



## Seminar - Bridge Game

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# Interactive Exercises : Classification

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# Machine Learning —— Classification

给定一个示例，将其归为垃圾邮件或者非垃圾邮件

例 0.40 (贝叶斯 Spam 过滤器) 如何确定一个电子邮件是 Spam?

- 假设我们有一个垃圾邮件的集合  $B$  和一个不是垃圾的邮件集合  $G$ . 利用贝叶斯公式来预测一个新的电子邮件是 Spam 的概率.
- 考察一个特定的单词  $\omega$ , 统计该单词在集合  $B$  和  $G$  中出现的次数分别为  $n_B(\omega)$  和  $n_G(\omega)$ .
- 设  $S$  是事件: 邮件为 Spam,  $E$  是事件: 邮件内容含单词  $\omega$ . 需计算  $P(S | E)$ .

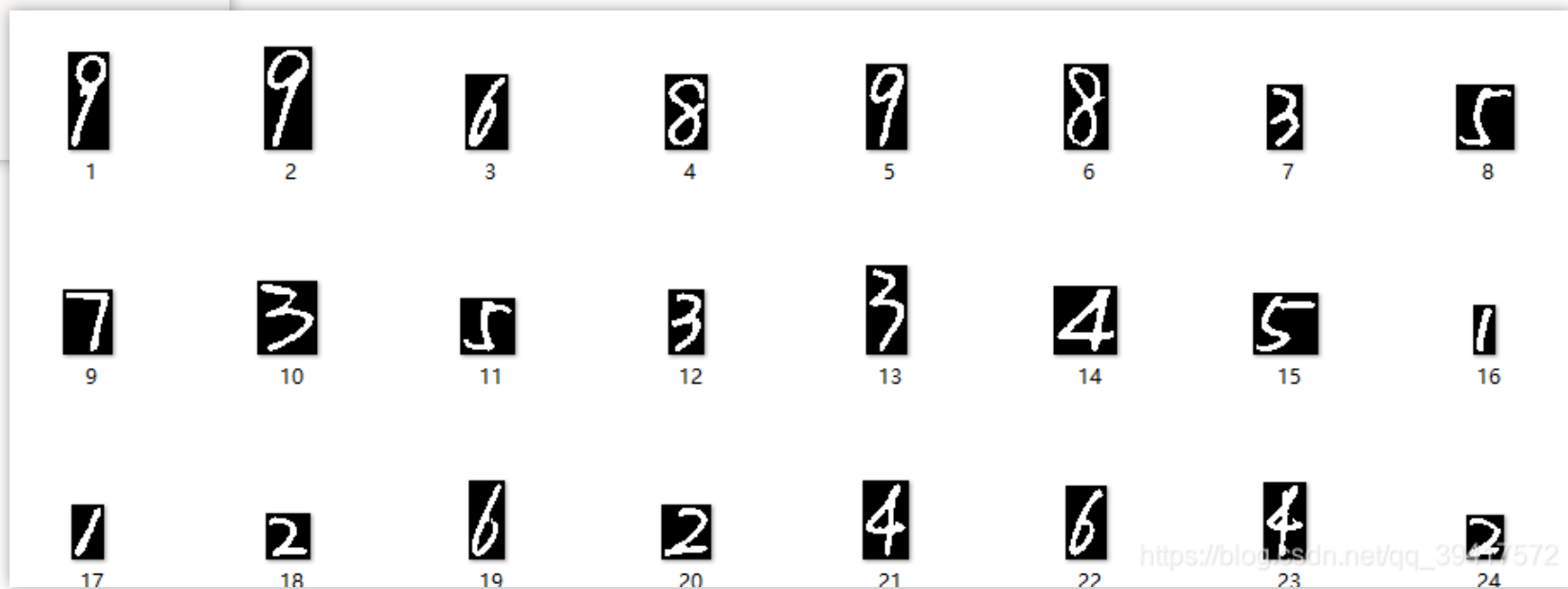
思路: 根据贝叶斯公式, 我们需要分别估算

- Spam 邮件中含有单词  $\omega$  的概率  $P(E | S)$
- 非 Spam 邮件中含有单词  $\omega$  的概率  $P(E | \bar{S})$
- 比较这两者的大小

给定 something —— 称为输入样本  
(Input)

给定一个手写字符的图片，将其分类为一个已知字符

输出一个类别 —— Label



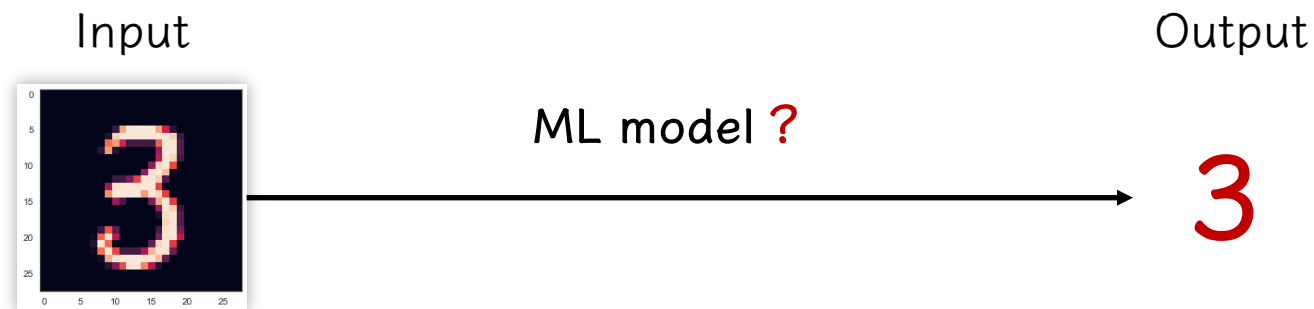
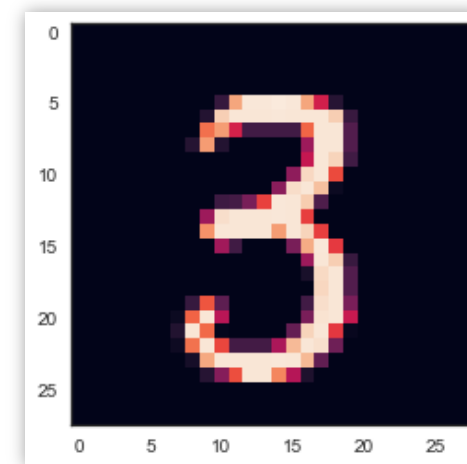
# Machine Learning —— Classification

□ 对于 Input 来讲，最重要的是 features

- 在垃圾邮件分类任务中，所要查找的单词，feature 是  $\omega$
- 在图像识别任务中，输入的是一张图片，features 是相对应的像素

□ 对于 Output

- 在垃圾邮件分类任务中，“是” or “否” 垃圾邮件
- 在图像识别任务中，输出是相对应的数字，e.g., 1, 2, 3, ...



# Binary Classification with Two Features

□ 抽象： $(X, Y) \rightarrow Z$

[-] Alibaba Cloud | TIANCHI 天池

Index	Height(Inches)	Weight(Pounds)	Gender
1	65.78331	112.9925	1
2	71.51521	136.4873	0
3	69.39874	153.0269	0
4	68.2166	142.3354	1
5	67.78781	144.2971	1
6	68.69784	123.3024	1
7	69.80204	141.4947	1
8	70.01472	136.4623	1

$X$  表示 Height

$Y$  表示 Weight

$Z$  表示 Gender (0 表示女生, 1 表示男生)

} features

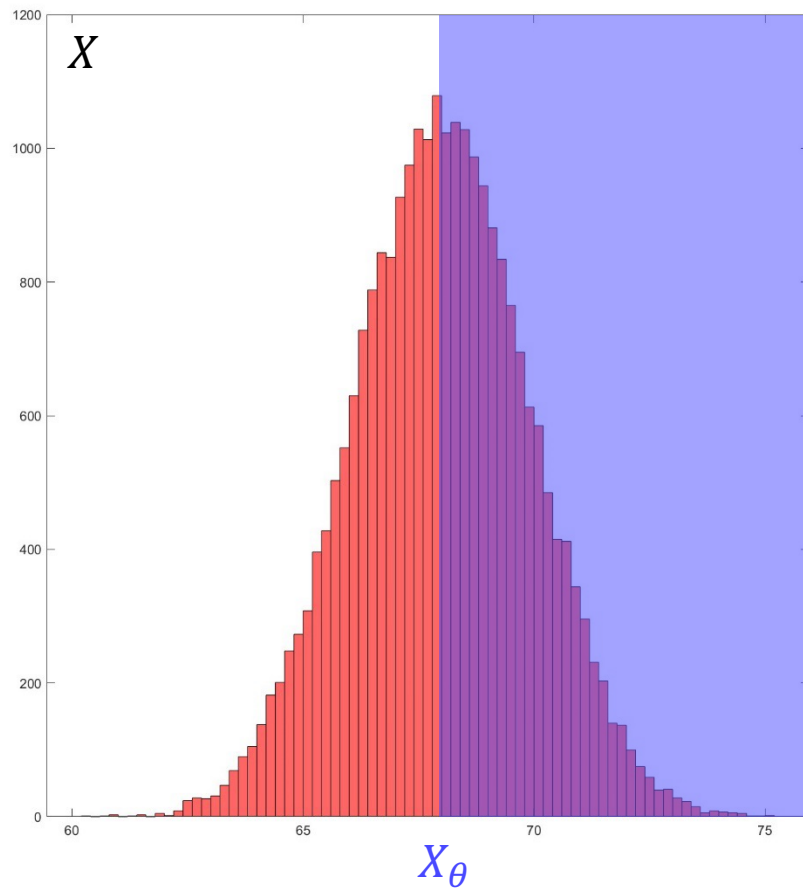
□ 根据《概率论与数理统计》所学的知识, 有哪些方法可以实现这个分类任务?

比如: 给定  $(X = 70.1111, Y = 141.3333)$ , 问: 对应的  $Z$  应该是多少?

- $Z = 1$  的概率?
- $Z = 0$  的概率?

# Classification with Univariate Feature

$$\square X \rightarrow Z \cap Y \rightarrow Z$$



IF **Red** refers to **1**, while **Blue** corresponds to **0**

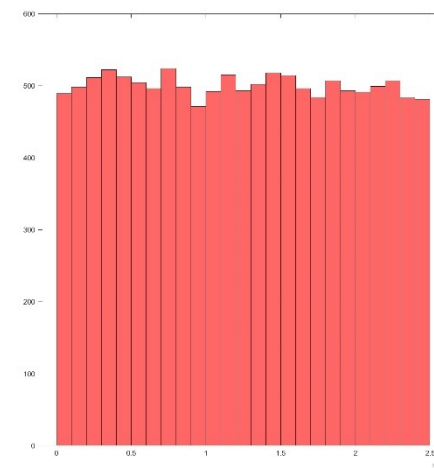
Then we have

$$X \geq X_\theta \rightarrow Z = 1$$

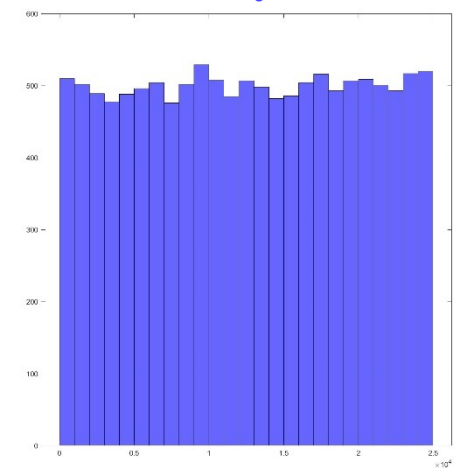
$$X < X_\theta \rightarrow Z = 0$$

Obviously, this case is ideal.

**Girl**



**Boy**



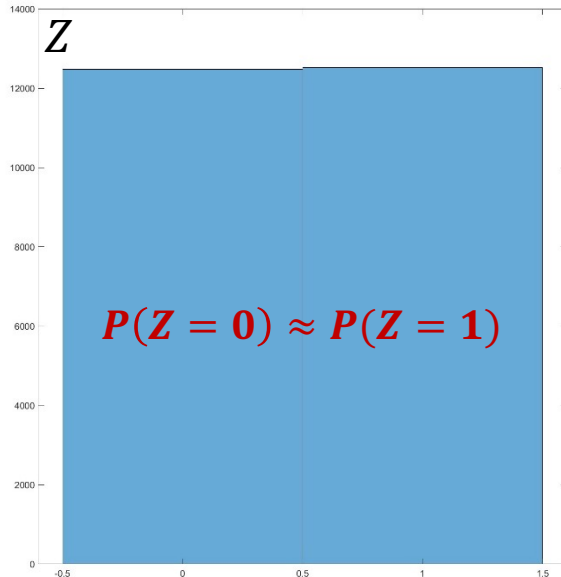
# Classification with Univariate Feature

## Conditional Probability:

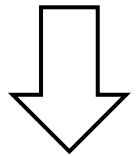
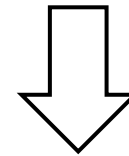
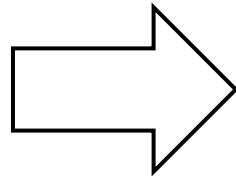
- First, compute  $P(Z | X = 70.1111)$
- Second, make a decision by compare  $P(Z = 1 | X = 70.1111)$  with  $P(Z = 0 | X = 70.1111)$

$$P(Z = 1 | X = 70.1111) = \frac{P(Z = 1, X = 70.1111)}{P(X = 70.1111)} = \frac{P(Z = 1)P(X = 70.1111 | Z = 1)}{P(X = 70.1111)}$$

$$P(Z = 0 | X = 70.1111) = \frac{P(Z = 0, X = 70.1111)}{P(X = 70.1111)} = \frac{P(Z = 0)P(X = 70.1111 | Z = 0)}{P(X = 70.1111)}$$



Compare  $P(X = 70.1111 | Z = 0)$  with  $P(X = 70.1111 | Z = 1)$



$$P(X = 70.1111 | Z = 0) = 0 \quad P(X = 70.1111 | Z = 1) = 0$$

What ?!!!

# Classification with Univariate Feature

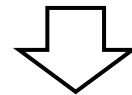
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## □ Conditional Probability:

- First, compute  $P(Z | X = 70.1111)$
- Second, make a decision by compare  $P(Z = 1 | X = 70.1111)$  with  $P(Z = 0 | X = 70.1111)$

## □ Improvement of Discretization :

- **Discrete  $X$ , Discrete  $Z$**
- Partition the range of variable  $X$  as  $x_1, x_2, \dots, x_n$ . For example, horizon  $\delta = 0.5$ ,  $x_1 = [60, 60.5)$
- Find  $70.1111 \in x_k$
- Compute  $P(Z = 1 | X = x_k)$  replacing  $P(Z = 1 | X = 70.1111)$
- Compare  $P(X = x_k | Z = 0)$  with  $P(X = x_k | Z = 1)$



$$P(X = x_k | Z = 0) = 0.0439 < P(X = x_k | Z = 1) = 0.0586$$

Identify  $Z = 1$ ?

## □ Depend heavily on the setting of the discretization horizon

horizon 0.2:  $0.0213 < 0.0254$   
horizon 0.12:  $0.0144 > 0.0141$

# Classification with Univariate Feature

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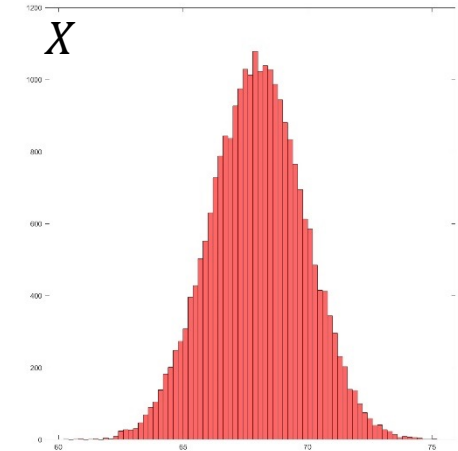
## □ Conditional Probability:

- First, compute  $P(Z | X = 70.1111)$
- Second, make a decision by compare  $P(Z = 1 | X = 70.1111)$  with  $P(Z = 0 | X = 70.1111)$

## □ Improvement of Continuum:

- Model  $(X, Z)$
- $P(Z \leq z | X = x) = \int_{-\infty}^z \frac{f(x,z)}{f_X(x)} dz$  ?
- We have challenges:
  - $Z$  is discrete
  - It is hard to obtain  $f(x, z)$ .

Assume  
Gaussian





# Classification with Univariate Feature

## Conditional Probability:

- First, compute  $P(Z | X = 70.1111)$
- Second, make a decision by compare  $P(Z = 1 | X = 70.1111)$  with  $P(Z = 0 | X = 70.1111)$

## Improvement of Continuum:

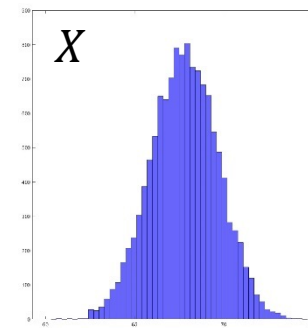
- Model  $(X, Z)$
- Continuous  $X$ , Discrete  $Z$

$$P(Z = 1 | X = x) = \frac{P(Z = 1, X = x)}{P(X = x)} = \frac{P(Z = 1)P(X = x | Z = 1)}{P(X = x)}$$
$$= \frac{P(Z = 1) \int_x^{x+\delta} f_{X|Z}(x|z = 1)dx}{P(X = x)}$$

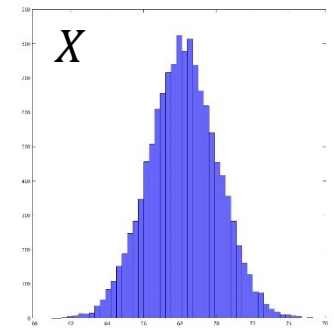
### Steps:

- $X$  is Gaussian,  $\mathcal{N}(67.9931, 3.6164)$
- $X|Z = 0$  is Gaussian,  $\mathcal{N}(67.8077, 3.5384)$
- $X|Z = 1$  is Gaussian,  $\mathcal{N}(68.1786, 3.6258)$
- Next ?

$Z = 0$



$Z = 1$



Assume Gaussian

$$\frac{x - 67.8007}{\sqrt{3.5384}}$$

VS

$$\frac{x - 68.1786}{\sqrt{3.6258}}$$

$$1.2282 - 0$$

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$$1.0148 - 0$$



$$Z = 0$$

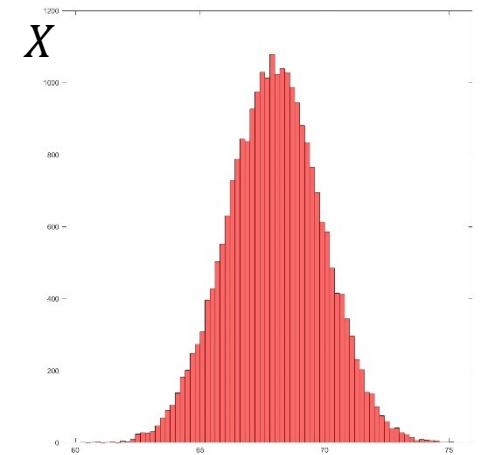
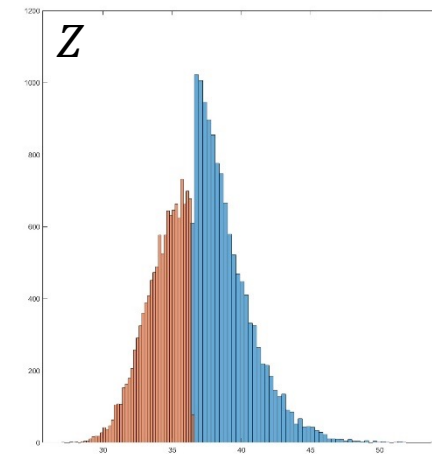
# Classification with Univariate Feature

## Conditional Probability:

- First, compute  $P(Z | X = 70.1111)$
- Second, make a decision by compare  $P(Z = 1 | X = 70.1111)$  with  $P(Z = 0 | X = 70.1111)$

## Improvement of Continuum:

- Model  $(X, Z)$
- Continuous  $X$ , Continuous  $Z$
- $E(Z | X = x) = \int_{-\infty}^{+\infty} \frac{f(x, z)}{f_X(x)} dz = \int_{-\infty}^{+\infty} z f_{Z|X}(z | X = x) dz$
- Steps:
  - $X$  is Gaussian,  $\mathcal{N}(67.9931, 3.6164)$
  - $Z$  also is continuous
  - compute  $f_{Z|X}(z | x) = ?$



Assume Gaussian

Even though we assume a continuous  $Z$ ,  
we cannot obtain the correlation coefficients  
between  $X$  and  $Z$ , RIGHT?

## 条件期望的性质

- **线性性.** 对任意常数  $a, b$  有  $\mathbb{E}(aX_1 + bX_2|Y) = a\mathbb{E}(X_1|Y) + b\mathbb{E}(X_2|Y)$ ;
- **函数型.** 对离散型随机向量  $(X, Y)$  和函数  $g(X)$ , 有

$$\mathbb{E}(g(X)|Y) = \sum_i g(x_i)P(X = x_i|Y = y)$$

对连续型随机向量  $(X, Y)$  和函数  $g(X)$ , 有

$$\mathbb{E}(g(X)|Y) = \int_{-\infty}^{+\infty} g(x)f(x|Y = y)dx$$

- 若随机向量  $(X, Y) \sim \mathcal{N}(\mu_x, \mu_y, \sigma_x^2, \sigma_y^2, \rho)$ , 则在  $Y = y$  的条件下随机变量  $X$  服从正态分布  $\mathcal{N}(\mu_x - \rho\sigma_x(y - \mu_y)/\sigma_y, (1 - \rho^2)\sigma_x^2)$ , 由此可得

$$\mathbb{E}(X|y) = \mu_x - \frac{\rho\sigma_x(y - \mu_y)}{\sigma_y}$$

# Classification with Univariate Feature

## Conditional Probability:

- First, compute  $P(Z | X = 70.1111)$
- Second, make a decision by compare  $P(Z = 1 | X = 70.1111)$  with  $P(Z = 0 | X = 70.1111)$

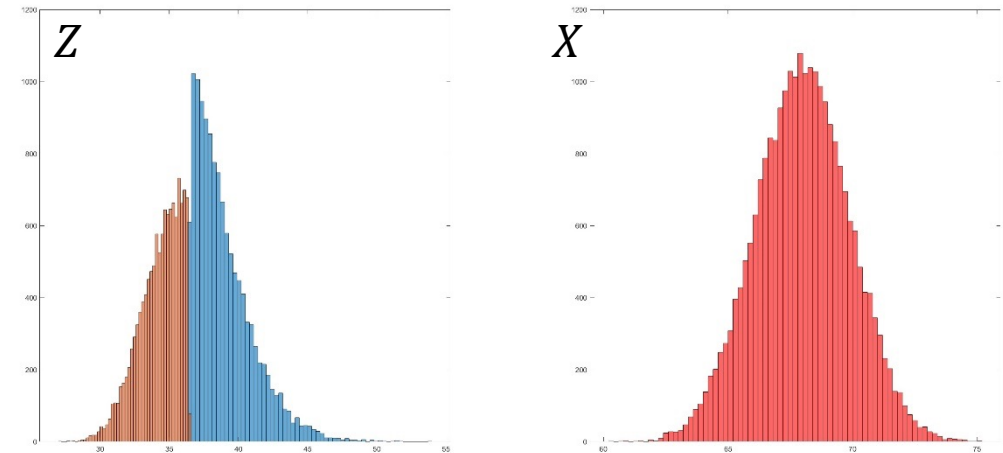
## Improvement of Continuum:

- Model  $(X, Z)$
- Continuous  $X$ , Continuous  $Z$

- $E(Z | X = x) = \int_{-\infty}^{+\infty} z \frac{f(x, z)}{f_X(x)} dz$

### Steps:

- $X$  is Gaussian,  $\mathcal{N}(67.9931, 3.6164)$
- $Z$  is Gaussian,  $\mathcal{N}(0.2027, 8.9741)$
- we can get the correlation coefficient  $\rho = 0.1103$
- compute  $(Z|X = x) \in \mathcal{N}(0.2027 - 0.1103 \times \frac{2.9957}{1.9017} \times (x - 67.9931), (1 - 0.1103^2) \times 8.9741)$
- compute  $(Z|X = 70.1111) \in \mathcal{N}(0.1653, 8.8645)$
- Next ?



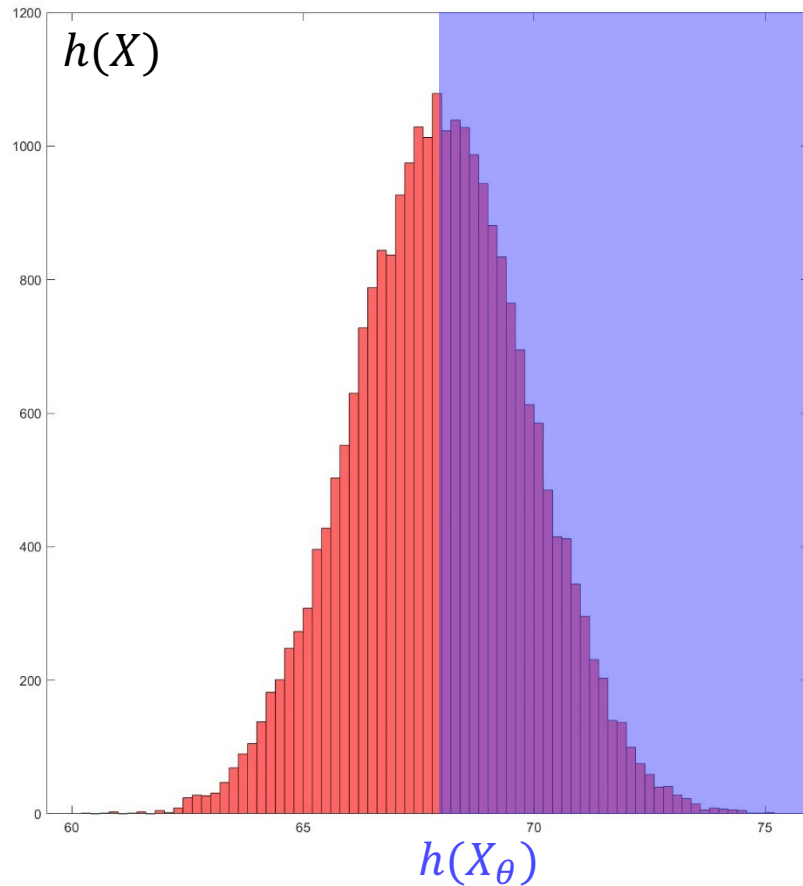
Assume Gaussian

# Classification with Univariate Feature

□ Possible: Is there a function  $h$  such that  $h(X)$  is obviously separable?

$$X \rightarrow h(X) \rightarrow Z$$

Q 1



# Classification with Multivariate Features

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□  $(X, Y) \rightarrow Z$  ?

- Is  $X$  independent to  $Y$ ?
- IF  $X$  is **independent** to  $Y$ , THEN we should make a classification, separately
- Select the maximum possibility

# Classification with Multivariate Features

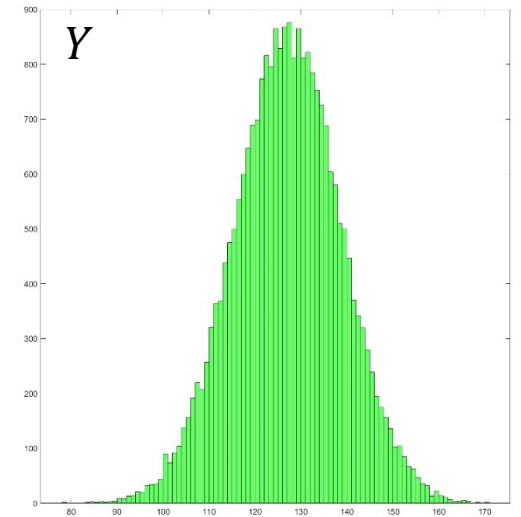
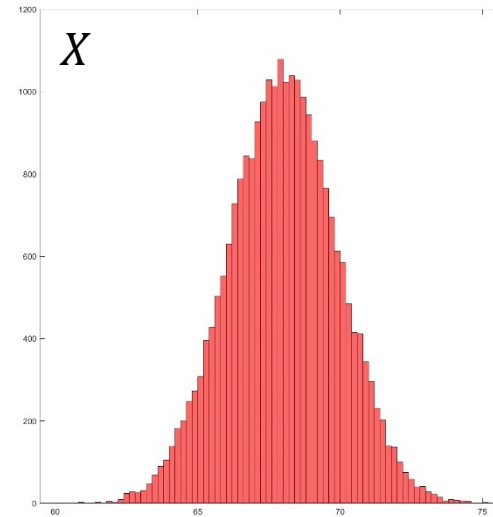
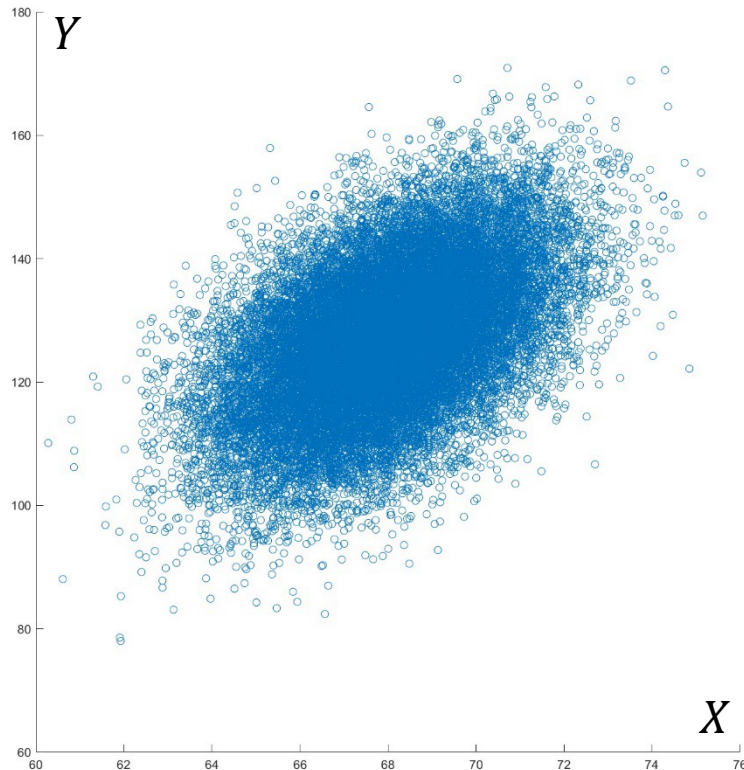
□  $(X, Y) \rightarrow Z$  ?

- Is  $X$  independent to  $Y$ ?
- It is observed that  $X$  is correlated to  $Y$ .

There are correlation, but we still cannot identify independency?

$$\mathbf{R}_{cor} = \begin{bmatrix} 1 & 0.529 \\ 0.529 & 1 \end{bmatrix}$$

$$\lambda_1 = \frac{1}{2}, u_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$
$$\lambda_2 = \frac{3}{2}, u_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$



Assume Gaussian

# Classification with Multivariate Features

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## □ $(X, Y) \rightarrow Z$ ?

- IF  $X$  is **dependent** to  $Y$ , THEN we should make a classification jointly
- **Discrete  $(X, Y)$ , Discrete  $Z$** 
  - Partition the range of variable  $X$  as  $x_1, x_2, \dots, x_n$ . For example, horizon  $\delta_1 = 0.5$ ,  $x_1 = [60, 60.5)$   
Partition the range of variable  $Y$  as  $y_1, y_2, \dots, y_n$ . For example, horizon  $\delta_2 = 2$ ,  $y_1 = [78, 80)$
  - Find  $(70.1111, 141.3333) \in (x_i, y_j)$
  - Compute  $P(Z = 0 \mid X = x_i, Y = y_j)$  and  $P(Z = 1 \mid X = x_i, Y = y_j)$
  - Compare  $P(X = x_i, Y = y_j \mid Z = 0)$  with  $P(X = x_i, Y = y_j \mid Z = 1)$



0.0066

>



0

Identify  $Z = 0$ ?

## □ Depend heavily on the setting of the discretization horizons

horizons (0.5, 1.5): 0.050 > 0  
horizons (0.5, 10): 0.0196 > 0  
horizons (0.2, 15): 0.0161 > 0.0088



# Classification with Multivariate Features

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## □ $(X, Y) \rightarrow Z$ ?

- IF  $X$  is **dependent** to  $Y$ , THEN we should make a classification jointly
- Provided Gaussian assumptions, we can obtain the  $f(x, y)$ 
  - $X$  is Gaussian,  $\mathcal{N}(67.9931, 3.6164)$
  - $Y$  is Gaussian,  $\mathcal{N}(127.0794, 135.9765)$
  - we can get the correlation coefficient  $\rho = 0.529$
  - compute  $(X, Y) \in \mathcal{N}((67.9931, 127.0794)^T, \mathbf{M}_{cov})$
  - **Next ?**

$$\mathbf{M}_{cov} = \begin{bmatrix} 3.6164 & 0.529 \\ 0.529 & 135.9765 \end{bmatrix}$$

## □ $(X, Y) \rightarrow Z$ ?

- Compare the possibility  
 $P(X = 70.1111, Y = 141.3333 \mid Z = 0)$  and  $P(X = 70.1111, Y = 141.3333 \mid Z = 1)$
- It is observed that both  $(X, Y) \mid Z = 0$  and  $(X, Y) \mid Z = 1$  obey Gaussian

# Classification with Multivariate Features

$Z = 0$



□  $(X, Y) \rightarrow Z$  ?

$$\mathcal{N}\left(\left(\frac{x - 67.8007}{\sqrt{3.5384}}, \frac{y - 137.4883}{\sqrt{79.1715}}\right), ?\right) \text{ VS } \mathcal{N}\left(\left(\frac{x - 68.1786}{\sqrt{3.6258}}, \frac{y - 119.6706}{\sqrt{83.0022}}\right), ?\right)$$

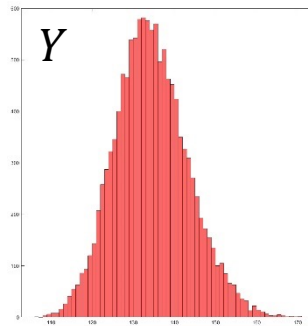
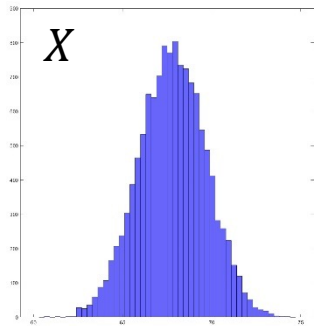


- Continuous  $(X, Y)$ , Discrete  $Z$

- Compare the possibility

$$P(X = 70.1111, Y = 141.3333 | Z = 0) \text{ and } P(X = 70.1111, Y = 141.3333 | Z = 1)$$

- It is observed that both  $(X, Y)|Z = 0$  and  $(X, Y)|Z = 1$  obey Gaussian



- Provided Gaussian assumptions, we can obtain the  $f(x, y|Z = 0)$

- $X|Z = 0$  is Gaussian,  $\mathcal{N}(67.8077, 3.5384)$

- $Y|Z = 0$  is Gaussian,  $\mathcal{N}(137.4883, 79.1715)$

- we can get the correlation coefficient  $\rho = 0.729$

- compute  $(X|Z = 0, Y|Z = 0) \in \mathcal{N}\left((67.8077, 137.4883)^T, \begin{pmatrix} 3.5384 & 12.2023 \\ 12.2023 & 79.1715 \end{pmatrix}\right)$

- Provided Gaussian assumptions, we can obtain the  $f(x, y|Z = 1)$

- $X|Z = 1$  is Gaussian,  $\mathcal{N}(68.1786, 3.6258)$

- $Y|Z = 1$  is Gaussian,  $\mathcal{N}(119.6706, 83.0022)$

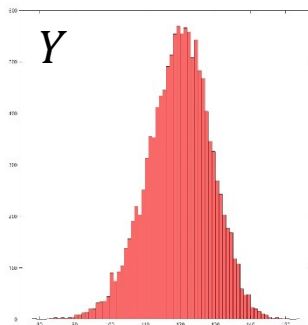
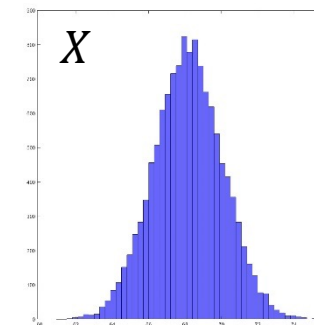
- we can get the correlation coefficient  $\rho = 0.7407$

- compute  $(X|Z = 1, Y|Z = 1) \in \mathcal{N}\left((68.1786, 119.6706)^T, \begin{pmatrix} 3.6258 & 12.8488 \\ 12.8488 & 83.0022 \end{pmatrix}\right)$

$$\int_{70.1111}^{70.1111+\delta_1} \int_{141.3333}^{141.3333+\delta_2} f(x, y|Z = 0) dx dy \text{ VS } \int_{70.1111}^{70.1111+\delta_1} \int_{141.3333}^{141.3333+\delta_2} f(x, y|Z = 1) dx dy$$

$Z = 0$

$Z = 1$



# Classification with Multivariate Features

$Z = 1$   
↑

□  $(X, Y) \rightarrow Z$  ?

$$\mathcal{N}\left(\left(\frac{x - 67.8007}{\sqrt{3.5384}}, \frac{y - 137.4883}{\sqrt{79.1715}}\right), ?\right) \quad \text{VS} \quad \mathcal{N}\left(\left(\frac{x - 68.1786}{\sqrt{3.6258}}, \frac{y - 119.6706}{\sqrt{83.0022}}\right), ?\right)$$

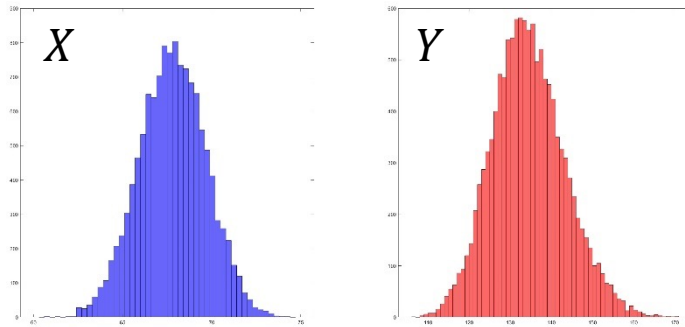


- Compare the possibility

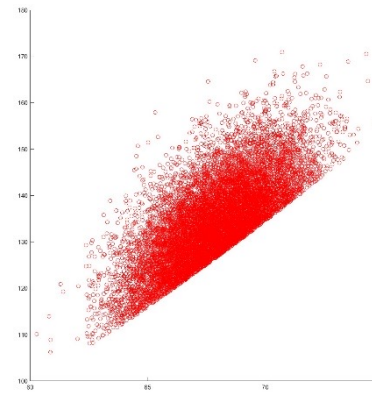
$$P(X = 70.1111, Y = 141.3333 \mid Z = 0) \text{ and } P(X = 70.1111, Y = 141.3333 \mid Z = 1)$$

- It is observed that both  $(X, Y) \mid Z = 0$  and  $(X, Y) \mid Z = 1$  obey Gaussian

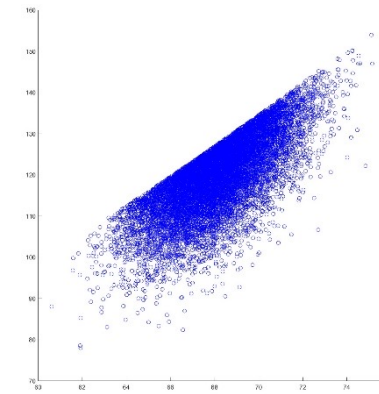
$Z = 0$



$Z = 0$

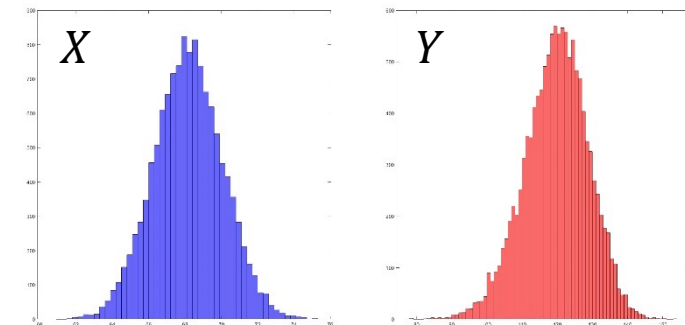


$Z = 1$



Why? (思考题)

$Z = 1$



# Classification with Multivariate Features

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## □ $(X, Y) \rightarrow Z$ ?

- IF  $X$  is **dependent** to  $Y$ , THEN we should make a classification jointly
- Provided Gaussian assumptions, we can obtain the  $f(x, y)$ 
  - $X$  is Gaussian,  $\mathcal{N}(67.9931, 3.6164)$
  - $Y$  is Gaussian,  $\mathcal{N}(127.0794, 135.9765)$
  - we can get the correlation coefficient  $\rho = 0.529$
  - compute  $(X, Y) \in \mathcal{N}((67.9931, 127.0794)^T, \mathbf{M}_{cov})$        $\mathbf{M}_{cov} = \begin{bmatrix} 3.6164 & 0.529 \\ 0.529 & 135.9765 \end{bmatrix}$
  - **Next ?**

## □ $(X, Y) \rightarrow Z$ ?

- Continuous  $(X, Y)$ , Continuous  $Z$
- 三维高斯建模

# Classification with Multivariate Features

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## □ $(X, Y) \rightarrow Z$ ?

- IF  $X$  is **dependent** to  $Y$ , THEN we should make a classification jointly
- Provided Gaussian assumptions, we can obtain the  $f(x, y)$ 
  - $X$  is Gaussian,  $\mathcal{N}(67.9931, 3.6164)$
  - $Y$  is Gaussian,  $\mathcal{N}(127.0794, 135.9765)$
  - we can get the correlation coefficient  $\rho = 0.529$
  - compute  $(X, Y) \in \mathcal{N}((67.9931, 127.0794)^T, \mathbf{M}_{cov})$        $\mathbf{M}_{cov} = \begin{bmatrix} 3.6164 & 0.529 \\ 0.529 & 135.9765 \end{bmatrix}$
  - **Next ?**

## □ $(X, Y) \rightarrow Z$ ?

- Image: If  $g(X, Y) \rightarrow Z$ , compute  $P(Z)$

Q 2

# Summary

## Bayesian formula

### □ Univariate Feature

- Discrete  $X$ , Discrete  $Z$   $Z = 1$
- Continuous  $X$ , Discrete  $Z$   $Z = 0$
- Continuous  $X$ , Continuous  $Z$   $Z = 0$

$$P(Z = 1 | X = x_k) = \frac{P(Z = 1, X = x_k)}{P(X = x_k)} = \frac{P(Z = 1)P(X = x_k | Z = 1)}{P(X = x_k)}$$

$$P(Z = 1 | X = x) = \frac{P(Z = 1, X = x)}{P(X = x)} = \frac{P(Z = 1)P(X = x | Z = 1)}{P(X = x)} = \frac{P(Z = 1) \int_{-\infty}^x f_{X|Z}(x|Z = 1) dx}{P(X = x)}$$

$$E(Z | X = x) = \int_{-\infty}^{+\infty} z \frac{f(x, z)}{f_X(x)} dz = \int_{-\infty}^{+\infty} z f_{Z|X}(z | X = x) dz$$

### □ Multivariate Features

- Discrete  $(X, Y)$ , Discrete  $Z$   $Z = 0$
- Continuous  $(X, Y)$ , Discrete  $Z$   $Z = 0$
- Continuous  $(X, Y)$ , Continuous  $Z$   $Z = 1$

$$P(Z = 1 | X = x_k, Y = y_k) = \frac{P(Z = 1, X = x_k, Y = y_k)}{P(X = x_k, Y = y_k)} = \frac{P(Z = 1)P(X = x_k, Y = y_k | Z = 1)}{P(X = x_k, Y = y_k)}$$

$$P(Z = 1 | X = x, Y = y) = \frac{P(Z = 1, X = x, Y = y)}{P(X = x, Y = y)} = \frac{P(Z = 1)P(X = x, Y = y | Z = 1)}{P(X = x, Y = y)} = \frac{P(Z = 1) \int_{-\infty}^y \int_{-\infty}^x f_{X,Y|Z}(x, y | Z = 1) dy dx}{P(X = x, Y = y)}$$

$$E(Z | X = x, Y = y) = \int_{-\infty}^{+\infty} z \frac{f(x, y, z)}{f_{X,Y}(x, y)} dz = \int_{-\infty}^{+\infty} z f_{Z|X,Y}(z | X = x, Y = y) dz$$

### □ Q3:

- 1. Which result is reliable ?
- 2. Which way is efficient?

# Summary

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□ **Q1:** Is there a function  $h$  such that  $h(X)$  is obviously separable?  $X \rightarrow h(X) \rightarrow Z$

□ **Q2:** Is there an apposite function  $g$  such that  $(X, Y) \rightarrow g(X, Y) \rightarrow Z$ , compute  $P(Z)$

- Statistics: given an explicit function before classification
- Classical ML: define a kernel function before classification
- Modern ML: represent the concerned function by model and data
  - representation learning
- Other ways?: directly construct the concerned function by ergodic algorithms e.g., the genetic algorithm
  - evolutionary learning

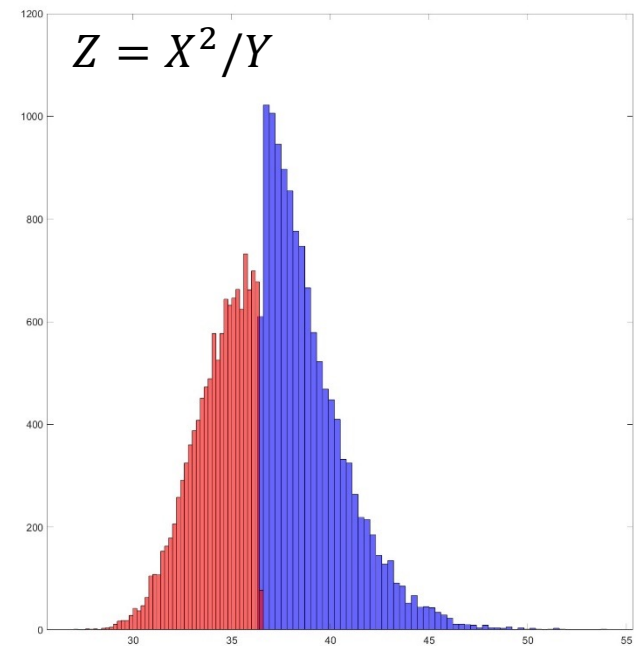
# Summary - genetic algorithm

- ❑ **Q1:** Is there a function  $h$  such that  $h(X)$  is obviously separable?  $X \rightarrow h(X) \rightarrow Z$
- ❑ **Q2:** Is there an apposite function  $g$  such that  $(X, Y) \rightarrow g(X, Y) \rightarrow Z$ , compute  $P(Z)$
- Other ways?: directly construct the concerned function by ergodic algorithms e.g., the genetic algorithm
  - evolutionary learning
  - $Z = X^2/Y$  is apposite

$$\frac{70.1111^2}{141.3333} = 34.7800 < E\left(\frac{X^2}{Y}\right) \quad \Rightarrow \quad Z = 0$$

— match the case of “Discrete  $(X, Y)$ , Discrete  $Z$ ”

Why?





Any Questions?