

## Module 18.3: Local Independencies in a Markov Network

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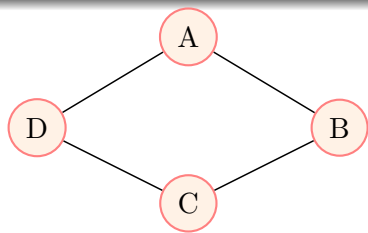
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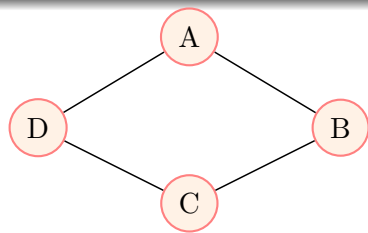
- Let us see this in the context of our original example



- In this example

$$P(A, B, C, D) =$$

$$\frac{1}{Z} [\phi_1(A, B) \phi_2(B, C) \phi_3(C, D) \phi_4(D, A)]$$

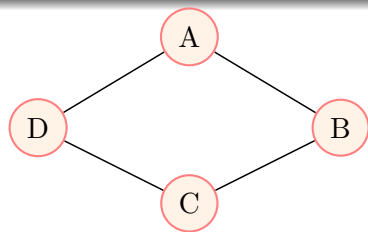


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$$P(A, B, C, D) = \frac{1}{Z} \underbrace{[\phi_1(A, B) \phi_2(B, C)]}_{\phi_5(B, \{A, C\})} \underbrace{[\phi_3(C, D) \phi_4(D, A)]}_{\phi_6(D, \{A, C\})}$$



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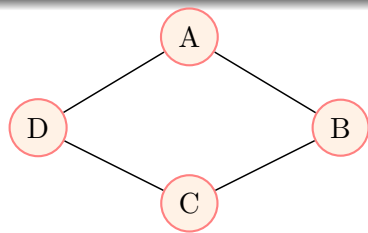
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- We can say that  $B \perp D | \{A, C\}$  which is indeed true

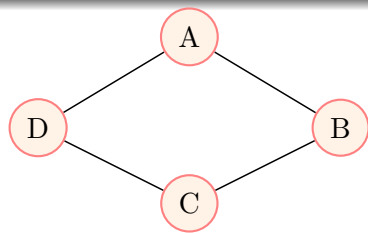




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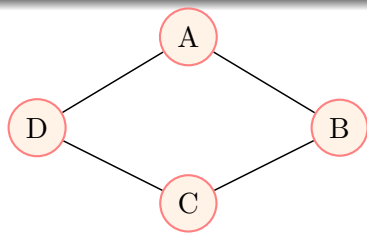


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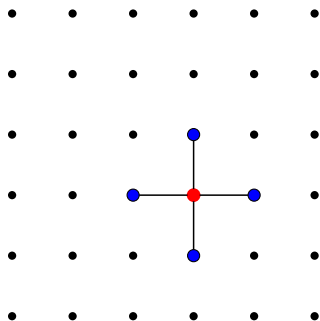
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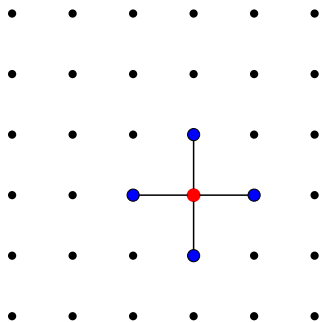
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- We can say that  $A \perp C | \{B, D\}$  which is indeed true

- For a given Markov network  $H$  we define Markov Blanket of a RV  $X$  to be the neighbors of  $X$  in  $H$

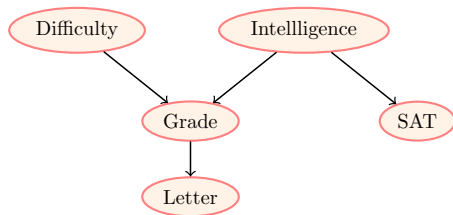




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- Analogous to the case of Bayesian Networks we can define the local independences associated with  $H$  to be

$$X \perp (U - \{X\} - MB_H) | MB_H(X)$$

## Bayesian network

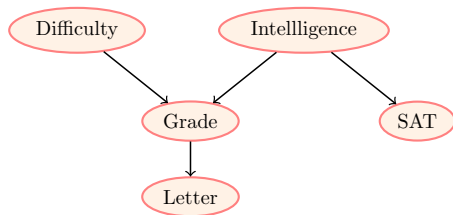


## Markov network

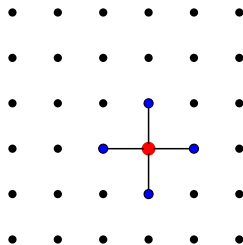
### Local Independencies

$$X_i \perp NonDescendants_{X_i} | Parent_{X_i}^G$$

## Bayesian network



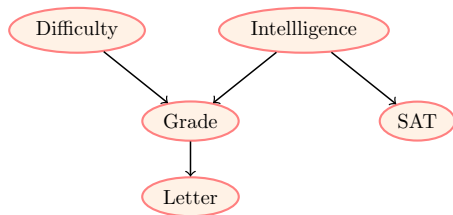
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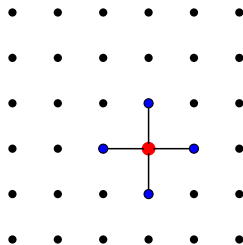
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