Deep Learning Theory and Software

Basics

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Deep Learning Revolution is Real

Geoffrey E Hinton

Yoshua Bengio

Yann LeCun

FATHERS OF THE DEEP LEARNING REVOLUTION RECEIVE ACM A.M. TURING AWARD (2019)

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.

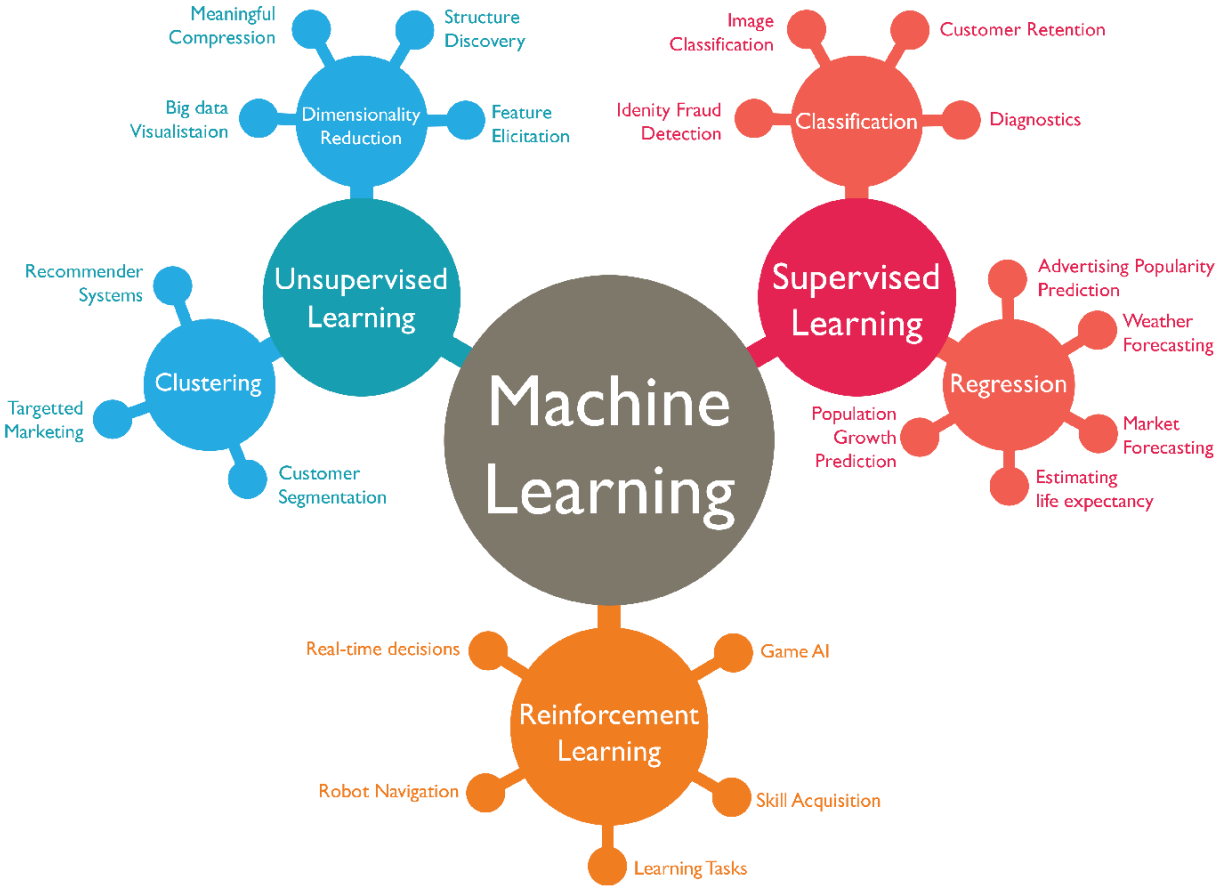
While the use of artificial neural networks as a tool to help computers recognize patterns and simulate human intelligence had been introduced in the 1980s, by the early 2000s, LeCun, Hinton and Bengio were among a small group who remained committed to this approach. Though their efforts to rekindle 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.

The ACM A.M. Turing Award, often referred to as the "Nobel Prize

Alan Turing (1912-1954)
Father of Computer Science

https://amturing.acm.org/

Machine Learning Overview

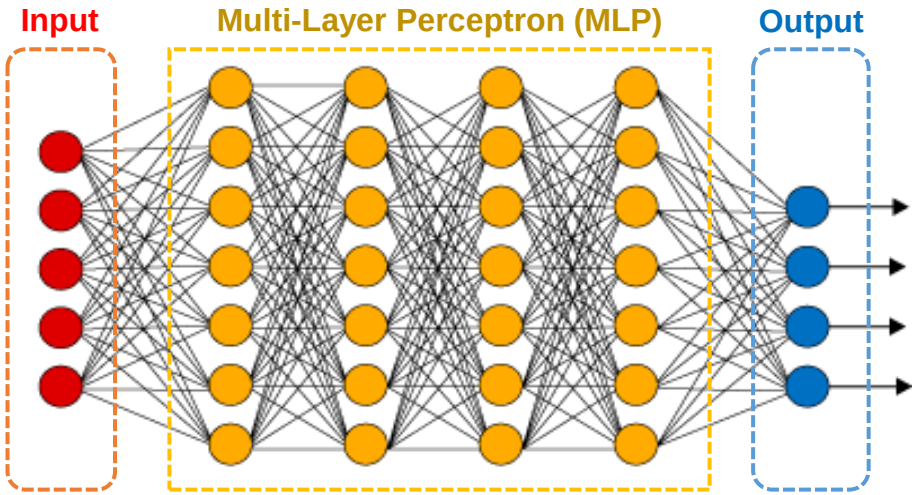


- How Deep Learning Works?
  - Deep Learning Computation Procedure

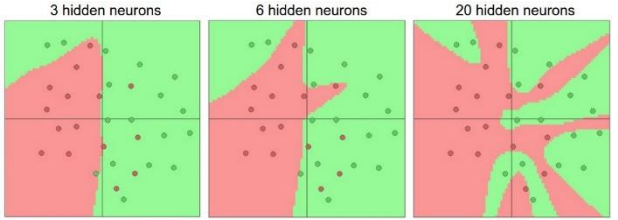
Deep Learning Model Setup
- MLP, CNN, RNN, GAN, or Customized
- # Hidden Layers, # Units, Input/Output, …
- Cost Function / Optimizer Selection

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



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



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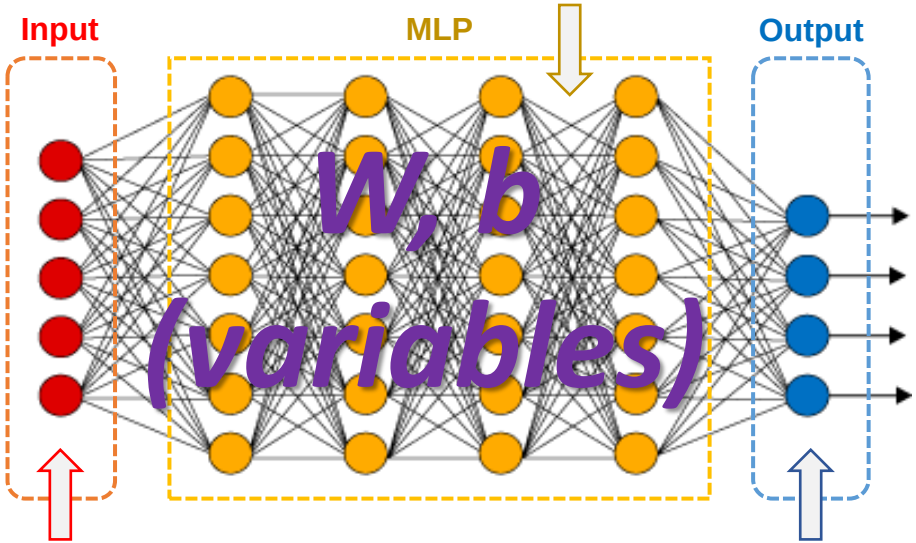
All weights in units are trained/set (under cost minimization)



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).

- How Deep Learning Works?
  - Deep Learning Computation Procedure

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Training (with Large-Scale Dataset)
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Inference / Testing (Real-Word Execution)
- Input: Real-World Input Data
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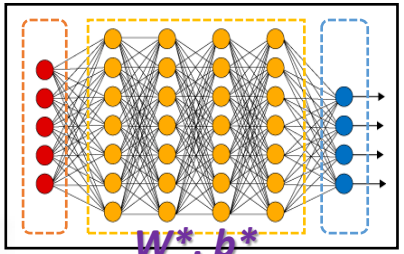
Trained Model



Intelligent Surveillance Platforms

INPUT: Real-Time Arrivals

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

- How Deep Learning Works?
  - Issue - **Overfitting**

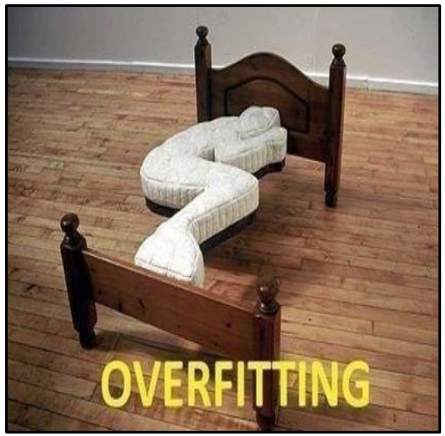
Deep Learning Model Setup
- MLP, CNN, RNN, GAN, or Custom
- # Hidden Layers, # Units, Input/Output, …
- Cost Function / Optimizer Selection

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

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

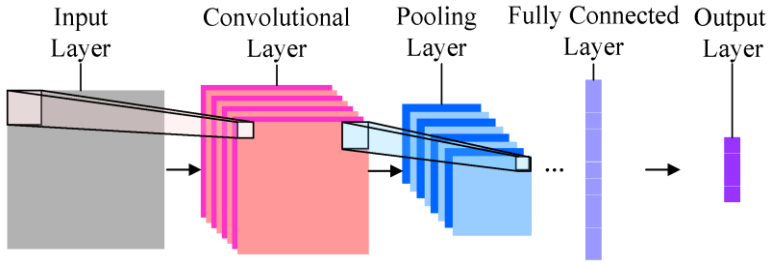
Situation becomes worse when the model (with insufficient training data) accurately fits on training data.



To Combat the Overfitting
- More training data
- Autoencoding (or variational auto-encoder (VAE))
- Droupout
- Regularization

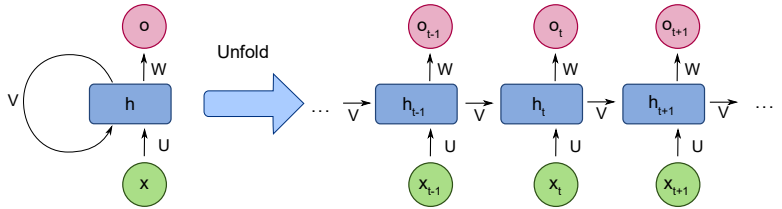
- Two Major Deep Learning Models → CNN vs. RNN

Convolutional Neural Network (CNN)



- 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**

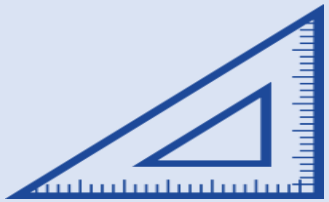
Recurrent Neural Network (RNN)



- 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**

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

Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions

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

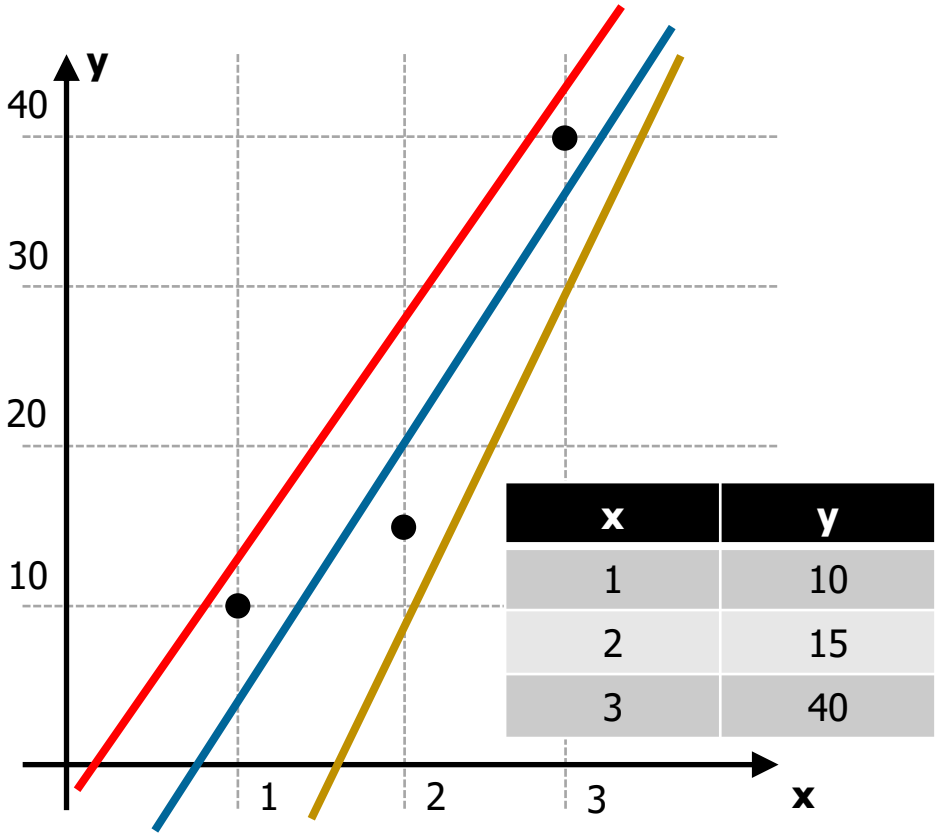
Advanced Topics

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

Deep Learning Basics and Software
Linear Regression
Linear Regression Theory

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

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



x	y
1	10
2	15
3	40

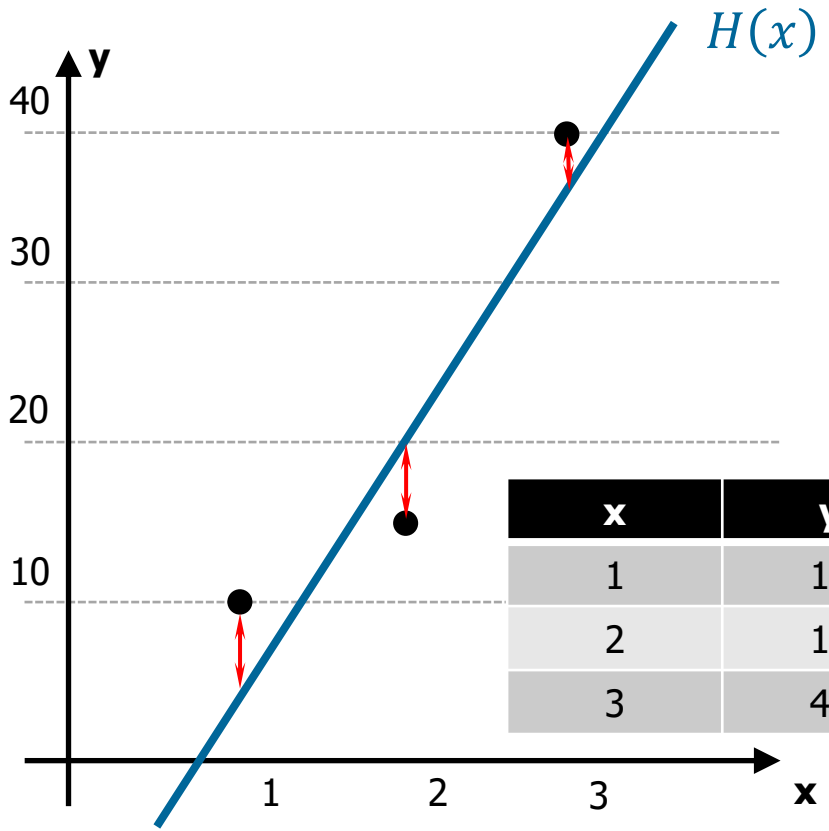
- Cost Function (or Loss Function)

m: The number of training data

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

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

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

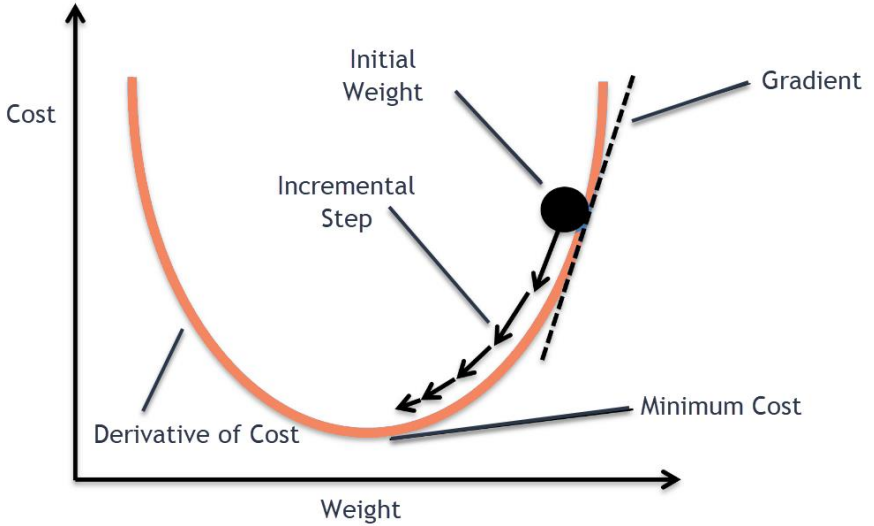


x	y
1	10
2	15
3	40

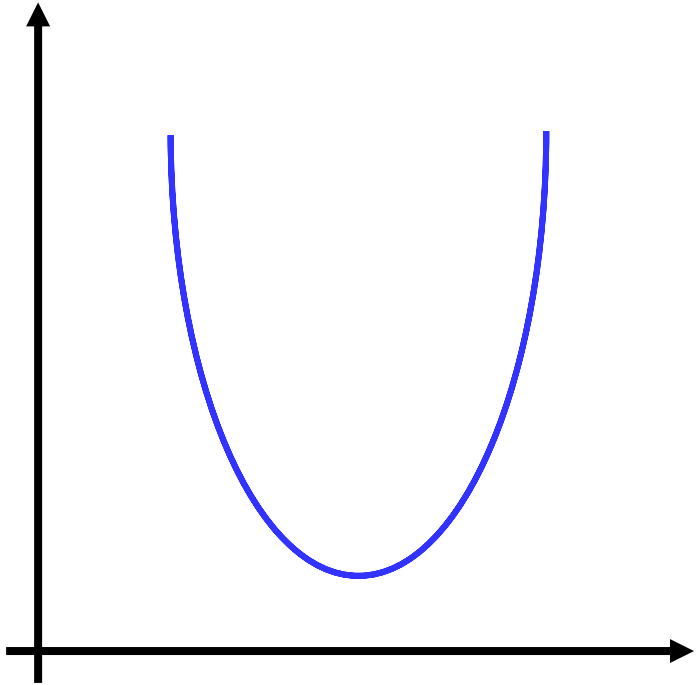
- Cost Function Minimization
  - Model: $H(x) = Wx + b$
  - Cost Function: $Cost(W, b) = \frac{1}{m}\sum_{i=1}^{m}\left(H\left(x^i\right) - y^i\right)^2 = \frac{1}{m}\sum_{i=1}^{m}\left(Wx^i + b - y^i\right)^2$
  - How to Minimize this Function? → **Gradient Descent Method**
    - Angle → Differentiation

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

α: Learning rate



- Learning Rates
  - Too large: Overshooting
  - Too small: taking very long time to converge
- How can we determine the learning rates?
  - Try several learning rates
    - Observe the cost function



- Multi-Variable Linear Regression
  - Model:

$$H(x_1, x_2, \dots, x_n) = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + b$$

  - Cost:

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

- Multi-Variable Linear Regression
  - Model:

$$H(x_1, x_2, \dots, x_n) = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + b \Rightarrow H(X) = XW + b$$

$$\begin{pmatrix} x_1 & x_2 \dots & x_n \end{pmatrix} \cdot \begin{pmatrix} w_1 \\ w_2 \\ \dots \\ w_n \end{pmatrix} = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n$$

X W

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

when $W = \begin{pmatrix} w_1 & w_2 \dots & w_n \end{pmatrix}$

Deep Learning Basics and Software
Linear Regression
Linear Regression Implementation

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

- **TensorFlow**
- PyTorch
- Keras

- **TensorFlow**
- PyTorch
- Keras

Linear Regression Implementation (TensorFlow)


```python
import tensorflow as tf
import numpy as np
x_data = np.array([[1,1],[2,2],[3,3]], dtype=np.float32)
y_data = np.array([[10],[20],[30]], dtype=np.float32)
W = tf.Variable(tf.random.normal([2,1]))
b = tf.Variable(tf.random.normal([1]))

def model_LinearRegression(x):
    return tf.matmul(x,W)+b

def cost_LinearRegression(model_x):
    return tf.reduce_mean(tf.square(model_x-y_data))

def train_optimization(x):
    with tf.GradientTape() as g:
        model = model_LinearRegression(x)
        cost = cost_LinearRegression(model)
    gradients = g.gradient(cost,[W,b])
    tf.optimizers.SGD(0.01).apply_gradients(zip(gradients,[W,b]))

for step in range(2001):
  train_optimization(x_data)

print('='*100)
x_test = np.array([[4,4]],dtype=np.float32)
model_test = model_LinearRegression(x_test)
print("model for [4,4]: ", model_test.numpy())
print('='*100)
```

- TensorFlow
- **PyTorch**
- Keras

Linear Regression Implementation (PyTorch)

```
1  import torch
2  x_train = torch.FloatTensor([[1,1], [2,2], [3,3]])
3  y_train = torch.FloatTensor([[10], [20], [30]])
4  W = torch.randn([2,1], requires_grad=True)
5  b = torch.randn([1], requires_grad=True)
6  optimizer = torch.optim.SGD([W, b], lr=0.01)
7
8  def model_LinearRegression(x):
9      return torch.matmul(x, W) + b
10
11 for step in range(2000):
12     prediction = model_LinearRegression(x_train)
13     cost = torch.mean((prediction - y_train) ** 2)
14     optimizer.zero_grad()
15     cost.backward()
16     optimizer.step()
17
18 x_test = torch.FloatTensor([[4,4]])
19 model_test = model_LinearRegression(x_test)
20 print("Model with [4] (expectation: 40): ", model_test.detach().item())
```

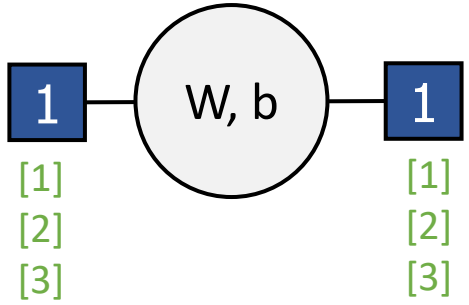
Linear Regression Implementation (PyTorch)


```python
import torch
import torch.nn as nn
import torch.nn.functional as F
x_train = torch.FloatTensor([[1,1], [2,2], [3,3]])
y_train = torch.FloatTensor([[10], [20], [30]])

class class_LinearRegression(nn.Module):
    def __init__(self):
        super().__init__()
        self.linear = nn.Linear(2,1)
    def forward(self, x):
        return self.linear(x)

model_LinearRegression = class_LinearRegression()
optimizer = torch.optim.SGD(model_LinearRegression.parameters(), lr=0.01)

for step in range(2000):
    prediction = model_LinearRegression(x_train)
    cost = F.mse_loss(prediction, y_train)
    optimizer.zero_grad()
    cost.backward()
    optimizer.step()

x_test = torch.FloatTensor([[4,4]])
model_test = model_LinearRegression(x_test)
print("Model with [4] (expectation: 40): ", model_test.detach().item())
```

- TensorFlow
- PyTorch
- **Keras**

Linear Regression Implementation (Keras)

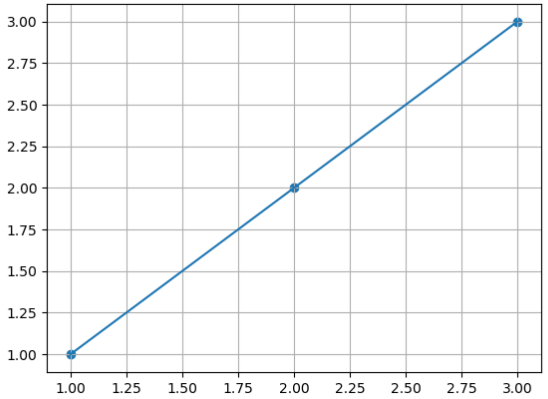

```python
import numpy as np
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import Dense

# Data
x_data = np.array([[1], [2], [3]])
y_data = np.array([[1], [2], [3]])
# Model, Cost, Train
model = Sequential()
model.add(Dense(1, input_dim=1))
model.compile(loss='mse', optimizer='adam')
model.fit(x_data, y_data, epochs=1000, verbose=0)
model.summary()
# Inference
print(model.get_weights())
print(model.predict(np.array([4])))
# Plot
plt.scatter(x_data, y_data)
plt.plot(x_data, y_data)
plt.grid(True)
plt.show()
```



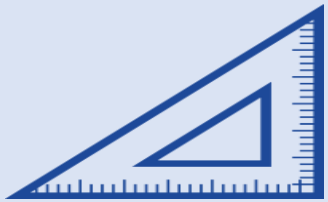
Model, Cost, Train

Linear Regression Implementation (Keras)


```
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: Con
version 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 sup
ports 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



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Binary Classification
Softmax Classification

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

Advanced Topics

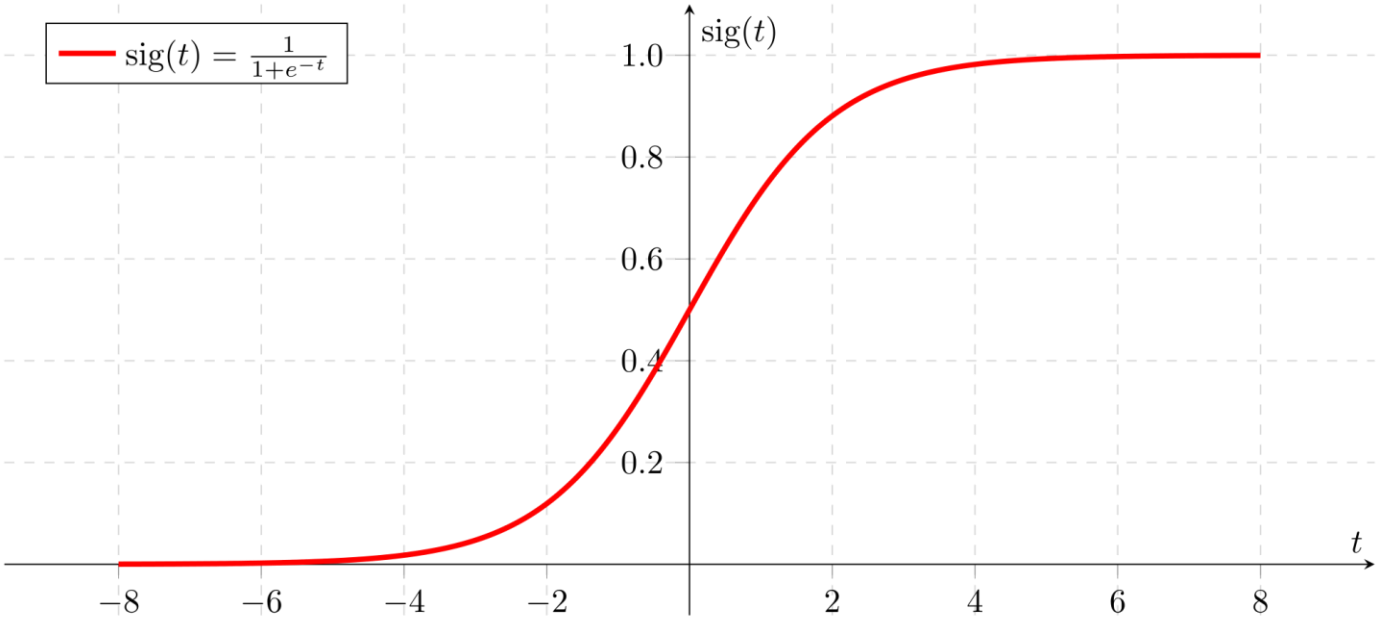
Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting

Deep Learning Basics and Software
Binary Classification
Binary Classification Theory

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

- Binary Classification Examples
  - **Spam Detection:** Spam [1] or Ham [0]
  - **Facebook Feed:** Show [1] or Hide [0]
  - **Credit Card Fraudulent Transaction Detection:** Fraud [1] or Legitimate [0]
  - **Tumor Image Detection in Radiology:** Malignant [1] or Benign [0]

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



Binary Classification

Linear Regression Model

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

Logistic/Sigmoid Function

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

Binary Classification Model

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

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

Linear Regression Model

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

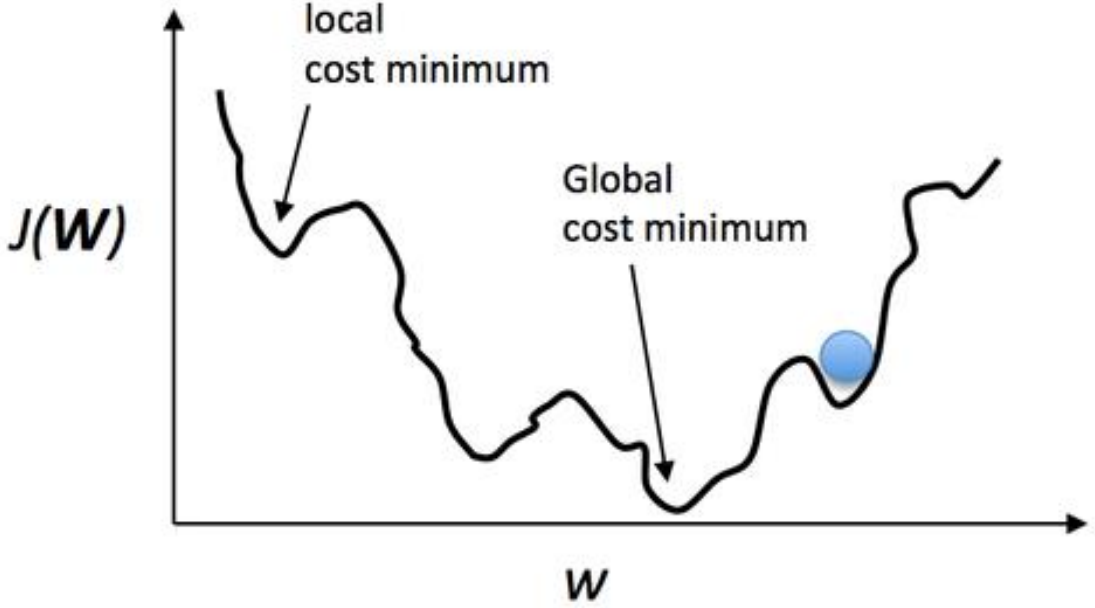
Gradient Descent Method can be used because $Cost(W,b)$ is convex (local minimum is global minimum).

Binary Classification Model

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

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

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



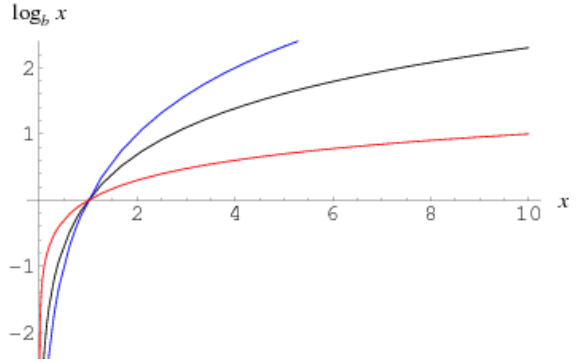
$$\text{Cost}(W)=\frac{1}{m}\sum c(H(x),y)$$

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

Understanding this Cost Function

Cost	0	∞	∞	0
$H(x)$	0	0	1	1
y	0	1	0	1

Log Function



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

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

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

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

Gradient Descent Method

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

Deep Learning Basics and Software
Binary Classification
Binary Classification Implementation

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

- **TensorFlow**
- PyTorch
- Keras

Binary Classification Implementation (TensorFlow)


```python
import tensorflow as tf
import numpy as np
x_train = np.array([[1,2], [2,3], [3,4], [4,4], [5,3], [6,2]], dtype=np.float32)
y_train = np.array([[0], [0], [0], [1], [1], [1]], dtype=np.float32)
W = tf.Variable(tf.random.normal([2,1]))
b = tf.Variable(tf.random.normal([1]))

def model_BinaryClassification(x):
    return tf.sigmoid(tf.matmul(x,W)+b)

def cost_BinaryClassification(model_x):
    return tf.reduce_mean((-1)*y_train*tf.math.log(model_x)+(-1)*(1.-y_train)*tf.math.log(1.-model_x))

def train_optimization(x):
    with tf.GradientTape() as g:
        model = model_BinaryClassification(x)
        cost = cost_BinaryClassification(model)
    gradients = g.gradient(cost,[W,b])
    tf.optimizers.SGD(0.01).apply_gradients(zip(gradients,[W,b]))

for step in range(2001):
  train_optimization(x_train)
  if step % 100 == 0:
      pred = model_BinaryClassification(x_train)
      loss = cost_BinaryClassification(pred)
      prediction = tf.cast(pred > 0.5, dtype=tf.float32)
      accuracy = tf.reduce_mean(tf.cast(tf.equal(prediction, y_train), dtype=tf.float32))
      print("Step: {},\t Accurray: {},\t Loss: {}".format(step,accuracy.numpy().flatten(),loss))

print('='*100)
x_test = np.array([[6,1]],dtype=np.float32)
model_test = model_BinaryClassification(x_test)
print("model for [6,1]: ", model_test.numpy())
print('='*100)
```

- TensorFlow
- **PyTorch**
- Keras

Binary Classification Implementation (PyTorch)

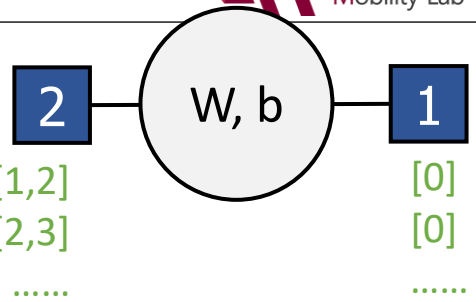
```
import torch
import numpy as np
x_train = torch.FloatTensor([[1,2], [2,3], [3,4], [4,4], [5,3], [6,2]])
y_train = torch.FloatTensor([[0], [0], [0], [1], [1], [1]])
W = torch.randn([2,1], requires_grad=True)
b = torch.randn([1], requires_grad=True)
optimizer = torch.optim.SGD([W, b], lr=0.01)

def model_BinaryClassification(x):
    return torch.sigmoid(torch.matmul(x, W) + b)

for step in range(2000):
    prediction = model_BinaryClassification(x_train)
    cost = torch.mean((-1)*y_train*torch.log(prediction)+(-1)*(1-y_train)*torch.log(1-prediction))
    optimizer.zero_grad()
    cost.backward()
    optimizer.step()

x_test = torch.FloatTensor([[6,1]])
model_test = model_BinaryClassification(x_test)
print("Model with [6,1] (expectation: 1) in sigmoid: ", model_test.detach().item())
model_test_binary = np.round(model_test>0.5).type(torch.float32)
print("Model with [6,1] (expectation: 1) in np.round: ", model_test_binary.detach().item())
```

Binary Classification Implementation (PyTorch)


```python
import torch
import torch.nn as nn
import torch.nn.functional as F
import numpy as np
x_train = torch.FloatTensor([[1,2], [2,3], [3,4], [4,4], [5,3], [6,2]])
y_train = torch.FloatTensor([[0], [0], [0], [1], [1], [1]])

class class_BinaryClassification(nn.Module):
    def __init__(self):
        super().__init__()
        self.linear1 = nn.Linear(2,3)
        self.linear2 = nn.Linear(3,1)
        self.sigmoid = nn.Sigmoid()
    def forward(self, x):
        return self.sigmoid(self.linear2(self.sigmoid(self.linear1(x))))

model_BinaryClassification = class_BinaryClassification()
optimizer = torch.optim.SGD(model_BinaryClassification.parameters(), lr=0.01)

for step in range(2000):
    prediction = model_BinaryClassification(x_train)
    cost = F.binary_cross_entropy(prediction, y_train)
    optimizer.zero_grad()
    cost.backward()
    optimizer.step()

x_test = torch.FloatTensor([[6,1]])
model_test = model_BinaryClassification(x_test)
print("Model with [6,1] (expectation: 1) in sigmoid: ", model_test.detach().item())
model_test_binary = np.round(model_test>0.5).type(torch.float32)
print("Model with [6,1] (expectation: 1) in np.round: ", model_test_binary.detach().item())
```

- TensorFlow
- PyTorch
- **Keras**

Binary Classification Implementation (Keras)



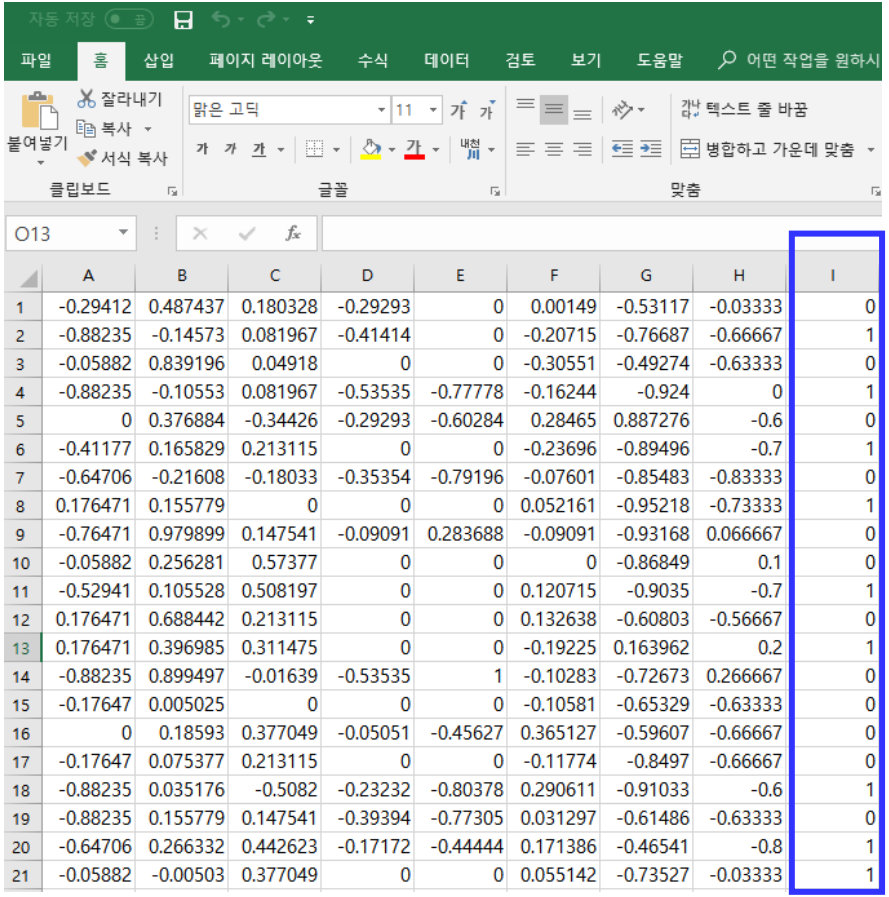

```python
import numpy as np
from keras.models import Sequential
from keras.layers import Dense

# Data
x_data = np.array([[1,2], [2,3], [3,1], [4,3], [5,3], [6,2]])
y_data = np.array([[0], [0], [0], [1], [1], [1]])
# Model, Cost, Train
model = Sequential()
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='sgd', metrics=['accuracy'])
model.fit(x_data, y_data, epochs=10000, verbose=1)
model.summary()
# Inference
print(model.get_weights())
print(model.predict(x_data))
```

Model, Cost, Train

Binary Classification Implementation (Keras)

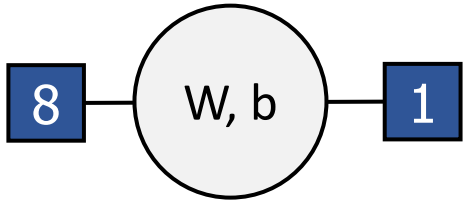

```
joongheon@joongheon-AB350M-Gaming-3: ~/Dropbox/codes_keras
6/6 [==============================] - 0s 107us/step - loss: 0.1504 - acc: 1.0000
Epoch 9992/10000
6/6 [==============================] - 0s 116us/step - loss: 0.1504 - acc: 1.0000
Epoch 9993/10000
6/6 [==============================] - 0s 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]]
```

CSV file



	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 (Keras)



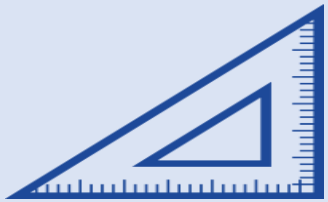

```
1  import numpy as np
2  from keras.models import Sequential
3  from keras.layers import Dense
4
5  # Data
6  xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
7  x_data = xy[:, 0:-1]
8  y_data = xy[:, [-1]]
9
10 # Model, Cost, Train
11 model = Sequential()
12 model.add(Dense(1, 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)


```
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

Advanced Topics

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

Deep Learning Basics and Software
Softmax Classification
Softmax Classification Theory

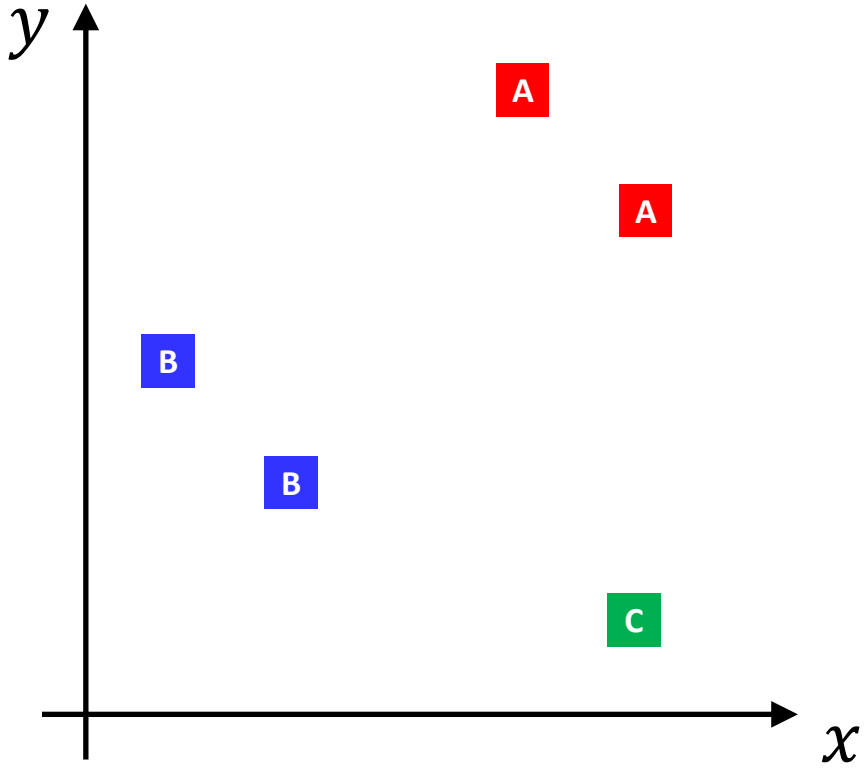
- **Softmax Classification Theory**
- Softmax Classification Implementation

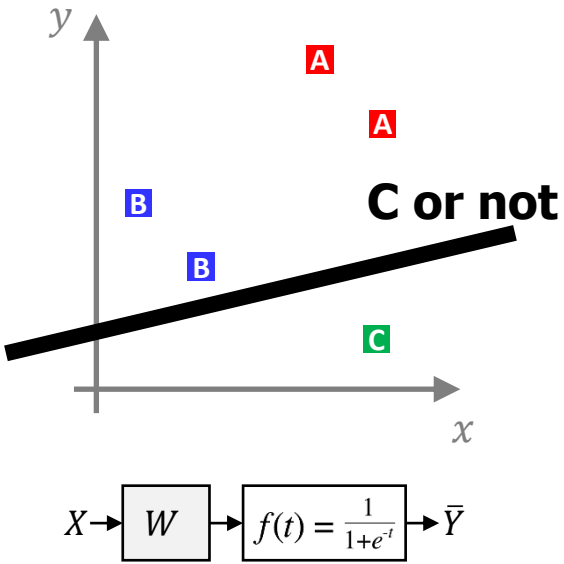
Regression (Examples)

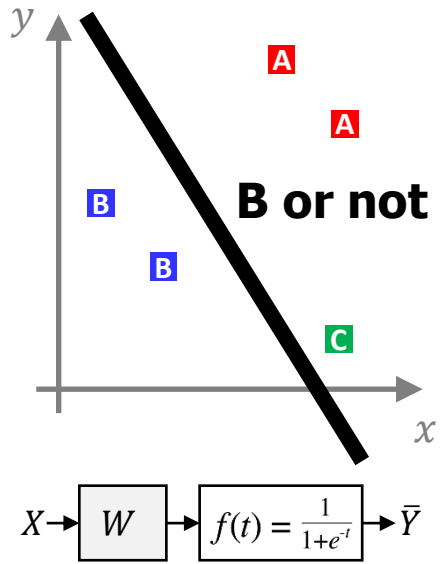
- Exam Score Prediction (Linear Regression)

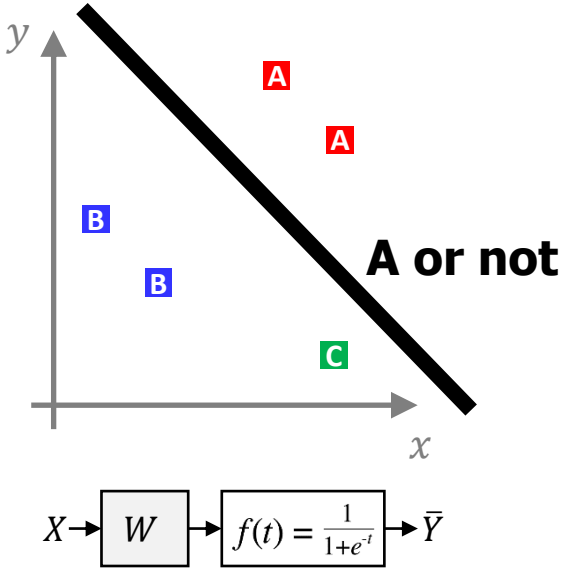
Classification (Examples)

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

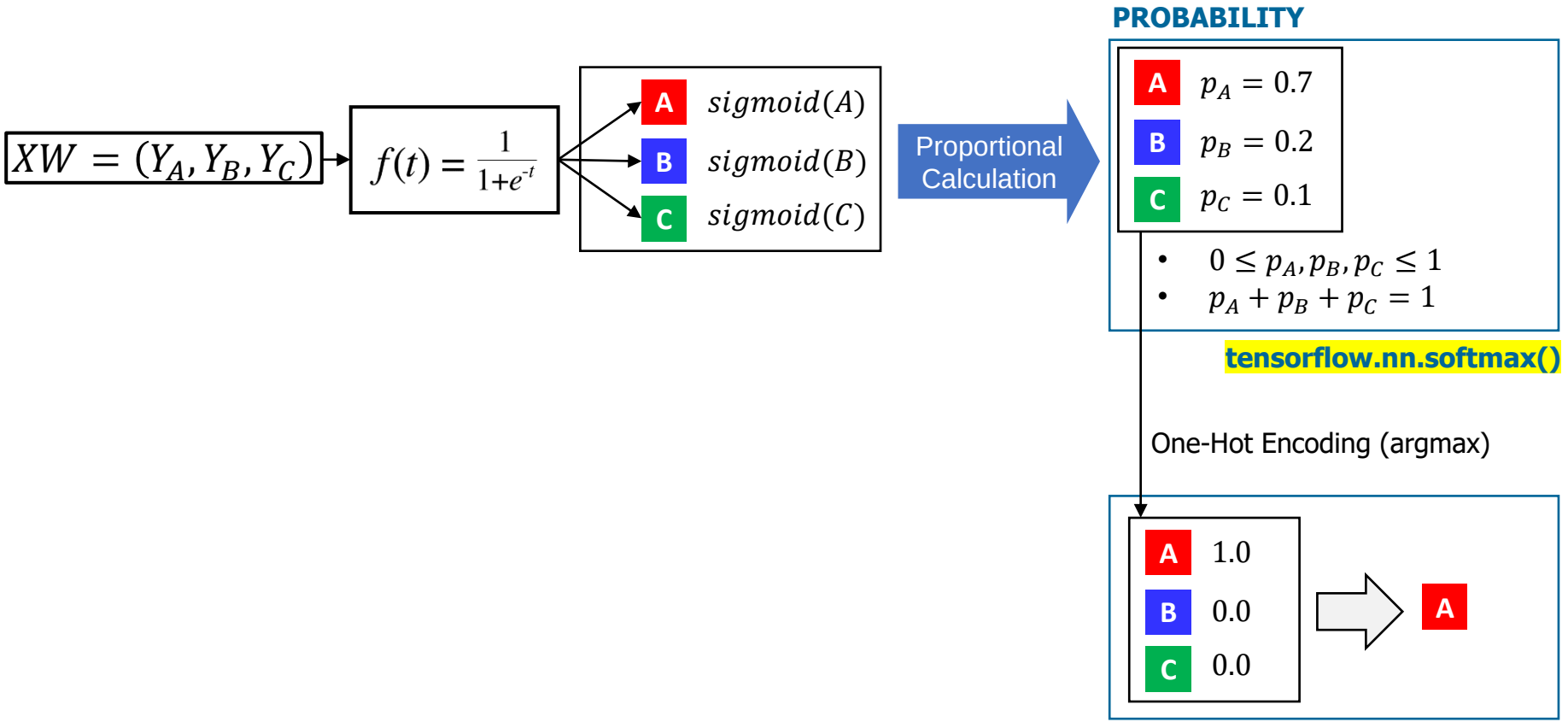

y
A
A
B
B
C
x







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


$XW = (Y_A, Y_B, Y_C)$
$f(t) = \frac{1}{1+e^{-t}}$
A $sigmoid(A)$
B $sigmoid(B)$
C $sigmoid(C)$
Proportional Calculation
PROBABILITY
A $p_A = 0.7$
B $p_B = 0.2$
C $p_C = 0.1$
$0 \le p_A, p_B, p_C \le 1$
$p_A + p_B + p_C = 1$
tensorflow.nn.softmax()
One-Hot Encoding (argmax)
A 1.0
B 0.0
C 0.0
A

- Cost Function: **Cross-Entropy**

$S(Y) = \bar{Y}$ (model)
0.7
0.2
0.1

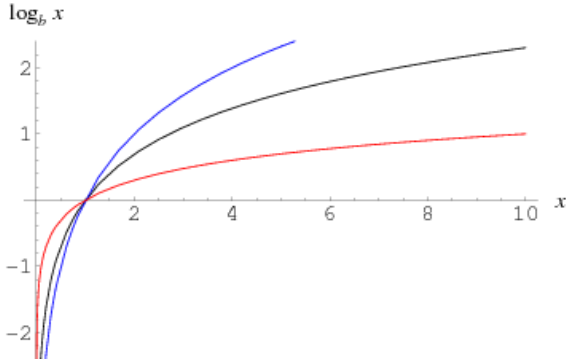
$$C(S, L) = -\sum_{\forall i} L_i \log(S_i)$$

$L = Y$ (real)
1.0
0.0
0.0

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]	$-1 \cdot \log 0 - 0 \cdot \log 0 - 0 \cdot \log 1 = \infty$

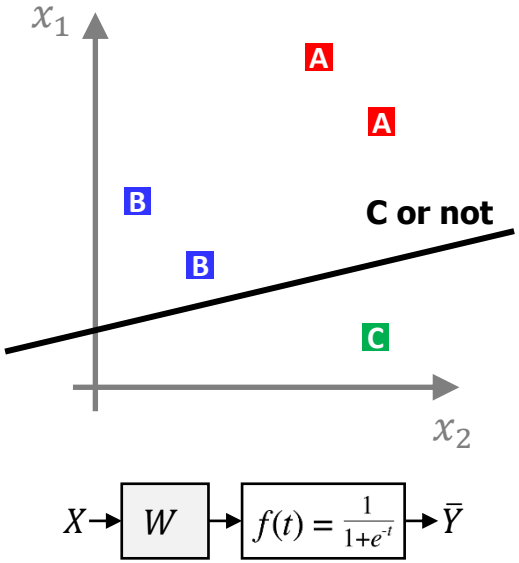
Log Function

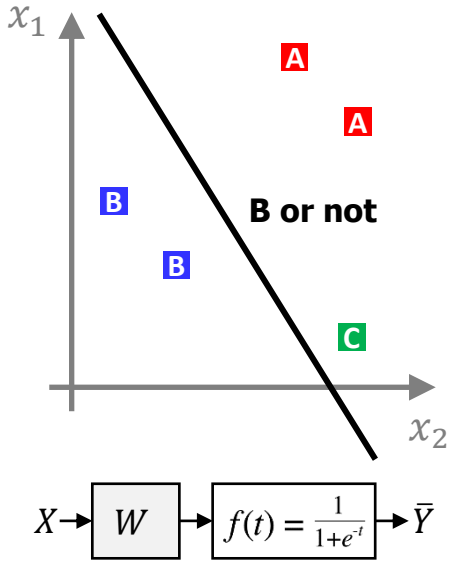


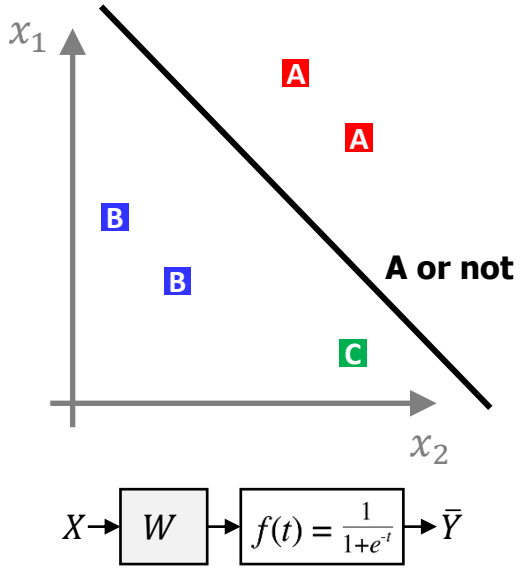
Deep Learning Basics and Software
Softmax Classification
Softmax Classification Implementation

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

- Implementation Example







- Implementation Example
  - Vector Representation

$$\begin{pmatrix} x_1 & x_2 & x_3 & x_4 \end{pmatrix} \cdot \begin{pmatrix} W_{A1} & W_{B1} & W_{C1} \\ W_{A2} & W_{B2} & W_{C2} \\ W_{A3} & W_{B3} & W_{C3} \\ W_{A4} & W_{B4} & W_{C4} \end{pmatrix} = \begin{pmatrix} S_A & S_B & S_C \end{pmatrix}$$

A B C

$$S_A \triangleq x_1 \cdot W_{A1} + x_2 \cdot W_{A2} + x_3 \cdot W_{A3} + x_4 \cdot W_{A4}$$
$$S_B \triangleq x_1 \cdot W_{B1} + x_2 \cdot W_{B2} + x_3 \cdot W_{B3} + x_4 \cdot W_{B4}$$
$$S_C \triangleq x_1 \cdot W_{C1} + x_2 \cdot W_{C2} + x_3 \cdot W_{C3} + x_4 \cdot W_{C4}$$

- **TensorFlow**
- PyTorch
- Keras

Softmax Classification Implementation (TensorFlow)


```python
import tensorflow as tf
import numpy as np
x_train = 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]], dtype=np.float32)
y_train = 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]], dtype=np.float32)
W = tf.Variable(tf.random.normal([4,3]))
b = tf.Variable(tf.random.normal([3]))

def model_SoftmaxClassificationLC(x):
    return tf.matmul(x,W)+b

def cost_SoftmaxClassification(model_x):
    return tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=model_x, labels=y_train))

def train_optimization(x):
    with tf.GradientTape() as g:
        model_LC = model_SoftmaxClassificationLC(x)
        cost = cost_SoftmaxClassification(model_LC)
    gradients = g.gradient(cost,[W,b])
    tf.optimizers.SGD(0.01).apply_gradients(zip(gradients,[W,b]))

for step in range(2001):
  train_optimization(x_train)
  if step % 100 == 0:
      pred = model_SoftmaxClassificationLC(x_train)
      loss = cost_SoftmaxClassification(pred)
      correct = tf.equal(tf.argmax(pred,1), tf.argmax(y_train,1))
      accuracy = tf.reduce_mean(tf.cast(correct,tf.float32))
      print("Step: {},\t Accurray: {},\t Loss: {}".format(step,accuracy.numpy().flatten(),loss))

print('='*100)
x_test = np.array([[1,8,8,8]],dtype=np.float32)
model_test = tf.nn.softmax(model_SoftmaxClassificationLC(x_test))
print("model for [1,8,8,8]: ", tf.argmax(model_test,1).numpy())
print('='*100)
```

- TensorFlow
- **PyTorch**
- Keras

Softmax Classification Implementation (PyTorch)

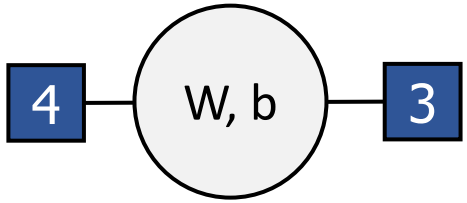

```python
import torch
import torch.nn as nn
import torch.nn.functional as F
import numpy as np
x_train = torch.FloatTensor([[1,2,1,1], [2,1,3,2], [3,1,3,4], [4,1,5,5], [1,7,5,5], [1,2,5,6], [1,6,6,6], [1,7,7,7]])
y_train = torch.FloatTensor([[0,0,1], [0,0,1], [0,0,1], [0,1,0], [0,1,0], [0,1,0], [1,0,0], [1,0,0]])
index_y = torch.argmax(y_train,1)
W = torch.randn([4,3], requires_grad=True)
b = torch.randn([3], requires_grad=True)
optimizer = torch.optim.SGD([W, b], lr=0.01)

def model_SoftmaxClassification(x):
    return F.softmax(torch.matmul(x, W) + b)

for step in range(50000):
    prediction = model_SoftmaxClassification(x_train)
    cost = F.cross_entropy(prediction, index_y)
    optimizer.zero_grad()
    cost.backward()
    optimizer.step()

x_test = torch.FloatTensor([[1,8,8,8]])
model_test = model_SoftmaxClassification(x_test)
index = torch.argmax(model_test.detach(),1).item()
if index == 0:
    print("Model with [1,8,8,8] is A.")
elif index == 1:
    print("Model with [1,8,8,8] is B.")
elif index == 2:
    print("Model with [1,8,8,8] is C.")
```

Softmax Classification Implementation (PyTorch)


```python
import torch
import torch.nn as nn
import torch.nn.functional as F
import numpy as np
x_train = torch.FloatTensor([[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]])
y_train = torch.FloatTensor([[0,0,1], [0,0,1], [0,0,1], [0,1,0], [0,1,0], [0,1,0], [1,0,0], [1,0,0]])
index_y = torch.argmax(y_train,1)

class class_SoftmaxClassification(nn.Module):
    def __init__(self):
        super().__init__()
        self.linear = nn.Linear(4,3)
    def forward(self, x):
        return F.softmax(self.linear(x))

model_SoftmaxClassification = class_SoftmaxClassification()
optimizer = torch.optim.SGD(model_SoftmaxClassification.parameters(), lr=0.01)

for step in range(50000):
    prediction = model_SoftmaxClassification(x_train)
    cost = F.cross_entropy(prediction, index_y)
    optimizer.zero_grad()
    cost.backward()
    optimizer.step()

x_test = torch.FloatTensor([[1,8,8,8]])
model_test = model_SoftmaxClassification(x_test)
index = torch.argmax(model_test.detach(),1)
if index == 0:
    print("Model with [1,8,8,8] is A.")
elif index == 1:
    print("Model with [1,8,8,8] is B.")
elif index == 2:
    print("Model with [1,8,8,8] is C.")
```

- TensorFlow
- PyTorch
- **Keras**

Softmax Classification Implementation (Keras)




```python
import numpy as np
from keras.models import Sequential
from keras.layers import Dense

# Data
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]])
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]])

# Model, Cost, Train
model = Sequential()
model.add(Dense(3, activation='softmax'))
model.compile(loss='categorical_crossentropy', optimizer='sgd', metrics=['accuracy'])
model.fit(x_data, y_data, epochs=10000, verbose=1)
model.summary()
# Inference
y_predict = model.predict(np.array([[1,11,7,9]]))
print(y_predict)
print("argmax: ", np.argmax(y_predict))
```

Model, Cost, Train

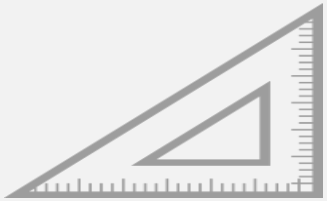
```
joongheon@joongheon-AB350M-Gaming-3: ~/Dropbox/codes_keras
8/8 [==============================] - 0s 96us/step - loss: 0.2581 - acc: 1.0000
Epoch 9989/10000
8/8 [==============================] - 0s 89us/step - loss: 0.2581 - acc: 1.0000
Epoch 9990/10000
8/8 [==============================] - 0s 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

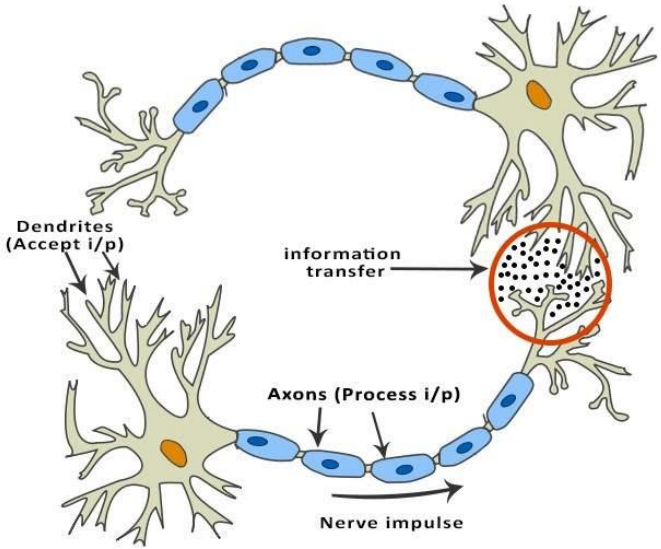
Advanced Topics

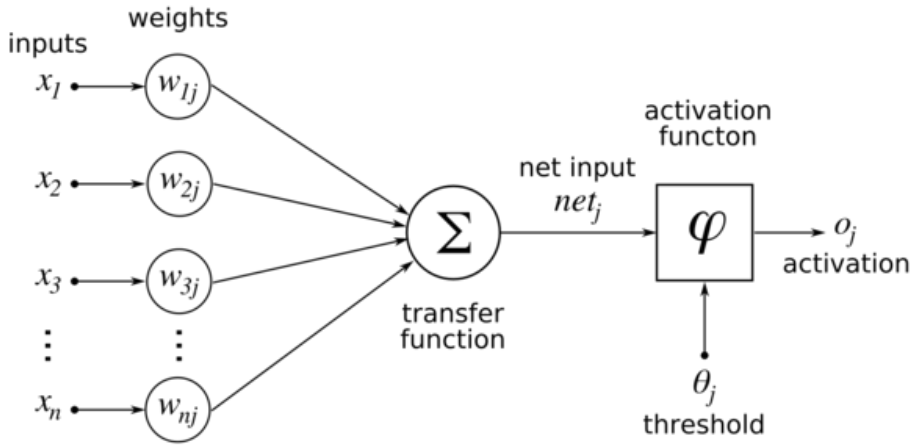
Gen. Adv. Network (GAN)
Interpolation
PCA/LDA
Overfitting

Deep Learning Basics and Software
Artificial Neural Networks (ANN)
ANN Theory

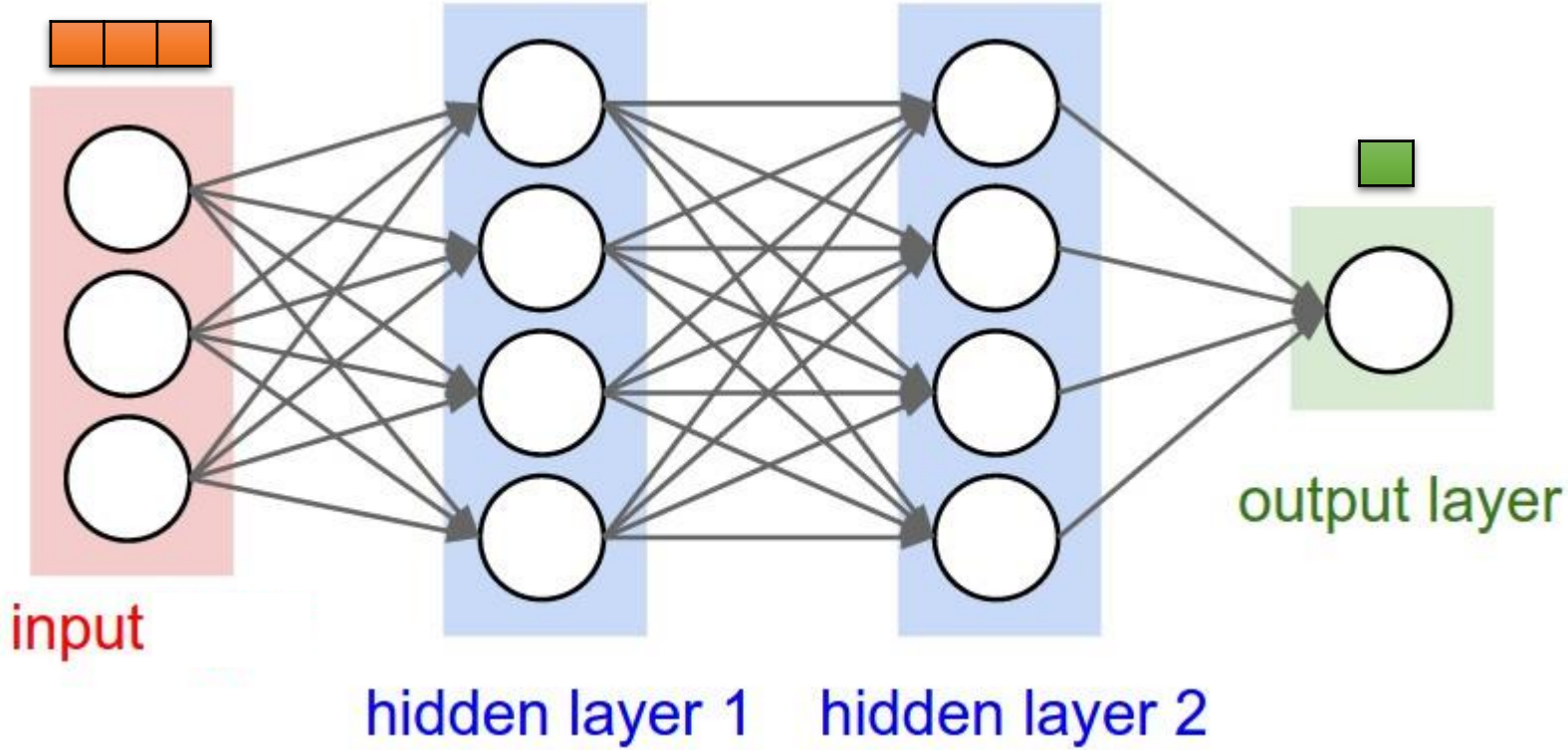
- **ANN Theory**
- ANN Implementation

- Human Brain (Neuron)



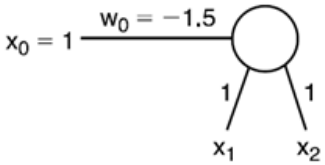


Binary Classification

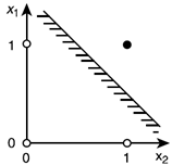

input
hidden layer 1
hidden layer 2
output layer

- Application to Logic Gate Design

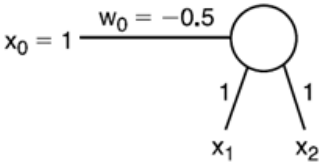
AND gate



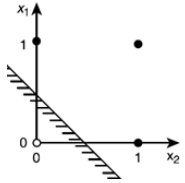
x_1	x_2	$W \cdot X$	y
0	0	−1.5	0
0	1	−0.5	0
1	0	−0.5	0
1	1	0.5	1



OR gate

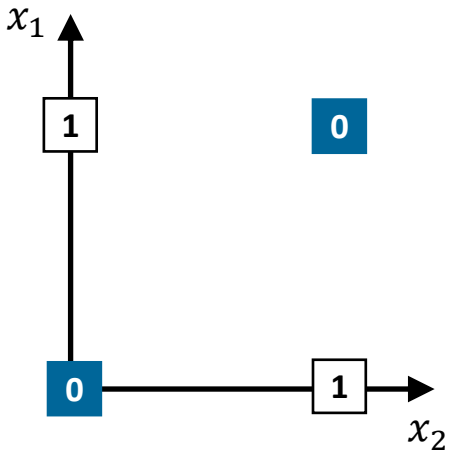


x_1	x_2	$W \cdot X$	y
0	0	−0.5	0
0	1	0.5	1
1	0	0.5	1
1	1	1.5	1



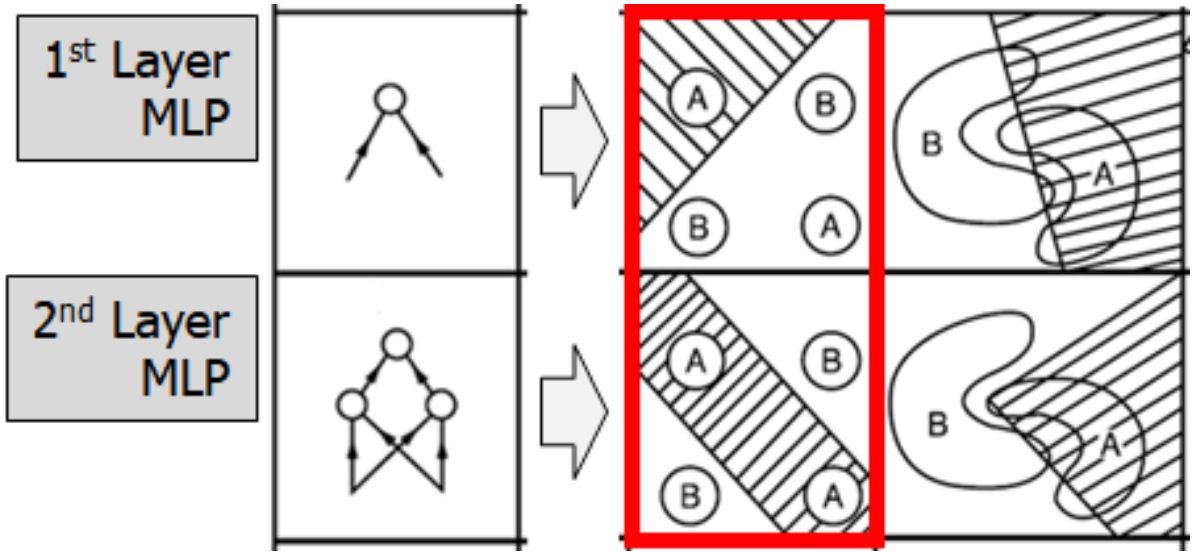
- **What about XOR?**

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

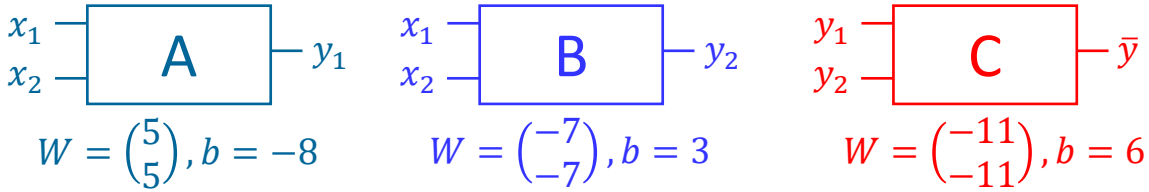


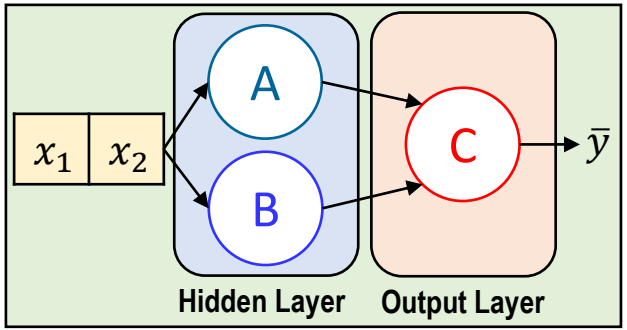
Mathematically proven by
Prof. Marvin Minsky at MIT (1969)

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

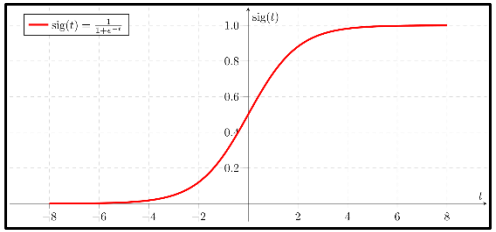


ANN: Solving XOR with MLP



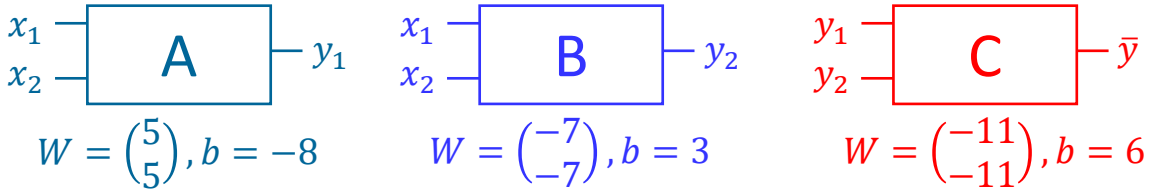


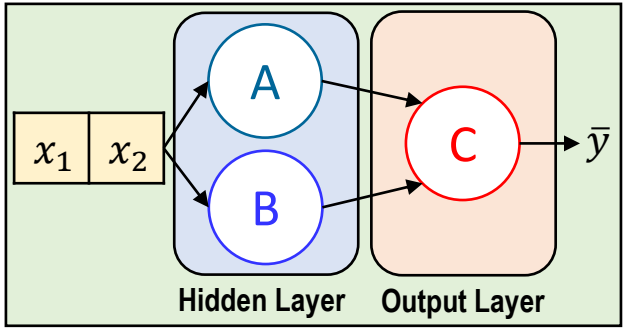
- $(x_1\ x_2) = (0\ 0)$
  - $(0\ 0)\begin{pmatrix} 5 \\ 5 \end{pmatrix} + (-8) = -8$, i.e., $y_1 = Sigmoid(-8) \cong 0$
  - $(0\ 0)\begin{pmatrix} -7 \\ -7 \end{pmatrix} + (3) = 3$, i.e., $y_2 = Sigmoid(3) \cong 1$
  - $(y_1\ y_2)\begin{pmatrix} -11 \\ -11 \end{pmatrix} + (6) = -11 + 6 = -5$, i.e., $\bar{y}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



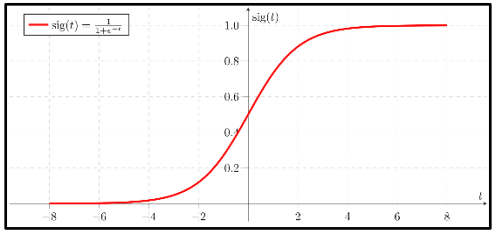
x_1	x_2	y_1	y_2	$\bar{y}$	XOR
0	0	**0**	**1**	**0**	**0**
0	1				**1**
1	0				**1**
1	1				**0**

ANN: Solving XOR with MLP



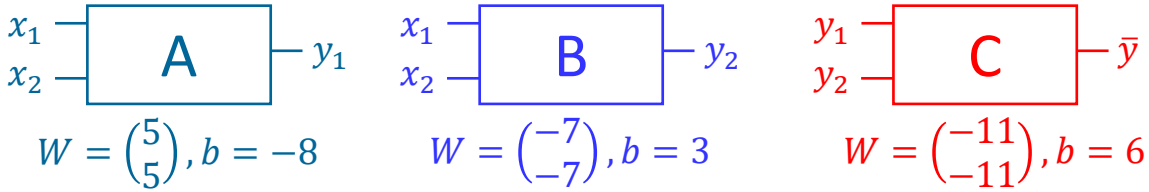


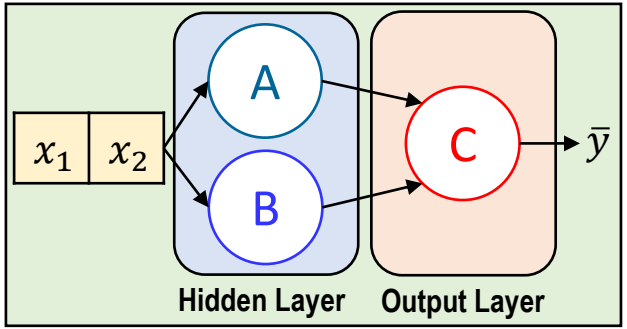
- $(x_1\ x_2) = (0\ 1)$
  - $(0\ 1)\begin{pmatrix} 5 \\ 5 \end{pmatrix} + (-8) = -3$, i.e., $y_1 = Sigmoid(-3) \cong 0$
  - $(0\ 1)\begin{pmatrix} -7 \\ -7 \end{pmatrix} + (3) = -4$, i.e., $y_2 = Sigmoid(-4) \cong 0$
  - $(y_1\ y_2)\begin{pmatrix} -11 \\ -11 \end{pmatrix} + (6) = 6$, i.e., $\bar{y} =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



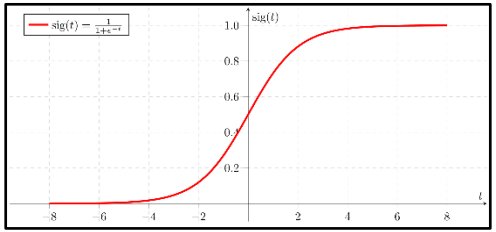
x_1	x_2	y_1	y_2	$\bar{y}$	XOR
0	0	**0**	**1**	**0**	**0**
0	1	**0**	**0**	**1**	**1**
1	0				**1**
1	1				**0**

ANN: Solving XOR with MLP



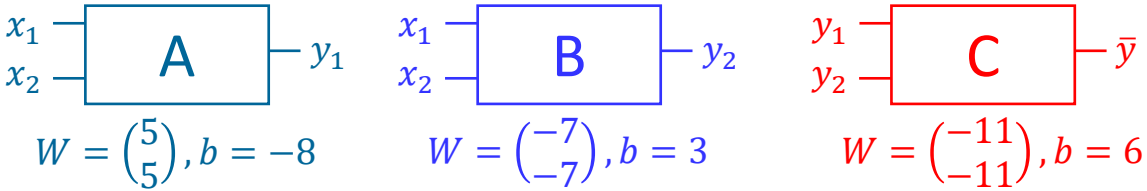


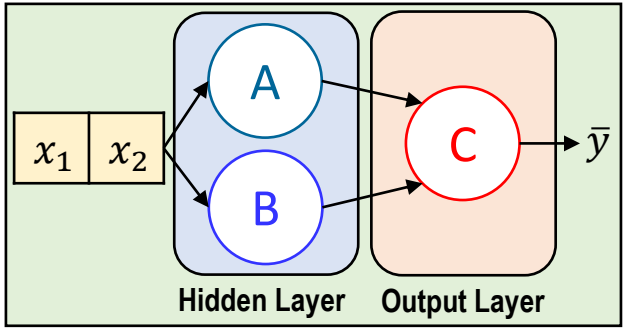
- $(x_1\ x_2) = (1\ 0)$
  - $(1\ 0)\begin{pmatrix} 5 \\ 5 \end{pmatrix} + (-8) = -3$, i.e., $y_1 = Sigmoid(-3) \cong 0$
  - $(1\ 0)\begin{pmatrix} -7 \\ -7 \end{pmatrix} + (3) = -4$, i.e., $y_2 = Sigmoid(-4) \cong 0$
  - $(y_1\ y_2)\begin{pmatrix} -11 \\ -11 \end{pmatrix} + (6) = 6$, i.e., $\bar{y} =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



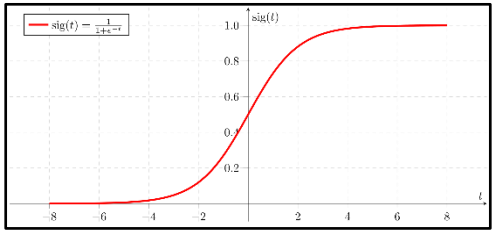
x_1	x_2	y_1	y_2	$\bar{y}$	XOR
0	0	**0**	**1**	**0**	**0**
0	1	**0**	**0**	**1**	**1**
1	0	**0**	**0**	**1**	**1**
1	1				**0**

ANN: Solving XOR with MLP



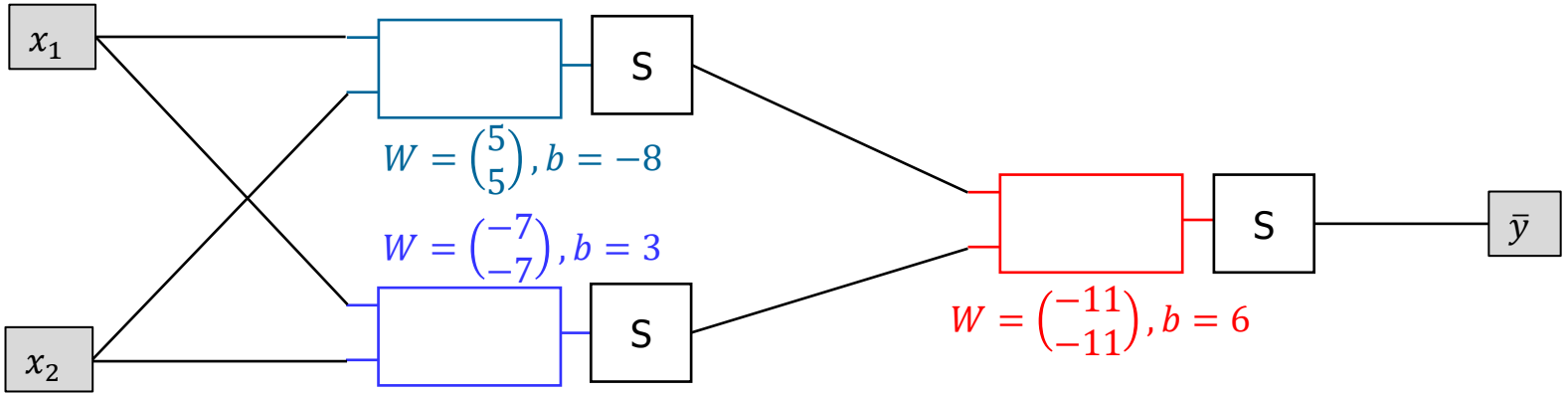


- $(x_1\ x_2) = (1\ 1)$
  - $(1\ 1)\begin{pmatrix} 5 \\ 5 \end{pmatrix} + (-8) = 2$, i.e., $y_1 = Sigmoid(2) \cong 1$
  - $(1\ 1)\begin{pmatrix} -7 \\ -7 \end{pmatrix} + (3) = -11$, i.e., $y_2 = Sigmoid(-11) \cong 0$
  - $(y_1\ y_2)\begin{pmatrix} -11 \\ -11 \end{pmatrix} + (6) = -5$, i.e., $\bar{y}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



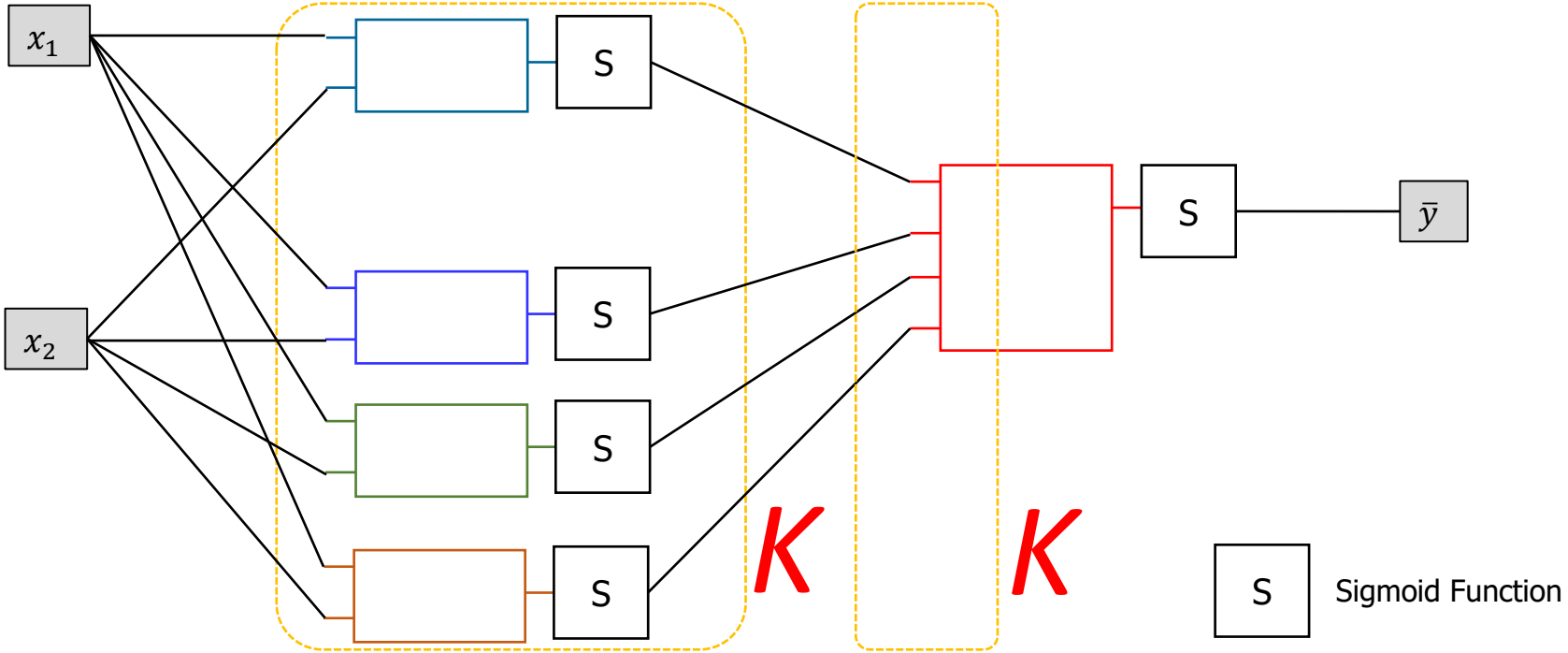
x_1	x_2	y_1	y_2	$\bar{y}$	XOR
0	0	0	1	0	0
0	1	0	0	1	1
1	0	0	0	1	1
1	1	1	0	0	0

ANN: Solving XOR with MLP (Forward Propagation)

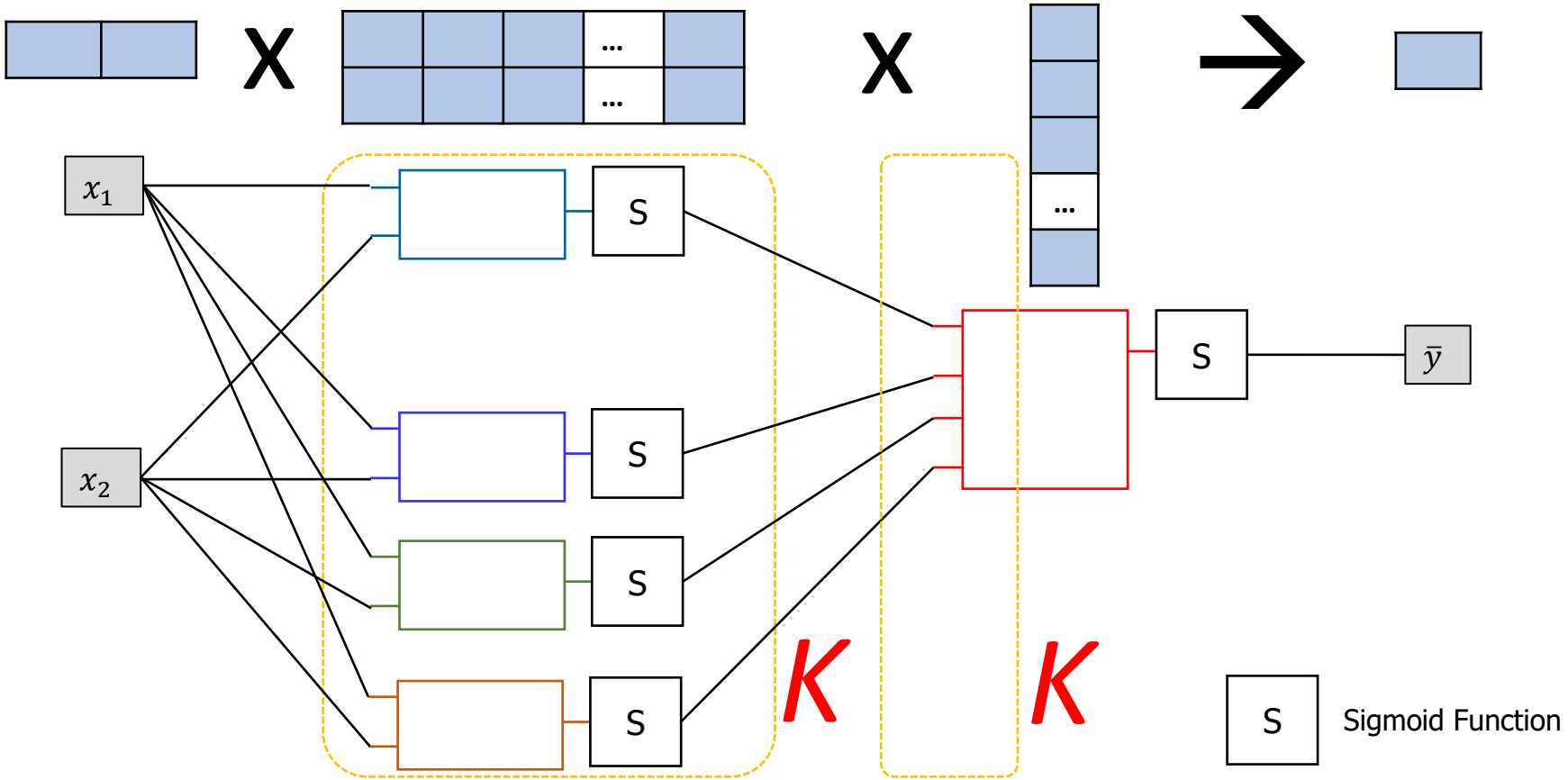


S Sigmoid Function

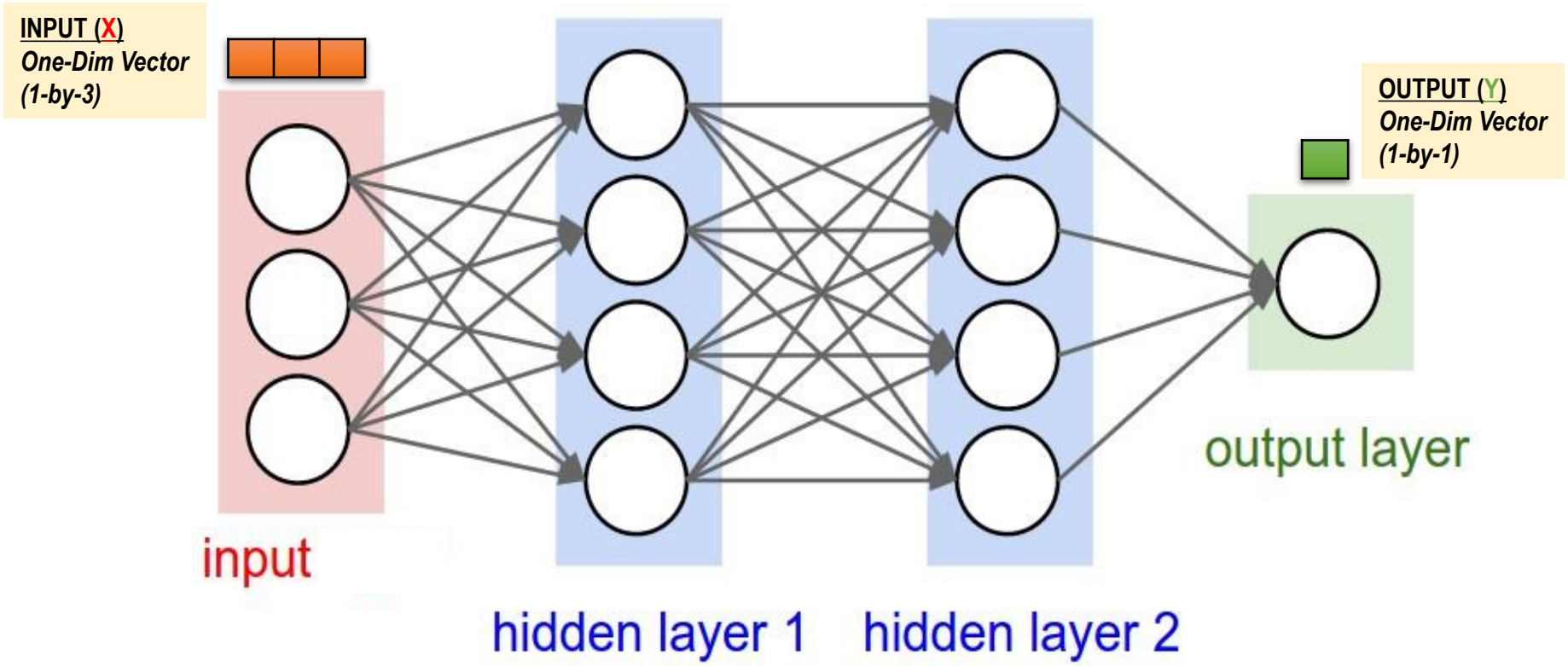
ANN: Solving XOR with MLP (Forward Propagation)



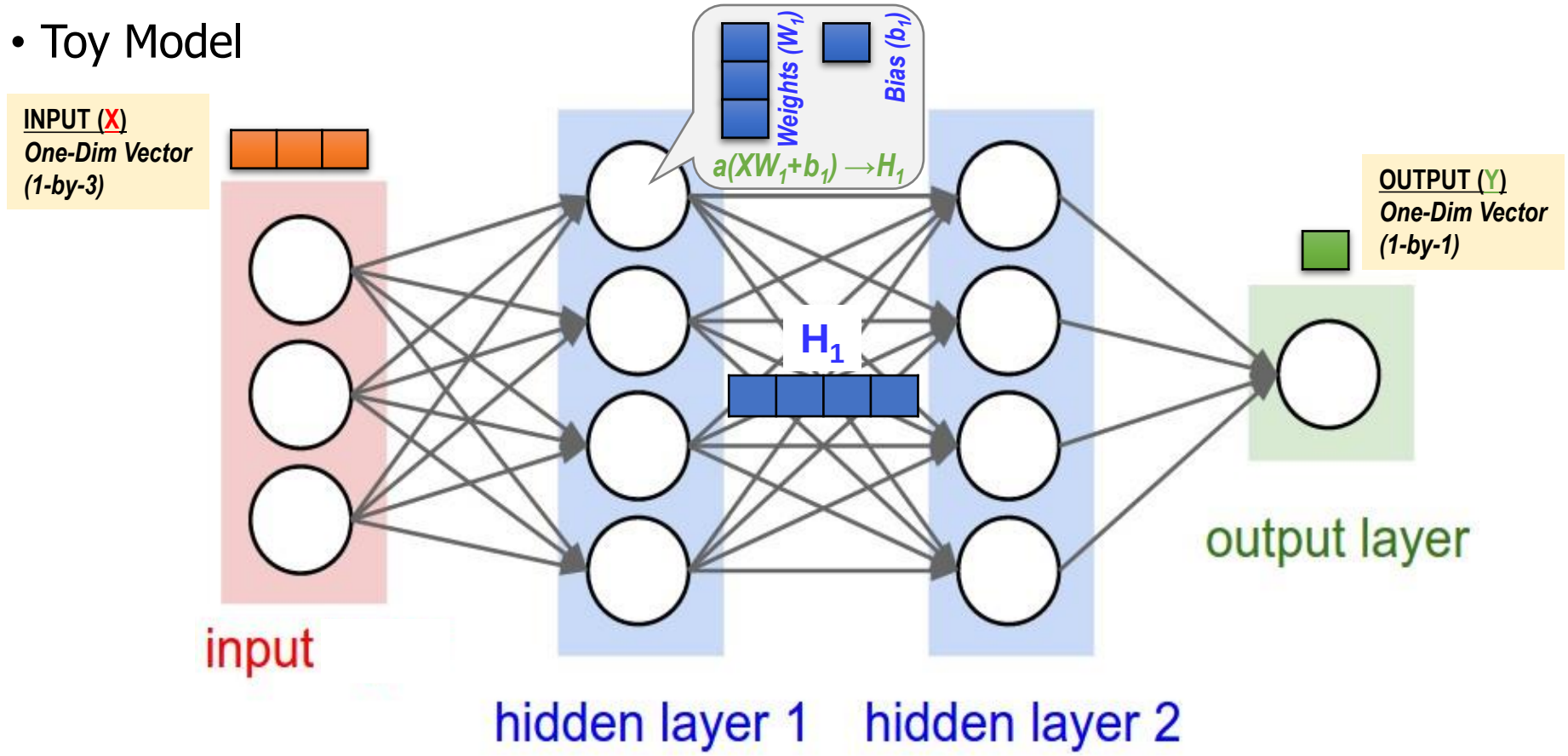
ANN: Solving XOR with MLP (Forward Propagation)



- Toy Model

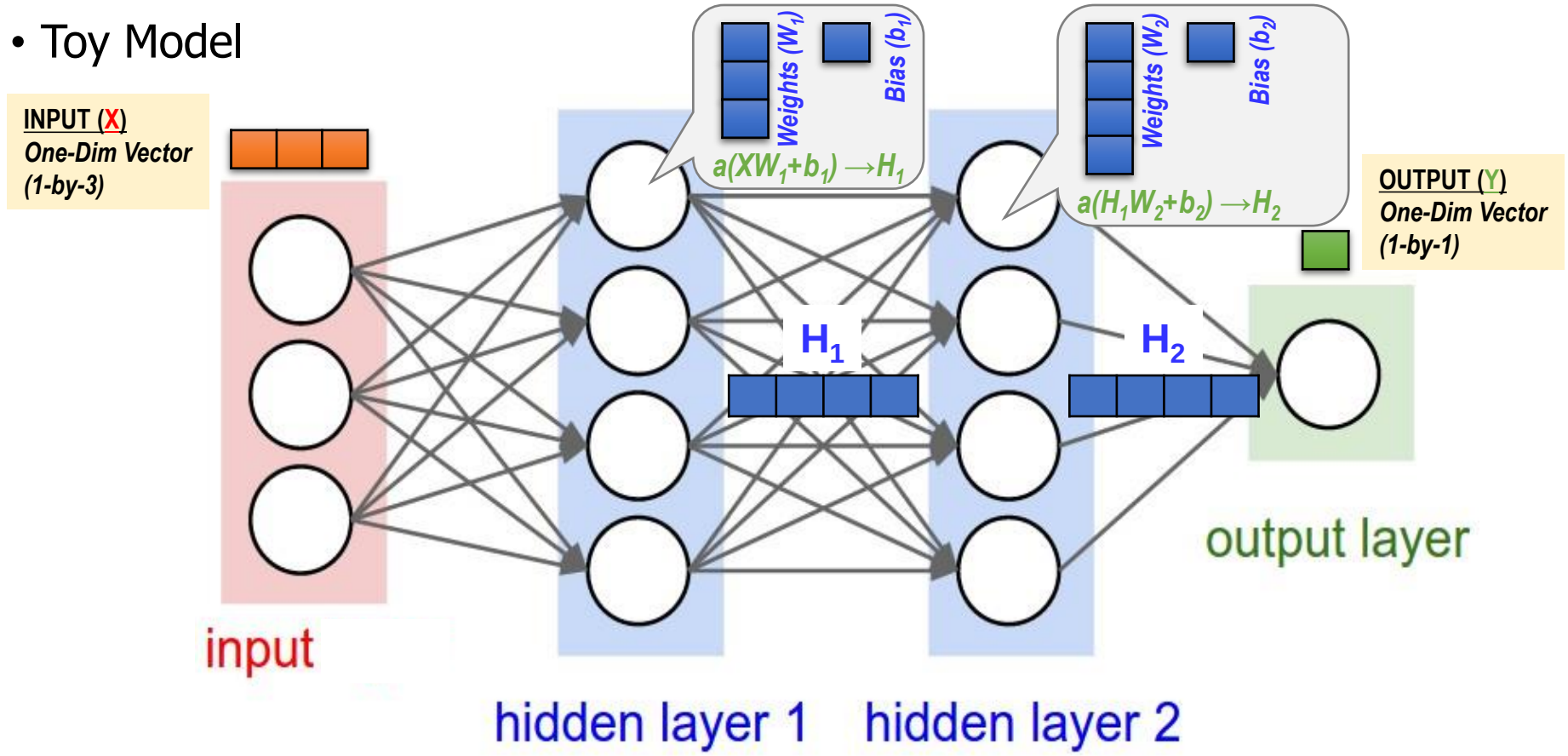

INPUT (X)
One-Dim Vector
(1-by-3)
OUTPUT (Y)
One-Dim Vector
(1-by-1)
input
hidden layer 1
hidden layer 2
output layer

- Toy Model


INPUT (X)
One-Dim Vector
(1-by-3)
Weights (W_1)
Bias (b_1)
$a(XW_1+b_1) \rightarrow H_1$
H_1
OUTPUT (Y)
One-Dim Vector
(1-by-1)
input
hidden layer 1
hidden layer 2
output layer

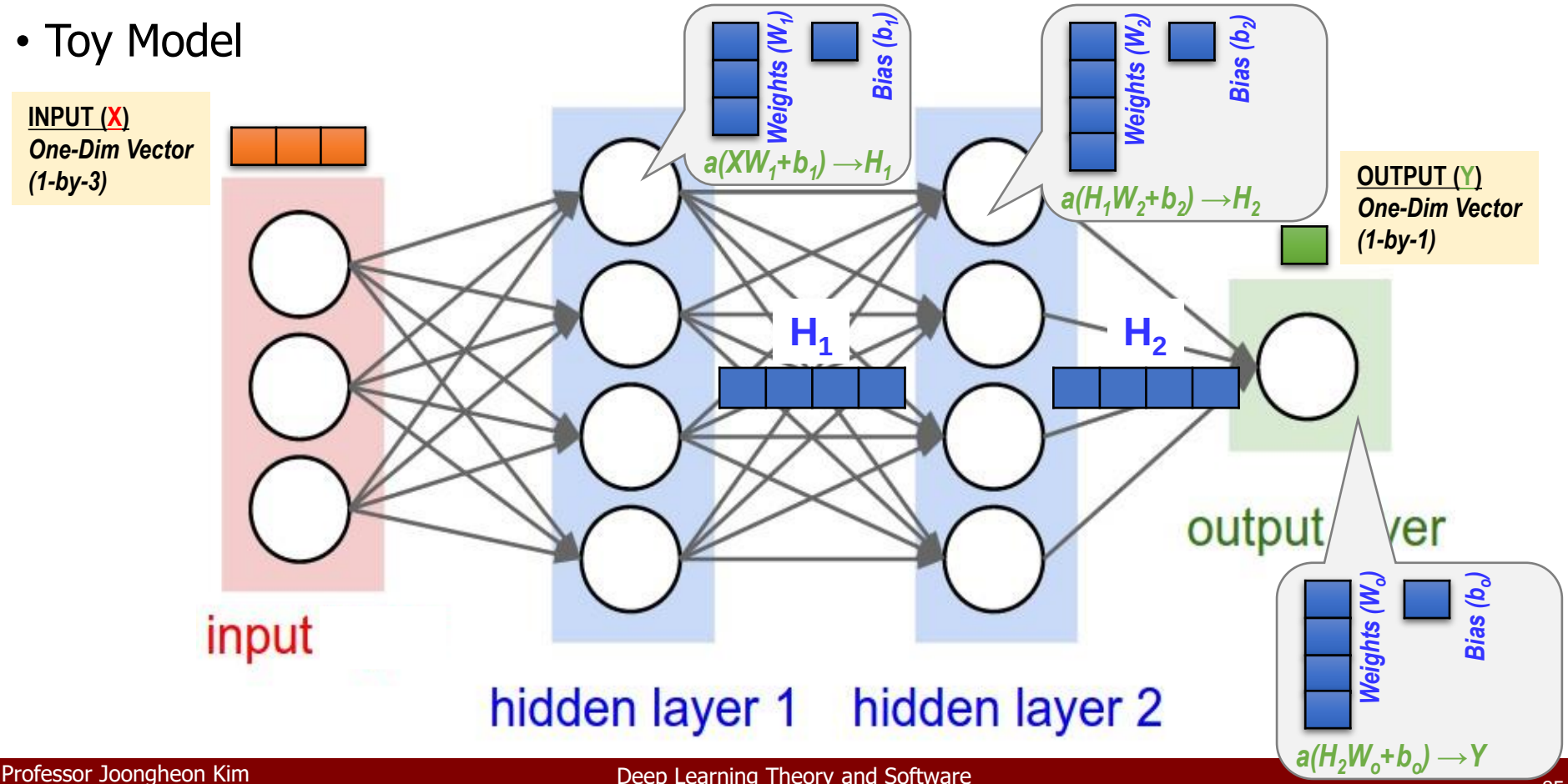
Conventional Deep Neural Network Training and Inference

- Toy Model



Conventional Deep Neural Network Training and Inference

- Toy Model



TensorFlow for ANN (XOR with ANN)

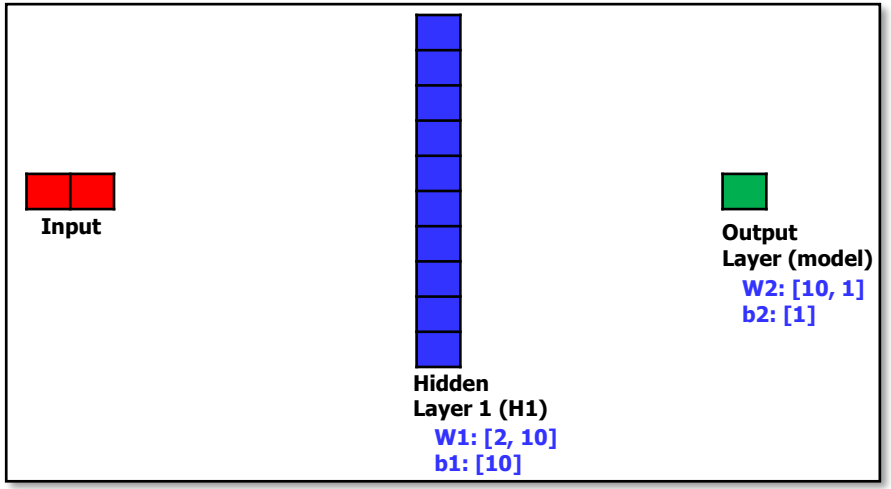
```python
#TensorFlow for ANN (XOR with ANN)
import tensorflow as tf
import numpy as np

x_train = np.array([[0,0], [0,1], [1,0], [1,1]], dtype=np.float32)
y_train = np.array([[0], [1], [1], [0]], dtype=np.float32)
W_h = tf.Variable(tf.random.normal([2,3]))
b_h =tf.Variable(tf.random.normal([3]))
W_o = tf.Variable(tf.random.normal([3,1]))
b_o =tf.Variable(tf.random.normal([1]))
train_step = 10001

def model_ANN_XOR(x):
  H1 = tf.sigmoid(tf.matmul(x,W_h)+b_h)
  return tf.sigmoid(tf.matmul(H1,W_o)+b_o)

def cost_ANN_XOR(model_x):
  return tf.reduce_mean((-1)*y_train*tf.math.log(model_x)+(-1)*(1.-y_train)*tf.math.log(1.-model_x))

def train_optimization(x):
  with tf.GradientTape() as g:
    model = model_ANN_XOR(x)
    cost = cost_ANN_XOR(model)
  gradients = g.gradient(cost,[W_h,W_o,b_h,b_o])
  tf.optimizers.SGD(0.1).apply_gradients(zip(gradients,[W_h,W_o,b_h,b_o]))

for step in range(train_step):
    train_optimization(x_train)

print('='*150)
x_test = np.array([[1,0],[0,1],[1,1],[0,0]], dtype = np.float32)
y_test = np.array([[1],[1],[0],[0]], dtype = np.float32)
model_test = model_ANN_XOR(x_test)
test_prediction = tf.cast(model_test > 0.5, dtype=tf.float32)
test_accuracy = tf.reduce_mean(tf.cast(tf.equal(test_prediction, y_test), dtype=tf.float32))
print("Test_Accurray: ", test_accuracy.numpy())
print('='*150)
```

PyTorch for ANN (XOR with ANN)

```
1  import torch
2  import numpy as np
3  x_train = torch.FloatTensor([[0,0], [0,1], [1,0], [1,1]])
4  y_train = torch.FloatTensor([[0], [1], [1], [0]])
5  W_h = torch.randn([2,3], requires_grad=True)
6  b_h = torch.randn([3], requires_grad=True)
7  W_o = torch.randn([3,1], requires_grad=True)
8  b_o = torch.randn([1], requires_grad=True)
9  optimizer = torch.optim.SGD([W_h, b_h, W_o, b_o], lr=0.01)
10
11 def model_ANN(x):
12     HL1 = torch.sigmoid(torch.matmul(x, W_h) + b_h)
13     Out = torch.sigmoid(torch.matmul(HL1, W_o) + b_o)
14     return Out
15
16 for step in range(200000):
17     prediction = model_ANN(x_train)
18     cost = torch.mean((-1)*y_train*torch.log(prediction)+(-1)*(1-y_train)*torch.log(1-prediction))
19     optimizer.zero_grad()
20     cost.backward()
21     optimizer.step()
22
23 model_test = model_ANN(x_train)
24 print(model_test.detach().numpy())
```

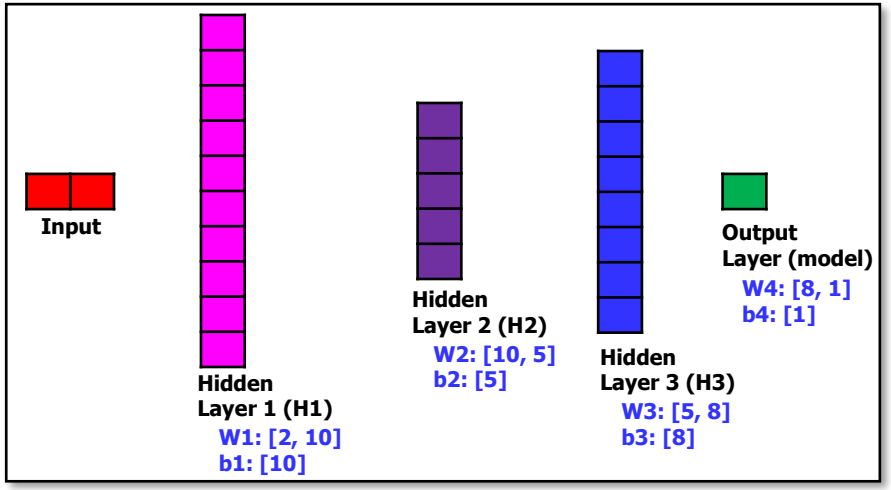
- **Wide** ANN for XOR

```
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)
```

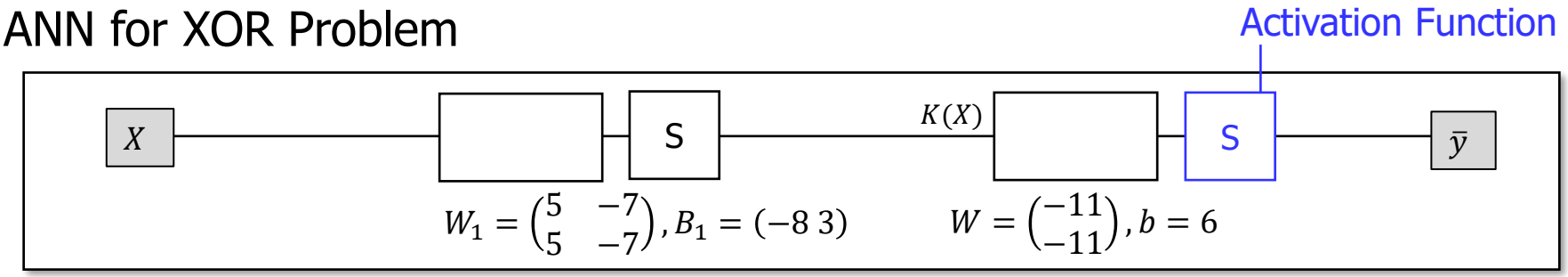


- **Deep** ANN for XOR

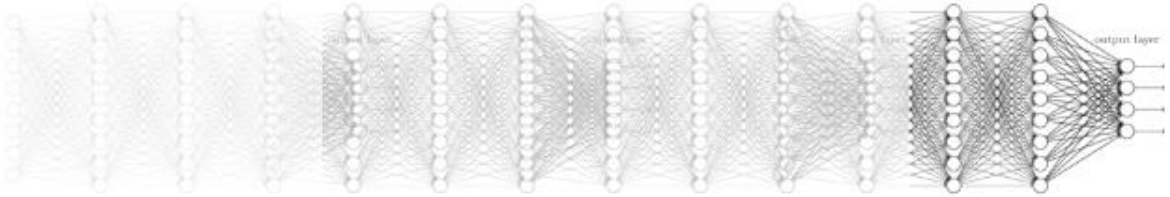
```
W1 = tf.Variable(tf.random_normal([2, 10]))
b1 = tf.Variable(tf.random_normal([10]))
H1 = tf.sigmoid(tf.matmul(X, W1) + b1)

W2 = tf.Variable(tf.random_normal([10, 5]))
b2 = tf.Variable(tf.random_normal([5]))
H2 = tf.sigmoid(tf.matmul(H1, W2) + b2)

W3 = tf.Variable(tf.random_normal([5, 8]))
b3 = tf.Variable(tf.random_normal([8]))
H3 = tf.sigmoid(tf.matmul(H2, W3) + b3)

W4 = tf.Variable(tf.random_normal([8, 1]))
b4 = tf.Variable(tf.random_normal([1]))
model = tf.sigmoid(tf.matmul(H3, W4) + b4)
```



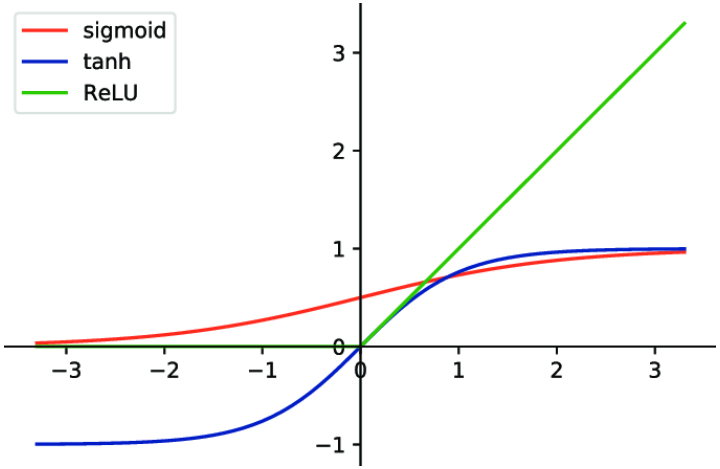
- ANN for XOR Problem

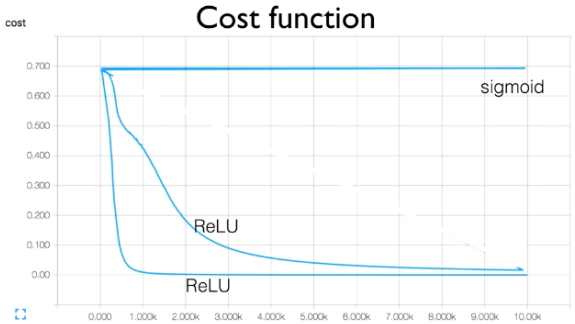


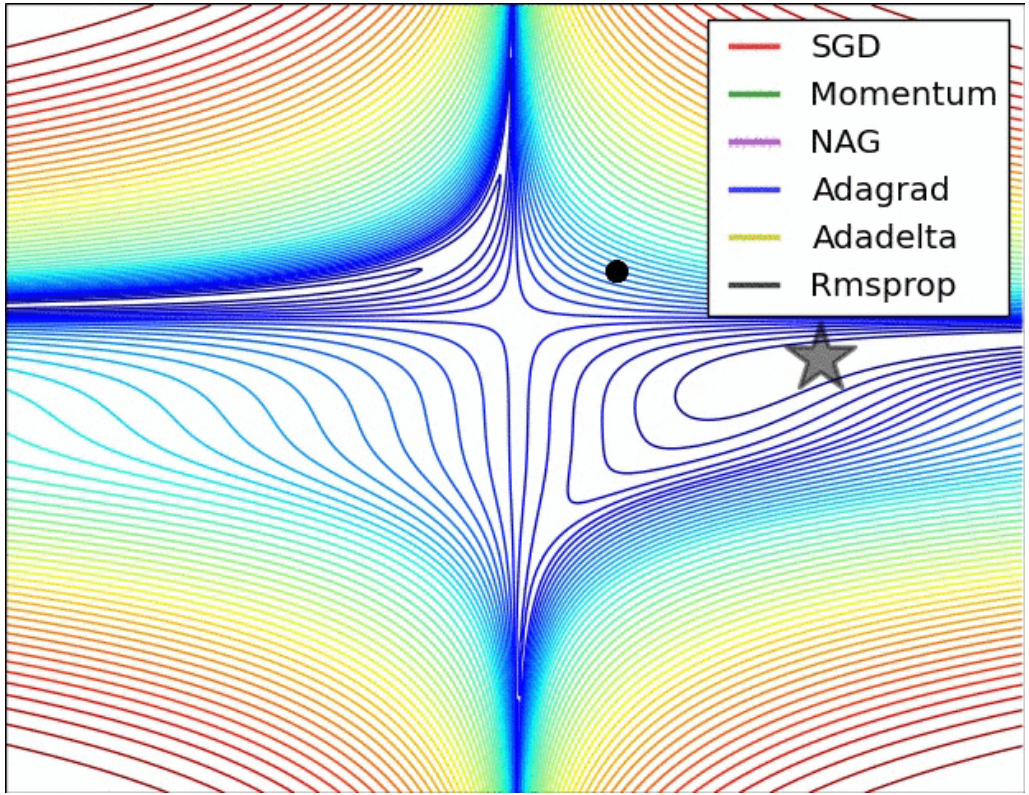
- Observation)
  - There exists cases when the accuracy is low even if the # layers is high. Why?
  - Answer)
    - The result of one ANN is the result of sigmoid function (**between 0 and 1**).
    - The numerous multiplication of this result converges to near zero.
      → **Gradient Vanishing Problem**



ANN: ReLU (Rectified Linear Unit)







- Deep Learning Revolution is Real

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

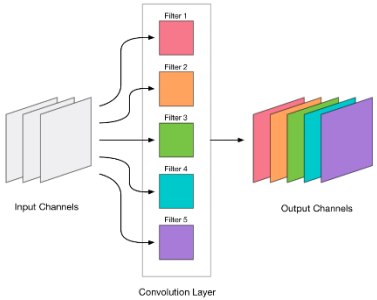
IMAGENET
14.2 million images

Big-Data

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

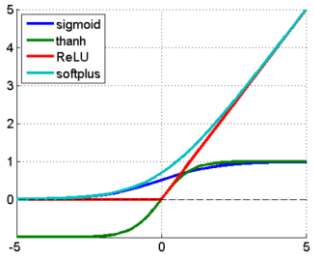
GPU

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

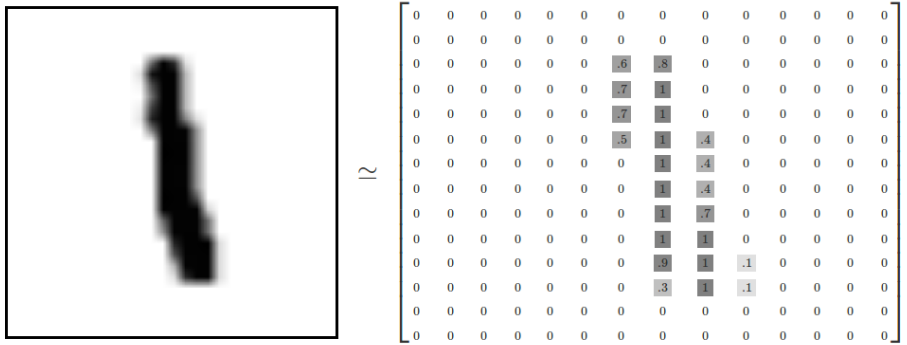
Deep Learning Theory and Software
Artificial Neural Networks (ANN)
ANN Implementation

- ANN Theory
- **ANN Implementation**

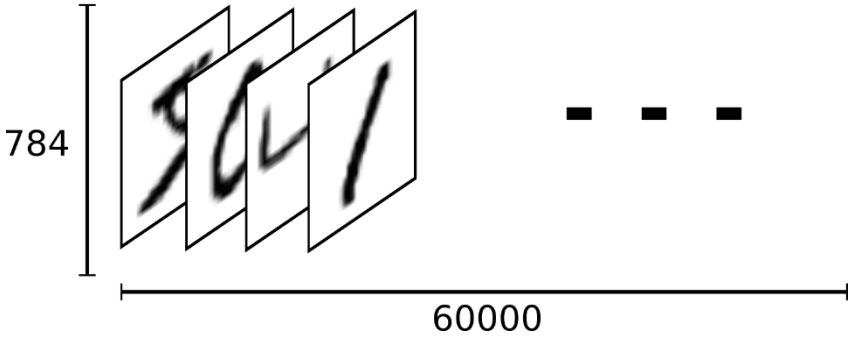
- MNIST Data Set
  - Hand-written images and their labels
    - For training: 55,000 (or 60,000)
    - For testing: 10,000

[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’

  - Image: 28-by-28 (pixels)



mnist.train.xs



- **TensorFlow**
- PyTorch
- Keras

ANN Implementation (TensorFlow)


```python
import tensorflow as tf
import numpy as np
import torch.nn as nn
from tensorflow.keras.datasets import mnist

batch_size = 128
nH1 = 256
nH2 = 256
nH3 = 256

(x_train, y_train), (x_test, y_test) =  mnist.load_data()
x_train, x_test = x_train.astype('float32'), x_test.astype('float32')
x_train, x_test = x_train.reshape([-1, 784]), x_test.reshape([-1, 784])
x_train, x_test = x_train / 255., x_test / 255.
y_train, y_test = tf.one_hot(y_train, depth=10), tf.one_hot(y_test, depth=10)
train_data = tf.data.Dataset.from_tensor_slices((x_train, y_train))
train_data = train_data.repeat().shuffle(5000).batch(batch_size)

class ANN(nn.Module):
  def __init__(self):
    self.W_1 = tf.Variable(tf.random.normal(shape=[784, nH1]))
    self.W_2 = tf.Variable(tf.random.normal(shape=[nH1, nH2]))
    self.W_3 = tf.Variable(tf.random.normal(shape=[nH2, nH3]))
    self.W_Out = tf.Variable(tf.random.normal(shape=[nH3, 10]))
    self.b_1 = tf.Variable(tf.random.normal(shape=[nH1]))
    self.b_2 = tf.Variable(tf.random.normal(shape=[nH2]))
    self.b_3 = tf.Variable(tf.random.normal(shape=[nH3]))
    self.b_Out = tf.Variable(tf.random.normal(shape=[10]))

  def __call__(self, x):
    # pytorch에서는 __forward__ tensor에서는 __call__ 사용
    H1_Out = tf.nn.relu(tf.matmul(x, self.W_1) + self.b_1)
    H2_Out = tf.nn.relu(tf.matmul(H1_Out, self.W_2) + self.b_2)
    H3_Out = tf.nn.relu(tf.matmul(H2_Out, self.W_3) + self.b_3)
    Out = tf.matmul(H2_Out, self.W_Out) + self.b_Out
    return Out
```

ANN Implementation (TensorFlow)

```
38  ANN_model = ANN()
39  optimizer = tf.optimizers.Adam(0.01)
40
41  def cost_ANN_mnist(x,y):
42      y = tf.cast(y, tf.int64)
43      loss = tf.nn.softmax_cross_entropy_with_logits(logits=x,labels=y)
44      return tf.reduce_mean(loss)
45
46  def accuracy(x,y):
47    correct = tf.equal(tf.argmax(x,1), tf.argmax(y,1))
48    accuracy = tf.reduce_mean(tf.cast(correct, tf.float32))
49    return accuracy
50
51  def train_optimization(x,y):
52    with tf.GradientTape() as g:
53      pred = ANN_model(x)
54      cost = cost_ANN_mnist(pred,y)
55    gradients = g.gradient(cost, vars(ANN_model).values(),unconnected_gradients=tf.UnconnectedGradients.ZERO)
56    #기존의 gradients와 다르게 뒤에 unconnected_gradients를 정의함으로써 연결되지 않는 그래디언트로 인한 오류를 없앤다.
57    optimizer.apply_gradients(zip(gradients, vars(ANN_model).values()))
58
59  for step, (batch_x, batch_y) in enumerate(train_data.take(300), 1):
60      train_optimization(batch_x, batch_y)
61      if step % 10 == 0:
62          pred = ANN_model(batch_x)
63          loss = cost_ANN_mnist(pred,batch_y)
64          acc = accuracy(pred, batch_y)
65          print("Step: {},\t Accurray: {},\t Loss: {}".format(step,acc.numpy().flatten(),loss.numpy().flatten()))
66  print('='*30)
67  print('Model test')
68  print("Test_Accurray: ",accuracy(ANN_model(x_test),y_test).numpy().flatten())
69  print('='*30)
```

- TensorFlow
- **PyTorch**
- Keras

ANN Implementation (PyTorch)


```python
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
import numpy as np
import pandas as pd
from sklearn.metrics import confusion_matrix
from torch.autograd import Variable

train_data = datasets.MNIST(root='../Data', train=True, download=True, transform=transforms.ToTensor())
test_data = datasets.MNIST(root='../Data', train=True, download=True, transform=transforms.ToTensor())
train_loader = DataLoader(train_data, batch_size=128, shuffle=True)
test_loader = DataLoader(test_data, batch_size=128, shuffle=False)

class ANNModel(nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim):
        super(ANNModel, self).__init__()
        self.net = nn.Sequential(nn.Linear(input_dim, hidden_dim),
                                 nn.ReLU(),
                                 nn.Linear(hidden_dim, hidden_dim),
                                 nn.ReLU(),
                                 nn.Linear(hidden_dim, hidden_dim),
                                 nn.ReLU(),
                                 nn.Linear(hidden_dim, output_dim)
                                 )
    def forward(self, x):
        return self.net(x)
```

ANN Implementation (PyTorch)

```
model = ANNModel(input_dim=784, hidden_dim=256, output_dim=10)
cost = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)
step = 0
loss_list = []
accuracy_list = []

for epoch in range(5):
    for i, (images, labels) in enumerate(train_loader):
        train = Variable(images.view(-1, 784))
        labels = Variable(labels)
        optimizer.zero_grad()
        outputs = model(train)
        loss = cost(outputs, labels)
        loss.backward()
        optimizer.step()
        step += 1
        if step % 50 == 0:
            correct = 0
            total = 0
            for images, labels in test_loader:
                test = Variable(images.view(-1, 784))
                outputs = model(test)
                predicted = torch.max(outputs.data,1)[1]
                total += len(labels)
                correct += (predicted == labels).sum()
            accuracy = correct.item() / total
            loss_list.append(loss.data.item())
            accuracy_list.append(accuracy)
            if step % 100 == 0:
                print("Step: {},\t Accurray: {},\t Loss: {}".format(step,accuracy,loss))
```

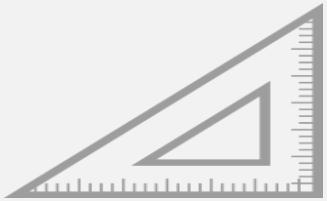
- TensorFlow
- PyTorch
- **Keras**

ANN Implementation (Keras)

```
from keras.utils import np_utils
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense
# MNIST data
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
print(train_images.shape, train_labels.shape, test_images.shape, test_labels.shape)
train_images = train_images.reshape(train_images.shape[0], 784).astype('float32')/255.0
test_images = test_images.reshape(test_images.shape[0], 784).astype('float32')/255.0
train_labels = np_utils.to_categorical(train_labels) # One-Hot Encoding
test_labels = np_utils.to_categorical(test_labels) # One-Hot Encoding
# Model
model = Sequential()
model.add(Dense(256, activation='relu')) # units=256, activation='relu'
model.add(Dense(256, activation='relu')) # units=256, activation='relu'
model.add(Dense(256, activation='relu')) # units=256, activation='relu'
model.add(Dense(10, activation='softmax')) # units=10, activation='softmax'
model.compile(loss='categorical_crossentropy', optimizer='sgd', metrics=['accuracy'])
# Training
model.fit(train_images, train_labels, epochs=5, batch_size=32, verbose=1)
# Testing
_, accuracy = model.evaluate(test_images, test_labels)
print('Accuracy: ', accuracy)
model.summary()
```

```
(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

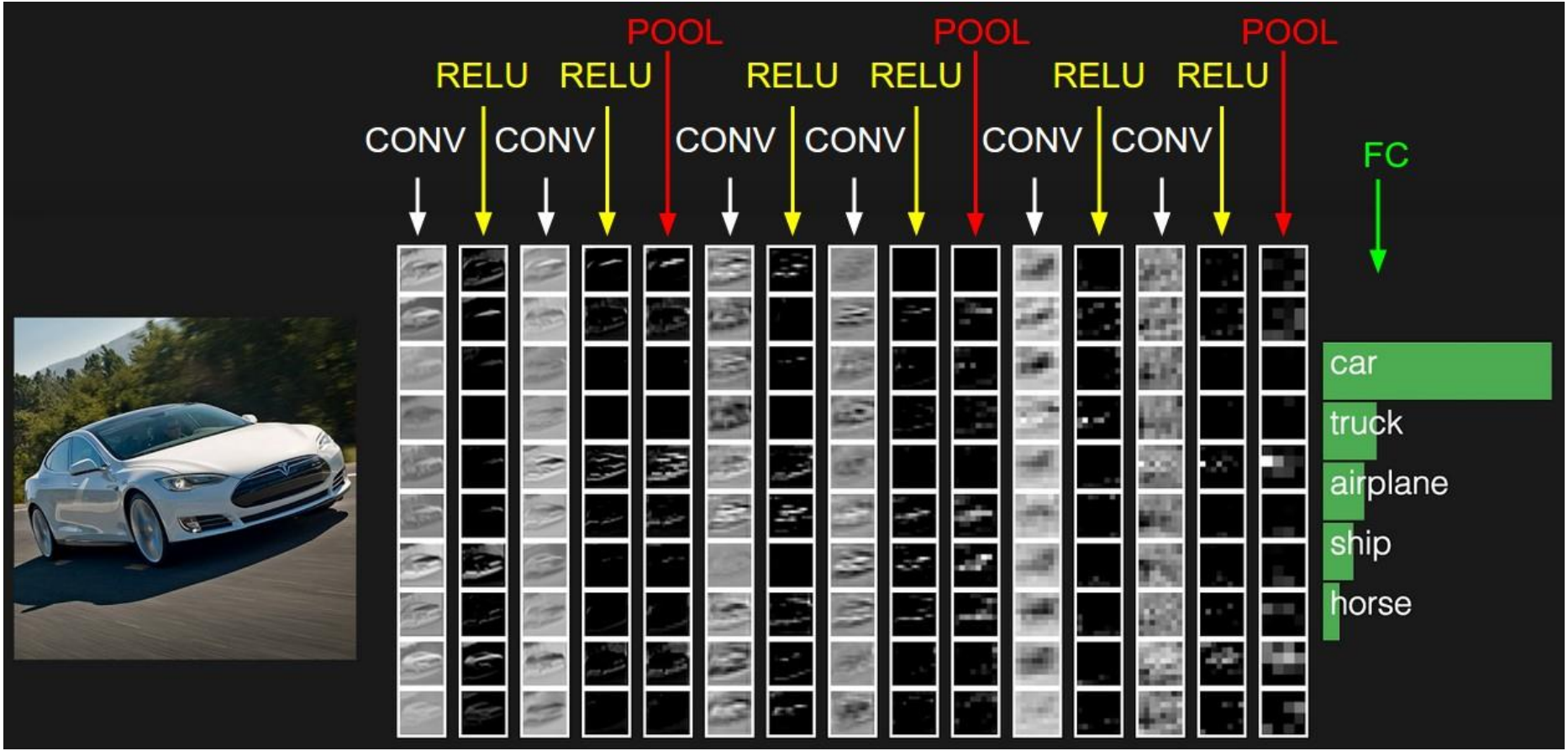
Neural Network (NN)
Convolutional NN (CNN)
CNN for CIFAR-10

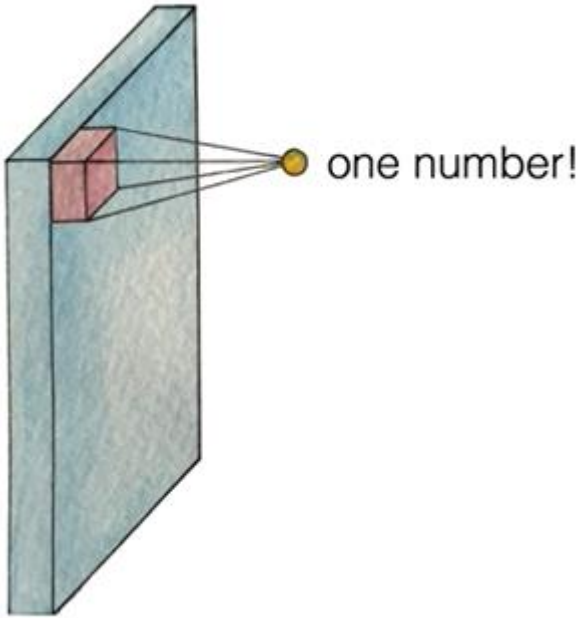
Advanced Topics

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

Deep Learning Theory and Software
Convolutional Neural Networks (CNN)
CNN Theory

- **CNN Theory**
- CNN Implementation

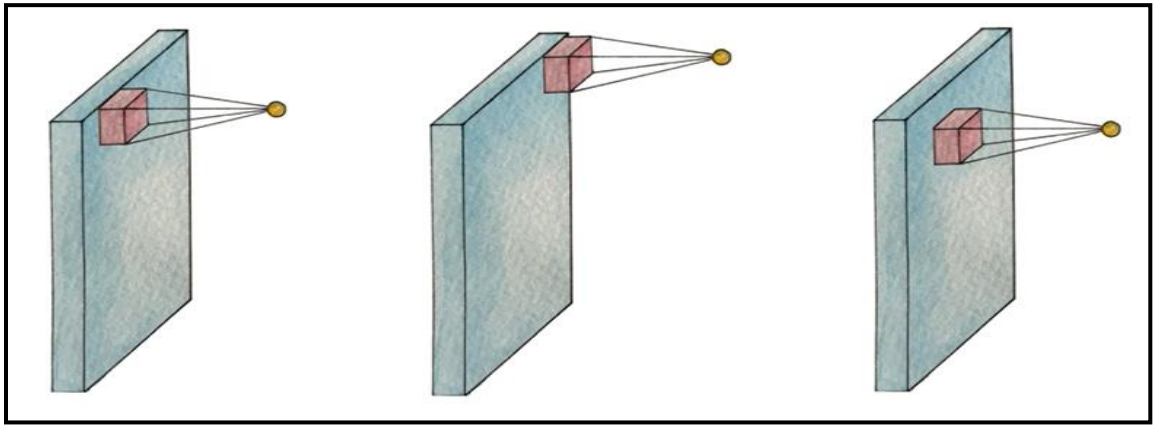

POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

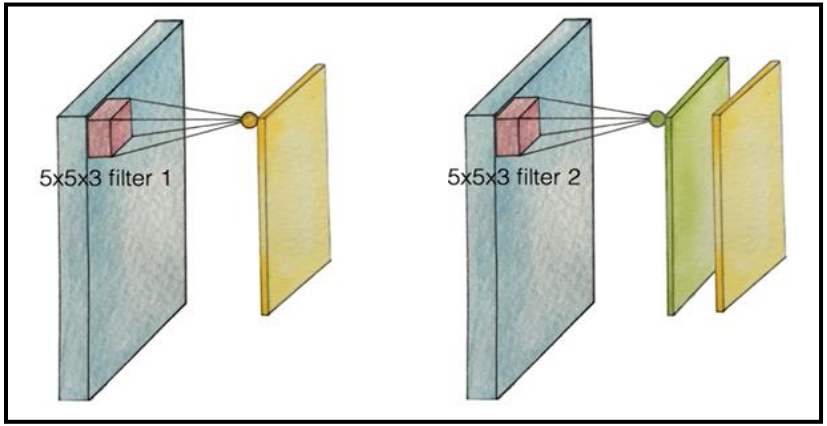


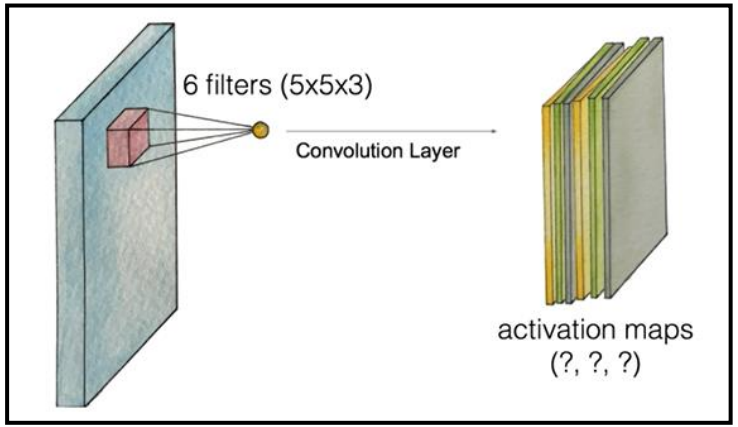
- Extracting **one point** with a filter

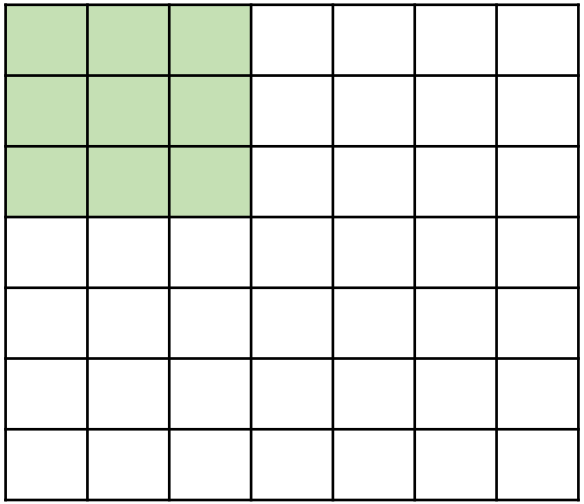
$$Wx + b$$

$$Y = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + b$$




5x5x3 filter 1
5x5x3 filter 2


6 filters (5x5x3)
Convolution Layer
activation maps
(?, ?, ?)

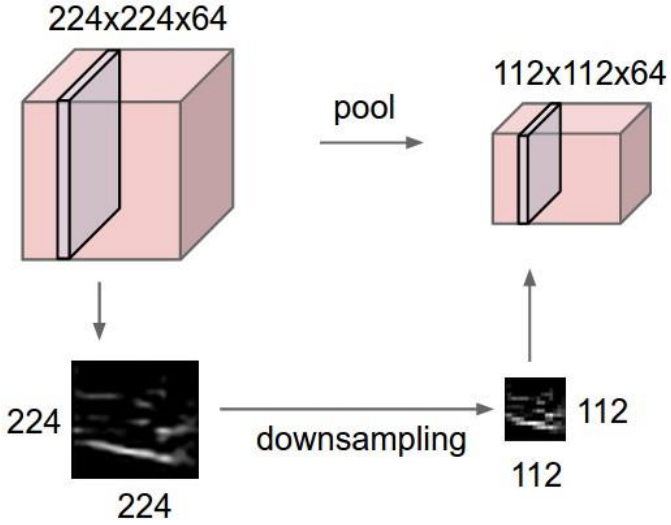


- Image Size: 7-by-7
- Filter Size: 3-by-3
- Strides (step-size of filter moving)
  - 1: 5*5=25
  - 2: 3*3=9
  - …
  - → Large strides loose information (value degrades).

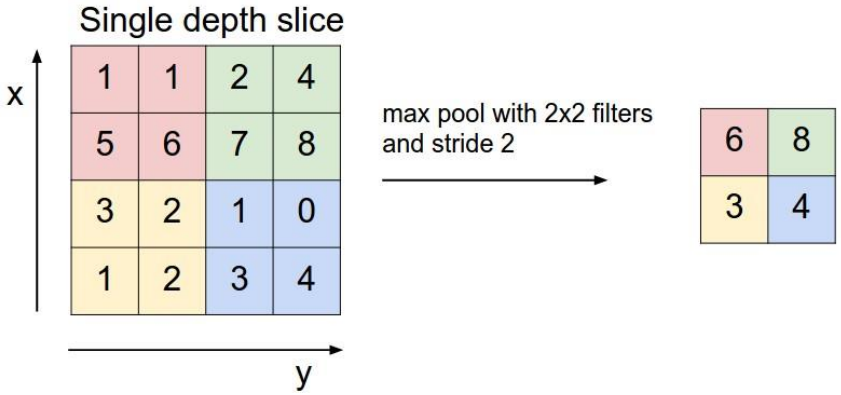
0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

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

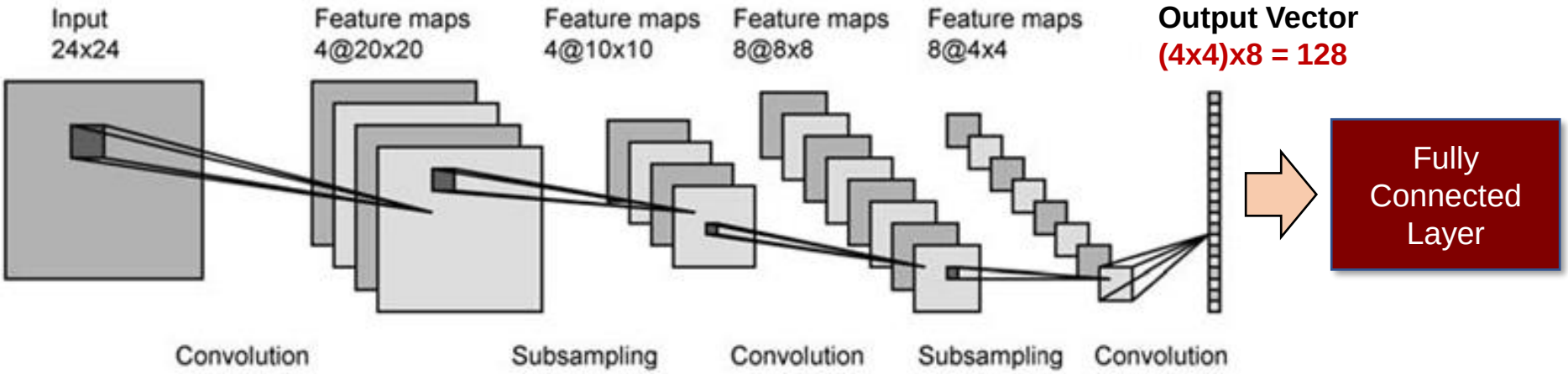
- Pooling Layer (Sampling)



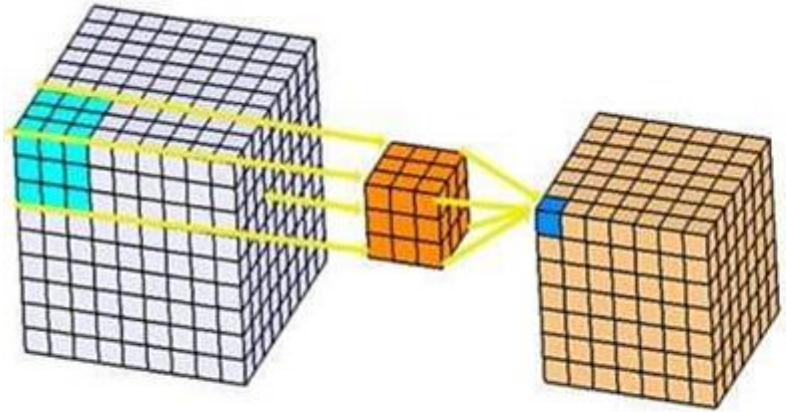
- Max Pooling Concept

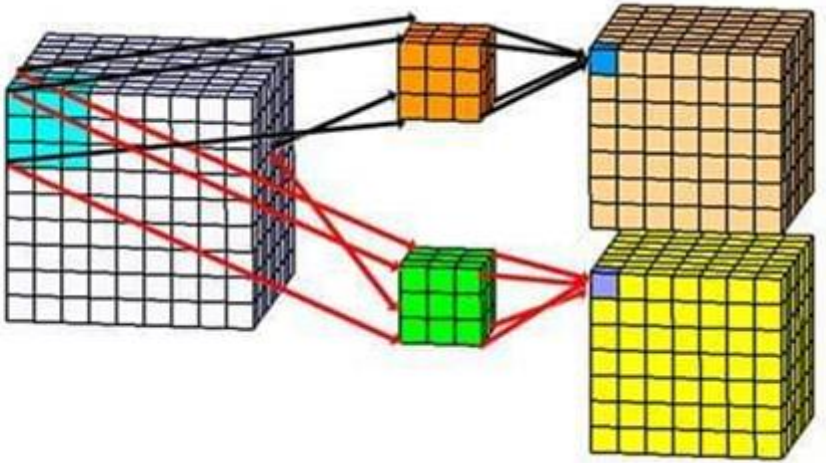


CNN: Example


Input
24x24
Feature maps
4@20x20
Feature maps
4@10x10
Feature maps
8@8x8
Feature maps
8@4x4
Output Vector
(4x4)x8 = 128
Fully Connected Layer
Convolution
Subsampling
Convolution
Subsampling
Convolution

- 3D Convolution

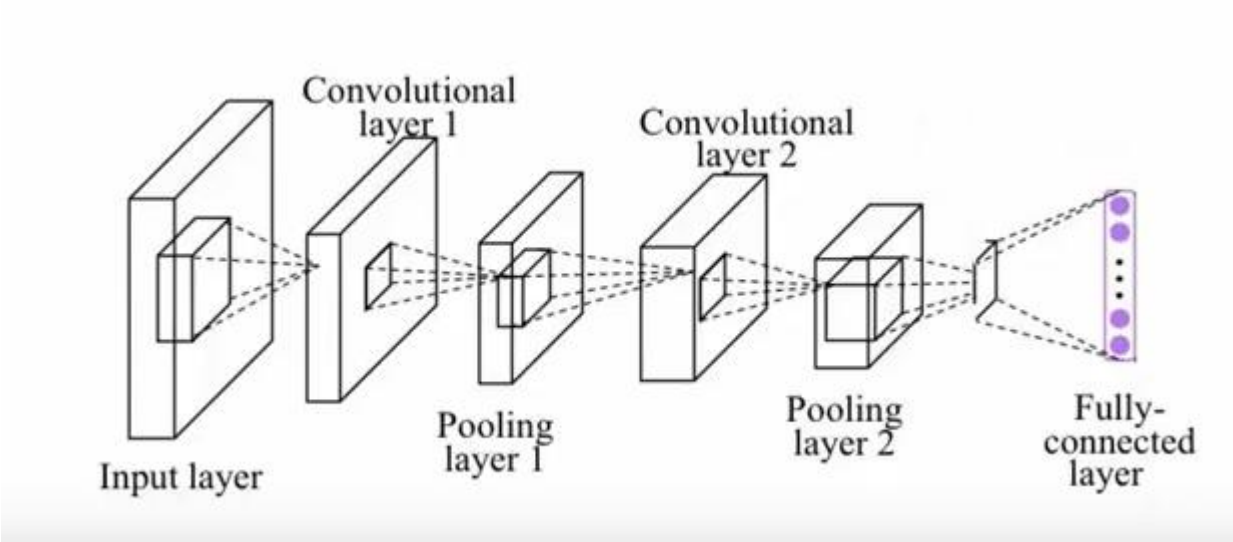




Deep Learning Theory and Software
Convolutional Neural Networks (CNN)
CNN Implementation

- CNN Theory
- **CNN Implementation**

- CNN for MNIST Image Classification



- **TensorFlow**
- Keras

CNN Implementation (TensorFlow)

```
#CNN Implementation (TensorFlow)
import tensorflow as tf
import numpy as np
import time
from tensorflow.keras.datasets import mnist
from tensorflow.keras import Model, layers

batch_size = 128
conv1_filters = 32
conv2_filters = 64
fc1_units = 1024

(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = np.array(x_train, np.float32), np.array(x_test, np.float32)
x_train, x_test = x_train / 255., x_test / 255.
train_data = tf.data.Dataset.from_tensor_slices((x_train, y_train))
train_data = train_data.repeat().shuffle(5000).batch(batch_size)
```

CNN Implementation (TensorFlow)


```
19  class CNN(Model):
20      def __init__(self):
21          super(CNN, self).__init__()
22          self.conv1 = layers.Conv2D(32, kernel_size=3, activation=tf.nn.relu) #(필터 사이즈 3-by-3으로 32개)
23          self.maxpool1 = layers.MaxPool2D(2, strides=2)
24          self.conv2 = layers.Conv2D(64, kernel_size=3, activation=tf.nn.relu) #(필터 사이즈 3-by-3으로 64개)
25          self.maxpool2 = layers.MaxPool2D(2, strides=2)
26          self.flatten = layers.Flatten()
27          self.fc1 = layers.Dense(1024)
28          self.dropout = layers.Dropout(rate=0.5)
29          self.out = layers.Dense(10)
30
31      def call(self, x, is_training=False):
32          x = tf.reshape(x, [-1, 28, 28, 1])
33          x = self.conv1(x)
34          x = self.maxpool1(x)
35          x = self.conv2(x)
36          x = self.maxpool2(x)
37          x = self.flatten(x)
38          x = self.fc1(x)
39          x = self.dropout(x, training=is_training)
40          x = self.out(x)
41          return x
42
43  CNN_model = CNN()
44  optimizer = tf.optimizers.Adam(0.01)
```

CNN Implementation (TensorFlow)

```
47  def cross_entropy_loss(x,y):
48      y = tf.cast(y, tf.int64)
49      loss = tf.nn.sparse_softmax_cross_entropy_with_logits(labels=y, logits=x) # loss에 softmax 가 포함
50      return tf.reduce_mean(loss)
51
52  def accuracy(x,y):
53      correct = tf.equal(tf.argmax(x, 1), tf.cast(y, tf.int64))
54      return tf.reduce_mean(tf.cast(correct, tf.float32), axis=-1)
55
56
57  def train_step(x, y):
58    with tf.GradientTape() as g:
59      y_pred = CNN_model.call(x)
60      loss = cross_entropy_loss(y_pred,y)
61      trainable_variables = CNN_model.trainable_variables
62    gradients = g.gradient(loss, trainable_variables)
63    optimizer.apply_gradients(zip(gradients,trainable_variables))
64
65  for step, (batch_x, batch_y) in enumerate(train_data.take(300), 1):
66      train_step(batch_x, batch_y)
67      if step % 10 == 0:
68          pred = CNN_model.call(batch_x)
69          loss = cross_entropy_loss(pred,batch_y)
70          acc = accuracy(pred, batch_y)
71          print("Step: {},\t Accurray: {},\t Loss: {}".format(step,acc.numpy().flatten(),loss.numpy().flatten()))
72  print('='*30)
73  print('Model test')
74  print("Test Accurray: ",accuracy(CNN_model(x_test),y_test).numpy().flatten())
75  print('='*30)
```

- TensorFlow
- **Keras**

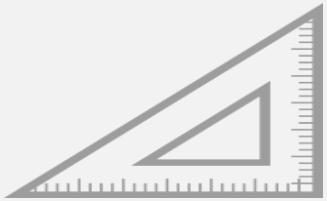
CNN Implementation (Keras)


```
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 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 14, 14, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (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

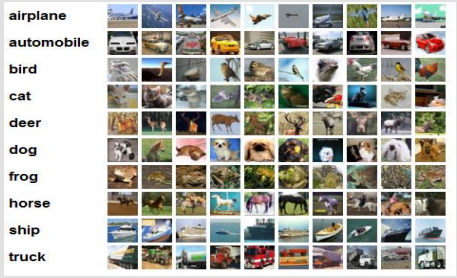
Advanced Topics

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

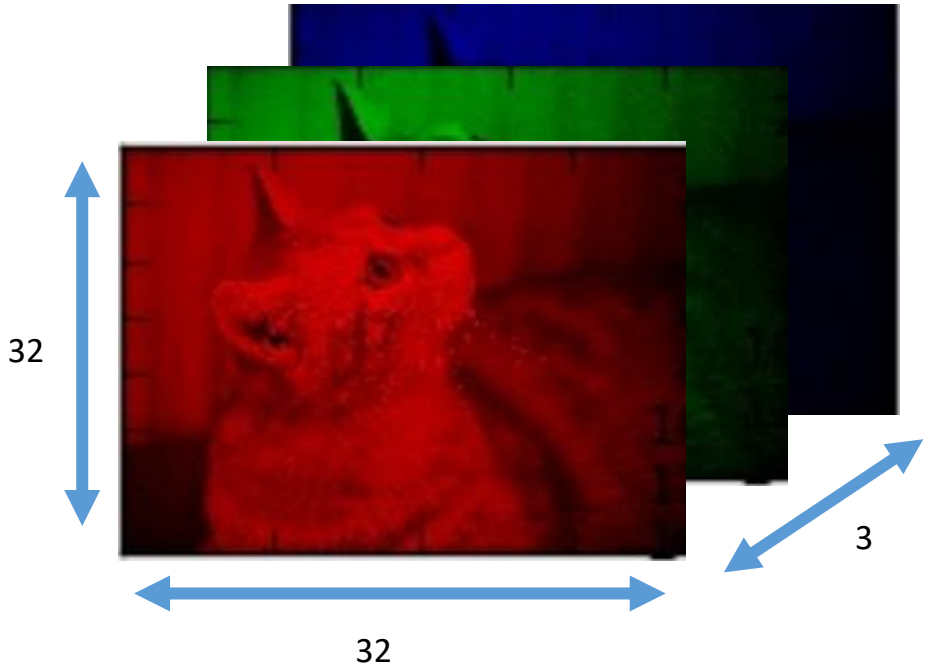
Deep Learning Theory and Software
CNN for CIFAR-10
CIFAR-10 Dataset

- **CIFAR-10 Dataset**

Image Dataset

	MNIST	CIFAR-10,100	IMAGENET
			
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	55,000	50,000	200,000

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

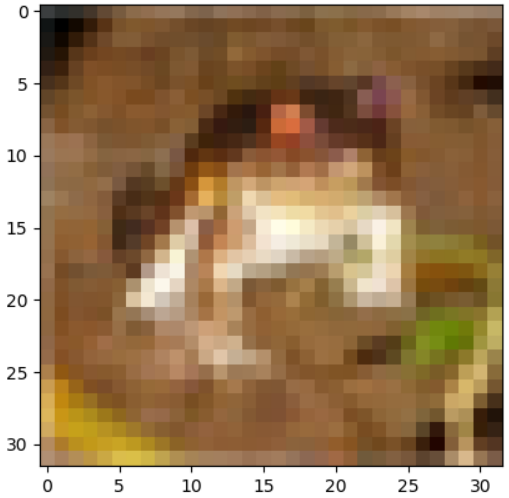


```
1  from keras.datasets import cifar10
2
3  (train_images, train_labels), (test_images, test_labels) = cifar10.load_data()
4  print('train_images', train_images.shape)
5  print('train_labels', train_labels.shape)
6  print('test_images', test_images.shape)
7  print('test_labels', test_labels.shape)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

```
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) → 3 channel RGB (32-by-32), 50000 images
    - (50000, 1) → 50000 labels (no one-hot encoding)
  - Test
    - (10000, 32, 32, 3) → 3 channel RGB (32-by-32), 10000 images
    - (10000, 1) → 10000 labels (no one-hot encoding)

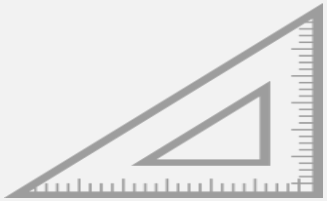
```
1  from keras.datasets import cifar10
2  from matplotlib import pyplot as plt
3
4  (train_images, train_labels), (test_images, test_labels) = cifar10.load_data()
5
6  plt.imshow(train_images[0])
7  plt.show()
```



Implementation 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

Advanced Topics

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

Deep Learning Theory and Software
Generative Adversarial Networks (GAN)
GAN Theory

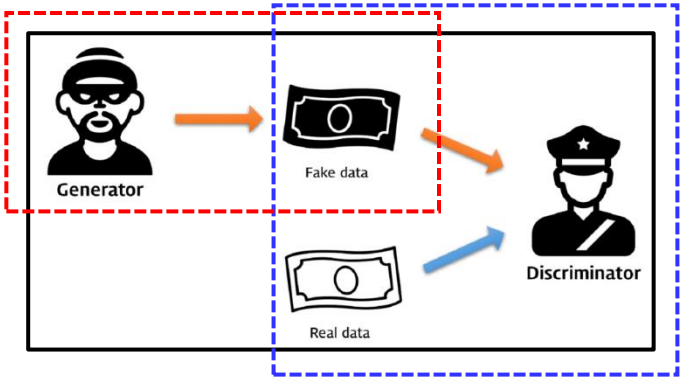
- **GAN Theory**
- GAN Implementation

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

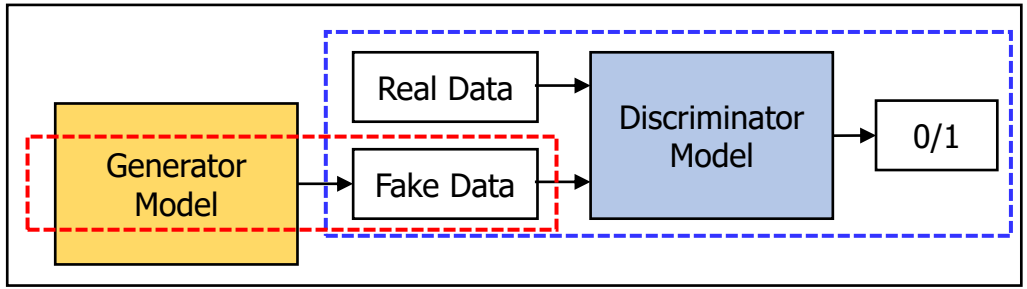
Performance Improvements via Competition

Generators

Discriminator



GAN architecture



Discriminator Model

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

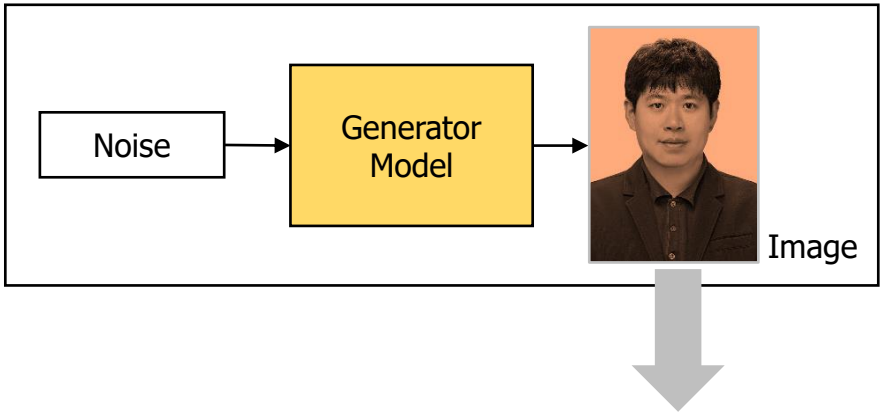
Supervised Learning

Generator Model

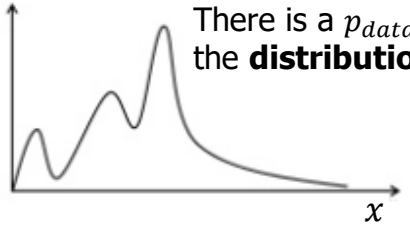
- The generative model learns **the distribution of training data**.

Unsupervised Learning

- Generative Model

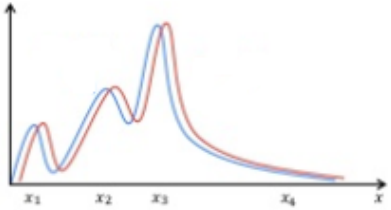


The generator model learns **the distribution of training data**.

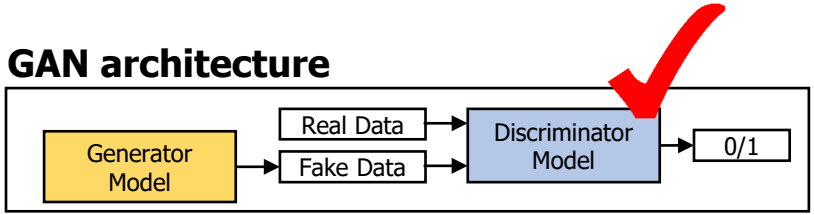


There is a $p_{data}(x)$ that represents the **distribution of actual images (training data)**.

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



GAN architecture



Objective of D

Sample x from real data distribution

Sample latent code x from Gaussian distribution

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

D should maximize V(D,G)

Maximize when D(x)=1

Maximize when D(G(z))=0

Training with REAL

x
Real Image

NN

D

D(x)

It should be high (close to 1).

The probability of that x came from the real data (0~1).

This D should classify a real image as real.

Training with FAKE

Fake image generated by G.

Random Noise (Latent Code)

z

NN

G

Fake Image

NN

D

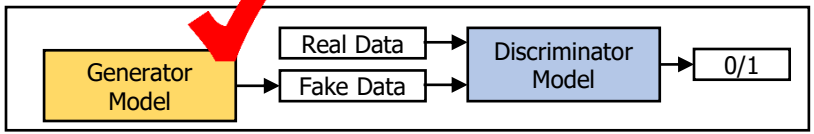
D(G(z))

Maybe low.

The G should create an image that is indistinguishable from real to receive D.

This D should classify a fake image as fake.

GAN architecture



Objective of G

G is independent to this part

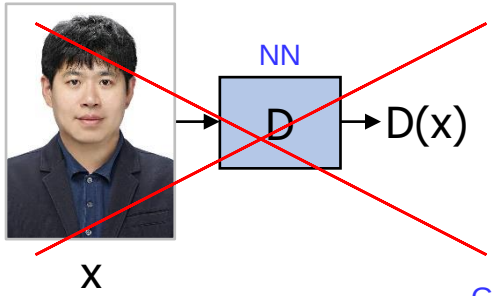
Sample latent code x from Gaussian distribution

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

G should minimize V(D,G)

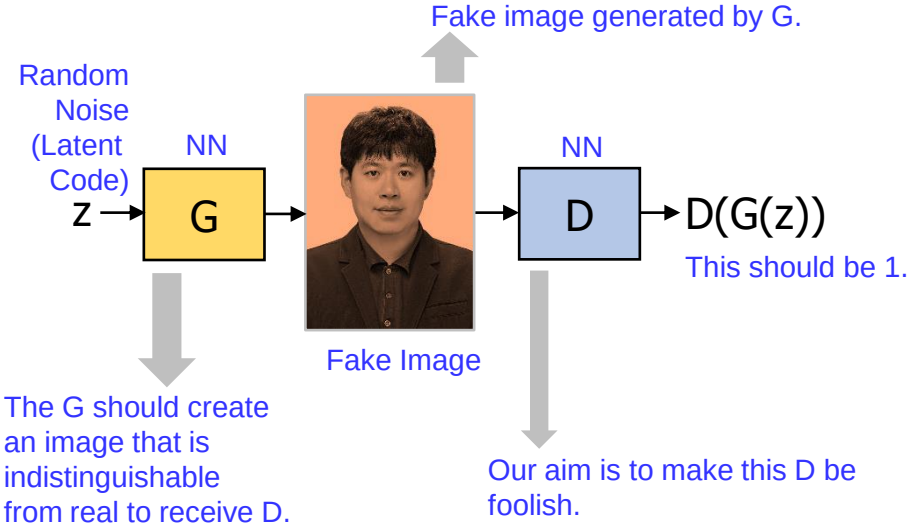
Minimum when D(G(z))=1

Training with REAL

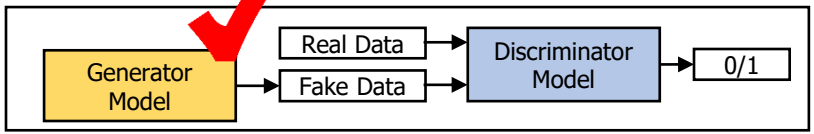


G has no inputs.

Training with FAKE



GAN architecture



Objective of G

G is independent to this part

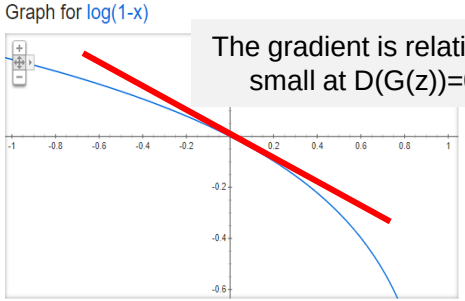
Sample latent code x from Gaussian distribution

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

G should minimize V(D,G)

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.



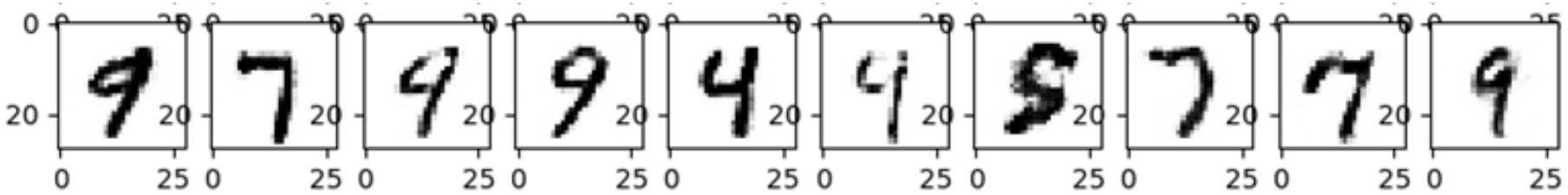
The gradient is relatively small at D(G(z))=0.

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

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

Deep Learning Theory and Software
Generative Adversarial Networks (GAN)
GAN Implementation

- GAN Theory
- **GAN Implementation**


0
20
0
25

```python
# MNIST data
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets("data_MNIST", one_hot=True)

import matplotlib.pyplot as plt
import numpy as np
import tensorflow as tf

# Training Params
num_steps = 100000
batch_size = 128

# Network Params
dim_image = 784 # 28*28 pixels
nHL_G = 256
nHL_D = 256
dim_noise = 100 # Noise data points

# A custom initialization (Xavier Glorot init)
def glorot_init(shape):
    return tf.random_normal(shape=shape, stddev=1. / tf.sqrt(shape[0] / 2.))
```

```
W = {
    'HL_G' : tf.Variable(glorot_init([dim_noise, nHL_G])),
    'OL_G' : tf.Variable(glorot_init([nHL_G, dim_image])),
    'HL_D' : tf.Variable(glorot_init([dim_image, nHL_D])),
    'OL_D' : tf.Variable(glorot_init([nHL_D, 1])),
}
b = {
    'HL_G' : tf.Variable(tf.zeros([nHL_G])),
    'OL_G' : tf.Variable(tf.zeros([dim_image])),
    'HL_D' : tf.Variable(tf.zeros([nHL_D])),
    'OL_D' : tf.Variable(tf.zeros([1])),
}

# Neural Network: Generator
def nn_G(x):
    HL = tf.nn.relu(tf.add(tf.matmul(x, W['HL_G']), b['HL_G']))
    OL = tf.nn.sigmoid(tf.add(tf.matmul(HL, W['OL_G']), b['OL_G']))
    return OL

# Neural Network: Discriminator
def nn_D(x):
    HL = tf.nn.relu(tf.add(tf.matmul(x, W['HL_D']), b['HL_D']))
    OL = tf.nn.sigmoid(tf.add(tf.matmul(HL, W['OL_D']), b['OL_D']))
    return OL

# Network Inputs
IN_G = tf.placeholder(tf.float32, shape=[None, dim_noise])
IN_D = tf.placeholder(tf.float32, shape=[None, dim_image])
```

```
52  # Build Generator Neural Network
53  sample_G = nn_G(IN_G)
54
55  # Build Discriminator Neural Network (one from noise input, one from generated samples)
56  D_real = nn_D(IN_D)
57  D_fake = nn_D(sample_G)
58  vars_G = [W['HL_G'], W['OL_G'], b['HL_G'], b['OL_G']]
59  vars_D = [W['HL_D'], W['
60
61  # Cost, Train
62  cost_G = -tf.reduce_mean(tf.log(D_fake))
63  cost_D = -tf.reduce_mean(tf.log(D_real) + tf.log(1. - D_fake))
64  train_G = tf.train.AdamOptimizer(0.0002).minimize(cost_G, var_list=vars_G)
65  train_D = tf.train.AdamOptimizer(0.0002).minimize(cost_D, var_list=vars_D)
```

G(z)

D(x)

D(G(z))

Objective of G

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

Objective of D

Sample x from real data distribution

Sample latent code x from Gaussian distribution

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

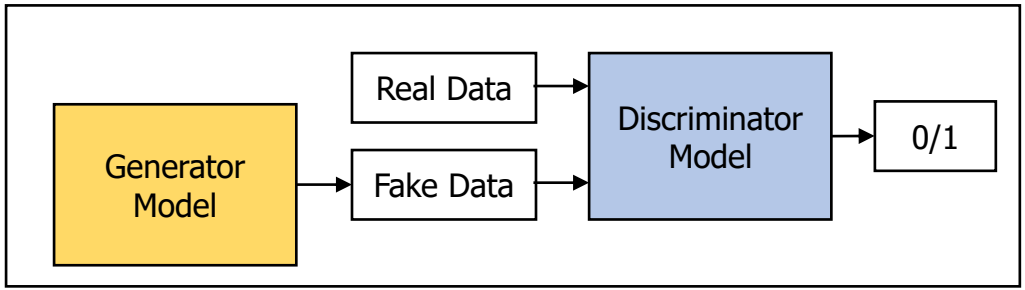
D should maximize V(D,G)

Maximize when D(x)=1

Maximize when D(G(z))=0

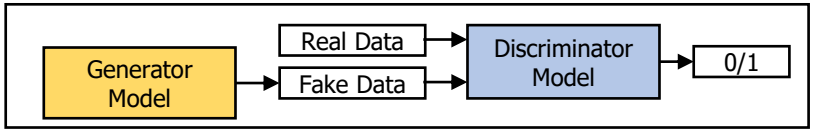
```
52  # Build Generator Neural Network
53  sample_G = nn_G(IN_G)
54
55  # Build Discriminator Neural Network (one from noise input, one from generated samples)
56  D_real = nn_D(IN_D)
57  D_fake = nn_D(sample_G)
58  vars_G = [W['HL_G'], W['OL_G'], b['HL_G'], b['OL_G']]
59  vars_D = [W['HL_D'], W['OL_D'], b['HL_D'], b['OL_D']]
60
61  # Cost, Train
62  cost_G = -tf.reduce_mean(tf.log(D_fake))
63  cost_D = -tf.reduce_mean(tf.log(D_real) + tf.log(1. - D_fake))
64  train_G = tf.train.AdamOptimizer(0.0002).minimize(cost_G, var_list=vars_G)
65  train_D = tf.train.AdamOptimizer(0.0002).minimize(cost_D, var_list=vars_D)
```

GAN architecture

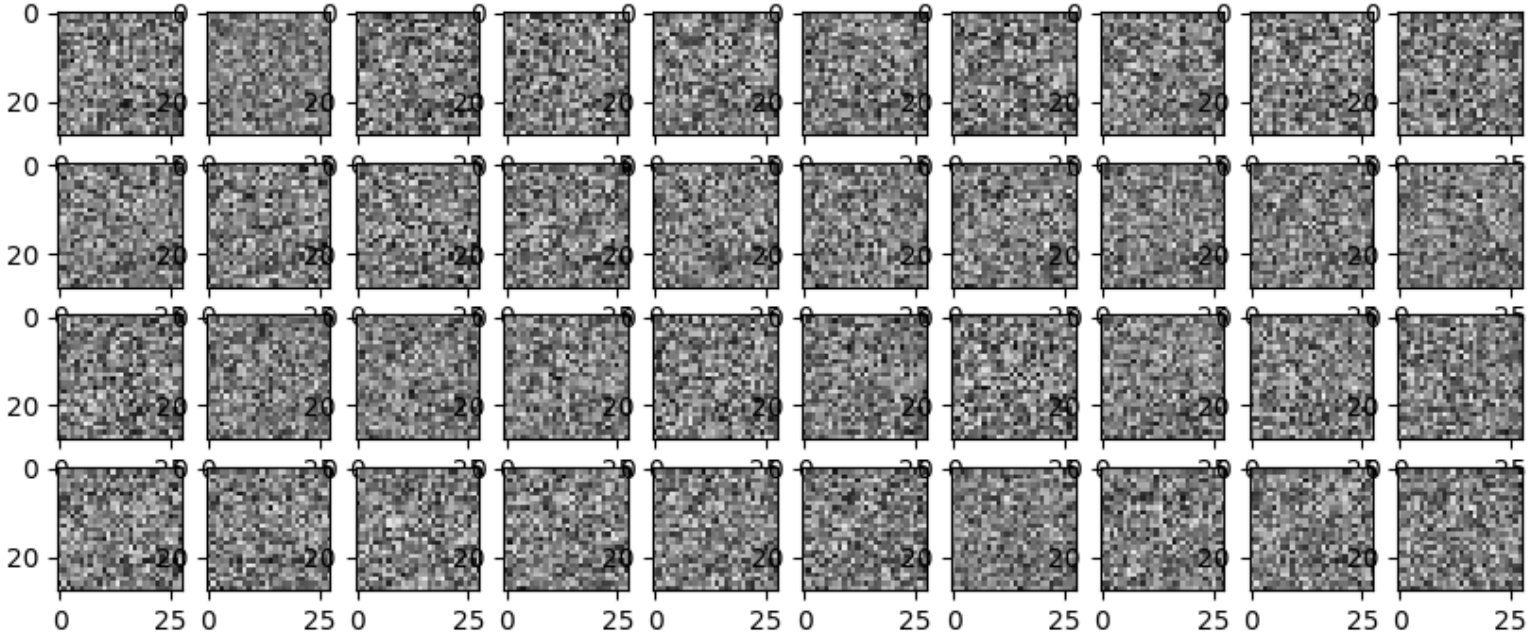


```
67  # Session
68  with tf.Session() as sess:
69      sess.run(tf.global_variables_initializer())
70      for i in range(1, num_steps+1):
71          # Get the next batch of MNIST data
72          batch_images, _ = mnist.train.next_batch(batch_size)
73          # Generate noise to feed to the generator G
74          z = np.random.uniform(-1., 1., size=[batch_size, dim_noise])
75          # Train
76          sess.run([train_G, train_D], feed_dict = {IN_D: batch_images, IN_G: z})
77          f, a = plt.subplots(4, 10, figsize=(10, 4))
78          for i in range(10):
79              z = np.random.uniform(-1., 1., size=[4, dim_noise])
80              g = sess.run([sample_G], feed_dict={IN_G: z})
81              g = np.reshape(g, newshape=(4, 28, 28, 1))
82              # Reverse colors for better display
83              g = -1 * (g - 1)
84              for j in range(4):
85                  # Generate image from noise. Extend to 3 channels for matplot figure.
86                  img = np.reshape(np.repeat(g[j][:, :, np.newaxis], 3, axis=2), newshape=(28, 28, 3))
87                  a[j][i].imshow(img)
88      f.show()
89      plt.draw()
90      plt.waitforbuttonpress()
```

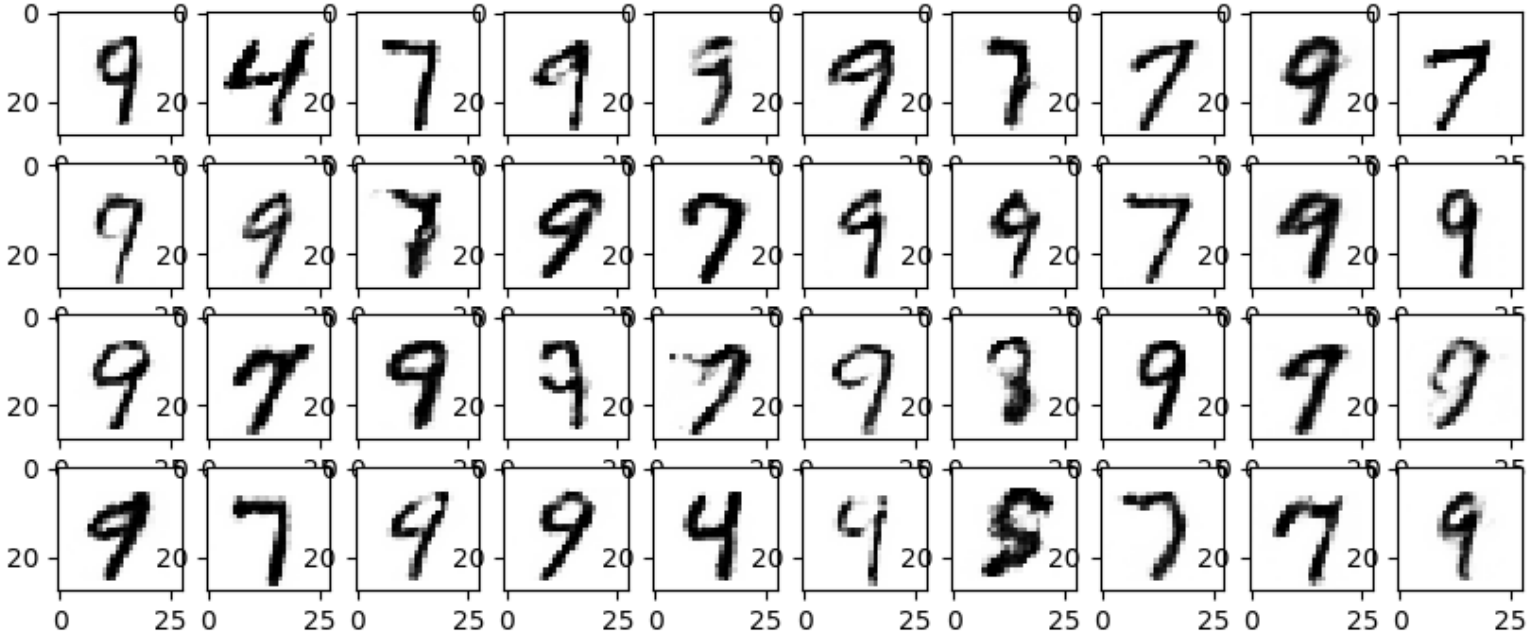
GAN architecture



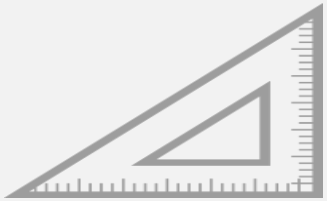
num_steps: 1



num_steps: 100000



Linear Functions



Linear Regression
Binary Classification
Softmax Classification

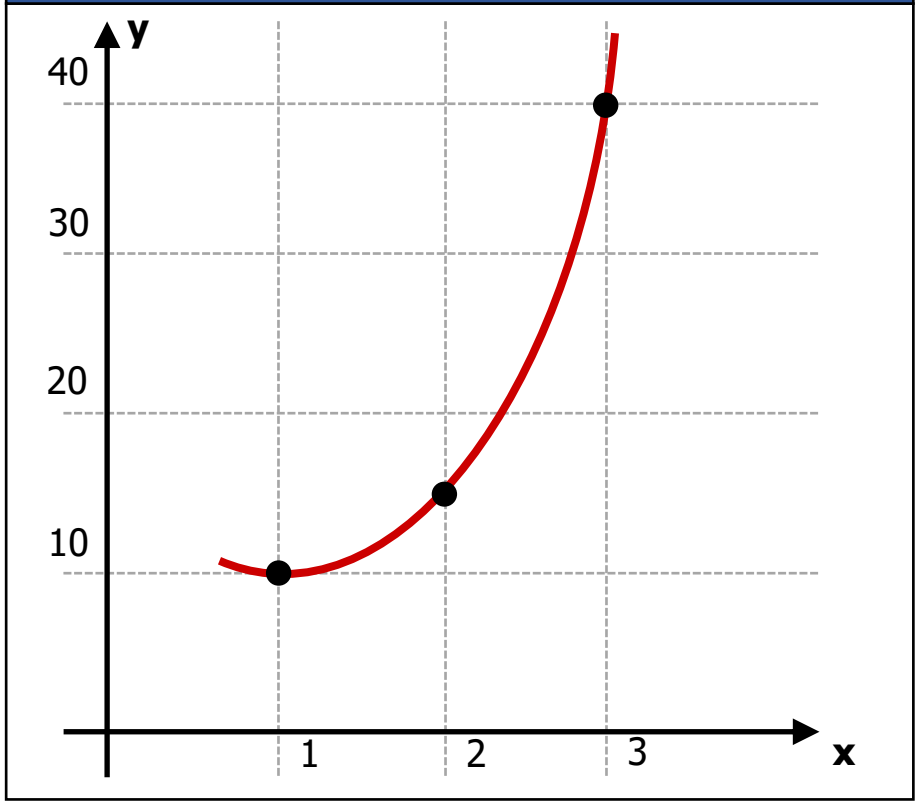
Nonlinear Functions

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

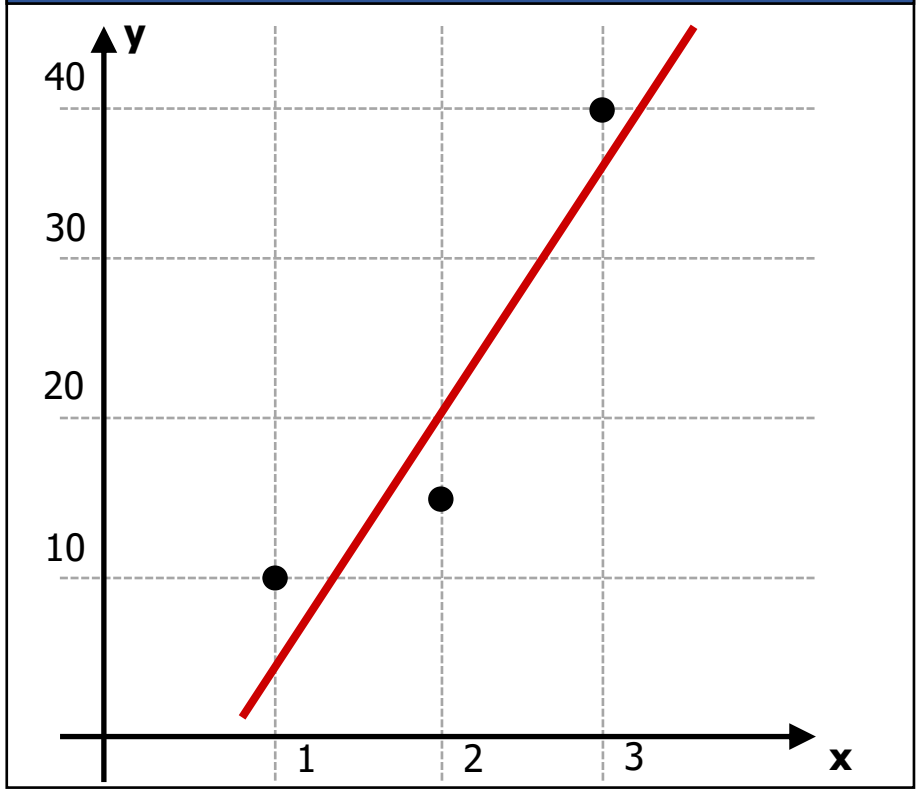
Advanced Topics

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

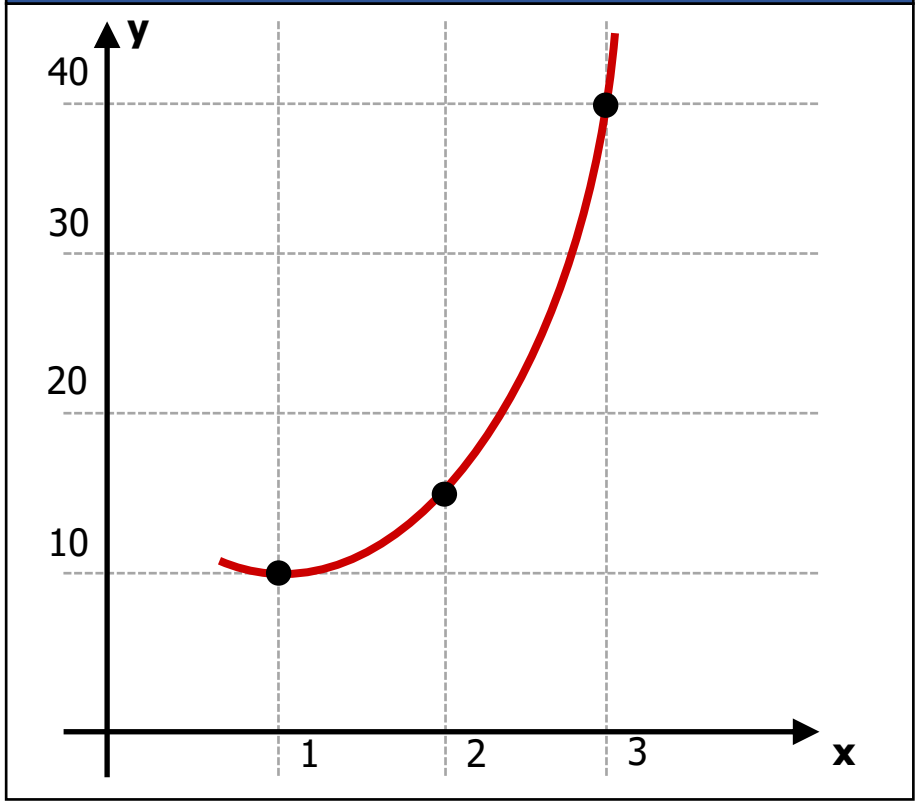
Interpolation



Linear Regression



Interpolation

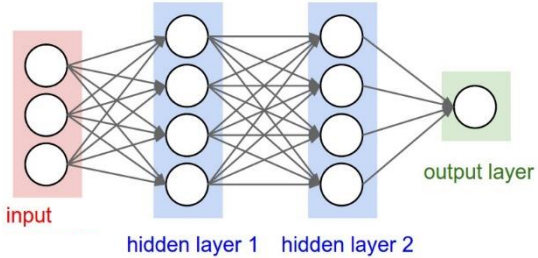


Interpolation with Polynomials

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

where three points are given.
→ Unique coefficients (a_0, a_1, a_2) can be calculated.

Is this related to
Neural Network Training?



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

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

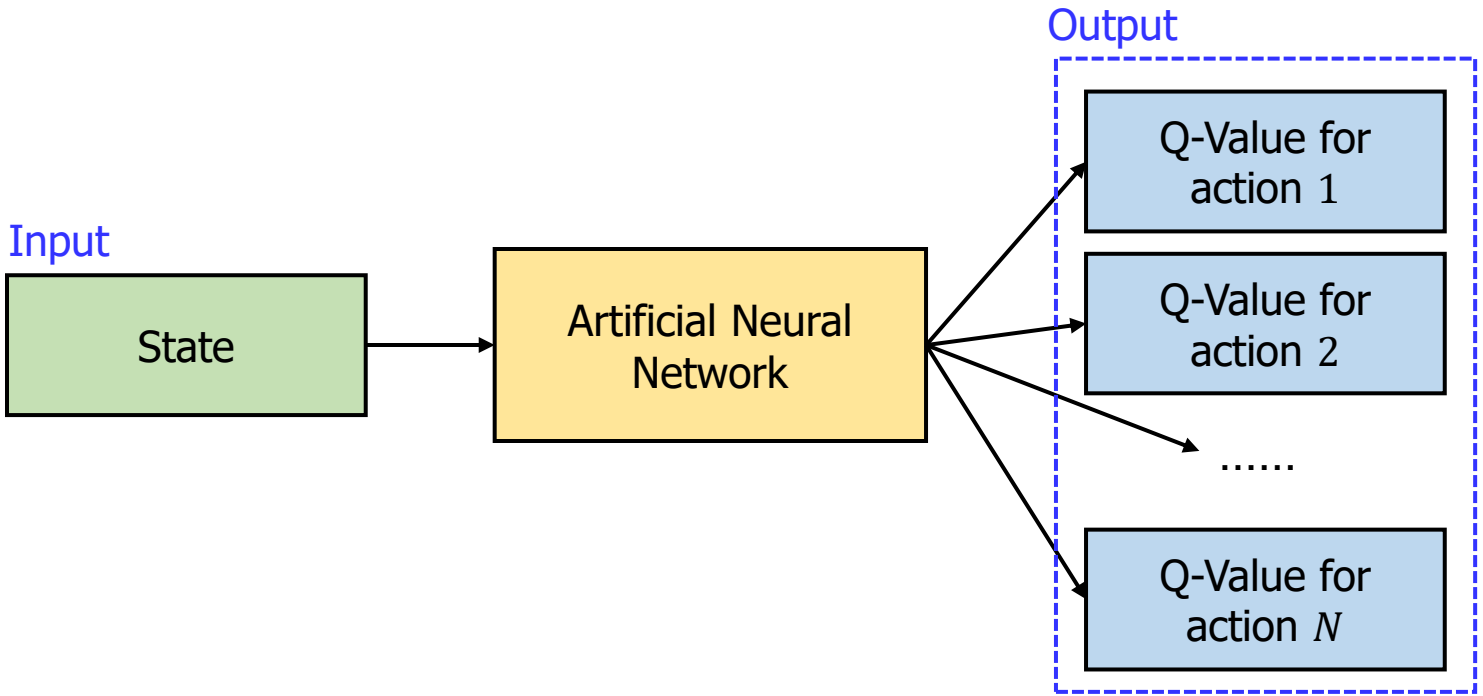
→ Find $W_1, b_1, W_2, b_2, W_o, b_o$

→ This is the mathematical meaning of neural network training.

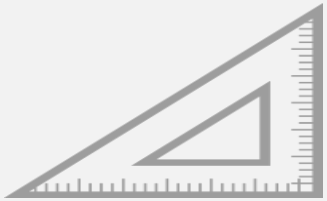
→ **Function Approximation**

→ The most well-known function approximation with neural network: **Deep Reinforcement Learning**

- 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
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Nonlinear Functions

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Advanced Topics

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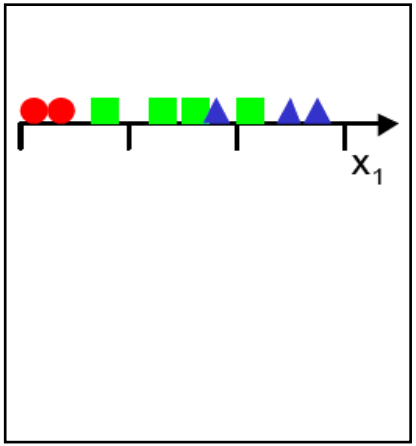
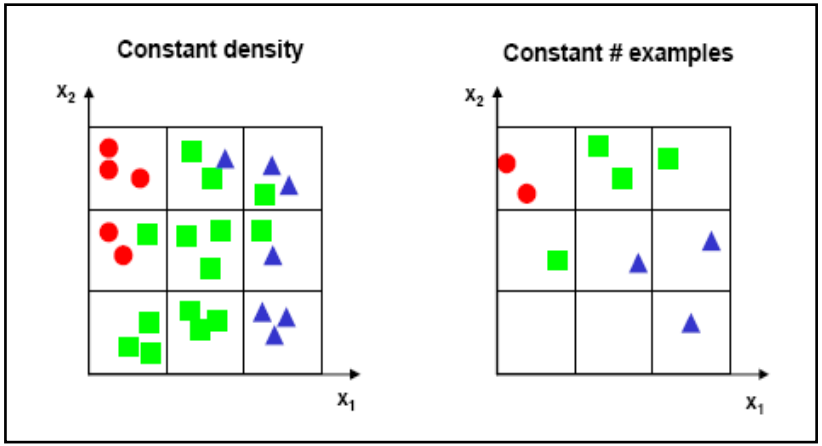
Overfitting

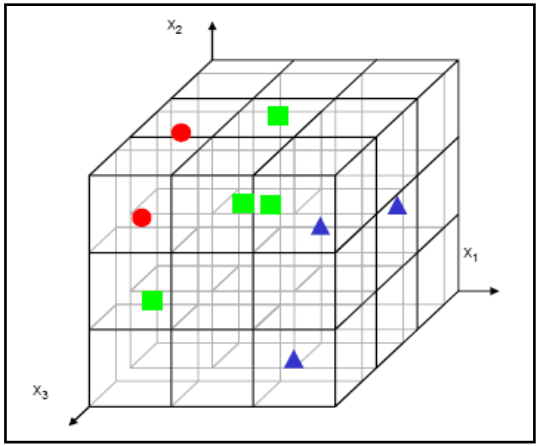
1D

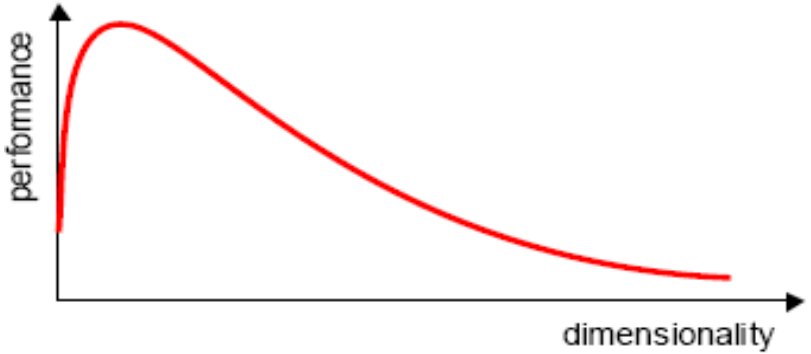

X1

2D

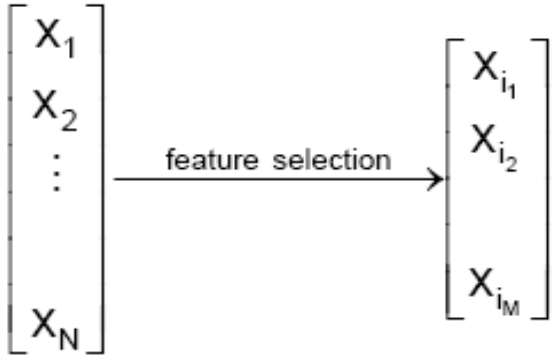

Constant density
X2
X1
Constant # examples
X2
X1

3D

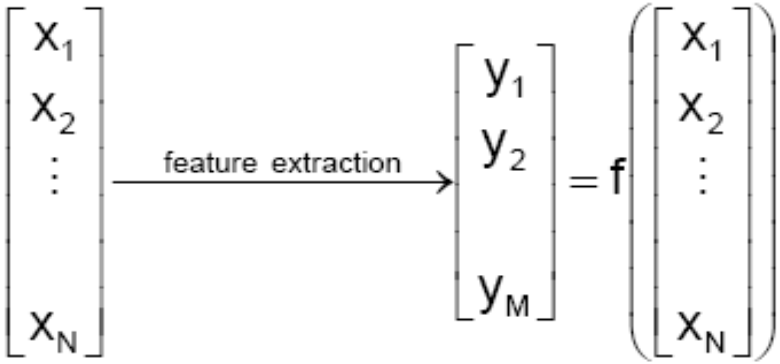

X2
X1
X3

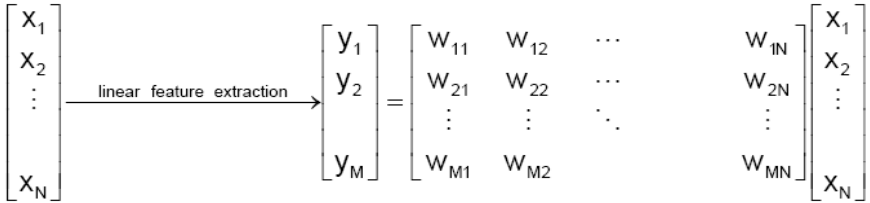

performance
dimensionality

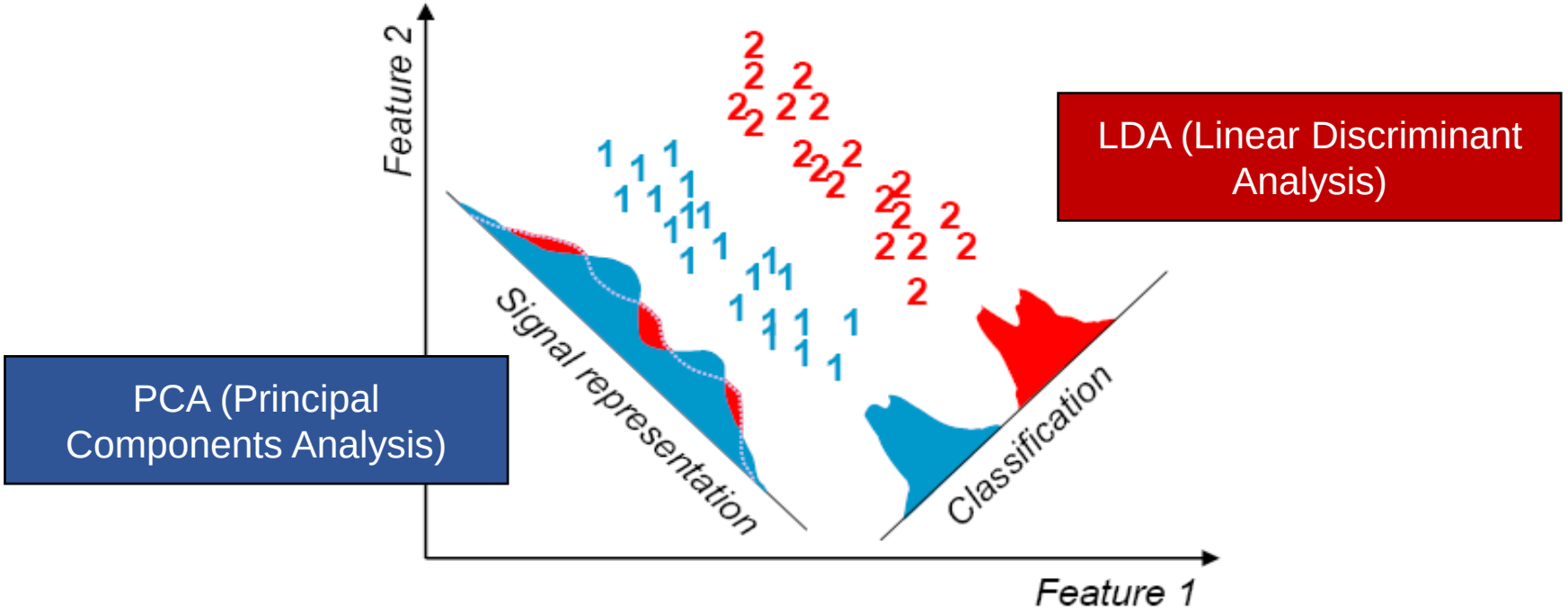
Feature Selection

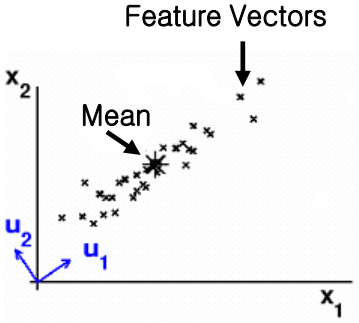


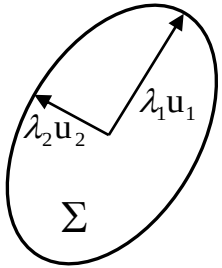
Feature Extraction





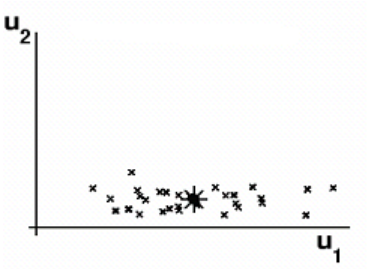

Feature 2
Feature 1
Signal representation
Classification
LDA (Linear Discriminant Analysis)
PCA (Principal Components Analysis)

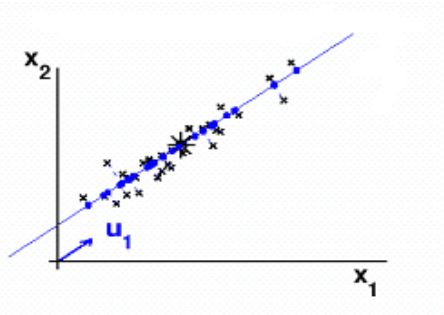


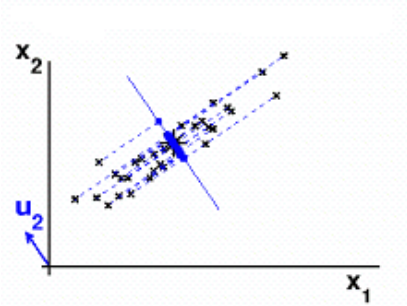


$$\Leftrightarrow \Sigma = [u_1 u_2] \times \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \times [u_1 u_2]^T$$

$$\lambda_1 > \lambda_2$$





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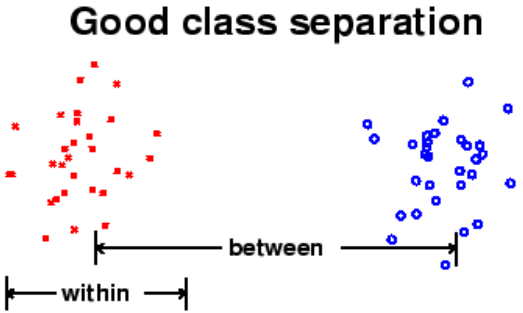
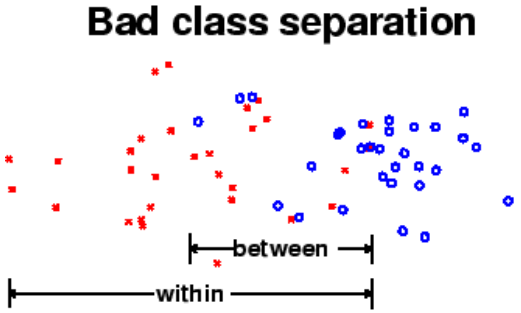
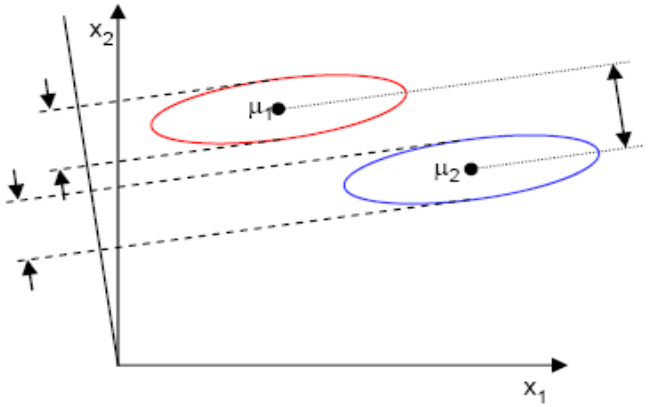
찍는, 순간 미친다! 푸딩 얼굴인식







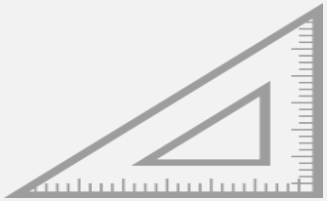
Fisher's linear discriminant function

$$J(\mathbf{w}) = \frac{\left|\tilde{\boldsymbol{\mu}}_1 - \tilde{\boldsymbol{\mu}}_2\right|^2}{\tilde{\mathbf{S}}_1^2 + \tilde{\mathbf{S}}_2^2}$$

→ Maximize!

→ Minimize!

Linear Functions



Linear Regression
Binary Classification
Softmax Classification

Nonlinear Functions

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CNN for CIFAR-10

Advanced Topics

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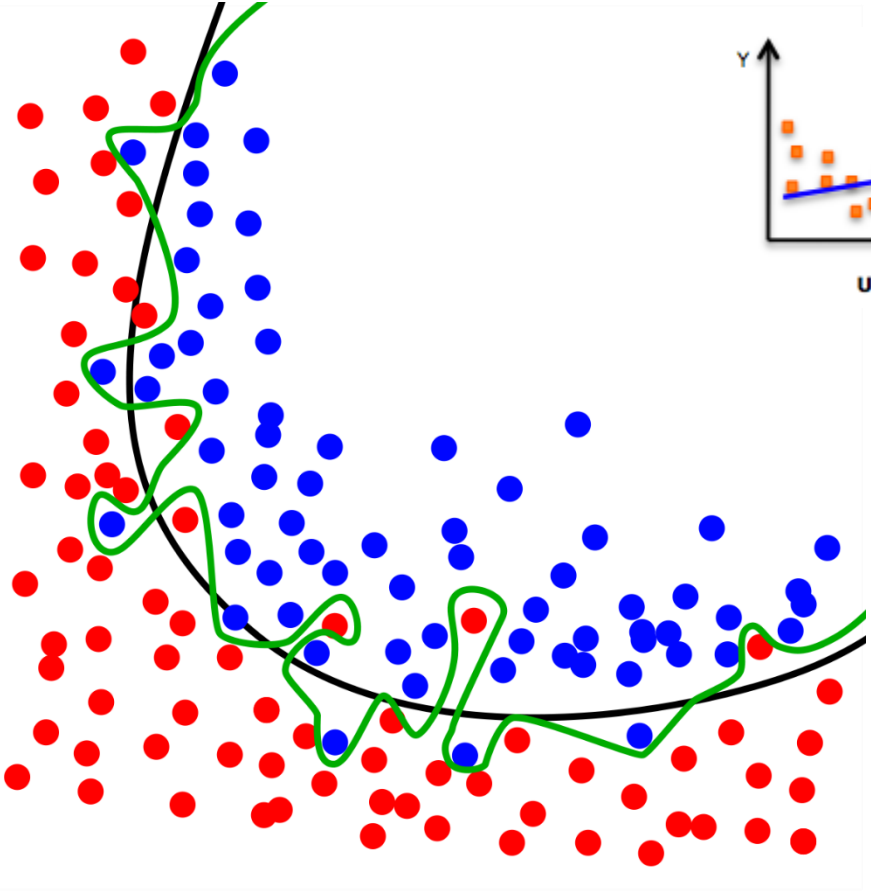
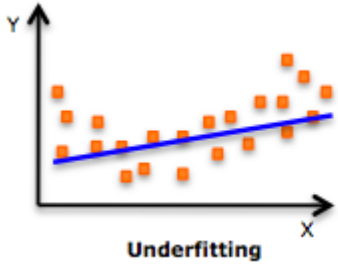
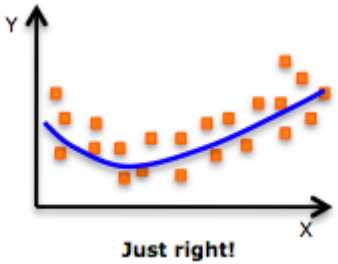
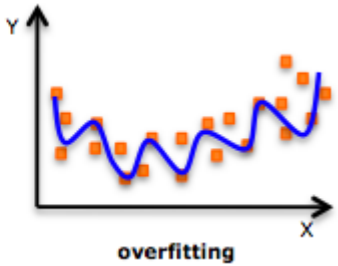
Interpolation
PCA/LDA
Overfitting

Overfitting

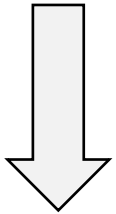




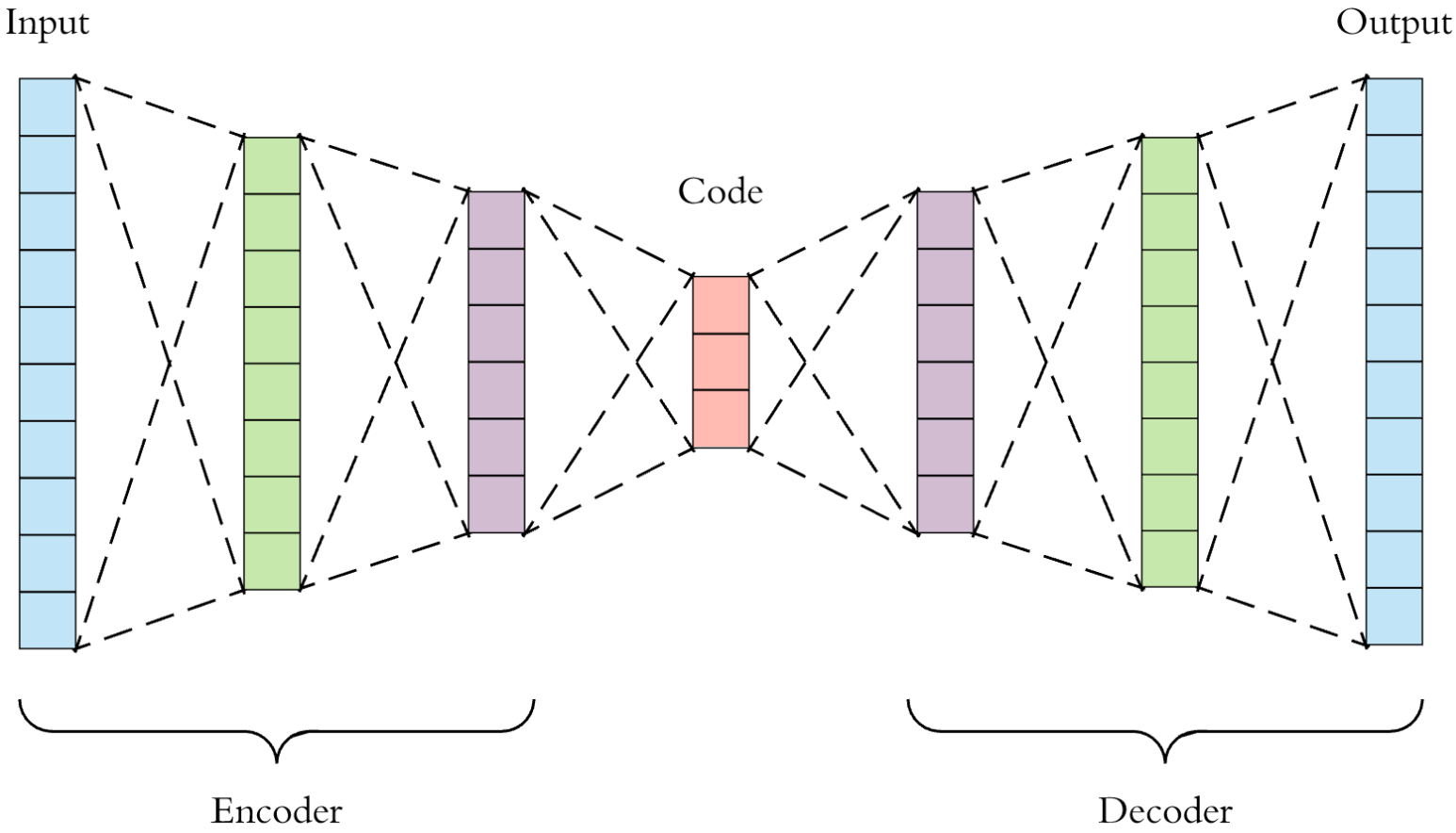




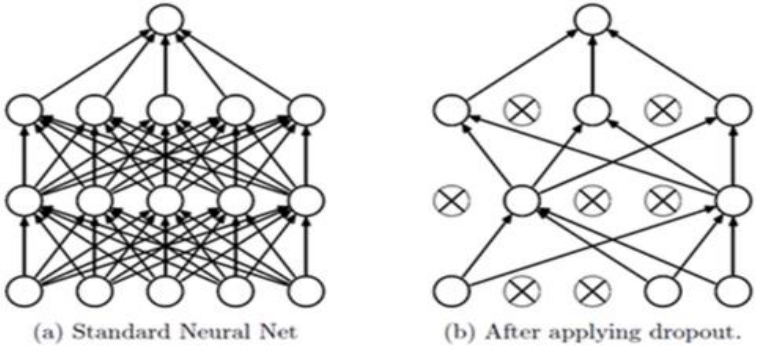
- How to overcome?
  - More training data
  - Reduce the number of features → autoencoding, dropout



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


Input
Output
Code
Encoder
Decoder

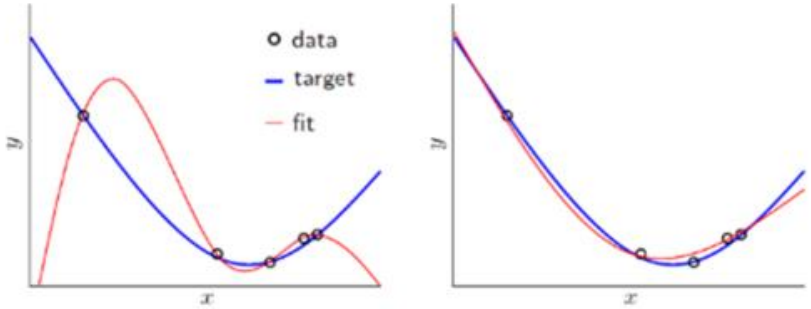
- Dropout
  - **tf.nn.dropout(layer, keep_prob=0.9)**



(a) Standard Neural Net

(b) After applying dropout.

- Regularization



(a) without regularization

(b) with regularization