Deep Learning for Applications

심스리얼리티 임직원을 위한 딥러닝 교육 과정

Dr. Kyong-Ha Lee (kyongha@kisti.re.kr)

KiSTi 한국과학기술정보연구원
Korea Institute of Science and Technology Information

강사 소개

- 이경하 (kyongha@kisti.re.kr)
  - 한국과학기술정보연구원
    초거대AI연구단장 /책임연구원
  - UST 응용AI 전공 전임부교수
  - 과기부 미래국방기술전략분과 위원
  - 한국정보과학회 학회지편집위원 및 이사 역임
  - 한국정보과학회 데이터소사이어티 상임이사 외

안 내

- 수업 진행 방식
  - 파워포인트 강의: 개념 및 이론
  - 실습: Google CoLab을 활용한 실습
    - Google 계정 보유 필요
    - Internet Browser(Google Chrome 또는 MS Edge)

- 강의 자료
  - GitHub을 이용한 자료 공유
  - https://github.com/bart7449/simsreality

Contents

Class1 : 인공지능 특히 뉴럴 네트워크에 대한 기초 개념과 구성요소를 강의와 실습을 통해 학습합니다.

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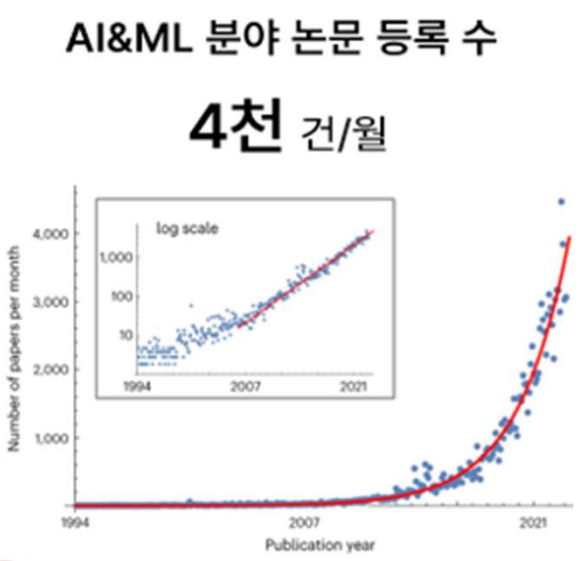
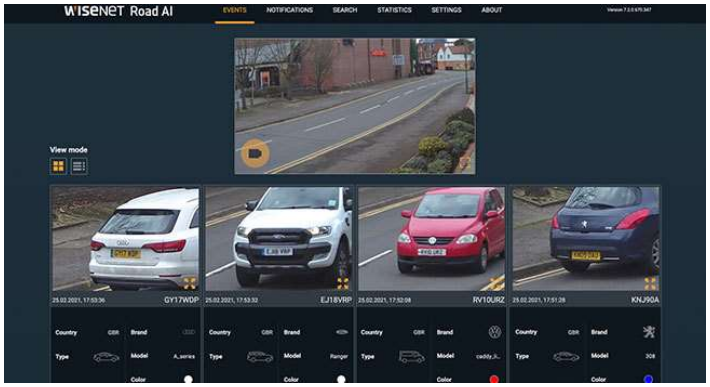
A Few Quates about Machine Learning

- **“A breakthrough in machine learning would be worth ten Microsofts” Bill Gates, Chairman, Microsoft)**
- **“Machine learning is the next Internet” (Tony Tether, Director, DARPA)**
- **Machine learning is the hot new thing” (John Hennessy, President, Stanford University)**
- **“Web rankings today are mostly a matter of machine learning” (Prabhakar Raghavan, Dir. Research, Yahoo)**

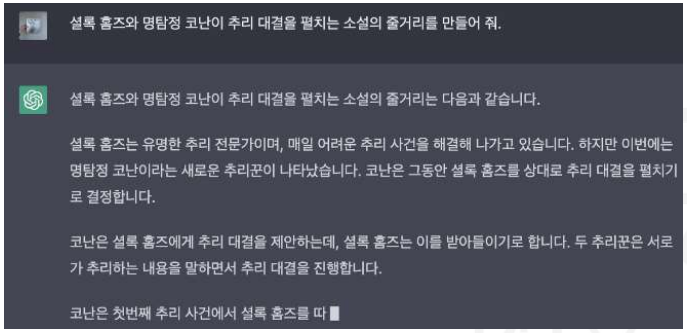


Application example

Vehicle Identification



Large Language Models

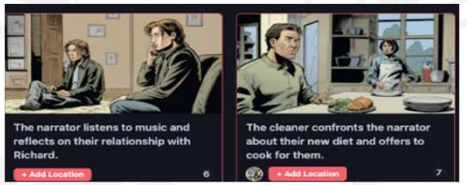


Stable Diffusion

Autonomous Driving

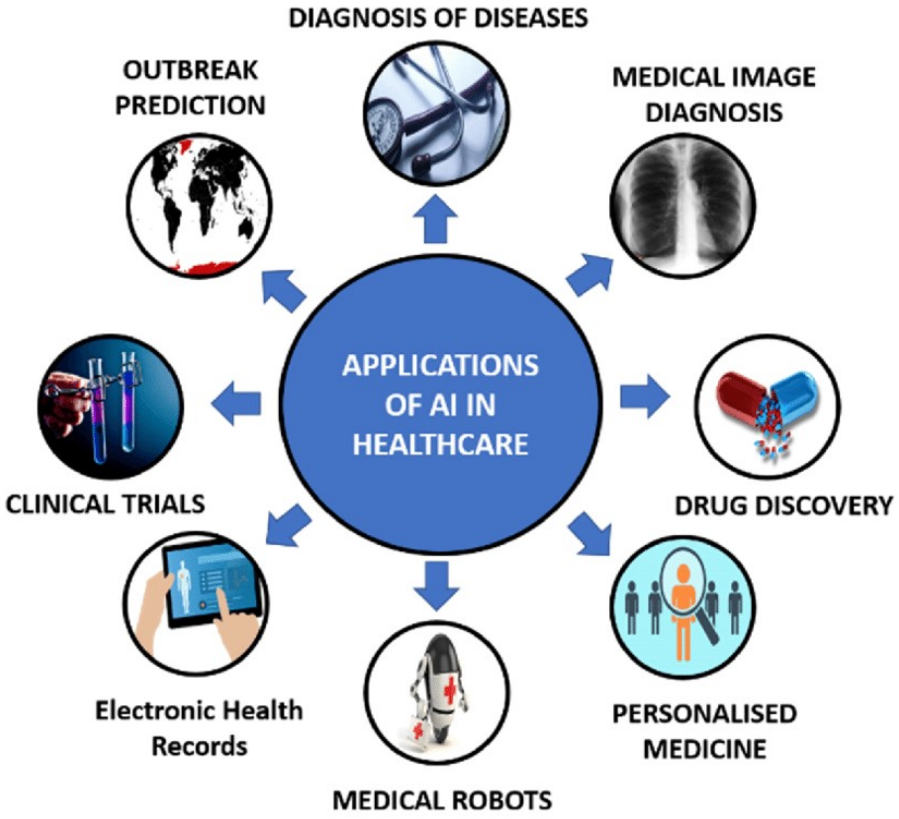
SORA (Text2Video)

Lore Machine (Story2Comic)



Udio (Text2Music)

Medical Applications



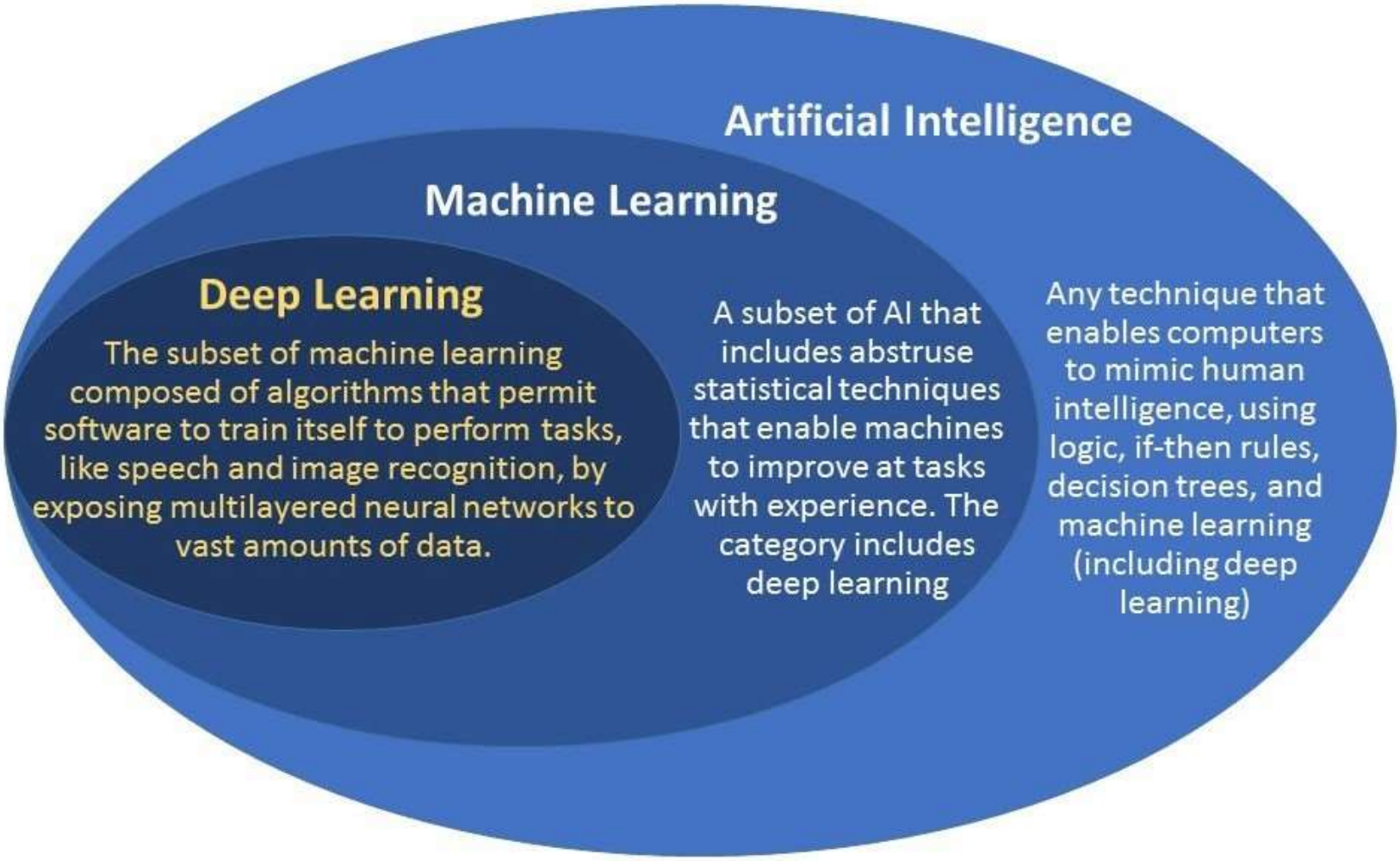
10 AI Applications That Could Change Health Care

APPLICATION	POTENTIAL ANNUAL VALUE BY 2026	KEY DRIVERS FOR ADOPTION
Robot-assisted surgery	$40B	Technological advances in robotic solutions for more types of surgery
Virtual nursing assistants	20	Increasing pressure caused by medical labor shortage
Administrative workflow	18	Easier integration with existing technology infrastructure
Fraud detection	17	Need to address increasingly compl service and payment fraud attemp
Dosage error reduction	16	Prevalence of medical errors, which leads to tangible penalties
Connected machines	14	Proliferation of connected machines/devices
Clinical trial participation	13	Patent cliff; plethora of data; outcomes-driven approach
Preliminary diagnosis	5	Interoperability/data architecture to enhance accuracy
Automated image diagnosis	3	Storage capacity; greater trust in AI technology
Cybersecurity	2	Increase in breaches; pressure to protect health data

SOURCE ACCENTURE

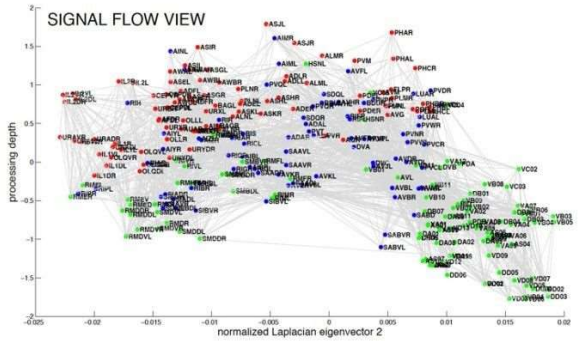
Harvard Business Review

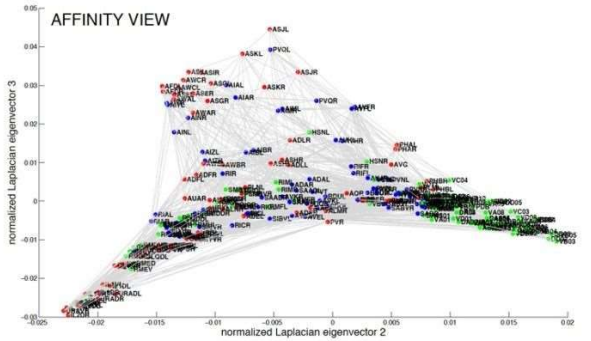
DL /ML/AI?


Artificial Intelligence
Any technique that enables computers to mimic human intelligence, using logic, if-then rules, decision trees, and machine learning (including deep learning)
Machine Learning
A subset of AI that includes abstruse statistical techniques that enable machines to improve at tasks with experience. The category includes deep learning
Deep Learning
The subset of machine learning composed of algorithms that permit software to train itself to perform tasks, like speech and image recognition, by exposing multilayered neural networks to vast amounts of data.

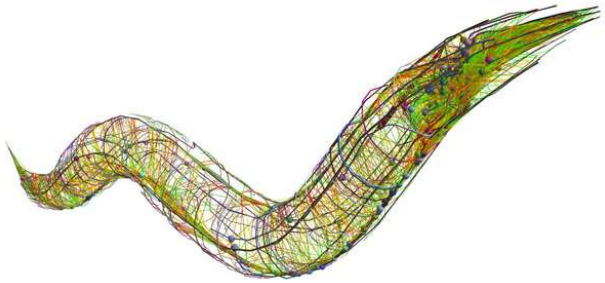
Interdisciplinary Linkage

- 예쁜 꼬마 선충(Caenorhabditis elegans)
  - 대표적인 유전학 모델
  - 노벨상 수상에 기여(3회)
    - 세포자살, RNAi, GFP
  - 다세포동물중 최초로 DNA서열이 다 밝혀진 동물
  - 302개 뉴런으로 구성된 신경계





- Connectome
  - 뇌 속에 있는 신경세포들의 연결을 종합적으로 표현한 <u>뇌지도</u>(또는 뇌 회로도)



Interdisciplinary Linkage

- Lego MindStorm으로 예쁜 꼬마선충의 뉴런연결정보를 구현하여 로봇 개발
  - 단순히 connectome을 구현한 것만으로 기본적인 움직임을 행함
- 생물학→ 전산학 →로봇, 기계공학 → 계산생물학 → 심리철학으로까지의 연구 촉발

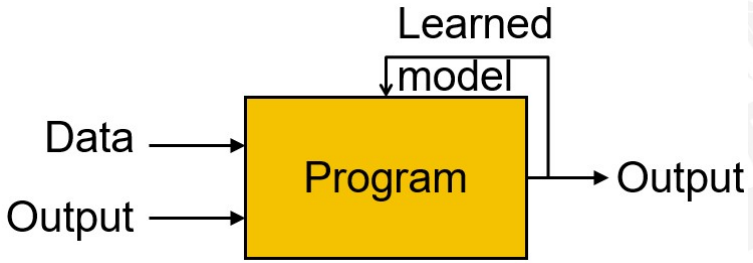
기계학습의 특성

- 기계학습(Machine Learning)의 정의
  - "환경(Environment, E)과의 상호작용을 통해서 축적되는 경험적인 데이터(Data, D)를 바탕으로 지식 즉 모델(Model, M)을 자동으로 구축하고 스스로 성능(Performance, P)을 향상하는 시스템" (Mitchell, 1997)

$$ML : D \xrightarrow{P} M$$

프로그래밍 방식과의 차이점

- 일반적인 컴퓨터 프로그램
  - 사람이 알고리즘 설계 및 코딩
  - 주어진 문제(데이터)에 대한 답 출력
- 머신 러닝 프로그램
  - 사람이 모델을 코딩
  - 기계학습 알고리즘을 통한 모델 학습
  - 데이터에 대한 프로그램을 출력



프로그래밍 방식과의 차이점

- Building ML program is more like gardening

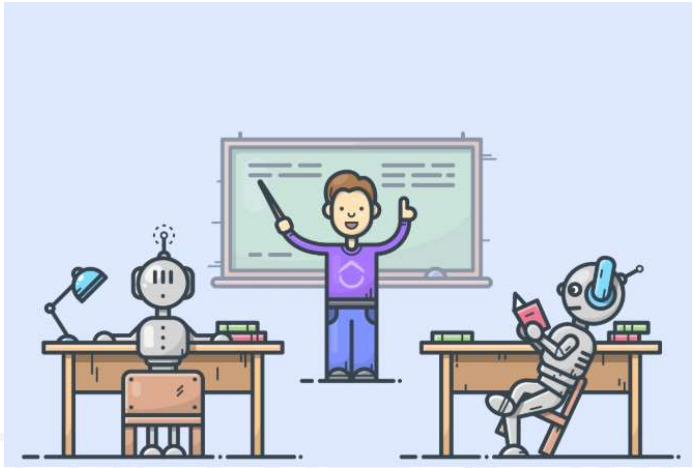
- Seeds = Algorithms
- Nutrients = Data
- Gardener = You
- Plants = Programs

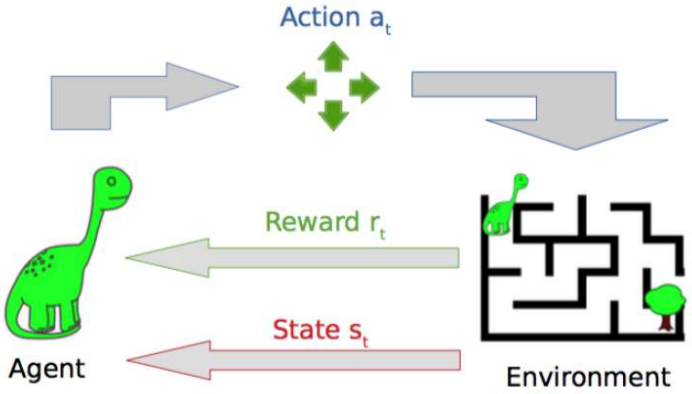
프로그래밍 방식과의 차이점

- 구성요소: 환경 E, 데이터 D, 모델 M, 성능지수 P
  - **환경(E)**: 학습 시스템이 상호작용하는 대상, 학습할 문제
  - **데이터(D)**: 환경과 상호작용을 통해 축적된 경험
    - 프로그램이 작성될 때 모든 가능한 입력을 고려하여 그 경우만을 다루는 것과 구별됨
  - **모델(M)**: 데이터를 모델링하는 학습 시스템의 구조
  - **성능지수(P)**: 학습 시스템의 성능 평가 지표
    - 학습 시스템이 목표를 이루기 위하여 최적화 해야 하는 지표

기계학습의 유형

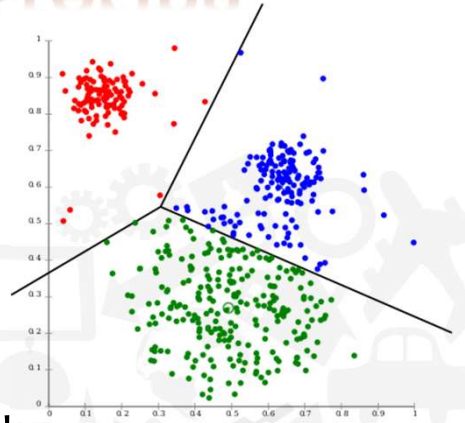
- Unsupervised learning
  - Training data does not include desired outputs
  - E.g., clustering
- **Supervised (inductive) learning**
  - Training data includes desired outputs
  - E.g., Classification, **regression/prediction**
- Semi-supervised learning
  - Training data includes a few desired outp
- Reinforcement learning
  - Rewards from sequence of actions



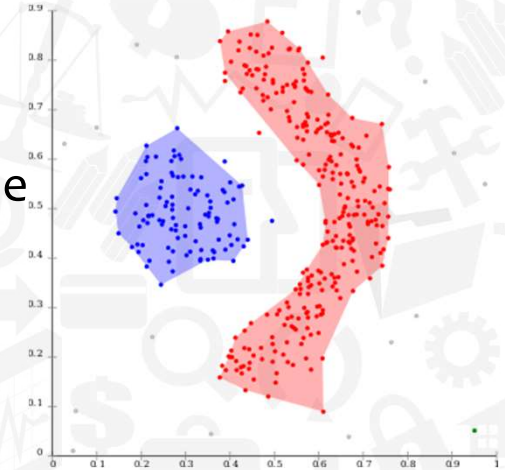


Unsupervised learnig 사례 -Clustering

- Definition
  - A task of grouping a set of objects in such a way that objects in the same cluster
- ***Centroid*-based clustering**
  - Each cluster is represented by a central vector
  - To find the ***k*** cluster centers and assign the objects to the nearest cluster center wrt. the squared distances from the cluster are minimized
  - e.g., ***k*-means**, RAM, CLARA, ...
- ***Density*-based clustering**
  - Clusters are defined as areas of higher density than the remainder of data set.
  - e.g., **DBSCAN** and OPTICS, ...
- Other clustering approaches also exist
  - hierarchical clustering and distribution-based approaches



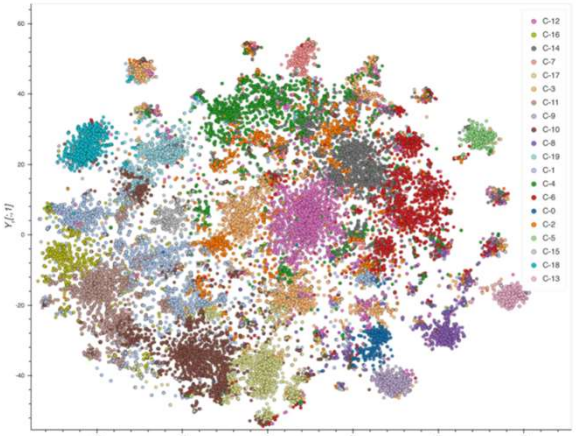
K-means



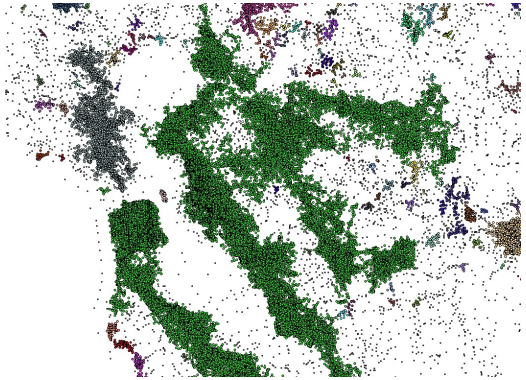
DBSCAN

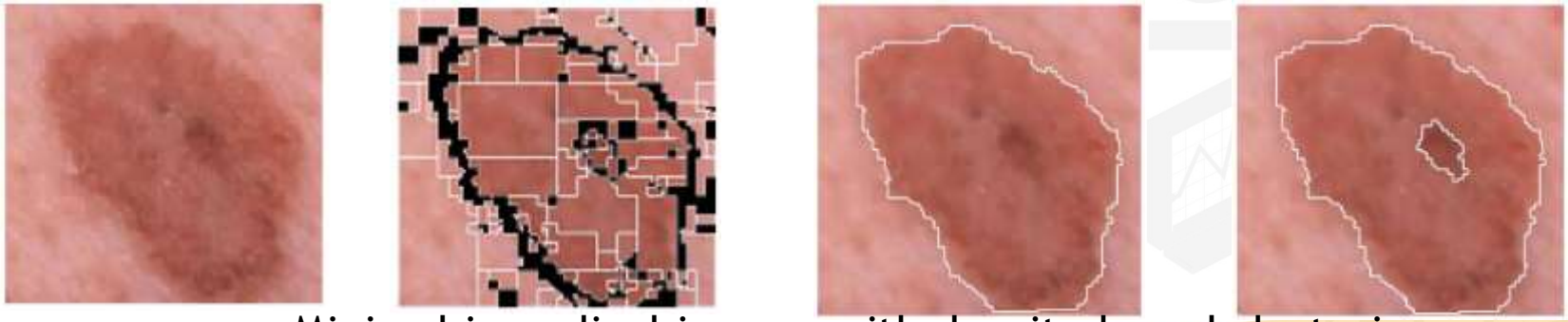
군집화 응용 사례

COVID-19
Literature
Clustering



Census survey
data





Mining biomedical images with density-based clustering

K-Means (Centroid-based clustering)

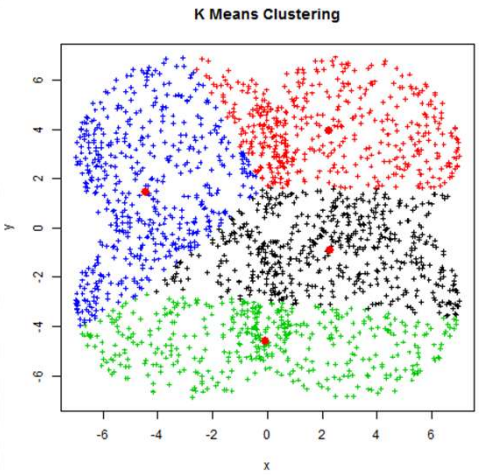
- Given a *k*, find a partition of *k* clusters to optimize the chosen partition criterion (cost function)
  - A heuristic approach : each cluster is represented by the centre of the cluster and the algorithm converges to stable centroids of clusters

0. Initialization : set seed points (randomly)

1. Find closest centroids
   - Assign each item to the cluster of the nearest seed point measured with a specific distance metric

2. Update centroid ***s***
   - Compute new seed points as the centroids(mean points) of the clusters of the current partition

3. Go back to Step 1 until no more new assignment
   - i.e., memberships in each cluster no longer change

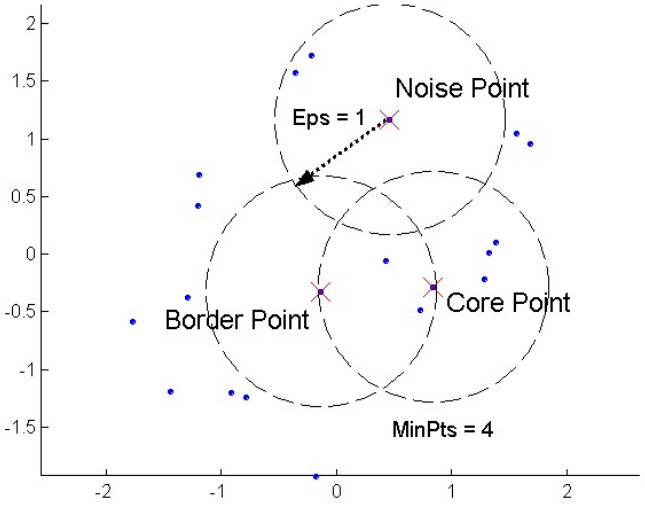


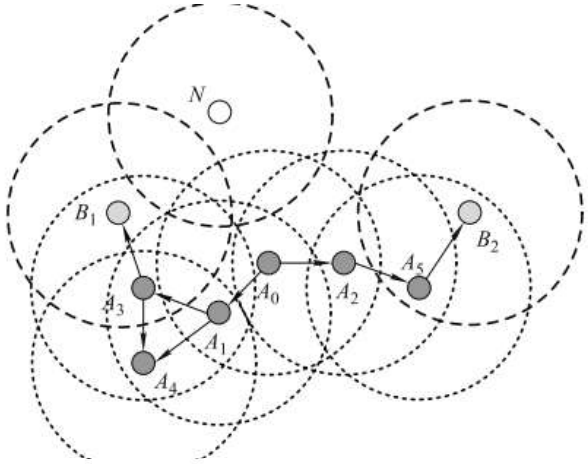
DBSCAN (Density-based clustering)

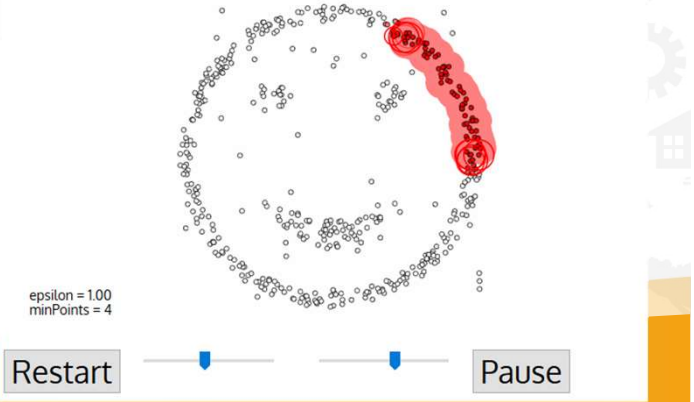
- Density = # of points within a specified radius ε (***Eps***)
- a core point is a point if it has more than a specified number of points (***MinPts***) within ***Eps***
  - points at the interior of a cluster
- A border point has fewer than ***MinPts*** within ***Eps***, but is in the neighborhood of a core point
- A noise point is any point that is not a core point or a border point
- Major features
  - Discover clusters of arbitrary shape
  - Handle noise
  - **One scan**
  - Need density parameters

DBSCAN

1. Create a graph whose nodes are the points to be clustered
2. For each core-point ***c*** create an edge from ***c*** to every point ***p*** in the ε-neighborhood of ***c***
3. Set ***N*** to the nodes of the graph;
4. If ***N*** does not contain any core points terminate
5. Pick a core point ***c*** in ***N***
6. Let ***X*** be the set of nodes that can be reached from ***c*** by going forward;
    1. create a cluster containing $X \cup \{c\}$
    2. $N = N/(X \cup \{c\})$
7. Continue with step 4

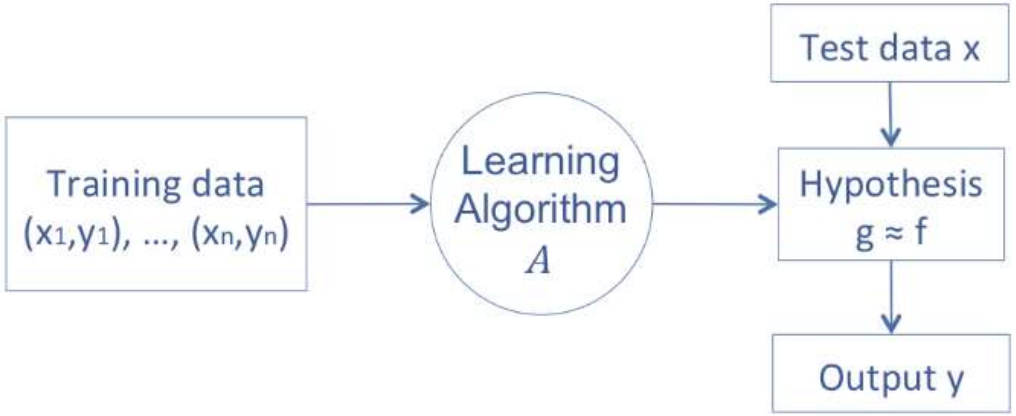






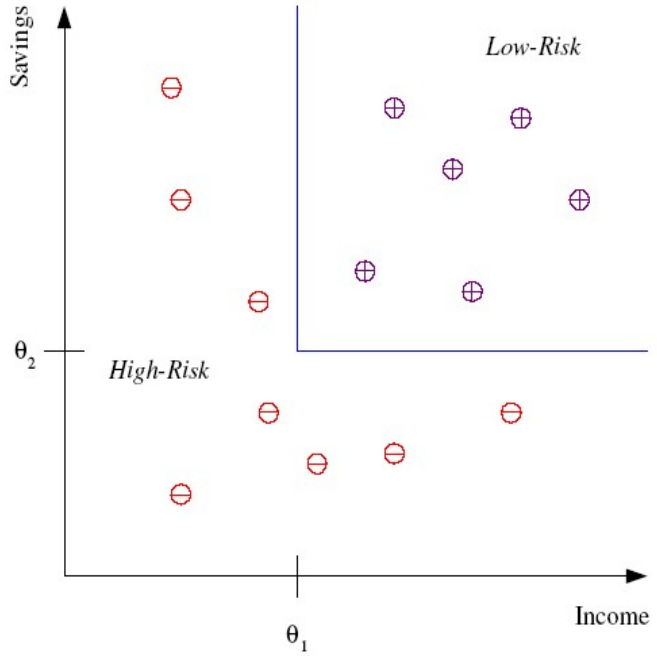
지도 학습(supervised learning)

- Given examples of a function (x, y) where $y = g(x)$
- Predict function ***f(x)*** for new examples ***X***
  - Discrete f(x) : **classification**
  - Continuous f(x) : **regression**
  - f(x) := probability(x) : **Probability estimation**



분류 (classification)

- Example: Credit scoring
- Differentiating between low-risk and high-risk customers from their *income* and *savings*

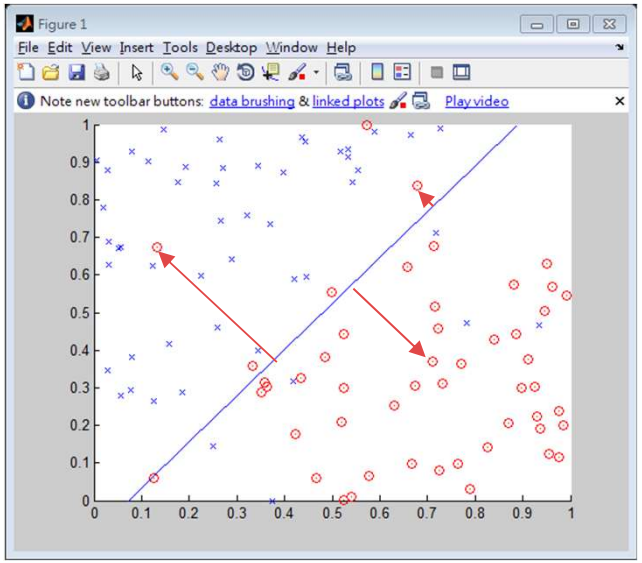


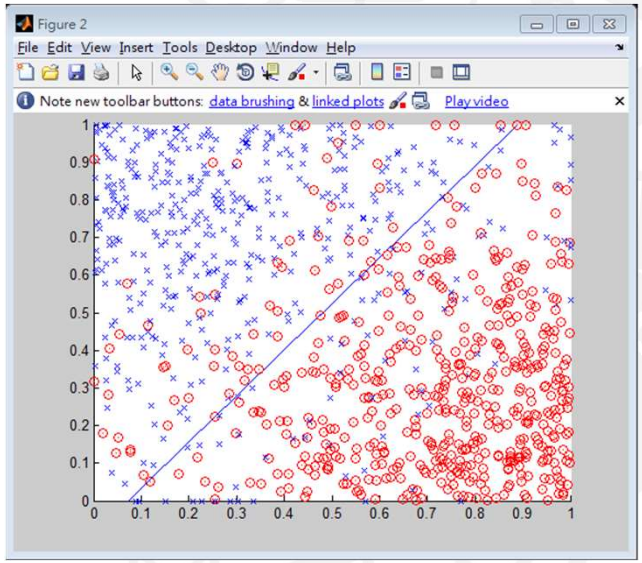
Discriminant: IF *income* > θ_1 AND *savings* > θ_2
THEN low-risk ELSE high-risk

Model

선형 분류기(Linear classifier)

- Classification decision is made based on the value of a linear combinations
  - If function(or model) is simple, error rate goes up.





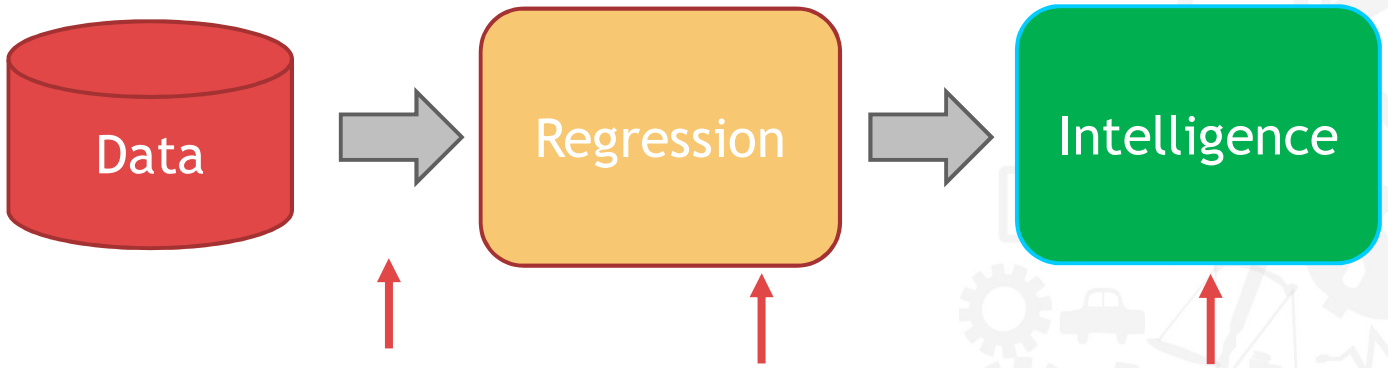
- More complicated function(or model) is required for guaranteeing a minimal error rate

분류의 응용 사례

- Face recognition: Pose, lighting, occlusion (glasses, beard), make-up, hair style
- Character recognition: Different handwriting styles.
- Speech recognition: Temporal dependency
  - Use of a dictionary or the syntax of the language.
  - Sensor fusion: Combine multiple modalities; eg, visual (lip image) and acoustic for speech
- Medical diagnosis: From symptoms to illnesses
- Web Advertising: Predict if a user clicks on an ad. on the Internet
- ….

회귀 분석(Regression Analysis)

From features to predictions



Input x:
Features derived from data

Learn x→ y
relationship

Predict y:
Continuous “output” or “response” to input

Prediction: Regression

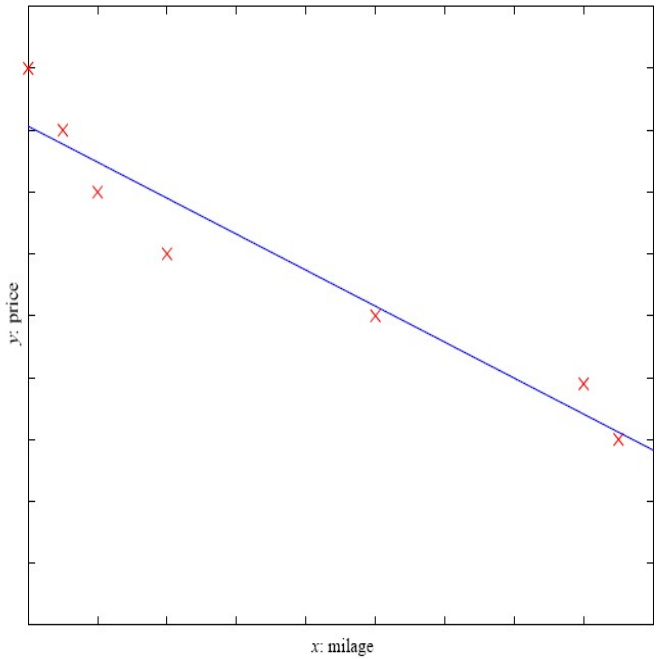
- Example: Price of a used car
- x : car attributes

  y : price

  $$y = g(x \mid \theta)$$

  g : ( ) model,

  θ : parameters



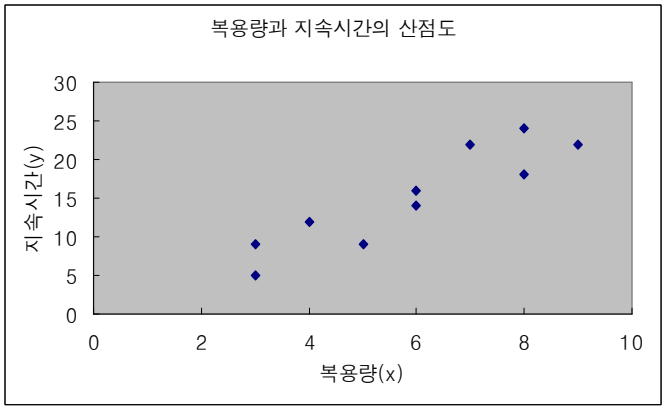
Regression

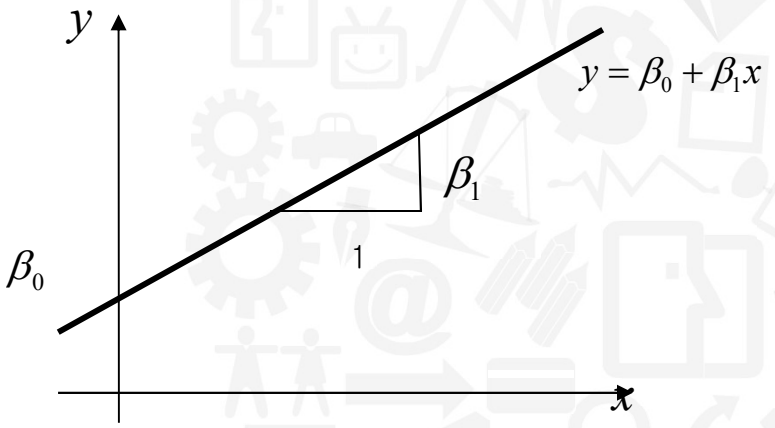
- x : 독립변수 (independent variable)
  - 원인
  - 특징(Feature)
- Y : 종속변수(depedent variable)
  - 결과 : 예측 가능

- 단순회귀분석(simple regression analysis)
  - 독립 변수 1개와 종속 변수 1개의 관계를 분석
- 다중회귀분석(multiple regression analysis)
  - 여러 독립변수와 하나의 종속 변수 사이의 관계를 규명

Regression examples

- 복용량에 따른 효과의 지속시간의 관계
  - x : 약품의 복용량
  - y : 효과가 지속되는 기간





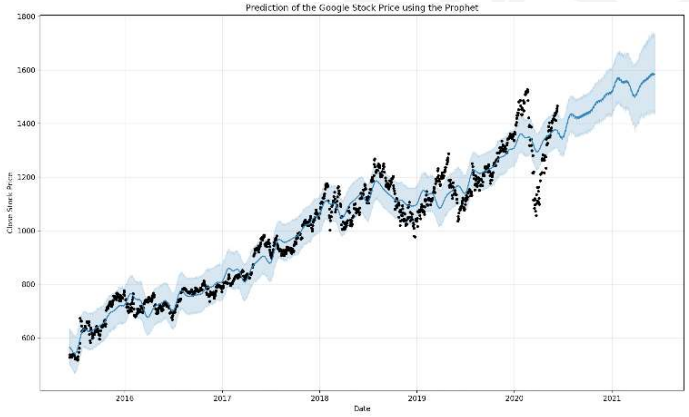
$$y = \beta_0 + \beta_1 x + \varepsilon$$

θ { β_0, β_1 : 회귀모수 (미지의 상수)
ε : 오차항 }

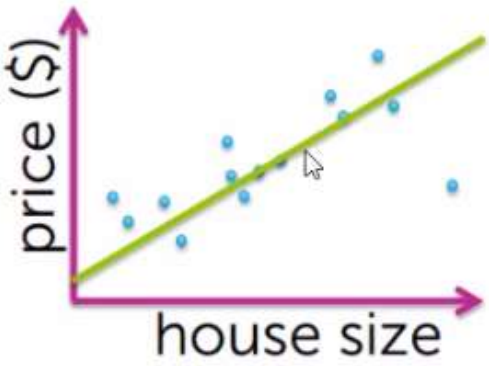
Regression examples

Stock Prediction

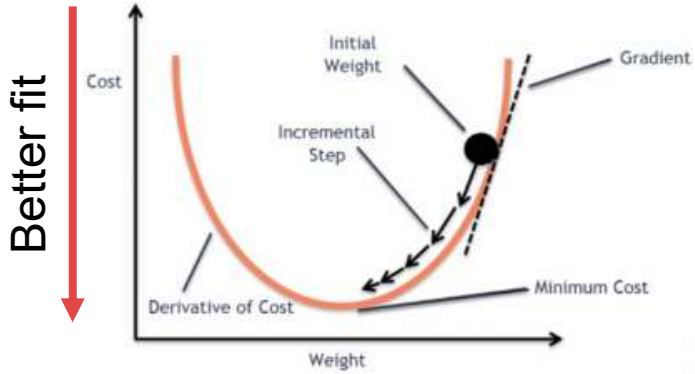
- Predict the price of a stock y
- Depends on x =
  - Recent history of stock price
  - News events
  - Related commodities



Simple Regression

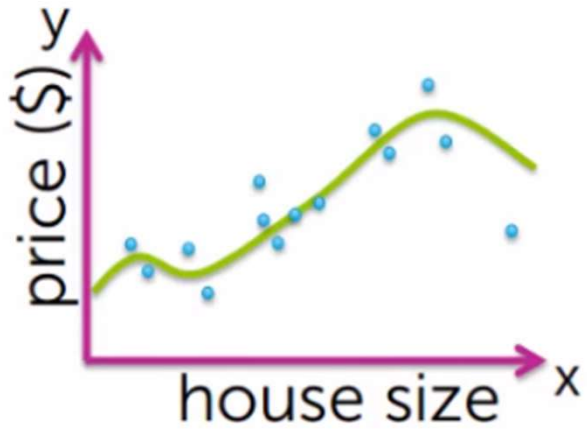


Define goodness-of-fit
Metric for each possible line

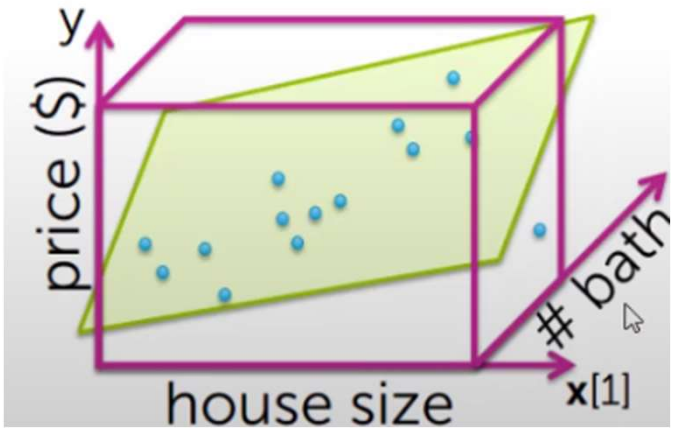


Gradient descent algorithm
Get estimated parameters
- interpret
- use to form predictions

Multiple regression



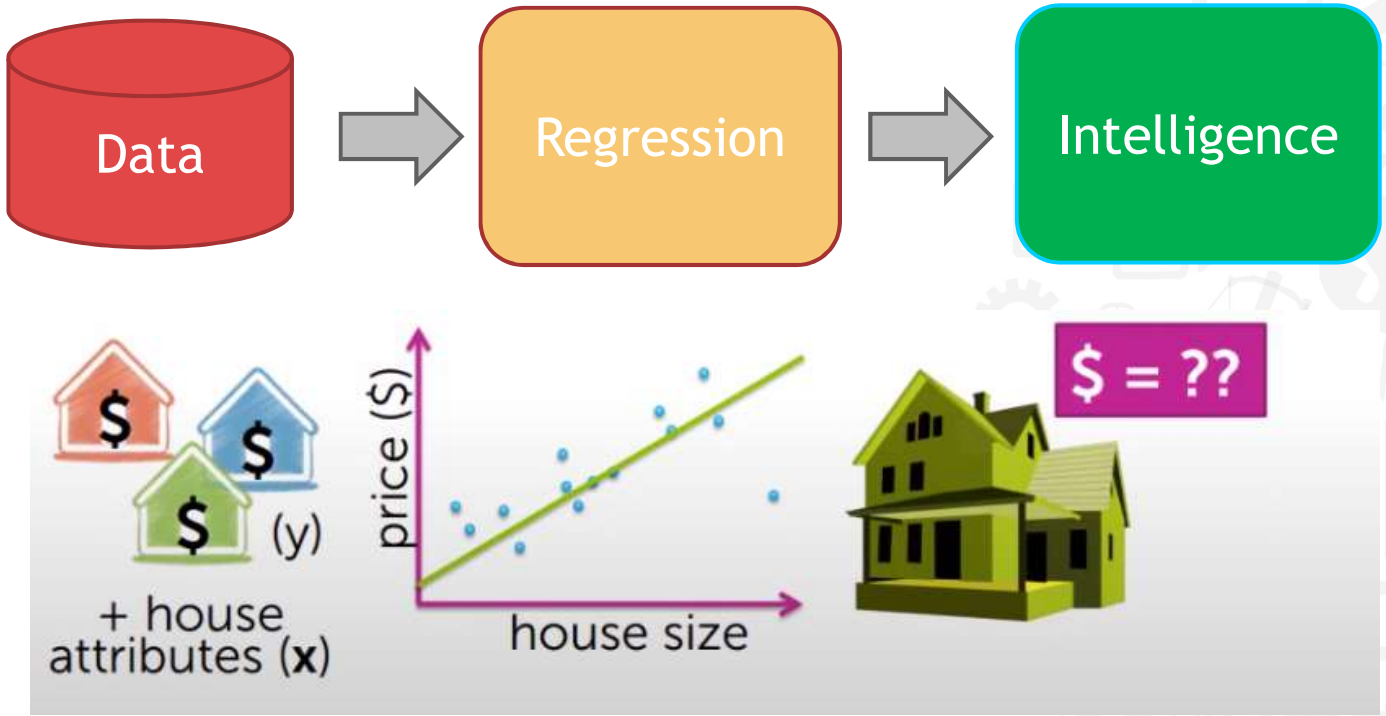
Fit more complex relationships than just a line



Incorporate more inputs

- Square feet
- Num. of bathrooms
- Num. of bedrooms
- Lot size
- Year built
- . . .

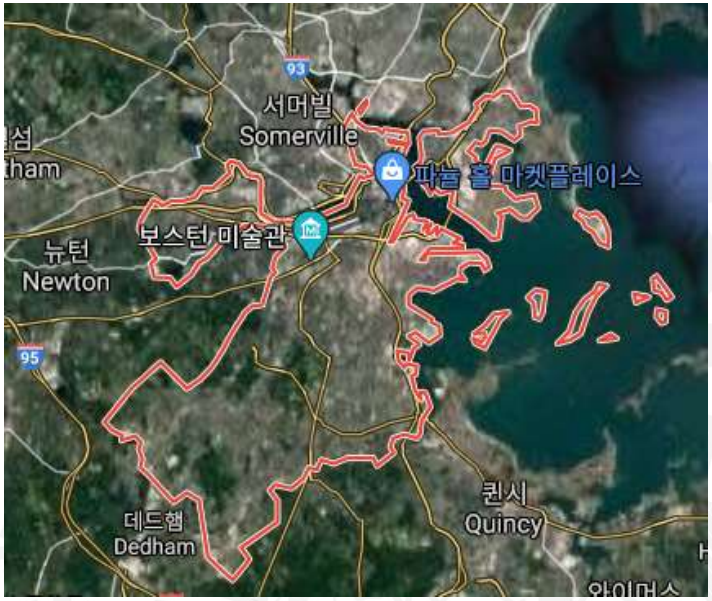
Lab 1: Predicting house price



Boston Housing Price Dataset

- Dr. Jason에 의해 작성된 1978년도 보스턴 교외지역부동산 관련 정보
  - 14개 변수(column)로 구성된 506개의 데이터(row)
    - 506 x 14 tabular data
  - 종속 변수 (1개)
    - MEDV : 1978년 보스턴 교외 506개 타운의 주택 가격 중앙값(단위 $1,000)
  - 독립 변수 (13개)
    - CRIM, INDUS, NOX, RM, LSTAT, B, PTRATIO, ZN, CHAS, AGE, RAD, DIS, TAX

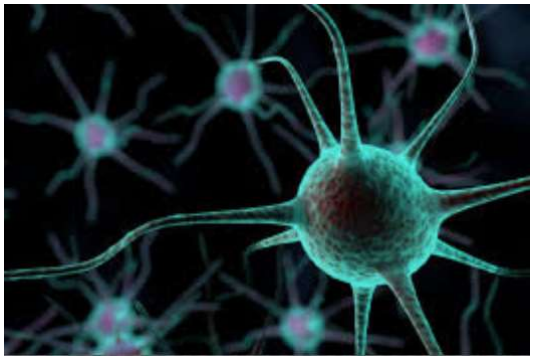
Features

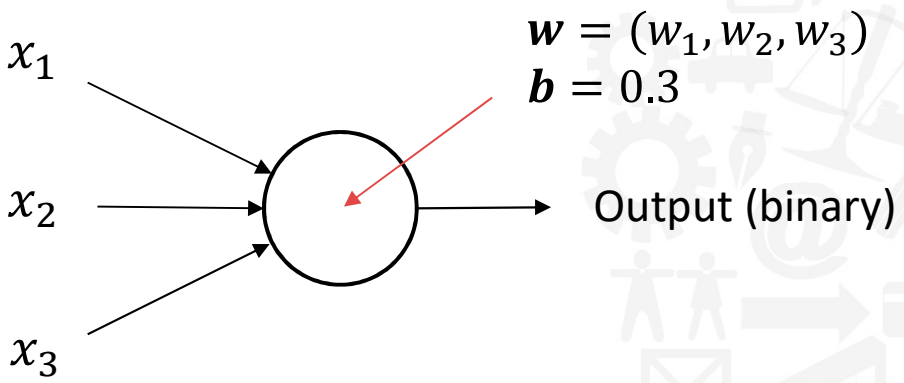


- CRIM : 범죄율
- INDUS: 비소매상업지역 면적 비율
- NOX: 일산화질소 농도
- RM : 주택당 방수
- LSTAT : 인구중 하위 계층 비율
- B : 인구중 흑인 비율
- PTRATIO: 학생/교사 비율
- ZN: 25,000 평방피트를 초과한 거주지역 비율
- CHAS : 찰스강의 경계에 위치한 경우 1 아니면 0
- AGE : 1940 년 이전에 건축된 주택의 비율
- RAD 방사형 고속도로까지의 거리
- DIS : 직업센터의 거리
- TAX : 재산세율

Neuron

- Basic building block for composition is a perceptron (artificial neuron) (Rosenblatt c.1960)
- Linear classifier
  - With a vector of weights *w* and a bias *b*



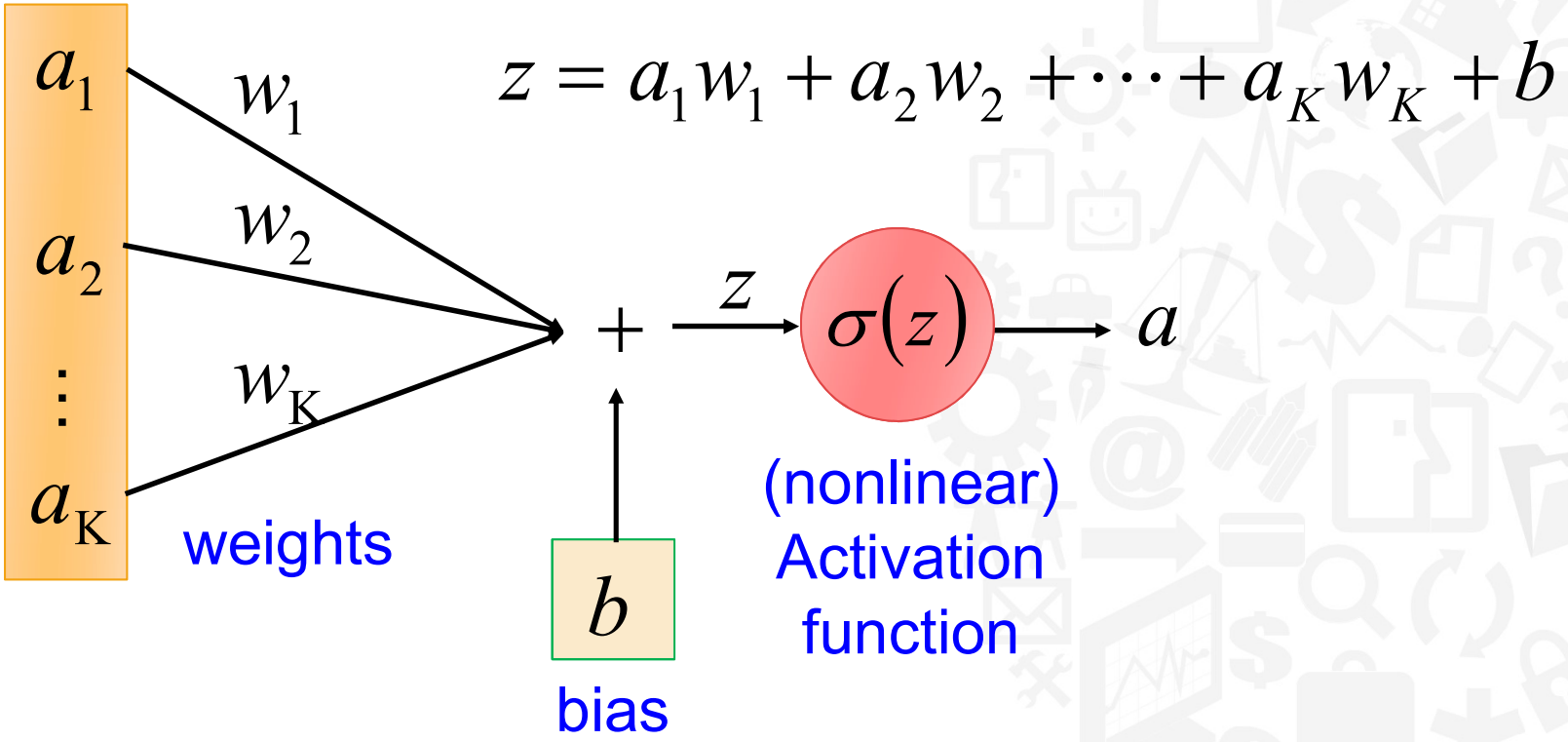


$$\text{output} = \begin{cases} 0 & \text{if } w \cdot x + b \leq 0 \\ 1 & \text{if } w \cdot x + b > 0 \end{cases}$$

$$w \cdot x \equiv \sum_j w_j x_j$$

Element of Neural Network

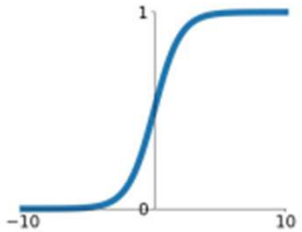
Neuron $f: R^K \rightarrow R$



Samples of Activation Functions

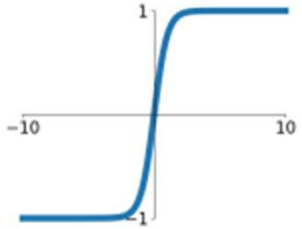
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



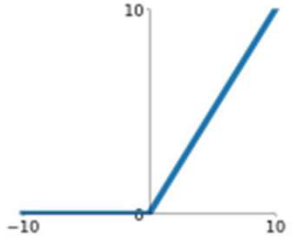
tanh

$$\tanh(x)$$



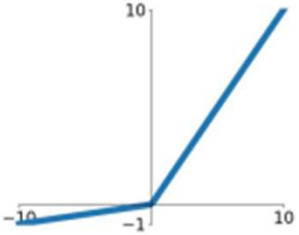
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

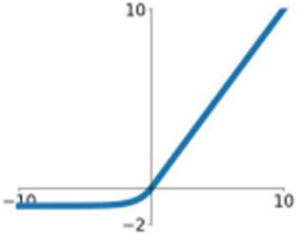


Maxout

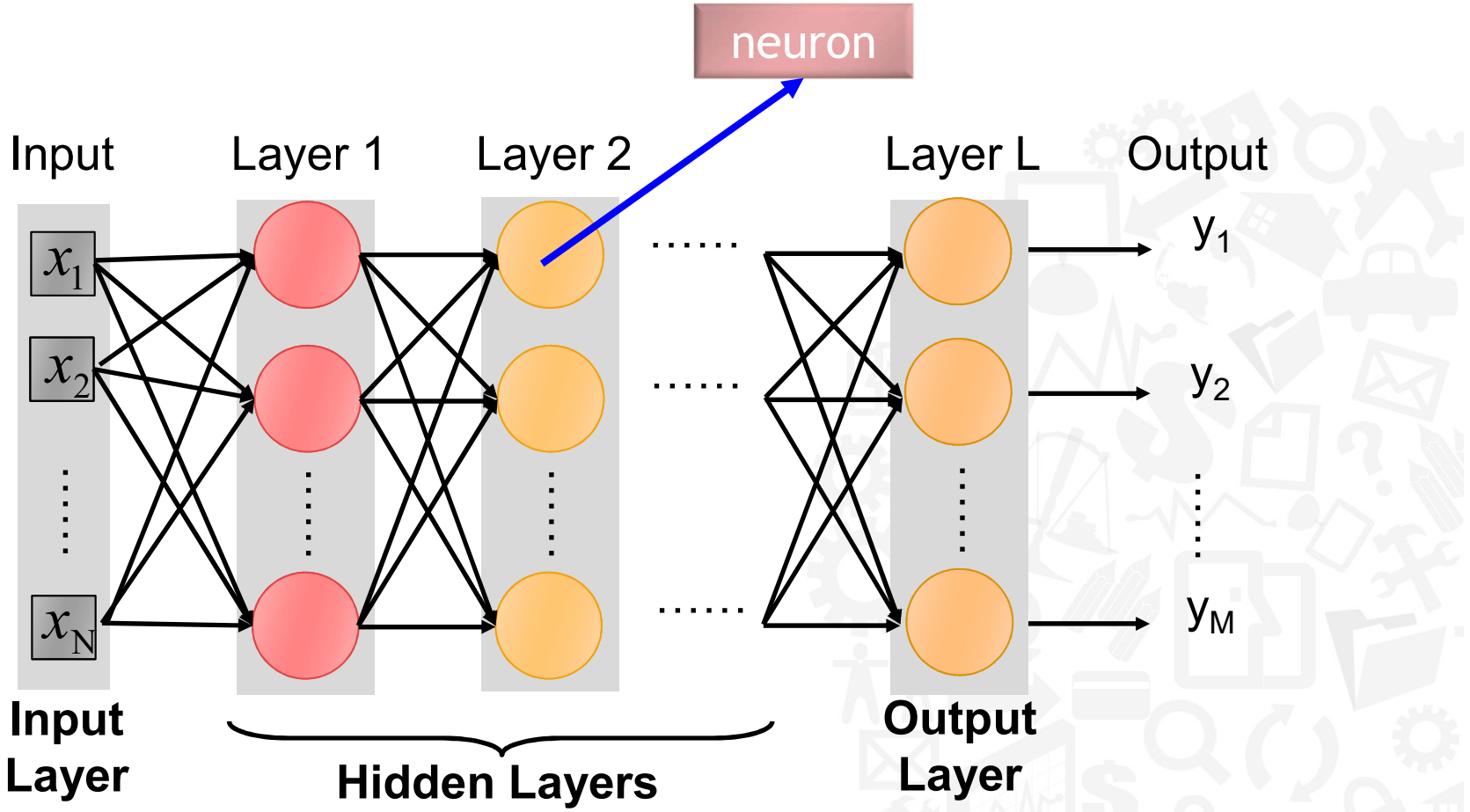
$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

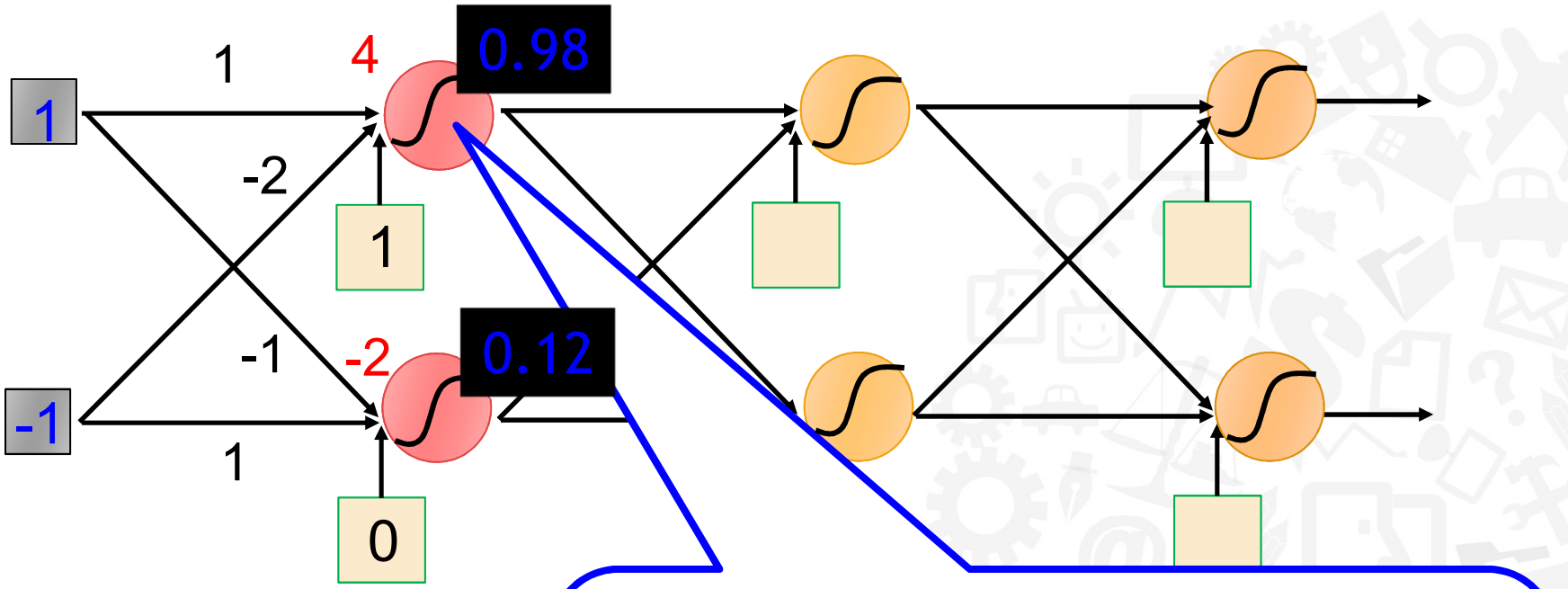


(Deep) Neural Network



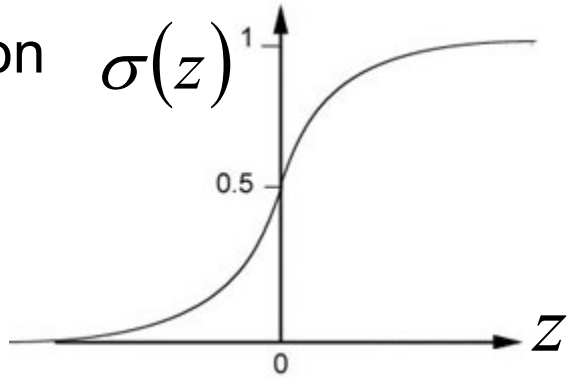
Deep means many hidden layers

Example of neural network

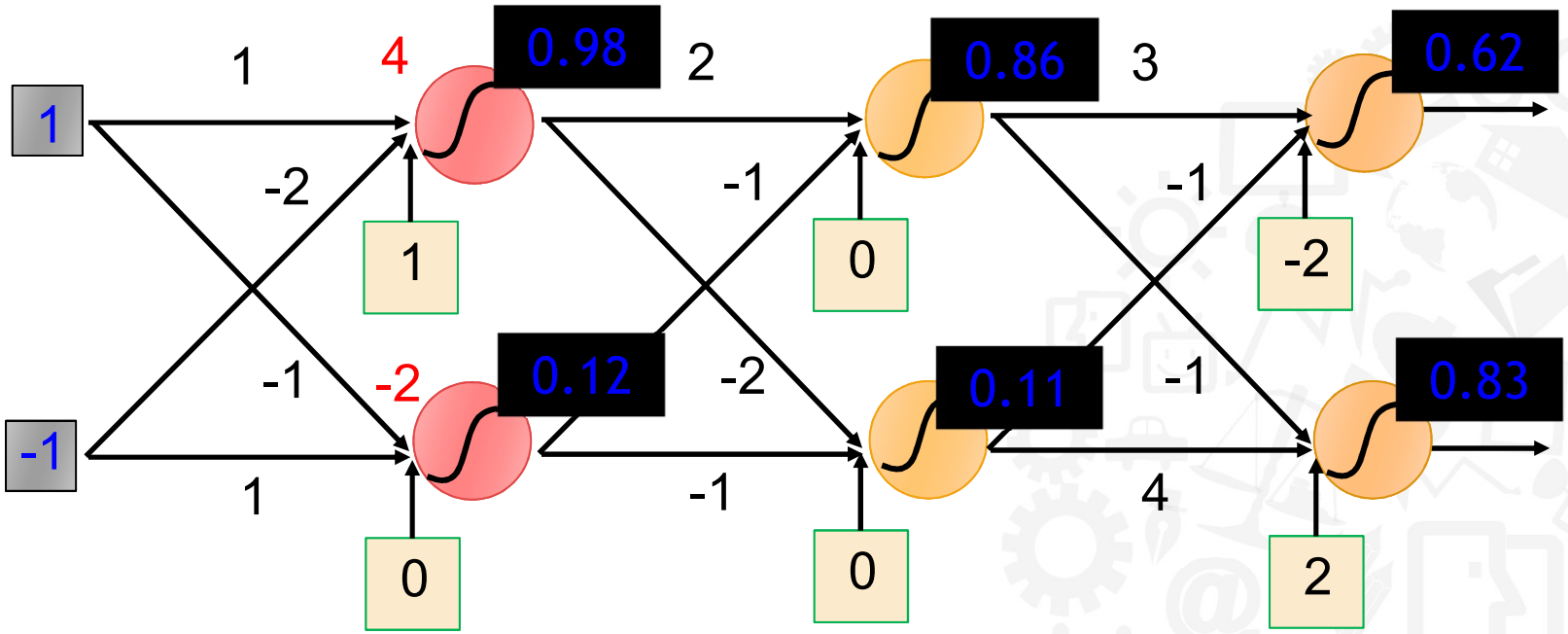


Sigmoid Function

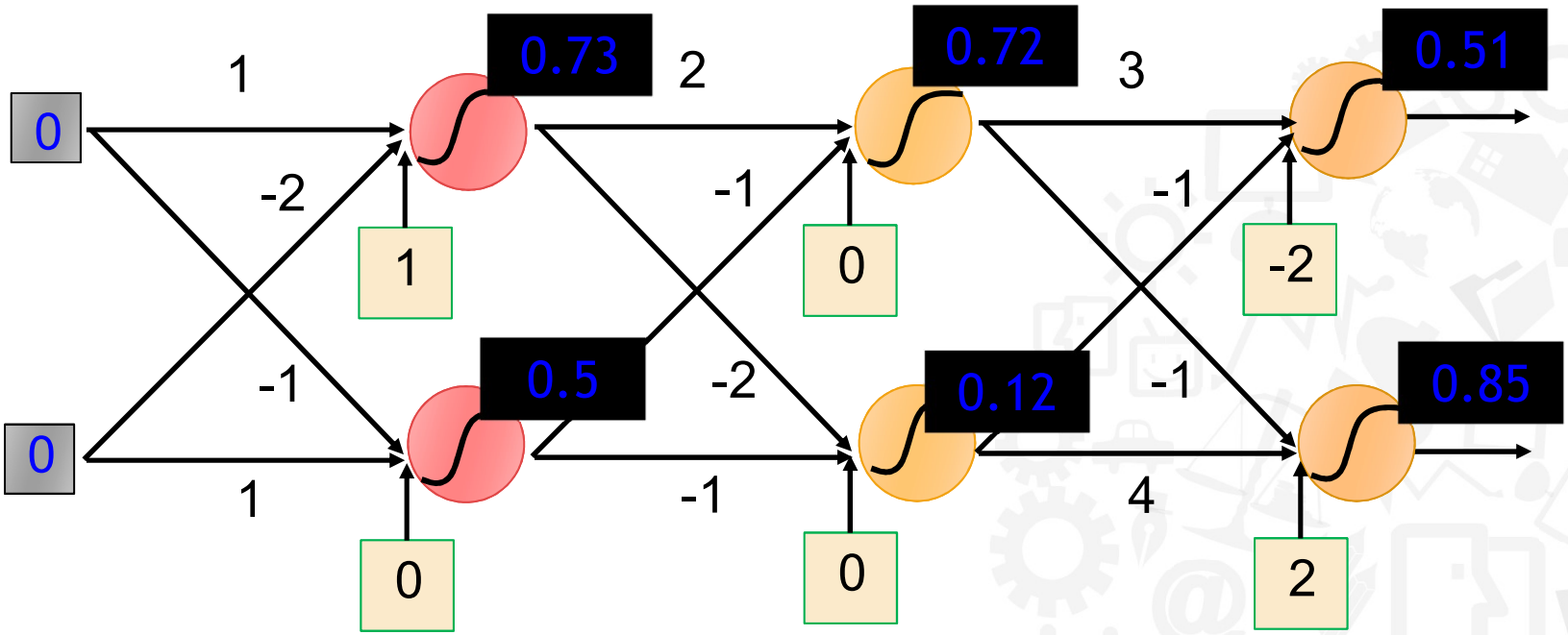
$$\sigma(z) = \frac{1}{1+e^{-z}}$$



Example of Neural network



Example of Neural network

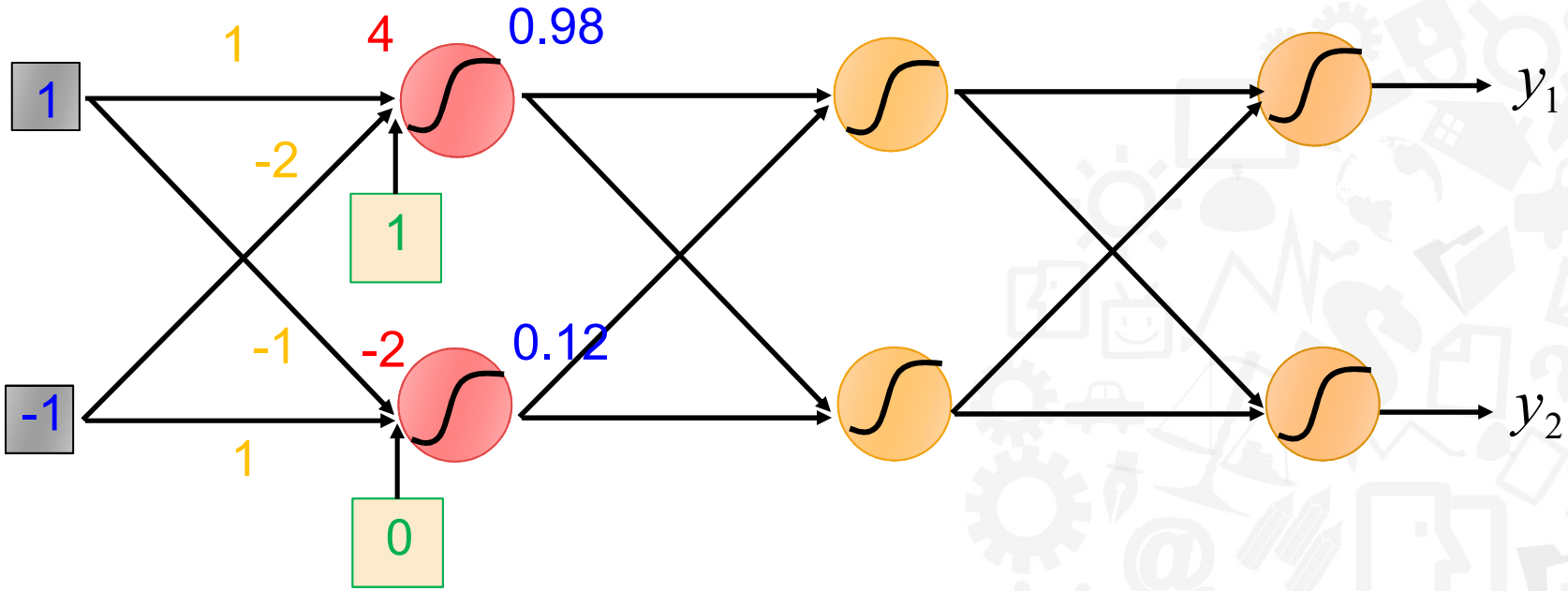


$f: R^2 \rightarrow R^2$

$$f\left(\begin{bmatrix}1\\-1\end{bmatrix}\right) = \begin{bmatrix}0.62\\0.83\end{bmatrix} \quad f\left(\begin{bmatrix}0\\0\end{bmatrix}\right) = \begin{bmatrix}0.51\\0.85\end{bmatrix}$$

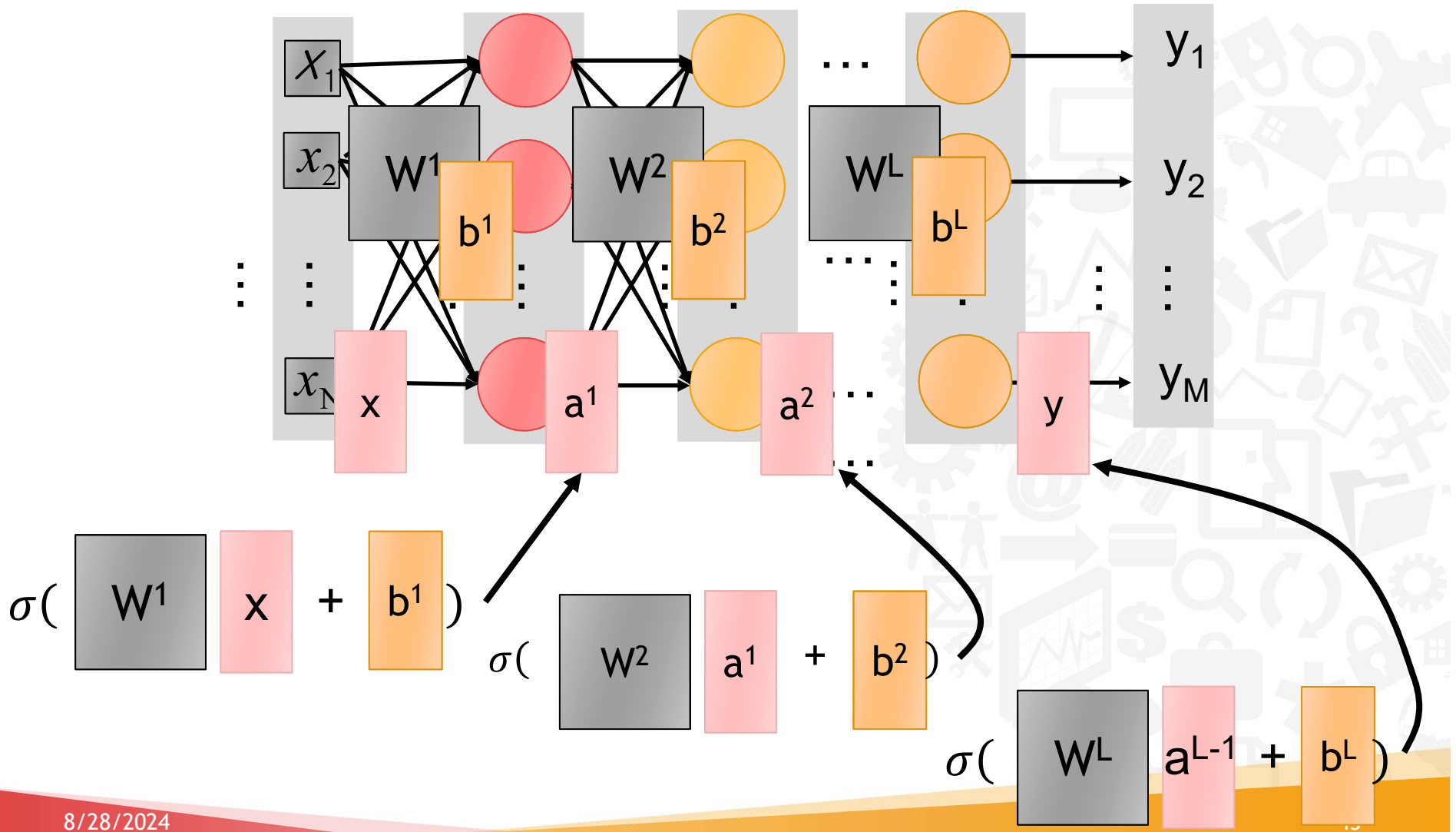
Different parameters define different function

Matrix operation

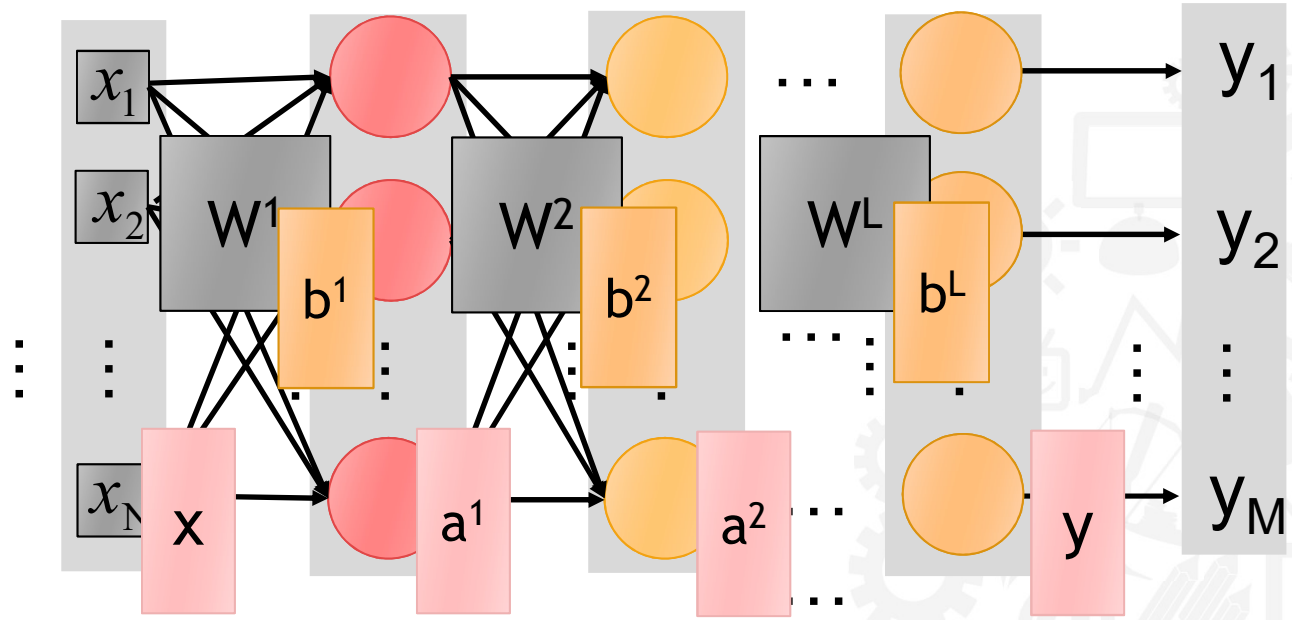


$$\sigma\left(\underbrace{\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{\begin{bmatrix} 4 \\ -2 \end{bmatrix}} \right) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

Neural network



Neural Network

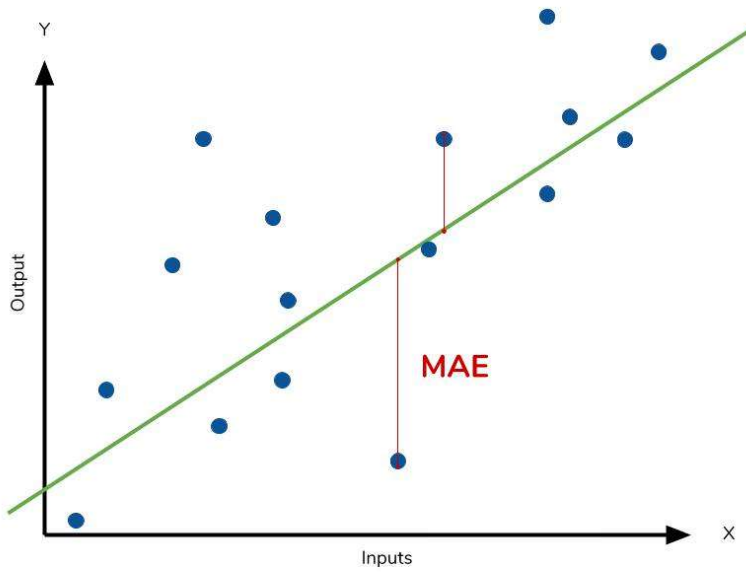


$$y = f(x)$$

Using parallel computing techniques to speed up matrix operation

$$= \sigma(W^L \cdots \sigma(W^2 \sigma(W^1 x + b^1) + b^2) \cdots + b^L)$$

Assessing the performance of the Model

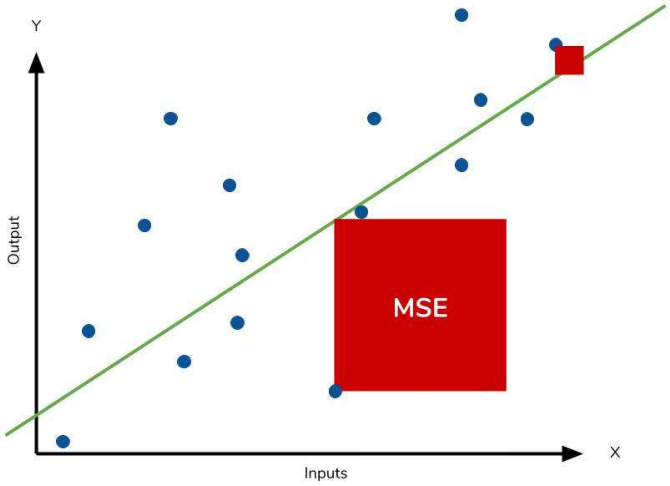


$$MAE = \frac{|y - \hat{y}|}{m}$$

- m : data points
- Y : vector of observed values
- $\hat{Y}$: vector of predicted values

- 절대값을 취하기 때문에 직관적
- MSE보다 특이치에 robust
- Regression 평가에 사용

Assessing the performance of the Model



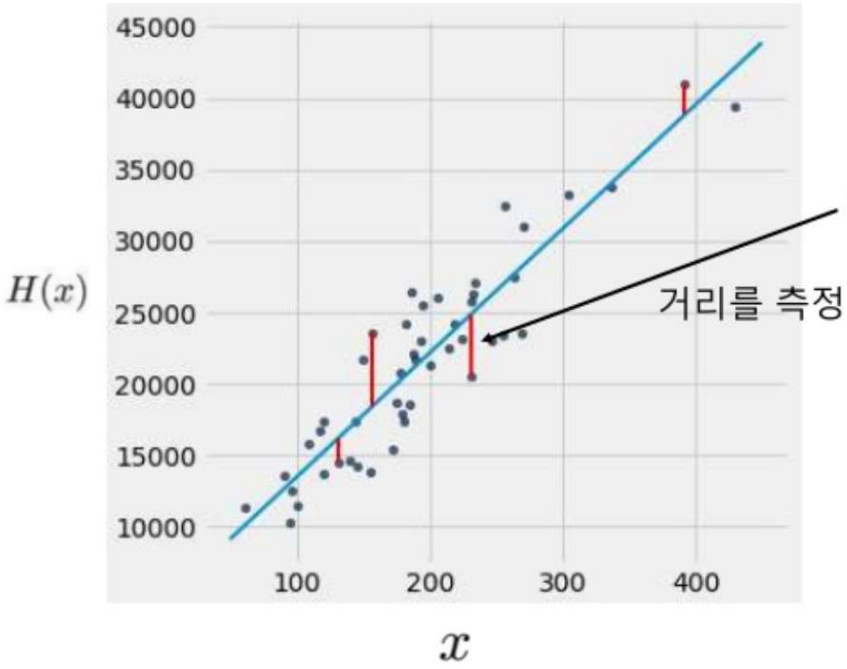
$$MSE = \frac{1}{m}\sum_{i=1}^{n}(\hat{Y} - Y)^2$$

- m : data points
- Y : vector of observed values
- $\hat{Y}$: vector of predicted values

- 모델의 예측값과 실제 값 차이 이의 면적의 합
- 특이치에 민감
- Training에 사용

How to minimize the cost?

- $MSE = \frac{1}{m}\sum_{i=1}^{n}(\hat{Y} - Y)^2$



$$H(x) = Wx + b$$

$$cost(W, b) = \frac{1}{m}\sum_{i=1}^{m}(H(x^{(i)}) - y^{(i)})^2$$

(m = data size, y = 실제값)

cost 함수

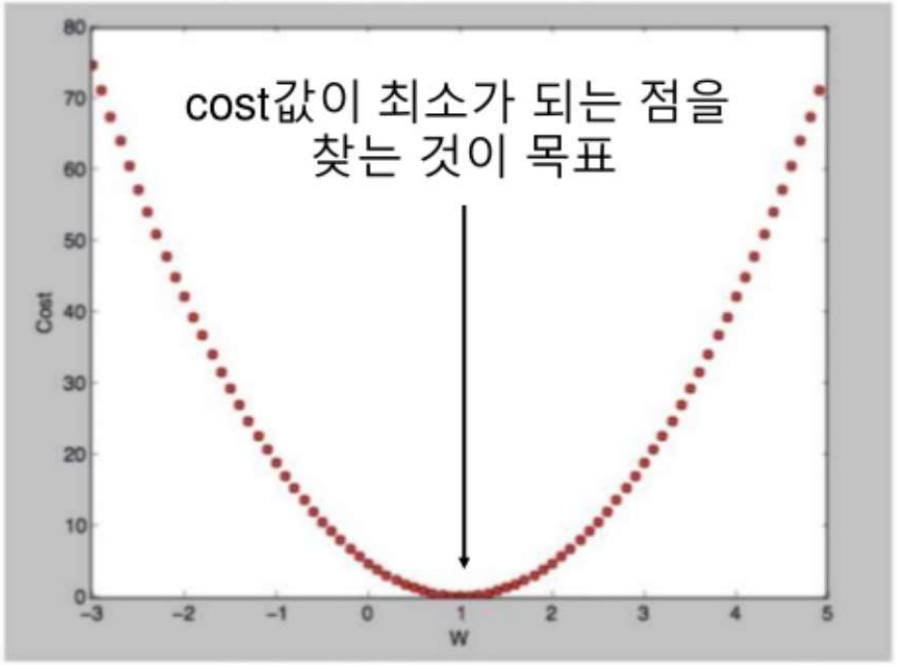
↓

W , b 의 함수

↓

Cost값을 작게 가지는 W , b 를 학습
= linear regression 의 학습

Cost function(or loss function)



(e.g. MSE)

$$H(x) = Wx$$

$$cost(W) = \frac{1}{m}\sum_{i=1}^{m}(Wx^{(i)} - y^{(i)})^2$$

무작위로 $H(x)$을 그어서
$cost(W)$ 가 최소가 되는 점을 찾는다?

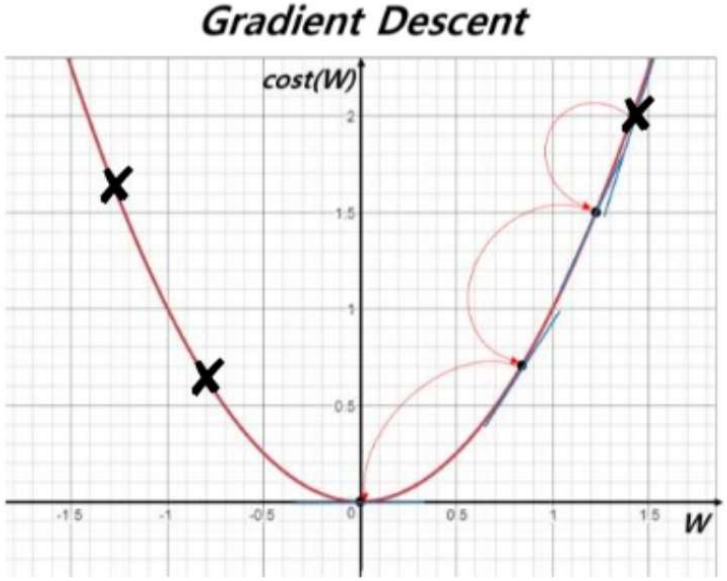
↓

$cost(W)$가 최소가 되는 점을
기계적으로 찾아내야 함

↓ optimization

Gradient descent algorithm

Gradient descent algorithm



✘ = 시작점

Step size, learning rate
= 수렴속도 조절

$$W := W - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(W \cdot x^{(i)} - y^{(i)} \right) \cdot x^{(i)}$$

$\frac{\partial cost(W)}{\partial W}$: 가파른 정도(slope)와 방향

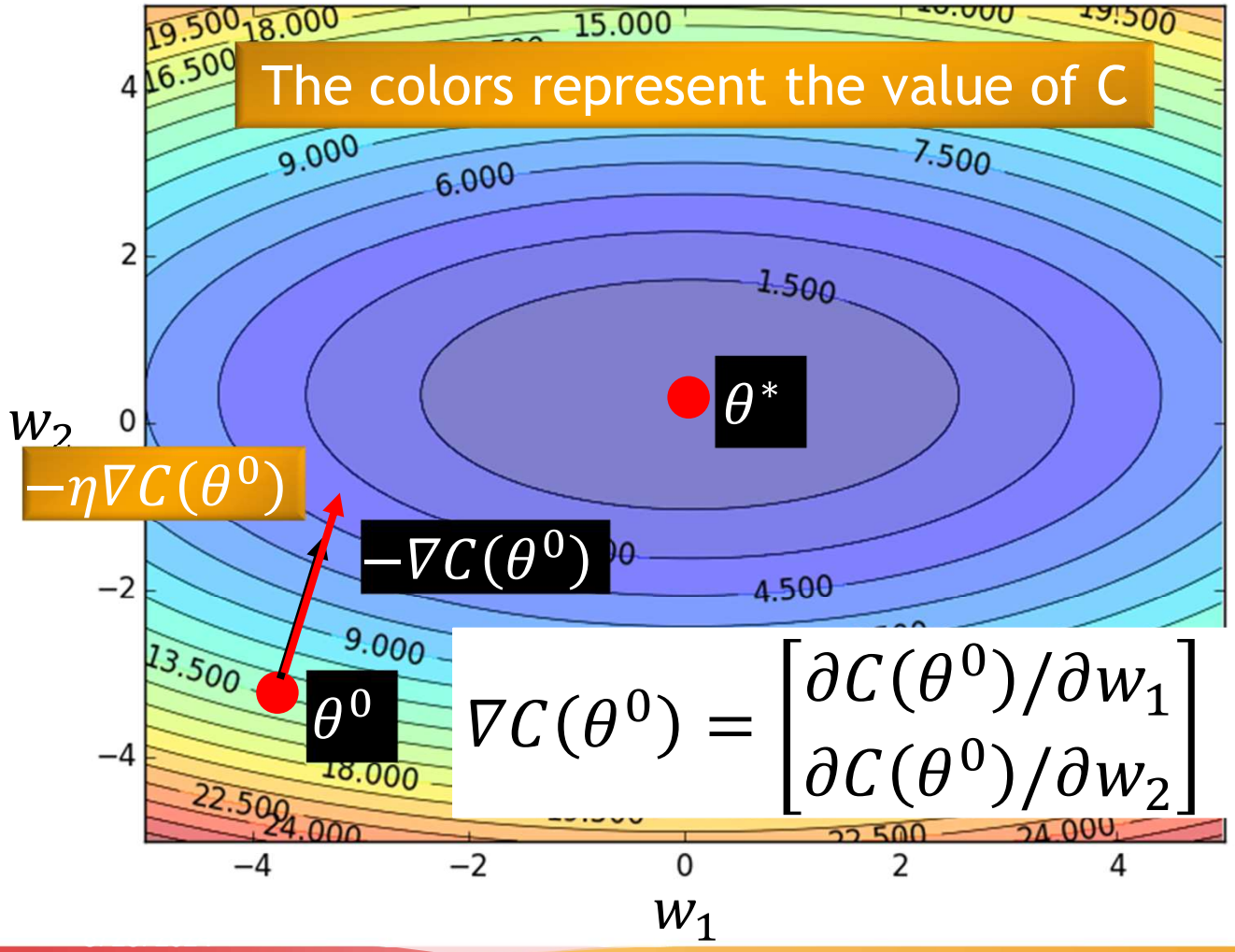
1. 시작점의 경사도에 따라 이동
2. 이동된 위치의 경사도를 따라 다시 이동
3. Cost(W)가 최소 즉 경사도 0인 지점까지 반복

Gradient Descent

Assume there are only two parameters w_1 and w_2 in a network.

$\theta = \{w_1, w_2\}$

Error surface



Randomly pick a starting point θ^0

Compute the negative gradient at θ^0

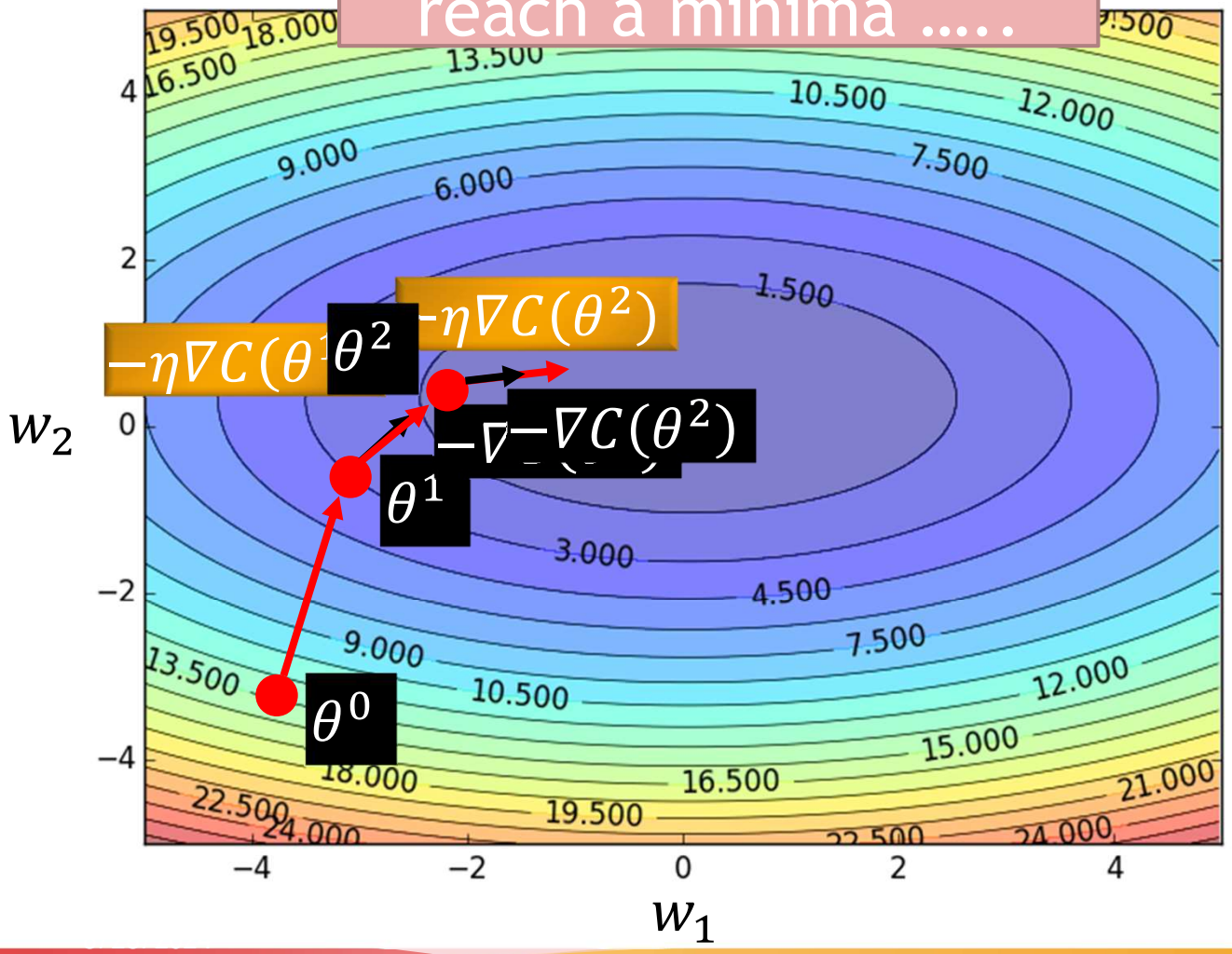
$-\nabla C(\theta^0)$

Times the learning rate η

$-\eta\nabla C(\theta^0)$

Gradient Descent

Eventually, we would reach a minima .....



Randomly pick a starting point θ^0

Compute the negative gradient at θ^0

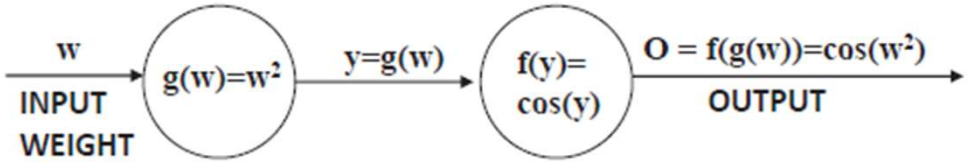
$-\nabla C(\theta^0)$

Times the learning rate η

$-\eta\nabla C(\theta^0)$

Backpropagation

- To compute the partial derivative of the loss function wrt. each intermediate weight
  - Not a simple matter with multi-layer architectures



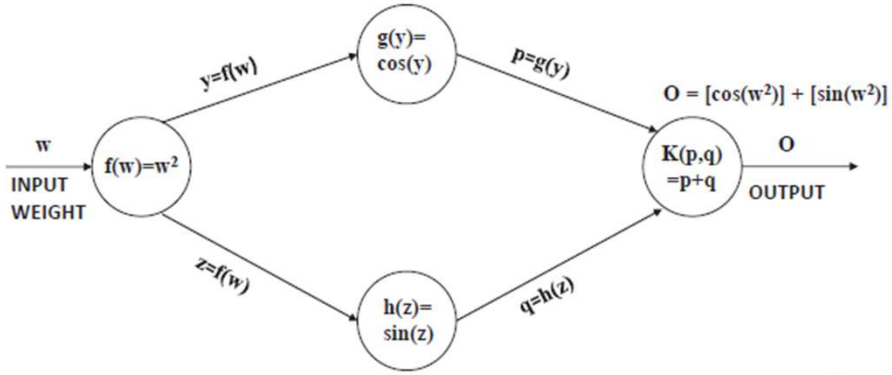
- In the univariate chain rule, we compute product of local derivatives

$$\frac{\partial f(g(w))}{\partial w} = \underbrace{\frac{\partial f(y)}{\partial y}}_{-sin(y)} \cdot \underbrace{\frac{\partial g(w)}{\partial w}}_{2w} = -2w \cdot \sin(y) = -2w \cdot \sin(w^2)$$

- Local derivatives are easy to compute because they care about their own inputs and outputs

Backpropagation

- Multivariate chain rule



$$\frac{\partial o}{\partial w} = \underbrace{\frac{\partial K(p,q)}{\partial p}}_{1} \cdot \underbrace{g'(y)}_{-\sin(y)} \cdot \underbrace{f'(w)}_{2w} + \underbrace{\frac{\partial K(p,q)}{\partial q}}_{1} \cdot \underbrace{h'(z)}_{\cos(z)} \cdot \underbrace{f'(w)}_{2w}$$

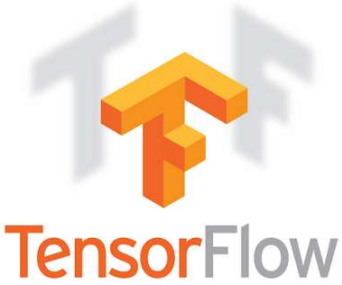
$$= -2w \cdot \sin(y) + 2w \cdot \cos(z)$$

$$= -2w \cdot \sin(w^2) + 2w \cdot \cos(w^2)$$

- Product of local derivatives along all paths from ***w*** to ***o***

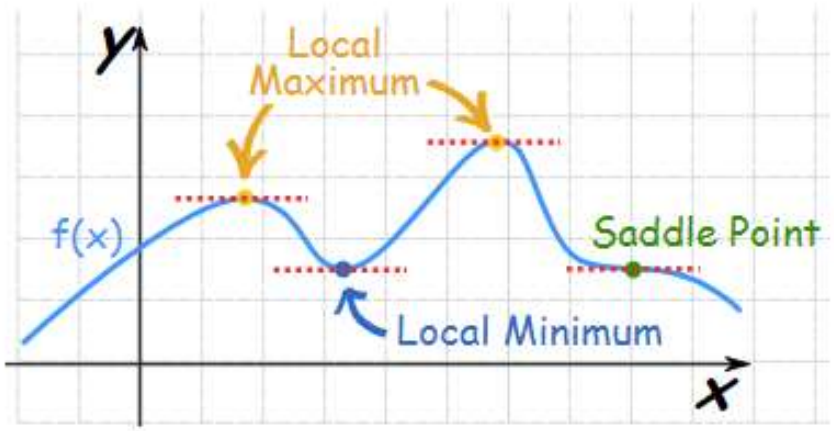
Backpropagation

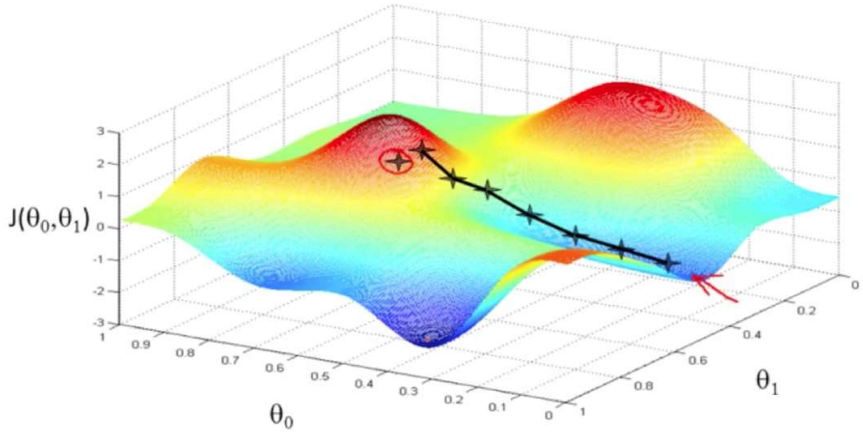
- A neural network can have millions of parameters
  - The size of today's NNs tends to increase
    - E.g., GPT-3 consists of 175B parameters
- Many toolkits can compute the gradients automatically



Local Minima

- Gradient descent never guarantee global minima

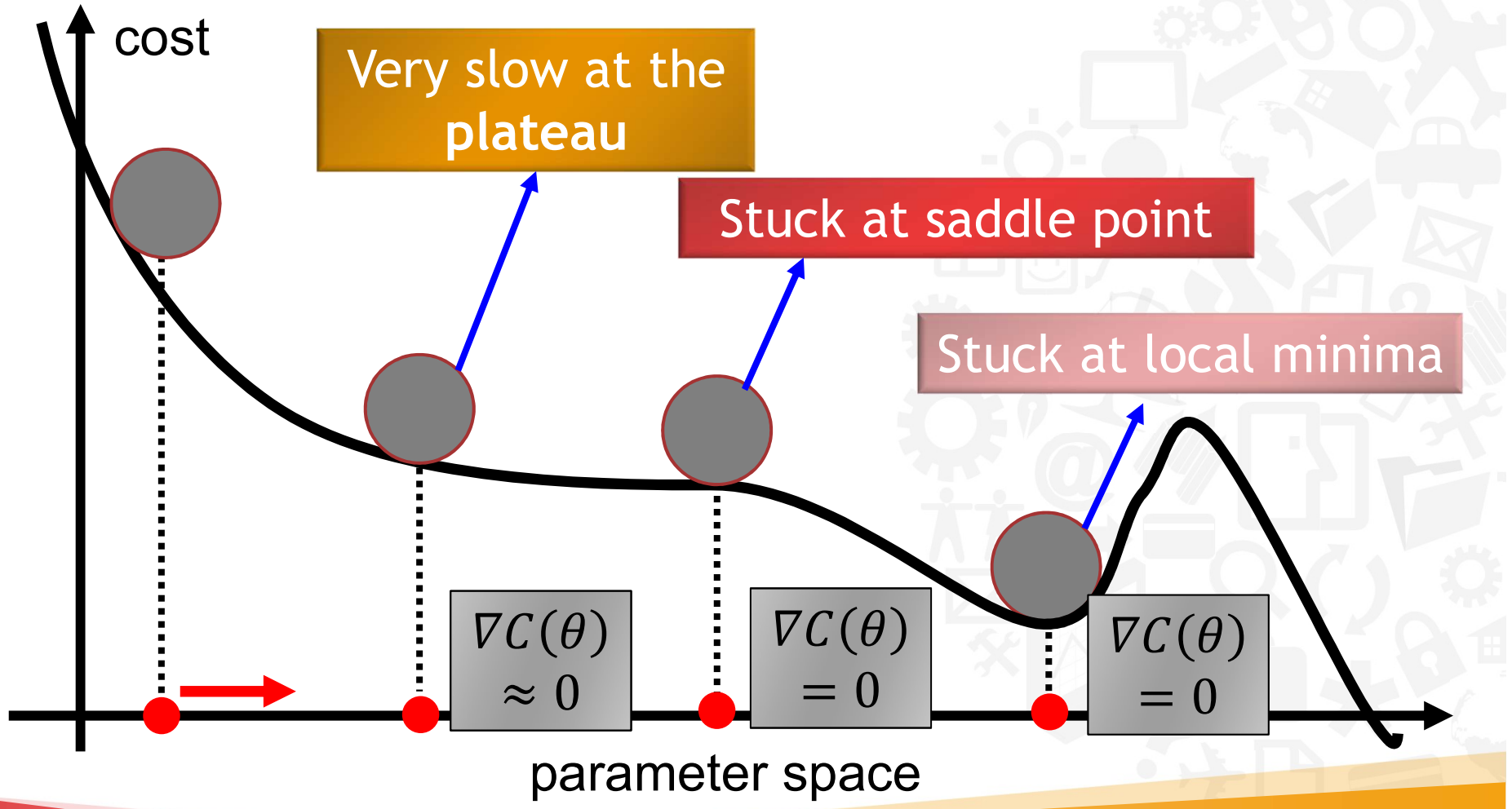




Different initial point θ^0

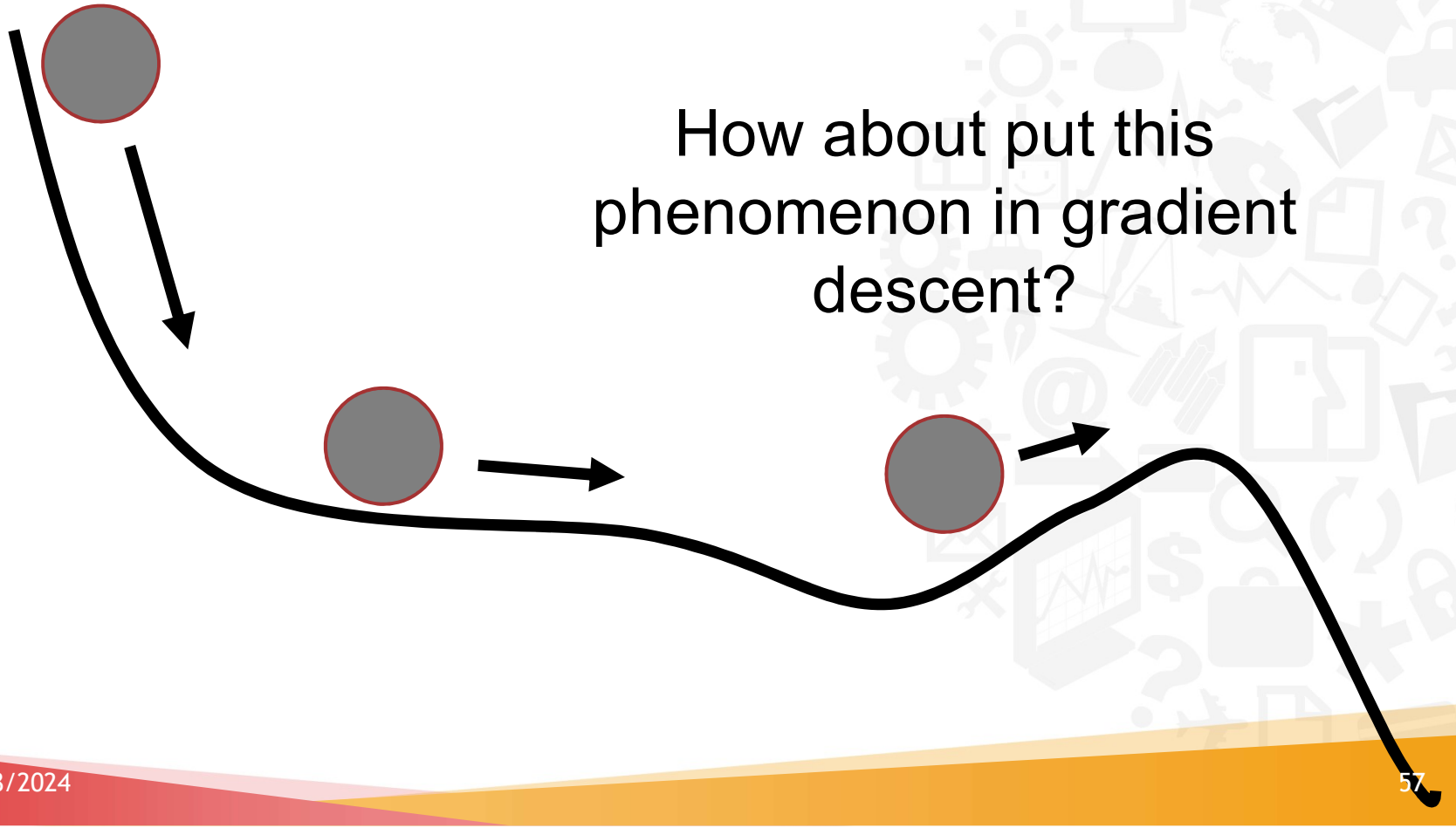
Reach different minima, so different results

Besides local minima .....



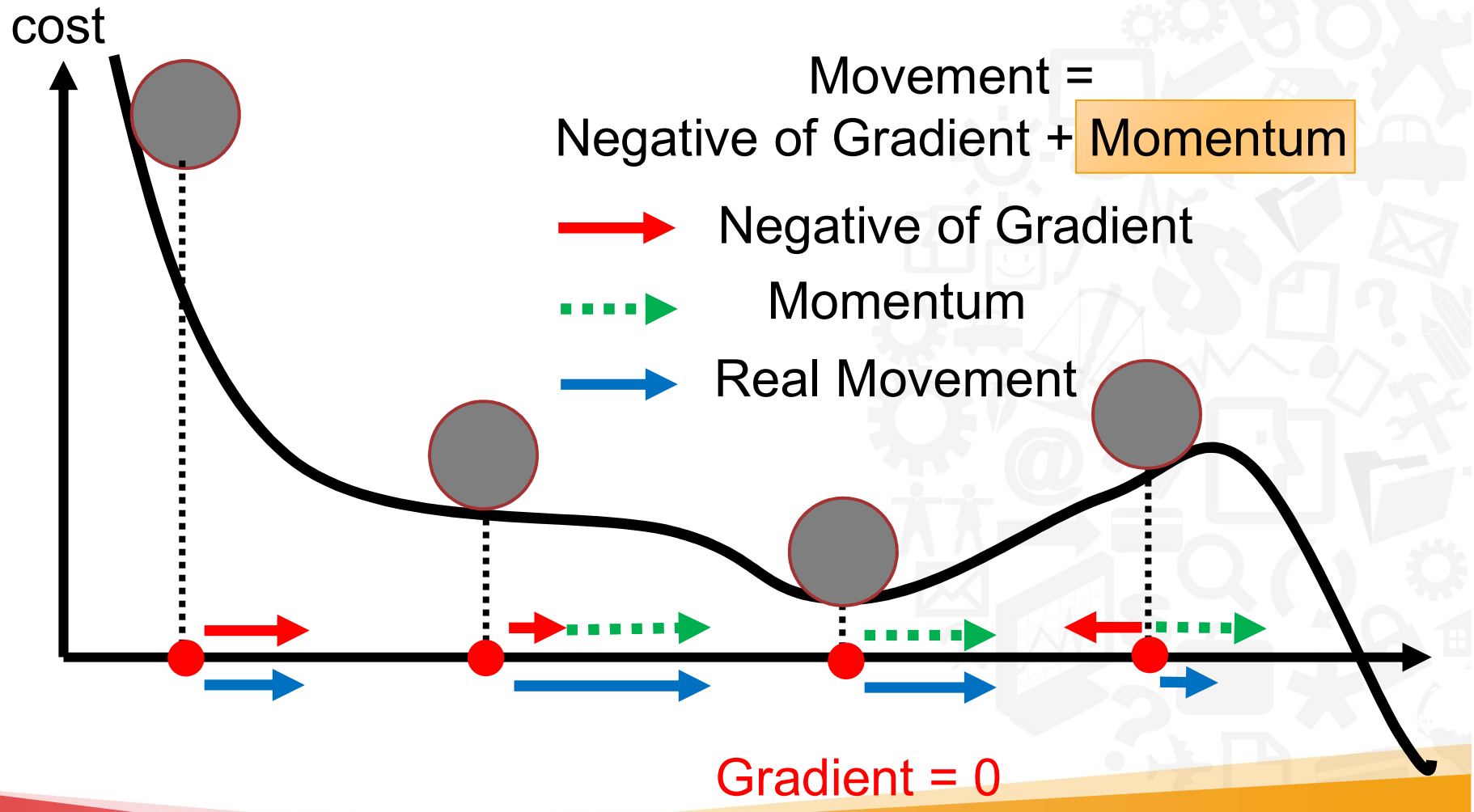
In physical world ……

- Momentum

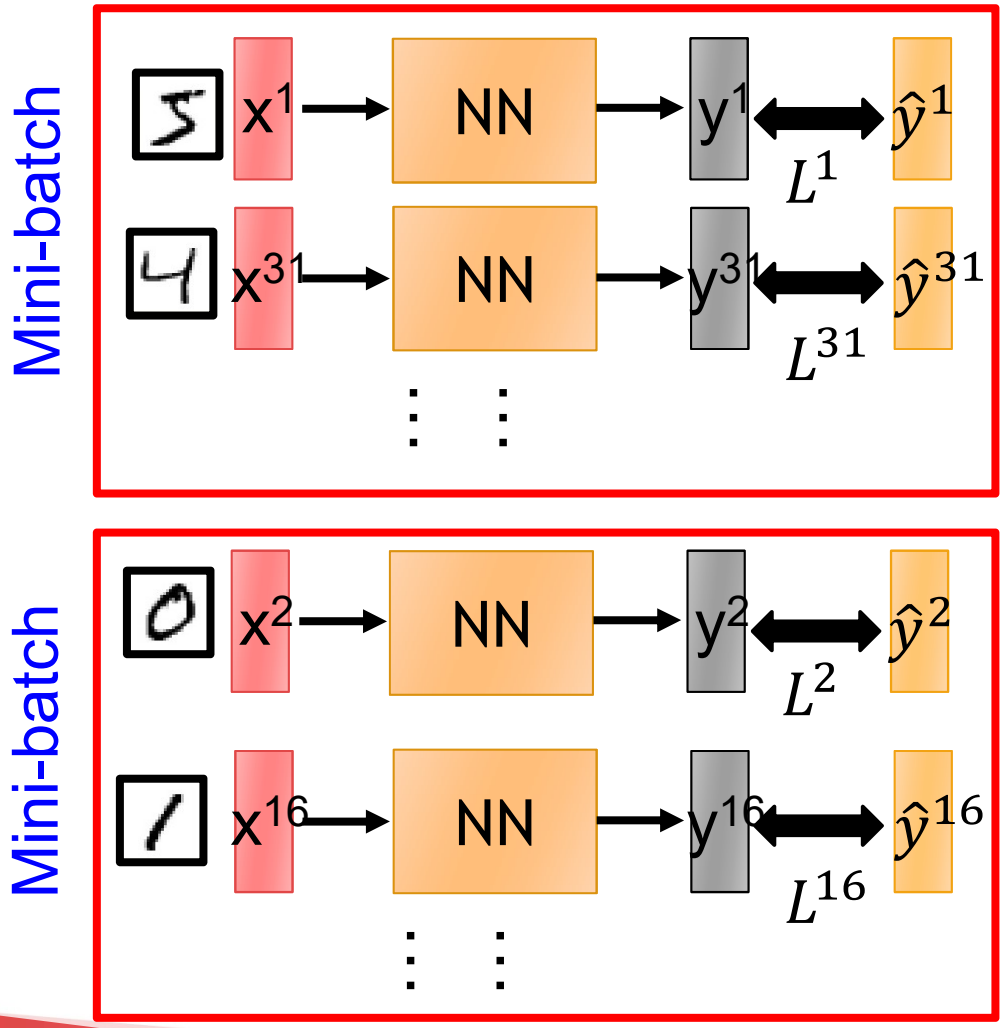


Momentum

Still not guarantee reaching global minima, but give some hope ……



Mini-batch



- Randomly initialize θ^0
- Pick the 1st batch

$$C = L^1 + L^{31} + \cdots$$

$$\theta^1 \leftarrow \theta^0 - \eta \nabla C(\theta^0)$$

- Pick the 2nd batch

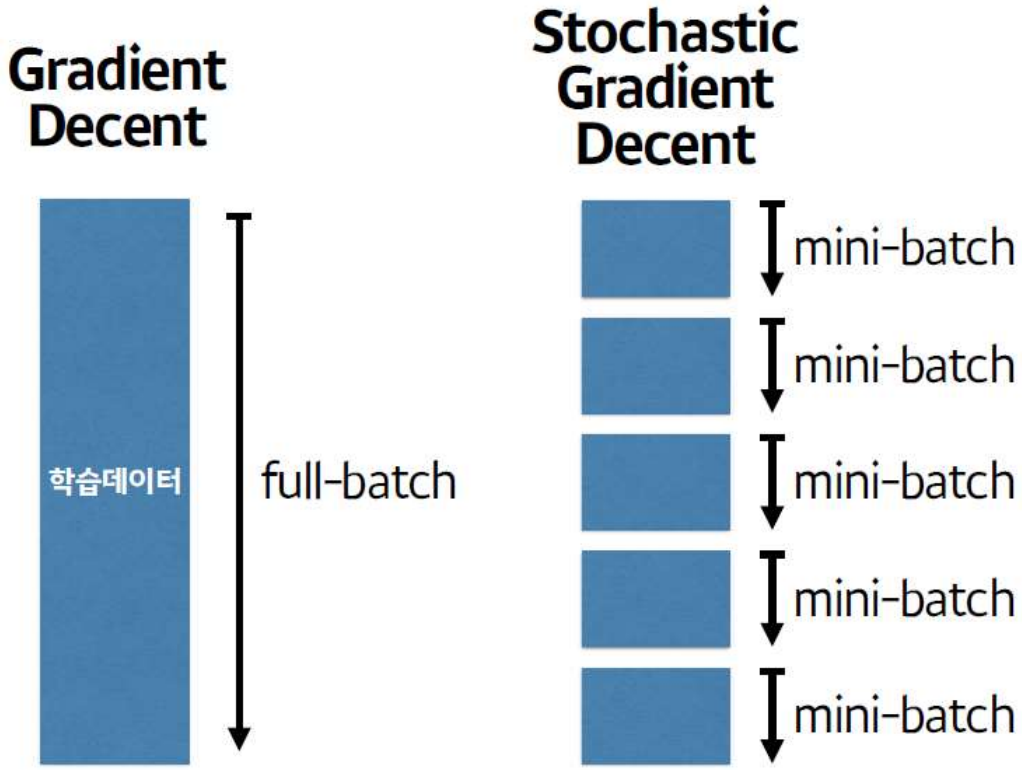
$$C = L^2 + L^{16} + \cdots$$

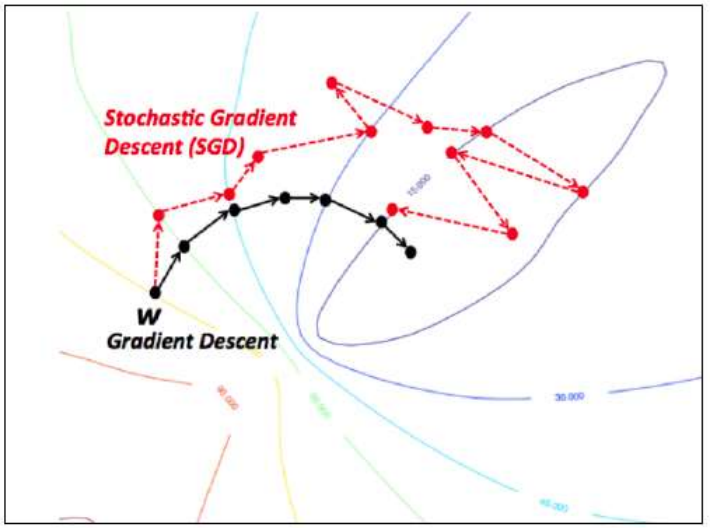
$$\theta^2 \leftarrow \theta^1 - \eta \nabla C(\theta^1)$$

⋮

C is different each time when we update parameters!

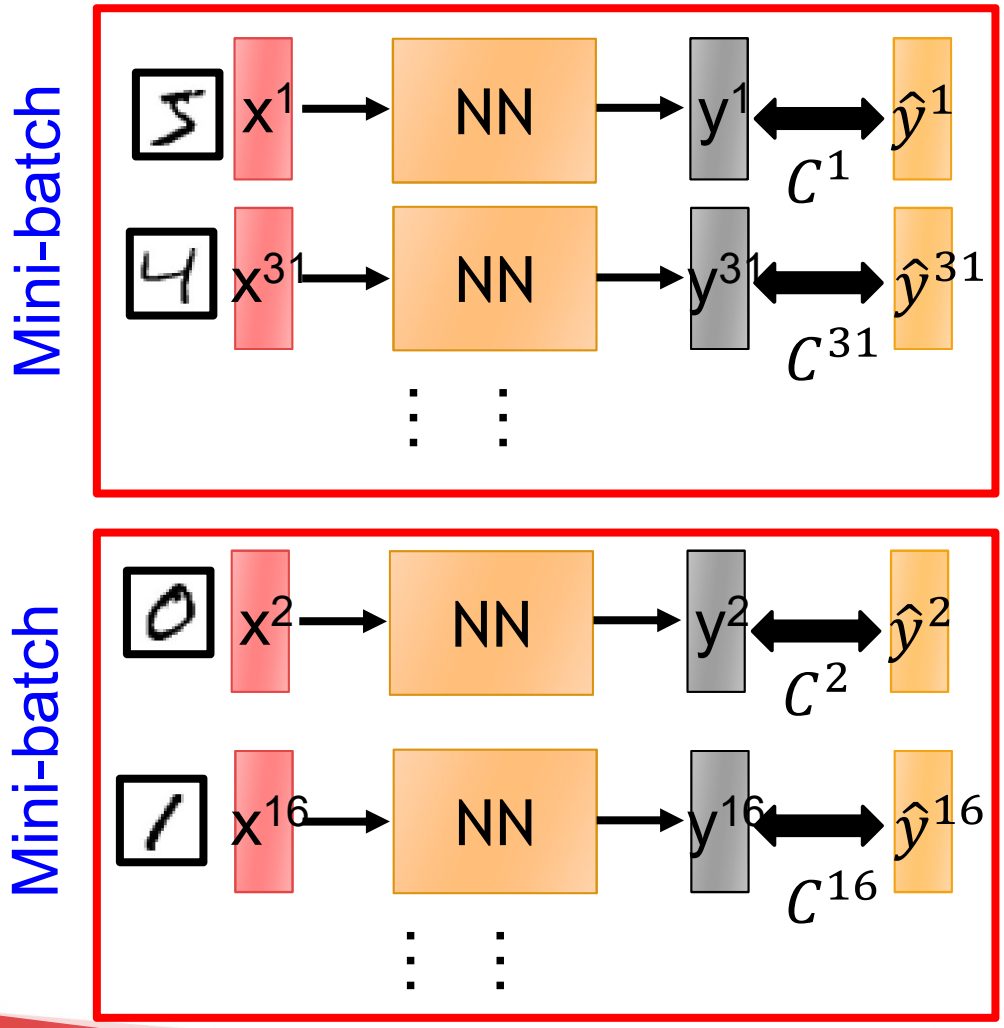
Mini-batch


Gradient Decent
학습데이터
full-batch
Stochastic Gradient Decent
mini-batch
mini-batch
mini-batch
mini-batch
mini-batch


Stochastic Gradient Descent (SGD)
W
Gradient Descent

Mini-batch

Faster **Better!**



- Randomly initialize θ^0
- Pick the 1st batch

  $C = C^1 + C^{31} + \cdots$

  $\theta^1 \leftarrow \theta^0 - \eta \nabla C(\theta^0)$
- Pick the 2nd batch

  $C = C^2 + C^{16} + \cdots$

  $\theta^2 \leftarrow \theta^1 - \eta \nabla C(\theta^1)$

  .
- Until all mini-batches have been picked

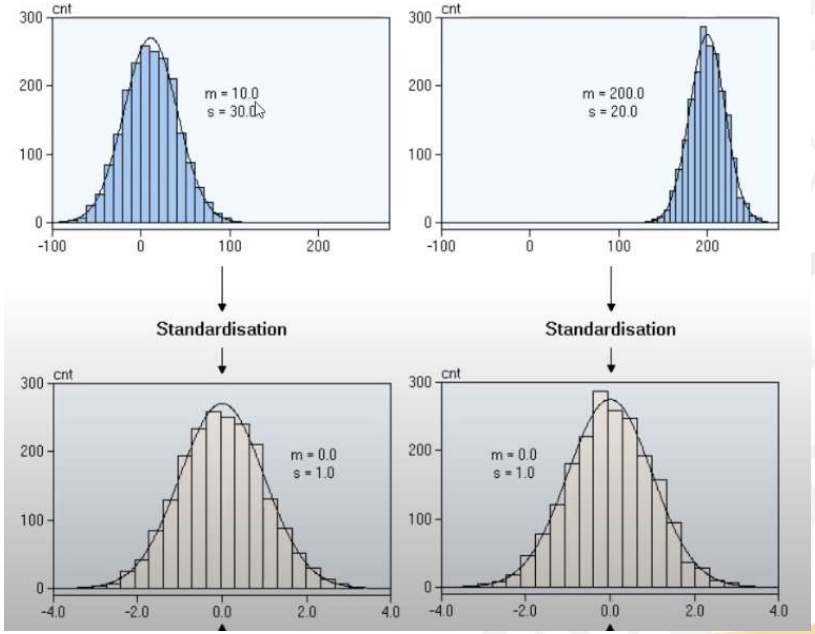
one epoch

Repeat the above process

Standardization

- 각 관찰값이 평균을 기준으로 어느정도 떨어져 있는지를 나타냄
  - 값의 scale이 다른 두 변수가 있을 때 scale 차이를 제거해주는 효과

$$x_{new} = \frac{x - \mu}{\sigma}$$

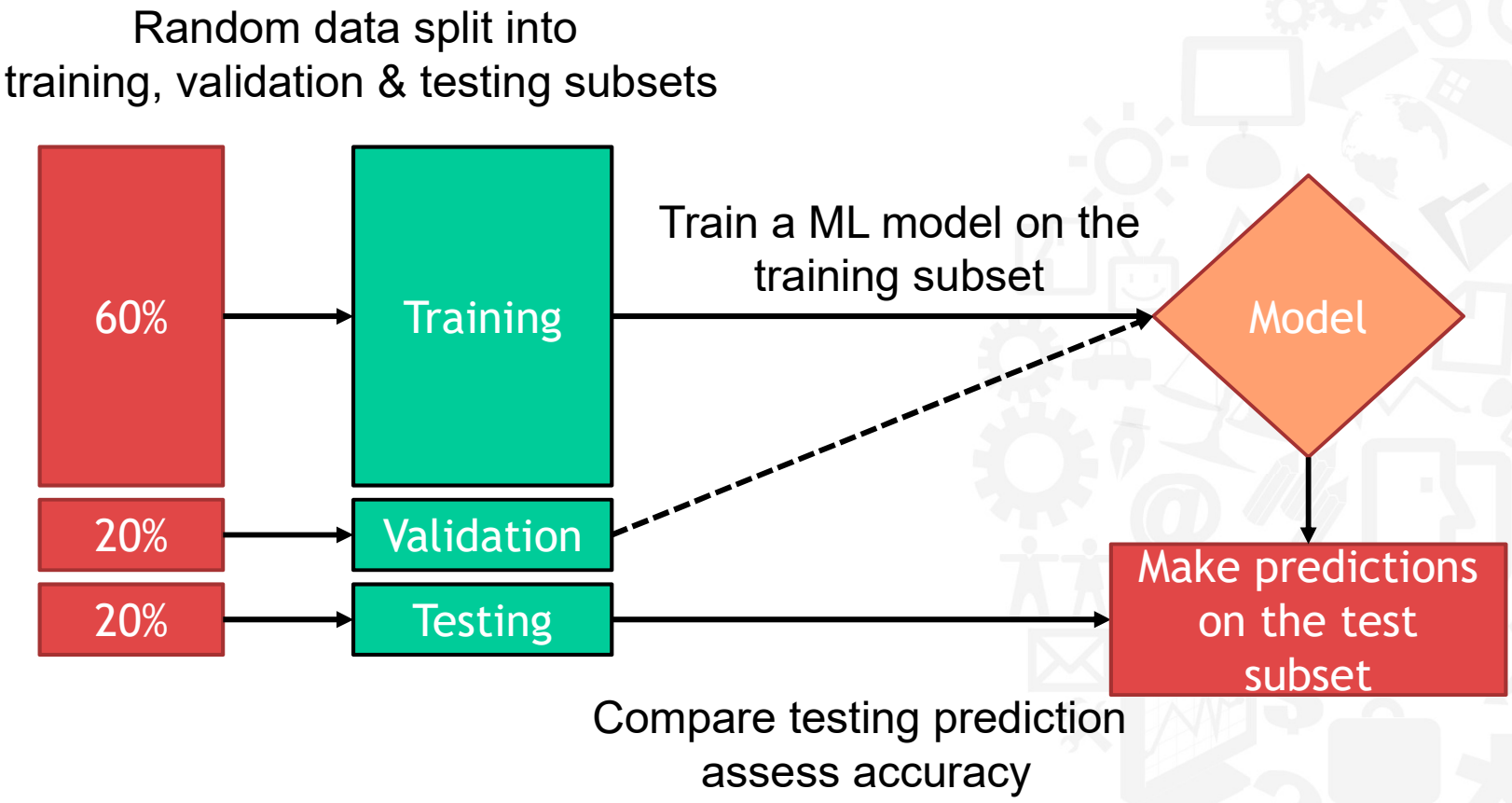


Normalization

- 정규화는 데이터의 범위를 0과 1로 변환하여 데이터 분포를 조정하는 방법
  - (해당 값- 최소값) / (최대값-최소값)
  - MinMax, Feature scaling 이라고도 함

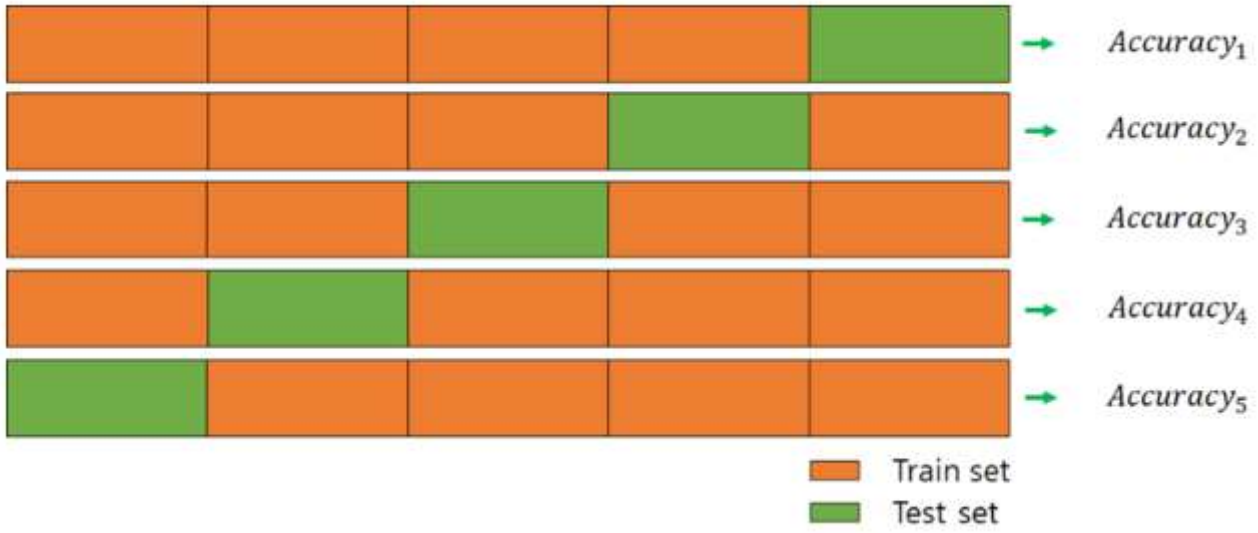
$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Training and testing splitting

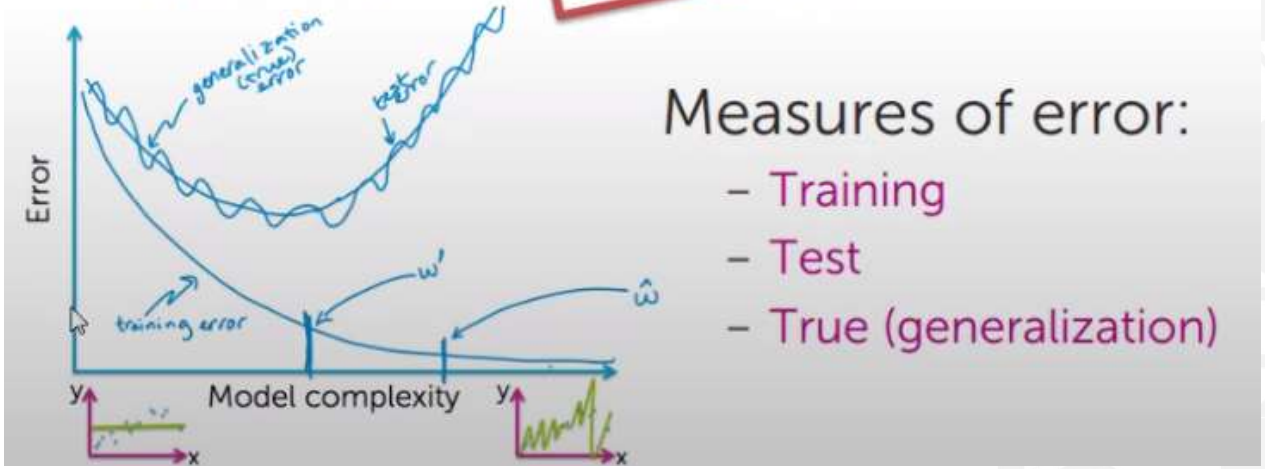


K-Folds Cross Validation

- 사용 이유
  - Test data 가 고정되어 있는 경우 test set에 overfit 될 수 있음
  - Dataset이 작은 경우 validation과 test set으로 데이터를 빼면 학습 데이터가 줄어드는 경우
-



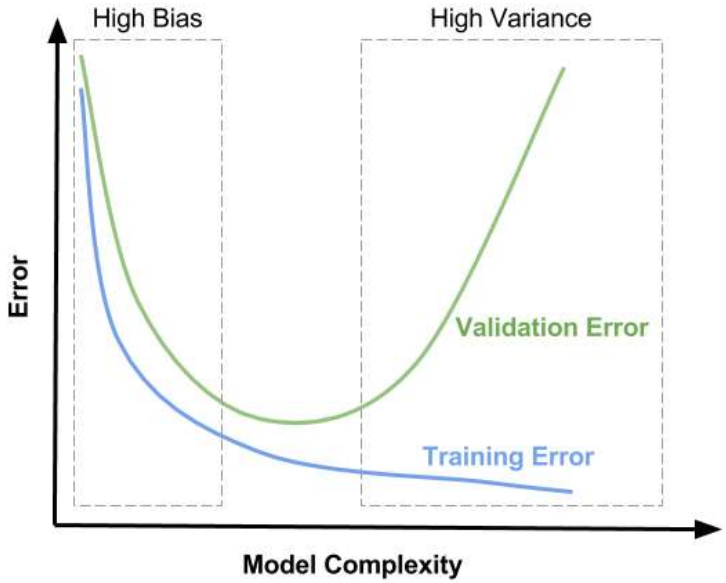
How do we determine the best fit line



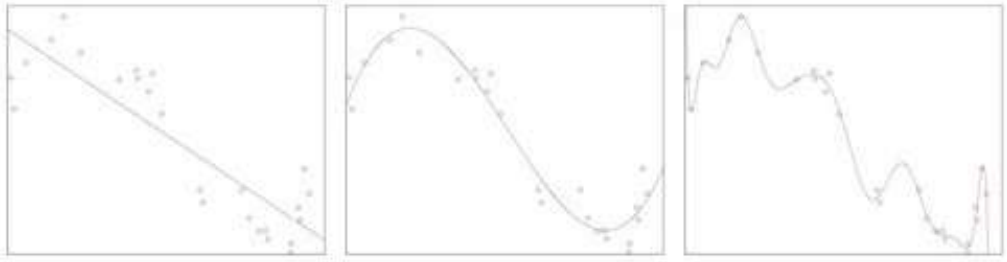
Measures of error:

- Training
- Test
- True (generalization)

Bias-Variance tradeoff



Model complexity



Error vs. amount of data

Bias-Variance tradeoff

- Bias (underfitting)
  - 추정값의 평균과 참값의 차이
  - 데이터 내에 있는 모든 정보를 고려하지 않음으로 인해 발생
- Variance (Overfitting)
  - 추정값의 평균과 추정값들간의 차이
  - 데이터 내에 있는 error나 noise까지 잘 잡아내도록 model fitting하여, 실제 관계없는 것까지 학습하는 경향

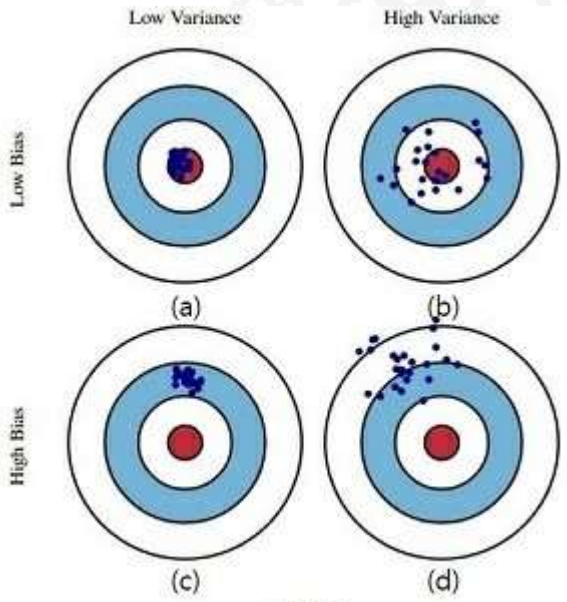


그림 1

LAB 1 : Housing Price Prediction