Neural Networks and Deep Learning

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한정호

Project Proposal

Topic | Neural Networks, Deep Learning

Description | We will learn basic concepts of neural network & deep learning and discuss as a team every friday 3-5pm (75 min: lecture / 45 min: discussion).

Expected Duration | 9 weeks (whole semester)

https://docs.google.com/spreadsheets/d/1UGbADy_LJ_xxtNhlWLFJKB1_Z8BFpPHPizxV6r5JNnE/edit#gid=0

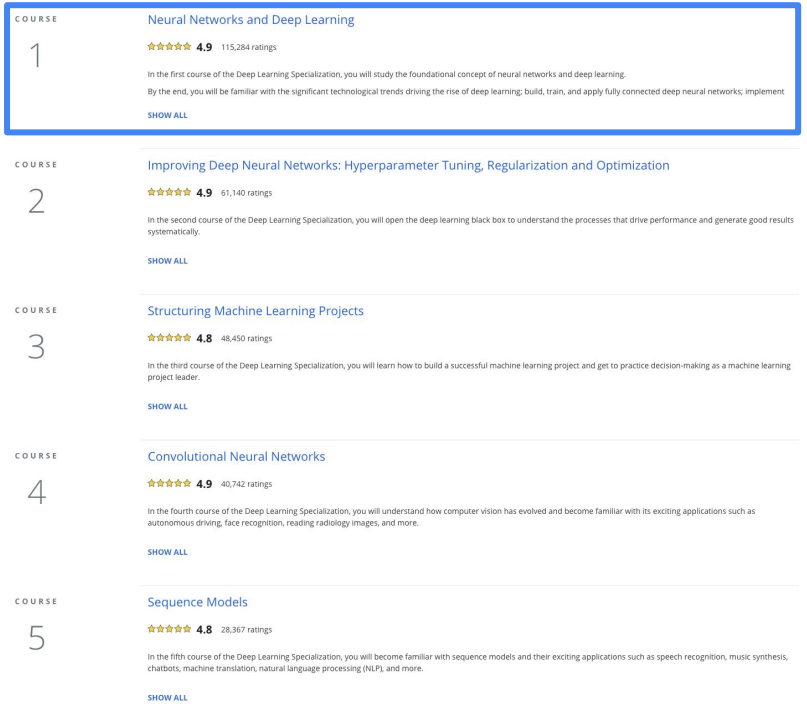
Team Member | 박시은, 오영빈, 최유진, 한정호

Timeline

Course 1: Neural Networks and Deep Learning (4-5 weeks)

Course 2 : Improving Deep Neural Networks: Hyperparameter Tuning, Regularization, and Optimization (4-5 weeks)

Coursera Deep Learning Specialization



https://www.coursera.org/specializations/deep-learning

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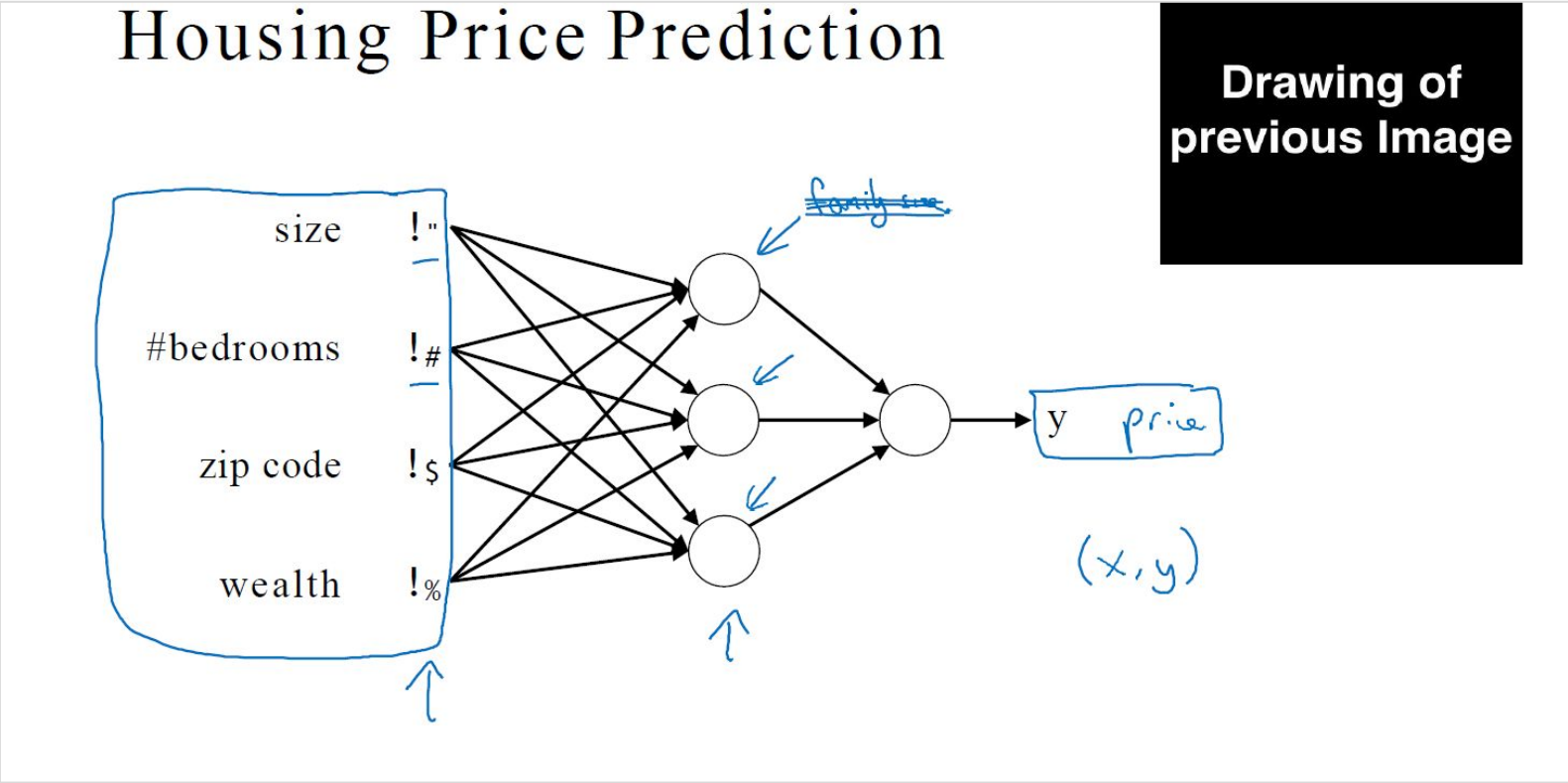
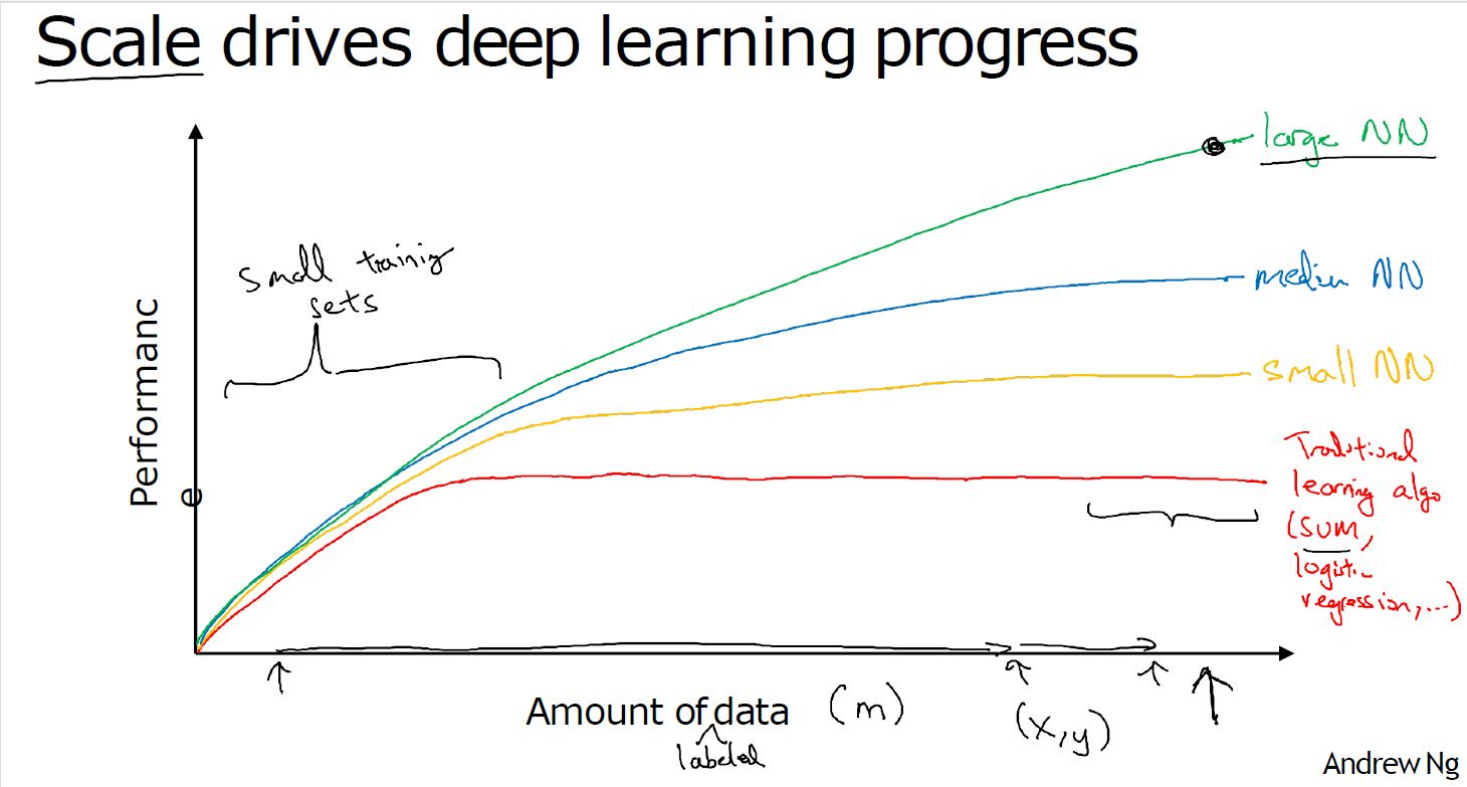
What is a Neural Network?

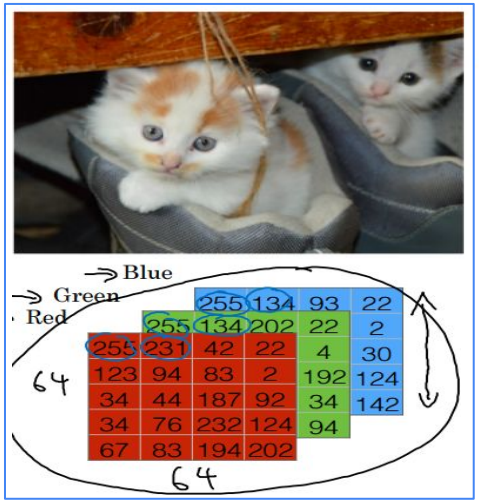


What is a Neural Network?



Binary classification

- Basics of neural network problem
- Supervised learning problem when the output y are all either zero or one.

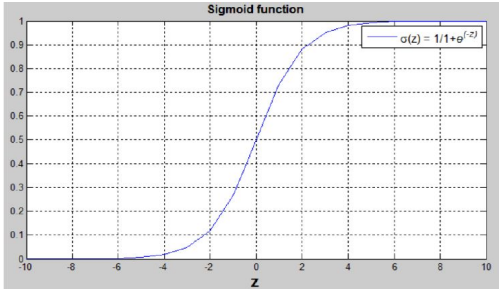


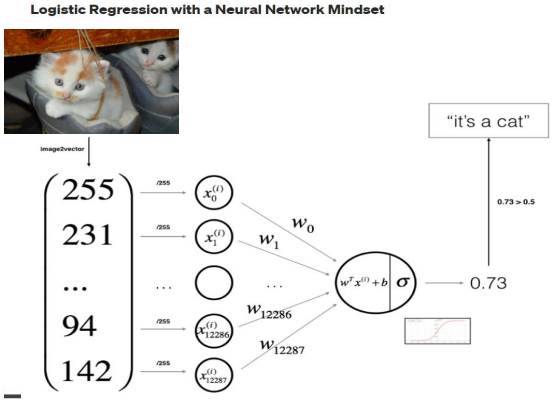
1 (cat) vs 0 (non cat)

y

Logistic regression

$$\hat{y}^{(i)} = \sigma(w^T x^{(i)} + b), \text{ where } \sigma(z^{(i)}) = \frac{1}{1 + e^{-z^{(i)}}}$$





Cost function

- Loss (error) function: computes the error for a single training example.

$$L(\hat{y}^{(i)}, y^{(i)}) = \frac{1}{2}(\hat{y}^{(i)} - y^{(i)})^2$$

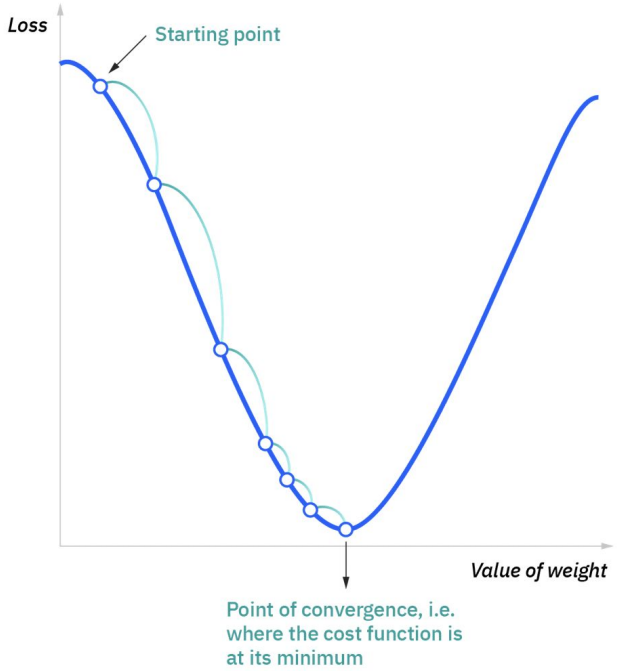
- Cost function: the average of the loss function of the entire training set.

- Goal: find the parameters w *and* b that minimize the overall cost function.

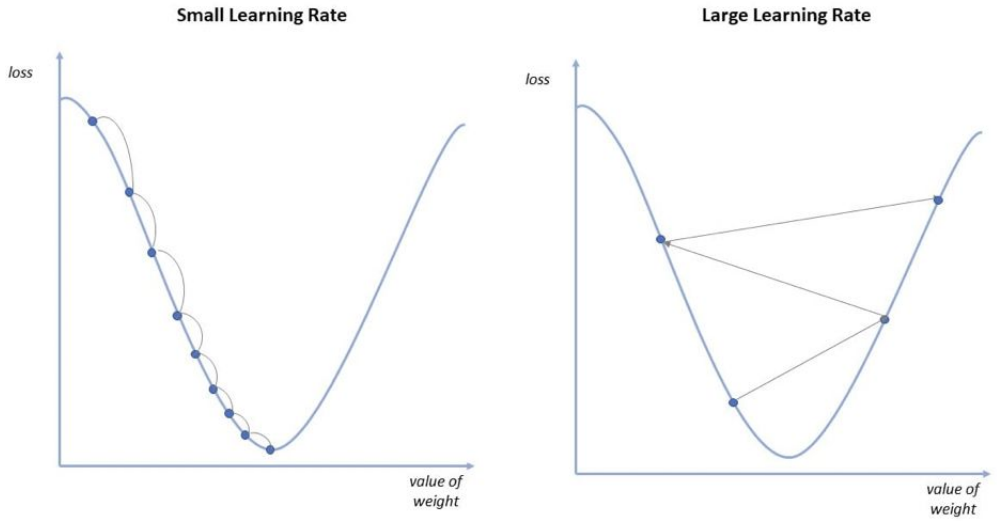
$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m} L(\hat{y}^{(i)}, y^{(i)}) = -\frac{1}{m}\sum_{i=1}^{m}[(y^{(i)}\log(\hat{y}^{(i)}) + (1 - y^{(i)})\log(1 - \hat{y}^{(i)})]$$

Gradient Descent

- Optimization algorithm to minimize cost function (convex)
- Take repeated steps in the opposite direction of the gradient of the function at the current point
- Repeat x<-x-α*f’(x)
  (α: learning rate, small positive number)
- Justification: The gradient points in the direction of the steepest ascent

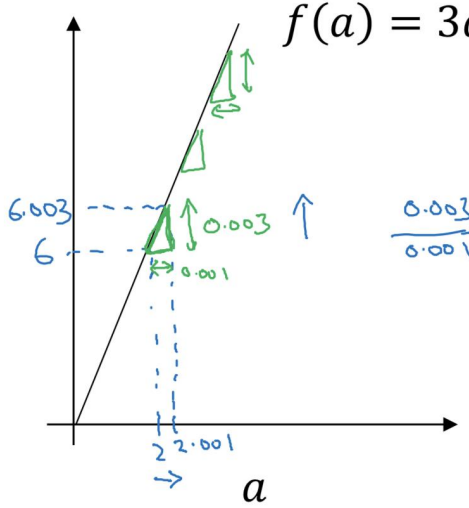


Gradient Descent



- Importance of making initial guess of optimal learning rate

Intuition about derivatives



$\frac{0.003}{0.001}$ $\frac{\text{height}}{\text{width}}$

→ slope (derivative) of $f(a)$ at $a=2$ is 3

→ $a = 2$ $f(a) = 6$

$a = 2.001$ $f(a) = 6.003$

→ $a = 5$ $f(a) = 15$

$a = 5.001$ $f(a) = 15.003$

slope at $a=5$ is also 3

$\frac{d f(a)}{da} = 3 = \frac{d}{da} f(a)$

0.001
0.000000001
0.000000000001

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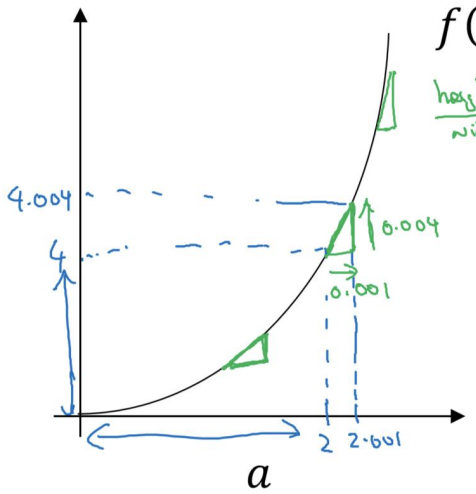
Intuition about derivatives



$$\frac{d}{da} a^2 = 2a$$

0.001

$(2a) \times 0.001$

0.001 ←

0.00000....01 ←

$a = 2$ $\quad f(a) = 4$

$a = 2.001$ $\quad f(a) \approx 4.004$

$(4.004\,001)$

slope (derivative) of $f(a)$ at $a = 2$ is 4.

$\frac{d}{da} f(a) = 4$ when $a = 2$.

$a = 5$ $\quad f(a) = 25$

$a = 5.001$ $\quad f(a) \approx 25.010$

$\frac{d}{da} f(a) = 10$ when $a = 5$

$\frac{d}{da} f(a) = \frac{d}{da} a^2 = 2a$

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Next Steps

- Python Implementation of Machine Learning
- Introduction to Neural Network

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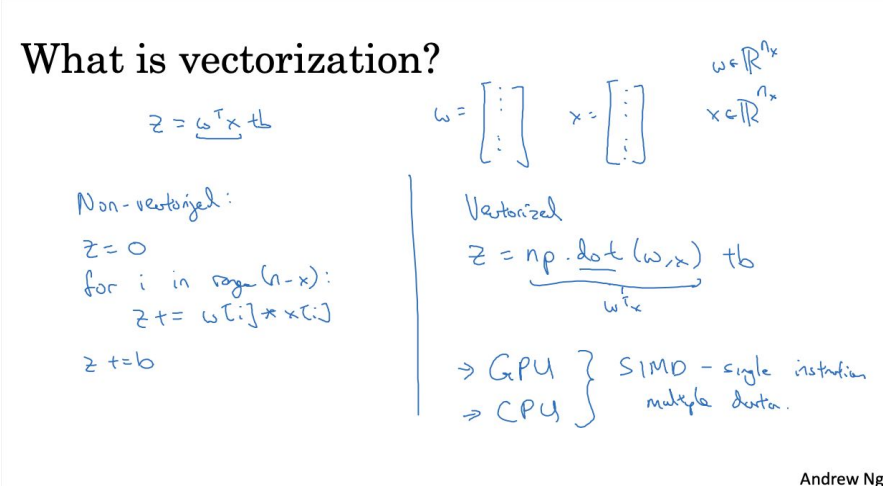
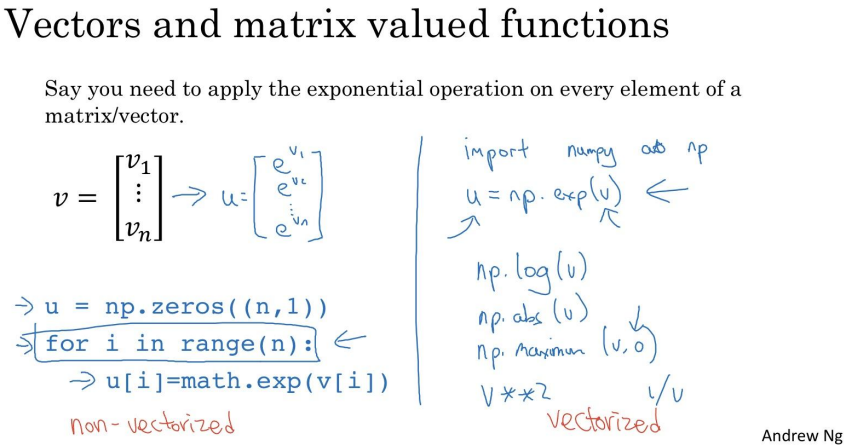
What is Vectorization?



- Iterative for loop vs vectorization
- Enables parallel processing
- Minimizes the running & execution time of code
- Vectorization Example:

https://colab.research.google.com/drive/1np5oDUVOmFPx8M-NScuEakZgDWjufuLe#scrollTo=nMUlJO0cjmPF

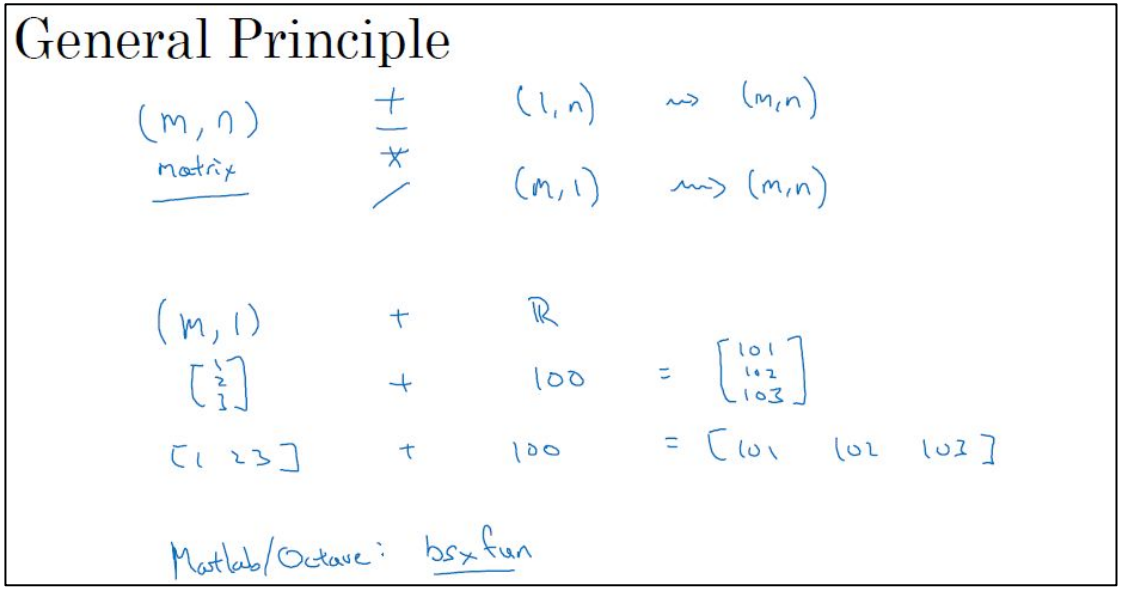
What is Vectorization?



- Whenever possible, remove explicit for loops
- Speed up data processing
- Implement by Python Numpy
- ex) np.exp(v), np.log(v), np.abs(v), np.square(v), np.maximum(v,0)

What is Broadcasting?

- numpy가 다른 모양의 행렬을 처리하는 방법



Broadcasting

- Python vs R

```
1 a = np.array([[1,4,7],
2               [2,5,8],
3               [3,6,9]])
4 print(a)
```

```
[[1 4 7]
 [2 5 8]
 [3 6 9]]
```

```
1 b = np.array([[1],
2               [2],
3               [3]])
4 print(b)
```

```
[[1]
 [2]
 [3]]
```

```
1 a+b
```

```
array([[ 2,  5,  8],
       [ 4,  7, 10],
       [ 6,  9, 12]])
```

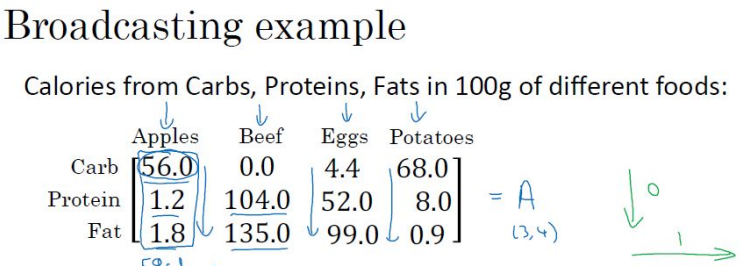
Python

```
> a <- matrix(data = 1:9, nrow = 3, ncol = 3)
> a
     [,1] [,2] [,3]
[1,]    1    4    7
[2,]    2    5    8
[3,]    3    6    9
> b <- matrix(data = 1:3, nrow = 3, ncol = 1)
> b
     [,1]
[1,]    1
[2,]    2
[3,]    3
> c <- a + b
Error in a + b : non-conformable arrays
```

R

Broadcasting

- 각 음식별 탄수화물, 단백질, 지방 칼로리 함량 (%)



- 백분율 계산 (matrix division)

```
# 총 칼로리 계산
# axis=0은 세로로 값을 더하라는 의미 (axis=1: 가로 합)
cal = A.sum(axis=0)
print(cal)
```

```
[ 59.  239.  155.4  76.9]
```

```
# 각 음식별 탄수화물, 단백질, 지방 칼로리 비율 (%)
percentage = 100*A/cal.reshape(1,4) # python broadcasting
                                    # M(3,4) / M(1,4)
percentage.round(2)
```

Matrix division

```
array([[94.92,  0.  ,  2.83, 88.43],
       [ 2.03, 43.51, 33.46, 10.4 ],
       [ 3.05, 56.49, 63.71,  1.17]])
```

- **주의할 점**: 아주 감지하기 힘든 버그나 또는 매우 이상하게 생긴 버그

Next Steps

- Neural Networks Overview
- Describe hidden units and hidden layers
- Use units with a non-linear activation function, such as tanh
- Implement forward and backward propagation
- Apply random initialization to your neural network
- Increase fluency in Deep Learning notations and Neural Network Representations
- Implement a 2-class classification neural network with a single hidden layer
- Compute the cross entropy loss

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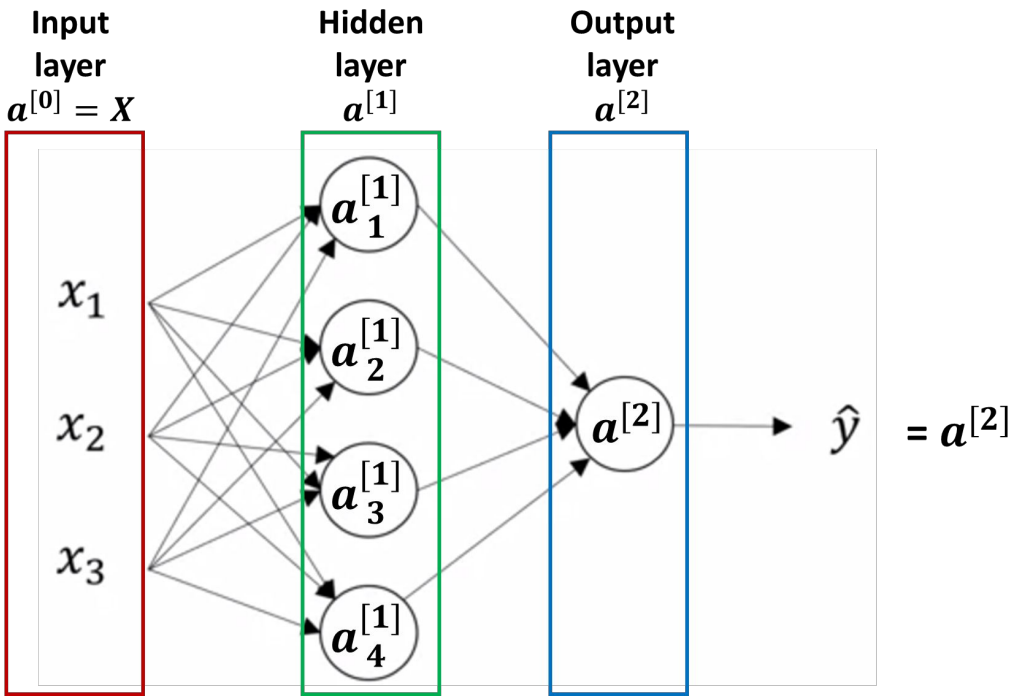
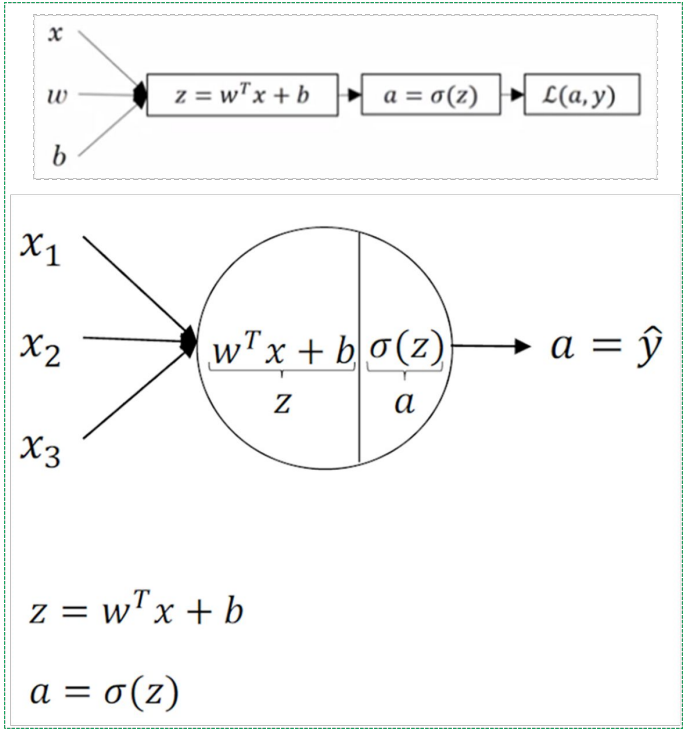
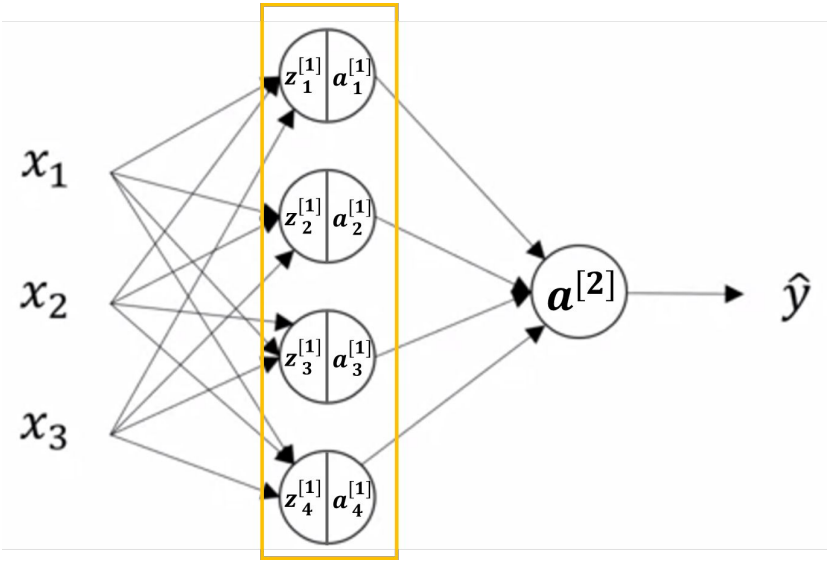
Neural Network Representation





Neural Network Representation



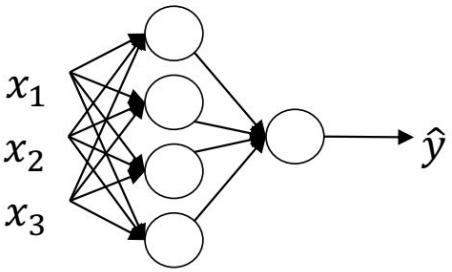
$$z_1^{[1]} = w_1^{[1]T}x + b_1^{[1]}, \quad a_1^{[1]} = \sigma(z_1^{[1]})$$
$$z_2^{[1]} = w_2^{[1]T}x + b_2^{[1]}, \quad a_2^{[1]} = \sigma(z_2^{[1]})$$
$$z_3^{[1]} = w_3^{[1]T}x + b_3^{[1]}, \quad a_3^{[1]} = \sigma(z_3^{[1]})$$
$$z_4^{[1]} = w_4^{[1]T}x + b_4^{[1]}, \quad a_4^{[1]} = \sigma(z_4^{[1]})$$

Vectorizing

$$z^{[1]} = \begin{bmatrix} w_1^{[1]T} \\ w_2^{[1]T} \\ w_3^{[1]T} \\ w_4^{[1]T} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1^{[1]} \\ b_2^{[1]} \\ b_3^{[1]} \\ b_4^{[1]} \end{bmatrix} = \begin{bmatrix} w_1^{[1]T}x \times b_1^{[1]} \\ w_2^{[1]T}x \times b_2^{[1]} \\ w_3^{[1]T}x \times b_3^{[1]} \\ w_4^{[1]T}x \times b_4^{[1]} \end{bmatrix} = \begin{bmatrix} z_1^{[1]} \\ z_2^{[1]} \\ z_3^{[1]} \\ z_4^{[1]} \end{bmatrix}$$

$$a^{[1]} = \begin{bmatrix} a_1^{[1]} \\ a_2^{[1]} \\ a_3^{[1]} \\ a_4^{[1]} \end{bmatrix} = \begin{bmatrix} \sigma(z_1^{[1]}) \\ \sigma(z_2^{[1]}) \\ \sigma(z_3^{[1]}) \\ \sigma(z_4^{[1]}) \end{bmatrix}$$

Vectorizing across multiple examples



$$z^{[1]} = W^{[1]}x + b^{[1]}$$
$$a^{[1]} = \sigma(z^{[1]})$$
$$z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$$
$$a^{[2]} = \sigma(z^{[2]})$$

$X \rightarrow a^{[2]} = \hat{y}$

$x^{(1)} \rightarrow a^{[2](1)} = \hat{y}^{(1)}$

$x^{(2)} \rightarrow a^{[2](2)} = \hat{y}^{(2)}$

$\vdots$

$x^{(m)} \rightarrow a^{[2](m)} = \hat{y}^{(m)}$

$a^{[2](i)}$ ← example i, ← layer 2

for $i = 1$ to m,

$z^{[1](i)} = W^{[1]}x^{(i)} + b^{[1]}$

$a^{[1](i)} = \sigma(z^{[1](i)})$

$z^{[2](i)} = W^{[2]}a^{[1](i)} + b^{[2]}$

$a^{[2](i)} = \sigma(z^{[2](i)})$

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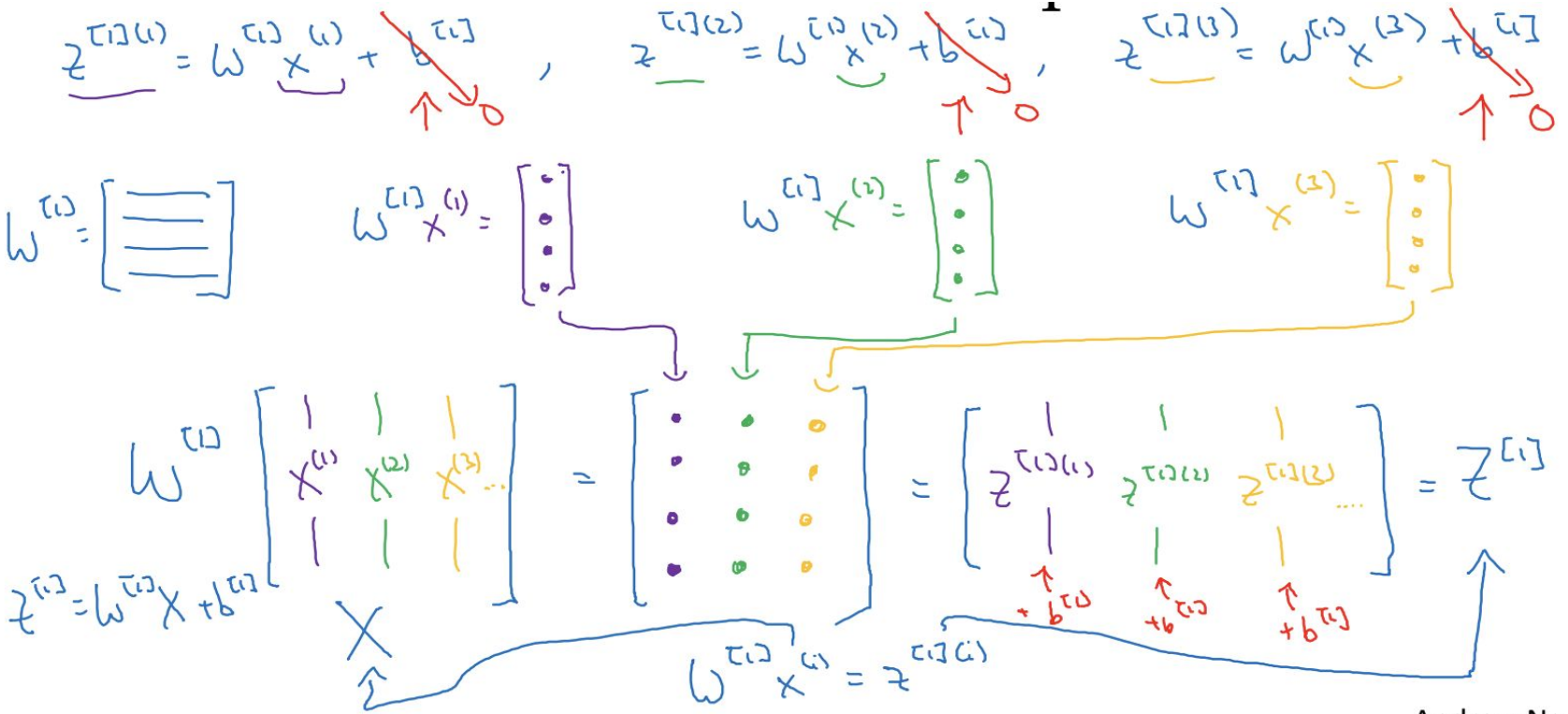
Explanation for Vectorized Implementation



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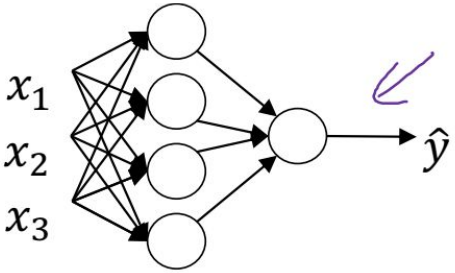
Recap for Vectorized Implementation



$$X = \begin{bmatrix} | & | & & | \\ x^{(1)} & x^{(2)} & \cdots & x^{(m)} \\ | & | & & | \end{bmatrix}$$

$$A^{[1]} = \begin{bmatrix} | & | & & | \\ a^{[1](1)} & a^{[1](2)} & \cdots & a^{[1](m)} \\ | & | & & | \end{bmatrix}$$

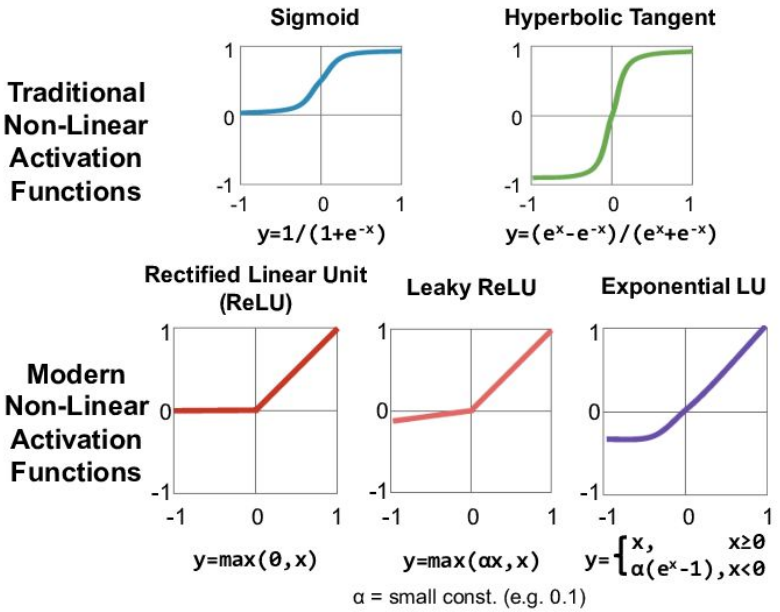
```
for i = 1 to m
```

$$z^{[1](i)} = W^{[1]} x^{(i)} + b^{[1]}$$
$$a^{[1](i)} = \sigma(z^{[1](i)})$$
$$z^{[2](i)} = W^{[2]} a^{[1](i)} + b^{[2]}$$
$$a^{[2](i)} = \sigma(z^{[2](i)})$$

$A^{[0]}$ $\quad X = a^{[0]} \quad x^{(i)} = a^{[0](i)}$

$$Z^{[1]} = W^{[1]} X + b^{[1]} \quad \leftarrow \quad w^{[1]} A^{[0]} + b^{[1]}$$
$$A^{[1]} = \sigma(Z^{[1]})$$
$$Z^{[2]} = W^{[2]} A^{[1]} + b^{[2]}$$
$$A^{[2]} = \sigma(Z^{[2]})$$

What is Activation Function?



Activation Function(활성함수)란?

- decides whether a neuron should be activated or not
- decides whether the neuron's input to the network is important or not in the process of prediction using simpler mathematical operations
- to derive output from a set of input values fed to a node (or a layer)
- Many types of activation functions (Sigmoid, tanh, ReLU, Leaky ReLU..)
- ReLU is the most used activation function nowadays (gradient vanishing issues of sigmoid and tanh functions)

What is Activation Function?

Why do we need non-linear activation functions?

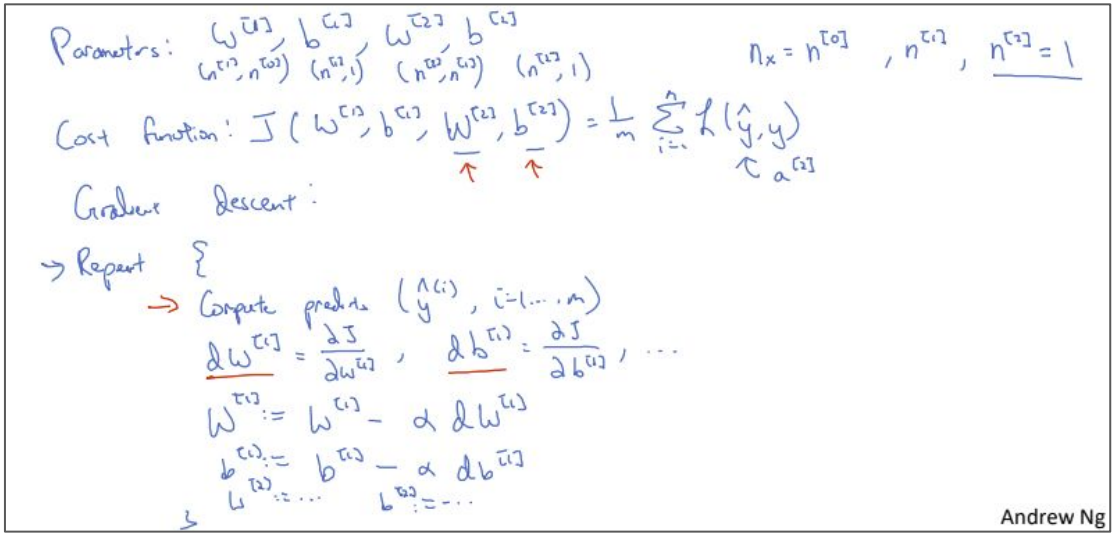
Activation function이 linear라면 hidden layer를 쓰는 이유가 사라지며, gradient descent를 쓰지 못하게 됨

ex) if activation function is h(x)=cx and y=h(h(h(x))) which is y=c^3x

c^3=a -> y=ax : return to linear function, one-layer network 와 동일하게 됨

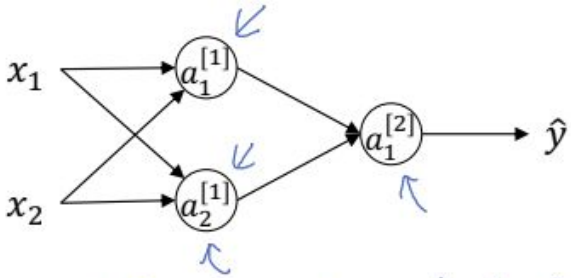
Gradient Descent for Neural Networks

1. Compute Loss function & Cost function with computed predictions
2. Compute derivative of cost function with respect to each parameter
3. Update parameters
4. Repeat this until they are converging.



Random initialization

- What happens if you initialize weights to zero?
- If a weight for w is initialized to zero, gradient descent won't work.
- Solution: Initialize weights randomly
- Usually use very small number, such as 0.01.



$W^{[1]} = np.random.randn((2,2)) * 0.01$

$b^{[1]} = np.zeros((2,1))$

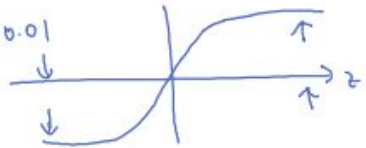
$W^{[2]} = np.random.randn((1,2)) * 0.01$

$b^{[2]} = 0$

100?

$z^{[1]} = W^{[1]} x + b^{[1]}$

$a^{[1]} = g^{[1]}(z^{[1]})$



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- 프로그래밍 과제 진행

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Motivation

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- Learn fundamentals of machine learning
- Hone Python programming skills

Week 1

Supervised Learning

Input(x)	Output (y)	Application
Home features	Price	Real Estate
Ad, user info	Click on ad? (0/1)	Online Advertising
Image	Object (1,...,1000)	Photo tagging
Audio	Text transcript	Speech recognition
English	Chinese	Machine translation
Image, Radar info	Position of other cars	Autonomous driving

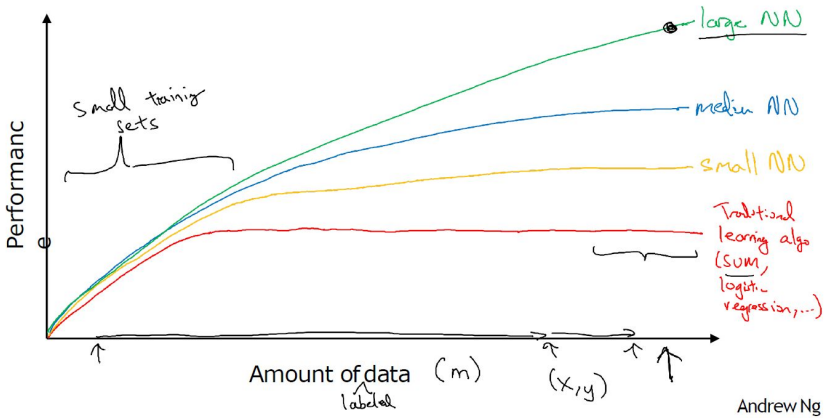
Standard NN

CNN

RNN

Custom/ Hybrid

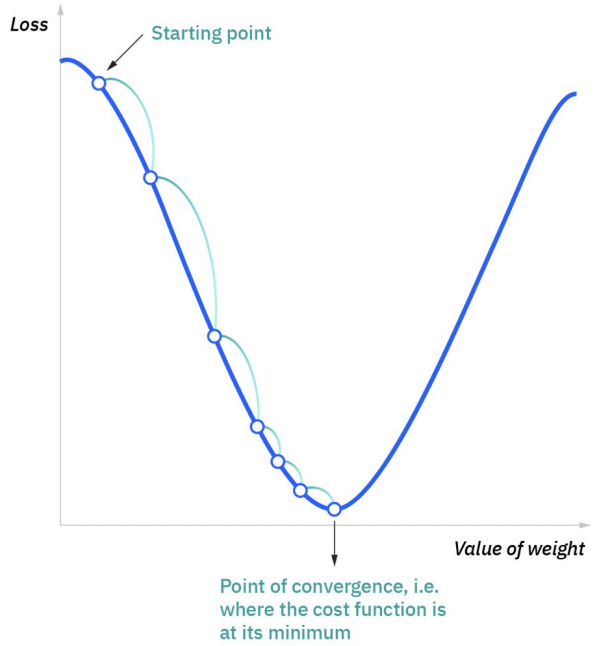
Scale drives deep learning progress



Week 2

Gradient Descent

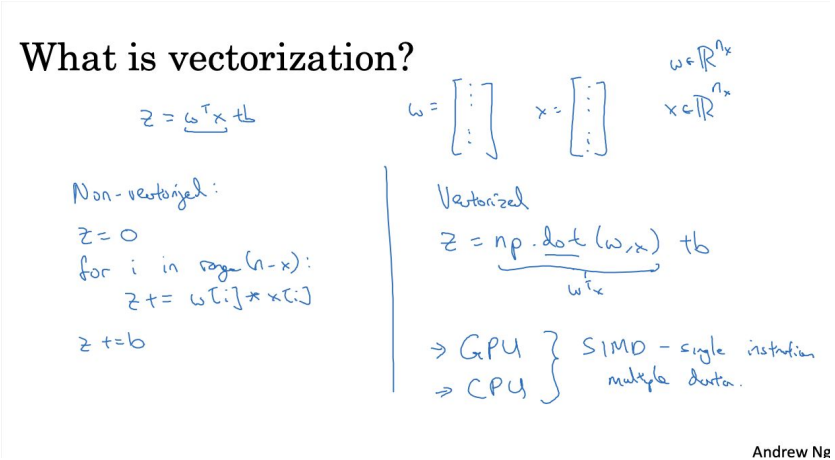
- Optimization algorithm to minimize cost function (convex)
- Take repeated steps in the opposite direction of the gradient of the function at the current point
- Repeat $x \leftarrow -x-\alpha * f'(x)$
  (α: learning rate, small positive number)
- Justification: The gradient points in the direction of the steepest ascent



Week 2

Vectorization

- Type of parallel processing–used to speed up the Python code without using loop
- Whenever possible, remove explicit for loops
- Minimizes the running & execution time of code
- Use built-in functions in Numpy
  ex) np.exp(v), np.log(v), np.abs(v), np.square(v), np.maximum(v,0)



Week 2

Broadcasting in Python

- How numpy treats arrays with different dimension during arithmetic operations
- Unique function in Python numpy

```
>>> a = np.array([1.0, 2.0, 3.0])
>>> b = np.array([2.0, 2.0, 2.0])
>>> a * b
array([2.,  4.,  6.])
```

Two arrays in same shape

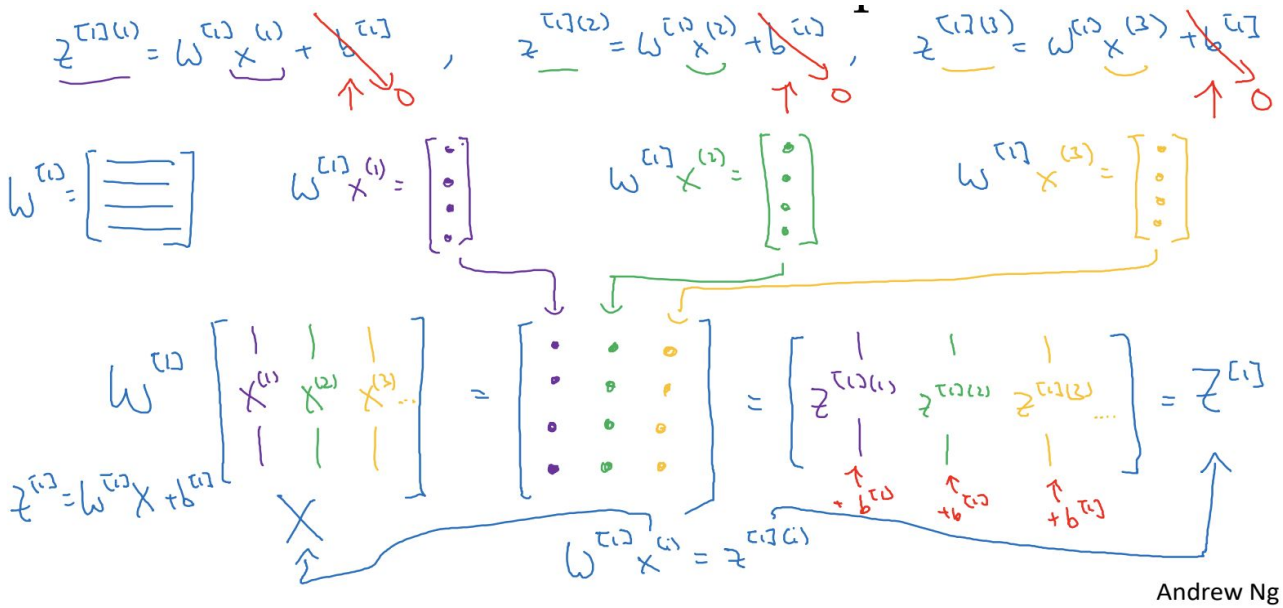
```
>>> a = np.array([1.0, 2.0, 3.0])
>>> b = 2.0
>>> a * b
array([2.,  4.,  6.])
```

Two arrays in different shapes

```
> a <- matrix(data = 1:9, nrow = 3, ncol = 3)
> a
     [,1] [,2] [,3]
[1,]    1    4    7
[2,]    2    5    8
[3,]    3    6    9
> b <- matrix(data = 1:3, nrow = 3, ncol = 1)
> b
     [,1]
[1,]    1
[2,]    2
[3,]    3
> c <- a + b
Error in a + b : non-conformable arrays
```

Week 3

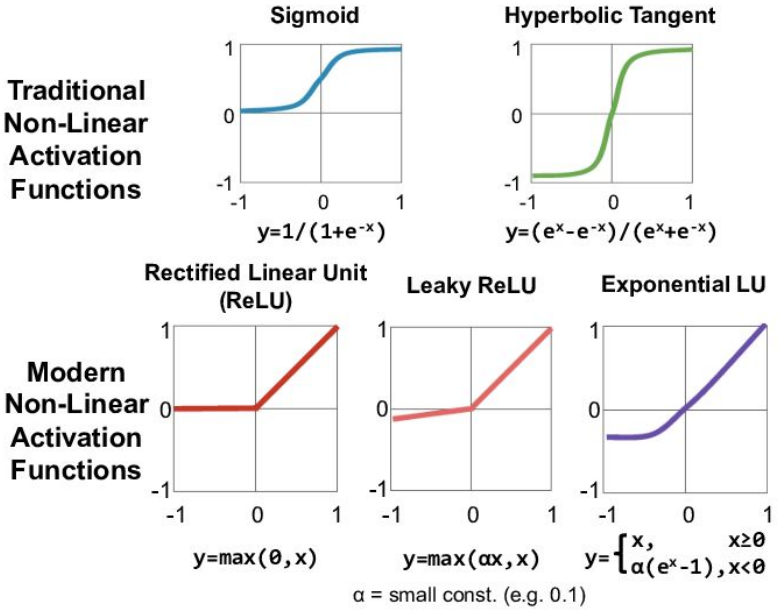
Explanation for Vectorized Implementation



Andrew Ng

Week 3

Non-linear Activation Function

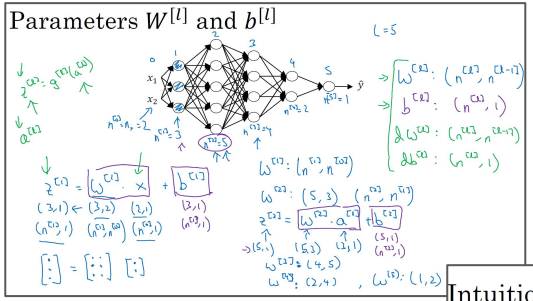


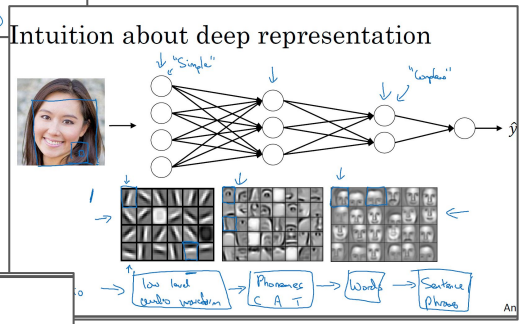
Activation Function(활성함수)란?

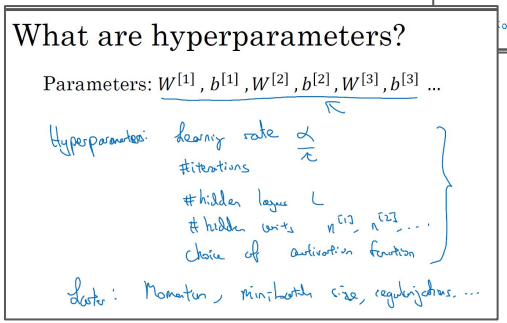
- decides whether a neuron should be activated or not
- decides whether the neuron's input to the network is important or not in the process of prediction using simpler mathematical operations
- to derive output from a set of input values fed to a node (or a layer)
- Many types of activation functions (Sigmoid, tanh, ReLU, Leaky ReLU..)
- ReLU is the most used activation function nowadays (gradient vanishing issues of sigmoid and tanh functions)

Week 4

- Forward propagation in a Deep Network
- Getting your matrix dimensions right
- Why deep representation?
- Parameters vs Hyperparameters
- What does this have to do with the brain?







Summary

- Familiarized with technological trends
- Built & trained deep neural networks
- Implemented neural network algorithms

Thank you