

Parametric Models

Part IV: Bayesian Belief Networks

Selim Aksoy
Bilkent University
Department of Computer Engineering
saksoy@cs.bilkent.edu.tr

Introduction

- Recall Bayesian minimum-error classification: Given an observation (feature) vector \mathbf{x} of a pattern and class-conditional densities $p(\mathbf{x}|w_i)$, assign it to the class with the highest posterior probability $P(w_i|\mathbf{x})$.
- We have studied different parametric models to estimate the class-conditional probability densities:
 - ▶ Univariate or multivariate Gaussians
 - ▶ Mixtures of Gaussians
 - ▶ Hidden Markov Models
- We will study a new class of models, Bayesian Belief Networks, to model the class-conditional densities.

Bayesian Networks

- *Bayesian networks (BN)* are probabilistic graphical models that are based on directed acyclic graphs.
- They provide a tool to deal with two problems: uncertainty and complexity.
- Hence, they provide a compact representation of joint probability distributions using a combination of graph theory and probability theory.
- The graph structure specifies statistical dependencies among the variables and the local probabilistic models specify how these variables are combined.

Bayesian Networks

- There are two components of a BN model: $\mathcal{M} = \{\mathcal{G}, \Theta\}$
 - ▶ Each node in the graph \mathcal{G} represents a random variable and edges represent conditional independence relationships.
 - ▶ The set Θ of parameters specifies the probability distributions associated with each variable.
- Edges represent “causation” so no directed cycles are allowed.
- Markov property: Each node is conditionally independent of its ancestors given its parents.

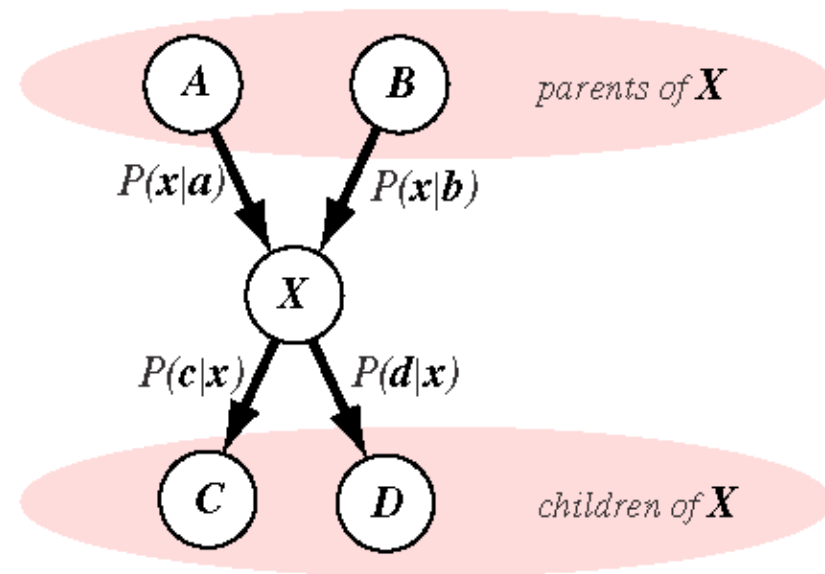


Figure 1: An example BN.

Bayesian Networks

- The joint probability of a set of variables x_1, \dots, x_n is given as

$$P(x_1, \dots, x_n) = \prod_{i=1}^n P(x_i | x_1, \dots, x_{i-1})$$

using the chain rule.

- The conditional independence relationships encoded in the Bayesian network state that a node x_i is conditionally independent of its ancestors given its parents π_i . Therefore,

$$P(x_1, \dots, x_n) = \prod_{i=1}^n P(x_i | \pi_i)$$

- Once we know the joint probability distribution encoded in the network, we can answer all possible inference questions about the variables using marginalization.

Bayesian Network Examples

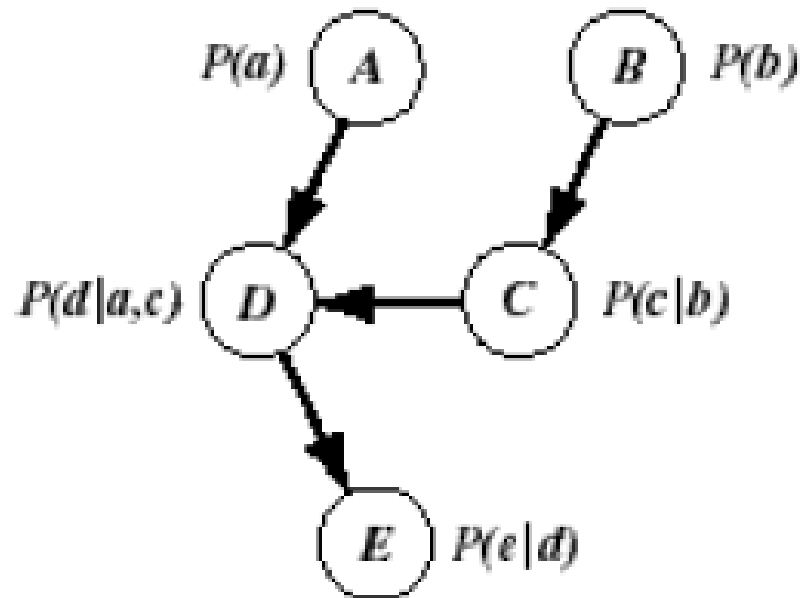


Figure 2: $P(a, b, c, d, e) = P(a)P(b)P(c|b)P(d|a, c)P(e|d)$

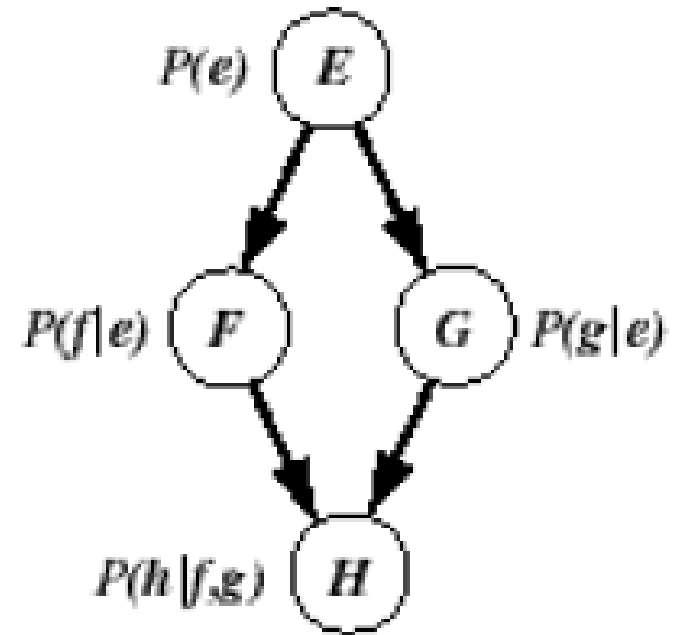


Figure 4: $P(e, f, g, h) = P(e)P(f|e)P(g|e)P(h|f, g)$

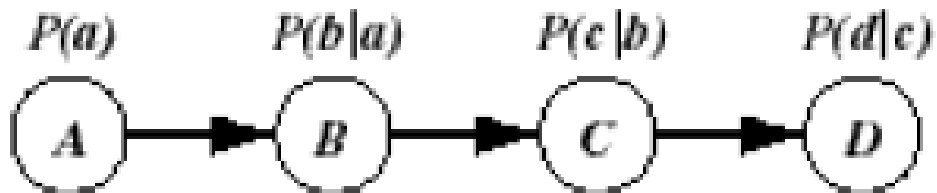


Figure 3:
 $P(a, b, c, d) = P(a)P(b|a)P(c|b)P(d|c)$

Bayesian Network Examples

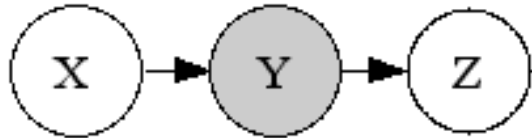


Figure 5: When y is given, x and z are conditionally independent. Think of x as the past, y as the present, and z is the future.

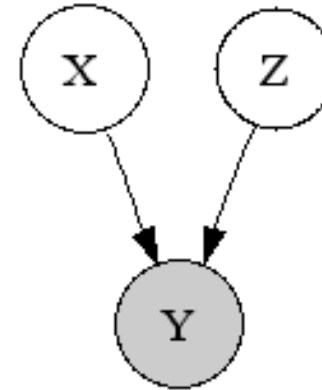


Figure 7: x and z are marginally independent, but when y is given, they are conditionally dependent. This is called explaining away.

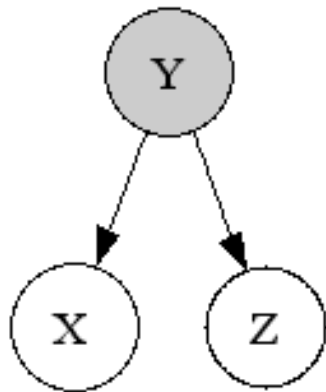


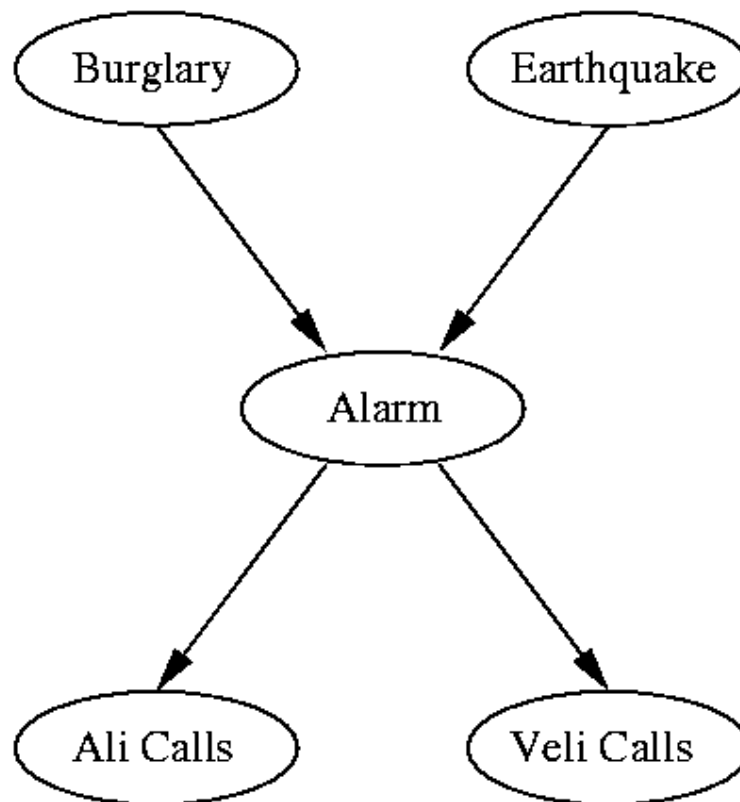
Figure 6: When y is given, x and z are conditionally independent. Think of y as the common cause of the two independent effects x and z .

Bayesian Network Examples

- You have a new burglar alarm installed at home.
- It is fairly reliable at detecting burglary, but also sometimes responds to minor earthquakes.
- You have two neighbors, Ali and Veli, who promised to call you at work when they hear the alarm.
- Ali always calls when he hears the alarm, but sometimes confuses telephone ringing with the alarm and calls too.
- Veli likes loud music and sometimes misses the alarm.
- Given the evidence of who has or has not called, we would like to estimate the probability of a burglary.

Bayesian Network Examples

$P(B=T)$	$P(B=F)$
0.001	0.999



$P(E=T)$	$P(E=F)$
0.002	0.998

B	E	$P(A=T)$	$P(A=F)$
T	T	0.95	0.05
T	F	0.94	0.06
F	T	0.29	0.71
F	F	0.001	0.999

A	$P(AC=T)$	$P(AC=F)$
T	0.90	0.10
F	0.05	0.95

A	$P(VC=T)$	$P(VC=F)$
T	0.70	0.30
F	0.01	0.99

Figure 8: The Bayesian network for the burglar alarm example. Burglary (B) and earthquakes (E) directly affect the probability of the alarm (A) going off, but whether or not Ali calls (AC) or Veli calls (VC) depends only on the alarm. (Russell and Norvig, Artificial Intelligence: A Modern Approach, 1995)

Bayesian Network Examples

- What is the probability that the alarm has sounded but neither a burglary nor an earthquake has occurred, and both Ali and Veli call?

$$P(AC, VC, A, \neg B, \neg E)$$

$$= P(AC|A)P(VC|A)P(A|\neg B, \neg E)P(\neg B)P(\neg E)$$

$$= 0.90 \times 0.70 \times 0.001 \times 0.999 \times 0.998$$

$$= 0.00062$$

(capital letters represent variables having the value true, and \neg represents negation)

Bayesian Network Examples

- What is the probability that there is a burglary given that Ali calls?

$$\begin{aligned}P(B|AC) &= \frac{P(B, AC)}{P(AC)} \\&= \frac{\sum_{vc} \sum_a \sum_e P(AC|a)P(vc|a)P(a|B, e)P(B)P(e)}{P(B, AC) + P(\neg B, AC)} \\&= \frac{0.00084632}{0.00084632 + 0.0513} \\&= 0.0162\end{aligned}$$

- What about if Veli also calls right after Ali hangs up?

$$P(B|AC, VC) = \frac{P(B, AC, VC)}{P(AC, VC)} = 0.29$$

Bayesian Network Examples

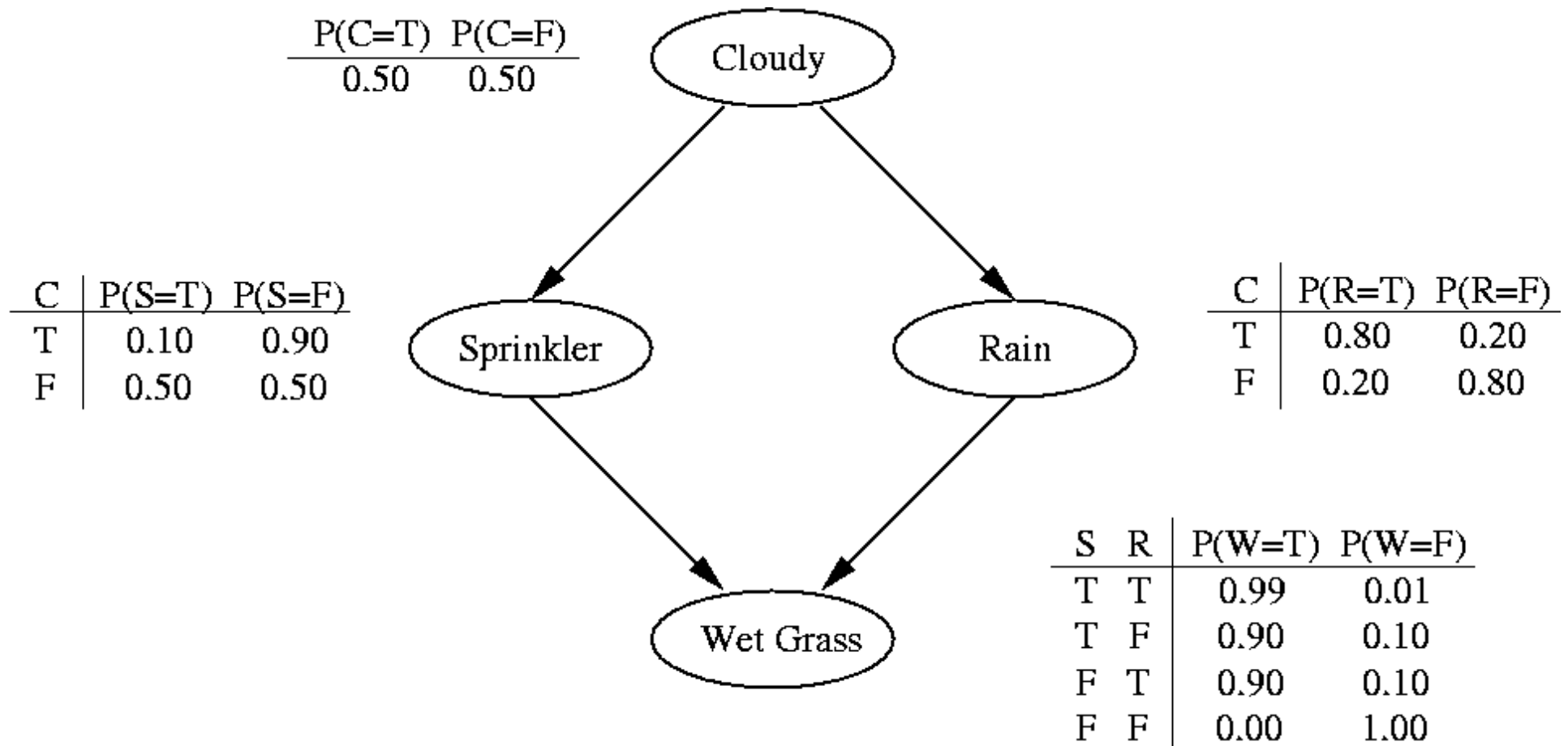


Figure 9: Another Bayesian network example. The event that the grass being wet ($W = \text{true}$) has two possible causes: either the water sprinkler is on ($S = \text{true}$) or it is raining ($R = \text{true}$). (Russell and Norvig, *Artificial Intelligence: A Modern Approach*, 1995)

Bayesian Network Examples

- Suppose we observe the fact that the grass is wet. There are two possible causes for this: either it is raining, or the sprinkler is on. Which one is more likely?

$$P(S|W) = \frac{P(S, W)}{P(W)} = \frac{0.2781}{0.6471} = 0.430$$

$$P(R|W) = \frac{P(R, W)}{P(W)} = \frac{0.4581}{0.6471} = 0.708$$

- We see that it is more likely that the grass is wet because it is raining.

Applications of Bayesian Networks

- Example applications include:
 - ▶ Machine learning
 - ▶ Statistics
 - ▶ Computer vision
 - ▶ Natural language processing
 - ▶ Speech recognition
 - ▶ Error-control codes
 - ▶ Bioinformatics
 - ▶ Medical diagnosis
 - ▶ Weather forecasting
- Example systems include:
 - ▶ PATHFINDER medical diagnosis system at Stanford
 - ▶ Microsoft Office assistant and troubleshooters
 - ▶ Space shuttle monitoring system at NASA Mission Control Center in Houston

Two Fundamental Problems for Bayesian Networks

- *Evaluation (inference) problem:* Given the model and the values of the observed variables, estimate the values of the hidden nodes.
- *Learning problem:* Given training data and prior information (e.g., expert knowledge, causal relationships), estimate the network structure, or the parameters of the probability distributions, or both.

Bayesian Network Evaluation Problem

- If we observe the “leaves” and try to infer the values of the hidden causes, this is called diagnosis, or bottom-up reasoning.
- If we observe the “roots” and try to predict the effects, this is called prediction, or top-down reasoning.
- *Exact inference* is an NP-hard problem because the number of terms in the summations (integrals) for discrete (continuous) variables grows exponentially with increasing number of variables.

Bayesian Network Evaluation Problem

- Some restricted class of networks, namely the singly connected networks where there is no more than one path between any two nodes, can be efficiently solved in time linear in the number of nodes.
- There are also clustering algorithms that convert multiply connected networks to single connected ones.
- However, *approximate inference* methods such as
 - ▶ sampling (Monte Carlo) methods
 - ▶ variational methods
 - ▶ loopy belief propagationhave to be used for most of the cases.

Bayesian Network Learning Problem

- The simplest situation is the one where the network structure is completely known (either specified by an expert or designed using causal relationships between the variables).
- Other situations with increasing complexity are known structure but unobserved variables, unknown structure with observed variables, and unknown structure with unobserved variables.

Table 1: Four cases in Bayesian network learning.

Structure	Observability	
	Full	Partial
Known	Maximum Likelihood Estimation	EM (or gradient ascent)
Unknown	Search through model space	EM + search through model space

Known Structure, Full Observability

- The joint pdf of the variables with parameter set Θ is

$$p(x_1, \dots, x_n | \Theta) = \prod_{i=1}^n P(x_i | \pi_i, \theta_i)$$

where θ_i is the vector of parameters for the conditional distribution of x_i and $\Theta = (\theta_1, \dots, \theta_n)$.

- Given training data $\mathcal{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_m\}$ where $\mathbf{x}_l = (x_{l1}, \dots, x_{ln})^T$, the log-likelihood of Θ with respect to \mathcal{X} can be computed as

$$\log L(\Theta | \mathcal{X}) = \sum_{l=1}^m \sum_{i=1}^n \log p(x_{li} | \pi_i, \theta_i)$$

Known Structure, Full Observability

- The likelihood decomposes according to the structure of the network so we can compute the MLEs for each node independently.
- An alternative is to assign a prior probability density function $p(\theta_i)$ to each θ_i and use the training data \mathcal{X} to compute the posterior distribution $p(\theta_i|\mathcal{X})$ and the Bayes estimate $E_{p(\theta_i|\mathcal{X})}[\theta_i]$.
- We will study the special case of discrete variables with discrete parents.

Known Structure, Full Observability

- Let each discrete variable x_i have r_i possible values (states) with probabilities

$$p(x_i = k | \pi_i = j, \theta_i) = \theta_{ijk} > 0$$

where $k \in \{1, \dots, r_i\}$, j is the state of x_i 's parents and $\theta_i = \{\theta_{ijk}\}$ specifies the parameters of the multinomial distribution for every combination of π_i .

- Given \mathcal{X} , the MLE of θ_{ijk} can be computed as

$$\hat{\theta}_{ijk} = \frac{N_{ijk}}{N_{ij}}$$

where N_{ijk} is the number of cases in \mathcal{X} in which $x_i = k$ and $\pi_i = j$, and $N_{ij} = \sum_{k=1}^{r_i} N_{ijk}$.

Known Structure, Full Observability

- Thus, learning just amounts to counting (in the case of multinomial distributions).
- For example, to compute the estimate for the W node in the water sprinkler example, we need to count

$$\#(W = T, S = T, R = T)$$

$$\#(W = T, S = T, R = F)$$

$$\#(W = T, S = F, R = T)$$

⋮

$$\#(W = F, S = F, R = F)$$

Known Structure, Full Observability

- Note that, if a particular event is not seen, it will be assigned a probability of 0.
- We can avoid this using the Bayes estimate with a Dirichlet($\alpha_{ij1}, \dots, \alpha_{ijr_i}$) prior (the conjugate prior for the multinomial) that gives

$$\hat{\theta}_{ijk} = \frac{\alpha_{ijk} + N_{ijk}}{\alpha_{ij} + N_{ij}}$$

where $\alpha_{ij} = \sum_{k=1}^{r_i} \alpha_{ijk}$ and $N_{ij} = \sum_{k=1}^{r_i} N_{ijk}$ as before.

- α_{ij} is sometimes called the equivalent sample size for the Dirichlet distribution.

Naive Bayesian Network

- When the dependencies among the features are unknown, we generally proceed with the simplest assumption that the features are conditionally independent given the class.
- This corresponds to the *naive Bayesian network* that gives the class-conditional probabilities

$$p(x_1, \dots, x_n | w) = \prod_{i=1}^n p(x_i | w)$$

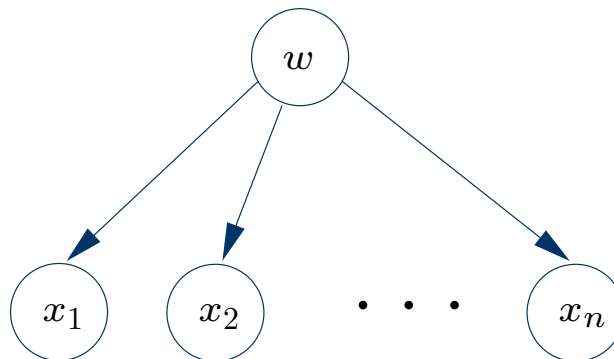


Figure 10: Naive Bayesian network structure. It looks like a very simple model but it often works quite well in practice.