10707
Deep Learning
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Graphical Models
Graphical Models

- Probabilistic graphical models provide a powerful framework for representing dependency structure between random variables.

- Graphical models offer several useful properties:
  - They provide a simple way to visualize the structure of a probabilistic model and can be used to motivate new models.
  - They provide various insights into the properties of the model, including conditional independence.
  - Complex computations (e.g. inference and learning in sophisticated models) can be expressed in terms of graphical manipulations.
Graphical Models

• A graph contains a set of nodes (vertices) connected by links (edges or arcs).

• In a probabilistic graphical model, each node represents a random variable, and links represent probabilistic dependencies between random variables.

• The graph specifies the way in which the joint distribution over all random variables decomposes into a product of factors, where each factor depends on a subset of the variables.

• Two types of graphical models:
  - Bayesian networks, also known as Directed Graphical Models (the links have a particular directionality indicated by the arrows).
  - Markov Random Fields, also known as Undirected Graphical Models (the links do not carry arrows and have no directional significance).

• Hybrid graphical models that combine directed and undirected graphical models, such as Deep Belief Networks.
Bayesian Networks

• Directed Graphs are useful for expressing causal relationships between random variables.

• Let us consider an arbitrary joint distribution $p(a, b, c)$ over three random variables $a,b$, and $c$.

• Note that at this point, we do not need to specify anything else about these variables (e.g. whether they are discrete or continuous).

• By application of the product rule of probability (twice), we get

$$p(a, b, c) = p(c|a, b)p(a, b) = p(c|a, b)p(b|a)p(a)$$

• This decomposition holds for any choice of the joint distribution.
Bayesian Networks

• By application of the product rule of probability (twice), we get

\[ p(a, b, c) = p(c|a, b)p(a, b) = p(c|a, b)p(b|a)p(a) \]

• Represent the joint distribution in terms of a simple graphical model:

- Introduce a node for each of the random variables.
- Associate each node with the corresponding conditional distribution in above equation.
- For each conditional distribution we add directed links to the graph from the nodes corresponding to the variables on which the distribution is conditioned.

• Hence for the factor \( p(c|a, b) \), there will be links from nodes a and b to node c.
• For the factor \( p(a) \), there will be no incoming links.
Bayesian Networks

• By application of the product rule of probability (twice), we get

\[
p(a, b, c) = p(c|a, b)p(a, b) = p(c|a, b)p(b|a)p(a)
\]

• If there is a link going from node a to node b, then we say that:
  - node a is a parent of node b.
  - node b is a child of node a.

• The joint distribution over K variables factorizes:

\[
p(x_1, \ldots, x_K) = p(x_K|x_1, \ldots, x_{K-1}) \cdots p(x_2|x_1)p(x_1)
\]

• If each node has incoming links from all lower numbered nodes, then the graph is fully connected; there is a link between all pairs of nodes.
Bayesian Networks

• **Absence of links** conveys certain information about the properties of the class of distributions that the graph conveys.

• Note that this graph is not fully connected (e.g. there is no link from $x_1$ to $x_2$).

• The joint distribution over $x_1, \ldots, x_7$ can be written as a product of a set of conditional distributions.

\[
p(x_1, \ldots, x_7) = p(x_1)p(x_2)p(x_3)p(x_4|x_1, x_2, x_3) \cdot p(x_5|x_1, x_3)p(x_6|x_4)p(x_7|x_4, x_5)
\]

• Note that according to the graph, $x_5$ will be conditioned only on $x_1$ and $x_3$. 
Factorization Property

- The joint distribution defined by the graph is given by the product of a conditional distribution for each node conditioned on its parents:

\[ p(x) = \prod_{k=1}^{K} p(x_k | \text{pa}_k) \]

where \( \text{pa}_k \) denotes a set of parents for the node \( x_k \).

- This equation expresses a key factorization property of the joint distribution for a directed graphical model.

- Important restriction: There must be no directed cycles!

- Such graphs are also called directed acyclic graphs (DAGs).
Bayesian Curve Fitting

• As an example, remember Bayesian polynomial regression model:

\[ y(x, \mathbf{w}) = \sum_{j=0}^{M} w_j x^j \]

• We are given inputs \( \mathbf{X} = \{x_1, x_2, \ldots, x_N\} \) and target values \( \mathbf{t} = [t_1, t_2, \ldots, t_N]^T \).

• Given the prior over parameters, the joint distribution is given by:

\[ p(\mathbf{t}, \mathbf{w}|\mathbf{X}) = p(\mathbf{w}) \prod_{i=1}^{N} p(t_i|y(\mathbf{w}, x_i)). \]
Graphical Representation

\[ p(t, w | X) = p(w) \prod_{i=1}^{N} p(t_n | y(w, x_n)) \].

- This distribution can be represented as a graphical model.
- Same representation using plate notation.
- Compact representation: we introduce a plate that represents \( N \) nodes of which only a single example \( t_n \) is shown explicitly.
- Note that \( w \) and \( t = [t_1, t_2, ..., t_N]^T \) represent random variables.
Graphical Representation

- It will often be useful to make the parameters of the model as well as random variables be explicit.

\[ p(t, w | x, \alpha, \sigma^2) = p(w | \alpha) \prod_{n=1}^{N} p(t_n | w, x_n, \sigma^2). \]

- Random variables will be denoted by open circles and deterministic parameters will be denoted by smaller solid circles.

\[ p(w | \alpha) = \mathcal{N}(w | 0, \alpha I), \]
\[ p(t_n | w, x_n, \sigma^2) = \mathcal{N}(t_n | y(w, x_n), \sigma^2), \]

\[ y(x, w) = \sum_{j=0}^{M} w_j x^j \]
Graphical Representation

• When we apply a graphical model to a problem in machine learning, we will set some of the variables to specific observed values (e.g. condition on the data).

For example, having observed the values of the targets \( \{t_n\} \) on the training data, we wish to infer the posterior distribution over parameters \( w \).

• In this example, we conditioned on observed data \( t = [t_1, t_2, \ldots, t_N]^T \) by shadowing the corresponding nodes.

\[
p(w|t) \propto p(w) \prod_{n=1}^{N} p(t_n|w)
\]
Predictive Distribution

• We may also be interested in making predictions for a new input value $\hat{x}$.

$$p(t|\hat{x}, x, t, \alpha, \sigma^2) \propto \int p(t, t, w|\hat{x}, x, \alpha, \sigma^2) \, dw$$

where the joint distribution of all of the random variables is given by:

$$p(t, t, w|\hat{x}, x, \alpha, \sigma^2) = \left[ \prod_{n=1}^{N} p(t_n|x_n, w, \sigma^2) \right] p(w|\alpha)p(t|\hat{x}, w, \sigma^2)$$

• Here we are setting the random variables in $t$ to the specific values observed in the data.
Ancestral Sampling

• Consider a joint distribution over $K$ random variables $p(x_1, x_2, \ldots, x_K)$ that factorizes as:

$$p(x) = \prod_{k=1}^{K} p(x_k | pa_k)$$

• Our goal is to draw a sample from this distribution.
• Start at the top and sample in order.

\[
\begin{align*}
\hat{x}_1 & \sim p(x_1) \\
\hat{x}_2 & \sim p(x_2) \\
\hat{x}_3 & \sim p(x_3) \\
\hat{x}_4 & \sim p(x_4 | \hat{x}_1, \hat{x}_2, \hat{x}_3) \\
\hat{x}_5 & \sim p(x_5 | \hat{x}_1, \hat{x}_3)
\end{align*}
\]

The parent variables are set to their sampled values.

• To obtain a sample from the marginal distribution, e.g. $p(x_2, x_5)$, we sample from the full joint distribution, retain $\hat{x}_2, \hat{x}_5$, and discard the remaining values.
Generative Models

• Higher-level nodes will typically represent latent (hidden) random variables.
• The primary role of the latent variables is to allow a complicated distribution over observed variables to be constructed from simpler (typically exponential family) conditional distributions.

Generative Model of an Image

Object Position Orientation

• Object identity, position, and orientation have independent prior probabilities.

• The image has a probability distribution that depends on the object identity, position, and orientation (likelihood function).

\[ P(Im, Ob, Po, Or) = P(Im|Ob, Po, Or)P(Ob)P(Po)P(Or) \]

• The graphical model captures the causal process, by which the observed data was generated (hence the name generative models).
Discrete Variables

• We now examine the discrete random variables.
• Assume that we have two discrete random variables $x_1$ and $x_2$, each of which has $K$ states.

$$p(x_1, x_2 | \mu) = \prod_{k=1}^{K} \prod_{l=1}^{K} \mu_{kl}^{x_{1k}x_{2l}}$$

• Using 1-of-$K$ encoding, we denote the probability of observing both $x_{1k}=1$, $x_{2l}=1$ by the parameter $\mu_{kl}$, where $x_{1k}$ denotes the $k^{th}$ component of $x_1$ (similarly for $x_2$).

• This distribution is governed by $K^2 - 1$ parameters.

• The total number of parameters that must be specified for an arbitrary joint distribution over $M$ random variables is $K^M - 1$ (corresponds to a fully connected graph).

• Grows exponentially in the number of variables $M$!
Discrete Variables

- General joint distribution: $K^2-1$ parameters.

\[
p(x_1, x_2 | \mu) = \prod_{k=1}^{K} \prod_{l=1}^{K} \mu_{k,l}^{x_{1,k} x_{2,l}}
\]

- Independent joint distribution: $2(K-1)$ parameters.

\[
\hat{p}(x_1, x_2 | \mu) = \prod_{k=1}^{K} \mu_{1,k}^{x_{1,k}} \prod_{l=1}^{K} \mu_{2,l}^{x_{2,l}}
\]

- We dropped the link between the nodes, so each variable is described by a separate multinomial distribution.
Discrete Variables

• In general:
  - Fully connected graphs have completely general distributions and have exponential $K^{M-1}$ number of parameters (too complex).
  - If there are no links, the joint distribution fully factorizes into the product of the marginals, and has $M(K-1)$ parameters (too simple).
  - Graphs that have an intermediate level of connectivity allow for more general distributions compared to the fully factorized one, while requiring fewer parameters than the general joint distribution.

• Let us look at the example of the chain graph.
• Consider an M-node Markov chain:

  $x_1 \rightarrow x_2 \rightarrow \ldots \rightarrow x_M$

  • The marginal distribution $p(x_1)$ requires K-1 parameters.

  • The remaining conditional distributions $p(x_i | x_{i-1})$, $i = 2, ..., M$ require K(K-1) parameters.

  • Total number of parameters: K-1 + (M-1)(K-1)K, which is quadratic in K and linear in the length M of the chain.

  • This graphical model forms the basis of a simple Hidden Markov Model.
Adding Priors

• We can turn a graph over discrete random variables into a Bayesian model by introducing Dirichlet priors for the parameters.
• From a graphical model point of view, each node acquires an additional parent representing the Dirichlet distribution over parameters.

\[
p\left(\{x_m, \mu_m\}\right) = p\left(x_1 | \mu_1\right) p\left(\mu_1\right) \prod_{m=2}^{M} p\left(x_m | x_{m-1}, \mu_m\right) p\left(\mu_m\right)
\]

\[
p(\mu_m) = \text{Dir}(\mu_m | \alpha_m)
\]
Shared Prior

- We can further share the common prior over the parameters governing the conditional distributions.

\[
p(\{x_m\}, \mu_1, \mu) = p(x_1 | \mu_1) p(\mu_1) \prod_{m=2}^{M} p(x_m | x_{m-1}, \mu) p(\mu)
\]
Parameterized Models

• We can use parameterized models to control exponential growth in the number of parameters.

If \( x_1, \ldots, x_M \) are discrete, \( K \)-state variables, \( p(y = 1 | x_1, \ldots, x_M) \) in general has \( O(K^M) \) parameters.

• We can obtain a more parsimonious form of the conditional distribution by using a logistic function acting on a linear combination of the parent variables:

\[
p(y = 1 | x_1, \ldots, x_M) = \sigma \left( w_0 + \sum_{i=1}^{M} w_i x_i \right) = \sigma(w^T x)
\]

• This is a more restricted form of conditional distribution, but it requires only \( M+1 \) parameters (linear growth in the number of parameters).
Linear Gaussian Models

• So far we worked with joint probability distributions over a set of discrete random variables (expressed as nodes in directed acyclic graphs).

• We now show how a multivariate Gaussian distribution can be expressed as a directed graph corresponding to a linear Gaussian model.

• Consider an arbitrary acyclic graph over D random variables, in which each node represent a single continuous Gaussian distribution with its mean given by the linear function of the parents:

\[
p(x_i | pa_i) = \mathcal{N} \left( x_i \left| \sum_{j \in pa_i} w_{ij} x_j + b_i, v_i \right. \right)
\]

where \( w_{ij} \) and \( b_i \) are parameters governing the mean, and \( v_i \) is the variance.
Linear Gaussian Models

• The log of the joint distribution takes form:

$$\ln p(x) = \sum_{i=1}^{D} \ln p(x_i | pa_i) = - \sum_{i=1}^{D} \frac{1}{2v_i} \left( x_i - \sum_{j \in pa_i} w_{ij} x_j - b_i \right)^2 + \text{const},$$

where ‘const’ denotes terms independent of $x$.

• This is a quadratic function of $x$, and hence the joint distribution $p(x)$ is a multivariate Gaussian.

• For example, consider a directed graph over three Gaussian variables with one missing link:

\[ x_1 \xrightarrow{} x_2 \xrightarrow{} x_3 \]
Computing the Mean

• We can determine the mean and covariance of the joint distribution. Remember:
  
  \[ p(x_i|\text{pa}_i) = \mathcal{N} \left( x_i \middle| \sum_{j \in \text{pa}_i} w_{ij} x_j + b_i, v_i \right) \]
  
  hence
  
  \[ x_i = \sum_{j \in \text{pa}_i} w_{ij} x_j + b_i + \sqrt{v_i} \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, 1), \]
  
  so its expected value:
  
  \[ \mathbb{E}[x_i] = \sum_{j \in \text{pa}_i} w_{ij} \mathbb{E}[x_j] + b_i. \]

• Hence we can find components: \( \mathbb{E}[\mathbf{x}] = [\mathbb{E}[x_1], ..., \mathbb{E}[x_D]] \) by doing ancestral pass: start at the top and proceed in order (see example):
Computing the Covariance

• We can obtain the i,j element of the covariance matrix in the form of a recursion relation:

\[
\text{cov}[x_i, x_j] = \mathbb{E}[(x_i - \mathbb{E}[x_i])(x_j - \mathbb{E}[x_j])]
\]

\[
= \mathbb{E} \left[ (x_i - \mathbb{E}[x_i]) \left( \sum_{k \in \text{pa}_j} w_{jk} (x_k - \mathbb{E}[x_k]) + \sqrt{\nu_i} \epsilon_j \right) \right]
\]

\[
= \sum_{k \in \text{pa}_j} w_{jk} \text{cov}[x_i, x_k] + I_{ij} \nu_j.
\]

• Consider two cases:

- There are no links in the graph (graph is fully factorized), so that \(w_{ij}\)'s are zero.
  In this case: \(\mathbb{E}[x] = [b_1, \ldots, b_D]^T\), and the covariance is diagonal \(\text{diag}(\nu_1, \ldots, \nu_D)\).
  The joint distribution represents D independent univariate Gaussian distributions.

- The graph is fully connected. The total number of parameters is \(D + D(D-1)/2\).
  The covariance corresponds to a general symmetric covariance matrix.
Bilinear Gaussian Model

• Consider the following model:

\[ u \sim \mathcal{N}(0, 1), \]
\[ v \sim \mathcal{N}(0, 1), \]
\[ r \sim \mathcal{N}(uv, 1). \]

\[ u_i \sim \mathcal{N}(0, 1), \quad i = 1, \ldots, N \]
\[ v_j \sim \mathcal{N}(0, 1), \quad j = 1, \ldots, M \]
\[ r_{ij} \sim \mathcal{N}(u_i v_j, 1). \]

• The mean is given by the product of two Gaussians.
Hierarchical Models
Conditional Independence

- We now look at the concept of conditional independence.
- \( a \) is independent of \( b \) given \( c \):
  \[
p(a|b, c) = p(a|c)
  \]
- Equivalently:
  \[
p(a, b|c) = p(a|b, c)p(b|c) = p(a|c)p(b|c)
  \]
- We will use the notation:
  \[a \perp \!\!\!\perp b \mid c\]

- An important feature of graphical models is that conditional independence properties of the joint distribution can be read directly from the graph without performing any analytical manipulations.

- The general framework for achieving this is called \( d \)-separation, where \( d \) stands for ‘directed’ (Pearl 1988).
Another example of conditional independence is provided by the concept of independent and identically distributed data.

Consider the problem of finding the posterior distribution over mean $\mu$ in Bayesian linear regression model.

Suppose that we condition on $\mu$ and consider the joint over observed variables.

If we integrate out $\mu$, the observations are no longer independent.
Markov Blanket in Directed Models

• The Markov blanket of a node is the minimal set of nodes that must be observed to make this node independent of all other nodes.

• In a directed model, the Markov blanket includes parents, children and co-parents (i.e. all the parents of the node’s children) due to explaining away.

\[
p(x_i | x_{\{j \neq i\}}) = \frac{p(x_1, \ldots, x_M)}{\int p(x_1, \ldots, x_M) \, dx_i} = \frac{\prod_k p(x_k | pa_k)}{\int \prod_k p(x_k | pa_k) \, dx_i}
\]

Factors independent of \(x_i\) cancel between numerator and denominator.
Directed Graphs as Distribution Filters

- We can view the graphical model as a filter.

\[ p(x) \rightarrow \text{filter} \rightarrow DF \]

- The joint probability distribution \( p(x) \) is allowed through the filter if and only if it satisfies the factorization property.

- Note: The fully connected graph exhibits no conditional independence properties at all.

- The fully disconnected graph (no links) corresponds to a joint distribution that factorizes into the product of marginal distributions.
Popular Models

Latent Dirichlet Allocation

One of the popular models for modeling word count vectors. We will see this model later.

Bayesian Probabilistic Matrix Factorization

One of the popular models for collaborative filtering applications.
Undirected Graphical Models

Directed graphs are useful for expressing causal relationships between random variables, whereas undirected graphs are useful for expressing soft constraints between random variables.

• The joint distribution defined by the graph is given by the product of non-negative potential functions over the maximal cliques (connected subset of nodes).

\[
p(x) = \frac{1}{\mathcal{Z}} \prod_C \phi_C(x_C)
\]

where the normalizing constant \( \mathcal{Z} \) is called a partition function.

• For example, the joint distribution factorizes:

\[
p(A, B, C, D) = \frac{1}{\mathcal{Z}} \phi(A, C)\phi(C, B)\phi(B, D)\phi(A, D)
\]

• Let us look at the definition of cliques.
Cliqu es

- The subsets that are used to define the potential functions are represented by **maximal cliques** in the undirected graph.

- **Clique**: a subset of nodes such that there exists a link between all pairs of nodes in a subset.

- **Maximal Clique**: a clique such that it is not possible to include any other nodes in the set without it ceasing to be a clique.

This graph has 5 cliques:

- Two maximal cliques:
  \[
  \{x_1, x_2, x_3\}, \{x_2, x_3, x_4\}.
  \]
Using Cliques to Represent Subsets

• If the potential functions only involve two nodes, an undirected graph has a nice representation.

• If the potential functions involve more than two nodes, using a different factor graph representation is much more useful.

• For now, let us consider only potential functions that are defined over two nodes.
Markov Random Fields (MRFs)

- Each potential function is a mapping from the joint configurations of random variables in a clique to non-negative real numbers.
- The choice of potential functions is not restricted to having specific probabilistic interpretations.

Potential functions are often represented as exponentials:

\[ p(x) = \frac{1}{\mathcal{Z}} \prod_C \phi_C(x_C) \]

where \( \mathcal{Z} \) is called an energy function.
MRFs with Hidden Variables

For many interesting real-world problems, we need to introduce hidden or latent variables.

- Our random variables will contain both visible and hidden variables \( x = (v, h) \).

\[
p(v) = \frac{1}{Z} \sum_h \exp(-E(v, h))
\]

- In general, computing both partition function and summation over hidden variables will be intractable, except for special cases.

- Parameter learning becomes a very challenging task.
Conditional Independence

- Conditional Independence is easier compared to directed models:

- Observation blocks a node.
- Two sets of nodes are conditionally independent if the observations block all paths between them.
Markov Blanket

- The Markov blanket of a node is simply all of the directly connected nodes.

  • This is simpler than in directed models, since there is no explaining away.

  • The conditional distribution of $x_i$ conditioned on all the variables in the graph is dependent only on the variables in the Markov blanket.
Conditional Independence and Factorization

• Consider two sets of distributions:
  – The set of distributions consistent with the conditional independence relationships defined by the undirected graph.
  – The set of distributions consistent with the factorization defined by potential functions on maximal cliques of the graph.

• The Hammersley-Clifford theorem states that these two sets of distributions are the same.

\[
p(x) = \frac{1}{Z} \prod_{C} \phi_{C}(x_{C})
\]
Interpreting Potentials

• In contrast to directed graphs, the potential functions do not have a specific probabilistic interpretation.

\[ p(x) = \frac{1}{\mathcal{Z}} \prod_{C} \phi_C(x_C) = \frac{1}{\mathcal{Z}} \exp(- \sum_{C} E(x_C)) \]

• This gives us greater flexibility in choosing the potential functions.

• We can view the potential function as expressing which configuration of the local variables are preferred to others.

• Global configurations with relatively high probabilities are those that find a good balance in satisfying the (possibly conflicting) influences of the clique potentials.

• So far we did not specify the nature of random variables, discrete or continuous.
Discrete MRFs

• MRFs with all discrete variables are widely used in many applications.

• MRFs with binary variables are sometimes called Ising models in statistical mechanics, and Boltzmann machines in machine learning.

... 

• Denoting the binary valued variable at node \( j \) by \( x_j \in \{0, 1\} \), the Ising model for the joint probabilities is given by:

\[
P_\theta(x) = \frac{1}{\mathcal{Z}(\theta)} \exp \left( \sum_{ij \in E} x_ix_j\theta_{ij} + \sum_{i \in V} x_i\theta_i \right)
\]

• The conditional distribution is given by logistic:

\[
P_\theta(x_i = 1|x_{-i}) = \frac{1}{1 + \exp(-\theta_i - \sum_{ij \in E} x_j\theta_{ij})},
\]

where \( x_{-i} \) denotes all nodes except for \( i \).

Hence the parameter \( \theta_{ij} \) measures the dependence of \( x_i \) on \( x_j \), conditional on the other nodes.
Example: Image Denoising

• Let us look at the example of noise removal from a binary image.

• Let the observed noisy image be described by an array of binary pixel values: $y_j \in \{-1, +1\}$, $i=1,\ldots,D$.

• We take a noise-free image $x_j \in \{-1, +1\}$, and randomly flip the sign of pixels with some small probability.

$$E(x, y) = h \sum_i x_i - \beta \sum_{i,j} x_i x_j - \eta \sum_i x_i y_i$$

$$p(x, y) = \frac{1}{Z} \exp\{-E(x, y)\}$$
Iterated Conditional Modes

- **Iterated conditional modes**: coordinate-wise gradient descent.

- Visit the unobserved nodes sequentially and set each $x$ to whichever of its two values has the lowest energy.
  - This only requires us to look at the Markov blanket, i.e. the connected nodes.
  - Markov blanket of a node is simply all of the directly connected nodes.
Gaussian MRFs

- We assume that the observations have a multivariate Gaussian distribution with mean $\mu$ and covariance matrix $\Sigma$.
  
  \[
  \mathcal{N}(x|\mu, \Sigma) = \frac{1}{(2\pi)^{D/2} |\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2}(x - \mu)^T \Sigma^{-1} (x - \mu) \right\}
  \]

- Since the Gaussian distribution represents at most second-order relationships, it automatically encodes a pairwise MRF. We rewrite:

  \[
  P(x) = \frac{1}{Z} \exp(-\frac{1}{2}x^T J x + g^T x),
  \]

  where

  \[
  J = \Sigma^{-1}, \quad \mu = J^{-1}g.
  \]

- The positive definite matrix $J$ is known as the information matrix and is sparse with respect to the given graph: 

  \[
  x^T J x = \sum_i J_{ii} x_i^2 + 2 \sum_{ij \in E} J_{ij} x_i x_j,
  \]

  if $(i, j) \neq E$, then $J_{ij} = 0$.

- The information matrix is sparse, but the covariance matrix is not sparse.
**Restricted Boltzmann Machines**

- For many real-world problems, we need to introduce hidden variables.
- Our random variables will contain *visible* and *hidden* variables \( x = (v, h) \).

**Stochastic binary visible variables** \( v \in \{0, 1\}^D \) are connected to stochastic binary hidden variables \( h \in \{0, 1\}^F \).

The energy of the joint configuration:

\[
E(v, h; \theta) = - \sum_{ij} W_{ij} v_i h_j - \sum_i b_i v_i - \sum_j a_j h_j
\]

\( \theta = \{W, a, b\} \) model parameters.

Probability of the joint configuration is given by the Boltzmann distribution:

\[
P_\theta(v, h) = \frac{1}{\mathcal{Z}(\theta)} \exp \left( - E(v, h; \theta) \right) = \frac{1}{\mathcal{Z}(\theta)} \prod_{ij} e^{W_{ij} v_i h_j} \prod_i e^{b_i v_i} \prod_j e^{a_j h_j}
\]

\( \mathcal{Z}(\theta) = \sum_{h,v} \exp \left( - E(v, h; \theta) \right) \) partition function potential functions
Restricted Boltzmann Machines

Inferring the distribution over the hidden variables is easy:

\[
P(h|v) = \prod_j P(h_j|v) \\
P(h_j = 1|v) = \frac{1}{1 + \exp(-\sum_i W_{ij}v_i - a_j)}
\]

Similarly:

\[
P(v|h) = \prod_i P(v_i|h) \\
P(v_i = 1|h) = \frac{1}{1 + \exp(-\sum_j W_{ij}h_j - b_i)}
\]

 Restricted: No interaction between hidden variables

Markov random fields, Boltzmann machines, log-linear models.
Restricted Boltzmann Machines

Observed Data
Subset of 25,000 characters

Learned $W$: “edges”
Subset of 1000 features

New Image: $p(h_7 = 1 | v)$

Represent: $\sigma(x) = \frac{1}{1+\exp(-x)}$
Logistic Function: Suitable for modeling binary images
Gaussian-Bernoulli RBMs

Define energy functions for various data modalities:

\[ E(v, h; \theta) = \sum_i \frac{(v_i - b_i)^2}{2\sigma_i^2} - \sum_{ij} W_{ij} h_j \frac{v_i}{\sigma_i} - \sum_j a_j h_j \]

\[ P_{\theta}(v, h) = \frac{1}{Z(\theta)} \exp(-E(v, h; \theta)) \]

\[ P(v_i = x|h) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(x - b_i - \sigma_i \sum_j W_{ij} h_j)^2}{2\sigma_i^2}\right) \]  
\text{Gaussian}

\[ P(h_j = 1|v) = \frac{1}{1 + \exp(-\sum_i W_{ij} \frac{v_i}{\sigma_i} - a_j)} \]  
\text{Bernoulli}
Gaussian-Bernoulli RBMs

Images: Gaussian-Bernoulli RBM

4 million unlabelled images

Learned features (out of 10,000)

Text: Multinomial-Bernoulli RBM

Reuters dataset:
804,414 unlabeled newswire stories

Bag-of-Words

Learned features: "topics"

russian
russia
moscow
yeltsin
soviet
clinton
house
president
bill
congress
computer
system
product
software
develop
trade
country
import
world
economy
stock
wall
street
point
dow
Relation to Directed Graphs

• Let us try to convert directed graph into an undirected graph:

\[ p(x) = p(x_1)p(x_2|x_1) \cdot p(x_3|x_2) \cdots p(x_N|x_{N-1}) \]

\[ p(x) = \frac{1}{Z} \psi_{1,2}(x_1, x_2) \psi_{2,3}(x_2, x_3) \cdots \psi_{N-1,N}(x_{N-1}, x_N) \]
Directed vs. Undirected

- Directed Graphs can be more precise about independencies than undirected graphs.

\[ p(\mathbf{x}) = p(x_1)p(x_2)p(x_3)p(x_4|x_1, x_2, x_3) \]

\[ p(\mathbf{x}) = \frac{1}{\mathcal{Z}} \psi(x_1, x_2, x_3, x_4) \]

- All the parents of \( x_4 \) can interact to determine the distribution over \( x_4 \).
- The directed graph represents independencies that the undirected graph cannot model.
- To represent the high-order interaction in the directed graph, the undirected graph needs a fourth-order clique.
- This fully connected graph exhibits no conditional independence properties.
Undirected vs. Directed

• Undirected Graphs can be more precise about independencies than directed graphs

• There is no directed graph over four variables that represents the same set of conditional independence properties.

\[
\begin{align*}
A \indep B \mid \emptyset \\
A \indep B \mid C \cup D \\
C \indep D \mid A \cup B
\end{align*}
\]
Directed vs. Undirected

• If every conditional independence property of the distribution is reflected in the graph and vice versa, then the graph is a perfect map for that distribution.

• Venn diagram:
  - The set of all distributions $P$ over a given set of random variables.
  - The set of distributions $D$ that can be represented as a perfect map using directed graph.
  - The set of distributions $U$ that can be represented as a perfect map using undirected graph.

• We can extend the framework to graphs that include both directed and undirected graphs.