

# PATTERN RECOGNITION USING PYTHON

## Multi-Layer Perceptron

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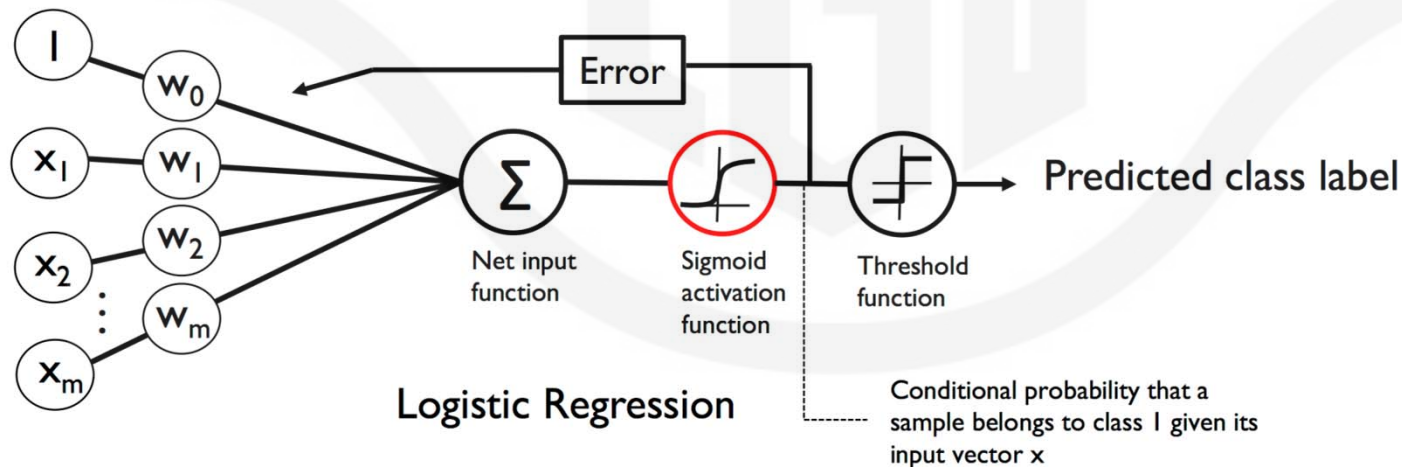
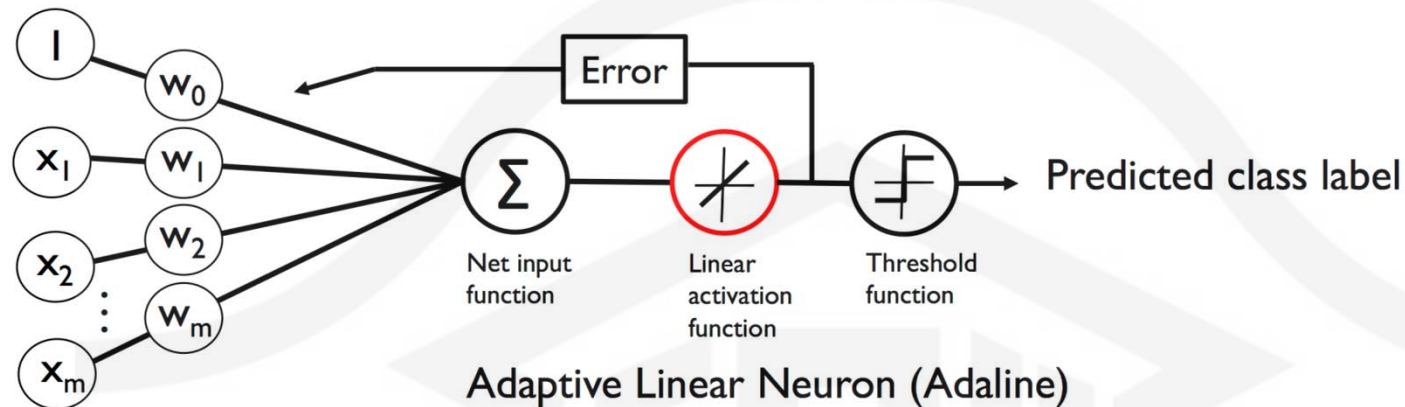
2019-Spring

# More Powerful Architectures

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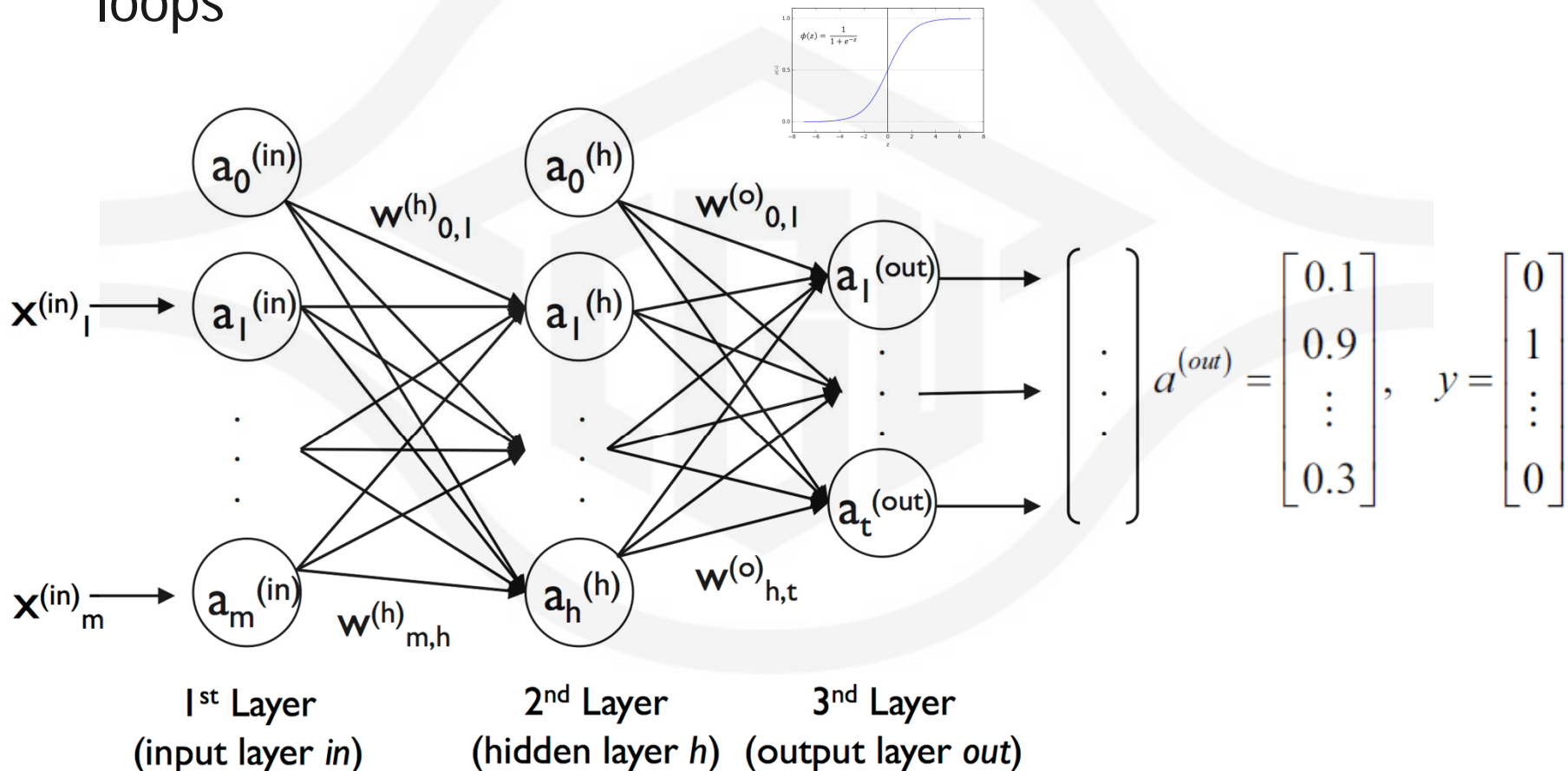
- Getting a conceptual understanding of multilayer neural networks
- Training a basic multilayer neural network for image classification

# Single-layer Perceptron Recap

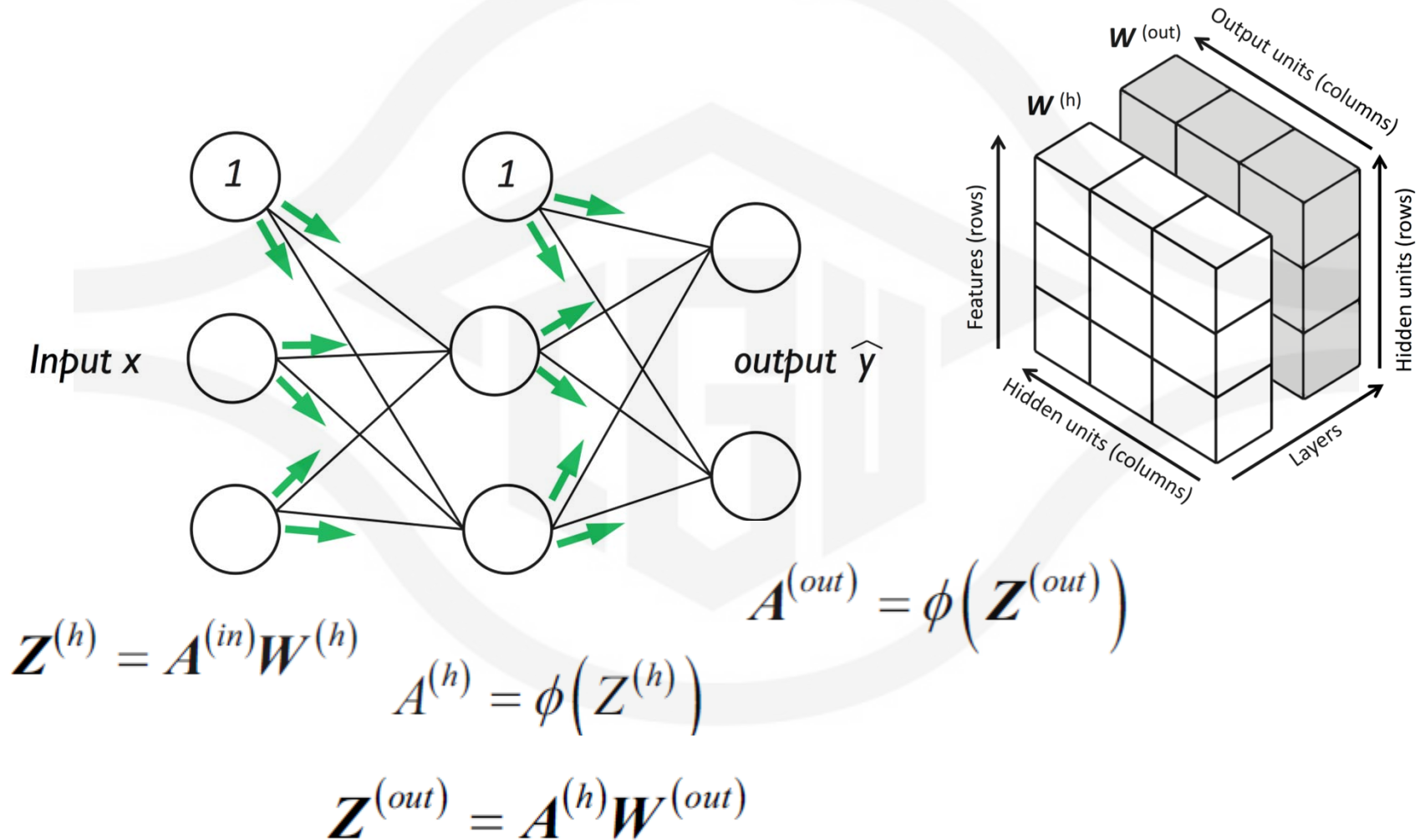


# Multi-layer Perceptron (Fully Connected Network)

- Each layer serves as the input to the next layer without loops



# Forward Propagation



# Training Neural Networks via Backpropagation

- Calculate the partial derivative of the parameters **W** with respect to each weight for every layer in the network

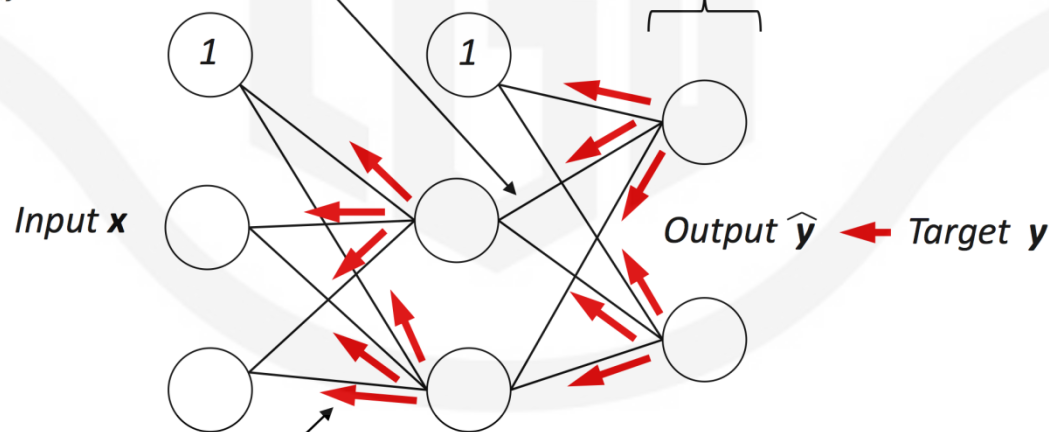
$$\frac{\partial}{\partial w_{j,i}^{(l)}} J(\mathbf{W}) \quad J(\mathbf{W}) = -\sum_{i=1}^n \sum_{j=1}^t y_j^{[i]} \log(a_j^{[i]}) + (1 - y_j^{[i]}) \log(1 - a_j^{[i]})$$

Compute the gradient:

$$\frac{\partial}{\partial w_{i,j}^{(out)}} J(\mathbf{W}) = a_j^{(h)} \delta_i^{(out)}$$

Error term of the output layer:

$$\delta^{(out)} = \mathbf{a}^{(out)} - \mathbf{y}$$



Compute the gradient:

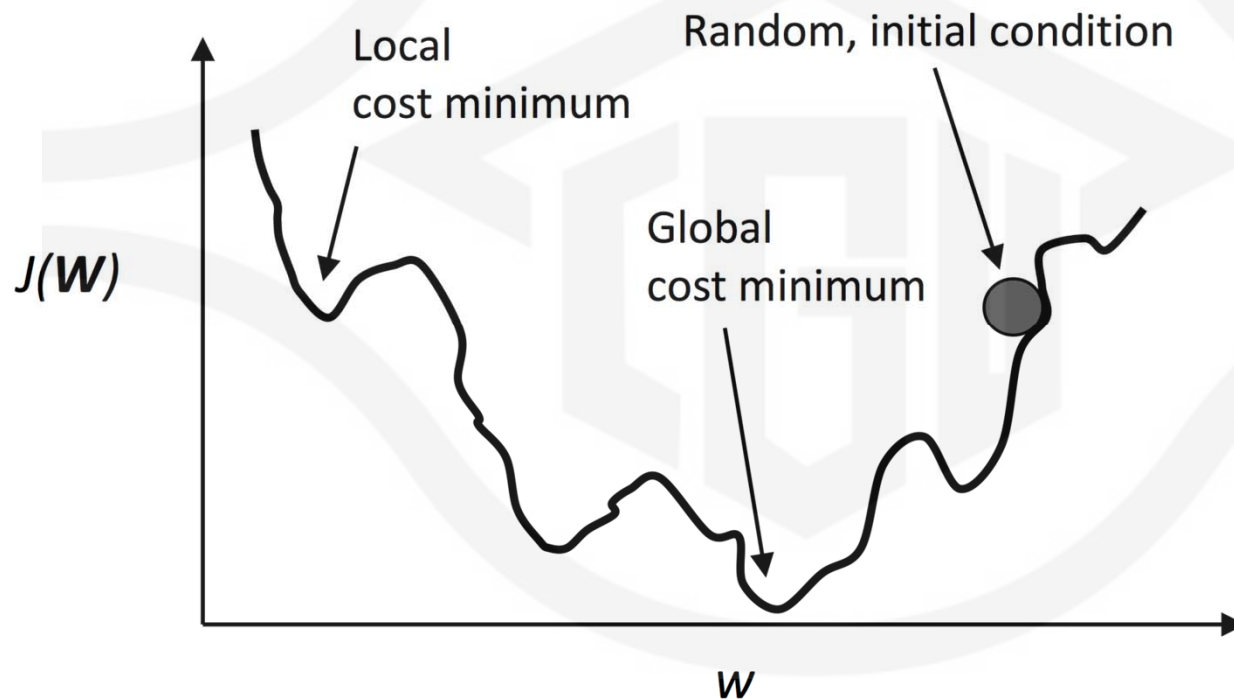
$$\frac{\partial}{\partial w_{i,j}^{(h)}} J(\mathbf{W}) = a_j^{(in)} \delta_i^{(h)}$$

Error term of the hidden layer:

$$\delta^{(h)} = \delta^{(out)} (\mathbf{W}^{(out)})^T \odot \frac{\partial \phi(z^{(h)})}{\partial z^{(h)}}$$

# Convergence in Neural Networks

- Non-convex loss function



# MLP Classifier utilize sklearn

- Classify wine data with MLP

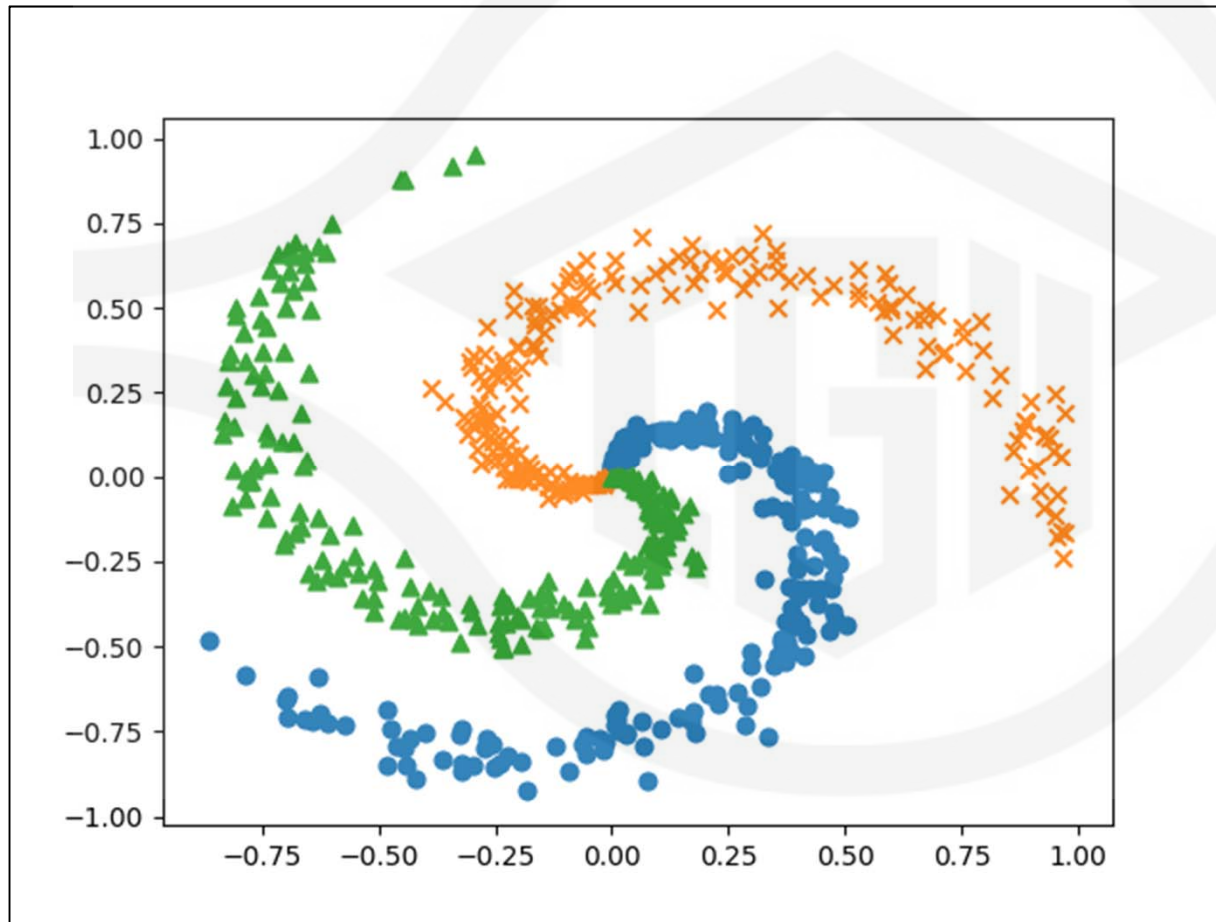
```
from sklearn.neural_network import MLPClassifier

mlp = MLPClassifier(hidden_layer_sizes=(50,), max_iter=500,
alpha=1e-4, solver='sgd', verbose=False, tol=1e-4,
random_state=1, learning_rate_init=0.1)
mlp.fit(X_train_std, y_train)
print("Training set score: %f" % mlp.score(mlp.fit(X_train_std,
y_train))
print("Test set score: %f" % mlp.score(mlp.fit(X_test_std,
y_test))
```

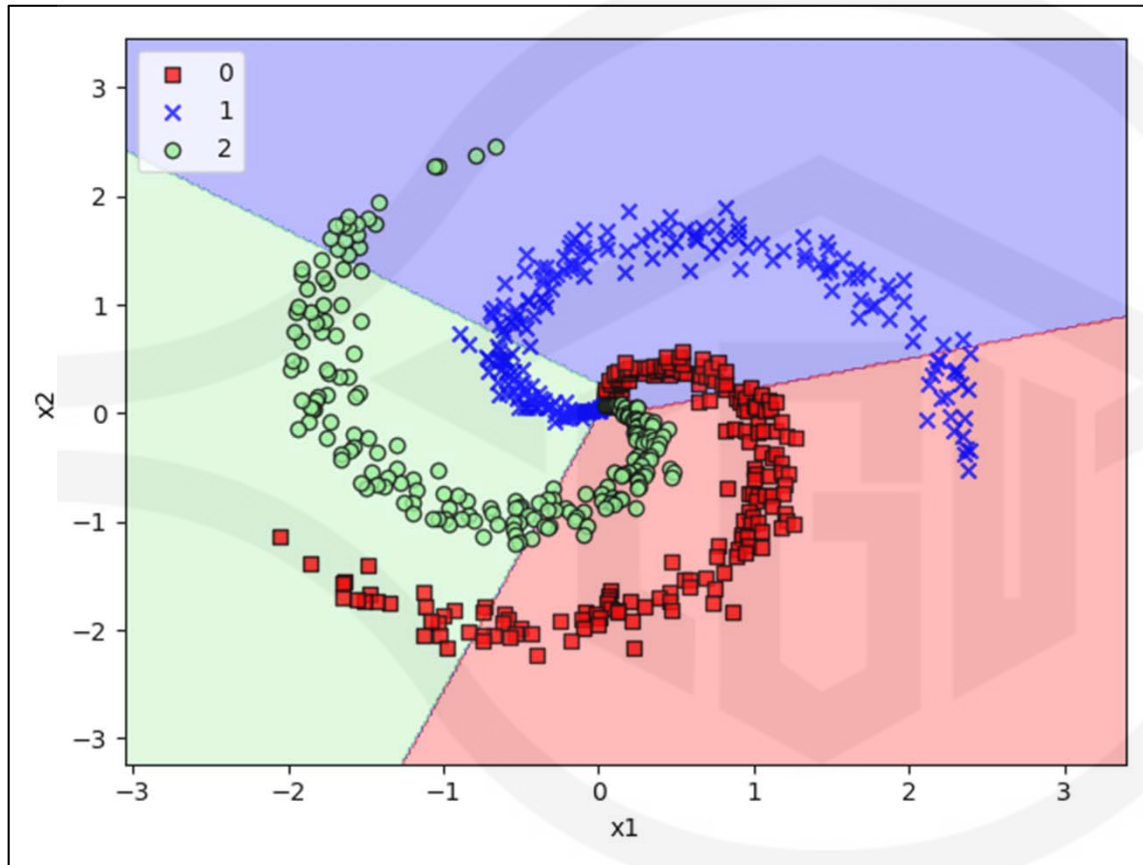


# Non-linear Data Classification

- Spiral Pattern

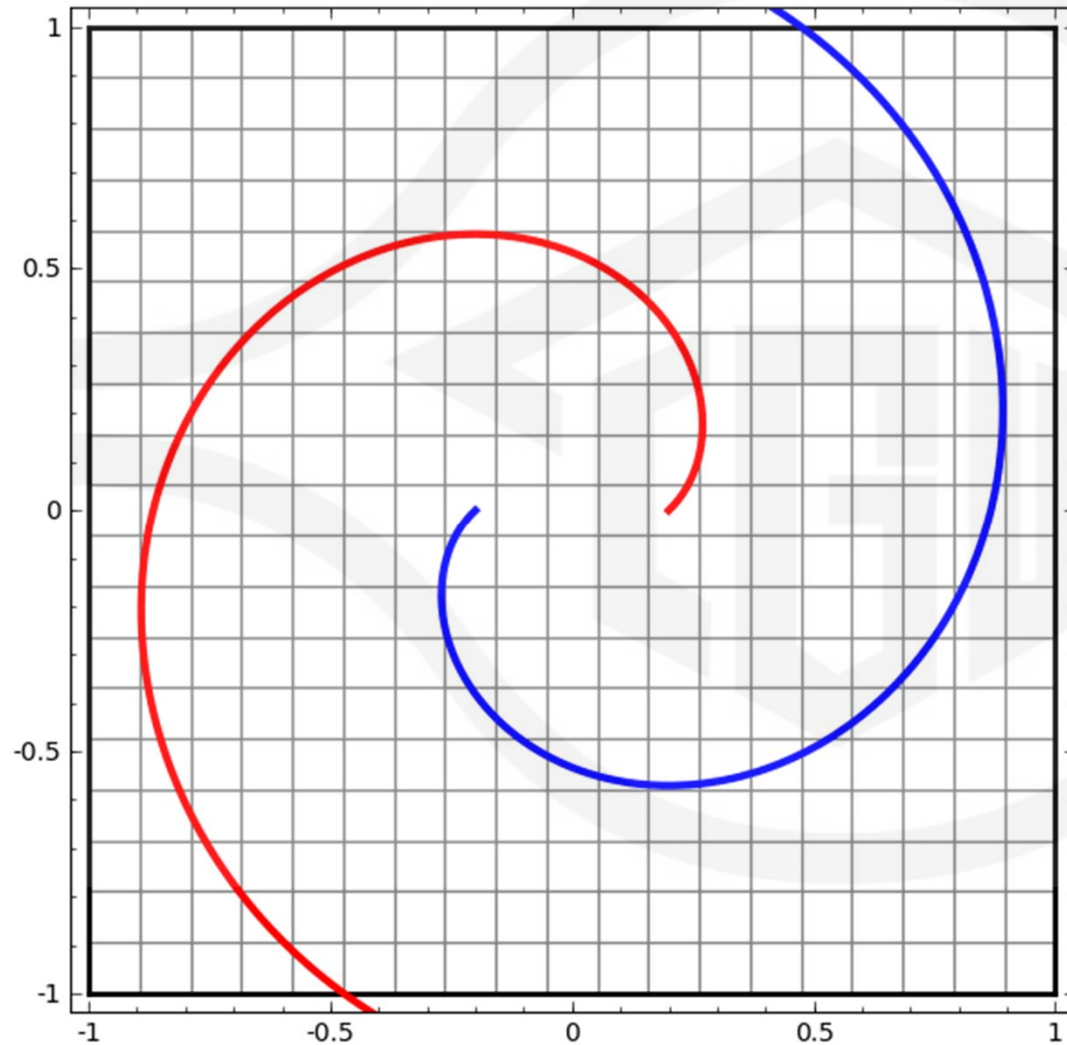


# General Classifier

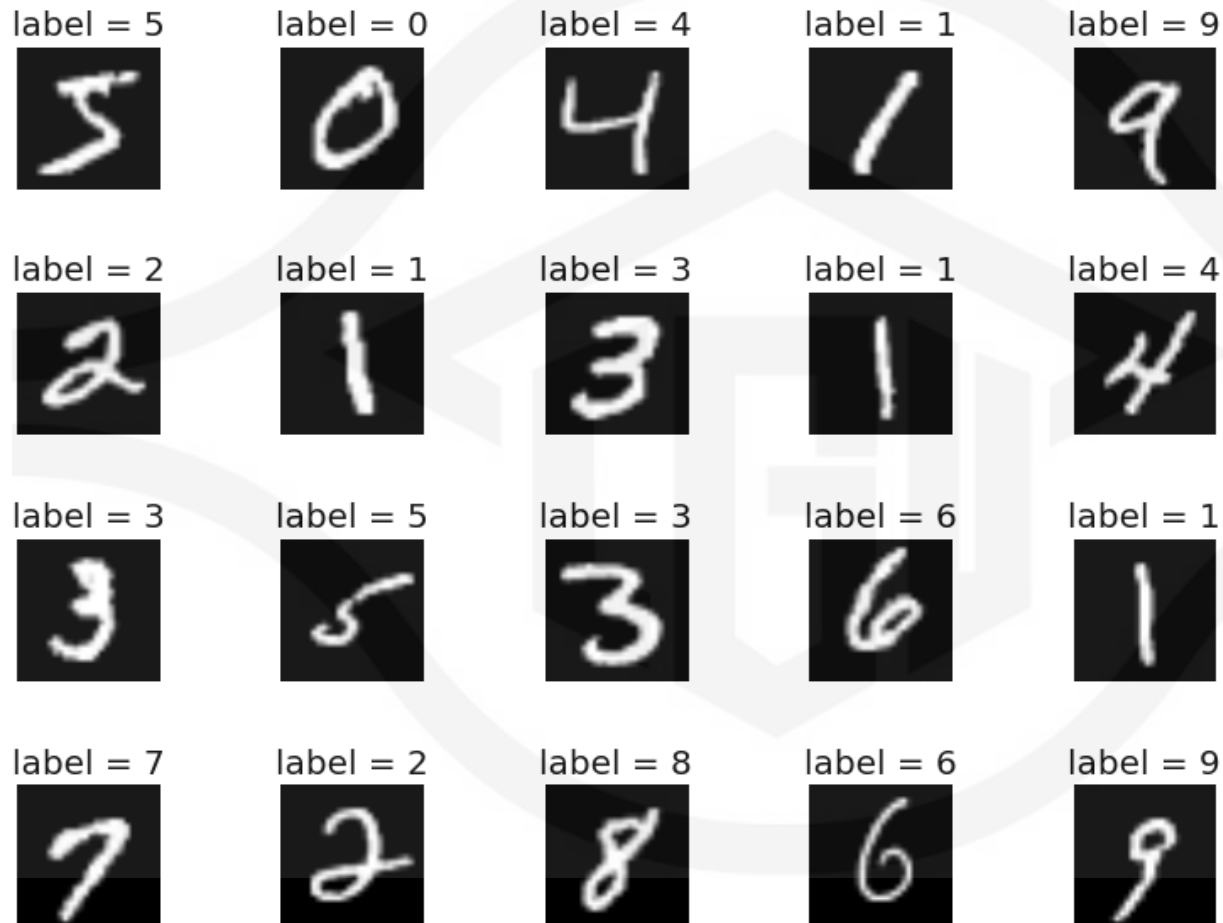


- Not Good, Try MLP Classifier ?

# The Ability of Non-linear Mapping



# Classifying Handwritten Digits



# Load MNIST Data & Preprocessing

- Dim = 784 (H28\*W28)

```
## Load dataset
df = pd.read_csv('mnist_784.csv', header=0)
y = df.iloc[:, -1].values
print(y.shape)
X = df.iloc[:, 0:-1].values
print(X.shape)
```

- 8 bits gray scale (0~255)

```
X = X / 255.
```

# Hidden Layer Setting

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- Hidden layer (100, 100)

```
## classifier MLP two hidden layer
from sklearn.neural_network import MLPClassifier
mlp2 = MLPClassifier(hidden_layer_sizes=(100, 100),
max_iter=50, alpha=1e-4, solver='sgd', verbose=False,
tol=1e-4, random_state=1, learning_rate_init=0.1)
mlp2.fit(X_train, y_train)
print('Two hidden layer')
print("Training set score: %f" % mlp2.score(X_train,
y_train))
print("Test set score: %f" % mlp2.score(X_test, y_test))
```

# Reference

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- Sebastian Raschka, Vahid Mirjalili. Python Machine Learning: Machine Learning and Deep Learning with Python, scikit-learn, and TensorFlow. Second Edition. Packt Publishing, 2017.