### Written Assignment 2

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I worked on this assignment with Wendy and Elise

### 1 Question 1: Vectorization

$$\theta = (\theta_0, \theta_1, \dots \theta_n)^T$$
$$x^{(i)} = (x_0, x_1 \dots x_n)^T$$
$$x_0 = 1$$

# 1.1 a) What is the vectorial expression for the multi-vareate linear regression hypothesis function?

the hypothesis function for multivareate linear regression is:

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \dots + \theta_n x_n$$

the parameters are n+1 feature vectors:

$$x = \begin{vmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{vmatrix}$$

$$heta = \left| egin{array}{c} heta_0 \\ heta_1 \\ heta_2 \\ heta_2 \\ heta_n \end{array} \right|$$

We can rewrite the hypothesis as:

$$h_{\theta}(x) = \theta^T X$$

because the hypthesis function is a matrix multiplication:

$$\left|\begin{array}{ccccc} \theta_0 & \theta_1 & \theta_2 & \dots & \theta_n \end{array}\right|$$

$$\left|\begin{array}{c} x_0 \\ x_1 \\ x_2 \\ \vdots \\ \vdots \\ x_n \end{array}\right|$$

### 1.2 b) What is the vectorized expression for the cost function?

the cost function is:

$$J(\theta) = 1/2m \sum_{i=1}^{m} (h_{\theta}(x^{(i)}) - y^{(i)})^{2}$$

but as the hypothesis has now changed to be:

$$h_{\theta}(x) = \theta^T X$$

rewrite the cost function to be:

$$J(\theta) = 1/2msum_{(i=1)}^{m} (\theta^{T} x^{(i)} - y^{(i)})^{2}$$

## 1.3 c) What is the vectorized expression for the gradient of the cost function?

To calculate the gradient:

$$\frac{\delta J(\theta)}{\delta \theta} = \begin{vmatrix} \frac{\delta J(\theta)}{\delta \theta_0} \\ \vdots \\ \vdots \\ \frac{\delta J(\theta)}{\delta \theta_n} \end{vmatrix}$$

which is:

$$\frac{\delta J(\theta)}{\delta \theta} = \begin{vmatrix} \frac{1}{m} \sum_{i=1}^{m} ((h_{\theta}(x^{(i)} - y^{(i)})) \\ \frac{1}{m} \sum_{i=1}^{m} ((h_{\theta}(x^{(i)} - y^{(i)}) \cdot x_1) \\ \vdots \\ \vdots \\ \frac{1}{m} \sum_{i=1}^{m} ((h_{\theta}(x^{(i)} - y^{(i)}) \cdot x_n) \end{vmatrix}$$

### 1.4 d) What is the vectorized expression for the $\theta$ update rule in the gradient descent procedure?

the update rule is now:

$$\theta_0 = \theta_0 - \alpha \frac{\delta J(\theta)}{\delta \theta_0} = \theta_0 - \alpha \cdot \frac{1}{m} \cdot \sum_{(i=1)}^m (h_{\theta}(x^{(i)} - y^{(i)}) x_0^{(i)}$$

where  $j \geq 1$ :

$$\theta_{j} = \theta - \alpha \cdot \frac{1}{m} \cdot \begin{bmatrix} \sum_{(i=1)}^{m} \theta^{T}(x^{(i)} - y^{(i)}) \cdot x_{2}^{(i)} \\ \sum_{(i=1)}^{m} \theta^{T}(x^{(i)} - y^{(i)}) \cdot x_{1}^{(i)} \\ \vdots \\ \sum_{(i=1)}^{m} \theta^{T}(x^{(i)} - y^{(i)}) \cdot x_{n}^{(i)} \end{bmatrix}$$

we simply add in the new hypothesis function

#### 2 Question 3: probability

#### 2.1 a. estimate mean and variance from data

the data set is: 2, 5, 7, 7, 9, 25 to calculate the mean:

$$\mu = \frac{1}{m} \sum_{i=1}^{m} x^{(i)}$$

$$\mu = \frac{1}{6} (2 + 5 + 7 + 7 + 9 + 25)$$

$$\mu = 9.17$$

to calculate the variance:

$$\sigma^{2} = \frac{1}{m} \sum_{(i=1)}^{m} (x^{(i)} - \mu)^{2}$$

$$\sigma^{2} = \frac{1}{6} \cdot (2 - 9.17)^{2} + (5 - 9.17)^{2} + (7 - 9.17)^{2} + (7 - 9.17)^{2} + (9 - 9.17)^{2} + (25 - 9.17)^{2}$$

$$\sigma^{2} = 54.81$$

#### 2.2 b) calculate the probability density function

$$X \sim N(\mu, \sigma^2)$$

is a random variable. calculate the probability density function:

$$fx^{(20)}$$

the probability density function is: CHECK THIS

$$\begin{split} fx^{(x)} &= \frac{1}{\sigma \cdot \sqrt{2\pi}} \cdot e^{-(\frac{(x-\mu)^2}{2 \cdot \sigma^2})} \\ fx^{(20)} &= \frac{1}{7.4 \cdot \sqrt{2\pi}} \cdot e^{-(\frac{(20-9.17)^2}{2 \cdot 54.81})} \\ fx^{(20)} &= 0.054 \cdot 0.343 \\ fx^{(20)} &= 0.0185 \end{split}$$

#### **2.3** c) calculate $fx_1...x_6(2,5,7,7,9,25)$

The variables are independent of each other and identically and normally distributed with  $\mu = 9.17$  and  $\sigma^2 = 54.81$   $fx_1...x_6(x_1...x_6)$  is the joint probability distribution function

#### 2.4 e) estimate the covariance

Cov(X, Y) = 0

Table 1: Table of values

$$Cov(X,Y) = \frac{\sum_{(i=1)}^{m} (x_i - \mu_x)(y_i - \mu_y)}{m-1}$$

$$\mu_x = 9.16$$

$$\mu_y = 6$$

$$Cov(X,Y) = \frac{((2-9.16) \cdot (5-9.16) \cdot (7-9.16) \cdot (7-9.16) \cdot (9-9.16) \cdot (25-9.16)) \cdot ((4-6) \cdot (4-6) \cdot (5-6) \cdot$$