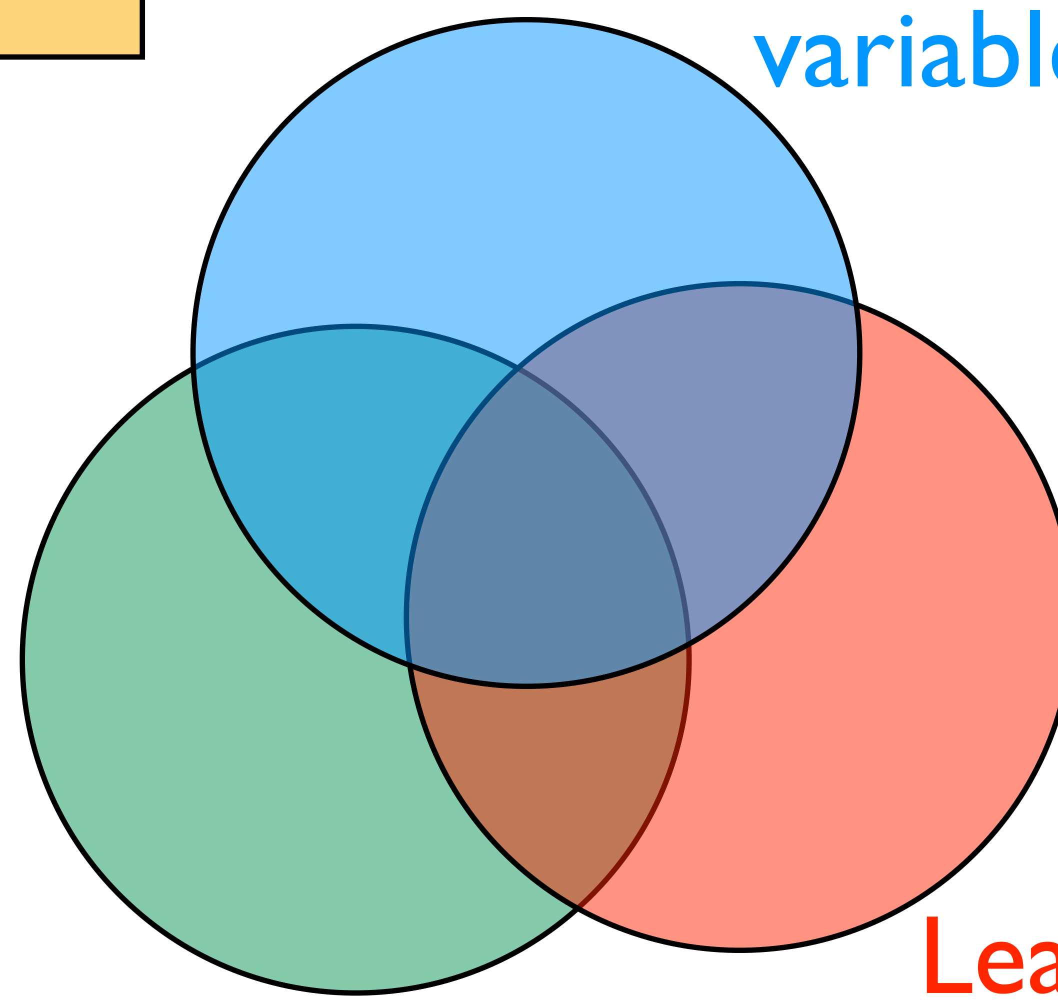
bornIn

person	city
ann	london
bob	york
eve	new york
tom	paris

cityIn

city	country
london	uk
york	uk
paris	usa

tuples as random variables



relational database

Learning

Example: Information Extraction

Recently-Learned Facts

twitter

Refresh

instance	iteration	date learned	confidence
kelly_andrews is a female	826	29-mar-2014	98.7
investment_next_year is an economic sector	829	10-apr-2014	95.3
shibenik is a geopolitical entity that is an organization	829	10-apr-2014	97.2
quality_web_design_work is a character trait	826	29-mar-2014	91.0
mercedes_benz_cls_by_carlsson is an automobile manufacturer	829	10-apr-2014	95.2
social_work is an academic program at the university rutgers_university	827	02-apr-2014	93.8
dante wrote the book the_divine_comedy	826	29-mar-2014	93.8
willie_aames was born in the city los_angeles	831	16-apr-2014	100.0
kitt_peak is a mountain in the state or province arizona	831	16-apr-2014	96.9
greenwich is a park in the city london	831	16-apr-2014	100.0

instances for many different relations

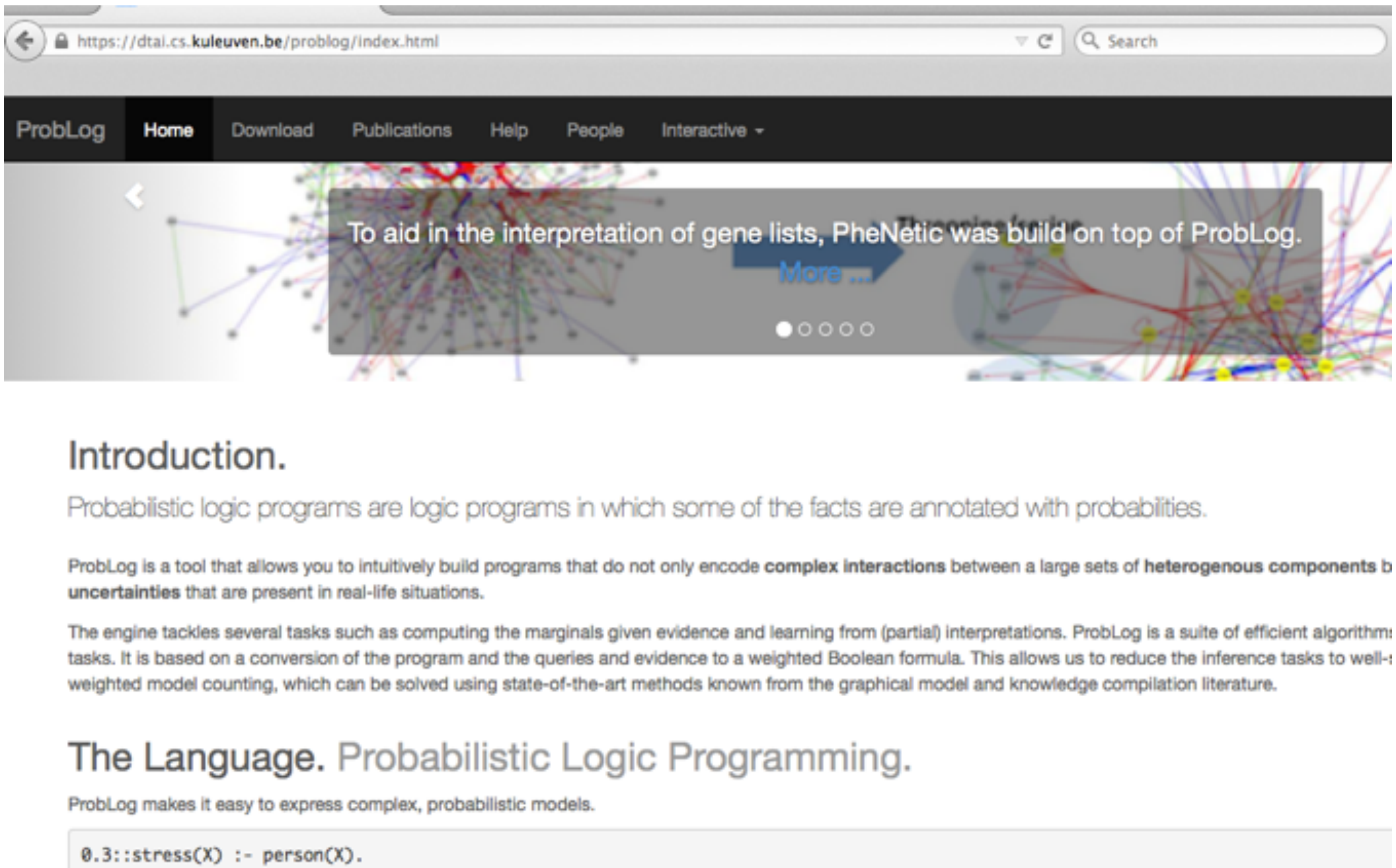
degree of certainty

NELL: http://rtw.ml.cmu.edu/rtw/

Distribution Semantics

- **probabilistic choices** + their **consequences**
- probability distribution over **possible worlds**
- how to efficiently answer **questions**?
  - most probable world (MPE inference)
  - probability of query (computing marginals)
  - probability of query given evidence

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



Part II : Inference

Inference

The challenge : disjoint sum problem

```
0.4::heads(1).
0.7::heads(2).
0.5::heads(3).
win :- heads(1).
win :- heads(2), heads(3).
```

$win \leftrightarrow h(1) \vee (h(2) \wedge h(3))$

$$P(win) = P(h(1) \vee (h(2) \wedge h(3))$$

$$=/= P(h(1)) + P(h(2) \wedge h(3))$$

should be

$$= P(h(1)) + P(h(2) \wedge h(3)) - P(h(1) \wedge h(2) \wedge h(3))$$

Inference

Map to Weighted Model Counting Problem and Solver

```
0.4::heads(1).
0.7::heads(2).
0.5::heads(3).
win :- heads(1).
win :- heads(2), heads(3).
```

$$\text{win} \leftrightarrow h(1) \lor (h(2) \land h(3))$$

Ground out

+ Put formula in CNF format

$$(\neg\text{win} \lor h(1) \lor h(2)) \land (\neg\text{win} \lor h(1) \lor h(3)) \land (\text{win} \lor \neg h(1)) \land (\text{win} \lor \neg h(2) \lor \neg h(3))$$

+ weights

+ call WMC

$h(1) \rightarrow 0.4$	$h(2) \rightarrow 0.7$	$h(3) \rightarrow 0.5$
$\neg h(1) \rightarrow 0.6$	$\neg h(2) \rightarrow 0.3$	$\neg h(3) \rightarrow 0.5$

Weighted Model Counting

$$WMC(\phi) = \sum_{I_V \models \phi} \prod_{l \in I_V} w(l)$$

Weighted Model Counting

propositional formula in conjunctive normal form (CNF)

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Weighted Model Counting

propositional formula in conjunctive normal form (CNF)

$$WMC(\phi) = \sum_{I_V \models \phi} \prod_{l \in I_V} w(l)$$

interpretations (truth value assignments) of propositional variables

Weighted Model Counting

propositional formula in conjunctive normal form (CNF)

$$WMC(\phi) = \sum_{I_V \models \phi} \prod_{l \in I_V} w(l)$$

interpretations (truth value assignments) of propositional variables

weight of literal

Weighted Model Counting

propositional formula in conjunctive normal form (CNF)

given by SRL model & query

$$WMC(\phi) = \sum_{I_V \models \phi} \prod_{l \in I_V} w(l)$$

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Weighted Model Counting

propositional formula in conjunctive normal form (CNF)

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weight of literal

interpretations (truth value assignments) of propositional variables

possible worlds

Weighted Model Counting

propositional formula in conjunctive normal form (CNF)

given by SRL model & query

$$WMC(\phi) = \sum_{I_V \models \phi} \prod_{l \in I_V} w(l)$$

interpretations (truth value assignments) of propositional variables

possible worlds

weight of literal

for p::f,
w(f) = p
w(not f) = 1−p

Weighte

$$P(Q) = \sum_{F \cup R \models Q} \prod_{f \in F} p(f) \prod_{f \notin F} 1 - p(f)$$

propositional formula in conjunctive normal form (CNF)

given by SRL model & query

$$WMC(\phi) = \sum_{I_V \models \phi} \prod_{l \in I_V} w(l)$$

interpretations (truth value assignments) of propositional variables

possible worlds

weight of literal

for p::f,
w(f) = p
w(not f) = 1−p

Weighted Model Counting

- Simple WMC solvers based on a generalisation of DPLL algorithm for SAT (Davis Putnam Logeman Loveland algorithm)
- Current solvers often use knowledge compilation (is also state of the art for inference in graphical models) — here an OBDD, many variations s-dDNNF, SDDs, …

$$\text{win} \leftrightarrow h(1) \vee (h(2) \wedge h(3))$$

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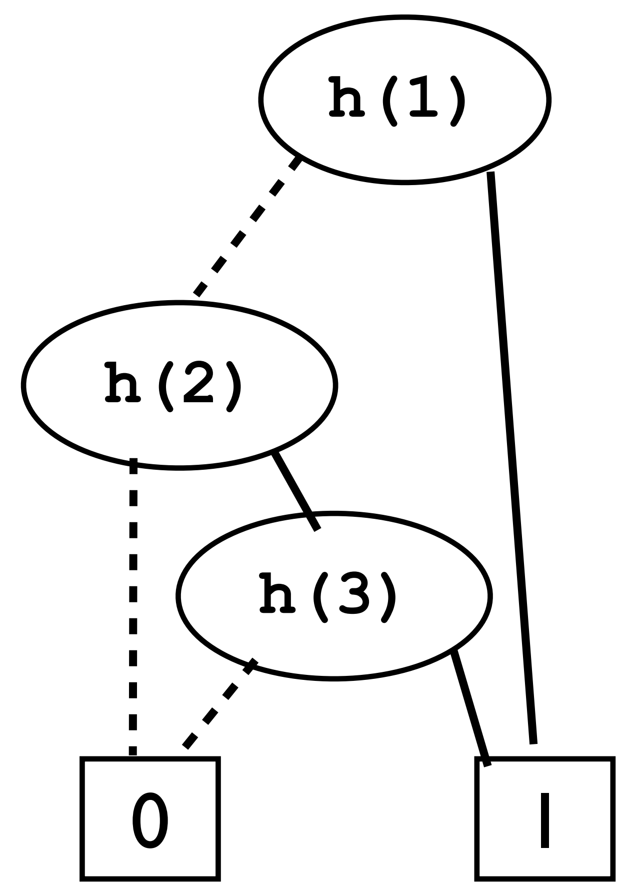
win ↔ h(1) ∨ (h(2) ∧ h(3))



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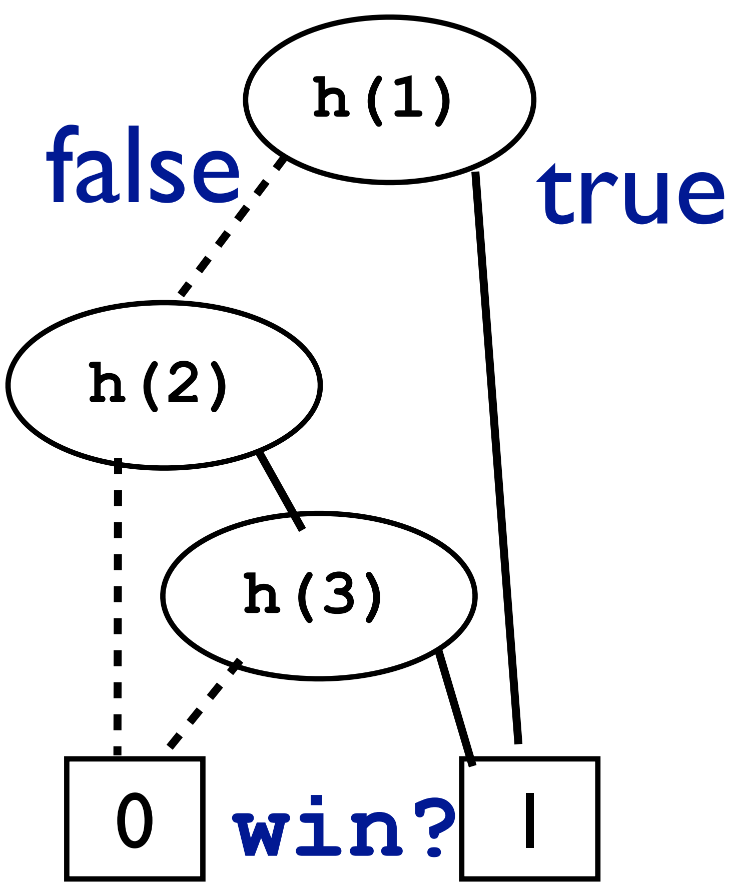

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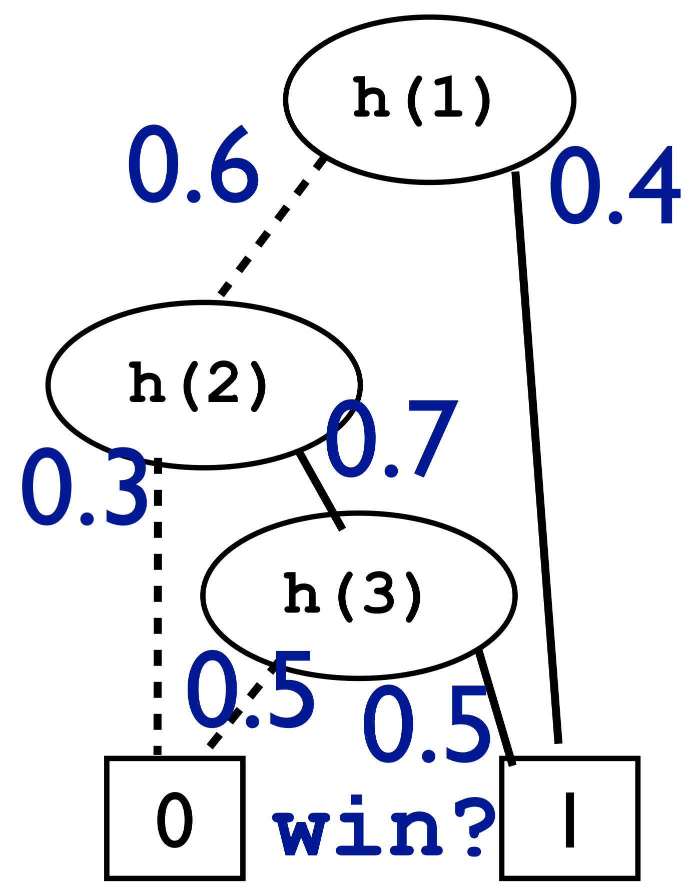
- Current solvers often use knowledge compilation (is also state of the art for inference in graphical models) — here an OBDD, many variations s-dDNNF, SDDs, …

P(**win**) = probability of reaching 1-leaf

win ↔ h(1) ∨ (h(2) ∧ h(3))



More inference

- Many variations / extensions
- Approximate inference
- Lifted inference
  - infected(X) :- contact(X,Y), sick(Y).

Part III : Learning
a. Parameters

Parameter Learning

e.g., webpage classification model

for each *CLASS1*, *CLASS2* and each *WORD*

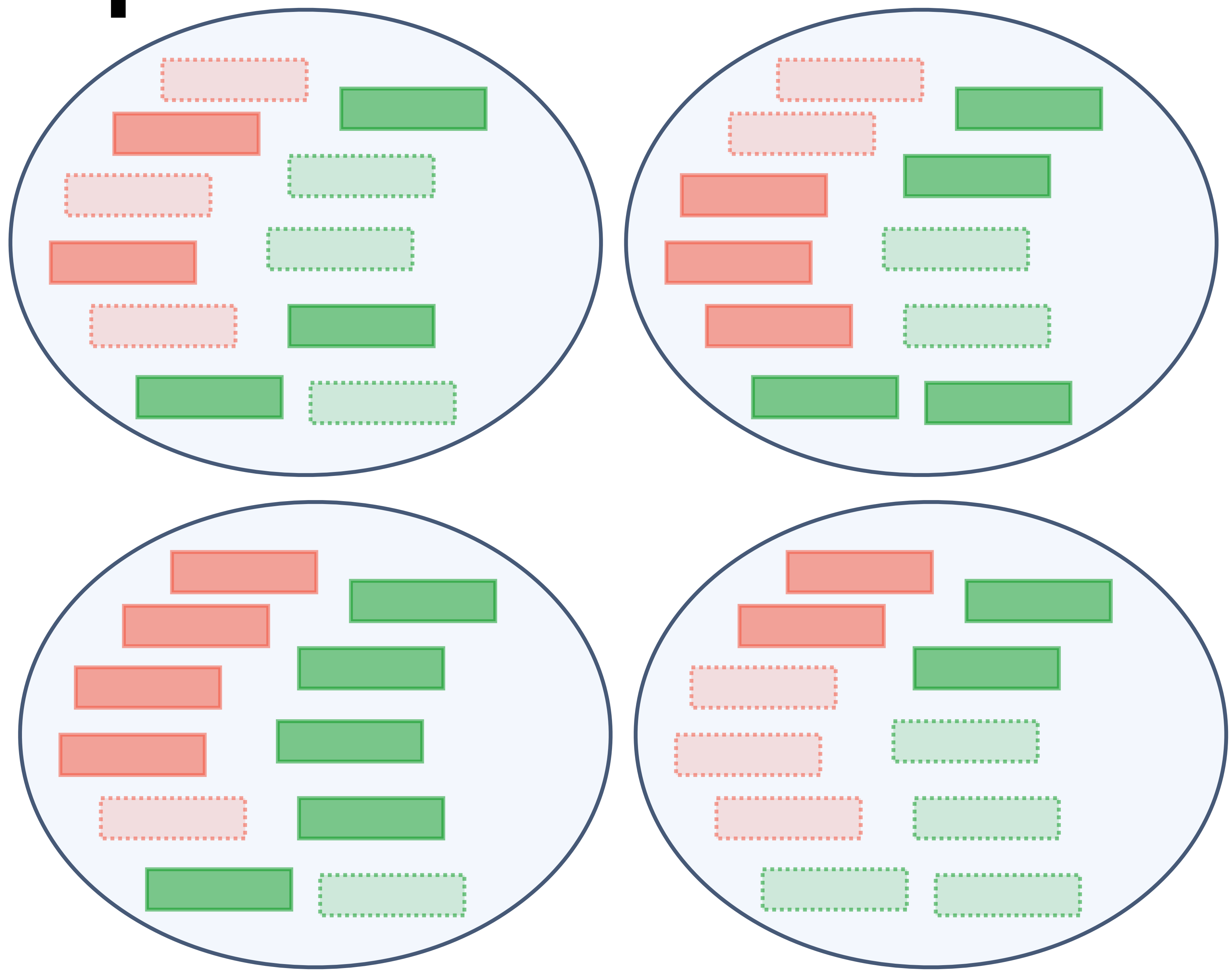
```
?? :: link_class(Source,Target,CLASS1,CLASS2).
?? :: word_class(WORD,CLASS).
```

```
class(Page,C)    :-   has_word(Page,W), word_class(W,C).

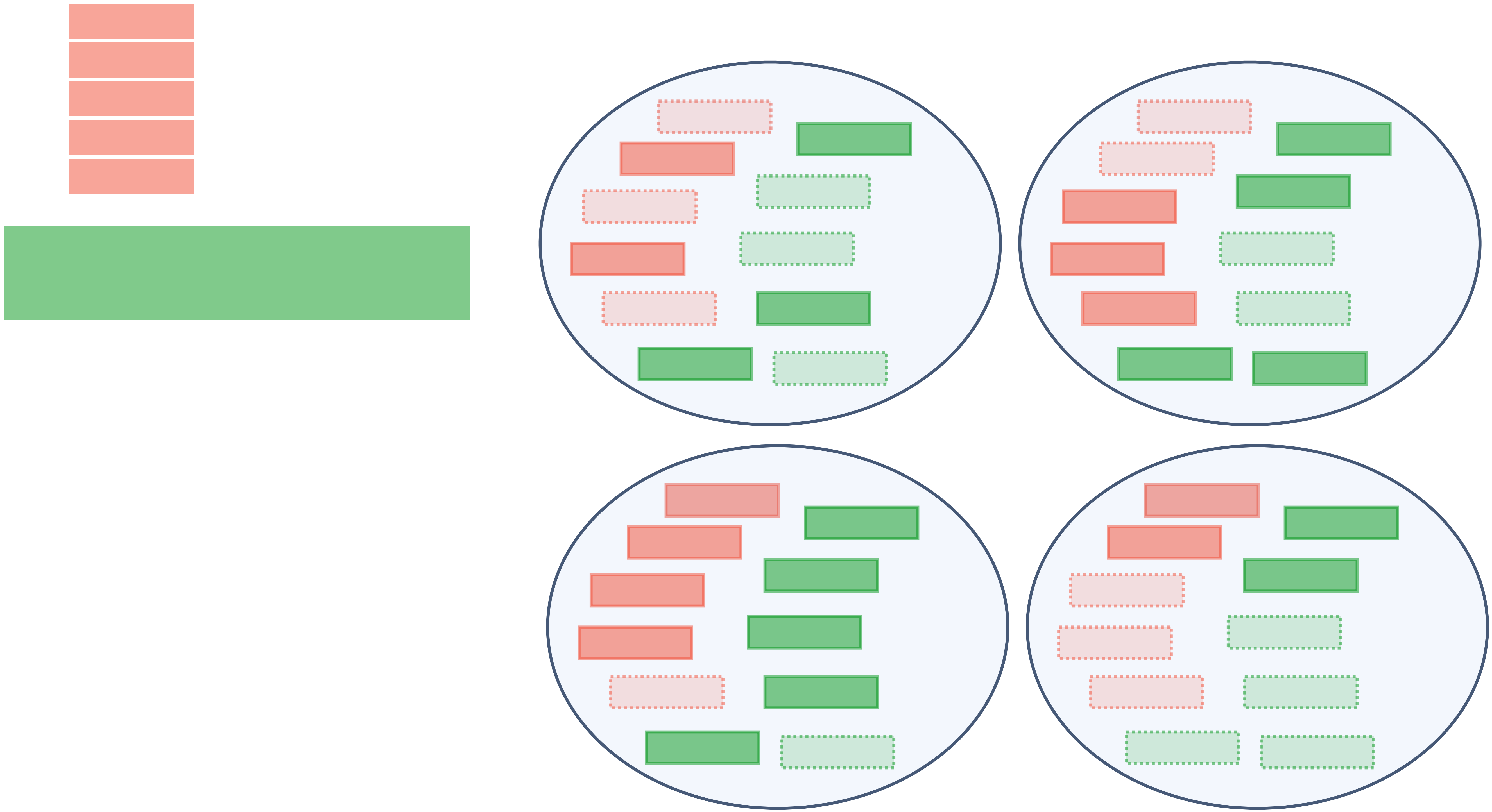
class(Page,C)         :-   links_to(OtherPage,Page),
    class(OtherPage,OtherClass),
                           link_class(OtherPage,Page,OtherClass,C).
```

Sampling Interpretations

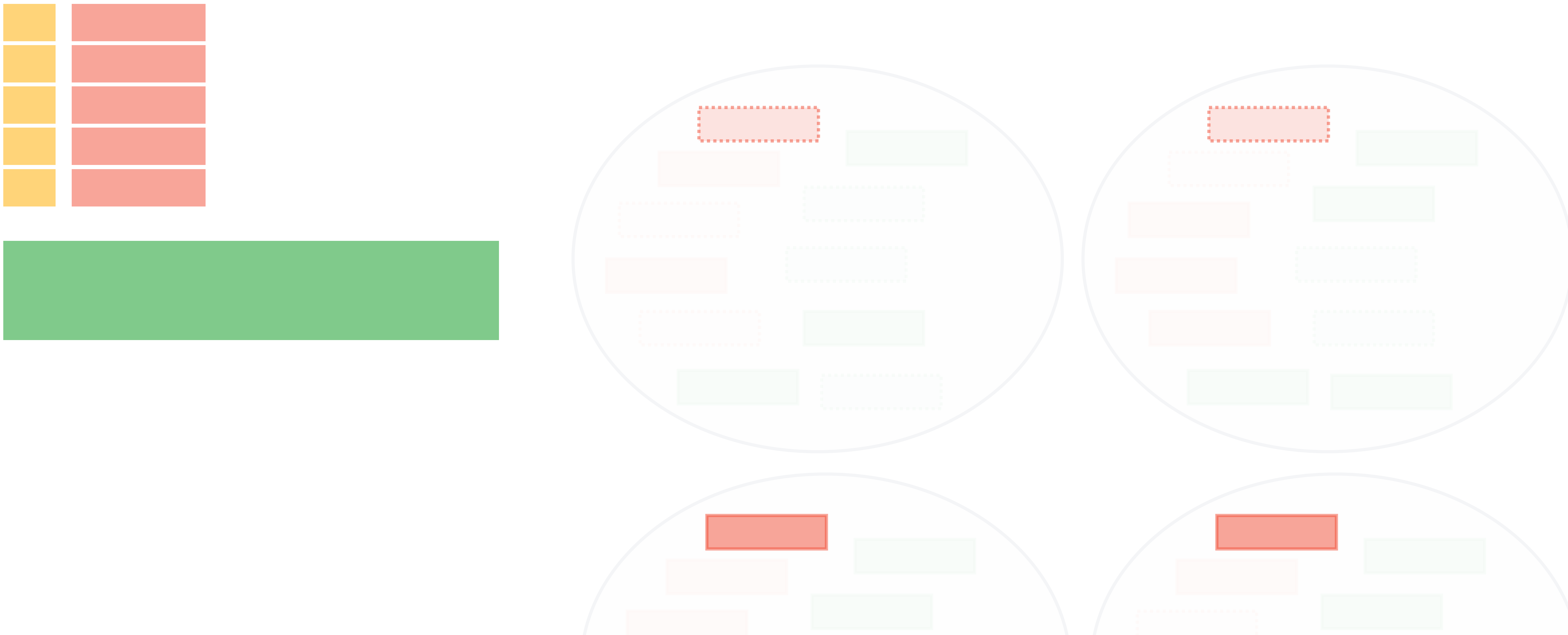
Sampling Interpretations



Parameter Estimation

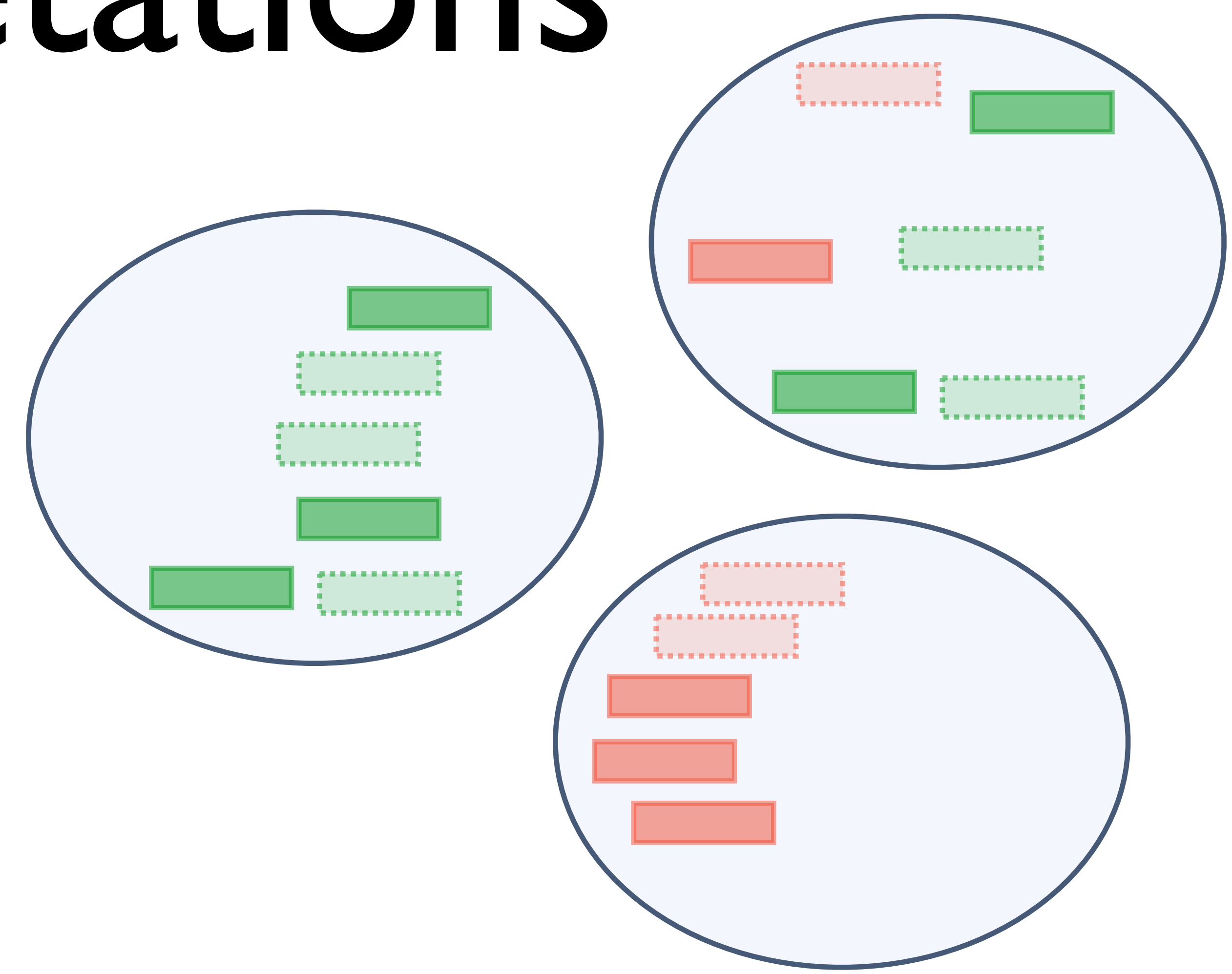


Parameter Estimation



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

Learning from partial interpretations



- Not all facts observed
- Soft-EM
- use **expected count** instead of **count**
- **P(Q |E) -- conditional queries !**

 [Gutmann et al, ECML 11; Fierens et al, TPLP 14]

Part III : Learning
b. Rules / Structure

Information Extraction in NELL

Recently-Learned Facts twitter

Refresh

instance	iteration	date learned	confidence
kelly_andrews is a female	826	29-mar-2014	98.7
investment_next_year is an economic sector	829	10-apr-2014	95.3
shibenik is a geopolitical entity that is an organization	829	10-apr-2014	97.2
quality_web_design_work is a character trait	826	29-mar-2014	91.0
mercedes_benz_cls_by_carlsson is an automobile manufacturer	829	10-apr-2014	95.2
social_work is an academic program at the university rutgers_university	827	02-apr-2014	93.8
dante wrote the book the_divine_comedy	826	29-mar-2014	93.8
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kitt_peak is a mountain in the state or province arizona	831	16-apr-2014	96.9
greenwich is a park in the city london	831	16-apr-2014	100.0

instances for many different relations

degree of certainty

NELL: http://rtw.ml.cmu.edu/rtw/

ProbFOIL

- Upgrade rule-learning to a probabilistic setting within a relational learning / inductive logic programming setting
  - Works with a probabilistic logic program instead of a deterministic one.
- Introduce ProbFOIL, an adaption of Quinlan's FOIL to this setting.
- Apply to probabilistic databases like NELL

Pro Log

surfing(X) :- not pop(X) and windok(X).

H

surfing(X) :- not pop(X) and sunshine(X).

pop(e1).   windok(e1).   sunshine(e1).   **B**

?-surfing(e1). **e**
no

B U H |=\= e   (H does not cover e)

An ILP example

ProbLog

a probabilistic Prolog

p1:: surfing(X) :- not pop(X) and windok(X).

H

p2:: surfing(X) :- not pop(X) and sunshine(X).

0.2::pop(e1).   0.7::windok(e1).   0.6::sunshine(e1).   **B**

?-P(surfing(e1)). **e**

gives (1-0.2) x 0.7 x p1 + (1-0.2) x 0.6 x (1-0.7) x p2 = P(B U H |= e)

not pop   x windok x p1 + not pop x sunshine x (not windok) x p1

probability that the example is covered

Inductive Probabilistic Logic Programming

Given

a set of example facts $e \in E$ together with the probability p that they hold

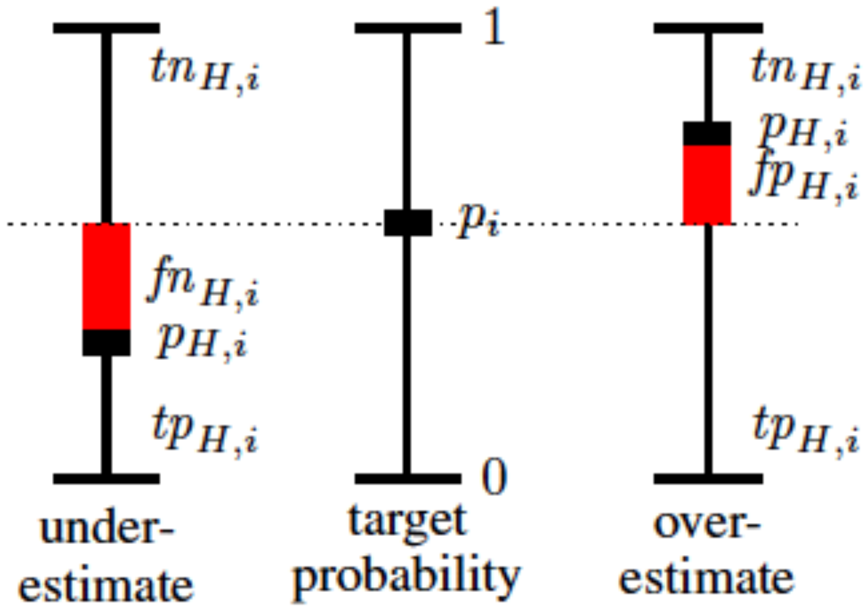
a background theory B in ProbLog

a hypothesis space L (a set of clauses)

Find

$$\arg\min_{H} loss(H, B, E) = \arg\min_{H} \sum_{e_i \in E} |P_s(B \cup H \models e) - p_i|$$

Adapt Rule-learner



Contingency table:
not only 1 / 0 values

Covering:
use multiple rules
to cover an example

Algorithm 1 The ProbFOIL$^+$ learning algorithm.

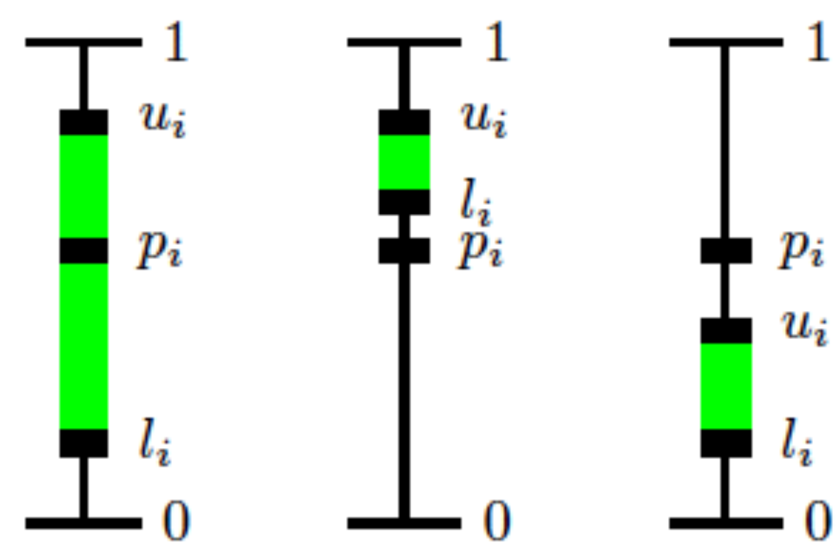
```
function PROBFOIL+(target)
  H := ∅
  while true do
    clause := LEARNRULE(H, target)
    if GSCORE(H) < GSCORE(H ∪ {clause}) then
      H := H ∪ {clause}
    else return H
function LEARNRULE(H, target)
  candidates := {x :: target ← true}
  best := (x :: target ← true)
  while candidates ≠ ∅ do
    next_cand := ∅
    for all x :: target ← body ∈ candidates do
      for all refinement ∈ ρ(target ← body) do
        if not REJECT(H, best, x :: target ← body) then
          next_cand := next_cand ∪ {x :: target ← body∧
                                    refinement}
          if LSCORE (H, x :: target ← body ∧ refinement) >
                                    LSCORE(H, best) then
            best := (x :: target ← body ∧ refinement)
    candidates := next_cand
  return best
```

Technical Novelty

p:: surfing(X) :- not pop(X) and windok(X).

$u_i = (p=1)$

$l_i = (p=0)$



(a) (b) (c)

ProbFOIL includes

a method to determine “optimal” p for a given rule

Experiments

Table 4: Precision for different experimental setups and parameters (A: $m = 1, p = 0.99$, B: $m = 1000, p = 0.90$).

Setting train/test/rule	athleteplaysforteam A	athleteplaysforteam B	athleteplayssport A	athleteplayssport B	teamplaysinleague A	teamplaysinleague B	athleteplaysinleague A	athleteplaysinleague B	teamplaysagainstteam A	teamplaysagainstteam B
1: det/det/det	74.00	69.36	94.14	93.47	96.29	82.15	80.95	74.14	73.40	73.86
2: det/prob/det	73.51	69.57	97.53	94.85	96.70	87.83	90.83	77.73	73.70	73.35
3: det/prob/prob	74.67	69.82	95.86	94.74	96.35	82.57	82.26	75.29	73.84	74.34
4: det/prob/prob	77.25	73.87	96.53	96.04	98.00	90.59	84.91	79.36	77.26	77.83
5: det/prob/prob	74.76	69.97	95.85	94.69	96.44	82.51	81.99	75.07	73.90	74.16
6: prob/prob/det	75.83	73.11	93.40	93.76	94.44	93.67	79.41	79.42	80.87	80.60
7: prob/prob/prob	78.31	73.72	95.62	95.10	98.84	91.86	96.94	79.49	85.78	81.81

Table 3: Learned relational rules for the different predicates (fold 1).

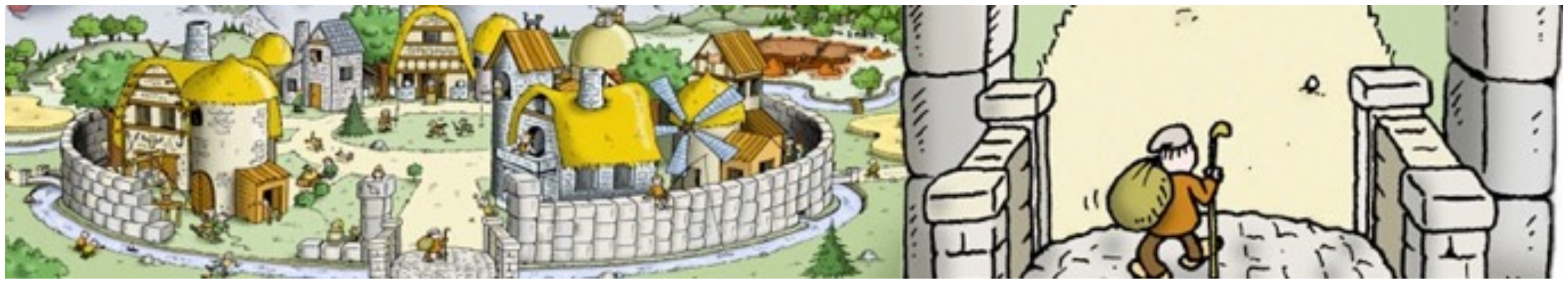
0.9375::athleteplaysforteam(A,B)	←	athleteledsportsteam(A,B).
0.9675::athleteplaysforteam(A,B)	←	athleteledsportsteam(A,V1), teamplaysagainstteam(B,V1).
0.9375::athleteplaysforteam(A,B)	←	athleteplayssport(A,V1), teamplayssport(B,V1).
0.5109::athleteplaysforteam(A,B)	←	athleteplaysinleague(A,V1), teamplaysinleague(B,V1).
0.9070::athleteplayssport(A,B)	←	athleteledsportsteam(A,V2), teamalsoknownas(V2,V1), teamplayssport(V1,B), teamplayssport(V2,B).
0.9070::athleteplayssport(A,B)	←	athleteplaysforteam(A,V2), teamalsoknownas(V2,V1), teamplayssport(V1,B), teamplayssport(V2,B),teamalsoknownas(V1,V2).
0.9070::athleteplayssport(A,B)	←	athleteplaysforteam(A,V1), teamplayssport(V1,B).
0.9286::athleteplaysinleague(A,B)	←	athleteledsportsteam(A,V1), teamplaysinleague(V1,B).
0.7868::athleteplaysinleague(A,B)	←	athleteplaysforteam(A,V2), teamalsoknownas(V2,V1), teamplaysinleague(V1,B).
0.9384::athleteplaysinleague(A,B)	←	athleteplayssport(A,V2), athleteplayssport(V1,V2), teamplaysinleague(V1,B).
0.9024::athleteplaysinleague(A,B)	←	athleteplaysforteam(A,V1), teamplaysinleague(V1,B).

ProbFOIL

- Upgrade rule-learning to a probabilistic setting within a relational learning / inductive logic programming setting
  - Works with a probabilistic logic program instead of a deterministic one.
- Introduce ProbFOIL, an adaption of Quinlan's FOIL to this setting.
- Apply to probabilistic databases like NELL

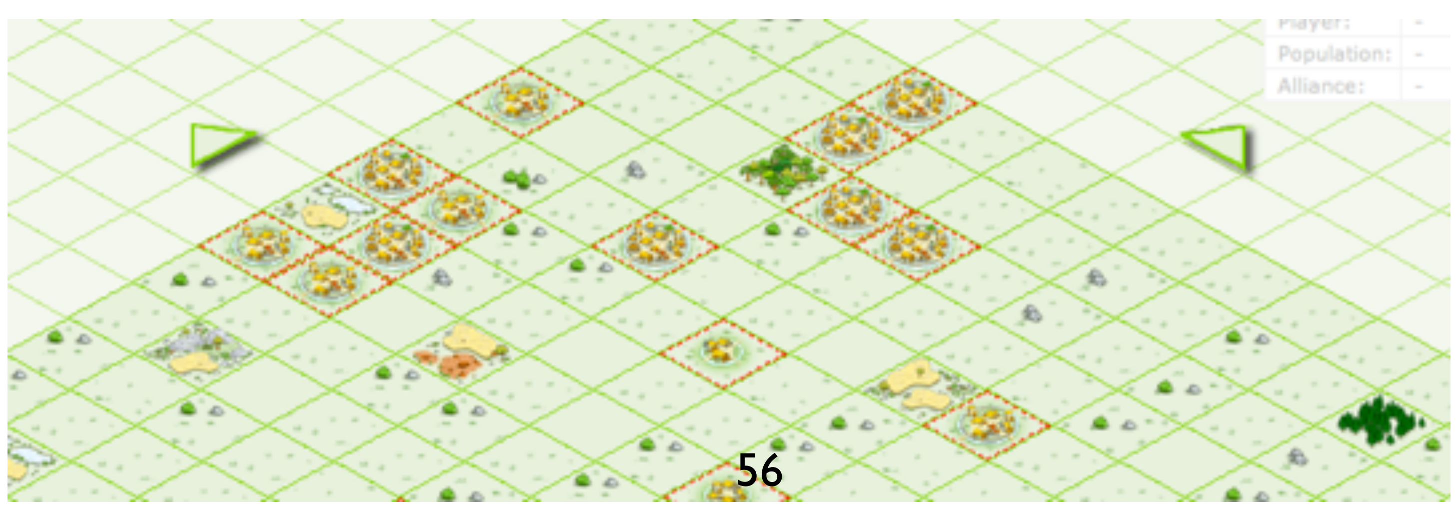
Part IV : Dynamics

Dynamics: Evolving Networks



- *Travian*: A massively multiplayer real-time strategy game
  - Commercial game run by TravianGames GmbH
  - ~3.000.000 players spread over different "worlds"
  - ~25.000 players in one world

[Thon et al. ECML 08]



World Dynamics

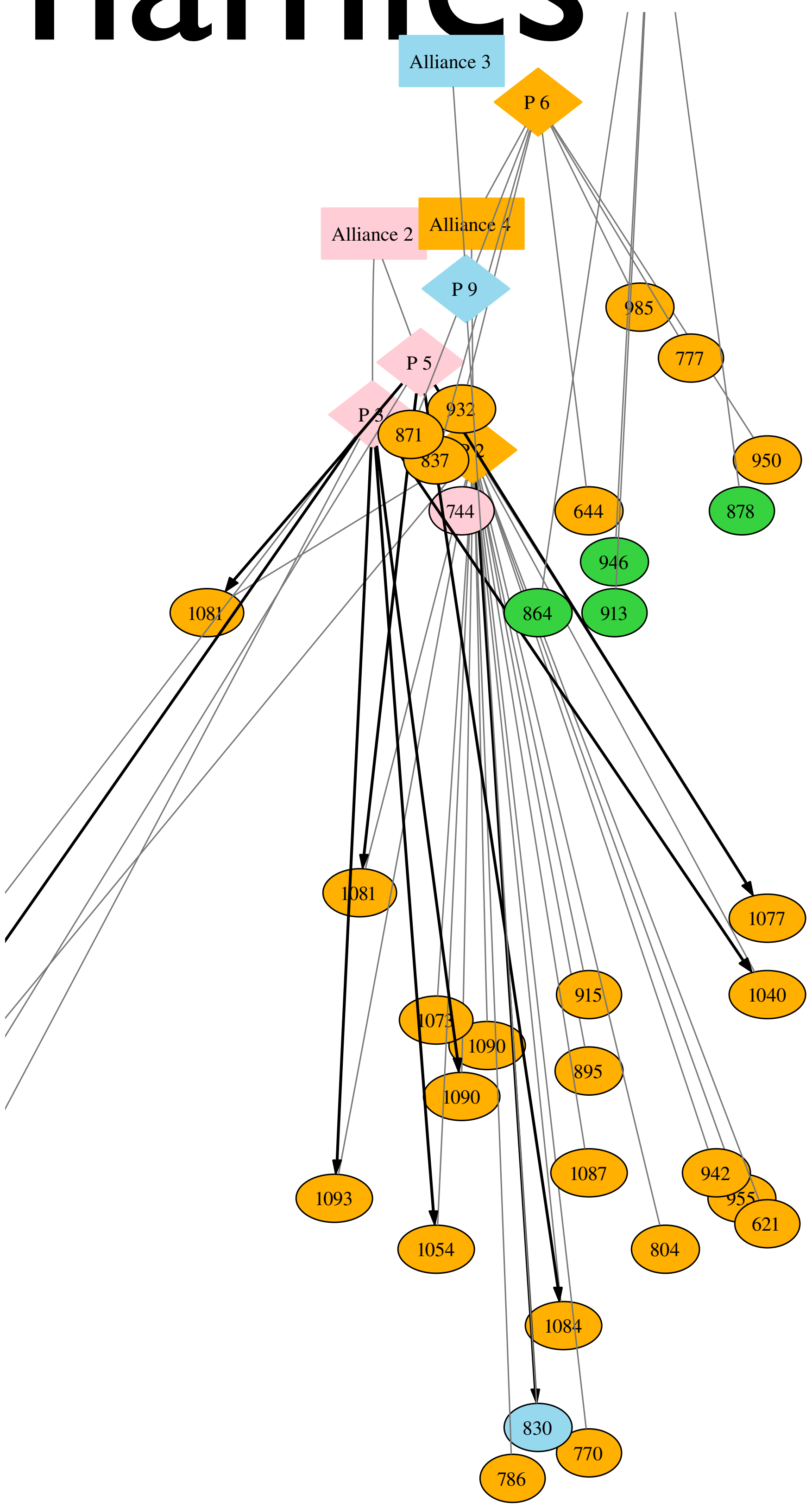
Fragment of world with

~10 alliances
~200 players
~600 cities

alliances color-coded

Can we build a model
of this world ?
Can we use it for playing
better ?

[Thon, Landwehr, De Raedt, ECML08]



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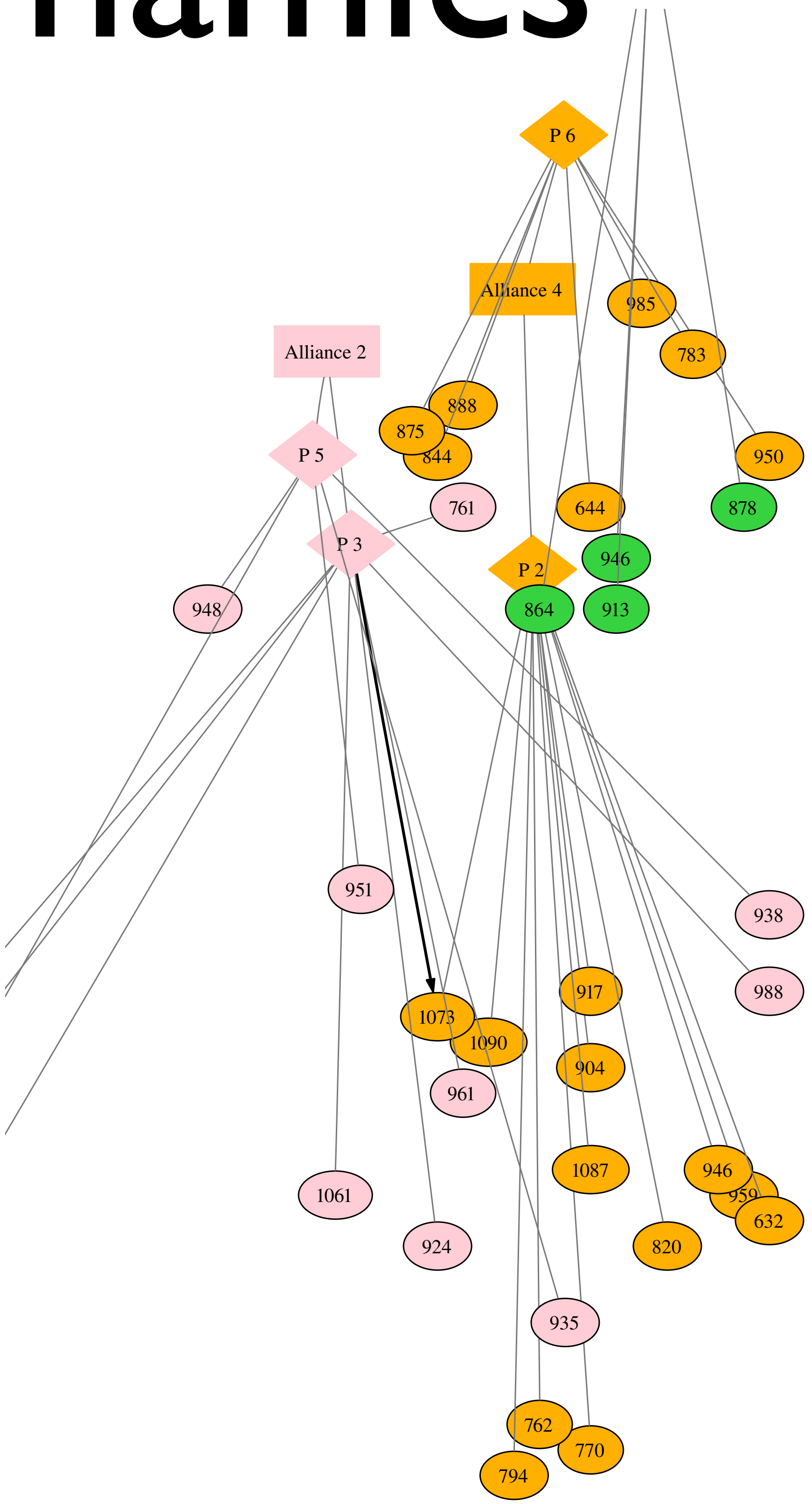

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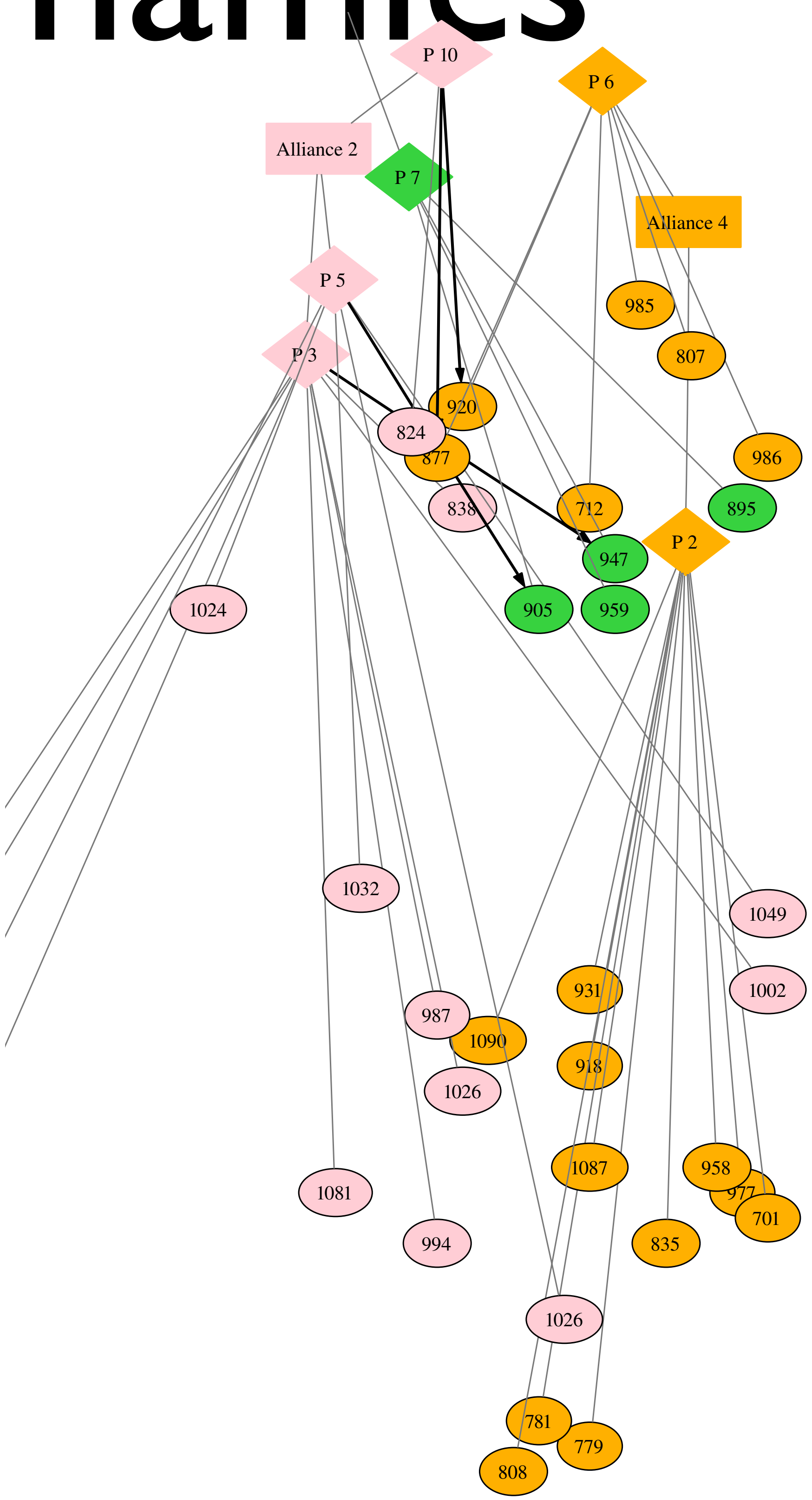

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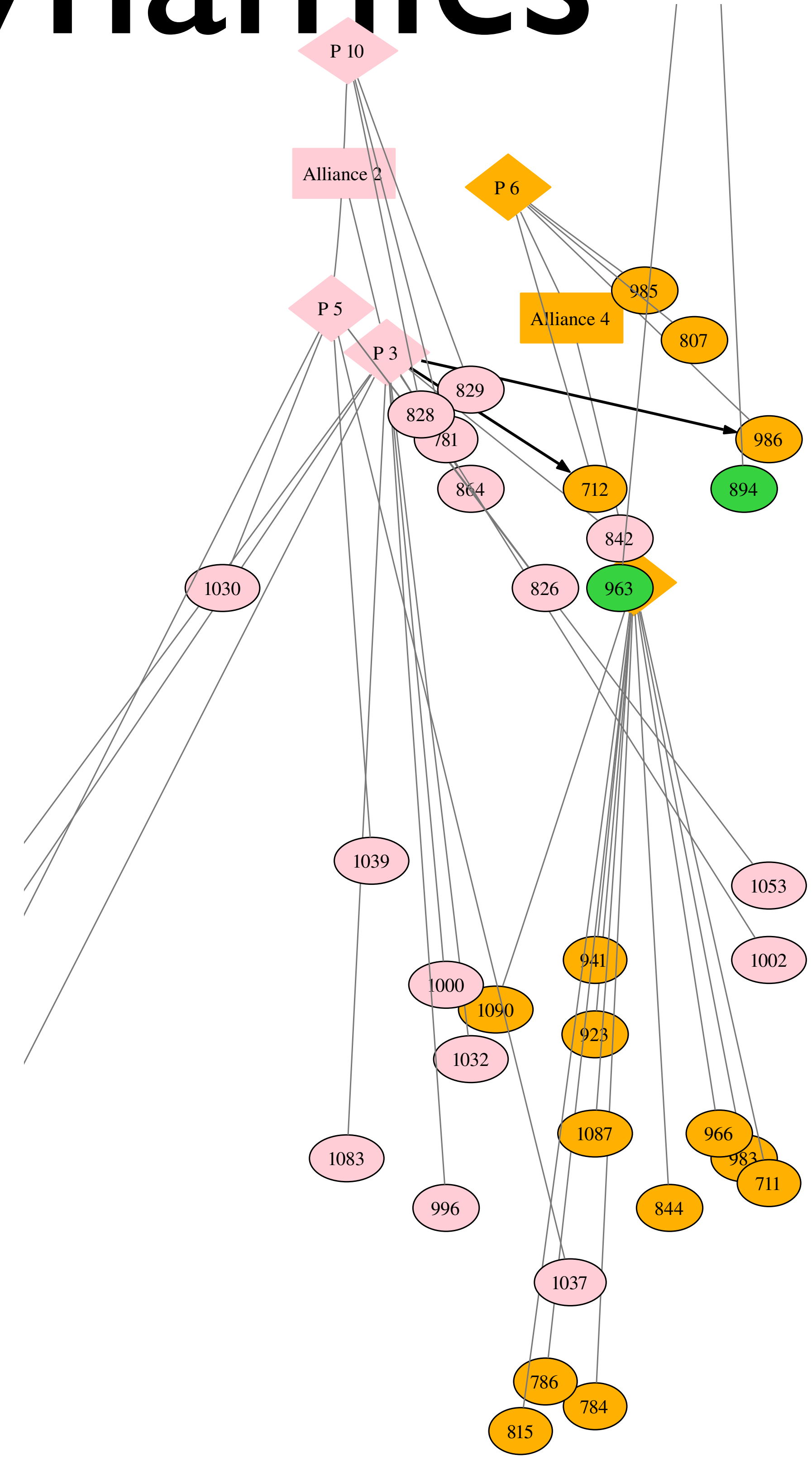

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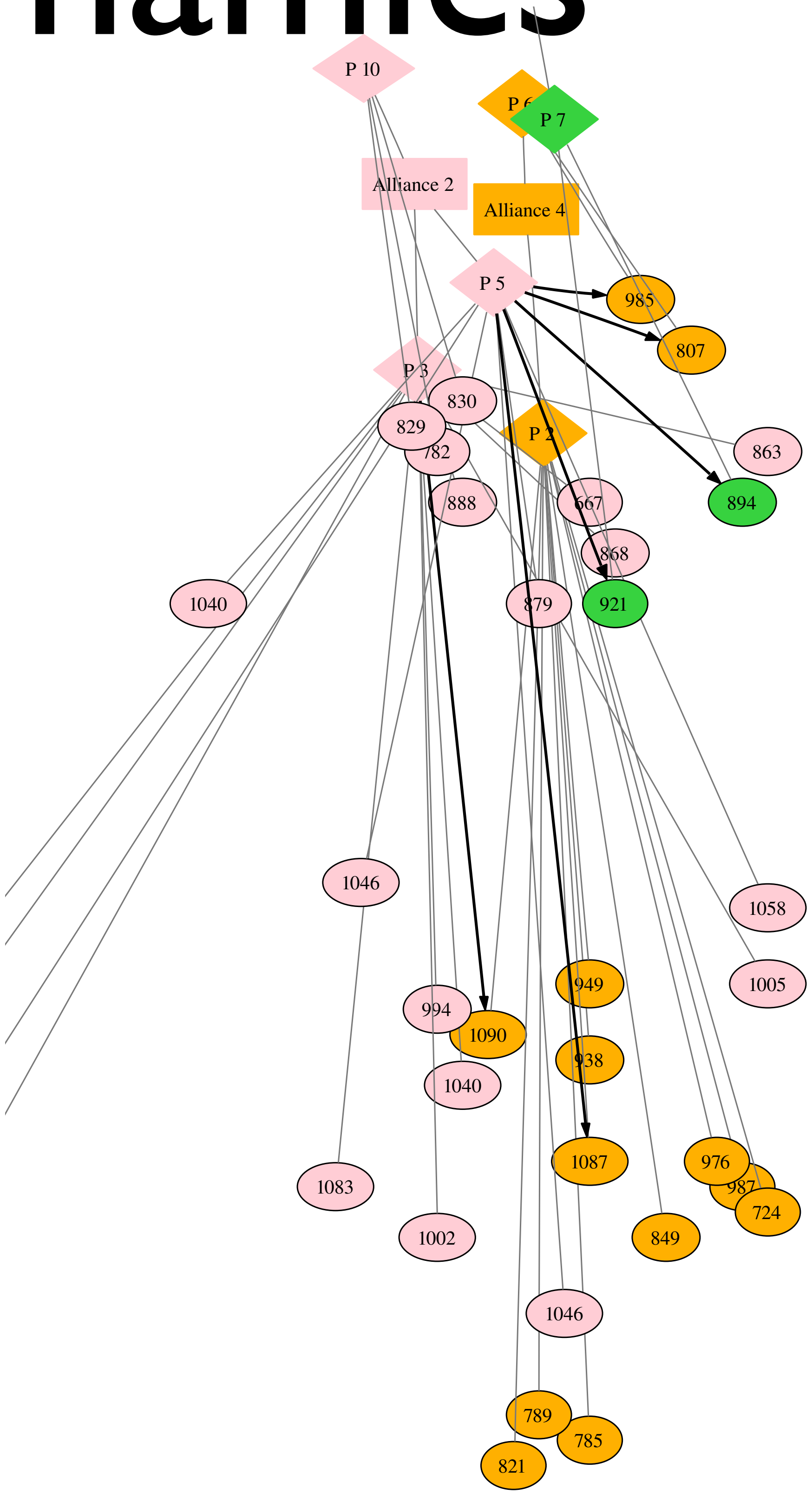

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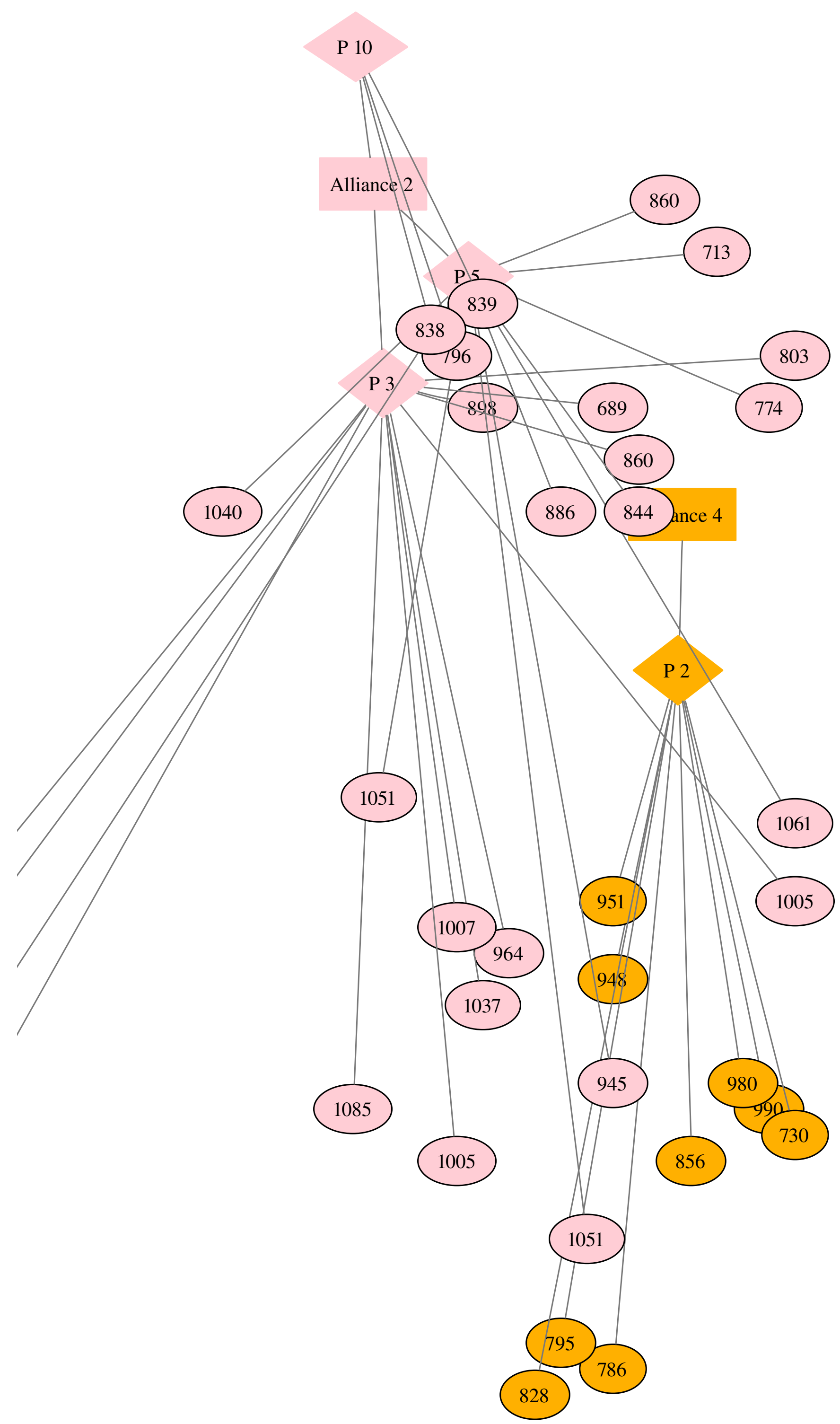
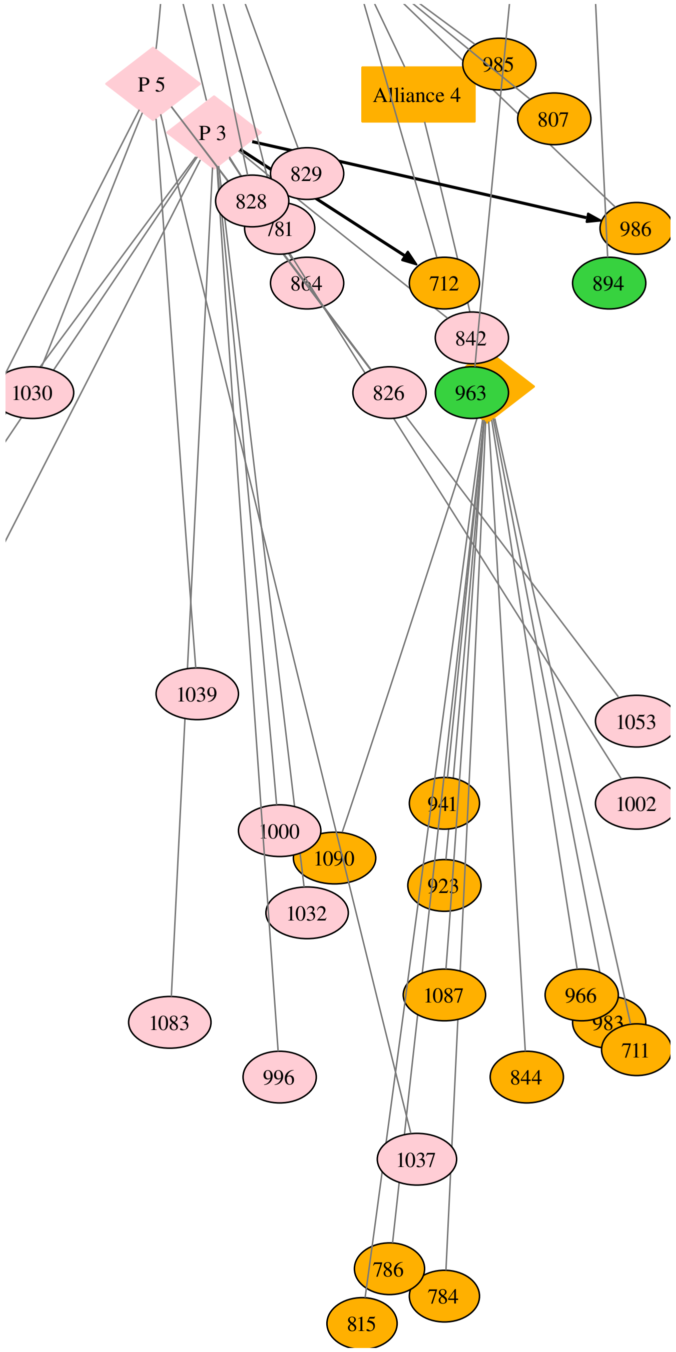


CPT-Rules

$$\underbrace{b_1, \ldots b_n}_{\text{cause}} \rightarrow \underbrace{h_1 : p_1 \vee \ldots \vee h_m : p_m}_{\text{effect}}$$

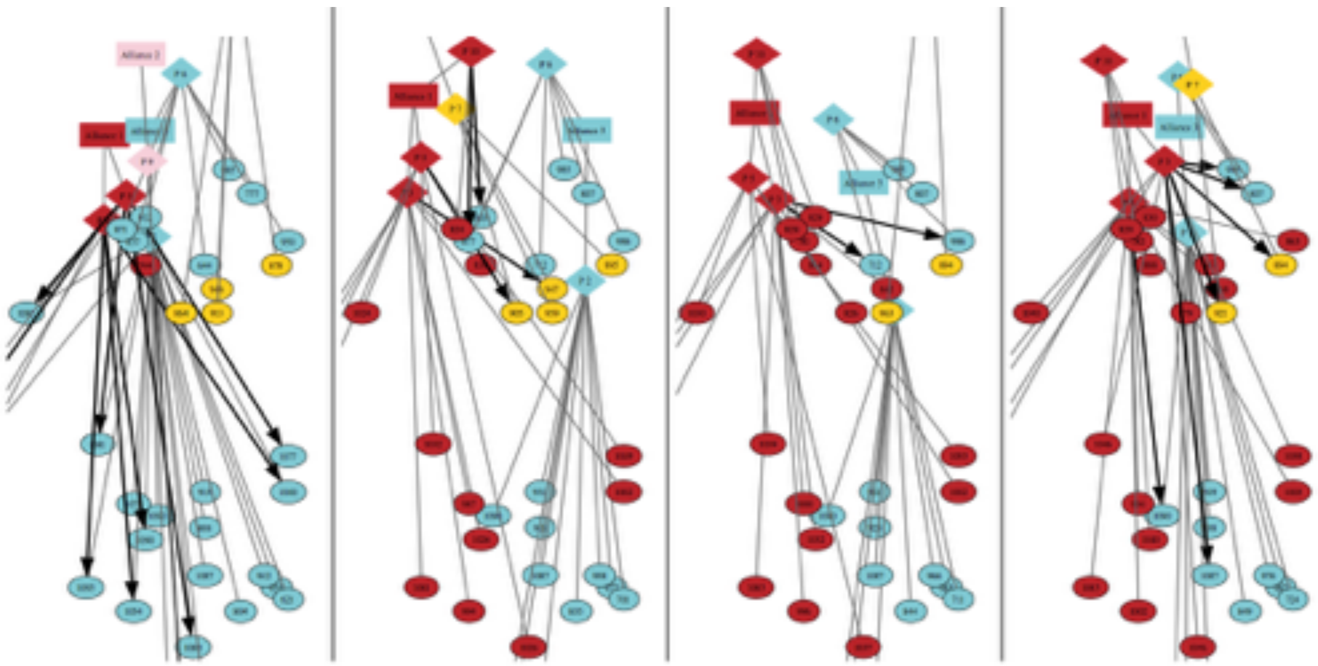
$$city(C, Owner), city(C2, Attacker), close(C, C2) \rightarrow$$
$$conquest(Attacker, C2) \;:\; p \;\vee\; nil \;:\; (1 - p)$$

conquer a city which is close
P(conquest(),Time+5) ?
learn parameters



Thon et al. MLJ 11

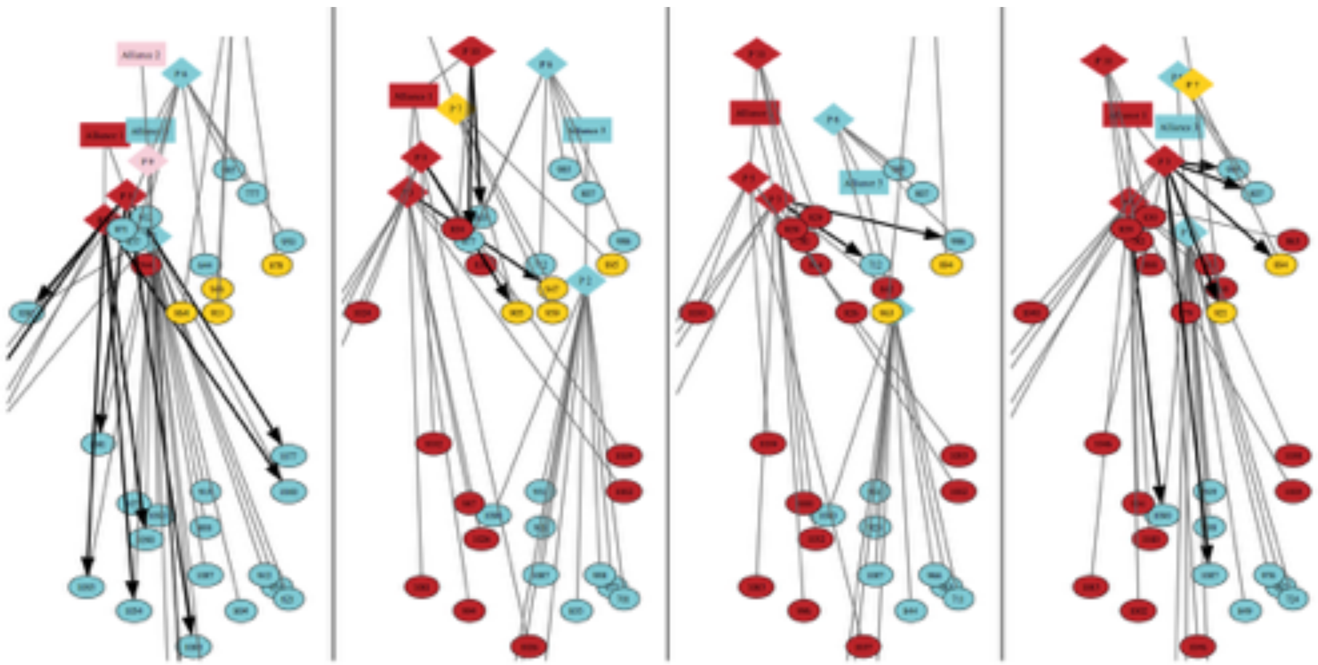
Causal Probabilistic Time-Logic (CPT-L)



how does the world change over time?

[Thon et al, MLJ 11]

Causal Probabilistic Time-Logic (CPT-L)



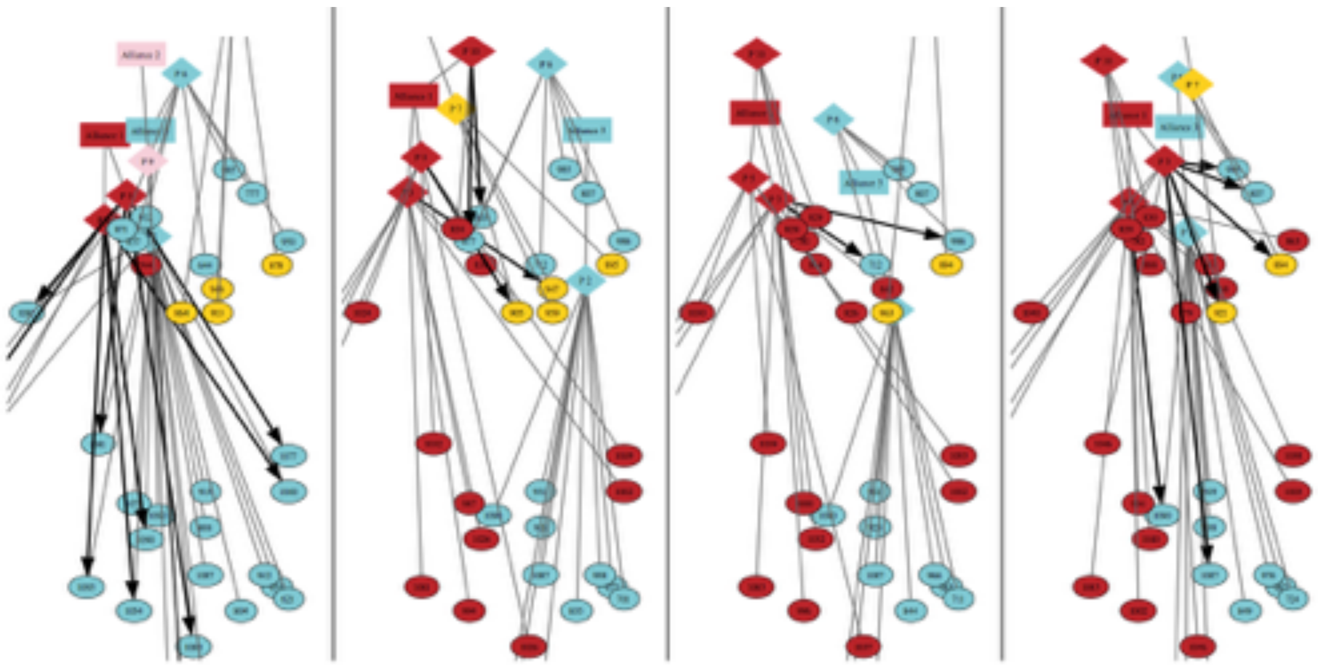
how does the world change over time?

```
0.4::conquest(Attacker,C); 0.6::nil :-
        city(C,Owner),city(C2,Attacker),close(C,C2).
```

if **cause** holds at time T

[Thon et al, MLJ 11]

Causal Probabilistic Time-Logic (CPT-L)



how does the world change over time?

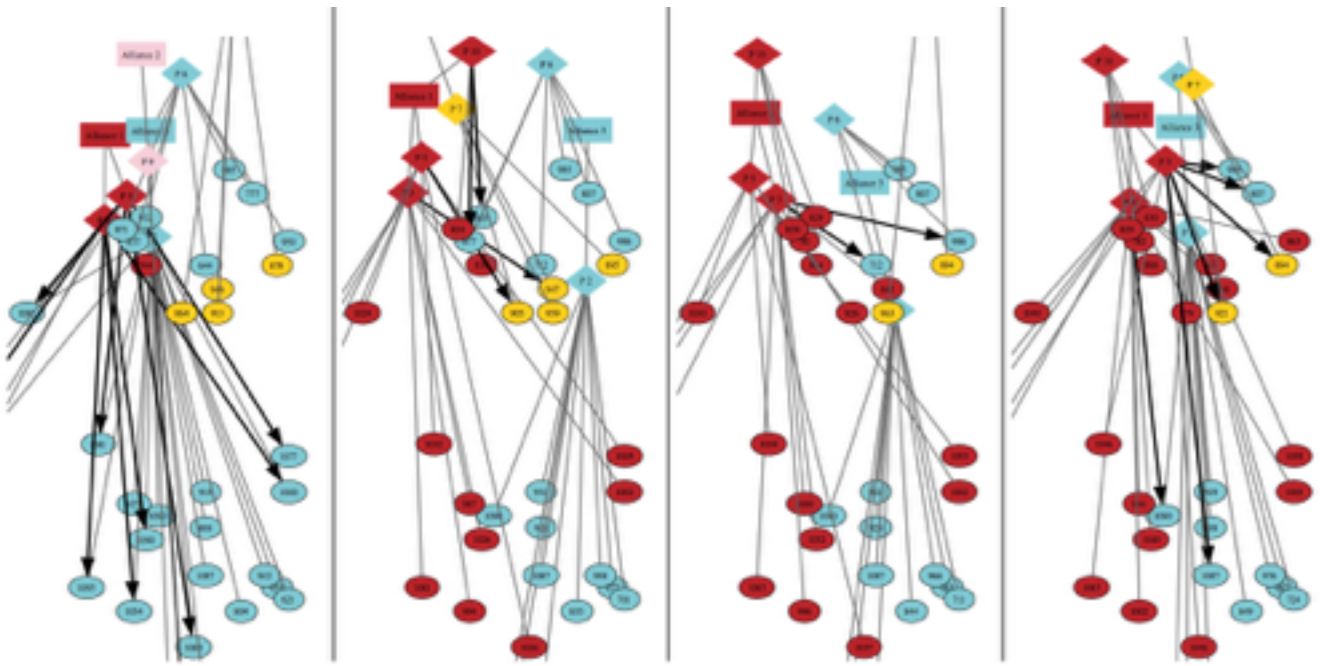
one of the **effects** holds at time T+1

```
0.4::conquest(Attacker,C); 0.6::nil :-
                city(C,Owner),city(C2,Attacker),close(C,C2).
```

if **cause** holds at time T

[Thon et al, MLJ 11]

Causal Probabilistic Time-Logic (CPT-L)



how does the world change over time?

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0.4::conquest(Attacker,C); 0.6::nil :-
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```

if **cause** holds at time T

[Thon et al, MLJ 11]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

random variable with Gaussian distribution

```
length(Obj) ~ gaussian(6.0,0.45) :- type(Obj,glass).
```

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

```
length(Obj) ~ gaussian(6.0,0.45) :- type(Obj,glass).
stackable(OBot,OTop) :-
      ≃length(OBot) ≥ ≃length(OTop),
      ≃width(OBot) ≥ ≃width(OTop).
```

comparing values of random variables

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

```
length(Obj) ~ gaussian(6.0,0.45) :- type(Obj,glass).
stackable(OBot,OTop) :-
      ≃length(OBot) ≥ ≃length(OTop),
      ≃width(OBot) ≥ ≃width(OTop).
ontype(Obj,plate) ~ finite([0 : glass, 0.0024 : cup,
                            0 : pitcher, 0.8676 : plate,
                            0.0284 : bowl, 0 : serving,
                            0.1016 : none])
                        :- obj(Obj), on(Obj,O2), type(O2,plate).
```

random variable with discrete distribution

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

```
length(Obj) ~ gaussian(6.0,0.45) :- type(Obj,glass).
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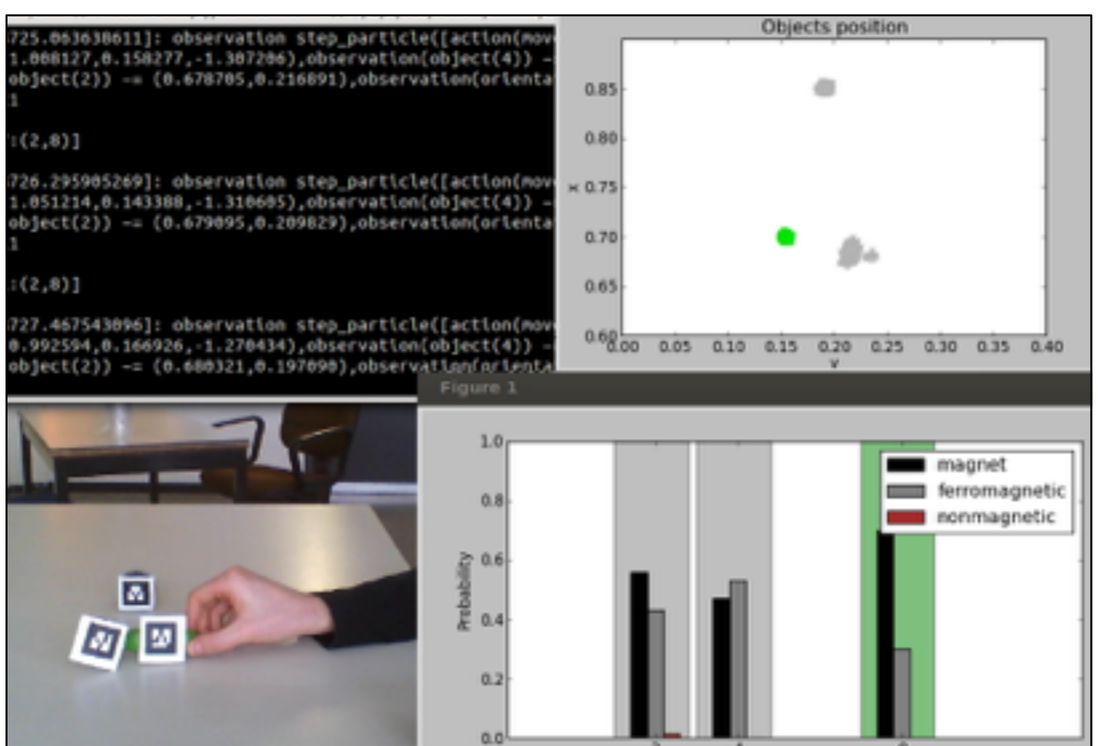
                         :- obj(Obj), on(Obj,O2), type(O2,plate).
```

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Relational State Estimation over Time

Magnetism scenario

- object tracking
- category estimation from interactions



[Nitti et al, IROS 13]

Relational State Estimation over Time

Magnetism scenario

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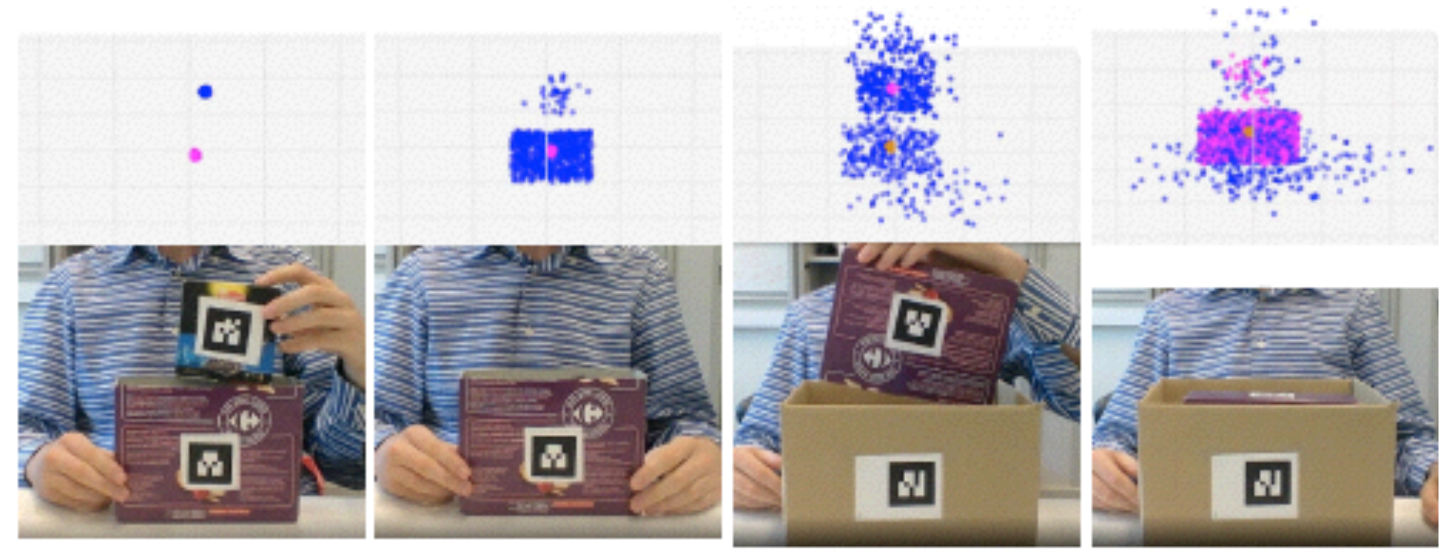
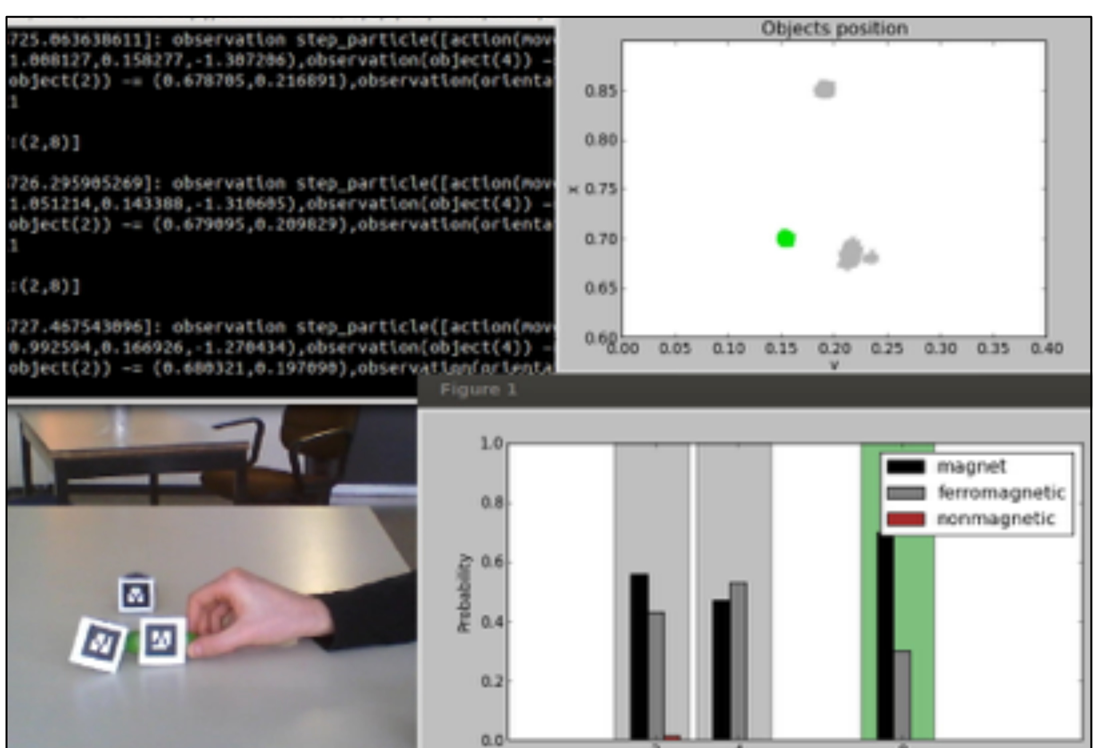
- category estimation from interactions



(a) cube on the box (b) cube inside the box (c) rotated box on a beige box (d) cube and box inside the beige box



Box scenario

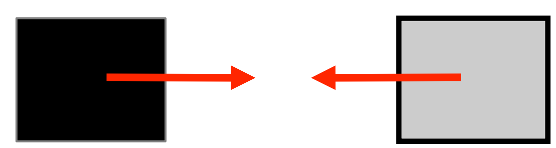
- object tracking even when invisible
- estimate spatial relations

[Nitti et al, IROS 13]

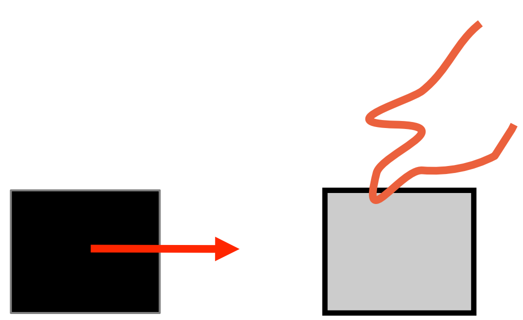
Magnetic scenario

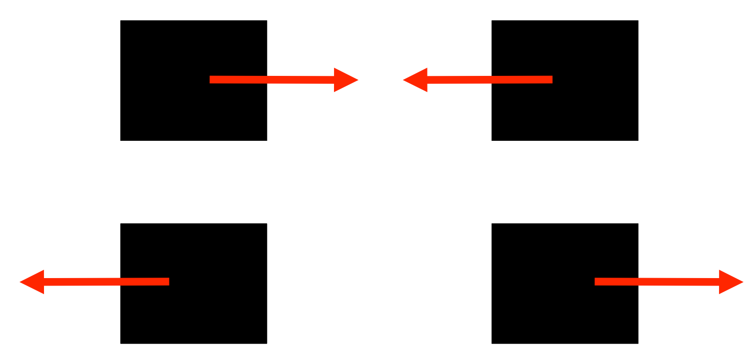
- 3 object types: magnetic, ferromagnetic, nonmagnetic

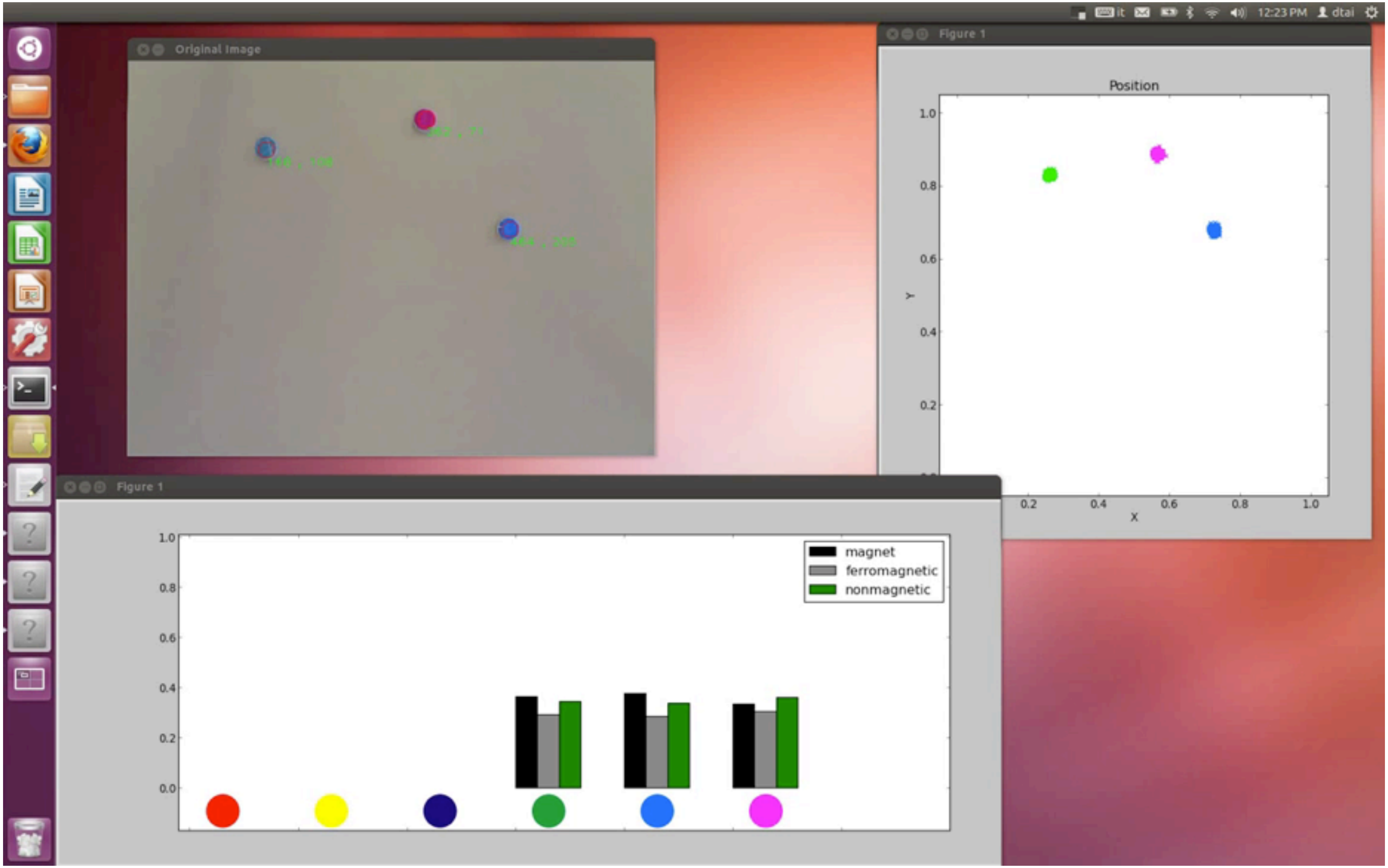
- Nonmagnetic objects do not interact
- A magnet and a ferromagnetic object attract each other

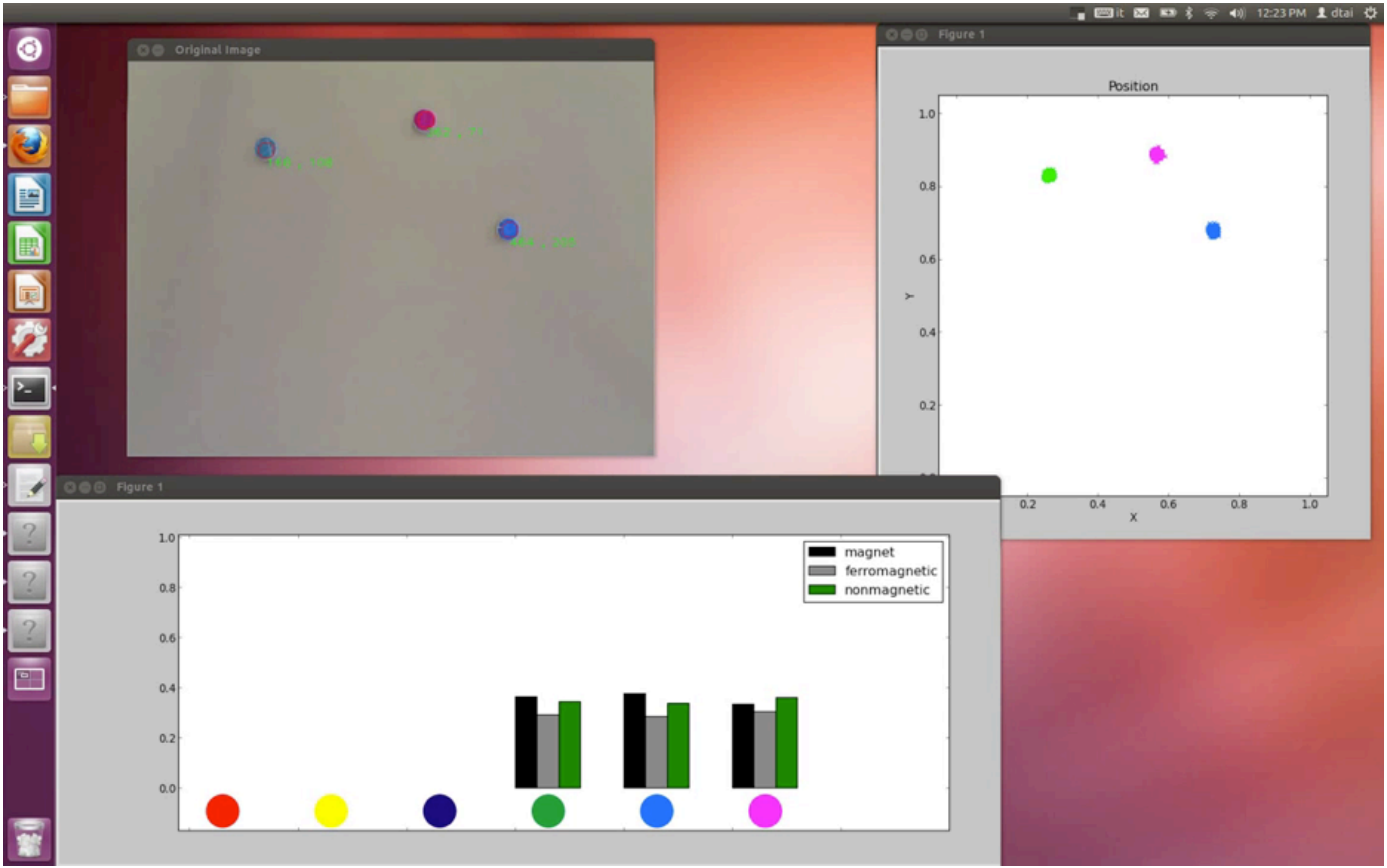


- Magnetic force that depends on the distance
- If an object is held magnetic force is compensated.






Original Image
Figure 1
Position
1.0
0.8
0.6
0.4
0.2
Y
0.2
0.4
0.6
0.8
1.0
X
Figure 1
magnet
ferromagnetic
nonmagnetic
1.0
0.8
0.6
0.4
0.2
0.0


Original Image
Figure 1
Position
1.0
0.8
0.6
0.4
0.2
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0.4
0.6
0.8
1.0
X
Y
Figure 1
magnet
ferromagnetic
nonmagnetic
1.0
0.8
0.6
0.4
0.2
0.0
12:23 PM
dtai

Magnetic scenario

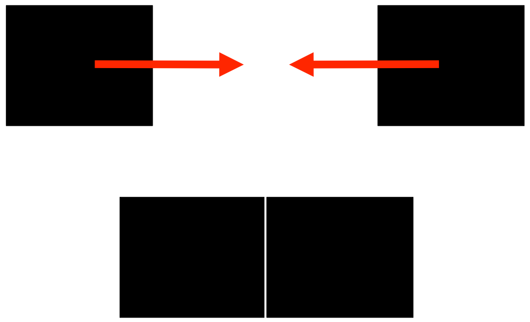
- 3 object types: magnetic, ferromagnetic, nonmagnetic

$\text{type}(X)_t \sim \text{finite}([1/3\text{:magnet}, 1/3\text{:ferromagnetic}, 1/3\text{:nonmagnetic}]) \leftarrow \text{object}(X).$

- 2 magnets attract or repulse

$\text{interaction}(A,B)_t \sim \text{finite}([0.5\text{:attraction}, 0.5\text{:repulsion}]) \leftarrow \text{object}(A), \text{object}(B), A<B, \text{type}(A)_t = \text{magnet}, \text{type}(B)_t = \text{magnet}.$

- Next position after attraction

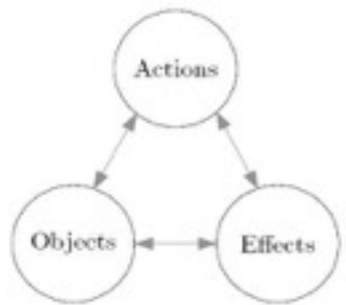


$\text{pos}(A)_{t+1} \sim \text{gaussian}(\text{middlepoint}(A,B)_t, \text{Cov}) \leftarrow \text{near}(A,B)_t, \text{not}(\text{held}(A)), \text{not}(\text{held}(B)), \text{interaction}(A,B)_t = \text{attr}, c/\text{dist}(A,B)_t^2 > \text{friction}(A)_t.$

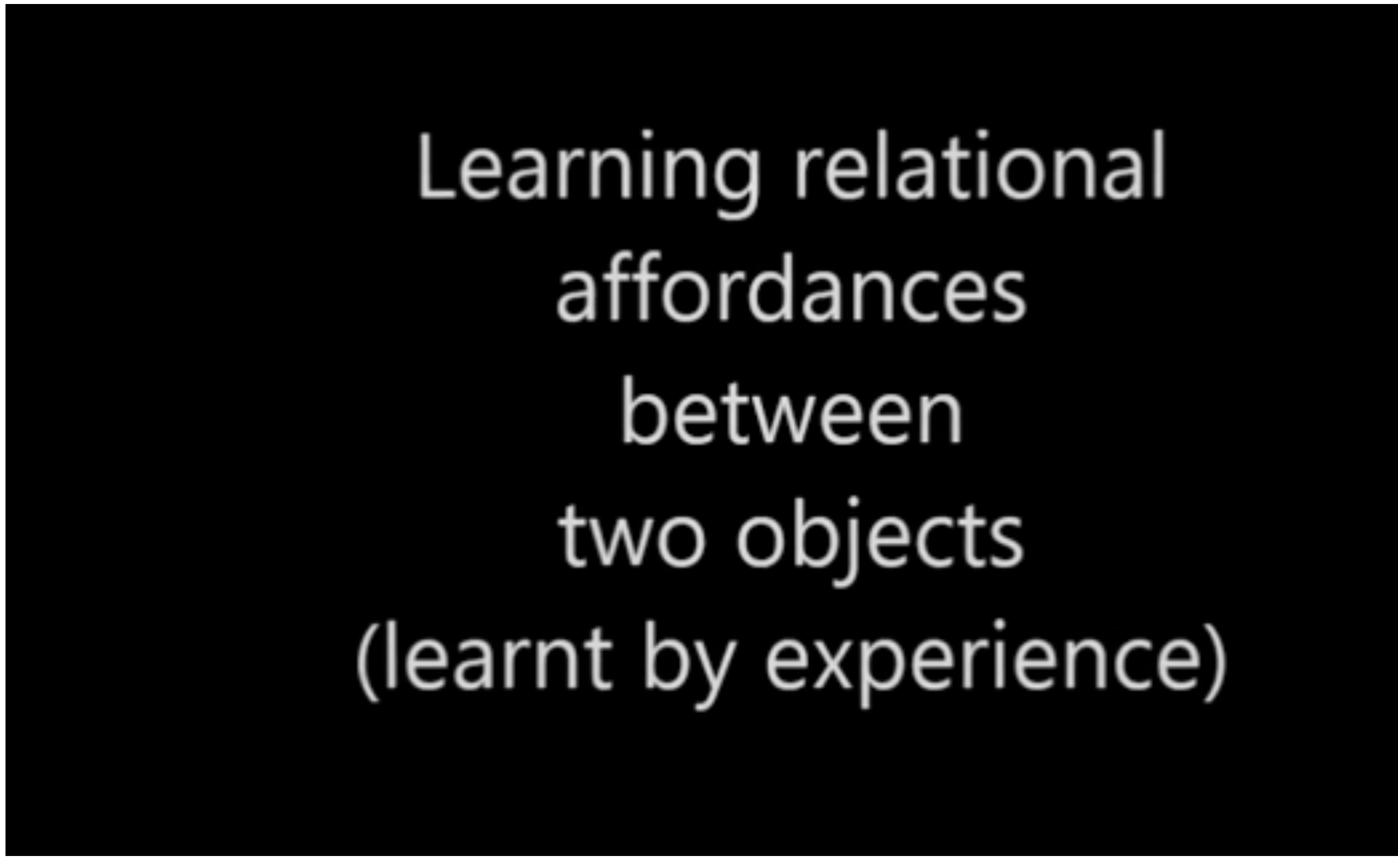
$\text{pos}(A)_{t+1} \sim \text{gaussian}(\text{pos}(A)_t, \text{Cov}) \leftarrow \text{not}(\ \text{attraction}(A,B)\ ).$

Learning relational affordances

Learn probabilistic model



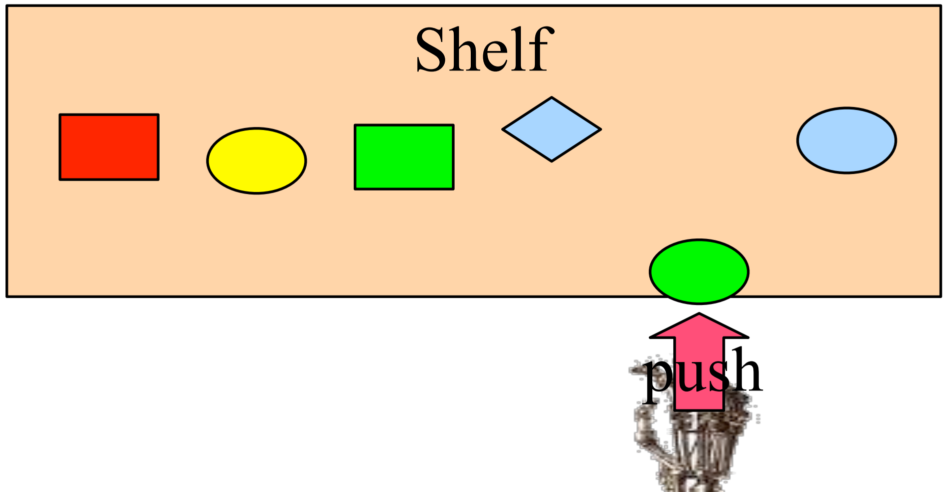
Inputs	Outputs	Function
(O, A)	E	Effect prediction
(O, E)	A	Action recognition/planning
(A, E)	O	Object recognition/selection

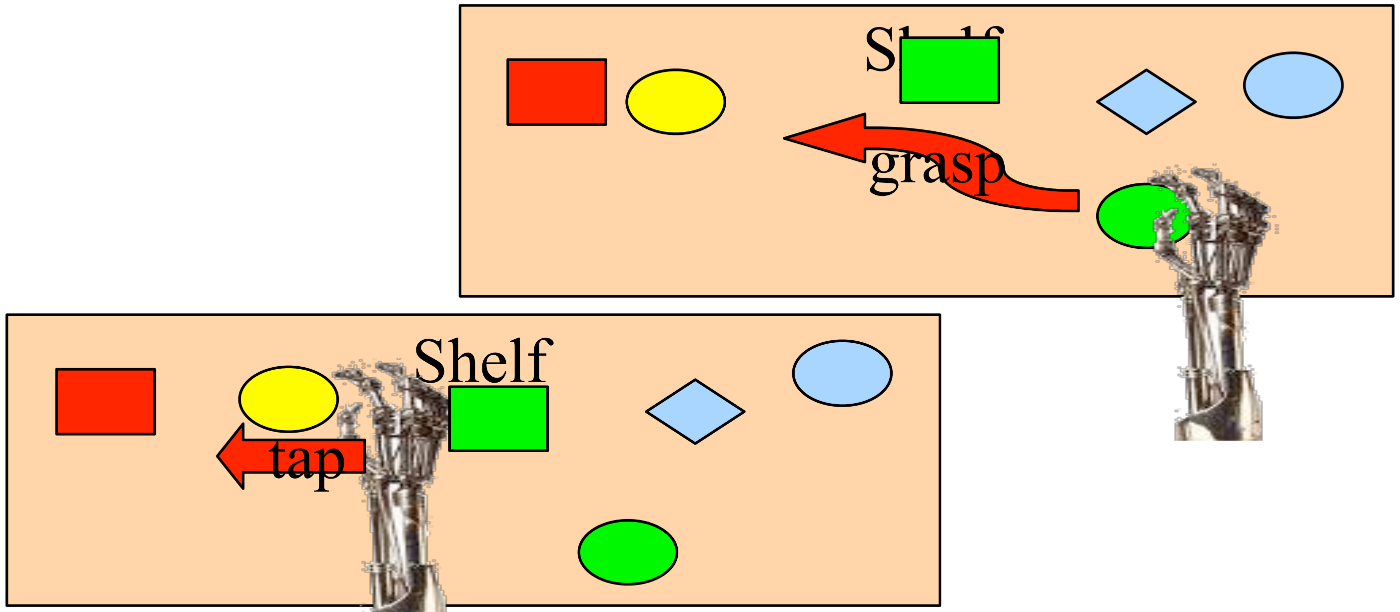


From two object interactions

Generalize to N

Moldovan et al. ICRA 12, 13, 14
Nitti et al, MLJ 16, 17; ECAI 16





Learning relational affordances

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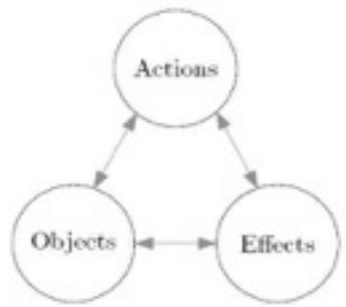

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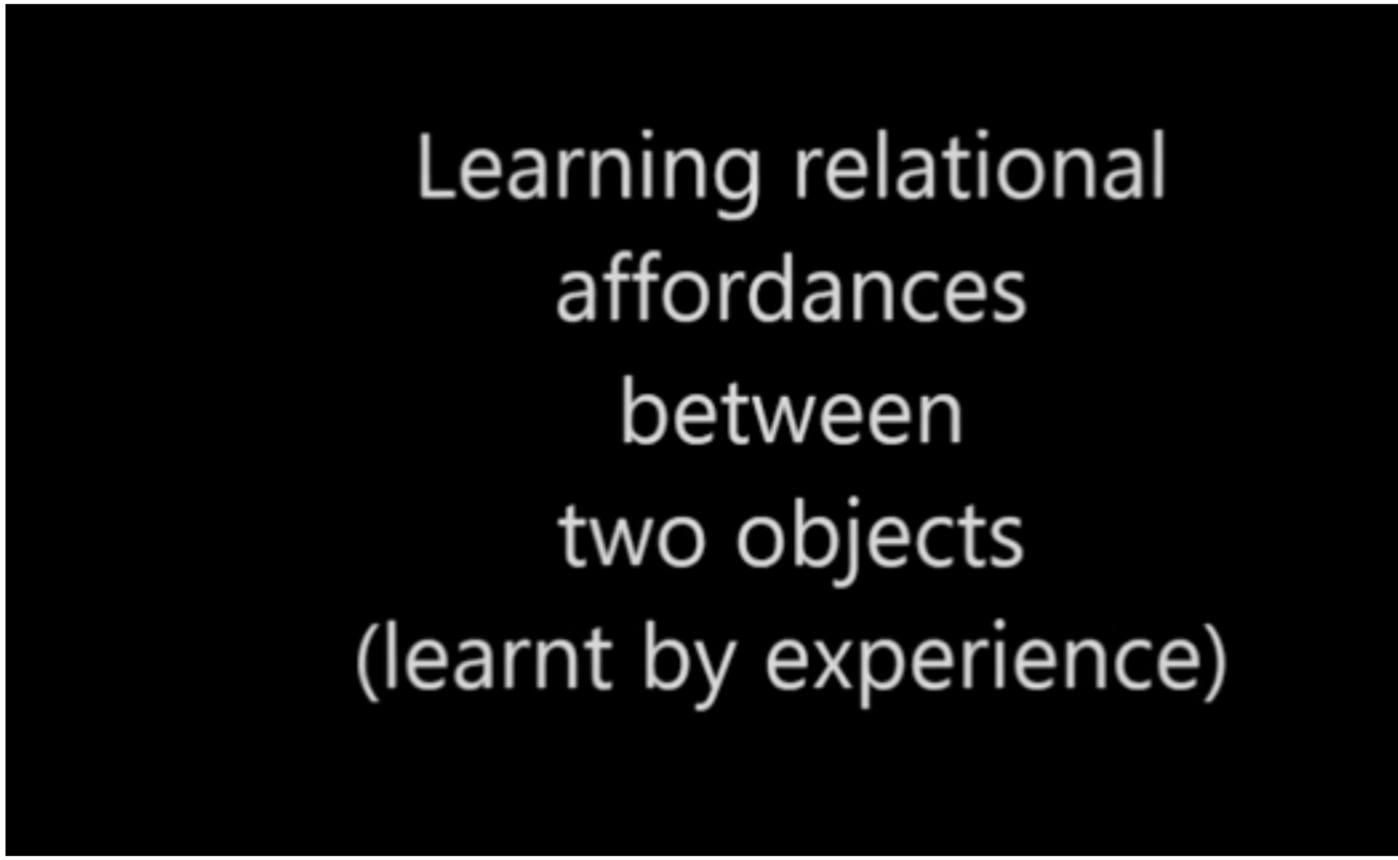

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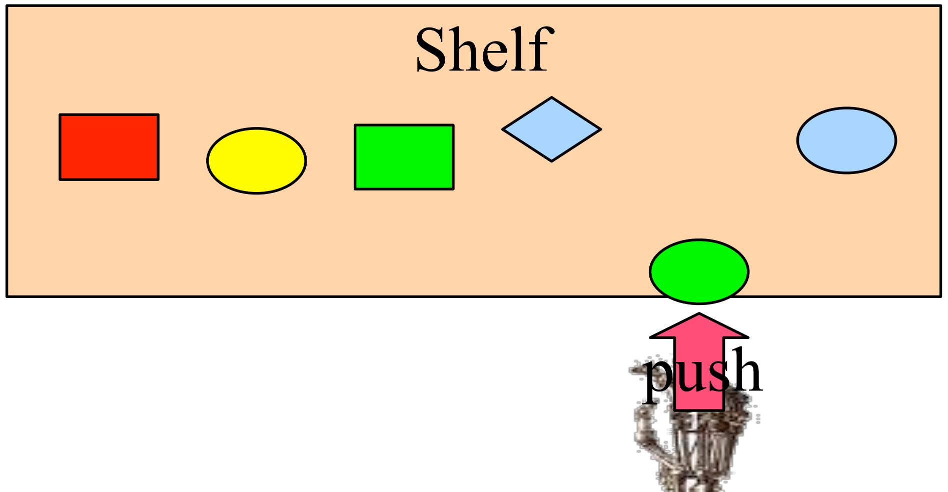
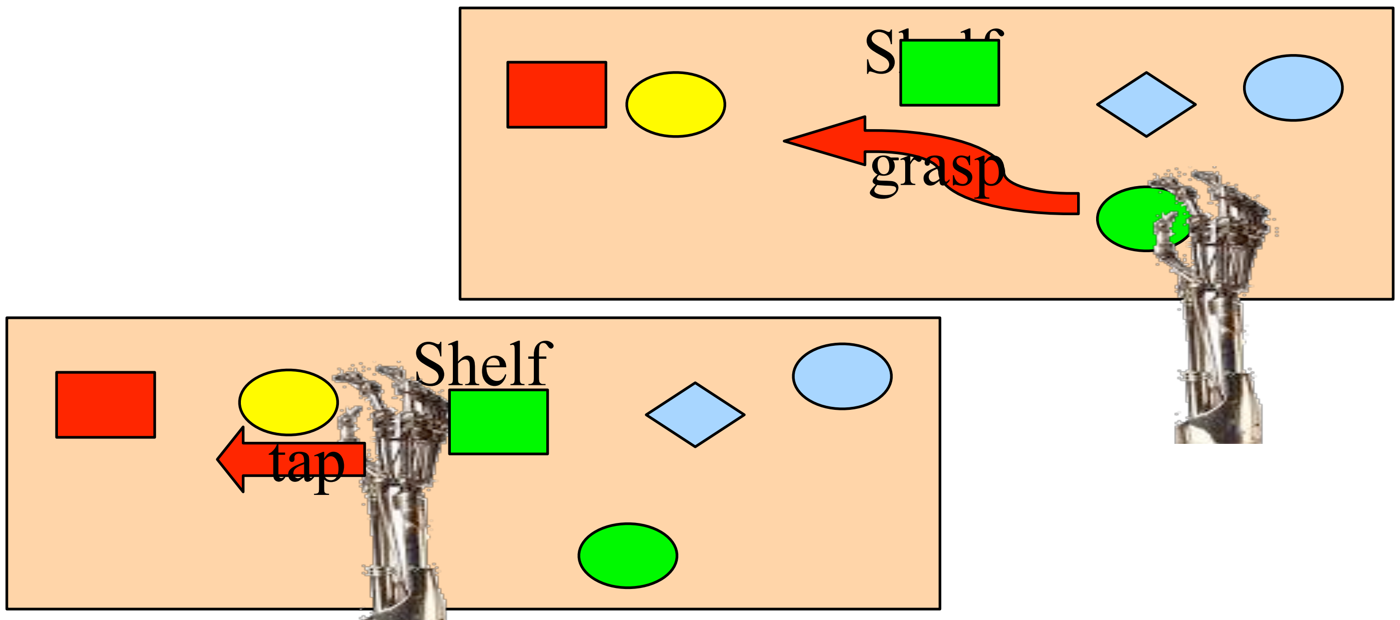
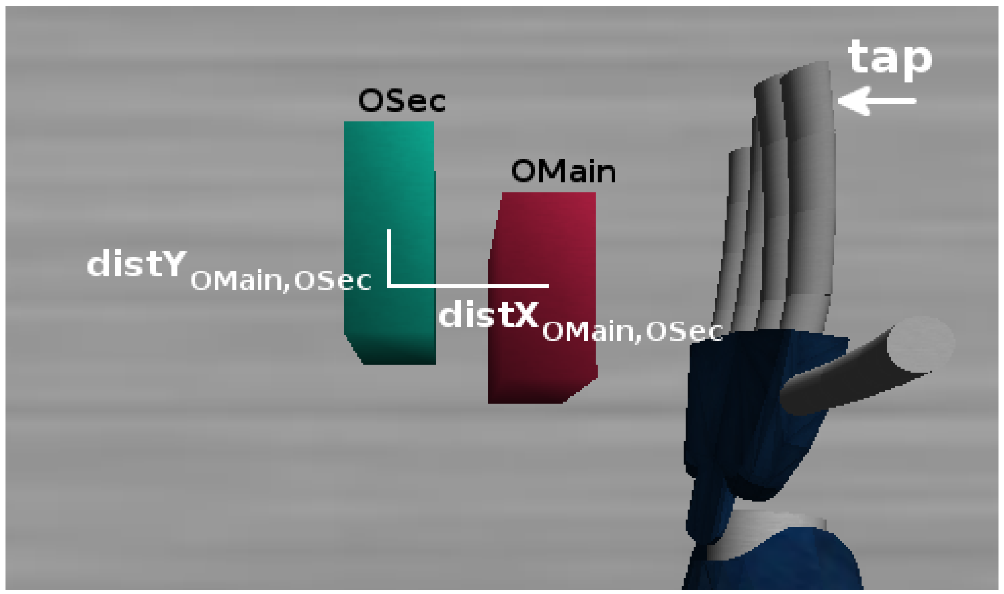




What is an affordance ?



Clip 8: Relational O before (l), and E after the action execution (r).

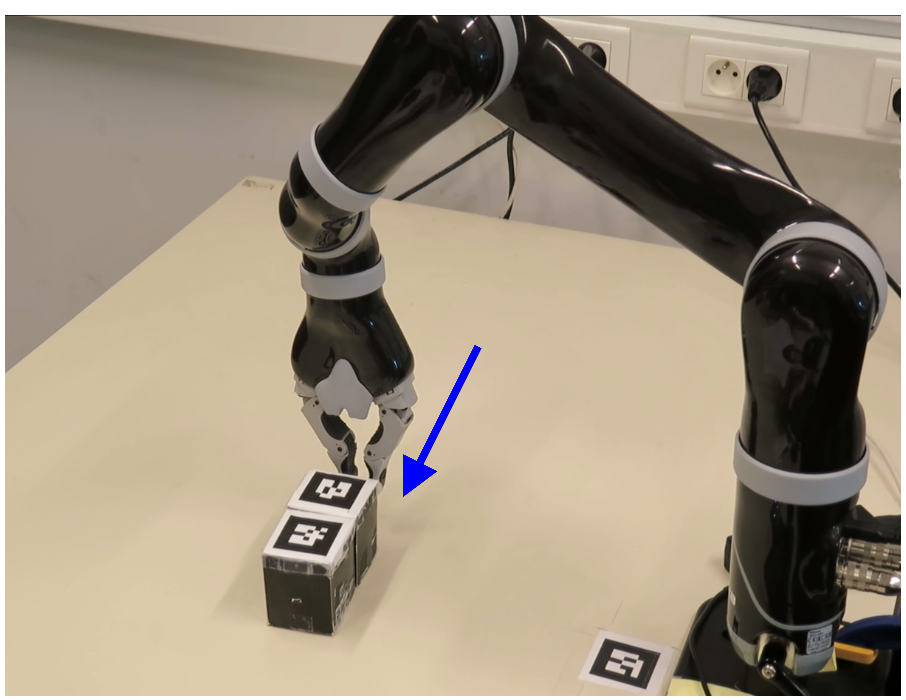
Table 1: Example collected O, A, E data for action in Figure 8

Object Properties	Action	Effects
$shape_{O_{Main}}$: $sprism$ $shape_{O_{Sec}}$: $sprism$ $distX_{O_{Main},O_{Sec}}$: $6.94cm$ $distY_{O_{Main},O_{Sec}}$: $1.90cm$	$tap(10)$	$displX_{O_{Main}}$: $10.33cm$ $displY_{O_{Main}}$: $-0.68cm$ $displX_{O_{Sec}}$: $7.43cm$ $displY_{O_{Sec}}$: $-1.31cm$

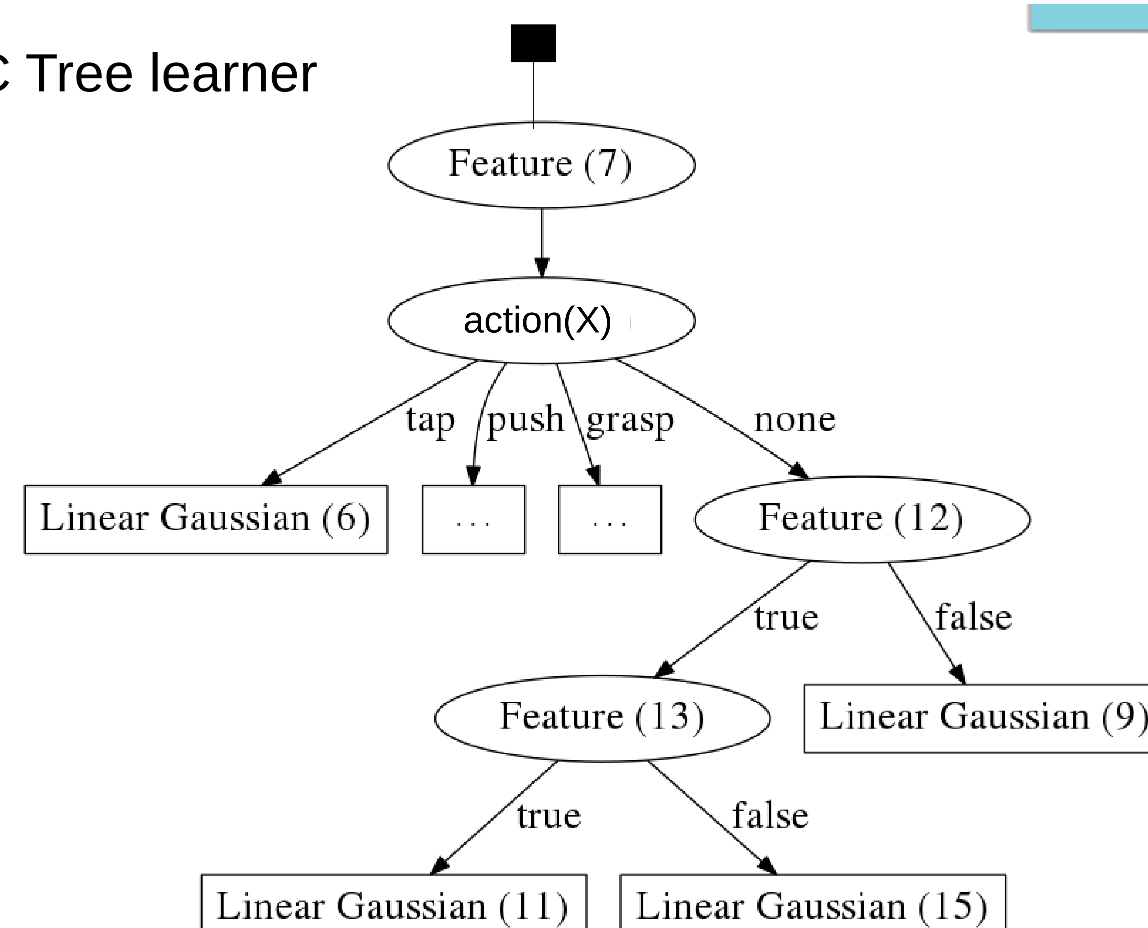
- Formalism — related to STRIPS but models delta
    - but also joint probability model over A, E, O

Relational Affordance Learning

- **Learning the Structure of Dynamic Hybrid Relational Models**
  Nitti, Ravkic, et al. ECAI 2016
  - Captures relations/affordances
  - Suited to learn affordances in
    robotics set-up, continuous and discrete variables
  - Planning in hybrid robotics domain

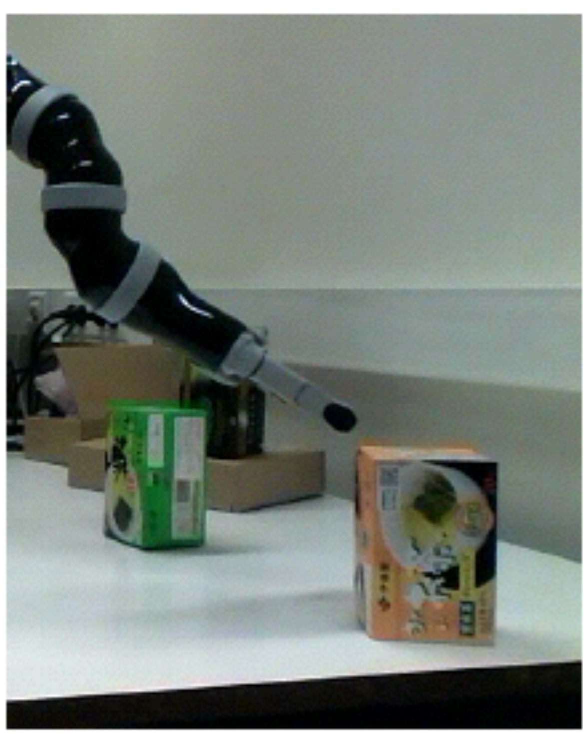


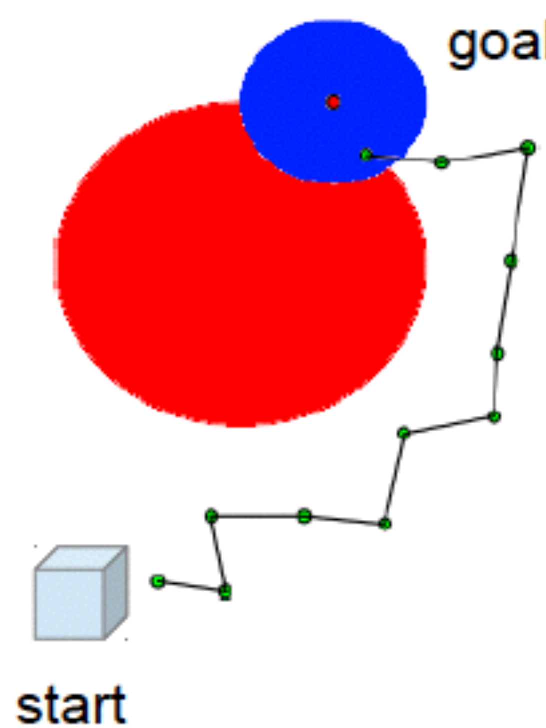
DDC Tree learner

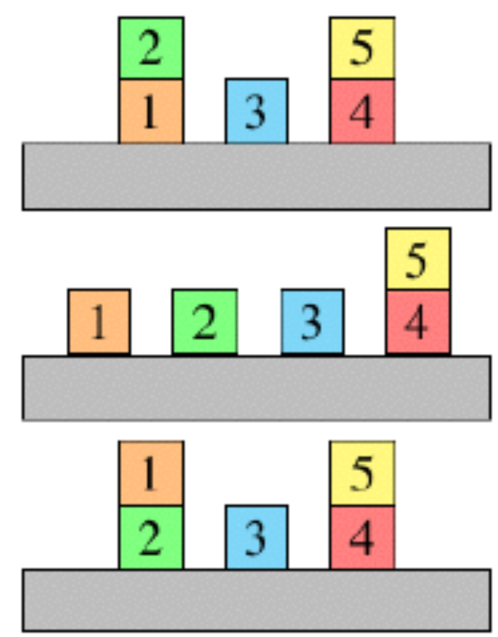


Planning

- Main task: probabilistic planning
  Find the best action to achieve the goal
- Discrete + continuous + relational representation



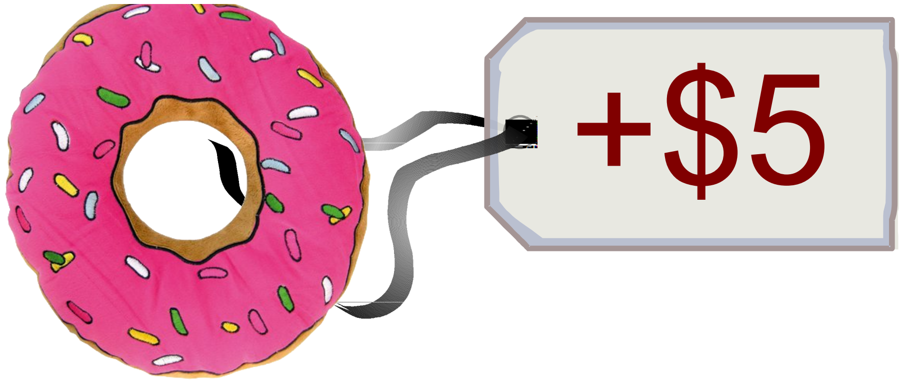




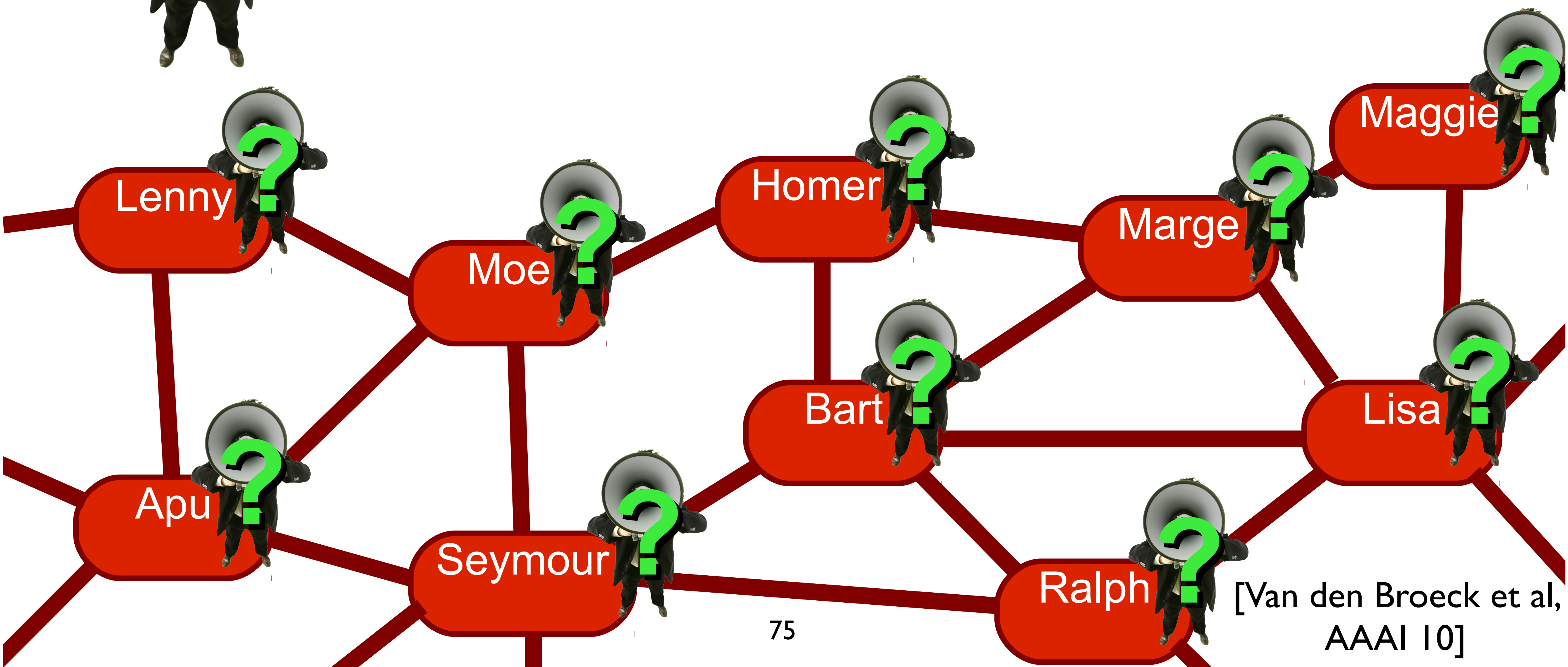
[Nitti et al ECML 15, MLJ 17]

Part V : Decisions

Viral Marketing

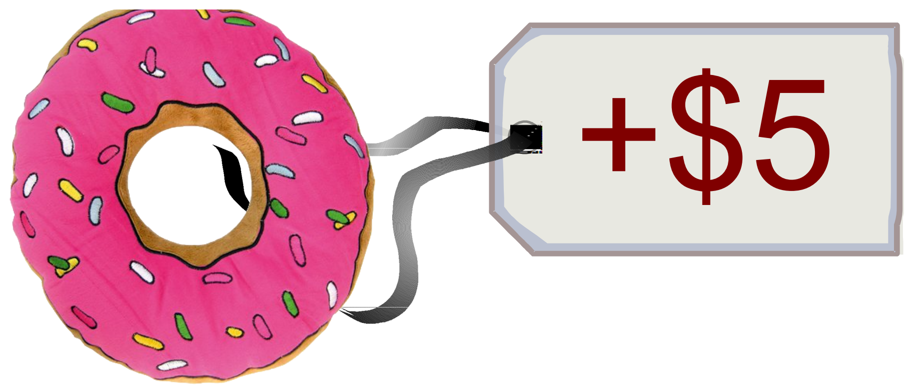


Which advertising strategy maximizes expected profit?

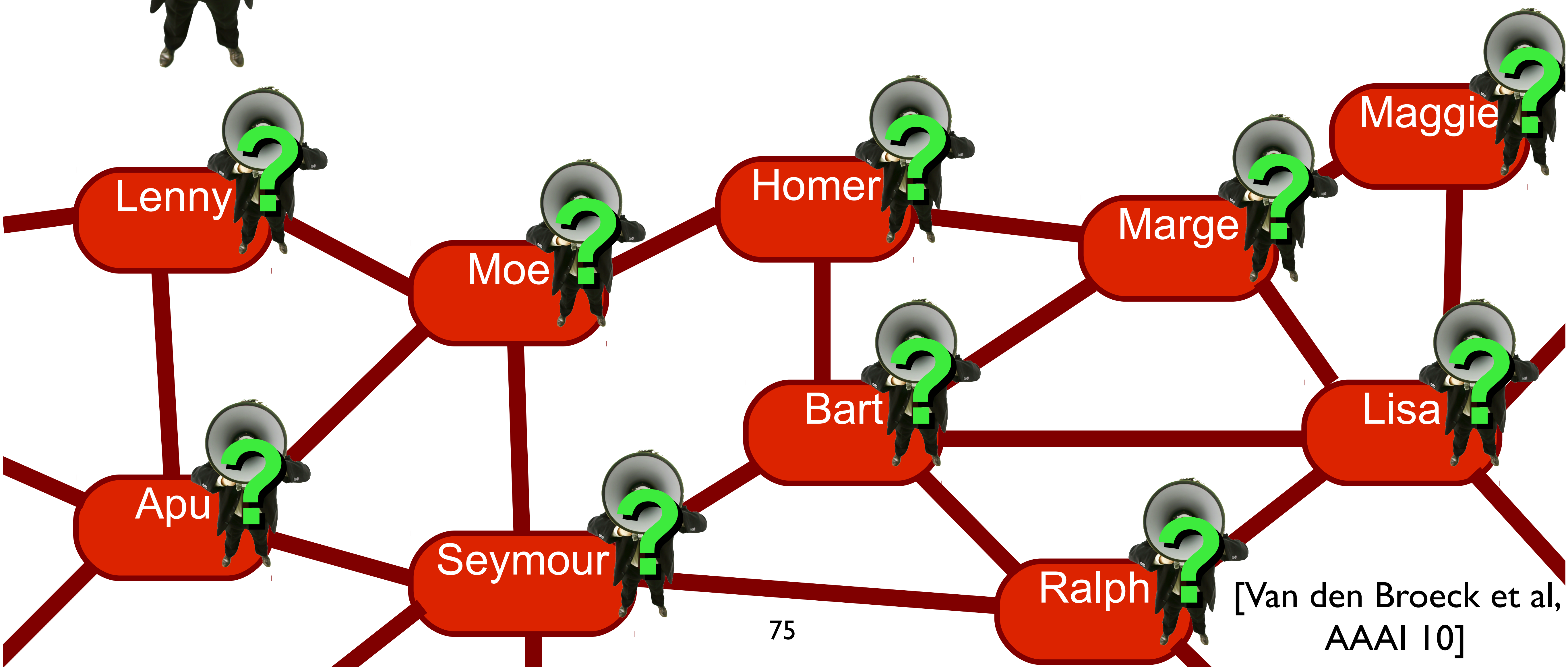


[Van den Broeck et al, AAAI 10]

Viral Marketing

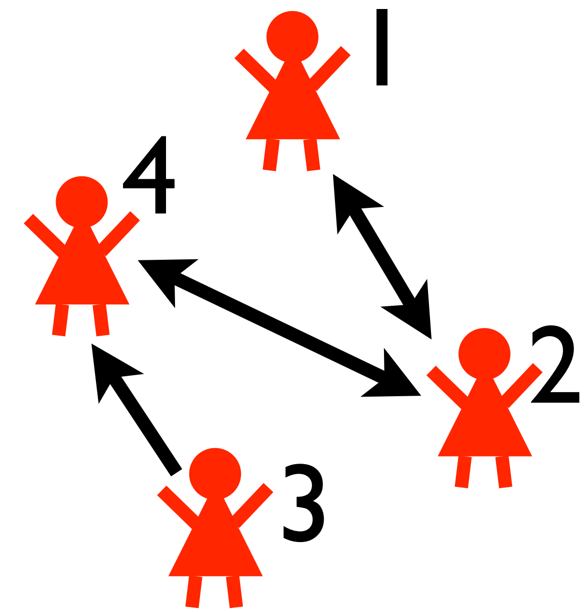


decide truth values of some atoms



[Van den Broeck et al, AAAI 10]

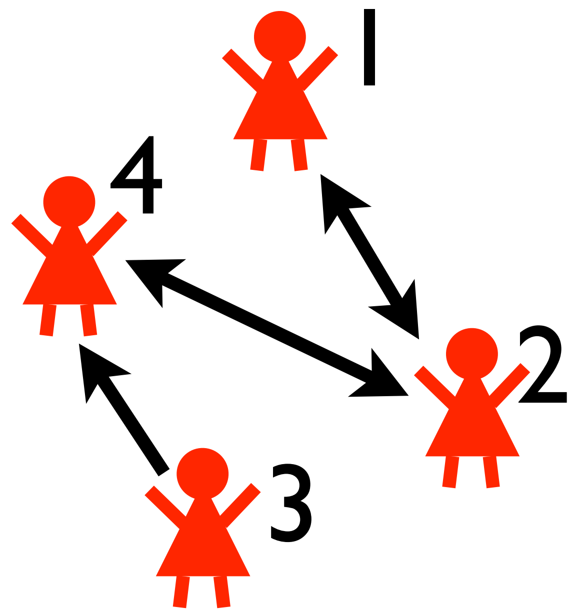
DTProbLog




```
person(1).
person(2).
person(3).
person(4).

friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

DTProbLog




```
? :: marketed(P) :- person(P).
```

decision fact: true or false?

```
person(1).
person(2).
person(3).
person(4).

friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

DTProbLog

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? :: marketed(P) :- person(P).
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0.3 :: buy_trust(X,Y) :- friend(X,Y).
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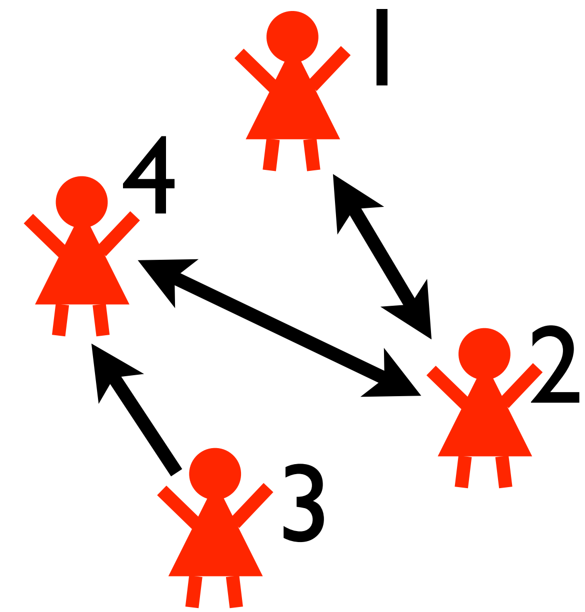
buys(X) :- friend(X,Y), buys(Y), buy_trust(X,Y).
buys(X) :- marketed(X), buy_marketing(X).
```

probabilistic facts
+ logical rules




```
person(1).
person(2).
person(3).
person(4).

friend(1,2).
friend(2,1).
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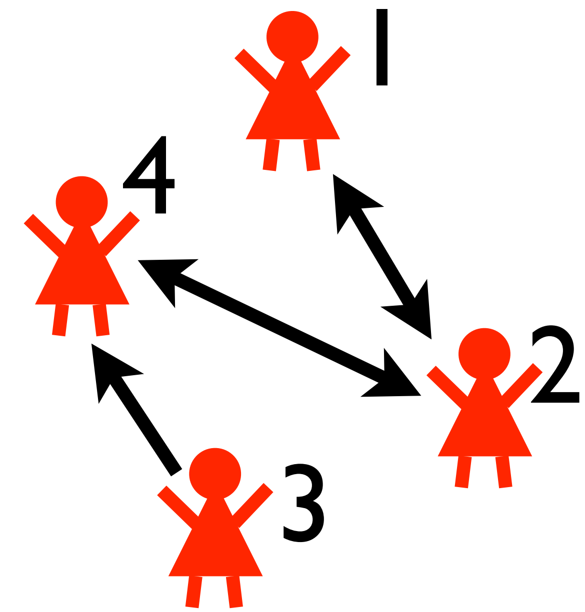
```

DTProbLog

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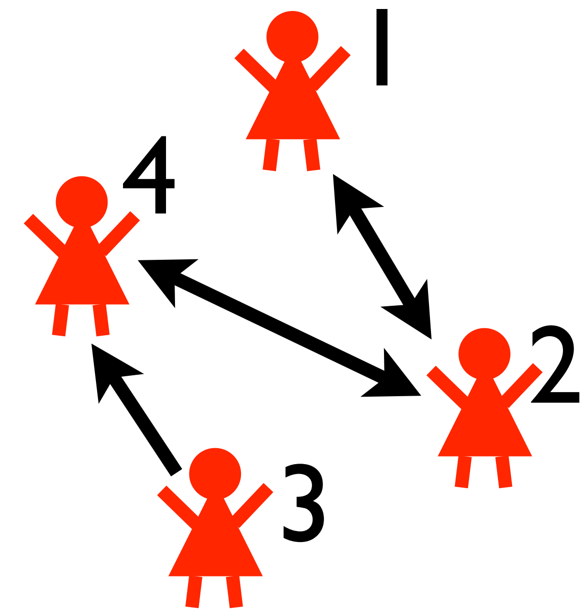
buys(P) => 5 :- person(P).
marketed(P) => -3 :- person(P).
```

utility facts: cost/reward if true

```
person(1).
person(2).
person(3).
person(4).

friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

DTProbLog

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person(4).

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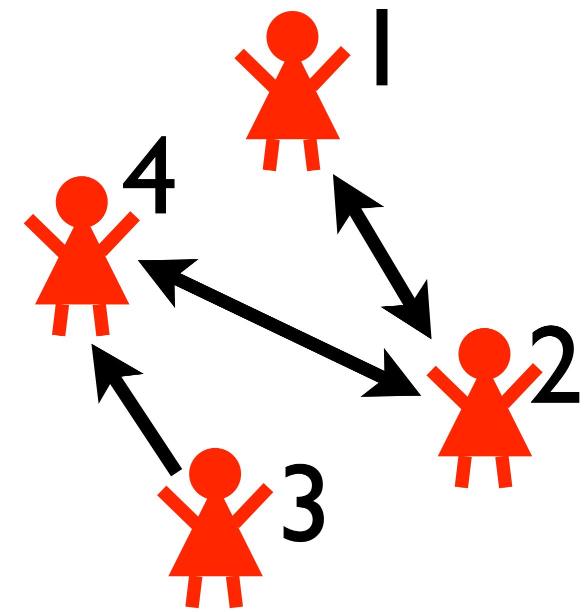
DTProbLog

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person(2).
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friend(2,4).
friend(3,4).
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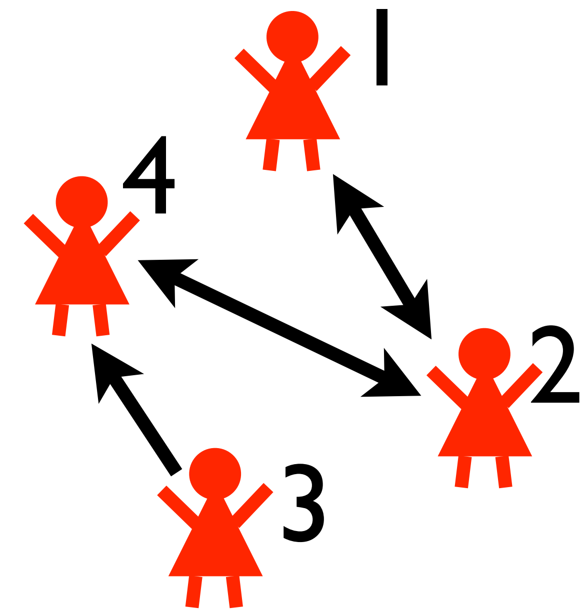
DTProbLog

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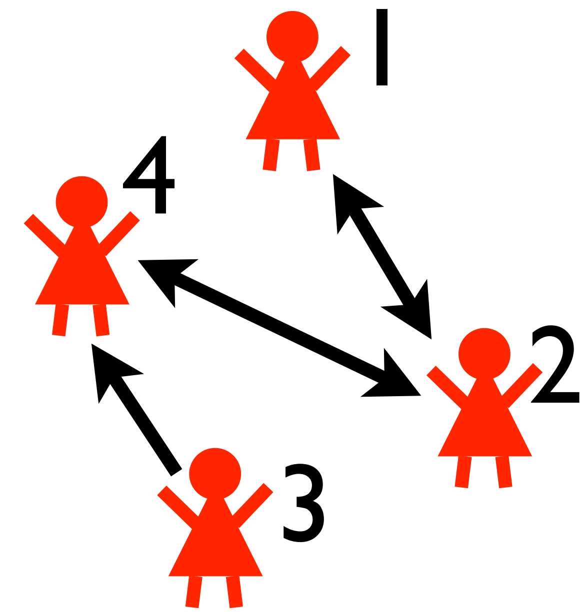
person(1).
person(2).
person(3).
person(4).

friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

```
marketed(1)          marketed(3)
```

DTProbLog

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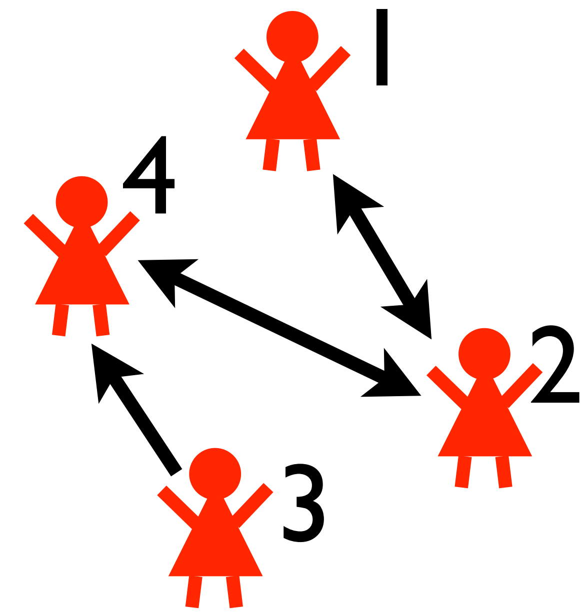
person(1).
person(2).
person(3).
person(4).

friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

```
marketed(1)          marketed(3)

    bt(2,1)    bt(2,4)          bm(1)
```

DTProbLog

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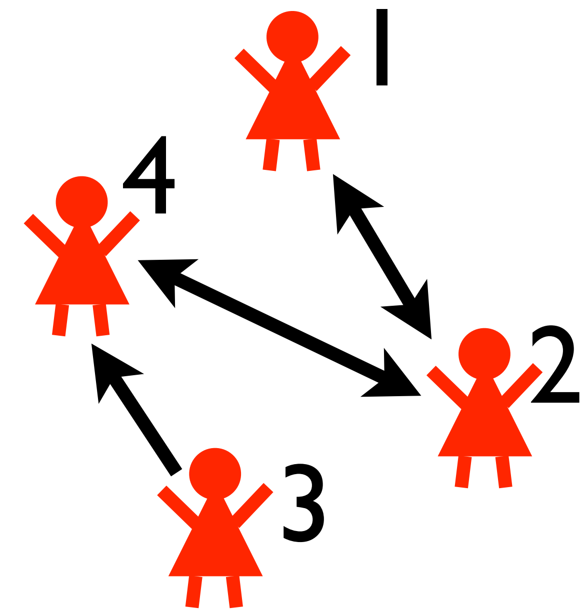
```
marketed(1)        marketed(3)

    bt(2,1)    bt(2,4)          bm(1)

buys(1)     buys(2)
```

DTProbLog

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person(2).
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person(4).

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friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

utility = −3 + −3 + 5 + 5 = 4

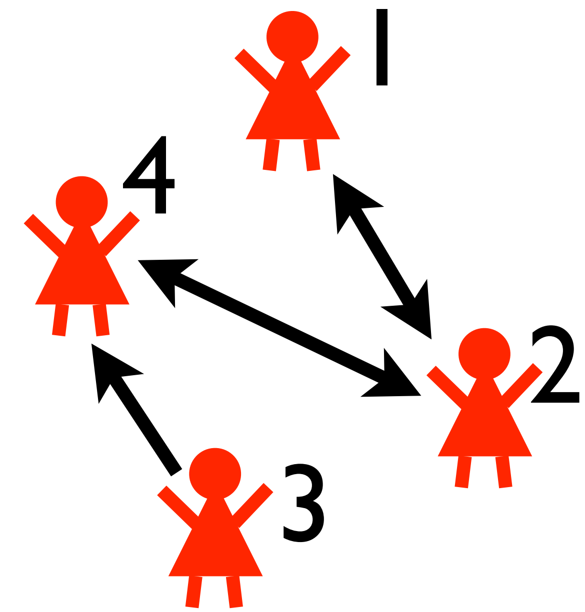
probability = 0.0032

```
marketed(1)          marketed(3)

    bt(2,1)    bt(2,4)          bm(1)

buys(1)     buys(2)
```

DTProbLog

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friend(2,1).
friend(2,4).
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```

utility = −3 + −3 + 5 + 5 = 4

probability = 0.0032

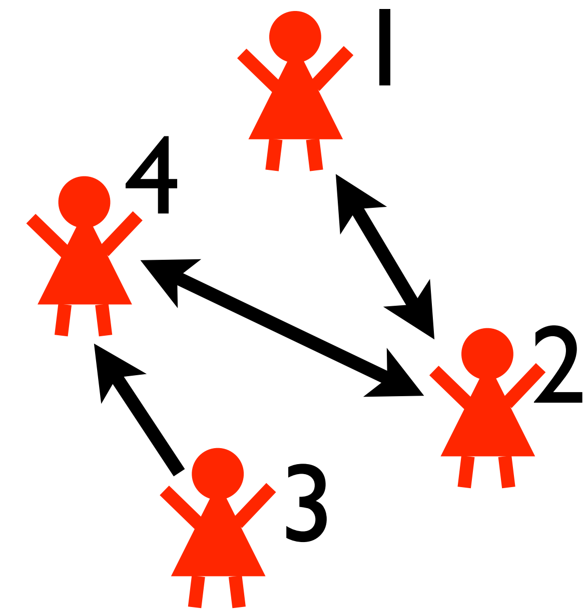
```
marketed(1)        marketed(3)

    bt(2,1)    bt(2,4)         bm(1)

buys(1)      buys(2)
```

world contributes 0.0032×4 to expected utility of strategy

DTProbLog

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person(2).
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person(4).

friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

task: find strategy that maximizes expected utility
solution: using ProbLog technology

Phenetic

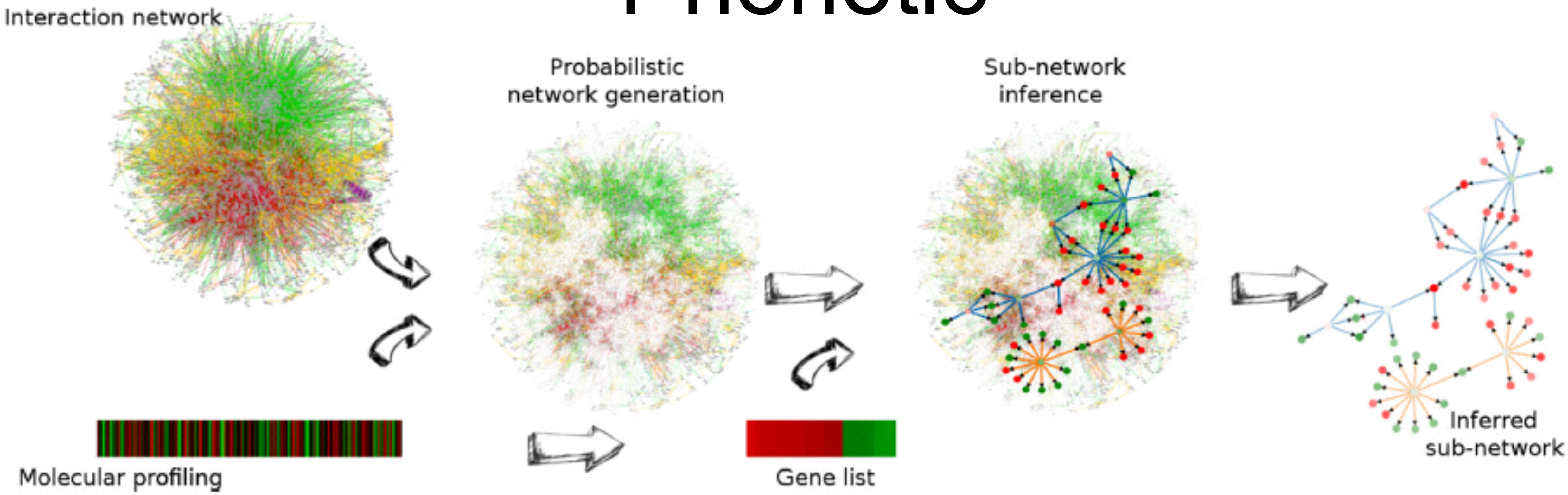


Figure 1. Overview of PheNetic, a web service for network-based interpretation of 'omics' data. The web service uses as input a genome wide interaction network for the organism of interest, a user generated molecular profiling data set and a gene list derived from these data. Interaction networks for a wide variety of organisms are readily available from the web server. Using the uploaded user-generated molecular data the interaction network is converted into a probabilistic network: edges receive a probability proportional to the levels measured for the terminal nodes in the molecular profiling data set. This probabilistic interaction network is used to infer the sub-network that best links the genes from the gene list. The inferred sub-network provides a trade-off between linking as many genes as possible from the gene list and selecting the least number of edges.

- Causes: Mutations
  - All related to similar phenotype
- Effects: Differentially expressed genes
- 27 000 cause effect pairs

- Interaction network:
  - 3063 nodes
    - Genes
    - Proteins
  - 16794 edges
    - Molecular interactions
    - Uncertain

- Goal: connect causes to effects through common subnetwork
  - = Find mechanism
- Techniques:
  - DTProbLog
  - Approximate inference

[De Maeyer et al., Molecular Biosystems 13, NAR 15]

Applications

- Medical reasoning (Peter Lucas et al)
- Knowledge base construction and Nell (De Raedt et al)
- Biology/Phenetic (De Maeyer et al, NAR 15)
- Robotics (Nitti et al., MLJ 16, MLJ 17, Moldovan et al. RA 17)
- Activity Recognition (Skarlatidis et al, TPLP 14)
- …

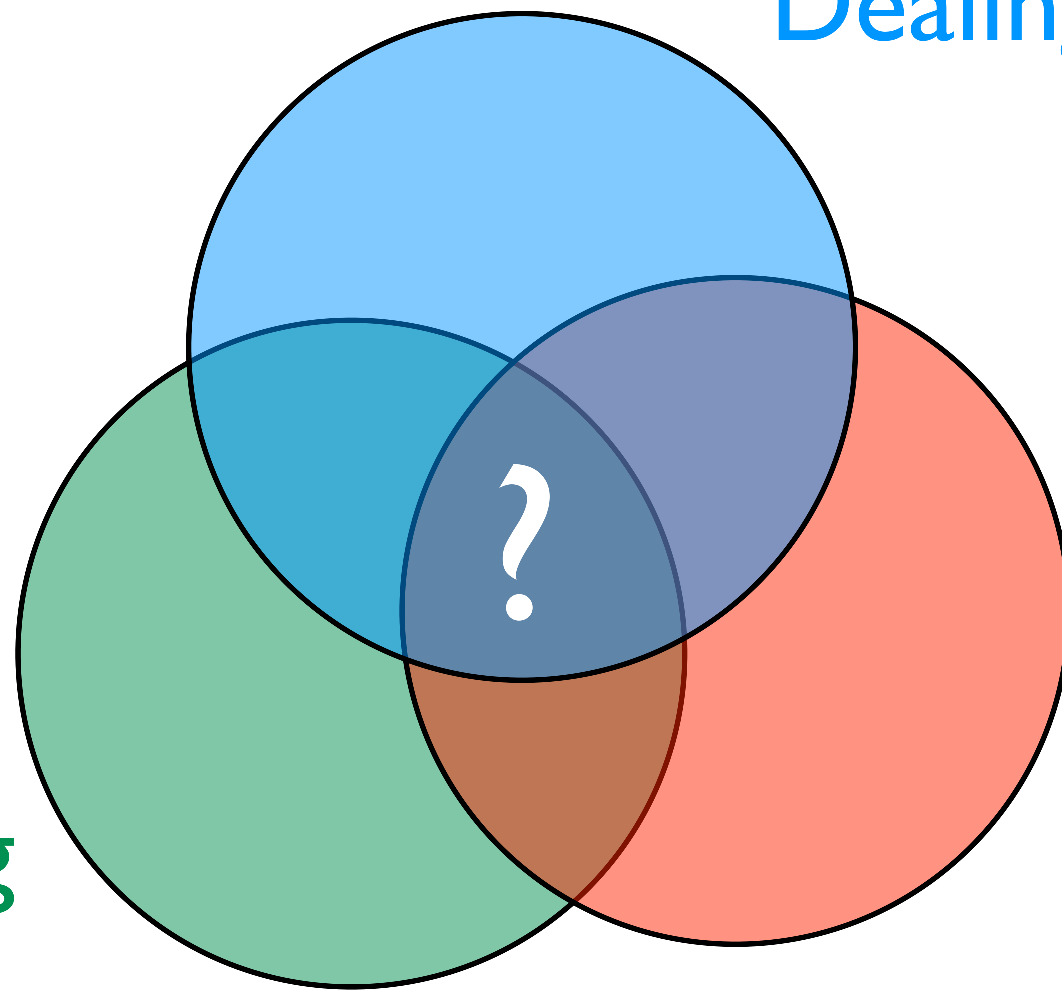
A key question in AI:

Dealing with uncertainty

- probability theory
- graphical models
- ...

Reasoning with relational data

- logic
- databases
- programming
- ...



Learning

- parameters
- structure

Statistical relational learning, probabilistic logic learning, probabilistic programming, ...

A key question in AI:

Dealing with uncertainty
- probability theory

dels

Reas
relat
- lo
- da
- pr
- ...

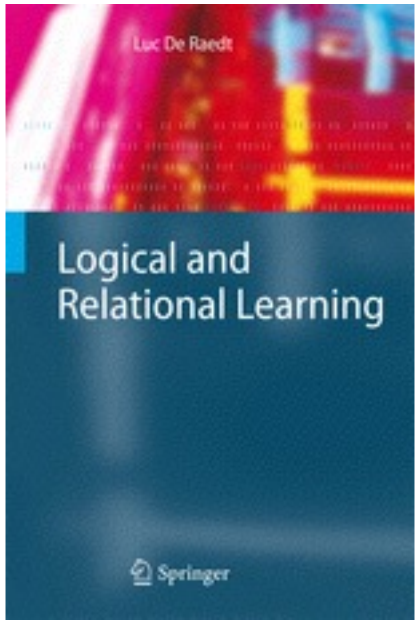
- Our answer: probabilistic (logic) programming
  = probabilistic choices + (logic) program
- Many languages, systems, applications, ...
- ... and much more to do!

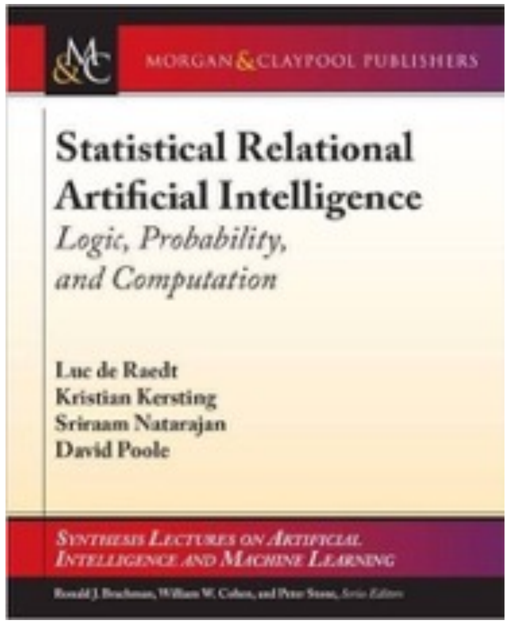
structure

Statistical relational learning, probabilistic logic learning, probabilistic programming, ...

Further Reading

- Logic and Learning
- Probabilistic programming
  - Logic programming and probabilistic databases
    - (ProbLog and DS as representatives)
  - http://dtai.cs.kuleuven.be/problog/ —
    - check also [DR & Kimmig, MLJ 15]
- Statistical relational AI and learning
  - Markov Logic





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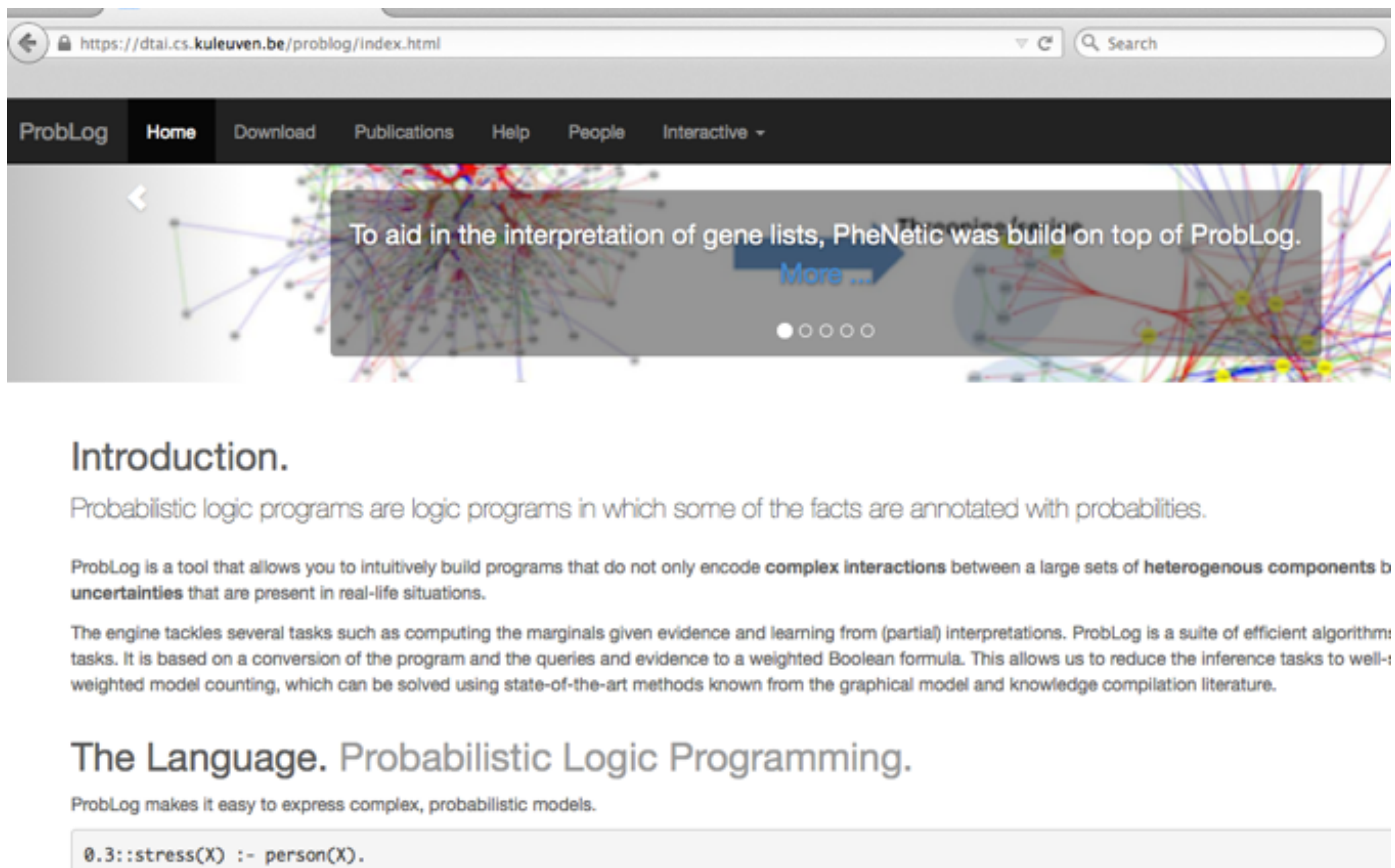
Bernd Gutmann
Manfred Jaeger
Gerda Janssens
Kristian Kersting
Angelika Kimmig
Theofrastos Mantadelis
Wannes Meert
Bogdan Moldovan
Siegfried Nijssen
Davide Nitti
Joris Renkens
Kate Revoredo
Ricardo Rocha
Vitor Santos Costa
Dimitar Shterionov
Ingo Thon
Hannu Toivonen
Guy Van den Broeck
Mathias Verbeke
Jonas Vlasselaer

Thanks !

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



PLP Systems

- **PRISM** http://sato-www.cs.titech.ac.jp/prism/
- **ProbLog2** http://dtai.cs.kuleuven.be/problog/
- Yap Prolog http://www.dcc.fc.up.pt/~vsc/Yap/ includes
  - **ProbLog1**
  - **cplint** https://sites.google.com/a/unife.it/ml/cplint
  - **CLP(BN)**
  - **LP2**
- **PITA** in XSB Prolog http://xsb.sourceforge.net/
- **AILog2** http://artint.info/code/ailog/ailog2.html
- **SLPs** http://stoics.org.uk/~nicos/sware/pepl
- **contdist** http://www.cs.sunysb.edu/~cram/contdist/
- **DC** https://code.google.com/p/distributional-clauses
- **WFOMC** http://dtai.cs.kuleuven.be/ml/systems/wfomc

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