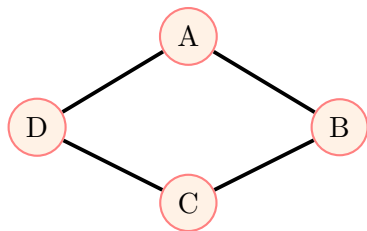
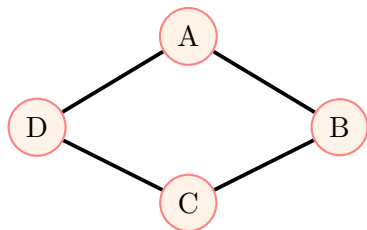


Module 18.1: Markov Networks: Motivation

- To motivate undirected graphical models let us consider a new example

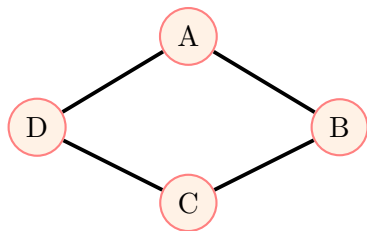


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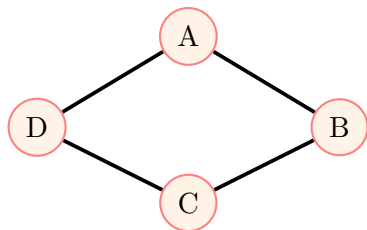
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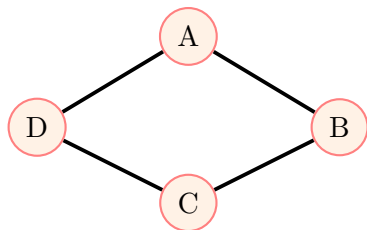
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- A, B, C, D are four students
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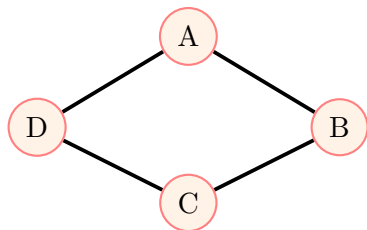
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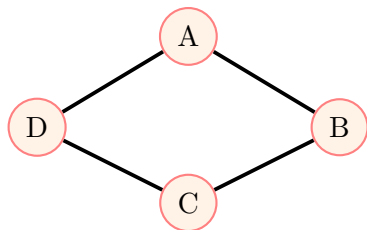
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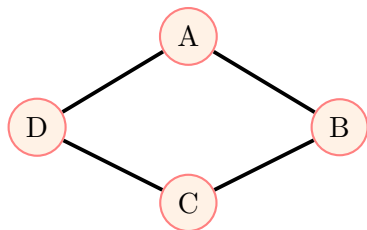
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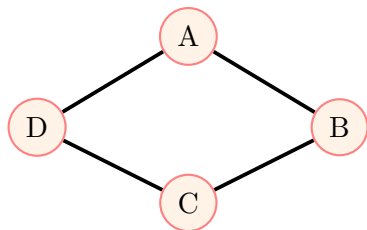
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- A, B, C, D are four students
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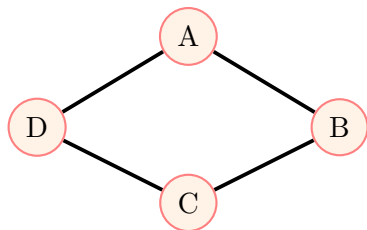
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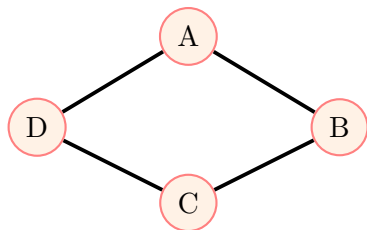
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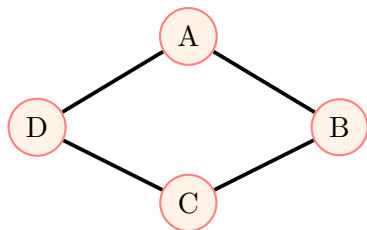
- To motivate undirected graphical models let us consider a new example
- Now suppose there was some misconception in the lecture due to some error made by the teacher

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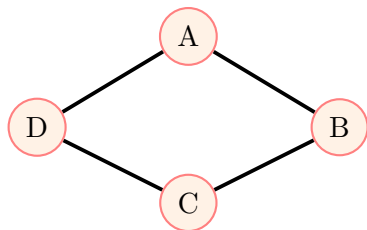
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- Now suppose there was some misconception in the lecture due to some error made by the teacher
- Each one of A, B, C, D could have independently cleared this misconception by thinking about it after the lecture



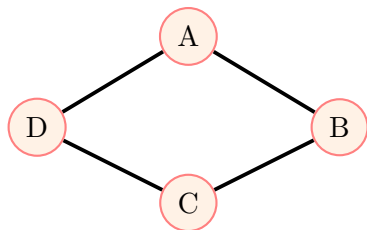
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- To motivate undirected graphical models let us consider a new example
- Now suppose there was some misconception in the lecture due to some error made by the teacher
- Each one of A, B, C, D could have independently cleared this misconception by thinking about it after the lecture
- In subsequent study pairs, each student could then pass on this information to their partner



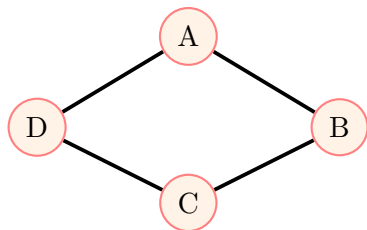
- We are now interested in knowing whether a student still has the misconception or not

- A, B, C, D are four students
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- B and C study together sometimes
- C and D study together sometimes
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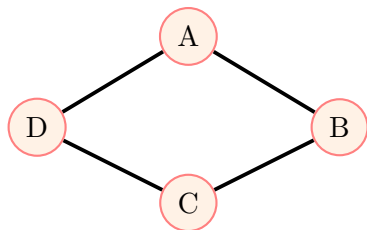
- We are now interested in knowing whether a student still has the misconception or not
- Or we are interested in $P(A, B, C, D)$

- A, B, C, D are four students
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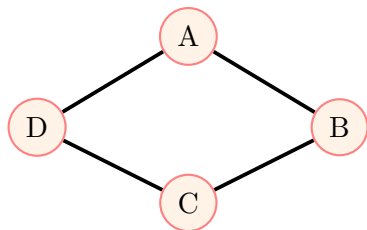
- We are now interested in knowing whether a student still has the misconception or not
- Or we are interested in $P(A, B, C, D)$
- where A, B, C, D can take values 0 (no misconception) or 1 (misconception)

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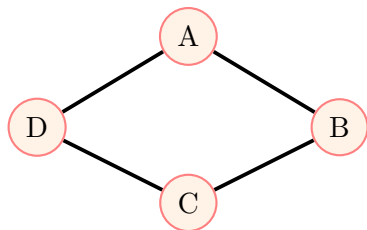
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- We are now interested in knowing whether a student still has the misconception or not
- Or we are interested in $P(A, B, C, D)$
- where A, B, C, D can take values 0 (no misconception) or 1 (misconception)
- How do we model this using a Bayesian Network ?



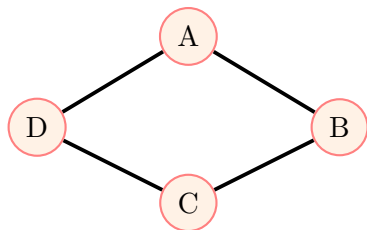
- First let us examine the conditional independencies in this problem

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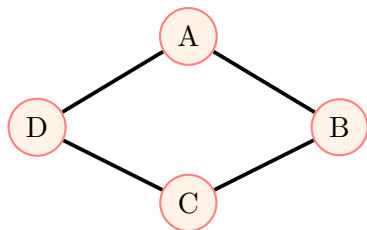
- First let us examine the conditional independencies in this problem
- $A \perp C | \{B, D\}$ (because A & C never interact)

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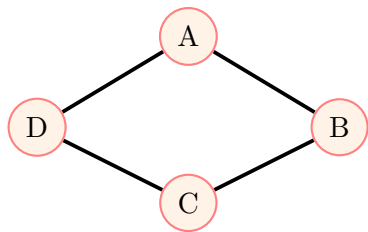
- First let us examine the conditional independencies in this problem
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- $B \perp D | \{A, C\}$ (because B & D never interact)

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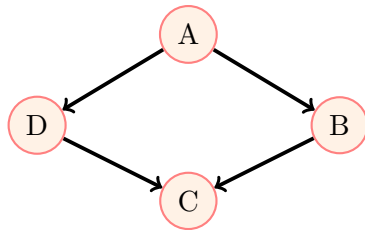
- First let us examine the conditional independencies in this problem
- $A \perp C | \{B, D\}$ (because A & C never interact)
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- There are no other conditional independencies in the problem

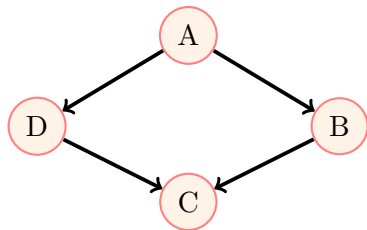


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- $B \perp D | \{A, C\}$ (because B & D never interact)
- There are no other conditional independencies in the problem
- Now let us try to represent this using a Bayesian Network

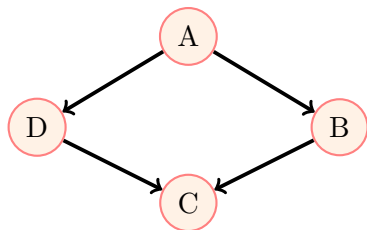
- How about this one?





- How about this one?
- Indeed, it captures the following in-dependencies relation

$$A \perp C | \{B, D\}$$



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- Indeed, it captures the following in-dependencies relation

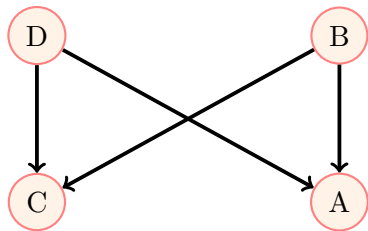
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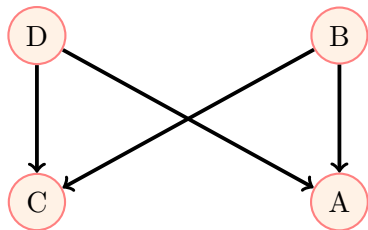
- But, it also implies that

$$B \not\perp D | \{A, C\}$$

- Let us try a different network

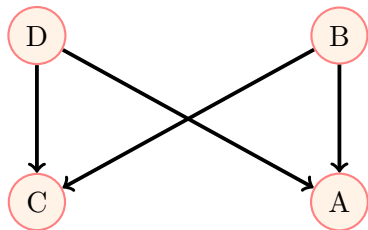
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- Let us try a different network
- Again

$$A \perp C | \{B, D\}$$

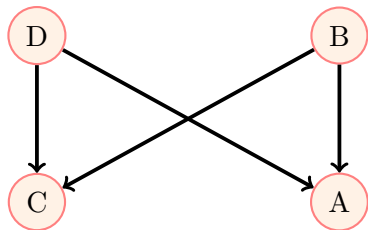


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$$A \perp C | \{B, D\}$$

- But

$$B \perp D (\text{unconditional})$$



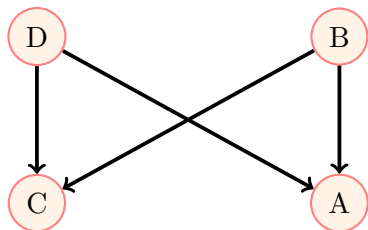
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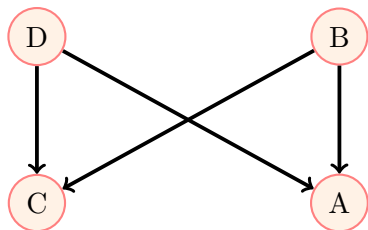
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- You can try other networks
- Turns out there is no Bayesian Network which can exactly capture independence relations that we are interested in



- **Perfect Map:** A graph G is a Perfect Map for a distribution P if the independence relations implied by the graph are exactly the same as those implied by the distribution

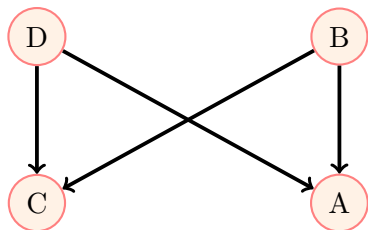
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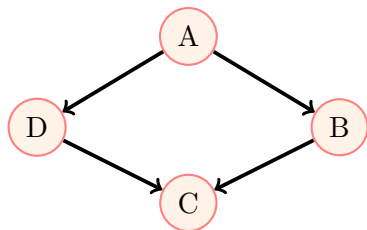
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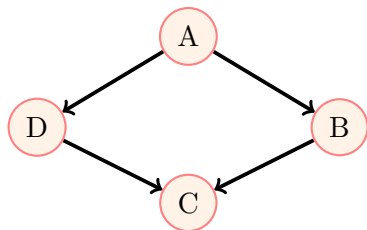
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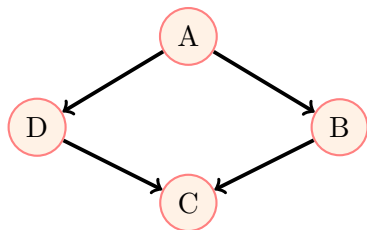
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- There is no Perfect Map for the distribution



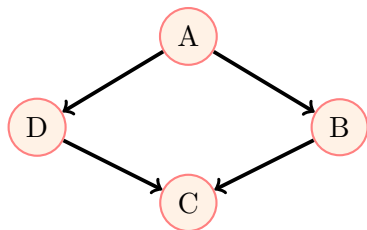
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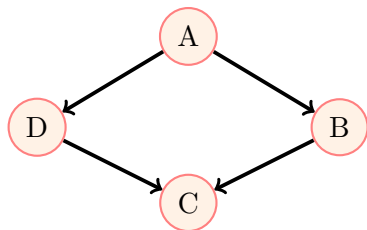
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- A directed edge between two nodes implies some kind of direction in the interaction



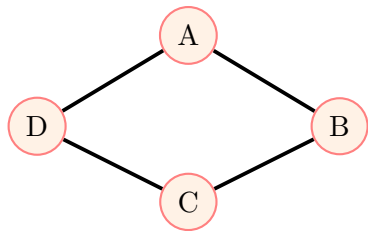
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- For example $A \rightarrow B$ could indicate that A influences B but not the other way round



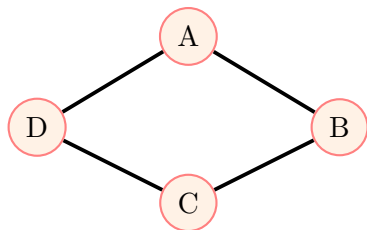
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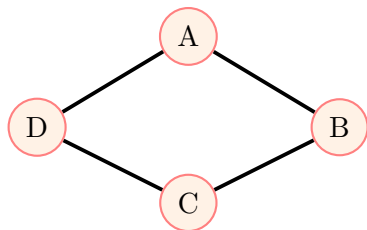
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- A directed edge between two nodes implies some kind of direction in the interaction
- For example $A \rightarrow B$ could indicate that A influences B but not the other way round
- But in our example A & B are equal partners (they both contribute to the study discussion)
- We want to capture the strength of this interaction (and there is no direction here)



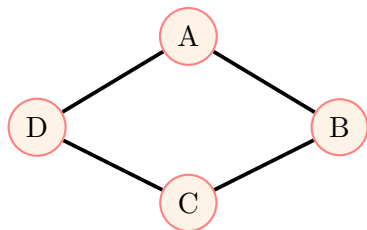
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- The Markov Network on the left exactly captures the interactions inherent in the problem



- We move on from Directed Graphical Models to Undirected Graphical Models
- Also known as **Markov Network**
- The Markov Network on the left exactly captures the interactions inherent in the problem
- But how do we parameterize this graph?