

# On the Power of Belief Propagation: A Constraint Propagation Perspective



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Rina  
Dechter

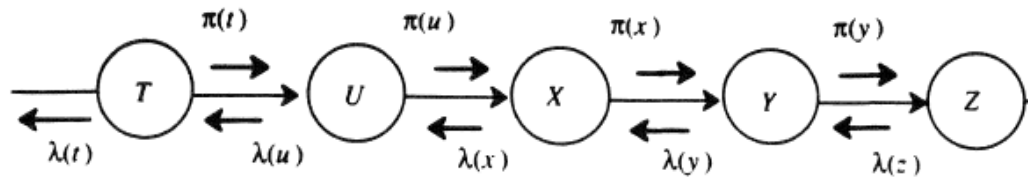
Bozhena  
Bidyuk

Robert  
Mateescu

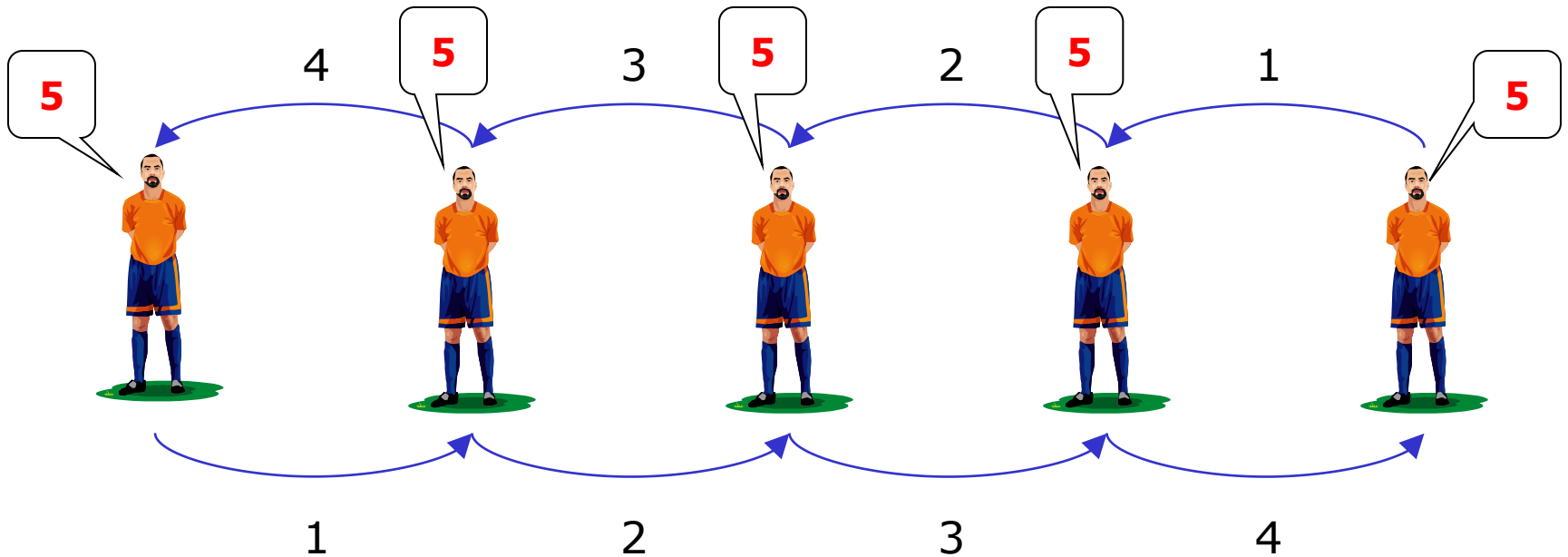
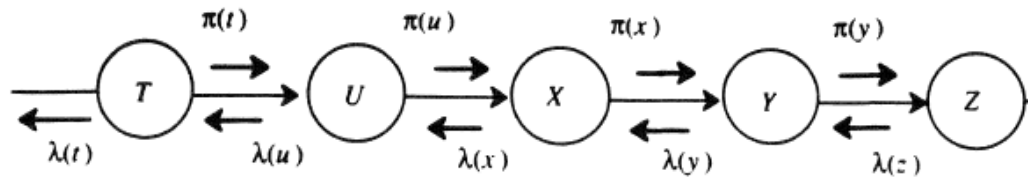
Emma  
Rollon



# Distributed Belief Propagation

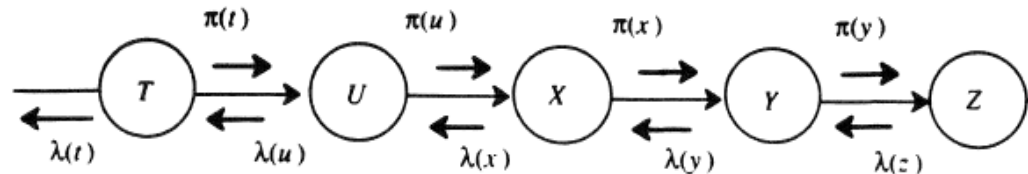


# Distributed Belief Propagation

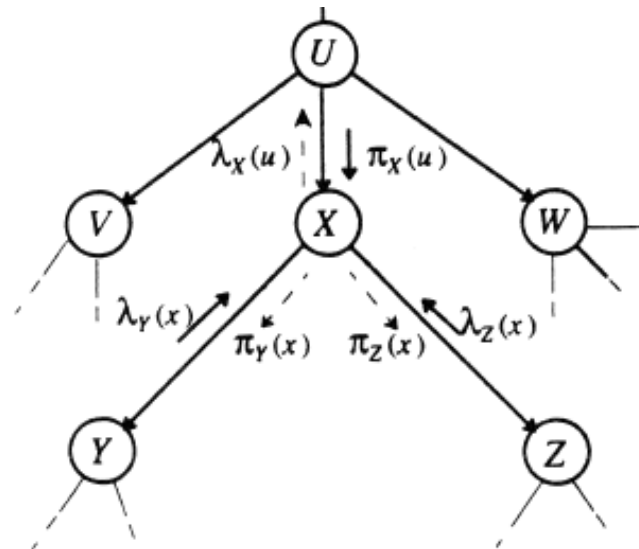


**How many people?**

# Distributed Belief Propagation



Causal support



Diagnostic support



**Figure 4.14.** Fragment of causal tree, showing incoming (solid arrows) and outgoing (broken arrows) messages at node  $X$ .

$$\mathbf{e} = \mathbf{e}_X^- \cup \mathbf{e}_X^+$$

$\mathbf{e}_X^-$  stands for the evidence contained in the tree rooted at  $X$ .  $\mathbf{e}_X^+$  stands for the evidence contained in the rest of the network.

# Belief Propagation in Polytrees

## EVIDENCE DECOMPOSITION

$e_{XY_j}^-$  stands for evidence contained in the subnetwork on the *head* side of the link  $X \rightarrow Y_j$ ,

$e_{U_i X}^+$  stands for evidence contained in the subnetwork on the *tail* side of the link  $U_i \rightarrow X$ .

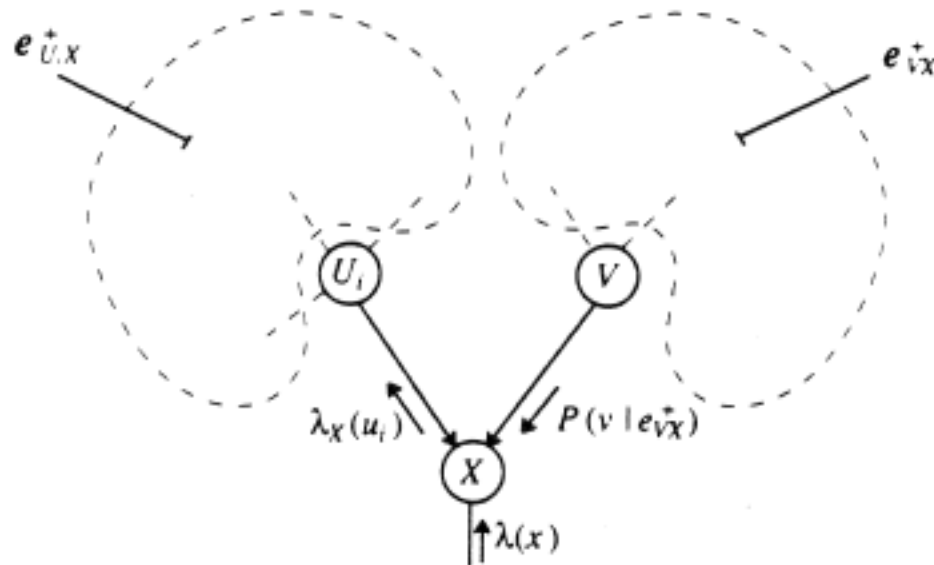
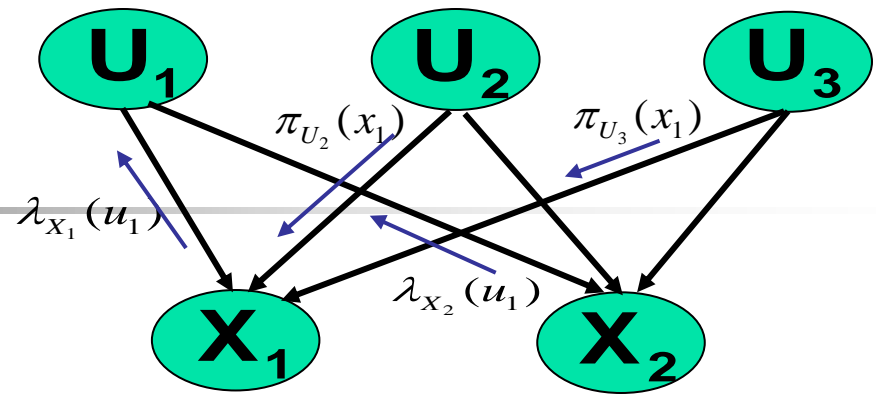


Figure 4.19. Variables, messages, and evidence sets used in the derivation of  $\lambda_X(u_i)$ .

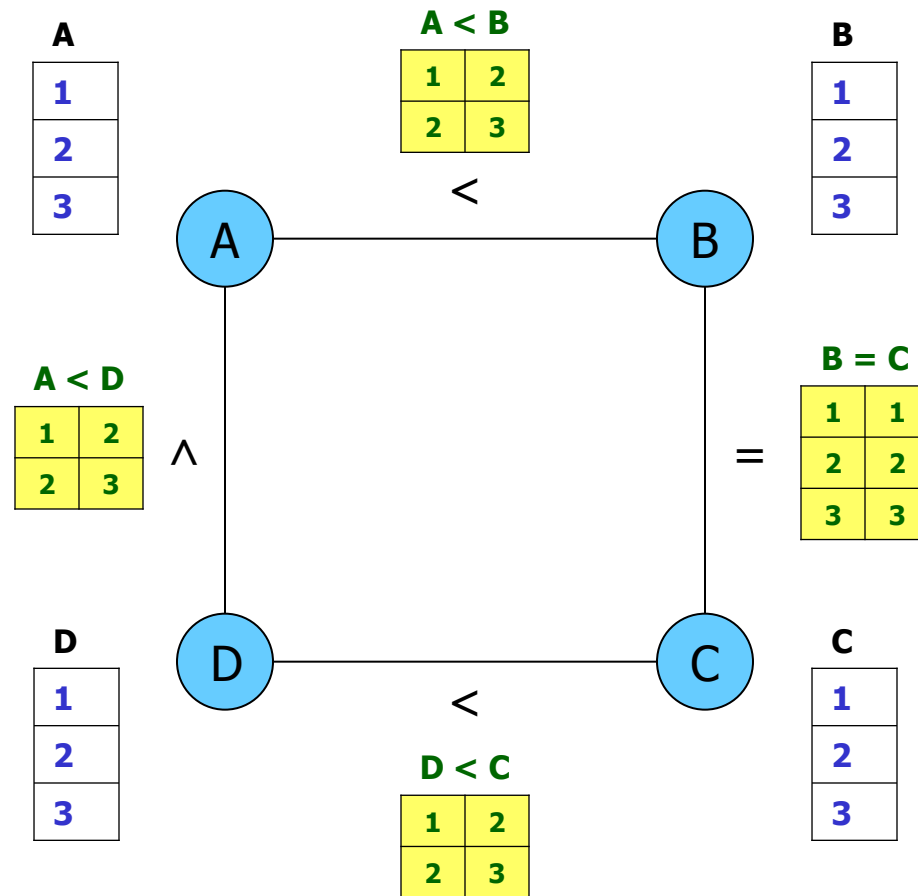
# BP on Loopy Graphs



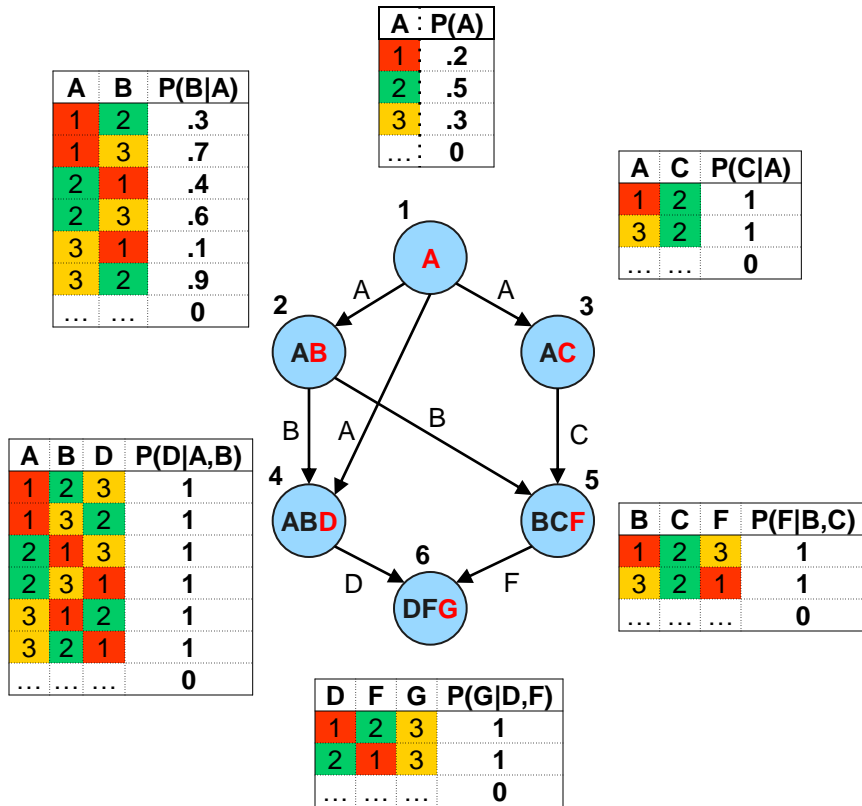
- Pearl (1988): use of BP to loopy networks
- McEliece, et. Al 1988: IBP's success on coding networks
- Lots of research into convergence ... and accuracy (?), but:
  - Why IBP works well for coding networks
  - Can we characterize other good problem classes
  - Can we have any guarantees on accuracy (even if converges)

# Arc-consistency

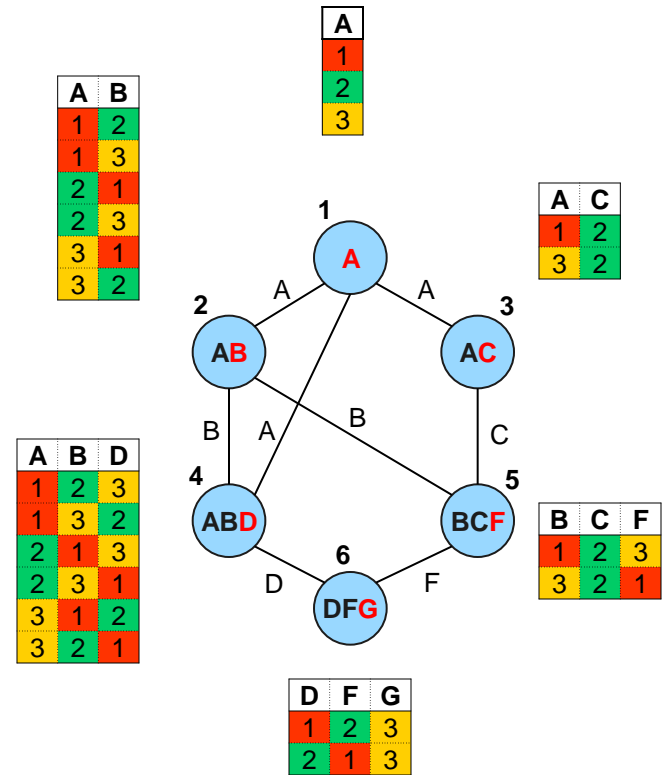
- Sound
- Incomplete
- Always converges (polynomial)



# Flattening the Bayesian Network



Belief network



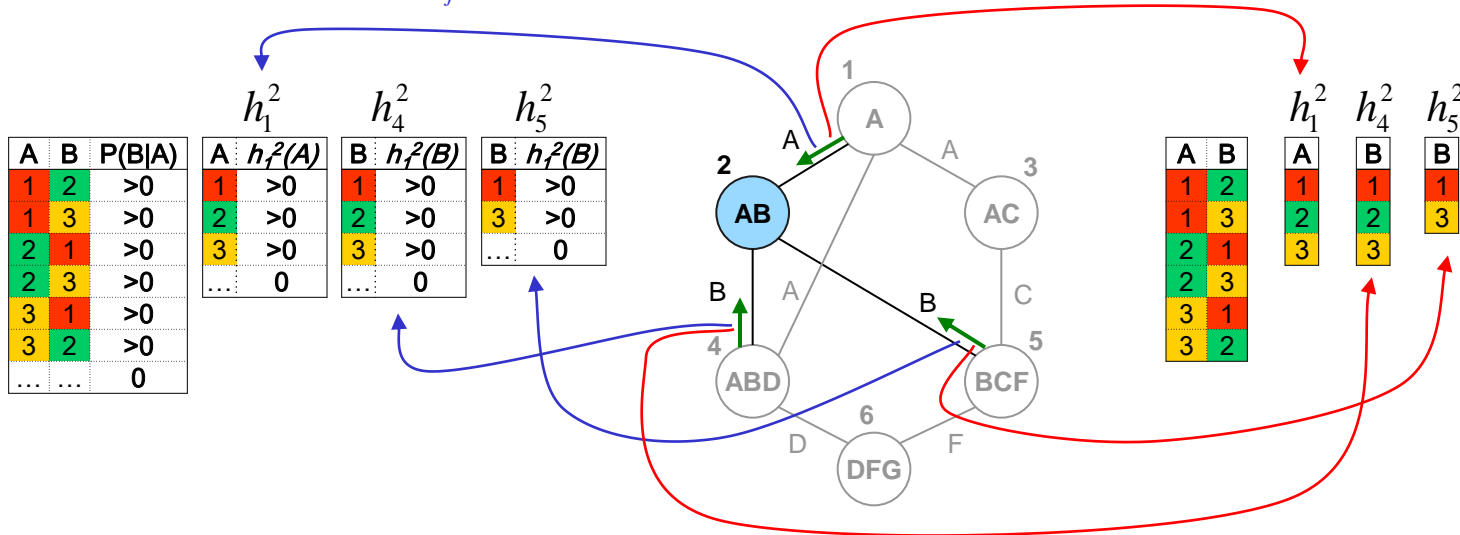
Flat constraint network



# Belief Zero Propagation = Arc-Consistency

$$h_i^j = \sum_{elim(i,j)} (p_i \cdot (\prod_{k \in ne_j(i)} h_k^i))$$

$$h_i^j = \pi_{lij} (R_i \bowtie (\bowtie_{k \in ne(i)} h_k^i))$$



Updated belief:

Updated relation:

$$Bel(A, B) = P(B | A) \cdot h_1^2 \cdot h_4^2 \cdot h_5^2 =$$

$$R(A, B) = R(A, B) \bowtie h_1^2 \bowtie h_4^2 \bowtie h_5^2 =$$

A	B	Bel(A,B)
1	3	>0
2	1	>0
2	3	>0
3	1	>0
...	...	0

A	B
1	3
2	1
2	3
3	1

# Flat Network - Example

$$R_1$$

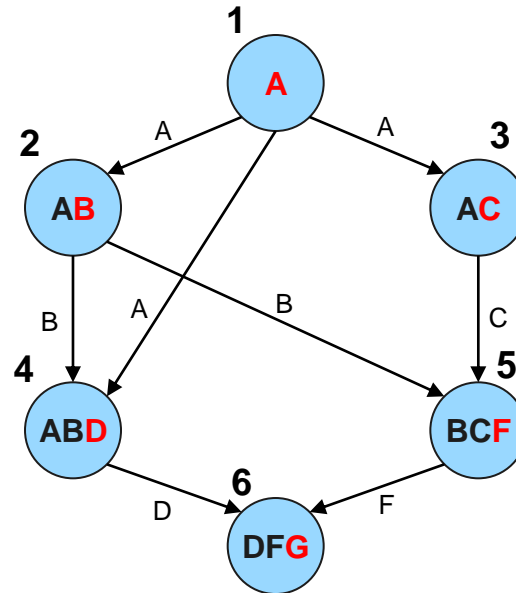
A	P(A)
1	.2
2	.5
3	.3
...	0

$$R_2$$

A	B	P(B A)
1	2	.3
1	3	.7
2	1	.4
2	3	.6
3	1	.1
3	2	.9
...	...	0

$$R_3$$

A	C	P(C A)
1	2	1
3	2	1
...	...	0



$$R_4$$

A	B	D	P(D A,B)
1	2	3	1
1	3	2	1
2	1	3	1
2	3	1	1
3	1	2	1
3	2	1	1
...	...	...	0

$$R_5$$

B	C	F	P(F B,C)
1	2	3	1
3	2	1	1
...	...	...	0

$$R_6$$

D	F	G	P(G D,F)
1	2	3	1
2	1	3	1
...	...	...	0

# IBP Example – Iteration 1

$$R_1$$

A	P(A)
1	>0
3	>0
...	0

 $R_2$ 

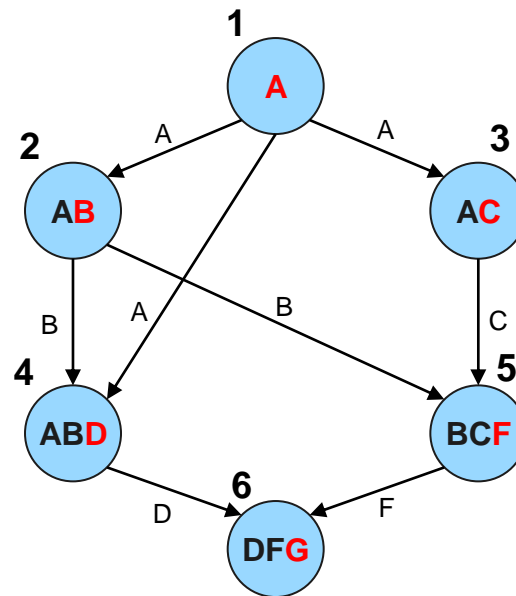
A	B	P(B A)
1	3	1
2	1	>0
2	3	>0
3	1	1
...	...	0

 $R_3$ 

A	C	P(C A)
1	2	1
3	2	1
...	...	0

 $R_4$ 

A	B	D	P(D A,B)
1	3	2	1
2	3	1	1
3	1	2	1
3	2	1	1
...	...	...	0


 $R_5$ 

B	C	F	P(F B,C)
1	2	3	1
3	2	1	1
...	...	...	0

 $R_6$ 

D	F	G	P(G D,F)
2	1	3	1
...	...	...	0

# IBP Example – Iteration 2

$$R_1$$

A	P(A)
1	>0
3	>0
...	0

$$R_2$$

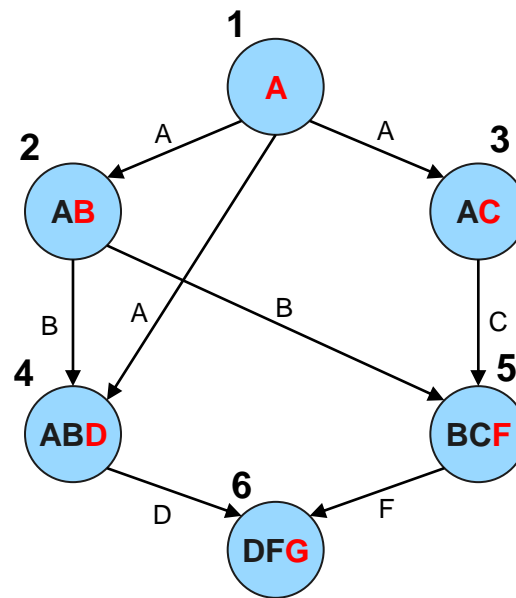
A	B	P(B A)
1	3	1
3	1	1
...	...	0

$$R_3$$

A	C	P(C A)
1	2	1
3	2	1
...	...	0

$$R_4$$

A	B	D	P(D A,B)
1	3	2	1
3	1	2	1
...	...	...	0



$$R_5$$

B	C	F	P(F B,C)
3	2	1	1
...	...	...	0

$$R_6$$

D	F	G	P(G D,F)
2	1	3	1
...	...	...	0

# IBP Example – Iteration 3

$$R_1$$

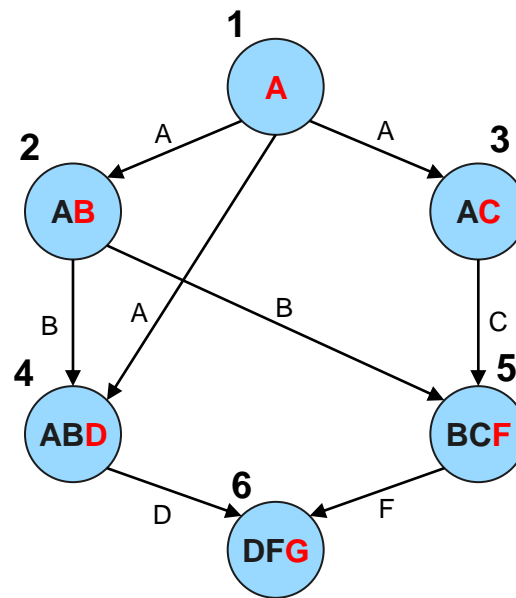
A	P(A)
1	>0
3	>0
...	0

$$R_2$$

A	B	P(B A)
1	3	1
...	...	0

$$R_3$$

A	C	P(C A)
1	2	1
3	2	1
...	...	0



$$R_4$$

A	B	D	P(D A,B)
1	3	2	1
3	1	2	1
...	...	...	0

$$R_5$$

B	C	F	P(F B,C)
3	2	1	1
...	...	...	0

$$R_6$$

D	F	G	P(G D,F)
2	1	3	1
...	...	...	0

# IBP Example – Iteration 4

 $R_1$ 

A	P(A)
1	1
...	0

 $R_2$ 

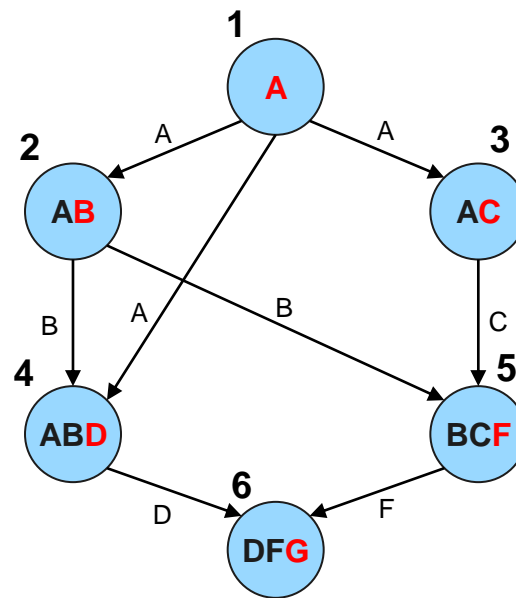
A	B	P(B A)
1	3	1
...	...	0

 $R_3$ 

A	C	P(C A)
1	2	1
3	2	1
...	...	0

 $R_4$ 

A	B	D	P(D A,B)
1	3	2	1
...	...	...	0


 $R_5$ 

B	C	F	P(F B,C)
3	2	1	1
...	...	...	0

 $R_6$ 

D	F	G	P(G D,F)
2	1	3	1
...	...	...	0

# IBP Example – Iteration 5

$$R_1$$

A	P(A)
1	1
...	0

A	B	C	D	F	G	Belief
1	3	2	2	1	3	1
...	...	...	...	...	...	0

$$R_2$$

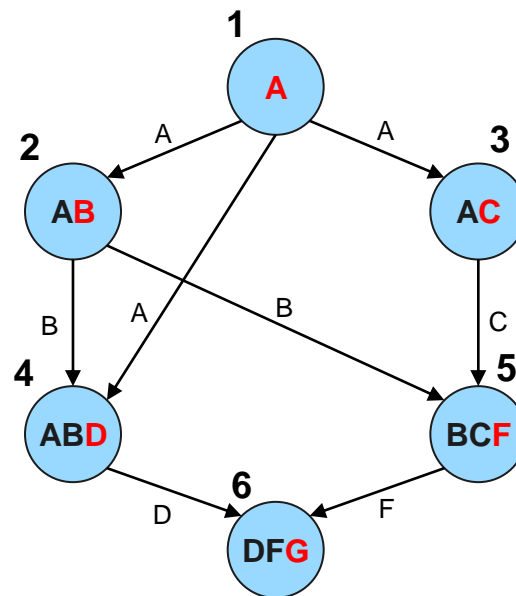
A	B	P(B A)
1	3	1
...	...	0

$$R_3$$

A	C	P(C A)
1	2	1
...	...	0

$$R_4$$

A	B	D	P(D A,B)
1	3	2	1
...	...	...	0



$$R_5$$

B	C	F	P(F B,C)
3	2	1	1
...	...	...	0

$$R_6$$

D	F	G	P(G D,F)
2	1	3	1
...	...	...	0



# IBP – Inference Power for Zero Beliefs

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- **Theorem:**

- Iterative BP performs arc-consistency on the flat network.

- **Soundness:**

- Inference of zero beliefs by IBP converges
  - All the inferred zero beliefs are correct

- **Incompleteness:**

- Iterative BP is as weak and as strong as arc-consistency

- **Continuity Hypothesis:** IBP is sound for zero  $\rightarrow$  IBP is accurate for extreme beliefs? Tested empirically





# Experimental Results

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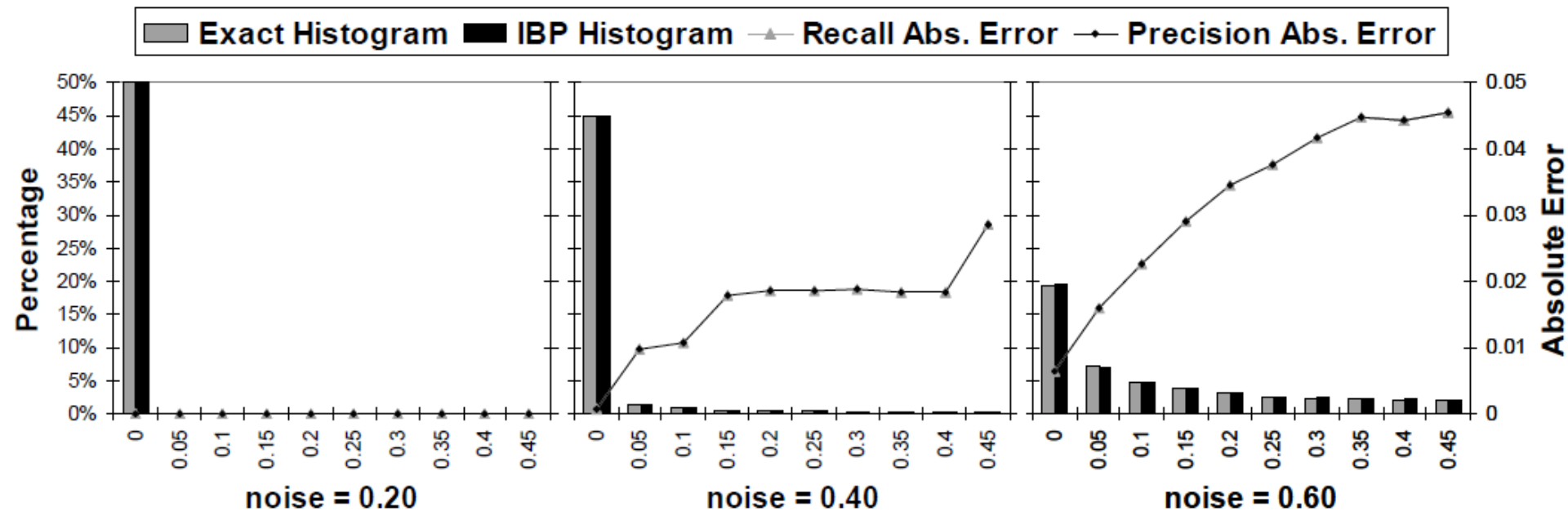
We investigated empirically if the results for zero beliefs extend to  $\varepsilon$ -small beliefs ( $\varepsilon > 0$ )

Have determinism?

- Network types:
  - YES** {
    - Coding
    - Linkage analysis\*
    - Grids\*
  - NO** {
    - Two-layer noisy-OR\*
    - CPCS54, CPCS360
- Measures:
  - Exact/IJGP histogram
  - Recall absolute error
  - Precision absolute error
- Algorithms:
  - IBP
  - IJGP

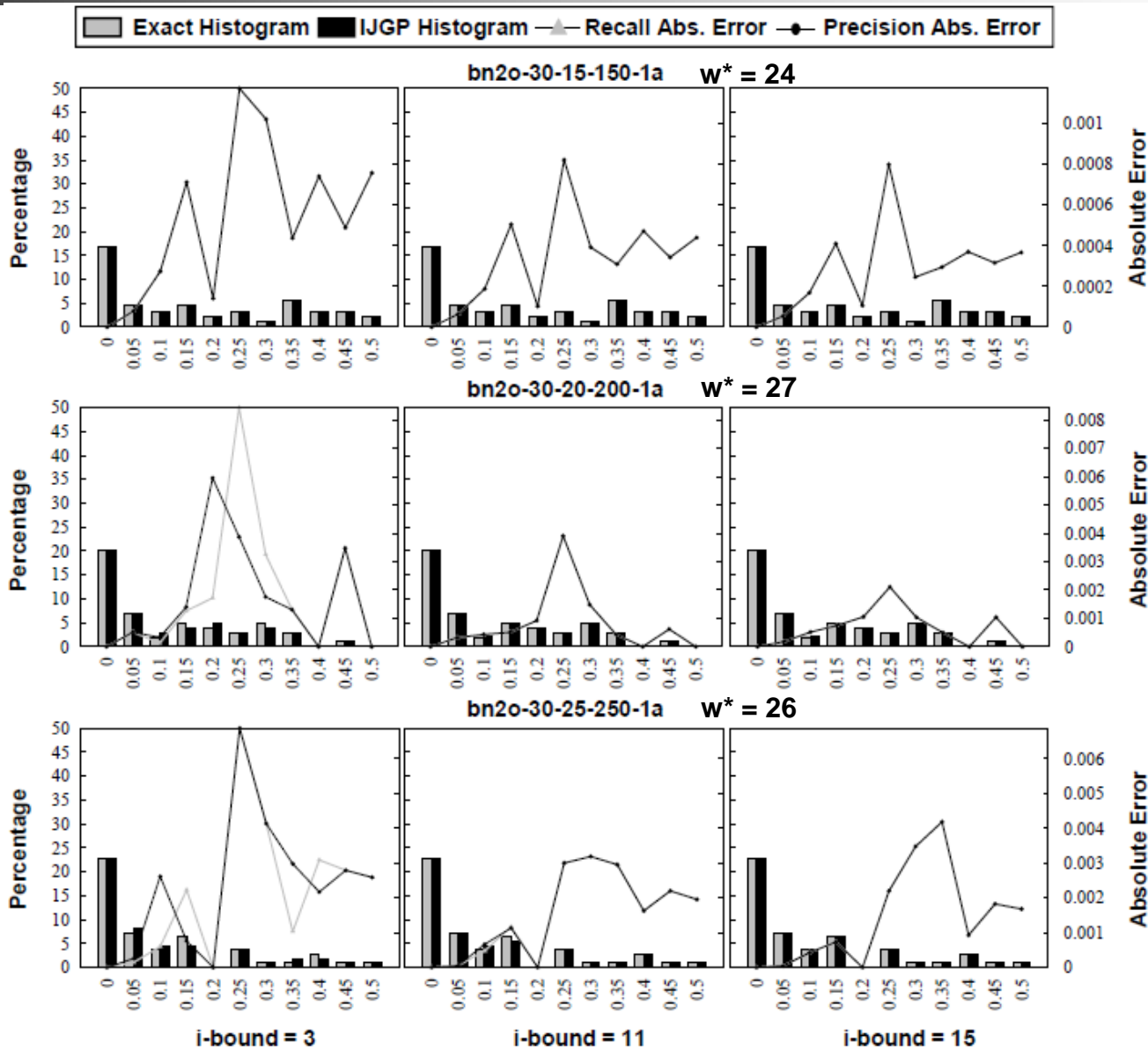
\* Instances from the UAI08 competition

# Networks with Determinism: Coding



N=200, 1000 instances,  $w^*=15$

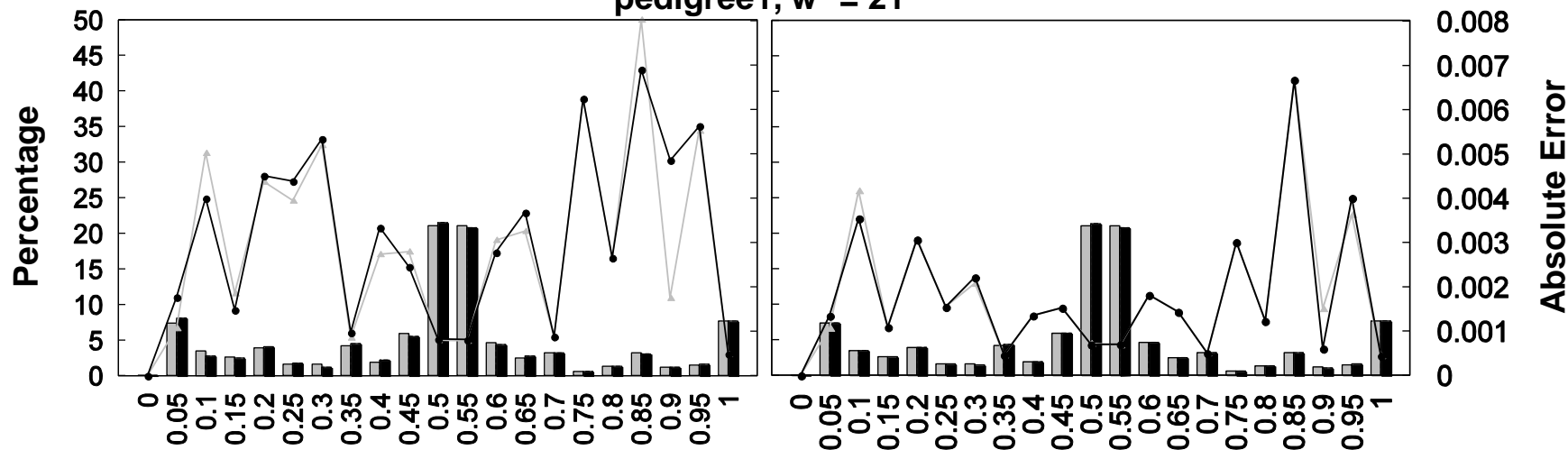
# Nets w/o Determinism: bn2o



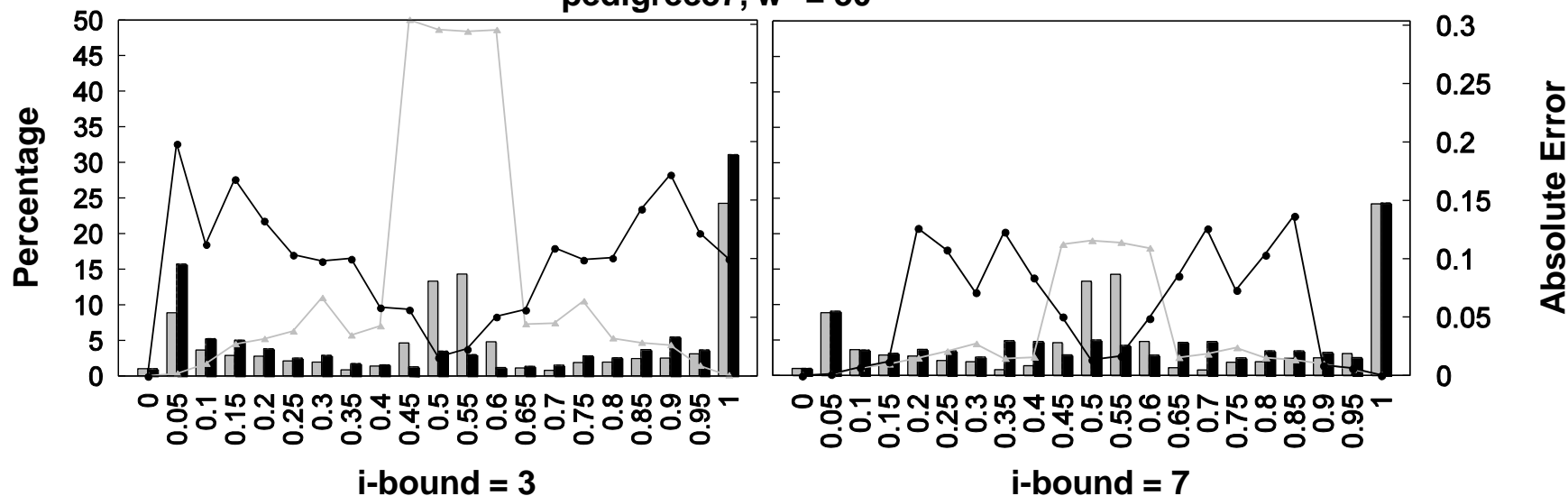
# Nets with Determinism: Linkage

Exact Histogram
  IJGP Histogram
  Recall Abs. Error
  Precision Abs. Error

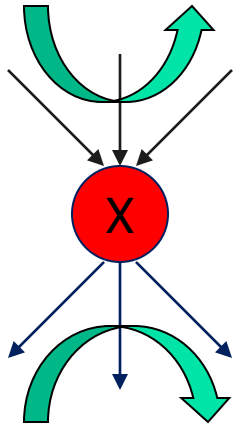
pedigree1,  $w^* = 21$



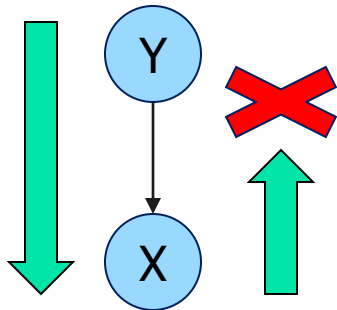
pedigree37,  $w^* = 30$



# The Cutset Phenomena & irrelevant nodes



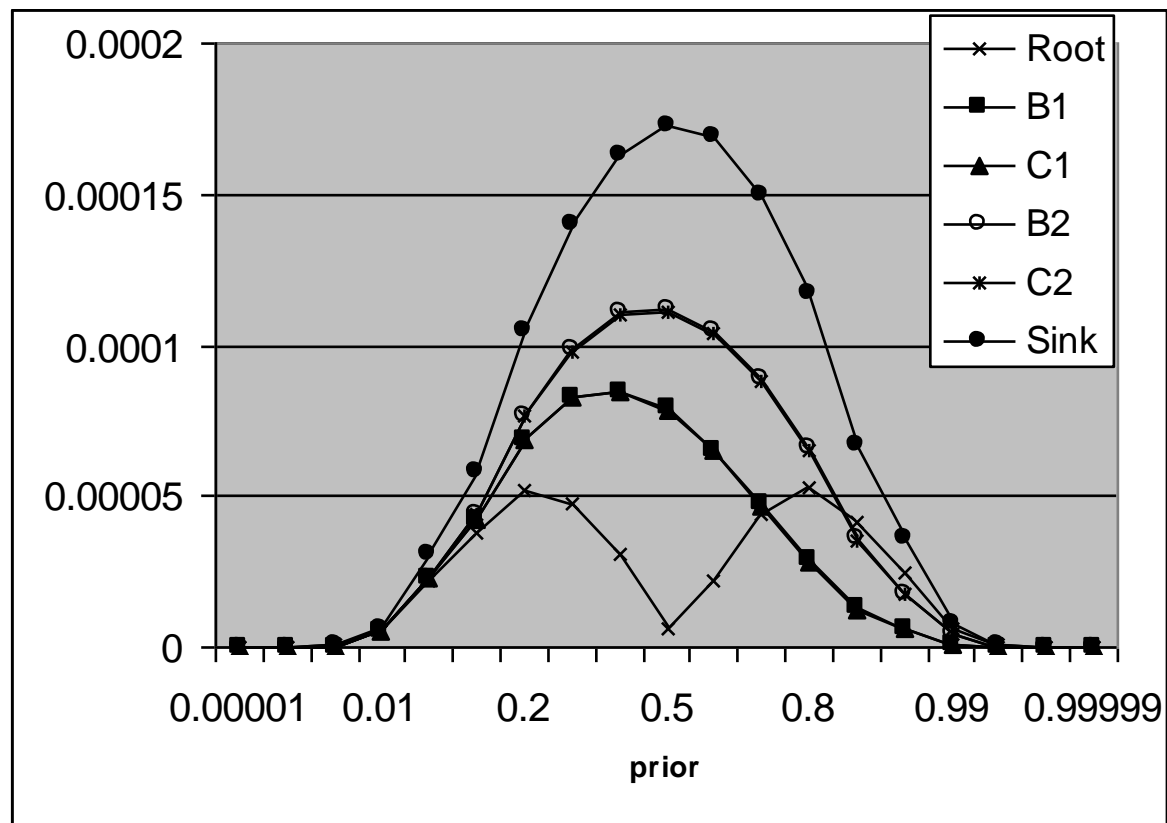
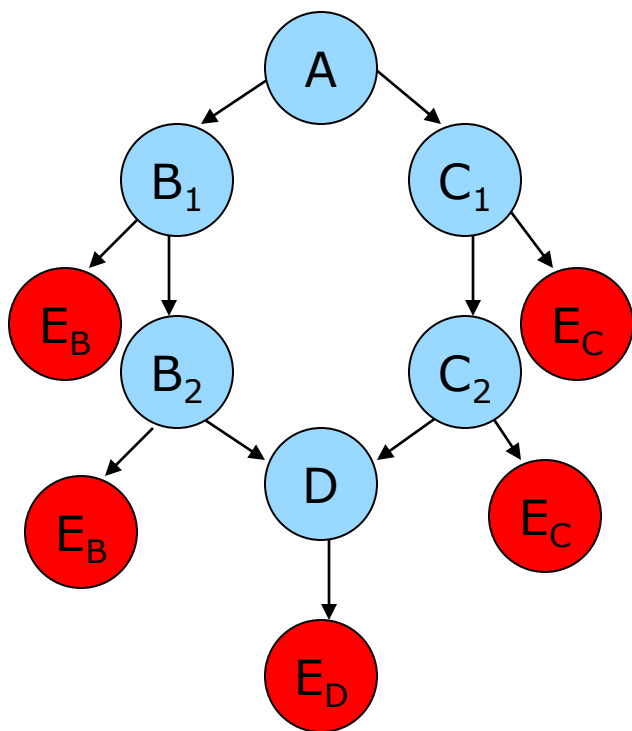
- **Observed variables** break the flow of inference
  - **IBP is exact when evidence variables form a cycle-cutset**



- **Unobserved variables** without observed descendants send zero-information to the parent variables – it is irrelevant
  - **In a network without evidence, IBP converges in one iteration top-down**

# Nodes with extreme support

Observed variables with xtreme priors or xtreme support can nearly-cut information flow:



Average Error vs. Priors



# Conclusion: For Networks with Determinism

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- IBP converges & sound for zero beliefs
- IBP's power to infer zeros is as weak or as strong as arc-consistency
- However: inference of extreme beliefs can be wrong.
- Cutset property (Bidyuk and Dechter, 2000):
  - Evidence and inferred singleton act like cutset
  - If zeros are cycle-cutset, all beliefs are exact
  - Extensions to epsilon-cutset were supported empirically.