

Introduction to Computer Science & Engineering

Lecture 12: A Few Basics of Learning Systems

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Introduction

if 문이나 while 문 없이 어떠한 데이터를
예측할 수 있는 것.

- What is machine learning?
 - ▶ Field of study that gives computers the ability to learn without being explicitly programmed
 - ▶ 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

E, T, P 3가지로 컴퓨터 프로그램 관행

Quick Example

- Suppose your email program watches which emails you do or do not mark as spam, based on that learns how to better filter spam. What is the task T in this example? And what is the experience E and the performance P ? 컴퓨터가 이해함 (숫자로 아쿠어인 Value)
- ▶ Classifying emails as spam or not spam Task T
- ▶ Watching you label emails as spam or not Experience E
- ▶ The number of emails correctly classified as spam/not spam Performance P

Machine Learning Algorithms

* Information system : 실제 데이터 분석고 활용 이용

machine Learning : 실제 Training Data 활용

- Supervised learning

지도식 학습방법

① Regression (연속)

② Classification (이산)

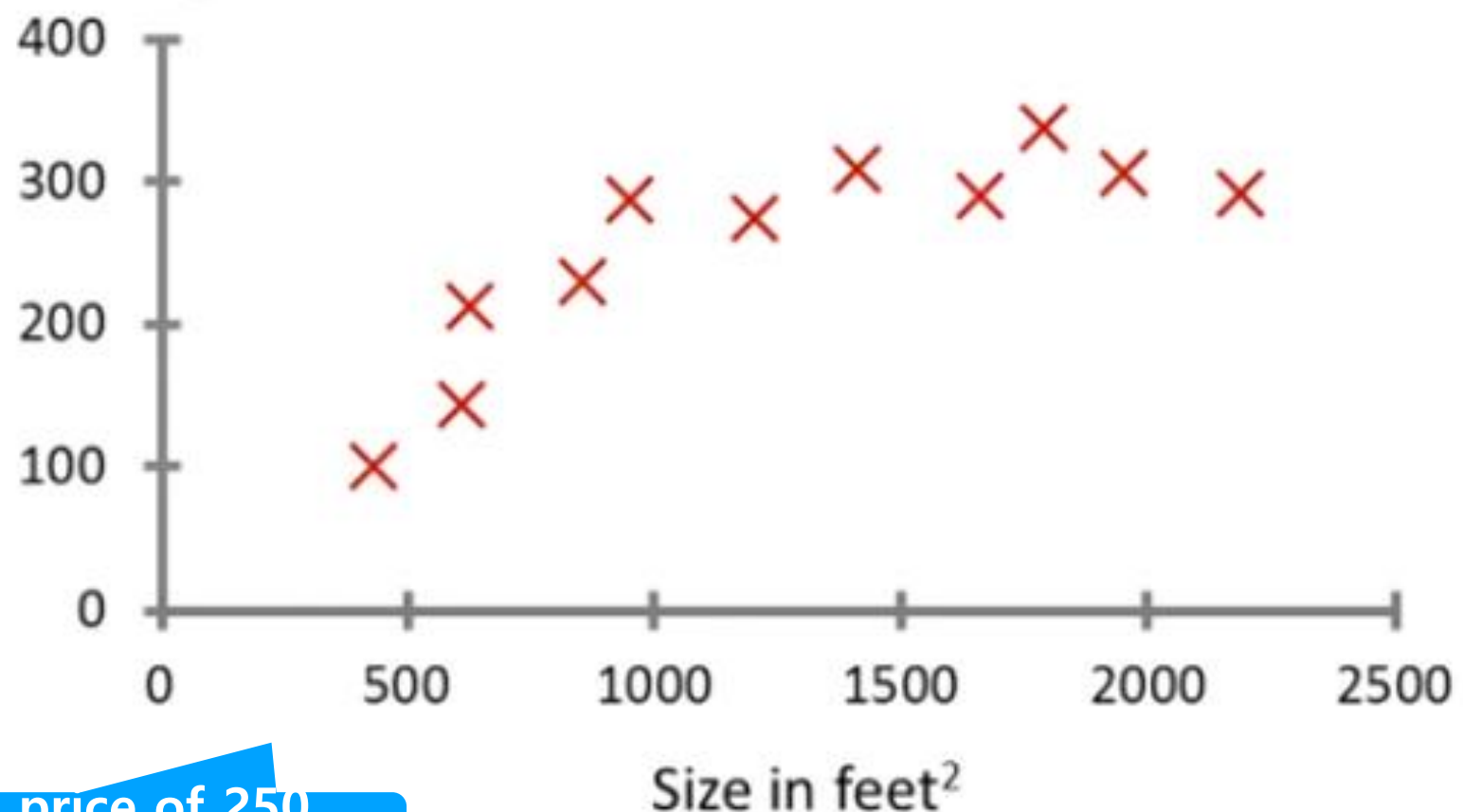
Housing price prediction.

이미 답을 알고있는 상태에서 학습

(Dataset이 이미 결과값을 포함함)

이미 정답 = 1900가
있을지 확인 가능)

Price (\$)
in 1000's



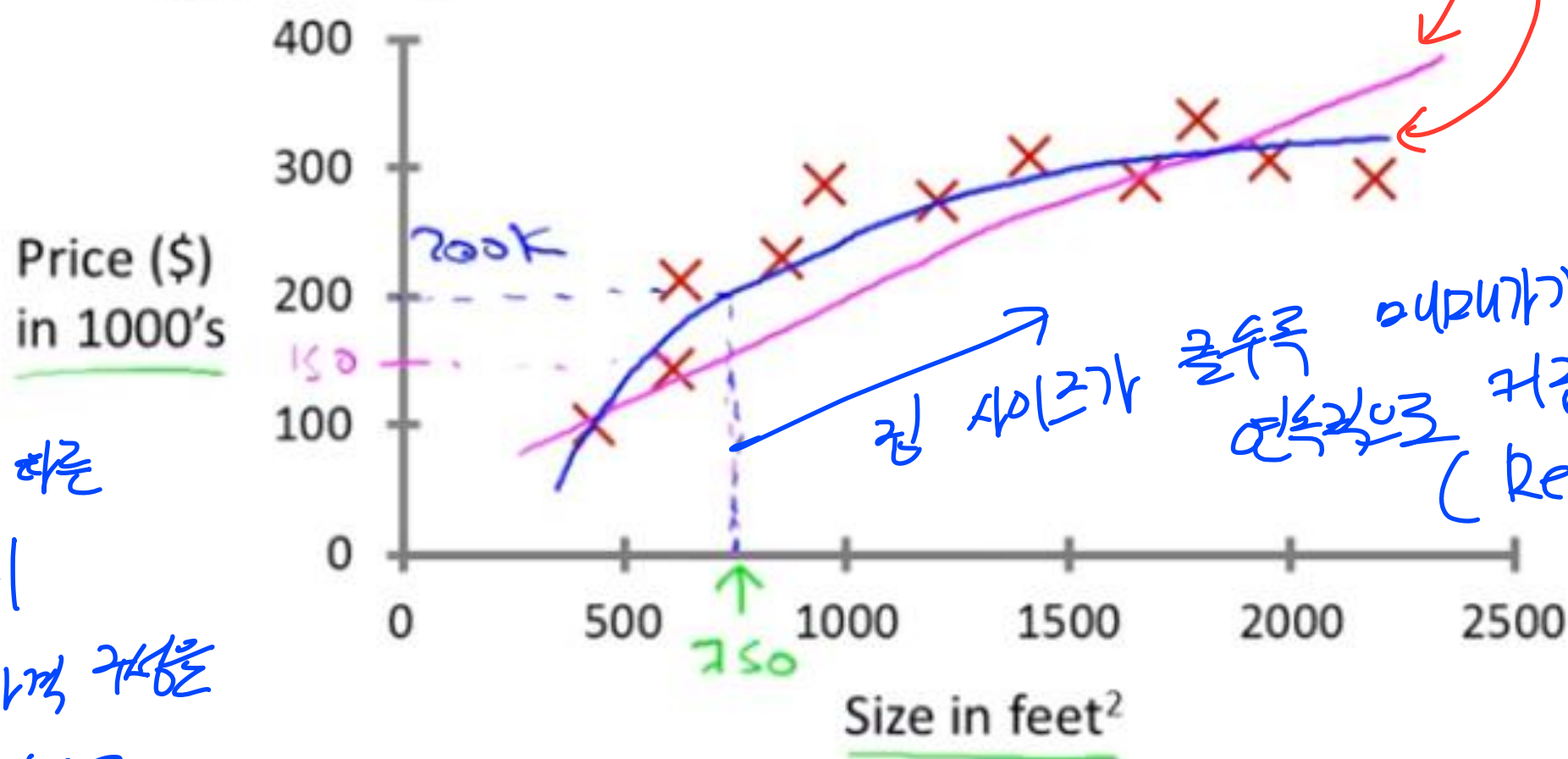
What is the price of 250
feet²?

Supervised Learning

Machine Learning 으로

예측한 value 이 대한 함수를

Housing price prediction.



ex) 집 사이즈에 따른
집의 가격분석 시
평가가 따른 가격 차이를
미리 알고 싶으므로

실제 집이 거래된 가격도 정확하게 알수있음.

이를 통해 평가지가 가격과 실제거래가격간의 cost (오차) 최소화.

Regression

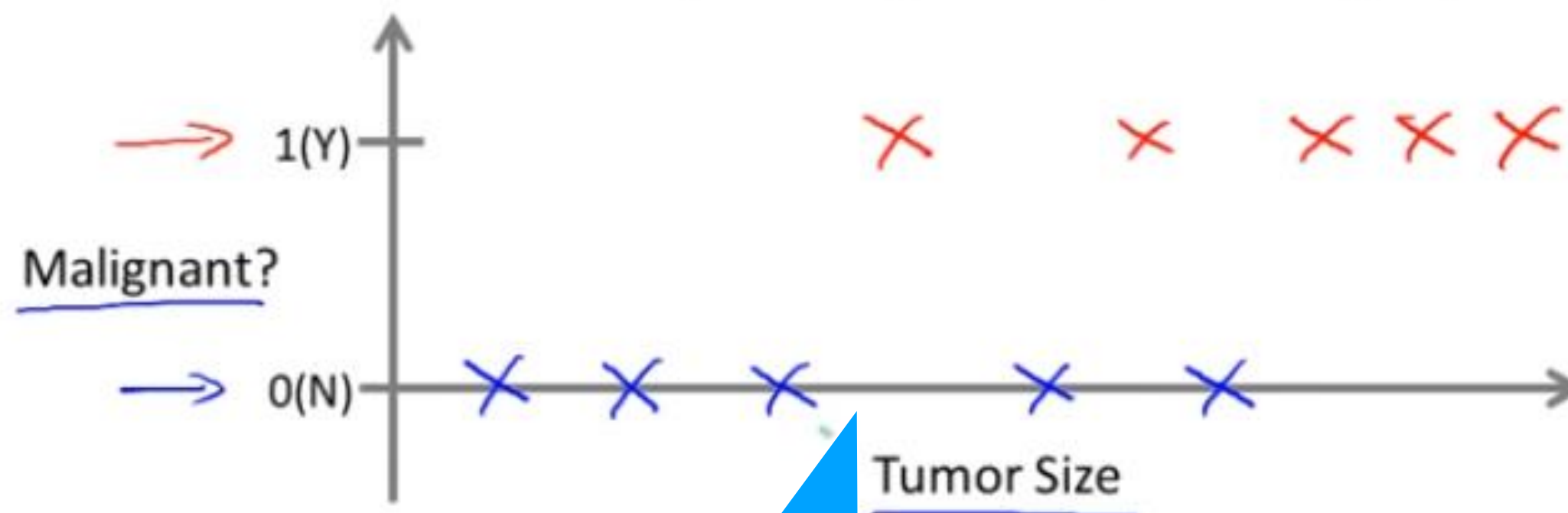
연속적인 output

- Right answers given
 - ▶ Called training set
학습된 데이터로 만든 집합
- The example is included in “regression”
 - ▶ Predict continuous valued output

Supervised Learning

입력(구조)이 여러 아피스트의 주어진 것 구분되는 것 Classification

Breast cancer (malignant, benign)



Would it be malignant if the tumor size is this much?

양성 크기를 기준으로

양성인지 아닌지 구분.

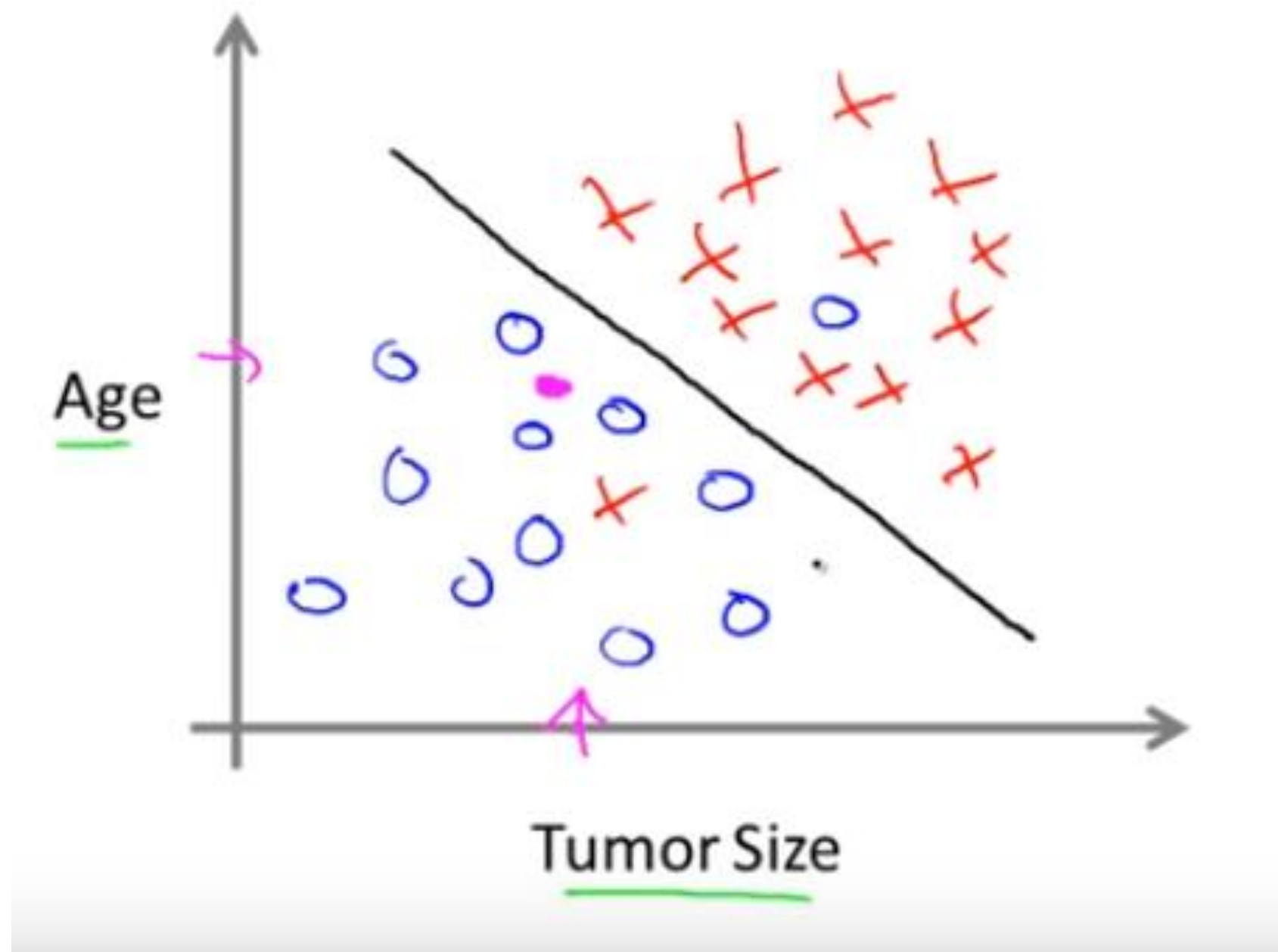
Classification

이산적인 output

- Discrete valued output
- Could be multiple
 - ▶ For example, cancer type 1, 2, 3, 4,...

Classification

- There can be multiple types of data



Unsupervised Learning

가설학습 \Rightarrow 우리가 답을 알고있지 않은 상태에서 학습하는 경우
(Data set 이 어떤 값이 들어있는지 모를때 사용)

Label 이 있어서 구분함

해만 비슷한

구체로 분류하는 것

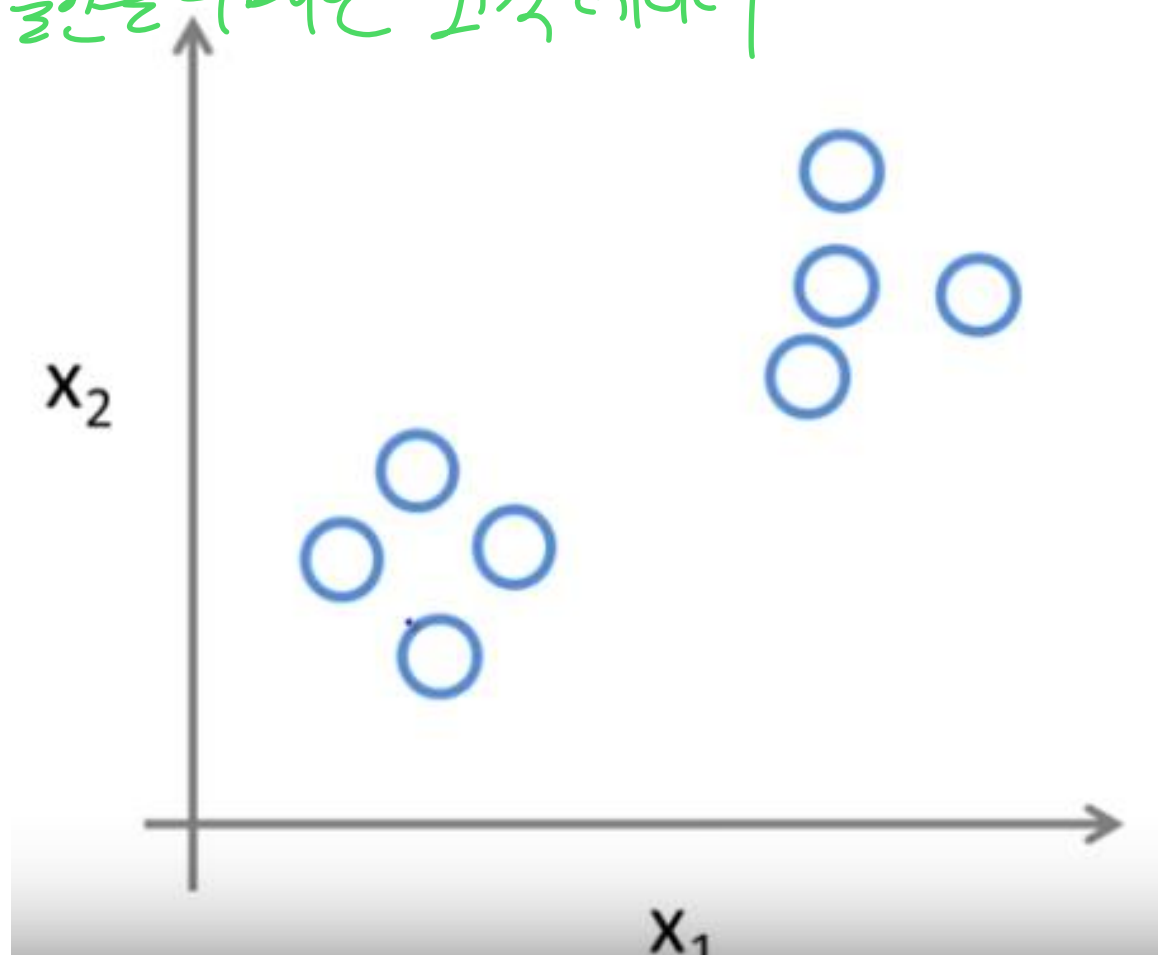
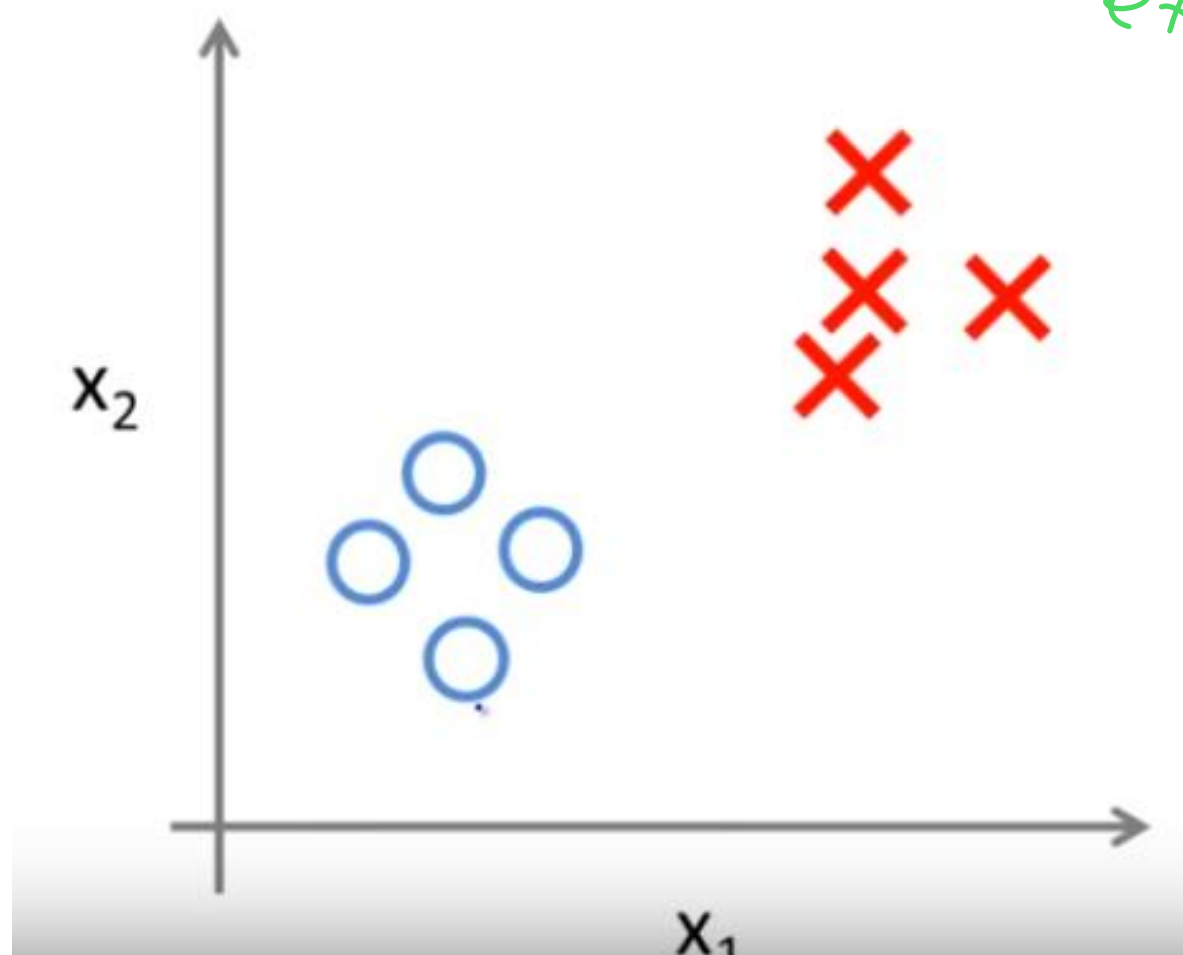
Label 구분이 안됨

(Clustering 이나 Grouping)

Supervised Learning

Unsupervised Learning

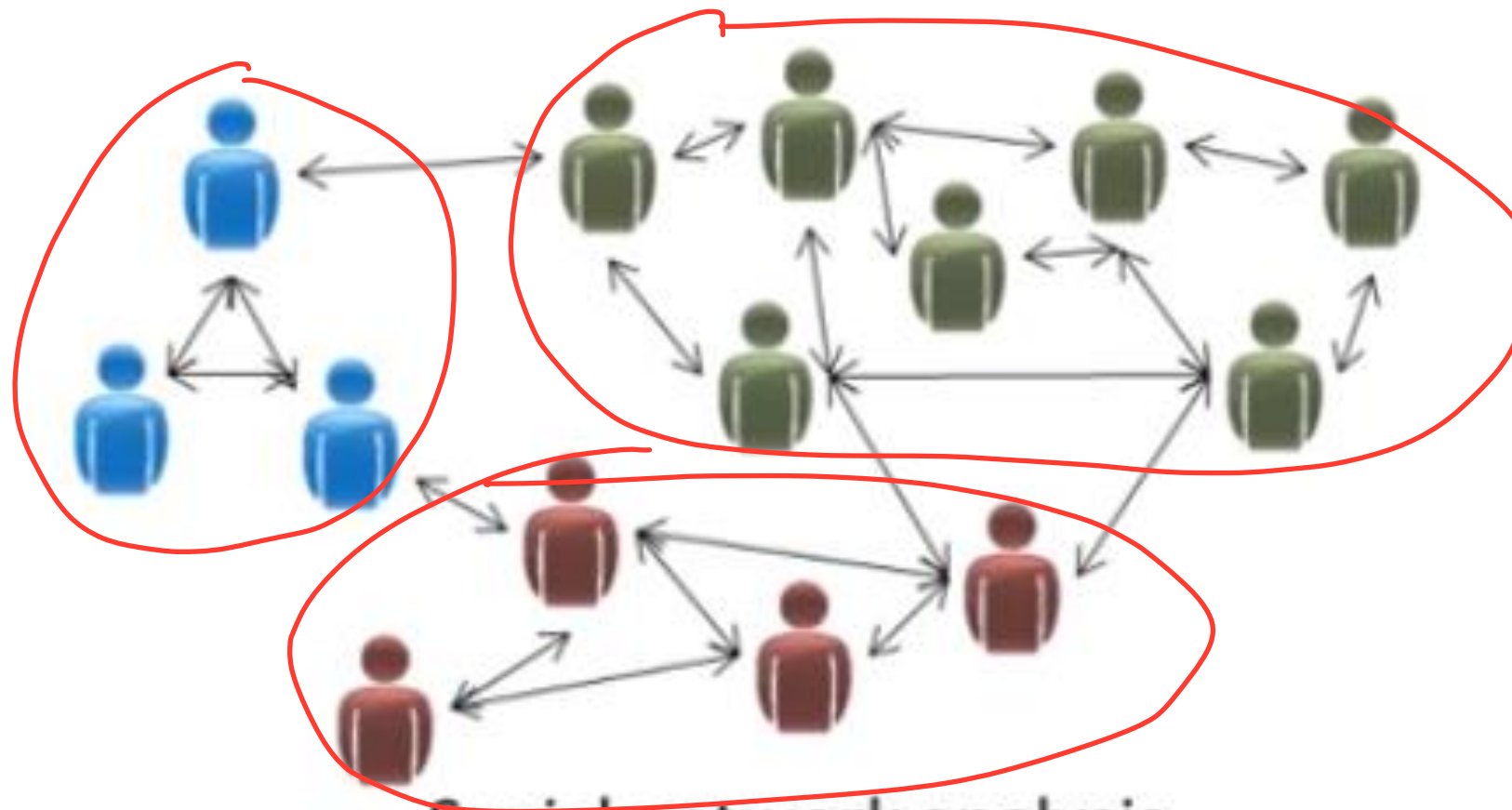
ex) 물건을 구분한 고객 데이터



Clustering

Group Name & 조직/계층
Group 별 구분 관리

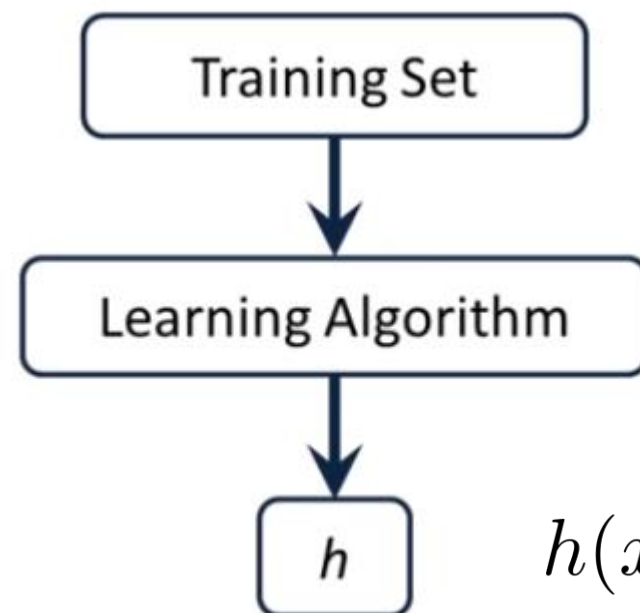
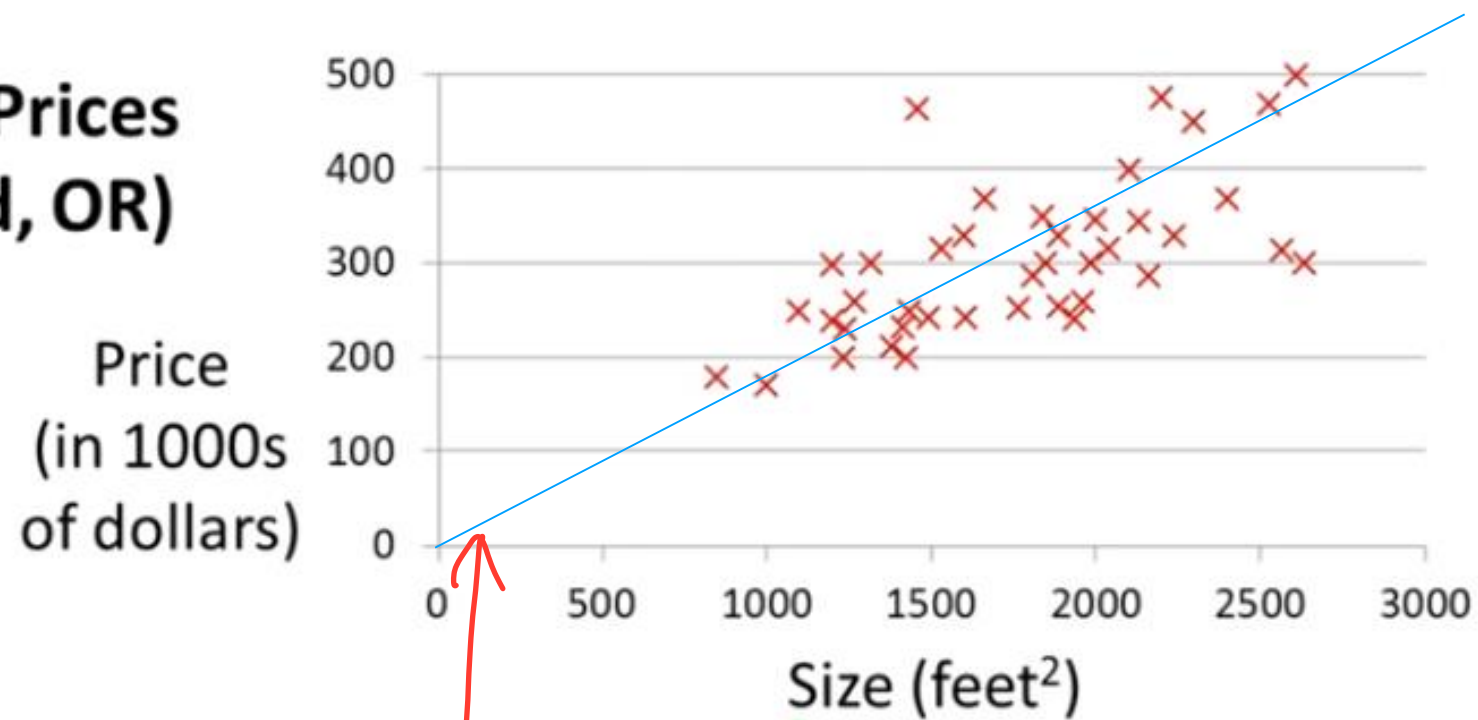
(Facebook)



Social network analysis

Linear Regression

Housing Prices (Portland, OR)



직선이 사이즈에 따른 값값

따라서 이 직선을 찾는것이 중요하게

우리가 직접 찾는게 아니라

알고리즘(머신)이 자동으로 찾아줄것임.

$$h(x) = ax + b$$

a, and b mean the parameters
of our function

Linear Regression

* 실제 환경은 supervised learning 이라고 하고, 그에 따른 $h(x) = Ax + b$ 를
원하므로 실제 환경은 값과 이 함수의 결과값을 비교하는데 Cost (오차)

- So, how to determine the parameters? 수직적으로 minimize 해서

- Principle

값을 줄이므로

$$\text{Cost} = (\text{예측값} - \text{실제값})^2$$
 (가이더스 방식)

- ▶ Choose the parameters so that $h(x)$ is close to the training data $\mathbf{t} = [t_1, t_2, \dots, t_N]$ for $\mathbf{x} = [x_1, x_2, \dots, x_N]$

* 제곱이 없으면 $h(x_i) < t_i$ 시

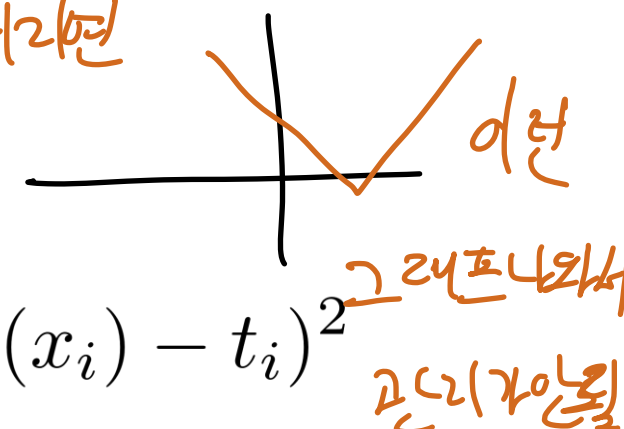
고려가 안되며 그냥다고
abs 취해버리면

- Find:

▶
$$\min \sum_{i=1}^N (h(x_i) - t_i)^2 \Rightarrow \text{최소값 구함}$$

$$h(x_i) = ax_i + b$$

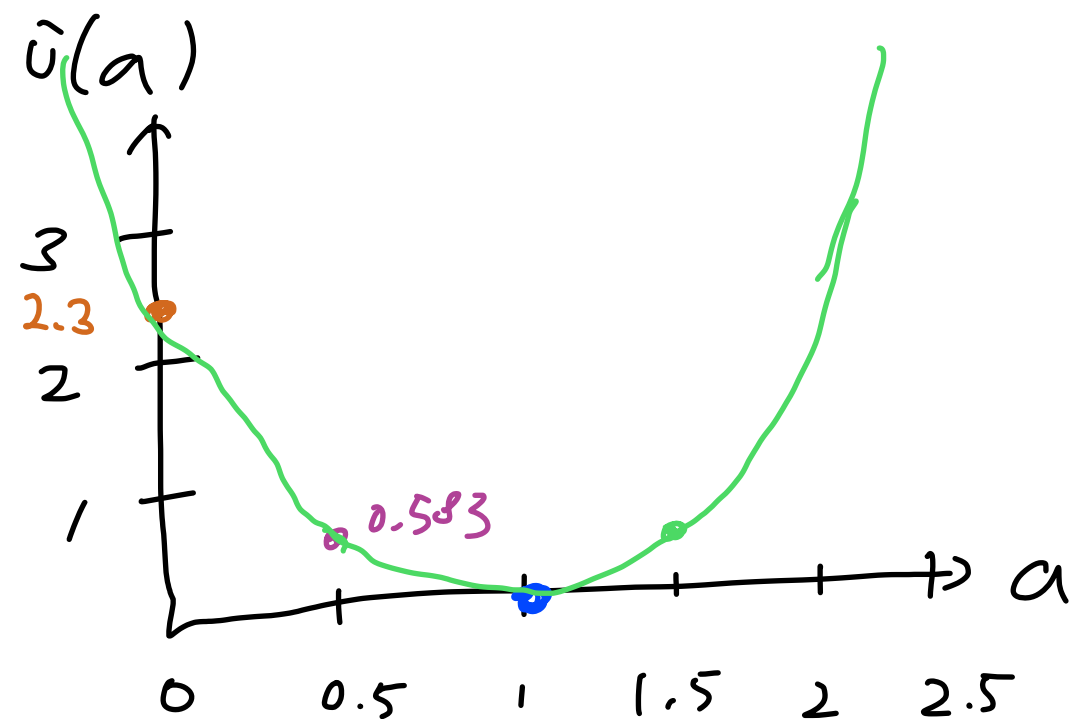
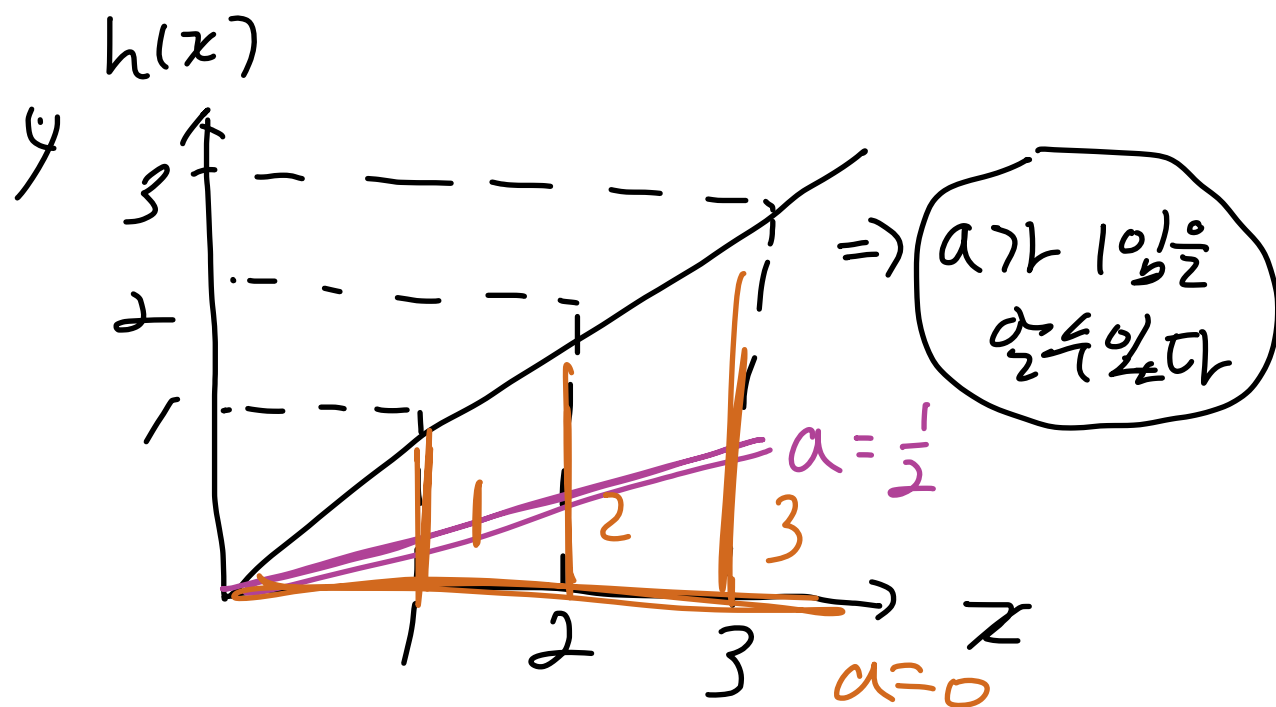
 실제 데이터



- We define the cost function $J(a, b) = \sum_{i=1}^N (h(x_i) - t_i)^2$

$\frac{1}{2N}$ 공짜이면 평균
 2N 미분을 왜 하냐
 제곱이 없었기 때문에
 그래프나워서 고려가 안됨
 Cost 줄이는
 J로 표시

$h(x) = ax$ 라 가정하면



실제결과인 $t_{\bar{x}}$ 와 $h(x)$ 가
동일하면 cost가 0일것.

$$J(a) = \sum_{\bar{x}=1}^N (h(x) - t_{\bar{x}})^2$$

$$h(x) = ax = 1 \times 3$$

$$J(1) = 0 \quad \text{0!}$$

$a = \frac{1}{2}$ 이면

$$\begin{aligned} J\left(\frac{1}{2}\right) &= \sum_{\bar{x}=1}^3 \left(\frac{1}{2}x - t_{\bar{x}}\right)^2 \\ &= \frac{1}{2 \cdot 3} \left[\left(\frac{1}{2} - 1\right)^2 + \left(\frac{2}{2} - 2\right)^2 + \left(\frac{3}{2} - 3\right)^2 \right] \\ &= \frac{1}{6} \cdot \left(\frac{1}{4} + 1 + \frac{9}{4}\right) = \frac{14}{24} \approx 0.583 \end{aligned}$$

$a = 0$ 이면

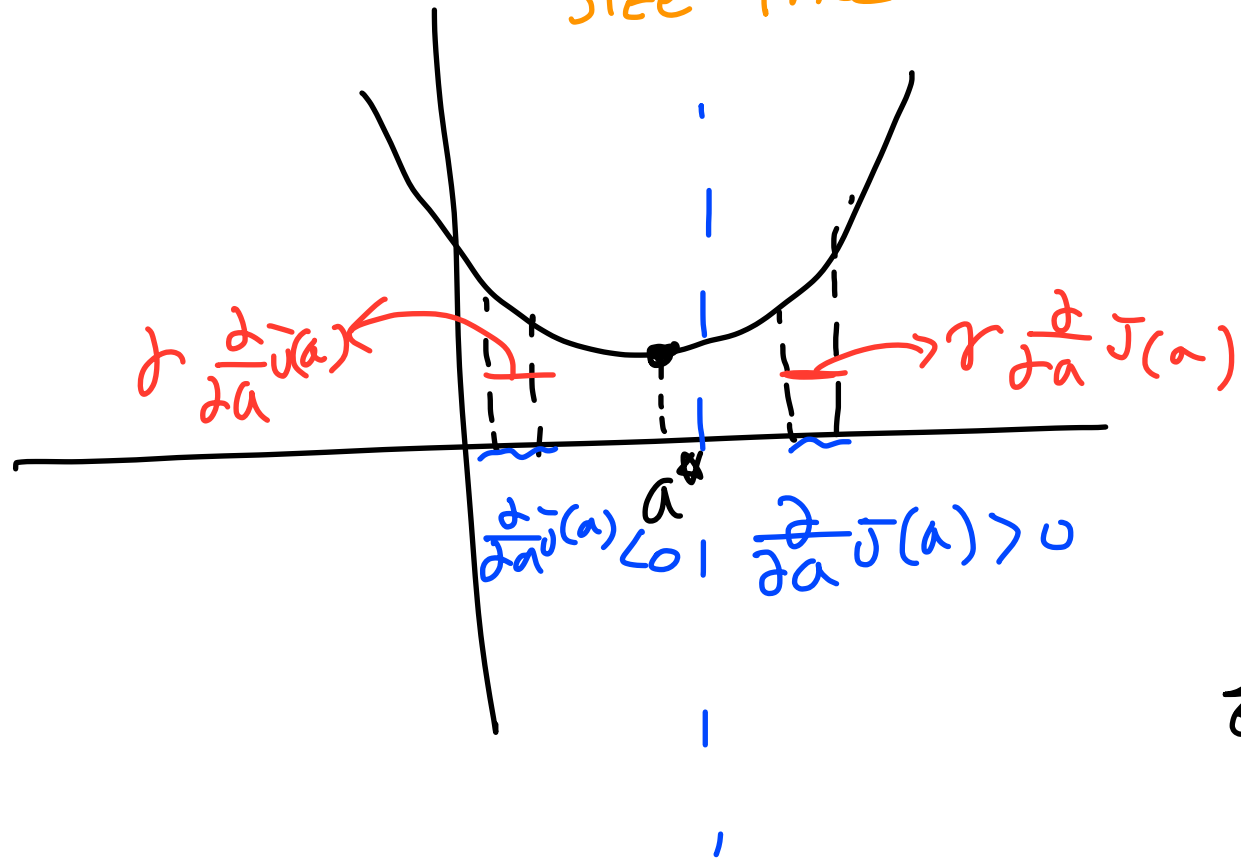
$$J(0) = \sum_{\bar{x}=1}^N (t_{\bar{x}})^2$$

$$\frac{1}{2 \cdot N} (1^2 + 2^2 + 3^2) = \frac{14}{6} \approx 2.3$$

$$J(a) = \sum_{i=1}^N (ax_i - t_i)^2$$

↓ ↓
Size Price

$$(h(x) = ax \text{ } \{ \text{can} \})$$



$$a_{\text{new}} = a - \gamma \frac{\partial}{\partial a} J(a, b)$$

하변할수록 a^* 에 가까워질.

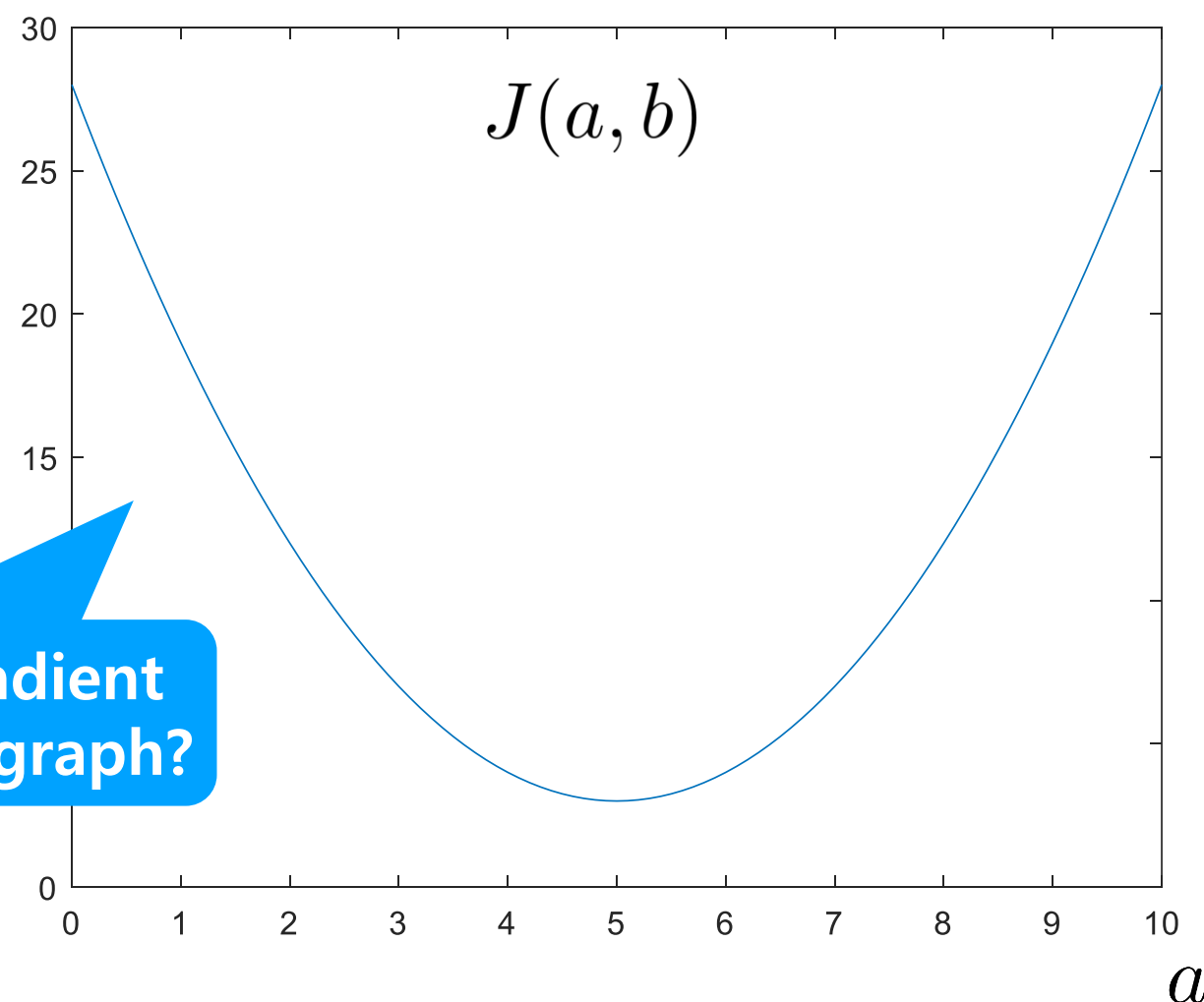
$$h(x) = a^* x \text{ 가 될것.}$$

Gradient Descent Approach

\Rightarrow Cost $\frac{1}{2} \sum_{i=1}^n \min_{\theta}$ minimizing 하는 방법.

- The parameters can be found iteratively

$$a_{\text{new}} = a - \gamma \frac{\partial}{\partial a} J(a, b)$$



How we apply gradient descent with this graph?

Think

- Try to think:
 - ▶ What happen if the step size gamma is too small?
 \Rightarrow 너무 조금 줄어서 오랜시간이 걸린다.
 - ▶ Or too big?
 \Rightarrow 평형문제가 발생한다.
 - ▶ When do we stop?
 \Rightarrow 더이상 줄어든기 않을때

Multi Dimensional Training

Data (변수가 여러개 일때)

Size (feet ²)	Number of bedrooms	Number of floors	Age of home (years)	Price (\$1000)
2104	5	1	45	460
1416	3	2	40	232
1534	3	2	30	315
852	2	1	36	178

How to model?

$$\mathbf{X} = \begin{bmatrix} 2104 & 5 & 1 & 45 \\ 1416 & 3 & 2 & 40 \\ 1534 & 3 & 2 & 30 \\ 852 & 2 & 1 & 36 \end{bmatrix} \quad \mathbf{y} = \begin{bmatrix} 460 \\ 232 \\ 315 \\ 178 \end{bmatrix}$$

Multivariate Linear Regression

- Our function is now

$$h(\mathbf{x}) = a_0 + a_1x_1 + a_2x_2 + a_3x_3$$

Three-variable regression

$$h(\mathbf{x}) = \mathbf{a}^T \mathbf{x}$$

$\mathbf{x} = [1, x_1, x_2, x_3]$
 $\mathbf{a} = [a_0, a_1, a_2, a_3]$

$$h(x) = a + bx \quad \text{matrix}$$

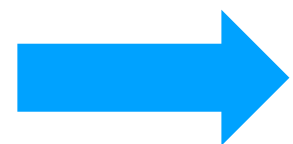
보통 1/3/5/7

가중

$$h(x) = [a \ b] \begin{bmatrix} 1 \\ x \end{bmatrix}$$

이제

$$h(x) = [a \ b \ c \ d] \begin{bmatrix} 1 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix}$$



Remaining question is now:

공백인 값 편미분 시작됨.

How to apply Gradient descent?

Matrix-based Reformulation

- Vector-form cost function

$$J(\bar{\theta}) = \sum_{i=1}^m (h_{\theta}(\mathbf{x}) - \mathbf{y})^2$$

- Gradient descent

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\bar{\theta})$$

- Find:

- ▶ $\min \sum_{i=1}^N (h(x_i) - t_i)^2$

- We define the cost function $J(a, b) = \sum_{i=1}^N (h(x_i) - t_i)^2$

Detail

- Assume we have one variable as before

$$\theta_0 \leftarrow \theta_0 - \alpha \frac{\partial}{\partial \theta_0} J(\bar{\theta})$$

$$\longleftrightarrow \theta_0 \leftarrow \theta_0 - \alpha \frac{\partial}{\partial \theta_0} \sum_{i=1}^m (h_{\theta}(\mathbf{x}_i) - y_i)^2$$

$$\longleftrightarrow \theta_0 \leftarrow \theta_0 - 2\alpha \sum_{i=1}^m (h_{\theta}(\mathbf{x}_i) - y_i)$$

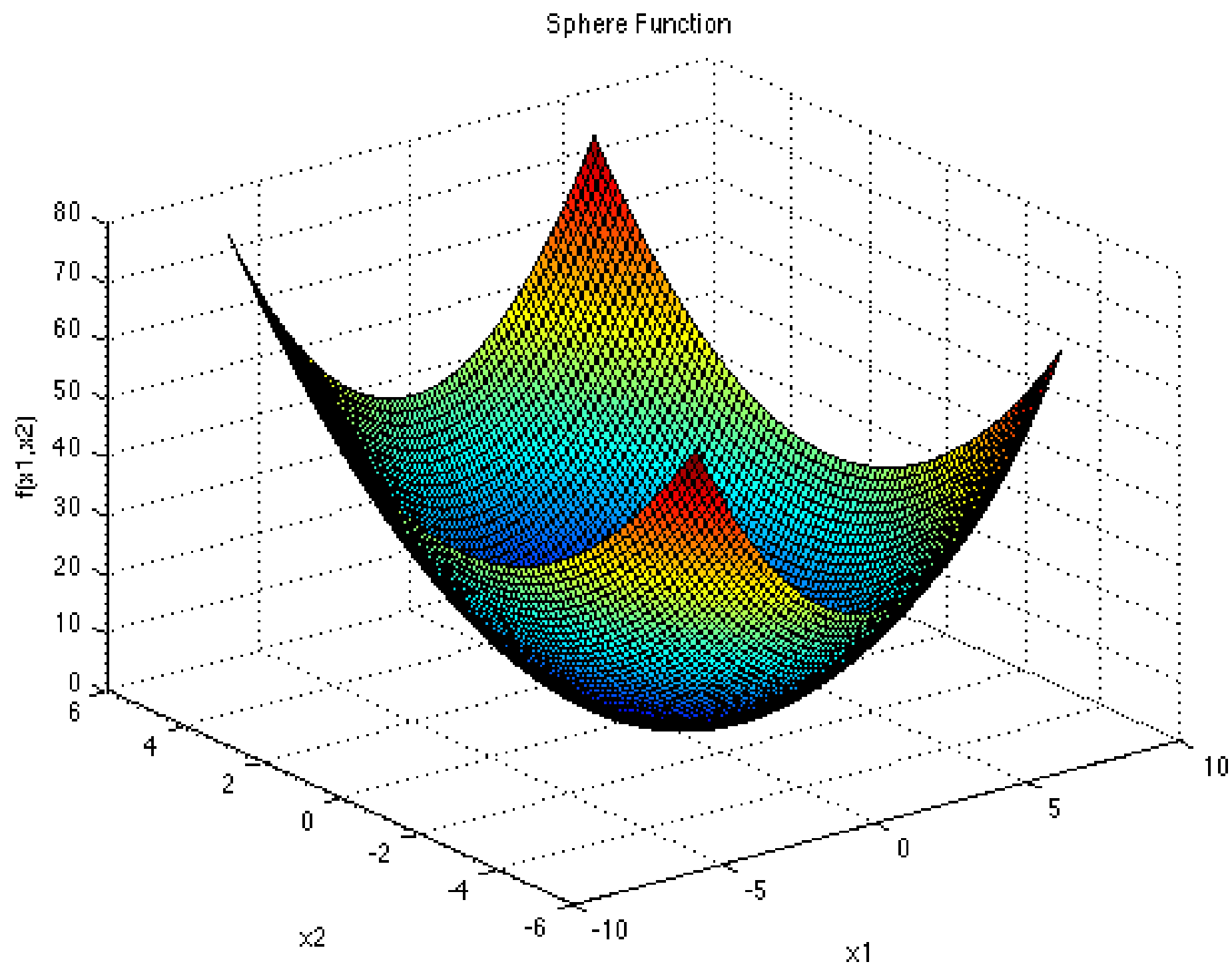
$$\theta_1 \leftarrow \theta_1 - \alpha \frac{\partial}{\partial \theta_1} J(\bar{\theta})$$

$$\longleftrightarrow \theta_1 \leftarrow \theta_1 - 2\alpha \sum_{i=1}^m (h_{\theta}(\mathbf{x}_i) - y_i) \mathbf{x}_i(1)$$

Multivariate Case

$$\theta_j \leftarrow \theta_j - 2\alpha \sum_{i=1}^m (h_{\theta}(\mathbf{x}_i) - y_i) \mathbf{x}_i(j)$$

Gradient Descent



Feature Scaling

→ 데이터를 다시 Normalize 해주

Feature Scaling

Idea: Make sure features are on a similar scale.

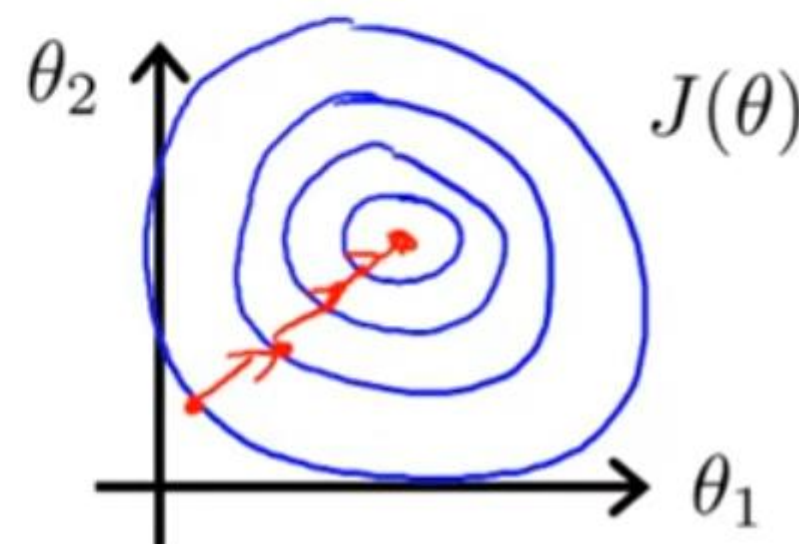
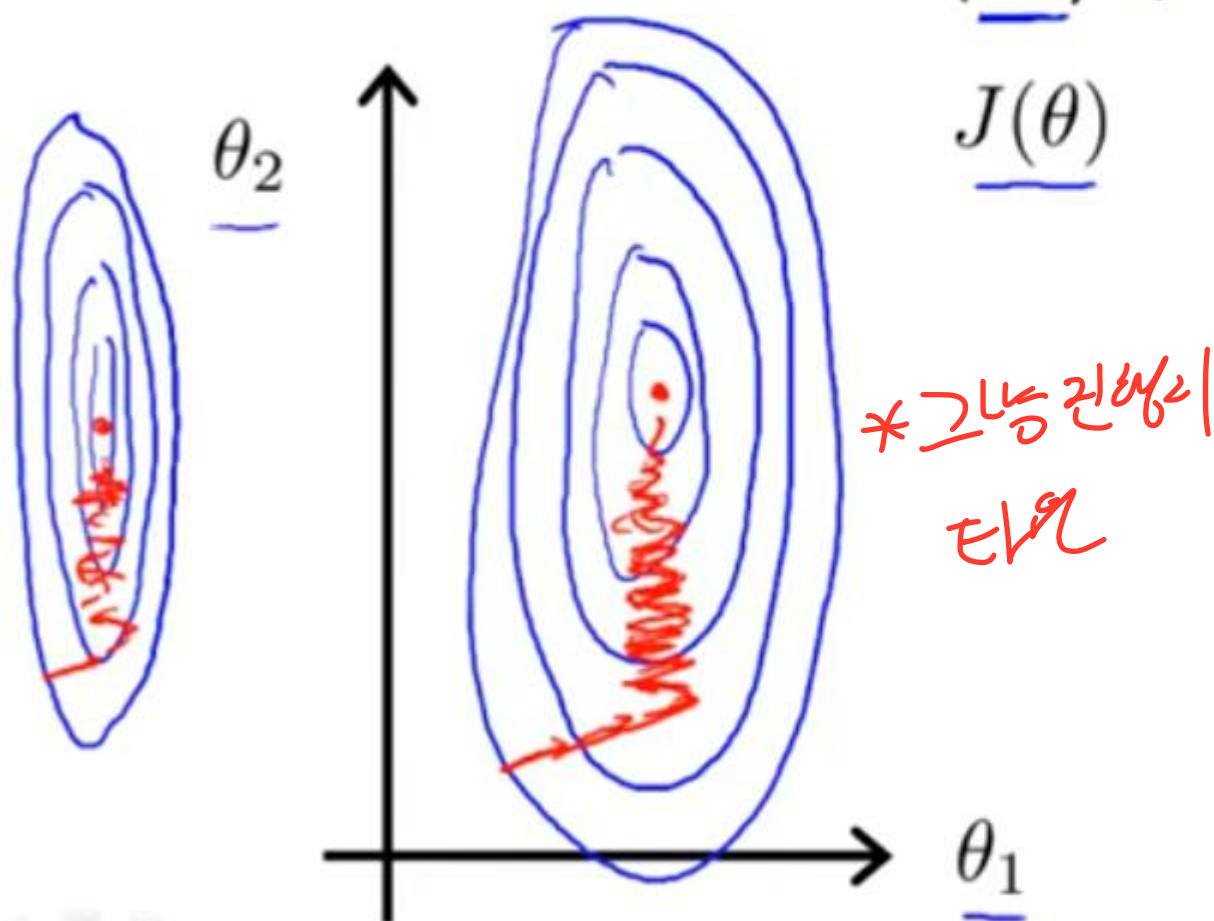
E.g. $x_1 = \text{size (0-2000 feet}^2)$ ←

$x_2 = \text{number of bedrooms (1-5)}$ ←

$$\rightarrow x_1 = \frac{\text{size (feet}^2)}{2000}$$

$$\rightarrow x_2 = \frac{\text{number of bedrooms}}{5}$$

* 리스케일링 후 원형



Andrew Ng

$$x_1 = \frac{\text{size} - 1000}{2000}$$

$$x_2 = \frac{\text{방수} - 2}{5}$$

Feature Normalization

$$x_1^{\text{new}} \leftarrow \frac{x_1 - \mu_1}{S_1}$$

Range (max - min)

Inf

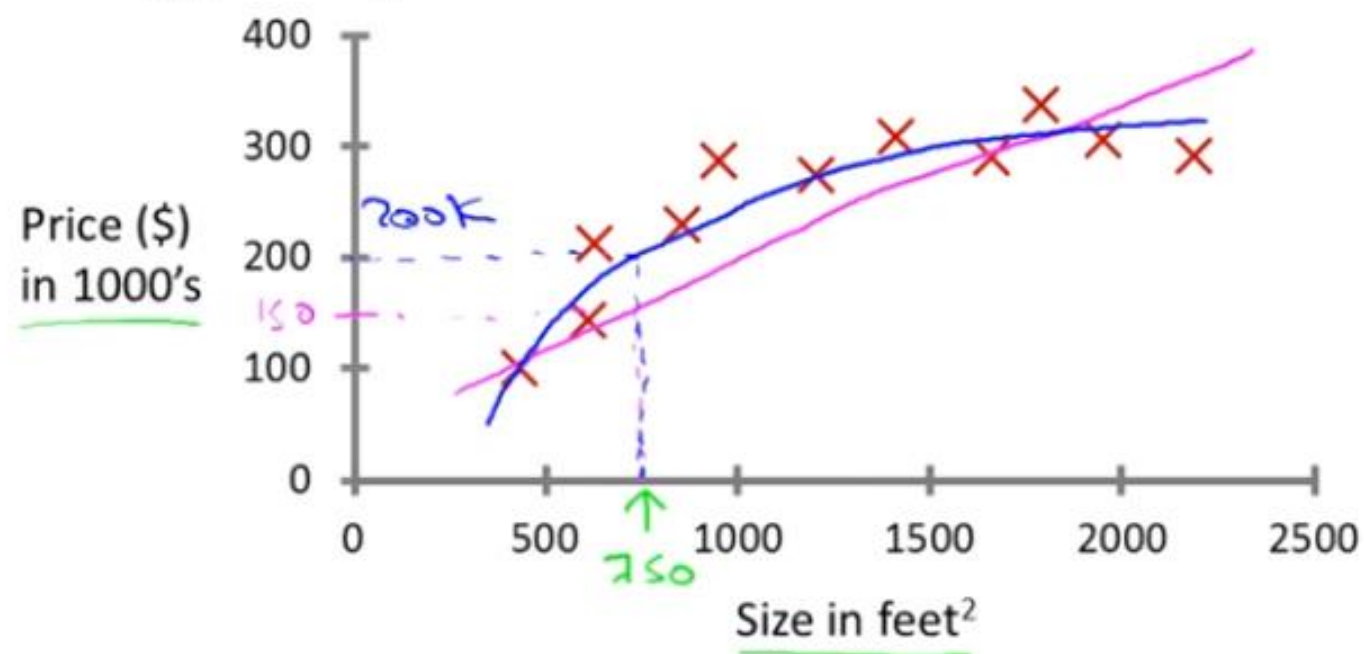
Polynomial Regression

- We use a polynomial function for regression

$$h_{\theta,2}(x) = \theta_0 + \theta_1 x + \theta_2 x^2$$

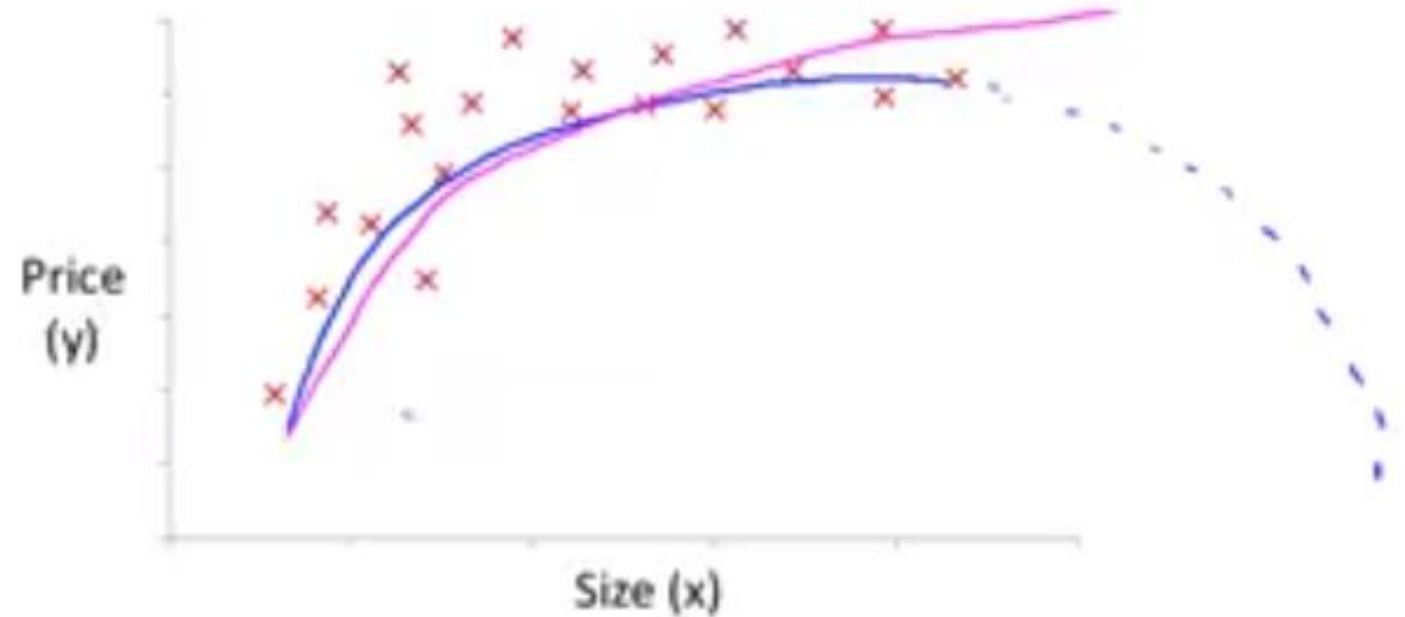
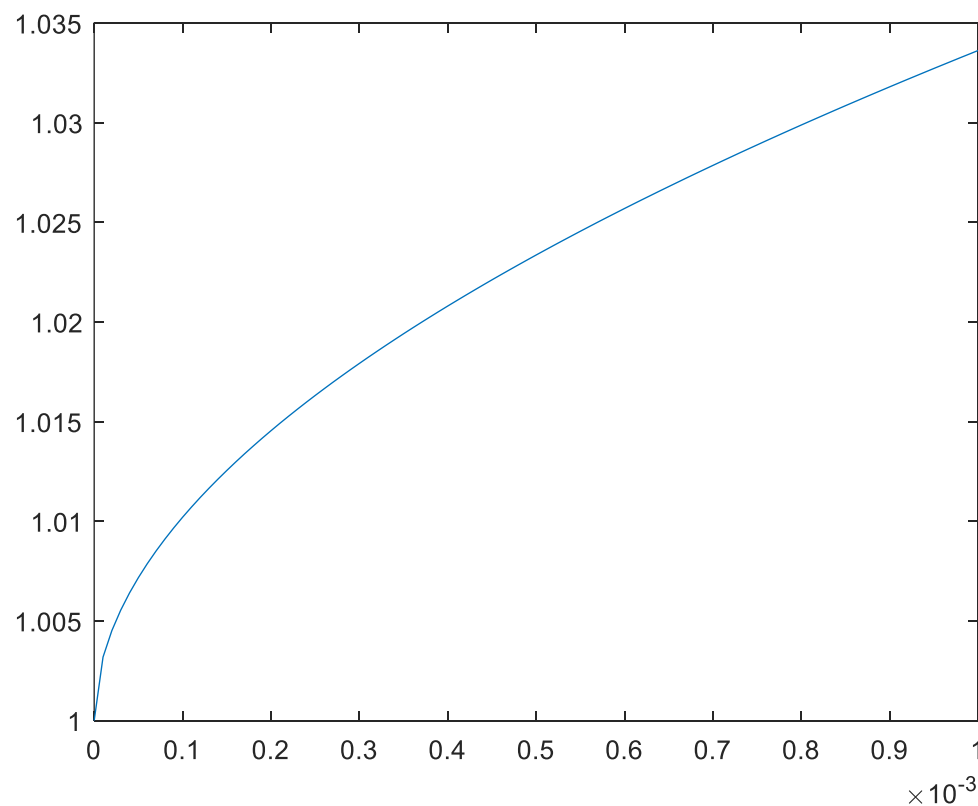
$$h_{\theta,3}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3$$

Housing price prediction.



Different Choice is Also Possible

$$h_{\theta,1/2}(x) = \theta_0 + \theta_1\sqrt{x} + \theta_2x$$



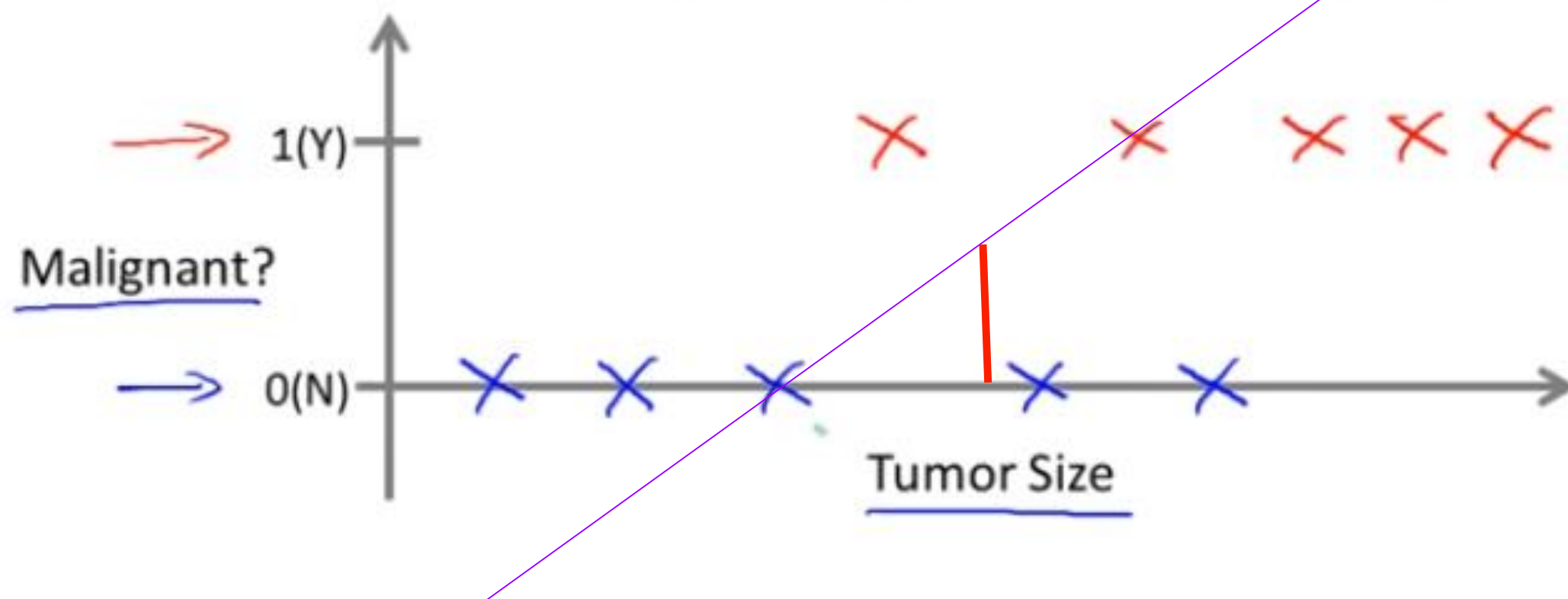
Normal Equation

- Any other [non-iterative] method?

Logistic Regression

- Regression for the classification problem

Breast cancer (malignant, benign)



Logistic Regression

$$0 \leq h_{\theta}(x) \leq 1$$

Logistic regression function



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

Sigmoid Function

- Or Logistic function

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

Could be interpreted as probability

