

# Business Analytics

## Naïve Bayes and Bayes Networks

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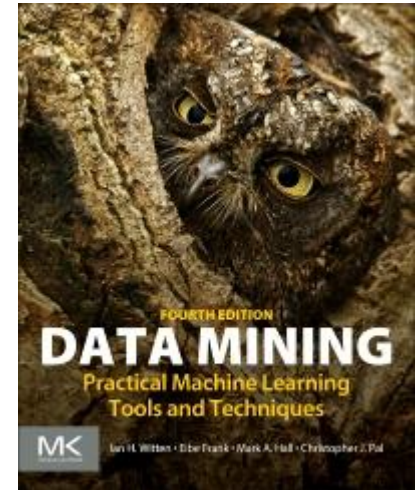
# Course Content

- Introduction
- Regression Analysis
- Regression Diagnostics
- Logistic and Poisson Regression
- **Naive Bayes and Bayesian Networks**
- Decision Tree Classifiers
- Data Preparation and Causal Inference
- Model Selection and Learning Theory
- Ensemble Methods and Clustering
- High-Dimensional Problems
- Association Rules and Recommenders
- Neural Networks



# Recommended Literature

- **Data Mining: Practical Machine Learning Tools and Techniques**
  - Ian H. Witten, Eibe Frank, Mark A. Hall, Christopher Pal
  - <http://www.cs.waikato.ac.nz/ml/weka/book.html>
  - Section: 4.1, 4.2, 9.1, 9.2
- **Alternative literature**
  - Machine Learning
    - Tom M. Mitchell, 1997
  - Data Mining: Introductory and Advanced Topics
    - Margaret H. Dunham, 2003



# Formal Definition of Classification

- **Classification:** Given a database  $D = \{x_1, x_2, \dots, x_n\}$  of tuples (items, records) and a set of classes  $C = \{C_1, C_2, \dots, C_m\}$ , the classification problem is to define a mapping  $f: D \rightarrow C$  where each  $x_i$  is assigned to one class. A class,  $C_j$ , contains precisely those tuples mapped to it; that is,  
$$C_j = \{x_i \mid f(x_i) = C_j, 1 \leq i \leq n, \text{ and } x_i \in D\}.$$
  - The *logistic regression* is used for classification.
- **Prediction** is similar, but usually implies a mapping to numeric values instead of a class  $C_j$

# Example Applications

- Determine if a bank customer for a loan is a low, medium, or high risk customer
- Churn prediction (typically a classification task)
- Determine if a sequence of credit card purchases indicates questionable behavior
- Identify customers that may be willing to purchase particular insurance policies
- Identify patterns of gene expression that indicate the patient has cancer
- Identify spam mail
- ...

# Algorithms for Classification

- Logistic Regression
- Statistical Modeling (e.g., Naïve Bayes)
- Decision Trees: Divide and Conquer
- Classification Rules (e.g. PRISM)
- Instance-Based Learning (e.g. kNN)
- Support Vector Machines
- ...



# Naïve Bayes Classifier

- Naive Bayes classifier takes all attributes into account
- Assumptions
  - All attributes equally important
  - All attributes independent
    - This means that knowledge about the value of a particular attribute doesn't tell us anything about the value of another attribute
- Although based on assumptions that are almost never correct, this scheme works often well in practice!



# Bayes Theorem: Some Notation

- Let  $\Pr[e]$  represent the prior or unconditional probability that proposition  $e$  is true.
  - Example: Let  $e$  represent that a customer is a high credit risk.  
 $\Pr[e] = 0.1$  means that there is a 10% chance a customer is a high credit risk.
- Probabilities of events change when we know something about the world
  - The notation  $\Pr[e|h]$  represents the conditional or posterior probability of  $e$
  - Read “the probability of  $e$  given that all we know is  $h$ .”
    - $\Pr[e = \textit{high risk} | h = \textit{unemployed}] = 0.60$
- The notation  $\Pr[E]$  is used to represent the probability distribution of all possible values of a random variable  $E$ 
  - E.g.:  $\Pr[\textit{Risk}] = \langle 0.7, 0.2, 0.1 \rangle$




# Conditional Probability



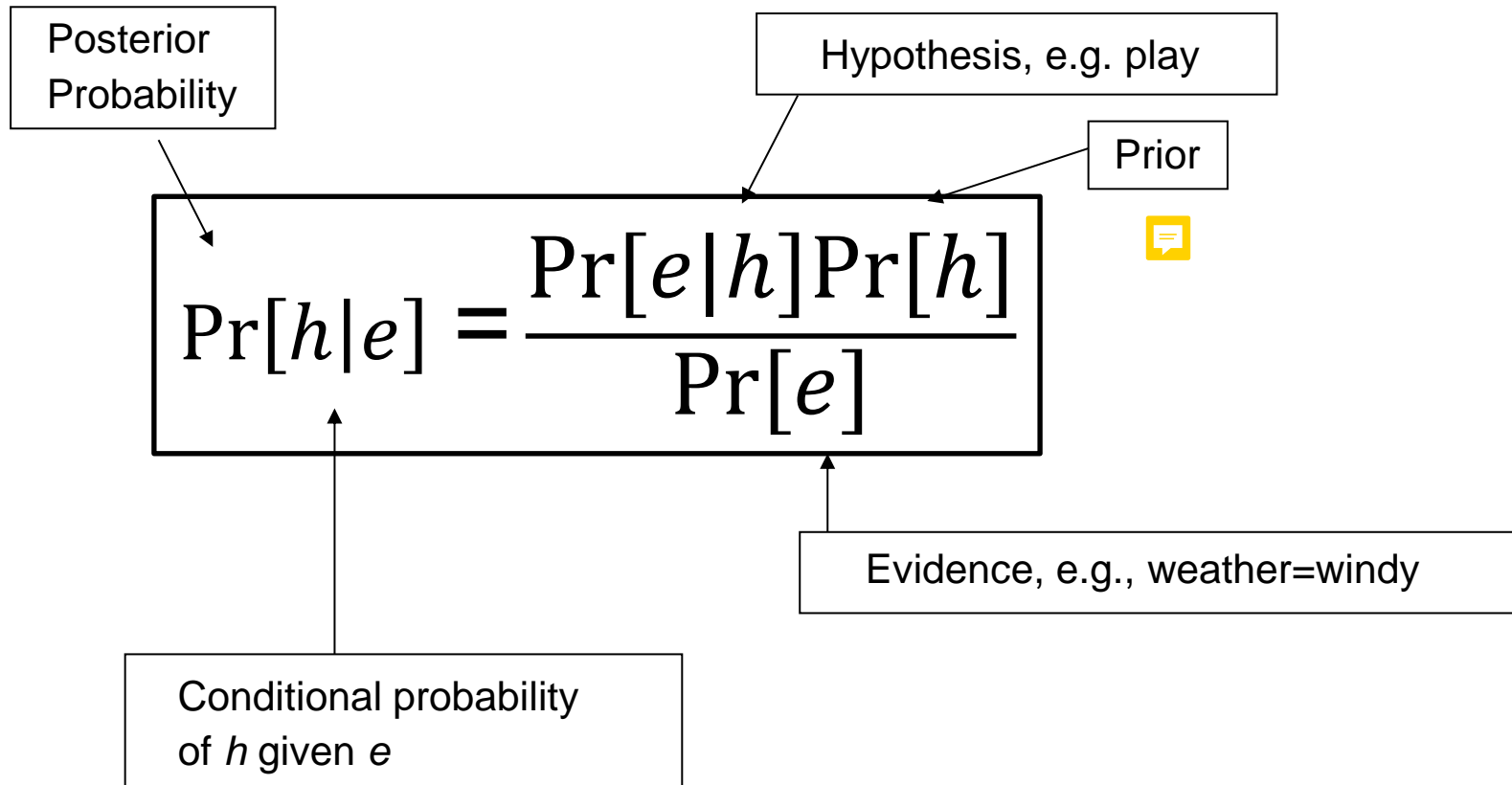
- Imagine that 5% of people of a given population own at least one TV. 2% of people own at least one TV and at least one computer. What is the probability that someone will own a computer, given that they also have a TV?
- Let  $a$  = “TV owner”,  $b$  = “computer owner”, then:
  - $\Pr[a] = 0.05$ ;  $\Pr[a \cap b] = 0.02$
  - $\Pr[b | a] = \Pr[a \cap b] / \Pr[a] = 0.4$
- If events  $a$  and  $b$  do not influence each other, then
  - $\Pr[a | b] = \Pr[a]$  and  $\Pr[a \cap b] = \Pr[a]P[b]$
  - For example, throw a coin two times

# Conditional Probability and Bayes Rule

- The product rule for conditional probabilities 
  - $\Pr[e|h] = \Pr[e \cap h] / \Pr[h]$
  - $\Pr[e \cap h] = \Pr[e|h]\Pr[h] = \Pr[h|e]\Pr[e]$  (product rule)
  - $\Pr[e \cap h] = \Pr[e]\Pr[h]$  (for independent random variables)
- Bayes' rule relates conditional probabilities
  - $\Pr[e \cap h] = \Pr[e|h]\Pr[h]$
  - $\Pr[e \cap h] = \Pr[h|e]\Pr[e]$

$$\Pr[h|e] = \frac{\Pr[e|h]\Pr[h]}{\Pr[e]}$$

# Bayes Theorem

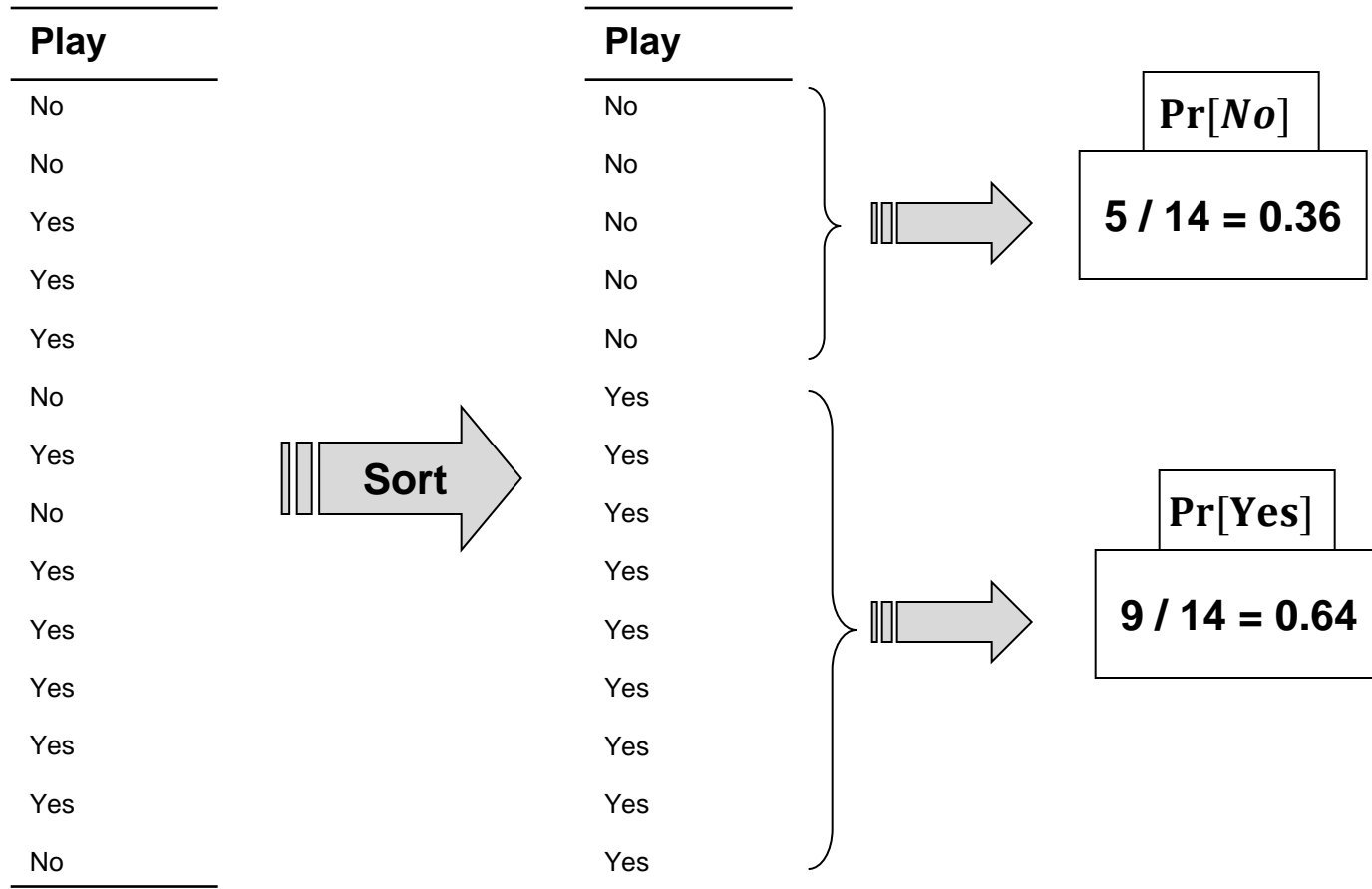


# Dataset



<b>Outlook</b>	<b>Temp</b>	<b>Humidity</b>	<b>Windy</b>	<b>Play</b>
Sunny	Hot	High	False	<b>No</b>
Sunny	Hot	High	True	<b>No</b>
Overcast	Hot	High	False	<b>Yes</b>
Rainy	Mild	High	False	<b>Yes</b>
Rainy	Cool	Normal	False	<b>Yes</b>
Rainy	Cool	Normal	True	<b>No</b>
Overcast	Cool	Normal	True	<b>Yes</b>
Sunny	Mild	High	False	<b>No</b>
Sunny	Cool	Normal	False	<b>Yes</b>
Rainy	Mild	Normal	False	<b>Yes</b>
Sunny	Mild	Normal	True	<b>Yes</b>
Overcast	Mild	High	True	<b>Yes</b>
Overcast	Hot	Normal	False	<b>Yes</b>
Rainy	Mild	High	True	<b>No</b>

# Frequency Tables



# Frequency Tables

Play

Outlook	Temp	Humidity	Windy	Play
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No

Outlook	No	Yes
Sunny	3	2
Overcast	0	4
Rainy	2	3

Temp	No	Yes
Hot	2	2
Mild	2	4
Cool	1	3

Humidity	No	Yes
High	4	3
Normal	1	6

Windy	No	Yes
False	2	6
True	3	3

# Naive Bayes – Probabilities

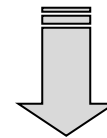
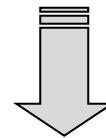
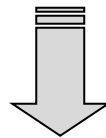
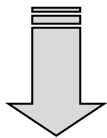
Frequency Tables

<i>Outlook</i>	No	Yes
Sunny	3	2
Overcast	0	4
Rainy	2	3

<i>Temp.</i>	No	Yes
Hot	2	2
Mild	2	4
Cool	1	3

<i>Humidity</i>	No	Yes
High	4	3
Normal	1	6

<i>Windy</i>	No	Yes
False	2	6
True	3	3



<i>Outlook</i>	No	Yes
Sunny	3/5	2/9
Overcast	0/5	4/9
Rainy	2/5	3/9

<i>Temp.</i>	No	Yes
Hot	2/5	2/9
Mild	2/5	4/9
Cool	1/5	3/9

<i>Humidity</i>	No	Yes
High	4/5	3/9
Normal	1/5	6/9

<i>Windy</i>	No	Yes
False	2/5	6/9
True	3/5	3/9

Likelihood Tables

# Predicting a New Day



Outlook	Temp.	Humidity	Windy	Play
sunny	cool	high	true	?

$$\begin{aligned} \Pr[\text{yes}|e] &= \Pr[\text{sunny}|\text{yes}] \times \Pr[\text{cool}|\text{yes}] \times \Pr[\text{high}|\text{yes}] \times \Pr[\text{true}|\text{yes}] \times \Pr[\text{yes}] / \Pr[e] \\ &= 2/9 \times 3/9 \times 3/9 \times 3/9 \times 9/14 = 0.0053 \Rightarrow 0.0053 / (0.0053 + 0.0206) = 0.205 \end{aligned}$$

$$\begin{aligned} \Pr[\text{no}|e] &= \Pr[\text{sunny}|\text{no}] \times \Pr[\text{cool}|\text{no}] \times \Pr[\text{high}|\text{no}] \times \Pr[\text{true}|\text{no}] \times \Pr[\text{no}] / \Pr[e] \\ &= 3/5 \times 1/5 \times 4/5 \times 3/5 \times 5/14 = 0.0206 \Rightarrow 0.0206 / (0.0053 + 0.0206) = 0.795 \end{aligned}$$

<i>Outlook</i>	No	Yes
Sunny	3/5	2/9
Overcast	0/5	4/9
Rainy	2/5	3/9

<i>Temp.</i>	No	Yes
Hot	2/5	2/9
Mild	2/5	4/9
Cool	1/5	3/9

<i>Humidity</i>	No	Yes
High	4/5	3/9
Normal	1/5	6/9

<i>Windy</i>	No	Yes
False	2/5	6/9
True	3/5	3/9



# Predicting a New Day - Formulas

- Again, given a new instance with
  - outlook=sunny
  - temperature=cool
  - humidity=high
  - windy=true
- If all explanatory attributes are independent and equally important they can be multiplied

$$\Pr[Play = yes] \cdot \prod_i \Pr[e_i | Play = yes]$$
$$= \frac{9}{14} \cdot \frac{2}{9} \cdot \frac{3}{9} \cdot \frac{3}{9} \cdot \frac{3}{9} = 0.0053$$

## Formulas Continued ...

- Similarly

$$\begin{aligned} & \Pr[Play = no] \cdot \prod_i \Pr[e_i | Play = no] \\ &= \frac{5}{14} \cdot \frac{3}{5} \cdot \frac{1}{5} \cdot \frac{4}{5} \cdot \frac{3}{5} = 0.0206 \end{aligned}$$

- Thus

$$\begin{aligned} h_{MAP} &= \underset{h \in \{Play=yes, Play=no\}}{arg \max} \Pr[h] \cdot \prod_i \Pr[e_i | h] \\ &= \{Play = no\} \end{aligned}$$

# Normalization

Note that we can normalize to get the *probabilities*:

$$\Pr[h|e_1, e_2, \dots, e_n] = \frac{\Pr[e_1, e_2, \dots, e_n|h] \cdot \Pr[h]}{\Pr[e_1, e_2, \dots, e_n]}$$

$$\frac{0.0053}{0.0053 + 0.0206} = 0.205 \quad h = \{Play = yes\}$$

$$\frac{0.0206}{0.0053 + 0.0206} = 0.795 \quad h = \{Play = no\}$$

$$\Pr[h | e] = \frac{\Pr[e_1 | h] \Pr[e_2 | h] \dots \Pr[e_n | h] \Pr[h]}{\Pr[e]}$$

# Naive Bayes - Summary

- Want to classify a new instance  $(e_1, e_2, \dots, e_n)$  into finite number of categories from the set  $h$ .
  - Choose the most likely classification using Bayes theorem
  - MAP (maximum a posteriori classification)
- Assign the most probable category  $h_{MAP}$  given  $(e_1, e_2, \dots, e_n)$ , i.e. the maximum likelihood

$$\begin{aligned} h_{MAP} &= \arg \max_{h \in H} \Pr[h|e_1, e_2, \dots, e_n] \\ &= \arg \max_{h \in H} \frac{\Pr[e_1, e_2, \dots, e_n|h] \cdot \Pr[h]}{\Pr[e_1, e_2, \dots, e_n]} \\ &= \arg \max_{h \in H} \Pr[e_1, e_2, \dots, e_n|h] \cdot \Pr[h] \end{aligned}$$



- “Naive Bayes” since the attributes are treated as independent
  - only then you can multiply the probabilities

$$\Pr[e_1, e_2, \dots, e_n|h] = \Pr[e_1|h] * \Pr[e_2|h] * \Pr[e_3|h] * \dots * \Pr[e_n|h]$$

# The Weather Data (yet again)

<i>Outlook</i>			<i>Temperature</i>			<i>Humidity</i>			<i>Windy</i>			<i>Play</i>	
Yes	No		Yes	No		Yes	No		Yes	No		Yes	No
Sunny	2	3	Hot	2	2	High	3	4	FALSE	6	2	9	5
Overcast	4	0	Mild	4	2	Normal	6	1	TRUE	3	3		
Rainy	3	2	Cool	3	1								

$$\Pr[Play = no] = \frac{5}{14}$$

$$\Pr[Outlook = overcast \mid Play = no] = \frac{0}{5}$$

$$\Pr[Temperature = cool \mid Play = no] = \frac{1}{5}$$

$$\Pr[Humidity = high \mid Play = no] = \frac{4}{5}$$

$$\Pr[Windy = true \mid Play = no] = \frac{3}{5}$$

# The Zero Frequency Problem

What if an attribute value doesn't occur with every class value

$$\Pr[\text{Outlook} = \text{overcast} \mid \text{no}] = 0$$



Remedy: add 1 to the numerator for every attribute value-class combination, and the probability can never be zero

$$\Pr[\text{no} \mid e] = 5/14 * 1/8 * 2/8 * 5/7 * 4/7 = 0.00456 \Rightarrow 27.84\%$$

$$\Pr[\text{yes} \mid e] = 9/14 * 5/12 * 4/12 * 4/11 * 4/11 = 0.01181 \Rightarrow 72.16\%$$

<i>Outlook</i>	No	Yes
Sunny	3+1	2+1
<i>Overcast</i>	0+1	4+1
Rainy	2+1	3+1

<i>Temp.</i>	No	Yes
Hot	2+1	2+1
Mild	2+1	4+1
<i>Cool</i>	1+1	3+1

<i>Humidity</i>	No	Yes
<i>High</i>	4+1	3+1
Normal	1+1	6+1

<i>Windy</i>	No	Yes
False	2+1	6+1
<i>True</i>	3+1	3+1

# Modified Probability Estimates

- In some cases adding a constant different from 1 might be more appropriate
- Example: attribute outlook for class no

$$\frac{3 + \mu/3}{5 + \mu}$$

*Sunny*

$$\frac{0 + \mu/3}{5 + \mu}$$

*Overcast*

$$\frac{2 + \mu/3}{5 + \mu}$$

*Rainy*

- Weights ( $w_p$ ) don't need to be equal (as long as their sum to 1)

$$\frac{3 + \mu w_1}{5 + \mu}$$

$$\frac{0 + \mu w_2}{5 + \mu}$$

$$\frac{2 + \mu w_3}{5 + \mu}$$

# Missing Values

- Training: instance is not included in frequency count for attribute value-class combination
- Classification: attribute will be omitted from calculation
- Example:



Outlook	Temp.	Humidity	Windy	Play
?	Cool	High	True	?

Likelihood of "yes" =  $3/9 \times 3/9 \times 3/9 \times 9/14 = 0.0238$

Likelihood of "no" =  $1/5 \times 4/5 \times 3/5 \times 5/14 = 0.0343$

$\Pr[\text{Play} = \text{"yes"} | e_2, e_3, e_4] = 0.0238 / (0.0238 + 0.0343) = 41\%$

$\Pr[\text{Play} = \text{"no"} | e_2, e_3, e_4] = 0.0343 / (0.0238 + 0.0343) = 59\%$



# Dealing with Numeric Attributes

- Usual assumption: attributes have a normal or Gaussian probability distribution (given the class)
- The probability density function for the normal distribution is defined by two parameters:



– The sample mean  $\mu$ :

$$\mu = \frac{1}{n} \sum_{i=1}^n x_i$$

– The standard deviation  $\sigma$ :

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \mu)^2}$$

– The density function  $f(x)$ :

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

# Statistics for the Weather Data

Outlook			Temperature		Humidity		Windy		Play				
	Yes	No		Yes	No		Yes	No		Yes	No		
Sunny	2	3		83	85		86	85	False	6	2	9	5
Overcast	4	0		70	80		96	90	True	3	3		
Rainy	3	2		68	65		80	70					
				...	...		...	...					
Sunny	2/9	3/5	mean	73	74.6	mean	79.1	86.2	False	6/9	2/5	9/14	5/14
Overcast	4/9	0/5	std dev	6.2	7.9	std dev	10.2	9.7	True	3/9	3/5		
Rainy	3/9	2/5											

- Calculate mean and std for Temperature when Play = yes; mean = 73, std = 6.2
- Example density value for Temperature = 66:

$$f(\text{temperature} = 66 | \text{yes}) = \frac{1}{\sqrt{2\pi}6.2} e^{-\frac{(66-73)^2}{2*6.2^2}} = 0.0340$$

# Classifying a New Day

- A new day:

Outlook	Temp.	Humidity	Windy	Play
Sunny	66	90	true	?

Likelihood of "yes" =  $2/9 \times 0.0340 \times 0.0221 \times 3/9 \times 9/14 = 0.000036$

Likelihood of "no" =  $3/5 \times 0.0291 \times 0.0380 \times 3/5 \times 5/14 = 0.000136$

$\Pr[\text{Play} = \text{"yes"} | e_1, \dots, e_4] = 0.000036 / (0.000036 + 0.000136) = 20.9\%$

$\Pr[\text{Play} = \text{"no"} | e_1, \dots, e_4] = 0.000136 / (0.000036 + 0.000136) = 79.1\%$

- Missing values during training: not included in calculation of mean and standard deviation

# Numeric Data: Unknown Distribution

- What if the data distribution does not follow a known distribution
- In this case we need a mechanism to estimate the density distribution
- A simple and intuitive approach is based on kernel density estimation
- Consider a random variable  $X$  whose distribution  $f(X)$  is unknown but a sample with a non-uniform distribution

$$\{x_1, x_2, \dots, x_n\}$$

# Kernel Density Estimation

We want to derive a function  $f(x)$  such that

(1)  $f(x)$  is a probability density function, i.e.

$$\int f(x)dx = 1$$

(2)  $f(x)$  is a smooth approximation of the data points in  $X$

(3)  $f(x)$  can be used to estimate values  $x^*$  which are not in  
 $\{x_1, x_2, \dots, x_n\}$

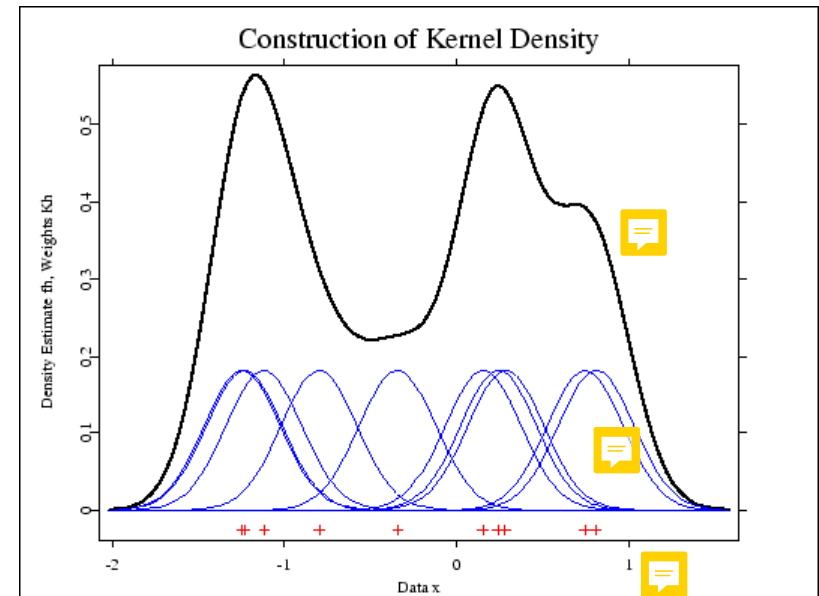
# Kernel Density Estimate

Rosenblatt-Parzen Kernel-Density-Estimator:

$$f(x) = \frac{1}{n} \sum_{i=1}^n K(x - x_i, h)$$

Where

$$K(t, h) = \frac{1}{\sqrt{2\pi}h} e^{-\frac{1}{2}\left(\frac{t}{h}\right)^2}$$



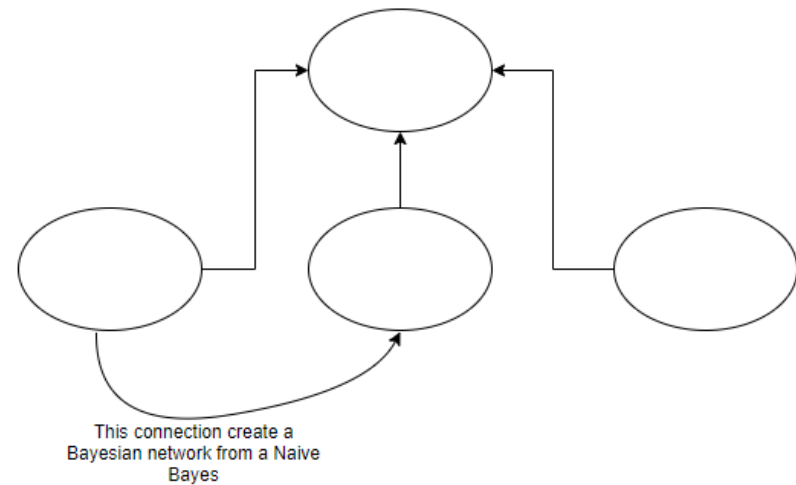
Adjust “ $h$ ” (aka bandwidth) to fit data

# Discussion of Naïve Bayes

- Naïve Bayes works surprisingly well (even if independence assumption is clearly violated)
  - Domingos, Pazzani: On the Optimality of the Simple Bayesian Classifier under Zero-One-Loss, Machine Learning (1997) 29.
- However: adding too many redundant attributes will cause problems (e.g., identical attributes)
  - Note also: many numeric attributes are not normally distributed
- Time complexity
  - Calculating conditional probabilities: Time  $O(n)$  where  $n$  is the number of instances
  - Calculating the class: Time  $O(cp)$  where  $c$  is the number of classes,  $p$  the attributes

# Bayesian (Belief) Networks: Multiple Variables with Depen

- Naïve Bayes assumption of conditional independence is restrictive
- Bayesian Belief network (Bayesian net) describe conditional independence among subsets of attributes: combining prior knowledge about dependencies among variables with observed training data
- Graphical representation: directed acyclic graph (DAG), one node for each attribute
  - Overall probability distribution factorized into component distributions
  - Graph's nodes hold component distributions (conditional distributions)





# Probability Laws

- Chain rule

- $\Pr[e_1, e_2, \dots, e_n] = \prod_{i=1, \dots, n} \Pr[e_i | e_{i-1}, \dots, e_1]$
- $\Pr[A, B, C, D, E] = \Pr[A] \Pr[B|A] \Pr[C|A, B] \Pr[D|A, B, C] \Pr[E|A, B, C, D]$
- The joint distribution is independent of the ordering


- Conditional independence

- $\Pr[h | e_1, e_2] = \Pr[h | e_2]$
- Example:
  - Rain causes people to use an umbrella and traffic to slow down
  - Umbrella is conditionally independent of traffic given rain
    - $Umbrella \perp\!\!\!\perp Traffic \mid Rain$
    - $\Pr[Umbrella, Traffic | Rain] = \Pr[Umbrella | Rain] * \Pr[Traffic | Rain]$
    - $\Pr[Umbrella | Rain, Traffic] = \Pr[Umbrella | Rain]$

# The Full Joint Distribution

$$\begin{aligned} & \Pr[e_1, \dots, e_n] \\ &= \Pr[e_n \mid e_{n-1}, \dots, e_1] \Pr[e_{n-1}, \dots, e_1] \\ &= \Pr[e_n \mid e_{n-1}, \dots, e_1] \Pr[e_{n-1} \mid e_{n-2}, \dots, e_1] \Pr[e_{n-2}, \dots, e_1] \\ &= \Pr[e_n \mid e_{n-1}, \dots, e_1] \Pr[e_{n-1} \mid e_{n-2}, \dots, e_1] \dots \Pr[e_2 \mid e_1] P[e_1] \\ &= \prod_{i=1}^n \Pr[e_i \mid e_{i-1}, \dots, e_1] \\ &= \prod_{i=1}^n \Pr[e_i \mid \text{parents}(e_i)] \end{aligned}$$

(Chain Rule)



From the chain rule  
to Bayesian networks

# Bayesian Network Assumptions

- $\Pr[e_1, e_2, \dots, e_n] = \Pr[E_1 = e_1 \wedge \dots \wedge E_n = e_n] =$

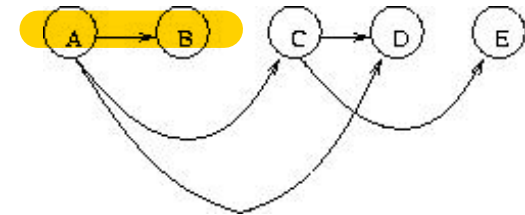
$$\prod_{i=1, \dots, n} \Pr[e_i | e_{i-1}, \dots, e_1] = \prod_{i=1, \dots, n} \Pr[e_i | \text{Parents}(e_i)]$$

- $\Pr[\text{Traffic, Rain, Umbrella}] =$

- $\Pr[T, R, U] = \Pr[R] * \Pr[T|R] * \Pr[U|R, T]$

- Considering conditional independence:

- $\Pr[T, R, U] = \Pr[R] * \Pr[T|R] * \Pr[U|R]$



- $\Pr[A, B, C, D, E] =$

- $\Pr[A] \Pr[B|A] \Pr[C|A, B] \Pr[D|A, B, C] \Pr[E|A, B, C, D] =$

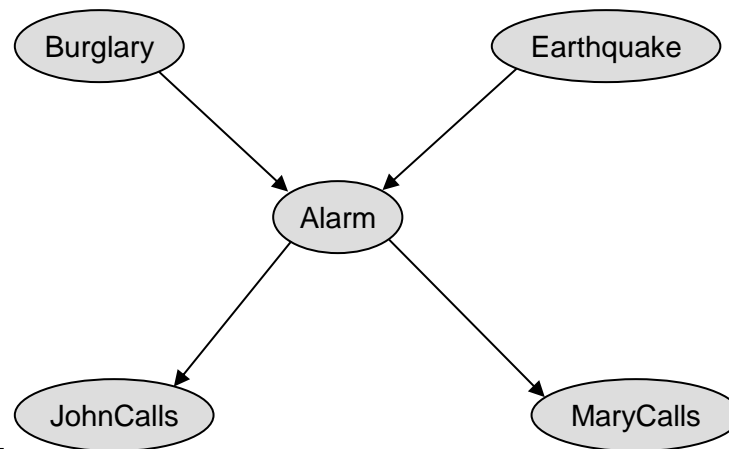
- $\Pr[A] \Pr[B|A] \Pr[C|A] \Pr[D|A, C] \Pr[E|C]$

# Example: Alarm

Your house has an alarm system against burglary. The house is located in the seismically active area and the alarm system can get occasionally set off by an earthquake. You have two neighbors, Mary and John, who do not know each other. If they hear the alarm they call you, but this is not guaranteed. They also call you from time to time just to chat.

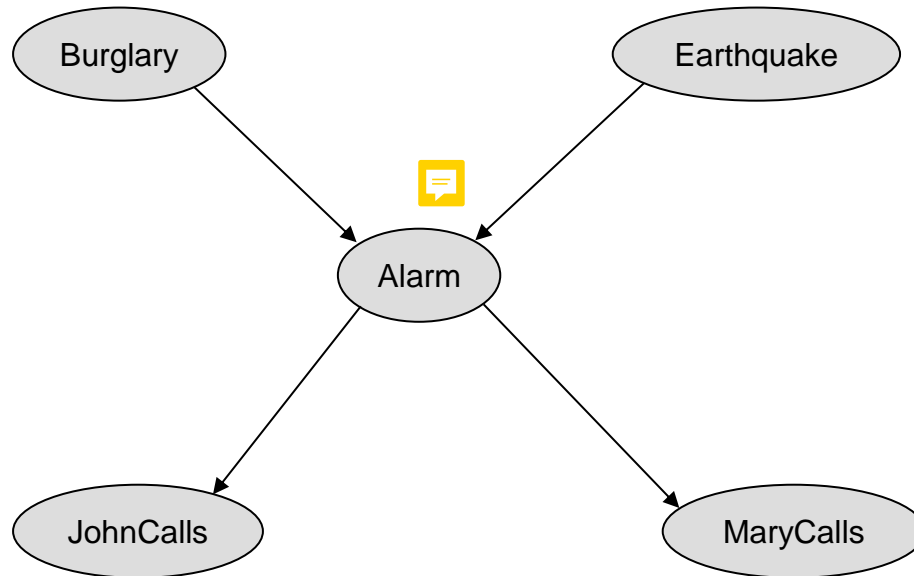
Five random variables

- A: Alarm
- B: Burglary
- E: Earthquake
- J: JohnCalls
- M: MaryCalls



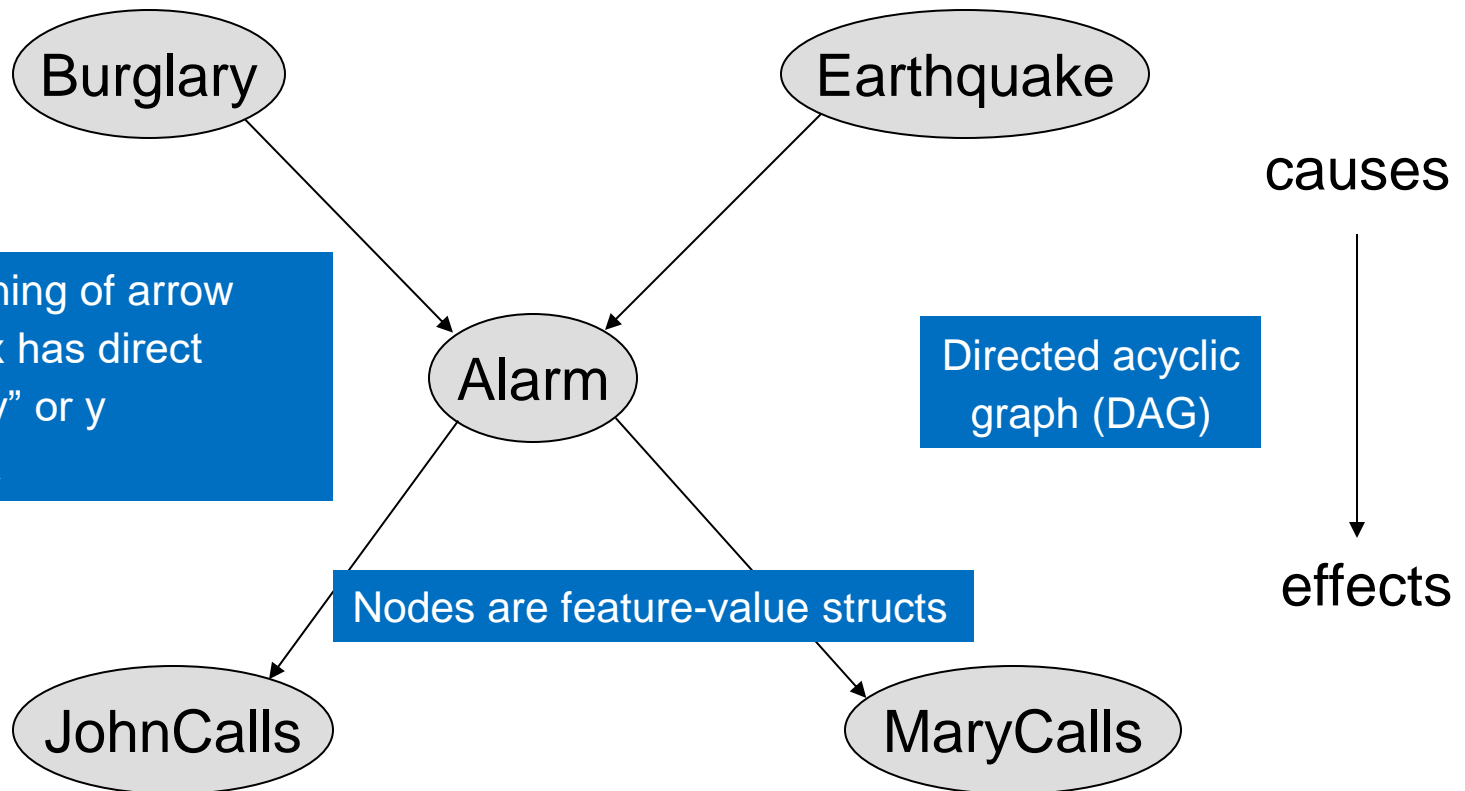
[illustration by Kevin Murphy]

# Example

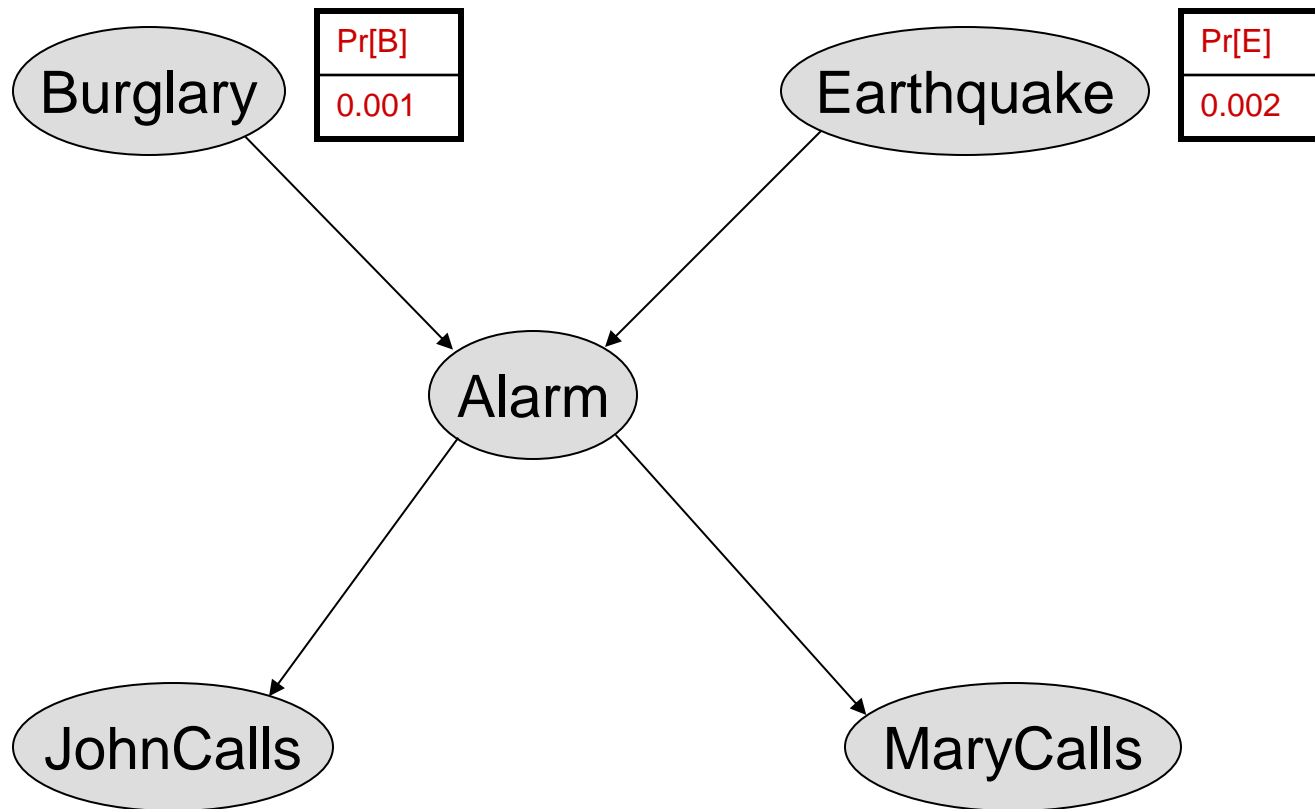


$$\begin{aligned} & \Pr(\text{JohnCalls}, \text{MaryCalls}, \text{Alarm}, \text{Burglary}, \text{Earthquake}) \\ &= \Pr(\text{JohnCalls} \mid \text{Alarm}) \Pr(\text{MaryCalls} \mid \text{Alarm}) \\ & \Pr(\text{Alarm} \mid \text{Burglary}, \text{Earthquake}) \Pr(\text{Burglary}) \Pr(\text{Earthquake}) \end{aligned}$$

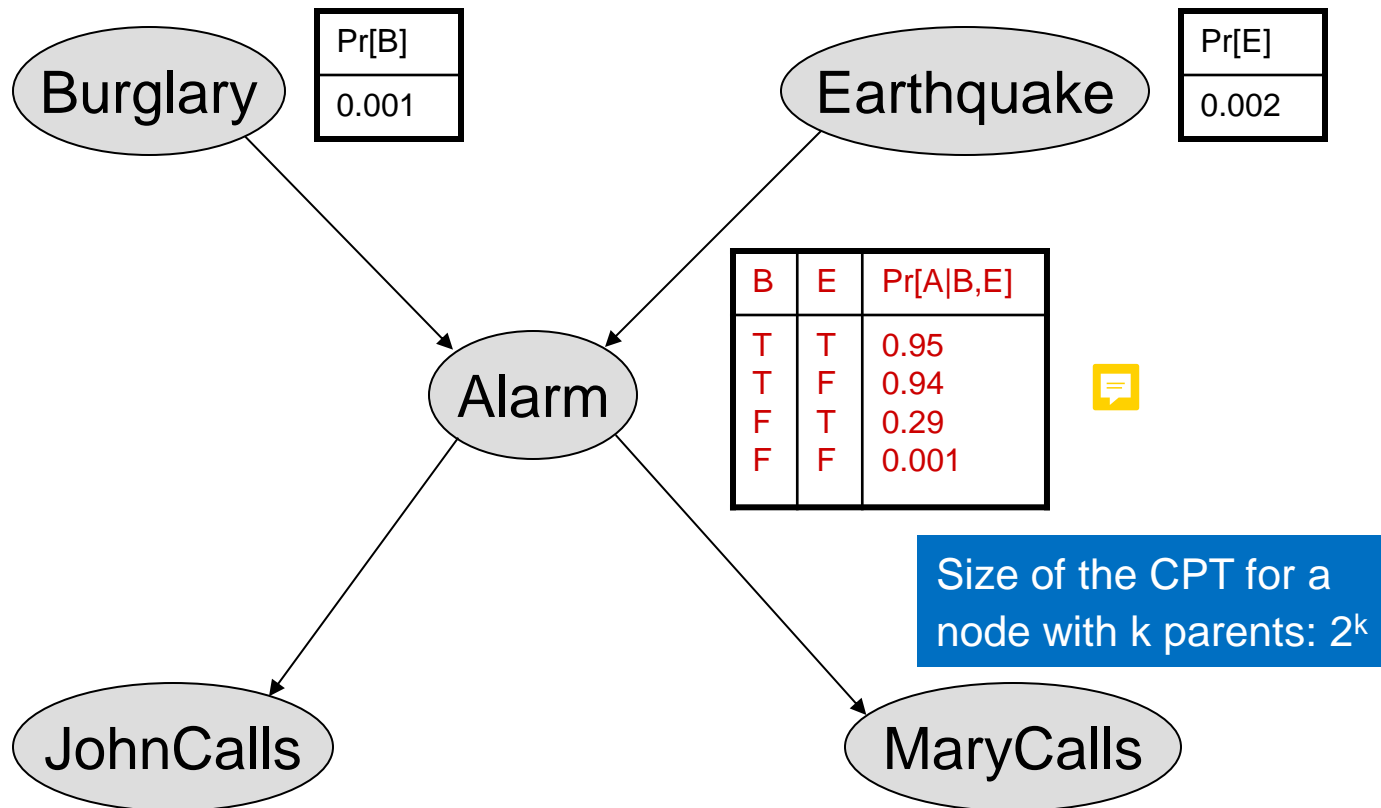
# A Simple Bayes Net



# Assigning Probabilities to Roots

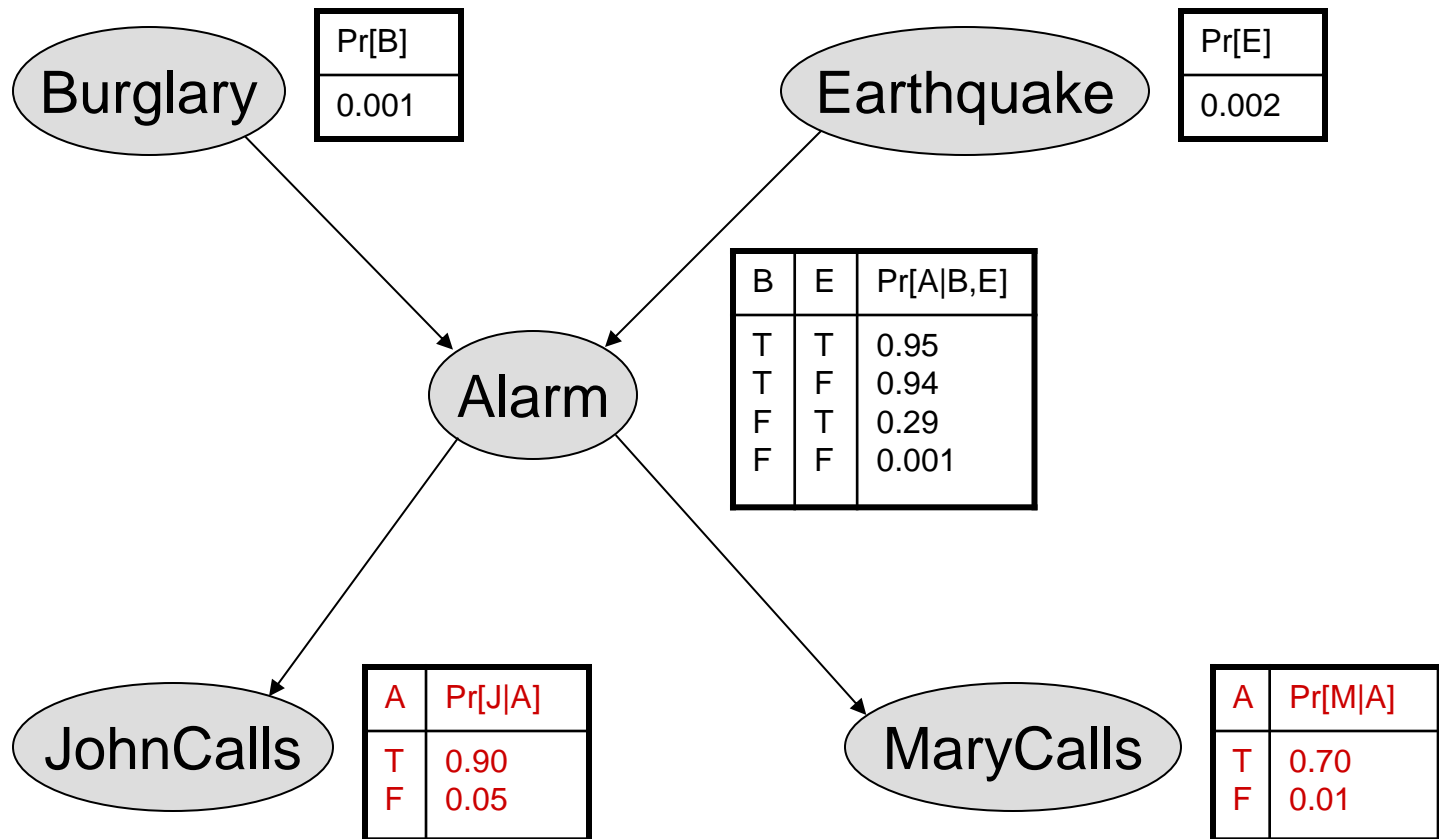


# Conditional Probability Tables

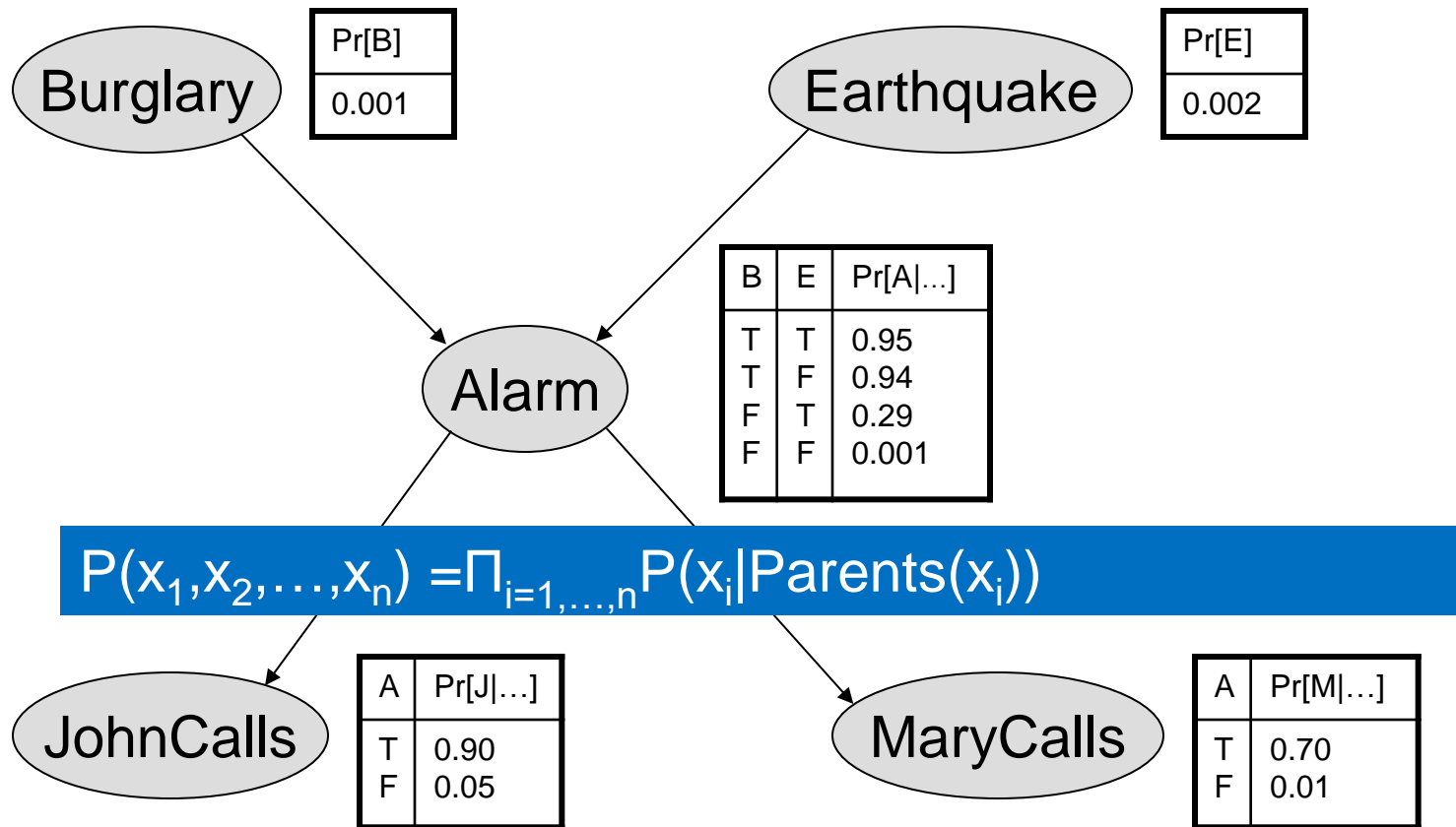




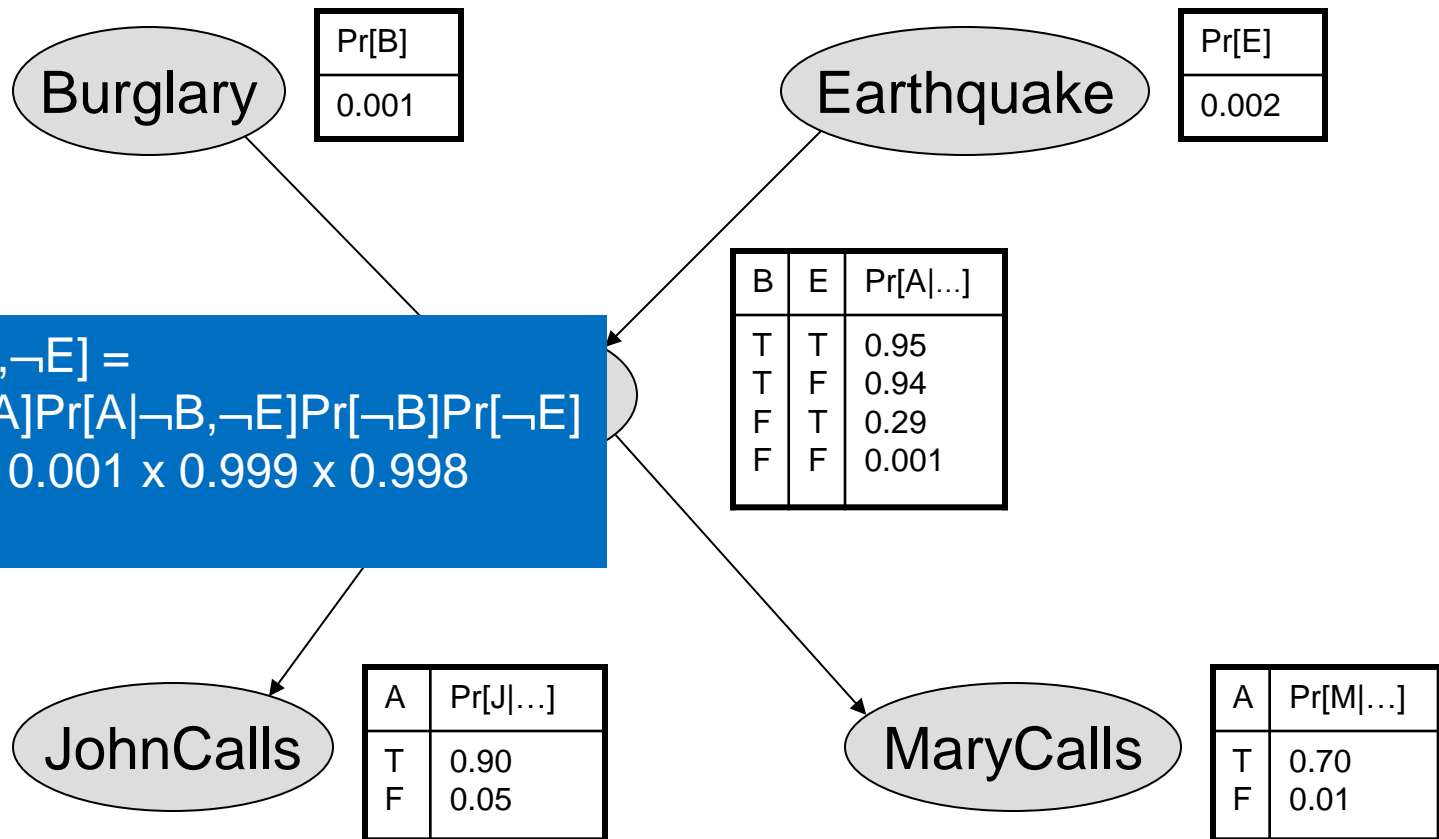
# Conditional Probability Tables



# What the BN Means



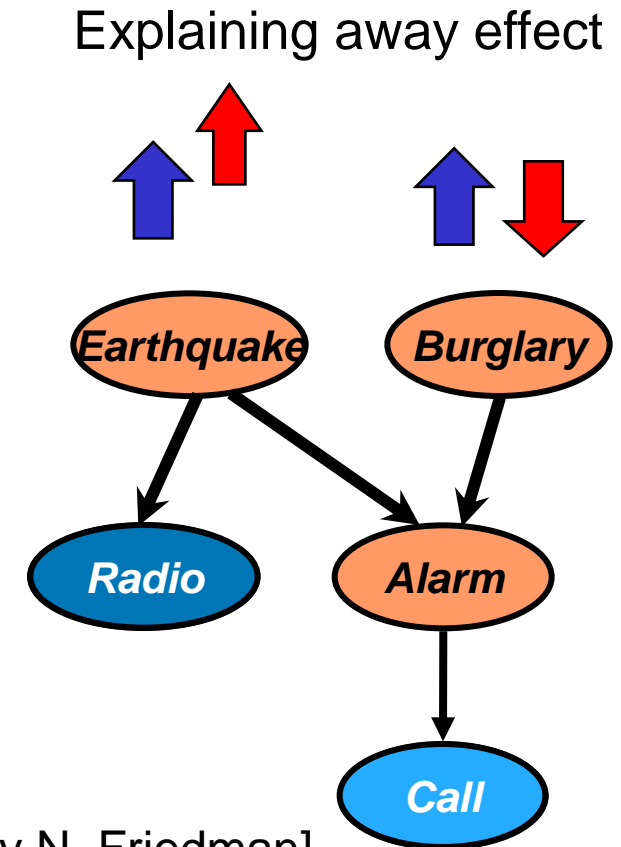
# Calculation of Joint Probability



$$\begin{aligned}
 &\Pr[J, M, A, \neg B, \neg E] = \\
 &\Pr[J|A]\Pr[M|A]\Pr[A|\neg B, \neg E]\Pr[\neg B]\Pr[\neg E] \\
 &= 0.9 \times 0.7 \times 0.001 \times 0.999 \times 0.998 \\
 &= 0.00062
 \end{aligned}$$

# Inference in Bayesian Networks

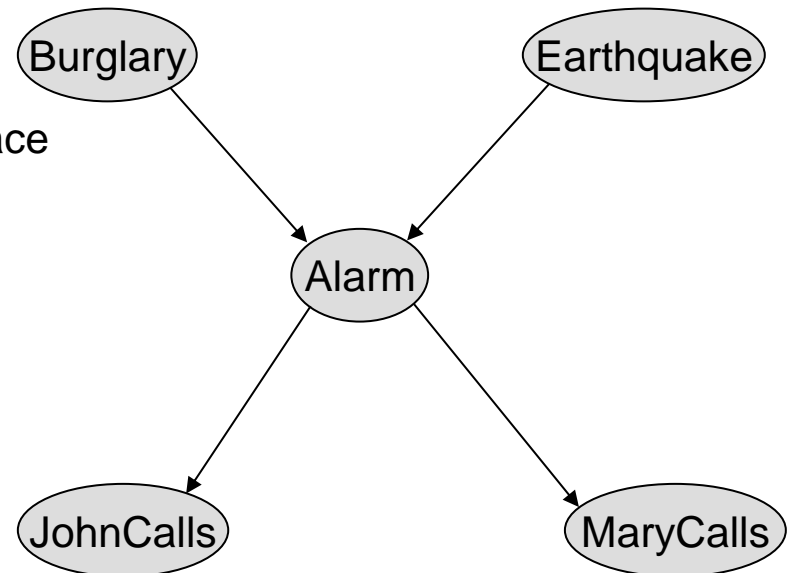
- Other than the joint probability of specific events, we may want to infer the probability of an event, given observations about a subset of other variables
- For such inference on the Bayesian Network, we need to consider the evidence and the topology of the network



[Figure by N. Friedman]

# Inference Rules: An Example

- If alarm is not observed, B and M calls are dependent:
  - My knowing that B has taken place increases my belief on M
  - My knowing that M called increases my belief on B
- If alarm is observed, B and M are conditionally independent:
  - If I already know that the alarm went off,
    - My further knowing that a burglary has taken place would not increase my belief on Mary's call
    - My further knowing that Mary called would not increase my belief on burglary
- d-separation determines whether a set of nodes  $X$  is independent of another set  $Y$  given a third set  $E$



# Learning Bayes Nets

- Method for evaluating the goodness of a given network
  - Measures maximize the joint probability of training data given the network (or the sum of the logarithms thereof)
  - Summarize the Log-Likelihood of training data based on the network
  - Example:
    - Akaike information Criterion (AIC):  $-2LL + 2K$
    - Minimize AIC, with  $K$ =number of parameters
- Method for searching through space of possible networks
  - Amounts to searching through sets of edges because nodes are fixed
  - Examples: K2, Tree Augmented Naive Bayes (TAN)

# Bayes Nets Summary

- Bayes Nets can handle dependencies among attributes
- Learning Bayes Nets is computationally complex
  - Network structure is given or not
  - All or only part of the variable values are observable in the training data
- Bayes Networks are the subject of much current research