

Welcome to

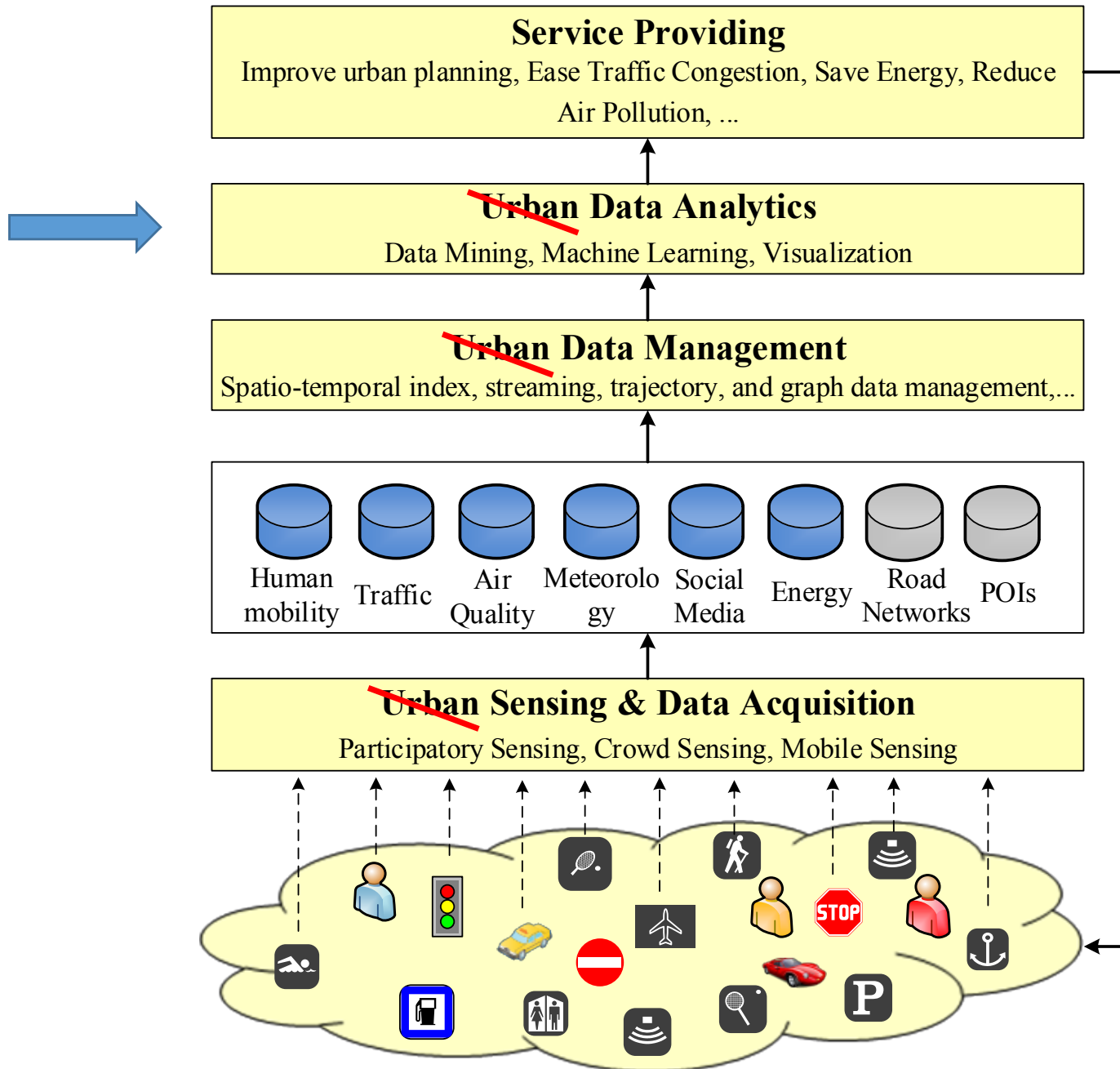
DS3010:
DS-III: Computational Data Intelligence
Classification
Prof. Yanhua Li

Time: 11:00am – 12:50pm M & R

Location: HL 114

D-term 2022

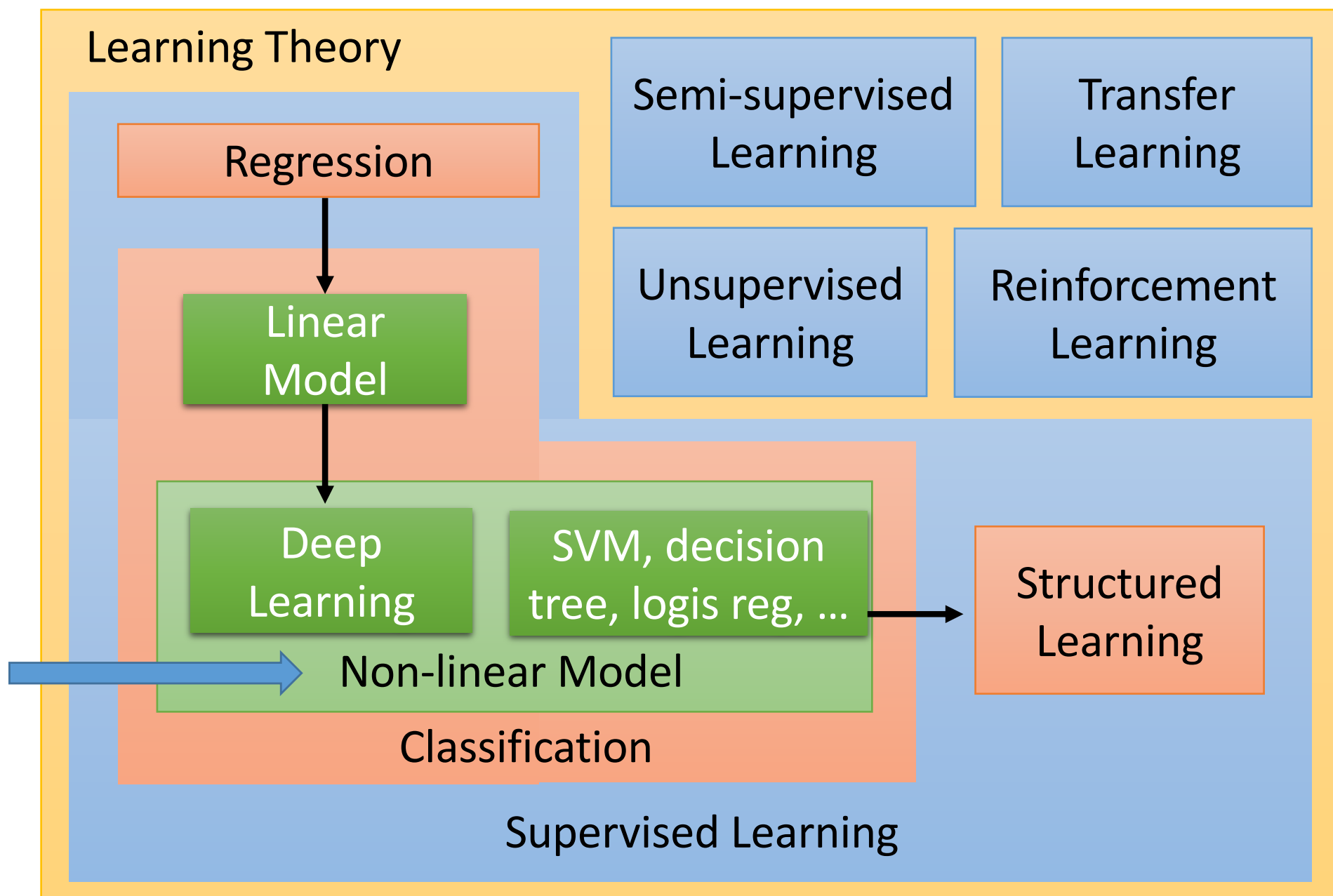
Data pipeline



Urban Computing: concepts, methodologies, and applications.
Zheng, Y., et al. *ACM transactions on Intelligent Systems and Technology*.

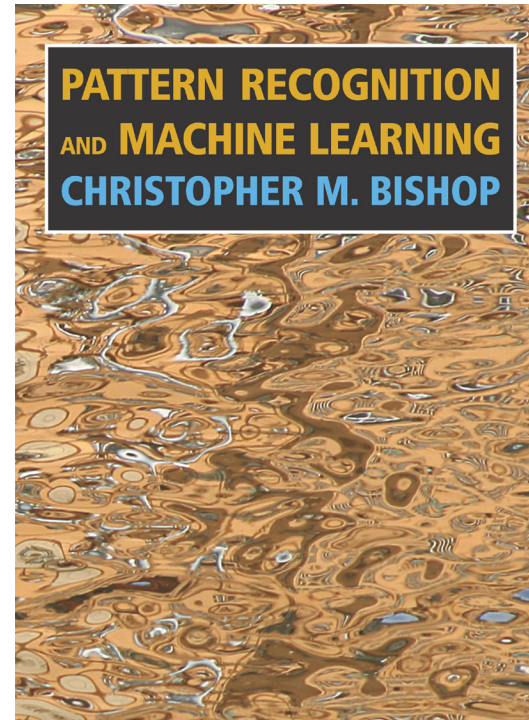
Learning Map

scenario task method



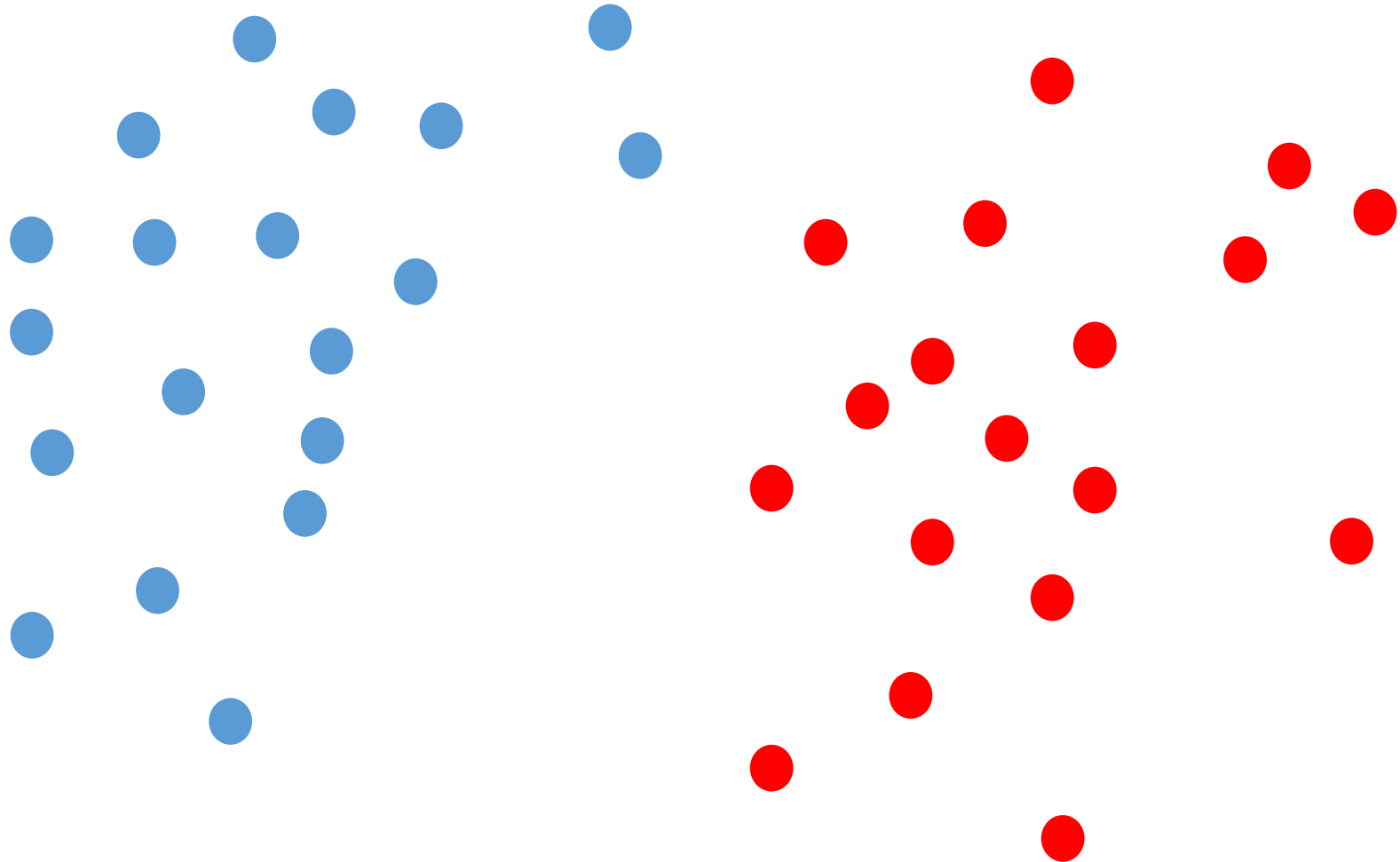
References

Classification
SVM (a much simplified
discussion)

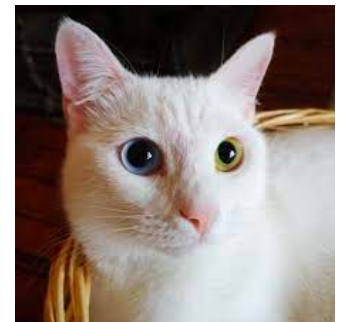


Bishop: Chapter 7.1

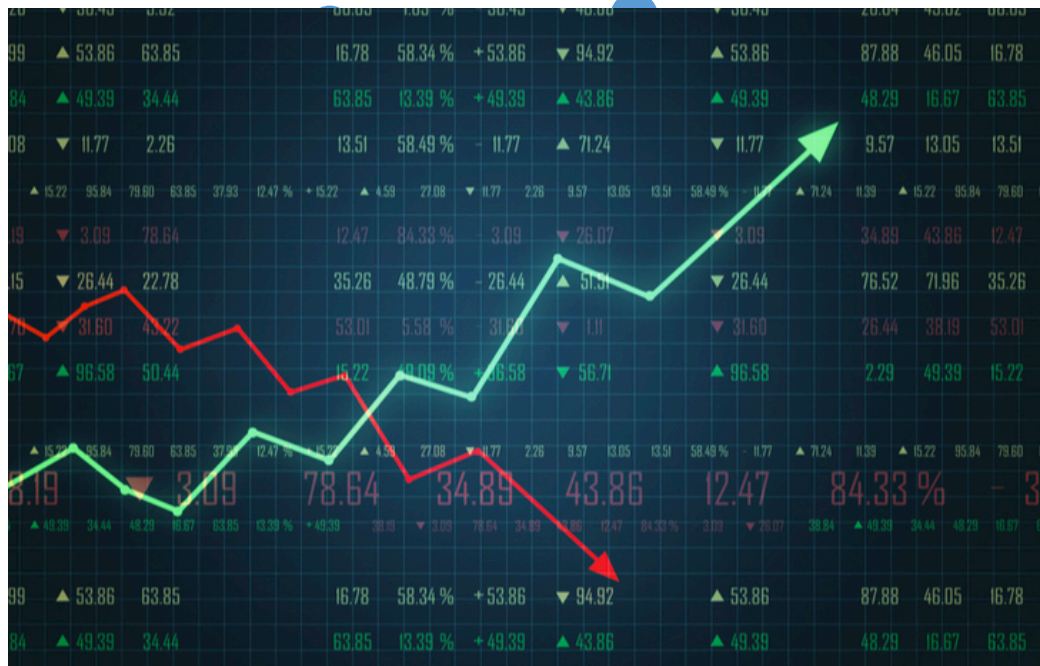
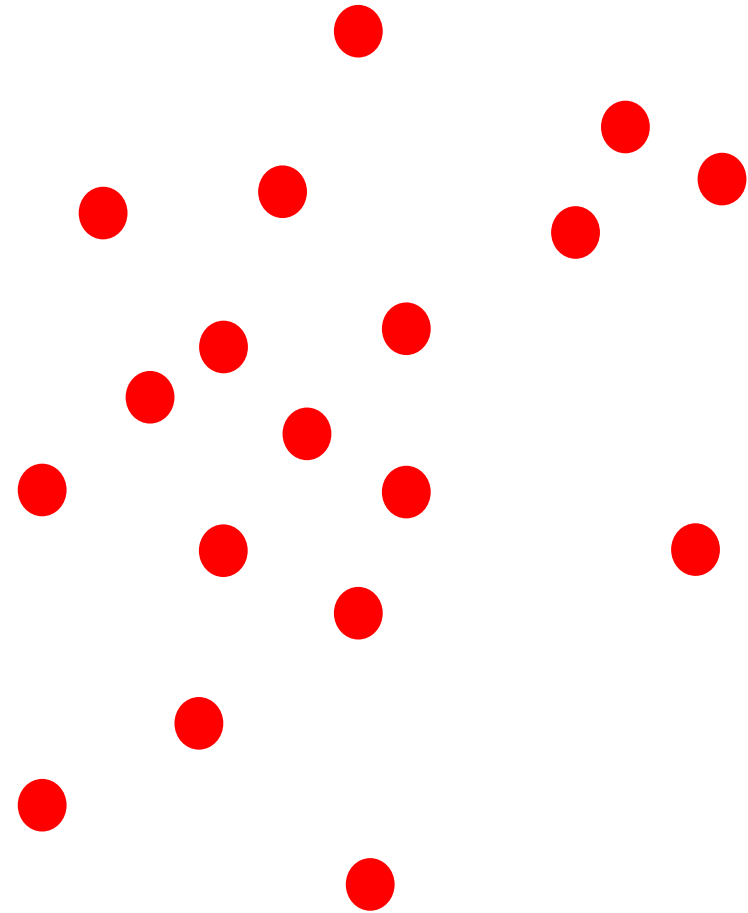
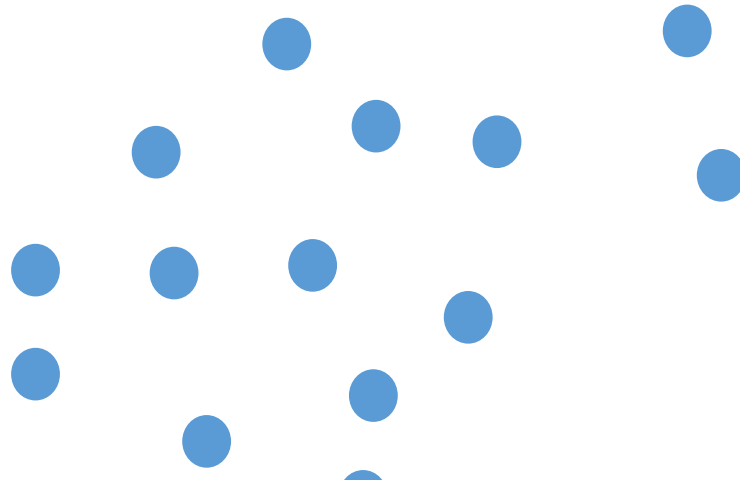
Support Vector Machine -- SVM



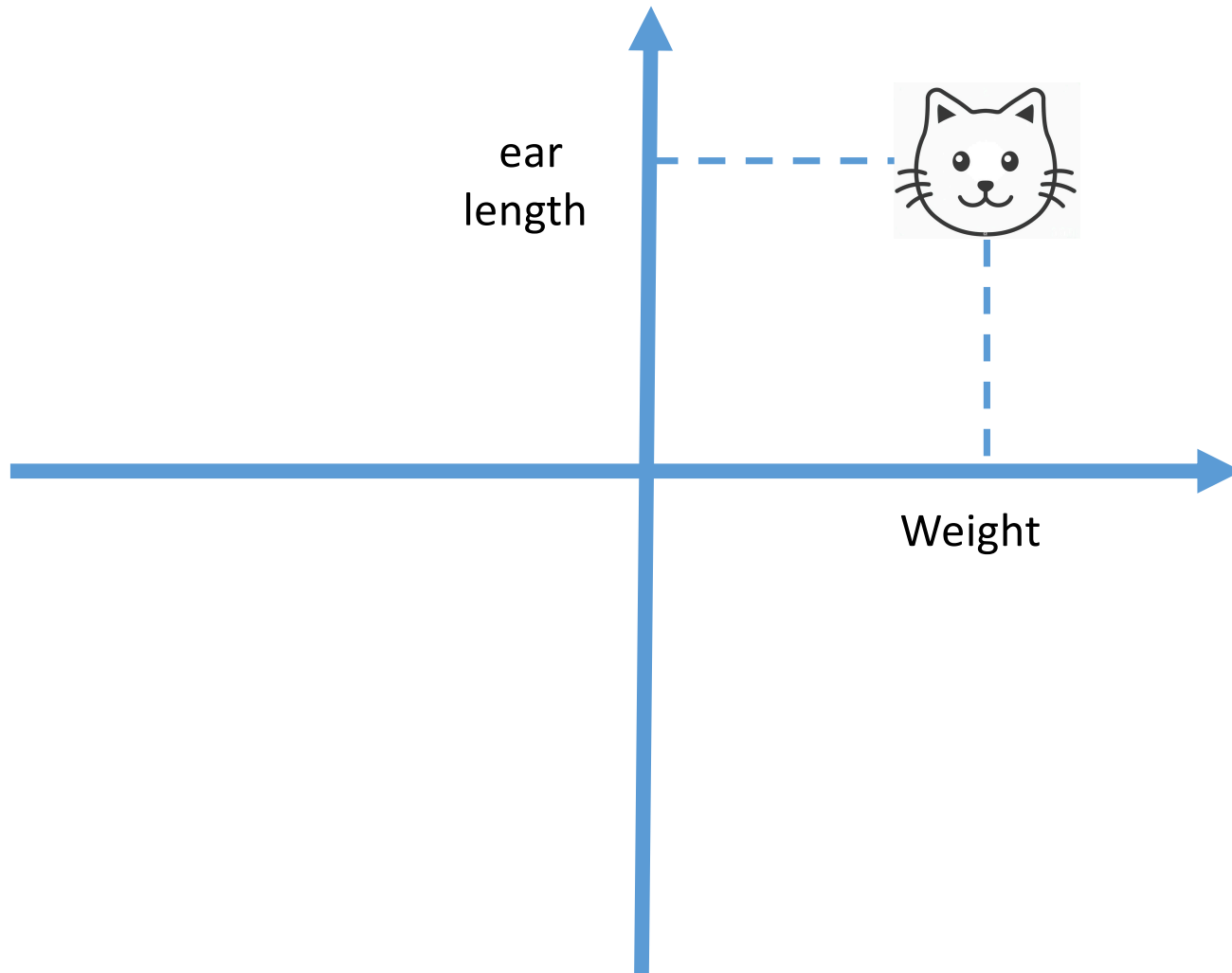
Support Vector Machine -- SVM



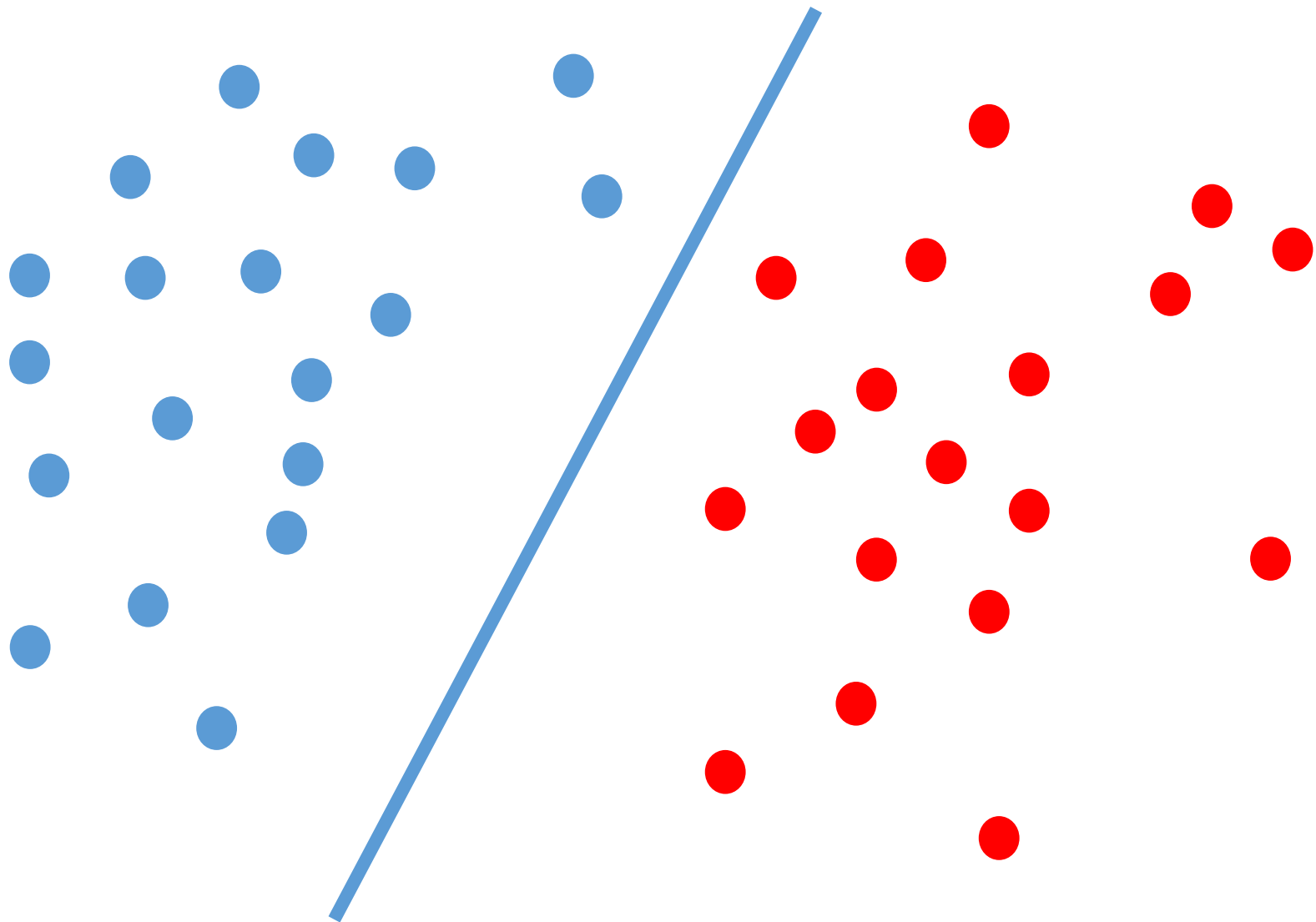
Support Vector Machine -- SVM



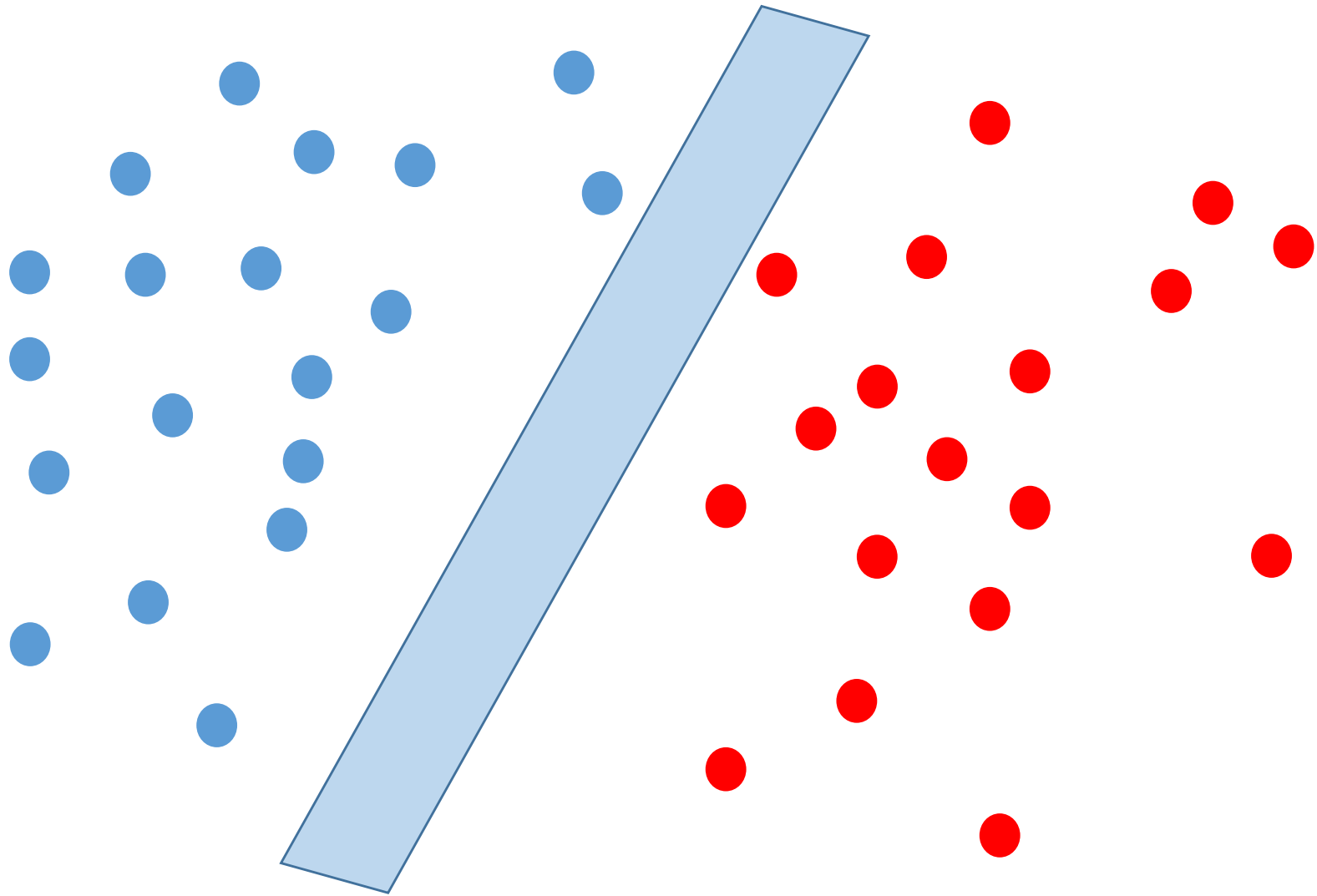
Support Vector Machine -- SVM



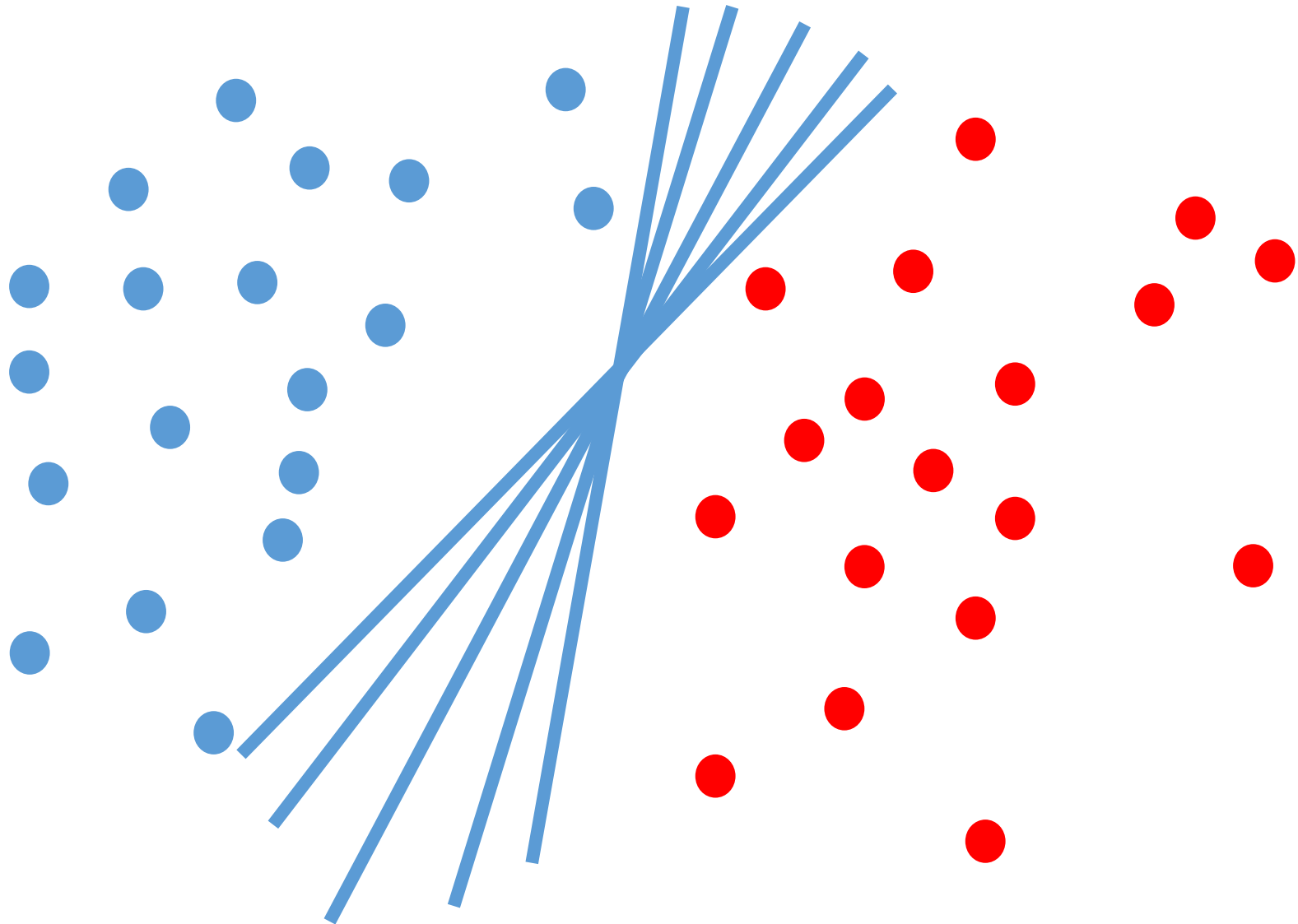
Support Vector Machine – SVM 1D



Support Vector Machine – SVM 2D

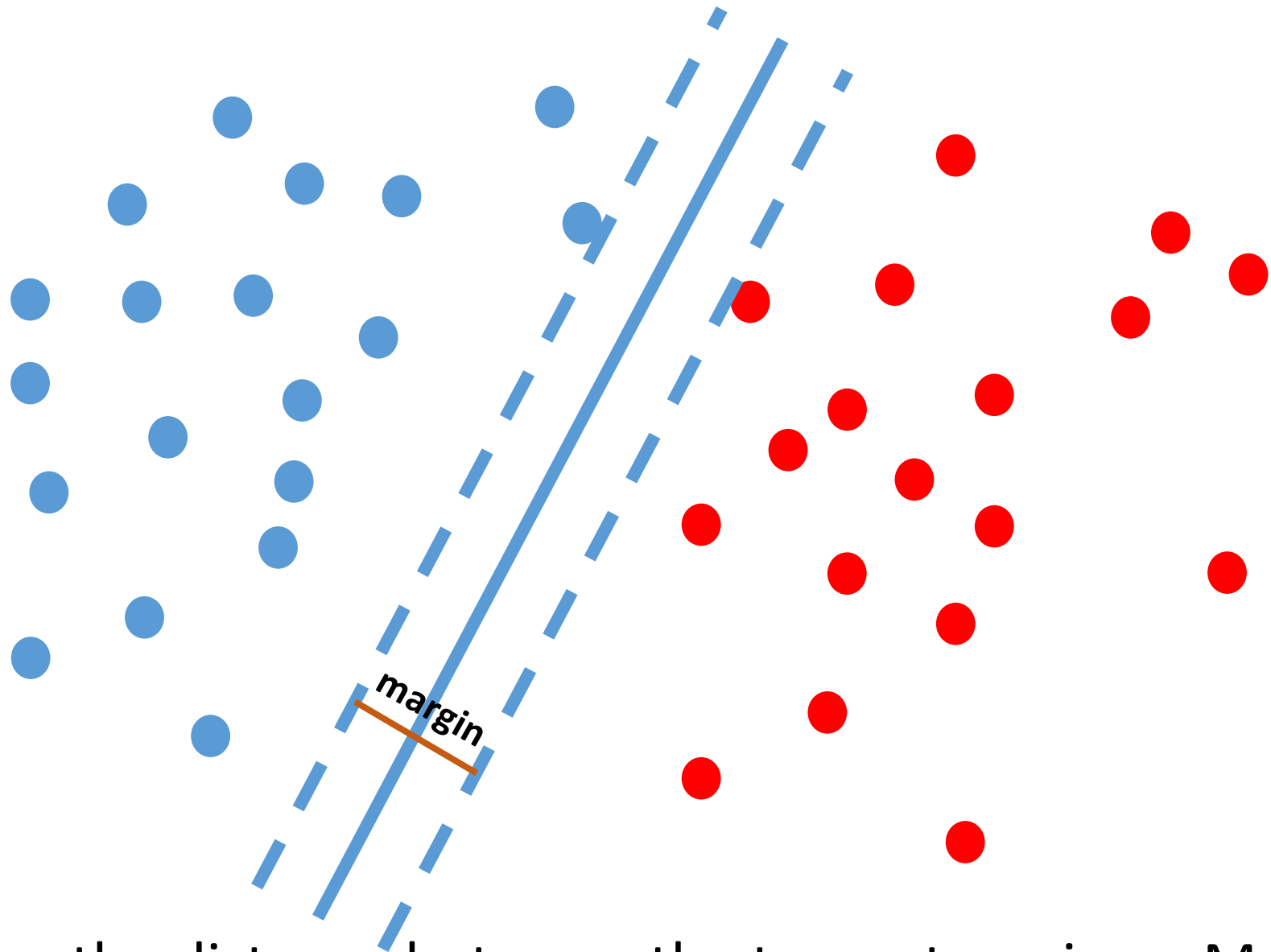


Support Vector Machine – SVM 1D



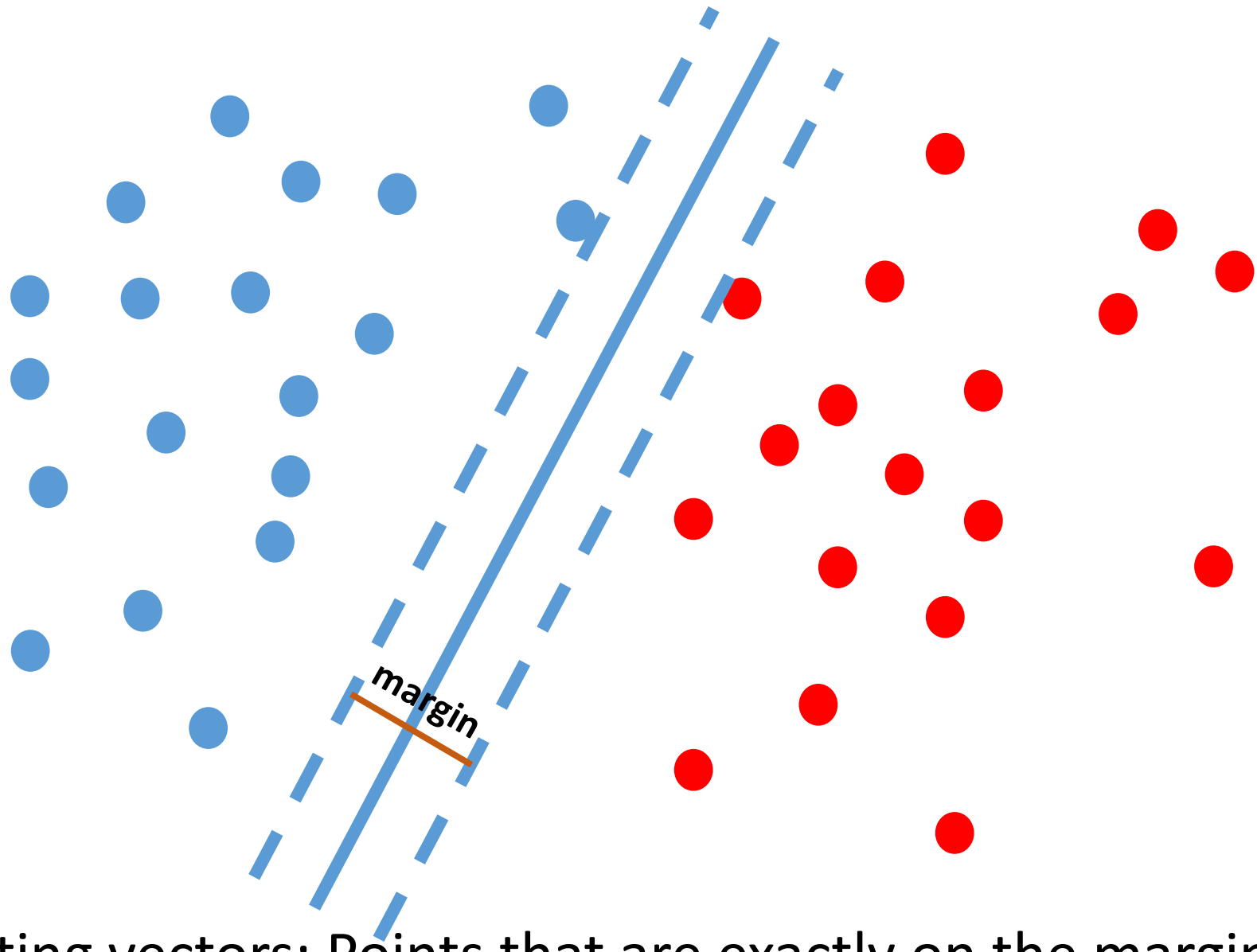
There could be multiple such hyper planes

Support Vector Machine – SVM 1D



Maximize the distance between the two categories -- Margin

Support Vector Machine – SVM 1D



Supporting vectors: Points that are exactly on the margin

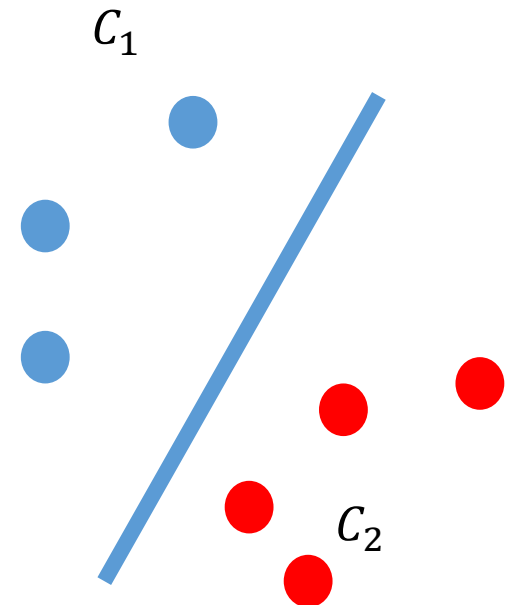
Support Vector Machine – SVM

Points	Feature 1	Feature 2	...	Category
1	0.97	0.27	...	
2	0.77	0.19	...	
3	0.33	0.85	...	
4	0.41	0.93	...	
5	0.27	0.32	...	

Supervised learning algorithm

Convex Optimization Problem

$$\begin{aligned} \min_{w,b} \quad & \|w\|^2 \\ \text{s.t.} \quad & w^T x + b \geq 1, \forall x \in C_1 \\ & w^T x + b \leq 1, \forall x \in C_2 \end{aligned}$$



Supervised learning algorithm

from sklearn import svm

```
from sklearn import svm
```

```
# features
```

```
X = [
```

```
    [-3, -1]
```

```
    [0, -2]
```

```
    [-2.5, 2]
```

```
    [-1, -1]
```

```
    [3, .5]
```

```
    [.5, 3]
```

```
    [3, 3]
```

```
]
```

```
# labels
```

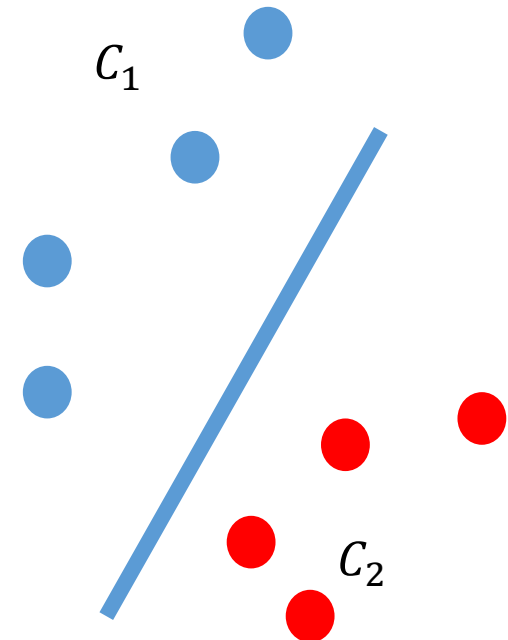
```
y = [0, 1, 0, 1, 1, 0, 1]
```

```
# fit
```

```
clf = svm.SVC(kernel='linear').fit(x,y)
```

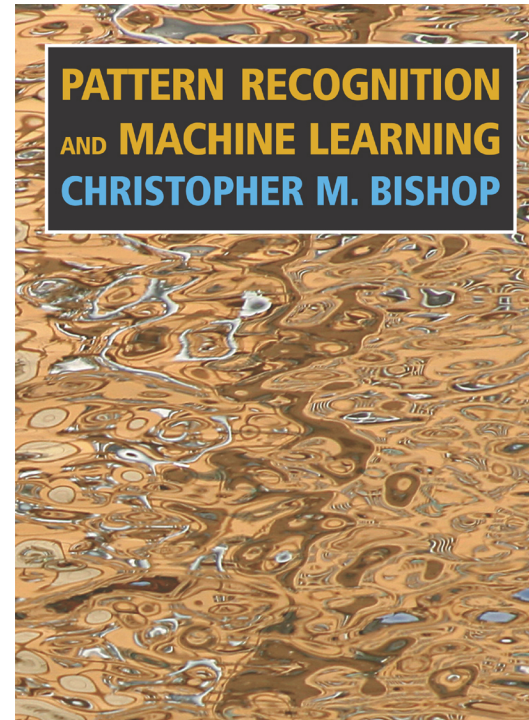
```
# predict
```

```
clf.predict([[2, 4]])
```



References

Classification
(Logistic regression)



Bishop: Chapter 4.3

Step 1: Function Set

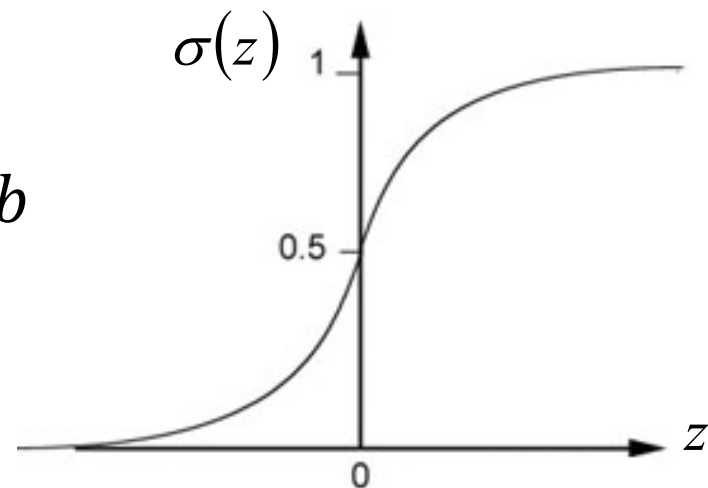
Function set: Including all different w and b

$$\left\{ \begin{array}{ll} z \geq 0 & \text{class 1} \\ z < 0 & \text{class 2} \end{array} \right.$$

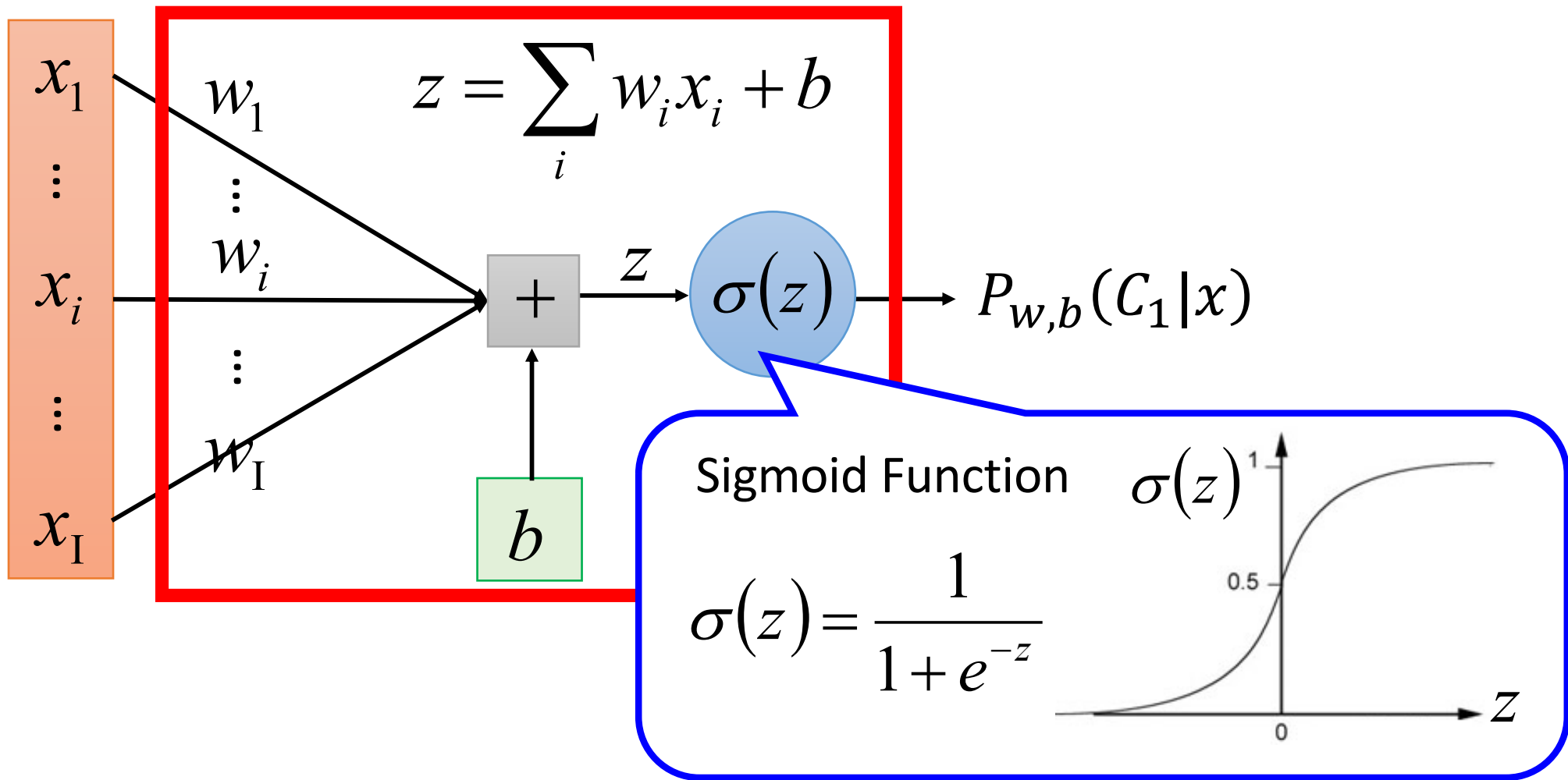
$$P_{w,b}(C_1|x) = \sigma(z)$$

$$z = w \cdot x + b = \sum_i w_i x_i + b$$

$$\sigma(z) = \frac{1}{1 + \exp(-z)}$$



Step 1: Function Set



Step 2: Goodness of a Function

Training
Data

x^1	x^2	x^3	$\dots \dots$	x^N
C_1	C_1	C_2		C_1

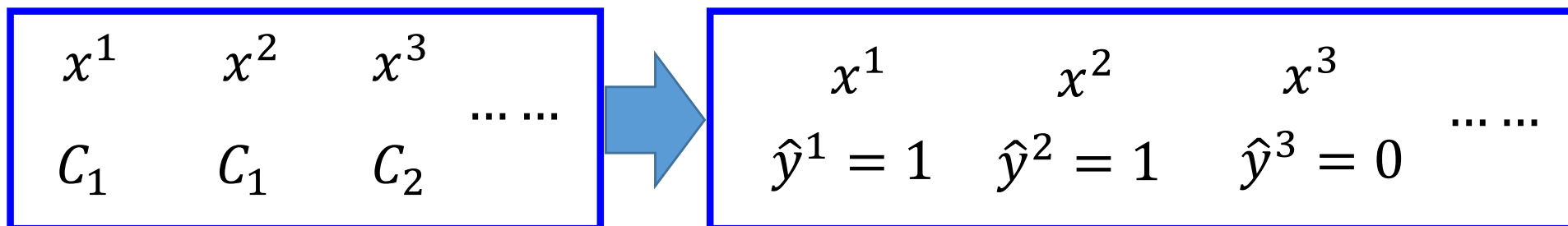
Assume the data is generated based on $f_{w,b}(x) = P_{w,b}(C_1|x)$

Given a set of w and b , what is its probability of generating the data?

$$L(w, b) = f_{w,b}(x^1)f_{w,b}(x^2)(1 - f_{w,b}(x^3)) \cdots f_{w,b}(x^N)$$

The most likely w^* and b^* is the one with the largest $L(w, b)$.

$$w^*, b^* = \arg \max_{w, b} L(w, b)$$



$\hat{y}^n$: 1 for class 1, 0 for class 2

$$L(w, b) = f_{w,b}(x^1) f_{w,b}(x^2) (1 - f_{w,b}(x^3)) \dots$$

$w^*, b^* = \arg \max_{w,b} L(w, b)$	=	$w^*, b^* = \arg \min_{w,b} -\ln L(w, b)$
--------------------------------------	---	---

$$-\ln L(w, b)$$

$$= -\ln f_{w,b}(x^1) \Rightarrow -\left[\boxed{1} \ln f(x^1) + \boxed{0} \ln(1 - f(x^1)) \right]$$

$$-\ln f_{w,b}(x^2) \Rightarrow -\left[\boxed{1} \ln f(x^2) + \boxed{0} \ln(1 - f(x^2)) \right]$$

$$-\ln(1 - f_{w,b}(x^3)) \Rightarrow -\left[\boxed{0} \ln f(x^3) + \boxed{1} \ln(1 - f(x^3)) \right]$$

$\vdots$

Step 2: Goodness of a Function

$$L(w, b) = f_{w,b}(x^1)f_{w,b}(x^2)(1 - f_{w,b}(x^3)) \cdots f_{w,b}(x^N)$$

$$-\ln L(w, b) = \ln f_{w,b}(x^1) + \ln f_{w,b}(x^2) + \ln(1 - f_{w,b}(x^3)) \cdots$$

$\hat{y}^n$: 1 for class 1, 0 for class 2

$$= \sum_n - \left[\hat{y}^n \ln f_{w,b}(x^n) + (1 - \hat{y}^n) \ln(1 - f_{w,b}(x^n)) \right]$$

Cross entropy between two Bernoulli distribution

Distribution p:

$$p(x = 1) = \hat{y}^n$$

$$p(x = 0) = 1 - \hat{y}^n$$



cross
entropy

Distribution q:

$$q(x = 1) = f(x^n)$$

$$q(x = 0) = 1 - f(x^n)$$

$$H(p, q) = - \sum_x [p(x) \ln(q(x)) + (1 - p(x)) \ln(1 - q(x))]$$

Step 2: Goodness of a Function

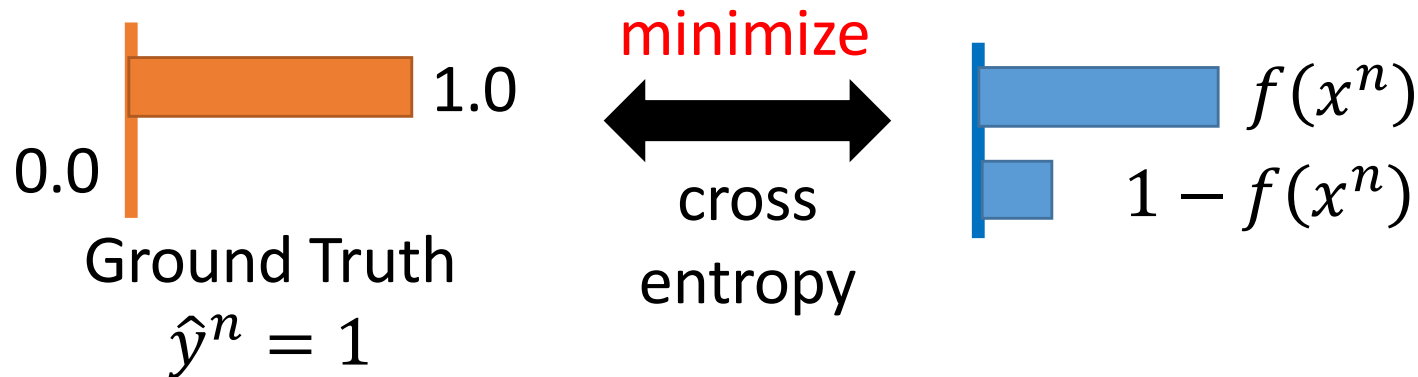
$$L(w, b) = f_{w,b}(x^1)f_{w,b}(x^2)\left(1 - f_{w,b}(x^3)\right)\cdots f_{w,b}(x^N)$$

$$-\ln L(w, b) = \ln f_{w,b}(x^1) + \ln f_{w,b}(x^2) + \ln\left(1 - f_{w,b}(x^3)\right) \cdots$$

$\hat{y}^n$: 1 for class 1, 0 for class 2

$$= \sum_n - \left[\hat{y}^n \ln f_{w,b}(x^n) + (1 - \hat{y}^n) \ln (1 - f_{w,b}(x^n)) \right]$$

Cross entropy between two Bernoulli distribution

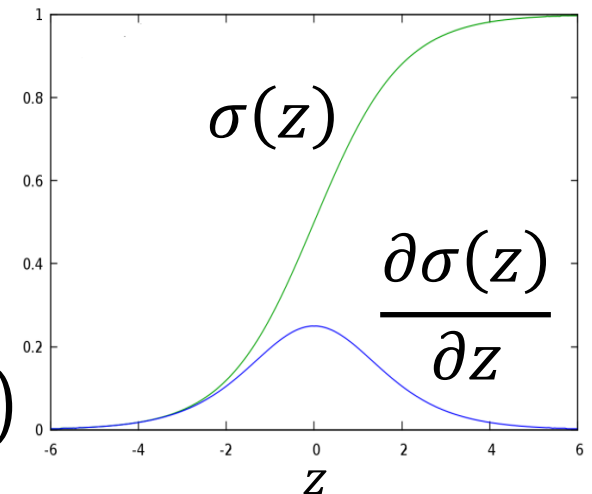


Step 3: Find the best function

$$\frac{-\ln L(w, b)}{\partial w_i} = \sum_n \left[\hat{y}^n \frac{\partial \ln f_{w,b}(x^n)}{\partial w_i} + (1 - \hat{y}^n) \frac{\partial \ln (1 - f_{w,b}(x^n))}{\partial w_i} \right]$$

$$\frac{\partial \ln f_{w,b}(x)}{\partial w_i} = \frac{\partial \ln f_{w,b}(x)}{\partial z} \frac{\partial z}{\partial w_i} \quad \frac{\partial z}{\partial w_i} = x_i$$

$$\frac{\partial \ln \sigma(z)}{\partial z} = \frac{1}{\sigma(z)} \frac{\partial \sigma(z)}{\partial z} = \frac{1}{\sigma(z)} \sigma(z)(1 - \sigma(z))$$



$$\begin{aligned} f_{w,b}(x) &= \sigma(z) \\ &= 1 / (1 + \exp(-z)) \end{aligned}$$

$$z = w \cdot x + b = \sum_i w_i x_i + b$$

Step 3: Find the best function

$$\frac{-\ln L(w, b)}{\partial w_i} = \sum_n - \left[\hat{y}^n \frac{(1 - f_{w,b}(x^n)) x_i^n}{\partial w_i} + (1 - \hat{y}^n) \frac{-f_{w,b}(x^n) x_i^n}{\partial w_i} \right]$$

$$\frac{\partial \ln(1 - f_{w,b}(x))}{\partial w_i} = \frac{\partial \ln(1 - f_{w,b}(x))}{\partial z} \frac{\partial z}{\partial w_i} \quad \frac{\partial z}{\partial w_i} = x_i$$

$$\frac{\partial \ln(1 - \sigma(z))}{\partial z} = - \frac{1}{1 - \sigma(z)} \frac{\partial \sigma(z)}{\partial z} = - \frac{1}{1 - \sigma(z)} \sigma(z) (1 - \sigma(z))$$

$$\begin{aligned} f_{w,b}(x) &= \sigma(z) \\ &= 1 / (1 + \exp(-z)) \end{aligned}$$

$$z = w \cdot x + b = \sum_i w_i x_i + b$$

Step 3: Find the best function

$$\begin{aligned}
 \frac{-\ln L(w, b)}{\partial w_i} &= \sum_n - \left[\hat{y}^n \frac{(1 - f_{w,b}(x^n)) x_i^n}{\partial w_i} + (1 - \hat{y}^n) \frac{-f_{w,b}(x^n) x_i^n}{\partial w_i} \right] \\
 &= \sum_n - \left[\hat{y}^n \frac{(1 - f_{w,b}(x^n)) x_i^n}{\partial w_i} - (1 - \hat{y}^n) \frac{f_{w,b}(x^n) x_i^n}{\partial w_i} \right] \\
 &= \sum_n - \left[\hat{y}^n - \cancel{\hat{y}^n f_{w,b}(x^n)} - f_{w,b}(x^n) + \cancel{\hat{y}^n f_{w,b}(x^n)} \right] \frac{x_i^n}{\partial w_i} \\
 &= \sum_n - \left(\hat{y}^n - f_{w,b}(x^n) \right) x_i^n
 \end{aligned}$$

Larger difference, larger update

$$w_i \leftarrow w_i - \eta \sum_n - \left(\hat{y}^n - f_{w,b}(x^n) \right) x_i^n$$

Multi-class Classification (3 classes as example)

$$C_1: w^1, b_1 \quad z_1 = w^1 \cdot x + b_1$$

$$C_2: w^2, b_2 \quad z_2 = w^2 \cdot x + b_2$$

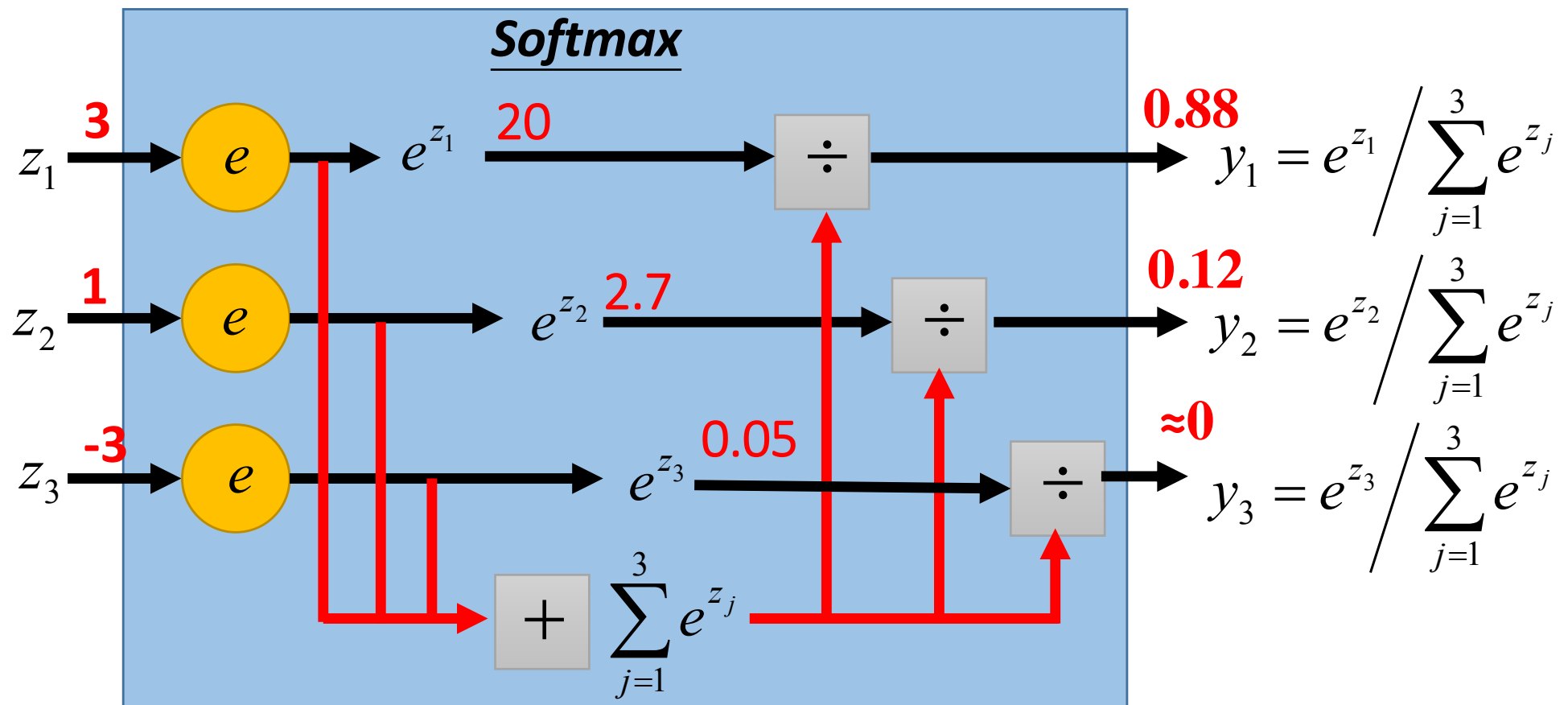
$$C_3: w^3, b_3 \quad z_3 = w^3 \cdot x + b_3$$

Probability:

$$\blacksquare 1 > y_i > 0$$

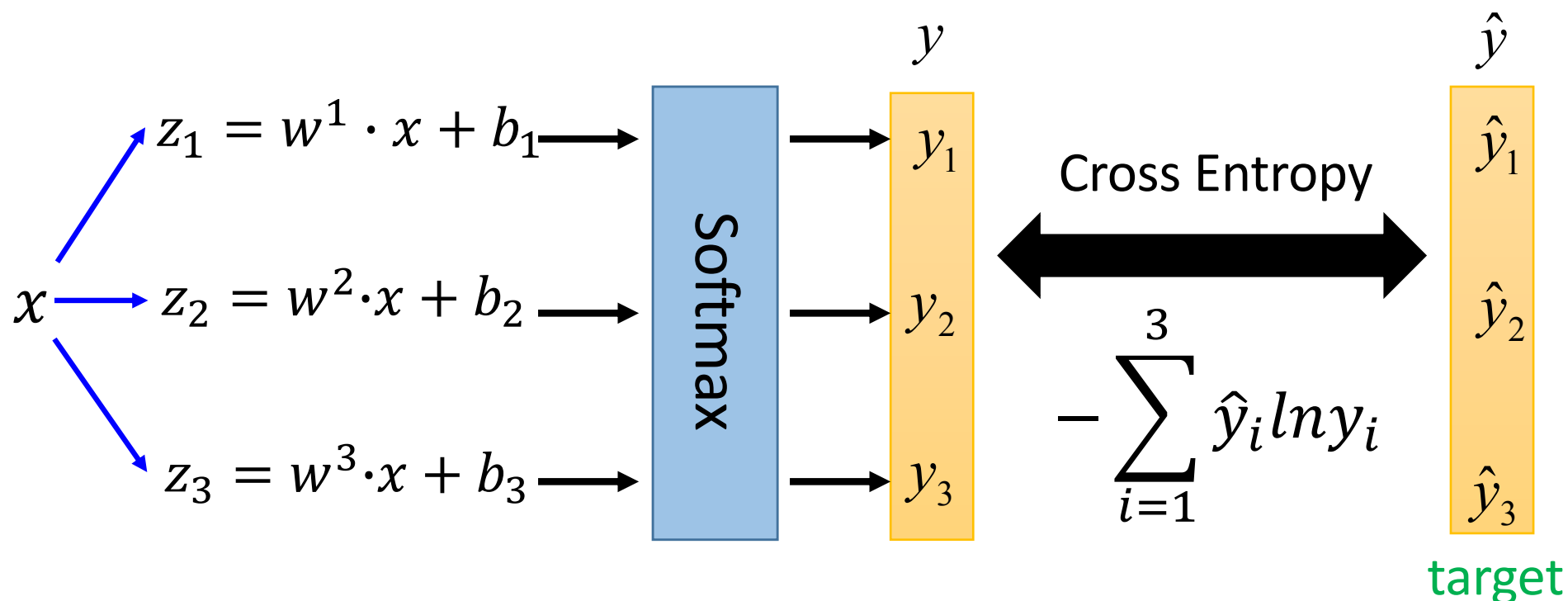
$$\blacksquare \sum_i y_i = 1$$

$$y_i = P(C_i | x)$$



Multi-class Classification (3 classes as example)

[Bishop, P209-210]



If $x \in \text{class 1}$

$$\hat{y} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

$$-\ln y_1$$

If $x \in \text{class 2}$

$$\hat{y} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

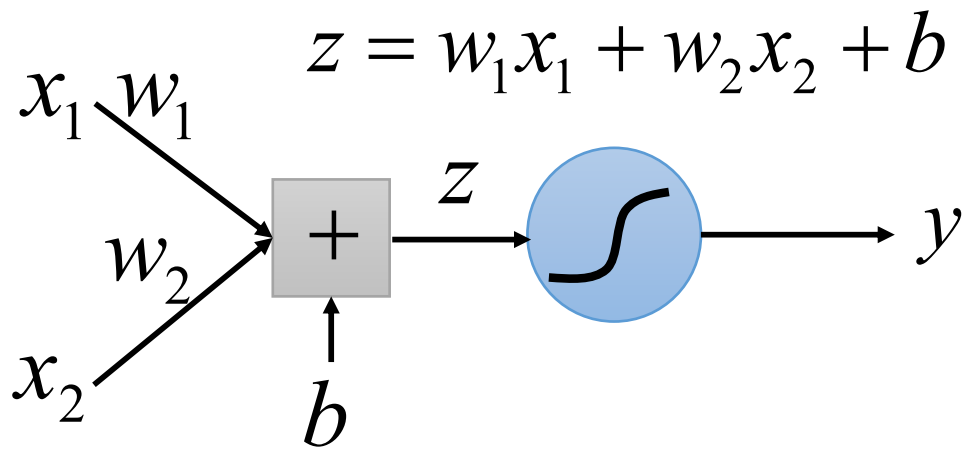
$$-\ln y_2$$

If $x \in \text{class 3}$

$$\hat{y} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

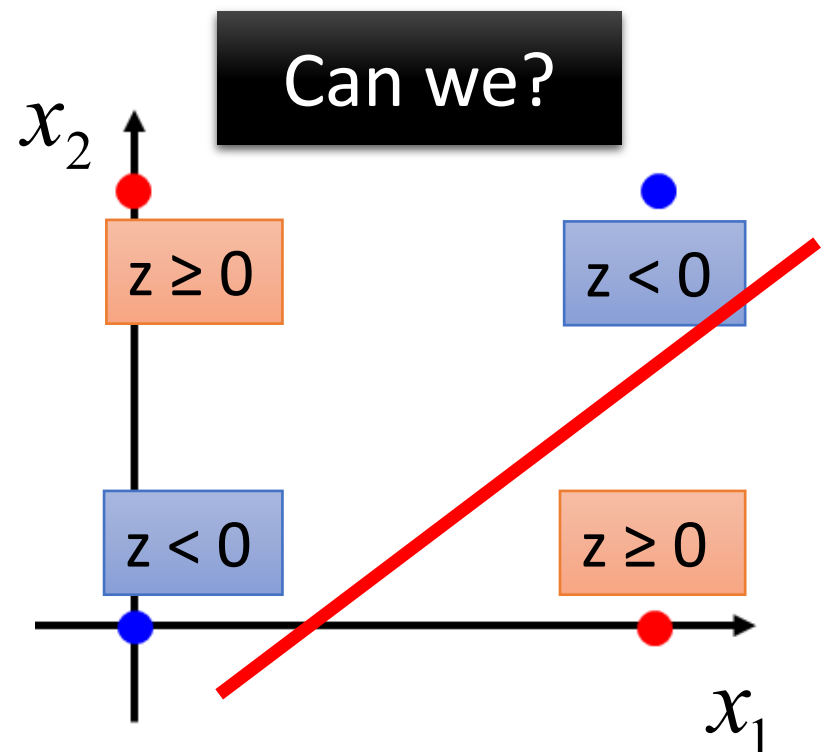
$$-\ln y_3$$

Limitation of Logistic Regression



$$\begin{cases} \text{Class1} & y \geq 0.5 \quad (z \geq 0) \\ \text{Class2} & y < 0.5 \quad (z < 0) \end{cases}$$

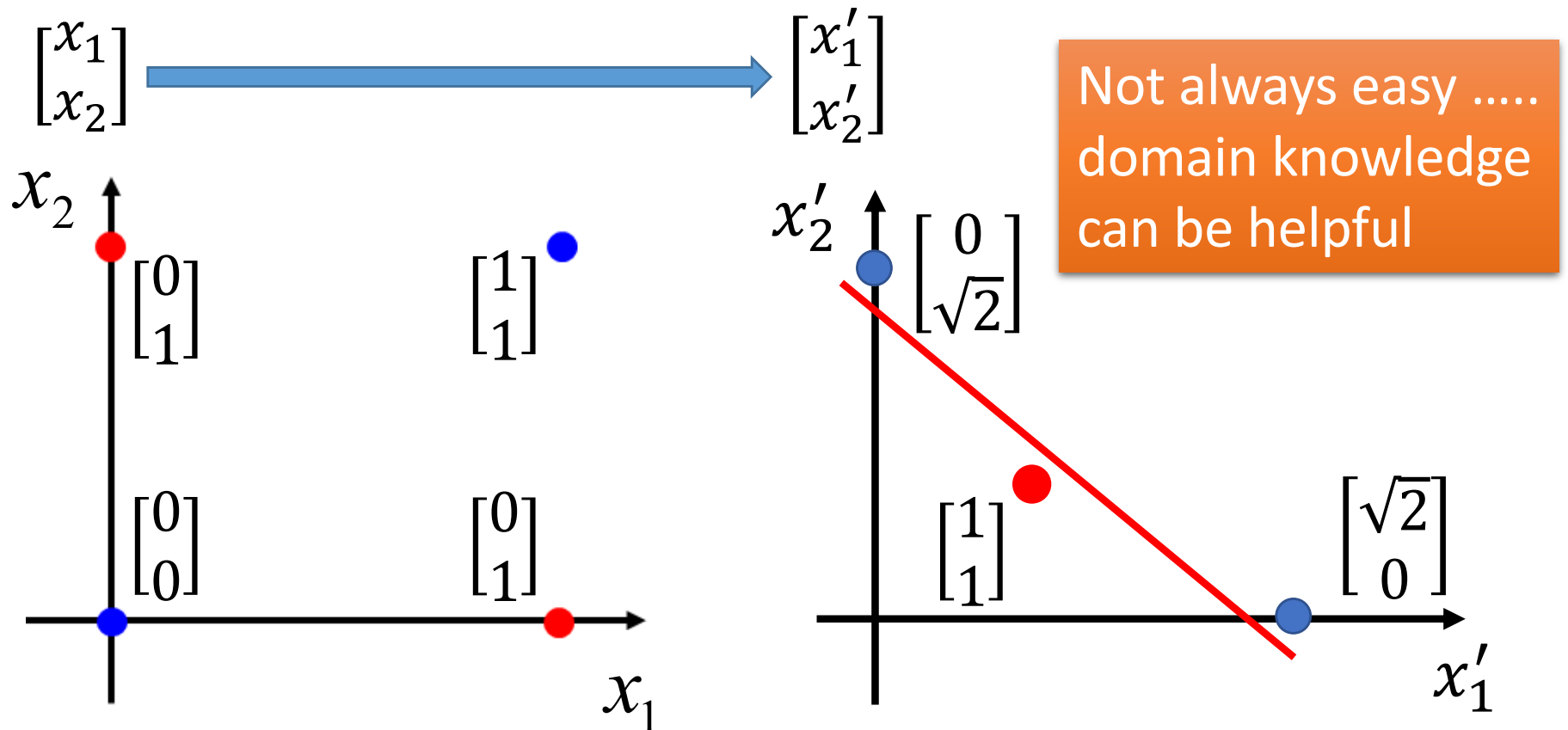
Input Feature		Label
x_1	x_2	
0	0	Class 2
0	1	Class 1
1	0	Class 1
1	1	Class 2



Limitation of Logistic Regression

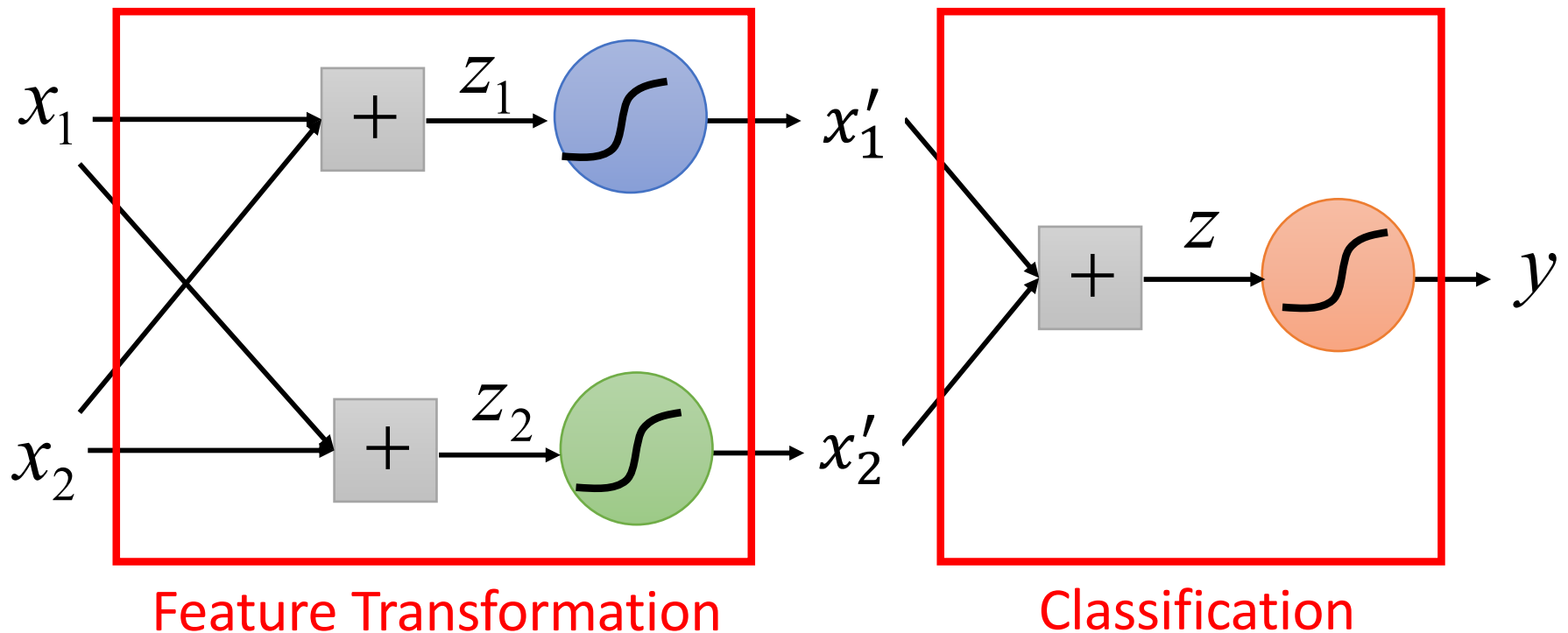
- **Feature transformation**

x'_1 : distance to $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$
 x'_2 : distance to $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$

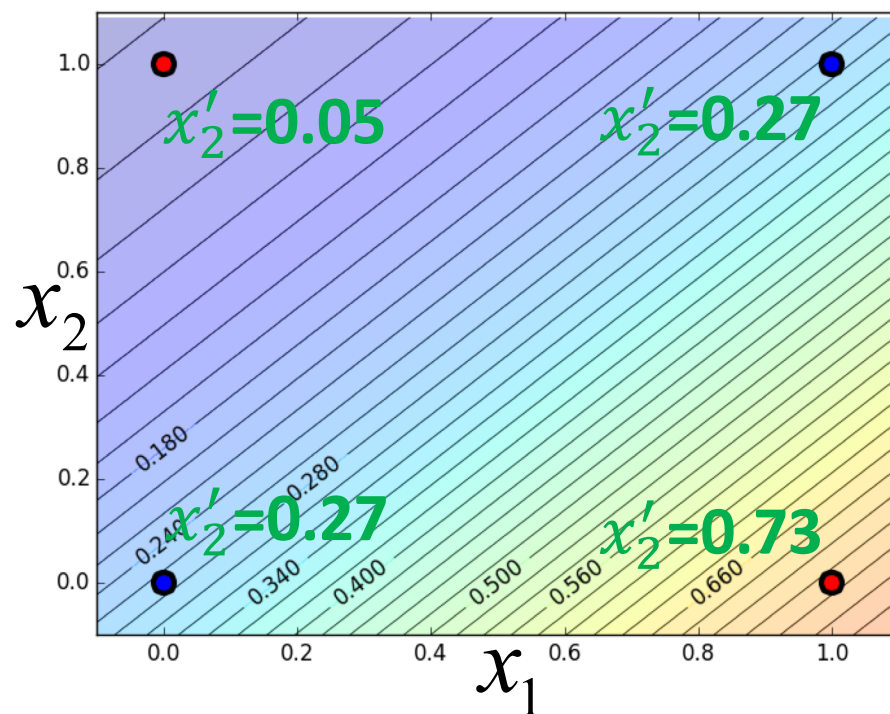
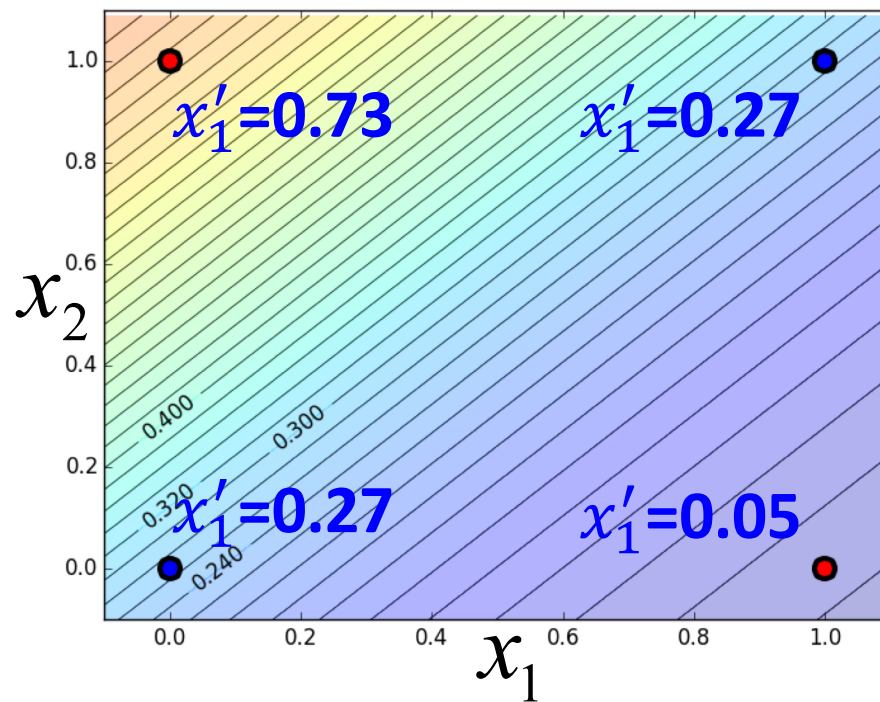
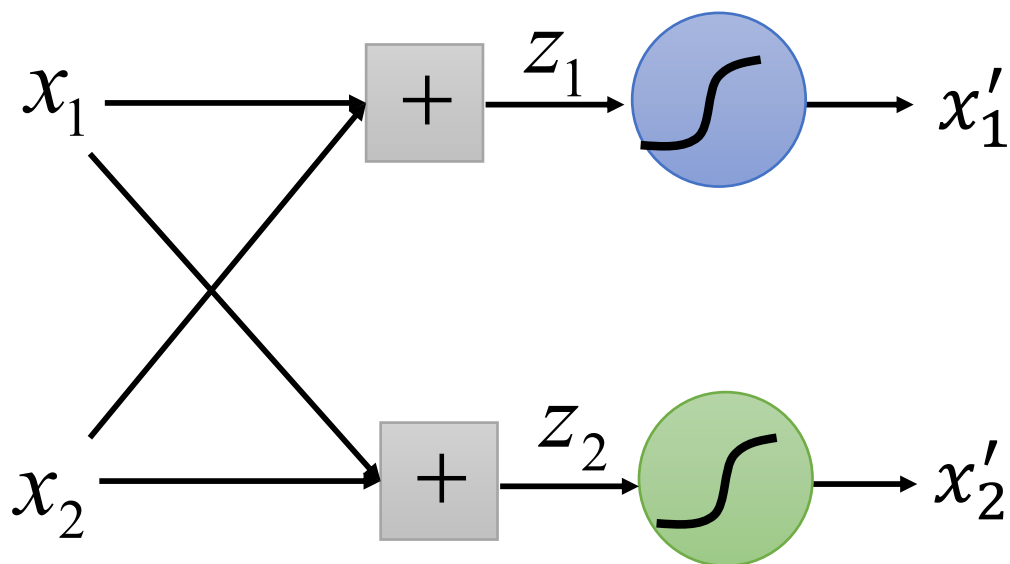
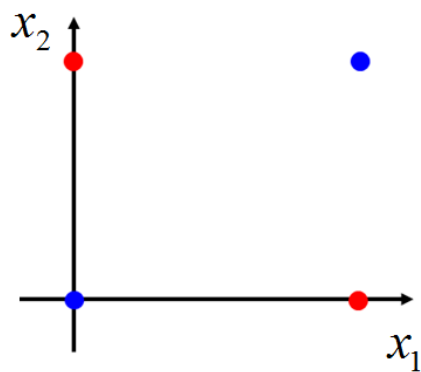


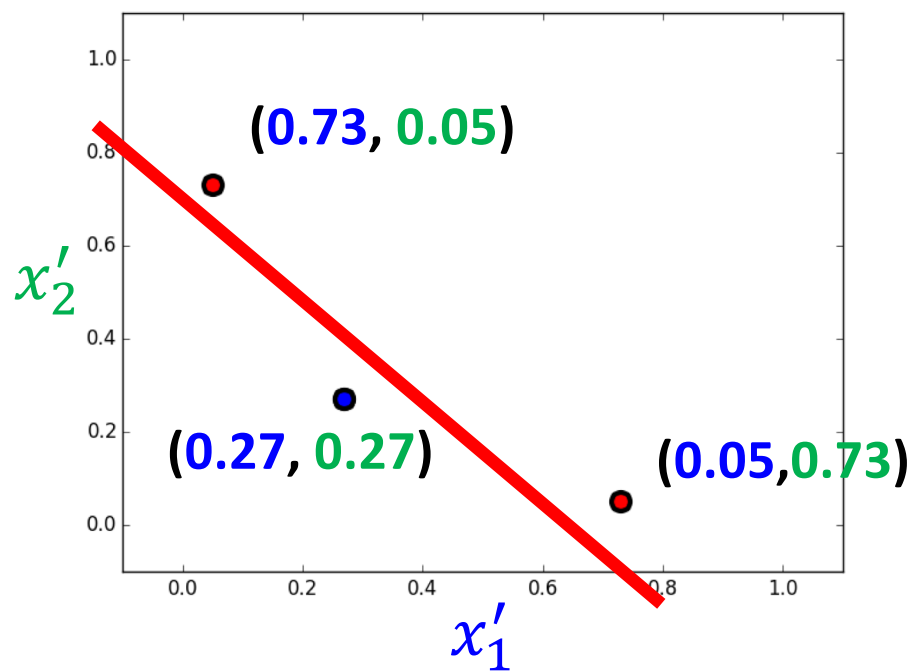
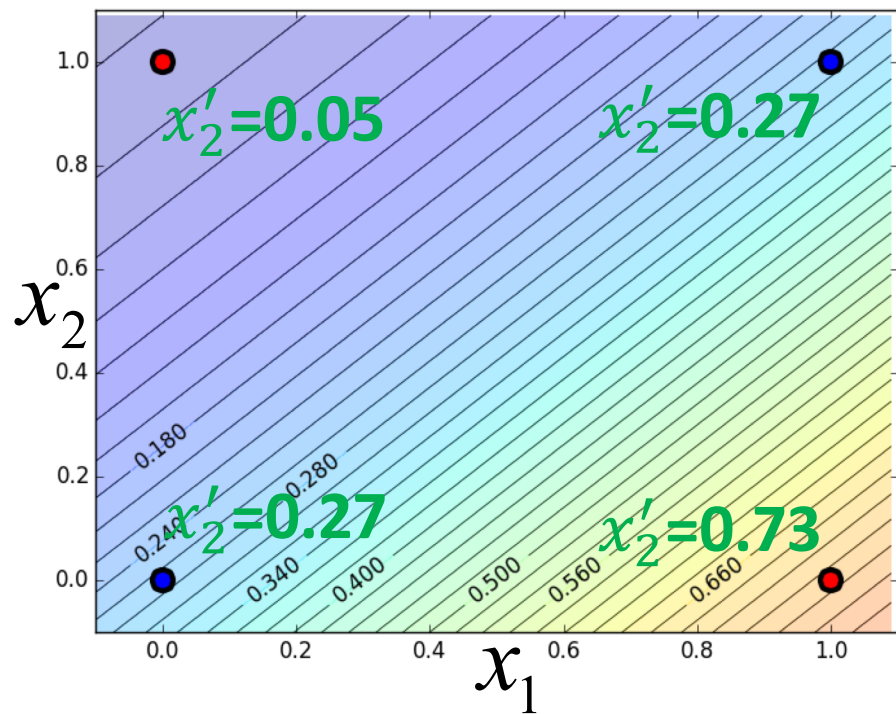
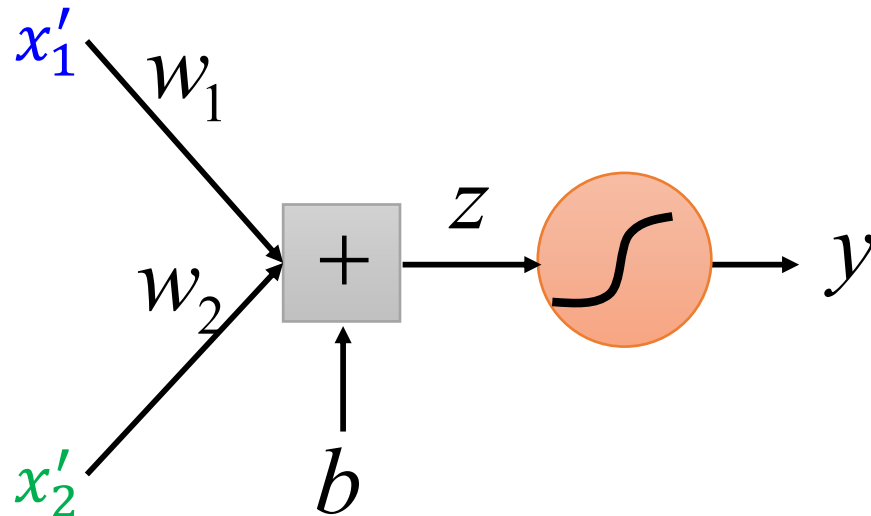
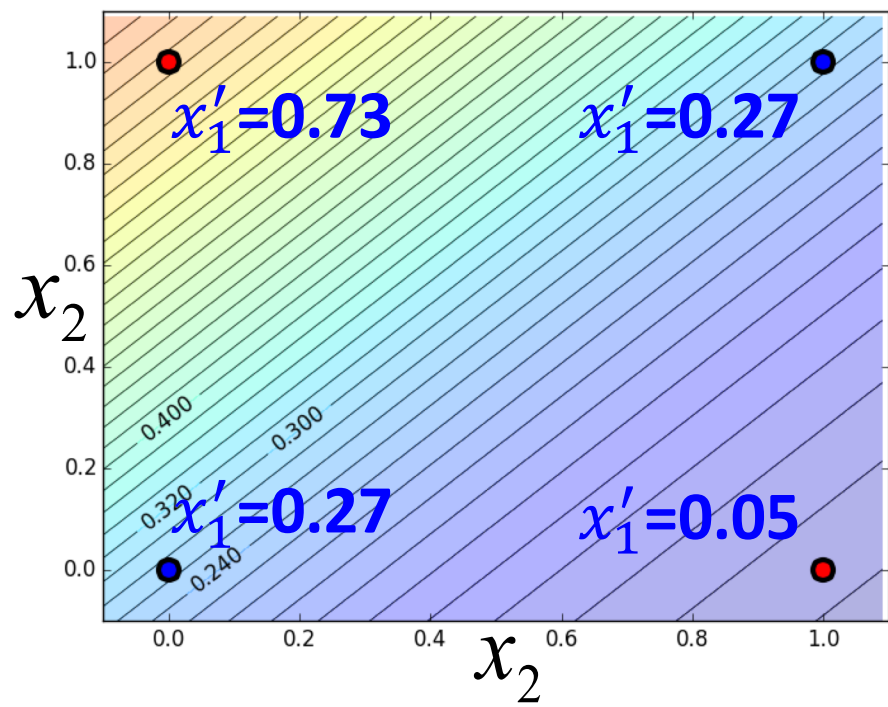
Limitation of Logistic Regression

- Cascading logistic regression models



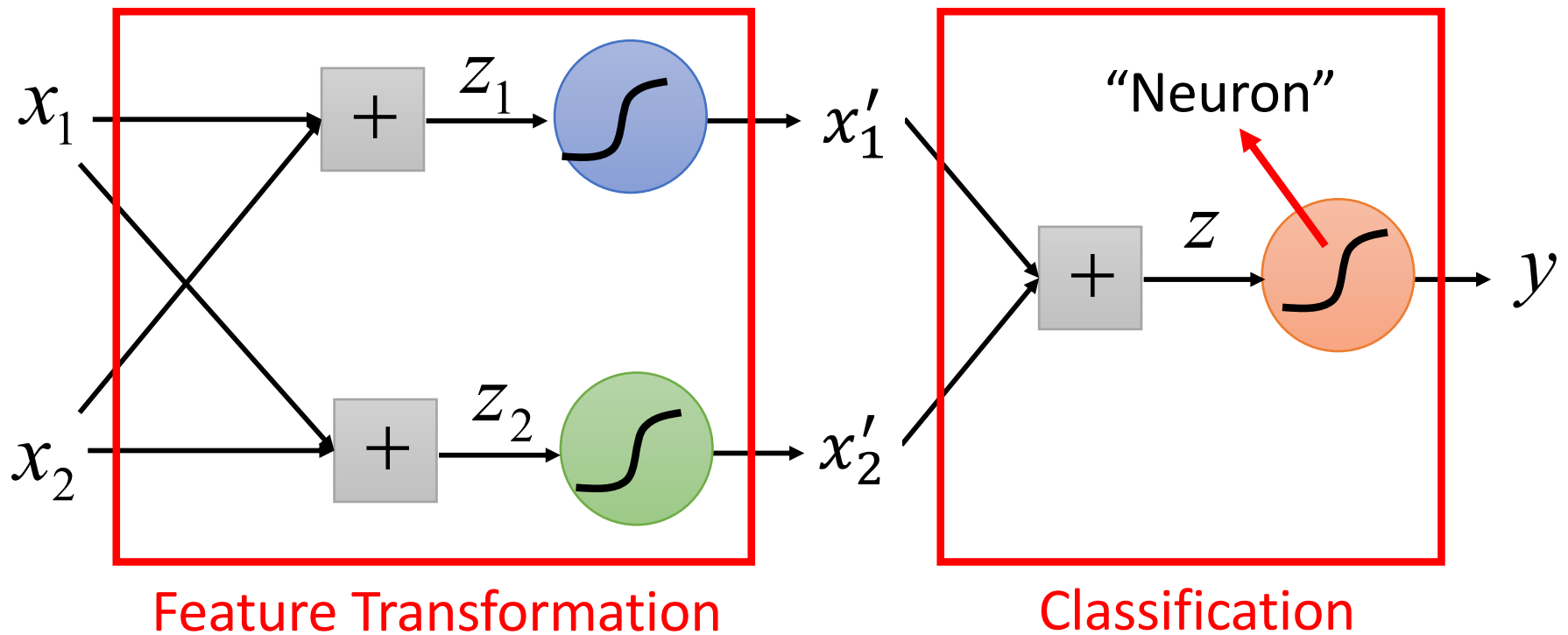
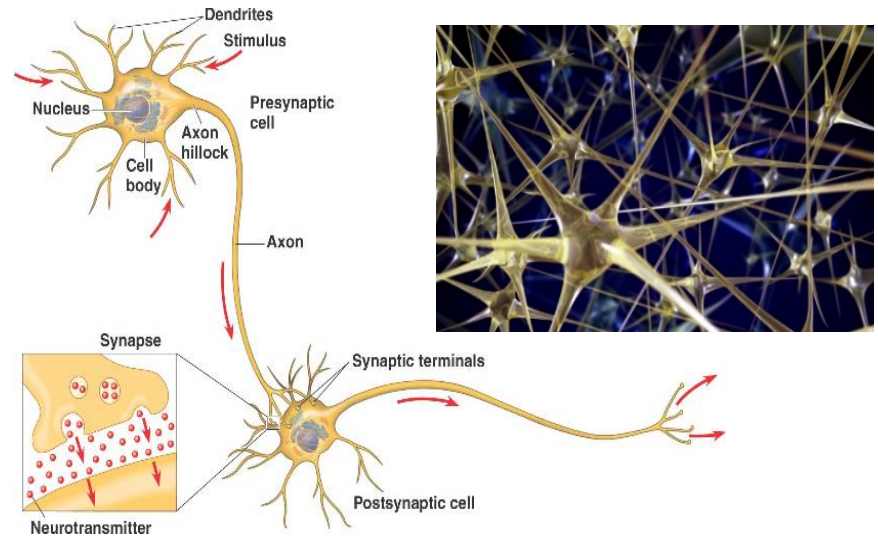
(ignore bias in this figure)





Deep Learning!

All the parameters of the logistic regressions are jointly learned.



Neural Network

Questions