## Homework Three

#### Kyle Kazemini

October 20, 2020

### Question 1

(a)

```
import numpy as np
import scipy as sp

x = np.genfromtxt('http://www.cs.utah.edu/~jeffp/teaching/FoDA/x.csv')
y = np.genfromtxt('http://www.cs.utah.edu/~jeffp/teaching/FoDA/y.csv')

(a, b) = np.polyfit(x, y, 1)
print(a, b)
```

From the given code, the coefficients for the model are 515.1222963490035 and -1095.6026286820393.

```
For x = 4: y = 515.122296349003(4) - 1095.6026286820393 = 964.886556714
```

For x = 8.5: y = 515.122296349003(8.5) - 1095.6026286820393 = 3282.93689028

(b)

```
import numpy as np
import scipy as sp

x = np.genfromtxt('http://www.cs.utah.edu/~jeffp/teaching/FoDA/x.csv')
y = np.genfromtxt('http://www.cs.utah.edu/~jeffp/teaching/FoDA/y.csv')

(a, b) = np.polyfit(x, y, 1)
print(a, b)

xTrain = np.resize(x, 80)
yTrain = np.resize(y, 80)

xTest = x[-20:]
yTest = y[-20:]

(c, d) = np.polyfit(xTrain, yTrain, 1)
print(c, d)
```

From the given code, the coefficients for the model are 492.83938094054713 and -991.1378015106926.

```
For x = 4: y = 492.83938094054713(4) - 991.1378015106926 = 980.219722251
```

For x = 8.5: y = 492.83938094054713(8.5) - 991.1378015106926 = 3197.99693648

(c)

```
xTrain = np.resize(x, 80)
yTrain = np.resize(y, 80)
xTest = x[-20:]
yTest = y[-20:]
(c, d) = np.polyfit(xTrain, yTrain, 1)
print(c, d)
print(x[0:20] - yTest)
print(LA.norm(x[0:20] - yTest))
print(xTrain[0:20] - yTest)
print(LA.norm(xTrain[0:20] - yTest))
\left[-1872.97566844 - 2124.20042923 - 2806.38564739 - 685.21763991 - 612.44185309 - 311.45530061 - 2073.90359254 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185309 - 412.44185000 - 412.44185000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.44180000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000 - 412.4418000
6329.50685967 - 1426.50893435 - 1752.68576377 - 3341.71890547 - 2172.88332434 - 1333.15364208 - 2482.68733743
-1677.87229317 -1953.870498 -1989.81298483 -1408.72616297 -1704.86156841 -1568.61698997 \\ ]
10396.231606675967
6329.50685967 - 1426.50893435 - 1752.68576377 - 3341.71890547 - 2172.88332434 - 1333.15364208 - 2482.68733743 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.50893435 - 1248.5089343 - 1248.5089343 - 1248.5089343 - 1248.5089343 - 1248.5089343 - 1248.5089343 - 1248.5089343 - 1248.5089343 - 1248.5089343 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.508934 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.50894 - 1248.5089 - 1248.50894 - 1248.50894 - 124
-1677.87229317 \ -1953.870498 \ -1989.81298483 \ -1408.72616297 \ -1704.86156841 \ -1568.61698997]
10396.231606675967
(d)
The first 3 rows of the matrix X_3 are:
  \begin{bmatrix} 1 & 3.64641412 & 13.2963359345 & 48.483947096 \end{bmatrix}
    1 \quad 9.76756879 \quad 95.4054000674 \quad 931.878808096
   1 2.72543008 7.42796912097
                                                                                                                    20.2444104756
coef = np.polyfit(xTrain, yTrain, 3)
print(coef)
[2.20876179\ 22.49361866\ 42.98550892\ 175.37688997]
Thus, the model is of the form 2.20876179 + 22.49361866x + 42.98550892x^2 + 175.37688997x^3.
print(xTrain[0:4] - coef)
print(LA.norm(xTrain[0:4] - coef))
print(xTest[0:4] - coef)
print(LA.norm(xTest[0:4] - coef))
[1.43765233\ \hbox{-} 12.72604987\ \hbox{-} 40.26007885\ \hbox{-} 171.33807389]
176.46990877821662
[3.98029592 - 16.25780541 - 35.44440414 - 172.10644721]
176.51372169996213
```

#### Question 2

(a)

The span of the columns of X is all of  $\mathbb{R}^n$  because the columns of X are linearly independent.

(b)

X is a square matrix because the number of rows n equals the number of columns n. By definition, the rank of a matrix is equal to the column rank. Since (a) shows that X has full column rank, X also has full rank. Thus, X is an invertible matrix.

(c)

Since Reginald chose the correct  $\hat{\alpha}$ , from the textbook we know this to be

$$\hat{\alpha} = (\tilde{X}^T \tilde{X})^{-1} \tilde{X}^T y$$

 $\hat{\alpha}$  is an *n* dimensional vector. Thus  $||X\hat{\alpha} - y||_2^2$  is the square of the 2-norm of the *n* dimensional vector  $X\hat{\alpha} - y$ . To be more specific, it's a scalar in  $\mathbb{R}$ .

(d)

Reginald is not necessarily correct. He may have an issue with overfitting the data. Although it looks like X predicts values for y well, Reginald hasn't tested X's prediction for a new value not in y. Cross-validation can be used here to ensure that X makes good predictions without overfitting.

# Question 3

(a)

```
def func1(x, y):
 return (x - y)**2 + x*y
def func1_grad(vx, vy):
 dfdx = 2*vx - vy
 dfdy = 2*vy - vx
 return np.array([dfdx, dfdy])
######## f1 ########
#initialize location and settings
v_{init} = np.array([2, 3])
num_iter = 20
values = np.zeros([num_iter, 2])
values[0,:] = v_init
v = v_{init}
gamma = 0.05
# actual gradient descent algorithm
for i in range(1, num_iter):
 v = v - gamma * func1_grad(v[0],v[1])
 values[i, :] = v
```

```
print(func1(v[0], v[1]))
print('\n')
Function values for each step:
6.1825
5.4821687499999999
4.877186453125\\
4.350745589335937
3.8897616734954097
3.48393186574361
3.125045871620225
2.8064799937505835\\
2.522824297718033
2.2696066633667744
2.043087476992105
1.8401059402222188
1.6579641941916723
1.4943392365774435
1.347215344339452
1.2148316957210588
1.095641320174279
0.9882785453901884
0.8915328656811666
(b)
def func2(x, y):
 return (1 - (y - 4))**2 + 35*((x + 6) - (y - 4)**2)**2
def func2_grad(vx, vy):
 dfdx = 70*(vx - (vy - 4)**2 + 6)
 dfdy = 2*((-70)*(vy - 4)*(vx - (vy - 4)**2 + 6) + vy - 5)
 return np.array([dfdx, dfdy])
######## f2 ########
#initialize location and settings
v_init = np.array([0, 2])
num_iter = 100
values = np.zeros([num_iter, 2])
values[0, :] = v_init
v = v_init
gamma = 0.0015
# actual gradient descent algorithm
for i in range(1,num_iter):
 v = v - gamma * func2_grad(v[0], v[1])
 values[i,:] = v
 print(func2(v[0], v[1]))
```

print('\n')

Function values for each step:

187.88006849523507

507.0224399254285

97.4687922498154

237.49697288060918

163.67331237471922

397.5295607383085

92.91856638516737

203.84546587090867

124.44105580352209

271.080602278776

98.95907069068228

201.39078707217467

97.62861798226827

191.17834664797255

88.27719160868917

164.68270551157514

81.25126770491809

145.1001259745785

74.5714162236261

107 0070001 5010

127.68726031521832

68.41053884855933

112.52686890847815

62.73791418295255

99.31273134192851

57.52379855993894

87.78384896359964

52.739191446705306

77.71665530217534

48.355989273410415

68.91925835864996

44.347125359484906

61.226658666804866

40.68667602849454

54.496735715292644

37.349934338528655

48.60686819081629

34.31345506468583

43.451081187215244

31.555074746514627

38.93763293113783

29.053910457193865

34.98696898146169

26.790340723278902

31.5299844010636

24.745971784329548

28.506544682212798

22.903592151697364

25.86422466532266

21.24711821379695

23.557231662398088

19.76153344310416

21.545484748545707

18.43282358438362

```
19.79382693000119
17.24791003621831
18.271350804783943
16.19458346727958
16.950821537976655
15.261439521275562\\
15.808183587525352
14.43781824628653
14.822139729090663
13.713748623429828\\
13.973792617426142
13.07989925935934\\
13.246340456271119
12.527535946853781
12.624819393264982
12.048486396374164\\
12.095886072745706\\
11.635112017061086
11.647634427091607
11.280286204802039
11.269441322940478
10.97737821016512
10.951836153071072\\
10.720241344280659
10.686389920354557
10.503204066801372
10.465619827931777\\
10.321062408896232\\
10.282905887018668\\
10.169072225061697
10.132416583721625
10.042939934603105
10.009041199220494
9.938810686491264\\
9.908326933963064
9.853253227611802
9.826419520702043
9.783241134806245
9.760006496960527
9.72613044490201\\
9.706262721998378
9.67963404785849
9.662798050615192
9.641793468778047
9.627607308926443
9.61094883880406
```

#### (c)

#initialize location and settings
v\_init = np.array([2, 3])

######## f1 ########

```
num_iter = 20
values = np.zeros([num_iter, 2])

values[0,:] = v_init
v = v_init

gamma = 0.2

# actual gradient descent algorithm
for i in range(1, num_iter):
    v = v - gamma * func1_grad(v[0],v[1])
    values[i, :] = v
    print(func1(v[0], v[1]))

print('\n')
```

Function value after 20 steps: 0.0012980742146342732

(d)

```
######## f2 ########
```

```
#initialize location and settings
v_init = np.array([0, 2])
num_iter = 100
values = np.zeros([num_iter, 2])

values[0, :] = v_init
v = v_init

gamma = 0.002201

# actual gradient descent algorithm
for i in range(1, num_iter):
    v = v - gamma * func2_grad(v[0], v[1])
    values[i,:] = v
    print(func2(v[0], v[1]))

print('\n')
```

Function value after 100 steps: 0.5027520844564334