CSE 473: Artificial Intelligence

Bayesian Networks

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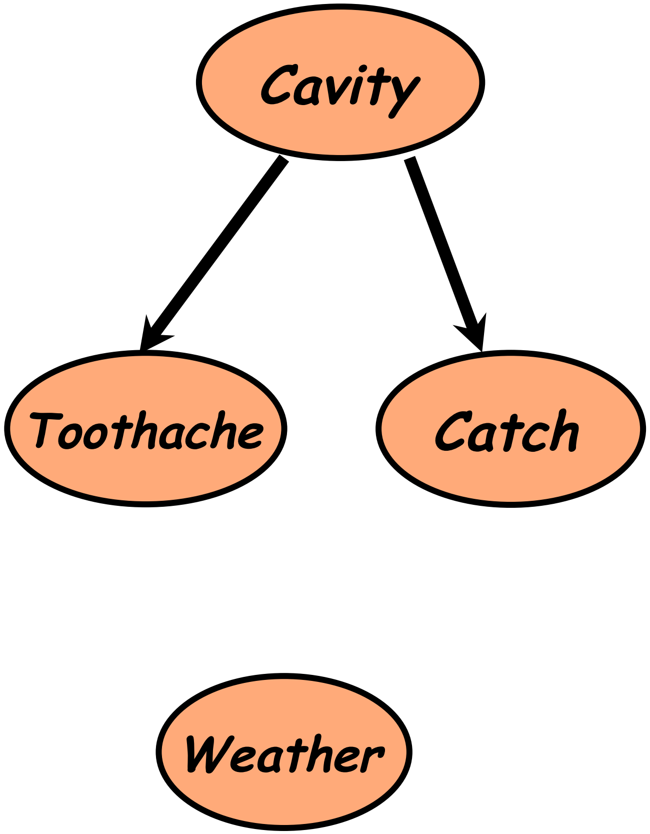
Many slides over the course adapted from either Luke Zettlemoyer, Pieter Abbeel, Dan Klein, Stuart Russell or Andrew Moore

Outline

- Probabilistic models (and inference)
  - Bayesian Networks (BNs)
  - Independence in BNs
  - Inference in BNs

Notation

- Nodes: variables (with domains)
  - Can be assigned (observed) or
  - unassigned (unobserved)
- Arcs: interactions
  - Indicate “direct influence” between variables
  - Formally: encode conditional independence (more later)

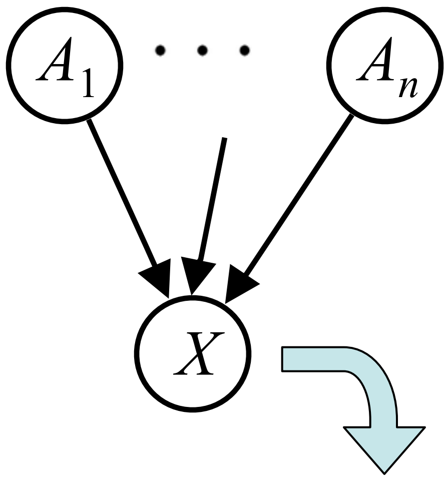


Bayes' Net Semantics

- Let's formalize the semantics of a Bayes' net
- A set of nodes, one per variable X
- A directed, acyclic graph
- A conditional distribution for each node
  - A collection of distributions over X, one for each combination of parents' values

$$P(X|a_1 \ldots a_n)$$

  - CPT: conditional probability table



$$P(X|A_1 \ldots A_n)$$

A Bayes net = Topology (graph) + Local Conditional Probabilities

Bayes Net Probabilities

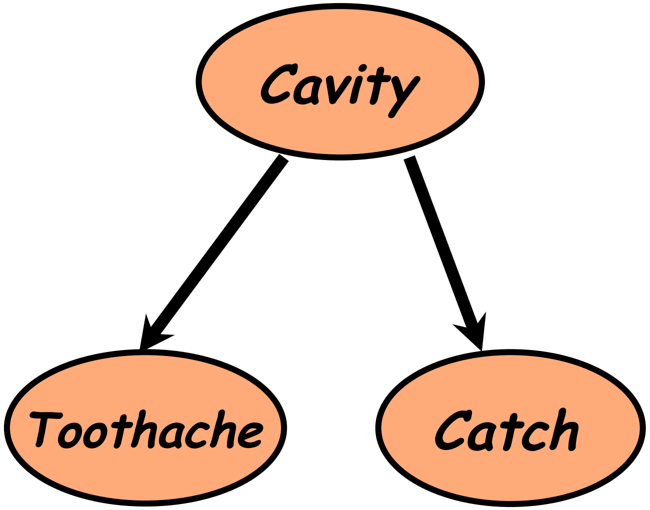
- Bayes nets compactly represent joint distributions (instead of big joint table)
  - A joint distribution using chain rule

$$P(x_1 \ldots x_n) = \prod_i P(x_i \mid parents(x_i))$$

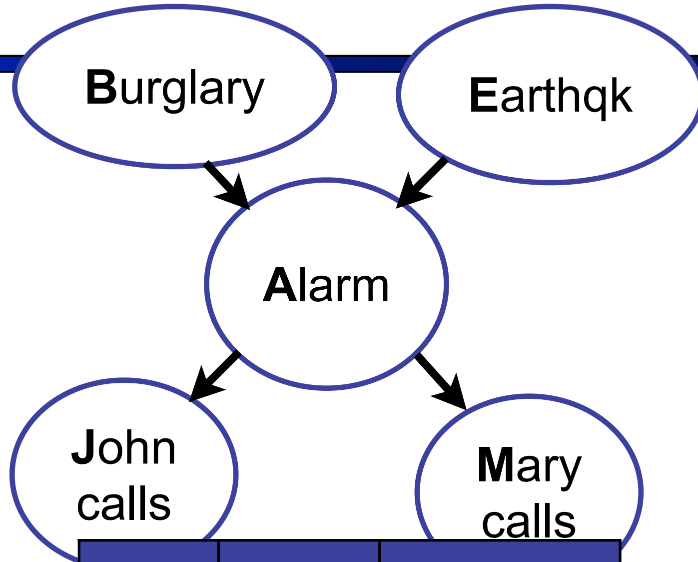
- {Cavity, Toothache, Catch}

  P(Cavity, Toothache, ~Catch) ?

P(Cavity, Toothache, ~Catch) =
P(cavity)P(toothache|cavity)
P(~catch|cavity)



Example: Alarm Network



B	P(B)
+b	0.001
¬b	0.999

E	P(E)
+e	0.002
¬e	0.998

A	J	P(J|A)
+a	+j	0.9
+a	¬j	0.1
¬a	+j	0.05
¬a	¬j	0.95

A	M	P(M|A)
+a	+m	0.7
+a	¬m	0.3
¬a	+m	0.01
¬a	¬m	0.99

B	E	A	P(A|B,E)
+b	+e	+a	0.95
+b	+e	¬a	0.05
+b	¬e	+a	0.94
+b	¬e	¬a	0.06
¬b	+e	+a	0.29
¬b	+e	¬a	0.71
¬b	¬e	+a	0.001
¬b	¬e	¬a	0.999

$$P(+b, -e, +a, -j, +m) =$$
$$P(+b)P(-e)P(+a|+b,-e)P(-j|+a)P(+m|+a) =$$
$$0.001 \times 0.998 \times 0.94 \times 0.1 \times 0.7$$

Size of a Bayes Net

- How big is a joint distribution over N Boolean variables?

  2^N

- How big is an N-node net if nodes have up to k parents?

  $O(N * 2^{k+1})$

- Both give you the power to calculate

$$P(X_1, X_2, \ldots X_n)$$

- BNs: Huge space savings!
- Also easier to elicit local CPTs
- Also faster to answer queries (coming)

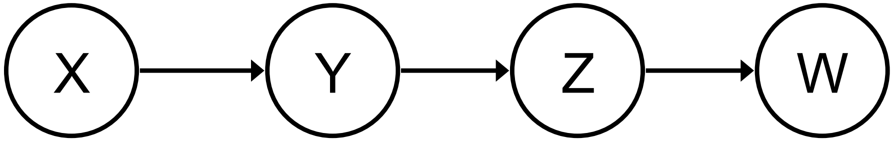
Bayes Nets: Assumptions

- Assumptions we are required to make to define the Bayes net when given the graph:

$$P(x_i|x_1 \cdots x_{i-1}) = P(x_i|parents(X_i))$$

- Beyond above "chain rule → Bayes net" conditional independence assumptions
  - Often additional conditional independences
  - They can be read off the graph
- Important for modeling: understand assumptions made when choosing a Bayes net graph

Independence in a BN

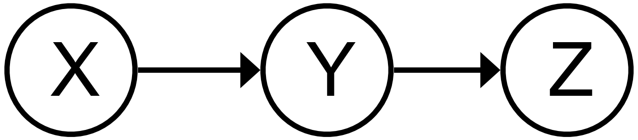


- Conditional independence assumptions directly from simplifications in chain rule:

- Additional implied conditional independence assumptions?

Independence in a BN

- Important question about a BN:
  - Are two nodes independent given certain evidence?
  - If yes, can prove using algebra (tedious in general)
  - If no, can prove with a counter example
  - Example:



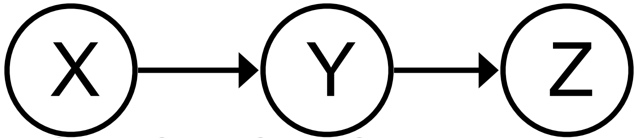
Causal Chains

- This configuration is a "causal chain"

X: Low pressure

Y: Rain

Z: Traffic



$$P(x, y, z) = P(x)P(y|x)P(z|y)$$

- Are X and Z independent?

- One example set of CPTs for which X is not independent of Z is sufficient to show this independence is not guaranteed.

- Example:
  - Low pressure causes rain causes traffic, high pressure causes no rain causes no traffic
  - In numbers:

    P(+y | +x) = 1, P(-y | - x) = 1,
    P(+z | +y) = 1, P(-z | -y) = 1

Causal Chains

- This configuration is a "causal chain"

$$X \rightarrow Y \rightarrow Z$$

X: Low pressure

Y: Rain

Z: Traffic

$$P(x,y,z) = P(x)P(y|x)P(z|y)$$

- Is X independent of Z given Y?

$$P(z|x,y) = \frac{P(x,y,z)}{P(x,y)} = \frac{P(x)P(y|x)P(z|y)}{P(x)P(y|x)}$$

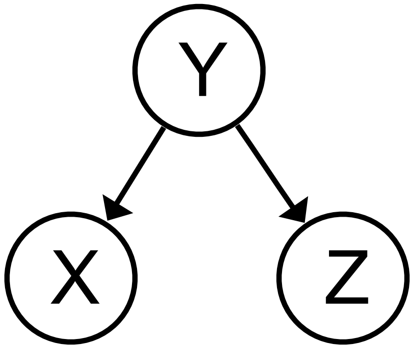
$$= P(z|y)$$

Yes!

- Evidence along the chain "blocks" the influence

Common Parent

- Another basic configuration: two effects of the same parent
  - Are X and Z independent?
  - Are X and Z independent given Y?



$$P(z|x,y) = \frac{P(x,y,z)}{P(x,y)} = \frac{P(y)P(x|y)P(z|y)}{P(y)P(x|y)}$$

$$= P(z|y)$$

Yes!

Y: Project due

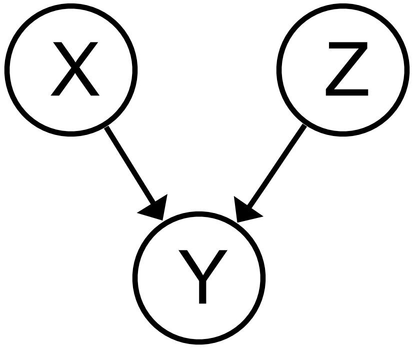
X: Newsgroup busy

Z: Lab full

- Observing the cause blocks influence between effects.

Common Effect

- Last configuration: two causes of one effect (v-structures)
  - Are X and Z independent?
    - Yes: the ballgame and the rain cause traffic, but they are not correlated
    - Still need to prove they must be (try it!)
  - Are X and Z independent given Y?
    - No: seeing traffic puts the rain and the ballgame in competition as explanation?
  - This is backwards from the other cases
    - Observing an effect activates influence between possible causes.



X: Raining

Z: Ballgame

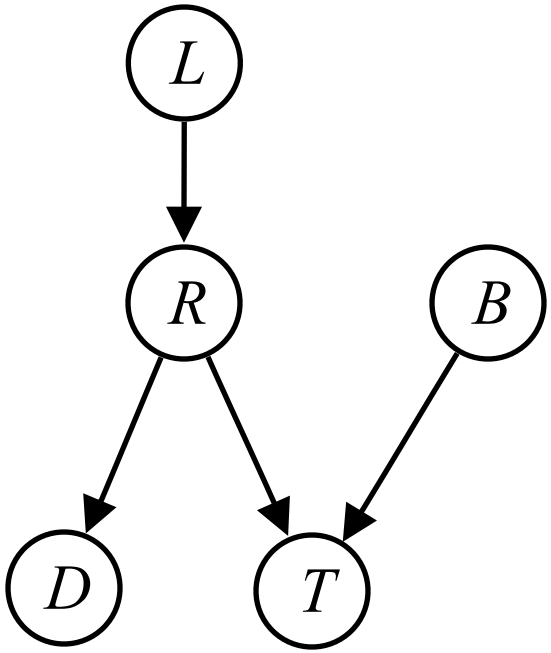
Y: Traffic

The General Case

- Any complex example can be analyzed using these three canonical cases
- General question: in a given BN, are two variables independent (given evidence)?
- Solution: analyze the graph

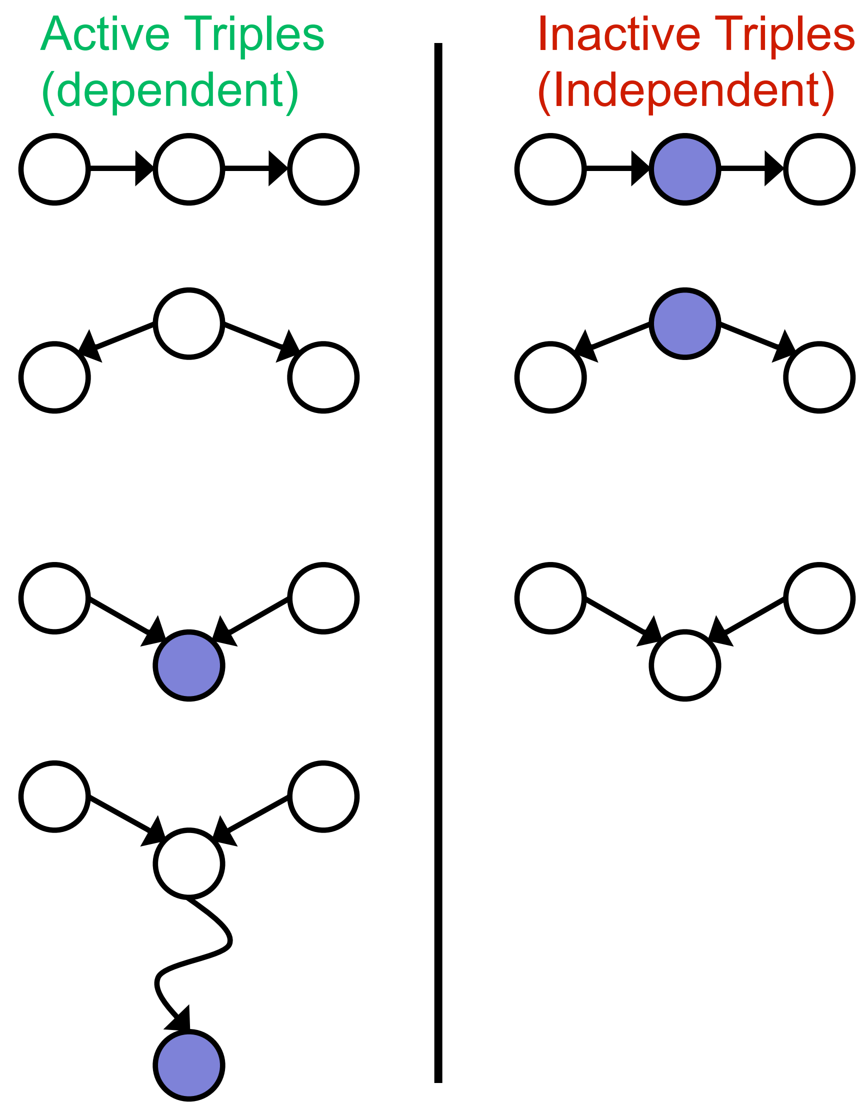
Reachability

- Recipe: shade evidence nodes
- Attempt 1: if two nodes are connected by an undirected path not blocked by a shaded node, they are conditionally independent
- Almost works, but not quite
  - Where does it break?
  - Answer: the v-structure at T doesn't count as a link in a path unless "active"



Reachability (D-Separation)

- Question: Are X and Y conditionally independent given evidence vars {Z}?
  - Yes, if X and Y “separated” by Z
  - Look for active paths from X to Y
  - No active paths = independence!
- A path is active if each triple is active:
  - Causal chain A → B → C where B is unobserved (either direction)
  - Common cause A ← B → C where B is unobserved
  - Common effect (aka v-structure) A → B ← C where B *or one of its descendents* is observed
- All it takes to block a path is a single inactive segment



D-Separation

- Query: $X_i \perp\!\!\!\perp X_j | \{X_{k_1}, ..., X_{k_n}\}$?
- Check all (undirected!) paths between X_i and X_j
  - If one or more active, then independence not guaranteed

$$X_i \not\perp\!\!\!\perp X_j | \{X_{k_1}, ..., X_{k_n}\}$$

- Otherwise (i.e. if all paths are inactive), then independence is guaranteed

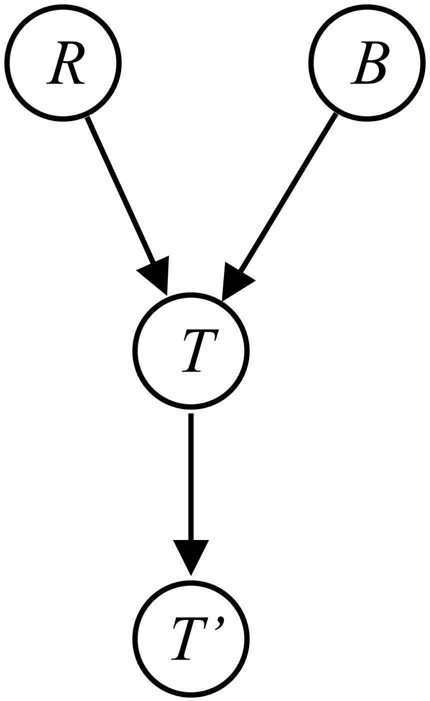
$$X_i \perp\!\!\!\perp X_j | \{X_{k_1}, ..., X_{k_n}\}$$

Example: Independent?

$R \perp\!\!\!\perp B$ Yes

$R \perp\!\!\!\perp B | T$

$R \perp\!\!\!\perp B | T'$



Example: Independent?

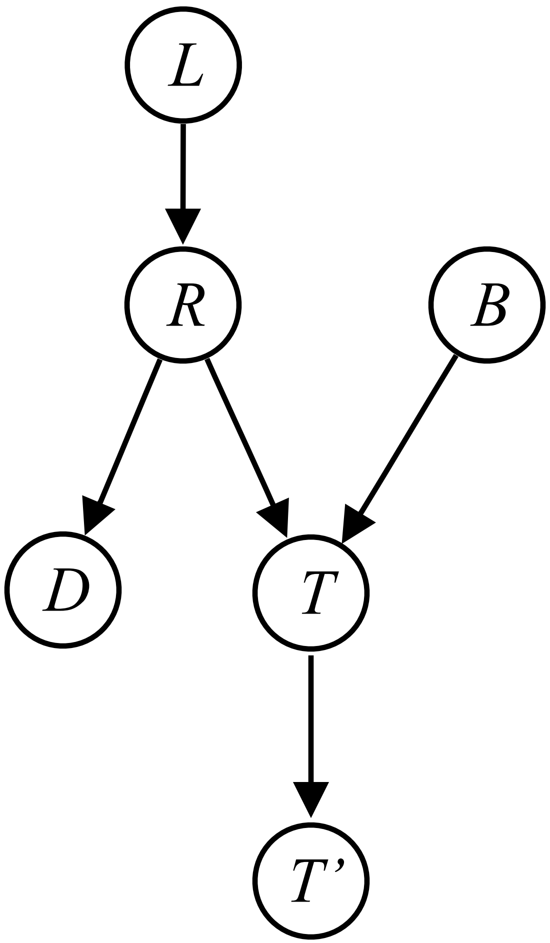
$L \perp\!\!\!\perp T' | T$ Yes

$L \perp\!\!\!\perp B$ Yes

$L \perp\!\!\!\perp B | T$

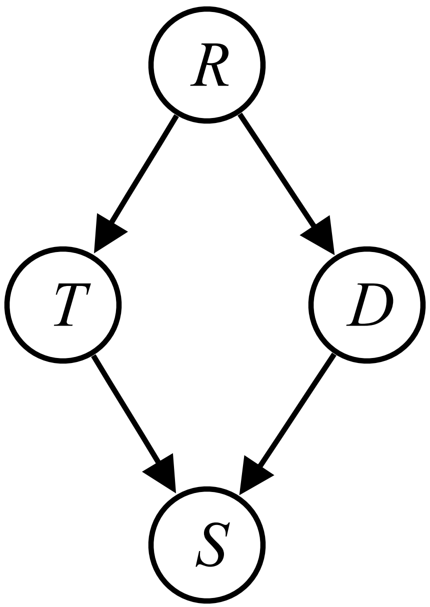
$L \perp\!\!\!\perp B | T'$

$L \perp\!\!\!\perp B | T, R$ Yes



Example

- Variables:
  - R: Raining
  - T: Traffic
  - D: Roof drips
  - S: I'm sad
- Questions:



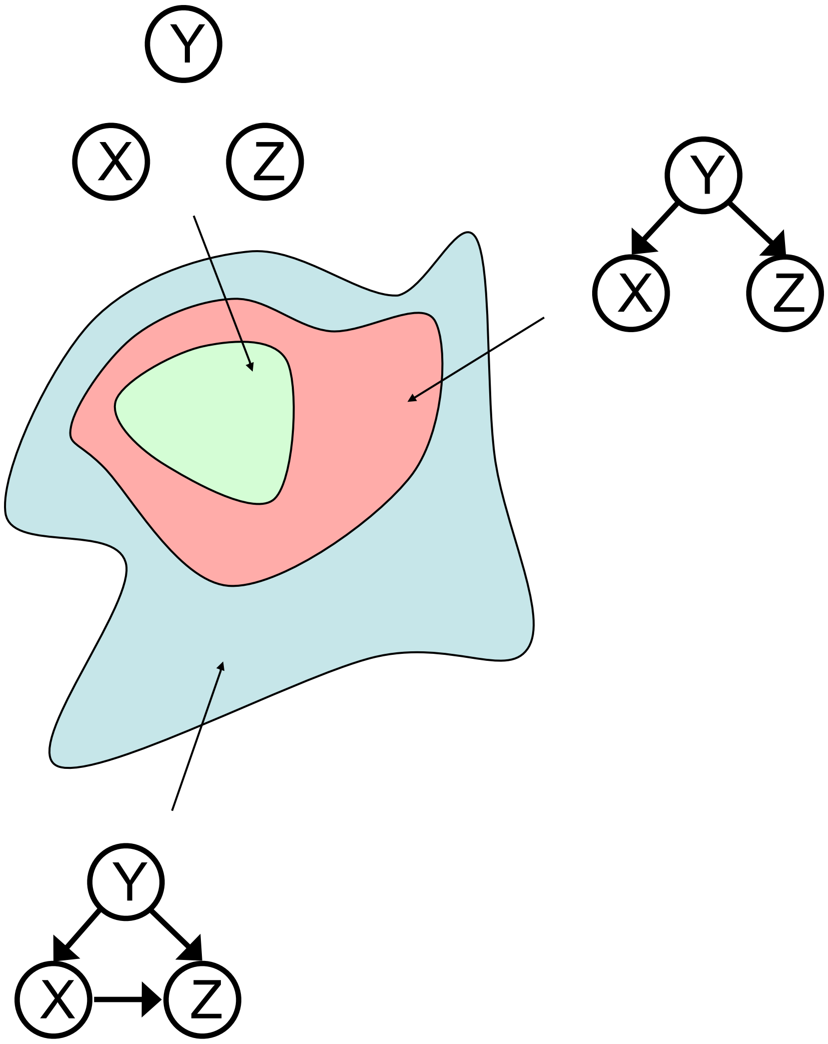
$$T \perp\!\!\!\perp D$$

$$T \perp\!\!\!\perp D | R$$ Yes

$$T \perp\!\!\!\perp D | R, S$$

Topology Limits Distributions

- Given some graph topology G, only certain joint distributions can be encoded
- The graph structure guarantees certain (conditional) independences
- (There might be more independence)
- Adding arcs increases the set of distributions, but has several costs
- Full conditioning can encode any distribution



Summary

- Bayes nets compactly encode joint distributions
- Guaranteed independencies of distributions can be deduced from BN graph structure
- D-separation gives precise conditional independence guarantees from graph alone
- A Bayes' net's joint distribution may have further (conditional) independence that is not detectable until you inspect its specific distribution