

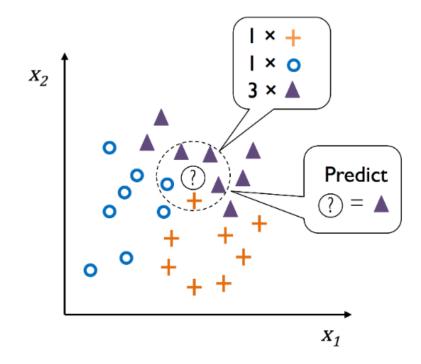
k-Nearest Neighbors, Multilayer Neural Network

Machine Learning

K-Nearest Neighbors

- What is the K-Nearest Neighbors?
 - In pattern recognition, the K-Nearest Neighbors algorithm(K-NN) is non-parametric method used for classification and regression

- Algorithm
- Choose the K and distance metric
- 2. Find K nearest neighbors for the test sample for test sample
- Assign classified label by majority vote



Load Iris Dataset

```
from sklearn import datasets
import numpy as np
iris = datasets.load_iris()
X = iris.data[50:150, [2, 3]]
y = iris.target[50:150]
print('Class labels:', np.unique(y))
Class labels: [1 2]
```

Splitting data into 70% training data & 30% test data

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
X, y, test_size=0.3, random_state=1, stratify=y)

print('Labels counts in y:', np.bincount(y))
print('Labels counts in y_train:', np.bincount(y_train))
print('Labels counts in y_test:', np.bincount(y_test))
Labels counts in y: [0 50 50]
Labels counts in y_train: [0 35 35]
Labels counts in y_test: [0 15 15]
```

Standardize the dataset

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
sc.fit(X_train)
X_train_std = sc.transform(X_train)
X_test_std = sc.transform(X_test)
```

Building a K-Nearest Neighbor and Training the model

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=5, p=2,metric='minkowski')
knn.fit(X_train, y_train)

KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski', metric_params=None, n_jobs=1, n_neighbors=5, p=2, weights='uniform')
```

Evaluation

```
# Train accuracy
acc = knn.score(X_train_std, y_train)
print("Train accuracy : %.4f" % acc)

Train accuracy : 0.9429

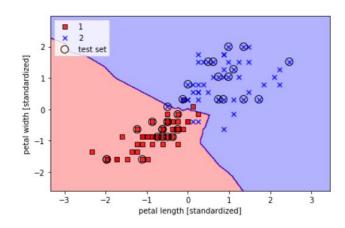
# Test accuracy
acc = knn.score(X_test_std, y_test)
print("Test accuracy : %.4f" % acc)

Test accuracy : 0.9667
```

Plotting decision boundary

```
X_combined_std = np.vstack((X_train_std, X_test_std))
y_combined = np.hstack((y_train, y_test))

plot_decision_regions(X_combined_std, y_combined,
classifier=knn, test_idx=range(70, 100))
plt.xlabel('petal length [standardized]')
plt.ylabel('petal width [standardized]')
plt.legend(loc='upper left')
plt.tight_layout()
plt.show()
```

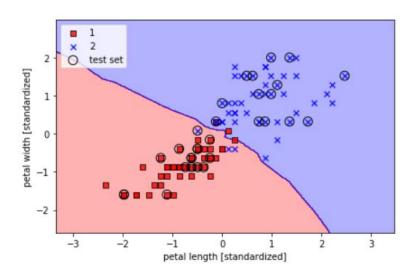


Try other k values

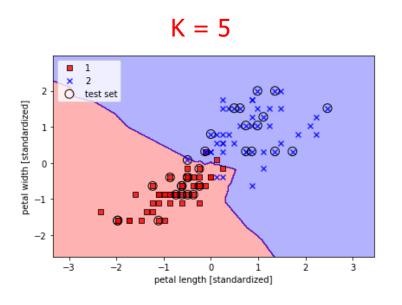
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n neighbors=9,
                           p=2,
                           metric='minkowski')
knn.fit(X train std, y train)
KNeighborsClassifier(algorithm='auto', leaf size=30, metric='minkowski',
                     metric params=None, n jobs=1, n neighbors=9, p=2,
                     weights='uniform')
# Train accuracy
acc = knn.score(X train std, y train)
print("Train accuracy : %.4f" % acc)
Train accuracy: 0.9286
# Test accuracy
acc = knn.score(X test_std, y_test)
print("Test accuracy : %.4f" % acc)
Test accuracy: 0.9667
```

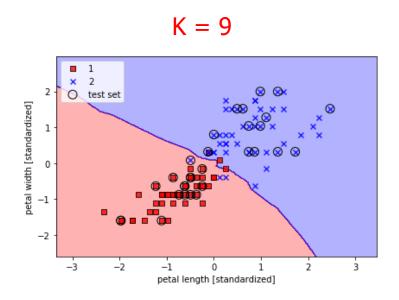
Try other k values

```
X_combined_std = np.vstack((X_train_std, X_test_std))
y_combined = np.hstack((y_train, y_test))
plot_decision_regions(X_combined_std, y_combined,
classifier=knn, test_idx=range(70, 100))
plt.xlabel('petal length [standardized]')
plt.ylabel('petal width [standardized]')
plt.legend(loc='upper left')
plt.tight_layout()
plt.show()
```



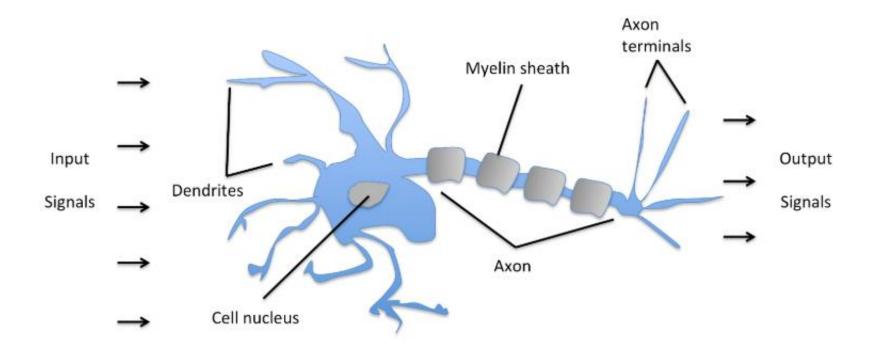
K: Number of Nearest Neighbors





The Neuron

Input signals accumulate and exceed a certain threshold value, an output signal is generated



- Analogy with human brain
 - Human
 - 10^{11} Neurons
 - 10⁴ synapses per neuron
 - 10¹⁶ operations per sec
 - 250M neurons per mm^3
 - 180,000km of "wires"



- $8*10^{12}$ operations per sec
- 5760 (small) cores
- \$2,000

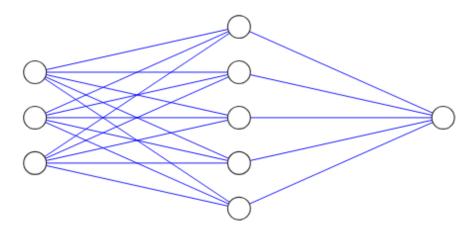




https://www.slideshare.net/braincreators/introduction-to-deep-neural-networks



- Neural Network : One hidden layer
 - A computer model of the human brain and nervous system



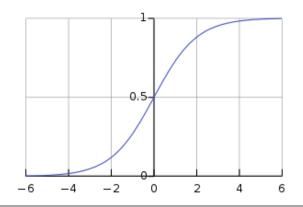
Input Layer ∈ R3

Hidden Layer ∈ R⁵

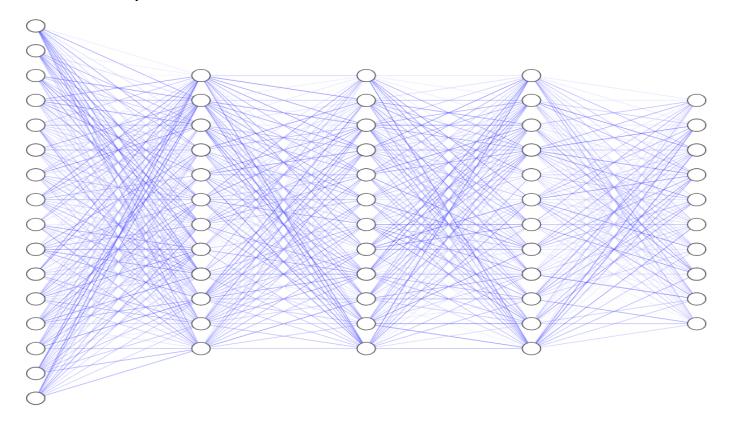
Output Layer ∈ R¹

Activation function : Sigmoid

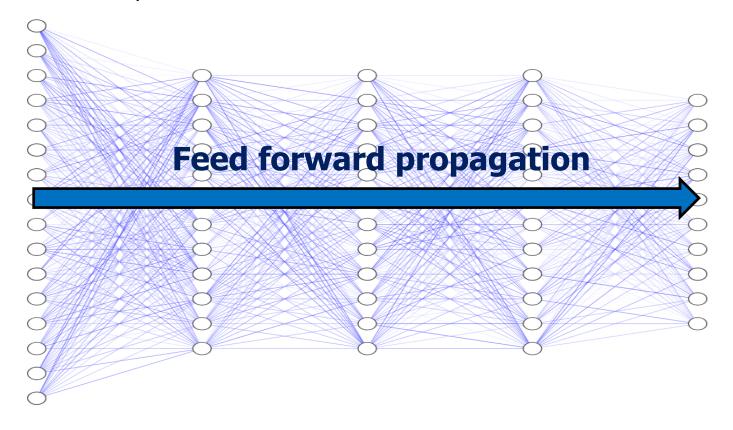
$$z = w_0 x_0 + w_1 x_1 + \dots + w_m x_m$$
$$\sigma(z) = \frac{1}{1 + e^{-z}}$$



- Deep Neural Network(Multi-layer Neural Networks)
 - A neural network with a certain level of complexity, a neural network with more than two layers

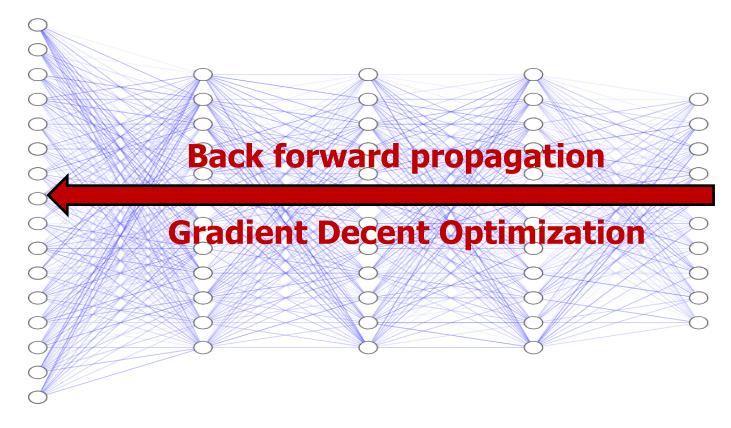


- Deep Neural Network(Multi-layer Neural Networks)
 - A neural network with a certain level of complexity, a neural network with more than two layers





- Deep Neural Network(Multi-layer Neural Networks)
 - A neural network with a certain level of complexity, a neural network with more than two layers





- Deep Neural Network(Multi-layer Neural Networks)
 - Activation function

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

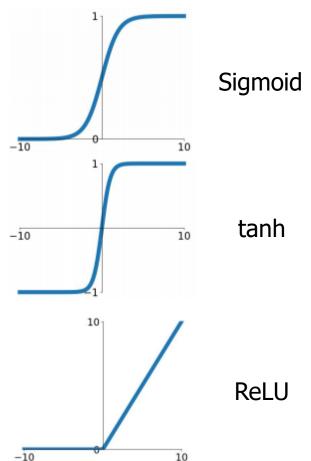
Leaky ReLU
$$max(0.1x, x)$$

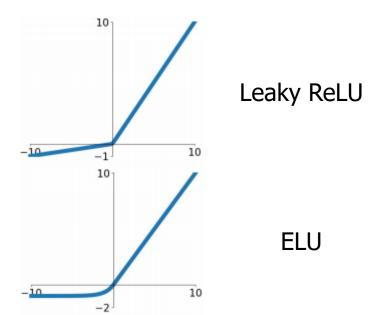
tanh
$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

ELU(Exponential Linear Unit)
$$\begin{cases} x, & x < 0 \\ \alpha(e^x - 1), & x \ge 0 \end{cases}$$

ReLU(Rectified Linear Unit) max(0, x)

- Deep Neural Network(Multi-layer Neural Networks)
 - Activation function







Load Iris Dataset

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X, y, test_size=0.3, random_state=1, stratify=y)

print('Labels counts in y:', np.bincount(y))
print('Labels counts in y_train:', np.bincount(y_train))
print('Labels counts in y_test:', np.bincount(y_test))
Labels counts in y: [0 50 50]
Labels counts in y_train: [0 35 35]
Labels counts in y_test: [0 15 15]
```

Standardize the dataset

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
sc.fit(X_train)
X_train_std = sc.transform(X_train)
X_test_std = sc.transform(X_test)
```

Building a Multi-layer Neural Network and Training the model



Loss curve

```
# plot the loss
plt.plot(mlp.loss_curve_)
plt.show()
```

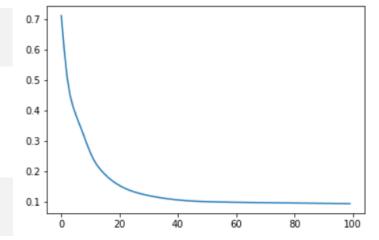
Evaluation

```
# Train accuracy
acc = mlp.score(X_train_std, y_train)
print("Train accuracy : %.4f" % acc)
```

Train accuracy: 0.9429

```
# Test accuracy
acc = mlp.score(X_test_std, y_test)
print("Test accuracy : %.4f" % acc)
```

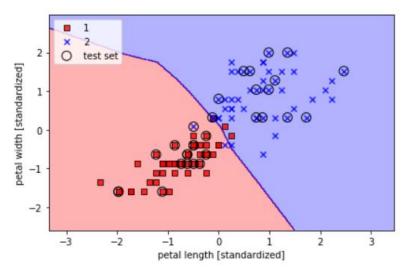
Test accuracy: 0.9667



Plotting decision boundary

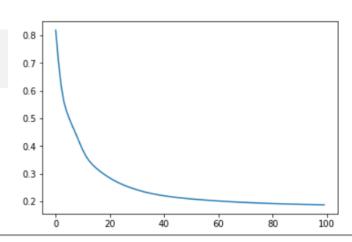
```
X_combined_std = np.vstack((X_train_std, X_test_std))
y_combined = np.hstack((y_train, y_test))

plot_decision_regions(X_combined_std, y_combined,
classifier=knn, test_idx=range(70, 100))
plt.xlabel('petal length [standardized]')
plt.ylabel('petal width [standardized]')
plt.legend(loc='upper left')
plt.tight_layout()
plt.show()
```



Try other regularization parameters (alpha) – (1)

```
# plot the loss
plt.plot(mlp.loss_curve_)
plt.show()
```



Try other regularization parameters (alpha) – (2)

```
# Train accuracy
acc = mlp.score(X_train_std, y_train)
print("Train accuracy : %.4f" % acc)

Train accuracy : 0.9286

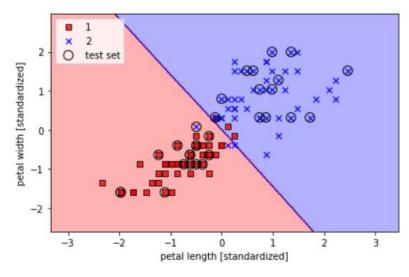
# Test accuracy
acc = mlp.score(X_test_std, y_test)
print("Test accuracy : %.4f" % acc)

Test accuracy : 0.9667
```

Try other regularization parameters (alpha) – (3)

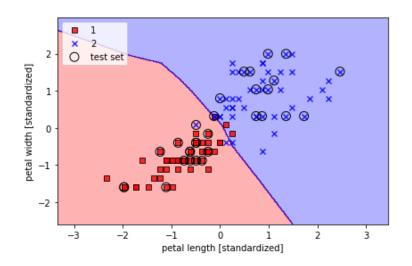
```
X_combined_std = np.vstack((X_train_std, X_test_std))
y_combined = np.hstack((y_train, y_test))

plot_decision_regions(X_combined_std, y_combined,
classifier=mlp, test_idx=range(70, 100))
plt.xlabel('petal length [standardized]')
plt.ylabel('petal width [standardized]')
plt.legend(loc='upper left')
plt.tight_layout()
plt.show()
```

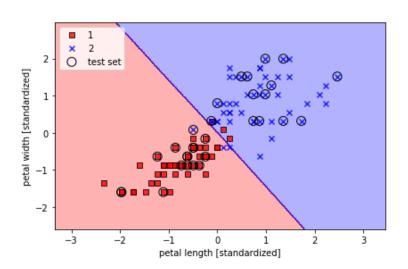


Regularization ratio - alpha

alpha = 1e-4

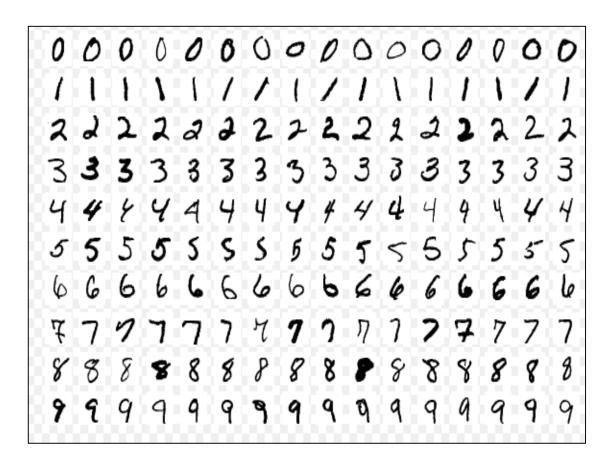


alpha = 1



MNIST dataset

- A set of 70,000 small handwritten digits
- 60,000 training images and 10,000 test images
- 28 x 28 grayscale pixels
- commonly used for training various imag e processing systems



Load MNIST Dataset

```
import matplotlib.pyplot as plt
import numpy as np
from scipy import io

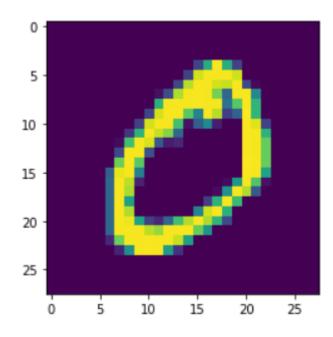
mnist = io.loadmat('mnist-original.mat')
mnist
```

Get X and y –(1)

```
X, y = mnist['data'], mnist['label']
X = np.array(X).T
y = np.array(y).T.ravel()
X.shape
# rescale the data, use the traditional train/test split
X_train, X_test = X[:60000], X[60000:]
y_train, y_test = y[:60000], y[60000:]
```

Get X and y – (2)

```
ex1 = X[0]
ex1_image = ex1.reshape(28, 28)
plt.imshow(ex1_image)
plt.show()
```



Splitting data into 60k training data & 10k test data

```
# rescale the data, use the traditional train/test split
X_train, X_test = X[:60000], X[60000:]
y_train, y_test = y[:60000], y[60000:]
```

Standardize the dataset

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
sc.fit(X_train)
X_train_std = sc.transform(X_train)
X_test_std = sc.transform(X_test)
```

Building a Multi-layer Neural Networks and Training the model

```
from sklearn.neural network import MLPClassifier
mlp = MLPClassifier(hidden layer sizes=(25,25), max iter=100, alpha=1e-4,
                      solver='sgd', verbose=10, tol=1e-4, random state=0,
                      learning rate init=.1)
mlp.fit(X train std, y train)
           Input: 784 dimensions
                                                            output: 10 dimensions
                                25 Neurons per Hidden layer(2)
```

Loss curve

```
# plot the loss
plt.plot(mlp.loss_curve_)
plt.show()
```

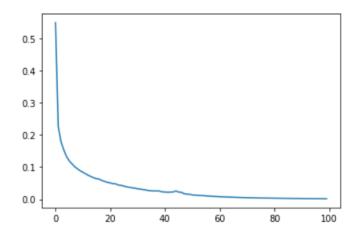
Evaluation

```
# Train accuracy
acc = mlp.score(X_train_std, y_train)
print("Train accuracy : %.4f" % acc)
```

Train accuracy : 1.0000

```
# Test accuracy
acc = mlp.score(X_test_std, y_test)
print("Test accuracy : %.4f" % acc)
```

Test accuracy: 0.9561

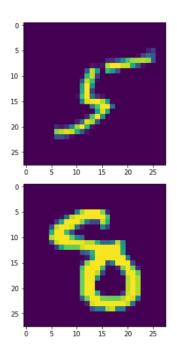


Classification example

```
%matplotlib inline
some_digit1 = X_train_std[35000]
some_digit_image1 = some_digit1.reshape(28, 28)
plt.imshow(some_digit_image1)
plt.show()

some_digit2 = X_train_std[50000]
some_digit_image2 = some_digit2.reshape(28, 28)
plt.imshow(some_digit_image2)
plt.show()
# classification
mlp.predict(sc.transform([some_digit1]))
# classification
mlp.predict(sc.transform([some_digit2]))

array([5.])
array([5.])
array([8.])
```



Visualization of MLP weights on MNIST

```
mlp.coefs [0].shape
(784, 25)
fig, axes = plt.subplots(5, 5)
# use global min / max to ensure all weights are shown on the same scale
vmin, vmax = mlp.coefs [0].min(), mlp.coefs [0].max()
for coef, ax in zip(mlp.coefs_[0].T, axes.ravel()):
    ax.matshow(coef.reshape(28, 28), cmap=plt.cm.gray, vmin=.5 * vmin, vmax=.5 * vmax)
    ax.set xticks(())
    ax.set yticks(())
plt.show()
```

Visualization of MLP weights on MNIST

```
mlp.coefs [1].shape
(25, 25)
fig, axes = plt.subplots(5, 5)
# use global min / max to ensure all weights are shown on the same scale
vmin, vmax = mlp.coefs [1].min(), mlp.coefs [1].max()
for coef, ax in zip(mlp.coefs_[1].T, axes.ravel()):
    ax.matshow(coef.reshape(5, 5), cmap=plt.cm.gray, vmin=.5 * vmin, vmax=.5 * vmax)
    ax.set xticks(())
    ax.set yticks(())
plt.show()
```

Visualization of MLP weights on MNIST

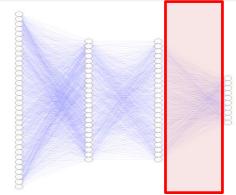
```
mlp.coefs_[2].shape

(25, 10)

fig, axes = plt.subplots(1, 10)
# use global min / max to ensure all weights are shown on the same scale
vmin, vmax = mlp.coefs_[2].min(), mlp.coefs_[2].max()

for coef, ax in zip(mlp.coefs_[2].T, axes.ravel()):
    ax.matshow(coef.reshape(5, 5), cmap=plt.cm.gray, vmin=.5 * vmin, vmax=.5 * vmax)
    ax.set_xticks(())
    ax.set_yticks(())
plt.show()
```





Submit

- To make sure if you have completed this practice,
 Submit your practice file(Week07_givencode.ipynb) to e-class.
- Deadline : tomorrow 11:59pm
- Modify your ipynb file name as "Week07_StudentNum_Name.ipynb"
 Ex) Week07_2020123456_홍일동.ipynb
- You can upload this file without taking the quiz, but homework will be provided like a quiz every three weeks, so it is recommended to take the quiz as well.

Quiz 1

- K-Nearest Neighbors
 - Dataset : Iris dataset(use all features)
 - Model : K-Nearest Neighbors
 - Find the hyperparameter that makes highest test accuracy(0.9556)
 - Number of Neighbors: 3, 5, 7, ...
 - distance metric : manhattan(p=1) / euclidean(p=2)

Quiz 2

- Multi-layer Neural Networks :
 - Dataset : MNIST dataset
 - Model : Multi-layer Neural Network
 - Find the hyperparameter that makes highest test accuracy
 - Number of hidden layers
 - Regularization ratio(alpha)