13주차(2/3)

Deep Neural Network 1

파이썬으로배우는기계학습

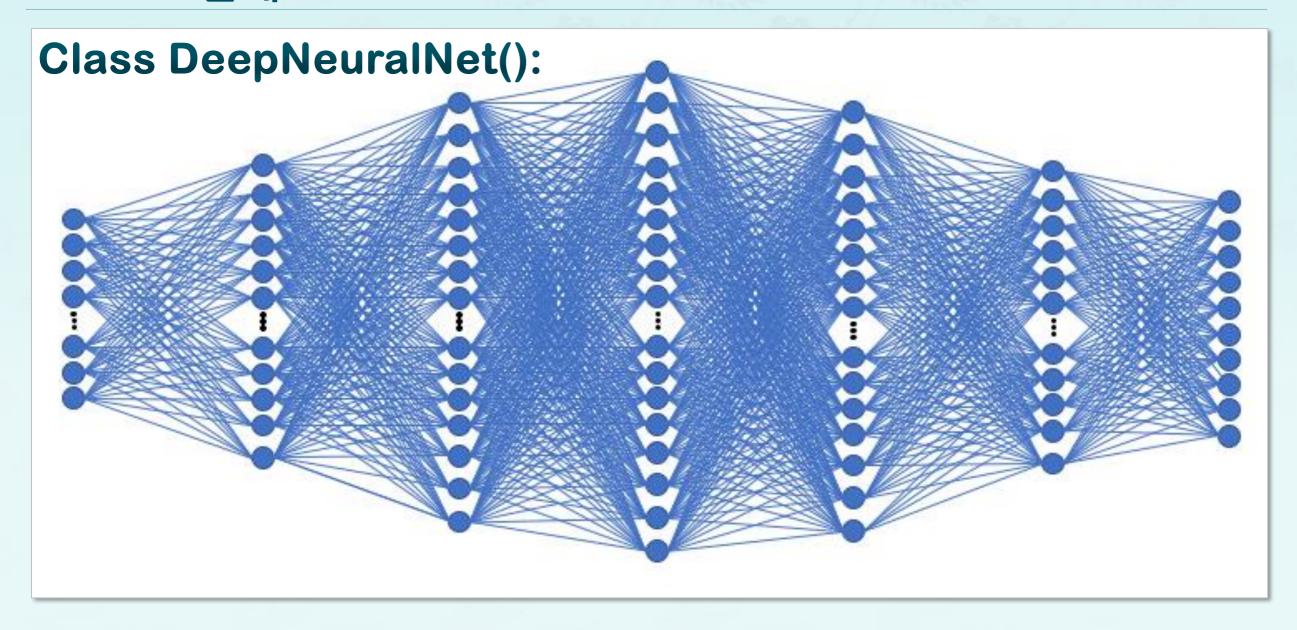
한동대학교 김영섭교수

Deep Neural Network 1

- 학습 목표
 - Deep Neural Network(심층신경망)을 학습한다.
 - 은닉층의 개수에 따른 성능을 확인한다.

- 학습 내용
 - 심층신경망 이해하기
 - 심층신경망 구현하기
 - 심층신경망 성능확인하기

1. DNN 클래스

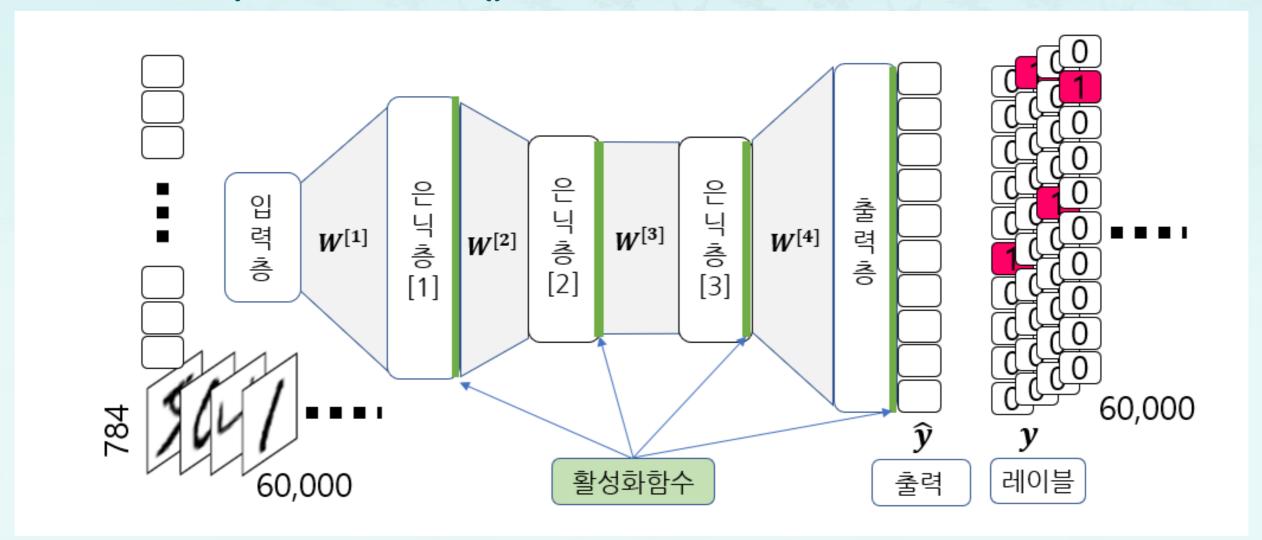


1. DNN 클래스

```
class DeepNeuralNet():
        """ implements a deep neural net.
            Users may specify any number of layers.
 4
            net_arch -- consists of a number of neurons in each layer
        11 11 11
 6
        def init (self, net arch, activate = None,
                     eta = 1.0, epochs = 100, random_seed = 1):
            pass
 9
10
        def forpass(self, A0):
11
            pass
12
13
        def backprop(self, Z, A, Y):
14
            pass
15
        def fit(self, X, y):
16
17
            pass
18
19
        def predict(self, X):
20
            pass
21
22
        def evaluate(self, Xtest, ytest):
23
            pass
```

2. DNN 활성화 함수

Class DeepNeuralNet():



2. DNN 활성화 함수: tanh

$$tanh(x) = \frac{1 - e^{-x}}{1 + e^{-x}} = \frac{2}{1 + e^{-2x}} - 1$$

```
def tanh(x):
        return (1.0 - np.exp(-2 * x))/(
               1.0 + np.exp(-2 * x))
   def tanh_d(x):
        return (1 + tanh(x)) * (1 - tanh(x))
 6
   def sigmoid(x):
       #x = np.clip(x, -500, 500)
       return 1 / (1 + np.exp((-x)))
10
11
12
   def sigmoid_d(x):
        return sigmoid(x) * (1 - sigmoid(x))
13
14
15
   def relu(x):
        return np.maximum(x, 0)
16
17
18
   def relu_d(x):
       x[x<=0] = 0
19
      x[x>0] = 1
20
21
        return x
```

2. DNN 활성화 함수: tanh

$$tanh(x) = \frac{1 - e^{-x}}{1 + e^{-x}} = \frac{2}{1 + e^{-2x}} - 1$$

$$\frac{d}{dx} \tanh(x) = 1 - \left(\frac{2}{1 + e^{-2x}} - 1\right)^2$$
= 1 - \tanh^2(x)

```
def tanh(x):
        return (1.0 - np.exp(-2 * x))/(
               1.0 + np.exp(-2 * x))
5 def tanh_d(x):
       return (1 + tanh(x)) * (1 - tanh(x))
   def sigmoid(x):
       \#x = np.clip(x, -500, 500)
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        return 1 / (1 + np.exp((-x)))
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   def sigmoid d(x):
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   def relu_d(x):
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      x[x<=0] = 0
      x[x>0] = 1
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21
        return x
```

2. DNN 활성화 함수: sigmoid

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

```
def tanh(x):
        return (1.0 - np.exp(-2 * x))/(
                1.0 + np.exp(-2 * x))
   def tanh_d(x):
        return (1 + tanh(x)) * (1 - tanh(x))
 8 def sigmoid(x):
       #x = np.clip(x, -500, 500)
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        return 1 / (1 + np.exp((-x)))
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   def sigmoid d(x):
        return sigmoid(x) * (1 - sigmoid(x))
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   def relu(x):
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```

2. DNN 활성화 함수: sigmoid

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

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

```
def tanh(x):
       return (1.0 - np.exp(-2 * x))/(
               1.0 + np.exp(-2 * x))
   def tanh_d(x):
       return (1 + tanh(x)) * (1 - tanh(x))
 8 def sigmoid(x):
    \#x = np.clip(x, -500, 500)
10 return 1 / (1 + np.exp((-x)))
12 def sigmoid_d(x):
       return sigmoid(x) * (1 - sigmoid(x))
   def relu(x):
16
       return np.maximum(x, 0)
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18
   def relu_d(x):
19
     x[x<=0] = 0
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21
       return x
```

2. DNN 활성화 함수: ReLU

$$Relu(x) = \begin{cases} x & if \ x \ge 0 \\ 0 & otherwise \end{cases}$$

```
def tanh(x):
        return (1.0 - np.exp(-2 * x))/(
                1.0 + np.exp(-2 * x))
 4
    def tanh_d(x):
        return (1 + tanh(x)) * (1 - tanh(x))
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   def sigmoid(x):
       #x = np.clip(x, -500, 500)
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        return np.maximum(x, 0)
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$$Relu(x) = \begin{cases} x & if \ x \ge 0 \\ 0 & otherwise \end{cases}$$

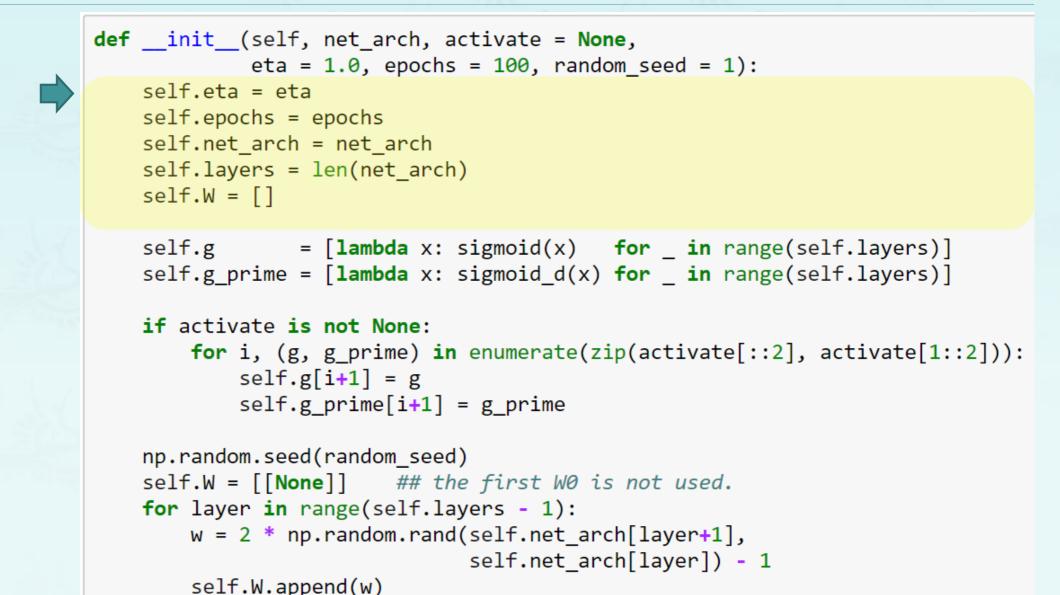
$$\frac{d}{dx}Relu(x) = \begin{cases} 1 & if \ x \ge 0 \\ 0 & otherwise \end{cases}$$

```
def tanh(x):
       return (1.0 - np.exp(-2 * x))/(
               1.0 + np.exp(-2 * x))
 4
   def tanh d(x):
       return (1 + tanh(x)) * (1 - tanh(x))
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   def sigmoid(x):
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        return x
```

```
def init (self, net arch, activate = None,
            eta = 1.0, epochs = 100, random seed = 1):
    self.eta = eta
   self.epochs = epochs
   self.net arch = net arch
   self.layers = len(net arch)
   self.W = []
   self.g = [lambda x: sigmoid(x) for _ in range(self.layers)]
   self.g prime = [lambda x: sigmoid d(x) for in range(self.layers)]
   if activate is not None:
       for i, (g, g_prime) in enumerate(zip(activate[::2], activate[1::2])):
           self.g[i+1] = g
           self.g prime[i+1] = g prime
   np.random.seed(random seed)
   self.W = [[None]] ## the first W0 is not used.
   for layer in range(self.layers - 1):
       w = 2 * np.random.rand(self.net_arch[layer+1],
                              self.net arch[layer]) - 1
       self.W.append(w)
```



```
def init (self, net arch, activate = None,
            eta = 1.0, epochs = 100, random seed = 1):
    self.eta = eta
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```

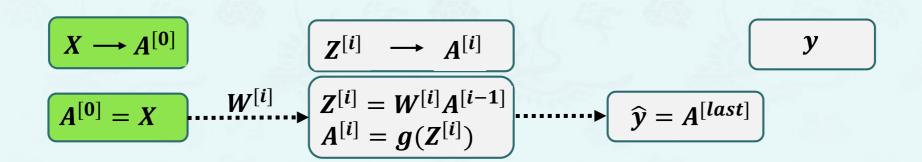
```
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            eta = 1.0, epochs = 100, random seed = 1):
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       self.W.append(w)
```

```
def init (self, net arch, activate = None,
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                             if activate is not None:
                                 for i, (g, g_prime) in enumerate(zip(activate[::2], activate[1::2])):
                                     self.g[i+1] = g
                                     self.g prime[i+1] = g prime
                             np.random.seed(random seed)
                             self.W = [[None]] ## the first W0 is not used.
                             for layer in range(self.layers - 1):
(뒷층 노드 수, 앞층 노드 수)
                                w = 2 * np.random.rand(self.net_arch[layer+1],
                                                       self.net arch[layer]) - 1
                                 self.W.append(w)
```

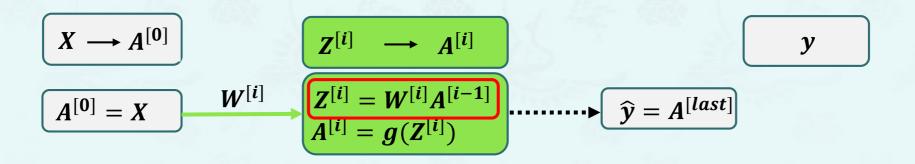
3. DNN 구현: fit() 메소드

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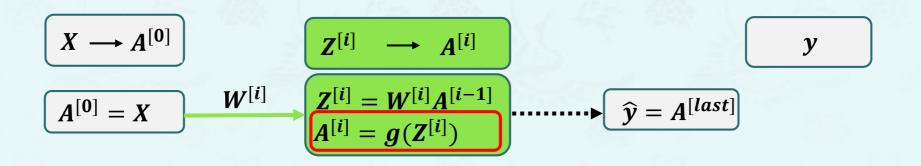
```
def forpass(self, A0):
    Z = [[None]] # Z0 is not used.
    A = [] # A0 = X0 is used.
    A.append(A0)
    for i in range(1, len(self.W)):
        z = np.dot(self.W[i], A[i-1])
        Z.append(z)
        a = self.g[i](z)
        A.append(a)
    return Z, A
```



```
def forpass(self, A0):
    Z = [[None]] # Z0 is not used.
    A = [] # A0 = X0 is used.
    A.append(A0)
    for i in range(1, len(self.W)):
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        z = np.dot(self.W[i], A[i-1])
        Z.append(z)
        a = self.g[i](z)
        A.append(a)
    return Z, A
```



3. DNN 구현: fit() 메소드

```
def backprop(self, Z, A, Y):
         E = [None for x in range(self.layers)]
         dZ = [None for x in range(self.layers)]
        11 = self.layers - 1
         error = Y - A[11]
         E[11] = error
         dZ[11] = error * self.g_prime[11](Z[11])
 9
        for i in range(self.layers-2, 0, -1):
10
             E[i] = np.dot(self.W[i+1].T, E[i+1])
11
12
             dZ[i] = E[i] * self.g prime[i](Z[i])
13
        m = Y.shape[0] # number of samples
14
                                                                                                                                    y
        for i in range(ll, 0, -1):
15
             self.W[i] += self.eta * np.dot(dZ[i], A[i-1].T) / m
16
17
         return error
                                                                            Z^{[i]} = W^{[i]}A^{[i-1]}
                                                                                                             \widehat{y} = A^{[last]}
                                                                           A^{[i]} = g(Z^{[i]})
                                                                       W^{[last]} += dZ^{[last]} \cdot A^{[last-1]T}
                            W^{[i]} += dZ^{[i]} \cdot A^{[i-1]T}
                                                                                                   E^{[last]} = y - \widehat{y}
                                                   E^{[i]} = W^{[i+1]T}E^{[i+1]}
                                                    dZ^{[i]} = E^{[i]}g'(Z^{[i]})
                                                                                            dZ^{[last]} = E^{[last]}g'(Z^{[last]})
```

```
1 def fit(self, X, y):
    def backprop(self, Z, A, Y):
                                                                           self.cost = []
         E = [None for x in range(self.layers)]
                                                                           for epoch in range(self.epochs):
        dZ = [None for x in range(self.layers)]
                                                                                Z, A = self.forpass(X)
                                                                               cost = self.backprop(Z, A, y)
        11 = self.layers - 1
                                                                                self.cost .append(np.sqrt(np.sum(cost * cost)))
        error = Y - A[11]
                                                                           return self
        E[11] = error
        dZ[11] = error * self.g_prime[11](Z[11])
 9
10
        for i in range(self.layers-2, 0, -1):
             E[i] = np.dot(self.W[i+1].T, E[i+1])
11
12
             dZ[i] = E[i] * self.g prime[i](Z[i])
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        m = Y.shape[0] # number of samples
                                                                                                                                 y
        for i in range(ll, 0, -1):
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             self.W[i] += self.eta * np.dot(dZ[i], A[i-1].T) / m
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         return error
                                                                          Z^{[i]} = W^{[i]}A^{[i-1]}
                                                                                                           \widehat{y} = A^{[last]}
                                                                         A^{[i]} = g(Z^{[i]})
                                                                     W^{[last]} += dZ^{[last]} \cdot A^{[last-1]T}
                            W^{[i]} += dZ^{[i]} \cdot A^{[i-1]T} \mid \bullet \cdots \bullet
                                                  E^{[i]} = W^{[i+1]T}E^{[i+1]}
                                                  dZ^{[i]} = E^{[i]}g'(Z^{[i]})
                                                                                          dZ^{[last]} = E^{[last]}g'(Z^{[last]})
```

```
def backprop(self, Z, A, Y):
         E = [None for x in range(self.layers)]
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         error = Y - A[11]
         E[11] = error
         dZ[11] = error * self.g_prime[11](Z[11])
         for i in range(self.layers-2, 0, -1):
              E[i] = np.dot(self.W[i+1].T, E[i+1])
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             dZ[i] = E[i] * self.g prime[i](Z[i])
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         m = Y.shape[0] # number of samples
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                                                                                                                                        y
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         return error
                                                                              Z^{[i]} = W^{[i]}A^{[i-1]}
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                                                                         W^{[last]} += dZ^{[last]} \cdot A^{[last-1]T}
                             W^{[i]} += dZ^{[i]} \cdot A^{[i-1]T} \mid \bullet \cdots \bullet
                                                                                                      E^{[last]} = y - \widehat{y}
                                                     E^{[i]} = W^{[i+1]T}E^{[i+1]}
                                                     dZ^{[i]} = E^{[i]}g'(Z^{[i]})
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def backprop(self, Z, A, Y):
         E = [None for x in range(self.layers)]
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        11 = self.layers - 1
         error = Y - A[11]
         E[11] = error
         dZ[11] = error * self.g_prime[11](Z[11])
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         for i in range(self.layers-2, 0, -1):
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             E[i] = np.dot(self.W[i+1].T, E[i+1])
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             dZ[i] = E[i] * self.g prime[i](Z[i])
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         m = Y.shape[0] # number of samples
14
                                                                                                                                     y
         for i in range(ll, 0, -1):
             self.W[i] += self.eta * np.dot(dZ[i], A[i-1].T) / m
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                                                                            Z^{[i]} = W^{[i]}A^{[i-1]}
         return error
                                                                                                             | \widehat{y} = A^{[last]} 
                                                                            A^{[i]} = g(Z^{[i]})
                                                                       W^{[last]} += dZ^{[last]} \cdot A^{[last-1]T}
                            W^{[i]} += dZ^{[i]} \cdot A^{[i-1]T}
                                                                                                   E^{[last]} = y - \widehat{y}
                                                   E^{[i]} = W^{[i+1]T}E^{[i+1]}
                                                    dZ^{[i]} = E^{[i]}g'(Z^{[i]})
                                                                                            dZ^{[last]} = E^{[last]}g'(Z^{[last]})
```

3. DNN 구현: fit() 메소드

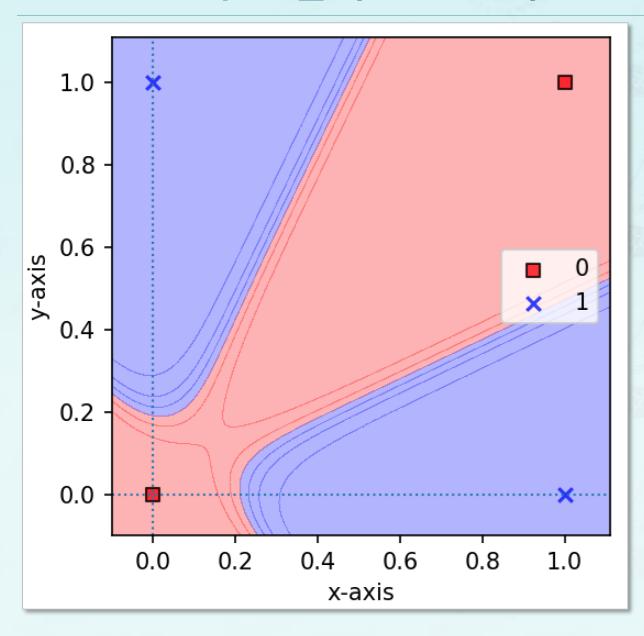
```
import joy
X = np.array([[0, 0, 1, 1], [0, 1, 0, 1]])
y = np.array([0, 1, 1, 0])
dnn = DeepNeuralNet([2, 4, 2, 1], eta = 0.5, epochs = 5000).fit(X, y)

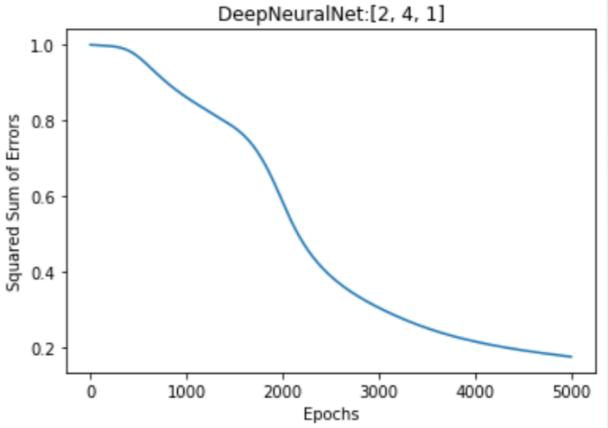
joy.plot_decision_regions(X.T, y, dnn)
plt.xlabel('x-axis')
plt.ylabel('y-axis')
plt.legend(loc='best')
plt.show()
```

[입력층, 은닉층, 은닉층, 출력층]의 노드 수

```
import joy
X = np.array([ [0, 0, 1, 1], [0, 1, 0, 1] ])
y = np.array([0, 1, 1, 0])
dnn = DeepNeuralNet([2, 4, 2, 1], eta = 0.5, epochs = 5000).fit(X, y)

joy.plot_decision_regions(X.T, y, dnn)
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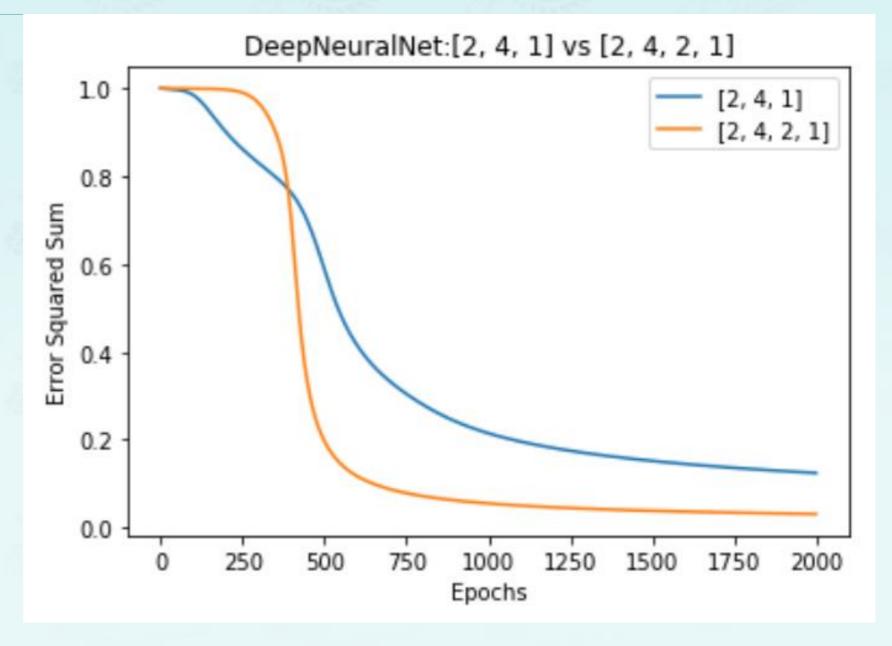




```
dnn1 = DeepNeuralNet([2,4,1], eta = 0.5, epochs = 5000).fit(X, y)
g = [sigmoid, sigmoid_d, sigmoid_d, sigmoid_d, sigmoid_d]
dnn2 = DeepNeuralNet([2,4,2,1], activate=g, eta = 0.5, epochs = 5000).fit(X, y)
plt.plot(range(len(dnn1.cost_)), dnn1.cost_, label='{}'.format(dnn1.net_arch))
plt.plot(range(len(dnn2.cost_)), dnn2.cost_, label='{}'.format(dnn2.net_arch))
plt.title('DeepNeuralNet:{} vs {}'.format(dnn1.net_arch, dnn2.net_arch))
plt.xlabel('Epochs')
plt.ylabel('Squared Sum of Errors')
plt.legend(loc='best')
plt.show()
```

```
dnn1 = DeepNeuralNet([2,4,1], eta = 0.5, epochs = 5000).fit(X, y)
g = [sigmoid, sigmoid_d, sigmoid_d, sigmoid_d, sigmoid_d]
dnn2 = DeepNeuralNet([2,4,2,1], activate=g, eta = 0.5, epochs = 5000).fit(X, y)
plt.plot(range(len(dnn1.cost_)), dnn1.cost_, label='{}'.format(dnn1.net_arch))
plt.plot(range(len(dnn2.cost_)), dnn2.cost_, label='{}'.format(dnn2.net_arch))
plt.title('DeepNeuralNet:{} vs {}'.format(dnn1.net_arch, dnn2.net_arch))
plt.xlabel('Epochs')
plt.ylabel('Squared Sum of Errors')
plt.legend(loc='best')
plt.show()
```

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g = [sigmoid, sigmoid_d, sigmoid_d, sigmoid_d, sigmoid_d]
dnn2 = DeepNeuralNet([2,4,2,1], activate=g, eta = 0.5, epochs = 5000).fit(X, y)
plt.plot(range(len(dnn1.cost_)), dnn1.cost_, label='{}'.format(dnn1.net_arch))
plt.plot(range(len(dnn2.cost_)), dnn2.cost_, label='{}'.format(dnn2.net_arch))
plt.title('DeepNeuralNet:{} vs {}'.format(dnn1.net_arch, dnn2.net_arch))
plt.xlabel('Epochs')
plt.ylabel('Squared Sum of Errors')
plt.legend(loc='best')
plt.show()
```



DNN 학습: 각 층별로 활성화 함수 지정

```
g1 = [tanh, tanh_d, sigmoid, sigmoid_d, sigmoid_d]
dnn1 = DeepNeuralNet([2,4,2,1], activate=g1, eta = 0.5, epochs = 5000).fit(X, y)
g2 = [sigmoid, sigmoid_d, sigmoid_d, sigmoid_d, sigmoid_d]
dnn2 = DeepNeuralNet([2,4,2,1], activate=g2, eta = 0.5, epochs = 5000).fit(X, y)
plt.plot(range(len(dnn1.cost_)), dnn1.cost_, label='[tanh, sigmoid, sigmoid]')
plt.plot(range(len(dnn2.cost_)), dnn2.cost_, label='[sigmoid, sigmoid, sigmoid]')
plt.title('DeepNeuralNet: tanh vs sigmoid')
plt.xlabel('Epochs')
plt.ylabel('Squared Sum of Errors')
plt.legend(loc='best')
plt.show()
```

DNN 학습: 각 층별로 활성화 함수 지정

```
g1 = [tanh, tanh_d, sigmoid, sigmoid_d, sigmoid, sigmoid_d]
dnn1 = DeepNeuralNet([2,4,2,1], activate=g1, eta = 0.5, epochs = 5000).fit(X, y)
g2 = [sigmoid, sigmoid_d, sigmoid_d, sigmoid_d, sigmoid_d]
dnn2 = DeepNeuralNet([2,4,2,1], activ
                                                         DeepNeuralNet: tanh vs sigmoid
plt.plot(range(len(dnn1.cost_)), dnn1
                                             1.0
                                                                        [tanh, sigmoid, sigmoid]
plt.plot(range(len(dnn2.cost_)), dnn2
                                                                        [sigmoid, sigmoid, sigmoid]
plt.title('DeepNeuralNet: tanh vs sig
                                             0.8
plt.xlabel('Epochs')
                                           Sum
plt.ylabel('Squared Sum of Errors')
                                           Error Squared
                                             0.6
plt.legend(loc='best')
plt.show()
                                             0.4
                                             0.2
                                             0.0
                                                      250
                                                           500
                                                                750
                                                                    1000
                                                                         1250
                                                                              1500
                                                                                   1750
                                                                                        2000
                                                                   Epochs
```

Deep Neural Network 1

- 학습 정리
 - 심층 신경망인 DeepNeuralNet 클래스 구현하기
 - 심층 신경망의 은닉층 갯수에 따른 성능을 확인하기

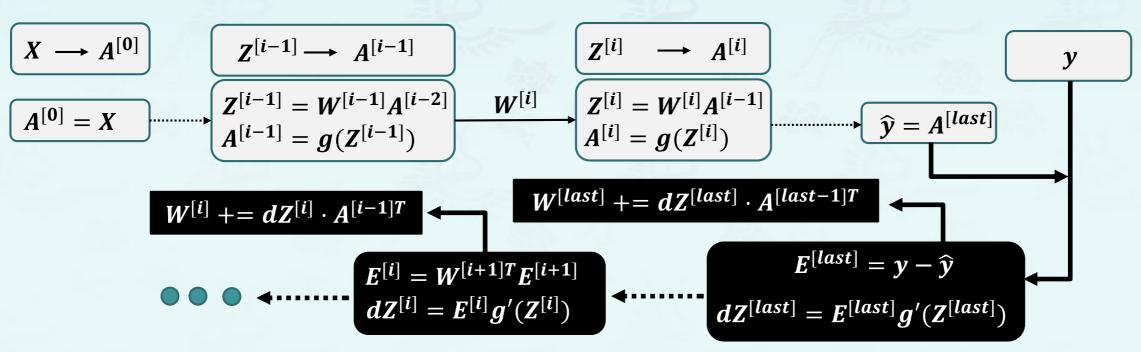
13-1 Deep Neural Network 2

13주차(2/3)

Deep Neural Network 1

파이썬으로배우는기계학습

한동대학교 김영섭교수



MNIST-Deep-Net

- 학습 목표
 - Batch Gradient와 Stochastic-GD, Mini-Batch-GD를 적용한다.
 - Dropout을 이용하여 과대적합을 피하는 방법을 학습한다.
 - MNIST-Fashion DataSet을 이용하여 Deep Neural Network를 테스트한다.
- 학습 내용
 - Batch Gradient, Stochastic-GD, Mini-Batch-GD
 - Dropout
 - MNIST-Fashion DataSet

Mini-Batch-GD: 개념 설명

- 배치 경사하강법
 - 모든 샘플들의 오차 총합



- 확률적 경사하강법
 - 각각의 샘플들의 오차



- 미니 배치 경사하강법
 - 특정 샘플들의 오차 총합

▶ 장점:

- Python이나 수치 계산 라이브러리가 대부분 큰 배열을 효율적으로 처리
- 자료 전송에서의 다량 전달로 인해 병목 현상 사라짐

Deep Neural Network

- 학습 정리
 - Batch Gradient와 Stochastic-GD, Mini-Batch-GD를 적용하기.
 - Dropout을 이용하여 과대적합을 피하는 방법을 학습하기.
 - MNIST-Fashion DataSet을 이용하여 Deep Neural Network를 테스트하기.

- 차시 예고
 - 12-3 Deep Neural Network 2