# Bayes classifier

#### Bayes classifier

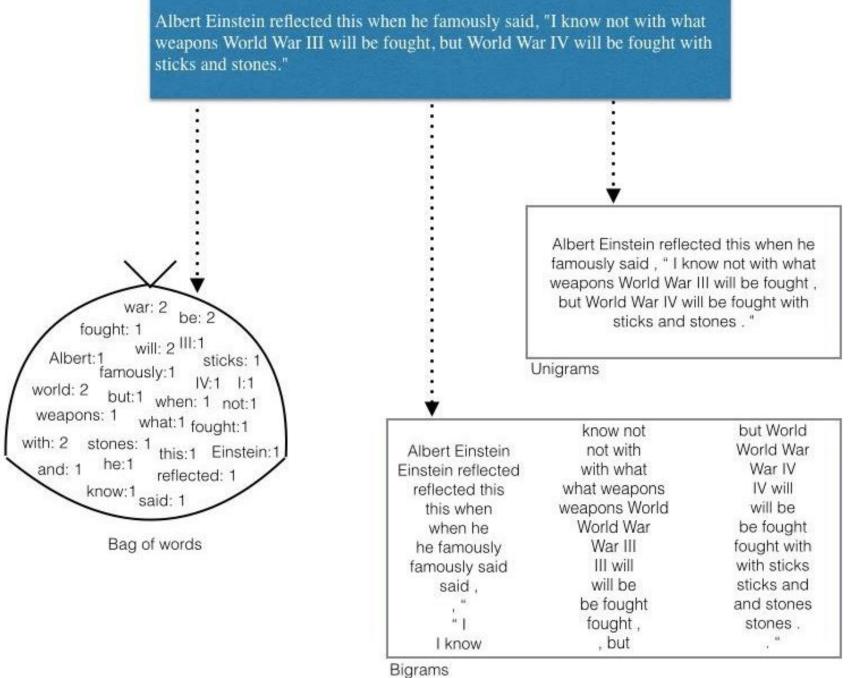
$$P(y|x) = \frac{P(y)P(x|y)}{P(x)}$$

$$y_{MAP} = \arg\max_{y \in Y} P(y|\mathbf{x}) = \arg\max_{y \in Y} \frac{P(y)P(\mathbf{x}|y)}{P(\mathbf{x})} = \arg\max_{y \in Y} P(y)P(\mathbf{x}|y)$$

$$\arg\max_{y\in Y} P(y)P(x|y) = \arg\max_{y\in Y} P(x_1, x_2, \dots, x_n|y)P(y)$$

Naïve assumption (features are independent):

$$P(x_1, x_2, ..., x_n | y) = P(x_1 | y) P(x_2 | y) P(x_3 | y) ... P(x_n | y)$$



#### Naïve Bayes classifier

$$P(x_1, x_2, ..., x_n | y) = P(x_1 | y) P(x_2 | y) P(x_3 | y) ... P(x_n | y)$$

$$y_{MAP} = \arg \max_{y \in Y} P(y)P(x|y)$$

$$y_{NB} = \arg \max_{y \in Y} P(y) \prod_{i} P(x_i|y)$$

#### Words in documents

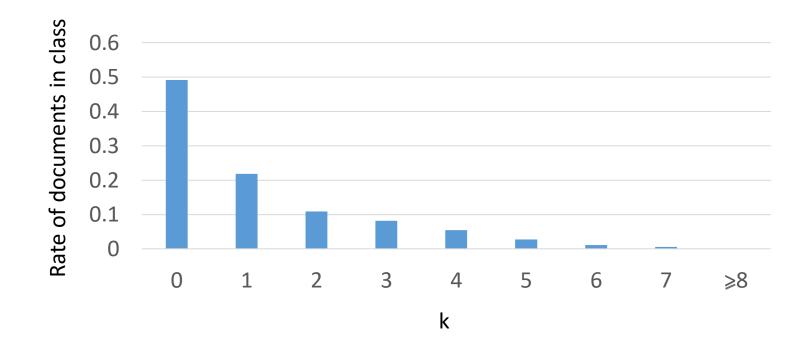
P(y) is the frequency of class y.

 $P(x_i = k | y)$  is the probability of value k of feature  $x_i$  in class y. Such as a proportion of documents in class with  $x_i = k$ .

$$P(x_i|y_j) = \frac{count(x_i,y_j)}{count(y_j)}$$

 $Problem - count(x_i, y_i) = 0$ 

$$\widehat{P}(x_i|y_j) = \frac{count(x_i,y_j)+1}{count(y_j)+K}$$



#### Bayes classifier with various types of features

Binary features:

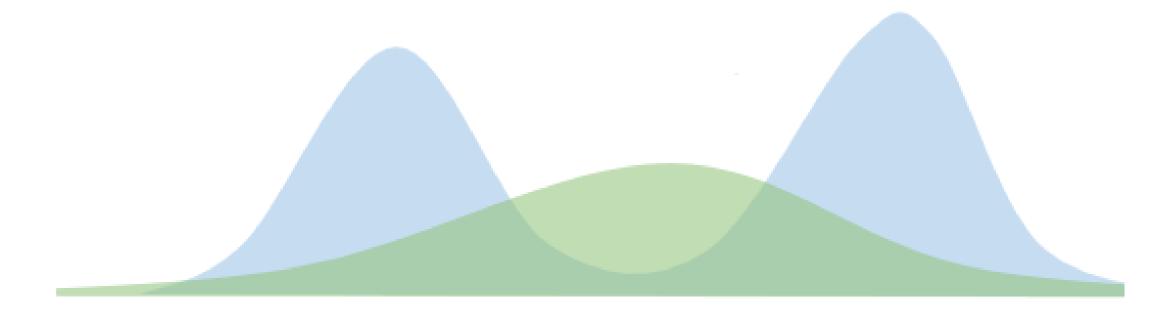
$$P(x_i|y) = P(x_i = 1|y)x_i + (1 - P(x_i = 1|y))(1 - x_i), \qquad x_i \in \{0,1\}$$

Distribution for continuous features:

$$p(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} e^{-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}}$$

#### Distribution evaluation

A simple option is to use sample mean and variance for  $\mu$  and  $\sigma$ .



A more complex option is expectation-maximization algorithm (EM) with Gaussian mixtures.

#### Expectation-maximization (EM)

Define Gaussian mixture of K distributions by:

 $\mu_k$  is the mean vector,  $\Sigma_k$  is the covariance matrix  $\alpha_k$  is the weight of distribution k, a probability that random point belongs to it.  $\Sigma \alpha_k = 1$ 

Affinity of object  $x_i$  to distribution k:

$$w_{ik} = P(\mu_k, \Sigma_k | \mathbf{x}_i) = \frac{p(\mathbf{x}_i | \mu_k, \Sigma_k) \cdot \alpha_k}{\sum_j p_j(\mathbf{x}_i | \mu_j, \Sigma_j) \cdot \alpha_j}$$

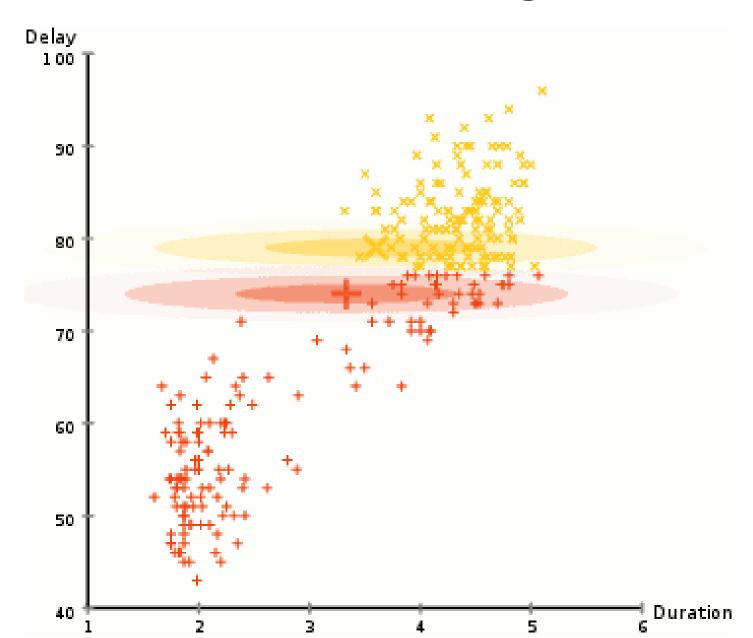
$$\alpha_k^{new} = \frac{\sum_{i=1}^N w_{ik}}{N} = \frac{N_k}{N}$$

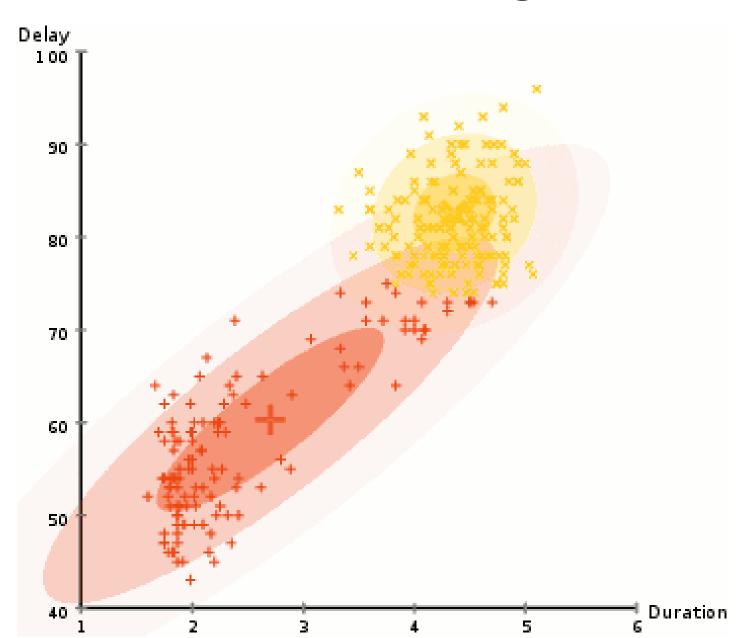
**E-Step:** calculate  $w_{ik}$ 

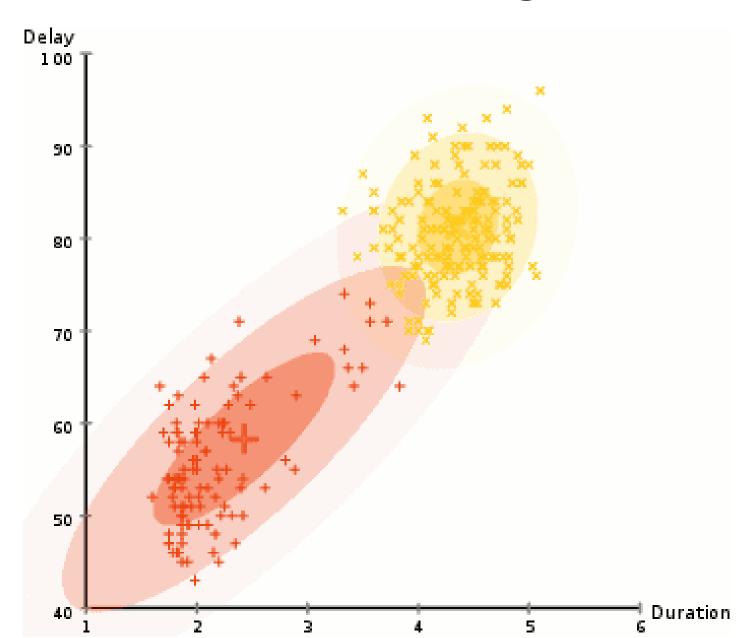
M-Step:

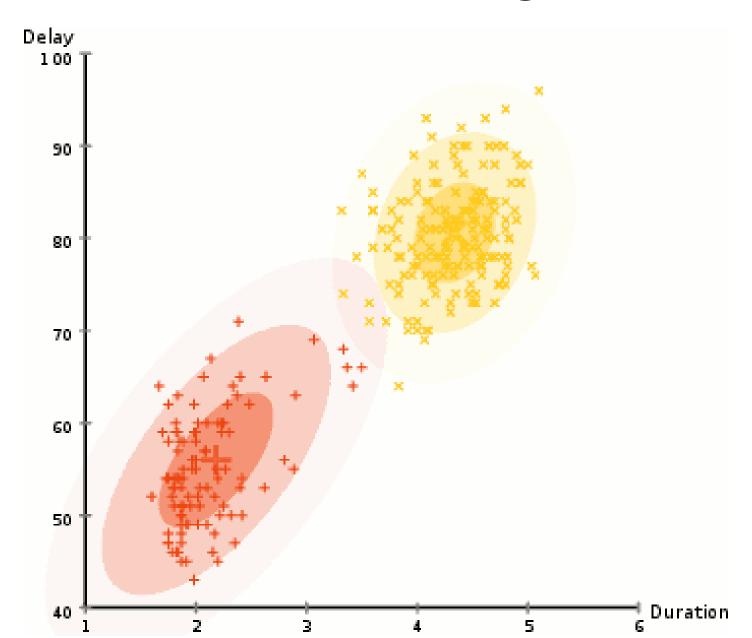
$$\mu_k^{new} = \left(\frac{1}{N_k}\right) \sum_{i=1}^N w_{ik} \cdot \mathbf{x}_i$$

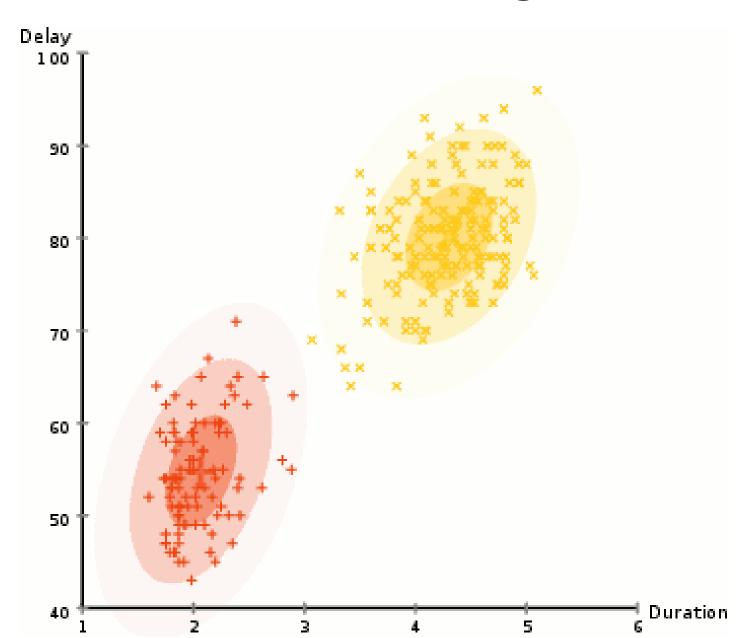
$$\Sigma_k^{new} = \left(\frac{1}{N_k}\right) \sum_{i=1}^N w_{ik} \cdot (\mathbf{x}_i - \boldsymbol{\mu}_k^{new}) (\mathbf{x}_i - \boldsymbol{\mu}_k^{new})^T$$

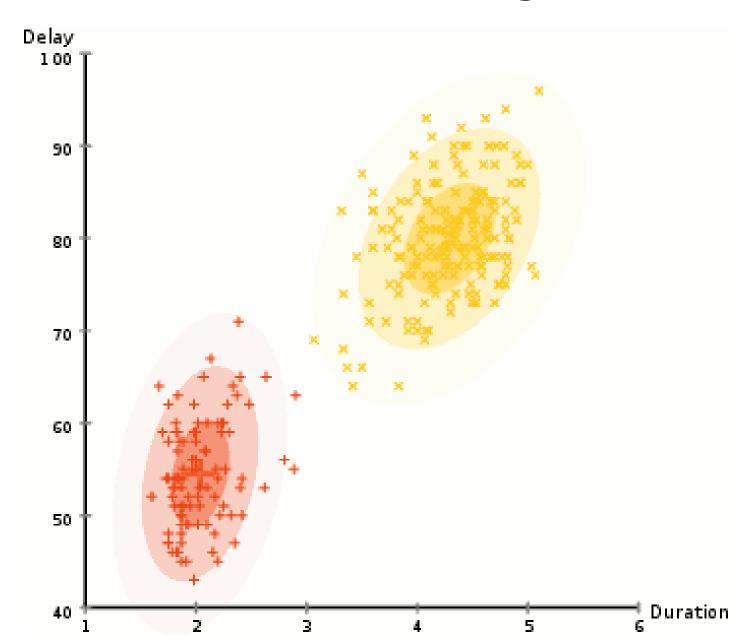


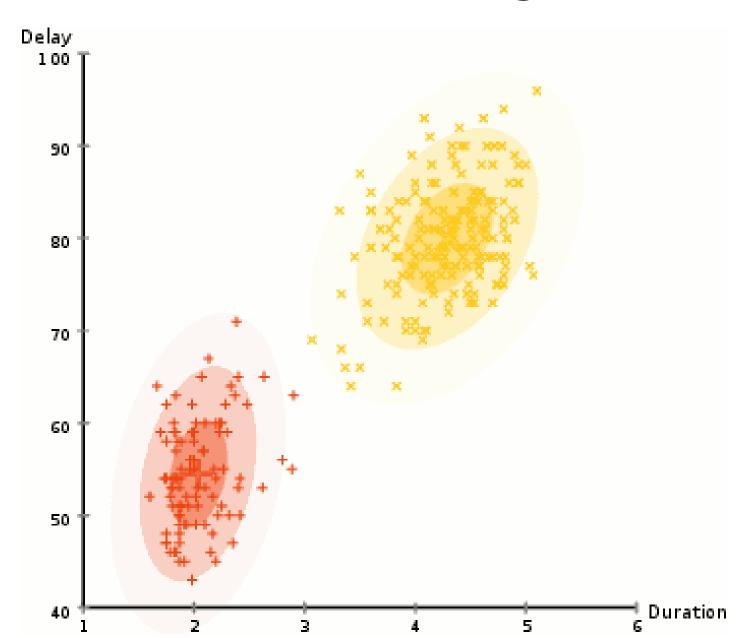


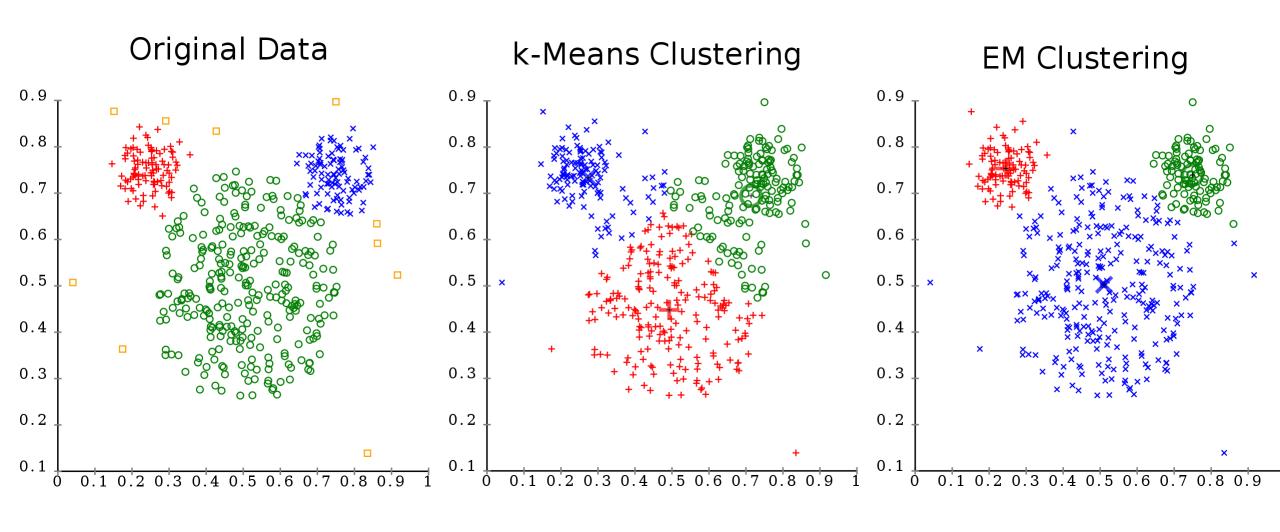












# Naïve Bayes is a very nice baseline!