

# Basics of Machine Learning

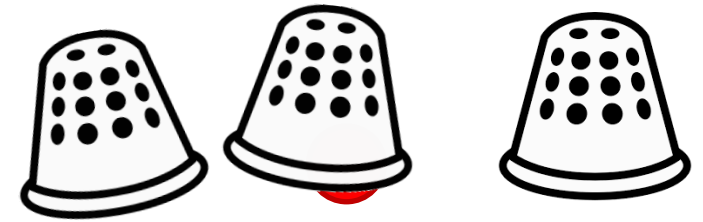
Dmitry Ryabokon, [github.com/dryabokon](https://github.com/dryabokon)





# Lesson 07

## Bayesian Approach



# Bayesian Approach

## Summary

- Approaches for ML
- Bayesian approach
- Classifying the independent binary features

# Approaches for ML

## Maximum Likelihood

$x_1, x_2, \dots, x_N$  features and  
 $k_1, k_2, \dots, k_N$  states

$k \in K = \{1, 2, \dots, K\}$  domain for  $k$

$p(x|k) = f(x, \mu_k)$  The model is parametrized by  
 $\mu_1, \mu_2, \dots, \mu_K$

input

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$$(\mu_1, \mu_2, \dots, \mu_K)^* = \arg \max_{\mu_1, \mu_2, \dots, \mu_K} \prod_{i=1}^N p(x_i, k_i)$$

output

# Approaches for ML

## Maximum Likelihood

$$\begin{aligned}\arg \max_{\mu_1, \mu_2, \dots, \mu_K} \prod_{i=1}^N p(x_i, k_i) &= \arg \max_{\mu_1, \mu_2, \dots, \mu_K} \left( \prod_{i=1}^N p(k_i) \cdot p(x_i | k_i) \right) = \arg \max_{\mu_1, \mu_2, \dots, \mu_K} \left( \prod_{i=1}^N p(x_i | k_i) \right) = \\ &= \arg \max_{\mu_1, \mu_2, \dots, \mu_K} \left( \prod_{x \in X_1} p(x|1) \times \prod_{x \in X_2} p(x|2) \times \prod_{x \in X_K} p(x|K) \right)\end{aligned}$$

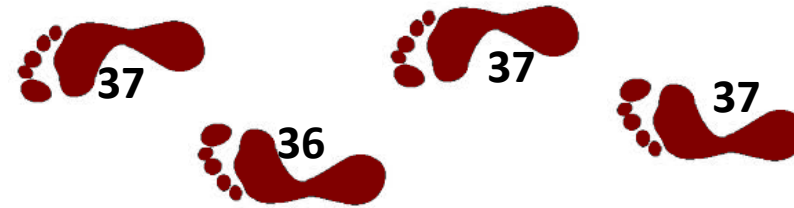
$$\mu_k^* = \arg \max_{\mu} \prod_{x \in X_k} f(x, \mu)$$

# Approaches for ML

## Maximum Likelihood: example



$$p(x|k=1) = f(x, \mu_1) \cong \exp\left\{-(x - \mu_1)^2\right\}$$



$$p(x|k=2) = f(x, \mu_2) \cong \exp\left\{-(x - \mu_2)^2\right\}$$

$$(\mu_1, \mu_2) = \arg \max \prod_{i=1}^7 p(x_i, k_i)$$

$$\mu_1 = \arg \max_{\mu} \exp\left\{-(45 - \mu)^2 - (46 - \mu)^2 - (45 - \mu)^2\right\}$$

# Approaches for ML

## Maximum Likelihood: example



$$\mu_1 = \arg \max_{\mu} \exp \left\{ - (45 - \mu)^2 - (46 - \mu)^2 - (45 - \mu)^2 \right\}$$

$$\mu_1 = \arg \min_{\mu} \left\{ (45 - \mu)^2 + (46 - \mu)^2 + (45 - \mu)^2 \right\}$$

$$\mu_1 = \frac{45 + 46 + 45}{3} = \langle x \rangle_{x_1}$$

# Approaches for ML

## Bias in training data

$x_1, x_2, \dots, x_N$  features and  
 $k_1, k_2, \dots, k_N$  states

$k \in K = \{1, 2, \dots, K\}$  domain for  $k$

$p(x|k) = f(x, \mu_k)$  The model is parametrized by  
 $\mu_1, \mu_2, \dots, \mu_K$

input

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$$\mu_1^* = \arg \max_{\mu} \left\{ \min_{x \in X_1} p(x|k=1, \mu) \right\}$$

output



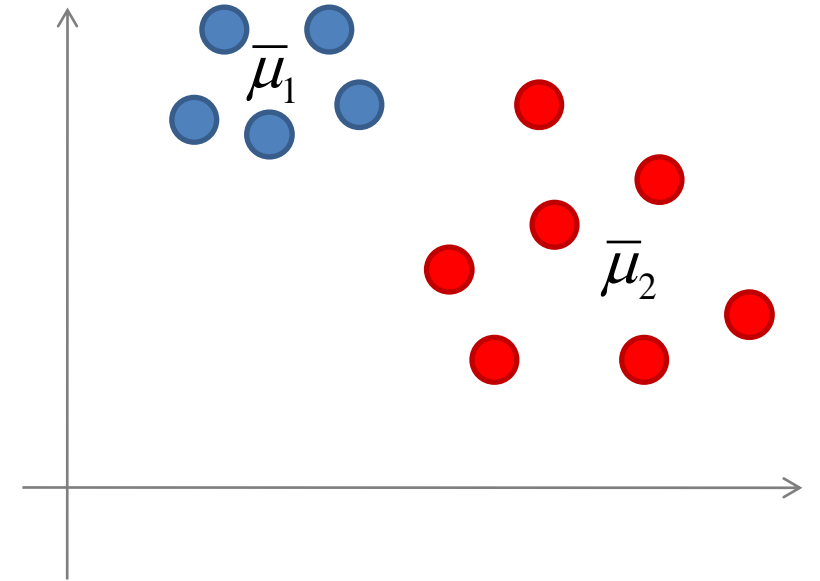
# Approaches for ML

## Bias in training data: example

$$p(x|k=1) = N(\bar{\mu}_1, 1)$$

$$p(x|k=2) = N(\bar{\mu}_2, 1)$$

$$\bar{\mu}_1^* = \arg \max_{\bar{\mu}} \left\{ \min_{x \in X_1} p(x|k=1, \bar{\mu}) \right\}$$



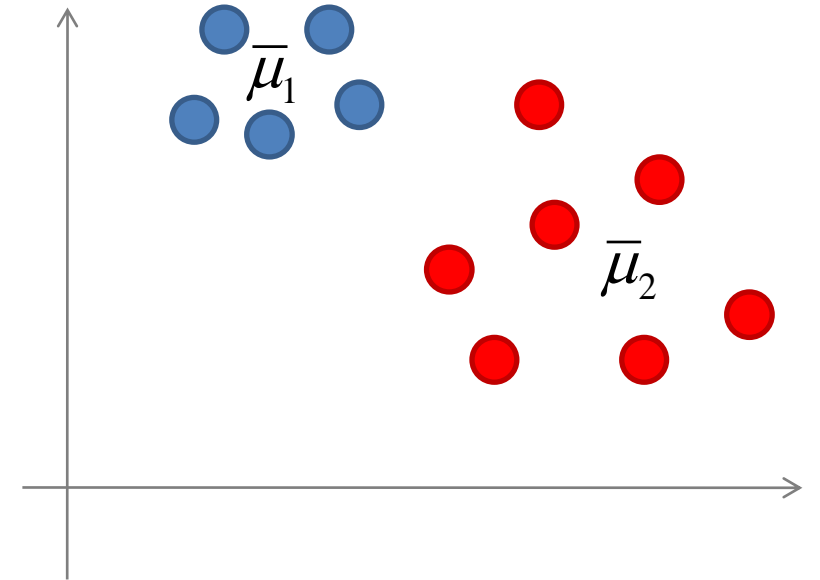
# Approaches for ML

## Bias in training data: example

$$p(x|k=1) = N(\bar{\mu}_1, 1)$$
$$p(x|k=2) = N(\bar{\mu}_2, 1)$$

$$\bar{\mu}_1^* = \arg \max_{\bar{\mu}} \left\{ \min_{x \in X_1} p(x|k=1, \bar{\mu}) \right\}$$

center of the circle that  
holds all the points from  $X_1$



# Approaches for ML

## ERM: Empirical risk minimization

$x_1, x_2, \dots, x_N$  features and  
 $k_1, k_2, \dots, k_N$  states

$k \in K = \{1, 2, \dots, K\}$  domain for  $k$

$W(k, k')$  penalty function

$q(x, \bar{\mu}) \in K$  decision strategy is parametrized by  $\mu$

# Approaches for ML

## ERM: Empirical risk minimization

$q(x, \bar{\mu}) \in K$  decision strategy is parametrized by  $\mu$

$$Risk(q(\bar{\mu})) = \sum_{x \in X} \sum_{k \in K} p(x, k) \cdot W(q(x, \bar{\mu}), k)$$

$$\cong \sum_{i=1}^N p(x_i, k_i) \cdot W(q(x_i, \bar{\mu}), k_i) = \sum_{i=1}^N W(q(x_i, \bar{\mu}), k_i)$$

$$\mu^* = \arg \min_{\mu} Risk q(\mu)$$

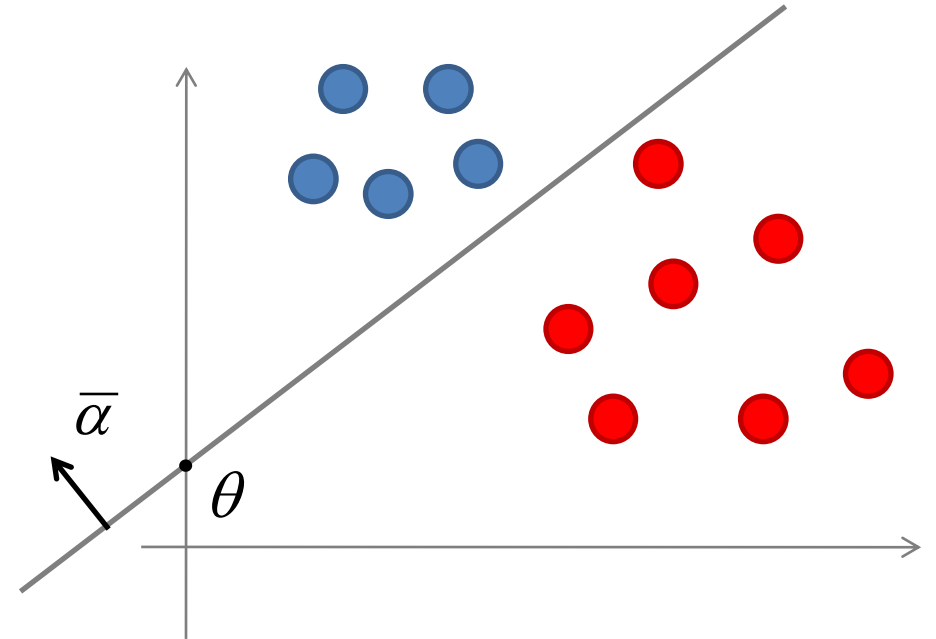
# Approaches for ML

## ERM: Empirical risk minimization

$$q(\bar{x}, \bar{\alpha}, \theta) = \begin{cases} -1 & \text{when } (\bar{x}, \bar{\alpha}) < \theta \\ +1 & \text{when } (\bar{x}, \bar{\alpha}) > \theta \end{cases}$$

$$W(k, k') = \begin{cases} 0 & k = k' \\ 1 & k \neq k' \end{cases}$$

$$\text{Risk}(q(\bar{\alpha}, \theta)) = \text{Number of errors}$$



# Bayesian approach



# Bayesian approach

## Definitions

$x \in X$       feature

$k \in K$       state (hidden)

$p(x, k)$       joint probability

$W : K \times K \rightarrow R$       penalty function

$q : X \rightarrow K$       decision strategy

$$Risk(q) = \sum_{k \in K} \sum_{x \in X} p(x, k) \cdot W(k, q(x))$$

# Bayesian approach

## The problem

$x \in X$  feature

$k \in K$  state (hidden)

$p(x, k)$  joint probability

$W : K \times K \rightarrow R$  penalty function

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$q : X \rightarrow K$  decision strategy

$$q^*(x) = \arg \min_{q(x)} Risk(q(x)) = \arg \min_{q(x)} \sum_{k \in K} \sum_{x \in X} p(x, k) \cdot W(k, q(x))$$

input

output



# Bayesian approach

## Some basics

$$p(x, k) = p(k) \cdot p(x|k) = p(x) \cdot p(k|x) \quad \text{joint probability}$$

$$p(x) = \sum_k p(k) \cdot p(x|k) \quad \text{law of total probability}$$

$$p(k|x) = \frac{p(k) \cdot p(x|k)}{\sum_{k'} p(k') \cdot p(x|k')} \quad \text{Bayes' theorem}$$

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$p(k)$  prior probability

$p(k|x)$  posterior probability

$p(x|k)$  conditional probability of  $x$ , assuming  $k$

$p(x)$  probability of  $x$

# Bayesian approach

## Example

$X = \{8, 9, 10, 11, 12\}$  time

$K = \{1\text{-revision}, 2\text{-free\_ride}\}$

$$p(k = 1 | x = 8) = 10\%$$

$$p(k = 2 | x = 8) = 90\%$$

$$W(k = 1, k' = 1) = 5 \quad W(k = 2, k' = 1) = 100$$

$$W(k = 1, k' = 2) = 5 \quad W(k = 2, k' = 2) = 0$$



# Bayesian approach

## Flexibility to not make a decision

$$W(k, k') = \begin{cases} 0 & \text{when } k = k' \\ 1 & \text{when } k \neq k' \\ \varepsilon & \text{when } k = \text{reject} \end{cases}$$

$$\begin{aligned} \text{Risk}(\text{reject}) &= \sum_{k \in K} p(k|x) \cdot W(k, \text{reject}) = \\ &= \sum_{k \in K} p(k|x) \cdot \varepsilon = \varepsilon \end{aligned}$$



# Bayesian approach

## Flexibility to not make a decision

$$\varepsilon = 0$$

*if*  $\min_k \text{Risk}(k) < \varepsilon$

*then*  ~~$k^* = \arg \min_k \sum_{k' \in K} p(k|x) \cdot W(k, k')$~~

*else* reject

$$\varepsilon = \infty$$

*if*  $\min_k \text{Risk}(k) < \varepsilon$

*then*  $k^* = \arg \min_k \sum_{k' \in K} p(k|x) \cdot W(k, k')$

*else* ~~reject~~

# Bayesian approach

## Decision strategies for different penalty functions

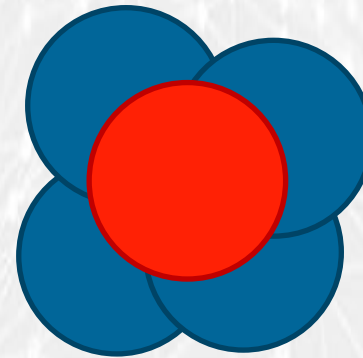
$$w(k, k') = |k - k'| \quad \text{median}$$

$$w(k, k') = (k - k')^2 \quad \text{average}$$

$$w(k, k') = \begin{cases} 0 & k = k' \\ 1 & k \neq k' \end{cases} \quad \text{the most probable sample}$$

$$w(k, k') = \begin{cases} 0 & |k - k'| < \Delta \\ 1 & |k - k'| \geq \Delta \end{cases} \quad \text{center of the most probable section } \Delta$$

# Classifying the independent binary features



# Classifying the independent binary features

## The problem

$\bar{x} = (x_1, x_2, \dots, x_N)$  feature – a set of independent binary values

$$p(\bar{x}|k) = p(x_1|k) \cdot p(x_2|k) \cdot \dots \cdot p(x_N|k)$$

$k \in K = \{1, 2\}$  Few states are possible

$$\frac{p(\bar{x}|k=1)}{p(\bar{x}|k=2)} \underset{2}{\overset{1}{\geq}} \theta$$

Decision strategy

# Classifying the independent binary features

## The problem

$$\log \frac{p(\bar{x}|k=1)}{p(\bar{x}|k=2)} = \log \frac{p(x_1|k=1) \cdot \dots \cdot p(x_n|k=1)}{p(x_1|k=2) \cdot \dots \cdot p(x_n|k=2)} = \log \frac{p(x_1|k=1)}{p(x_1|k=2)} + \dots + \log \frac{p(x_n|k=1)}{p(x_n|k=2)} =$$

$$x_1 \cdot \log \frac{p(x_1=1|k=1) \cdot p(x_1=0|k=2)}{p(x_1=1|k=2) \cdot p(x_1=0|k=1)} + \log \frac{p(x_1=0|k=1)}{p(x_1=0|k=2)} +$$

$\vdots$

$$x_n \cdot \log \frac{p(x_n=1|k=1) \cdot p(x_n=0|k=2)}{p(x_n=1|k=2) \cdot p(x_n=0|k=1)} + \log \frac{p(x_n=0|k=1)}{p(x_n=0|k=2)}$$



# Classifying the independent binary features

## Decision rule

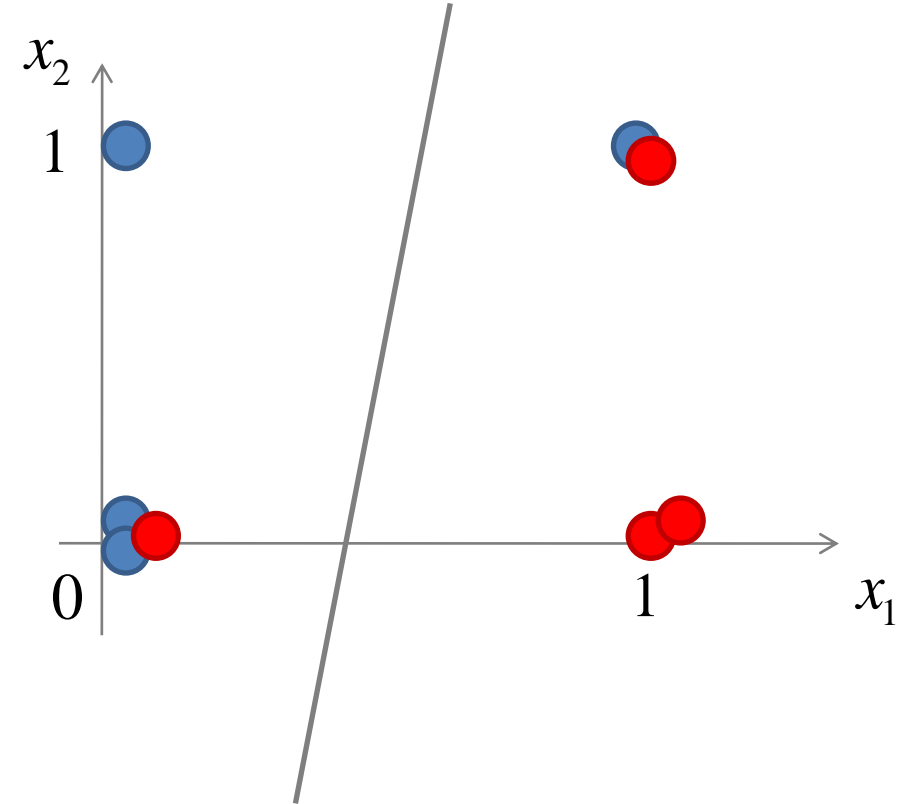
$$\sum_{i=1}^N x_i \cdot \log \frac{p(x_i = 1|k = 1) \cdot p(x_i = 0|k = 2)}{p(x_i = 1|k = 2) \cdot p(x_i = 0|k = 1)} + \log \frac{p(x_i = 0|k = 1)}{p(x_i = 0|k = 2)} \underset{2}{\overset{1}{\geq \leq}} \log \theta$$

$$\sum_{i=1}^N x_i \cdot a_i \underset{2}{\overset{1}{\geq \leq}} \theta'$$

# Classifying the independent binary features

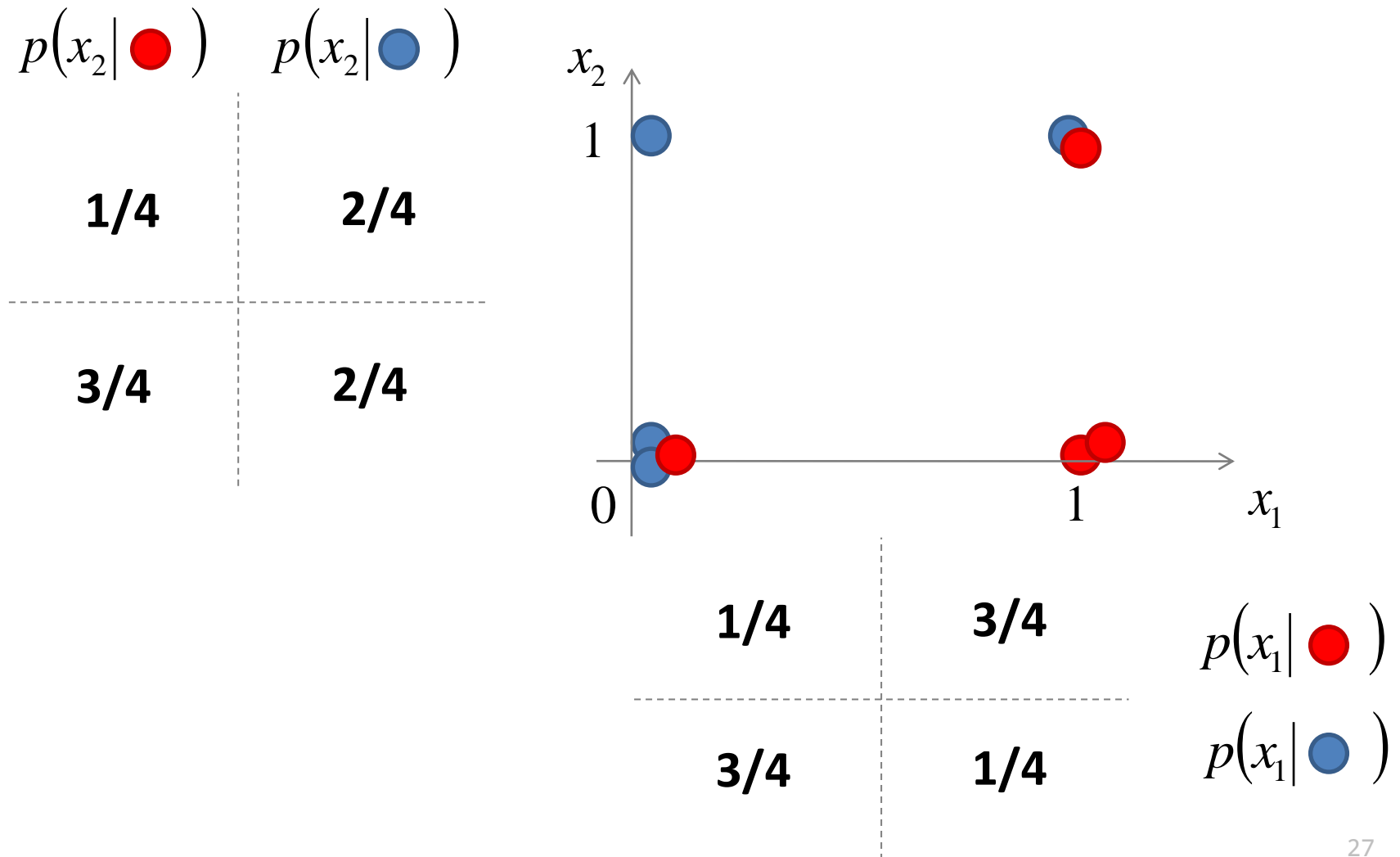
## Example

$$\sum_{i=1}^N x_i \cdot a_i \begin{matrix} \geq \\ \leq \end{matrix} \begin{matrix} 1 \\ 2 \end{matrix} \theta'$$



# Classifying the independent binary features

## Example

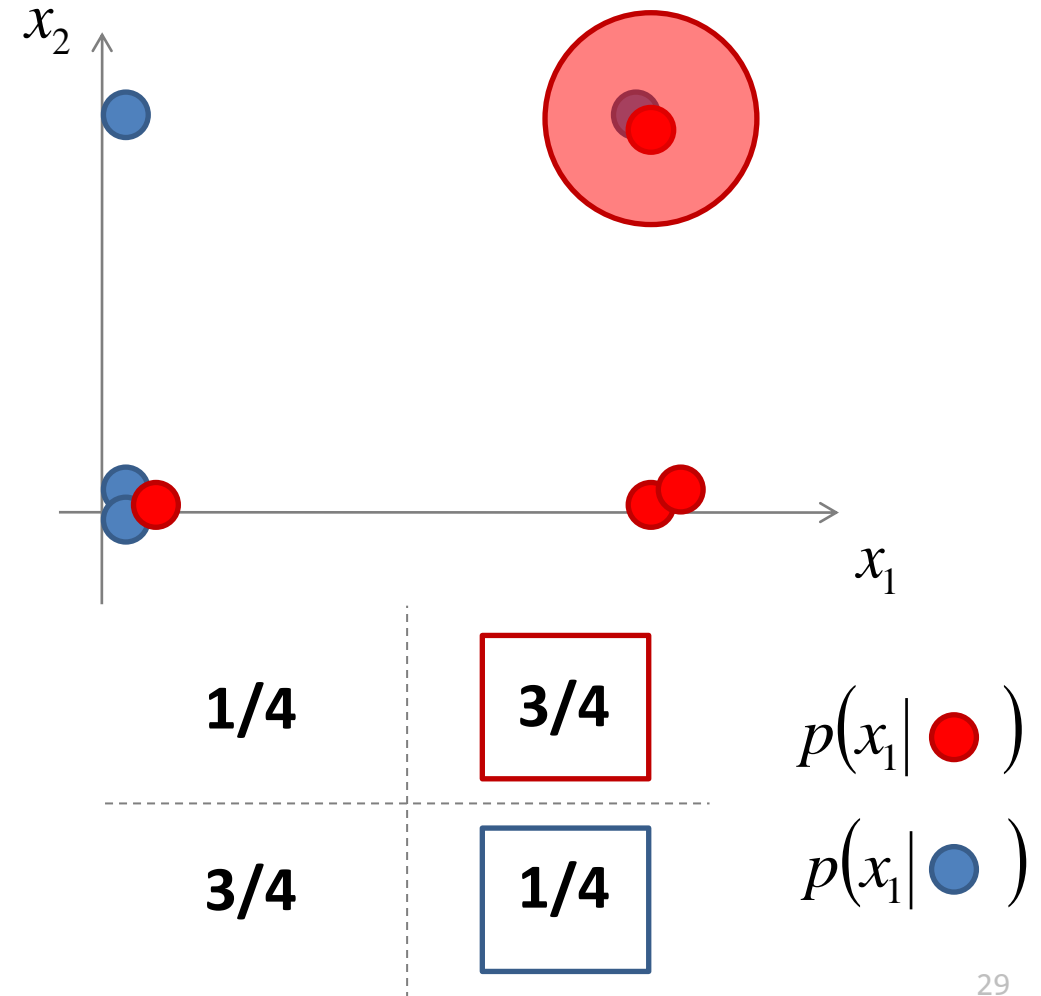
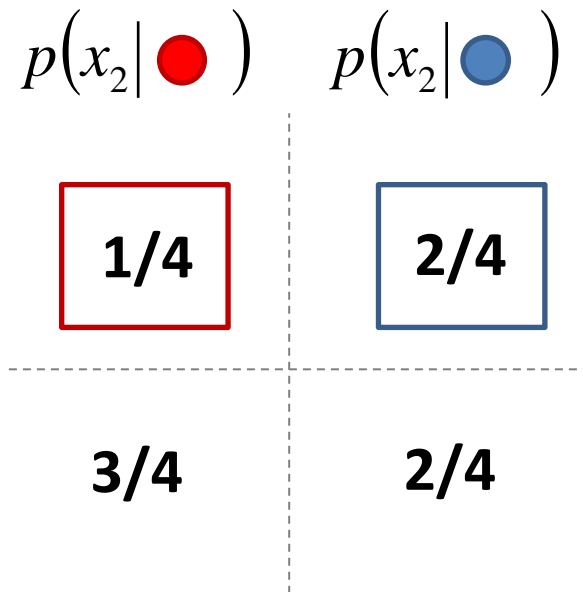


## Example



# Classifying the independent binary features

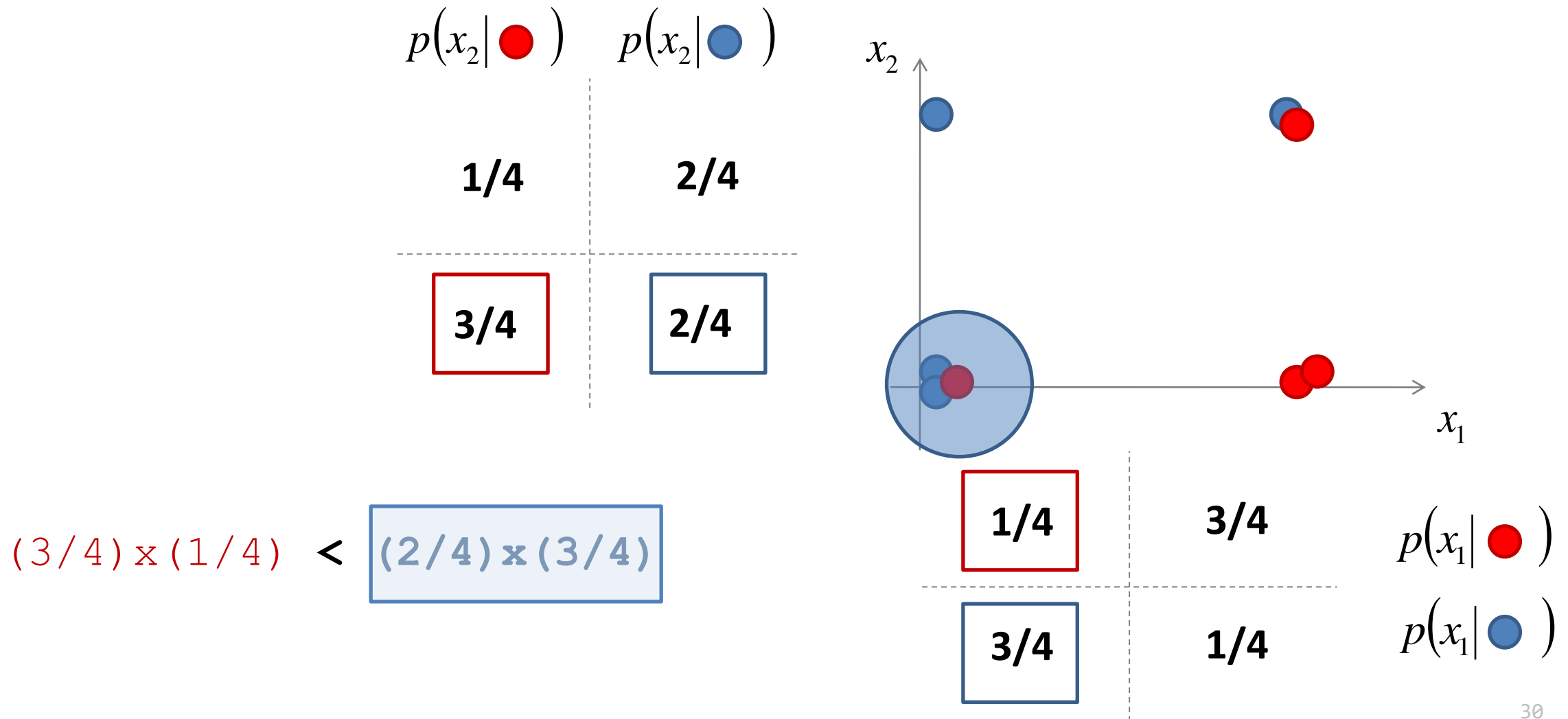
## Example



$$(1/4) \times (3/4) > (2/4) \times (1/4)$$

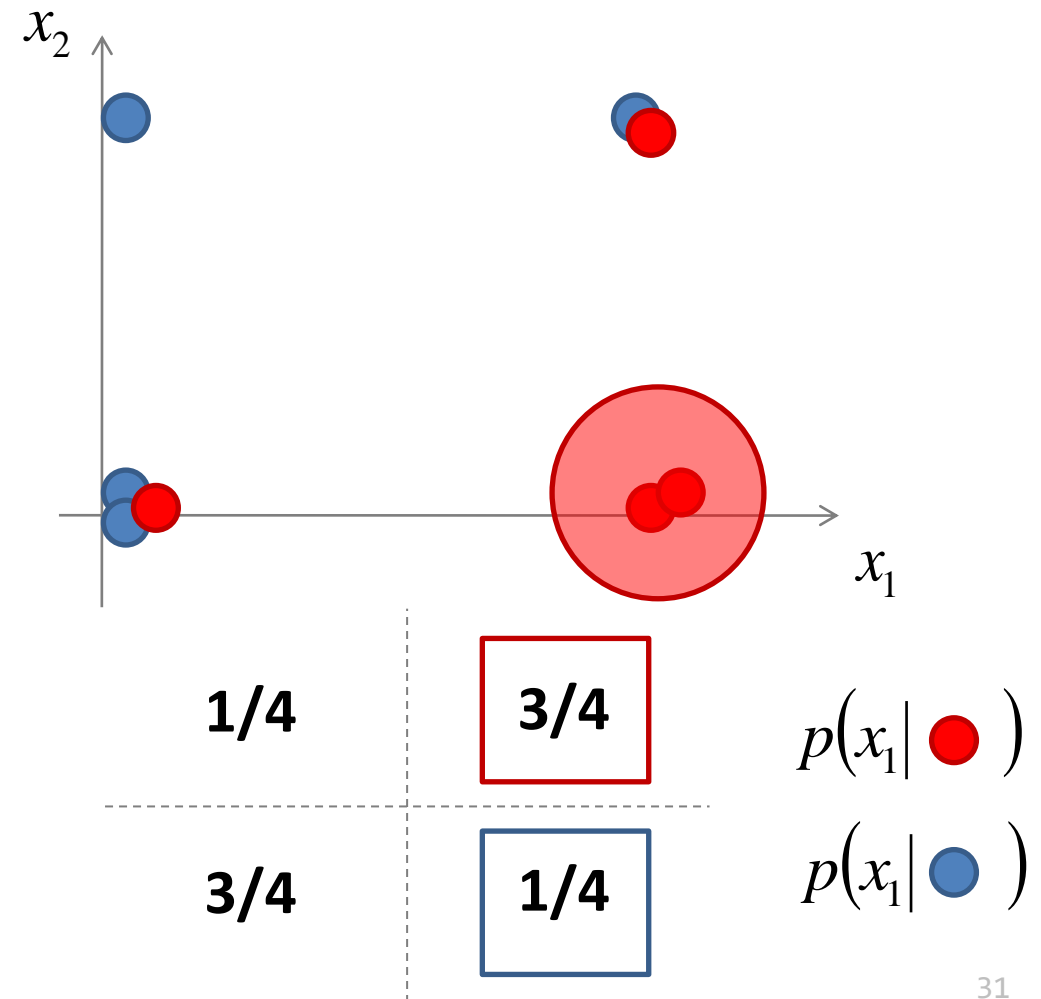
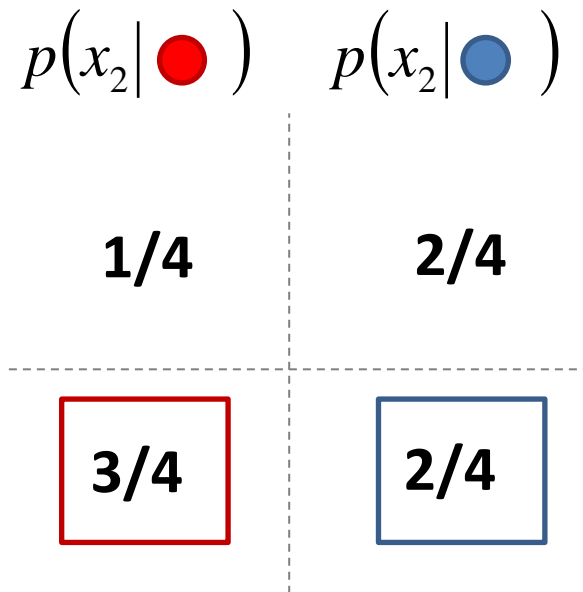
# Classifying the independent binary features

## Example



# Classifying the independent binary features

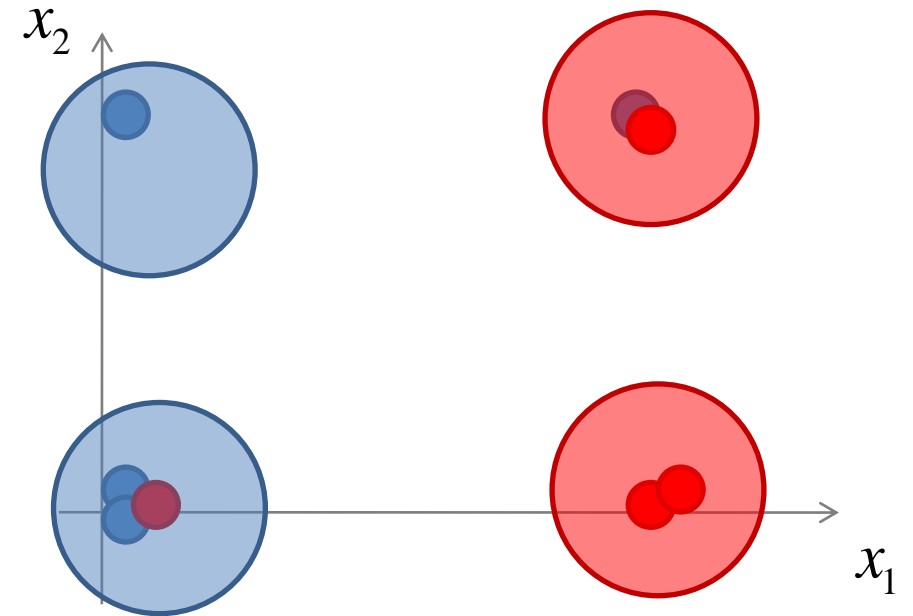
## Example



$$(3/4) \times (3/4) > (2/4) \times (1/4)$$

# Classifying the independent binary features

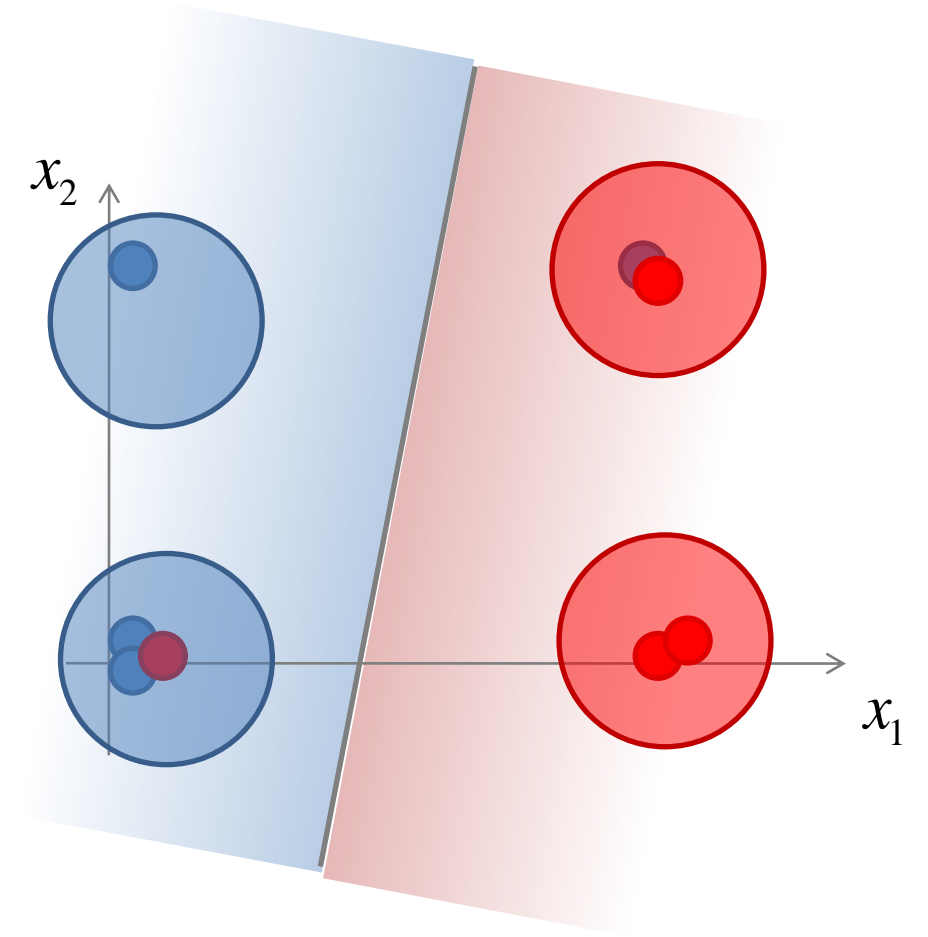
## Example





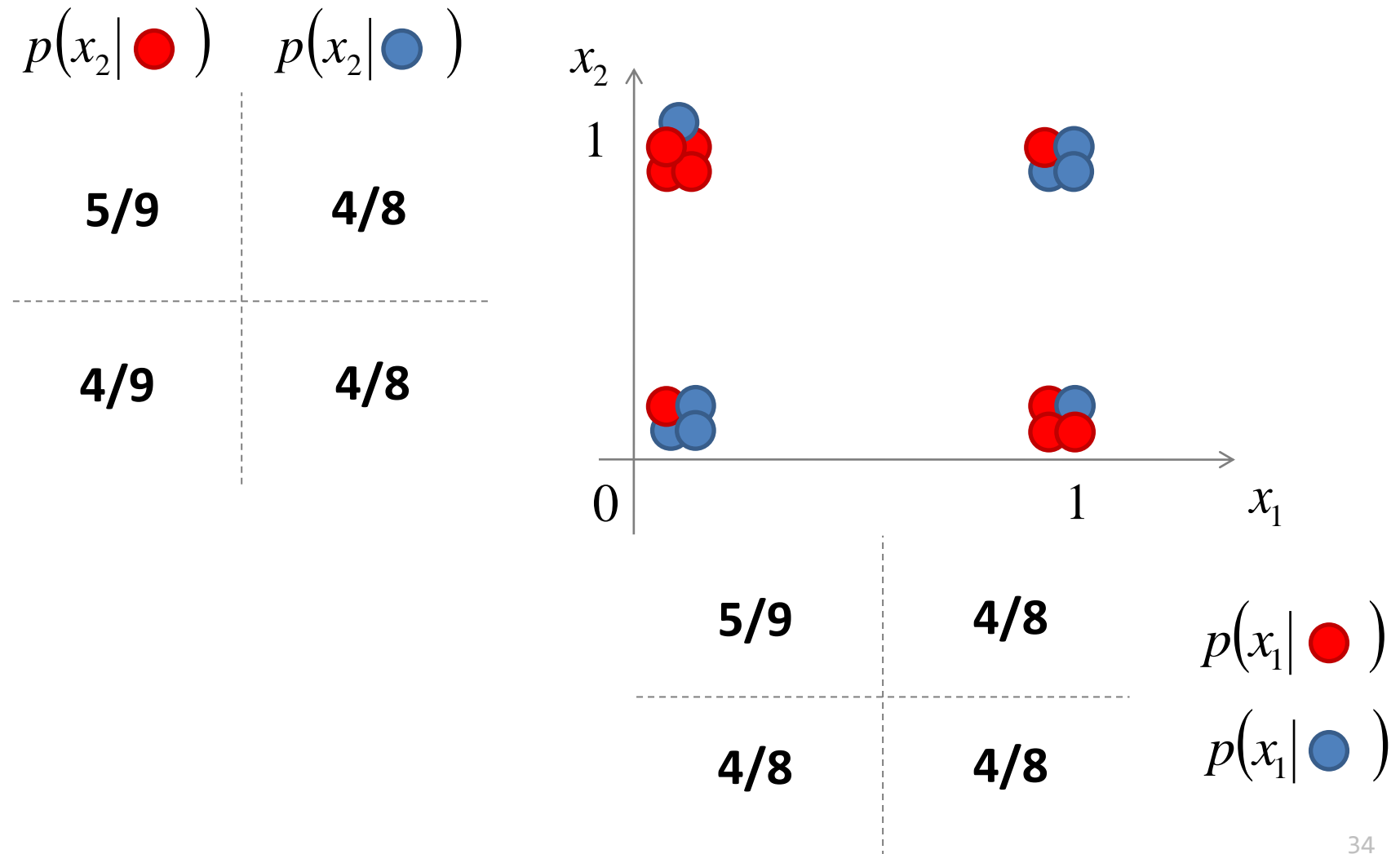
# Classifying the independent binary features

## Example



# Classifying the independent binary features

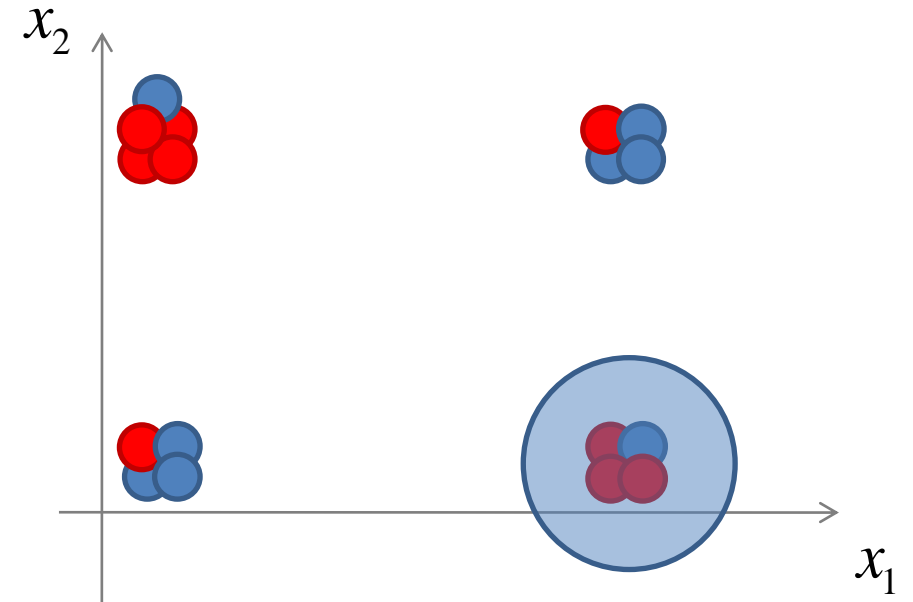
## Another example



# Classifying the independent binary features

## Another example

$$p(x_2 | \bullet) \quad p(x_2 | \bullet)$$



$$(4/9) \times (4/9) <$$

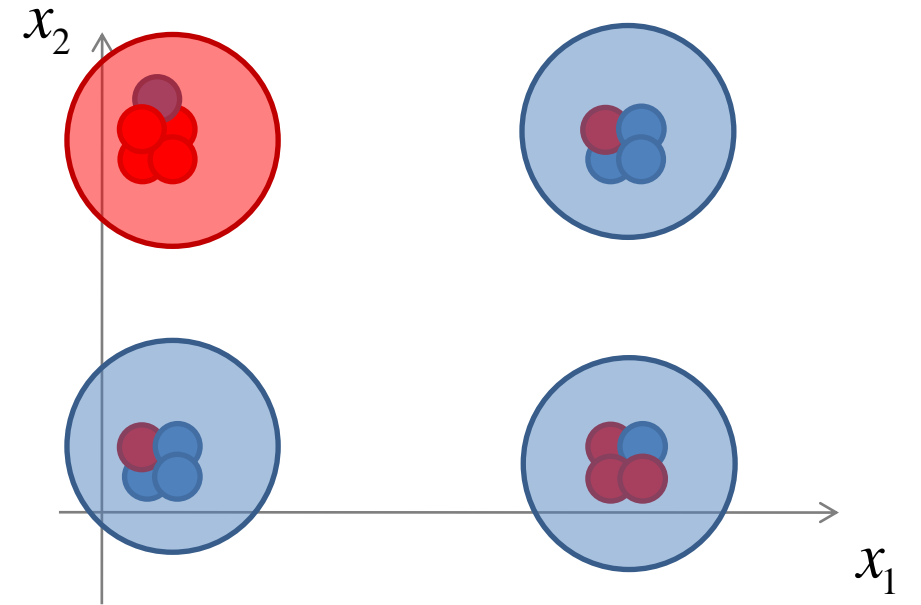
$$(4/8) \times (4/8)$$

$$p(x_1 | \bullet)$$

$$p(x_1 | \bullet)$$

# Classifying the independent binary features

## Another example



# Classifying the independent binary features

## Another example

