

# T1: Data models and query languages

## L6: Datalog vs. Stable models

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CS7240 Principles of scalable data management (sp20)

<https://northeastern-datalab.github.io/cs7240/sp20/>

Version 1/24/2020

# Outline: Datalog

- Datalog
  - Datalog rules
  - Recursion
  - Semantics
  - Datalog<sup>¬</sup>: Negation, stratification
  - Datalog<sup>±</sup>
  - Stable model semantics (Answer set programming)
  - Datalog vs. RA
  - Naive and Semi-naive evaluation

# Answer Set Programming

- Programming paradigm that can model AI problems (e.g, planning, combinatorics)
- Basic idea
  - Allow non-stratified negation and encode problem (specification & "instance") as logic program rules
  - Solutions are **stable models** of the program
- Semantics based on Possible Worlds and Stable Models
  - Given an answer set program, there can be **multiple solutions** (stable models, answer sets)
  - Each model: assignment of true/false value to propositions to make all formulas true.
  - Captures default reasoning, non-monotonic reasoning, constrained optimization, exceptions, weak exceptions, preferences, etc., in a natural way
- Finding stable models of answer set programs is not easy
  - Current systems CLASP, DLV, Smodels, etc., extremely sophisticated
  - Work by grounding the program, suitably transforming it to a propositional theory whose models are stable models of the original program
  - These models found using a SAT solver

# Rules with Negation

- Closed world assumption
  - If a fact does not logically follow from a set of Datalog clauses, then we conclude that the negation of this fact is true.
- Problem: multiple minimal models ("Herbrand models")
  - `boring(chess) :- not interesting(chess)`
  - $H_a = \{interesting(chess)\}$ ,  $H_b = \{boring(chess)\}$

# Semantics: Informally

- Informally, a **stable model**  $M$  of a ground program  $P$  is a set of ground atoms such that

1. Every rule is satisfied:

i.e., for any rule in  $P$

$A :- B_1, \dots, B_m, \text{not } C_1, \dots, \text{not } C_n.$

if each  $B_j$  is satisfied ( $B_j$ 's are in  $M$ ) and **no**  $C_i$  is satisfied (i.e. no  $C_i$  is in  $M$ ), then  $A$  is in  $M$ .

2. Every  $A \in M$  can be derived from a rule by a "**non-circular reasoning**" (informal for: we are looking for **minimal models**)

$\langle \{a\} \rangle \{ \}$

$a :- a$

# Semantics: "non-circular" more formally

Idea: you guess a set of atoms. You then verify it is indeed exactly the set of atoms that "can be derived."

The **reduct** of  $P$  w.r.t  $M$  is:

$$P^M = \left\{ \begin{array}{l} \boxed{h \text{ :- } b_1, \dots, b_m.} \mid \\ \boxed{h \text{ :- } b_1, \dots, b_m, \text{ not } c_1, \dots, \text{ not } c_n.} \in P \wedge \text{no } C_i \in M \end{array} \right\}$$

$M$  is a **stable model** of  $P$  iff  $M$  is the least model of  $P^M$

# Examples



edge (a, b):-

P1: a :- a.

~~M={a}~~ not a stable model (not minimal, derivation of a is based on a circular reasoning)

M={} stable model

P2: a :- ~~not~~ b.

M={a} only stable model  
~~M={a}~~

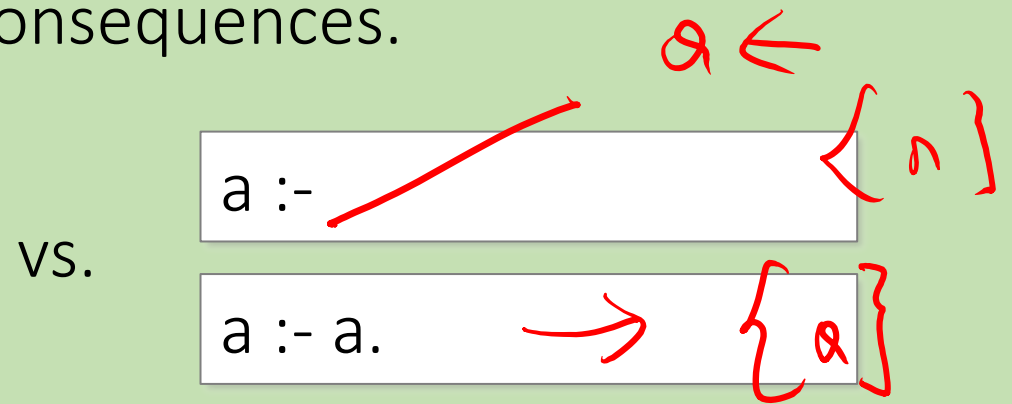
P3: a :- ~~not~~ a.

{ } ↔ { 0 }

{ a }

has no stable model

For a normal program without negation ("positive program"), its least model is the set of its atomic consequences.



# Examples



P4:  
a :- not b.  
b :- not a.

$M_1 = \{a\}$

$M_2 = \{b\}$

*two stable models*

~~$a : \neg b$~~

$a \leftarrow$

~~$b : \neg a$~~

P5:  
~~a :- not b.~~  
~~b :- not a.~~  
~~a :- not a.~~

$M = \{a\}$

*only stable model*

$a : \neg a$

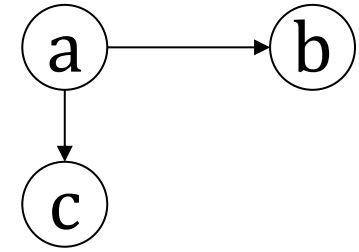
$a :$



# 3-colorability



Q: For a graph  $(V, E)$  find an assignment of one of 3 colors to each vertex such that no adjacent vertices share a color.



?

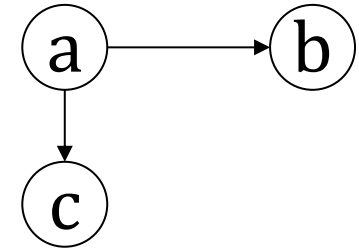
Convention in ASP:  
Capital letters are  
variables, small  
letters constants

Cp.  $edge(x,a)$   
vs.  $edge(x,'a')$

# 3-colorability



Q: For a graph  $(V, E)$  find an assignment of one of 3 colors to each vertex such that no adjacent vertices share a color.



vertex(a). vertex(b). vertex(c). edge(a,b). edge(a,c).

?

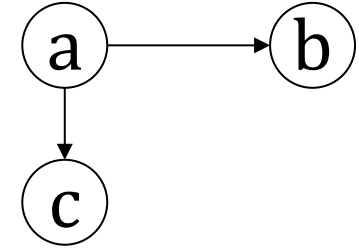
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# 3-colorability



Q: For a graph  $(V, E)$  find an assignment of one of 3 colors to each vertex such that no adjacent vertices share a color.



`vertex(a).` `vertex(b).` `vertex(c).` `edge(a,b).` `edge(a,c).`

`color(V,1) :- not color(V,2), not color(V,3), vertex(V).`

`color(V,2) :- not color(V,3), not color(V,1), vertex(V).`

`color(V,3) :- not color(V,1), not color(V,2), vertex(V).`

?

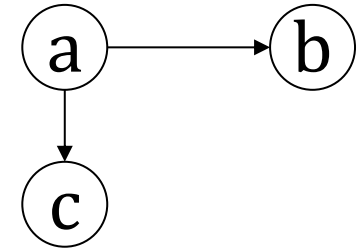
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*Cp. `edge(X,a)`  
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# 3-colorability



Q: For a graph  $(V, E)$  find an assignment of one of 3 colors to each vertex such that no adjacent vertices share a color.



*E, B*

`vertex(a). vertex(b). vertex(c). edge(a,b). edge(a,c).`

`color(V,1) :- not color(V,2), not color(V,3), vertex(V).`

`color(V,2) :- not color(V,3), not color(V,1), vertex(V).`

`color(V,3) :- not color(V,1), not color(V,2), vertex(V).`

`:- edge(V,U), color(V,C), color(U,C).`

Convention in ASP:  
Capital letters are  
variables, small  
letters constants

Cp. `edge(X,a)`  
vs. `edge(x,'a')`



# Data Conflict Resolution Using Trust Mappings

SIGMOD 2010

Paper: <http://portal.acm.org/citation.cfm?id=1807167.1807193>

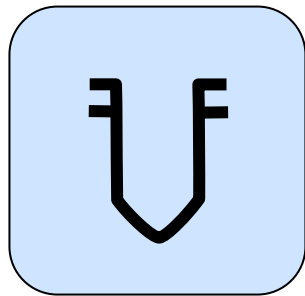
Full version with proofs: <http://arxiv.org/pdf/1012.3320>

Old Project web page: <https://db.cs.washington.edu/projects/beliefdb/>

# Problem in social data: often no single ground truth

## The Indus Script\*

What is the origin  
of this glyph?



\* Current state of knowledge on the Indus Script: Rao et al., Science 324(5931):1165, May 2009

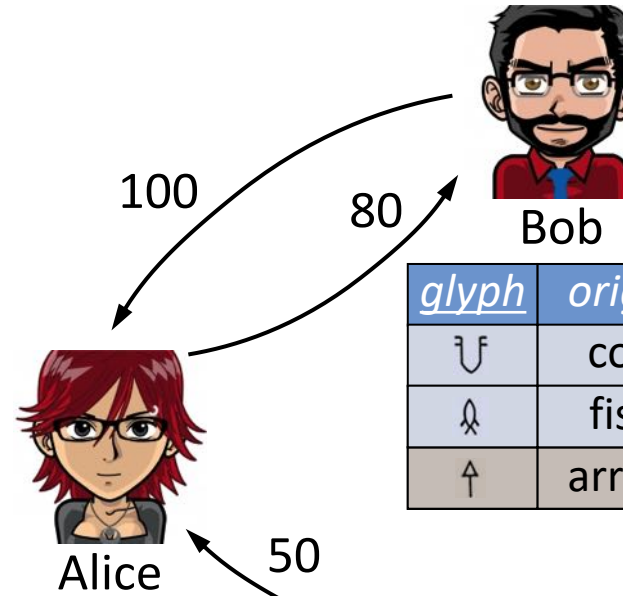
# Background: Conflicts & Trust in Community DBs

## Conflicting beliefs

<i>glyph</i>	<i>origin</i>
∪	ship hull
∪	cow
∪	jar
⊗	fish
⊗	knot
↑	arrow

“Beliefs”: annotated  
(key,value) pairs

Alice  
Bob  
Charlie  
Bob  
Charlie  
Charlie



<i>glyph</i>	<i>origin</i>
∪	cow
⊗	fish
↑	arrow

Bob

“Explicit belief”

## Trust mappings

Alice ← Bob	(100)
Alice ← Charlie	(50)
Bob ← Alice	(80)

Priorities

<i>glyph</i>	<i>origin</i>
∪	ship hull
⊗	fish
↑	arrow

“Implicit belief”

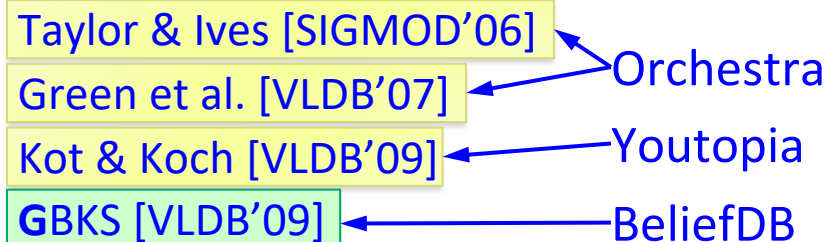
Alice



Charlie

<i>glyph</i>	<i>origin</i>
∪	jar
⊗	knot
↑	arrow

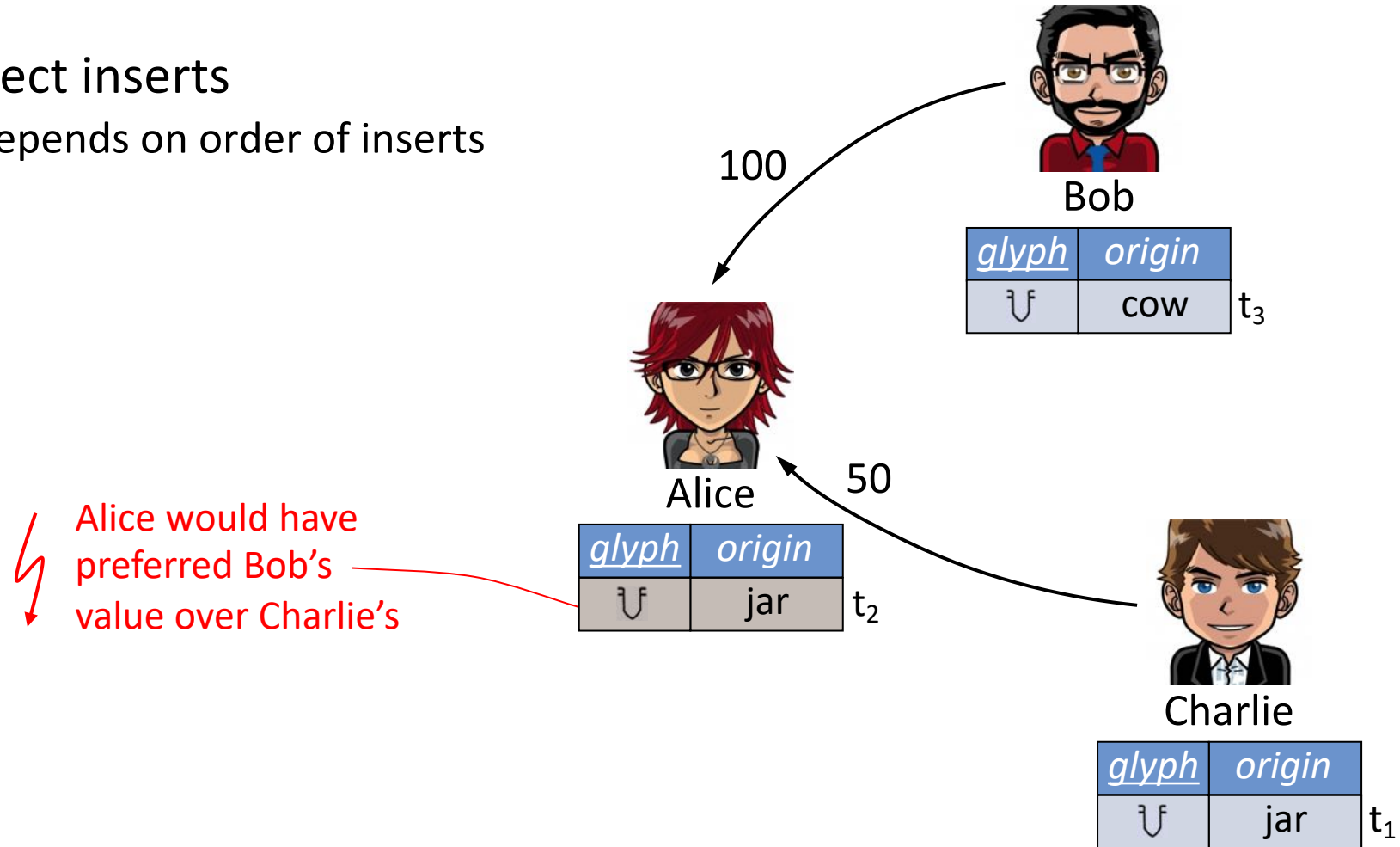
## Recent work on community databases:



# Limitations of previous work: transient effects

## 1. Incorrect inserts

- Value depends on order of inserts

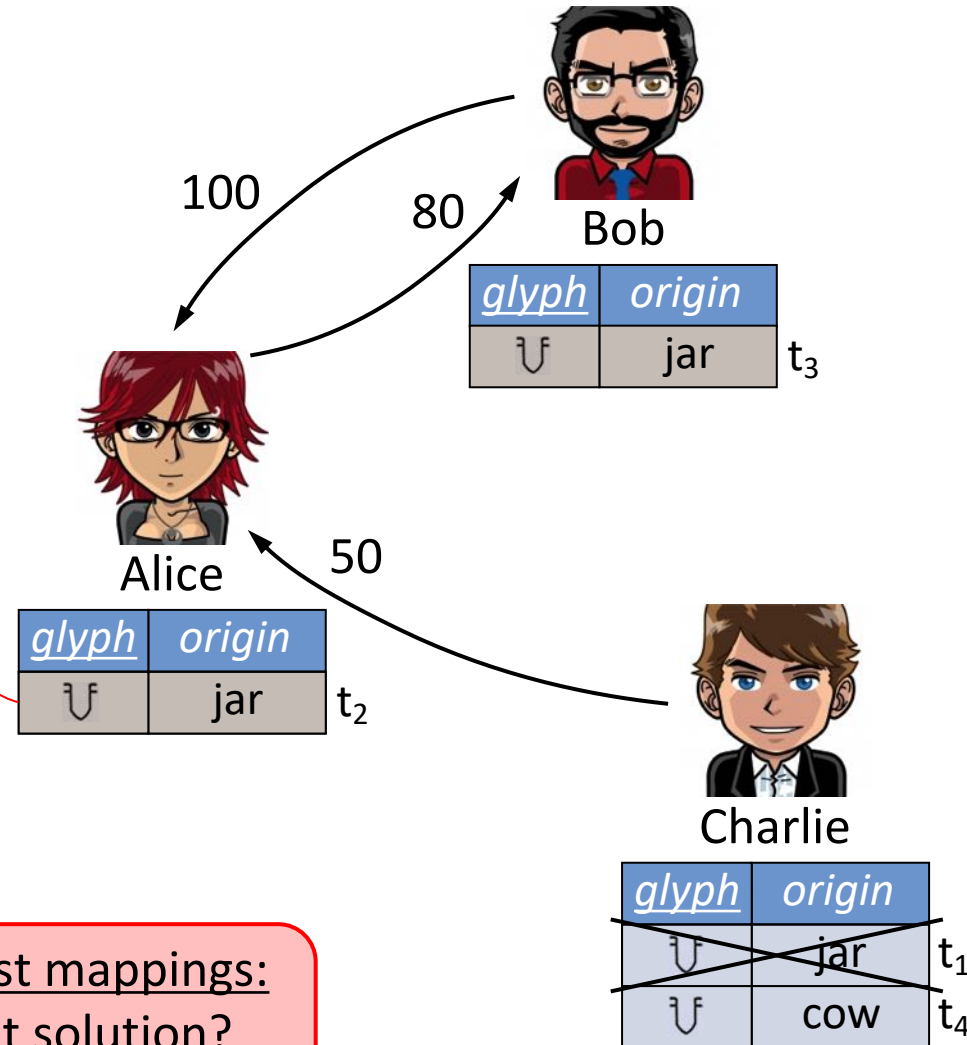




# Limitations of previous work: transient effects

1. Incorrect inserts
  - Value depends on order of inserts
2. Incorrect updates
  - Mis-handling of revokes

⚡ Alice and Bob trust each other most, but have lost “justification” for their beliefs



## Automatic conflict resolution with trust mappings:

1. How to define a globally consistent solution?
2. How to calculate it efficiently?
- (3. Several extensions)

GS [Sigmoid'10]

# Agenda

## 1. Stable solutions

- how to define a unique and consistent solution?

## 2. Resolution algorithm

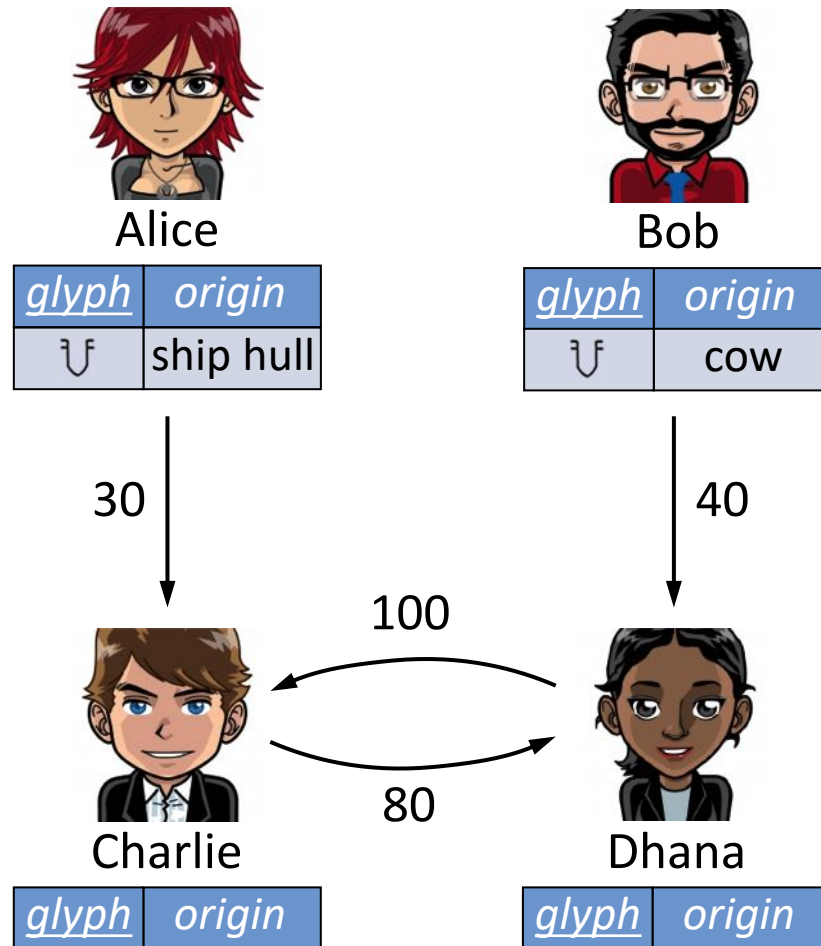
- how to calculate the solution efficiently?

## 3. Extensions

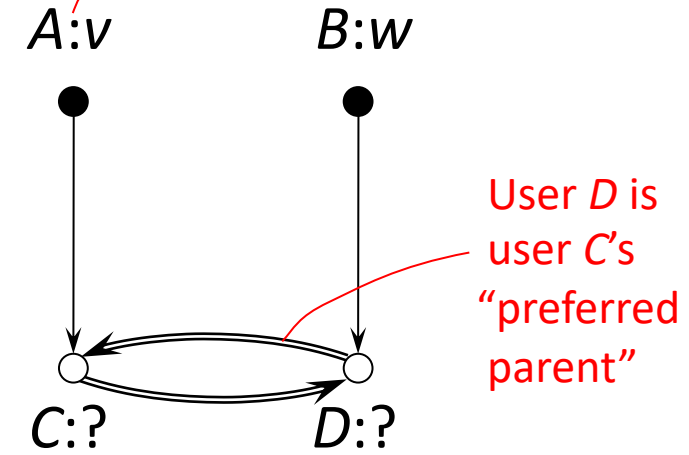
- how to deal with “negative beliefs”?

# Binary Trust Networks (BTNs)

To simplify presentation: focus on binary TNs



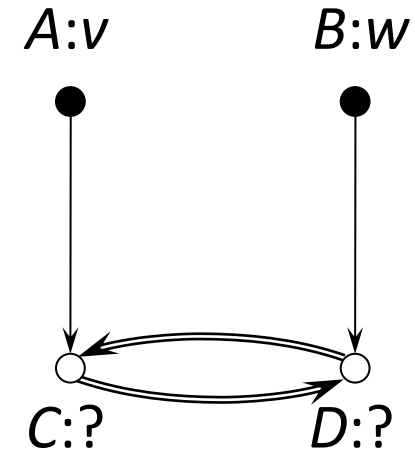
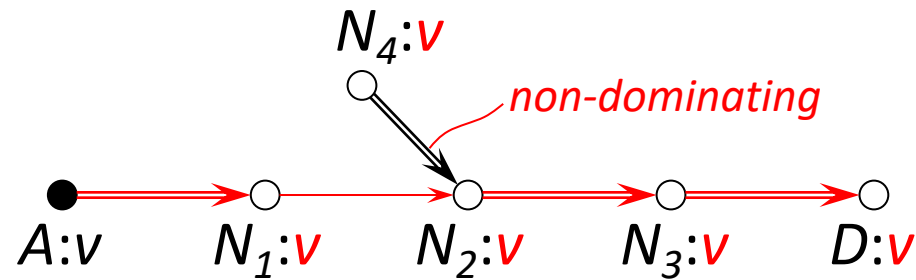
User A has explicit belief  $v$



Focus on one single key (we ignore the glyph)

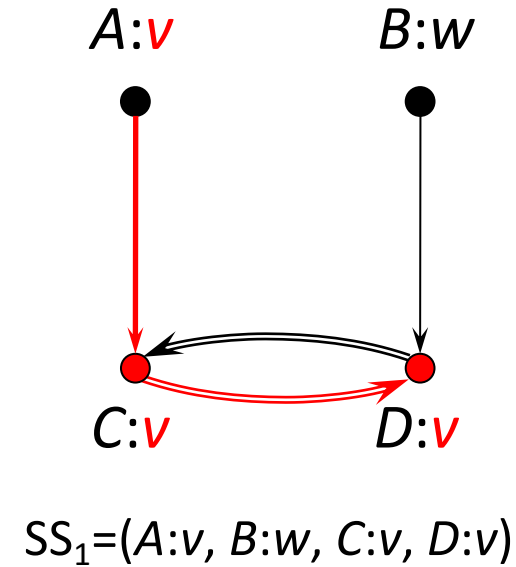
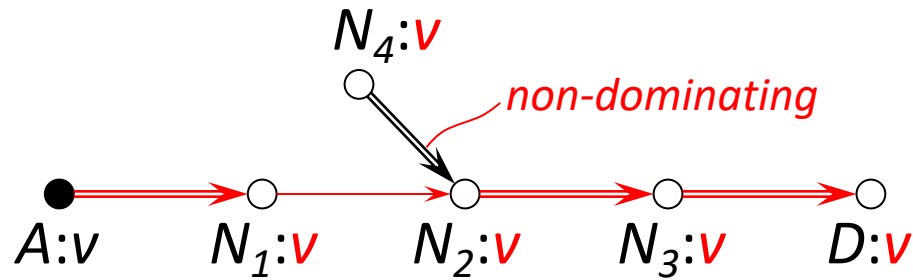
# The definition of a globally consistent solution

- Stable solution
  - assignment of values to each node, s.t. each belief has a “*non-dominated lineage*” to an explicit belief



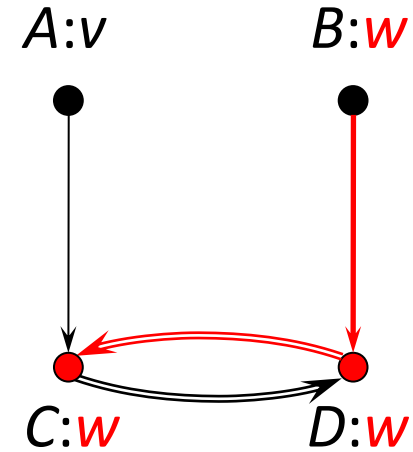
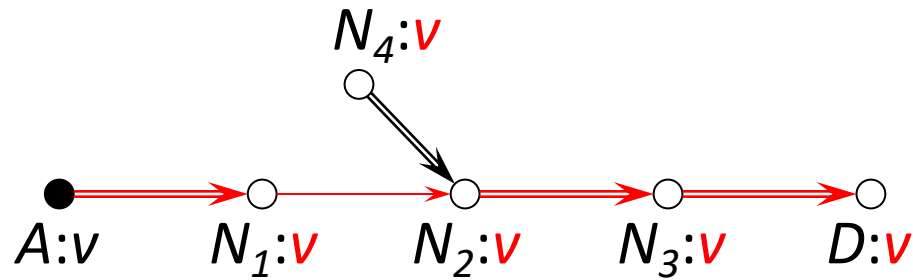
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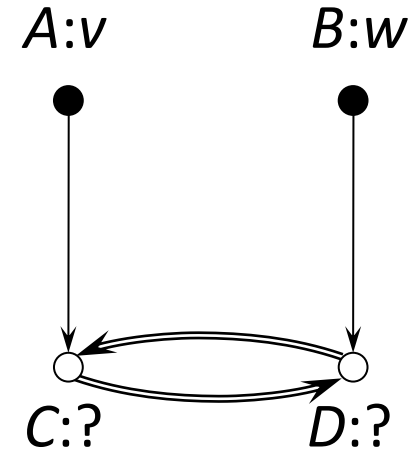
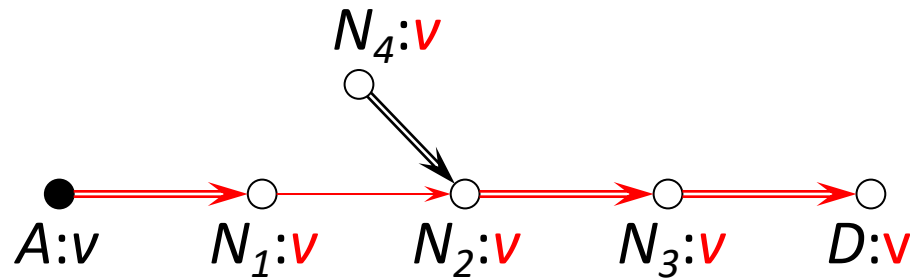


$SS_1 = (A:v, B:w, C:v, D:v)$   
 $SS_2 = (A:v, B:w, C:w, D:w)$

# Possible and certain values from all stable solutions

- **Stable solution**

- assignment of values to each node, s.t. each belief has a “*non-dominated lineage*” to an explicit belief



$SS_1 = (A:v, B:w, C:v, D:v)$   
 $SS_2 = (A:v, B:w, C:w, D:w)$

- **Possible / Certain semantics**

- a stable solution determines, for each node, a possible value (“**poss**”)
- certain value (“**cert**”) = intersection of all stable solutions, per user

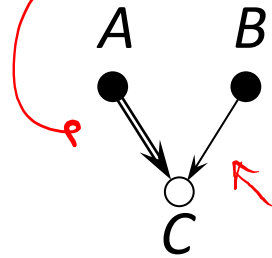
$X$	$\text{poss}(X)$	$\text{cert}(X)$
$A$	$\{v\}$	$\{v\}$
$B$	$\{w\}$	$\{w\}$
$C$	$\{v, w\}$	$\emptyset$
$D$	$\{v, w\}$	$\emptyset$

Handwritten table:

poss	(v, w)
A	v
C	v
C	w

# Logic programs (LP) with stable model semantics

- LPs can capture this semantics.



```
P(C,x) :- P(A,x)
F(C,B,y) :- P(B,y), P(C,x), x≠y
P(C,y) :- P(B,y), ¬F(C,B,y)
```

- There exist powerful and free LP solver available.
- Previous work on peer data exchange suggest using LPs.

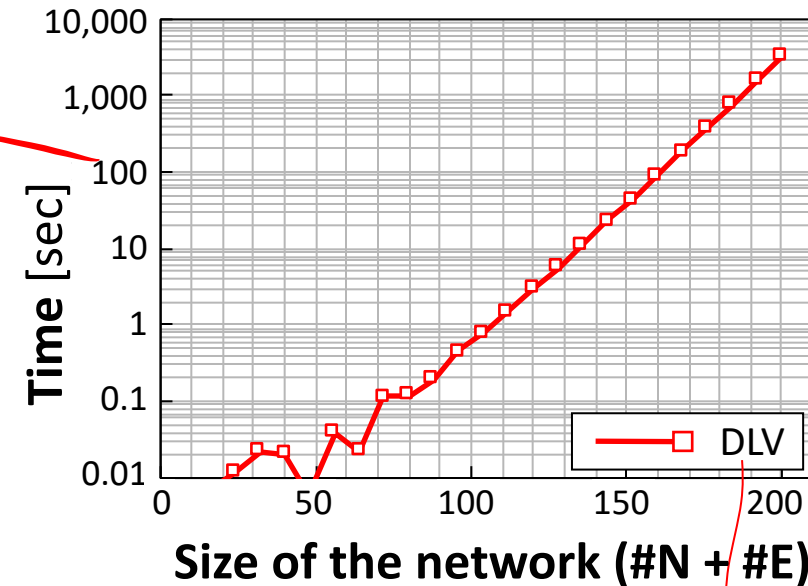
Greco et al. [TKDE'03]

Arenas et al. [TLP'03]

Barcelo, Bertossi [PADL'03]

Bertossi, Bravo [LPAR'07]

But solving LPs is hard 😞

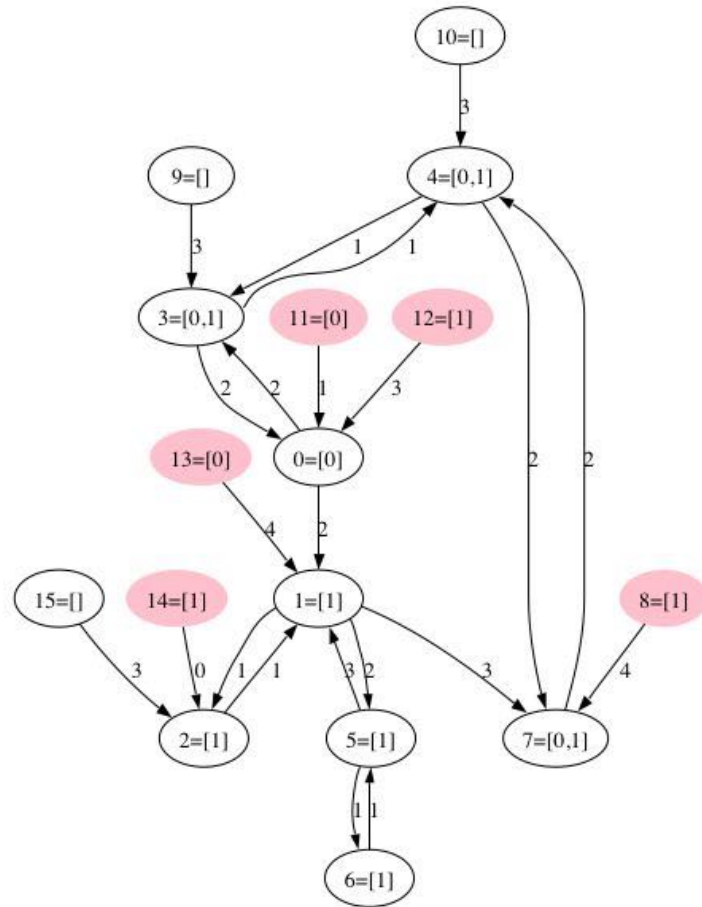


State-of-the-art LP solver

Yet surprisingly, our problem allows a PTIME solution 😊



# DLV example



Size: 38

## input.txt

```
% --- Insert explicit beliefs ---
possH(h8_0,1).
possH(h11_0,0).
possH(h12_0,1).
possH(h13_0,0).
possH(h14_0,1).
% --- Node: 0 ---
possH(h0_1,X) :- possH(h0_0,X).
block(h0_1,11,X) :- poss(11,X), possH(h0_1,Y), Y!=X.
possH(h0_1,X) :- poss(11,X), not block(h0_1,11,X).
possH(h0_2,X) :- possH(h0_1,X).
block(h0_2,3,X) :- poss(3,X), possH(h0_2,Y), Y!=X.
possH(h0_2,X) :- poss(3,X), not block(h0_2,3,X).
possH(h0_3,X) :- possH(h0_2,X).
block(h0_3,12,X) :- poss(12,X), possH(h0_3,Y), Y!=X.
possH(h0_3,X) :- poss(12,X), not block(h0_3,12,X).
poss(0,X) :- possH(h0_3,X).
% --- Node: 1 ---
possH(h1_1,X) :- possH(h1_0,X).
block(h1_1,2,X) :- poss(2,X), possH(h1_1,Y), Y!=X.
possH(h1_1,X) :- poss(2,X), not block(h1_1,2,X).
possH(h1_2,X) :- possH(h1_1,X).
block(h1_2,0,X) :- poss(0,X), possH(h1_2,Y), Y!=X.
possH(h1_2,X) :- poss(0,X), not block(h1_2,0,X).
possH(h1_3,X) :- possH(h1_2,X).
block(h1_3,5,X) :- poss(5,X), possH(h1_3,Y), Y!=X.
possH(h1_3,X) :- poss(5,X), not block(h1_3,5,X).
possH(h1_4,X) :- possH(h1_3,X).
block(h1_4,13,X) :- poss(13,X), possH(h1_4,Y), Y!=X.
possH(h1_4,X) :- poss(13,X), not block(h1_4,13,X).
poss(1,X) :- possH(h1_4,X).
% --- Node: 2 ---
.....
% --- Node: 13 ---
poss(13,X) :- possH(h13_0,X).
% --- Node: 14 ---
poss(14,X) :- possH(h14_0,X).
% --- Node: 15 ---
poss(15,X) :- possH(h15_0,X).
```

## query.txt

```
poss(X,U) ?
```

## Executing program

```
./dlv.bin - brave
input.txt. query-.txt
```

## Result

```
Macintosh-2:DLV gat1
8, 1
11, 0
12, 1
13, 0
14, 1
0, 0
1, 1
2, 1
3, 0
3, 1
4, 0
4, 1
5, 1
6, 1
7, 0
7, 1
```

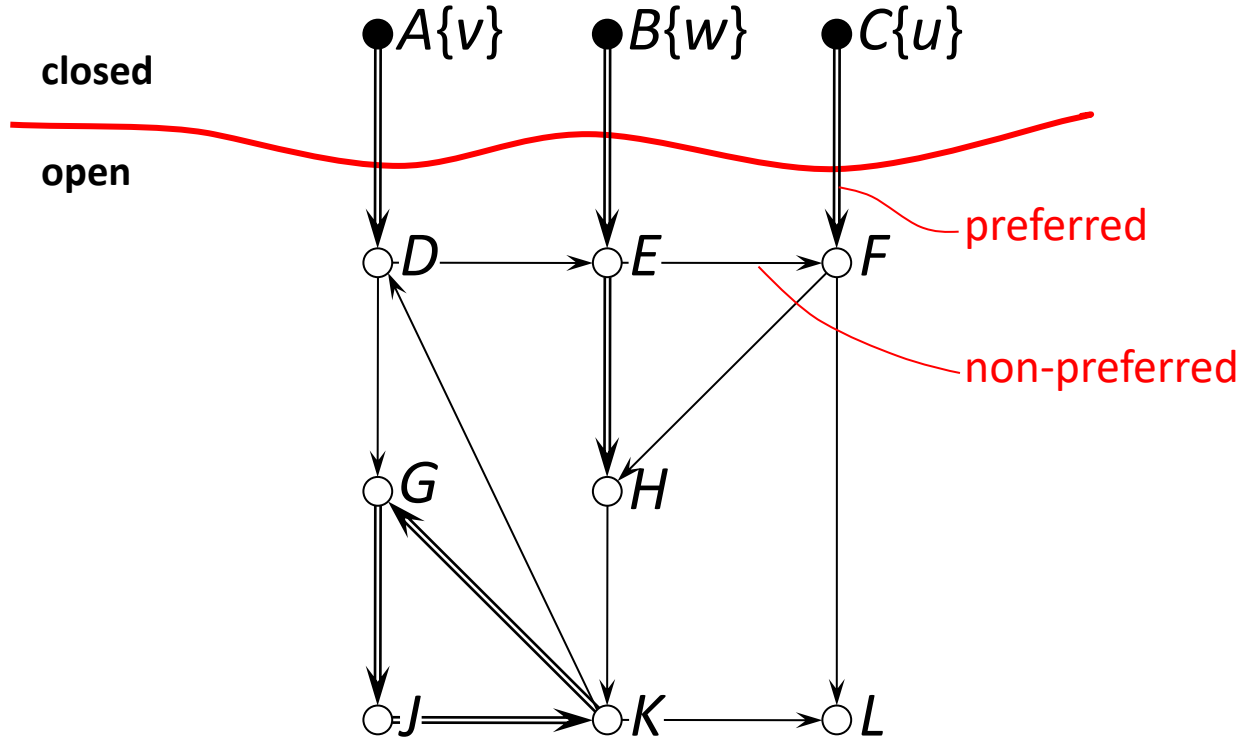
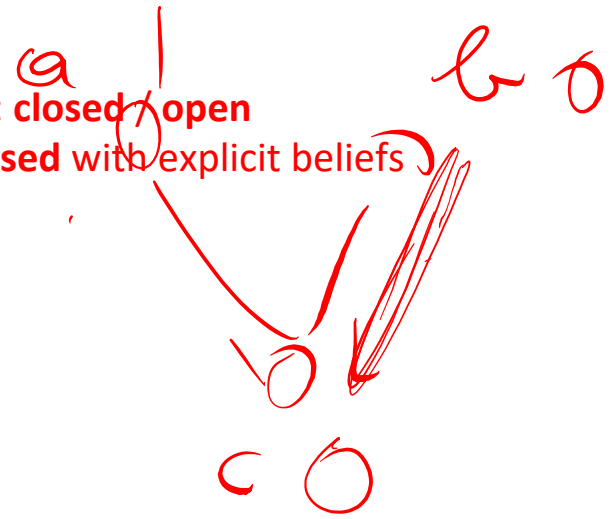
# Agenda

1. Stable solutions
  - how to define a unique and consistent solution?
2. Resolution algorithm
  - how to calculate the solution efficiently?
3. Extensions
  - how to deal with “negative beliefs”?

# Resolution Algorithm

Focus on binary trust network

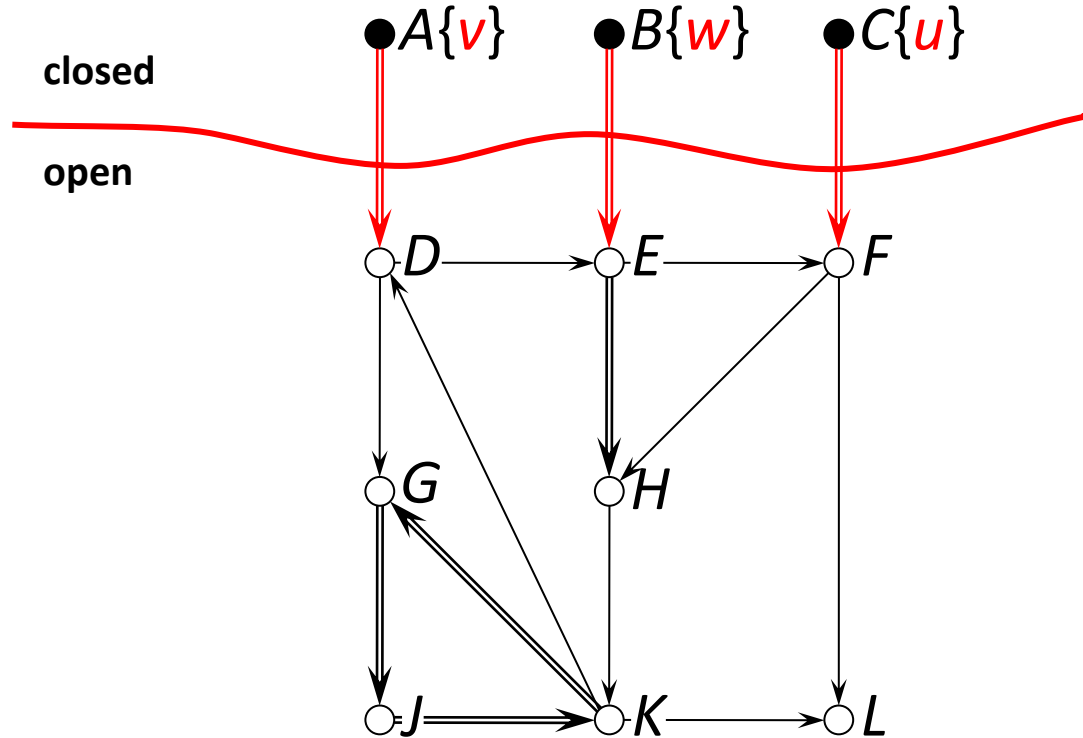
- Keep 2 sets: **closed** / **open**  
Initialize **closed** with explicit beliefs



<i>X</i>	poss( <i>X</i> )	cert( <i>X</i> )
<i>A</i>	{ <i>v</i> }	{ <i>v</i> }
<i>B</i>	{ <i>w</i> }	{ <i>w</i> }
<i>C</i>	{ <i>u</i> }	{ <i>u</i> }
<i>D</i>	?	?
<i>E</i>	?	?
<i>F</i>	?	?
<i>G</i>	?	?
<i>H</i>	?	?
<i>J</i>	?	?
<i>K</i>	?	?
<i>L</i>	?	?

# Resolution Algorithm

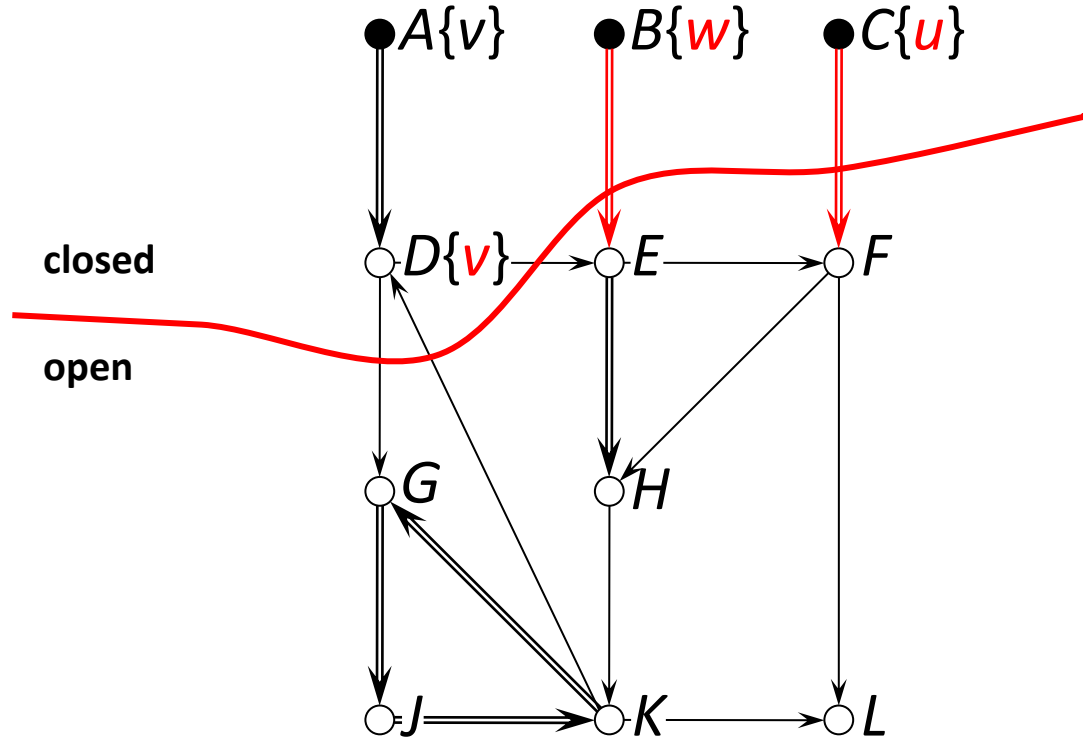
- Keep 2 sets: **closed** / **open**  
Initialize **closed** with explicit beliefs
- MAIN  
Step 1: if  $\exists$  preferred edges from **open** to **closed**  
→ follow



$X$	$\text{poss}(X)$	$\text{cert}(X)$
$A$	$\{v\}$	$\{v\}$
$B$	$\{w\}$	$\{w\}$
$C$	$\{u\}$	$\{u\}$
$D$	?	?
$E$	?	?
$F$	?	?
$G$	?	?
$H$	?	?
$J$	?	?
$K$	?	?
$L$	?	?

# Resolution Algorithm

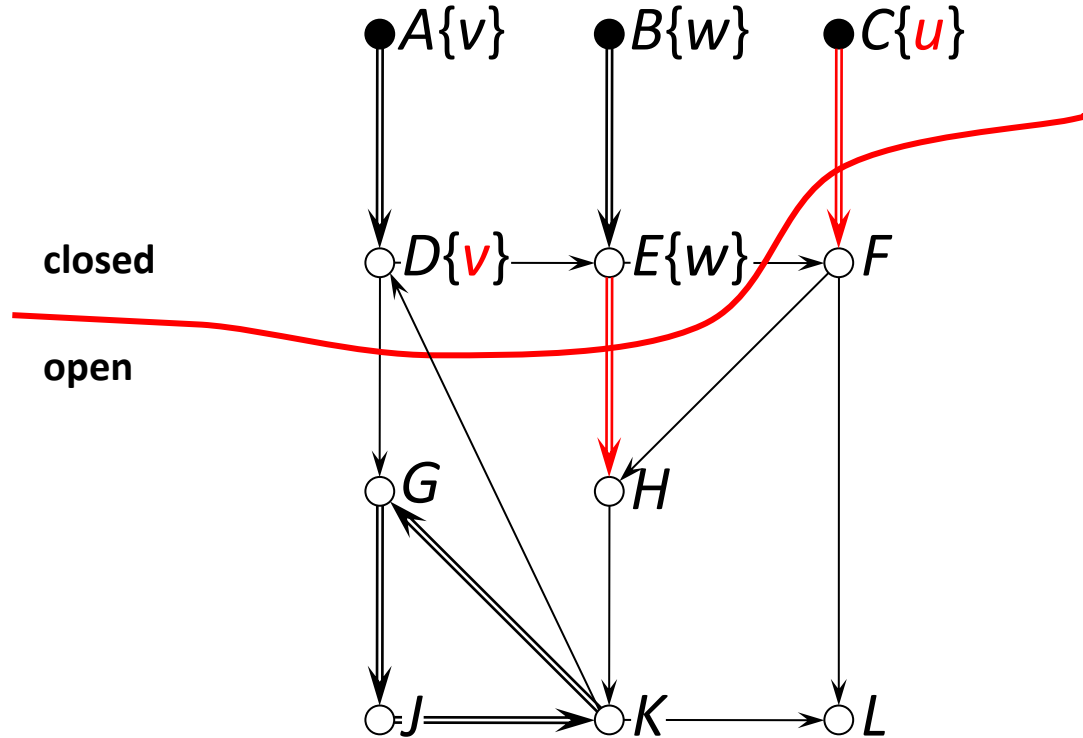
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→ follow



$X$	$\text{poss}(X)$	$\text{cert}(X)$
A	{v}	{v}
B	{w}	{w}
C	{u}	{u}
D	{v}	{v}
E	?	?
F	?	?
G	?	?
H	?	?
J	?	?
K	?	?
L	?	?

# Resolution Algorithm

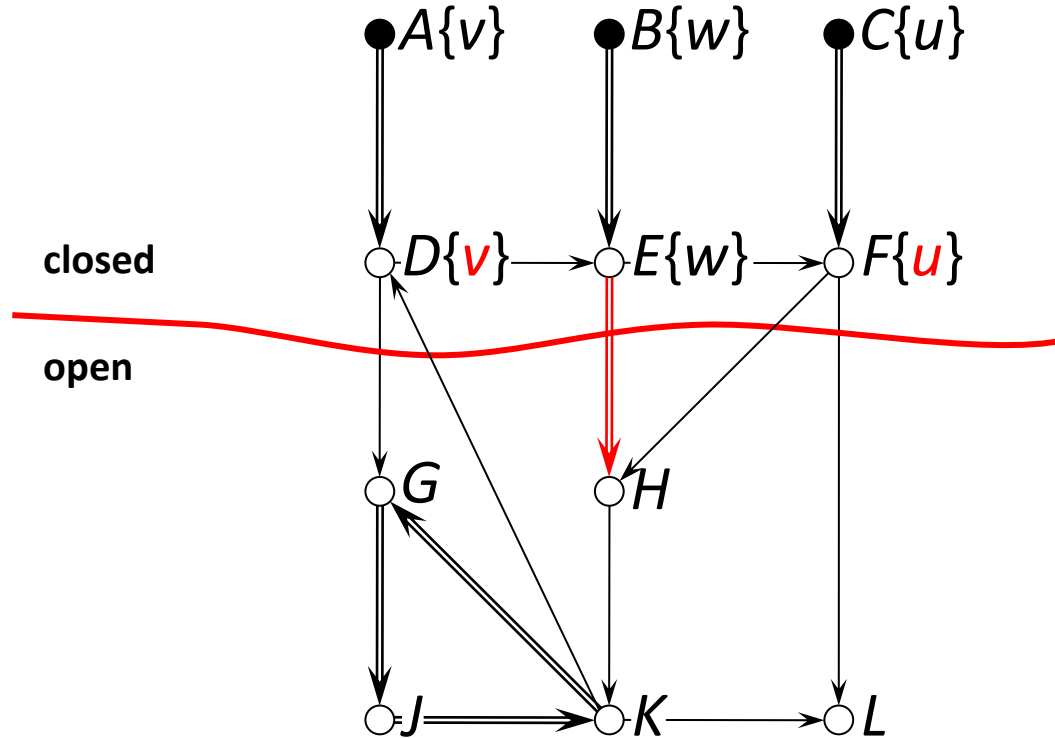
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$C$	$\{u\}$	$\{u\}$
$D$	$\{v\}$	$\{v\}$
$E$	$\{w\}$	$\{w\}$
$F$	?	?
$G$	?	?
$H$	?	?
$J$	?	?
$K$	?	?
$L$	?	?

# Resolution Algorithm

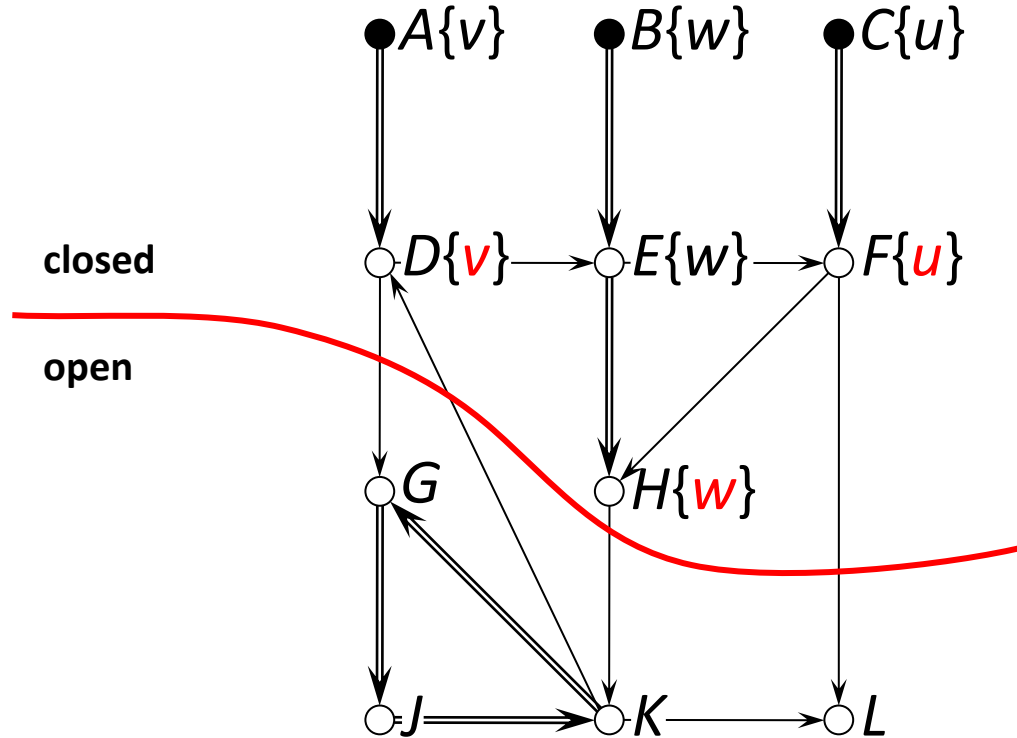
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$B$	$\{w\}$	$\{w\}$
$C$	$\{u\}$	$\{u\}$
$D$	$\{v\}$	$\{v\}$
$E$	$\{w\}$	$\{w\}$
$F$	$\{u\}$	$\{u\}$
$G$	?	?
$H$	?	?
$J$	?	?
$K$	?	?
$L$	?	?

# Resolution Algorithm

- Keep 2 sets: **closed** / **open**  
Initialize **closed** with explicit beliefs
- MAIN  
Step 1: if  $\exists$  preferred edges from **open** to **closed**  
→ follow



Now we are stuck!

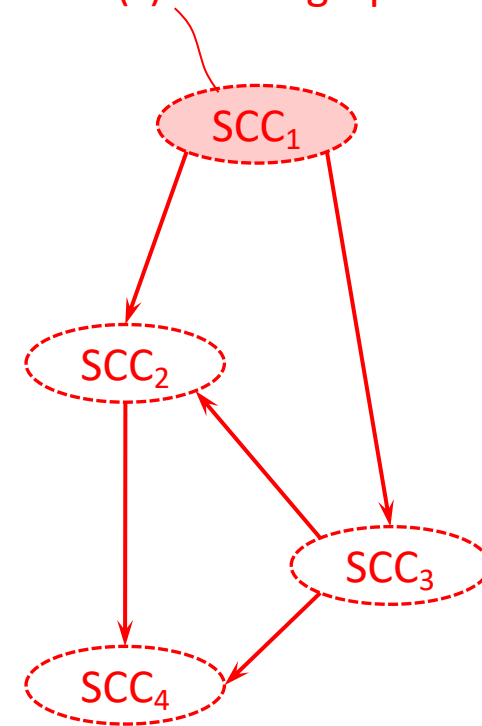
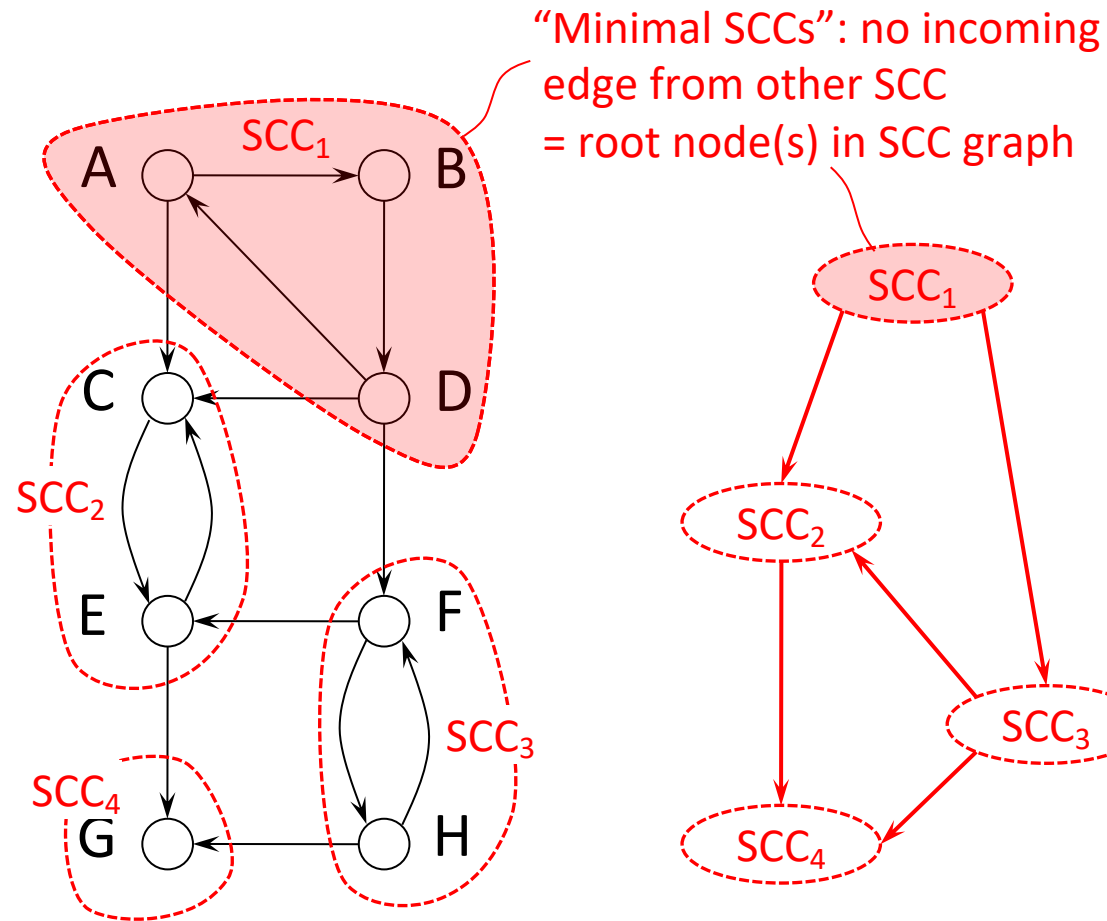
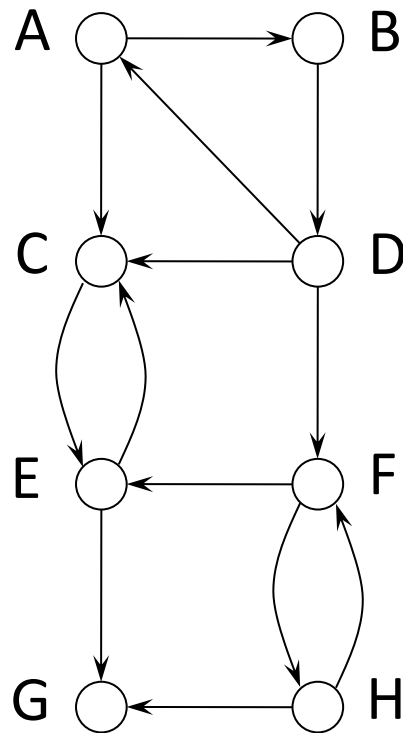
$X$	$\text{poss}(X)$	$\text{cert}(X)$
$A$	$\{v\}$	$\{v\}$
$B$	$\{w\}$	$\{w\}$
$C$	$\{u\}$	$\{u\}$
$D$	$\{v\}$	$\{v\}$
$E$	$\{w\}$	$\{w\}$
$F$	$\{u\}$	$\{u\}$
$G$	?	?
$H$	$\{w\}$	$\{w\}$
$J$	?	?
$K$	?	?
$L$	?	?



# Detail: Strongly Connected Components (SCCs)

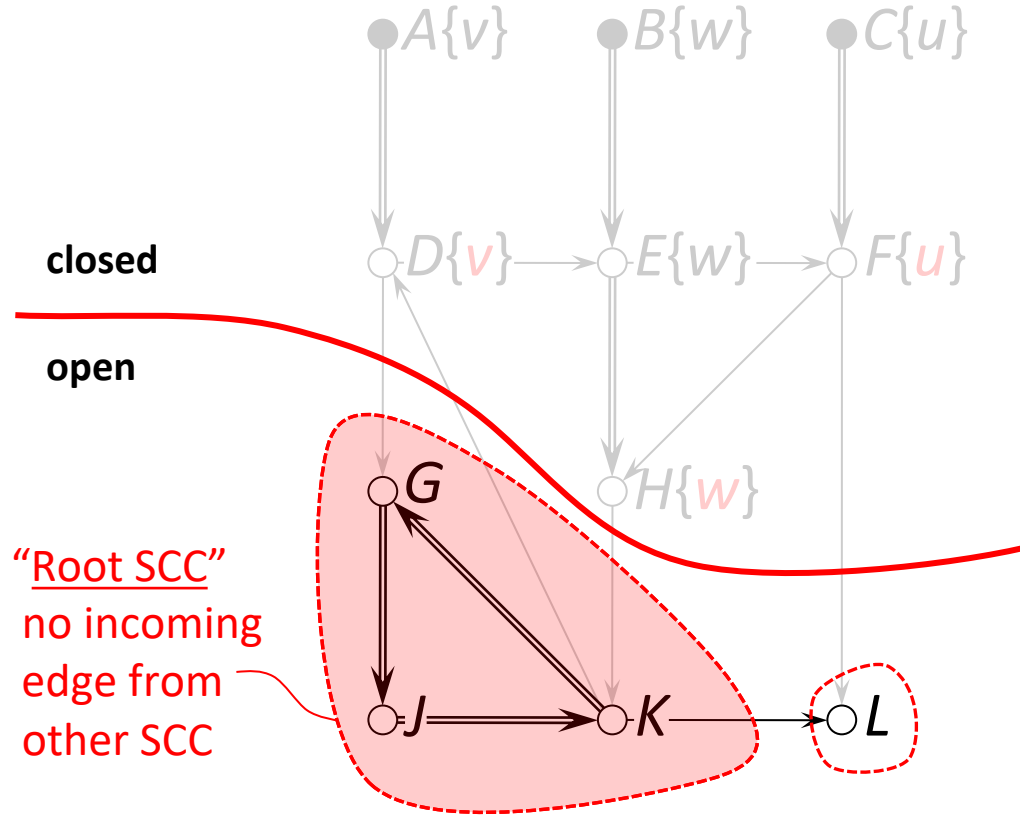
For every cyclic or acyclic directed graph:

- The Strongly Connected Components graph is a DAG
- can be calculated in  $O(n)$  Tarjan [1972]



# Resolution Algorithm

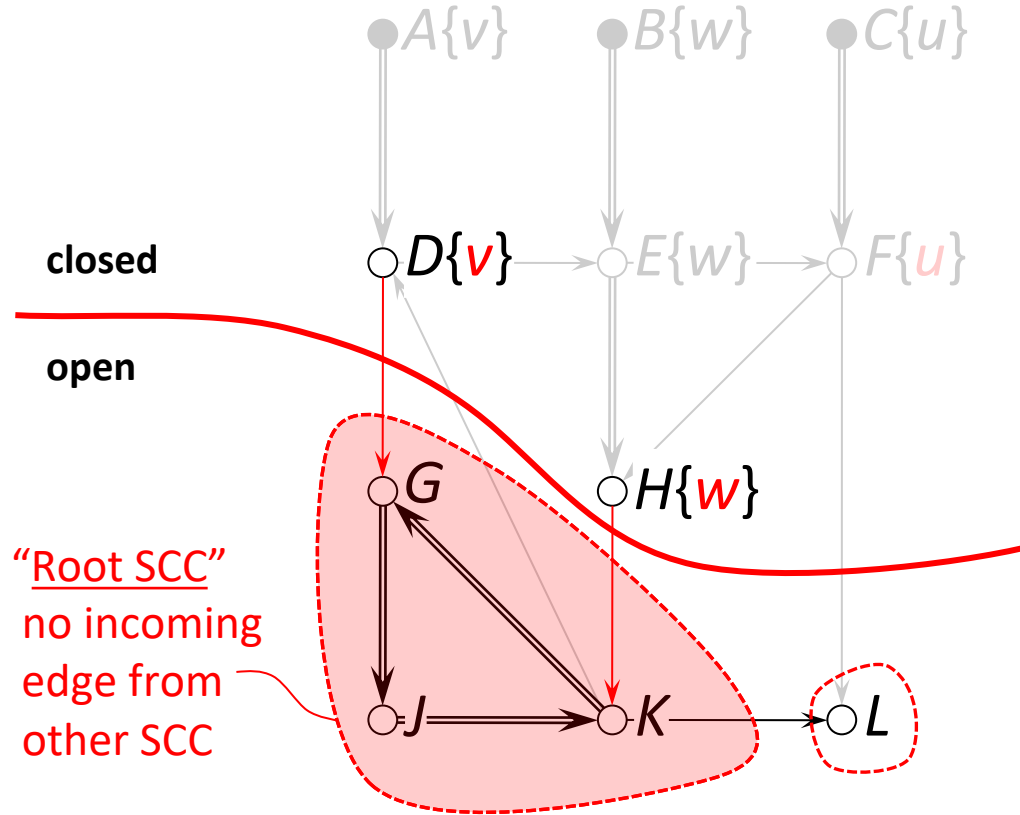
- Keep 2 sets: **closed** / **open**  
Initialize **closed** with explicit beliefs
- MAIN
  - Step 1: if  $\exists$  preferred edges from **open** to **closed**  
→ follow
  - Step 2: else  
→ construct SCC graph of **open**



$X$	$\text{poss}(X)$	$\text{cert}(X)$
A	{v}	{v}
B	{w}	{w}
C	{u}	{u}
D	{v}	{v}
E	{w}	{w}
F	{u}	{u}
G	?	?
H	{w}	{w}
J	?	?
K	?	?
L	?	?

# Resolution Algorithm

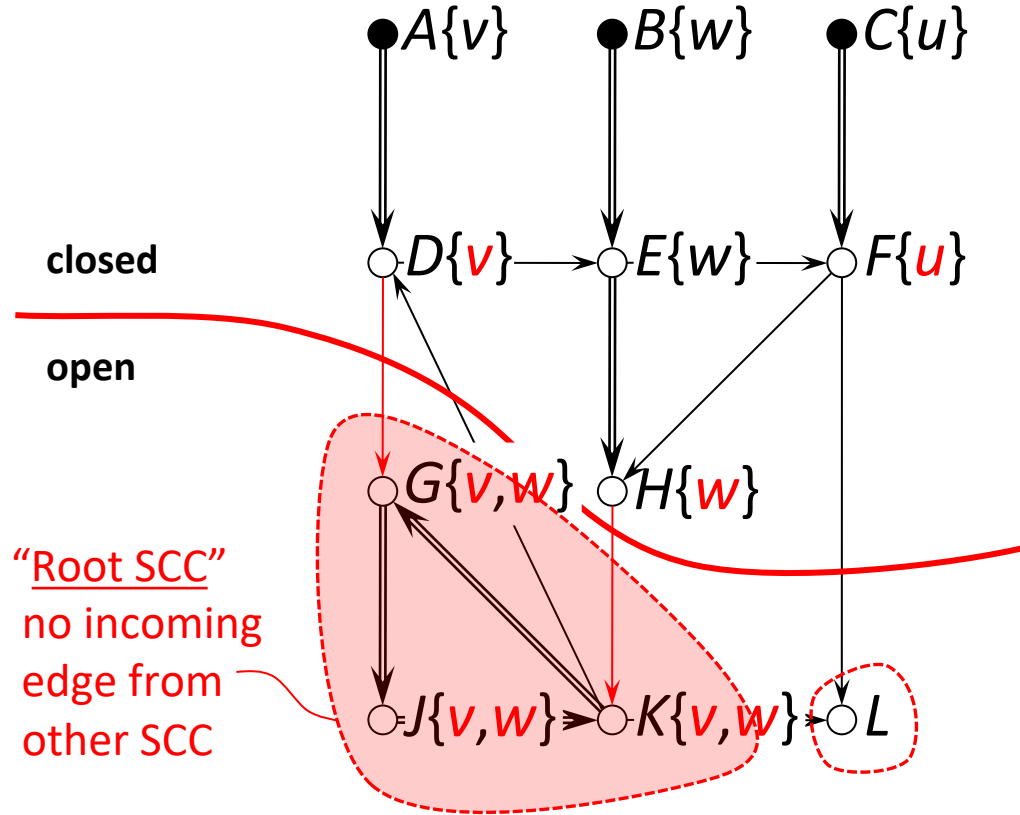
- Keep 2 sets: **closed** / **open**  
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$X$	$\text{poss}(X)$	$\text{cert}(X)$
A	{v}	{v}
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C	{u}	{u}
D	{v}	{v}
E	{w}	{w}
F	{u}	{u}
G	?	?
H	{w}	{w}
J	?	?
K	?	?
L	?	?

# Resolution Algorithm

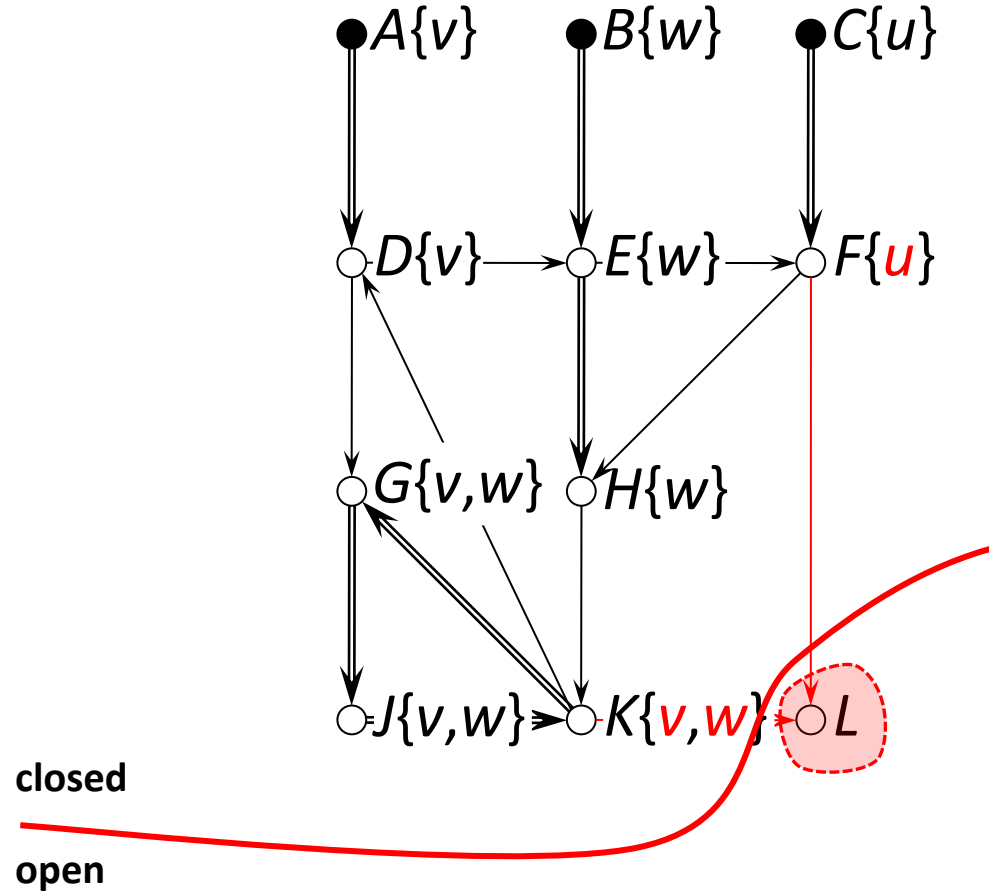
- Keep 2 sets: **closed** / **open**  
Initialize **closed** with explicit beliefs
- MAIN
  - Step 1: if  $\exists$  preferred edges from **open** to **closed**  
→ follow
  - Step 2: else  
→ construct SCC graph of **open**  
→ resolve minimum SCCs



$X$	$\text{poss}(X)$	$\text{cert}(X)$
$A$	$\{v\}$	$\{v\}$
$B$	$\{w\}$	$\{w\}$
$C$	$\{u\}$	$\{u\}$
$D$	$\{v\}$	$\{v\}$
$E$	$\{w\}$	$\{w\}$
$F$	$\{u\}$	$\{u\}$
$G$	$\{v, w\}$	$\emptyset$
$H$	$\{w\}$	$\{w\}$
$J$	$\{v, w\}$	$\emptyset$
$K$	$\{v, w\}$	$\emptyset$
$L$	$?$	$?$

# Resolution Algorithm

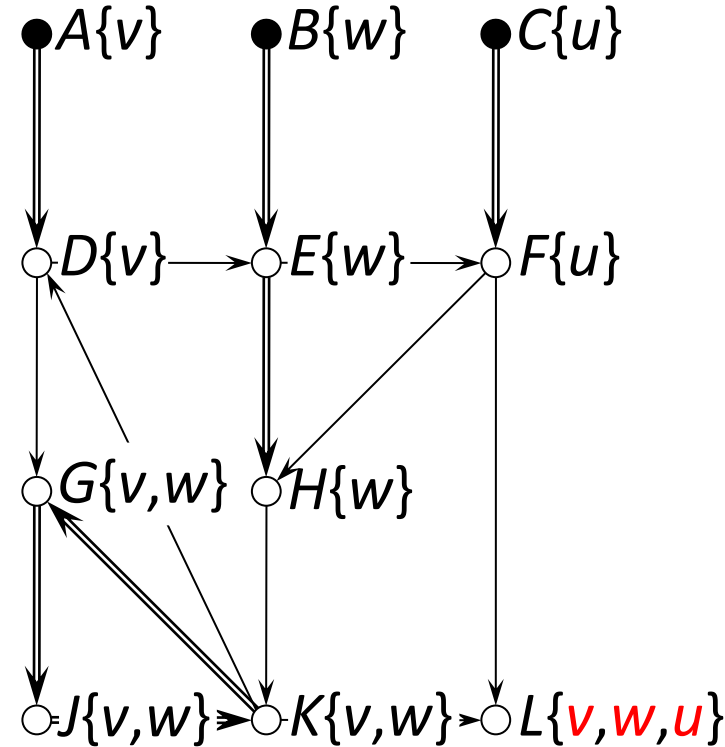
- Keep 2 sets: **closed** / **open**  
Initialize **closed** with explicit beliefs
- MAIN
  - Step 1: if  $\exists$  preferred edges from **open** to **closed**  
→ follow
  - Step 2: else  
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$X$	$\text{poss}(X)$	$\text{cert}(X)$
$A$	$\{v\}$	$\{v\}$
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$C$	$\{u\}$	$\{u\}$
$D$	$\{v\}$	$\{v\}$
$E$	$\{w\}$	$\{w\}$
$F$	$\{u\}$	$\{u\}$
$G$	$\{v, w\}$	$\emptyset$
$H$	$\{w\}$	$\{w\}$
$J$	$\{v, w\}$	$\emptyset$
$K$	$\{v, w\}$	$\emptyset$
$L$	$?$	$?$

# Resolution Algorithm

- Keep 2 sets: **closed** / **open**  
Initialize **closed** with explicit beliefs
- MAIN
  - Step 1: if  $\exists$  preferred edges from **open** to **closed**  
→ follow
  - Step 2: else  
→ construct SCC graph of **open**  
→ resolve minimum SCCs



closed

open

Can be implemented  
in current DBMS with  
transitive closure ☺

**PTIME** resolution algorithm  
 **$O(n^2)$**  worst case  
 **$O(n)$**  on reasonable graphs

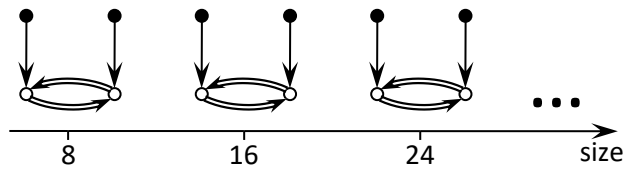
$X$	<b>poss</b> ( $X$ )	<b>cert</b> ( $X$ )
A	{v}	{v}
B	{w}	{w}
C	{u}	{u}
D	{v}	{v}
E	{w}	{w}
F	{u}	{u}
G	{v,w}	$\emptyset$
H	{w}	{w}
J	{v,w}	$\emptyset$
K	{v,w}	$\emptyset$
L	{v,w,u}	$\emptyset$

# Experiments on large network data

## Calculating **poss** / **cert** for fixed key

- **DLV**: State-of-the art logic programming solver
- **RA**: Resolution algorithm

## Network 1: "Oscillators"

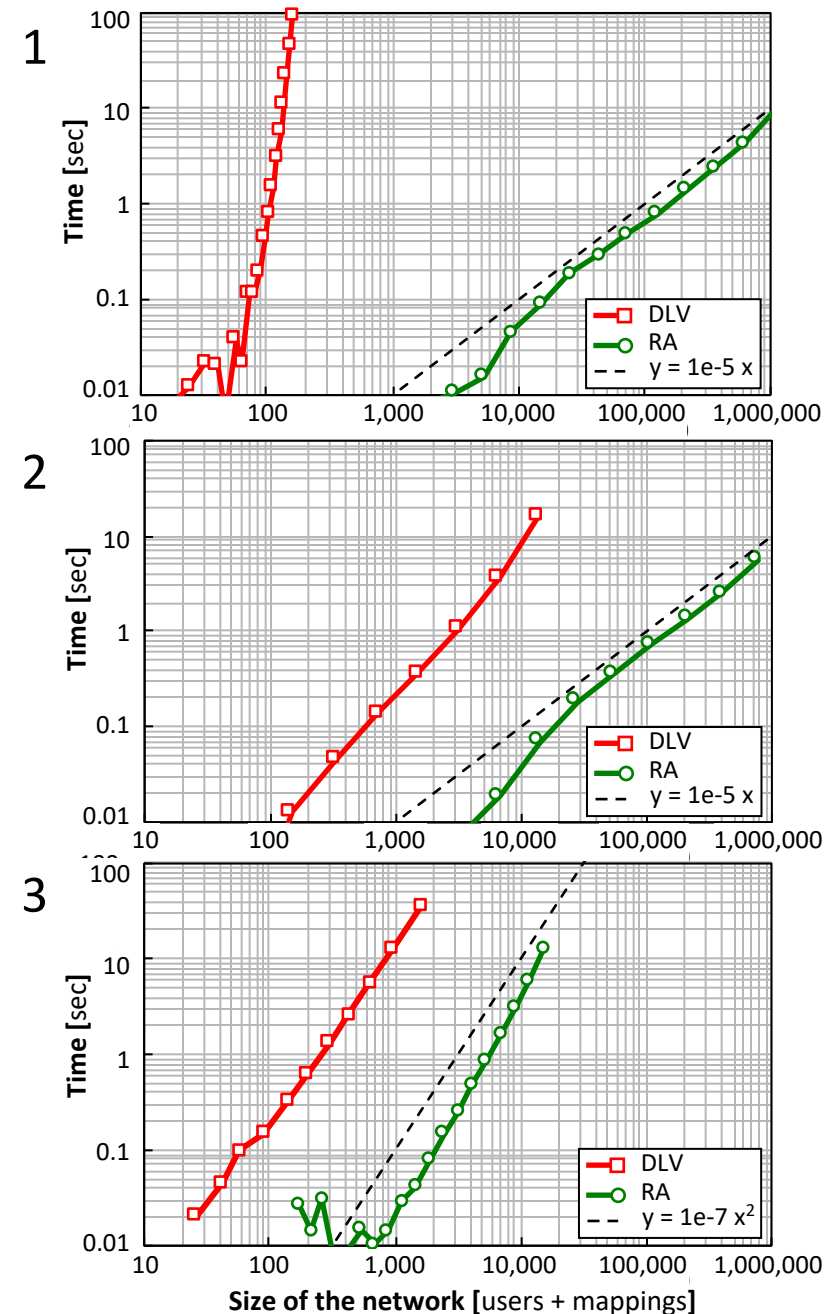
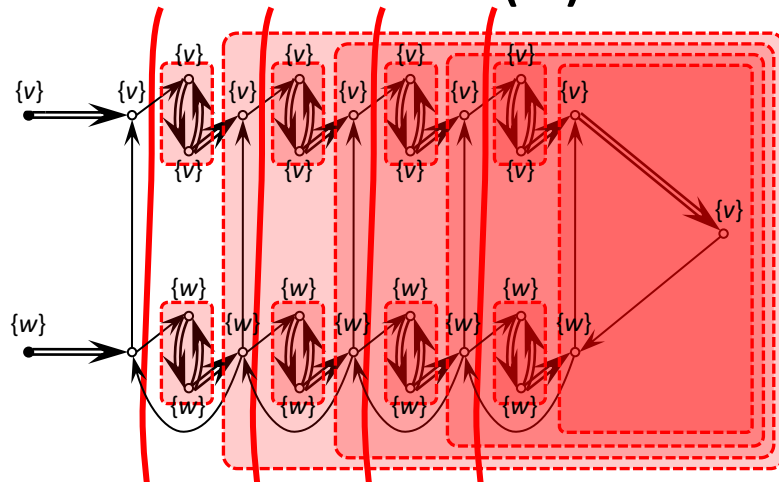


## Network 2: "Web link data"

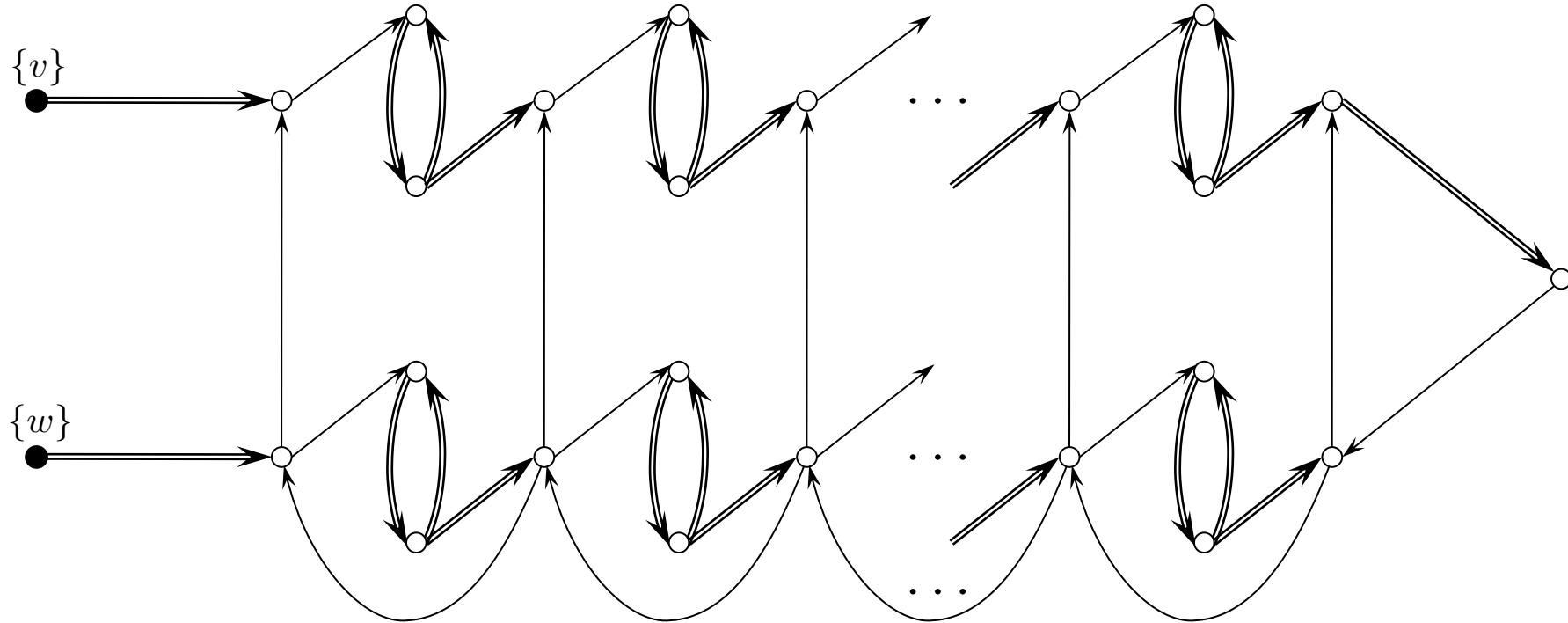
Web data set with 5.4m links between 270k domain names. Approach:

- Sample links with increasing ratio
- Include both nodes in sample
- Assign explicit beliefs randomly

## Network 3: "Worst case" $O(n^2)$

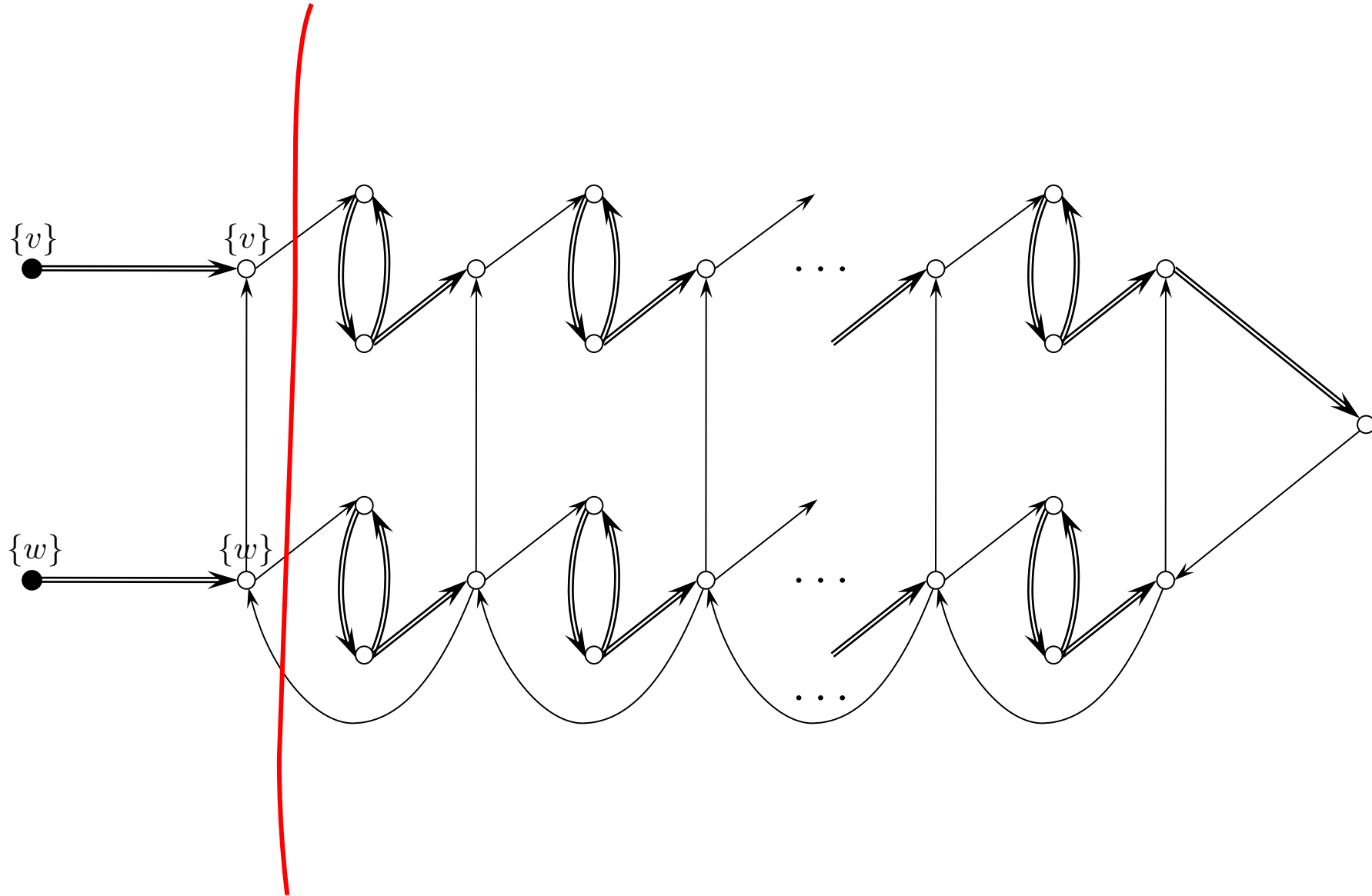


# $O(n^2)$ -worst-case for Resolution Algorithm

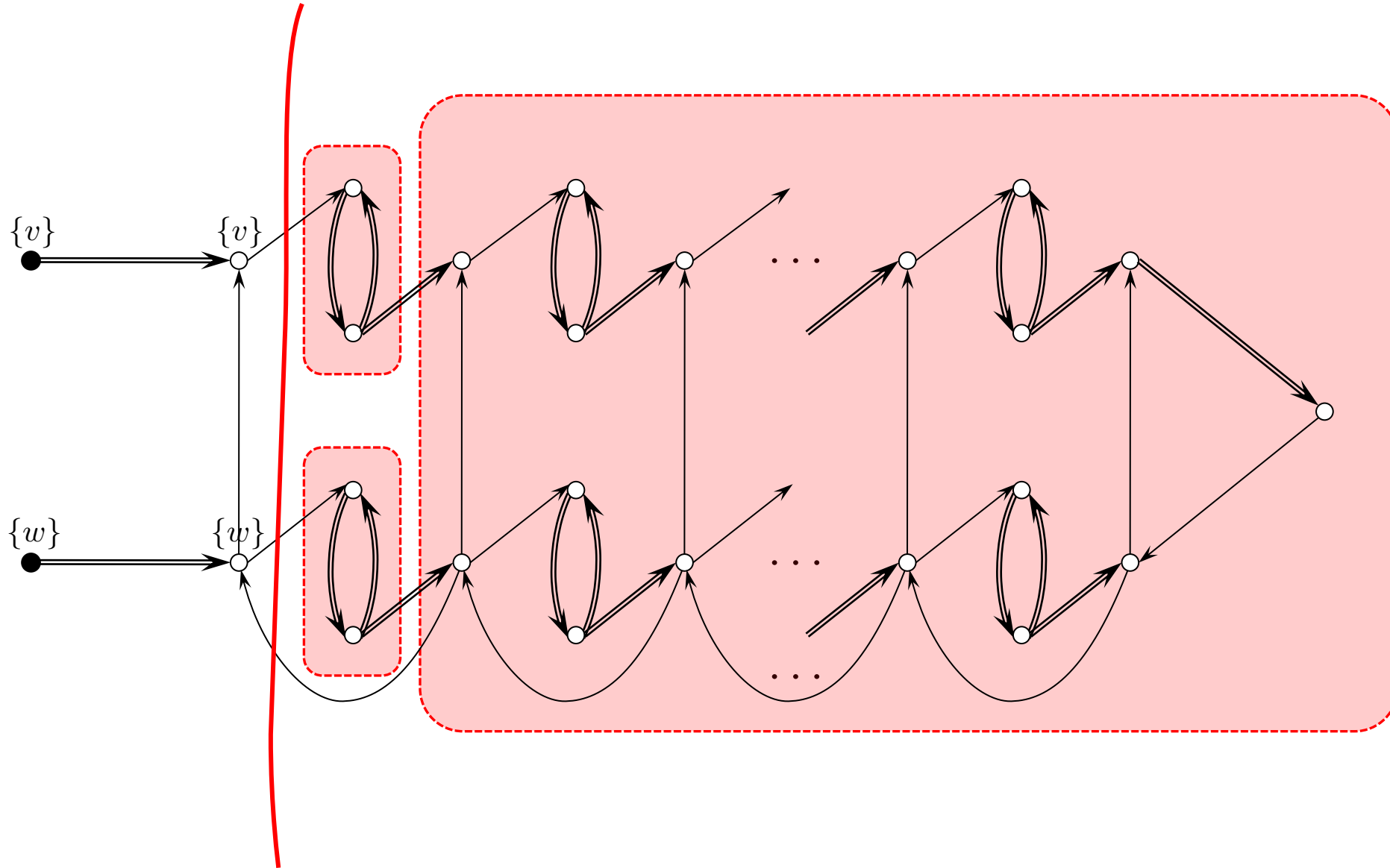




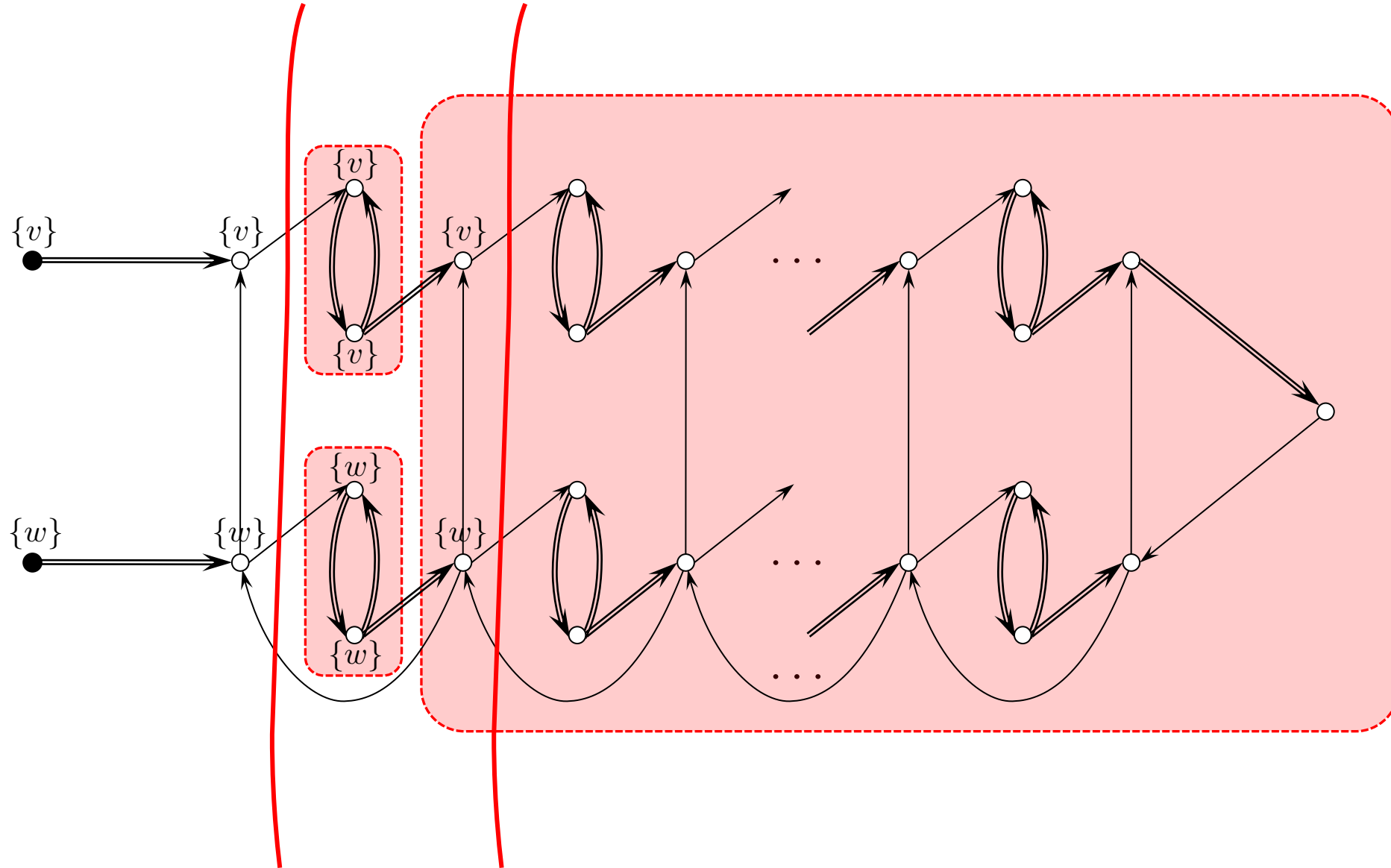
# $O(n^2)$ -worst-case for Resolution Algorithm



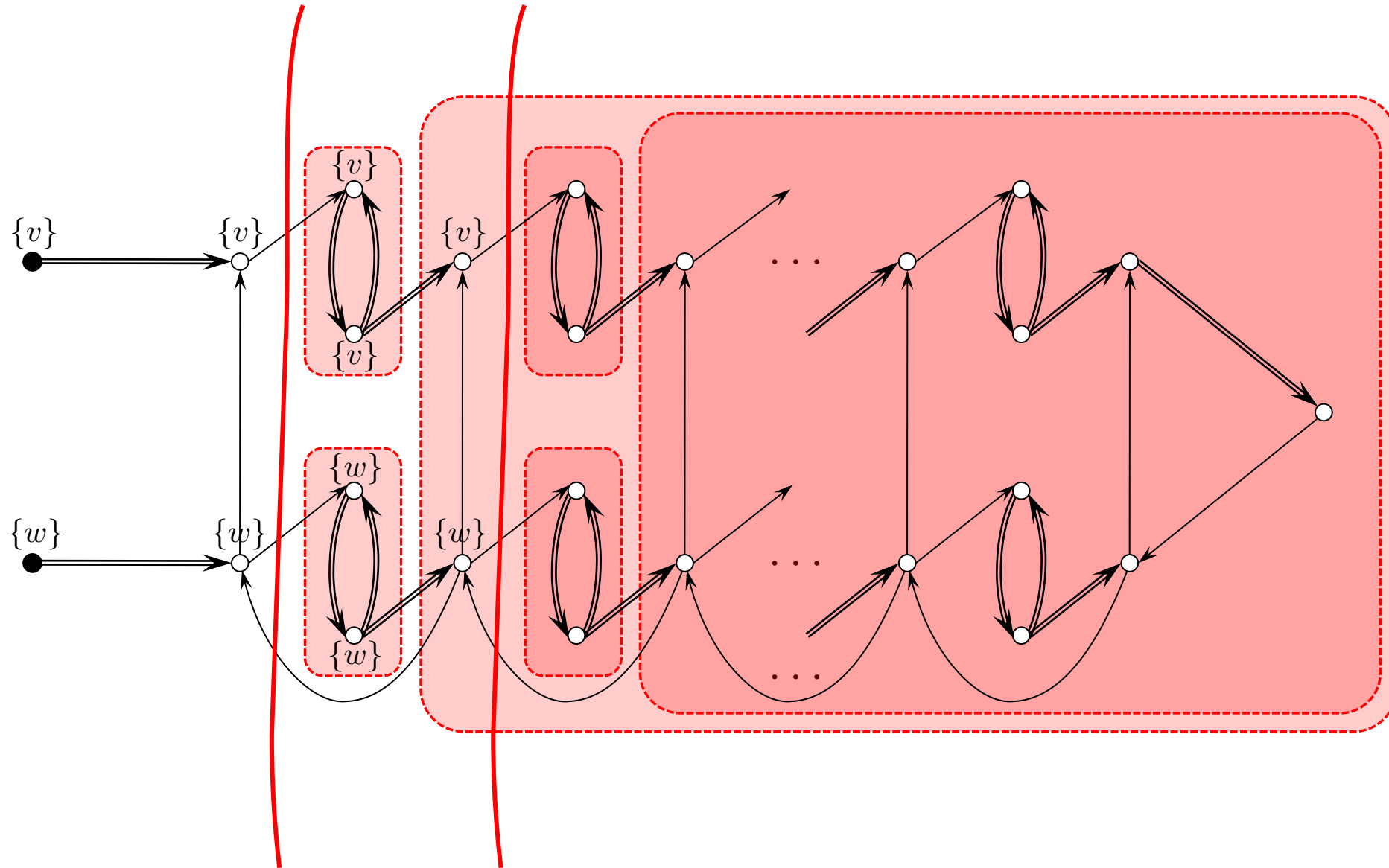
# $O(n^2)$ -worst-case for Resolution Algorithm



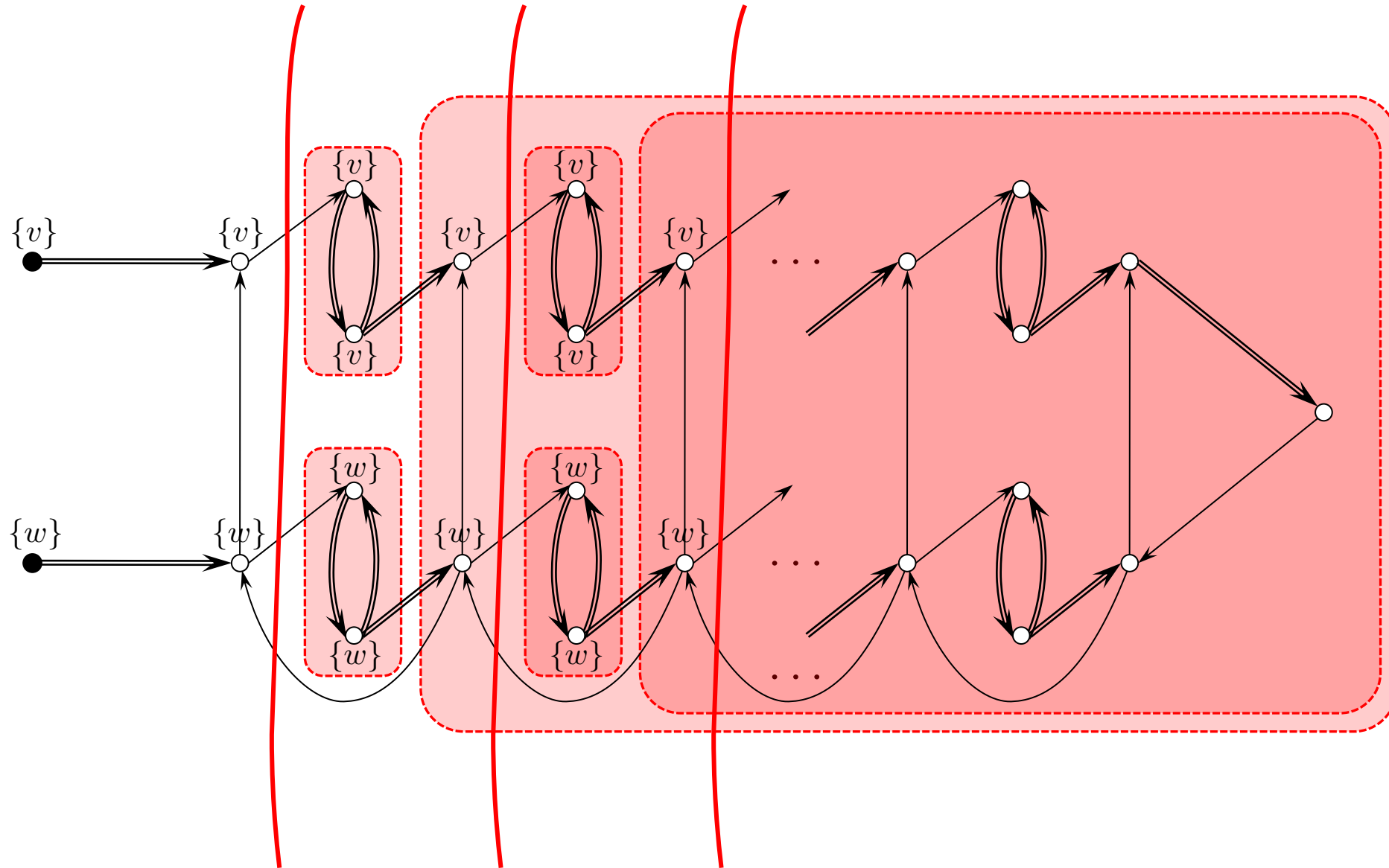
# $O(n^2)$ -worst-case for Resolution Algorithm



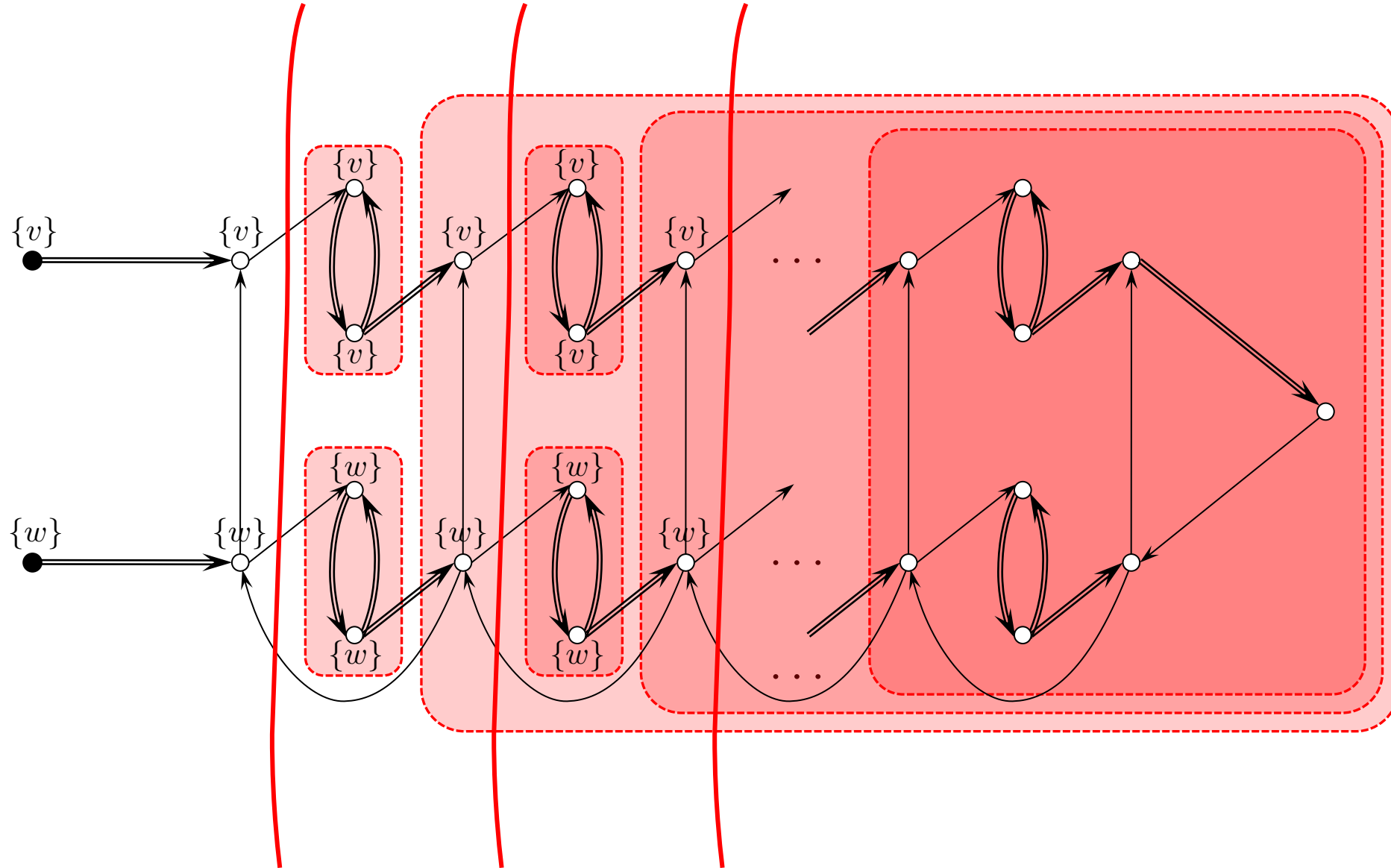
# $O(n^2)$ -worst-case for Resolution Algorithm



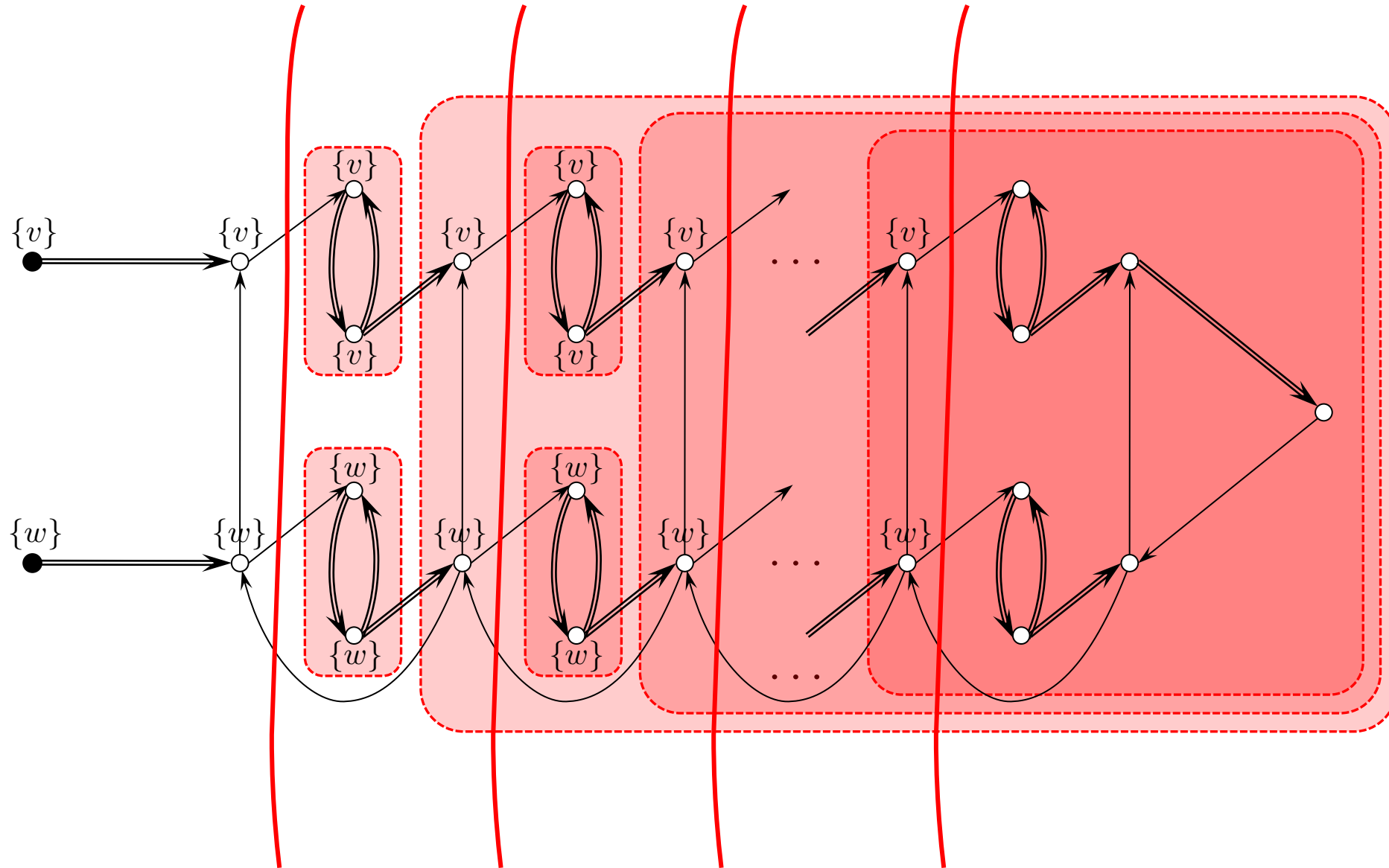
# $O(n^2)$ -worst-case for Resolution Algorithm



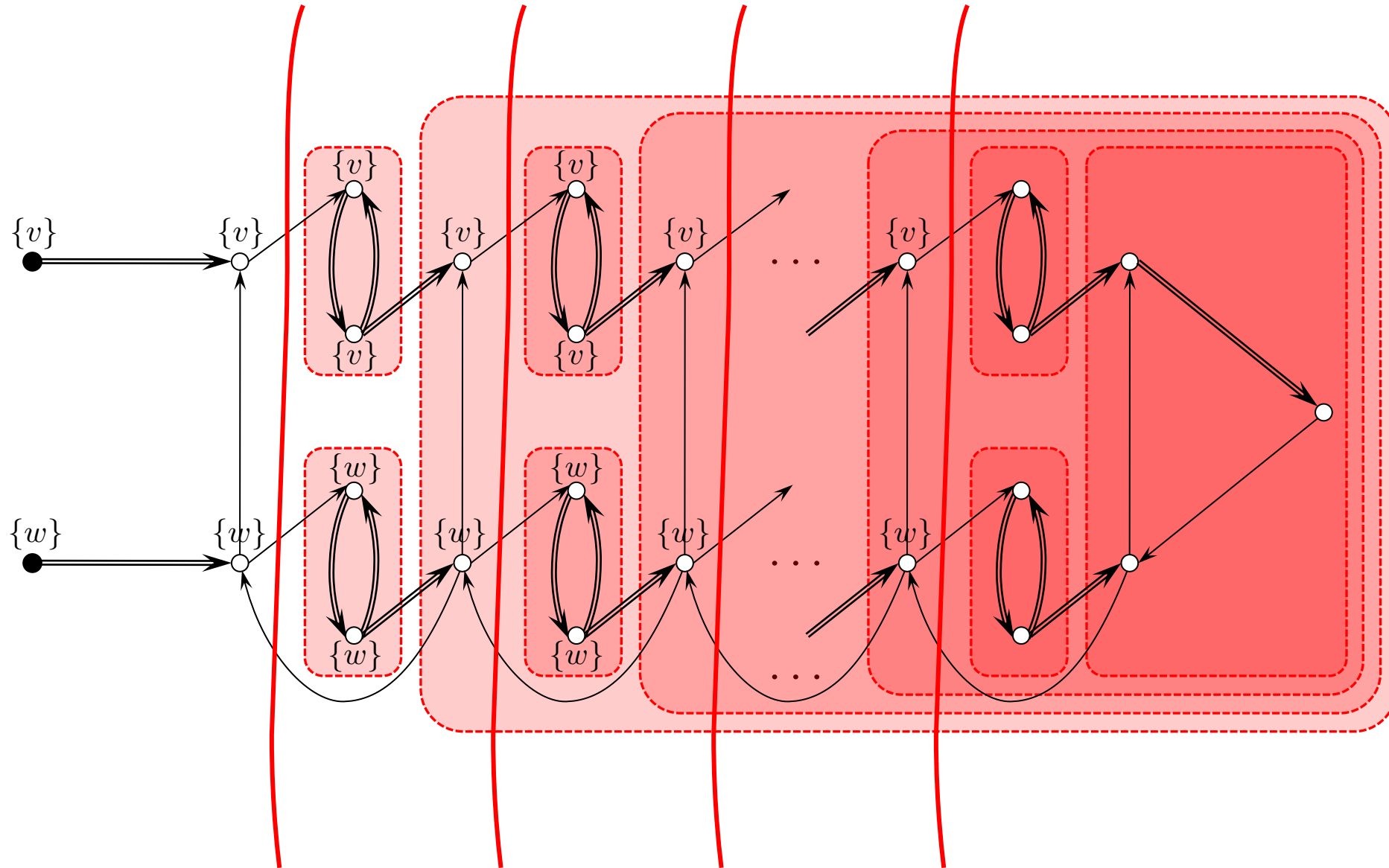
# $O(n^2)$ -worst-case for Resolution Algorithm



# $O(n^2)$ -worst-case for Resolution Algorithm

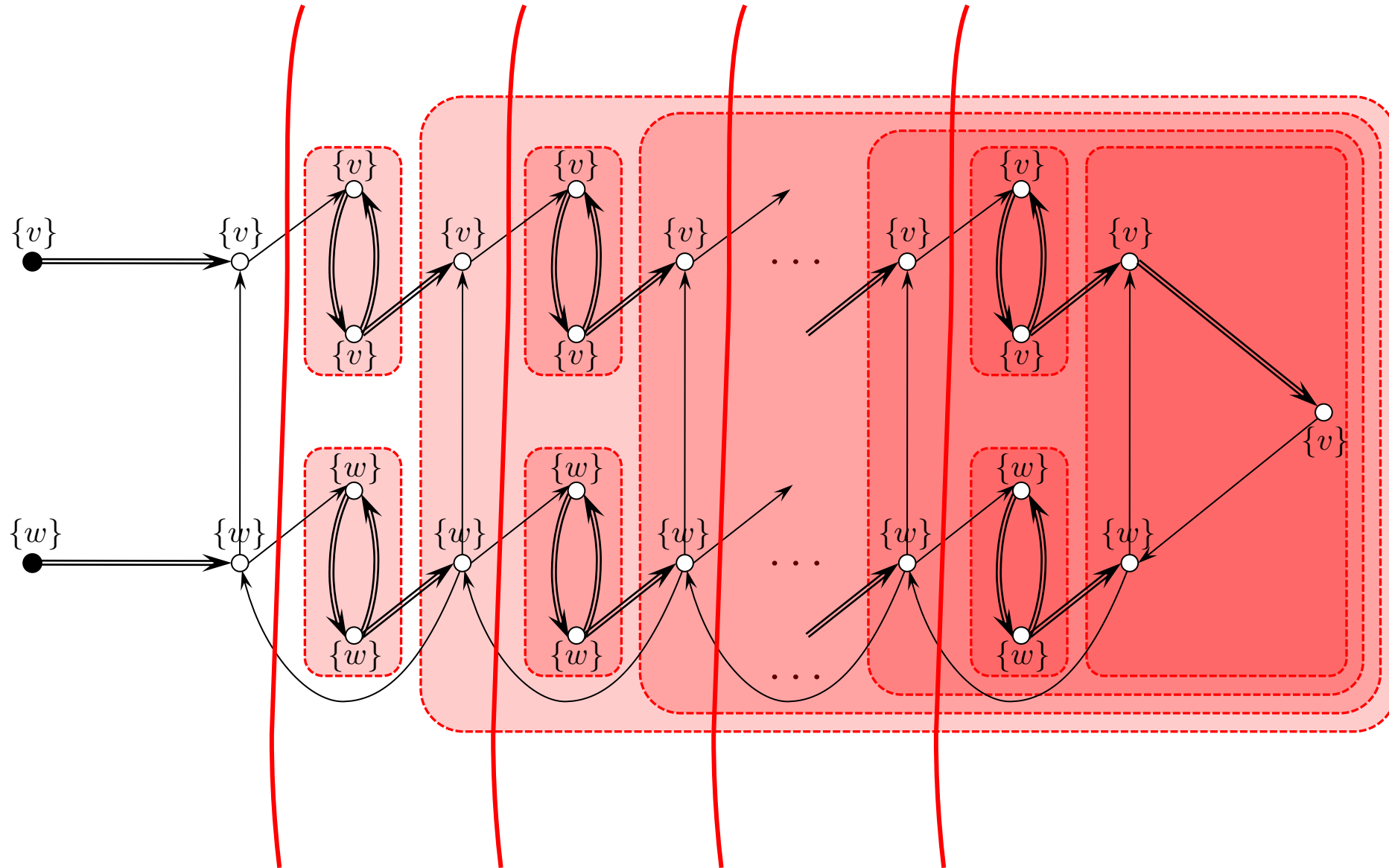


# $O(n^2)$ -worst-case for Resolution Algorithm





# $O(n^2)$ -worst-case for Resolution Algorithm

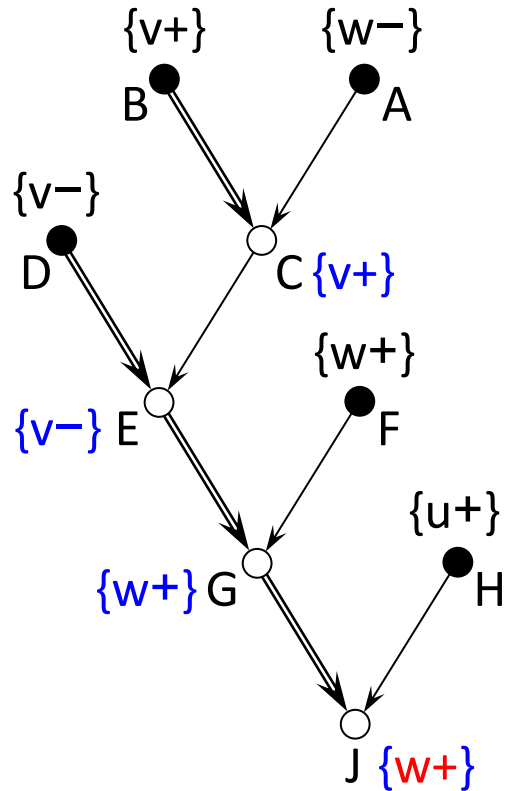


# Agenda

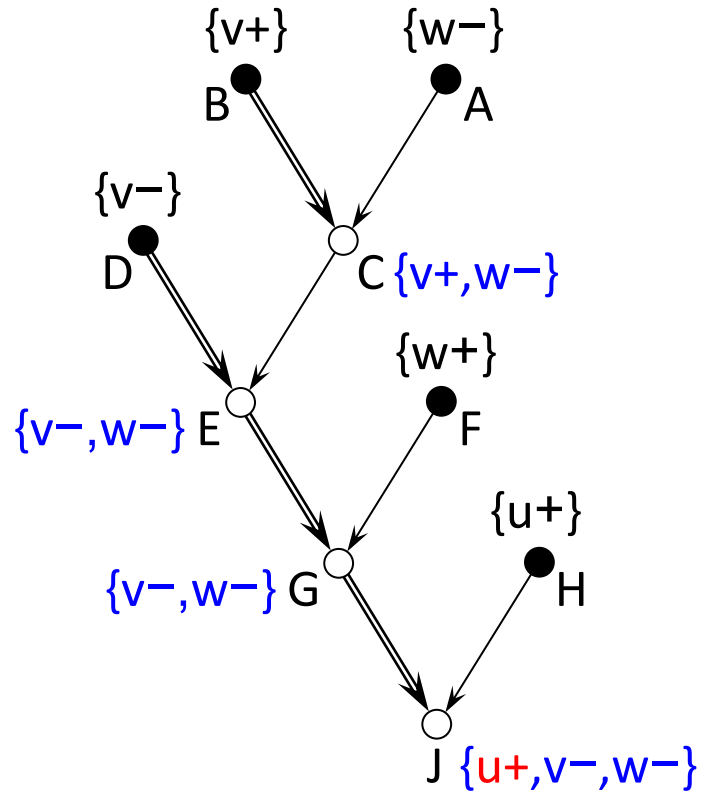
1. Stable solutions
  - how to define a unique and consistent solution?
2. Resolution algorithm
  - how to calculate the solution efficiently?
3. Extensions
  - how to deal with “negative beliefs”?

# 3 semantics for negative beliefs

## Agnostic



## Eclectic



w/o cycles\*

**O(n)**

w cycles

**NP-hard**

**O(n)**

**NP-hard**

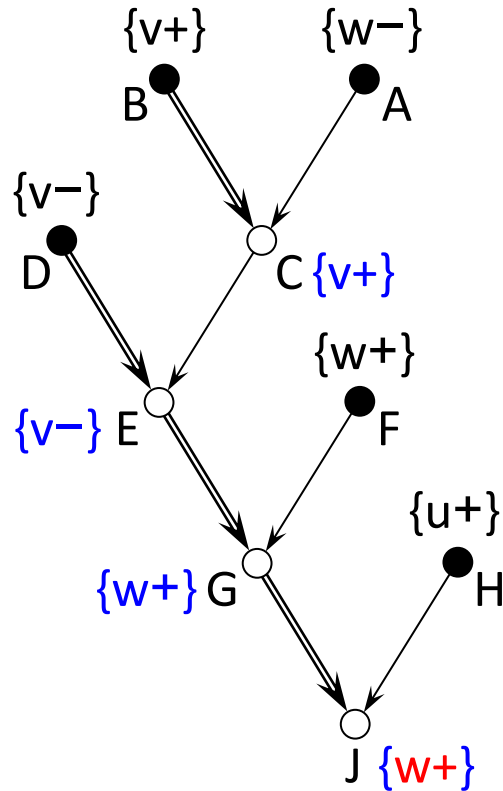
\* assuming total order on parents for each node

# 3 semantics for negative beliefs

Our recommendation



**Agnostic**



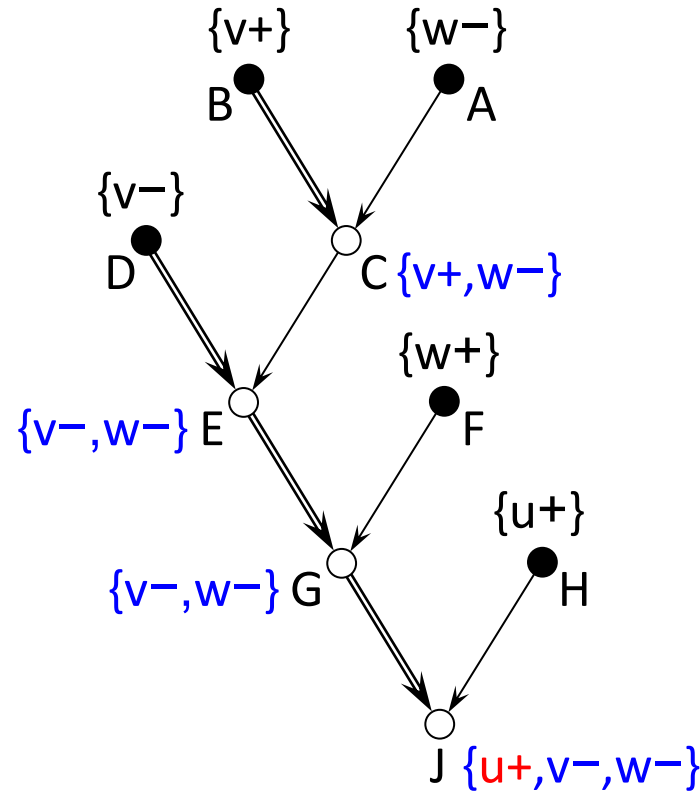
w/o cycles\*

$O(n)$

w cycles

NP-hard

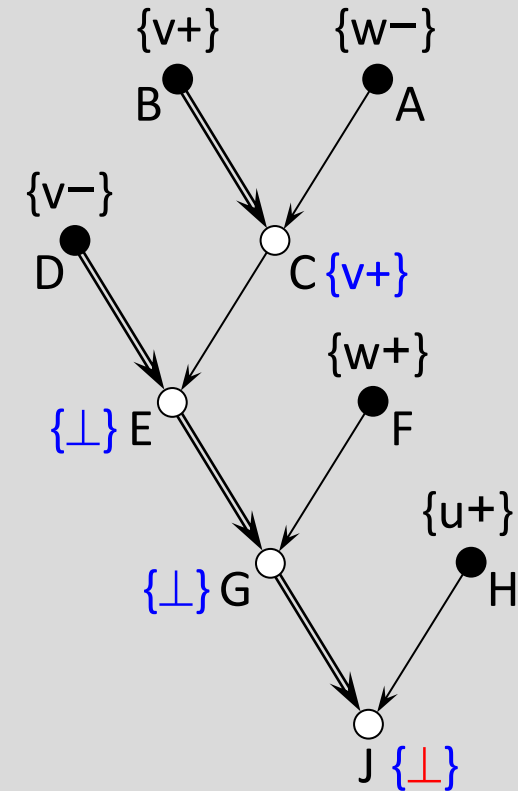
**Eclectic**



$O(n)$

NP-hard

**Skeptic**



$O(n)$

$O(n^2)$

with a variation of resolution algorithm

\* assuming total order on parents for each node

# Take-aways automatic conflict resolution

## Problem

- Given explicit beliefs & trust mappings, how to assign consistent value assignment to users?

## Our solution

- Stable solutions with possible/certain value semantics
- PTIME algorithm [ $O(n^2)$  worst case,  $O(n)$  experiments]
- Several extensions
  - negative beliefs: 3 semantics, two hard, one  $O(n^2)$

- bulk inserts
- agreement checking
- consensus value
- lineage computation

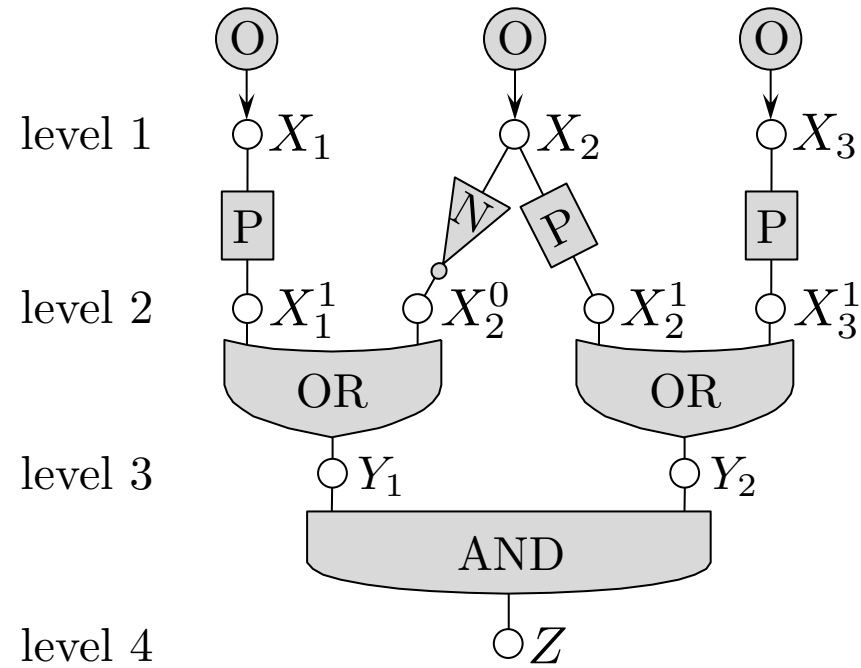
in the paper & TR

<https://db.cs.washington.edu/projects/beliefdb/>

details

# Fig\_ComplexityExampleLong

8-17-2010



Encoding

$$(0/1) = (a+/b+)$$

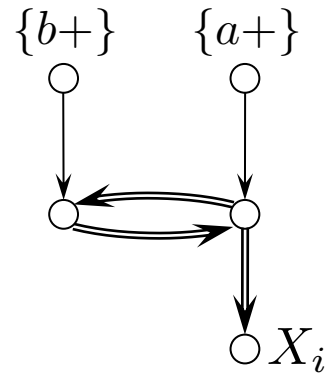
$$(0/1) = (c+/d+)$$

$$(0/1) = (e+/d+)$$

$$(0/1) = (e+/f+)$$

# Fig\_ComplexityOscillator

8-16-2010



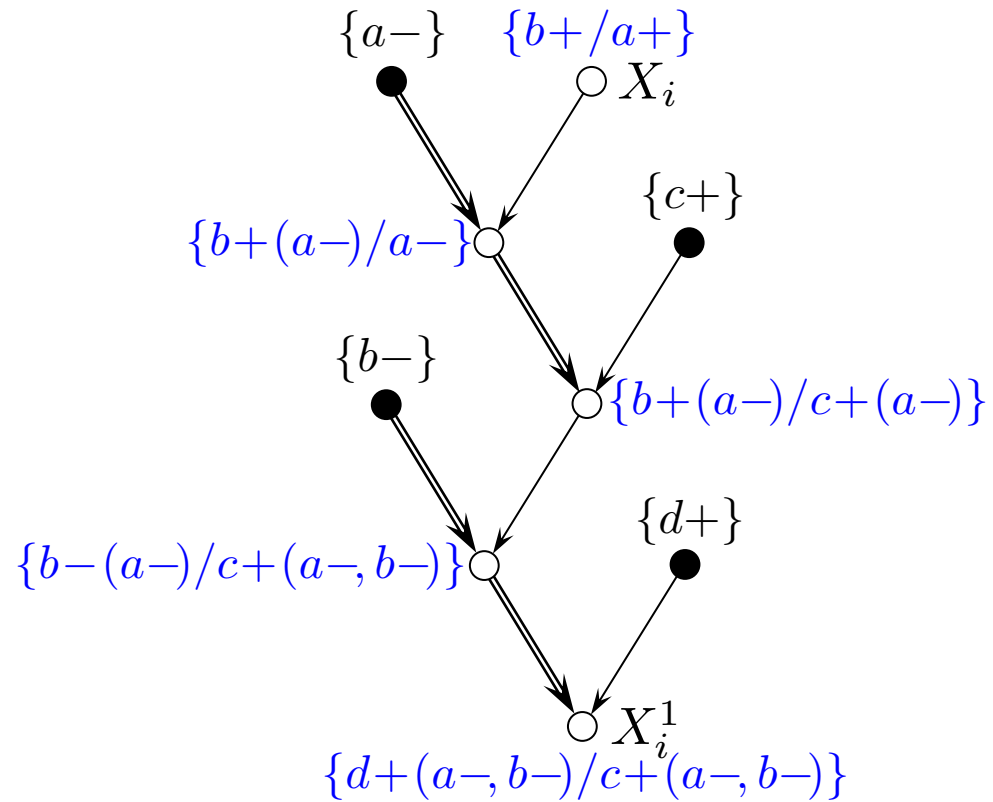


# Fig\_ComplexityPassLong

8-17-2010

Encoding

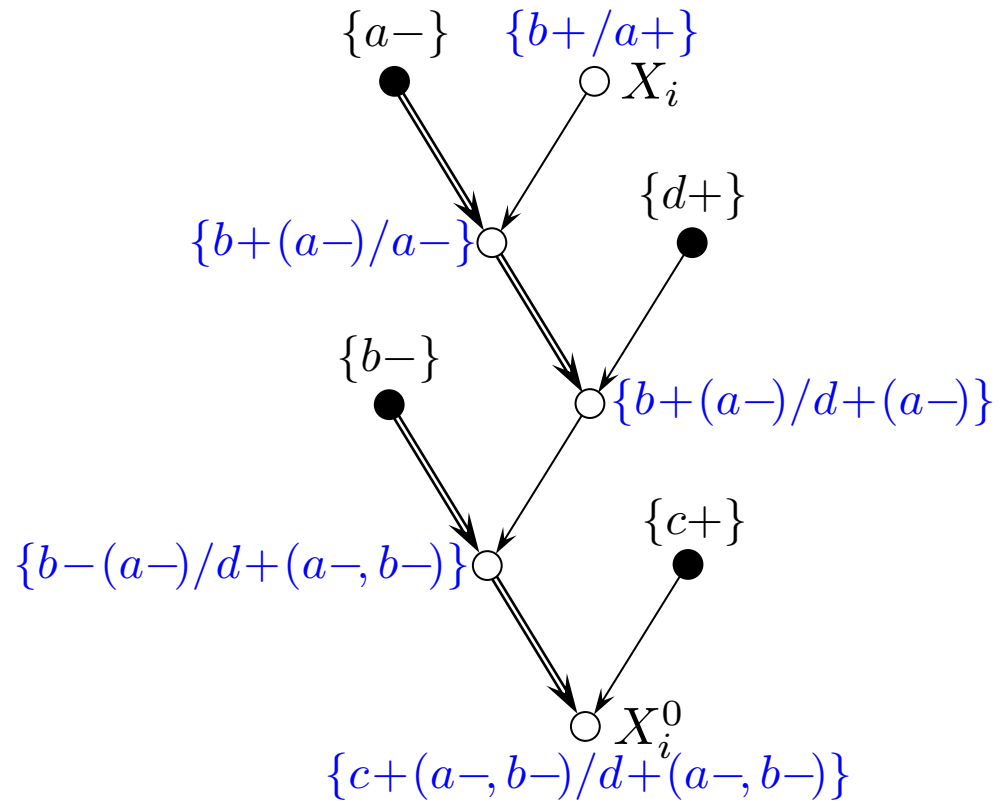
(0/1) = (a+/b+)



(0/1) = (c+/d+)

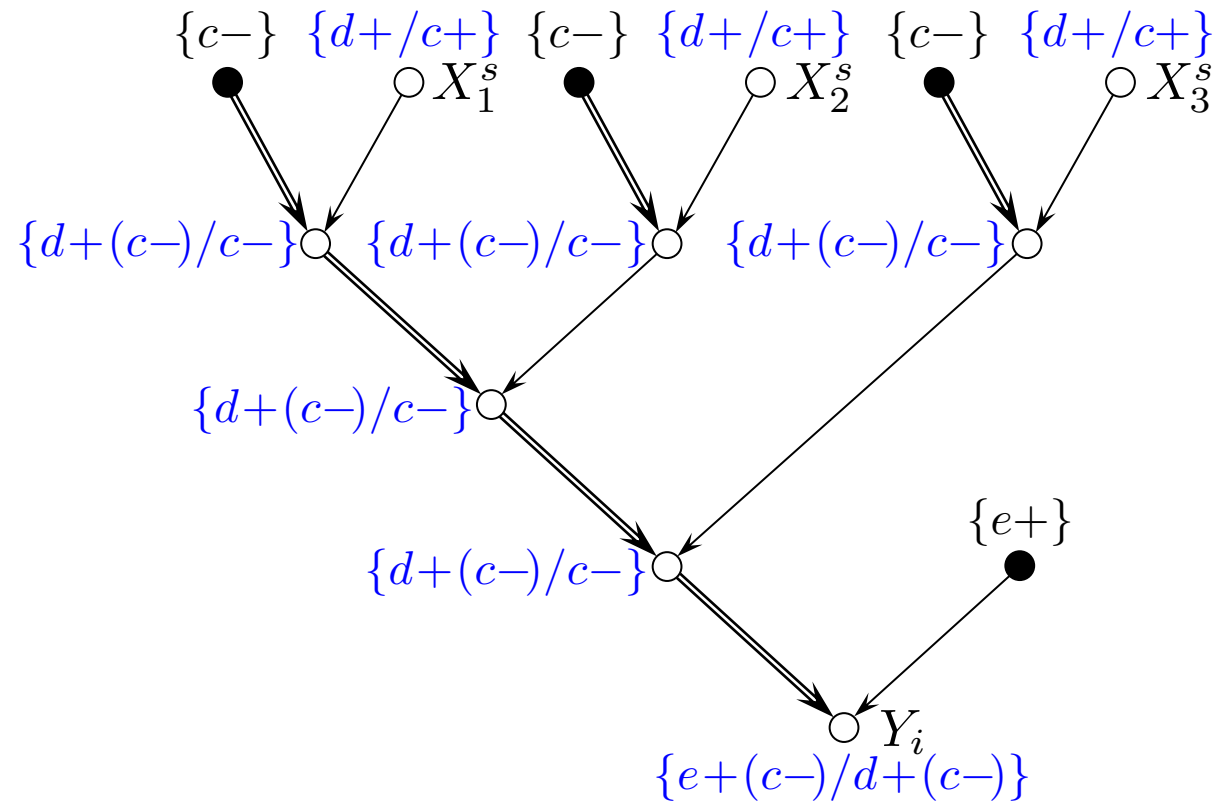
# Fig\_ComplexityNotLong

8-17-2010



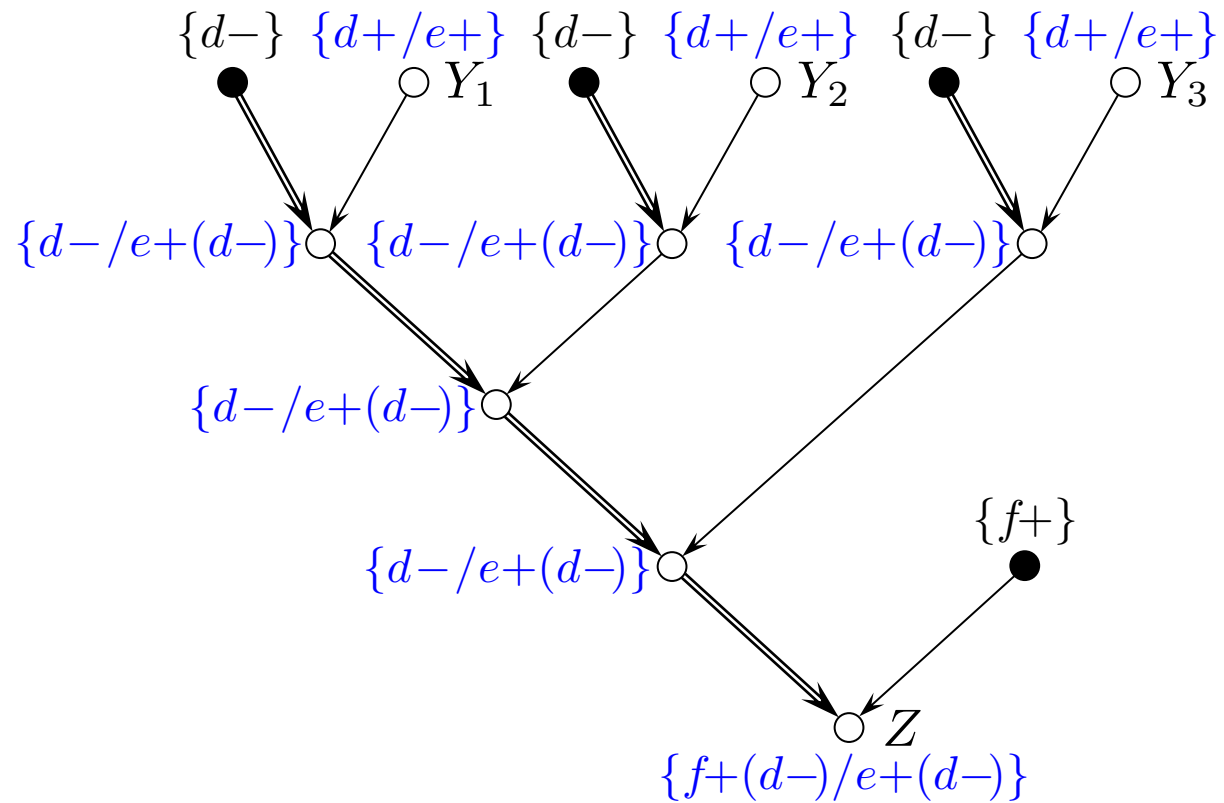
# Fig\_ComplexityOrLong

8-17-2010



# Fig\_ComplexityAndLong

8-17-2010



DEFINITION 3.1 (CONSISTENCY). *Two beliefs  $b_1, b_2$  are conflicting ( $b_1 \not\leftrightarrow b_2$ ) if they are either distinct positive beliefs  $v+, w+$ , or one is  $v+$  and the other is  $v-$ . Otherwise,  $b_1, b_2$  are consistent ( $b_1 \leftrightarrow b_2$ ). A set of beliefs  $B$  is called consistent if any two beliefs  $b_1, b_2 \in B$  are consistent.*

DEFINITION 3.2 (PREFERRED UNION). *Given two consistent sets of beliefs  $B_1, B_2$ , their preferred union is:*

$$B_1 \vec{\cup} B_2 = B_1 \cup \{b_2 \mid b_2 \in B_2. (\forall b_1 \in B_1. b_1 \leftrightarrow b_2)\}$$

be a consistent set of positive and/or negative beliefs. For each paradigm  $\sigma \in \{\text{Agnostic}, \text{Eclectic}, \text{Skeptical}\}$  (abbreviated by  $\{\mathbf{A}, \mathbf{E}, \mathbf{S}\}$ ), the *normal form*  $Norm_\sigma(B)$  is:

$$Norm_{\mathbf{A}}(B) = \begin{cases} \{v+\} & \text{if } \exists v+ \in B \\ B & \text{otherwise} \end{cases}$$

$$Norm_{\mathbf{E}}(B) = B$$

$$Norm_{\mathbf{S}}(B) = \begin{cases} \{v+\} \cup (\perp - \{v-\}) & \text{if } \exists v+ \in B \\ B & \text{otherwise} \end{cases}$$

The *preferred union specialized to the paradigm*  $\sigma$  is:

$$B_1 \vec{\cup}_\sigma B_2 = Norm_\sigma (Norm_\sigma(B_1) \vec{\cup} Norm_\sigma(B_2)) \quad (1)$$

For example:

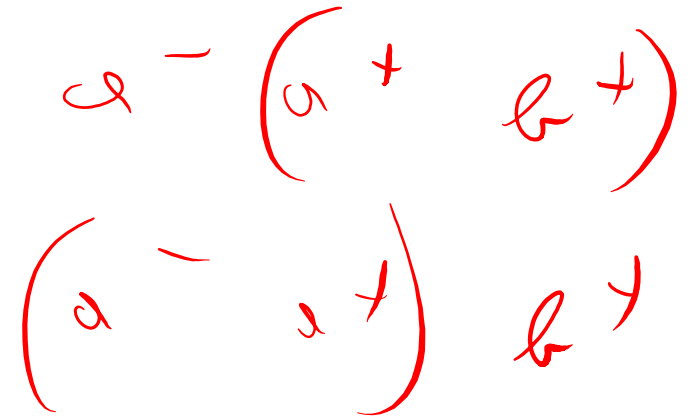
$$\{a-\} \vec{\cup}_{\mathbf{A}} \{b+\} = \{b+\}$$

$$\{a-\} \vec{\cup}_{\mathbf{E}} \{b+\} = \{b+, a-\}$$

$$\{a-\} \vec{\cup}_{\mathbf{S}} \{b+\} = \{b+, a-, c-, d-, \dots\}$$

$$\{b-\} \vec{\cup}_{\mathbf{S}} \{b+\} = \perp$$

A puzzling question is why is the **Skeptic** paradigm in PTIME, while the other two are hard. It is easy to see that the Boolean gates in Fig. 7 no longer work under **Skeptic**, but we do not consider this a satisfactory explanation. While we cannot give an ultimate cause, we point out one interesting difference. The preferred union for **Skeptic** is *as-associative*, while it is not associative for either **Agnostic** nor **Eclectic**. For example, consider the two expressions  $B_1 = \{a-\} \vec{\cup}_\sigma (\{a+\} \vec{\cup}_\sigma \{b+\})$ ,  $B_2 = (\{a-\} \vec{\cup}_\sigma \{a+\}) \vec{\cup}_\sigma \{b+\}$ . For **Agnostic**, we have  $B_2 = \{b+\}$ , for **Eclectic**  $B_2 = \{a-, b+\}$ , while for both  $B_1 = \{a-\}$ . By contrast, one can show that  $\vec{\cup}_s$  is associative. Associativity as a desirable property during data merging was pointed out in [14].



# The issue of associativity

null appears in a join column. No matter what choice is taken,  $\bowtie$  is not associative. Consider the relations

$q$	$r$	$s$
$\begin{array}{c c} A & B \\ \hline 1 & 2 \end{array}$	$\begin{array}{c c} B & C \\ \hline 2 & 3 \end{array}$	$\begin{array}{c c} A & C \\ \hline 1 & 4 \end{array}$

Computing  $(q \bowtie r) \bowtie s$  we get

$q'$
$\begin{array}{c c c} A & B & C \\ \hline 1 & 2 & 3 \\ 1 & \perp & 4 \end{array}$

while  $q \bowtie (r \bowtie s)$  gives

$q''$
$\begin{array}{c c c} A & B & C \\ \hline 1 & 2 & 4 \\ \perp & 2 & 3 \end{array}$

$$\{a^-\} \bar{U}_a (\{a\} \bar{U}_a \{b\}) = \{a^-\}$$

$$(\{a^-\} \bar{U}_a \{a\}) \bar{U}_a \{b\} = \{b\}$$

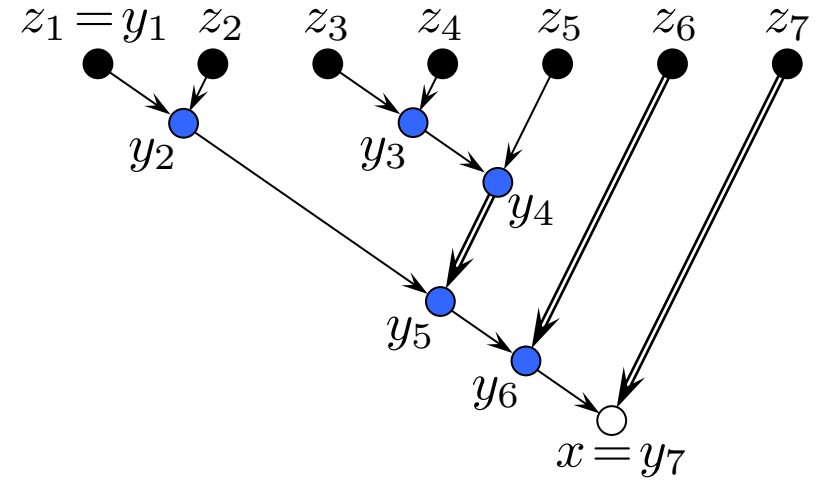
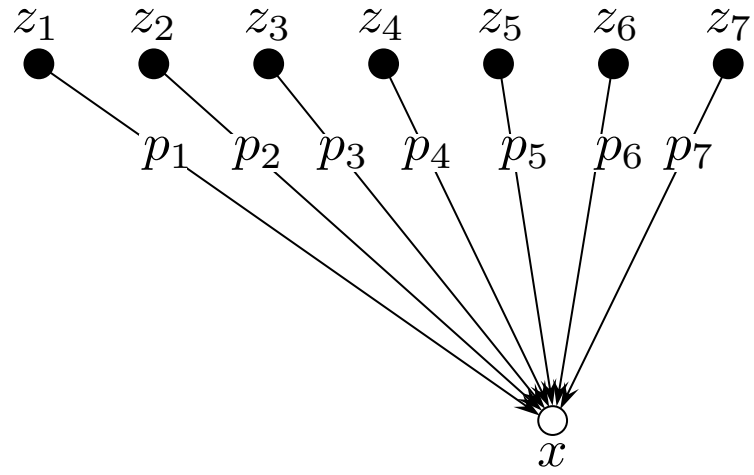
left outer join example from p392 in "Maier. The theory of relational databases, 1983."

right preferred union example from "Gatterbauer, Suciu. Conflict resolution using trust mapping. SIGMOD 2010."



backup

# Binarization example



$$p_1 = p_2 < p_3 = p_4 = p_5 < p_6 < p_7$$

# Binarization for Resolution Algorithm\*

## Example Trust Network (TN)

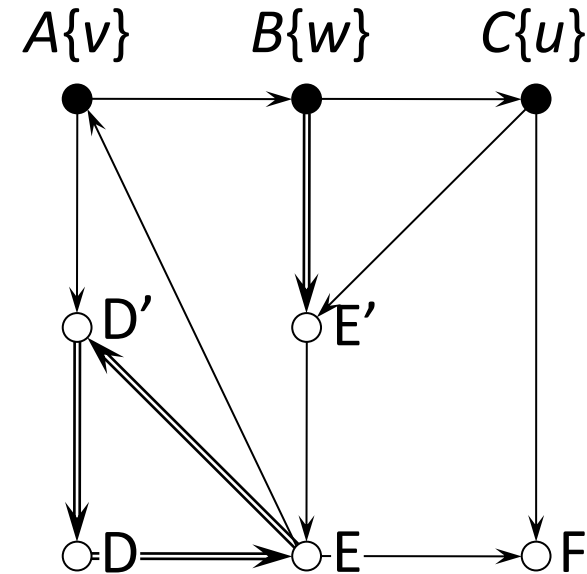
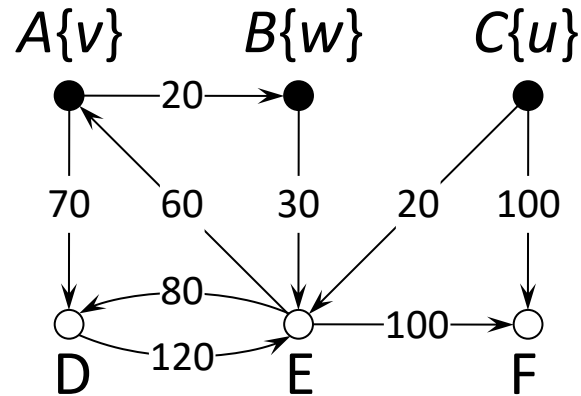
6 nodes, 9 arcs (size 15)

3 explicit beliefs: A:v, B:w, C:u

## Corresponding Binary TN (BTN)

8 nodes, 12 arcs (size 20)

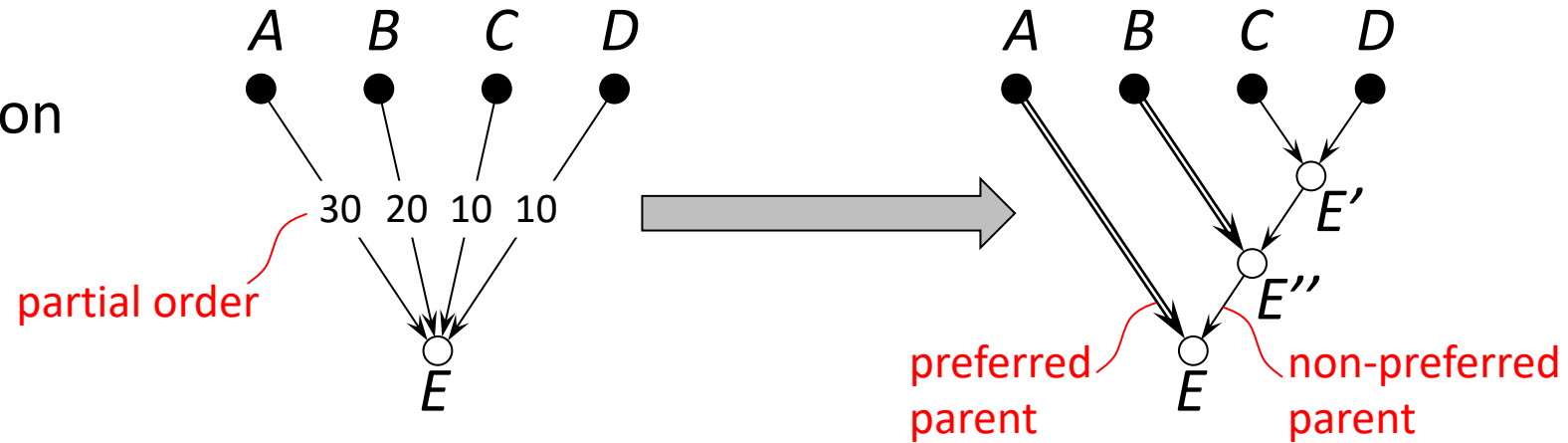
Size increase (N+E):  $\leq 3$



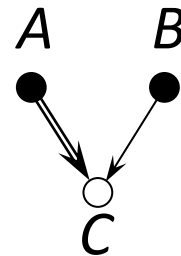
\* Note that binarization is not necessary, but greatly simplifies the presentation

# Logic programs with stable model semantics

Step 1:  
Binarization



Step 2:  
Logic program

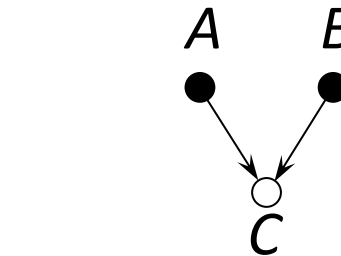


1: accept all **poss** of preferred parent

$P(C,x) :- P(A,x)$

$F(C,B,y) :- P(B,y), P(C,x), x \neq y$

$P(C,y) :- P(B,y), \neg F(C,B,y)$



$F(C,A,y) :- P(A,y), P(C,x), x \neq y$

$P(C,y) :- P(A,y), \neg F(C,A,y)$

$F(C,B,y) :- P(B,y), P(C,x), x \neq y$

$P(C,y) :- P(B,y), \neg F(C,B,y)$

2: accept **poss** from non-preferred parent, that are not conflicting with an existing value

# Binarization for Resolution Algorithm\*

## Example Trust Network (TN)

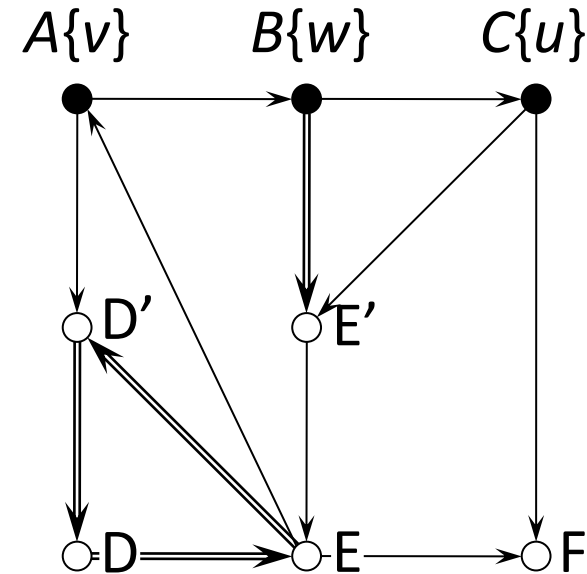
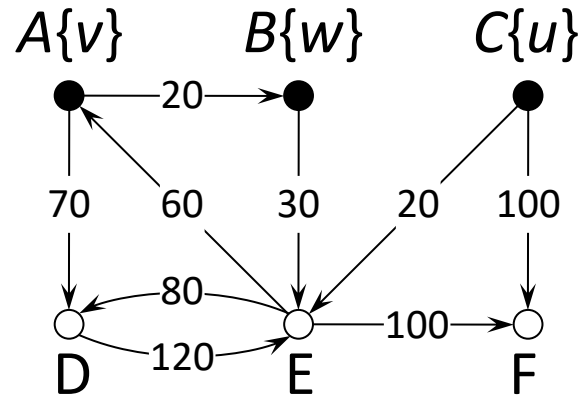
6 nodes, 9 arcs (size 15)

3 explicit beliefs: A:v, B:w, C:u

## Corresponding Binary TN (BTN)

8 nodes, 12 arcs (size 20)

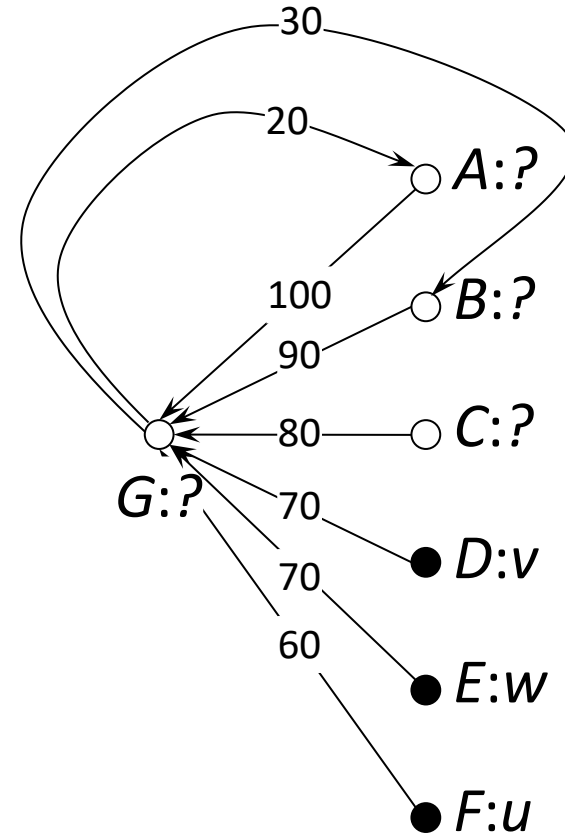
Size increase :  $\leq 3$



\* Note that binarization is not necessary, but greatly simplifies the presentation

# Stable solutions: example 2

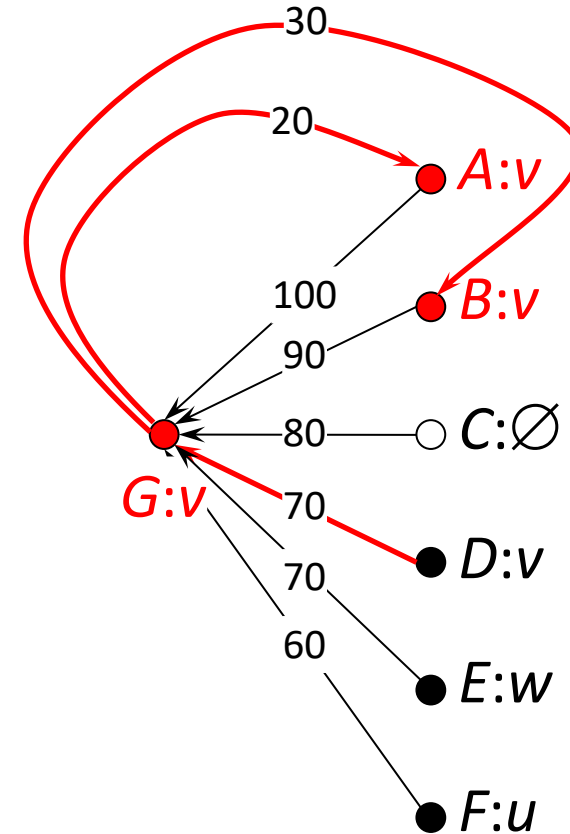
- Priority trust network (TN)
  - assume a fixed key
  - users (nodes):  $A, B, C$
  - values (beliefs):  $v, w, u$
  - trust mappings (arcs) from “parents”
- Stable solution
  - assignment of values to each node\*, s.t. each belief has a “non-dominated lineage” to an explicit belief
- Certain values
  - all stable solution determine, for each node, a possible value (“poss”)
  - certain value (“cert”) = intersection of all stable solutions



\* each node with at least one ancestor with explicit belief

# Stable solutions: example 2

- Priority trust network (TN)
  - assume a fixed key
  - users (nodes):  $A, B, C$
  - values (beliefs):  $v, w, u$
  - trust mappings (arcs) from “parents”
- Stable solution
  - assignment of values to each node\*, s.t. each belief has a “non-dominated lineage” to an explicit belief
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  - all stable solution determine, for each node, a possible value (“poss”)
  - certain value (“cert”) = intersection of all stable solutions

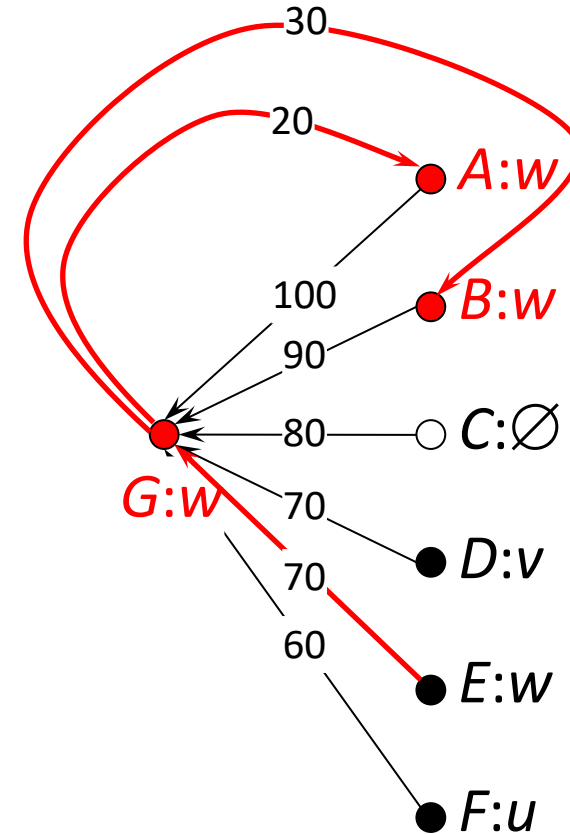


$$\text{poss}(G) = \{v, \dots\}$$

\* each node with at least one ancestor with explicit belief

# Stable solutions: example 2

- Priority trust network (TN)
  - assume a fixed key
  - users (nodes):  $A, B, C$
  - values (beliefs):  $v, w, u$
  - trust mappings (arcs) from “parents”
- Stable solution
  - assignment of values to each node\*, s.t. each belief has a “non-dominated lineage” to an explicit belief
- Certain values
  - all stable solution determine, for each node, a possible value (“poss”)
  - certain value (“cert”) = intersection of all stable solutions



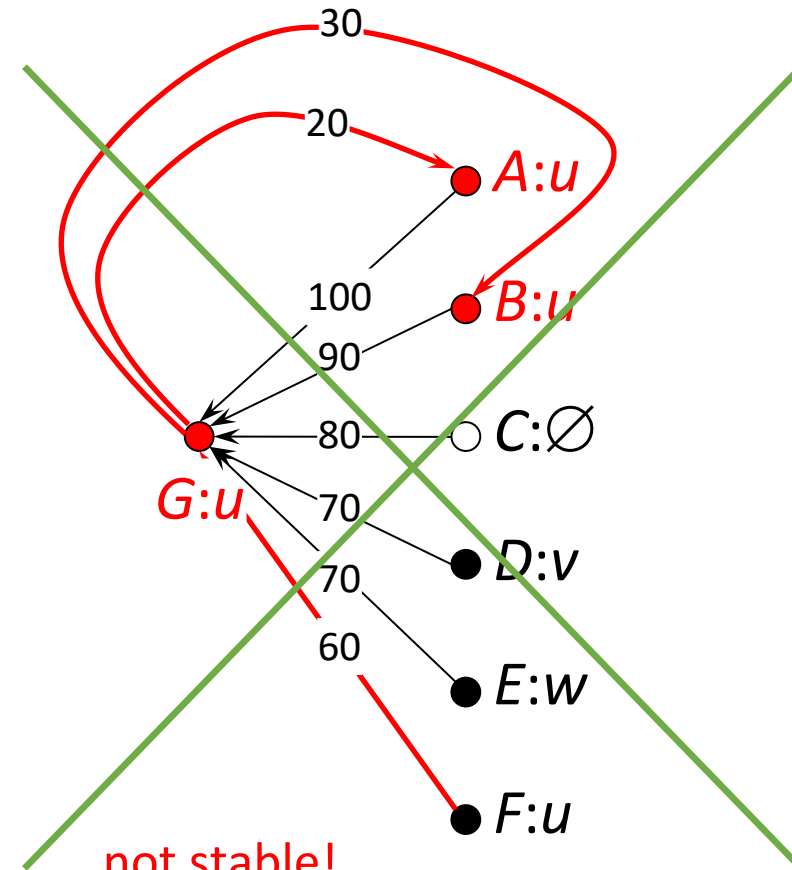
$$\text{poss}(G) = \{v, w, \dots\}$$

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$$\text{poss}(G) = \{v, w\}$$

$$\text{cert}(G) = \emptyset$$

\* each node with at least one ancestor with explicit belief