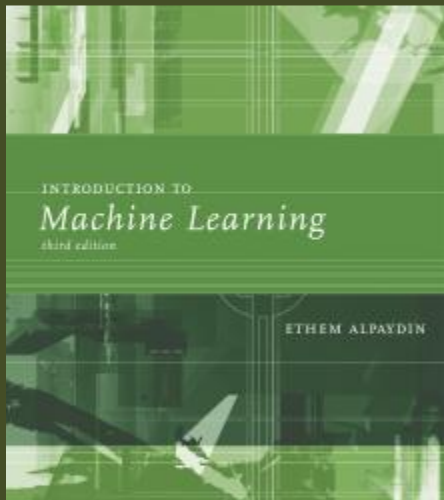


Lecture Slides for

INTRODUCTION TO MACHINE LEARNING

3RD EDITION

ETHEM ALPAYDIN

alpaydin@boun.edu.tr
http://www.cmpe.boun.edu.tr/~ethem/i2ml3e

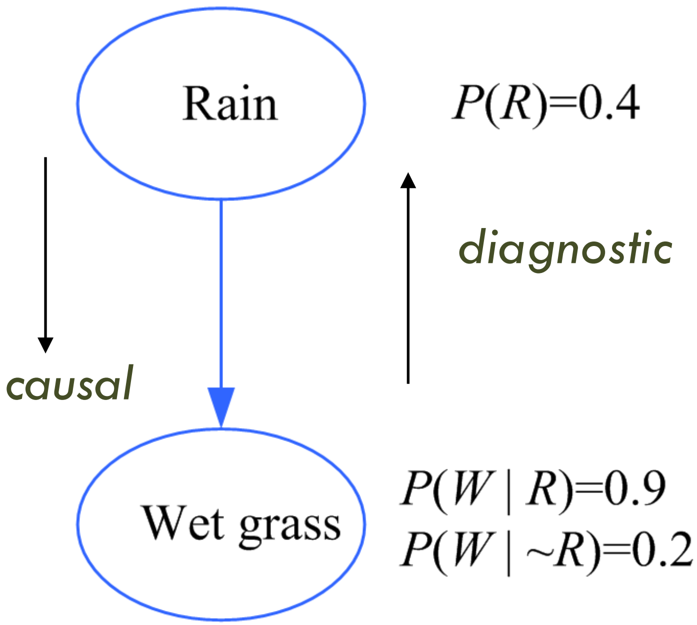
CHAPTER 16:

GRAPHICAL MODELS

Graphical Models

- Aka Bayesian networks, probabilistic networks
- Nodes are hypotheses (random vars) and the probabilities corresponds to our belief in the truth of the hypothesis
- Arcs are direct influences between hypotheses
- The structure is represented as a directed acyclic graph (DAG)
- The parameters are the conditional probabilities in the arcs (Pearl, 1988, 2000; Jensen, 1996; Lauritzen, 1996)

Causes and Bayes' Rule



Diagnostic inference:
Knowing that the grass is wet, what is the probability that rain is the cause?

$$
\begin{aligned}
P(R \mid W) &= \frac{P(W \mid R)P(R)}{P(W)} \\
&= \frac{P(W \mid R)P(R)}{P(W \mid R)P(R) + P(W \mid \sim R)P(\sim R)} \\
&= \frac{0.9 \times 0.4}{0.9 \times 0.4 + 0.2 \times 0.6} = 0.75
\end{aligned}
$$

Conditional Independence

- X and Y are independent if

$$P(X,Y)=P(X)P(Y)$$

- X and Y are conditionally independent given Z if

$$P(X,Y\,|\,Z)=P(X\,|\,Z)P(Y\,|\,Z)$$

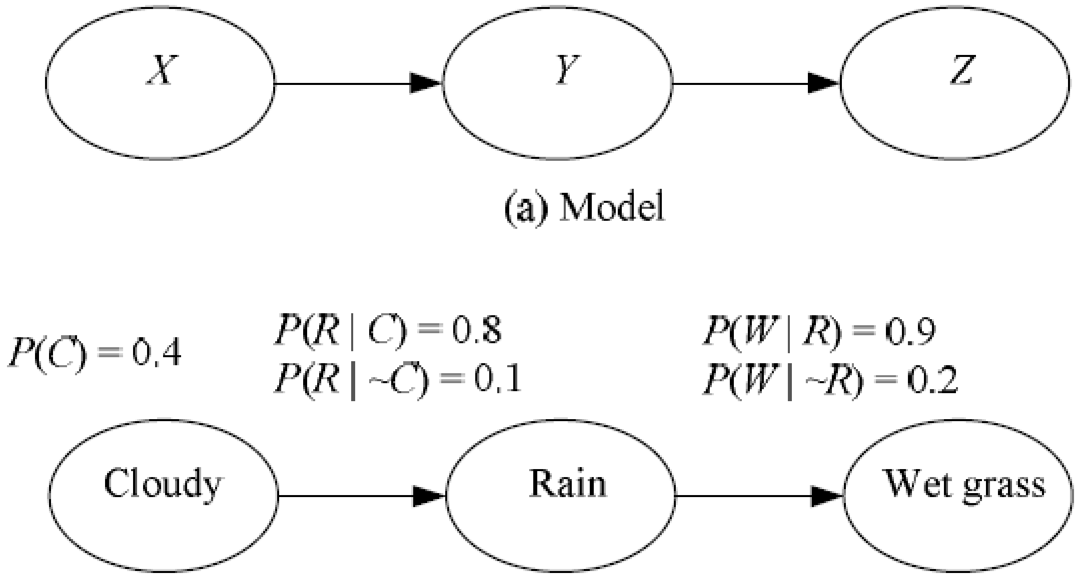
or

$$P(X\,|\,Y,Z)=P(X\,|\,Z)$$

- Three canonical cases: Head-to-tail, Tail-to-tail, head-to-head

Case 1: Head-to-Head

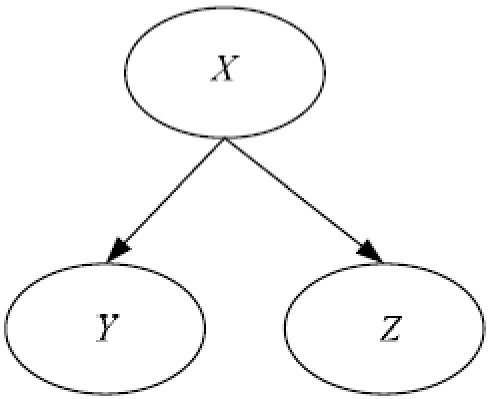
- $P(X,Y,Z)=P(X)P(Y|X)P(Z|Y)$

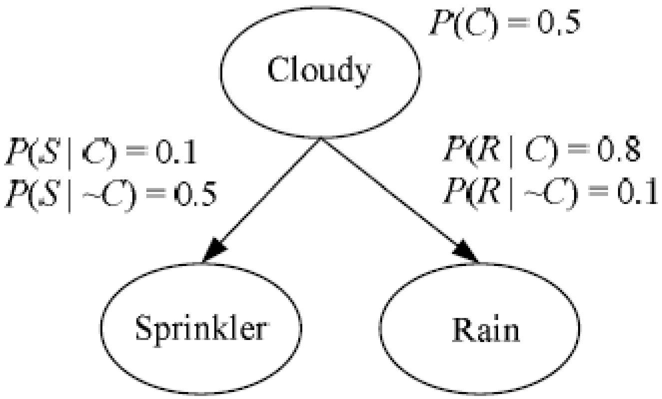


- $P(W|C)=P(W|R)P(R|C)+P(W|{\sim}R)P({\sim}R|C)$

Case 2: Tail-to-Tail

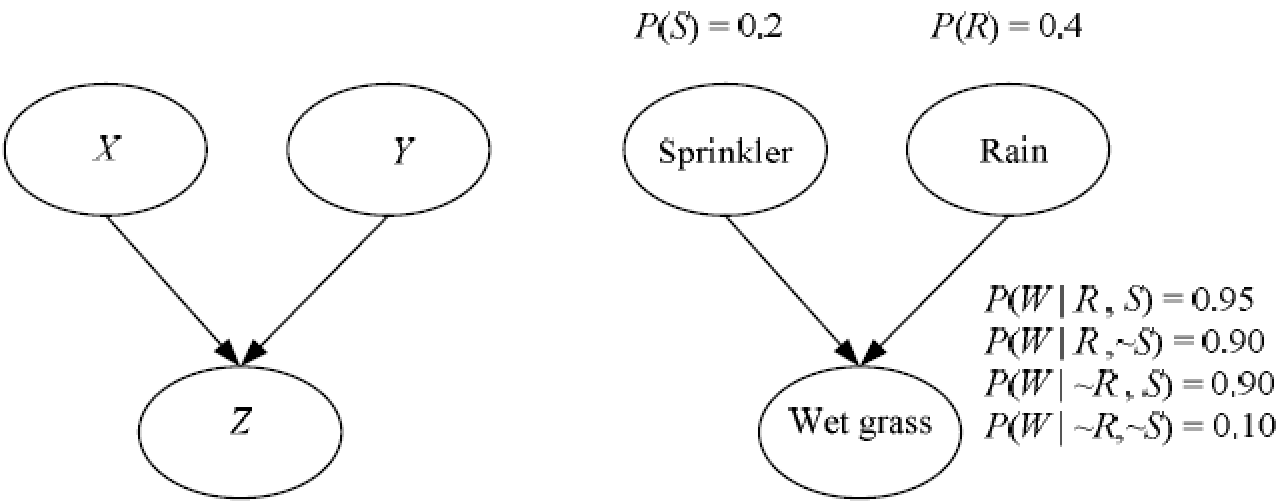
- $P(X,Y,Z) = P(X)P(Y \mid X)P(Z \mid X)$





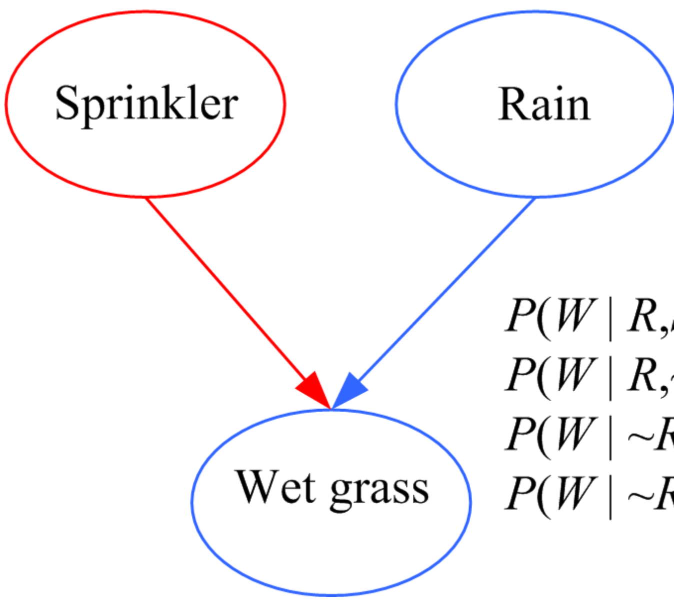
Case 3: Head-to-Head

- $P(X,Y,Z)=P(X)P(Y)P(Z|X,Y)$



Causal vs Diagnostic Inference

$P(S)=0.2$ $P(R)=0.4$



$P(W \mid R,S)=0.95$
$P(W \mid R,\sim S)=0.90$
$P(W \mid \sim R,S)=0.90$
$P(W \mid \sim R,\sim S)=0.10$

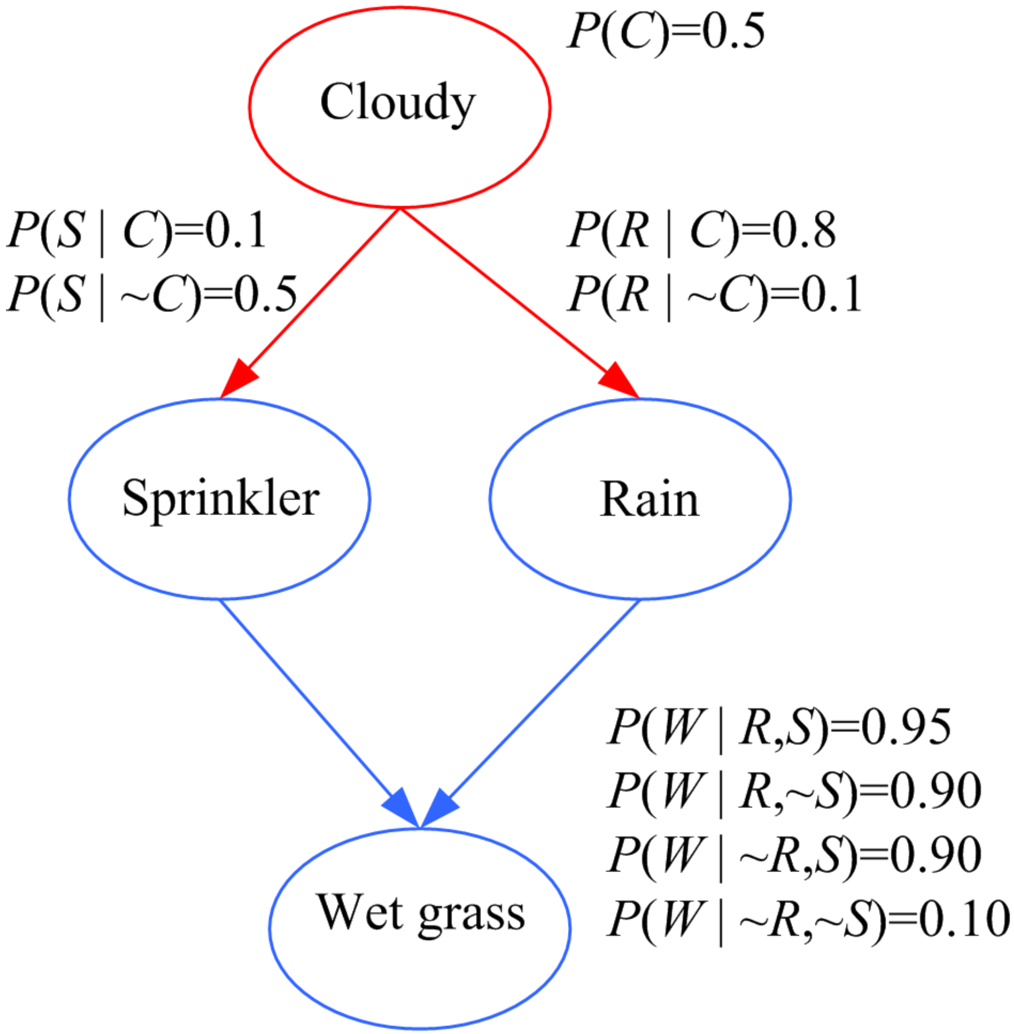
Causal inference: If the sprinkler is on, what is the probability that the grass is wet?

$$P(W|S) = P(W|R,S)\,P(R|S) + P(W|\sim R,S)\,P(\sim R|S)$$
$$= P(W|R,S)\,P(R) + P(W|\sim R,S)\,P(\sim R)$$
$$= 0.95\ 0.4 + 0.9\ 0.6 = 0.92$$

Diagnostic inference: If the grass is wet, what is the probability that the sprinkler is on? $P(S|W) = 0.35 > 0.2\ P(S)$

$P(S|R,W) = 0.21$ *Explaining away: Knowing that it has rained decreases the probability that the sprinkler is on.*

Causes



Causal inference:

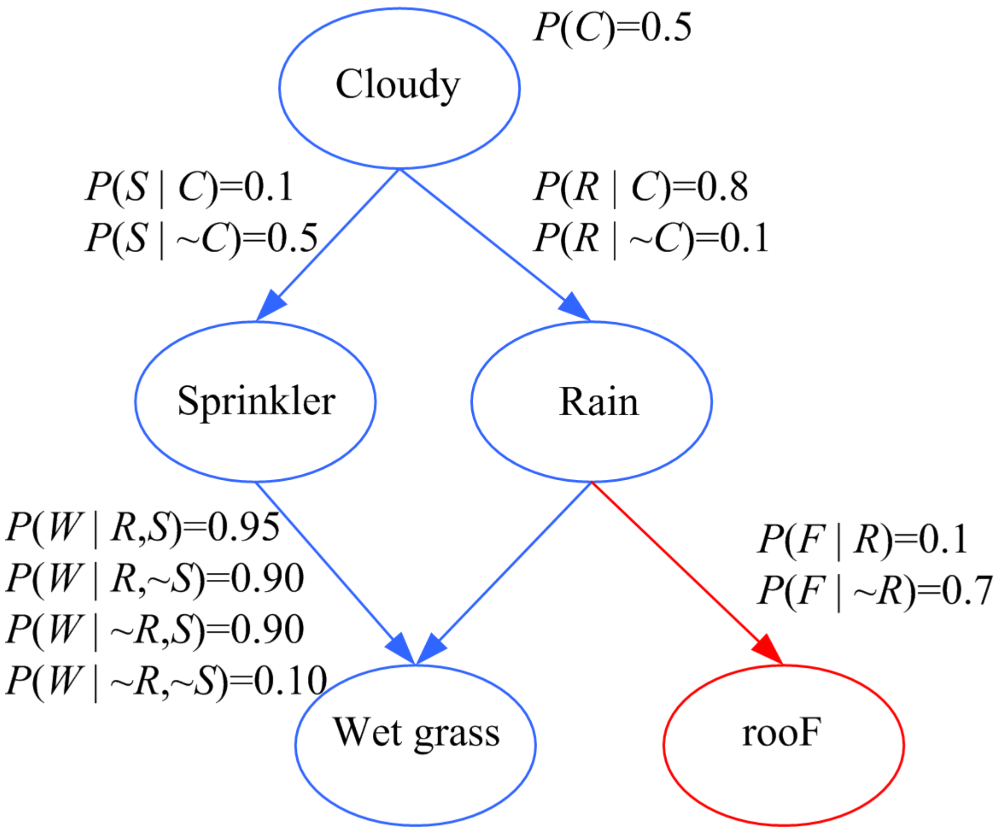
$$P(W|C) = P(W|R,S)\,P(R,S|C) + P(W|{\sim}R,S)\,P({\sim}R,S|C) + P(W|R,{\sim}S)\,P(R,{\sim}S|C) + P(W|{\sim}R,{\sim}S)\,P({\sim}R,{\sim}S|C)$$

and use the fact that

$$P(R,S|C) = P(R|C)\,P(S|C)$$

Diagnostic: $P(C|W) = ?$

Exploiting the Local Structure



$P(F \mid C) = ?$

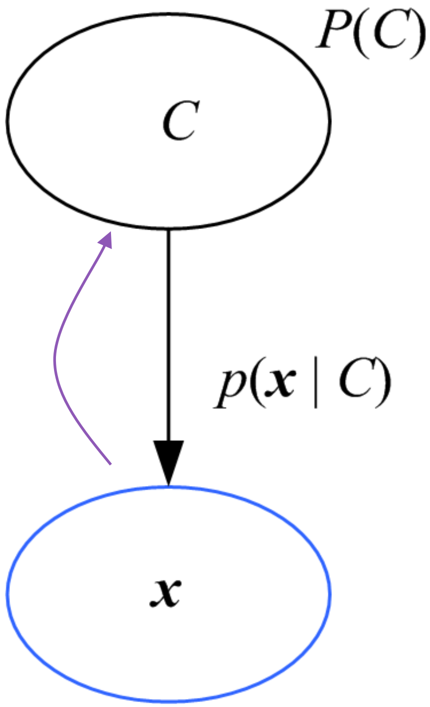
$$P(C,S,R,W,F) = P(C)P(S|C)P(R|C)P(W|S,R)P(F|R)$$

$$P(X_1,\ldots X_d) = \prod_{i=1}^{d} P(X_i \mid \text{parents}(X_i))$$

Classification

diagnostic

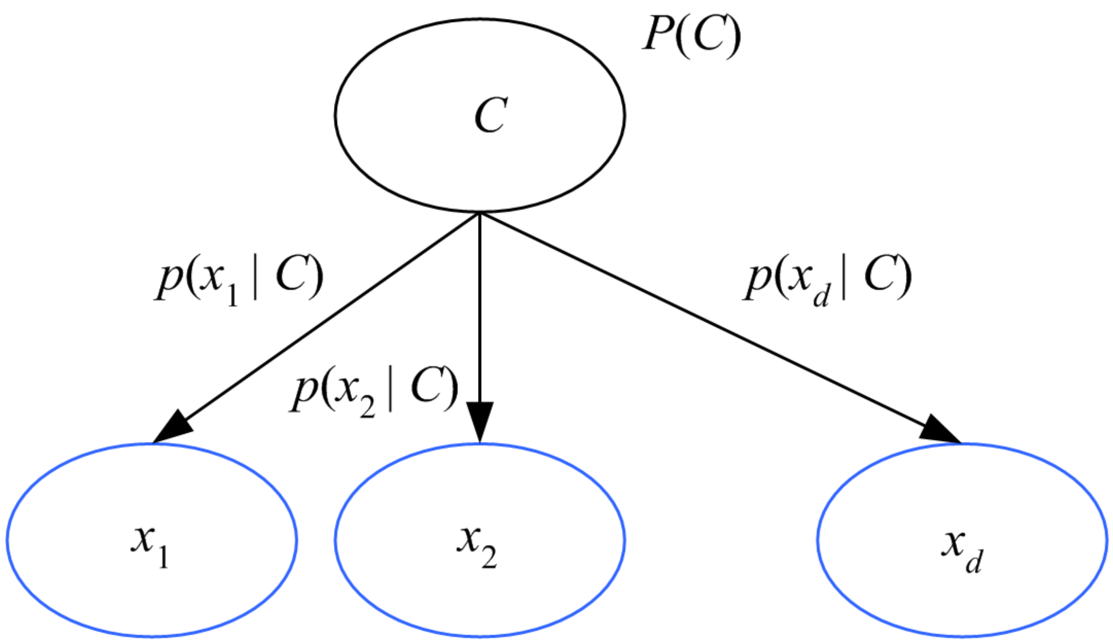
P (C | x)



Bayes' rule inverts the arc:

$$P(C \mid \mathbf{x}) = \frac{p(\mathbf{x} \mid C)P(C)}{p(\mathbf{x})}$$

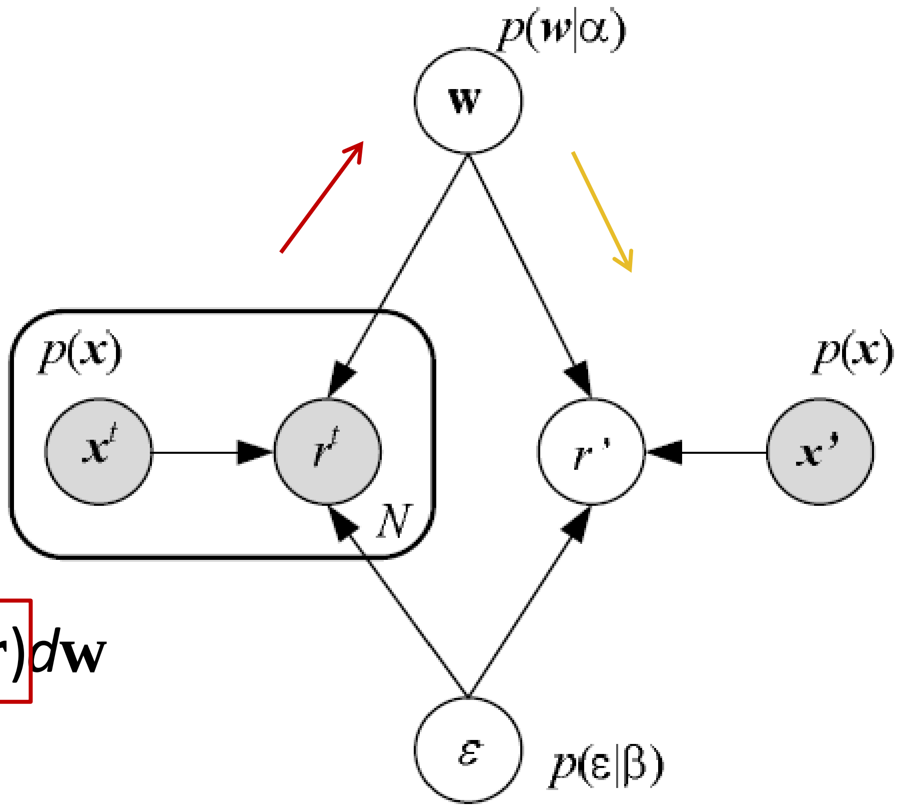
Naive Bayes' Classifier



Given C, x_i are independent:

$$p(\mathbf{x} \mid C) = p(x_1 \mid C)\, p(x_2 \mid C) \ldots p(x_d \mid C)$$

Linear Regression



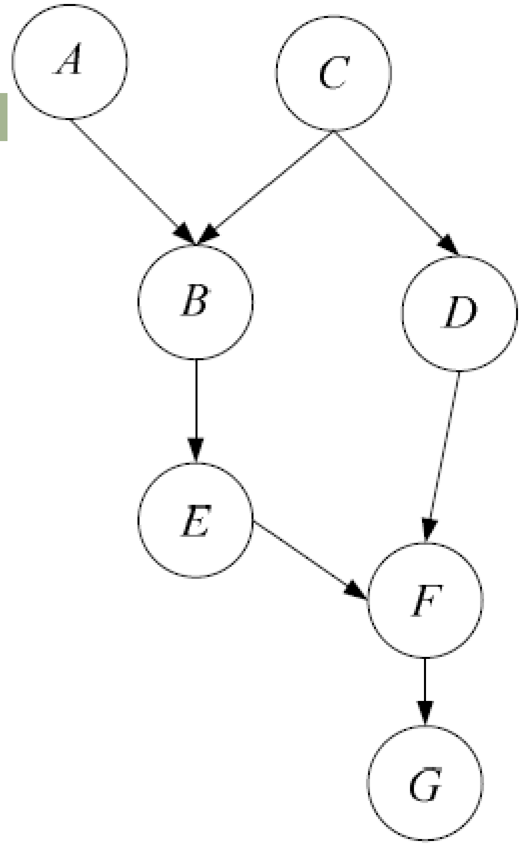
$$p(r'|\mathbf{x}',\mathbf{r},\mathbf{X}) = \int p(r'|\mathbf{x}',\mathbf{w})\,p(\mathbf{w}|\mathbf{X},\mathbf{r})\,d\mathbf{w}$$

$$= \int p(r'|\mathbf{x}',\mathbf{w}) \frac{p(\mathbf{r}|\mathbf{X},\mathbf{w})p(\mathbf{w})}{p(\mathbf{r})} d\mathbf{w}$$

$$\propto \int p(r'|\mathbf{x}',\mathbf{w}) \prod_t p(r^t|\mathbf{x}^t,\mathbf{w})p(\mathbf{w})d\mathbf{w}$$

d-Separation

- A path from node *A* to node *B* is blocked if
  a) The directions of edges on the path meet head-to-tail (case 1) or tail-to-tail (case 2) and the node is in C, or
  b) The directions of edges meet head-to-head (case 3) and neither that node nor any of its descendants is in C.
- If all paths are blocked, *A* and *B* are d-separated (conditionally independent) given C.



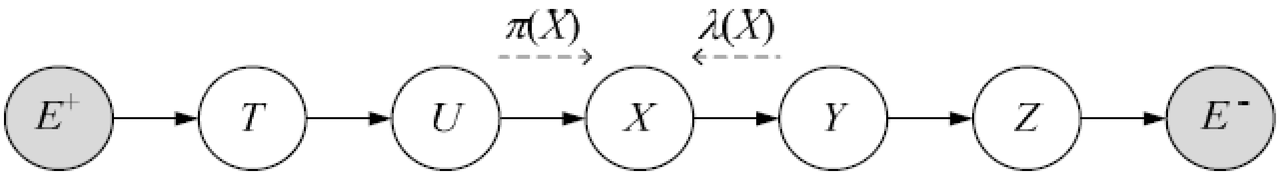
BCDF is blocked given C.

BEFG is blocked by *F*.

BEFD is blocked unless *F* (or G) is given.

Belief Propagation (Pearl, 1988)

- Chain:



$$P(X|E)=\frac{P(E|X)P(X)}{P(E)}=\frac{P(E^+,E^-|X)P(X)}{P(E)}$$

$$=\frac{P(E^+|X)P(E^-|X)P(X)}{P(E)}=\alpha\pi(X)\lambda(X)$$

$$\pi(X)=\sum_U P(X|U)\pi(U)$$

$$\lambda(X)=\sum_Y P(Y|X)\lambda(Y)$$

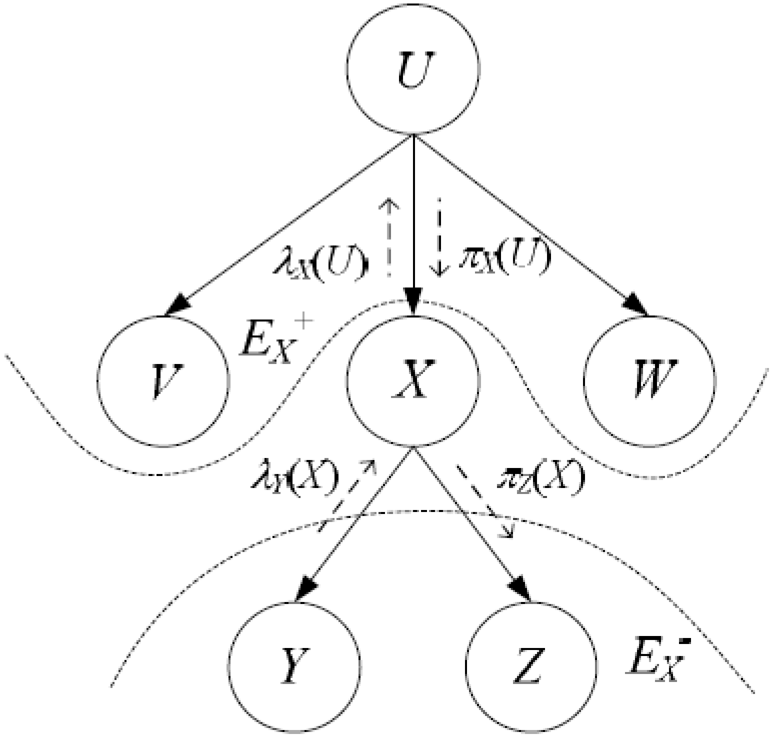
Trees

$$\lambda(X) = P(E_X^- \mid X) = \lambda_Y(X)\lambda_Z(X)$$

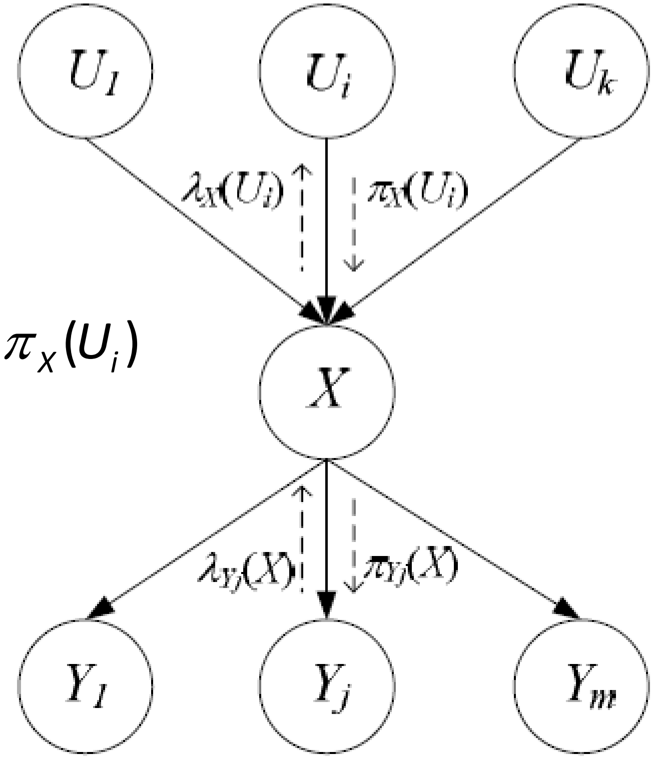
$$\lambda_X(U) = \sum_X \lambda(X) P(X \mid U)$$

$$\pi(X) = P(X \mid E_X^+) = \sum_U P(X \mid U)\pi_X(U)$$

$$\pi_y(X) = \alpha \lambda_Z(X)\pi(X)$$



Polytrees



$$\pi(X) = P(X \mid E_X^+) = \sum_{U_1}\sum_{U_2}\cdots\sum_{U_k} P(X \mid U_1, U_2, \cdots, U_k) \prod_{i=1}^{k} \pi_X(U_i)$$

$$\pi_{y_j}(X) = \alpha \prod_{s \neq j} \lambda_{Y_s}(X)\pi(X)$$

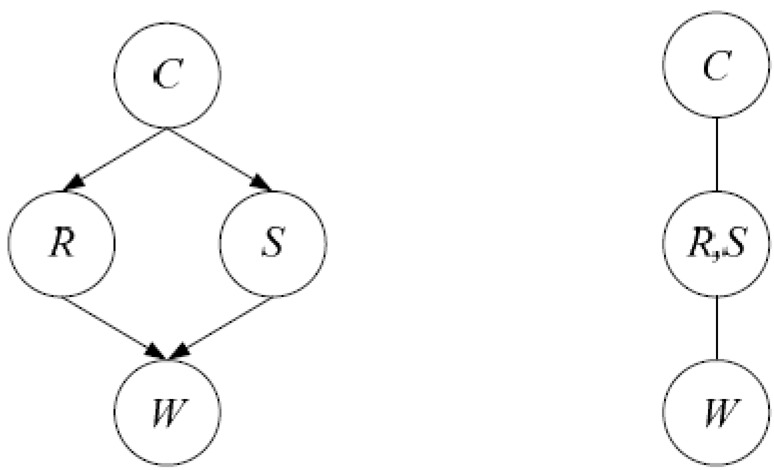
$$\lambda_X(U_i) = \beta \sum_X \lambda(X) \sum_{U_{r \neq i}} P(X \mid U_1, U_2, \cdots, U_k) \prod_{r \neq i} \pi_X(U_r)$$

$$\lambda(X) = \prod_{j=1}^{m} \lambda_{Y_j}(X)$$

How can we model $P(X \mid U_1, U_2, \ldots, U_k)$ cheaply?

Junction Trees

- If *X* does not separate E^+ and E^-, we convert it into a junction tree and then apply the polytree algorithm



Tree of moralized, clique nodes

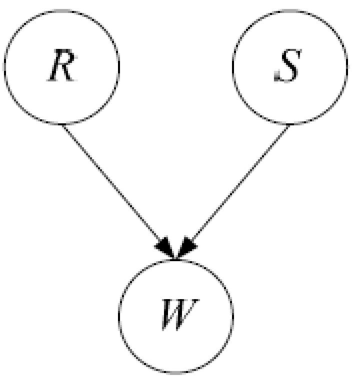
Undirected Graphs: Markov Random Fields

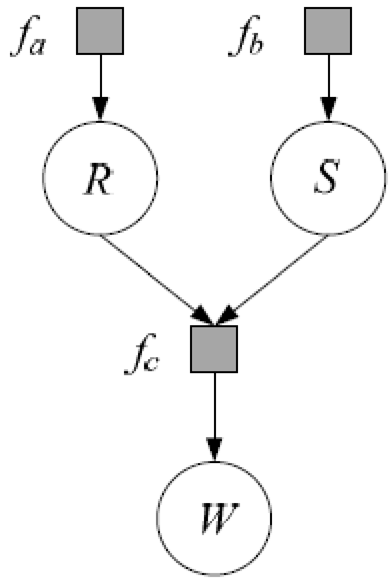
- In a Markov random field, dependencies are symmetric, for example, pixels in an image
- In an undirected graph, *A* and *B* are independent if removing C makes them unconnected.
- Potential function $\psi_c(X_c)$ shows how favorable is the particular configuration *X* over the clique C
- The joint is defined in terms of the clique potentials

$$p(X) = \frac{1}{Z}\prod_{C}\psi_C(X_C) \text{ where normalizer } Z = \sum_{X}\prod_{C}\psi_C(X_C)$$

Factor Graphs

- Define new factor nodes and write the joint in terms of them





$$p(X) = \frac{1}{Z} \prod_{s} f_s(X_s)$$

Learning a Graphical Model

- Learning the conditional probabilities, either as tables (for discrete case with small number of parents), or as parametric functions
- Learning the structure of the graph: Doing a state-space search over a score function that uses both goodness of fit to data and some measure of complexity

Influence Diagrams