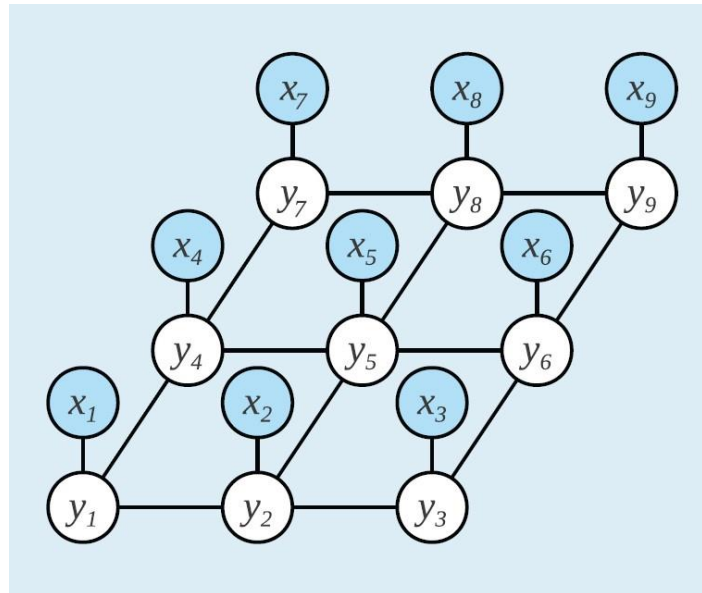


Probabilistic Graphical Models in Bioinformatics

Lecture 3: Bayesian network representation-2



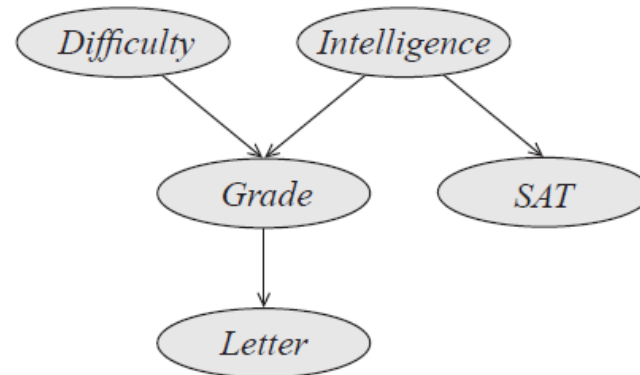
Independencies in Graphs

Review: local independencies in BNs

- Bayesian network G encodes the following set of local independencies for each variable X_i

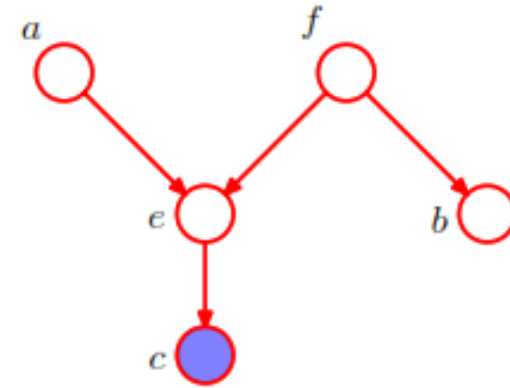
$$X_i \perp \text{NonDescendants}_{X_i} \mid \text{Pa}_G(X_i)$$

$$\begin{aligned} L &\perp I, D, S \mid G \\ G &\perp S \mid D, I \\ S &\perp L, G, D \mid I \\ I &\perp D \\ D &\perp I, S \end{aligned}$$



Independencies in Graphs

- Question: In a general DAG, is X dependence of Y given Z ?
 - In the following DAG, are a and b independent given c ?



- D-separation
 - to check whether an independence assertion $X \perp Y \mid Z$ is implied by a given DAG.

Independencies in Graphs- simple examples

- Direct connection
 - $X \rightarrow Y$ or $Y \rightarrow X$

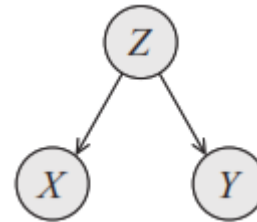
- Three-node networks



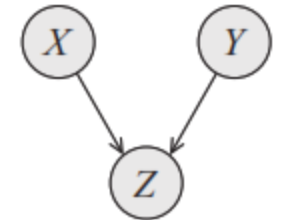
Indirect causal
effect



Indirect evidential
effect



common cause



common effect
or v-structure

$$X \perp Y \mid Z$$

$$X \not\perp Y$$

$$X \not\perp Y \mid Z$$

$$X \perp Y$$

The joint distribution corresponding to the following graph is

$$P(X, Y, Z) = P(X)P(Z|X)P(Y | Z)$$

Case 1: first we show X and Y are independent given Z

$$\begin{aligned} P(X, Y | Z) &= \frac{P(X, Y, Z)}{P(Z)} = \frac{P(X)P(Z|X)P(Y | Z)}{P(Z)} = \frac{P(X, Z)}{P(Z)} P(Y | Z) \\ &= P(X | Z)P(Y | Z) \end{aligned}$$

Hence $X \perp Y | Z$



Case 2: then we first show X and Y are marginally dependent

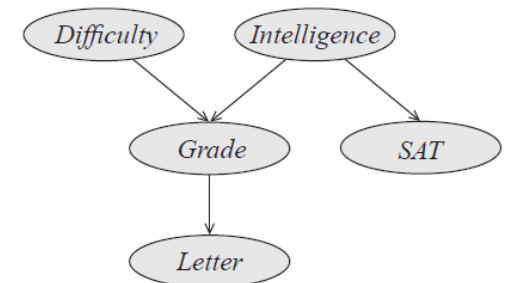
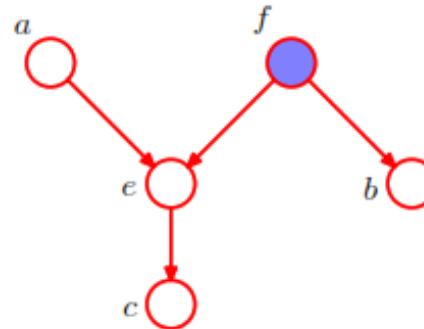
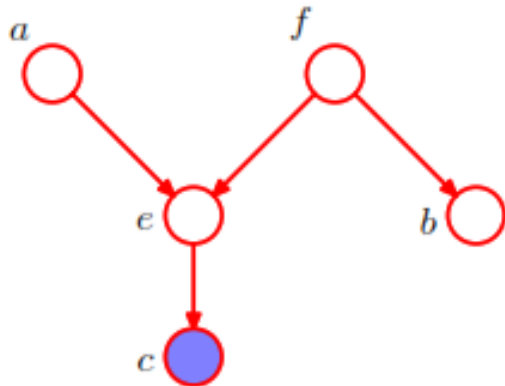
$$\begin{aligned} P(X, Y) &= \sum_Z P(X)P(Z|X)P(Y | Z) = P(X) \sum_Z P(Z|X)P(Y | Z) \\ &= P(X) \sum_Z P(Z|X)P(Y | Z, X) = P(X) \sum_Z P(Y, Z | X) = P(X)P(Y | X) \end{aligned}$$

which in general does not factorize to $P(X)P(Y)$ hence $X \not\perp Y$

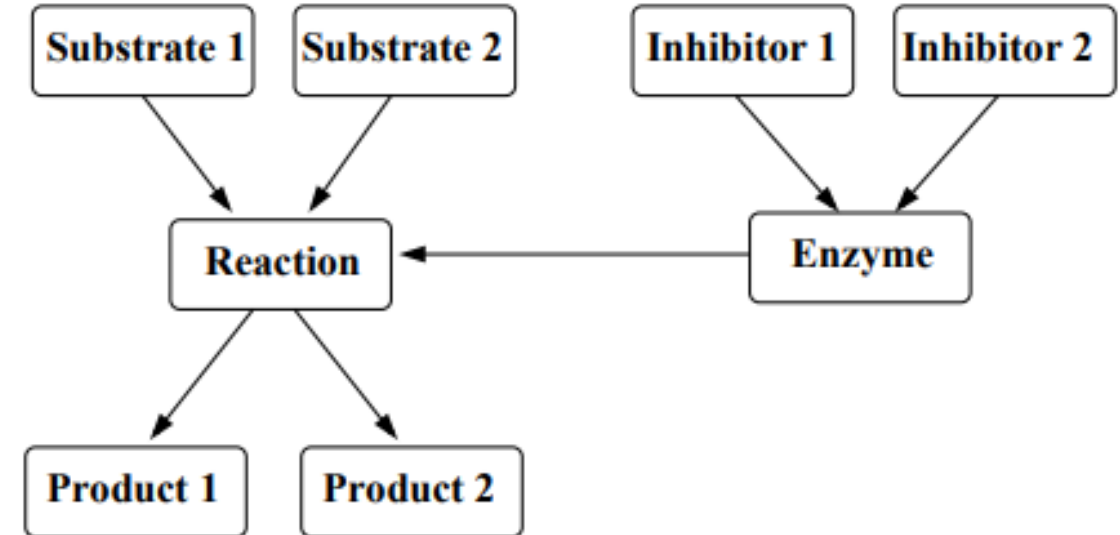
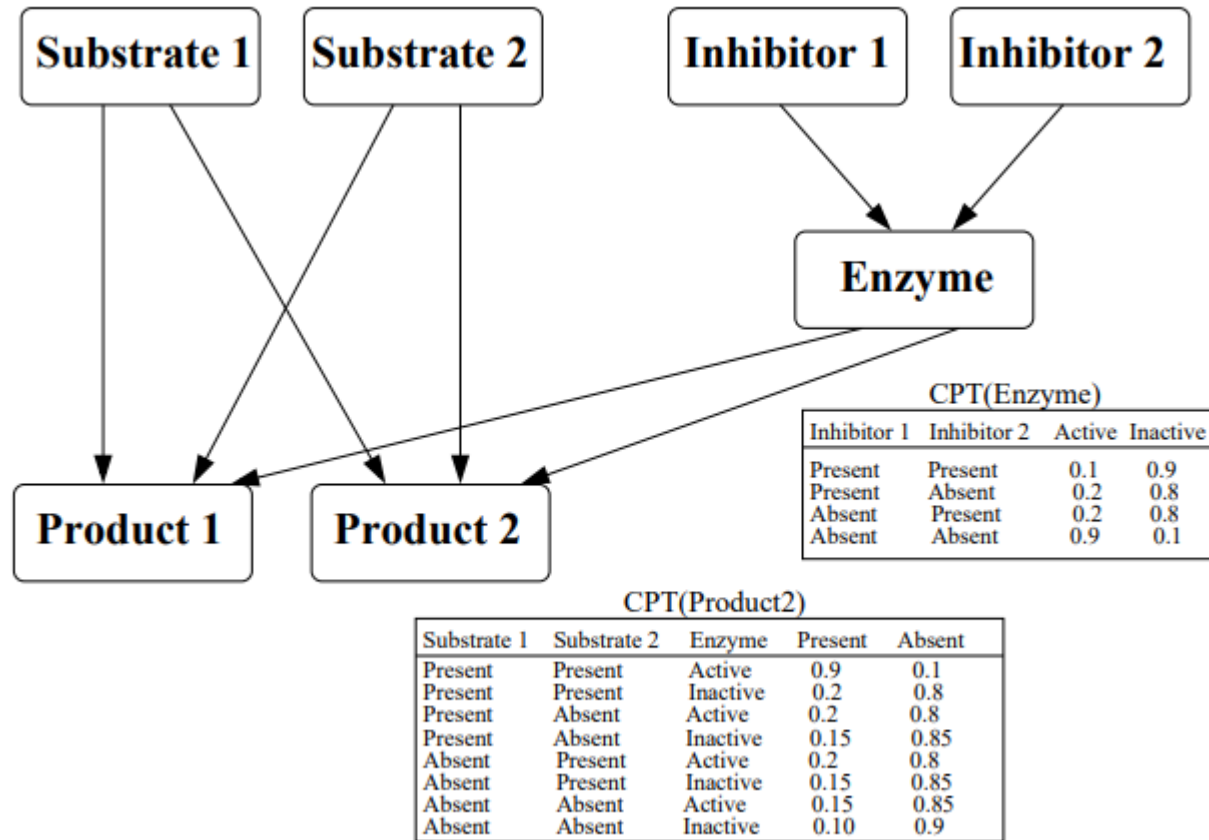
Homework: redo the above derivations for common cause and v-structure cases.

D-separation

- **Active trail:** A trail $X_1 - X_2 - \dots - X_n$ is active given Z if
 - For any v-structure $X_{i-1} \rightarrow X_i \leftarrow X_{i+1}$, then X_i or one of its descendants are in Z ;
 - No other node along the trail is in Z .
- **D-separation:** Let X, Y, Z be three sets of node in the input graph. X and Y are d-separated given Z if there is no active trail between any node $X \in X$ and $Y \in Y$ given Z .



Example: a Bayesian network for a single reaction metabolic pathway



Another possibility

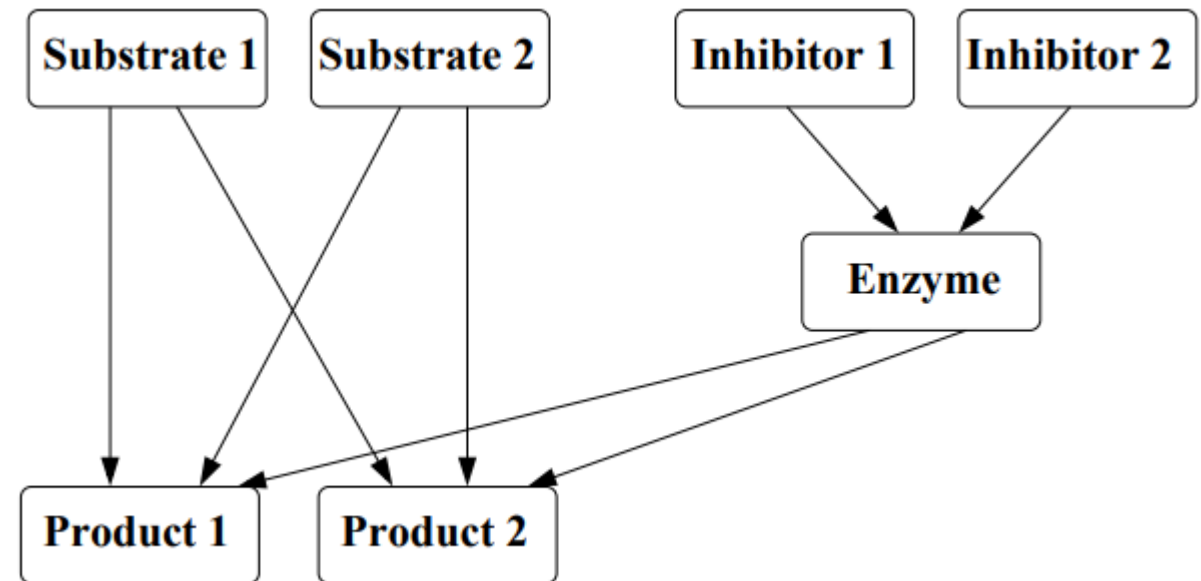
[Tamaddoni-Nezhad, 2003]

Example: a Bayesian network for a single reaction metabolic pathway

Check the following Independence statements:

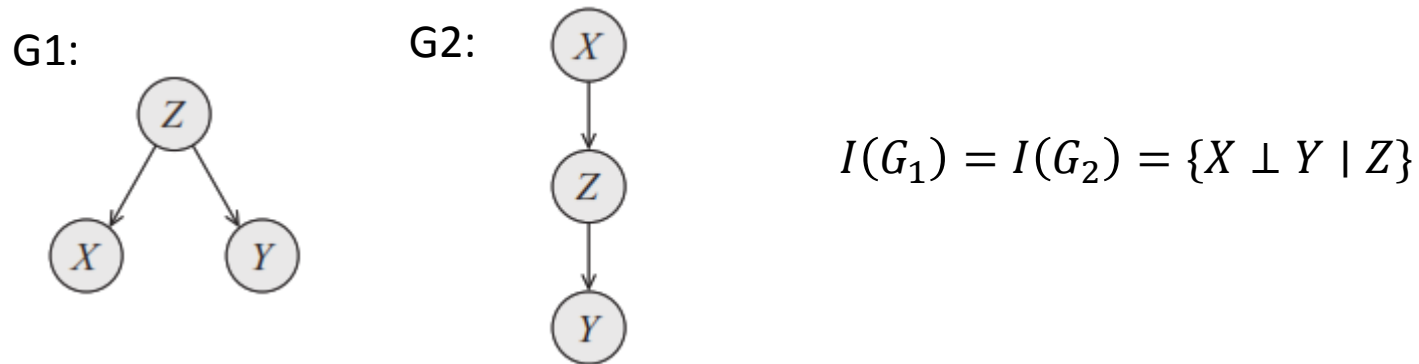
- $P_1 \perp P_2$
- $P_1 \perp P_2 \mid E$
- $P_1 \perp P_2 \mid E, S_1$
- $P_1 \perp P_2 \mid E, S_1, S_2$

- $S_1 \perp I_1$
- $S_1 \perp I_1 \mid P_1$
- $S_1 \perp I_1 \mid E$
- $S_1 \perp I_1 \mid P_1, P_2, E$



I-Equivalence

- Same set of conditional independence assertions for different BN structures

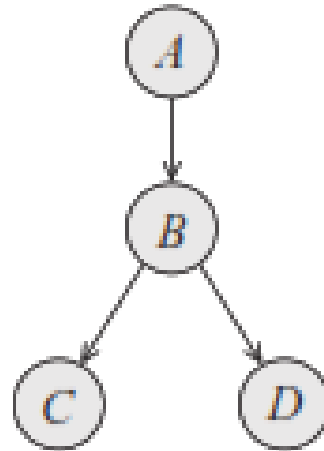


- Theorem:** If two BN graphs have the **same skeleton** and the **same set of v-structures** then they are I-equivalent



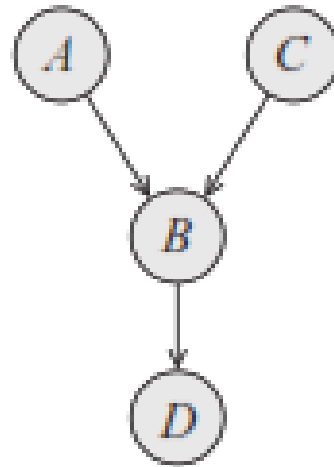
I-Equivalence

- **Question:** Find I-equivalent BNs of the following BN



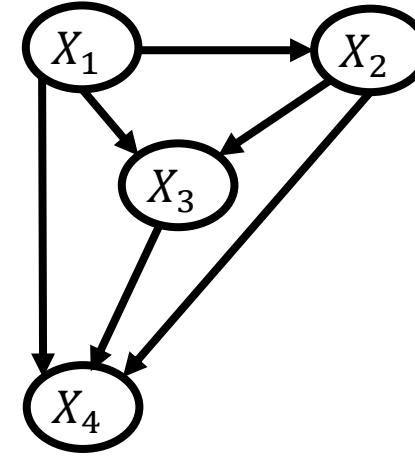
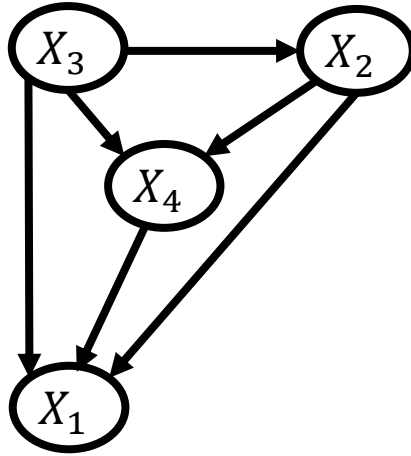
I-Equivalence

- **Question:** Find I-equivalent BNs of the following BN



I-Equivalence

- **Question:** Are the following BNs I-equivalent?

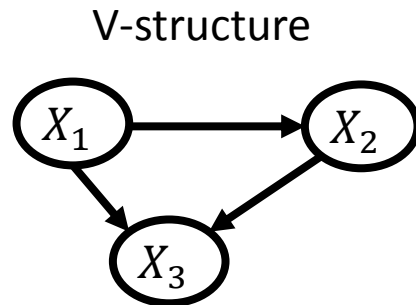


- Factorize the joint distribution according to each of the BNs.

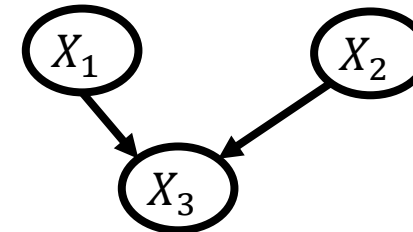
Any two complete graphs are I-equivalent but is not detected by the criterion of previous theorem!

I-Equivalence

- **Definition:** A v-structure $X \rightarrow Z \leftarrow Y$ is an immorality if there is no direct edge between X and Y . If there is such an edge, it is called a covering edge for the v-structure.



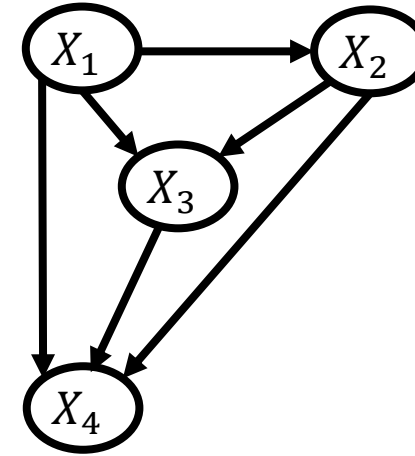
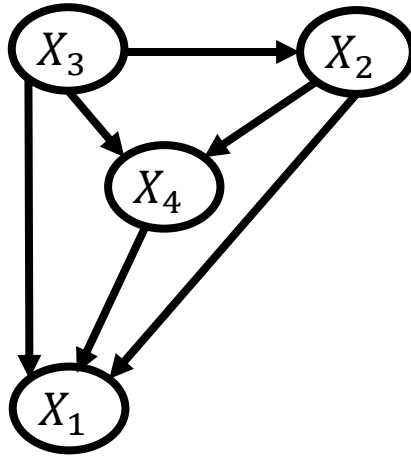
v-structure and immorality



- **Theorem:** Two BN graphs have the **same skeleton** and the **same set of immoralities** if and only if they are I-equivalent.

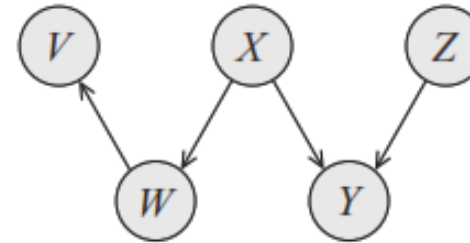
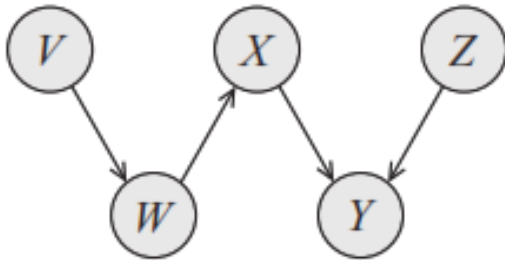
I-Equivalence

- **Question:** Are the following BNs I-equivalent?



I-Equivalence

- **Question:** Are the following BNs I-equivalent?



Markov blanket

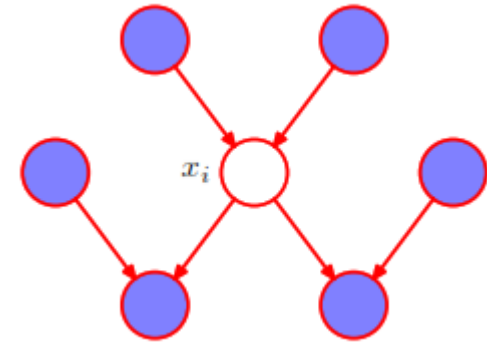
- Markov blanket of a node is the set of its parents, co-parents, and children.

$$P(X_i | X_{k \neq i}) = P(X_i | X_{\text{MB}(i)})$$

Sketch of the proof:

$$\begin{aligned} P(X_i | X_{n \neq i}) &= \frac{P(X_1, \dots, X_n)}{\sum_{X_i} P(X_1, \dots, X_n)} \\ &= \frac{\prod_k P(X_k | \text{Par}(X_k))}{\sum_{X_i} \prod_k P(X_k | \text{Par}(X_k))} \end{aligned}$$

Factors not depending on X_i can be taken outside summation
and are canceled between numerator and denominator



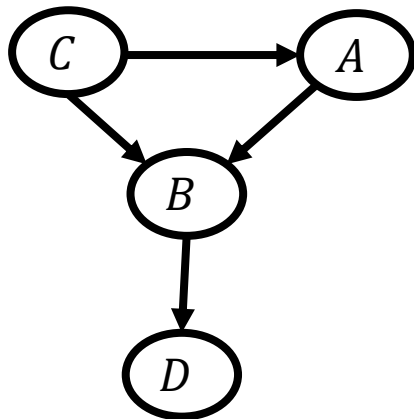
From Distributions to Graphs

From Distributions to Graphs

- **Question:** Given a distribution P (e.g. in terms of independence assertions), to what extent can we construct a graph G whose independencies reasonably represent independencies in P ?
- Two approaches
 - Minimal I-maps
 - Perfect maps

Minimal I-maps

- A graph \mathcal{K} is a minimal I-map for a set of independencies I if
 - A. it is an I-map for I , *i.e.* $I(\mathcal{K}) \subseteq I$.
 - B. and removal a single edge from graph \mathcal{K} makes it not an I-map.
- **Example:** given the set of independencies $I = \{A \perp B, D \perp A, C \mid B\}$



Question: what is $I(\mathcal{K})$?

\mathcal{K} : a minimal I-map for I

Minimal I-maps

- Algorithm to obtain minimal I-map
 - It depends on a given ordering of the variables
 - Obtained minimal I-maps are not unique.

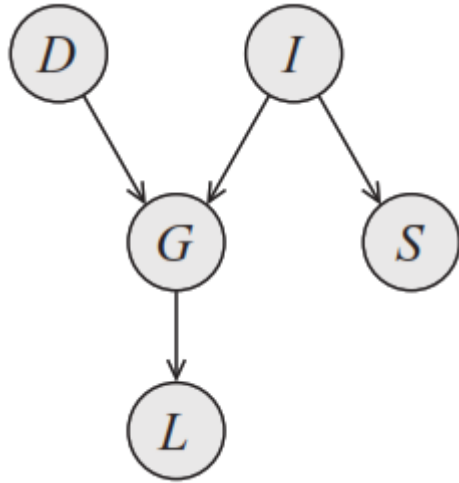
Algorithm 3.2 Procedure to build a minimal I-map given an ordering

```

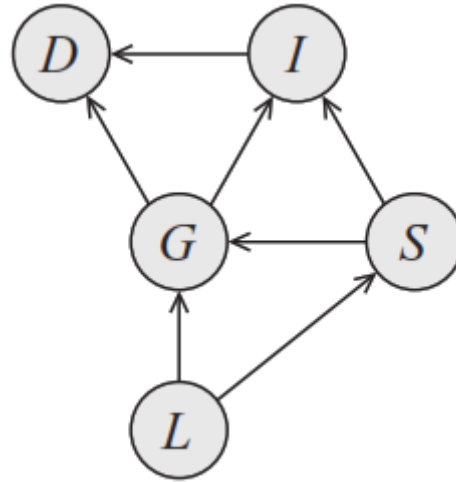
Procedure Build-Minimal-I-Map (
   $X_1, \dots, X_n$  // an ordering of random variables in  $\mathcal{X}$ 
   $\mathcal{I}$  // Set of independencies
)
1  Set  $\mathcal{G}$  to an empty graph over  $\mathcal{X}$ 
2  for  $i = 1, \dots, n$ 
3     $U \leftarrow \{X_1, \dots, X_{i-1}\}$  //  $U$  is the current candidate for parents of  $X_i$ 
4    for  $U' \subseteq \{X_1, \dots, X_{i-1}\}$ 
5      if  $U' \subset U$  and  $(X_i \perp \{X_1, \dots, X_{i-1}\} - U' \mid U') \in \mathcal{I}$  then
6         $U \leftarrow U'$ 
7      // At this stage  $U$  is a minimal set satisfying  $(X_i \perp$ 
8         $\{X_1, \dots, X_{i-1}\} - U \mid U)$ 
9      // Now set  $U$  to be the parents of  $X_i$ 
10     for  $X_j \in U$ 
11       Add  $X_j \rightarrow X_i$  to  $\mathcal{G}$ 
12  return  $\mathcal{G}$ 

```

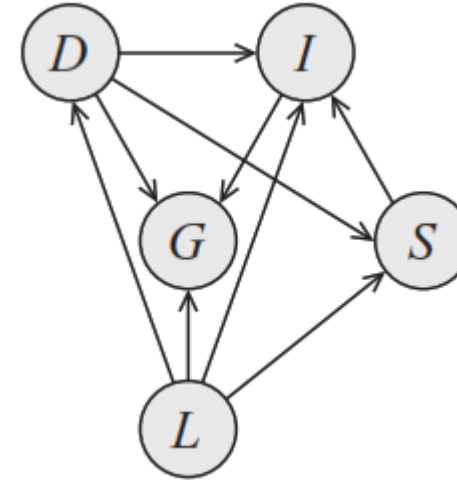
Examples of minimal I-maps



D, I, S, G, L



L, S, G, I, D



L, D, S, I, G

- Minimal I-maps **fail** to capture some or all of independencies that hold in the distribution.

Perfect maps

- A graph \mathcal{K} is a perfect map for P if $I(\mathcal{K}) = I(P)$.
- Existence of P-maps: not every distribution has a P-map.
- Example:

$$P(x, y, z) = \begin{cases} 1/12 & x \oplus y \oplus z = \textit{false} \\ 1/6 & x \oplus y \oplus z = \textit{true} \end{cases}$$

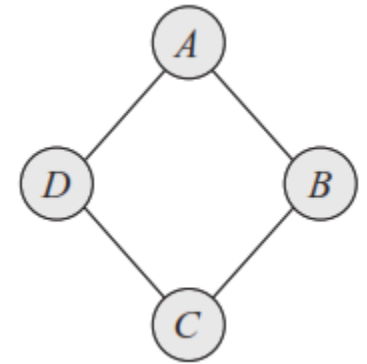
$$I(P) = \{ X \perp Y, X \perp Z, Y \perp Z \}$$

Important: Note the pair X and Y are not independent given Z . The same is true for other pairs.

Question: find a Bayesian network G with $I(G) = I(P)$. Is it possible?

Existence of P-maps- misconception example

1. Four students study in pairs Alice and Bob; Bob and Charles; Charles and Debbie; Debbie and Alice.
2. Professor accidentally misspoke in the class, leading to a possible misconception
3. Students may have figured out the problem by reading the textbook
4. Students transmits their understanding to their partners

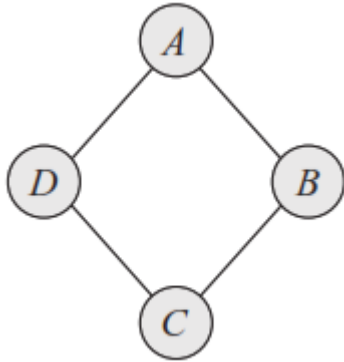


Study pairs
for students

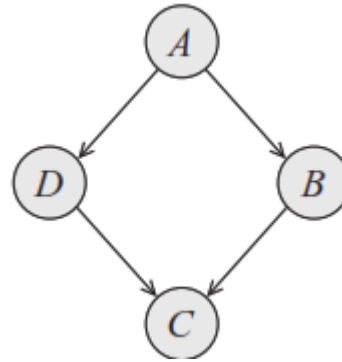
$$A \perp C \mid D, B$$

$$B \perp D \mid A, C$$

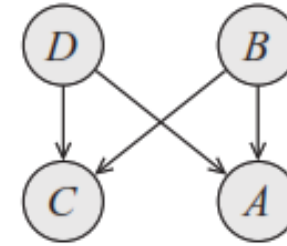
Failed attempts to identify a P-map for the misconception example



Study pairs
for students



First attempt



Second attempt

