실습을 통해 기초부터 배우는 머신러닝

18.12.01 – 18.12.29 (토 , 13:00 ~ 18:00)

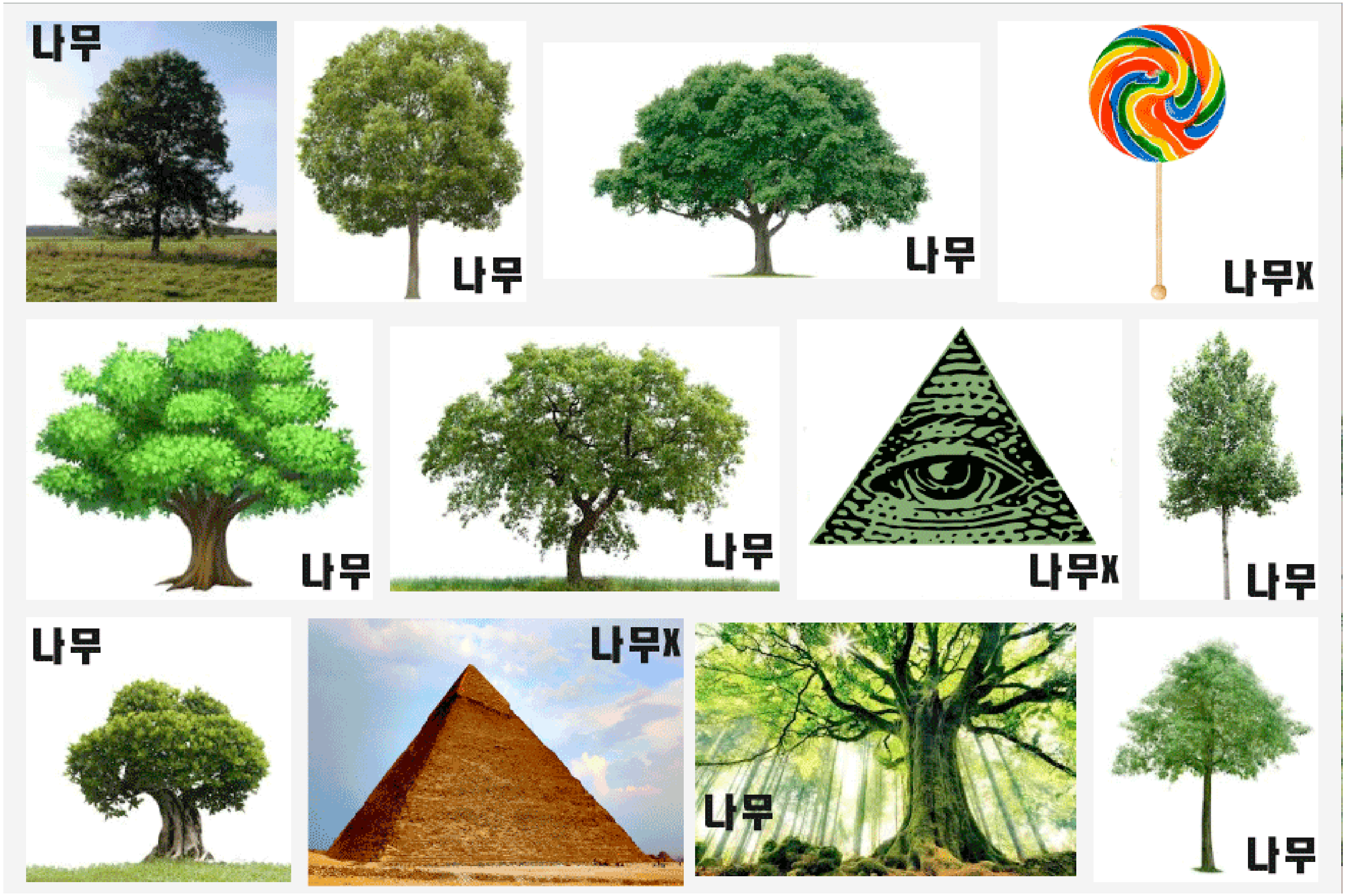
Week 3

Agenda

1. Introduction
2. What’s & Why ML?
3. Categorization of ML
4. Linear Regression
5. Logistic Regression
6. Practice

How do we learn?

Learning process



Can you guess what it is?

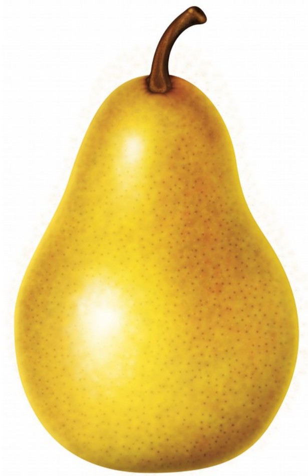
There are many fruits here!

딸기

바나나

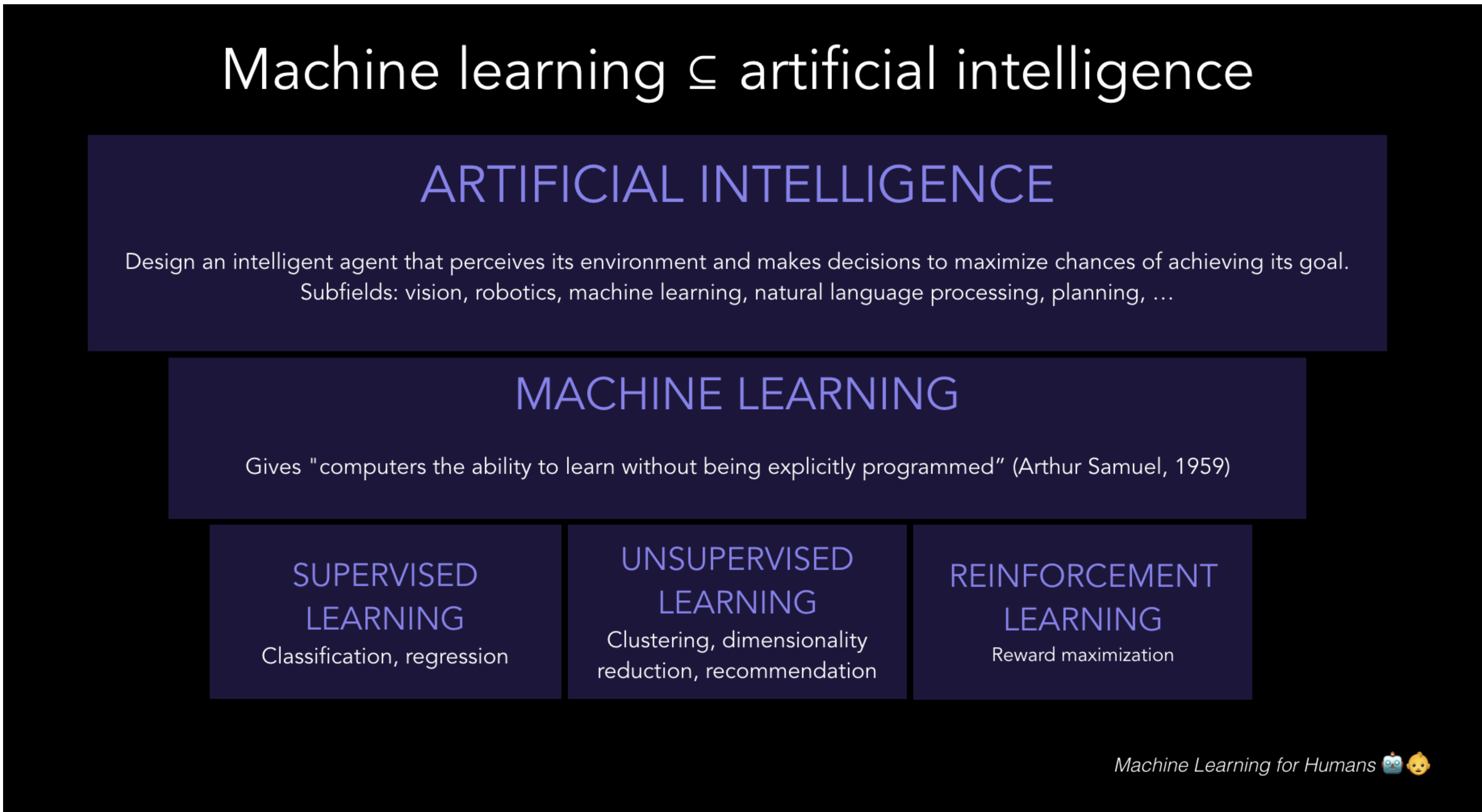
포도

사과



배

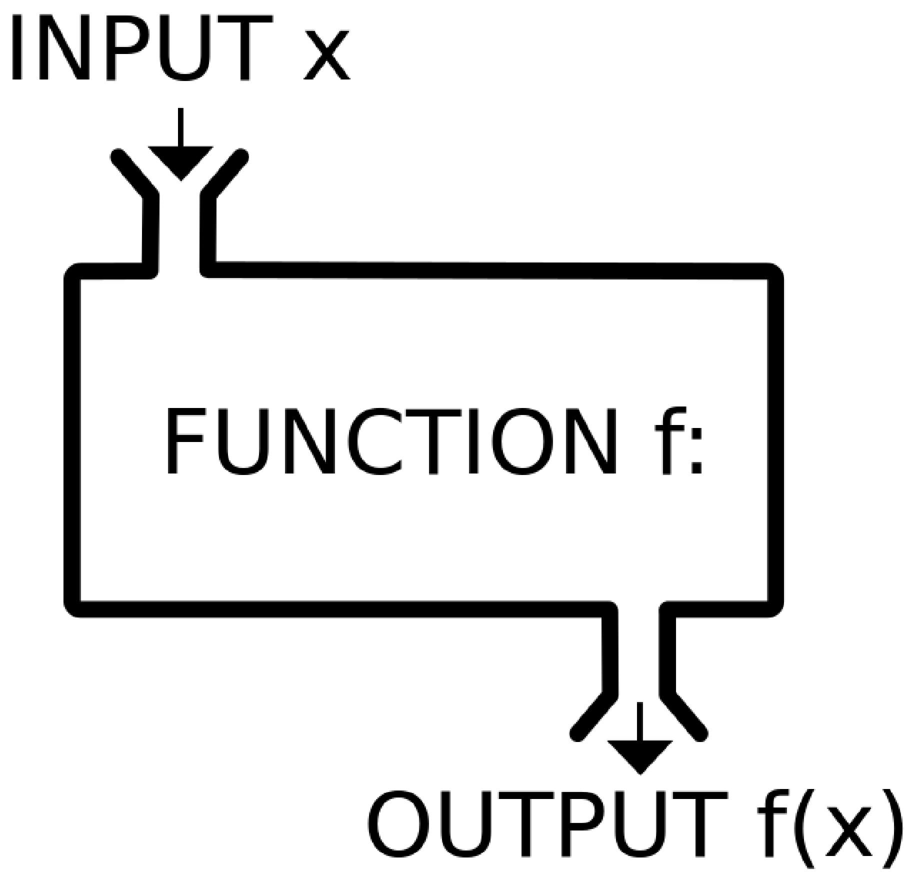
What’s machine learning?



What's machine learning?

- 기계가 **일일이 코드로 명시하지 않은 동작**을 데이터로부터 학습하여 실행할 수 있도록 하는 알고리즘을 개발하는 연구 분야 – Arthur Samuel, 1959
- 만약 작업 T 에 대해 기준 P 로 측정한 **성능**이 경험 E 로 인해 **향상**되었다면 , 그 프로그램은 작업 T 에 대해 기준 P 의 관점에서 **경험** E 로부터 **배웠다** – Tom Mitchell, 1998
- 데이터로부터 **패턴**을 **학습**하여 **새로운 데이터**에 대해 적절한 작업을 수행하는 일련의 알고리즘이나 처리 과정

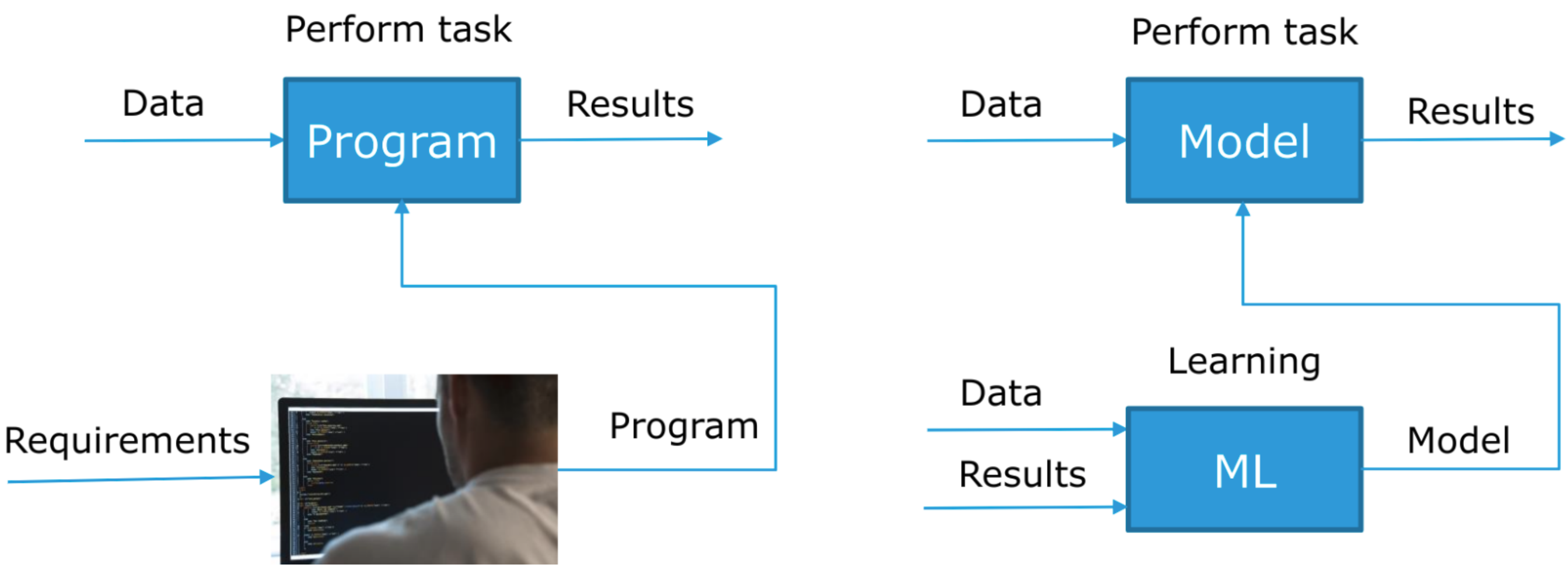
What’s machine learning?



Through Machine Learning ?

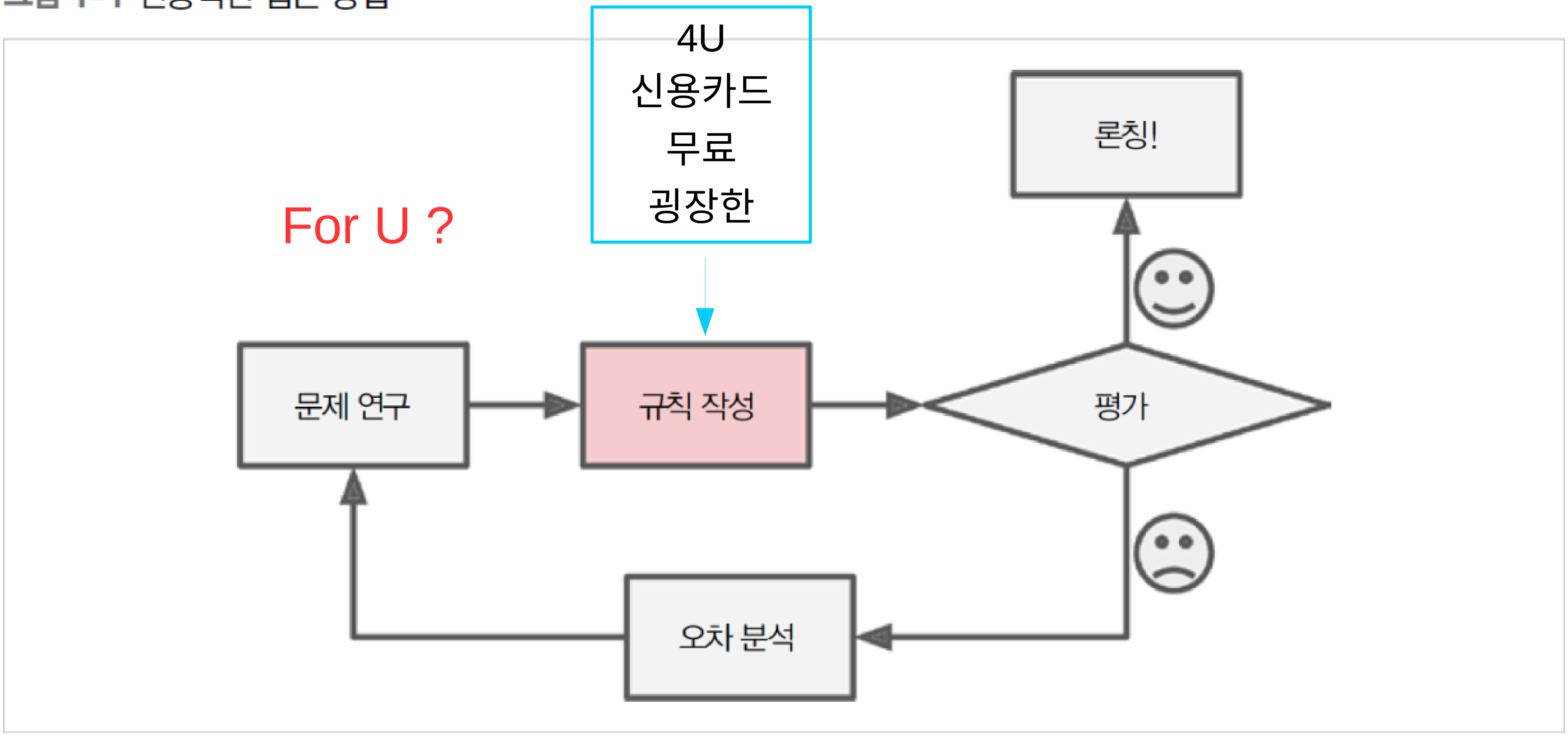
입력 값으로부터 원하는 결과 값을
출력해주는 함수를 얻는 것 !!!

What’s different from programming



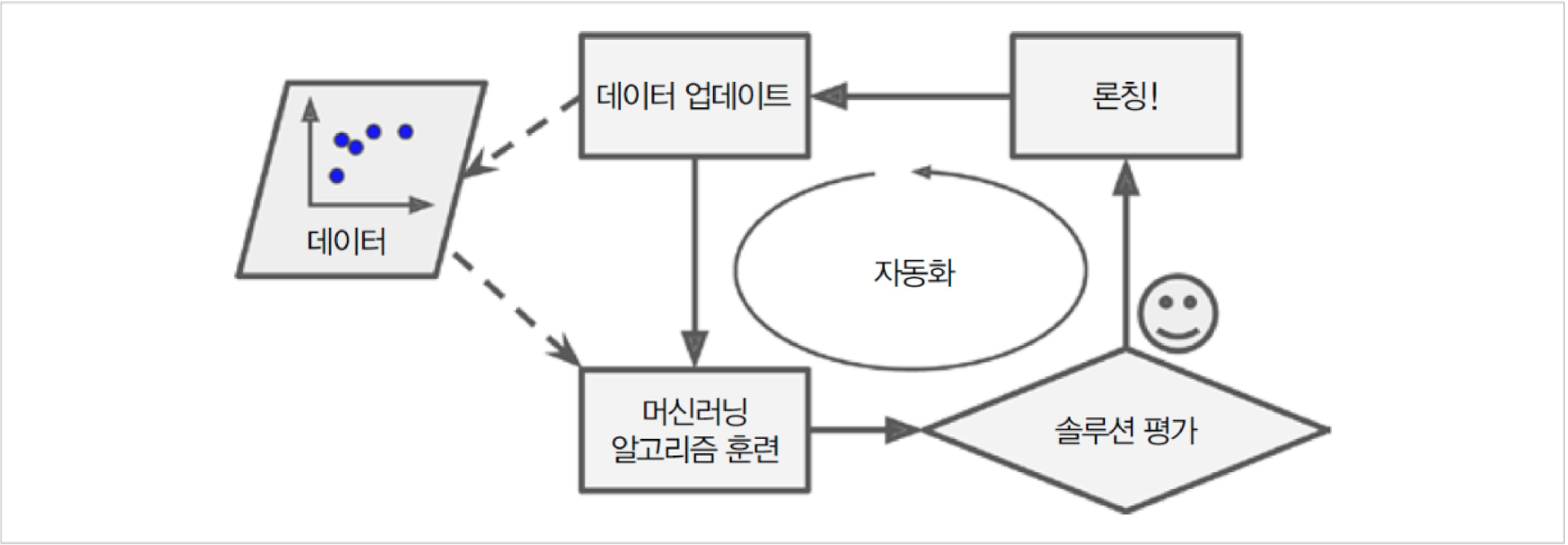
Example – spam filter

그림 1-1 전통적인 접근 방법



Example – spam filter

그림 1-3 자동으로 변화에 적응함



ML is good for...

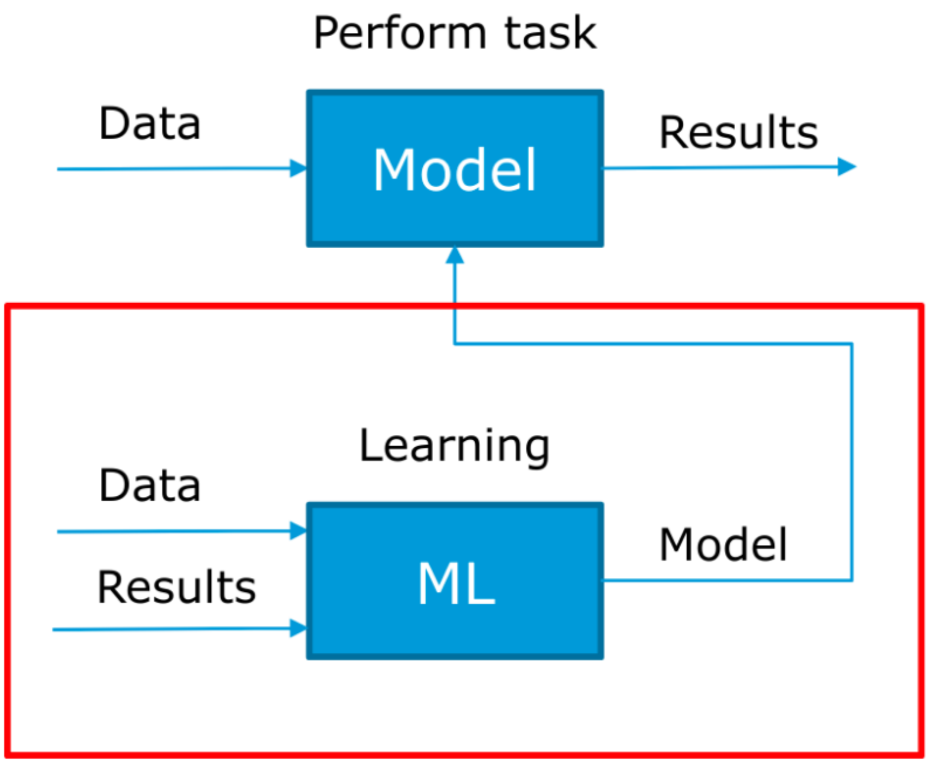
- 기존 솔루션으로는 많은 수동 조정과 규칙이 필요한 문제

  ex) 스팸 필터

- 전통적인 방식으로는 해결하기 어려운 복잡한 문제

  ex) 이미지 분류 , 음성 인식

What’s learning?

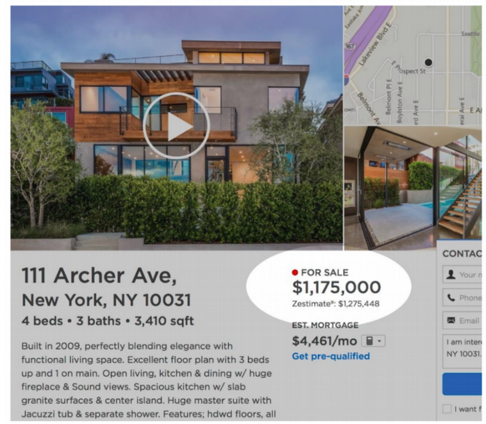


- Different Machine Learning techniques for different kinds of tasks

- Learning is finding which model’s parameters represent best the input-output mapping

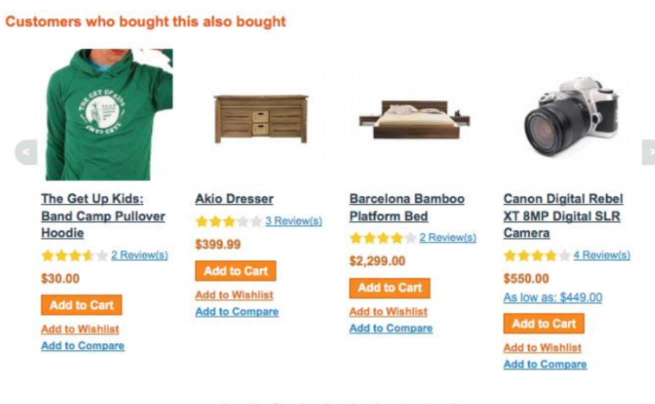
Which tasks can ML perform?

Spam Filter

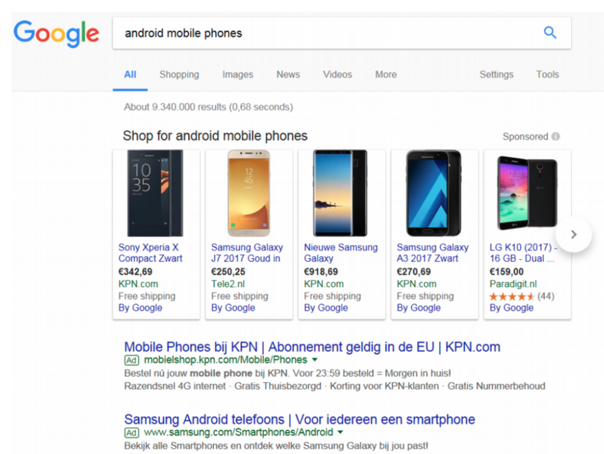


Real Estate

Predict at which price a property will be sold



Recommendation Engine



Advertising

Predict which ads you are more likely to click on

Which tasks can ML perform?

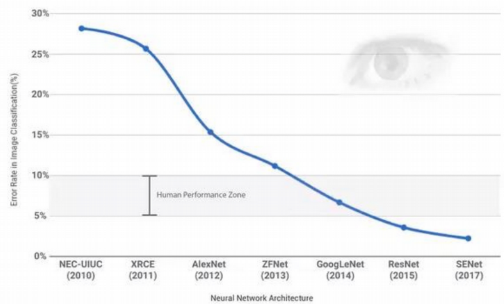
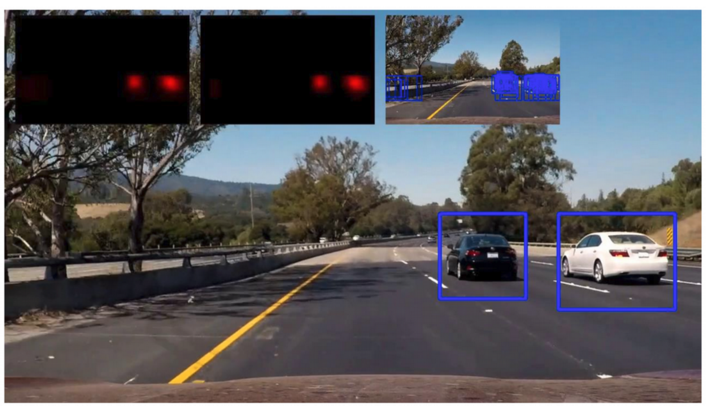
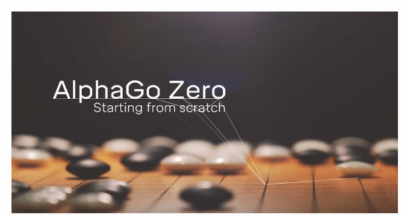


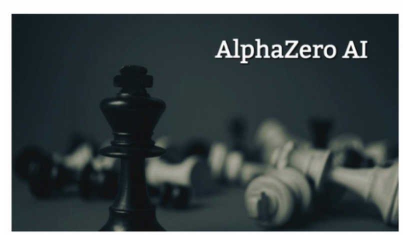
Image Classification

Speech Recognition
& Synthesis

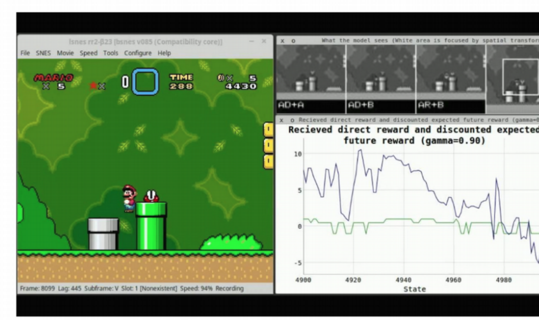


Self-driving cars

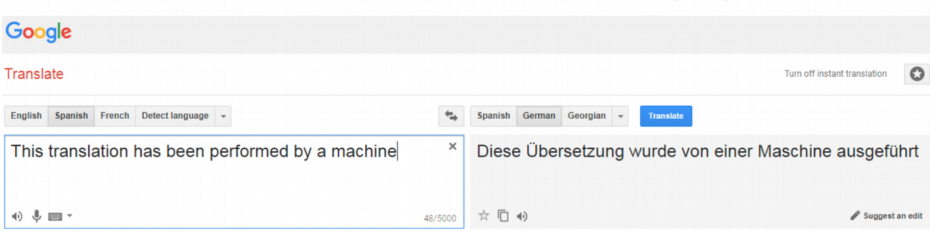




Playing Games



Language Translation



Why machine learning now?

- Amount of data(Big data)
- Computing power(GPU)
- Improved Algorithms

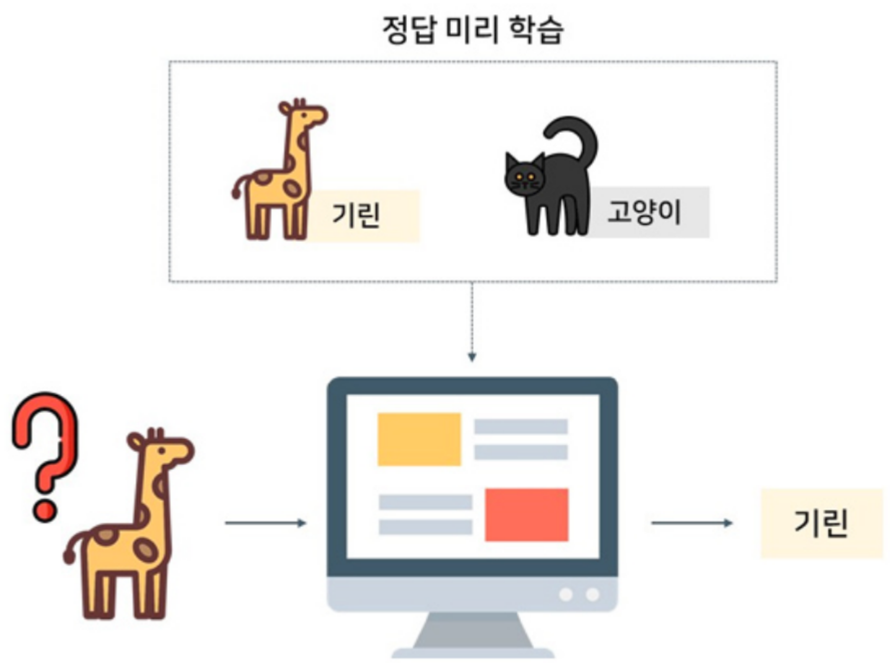
Categorization of ML

머신러닝의 분류

Categorization of ML

- **지도학습 (Supervised Learning)**

  : 정답이 주어진 상태에서 학습하는 알고리즘

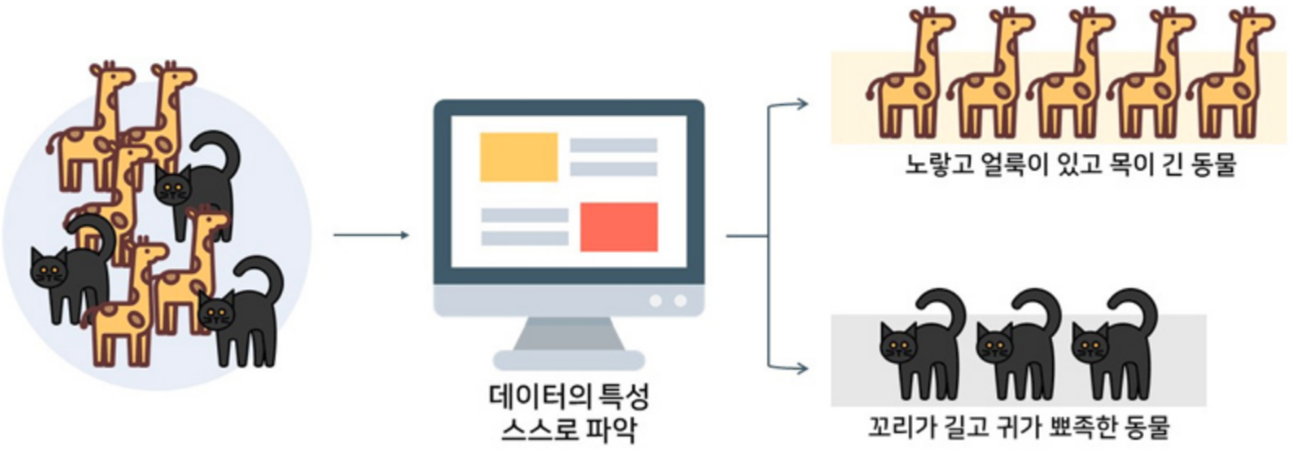


지도학습의 학습방식

Categorization of ML

- 비지도 학습 (Unsupervised Learning)

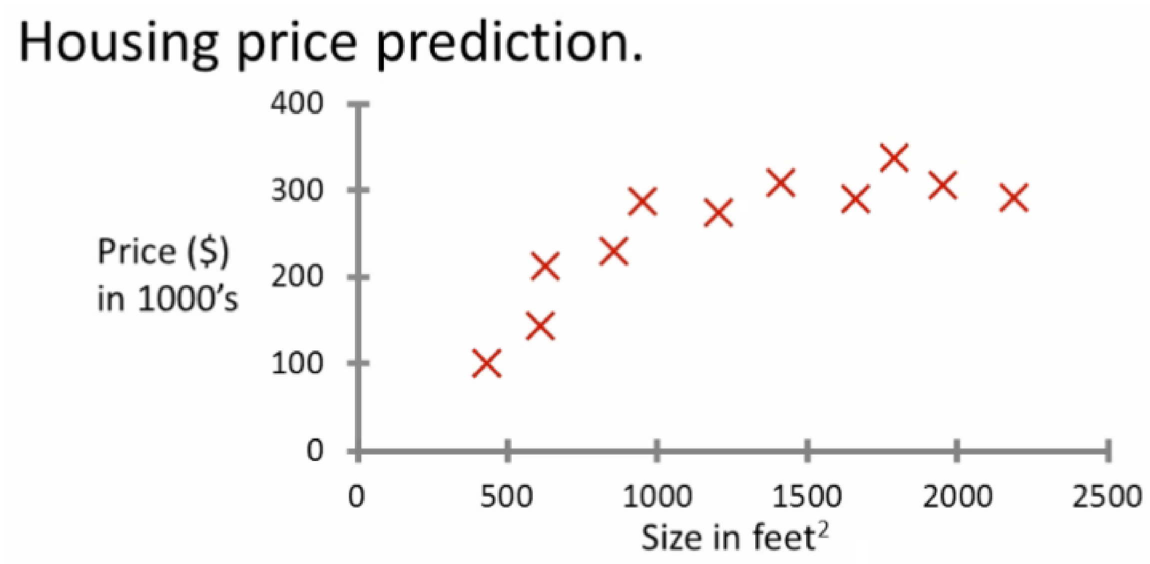
  : 정답이 주어지지 않은 상태에서 학습하는 알고리즘

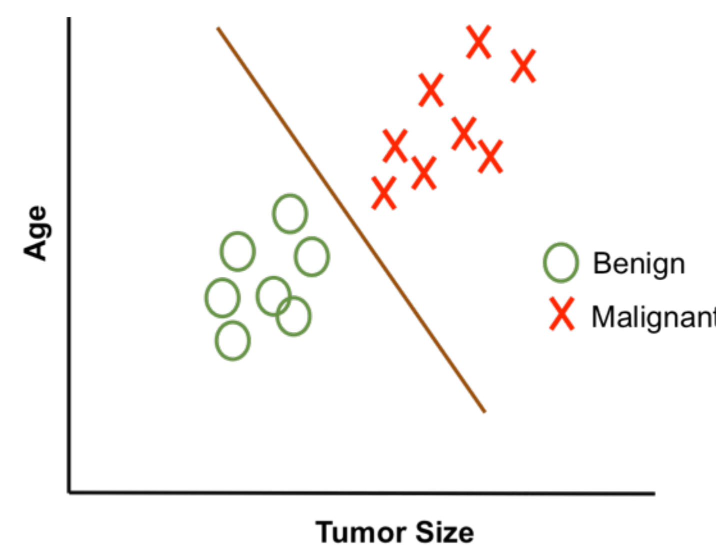


비지도학습의 학습방식

Supervised learning

- 데이터 (입력) 에 대한 레이블 (정답) 이 존재
- 정답 종류에 따라 분류 또는 회귀

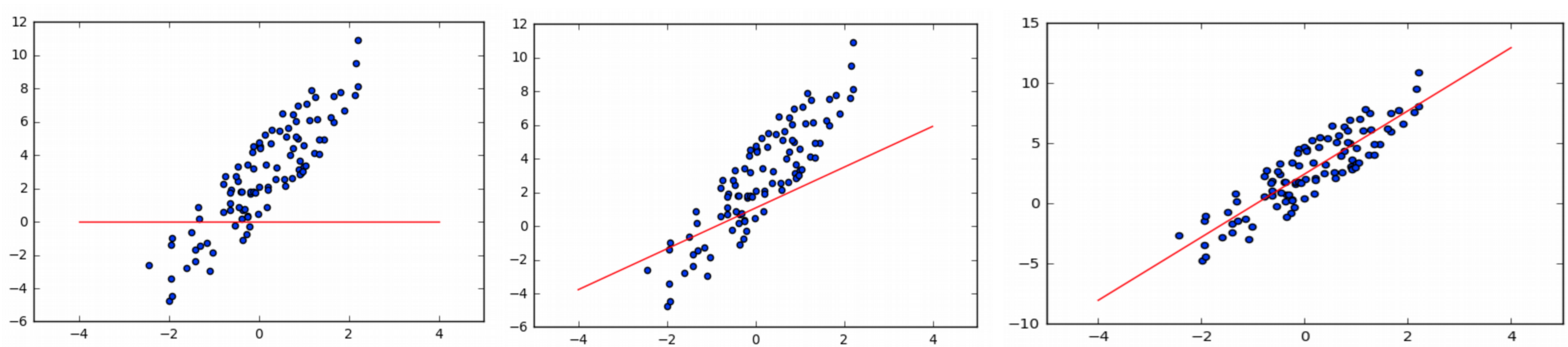




Linear Regression(Supervised)

- 다음 중 데이터를 가장 잘 표현하는 함수 (직선) 는 ?

  ex) 키와 몸무게



What’s linear regression?

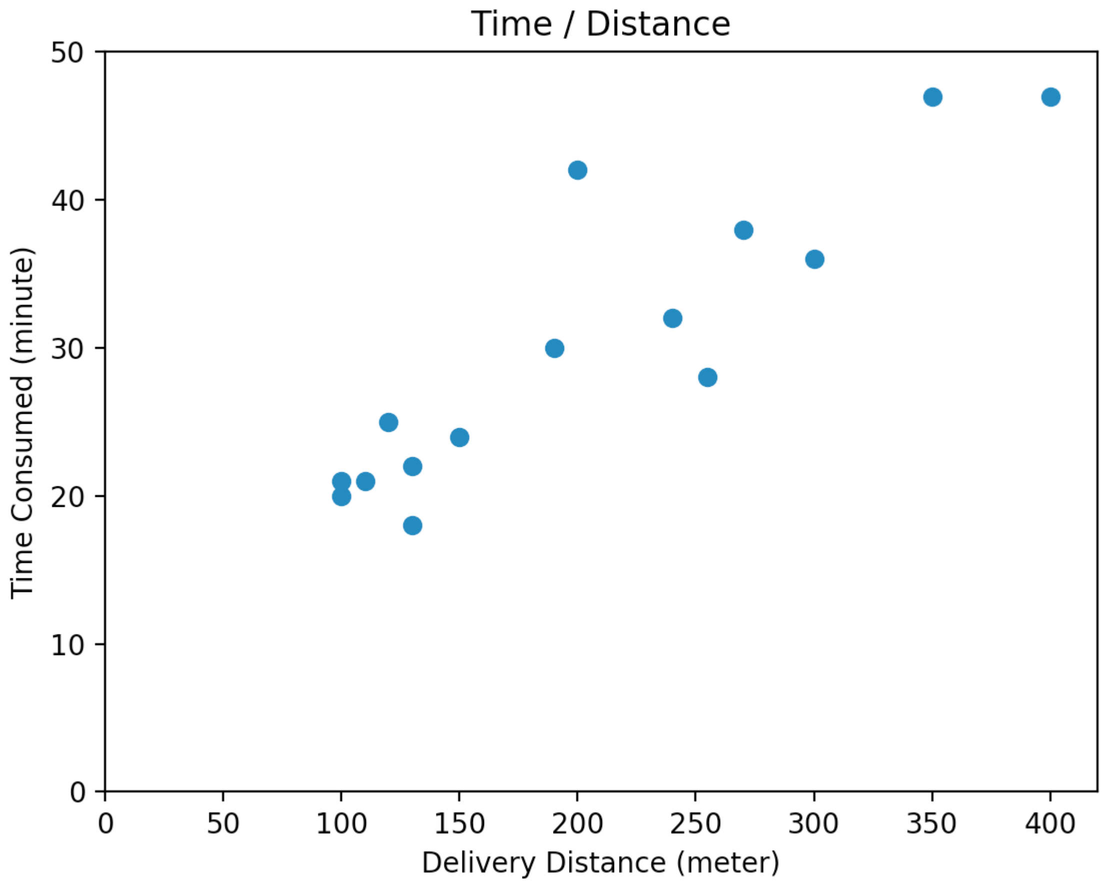
- 연속형 (수치) 값을 예측하기 위한 모델
- 주어진 데이터로부터 입력 (x) 와 출력 (y) 사이의 선형 관계를 분석하는 것

$$Y(\text{키}) = a * X(\text{몸무게}) + b$$

$$y = f(\theta_0 x_1 + \theta_1 x_2 + \ldots + \theta_n x_n)$$

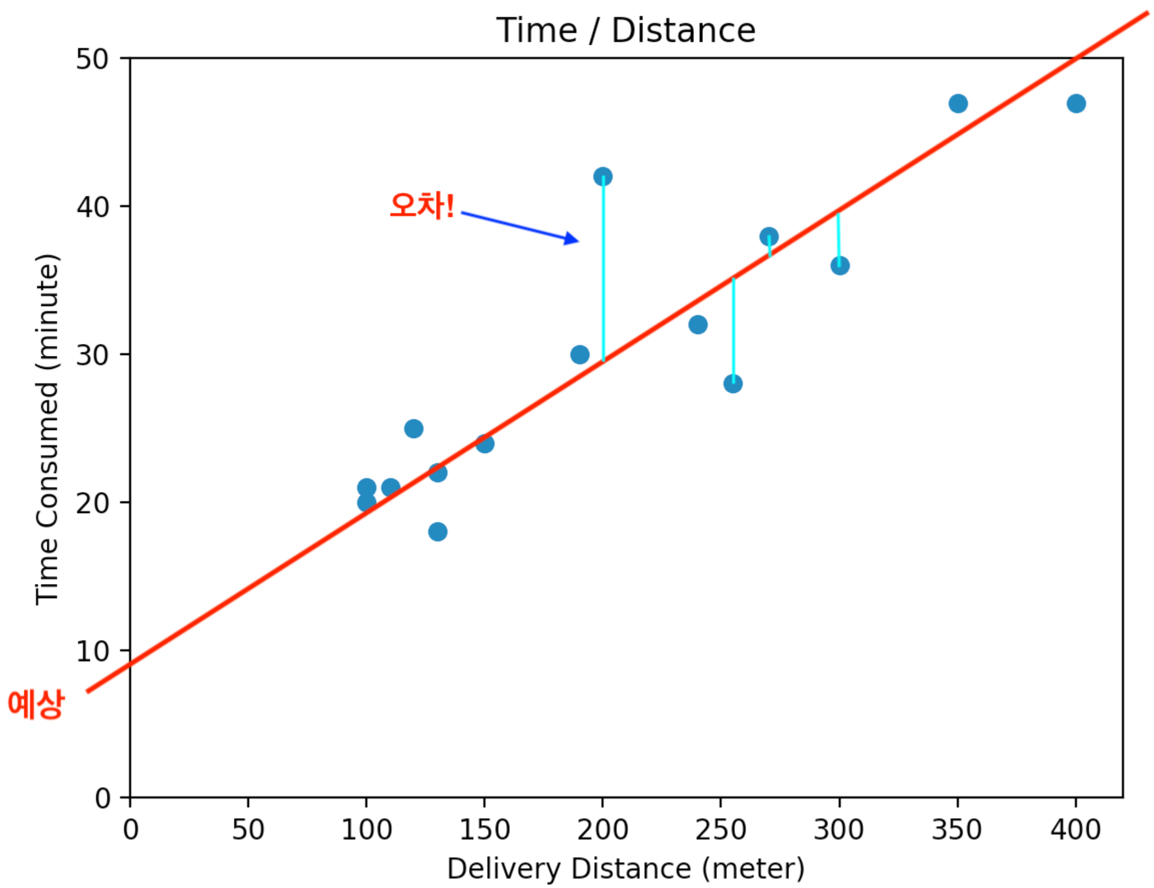
Linear Regression(Supervised)

- (배달 시간) 50m 거리 일 때는 ?



Linear Regression(Supervised)

- **예상 : 약 13 분 ?**



오차가 최소가 되는
직선 찾기 !

$$Y(\text{배달시간}) = a * X(\text{거리}) + b$$

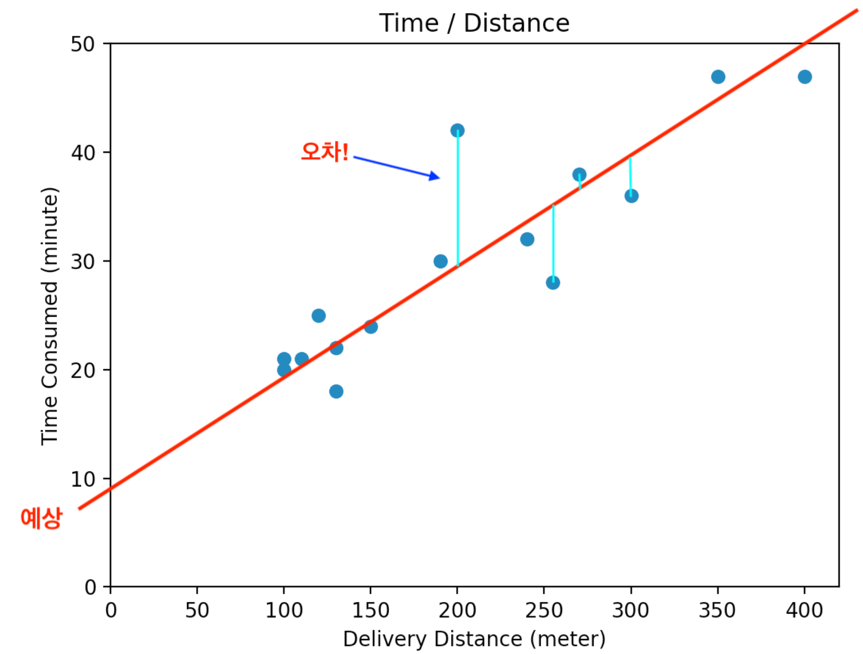
Linear Regression(Supervised)

- **가설 (hypothesis)**

$$h_\theta(x) = \theta_0 + \theta_1 x \; (\theta_i : \text{Parameter})$$

- **비용 함수 (cost function)**

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



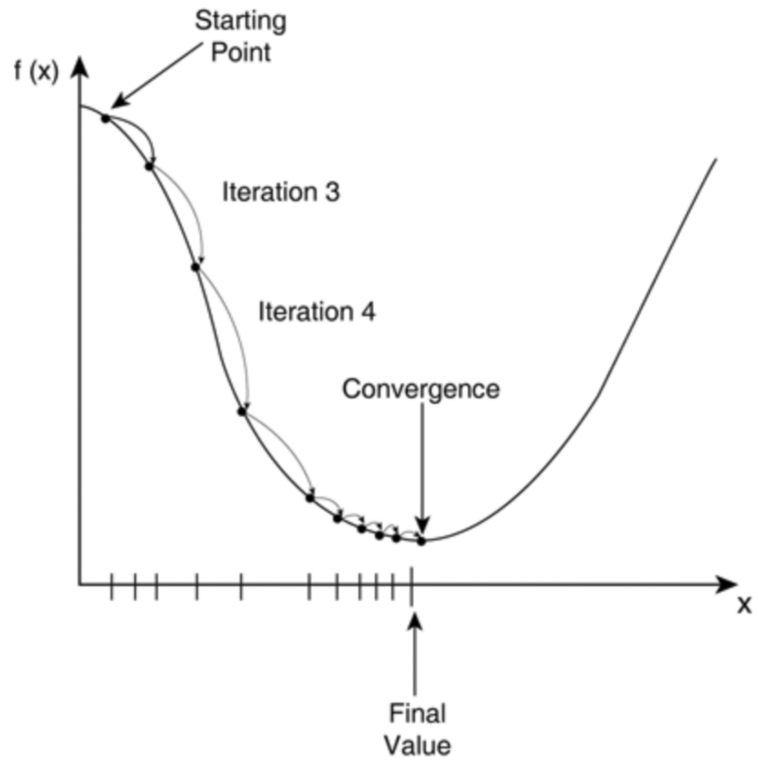
오차를 최소화하는 파라미터 (Θ) 를 찾는 것이 목적 !

= 데이터를 가장 잘 설명하는 모델을 찾는다 (model fitting)

How to minimize cost function?

- 경사하강법 (Gradient descent)

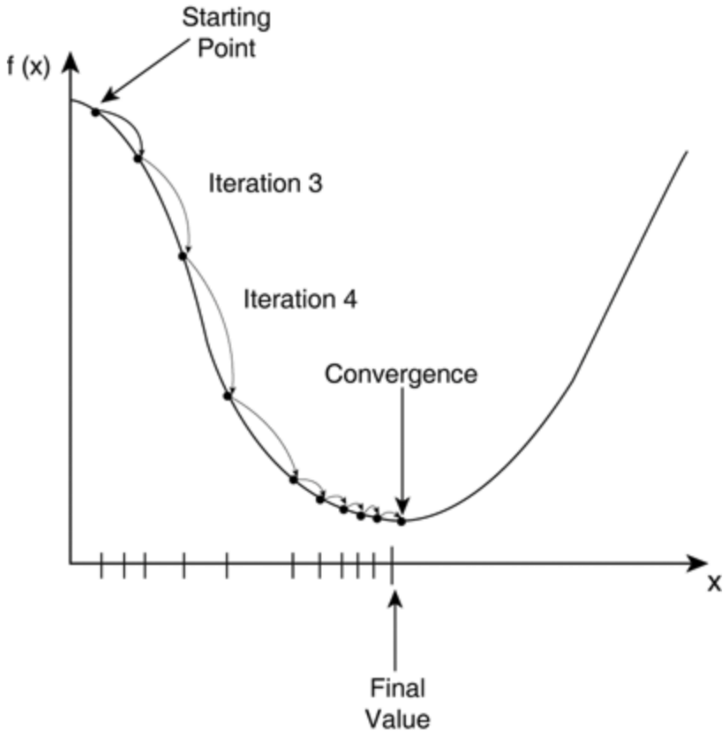
  : 비용 함수를 최소화하기 위한 최적화 알고리즘 (기울기로 함수의 최솟값을 찾는다)



Gradient Descent Algorithm

$h_\theta(x) = \theta_0 + \theta_1 x$ (θ_i : Parameter)

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



1. 파라미터 초기화
2. 해당 파라미터에 대한 기울기 계산
3. 파라미터 업데이트
4. 비용 함수가 수렴할 때까지 (최솟값을 가질 때까지) 반복

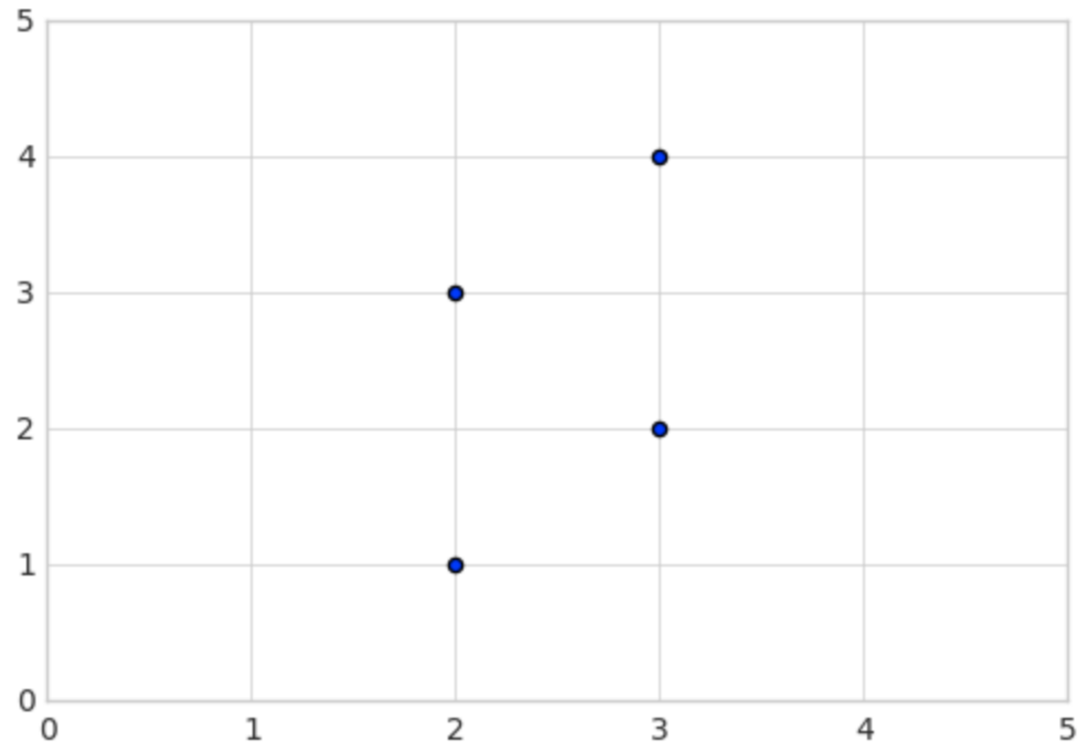
repeat until convergence {

$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$ (for j=0 and j=1)

}

α : learning rate(학습률)

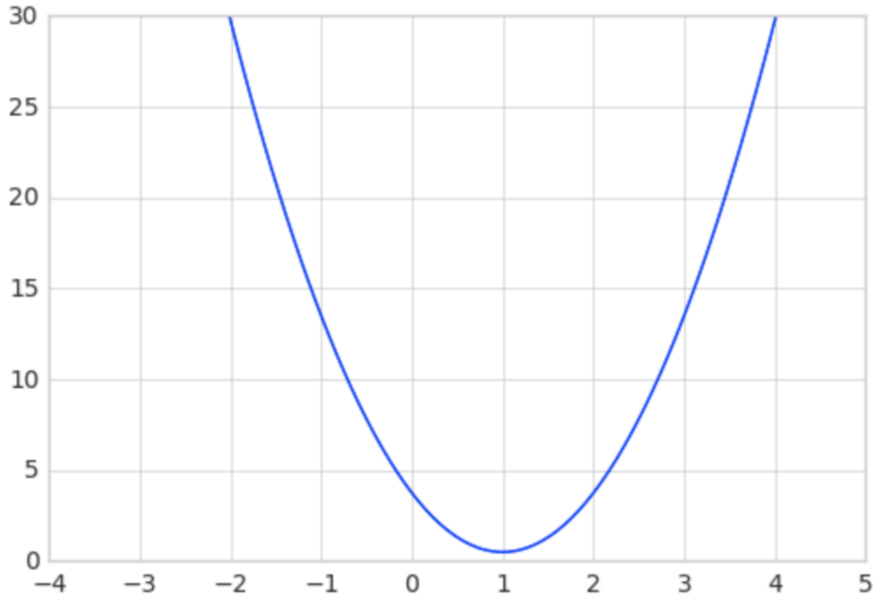
Gradient descent example



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

$$J(\theta_1) = \frac{1}{2*4} \sum_{i=1}^{4} (h_\theta(x^i) - y^i)^2 = \frac{1}{8}(26\theta_1^2 - 52\theta_1 + 30)$$

Gradient descent example



$$J(\theta_1) = \frac{1}{8}(26\theta_1^2 - 52\theta_1 + 30)$$

θ_1 의 초깃값 = 0 , $\alpha = 0.1$

```
for i in range(38):
    theta = update_theta(theta, alpha)
    print (theta)
```

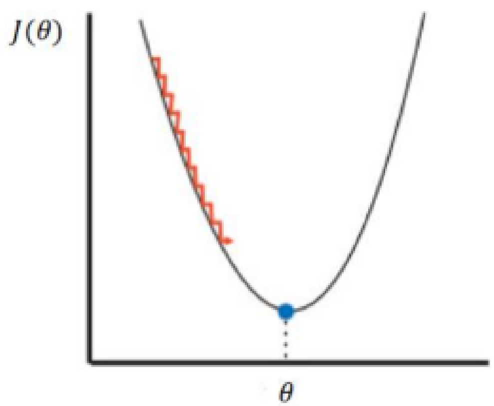
```
0.65
0.8775000000000001
0.957125
0.98499375
0.9947478125
0.998161734375
0.99935660703125
0.9997748124609375
0.9999211843613282
0.9999724145264649
0.9999903450842628
0.9999966207794919
0.9999988172728221
0.9999995860454878
0.9999998551159207
0.9999999492905722
0.9999999822517003
0.9999999937880951
0.9999999978258333
0.9999999992390416
0.9999999997336646
0.9999999999067826
0.9999999999673739
0.9999999999885809
0.9999999999960033
0.9999999999986011
0.9999999999995104
0.9999999999998286
0.99999999999994
0.999999999999979
0.9999999999999927
0.9999999999999974
0.9999999999999991
0.9999999999999997
0.9999999999999999
1.0
1.0
1.0
```

Learning rate(학습률)

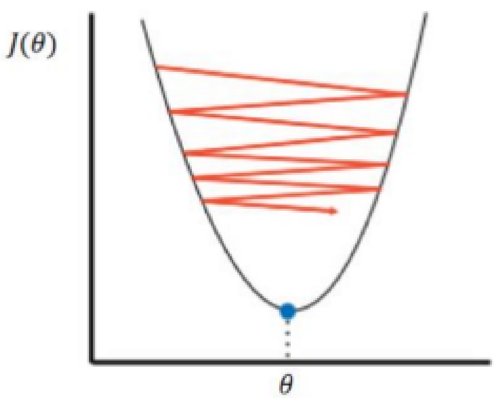
- 얼마나 많이 이동할 것인가 ?

```
theta = 0
alpha = 0.5
for i in range(10):
    theta = update_theta(theta, alpha)
    print (theta)
```

```
3.25
-4.0625
12.390625
-24.62890625
58.6650390625
-128.746337890625
292.92926025390625
-655.8408355712891
1478.8918800354004
-3324.256730079651
```

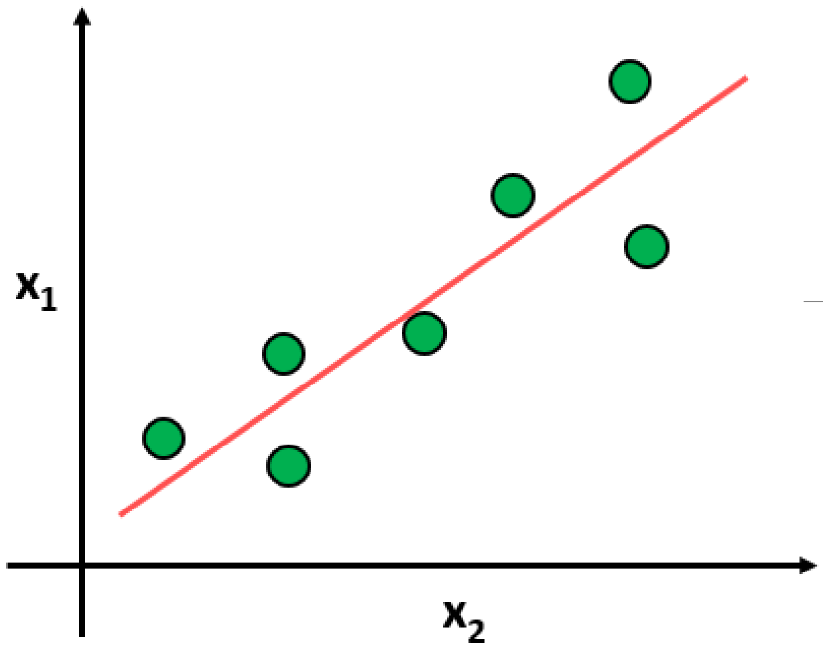


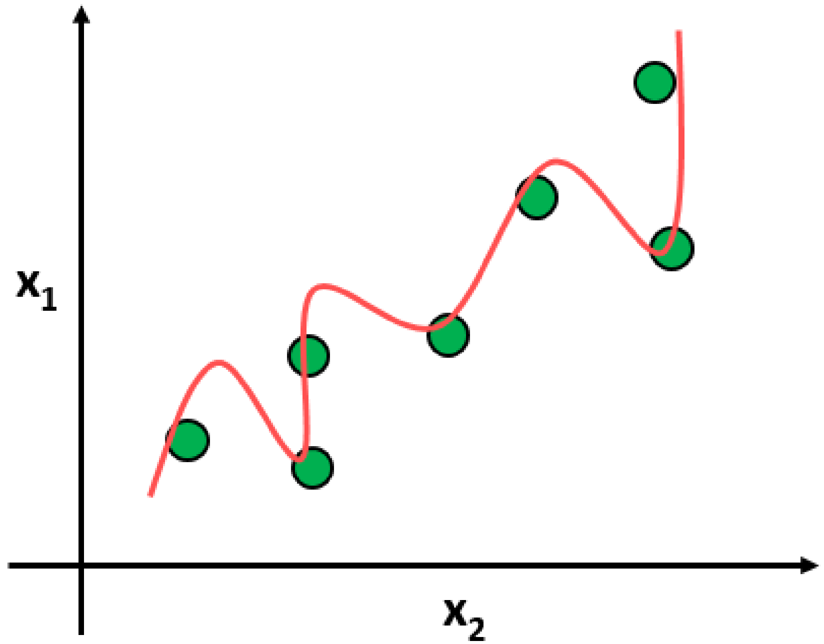
Too small: converge very slowly



Too big: overshoot and even diverge

Why not?

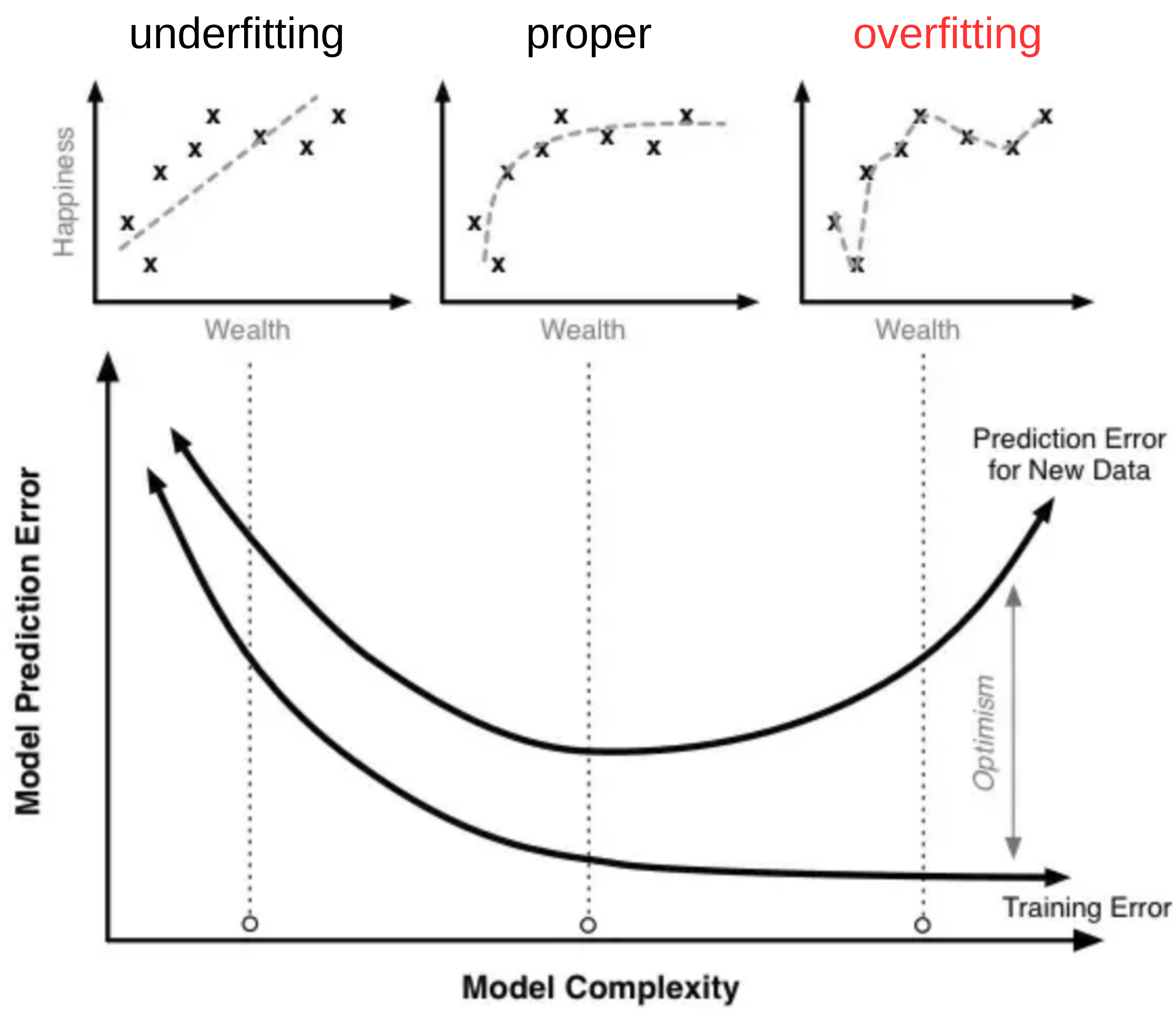




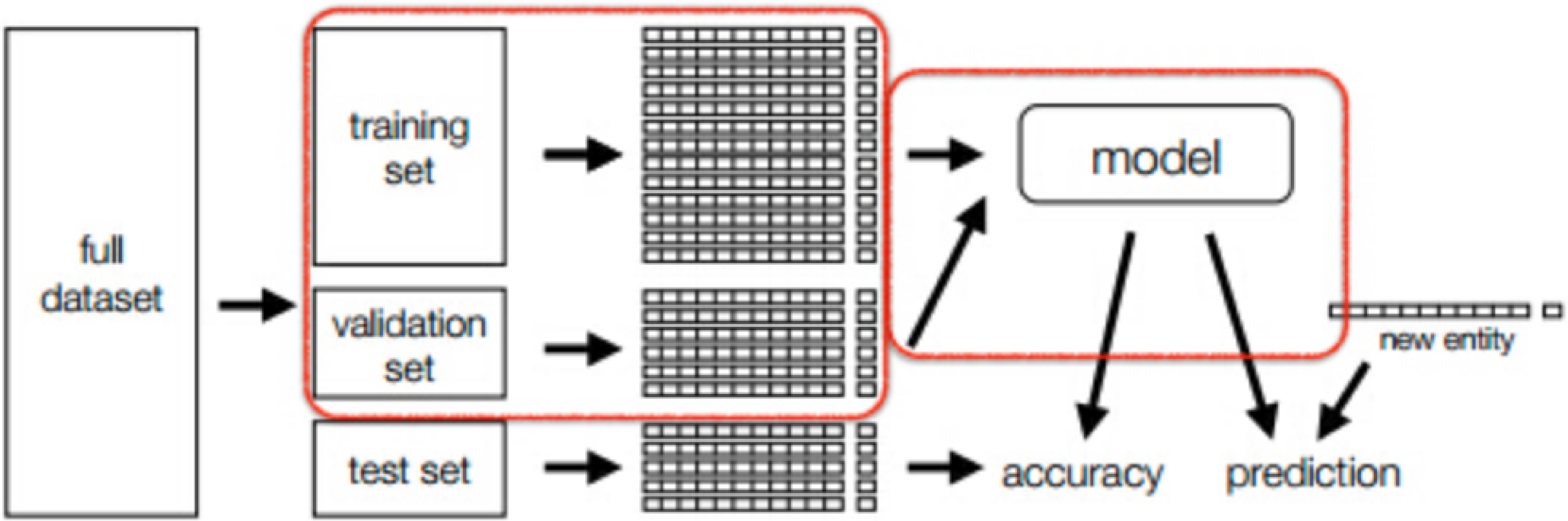
y = wx + b

y = w1x1 + w2x2 + … + w9x9 +b

Model complexity



Data set includes ...



Training set : 모델 학습

Validation set : 모델 선택 / Hyper parameter 최적화

Test set : 오직 평가

Logistic Regression(Supervised)

- 분류 문제를 해결하기 위한 모델 (주로 이진 분류)

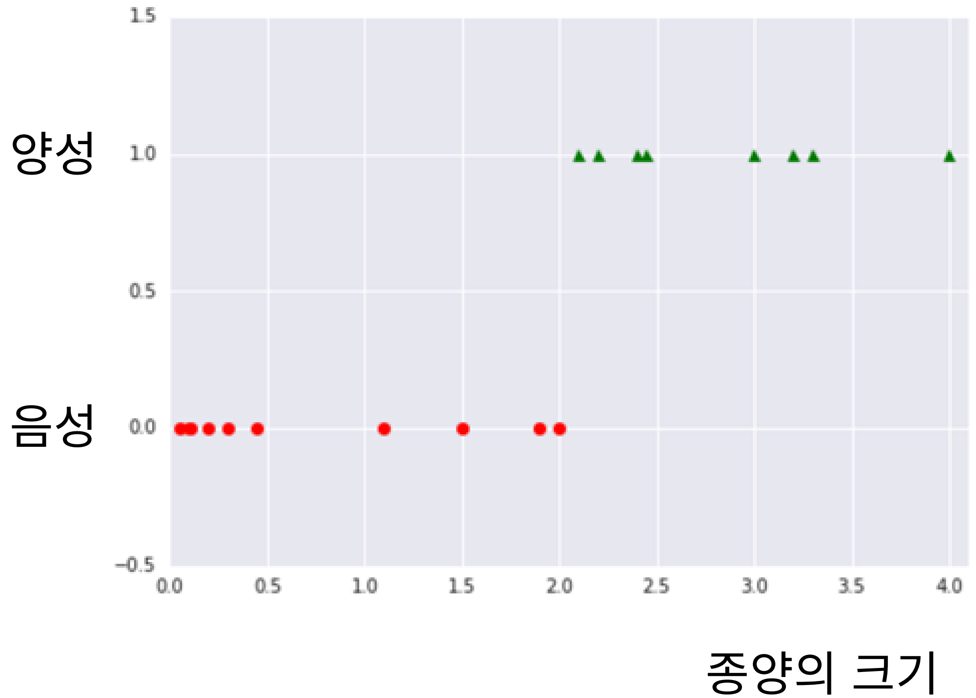
  ex) 스팸 메일 분류 , 질병 양성 / 음성 분류 등
- 결과 값을 0 또는 1 로 표현
- 특정 범주 (0 또는 1) 에 속할 확률을 계산

Logistic Regression(Supervised)

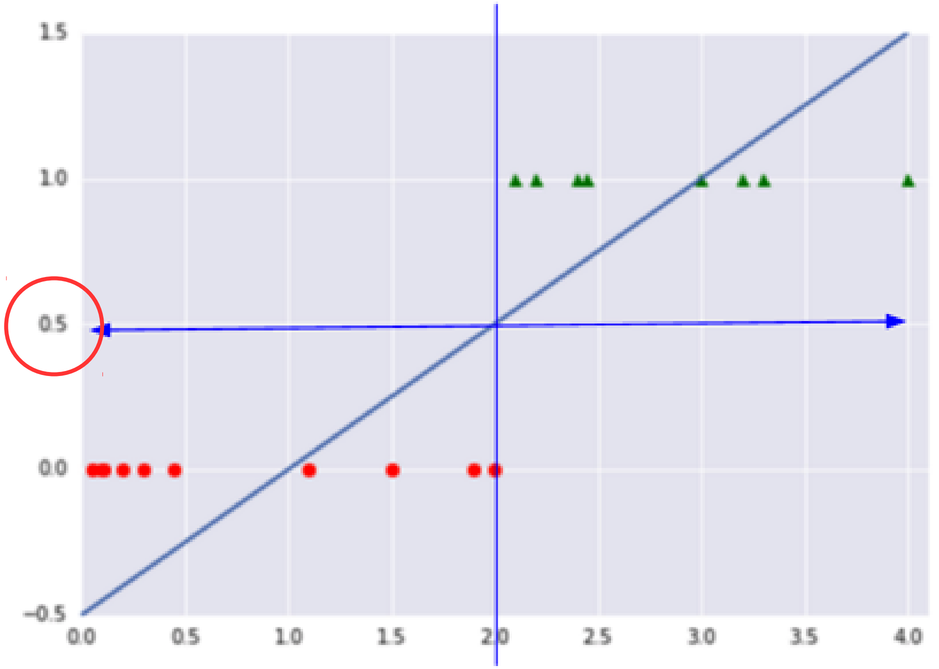
- 고객이 5 년 내에 사망할 확률 ?

Sex	Age	Diabetes	...	Life span
Male	20	Yes	...	65
Female	40	Yes	...	68
Male	60	No	...	64

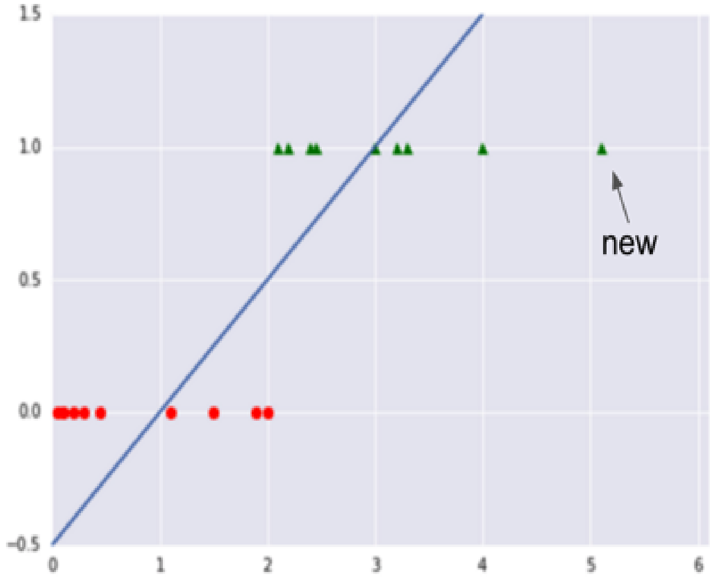
Logistic Regression(Supervised)

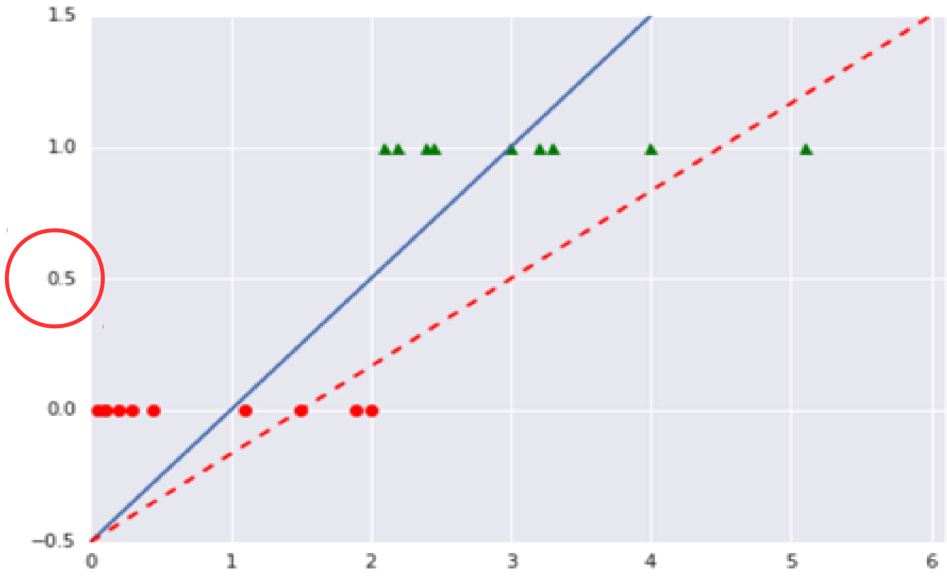


Linear Regression?



Logistic Regression(Supervised)

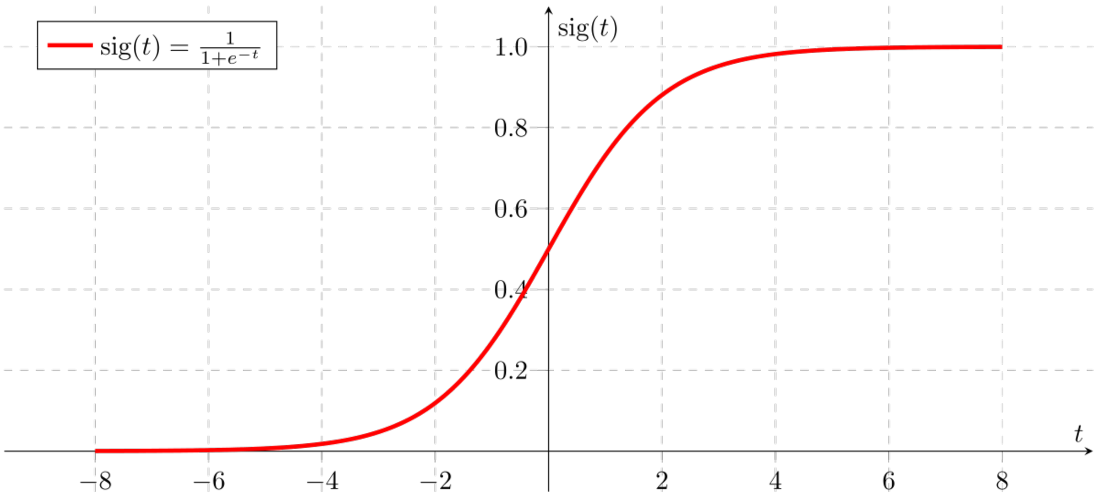




Linear regression for classification?

Problem 1) Threshold 2) Range

Logistic Regression(Supervised)



Q. 양성 VS 음성 ?

$$h = p\left(Y = 양성 \middle| X = 데이터\right)$$

If h > 0.5 → 양성

If h < 0.5 → 음성

t = a*X + b

h = sigmoid (t)

t > 0 → 양성 (y=1)

t < 0 → 음성 (y=0)

Logistic Regression(Supervised)

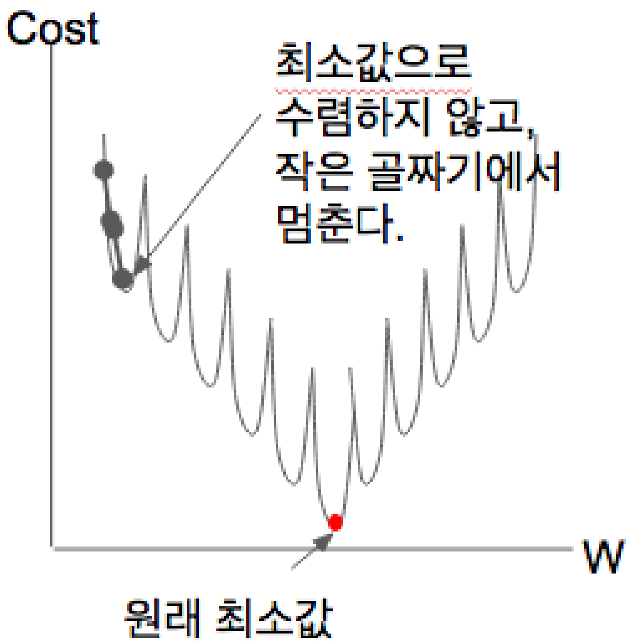
- **가설 (hypothesis)**

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

- **비용 함수 (cost function)**

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

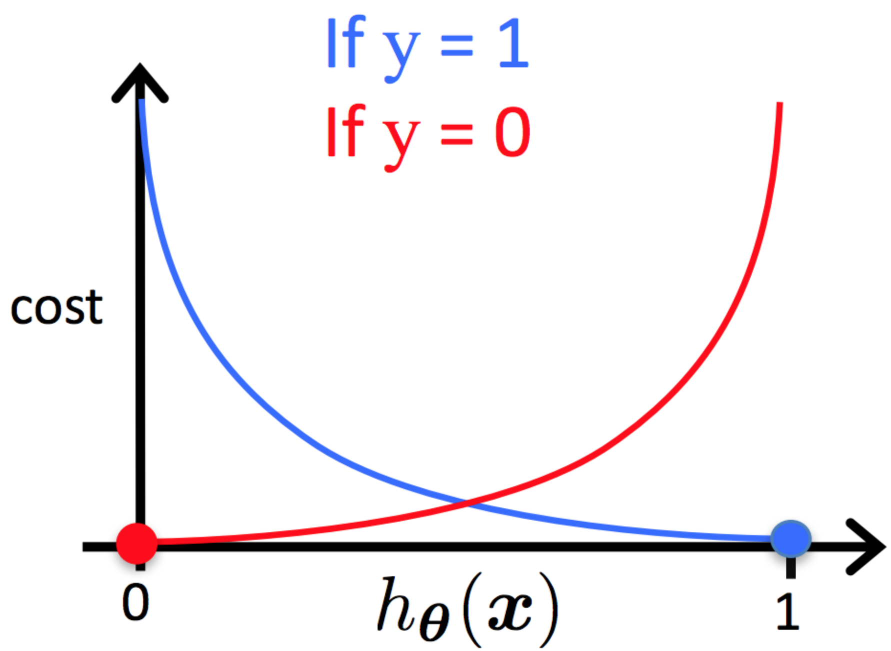
새로운 비용 함수 필요



Logistic Regression(Supervised)

- **비용 함수 (cost function)**

$$\mathrm{Cost}(h_\theta(x), y) = \begin{cases} -\log(h_\theta(x)) & \text{if } y = 1 \\ -\log(1 - h_\theta(x)) & \text{if } y = 0 \end{cases}$$



Logistic Regression(Supervised)

- 비용 함수 (cost function)

$$\mathrm{Cost}(h_\theta(x), y) = \begin{cases} -\log(h_\theta(x)) & \text{if } y = 1 \\ -\log(1 - h_\theta(x)) & \text{if } y = 0 \end{cases}$$

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

비용 함수 (오차) 를 최소화 하는 파라미터 (θ) 를 찾는다 .

→ 경사 하강법 (Gradient descent)

Calculating Gradient

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

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

$$= \frac{1}{m}[\sum_{i=1}^{m} -y^{(i)} \log(\frac{1}{1+e^{-(\theta^T x^{(i)}+b)}}) - (1-y^{(i)}) \log(1-\frac{1}{1+e^{-(\theta^T x^{(i)}+b)}})]$$

$$= \frac{1}{m}[\sum_{i=1}^{m} -y^{(i)} (\log 1 - log(1+e^{-(\theta^T x^{(i)}+b)})) - (1-y^{(i)}) \log(\frac{e^{-(\theta^T x^{(i)}+b)}}{1+e^{-(\theta^T x^{(i)}+b)}})]$$

$$= \frac{1}{m}[\sum_{i=1}^{m} y^{(i)} log(1+e^{-(\theta^T x^{(i)}+b)}) - (1-y^{(i)}) \log(e^{-(\theta^T x^{(i)}+b)}) + (1-y^{(i)}) \log(1+e^{-(\theta^T x^{(i)}+b)})]$$

$$= \frac{1}{m}[\sum_{i=1}^{m} (1-y^{(i)})(\theta^T x^{(i)}+b) + \log(1+e^{-(\theta^T x^{(i)}+b)})]$$

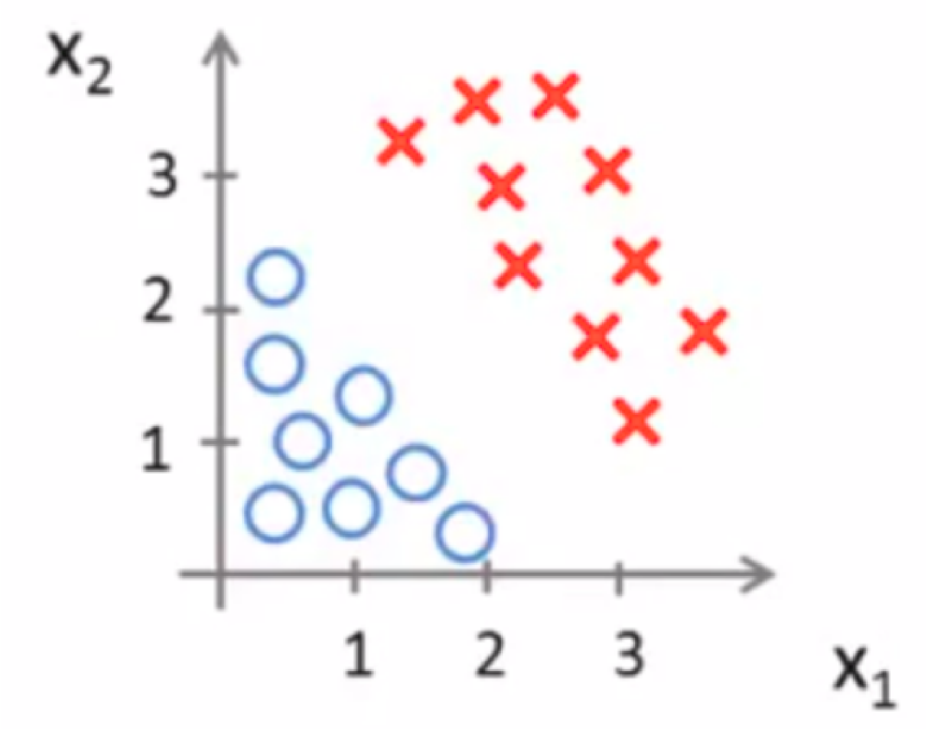
$$= \frac{1}{m}[\sum_{i=1}^{m} \log e^{\theta^T x^{(i)}+b} - y^{(i)}(\theta^T x^{(i)}+b) + \log(1+e^{-(\theta^T x^{(i)}+b)})]$$

$$= \frac{1}{m}[\sum_{i=1}^{m} \log(e^{\theta^T x^{(i)}+b}+1) - y^{(i)}(\theta^T x^{(i)}+b)]$$

$$\frac{\partial J(\theta)}{\partial \theta_j} = \frac{1}{m}[\sum_{i=1}^{m} \frac{x_j e^{\theta^T x^{(i)}+b}}{e^{\theta^T x^{(i)}+b}+1} - y^{(i)} x_j] = \frac{1}{m} x_j \sum_{i=1}^{m} [\frac{1}{1+e^{-(\theta^T x^{(i)}+b)}} - y^{(i)}] = \frac{1}{m} x_j \sum_{i=1}^{m} [h_\theta(x^{(i)}) - y^{(i)}]$$

$$\frac{\partial J(\theta)}{\partial b} = \frac{1}{m}[\sum_{i=1}^{m} \frac{e^{\theta^T x^{(i)}+b}}{e^{\theta^T x^{(i)}+b}+1} - y^{(i)}] = \frac{1}{m} \sum_{i=1}^{m} [\frac{1}{1+e^{-(\theta^T x^{(i)}+b)}} - y^{(i)}] = \frac{1}{m} \sum_{i=1}^{m} [h_\theta(x^{(i)}) - y^{(i)}]$$

Decision Boundary



$$h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$$

$$\theta = \begin{bmatrix} -3 \\ 1 \\ 1 \end{bmatrix}$$

predict "$y = 1$" if $-3 + x_1 + x_2 \geq 0$

$\Leftrightarrow x_1 + x_2 \geq 3$

the line $x_1 + x_2 = 3$ we call that "Decision boundary"