

Graphical Models

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Probabilistic Models

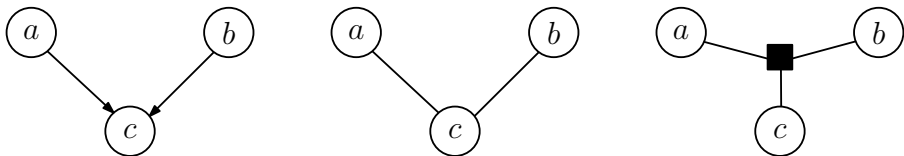
Previously we saw:

- ▶ Probabilistic model is a **joint distribution** $p(\mathbf{x}, \mathbf{z})$.
- ▶ We make factorisation assumptions to specify the model.
- ▶ Factorisation assumptions help simplify the posterior.

Graphical models help us to:

- ▶ visualise (conditional) independence,
- ▶ specify models with the right structure,
- ▶ find (conditional) independence when conditioning,
- ▶ do inference automatically and efficiently.

Probabilistic Graphical Models



Three types of probabilistic graphical models:

- ▶ **Bayesian networks** (directed graphical models)
 - ▶ **Markov random fields** (undirected graphical models)
 - ▶ **Factor graphs**
 - ▶ **Nodes:** (Sets of) random variables
 - ▶ **Edges:** Probabilistic/functional relations between variables
- ▶ Graph captures the **way in which the joint distribution over all random variables can be decomposed** into a product of factors depending only on a subset of these variables

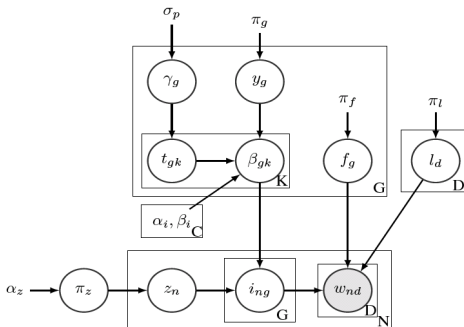
Importance of Visualization

$$Pr(\{y_g, \gamma_g, t_{gk}, \beta_{gk}, l_d, f_g, z_n, i_{ng}\} | \{w_{nd}\}) = \prod_g^G p(y_g | \rho) p(\gamma_g | \sigma) p(f_g | \alpha) \cdot$$

$$\prod_k^K p(t_{gk} | \gamma_g) p(\beta_{gk} | t_{gk}, y_g) p(\kappa | \alpha) \prod_d^D p(l_d | \kappa) p(\pi | \alpha) \prod_n^N p(z_n | \pi)$$

$$\prod_n^N \prod_g^G p(i_{ng} | \beta, z_n) \prod_n^N \prod_d^D p(w_{nd} | i_{ng}, f, l_d)]$$

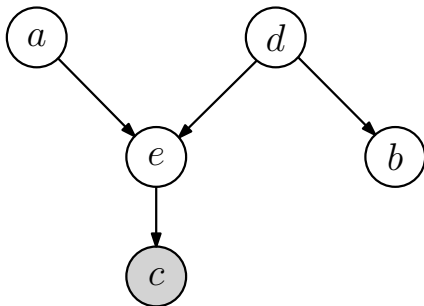
From Kim et al. (NIPS, 2015)



From Kim et al. (NIPS, 2015)

Expressing Factorisations as Graphs

Directed Graphical Models



- ▶ Nodes: Random variables
- ▶ Shaded nodes: Observed random variables
- ▶ Unshaded nodes: Unobserved (latent) random variables
- ▶ Directed arrow from a to b : Conditional distribution $p(b|a)$.

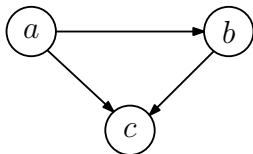
Skill: From Joints to Graphs

Consider the joint distribution

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

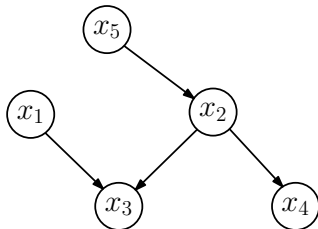
Building the corresponding graphical model:

1. Create a node for all random variables
2. For each conditional distribution, we add a directed link (arrow) to the graph from the nodes corresponding to the variables on which the distribution is conditioned on



► Graph layout depends on the choice of factorization

Skill: From Graphs to Joints



- ▶ Joint distribution is the product of a set of conditionals, one for each node in the graph
- ▶ Each conditional depends only on the parents of the corresponding node in the graph

$$p(x_1, x_2, x_3, x_4, x_5) = p(x_1)p(x_5)p(x_2|x_5)p(x_3|x_1, x_2)p(x_4|x_2)$$

In general: $p(\mathbf{x}) = p(x_1, \dots, x_K) = \prod_{k=1}^K p(x_k | \text{parents}(x_k))$

What is **the** graphical model?

Remember, a model is defined simply by its joint distribution, which often is just between data and a latent variable:

$$p(\mathbf{x}, \mathbf{z}) \quad (1)$$

We can factorise this in two distinct, but equally valid ways:

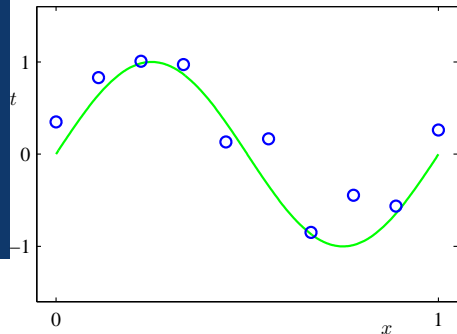
$$p(\mathbf{x}, \mathbf{z}) = p(\mathbf{x}|\mathbf{z})p(\mathbf{z}) = p(\mathbf{x})p(\mathbf{z}|\mathbf{x}) \quad (2)$$



Which one is correct? Depends on which conditional you specified!

$$p(\mathbf{x}, \mathbf{z}) = p(\mathbf{x}|\mathbf{z}) p(\mathbf{z}) = p(\mathbf{x}) p(\mathbf{z}|\mathbf{x}) \quad (3)$$

Graphical Model for (Bayesian) Linear Regression



From PRML (Bishop, 2006)

We are given a data set $(x_1, y_1), \dots, (x_N, y_N)$ where

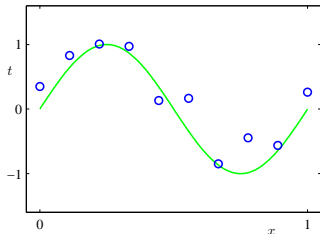
$$y_i = f(x_i) + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \sigma^2)$$

with f unknown.

► Find a (regression) model that explains the data

- Consider **polynomials** $f(x) = \sum_{j=0}^M w_j x^j$ with parameters $\mathbf{w} = [w_0, \dots, w_M]^\top$.
- **Bayesian linear regression**: Place a conjugate Gaussian prior on the parameters: $p(\mathbf{w}) = \mathcal{N}(\mathbf{0}, \alpha^2 \mathbf{I})$

Graphical Model for Linear Regression

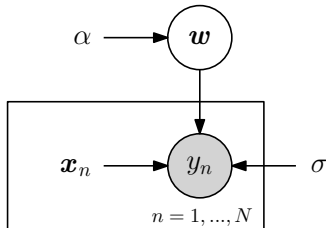
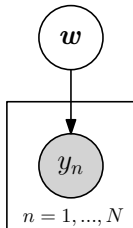
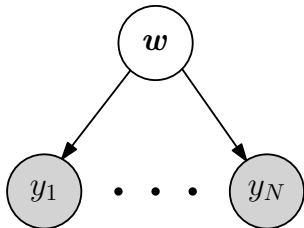


From PRML (Bishop, 2006)

$$p(y_i | \mathbf{w}, x_i) = \mathcal{N}(y_i | f_{\mathbf{w}}(x_i), \sigma^2)$$

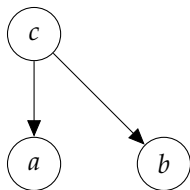
$$f(x) = \sum_{j=0}^M w_j x^j$$

$$p(\mathbf{w}) = \mathcal{N}(\mathbf{0}, \alpha^2 \mathbf{I})$$



Finding Conditional Independence

Conditional Independence



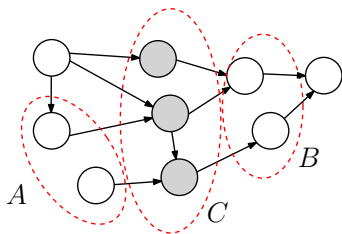
$$\begin{aligned} a \perp\!\!\!\perp b|c &\iff p(a,b|c) = p(a|c)p(b|c) \\ &\iff p(a|b,c) = p(a|c) \end{aligned}$$

- ▶ (Conditional) independence allows for a **factorization of the joint distribution** ► More efficient inference

$$\mathbb{E}_{p(a,b|c)}[f(a)g(b)] = \mathbb{E}_{p(a|c)}[f(a)] \cdot \mathbb{E}_{p(b|c)}[g(b)] \quad (4)$$

- ▶ **Conditional independence** properties of the joint distribution can be read directly from the graph without analytical manipulations!
► **d-separation** (Pearl, 1988)

D-Separation (Directed Graphs)



Directed, acyclic graph in which A, B, C are arbitrary, non-intersecting sets of nodes. Does $A \perp\!\!\!\perp B | C$ hold?

Note: C is observed if we condition on it (and the nodes in the GM are shaded)

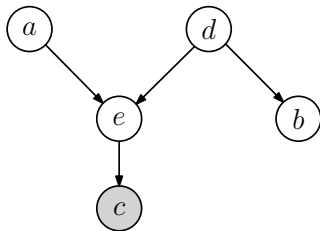
► Consider **all possible paths** from any node in A to any node in B .

Any such **path is blocked** if it includes a node such that either

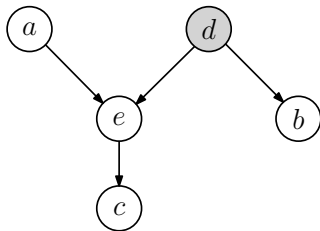
- ▶ Arrows on the path meet either **head-to-tail** or **tail-to-tail** at the node, and the node is in the set C or
- ▶ Arrows meet **head-to-head** at the node and neither the node nor any of its descendants is in the set C

If **all paths are blocked**, then A is **d-separated** (conditionally indep.) from B by C , and the joint distribution satisfies $A \perp\!\!\!\perp B | C$.

Exam skill: Find conditional independencies



(a) $a \perp\!\!\!\perp b|c?$

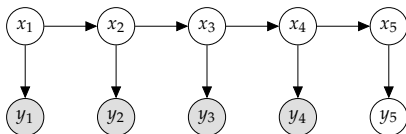


(b) $a \perp\!\!\!\perp b|d?$

A path is **blocked** if it includes a node such that either

- ▶ The arrows on the path meet either head-to-tail or tail-to-tail at the node, and the node is in the set C (observed) or
- ▶ The arrows meet head-to-head at the node, and neither the node nor any of its descendants is in the set C (observed)

Markov Chains



$$p(\{x_t\}_{t=1}^5, \{y_t\}_{t=1}^5) = p(x_1) \left[\prod_{t=2}^5 p(x_t | x_{t-1}) \right] \left[\prod_{t=1}^5 p(y_t | x_t) \right] \quad (5)$$

How do we compute the posterior on x_5 (so we can predict y_5)?

- ▶ We note that $x_4 \perp\!\!\!\perp \{x_t\}_{t=1}^2, \{y_t\}_{t=1}^3 | x_3$ (blocked path, tail-to-tail)
 $p(x_4 | \{y_t\}_{t=1}^4) = \int p(x_4 | x_3, y_4) p(x_3 | \{y_t\}_{t=1}^3) dx_3$
- ▶ This can be applied recursively!
- ▶ Finding the posterior can be done in linear time!

Recommended Reading

Bishop: Pattern Recognition and Machine Learning, Chapter 8
Directed graphical models

References I

Not examinable from here

Factor Graphs

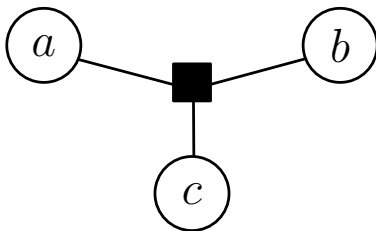
A different graphical representation

Good references:

Kschischang et al.: Factor Graphs and the Sum-Product Algorithm. IEEE Transactions on Information Theory (2001)

Loeliger: An Introduction to Factor Graphs. IEEE Signal Processing Magazine, (2004)

Factor Graphs



- ▶ (Un)directed graphical models express a global function of several variables as a product of factors over subsets of those variables
- ▶ Factor graphs make this decomposition explicit by introducing **additional nodes for the factors** themselves

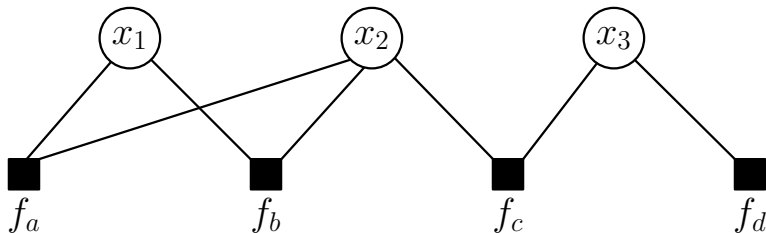
Factorizing the Joint

The joint distribution is a product of factors:

$$p(\mathbf{x}) = \prod_s f_s(\mathbf{x}_s)$$

- ▶ $\mathbf{x} = (x_1, \dots, x_n)$
- ▶ \mathbf{x}_s : Subset of variables
- ▶ f_s : Factor; non-negative function of the variables \mathbf{x}_s
- ▶ Building a factor graph as a **bipartite graph**:
 - ▶ Nodes for all random variables (same as in (un)directed graphical models)
 - ▶ Additional nodes for factors (black squares) in the joint distribution
- ▶ Undirected links connecting each factor node to all of the variable nodes the factor depends on

Example



$$p(\mathbf{x}) = f_a(x_1, x_2) f_b(x_1, x_2) f_c(x_2, x_3) f_d(x_3)$$

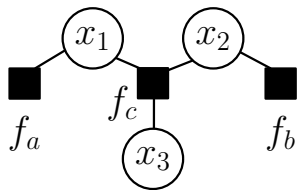
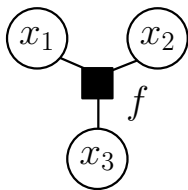
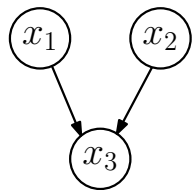
► Efficient inference algorithms for factor graphs (e.g., **sum-product algorithm**)

Directed Graphical Model \rightarrow Factor Graph

1. Take variable nodes from Bayesian network
2. Create additional factor nodes corresponding to the conditional distributions
3. Add appropriate links

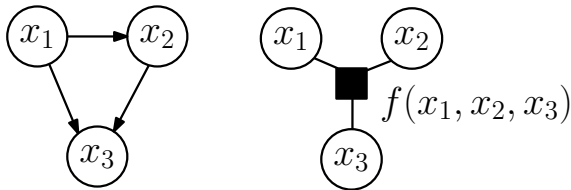
Not unique

Example: Directed Graph \rightarrow Factor Graph



- ▶ Directed graph with factorization $p(x_1)p(x_2)p(x_3|x_1, x_2)$
- ▶ Factor graph with factor $f(x_1, x_2, x_3) = p(x_1)p(x_2)p(x_3|x_1, x_2)$
- ▶ Factor graph with factors $f_a = p(x_1)$, $f_b = p(x_2)$, $f_c = p(x_3|x_1, x_2)$

Removing Cycles



$$p(x_3|x_2, x_1)p(x_2|x_1)p(x_1) = f_a(x_1, x_2, x_3)f_b(x_1, x_2)f_c(x_2) = f(x_1, x_2, x_3) \quad (6)$$

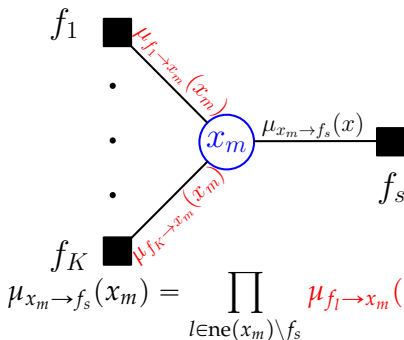
- Local cycles in an (un)directed graph (due to links connecting parents of a node) can be removed on conversion to a factor graph

Exact Inference in Factor Graphs

Sum-Product Algorithm for Factor Graphs

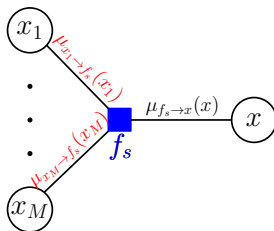
- ▶ Factor graphs give a **uniform treatment to message passing**, which is used for inference in graphs
- ▶ Inference: Find (marginal) posterior distributions
- ▶ Idea: **Local message passing** between nodes and factors
- ▶ Two different types of messages:
 - ▶ Messages $\mu_{x \rightarrow f}(x)$ from variable nodes to factors
 - ▶ Messages $\mu_{f \rightarrow x}(x)$ from factors to variable nodes
- ▶ Repeated sending of these messages through the graph converges
- ▶ Factors transform messages into evidence for the receiving node

Variable-to-Factor Message



- ▶ Take the product of all **incoming messages along all other links**
- ▶ A variable node can send a message to a factor node once it has received messages from all other neighboring factors
- ▶ The message that a node sends to a factor is made up of the messages that it receives from all other factors.

Factor-to-Variable Message



$$\mu_{f_s \rightarrow x}(x) = \sum_{x_1} \cdots \sum_{x_M} f_s(x, x_1, \dots, x_M) \prod_{m \in \text{ne}(f_s) \setminus x} \mu_{x_m \rightarrow f_s}(x_m)$$

- ▶ Take the product of the incoming messages along all other links coming into the factor node
- ▶ Multiply by the factor associated with that node
- ▶ Marginalize over all variables associated with the incoming messages

Initialization

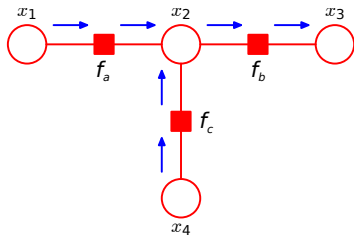
- ▶ If the leaf node is a **variable node**, initialize the corresponding messages to 1:

$$\mu_{x \rightarrow f}(x) = 1$$

- ▶ If the leaf node is a **factor node**, the message should be

$$\mu_{f \rightarrow x}(x) = f(x)$$

Example (1)



From PRML (Bishop, 2006)

$$\mu_{x_1 \rightarrow f_a}(x_1) = 1$$

$$\mu_{f_a \rightarrow x_2}(x_2) = \sum_{x_1} f_a(x_1, x_2) \cdot 1$$

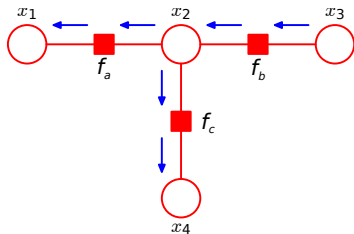
$$\mu_{x_4 \rightarrow f_c}(x_4) = 1$$

$$\mu_{f_c \rightarrow x_2}(x_2) = \sum_{x_4} f_c(x_2, x_4) \cdot 1$$

$$\mu_{x_2 \rightarrow f_b}(x_2) = \mu_{f_a \rightarrow x_2}(x_2) \mu_{f_c \rightarrow x_2}(x_2)$$

$$\mu_{f_b \rightarrow x_3}(x_3) = \sum_{x_2} f_b(x_2, x_3) \mu_{x_2 \rightarrow f_b}(x_2)$$

Example (2)



From PRML (Bishop, 2006)

$$\mu_{x_3 \rightarrow f_b}(x_3) = 1$$

$$\mu_{f_b \rightarrow x_2}(x_2) = \sum_{x_3} f_b(x_2, x_3) \cdot 1$$

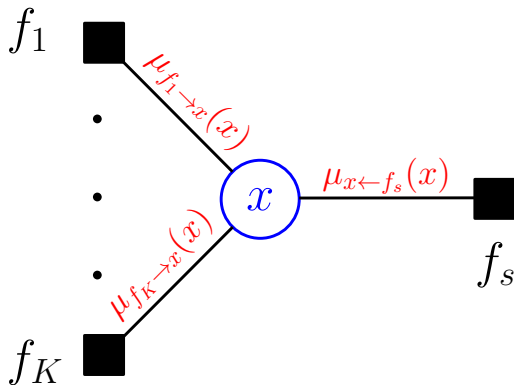
$$\mu_{x_2 \rightarrow f_a}(x_2) = \mu_{f_b \rightarrow x_2}(x_2) \mu_{f_c \rightarrow x_2}(x_2)$$

$$\mu_{f_a \rightarrow x_1}(x_1) = \sum_{x_2} f_a(x_1, x_2) \mu_{x_2 \rightarrow f_a}(x_2)$$

$$\mu_{x_2 \rightarrow f_c}(x_2) = \mu_{f_a \rightarrow x_2}(x_2) \mu_{f_b \rightarrow x_2}(x_2)$$

$$\mu_{f_c \rightarrow x_4}(x_4) = \sum_{x_2} f_c(x_2, x_4) \mu_{x_2 \rightarrow f_c}(x_2)$$

Marginals



For a single variable node the marginal is given as the **product of all incoming messages**:

$$p(x) = \prod_{f_i \in \text{ne}(x)} \mu_{f_i \rightarrow x}(x)$$

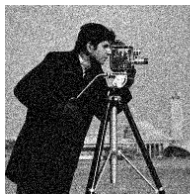
Observed Variables ► Posterior

- Thus far, we have focused on the case where all variables are unobserved.
- Posterior is always conditioned on observations
- Partition $x = h \cup v$, h : hidden variables, v : visible variables with observations \hat{v}
- $p(v = \hat{v}) = \prod_i I(v_i = \hat{v}_i)$
- $p(x)p(v = \hat{v}) = p(h, v = \hat{v}) \propto p(h|v = \hat{v})$
- **Marginal posteriors** $p(h_i|v = \hat{v})$ can be obtained via sum-product algorithm and some local computations
- (Koller & Friedman, 2009)

Exact Inference in (Un)Directed Graphical Models

- ▶ Loops are possible ►► **Junction Tree Algorithm** (Lauritzen & Spiegelhalter, 1988)
- ▶ Alternative: **Loopy Belief Propagation** (Frey & MacKay 1998)

Applications of Inference in Graphical Models



- ▶ **Ranking:** TrueSkill (Herbrich et al., 2007)
- ▶ **Computer vision:** de-noising, segmentation, semantic labeling, ... (e.g., Sucar & Gillies, 1994; Shotton et al., 2006; Szeliski et al., 2008)
- ▶ **Coding theory:** Low-density parity-check codes, turbo codes, ... (e.g., McEliece et al., 1998)
- ▶ **Linear algebra:** Solve linear equation systems (Shental et al., 2008)
- ▶ **Signal processing:** Iterative state estimation (e.g., Bickson et al., 2007; Deisenroth & Mohamed, 2012)