

**CS 6347**

**Lecture 4**

**Markov Random Fields**

# Recap

- Announcements
  - First homework is available on eLearning
- Last Time
  - Bayesian networks
  - Introduction to MRFs
- Today
  - More MRFs

# Markov Random Fields (MRFs)

- A **Markov random field** is an undirected graphical model
  - Undirected graph  $G = (V, E)$
  - One node for each random variable
  - Potential function or "factor" associated with cliques,  $C$ , of the graph
  - Nonnegative potential functions represent interactions and need not correspond to conditional probabilities (may not even sum to one)

# Markov Random Fields (MRFs)

- A **Markov random field** is an undirected graphical model
  - Corresponds to a **factorization** of the joint distribution

$$p(x_1, \dots, x_n) = \frac{1}{Z} \prod_{c \in C} \psi_c(x_c)$$

$$Z = \sum_{x'_1, \dots, x'_n} \prod_{c \in C} \psi_c(x'_c)$$

# Markov Random Fields (MRFs)

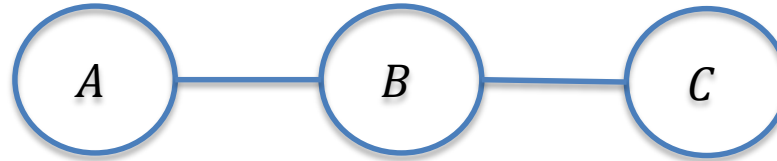
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Normalizing constant,  $Z$ , often called the **partition function**

# Independence Assertions

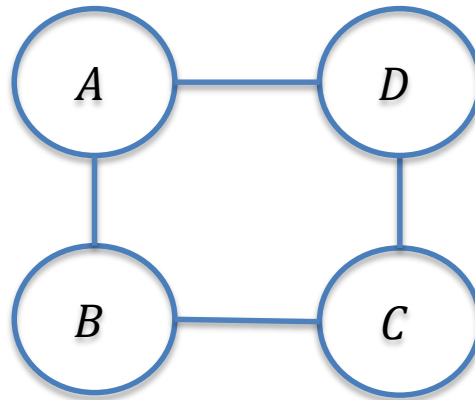


$$p(x_A, x_B, x_C) = \frac{1}{Z} \psi_{AB}(x_A, x_B) \psi_{BC}(x_B, x_C)$$

- How does separation imply independence?
- Showed that  $A \perp C \mid B$  on board last lecture

# Independence Assertions

- If  $X \subseteq V$  is **graph separated** from  $Y \subseteq V$  by  $Z \subseteq V$ , (i.e., all paths from  $X$  to  $Y$  go through  $Z$ ) then  $X \perp Y \mid Z$
- What independence assertions follow from this MRF?



# Independence Assertions

- Each variable is independent of all of its non-neighbors given its neighbors
  - All paths leaving a single variable must pass through some neighbor
- If the joint probability distribution,  $p$ , factorizes with respect to the graph  $G$ , then  $G$  is an **I-map** for  $p$
- If  $G$  is an I-map of a strictly positive distribution  $p$ , then  $p$  factorizes with respect to the graph  $G$ 
  - Hamersley-Clifford Theorem

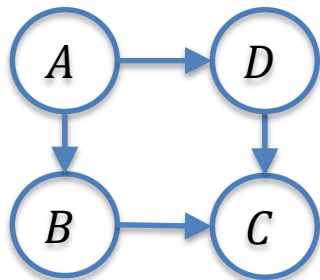


# BNs vs. MRFs

Property	Bayesian Networks	Markov Random Fields
Factorization	Conditional Distributions	Potential Functions
Distribution	Product of Conditional Distributions	Normalized Product of Potentials
Cycles	Not Allowed	Allowed
Partition Function	1	Potentially NP-hard to Compute
Independence Test	d-Separation	Graph Separation

# Moralization

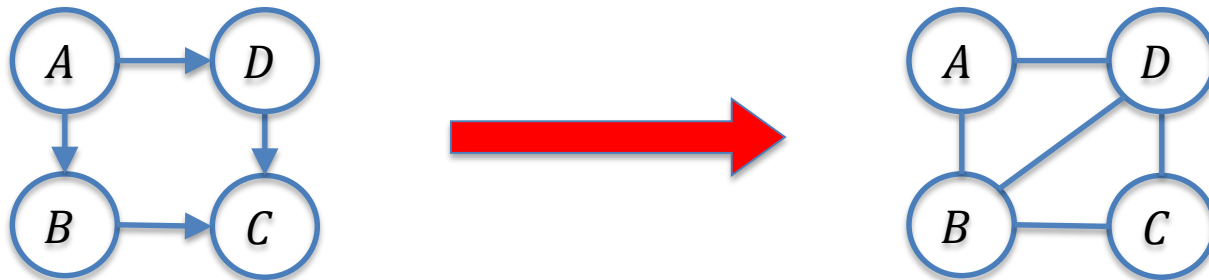
- Every Bayesian network can be converted into an MRF with some possible loss of independence information
  - Remove the direction of all arrows in the network
  - If  $A$  and  $B$  are parents of  $C$  in the Bayesian network, we add an edge between  $A$  and  $B$  in the MRF
- This procedure is called "**moralization**" because it "marries" the parents of every node



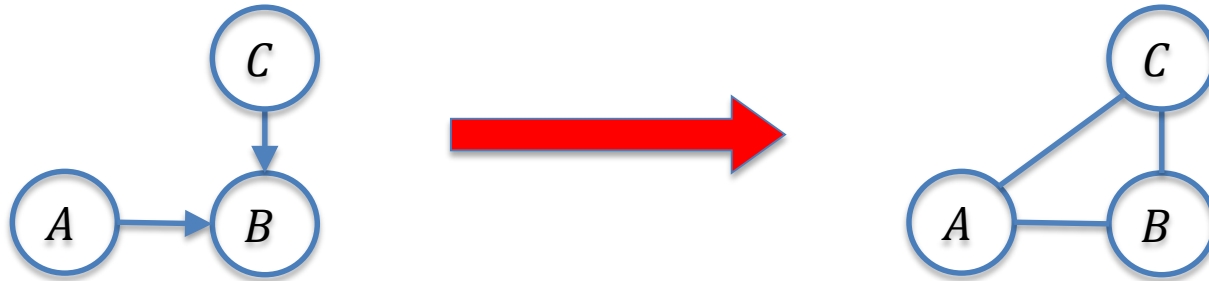
?

# Moralization

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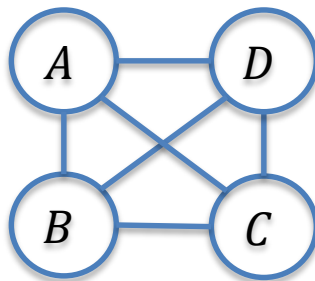
# Moralization



- What independence information is lost?

# Factorizations

- Many factorizations over the same graph may represent the same joint distribution
  - Some are better than others (e.g., they more compactly represent the distribution)
  - Simply looking at the graph is not enough to understand which specific factorization is being assumed

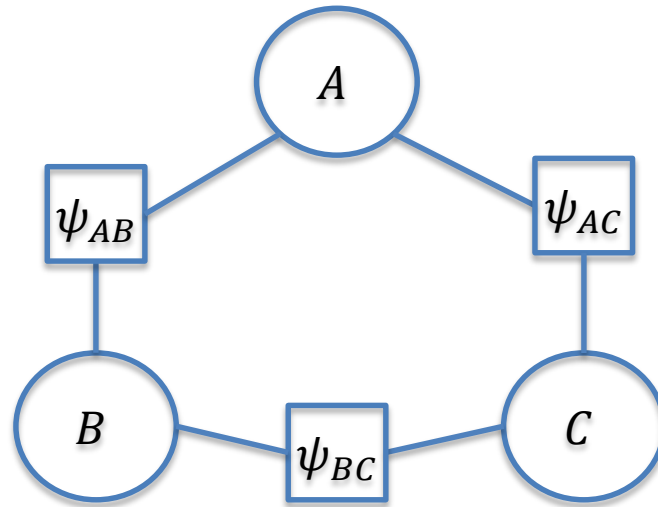


# Factor Graphs

- Factor graphs are used to explicitly represent a given factorization over a given graph
  - Not a different model, but rather different way to visualize an MRF
  - Undirected bipartite graph with two types of nodes: variable nodes (circles) and factor nodes (squares)
  - Factor nodes are connected to the variable nodes on which they depend

# Factor Graphs

$$p(x_A, x_B, x_C) = \frac{1}{Z} \psi_{AB}(x_A, x_B) \psi_{BC}(x_B, x_C) \psi_{AC}(x_A, x_C)$$



# MRF Examples

- Given a graph  $G = (V, E)$ , express the following as probability distributions that factorize over  $G$ 
  - Uniform distribution over independent sets
  - Uniform distribution over vertex covers
  - Express the uniform distribution over matchings (i.e., subsets of edges such that no two edges in the set have a common endpoint) as a factor graph

*(done on the board)*



# Conditional Random Fields (CRFs)

- Undirected graphical models that represent conditional probability distributions  $p(Y | X)$ 
  - Potentials can depend on both  $X$  and  $Y$

$$p(Y | X) = \frac{1}{Z(x)} \prod_{c \in C} \psi_c(x_c, y_c)$$

$$Z(x) = \sum_{y'} \prod_{c \in C} \psi_c(x_c, y'_c)$$

# Log-Linear Models

- CRFs often assume that the potentials are log-linear functions

$$\psi_c(x_c, y_c) = \exp(w \cdot f_c(x_c, y_c))$$

$f_c$  is referred to as a **feature vector** and  $w$  is some vector of feature weights

- The feature weights are typically learned from data
- CRFs don't require us to model the full joint distribution (which may not be possible anyhow)

# Conditional Random Fields (CRFs)

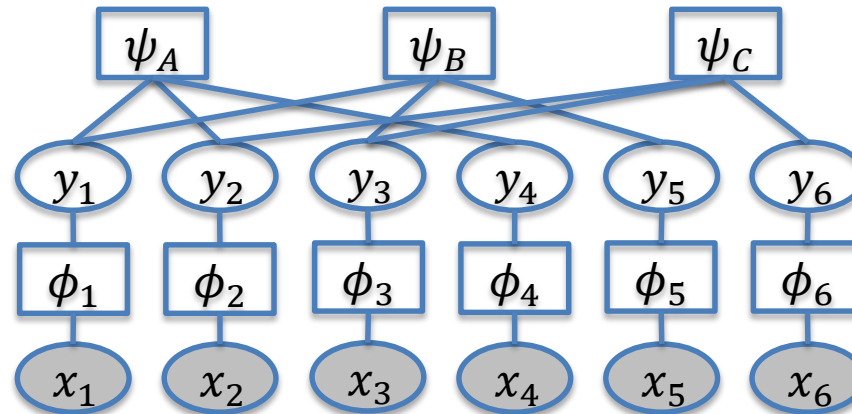
- **Binary image segmentation**
  - Label the pixels of an image as belonging to the foreground or background
  - +/- correspond to foreground/background
  - Interaction between neighboring pixels in the image depends on how similar the pixels are
    - Similar pixels should preference having the same spin (i.e., being in the same part of the image)

# Conditional Random Fields (CRFs)

- **Binary image segmentation**
  - This can be modeled as a CRF where the image information (e.g., pixel colors) is observed, but the segmentation is unobserved
  - Because the model is conditional, we don't need to describe the joint probability distribution of (natural) images and their foreground/background segmentations
  - CRFs will be particularly important when we want to learn graphical models from observed data

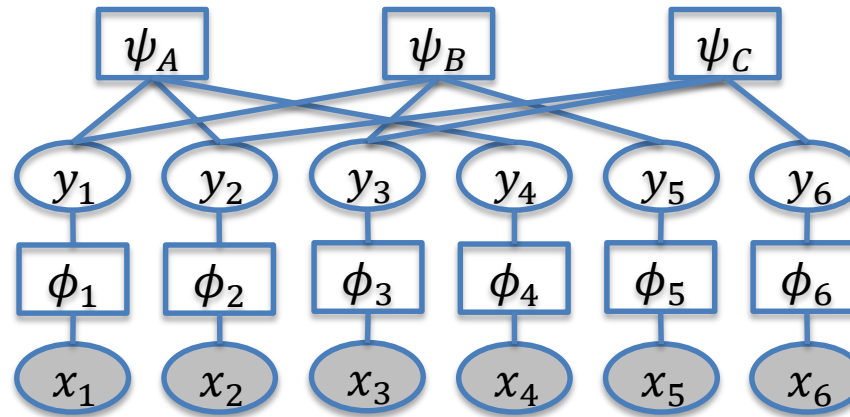
# Low Density Parity Check Codes

- Want to send a message across a noisy channel in which bits can be flipped with some probability – use error correcting codes



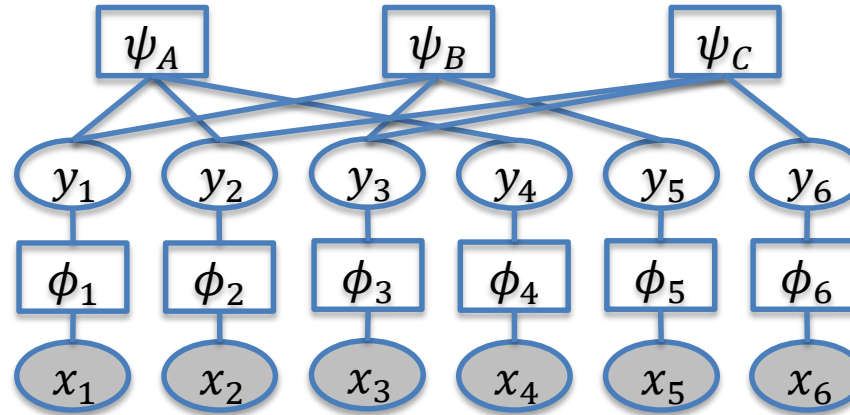
- $\psi_A, \psi_B, \psi_C$  are all parity check constraints: they equal one if their input contains an even number of ones and zero otherwise
- $\phi_i(x_i, y_i) = p(y_i|x_i)$ , the probability that the  $i$ th bit was flipped during transmission

# Low Density Parity Check Codes



- The parity check constraints enforce that the  $y$ 's can only be one of a few possible codewords: 000000, 001011, 010101, 011110, 100110, 101101, 110011, 111000
- Decoding the message that was sent is equivalent to computing the most likely codeword under the joint probability distribution

# Low Density Parity Check Codes



- Most likely codeword is given by MAP inference

$$\arg \max_y p(y|x)$$

- Do we need to compute the partition function for MAP inference?