

Probabilistic Graphical Models

Relationship between the directed & undirected models

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Learning Objective

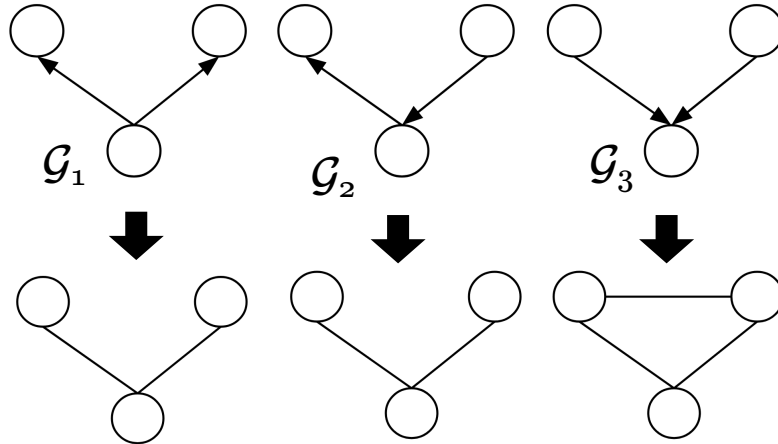
understand the relationship between CIs
in directed and undirected models.

convert

Markov network	\Rightarrow	Bayes-net
Markov network	\Leftarrow	Bayes-net

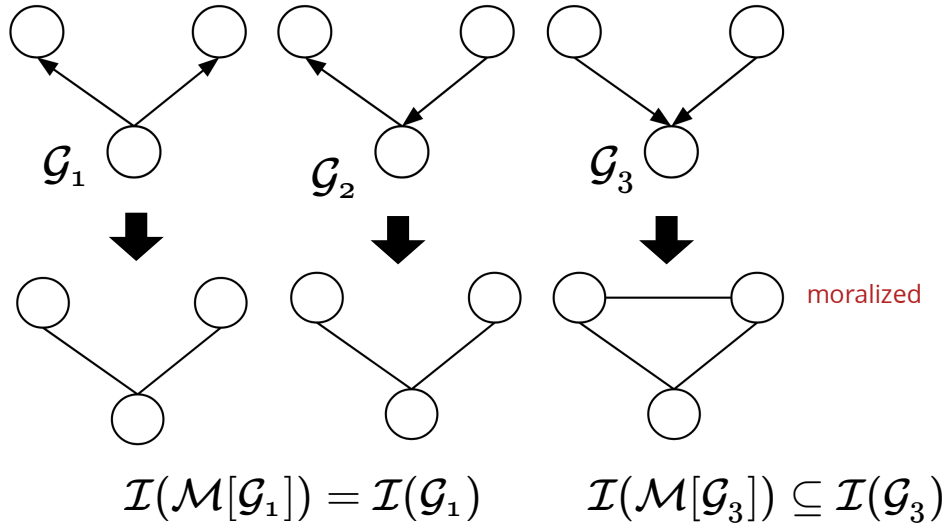
1. From Bayesian to Markov networks

build an I-map for the following



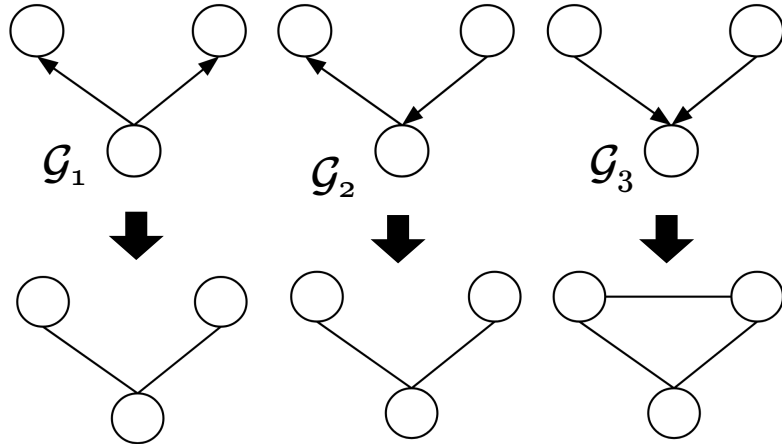
1. From Bayesian to Markov networks

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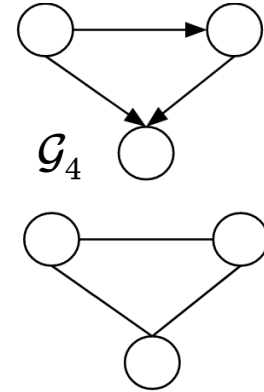
build an I-map for the following



$$\mathcal{I}(\mathcal{M}[\mathcal{G}_1]) = \mathcal{I}(\mathcal{G}_1)$$

$$\mathcal{I}(\mathcal{M}[\mathcal{G}_3]) \subseteq \mathcal{I}(\mathcal{G}_3)$$

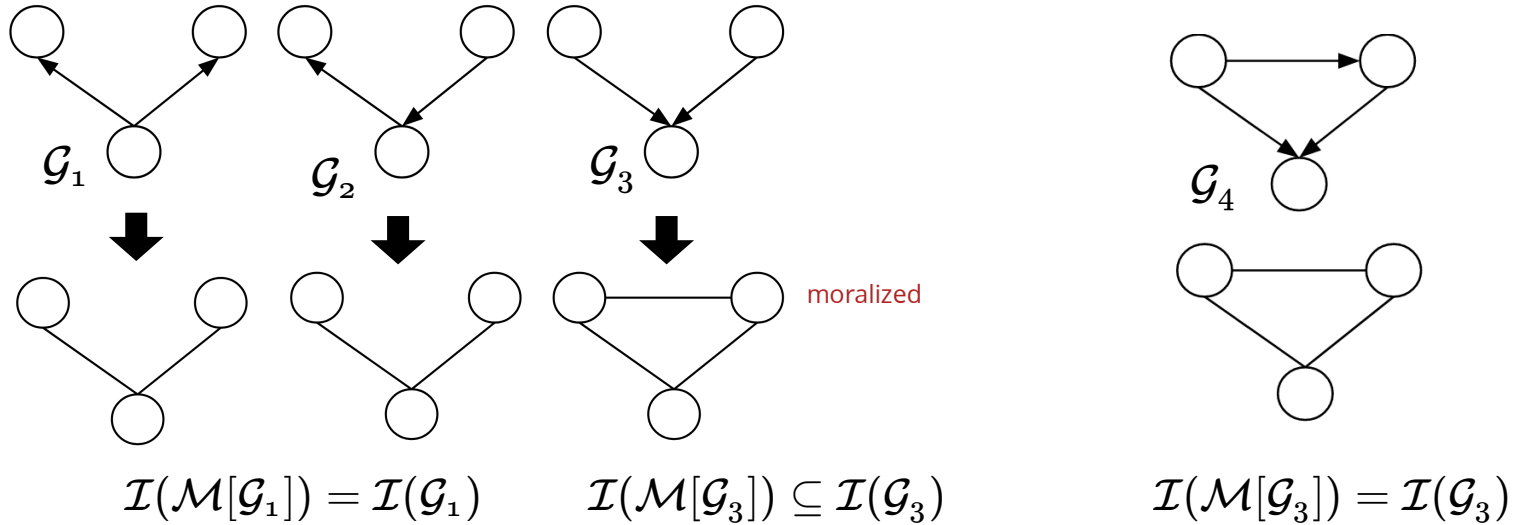
moralized



$$\mathcal{I}(\mathcal{M}[\mathcal{G}_3]) = \mathcal{I}(\mathcal{G}_3)$$

1. From Bayesian to Markov networks

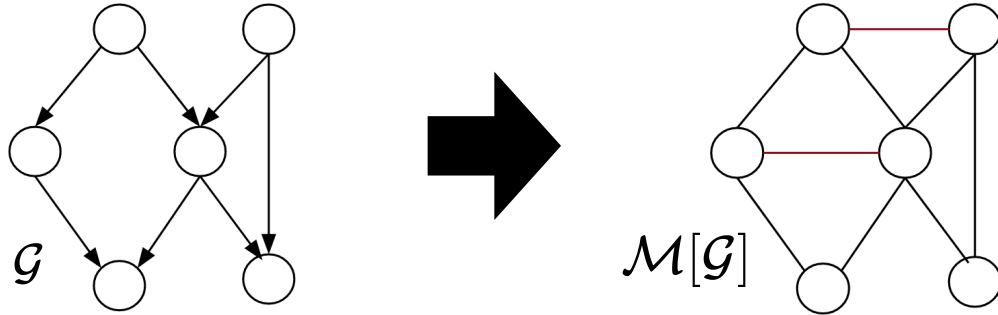
build an I-map for the following



Moralize $\mathcal{G} \rightarrow \mathcal{M}(\mathcal{G})$: connect parents keep the skeleton

From **Bayesian** to **Markov** networks

moralize & keep the skeleton

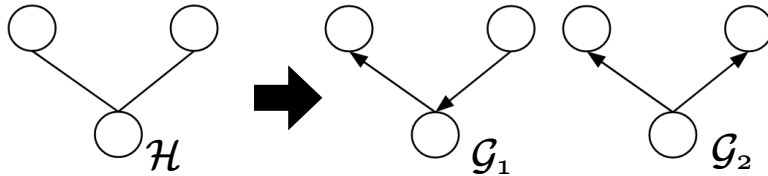


for moral \mathcal{G} , we get a perfect map $\mathcal{I}(\mathcal{M}[\mathcal{G}]) = \mathcal{I}(\mathcal{G})$

- *directed and undirected CI tests are equivalent*

2. From Markov to Bayesian networks

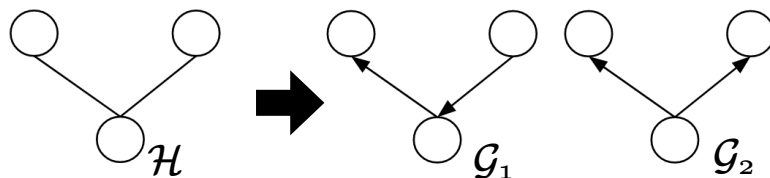
minimal examples 1.



$$\mathcal{I}(\mathcal{G}_1) = \mathcal{I}(\mathcal{G}_2) = \mathcal{I}(\mathcal{H})$$

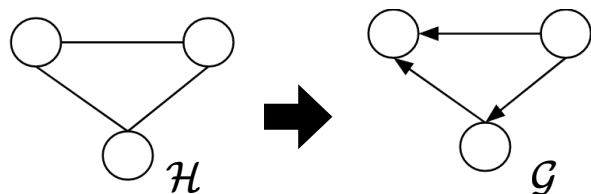
2. From Markov to Bayesian networks

minimal examples 1.



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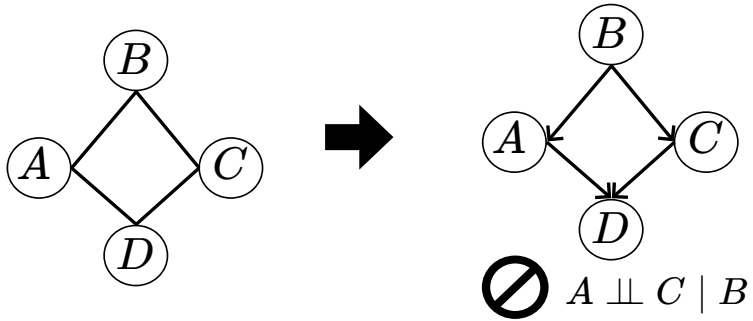
minimal examples 2.



$$\mathcal{I}(\mathcal{G}) = \mathcal{I}(\mathcal{H})$$

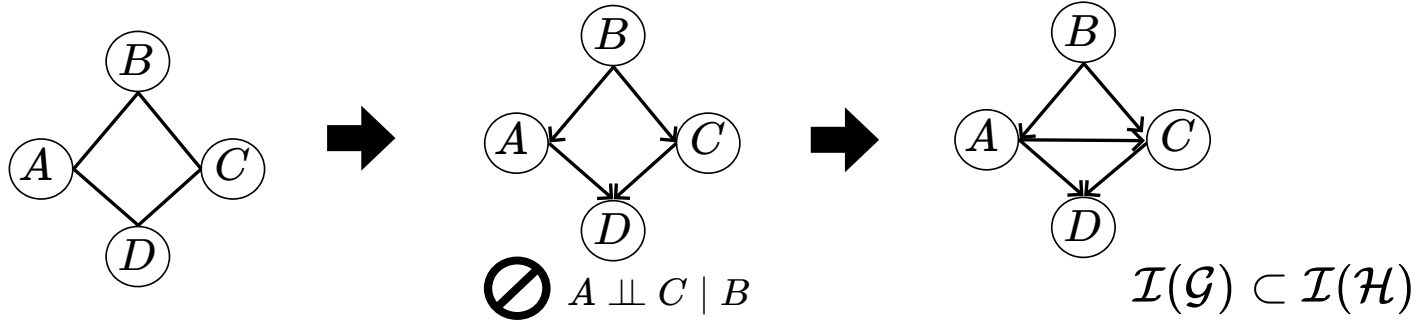
From Markov to Bayesian networks

minimal examples 3.



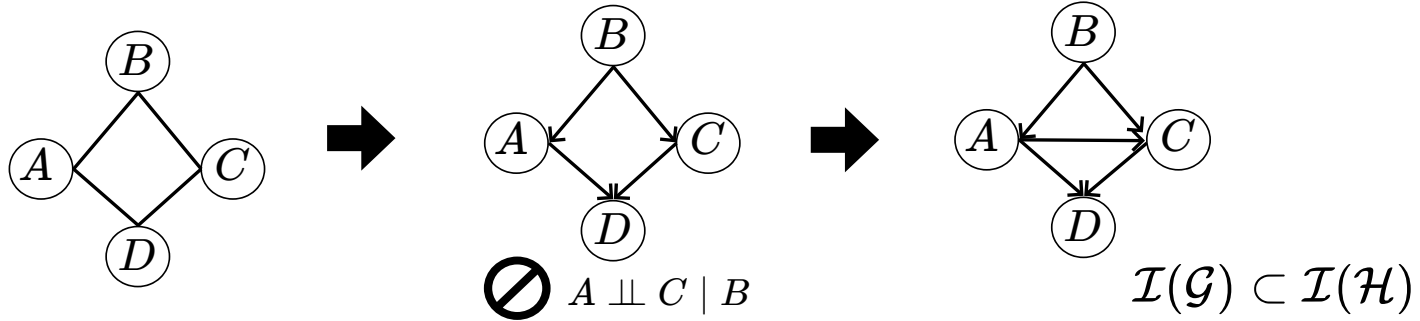
From Markov to Bayesian networks

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From Markov to Bayesian networks

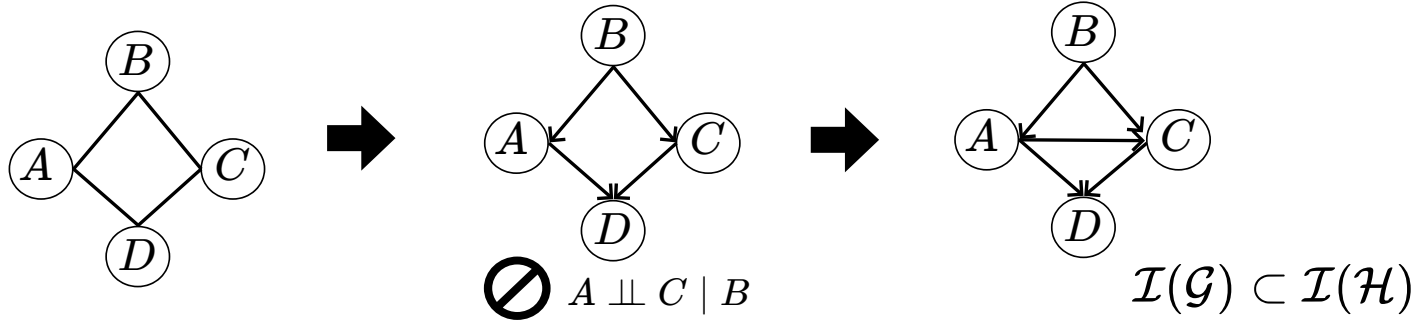
minimal examples 3.



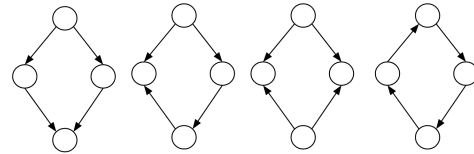
- if adding direction creates immoralities, we have to moralize

From Markov to Bayesian networks

minimal examples 3.

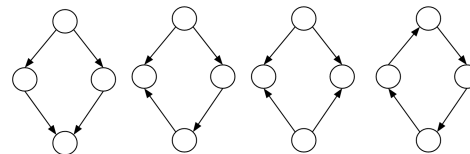


- if adding direction creates immoralities, we have to moralize
- any non-triangulated loop > 3 creates immorality
- have to triangulate the loops

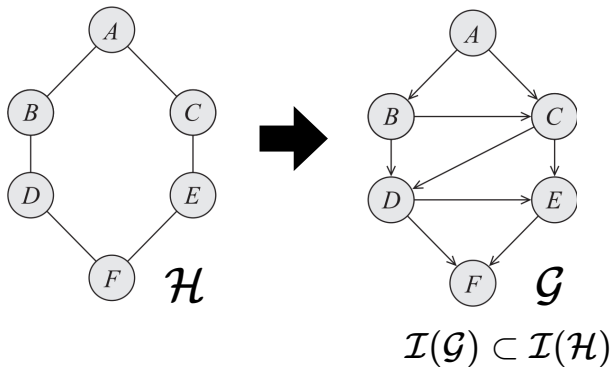


From Markov to Bayesian networks

- any non-triangulated loop > 3 creates immorality
- have to **triangulate** the loops



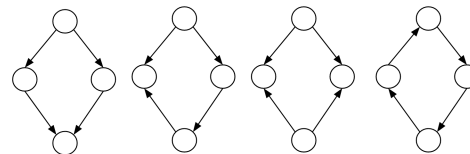
examples 4.



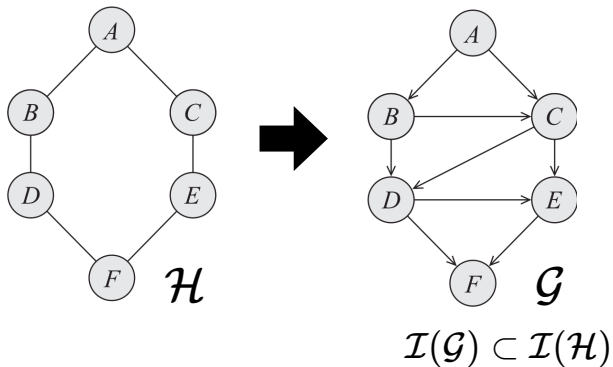
\mathcal{H}

From Markov to Bayesian networks

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examples 4.

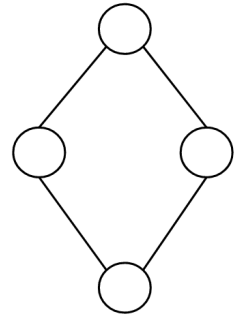


a graph \mathcal{H} is **chordal** if all loops > 3 have a "chord"

Chordal = Markov \cap Bayesian networks

\mathcal{H} is **not chordal**, then $\mathcal{I}(\mathcal{G}) \neq \mathcal{I}(\mathcal{H})$ for **every** \mathcal{G}

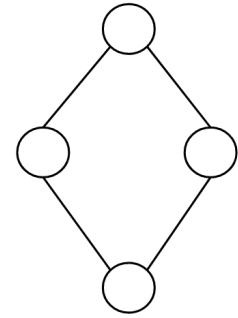
- no *perfect MAP* in the form of Bayes-net



Chordal = Markov \cap Bayesian networks

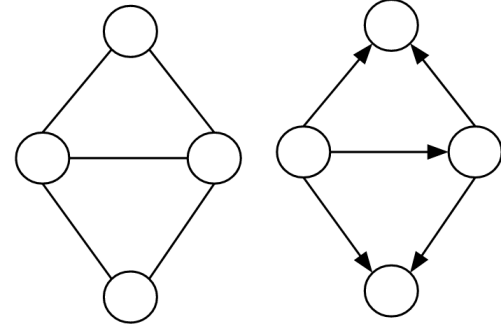
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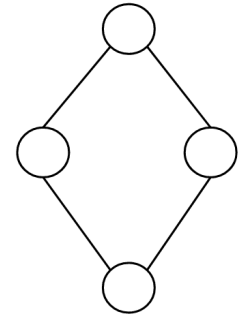
- has a Bayes-net perfect map



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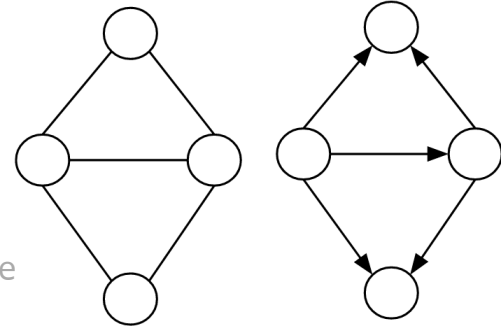
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\mathcal{H} is **chordal**, then $\mathcal{I}(\mathcal{G}) = \mathcal{I}(\mathcal{H})$ for **some** \mathcal{G}

- has a Bayes-net perfect map



need clique-trees to build these

directed

- parameter-estimation is easy
- can represent causal relations
- better for encoding expert domain knowledge

undirected

- simpler CI semantics
- less interpretable form for local factors
- less restrictive in structural form (loops)

Summary

- directed to undirected:
 - moralize
- undirected to directed:
 - triangulate
- Chordal graphs = Markov \cap Bayesian networks
 - p-maps in both directions

Bonus

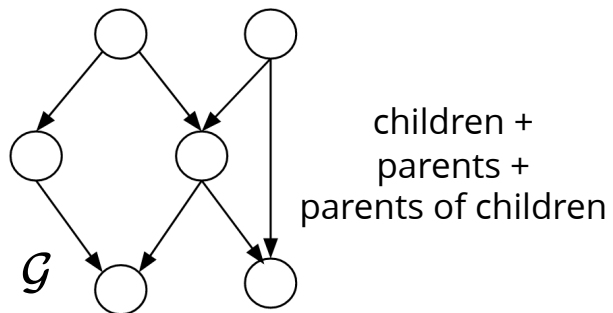
From Bayesian to Markov networks

alternative approach

- in both directed and undirected models

$$X_i \perp \text{every other var.} \mid MB(X_i)$$

- connect each node to its **Markov blanket**



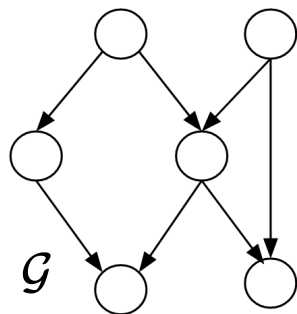
From Bayesian to Markov networks

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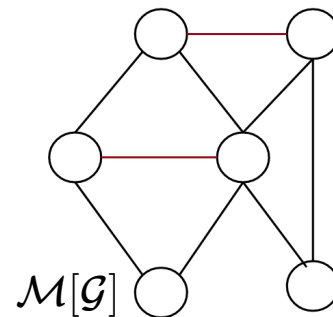
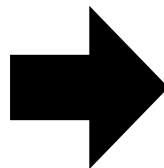
- in both directed and undirected models

$$X_i \perp \text{every other var.} \mid MB(X_i)$$

- connect each node to its **Markov blanket**



children +
parents +
parents of children



- gives the same moralized graph