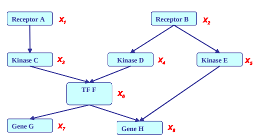
Machine Learning

10-701/15-781, Spring 2010

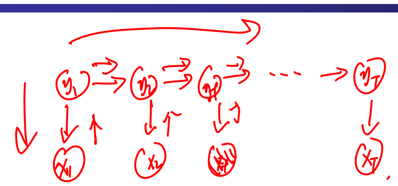
Bayesian Networks

Eric Xing



Lecture 13, March 1, 2010

Reading: Chap. 8, C.B book



① $P(X_1 \cdots X_T, y_1 \cdots y_T)$

$= P(y_1)P(X_1|y_1)P(y_2|y_1)P(X_2|y_2) \cdots$

$P(X_T|y_T)$

② $P(X_t | y_t, X_1 \cdots X_{t-1}, y_1 \cdots y_{t-1})$

$= P(X_t|y_t)$

$P(y_t | y_{t-1} \cdots y_1, X_1 \cdots X_{t-1})$

$= P(y_t|y_{t-1})$

③ $P(y_t | X_1 \cdots X_T)$

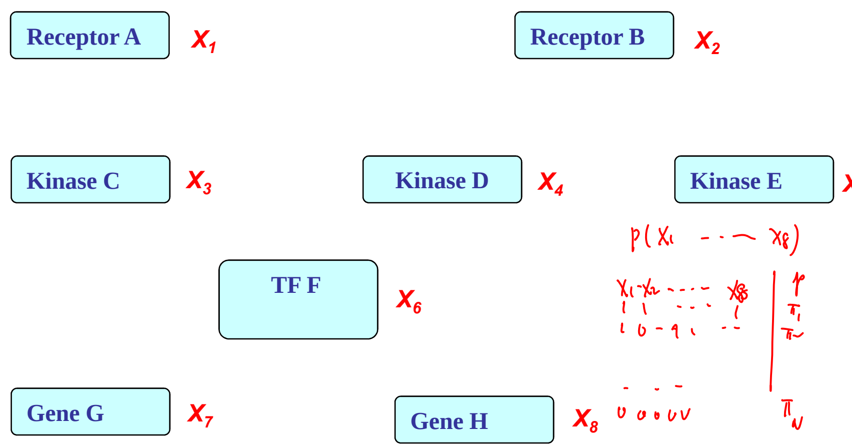
Belief Prop

message passing.

What is a Bayesian Network?

--- example from a signal transduction pathway

- A possible world for cellular signal transduction:



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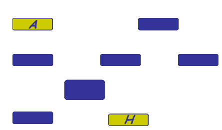
Recap of Basic Prob. Concepts

- **Representation: what is the joint probability dist. on multiple variables?**

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



  - **How many state configurations in total? --- 2^8**
  - **Are they all needed to be represented?**
  - **Do we get any scientific/medical insight?**

- **Learning: where do we get all this probabilities?**
  - **Maximal-likelihood estimation? but how many data do we need?**
  - **Where do we put domain knowledge in terms of plausible relationships between variables, and plausible values of the probabilities?**

- **Inference: If not all variables are observable, how to compute the conditional distribution of latent variables given evidence?**
  - **Computing $p(H|A)$ would require summing over all 2^6 configurations of the unobserved variables**

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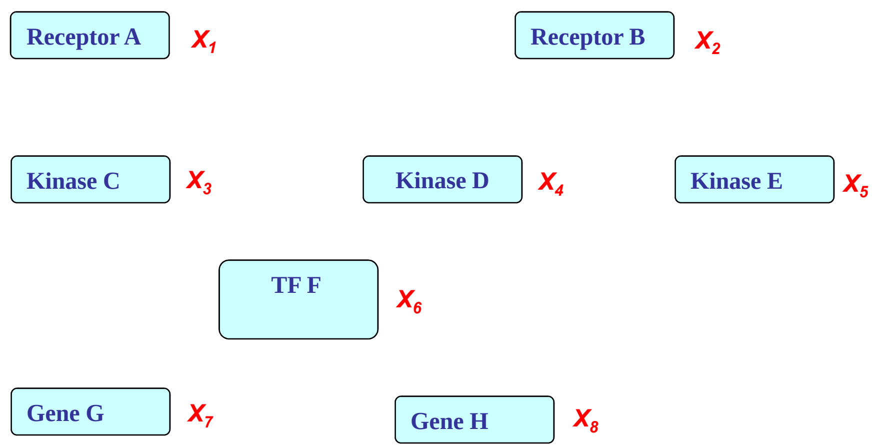
What is a Bayesian Network?

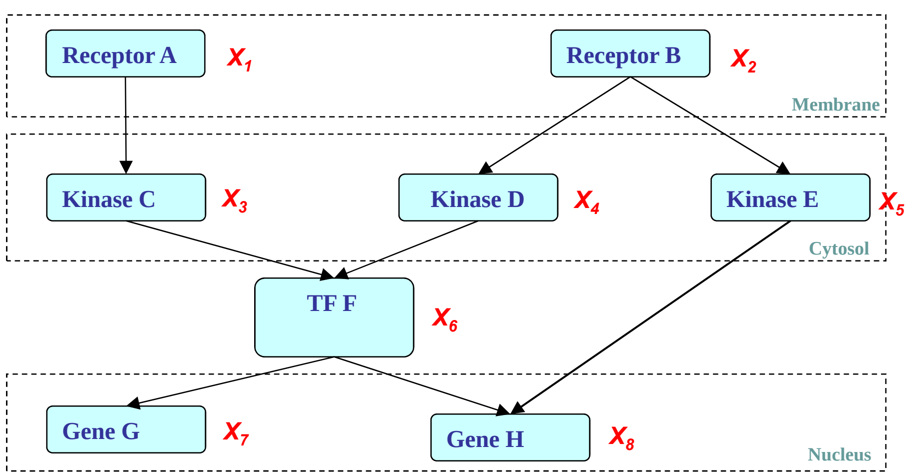
--- example from a signal transduction pathway

- A possible world for cellular signal transduction:



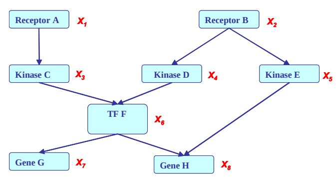
BN: Structure Simplifies Representation

- Dependencies among variables



Bayesian Network

- If X_i's are **conditionally independent** (as described by a **BN**), the joint can be factored to a product of simpler terms, e.g.,



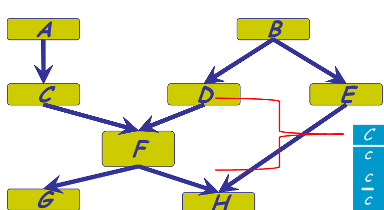
$$P(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8)$$
$$= P(X_1)\,P(X_2)\,P(X_3|\,X_1)\,P(X_4|\,X_2)\,P(X_5|\,X_2)\,P(X_6|\,X_3, X_4)\,P(X_7|\,X_6)\,P(X_8|\,X_5, X_6)$$

- **Why we may favor a BN?**
  - **Representation cost: how many probability statements are needed?**

    ~~2+2+4+4+4+8+4+8=~~36, an 8-fold reduction from 2^8!
  - **Algorithms for systematic and efficient inference/learning computation**
    - **Exploring the graph structure and probabilistic semantics**
  - **Incorporation of domain knowledge and causal (logical) structures**

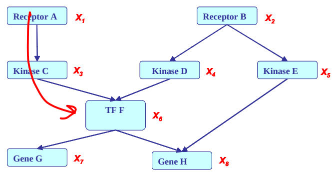
Specification of a BN

- There are two components to any GM:
  - the *qualitative* specification
  - the *quantitative* specification



C	D	P(F | C,D)	
c	d	0.9	0.1
c	$\bar{d}$	0.2	0.8
$\bar{c}$	d	0.9	0.1
$\bar{c}$	$\bar{d}$	0.01	0.99

Bayesian Network: Factorization Theorem



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

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

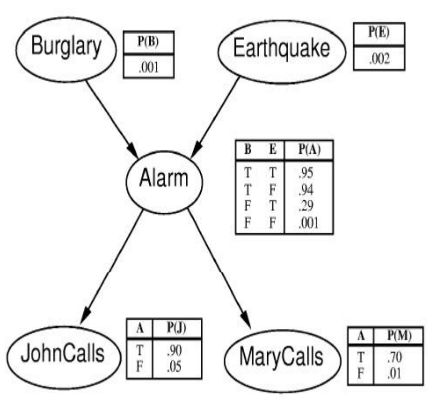
- **Theorem:**

  Given a DAG, The most general form of the probability distribution that is consistent with the (probabilistic independence properties encoded in the) graph factors according to "node given its parents":

$$P(\mathbf{X}) = \prod_i P(X_i \mid \mathbf{X}_{\pi_i})$$

  where $\mathbf{X}_{\pi_i}$ is the set of parents of xi. d is the number of nodes (variables) in the graph.

Examples



P(B)
.001

P(E)
.002

B	E	P(A)
T	T	.95
T	F	.94
F	T	.29
F	F	.001

A	P(J)
T	.90
F	.05

A	P(M)
T	.70
F	.01

P(B, E, A, J, M)

= P(B)P(E)P(A|E,B)P(J|A)P(M|A)

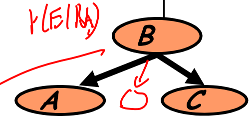
P(M|B)

Qualitative Specification

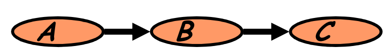
- Where does the qualitative specification come from?
  - Prior knowledge of causal relationships
  - Prior knowledge of modular relationships
  - Assessment from experts
  - Learning from data
  - We simply link a certain architecture (e.g. a layered graph)
  - …

Local Structures & Independencies

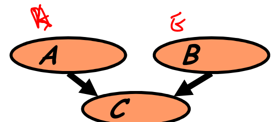
- Common parent
  - Fixing B decouples A and C
    "given the level of gene B, the levels of A and C are independent"



- Cascade
  - Knowing B decouples A and C
    "given the level of gene B, the level gene A provides no extra prediction value for the level of gene C"

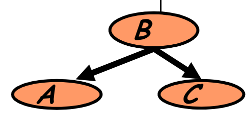


- V-structure
  - Knowing C couples A and B
    because A can "explain away" B w.r.t. C
    "If A correlates to C, then chance for B to also correlate to B will decrease"



- The language is compact, the concepts are rich!

A simple justification

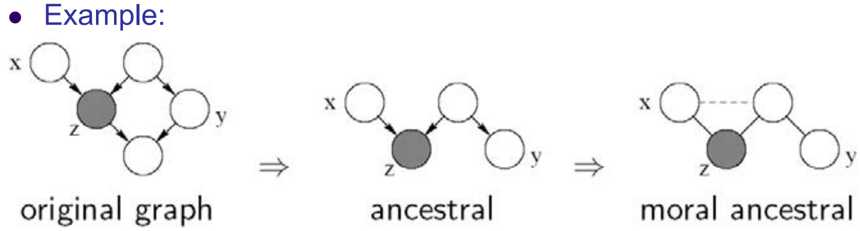


Graph separation criterion

- D-separation criterion for Bayesian networks (D for Directed edges):

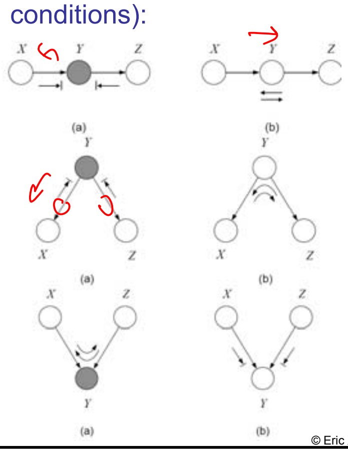
  Definition: variables x and y are *D-separated* (conditionally independent) given z if they are separated in the *moralized* ancestral graph

- Example:



Global Markov properties of DAGs

- X is **d-separated** (directed-separated) from Z given Y if we can't send a ball from any node in X to any node in Z using the "*Bayes-ball*" algorithm illustrated bellow (and plus some boundary conditions):



- **Defn: $\mathcal{I}(G)$=all independence properties that correspond to d-separation:**

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

- **D-separation is sound and complete**

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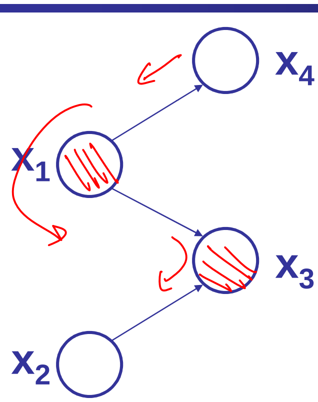
Example:



- Complete the I(G) of this graph:

$X_4 \perp X_2 \mid \phi$

$X_1 \perp X_2 \mid \phi$

$X_4 \perp X_3 \mid X_1$

$X_4 \perp X_2 \mid X_1, X_3$

Essentially: A BN is a database of Pr. Independence statements among variables.

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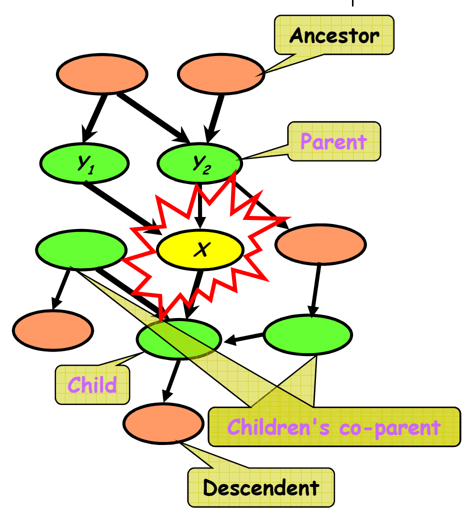
Bayesian Network: Conditional Independence Semantics

Structure: *DAG*

- **Meaning: a node is conditionally independent of every other node in the network outside its Markov blanket**
- **Local conditional distributions (CPD) and the DAG completely determine the joint dist.**
- **Give causality relationships, and facilitate a generative process**



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Towards quantitative specification of probability distribution

- Separation properties in the graph imply independence properties about the associated variables
- For the graph to be useful, any conditional independence properties we can derive from the graph should hold for the probability distribution that the graph represents
- **The Equivalence Theorem**

  For a graph G,

  Let $\mathcal{D}_1$ denote the family of all distributions that satisfy I(G),

  Let $\mathcal{D}_2$ denote the family of all distributions that factor according to G,

  Then $\mathcal{D}_1 \equiv \mathcal{D}_2$.

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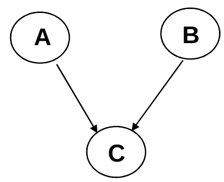
Quantitative Specification



↔ p(A,B,C) =

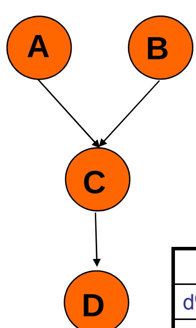
=P(A)P(B)P(C|A,B)

Conditional probability tables (CPTs)

a^0	0.75
a^1	0.25

b^0	0.33
b^1	0.67

P(a,b,c.d) =
P(a)P(b)P(c|a,b)P(d|c)



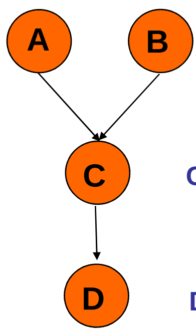
	a^0b^0	a^0b^1	a^1b^0	a^1b^1
c^0	0.45	1	0.9	0.7
c^1	0.55	0	0.1	0.3

	c^0	c^1
d^0	0.3	0.5
d^1	07	0.5

Conditional probability density func. (CPDs)

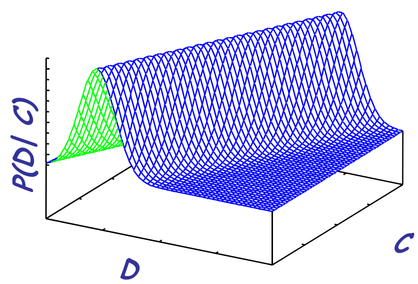
$A \sim N(\mu_a, \Sigma_a)$ $B \sim N(\mu_b, \Sigma_b)$

$P(a,b,c.d) = P(a)P(b)P(c|a,b)P(d|c)$

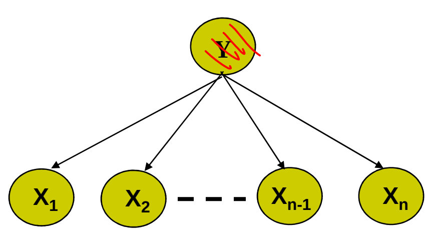


$C \sim N(A+B, \Sigma_c)$

$D \sim N(\mu_a+C, \Sigma_a)$



Conditional Independencies



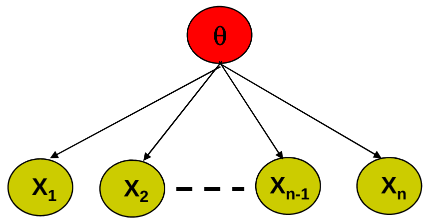
Label

Features

What is this model

1. **When Y is observed?** NB
2. **When Y is unobserved?** Mixture

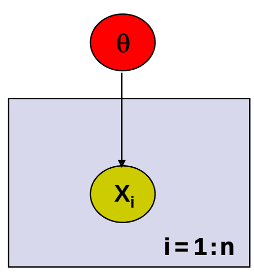
Conditionally Independent Observations



Model parameters

Data = $\{y_1, \ldots y_n\}$

"Plate" Notation



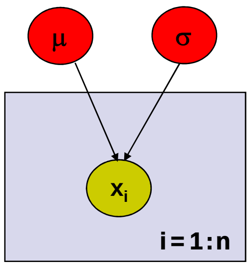
Model parameters

Data = $\{x_1, \ldots x_n\}$

Plate = rectangle in graphical model

variables within a plate are replicated
in a conditionally independent manner

Example: Gaussian Model



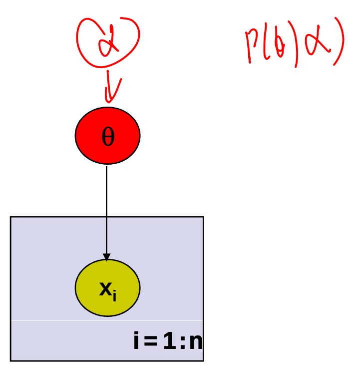
Generative model:

$$p(x_1,\dots x_n \mid \mu, \sigma) = \prod p(x_i \mid \mu, \sigma)$$
$$= p(\text{data} \mid \text{parameters})$$
$$= p(D \mid \theta)$$

where $\theta = \{\mu, \sigma\}$

- Likelihood = p(data | parameters)
  $= p(D \mid \theta)$
  $= L(\theta)$
- Likelihood tells us how likely the observed data are conditioned on a particular setting of the parameters
  - Often easier to work with $\log L(\theta)$

Bayesian models



Example: modeling text

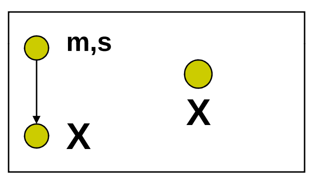
A Hierarchical Phrase-Based Model for Statistical Machine Translation

We present a statistical phrase-based Translation model that uses *hierarchical phrases*—phrases that contain sub-phrases. The model is formally a synchronous context-free grammar but is learned from a bitext without any syntactic information. Thus it can be seen as a shift to the *formal* machinery of syntax based translation systems without any *linguistic* commitment. In our experiments using BLEU as a metric, the hierarchical Phrase based model achieves a relative Improvement of 7.5% over Pharaoh, a state-of-the-art phrase-based system.

More examples

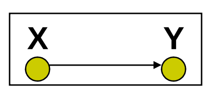
Density estimation

Parametric and nonparametric methods



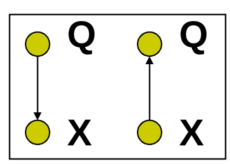
Regression

Linear, conditional mixture, nonparametric



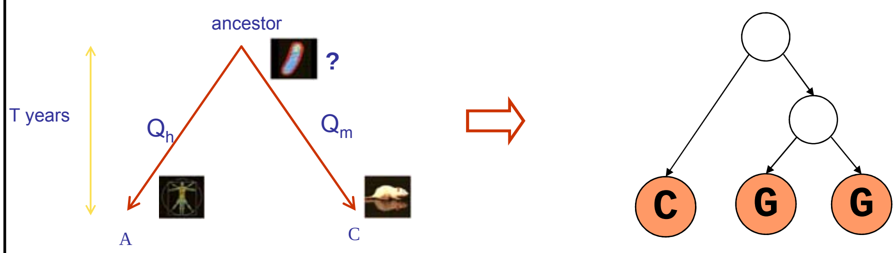
Classification

Generative and discriminative approach



Example, con'd

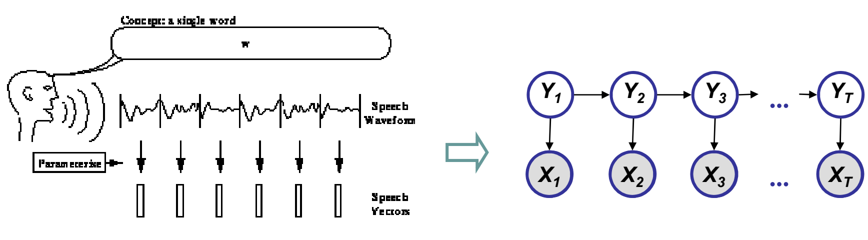
- Evolution



Tree Model

Example, con'd

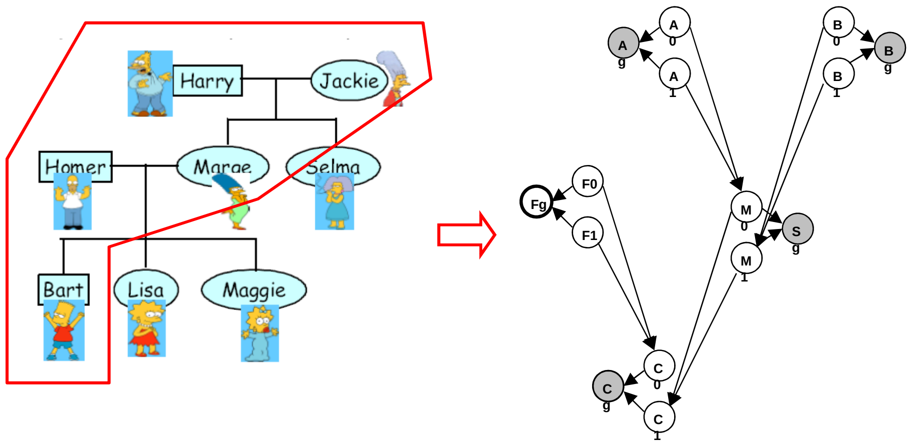
- Speech recognition



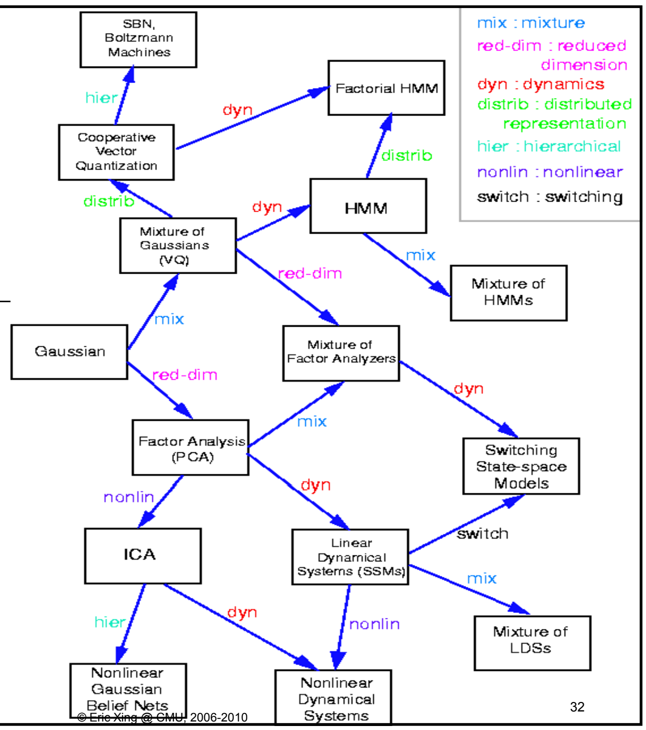
Hidden Markov Model

Example, con'd

- Genetic Pedigree



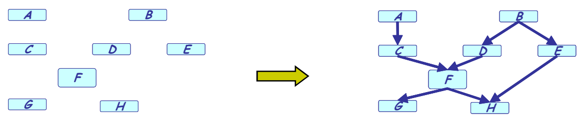
An (incomplete) genealogy of BNs



(Picture by Zoubin Ghahramani and Sam Roweis)

BN and Graphical Models

- A Bayesian network is a special case of **Graphical Models**
- A Graphical Model refers to a family of distributions on a set of random variables that are **compatible** with all the probabilistic independence propositions encoded by a graph that connects these variables
- It is a smart way to write/specify/compose/design exponentially-large probability distributions without paying an exponential cost, and at the same time endow the distributions with structured semantics



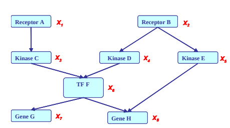
$P(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8)$

$P(X_{1:8}) = P(X_1)P(X_2)P(X_3 \mid X_1 X_2)P(X_4 \mid X_2)P(X_5 \mid X_2)$
$P(X_6 \mid X_3, X_4)P(X_7 \mid X_6)P(X_8 \mid X_5, X_6)$

Two types of GMs

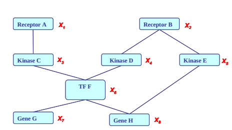
- **Directed edges give causality relationships (Bayesian Network or Directed Graphical Model):**

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



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

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



Probabilistic Inference

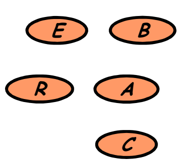
- Computing statistical queries regarding the network, e.g.:
  - Is node X independent on node Y given nodes Z,W ?
  - What is the probability of X=true if (Y=false and Z=true)?
  - What is the joint distribution of (X,Y) if Z=false?
  - What is the likelihood of some full assignment?
  - What is the most likely assignment of values to all or a subset the nodes of the network?

- General purpose algorithms exist to fully automate such computation
  - Computational cost depends on the topology of the network
  - Exact inference:
    - The junction tree algorithm
  - Approximate inference;
    - Loopy belief propagation, variational inference, Monte Carlo sampling

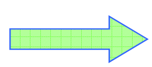
Learning BNs (or GMs)

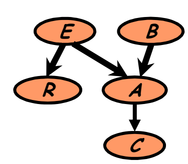
The goal:

Given set of independent samples (*assignments* of random variables), find the *best* (the most likely?) Bayesian Network (both DAG and CPDs)



(B,E,A,C,R)=(T,F,F,T,F)
(B,E,A,C,R)=(T,F,T,T,F)
....
(B,E,A,C,R)=(F,T,T,T,F)



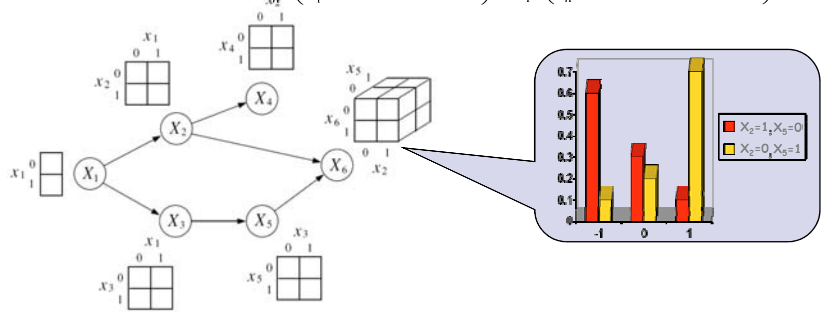


E	B	P(A | E,B)	
e	b	0.9	0.1
e	$\bar{b}$	0.2	0.8
$\bar{e}$	b	0.9	0.1
$\bar{e}$	$\bar{b}$	0.01	0.99

MLE for general BN parameters

- If we assume the parameters for each CPD are globally independent, and all nodes are **fully observed**, then the log-likelihood function decomposes into a sum of local terms, one per node:

$$\ell(\theta; D) = \log p(D \mid \theta) = \log \prod_n \left(\prod_i p(x_{n,i} \mid \mathbf{x}_{n,\pi_i}, \theta_i) \right) = \sum_i \left(\sum_n \log p(x_{n,i} \mid \mathbf{x}_{n,\pi_i}, \theta_i) \right)$$

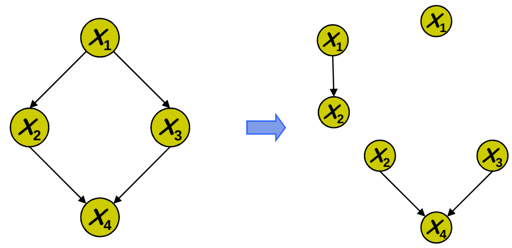


Example: decomposable likelihood of a directed model

- Consider the distribution defined by the directed acyclic GM:

$$p(x \mid \theta) = p(x_1 \mid \theta_1) p(x_2 \mid x_1, \theta_1) p(x_3 \mid x_1, \theta_3) p(x_4 \mid x_2, x_3, \theta_1)$$

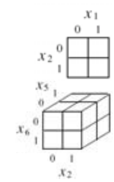
- This is exactly like learning four separate small BNs, each of which consists of a node and its parents.



E.g.: MLE for BNs with tabular CPDs

- Assume each CPD is represented as a table (multinomial) where

$$\theta_{ijk} \overset{\text{def}}{=} p(X_i = j \mid X_{\pi_i} = k)$$



  - Note that in case of multiple parents, $\mathbf{X}_{\pi_i}$ will have a composite state, and the CPD will be a high-dimensional table
  - The sufficient statistics are counts of family configurations

$$n_{ijk} \overset{\text{def}}{=} \sum_n x_{n,i}^j x_{n,\pi_i}^k$$

- The log-likelihood is $\ell(\theta; D) = \log \prod_{i,j,k} \theta_{ijk}^{n_{ijk}} = \sum_{i,j,k} n_{ijk} \log \theta_{ijk}$

- Using a Lagrange multiplier to enforce $\sum_j \theta_{ijk} = 1$, we get: $\theta_{ijk}^{ML} = \dfrac{n_{ijk}}{\sum_{i,j',k} n_{ij'k}}$

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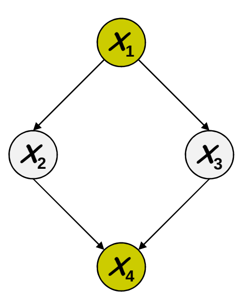
What if some nodes are not observed?

- Consider the distribution defined by the directed acyclic GM:

$$p(x \mid \theta) = p(x_1 \mid \theta_1) p(x_2 \mid x_1, \theta_1) p(x_3 \mid x_1, \theta_3) p(x_4 \mid x_2, x_3, \theta_1)$$



- Need to compute $p(x_H|x_V)$ → inference

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Summary

- Represent dependency structure with a directed acyclic graph
  - Node <-> random variable
  - Edges encode dependencies
    - Absence of edge -> conditional independence
  - Plate representation
  - A BN is a database of prob. Independence statement on variables

- The factorization theorem of the joint probability
  - Local specification → globally consistent distribution
  - Local representation for exponentially complex state-space
- Support efficient inference and learning – next lecture