Assigment 3 - Coder

This assigment 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

In [32]:

```
import numpy as np
import matplotlib.pylab as plt
%matplotlib inline
```

1. Create a 4 dimensional data set with 64 elements and show all 4 scatter 2D plots of the data x_1 vs. y, x_2 vs. y, x_3 vs. y, x_4 vs. y

In [33]:

```
n = 64
x = np.linspace(0, 1, n) + np.random.rand(4, n)
x = np.vstack([x, np.ones(len(x.T))]).T
y = np.linspace(0, 1, n) + np.random.rand(n) - 1
```

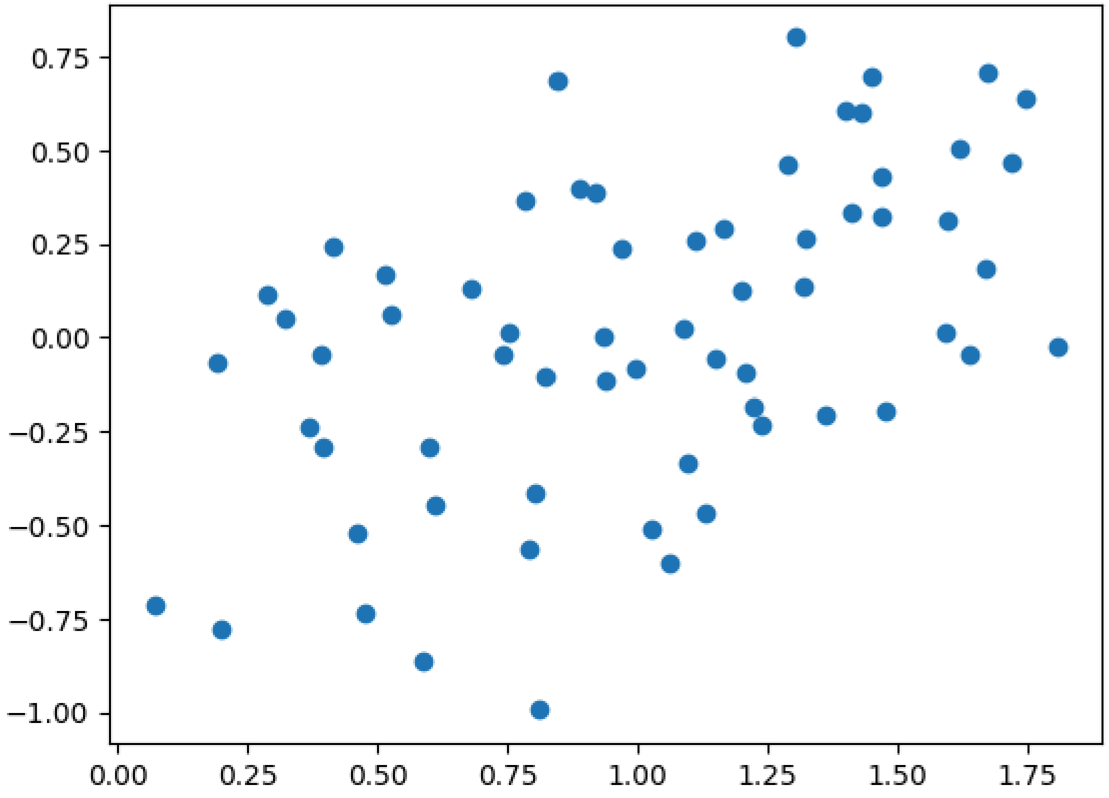
x_1 vs. y

In [34]:

```
plt.scatter(x.T[0],y)
```

Out[34]:

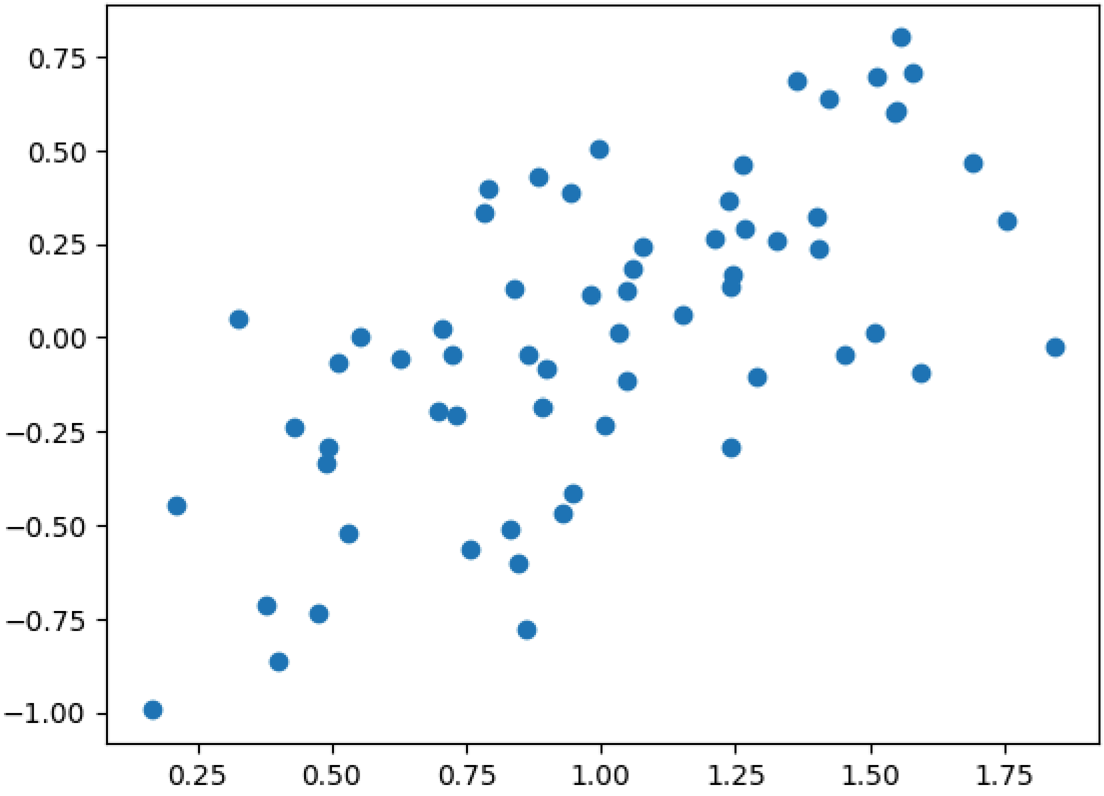
```
<matplotlib.collections.PathCollection at 0x29b06acb2d0>
```



x_2 vs. y

```
In [35]: plt.scatter(x.T[1],y)
```

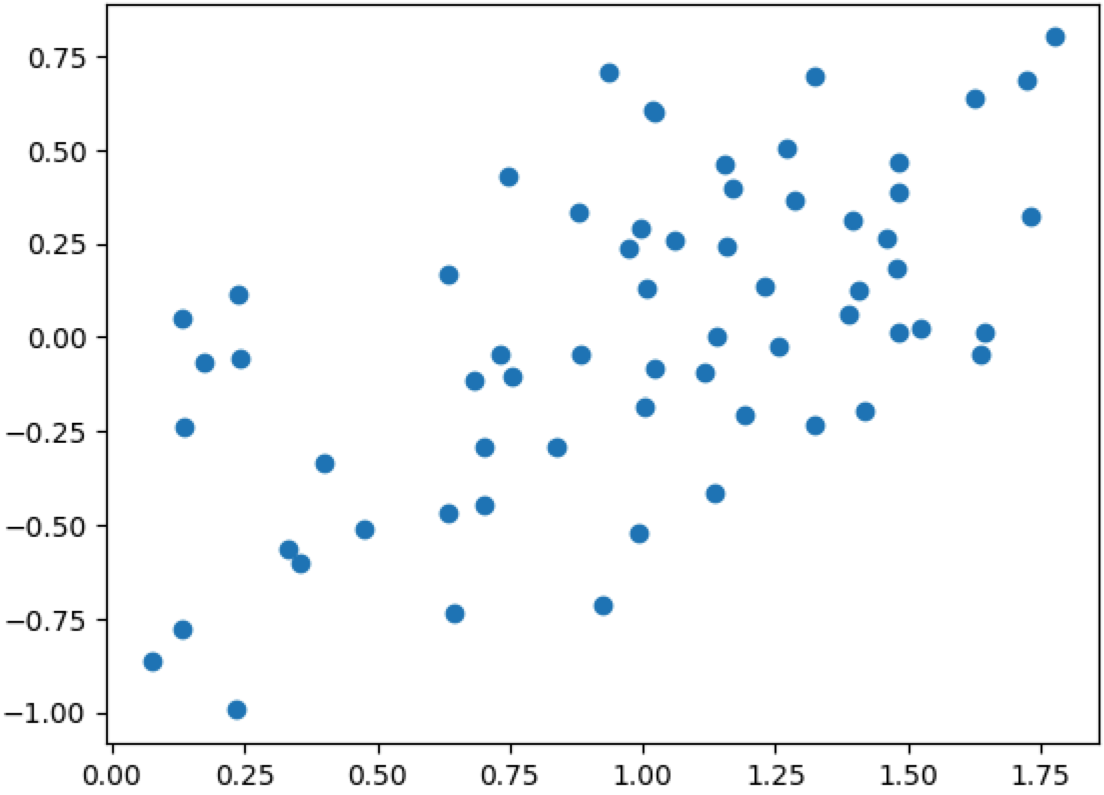
```
Out[35]: <matplotlib.collections.PathCollection at 0x29b06ad2450>
```



x_3 vs. y

```
In [36]: plt.scatter(x.T[2],y)
```

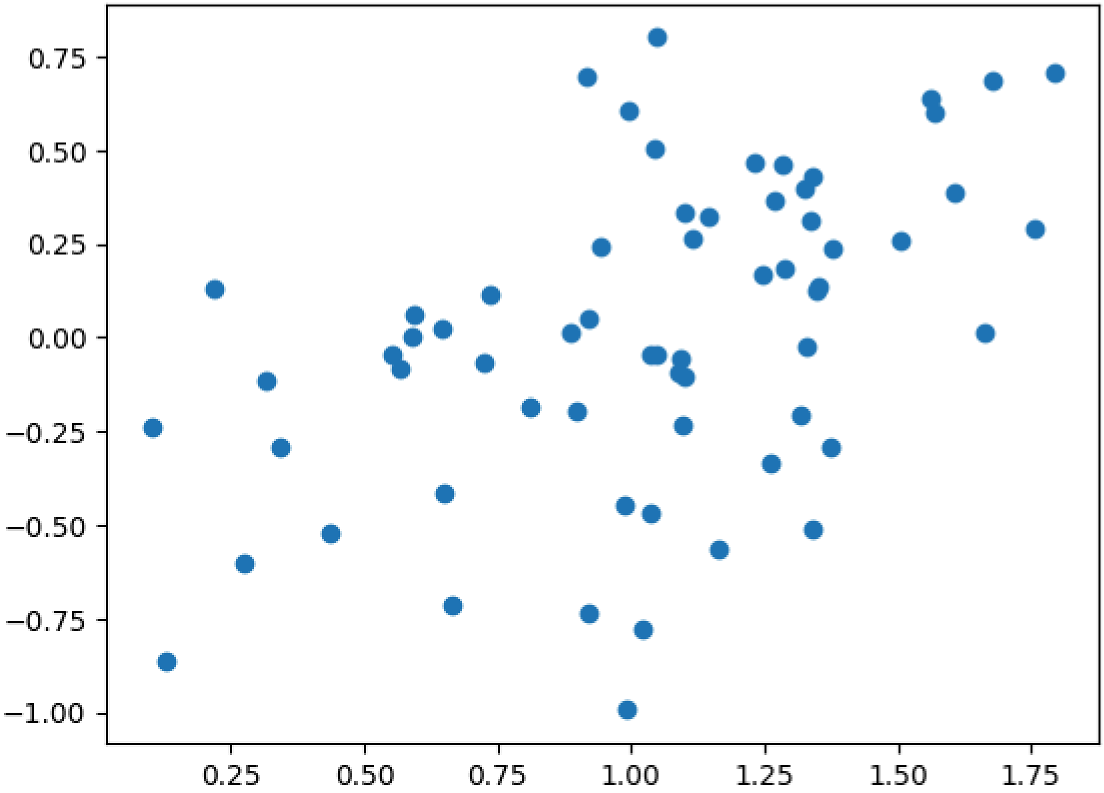
```
Out[36]: <matplotlib.collections.PathCollection at 0x29b07316fd0>
```



x_4 vs. y

In [37]:
```
plt.scatter(x.T[3],y)
```

Out[37]:
```
<matplotlib.collections.PathCollection at 0x29b073975d0>
```



2. Create a Linear Regression model (LIKE WE DID IN CLASS) to fit the data. *Use the example from Lesson 3 and DO NOT USE a library that calculates automatically*. We are expecting 5 coefficients to describe the linear model.

```
In [38]: left = np.linalg.inv(np.dot(x.T, x))
         right = np.dot(y.T, x)
         beta = np.dot(left, right)
         beta
```

```
Out[38]: array([ 0.03323277,  0.41481994,  0.24327771,  0.16603724, -0.8506729 ])
```

After creating the model (finding the coefficients), calculate a new column $y_p = \Sigma\beta_n \cdot x_n$

```
In [39]: pred = np.dot(x, beta)
         pred
```

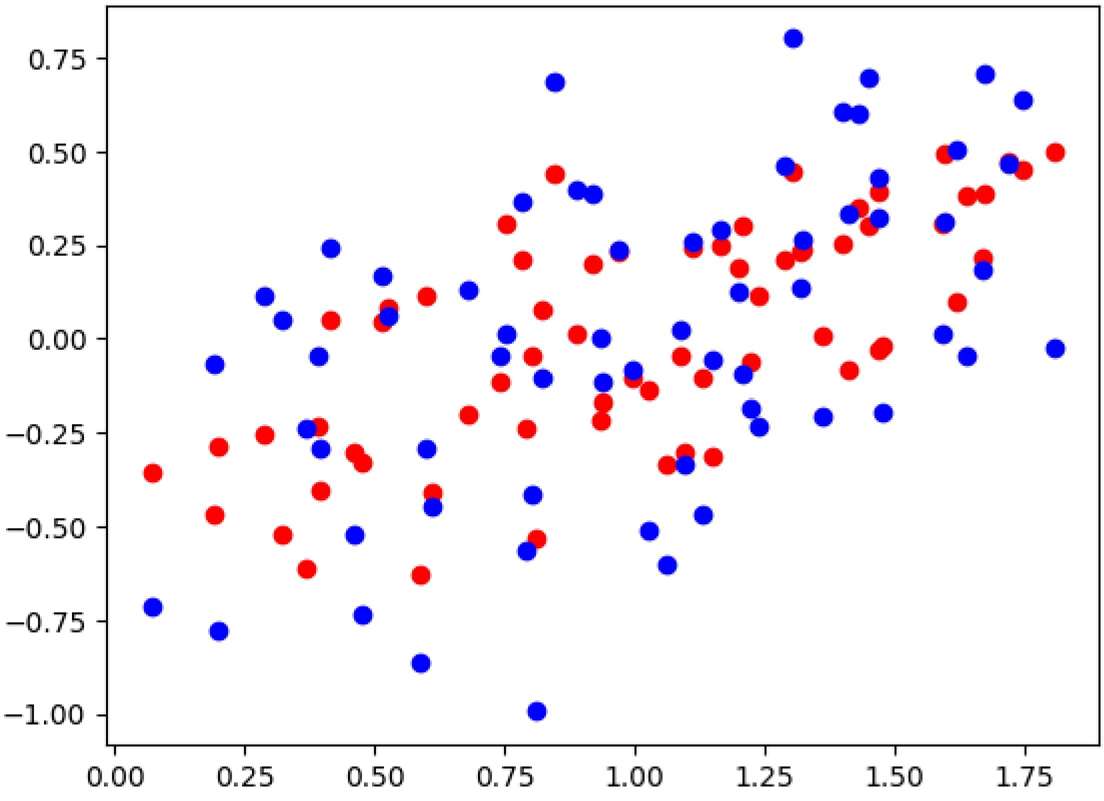
```
Out[39]: array([-0.5342546 , -0.62630097, -0.60965778, -0.35595807, -0.51928145,
                -0.28387396, -0.33202531, -0.46913572, -0.25439715, -0.23036245,
                -0.40850247, -0.31230595, -0.19820476, -0.32889708, -0.16658416,
                -0.10218576, -0.30215634, -0.4042707 , -0.30474669, -0.23748438,
                -0.04705607,  0.04373898, -0.10214601,  0.0480595 , -0.13400978,
                -0.11720262, -0.08285935,  0.11653222, -0.06172786,  0.23245796,
                 0.08014361,  0.0771893 , -0.21519871,  0.0071616 ,  0.21066399,
                 0.30863008, -0.04363147,  0.23006232, -0.01752713,  0.11268869,
                 0.0116793 , -0.03135073,  0.09777855,  0.34749077,  0.30302729,
                 0.21806285,  0.21216154,  0.19783639,  0.29905805,  0.44104019,
                 0.38006217,  0.18925213,  0.45339176,  0.3848098 ,  0.25261937,
                 0.24728547,  0.24506539,  0.30734035,  0.44417662,  0.491332  ,
                 0.49966149,  0.39075817,  0.47230141,  0.23652012])
```

3. Plot the model's prediction as a different color on top of the scatter plot from Q1 in 2D for all 4 of the dimensions ($x_1 \rightarrow y_p, x_2 \rightarrow y_p, x_3 \rightarrow y_p, x_4 \rightarrow y_p$)

x_1 vs. y_p

```
In [40]: plt.scatter(x.T[0], pred, c='red')
         plt.scatter(x.T[0], y, c='b')
```

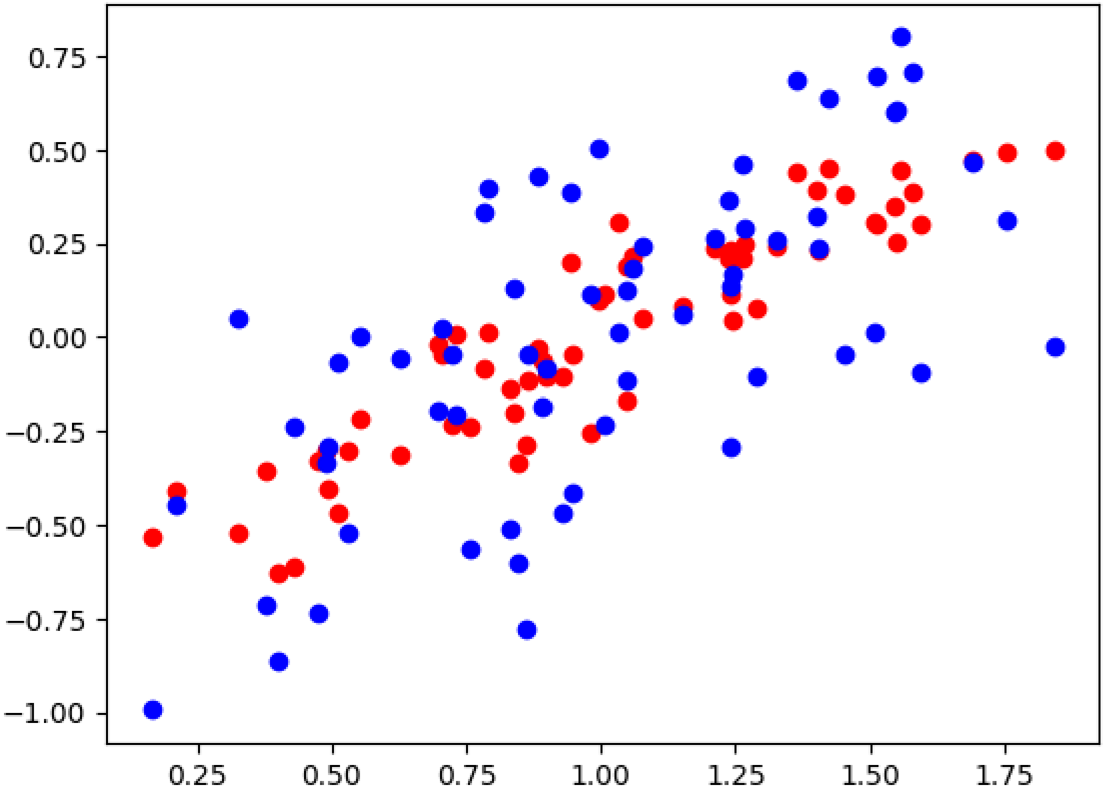
```
Out[40]: <matplotlib.collections.PathCollection at 0x29b0736b050>
```



x_2 vs. y_p

```
In [41]: plt.scatter(x.T[1], pred, c='red')
         plt.scatter(x.T[1], y, c='b')
```

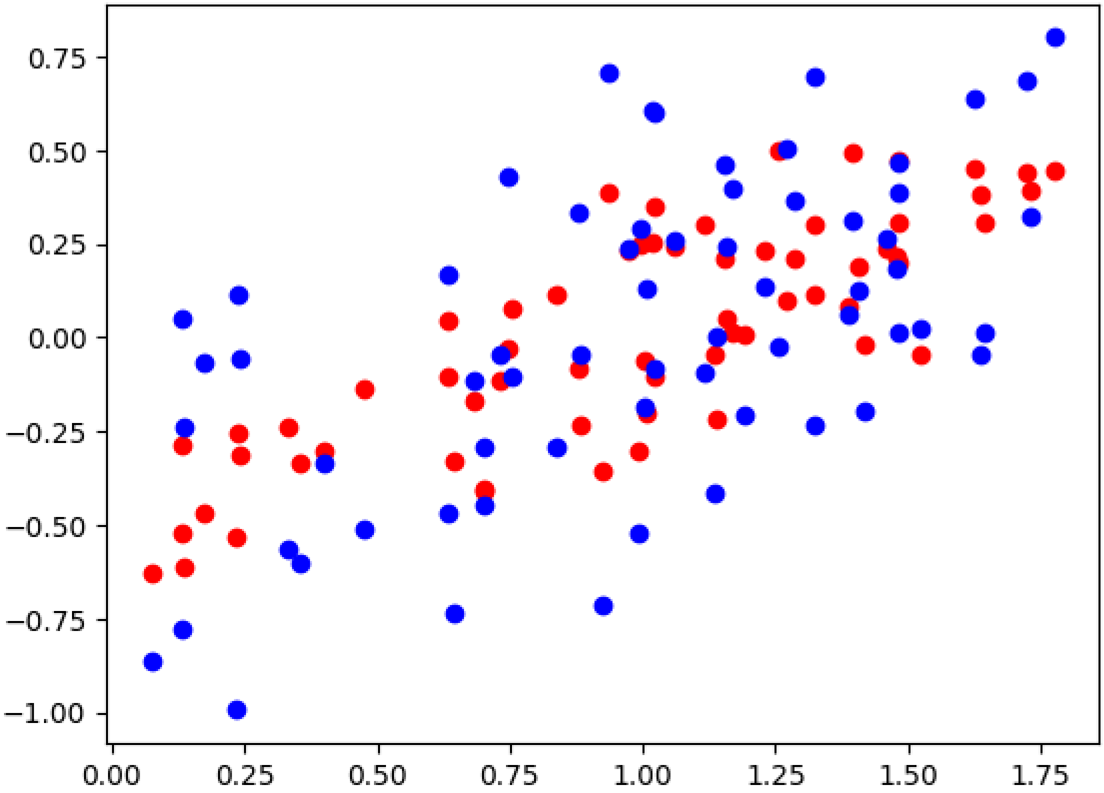
```
Out[41]: <matplotlib.collections.PathCollection at 0x29b07110750>
```



x_3 vs. y_p

```
In [42]: plt.scatter(x.T[2], pred, c='red')
         plt.scatter(x.T[2], y, c='b')
```

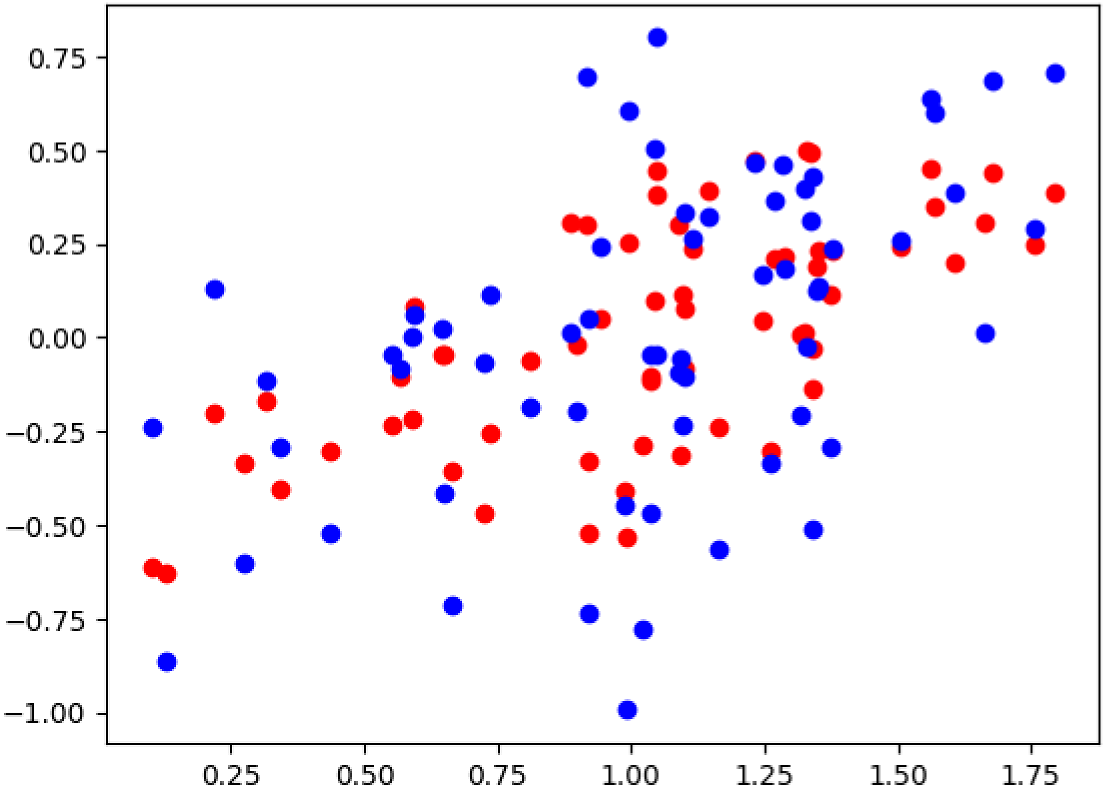
```
Out[42]: <matplotlib.collections.PathCollection at 0x29b0745c410>
```



x_4 vs. y_p

```
In [43]: plt.scatter(x.T[3], pred, c='red')
         plt.scatter(x.T[3], y, c='b')
```

```
Out[43]: <matplotlib.collections.PathCollection at 0x29b07206bd0>
```



4. Read in `mlnn/data/Credit.csv` with Pandas and build a Linear Regression 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 (Column `Rating`)

In [44]:

```
import pandas as pd
credit = pd.read_csv('../data/Credit.csv')
credit.head()
```

Out[44]:

	Unnamed: 0	Income	Limit	Rating	Cards	Age	Education	Gender	Student	Married
0	1	14.891	3606	283	2	34	11	Male	No	Yes
1	2	106.025	6645	483	3	82	15	Female	Yes	Yes
2	3	104.593	7075	514	4	71	11	Male	No	No
3	4	148.924	9504	681	3	36	11	Female	No	No
4	5	55.882	4897	357	2	68	16	Male	No	Yes

Choose multiple columns as inputs beyond `Income` and `Limit` but clearly, don't use `Rating`

In [45]:

```
columns = ['Income', 'Limit', 'Cards', 'Age', 'Education', 'Balance']
credx = credit[columns].values

credx = np.vstack([credx.T, np.ones(len(credx))]).T
credx
```

Out[45]:

```
array([[1.48910e+01, 3.60600e+03, 2.00000e+00, ..., 1.10000e+01,
        3.33000e+02, 1.00000e+00],
       [1.06025e+02, 6.64500e+03, 3.00000e+00, ..., 1.50000e+01,
        9.03000e+02, 1.00000e+00],
       [1.04593e+02, 7.07500e+03, 4.00000e+00, ..., 1.10000e+01,
        5.80000e+02, 1.00000e+00],
       ...,
       [5.78720e+01, 4.17100e+03, 5.00000e+00, ..., 1.20000e+01,
        1.38000e+02, 1.00000e+00],
       [3.77280e+01, 2.52500e+03, 1.00000e+00, ..., 1.30000e+01,
        0.00000e+00, 1.00000e+00],
       [1.87010e+01, 5.52400e+03, 5.00000e+00, ..., 7.00000e+00,
        9.66000e+02, 1.00000e+00]])
```

In [46]:

```
credy = credit['Rating']
credy
```

Out[46]:

```
0      283
1      483
2      514
3      681
4      357
      ... 
395    307
396    296
397    321
398    192
399    415
Name: Rating, Length: 400, dtype: int64
```

In [47]:

```
credleft = np.linalg.inv(np.dot(credx.T, credx))
credright = np.dot(credy.T, credx)
credbeta = np.dot(credleft, credright)
credbeta
```

Out[47]:

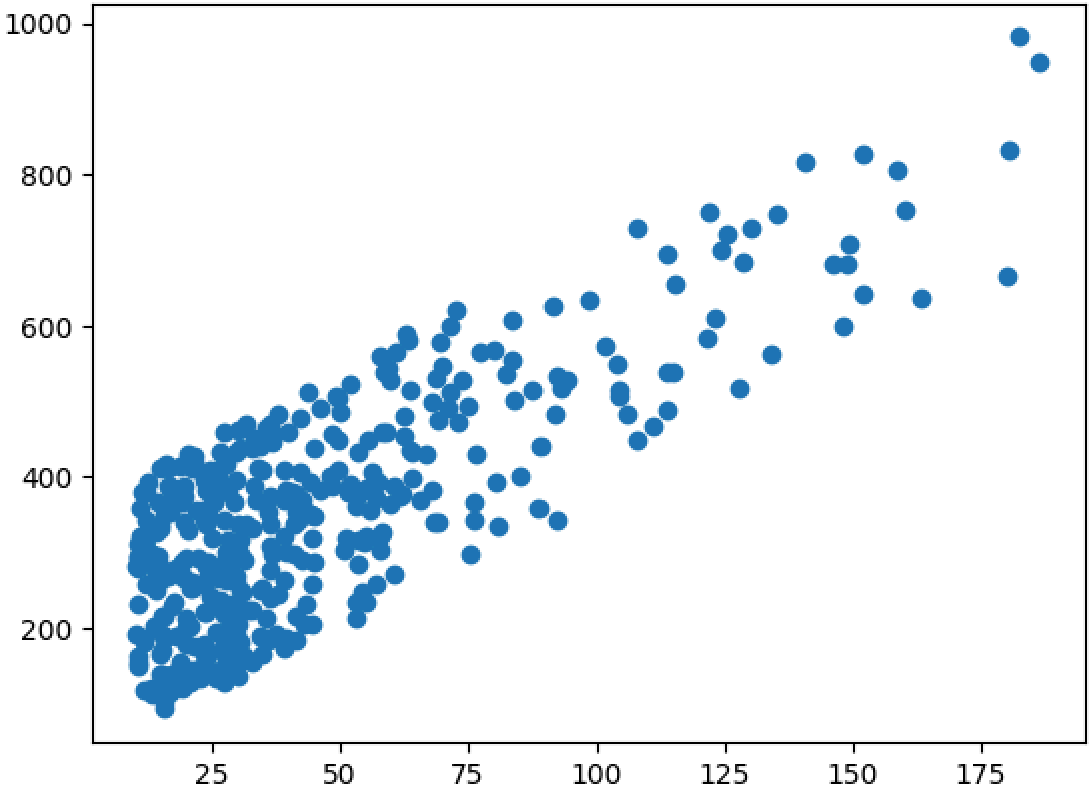
```
array([ 9.48157743e-02,  6.42304413e-02,  4.67706085e+00,  8.06617460e-03,
       -2.30863025e-01,  8.18115721e-03,  3.10522106e+01])
```

5. Plot your results using scatter plots (just like in class). Show as many of your columns vs. credit rating that you can.

Income vs Credit Rating

```
In [48]: plt.scatter(credx.T[0],credy)
```

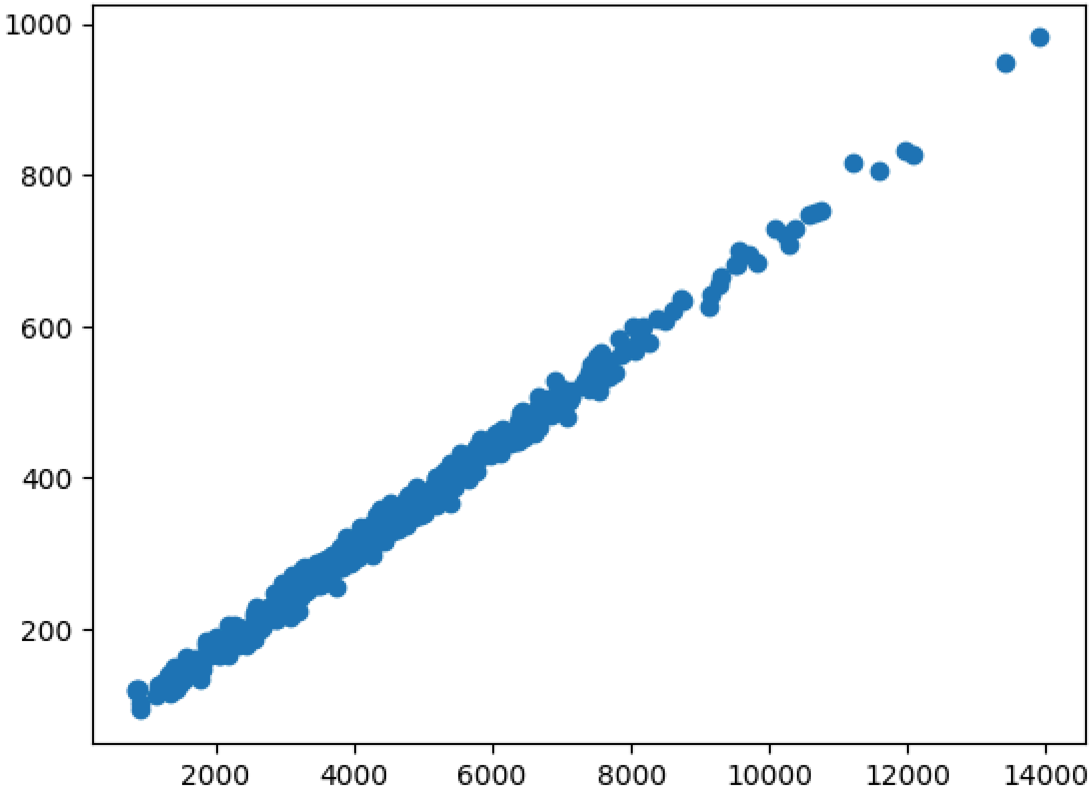
```
Out[48]: <matplotlib.collections.PathCollection at 0x29b0727c110>
```



Limit vs Credit Rating

```
In [49]: plt.scatter(credx.T[1],credy)
```

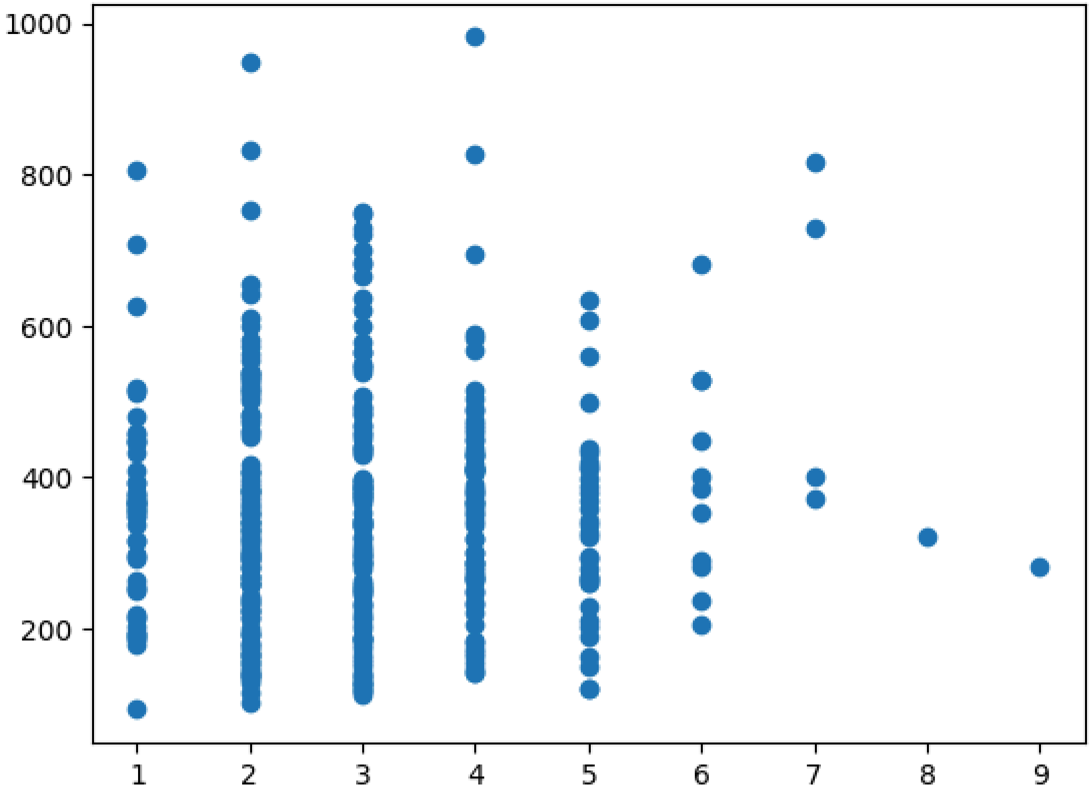
```
Out[49]: <matplotlib.collections.PathCollection at 0x29b07639890>
```



Cards vs Credit Rating

```
In [50]: plt.scatter(credx.T[2],credy)
```

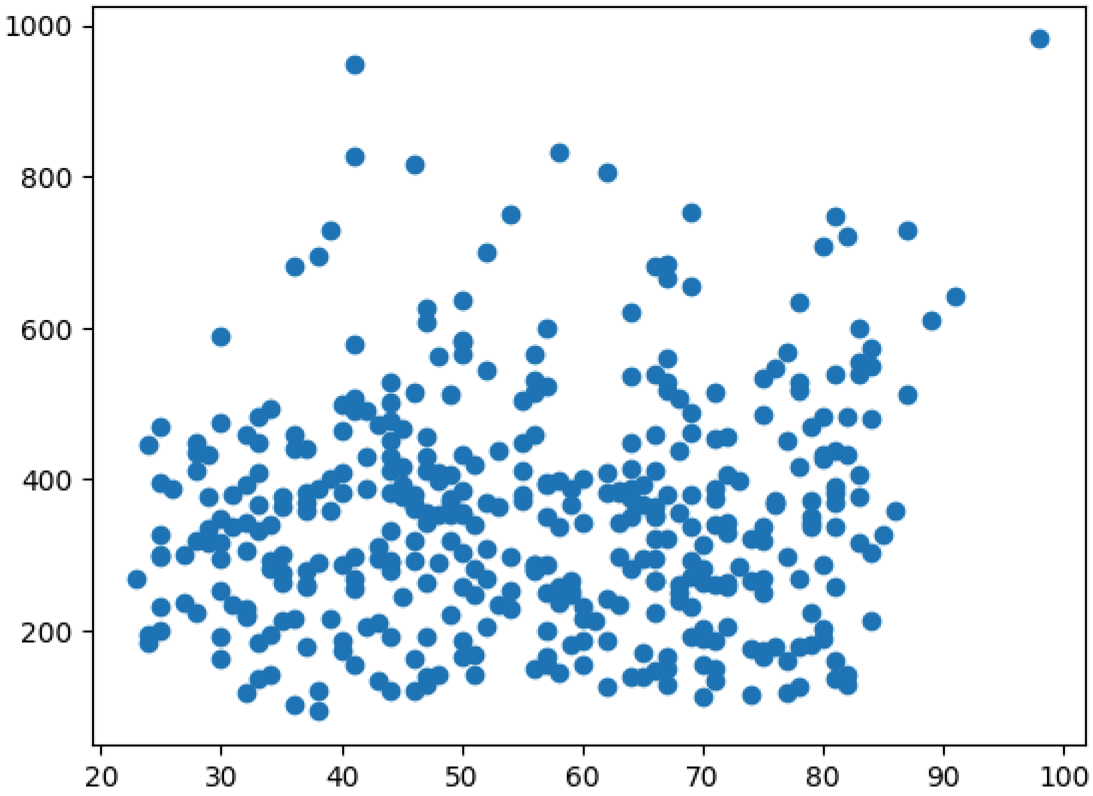
```
Out[50]: <matplotlib.collections.PathCollection at 0x29b076df690>
```



Age vs Credit Rating

```
In [51]: plt.scatter(credx.T[3],credy)
```

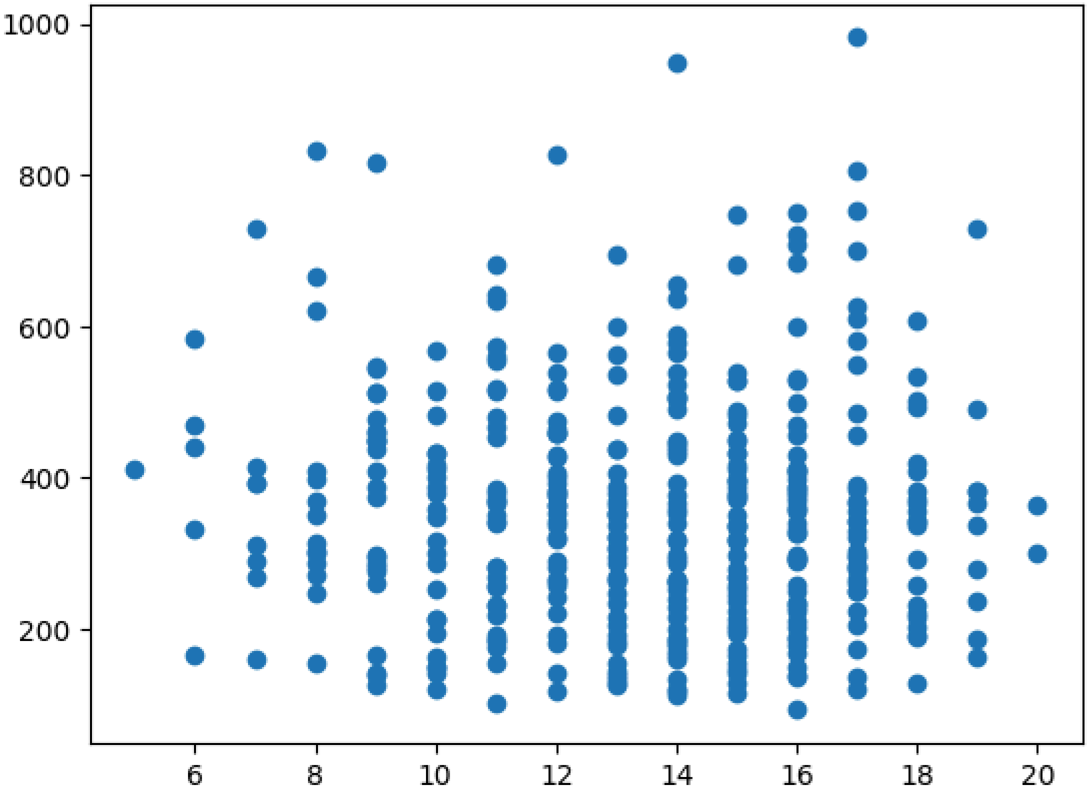
```
Out[51]: <matplotlib.collections.PathCollection at 0x29b07364610>
```



Education vs Credit Rating

```
In [52]: plt.scatter(credx.T[4],credy)
```

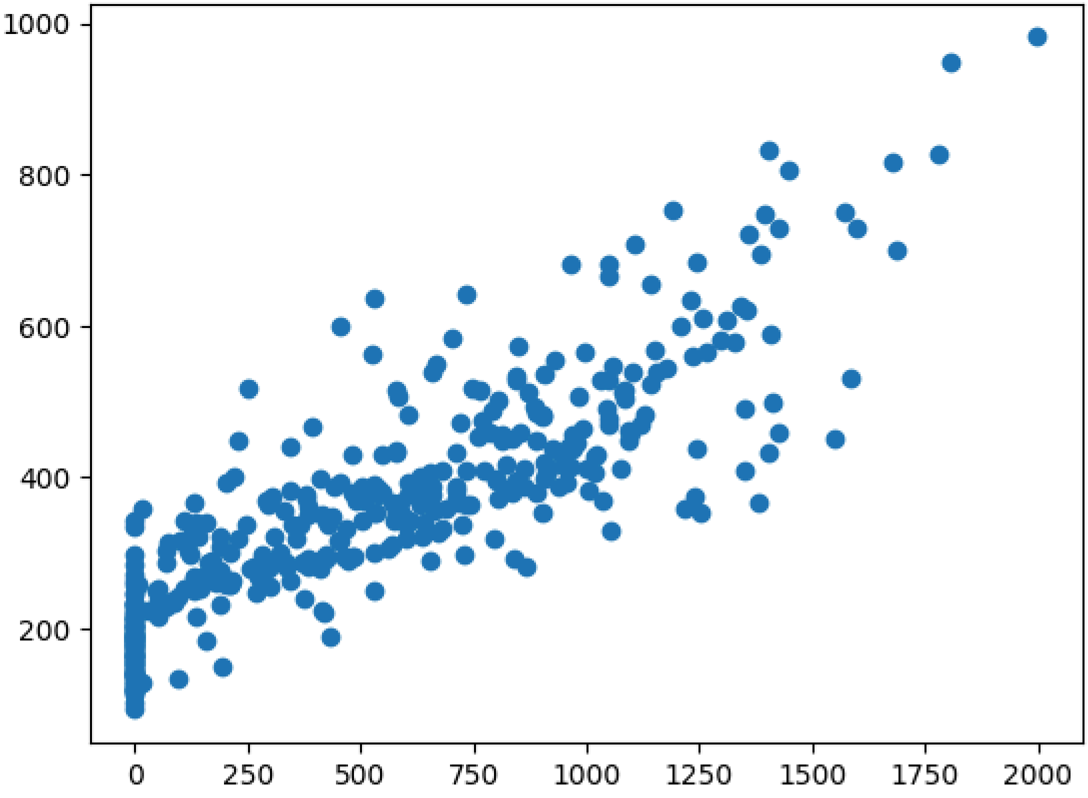
```
Out[52]: <matplotlib.collections.PathCollection at 0x29b0879f410>
```



Balance vs Credit Rating

```
In [53]: plt.scatter(credx.T[5],credy)
```

```
Out[53]: <matplotlib.collections.PathCollection at 0x29b0748fcd0>
```


1000
800
600
400
200
0
250
500
750
1000
1250
1500
1750
2000