3-Copy1

February 9, 2020

1 Assigment 3

This assignment focuses on getting comfortable with working with multidimensional data and linear regression. Key items include: - Creating random n-dimensional data - Creating a Model that can handle the data - Plot a subset of the data along with the prediction - Using a Dataset to read in and choose certain columns to produce a model - Create several models from various combinations of columns - Plot a few of the results - BONUS: Perform all the plots in 3D instead of 2D

1.1 1. Create a 4 dimensional data set with 64 elements and show 2D plots of the data $x_1 \rightarrow y, x_2 \rightarrow y$, etc.

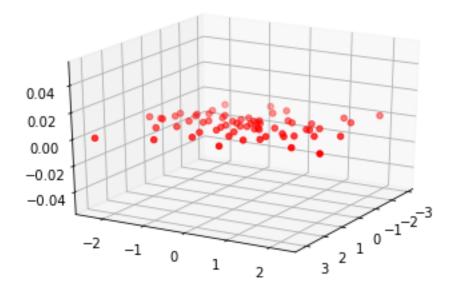
```
import numpy as np
np.warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

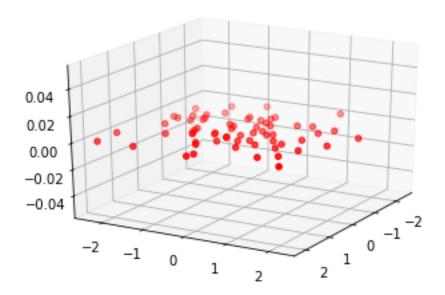
x = np.random.randn(4,64)
x = np.vstack([x, np.ones(len(x.T))]).T
y = np.random.randn(64)

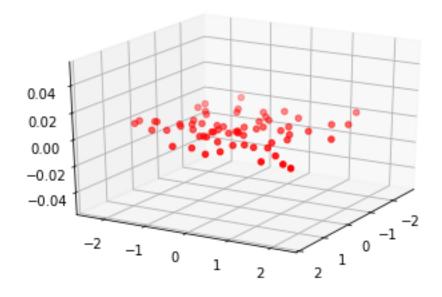
for index, np_array in enumerate(x):
    if index < len(x.T):
        fig = plt.figure()
        ax = fig.add_subplot(111, projection='3d')
        ax.view_init(23, 30)
        ax.scatter(x.T[index], y, zdir='z', c='r')
        print(fig)</pre>
```

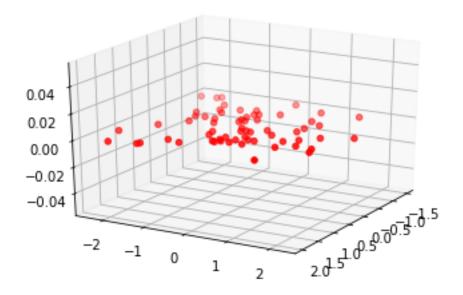
Figure (432x288)
Figure (432x288)

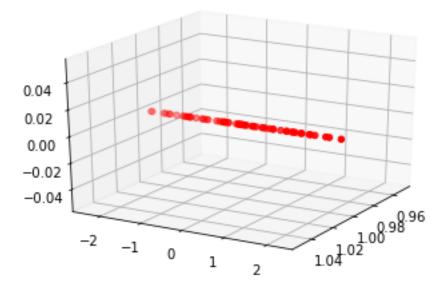
Figure(432x288)
Figure(432x288)
Figure(432x288)











1.2 2. Create a model to fit the data. Hint: follow the example from Lesson 3

```
[163]: left = np.linalg.inv(np.dot(x.T, x))
    right = np.dot(y.T, x)
    beta = np.dot(left, right)

    print(right)
    print(left)
    print(beta)
```

```
[-17.89295222 3.14936286 14.42326991 3.39140895 -12.30861914]
[[ 0.0150527 0.00390433 -0.00305523 0.00446507 -0.00091556]
[ 0.00390433 0.01575172 0.00025808 -0.00094911 0.00084603]
[-0.00305523 0.00025808 0.01496104 0.00068711 0.00201285]
[ 0.00446507 -0.00094911 0.00068711 0.02293804 -0.00528972]
[-0.00091556 0.00084603 0.00201285 -0.00528972 0.01719666]]
[-0.27469529 -0.0301621 0.24882179 0.06992943 -0.18152823]
```

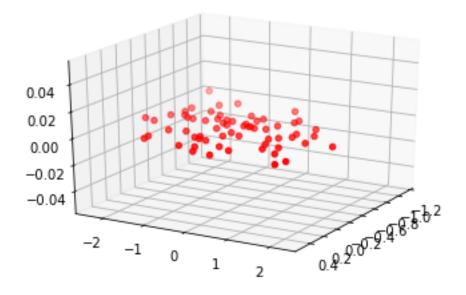
1.3 3. Plot the model's prediction in 2D for 2 of the dimensions $(x_1 \to y_p, x_2 \to y_p)$ along with the original points

```
[164]: pred = np.dot(x, beta)
  print(pred)
  fig = plt.figure()
  ax = fig.add_subplot(111, projection='3d')
  ax.view_init(23, 30)
```

```
ax.scatter(pred.T, y, zdir='z', c='r')
```

```
 \begin{bmatrix} -0.5720941 & -0.38111809 & -0.40764074 & 0.50066274 & -0.32042538 & -0.32644179 \\ -0.59919781 & -0.32619558 & -1.12701497 & -0.40182229 & -0.16359414 & -0.28948547 \\ 0.27049832 & -0.45026039 & -0.77297884 & -0.51153857 & 0.09450326 & -0.3232093 \\ 0.24502731 & -0.33704961 & 0.04961593 & 0.17004382 & -0.22092678 & 0.05045144 \\ -0.11237741 & -0.5781343 & -0.41774533 & -0.88991427 & -0.32621739 & 0.13025713 \\ -0.32544862 & -0.11908192 & -0.48507774 & -0.30497036 & 0.08280616 & -0.13398027 \\ -0.17212076 & -0.50038633 & 0.15357864 & 0.38777843 & 0.48857992 & -0.59382615 \\ 0.38105966 & -0.31287943 & -0.08699377 & 0.00201545 & 0.17105593 & 0.36019618 \\ 0.47573013 & -0.33156489 & -0.49948389 & -0.13422635 & 0.34338822 & -0.32232919 \\ 0.32984158 & 0.26798169 & -0.89386191 & -0.60916991 & -0.65993757 & -0.34061172 \\ -0.14867946 & -0.06151375 & 0.01583813 & -0.38800266 \end{bmatrix}
```

[164]: <mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x13986c080>



1.4 4. Read in mlnn/data/Credit.csv with Pandas and create a model to predict Credit Rating (Rating). Use only the numeric columns in your model, but feel free to experiment which which columns you believe are better predicters of Credit Rating

```
[165]: import pandas as pd
    credit = pd.read_csv('../data/Credit.csv')
    print(credit.head(10))
```

Unnamed: O Income Limit Rating Cards Age Education Gender Student \

```
0
             1
                 14.891
                           3606
                                      283
                                                2
                                                    34
                                                                 11
                                                                       Male
                                                                                  No
1
                106.025
                           6645
                                      483
                                                3
                                                    82
                                                                     Female
             2
                                                                 15
                                                                                 Yes
2
                104.593
                                                4
             3
                           7075
                                      514
                                                    71
                                                                 11
                                                                       Male
                                                                                  No
3
             4
                148.924
                           9504
                                      681
                                                3
                                                    36
                                                                 11
                                                                    Female
                                                                                  No
4
             5
                 55.882
                           4897
                                                2
                                                                       Male
                                      357
                                                    68
                                                                 16
                                                                                  No
5
             6
                 80.180
                           8047
                                      569
                                                4
                                                    77
                                                                 10
                                                                       Male
                                                                                  No
             7
6
                 20.996
                           3388
                                      259
                                                2
                                                    37
                                                                 12
                                                                    Female
                                                                                  No
                 71.408
7
                                                2
                                                                       Male
             8
                           7114
                                      512
                                                    87
                                                                  9
                                                                                  No
8
             9
                 15.125
                           3300
                                      266
                                                5
                                                    66
                                                                 13 Female
                                                                                  No
9
                 71.061
                           6819
                                      491
                                                3
                                                                 19
                                                                     Female
            10
                                                    41
                                                                                 Yes
  Married
                    Ethnicity
                                Balance
      Yes
                                     333
                    Caucasian
```

```
0
1
      Yes
                        Asian
                                    903
2
       No
                        Asian
                                    580
3
       No
                        Asian
                                    964
4
      Yes
                    Caucasian
                                    331
5
       No
                    Caucasian
                                   1151
6
       No
           African American
                                    203
7
       No
                        Asian
                                    872
8
       No
                    Caucasian
                                    279
9
      Yes
            African American
                                   1350
```

```
[166]: # Create features for model.
X = credit[['Income', 'Limit','Cards','Age']].as_matrix()
X = np.vstack([X.T, np.ones(len(X))]).T
```

```
[167]: y = credit['Rating']
beta = np.linalg.lstsq(X,y)[0]
pred = np.dot(X, beta)

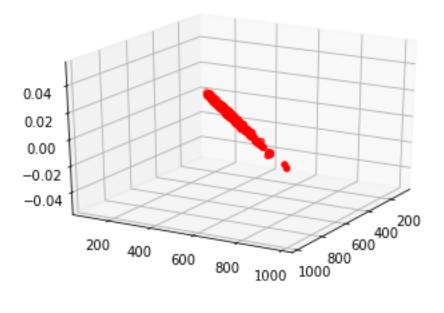
print(pred.shape)
```

(400,)

1.4.1 5. Plot your results (Bonus if you use 3D plots). Show as many of your columns vs. credit rating that you can.

```
[168]: fig = plt.figure()
   ax = fig.add_subplot(111, projection='3d')
   ax.view_init(23, 30)
   ax.scatter(pred.T, y, zdir='z', c='r')
```

[168]: <mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x1394b33c8>



[]: