

## ML HW3

1,2,3:

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1. [b]

$$E_D[E_{in}(w_{lin})] = \sigma^2 \left(1 - \frac{d+1}{N}\right) \quad d=11, \sigma=0.1$$

$$0.1^2 \left(1 - \frac{11+1}{N}\right) \geq 0.006$$

$$0.4 \geq \frac{12}{N}, \quad N \geq \frac{12}{0.4} = 30$$

2. [a]

normal equation  $X^T X w = X^T y$

(a) only one solution for the normal equation

(b)  $\nabla E_{in}(w) = 0$

(c)  $\nabla E_{in}(w) = 0$

(d) not unique  $\nabla E_{in}(w) = 0$

3.

$$\hat{y} = Hy = Xw_{LIN}$$

(a)  $X \rightarrow ZX, \hat{y} \rightarrow Z\hat{y}, H \rightarrow ZH$

(b)  $X = \begin{bmatrix} x_1^1 & x_1^2 & x_1^3 \\ x_2^1 & x_2^2 & x_2^3 \\ x_3^1 & x_3^2 & x_3^3 \end{bmatrix} \rightarrow \begin{bmatrix} x_1^1 & 2x_1^2 & 3x_1^3 \\ x_2^1 & 2x_2^2 & 3x_2^3 \\ x_3^1 & 2x_3^2 & 3x_3^3 \end{bmatrix}$

[ ]

4,5:

4. [e]

$\Pr(|V - \theta| > \epsilon) \leq 2 \exp(-2\epsilon^2 N) \rightarrow$  by Hoeffding

$V$  maximizes likelihood  $(\theta)$  over all  $\hat{\theta} \in [0, 1]$

$\rightarrow$  because  $V$  is  $\rightarrow \theta$ .

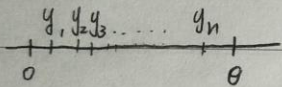
$V$  minimizes  $E_{in}(\hat{y}) = \frac{1}{N} \sum_{n=1}^N (\hat{y} - y_n)^2$  over all  $\hat{y} \in \mathbb{R}$

$$\frac{\partial E_{in}(\hat{y})}{\partial \hat{y}} = \frac{2}{N} \sum_{n=1}^N (\hat{y} - y_n) = 2 \left( \frac{\sum_{n=1}^N \hat{y}}{N} - \frac{\sum_{n=1}^N y_n}{N} \right) = 2 \left( A - \frac{1}{N} \sum_{n=1}^N y_n \right)$$

$$\nabla E_{in}(\theta) = 2 \left( 0 - \frac{\sum_{n=1}^N y_n}{N} \right) = -2V, \quad 2V = -\nabla E_{in}(\theta)$$

$$\theta = V$$

5. [a]



$\forall n \in (1, N), \dots$

$$P(y_n | \theta) = \frac{1}{\theta}$$

For any  $\hat{\theta} \geq \max(y_1, y_2, \dots, y_N)$

$$P(y_n | \hat{\theta}) = \frac{1}{\hat{\theta}}$$

the likelihood of generating the data set  $(y_1, y_2, \dots, y_N)$  is

$$\prod_{n=1}^N P(y_n | \hat{\theta}) = \prod_{n=1}^N \frac{1}{\hat{\theta}} = \left( \frac{1}{\hat{\theta}} \right)^N$$

6,7:

6. [b]

$$\text{err}(w, x, y) = \frac{y w^T x (\text{sign}(w^T x) \neq y)}{1}$$

$$= \max(0, -y w^T x)$$

$$E(w) = \sum_{n=1}^N \text{err}(w, x_n, y_n)$$

$$w_{t+1} = w_t + \eta \nabla E(w_t)$$

$$\nabla E(w) = \frac{1}{N} \sum_{n=1}^N \frac{\partial \text{err}(w, x_n, y_n)}{\partial w} = \frac{1}{N} \sum_{n=1}^N \frac{\partial \max(0, -y_n w^T x_n)}{\partial w}$$

$$= \frac{1}{N} \sum_{n=1}^N \begin{cases} -y_n x_n & \text{if } -y_n w^T x_n > 0 \\ 0 & \text{otherwise} \end{cases}$$

7. [a]

$$\text{err} = e^{(-y w^T x)}$$

Gradient descent:

$$E_{\text{in}}(w) = \frac{1}{N} \sum_{n=1}^N \text{err}(w, x_n, y_n) \rightarrow \frac{1}{N} \sum_{n=1}^N \text{err}_{\text{exp}}(w, x_n, y_n) \rightarrow \frac{1}{N} \sum_{n=1}^N e^{-y_n w^T x_n}$$

$$\nabla E_{\text{in}}(w) = \frac{1}{N} \sum_{n=1}^N \frac{\partial e^{-y_n w^T x_n}}{\partial w} = \frac{1}{N} \sum_{n=1}^N e^{-y_n w^T x_n} \cdot (-y_n x_n)$$

$$w_{t+1} = w_t + \eta \nabla E_{\text{in}}(w) = w_t - \eta \frac{1}{N} \sum_{n=1}^N e^{-y_n w^T x_n} \cdot (-y_n x_n)$$

SGD: randomly pick one  $x$ :

$$w_{t+1} = w_t - \eta (-y_n x_n) e^{-y_n w^T x_n}$$

$$= -\nabla \text{err}_{\text{exp}}(w, x_n, y_n) = \eta (y_n x_n) \exp(-y_n w^T x_n)$$

8,9:



8. [b]

$$E(w) \approx E(u) + b_E(u)^T (w-u) + \frac{1}{2} (w-u)^T A_E(u) (w-u)$$

$$w = u + v, \text{ s.t. } \nabla E(w) = \vec{0}$$

$$\frac{\partial E(w)}{\partial w} = 0 + \frac{\partial b_E(u)^T (w-u)}{\partial w} + \frac{1}{2} \frac{\partial (w-u)^T A_E(u) (w-u)}{\partial w}$$

$$= b_E(u)^T + \cancel{2} A_E(u)^T (w-u) \cdot \frac{1}{\cancel{2}}$$

$$\left. \frac{\partial E(w)}{\partial w} \right|_{u+v} = b_E(u)^T + A_E(u)^T v = \vec{0}$$

$$A_E(u)^T v = -b_E(u)^T$$

$$v = -(A_E(u)^T)^{-1} b_E(u)^T$$

9. [b]

second-order Taylor-expansion of  $E(w)$  around  $w_*$

$$E(w) \approx E(w_*) + b_E(w_*)^T (w-w_*) + \frac{1}{2} (w-w_*)^T A_E(w_*) (w-w_*)$$

$$\nabla E(w) = b_E(w_*)^T + A_E(w_*)^T (w-w_*) = 0$$

for linear regression:

$$\nabla E(w_*) = \frac{2}{N} (X^T X w_* - X^T y) = 0$$

$$A_E(w_*) = \nabla^2 E(w_*) = \frac{\partial}{\partial w_*} \left( \frac{2}{N} (X^T X w_* - X^T y) \right)$$

$$= \frac{2}{N} X^T X$$

10:

10. [b]

$$h_y(x) = \frac{e^{(w_y^T x)}}{\sum_{i=1}^K e^{(w_i^T x)}}$$

$$w = \begin{bmatrix} w_1 & w_2 & \dots & w_K \end{bmatrix}$$

$$\text{err}(w, x, y) = -\ln h_y(x) = -\sum_{k=1}^K \mathbb{I}[y=k] \ln h_k(x)$$

$$h_y(x) \propto \prod_{n=1}^N h_{y_n}(x_n) = \prod_{n=1}^N \frac{e^{w_y^T x_n}}{\sum_{i=1}^K e^{w_i^T x_n}} \propto \frac{e^{w_y^T x}}{\sum_{i=1}^K e^{w_i^T x}}$$

$$D = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$$

$$\frac{\partial \text{err}(w, x, y)}{\partial w_k} = \frac{-\sum_{k=1}^K \frac{\partial \mathbb{I}[y=k] \ln h_k(x)}{\partial w_k}}{\partial w_k}$$

$$= \frac{-\sum_{k=1}^K \mathbb{I}[y=k] (w_k^T x - \ln \sum_{i=1}^K e^{w_i^T x})}{\partial w_k}$$

$$= \frac{-\mathbb{I}[y=k] w_k^T x}{\partial w_k} + \frac{\mathbb{I}[y=k] \frac{\partial \ln \sum_{i=1}^K e^{w_i^T x}}{\partial w_k}}{\partial w_k} \mathbb{I}[y=k]$$

$$= -\mathbb{I}[y=k] x_i + \frac{\mathbb{I}[y=k] \frac{\partial \ln \sum_{i=1}^K e^{w_i^T x}}{\partial w_k}}{\frac{\partial \sum_{i=1}^K e^{w_i^T x}}{\partial w_k}} \mathbb{I}[y=k]$$

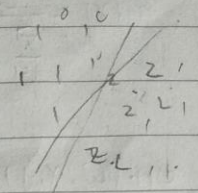
$$= -\mathbb{I}[y=k] x_i + \mathbb{I}[y=k] \frac{1}{\sum_{i=1}^K e^{w_i^T x}} \cdot x_i e^{w_k^T x}$$

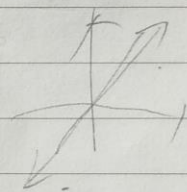
$$= -\mathbb{I}[y=k] x_i + \mathbb{I}[y=k] \frac{e^{w_k^T x}}{\sum_{i=1}^K e^{w_i^T x}} \cdot x_i$$

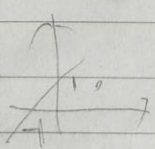
$$= -\mathbb{I}[y=k] x_i + \mathbb{I}[y=k] h_k(x) x_i$$

$$= (h_k(x) - \mathbb{I}[y=k]) x_i$$

$y = \{1, 2\}$   
 $D = \{(x_1, y_1), (x_2, y_2) \dots (x_N, y_N)\}$   
 for  $y = 1$   $y' = -1$   
 $P(x_1) h(w_1^* \cdot x_1) \times P(x_2) h(w_1^* \cdot x_2) \dots P(x_N) h(w_1^* \cdot x_N)$   
 $= P(x_1) h(y_1 w_1^* \cdot x_1) \times P(x_2) h(y_2 w_1^* \cdot x_2) \dots P(x_N) h(y_N w_1^* \cdot x_N)$   
 $\downarrow$   
 $\nabla E_{in}(w_1^*) = \frac{1}{N} \sum_{n=1}^N \theta(-y_n w_1^* \cdot x_n) (-y_n x_n) = 0$   
 for  $y = 2$   $y' = 1$   
 $\nabla E_{in}(w_2^*) = \frac{1}{N} \sum_{n=1}^N \theta(-y_n w_2^* \cdot x_n) (-y_n x_n) = 0$   
 $w_2^* = -w_1^*$   
 $w_2^* = \frac{1}{2} (w_2^* - w_1^*)$





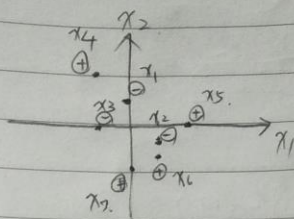


$x - y = -1$   
 $x - y + 1 = 0$   
 $\begin{bmatrix} 1 & -1 \end{bmatrix}^T x$

12:



12. [e]



$\times [a] -9 - x_1 + 2x_1^2 - 2x_1x_2 + 3x_2^2$

$[e] -7 + 2x_1^2 - 2x_1x_2 + 3x_2^2$

$x_1(0,1) = -9 - 0 + 0 - 0 + 3 < 0$

$x_2(1,-0.5) = -9 - 1 + 2 + 1 + 0.75 < 0$

$x_3(-1,0) = -9 + 1 + 2 - 0 + 0 < 0$

$x_4(-1,2) = -9 + 1 + 2 + 4 + 12 > 0$

$x_5(2,0) = -9 - 2 + 8 - 0 + 0 < 0$

$\times [b] -5 - x_1 + 2x_2 + 3x_1^2 - 7x_1x_2 + 2x_2^2$

$x_1(0,1) < 0$

$x_2(1,-0.5) = -5 - 1 - 1 + 3 - 3.5 + 0.5 < 0$

$x_3(-1,0) = -5 + 1 + 3 < 0$

$x_4(-1,2) = -5 + 1 + 4 + 3 + 14 + 8 > 0$

$x_5(2,0) = -5 - 2 + 12 > 0$

$x_6(1,-1.5) = -5 - 1 - 3 + 3 + 10.5 + 4.5 > 0$

$x_7(0,-2) = -5 - 4 < 0$

$\times [c] 9 - x_1 + 4x_2 + 2x_1^2 - 2x_1x_2 + 3x_2^2$

$x_1(0,1) = 9 + 4 > 0$

$x_4(-1,2) = 9 + 1 + 8 + 2 > 0$

$\times [d] 2 - x_1 - 4x_2 - 2x_1^2 + 7x_1x_2 - 4x_2^2$

$x_1(0,1) = 2 - 4 - 4 < 0$

$x_2(1,-0.5) = 2 - 1 + 2 - 2 - 3.5 - 1 < 0$

$x_3(-1,0) = 2 + 1 - 2 > 0$

13:

13.

$$\chi_1 = [\chi_1^1 \chi_2^1 \dots \chi_k^1 \dots \chi_d^1]$$

$$\chi_2 = [\chi_1^2 \chi_2^2 \dots \chi_k^2 \dots \chi_d^2]$$

$$\chi_3 = [\chi_1^3 \chi_2^3 \dots \chi_k^3 \dots \chi_d^3]$$

$$\phi = (1, \chi_k)$$

$d_{vc}(H_k)$  in  $n$ -D pla is  $n+1$

$$n=1, d_{vc}(H_k) = 2$$

tightest UB of  $d_{vc}(\bigcup_{k=1}^d H_k)$

$$= d_{vc}(H_1) \cup d_{vc}(H_2) \cup d_{vc}(H_3) \cup \dots \cup d_{vc}(H_d)$$

$$\leq d_{vc}(H_1) + d_{vc}(H_2) + \dots + d_{vc}(H_d)$$

$$\leq 2 \times d$$



14:

```
import numpy as np

X0 = np.ones([1000,1])
train = np.genfromtxt('train.txt', delimiter='\t')
train = np.append(X0 , train ,axis=1)
X = np.hsplit(train,[11])[0]  ## separate the array into two part on the
base of the nth column
Y = np.hsplit(train,[11])[1]
Wlin = np.dot(np.linalg.pinv(X) , Y)

E = np.dot(X , Wlin) - Y
print(E)
Ein = 0
for i in range(len(E)):
    Ein += (E[i][0]) ** 2/len(E)

print(Ein)
```

15:

```
import numpy as np
from random import randint

X0 = np.ones([1000,1])
train = np.genfromtxt('train.txt', delimiter='\t')
train = np.append(X0 , train ,axis=1)
X = np.hsplit(train,[11])[0]  ## separate the array into two part on the
base of the nth column
Y = np.hsplit(train,[11])[1]
Wlin = np.dot(np.linalg.pinv(X) , Y)

E = np.dot(X , Wlin) - Y
Einlin = 0
for i in range(len(E)):
    Einlin += (E[i][0]) ** 2/len(E)

n = 0.001
count = 0
times_avg = 0
while count < 1000:
    print(count)
    times = 0
    ratio = 100
    Wt = np.zeros([11,1])
    while ratio > 1.01:
        rand = randint(0,999)
        E = np.dot(X , Wt) - Y
        Einwt = 0
        for i in range(len(E)):
            Einwt += (E[i][0]) ** 2/len(E)
        x = X[rand].reshape((1,11))  # what the hell is it????

        Ein_grad = 2*(np.dot(x,Wt) - Y[rand][0]) * np.transpose(x)
        Wt = Wt- n*Ein_grad
        ratio = Einwt / Einlin
        times += 1
```

```

        times_avg += times/1000
        count += 1

print(times_avg)

```

16:

```

import numpy as np
from random import randint

X0 = np.ones([1000,1])
train = np.genfromtxt('train.txt', delimiter='\t')
train = np.append(X0 , train ,axis=1)
X = np.hsplit(train,[11])[0]  ## separate the array into two part on the
base of the nth column
Y = np.hsplit(train,[11])[1]

def sigmoid(h):
    ans = 1/(1+np.exp(-h))
    return ans

n = 0.001
count = 0
Ein_avg = 0
while count < 1000:
    print(count)
    times = 0
    Wt = np.zeros([11,1])
    while times < 500:
        rand = randint(0,999)
        x = X[rand].reshape((1,11))  # what the hell is it????
        Ein_grad = sigmoid(-
Y[rand][0] * np.dot(x,Wt)) * Y[rand][0] * np.transpose(x)
        Wt = Wt + n*Ein_grad
    times += 1
    count += 1
    Ein_avg += Ein_grad/500

```



```

        times += 1

    Einwt = 0
    for i in range(1000):
        x = X[i].reshape((1,11))
        CE_error = np.log(1+np.exp(-Y[i][0] * np.dot(x,Wt)[0][0]))
        Einwt += CE_error/1000

    Ein_avg += Einwt/1000
    count += 1

print(Ein_avg)

```

17:

```

import numpy as np
from random import randint

X0 = np.ones([1000,1])
train = np.genfromtxt('train.txt', delimiter='\t')
train = np.append(X0 , train ,axis=1)
X = np.hsplit(train,[11])[0]  ## separate the array into two part on the
base of the nth column
Y = np.hsplit(train,[11])[1]
Wlin = np.dot(np.linalg.pinv(X) , Y)

def sigmoid(h):
    ans = 1/(1+np.exp(-h))
    return ans

n = 0.001
count = 0
Ein_avg = 0
while count < 1000:
    print(count)
    times = 0
    Wt = Wlin
    while times < 500:
        rand = randint(0,999)
        x = X[rand].reshape((1,11))  # what the hell is it????

```

```

        Ein_grad = sigmoid(-
Y[rand][0] * np.dot(x,Wt)) * Y[rand][0] * np.transpose(x)
        Wt = Wt + n*Ein_grad
        times += 1

    Einwt = 0
    for i in range(1000):
        x = X[i].reshape((1,11))
        CE_error = np.log(1+np.exp(-Y[i][0] * np.dot(x,Wt)[0][0]))
        Einwt += CE_error/1000

    Ein_avg += Einwt/1000
    count += 1

print(Ein_avg)

```

18:

```

import numpy as np

X0_train = np.ones([1000,1])
X0_test = np.ones([3000,1])
train = np.genfromtxt('train.txt', delimiter='\t')
test = np.genfromtxt('test.txt', delimiter='\t')
train = np.append(X0_train , train ,axis=1)
test = np.append(X0_test , test ,axis=1)

X_train = np.hsplit(train,[11])[0]  ## separate the array into two part
on the base of the nth column
Y_train = np.hsplit(train,[11])[1]
X_test = np.hsplit(test,[11])[0]  ## separate the array into two part o
n the base of the nth column
Y_test = np.hsplit(test,[11])[1]
Wlin = np.dot(np.linalg.pinv(X_train) , Y_train)

def sign(s):
    if s >= 0:
        return 1
    else:
        return -1

```

```

E_train = np.dot(X_train , Wlin) * Y_train #
E_test = np.dot(X_test , Wlin) * Y_test
Ein = 0
Eout = 0
for i in range(1000):
    if sign(E_train[i]) == -1:
        Ein += 1/1000
    if sign(E_test[i]) == -1:
        Eout += 1/1000

print(Ein)
print(Eout)
print(abs(Ein-Eout))

```

19:

```

import numpy as np

X0_train = np.ones([1000,1])
X0_test = np.ones([3000,1])
train = np.genfromtxt('train.txt', delimiter='\t')
test = np.genfromtxt('test.txt', delimiter='\t')
train = np.append(X0_train , train ,axis=1)
test = np.append(X0_test , test ,axis=1)

X_train = np.hsplit(train,[11])[0] ## separate the array into two part
on the base of the nth column
Y_train = np.hsplit(train,[11])[1]
X_test = np.hsplit(test,[11])[0] ## separate the array into two part o
n the base of the nth column
Y_test = np.hsplit(test,[11])[1]
Wlin = np.dot(np.linalg.pinv(X_train) , Y_train)

def sign(s):
    if s >= 0:

```



```

        return 1
    else:
        return -1

E_train = np.dot(X_train , Wlin) * Y_train #
E_test = np.dot(X_test , Wlin) * Y_test
Ein = 0
Eout = 0
for i in range(1000):
    if sign(E_train[i]) == -1:
        Ein += 1/1000
    if sign(E_test[i]) == -1:
        Eout += 1/1000

print(Ein)
print(Eout)
print(abs(Ein-Eout))

```

20:

```

import numpy as np

X0_train = np.ones([1000,1])
X0_test = np.ones([3000,1])

train = np.genfromtxt('train.txt', delimiter='\t')
X_train = np.hsplit(train,[10])[0] ## separate the array into two part
on the base of the nth column
Y_train = np.hsplit(train,[10])[1]
test = np.genfromtxt('test.txt', delimiter='\t')
X_test = np.hsplit(test,[10])[0] ## separate the array into two part o
n the base of the nth column
Y_test = np.hsplit(test,[10])[1]

Q = 10
Z_train = X0_train

```

```

Z_test = X0_test
for q in range(1,Q+1):
    Z_train2 = np.power(X_train , q)
    Z_test2 = np.power(X_test , q)
    Z_train = np.append(Z_train , Z_train2 ,axis = 1)
    Z_test = np.append(Z_test , Z_test2 ,axis = 1)

g = np.dot(np.linalg.pinv(Z_train) , Y_train)

def sign(s):
    if s >= 0:
        return 1
    else:
        return -1

E_train = np.dot(Z_train , g) * Y_train #
E_test = np.dot(Z_test , g) * Y_test
Ein = 0
Eout = 0
for i in range(1000):
    if sign(E_train[i]) == -1:
        Ein += 1/1000
for i in range(3000):
    if sign(E_test[i]) == -1:
        Eout += 1/3000

print(Ein)
print(Eout)

print(abs(Ein-Eout))

```