

Graphical Models

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Probabilistic Models

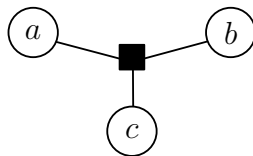
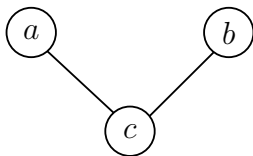
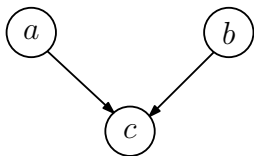
Previously we saw:

- ▶ 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.

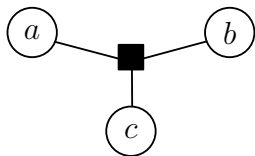
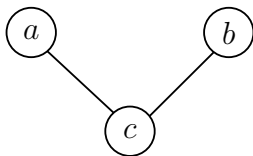
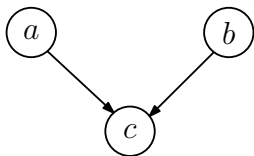
Probabilistic Graphical Models



Three types of probabilistic graphical models:

- ▶ Bayesian networks (directed graphical models)
- ▶ Markov random fields (undirected graphical models)
- ▶ Factor graphs

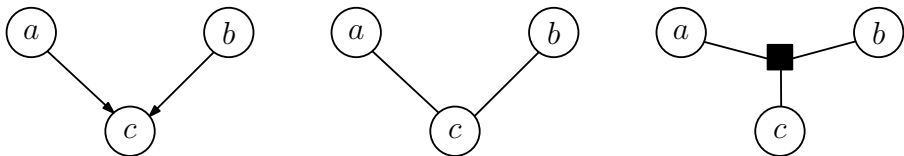
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- ▶ **Edges:** Probabilistic/functional relations between variables

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 - ▶ **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

$$\begin{aligned} Pr(\{y_g, \gamma_g, t_{gk}, \beta_{gk}, l_d, f_g, z_n, i_{ng}\} | \{w_{nd}\}) &= \prod_g^G p(y_g | \rho) p(\gamma_g | \sigma) p(f_g | \alpha) \cdot \\ &\left[\prod_k^K p(t_{gk} | \gamma_g) p(\beta_{gk} | t_{gk}, y_g) \right] p(\kappa | \alpha) \prod_d^D p(l_d | \kappa) p(\pi | \alpha) \prod_n^N p(z_n | \pi) \\ &\prod_n^N \prod_g^G p(i_{ng} | \beta, z_n) \prod_n^N \prod_d^D p(w_{nd} | i_{ng}, f, l_d) \end{aligned}$$

From Kim et al. (NIPS, 2015)

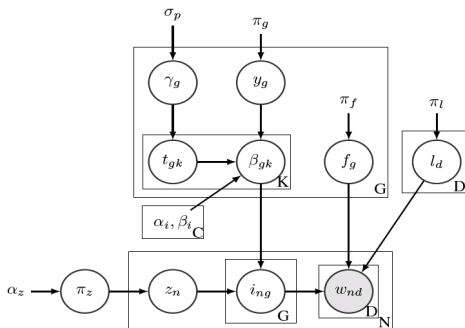
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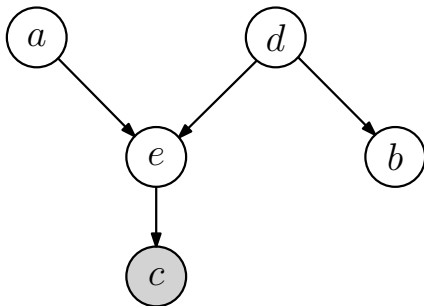
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Expressing Factorisations as Graphs

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 $p(b|a)$.

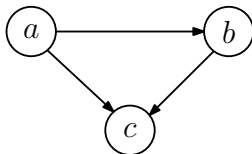
Skill: From Joints to Graphs

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



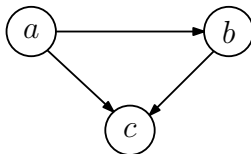
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Building the corresponding graphical model:

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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



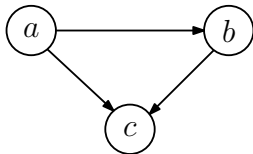
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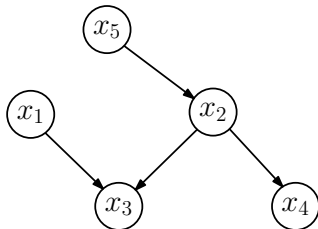
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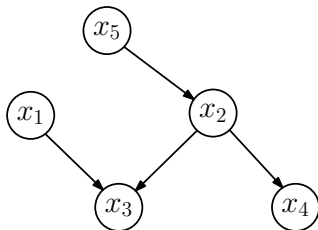
► Graph layout depends on the choice of factorization

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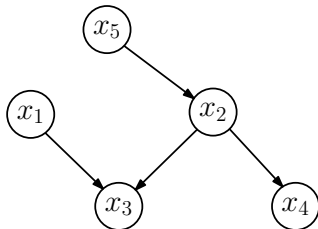
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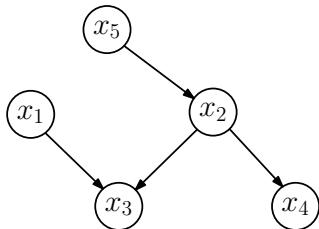
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$$p(x_1, x_2, x_3, x_4, x_5) = p(x_1)p(x_5)p(x_2|x_5)p(x_3|x_1, x_2)p(x_4|x_2)$$

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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:

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

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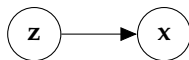
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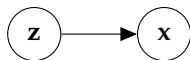
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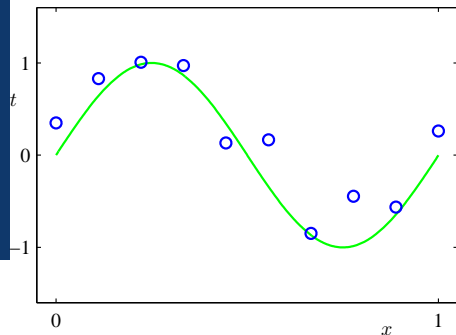
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Which one is correct? Depends on which conditional you specified!

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

Graphical Model for (Bayesian) Linear Regression



From PRML (Bishop, 2006)

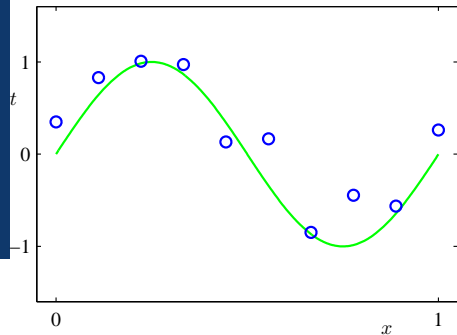
We are given a data set $(x_1, y_1), \dots, (x_N, y_N)$ where

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

with f unknown.

►► Find a (regression) model that explains the data

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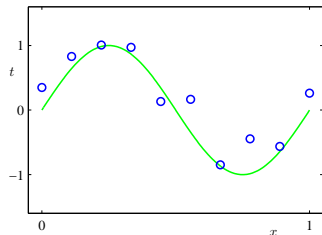
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- Consider **polynomials** $f(x) = \sum_{j=0}^M w_j x^j$ with parameters $\mathbf{w} = [w_0, \dots, w_M]^\top$.
- **Bayesian linear regression**: Place a conjugate Gaussian prior on the parameters: $p(\mathbf{w}) = \mathcal{N}(\mathbf{0}, \alpha^2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

Graphical Model for Linear Regression



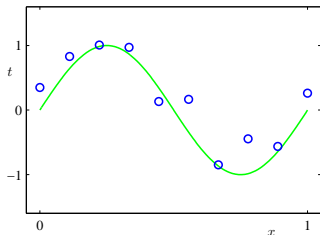
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$$p(y_i | \mathbf{w}, x_i) = \mathcal{N}(y_i | f_{\mathbf{w}}(x_i), \sigma^2)$$

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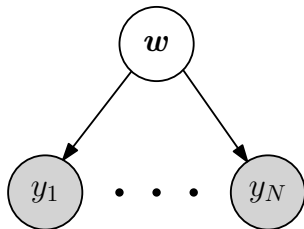


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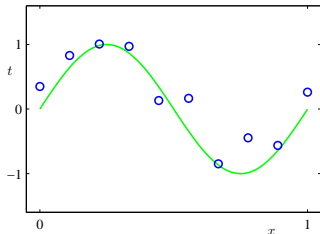
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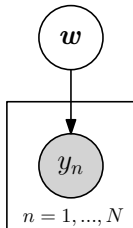
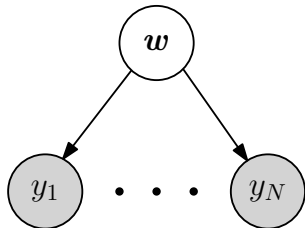


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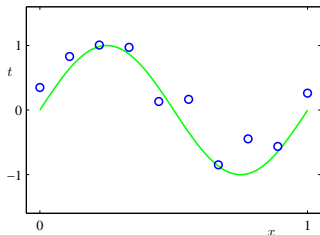
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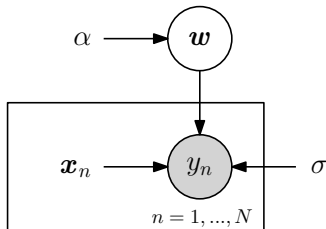
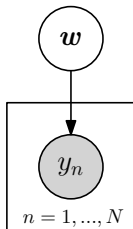
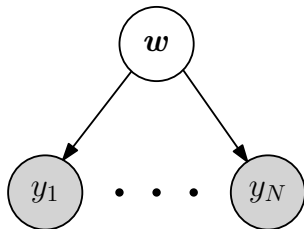


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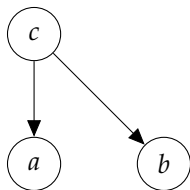
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Finding Conditional Independence

Conditional Independence



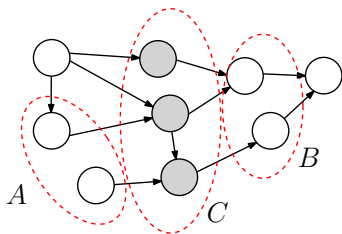
$$\begin{aligned} a \perp\!\!\!\perp b|c &\iff p(a,b|c) = p(a|c)p(b|c) \\ &\iff p(a|b,c) = p(a|c) \end{aligned}$$

- ▶ (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)

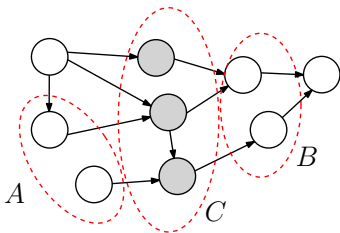
D-Separation (Directed Graphs)



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)

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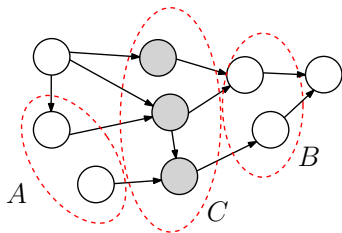


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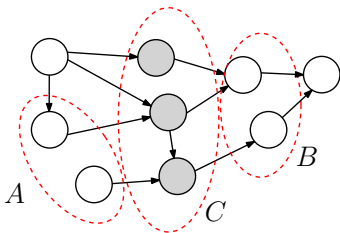
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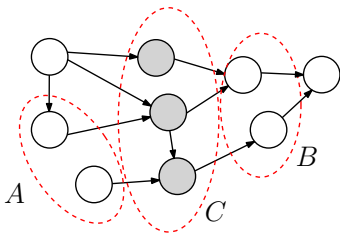
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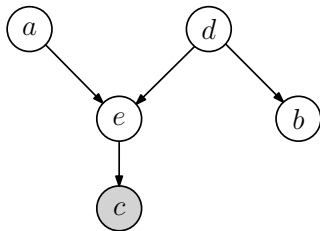
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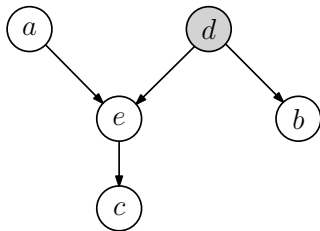
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If **all paths are blocked**, then A is **d-separated** (conditionally indep.) from B by C , and the joint distribution satisfies $A \perp\!\!\!\perp B | C$.

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
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(Hidden) Markov Models

- ▶ Models of time-varying phenomena (time series)
- ▶ Conditional Independencies are crucial

Time-series models

Many phenomena vary over time:

- ▶ Dynamical systems
 - ▶ motion of stars in the sky, that you want to understand
 - ▶ motion of a robot arm, that you want to control
- ▶ Audio signals
- ▶ Communication signals
- ▶ Price of assets over time

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More generally, we can think about **sequence** models:

- ▶ DNA sequences
- ▶ Language

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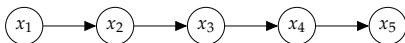
- ▶ To simplify the specification of the model, we can **assume** that x_t is the **state** of the dynamical system.
- ▶ The state is a variable that, if known, determines **everything** there is to know about future states.
- ▶ In other words, $x_{t+T} \perp\!\!\!\perp x_{t-\tau} | x_t$ for $t, T > 0$.

Markov Chains

We can express this assumption with the factorisation:

$$p(x_1, \dots, x_5) = p(x_1) \prod_{t=2}^5 p(x_t | x_{t-1}) \quad (6)$$

With the corresponding graphical model:



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With the corresponding graphical model:



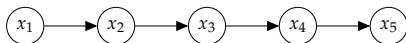
Exercise: Show that $x_4 \perp\!\!\!\perp x_1 | x_3$.

Markov Chains

We can express this assumption with the factorisation:

$$p(x_1, \dots, x_5) = p(x_1) \prod_{t=2}^5 p(x_t | x_{t-1}) \quad (6)$$

With the corresponding graphical model:



Exercise: Show that $x_4 \perp\!\!\!\perp x_1 | x_3$.

► Single path from x_4 to x_1 , blocked by rule 1 since x_3 is observed.

Hidden Markov Models

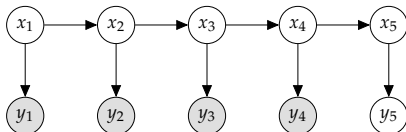
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Hidden Markov Models

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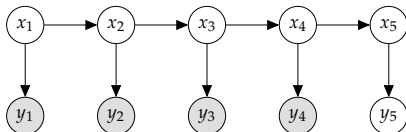
Hidden Markov Models

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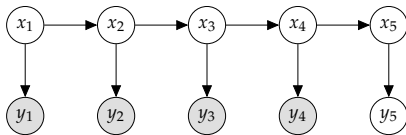
Hidden Markov Models

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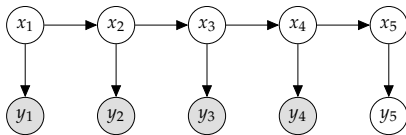
$$p(\{x_t\}_{t=1}^5, \{y_t\}_{t=1}^5) = p(x_1) \left[\prod_{t=2}^5 p(x_t|x_{t-1}) \right] \left[\prod_{t=1}^5 p(y_t|x_t) \right] \quad (7)$$

Hidden Markov Models



Exercise: Is $y_i \perp\!\!\!\perp y_j$ for $i \neq j$?

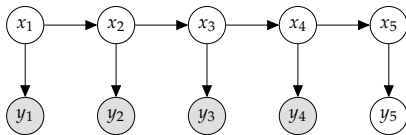
Hidden Markov Models



Exercise: Is $y_i \perp\!\!\!\perp y_j$ for $i \neq j$?

► No! y_i is connected by an open path to y_j .

Hidden Markov Models



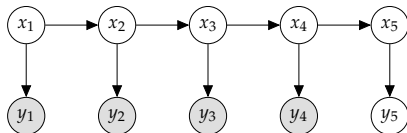
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Observe:

- We have specified a complex joint on observables $p(y_1, \dots, y_T)$.

Hidden Markov Models



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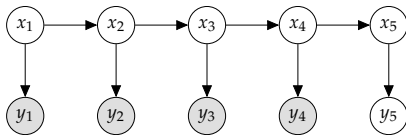
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Observe:

- We have specified a complex joint on observables $p(y_1, \dots, y_T)$.
- But **simpler** structure than an “always true” factorisation, e.g.:

$$p(y_1, \dots, y_T) \stackrel{\text{AT}}{=} p(y_1)p(y_2|y_1)p(y_3|y_2, y_1) \prod_{t=4}^T p(y_t|y_1, \dots, y_{t-1}) \quad (8)$$

Hidden Markov Models



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- We never needed to specify a function on more than 2 variables! ($p(x_t|x_{t-1})$ vs e.g. $p(y_t|y_1, \dots, y_{t-1})$).

Hidden Markov Models: Example Applications

- ▶ Figuring out the trajectory of a projectile from RADAR observations (e.g. spacecraft).
 - ▶ State is the location and speed of a projectile
 - ▶ $p(x_t|x_{t-1})$ is determined by Newton's laws, plus uncertainty from unknown forces acting on the object.
 - ▶ This is an example of physics-inspired model, where latent variables have physical interpretation.
- ▶ Stock market models
 - ▶ Posit some hypothetical “market state”, which *if you knew it* would predict the future well.
 - ▶ No “real” way in which the state “exists”, but it can help with prediction!

Hidden Markov Models: Two Questions

- ▶ Given all observations, what is our belief on the latent at time t ?
I.e. find $p(x_t|y_{1:t})$.
- ▶ How can we predict into the future?
I.e. find $p(y_{t+1}|y_{1:t})$.

Filtering Distribution

Systematic method: Probability of Everything

$$\begin{aligned} p(x_t|y_{1:t}) &\stackrel{\text{AT}}{=} \int \frac{p(x_1, \dots, x_t, y_1, \dots, y_t)}{p(y_1, \dots, y_t)} dx_1 \dots x_{t-1} \\ &\stackrel{\text{MA}}{=} \int \frac{p(x_1) \left[\prod_{t=2}^t p(x_t|x_{t-1}) \right] \left[\prod_{t=1}^t p(y_t|x_t) \right]}{p(y_1, \dots, y_t)} dx_1 \dots x_{t-1} \\ p(y_1, \dots, y_t) &= \int p(x_1) \left[\prod_{t=2}^t p(x_t|x_{t-1}) \right] \left[\prod_{t=1}^t p(y_t|x_t) \right] dx_1 \dots x_t \end{aligned}$$

- ▶ In principle, we could compute this (everything is specified in a density from the model specification!)
- ▶ Lots of sums/integrals though! Very slow to compute!
- ▶ Could rearrange the sums to speed things up?

Recursive Filtering

You can actually get a recursive equation to solve this problem, which is much easier to compute:

$$\text{Step 1: } p(x_t | y_1, \dots, y_{t-1}) = \int p(x_t | x_{t-1}) p(x_{t-1} | y_1, \dots, y_{t-1}) dy_{1:t-1}$$

$$\text{Step 2: } p(x_t | y_1, \dots, y_t) = \frac{p(y_t | x_t) p(x_t | y_{1:t-1})}{p(y_t | y_{1:t-1})}$$

- ▶ Only needs one sum/integral.
- ▶ See `exercises.pdf` (question 9) for full derivation.
- ▶ Look at `hmm-demo.ipynb` for alternative derivation and code demonstrating the model.

HMM Demo

Demo `hmm-demo.ipynb`. TODO: Save figures from ipynb and put in slides.

Algorithms on Graphs

- ▶ It took some effort to derive the recursive algorithm for efficient filtering.
- ▶ Algorithms on graphs can discover these **efficient** algorithms **automatically**!
- ▶ ►► Belief Propagation (not examinable)

Conclusion

- ▶ Skill: Conditionals to Graphical Model
- ▶ Skill: Graphical model to Conditionals
- ▶ Skill: Conditional Independence from Graphical Model
- ▶ Skill: Simplification of Posteriors using Conditional Independencies

Further Reading

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

References I

- [1] C. M. Bishop. *Pattern Recognition and Machine Learning*. Information Science and Statistics. Springer-Verlag, 2006.
- [2] B. Kim, J. A. Shah, and F. Doshi-Velez. Mind the Gap: A Generative Approach to Interpretable Feature Selection and Extraction. In C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, pages 2260–2268. 2015.
- [3] J. Pearl. *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. Morgan Kaufmann, 1988.

Not examinable from here

Factor Graphs

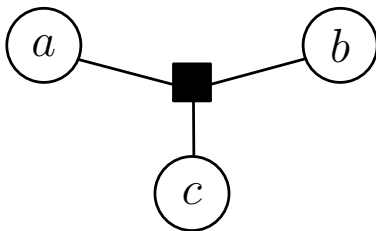
A different graphical representation

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

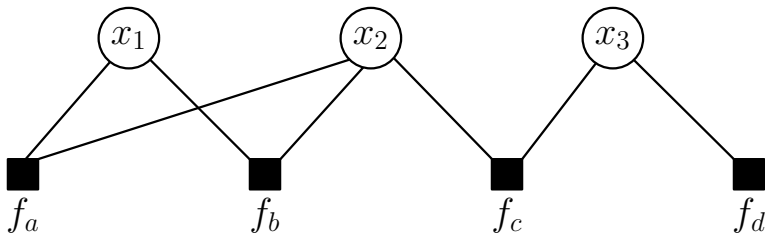
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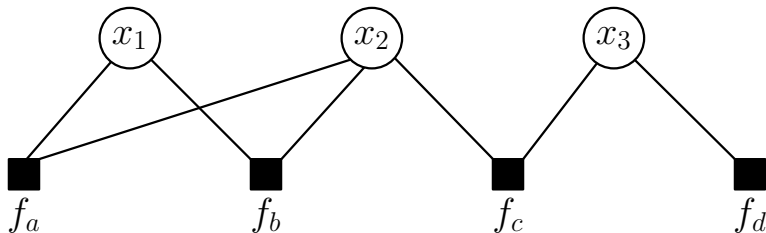
- ▶ $\mathbf{x} = (x_1, \dots, x_n)$
- ▶ \mathbf{x}_s : Subset of variables
- ▶ f_s : Factor; non-negative function of the variables \mathbf{x}_s
- ▶ Building a factor graph as a **bipartite graph**:
 - ▶ Nodes for all random variables (same as in (un)directed graphical models)
 - ▶ Additional nodes 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



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

Example



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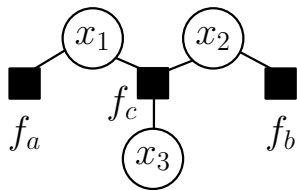
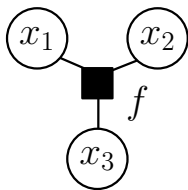
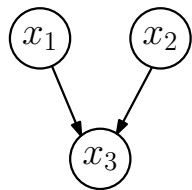
► Efficient inference algorithms for factor graphs (e.g., **sum-product algorithm**)

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

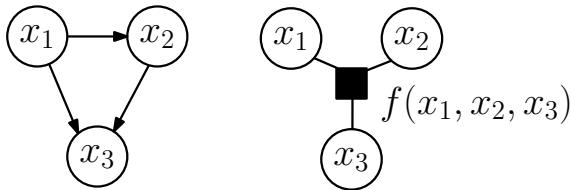
Not unique

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



$$p(x_3|x_2, x_1)p(x_2|x_1)p(x_1) = f_a(x_1, x_2, x_3)f_b(x_1, x_2)f_c(x_2) = f(x_1, x_2, x_3) \quad (9)$$

- 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

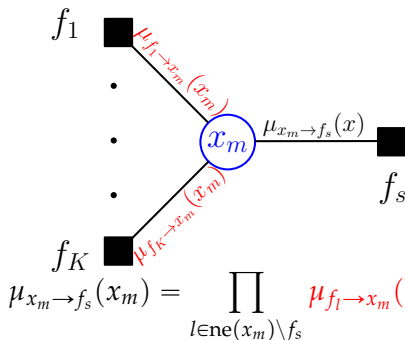
Sum-Product Algorithm for Factor Graphs

- ▶ 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

Sum-Product Algorithm for Factor Graphs

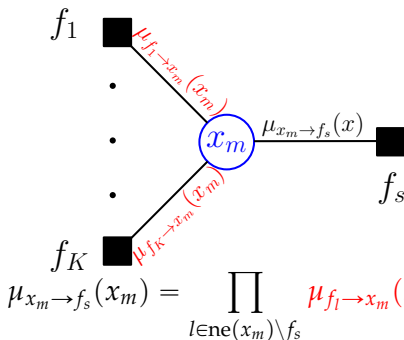
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- ▶ Two different types of messages:
 - ▶ Messages $\mu_{x \rightarrow f}(x)$ from variable nodes to factors
 - ▶ Messages $\mu_{f \rightarrow x}(x)$ from factors to variable nodes
- ▶ Repeated sending of these messages through the graph converges
- ▶ Factors transform messages into evidence for the receiving node

Variable-to-Factor Message



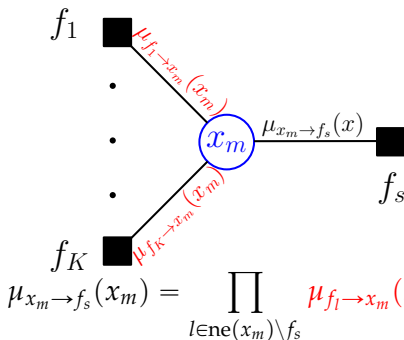
- Take the product of all **incoming messages along all other links**

Variable-to-Factor Message



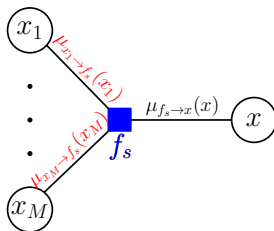
- ▶ Take the product of all **incoming messages along all other links**
- ▶ A variable node can send a message to a factor node once it has received messages from all other neighboring factors

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.

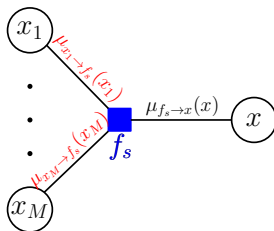
Factor-to-Variable Message



$$\mu_{f_s \rightarrow x}(x) = \prod_{m \in \text{ne}(f_s) \setminus x} \mu_{x_m \rightarrow f_s}(x_m)$$

- Take the product of the incoming messages along all other links coming into the factor node

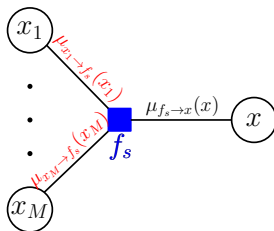
Factor-to-Variable Message



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

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

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

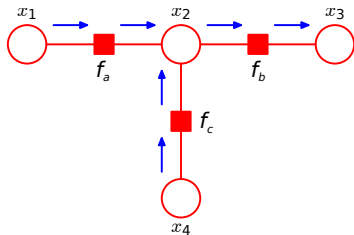
- ▶ If the leaf node is a **variable node**, initialize the corresponding messages to 1:

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

- ▶ 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)

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

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

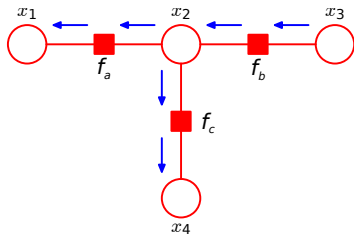
$$\mu_{x_4 \rightarrow f_c}(x_4) = 1$$

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

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

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

Example (2)



From PRML (Bishop, 2006)

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

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

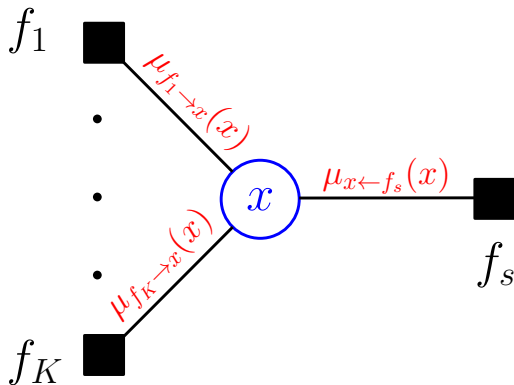
$$\mu_{x_2 \rightarrow f_a}(x_2) = \mu_{f_b \rightarrow x_2}(x_2) \mu_{f_c \rightarrow x_2}(x_2)$$

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

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

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

Marginals



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

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

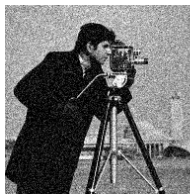
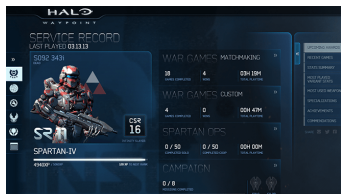
Observed Variables ► Posterior

- 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)