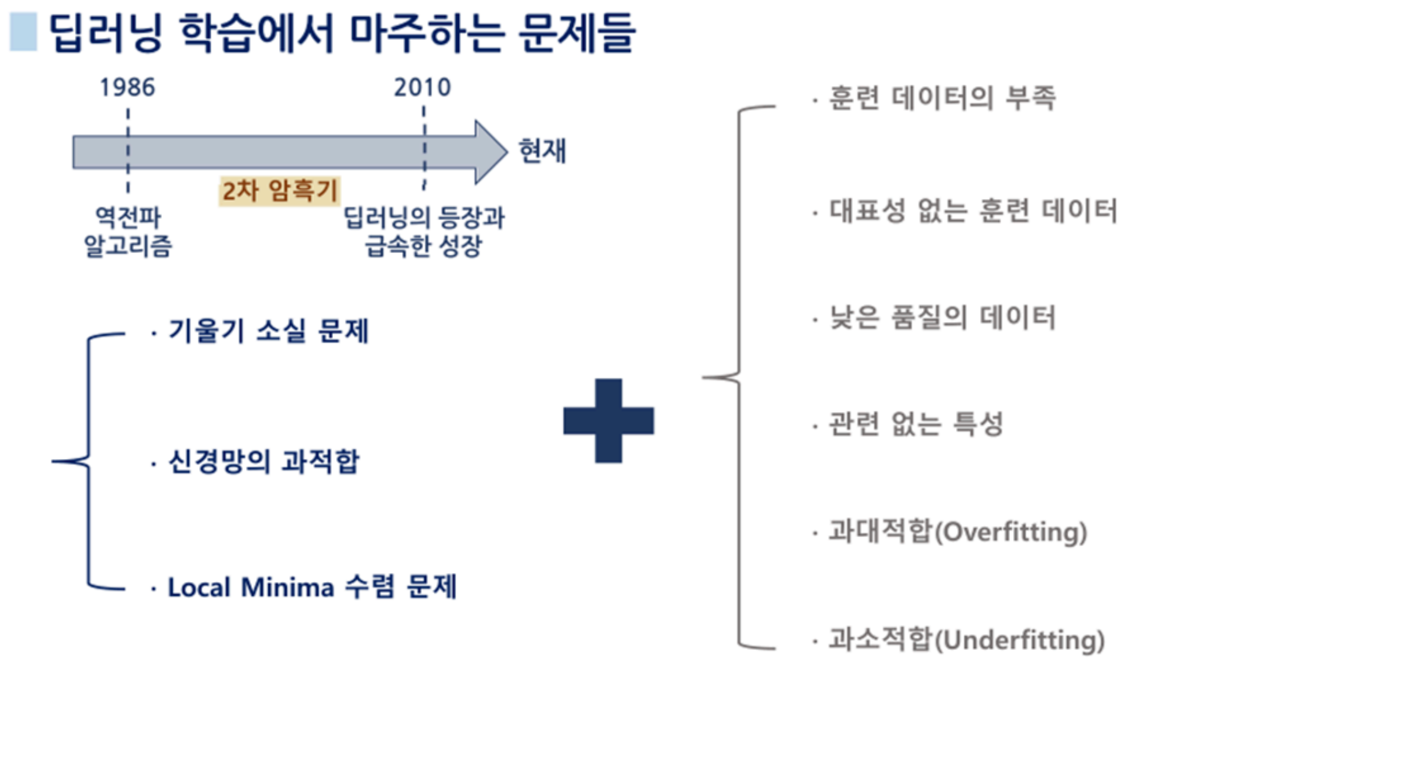
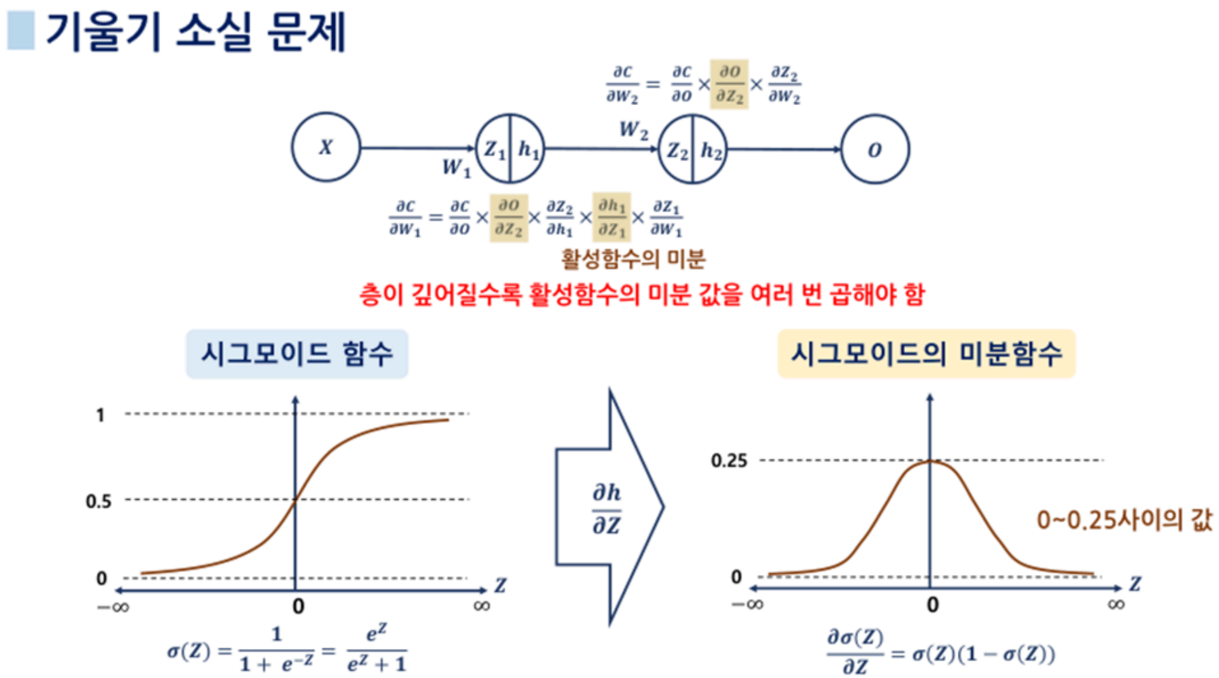
17강. 딥러닝 학습에서 마주하는 문제들

- 기울기 소실 문제
- RELU / 배치정규화
- 드롭아웃 / 데이터 증강 / 규제 / 조기종료
- 경사하강법 옵티마이저(Optimizer)

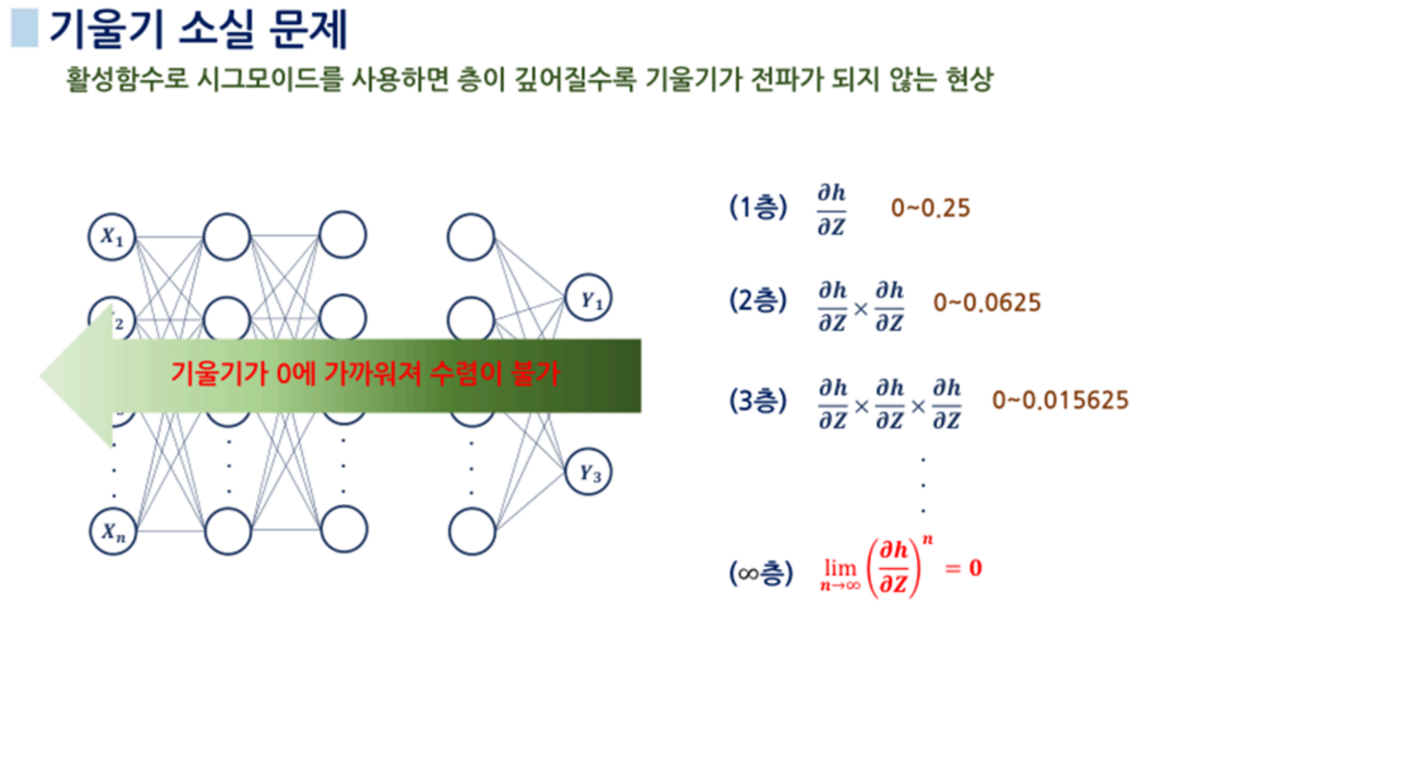


기울기 소실(Gradient Vanishing)와 기울기 폭주(Gradient Exploding)



기울기 소실 문제
$\frac{\partial C}{\partial W_2} = \frac{\partial C}{\partial O} \times \frac{\partial O}{\partial Z_2} \times \frac{\partial Z_2}{\partial W_2}$
X
W_1
Z_1 h_1
W_2
Z_2 h_2
O
$\frac{\partial C}{\partial W_1} = \frac{\partial C}{\partial O} \times \frac{\partial O}{\partial Z_2} \times \frac{\partial Z_2}{\partial h_1} \times \frac{\partial h_1}{\partial Z_1} \times \frac{\partial Z_1}{\partial W_1}$
활성함수의 미분
층이 깊어질수록 활성함수의 미분 값을 여러 번 곱해야 함
시그모이드 함수
시그모이드의 미분함수
1
0.5
0
$-\infty$
0
∞
Z
$\sigma(Z) = \frac{1}{1+e^{-Z}} = \frac{e^Z}{e^Z+1}$
$\frac{\partial h}{\partial Z}$
0.25
0~0.25사이의 값
$\frac{\partial \sigma(Z)}{\partial Z} = \sigma(Z)(1-\sigma(Z))$

순전파/역전파

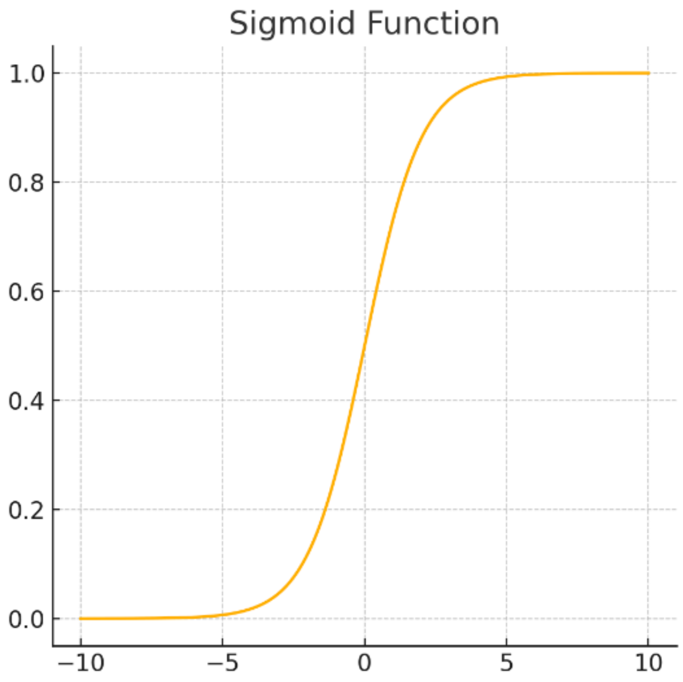


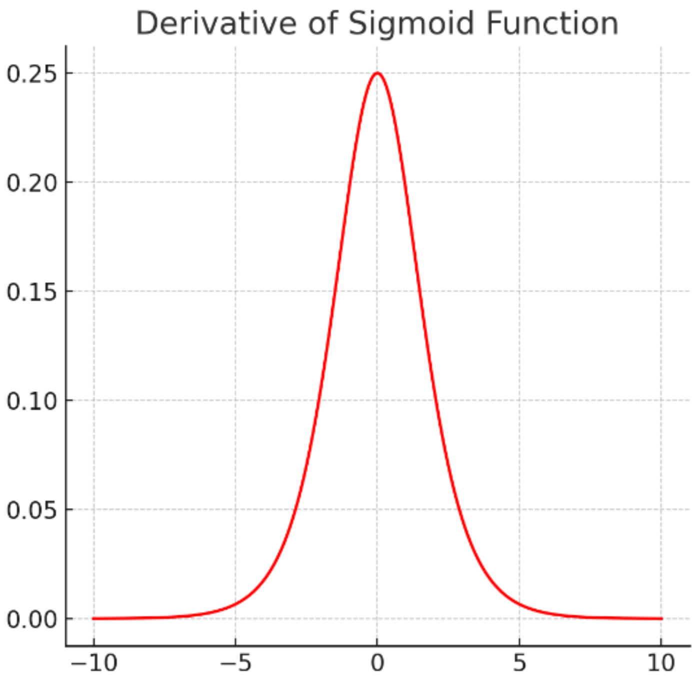
기울기 소실(Gradient Vanishing)과 폭주(Exploding)를 완화하는 방법

활성화 함수

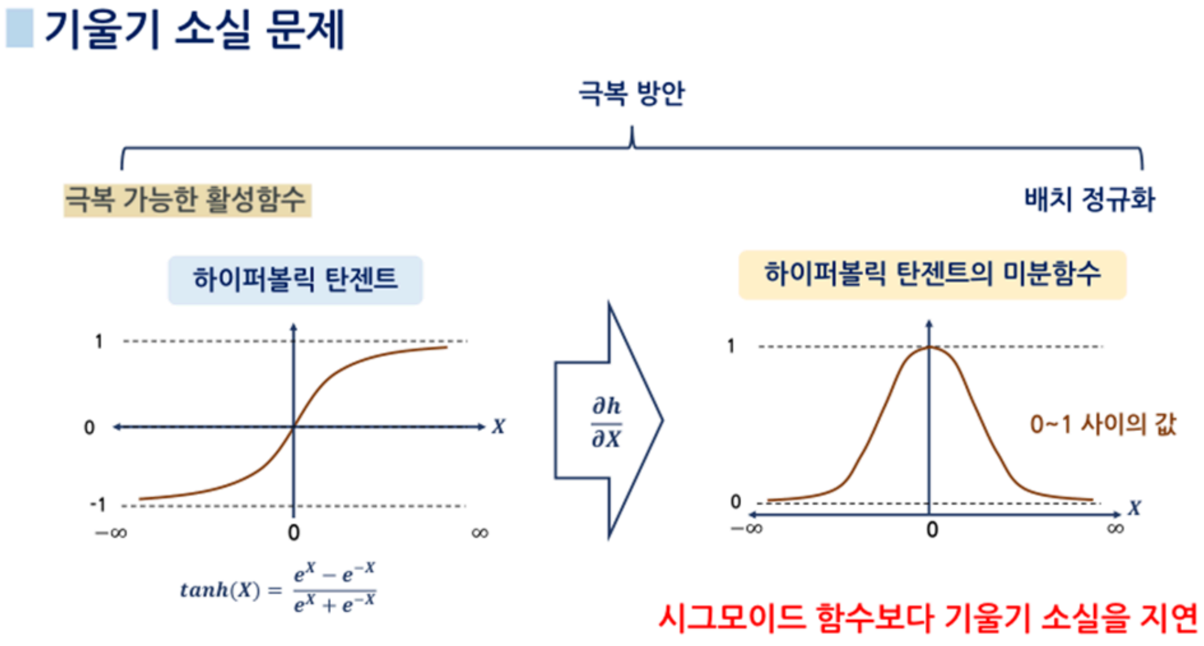
- Sigmoid나 tanh와 같은 활성화 함수는 입력 값이 매우 크거나 작을 때 출력의 변화가 매우 작음

> - 예를 들어 Sigmoid의 도함수의 경우 아래와 같이 σ(x)가 0 또는 1에 가까워지면 도함수가 0에 가까워짐
> - 이러한 활성화 함수들은 입력 값이 크거나 작을 때 기울기를 거의 0으로 만들기 때문에, 역전파 동안 기울기가 점점 더 작아짐





$$W_i = W_{i-1} - \eta \frac{\delta Error}{\delta W}$$



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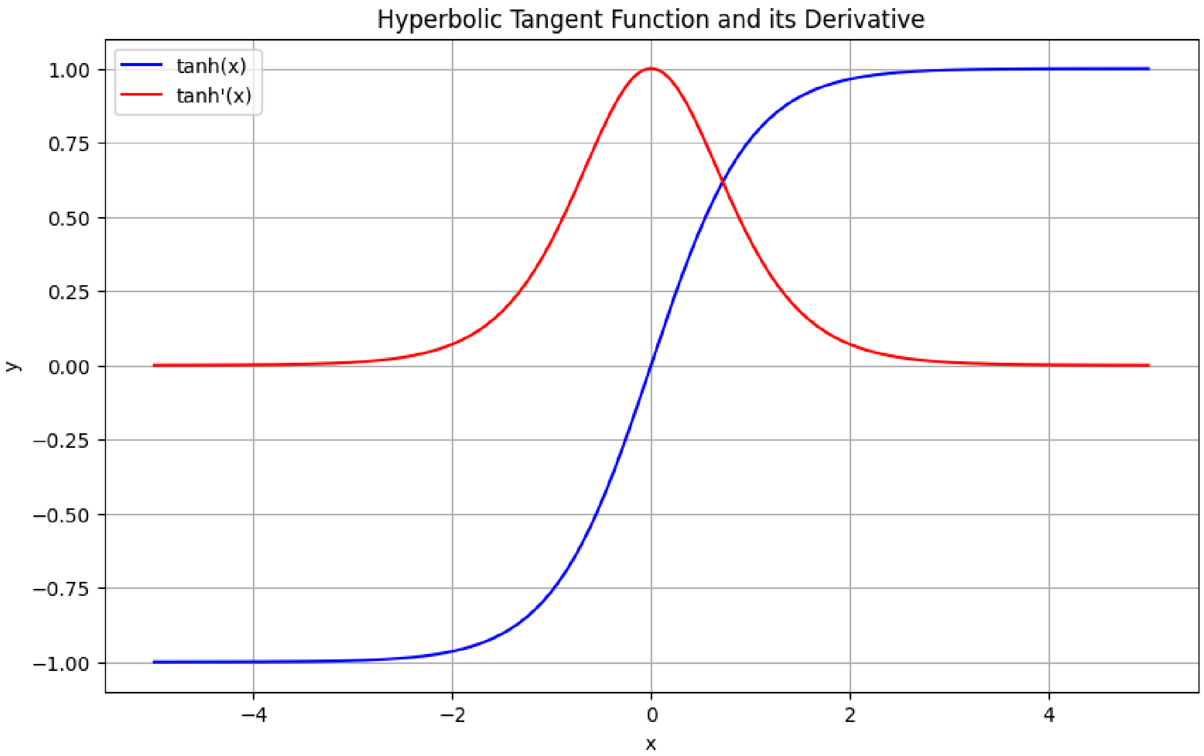
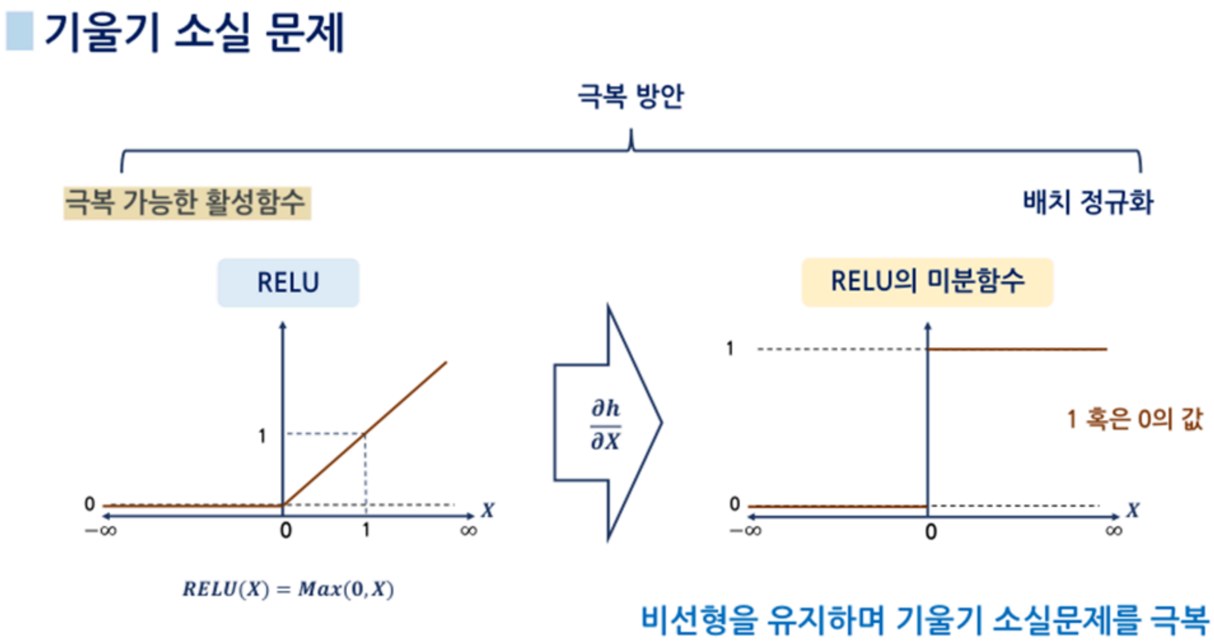
hyperbolic tangent function and its derivative

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

# Define the hyperbolic tangent function and its derivative
def tanh(x):
    return np.tanh(x)

def tanh_derivative(x):
    return 1 - np.tanh(x)**2

# Generate x values
x = np.linspace(-5, 5, 400)

# Calculate y values for tanh and its derivative
y_tanh = tanh(x)
```

```python
y_tanh_derivative = tanh_derivative(x)

# Create the plot
plt.figure(figsize=(10, 6))
plt.plot(x, y_tanh, label='tanh(x)', color='blue')
plt.plot(x, y_tanh_derivative, label="tanh'(x)", color='red')

# Add labels and title
plt.xlabel('x')
plt.ylabel('y')
plt.title('Hyperbolic Tangent Function and its Derivative')

# Add grid and legend
plt.grid(True)
plt.legend()

# Show the plot
plt.show()
```

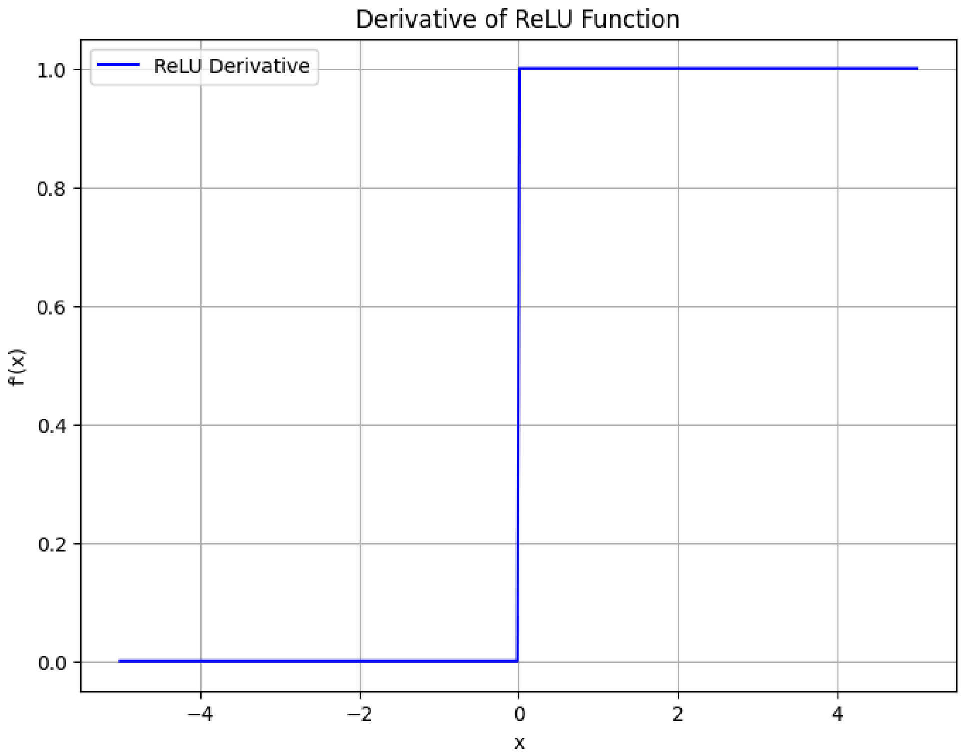




ReLU(Rectified Linear Unit) function and its derivative

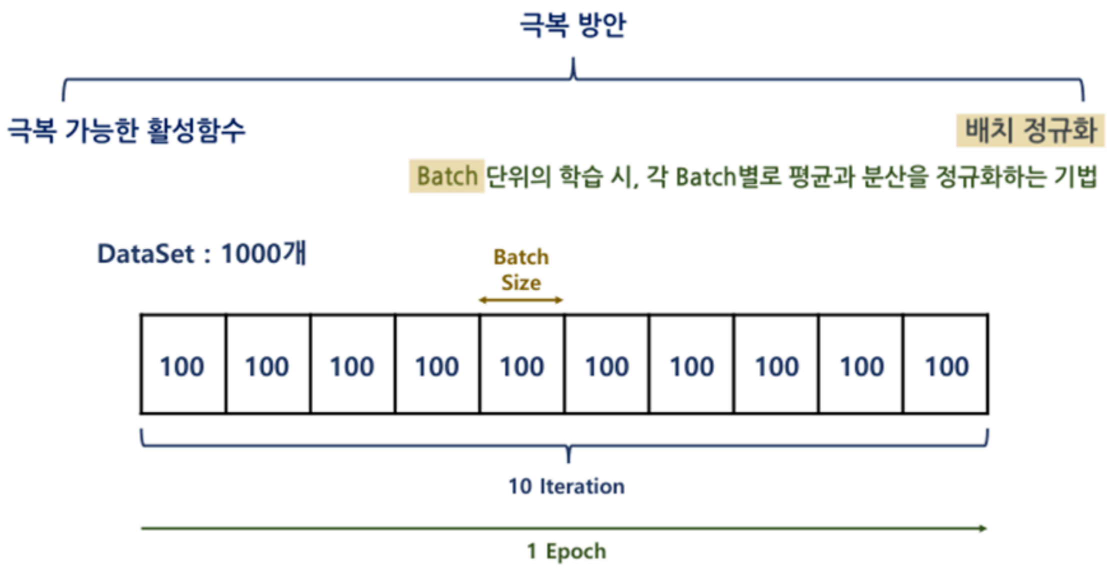
```
import numpy as np
import matplotlib.pyplot as plt

def relu_derivative(x):
  """
  Calculates the derivative of the ReLU function.

  Args:
    x: A numpy array of input values.

  Returns:
    A numpy array of the corresponding derivative values.
  """
  return np.where(x > 0, 1, 0)

```

```
# Generate x values
x = np.linspace(-5, 5, 400)
# Calculate ReLU derivative
y = relu_derivative(x)

# Create the plot
plt.figure(figsize=(8, 6))
plt.plot(x, y, label='ReLU Derivative', color='blue')
plt.xlabel('x')
plt.ylabel('f₩'(x)')
plt.title('Derivative of ReLU Function')
plt.grid(True)
plt.legend()
plt.show()
```



배치정규화

기울기 소실 문제



Epoch, Iteration, Batch size 개념

- Batch Size

> - 사람이 문제 풀이를 통해 학습해 나가는 과정에서 몇 개의 문제를 한 번에 쭉 풀고 채점할지를 결정하는 것과 같음
> - 총 100개의 문제가 있을 때, 20개씩 풀고 채점한다면 Batch 크기는 20
> - 전체 데이터가 3,000개이고 Batch 크기가 300이라면, 데이터를 300개씩 활용하여 모델을 점차 학습시켜 나감
> - 사람은 문제를 풀고 채점을 하면서 문제를 틀린 이유나 맞춘 원리를 학습함!!!!1

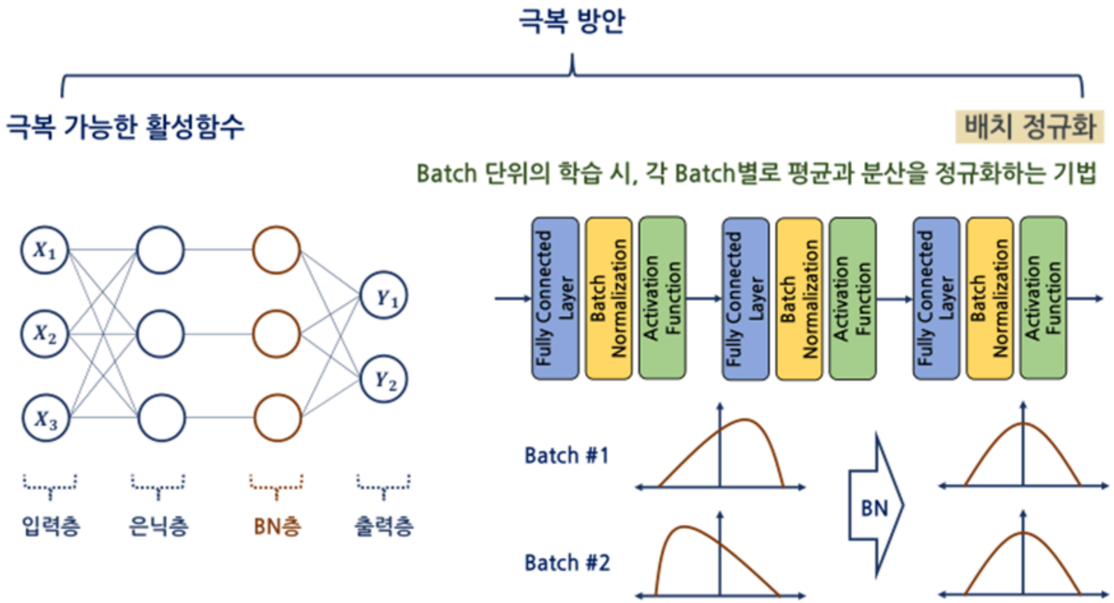
- Iteration - 전체 데이터에 대해 총 Batch의 수를 의미

> - Batch 크기가 300이고 전체 데이터 개수가 3,000이라면 전체 데이터셋을 학습시키기 위해서는 총 10개의 Batch가 필요함
> - 10번에 걸쳐 파라미터를 업데이트해야 되니까 즉, Iteration의 수는 10임

- Epoch - 전체 데이터셋을 학습한 횟수를 의미

> - 사람이 문제집으로 공부하는 상황에서 문제집에 있는 모든 문제를 처음부터 끝까지 풀고, 채점까지 마친 횟수를 의미
> - 전체 데이터셋을 1회 활용하여 모델을 학습했다면 Epoch는 1임

기울기 소실 문제



Batch normalization

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

def batch_normalization(x, gamma, beta, epsilon=1e-8):
    """
    Performs batch normalization on the input data.

```

```
    Args:
      x: Input data (numpy array).
      gamma: Scale parameter (numpy array).
      beta: Shift parameter (numpy array).
      epsilon: Small constant for numerical stability.

    Returns:
      Normalized data (numpy array).
    """
    mean = np.mean(x)
    variance = np.var(x)
    x_norm = (x - mean) / np.sqrt(variance + epsilon)
    out = gamma * x_norm + beta
    return out

# Generate random data
np.random.seed(42)
x = np.random.normal(10, 5, 1000)

print(x)

# Set gamma and beta parameters
gamma = 1.0
beta = 0.0

# Apply batch normalization
x_normalized = batch_normalization(x, gamma, beta)

# Plot the original and normalized data
plt.figure(figsize=(10, 5))

plt.subplot(1, 2, 1)
plt.hist(x, bins=50)
plt.title("Original Data")

plt.subplot(1, 2, 2)
plt.hist(x_normalized, bins=50)
plt.title("Normalized Data")

plt.show()
```

```
 15.15499761 14.6564006   5.80391238  8.45393812 11.65631716 14.87772564
  7.60412881  9.07170512  4.46832513  4.01896688 14.06262911 16.78120014
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```
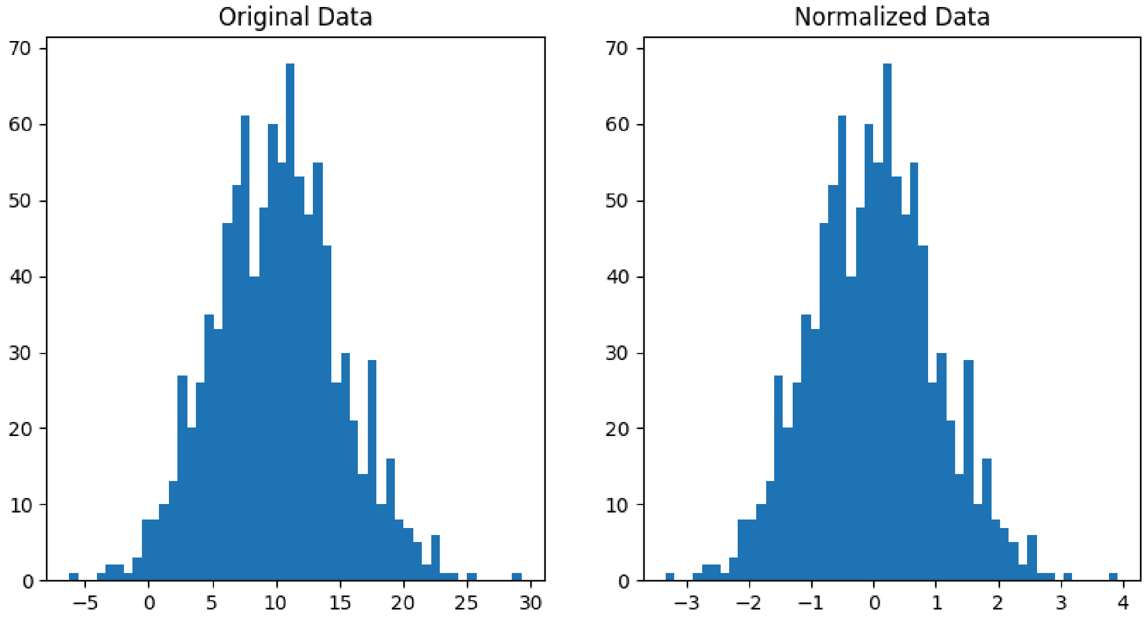
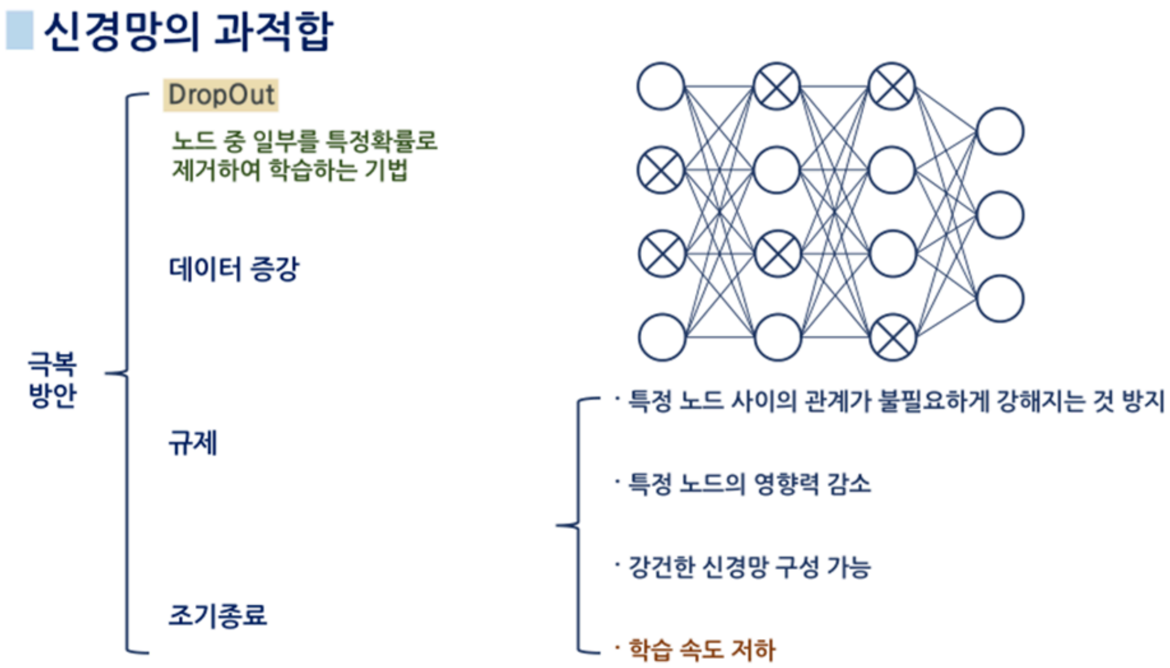

```
 18.98843263 13.20421431  7.14410505 12.86291391]
```



드롭아웃



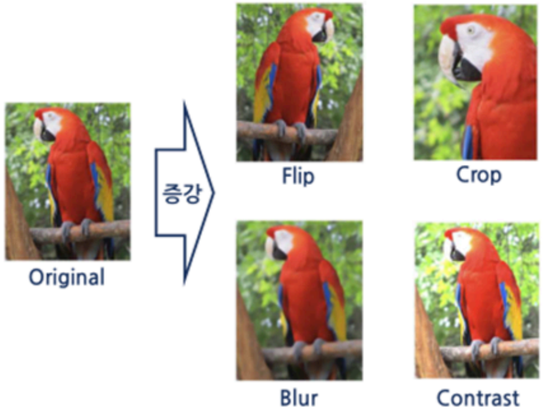
데이터 증강(Data Augmentation)이해

신경망의 과적합

극복 방안

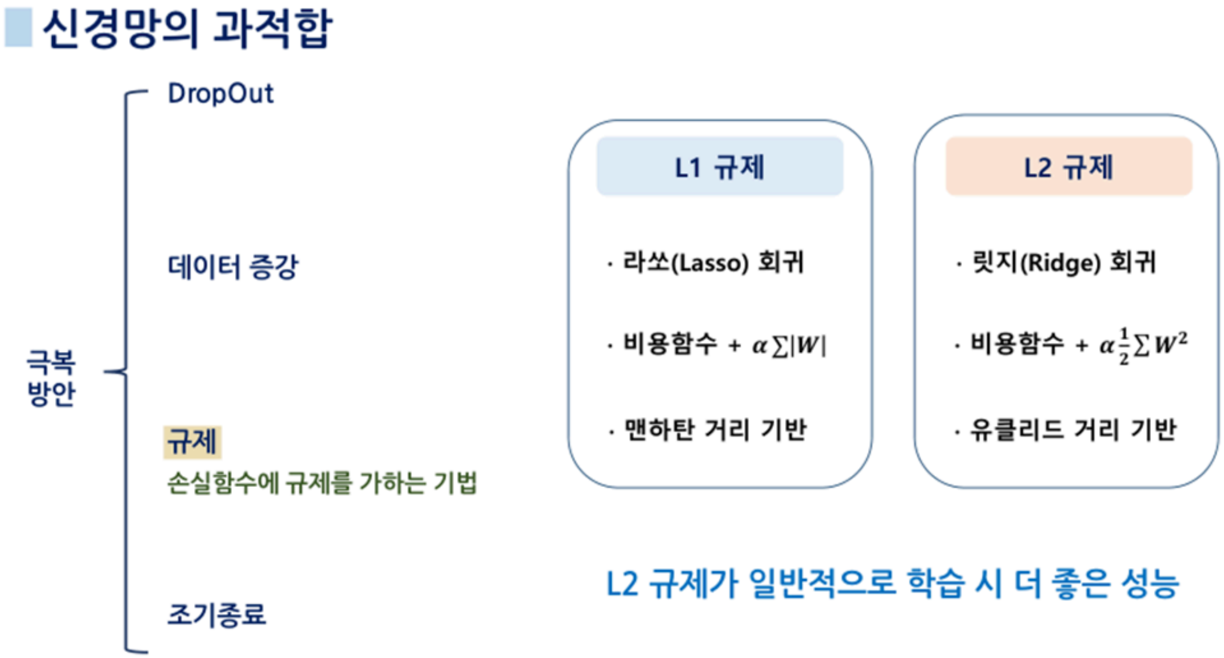
- DropOut
- 데이터 증강

  기존 데이터에서 새로운 데이터를 인위적으로 생성하여 데이터 양을 증가시키는 기법

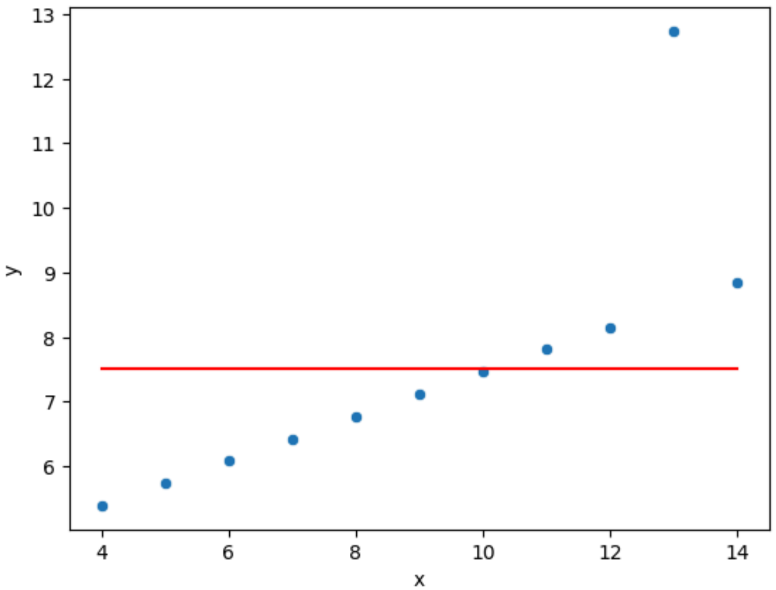


- 규제
- 조기종료

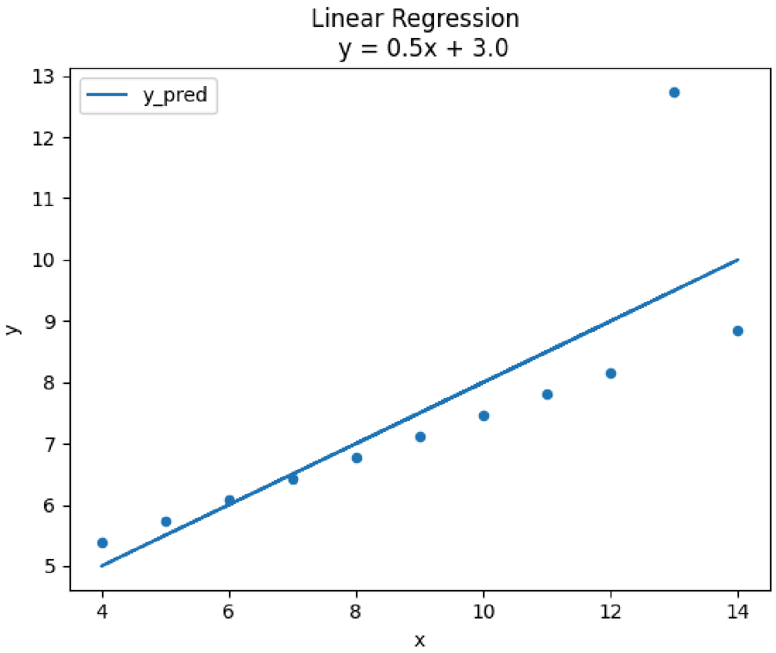
※ 출처 : What is image augmentation and how it can improve the performance of deep neural networks'
Link - [What is image augmentation - Albumentations Documentation]




```python
# 데이터 불러오기
import seaborn as sns

ans = sns.load_dataset('anscombe').query('dataset=="III"')
baseline = ans.y.mean() # 기준 모델
sns.lineplot(x='x', y=baseline, data=ans, color='red'); # 기준 모델 시각화
sns.scatterplot(x='x', y='y', data=ans);
```

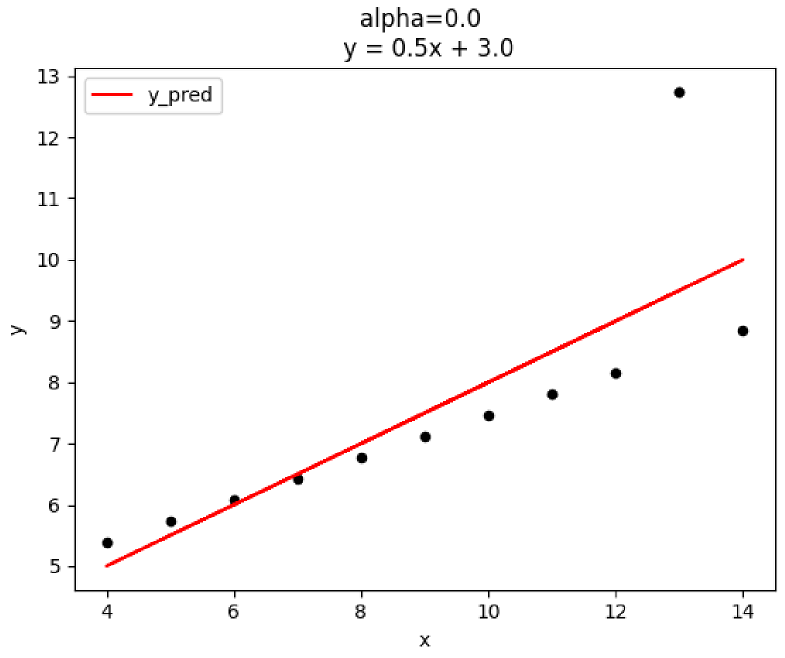


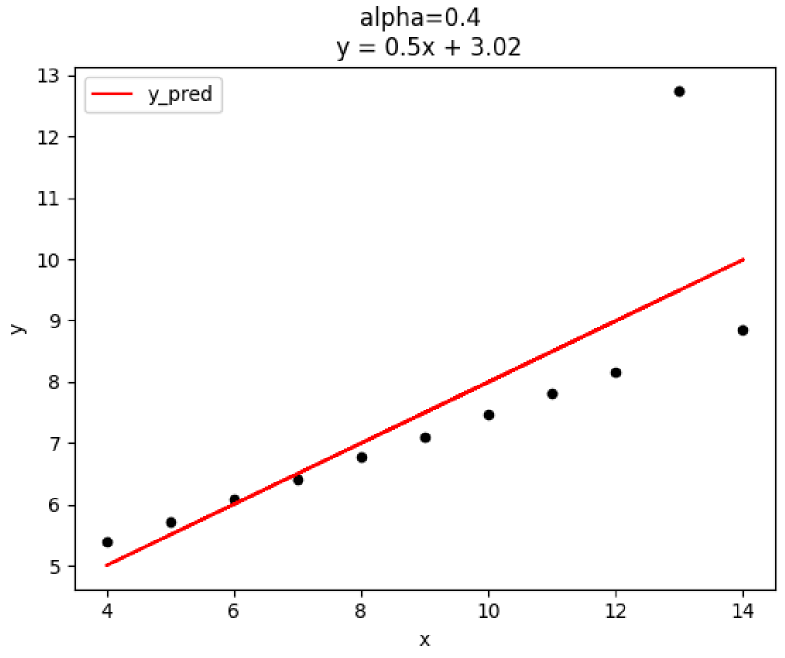

```
# 다중 선형 회귀(OLS)
from sklearn.linear_model import LinearRegression
%matplotlib inline

ax = ans.plot.scatter('x', 'y')

# OLS
ols = LinearRegression()
ols.fit(ans[['x']], ans['y'])

# 회귀계수와 intercept 확인
m = ols.coef_[0].round(2)
b = ols.intercept_.round(2)
title = f'Linear Regression \n y = {m}x + {b}'

# 훈련 데이터로 예측
ans['y_pred'] = ols.predict(ans[['x']])

ans.plot('x', 'y_pred', ax=ax, title=title);
```

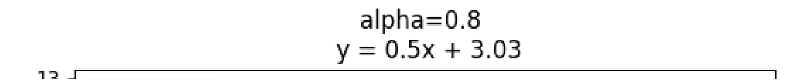


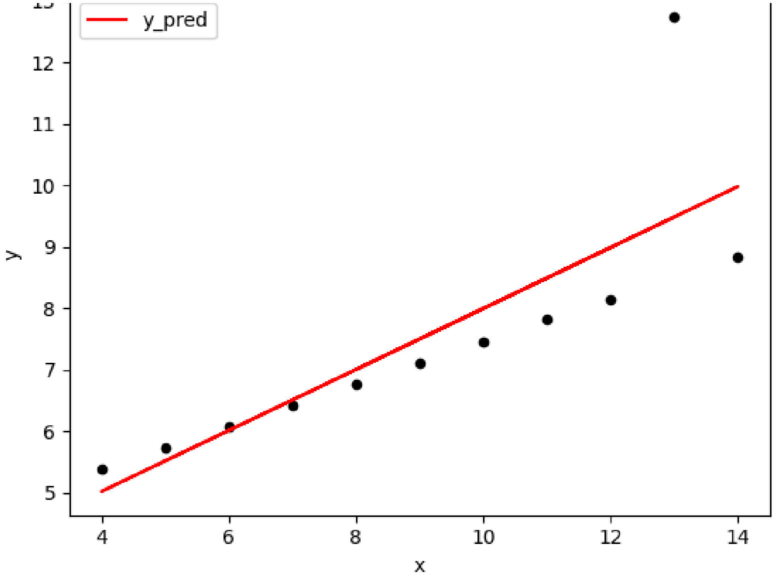

```python
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import Ridge

# 데이터셋 load
df = sns.load_dataset('anscombe').query('dataset=="III"')

# λ 값을 변화 시키면서 회귀 계수의 변화를 확인
def ridge_ans(alpha):
    ridge = Ridge(alpha=alpha)
#     ridge = Ridge(alpha=alpha, normalize=True)
    ridge.fit(df[['x']], df['y'])

    df['y_pred'] = ridge.predict(df[['x']])

    #시각화 표현
    m = ridge.coef_[0].round(2)
    b = ridge.intercept_.round(2)
    title = f'alpha={alpha} ₩n y = {m}x + {b}'

    ax = df.plot.scatter('x', 'y', c='black')
    df.plot('x', 'y_pred', ax=ax, c='r', title=title)

    plt.show()

```

```
alphas = np.arange(0, 2.1, 0.4)
for alpha in alphas:
    ridge_ans(alpha=alpha)
```

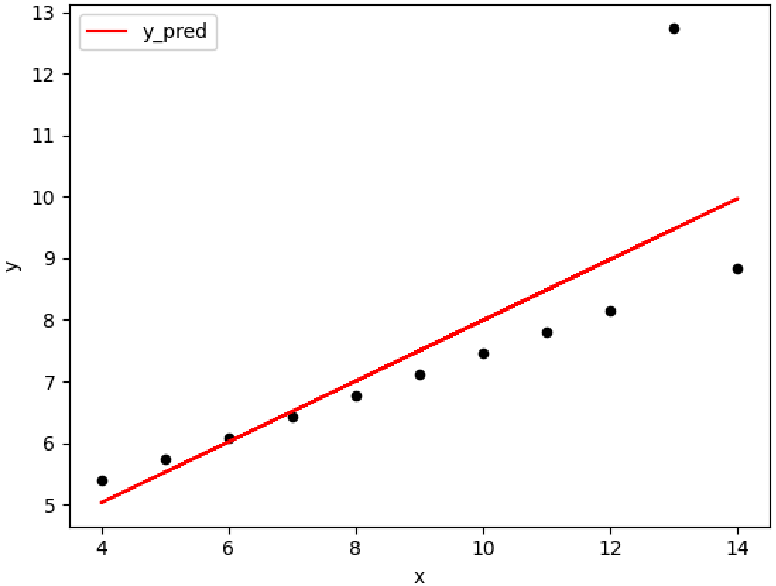

alpha=0.0
y = 0.5x + 3.0
y_pred
y
x


alpha=0.4
y = 0.5x + 3.02
y_pred
y
x

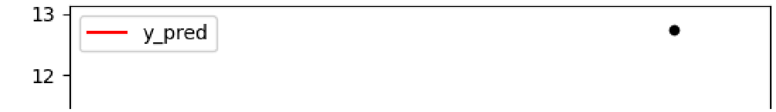

alpha=0.8
y = 0.5x + 3.03

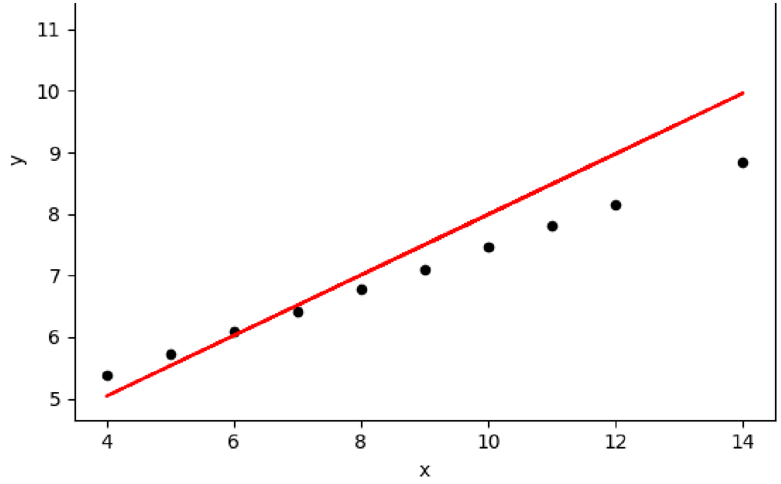


alpha=1.2000000000000002
y = 0.49x + 3.05



alpha=1.6
y = 0.49x + 3.07





alpha=2.0
y = 0.49x + 3.08