School of Computer Science
Carnegie Mellon

Probabilistic Graphical Models

Representation of undirected GM

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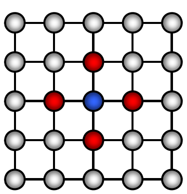
Lecture 3, February 22, 2014

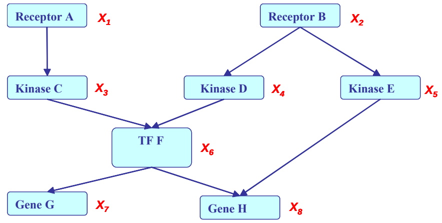


Reading: KF-chap4

Two types of GMs

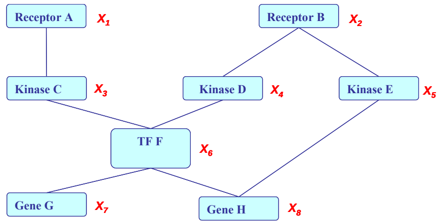
- **Directed edges** give **causality** relationships (Bayesian Network or Directed Graphical Model):

$$P(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8)$$
$$= P(X_1)\,P(X_2)\,P(X_3|\,X_1)\,P(X_4|\,X_2)\,P(X_5|\,X_2)\,P(X_6|\,X_3, X_4)\,P(X_7|\,X_6)\,P(X_8|\,X_5, X_6)$$



- **Undirected edges** simply give **correlations** between variables (Markov Random Field or Undirected Graphical model):

$$P(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8)$$
$$= 1/Z\ \exp\{E(X_1)+E(X_2)+E(X_3, X_1)+E(X_4, X_2)+E(X_5, X_2) + E(X_6, X_3, X_4)+E(X_7, X_6)+E(X_8, X_5, X_6)\}$$



Review: independence properties of DAGs

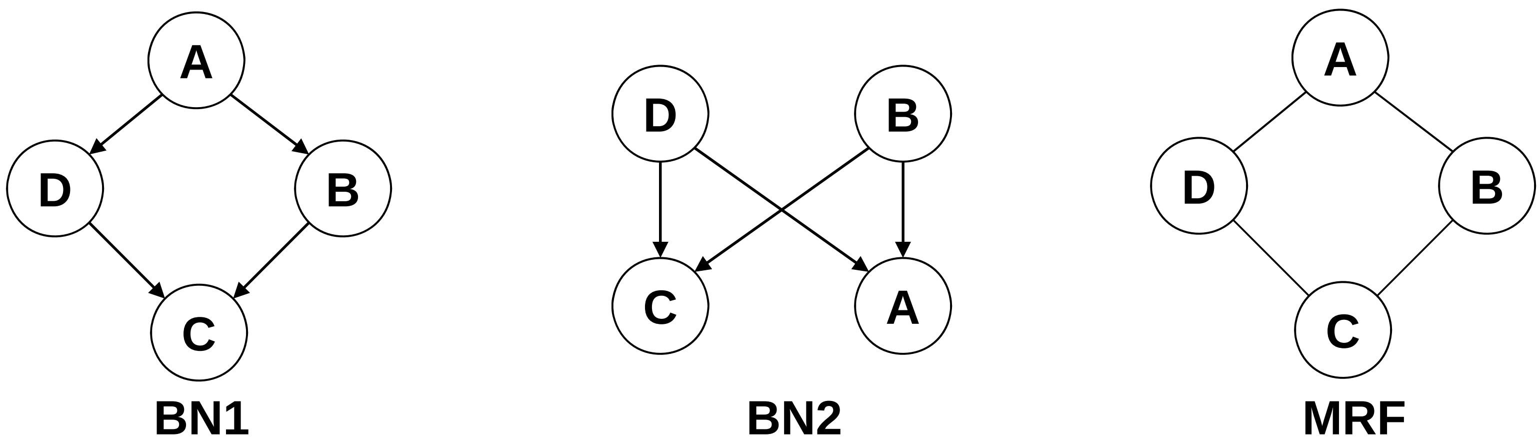
- Defn: let $\mathcal{I}_l(\mathcal{G})$ be the set of local independence properties encoded by DAG $\mathcal{G}$, namely:

$$\mathrm{I}(G) = \left\{ X \perp Z \middle| Y : \mathrm{dsep}_G(X; Z \middle| Y) \right\}$$

- Defn: A DAG $\mathcal{G}$ is an **I-map** (independence-map) of P if $\mathcal{I}_l(\mathcal{G}) \subseteq \mathcal{I}(P)$
- A fully connected DAG $\mathcal{G}$ is an I-map for any distribution, since $\mathcal{I}_l(\mathcal{G}) = \emptyset \subseteq \mathcal{I}(P)$ for any P.
- Defn: A DAG $\mathcal{G}$ is a minimal I-map for P if it is an I-map for P, and if the removal of even a single edge from $\mathcal{G}$ renders it not an I-map.
- A distribution may have several minimal I-maps
  - Each corresponding to a specific node-ordering

P-maps

- Defn: A DAG G is a **perfect map** (P-map) for a distribution P if $I(P)=I(G)$.
- Thm: not every distribution has a perfect map as DAG.
  - Pf by counterexample. Suppose we have a model where
    $A \perp C \mid \{B,D\}$, and $B \perp D \mid \{A,C\}$.
    This cannot be represented by any Bayes net.
    - e.g., BN1 wrongly says $B \perp D \mid A$, BN2 wrongly says $B \perp D$.



P-maps

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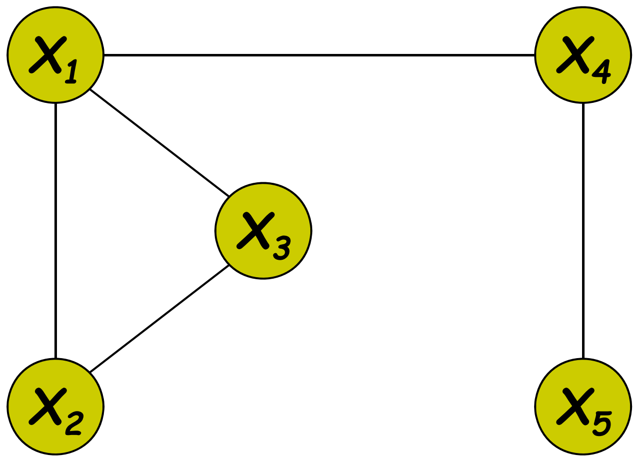
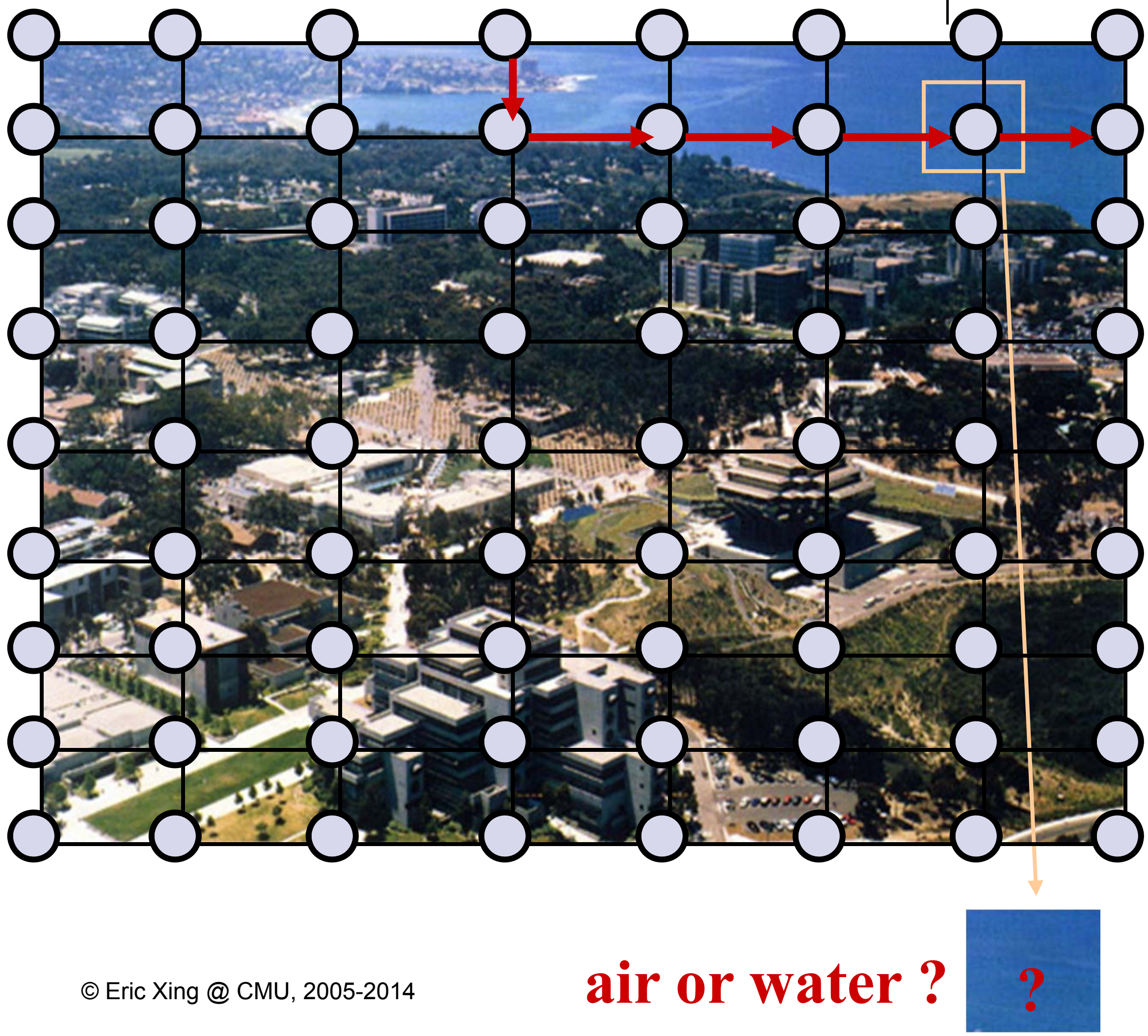
    This cannot be represented by any Bayes net.
    - e.g., BN1 wrongly says $B \perp D \mid A$, BN2 wrongly says $B \perp D$.
  - The fact that G is a minimal I-map for P is far from a guarantee that G captures the independence structure in P
  - The P-map of a distribution *is* unique up to I-equivalence between networks. That is, a distribution P can have many P-maps, but all of them are I-equivalent.

Undirected graphical models (UGM)



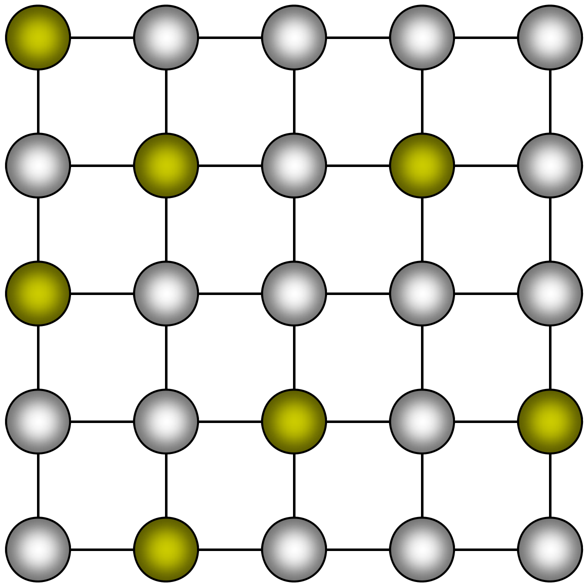
- Pairwise (non-causal) relationships
- Can write down model, and score specific configurations of the graph, but no explicit way to generate samples
- Contingency constrains on node configurations

A Canonical Examples: understanding complex scene ...



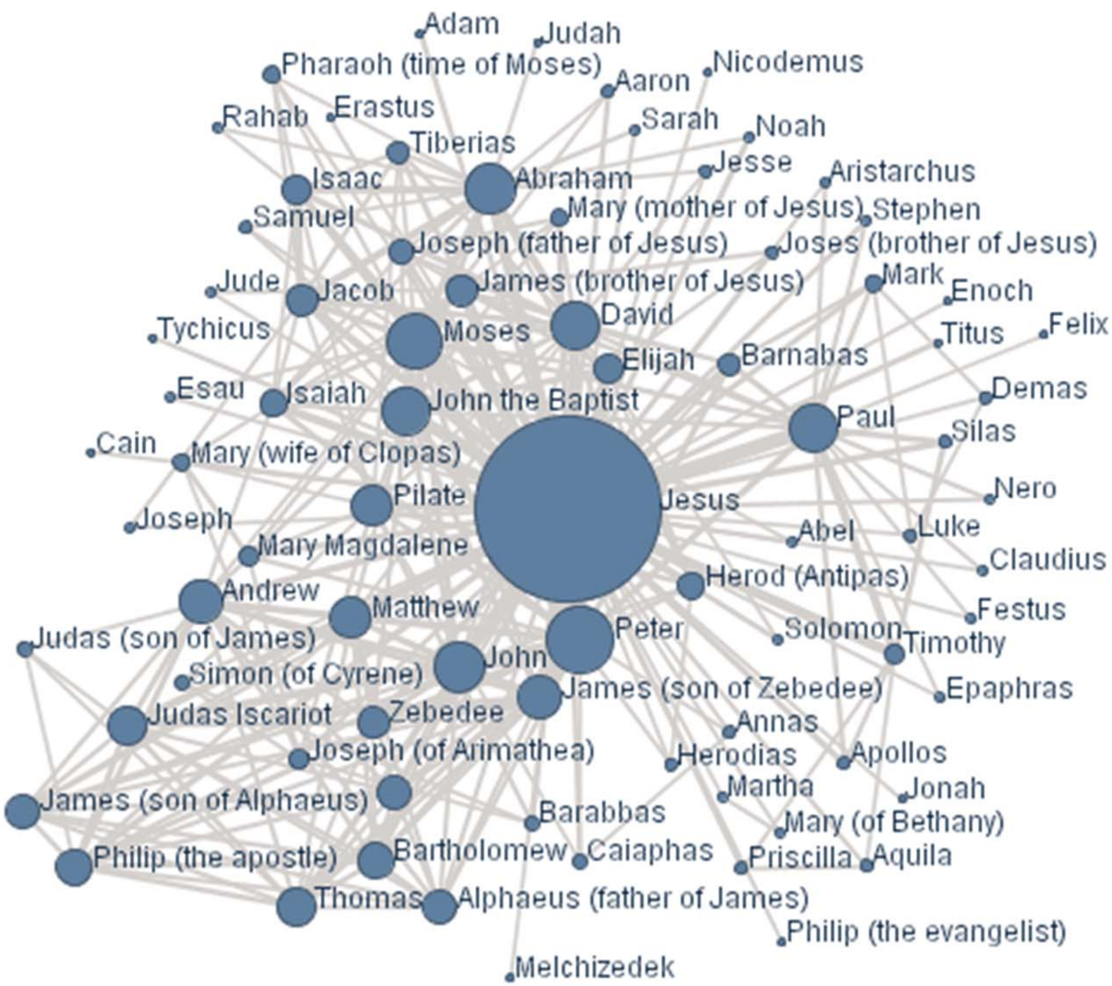
Canonical example

- The grid model



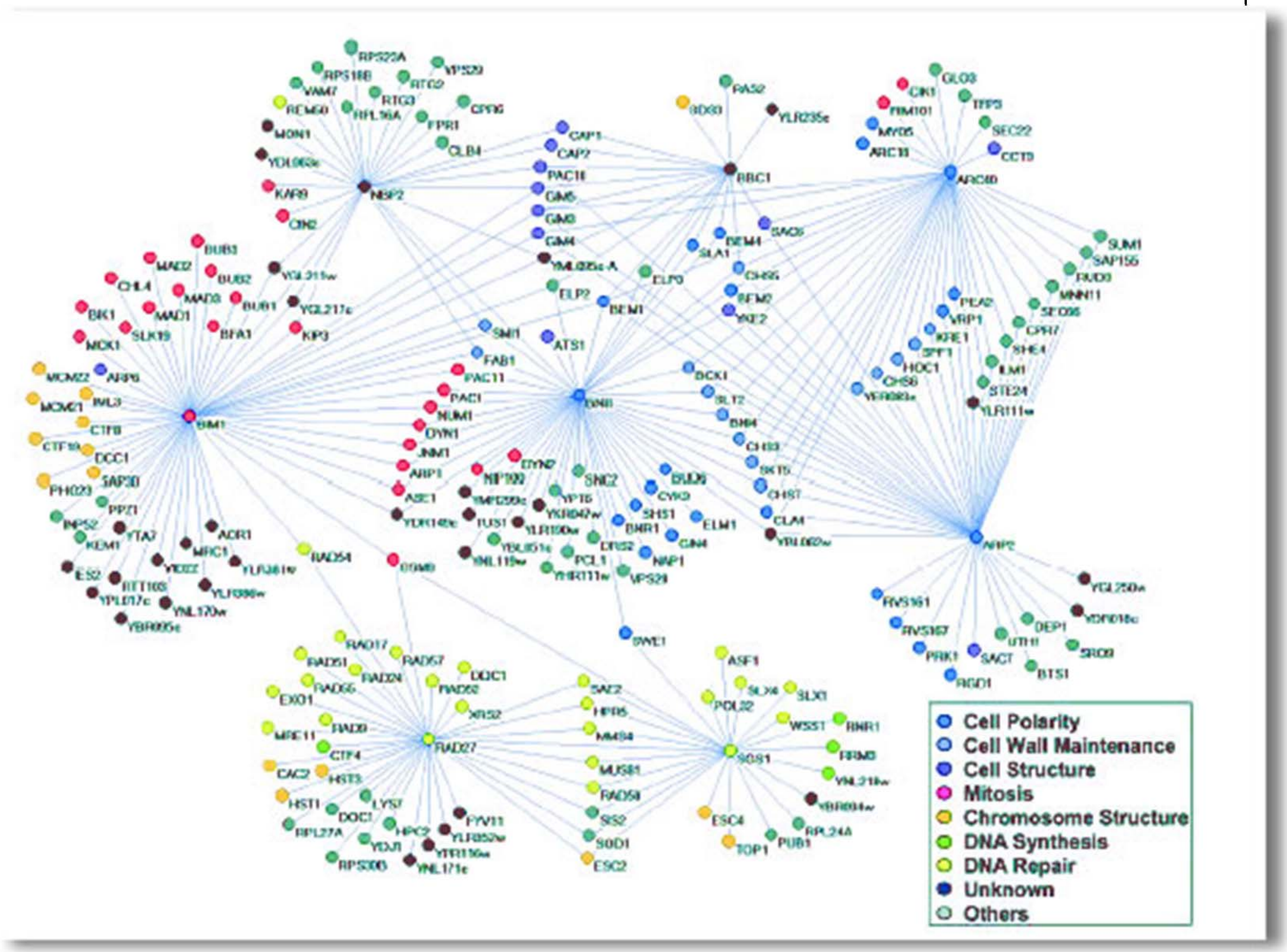
- Naturally arises in image processing, lattice physics, etc.
- Each node may represent a single "pixel", or an atom
  - The states of adjacent or nearby nodes are "coupled" due to pattern continuity or electro-magnetic force, etc.
  - Most likely joint-configurations usually correspond to a "low-energy" state

Social networks

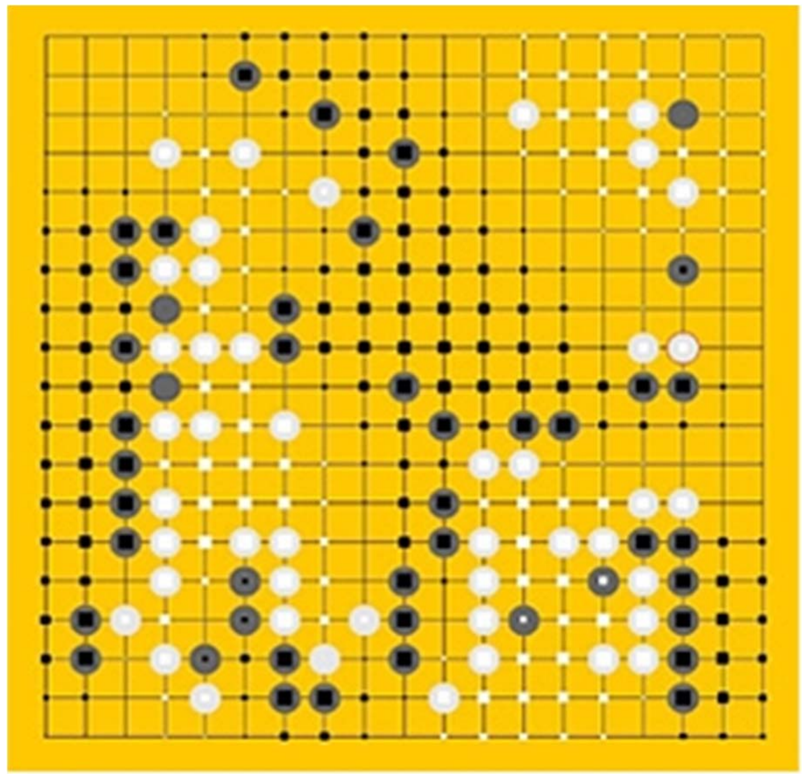


The New Testament Social Networks

Protein interaction networks

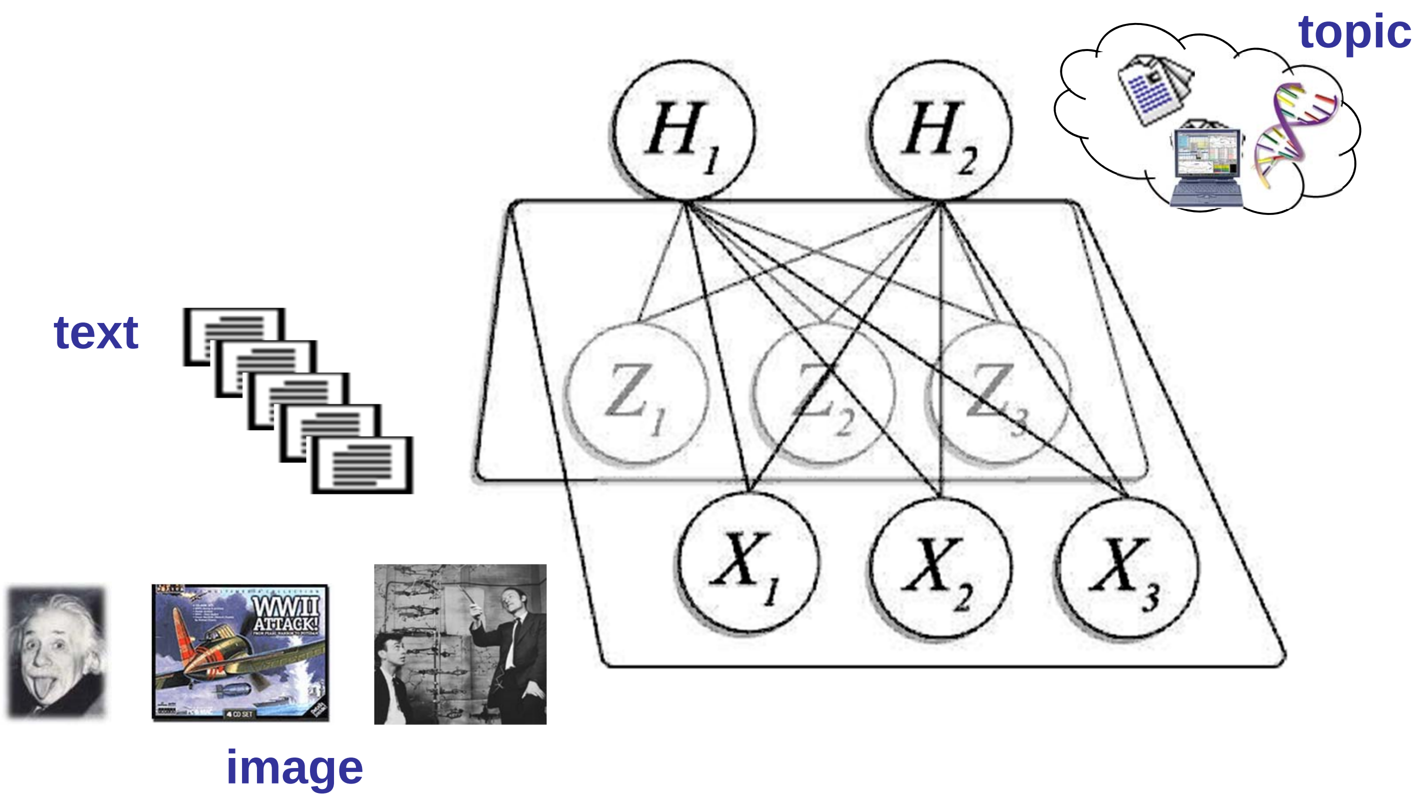


Modeling Go



This is the middle position of a Go game. Overlaid is the estimate for the probability of becoming black or white for every intersection. Large squares mean the probability is higher.

Information retrieval



Representation

- Defn: an undirected graphical model represents a distribution $P(X_1, \ldots, X_n)$ defined by an undirected graph H, and a set of positive ***potential functions*** y_c associated with the cliques of H, s.t.

$$P(x_1, \ldots, x_n) = \frac{1}{Z} \prod_{c \in C} \psi_c(\mathbf{x}_c)$$

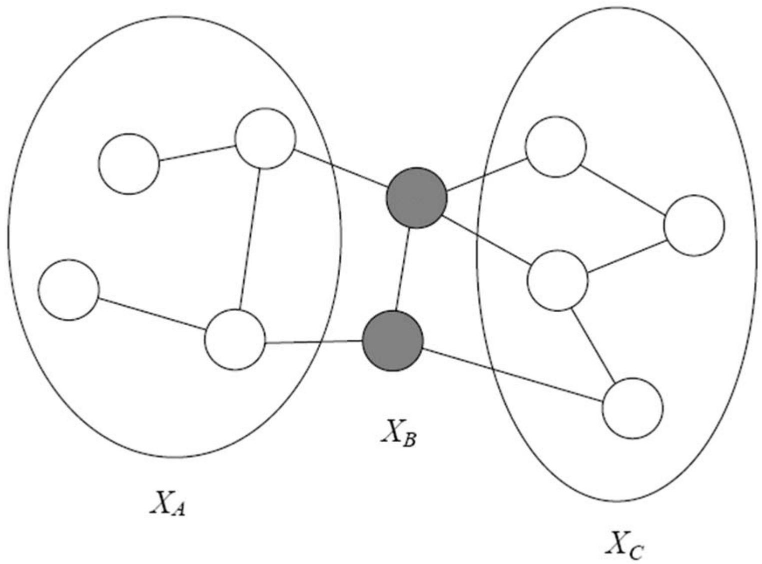
where Z is known as the partition function:

$$Z = \sum_{x_1, \ldots, x_n} \prod_{c \in C} \psi_c(\mathbf{x}_c)$$

- Also known as Markov Random Fields, Markov networks …
- The ***potential function*** can be understood as an contingency function of its arguments assigning "pre-probabilistic" score of their joint configuration.

Global Markov Independencies

- Let *H* be an undirected graph:



- *B* ***separates*** *A* and *C* if every path from a node in *A* to a node in *C* passes through a node in *B*: $\mathrm{sep}_H(A;C|B)$
- A probability distribution satisfies the ***global Markov property*** if for any disjoint *A*, *B*, *C*, such that *B* separates *A* and *C*, *A* is independent of *C* given *B:* $\mathrm{I}(H) = \{A \perp C | B : \mathrm{sep}_H(A;C|B)\}$

Local Markov independencies

- For each node $X_i \in \mathbf{V}$, there is *unique Markov blanket* of X_i, denoted MB_{X_i}, which is the set of neighbors of X_i in the graph (those that share an edge with X_i)

- **Defn:**

  The *local Markov independencies* associated with H is:

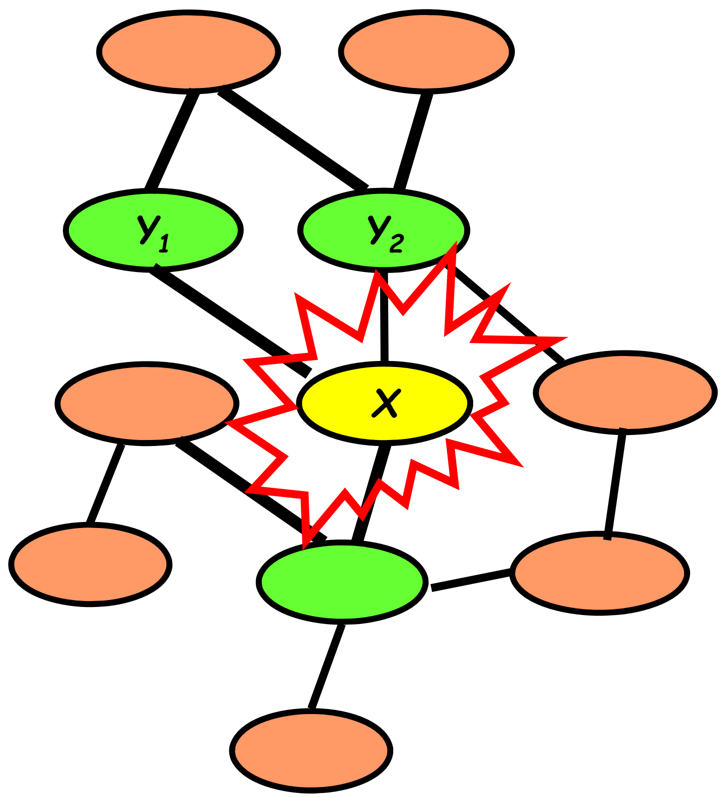
  $$I_\ell(H): \{X_i \perp \mathbf{V} - \{X_i\} - MB_{X_i} \mid MB_{X_i} : \forall\ i\},$$

  In other words, X_i is independent of the rest of the nodes in the graph given its immediate neighbors

Summary: Conditional Independence Semantics in an MRF

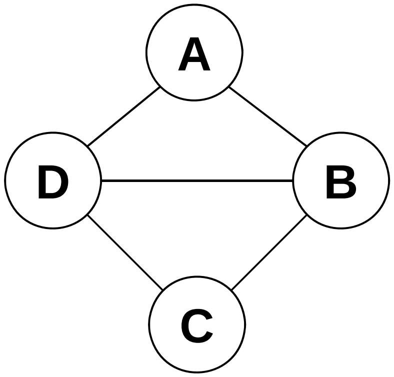
Structure: an *undirected graph*

- Meaning: a node is conditionally independent of every other node in the network given its Directed neighbors
- Local contingency functions (potentials) and the cliques in the graph completely determine the joint dist.
- Give correlations between variables, but no explicit way to generate samples



I. Quantitative Specification: Cliques

- For $G=\{V,E\}$, a complete subgraph (clique) is a subgraph $G'=\{V'\subseteq V, E'\subseteq E\}$ such that nodes in V' are fully interconnected
- A (maximal) clique is a complete subgraph s.t. any **superset** $V''\supset V'$ is not complete.
- A sub-clique is a not-necessarily-maximal clique.



- Example:
  - max-cliques = $\{A,B,D\}$, $\{B,C,D\}$,
  - sub-cliques = $\{A,B\}$, $\{C,D\}$, …→ all edges and singletons

Gibbs Distribution and Clique Potential

- Defn: an undirected graphical model represents a distribution $P(X_1,\ldots,X_n)$ defined by an undirected graph H, and **a set** of positive ***potential functions*** ψ_c associated with cliques of H, s.t.

$$P(x_1,\ldots,x_n) = \frac{1}{Z}\prod_{c \in C} \psi_c(\mathbf{x}_c)$$

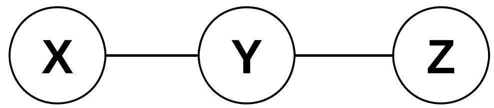
(A Gibbs distribution)

where Z is known as the partition function:

$$Z = \sum_{x_1,\ldots,x_n} \prod_{c \in C} \psi_c(\mathbf{x}_c)$$

- Also known as Markov Random Fields, Markov networks …
- The ***potential function*** can be understood as an contingency function of its arguments assigning "pre-probabilistic" score of their joint configuration.

Interpretation of Clique Potentials



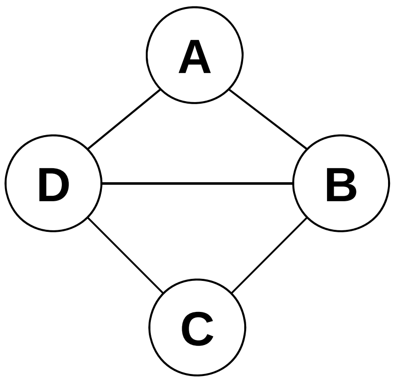
- The model implies $X \perp Z | Y$. This independence statement implies (by definition) that the joint must factorize as:

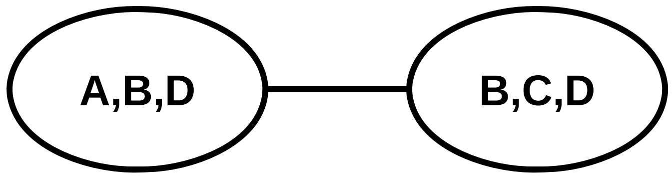
$$p(x,y,z) = p(y)p(x|y)p(z|y)$$

- We can write this as: $p(x,y,z) = p(x,y)p(z|y)$, but $p(x,y,z) = p(x|y)p(z,y)$
  - **cannot** have all potentials be marginals
  - **cannot** have all potentials be conditionals

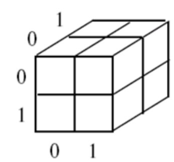
- The positive clique potentials can only be thought of as general "compatibility", "goodness" or "happiness" functions over their variables, but not as probability distributions.

Example UGM – using max cliques





$\psi_c(\mathbf{x}_{124})$ $\psi_c(\mathbf{x}_{234})$

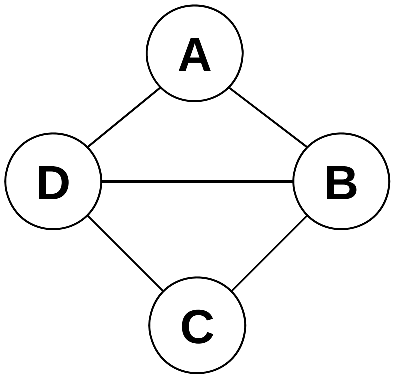


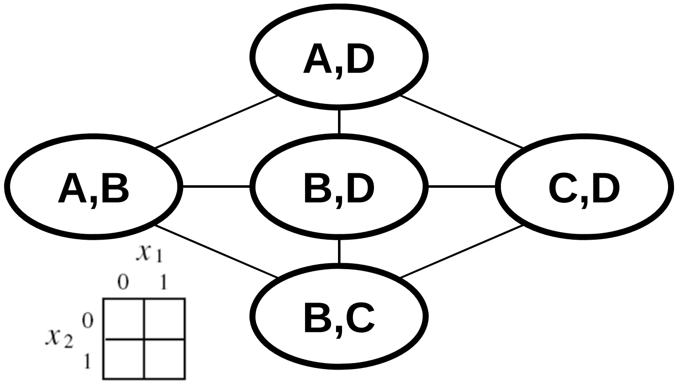
$$P'(x_1, x_2, x_3, x_4) = \frac{1}{Z}\psi_c(\mathbf{x}_{124}) \times \psi_c(\mathbf{x}_{234})$$

$$Z = \sum_{x_1, x_2, x_3, x_4} \psi_c(\mathbf{x}_{124}) \times \psi_c(\mathbf{x}_{234})$$

- For discrete nodes, we can represent $P(X_{1:4})$ as two 3D tables instead of one 4D table

Example UGM – using subcliques





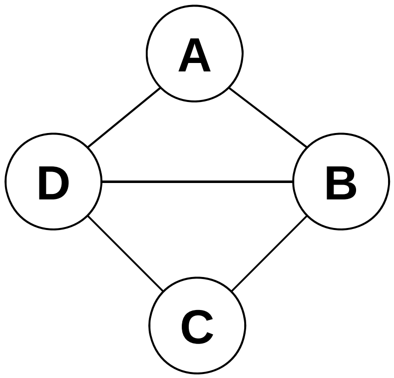
$$P''(x_1, x_2, x_3, x_4) = \frac{1}{Z} \prod_{ij} \psi_{ij}(\mathbf{x}_{ij})$$

$$= \frac{1}{Z} \psi_{12}(\mathbf{x}_{12}) \psi_{14}(\mathbf{x}_{14}) \psi_{23}(\mathbf{x}_{23}) \psi_{24}(\mathbf{x}_{24}) \psi_{34}(\mathbf{x}_{34})$$

$$Z = \sum_{x_1, x_2, x_3, x_4} \prod_{ij} \psi_{ij}(\mathbf{x}_{ij})$$

- We can represent $P(X_{1:4})$ as 5 2D tables instead of one 4D table
- Pair MRFs, a popular and simple special case
- I(P') vs. I(P") ? D(P') vs. D(P")

Example UGM – canonical representation



$$P(x_1, x_2, x_3, x_4)$$
$$= \frac{1}{Z}\psi_c(\mathbf{x}_{124}) \times \psi_c(\mathbf{x}_{234})$$
$$\times \psi_{12}(\mathbf{x}_{12})\psi_{14}(\mathbf{x}_{14})\psi_{23}(\mathbf{x}_{23})\psi_{24}(\mathbf{x}_{24})\psi_{34}(\mathbf{x}_{34})$$
$$\times \psi_1(x_1)\psi_2(x_2)\psi_3(x_3)\psi_4(x_4)$$

$$Z = \sum_{x_1, x_2, x_3, x_4} \begin{array}{l} \psi_c(\mathbf{x}_{124}) \times \psi_c(\mathbf{x}_{234}) \\ \times \psi_{12}(\mathbf{x}_{12})\psi_{14}(\mathbf{x}_{14})\psi_{23}(\mathbf{x}_{23})\psi_{24}(\mathbf{x}_{24})\psi_{34}(\mathbf{x}_{34}) \\ \times \psi_1(x_1)\psi_2(x_2)\psi_3(x_3)\psi_4(x_4) \end{array}$$

- **Most general, subsume P' and P" as special cases**
- **I(P) vs. I(P') vs. I(P")**
  D(P) vs. D(P') vs. D(P")

Hammersley-Clifford Theorem

- If arbitrary potentials are utilized in the following product formula for probabilities,

$$P(x_1,\ldots,x_n) = \frac{1}{Z}\prod_{c\in C}\psi_c(\mathbf{x}_c)$$

$$Z = \sum_{x_1,\ldots,x_n}\prod_{c\in C}\psi_c(\mathbf{x}_c)$$

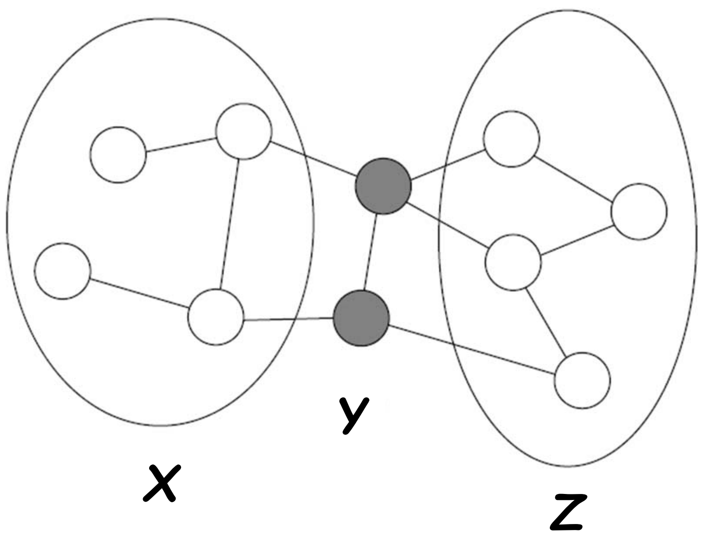
  then the family of probability distributions obtained is exactly that set which **respects** the *qualitative specification* (the conditional independence relations) described earlier

- **Thm :** Let P be a positive distribution over $\mathbf{V}$, and *H* a Markov network graph over $\mathbf{V}$. If *H* is an I-map for P, then P is a Gibbs distribution over *H*.

II: Independence properties: global independencies

- Let us return to the question of what kinds of distributions can be represented by undirected graphs (ignoring the details of the particular parameterization).
- Defn: the global Markov properties of a UG *H* are

$$\mathrm{I}(H) = \left\{ X \perp Z \middle| Y \right) : \mathrm{sep}_H \left(X ; Z \middle| Y \right) \right\}$$



- Is this definition sound and complete?

Soundness and completeness of global Markov property

- Defn: An UG H is an I-map for a distribution P if $I(H) \subseteq I(P)$, i.e., P entails $I(H)$.
- Defn: P is a Gibbs distribution over H if it can be represented as

$$P(x_1, \ldots, x_n) = \frac{1}{Z} \prod_{c \in C} \psi_c(\mathbf{x}_c)$$

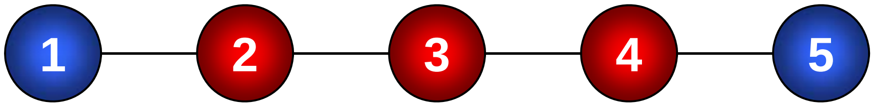
- Thm (soundness): If P is a Gibbs distribution over H, then H is an I-map of P.
- Thm (completeness): If $\neg \mathrm{sep}_H(X; Z \mid Y)$, then $X \not\perp_P Z \mid Y$ in ***some*** P that factorizes over H.

Local and global Markov properties revisit

- For directed graphs, we defined I-maps in terms of local Markov properties, and derived global independence.
- For undirected graphs, we defined I-maps in terms of global Markov properties, and will now derive local independence.
- Defn: The *pairwise Markov independencies* associated with UG $H = (V;E)$ are

$$\mathrm{I}_p(H) = \left\{ X \perp Y \middle| V \setminus \{X, Y\} : \{X, Y\} \notin E \right\}$$

- e.g., $X_1 \perp X_5 | \{X_2, X_3, X_4\}$

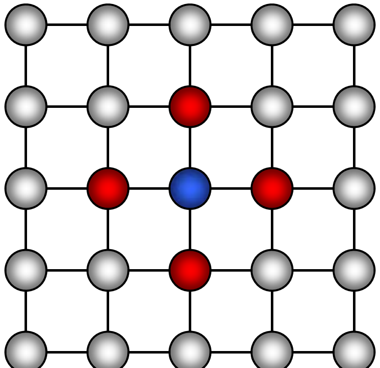


Local Markov properties

- A distribution has the *local Markov property* w.r.t. a graph H=(**V**,**E**) if the conditional distribution of variable given its neighbors is independent of the remaining nodes

$$\mathrm{I}_l(H) = \left\{ X \perp \mathbf{V} \setminus \left(X \cup N_H(X) \right) \middle| N_H(X)) : X \in \mathbf{V} \right\}$$

- **Theorem** (Hammersley-Clifford): If the distribution is strictly positive and satisfies the local Markov property, then it factorizes with respect to the graph.
- $N_H(X)$ is also called the Markov blanket of X.



Relationship between local and global Markov properties

- Thm 5.5.5. If $P \models I_l(H)$ then $P \models I_p(H)$.
- Thm 5.5.6. If $P = I(H)$ then $P \models I_l(H)$.
- Thm 5.5.7. If $P > 0$ and $P \models I_p(H)$, then $P \models I(H)$.

- **Corollary (5.5.8):** The following three statements are equivalent for a *positive distribution* P:

  $P \models I_l(H)$
  $P \models I_p(H)$
  $P \models I(H)$

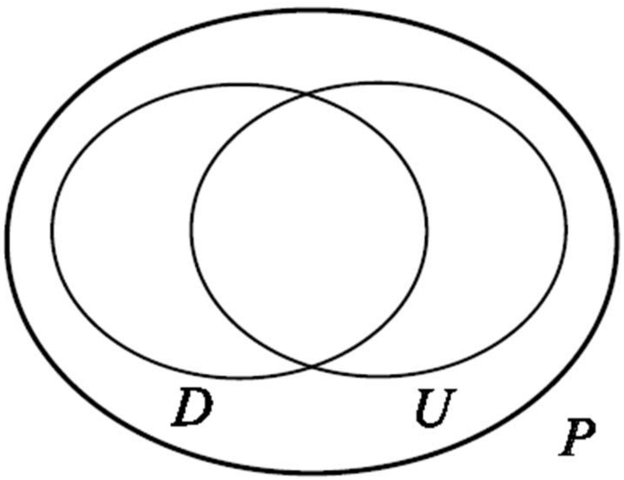
  - This equivalence relies on the positivity assumption.
  - We can design a distribution locally

Perfect maps

- Defn: A Markov network H is a perfect map for P if for any X; Y;Z we have that

$$\mathrm{sep}_H(X;Z|Y) \Leftrightarrow P \models (X \perp Z \mid Y)$$

- Thm: not every distribution has a perfect map as UGM.
  - Pf by counterexample. No undirected network can capture all and only the independencies encoded in a v-structure $X \rightarrow Z \leftarrow Y$.



Exponential Form

- Constraining clique potentials to be positive could be inconvenient (e.g., the interactions between a pair of atoms can be either attractive or repulsive). We represent a clique potential $\psi_c(\mathbf{x}_c)$ in an unconstrained form using a real-value "energy" function $\phi_c(\mathbf{x}_c)$:

$$\psi_c(\mathbf{x}_c) = \exp\{-\phi_c(\mathbf{x}_c)\}$$

  For convenience, we will call $\phi_c(\mathbf{x}_c)$ a potential when no confusion arises from the context.

- This gives the joint a nice additive strcuture

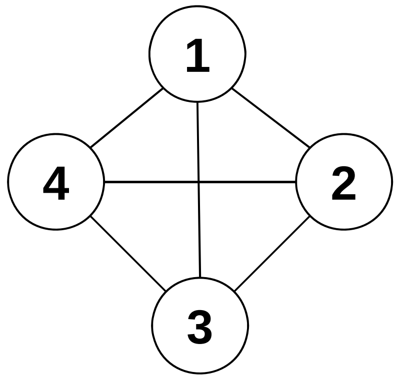
$$p(\mathbf{x}) = \frac{1}{Z}\exp\left\{-\sum_{c\in C}\phi_c(\mathbf{x}_c)\right\} = \frac{1}{Z}\exp\{-H(\mathbf{x})\}$$

  where the sum in the exponent is called the "free energy":

$$H(\mathbf{x}) = \sum_{c\in C}\phi_c(\mathbf{x}_c)$$

- In physics, this is called the "Boltzmann distribution".
- In statistics, this is called a log-linear model.

Example: Boltzmann machines



- A fully connected graph with pairwise (edge) potentials on binary-valued nodes (for $x_i \in \{-1,+1\}$ or $x_i \in \{0,1\}$) is called a Boltzmann machine

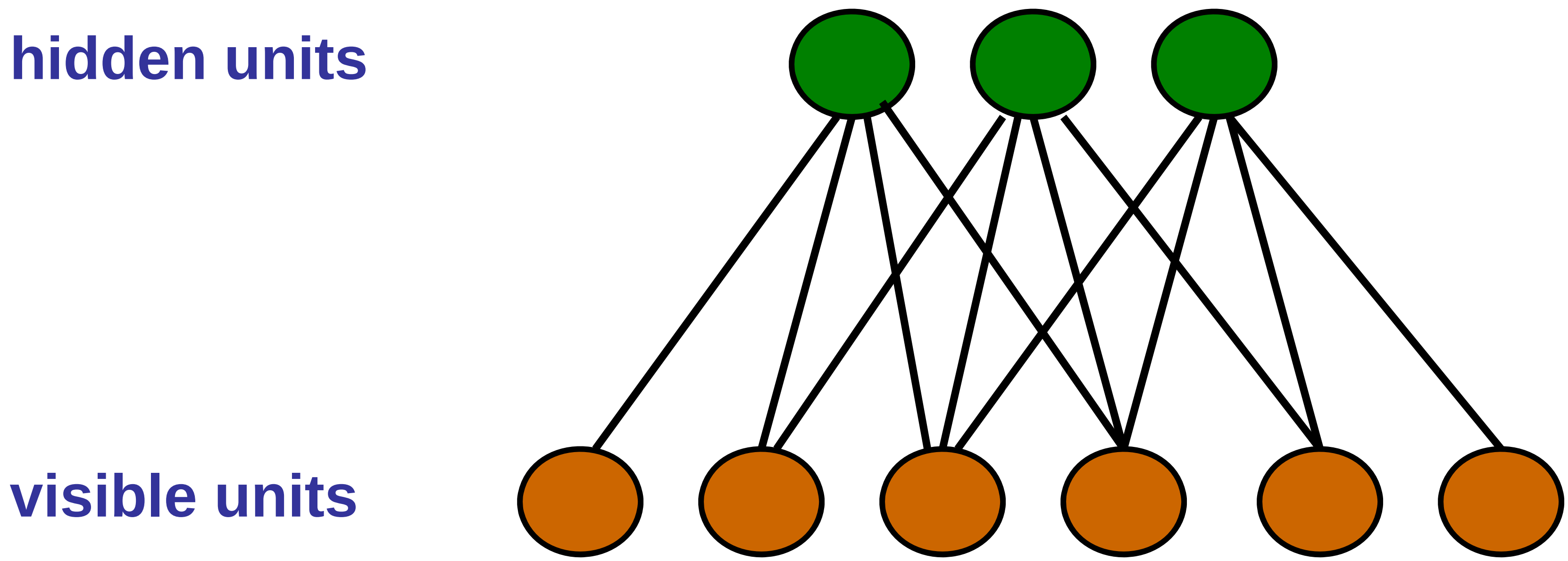
$$P(x_1, x_2, x_3, x_4) = \frac{1}{Z} \exp\left\{ \sum_{ij} \phi_{ij}(x_{i,} x_j) \right\}$$

$$= \frac{1}{Z} \exp\left\{ \sum_{ij} \theta_{ij} x_i x_j + \sum_i \alpha_i x_i + C \right\}$$

- Hence the overall energy function has the form:

$$H(x) = \sum_{ij} (x_i - \mu) \Theta_{ij} (x_j - \mu) = (x - \mu)^T \Theta (x - \mu)$$

Restricted Boltzmann Machines



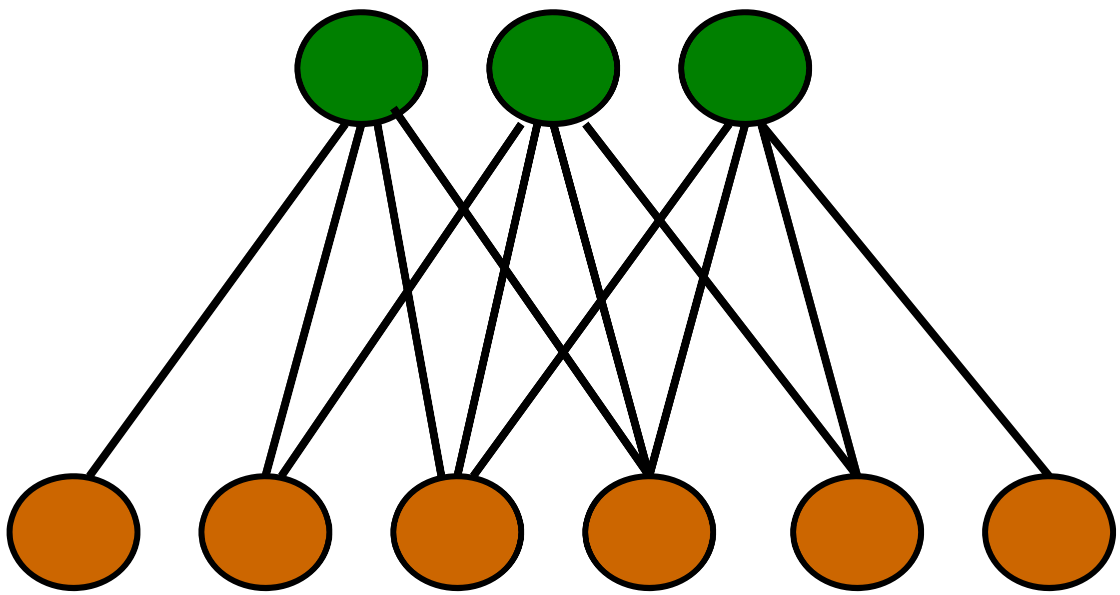
$$p(x,h\,|\,\theta) = \exp\left\{ \sum_i \theta_i \phi_i(x_i) + \sum_j \theta_j \phi_j(h_j) + \sum_{i,j} \theta_{i,j} \phi_{i,j}(x_i, h_j) - A(\boldsymbol{\theta}) \right\}$$

Restricted Boltzmann Machines

The Harmonium (Smolensky –'86)

hidden units

visible units



History:

Smolensky ('86), Proposed the architechture.

Freund & Haussler ('92), The "Combination Machine" (binary), learning with projection pursuit.

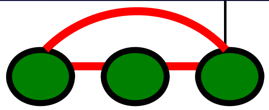
Hinton ('02), The "Restricted Boltzman Machine" (binary), learning with contrastive divergence.

Marks & Movellan ('02), Diffusion Networks (Gaussian).

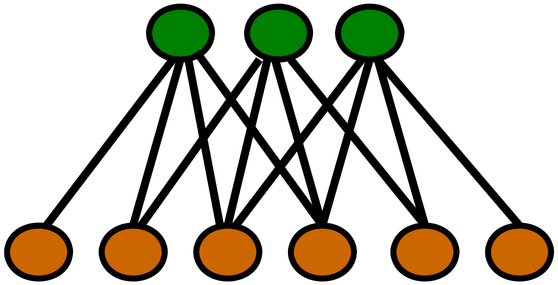
Welling, Hinton, Osindero ('02), "Product of Student-T Distributions" (super-Gaussian)

Properties of RBM

- Factors are marginally *dependent*.

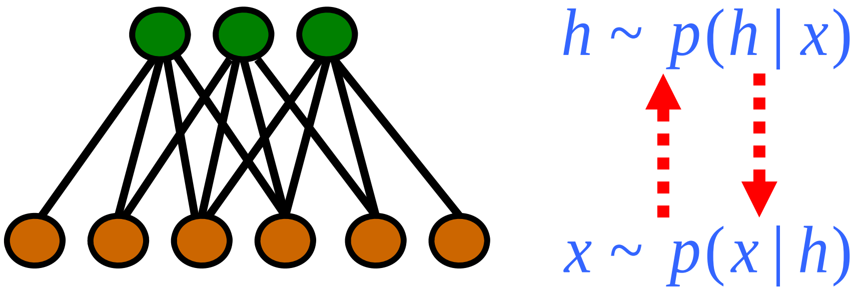


- Factors are conditionally *independent* given observations on the visible nodes.

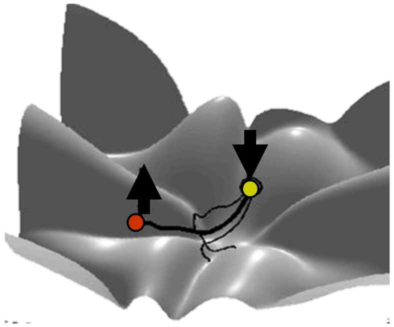


$$P(\ell \mid \mathbf{w}) = \prod_i P(\ell_i \mid \mathbf{w})$$

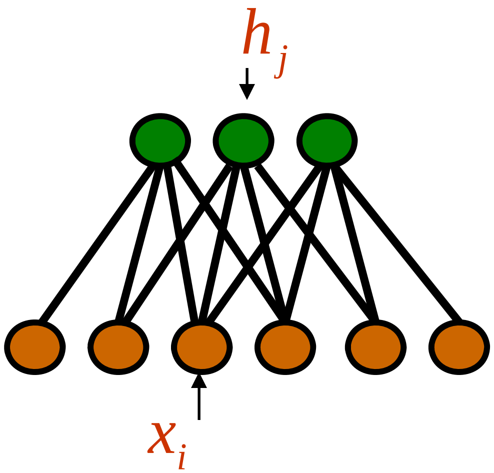
- Iterative Gibbs sampling.



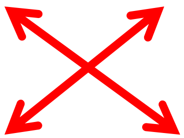
- Learning with contrastive divergence



A Constructive Definition



$$p_{\text{ind}}(\mathbf{h}) \propto \prod_j \exp\{\ \theta_j g_j(h_j)\ \}$$

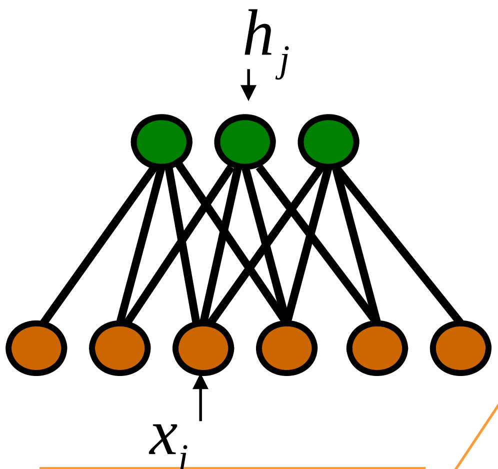


how do we couple them?

$$p_{\text{ind}}(\mathbf{x}) \propto \prod_i \exp\{\ \theta_i f_i(x_i)\ \}$$

$$p(x,h\,|\,\theta) = \exp\{\ \sum_i \vec{\theta}_i \vec{f}_i(x_i) + \sum_j \vec{\lambda}_j \vec{g}_j(h_j) + \sum_{i,j} \vec{f}_i^{\,T}(x_i)\mathbf{W}_{i,j}\vec{g}_j(h_j)\ \}$$

A Constructive Definition



$$p(\mathbf{x}\,|\,\mathbf{h}) = \prod_i p(x_i\,|\,\mathbf{h}),$$

$$p(x_i\,|\,\mathbf{h}) = \exp\{\ \sum_a \hat{\theta}_{ia} f_{ia}(x_i) + A_i(\{\hat{\theta}_{ia}\})\ \}$$

$$\hat{\theta}_{ia} = \theta_{ia} + \sum_{jb} W_{ia}^{jb} g_{jb}(h_j) = \theta_{ia} + \sum_j \vec{W}_{ia}^{j} \vec{g}_j(h_j)$$

$$p(\mathbf{h}\,|\,\mathbf{x}) = \prod_j p(h_j\,|\,\mathbf{x})$$

$$p(h_j\,|\,\mathbf{x}) = \exp\{\ \sum_b \hat{\lambda}_{jb} g_{jb}(h_j) + B_j(\{\hat{\lambda}_{jb}\})\ \}$$

$$\hat{\lambda}_{jb} = \lambda_{jb} + \sum_{ia} W_{ia}^{jb} f_{ia}(x_i) = \lambda_{jb} + \sum_i \vec{W}_i^{jb} \vec{f}_i(x_i)$$

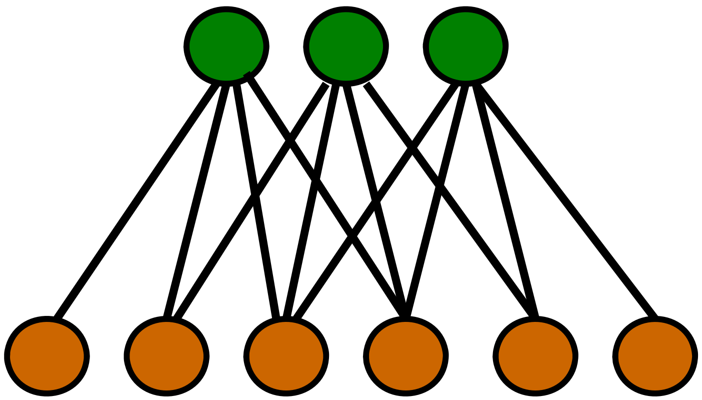
coupling in the log-domain with shifted parameters

vector of local sufficient statistics (features)

They map to the RBM random field:

$$p(x,h\,|\,\theta) = \exp\{\ \sum_i \vec{\theta}_i \vec{f}_i(x_i) + \sum_j \vec{\lambda}_j \vec{g}_j(h_j) + \sum_{i,j} \vec{f}_i^{\,T}(x_i)\mathbf{W}_{i,j}\vec{g}_j(h_j)\ \}$$

An RBM for Text Modeling



h_j = 3: topic j has strength 3

$h_j \in \mathbf{R}, \qquad \langle h_j \rangle = \Sigma_i W_{i,j} x_i$

x_i = n: word i has count n

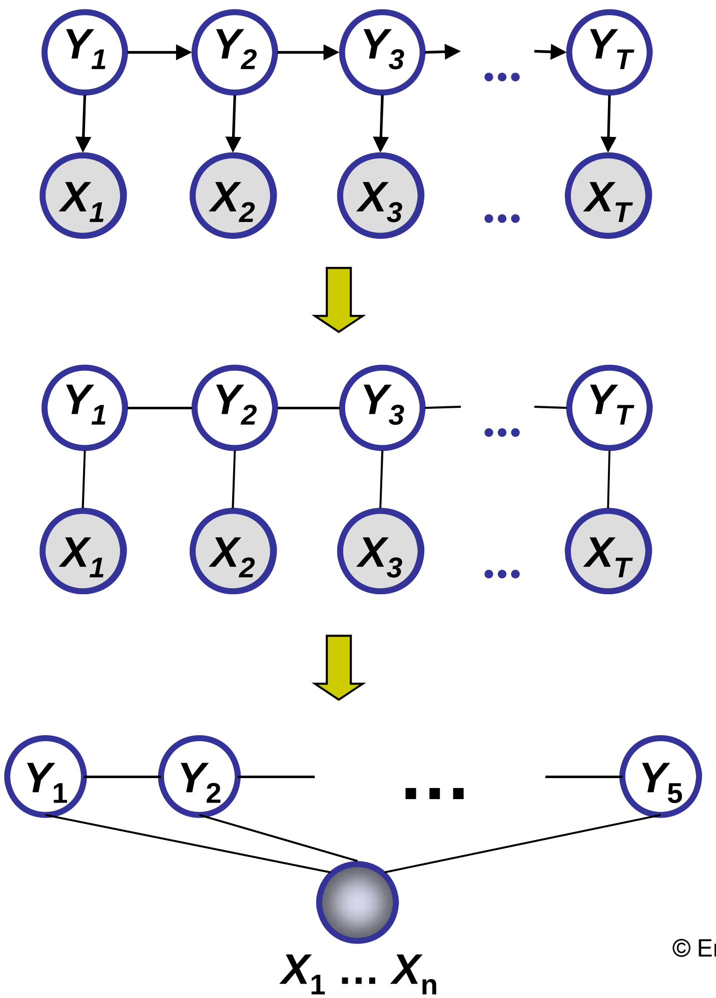
$x_i \in \mathbf{I}$

$$p(\mathbf{h} \mid \mathbf{x}) = \prod_j \text{Normal}_{h_j} \left[\sum_i \vec{W}_{ij} \vec{x}_i, 1 \right]$$

$$p(\mathbf{x} \mid \mathbf{h}) = \prod_i \text{Bi}_{x_i} \left[N, \frac{\exp(\alpha_j + \Sigma_j W_{ij} h_j)}{1+\exp(\alpha_j + \Sigma_j W_{ij} h_j)} \right]$$

$$\Rightarrow p(\mathbf{x}) \propto \exp\left\{ \left(\Sigma_i \alpha_i x_i - \log \Gamma(x_i) - \log \Gamma(N - x_i) \right) + \tfrac{1}{2} \Sigma_j \left(\Sigma_i W_{i,j} x_i \right)^2 \right\}$$

Conditional Random Fields



- Discriminative

$$p_\theta(y \mid x) = \frac{1}{Z(\theta, x)} \exp\left\{ \sum_c \theta_c f_c(x, y_c) \right\}$$

- Doesn't assume that features are independent

- When labeling X_i future observations are taken into account

Conditional Models

- Conditional probability P(label sequence $\mathbf{y}$ | observation sequence $\mathbf{x}$) rather than joint probability $P(\mathbf{y}, \mathbf{x})$
  - Specify the probability of possible label sequences given an observation sequence

- Allow arbitrary, non-independent features on the observation sequence $\mathbf{X}$

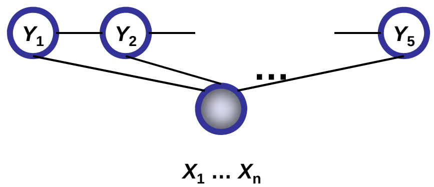
- The probability of a transition between labels may depend on past and future observations

- Relax strong independence assumptions in generative models

Conditional Distribution

- If the graph $G = (V, E)$ of $\mathbf{Y}$ is a tree, the conditional distribution over the label sequence $\mathbf{Y} = \mathbf{y}$, given $\mathbf{X} = \mathbf{x}$, by the Hammersley Clifford theorem of random fields is:

$$p_\theta(\mathrm{y} \mid \mathrm{x}) \propto \exp\left(\sum_{e \in E, k} \lambda_k f_k(e, \mathrm{y}|_e, \mathrm{x}) + \sum_{v \in V, k} \mu_k g_k(v, \mathrm{y}|_v, \mathrm{x}) \right)$$



  - x is a data sequence
  - y is a label sequence
  - *v* is a vertex from vertex set V = set of label random variables
  - *e* is an edge from edge set E over V
  - f_k and g_k are given and fixed. g_k is a Boolean vertex feature; f_k is a Boolean edge feature
  - *k* is the number of features
  - $\theta = (\lambda_1, \lambda_2, \cdots, \lambda_n; \mu_1, \mu_2, \cdots, \mu_n); \lambda_k$ and μ_k are parameters to be estimated
  - $\mathrm{y}|_e$ is the set of components of y defined by edge *e*
  - $\mathrm{y}|_v$ is the set of components of y defined by vertex *v*

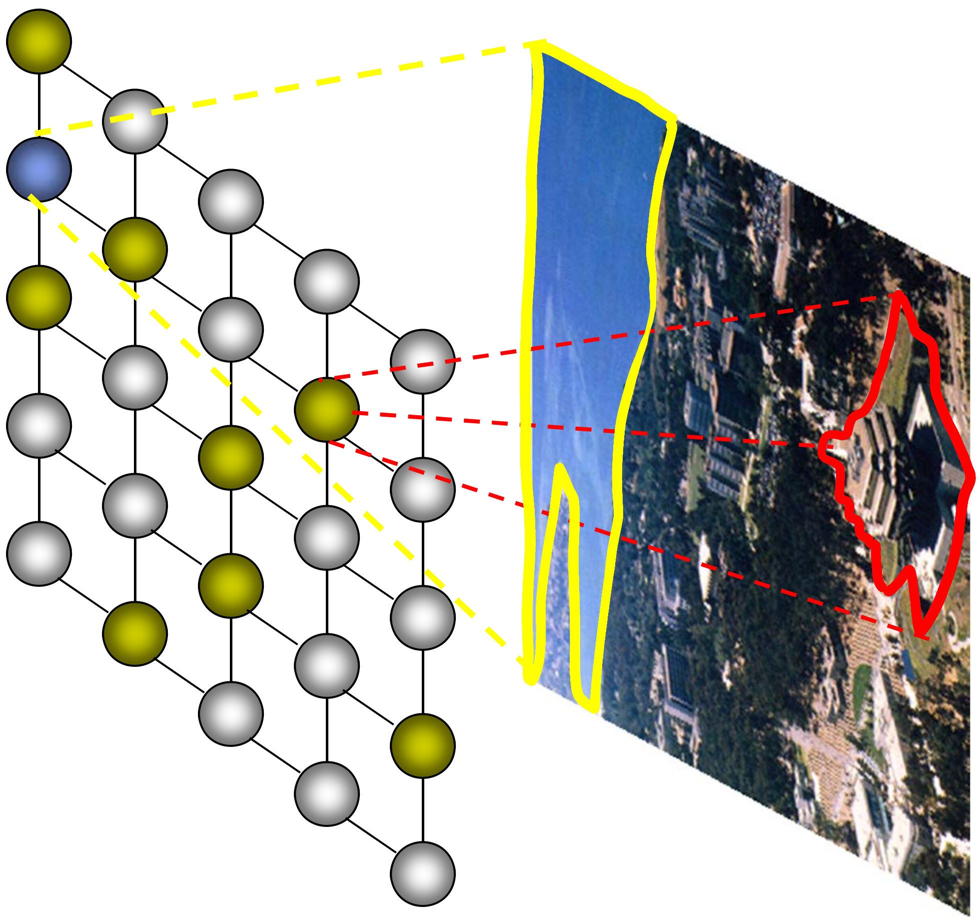
Conditional Distribution (cont'd)

- CRFs use the observation-dependent normalization $Z(\mathbf{x})$ for the conditional distributions:

$$p_\theta(\mathrm{y} \mid \mathrm{x}) = \frac{1}{Z(\mathrm{x})} \exp\left(\sum_{e \in E, k} \lambda_k f_k(e, \mathrm{y}|_e, \mathrm{x}) + \sum_{v \in V, k} \mu_k g_k(v, \mathrm{y}|_v, \mathrm{x}) \right)$$

  - $Z(\mathbf{x})$ is a normalization over the data sequence x

Conditional Random Fields



$$p_\theta(y \mid x) = \frac{1}{Z(\theta, x)} \exp\left\{ \sum_c \theta_c f_c(x, y_c) \right\}$$

- Allow arbitrary dependencies on input
- Clique dependencies on labels
- Use approximate inference for general graphs

Summary

- Undirected graphical models capture “relatedness”, “coupling”, “co-occurrence”, “synergism”, etc. between entities
- Local and global independence properties identifiable via graph separation criteria
- Defined on clique potentials
- Generally intractable to compute likelihood due to presence of “partition function”
  - Therefore not only inference, but also likelihood-based learning is difficult in general
- Can be used to define either joint or conditional distributions
- Important special cases:
  - Ising models
  - RBM
  - CRF