

# ENPM808A – Introduction to Machine Learning

## Homework – 1

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1.

```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from sklearn import linear_model
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split

df = pd.read_excel('mlr05.xls')

X = df.drop('X1', axis =1)
Y = df.X1

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2)

model = linear_model.LinearRegression()
model.fit(X_train, Y_train)

Y_pred_train = model.predict(X_train)
Y_pred_test = model.predict(X_test)

full = linear_model.LinearRegression()
full.fit(X, Y)
full_pred = model.predict(X)

plt.figure(figsize=(5,11))

# 2 row, 1 column, plot 1
plt.subplot(2, 1, 1)
plt.scatter(x=Y_train, y=Y_pred_train, c="#7CAE00", alpha=0.3)

z = np.polyfit(Y_train, Y_pred_train, 1)
p = np.poly1d(z)
plt.plot(Y_test,p(Y_test), "#F8766D")

plt.ylabel('Predicted Sales')

# 2 row, 1 column, plot 2
```

```

plt.subplot(2, 1, 2)
plt.scatter(x=Y_test, y=Y_pred_test, c="#619CFF", alpha=0.3)

z = np.polyfit(Y_test, Y_pred_test, 1)
p = np.poly1d(z)
plt.plot(Y_test, p(Y_test), "#F8766D")

plt.ylabel('Predicted Sales')
plt.xlabel('Experimental Sales')

plt.savefig('plot_vertical_Sales.png')
plt.savefig('plot_vertical_Sales.pdf')
plt.show()

plt.figure(figsize=(11,5))

# 1 row, 2 column, plot 1
plt.subplot(1, 2, 1)
plt.scatter(x=Y_train, y=Y_pred_train, c="#7CAE00", alpha=0.3)

z = np.polyfit(Y_train, Y_pred_train, 1)
p = np.poly1d(z)
plt.plot(Y_test, p(Y_test), "#F8766D")

plt.ylabel('Predicted Sales')
plt.xlabel('Experimental Sales')

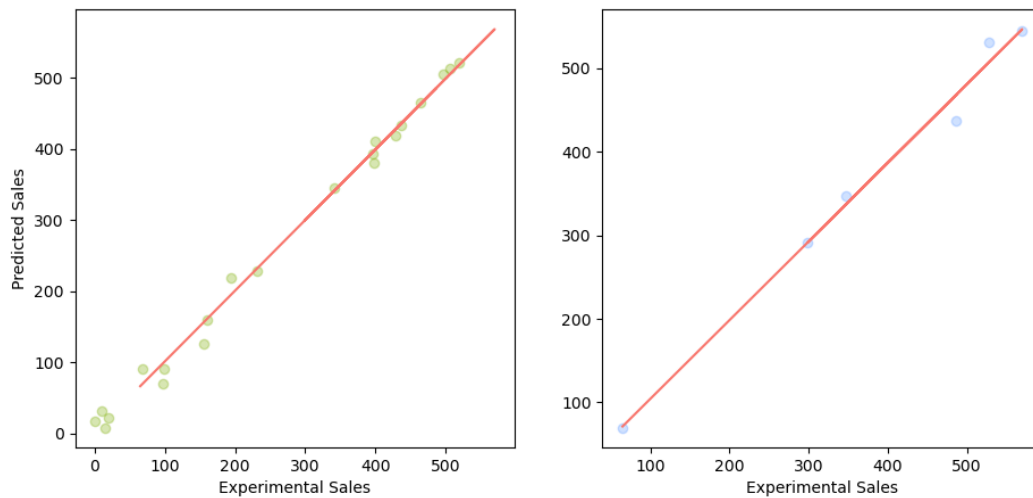
# 1 row, 2 column, plot 2
plt.subplot(1, 2, 2)
plt.scatter(x=Y_test, y=Y_pred_test, c="#619CFF", alpha=0.3)

z = np.polyfit(Y_test, Y_pred_test, 1)
p = np.poly1d(z)
plt.plot(Y_test, p(Y_test), "#F8766D")

plt.xlabel('Experimental Sales')

plt.savefig('plot_horizontal_Sales.png')
plt.savefig('plot_horizontal_Sales.pdf')
plt.show()

```



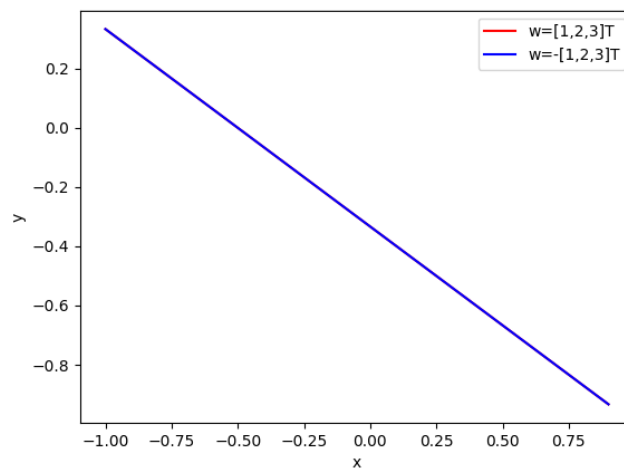
2.a. Using analytics geo.,  $w^T x = 0$ .  $h(x) = +1$  and  $h(x) = -1$  are separated by a straight line because there are points on one side of the line  $w^T x > 0$  and same for  $w^T x < 0$ . The slope  $a$  and intercept  $b$  can be expressed in  $w_0, w_1, w_2$  as:

$$w^T x = w_0 + w_1 x_1 + w_2 x_2 = 0$$

when  $w_2 \neq 0$

$$x_2 = -\frac{w_0}{w_2} - \frac{w_1}{w_2} x$$

2.b.



3.

Q3  $\rightarrow$  Let  $w^* = \operatorname{argmin} \{ \|w\| : \langle w, x_i \rangle y_i \geq 1, \forall i \in [1:n] \}$   
 The idea of the proof is to show that after performing  $T$  iterations, the cosine of the angle between  $w^*$  and  $w^{(T+1)}$  is at least  $\frac{\sqrt{T}}{RB}$ , i.e.,

$$\cos(\angle(w^*, w^{(T+1)})) = \frac{\langle w^*, w^{(T+1)} \rangle}{\|w^*\| \|w^{(T+1)}\|} \geq \frac{\sqrt{T}}{RB}$$

hence,  $T \leq (RB)^2$

To show this, we first show that  $\langle w^*, w^{(T+1)} \rangle \geq T$ . Initially, we have  $\langle w^*, w^{(1)} \rangle = 0$   
 at iteration  $t$ , after updating  $w^{(t+1)}$  based on example  $i$  we have

$$\langle w^*, w^{(t+1)} \rangle - \langle w^*, w^{(t)} \rangle = \langle w^*, w^{(t)} + y_i x_i \rangle - \langle w^*, w^{(t)} \rangle$$

$$\begin{aligned} &= \langle w^*, y_i x_i \rangle \\ &\geq 1 \end{aligned}$$

Therefore, after  $T$  iterations, we have  
 $\langle w^*, w^{(T+1)} \rangle \geq T$

Now we upper bound  $\|w^{(T+1)}\|$ . At each iteration  $t$ , we have

$$\begin{aligned} \|w^{(t+1)}\|^2 &= \|w^{(t)} + y_i x_i\|^2 \\ &= \|w^{(t)}\|^2 + \|y_i x_i\|^2 + 2y_i \langle w^{(t)}, x_i \rangle \\ &\leq \|w^{(t)}\|^2 + \|y_i x_i\|^2 \end{aligned}$$

$$\leq \|w^{(t)}\|^2 + R^2$$

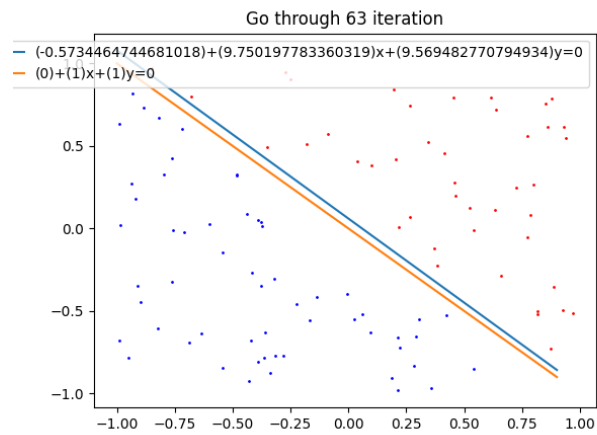
Since  $\|w^{(1)}\|^2 = 0$ , after  $T$  iterations we have  
 $\|w^{(T+1)}\|^2 \leq TR^2$   
 i.e.,  $\|w^{(T+1)}\| \leq \sqrt{TR}$

Combining the above we have

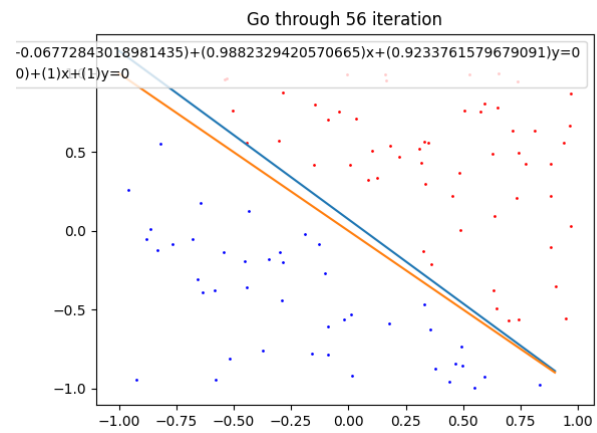
$$\begin{aligned} \frac{\langle w^*, w^{(T+1)} \rangle}{\|w^*\| \|w^{(T+1)}\|} &\geq \frac{T}{B\sqrt{TR}} \\ &= \frac{\sqrt{T}}{RB} \end{aligned}$$

4. The question requires a consideration of the "deviation distance" when updating. In the process of trying, I found that taking 100 for  $\eta$  would cause the number to be too large, so here we take 1, 0.1, 0.01, 0.0001

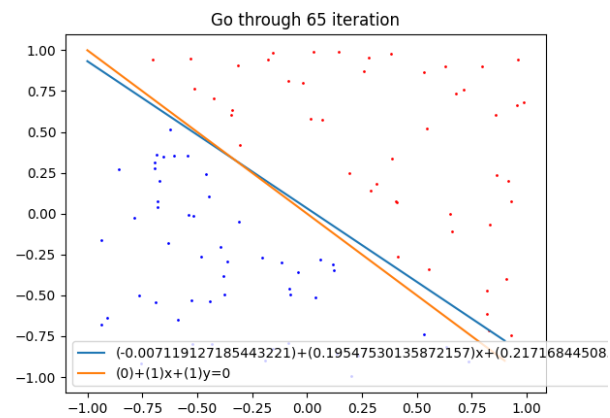
$n = 1$ , time error rate = 0.0



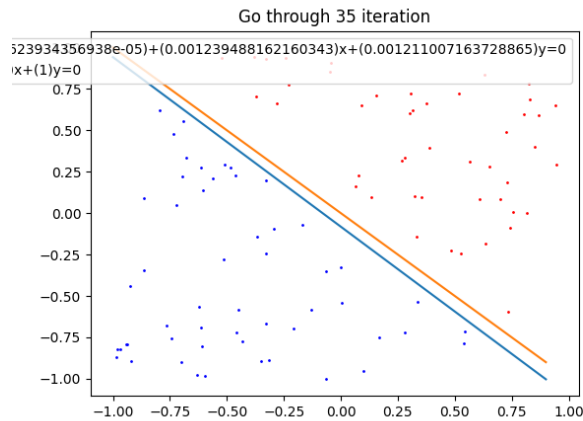
$n = 0.1$ , time error rate = 0.0022



$n = 0.01$ , time error rate = 0.002



$n = 0.0001$ , time error rate = 0.0001



5.1. Using binomial distribution, there are two kinds of marbles in the box, 90% are red marbles, 10% are green marbles, now we take 10, and ask the probability that the number of red marbles is less than or equal to 1.

$$P = 0.1^{10} + C_{10}^1 \times 0.1^9 \times 0.9 \approx 9 \times 10^{-9} \quad \text{where } P \text{ is the Probability}$$

5.2. Using Hoeffding Inequality:

$$\mathbb{P}[|\nu - \mu| > \epsilon] \leq 2e^{-2\epsilon^2 N} \quad \text{for any } \epsilon > 0.$$

Substituting the values:

$$\mathbb{P}[v \leq 0.1] = \mathbb{P}[0.9 - v \geq 0.8] = \mathbb{P}[\mu - v \geq 0.8] \leq \mathbb{P}[|\mu - v| \geq 0.8] \leq 2e^{-2 \times 0.8^2 \times 10} \approx 5.5215451440744015 \times 10^{-6}$$

This is a loose upper bound than the 5.1 (Exercise 1.8) as Hoeffding inequality is universal. Thus, the upper bound must be loose.