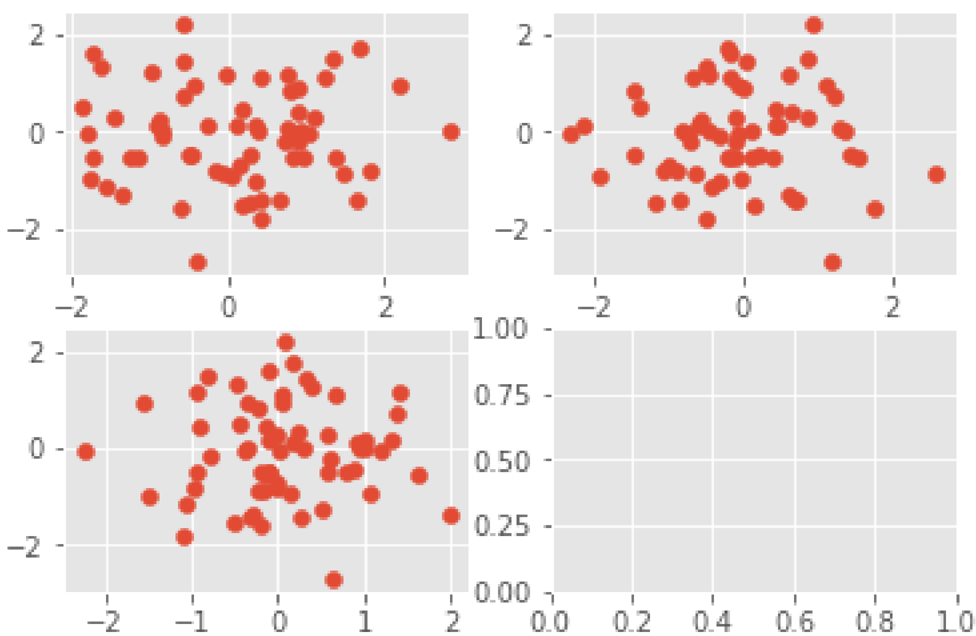
HW3

May 20, 2017

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

In [44]:
```
import numpy as np
import pandas as pd

s = pd.DataFrame(np.random.randn(64,4))
s.rename(columns={0: 'x1',1: 'x2',2:'x3',3:'y'}, inplace=True)

import matplotlib.pyplot as plt
plt.style.use('ggplot')

fig, ax = plt.subplots(2,2)
ax[0,0].scatter(s['x1'], s['y'])
ax[0,1].scatter(s['x2'], s['y'])
ax[1,0].scatter(s['x3'], s['y'])

plt.show()
```



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

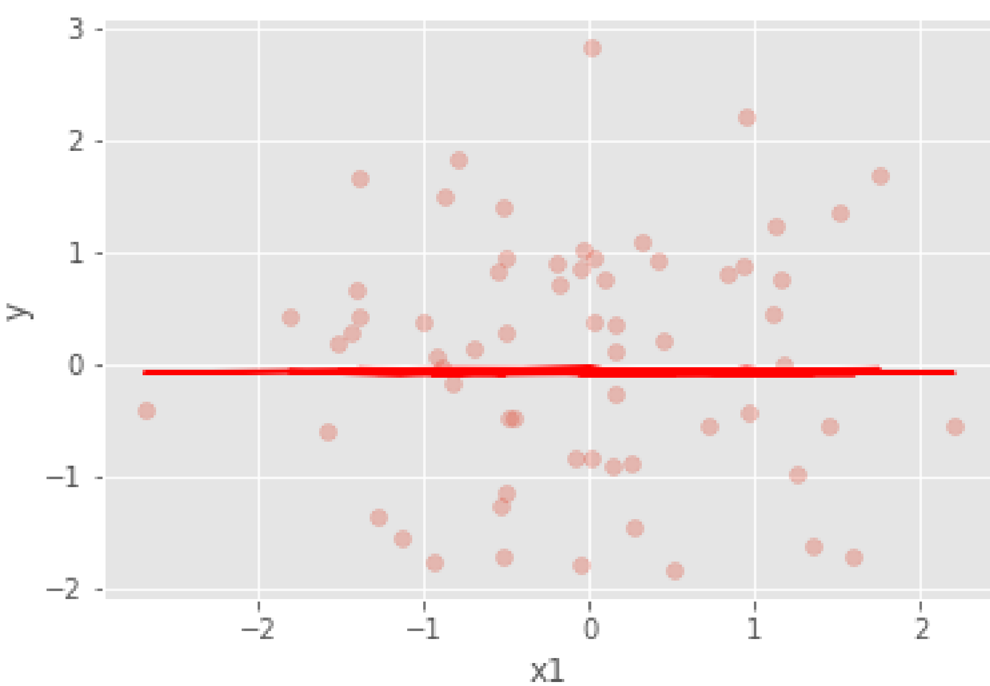
```
In [47]: import statsmodels.api as sm
         X = sm.add_constant(s)
         X.drop('y',axis =1,inplace=True)
         est = sm.OLS(y, X).fit()
         est.summary()
```

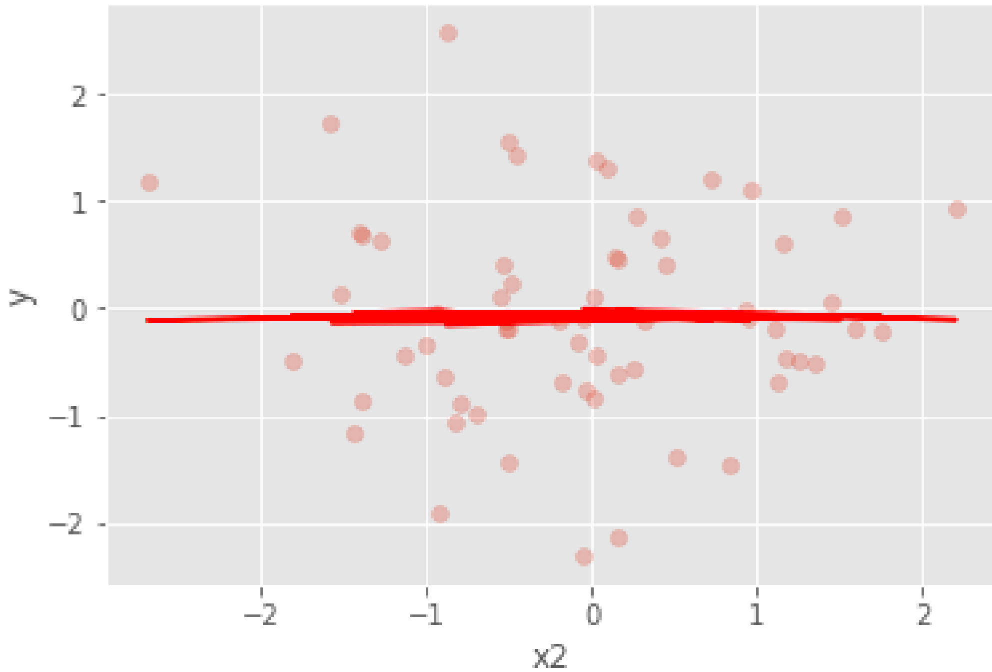
```
Out[47]: <class 'statsmodels.iolib.summary.Summary'>
         """
                                     OLS Regression Results
         ==============================================================================
         Dep. Variable:                      y   R-squared:                       0
         Model:                            OLS   Adj. R-squared:                 -0
         Method:                 Least Squares   F-statistic:                    0.0
         Date:                Sat, 20 May 2017   Prob (F-statistic):              0
         Time:                        11:24:04   Log-Likelihood:                -90
         No. Observations:                  64   AIC:                             1
         Df Residuals:                      60   BIC:                             1
         Df Model:                           3
         Covariance Type:            nonrobust
         ==============================================================================
                          coef    std err          t      P>|t|      [95.0% Conf. I
         ------------------------------------------------------------------------------
         const         -0.0771      0.129     -0.599      0.551        -0.334      0
         x1             0.0208      0.120      0.174      0.862        -0.218      0
         x2            -0.0349      0.137     -0.255      0.800        -0.309      0
         x3             0.0049      0.160      0.031      0.976        -0.316      0
         ==============================================================================
         Omnibus:                        0.163   Durbin-Watson:                   1
         Prob(Omnibus):                  0.922   Jarque-Bera (JB):                0
         Skew:                           0.040   Prob(JB):                        0
         Kurtosis:                       2.641   Cond. No.
         ==============================================================================

         Warnings:
         [1] Standard Errors assume that the covariance matrix of the errors is cor
         """
```

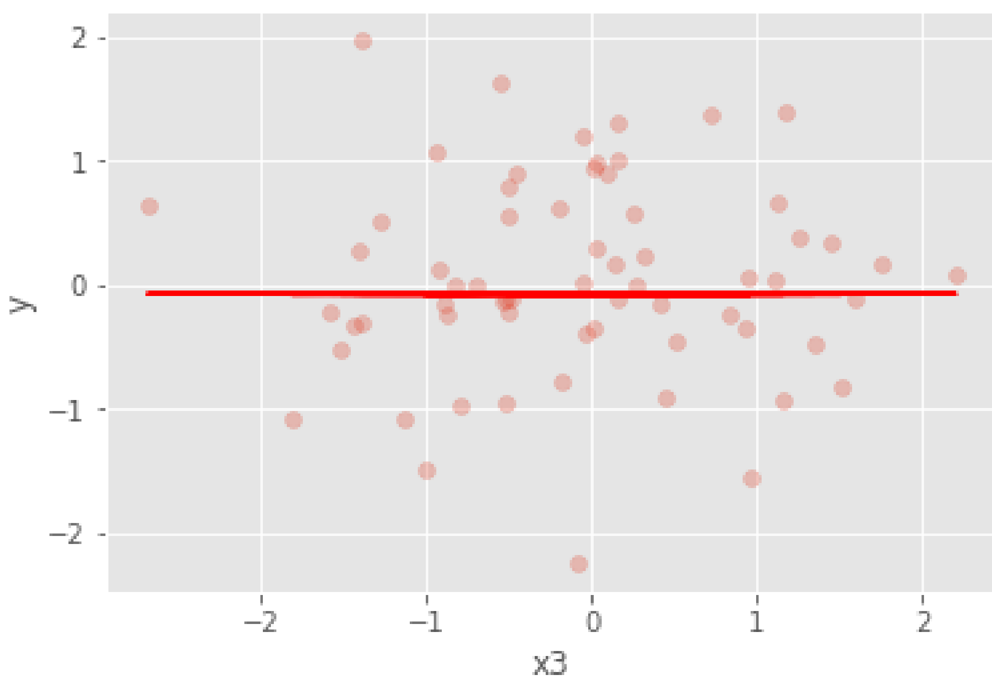
3. Plot the model's prediction in 2D for 2 of the dimensions ($x_1 \to y_p, x_2 \to y_p$) along with the original points

```
In [54]: X1 = s['x1']
         X1 = sm.add_constant(X1)
         est1 = sm.OLS(s['y'], X1).fit()
         plt.scatter(s['y'], s['x1'], alpha=0.3)
```

```
plt.xlabel('x1')
plt.ylabel('y')
plt.plot(s['y'], est1.params[0] + est1.params[1] *X1['x1'], 'r')

plt.show()

X2 = s['x2']
X2 = sm.add_constant(X2)
est2 = sm.OLS(s['y'], X2).fit()
plt.scatter(s['y'], s['x2'], alpha=0.3)
plt.xlabel('x2')
plt.ylabel('y')
plt.plot(s['y'], est2.params[0] + est2.params[1] *X2['x2'], 'r')

plt.show()

X3 = s['x3']
X3 = sm.add_constant(X3)
est3 = sm.OLS(s['y'], X3).fit()
plt.scatter(s['y'], s['x3'], alpha=0.3)
plt.xlabel('x3')
plt.ylabel('y')
plt.plot(s['y'], est3.params[0] + est3.params[1] *X3['x3'], 'r')

plt.show()
```




2
1
0
−1
−2
y
−2
−1
0
1
2
x2


2
1
0
−1
−2
y
−2
−1
0
1
2
x3

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

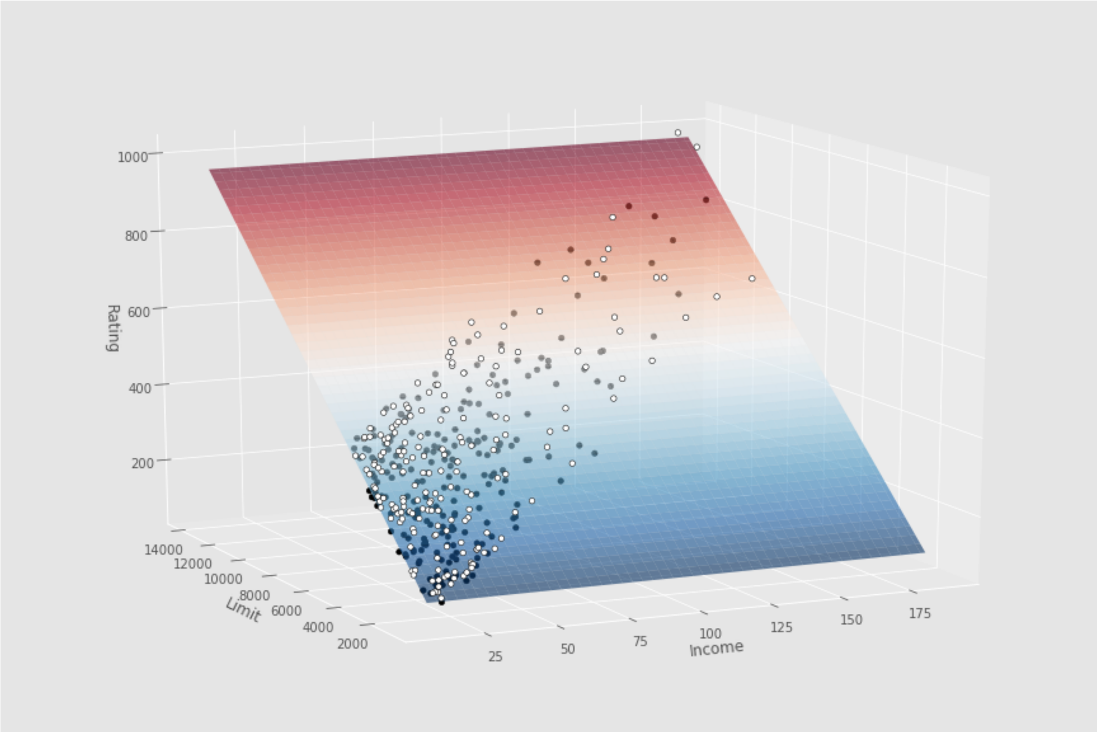
In [77]:
```
Credit = pd.read_csv("/Users/e_chertow/Documents/Ahmed/Documents/JhuMachin
X = Credit[['Income', 'Limit']]
X = sm.add_constant(X)
y = Credit['Rating']
estCredit = sm.OLS(y, X).fit()
estCredit.summary()
```

Out[77]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Rating   R-squared:                       0
Model:                            OLS   Adj. R-squared:                  0
Method:                 Least Squares   F-statistic:                 3.170
Date:                Sat, 20 May 2017   Prob (F-statistic):
Time:                        15:40:15   Log-Likelihood:                -15
No. Observations:                 400   AIC:                             3
Df Residuals:                     397   BIC:                             3
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. I
------------------------------------------------------------------------------
const         38.7419      1.439     26.918      0.000      35.912     41
Income         0.0207      0.028      0.729      0.467      -0.035      0
Limit          0.0666      0.000    153.124      0.000       0.066      0
==============================================================================
Omnibus:                        7.285   Durbin-Watson:                   2
Prob(Omnibus):                  0.026   Jarque-Bera (JB):                5
Skew:                           0.158   Prob(JB):                       0.
Kurtosis:                       2.532   Cond. No.                     1.24
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is cor
[2] The condition number is large, 1.24e+04. This might indicate that ther
strong multicollinearity or other numerical problems.
"""
```

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

In [74]:
```
## Create the 3d plot

from mpl_toolkits.mplot3d import Axes3D
```

```
xx1, xx2 = np.meshgrid(np.linspace(X.Income.min(), X.Income.max(), 100),
                       np.linspace(X.Limit.min(), X.Limit.max(), 100))

Z = estCredit.params[0] + estCredit.params[1] * xx1 + estCredit.params[2]

fig = plt.figure(figsize=(12, 8))
ax = Axes3D(fig, azim=-115, elev=15)


surf = ax.plot_surface(xx1, xx2, Z, cmap=plt.cm.RdBu_r, alpha=0.6, linewic


resid = y - estCredit.predict(X)

ax.scatter(X[resid >= 0].Income, X[resid >= 0].Limit, y[resid >= 0], color
ax.scatter(X[resid < 0].Income, X[resid < 0].Limit, y[resid < 0], color='k

ax.set_xlabel('Income')
ax.set_ylabel('Limit')
ax.set_zlabel('Rating')

plt.show()
```



In [ ]: