CNN for CV

AI for CV Group
2020

Week 3-5.
Classical Machine Learning

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B. Unsupervised Learning

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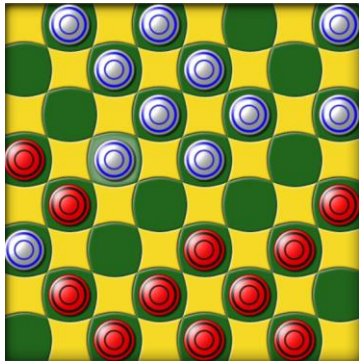
O. Reading Parts: AdaBoost / Haar Feature

I. Introduction To Machine Learning

I. Intro To ML

Arthur Samuel: Field of study that gives computers the ability to learn without being explicitly programmed.

1959



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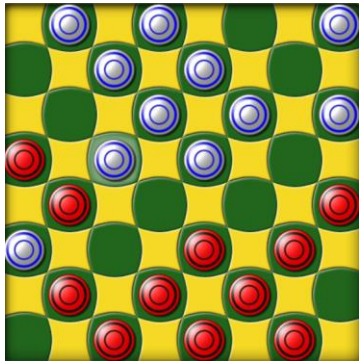

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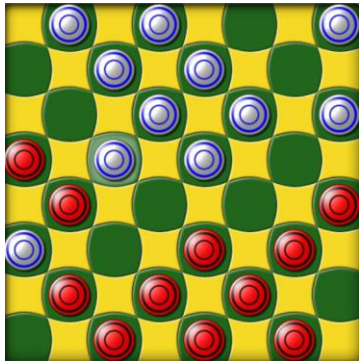

Tom Mitchell: Well-posed Learning Problem: A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E. 1998

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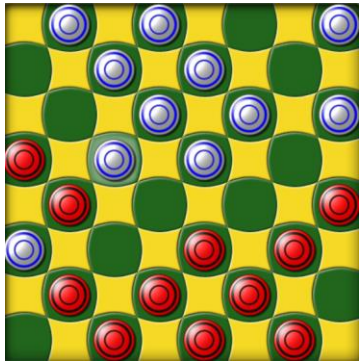

1. A solution exists; 2. Solution is unique; 3. Solution's behavior is continuous.

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I. Intro To ML

ML Algorithms:

- Supervised Learning
- Unsupervised Learning

Others:

- Reinforcement Learning
- Recommender Systems

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I. Intro To ML

A. Supervised Learning:

I. Intro To ML

A. Supervised Learning:

Who supervises who?

Who is supervised by whom?

I. Intro To ML

A. Supervised Learning:

Who supervises who?

A “teacher” supervises “me”.

Who is supervised by whom?

“I” am supervised by a “teacher”.

I. Intro To ML

A. Supervised Learning:

Who supervises who?

A “teacher” supervises “me”.

A “standard” supervises the “system”.

Who is supervised by whom?

“I” am supervised by a “teacher”.

The “system” is supervised by the “standard”.

I. Intro To ML

A. Supervised Learning:

There is an answer as our standard!

Who supervises who?

A “teacher” supervises “me”.

A “standard” supervises the “system”.

Who is supervised by whom?

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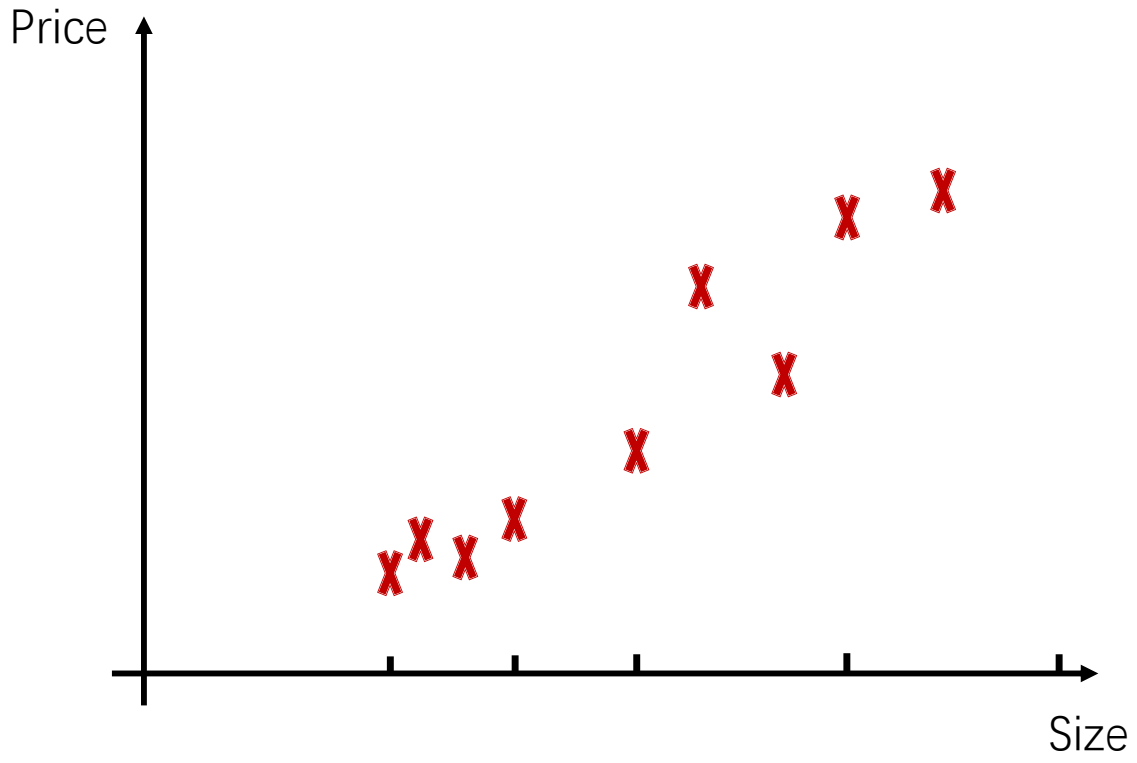

I. Intro To ML

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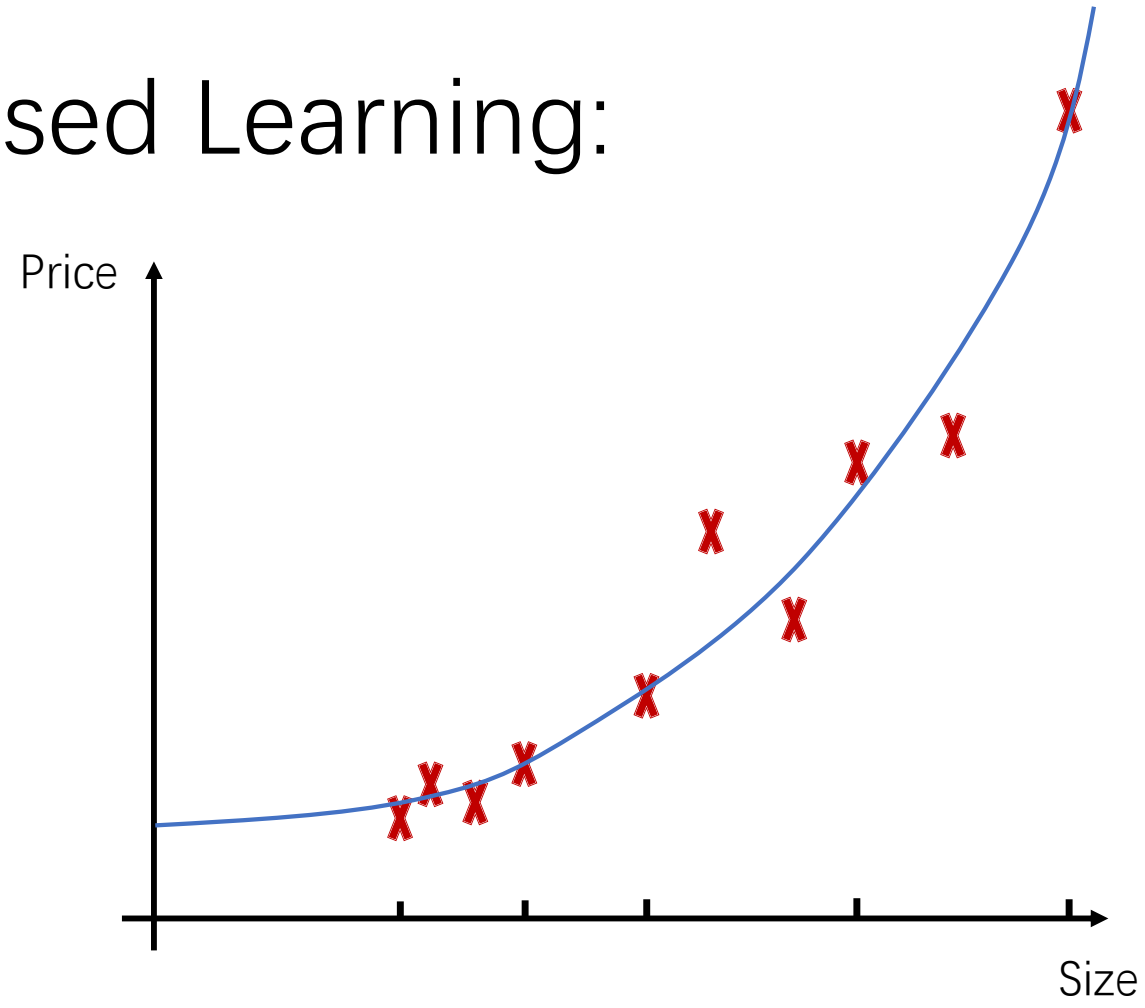
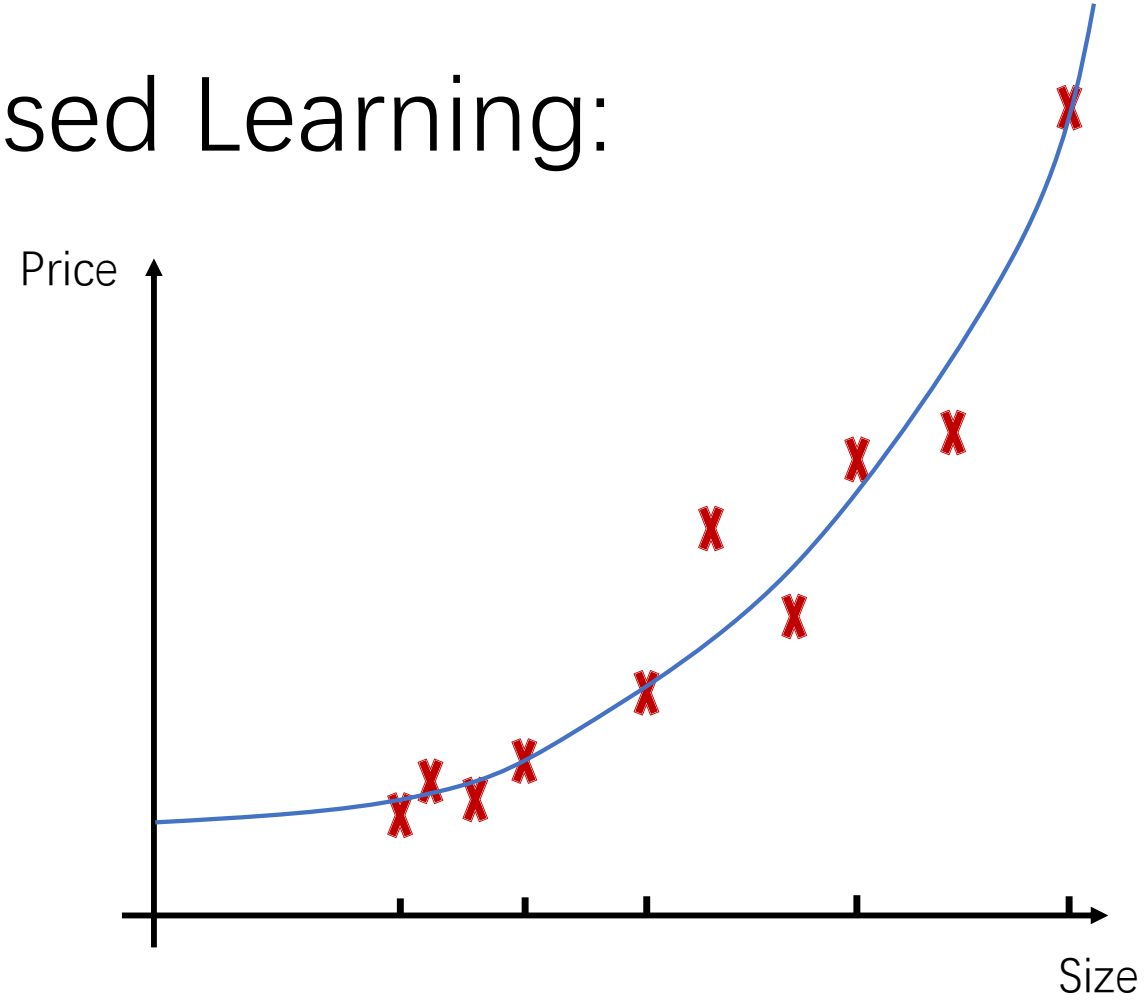


I. Intro To ML

A. Supervised Learning:

Regression



I. Intro To ML

A. Supervised Learning:

Regression

Object Detection

Keypoint Detection

Prediction (age, charm, counting)

.....

I. Intro To ML

A. Supervised Learning:

Regression

Object Detection

Keypoint Detection

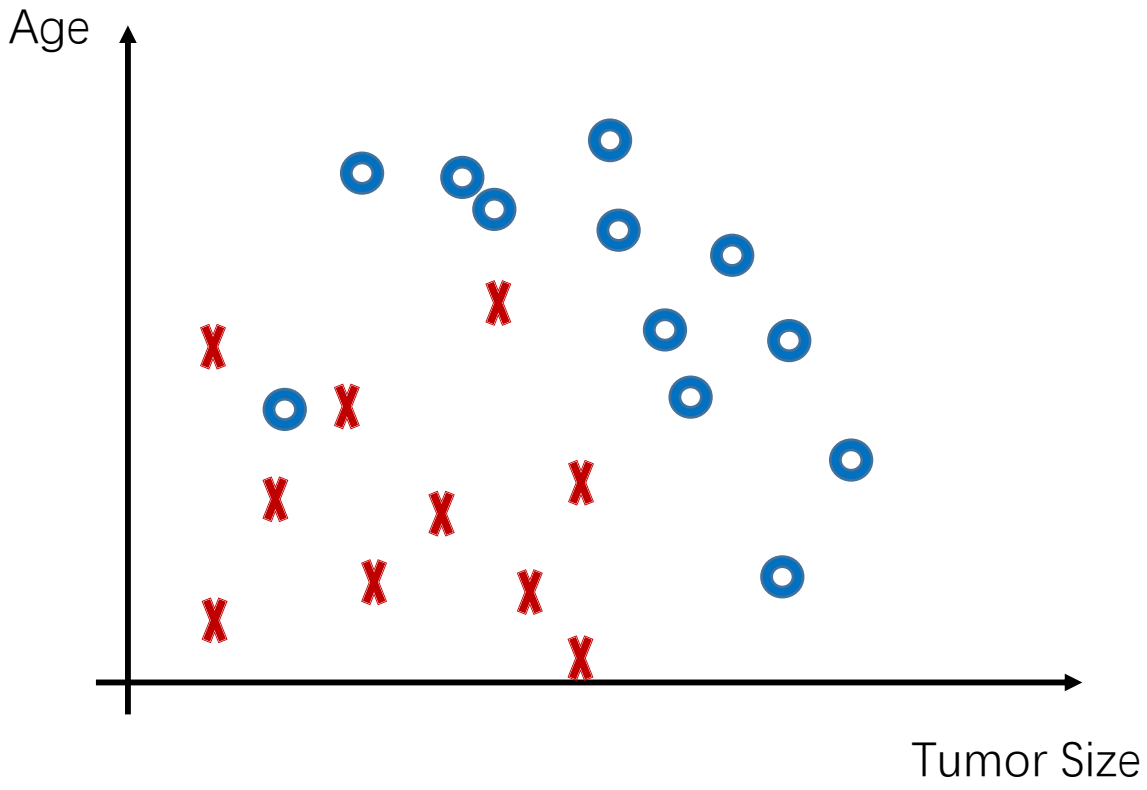
Prediction (age, charm, counting)

……

Give out numbers

I. Intro To ML

A. Supervised Learning:



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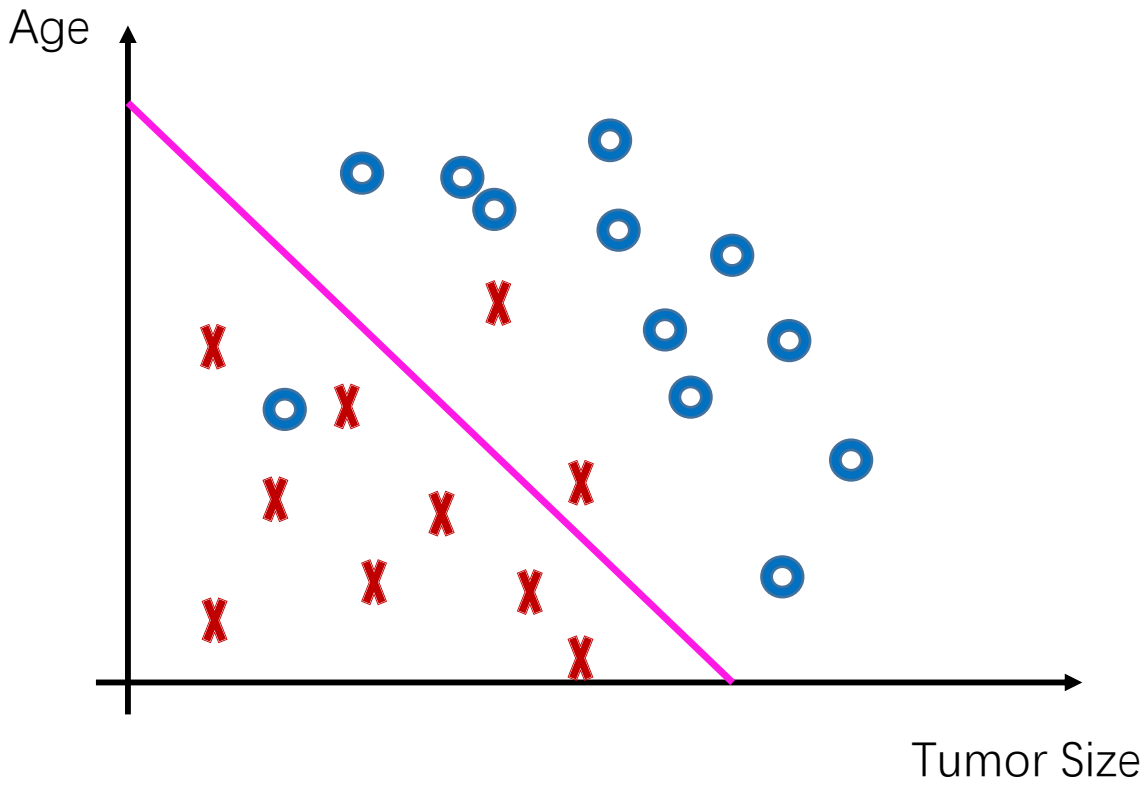

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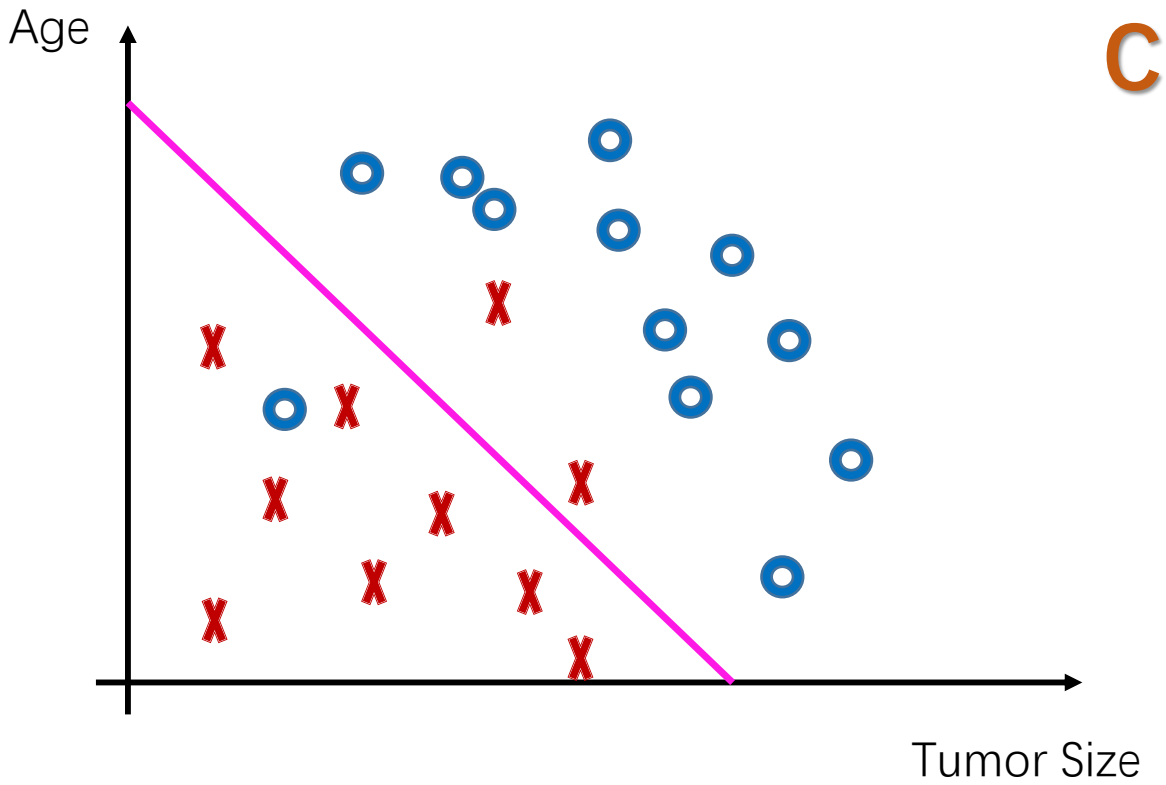


Classification

I. Intro To ML

A. Supervised Learning:

Classification

Image/Video Classification

Segmentation

.....

I. Intro To ML

B. Unsupervised Learning:

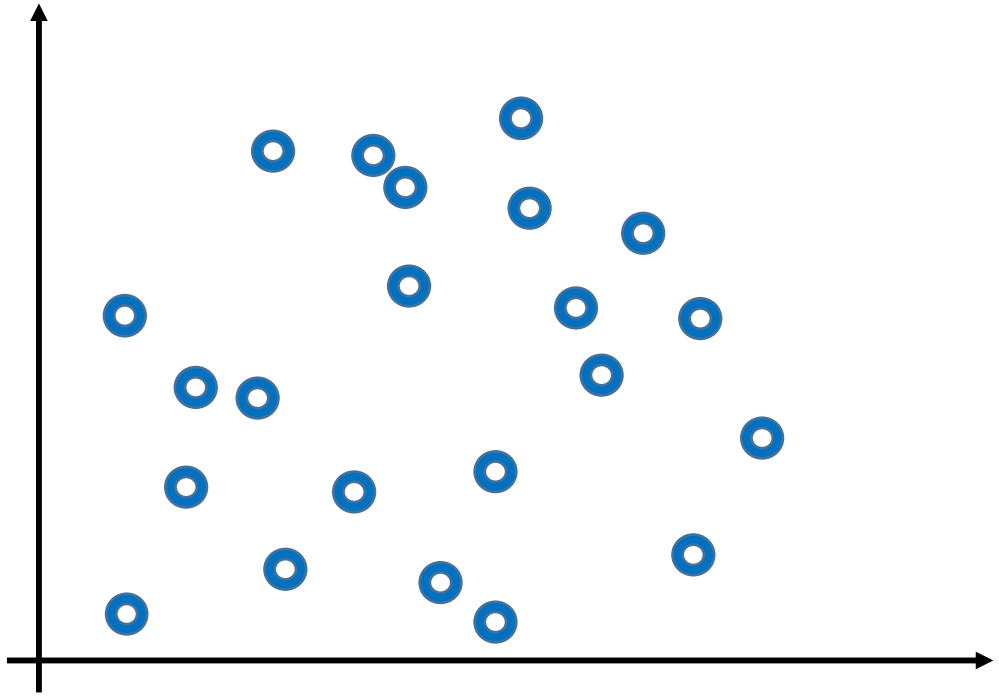
I. Intro To ML

B. Unsupervised Learning:

There is no answers as our standards!

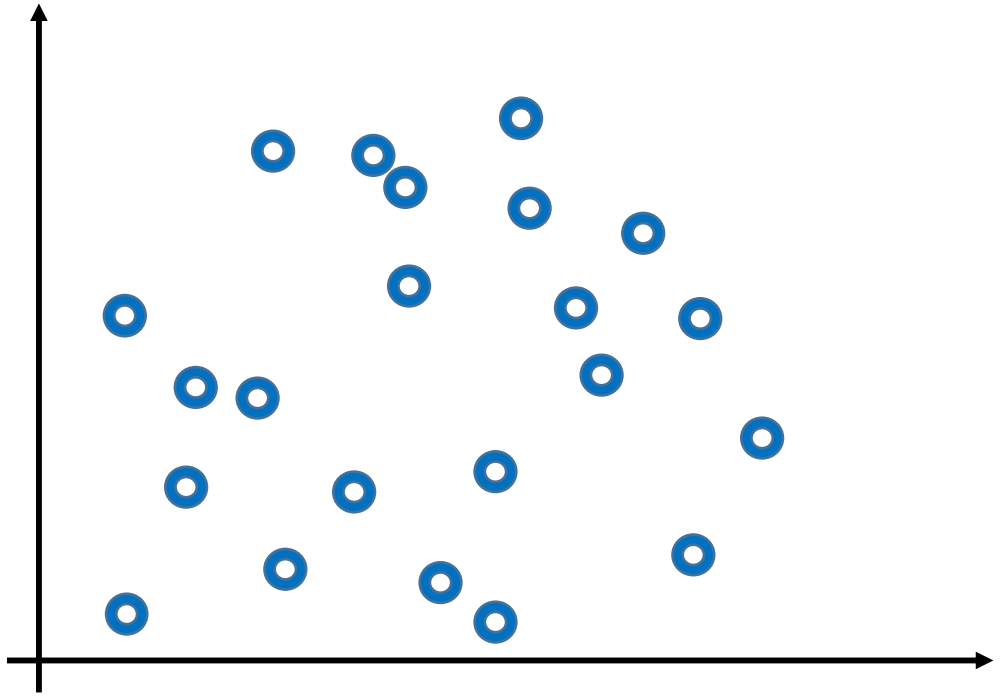
I. Intro To ML

B. Unsupervised Learning:



I. Intro To ML

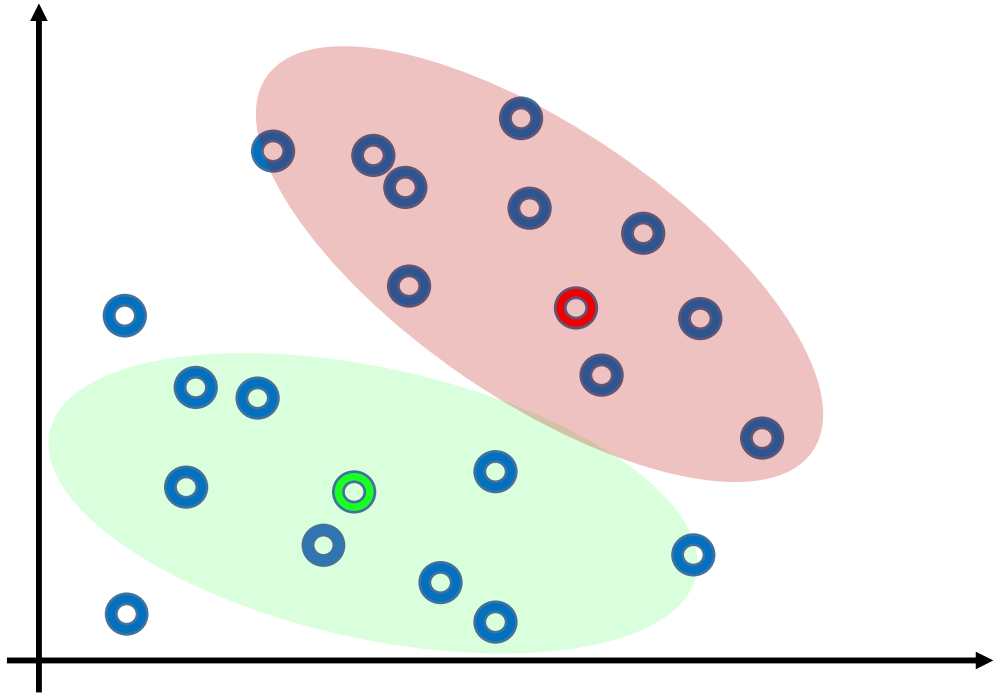
B. Unsupervised Learning:



Clustering

I. Intro To ML

B. Unsupervised Learning:



Clustering

I. Intro To ML

B. Unsupervised Learning:

Q: How to type a video within 1,000,000,000 videos in a short time?

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Q: How to type a video within 1,000,000,000 videos in a short time?

A: That's classification. We build a model to classify the video.

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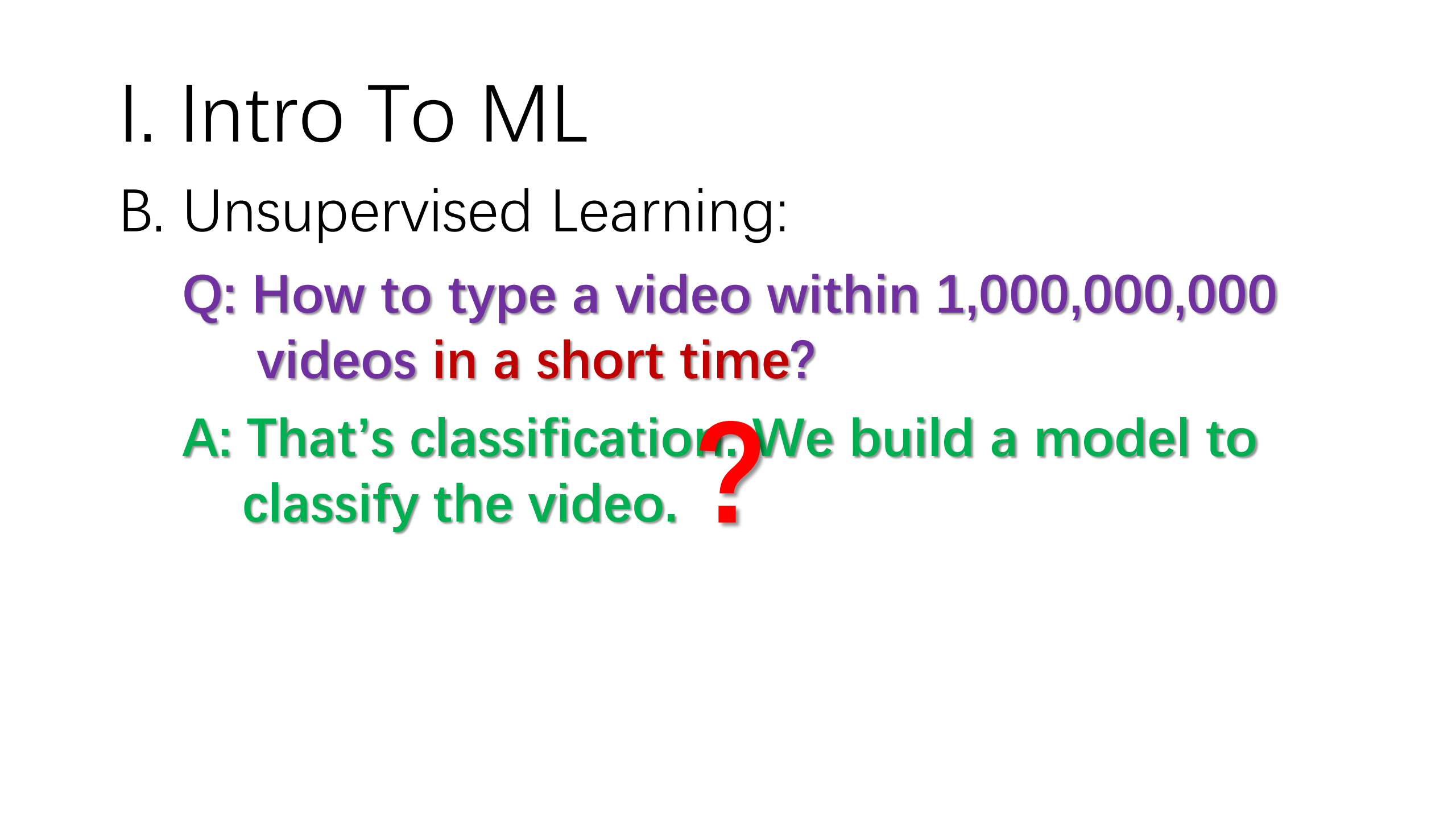


I. Intro To ML

B. Unsupervised Learning:

Q: How to type a video within 1,000,000,000 videos in a short time?

A: That's classification. We build a model to classify the video.

P: 1. Who labels the data?

2. Videos are changing. We'll be training all the rest time in the universe.

I. Intro To ML

B. Unsupervised Learning:

Q: How to type a video within 1,000,000,000 videos in a short time?

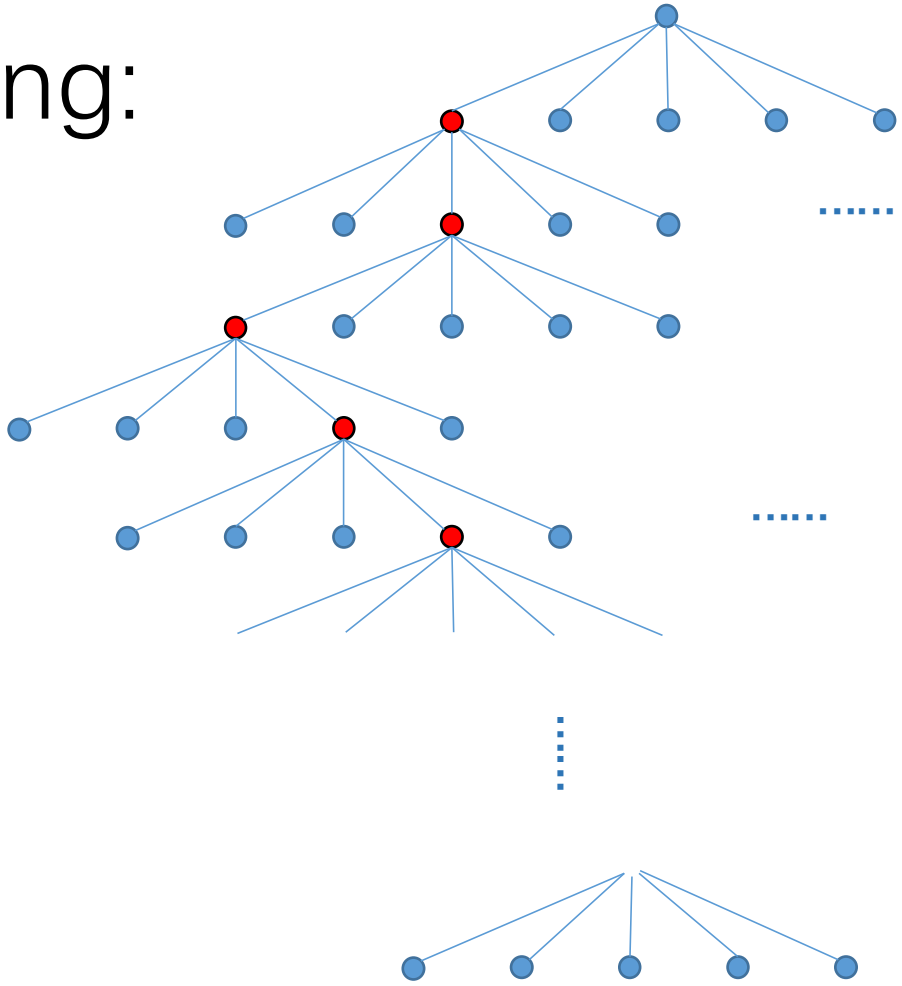
A: Clustering

I. Intro To ML

B. Unsupervised Learning:

Q: How to type a video within 1,000,000,000 videos in a short time?

A: Clustering per level.
Root the center.
Recurse.



II. Supervised Learning

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C. Linear Regression:

II. Supervised Learning

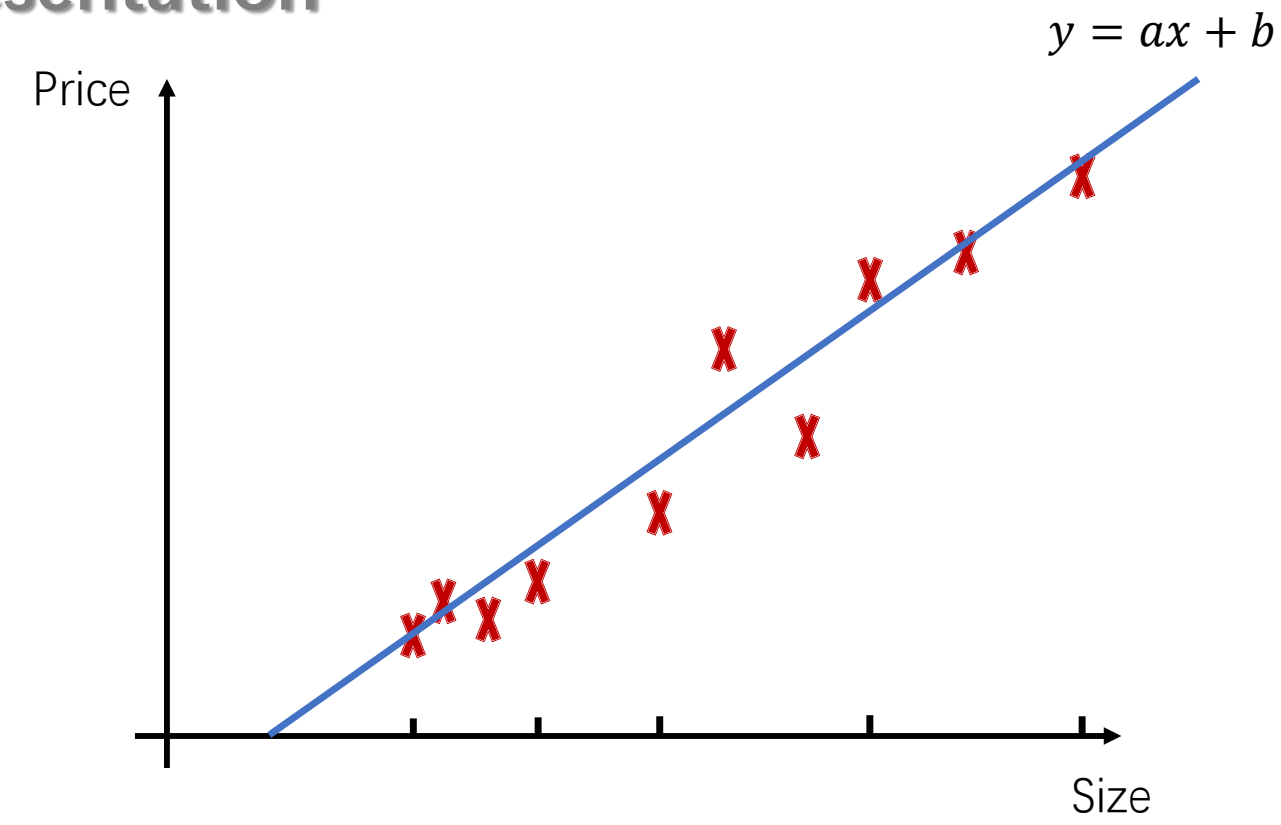
C. Linear Regression:

Regression: Fit A Line

II. Supervised Learning

C. Linear Regression:

C1. Representation



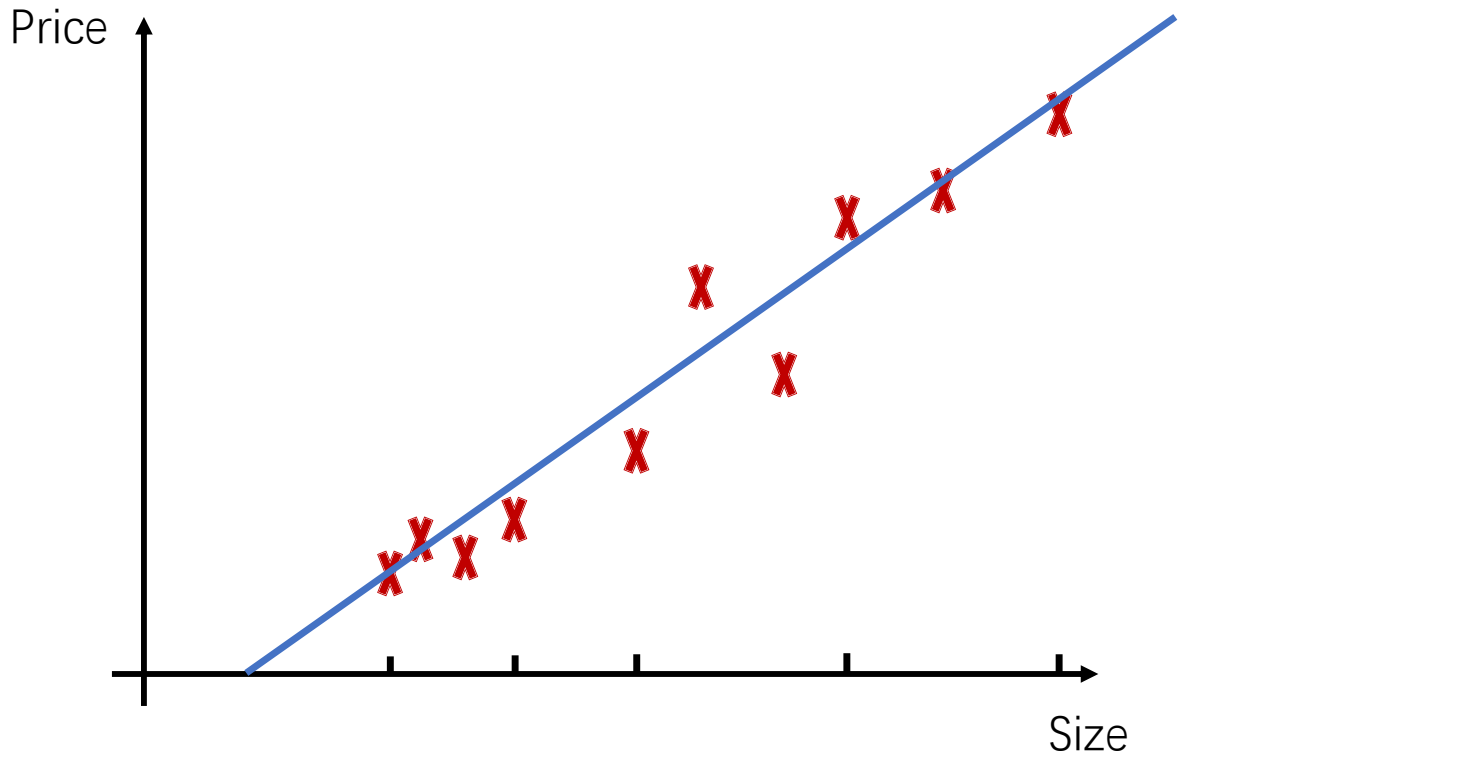
II. Supervised Learning

C. Linear Regression:

C1. Representation

What shape the line?

$y = ax + b$



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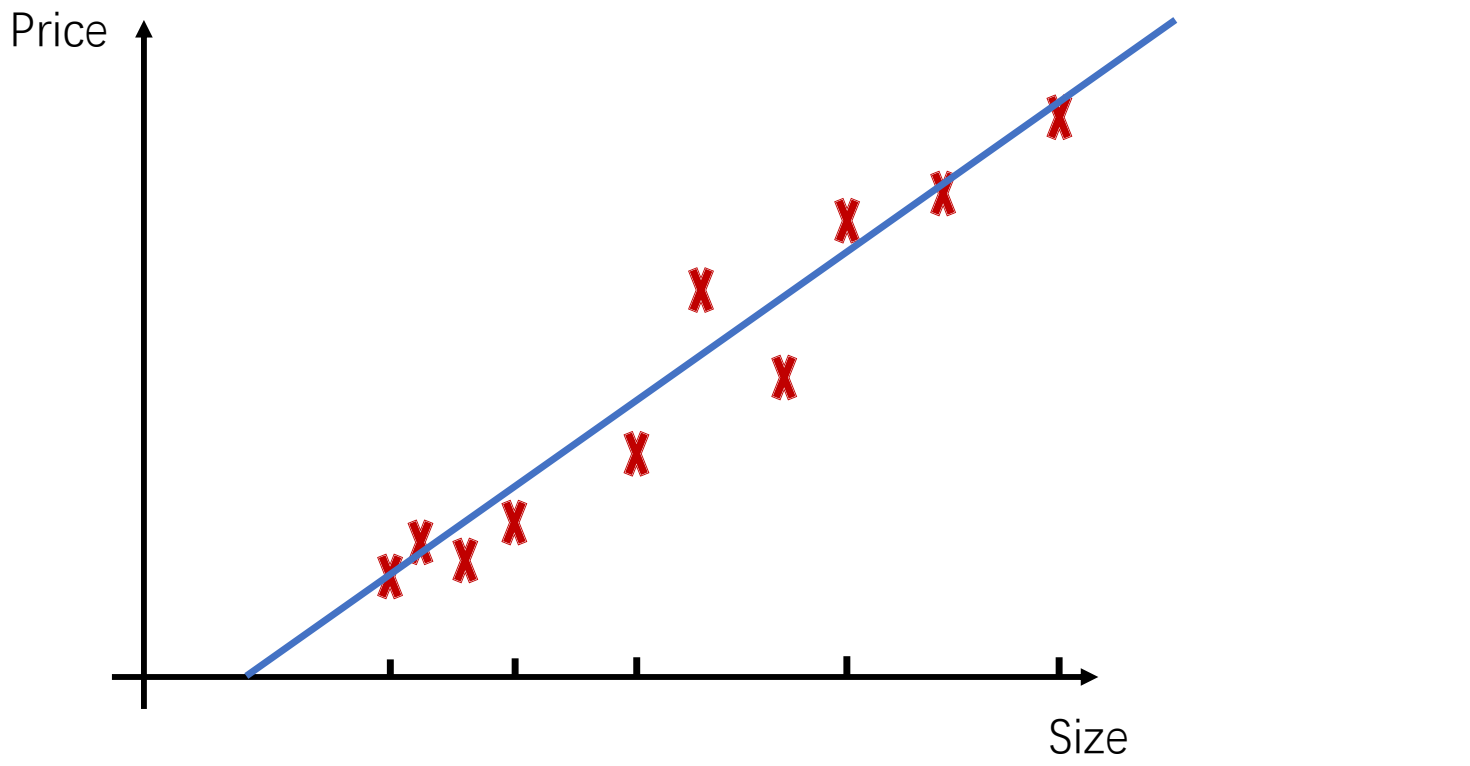


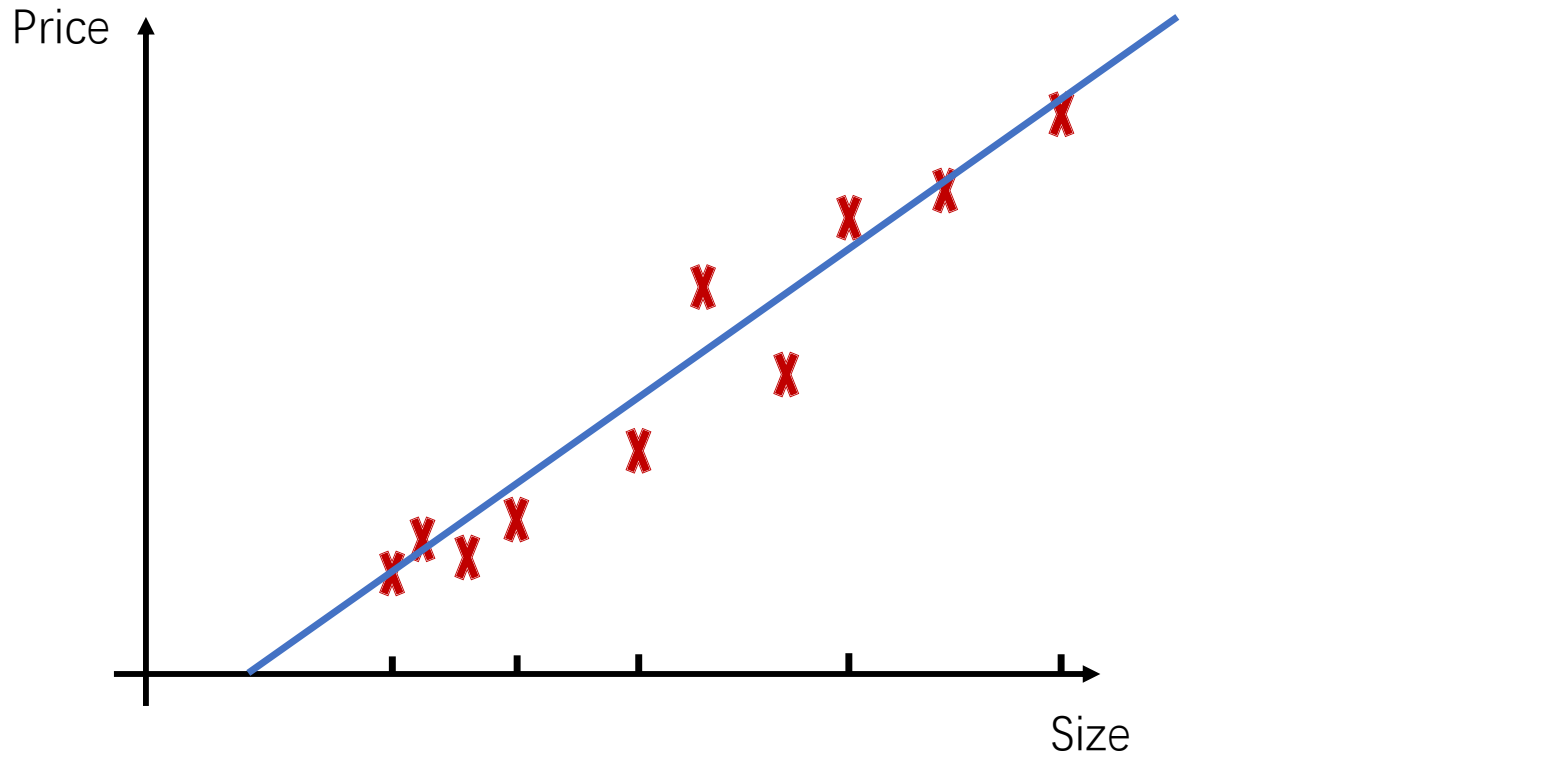
II. Supervised Learning

C. Linear Regression:

C1. Representation

Let's give a & b a name:

$y = ax + b$



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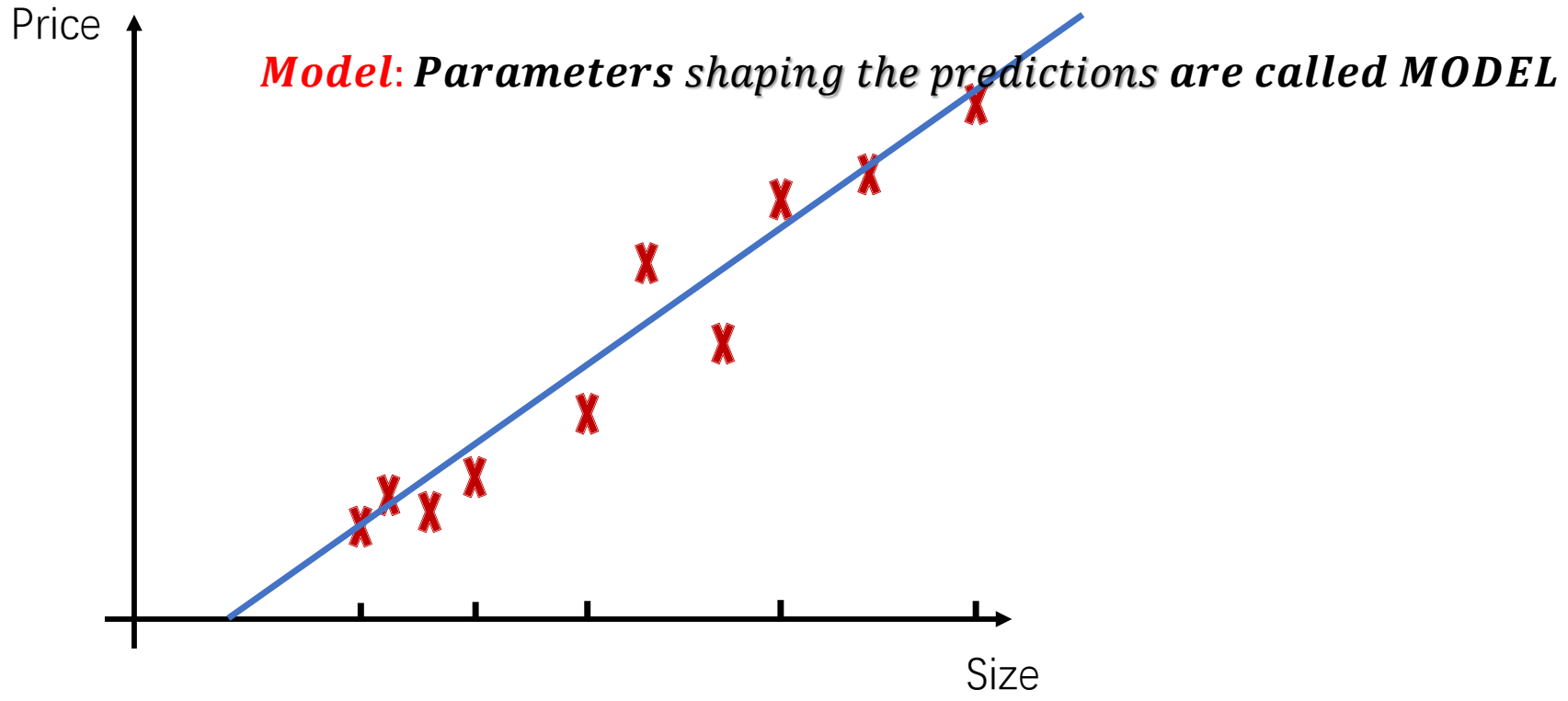

Model: ***Parameters shaping the predictions are called MODEL***

II. Supervised Learning

C. Linear Regression:

C1. Representation

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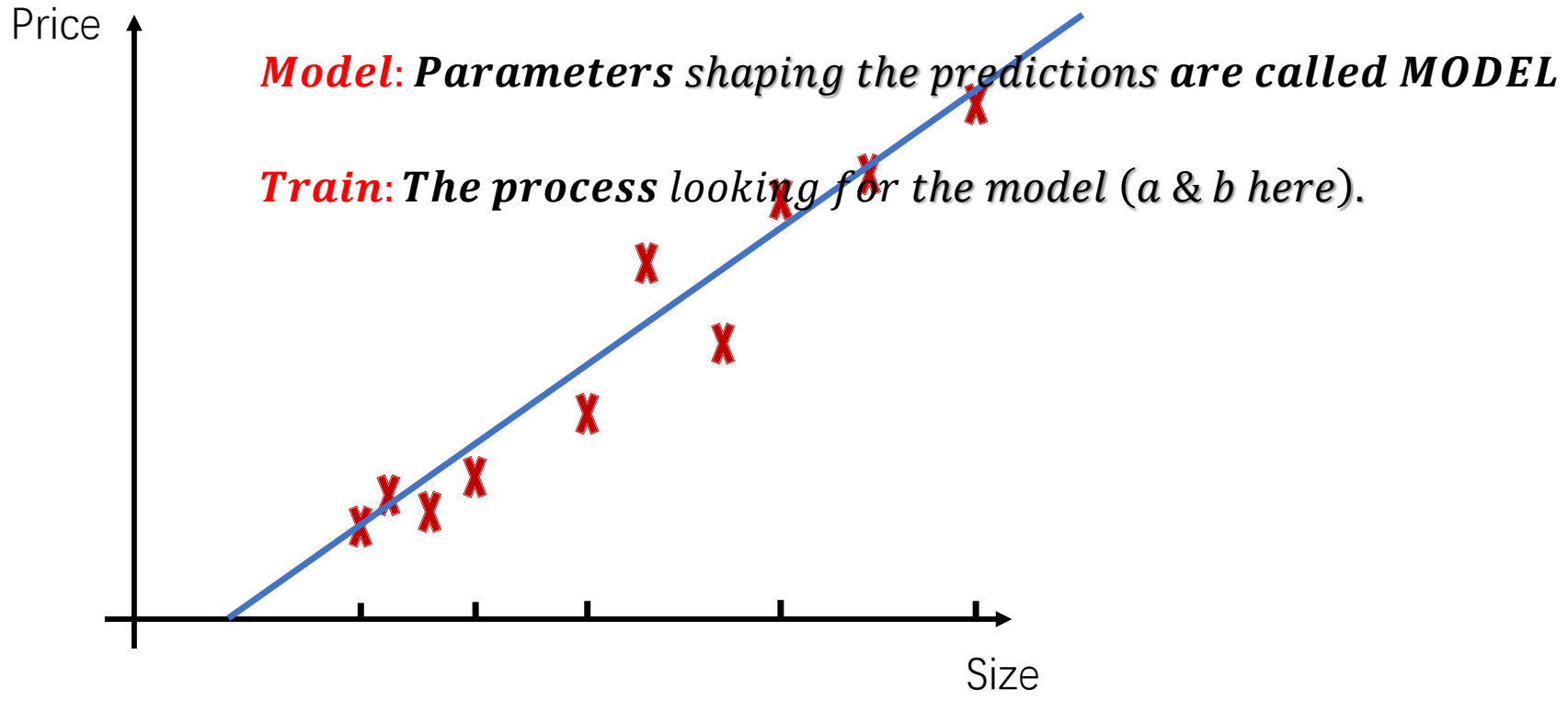


Model: ***Parameters*** *shaping the predictions* ***are called MODEL***

Train: ***The process*** *looking for the model* (*a* & *b here*).

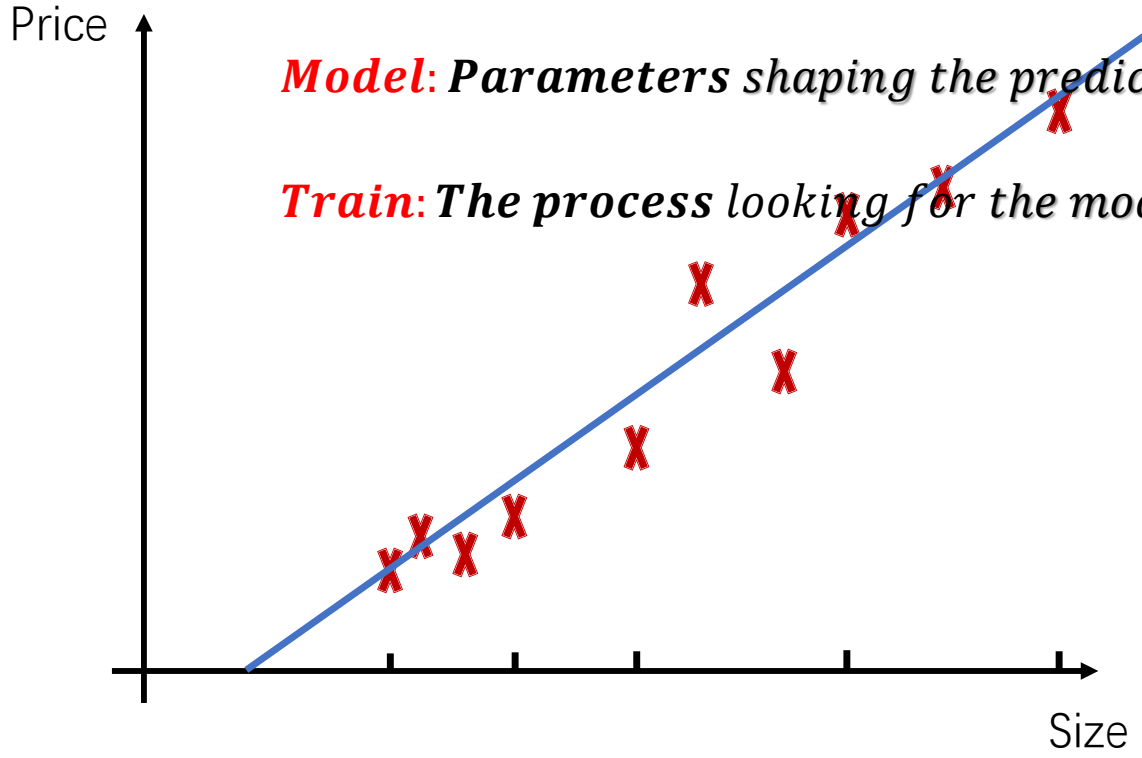
II. Supervised Learning

C. Linear Regression:

C1. Representation

For generalizing purpose:

$h_\theta(x) = \theta_0 + \theta_1 x$



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C1. Representation

For generalizing purpose:

Hypotheses $h_\theta(x) = \theta_0 + \theta_1 x$

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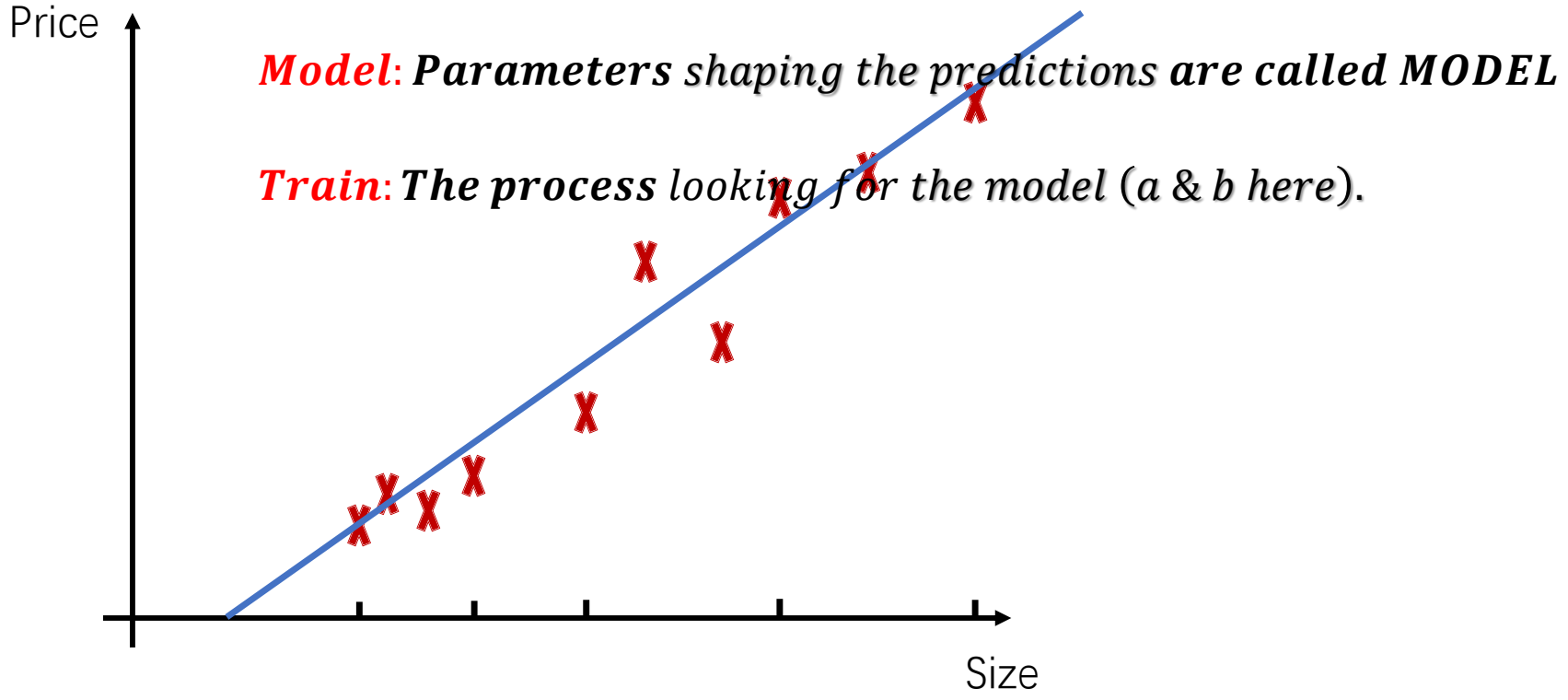

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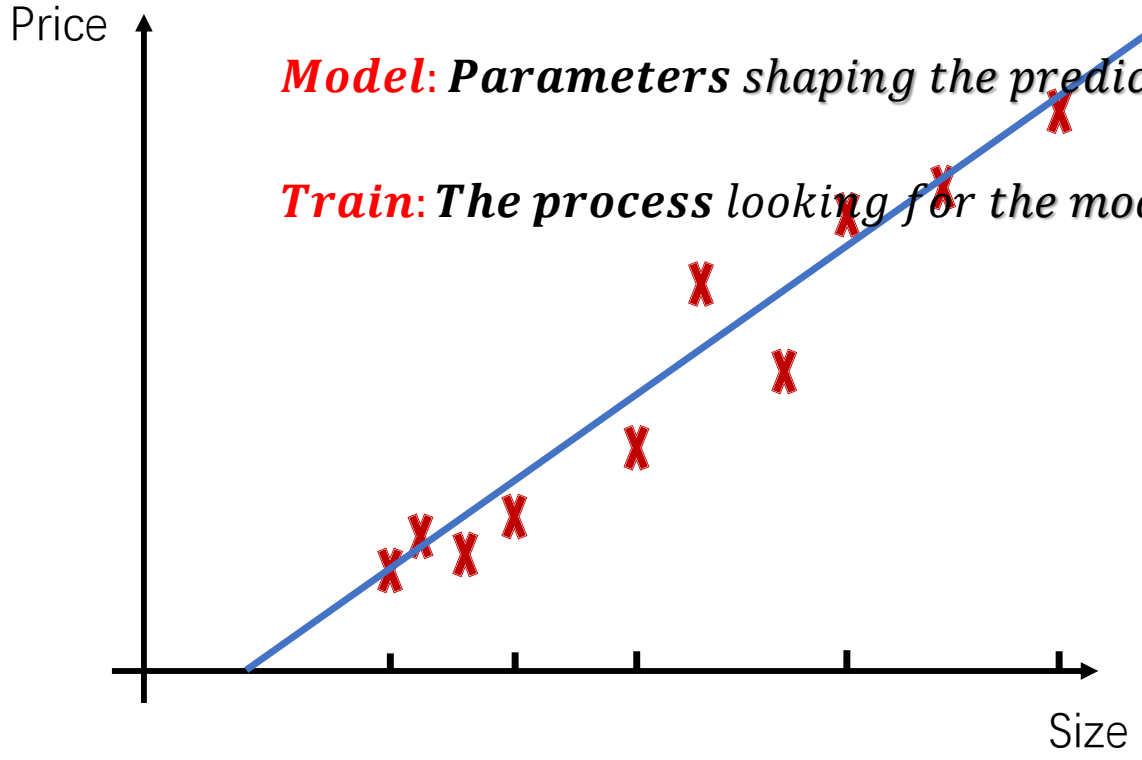

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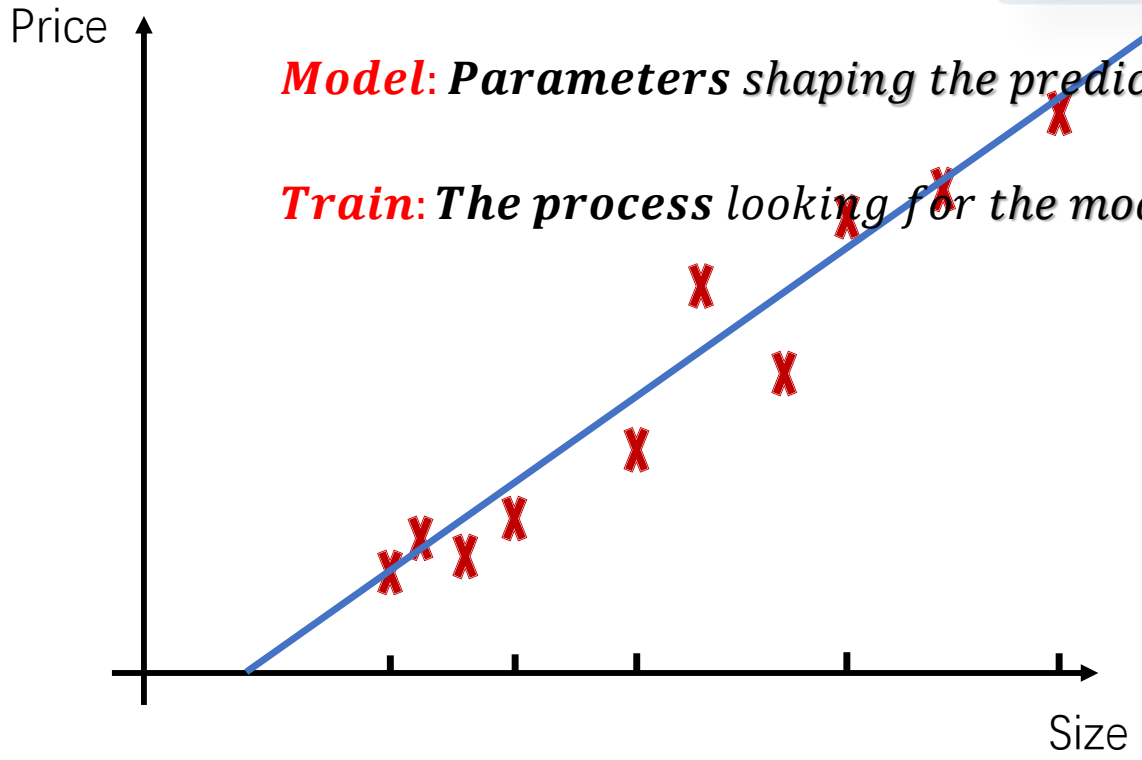
C. Linear Regression:

C1. Representation

For generalizing purpose:

$$h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$$



Model: ***Parameters*** *shaping the predictions* ***are called MODEL***

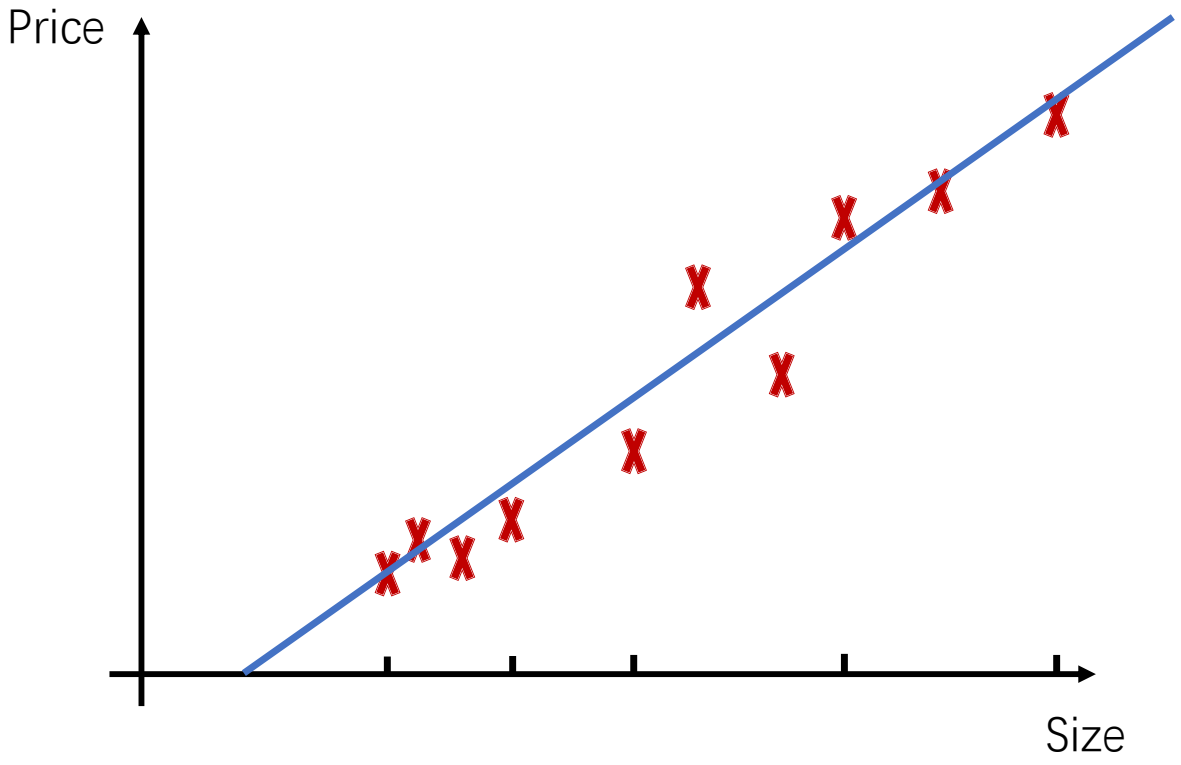
Train: ***The process*** *looking for the model* (*a* & *b here*).

II. Supervised Learning

C. Linear Regression:

C2. How to choose θ-Cost Function

$$h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$$



II. Supervised Learning

C. Linear Regression:

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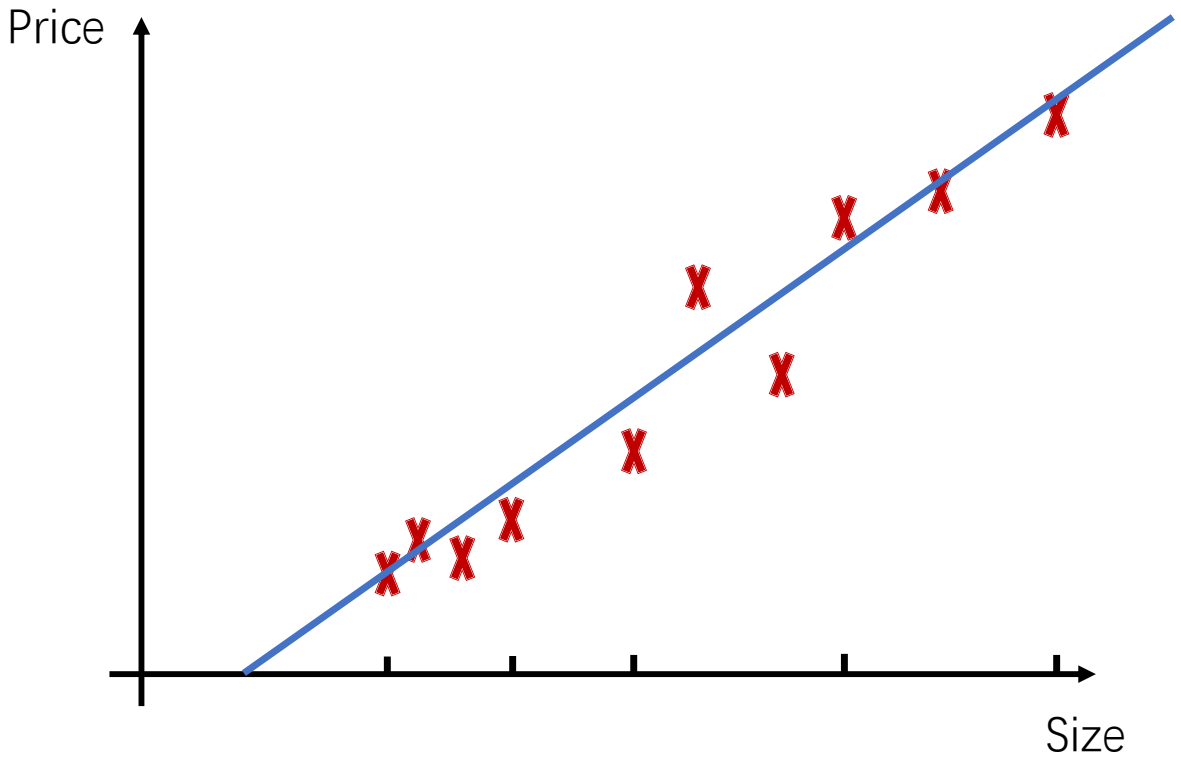


Cost:

Difference between hypotheses and reality

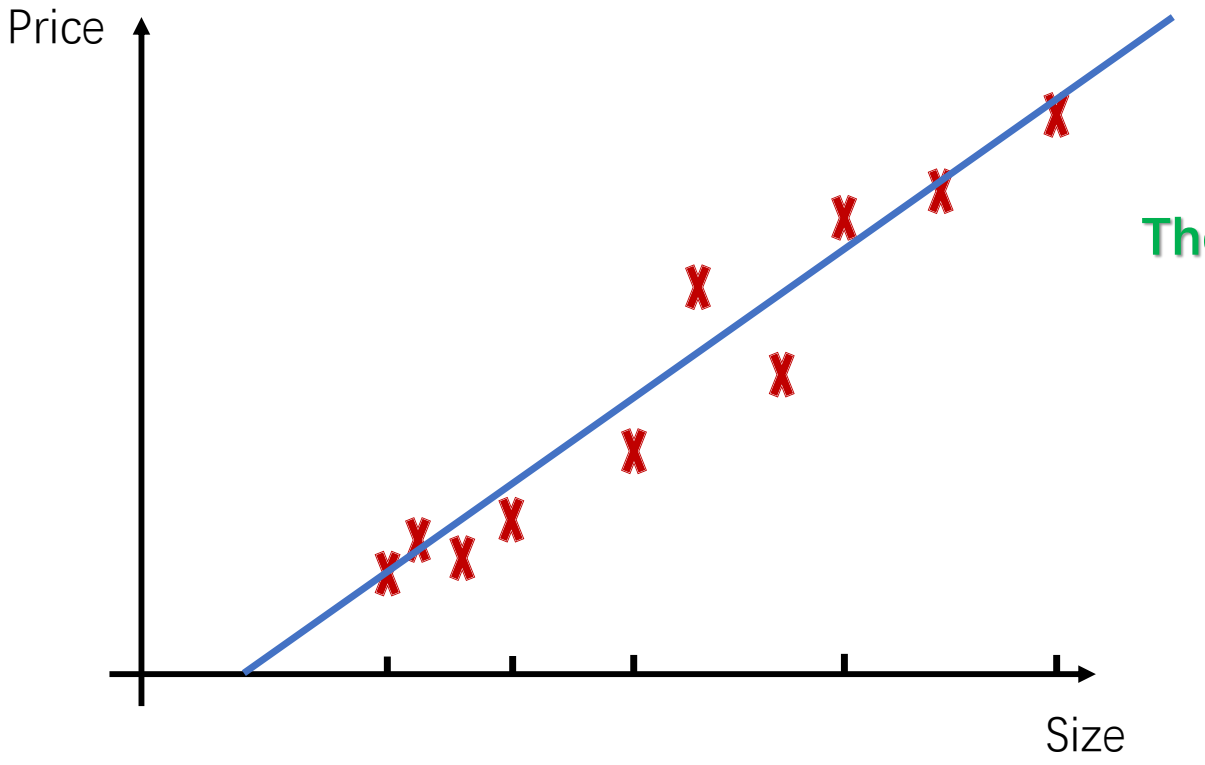
Label data

II. Supervised Learning

C. Linear Regression:

C2. How to choose θ-Cost Function

$$h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$$



Cost:

Difference between hypotheses and reality

Label data

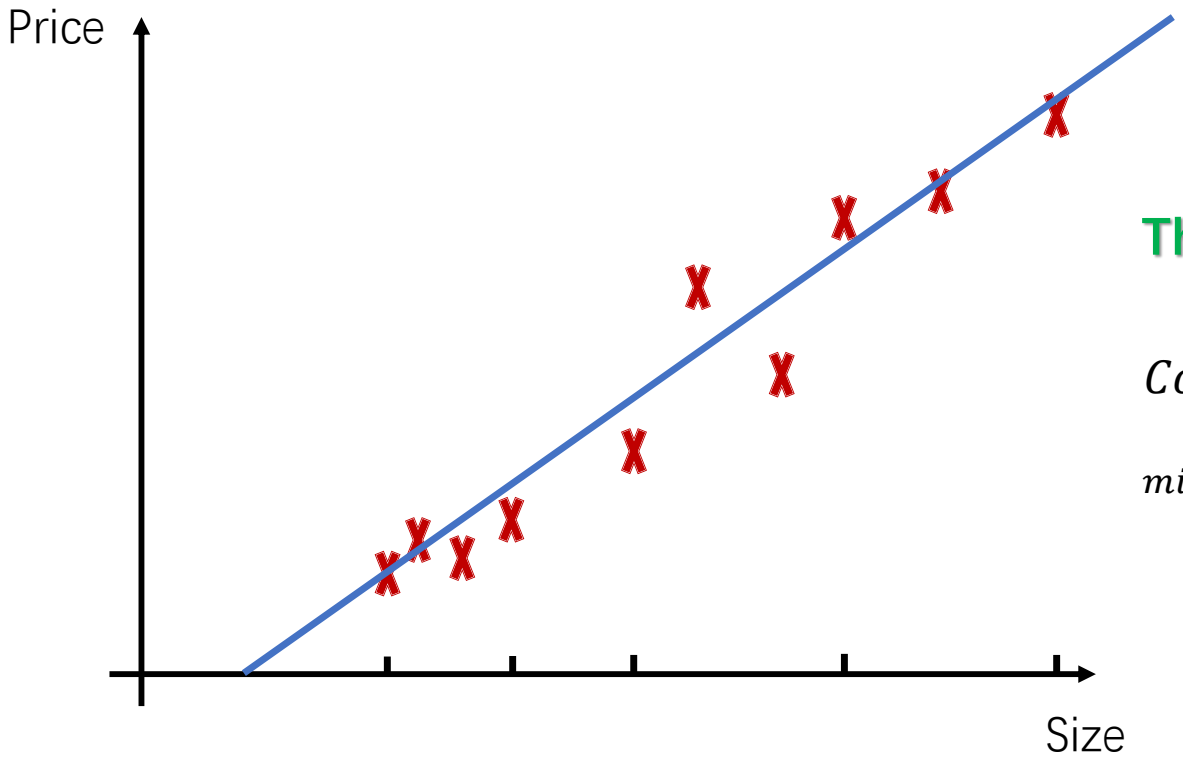
The less the difference/cost, the better the model

II. Supervised Learning

C. Linear Regression:

C2. How to choose θ-Cost Function

$$h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$$



Cost:

Difference between hypotheses and reality

Label data

The less the difference/cost, the better the model

$$Cost = J(\theta_0, \theta_1) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2$$

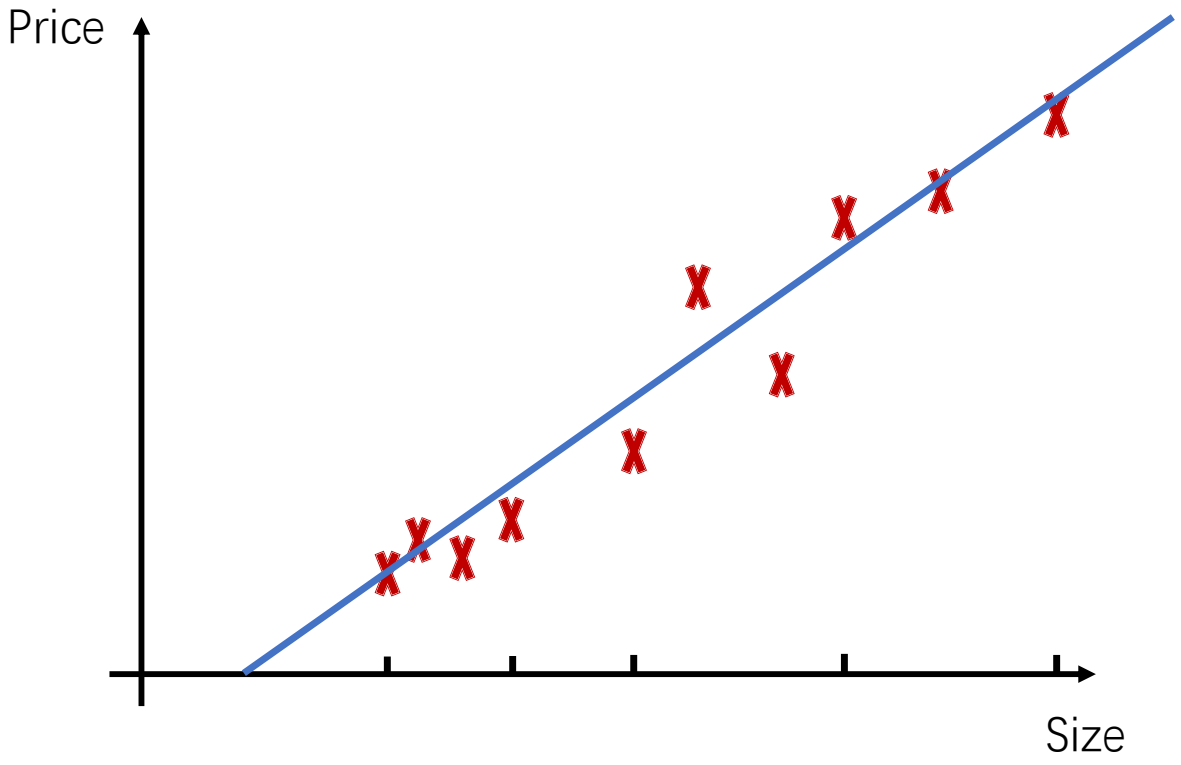
$$\underset{\theta_0,\theta_1}{minimize} J(\theta_0, \theta_1)$$

Squared Error Function

II. Supervised Learning

C. Linear Regression:

C2. How to choose θ-Cost Function



Hypothesis: $h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$

Parameters: θ_0, θ_1

Cost Func: $J(\theta_0, \theta_1) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2$

Goal: $\underset{\theta_0,\theta_1}{minimize} J(\theta_0, \theta_1)$

II. Supervised Learning

C. Linear Regression:

C3. How to calculate-Gradient Descent

Gradient Descent Algo:

$while\ not\ converge\ \{$

$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \qquad for\ j = 0\ and\ j = 1$$

$\}$

$$\text{temp0} := \theta_0 - \alpha \frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1)$$
$$\text{temp1} := \theta_1 - \alpha \frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1)$$
$$\theta_0 := \text{temp0}$$
$$\theta_1 := \text{temp1}$$

Hypothesis: $h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$

Parameters: θ_0, θ_1

Cost Func: $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i)^2$

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II. Supervised Learning

C. Linear Regression:

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$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \qquad for\ j = 0\ and\ j = 1$$

$\}$

$$\frac{\partial}{\partial \theta_0} J(\theta_0) =$$

$$\frac{\partial}{\partial \theta_1} J(\theta_1) =$$

Hypothesis: $h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$

Parameters: θ_0, θ_1

Cost Func: $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i)^2$

Goal: $\underset{\theta_0, \theta_1}{minimize} J(\theta_0, \theta_1)$

II. Supervised Learning

C. Linear Regression:

C3. How to calculate-Gradient Descent

Gradient Descent Algo:

$while\ not\ converge\ \{$

$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \qquad for\ j = 0\ and\ j = 1$$

$\}$

$$\frac{\partial}{\partial \theta_0} J(\theta_0) = \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i)$$

$$\frac{\partial}{\partial \theta_1} J(\theta_1) = \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i) \cdot x^i$$

Hypothesis: $h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$

Parameters: θ_0, θ_1

Cost Func: $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i)^2$

Goal: $\underset{\theta_0, \theta_1}{minimize} J(\theta_0, \theta_1)$

II. Supervised Learning

Explain

C. Linear Regression:

C3. Illustration-Gradient Descent

Hypothesis: $h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$

Parameters: θ_0, θ_1

Cost Func: $J(\theta_0, \theta_1) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2$

Goal: $\underset{\theta_0,\theta_1}{minimize} J(\theta_0, \theta_1)$

$J(\theta_j)$: ***Quadratic Function***

$\frac{d}{d\theta_j}J(\theta_j)$: ***Slope***

$\theta_j = \theta_j - \alpha\frac{\partial}{\partial\theta_j}J(\theta)$: ***Gradient Descent***

$\theta_1 > extreme$

$\theta_1 < extreme$

II. Supervised Learning

Explain

C. Linear Regression:

C3. Illustration-Gradient Descent

Hypothesis: $h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$

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$\frac{d}{d\theta_j}J(\theta_j)$: ***Slope***

$\theta_j = \theta_j - \alpha\frac{\partial}{\partial\theta_j}J(\theta)$: ***Gradient Descent***

α: *too small*

α: *too big*

II. Supervised Learning

Explain

C. Linear Regression:

C3. Illustration-Gradient Descent

Hypothesis: $h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$

Parameters: θ_0, θ_1

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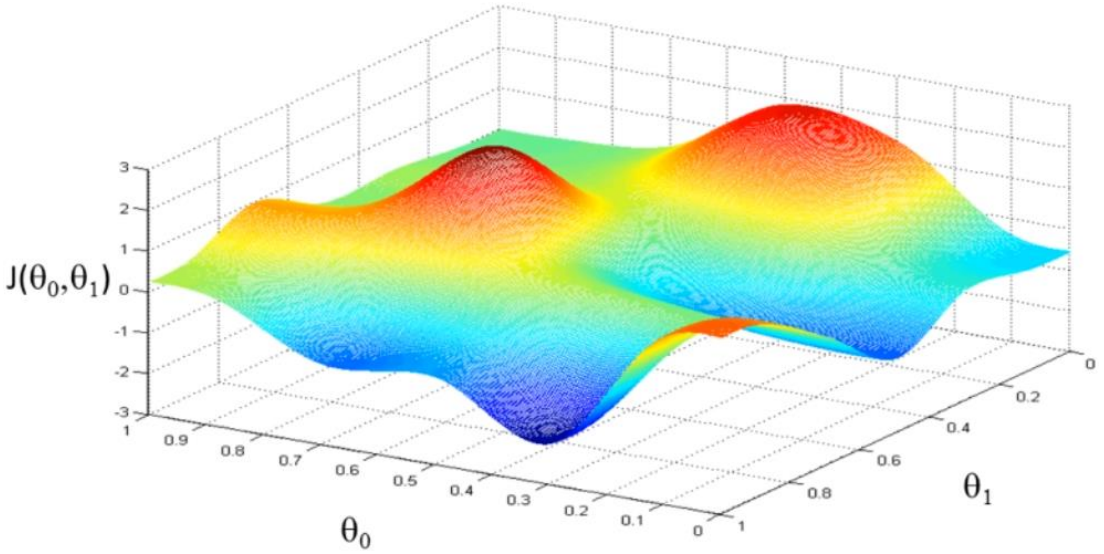

II. Supervised Learning

Explain

C. Linear Regression:

C3. Illustration-Gradient Descent

Hypothesis: $h_\theta(x^i) = \theta_0 + \theta_1 x^i = \boldsymbol{\theta x^i}$

Parameters: θ_0, θ_1

Cost Func: $J(\theta_0, \theta_1) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2$

Goal: $\underset{\theta_0,\theta_1}{minimize} J(\theta_0, \theta_1)$

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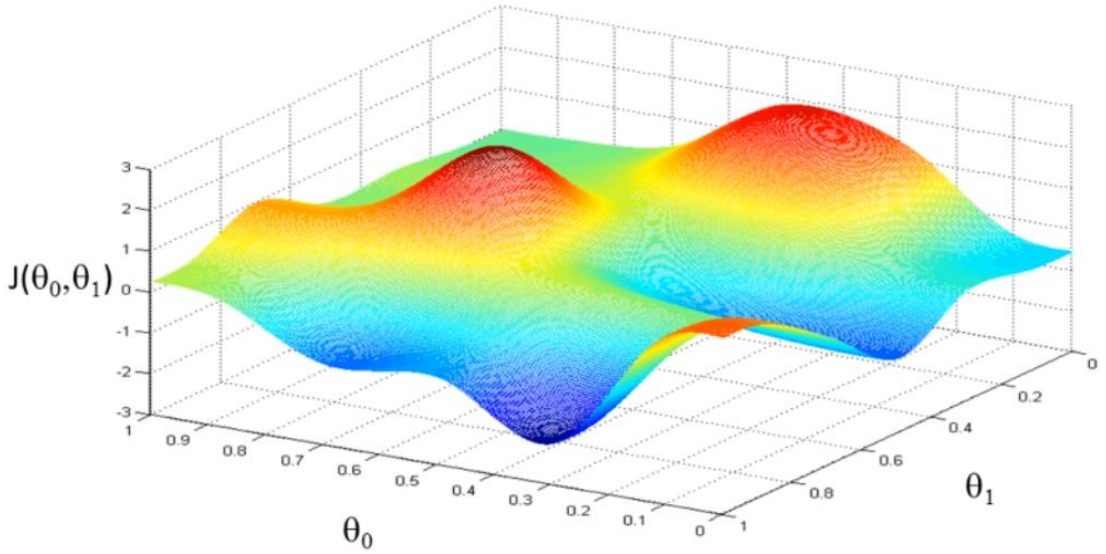
$\theta_j = \theta_j - \alpha\frac{\partial}{\partial\theta_j}J(\theta)$: ***Gradient Descent***



Get to local minimum

II. Supervised Learning

C. Linear Regression:

C4. Extension-Multiple Variables

Price:

Size

II. Supervised Learning

C. Linear Regression:

C4. Extension-Multiple Variables

Price:

Size, Community, Floor, Far, School, Hospital,

Subway, Traffic, Business, Entertainment,

Market, Policy, ……

II. Supervised Learning

C. Linear Regression:

C4. Extension-Multiple Variables

Price:

x_1 x_2 x_3 x_4 x_5 x_6

Size, Community, Floor, Far, School, Hospital,

x_7 x_8 x_9 x_{10}

Subway, Traffic, Business, Entertainment,

x_{11} x_{12} x_n

Market, Policy, ……

$x_0 = 1$

II. Supervised Learning

C. Linear Regression:

C4. Extension-Multiple Variables

Price:

x_1 x_2 x_3 x_4 x_5 x_6

Size, Community, Floor, Far, School, Hospital,

x_7 x_8 x_9 x_{10}

Subway, Traffic, Business, Entertainment,

x_{11} x_{12} x_n

Market, Policy, ……

$x_0 = 1$

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n = \boldsymbol{\theta}^T \boldsymbol{x}$$

II. Supervised Learning

C. Linear Regression:

C4. Extension-Multiple Variables

Explain

Hypothesis:

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n = \boldsymbol{\theta}^T \boldsymbol{x}$$

$$h_\theta(x^i) = \theta_0 + \theta_1 x_1^i + \theta_2 x_2^i + \cdots + \theta_n x_n^i = \boldsymbol{\theta}^T \boldsymbol{x}^i$$

n: $dimension's\ total\ number$
j: $dimension\ id\ of\ a\ sample$
m: $sample's\ total\ number$
i: $sample's\ id$

Gradient Descent:

$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_j)$$

$$= \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i) \cdot x_j^i$$

II. Supervised Learning

Explain: Why Elongated

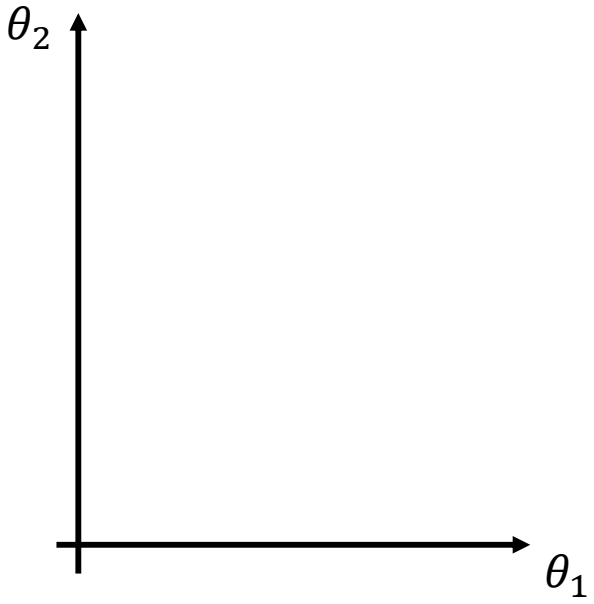
C. Linear Regression:

C5. Practice-Feature Scaling

E.G.:

$x_1 = (0, 500)$ — $size$

$x_2 = (0,10)$ — $\#\ of\ bedrooms$



II. Supervised Learning

Explain: Why Zigzag

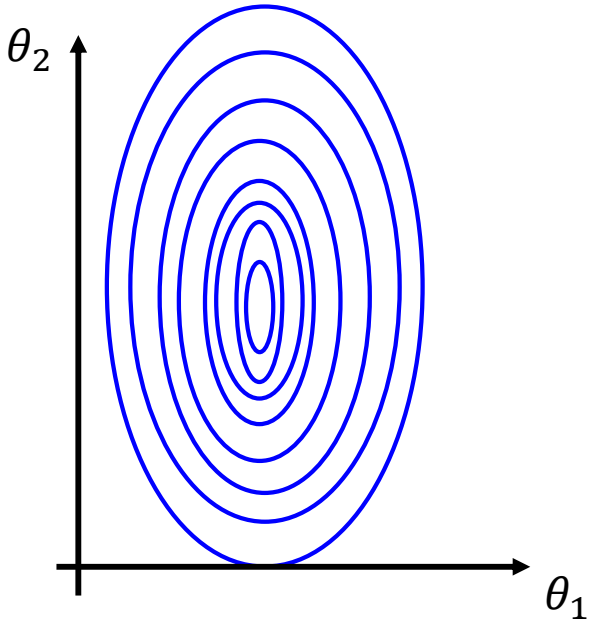
C. Linear Regression:

C5. Practice-Feature Scaling

E.G.:

$x_1 = (0, 500)$ — $size$

$x_2 = (0,10)$ — $\#\ of\ bedrooms$



Why Elongated Ellipse?

Why Zigzag?

Why the gradient along with the "narrow" dimension won't be exploded?

II. Supervised Learning

C. Linear Regression:

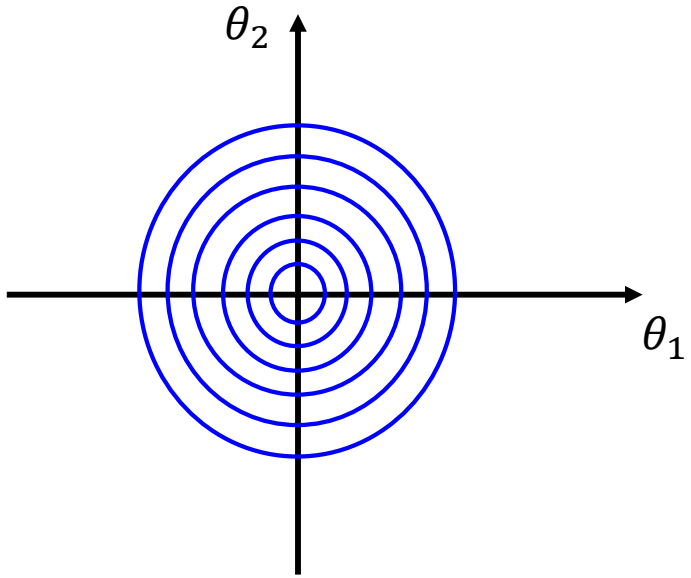
C5. Practice-Feature Scaling

E.G.:

$x_1 = (0, 500)$ — $size$

$x_2 = (0,10)$ — $\#\ of\ bedrooms$

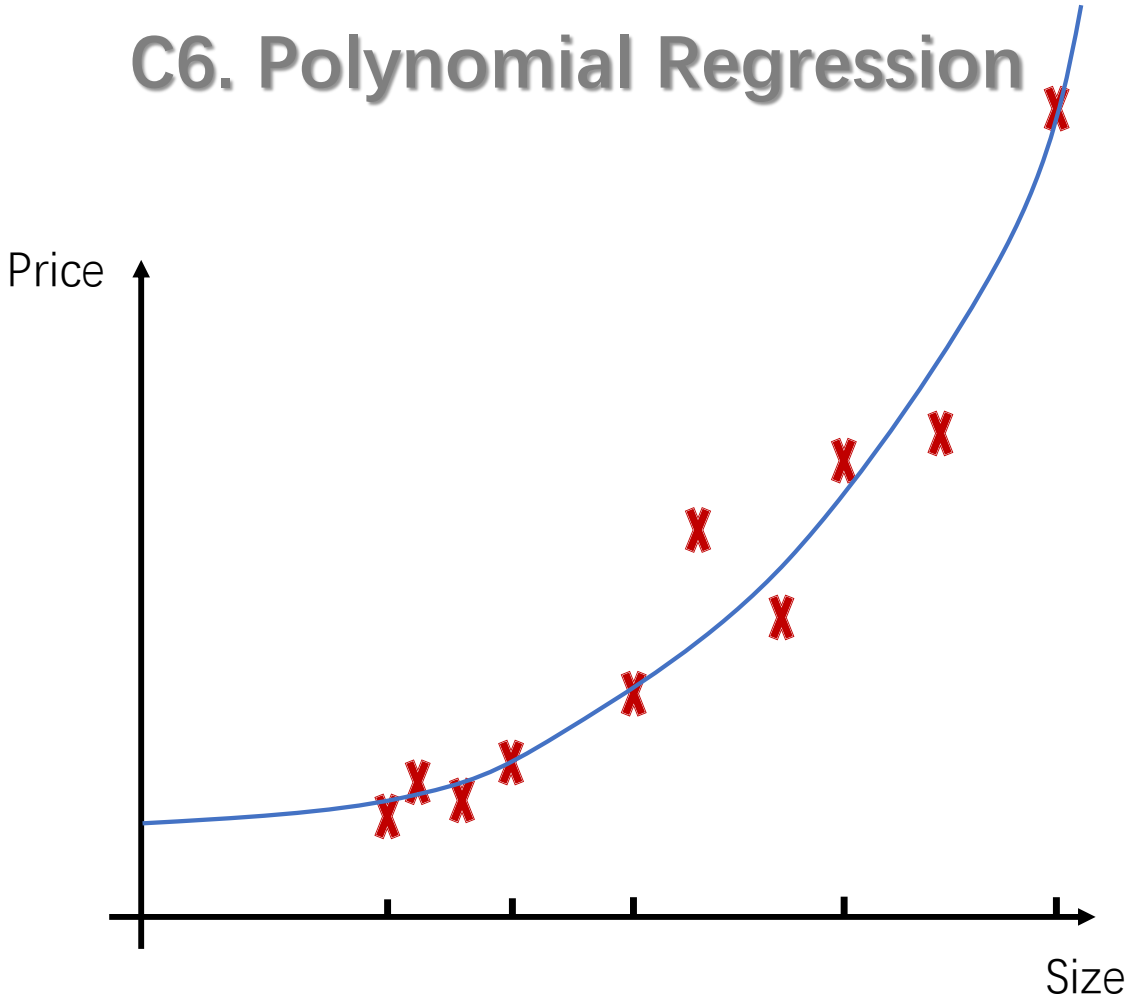
$$x_j' = \frac{x_j - \bar{x_j}}{\sigma_j} \quad s.t\ N\sim(0,1)$$



II. Supervised Learning

C. Linear Regression:

C6. Polynomial Regression



$$h_\theta(x) = \theta_0 + \theta_1 x + \theta_1 x^2$$

$$= \theta_0 + \theta_1(size) + \theta_1(size)^2$$

$$= \theta_0 + \theta_1 x_1 + \theta_1 x_2$$

II. Supervised Learning

C. Linear Regression:

C7. Normal Equation

$$h_\theta(x) = \theta_0 x_0 + \theta_1 x_1 + \cdots + \theta_n x_n$$

$$J(\theta_{0\ldots n}) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2$$

$$\begin{pmatrix}\theta_0\\ \theta_1\\ \ldots\\ \theta_n\end{pmatrix} \in \mathbb{R}^{n+1}$$

$$h_\theta(x) = \theta^T x$$

$$J(\theta) = \frac{1}{2m}(X\theta - y)^T(X\theta - y)$$

$$J(\theta) = ((X\theta)^T - y^T)(X\theta - y)$$

$$J(\theta) = (X\theta)^T X\theta - (X\theta)^T y - y^T(X\theta) + y^T y$$

$$J(\theta) = \theta^T X^T X\theta - 2(X\theta)^T y + y^T y$$

$$\frac{\partial J}{\partial \theta} = 2X^T X\theta - 2X^T y = 0$$

$$X^T X\theta = X^T y$$

$$\theta = (X^T X)^{-1} X^T y$$

II. Supervised Learning

D. Logistic Regression:

II. Supervised Learning

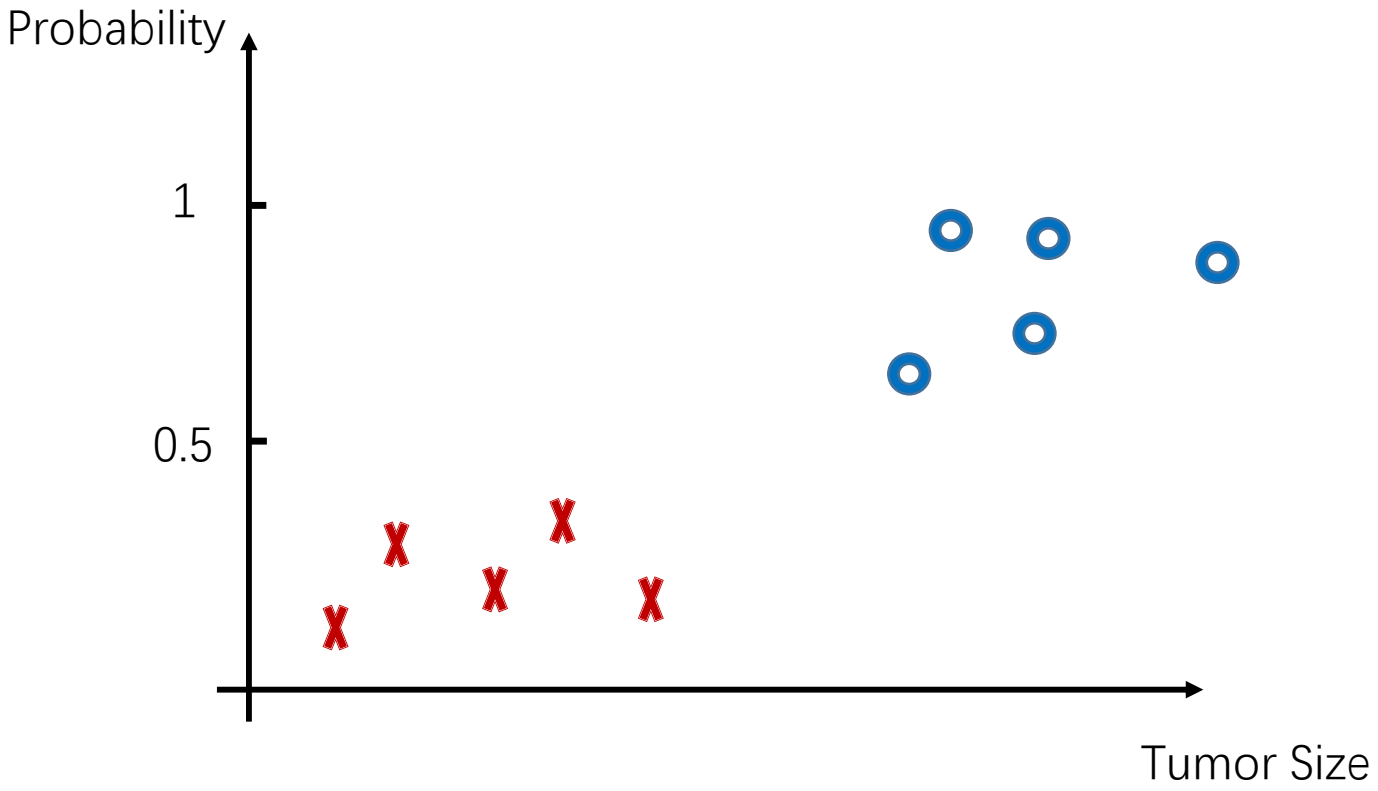
D. Logistic Regression:

Classification

II. Supervised Learning

D. Logistic Regression:

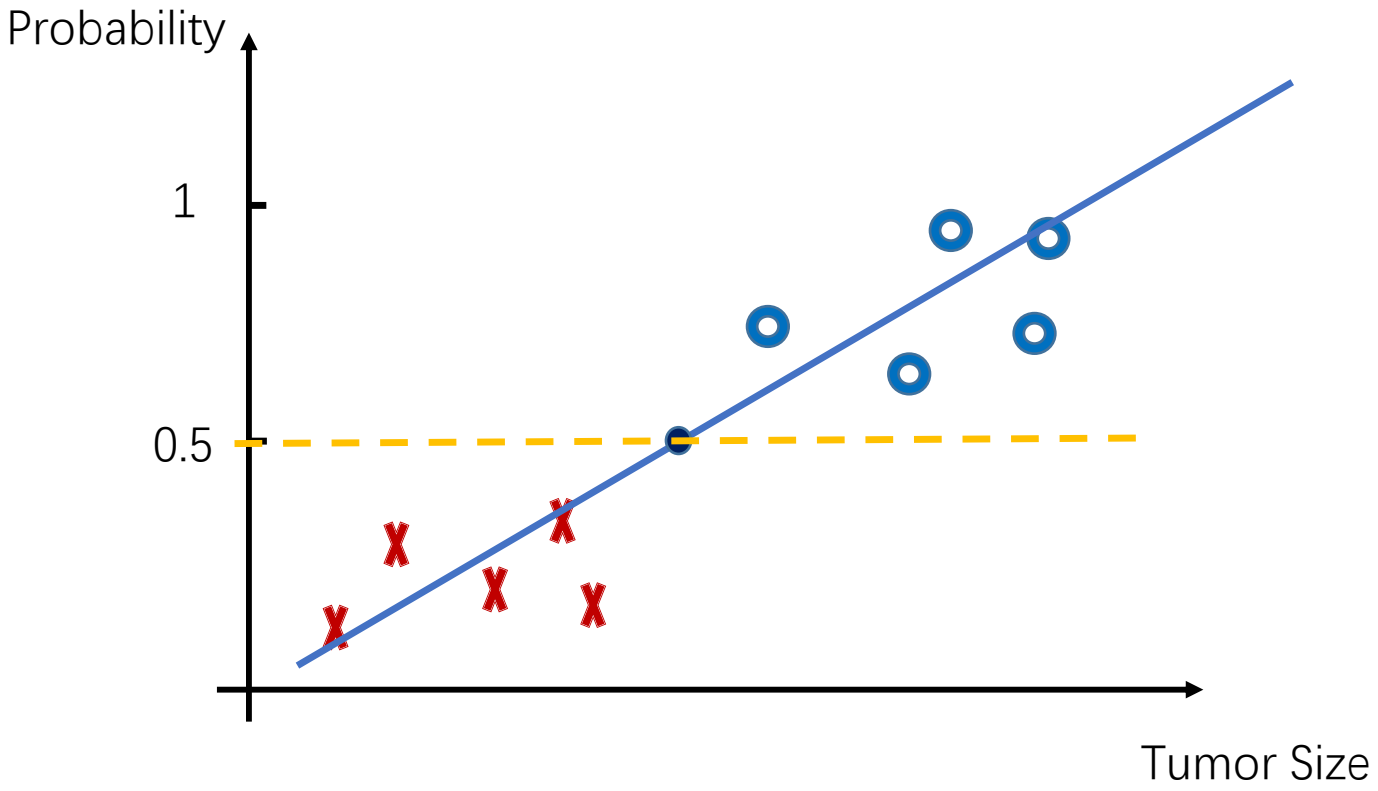
D1. 2 Classes



II. Supervised Learning

D. Logistic Regression:

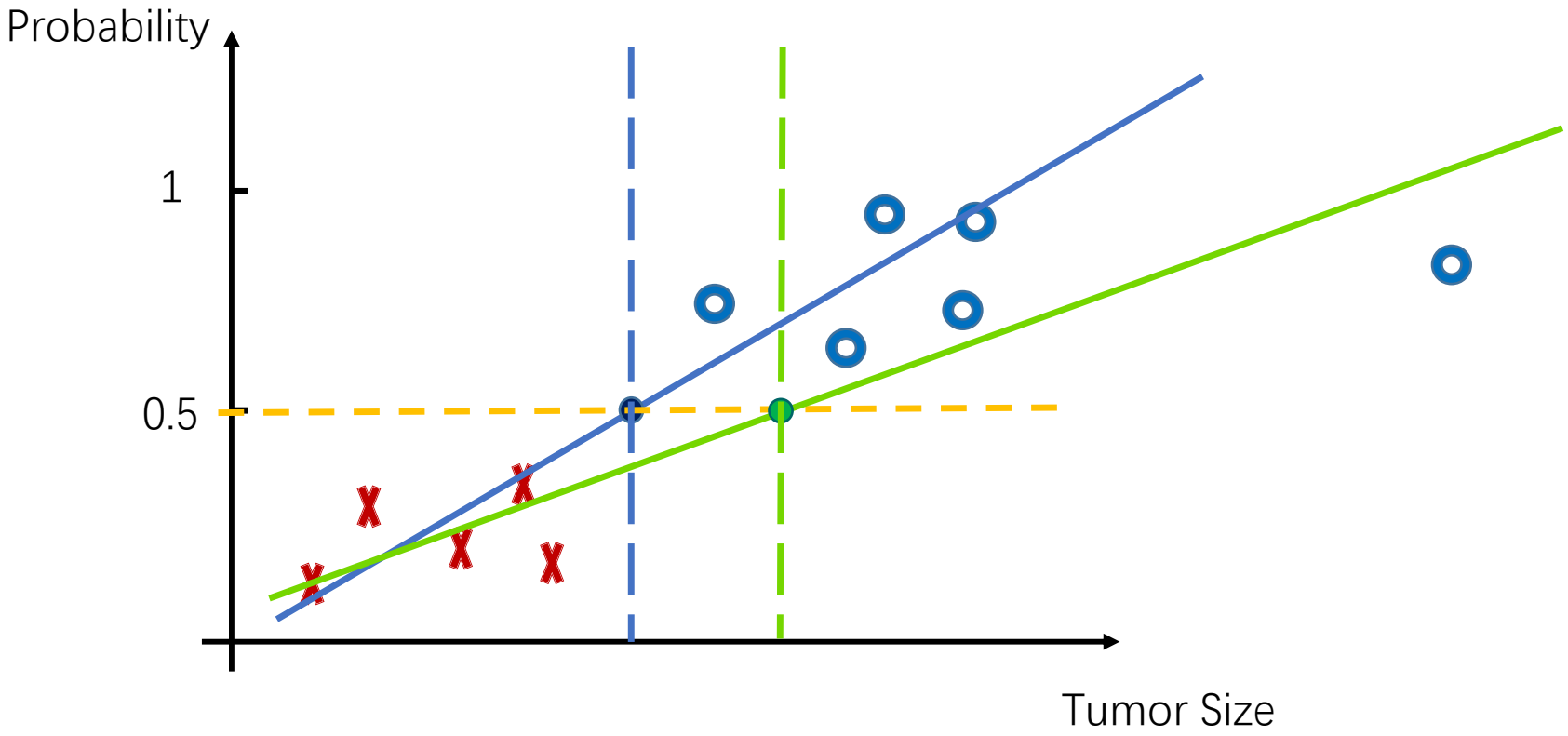
D1. 2 Classes



II. Supervised Learning

D. Logistic Regression:

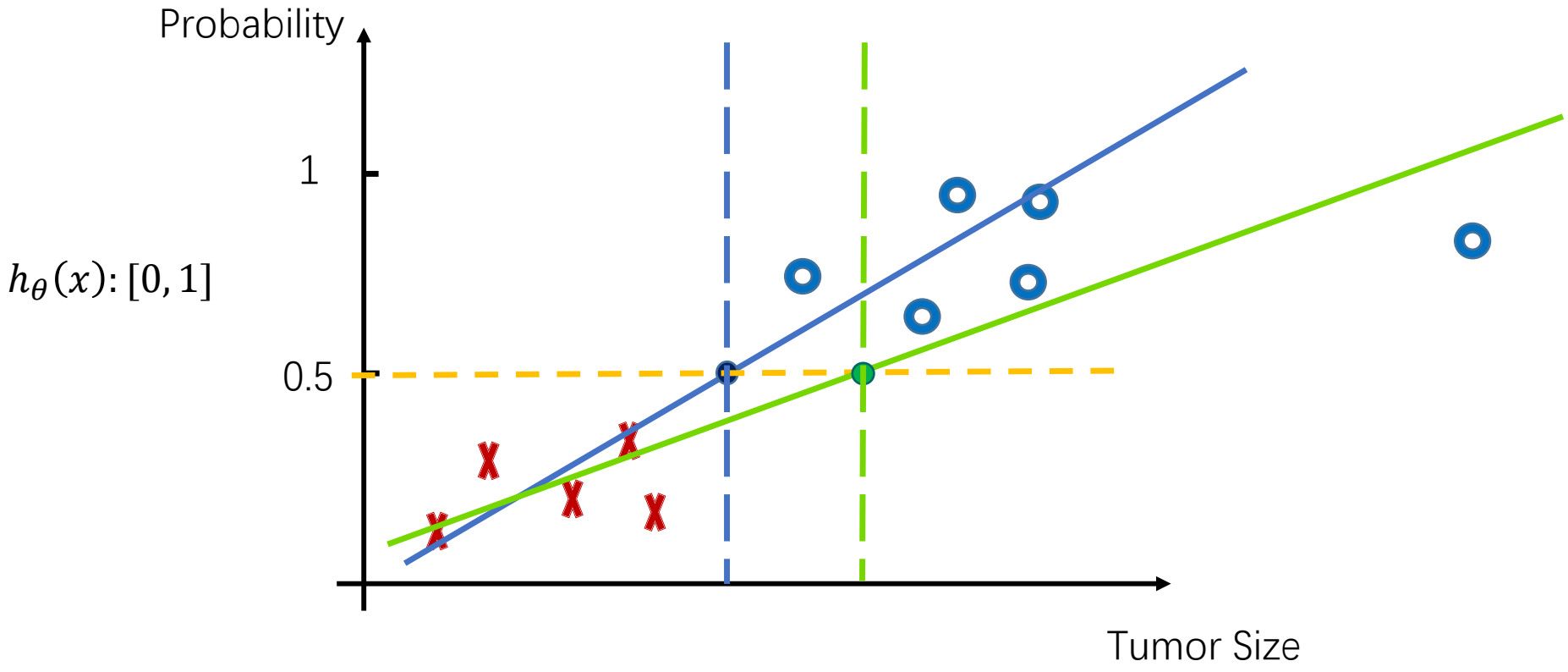
D1. 2 Classes



II. Supervised Learning

D. Logistic Regression:

D1. 2 Classes



II. Supervised Learning

D. Logistic Regression:

D1. 2 Classes

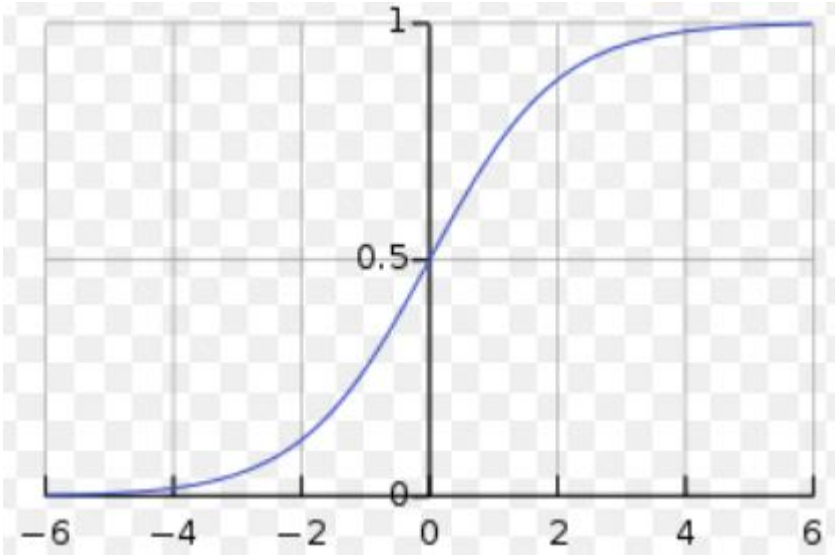
Hypothesis:

$$h_\theta(x) = g(\theta^T x)$$

$$= g(z)$$

$$= \frac{1}{1 + e^{-z}}$$

$$= \frac{1}{1 + e^{-\theta^T x}}$$



Sigmoid Function
Logistic Function

II. Supervised Learning

D. Logistic Regression:

D1. 2 Classes

Hypothesis:

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

Cost Function:

$$J(\theta) = \begin{cases} -\log(h_\theta(x)) & if\ y = 1 \\ -\log\left(1 - h_\theta(x)\right) & if\ y = 0 \end{cases}$$

For single sample

II. Supervised Learning

Explain: h(x)'s shape

D. Logistic Regression:

D1. 2 Classes

Hypothesis:

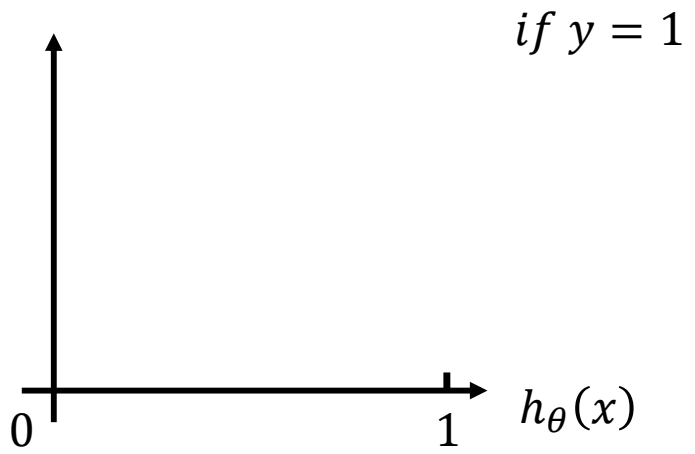
$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

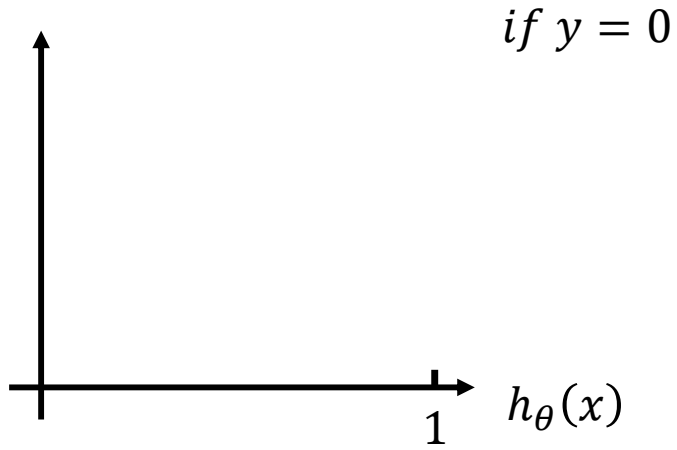
Cost Function:

$$J(\theta) = \begin{cases} -\log(h_\theta(x)) & if\ y = 1 \\ -\log\left(1 - h_\theta(x)\right) & if\ y = 0 \end{cases}$$

$$J(\theta) = (h_\theta(x) - y)^2$$ Linear Regression

For single sample





II. Supervised Learning

Explain: why can write together

D. Logistic Regression:

D1. 2 Classes

Hypothesis:

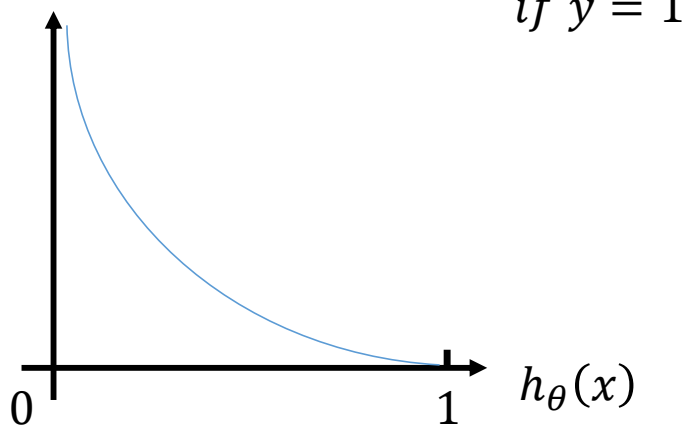
$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

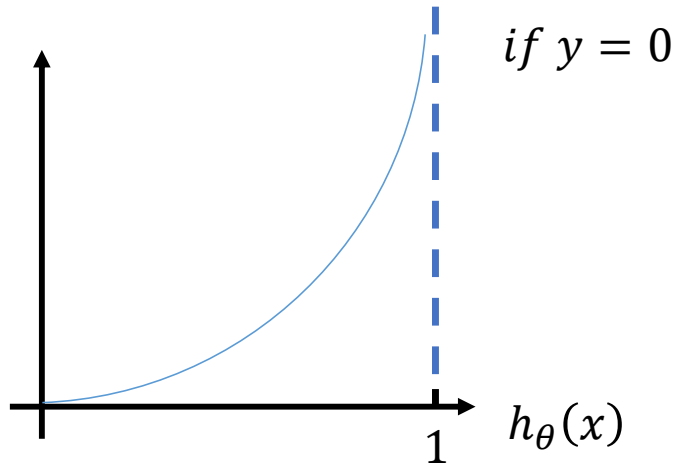
Cost Function:

$$J(\theta) = -ylog\big(h_\theta(x)\big) - (1-y)log\big(1 - h_\theta(x)\big)$$

$$J(\theta) = (h_\theta(x) - y)^2$$ Linear Regression

For single sample





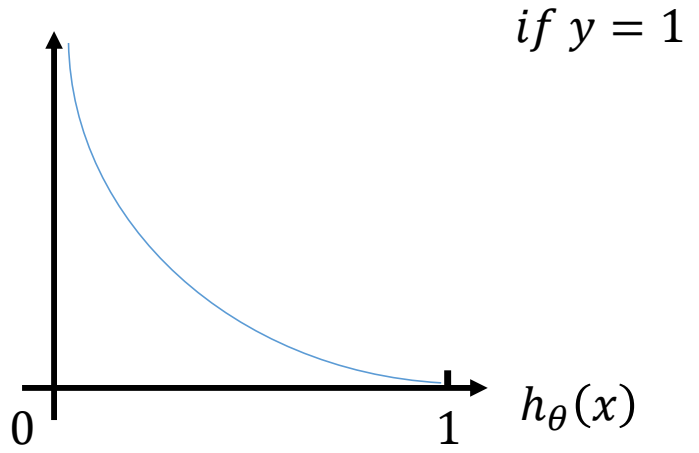
II. Supervised Learning

D. Logistic Regression:

D1. 2 Classes

Hypothesis:

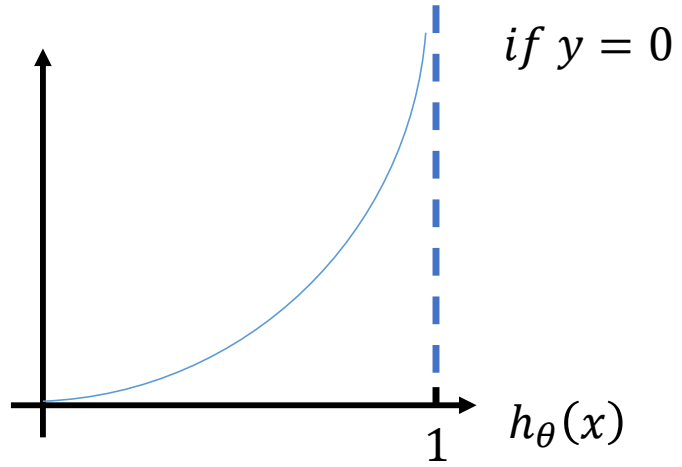
$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$



Cost Function:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^i log\left(h_\theta(x^i)\right) + (1 - y^i) log\left(1 - h_\theta(x^i)\right)]$$

$$J(\theta) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2$$ Linear Regression



For samples

Explain: derivative

II. Supervised Learning

D. Logistic Regression:

D1. 2 Classes

Hypothesis:

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

Gradient Descent:

$$\frac{\partial}{\partial \theta_j} J(\theta_j) = \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i) \cdot x_j$$

Cost Function:

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^{m} [y^i log\left(h_\theta(x^i)\right) + (1 - y^i) log\left(1 - h_\theta(x^i)\right)]$$

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i)^2$$ Linear Regression

For samples

II. Supervised Learning

Explain: derivative

D. Logistic Regression:

D1. 2 Classes

Hypothesis:

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

Cost Function:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^i log\left(h_\theta(x^i)\right) + (1 - y^i) log\left(1 - h_\theta(x^i)\right)]$$

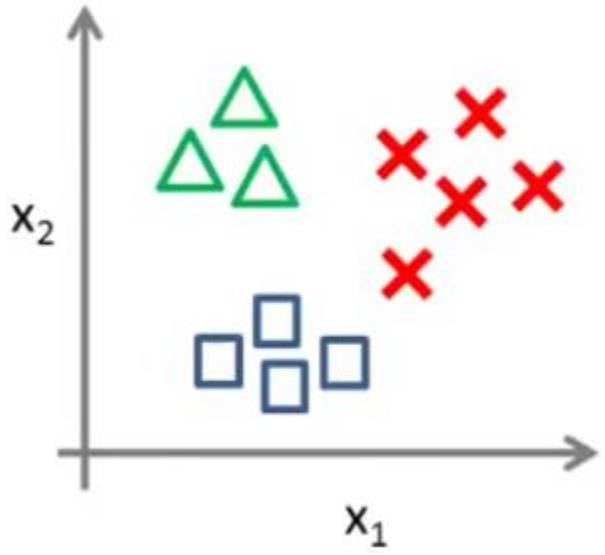
Gradient Descent:

$$\frac{\partial}{\partial \theta_j} J(\theta_j) = \frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i) \cdot x_j$$

II. Supervised Learning

D. Logistic Regression:

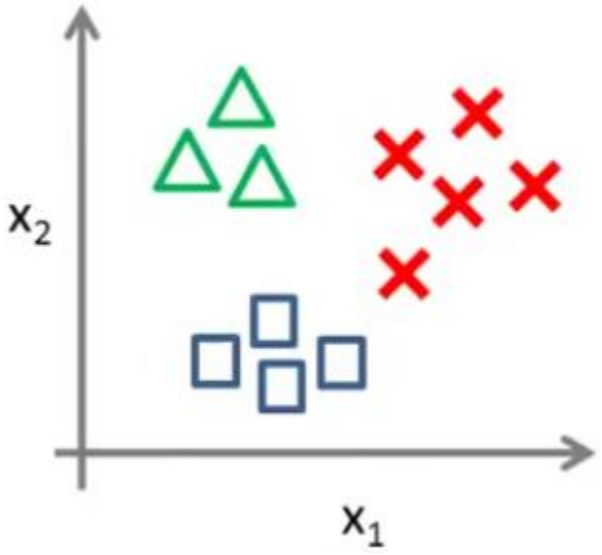
D2. Multi-Classes

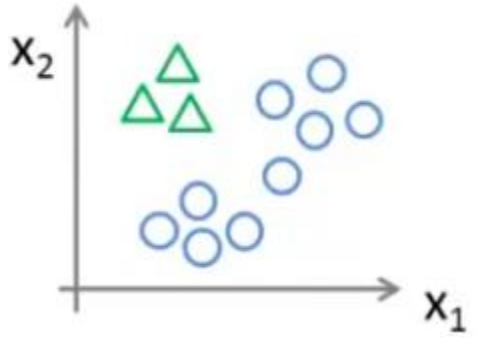


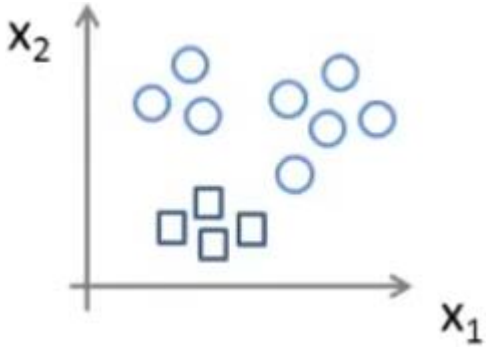
II. Supervised Learning

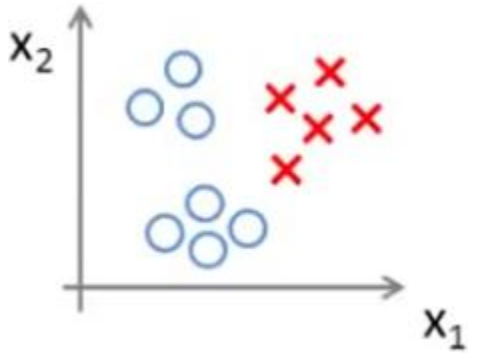
D. Logistic Regression:

D2. Multi-Classes





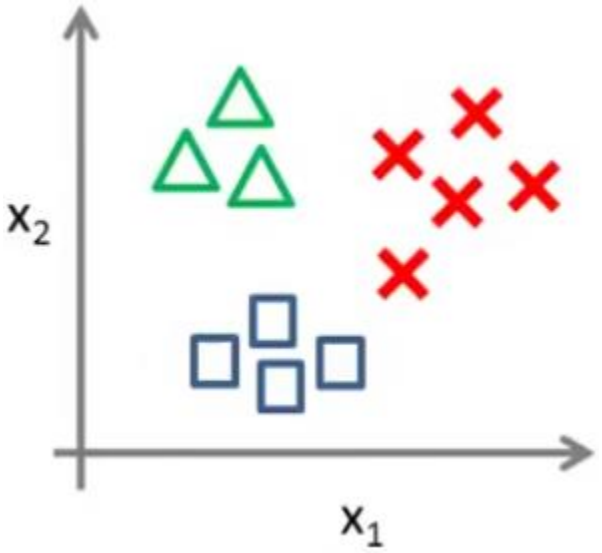




II. Supervised Learning

D. Logistic Regression:

D2. Multi-Classes



Train a logistic regression classifier $h_\theta^{(i)}(x)$ for each class i to predict the probability that $y = i$.

On a new input x, to make a prediction, pick the class i that maximizes

$$\max_i h_\theta^{(i)}(x)$$

II. Supervised Learning

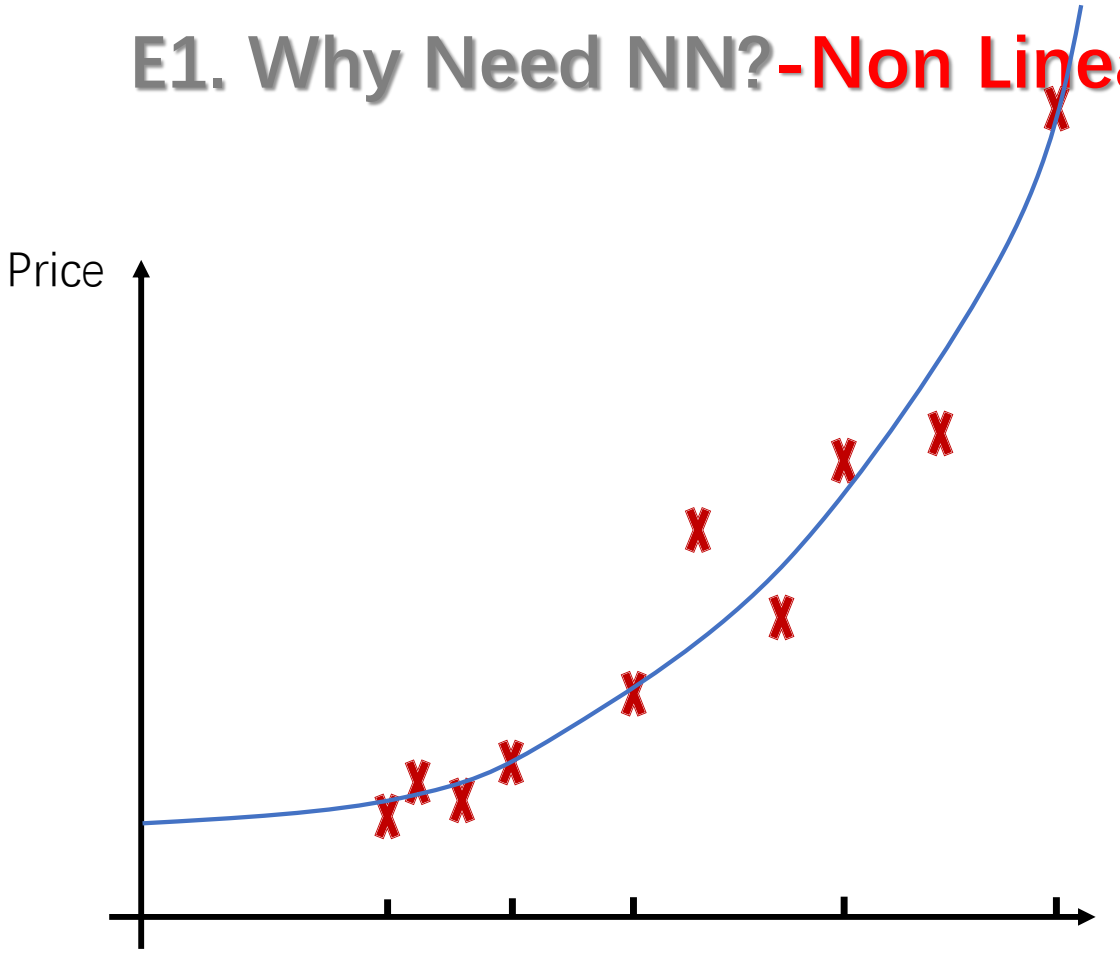
Linear Regression:

Implementation from scratch

II. Supervised Learning

E. Neural Network:

E1. Why Need NN?-Non Linear



$$h_\theta(x) = \theta_0 + \theta_1 x + \theta_1 x^2$$

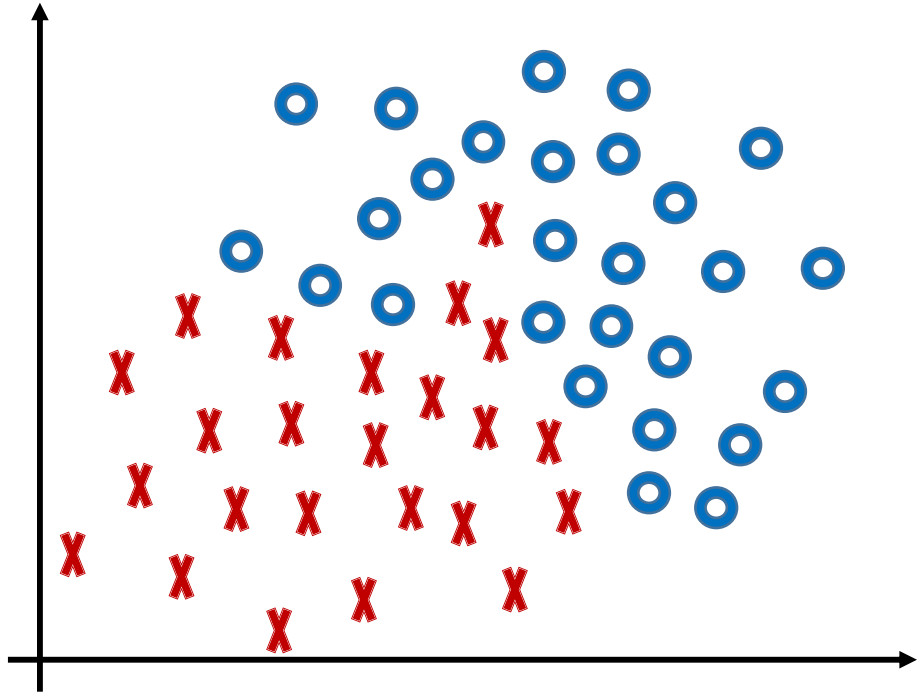
$$= \theta_0 + \theta_1(size) + \theta_1(size)^2$$

$$= \theta_0 + \theta_1 x_1 + \theta_1 x_2$$

II. Supervised Learning

E. Neural Network:

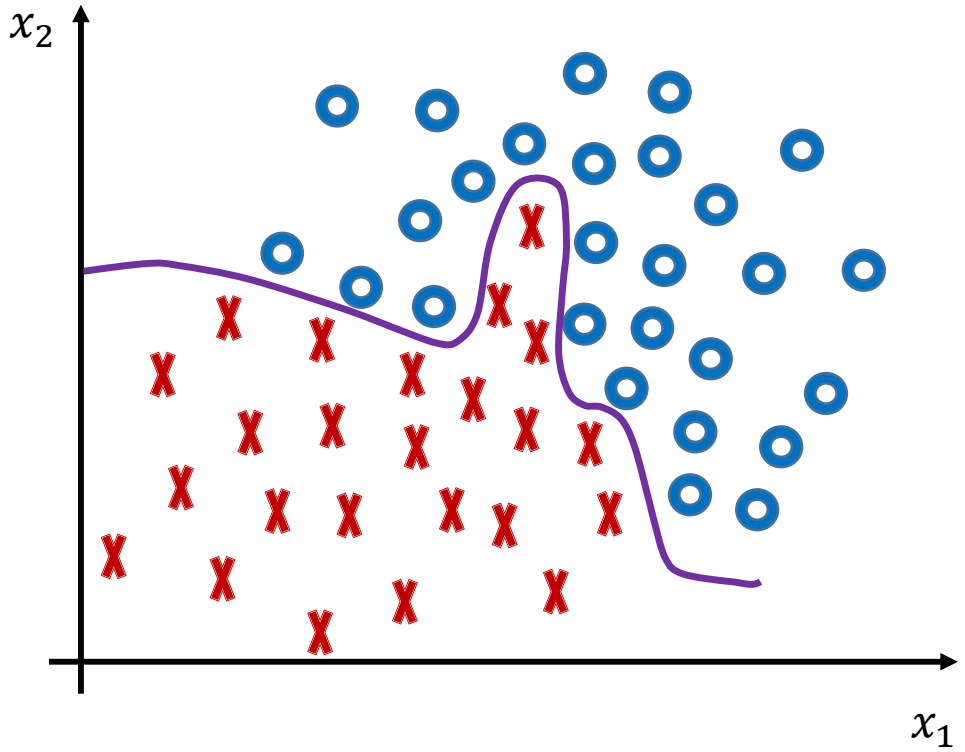
E1. Why Need NN?-Non Linear



II. Supervised Learning

E. Neural Network:

E1. Why Need NN?-Non Linear

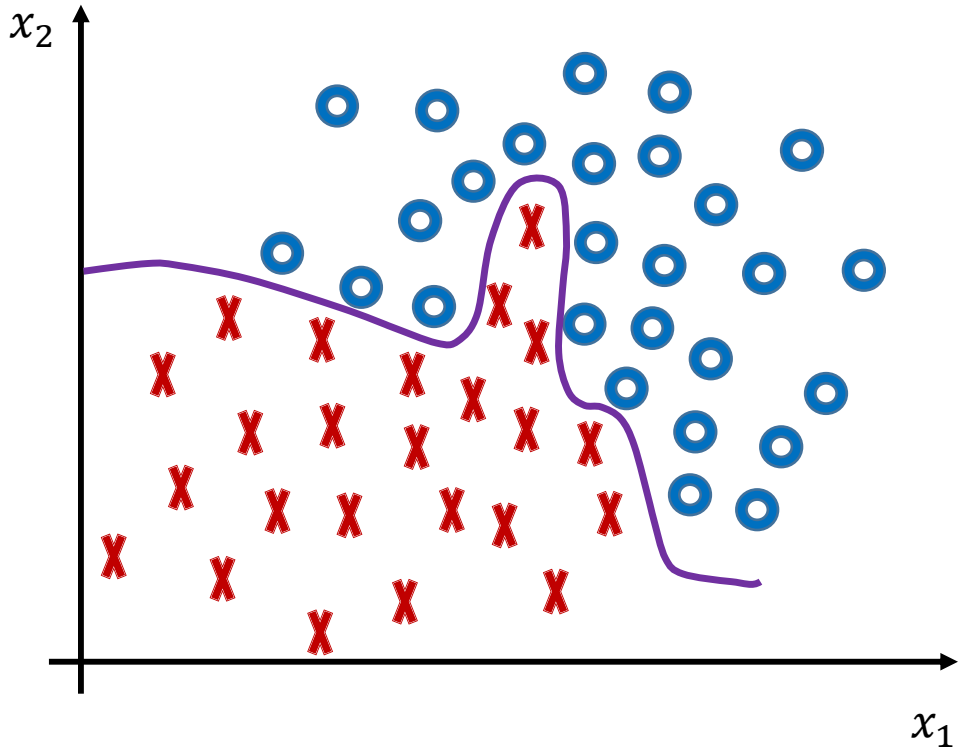


$$h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_1 x_2 + \theta_3 x_1 x_2 + \theta_4 x_1^2 x_2 + \theta_5 x_1^3 x_2 + \theta_6 x_1 x_2^2 + \cdots)$$

II. Supervised Learning

E. Neural Network:

E1. Why Need NN?-Non Linear

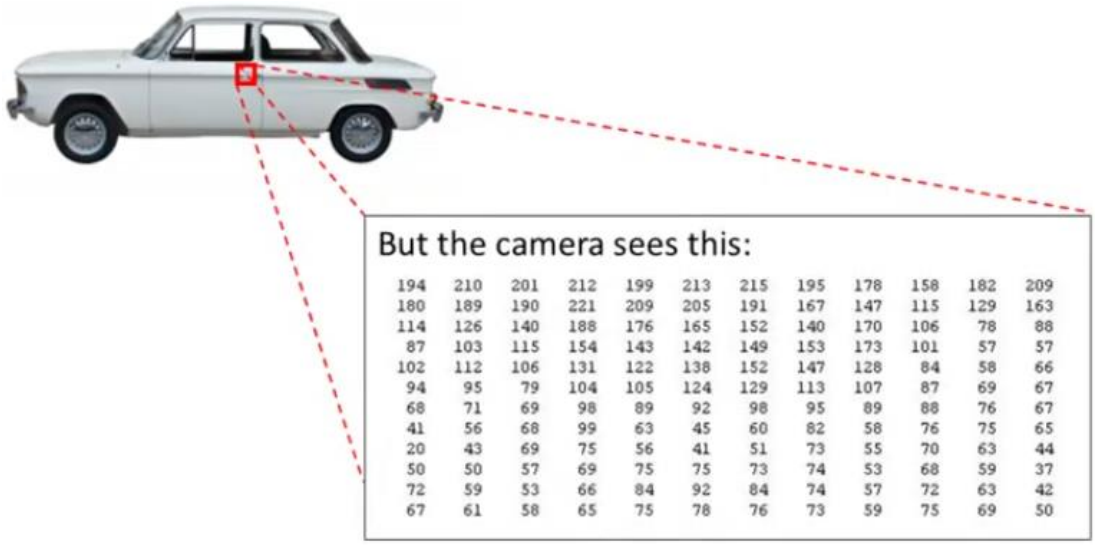


$$h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_1 x_2 + \theta_3 x_1 x_2 + \theta_4 x_1^2 x_2 + \theta_5 x_1^3 x_2 + \theta_6 x_1 x_2^2 + \cdots)$$

II. Supervised Learning

E. Neural Network:

E1. Why Need NN?-Non Linear



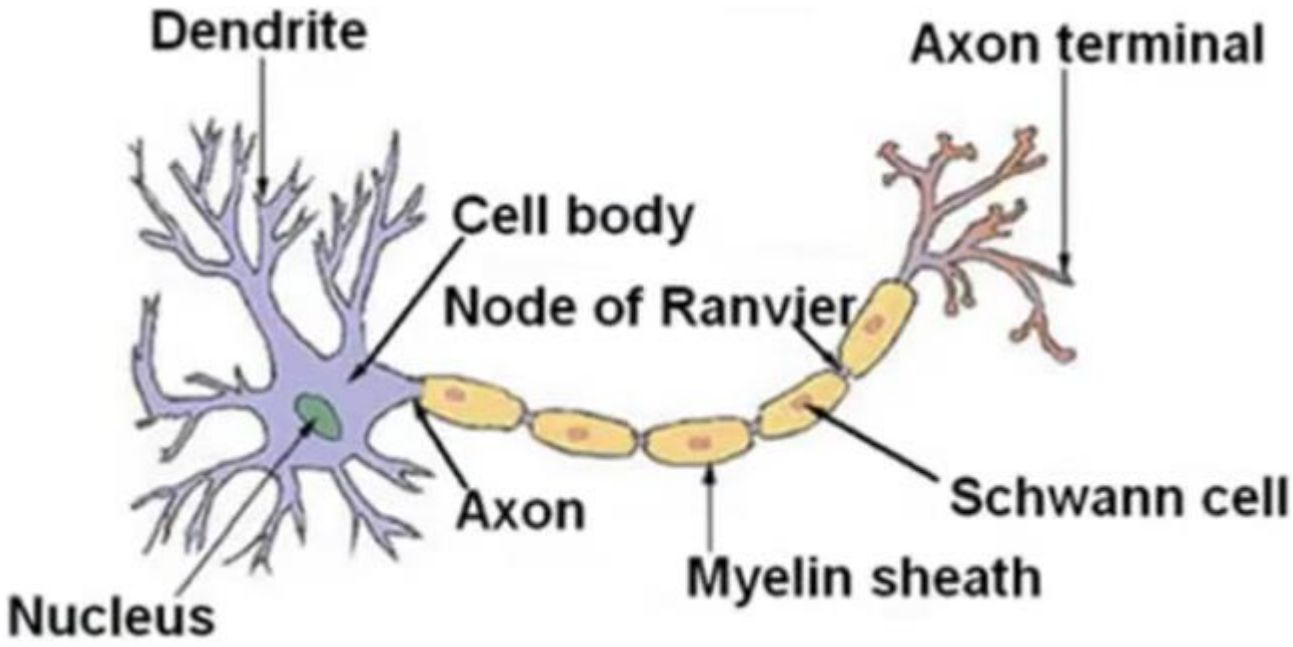
Not possible by just combining features

Need advanced techs

II. Supervised Learning

E. Neural Network:

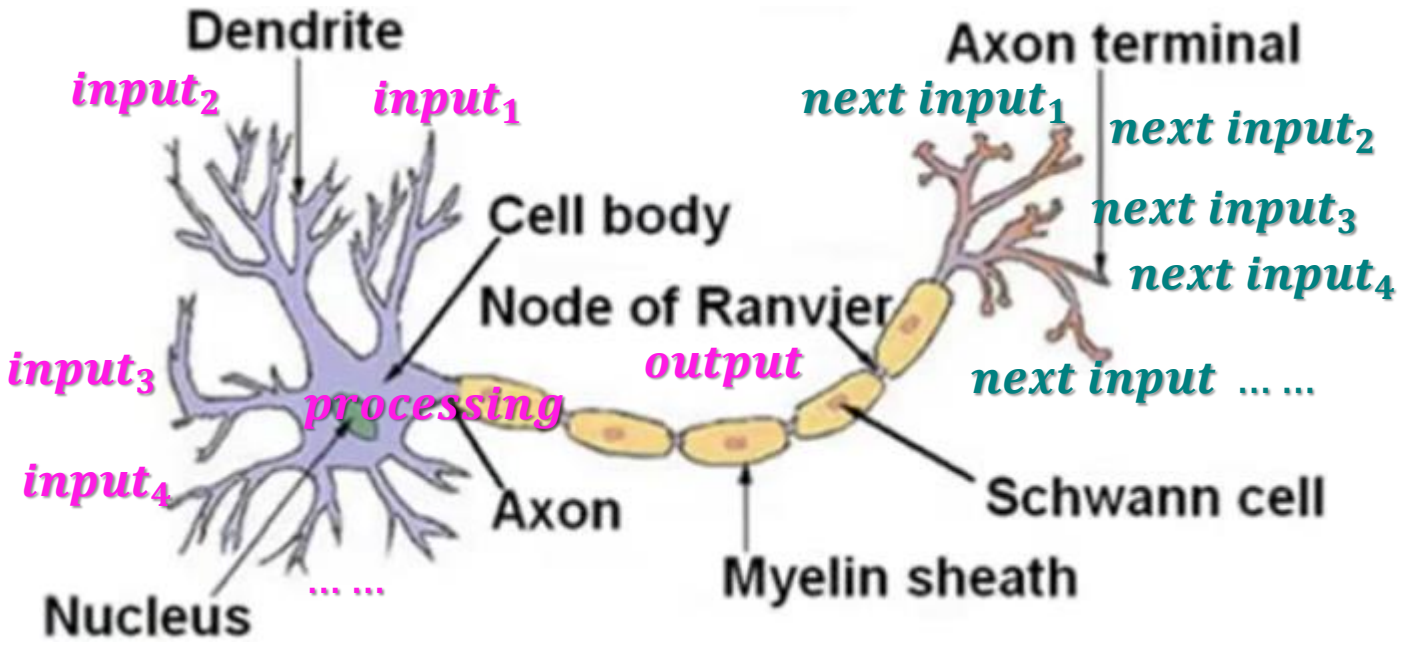
E1. Why Need NN?-Mimic Brain



II. Supervised Learning

E. Neural Network:

E1. Why Need NN?-Mimic Brain



II. Supervised Learning

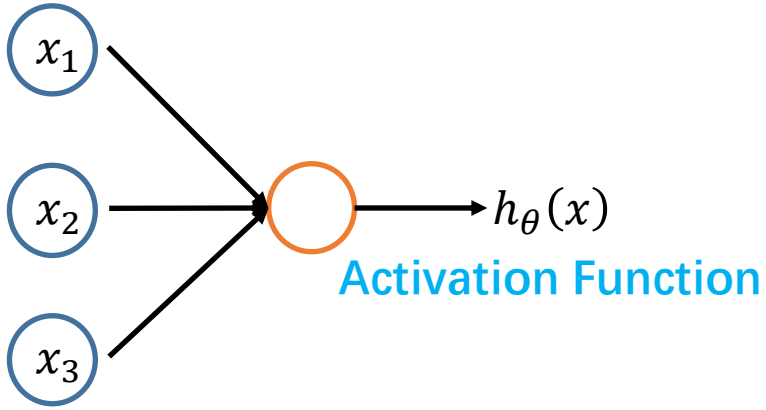
Explain: bias

E. Neural Network:

E2. Logistic Unit

$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \qquad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$

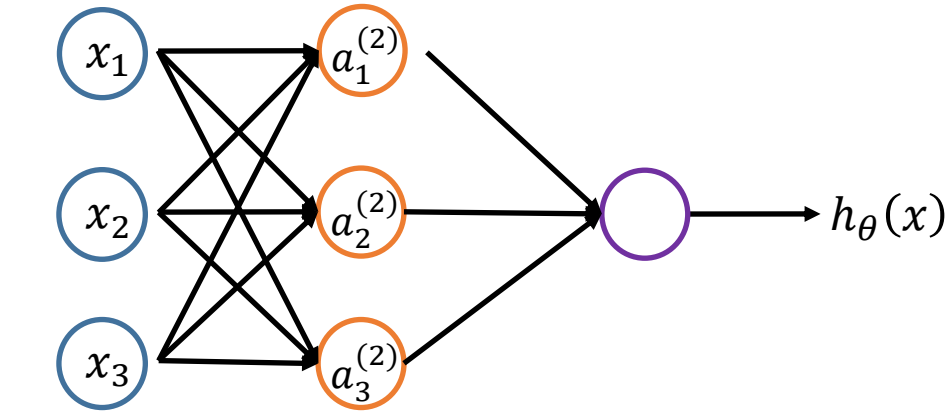
feature weights



II. Supervised Learning

E. Neural Network:

E3. Neural Network



II. Supervised Learning

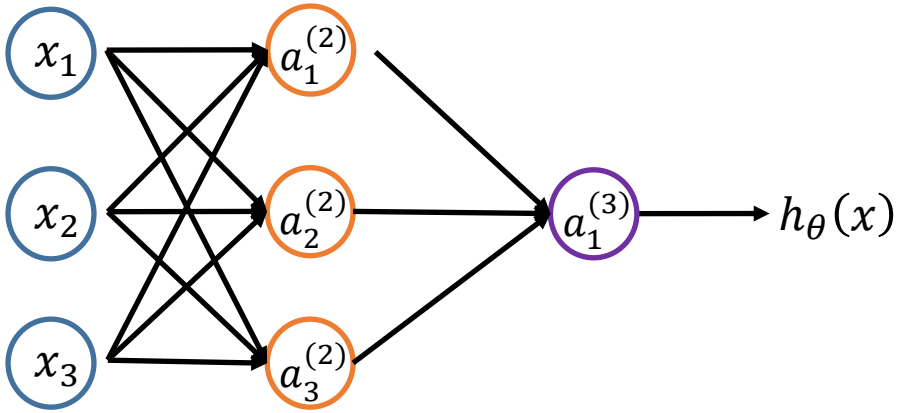
Explain: formulas

E. Neural Network:

E3. Neural Network

$a_i^{(j)} = "activation"\ of\ unit\ \boldsymbol{i}\ in\ layer\ \boldsymbol{j}$

$\theta^{(j)} = \boldsymbol{matrix}\ of\ weights\ controlling\ function\ mapping\ from\ layer\ j\ to\ layer\ j+1$



Layer 2:

$$a_1^{(2)} = g(\theta_{10}^{(1)}x_0 + \theta_{11}^{(1)}x_1 + \theta_{12}^{(1)}x_2 + \theta_{13}^{(1)}x_3)$$

$$a_2^{(2)} = g(\theta_{20}^{(1)}x_0 + \theta_{21}^{(1)}x_1 + \theta_{22}^{(1)}x_2 + \theta_{23}^{(1)}x_3)$$

$$a_3^{(2)} = g(\theta_{30}^{(1)}x_0 + \theta_{31}^{(1)}x_1 + \theta_{32}^{(1)}x_2 + \theta_{33}^{(1)}x_3)$$

Layer 3:

$$h_\theta(x) = a_1^{(3)} = g(\theta_{10}^{(2)}a_0^{(2)} + \theta_{11}^{(2)}a_1^{(2)} + \theta_{12}^{(2)}a_2^{(2)} + \theta_{13}^{(2)}a_3^{(2)})$$

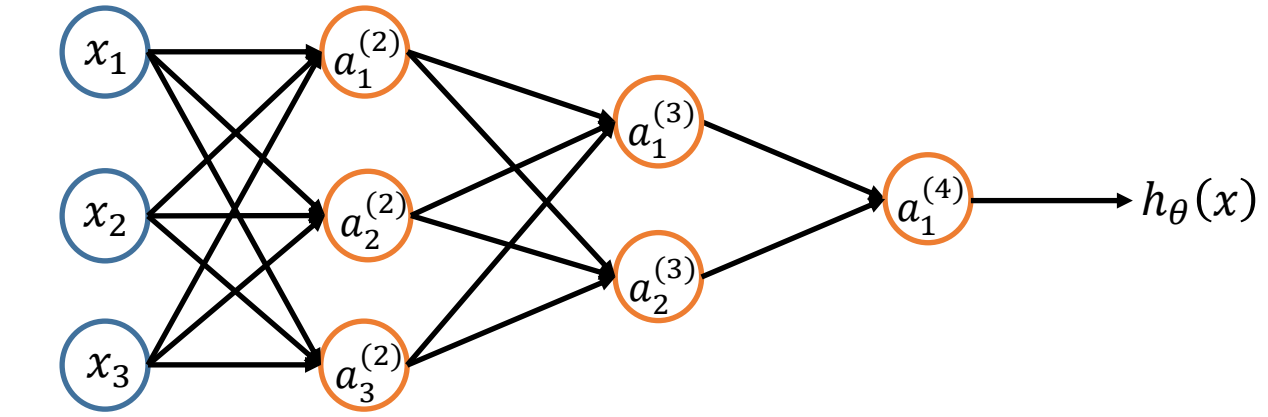
II. Supervised Learning

E. Neural Network:

E3. Neural Network

$a_i^{(j)} = \text{"activation" of unit } \boldsymbol{i} \text{ in layer } \boldsymbol{j}$

$\theta^{(j)} = \boldsymbol{matrix}\ of\ weights\ controlling\ function\ mapping\ from\ layer\ j\ to\ layer\ j+1$



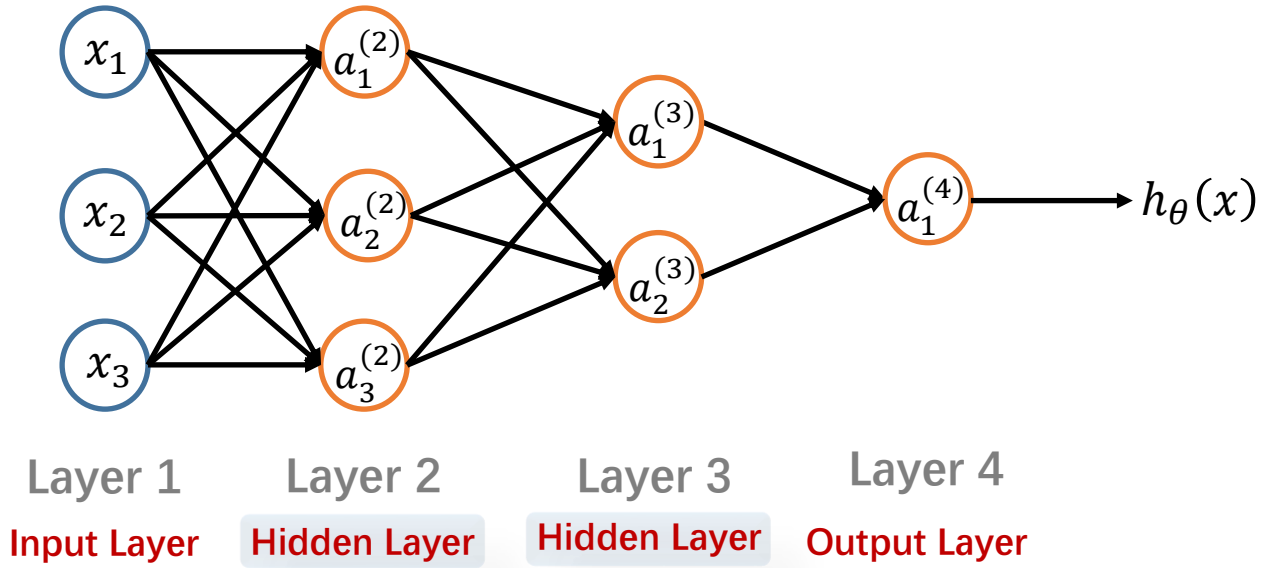
II. Supervised Learning

E. Neural Network:

E3. Neural Network

$a_i^{(j)} = \text{"activation" of unit } \boldsymbol{i} \text{ in layer } \boldsymbol{j}$

$\theta^{(j)} = \boldsymbol{matrix} \text{ of weights controlling function mapping from layer } j \text{ to layer } j+1$

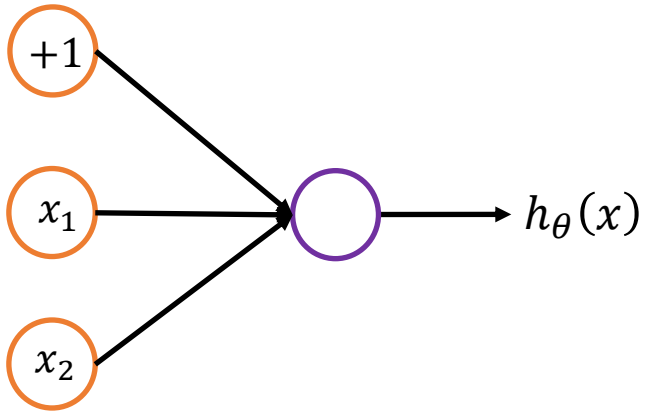


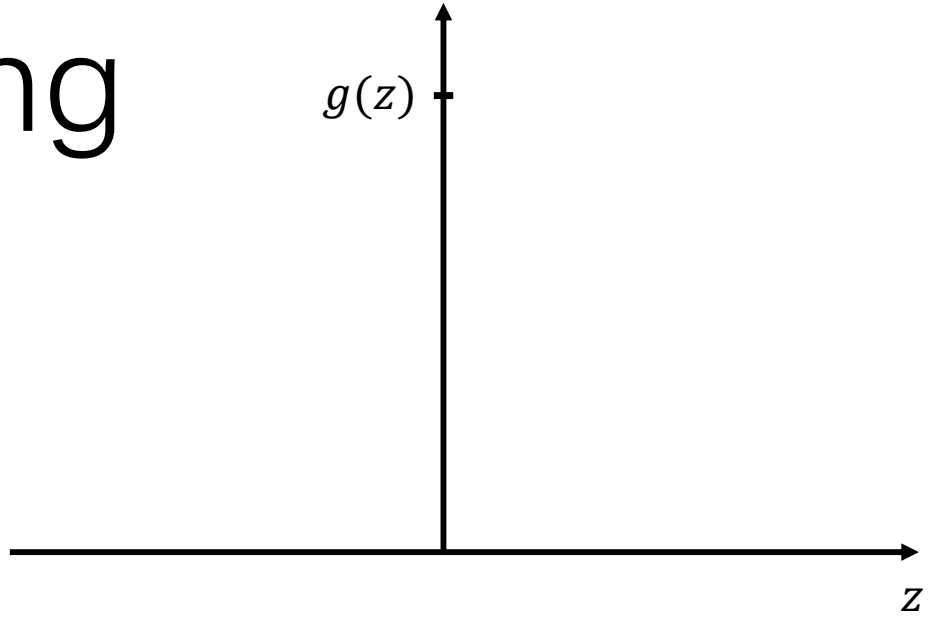
II. Supervised Learning

E. Neural Network:

E3. Neural Network-E.G: AND

$$y = x_1 \,\&\, x_2, \quad x_1, x_2 \in \{0, 1\}$$





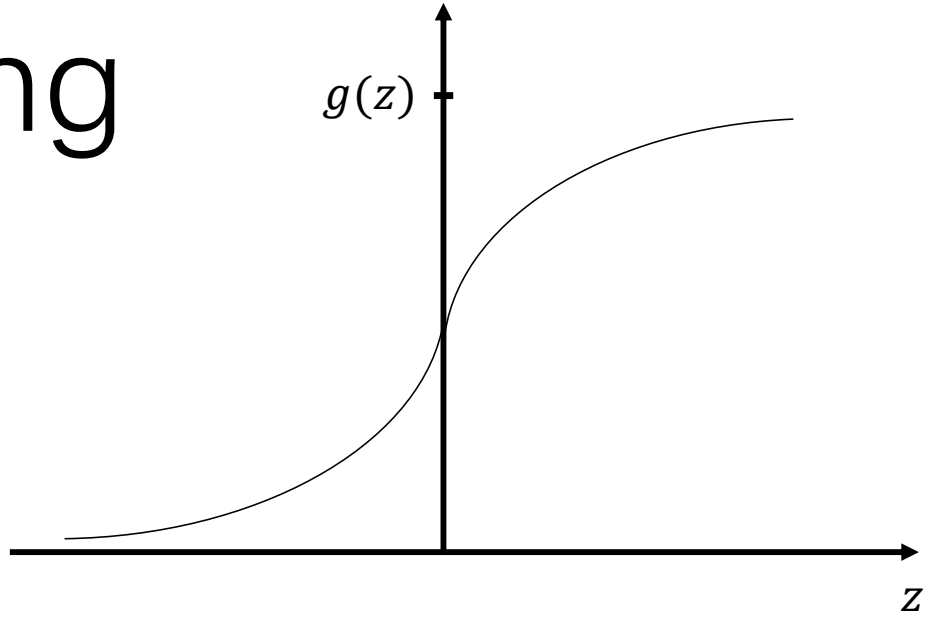
x_1	x_2	$h_\theta(x)$
0	0	
0	1	
1	0	
1	1	

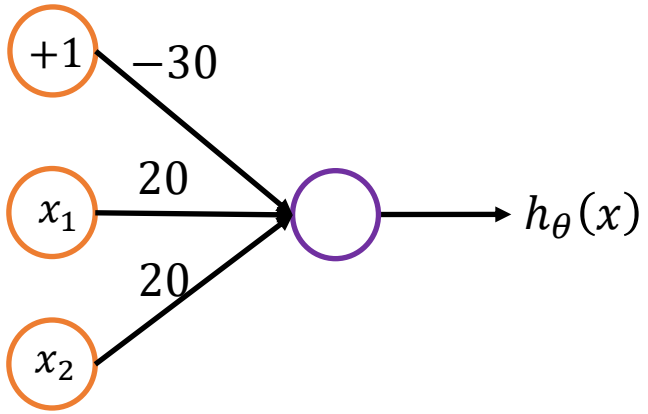
II. Supervised Learning

E. Neural Network:

E3. Neural Network-E.G: AND

$y = x_1 \,\&\, x_2, \quad x_1, x_2 \in \{0, 1\}$





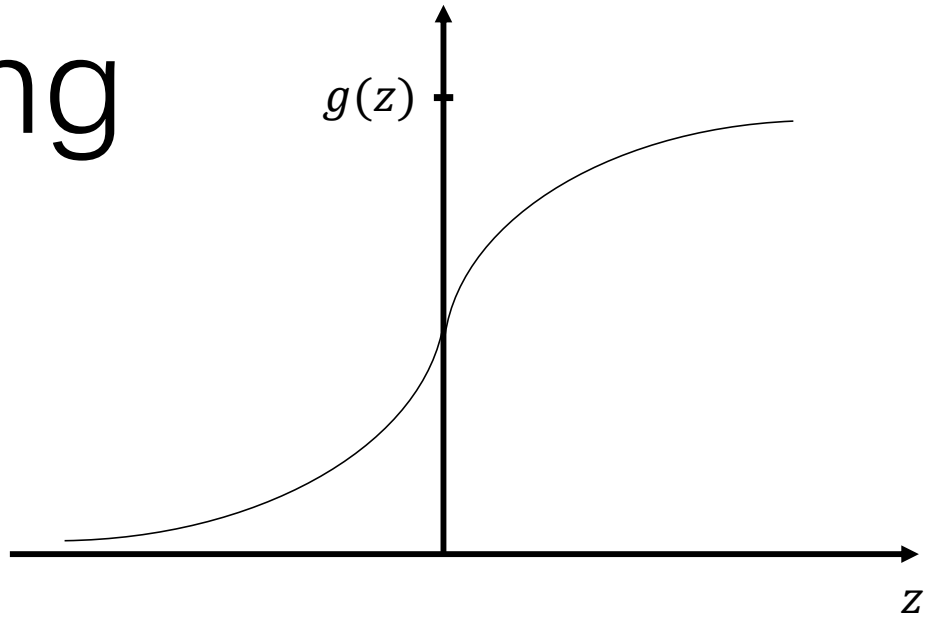
x_1	x_2	$h_\theta(x)$
0	0	
0	1	
1	0	
1	1	

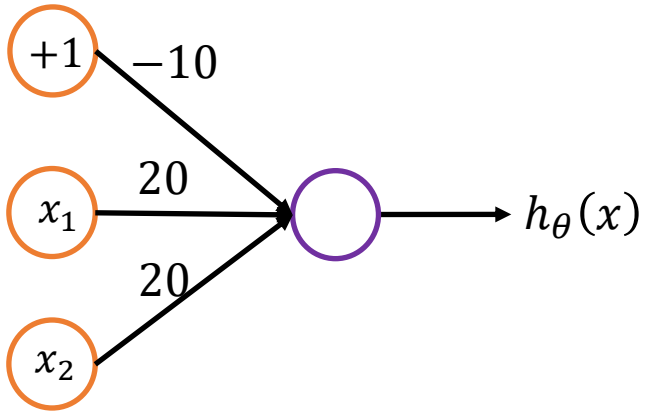
II. Supervised Learning

E. Neural Network:

E3. Neural Network-E.G: OR

$y = x_1 \mid x_2, \quad x_1, x_2 \in \{0, 1\}$





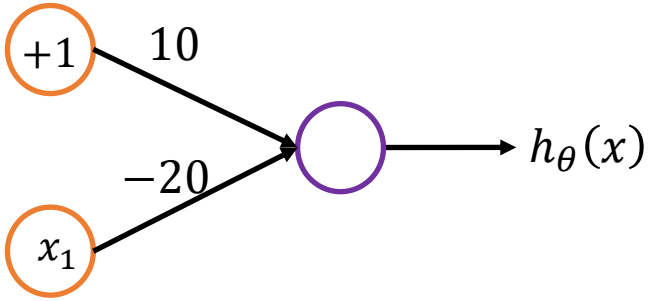
x_1	x_2	$h_\theta(x)$
0	0	
0	1	
1	0	
1	1	

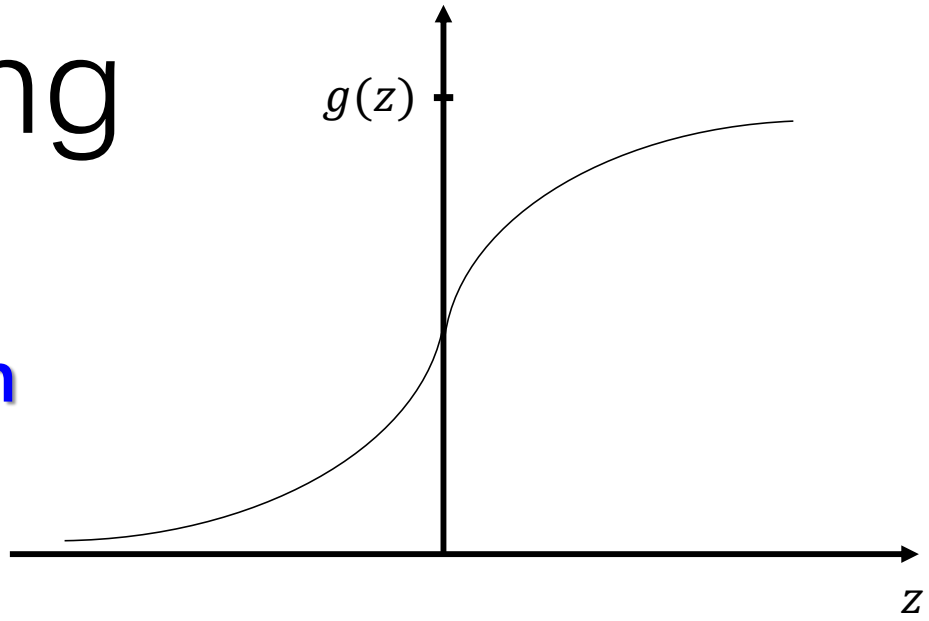
II. Supervised Learning

E. Neural Network:

E3. Neural Network-E.G: Negation

$y = !\,x_1, \quad x_1 \in \{0, 1\}$





x_1	$h_\theta(x)$
0	
1	

Explain: xnor

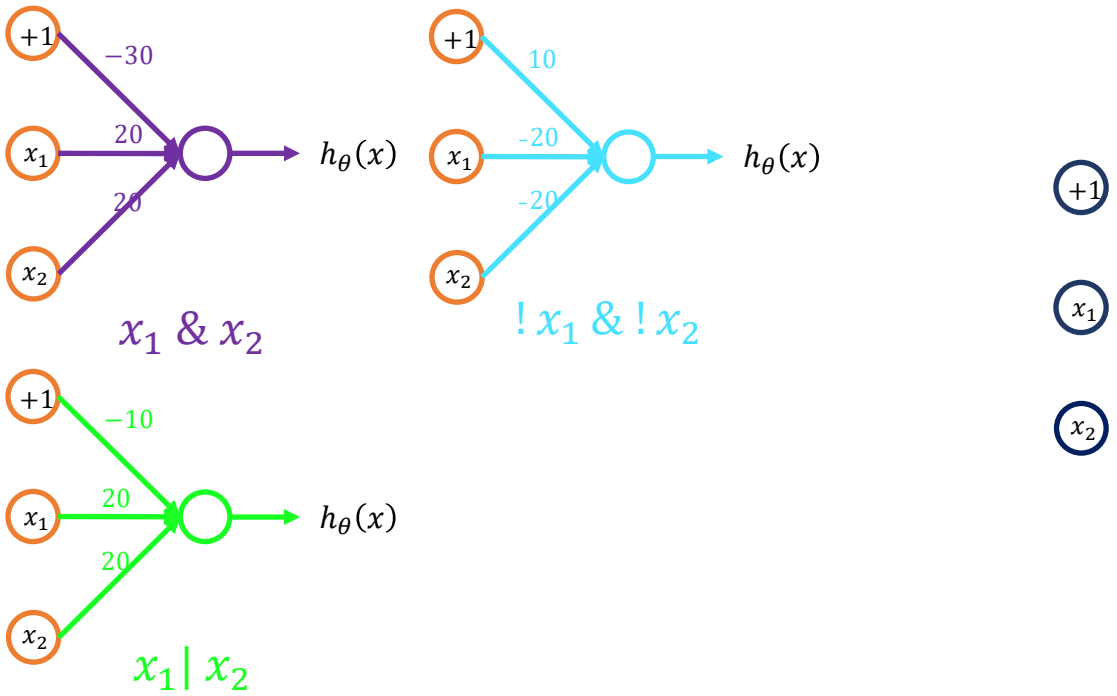
II. Supervised Learning

E. Neural Network:

E3. Neural Network-E.G: Combination

$y = x_1 \ \mathbf{XNOR}\ x_2, \quad x_1, x_2 \in \{0, 1\}$

x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\theta(x)$
0	0			
0	1			
1	0			
1	1			



II. Supervised Learning

E. Neural Network:

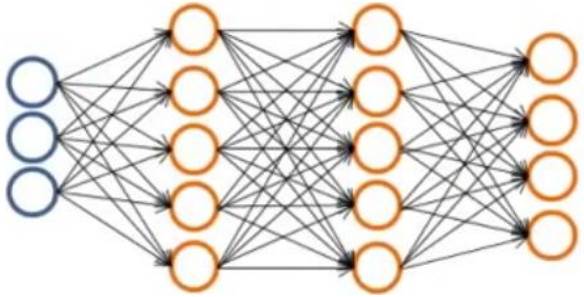
E3. Neural Network-E.G: Classification

Pedestrian

Car

Motorcycle

Truck



$h_\Theta(x) \in \mathbb{R}^4$

Want $h_\Theta(x) \approx \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, $h_\Theta(x) \approx \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$, $h_\Theta(x) \approx \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$, etc.

when pedestrian when car when motorcycle

II. Supervised Learning

E. Neural Network:

E4. Gradient Descent

Cost Function:

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m,}\sum_{k=1}^{K} y_k^i log(h_\theta(x^i))_k + \left(1 - y_k^i\right) log(1 - \left(h_\theta(x^i)\right)_k)\right]$$

i: $sample\ ID$

m: # $of\ samples$

k: $output\ ID$

K: # $of\ outputs$

II. Supervised Learning

F. Back Propagation:

Explain: scratch
Intuitive Chain rule

II. Supervised Learning

F. Back Propagation:

Chain Rule

Explain: Theoretical Math Chain rule

II. Supervised Learning

F. Back Propagation:

F1. Chain Rule

Explain: real e.g1
Math Chain rule

II. Supervised Learning

F. Back Propagation:

F1. Chain Rule-Real Example

Explain: real e.g2
Math Chain rule

II. Supervised Learning

F. Back Propagation:

F1. Chain Rule-Real Example

Explain: real e.g3
Math Chain rule

II. Supervised Learning

F. Back Propagation:

F1. Chain Rule-Real Example

Explain:
Chain rule problems

II. Supervised Learning

F. Back Propagation:

F1. Chain Rule-Problems

II. Supervised Learning

F. Back Propagation:

F2. Implementation: NN

II. Supervised Learning

G. Regularization:

G1. What Is Regularization

Linear Regression: $J(\theta) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2$

Logistic Regression: $J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^i log\left(h_\theta(x^i)\right) + (1 - y^i) log\left(1 - h_\theta(x^i)\right)]$

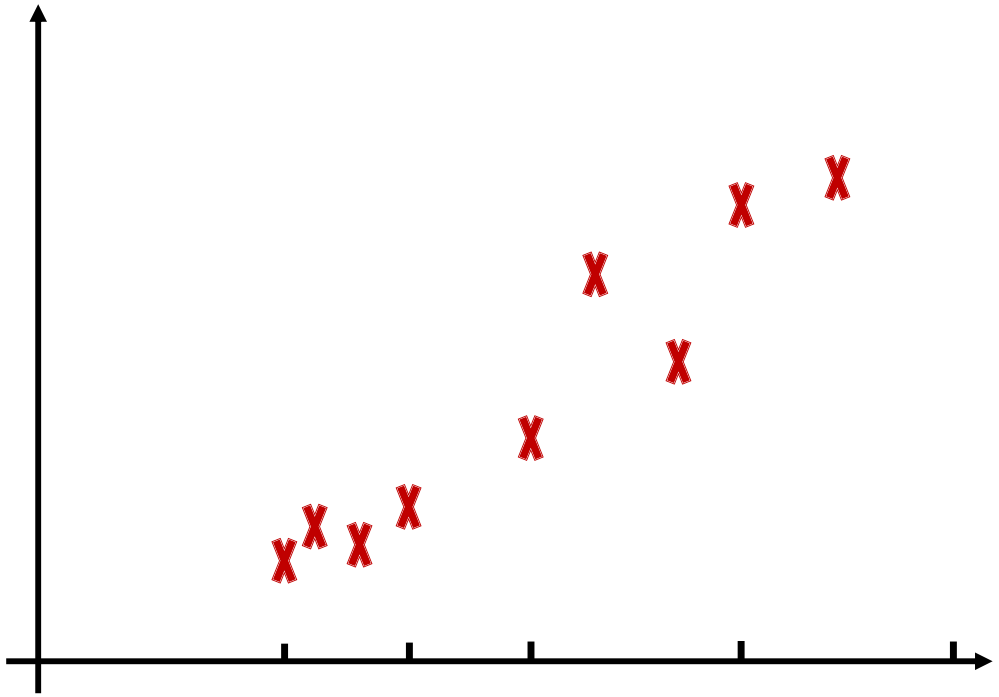
Neural Network: $J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m,}\sum_{k=1}^{K} y_k^i log(h_\theta(x^i))_k + \left(1 - y_k^i\right) log(1 - \left(h_\theta(x^i)\right)_k)\right]$

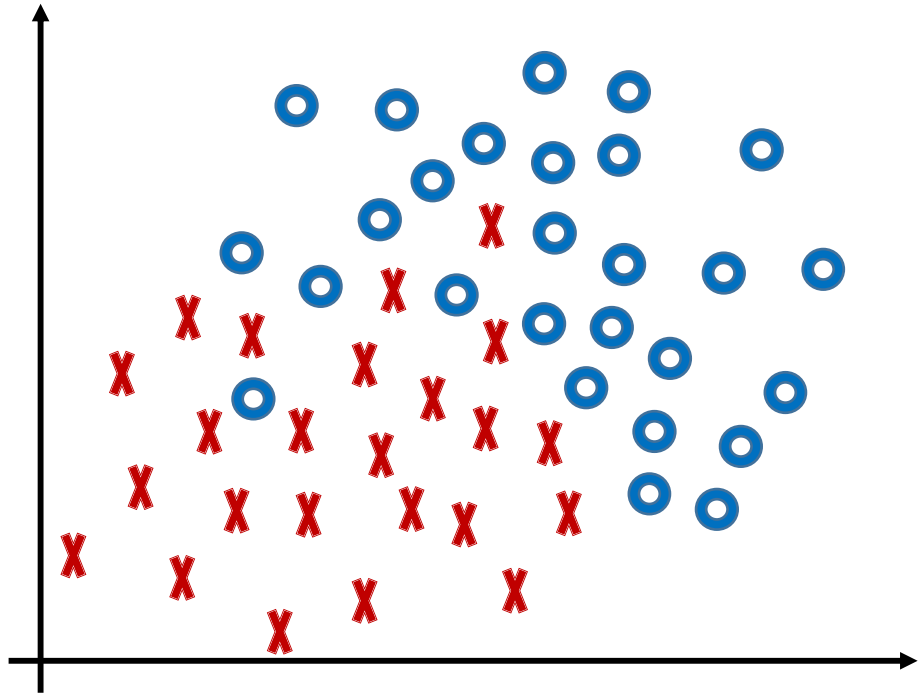
Explain: Fit to what
Extension
Overfit & prevension

II. Supervised Learning

G. Regularization:

G1. What Is Regularization





II. Supervised Learning

G. Regularization:

G1. What Is Regularization

Linear Regression:

$$J(\theta) = \frac{1}{2m}\left[\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2 + \lambda\sum_{j=1}^{n}\theta_j^2\right]$$

Logistic Regression:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^i log\left(h_\theta(x^i)\right) + (1-y^i)log\left(1-h_\theta(x^i)\right)] + \frac{\lambda}{2m}\sum_{j=1}^{n}\theta_j^2$$

Neural Network:

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m,}\sum_{k=1}^{K} y_k^i \log(h_\theta(x^i))_k + \left(1-y_k^i\right) log(1-\left(h_\theta(x^i)\right)_k)\right]$$
$$+\frac{\lambda}{2m}\sum_{l=1}^{L-1,}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}(\theta_{ji}^l)^2$$

Explain: theta, lambda effects

II. Supervised Learning

G. Regularization:

G1. What Is Regularization

Linear Regression:

$$J(\theta) = \frac{1}{2m}\left[\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2 + \lambda\sum_{j=1}^{n}\theta_j^2\right]$$

Gradient Descent:

$$while\ not\ converge\ \{$$

$$\theta_j = \theta_j - \alpha\left[\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)\cdot x^i + \frac{\lambda}{m}\theta_j\right]$$

$$\}$$

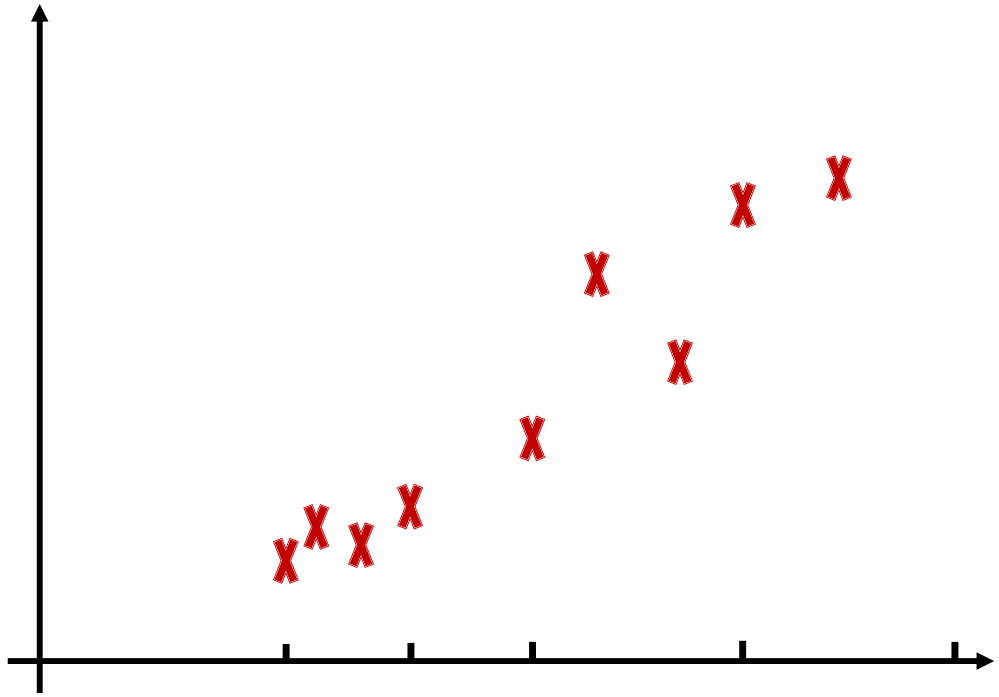
$$\theta_j = \theta_j\left(1 - \alpha\frac{\lambda}{m}\right) - \alpha\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)\cdot x^i$$

Explain:
Restrain can be better

II. Supervised Learning

G. Regularization:

G1. What Is Regularization

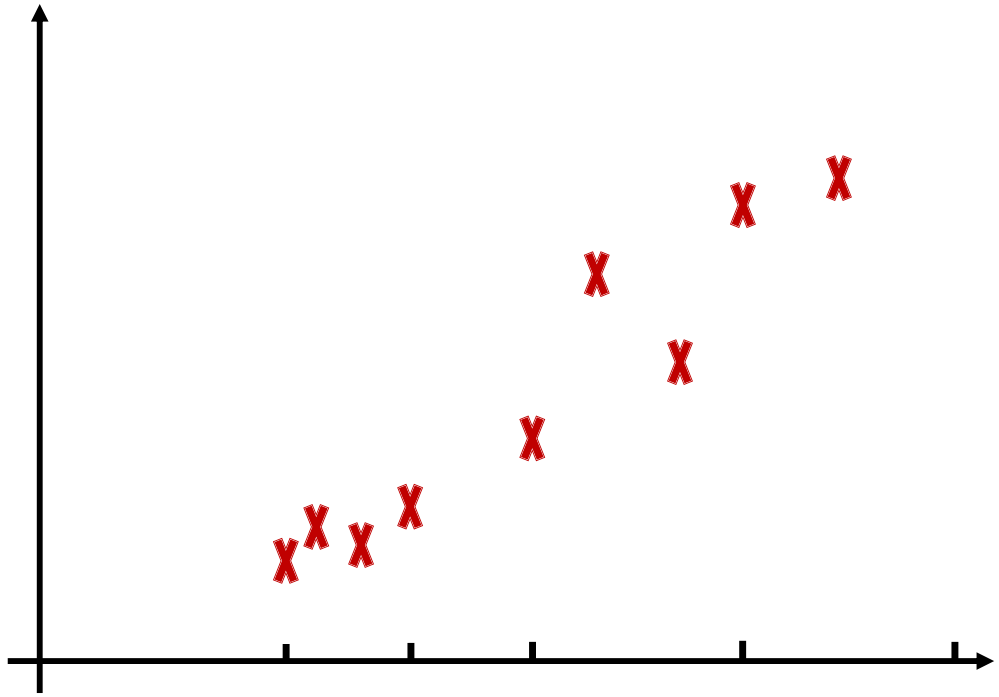


Explain:
Restrain can be better

II. Supervised Learning

G. Regularization:

G1. What Is Regularization



为了拟合不同点，overfit的函数往往需要在相对较小的区间内迅速变化，因而需要较大的梯度。为了保证较大的梯度，只能令权重较大。

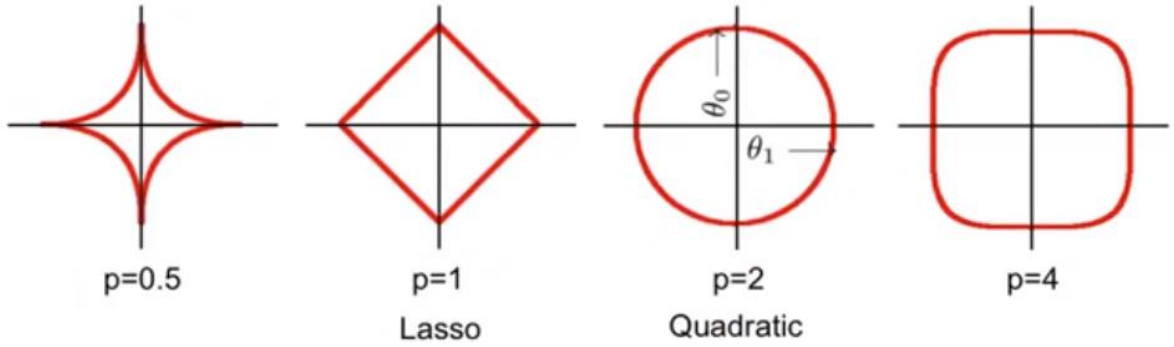
因而，Regularization保证了较小的权重，所以能够起到防止overfit的作用。

II. Supervised Learning

G. Regularization:

G2. Type Of Regularization

Lp Norm: $\left(\sum_i |\theta_i|^p\right)^{\frac{1}{p}}$



L2 Regularization: $\|\theta\|^2$ Ridge Regression

L1 Regularization: $\|\theta\|$ Lasso Regression

II. Supervised Learning

G. Regularization:

G2. Type Of Regularization

L1 Regularization:

Linear Regression:

$$J(\theta) = \frac{1}{2m}\left[\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2 + \lambda\sum_{j=1}^{n}\|\theta_j\|_1\right]$$

Logistic Regression:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^i log\left(h_\theta(x^i)\right) + (1-y^i) log\left(1-h_\theta(x^i)\right)] + \frac{\lambda}{2m}\sum_{j=1}^{n}\|\theta_j\|_1$$

Neural Network:

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m,}\sum_{k=1}^{K} y_k^i \log(h_\theta(x^i))_k + \left(1-y_k^i\right) log(1-\left(h_\theta(x^i)\right)_k)\right]$$
$$+\frac{\lambda}{2m}\sum_{l=1}^{L-1,}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}\|\theta_j\|_1$$

Explain:
L1 Pattern

II. Supervised Learning

G. Regularization:

G2. Type Of Regularization

L1 Regularization:

Linear Regression:

$$J(\theta) = \frac{1}{2m}\left[\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2 + \lambda\sum_{j=1}^{n}\|\theta_j\|_1\right]$$

Gradient Descent:

$$while\ not\ converge\ \{$$

$$\theta_j = \theta_j - \alpha\left[\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)\cdot x^i + \frac{\lambda}{m}sgn(\theta_j)\right]$$

$$\}$$

$$\theta_j = \theta_j - \alpha\frac{\lambda}{m}sgn(\theta_j) - \alpha\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)\cdot x^i$$

II. Supervised Learning

G. Regularization:

G2. Type Of Regularization

The Figure 3.11 from *Elements of Statistical Learning* by Hastie, Tibshirani, and Friedman is very illustrative:

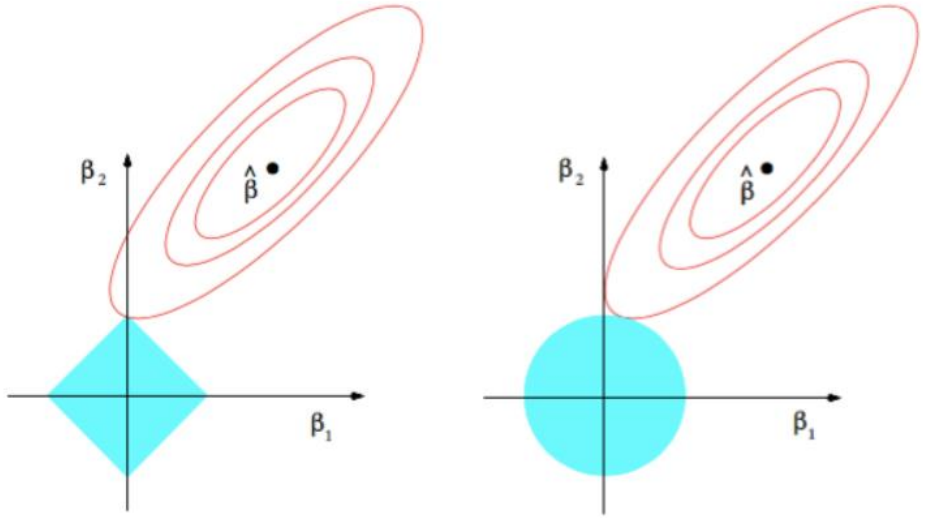


FIGURE 3.11. *Estimation picture for the lasso (left) and ridge regression (right). Shown are contours of the error and constraint functions. The solid blue areas are the constraint regions* $|\beta_1| + |\beta_2| \leq t$ *and* $\beta_1^2 + \beta_2^2 \leq t^2$*, respectively, while the red ellipses are the contours of the least squares error function.*

II. Supervised Learning

G. Regularization:

G2. Type Of Regularization

L1 Sparsity Theoretical Explanation: [Link 1]

II. Supervised Learning

G. Regularization:

G2. Type Of Regularization

L2 regularization	L1 regularization
Computational efficient due to having analytical solutions	Computational inefficient on non-sparse cases
Non-sparse outputs	Sparse outputs
No feature selection	Built-in feature selection

Explain:
SVM 1 fundamental

II. Supervised Learning

H. SVM:

H1. Basic SVM: Support Vector Machine

Explain:
SVM 2 fundamental

II. Supervised Learning

H. SVM:

H1. Basic SVM

Explain:
SVM 3 fundamental

II. Supervised Learning

H. SVM:

H1. Basic SVM

Explain:
SVM soft margin

II. Supervised Learning

H. SVM:

H2. Soft margin

Explain:
SVM soft margin

II. Supervised Learning

H. SVM:

H3. Kernel

II. Supervised Learning

H. SVM:

H3. Kernel

Type	Expression: $\kappa(x_i, x_j)$	Parameters
linear		
polynomial		
Gaussian (RBF)		
Laplacian		
Sigmoid		

II. Supervised Learning

H. SVM:

H4. Applying SVM

n: # of features, m: # of samples

- **n~ & n > m: logistic regression || SVM w/o kernel**
- **n_, m-: SVM w kernel**
- **n_, m~: add more features, then logistic || SVM w/o kernel**
- **Usually, SVM is not so good for large # of samples.**
- **NN can handle. Always.**

- **See L3**

Summary: Supervised Learning

II. Supervised Learning

Summary:

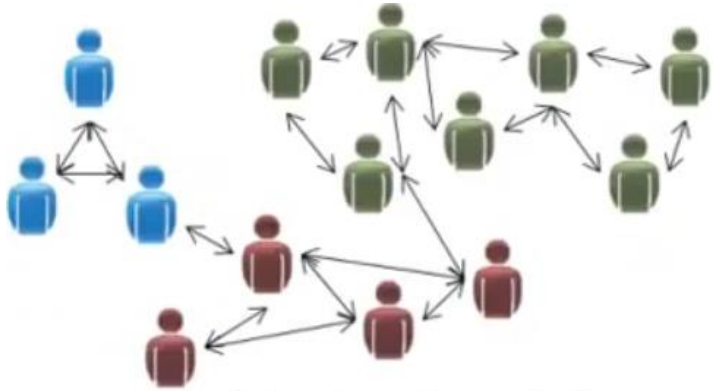
- **Linear Regression**
- **Logistic Regression / Classification**
- **L2 Loss**
- **Sigmoid Function**
- **Cross Entropy / Multi-Label**
- **Neural Network**
- **L1 / L2 Regularization**
- **Overfit / Zigzag**
- **BP / Cost Function / Hypothesis**
- **Gradient Vanishing / Explosion**
- **SVM / Kernel / Derivation**
- **Normal Equation**

III. Unsupervised Learning

III. Unsupervised Learning

I. K-Means:

I1. Clustering



Social network analysis

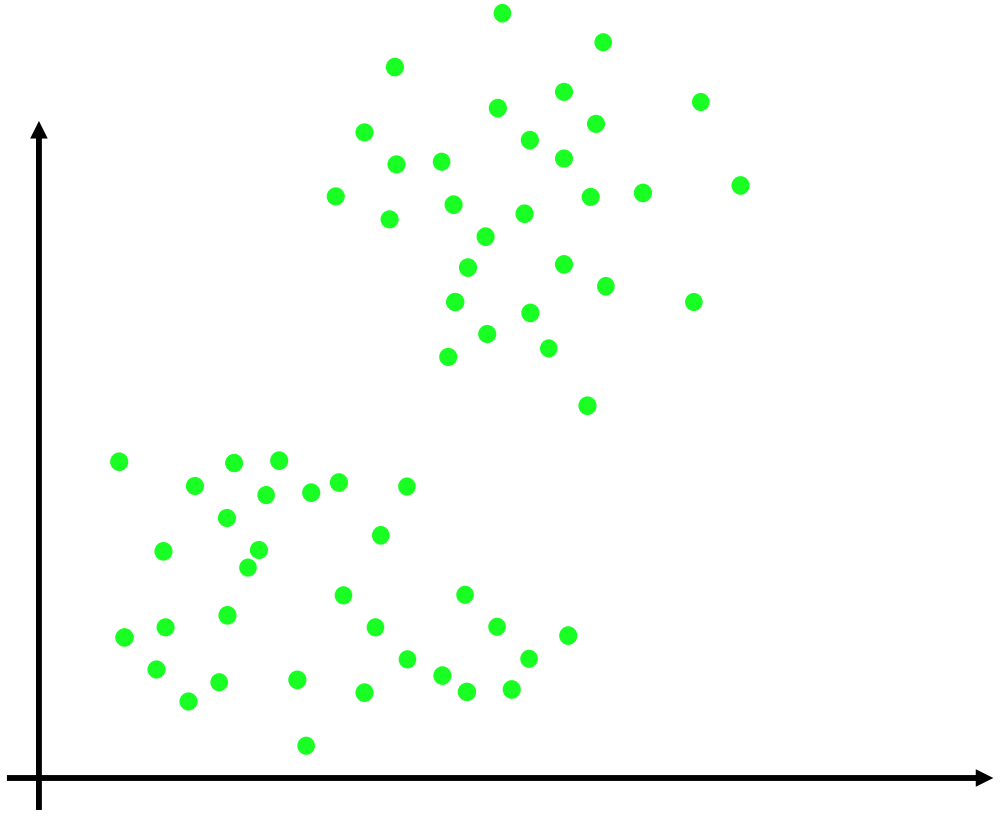
Organize computing clusters

Astronomical data analysis

III. Unsupervised Learning

I. K-Means:

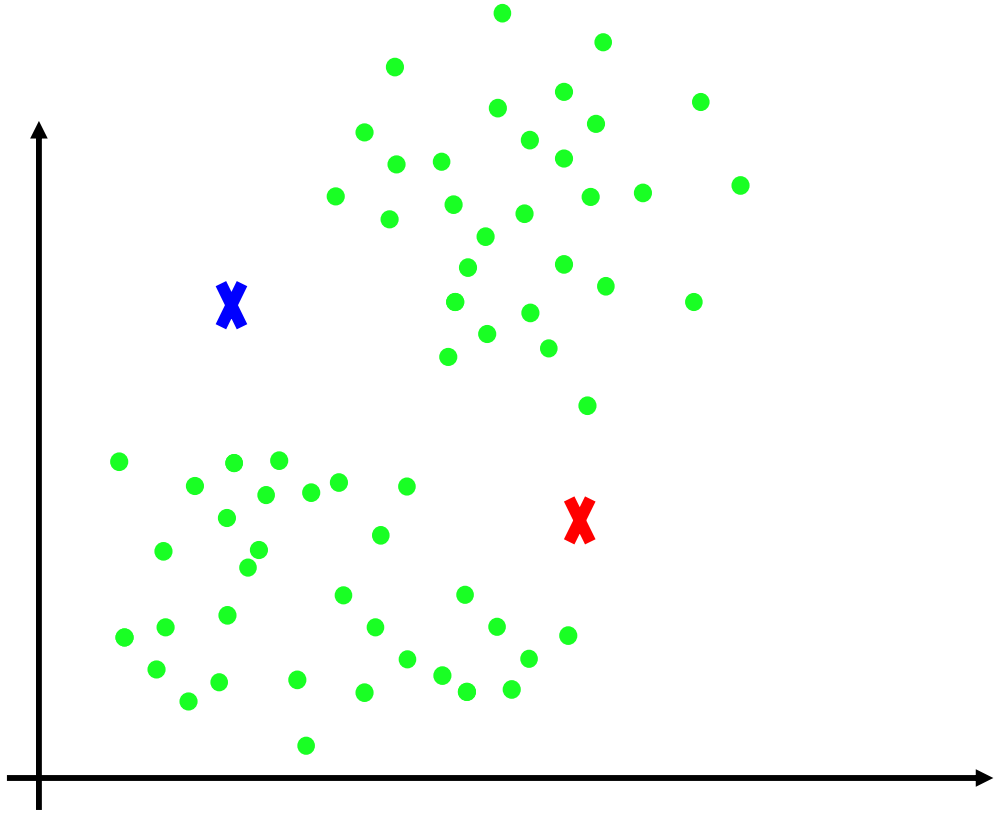
I2. K-Means



III. Unsupervised Learning

I. K-Means:

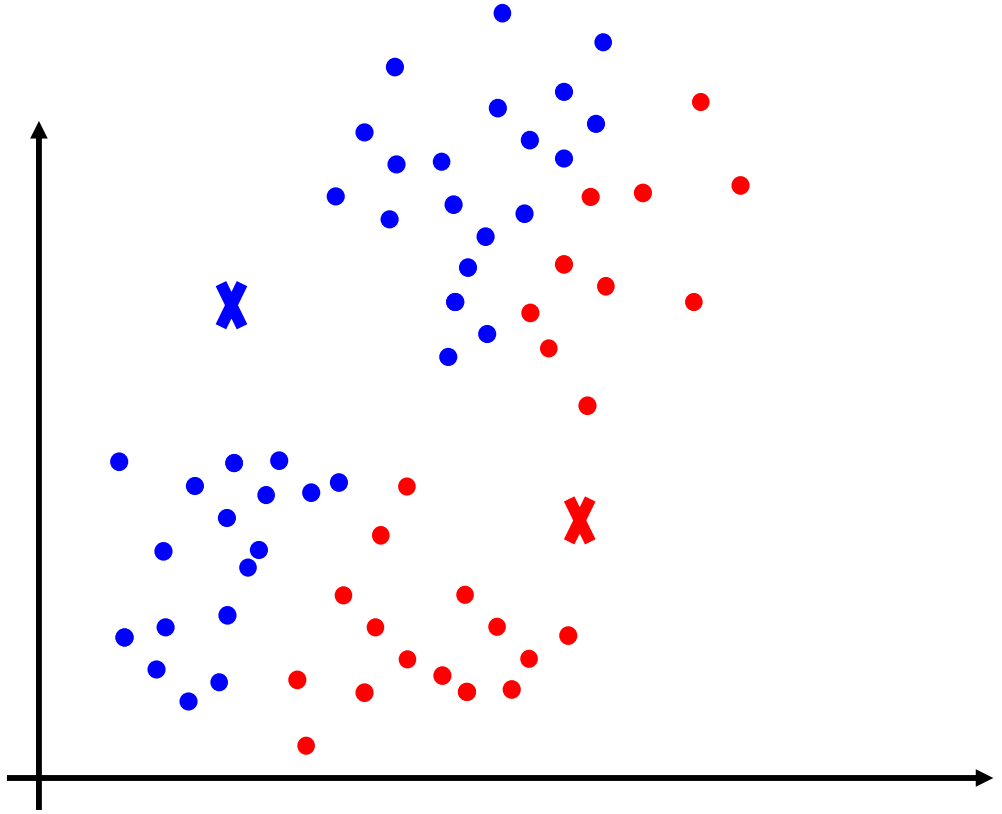
I2. K-Means



III. Unsupervised Learning

I. K-Means:

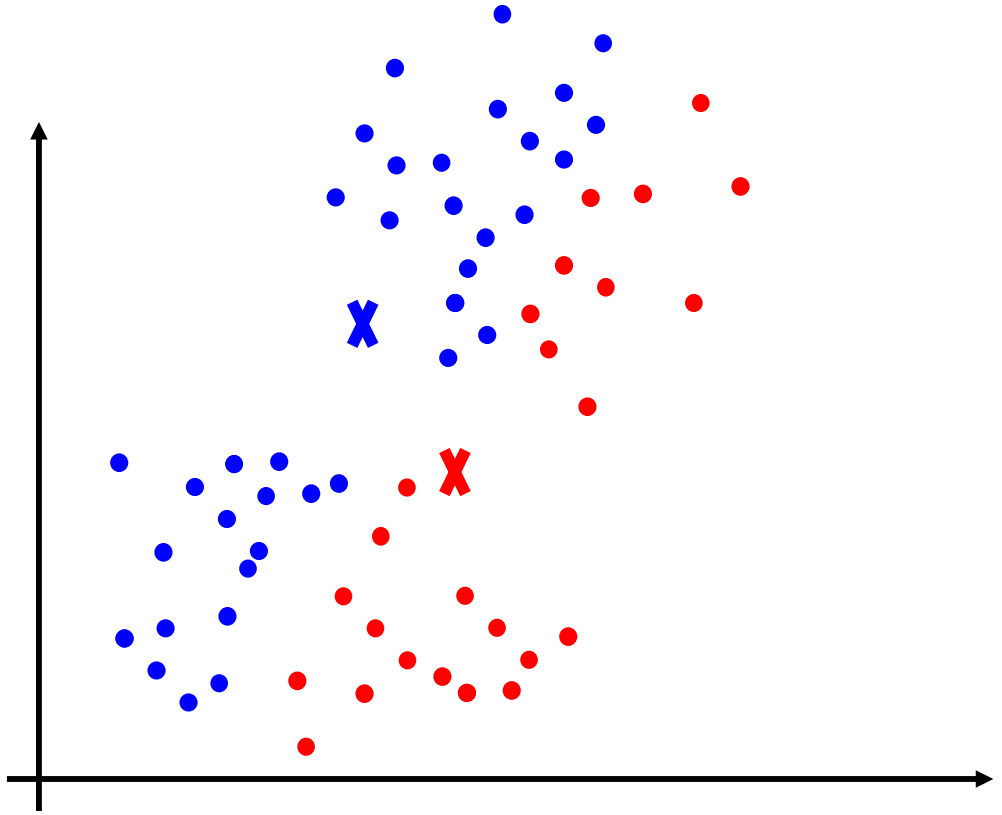
I2. K-Means



III. Unsupervised Learning

I. K-Means:

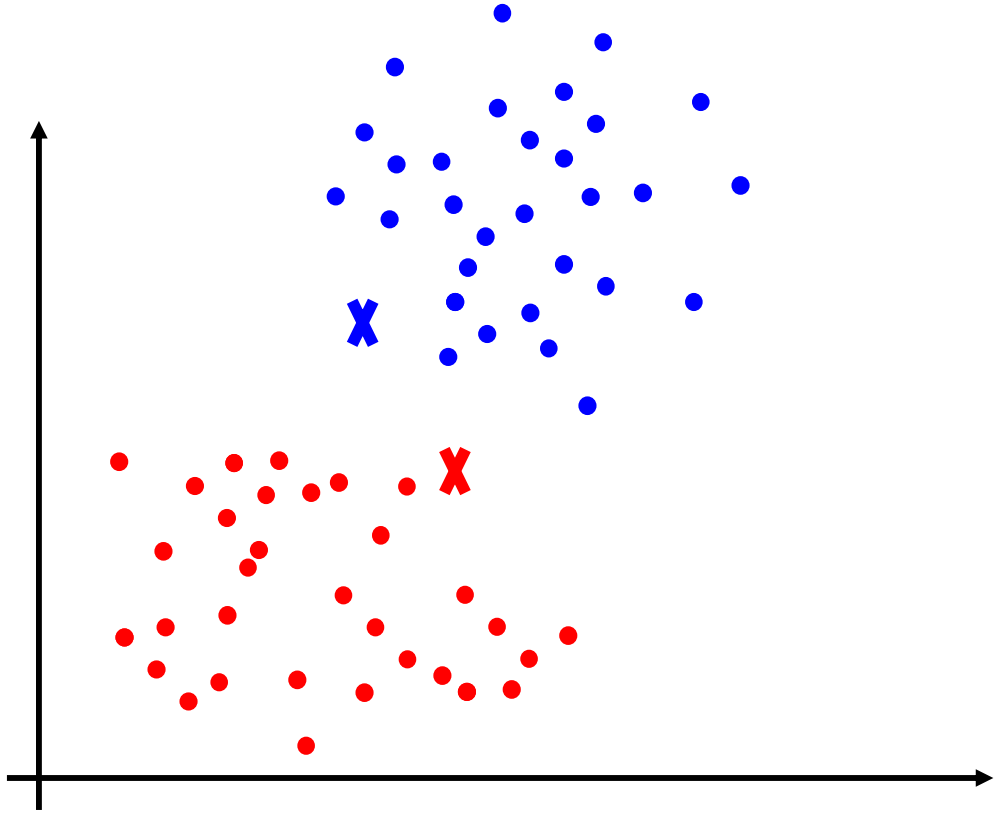
I2. K-Means



III. Unsupervised Learning

I. K-Means:

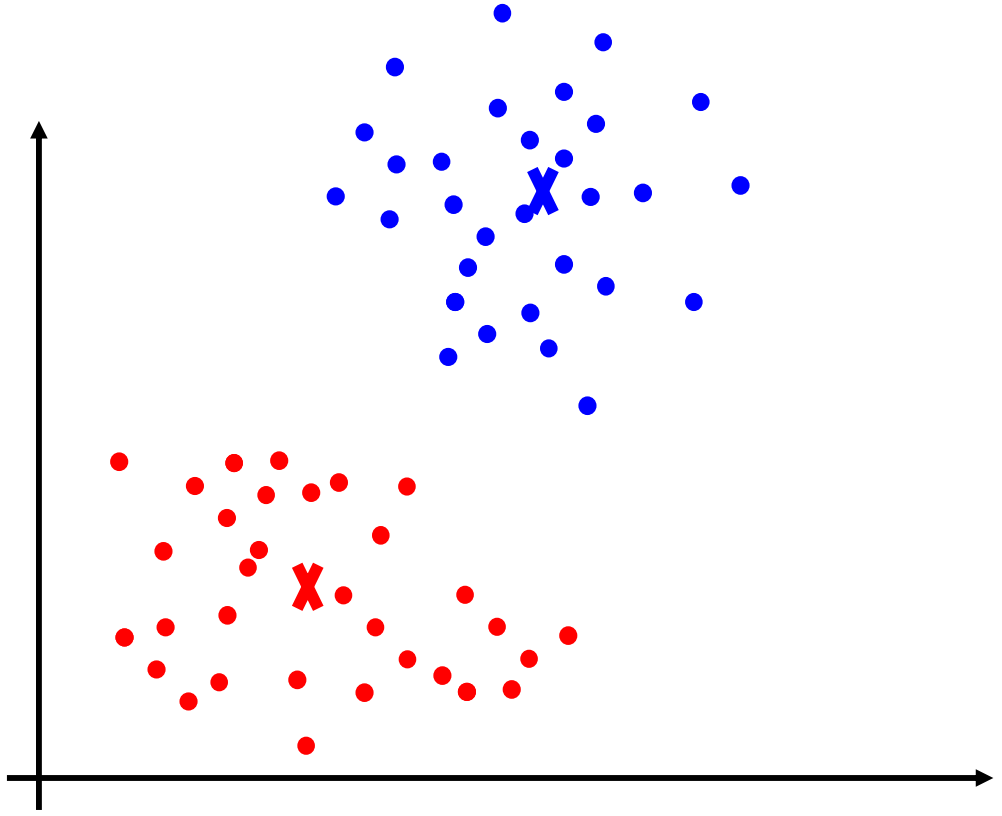
I2. K-Means



III. Unsupervised Learning

I. K-Means:

I2. K-Means



III. Unsupervised Learning

I. K-Means:

I2. K-Means

Input: K: # of clusters
X: samples

Start: Randomly initialize K centroids $c_1, c_2, \cdots, c_K \epsilon \mathbb{R}^n$

While: c_i not converging {
【step 1: update assignment for each sample x_i】
for i = 1 to m:
$\underset{k}{argmin}(\|x_i - c_k\|)$
【step 2: update centroids】
for k = 1 to K:
c_k = mean of points assigned to cluster k
}

III. Unsupervised Learning

I. K-Means:

I2. K-Means

Implement: K-Means

Explain:
K-Means++

III. Unsupervised Learning

I. K-Means:

I3. K-Means-improved

Assignment!

Problems:

1. **Initialized seeds/centroids. K-Means++ [2007, Arthur & Vassilvitskii]**

1a. Take one center c_1, chosen uniformly at random from $\mathcal{X}$.
1b. Take a new center c_i, choosing $x \in \mathcal{X}$ with probability $\frac{D(x)^2}{\sum_{x \in \mathcal{X}} D(x)^2}$.
1c. Repeat Step 1b. until we have taken k centers altogether.

E.g.:

Explain:
K-Means++

III. Unsupervised Learning

I. K-Means:

I3. K-Means-improved

Problems:

1. **Initialized seeds/centroids.** **-K-Means++**

E.g.:

Explain:
K-Means++

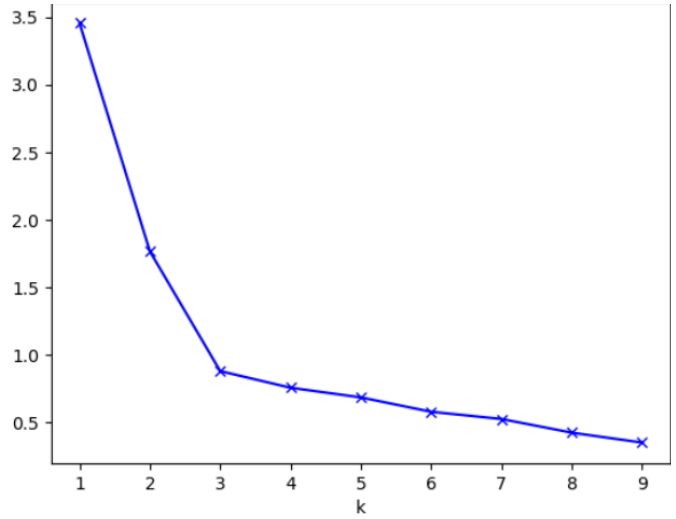
III. Unsupervised Learning

I. K-Means:

I3. K-Means-improved

Problems:

1. **Initialized seeds/centroids.**
2. **K chosen. elbow method / more / ISODATA**



III. Unsupervised Learning

I. K-Means:

I3. K-Means-improved

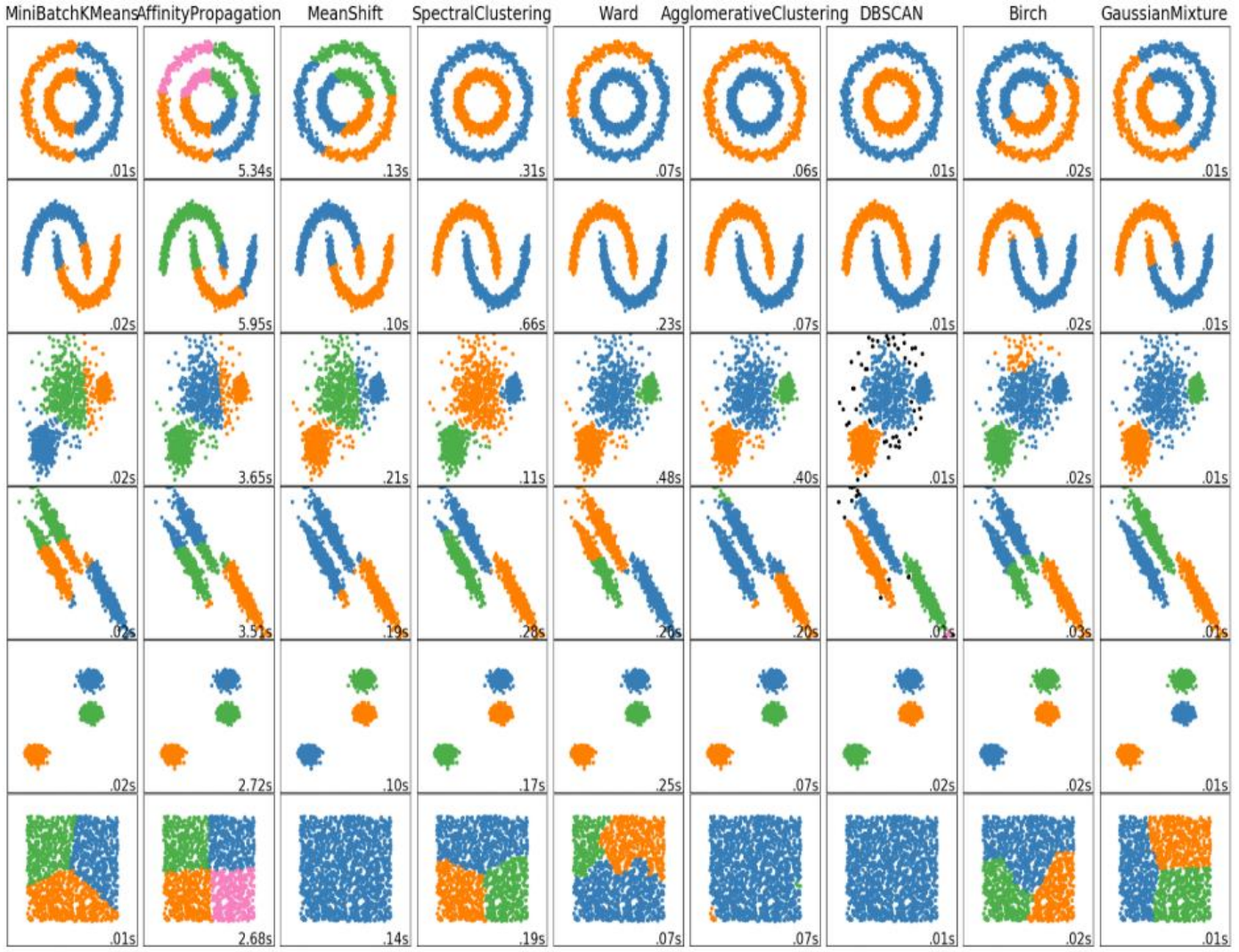
Problems:

1. Initialized seeds/centroids.
2. K chosen.
3. Not good for structural distribution
4. Slow when # of samples is big

III. Unsupervised Learning

I. K-Means:

I4. Modern Methods



A comparison of the clustering algorithms in scikit-learn

III. Unsupervised Learning

I. K-Means:

I5. kNN

Decide a sample according to its k nearest neighbors
[Lazy-learning]

Explain:
kNN

III. Unsupervised Learning

I. K-Means:

I6. Comparison

kNN	K-Means
1. Classification / Regression 2. Supervised (Labeled)	1. Clustering 2. Unsupervised(Unlabeled)
Memory-based learning (Needless to learn)	Have to learn
k: k neighbors	k: k clusters
Need to find Nearest Samples (NN), use KD-Tree sometimes.	

IV. Concepts & Problems

Explain:
Split

IV. Concepts & Problems

J. Training / Validation / Test Set

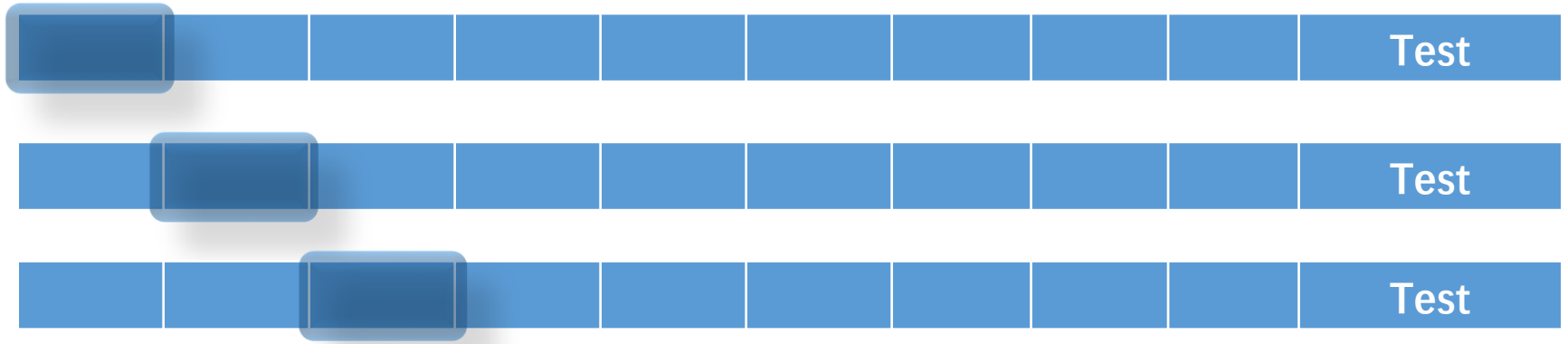
Target: To find a really good model

IV. Concepts & Problems

J. Training / Validation / Test Set

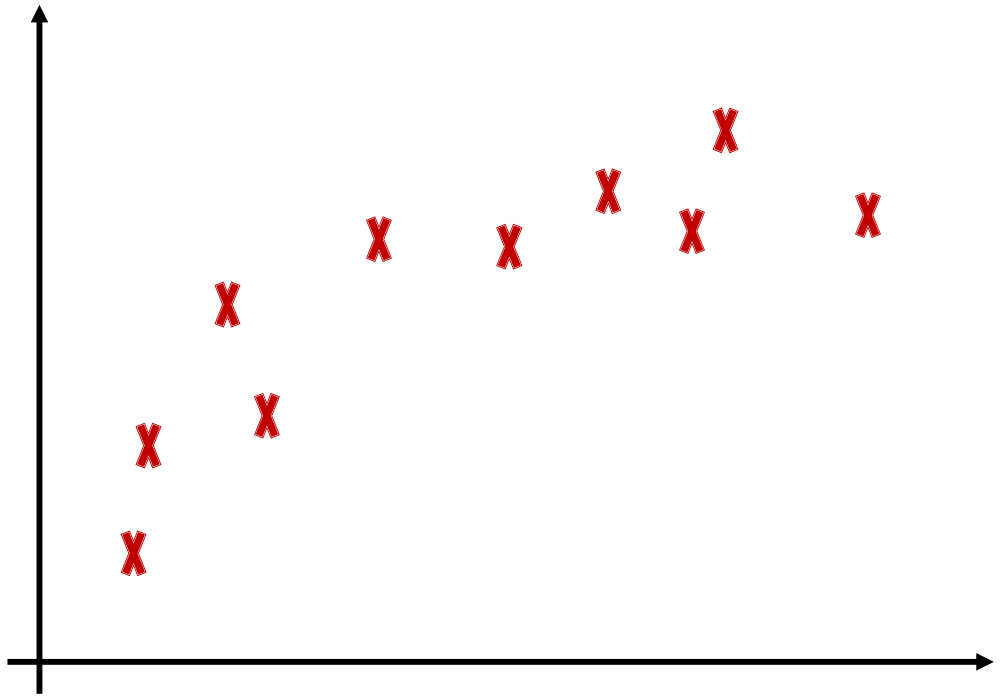
Explain:
Better model |
Hyperparameter
2 ways
ratio

Target: To find a really good model



IV. Concepts & Problems

K. Underfit / Overfit



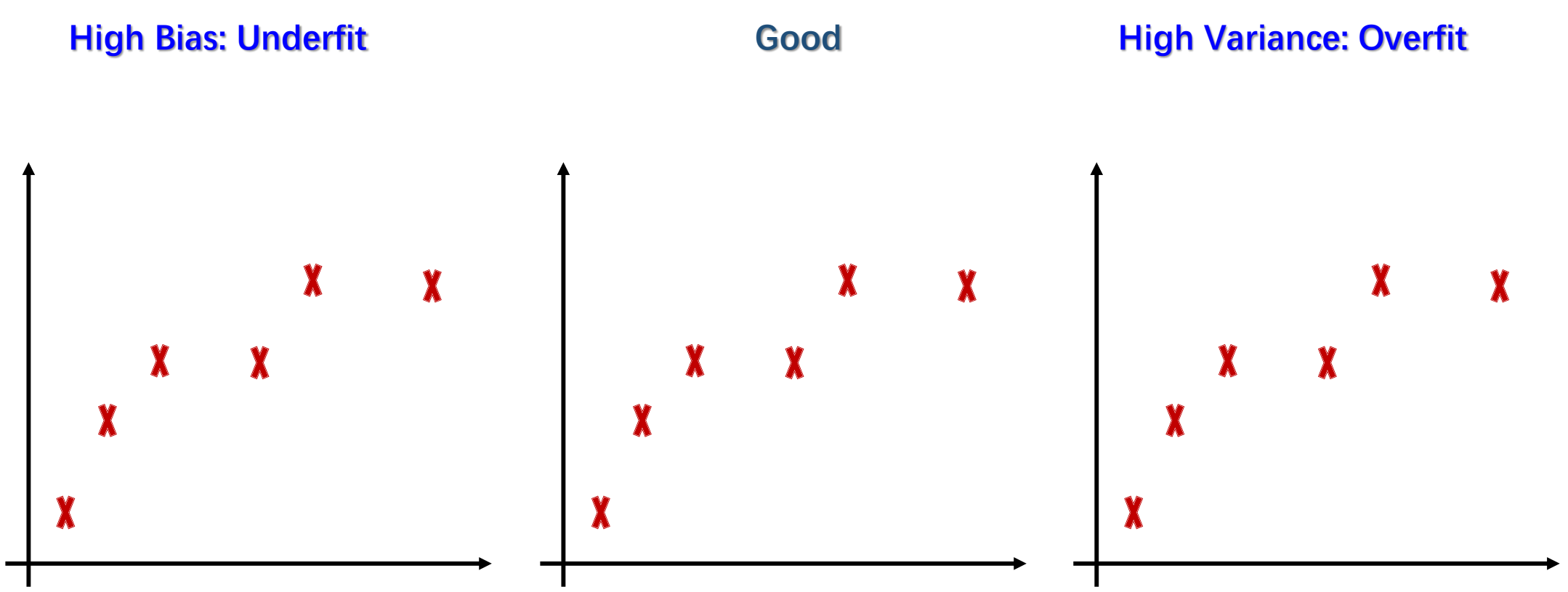
IV. Concepts & Problems

K. Underfit / Overfit

	Underfit	Overfit	
Phenomenon	1. Not good even when training	1. Very good when training, bad when validating	
Reasons	1. Model's too simple 2. Data's too complex 3. Gradient/Weight's too small 4. Parameters' too less 5. Too much regularization	1. Model's too complex 2. Data's too simple 3. Gradient/ Weight's too big 4. Parameters' too many 5. Less regularization	
Solutions	1. More complex structure 2. Less data 3. Simple data 4. Less regularization	1. Simpler structure 2. More data 3. Complex data 4. More regularization 5. Dropout 6. Batch Norm 7. Perturb Label 8. Noise	9. Early stop 10. ……

IV. Concepts & Problems

L. Bias / Variance



Explain: Diagnose Bias Variance

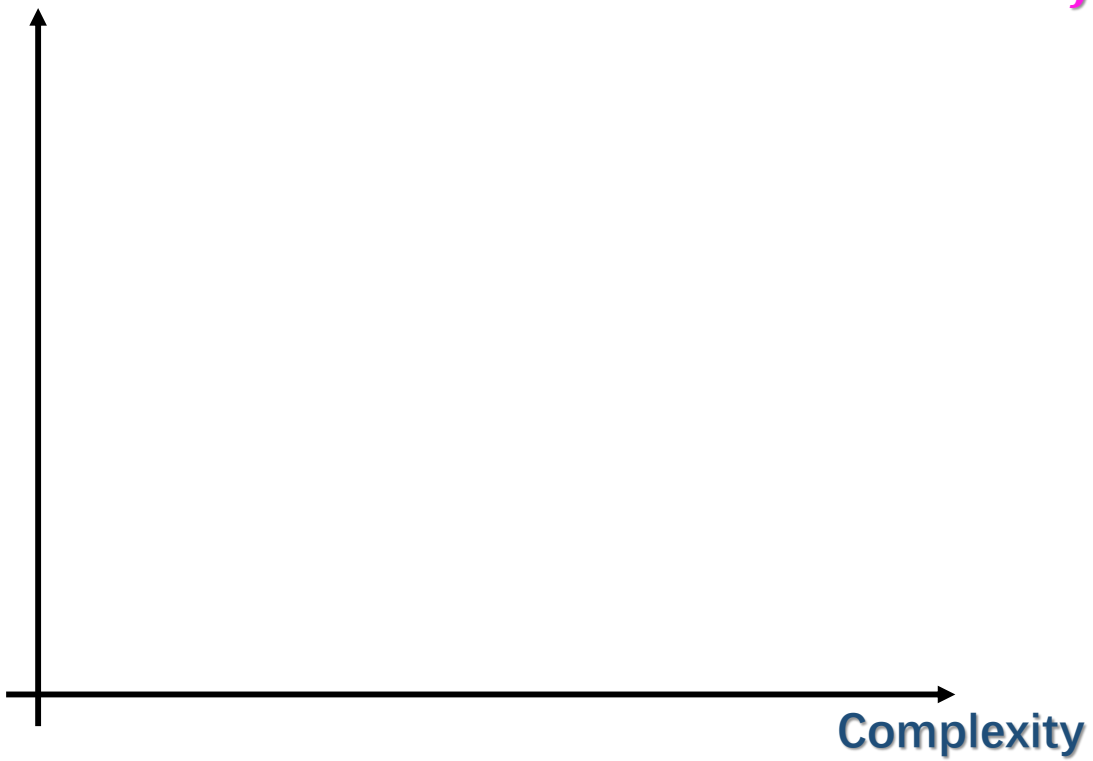
IV. Concepts & Problems

L. Bias / Variance

L1. Complexity

$J_{train}(\theta)$

$J_{test}(\theta)$



Explain: regularization
Bias Variance

IV. Concepts & Problems

L. Bias / Variance

L2. Regularization

$$J(\theta) = \frac{1}{2m}\left[\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2 + \lambda\sum_{j=1}^{n}\theta_j^2\right]$$

Explain: SVM
Bias / Variance

IV. Concepts & Problems

L. Bias / Variance

L3. Applying SVM

$$\begin{cases} \min_{\theta}\left(\frac{1}{2}\|\theta\|^2 + C\sum_{i}^{m}\xi_i\right) \\ s.t. \begin{cases} y_i\left(\theta\phi(x_i)\right) \geq 1 - \xi_i \\ \xi_i \geq 0 \end{cases} \end{cases}$$

Explain: why
No sample in bias

IV. Concepts & Problems

L. Bias / Variance

L4. In Sum

To reduce high variance	$+\lambda$
	-complexity
	+samples
To reduce high bias	+complexity
	$-\lambda$

IV. Concepts & Problems

M. Gradient Vanishing / Explosion

V. Other Classical ML Tools

V. Other Classical ML Tools

N. Decision Tree:

Some concepts:

- $\boldsymbol{Entropy}$: 随机变量的不确定，称“(信息)熵”，也“即系统混乱程度”

$$\boldsymbol{H(Y) = -\sum_{i=1}^{n} p_i log p_i}$$

- $\boldsymbol{Conditional\ Entropy}$: 随机变量X条件下Y的不确定性

$$\boldsymbol{H(Y|X) = -\sum_{i=1}^{n} p_i H(Y|X = x_i), p_i = P(X = x_i)}$$

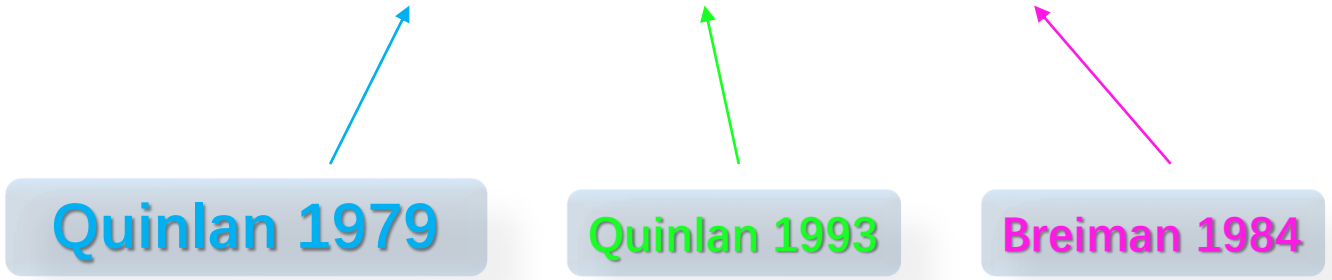
- $\boldsymbol{Information\ Gain}$: 信息增益：信息F对系统带来信息G

$$\boldsymbol{G(Y|X) = H(Y) - H(Y|X)}$$

V. Other Classical ML Tools

N. Decision Tree: ID3 / C4.5 / CART

History:



I: Iterative

D: Dichotomiser

3: 3rd generation of inductive learning

V. Other Classical ML Tools

N. Decision Tree: ID3

E.G.: 女婿受丈母娘欢迎度

ID	Appearance	Income	Age	Profession	是否受欢迎
1	Good	Low	Older	Steady	N
2	Good	Low	Older	Unstable	N
3	Great	Low	Older	Steady	Y
4	Ah	Good	Older	Steady	Y
5	Ah	Great	Younger	Steady	Y
6	Ah	Great	Younger	Unstable	N
7	Great	Great	Younger	Unstable	Y
8	Good	Good	Older	Steady	N
9	Good	Great	Younger	Steady	Y
10	Ah	Good	Younger	Steady	Y
11	Good	Good	Younger	Unstable	Y
12	Great	Good	Older	Unstable	Y
13	Great	Low	Younger	Steady	Y
14	Ah	Good	Older	Unstable	N

Target:

是否受欢迎: {Y:9, N:5}

Attribute:

Appearance: { Ah: 5=3Y+2N,
Good: 5=2Y+3N,
Great: 4=4Y}

Income: { Low: 4=2Y+2N,
Good: 6=4Y+2N,
Great: 4=3Y+1N}

Age: { Younger: 7=3Y+4N,
Older: 7=4Y+2N}

Profession: { Unstable: 6=3Y+3N,
Steady: 8=6Y+2N}

V. Other Classical ML Tools

N. Decision Tree: ID3

E.G.: 女婿受丈母娘欢迎度

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Age: { Younger: 7=3Y+4N,
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Profession: { Unstable: 6=3Y+3N,
Steady: 8=6Y+2N}

- ***Entropy***: $H(Y) = -\sum_{i=1}^{n} p_i log p_i$
- ***Conditional Entropy***: $H(Y|X) = -\sum_{i=1}^{n} p_i H(Y|X = x_i), p_i = P(X = x_i)$

a. Calculate the entropy of the system

$$H(D) = -\sum_{k=1}^{K} p_k log p_k = -\frac{9}{14}\log(\frac{9}{14}) - \frac{5}{14}\log(\frac{5}{14}) = 0.94$$

b. Calculate entropies for each feature

$$Appearance:\ H(F_{Great}) = -\frac{4}{4}\log\left(\frac{4}{4}\right) = 0$$

$$H(F_{Good}) = -\frac{2}{5}\log\left(\frac{2}{5}\right) - \frac{3}{5}\log\left(\frac{3}{5}\right) = 0.971$$

$$H(F_{Ah}) = -\frac{3}{5}\log\left(\frac{3}{5}\right) - \frac{2}{5}\log\left(\frac{2}{5}\right) = 0.971$$

$$\boldsymbol{H(D|F_{App})} = \frac{4}{14}H(F_{Great}) + \frac{5}{14}H(F_{Good}) + \frac{5}{14}H(F_{Ah}) = \mathbf{0.693}$$

V. Other Classical ML Tools

N. Decision Tree: ID3

E.G.: 女婿受丈母娘欢迎度

Target:

是否受欢迎: {Y:9, N:5}

Attribute:

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Age: { Younger: 7=3Y+4N,
Older: 7=4Y+2N}

Profession: { Unstable: 6=3Y+3N,
Steady: 8=6Y+2N}

- ***Entropy***: $H(Y) = -\sum_{i=1}^{n} p_i log p_i$
- ***Conditional Entropy***: $H(Y|X) = -\sum_{i=1}^{n} p_i H(Y|X = x_i), p_i = P(X = x_i)$

a. Calculate the entropy of the system

$$H(D) = -\sum_{k=1}^{K} p_k log p_k = -\frac{9}{14}\log(\frac{9}{14}) - \frac{5}{14}\log(\frac{5}{14}) = 0.94$$

b. Calculate entropies for each feature

$H(D|F_{App}) = 0.693$ $H(D|F_{Age}) = 0.789$

$H(D|F_{Inc}) = 0.911$ $H(D|F_{Job}) = 0.892$

c. Get Info Gain & d. Split feature with max gain

$G(D|F_{App}) = H(D) - H(D|F_{App}) = 0.94 - 0.693 = 0.246$

$G(D|F_{Inc}) = H(D) - H(D|F_{Inc}) = 0.94 - 0.911 = 0.029$

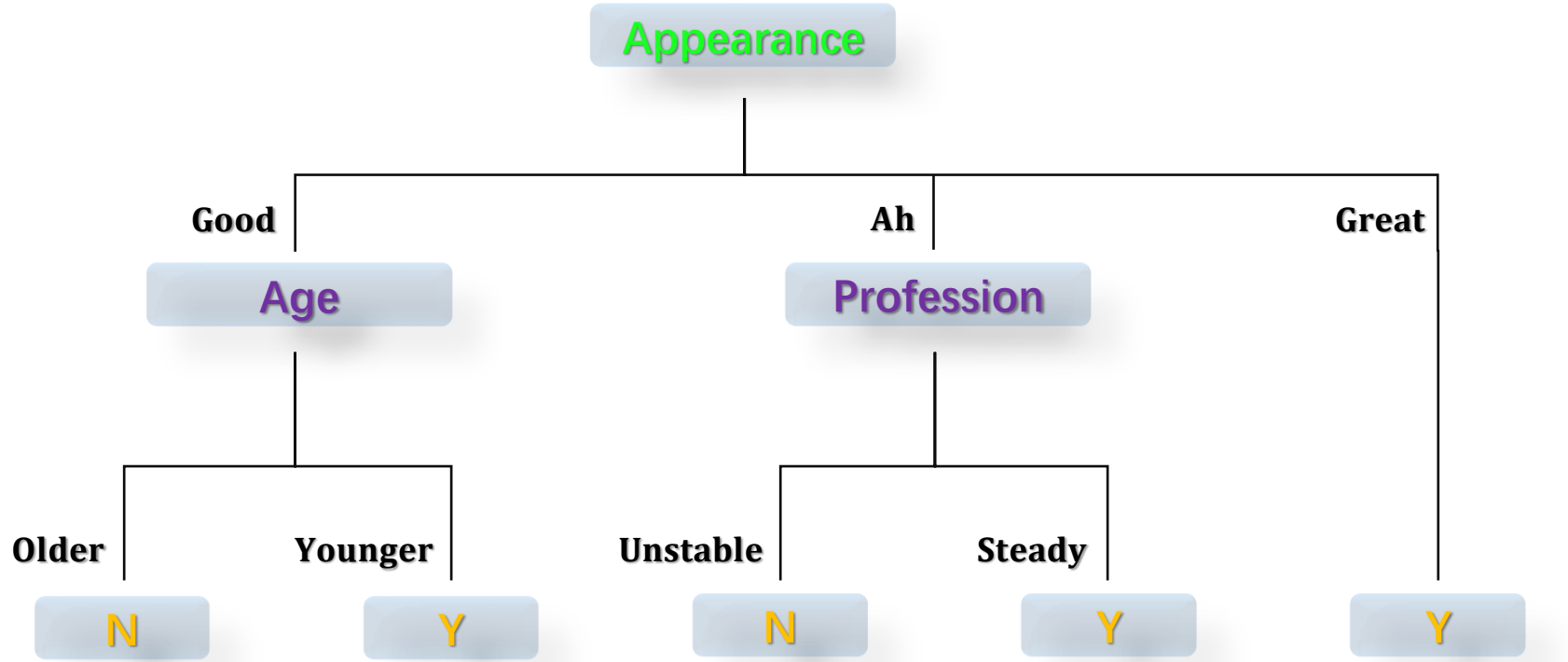
$G(D|F_{Age}) = H(D) - H(D|F_{Age}) = 0.94 - 0.798 = 0.151$

$G(D|F_{Job}) = H(D) - H(D|F_{Job}) = 0.94 - 0.892 = 0.048$

V. Other Classical ML Tools

N. Decision Tree: ID3

E.G.: 女婿受丈母娘欢迎度



V. Other Classical ML Tools

N. Decision Tree: ID3

Pros & Cons:

Pros: 1. Easy to understand
2. Classification + Regression

Cons: 1. Discrete
2. Prone to overfit
3. NP-Complete [Greedy algorithm: local optimum]
4. Usually easy to choose features having more attributes

Solutions: 1. Prune
2. # in leaf node
3. C4.5

V. Other Classical ML Tools

N. Decision Tree: ID3 / C4.5 / CART

More than ID3:

Except Gain:

- $SplitInformation(D|F) = -\sum_{i=1}^{n} \frac{|D_i|}{|D|} log \frac{|D_i|}{|D|}$
- $GainRatio(D|F) = \frac{G(D|F)}{SplitInformation(D|F)}$
- $Choose\ argmax$

V. Other Classical ML Tools

N. Decision Tree: ID3 / C4.5 / CART

It's a binary tree:

a. **Calculate the Gini Index**

$$Gini(D) = \sum_{k=1}^{K} p_k(1 - p_k) = 1 - \sum_{k=1}^{K} p_k^2$$

b. **Calculate conditional Gini Index for each feature**

$$Gini(D|F) = \frac{D_1}{D} Gini(D_1) + \frac{D_2}{D} Gini(D_2)$$

c. **Split feature with min Gini Index**

V. Other Classical ML Tools

N. Decision Tree: ID3 / C4.5 / CART

E.G.: 女婿受丈母娘欢迎度

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8	Good	Good	Older	Steady	N
9	Good	Great	Younger	Steady	Y
10	Ah	Good	Younger	Steady	Y
11	Good	Good	Younger	Unstable	Y
12	Great	Good	Older	Unstable	Y
13	Great	Low	Younger	Steady	Y
14	Ah	Good	Older	Unstable	N

Target:

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Profession: { Unstable: 6=3Y+3N,
Steady: 8=6Y+2N}

V. Other Classical ML Tools

N. Decision Tree: ID3 / C4.5 / CART

E.G.: 女婿受丈母娘欢迎度

Target:

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Attribute:

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Good: 6=4Y+2N,
Great: 4=3Y+1N}

Age: { Younger: 7=3Y+4N,
Older: 7=4Y+2N}

Profession: { Unstable: 6=3Y+3N,
Steady: 8=6Y+2N}

a. Calculate Gini Index for Profession

$$Gini(F_{Unstable}) = 1 - (\frac{3}{6})^2 - (\frac{3}{6})^2$$

$$Gini(F_{Steady}) = 1 - (\frac{2}{8})^2 - (\frac{6}{8})^2$$

$$Gini(D|F_{Job}) = \frac{6}{14} Gini(F_{Unstable}) + \frac{8}{14} Gini(F_{Steady}) = A$$

b. Calculate Gini Index for Appearance [> 2 *branches*]

1. $Ah|Good, Great :=> B_1$
2. $Good|Ah, Great :=> B_2$
3. $Great|Ah, Good :=> B_3$

$$B = \min(B_1, B_2, B_3)$$

c. Split Feature according to min Gini Index

Split feature ID = $argmin\{A, B, C, \dots\}$)

V. Other Classical ML Tools

O. Reading Parts: AdaBoost / Haar Feature

- **AdaBoost:** adaptive boost [1995, Freund & Schapire]
  [source paper / explanation]

- **Haar Feature:** [2001 Viola & Jones]
  [source paper / explanation]