Assigment 3

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

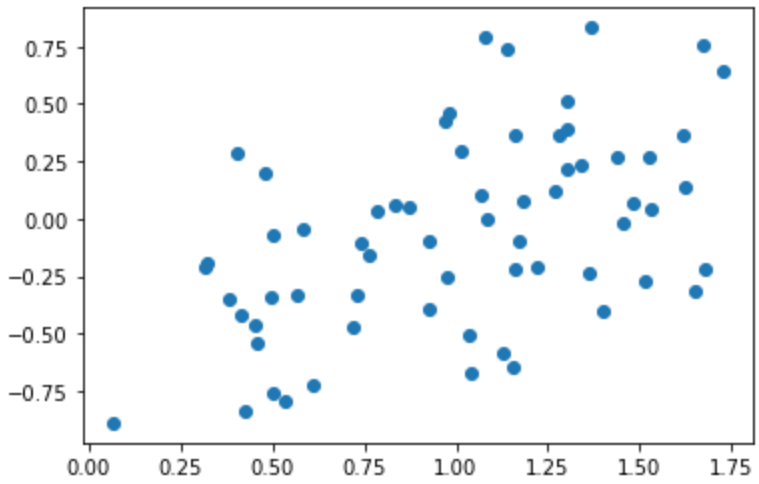
In [1]:
```
import numpy as np
import matplotlib.pylab as plt
%matplotlib inline
```

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 [2]:
```
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
```

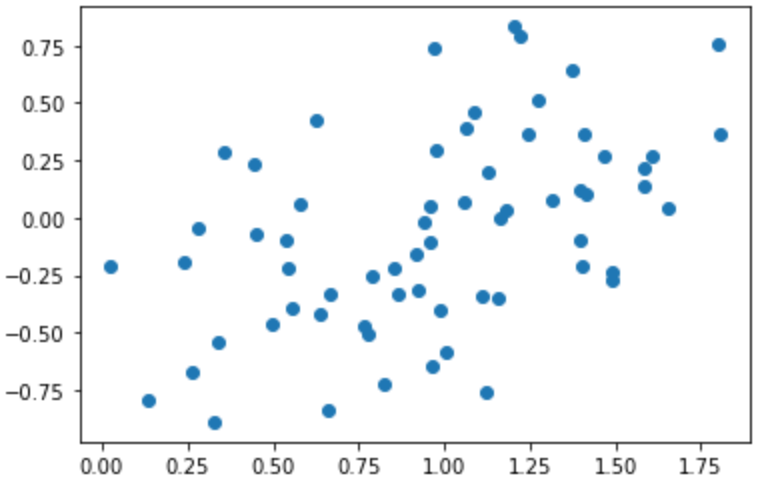
In [3]:
```
plt.scatter(x.T[0], y)
```

Out[3]:
```
<matplotlib.collections.PathCollection at 0x7f9a386854c0>
```



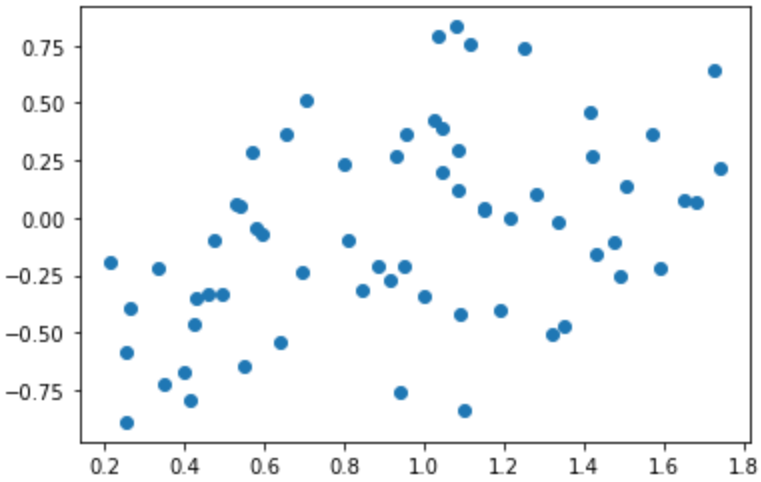
In [4]:
```
plt.scatter(x.T[1], y)
```

Out[4]:
```
<matplotlib.collections.PathCollection at 0x7f9a484d1af0>
```



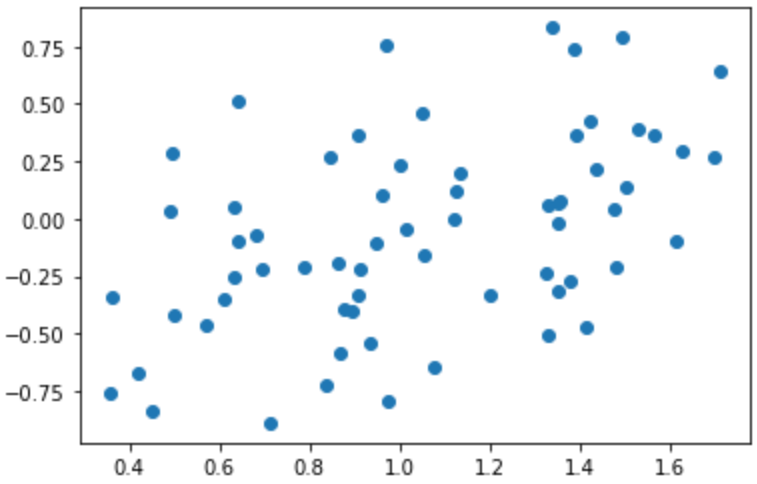
In [5]:
```
plt.scatter(x.T[2], y)
```

Out[5]:
```
<matplotlib.collections.PathCollection at 0x7f9a6ab75610>
```



In [6]:
```
plt.scatter(x.T[3], y)
```

Out[6]:
```
<matplotlib.collections.PathCollection at 0x7f9a6ac87520>
```



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.

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

In [7]:
```
left = np.linalg.inv(np.dot(x.T, x))
```

In [8]:
```
right = np.dot(y.T, x)
```

In [9]:
```
beta = np.dot(left, right)
beta
```

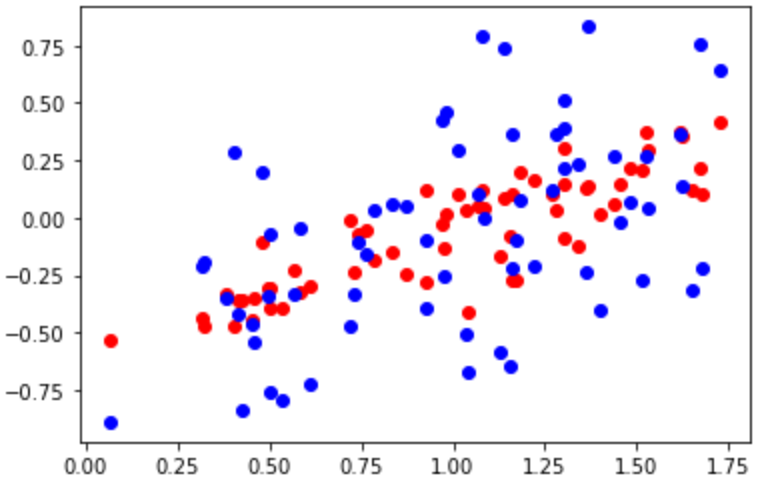
Out[9]:
```
array([ 0.19910577,  0.17422601,  0.1333519 ,  0.2471695 , -0.81746548])
```

In [10]:
```
pred = np.dot(x, beta)
```

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 ($x_1 \rightarrow y_p, x_2 \rightarrow y_p, x_3 \rightarrow y_p, x_4 \rightarrow y_p$)

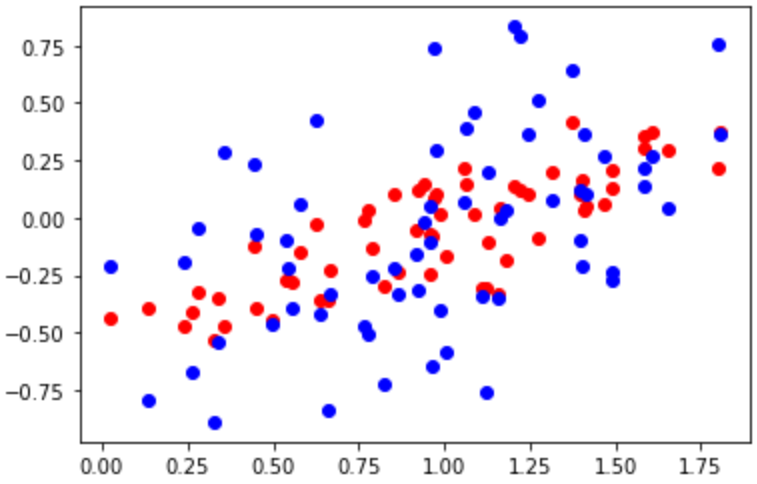
In [11]:
```
plt.scatter(x.T[0], pred, c='red')
plt.scatter(x.T[0], y, c='b')
```

Out[11]:
```
<matplotlib.collections.PathCollection at 0x7f9a48685310>
```



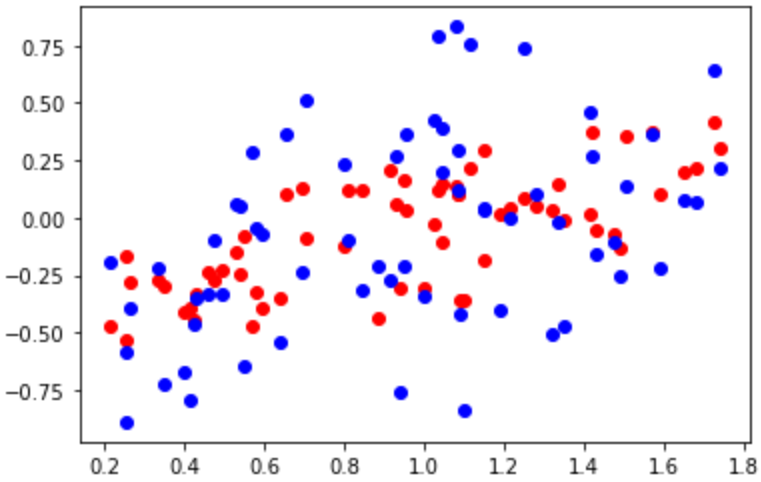
In [12]:
```
plt.scatter(x.T[1], pred, c='red')
plt.scatter(x.T[1], y, c='b')
```

Out[12]:
```
<matplotlib.collections.PathCollection at 0x7f9a486eeca0>
```



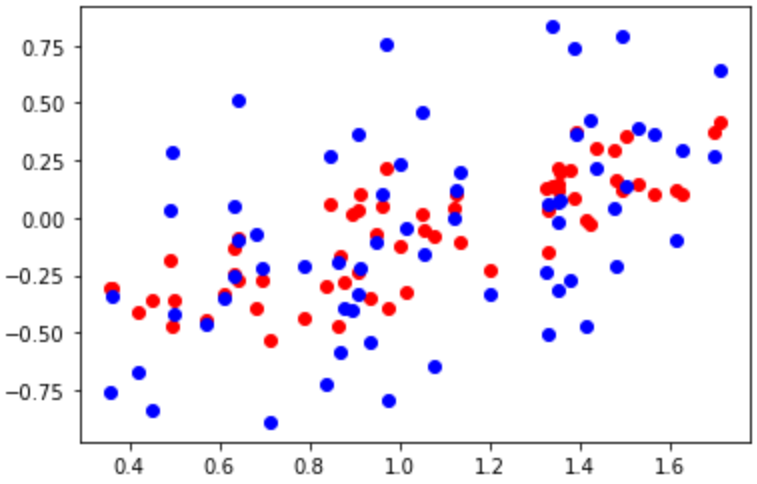
In [13]:
```
plt.scatter(x.T[2], pred, c='red')
plt.scatter(x.T[2], y, c='b')
```

Out[13]:
```
<matplotlib.collections.PathCollection at 0x7f9a48781b20>
```



In [14]:
```
plt.scatter(x.T[3], pred, c='red')
plt.scatter(x.T[3], y, c='b')
```

Out[14]:
```
<matplotlib.collections.PathCollection at 0x7f9a386bcee0>
```



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 [15]:
```
import pandas as pd
credit = pd.read_csv('../data/Credit.csv',index_col=0)
credit.head()
```

Out[15]:

	Income	Limit	Rating	Cards	Age	Education	Gender	Student	Married	Ethnicity	Balance
1	14.891	3606	283	2	34	11	Male	No	Yes	Caucasian	333
2	106.025	6645	483	3	82	15	Female	Yes	Yes	Asian	903
3	104.593	7075	514	4	71	11	Male	No	No	Asian	580
4	148.924	9504	681	3	36	11	Female	No	No	Asian	964
5	55.882	4897	357	2	68	16	Male	No	Yes	Caucasian	331

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

In [16]:
```
columns = ['Income', 'Limit','Age','Education','Balance']
X = credit[columns].values

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

Out[16]:
```
array([[1.48910e+01, 3.60600e+03, 3.40000e+01, 1.10000e+01, 3.33000e+02,
        1.00000e+00],
       [1.06025e+02, 6.64500e+03, 8.20000e+01, 1.50000e+01, 9.03000e+02,
        1.00000e+00],
       [1.04593e+02, 7.07500e+03, 7.10000e+01, 1.10000e+01, 5.80000e+02,
        1.00000e+00],
       ...,
       [5.78720e+01, 4.17100e+03, 6.70000e+01, 1.20000e+01, 1.38000e+02,
        1.00000e+00],
       [3.77280e+01, 2.52500e+03, 4.40000e+01, 1.30000e+01, 0.00000e+00,
        1.00000e+00],
       [1.87010e+01, 5.52400e+03, 6.40000e+01, 7.00000e+00, 9.66000e+02,
        1.00000e+00]])
```

In [17]:
```
y = credit['Rating']
y
```

Out[17]:
```
1      283
2      483
3      514
4      681
5      357
      ...
396    307
397    296
398    321
399    192
400    415
Name: Rating, Length: 400, dtype: int64
```

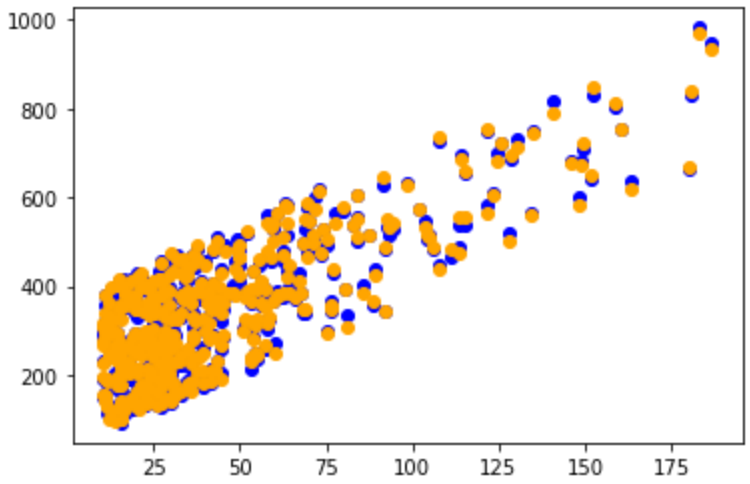
In [18]:
```
left_2 = np.linalg.inv(np.dot(X.T, X))
right_2 = np.dot(y.T, X)
```

```
beta_2 = np.dot(left_2, right_2)
pred_2 = np.dot(X, beta_2)
```

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

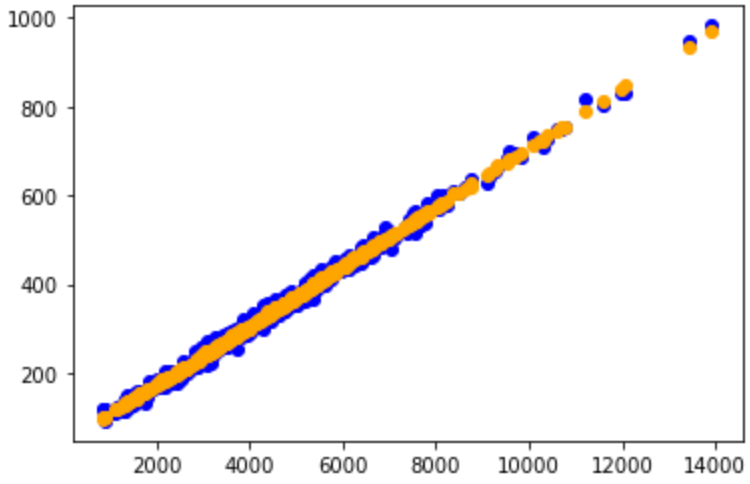
In [19]:
```
plt.scatter(X.T[0], y, c='b')
plt.scatter(X.T[0], pred_2, c='orange')
```

Out[19]:
```
<matplotlib.collections.PathCollection at 0x7f9a6b43d6a0>
```



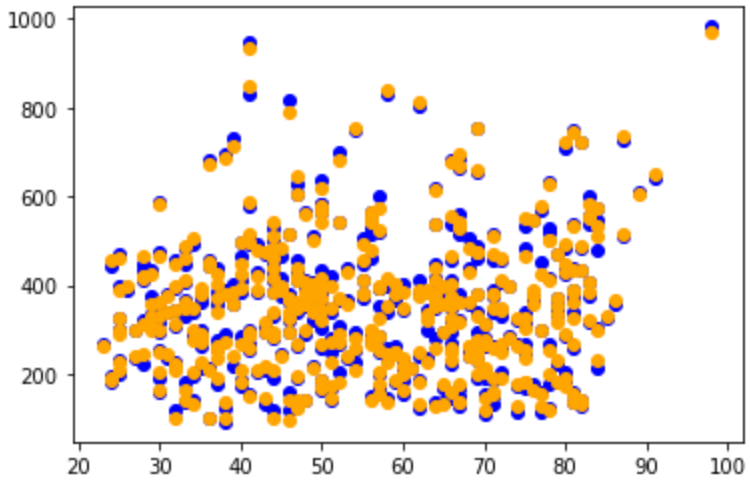
In [20]:
```
plt.scatter(X.T[1], y, c='b')
plt.scatter(X.T[1], pred_2, c='orange')
```

Out[20]:
```
<matplotlib.collections.PathCollection at 0x7f9a38d091c0>
```



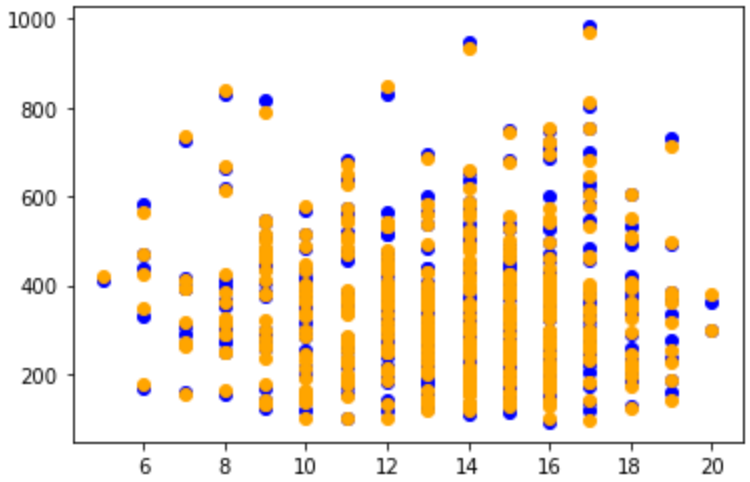
In [21]:
```
plt.scatter(X.T[2], y, c='b')
plt.scatter(X.T[2], pred_2, c='orange')
```

Out[21]:
```
<matplotlib.collections.PathCollection at 0x7f9a38d68b50>
```



In [22]:
```
plt.scatter(X.T[3], y, c='b')
plt.scatter(X.T[3], pred_2, c='orange')
```

Out[22]: <matplotlib.collections.PathCollection at 0x7f9a38d52940>



In [23]:
```
plt.scatter(X.T[4], y, c='b')
plt.scatter(X.T[4], pred_2, c='orange')
```

Out[23]: <matplotlib.collections.PathCollection at 0x7f9a38e9eb80>