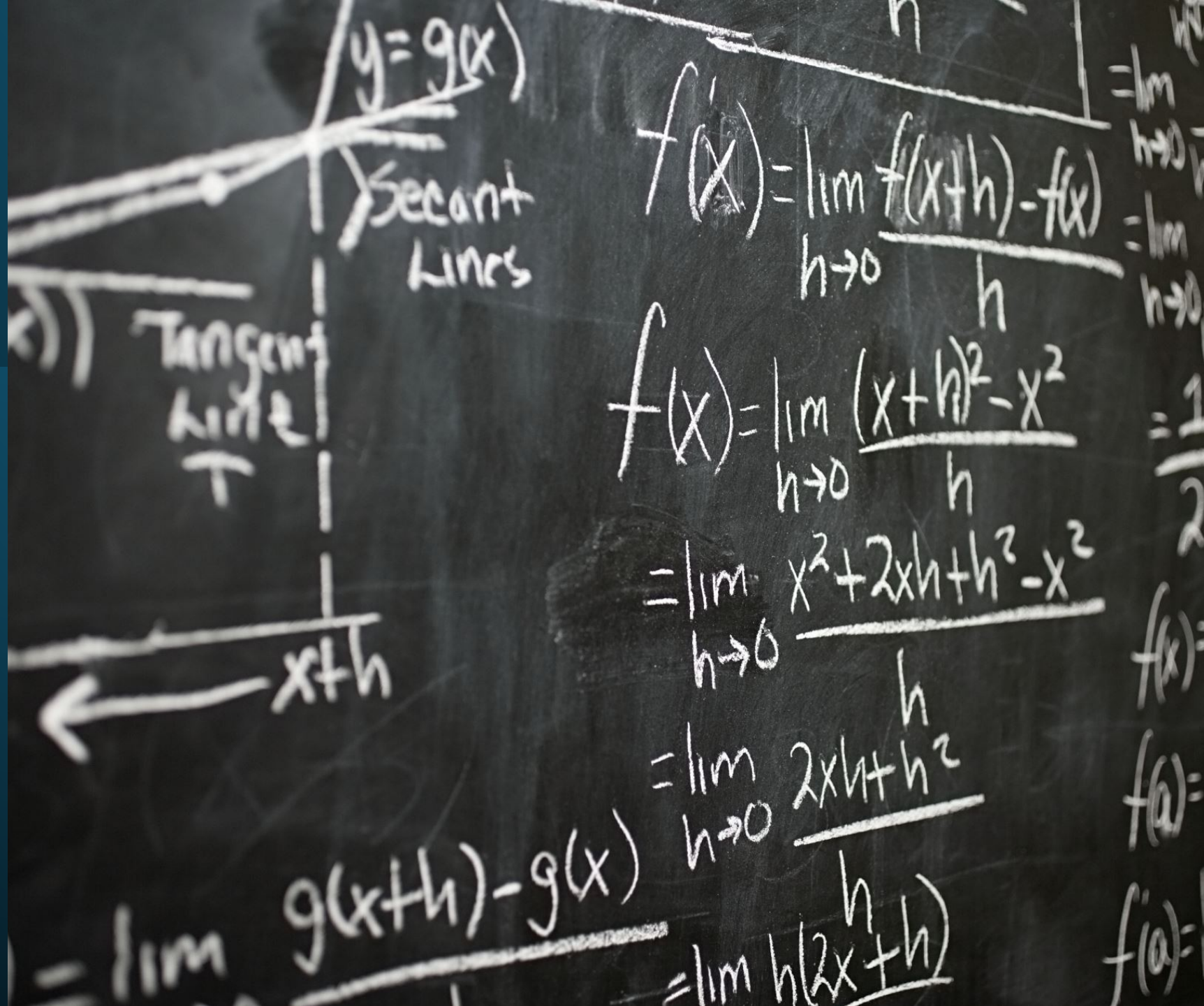


Based on Baye's  
theorem

# Naïve Bayesian Classifier



# Bayes' Theorem

- $$P(H|X) = \frac{P(X|H) \cdot P(H)}{P(X)}$$
- $X$ : Data tuple
- $H$ : Hypothesis that the data tuple  $X$  belongs to a specified class  $C$
- $P(H|X)$ : Posterior probability
- $P(H)$ : Prior probability
- $P(X|H)$ : Likelihood
- $P(X)$ : Evidence



# Naïve Bayesian Classification

- **Assumption:** Attributes are conditionally independent given the class (i.e. no dependence relationships among the attributes)

- **Formula:**

$$P(C_i|X) = \frac{P(X|C_i) \cdot P(C_i)}{P(X)}$$

- Since  $P(X)$  is constant, we maximize:

$$P(X|C_i) \cdot P(C_i)$$

# Naïve Bayes Classifier Formula

- 

$$P(X|C_i) = \prod_{k=1}^n P(x_k|C_i)$$

- $x_k$ : value of attribute  $k$
- $n$ : number of attributes
- **Class label prediction:**

$$\operatorname{argmax}_{C_i} \left[ P(C_i) \prod_{k=1}^n P(x_k|C_i) \right]$$

# Example: *AllElectronics* Customer Database

RID	age	income	student	credit_rating	buys_computer
1	youth	high	no	fair	no
2	youth	high	no	excellent	no
3	middle_aged	high	no	fair	yes
4	senior	medium	no	fair	yes
5	senior	low	yes	fair	yes
6	senior	low	yes	excellent	no
7	middle_aged	low	yes	excellent	yes
8	youth	medium	no	fair	no
9	youth	low	yes	fair	yes
10	senior	medium	yes	fair	yes
11	youth	medium	yes	excellent	yes
12	middle_aged	medium	no	excellent	yes
13	middle_aged	high	yes	fair	yes
14	senior	medium	no	excellent	no

# Class Priors

- $C_1$ : *buys computer = yes*
- $C_2$ : *buys computer = no*
- The tuple we wish to classify is
  - $X = (\text{age} = \text{youth}, \text{income} = \text{medium}, \text{student} = \text{yes}, \text{credit rating} = \text{fair})$
- $P(\text{buys computer} = \text{yes}) = \frac{9}{14} = 0.643$
- $P(\text{buys computer} = \text{no}) = \frac{5}{14} = 0.357$

# Likelihoods

- $P(\text{age} = \text{youth} | \text{buys computer} = \text{yes}) = \frac{2}{9} = 0.22$
- $P(\text{age} = \text{youth} | \text{buys computer} = \text{no}) = \frac{3}{5} = 0.60$
- $P(\text{income} = \text{medium} | \text{buys computer} = \text{yes}) = \frac{4}{9} = 0.44$
- $P(\text{income} = \text{medium} | \text{buys computer} = \text{no}) = \frac{2}{5} = 0.40$
- $P(\text{student} = \text{yes} | \text{buys computer} = \text{yes}) = \frac{6}{9} = 0.667$
- $P(\text{student} = \text{yes} | \text{buys computer} = \text{no}) = \frac{1}{5} = 0.200$
- $P(\text{credit rating} = \text{fair} | \text{buys computer} = \text{yes}) = \frac{6}{9} = 0.667$
- $P(\text{credit rating} = \text{fair} | \text{buys computer} = \text{no}) = \frac{2}{5} = 0.400$

# Likelihoods...

- $P(X|\text{buys computer} = \text{yes}) =$   
 $P(\text{age} = \text{youth}|\text{buys computer} = \text{yes}) \times$   
 $P(\text{income} = \text{medium}|\text{buys computer} = \text{yes}) \times$   
 $P(\text{student} = \text{yes}|\text{buys computer} = \text{yes}) \times$   
 $P(\text{credit rating} = \text{fair}|\text{buys computer} = \text{yes})$   
 $= 0.222 \times 0.444 \times 0.667 \times 0.667 = 0.044$
- $P(X|\text{buys computer} = \text{no}) = P(\text{age} = \text{youth}|\text{buys computer} = \text{no}) \times$   
 $P(\text{income} = \text{medium}|\text{buys computer} = \text{no}) \times$   
 $P(\text{student} = \text{yes}|\text{buys computer} = \text{no}) \times$   
 $P(\text{credit rating} = \text{fair}|\text{buys computer} = \text{no})$   
 $= 0.60 \times 0.40 \times 0.20 \times 0.40 = 0.019$



# Classify Tuple

- - $P(X|buys\ computer = yes) \cdot P(buys\ computer = yes) = 0.044 \times 0.643 = 0.028$
  - $P(X|buys\ computer = no) \cdot P(buys\ computer = no) = 0.019 \times 0.357 = 0.007$
  - **Prediction:**  $buys\ computer = yes$  for tuple  $X$ .

# Advantages and Disadvantages

- Fast, simple, works well with high-dimensional data
- Handles both continuous and discrete data
- Robust to noise
- Independence assumption often violated