



Smart Mobile Platform

Deep Neural Network (DNN)

Prof. Joongheon Kim
Korea University, School of Electrical Engineering
<https://joongheon.github.io>
joongheon@korea.ac.kr



Deep Learning Revolution is Real

Geoffrey E Hinton



Yoshua Bengio



Yann LeCun



FATHERS OF THE DEEP LEARNING REVOLUTION RECEIVE ACM A.M. TURING AWARD

Bengio, Hinton, and LeCun Ushered in Major Breakthroughs in Artificial Intelligence

ACM named **Yoshua Bengio**, **Geoffrey Hinton**, and **Yann LeCun** recipients of the 2018 ACM A.M. Turing Award for conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing. Bengio is Professor at the University of Montreal and Scientific Director at Mila, Quebec's Artificial Intelligence Institute; Hinton is VP and Engineering Fellow of Google, Chief Scientific Adviser of The Vector Institute, and University Professor Emeritus at the University of Toronto; and LeCun is Professor at New York University and VP and Chief AI Scientist at Facebook.

Working independently and together, Hinton, LeCun and Bengio developed conceptual foundations for the field, identified surprising phenomena through experiments, and contributed engineering advances that demonstrated the practical advantages of deep neural networks. In recent years, deep learning methods have been responsible for astonishing breakthroughs in computer vision, speech recognition, natural language processing, and robotics—among other applications.

While the use of artificial neural networks as a tool to help computers recognize patterns and simulate human intelligence had been introduced in the 1980s, by the early 2000s, LeCun, Hinton and Bengio were among a small group who remained committed to this approach. Though their efforts to rekindle the AI community's interest in neural networks were initially met with skepticism, their ideas recently resulted in major technological advances, and their methodology is now the dominant paradigm in the field.

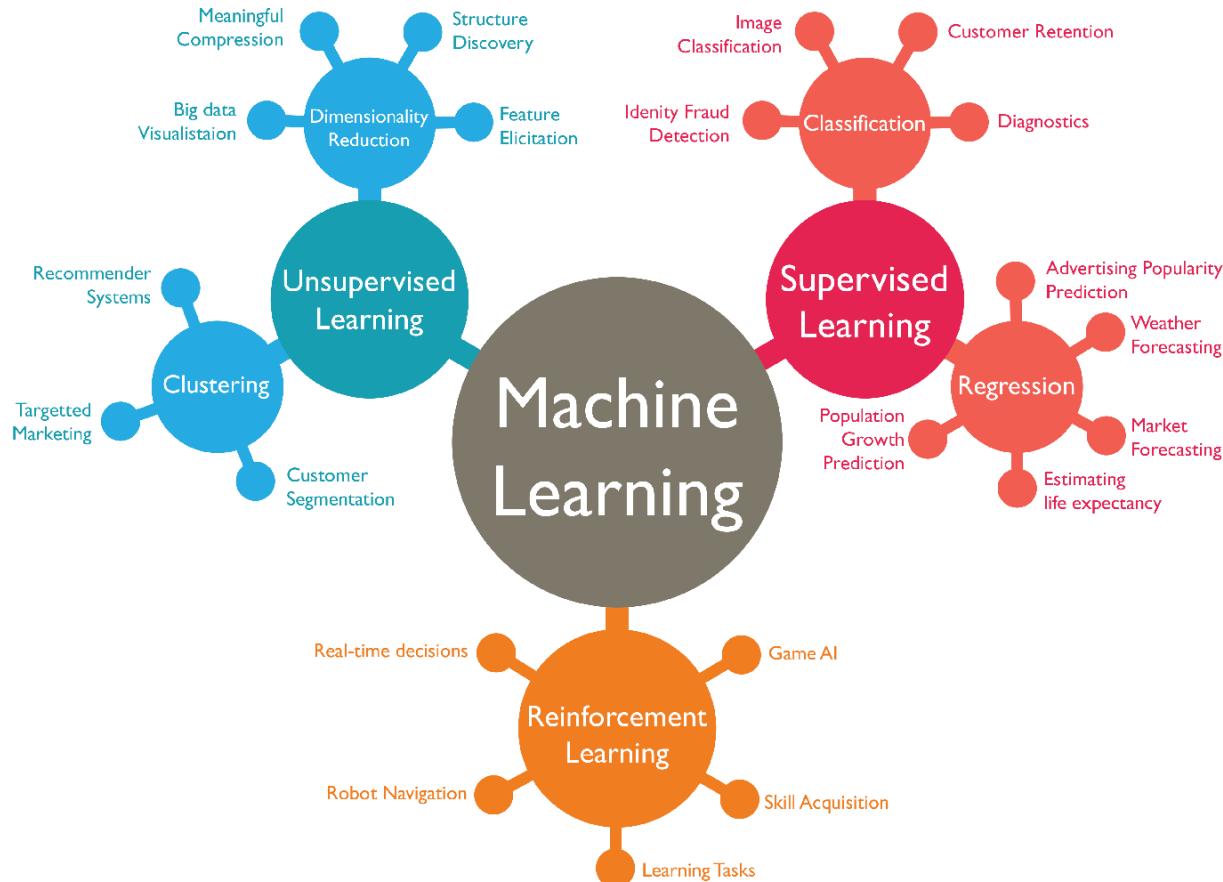


Alan Turing (1912-1954)
Father of Computer Science

<https://amturing.acm.org/>



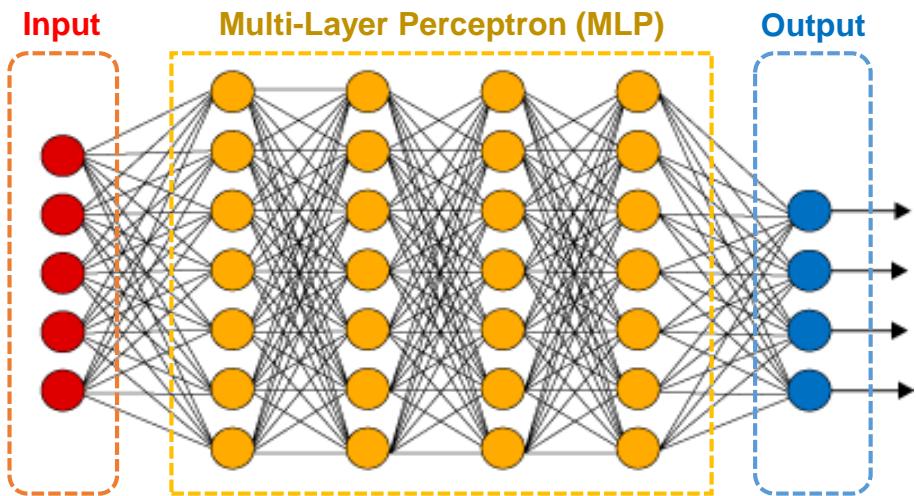
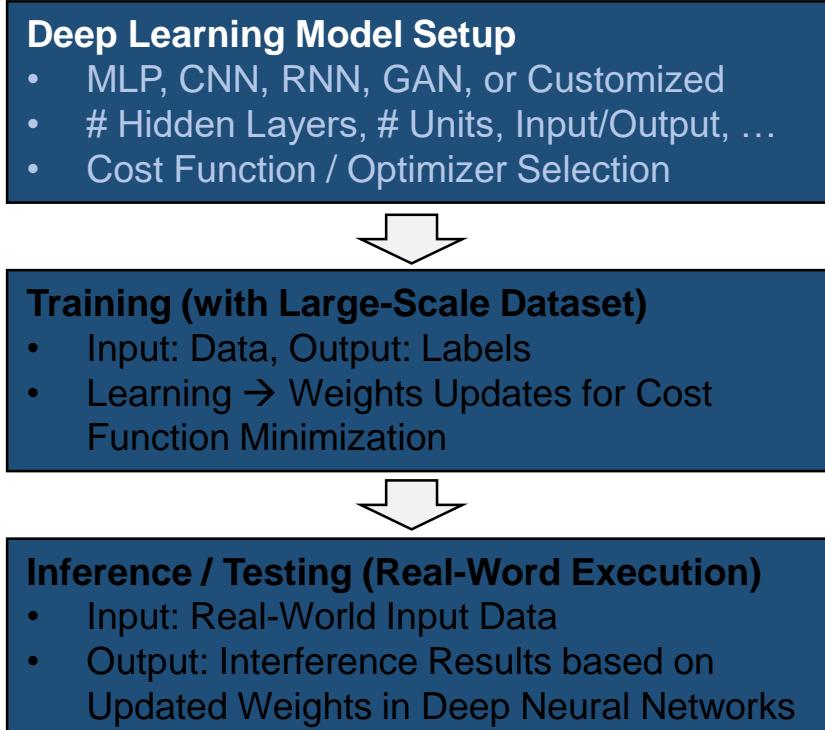
Machine Learning Overview



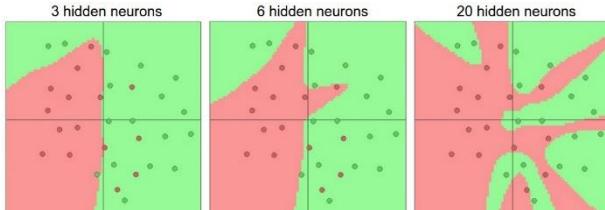


Introduction

- How Deep Learning Works?
 - Deep Learning Computation Procedure



Non-Linear Training (Weights Updates) for Cost Minimization: GD, SGD, Adam, etc.





Introduction

- How Deep Learning Works?
 - Deep Learning Computation Procedure

Deep Learning Model Setup

- MLP, CNN, RNN, GAN, or Customized
- # Hidden Layers, # Units, Input/Output, ...
- Cost Function / Optimizer Selection



Training (with Large-Scale Dataset)

- Input: Data, Output: Labels
- Learning → Weights Updates for Cost Function Minimization



Inference / Testing (Real-Word Execution)

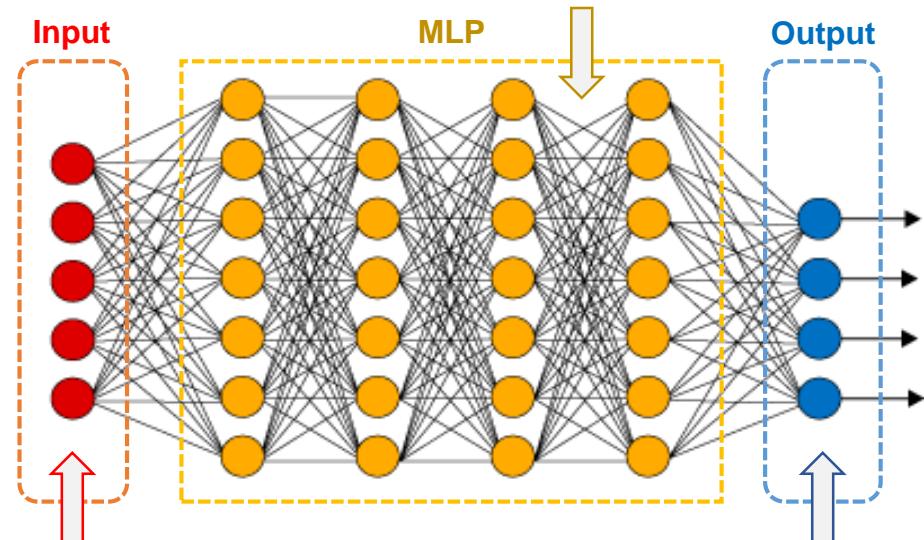
- Input: Real-World Input Data
- Output: Interference Results based on Updated Weights in Deep Neural Networks

All weights in units are trained/set (under cost minimization)

Input

MLP

Output



INPUT: Data

- One-Dimension Vector

OUTPUT: Labels

- One-Hot Encoding

We need a lot of training data for generality
(otherwise, we will suffer from overfitting problem).

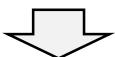


Introduction

- How Deep Learning Works?
 - Deep Learning Computation Procedure

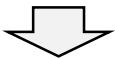
Deep Learning Model Setup

- MLP, CNN, RNN, GAN, or Customized
- # Hidden Layers, # Units, Input/Output, ...
- Cost Function / Optimizer Selection



Training (with Large-Scale Dataset)

- Input: Data, Output: Labels
- Learning → Weights Updates for Cost Function Minimization

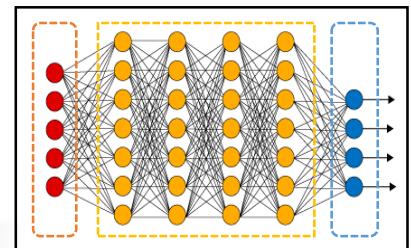


Inference / Testing (Real-Word Execution)

- Input: Real-World Input Data
- Output: Inference Results based on Updated Weights in Deep Neural Networks



Trained Model



Intelligent
Surveillance
Platforms

INPUT: Real-Time Arrivals

OUTPUT: Inference

- Computation Results based on (i) INPUT and (ii) trained weights in units (trained model).



Introduction

- How Deep Learning Works?

- Issue - **Overfitting**

Deep Learning Model Setup

- MLP, CNN, RNN, GAN, or Custom
- # Hidden Layers, # Units, Input/Output, ...
- Cost Function / Optimizer Selection

What if we do not have enough data for training (not enough to derive Gaussian/normal distribution)?

Training (with Large-Scale Dataset)

- Input: Data, Output: Labels
- Learning → Weights Updates for Cost Function Minimization

Situation becomes worse when the model (with insufficient training data) accurately fits on training data.



Inference / Testing (Real-Word Execution)

- Input: Real-World Input Data
- Output: Inference Results based on Updated Weights in Deep Neural Networks

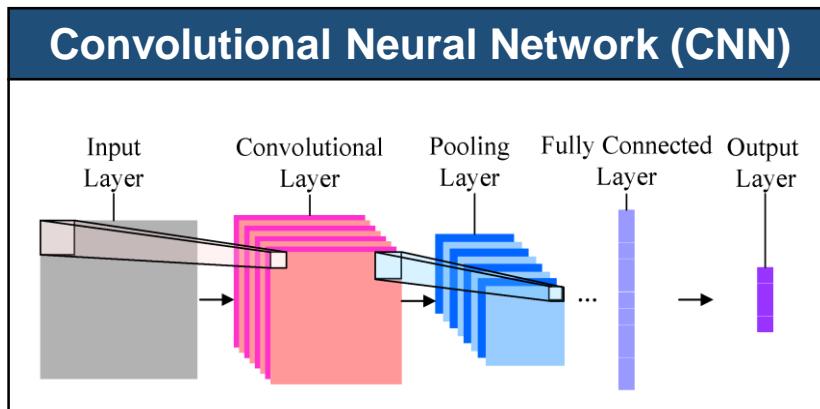
To Combat the Overfitting

- More training data
- Autoencoding (or variational auto-encoder (VAE))
- Dropout
- Regularization

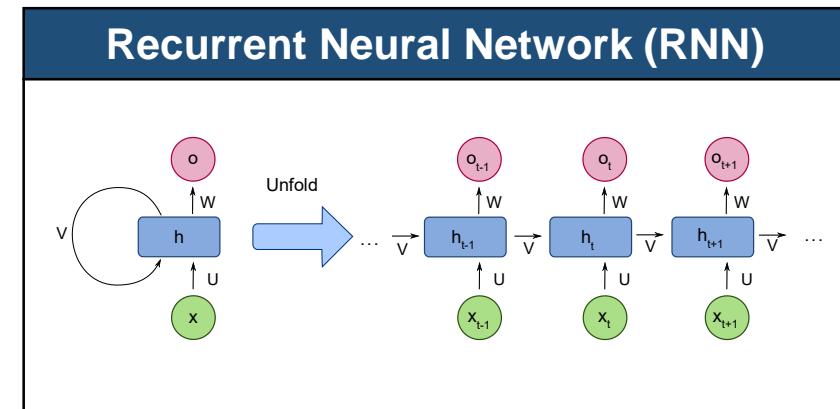


Introduction

- Two Major Deep Learning Models → CNN vs. RNN



- In conventional neural network architectures, the input should be one-dimensional vector.
- In many applications, the input should be multi-dimensional (e.g., 2D for images). Thus, we need architectures in order to recognize the features in high-dimensional data.
- Mainly used for **visual information learning**

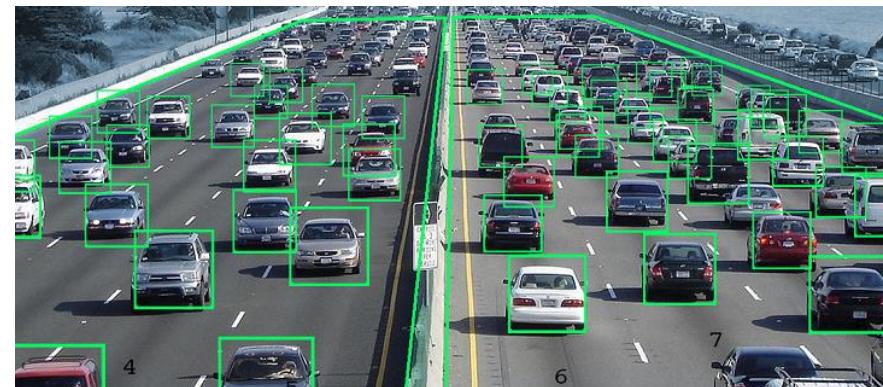


- In conventional neural network architectures, there is no way to introduce the concept of time.
- The time index can be represented as the chain of neural network models.
- The representative models are LSTM and GRU.
- Mainly used for **time-series information learning**



Visual Learning

- Object Recognition
- Style Transfer
- Deblurring and Denoising
- Super-Resolution
- ...





Speech/Language Learning

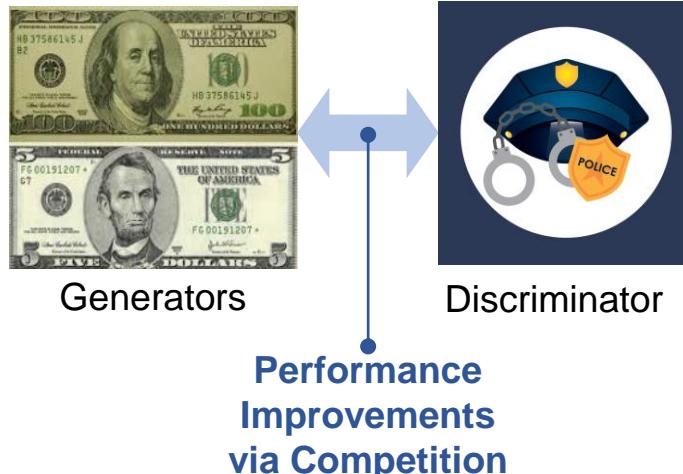
- Speech Recognition
- Machine Translation
- Information Retrieval
- ...





Deep Learning: Generative Models

- An Emerging Direction, Generative Adversarial Network (GAN)
 - Training both of **generator** and **discriminator**; and then generates samples which are similar to the original samples.



Deep Learning Basics and Software Software Installation and Examples

- **Python/TensorFlow/Keras Installation**
- Python/TensorFlow Examples



- Preparation
 - Python Download: [python-3.5.3-amd64.exe](#)
 - Anaconda Download: [Anaconda3-5.2.0-Windows-x86_64.exe](#)
- Installation Procedure
 - [1] Python Installation
 - [2] Conda Environment Setup
 - Execute the downloaded **Anaconda EXE as admin**
 - Execute **Anaconda Prompt** as admin
 - [3] TensorFlow Installation





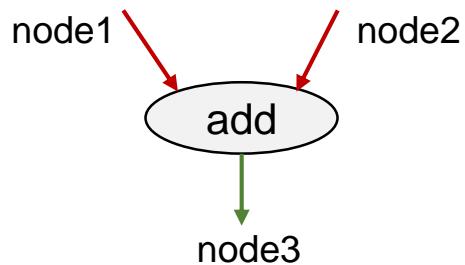
- Installation Procedure
 - [1] Python Installation
 - [2] Conda Environment Setup
 - **[3] TensorFlow Installation**
 - **> conda create -n tensorflow python=3.5**
 - Proceed([y]/n)? y
 - **> pip install tensorflow**
 - **> pip install keras**

Deep Learning Basics and Software Software Installation and Examples

- Python/TensorFlow/Keras Installation
- **Python/TensorFlow Examples**



- Quick Start Example



- **add** is a node which represents addition operation
 - **node1**: input tensor
 - **node2**: input tensor
 - **node3**: resultant tensor

```
ex_add.py
1 import tensorflow as tf
2 # Create nodes in computation graph
3 node1 = tf.constant(3, dtype=tf.int32)
4 node2 = tf.constant(5, dtype=tf.int32)
5 node3 = tf.add(node1, node2)
6
7 # Create session object
8 sess = tf.Session()
9 print("node1 + node2 = ", sess.run(node3))
10 # Close the session
11 sess.close()
```



Python/TensorFlow Examples

- Quick Start Example

```
ex_add.py
1 import tensorflow as tf
2 # Create nodes in computation graph
3 node1 = tf.constant(3, dtype=tf.int32)
4 node2 = tf.constant(5, dtype=tf.int32)
5 node3 = tf.add(node1, node2)
6
7 # Create session object
8 sess = tf.Session()
9 print("node1 + node2 = ", sess.run(node3))
10 # Close the session
11 sess.close()
```

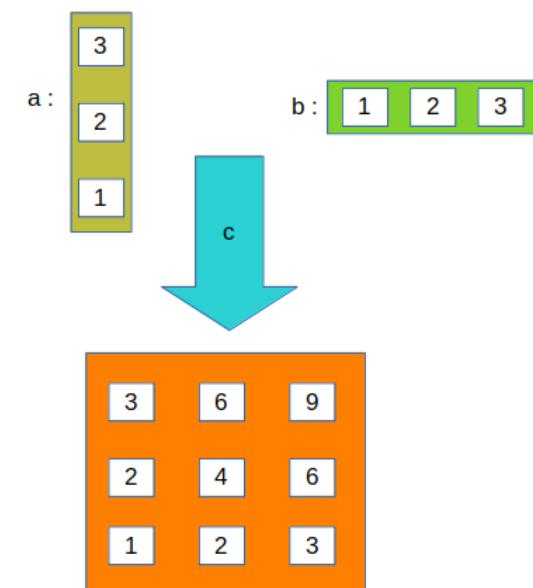
```
ex_add2.py
1 import tensorflow as tf
2 # Create nodes in computation graph
3 node1 = tf.constant(3, dtype=tf.int32)
4 node2 = tf.constant(5, dtype=tf.int32)
5 node3 = tf.add(node1, node2)
6
7 # Create session object
8 with tf.Session() as sess:
9     print("node1 + node2 = ", sess.run(node3))
```



Python/TensorFlow Examples

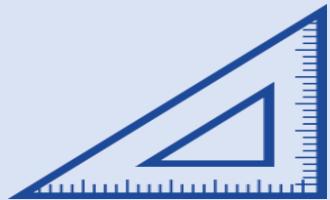
- Example: Placeholder

```
ex_placeholder.py
1 import tensorflow as tf
2
3 # Create nodes in computation graph
4 a = tf.placeholder(tf.int32, shape=(3,1))
5 b = tf.placeholder(tf.int32, shape=(1,3))
6 c = tf.matmul(a, b)
7
8 # Run computation graph
9 with tf.Session() as sess:
10     print(sess.run(c, feed_dict={a: [[3], [2], [1]], b: [[1, 2, 3]]}))
```





Linear Functions



Linear Regression

Binary Classification

Softmax Classification

Nonlinear Functions



Neural Network (NN)

Convolutional NN (CNN)

CNN for CIFAR-10

Recurrent NN (RNN)

Advanced Topics



Gen. Adv. Network (GAN)

Interpolation

PCA/LDA

Overfitting

Deep Learning Basics and Software

Linear Regression

Linear Regression Theory

- **Linear Regression Theory**
- Linear Regression Implementation



Regression (Examples)

- Exam Score Prediction (Linear Regression)



Classification (Examples)

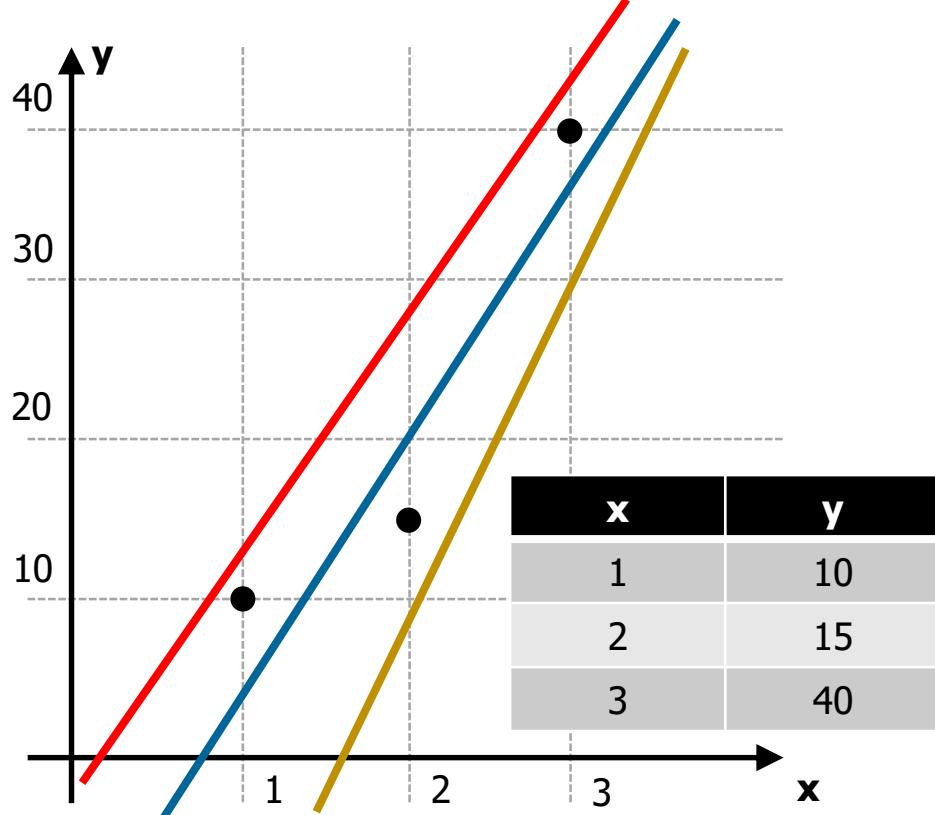
- Pass/Fail (Binary Classification)
- Letter Grades (Multi-Level Classification)





Linear Regression

- Linear model: $H(x) = Wx + b$
- Which model is the best among the given three?



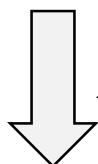


Linear Regression

- Cost Function (or Loss Function)
 - How to fit the line to training data
 - The difference between model values and real measurements:

m : The number of training data

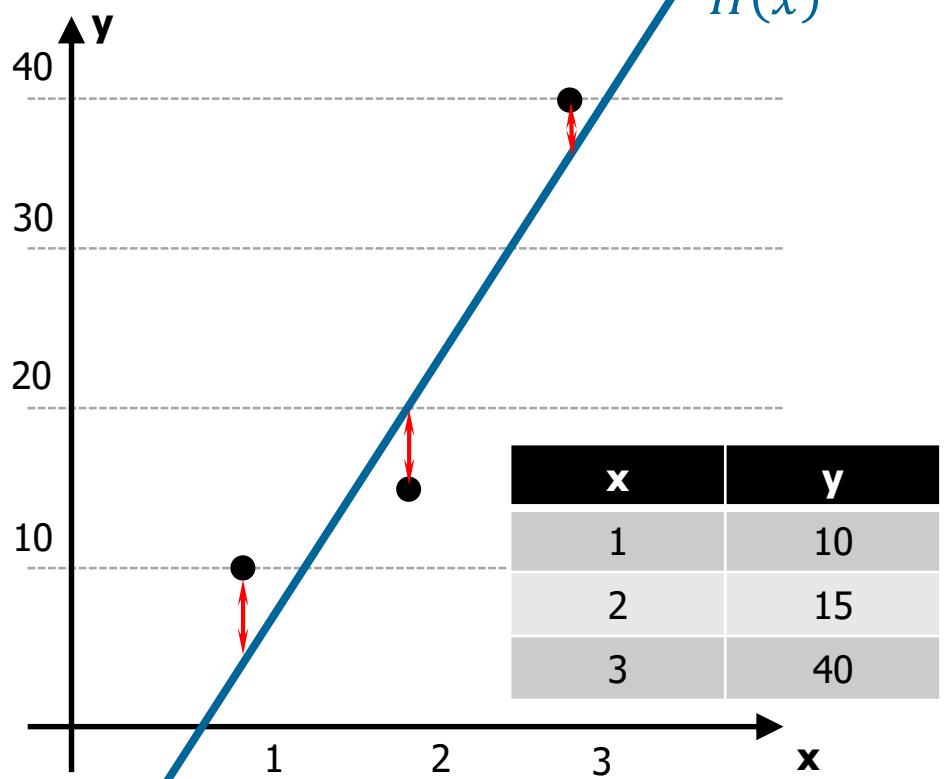
$$\frac{1}{m} \sum_{i=1}^m (H(x^i) - y^i)^2$$



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

$$\text{Cost}(W, b) =$$

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





Linear Regression

- Cost Function Minimization

- Model: $H(x) = Wx + b$

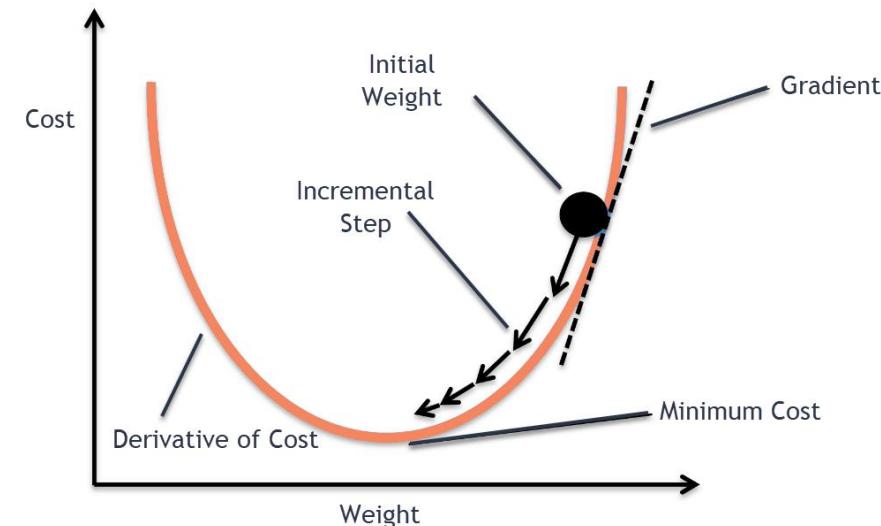
- Cost Function: $Cost(W, b) = \frac{1}{m} \sum_{i=1}^m (H(x^i) - y^i)^2 = \frac{1}{m} \sum_{i=1}^m (Wx^i + b - y^i)^2$

- How to Minimize this Function? → **Gradient Descent Method**

- Angle → Differentiation

$$W \leftarrow W - \alpha \frac{\partial}{\partial W} Cost(W)$$

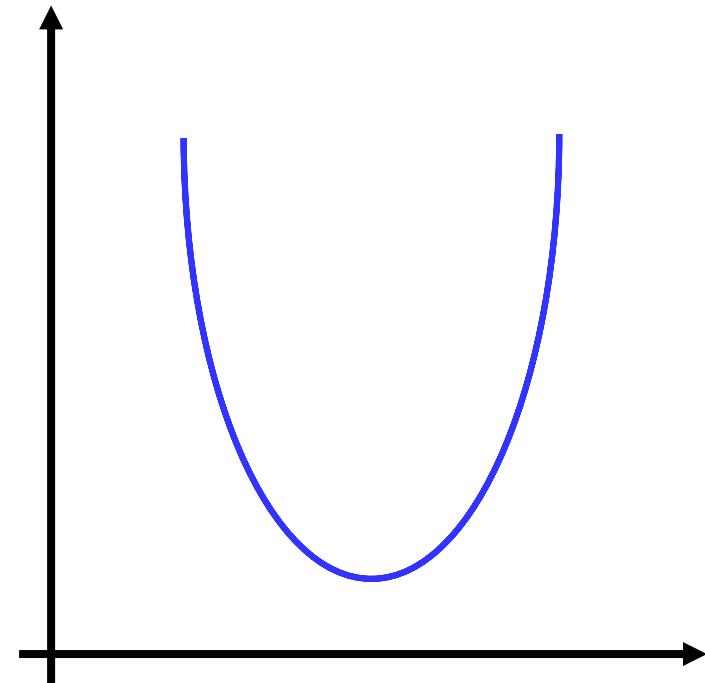
α : Learning rate





Linear Regression

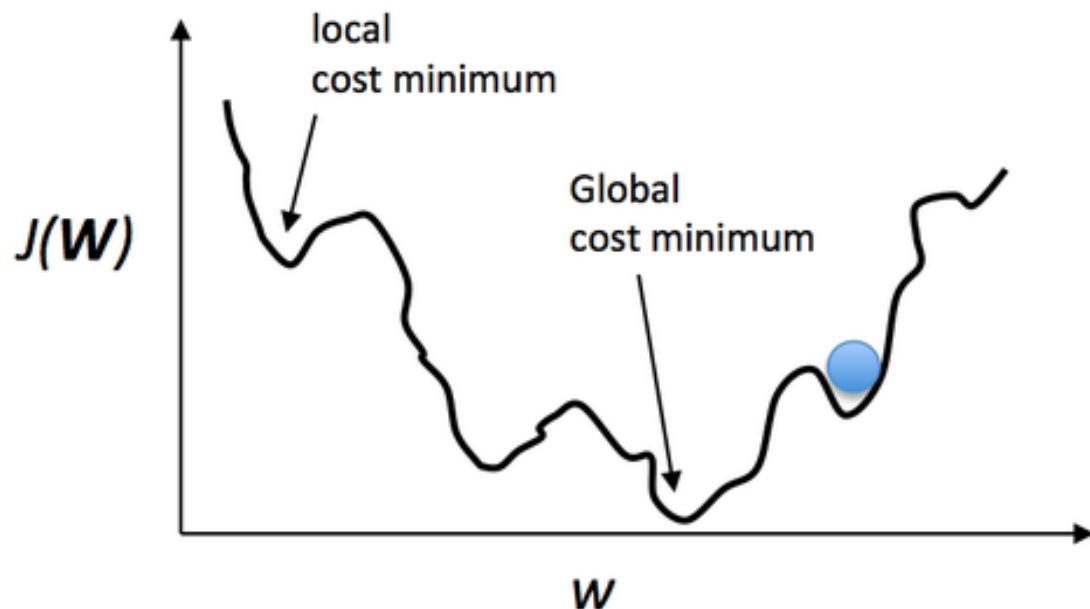
- Learning Rates
 - Too large: Overshooting
 - Too small: takes too long, stops in the middle
- How can we determine the learning rates?
 - Try several learning rates
 - Observe the cost function
 - Check it goes down in a reasonable rate





Linear Regression

- Cost Function Minimization
 - Gradient Descent Method is only good for convex functions.





- Multi-Variable Linear Regression

- Model:

$$H(x_1, x_2, \dots, x_n) = w_1x_1 + w_2x_2 + \dots + w_nx_n + b$$

- Cost:

$$Cost(W, b) = \frac{1}{m} \sum_{i=1}^m (H(x_1^i, x_2^i, \dots, x_n^i) - y^i)^2$$



Linear Regression

- Multi-Variable Linear Regression

- Model:

$$H(x_1, x_2, \dots, x_n) = w_1x_1 + w_2x_2 + \dots + w_nx_n + b$$

$$\Rightarrow H(X) = XW + b$$

$$(x_1 \quad x_2 \dots \quad x_n) \cdot \begin{pmatrix} w_1 \\ w_2 \\ \dots \\ w_n \end{pmatrix} = w_1x_1 + w_2x_2 + \dots + w_nx_n$$

X

W



$$H(X) = XW^T + b$$

$$\text{when } W = (w_1 \quad w_2 \dots \quad w_n)$$



Deep Learning Basics and Software

Linear Regression

Linear Regression Implementation

- Linear Regression Theory
- Linear Regression Implementation



Linear Regression Implementation (TensorFlow)

- TensorFlow
 - **Linear Regression**
- Keras
 - Linear Regression



Linear Regression Implementation (TensorFlow)

```

1 import tensorflow as tf
2
3 x_data = [[1,1], [2,2], [3,3]]
4 y_data = [[10], [20], [30]]
5 X = tf.placeholder(tf.float32, shape=[None, 2])
6 Y = tf.placeholder(tf.float32, shape=[None, 1])
7
8 W=tf.Variable(tf.random_normal([2,1]))
9 b=tf.Variable(tf.random_normal([1]))
10
11 model = tf.matmul(X,W)+b
12 cost = tf.reduce_mean(tf.square(model - Y))
13 train = tf.train.GradientDescentOptimizer(0.01).minimize(cost)
14
15 with tf.Session() as sess:
16     sess.run(tf.global_variables_initializer())
17     # Training
18     for step in range(2001):
19         c, W_, b_, _ = sess.run([cost, W, b, train], feed_dict={X: x_data, Y: y_data})
20         print(step, c, W_, b_)
21     # Testing
22     print(sess.run(model, feed_dict={X: [[4,4]]}))

```

Model, Cost, Train



Linear Regression Implementation (TensorFlow)

```
[4.667964 ]] [0.014943]
1991 3.1940912e-05 [[5.325548 ]]
[4.6679726]] [0.01490401]
1992 3.1772186e-05 [[5.3255568]
[4.667981 ]] [0.0148651]
1993 3.1603915e-05 [[5.3255653]
[4.6679897]] [0.01482627]
1994 3.143936e-05 [[5.325574 ]]
[4.6679983]] [0.01478756]
1995 3.1277286e-05 [[5.3255825]
[4.668007 ]] [0.01474891]
1996 3.1110336e-05 [[5.325591 ]]
[4.6680155]] [0.01471035]
1997 3.095236e-05 [[5.325599 ]
[4.6680236]] [0.01467189]
1998 3.079518e-05 [[5.325608]
[4.668032]] [0.01463356]
1999 3.062387e-05 [[5.325616 ]]
[4.6680403]] [0.01459529]
2000 3.0467529e-05 [[5.325624 ]
[4.6680484]] [0.01455714]
[[39.989246]]
```



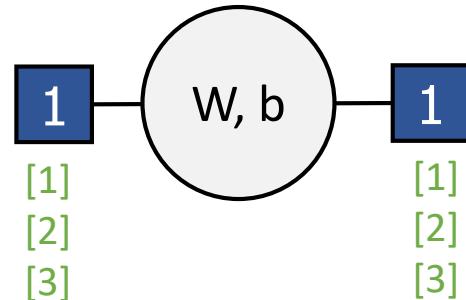
Linear Regression Implementation (Keras)

- TensorFlow
 - Linear Regression
- Keras
 - Linear Regression



Linear Regression Implementation (Keras)

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 from keras.models import Sequential
4 from keras.layers import Dense
5
6 # Data
7 x_data = np.array([[1], [2], [3]])
8 y_data = np.array([[1], [2], [3]])
9 # Model, Cost, Train
10 model = Sequential()
11 model.add(Dense(1, input_dim=1))
12 model.compile(loss='mse', optimizer='adam')
13 model.fit(x_data, y_data, epochs=1000, verbose=0)    Model, Cost, Train
14 model.summary()
15 # Inference
16 print(model.get_weights())
17 print(model.predict(np.array([4])))
18 # Plot
19 plt.scatter(x_data, y_data)
20 plt.plot(x_data, y_data)
21 plt.grid(True)
22 plt.show()
```

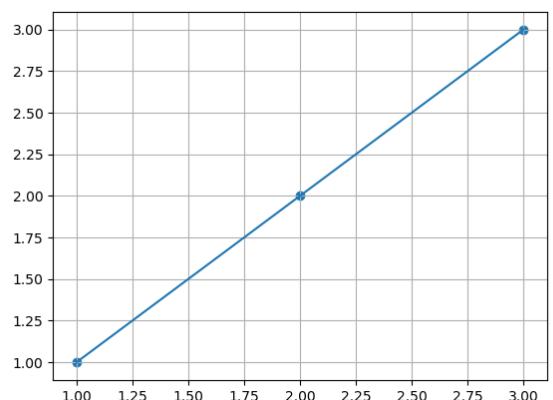




Linear Regression Implementation (Keras)

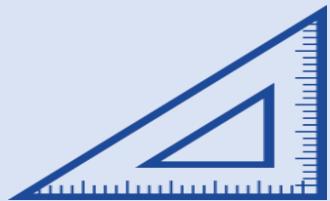
```
x - joongheon@joongheon-AB350M-Gaming-3: ~/Dropbox/codes_keras
joongheon@joongheon-AB350M-Gaming-3:~/Dropbox/codes_keras$ python keras_linearregression.py
/home/joongheon/anaconda3/lib/python3.6/site-packages/h5py/_init_.py:36: FutureWarning: Conversion of the second argument of issubdtype from `float` to `np.floating` is deprecated. In future, it will be treated as `np.float64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
2019-06-29 16:39:04.566966: I tensorflow/core/platform/cpu_feature_guard.cc:141] Your CPU supports instructions that this TensorFlow binary was not compiled to use: AVX2 FMA
Layer (type)          Output Shape         Param #
=====
dense_1 (Dense)      (None, 1)           2
=====
Total params: 2
Trainable params: 2
Non-trainable params: 0

[array([[0.999888]], dtype=float32), array([0.00024829], dtype=float32)]
[[3.9998002]]
joongheon@joongheon-AB350M-Gaming-3:~/Dropbox/codes_keras$
```





Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions



Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10
Recurrent NN (RNN)

Advanced Topics



Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting

Deep Learning Basics and Software

Binary Classification

Binary Classification Theory

- **Binary Classification Theory**
- Binary Classification Implementation



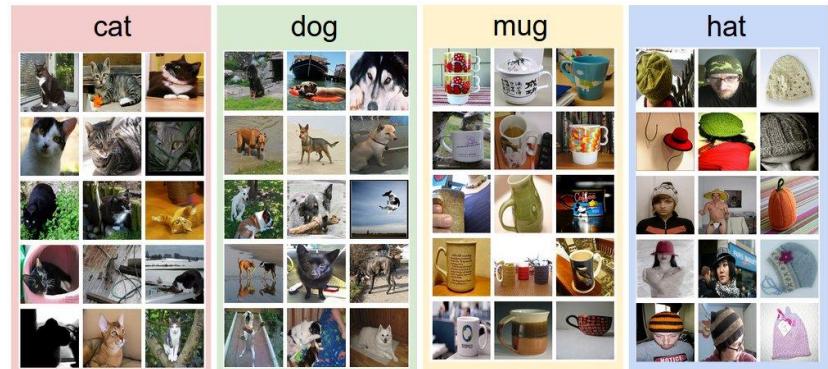
Regression (Examples)

- Exam Score Prediction (Linear Regression)



Classification (Examples)

- Pass/Fail (Binary Classification)
- Letter Grades (Multi-Level Classification)



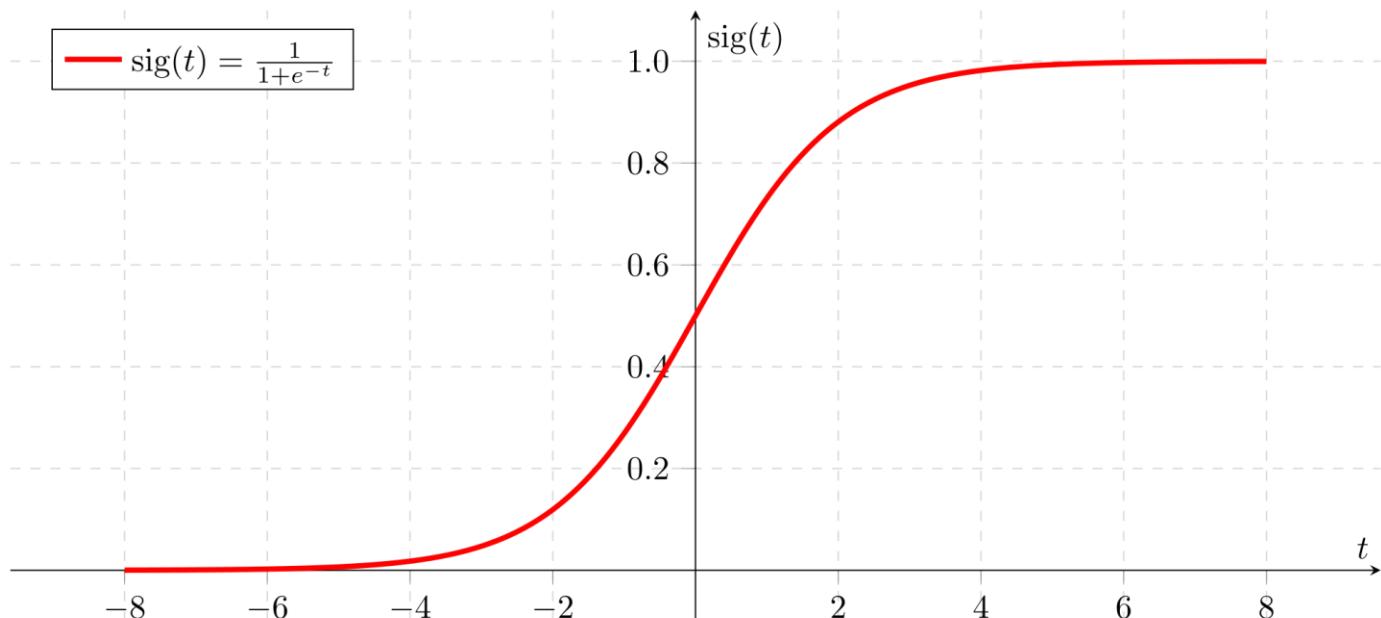


- Binary Classification Examples
 - **Spam Detection:** Spam [1] or Ham [0]
 - **Facebook Feed:** Show [1] or Hide [0]
 - Facebook learns with your like-articles; and shows your favors.
 - **Credit Card Fraudulent Transaction Detection:** Fraud [1] or Legitimate [0]
 - **Tumor Image Detection in Radiology:** Malignant [1] or Benign [0]



Binary Classification

- Binary Classification Basic Idea
 - Step 1) Linear regression with $H(x) = Wx + b$
 - Step 2) **Logistic/sigmoid function ($\text{sig}(t)$)** based on the result of Step 1.





Binary Classification

Model

$$H(x) = Wx + b \text{ or } H(X) = W^T X$$

Logistic Model

$$g(X) = \frac{1}{1 + e^{-W^T X}}$$

Logistic/Sigmoid Function

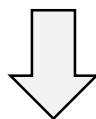
$$g(z) = \frac{1}{1 + e^{-z}}$$



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

Hypothesis

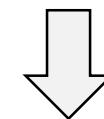
$$H(x) = Wx + b \text{ or } H(X) = W^T X$$



Gradient Descent Method can be used because $\text{Cost}(W, b)$ is convex (local minimum is global minimum).

Logistic Hypothesis

$$g(z) = \frac{1}{1 + e^{-W^T X}}$$



Gradient Descent Method can not be used because $\text{Cost}(W, b)$ is non-convex. **New Cost Function is required.**



Binary Classification

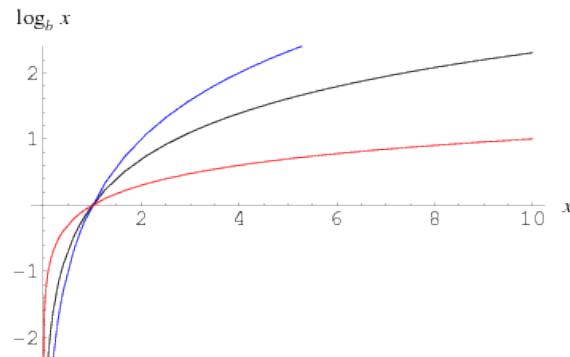
$$\text{Cost}(W) = \frac{1}{m} \sum c(H(x), y)$$

$$c(H(x), y) = \begin{cases} -\log(H(x)), & y = 1 \\ -\log(1 - H(x)), & y = 0 \end{cases}$$

Understanding this Cost Function

Cost	0	∞	∞	0
$H(x)$	0	0	1	1
y	0	1	0	1

Log Function

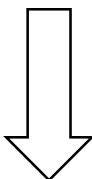




Binary Classification

$$\text{Cost}(W) = \frac{1}{m} \sum c(H(x), y)$$

$$c(H(x), y) = \begin{cases} -\log(H(x)), & y = 1 \\ -\log(1 - H(x)), & y = 0 \end{cases}$$



$$c(H(x), y) = -y \log(H(x)) - (1 - y) \log(1 - H(x))$$



$$\text{Cost}(W) = -\frac{1}{m} \sum y \log(H(x)) + (1 - y) \log(1 - H(x))$$



Gradient Descent Method

$$W \leftarrow W - \alpha \frac{\partial}{\partial W} \text{Cost}(W)$$

Deep Learning Basics and Software

Binary Classification

Binary Classification Implementation

- Binary Classification Theory
- **Binary Classification Implementation**

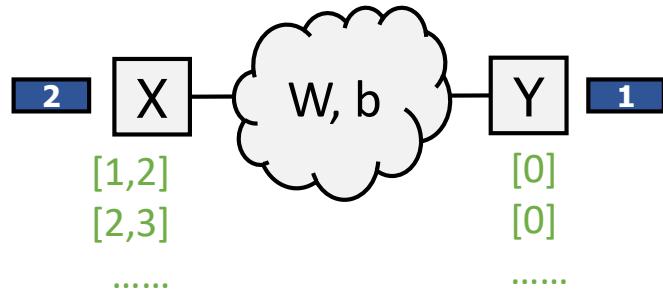


- TensorFlow
 - **Binary Classification**
 - Binary Classification (using CSV File)
- Keras
 - Binary Classification
 - Binary Classification (using CSV File)

Binary Classification Implementation (TensorFlow)



```
1 import tensorflow as tf
2
3 x_data = [[1,2], [2,3], [3,1], [4,3], [5,3], [6,2]]
4 y_data = [[0], [0], [0], [1], [1], [1]]
5 X = tf.placeholder(tf.float32, shape=[None, 2])
6 Y = tf.placeholder(tf.float32, shape=[None, 1])
7 W = tf.Variable(tf.random_normal([2,1]))
8 b = tf.Variable(tf.random_normal([1]))
9
10 model = tf.sigmoid(tf.add(tf.matmul(X,W),b))
11 cost = tf.reduce_mean((-1)*Y*tf.log(model) + (-1)*(1-Y)*tf.log(1-model))
12 train = tf.train.GradientDescentOptimizer(0.01).minimize(cost)
13
14 prediction = tf.cast(model > 0.5, dtype=tf.float32)
15 accuracy = tf.reduce_mean(tf.cast(tf.equal(prediction, Y), dtype=tf.float32))
16
17 with tf.Session() as sess:
18     sess.run(tf.global_variables_initializer())
19     # Training
20     for step in range(10001):
21         cost_val, train_val = sess.run([cost, train], feed_dict={X: x_data, Y: y_data})
22         print(step, cost_val)
23     # Testing
24     h, c, a = sess.run([model, prediction, accuracy], feed_dict={X: x_data, Y: y_data})
25     print("\nModel: ", h, "\nCorrect: ", c, "\nAccuracy: ", a)
```



Model, Cost, Train



Binary Classification Implementation (TensorFlow)

```
1 import tensorflow as tf
2
3 x_data = [[1,2], [2,3], [3,1],
4 y_data = [[0], [0], [0], [1], [
5 X = tf.placeholder(tf.float32,
6 Y = tf.placeholder(tf.float32,
7 W = tf.Variable(tf.random_norma
8 b = tf.Variable(tf.random_norma
9
10 model = tf.sigmoid(tf.add(tf.ma
11 cost = tf.reduce_mean((-1)*Y*tf
12 train = tf.train.GradientDescer
13
14 prediction = tf.cast(model > 0.5, dtype=tf.float32)
15 accuracy = tf.reduce_mean(tf.cast(tf.equal(prediction, Y), dtype=tf.float32))
16
17 with tf.Session() as sess:
18     sess.run(tf.global_variables_initializer())
19     # Training
20     for step in range(10001):
21         cost_val, train_val = sess.run([cost, train], feed_dict={X: x_data, Y: y_data})
22         print(step, cost_val)
23     # Testing
24     h, c, a = sess.run([model, prediction, accuracy], feed_dict={X: x_data, Y: y_data})
25     print("\nModel: ", h, "\nCorrect: ", c, "\nAccuracy: ", a)
```

prediction

- Checking whether the first argument of **tf.cast** is true or not.
 - If true (model > 0.5), the result of **tf.cast** is **1.0**. Otherwise, the result of **tf.cast** is **0.0**.

accuracy

- **tf.equal()**
 - It returns **True** when **prediction == Y**. Otherwise, it returns **False**.
 - Accuracy: The average of T/F (= 1/0) values.

Binary Classification Implementation (TensorFlow)

```
1 import tensorflow as tf
2
3 x_data = [[1,2], [2,3], [3,1], [4,3], [5,3], [6,2]]
4 y_data = [[0], [0], [0], [1], [1], [1]]
5 X = tf.placeholder(tf.float32, shape=[None, 2])
6 Y = tf.placeholder(tf.float32, shape=[None, 1])
7 W = tf.Variable(tf.random_normal([2,1]))
8 b = tf.Variable(tf.random_normal([1]))
9
10 model = tf.sigmoid(tf.add(tf.matmul(X,W),b))
11 cost = tf.reduce_mean((-1)*Y*tf.log(model) + (-1)*(1-Y)*tf.log(1-model))
12 train = tf.train.GradientDescentOptimizer(0.01).minimize(cost)
13
14 prediction = tf.cast(model > 0.5, dtype=tf.float32)
15 accuracy = tf.reduce_mean(tf.cast(tf.equal(prediction, Y), dtype=tf.float32))
16
17 with tf.Session() as sess:
18     sess.run(tf.global_variables_initializer())
19     # Training
20     for step in range(10001):
21         cost_val, train_val = sess.run([cost, train], feed_dict={X: x_data, Y: y_data})
22         print(step, cost_val)
23     # Testing
24     h, c, a = sess.run([model, prediction, accuracy], feed_dict={X: x_data, Y: y_data})
25     print("\nModel: ", h, "\nCorrect: ", c, "\nAccuracy: ", a)
```

9985 0.1493395
9986 0.14932828
9987 0.14931704
9988 0.14930585
9989 0.14929464
9990 0.1492834
9991 0.14927219
9992 0.14926098
9993 0.14924978
9994 0.14923854
9995 0.14922734
9996 0.14921615
9997 0.14920495
9998 0.14919376
9999 0.1491826
10000 0.1491714

Model: [[0.0306041]
[0.15866211]
[0.30421484]
[0.7816807]
[0.93976283]
[0.9802319]]
Correct: [[0.]
[0.]
[1.]
[1.]
[1.]]
Accuracy: 1.0

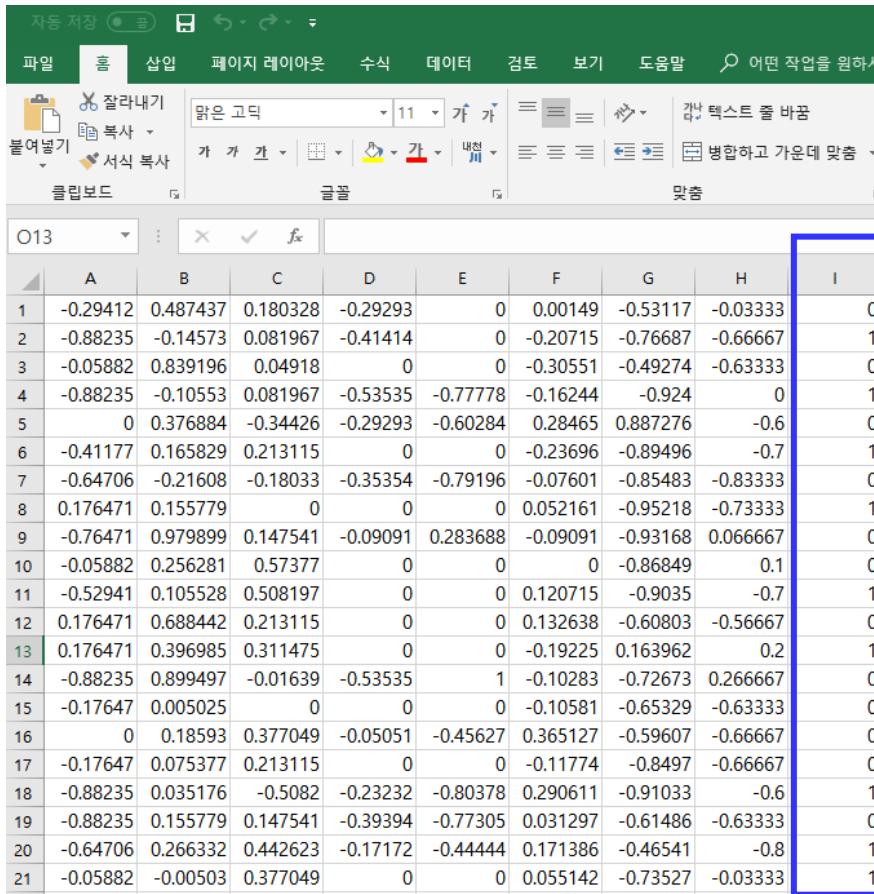


- TensorFlow
 - Binary Classification
 - **Binary Classification (using CSV File)**
- Keras
 - Binary Classification
 - Binary Classification (using CSV File)



Binary Classification Implementation (TensorFlow)

CSV file



O13	A	B	C	D	E	F	G	H	I
1	-0.29412	0.487437	0.180328	-0.29293	0	0.00149	-0.53117	-0.03333	0
2	-0.88235	-0.14573	0.081967	-0.41414	0	-0.20715	-0.76687	-0.66667	1
3	-0.05882	0.839196	0.04918	0	0	-0.30551	-0.49274	-0.63333	0
4	-0.88235	-0.10553	0.081967	-0.53535	-0.77778	-0.16244	-0.924	0	1
5	0	0.376884	-0.34426	-0.29293	-0.60284	0.28465	0.887276	-0.6	0
6	-0.41177	0.165829	0.213115	0	0	-0.23696	-0.89496	-0.7	1
7	-0.64706	-0.21608	-0.18033	-0.35354	-0.79196	-0.07601	-0.85483	-0.83333	0
8	0.176471	0.155779	0	0	0	0.052161	-0.95218	-0.73333	1
9	-0.76471	0.979899	0.147541	-0.09091	0.283688	-0.09091	-0.93168	0.066667	0
10	-0.05882	0.256281	0.57377	0	0	0	-0.86849	0.1	0
11	-0.52941	0.105528	0.508197	0	0	0.120715	-0.9035	-0.7	1
12	0.176471	0.688442	0.213115	0	0	0.132638	-0.60803	-0.56667	0
13	0.176471	0.396985	0.311475	0	0	-0.19225	0.163962	0.2	1
14	-0.88235	0.899497	-0.01639	-0.53535	1	-0.10283	-0.72673	0.266667	0
15	-0.17647	0.005025	0	0	0	-0.10581	-0.65329	-0.63333	0
16	0	0.18593	0.377049	-0.05051	-0.45627	0.365127	-0.59607	-0.66667	0
17	-0.17647	0.075377	0.213115	0	0	-0.11774	-0.8497	-0.66667	0
18	-0.88235	0.035176	-0.5082	-0.23232	-0.80378	0.290611	-0.91033	-0.6	1
19	-0.88235	0.155779	0.147541	-0.39394	-0.77305	0.031297	-0.61486	-0.63333	0
20	-0.64706	0.266332	0.442623	-0.17172	-0.44444	0.171386	-0.46541	-0.8	1
21	-0.05882	-0.00503	0.377049	0	0	0.055142	-0.73527	-0.03333	1



Binary Classification Implementation (TensorFlow)

```

1 import tensorflow as tf
2 import numpy as np
3
4 xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
5 x_data = xy[:, 0:-1]
6 y_data = xy[:, [-1]]

```

CSV data loading

```

7
8 X = tf.placeholder(tf.float32, shape=[None, x_data.shape[1]])
9 Y = tf.placeholder(tf.float32, shape=[None, 1])
10 W = tf.Variable(tf.random_normal([x_data.shape[1], 1]))
11 b = tf.Variable(tf.random_normal([1]))
12

```

$x_data.shape[1] == 8$

```

13 model = tf.sigmoid(tf.matmul(X, W) + b)
14 cost = tf.reduce_mean((-1)*Y*tf.log(model) + (-1)*(1-Y)*tf.log(1-model))
15 train = tf.train.GradientDescentOptimizer(0.01).minimize(cost)
16

```

Model, Cost, Train

```

17 prediction = tf.cast(model > 0.5, dtype=tf.float32)
18 accuracy = tf.reduce_mean(tf.cast(tf.equal(prediction, Y), dtype=tf.float32))
19
20 with tf.Session() as sess:
21     sess.run(tf.global_variables_initializer())
22     # Training
23     for step in range(100001):
24         c, _ = sess.run([cost, train], feed_dict={X: x_data, Y: y_data})
25         print(step, c)
26     # Testing
27     h, c, a = sess.run([model, prediction, accuracy], feed_dict={X: x_data, Y: y_data})
28     print("\nHypothesis: ", h, "\nCorrect (Y): ", c, "\nAccuracy: ", a)

```

[0.]
[1.]
[1.]
[1.]
[1.]
[1.]
[1.]
[1.]

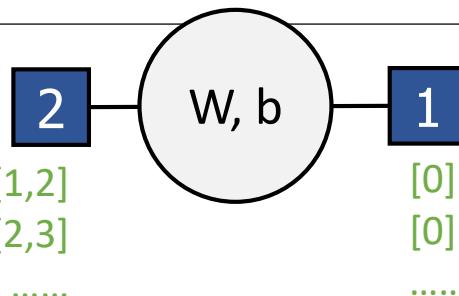
Accuracy: 0.76943344



Binary Classification Implementation (Keras)

- TensorFlow
 - Binary Classification
 - Binary Classification (using CSV File)
- Keras
 - **Binary Classification**
 - Binary Classification (using CSV File)

Binary Classification Implementation (Keras)



```
1 import numpy as np
2 from keras.models import Sequential
3 from keras.layers import Dense
4
5 # Data
6 x_data = np.array([[1,2], [2,3], [3,1], [4,3], [5,3], [6,2]])
7 y_data = np.array([[0], [0], [0], [1], [1], [1]])
8 # Model, Cost, Train
9 model = Sequential()
10 model.add(Dense(1, activation='sigmoid'))
11 model.compile(loss='binary_crossentropy', optimizer='sgd', metrics=['accuracy'])
12 model.fit(x_data, y_data, epochs=10000, verbose=1)
13 model.summary()
14 # Inference
15 print(model.get_weights())
16 print(model.predict(x_data))
```

Model, Cost, Train



Binary Classification Implementation (Keras)

```
joongheon@joongheon-AB350M-Gaming-3: ~/Dropbox/codes_keras
6/6 [=====] - 0s 107us/step - loss: 0.1504 - acc: 1.0000
Epoch 9992/10000
6/6 [=====] - 0s 116us/step - loss: 0.1504 - acc: 1.0000
Epoch 9993/10000
6/6 [=====] - 0s 96us/step - loss: 0.1504 - acc: 1.0000
Epoch 9994/10000
6/6 [=====] - 0s 102us/step - loss: 0.1504 - acc: 1.0000
Epoch 9995/10000
6/6 [=====] - 0s 97us/step - loss: 0.1504 - acc: 1.0000
Epoch 9996/10000
6/6 [=====] - 0s 101us/step - loss: 0.1504 - acc: 1.0000
Epoch 9997/10000
6/6 [=====] - 0s 102us/step - loss: 0.1504 - acc: 1.0000
Epoch 9998/10000
6/6 [=====] - 0s 101us/step - loss: 0.1503 - acc: 1.0000
Epoch 9999/10000
6/6 [=====] - 0s 104us/step - loss: 0.1503 - acc: 1.0000
Epoch 10000/10000
6/6 [=====] - 0s 102us/step - loss: 0.1503 - acc: 1.0000

-----  

Layer (type)           Output Shape        Param #  

-----  

dense_1 (Dense)        (None, 1)           3  

-----  

Total params: 3  

Trainable params: 3  

Non-trainable params: 0  

-----  

[[array([[1.4663278],  

       [0.3097024]], dtype=float32), array([-5.5251], dtype=float32)]  

 [[0.03108752]  

 [0.15931448]  

 [0.30652532]  

 [0.780626 ]  

 [0.9390975 ]  

 [0.98000884]]
```



Binary Classification Implementation (Keras)

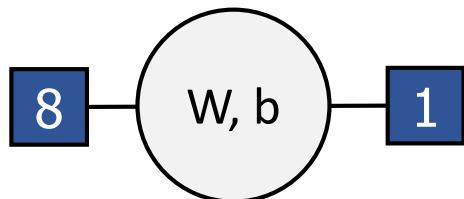
- TensorFlow
 - Binary Classification
 - Binary Classification (using CSV File)
- Keras
 - Binary Classification
 - **Binary Classification (using CSV File)**

Binary Classification Implementation (Keras)



```
1 import numpy as np
2 from keras.models import Sequential
3 from keras.layers import Dense
4
5 # Data
6 xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
7 x_data = xy[:, :-1]
8 y_data = xy[:, [-1]]
9
10 # Model, Cost, Train
11 model = Sequential()
12 model.add(Dense(1, activation='sigmoid'))
13 model.compile(loss='binary_crossentropy', optimizer='sgd', metrics=['accuracy'])
14 model.fit(x_data, y_data, epochs=1000, verbose=1)
15 model.summary()
```

Model, Cost, Train





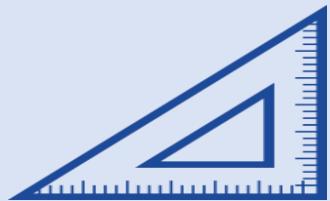
Binary Classification Implementation (Keras)

```
x -o joongheon@joongheon-AB350M-Gaming-3: ~/Dropbox/codes_keras
759/759 [=====] - 0s 18us/step - loss: 0.4725 - acc: 0.7694
Epoch 988/1000
759/759 [=====] - 0s 23us/step - loss: 0.4724 - acc: 0.7694
Epoch 989/1000
759/759 [=====] - 0s 23us/step - loss: 0.4724 - acc: 0.7694
Epoch 990/1000
759/759 [=====] - 0s 21us/step - loss: 0.4724 - acc: 0.7694
Epoch 991/1000
759/759 [=====] - 0s 20us/step - loss: 0.4724 - acc: 0.7708
Epoch 992/1000
759/759 [=====] - 0s 23us/step - loss: 0.4724 - acc: 0.7694
Epoch 993/1000
759/759 [=====] - 0s 21us/step - loss: 0.4724 - acc: 0.7708
Epoch 994/1000
759/759 [=====] - 0s 24us/step - loss: 0.4724 - acc: 0.7708
Epoch 995/1000
759/759 [=====] - 0s 24us/step - loss: 0.4724 - acc: 0.7708
Epoch 996/1000
759/759 [=====] - 0s 22us/step - loss: 0.4724 - acc: 0.7708
Epoch 997/1000
759/759 [=====] - 0s 22us/step - loss: 0.4724 - acc: 0.7694
Epoch 998/1000
759/759 [=====] - 0s 21us/step - loss: 0.4724 - acc: 0.7694
Epoch 999/1000
759/759 [=====] - 0s 21us/step - loss: 0.4724 - acc: 0.7708
Epoch 1000/1000
759/759 [=====] - 0s 24us/step - loss: 0.4724 - acc: 0.7708
```

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 1)	9
Total params:	9	
Trainable params:	9	
Non-trainable params:	0	



Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions



Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10
Recurrent NN (RNN)

Advanced Topics



Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting

Deep Learning Basics and Software

Softmax Classification

Softmax Classification Theory

- **Softmax Classification Theory**
- Softmax Classification Implementation



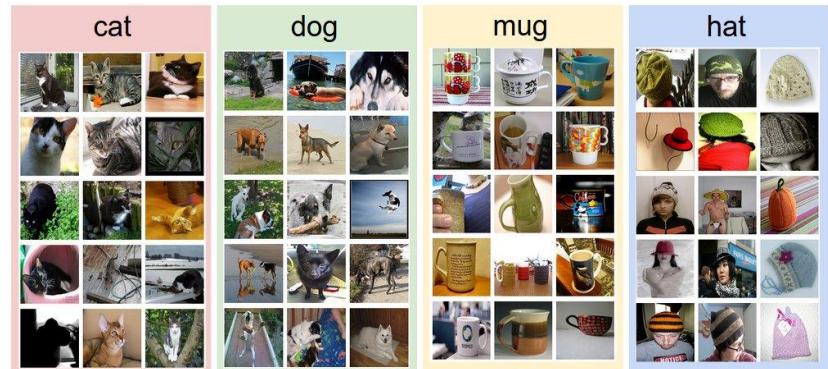
Regression (Examples)

- Exam Score Prediction (Linear Regression)



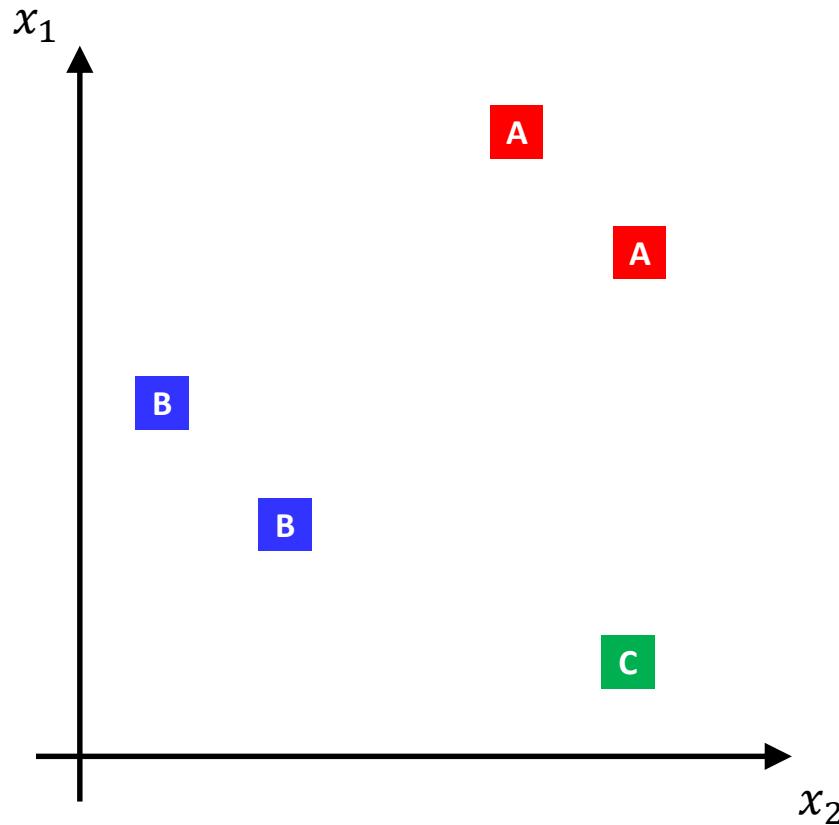
Classification (Examples)

- Pass/Fail (Binary Classification)
- Letter Grades (Multi-Level Classification)



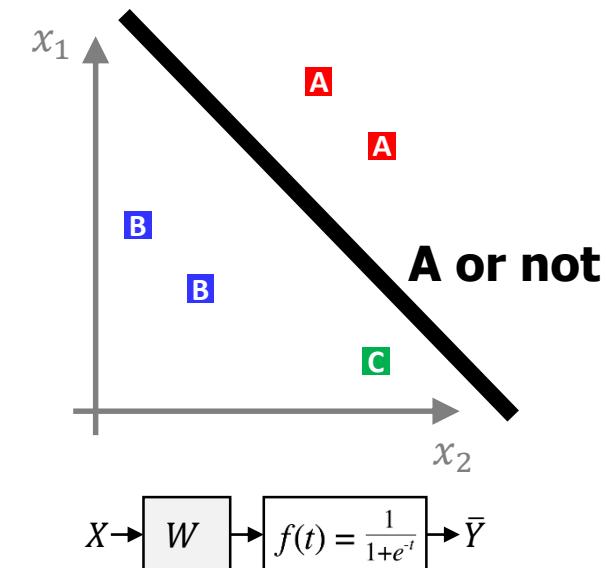
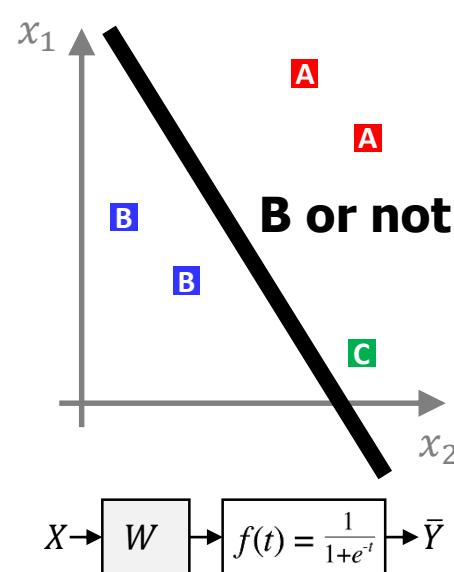
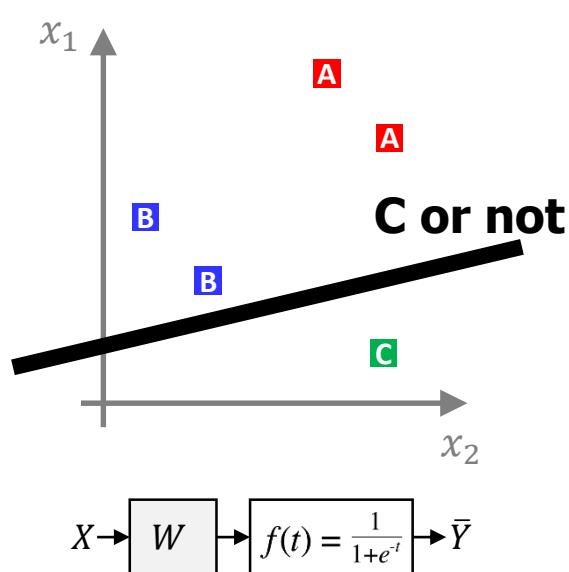


Multinomial Classification (Softmax Classification)





Multinomial Classification (Softmax Classification)

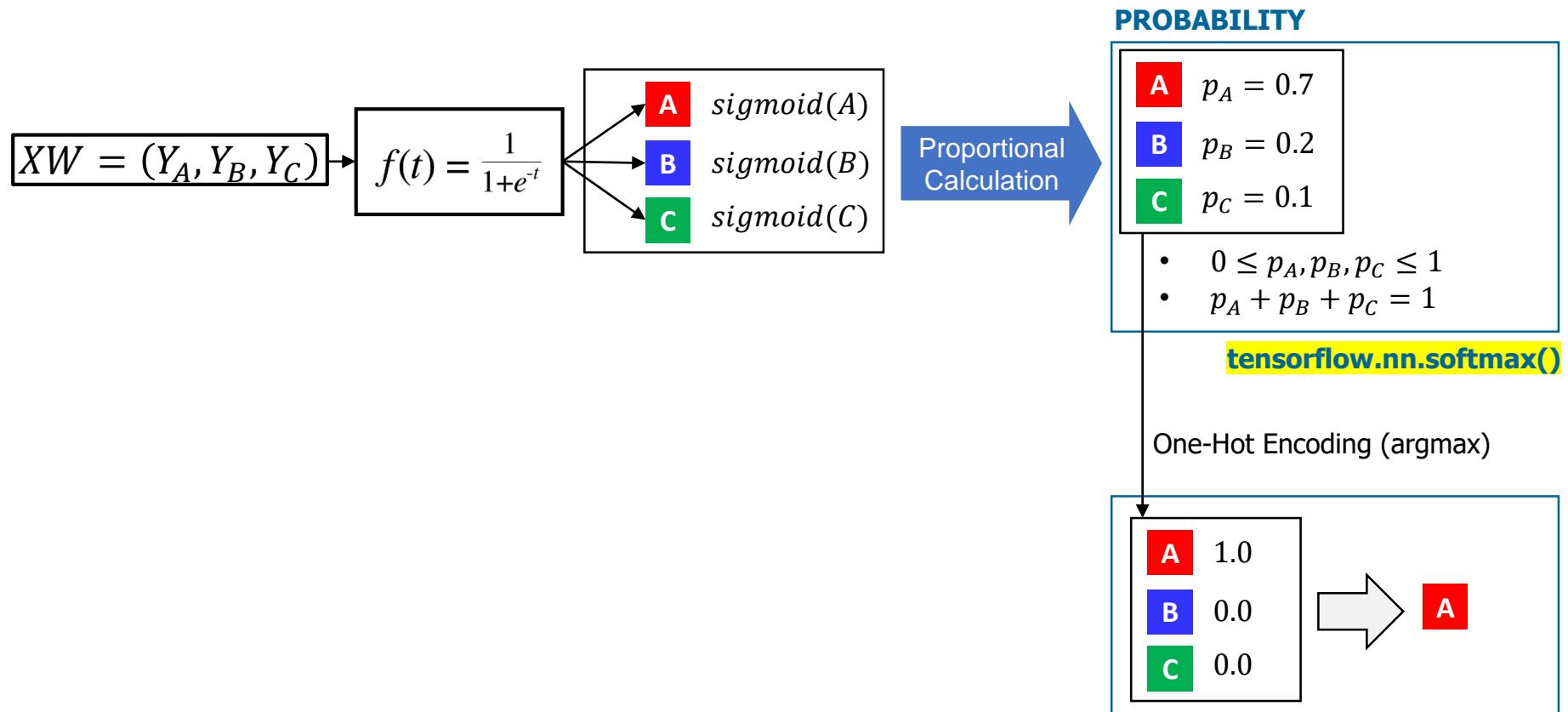


$$\begin{pmatrix} x_1 & x_2 \end{pmatrix} \cdot \begin{pmatrix} A \\ B \\ C \end{pmatrix} = \begin{pmatrix} x_1 \cdot W_{A1} + x_2 \cdot W_{A2} \\ x_1 \cdot W_{B1} + x_2 \cdot W_{B2} \\ x_1 \cdot W_{C1} + x_2 \cdot W_{C2} \end{pmatrix}$$

The matrix multiplication is shown with colored boxes: red for A, blue for B, and green for C. The resulting vector components are also color-coded: red for A, blue for B, and green for C.



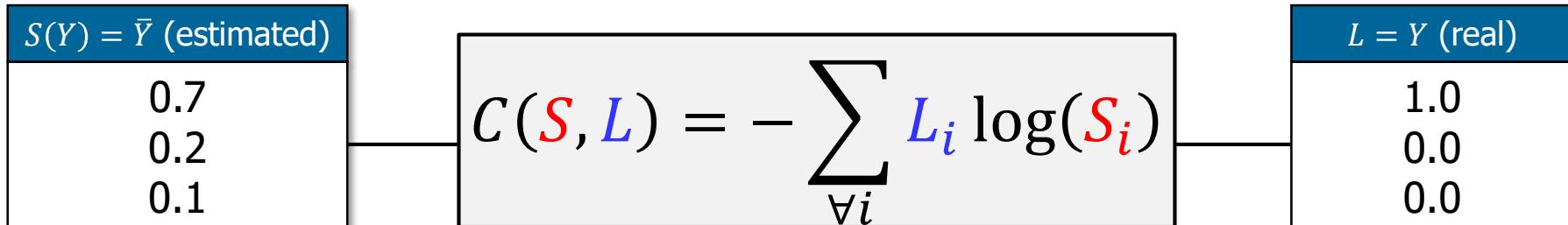
Multinomial Classification (Softmax Classification)





Multinomial Classification (Softmax Classification)

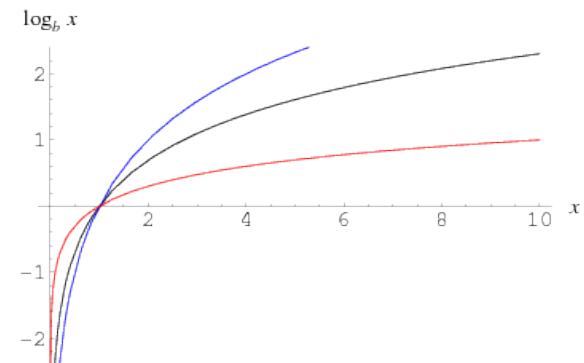
- Cost Function: **Cross-Entropy**



Understanding this Cost Function

L	S	Cost
[1,0,0]	[1,0,0]	$-1 \cdot \log 1 - 0 \cdot \log 0 - 0 \cdot \log 0 = 0$
	[0,1,0]	$-1 \cdot \log 0 - 0 \cdot \log 1 - 0 \cdot \log 0 = \infty$
	[0,0,1]	$-1 \cdot \log 0 - 0 \cdot \log 0 - 0 \cdot \log 1 = \infty$

Log Function



Deep Learning Basics and Software

Softmax Classification

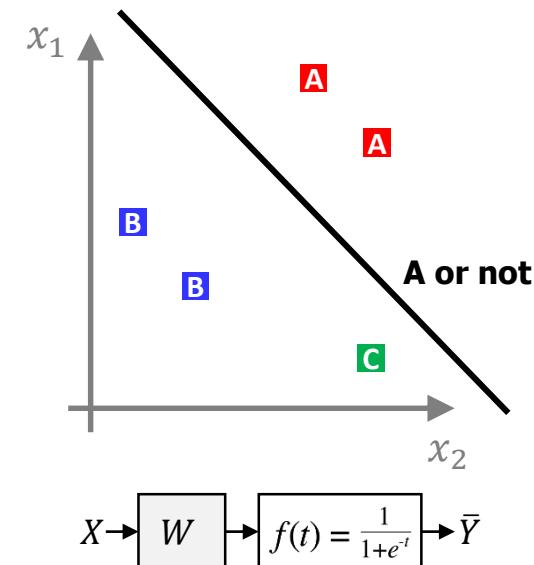
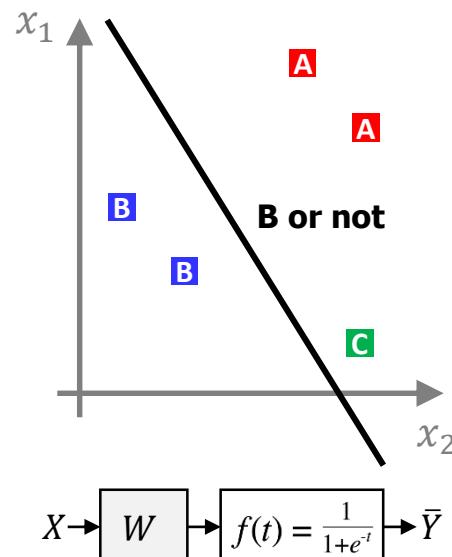
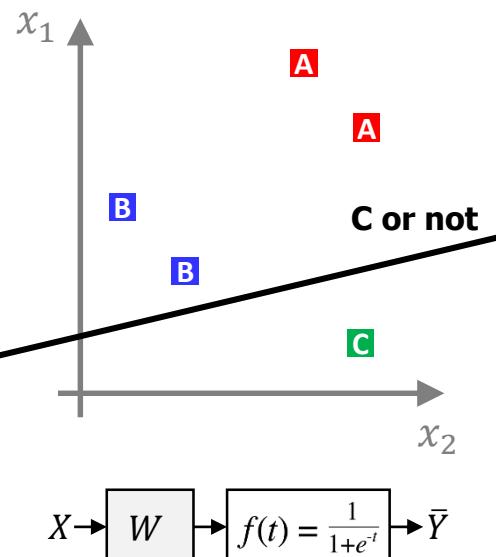
Softmax Classification Implementation

- Softmax Classification Theory
- Softmax Classification Implementation



Softmax Classification Implementation (TensorFlow)

- Implementation Example





Softmax Classification Implementation (TensorFlow)

- Implementation Example
 - Vector Representation

$$\begin{pmatrix} x_1 & x_2 & x_3 & x_4 \end{pmatrix} \cdot \begin{pmatrix} A \\ B \\ C \end{pmatrix} = \begin{pmatrix} S_A & S_B & S_C \end{pmatrix}$$

The diagram illustrates the softmax classification process. On the left, a vector $\begin{pmatrix} x_1 & x_2 & x_3 & x_4 \end{pmatrix}$ is multiplied by a weight matrix. The weight matrix is partitioned into three columns labeled A, B, and C. Column A (red border) contains weights $W_{A1}, W_{A2}, W_{A3}, W_{A4}$. Column B (blue border) contains weights $W_{B1}, W_{B2}, W_{B3}, W_{B4}$. Column C (green border) contains weights $W_{C1}, W_{C2}, W_{C3}, W_{C4}$. The result of the multiplication is a vector $\begin{pmatrix} S_A & S_B & S_C \end{pmatrix}$, where S_A, S_B, S_C represent the scores for categories A, B, and C respectively.

$$S_A \triangleq x_1 \cdot W_{A1} + x_2 \cdot W_{A2} + x_3 \cdot W_{A3} + x_4 \cdot W_{A4}$$

$$S_B \triangleq x_1 \cdot W_{B1} + x_2 \cdot W_{B2} + x_3 \cdot W_{B3} + x_4 \cdot W_{B4}$$

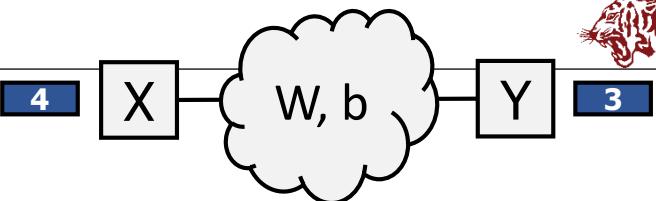
$$S_C \triangleq x_1 \cdot W_{C1} + x_2 \cdot W_{C2} + x_3 \cdot W_{C3} + x_4 \cdot W_{C4}$$



Softmax Classification Implementation (TensorFlow)

- TensorFlow
 - **Softmax Classification (with Given Cost Function)**
- Keras
 - Softmax Classification

Softmax Classification Implementation (TensorFlow)



```
1 import tensorflow as tf
2
3 x_data = [[1,2,1,1], [2,1,3,2], [3,1,3,4], [4,1,5,5], [1,7,5,5], [1,2,5,6], [1,6,6,6], [1,7,7,7]] # vectors
4 y_data = [[0,0,1], [0,0,1], [0,0,1], [0,1,0], [0,1,0], [0,1,0], [1,0,0], [1,0,0]] # one hot encoding
5 X = tf.placeholder(tf.float32, shape=[None, 4])
6 Y = tf.placeholder(tf.float32, shape=[None, 3])
7 W = tf.Variable(tf.random_normal([4, 3]))
8 b = tf.Variable(tf.random_normal([3]))
9
10 model_LC = tf.add(tf.matmul(X,W),b)
11 model = tf.nn.softmax(model_LC)
12 cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits_v2(logits=model_LC, labels=Y))
13 train = tf.train.GradientDescentOptimizer(0.1).minimize(cost)
14
15 with tf.Session() as sess:
16     sess.run(tf.global_variables_initializer())
17     # Training
18     for step in range(2001):
19         c, _ = sess.run([cost, train], feed_dict={X: x_data, Y: y_data})
20         print(step, c)
21     # Testing
22     test1 = sess.run(model, feed_dict={X: [[1,11,7,9]]})
23     print(test1, sess.run(tf.argmax(test1, 1)))
```

Model, Cost, Train

1988	0.16142774
1989	0.16136909
1990	0.16131032
1991	0.16125184
1992	0.16119315
1993	0.16113463
1994	0.16107623
1995	0.16101775
1996	0.16095944
1997	0.1609011
1998	0.16084275
1999	0.16078432
2000	0.16072604

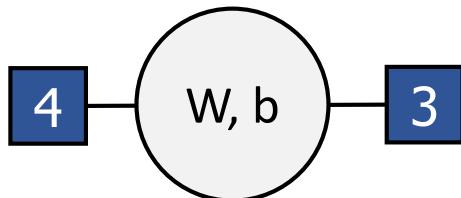
[[7.2217123e-03 9.9276876e-01 9.6337890e-06]] [1]



Softmax Classification Implementation (Keras)

- TensorFlow
 - Softmax Classification (with Given Cost Function)
- Keras
 - **Softmax Classification**

Softmax Classification Implementation (Keras)



```
1 import numpy as np
2 from keras.models import Sequential
3 from keras.layers import Dense
4
5 # Data
6 x_data = np.array([[1,2,1,1], [2,1,3,2], [3,1,3,4], [4,1,5,5], [1,7,5,5], [1,2,5,6], [1,6,6,6], [1,7,7,7]])
7 y_data = np.array([[0,0,1], [0,0,1], [0,0,1], [0,1,0], [0,1,0], [0,1,0], [1,0,0], [1,0,0]])
8
9 # Model, Cost, Train
10 model = Sequential()
11 model.add(Dense(3, activation='softmax'))
12 model.compile(loss='categorical_crossentropy', optimizer='sgd', metrics=['accuracy'])
13 model.fit(x_data, y_data, epochs=10000, verbose=1)
14 model.summary()
15 # Inference
16 y_predict = model.predict(np.array([[1,11,7,9]]))
17 print(y_predict)
18 print("argmax: ", np.argmax(y_predict))
```

Model, Cost, Train



Softmax Classification Implementation (Keras)

```
joongheon@joongheon-AB350M-Gaming-3: ~/Dropbox/codes_keras
8/8 [=====] - 0s 96us/step - loss: 0.2581 - acc: 1.0000
Epoch 9989/10000
8/8 [=====] - 0s 89us/step - loss: 0.2581 - acc: 1.0000
Epoch 9990/10000
8/8 [=====] - 0s 87us/step - loss: 0.2581 - acc: 1.0000
Epoch 9991/10000
8/8 [=====] - 0s 76us/step - loss: 0.2580 - acc: 1.0000
Epoch 9992/10000
8/8 [=====] - 0s 80us/step - loss: 0.2580 - acc: 1.0000
Epoch 9993/10000
8/8 [=====] - 0s 69us/step - loss: 0.2580 - acc: 1.0000
Epoch 9994/10000
8/8 [=====] - 0s 69us/step - loss: 0.2580 - acc: 1.0000
Epoch 9995/10000
8/8 [=====] - 0s 68us/step - loss: 0.2580 - acc: 1.0000
Epoch 9996/10000
8/8 [=====] - 0s 74us/step - loss: 0.2580 - acc: 1.0000
Epoch 9997/10000
8/8 [=====] - 0s 69us/step - loss: 0.2580 - acc: 1.0000
Epoch 9998/10000
8/8 [=====] - 0s 70us/step - loss: 0.2579 - acc: 1.0000
Epoch 9999/10000
8/8 [=====] - 0s 66us/step - loss: 0.2579 - acc: 1.0000
Epoch 10000/10000
8/8 [=====] - 0s 66us/step - loss: 0.2579 - acc: 1.0000

Layer (type)          Output Shape         Param #
=====
dense_1 (Dense)      (None, 3)            15
=====
Total params: 15
Trainable params: 15
Non-trainable params: 0
-----
[[1.3161632e-01 8.6831880e-01 6.4874497e-05]]
argmax: 1
```



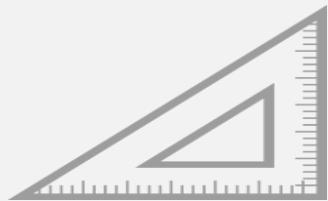
- Keras Tips
 - Parameter Setting Table

	[activation] setting in [Dense] keras.layers in [add] function	[loss] setting in [compile] function
Linear Regression		mse
Binary Classification	sigmoid	binary_crossentropy
Softmax Classification	softmax	categorical_crossentropy

- Optimizer
 - **sgd** // stochastic gradient descent optimizer
 - **adam** // adam optimizer



Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions



Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10
Recurrent NN (RNN)

Advanced Topics



Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting

Deep Learning Basics and Software

Artificial Neural Networks (ANN)

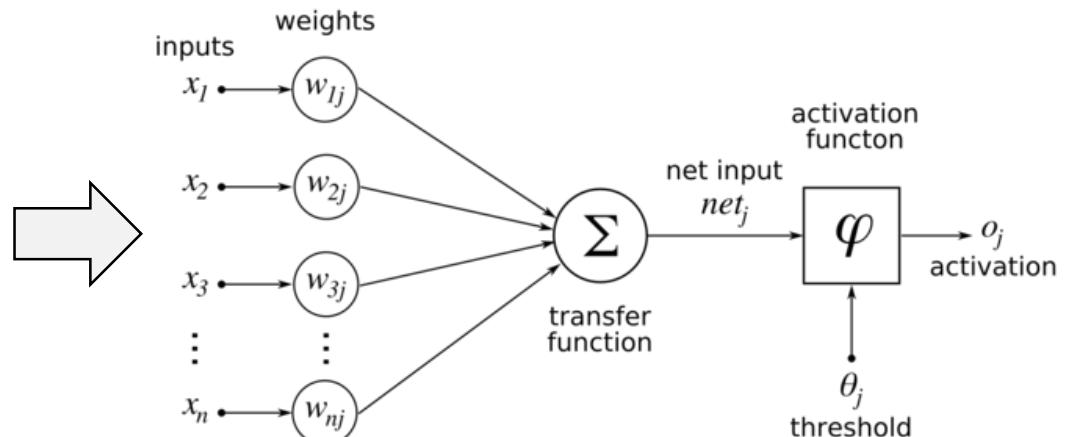
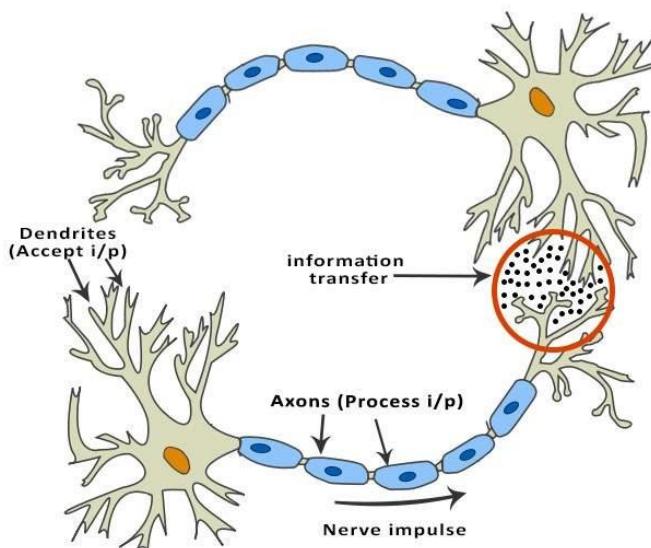
ANN Theory

- **ANN Theory**
- ANN Implementation

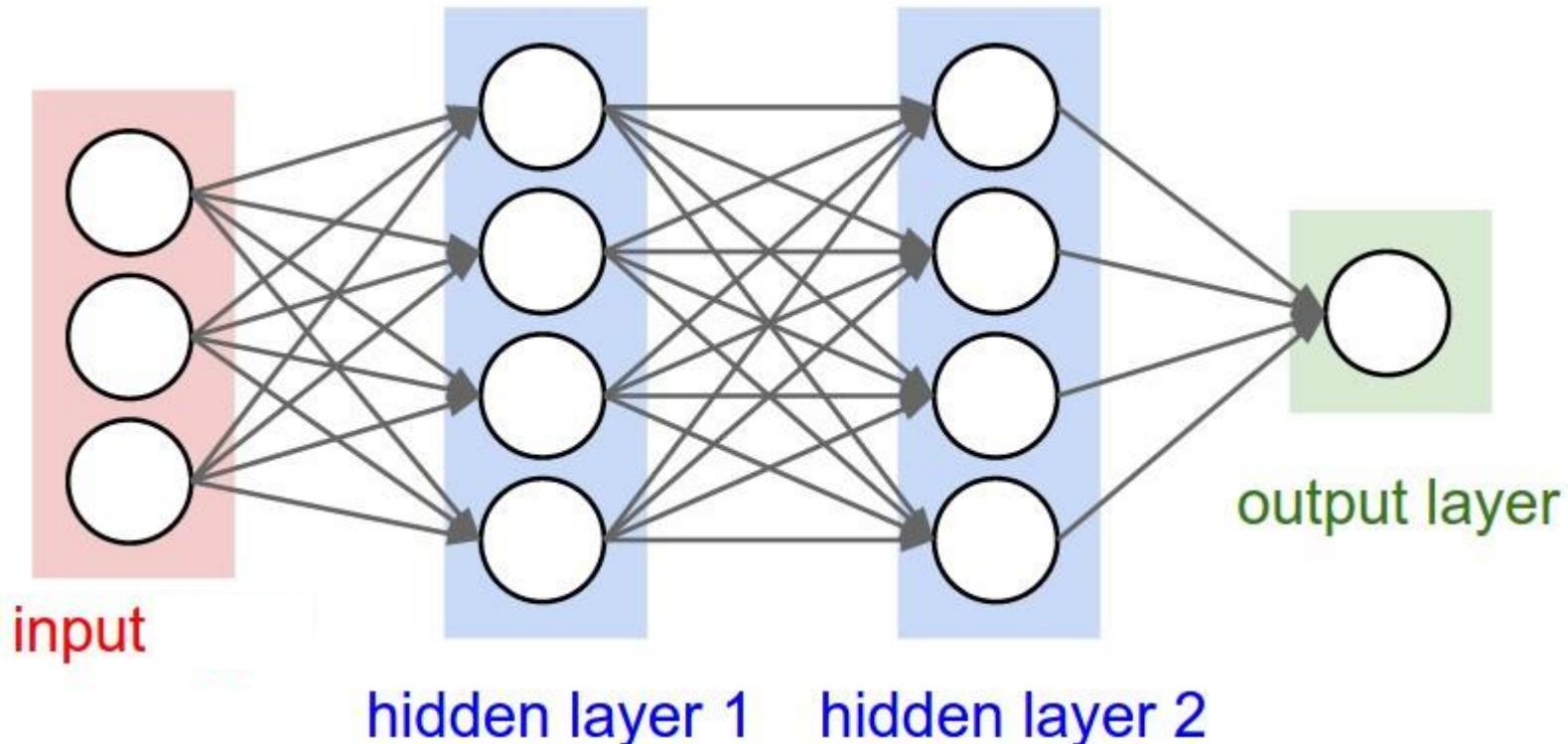


Artificial Neural Networks (ANN): Introduction

- Human Brain (Neuron)



Binary Classification

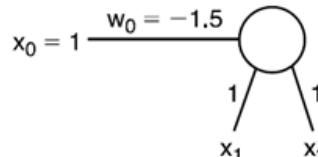




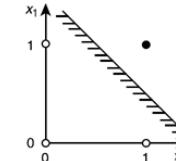
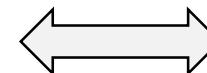
Artificial Neural Networks (ANN): Multilayer Perceptron

- Application to Logic Gate Design

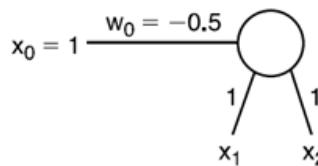
AND
gate



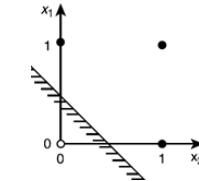
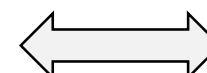
x_1	x_2	$W \cdot X$	y
0	0	-1.5	0
0	1	-0.5	0
1	0	-0.5	0
1	1	0.5	1



OR
gate



x_1	x_2	$W \cdot X$	y
0	0	-0.5	0
0	1	0.5	1
1	0	0.5	1
1	1	1.5	1

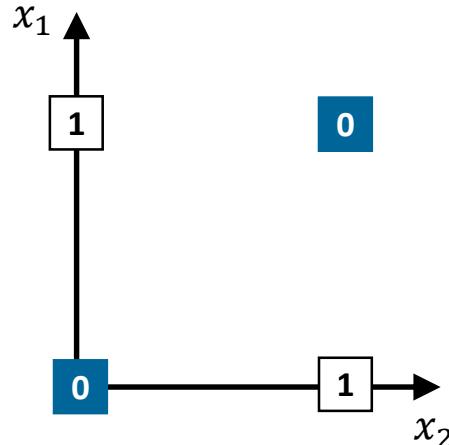


- What about XOR?

Artificial Neural Networks (ANN): Multilayer Perceptron



x_1	x_2	XOR
0	0	0
0	1	1
1	0	1
1	1	0

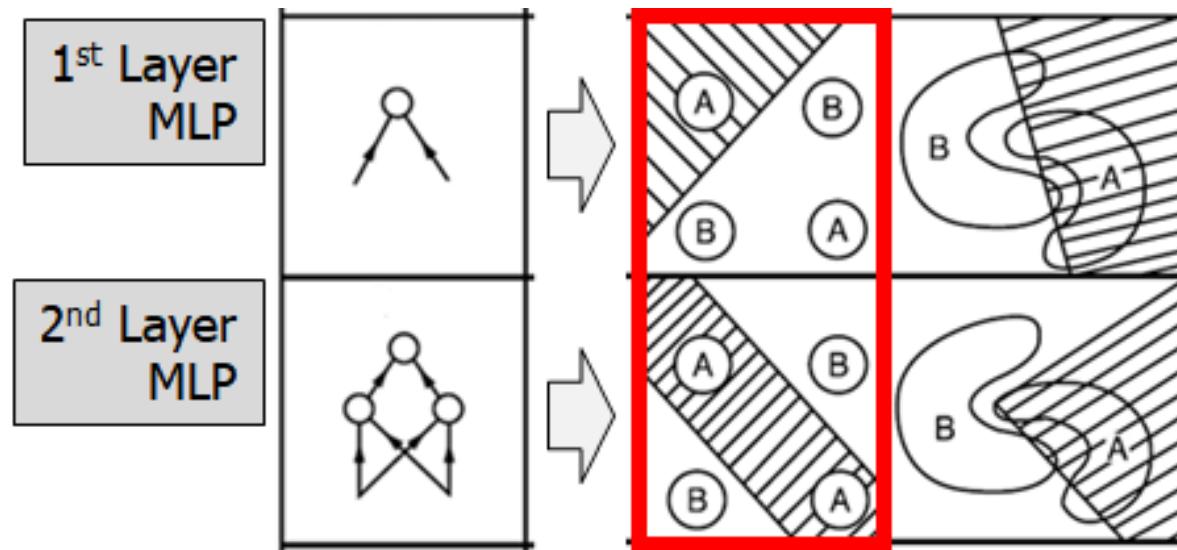


Mathematically proven by
Prof. Marvin Minsky at MIT (1969)



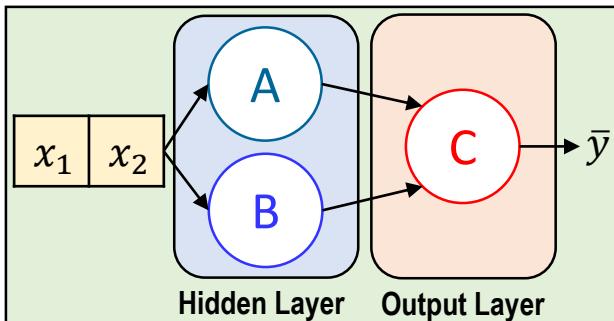
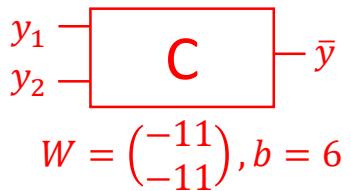
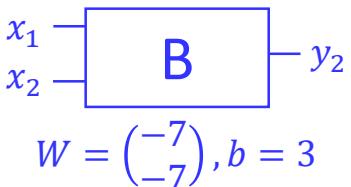
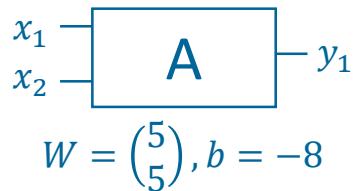
Artificial Neural Networks (ANN): Multilayer Perceptron

- Multilayer Perceptron (MLP)
 - Proposed by Prof. Marvin Minsky at MIT (1969)
 - Can solve XOR Problem

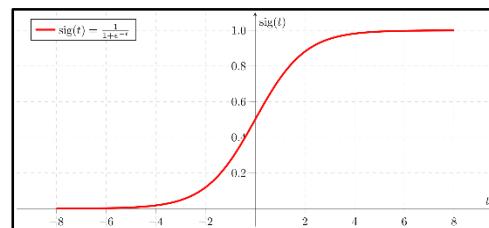




ANN: Solving XOR with MLP



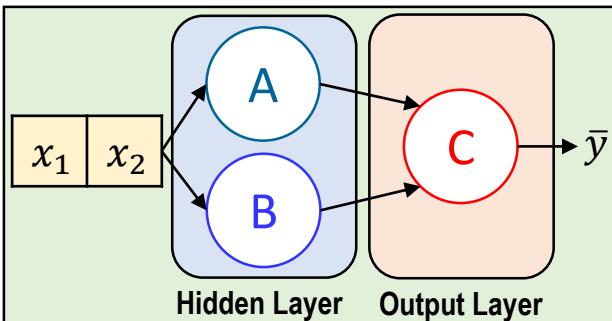
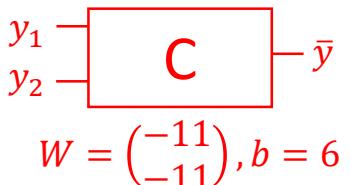
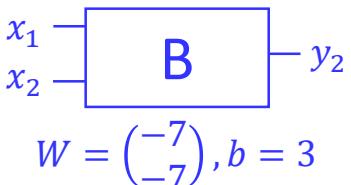
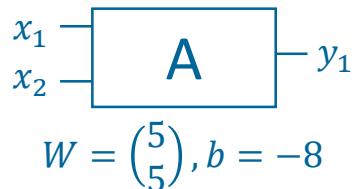
- $(x_1 \ x_2) = (0 \ 0)$
 - $(0 \ 0) \begin{pmatrix} 5 \\ 5 \end{pmatrix} + (-8) = -8$, i.e., $y_1 = \text{Sigmoid}(-8) \cong 0$
 - $(0 \ 0) \begin{pmatrix} -7 \\ 7 \end{pmatrix} + (3) = 3$, i.e., $y_2 = \text{Sigmoid}(3) \cong 1$
 - $(y_1 \ y_2) \begin{pmatrix} -11 \\ 11 \end{pmatrix} + (6) = -11 + 6 = -5$, i.e., $\bar{y} = \text{Sigmoid}(-5) \cong 0$



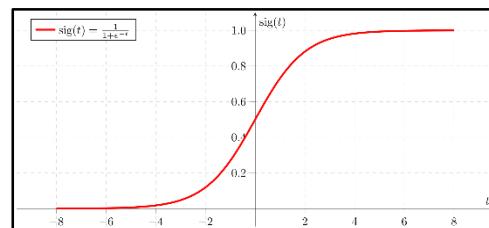
x_1	x_2	y_1	y_2	\bar{y}	XOR
0	0	0	1	0	0
0	1				1
1	0				1
1	1				0



ANN: Solving XOR with MLP



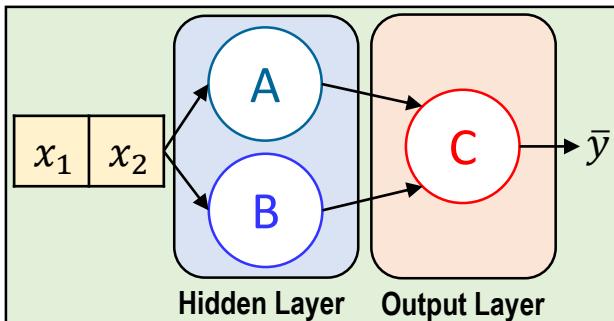
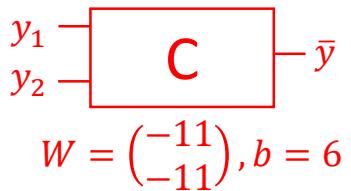
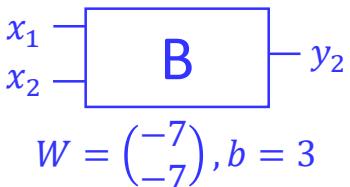
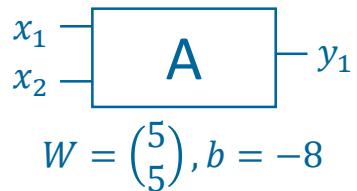
- $(x_1 \ x_2) = (0 \ 1)$
 - $(0 \ 1) \begin{pmatrix} 5 \\ 5 \end{pmatrix} + (-8) = -3$, i.e., $y_1 = Sigmoid(-3) \cong 0$
 - $(0 \ 1) \begin{pmatrix} -7 \\ -7 \end{pmatrix} + (3) = -4$, i.e., $y_2 = Sigmoid(-4) \cong 0$
 - $(y_1 \ y_2) \begin{pmatrix} -11 \\ -11 \end{pmatrix} + (6) = 6$, i.e., $\bar{y} = Sigmoid(6) \cong 1$



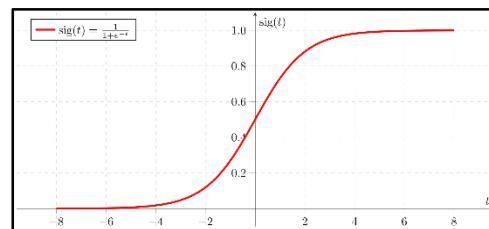
x_1	x_2	y_1	y_2	\bar{y}	XOR
0	0	0	1	0	0
0	1	0	0	1	1
1	0				1
1	1				0



ANN: Solving XOR with MLP



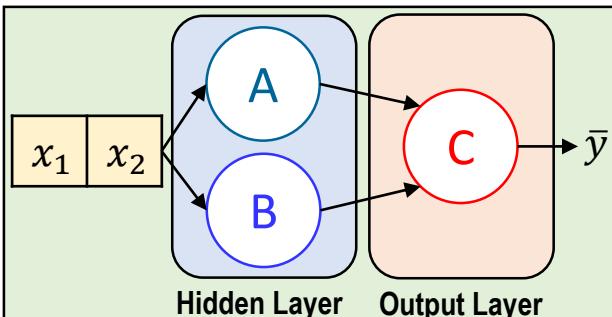
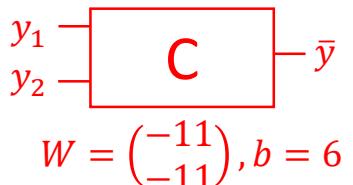
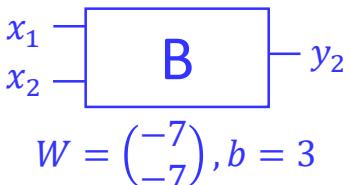
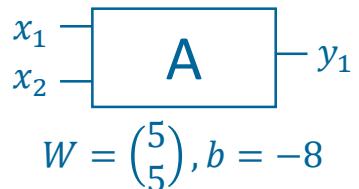
- $(x_1 \ x_2) = (1 \ 0)$
 - $(1 \ 0) \begin{pmatrix} 5 \\ 5 \end{pmatrix} + (-8) = -3$, i.e., $y_1 = Sigmoid(-3) \cong 0$
 - $(1 \ 0) \begin{pmatrix} -7 \\ -7 \end{pmatrix} + (3) = -4$, i.e., $y_2 = Sigmoid(-4) \cong 0$
 - $(y_1 \ y_2) \begin{pmatrix} -11 \\ -11 \end{pmatrix} + (6) = 6$, i.e., $\bar{y} = Sigmoid(6) \cong 1$



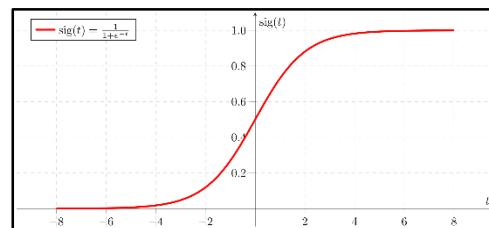
x_1	x_2	y_1	y_2	\bar{y}	XOR
0	0	0	1	0	0
0	1	0	0	1	1
1	0	0	0	1	1
1	1				0



ANN: Solving XOR with MLP



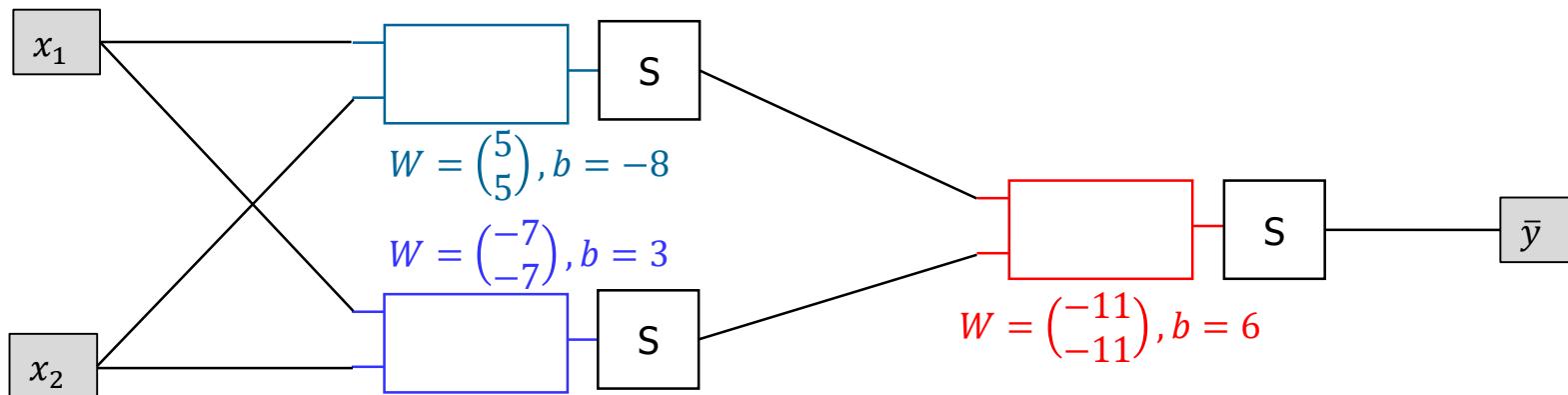
- $(x_1 \ x_2) = (1 \ 1)$
 - $(1 \ 1) \begin{pmatrix} 5 \\ 5 \end{pmatrix} + (-8) = 2$, i.e., $y_1 = Sigmoid(2) \cong 1$
 - $(1 \ 1) \begin{pmatrix} -7 \\ -7 \end{pmatrix} + (3) = -11$, i.e., $y_2 = Sigmoid(-11) \cong 0$
 - $(y_1 \ y_2) \begin{pmatrix} -11 \\ -11 \end{pmatrix} + (6) = -5$, i.e., $\bar{y} = Sigmoid(-5) \cong 0$



x_1	x_2	y_1	y_2	\bar{y}	XOR
0	0	0	1	0	0
0	1	0	0	1	1
1	0	0	0	1	1
1	1	1	0	0	0



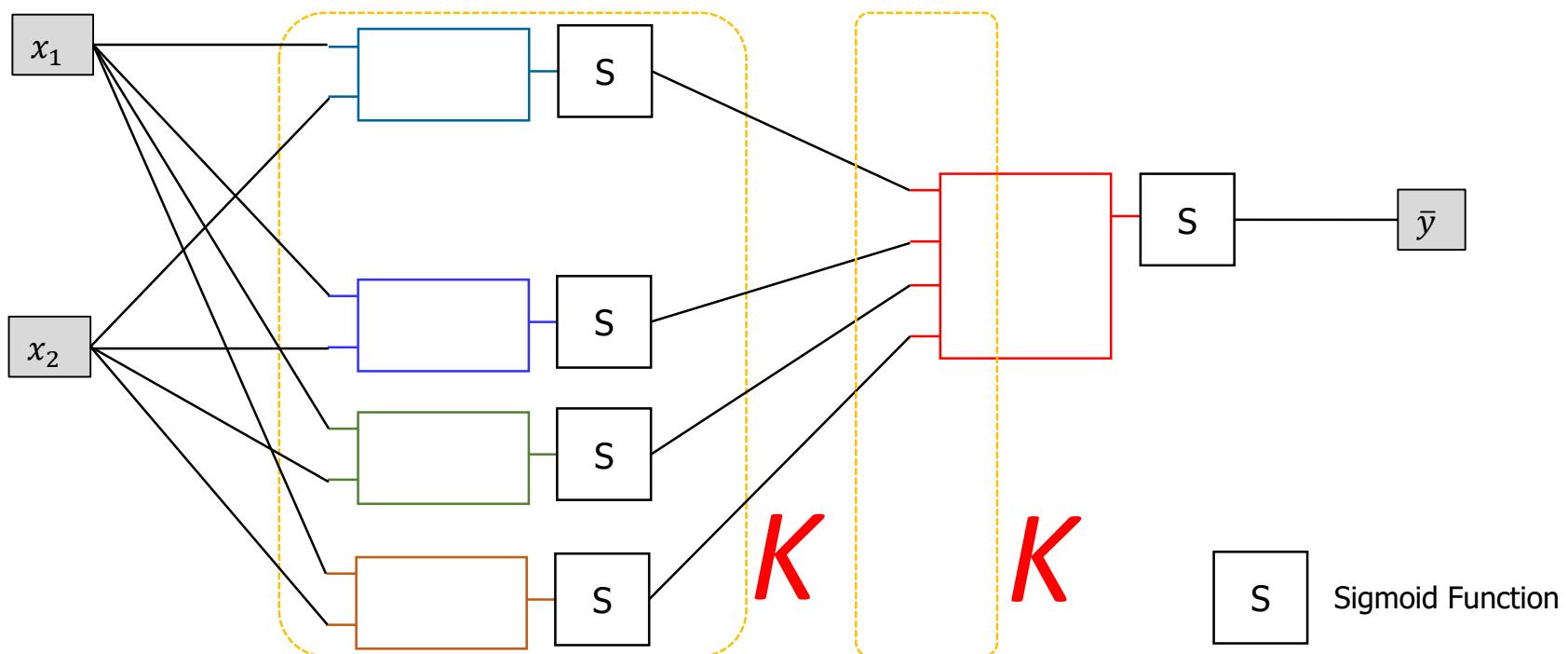
ANN: Solving XOR with MLP (Forward Propagation)



S Sigmoid Function

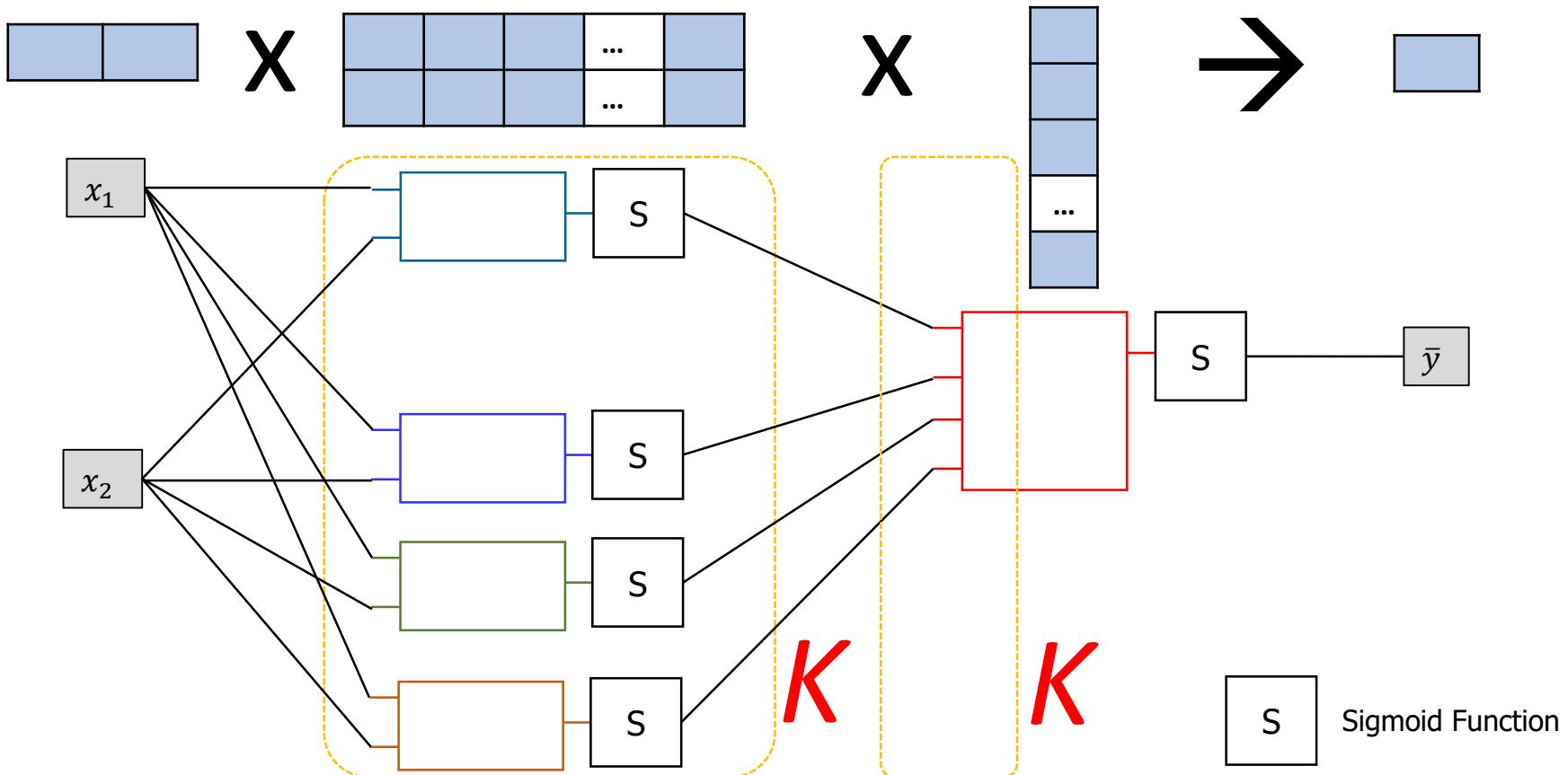


ANN: Solving XOR with MLP (Forward Propagation)





ANN: Solving XOR with MLP (Forward Propagation)



TensorFlow for ANN (XOR with Binary Classification)

0	1.0826586
2000	0.6931472
4000	0.6931472
6000	0.6931472
8000	0.6931472
10000	0.6931472
12000	0.6931472
14000	0.6931472
16000	0.6931472
18000	0.6931472
20000	0.6931472
	[[0.5]]
	[0.5]
	[0.5]
	[0.5]
	[0.5]
	[0.]
	[0.]
	[0.]
	0.5

```
1 import tensorflow as tf
2
3 x_data = [[0,0], [0,1], [1,0], [1,1]]
4 y_data = [[0], [1], [1], [0]]
5 X = tf.placeholder(tf.float32, shape=[None, 2])
6 Y = tf.placeholder(tf.float32, shape=[None, 1])
7 W = tf.Variable(tf.random_normal([2,1]))
8 b = tf.Variable(tf.random_normal([1]))
9 model = tf.sigmoid(tf.matmul(X,W)+b)
10 cost = tf.reduce_mean((-1)*Y*tf.log(model) + (-1)*(1-Y)*tf.log(1-model))
11 train = tf.train.GradientDescentOptimizer(0.1).minimize(cost)
12
13 prediction = tf.cast(model > 0.5, dtype=tf.float32)
14 accuracy = tf.reduce_mean(tf.cast(tf.equal(prediction, Y), dtype=tf.float32))
15
16 with tf.Session() as sess:
17     sess.run(tf.global_variables_initializer())
18     # Training
19     for step in range(20001):
20         c, _ = sess.run([cost, train], feed_dict={X: x_data, Y: y_data})
21         if step % 2000 == 0:
22             print(step, c)
23     # Testing
24     m, p, a = sess.run([model, prediction, accuracy], feed_dict={X: x_data, Y: y_data})
25     print(m,p,a)
```

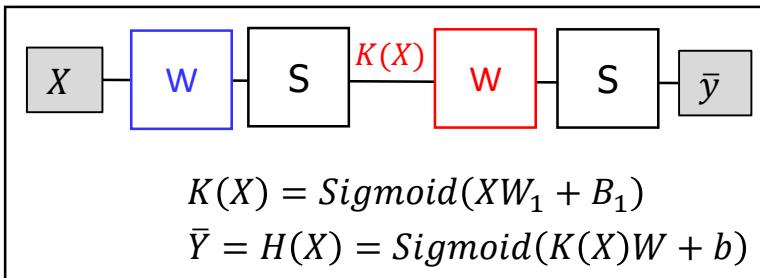


TensorFlow for ANN (XOR with ANN)

```

1 import tensorflow as tf
2
3 x_data = [[0,0], [0,1], [1,0], [1,1]]
4 y_data = [[0], [1], [1], [0]]
5 X = tf.placeholder(tf.float32, shape=[None, 2])
6 Y = tf.placeholder(tf.float32, shape=[None, 1])
7 W_h = tf.Variable(tf.random_normal([2,3]))
8 b_h = tf.Variable(tf.random_normal([3]))
9 H1 = tf.sigmoid(tf.matmul(X,W_h)+b_h)
10 W_o = tf.Variable(tf.random_normal([3,1]))
11 b_o = tf.Variable(tf.random_normal([1]))
12 model = tf.sigmoid(tf.matmul(H1,W_o)+b_o)
13 cost = tf.reduce_mean((-1)*Y*tf.log(model) + (-1)*(1-Y)*tf.log(1-model))
14 train = tf.train.GradientDescentOptimizer(0.1).minimize(cost)
15
16 prediction = tf.cast(model > 0.5, dtype=tf.float32)
17 accuracy = tf.reduce_mean(tf.cast(tf.equal(prediction, Y), dtype=tf.float32))
18
19 with tf.Session() as sess:
20     sess.run(tf.global_variables_initializer())
21     # Training
22     for step in range(20001):
23         c, _ = sess.run([cost, train], feed_dict={X: x_data, Y: y_data})
24         if step % 2000 == 0:
25             print(step, c)
26     # Testing
27     m, p, a = sess.run([model, prediction, accuracy], feed_dict={X: x_data, Y: y_data})
28     print(m,p,a)

```



```

0 0.86801255
2000 0.27334553
4000 0.046823796
6000 0.02246793
8000 0.0143708335
10000 0.010443565
12000 0.008153362
14000 0.0066633224
16000 0.0056207716
18000 0.0048525333
20000 0.004264111
[[0.00480547]
 [0.99502313]
 [0.9966924 ]
 [0.00392833]] [[0.]
 [1.]
 [1.]
 [0.]] 1.0

```



TensorFlow for ANN (XOR with ANN)

- **Wide ANN for XOR**

```
W1 = tf.Variable(tf.random_normal([2, 10]))
b1 = tf.Variable(tf.random_normal([10]))
H1 = tf.sigmoid(tf.matmul(X, W1) + b1)

W2 = tf.Variable(tf.random_normal([10, 1]))
b2 = tf.Variable(tf.random_normal([1]))
model = tf.sigmoid(tf.matmul(H1, W2) + b2)
```

[2,10], [10,1]

Hypothesis:

```
[[ 0.00358802]
 [ 0.99366933]
 [ 0.99204296]
 [ 0.0095663 ]]
```

Correct:

```
[[ 0.]
 [ 1.]
 [ 1.]
 [ 0.]]
```

Accuracy: 1.0

[2,2], [2,1]

Hypothesis:

```
[[ 0.01338218]
 [ 0.98166394]
 [ 0.98809403]
 [ 0.01135799]]
```

Correct:

```
[[ 0.]
 [ 1.]
 [ 1.]
 [ 0.]]
```

Accuracy: 1.0



TensorFlow for ANN (XOR with ANN)

- **Deep ANN for XOR**

```
W1 = tf.Variable(tf.random_normal([2, 10]))
b1 = tf.Variable(tf.random_normal([10]))
H1 = tf.sigmoid(tf.matmul(X, W1) + b1)

W2 = tf.Variable(tf.random_normal([10, 10]))
b2 = tf.Variable(tf.random_normal([10]))
H2 = tf.sigmoid(tf.matmul(H1, W2) + b2)

W3 = tf.Variable(tf.random_normal([10, 10]))
b3 = tf.Variable(tf.random_normal([10]))
H3 = tf.sigmoid(tf.matmul(H2, W3) + b3)

W4 = tf.Variable(tf.random_normal([10, 1]))
b4 = tf.Variable(tf.random_normal([1]))
model = tf.sigmoid(tf.matmul(H3, W4) + b4)
```

4 layers

Hypothesis:
[[7.80e-04]
[9.99e-01]
[9.98e-01]
[1.55e-03]]

Correct:

[[0.]
[1.]
[1.]
[0.]]

Accuracy: 1.0

2 layers

Hypothesis:
[[0.01338218]
[0.98166394]
[0.98809403]
[0.01135799]]

Correct:

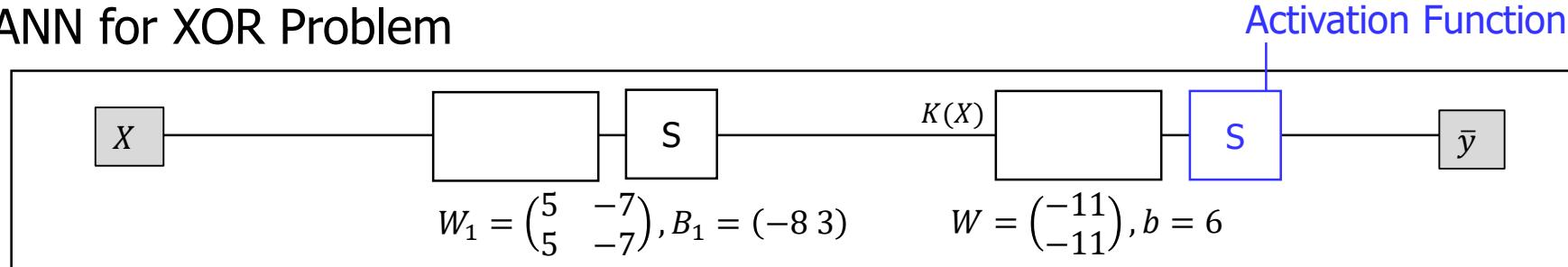
[[0.]
[1.]
[1.]
[0.]]

Accuracy: 1.0



ANN: ReLU (Rectified Linear Unit)

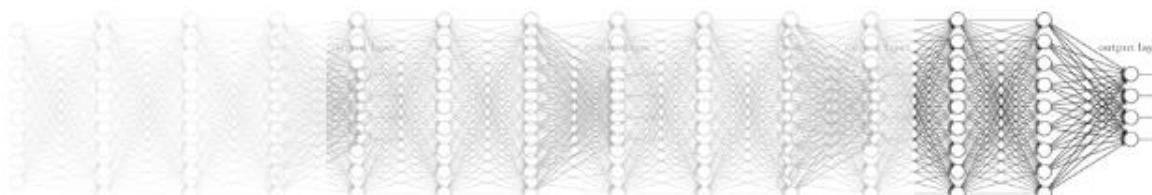
- ANN for XOR Problem



- Observation)

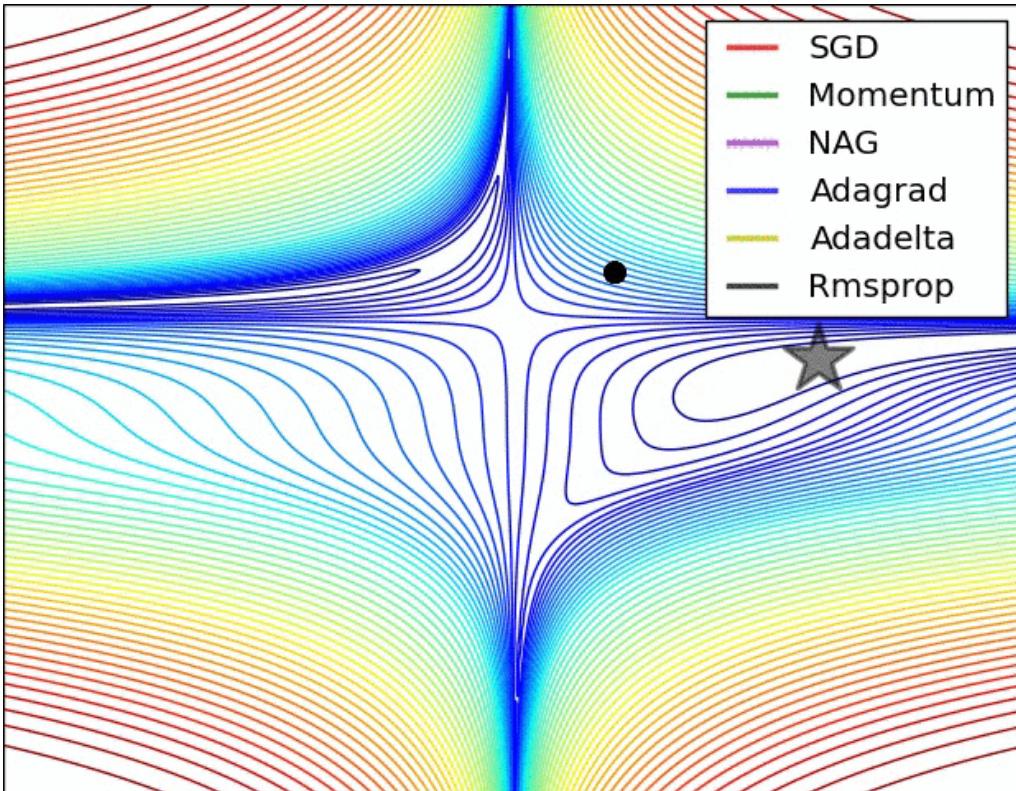
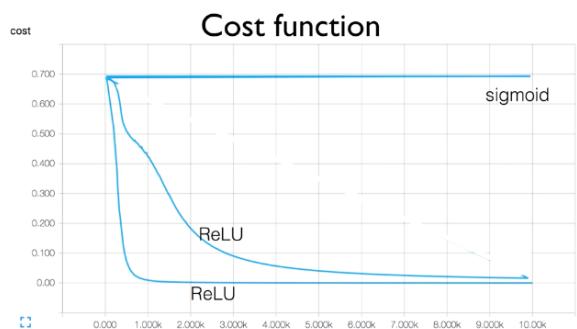
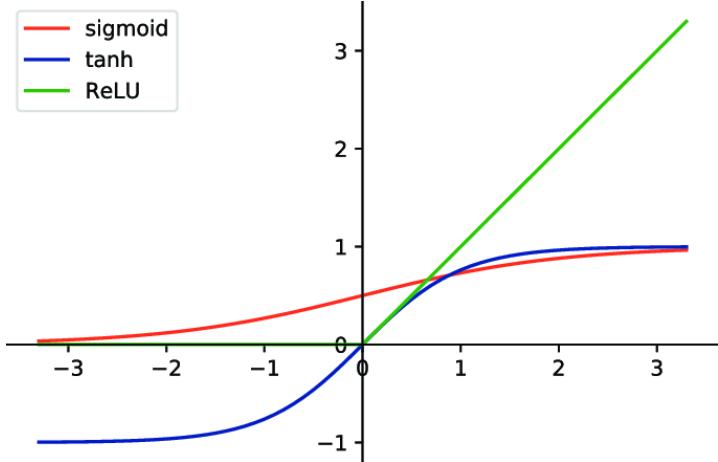
- There exists cases when the accuracy is low even if the # layers is high. Why?
- Answer)

- The result of one ANN is the result of sigmoid function (**between 0 and 1**).
- The numerous multiplication of this result converges to near zero.
→ **Gradient Vanishing Problem**





ANN: ReLU (Rectified Linear Unit)





- ReLU

```
# input place holders
X = tf.placeholder(tf.float32, [None, 784])
Y = tf.placeholder(tf.float32, [None, 10])

# weights & bias for NN layers
W1 = tf.Variable(tf.random_normal([784, 256]))
b1 = tf.Variable(tf.random_normal([256]))
L1 = tf.nn.relu(tf.matmul(X, W1) + b1)

W2 = tf.Variable(tf.random_normal([256, 256]))
b2 = tf.Variable(tf.random_normal([256]))
L2 = tf.nn.relu(tf.matmul(L1, W2) + b2)

W3 = tf.Variable(tf.random_normal([256, 10]))
b3 = tf.Variable(tf.random_normal([10]))

model_LC = tf.matmul(L2, W3) + b3
cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits_v2(logits=model_LC, labels=Y))
train = tf.train.AdamOptimizer(0.01).minimize(cost)
```



ANN: Deep Learning

- Deep Learning Revolution is Real

Our **labeled datasets** were **too small**.

IMAGENET
14.2 million images



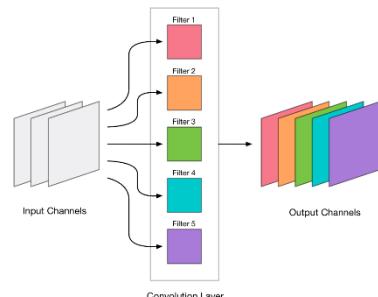
Big-Data

Our **computers** were millions of times **too slow**.



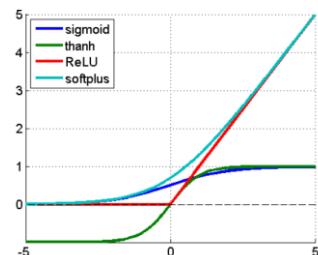
GPU

We only consider **one-dimensional vector** as an input.



Convolution Layers for Multi-Dimensional Inputs

We used the **wrong type of non-linearity (activation function)**.



ReLU for solving Gradient Vanishing Problem

Deep Learning Theory and Software

Artificial Neural Networks (ANN)

ANN Implementation

- ANN Theory
- **ANN Implementation**



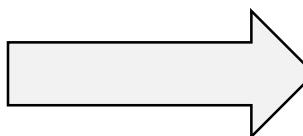
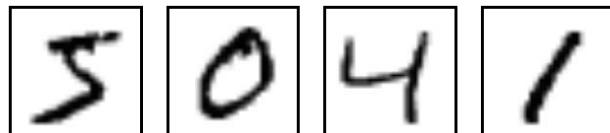
ANN Implementation (TensorFlow)

- TensorFlow
 - **MLP for MNIST**
 - MLP for MNIST (tensorflow.layers.dense)
- Keras
 - MLP for MNIST



- MNIST Data Set

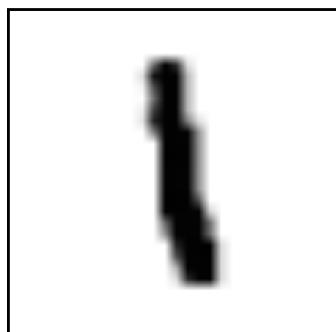
- Hand written images and their labels
 - For training: 55,000
 - For testing: 5,000



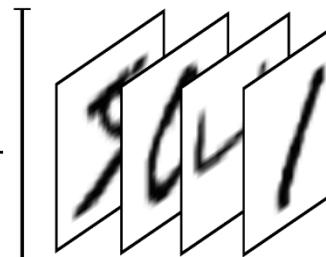
[0,0,0,0,0,1,0,0,0,0]	→	'5'
[1,0,0,0,0,0,0,0,0,0]	→	'0'
[0,0,0,0,1,0,0,0,0,0]	→	'4'
[0,1,0,0,0,0,0,0,0,0]	→	'1'

mnist.train.xs

- Image: 28-by-28 (pixels)



784



60000



ANN Implementation (TensorFlow)

```
1 # MNIST
2 from tensorflow.examples.tutorials.mnist import input_data
3 mnist = input_data.read_data_sets("data_MNIST", one_hot = True)
4
5 # Setting
6 import tensorflow as tf
7 import time
8 num_steps = 5000
9 batch_size = 128
10 nH1 = 256
11 nH2 = 256
12 nH3 = 256
13
14 X = tf.placeholder("float", [None, 784])
15 Y = tf.placeholder("float", [None, 10])
16
```



ANN Implementation (TensorFlow)

```
17 def mlp_LC(img):
18     HL1 = tf.nn.relu(tf.add(tf.matmul(img, W['HL1']), b['HL1']))
19     HL2 = tf.nn.relu(tf.add(tf.matmul(HL1, W['HL2']), b['HL2']))
20     HL3 = tf.nn.relu(tf.add(tf.matmul(HL2, W['HL3']), b['HL3']))
21     Out = tf.matmul(HL3, W['Out']) + b['Out']
22     return Out
23 W = {
24     'HL1' : tf.Variable(tf.random_normal([784, nH1])),
25     'HL2' : tf.Variable(tf.random_normal([nH1, nH2])),
26     'HL3' : tf.Variable(tf.random_normal([nH2, nH3])),
27     'Out' : tf.Variable(tf.random_normal([nH3, 10]))
28 }
29 b = {
30     'HL1' : tf.Variable(tf.random_normal([nH1])),
31     'HL2' : tf.Variable(tf.random_normal([nH2])),
32     'HL3' : tf.Variable(tf.random_normal([nH3])),
33     'Out' : tf.Variable(tf.random_normal([10]))
34 }
```



ANN Implementation (TensorFlow)

```
36 # Model, Cost, Train
37 model_LC = mlp_LC(X)
38 model = tf.nn.softmax(model_LC)
39 cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=model_LC, labels=Y))
40 train = tf.train.AdamOptimizer(0.01).minimize(cost)
41
42 # Accuracy Computation
43 accuracy = tf.reduce_mean(tf.cast(tf.equal(tf.argmax(model, 1), tf.argmax(Y,1)), tf.float32))
44
45 # Session
46 with tf.Session() as sess:
47     sess.run(tf.global_variables_initializer())
48     # Train
49     t1 = time.time()
50     for step in range(1, num_steps+1):
51         train_images, train_labels = mnist.train.next_batch(batch_size)
52         sess.run(train, feed_dict={X: train_images, Y: train_labels})
53         if step % 500 == 0:
54             print(step)
55             print("Training Time (seconds): ", t2-t1)
56             print("Testing Accuracy: ", sess.run(accuracy, feed_dict={X: mnist.test.images, Y: mnist.test.labels}))
57
```

500
1000
1500
2000
2500
3000
3500
4000
4500
5000
Training Time (seconds): 14.891910552978516
Testing Accuracy: 0.9581

- Line 48:
 - **batch_train_images**: matrix for **mnist.train.next_batch**: (batch_size)-by-(784) → *image data*
 - **batch_train_labels**: matrix for **mnist.train.next_batch**: (batch_size)-by-(10) → *image labels*
- Line 54:
 - **Testing** with **mnist.test.images** and **mnist.test.labels**



- TensorFlow
 - MLP for MNIST
 - **MLP for MNIST (tensorflow.layers.dense)**
- Keras
 - MLP for MNIST



ANN Implementation (TensorFlow)

```
17 def mlp_LC(img):
18     HL1 = tf.nn.relu(tf.add(tf.matmul(img, W['HL1']), b['HL1']))
19     HL2 = tf.nn.relu(tf.add(tf.matmul(HL1, W['HL2']), b['HL2']))
20     HL3 = tf.nn.relu(tf.add(tf.matmul(HL2, W['HL3']), b['HL3']))
21     Out = tf.matmul(HL3, W['Out']) + b['Out']
22     return Out
23 W = {
24     'HL1' : tf.Variable(tf.random_normal([784, nH1])),
25     'HL2' : tf.Variable(tf.random_normal([nH1, nH2])),
26     'HL3' : tf.Variable(tf.random_normal([nH2, nH3])),
27     'Out' : tf.Variable(tf.random_normal([nH3, 10]))
28 }
29 b = {
30     'HL1' : tf.Variable(tf.random_normal([nH1])),
31     'HL2' : tf.Variable(tf.random_normal([nH2])),
32     'HL3' : tf.Variable(tf.random_normal([nH3])),
33     'Out' : tf.Variable(tf.random_normal([10]))
34 }
```



`tensorflow.layers.dense`

```
17 def mlp_LC(img):
18     HL1 = tf.layers.dense(inputs=img, units=nH1, activation=tf.nn.relu)
19     HL2 = tf.layers.dense(inputs=HL1, units=nH2, activation=tf.nn.relu)
20     HL3 = tf.layers.dense(inputs=HL2, units=nH3, activation=tf.nn.relu)
21     Out = tf.layers.dense(inputs=HL3, units=10, activation=None)
22     return Out
```



ANN Implementation (TensorFlow)

- TensorFlow
 - MLP for MNIST
 - MLP for MNIST (`tensorflow.layers.dense`)
- Keras
 - **MLP for MNIST**



ANN Implementation (Keras)

```
1  from keras.utils import np_utils
2  from keras.datasets import mnist
3  from keras.models import Sequential
4  from keras.layers import Dense
5  # MNIST data
6  (train_images, train_labels), (test_images, test_labels) = mnist.load_data()
7  print(train_images.shape, train_labels.shape, test_images.shape, test_labels.shape)
8  train_images = train_images.reshape(train_images.shape[0], 784).astype('float32')/255.0
9  test_images = test_images.reshape(test_images.shape[0], 784).astype('float32')/255.0
10 train_labels = np_utils.to_categorical(train_labels) # One-Hot Encoding
11 test_labels = np_utils.to_categorical(test_labels) # One-Hot Encoding
12 # Model
13 model = Sequential()
14 model.add(Dense(256, activation='relu')) # units=256, activation='relu'
15 model.add(Dense(256, activation='relu')) # units=256, activation='relu'
16 model.add(Dense(256, activation='relu')) # units=256, activation='relu'
17 model.add(Dense(10, activation='softmax')) # units=10, activation='softmax'
18 model.compile(loss='categorical_crossentropy', optimizer='sgd', metrics=['accuracy'])
19 # Training
20 model.fit(train_images, train_labels, epochs=5, batch_size=32, verbose=1)
21 # Testing
22 _, accuracy = model.evaluate(test_images, test_labels)
23 print('Accuracy: ', accuracy)
24 model.summary()
```



ANN Implementation (Keras)

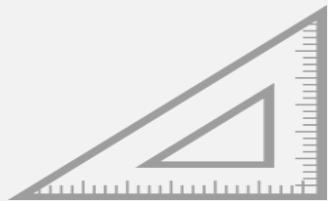
```
(60000, 28, 28) (60000,) (10000, 28, 28) (10000,)

Epoch 1/5
2019-08-04 21:38:20.386123: I tensorflow/core/platform/cpu_feature_guard.cc:141] Your CPU
supports instructions that this TensorFlow binary was not compiled to use: AVX2 FMA
60000/60000 [=====] - 5s 87us/step - loss: 0.6131 - acc: 0.8331
Epoch 2/5
60000/60000 [=====] - 5s 85us/step - loss: 0.2544 - acc: 0.9269
Epoch 3/5
60000/60000 [=====] - 5s 85us/step - loss: 0.1971 - acc: 0.9426
Epoch 4/5
60000/60000 [=====] - 5s 85us/step - loss: 0.1610 - acc: 0.9529
Epoch 5/5
60000/60000 [=====] - 5s 85us/step - loss: 0.1356 - acc: 0.9608
10000/10000 [=====] - 0s 32us/step
Accuracy: 0.9602

Layer (type)          Output Shape         Param #
=====
dense_1 (Dense)      (None, 256)          200960
dense_2 (Dense)      (None, 256)          65792
dense_3 (Dense)      (None, 256)          65792
dense_4 (Dense)      (None, 10)           2570
=====
Total params: 335,114
Trainable params: 335,114
Non-trainable params: 0
```



Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions



Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10
Recurrent NN (RNN)

Advanced Topics



Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting

Deep Learning Theory and Software

Convolutional Neural Networks (CNN)

CNN Theory

- **CNN Theory**
- CNN Implementation

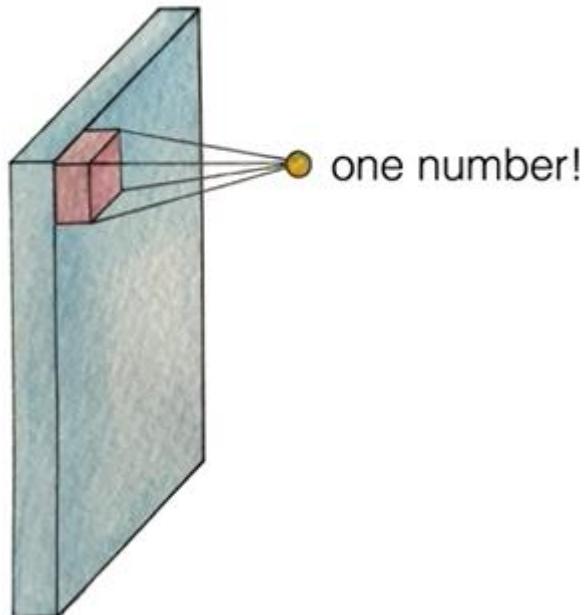


CNN: Convolution

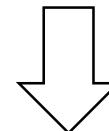




- Extracting **one point** with a filter



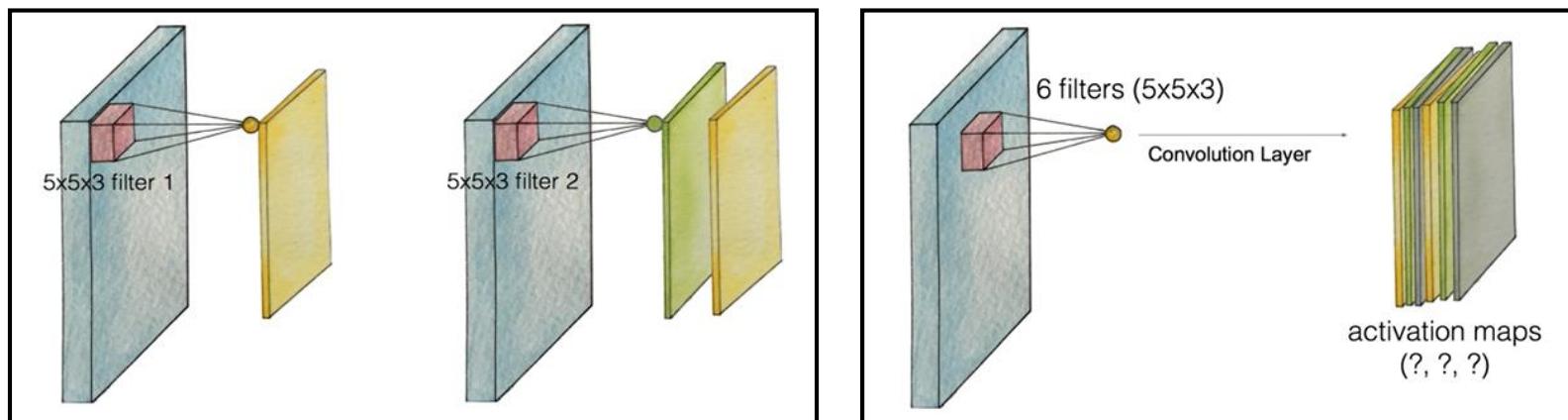
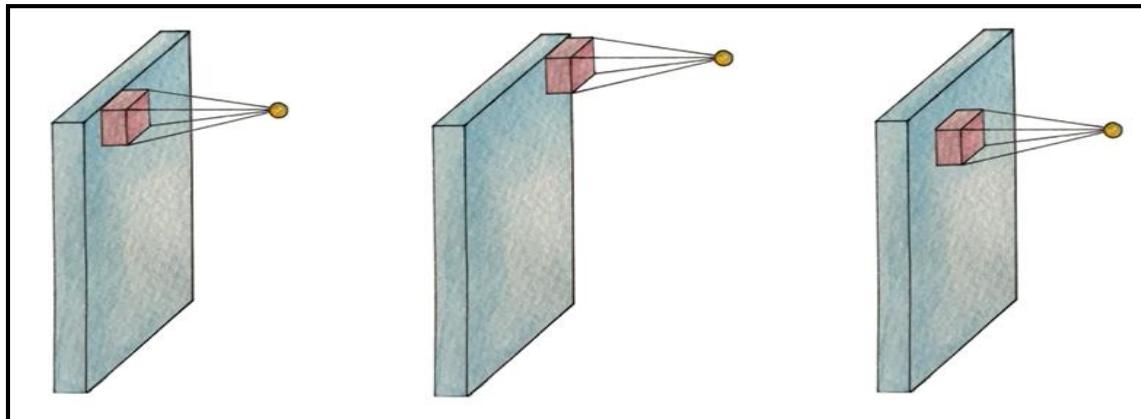
$$Wx + b$$

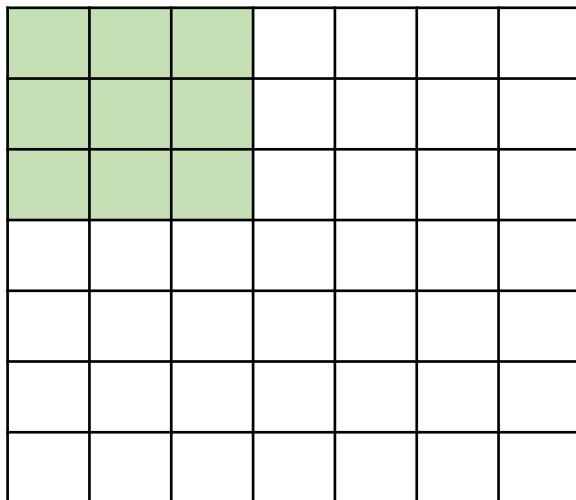


$$Y = w_1x_1 + w_2x_2 + \cdots + w_nx_n + b$$



CNN: Convolution





- Image Size: 7-by-7
- Filter Size: 3-by-3
- Strides (step-size of filter moving)
 - 1: $5 \times 5 = 25$
 - 2: $3 \times 3 = 9$
 - ...
 - → Large strides loose information (value degrades).



- Padding

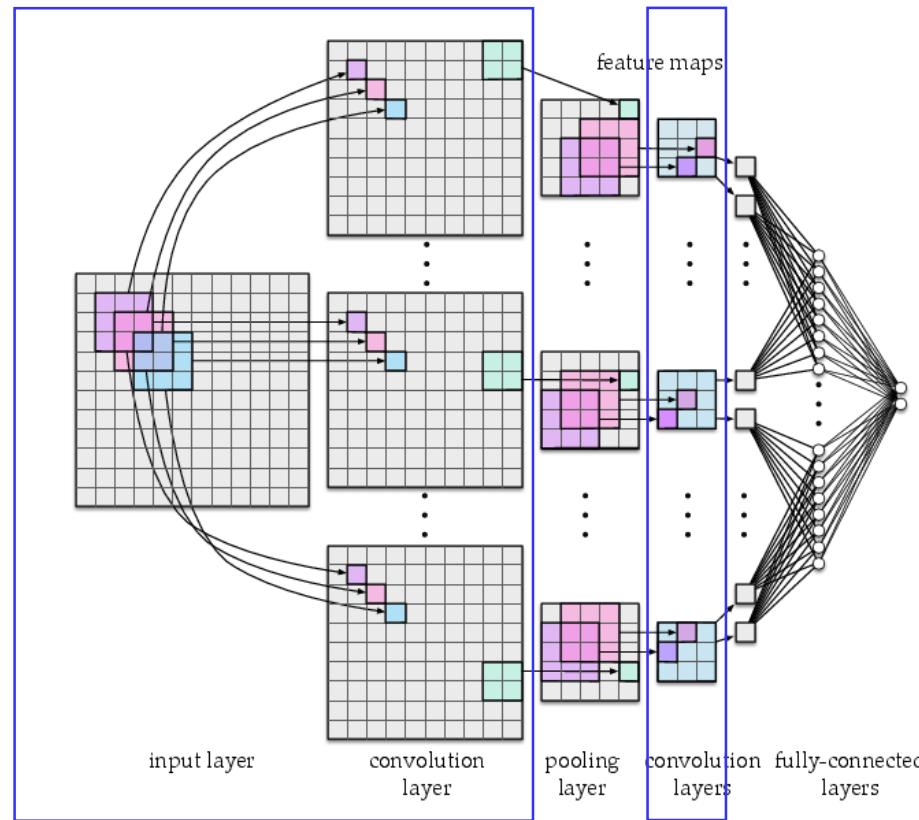
- Marking for the image areas
- Preventing the case where the sizes of return images becomes smaller.

0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0



CNN: Convolution

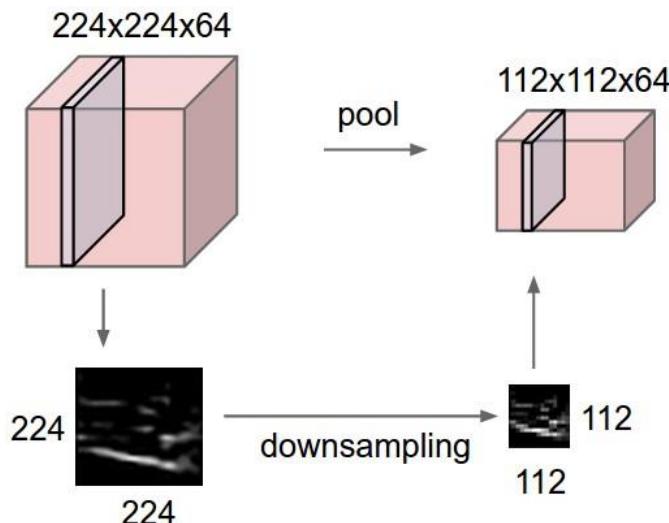
- From one image, multiple filters can be used for swiping the entire image.



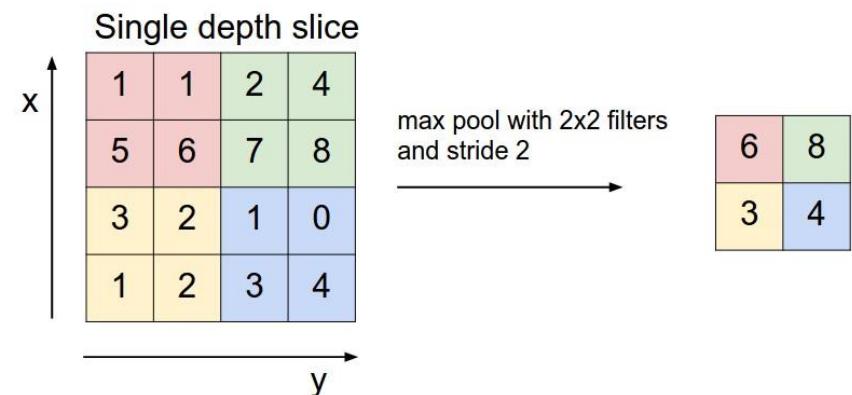


CNN: Max Pooling

- Pooling Layer (Sampling)

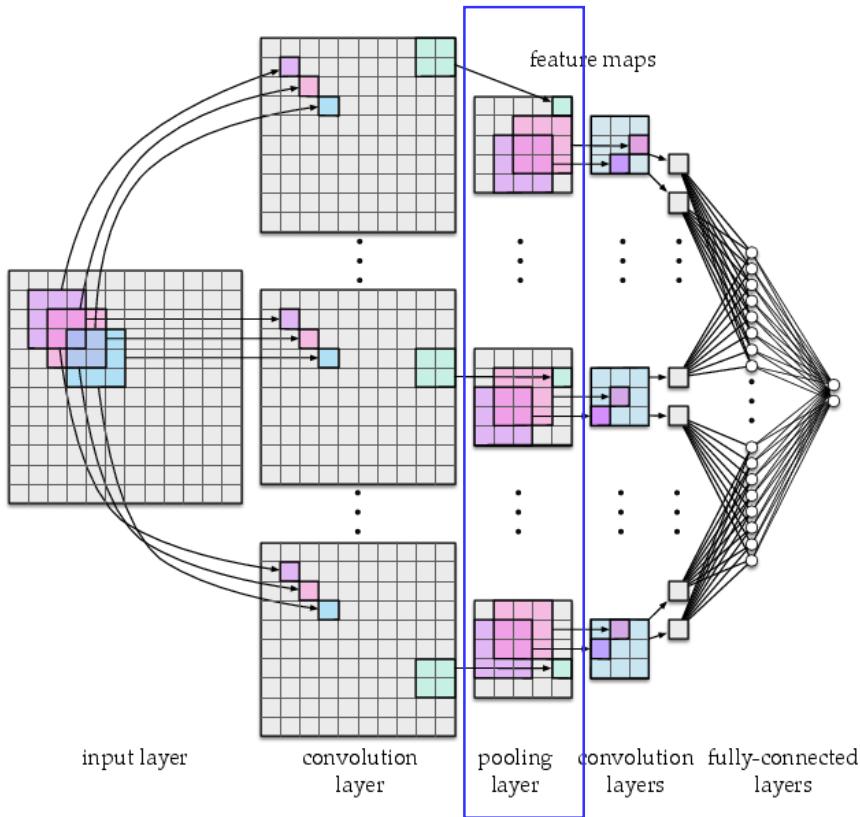


- Max Pooling Concept



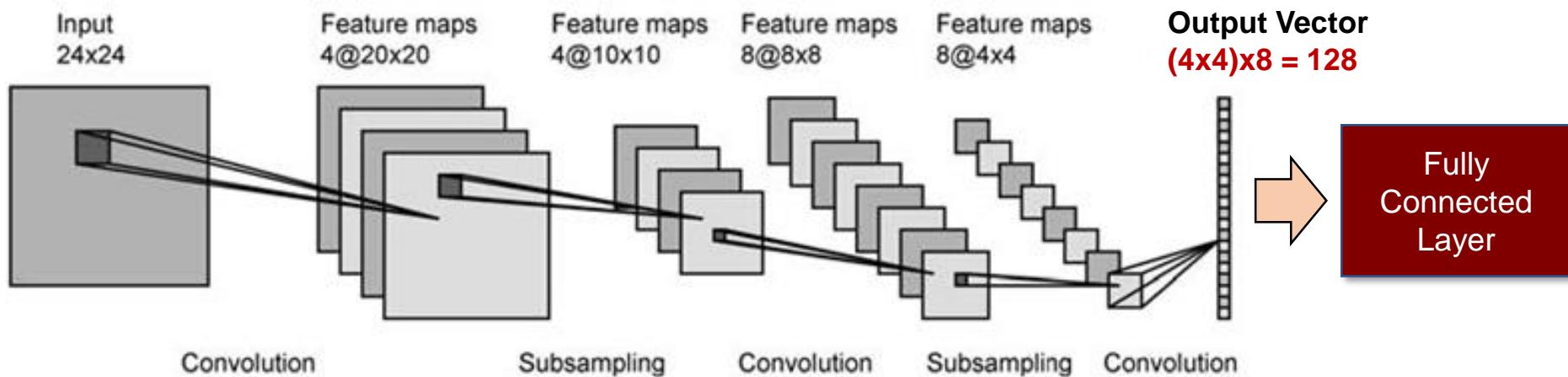


CNN: Max Pooling



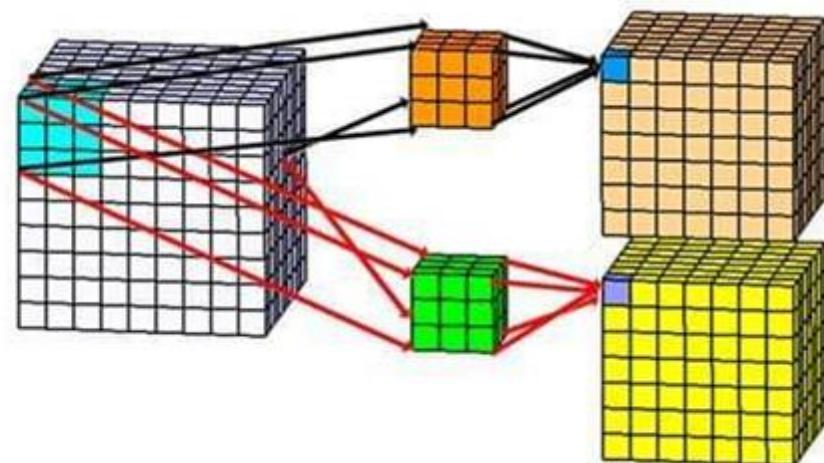
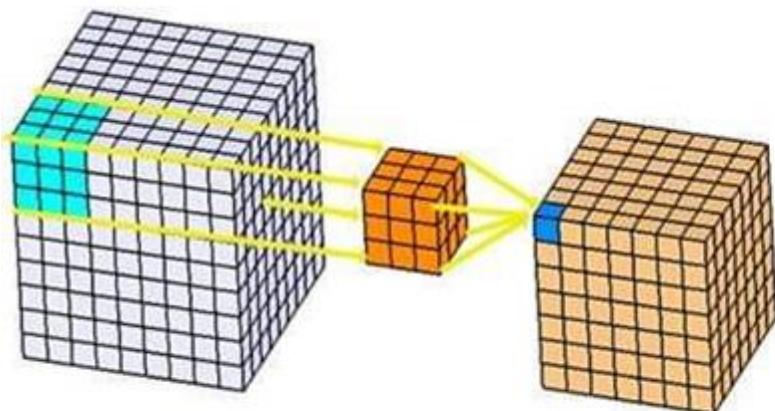


CNN: Example





- 3D Convolution



Deep Learning Theory and Software

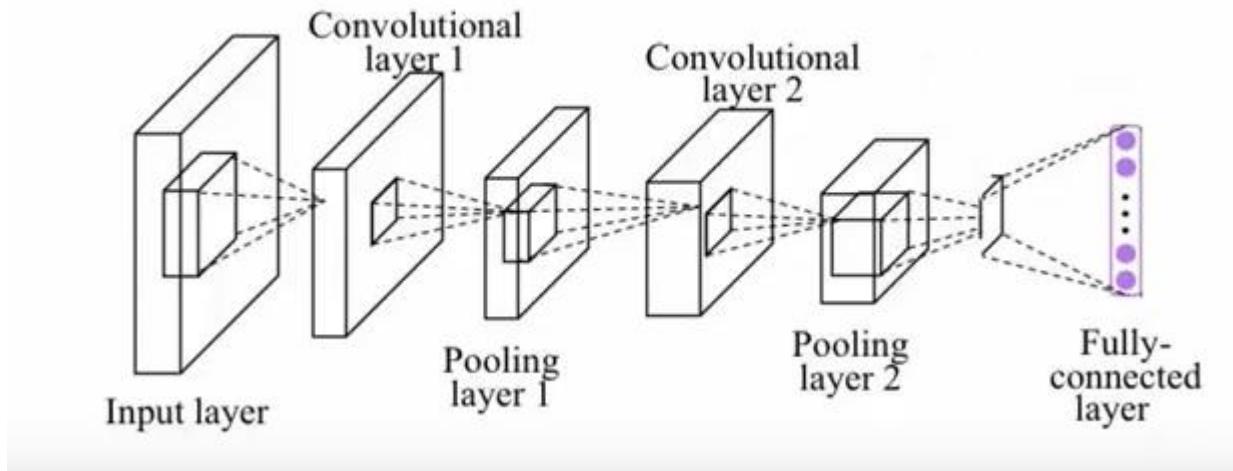
Convolutional Neural Networks (CNN)

CNN Implementation

- CNN Theory
- CNN Implementation

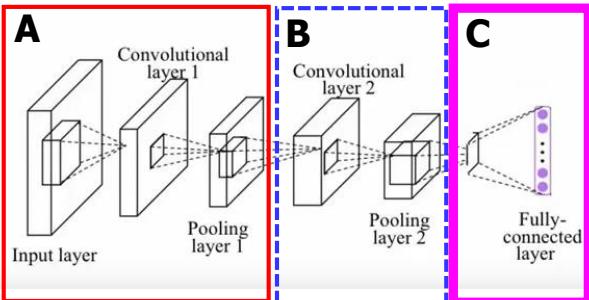


- CNN for MNIST Image Classification





CNN Implementation (TensorFlow)



```

A
# Convolution Layer 1
W1 = tf.Variable(tf.random_normal([3,3,1,32], stddev=0.01))
CL1 = tf.nn.conv2d(X_img, W1, strides=[1,1,1,1], padding='SAME')
CL1 = tf.nn.relu(CL1)

# Pooling Layer 1
PL1 = tf.nn.max_pool(CL1, ksize=[1,2,2,1], strides=[1,2,2,1], padding='SAME')

B
# Convolution Layer 2
W2 = tf.Variable(tf.random_normal([3,3,32,64], stddev=0.01))
CL2 = tf.nn.conv2d(PL1, W2, strides=[1,1,1,1], padding='SAME')
CL2 = tf.nn.relu(CL2)

# Pooling Layer 2
PL2 = tf.nn.max_pool(CL2, ksize=[1,2,2,1], strides=[1,2,2,1], padding='SAME')

C
# Fully Connected (FC) Layer
L_flat = tf.reshape(PL2, [-1, 7*7*64])
W3 = tf.Variable(tf.random_normal([7*7*64,10], stddev=0.01))
b3 = tf.Variable(tf.random_normal([10]))

```



CNN Implementation (TensorFlow)

- TensorFlow
 - **CNN for MNIST**
 - CNN for MNIST (with tensorflow.layers)
- Keras
 - CNN for MNIST



CNN Implementation (TensorFlow)

```
1 from tensorflow.examples.tutorials.mnist import input_data
2 mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
3
4 import tensorflow as tf
5 import time
6
7 training_epochs = 15
8 batch_size = 100
9
10 X = tf.placeholder(tf.float32, [None, 784])
11 Y = tf.placeholder(tf.float32, [None, 10])
12 X_img = tf.reshape(X, [-1, 28, 28, 1])
13
14 # Convolution Layer 1
15 W1 = tf.Variable(tf.random_normal([3,3,1,32], stddev=0.01))
16 CL1 = tf.nn.conv2d(X_img, W1, strides=[1,1,1,1], padding='SAME')
17 CL1 = tf.nn.relu(CL1)
18 # Pooling Layer 1
19 PL1 = tf.nn.max_pool(CL1, ksize=[1,2,2,1], strides=[1,2,2,1], padding='SAME')
20 # Convolution Layer 2
21 W2 = tf.Variable(tf.random_normal([3,3,32,64], stddev=0.01))
22 CL2 = tf.nn.conv2d(PL1, W2, strides=[1,1,1,1], padding='SAME')
23 CL2 = tf.nn.relu(CL2)
24 # Pooling Layer 2
25 PL2 = tf.nn.max_pool(CL2, ksize=[1,2,2,1], strides=[1,2,2,1], padding='SAME')
26 # Fully Connected (FC) Layer
27 L_flat = tf.reshape(PL2, [-1,7*7*64])
28 W3 = tf.Variable(tf.random_normal([7*7*64,10], stddev=0.01))
29 b3 = tf.Variable(tf.random_normal([10]))
```



CNN Implementation (TensorFlow)

```
31 # Model, Cost, Train
32 model_LC = tf.matmul(L_flat, W3) + b3
33 model = tf.nn.softmax(model_LC)
34 cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits_v2(logits=model_LC, labels=Y))
35 train = tf.train.AdamOptimizer(0.01).minimize(cost)
36
37 # Accuracy
38 accuracy = tf.reduce_mean(tf.cast(tf.equal(tf.argmax(model, 1), tf.argmax(Y, 1)), tf.float32))
39
40 # Session
41 with tf.Session() as sess:
42     sess.run(tf.global_variables_initializer())
43     # Training
44     t1 = time.time()
45     for epoch in range(training_epochs):
46         total_batch = int(mnist.train.num_examples / batch_size)
47         for i in range(total_batch):
48             train_images, train_labels = mnist.train.next_batch(batch_size)
49             c, _ = sess.run([cost, train], feed_dict={X: train_images, Y: train_labels})
50             if i % 10 == 0:
51                 print('epoch:', epoch, ', batch number:', i)
52     t2 = time.time()
53     # Testing
54     print('Training Time (Seconds): ', t2-t1)
55     print('Accuracy: ', sess.run(accuracy, feed_dict={X: mnist.test.images, Y: mnist.test.labels}))
```

epoch: 14 , batch number: 520
epoch: 14 , batch number: 530
epoch: 14 , batch number: 540
Training Time (Seconds): 275.65979075431824
Accuracy: 0.9858



- TensorFlow
 - CNN for MNIST
 - **CNN for MNIST (with tensorflow.layers)**
- Keras
 - CNN for MNIST



CNN Implementation (TensorFlow)

```
# Convolution Layer 1
W1 = tf.Variable(tf.random_normal([3,3,1,32], stddev=0.01))
CL1 = tf.nn.conv2d(X_img, W1, strides=[1,1,1,1], padding='SAME')
CL1 = tf.nn.relu(CL1)
# Pooling Layer 1
PL1 = tf.nn.max_pool(CL1, ksize=[1,2,2,1], strides=[1,2,2,1], padding='SAME')
# Convolution Layer 2
W2 = tf.Variable(tf.random_normal([3,3,32,64], stddev=0.01))
CL2 = tf.nn.conv2d(PL1, W2, strides=[1,1,1,1], padding='SAME')
CL2 = tf.nn.relu(CL2)
# Pooling Layer 2
PL2 = tf.nn.max_pool(CL2, ksize=[1,2,2,1], strides=[1,2,2,1], padding='SAME')
# Fully Connected (FC) Layer
L_flat = tf.reshape(PL2, [-1,7*7*64])
W3 = tf.Variable(tf.random_normal([7*7*64,10], stddev=0.01))
b3 = tf.Variable(tf.random_normal([10]))
```

`tensorflow.layers.conv2d`

`tensorflow.layers.max_pooling2d`

```
# Convolution Layer 1
CL1 = tf.layers.conv2d(inputs=X_img, filters=32, kernel_size=[3,3], padding='SAME', strides=1, activation=tf.nn.relu)
# Pooling Layer 1
PL1 = tf.layers.max_pooling2d(inputs=CL1, pool_size=[2,2], padding='SAME', strides=2)
# Convolution Layer 2
CL2 = tf.layers.conv2d(inputs=PL1, filters=64, kernel_size=[3,3], padding='SAME', strides=1, activation=tf.nn.relu)
# Pooling Layer 1
PL2 = tf.layers.max_pooling2d(inputs=CL2, pool_size=[2,2], padding='SAME', strides=2)
# Fully Connected (FC) Layer
L_flat = tf.reshape(PL2, [-1,7*7*64])
W3 = tf.Variable(tf.random_normal([7*7*64,10], stddev=0.01))
b3 = tf.Variable(tf.random_normal([10]))
```



CNN Implementation (Keras)

- TensorFlow
 - CNN for MNIST
 - CNN for MNIST (with tensorflow.layers)
- Keras
 - **CNN for MNIST**



CNN Implementation (Keras)

```
1  from keras.utils import np_utils
2  from keras.datasets import mnist
3  from keras.models import Sequential
4  from keras.layers import Conv2D, pooling, Flatten, Dense
5  # MNIST data
6  (train_images, train_labels), (test_images, test_labels) = mnist.load_data()
7  print(train_images.shape, train_labels.shape, test_images.shape, test_labels.shape)
8  train_images = train_images.reshape(train_images.shape[0], 28,28,1).astype('float32')/255.0
9  test_images = test_images.reshape(test_images.shape[0], 28,28,1).astype('float32')/255.0
10 train_labels = np_utils.to_categorical(train_labels) # One-Hot Encoding
11 test_labels = np_utils.to_categorical(test_labels) # One-Hot Encoding
12 # Model
13 model = Sequential()
14 model.add(Conv2D(32, (3,3), padding='same', strides=(1,1), activation='relu', input_shape=(28,28,1)))
15 print(model.output_shape)
16 model.add(pooling.MaxPooling2D(pool_size=(2,2)))
17 print(model.output_shape)
18 model.add(Conv2D(64, (3,3), padding='same', strides=(1,1), activation='relu'))
19 print(model.output_shape)
20 model.add(pooling.MaxPooling2D(pool_size=(2,2)))
21 print(model.output_shape)
22 model.add(Flatten())
23 model.add(Dense(10, activation='softmax')) # units=10, activation='softmax'
24 model.compile(loss='categorical_crossentropy', optimizer='sgd', metrics=['accuracy'])
25 # Training
26 model.fit(train_images, train_labels, epochs=5, batch_size=32, verbose=1)
27 # Testing
28 _, accuracy = model.evaluate(test_images, test_labels)
29 print('Accuracy: ', accuracy)
30 model.summary()
```



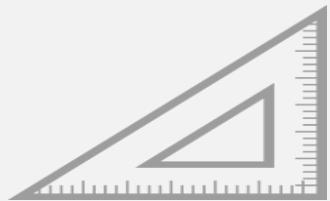
CNN Implementation (Keras)

```
(60000, 28, 28) (60000,) (10000, 28, 28) (10000,)  
(None, 28, 28, 32)  
(None, 14, 14, 32)  
(None, 14, 14, 64)  
(None, 7, 7, 64)  
Epoch 1/5  
2019-08-04 22:30:43.603681: I tensorflow/core/platform/cpu_feature_guard.cc:141] Your CPU  
supports instructions that this TensorFlow binary was not compiled to use: AVX2 FMA  
60000/60000 [=====] - 22s 359us/step - loss: 0.5194 - acc: 0.8502  
Epoch 2/5  
60000/60000 [=====] - 21s 357us/step - loss: 0.1657 - acc: 0.9506  
Epoch 3/5  
60000/60000 [=====] - 21s 358us/step - loss: 0.1138 - acc: 0.9668  
Epoch 4/5  
60000/60000 [=====] - 21s 357us/step - loss: 0.0914 - acc: 0.9733  
Epoch 5/5  
60000/60000 [=====] - 22s 362us/step - loss: 0.0786 - acc: 0.9762  
10000/10000 [=====] - 1s 117us/step  
Accuracy: 0.9774
```

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 28, 28, 32)	320
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_2 (Conv2D)	(None, 14, 14, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 7, 7, 64)	0
flatten_1 (Flatten)	(None, 3136)	0
dense_1 (Dense)	(None, 10)	31370
Total params:	50,186	
Trainable params:	50,186	
Non-trainable params:	0	



Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions



Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10
Recurrent NN (RNN)

Advanced Topics



Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting



Deep Learning Theory and Software

CNN for CIFAR-10

CIFAR-10 Dataset

- **CIFAR-10 Dataset**

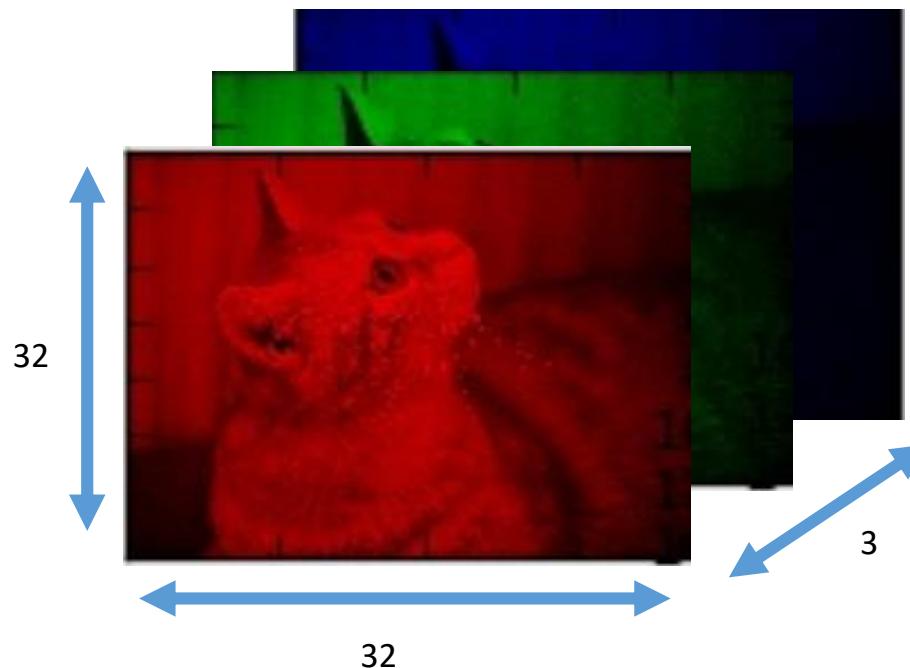


Image Dataset

	MNIST	CIFAR-10,100	IMAGENET																				
	<pre>0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9</pre>	<table border="1"> <tr><td>airplane</td><td></td></tr> <tr><td>automobile</td><td></td></tr> <tr><td>bird</td><td></td></tr> <tr><td>cat</td><td></td></tr> <tr><td>deer</td><td></td></tr> <tr><td>dog</td><td></td></tr> <tr><td>frog</td><td></td></tr> <tr><td>horse</td><td></td></tr> <tr><td>ship</td><td></td></tr> <tr><td>truck</td><td></td></tr> </table>	airplane		automobile		bird		cat		deer		dog		frog		horse		ship		truck		
airplane																							
automobile																							
bird																							
cat																							
deer																							
dog																							
frog																							
horse																							
ship																							
truck																							
Num Channel	1 (Gray scale)	3 (R, G, B)	3 (R, G, B)																				
Num Classes	10	10 , 100	1000																				
Resolution	28 * 28	32 * 32	(256 * 256)																				
Num Training Set	50,000	50,000	200,000																				



- RGB 3 channel image (32-by-32-by-3 matrix)





```
1 from keras.datasets import cifar10
2
3 (train_images, train_labels), (test_images, test_labels) = cifar10.load_data()
4 print('train_images', train_images.shape)
5 print('train_labels', train_labels.shape)
6 print('test_images', test_images.shape)
7 print('test_labels', test_labels.shape)
```

```
train_images (50000, 32, 32, 3)
train_labels (50000, 1)
test_images (10000, 32, 32, 3)
test_labels (10000, 1)
```

- CIFAR-10

- Train

- $(50000, 32, 32, 3) \rightarrow$ 3 channel RGB (32-by-32), 50000 images
 - $(50000, 1) \rightarrow$ 50000 labels (no one-hot encoding)

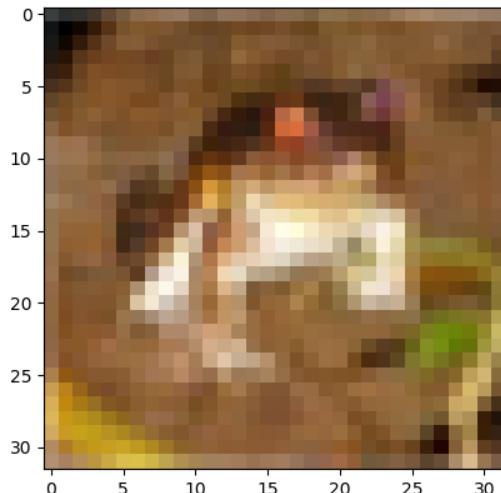
- Test

- $(10000, 32, 32, 3) \rightarrow$ 3 channel RGB (32-by-32), 10000 images
 - $(10000, 1) \rightarrow$ 10000 labels (no one-hot encoding)



CIFAR-10

```
1 from keras.datasets import cifar10
2 from matplotlib import pyplot as plt
3
4 (train_images, train_labels), (test_images, test_labels) = cifar10.load_data()
5
6 plt.imshow(train_images[0])
7 plt.show()
```





Implementation

- CIFAR-10 Classification Implementation
 - **TensorFlow**
 - Keras



Implementation for CIFAR-10 (TensorFlow)

```
1  from keras.utils import np_utils
2  from keras.datasets import cifar10
3  import tensorflow as tf
4  import time
5
6  (train_images, train_labels), (test_images, test_labels) = cifar10.load_data()
7  train_labels = np_utils.to_categorical(train_labels) # One-Hot Encoding
8  test_labels = np_utils.to_categorical(test_labels) # One-Hot Encoding
9
10 training_epochs = 15
11 batch_size = 100
12
13 X = tf.placeholder(tf.float32, [None, 32, 32, 3])
14 Y = tf.placeholder(tf.float32, [None, 10])
15 X_img = tf.reshape(X, [-1, 32, 32, 3])
16
17 # Convolution Layer 1
18 W1 = tf.Variable(tf.random_normal([3, 3, 3, 32], stddev=0.01))
19 CL1 = tf.nn.conv2d(X_img, W1, strides=[1, 1, 1, 1], padding='SAME')
20 CL1 = tf.nn.relu(CL1)
21 # Pooling Layer 1
22 PL1 = tf.nn.max_pool(CL1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')
23 # Convolution Layer 2
24 W2 = tf.Variable(tf.random_normal([3, 3, 32, 64], stddev=0.01))
25 CL2 = tf.nn.conv2d(PL1, W2, strides=[1, 1, 1, 1], padding='SAME')
26 CL2 = tf.nn.relu(CL2)
27 # Pooling Layer 2
28 PL2 = tf.nn.max_pool(CL2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')
29 # Fully Connected (FC) Layer
30 L_flat = tf.reshape(PL2, [-1, 8*8*64])
31 W3 = tf.Variable(tf.random_normal([8*8*64, 10], stddev=0.01))
32 b3 = tf.Variable(tf.random_normal([10]))
```



Implementation for CIFAR-10 (TensorFlow)

```
34 # Model, Cost, Train
35 model_LC = tf.matmul(L_flat, W3) + b3
36 model = tf.nn.softmax(model_LC)
37 cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=model_LC, labels=Y))
38 train = tf.train.AdamOptimizer(0.01).minimize(cost)
39
40 # Accuracy
41 accuracy = tf.reduce_mean(tf.cast(tf.equal(tf.argmax(model, 1), tf.argmax(Y, 1)), tf.float32))
42
43 # Session
44 with tf.Session() as sess:
45     sess.run(tf.global_variables_initializer())
46     # Training
47     t1 = time.time()
48     for epoch in range(training_epochs):
49         total_batch = int(train_images.shape[0] / batch_size)
50         for i in range(total_batch):
51             batch_train_images = train_images[i*batch_size:(i+1)*batch_size]
52             batch_train_labels = train_labels[i*batch_size:(i+1)*batch_size]
53             c, _ = sess.run([cost, train], feed_dict={X: batch_train_images, Y: batch_train_labels})
54             if i % 10 == 0:
55                 print('epoch:', epoch, ', batch number:', i)
56     t2 = time.time()
57     # Testing
58     print('Training Time (Seconds): ', t2-t1)
59     total_batch = int(test_images.shape[0] / batch_size)
60     for i in range(total_batch):
61         batch_test_images = test_images[i*batch_size:(i+1)*batch_size]
62         batch_test_labels = test_labels[i*batch_size:(i+1)*batch_size]
63     print('Accuracy: ', sess.run(accuracy, feed_dict={X: batch_test_images, Y: batch_test_labels}))
```



Implementation

- CIFAR-10 Classification Implementation
 - TensorFlow
 - **Keras**

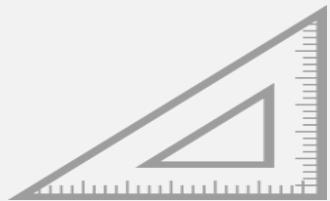


Implementation for CIFAR-10 (Keras)

```
1 from keras.utils import np_utils
2 from keras.datasets import cifar10
3 from keras.models import Sequential
4 from keras.layers import Conv2D, pooling, Flatten, Dense
5 # MNIST data
6 (train_images, train_labels), (test_images, test_labels) = cifar10.load_data()
7 print(train_images.shape, train_labels.shape, test_images.shape, test_labels.shape)
8
9 train_images = train_images.reshape(train_images.shape[0], 32,32,3).astype('float32')/255.0
10 test_images = test_images.reshape(test_images.shape[0], 32,32,3).astype('float32')/255.0
11
12 train_labels = np_utils.to_categorical(train_labels) # One-Hot Encoding
13 test_labels = np_utils.to_categorical(test_labels) # One-Hot Encoding
14 # Model
15 model = Sequential()
16 model.add(Conv2D(32, (3,3), padding='same', strides=(1,1), activation='relu', input_shape=(32,32,3)))
17 model.add(pooling.MaxPooling2D(pool_size=(2,2)))
18 model.add(Conv2D(64, (3,3), padding='same', strides=(1,1), activation='relu'))
19 model.add(pooling.MaxPooling2D(pool_size=(2,2)))
20 model.add(Flatten())
21 model.add(Dense(10, activation='softmax')) # units=10, activation='softmax'
22 model.compile(loss='categorical_crossentropy', optimizer='sgd', metrics=['accuracy'])
23 # Training
24 model.fit(train_images, train_labels, epochs=5, batch_size=32, verbose=1)
25 # Testing
26 _, accuracy = model.evaluate(test_images, test_labels)
27 print('Accuracy: ', accuracy)
28 model.summary()
```



Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions



Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10
Recurrent NN (RNN)

Advanced Topics



Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting

Deep Learning Theory and Software

Recurrent Neural Networks (CNN)

RNN Theory

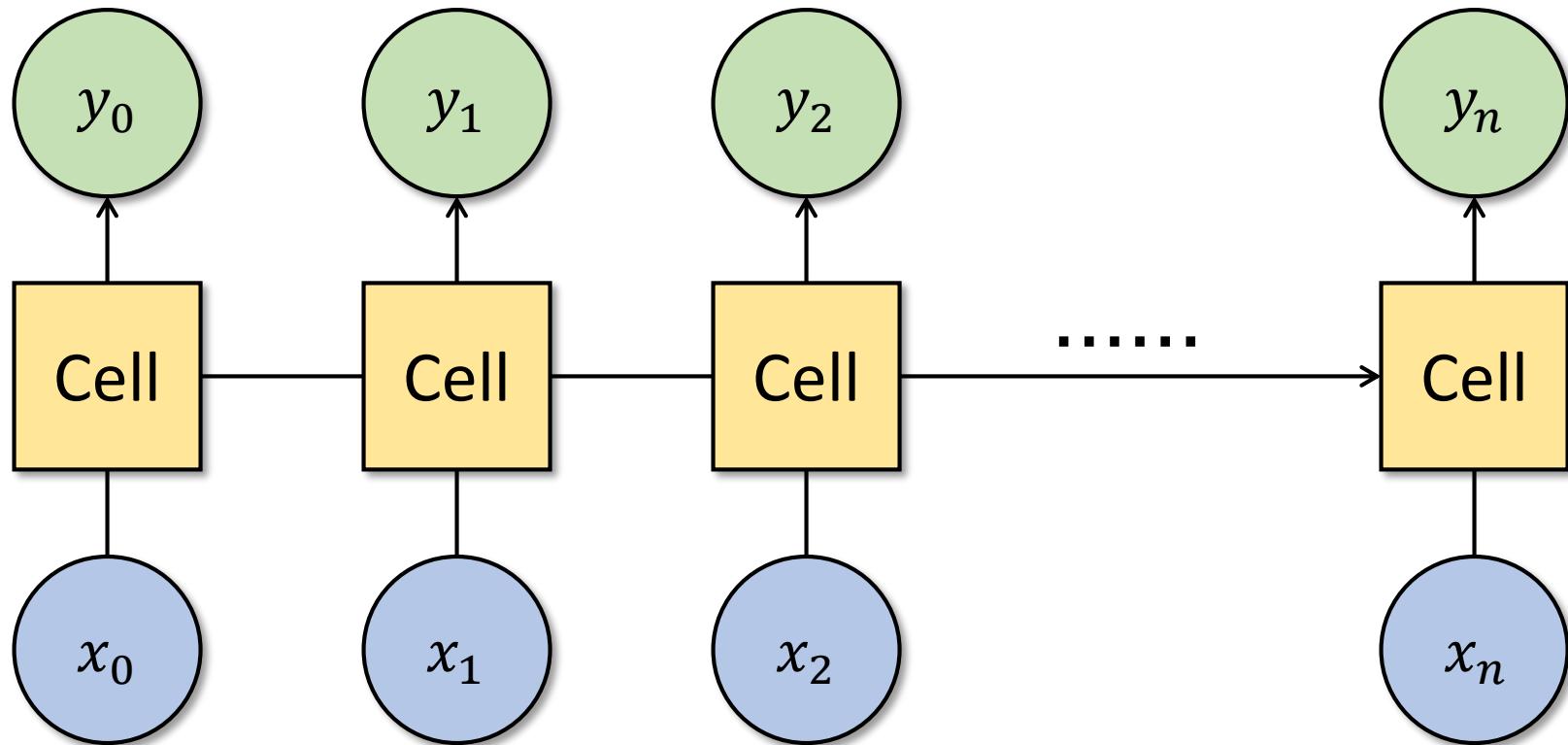
- **RNN Theory**
- RNN Implementation



- Sequence Data

- We don't understand one word only.
We understand based on the previous words + this word (time series).
- ANN/CNN cannot do this.

Recurrent Neural Networks (RNN): Introduction



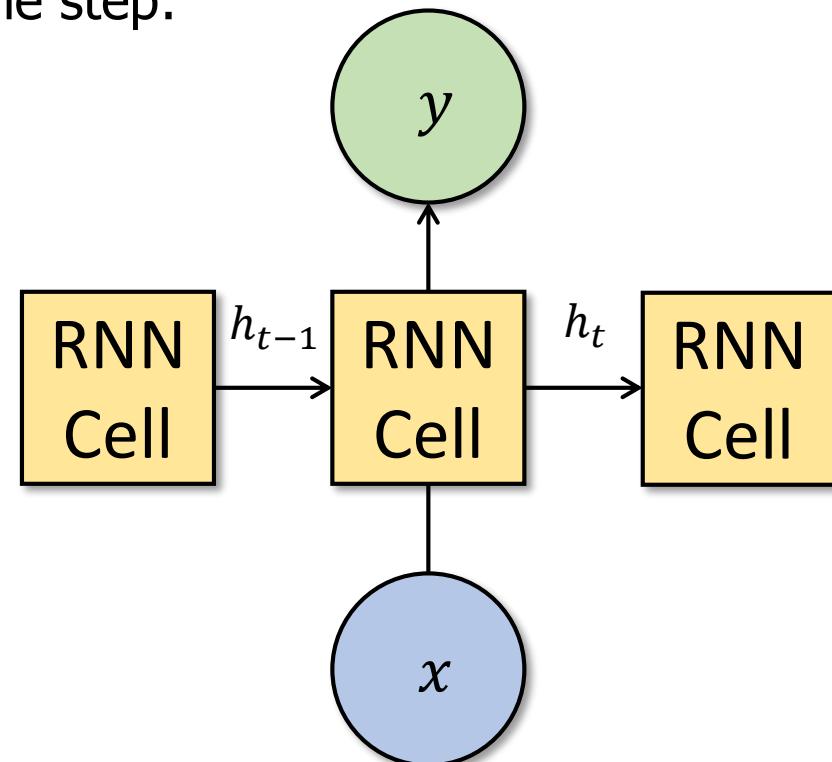


Recurrent Neural Networks (RNN): Introduction

- We can process a sequence of vector \vec{x} by applying a recurrence formula at every time step:

$$h_t = f_W(h_{t-1}, x_t)$$

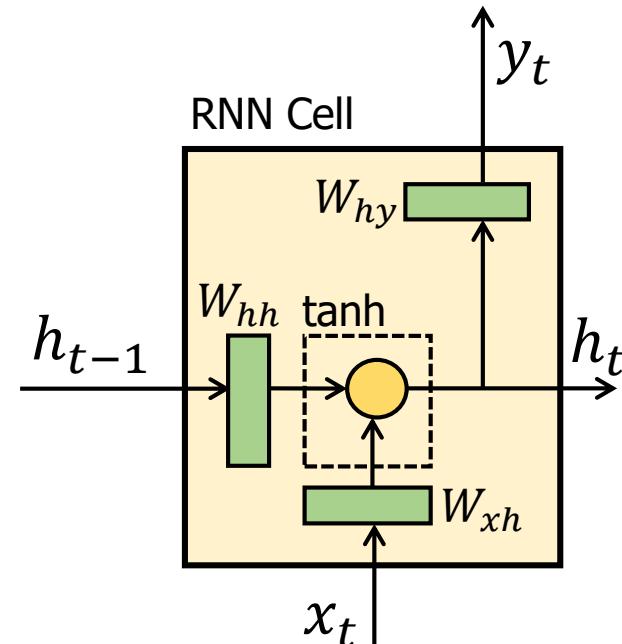
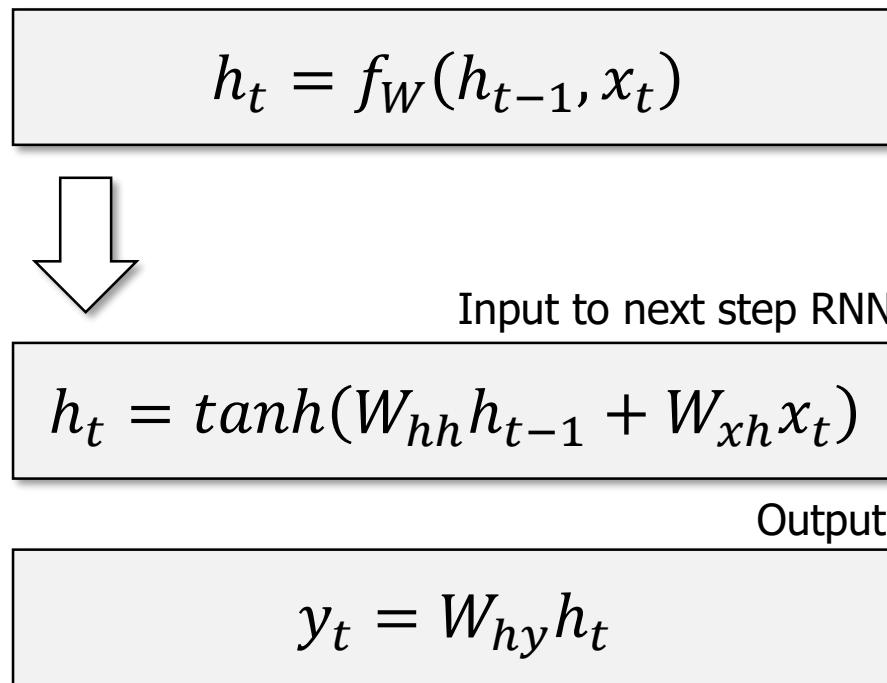
- h_t : New state
- $f_W(\cdot)$: Some function with parameters W
 - Equivalent to all RNN functions
- h_{t-1} : Old state
- x_t : Input vector at some time step





Recurrent Neural Networks (RNN): Introduction

- The state consists of a single hidden vector \vec{h}





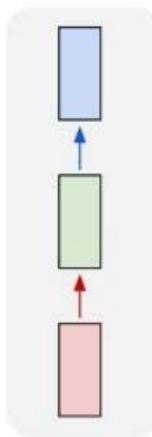
- RNN applications
 - Language Modeling
 - Speech Recognition
 - Machine Translation
 - Question Answering (QA) Systems
 - Conversation Modeling
 - Image/Video Captioning
 - Image/Music/Dance Generation



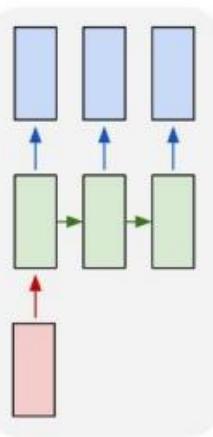
RNN: Applications

- RNN offers a lot of flexibility.

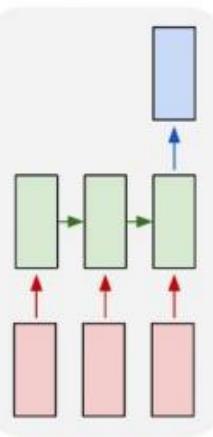
one to one



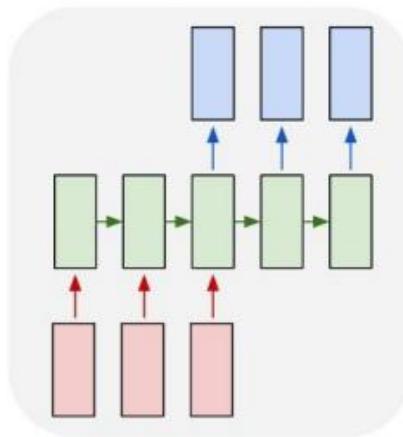
one to many



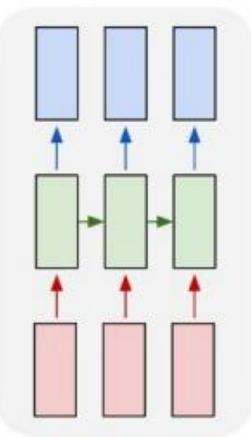
many to one



many to many



many to many





RNN: Applications

- RNN offers a lot of flexibility.

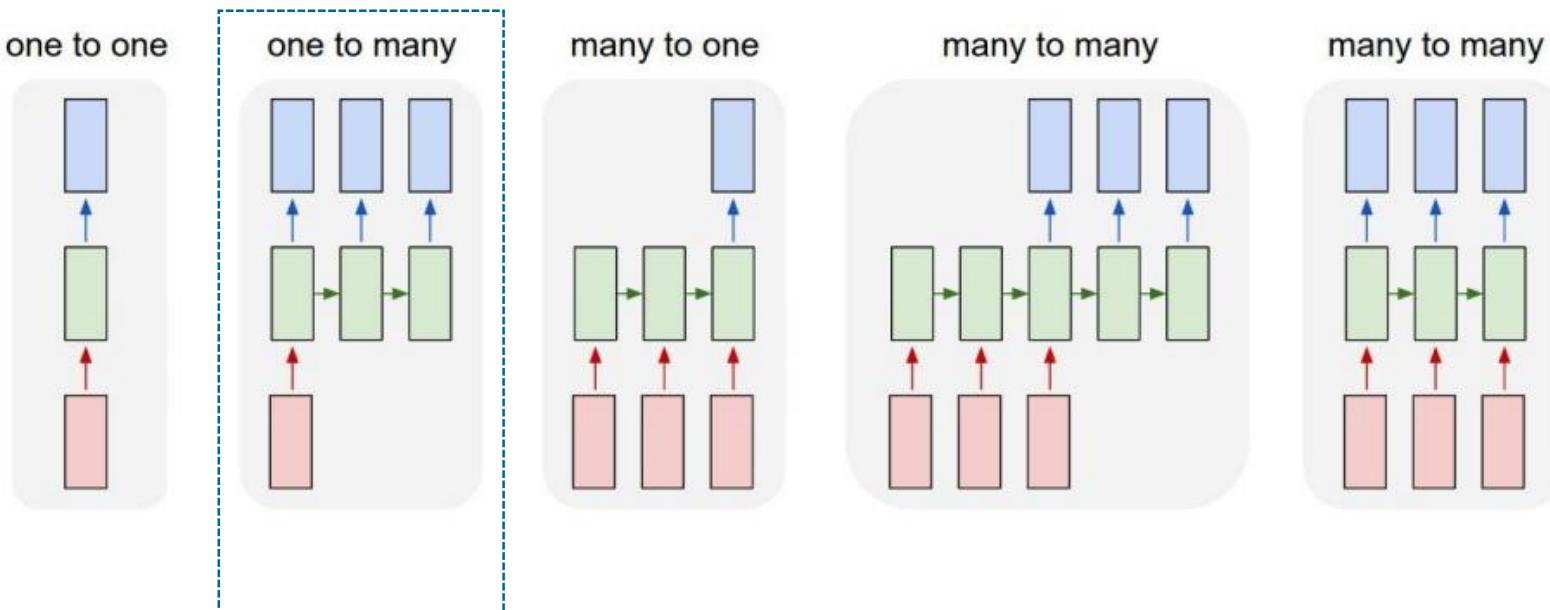


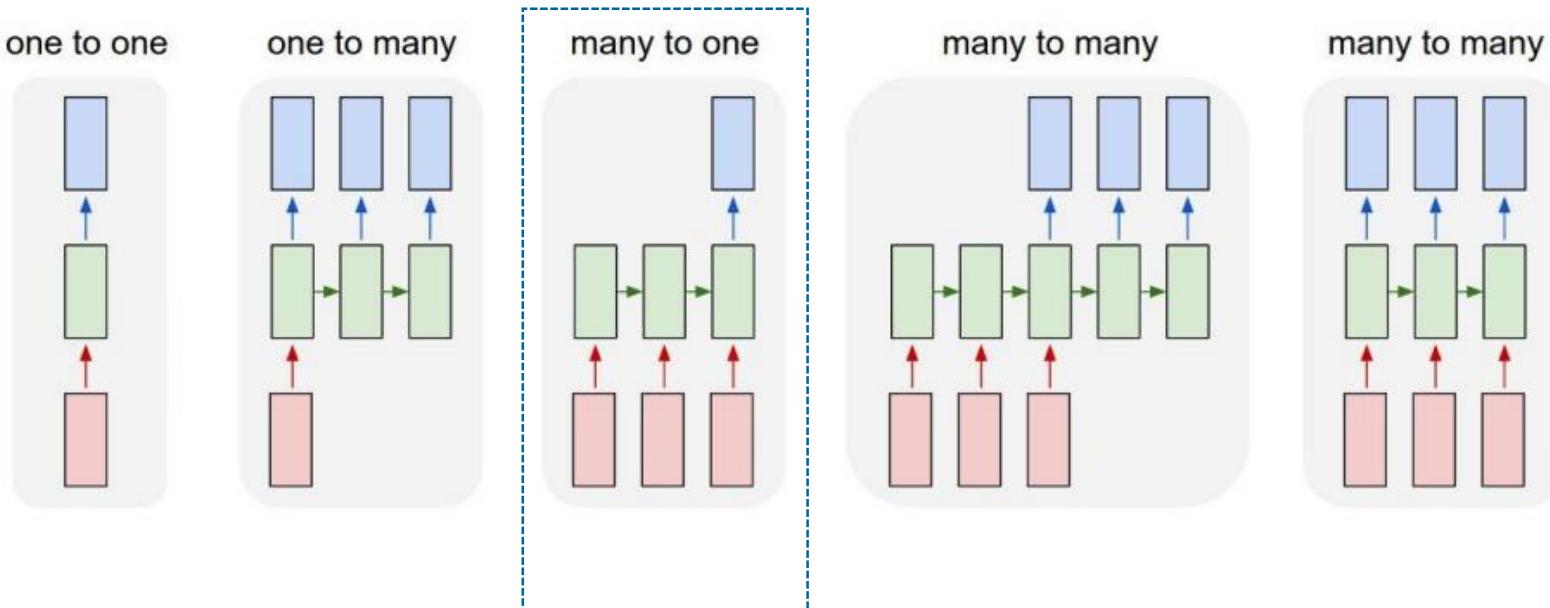
Image Captioning

- Deriving a sequence of words from one image



RNN: Applications

- RNN offers a lot of flexibility.



Sentiment Classification

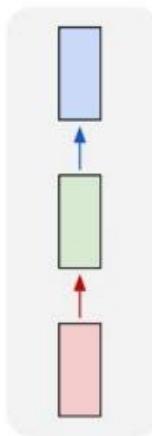
- Deriving a sentiment from several sentences
- Affective computing



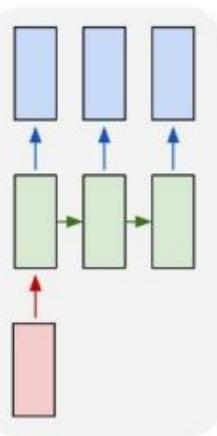
RNN: Applications

- RNN offers a lot of flexibility.

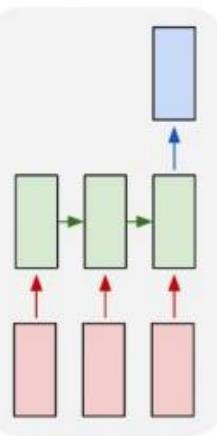
one to one



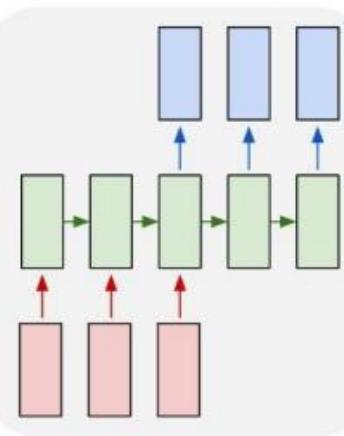
one to many



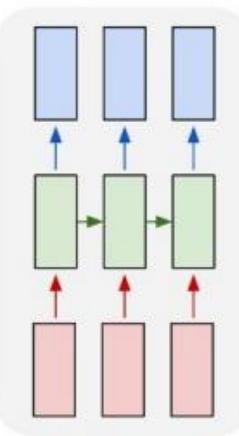
many to one



many to many



many to many



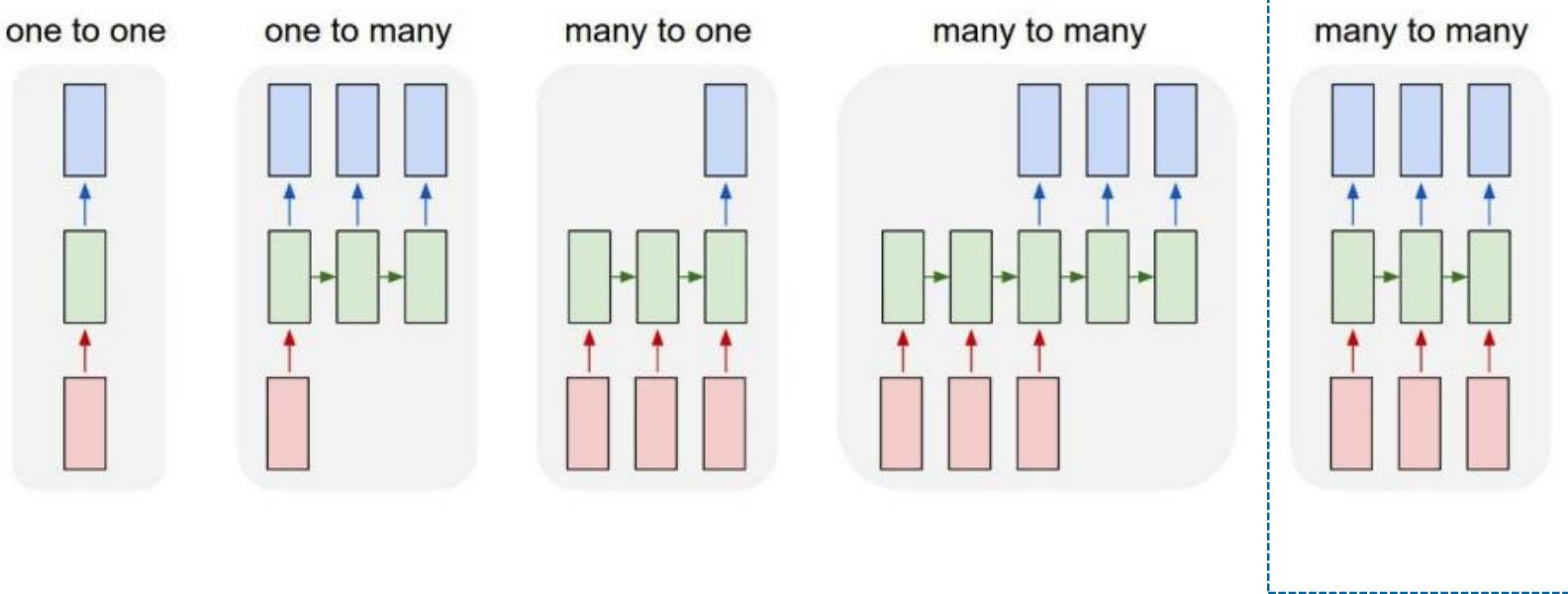
Machine Translation

- Deriving a sequence of words from the other sequence of words



RNN: Applications

- RNN offers a lot of flexibility.



Video Classification on frame level

- Deriving video descriptions from individual frames

Deep Learning Theory and Software

Recurrent Neural Networks (CNN)

RNN Implementation

- RNN Theory
- RNN Implementation



RNN Implementation (TensorFlow)

- TensorFlow
 - **RNN Basic**
- Keras
 - RNN Learning (LSTM)

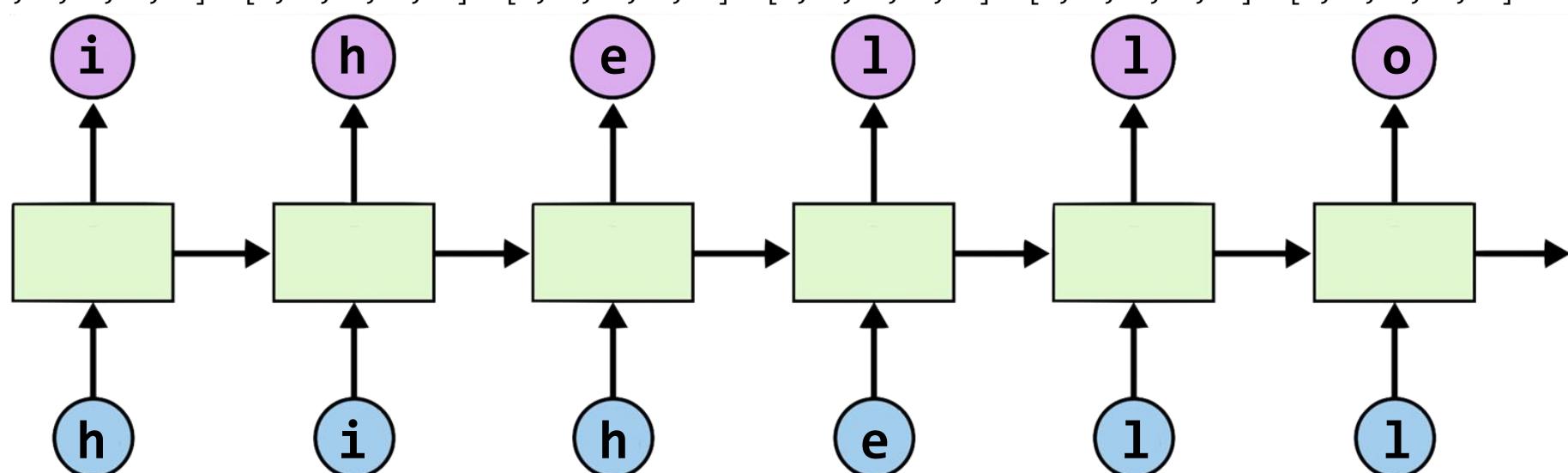
RNN Implementation (TensorFlow)

- Teach RNN 'hihello' (example)

[1, 0, 0, 0, 0]	# h 0
[0, 1, 0, 0, 0]	# i 1
[0, 0, 1, 0, 0]	# e 2
[0, 0, 0, 1, 0]	# l 3
[0, 0, 0, 0, 1]	# o 4



[0, 1, 0, 0, 0] [1, 0, 0, 0, 0] [0, 0, 1, 0, 0] [0, 0, 0, 1, 0] [0, 0, 0, 1, 0] [0, 0, 0, 0, 1]





RNN Implementation (TensorFlow)

```
1 import tensorflow as tf
2 import numpy as np
3 sample = " My name is Joongheon Kim."
4 idx2char = list(set(sample)) # index -> char
5 print(idx2char)
6 char2idx = {c: i for i, c in enumerate(idx2char)} # char -> index
7 print(char2idx)
8 # hyper parameters
9 dic_size = len(char2idx) # RNN input size (one hot size)
10 print(dic_size)
11 hidden_size = len(char2idx) # RNN output size
12 num_classes = len(char2idx) # final output size (RNN or softmax, etc.)
13 batch_size = 1 # one sample data, one batch
14 sequence_length = len(sample) - 1 # number of RNN rollings (unit #)
15 print(sequence_length)
16 sample_idx = [char2idx[c] for c in sample] # char to index
17 print(sample_idx)
18 x_data = [sample_idx[:-1]] # X data sample (0 ~ n-1)
19 y_data = [sample_idx[1:]] # Y label sample (1 ~ n)
20 X = tf.placeholder(tf.int32, [None, sequence_length]) # X data
21 Y = tf.placeholder(tf.int32, [None, sequence_length]) # Y label
22 x_one_hot = tf.one_hot(X, num_classes) # one hot: 1 -> 0 1 0 0 0 0 0 ... 0
```

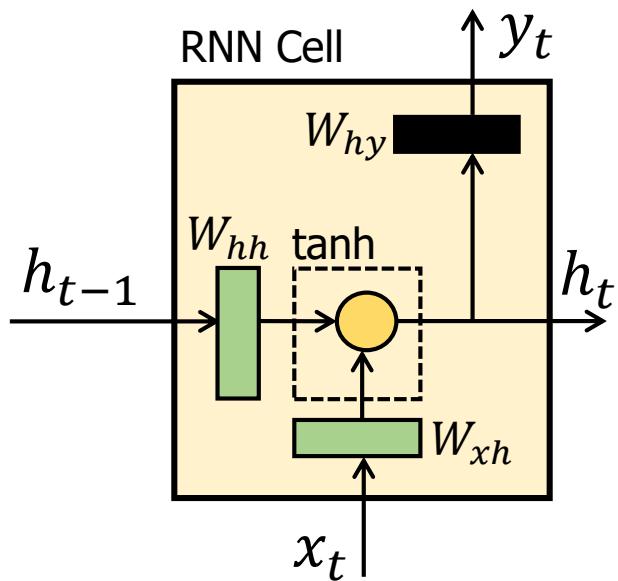


RNN Implementation (TensorFlow)

```

23 # cell and RNN
24 cell = tf.contrib.rnn.BasicRNNCell(num_units=hidden_size)
25 outputs, _states = tf.nn.dynamic_rnn(cell, x_one_hot, dtype=tf.float32)
26 # FC layer
27 X_for_fc = tf.reshape(outputs, [-1, hidden_size])
28 outputs = tf.contrib.layers.fully_connected(X_for_fc, num_classes, activation_fn=None)
29 # reshape out for sequence_loss
30 outputs = tf.reshape(outputs, [batch_size, sequence_length, num_classes])
31 sequence_loss = tf.contrib.seq2seq.sequence_loss(logits=outputs, targets=Y, weights=tf.ones([batch_size, sequence_length]))
32 cost = tf.reduce_mean(sequence_loss)
33 train = tf.train.AdamOptimizer(0.1).minimize(cost)
34 prediction = tf.argmax(outputs, axis=2)

```





RNN Implementation (TensorFlow)

```
36     with tf.Session() as sess:  
37         sess.run(tf.global_variables_initializer())  
38         for i in range(20):  
39             l, _ = sess.run([cost, train], feed_dict={X: x_data, Y: y_data})  
40             result = sess.run(prediction, feed_dict={X: x_data})  
41             # print char using dic  
42             result_str = [idx2char[c] for c in np.squeeze(result)]  
43             print(i, ", loss:", l, ", Prediction:", ''.join(result_str))
```



RNN Implementation (TensorFlow)

```
['e', 'n', 'm', 'J', ' ', 'y', 'h', 's', 'i', 'g', 'K', 'M', '.', 'o', 'a']
{'e': 0, 'n': 1, 'm': 2, 'J': 3, ' ': 4, 'y': 5, 'h': 6, 's': 7, 'i': 8, 'g': 9, 'K': 10, 'M': 11, '.': 12, 'o': 13, 'a': 14}
15
25
[4, 11, 5, 4, 1, 14, 2, 0, 4, 8, 7, 4, 3, 13, 13, 1, 9, 6, 0, 13, 1, 4, 10, 8, 2, 12]
WARNING:tensorflow:From C:/Users/CAU/Desktop/untitled4.py:31: BasicRNNCell.__init__ (from
tensorflow.python.ops.rnn_cell_impl) is deprecated and will be removed in a future version.
Instructions for updating:
This class is equivalent as tf.keras.layers.SimpleRNNCell, and will be replaced by that in Tensorflow 2.0.
0 , loss: 2.7530553 , Prediction: iyaaaaeansssoonnieanaaeme
1 , loss: 2.2681878 , Prediction: omnomme ssoJoohgie n Mo.
2 , loss: 1.9158436 , Prediction: omngme n oJoongheonnheme
3 , loss: 1.4575784 , Prediction: ooname mn JoongheonKeme
4 , loss: 1.1863785 , Prediction: yoname e JoongheongKem.
5 , loss: 0.8737224 , Prediction: Jy name e JoongheongKem.
6 , loss: 0.6875408 , Prediction: Jy name es Joongheon Kim.
7 , loss: 0.56999004 , Prediction: My name es Joonaheon Kim.
8 , loss: 0.38090125 , Prediction: My name is Joongheon Kim.
9 , loss: 0.26949963 , Prediction: My name is Joongheon Kim.
10 , loss: 0.17376524 , Prediction: My name is Joongheon Kim.
11 , loss: 0.12433112 , Prediction: My name is Joongheon Kim.
12 , loss: 0.09018694 , Prediction: My name is Joongheon Kim.
13 , loss: 0.06243824 , Prediction: My name is Joongheon Kim.
14 , loss: 0.044248596 , Prediction: My name is Joongheon Kim.
15 , loss: 0.0328589 , Prediction: My name is Joongheon Kim.
16 , loss: 0.024894495 , Prediction: My name is Joongheon Kim.
17 , loss: 0.018896589 , Prediction: My name is Joongheon Kim.
18 , loss: 0.014688267 , Prediction: My name is Joongheon Kim.
19 , loss: 0.012020792 , Prediction: My name is Joongheon Kim.
```



RNN Implementation (Keras)

- TensorFlow
 - RNN Basic
- Keras
 - **RNN Learning (LSTM)**



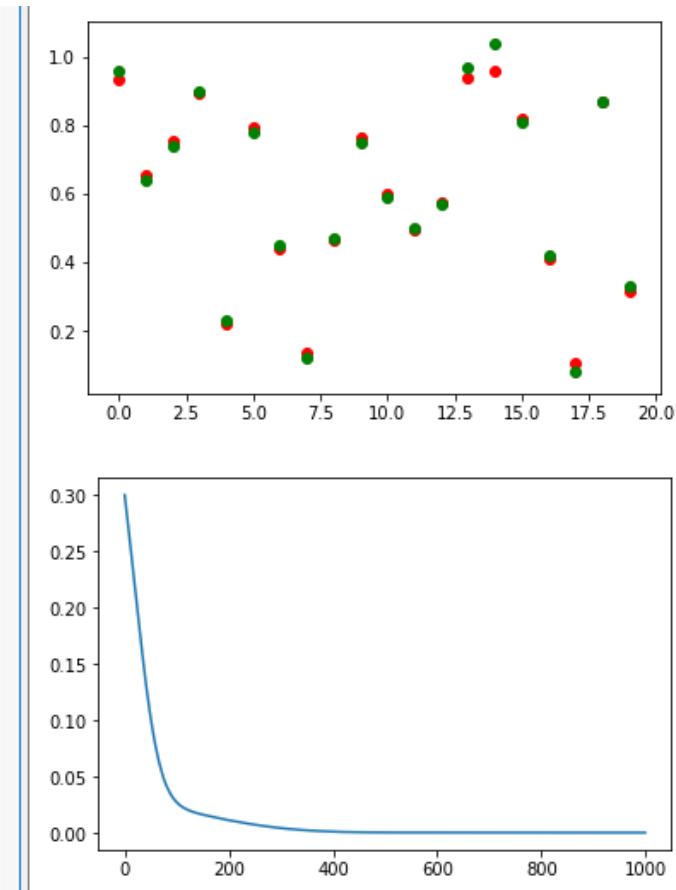
RNN Implementation (Keras)

```
1 from keras.models import Sequential
2 from keras.layers import LSTM
3 from sklearn.model_selection import train_test_split # pip install -U scikit-learn
4 import numpy as np
5 import matplotlib.pyplot as plt
6
7 x_data = [[[((i+j)/100) for i in range(5)] for j in range(100)]]
8 y_data = [(i+5)/100 for i in range(100)]
9 x_data = np.array(x_data, dtype=float)
10 y_data = np.array(y_data, dtype=float)
11 x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.2)
12 model=Sequential()
13 model.add(LSTM(1, input_dim=1, input_length=5, return_sequences = False))
14 model.compile(loss='mse', optimizer='adam')
15 model.summary()
16 history = model.fit(x_train, y_train, epochs=1000, verbose=0)
17 y_predict = model.predict(x_test)
18 plt.scatter(range(20), y_predict, c='r')
19 plt.scatter(range(20), y_test, c='g')
20 plt.show()
21 plt.plot(history.history['loss']))
22 plt.show()
```

x_data: 100-by-5 samples
y_data: 100-by-1 samples

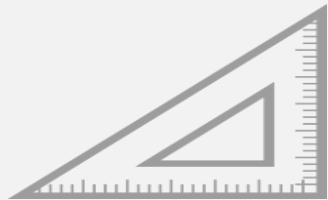


RNN Implementation (Keras)





Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions



Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10
Recurrent NN (RNN)

Advanced Topics



Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting

Deep Learning Theory and Software

Generative Adversarial Networks (GAN)

GAN Theory

- **GAN Theory**
- GAN Implementation



GAN Introduction

- GAN: Generative Adversarial Network
- Training both of **generator** and **discriminator**; and then generates samples which are similar to the original samples



Performance
Improvements via
Competition

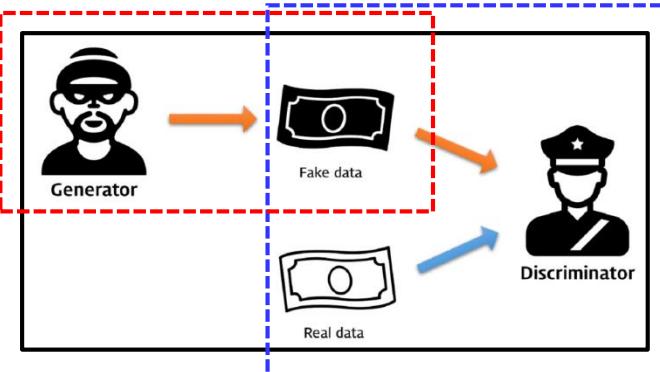


Generators

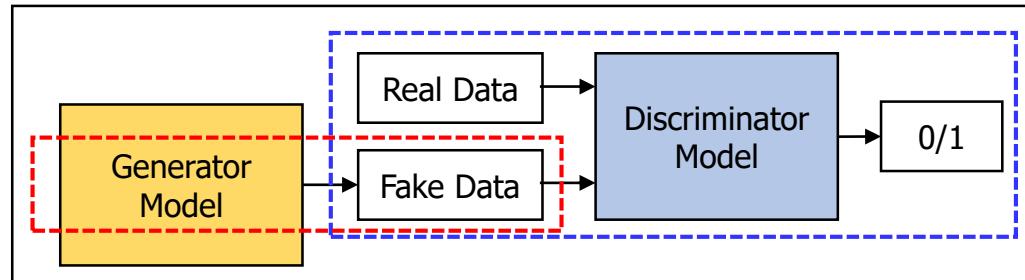
Discriminator



GAN Introduction



GAN architecture



Discriminator Model

- The discriminative model learns **how to classify** input to its class (fake → fake class, real → real class).
- Binary classifier.

Supervised Learning

Generator Model

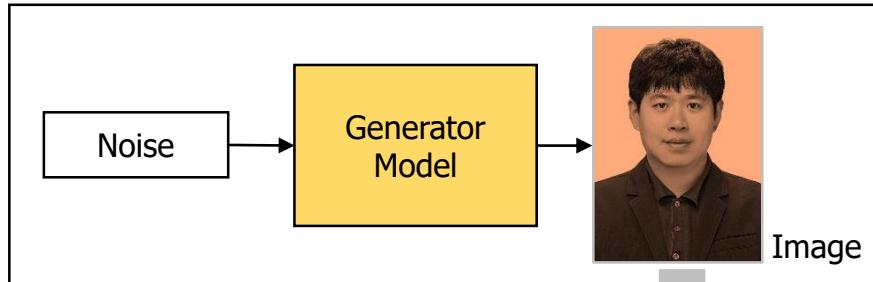
- The generative model learns **the distribution of training data**.

Unsupervised Learning

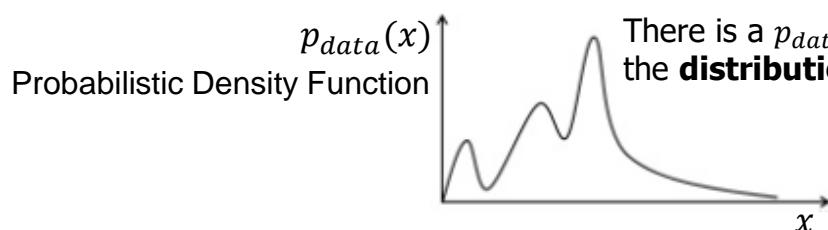


GAN Introduction

- Generative Model

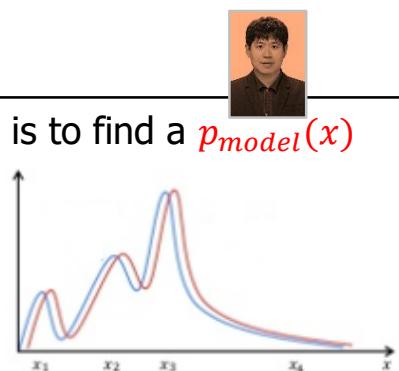


The generator model learns **the distribution of training data**.



There is a $p_{data}(x)$ that represents
the **distribution of actual images (training data)**.

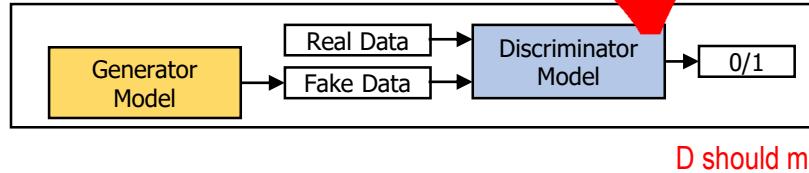
The goal of the generative model is to find a $p_{model}(x)$
that approximates $p_{data}(x)$ well.





GAN Introduction

GAN architecture



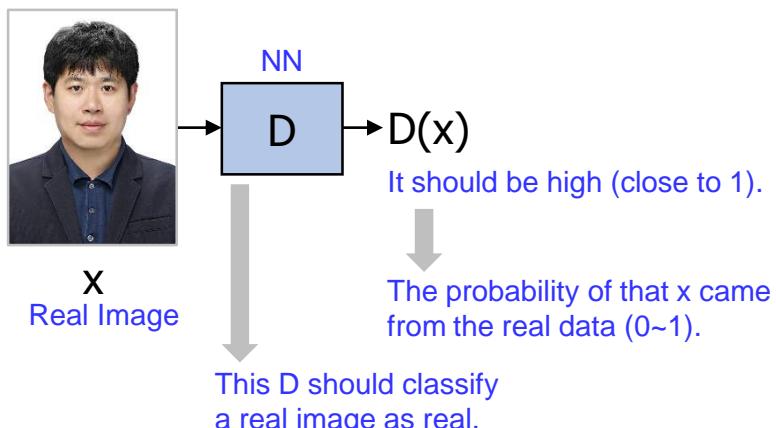
Objective of D

$$\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

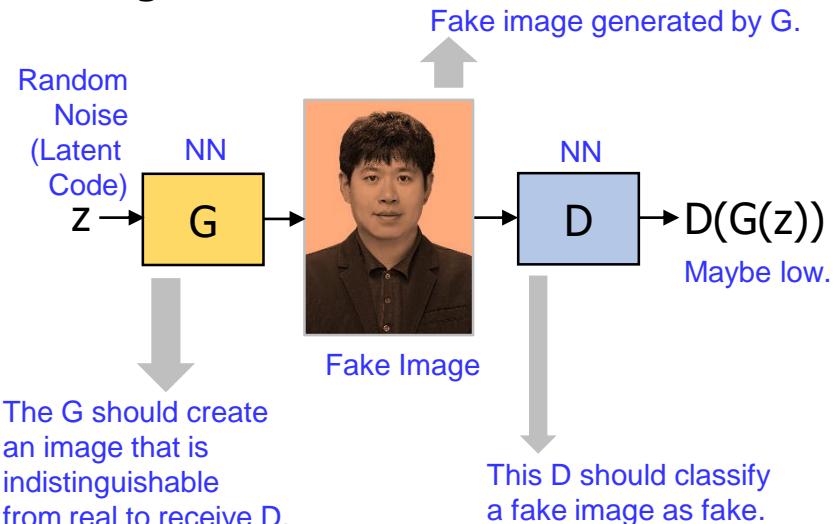
Red annotations explain the objective:

- "D should maximize $V(D,G)$ " is below the first term $E_{x \sim p_{data}(x)}[\log D(x)]$.
- "Maximize when $D(x)=1$ " is below the second term $E_{z \sim p_z(z)}[\log(1 - D(G(z)))]$.
- "Maximize when $D(G(z))=0$ " is also below the same term.

Training with REAL



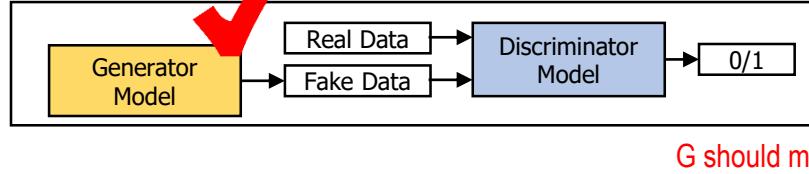
Training with FAKE





GAN Introduction

GAN architecture



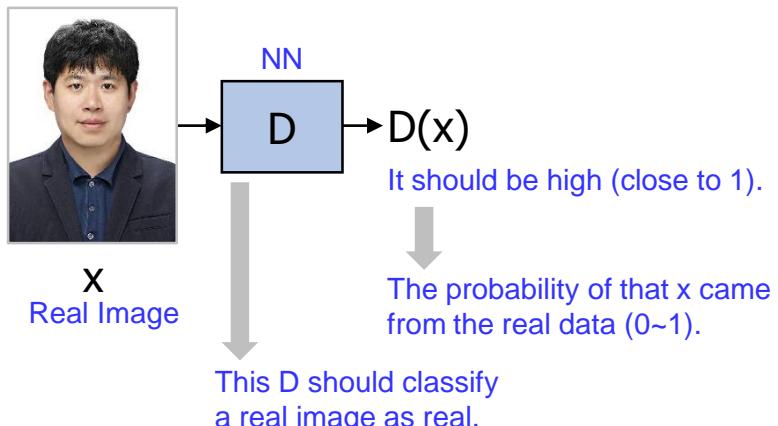
Objective of G

$$\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

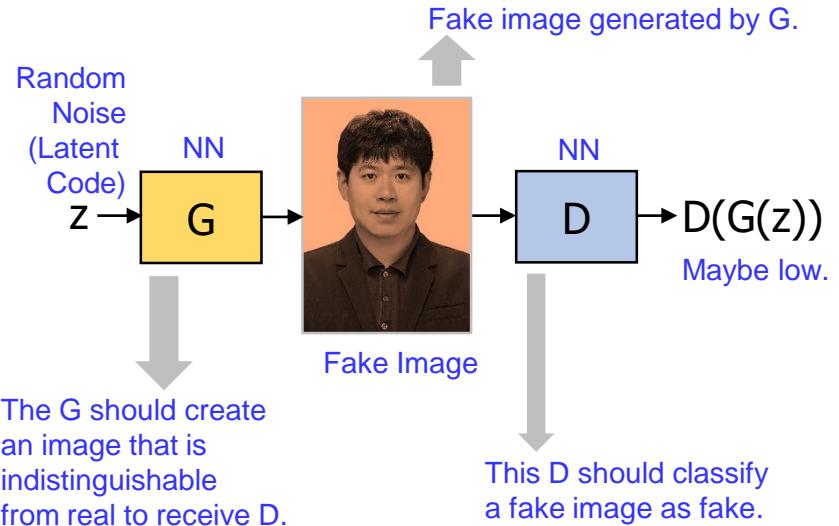
G should minimize $V(D, G)$

Sample latent code x from Gaussian distribution
Minimum when $D(G(z))=1$

Training with REAL



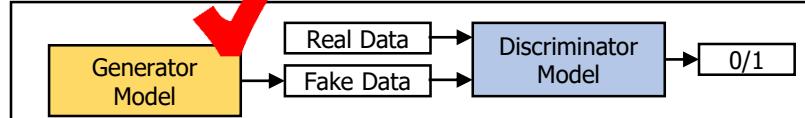
Training with FAKE





GAN Introduction

GAN architecture



Objective of G

G should minimize V(D,G)

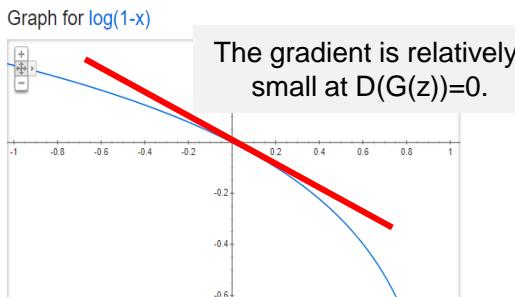
G is independent to this part

$\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))]$

Sample latent code x from Gaussian distribution

Minimum when $D(G(z))=1$

- At the beginning of training, the D can clearly classify the generated image as fake because the quality of the image is very low.
- This means $D(G(z))$ is almost zero at early stage of training.



$$\min_G E_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

$$\max_G E_{z \sim p_z(z)}[\log(D(G(z)))]$$

Deep Learning Theory and Software

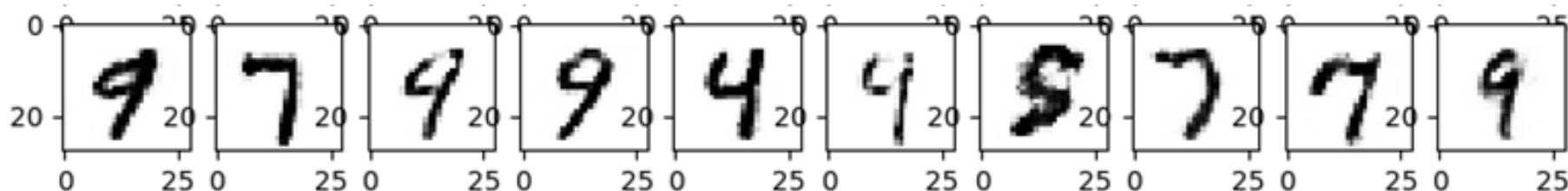
Generative Adversarial Networks (GAN)

GAN Implementation

- GAN Theory
- GAN Implementation



GAN Introduction (TensorFlow for GAN)





GAN Introduction (TensorFlow for GAN)

```
1 # MNIST data
2 from tensorflow.examples.tutorials.mnist import input_data
3 mnist = input_data.read_data_sets("data_MNIST", one_hot=True)
4
5 import matplotlib.pyplot as plt
6 import numpy as np
7 import tensorflow as tf
8
9 # Training Params
10 num_steps = 100000
11 batch_size = 128
12
13 # Network Params
14 dim_image = 784 # 28*28 pixels
15 nHL_thief = 256
16 nHL_police = 256
17 dim_noise = 100 # Noise data points
18
19 # A custom initialization (see Xavier Glorot init)
20 def glorot_init(shape):
21     return tf.random_normal(shape=shape, stddev=1. / tf.sqrt(shape[0] / 2.))
```



GAN Introduction (TensorFlow for GAN)

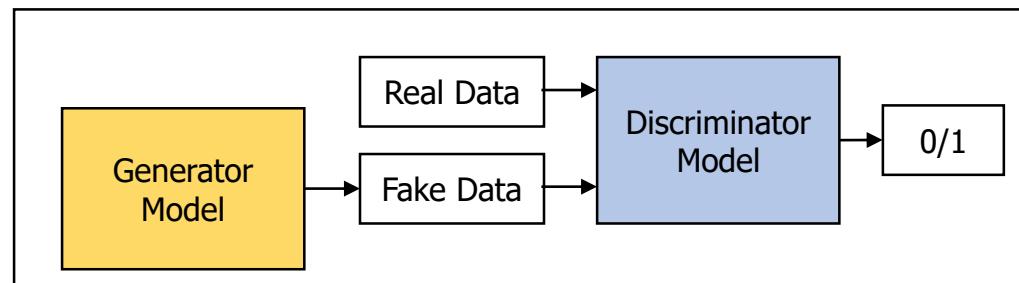
```
23  W = {
24      'HL_thief' : tf.Variable(glorot_init([dim_noise, nHL_thief])), 
25      'OL_thief' : tf.Variable(glorot_init([nHL_thief, dim_image])), 
26      'HL_police': tf.Variable(glorot_init([dim_image, nHL_police])), 
27      'OL_police': tf.Variable(glorot_init([nHL_police, 1])), 
28  }
29  b = {
30      'HL_thief' : tf.Variable(tf.zeros([nHL_thief])), 
31      'OL_thief' : tf.Variable(tf.zeros([dim_image])), 
32      'HL_police': tf.Variable(tf.zeros([nHL_police])), 
33      'OL_police': tf.Variable(tf.zeros([1])), 
34  }
35
36  # Neural Network: Thief
37  def nn_thief(x):
38      HL = tf.nn.relu(tf.add(tf.matmul(x, W['HL_thief']), b['HL_thief']))
39      OL = tf.nn.sigmoid(tf.add(tf.matmul(HL, W['OL_thief']), b['OL_thief']))
40      return OL
41
42  # Neural Network: Police
43  def nn_police(x):
44      HL = tf.nn.relu(tf.add(tf.matmul(x, W['HL_police']), b['HL_police']))
45      OL = tf.nn.sigmoid(tf.add(tf.matmul(HL, W['OL_police']), b['OL_police']))
46      return OL
47
48  # Network Inputs
49  IN_THIEF = tf.placeholder(tf.float32, shape=[None, dim_noise])
50  IN_POLICE = tf.placeholder(tf.float32, shape=[None, dim_image])
```



GAN Introduction (TensorFlow for GAN)

```
52 # Build Thief/Generator Neural Network
53 sample_thief = nn_thief(IN_THIEF)
54
55 # Build Police/Discriminator Neural Network (one from noise input, one from generated samples)
56 police_data_real = nn_police(IN_POLICE)
57 police_data_fake = nn_police(sample_thief)
58 vars_thief = [W['HL_thief'], W['OL_thief'], b['HL_thief'], b['OL_thief']]
59 vars_police = [W['HL_police'], W['OL_police'], b['HL_police'], b['OL_police']]
60
61 # Cost, Train
62 cost_thief = -tf.reduce_mean(tf.log(police_data_fake))
63 cost_police = -tf.reduce_mean(tf.log(police_data_real) + tf.log(1. - police_data_fake))
64 train_thief = tf.train.AdamOptimizer(0.0002).minimize(cost_thief, var_list=vars_thief)
65 train_police = tf.train.AdamOptimizer(0.0002).minimize(cost_police, var_list=vars_police)
```

GAN architecture





GAN Introduction (TensorFlow for GAN)

```

52 # Build Thief/Generator Neural Network          G(z)
53 sample_thief = nn_thief(IN_THIEF)             D(x)
54
55 # Build Police/Discriminator Neural Network (one from noise input, one from generated samples)
56 police_data_real = nn_police(IN_POLICE)        D(G(z))
57 police_data_fake = nn_police(sample_thief)
58 vars_thief = [W['HL_thief']]
59 vars_police = [W['HL_police']]
60
61 # Cost, Train
62 cost_thief = -tf.reduce_mean(tf.log(police_data_fake))
63 cost_police = -tf.reduce_mean(tf.log(police_data_real) + tf.log(1. - police_data_fake))
64 train_thief = tf.train.AdamOptimizer(0.0002).minimize(cost_thief, var_list=vars_thief)
65 train_police = tf.train.AdamOptimizer(0.0002).minimize(cost_police, var_list=vars_police)

```

Objective of G

$$\max_G E_{z \sim p_z(z)} [\log(D(G(z)))]$$

Objective of D

$$\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

D should maximize $V(D, G)$

Sample x from real data distribution

Sample latent code x from Gaussian distribution

Maximize when $D(x)=1$

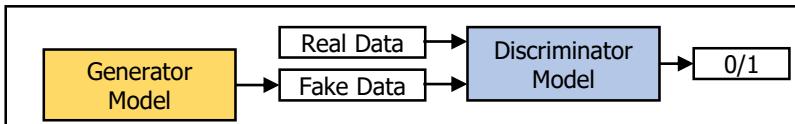
Maximize when $D(G(z))=0$

GAN Introduction (TensorFlow for GAN)



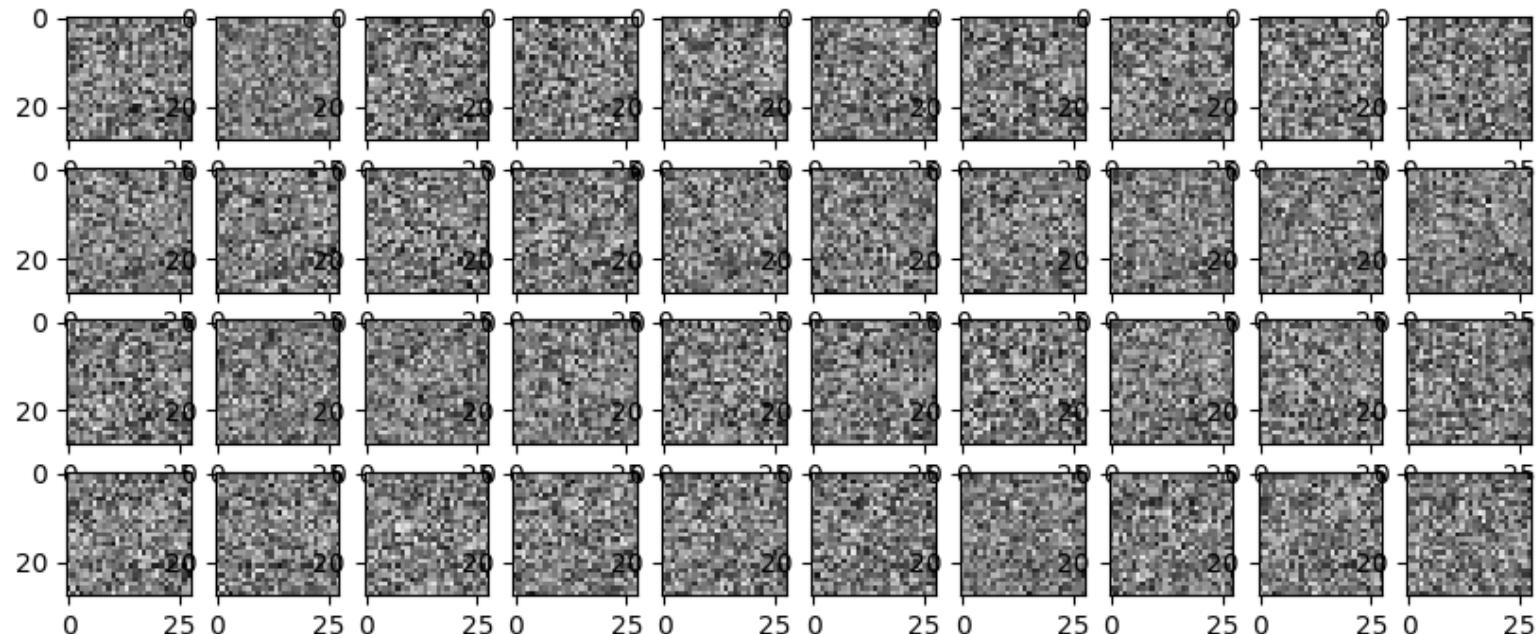
```
67 # Session
68 with tf.Session() as sess:
69     sess.run(tf.global_variables_initializer())
70     for i in range(1, num_steps+1):
71         # Prepare Data
72         # Get the next batch of MNIST data (only images are needed, not labels)
73         batch_images, _ = mnist.train.next_batch(batch_size)
74         # Generate noise to feed to the generator/thief
75         z = np.random.uniform(-1., 1., size=[batch_size, dim_noise])
76         # Train
77         sess.run([train_thief, train_police], feed_dict = {IN_POLICE: batch_images, IN_THIEF: z})
78         # Generate images from noise, using the generator network.
79         f, a = plt.subplots(4, 10, figsize=(10, 4))
80         for i in range(10):
81             # Noise input
82             z = np.random.uniform(-1., 1., size=[4, dim_noise])
83             g = sess.run([sample_thief], feed_dict={IN_THIEF: z})
84             g = np.reshape(g, newshape=(4, 28, 28, 1))
85             # Reverse colors for better display
86             g = -1 * (g - 1)
87             for j in range(4):
88                 # Generate image from noise. Extend to 3 channels for matplotlib figure.
89                 img = np.reshape(np.repeat(g[j][:, :, np.newaxis], 3, axis=2), newshape=(28, 28, 3))
90                 a[j][i].imshow(img)
91             print(i)
92         f.show()
93         plt.draw()
94         plt.waitforbuttonpress()
```

GAN architecture





num_steps: 1



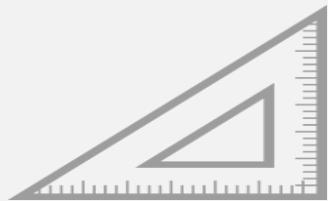


num_steps: 100000





Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions



Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10
Recurrent NN (RNN)

Advanced Topics

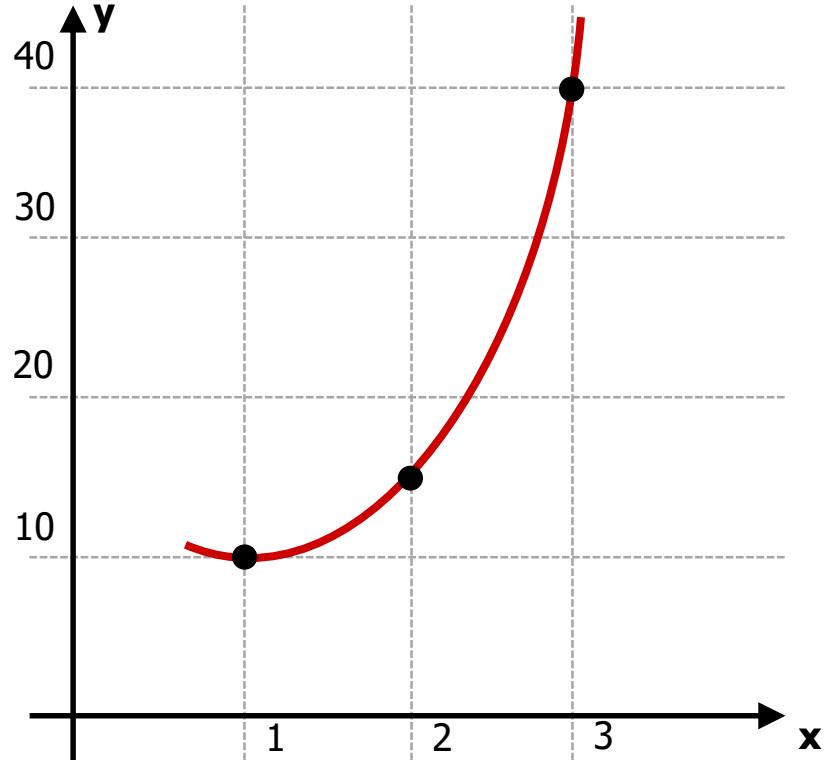


Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting

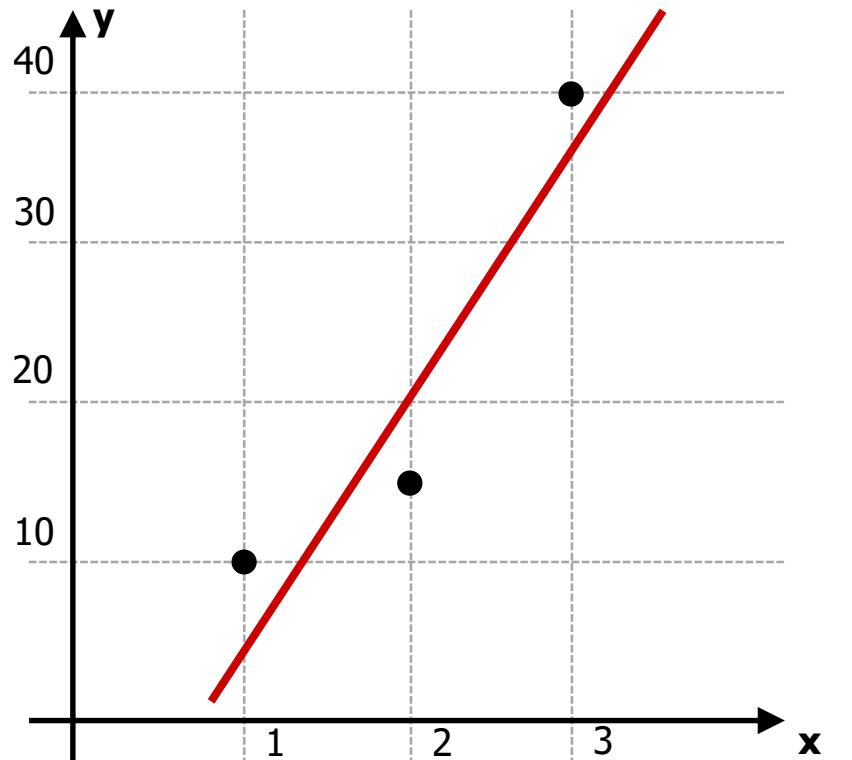


Interpolation vs. Linear Regression

Interpolation



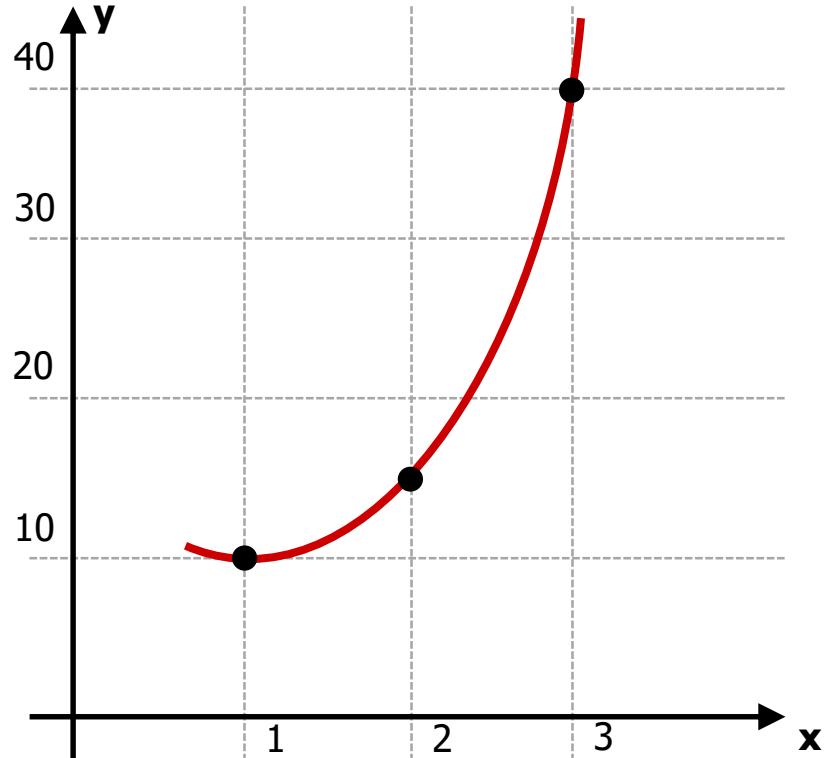
Linear Regression





Interpolation vs. Linear Regression

Interpolation



Interpolation with Polynomials

$$y = a_2 x^2 + a_1 x^1 + a_0$$

where three points are given.

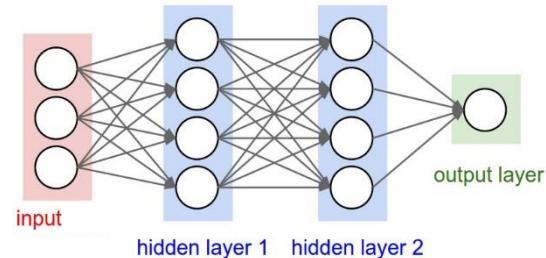
→ Unique coefficients (a_0, a_1, a_2) can be calculated.



Is this related to
Neural Network Training?



Interpolation and Neural Network Training



$$Y = a(a(a(X \cdot W_1 + b_1) \cdot W_2 + b_2) \cdot W_o + b_o)$$

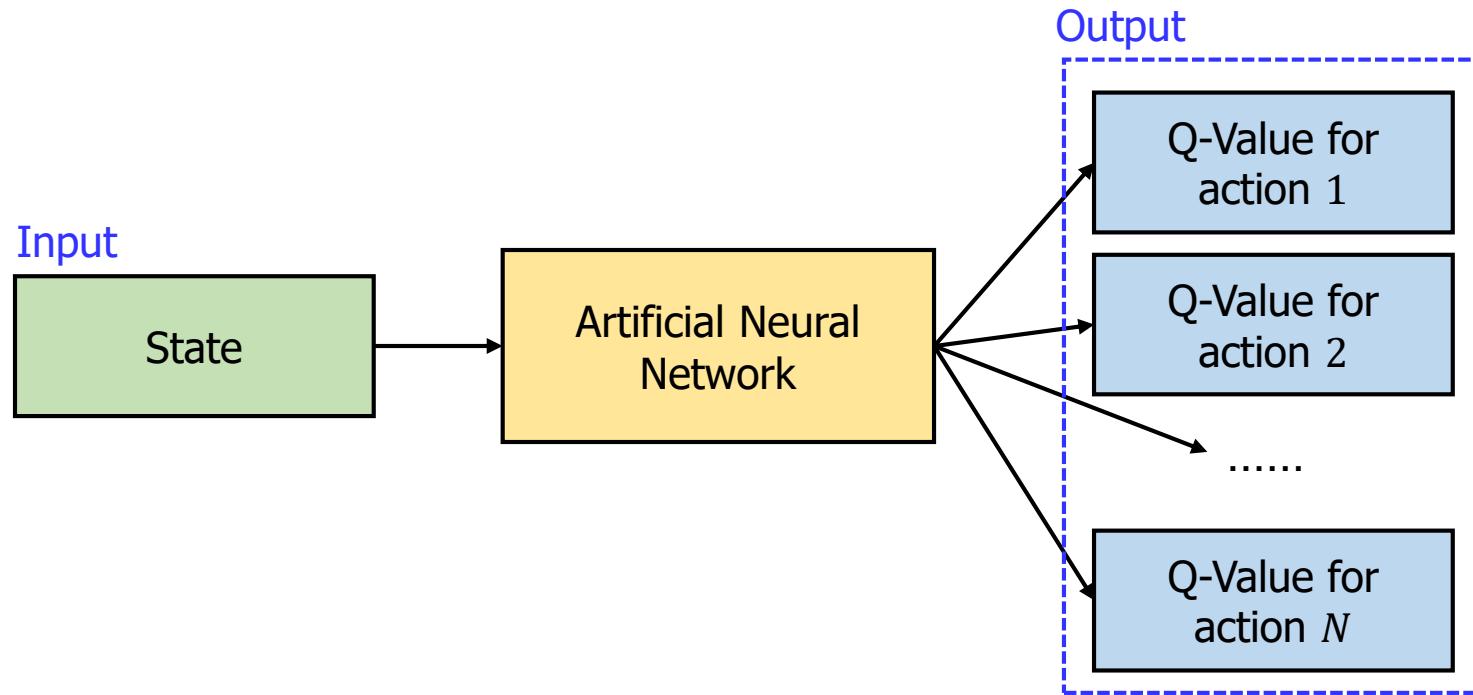
where training data/labels (X : data, Y : labels) are given.

- Find $W_1, b_1, W_2, b_2, W_o, b_o$
- This is the mathematical meaning of neural network training.
- **Function Approximation**
- The most well-known function approximation with neural network:
Deep Reinforcement Learning



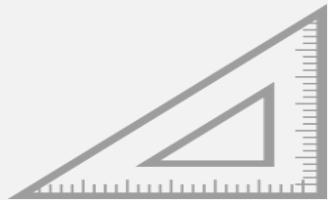
Example (Deep Reinforcement Learning)

- It is inefficient to make the Q-table for each state-action pair.
→ ANN is used to **approximate the Q-function**.





Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions



Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10
Recurrent NN (RNN)

Advanced Topics

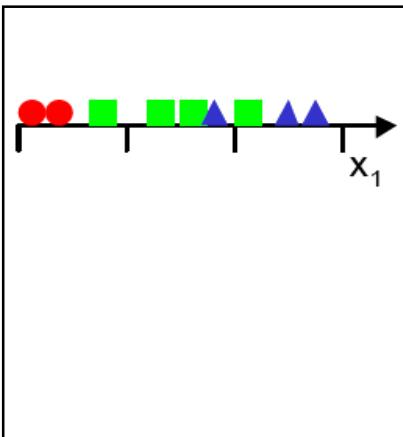


Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting

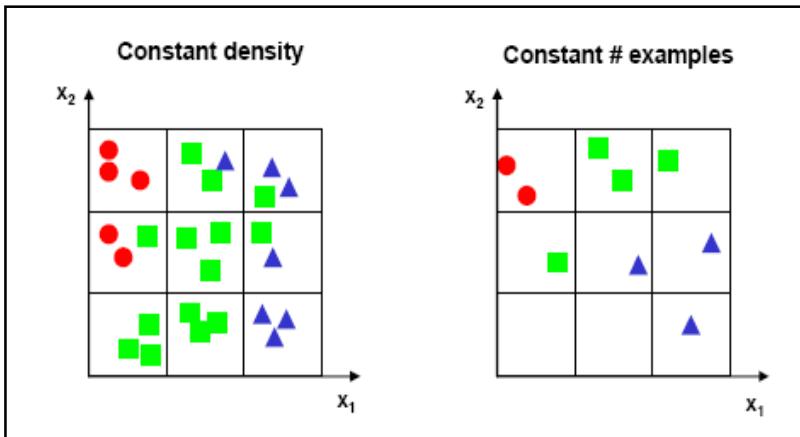


Curse of Dimensionality

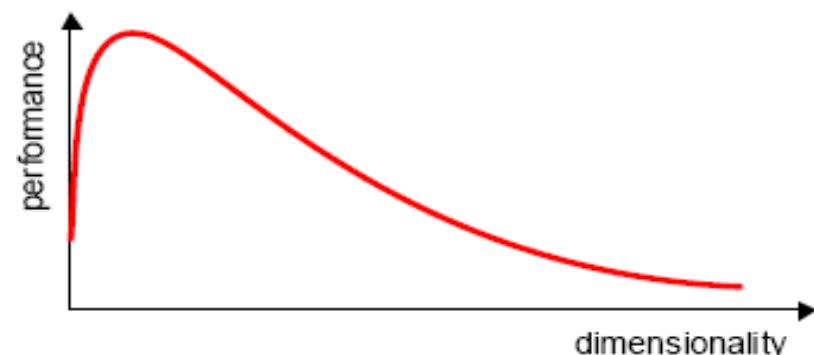
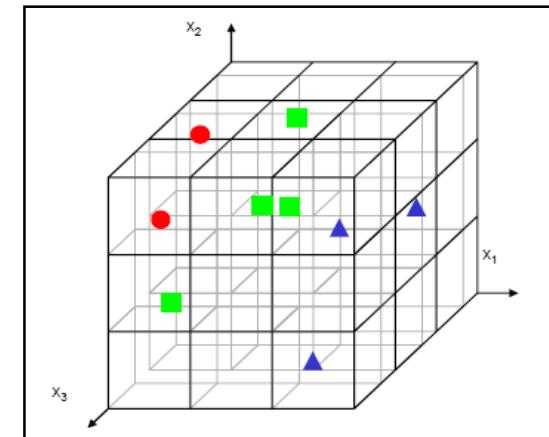
1D



2D



3D





Feature Selection

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} \xrightarrow{\text{feature selection}} \begin{bmatrix} x_{i_1} \\ x_{i_2} \\ \vdots \\ x_{i_M} \end{bmatrix}$$

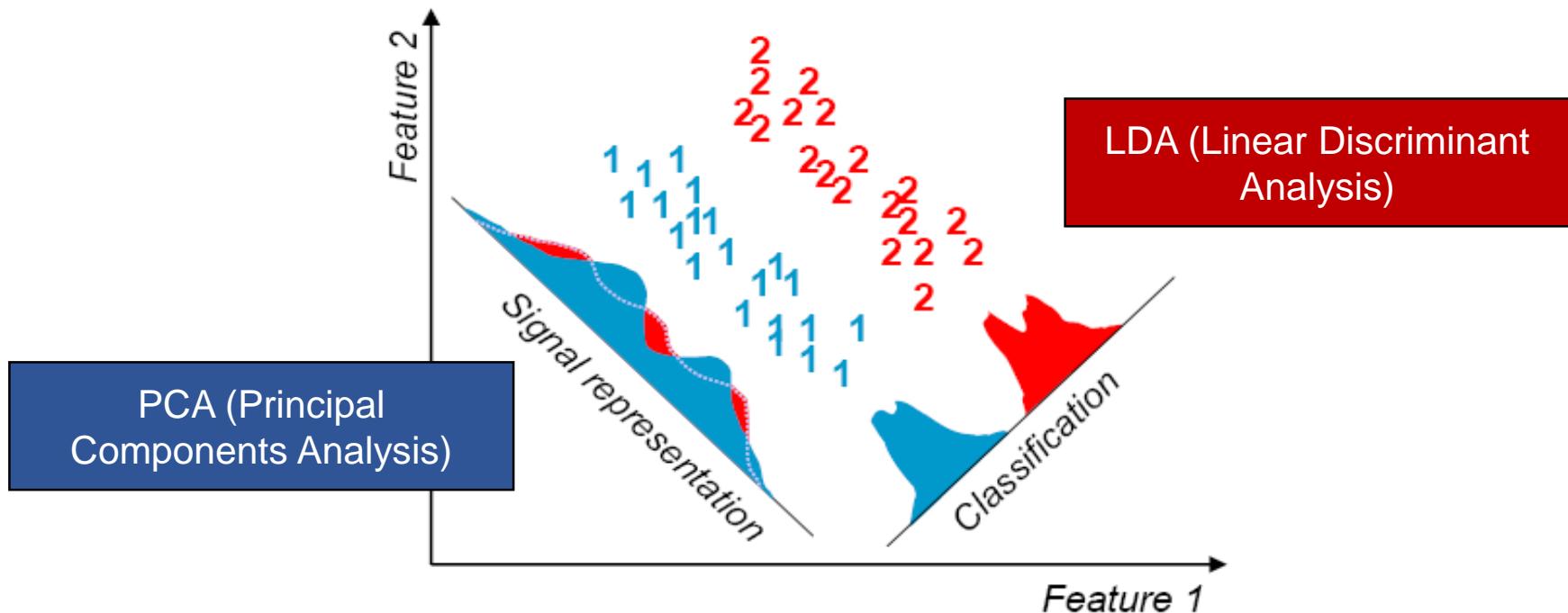
Feature Extraction

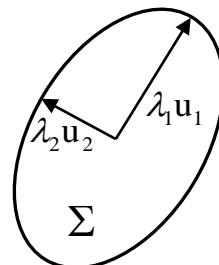
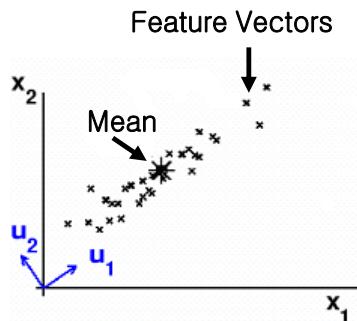
$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} \xrightarrow{\text{feature extraction}} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = f \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix}$$

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} \xrightarrow{\text{linear feature extraction}} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1N} \\ w_{21} & w_{22} & \cdots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{M1} & w_{M2} & \cdots & w_{MN} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}$$



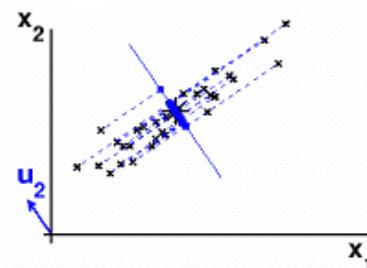
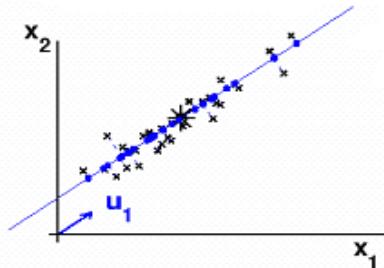
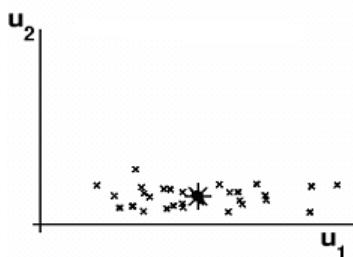
Dimensionally Reduction: PCA and LDA





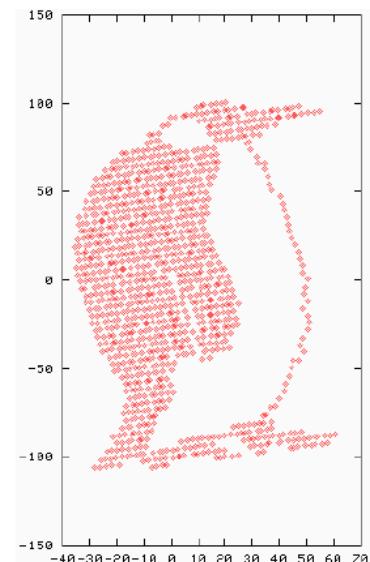
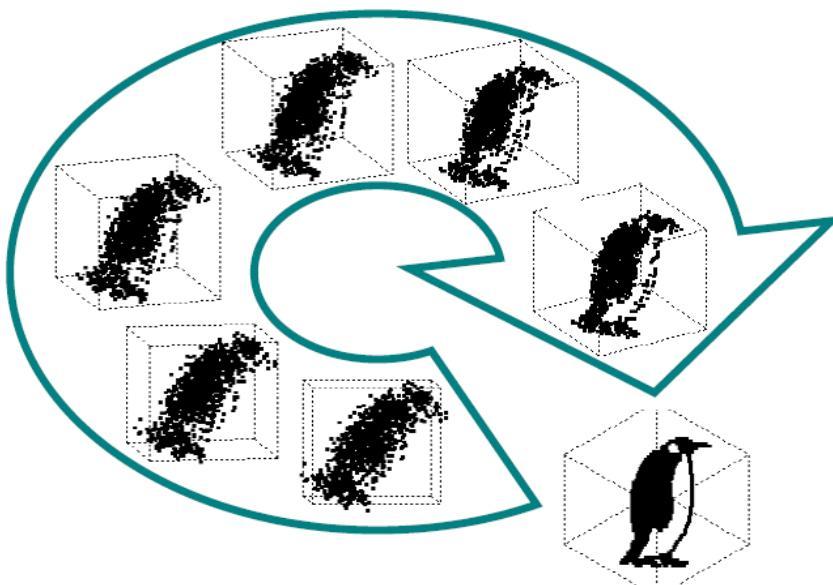
$$\Leftrightarrow \Sigma = [u_1 u_2] \times \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \times [u_1 u_2]^\top$$

$$\lambda_1 > \lambda_2$$





PCA Example





PCA Example: Face Recognition

얼굴인식 결과



35세 남자



얼굴인식 결과



40세 남자



닮 . 은 . 연 . 예 . 인

72%

이병현
남 41세



얼핏보면 연예인으로
착각하겠어요~



작는, 순간 놀진다! 푸딩 얼굴인식

닮 . 은 . 연 . 예 . 인

46%

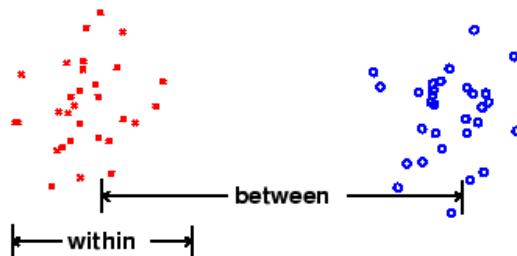
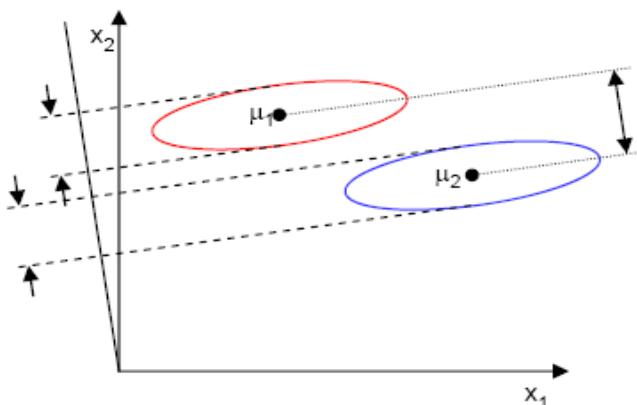
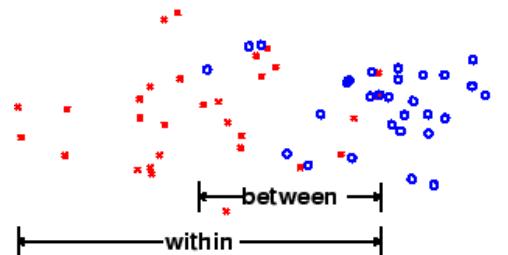
엄앵란
여 75세



그다지 닮진 않았지만
굳이 한명을 뽑자면...



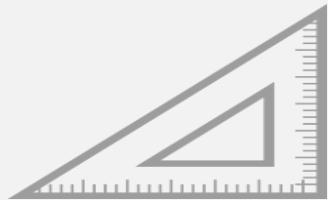
작는, 순간 놀진다! 푸딩 얼굴인식

**Good class separation****Bad class separation****Fisher's linear discriminant function**

$$J(\mathbf{w}) = \frac{|\tilde{\mu}_1 - \tilde{\mu}_2|^2}{\tilde{S}_1^2 + \tilde{S}_2^2} \rightarrow \text{Maximize!}$$
$$\rightarrow \text{Minimize!}$$



Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions



Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10
Recurrent NN (RNN)

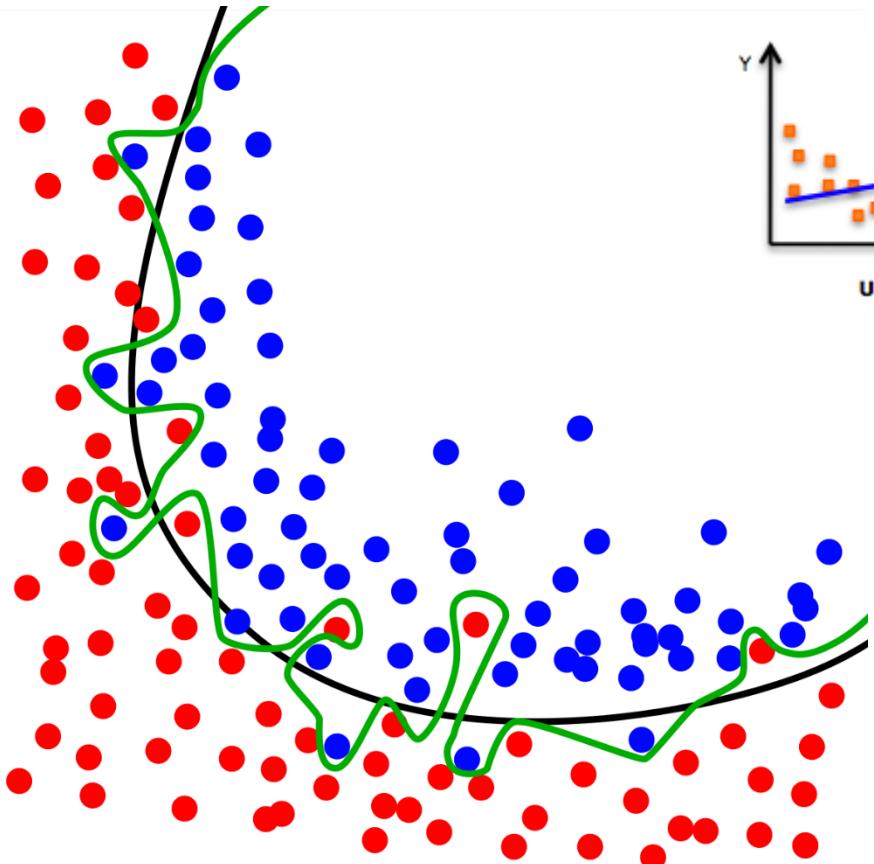
Advanced Topics



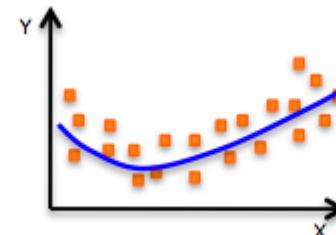
Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting



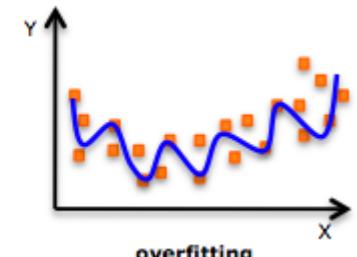
Overfitting



Underfitting



Just right!

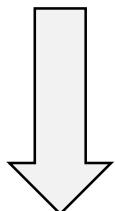


overfitting



Overfitting

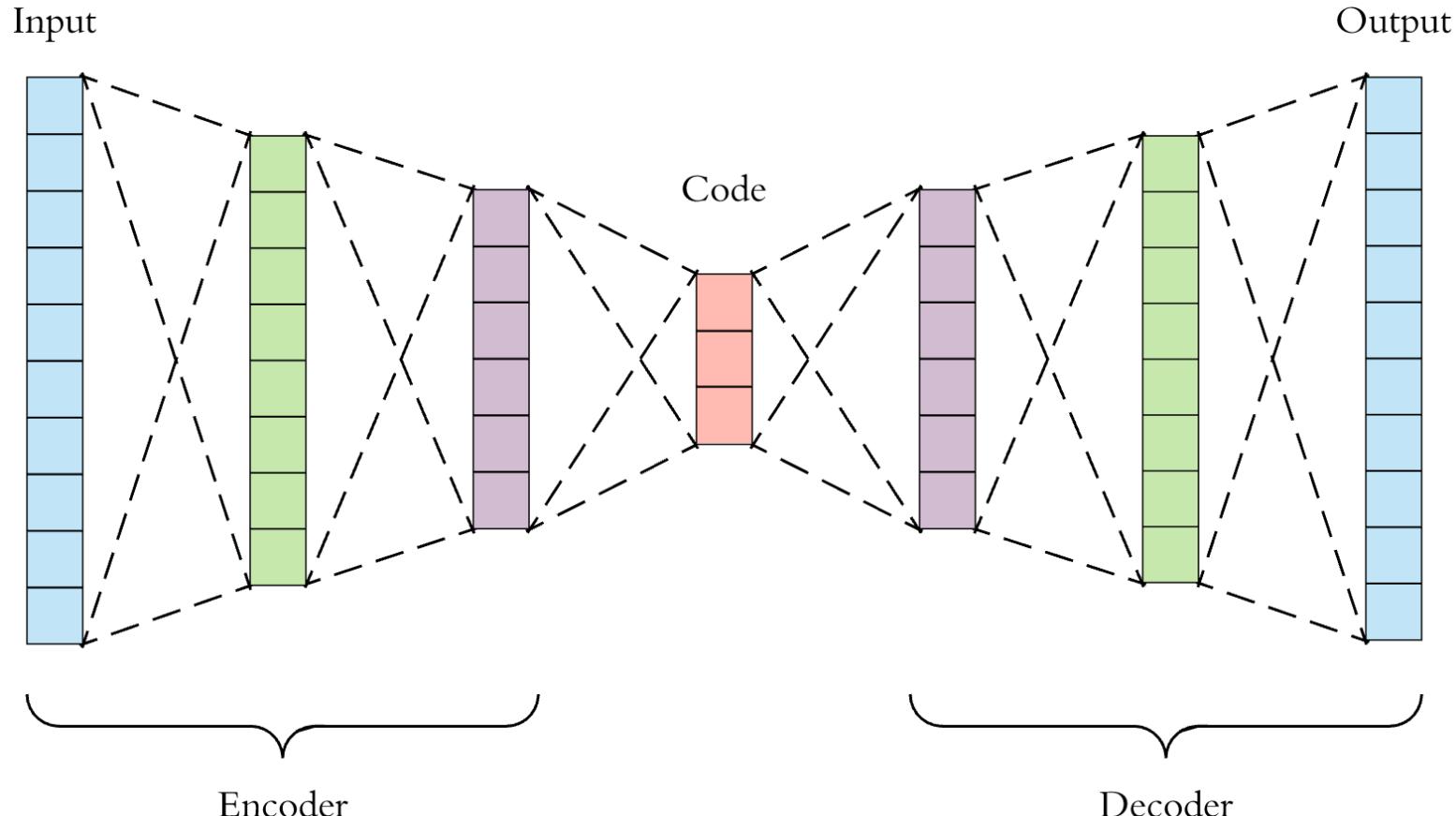
- How to overcome?
 - More training data
 - Reduce the number of features → autoencoding, dropout
 - Regularization



- **Autoencoding**
- **Dropout**
- **Regularization**



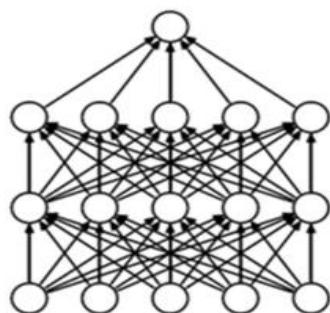
Autoencoding



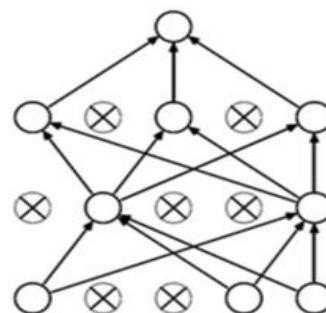


Dropout and Regularization

- Dropout
 - `tf.nn.dropout(layer, keep_prob=0.9)`

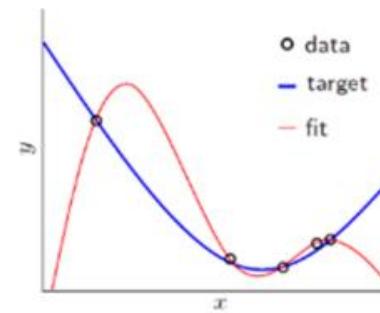


(a) Standard Neural Net

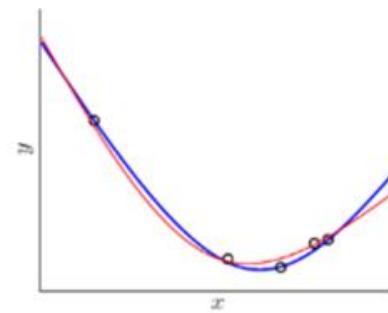


(b) After applying dropout.

- Regularization



(a) without regularization



(b) with regularization