ProbLog: a probabilistic programming language for data analysis

CATCH meeting 04.10.13

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DTAI
MACHINE LEARNING

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Research Foundation – Flanders

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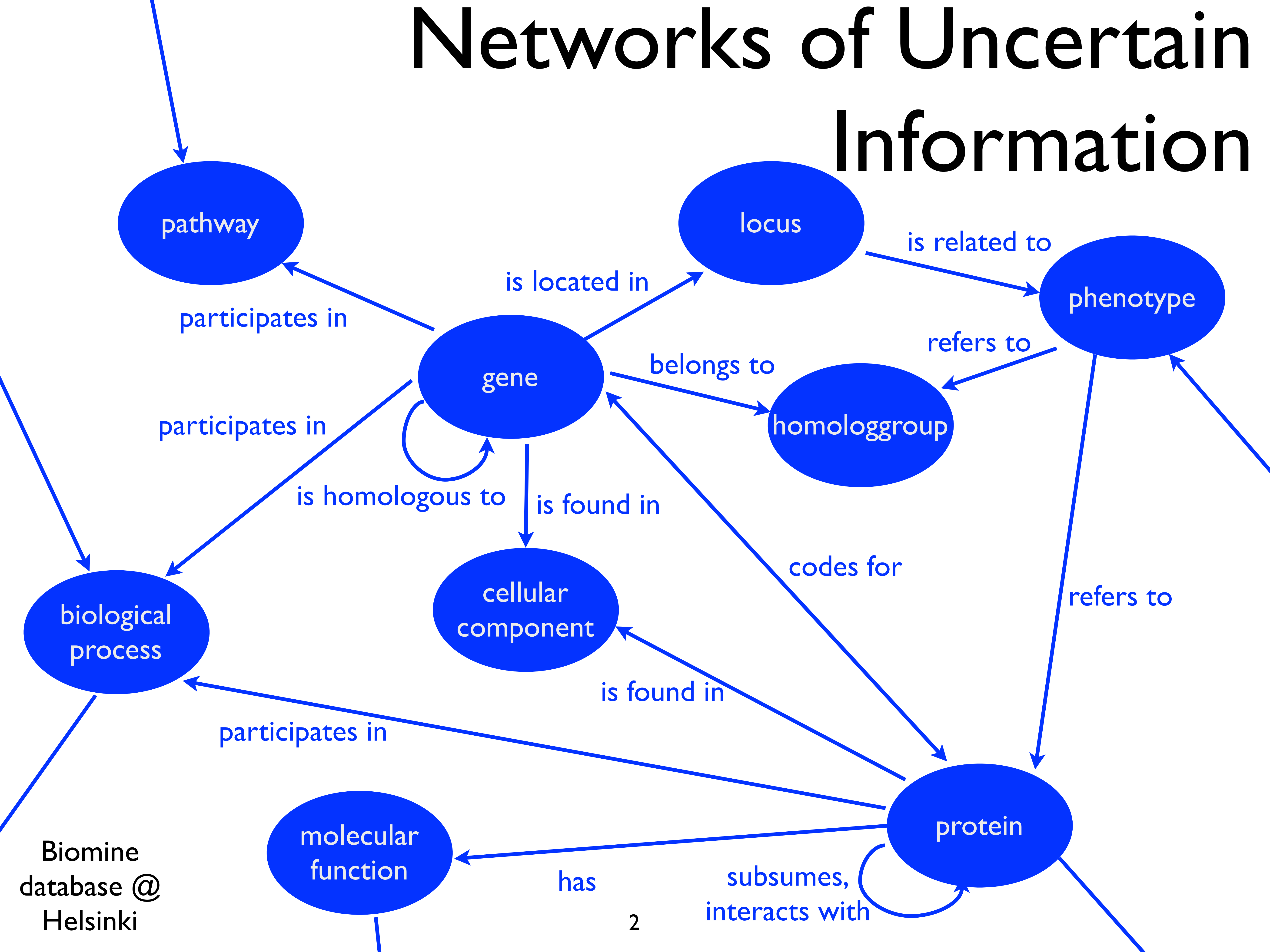
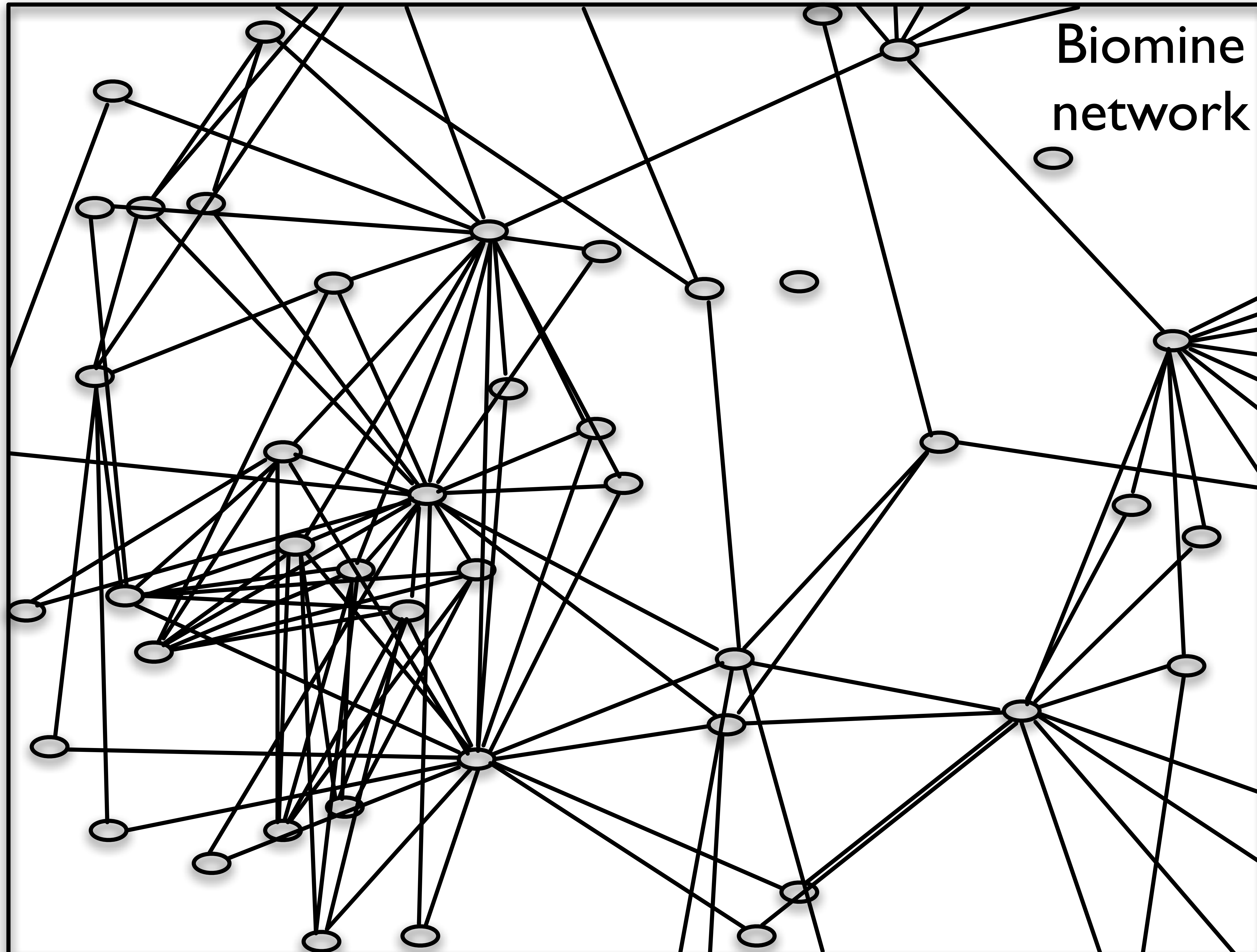
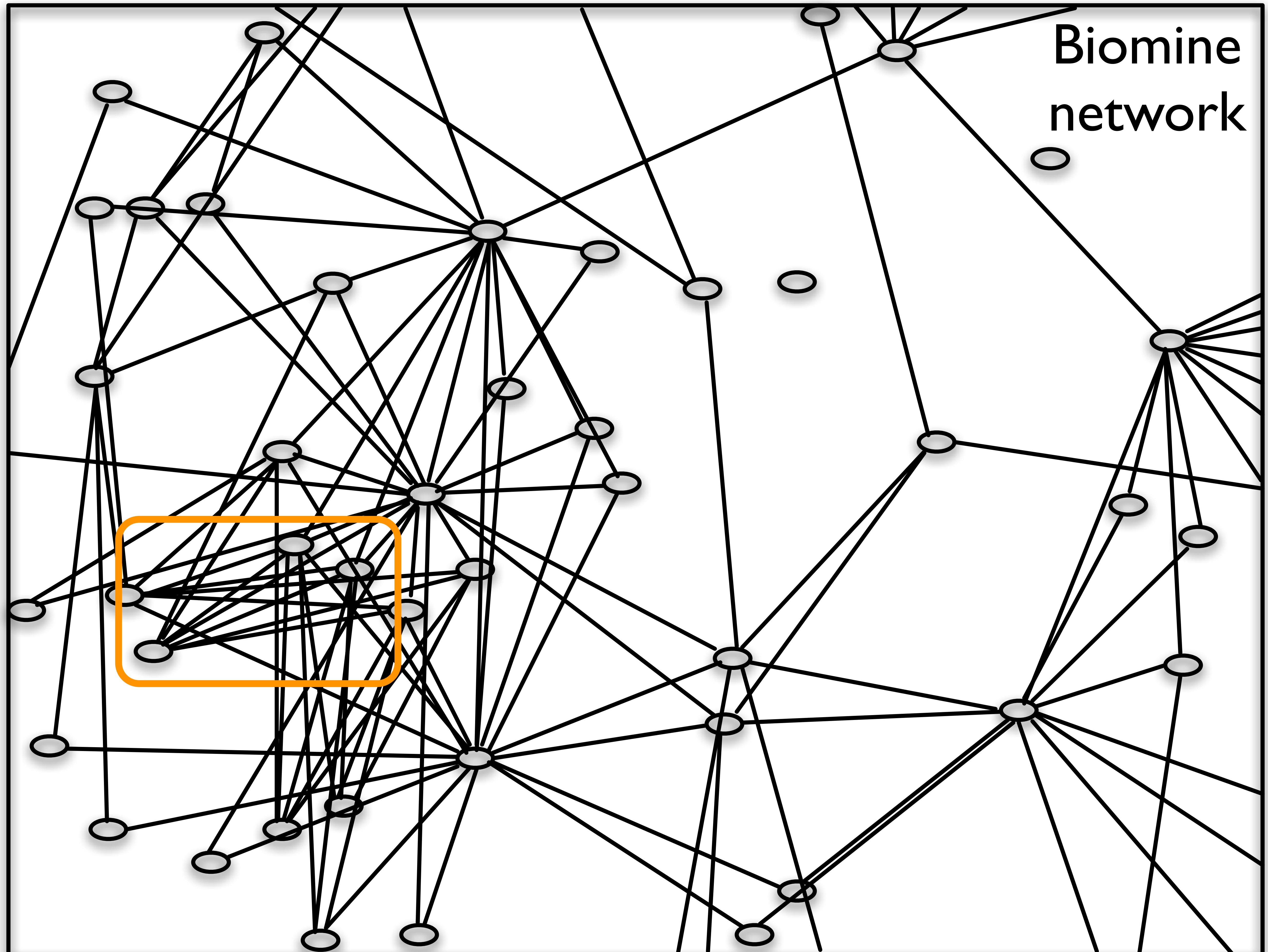
Networks of Uncertain Information

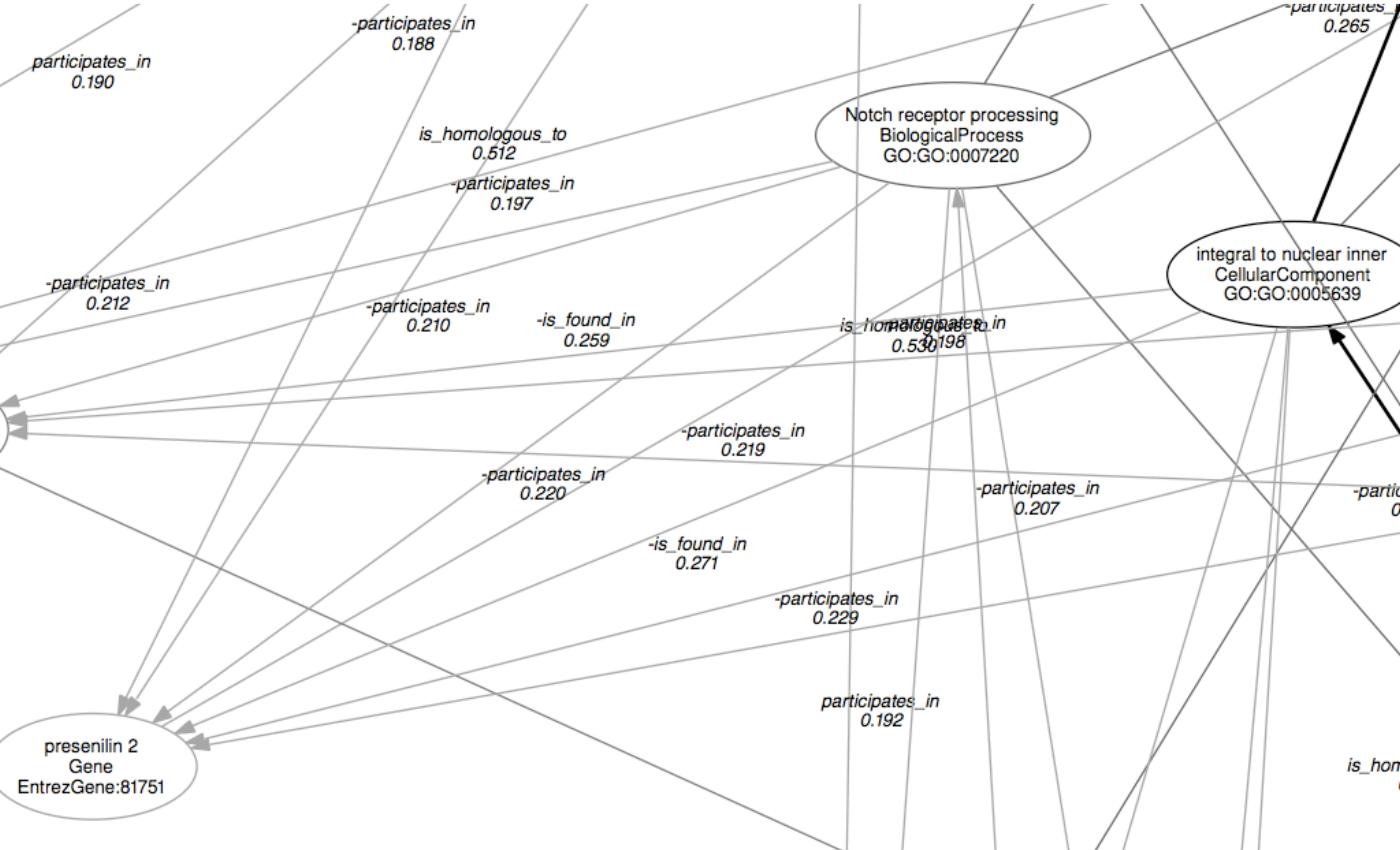


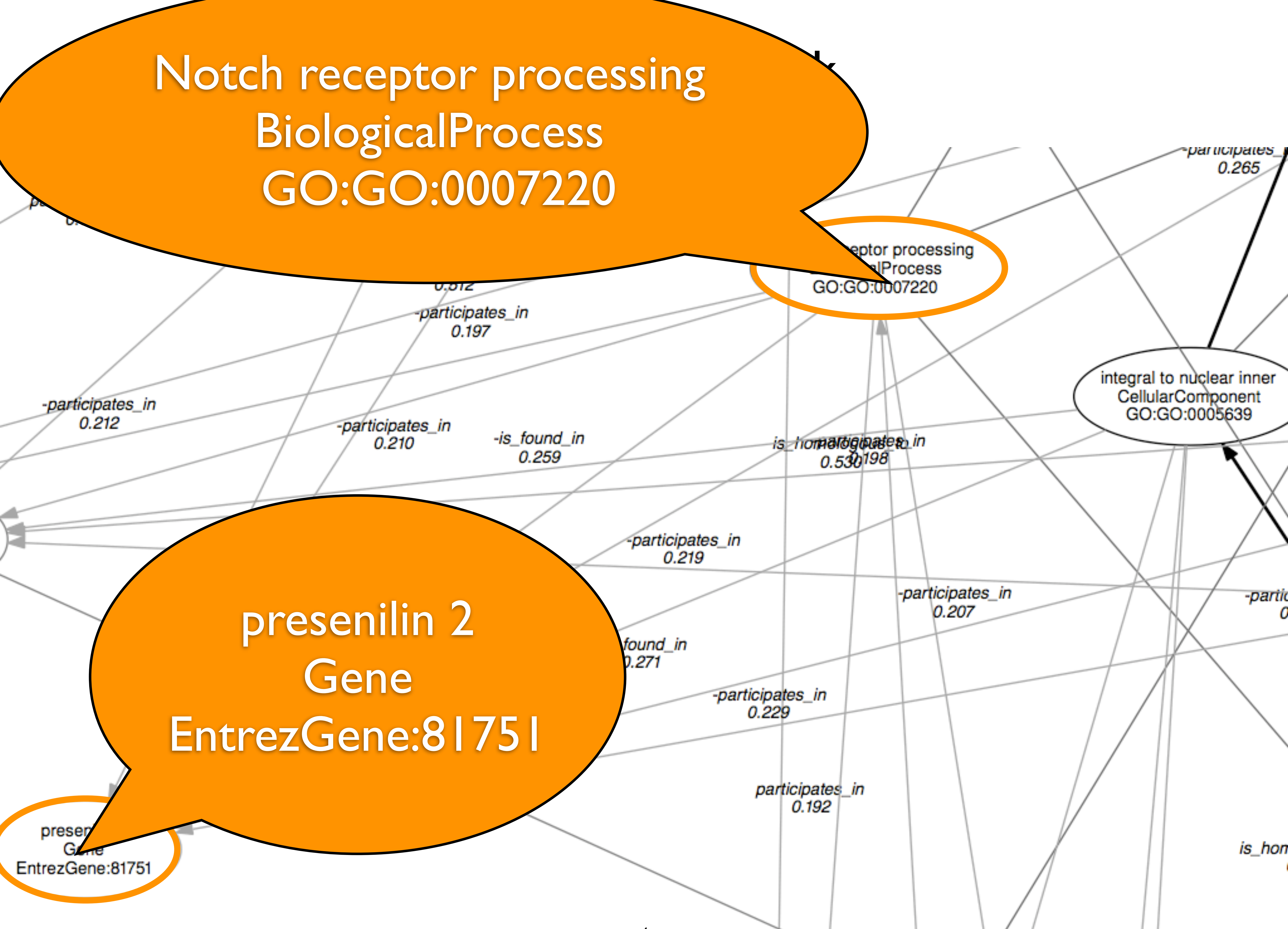
Biomine database @ Helsinki


Biomine
network

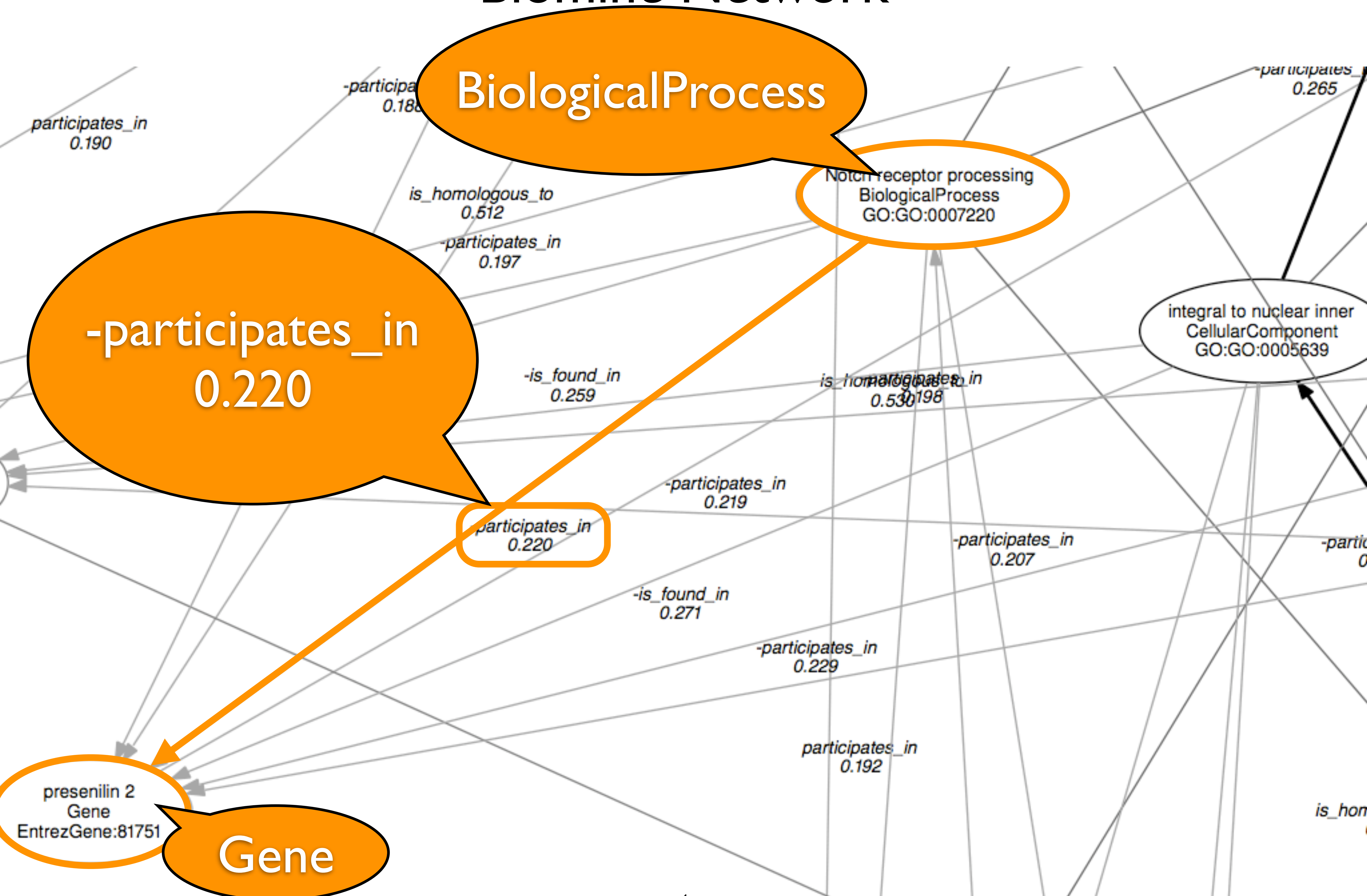

Biomine
network

Biomine Network

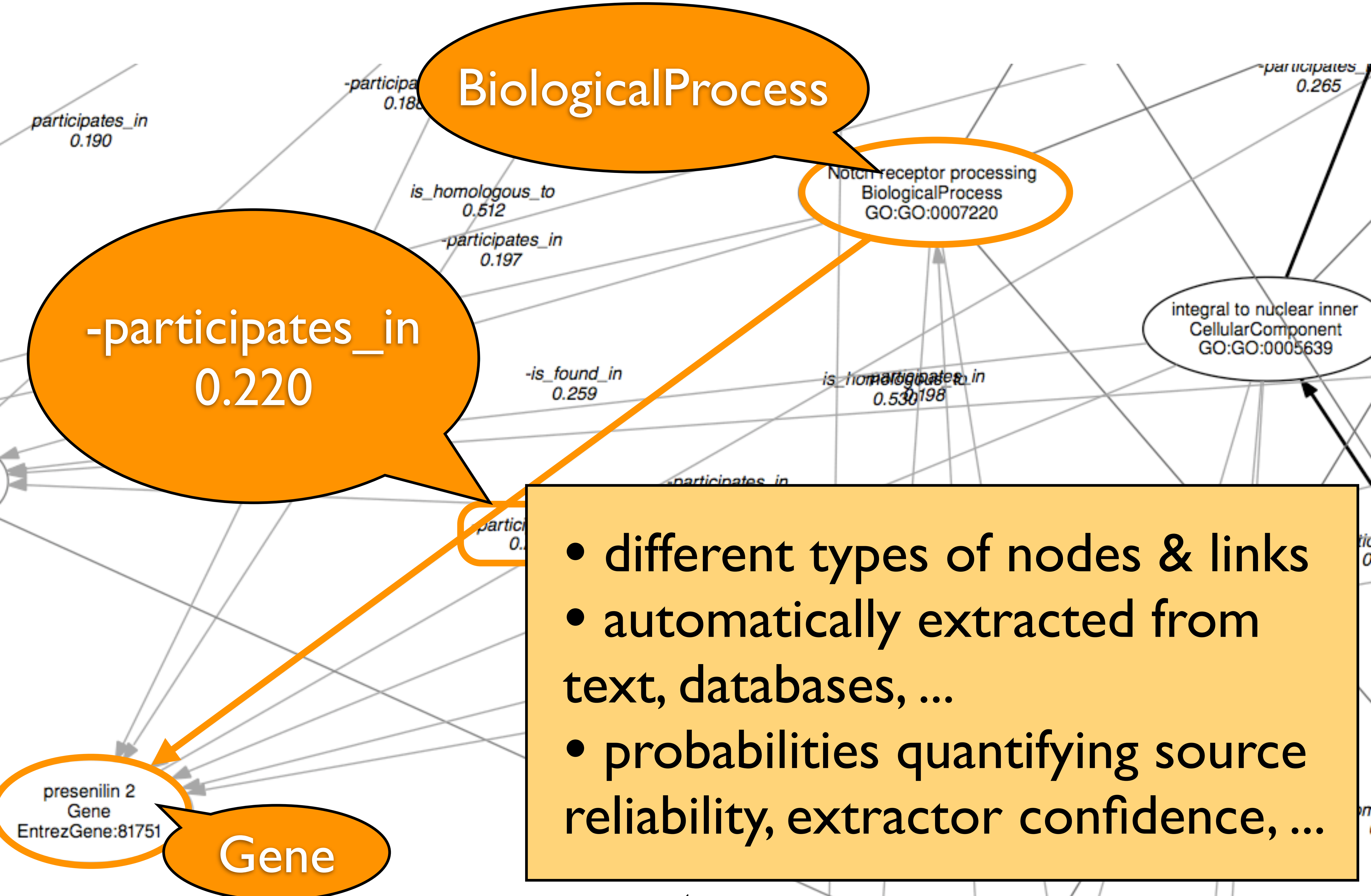



Notch receptor processing
BiologicalProcess
GO:GO:0007220
presenilin 2
Gene
EntrezGene:81751
GO:GO:0007220
integral to nuclear inner
CellularComponent
GO:GO:0005639
-participates_in
0.197
-participates_in
0.212
-participates_in
0.210
-is_found_in
0.259
-participates_in
0.219
-participates_in
0.207
-participates_in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

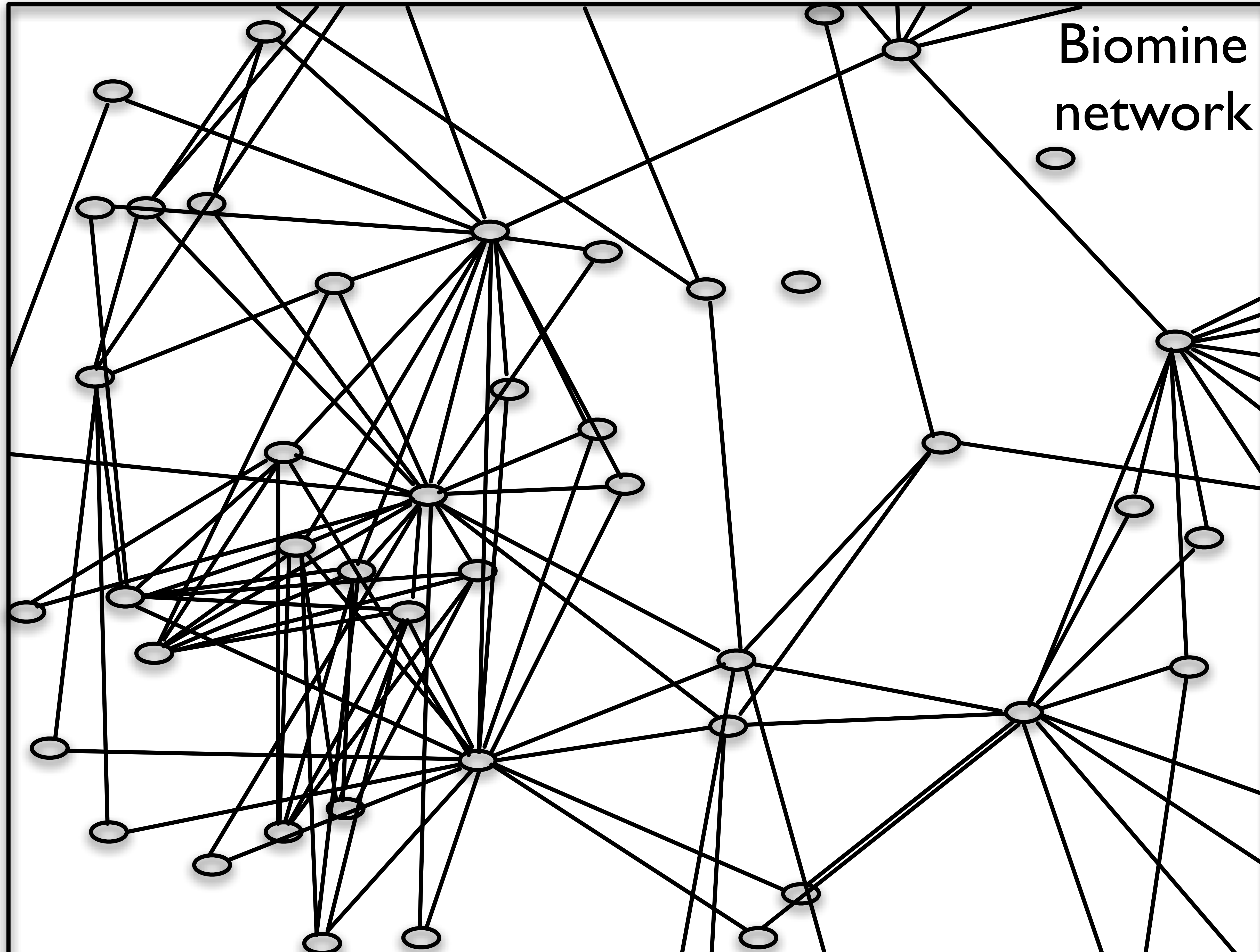
Biomine Network



Biomine Network



- different types of nodes & links
- automatically extracted from text, databases, ...
- probabilities quantifying source reliability, extractor confidence, ...


Biomine
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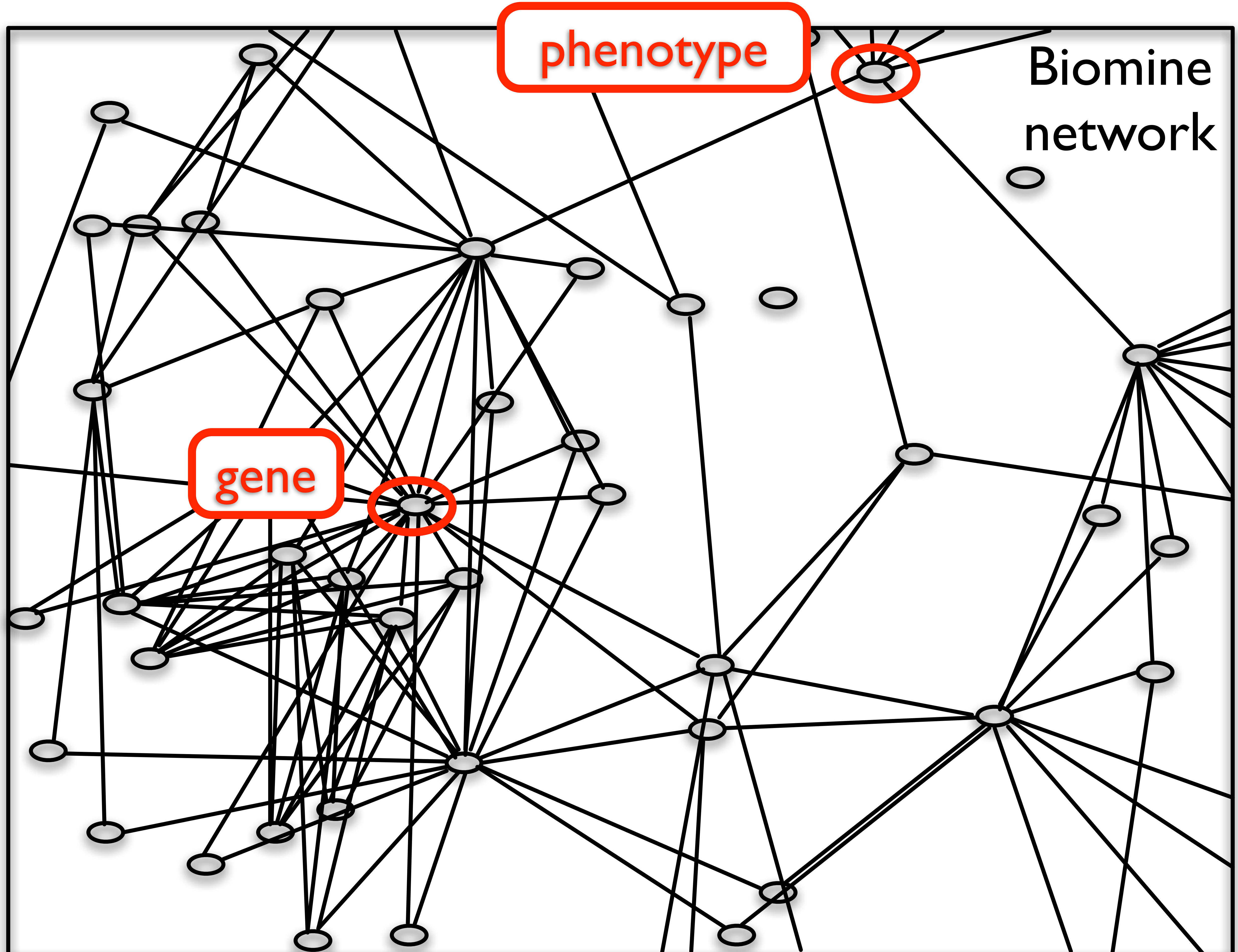
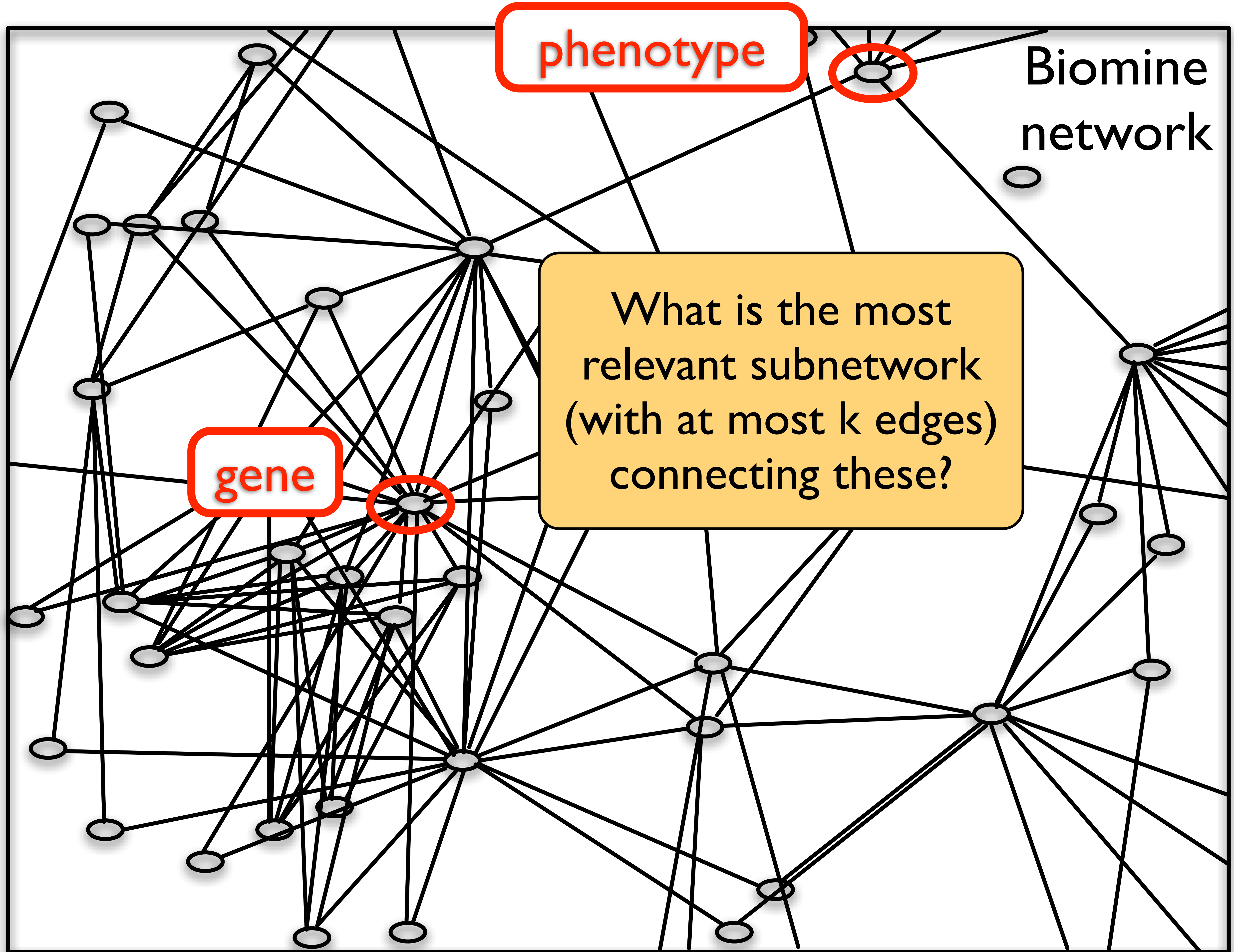
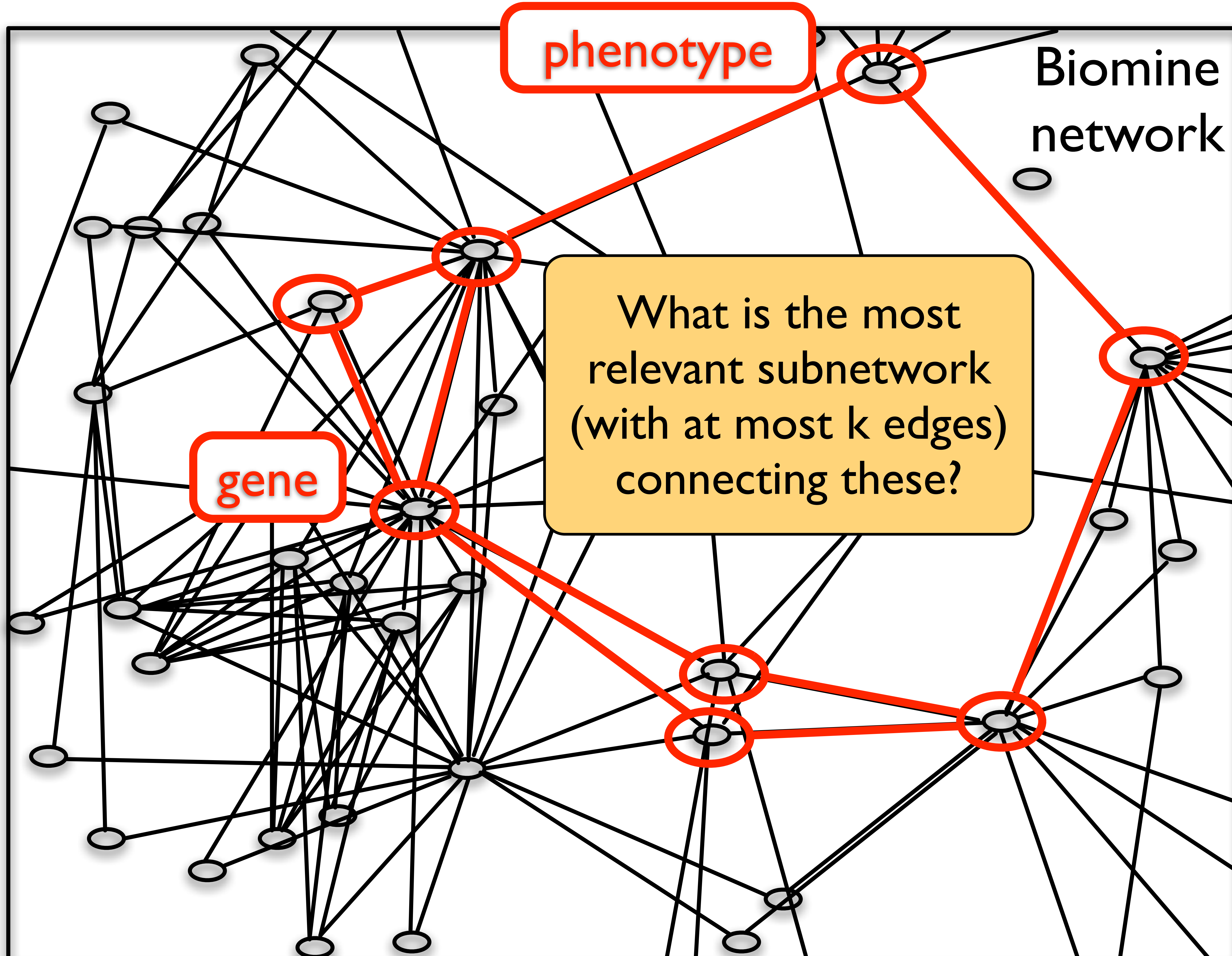

phenotype
Biomine
network
gene


phenotype
Biomine
network
What is the most
relevant subnetwork
(with at most k edges)
connecting these?
gene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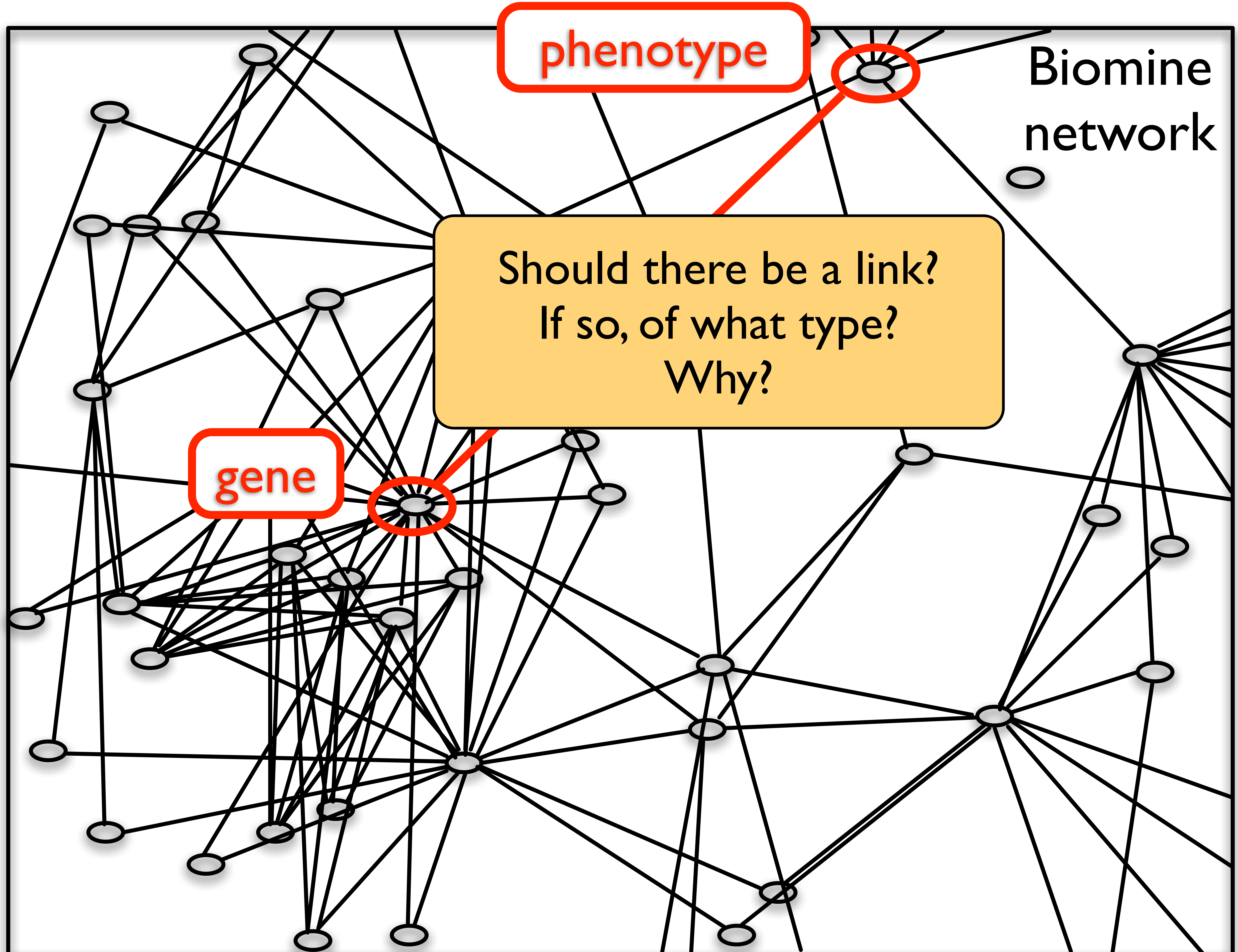
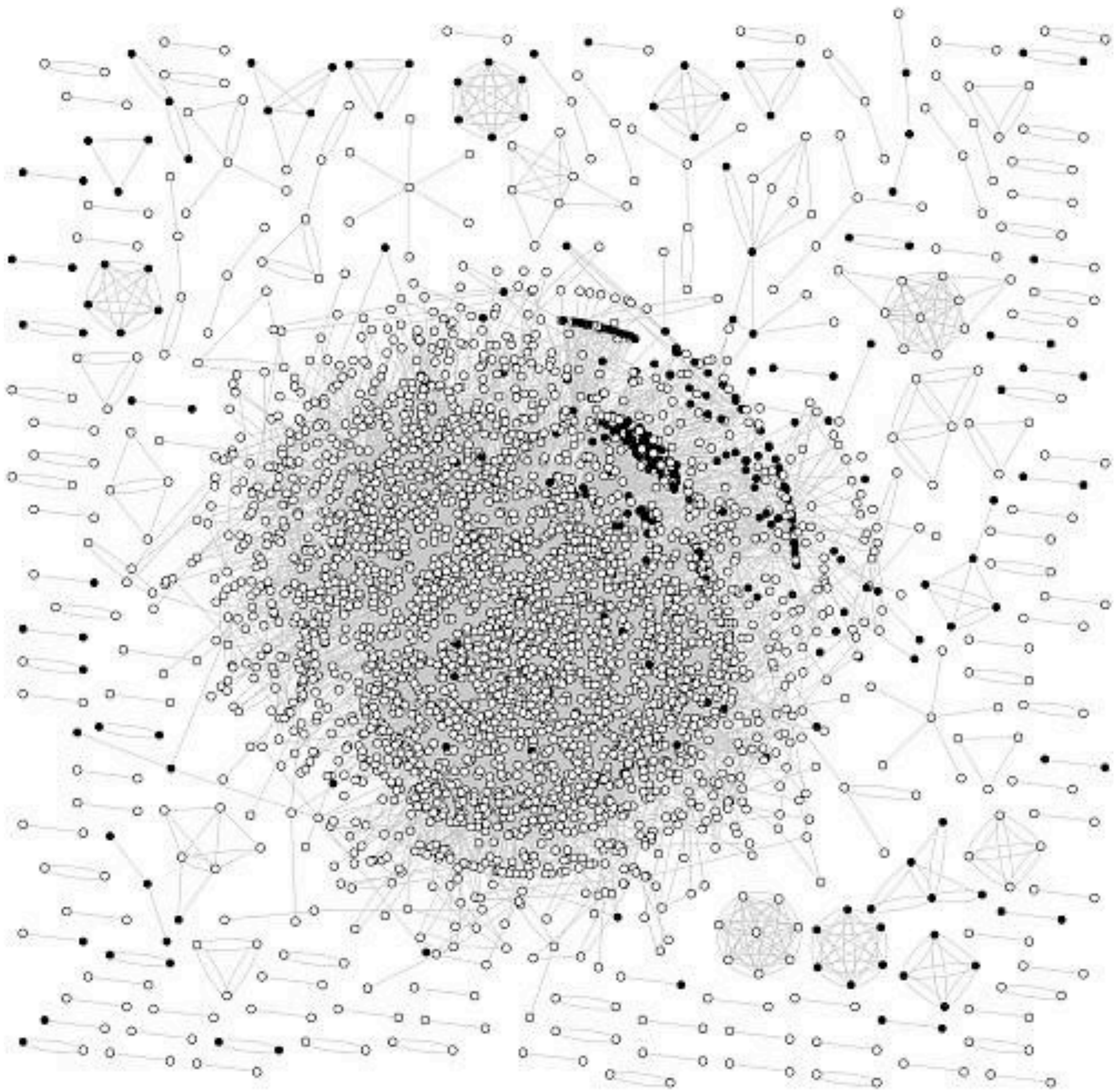

phenotype
Biomine network
Should there be a link?
If so, of what type?
Why?
gene

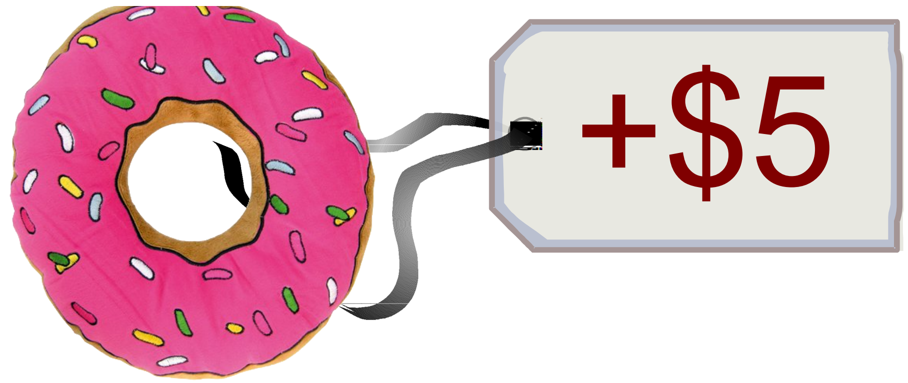
Node Classification



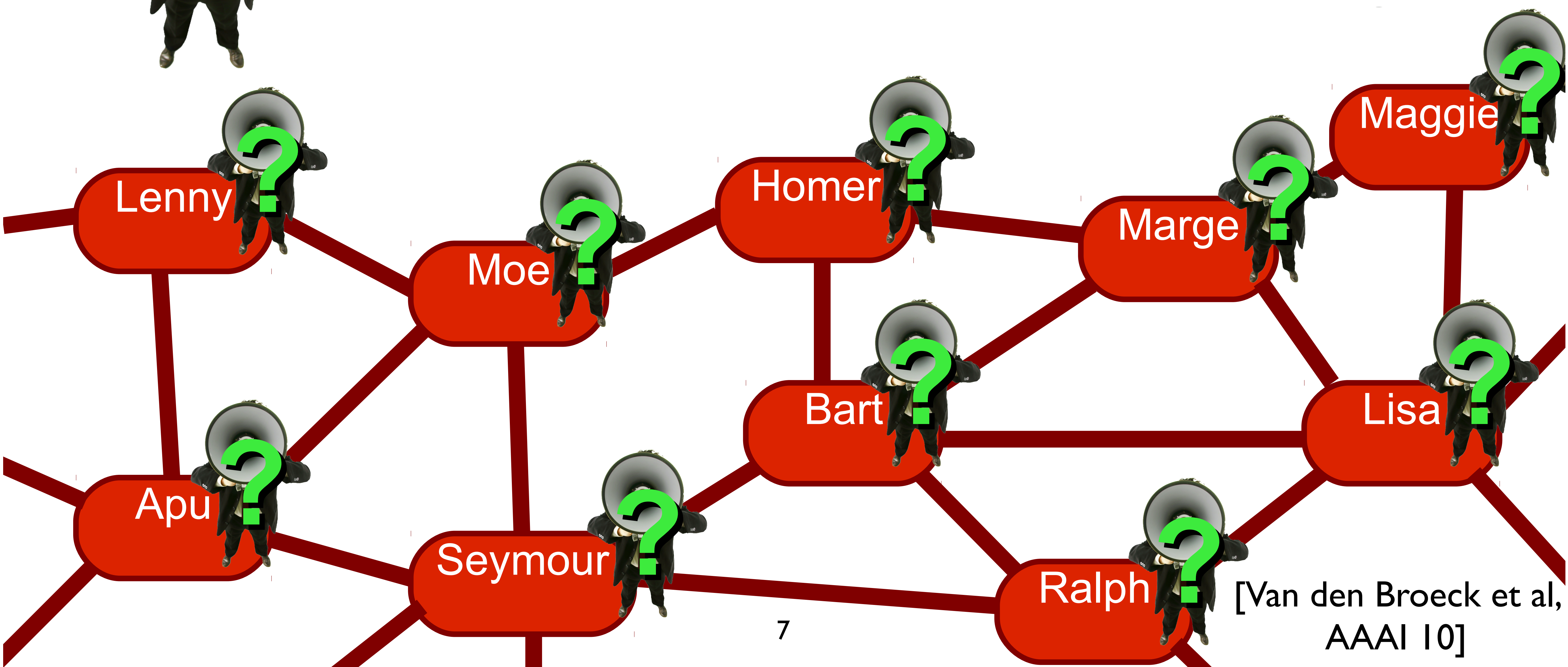
Can we predict the type of a node given information on its neighbors?

e.g., the type of a webpage given its links and the words on the page?

Viral Marketing

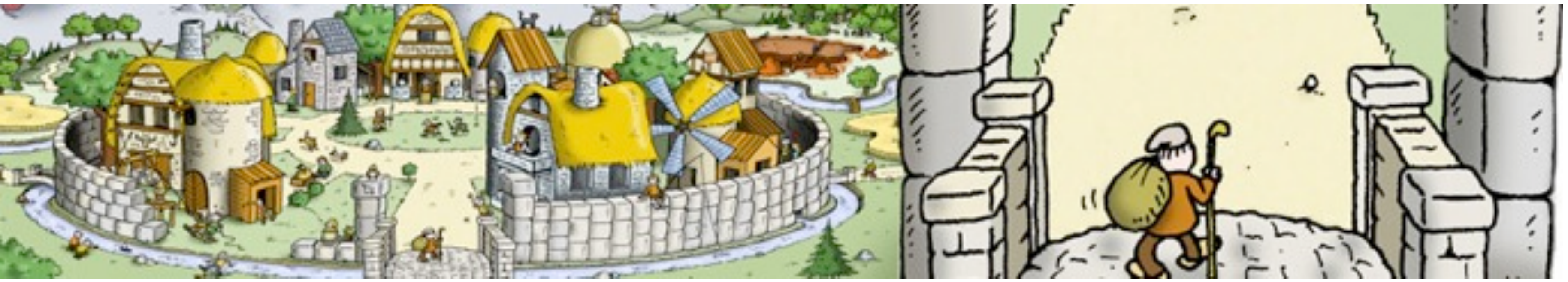


Which advertising strategy maximizes expected profit?



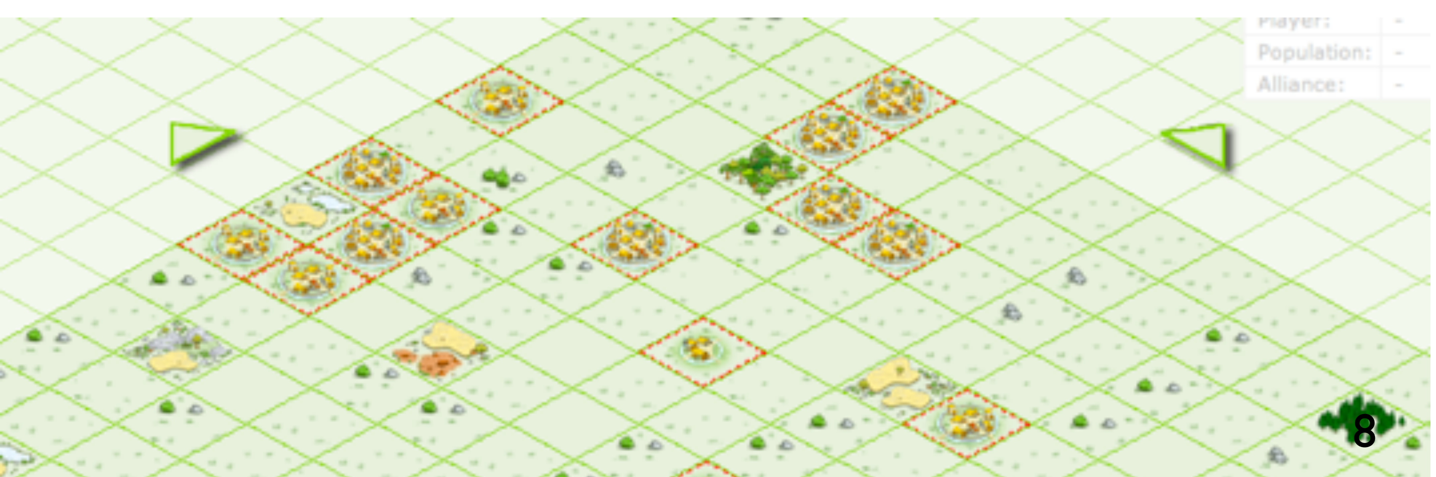
[Van den Broeck et al, AAAI 10]

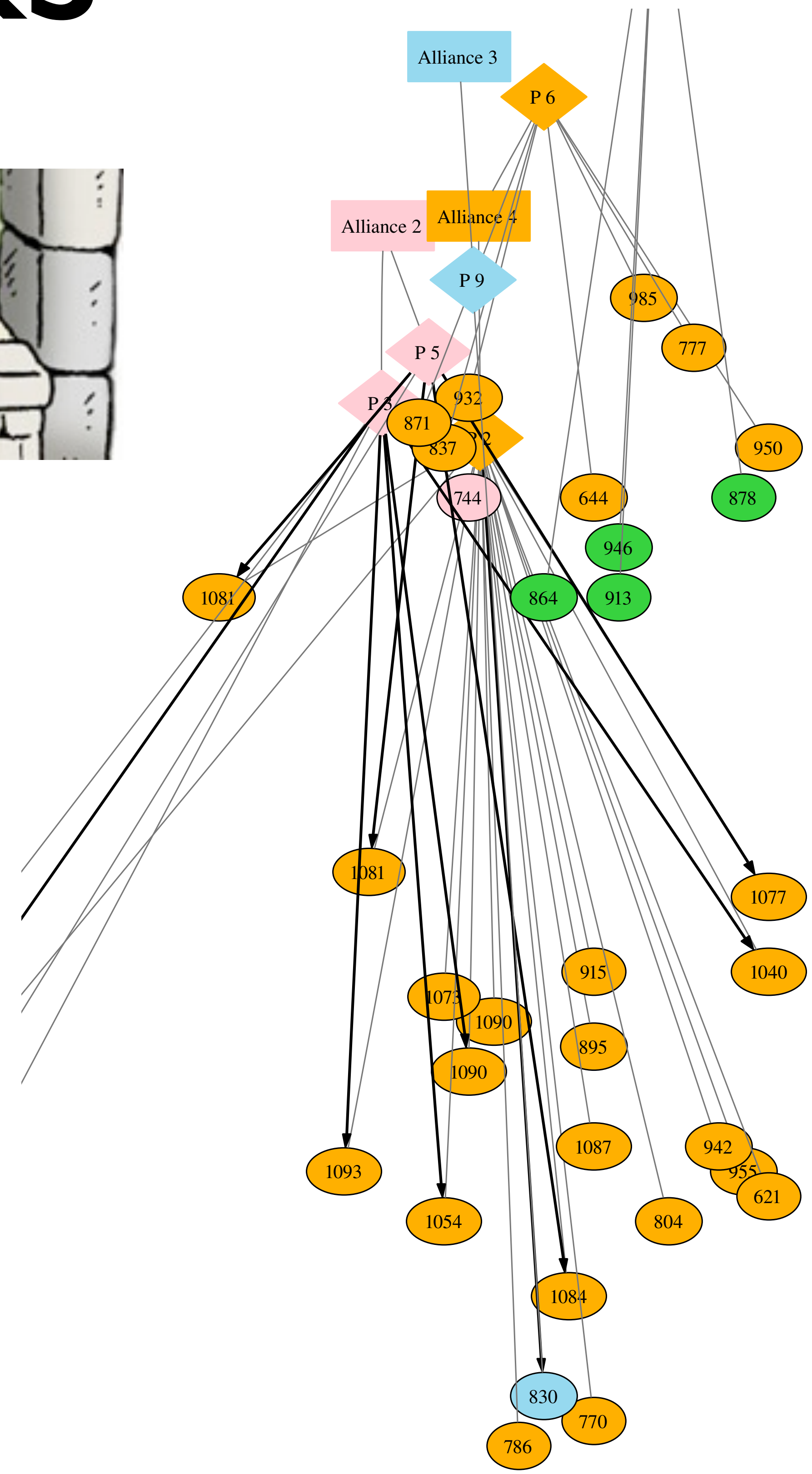
Dynamic networks



Travian: A massively multiplayer real-time strategy game

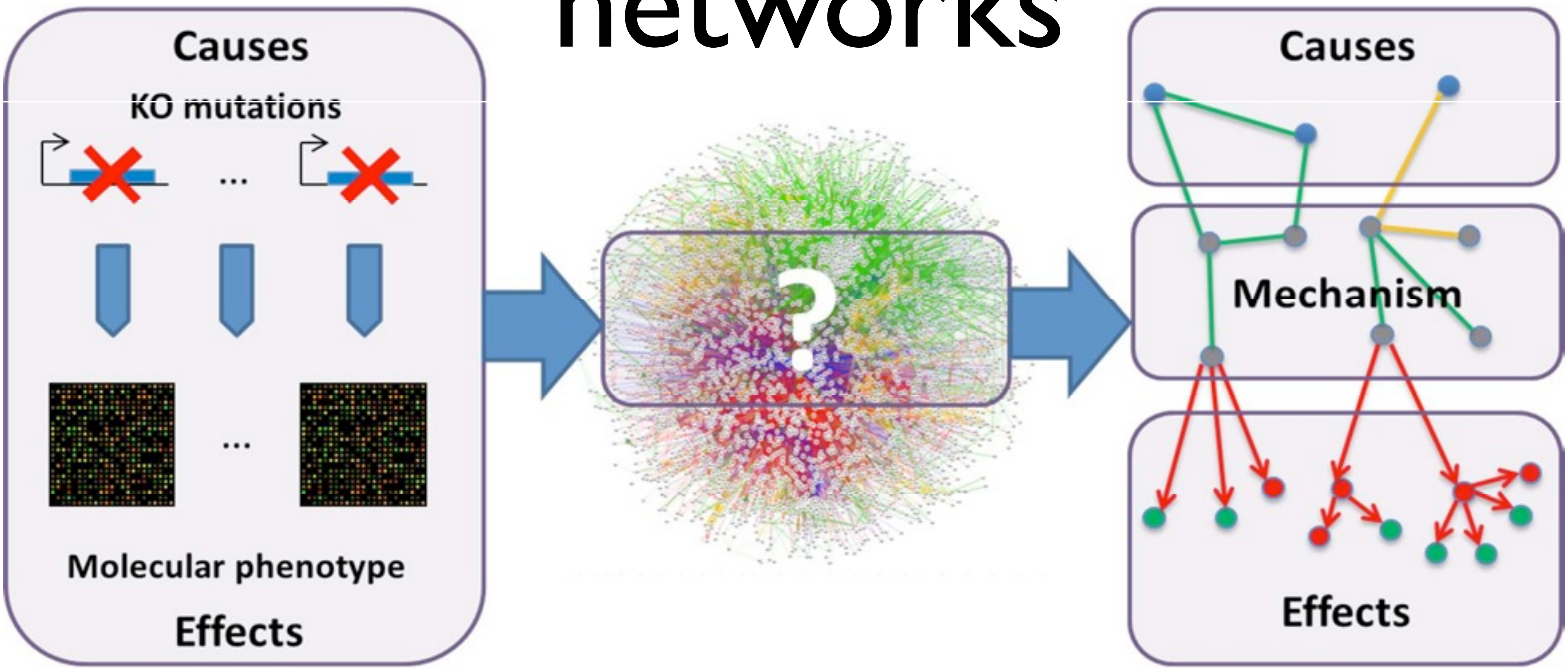
Can we build a model of this world ? Can we use it for playing better ?





[Thon et al, MLJ 11]

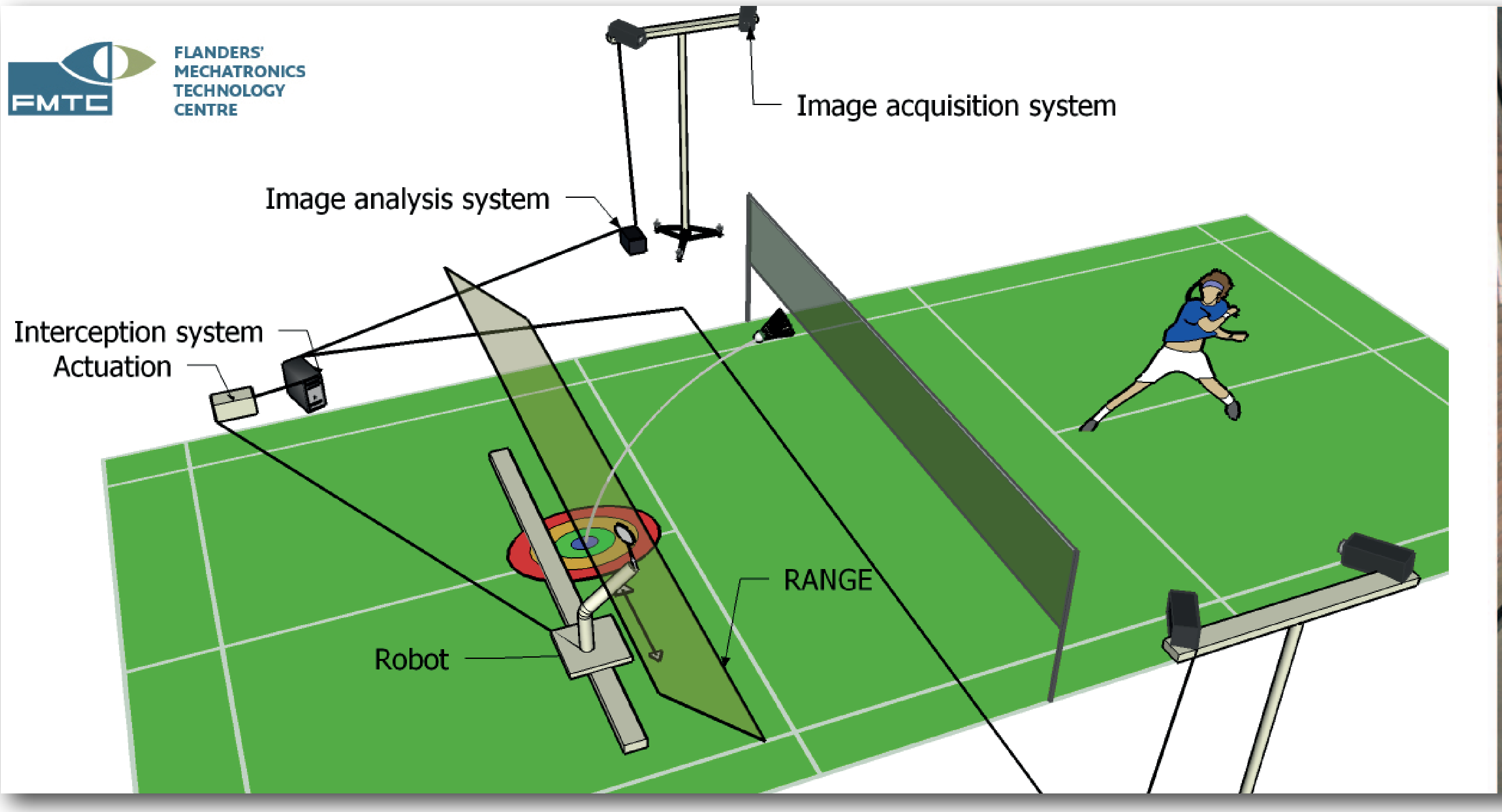
Molecular interaction networks

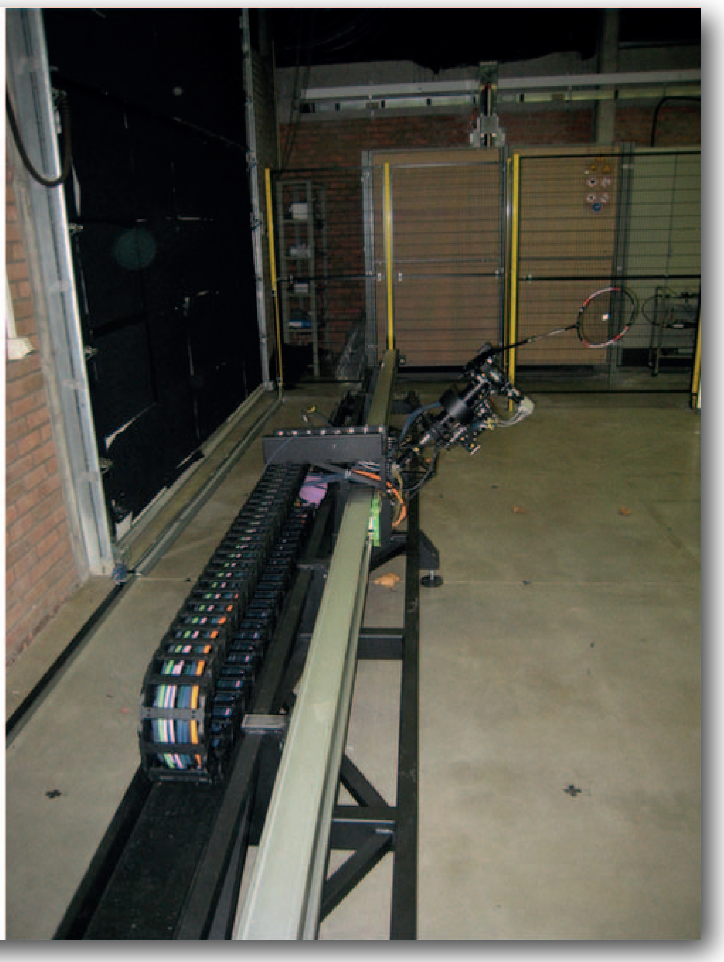


Can we find the mechanism connecting causes to effects?

[De Maeyer at al, Molecular Biosystems 13]

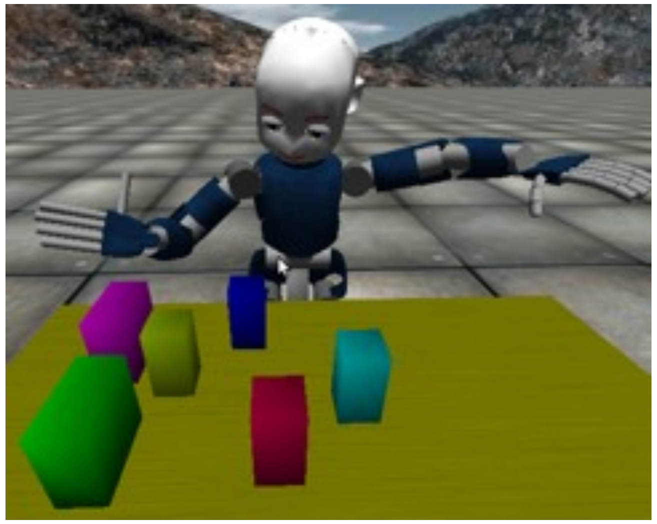
Diagnosing machine failures



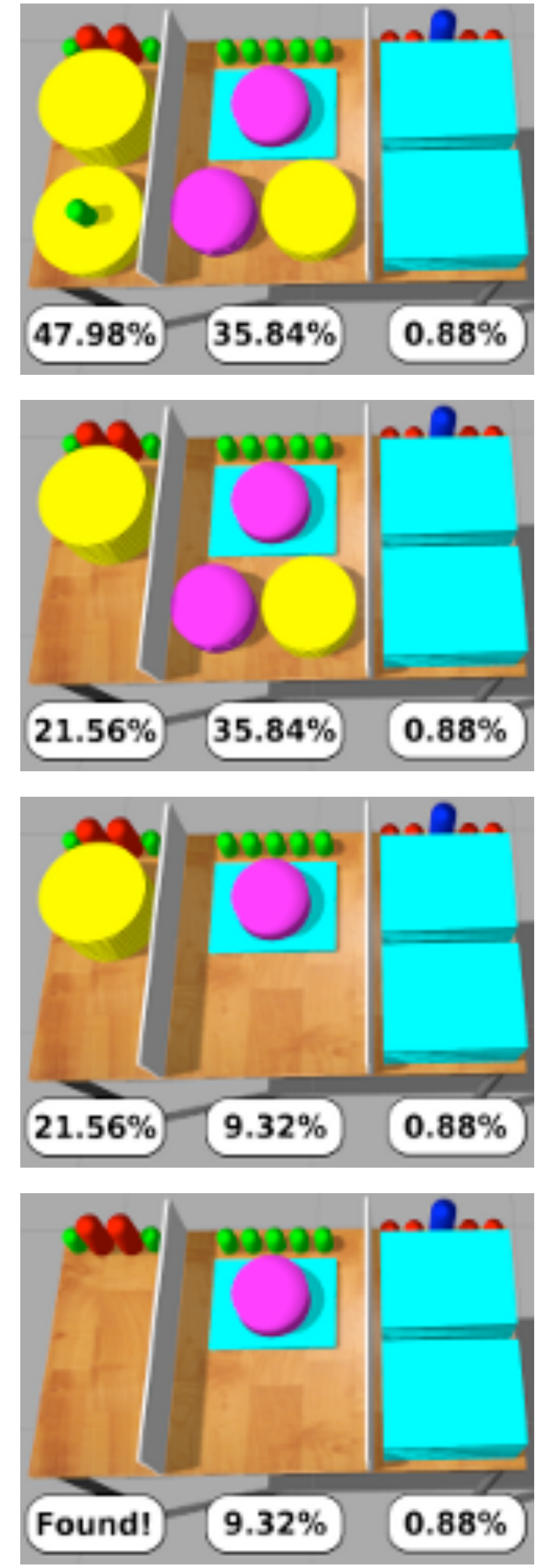


Can we build a model of the robot's working and use it to find causes of failures?

[Schramm, Meert and Driessens]



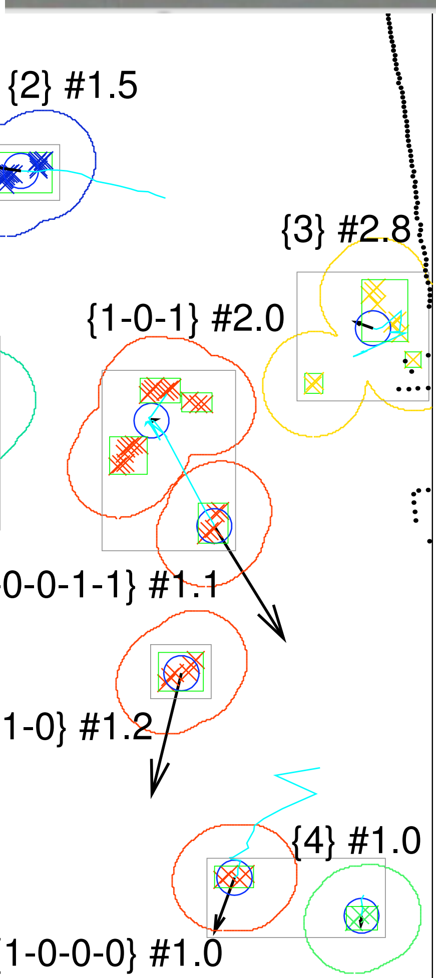
Robotics



- How to achieve a specific configuration of objects on the shelf?
- Where's the orange mug?
- Where's something to serve soup in?

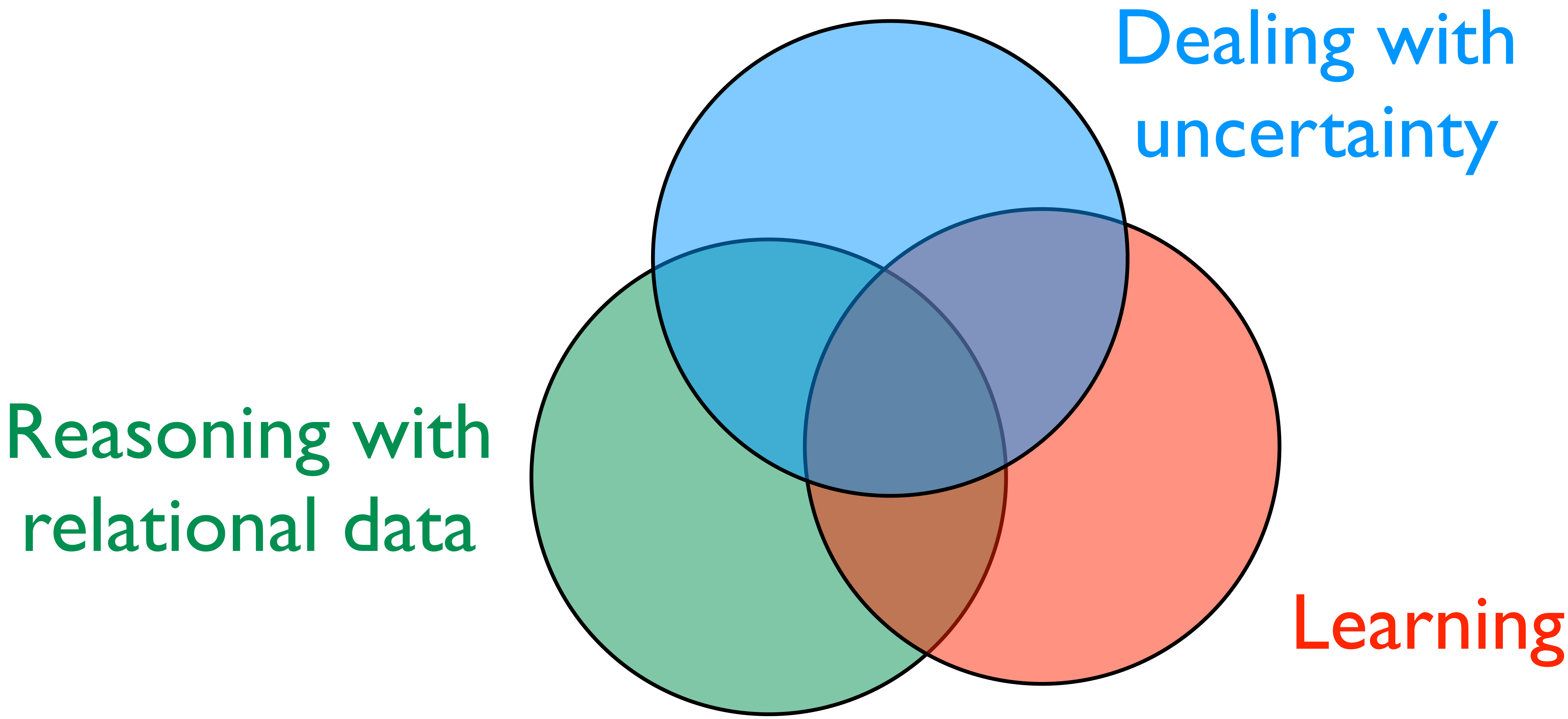
[Moldovan et al]

Analyzing Video Data



- Track people or objects over time? Even if temporarily hidden?
- Recognize activities?
- Infer object properties?

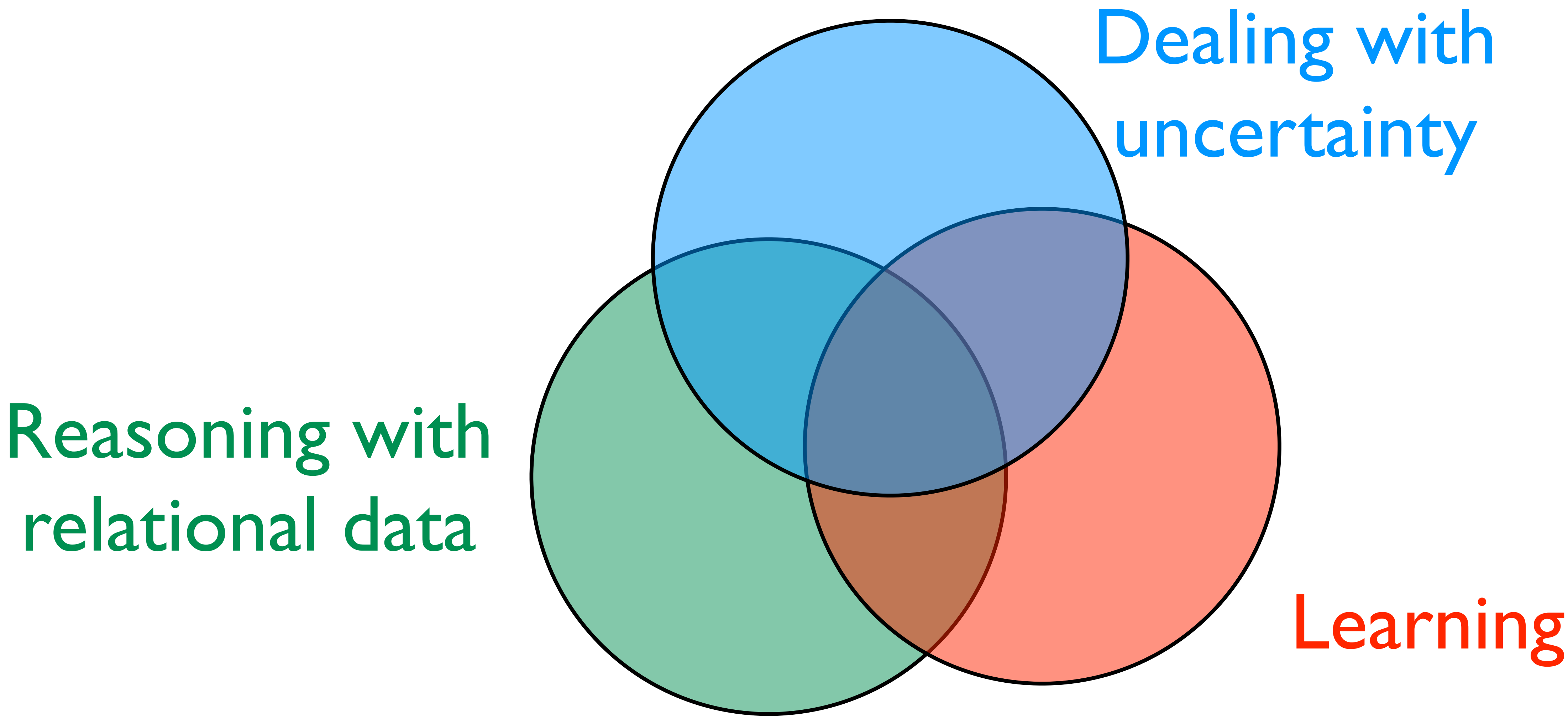
Common theme



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

ProbLog

probabilistic Prolog



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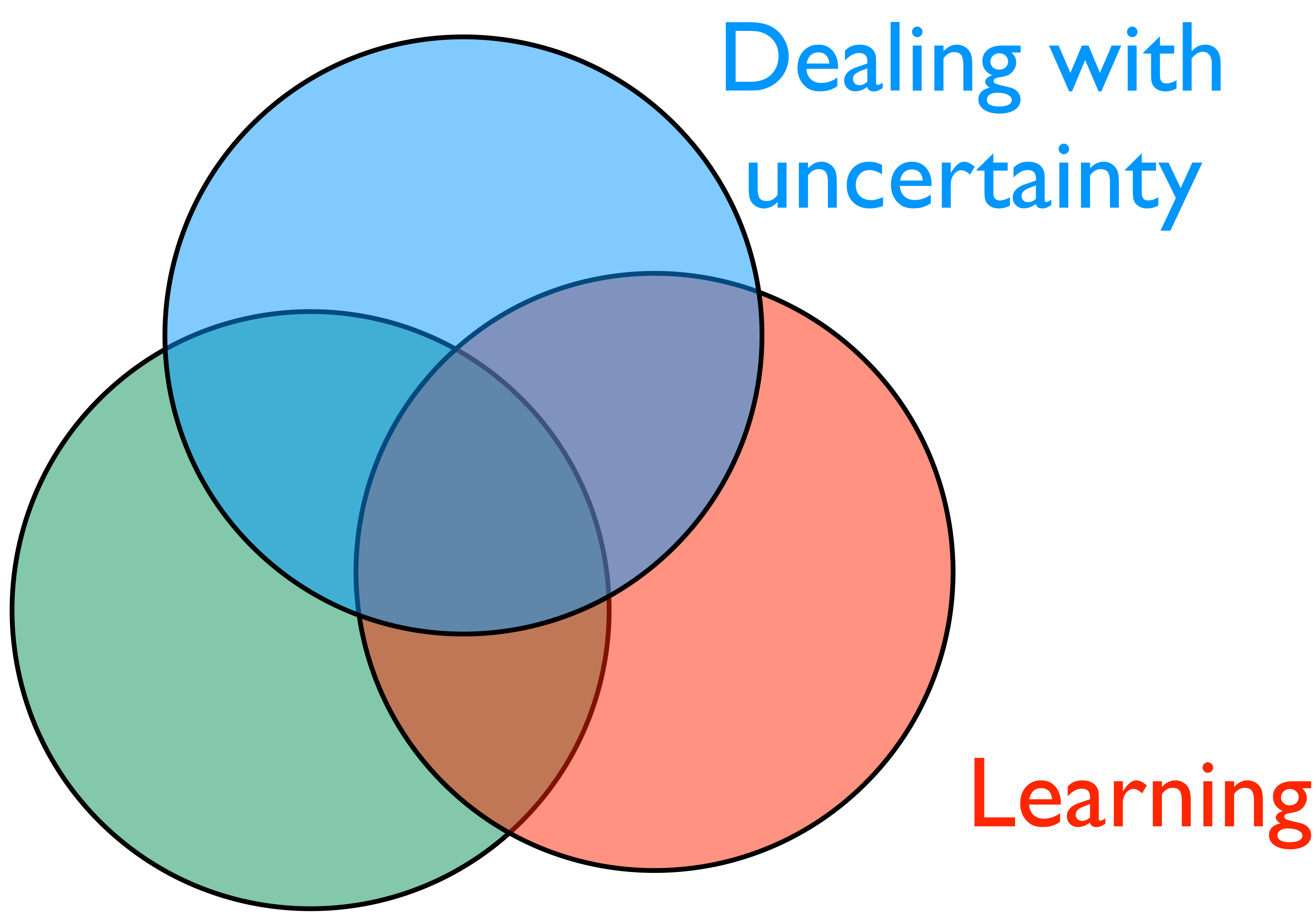


```
stress(ann).
influences(ann,bob).
influences(bob,carl).

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

ProbLog

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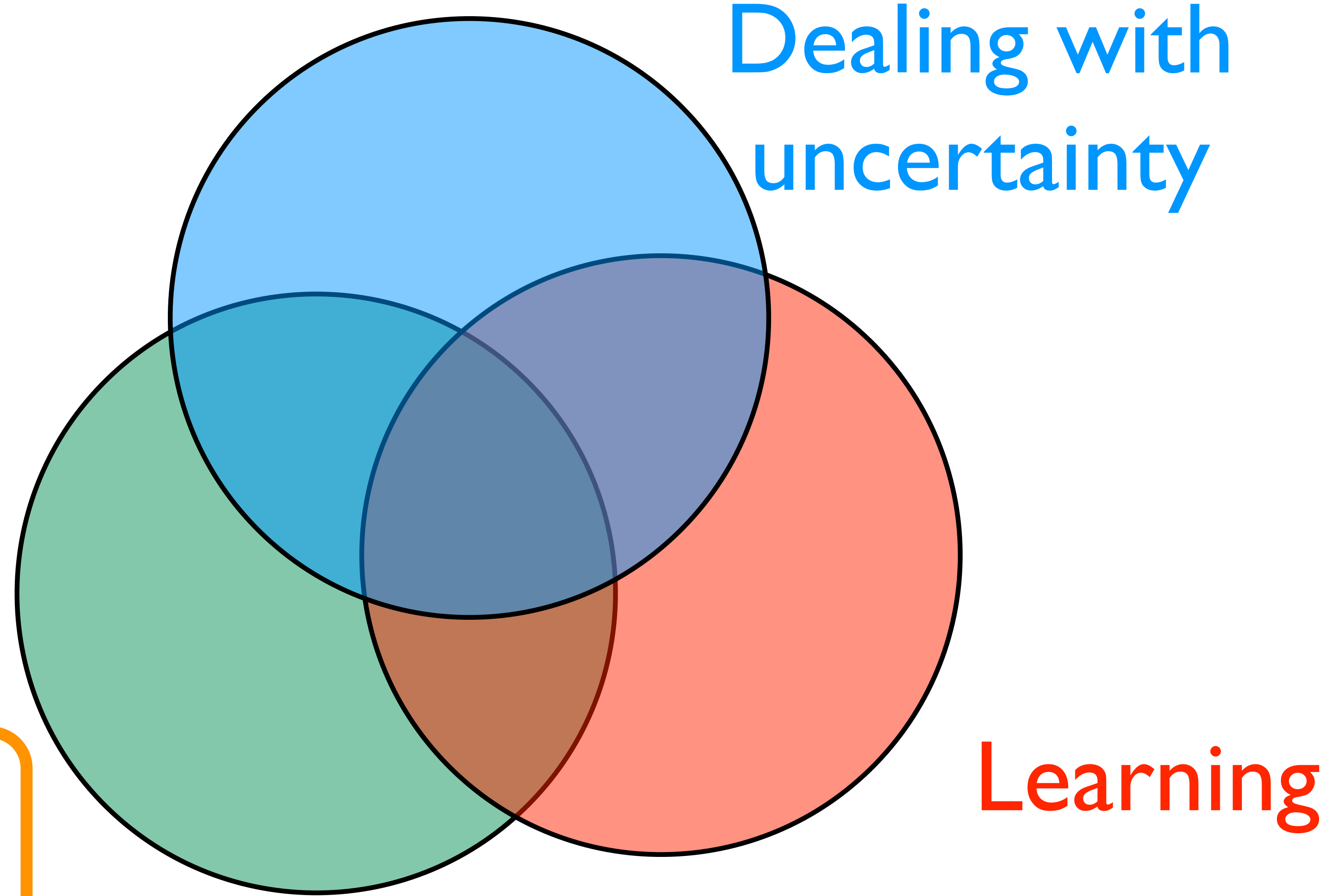


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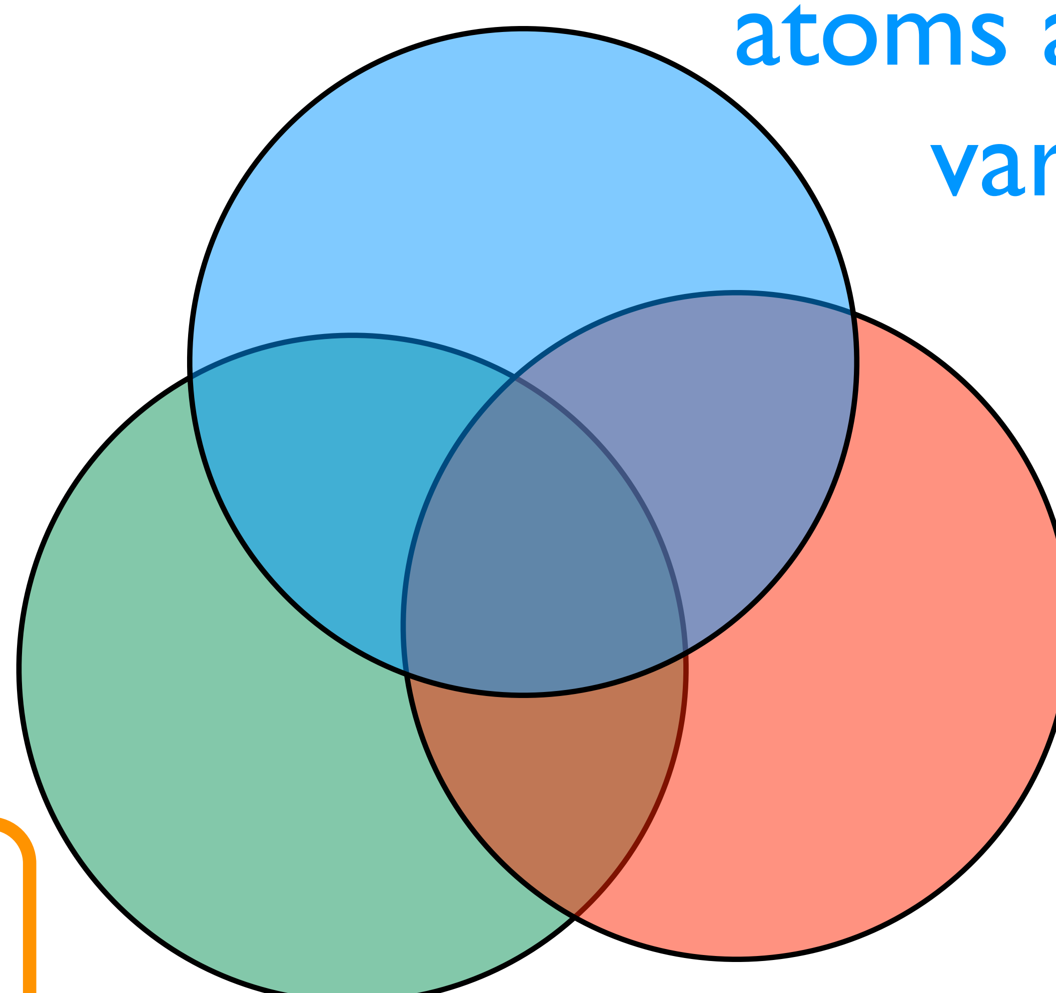
ProbLog

probabilistic Prolog

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

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ProbLog

probabilistic Prolog

several possible worlds

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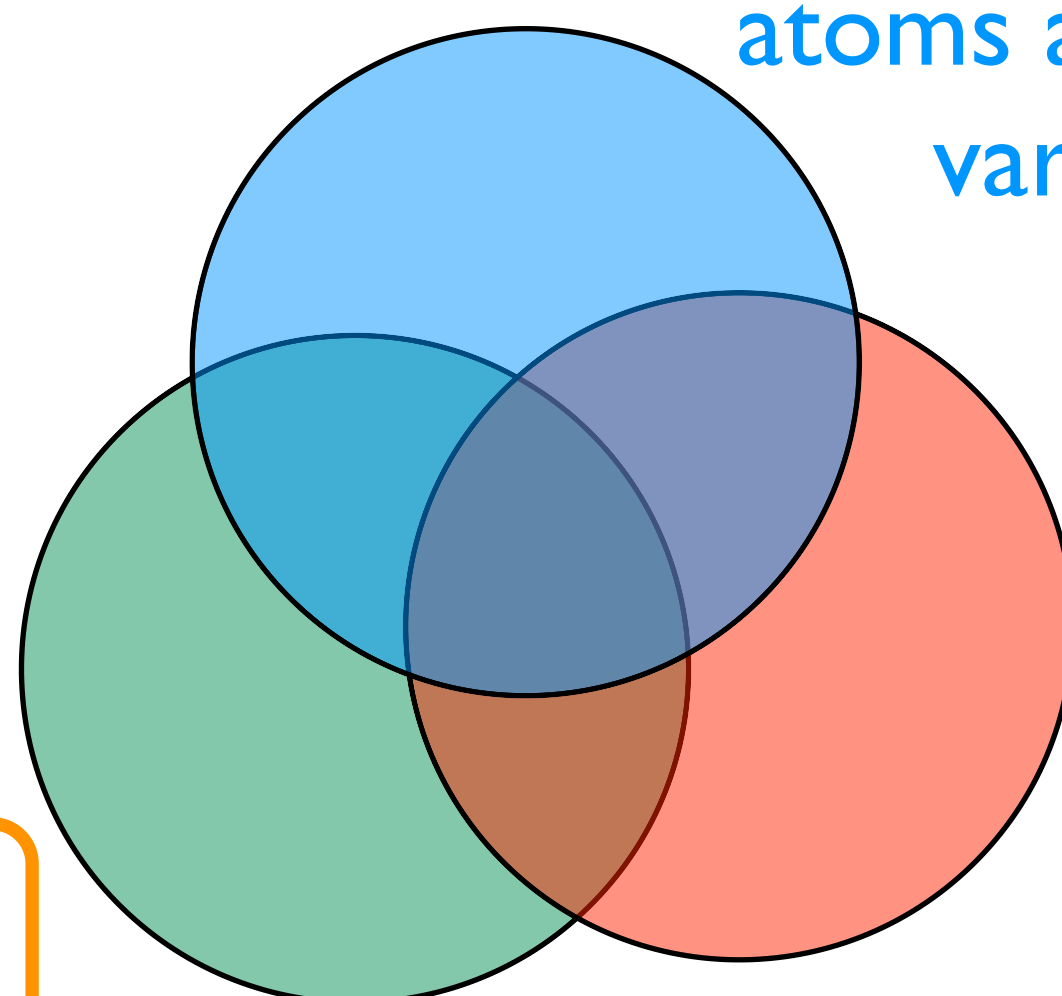
atoms as random variables



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

several possible worlds

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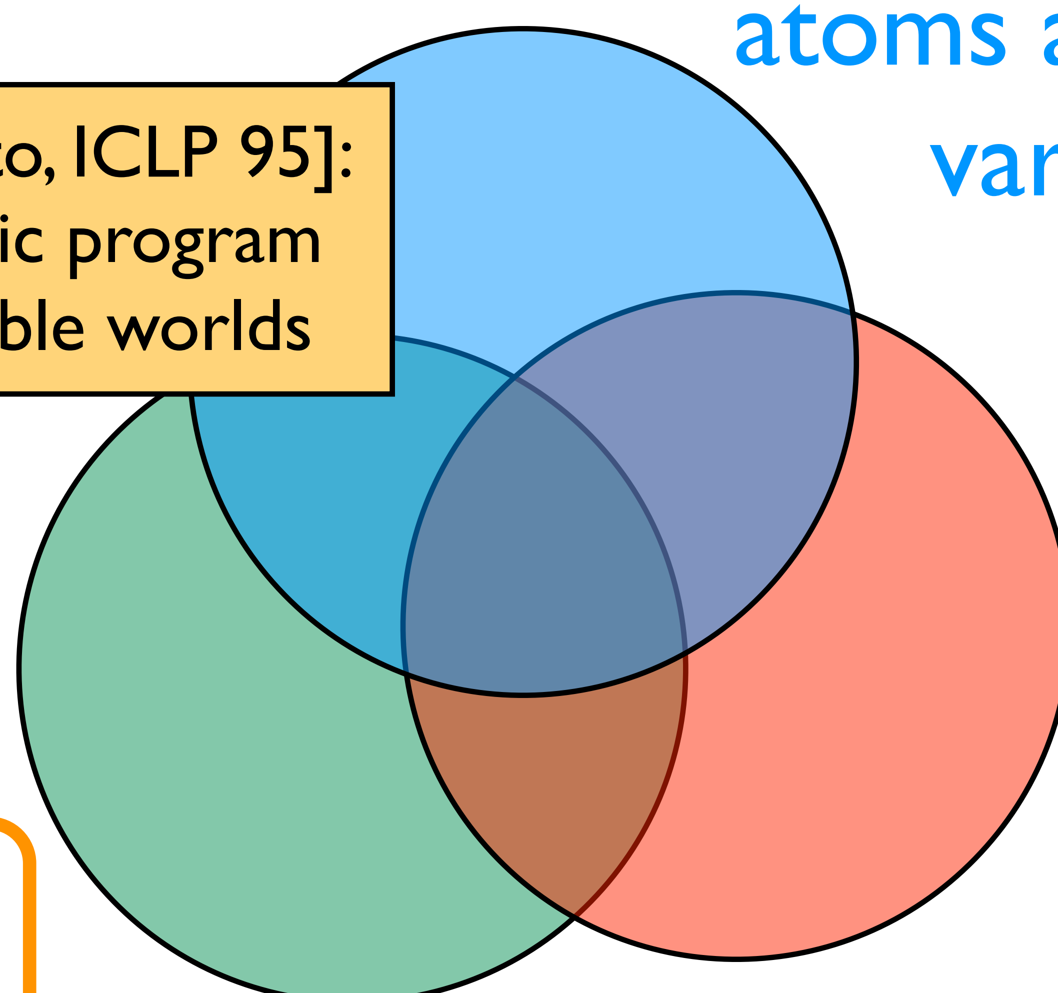
atoms as random variables

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



Prolog / logic programming

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ProbLog

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Distribution Semantics [Sato, ICLP 95]:
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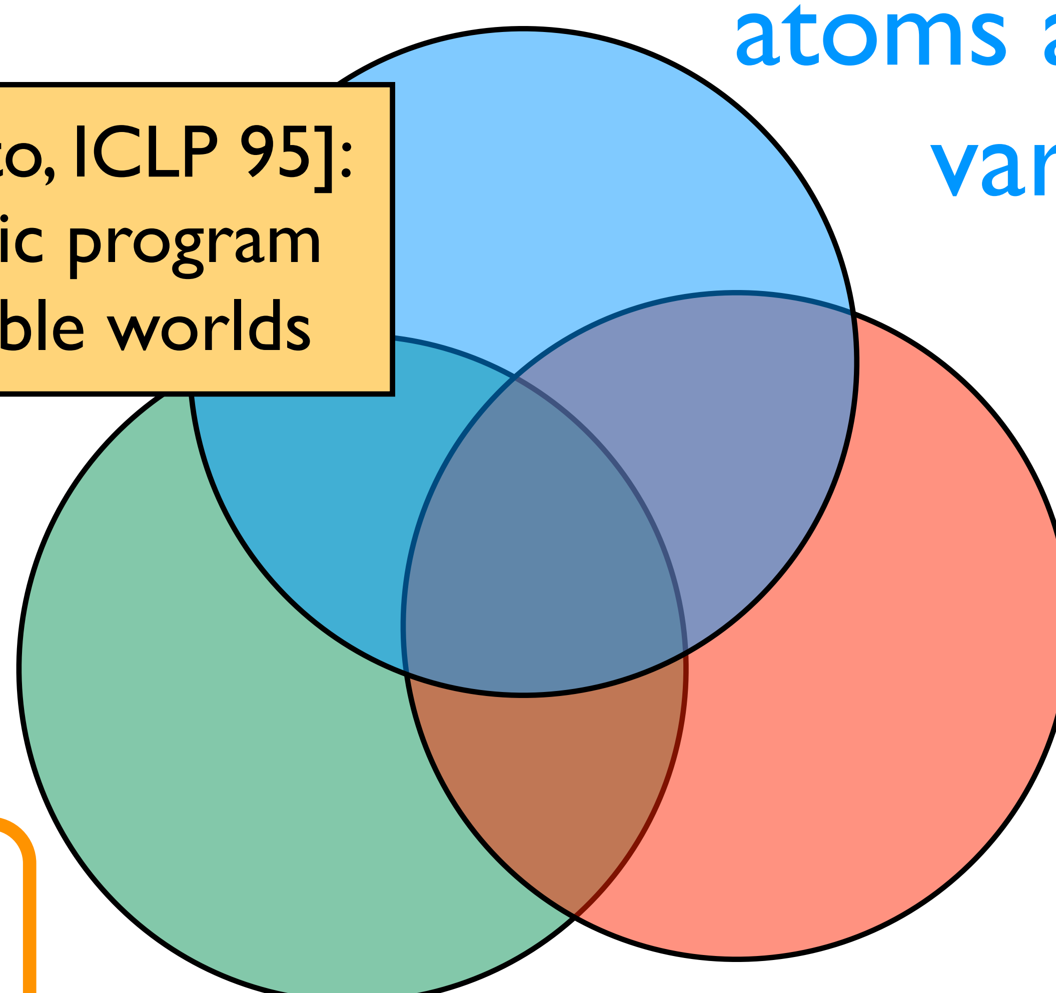

Prolog / logic programming

adapted relational learning techniques

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

one world

```
smokes(X) :- stress(X).
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```

Overview

- ProbLog Basics
  - ProbLog by example
  - Inference
  - Parameter Learning
- Selected Topics
  - Upgrading relational learning
  - Dynamics under uncertainty
  - Continuous-valued random variables
  - Decision making
  - Constraints

Overview

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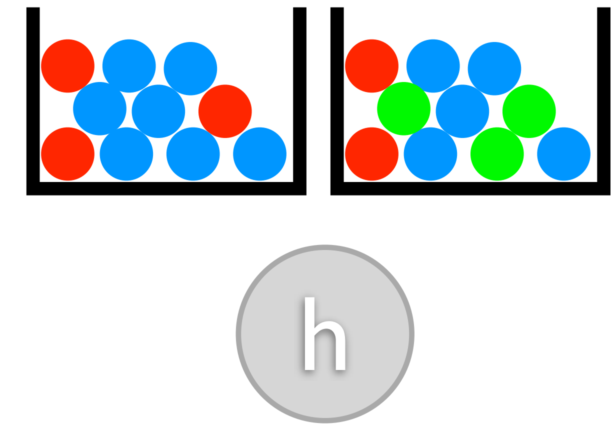
ProbLog by example:

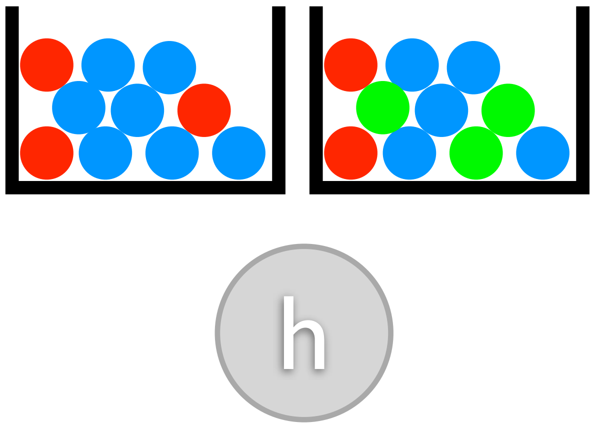
A bit of gambling



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

ProbLog by example:

A bit of gambling



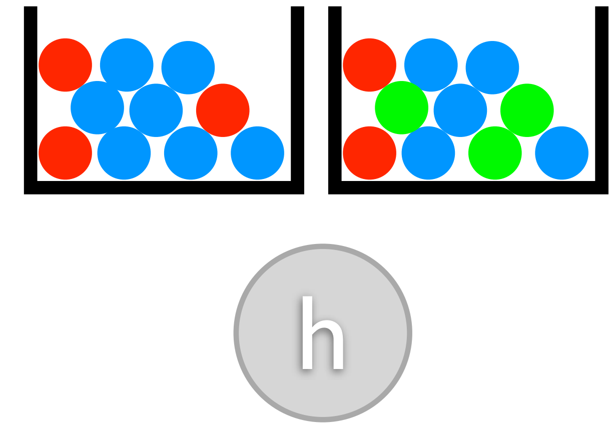
- toss (biased) coin & draw ball from each urn
- win if (heads and a red ball) or (two balls of same color)

```
0.4 :: heads.
```

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

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)

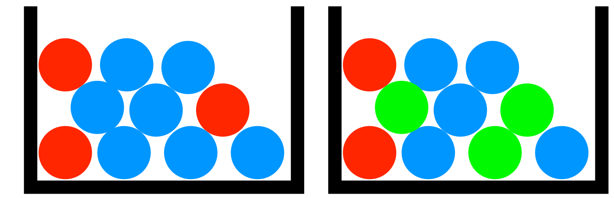
```
0.4 :: heads.
```

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) <- true.
```

ProbLog by example:

A bit of gambling



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0.2 :: col(2,red); 0.3 :: col(2,green);
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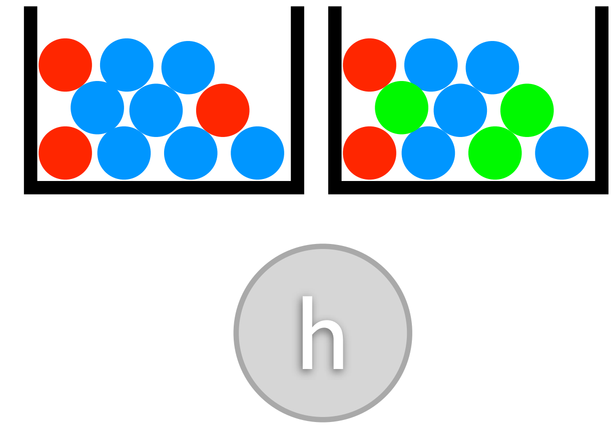
```

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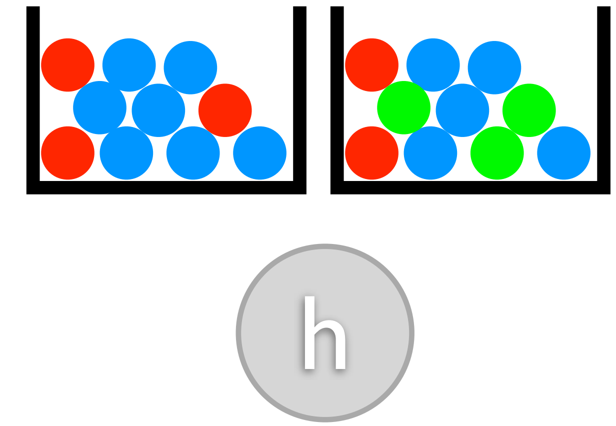
win :- heads, col(_,red).
```

logical rule encoding background knowledge

ProbLog by example:

A bit of gambling



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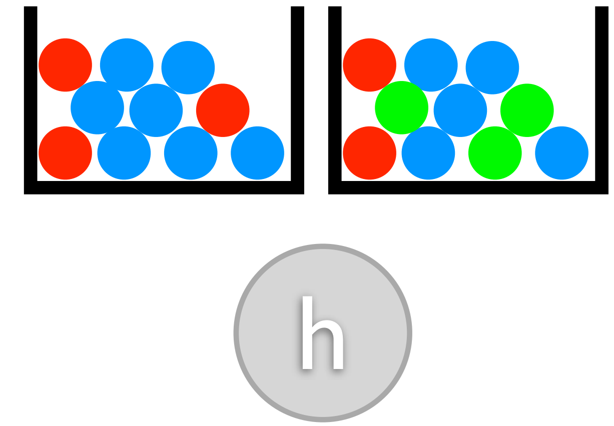
win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

logical rule encoding background knowledge

ProbLog by example:

A bit of gambling



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probabilistic choices

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consequences

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

Questions

```
0.4 :: heads.

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```

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

Questions

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marginal probability

- Probability of `win`?

query

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marginal probability

- Probability of **`win`**?

conditional probability

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

evidence

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

Questions

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marginal probability

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conditional probability

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- Most probable world where `win` is true?

MPE inference

Possible Worlds

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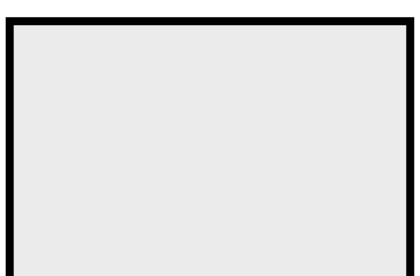

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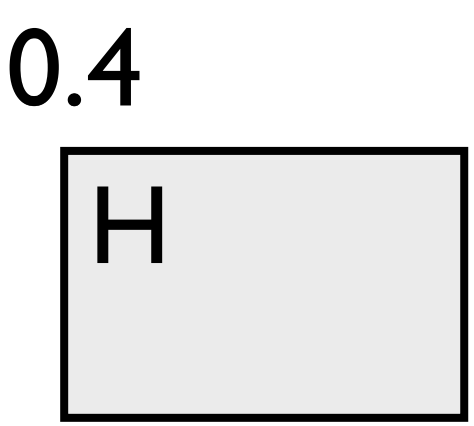

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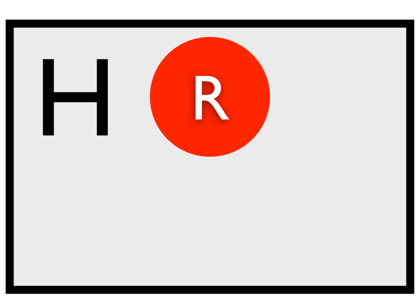
0.4×0.3



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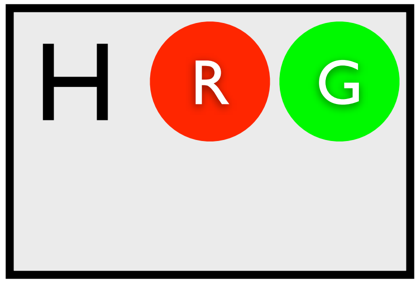
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

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

$0.4 \times 0.3 \times 0.3$



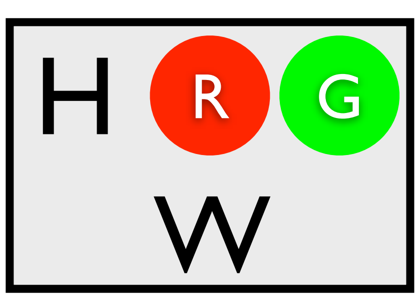
Possible Worlds

```
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).
```

$0.4 \times 0.3 \times 0.3$



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).
```

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

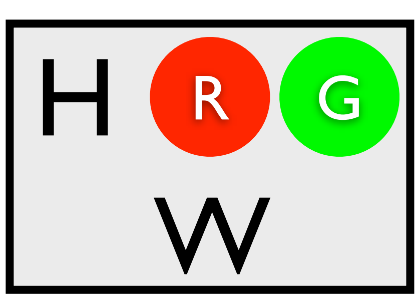
Possible Worlds

```
0.4 :: heads.

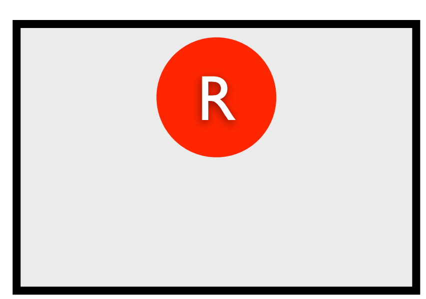
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

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

$0.4 \times 0.3 \times 0.3$



$(1-0.4)\times 0.3$



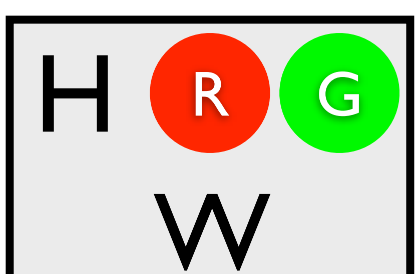
Possible Worlds

```
0.4 :: heads.

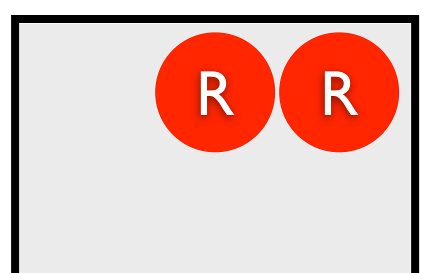
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

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

$0.4 \times 0.3 \times 0.3$



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



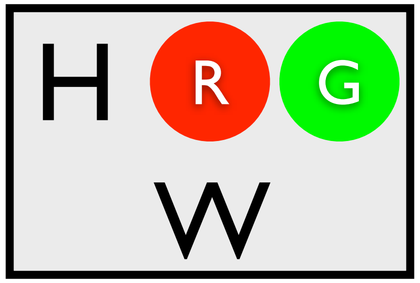
Possible Worlds

```
0.4 :: heads.

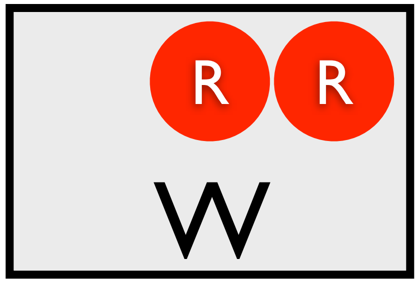
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

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

$0.4 \times 0.3 \times 0.3$



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



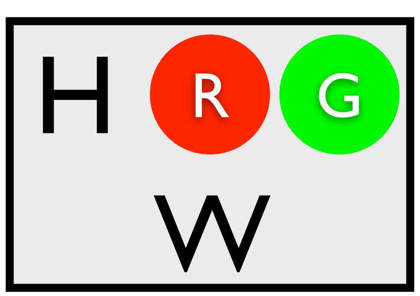
Possible Worlds

```
0.4 :: heads.

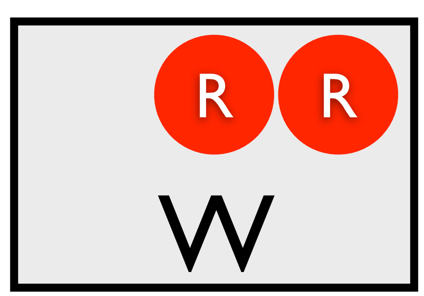
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

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

$0.4 \times 0.3 \times 0.3$



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



$(1-0.4)$

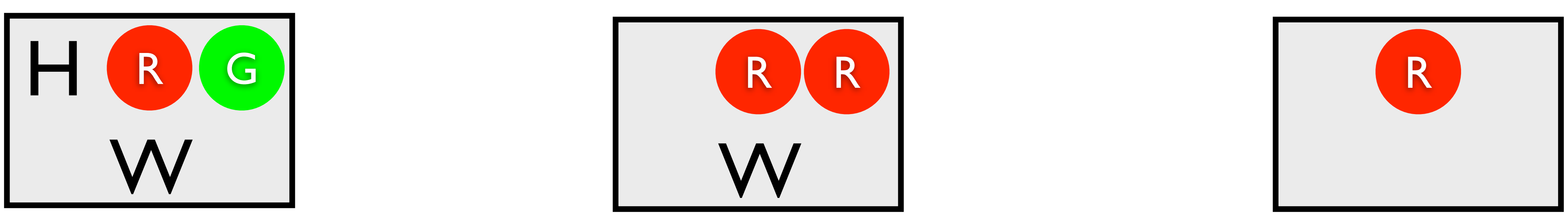
Possible Worlds

```
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).
```

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



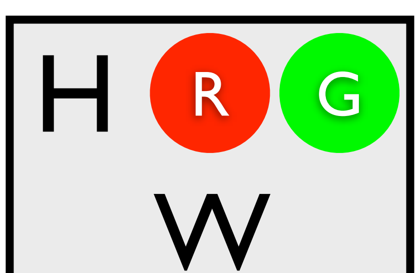
Possible Worlds

```
0.4 :: heads.

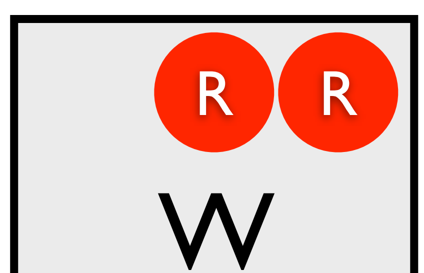
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

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

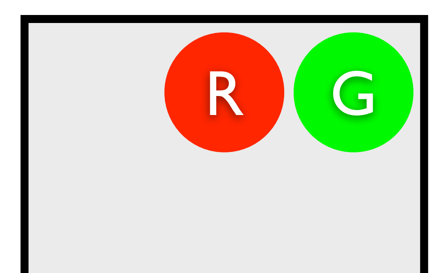
$0.4 \times 0.3 \times 0.3$



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



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



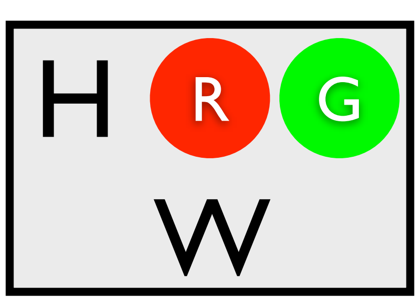
Possible Worlds

```
0.4 :: heads.

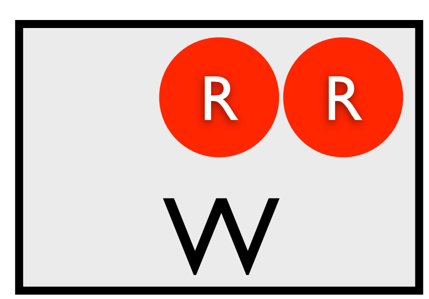
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

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

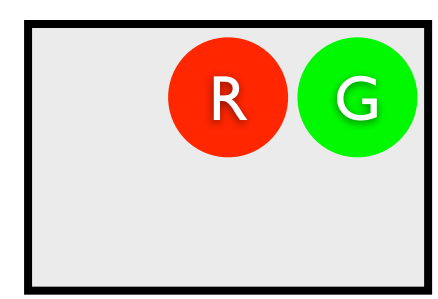
$0.4 \times 0.3 \times 0.3$



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



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



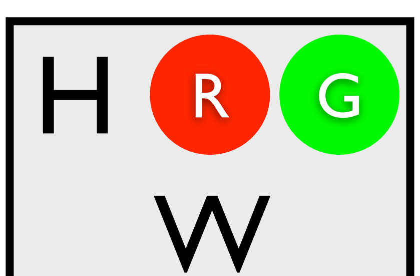
Possible Worlds

```
0.4 :: heads.

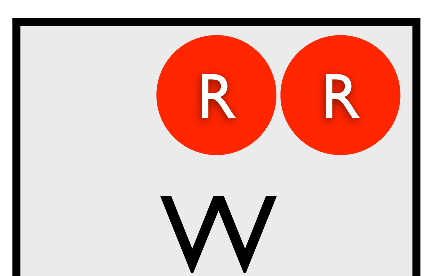
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

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

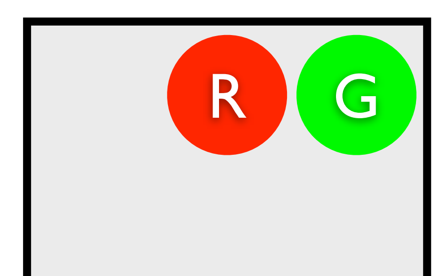
$0.4 \times 0.3 \times 0.3$



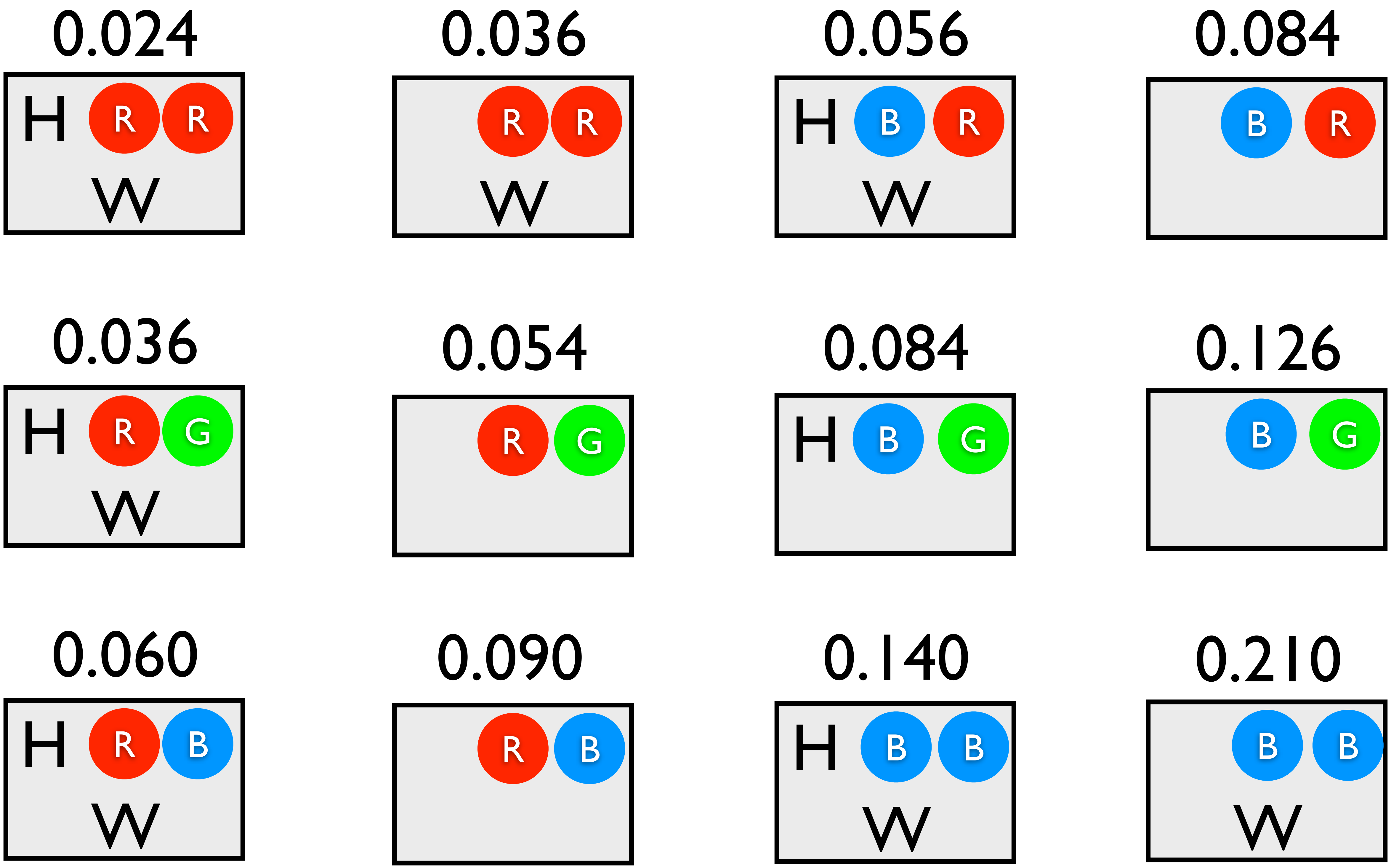
$(1-0.4)\times 0.3 \times 0.2$



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

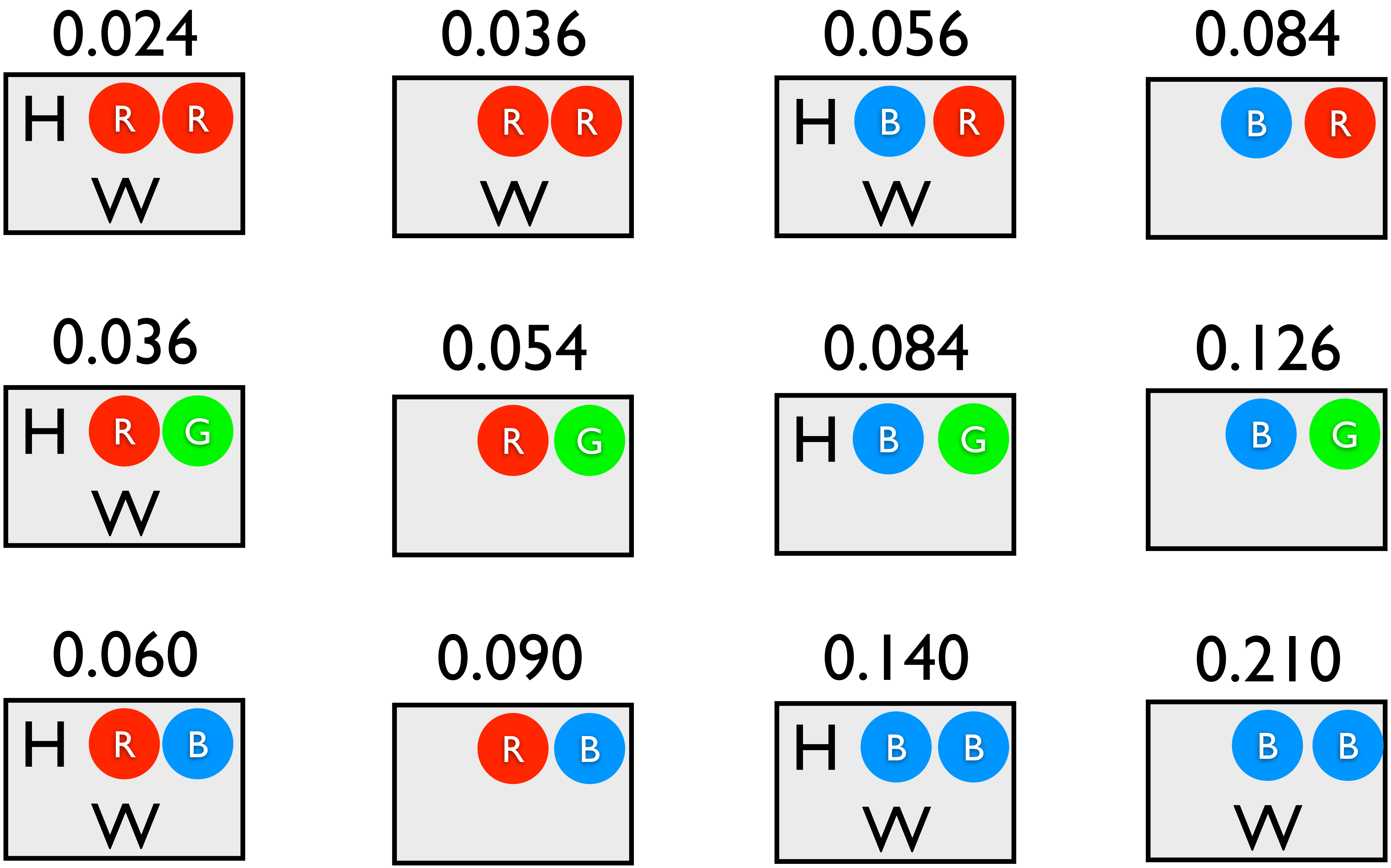


All Possible Worlds



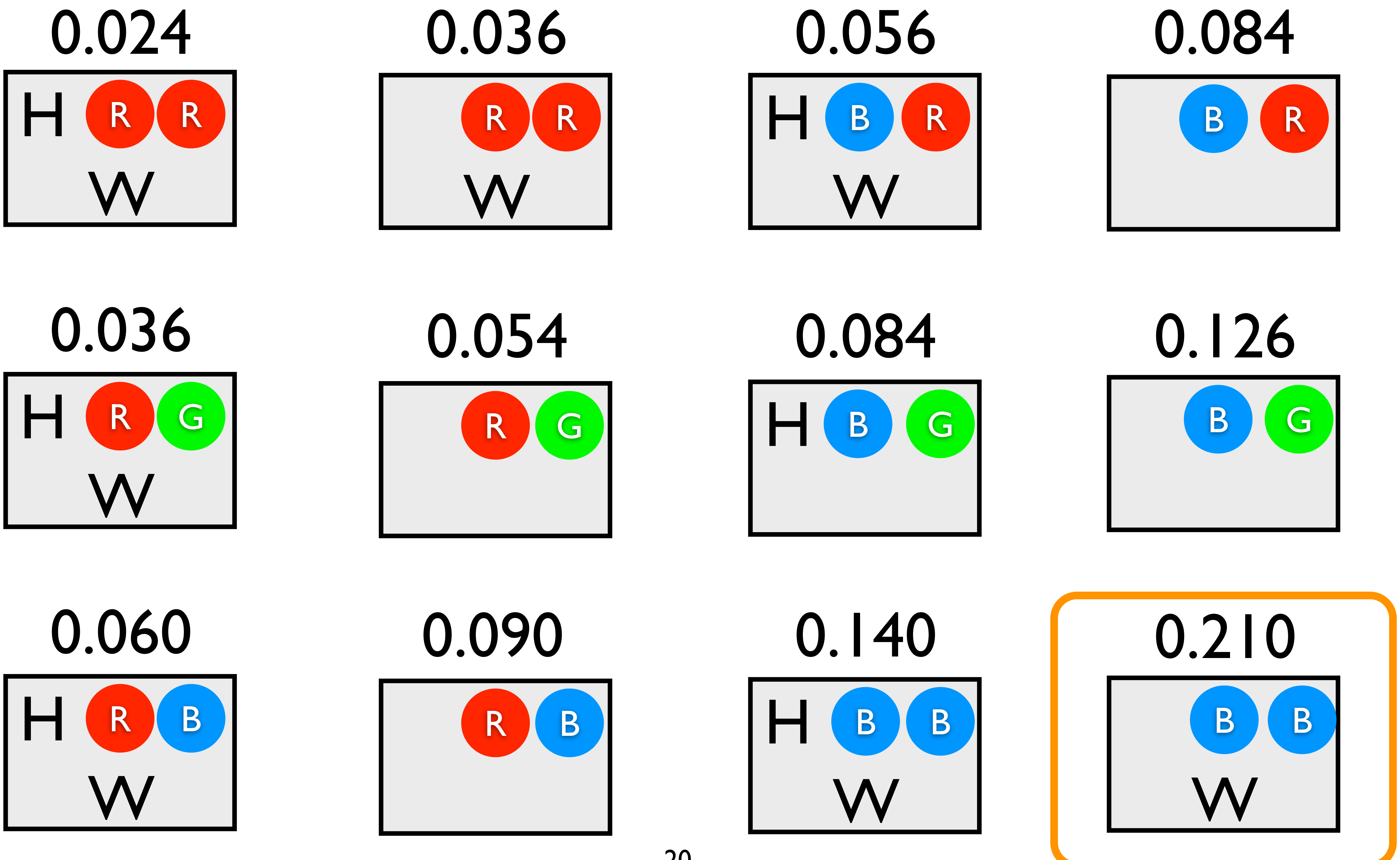
Most likely world where **`win`** is true?

MPE Inference



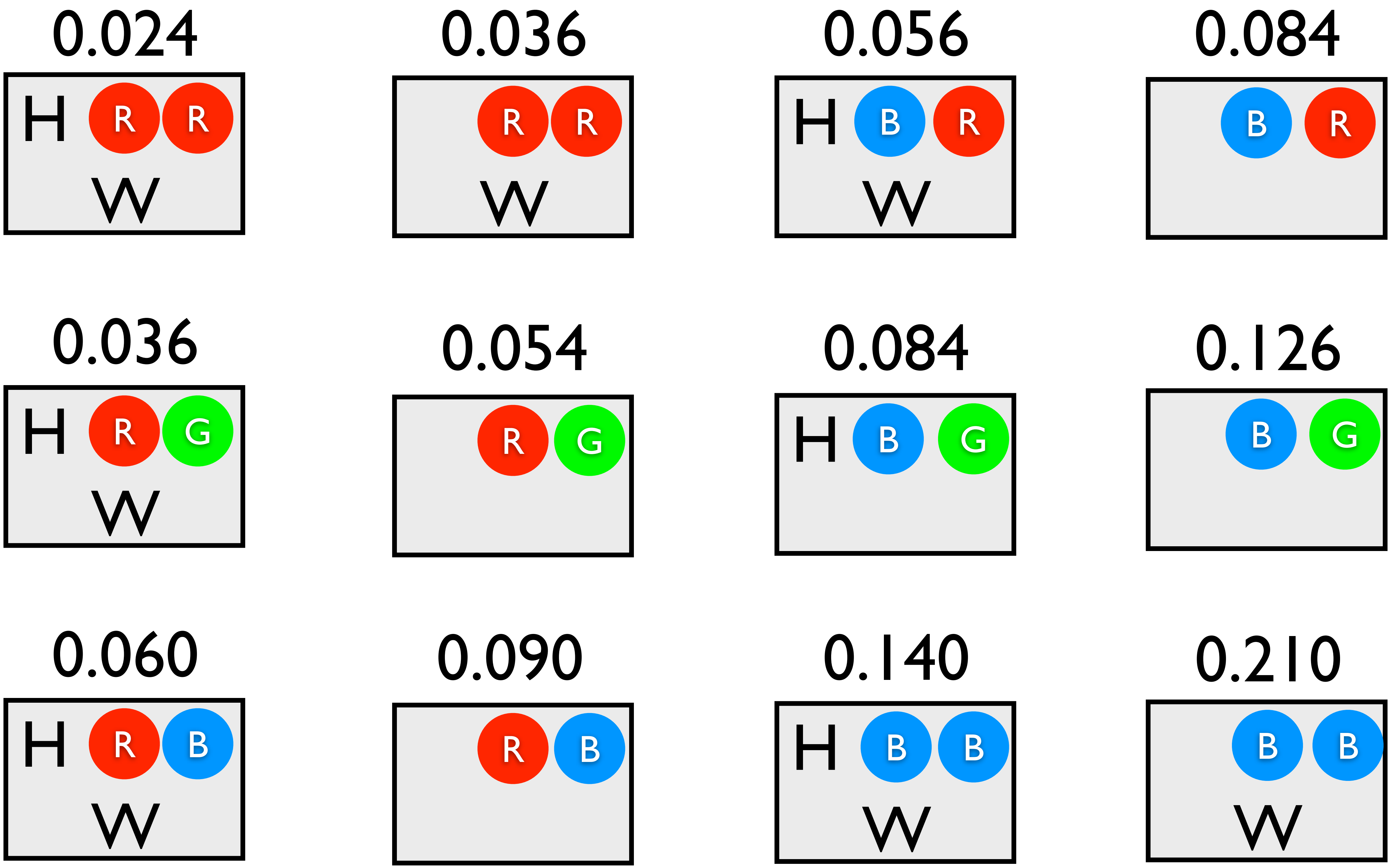
Most likely world where **`win`** is true?

MPE Inference



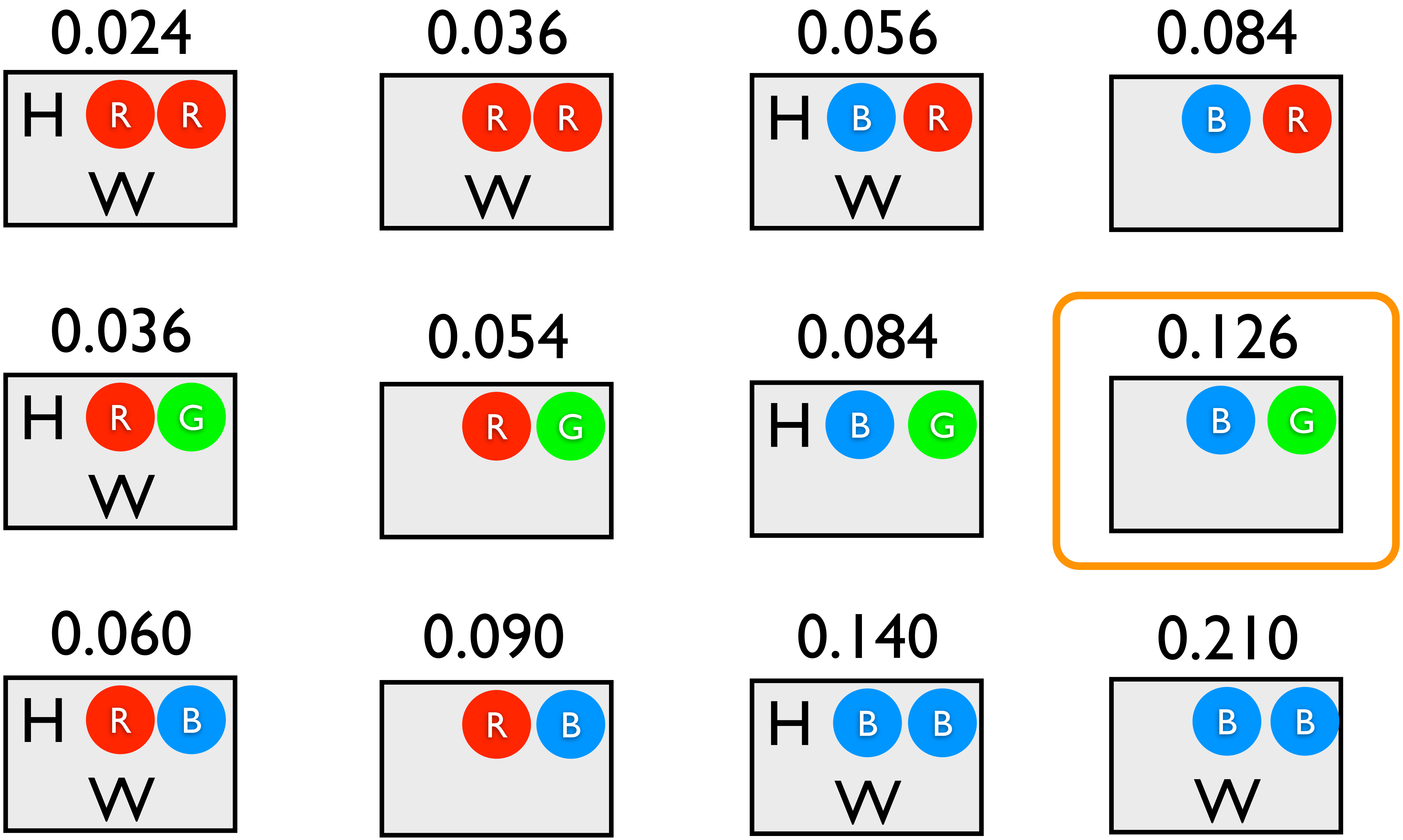
Most likely world where `col(2,blue)` is false?

MPE Inference



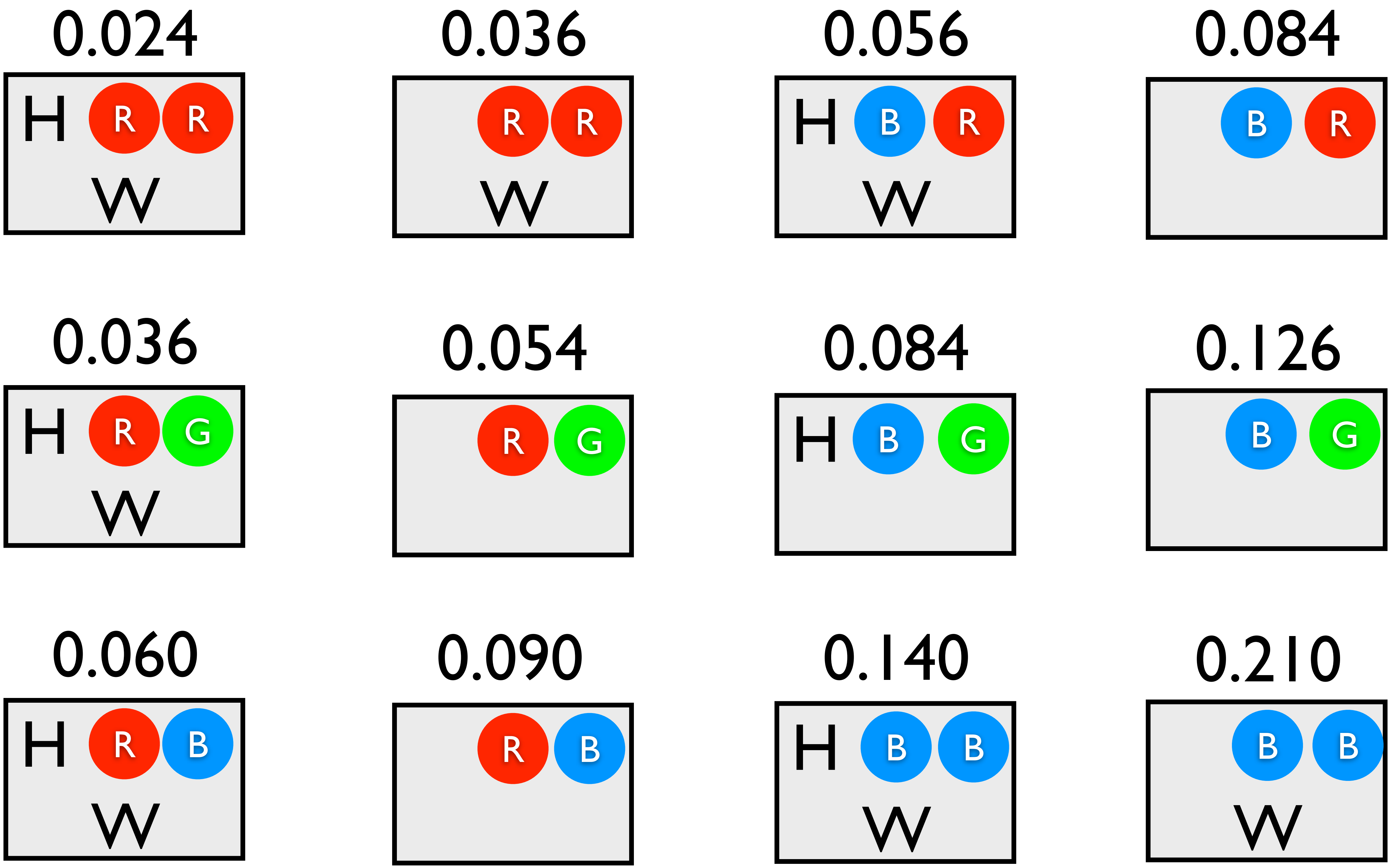
Most likely world where `col(2,blue)` is false?

MPE Inference



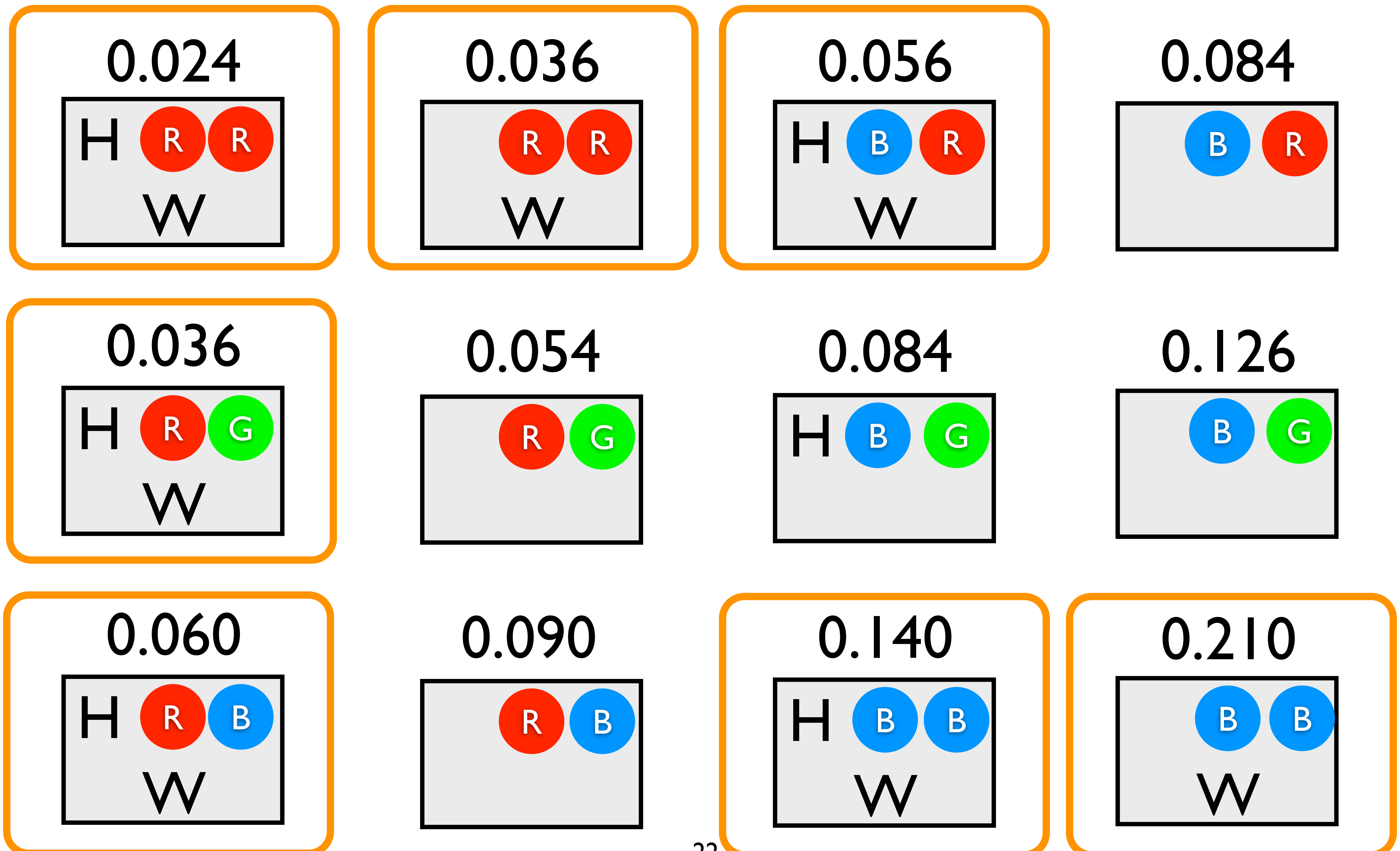
P(win)=?

Marginal Probability



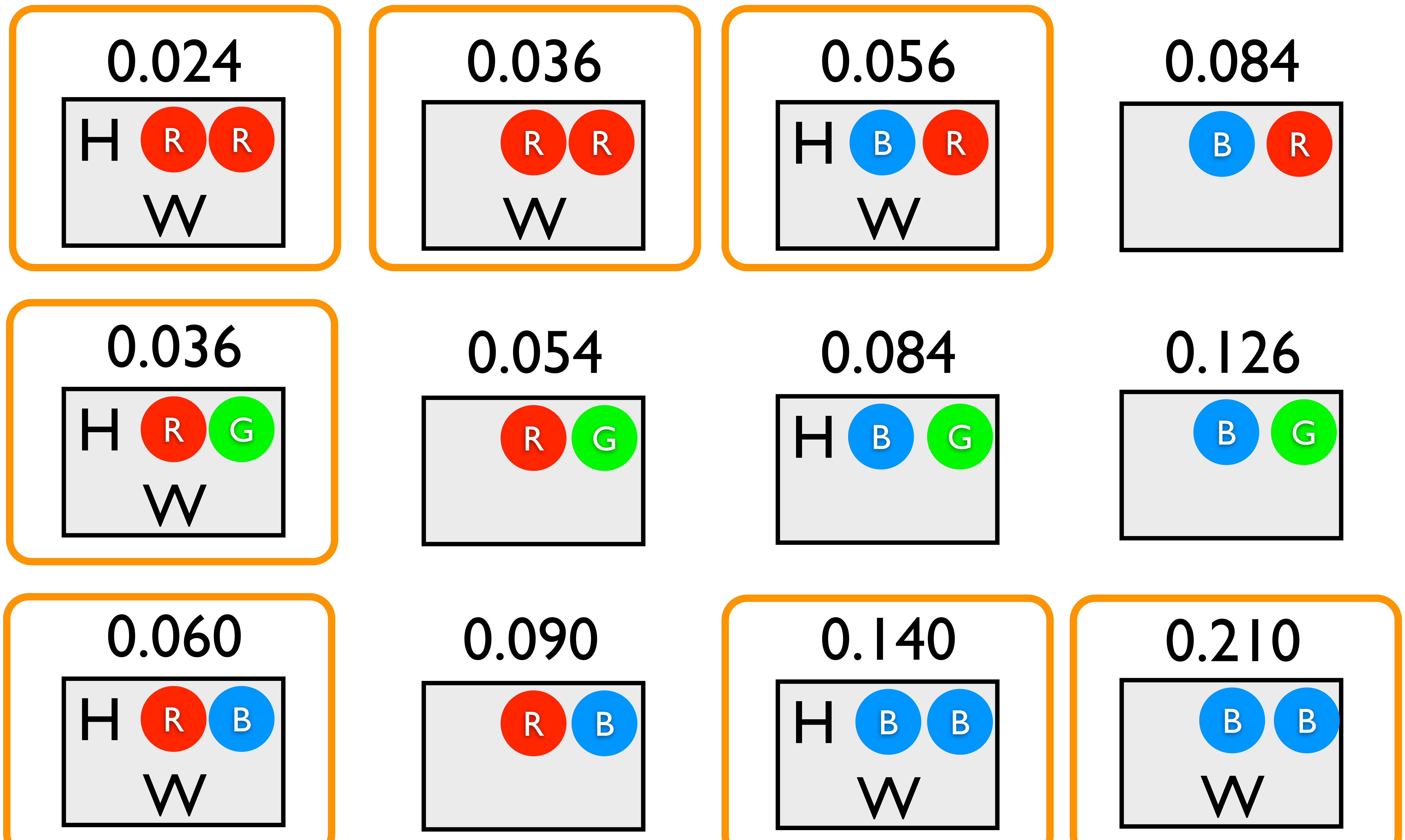
$P(\underline{\text{win}}) = \sum$

Marginal Probability



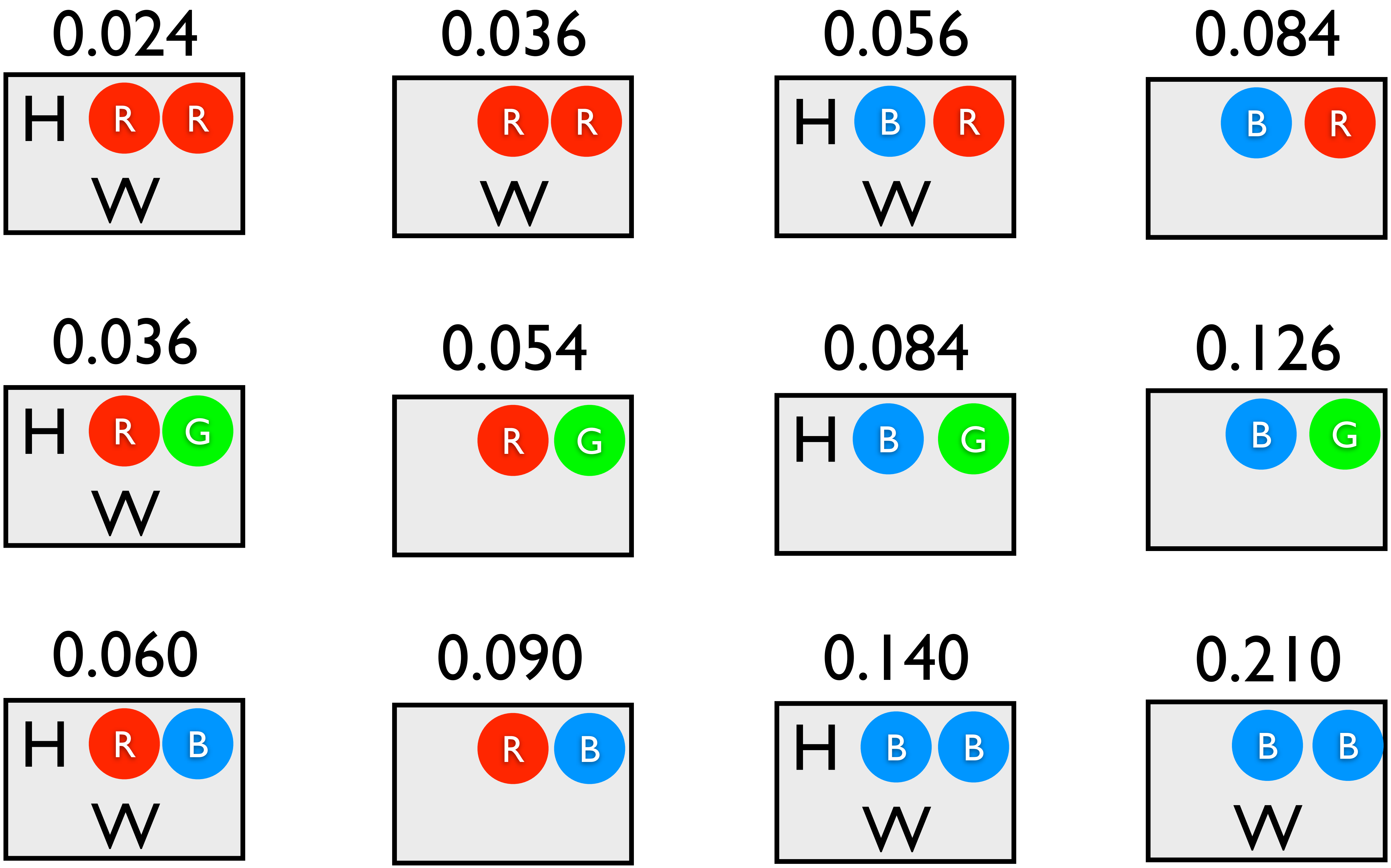
$P(\underline{win}) = \sum = 0.562$

Marginal Probability



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

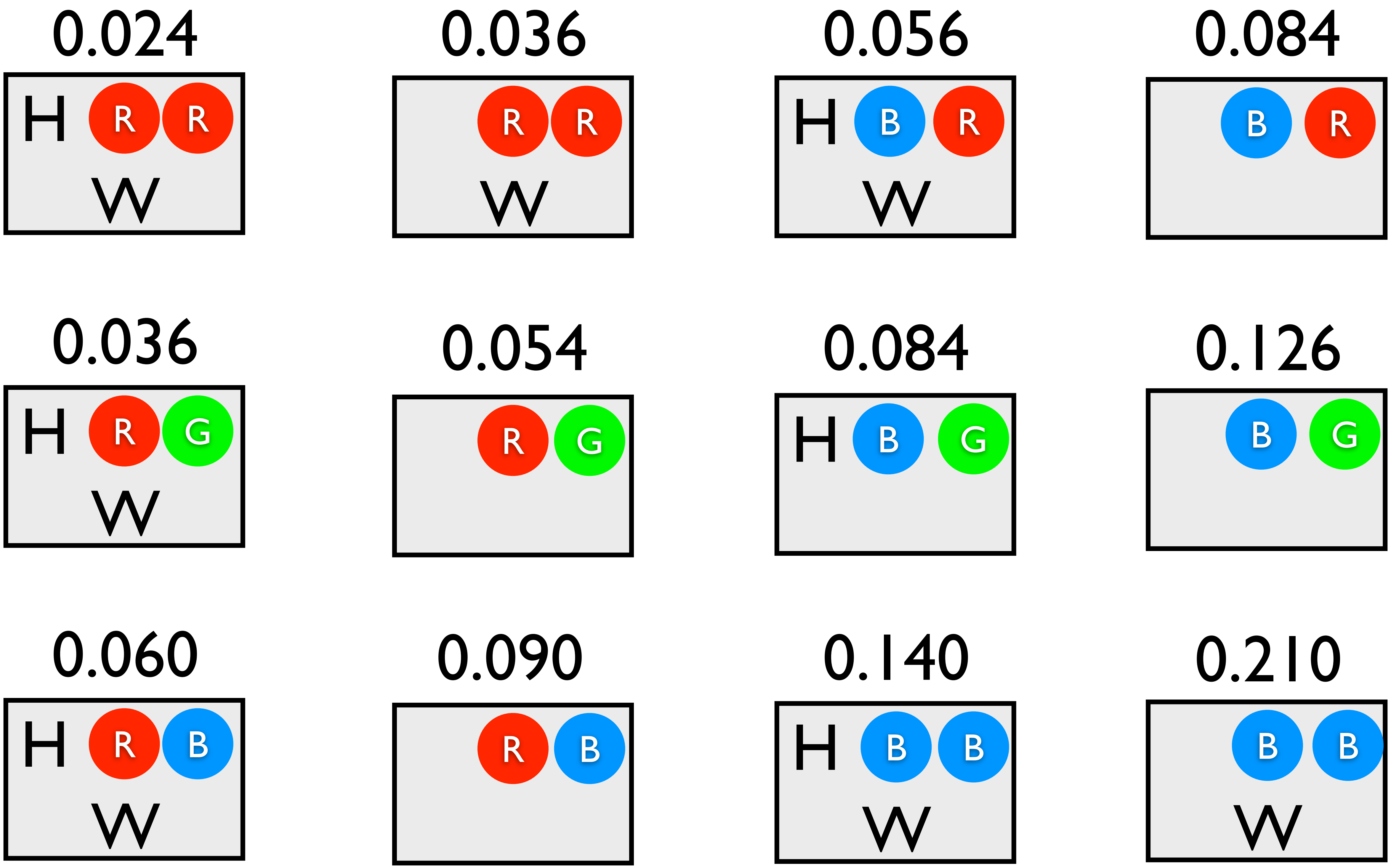
Conditional Probability



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

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

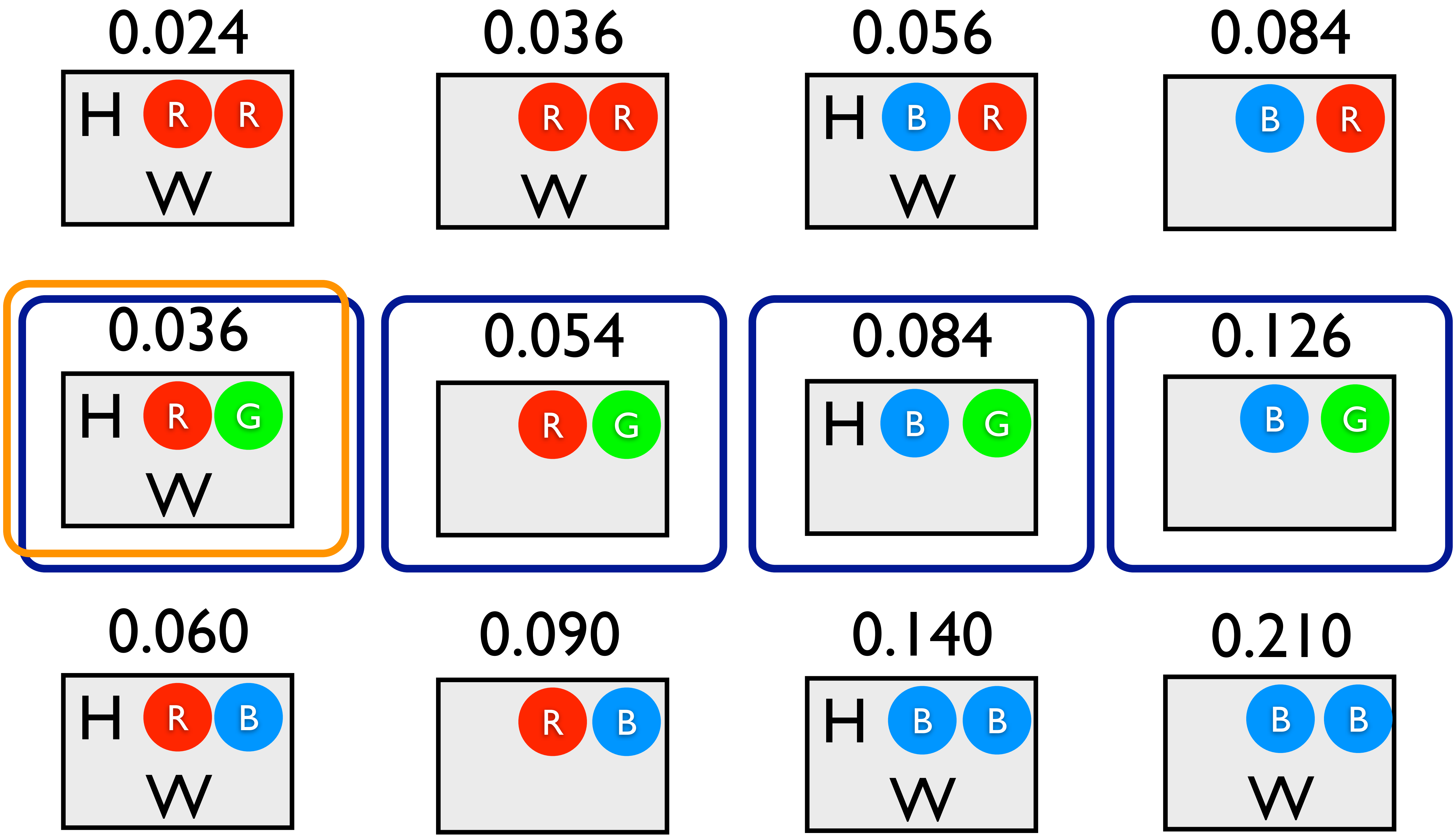
Conditional Probability



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

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

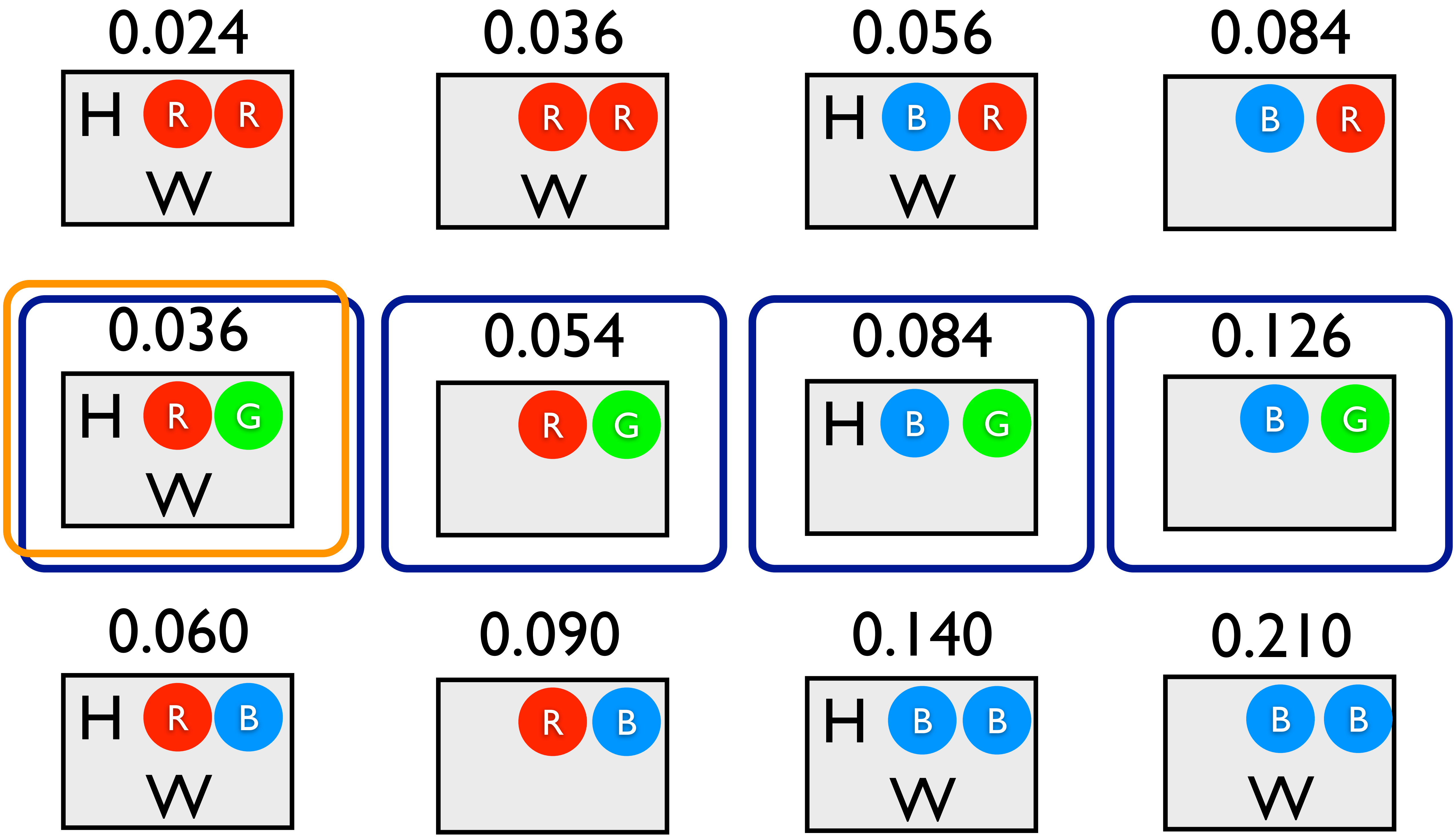
Conditional Probability



Conditional Probability

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

$= 0.036/0.3 = 0.12$



ProbLog by example:

Rain or sun?

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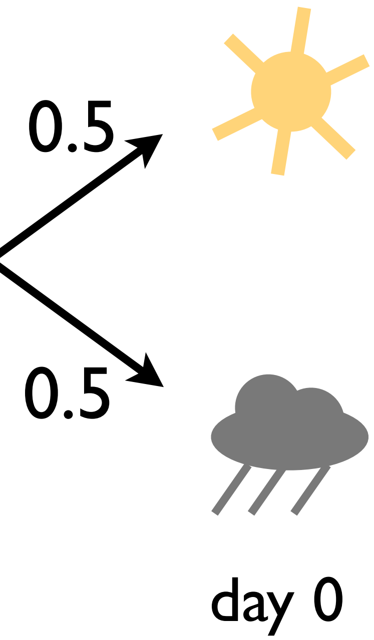
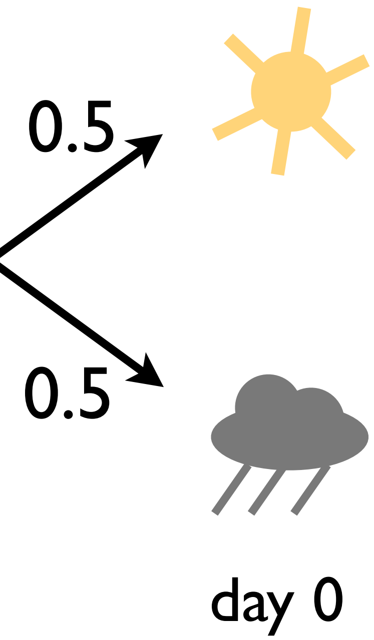
Rain or sun?



ProbLog by example:

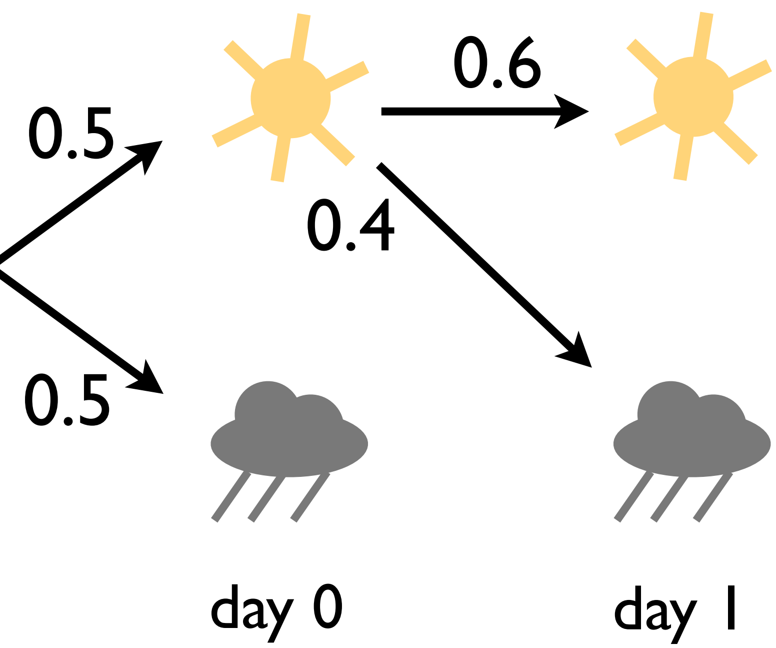
Rain or sun?




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

ProbLog by example:

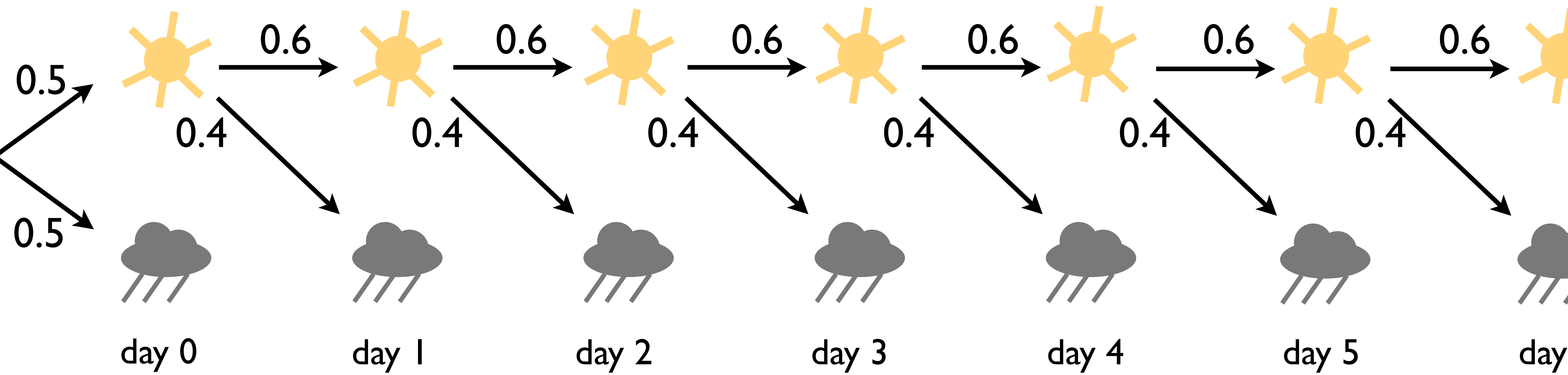
Rain or sun?




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

ProbLog by example:

Rain or sun?

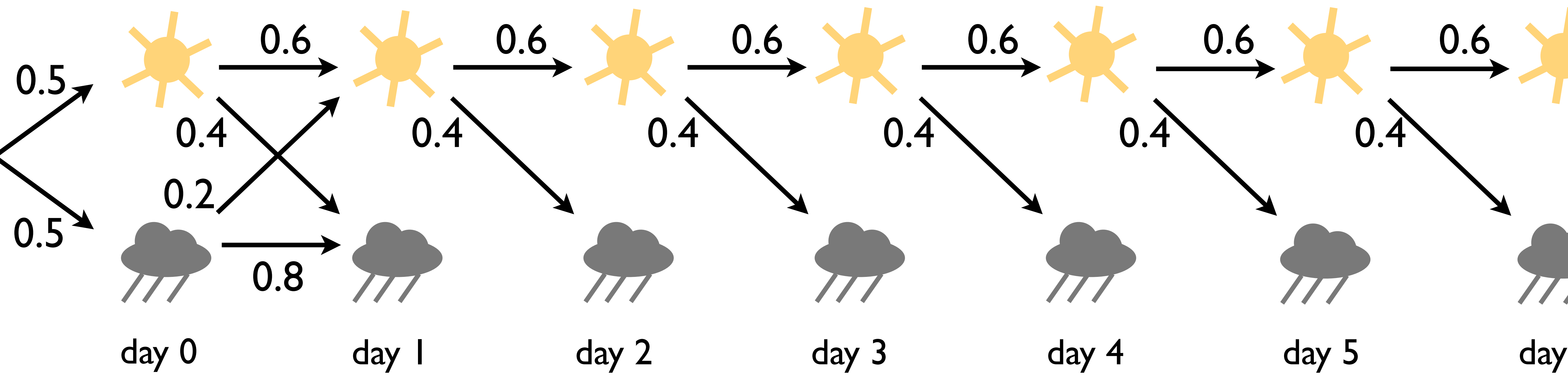



```
0.5::weather(sun,0) ; 0.5::weather(rain,0) <- true.

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?

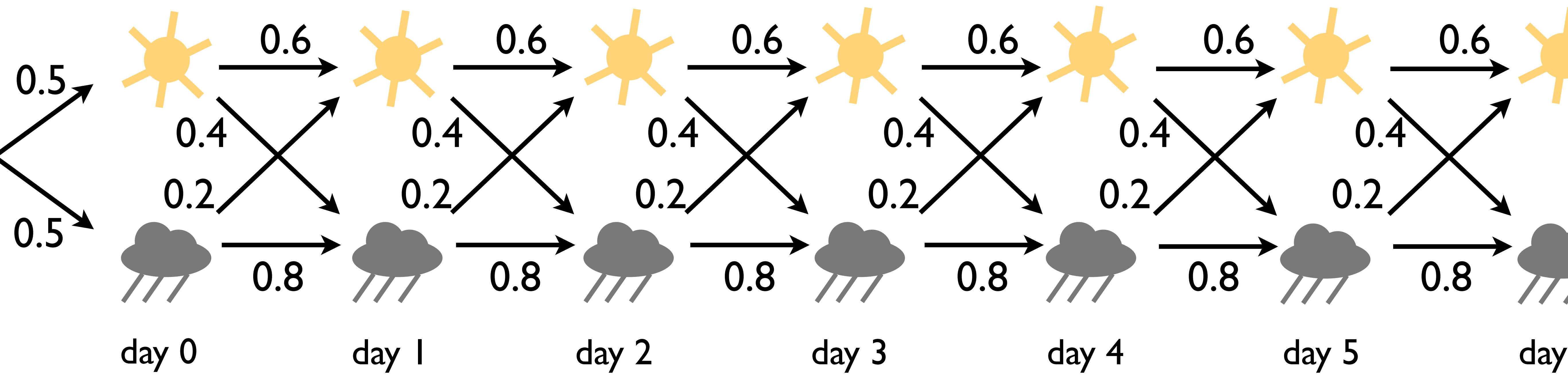



```
0.5::weather(sun,0) ; 0.5::weather(rain,0) <- true.

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

ProbLog by example:

Rain or sun?

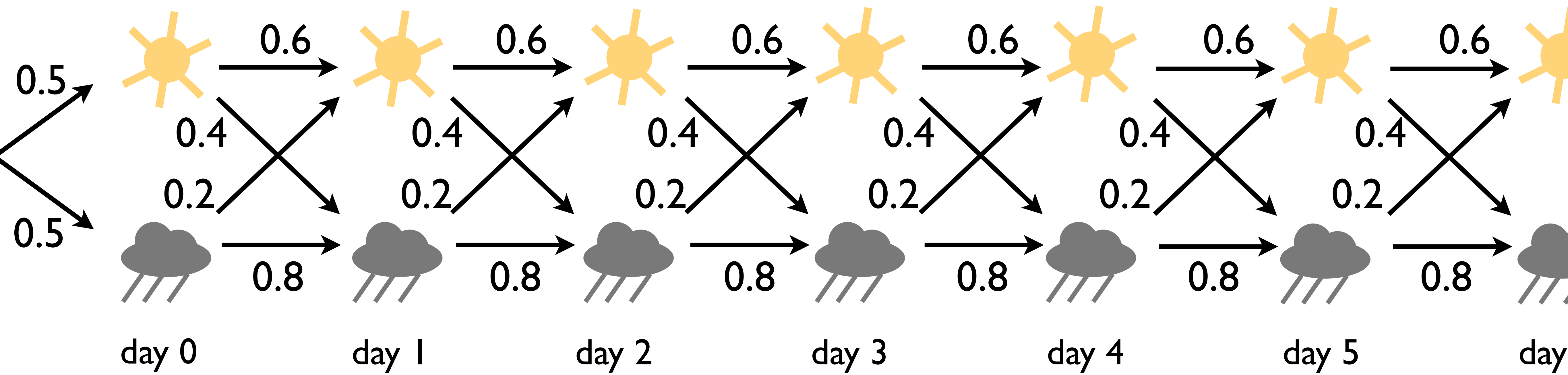



```
0.5::weather(sun,0) ; 0.5::weather(rain,0) <- true.

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?



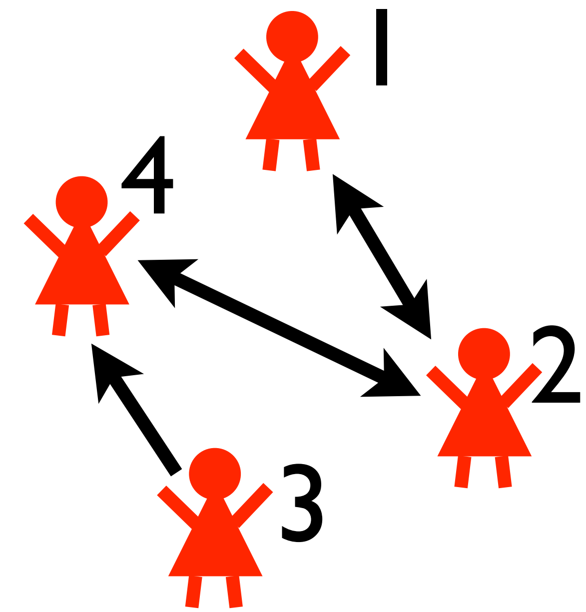

```
0.5::weather(sun,0) ; 0.5::weather(rain,0) <- true.

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 suffice to answer any given ground query

ProbLog by example:

Friends & smokers

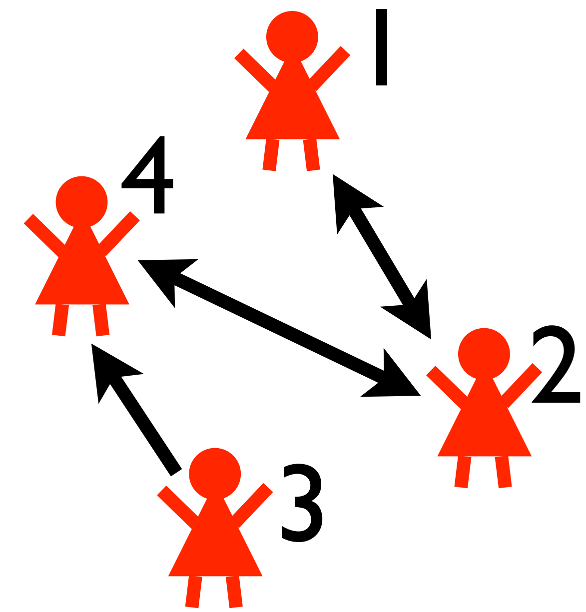



```
person(1).
person(2).
person(3).
person(4).

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

ProbLog by example:

Friends & smokers



typed probabilistic facts

= a probabilistic fact for each grounding

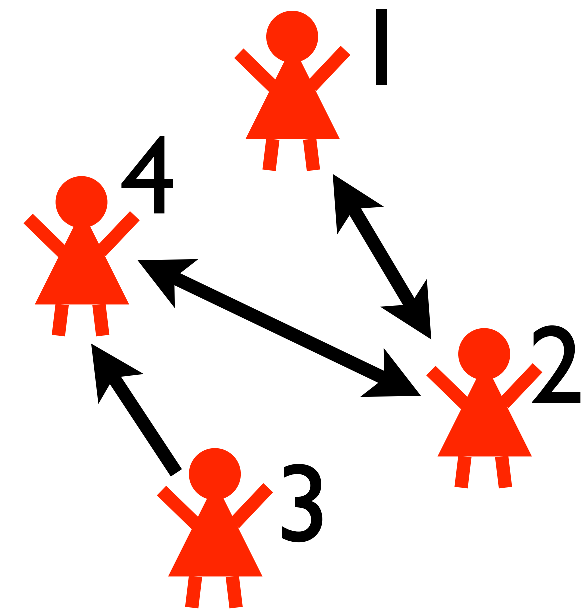
```
0.3::stress(X):- person(X).
0.2::influences(X,Y):-
             person(X), person(Y).
```

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

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

ProbLog by example:

Friends & smokers



typed probabilistic facts

= a probabilistic fact for each grounding

```
0.3::stress(X):- person(X).
0.2::influences(X,Y):-
             person(X), person(Y).
```

```
0.3::stress(1).
0.3::stress(2).
0.3::stress(3).
0.3::stress(4).
```

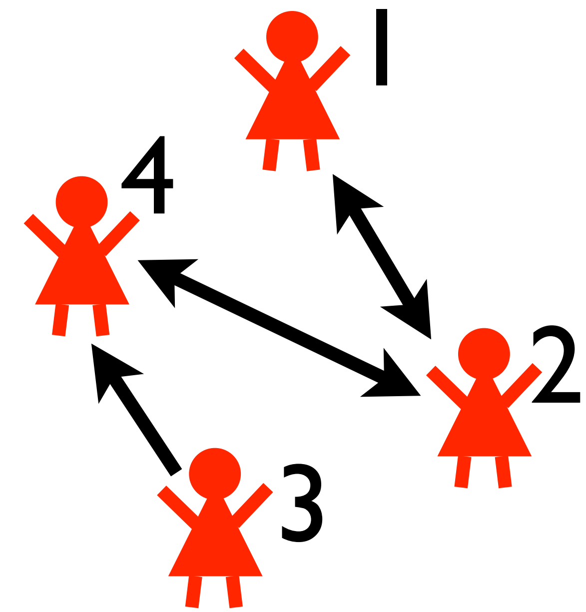
```
0.2::influences(1,1).
0.2::influences(1,2).
0.2::influences(1,3).
0.2::influences(1,4).
0.2::influences(2,1).
...
0.2::influences(4,2).
0.2::influences(4,3).
0.2::influences(4,4).
```

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

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

ProbLog by example:

Friends & smokers




```
0.3::stress(X):- person(X).
0.2::influences(X,Y):-
            person(X), person(Y).

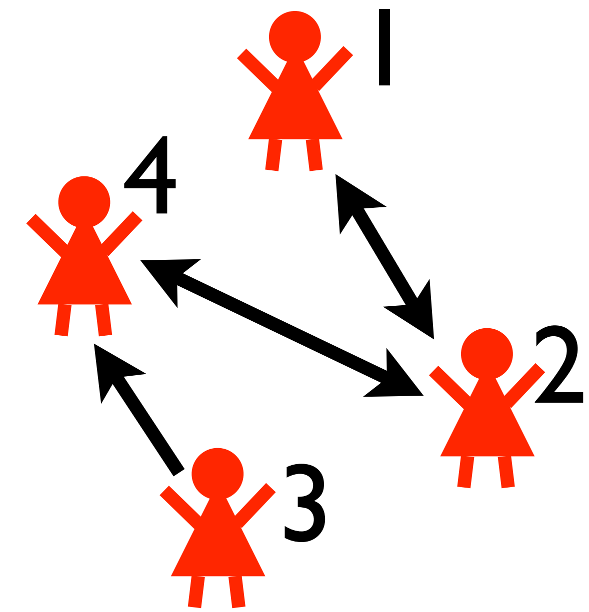
smokes(X) :- stress(X).
smokes(X) :-
     friend(X,Y), influences(Y,X), smokes(Y).
```

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

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

ProbLog by example:

Friends & smokers




```
0.3::stress(X):- person(X).
0.2::influences(X,Y):-
            person(X), person(Y).

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

0.4::asthma(X) <- smokes(X).
```

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

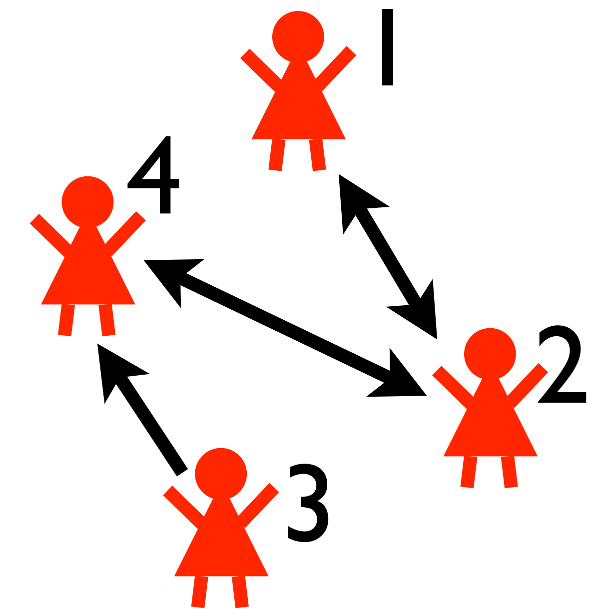
friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

annotated disjunction with implicit head atom:

with probability 0.6, nothing happens

ProbLog by example:

Friends & smokers




```
0.3::stress(X):- person(X).
0.2::influences(X,Y):-
            person(X), person(Y).

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

0.4::asthma(X) <- smokes(X).
```

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

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

ProbLog by example:

Limited Luggage

```
weight(skis,6).
weight(boots,4).
weight(helmet,3).
weight(gloves,2).
```

ProbLog by example:

Limited Luggage

```
weight(skis,6).
weight(boots,4).
weight(helmet,3).
weight(gloves,2).

P::pack(Item) :- weight(Item,Weight), P is 1.0/Weight.
```

flexible probability:

computed from the weight of the item

ProbLog by example:

Limited Luggage

```
weight(skis,6).          1/6::pack(skis).
weight(boots,4).         1/4::pack(boots).
weight(helmet,3).        1/3::pack(helmet).
weight(gloves,2).        1/2::pack(gloves).

P::pack(Item) :- weight(Item,Weight), P is 1.0/Weight.
```

flexible probability:

computed from the weight of the item

ProbLog by example:

Limited Luggage

```
weight(skis,6).
weight(boots,4).
weight(helmet,3).
weight(gloves,2).

P::pack(Item) :- weight(Item,Weight),  P is 1.0/Weight.

excess(Limit) :- excess([skis,boots,helmet,gloves],Limit).
```

list of all items

ProbLog by example:

Limited Luggage

```
weight(skis,6).
weight(boots,4).
weight(helmet,3).
weight(gloves,2).

P::pack(Item) :- weight(Item,Weight),  P is 1.0/Weight.

excess(Limit) :- excess([skis,boots,helmet,gloves],Limit).

excess([],Limit) :- Limit<0.
excess([I|R],Limit) :-
   pack(I), weight(I,W), L is Limit-W, excess(R,L).
excess([I|R],Limit) :-
   \+pack(I), excess(R,Limit).
```

ProbLog by example:

Limited Luggage

```
weight(skis,6).
weight(boots,4).
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excess([I|R],Limit) :-
   \+pack(I), excess(R,Limit).
```

pack first item, decrease limit by its weight, and continue with rest of items

ProbLog by example:

Limited Luggage

```
weight(skis,6).
weight(boots,4).
weight(helmet,3).
weight(gloves,2).

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excess([I|R],Limit) :-
   \+pack(I), excess(R,Limit).
```

do **not** pack first item,
continue with rest of items

ProbLog by example:

Limited Luggage

```
weight(skis,6).
weight(boots,4).
weight(helmet,3).
weight(gloves,2).

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excess([I|R],Limit) :-
   \+pack(I), excess(R,Limit).
```

no items left: did we add too much?

ProbLog by example:

Limited Luggage

```
weight(skis,6).
weight(boots,4).
weight(helmet,3).
weight(gloves,2).

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excess([I|R],Limit) :-
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```

ProbLog

- **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

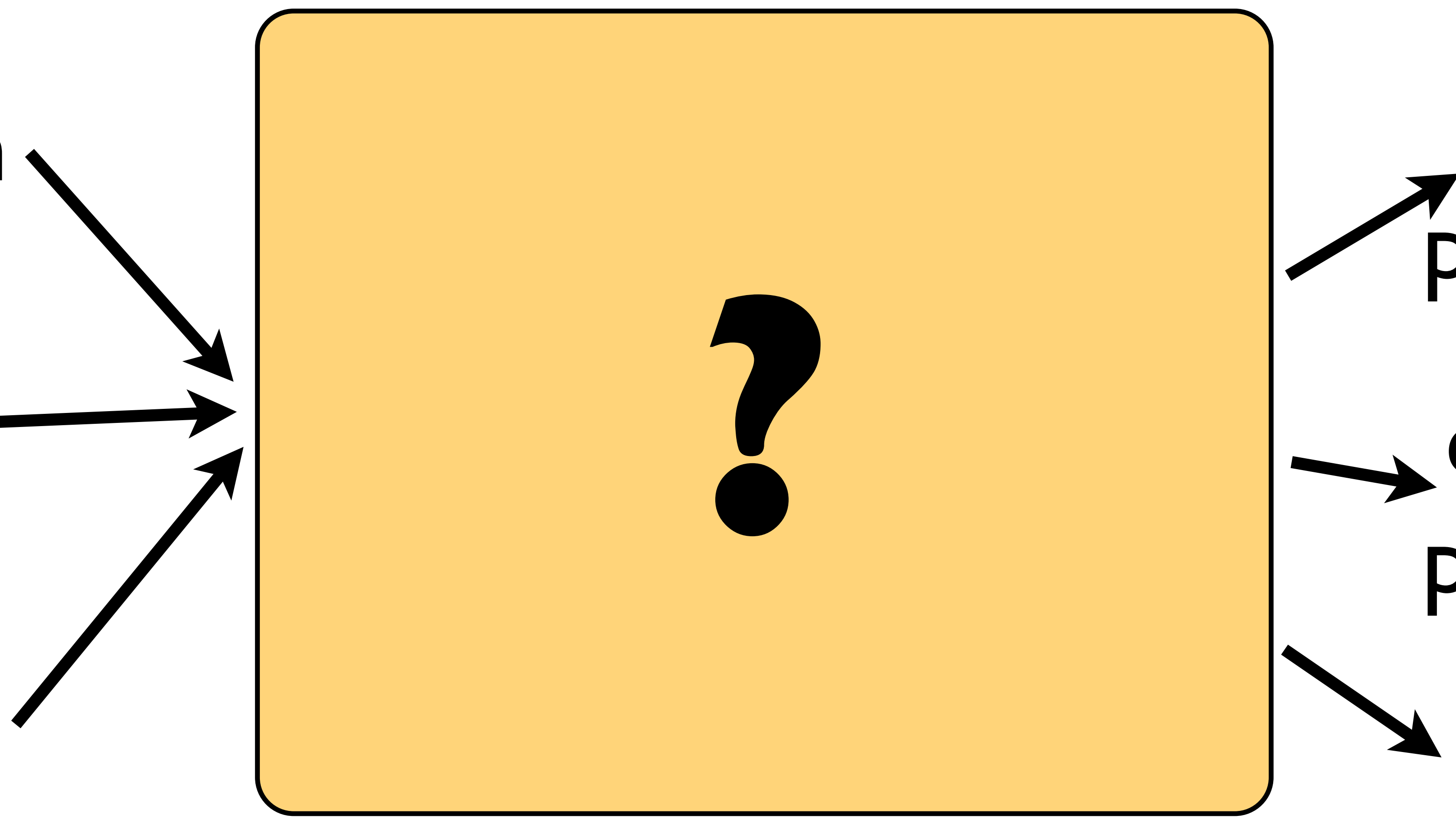
Answering Questions

Given:

program

queries

evidence



Find:

marginal probabilities

conditional probabilities

MPE state

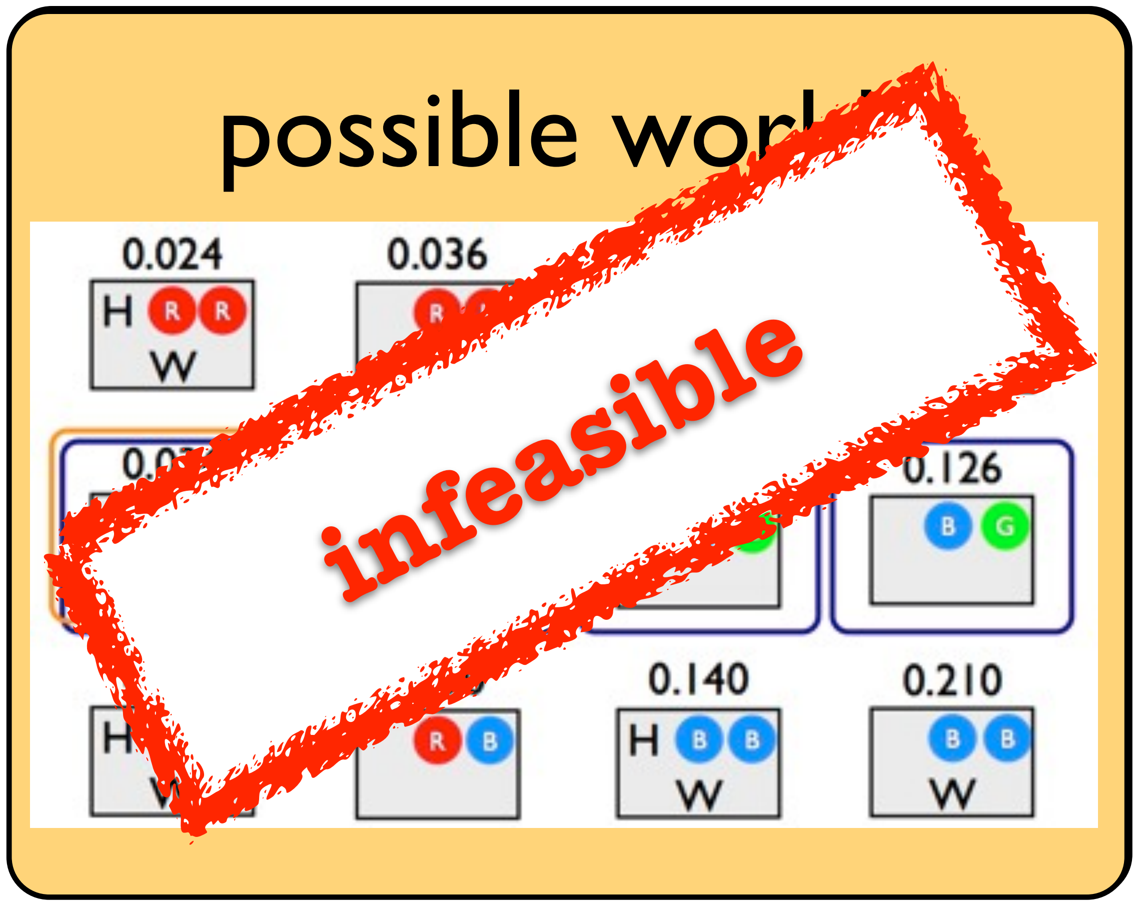
Answering Questions

Given:

program

queries

evidence



Find:

marginal probabilities

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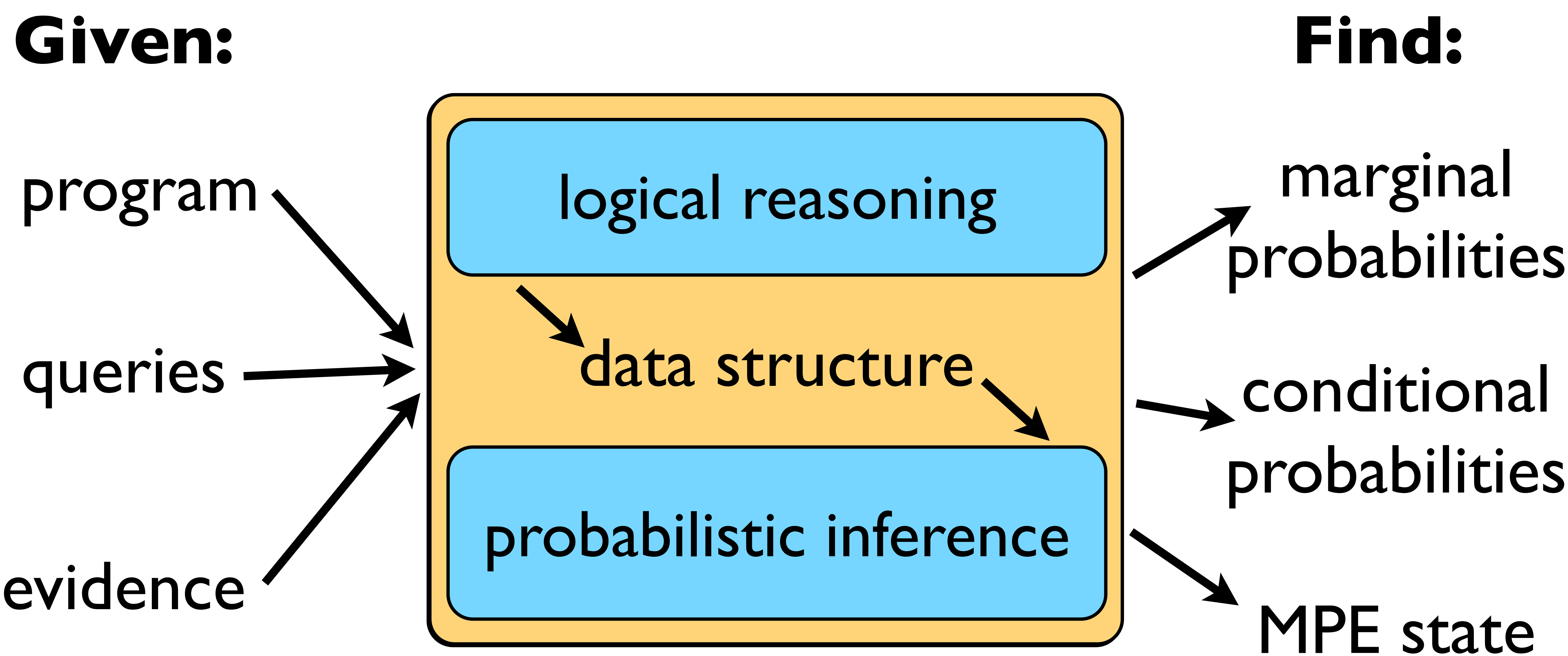
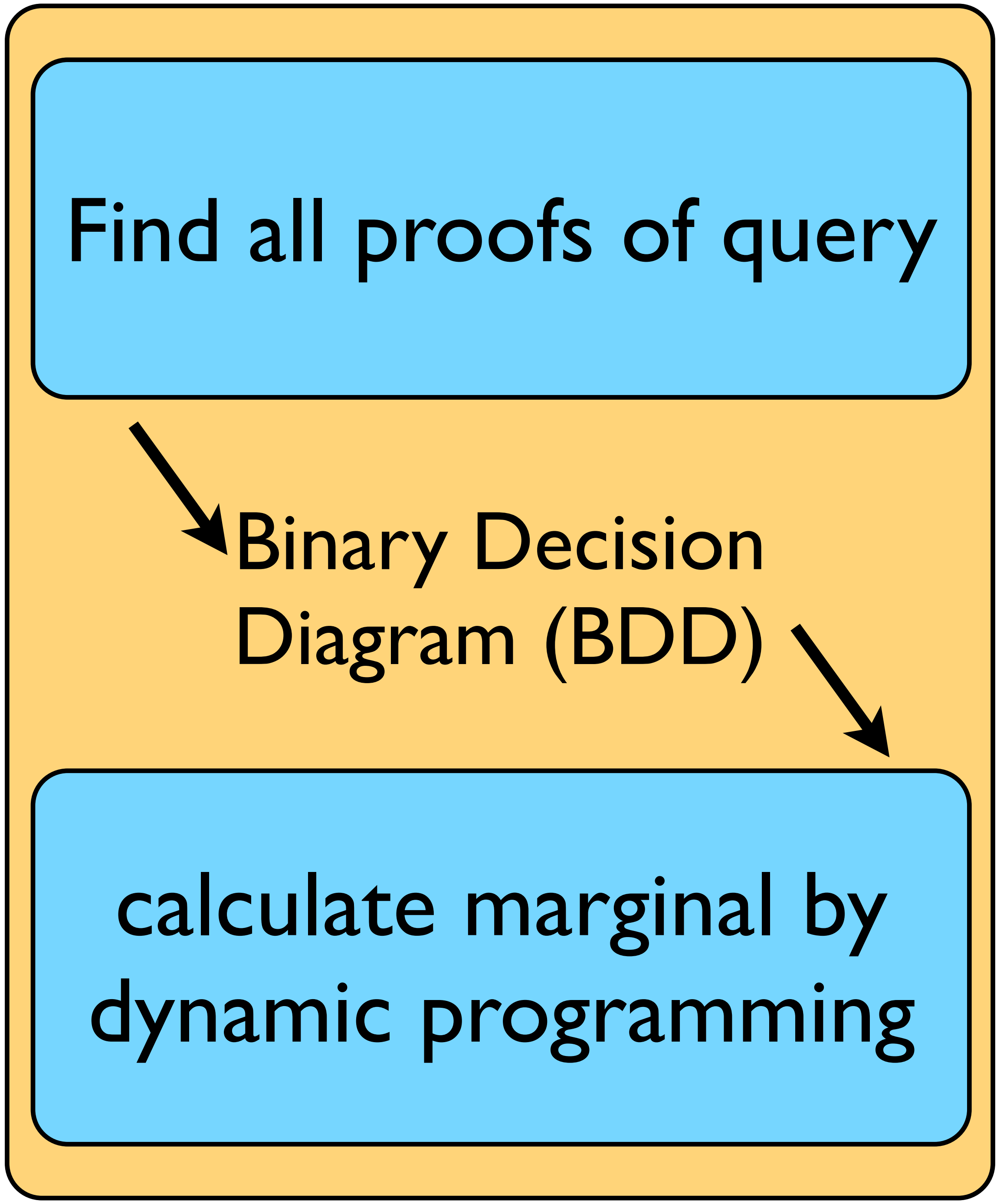
Answering Questions



Initial Approach
(ProbLog1)



 [De Raedt et al, IJCAI 07; Kimmig et al, TPLP 11]

Initial Approach
(ProbLog1)

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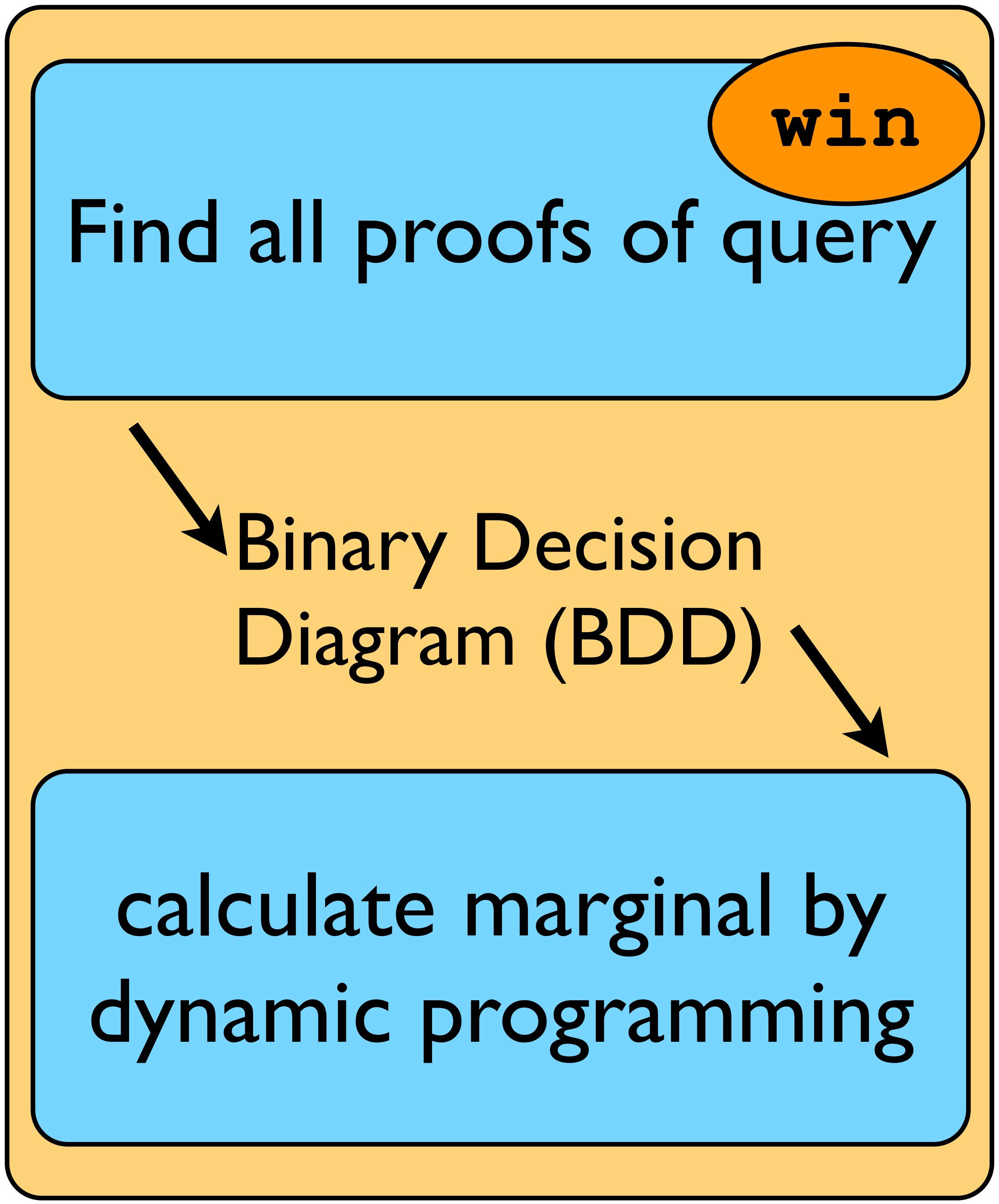
```



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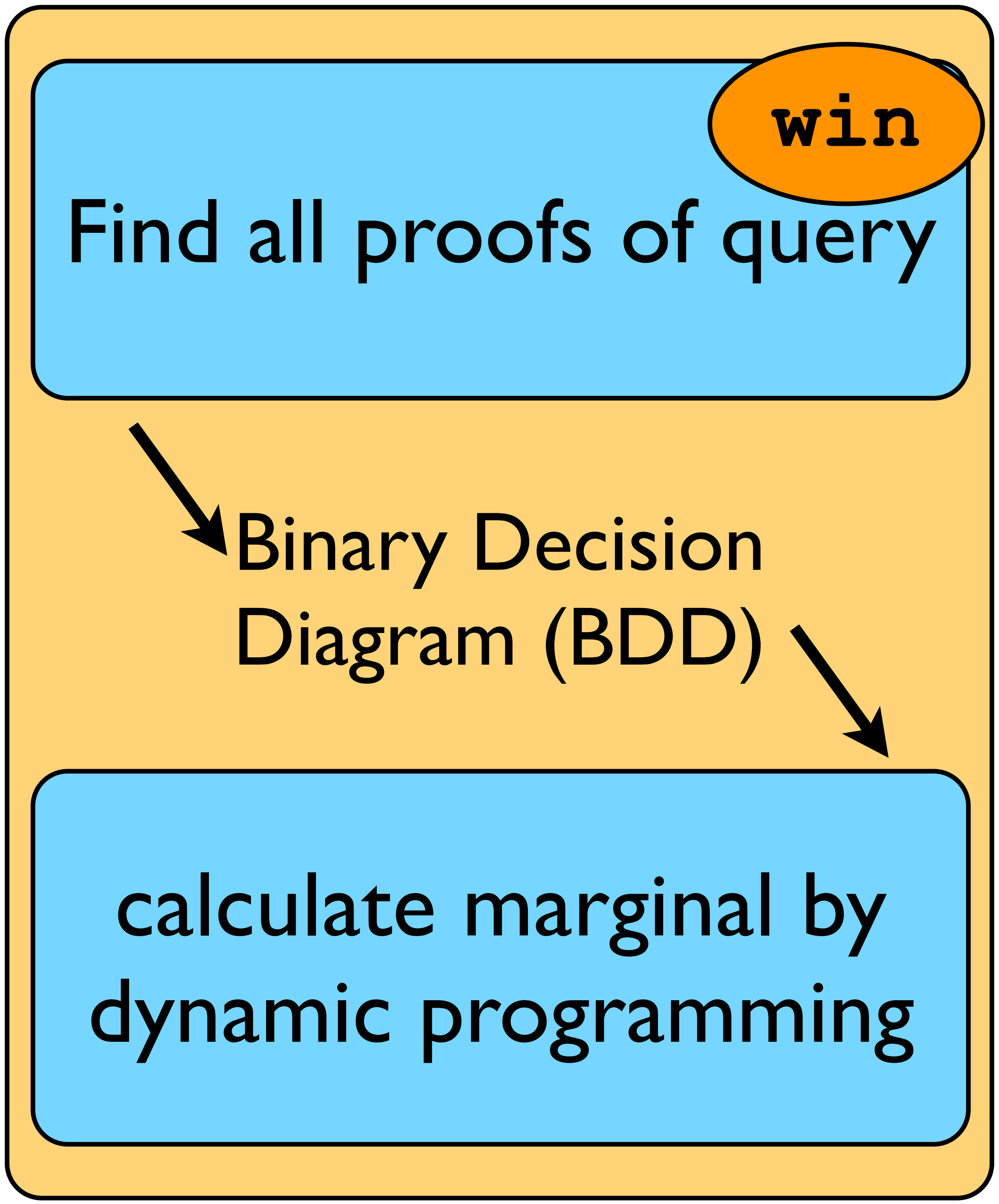


```
heads(1)
heads(2)  & heads(3)
```


[De Raedt et al, IJCAI 07; Kimmig et al, TPLP 11]

Initial Approach
(ProbLog1)

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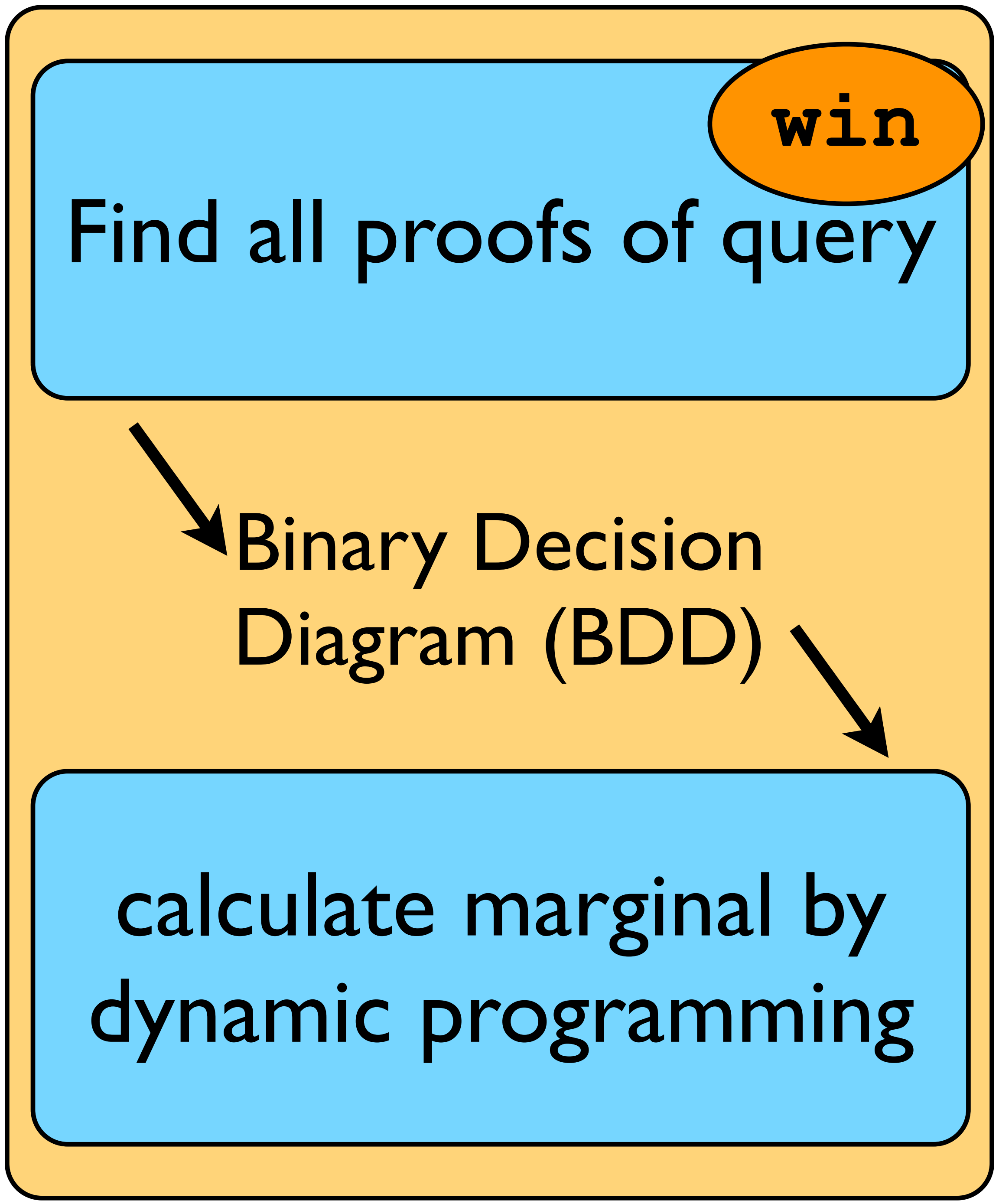


```
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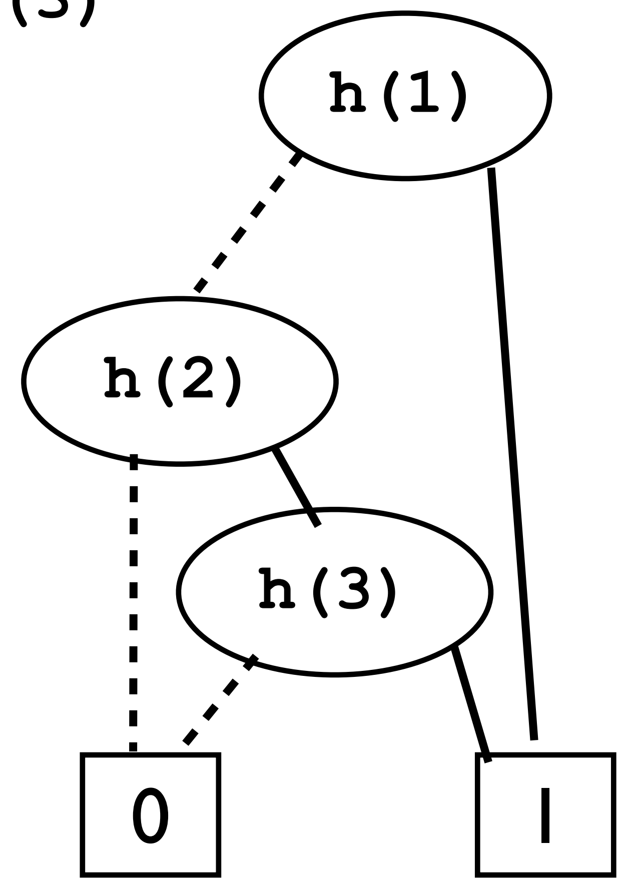

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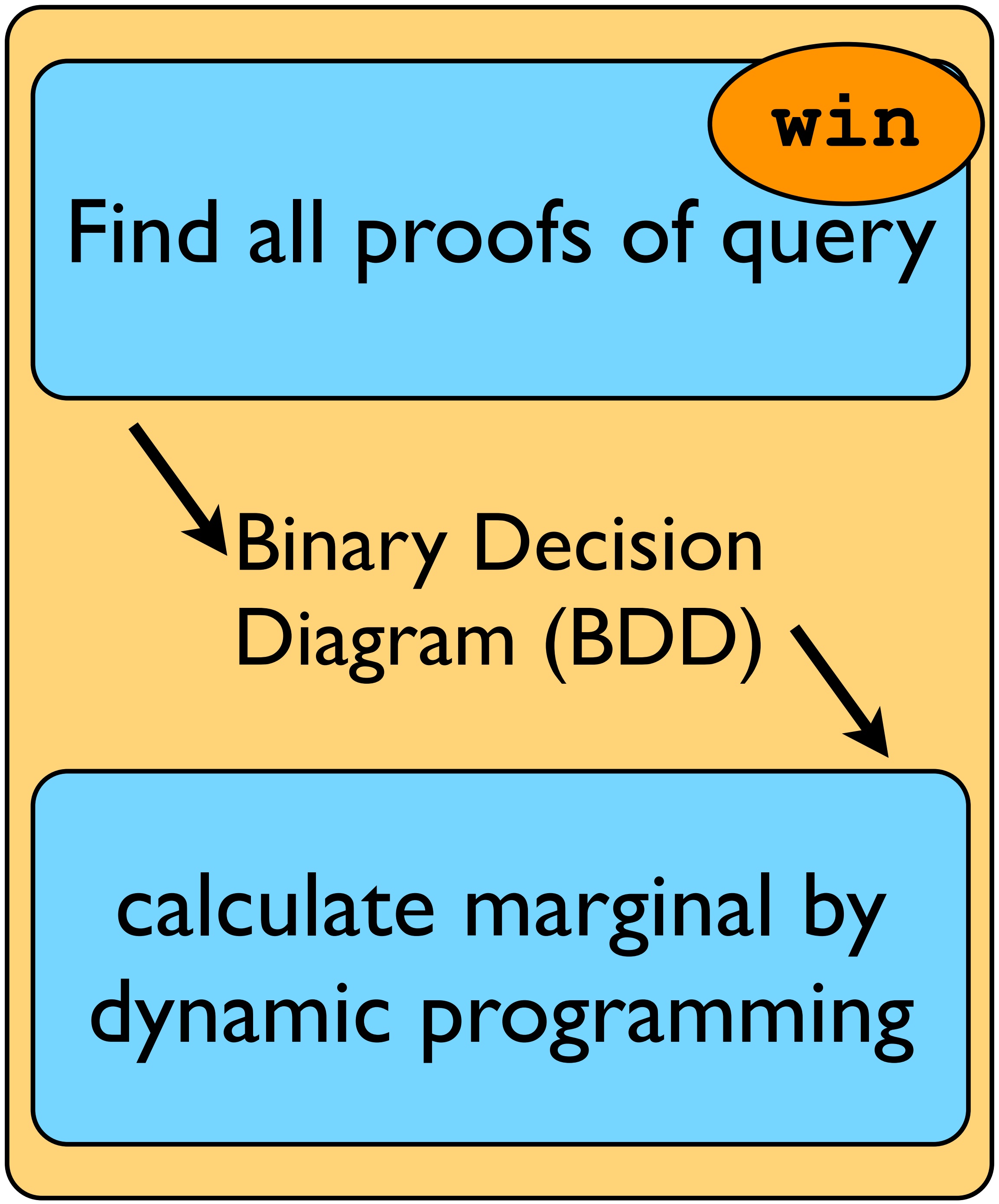


```
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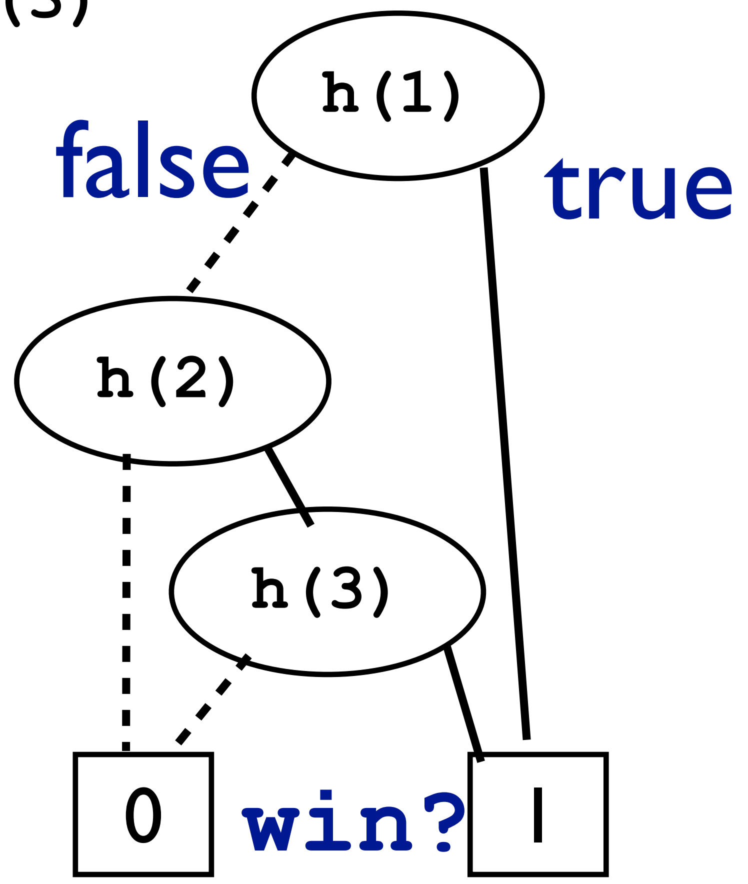
heads(2) & heads(3)
```



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Initial Approach

(ProbLog1)

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

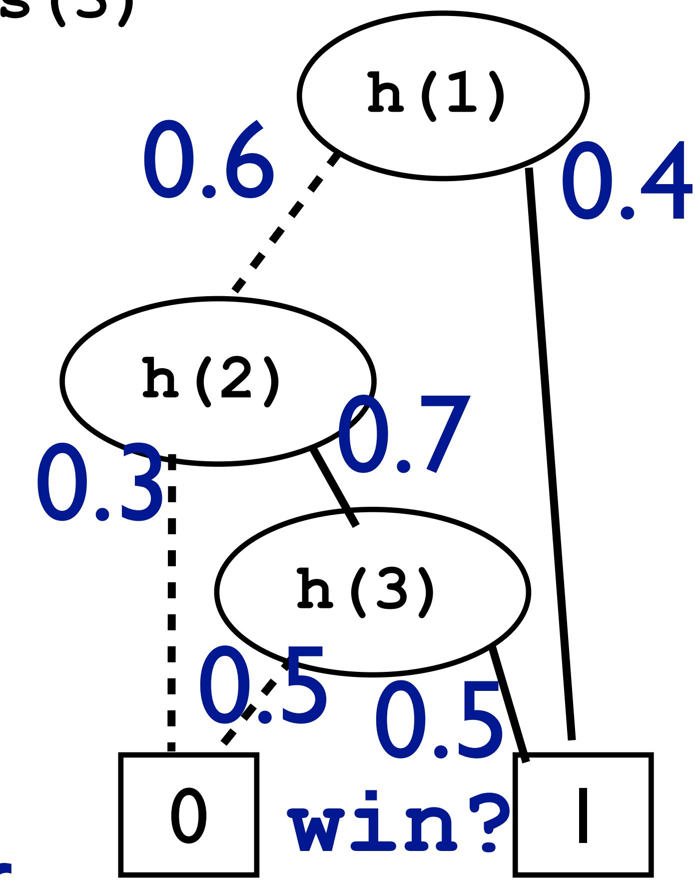
win

Find all proofs of query

→ Binary Decision Diagram (BDD) →

calculate marginal by dynamic programming

```
heads(1)
heads(2) & heads(3)
```

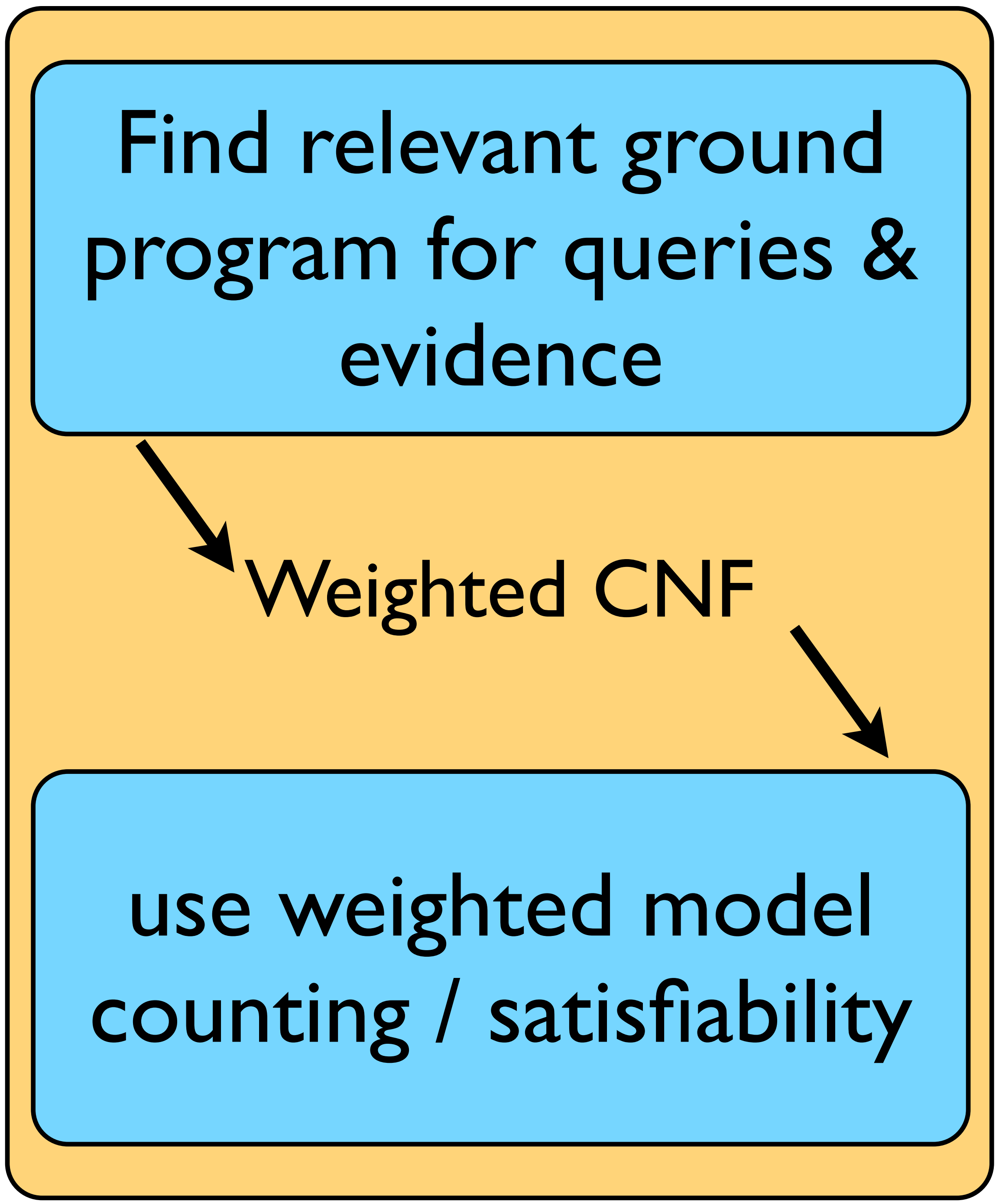


P(**win**) = probability of reaching 1-leaf

 [De Raedt et al, IJCAI 07; Kimmig et al, TPLP 11]

Current Approach

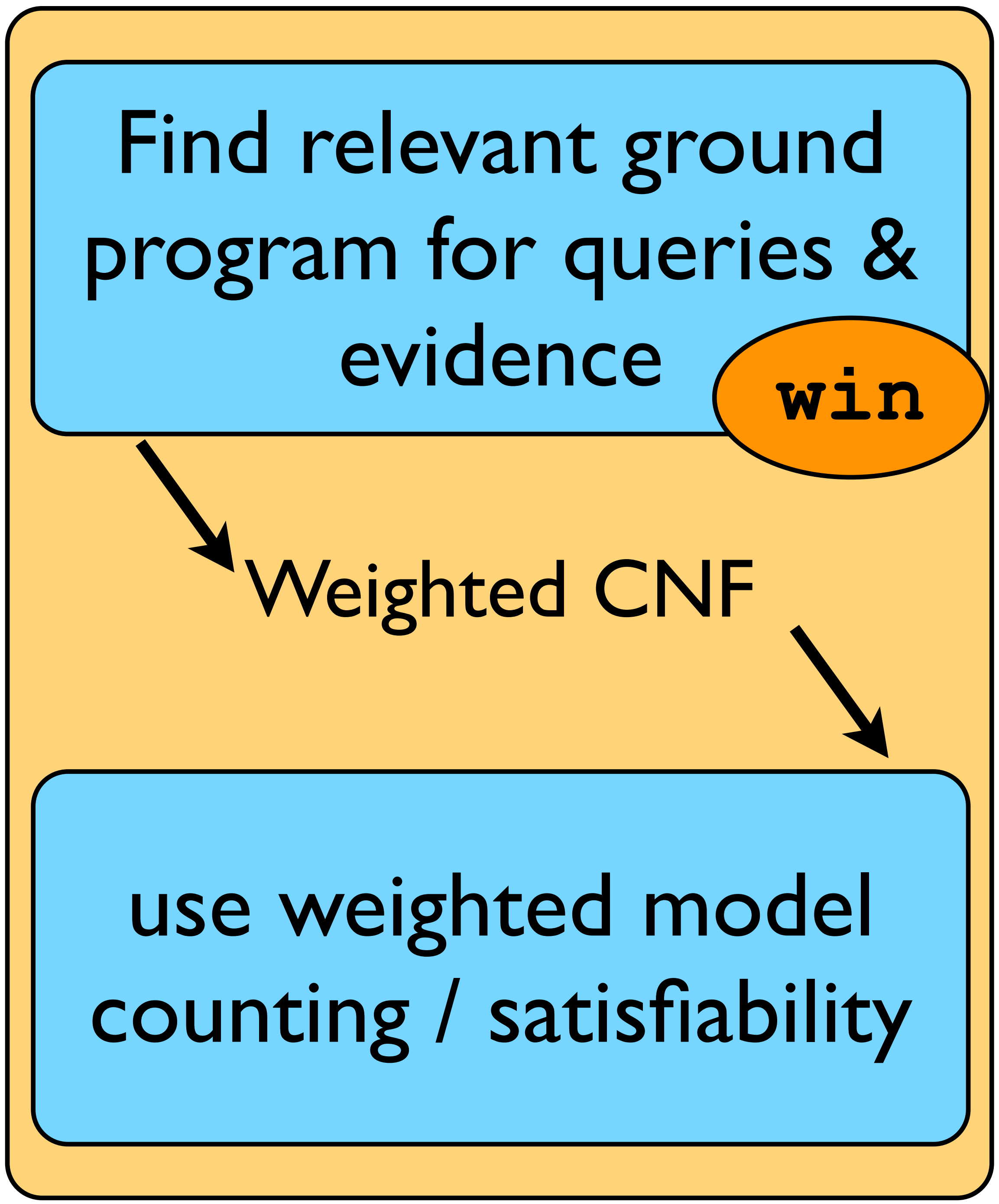
(ProbLog2)



[Fierens et al, TPLP 13]

Current Approach
(ProbLog2)

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



[Fierens et al, TPLP 13]

Current Approach
(ProbLog2)

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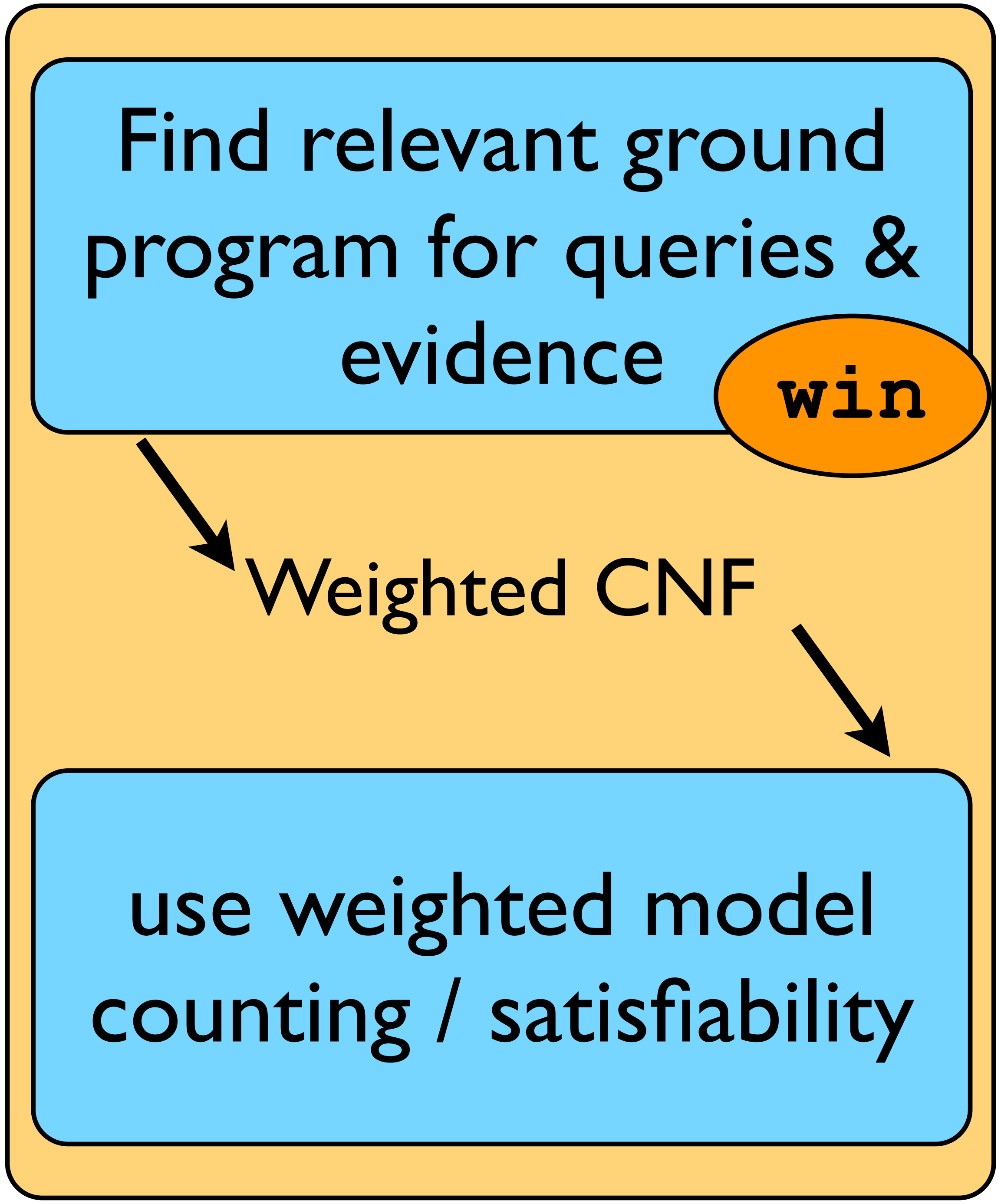
```

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win :- heads(1).
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[Fierens et al, TPLP 13]

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(ProbLog2)

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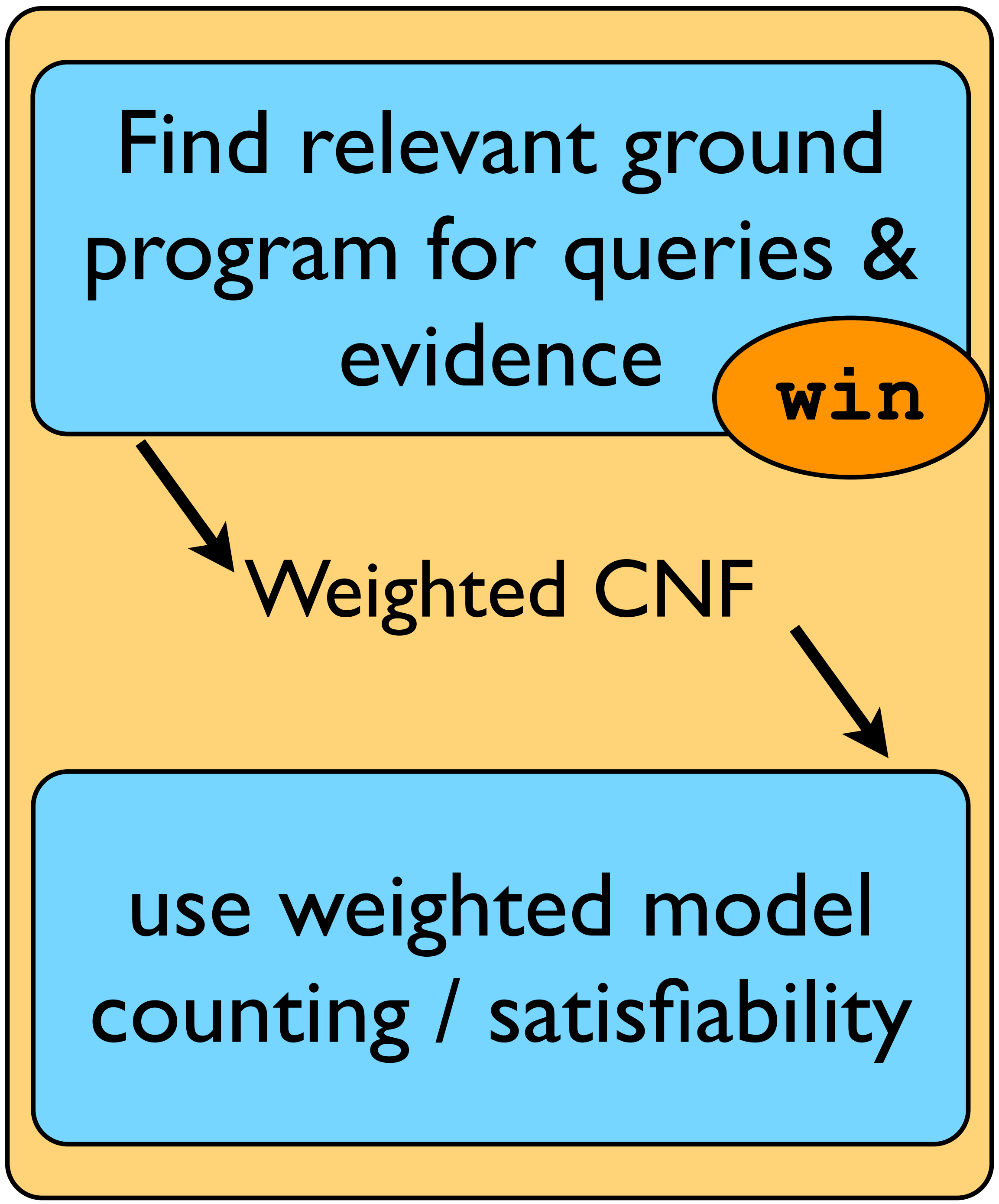


```
win :- heads(1).
win :- heads(2), heads(3).
```

↓

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

[Fierens et al, TPLP 13]

Current Approach
(ProbLog2)

```
0.4::heads(1).
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win :- heads(1).
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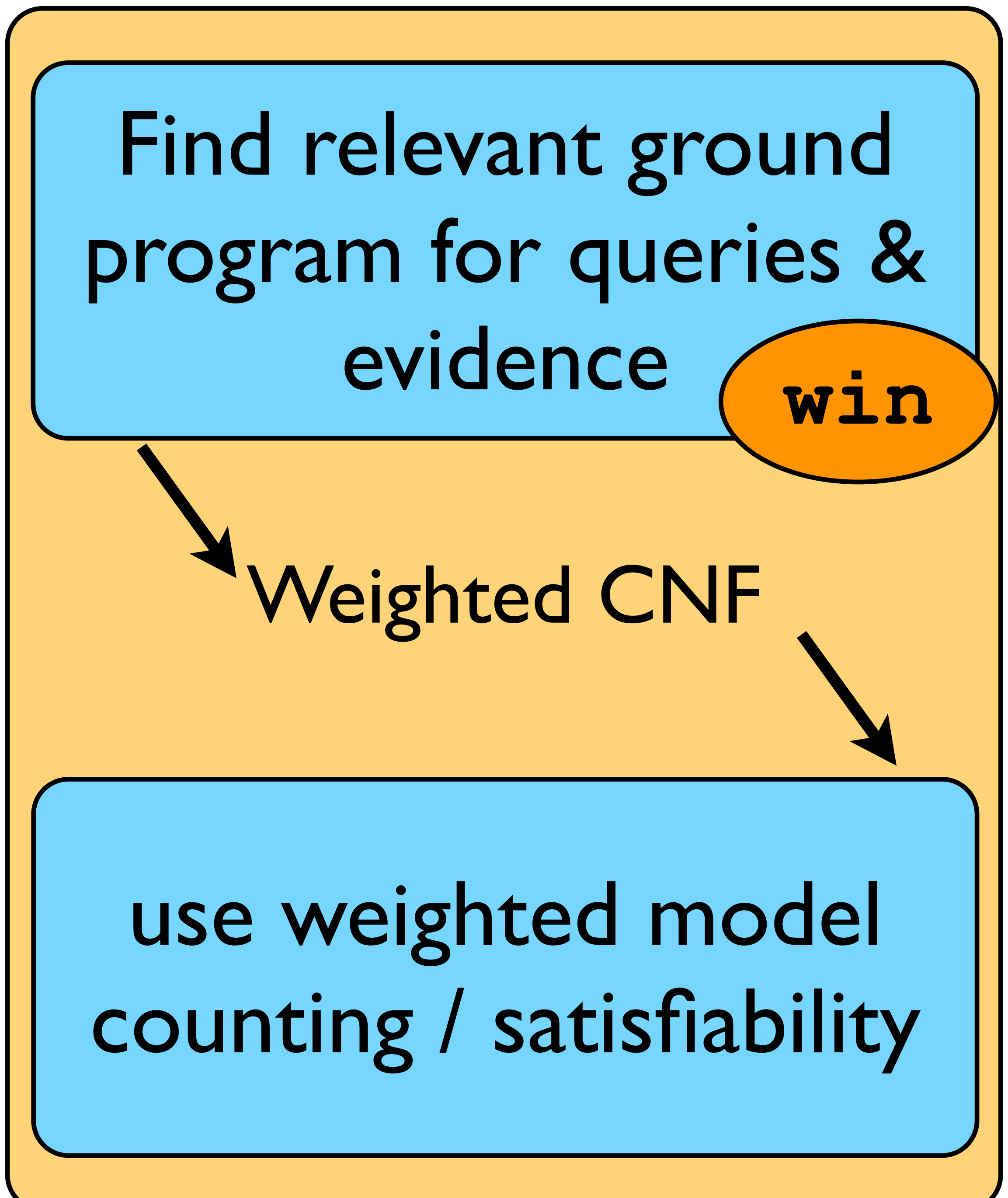



```
win :- heads(1).
win :- heads(2), heads(3).
```

↓

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

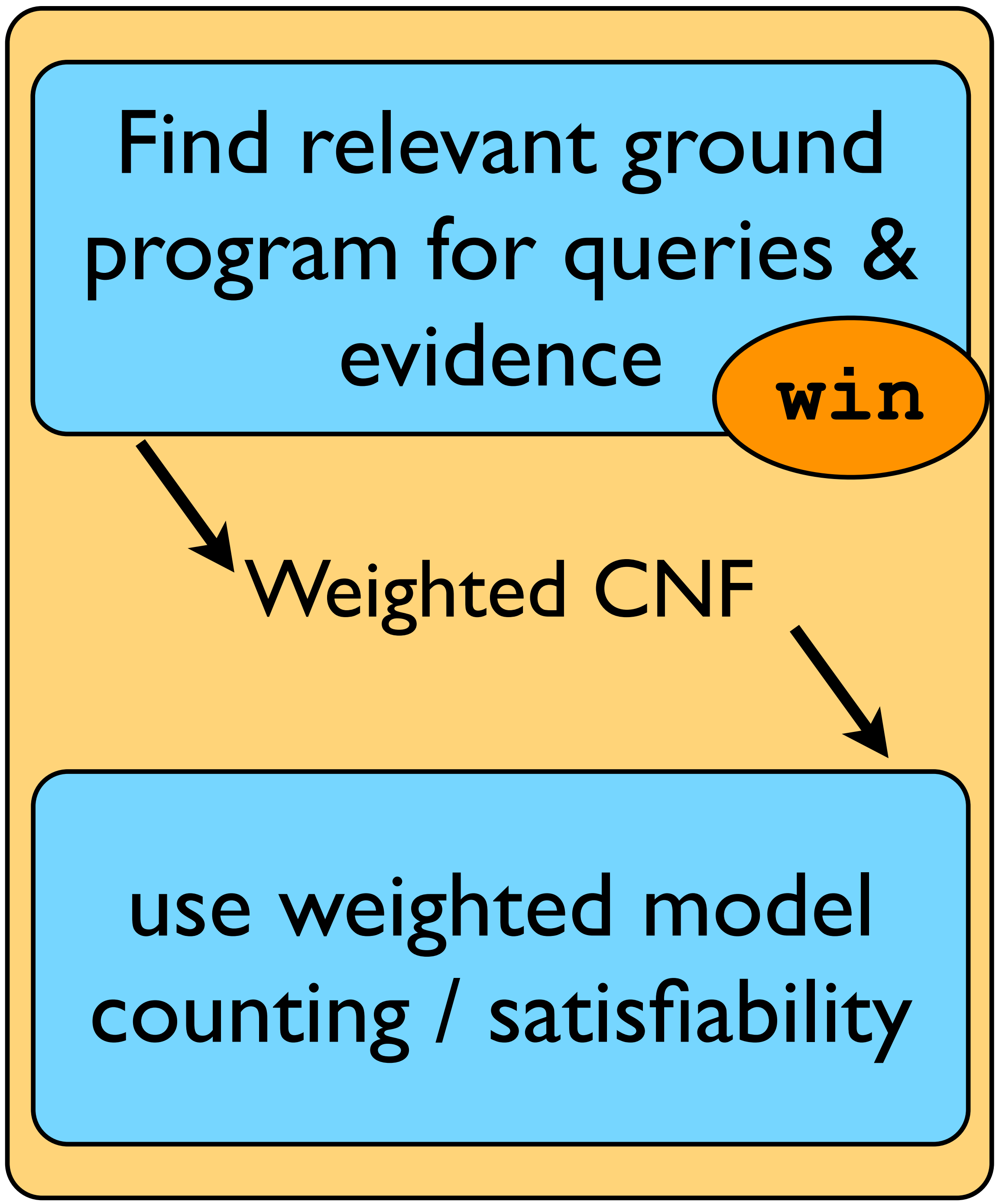
↓

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

[Fierens et al, TPLP 13]

Current Approach
(ProbLog2)

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




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

↓

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

↓

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

$h(1) \to 0.4$ $h(2) \to 0.7$ $h(3) \to 0.5$

$\neg h(1) \to 0.6$ $\neg h(2) \to 0.3$ $\neg h(3) \to 0.5$

[Fierens et al, TPLP 13]

Current Approach

(ProbLog2)

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

Find relevant ground program for queries & evidence **win**

↓

Weighted CNF

↓

use weighted model counting / satisfiability

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

↓

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

↓

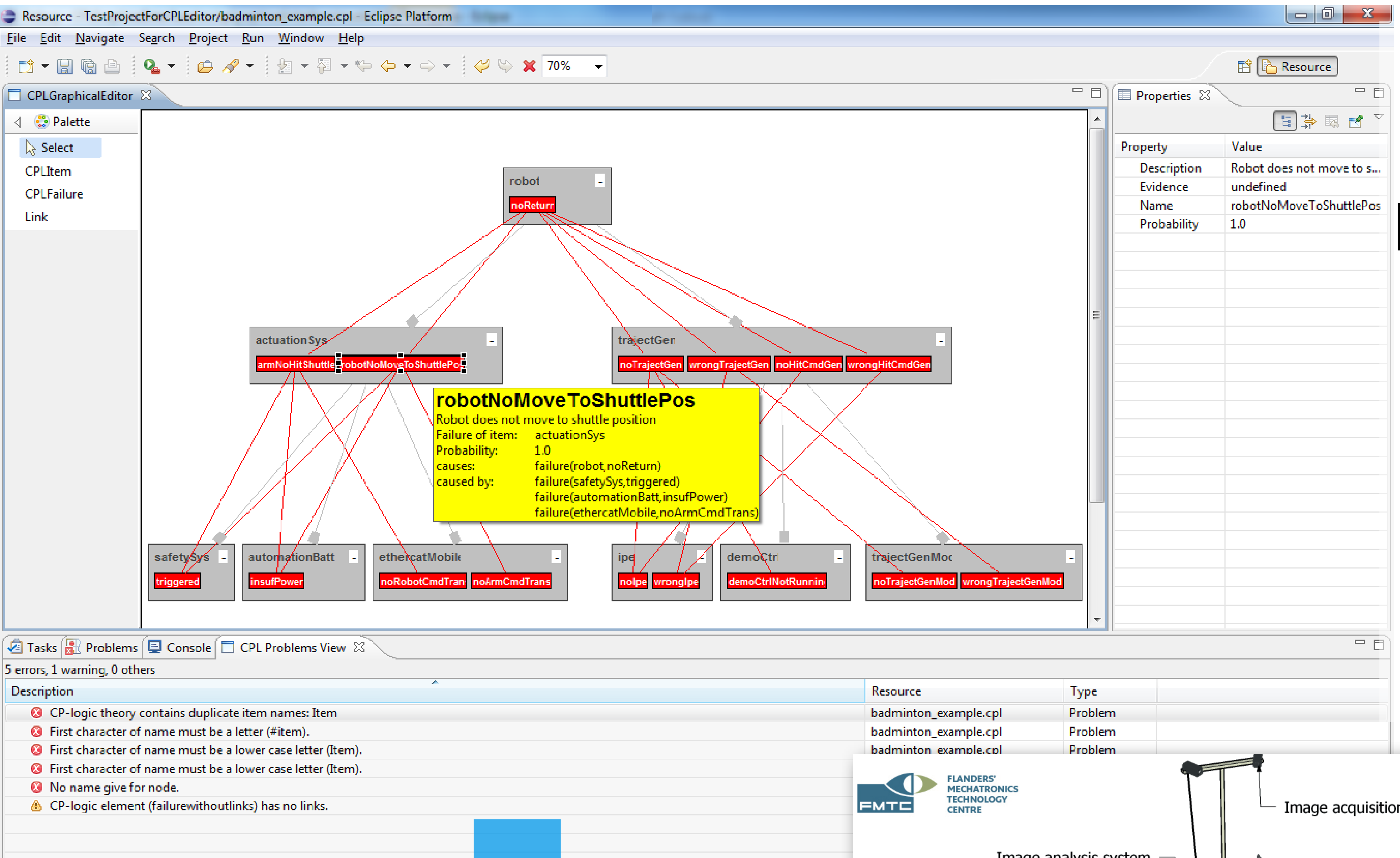
$$(\neg win \lor h(1) \lor h(2)) \land (\neg win \lor h(1) \lor h(3)) \land (win \lor \neg h(1)) \land (win \lor \neg h(2) \lor \neg h(3))$$

use standard tool

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

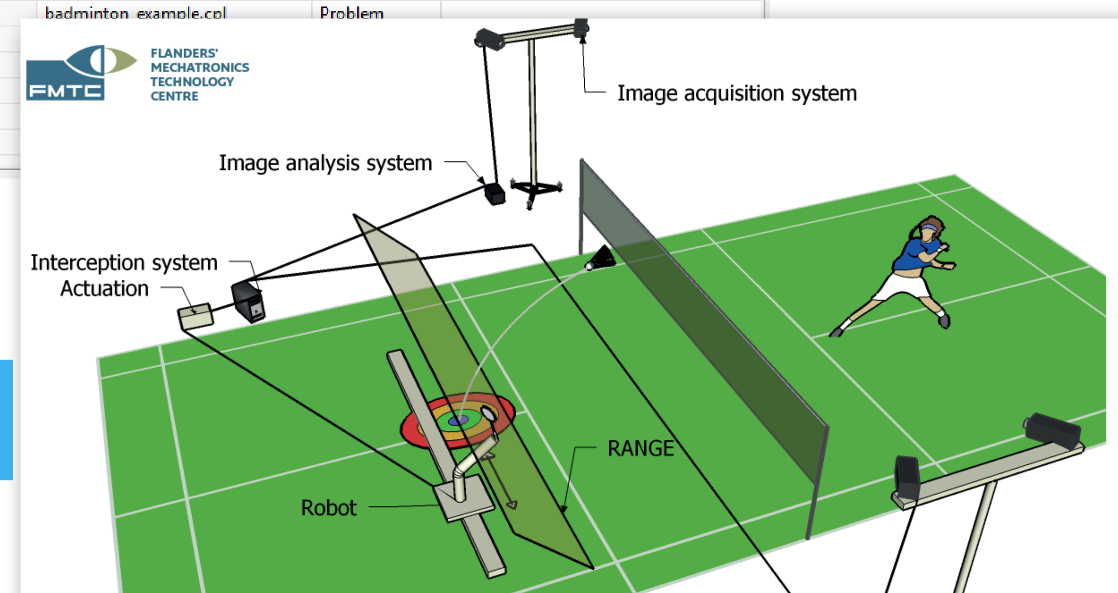
[Fierens et al, TPLP 13]

Diagnostics for Prognostics



Visual representation of a ProbLog diagnostics program

The GUI knows how to interpret certain predicates (e.g. failure, partof)



Find most probable reason of a failure given a set of sensor measurements

[Schramm, Meert & Driessens]

ProbLog for activity recognition from video

CAVIAR-INRIA human activity dataset

28 videos
≈ 26.500 frames

- Separation between low-level events (LLE) and high-level events (HLE)
  - LLE: *walking, running, active, inactive, abrupt*
  - HLE: *meeting, moving, fighting, leaving_object*
- Probabilistic Logic approach: *Event Calculus in ProbLog* (Prob-EC) to infer the high-level events from an **algebra** of low-level events.
- Example:

$$
\begin{gathered}
initiatedAt(fighting(P_1, P_2) = true, T) \leftarrow \\
happensAt(abrupt(P_1), T), \\
holdsAt(close(P_1, P_2, 44) = true, T), \\
not\ happensAt(inactive(P_2), T).
\end{gathered}
$$

[Skarlatidis et al, TPLP 13]

Parameter Learning

e.g., webpage classification model

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

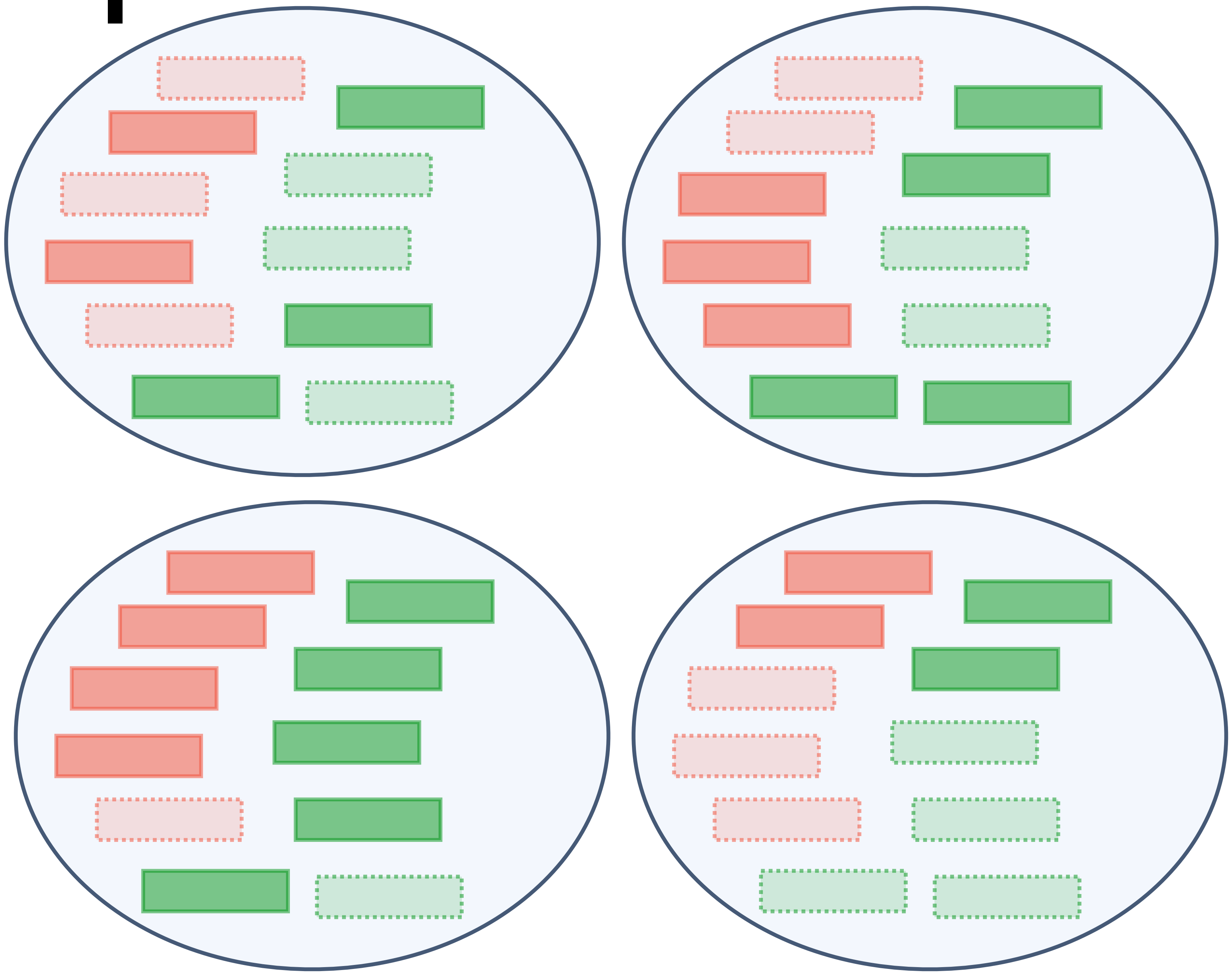
```
?? :: link_class(Source,Target,CLASS1,CLASS2).
?? :: word_class(WORD,CLASS).
```

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

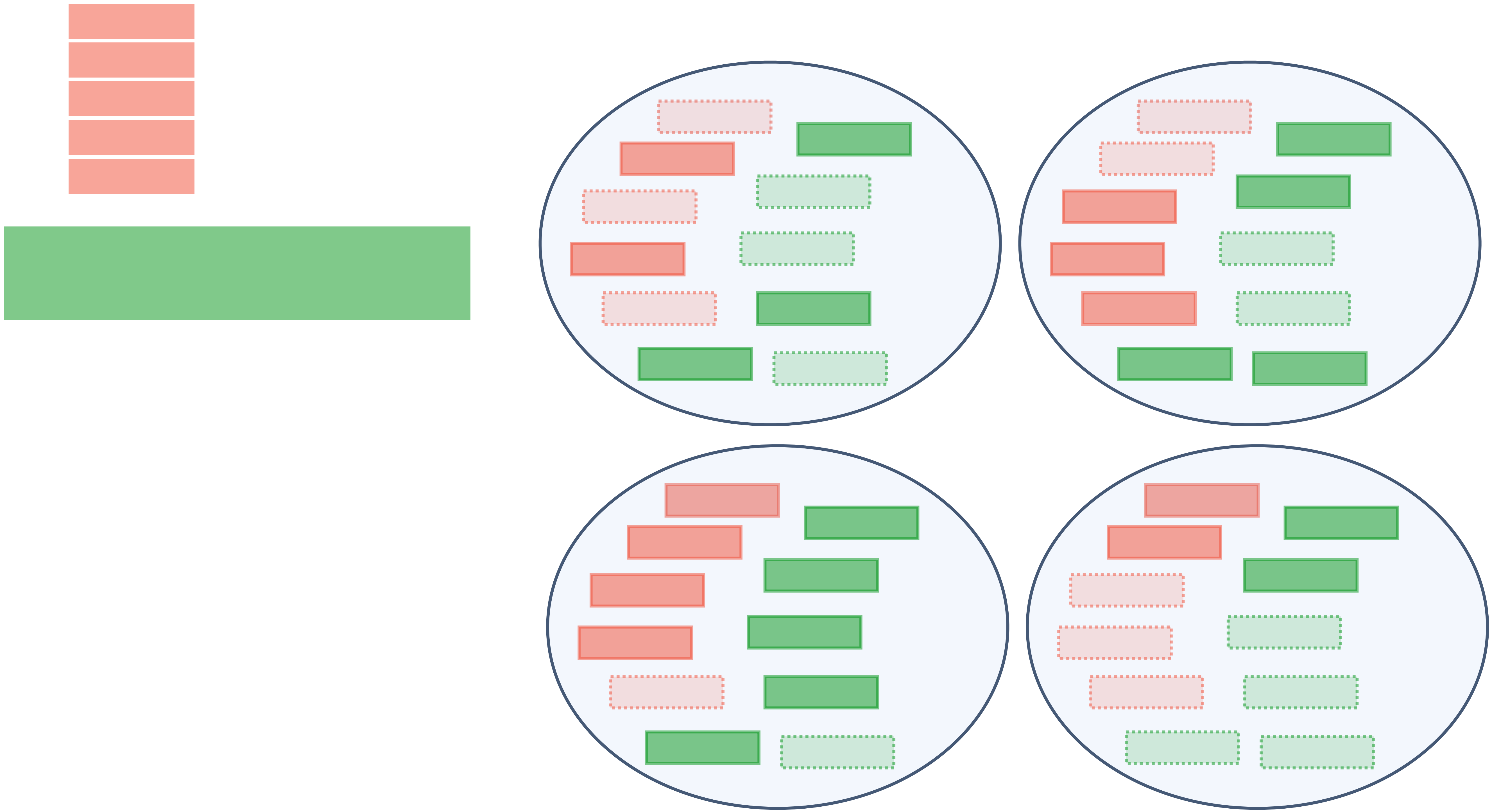
class(Page,C)       :-  links_to(OtherPage,Page),
                        class(OtherPage,OtherClass),
                        link_class(OtherPage,Page,OtherClass,C).
```

Sampling Interpretations

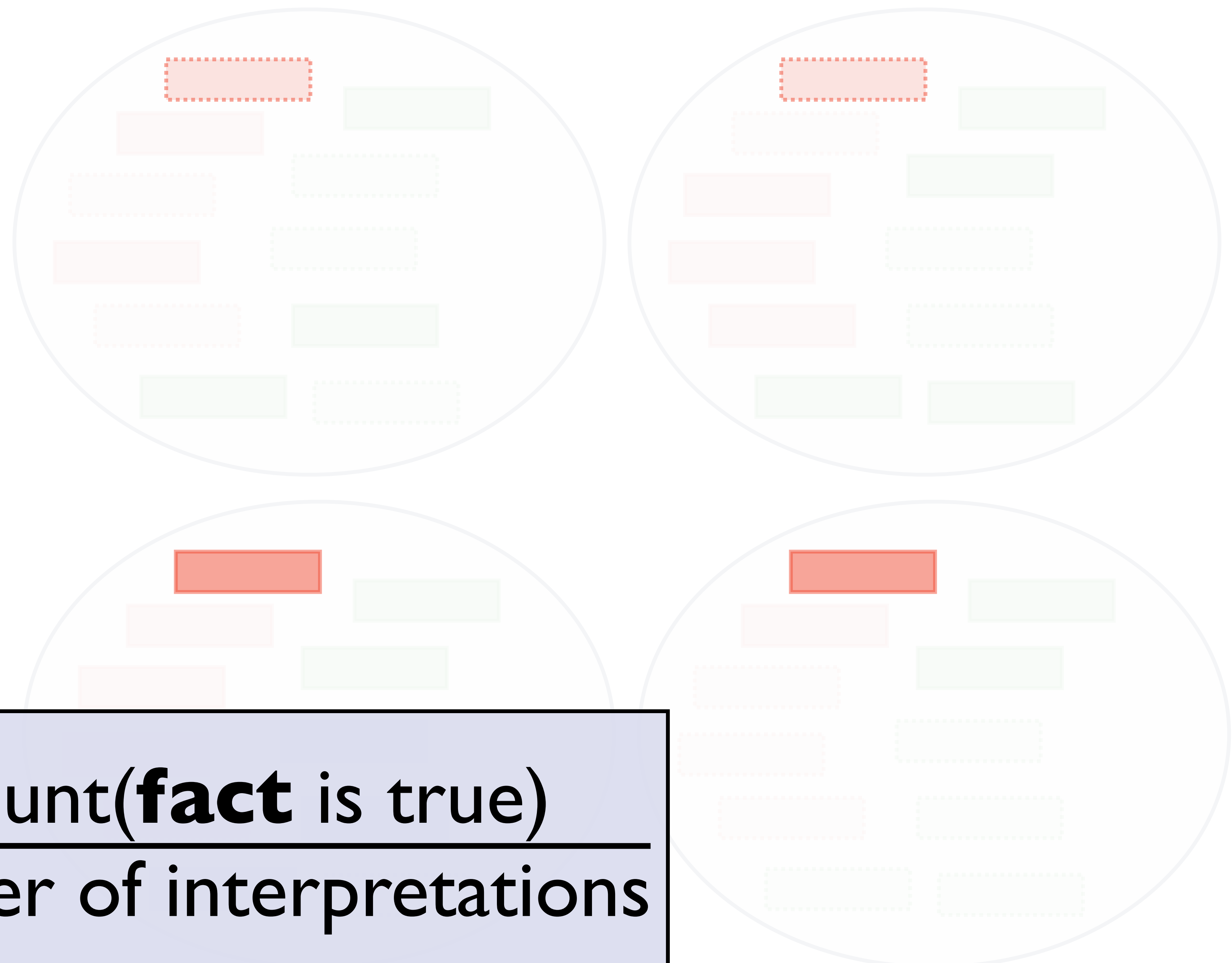
Sampling Interpretations



Parameter Estimation

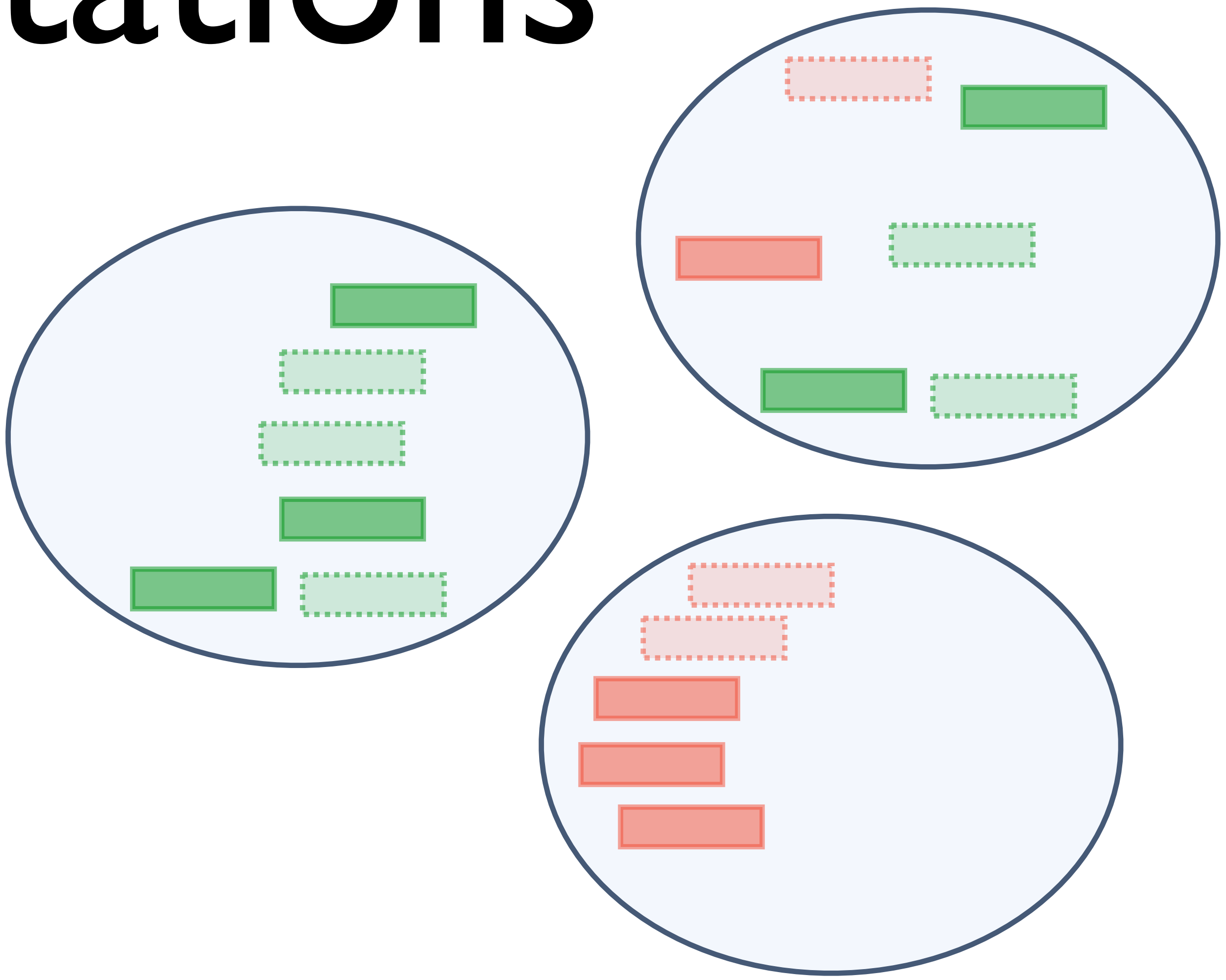


Parameter Estimation



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

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 13]

Overview

- ProbLog Basics
  - ProbLog by example
  - Inference
  - Parameter Learning

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Upgrading relational learning

	Prolog
	
	`infl(a,b).`
	`...`
		ProbLog
		
		`0.4::infl(a,b).`
		`...`

Reasoning	query true? yes/no	query true? with probability P

Upgrading relational learning

	Prolog
	
	`infl(a,b).`
	`...`
		ProbLog
		
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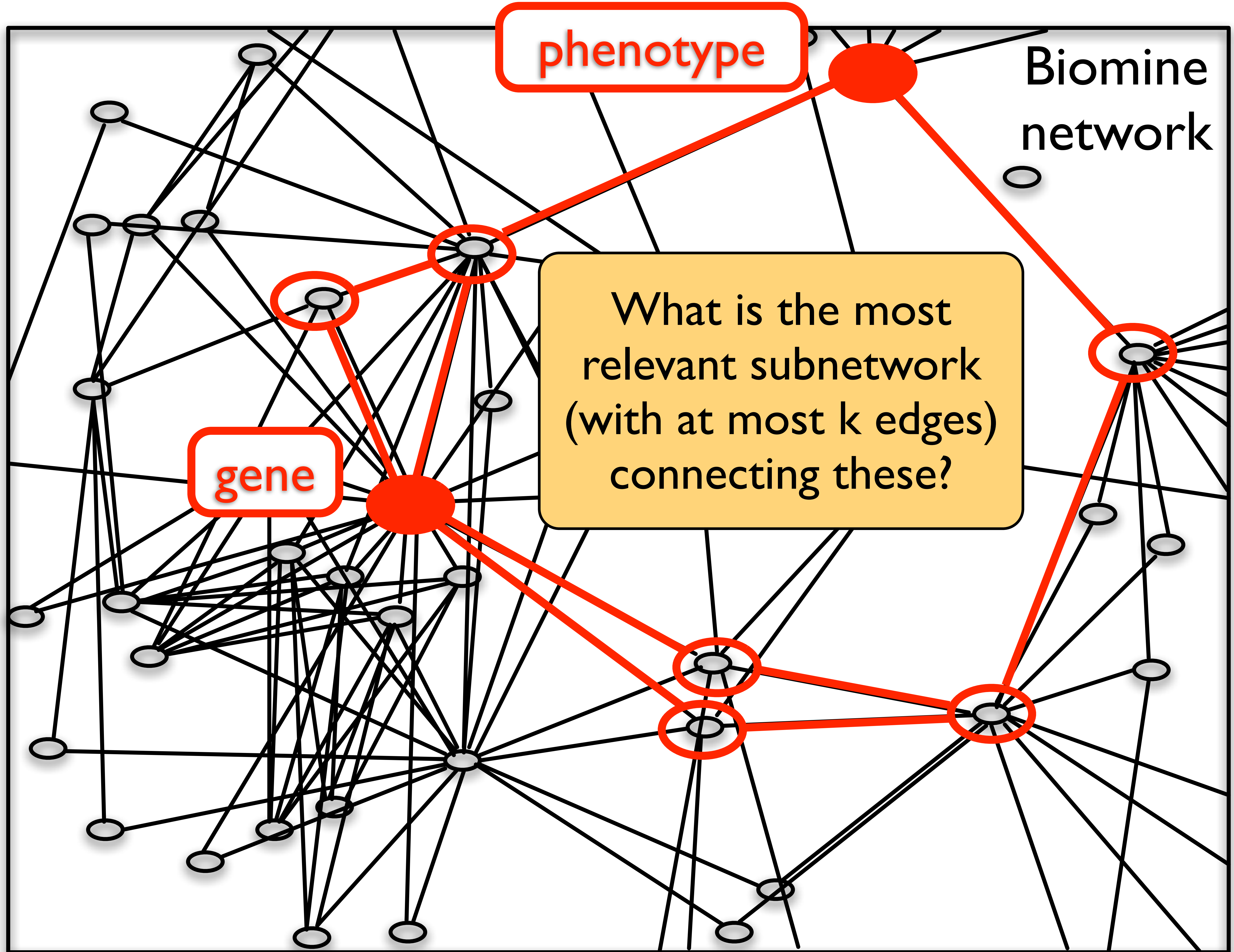
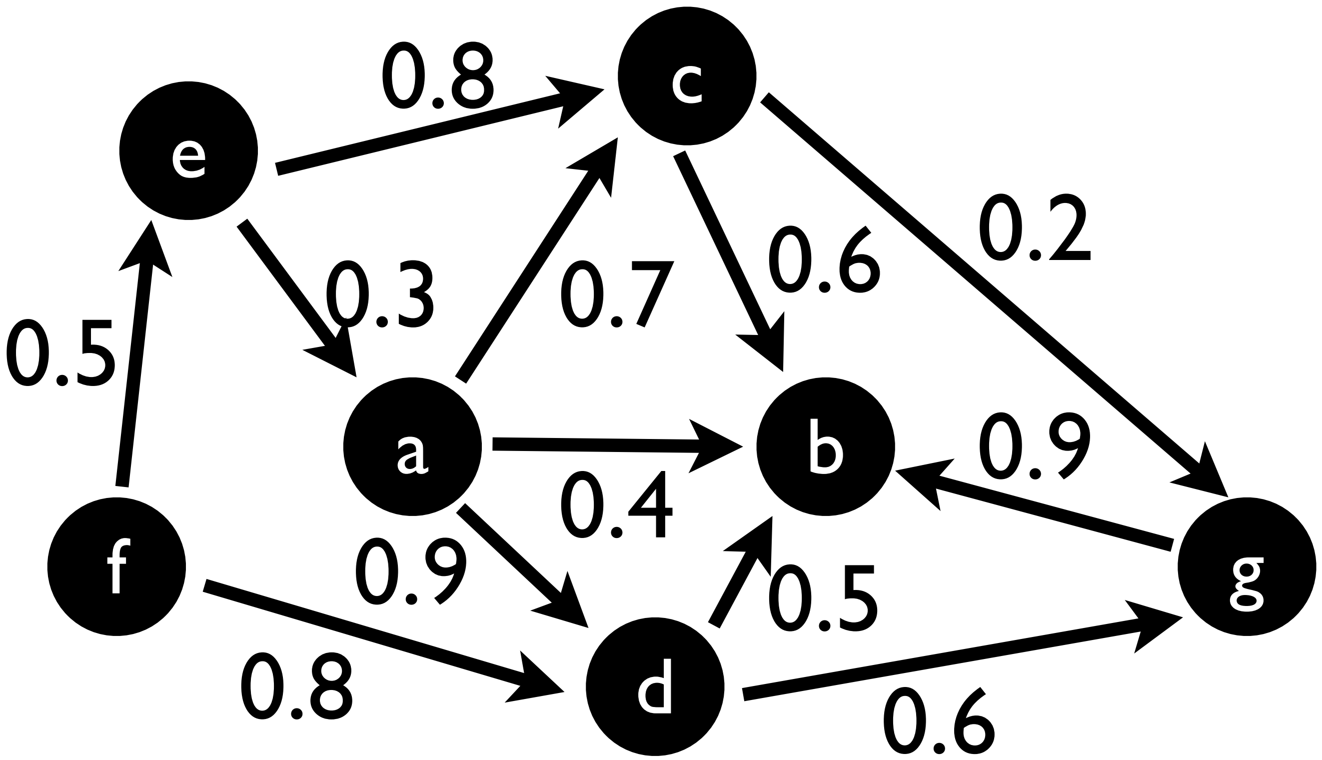
		`...`

Reasoning	query true? yes/no	query true? with probability P
Machine Learning	example covered? yes/no	example covered? with probability P


phenotype
Biomine network
What is the most relevant subnetwork (with at most k edges) connecting these?
gene

Theory compression

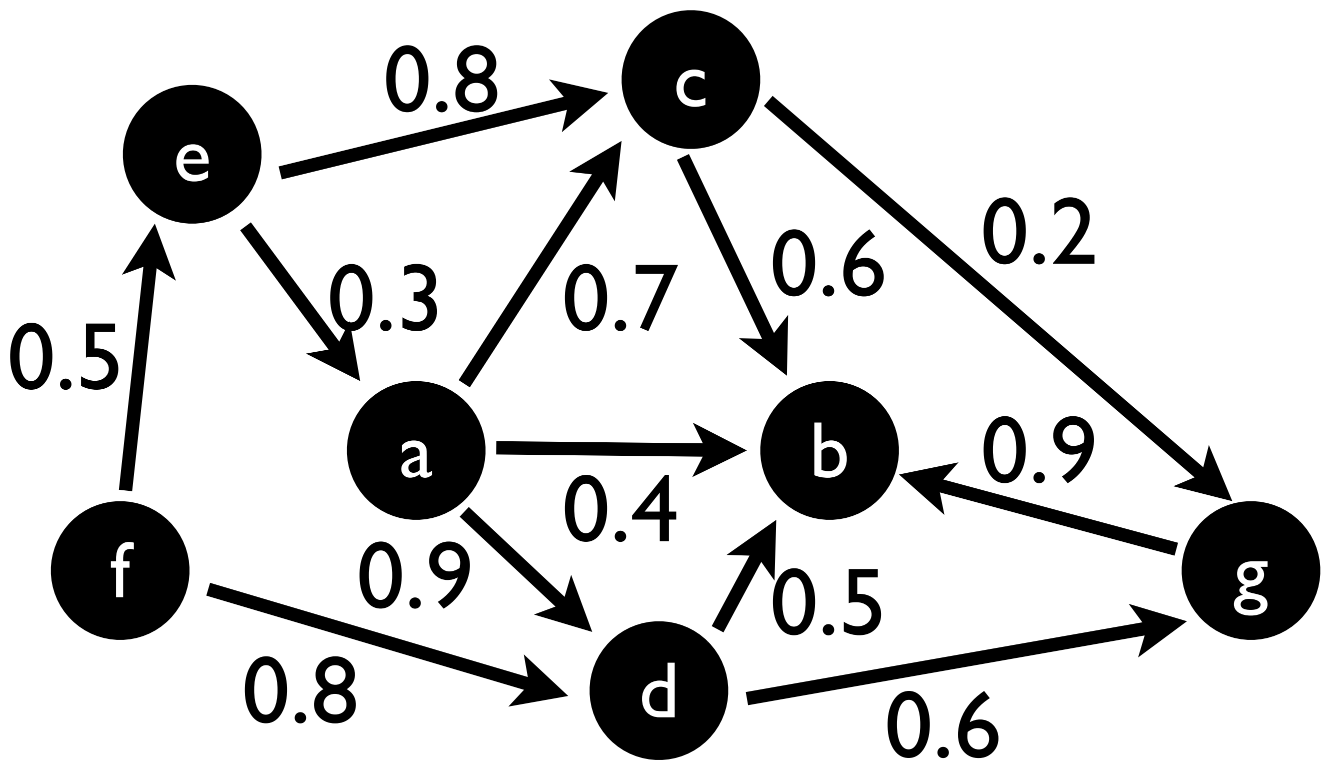



```
path(X,Y) :- edge(X,Y).
path(X,Y) :- edge(X,Z), path(Z,Y).

0.8::edge(e,c).
0.3::edge(e,a).
...
```

[De Raedt et al, MLJ 08]

Theory compression

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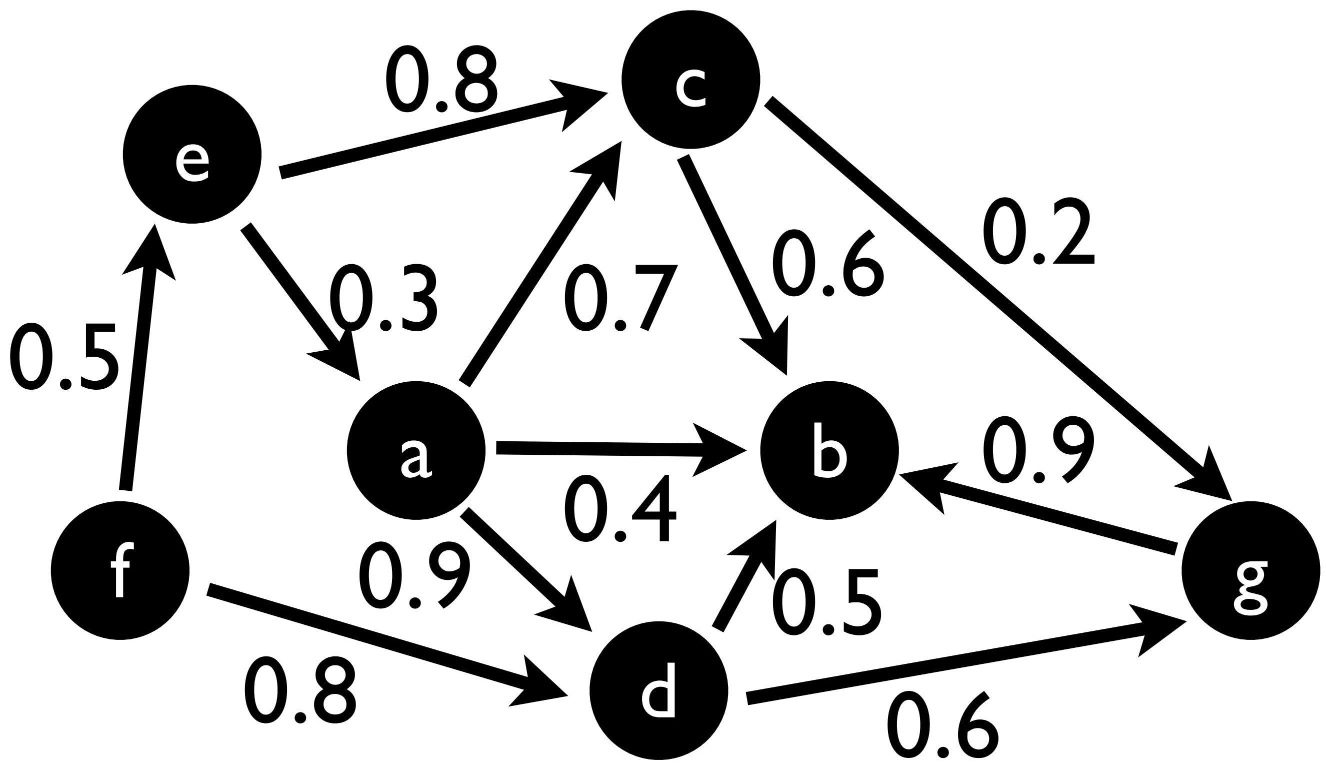
best subnetwork of at most 5 edges where **`path(a,b)`** but not **`path(e,g)`**?

[De Raedt et al, MLJ 08]

Theory compression

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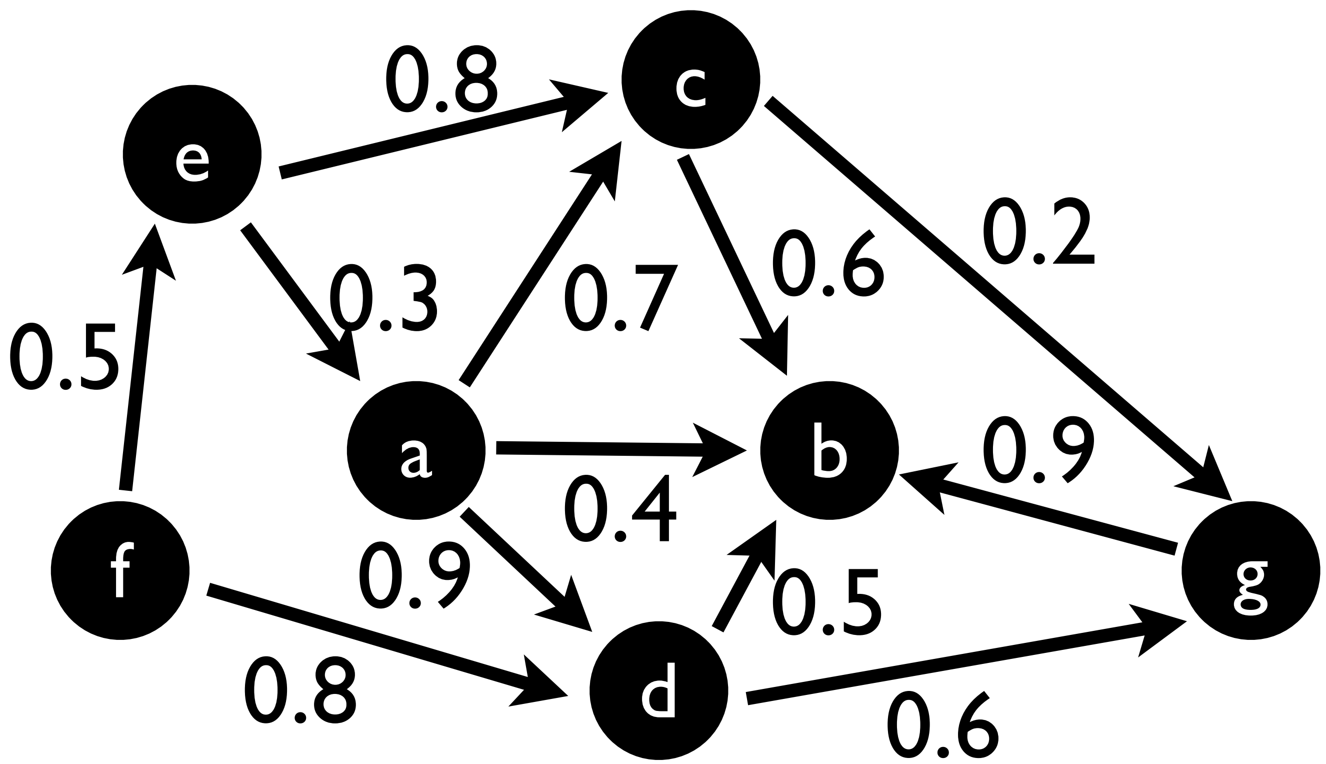
best subnetwork of at most 5 edges where **`path(a,b)`** but not **`path(e,g)`**?

- build inference data structures for all examples
- simulate edge deletion by setting probability to 0
- greedily delete the one that maximizes $\prod_{pos} P - \prod_{neg} (1-P)$

[De Raedt et al, MLJ 08]

Theory compression

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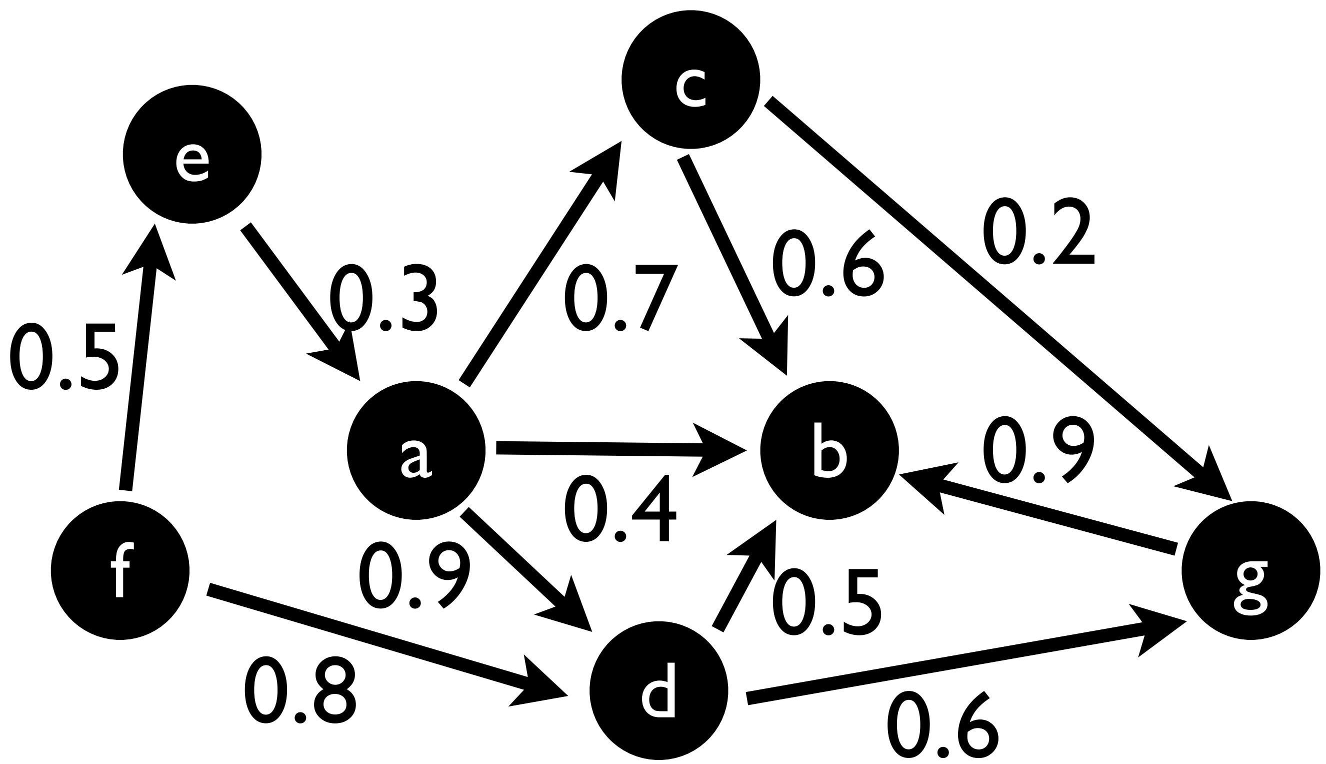


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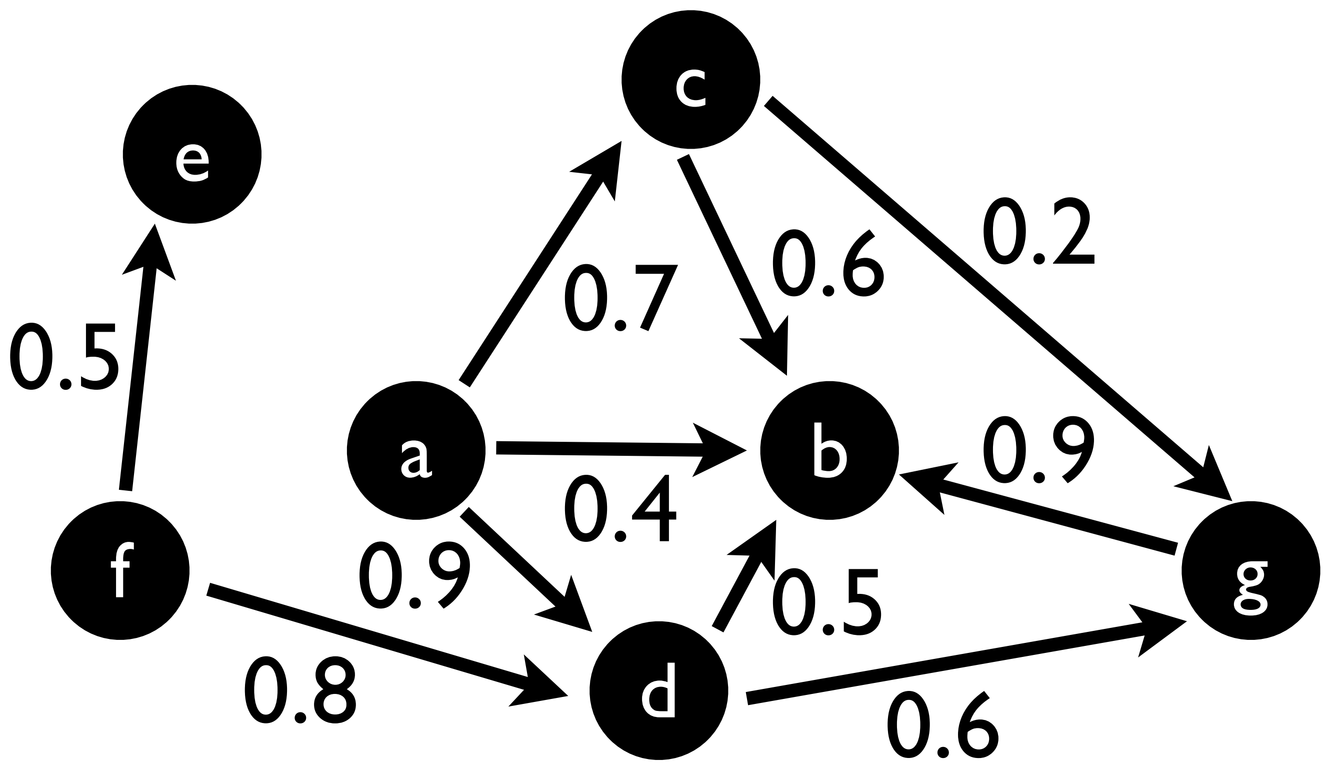
- greedily delete the one that maximizes $\prod_{pos} P - \prod_{neg} (1-P)$

[De Raedt et al, MLJ 08]

Theory compression




```
path(X,Y) :- edge(X,Y).
path(X,Y) :- edge(X,Z), path(Z,Y).

0.8::edge(e,c).
0.3::edge(e,a).
...
```

best subnetwork of at most 5 edges where **`path(a,b)`** but not **`path(e,g)`**?

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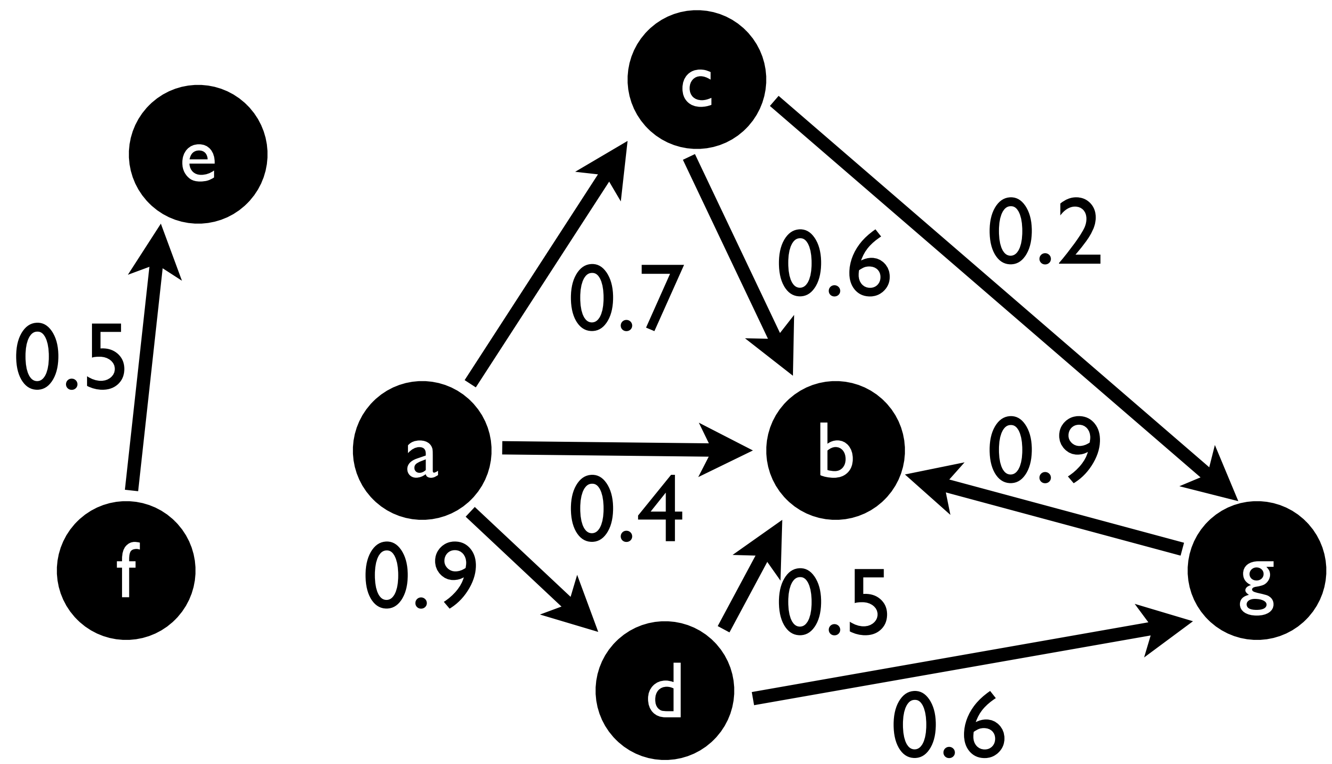


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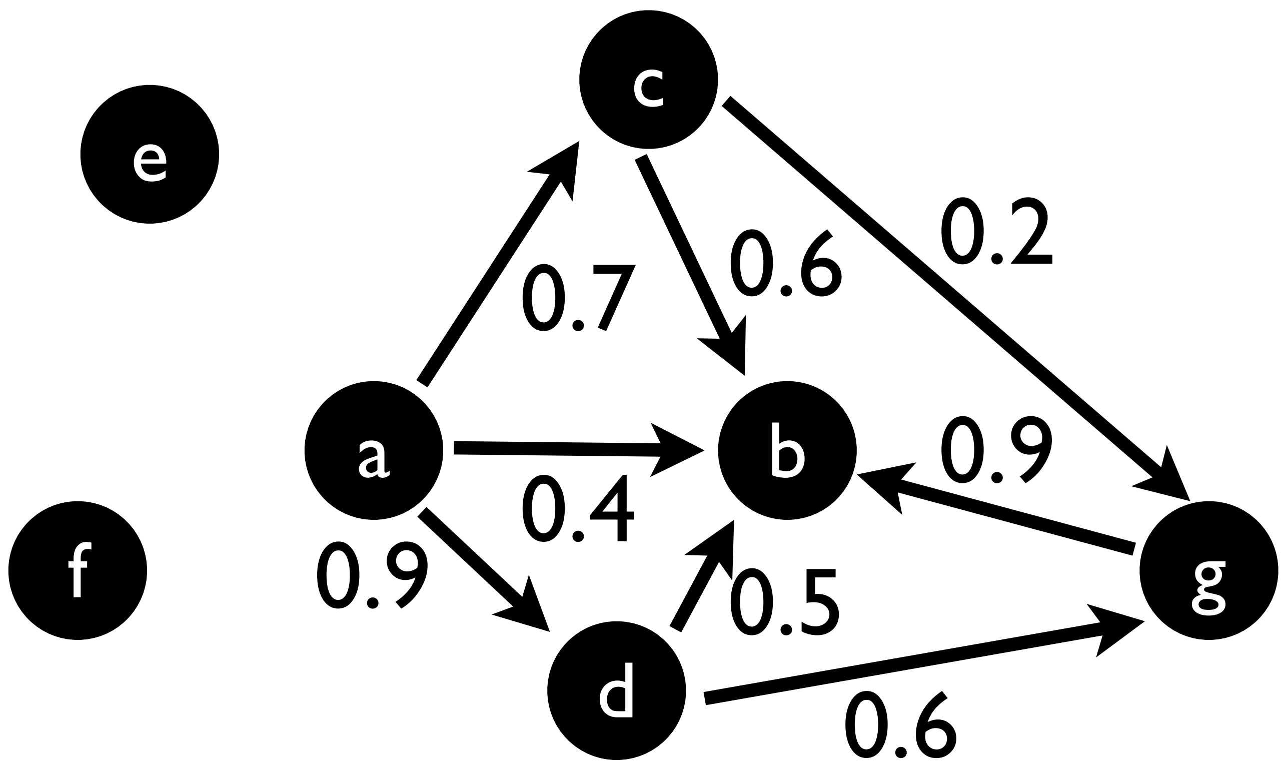


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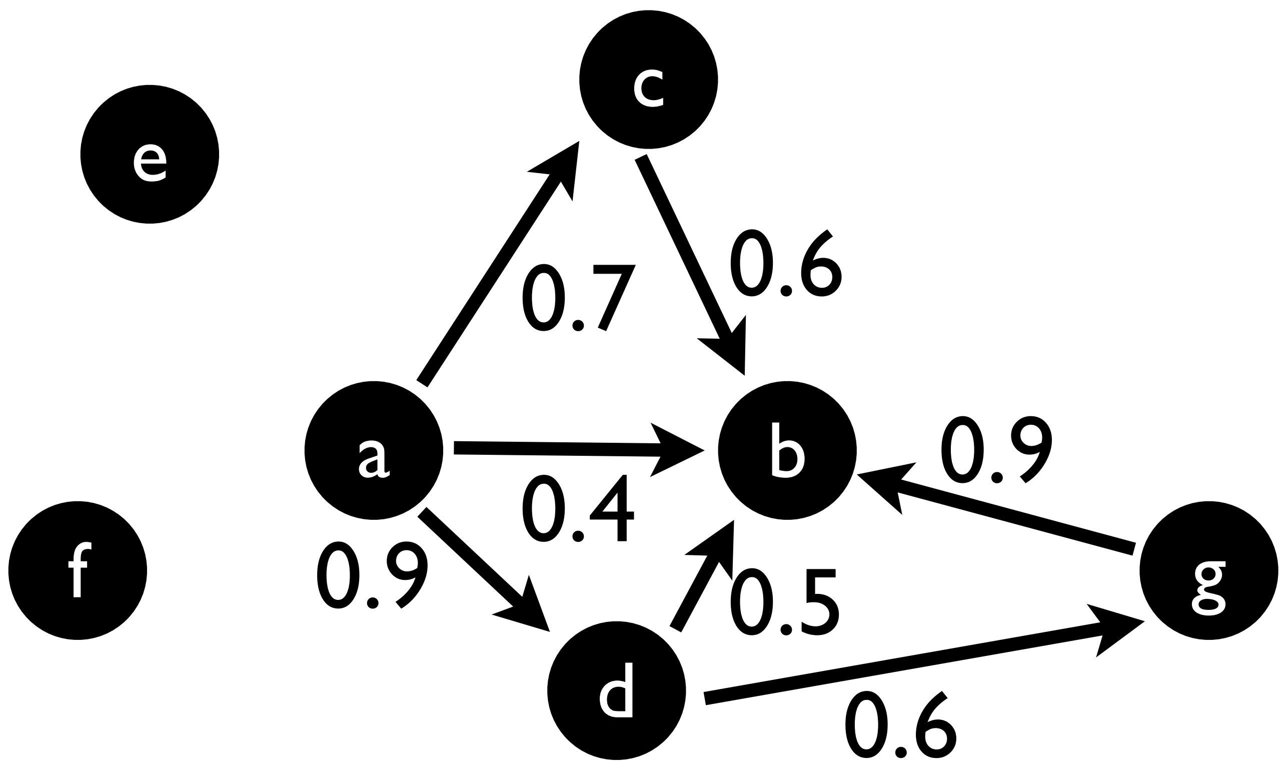


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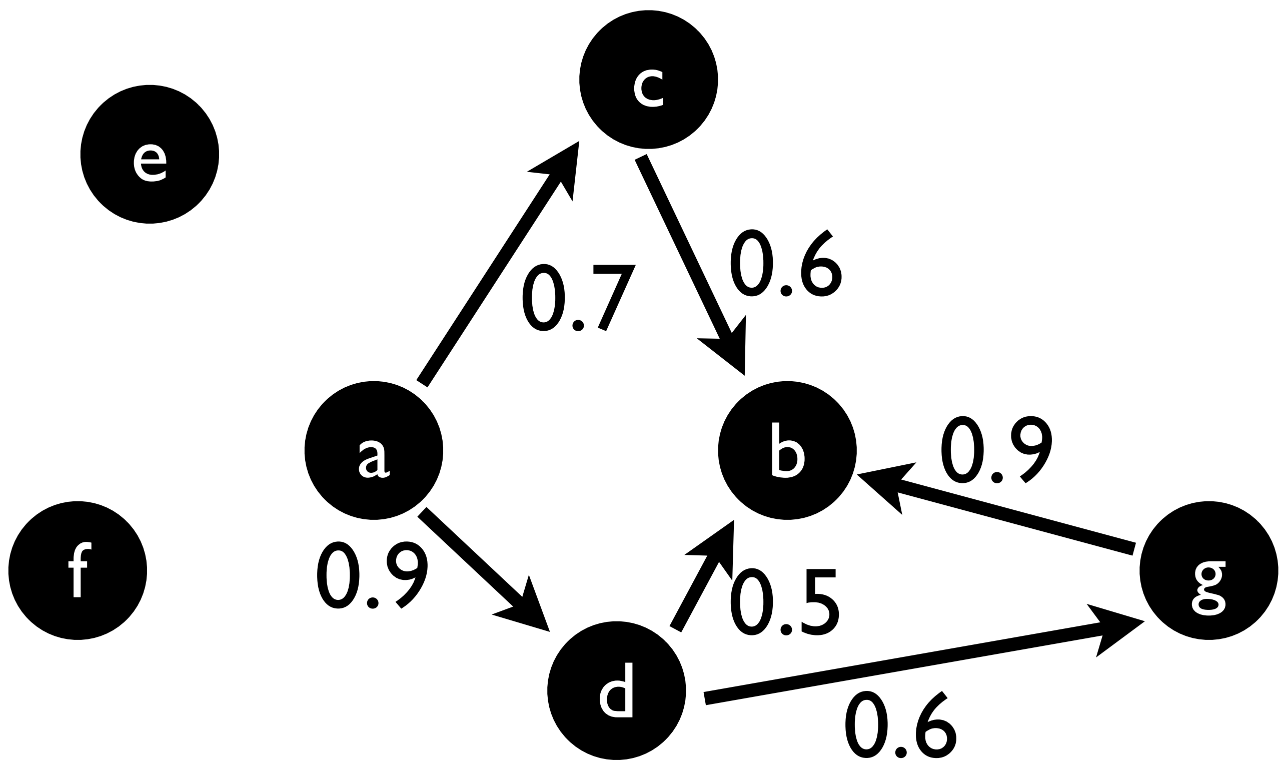


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...
```

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[De Raedt et al, MLJ 08]

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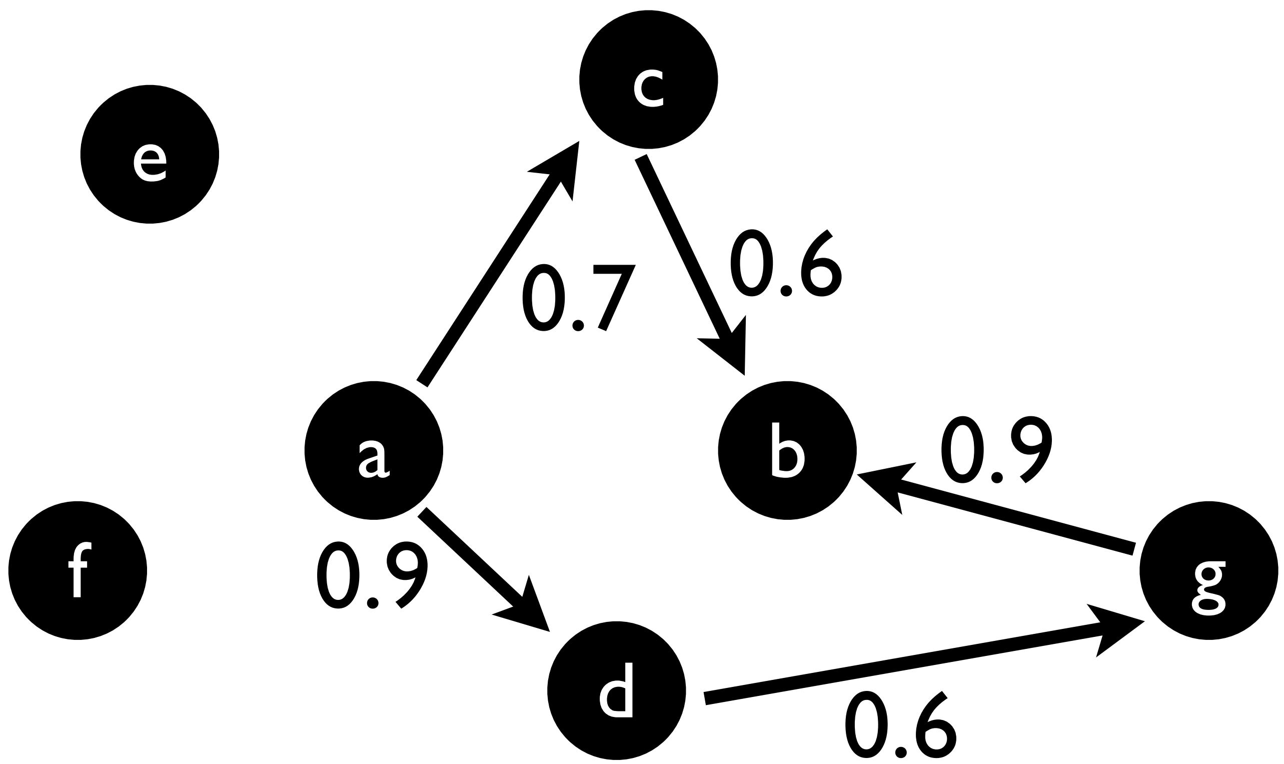


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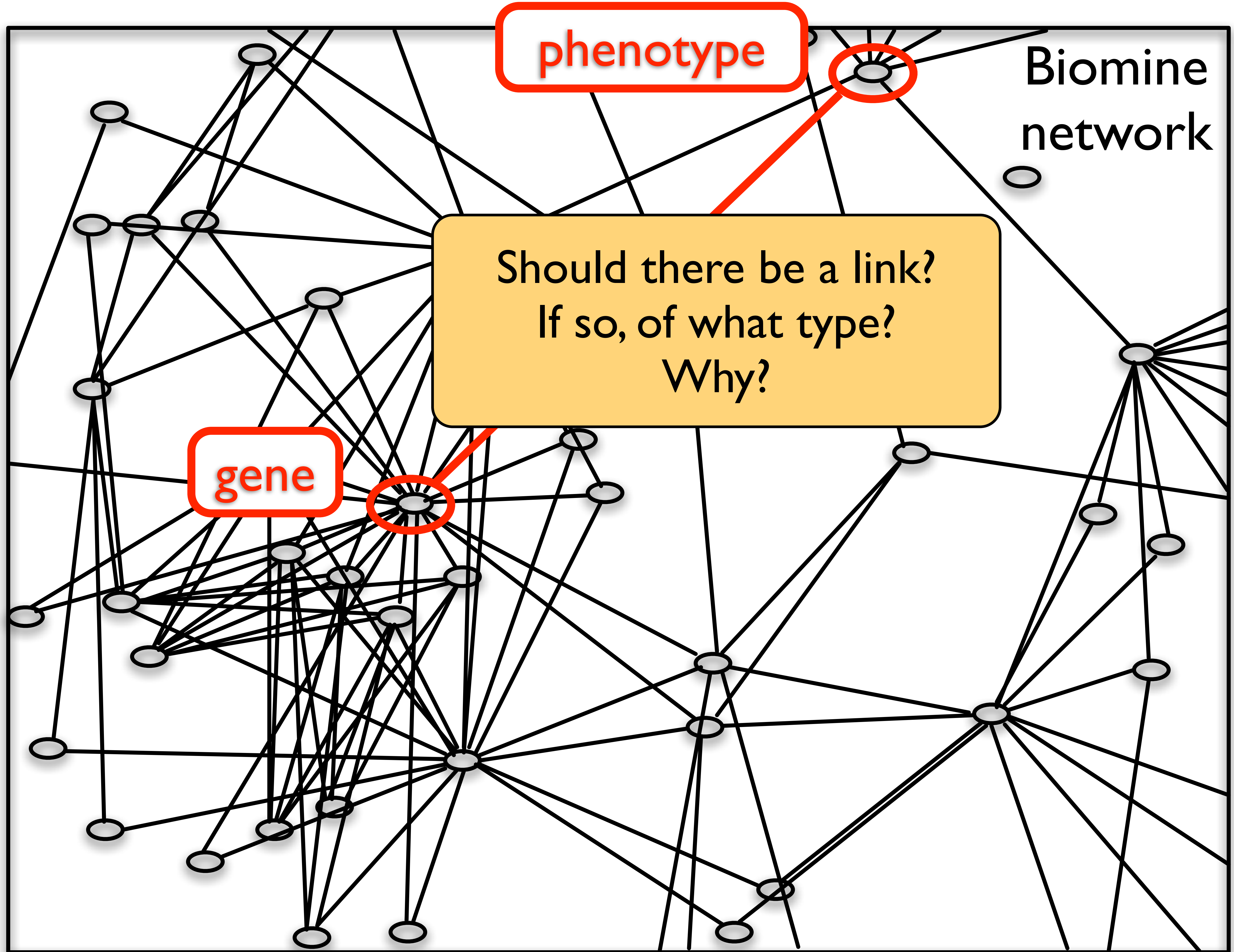
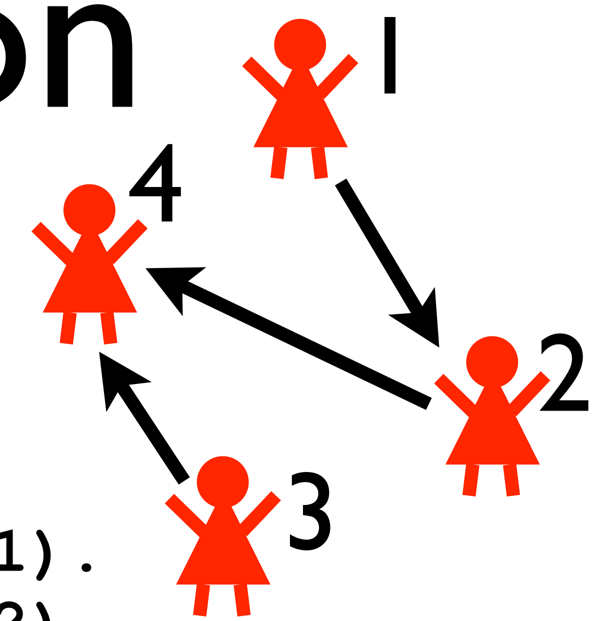

phenotype
Biomine
network
Should there be a link?
If so, of what type?
Why?
gene

Learning Patterns

- **Probabilistic Explanation Based Learning**: example + background theory → rule
- **Probabilistic Query Mining**: pos./neg. examples → set of independent rules
- **Probabilistic Rule Learning**: probabilistic examples → (probabilistic) concept definition

Probabilistic explanation based learning



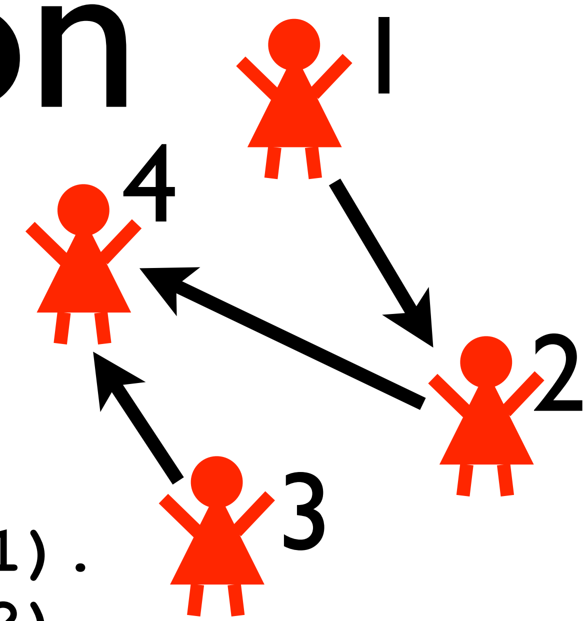

```
smokes(X) :- stress(X).
smokes(X) :-
     influences(Y,X), smokes(Y).
```

```
0.4::stress(1).
0.9::stress(2).
0.5::stress(3).
0.2::stress(4).

0.8::influences(1,2).
0.7::influences(2,4).
0.5::influences(3,4).
```


[Kimmig et al, ECML 07]

Probabilistic explanation based learning

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```
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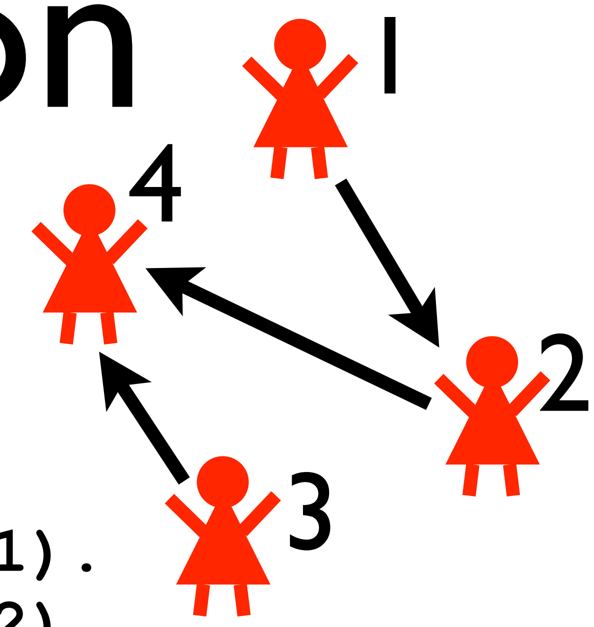
0.9::stress(2).
0.5::stress(3).
0.2::stress(4).

0.8::influences(1,2).
0.7::influences(2,4).
0.5::influences(3,4).
```

example `smokes(4)`

[Kimmig et al, ECML 07]

Probabilistic explanation based learning




```
smokes(X) :- stress(X).
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```

```
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0.2::stress(4).

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0.7::influences(2,4).
0.5::influences(3,4).
```

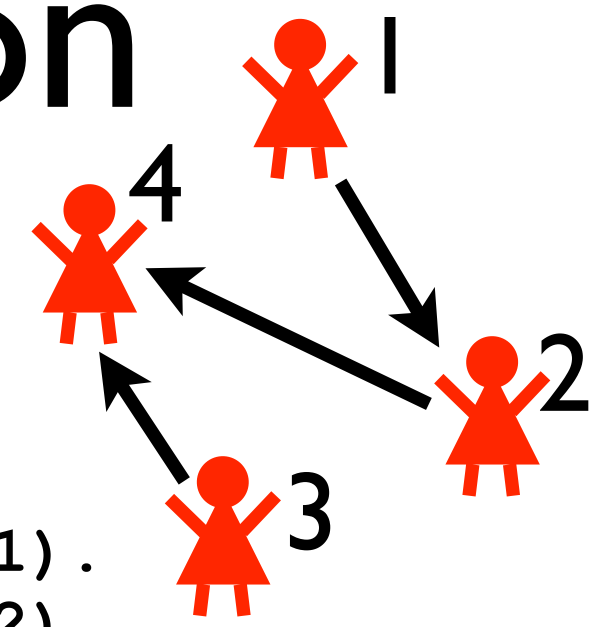
example `smokes(4)`

proofs

```
stress(4)
influences(2,4) & stress(2)
influences(2,4) & influences(1,2) & stress(1)
influences(3,4) & stress(3)
```


[Kimmig et al, ECML 07]

Probabilistic explanation based learning

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0.8::influences(1,2).
0.7::influences(2,4).
0.5::influences(3,4).
```

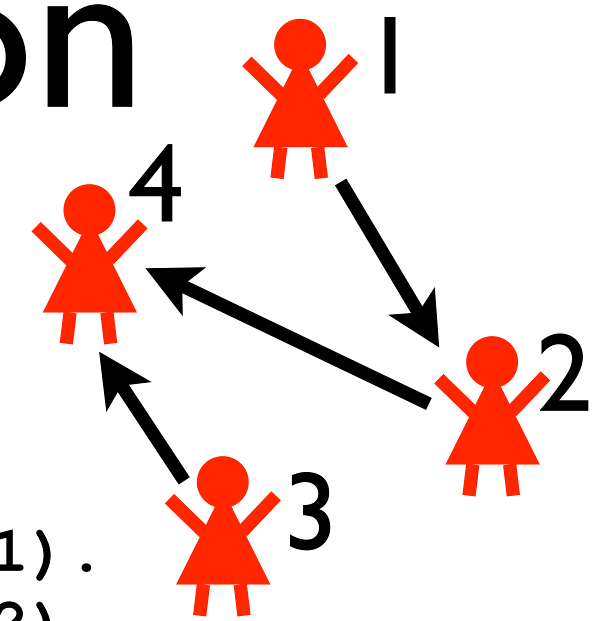
example `smokes(4)`

proofs

0.200	`stress(4)`
0.630	`influences(2,4) & stress(2)`
0.224	`influences(2,4) & influences(1,2) & stress(1)`
0.250	`influences(3,4) & stress(3)`

[Kimmig et al, ECML 07]

Probabilistic explanation based learning

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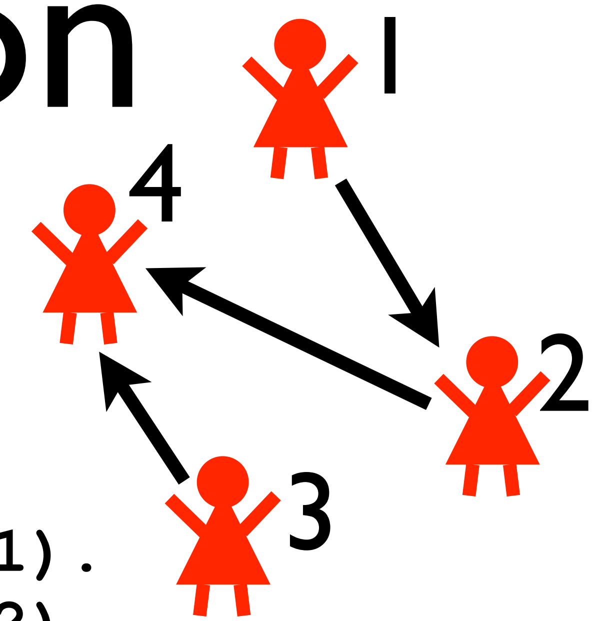
specific explanation `smokes(4) if influences(2,4) & stress(2)`

[Kimmig et al, ECML 07]

Probabilistic explanation based learning

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0.7::influences(2,4).
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```

example `smokes(4)`

proofs

0.200 `stress(4)`
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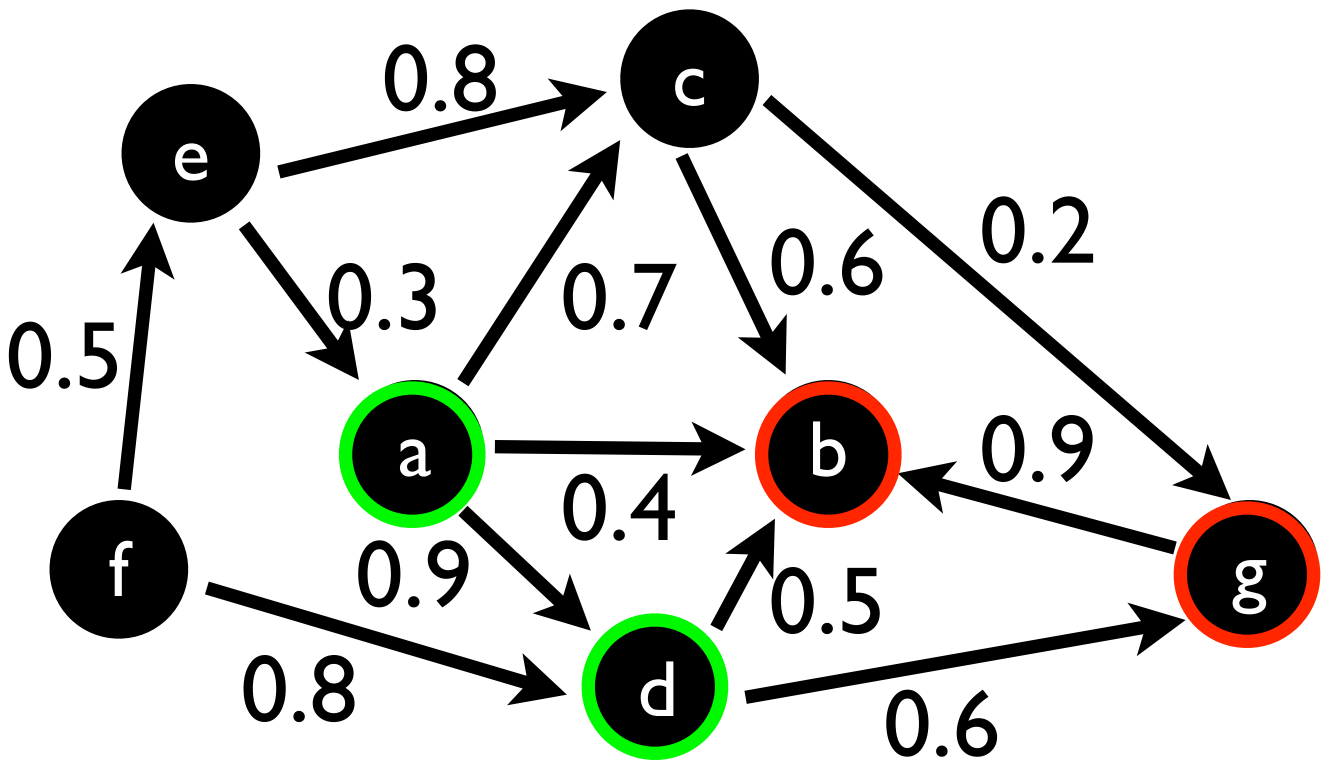
specific explanation `smokes(4) if influences(2,4) & stress(2)`

general explanation `smokes(A) if influences(B,A) & stress(B)`

[Kimmig et al, ECML 07]

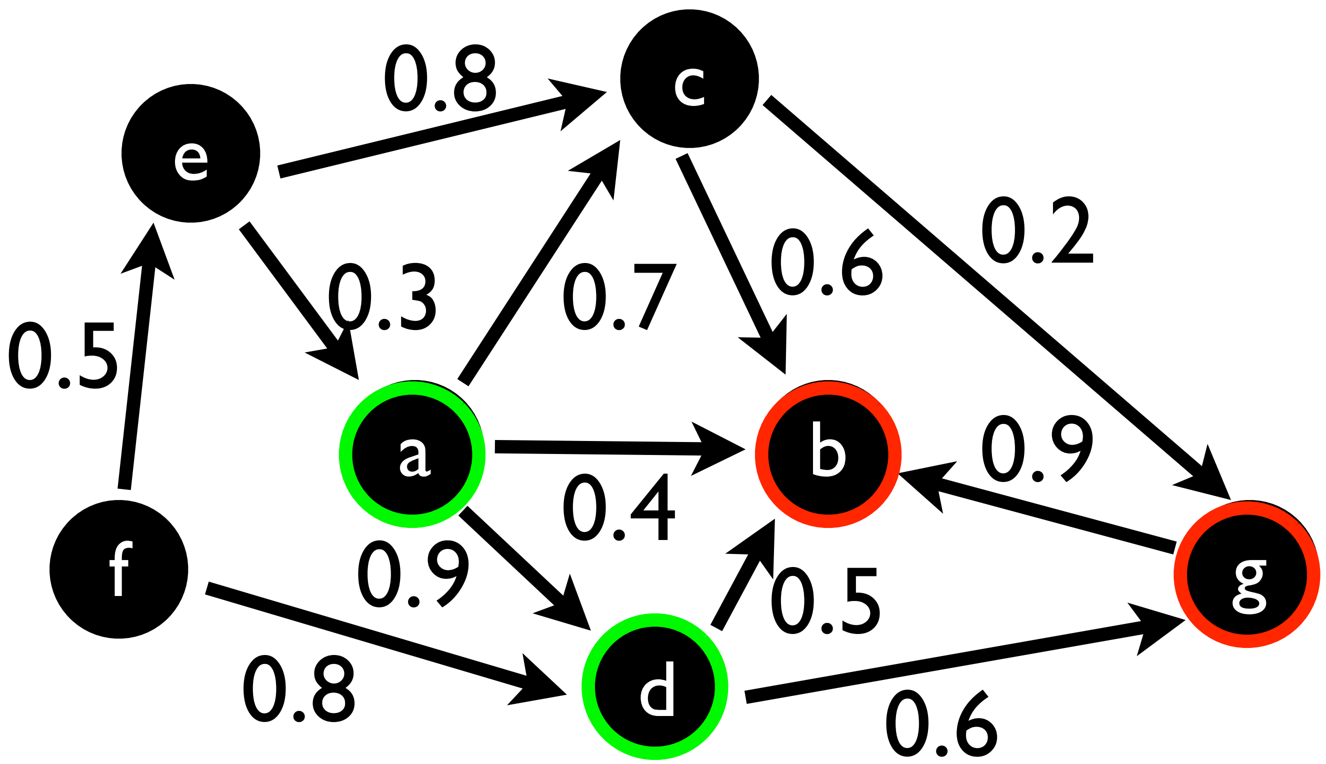
Probabilistic query mining




```
pos(a).    not pos(b).
pos(d).    not pos(g).
```


[Kimmig and De Raedt, IJCAI 09]

Probabilistic query mining




```
pos(a).    not pos(b).
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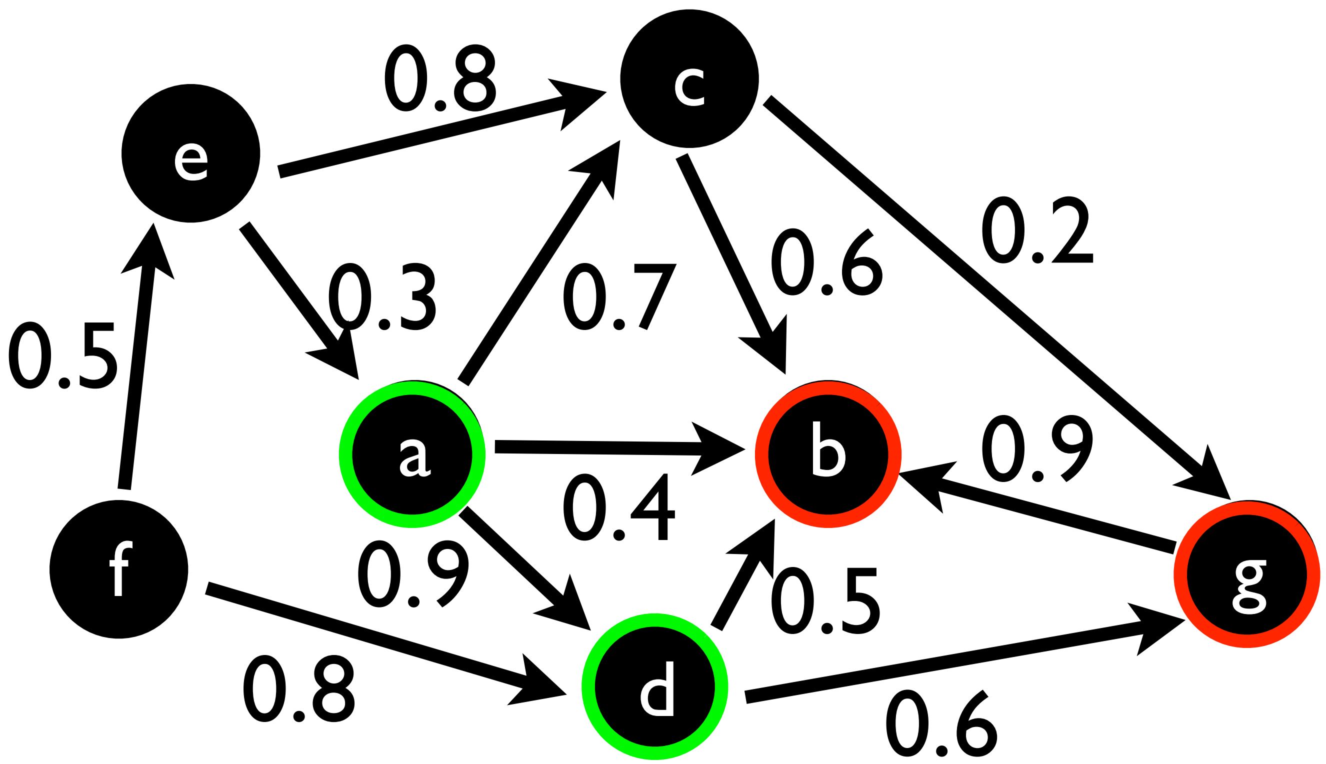
```

subgraph queries that maximize $\sum_{pos} P - \sum_{neg} P$?

[Kimmig and De Raedt, IJCAI 09]

Probabilistic query mining




```
pos(a).    not pos(b).
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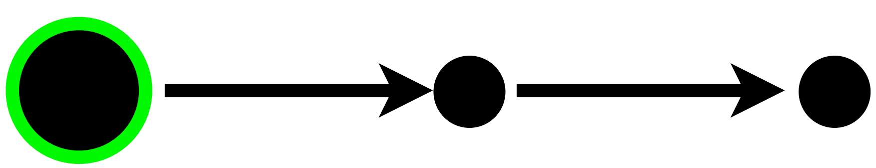
```

subgraph queries that maximize $\sum_{pos} P - \sum_{neg} P$?

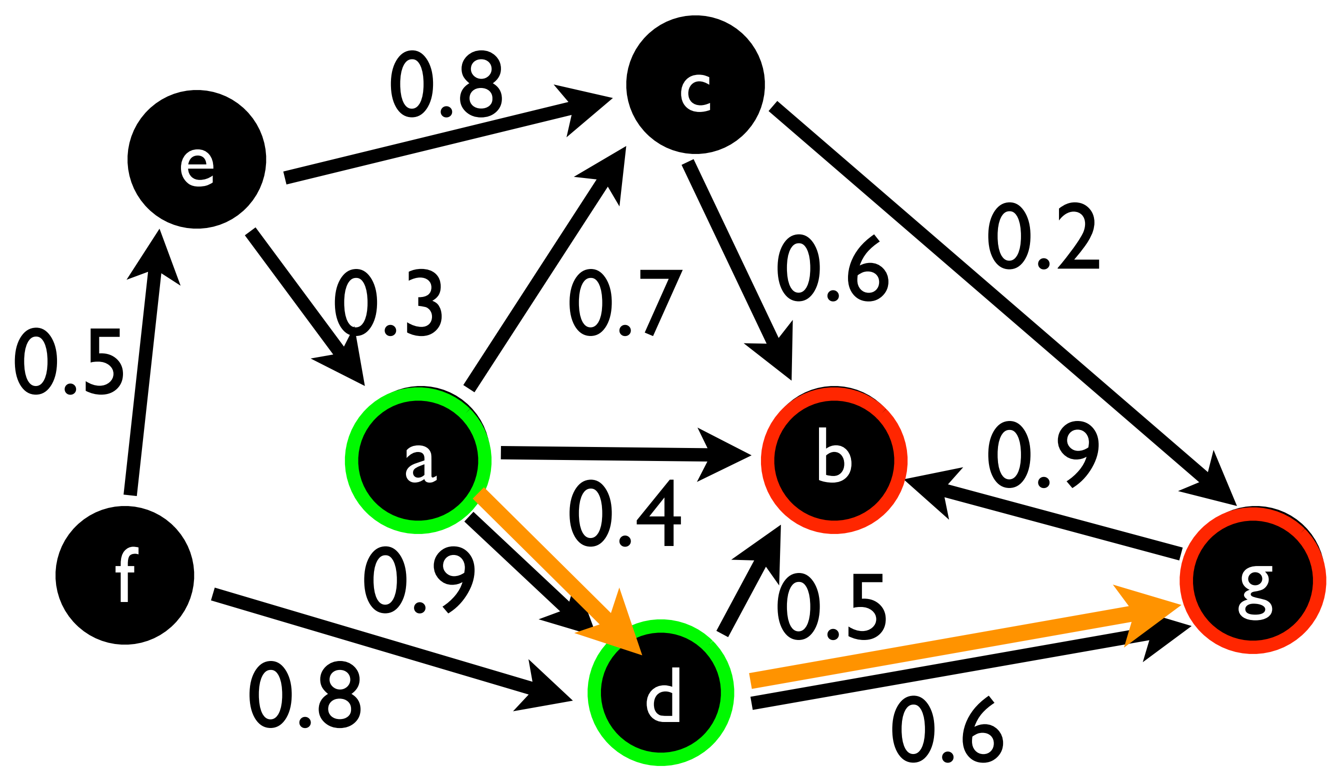
```
pos(X) :- edge(X,Y),edge(Y,Z).
```



1.08

[Kimmig and De Raedt, IJCAI 09]

Probabilistic query mining



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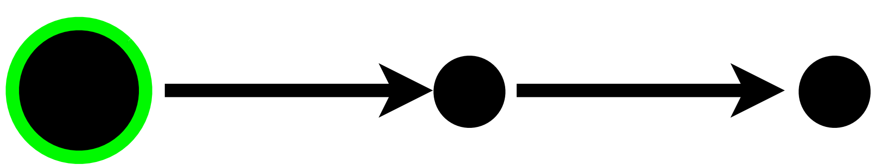
subgraph queries that maximize $\sum_{pos} P - \sum_{neg} P$?

`pos(X) :- edge(X,Y),edge(Y,Z).`



1.08

a-d-g 0.54

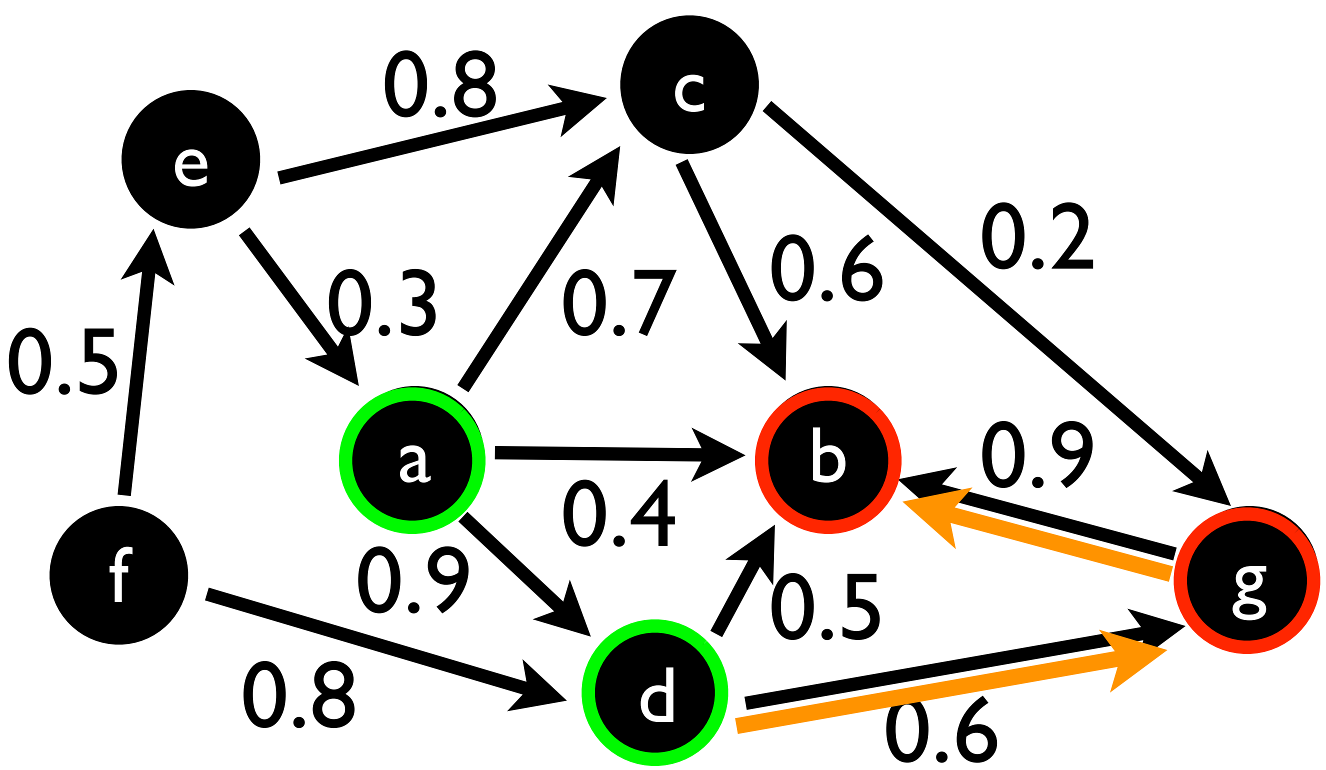
d-g-b 0.54

b-

g-

[Kimmig and De Raedt, IJCAI 09]

Probabilistic query mining

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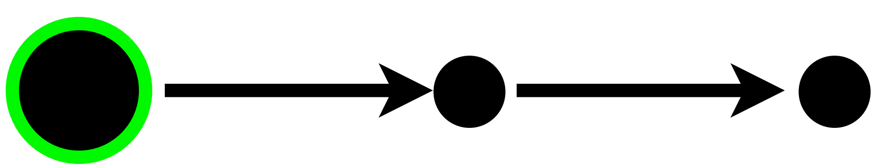

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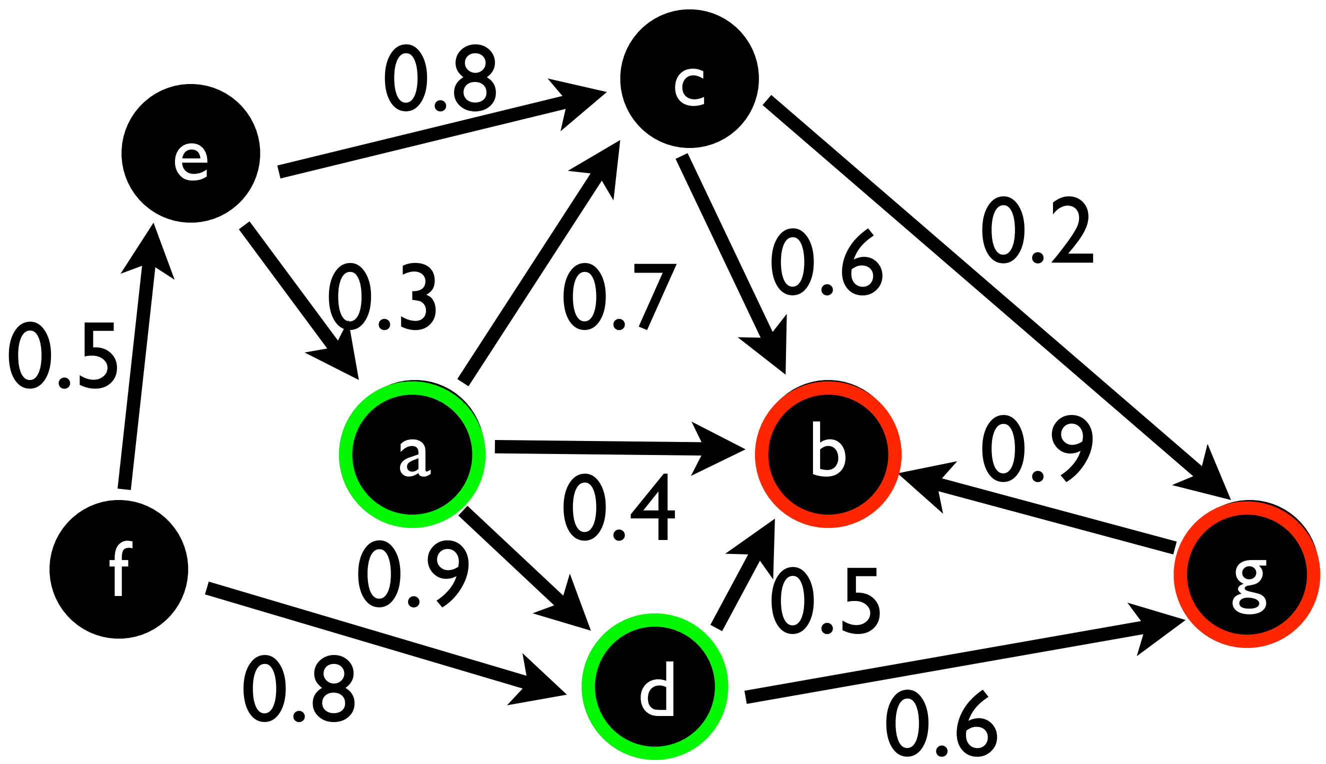


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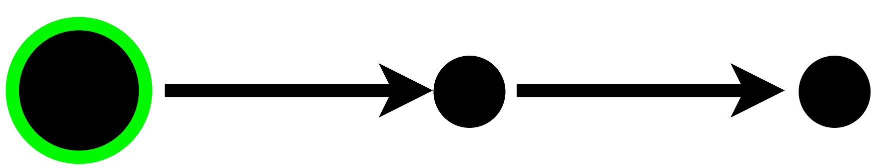

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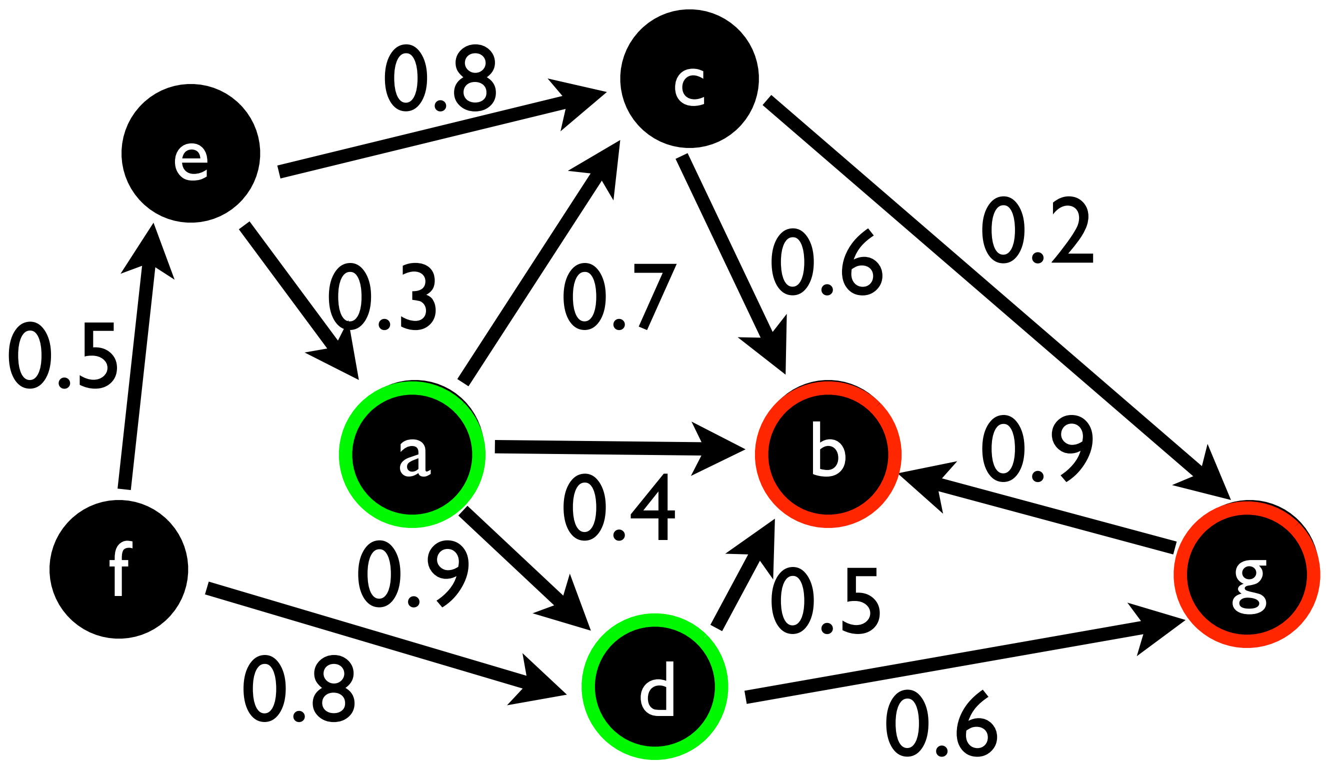


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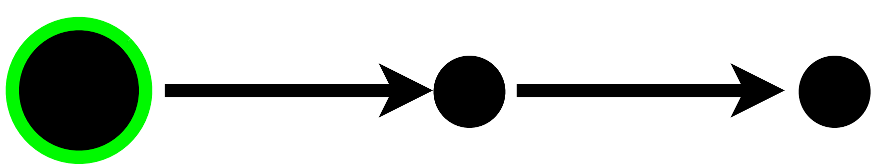

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g-

```
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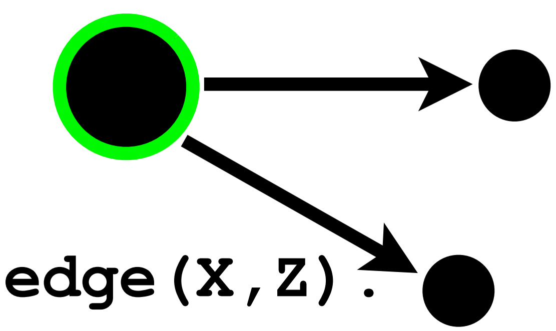
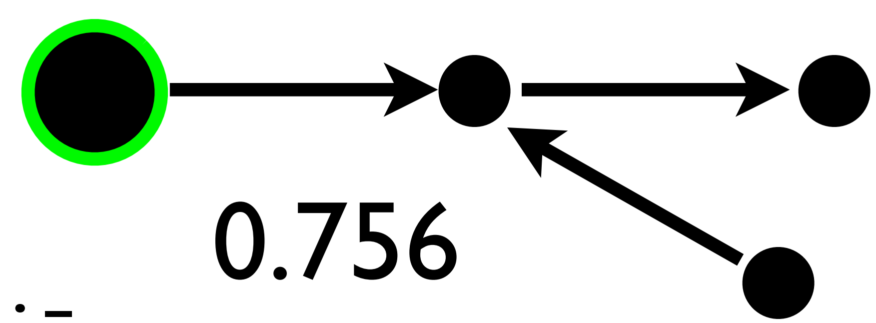
```



0.93



0.756

```
pos(X) :-
edge(X,Y),edge(Y,Z),edge(W,Y).
```


[Kimmig and De Raedt, IJCAI 09]

ProbFOIL

- Upgrading FOIL to learn a set of rules from **probabilistic** facts

[De Raedt and Thon, ILP 10; Dries et al]

ProbFOIL

- Upgrading FOIL to learn a set of rules from **probabilistic** facts

```
  0.4987::rain(1).
 0.3591::windok(1).
0.4534::sunshine(1).
0.3257::surfing(1).
  0.7391::rain(2).
 0.6022::windok(2).
0.9837::sunshine(2).
0.2592::surfing(2).
  0.2898::rain(3).
 0.7423::windok(3).
0.2275::sunshine(3).
0.5688::surfing(3).
        ...
```

[De Raedt and Thon, ILP 10; Dries et al]

ProbFOIL

- Upgrading FOIL to learn a set of rules from **probabilistic** facts

```
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0.3591::windok(1).
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0.2592::surfing(2).
0.2898::rain(3).
0.7423::windok(3).
0.2275::sunshine(3).
0.5688::surfing(3).
...
```

```
surfing(X) :-
    \+ rain(X), windok(X).
surfing(X) :-
    \+ rain(X), sunshine(X).
```

[De Raedt and Thon, ILP 10; Dries et al]

ProbFOIL

- Upgrading FOIL to learn a set of rules from **probabilistic** facts

```
0.7::father(piet, wim).
0.9::father(bart, pieter).
0.6::father(tom, greet).
mother(emma,piet).
mother(emma,greet).
mother(greet,pieter).
grandmother(emma,ilse).
0.7::grandmother(emma,wim).
....
```

[De Raedt and Thon, ILP 10; Dries et al]

ProbFOIL

- Upgrading FOIL to learn a set of rules from **probabilistic** facts

```
0.7::father(piet, wim).
0.9::father(bart, pieter).
0.6::father(tom, greet).
mother(emma,piet).
mother(emma,greet).
mother(greet,pieter).
grandmother(emma,ilse).
0.7::grandmother(emma,wim).
....
```

```
grandmother(X,Y) :-
    mother(X,Z),
    father(Z,Y).
```

[De Raedt and Thon, ILP 10; Dries et al]

Prob2FOIL

- Learning **probabilistic rules** from probabilistic facts

```
  0.4987::rain(1).
 0.3591::windok(1).
0.4534::sunshine(1).
 0.3257::surfing(1).
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 0.6022::windok(2).
0.9837::sunshine(2).
 0.2592::surfing(2).
  0.2898::rain(3).
 0.7423::windok(3).
0.2275::sunshine(3).
 0.5688::surfing(3).
        ...
```

Prob2FOIL

- Learning **probabilistic rules** from probabilistic facts

```
 0.4987::rain(1).
0.3591::windok(1).
0.4534::sunshine(1).
0.3257::surfing(1).
 0.7391::rain(2).
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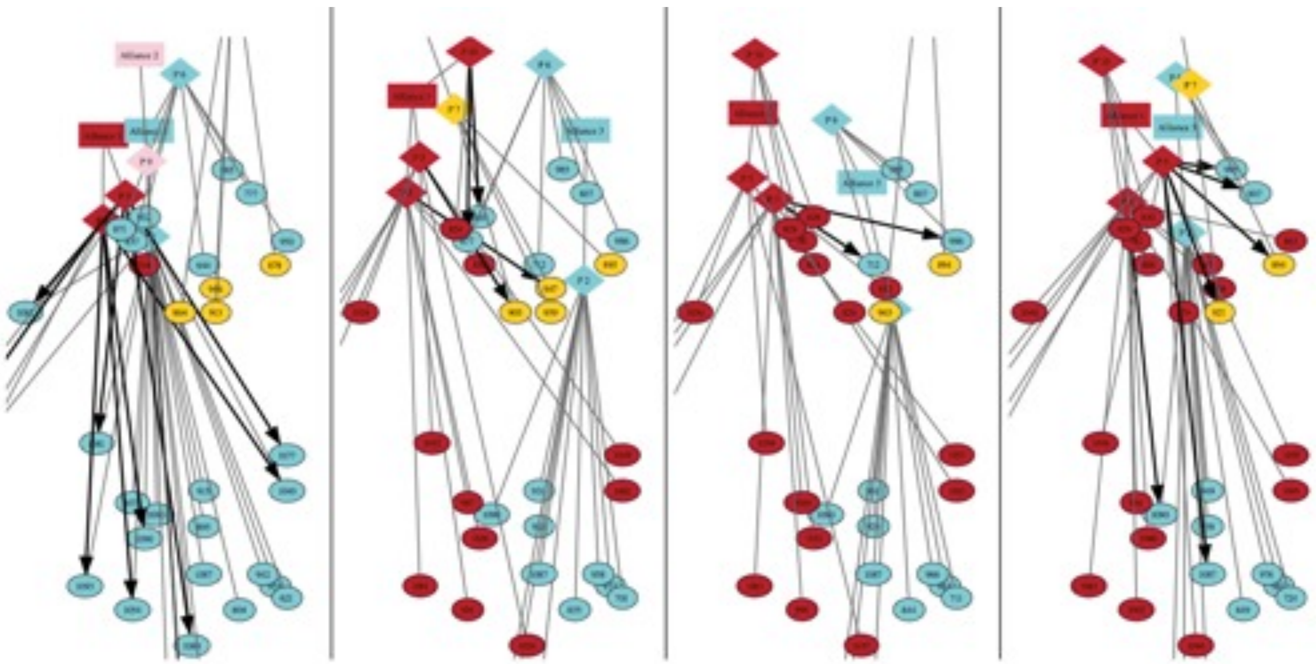
0.2592::surfing(2).
 0.2898::rain(3).
0.7423::windok(3).
0.2275::sunshine(3).
0.5688::surfing(3).
       ...
```

```
0.7023::surfing(A) <-
               \+rain(A).
0.01243::surfing(A) <-
               true.
```

Overview

- ProbLog Basics
  - ProbLog by example
  - Inference
  - Parameter Learning
- Selected Topics
  - Upgrading relational learning
  - Dynamics under uncertainty
  - Continuous-valued random variables
  - Decision making
  - Constraints

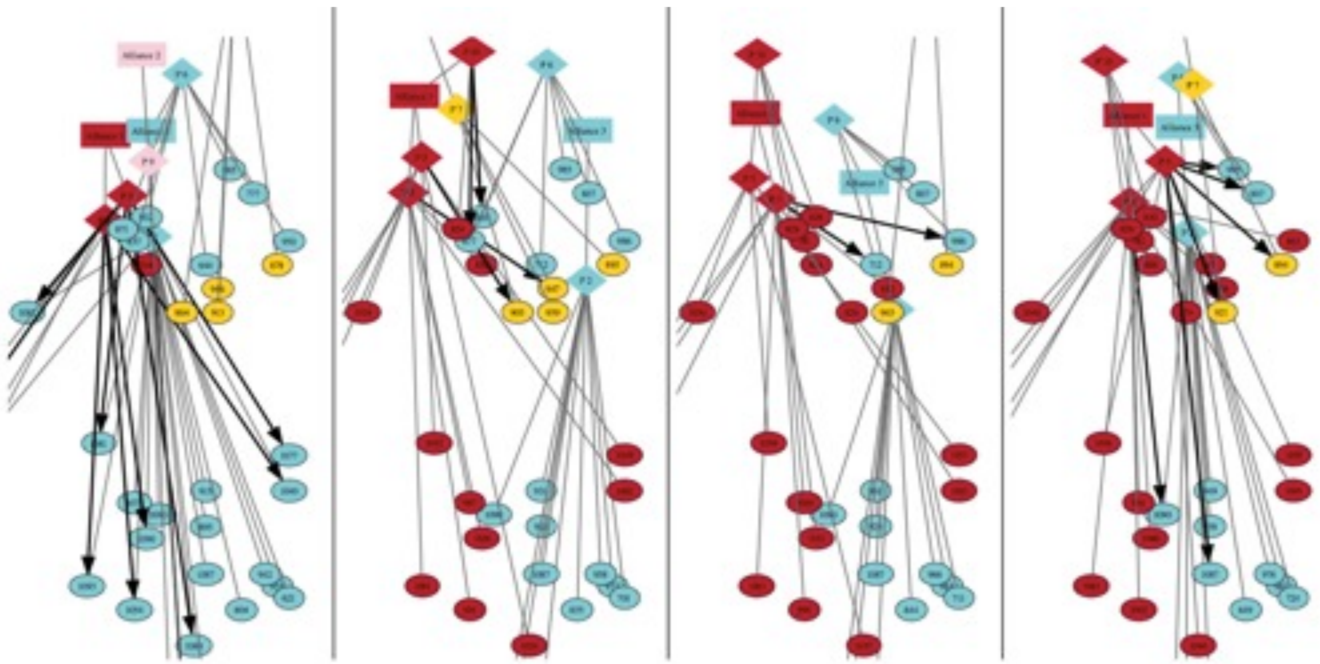
Causal Probabilistic Time-Logic (CPT-L)



how does the world change over time?

[Thon et al, MLJ 11]

Causal Probabilistic Time-Logic (CPT-L)



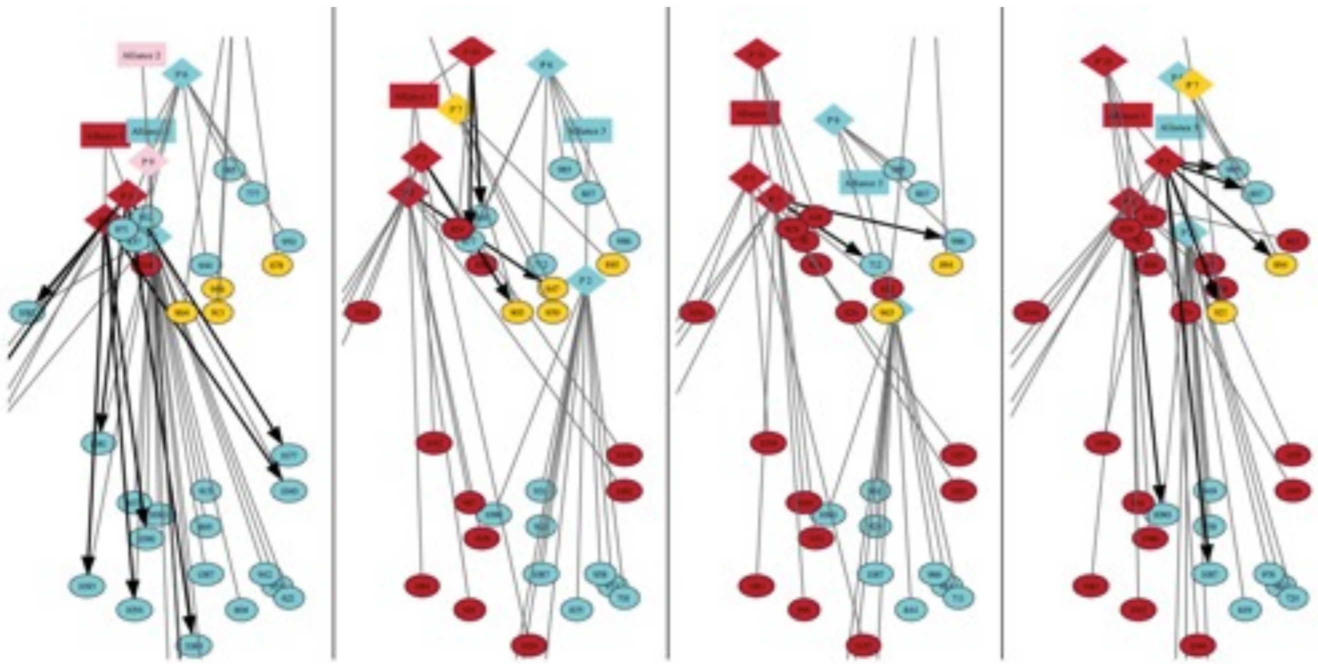
how does the world change over time?

```
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 <-
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if **cause** holds at time T

[Thon et al, MLJ 11]

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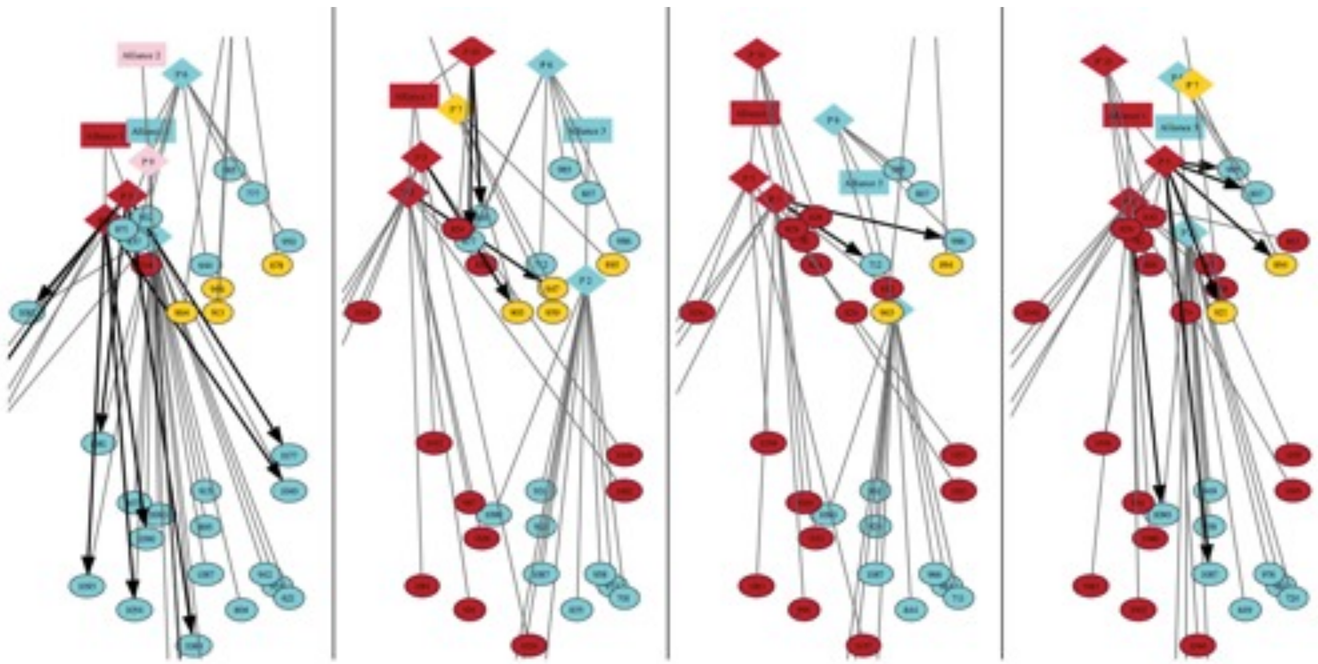

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```
0.4::conquest(Attacker,C); 0.6::nil <-
              city(C,Owner),city(C2,Attacker),close(C,C2).
```

if **cause** holds at time T

[Thon et al, MLJ 11]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables
- Inference: particle filter

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

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- Discrete- and continuous-valued random variables
- Inference: particle filter

random variable with Gaussian distribution

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

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

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables
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```
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]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables
- Inference: particle filter

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

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables
- Inference: particle filter

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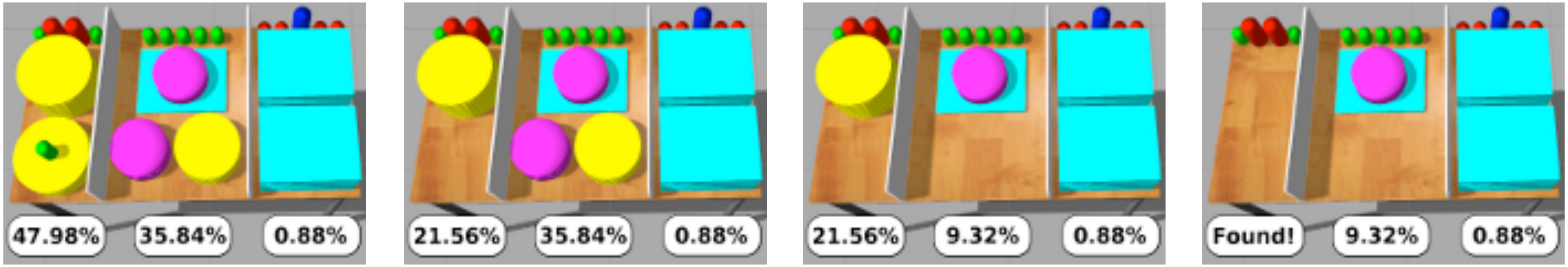
                        :- obj(Obj), on(Obj,O2), type(O2,plate).
```

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

Occluded Object Search

- DC model of objects and their spatial arrangement
- different types of objects suitable for different tasks
- shelves with objects of different shape and size
- given a task, find an object to perform that task

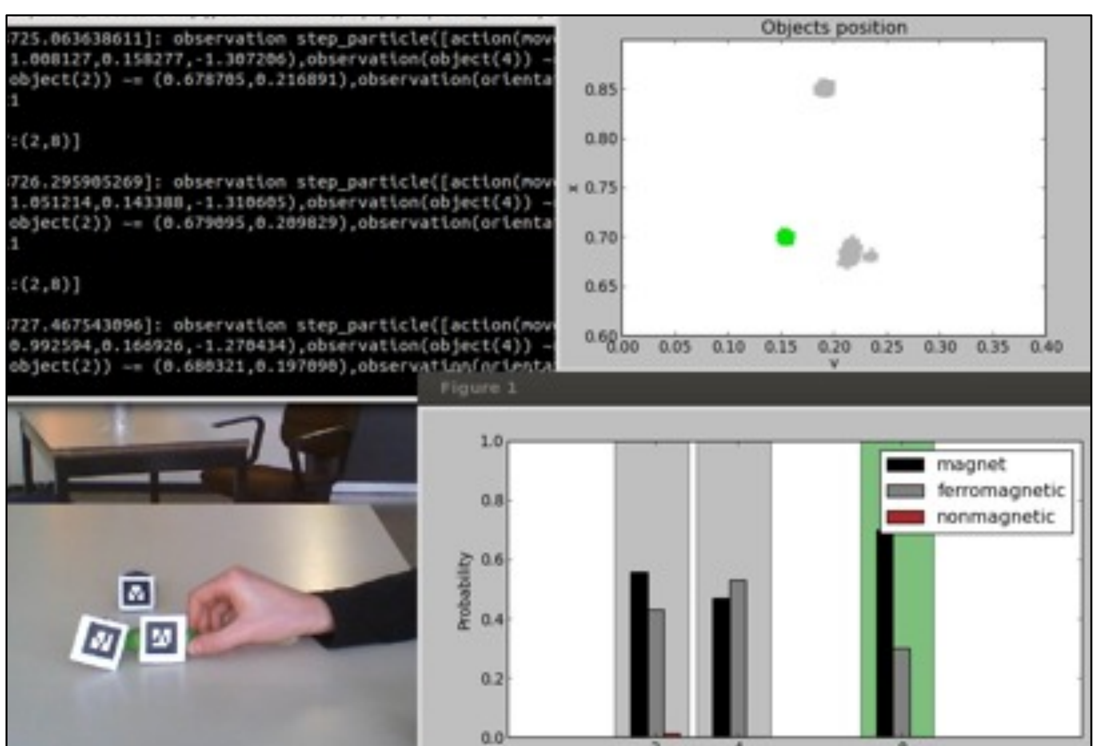


[Moldovan et al]

Relational State Estimation over Time

Magnetism scenario

- object tracking
- category estimation from interactions



[Nitti et al, IEEE/RSJ 13]

Relational State Estimation over Time

Magnetism scenario

- object tracking
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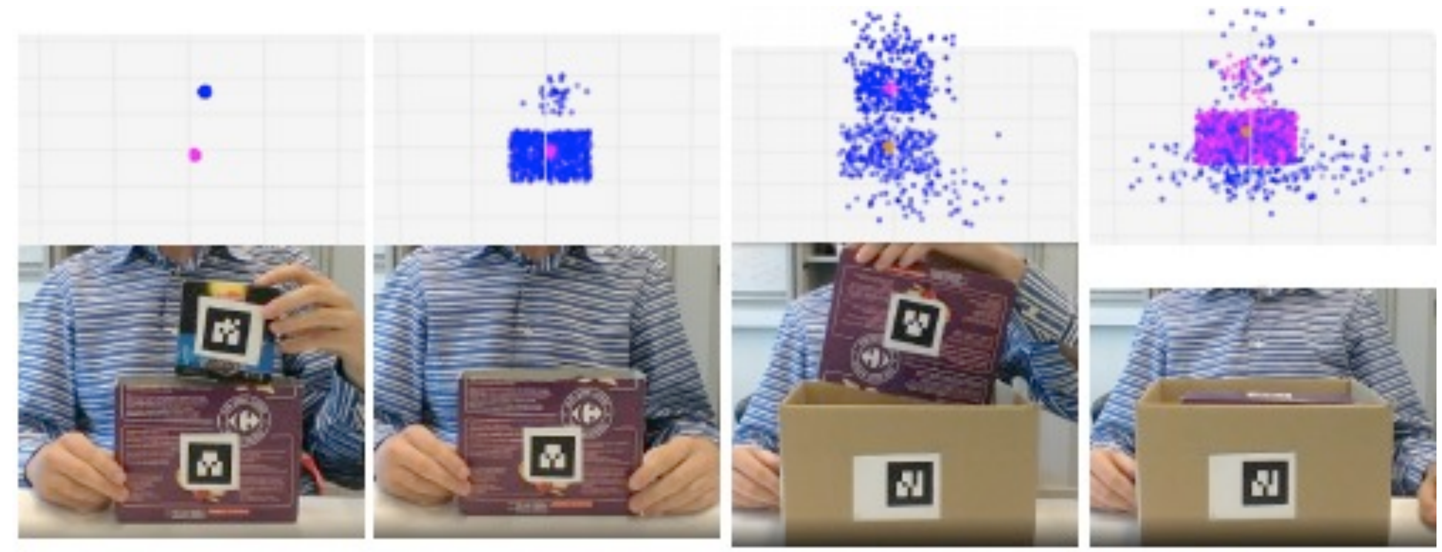
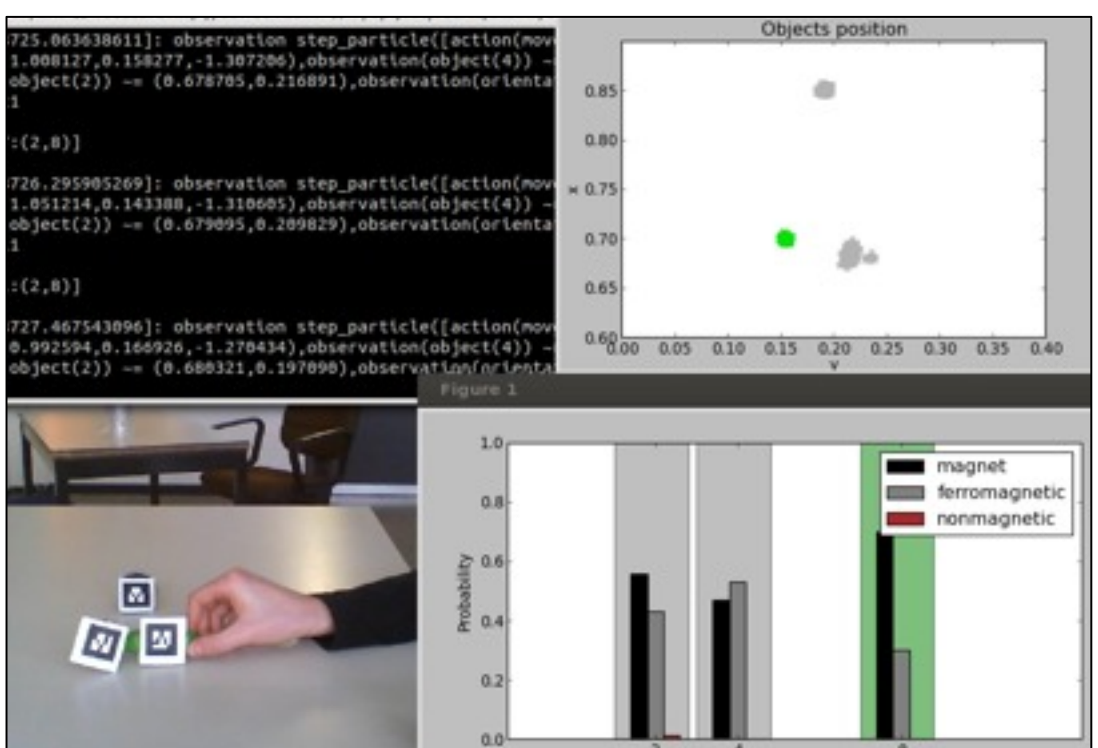


(a) cube on the box (b) cube inside the box (c) rotated box on a beige box (d) cube and box inside the beige box

Box scenario

- object tracking even when invisible
- estimate spatial relations



[Nitti et al, IEEE/RSJ 13]

Overview

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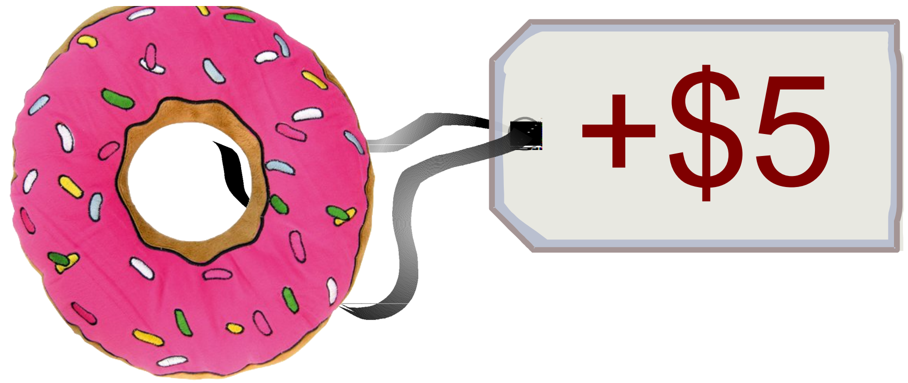
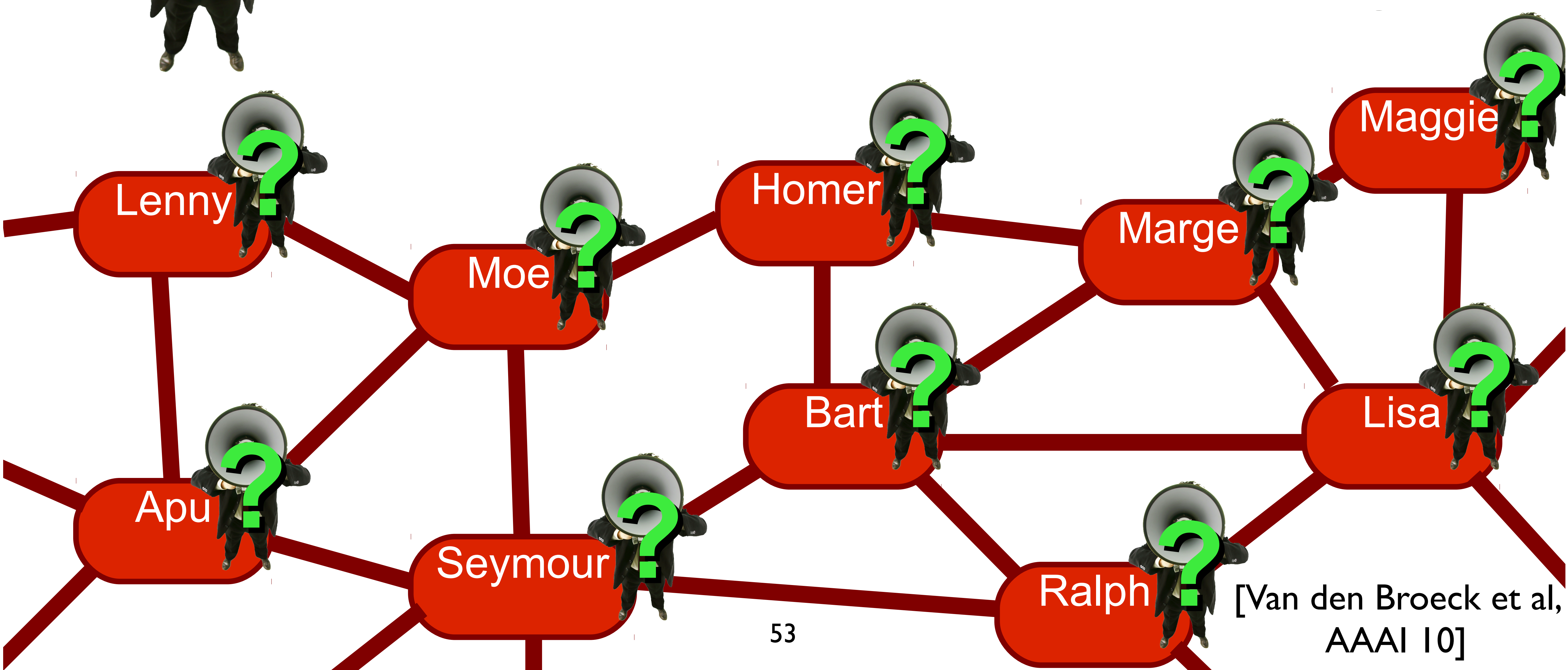
Viral Marketing

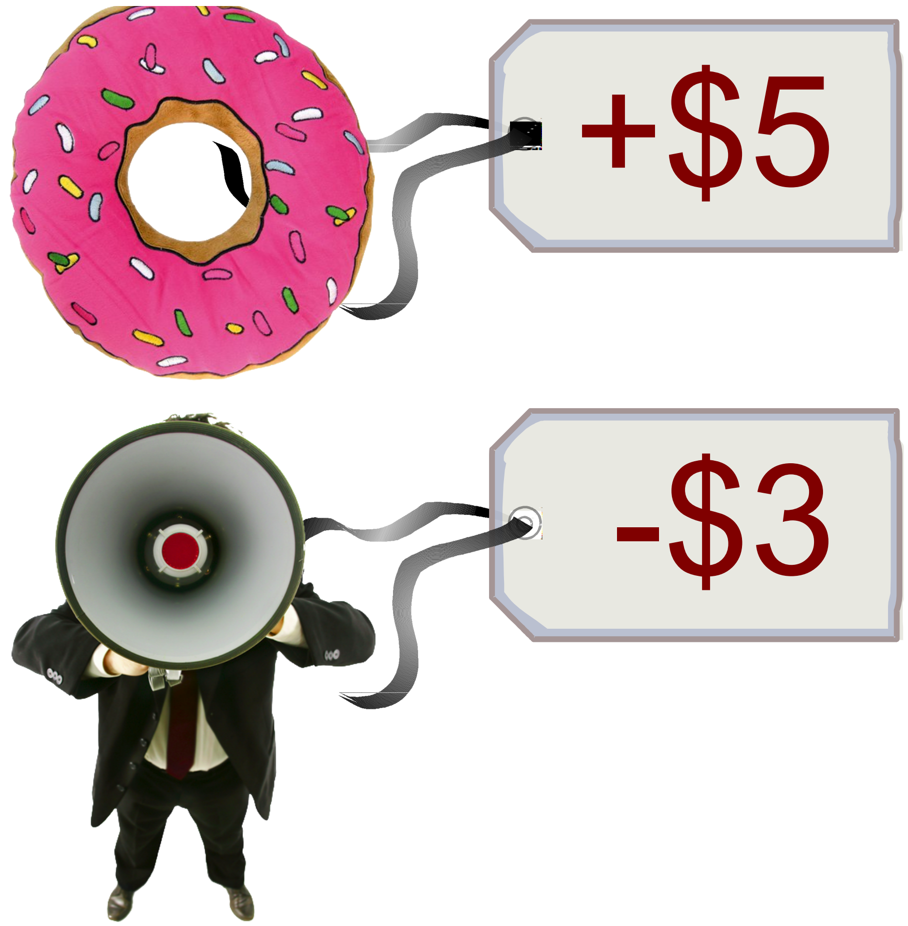


Which advertising strategy maximizes expected profit?

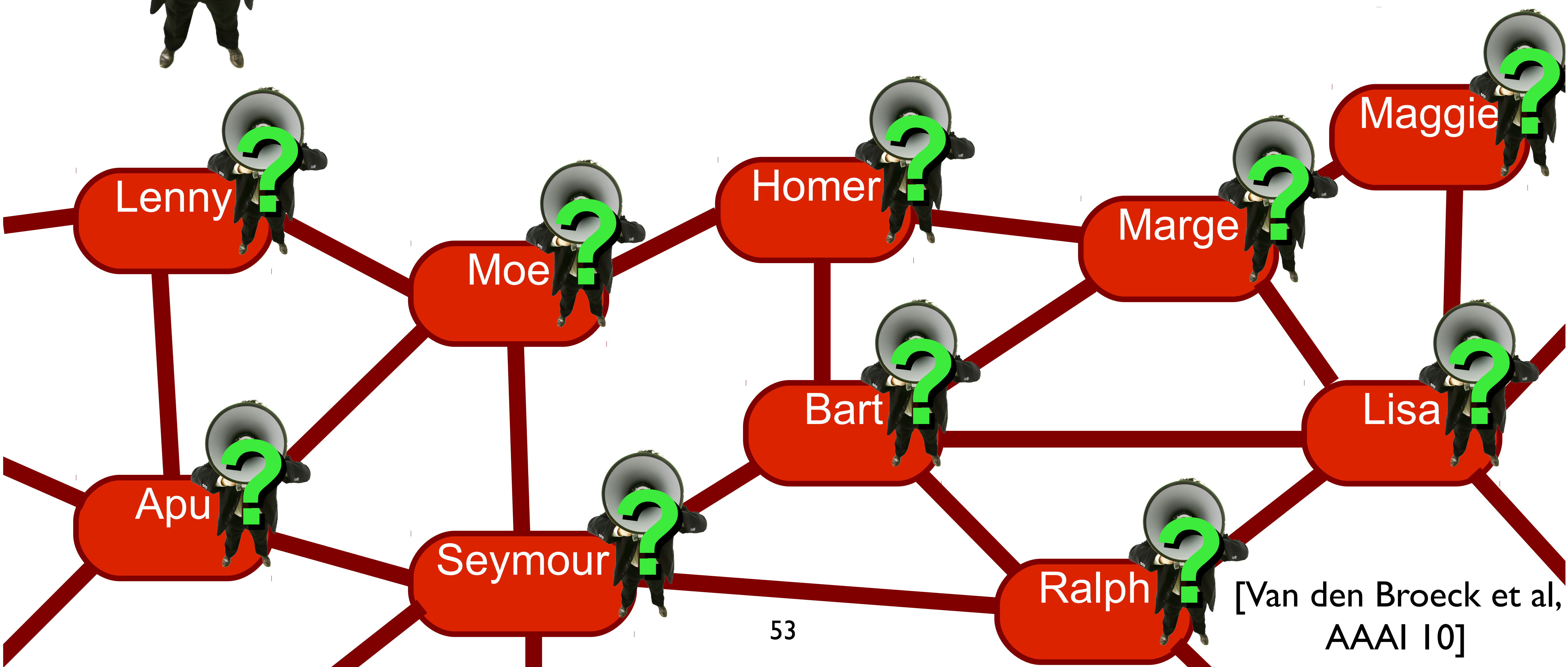


[Van den Broeck et al, AAAI 10]

Viral Marketing

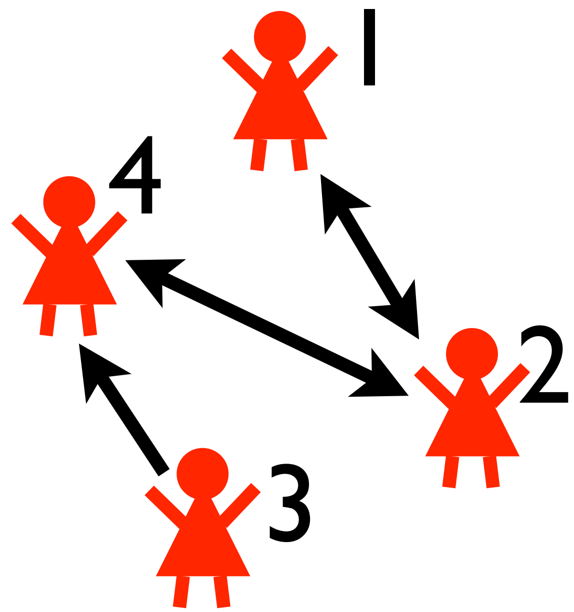


decide truth values of some atoms



[Van den Broeck et al, AAAI 10]

DTProbLog



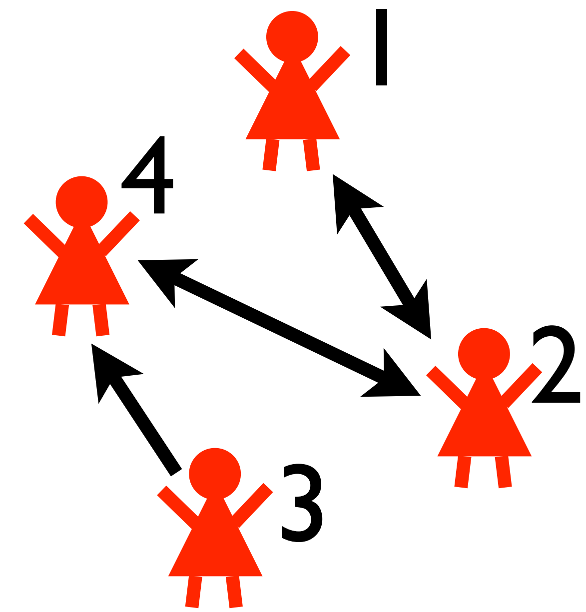

```
person(1).
person(2).
person(3).
person(4).

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?

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DTProbLog

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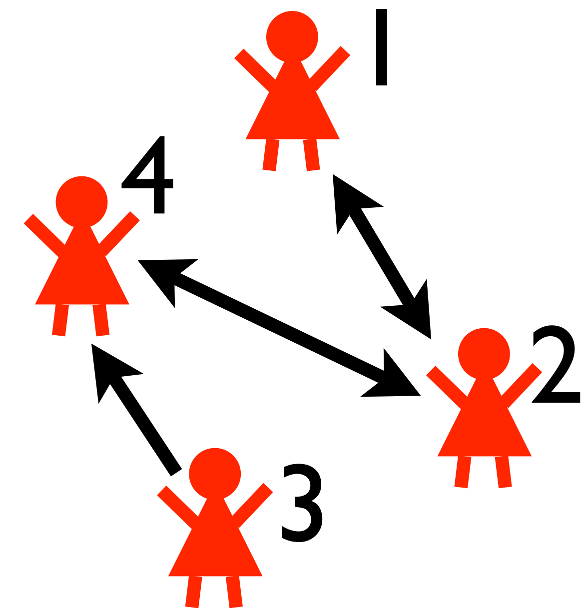
buys(X) :- marketed(X), buy_marketing(X).
```

probabilistic facts
+ logical rules

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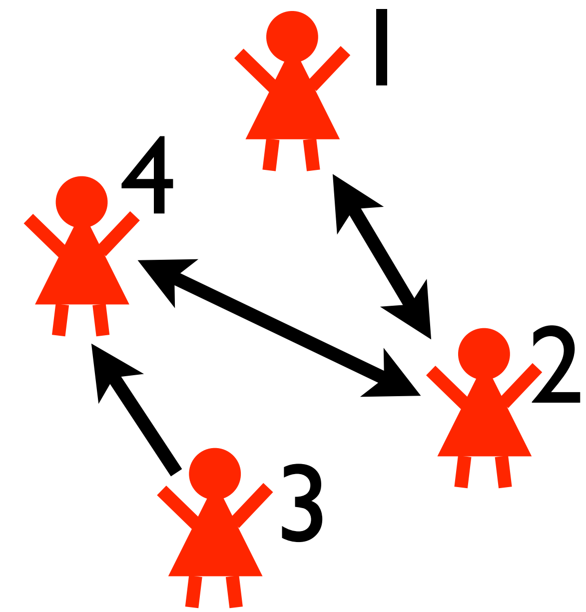


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buys(P) => 5 :- person(P).
marketed(P) => -3 :- person(P).
```

utility facts: cost/reward if true

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person(1).
person(2).
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friend(2,1).
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DTProbLog

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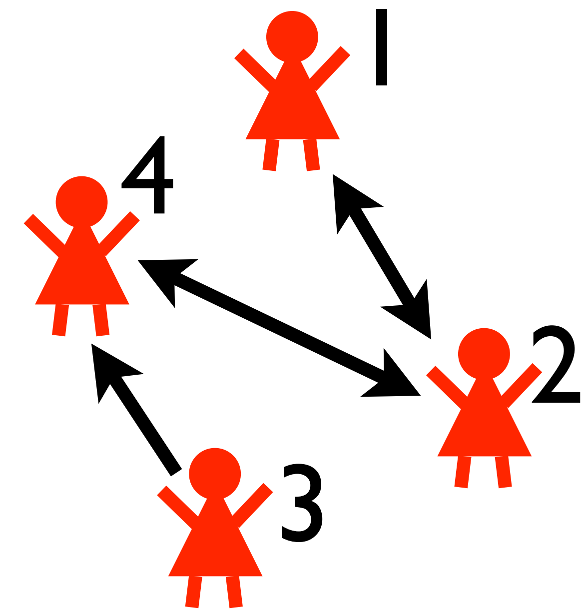


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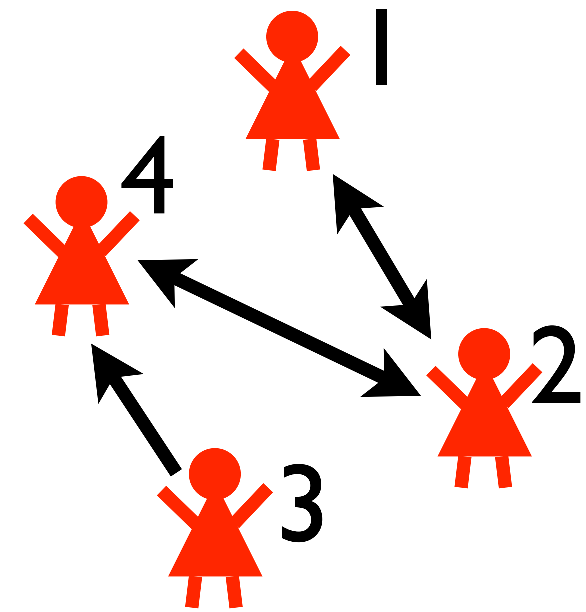


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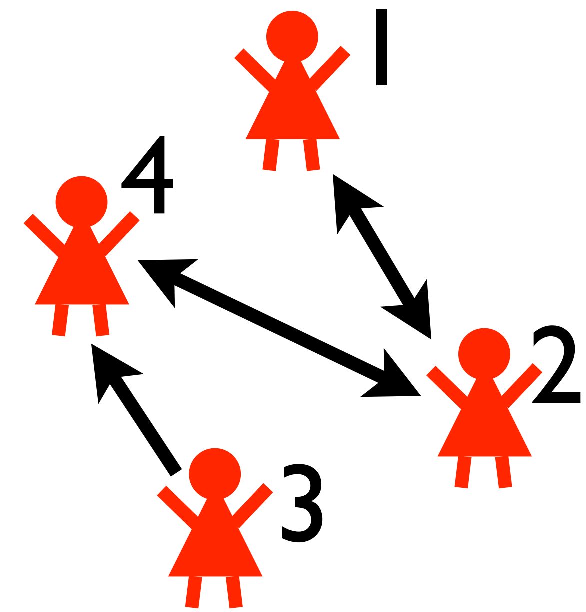


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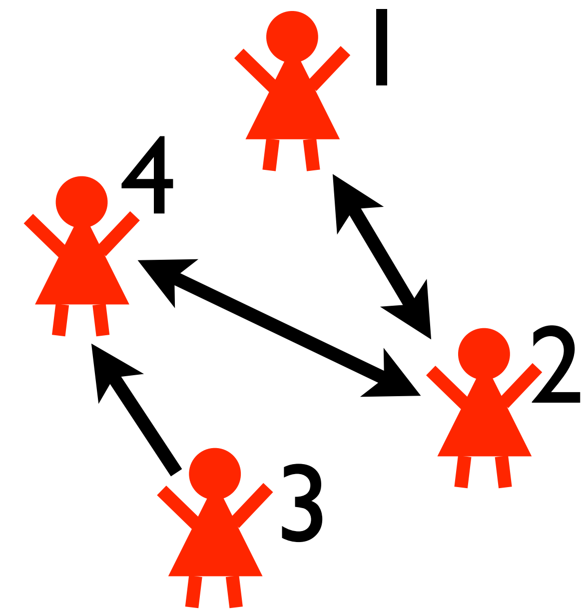
```

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

DTProbLog

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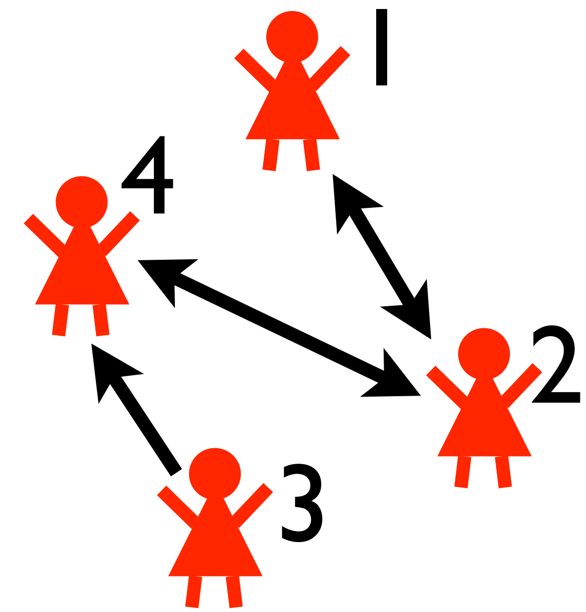
```

```
marketed(1)          marketed(3)

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

DTProbLog

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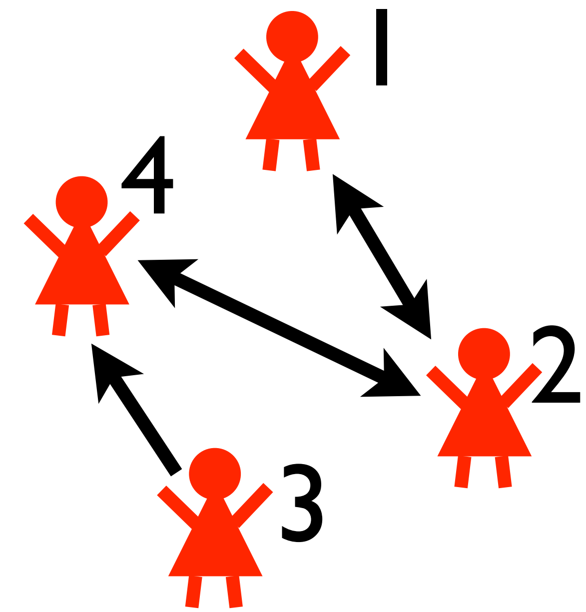
buys(1)      buys(2)
```

DTProbLog

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```

utility = −3 + −3 + 5 + 5 = 4

probability = 0.0032

```
marketed(1)        marketed(3)

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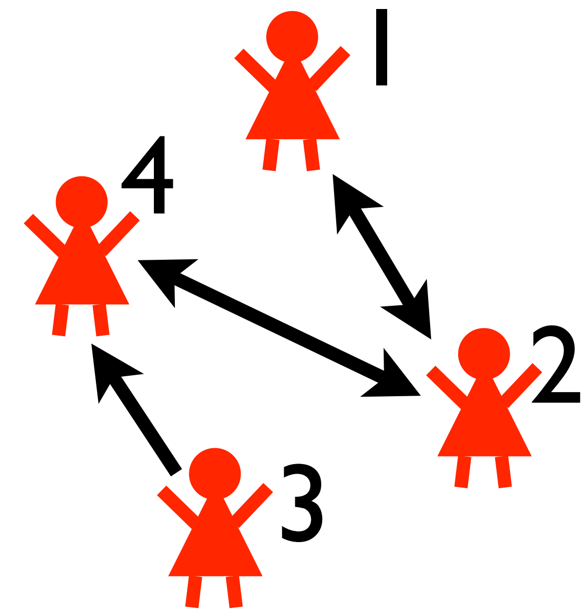
DTProbLog

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```
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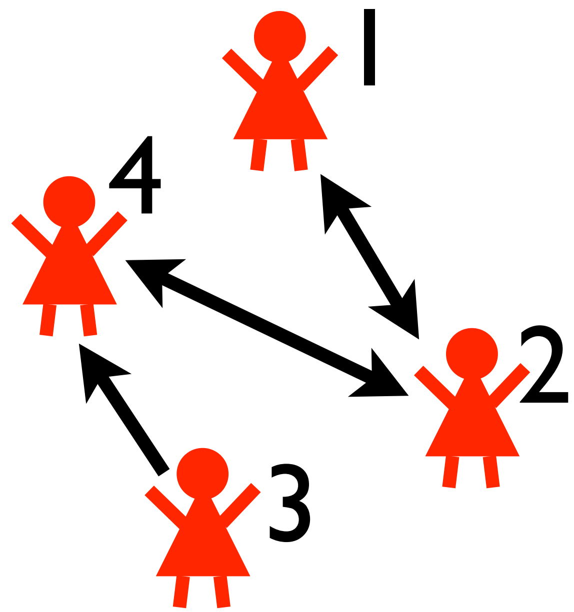
buys(1)     buys(2)
```

world contributes 0.0032×4 to expected utility of strategy

DTProbLog

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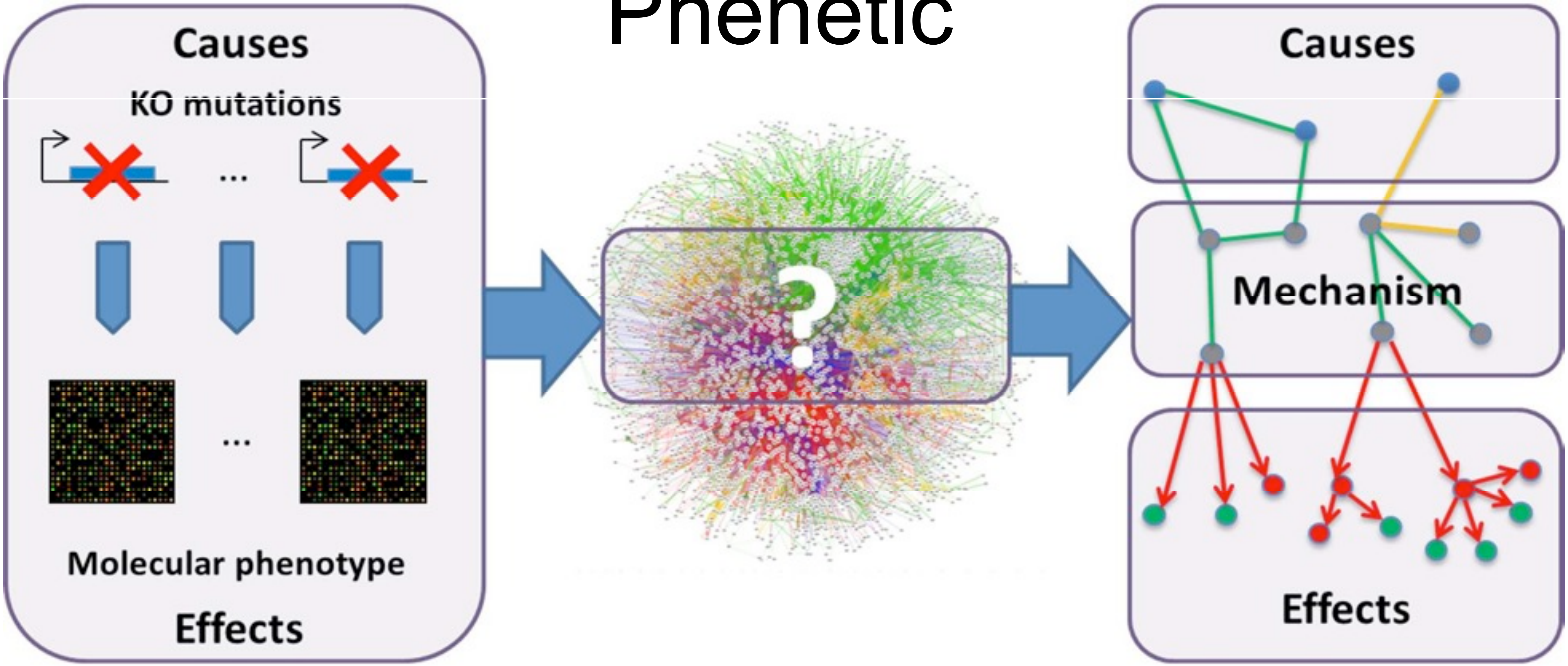
friend(4,2).
```

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

Phenetic



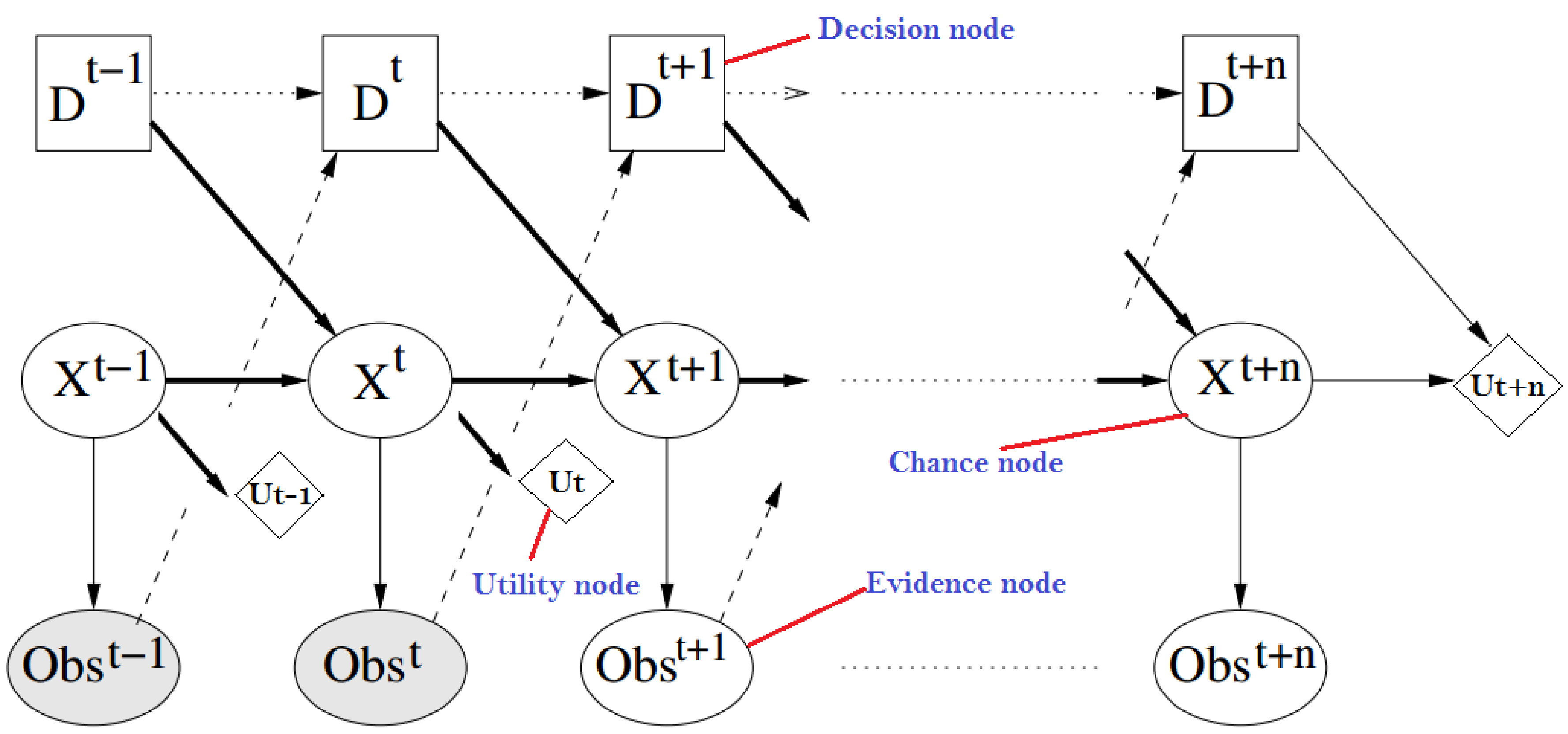
- Causes: Mutations
  - All related to similar phenotype
- Effects: Differentially expressed genes
- 27 000 cause effect pairs

- 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]

Dynamic Decision Network



Use non-functional requirements and quality of context to make decisions based on the outcome of previous decisions

Pick-a-caregiver scenario:
Decide which caregiver to call in case of an emergency by optimising over the probability distribution over her availability and locality and the non-functional requirements evaluated on previous decisions.

[Naqvi, Preuveneers, Meert & Berbers]

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  - Continuous-valued random variables
  - Decision making
  - Constraints

cProbLog: constraints on possible worlds

```
weight(skis,6).
weight(boots,4).
weight(helmet,3).
weight(gloves,2).

P::pack(Item) :-
  weight(Item,Weight),
  P is 1.0/Weight.

excess(Limit) :- ...

not excess(10).
pack(helmet) v pack(boots).
```


[Fierens et al, PP 12; Shterionov et al]

cProbLog: constraints on possible worlds

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weight(skis,6).
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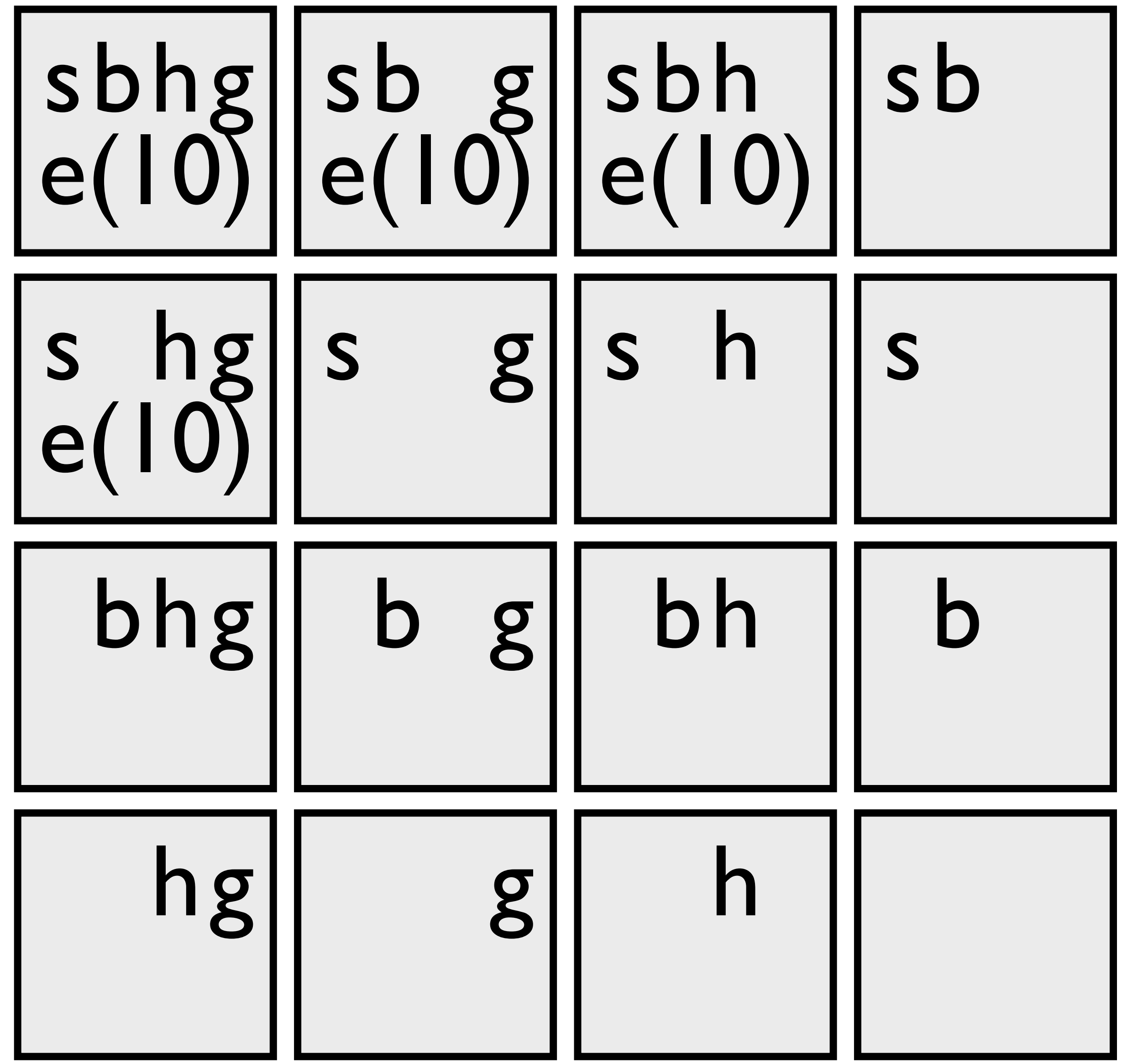
```

distribution over **all** possible worlds



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```

sbhg e(10)	sb g e(10)	sbh e(10)	sb
s hg e(10)	s g	s h	s
bhg	b g	bh	b
hg	g	h	

constraints as first-order logic formulas

[Fierens et al, PP 12; Shterionov et al]

cPobLog: constraints on possible worlds

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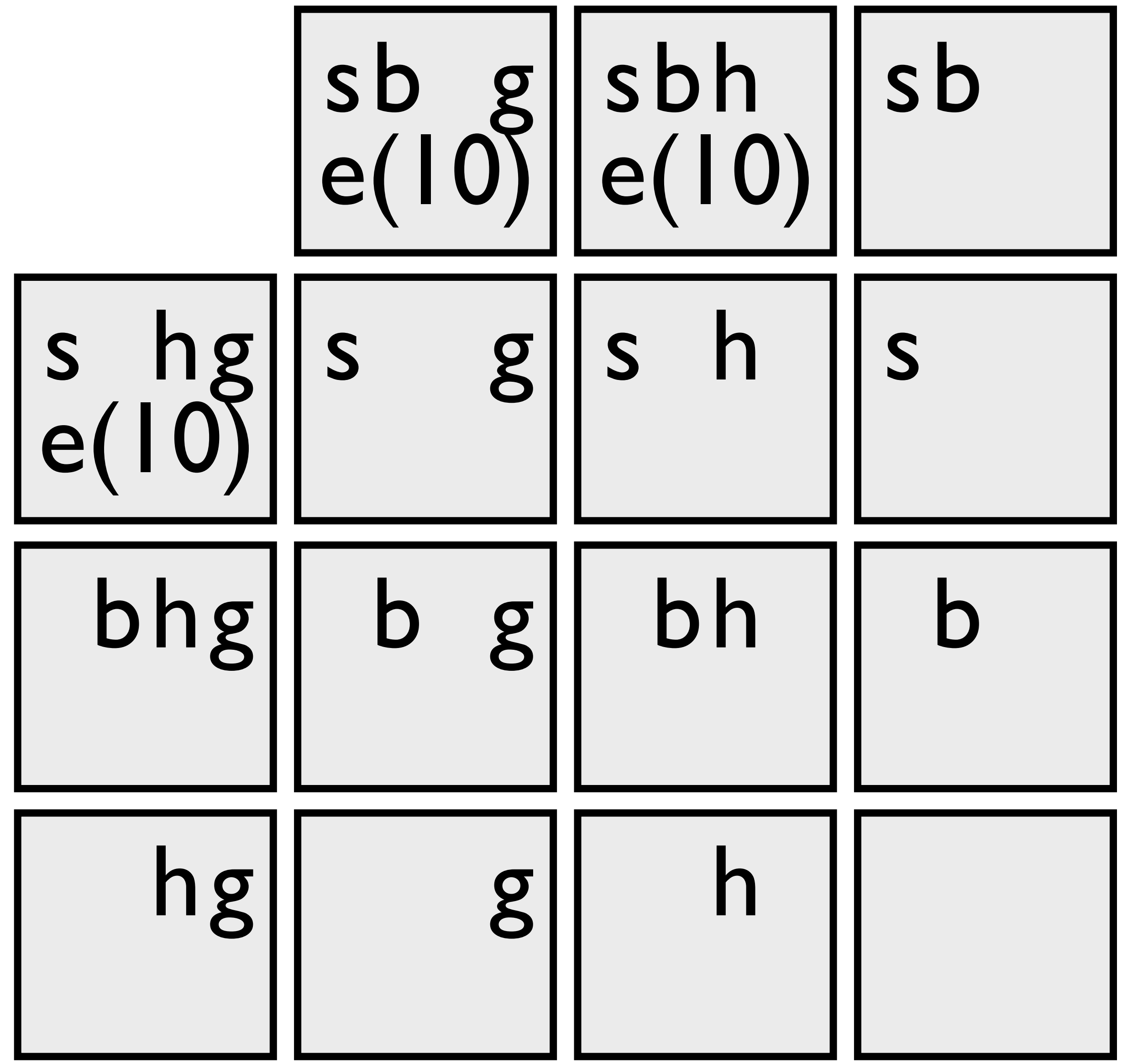
constraints as first-order logic formulas



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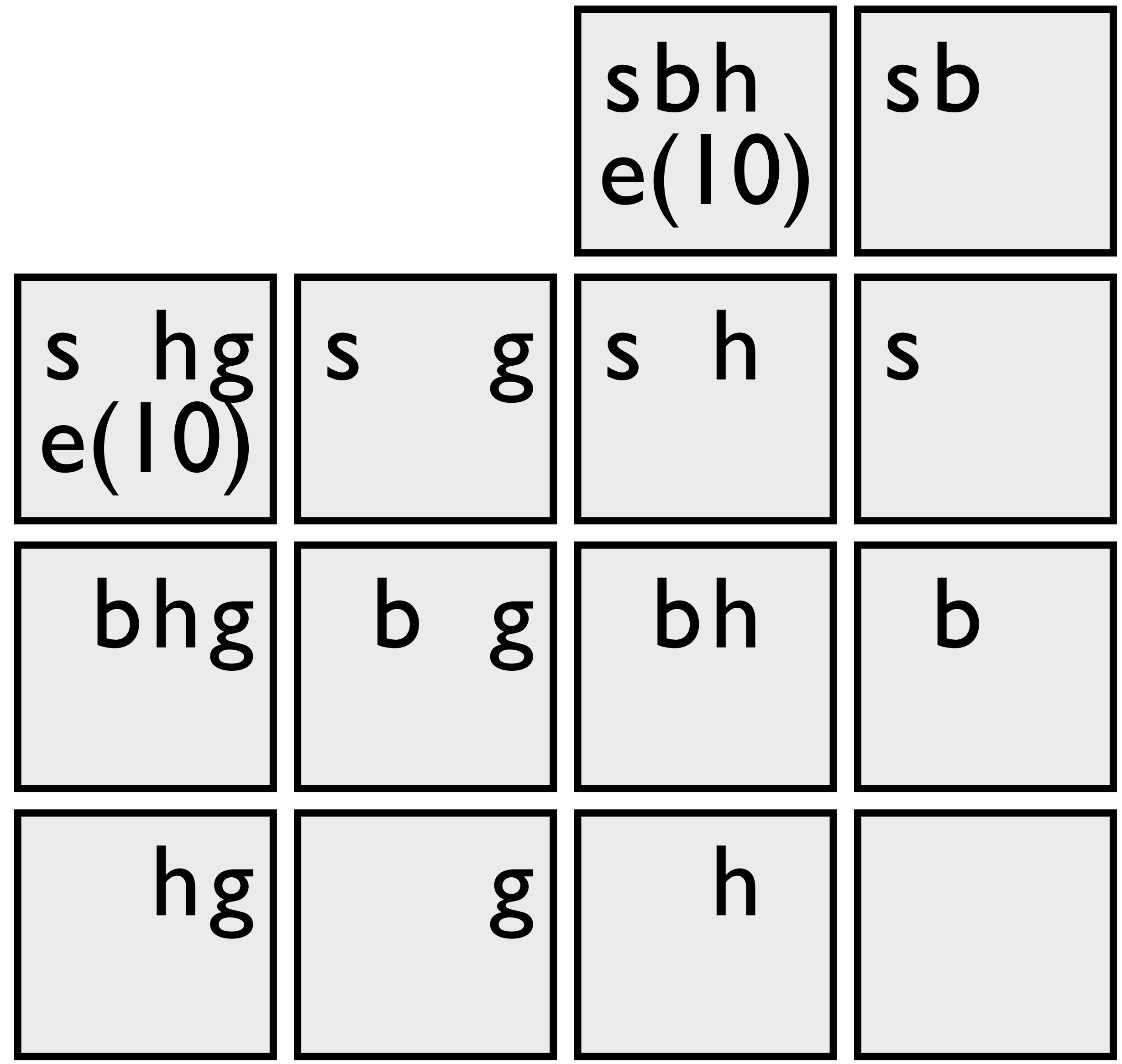

constraints as first-order logic formulas

[Fierens et al, PP 12; Shterionov et al]

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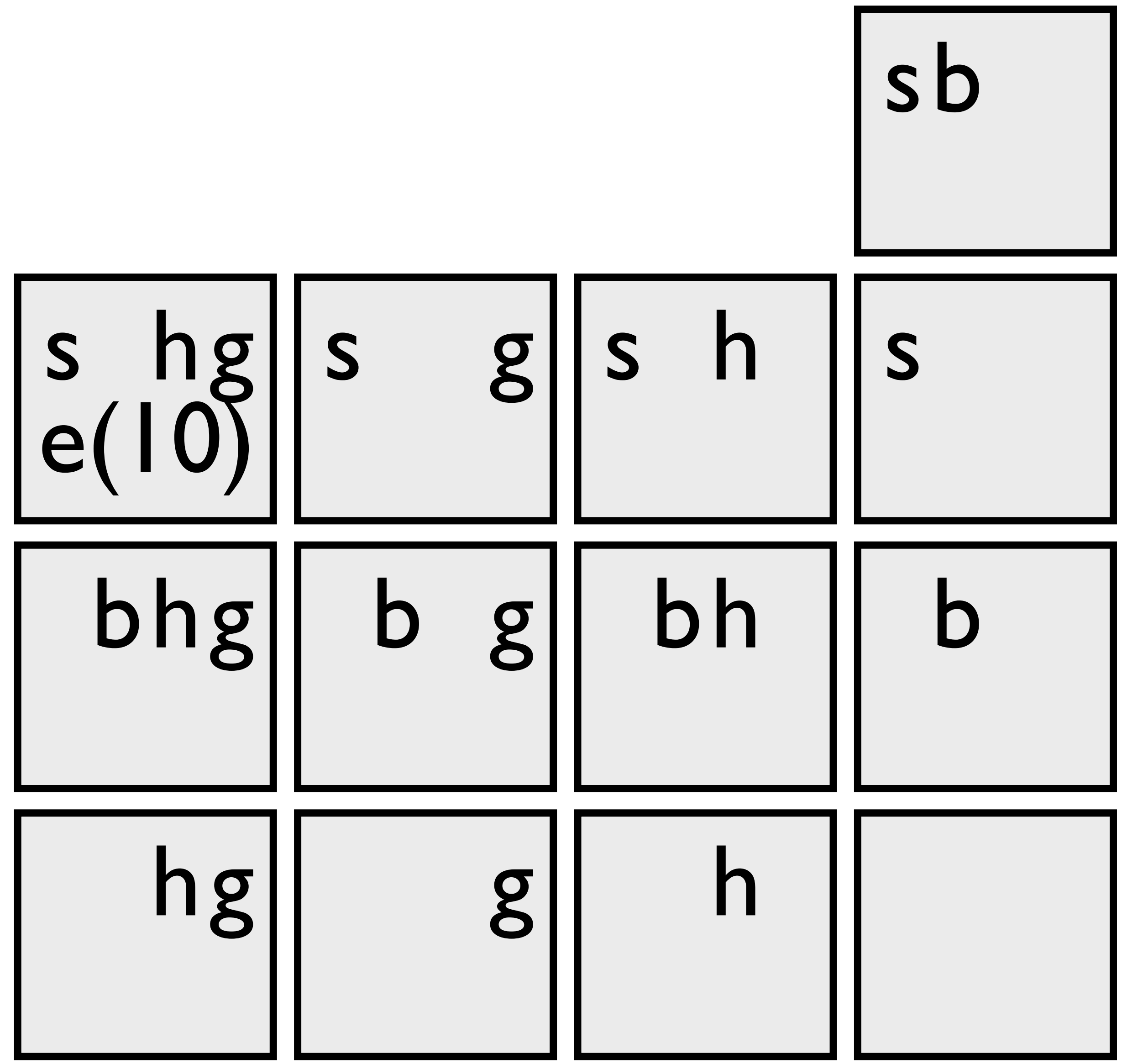

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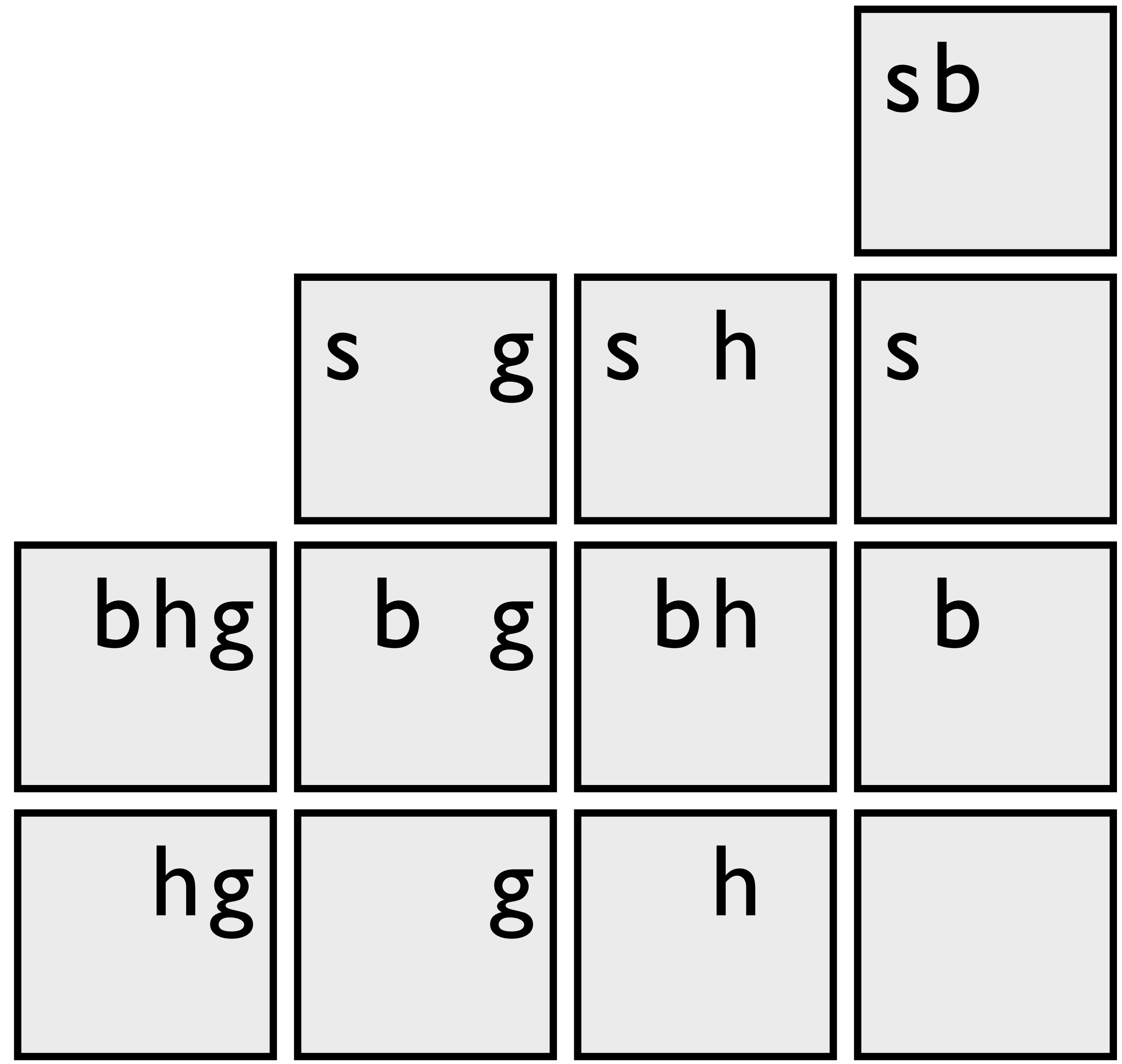

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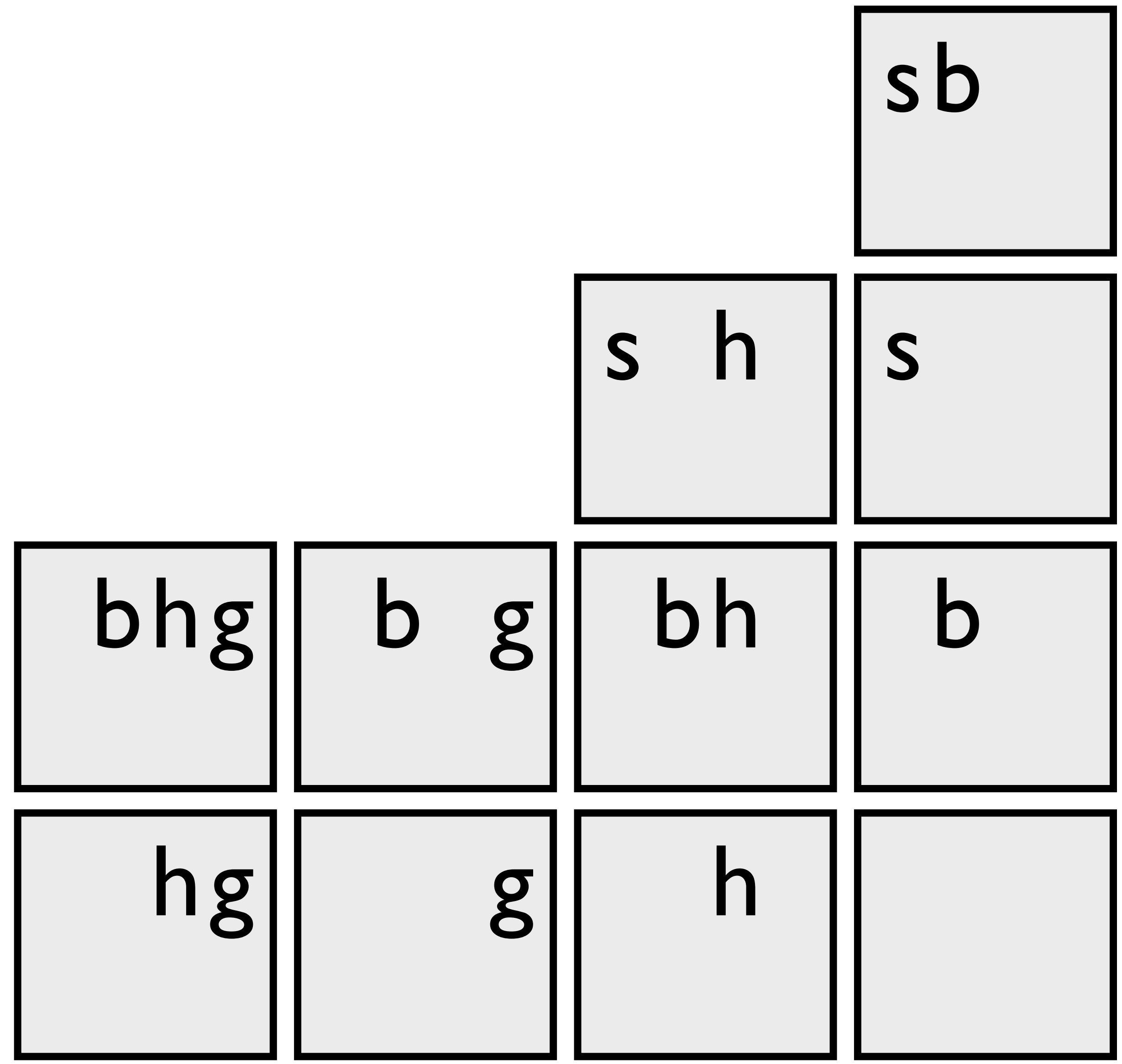

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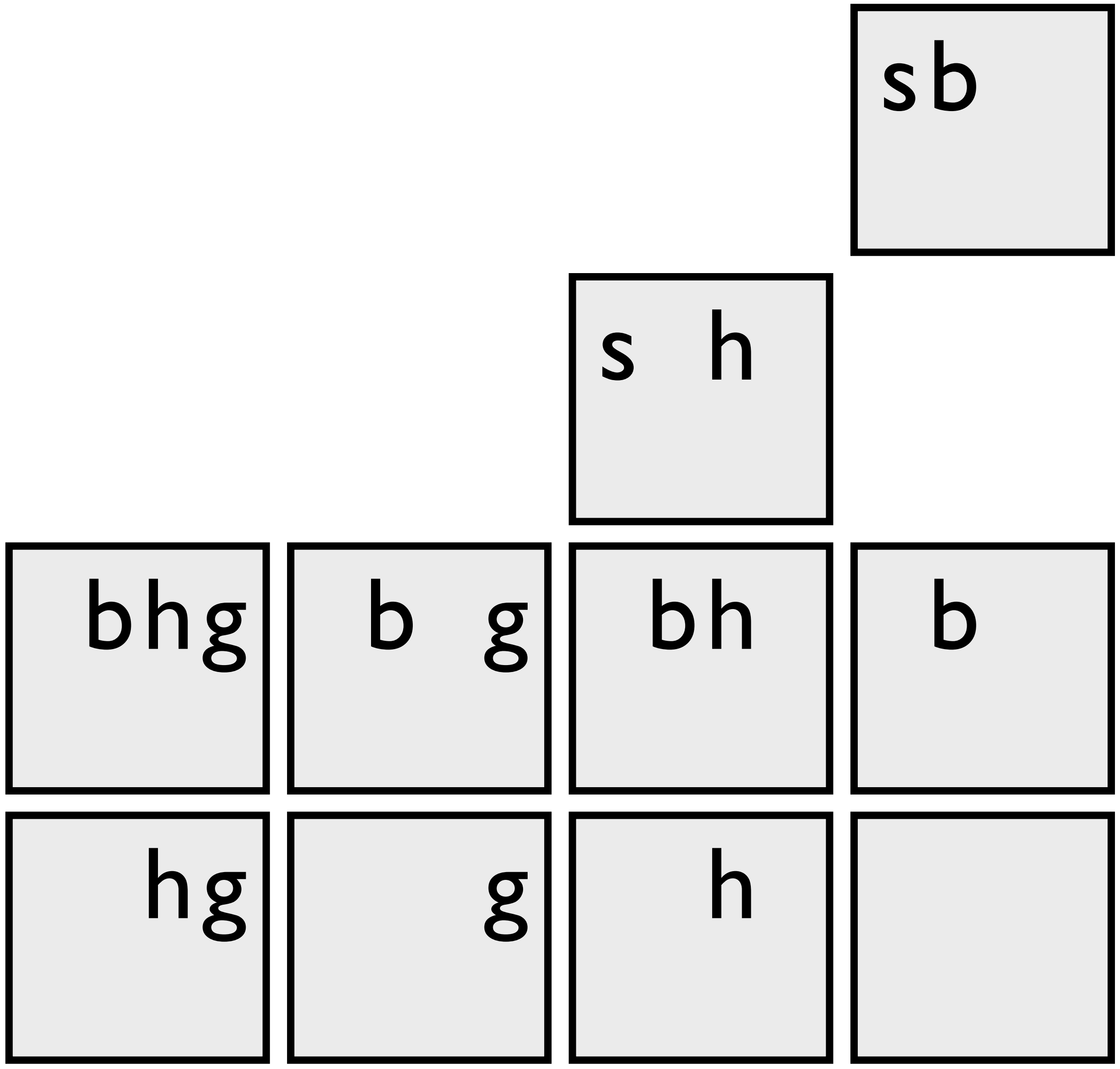
```

constraints as first-order logic formulas



[Fierens et al, PP 12; Shterionov et al]

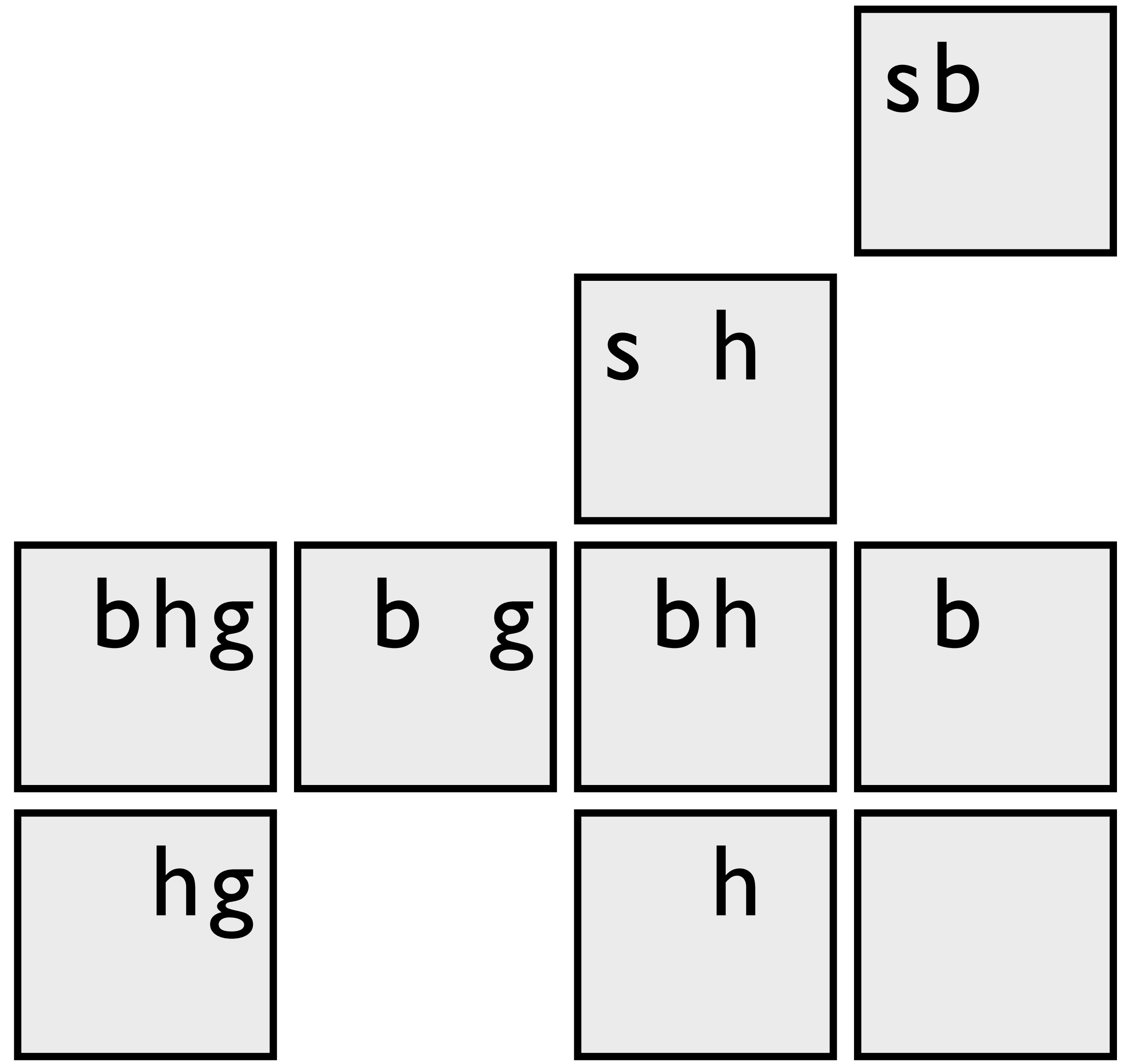
cProbLog: constraints on possible worlds

```
weight(skis,6).
weight(boots,4).
weight(helmet,3).
weight(gloves,2).

P::pack(Item) :-
   weight(Item,Weight),
   P is 1.0/Weight.

excess(Limit) :- ...

not excess(10).
pack(helmet) v pack(boots).
```



constraints as first-order logic formulas

[Fierens et al, PP 12; Shterionov et al]

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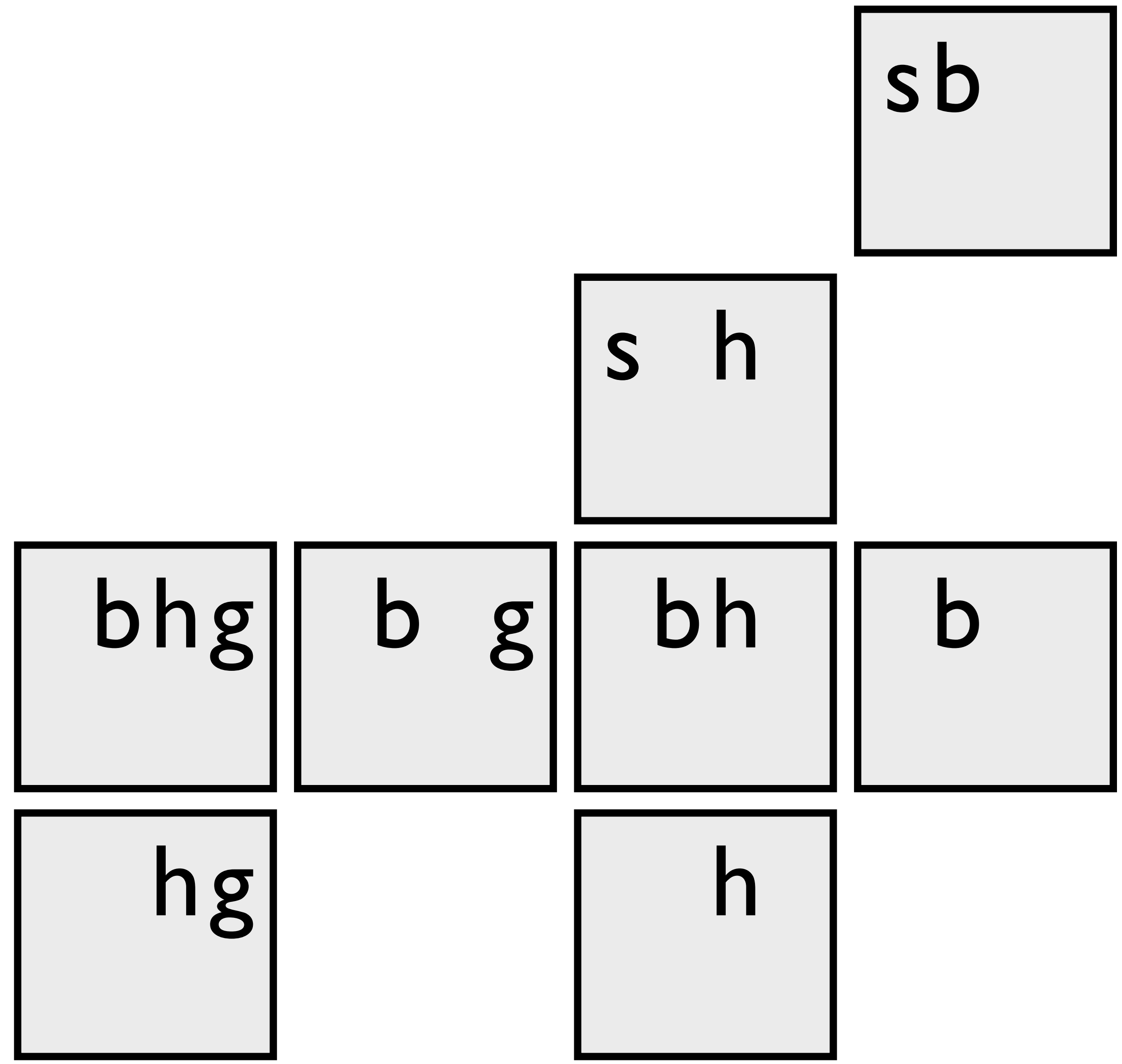

[Fierens et al, PP 12; Shterionov et al]

cProbLog: constraints on possible worlds

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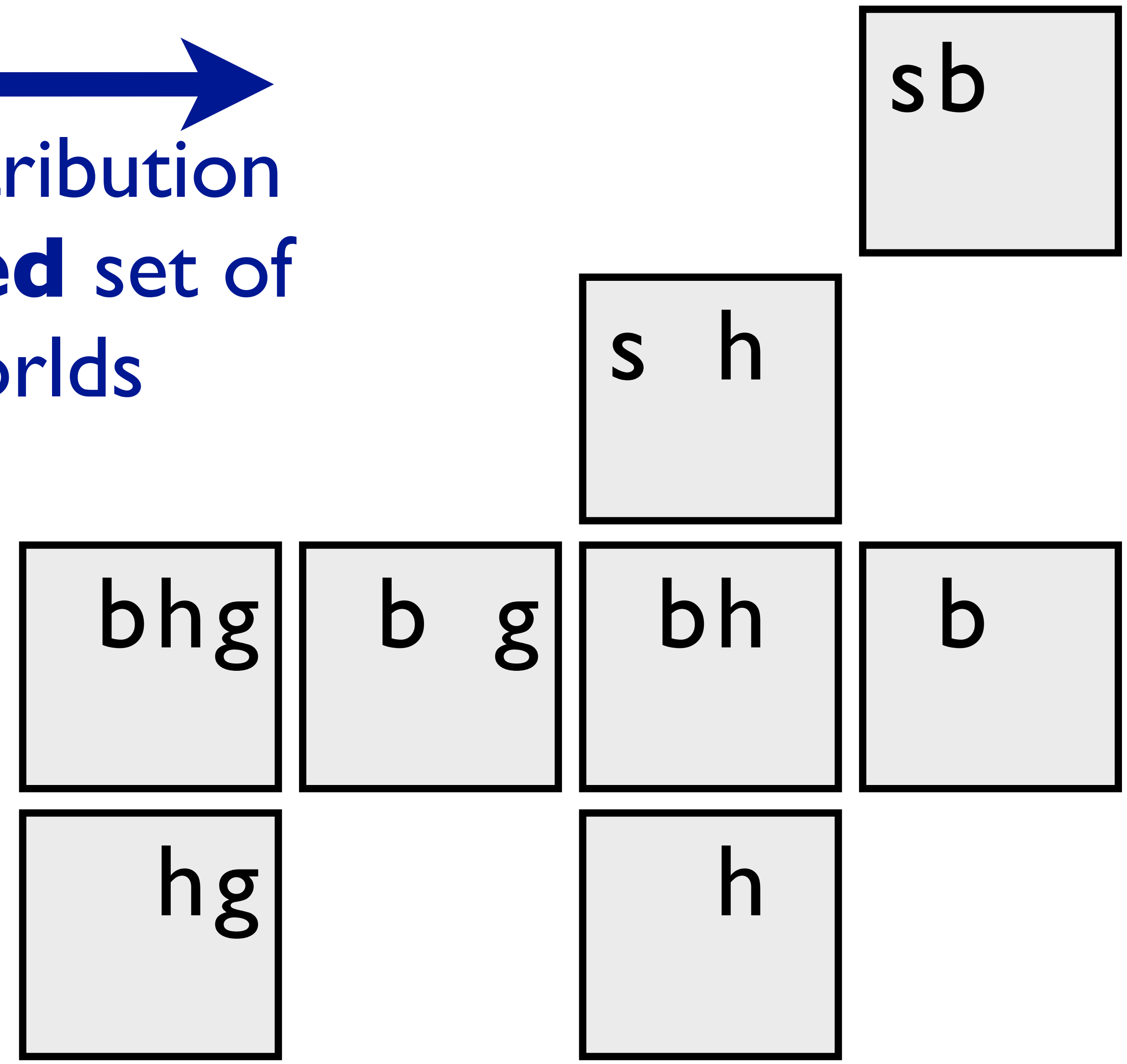
normalized distribution over **restricted** set of possible worlds



constraints as first-order logic formulas

[Fierens et al, PP 12; Shterionov et al]

Summary

- ProbLog Basics
  - ProbLog = probabilistic choices + logical consequences
  - Inference: MPE, marginals, conditional probabilities
  - Parameter learning from (partial) interpretations
- Selected Topics
  - Upgrading relational learning
  - Dynamics under uncertainty
  - Continuous-valued random variables
  - Decision making
  - Constraints

Getting started

- http://dtai.cs.kuleuven.be/problog
  - interactive tutorial
  - online interface for inference and parameter estimation
  - offline version for download

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Daan Fierens
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Thanks!

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