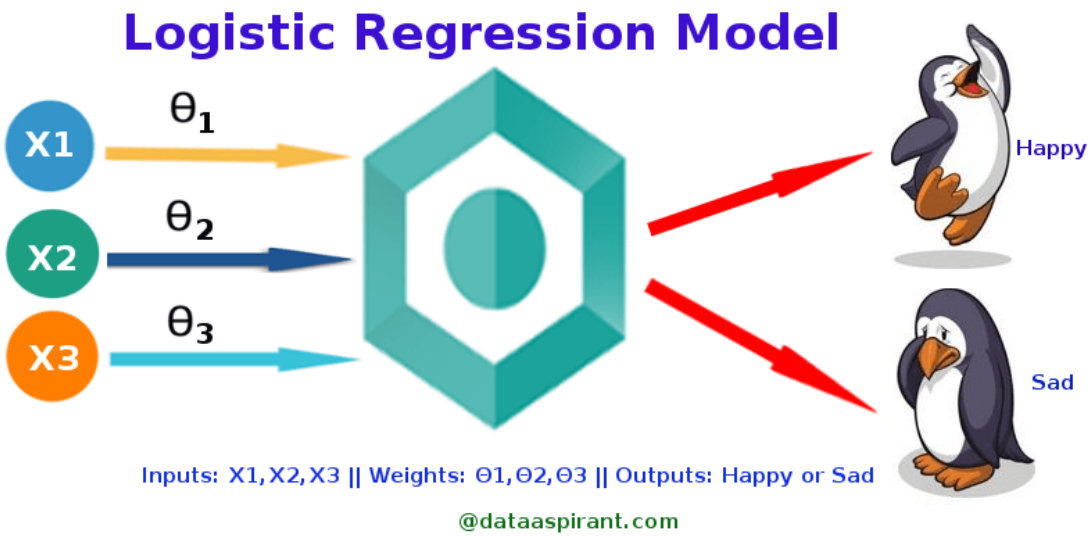
# 이항 분류 및 다항 분류

# 파일

- **10W-1-classcification.ipynb**

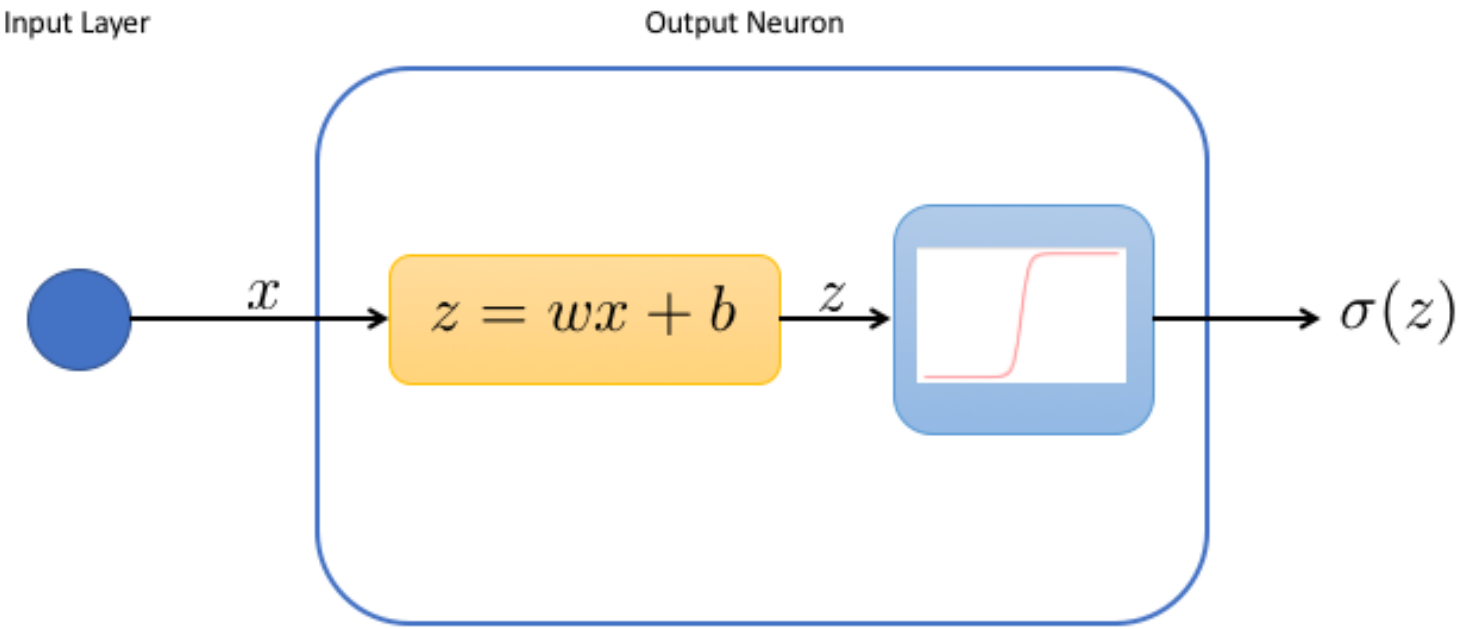
# 이진(이항) 분류

- **두 가지로 분류하는 방법**
  - PASS / FAIL
  - SPAM / HAM
  - 긍정positive과 부정 negative
    - **리뷰 텍스트를 기반으로 영화 리뷰**
  - 로지스틱 회귀라고도 부름

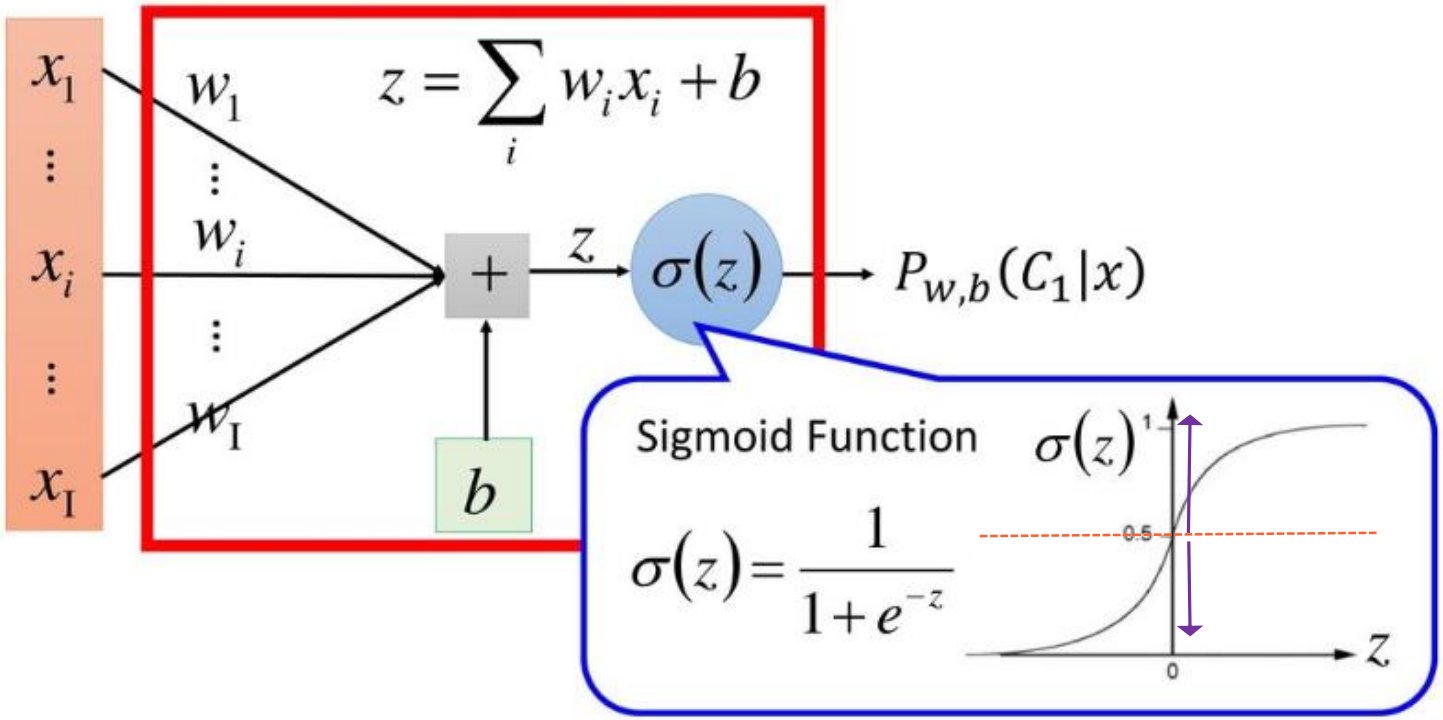



- **결과 기술 방식**
  - 4 개의 결과
    - **일반 레이블 방식**
      - **[0, 1, 0, 1]**
    - **One Hot Encoding 방식**
      - **[[1, 0], [0, 1], [1, 0], [0, 1]]**

# 이진 분류 개념



# 이진 분류 활성화 함수

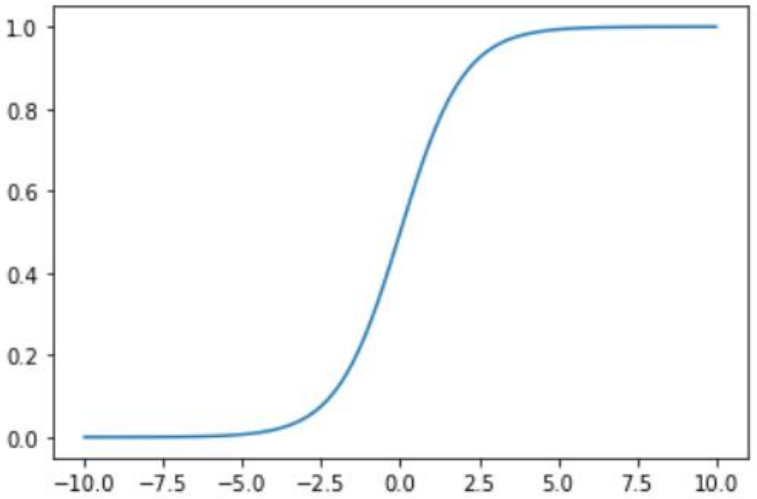

$x_1$
$x_i$
$x_I$
$w_1$
$w_i$
$w_I$
$z = \sum_i w_i x_i + b$
+
$b$
$z$
$\sigma(z)$
$P_{w,b}(C_1|x)$
Sigmoid Function
$\sigma(z) = \frac{1}{1+e^{-z}}$
$\sigma(z)$
1
0.5
0
$z$

# 시그모이드 함수

- **이진분류 모델의 출력층에 주로 사용되는 활성화 함수**
  - 0과 1사이의 값으로 출력
  - 출력 값이 특정 임계값(예를 들어 0.5) 이상이면 양성
    - **이하이면 음성이라고 판별**

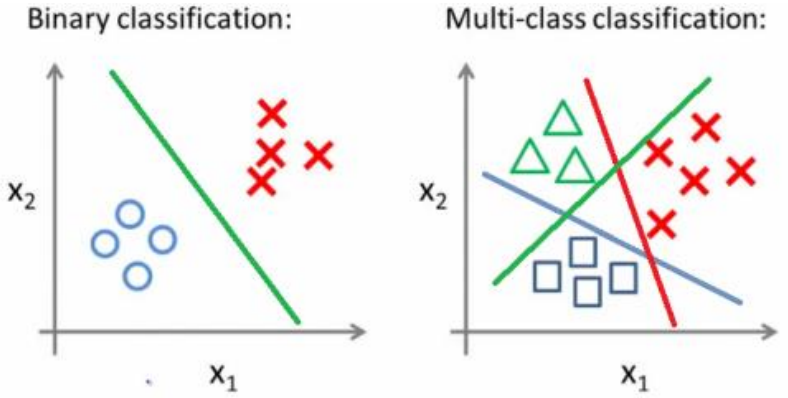
$$f(x) = \frac{1}{1 + e^{-x}}$$

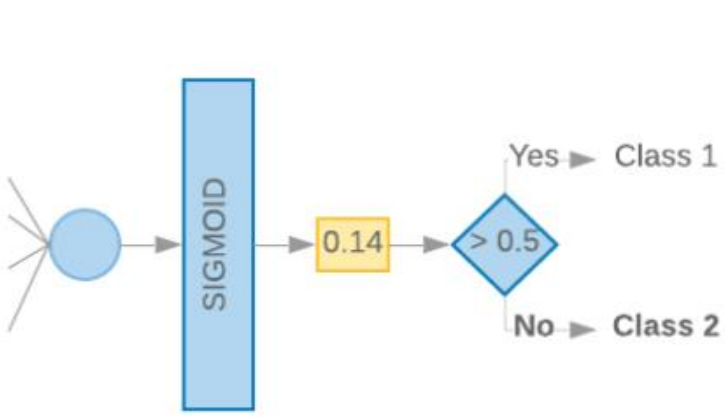
```
import numpy as np
import matplotlib.pyplot as plt

x = np.linspace(-10, 10, 100)
y = 1 / ( 1 + np.exp(-x) )
plt.plot(x, y)
plt.show()
```

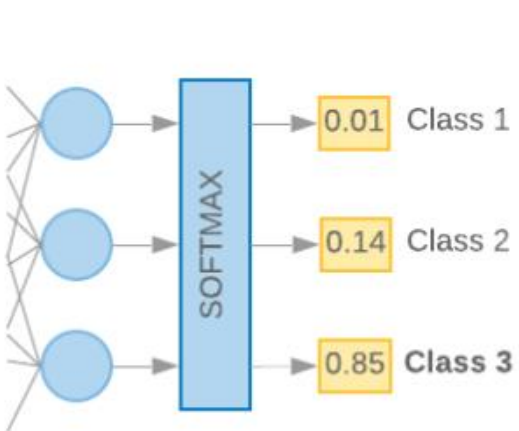


# 이진 분류와 다중 분류

- **시그모이드 함수와 소프트맥스 함수**

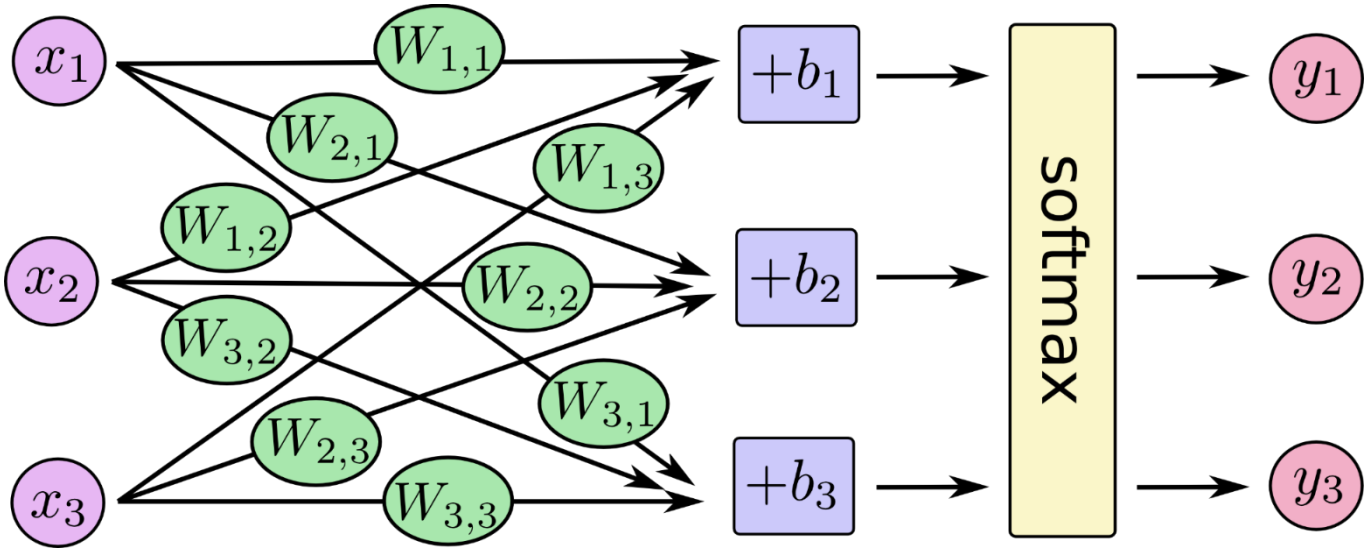


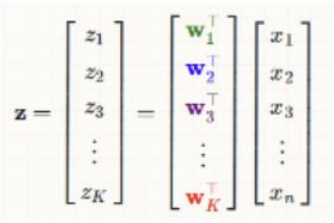
# 소프트맥스 함수

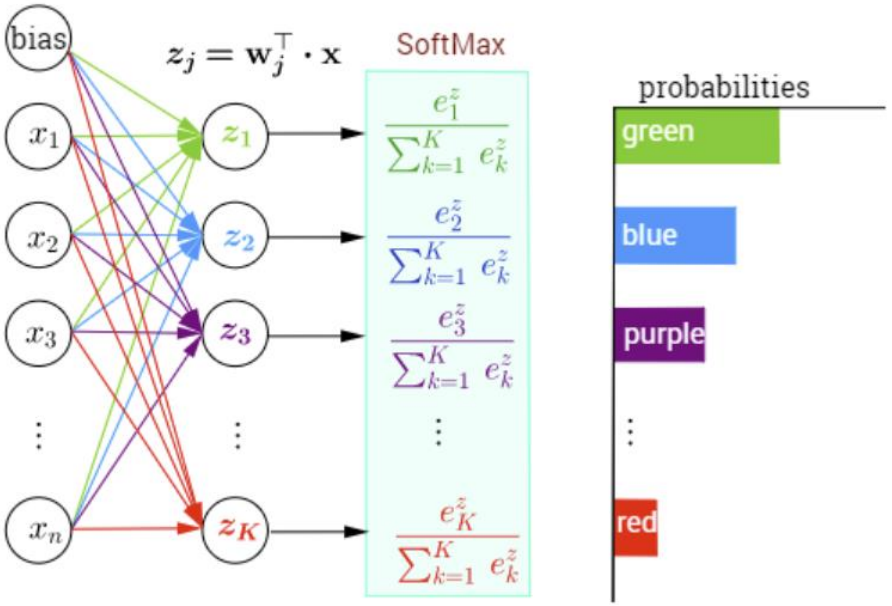
- **분류의 마지막 활성화 함수로 사용**
  - 모든 yi의 합은 1
    - **각각의 yi는 그 분류의 확률**



# 소프트맥스 함수

- **뉴런의 결과를 e의 지수승으로 하여 모든 합으로 나눈 결과**
  - $\exp(x_i)$ / tf.reduce_sum(exp(x))




The softmax as

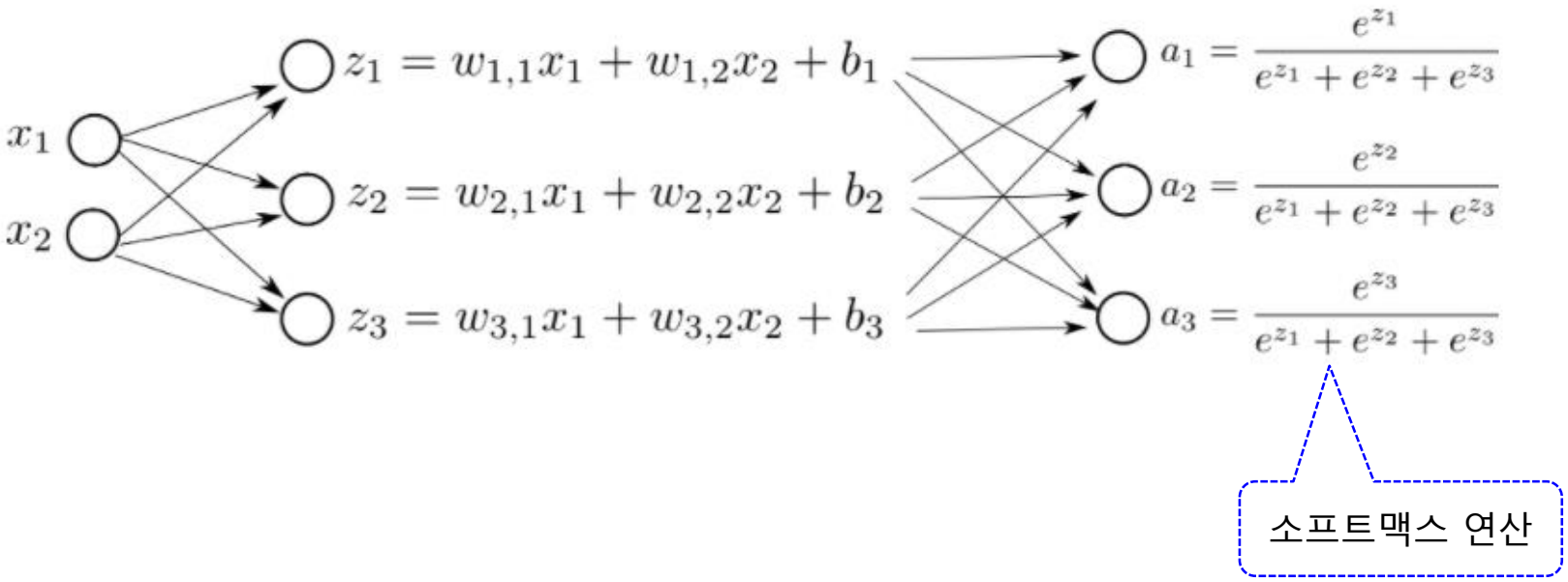
$$\sigma(j) = \frac{\exp(\mathbf{w}_j^\top \mathbf{x})}{\sum_{k=1}^{K} \exp(\mathbf{w}_k^\top \mathbf{x})} = \frac{\exp(z_j)}{\sum_{k=1}^{K} \exp(z_k)}$$

This will result in a normalization of the output adding up to 1, interpretable as a probability mass functionn.



http://rinterested.github.io/statistics/softmax.html

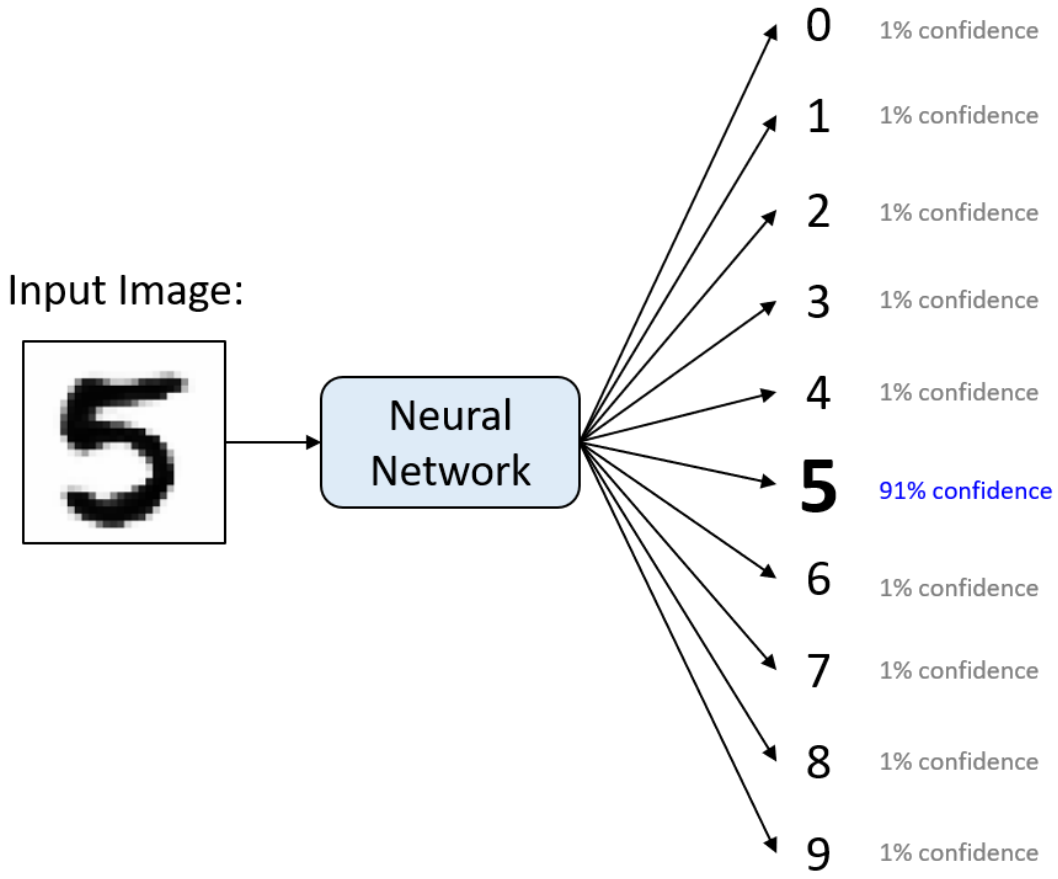
# 소프트맥스의 이해




$$\frac{\exp(z_j)}{\sum_{k=1}^{K} \exp(z_k)}$$

# 대표적 다중 분류

- **MNIST 손글씨**



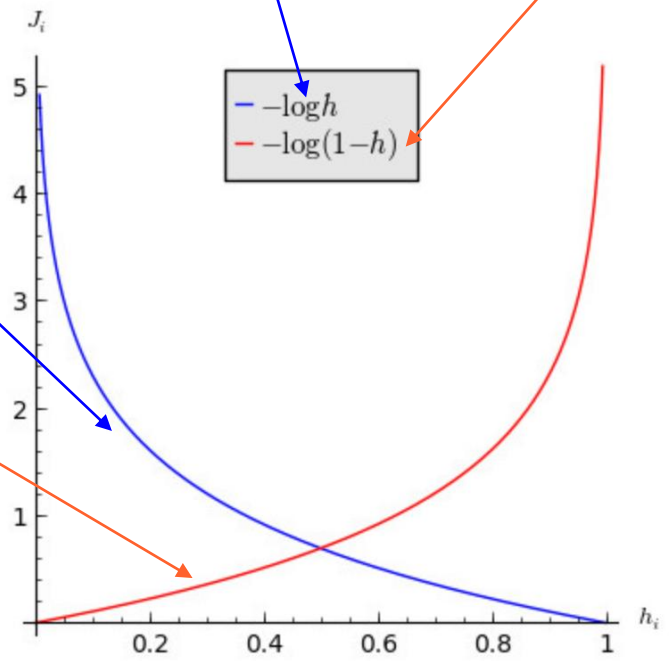
# 분류에서의 손실 함수로 활용되는 엔트로피의 이해

- **이진 분류에서의 바이너리 크로스 엔트로피의 이해**
  - 예측 값 H(x): 0 <= H(x) <= 1
  - 실제 데이터의 결과 값인 y
    - **y=1일 때**
      - **예측 값이 1에 가까워질수록 cost function의 값은 작아져야 함**
      - **반대로 0에 가까워질수록 cost function의 값이 무한대로 증가하게 되어 예측이 틀렸다는 것을 보여주어야 함**
    - **y= 0일 때**
      - **예측이 0으로 맞게 되면 cost function은 매우 작은 값을 가지고**
      - **반대로 예측이 1로 하게 되어 예측에 실패할 경우 cost 값이 무한대로 증가하여 틀렸다는 것을 알 수 있게 해야 함**

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

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

$$C(H(x), y) = -ylog(H(x)) - (1 - y)log(1 - H(x))$$

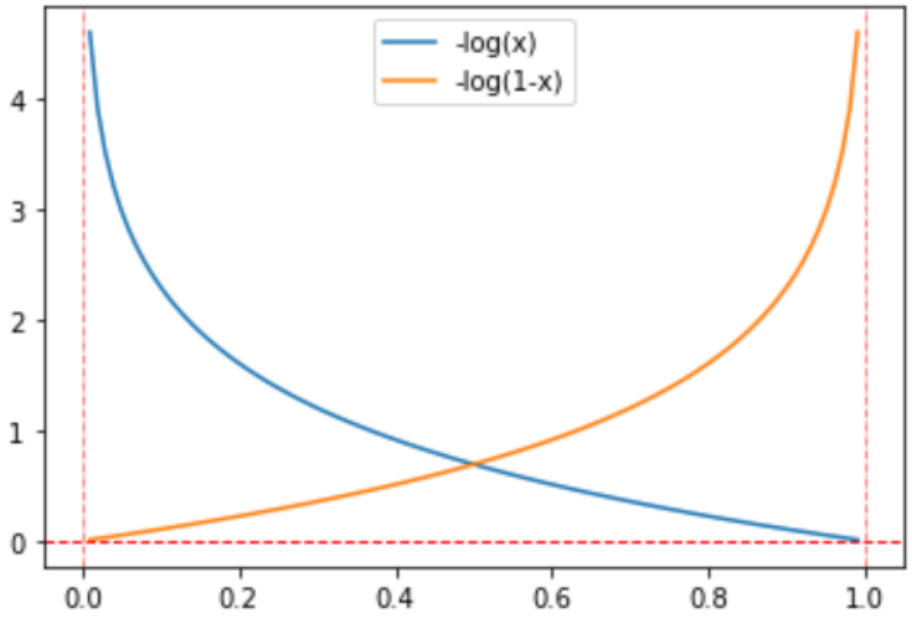





https://wikidocs.net/35476

# 바이너리 크로스 엔트로피 손실 함수 직접 그리기

- **Cross entropy**

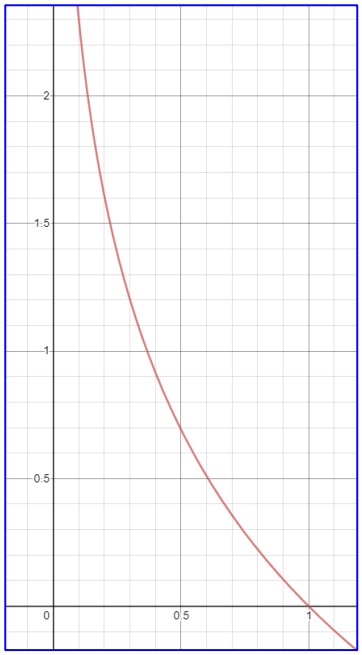



```
import numpy as np
import matplotlib.pyplot as plt

alpha = 0.1e-1
x = np.linspace(0+alpha, 1-alpha, 100)
y1 = -np.log(x)
y2 = -np.log(1-x)

plt.axhline(y=0, color='r', linestyle='--',linewidth=1)
plt.axvline(x=1, color='r', linestyle='-.',linewidth=.5)
plt.axvline(x=0, color='r', linestyle='-.',linewidth=.5)
plt.plot(x, y1, label='-log(x)')
plt.plot(x, y2, label='-log(1-x)')
plt.legend(loc='best')
plt.show()
```

# 크로스 엔트로피

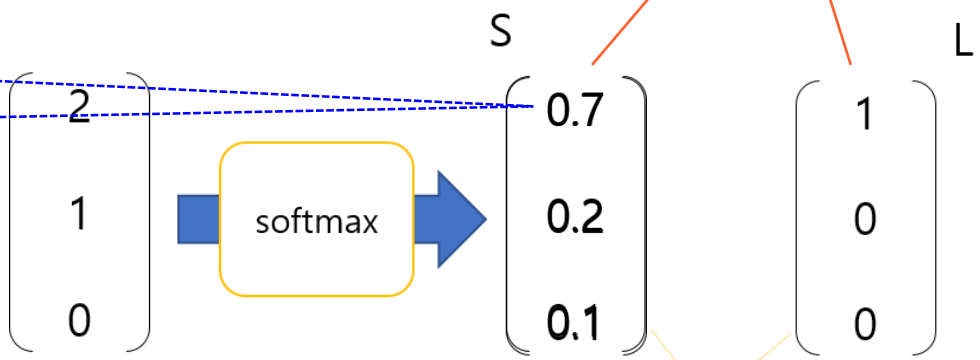
- **비용함수: Cross entropy**
  - y: 는 실제값(정답)
  - k: 클래스의 개수로 정의, 3
  - yj: 실제값 원-핫 벡터의 j번째 인덱스를 의미
  - pj: 샘플 데이터가 j번째 클래스일 확률

$$cost(W) = -\sum_{j=1}^{k} y_j \, log(p_j)$$



https://www.desmos.com/calculator?lang=ko

만일 07보다 작다면 손실함수인 앤트로피는 더 커짐

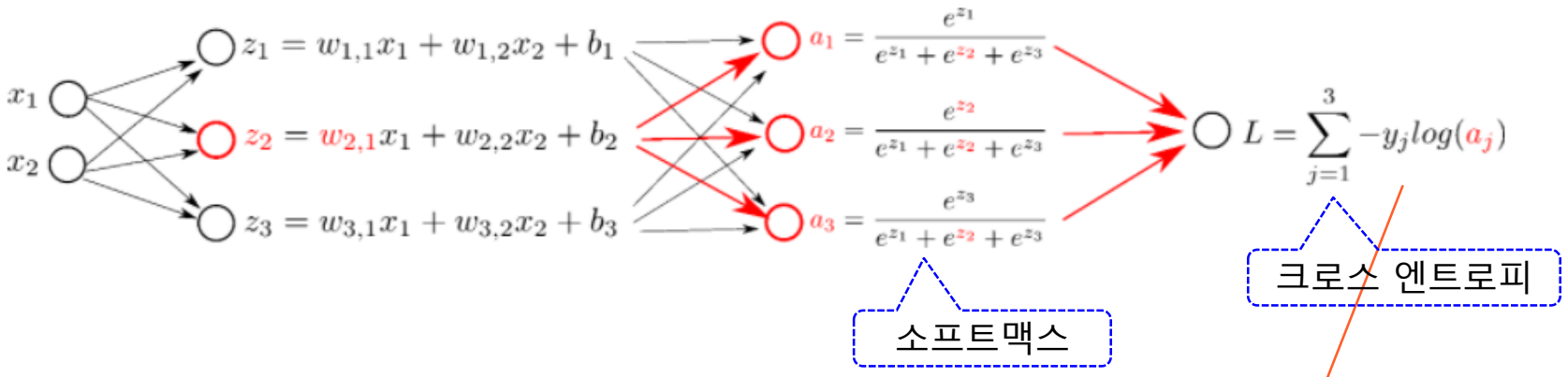


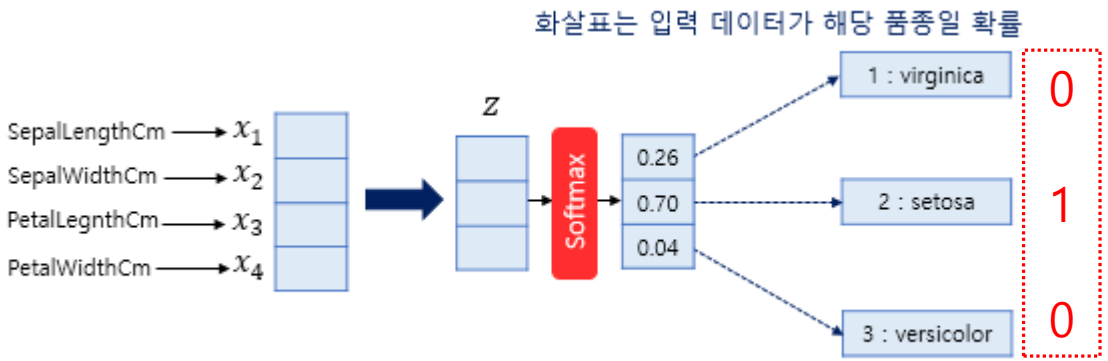

$$\text{softmax}(x)_i = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

$$cost(W) = -\sum_{j=1}^{k} y_j \, log(p_j) \quad -(1 * log0.7 + 0 * log0.2 + 0 * log0.1)$$

https://www.youtube.com/watch?v=jMU9G5WEtBc&feature=youtu.be
이해를 돕기 위한 동영상: 성김비디오

# 소프트맥스와 엔트로피의 계산 이해




- ( (0 * log0.26) + (1 * log0.70) + (0 * log0.04) )

# 텐서플로 Softmax 계산

- **확률 값**
  - 결과를 모두 더하면 1

```
import tensorflow as tf
import numpy as np

a = np.array([[0.3, 2.9, 4.0]])
sm = tf.keras.activations.softmax(tf.convert_to_tensor(a))
print(sm.numpy())
```

```
[[0.01821127 0.24519181 0.73659691]]
```

# 텐서플로로 크로스 엔트로피 손실 함수 계산

- **tf.keras.losses.categorical_crossentropy**
  - 정답
    - **y_true = [[0, 1, 0], [0, 0, 1]]**
  - 예측
    - **y_pred = [[0.05, 0.95, 0], [0.1, 0.8, 0.1]]**
  - 함수 적용
    - **loss = tf.keras.losses.categorical_crossentropy(y_true, y_pred)**
  - 결과
    - **loss.numpy()**

```
1 import tensorflow as tf
2
3 y_true = [[0, 1, 0], [0, 0, 1]]
4 y_pred = [[0.05, 0.95, 0], [0.1, 0.8, 0.1]]
5 loss = tf.keras.losses.categorical_crossentropy(y_true, y_pred)
6 loss.numpy()
```

```
array([0.05129331, 2.3025851 ], dtype=float32)
```

정답이 2인데, 정답을 1이 0.8로 예측

정답이 2인데, 정답을 1이 0.8로
예측해 손실 값이 매우 큼

# 일반 값 사용 크로스 엔트로피 손실 함수

- **tf.keras.losses.categorical_crossentropy**
  - 정답: 원 핫 인코딩 유형
    - **y_true = [[0, 1, 0], [0, 0, 1]]**
- **tf.keras.losses.sparse_categorical_crossentropy**
  - 정답: 일반 유형
    - **y_true = [[1], [2]]**

```
import tensorflow as tf

# y_true = [[0, 1, 0], [0, 0, 1]]
y_true = [[1], [2]]
y_pred = [[0.05, 0.95, 0], [0.1, 0.8, 0.1]]
loss = tf.keras.losses.sparse_categorical_crossentropy(y_true, y_pred)
loss.numpy()
```

# 일반 값을 원핫으로 변환

- **일반 값을 원핫으로 변환해 크로스 엔트로피 손실 함수**

```
import tensorflow as tf

y_true = [[1], [2]]
y_true = tf.one_hot(y_true, depth=3)
print(y_true)
y_true = tf.reshape(y_true, [-1, 3])
print(y_true)
y_pred = [[0.05, 0.95, 0], [0.1, 0.8, 0.1]]

loss = tf.keras.losses.categorical_crossentropy(y_true, y_pred)
loss.numpy()
```

```
tf.Tensor(
[[[0. 1. 0.]]

 [[0. 0. 1.]]], shape=(2, 1, 3), dtype=float32)
tf.Tensor(
[[0. 1. 0.]
 [0. 0. 1.]], shape=(2, 3), dtype=float32)
array([0.05129331, 2.3025851 ], dtype=float32)
```

# 크로스 엔트로피 손실 값 직접 계산

$$cost(W) = -\sum_{j=1}^{k} y_j \, log(p_j)$$

S

$$\begin{pmatrix} 0.7 \\ 0.2 \\ 0.1 \end{pmatrix}$$

L

$$\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

$$H(p,q) = -\sum_{x} p(x) \log q(x).$$

$$-(1 * log0.7 + 0 * log0.2 + 0 * log0.1)$$

```
import tensorflow as tf
import numpy as np

y_true = tf.reshape(tf.one_hot([[1], [2]], depth=3), [-1, 3])
y_pred = [[0.05, 0.95, 0], [0.1, 0.8, 0.1]]

loss = tf.keras.losses.categorical_crossentropy(y_true, y_pred)
print(loss.numpy())

print(-np.log(0.95), -np.log(0.1))
```

```
[0.05129331 2.3025851 ]
0.05129329438755058 2.302585092994045
```

# 엔트로피

- **불확실성의 척도**
- **정보이론**
  - 엔트로피는 불확실성을 나타내며
  - 엔트로피가 높다는 것은 정보가 많고, 확률이 낮다는 것을 의미
- **Cross-Entropy**

$$H_p(q) = -\sum_{i=1}^{n} q(x_i) log p(x_i)$$

- **크로스 엔트로피는 실제 분포에 대하여 알지 못하는 상태에서**
  - 모델링을 통하여 구한 분포인 p를 통하여 q를 예측하는 것
  - q와 p가 모두 들어가서 크로스 엔트로피
- **머신러닝**
  - 실제 환경의 결과 값 q, 예측값(관찰값) p
  - 실제값과 예측값이 맞는 경우에는 0으로 수렴
  - 값이 틀릴 경우에는 값이 커지기 때문에, 실제 값과 예측 값의 차이를 줄이기 위한 엔트로피

# 5장 분류

# 이항 분류:
# 레드 와인과
# 화이트 와인 구분

# 파일

- **10W-2-wine-classcification.ipynb**

# 화인 데이터 셋

- **캘리포니아 어바인 대학 제공**
- **특징 12 개, p108**
  - ['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
  - 'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
  - 'pH', 'sulphates', 'alcohol', 'quality']

```
# 5.1 와인 데이터셋 불러오기
import pandas as pd
red = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-
databases/wine-quality/winequality-red.csv', sep=';')
white = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-
databases/wine-quality/winequality-white.csv', sep=';')
print(red.head())
print(white.head())
```

# 와인 데이터셋 합치기

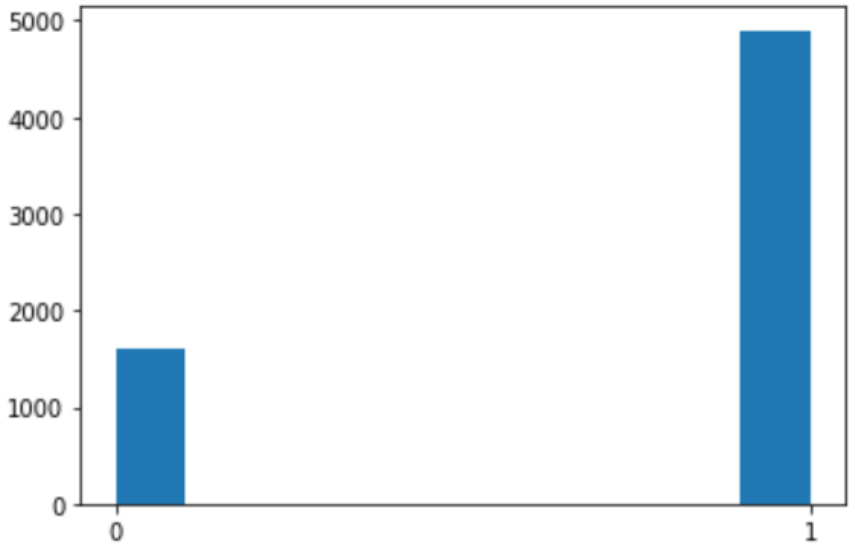
- **두 데이터를 합하여**
  - 메소드 pd.concat()
- **와인 구분, 열 type 추가**
  - 레드 와인: 0
  - 화이트 와인: 1

```
# 5.2 와인 데이터셋 합치기
red['type'] = 0
white['type'] = 1
print(red.head(2))
print(white.head(2))

wine = pd.concat([red, white])
print(wine.describe())
```

```
   fixed acidity  volatile acidity  citric acid  ...  alcohol  quality  type
0            7.4              0.70         0.0  ...      9.4        5     0
1            7.8              0.88         0.0  ...      9.8        5     0

[2 rows x 13 columns]
   fixed acidity  volatile acidity  citric acid  ...  alcohol  quality  type
0            7.0              0.27         0.36  ...      8.8        6     1
1            6.3              0.30         0.34  ...      9.5        6     1

[2 rows x 13 columns]
       fixed acidity  volatile acidity  ...      quality         type
count    6497.000000       6497.000000  ...  6497.000000  6497.000000
mean        7.215307          0.339666  ...     5.818378     0.753886
std         1.296434          0.164636  ...     0.873255     0.430779
min         3.800000          0.080000  ...     3.000000     0.000000
25%         6.400000          0.230000  ...     5.000000     1.000000
50%         7.000000          0.290000  ...     6.000000     1.000000
75%         7.700000          0.400000  ...     6.000000     1.000000
max        15.900000          1.580000  ...     9.000000     1.000000

[8 rows x 13 columns]
```

# 레드 와인 화이트 와인 수

```
# 5.3 레드 와인과 화이트 와인 type 히스토그램
import matplotlib.pyplot as plt
plt.hist(wine['type'])
plt.xticks([0, 1])
plt.show()

print(wine['type'].value_counts())
```




```
1    4898
0    1599
Name: type, dtype: int64
```

# 정규화

- **정규화 이후**
  - 최소 0, 최대 1

```
# 5.5 데이터 정규화
wine_norm = (wine - wine.min()) / (wine.max() - wine.min())
print(wine_norm.head())
print(wine_norm.describe())
```

```
   fixed acidity  volatile acidity  citric acid  ...   alcohol   quality  type
0       0.297521          0.413333     0.000000  ...  0.202899  0.333333   0.0
1       0.330579          0.533333     0.000000  ...  0.260870  0.333333   0.0
2       0.330579          0.453333     0.024096  ...  0.260870  0.333333   0.0
3       0.611570          0.133333     0.337349  ...  0.260870  0.500000   0.0
4       0.297521          0.413333     0.000000  ...  0.202899  0.333333   0.0

[5 rows x 13 columns]
       fixed acidity  volatile acidity  ...      quality         type
count    6497.000000       6497.000000  ...  6497.000000  6497.000000
mean        0.282257          0.173111  ...     0.469730     0.753886
std         0.107143          0.109758  ...     0.145543     0.430779
min         0.000000          0.000000  ...     0.000000     0.000000
25%         0.214876          0.100000  ...     0.333333     1.000000
50%         0.264463          0.140000  ...     0.500000     1.000000
75%         0.322314          0.213333  ...     0.500000     1.000000
max         1.000000          1.000000  ...     1.000000     1.000000

[8 rows x 13 columns]
```

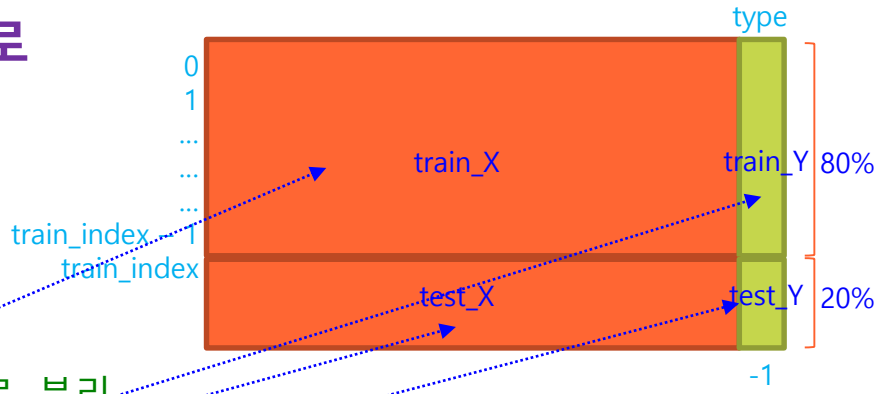
# 레드와인과 화이트 와인 행 섞기

```
# 5.6 데이터 섞은 후 numpy array로 변환
import numpy as np

wine_shuffle = wine_norm.sample(frac=1)
print(wine_shuffle.head())
wine_np = wine_shuffle.to_numpy()
print(wine_np[:5])
```

```
      fixed acidity  volatile acidity  citric acid  ...   alcohol   quality  type
464        0.636364          0.156667     0.325301  ...  0.173913  0.500000   0.0
4256       0.181818          0.166667     0.156627  ...  0.173913  0.333333   1.0
441        0.190083          0.200000     0.120482  ...  0.347826  0.500000   1.0
3676       0.123967          0.146667     0.180723  ...  0.811594  0.666667   1.0
165        0.330579          0.366667     0.289157  ...  0.217391  0.333333   0.0

[5 rows x 13 columns]
[[0.63636364 0.15666667 0.3253012  0.02300613 0.12458472 0.01388889
  0.02073733 0.22344322 0.20155039 0.26966292 0.17391304 0.5
  0.        ]
 [0.18181818 0.16666667 0.15662651 0.0690184  0.06976744 0.05208333
  0.26036866 0.13591671 0.33333333 0.10674157 0.17391304 0.33333333
  1.        ]
 [0.19008264 0.2        0.12048193 0.09202454 0.03986711 0.08333333
  0.30184332 0.12897629 0.4496124  0.26404494 0.34782609 0.5
  1.        ]
 [0.12396694 0.14666667 0.18072289 0.00920245 0.03322259 0.08333333
  0.20046083 0.00597648 0.45736434 0.1011236  0.8115942  0.66666667
  1.        ]
 [0.33057851 0.36666667 0.28915663 0.01687117 0.15116279 0.04513889
  0.20737327 0.17331791 0.36434109 0.2247191  0.2173913  0.33333333
  0.        ]]
```

# 학습 데이터와 테스트 데이터 분리

- 특징에서 마지막 값을 정답으로
- 정답을 원 핫 인코딩으로




```
# 5.7 train 데이터와 test 데이터로 분리
import tensorflow as tf
train_idx = int(len(wine_np) * 0.8)

train_X, train_Y = wine_np[:train_idx, :-1], wine_np[:train_idx, -1]
test_X, test_Y = wine_np[train_idx:, :-1], wine_np[train_idx:, -1]
print(train_X[0])
print(train_Y[0])
print(test_X[0])
print(test_Y[0])

train_Y = tf.keras.utils.to_categorical(train_Y, num_classes=2)
test_Y = tf.keras.utils.to_categorical(test_Y, num_classes=2)
print(train_Y[0])
print(test_Y[0])
```

정답 제외

정답만

# 원 핫 인코딩

```
y = [0, 1, 2, 3]
tf.keras.utils.to_categorical(y, num_classes=4)
```

```
array([[1., 0., 0., 0.],
       [0., 1., 0., 0.],
       [0., 0., 1., 0.],
       [0., 0., 0., 1.]], dtype=float32)
```

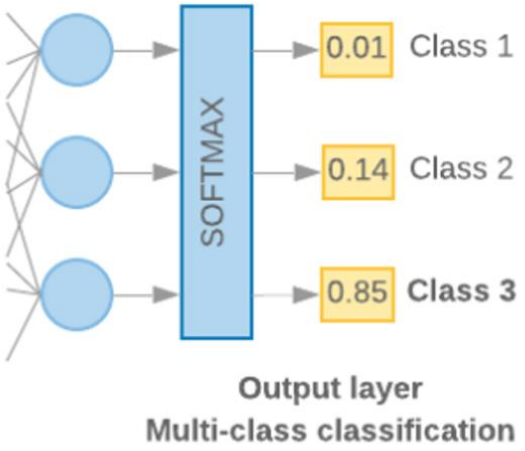
# 딥러닝 모델

```
# 5.8 와인 데이터셋 분류 모델 생성
import tensorflow as tf
model = tf.keras.Sequential([
    tf.keras.layers.Dense(units=48, activation='relu', input_shape=(12,)),
    tf.keras.layers.Dense(units=24, activation='relu'),
    tf.keras.layers.Dense(units=12, activation='relu'),
    tf.keras.layers.Dense(units=2, activation='softmax')
])

model.compile(optimizer = tf.keras.optimizers.Adam(lr=0.07),
              loss='categorical_crossentropy', metrics=['accuracy'])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 48)                624
_________________________________________________________________
dense_1 (Dense)              (None, 24)                1176
_________________________________________________________________
dense_2 (Dense)              (None, 12)                300
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 26
=================================================================
Total params: 2,126
Trainable params: 2,126
Non-trainable params: 0
_________________________________________________________________
```

# 분류에서의 활성화 함수

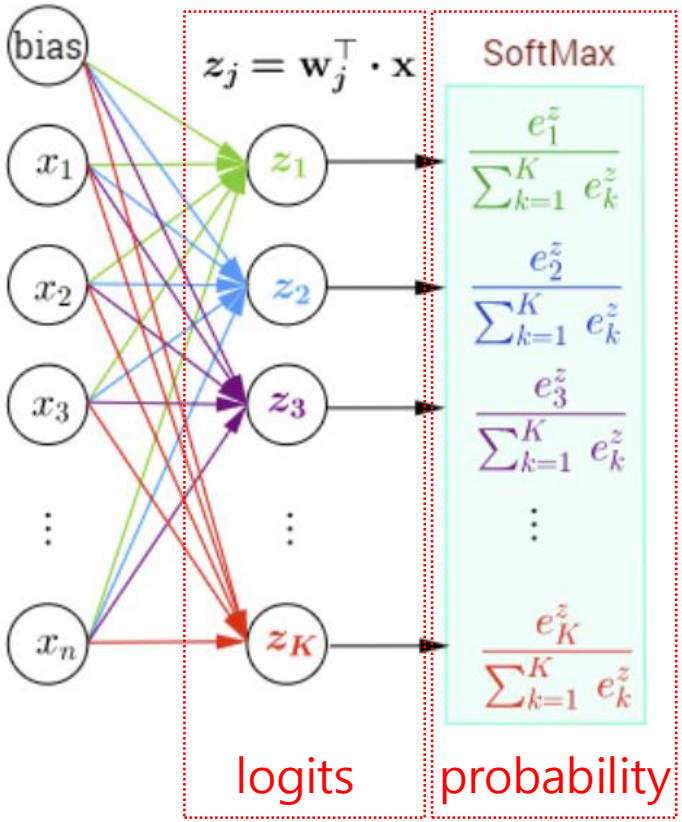
- **마지막 층은**
  - 소프트맥스 함수
    - **결과의 총합은 1**
    - **큰 값을 강조하고 작은 값은 약화시키는 효과**




```
# 5.8 와인 데이터셋 분류 모델 생성
import tensorflow as tf
model = tf.keras.Sequential([
    tf.keras.layers.Dense(units=48, activation='relu', input_shape=(12,)),
    tf.keras.layers.Dense(units=24, activation='relu'),
    tf.keras.layers.Dense(units=12, activation='relu'),
    tf.keras.layers.Dense(units=2, activation='softmax')
])

model.compile(optimizer = tf.keras.optimizers.Adam(lr=0.07),
              loss='categorical_crossentropy', metrics=['accuracy'])
model.summary()
```

# 소프트맥스 함수

$$\mathbf{z} = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ \vdots \\ z_K \end{bmatrix} = \begin{bmatrix} \mathbf{w}_1^\top \\ \mathbf{w}_2^\top \\ \mathbf{w}_3^\top \\ \vdots \\ \mathbf{w}_K^\top \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}$$





The softmax as

$$\sigma(j) = \frac{\exp(\mathbf{w}_j^\top \mathbf{x})}{\sum_{k=1}^K \exp(\mathbf{w}_k^\top \mathbf{x})} = \frac{\exp(z_j)}{\sum_{k=1}^K \exp(z_k)}$$

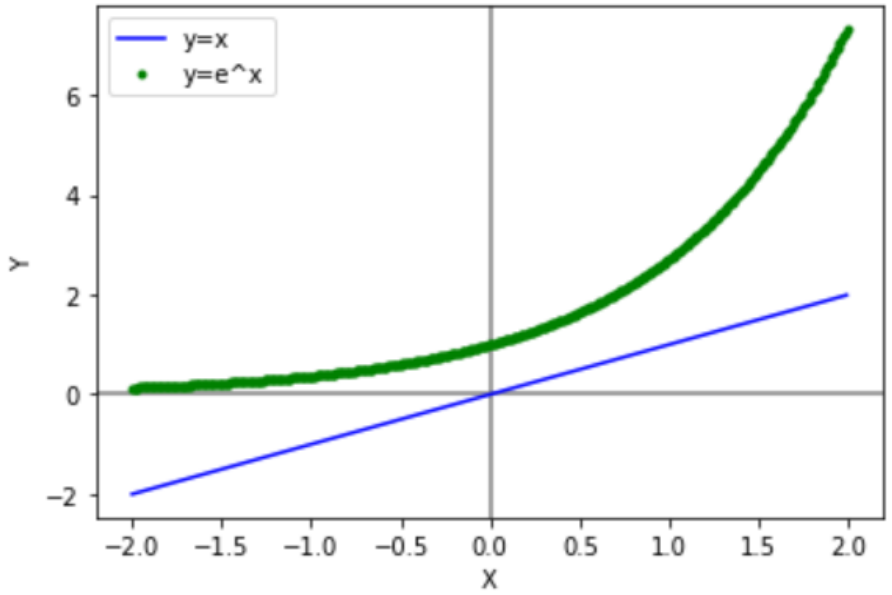
This will result in a normalization of the output adding up to 1, interpretable as a probability mass functionn.



http://rinterested.github.io/statistics/softmax.html

# 지수승 $e^x$ 효과

- **자연수 e를 밑으로 하는 지수 함수**
  - 음수는 양수로
  - 작은 수는 작게, 큰 수는 더욱 크게




```
# 그림 5.5 출력 코드
import matplotlib.pyplot as plt
import math
import numpy as np
x = np.arange(-2, 2, 0.01)
e_x = math.e ** x

plt.axhline(0, color='gray')
plt.axvline(0, color='gray')
plt.plot(x, x, 'b-', label='y=x')
plt.plot(x, e_x, 'g.', label='y=e^x')
plt.xlabel('X')
plt.ylabel('Y')
plt.legend()
plt.show()
```

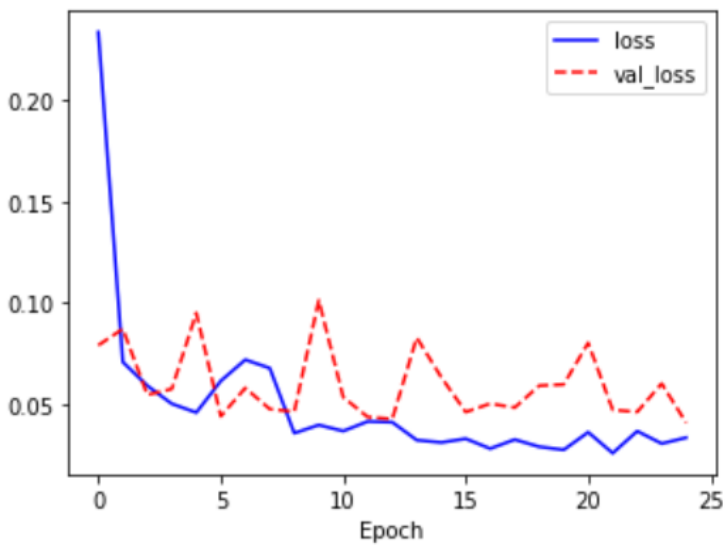
# 학습

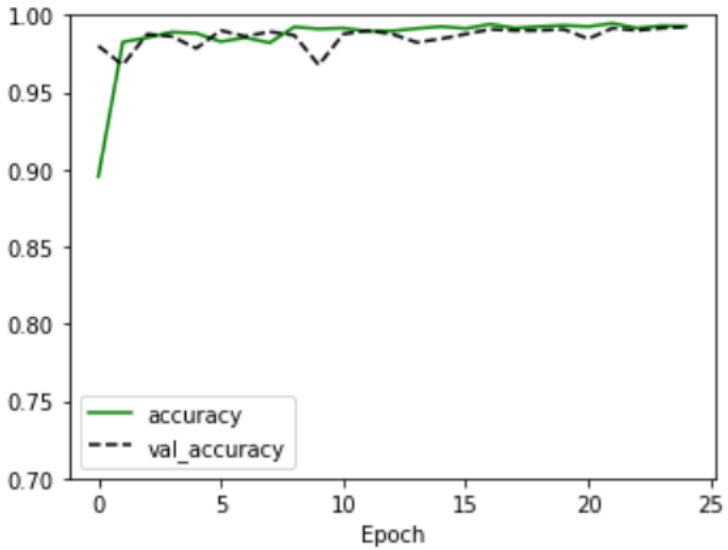
```
# 5.9 와인 데이터셋 분류 모델 학습
history = model.fit(train_X, train_Y, epochs=25, batch_size=32, validation_split=0.25)
```

```
Epoch 22/25
122/122 [==============================] - 0s 2ms/step - loss: 0.0320 - accuracy: 0.9933 - val_loss: 0.0272 - val_accuracy: 0.9946
Epoch 23/25
122/122 [==============================] - 0s 2ms/step - loss: 0.0334 - accuracy: 0.9913 - val_loss: 0.1146 - val_accuracy: 0.9638
Epoch 24/25
122/122 [==============================] - 0s 2ms/step - loss: 0.0428 - accuracy: 0.9900 - val_loss: 0.0526 - val_accuracy: 0.9931
Epoch 25/25
122/122 [==============================] - 0s 2ms/step - loss: 0.0394 - accuracy: 0.9879 - val_loss: 0.0325 - val_accuracy: 0.9946
```

# 학습 과정 시각화

```
# 5.10 분류 모델 학습 결과 시각화
import matplotlib.pyplot as plt
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], 'b-', label='loss')
plt.plot(history.history['val_loss'], 'r--', label='val_loss')
plt.xlabel('Epoch')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], 'g-', label='accuracy')
plt.plot(history.history['val_accuracy'], 'k--', label='val_accuracy')
plt.xlabel('Epoch')
plt.ylim(0.7, 1)
plt.legend()

plt.show()
```



# 평가

```
1 # 5.11 분류 모델 평가
2 model.evaluate(test_X, test_Y)
```

```
41/41 [==============================] - 0s 1ms/step - loss: 0.0316 - accuracy: 0.9915
[0.0315738245844841, 0.9915384650230408]
```

# 다항 분류:
# 와인 품질 분류

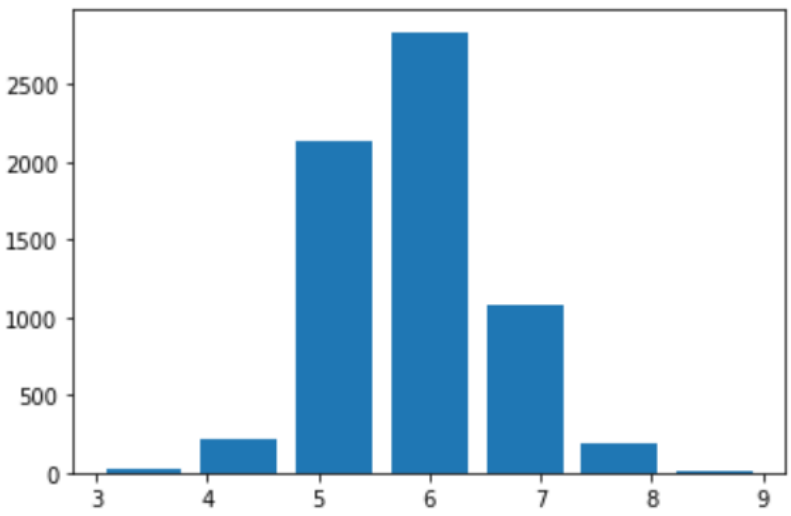
# 와인 데이터 셋의 'quality'

- **등급 3~9**
  - 이 모든 등급을 예측하기에는 등급에 따른 데이터 수 차이가 큼
    - **다시 등급을 3개 정도로 나누어 예측**

```
[20]  1 # 5.12 품질 데이터 확인
      2 print(wine['quality'].describe())
      3 print(wine['quality'].value_counts())
```

```
count    6497.000000
mean        5.818378
std         0.873255
min         3.000000
25%         5.000000
50%         6.000000
75%         6.000000
max         9.000000
Name: quality, dtype: float64
6    2836
5    2138
7    1079
4     216
8     193
3      30
9       5
Name: quality, dtype: int64
```

```
[21]  1 # 5.13 품질 히스토그램 시각화
      2 import matplotlib.pyplot as plt
      3 plt.hist(wine['quality'], bins=7, rwidth=0.8)
      4 plt.show()
```



# 새로운 등급인 new_quality를 생성

- **조건에 맞는 값을 새로운 열에 추가**
  - df.loc[ data['컬럼'] 조건, '새로운 컬럼명' ] = '값'

```
# 5.14 품질을 3개의 범주(좋음, 보통, 나쁨)로 재분류
wine.loc[wine['quality'] <= 5, 'new_quality'] = 0
wine.loc[wine['quality'] == 6, 'new_quality'] = 1
wine.loc[wine['quality'] >= 7, 'new_quality'] = 2

print(wine['new_quality'].describe())
print(wine['new_quality'].value_counts())
```

```
count    6497.000000
mean        0.829614
std         0.731124
min         0.000000
25%         0.000000
50%         1.000000
75%         1.000000
max         2.000000
Name: new_quality, dtype: float64
1.0    2836
0.0    2384
2.0    1277
Name: new_quality, dtype: int64
```

# 정규화와 원핫 인코딩

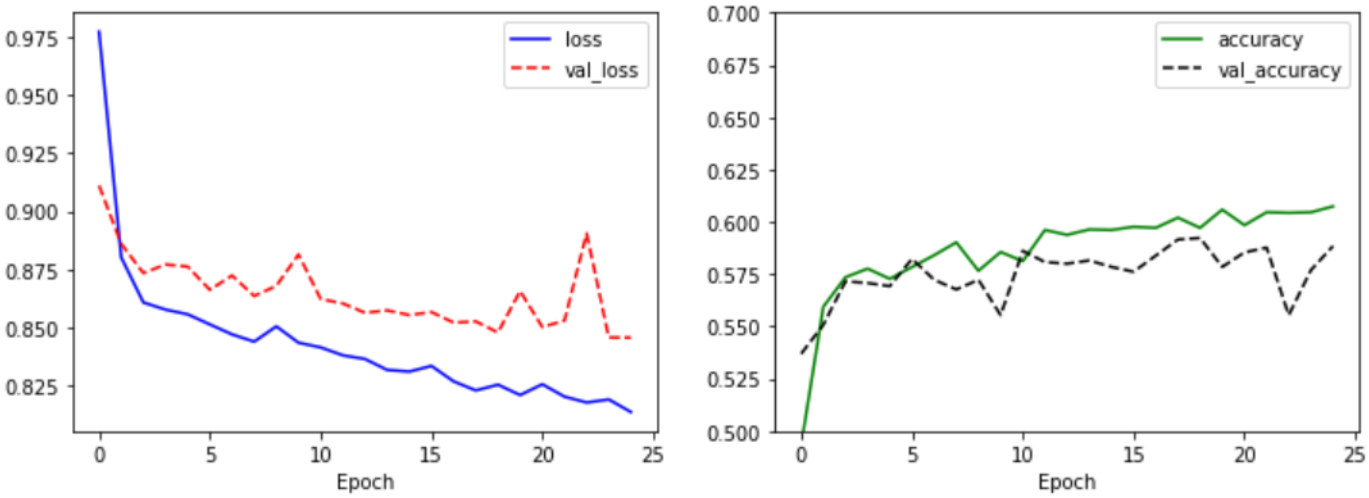
```
# 5.15 데이터 정규화 및 train, test 데이터 분리
del wine['quality']
wine_backup = wine.copy()
wine_norm = (wine - wine.min()) / (wine.max() - wine.min())
wine_norm['new_quality'] = wine_backup['new_quality']
wine_shuffle = wine_norm.sample(frac=1)
wine_np = wine_shuffle.to_numpy()

train_idx = int(len(wine_np) * 0.8)
train_X, train_Y = wine_np[:train_idx, :-1], wine_np[:train_idx, -1]
test_X, test_Y = wine_np[train_idx:, :-1], wine_np[train_idx:, -1]
train_Y = tf.keras.utils.to_categorical(train_Y, num_classes=3)
test_Y = tf.keras.utils.to_categorical(test_Y, num_classes=3)
```

# 딥러닝 모델

```
# 5.16 와인 데이터셋 다항 분류 모델 생성 및 학습
model = tf.keras.Sequential([
    tf.keras.layers.Dense(units=48, activation='relu', input_shape=(12,)),
    tf.keras.layers.Dense(units=24, activation='relu'),
    tf.keras.layers.Dense(units=12, activation='relu'),
    tf.keras.layers.Dense(units=3, activation='softmax')
])

model.compile(optimizer=tf.keras.optimizers.Adam(lr=0.003),
              loss='categorical_crossentropy', metrics=['accuracy'])

history = model.fit(train_X, train_Y, epochs=25, batch_size=32,
                    validation_split=0.25)
```

# 학습 과정 시각화

```
# 5.17 다항 분류 모델 학습 결과 시각화
import matplotlib.pyplot as plt
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], 'b-', label='loss')
plt.plot(history.history['val_loss'], 'r--', label='val_loss')
plt.xlabel('Epoch')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], 'g-', label='accuracy')
plt.plot(history.history['val_accuracy'], 'k--', label='val_accuracy')
plt.xlabel('Epoch')
plt.ylim(0.5, 0.7)
plt.legend()

plt.show()
```



# 평가

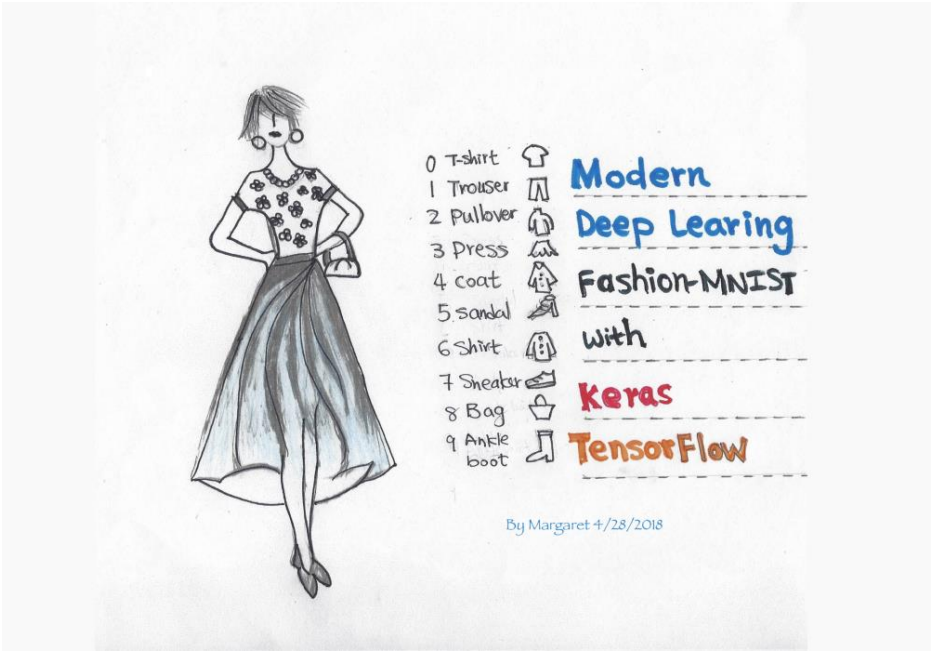
```
1 # 5.18 다항 분류 모델 평가
2 model.evaluate(test_X, test_Y)
```

```
41/41 [==============================] - 0s 1ms/step - loss: 0.8130 - accuracy: 0.6023
[0.812984824180603, 0.6023076772689819]
```

# 다항 분류: 패션 MNIST

# Fashion-MNIST 데이터 저장

- 미리 섞여진 fashoin-mnist의 학습 데이터와 테스트 데이터 로드




```
# 필요 모듈 임포트
# tensorflow와 tf.keras를 임포트합니다
import tensorflow as tf
from tensorflow import keras

# ① 문제와 정답 데이터 지정
fashion_mnist = keras.datasets.fashion_mnist
(train_images, train_labels), (test_images, test_labels) = fashion_mnist.load_data()
# 10 개의 분류 이름 지정
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']

# 데이터 전처리
# 샘플 값을 정수(0~255)에서 부동소수(0~1)로 변환
train_images, test_images = train_images / 255.0, test_images / 255.0
```

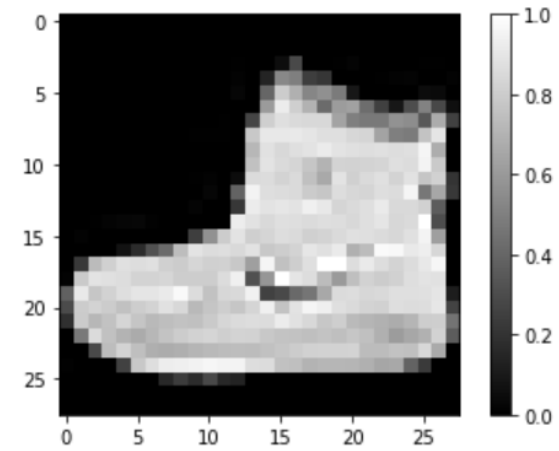
# 데이터셋 불러오기

```
[34]  1 # 5.19 Fashion MNIST 데이터셋 불러오기
      2 fashion_mnist = tf.keras.datasets.fashion_mnist
      3 (train_X, train_Y), (test_X, test_Y) = fashion_mnist.load_data()
      4
      5 print(len(train_X), len(test_X))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz
32768/29515 [================================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz
26427392/26421880 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx1-ubyte.gz
8192/5148 [===============================================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz
4423680/4422102 [==============================] - 0s 0us/step
60000 10000
```

# 데이터 확인

[41]
```
# 5.20 데이터 확인
import matplotlib.pyplot as plt
plt.imshow(train_X[0], cmap='gray')
plt.colorbar()
plt.show()

print(train_Y[0])
```




9

[43]
```
# 10 개의 분류 이름 지정
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']

print(class_names[train_Y[0]])
```

Ankle boot

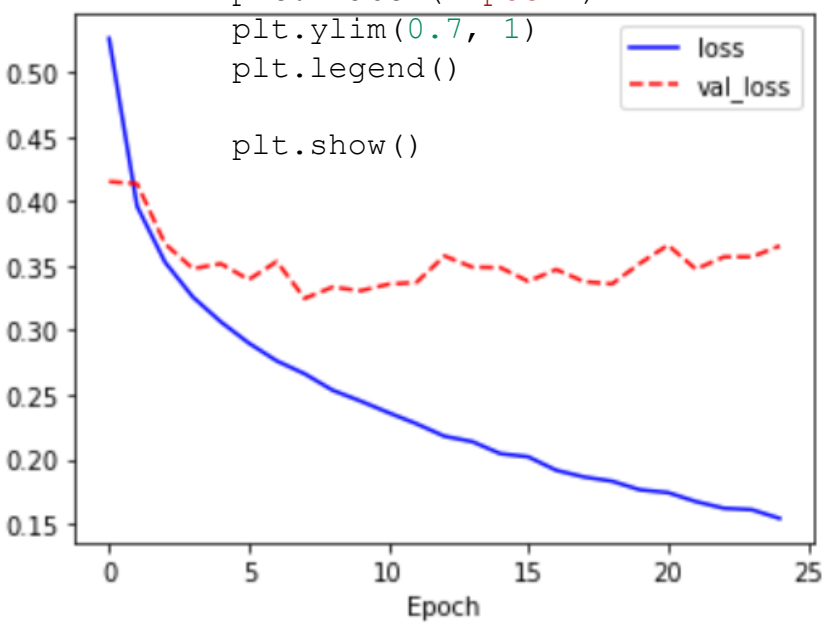
# 정규화, 모델 생성과 학습

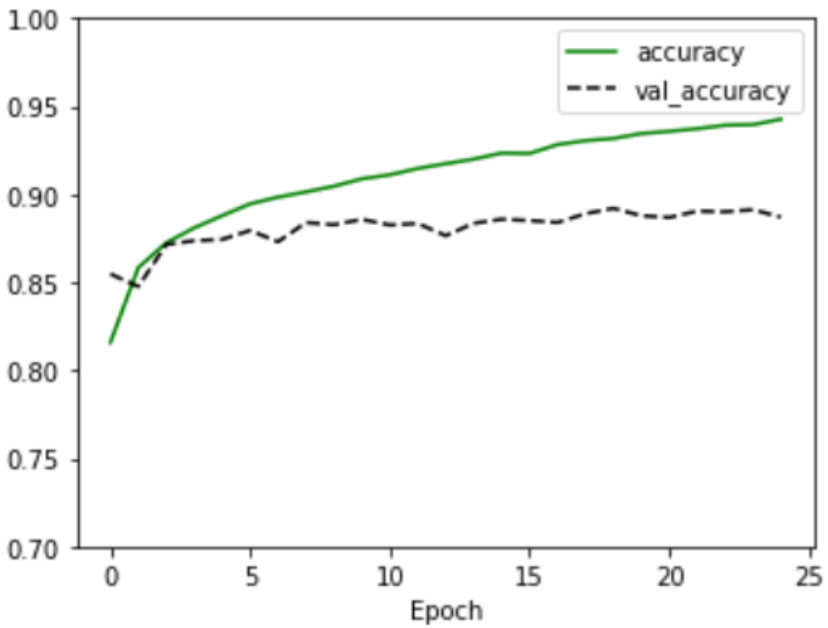
- loss='sparse_categorical_crossentropy'
  - 정답을 원핫인코딩 불필요

```
# 5.21 데이터 정규화
train_X = train_X / 255.0
test_X = test_X / 255.0

print(train_X[0])
# 5.22 Fashion MNIST 분류 모델
model = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape=(28,28)),
    tf.keras.layers.Dense(units=128, activation='relu'),
    tf.keras.layers.Dense(units=10, activation='softmax')
])

model.compile(optimizer=tf.keras.optimizers.Adam(),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.summary()
# 5.23 Fashion MNIST 분류 모델 학습
history = model.fit(train_X, train_Y, epochs=25, validation_split=0.25)
```

# 시각화

```
# 5.24 Fashion MNIST 분류 모델 학습 결과 시각화
import matplotlib.pyplot as plt
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], 'b-', label='loss')
plt.plot(history.history['val_loss'], 'r--', label='val_loss')
plt.xlabel('Epoch')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], 'g-', label='accuracy')
plt.plot(history.history['val_accuracy'], 'k--
', label='val_accuracy')
plt.xlabel('Epoch')
plt.ylim(0.7, 1)
plt.legend()

plt.show()
```



# 평가

```
[40]  1 # 5.25 Fashion MNIST 분류 모델 평가
      2 model.evaluate(test_X, test_Y)
```

```
313/313 [==============================] - 0s 1ms/step - loss: 0.4018 - accuracy: 0.8823
[0.40182268619537354, 0.8823000192642212]
```