In [187…

```
import numpy as np
import matplotlib.pylab as plt
%matplotlib inline
plt.rcParams["figure.figsize"] = (20, 10)
```

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

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 [446…

```
n = int(64/4)
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 [447…

```
pd.DataFrame(x, y)
```

Out[447]:

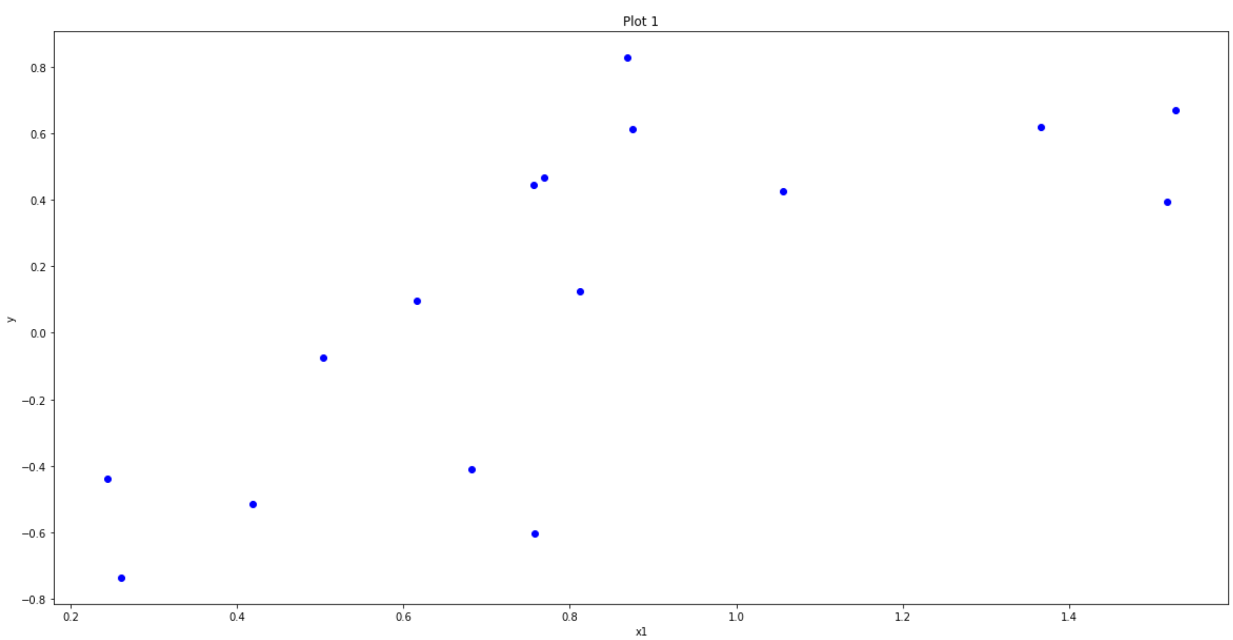
	0	1	2	3	4
-0.440913	0.244570	0.005403	0.281290	0.407163	1.0
-0.514138	0.418269	0.263092	0.855919	1.066581	1.0
0.096028	0.616166	0.274144	0.210308	0.799476	1.0
-0.737820	0.260726	0.806225	0.658060	0.370272	1.0
-0.603832	0.758140	0.980953	0.811179	0.325393	1.0
-0.409980	0.681304	0.357621	0.973961	0.800355	1.0
-0.074758	0.503153	1.374734	1.340003	1.128157	1.0
0.427148	1.055815	1.319453	0.535363	1.084118	1.0
0.445403	0.756377	0.772325	0.900750	1.165129	1.0
0.126219	0.812471	0.835400	0.659985	1.584452	1.0
0.393982	1.517185	1.393197	0.878941	1.260400	1.0
0.468382	0.769135	1.212065	1.497595	1.651748	1.0
0.612232	0.875060	0.873142	1.028633	1.745439	1.0
0.829757	0.869367	1.543514	1.467143	0.919392	1.0
0.671672	1.527336	1.418012	0.955373	1.678225	1.0
0.619556	1.365538	1.265482	1.220737	1.884882	1.0

In [504…

```
plt.scatter(x.T[0], y, c = "blue")
plt.xlabel("x1")
plt.ylabel("y")
plt.title("Plot 1")
```

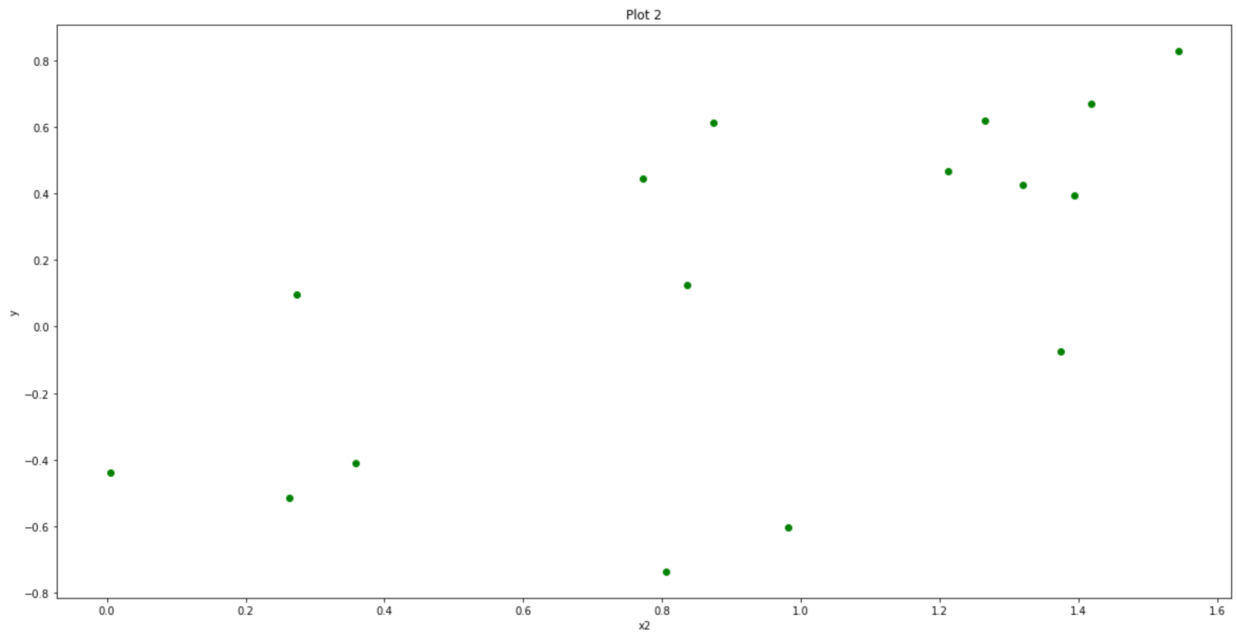
Out[504]:

```
Text(0.5, 1.0, 'Plot 1')
```



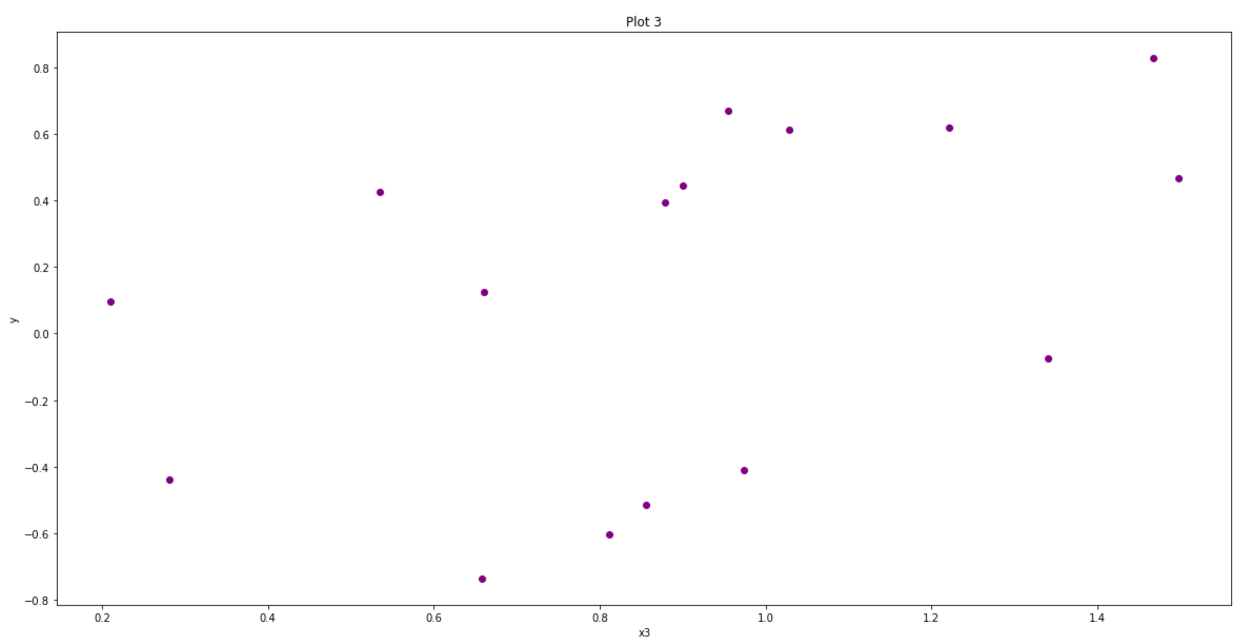
In [476…
```
plt.scatter(x.T[1], y, c = "green")
plt.xlabel("x2")
plt.ylabel("y")
plt.title("Plot 2")
```

Out[476]: Text(0.5, 1.0, 'Plot 2')



In [479…
```
plt.scatter(x.T[2], y, c = "purple")
plt.xlabel("x3")
plt.ylabel("y")
plt.title("Plot 3")
```

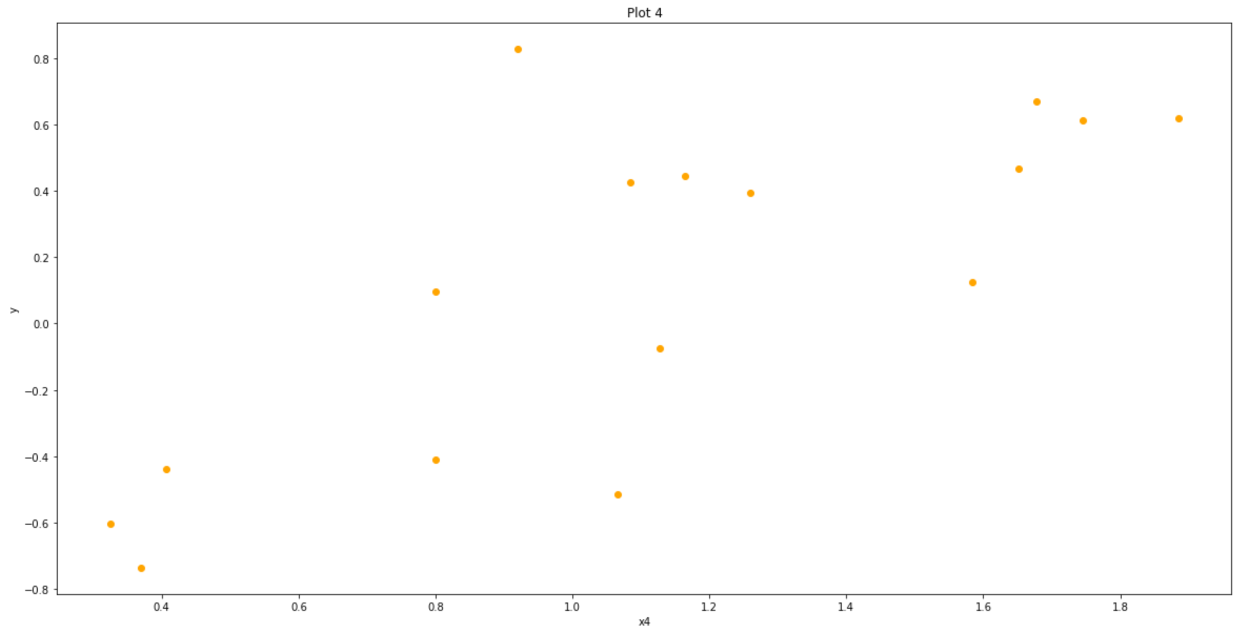
Out[479]: Text(0.5, 1.0, 'Plot 3')



In [481…
```
plt.scatter(x.T[3], y, c= "orange")
plt.xlabel("x4")
```

```
plt.ylabel("y")
plt.title("Plot 4")
```

Out[481]: Text(0.5, 1.0, 'Plot 4')



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 [482…

```
left = np.linalg.inv(np.dot(x.T, x))
right = np.dot(y.T, x)
```

In [483…

```
beta = np.dot(left, right)
beta
```

Out[483]: array([0.27435259, 0.32153046, -0.0725681 , 0.52025182, -0.91577791])

In [484…

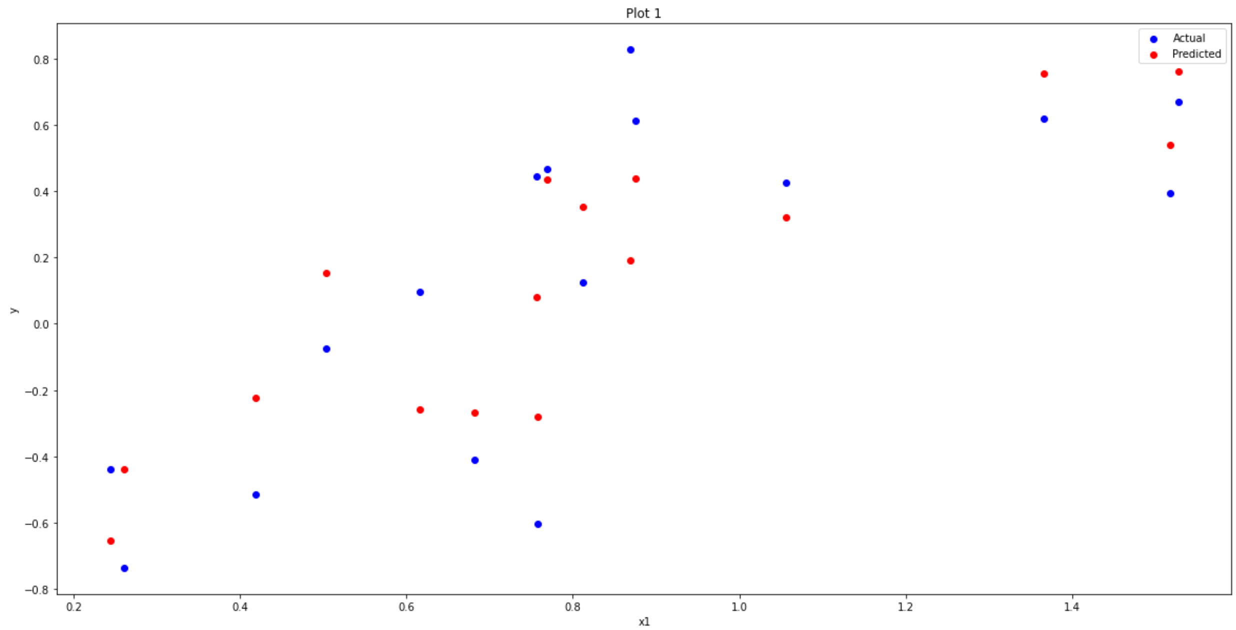
```
pred = np.dot(x, beta)
```

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 [499…

```
plt.scatter(x.T[0], y, c = "blue")
plt.scatter(x.T[0], pred, c="red")
plt.xlabel("x1")
plt.ylabel("y")
plt.title("Plot 1")
plt.legend(labels = ["Actual", "Predicted"])
```

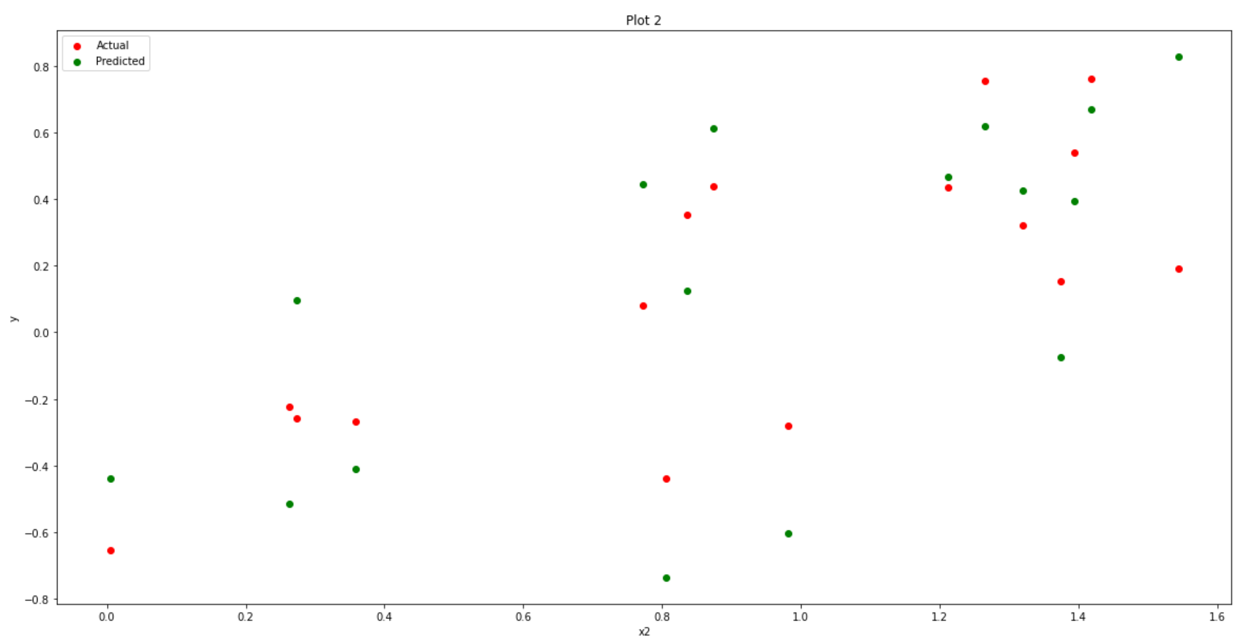
Out[499]: <matplotlib.legend.Legend at 0x2b6b4714f70>



In [500…

```
plt.scatter(x.T[1], pred, c="red")
plt.scatter(x.T[1], y, c="green")
plt.xlabel("x2")
plt.ylabel("y")
plt.title("Plot 2")
plt.legend(labels = ["Actual", "Predicted"])
```

Out[500]: <matplotlib.legend.Legend at 0x2b6b47a1a20>

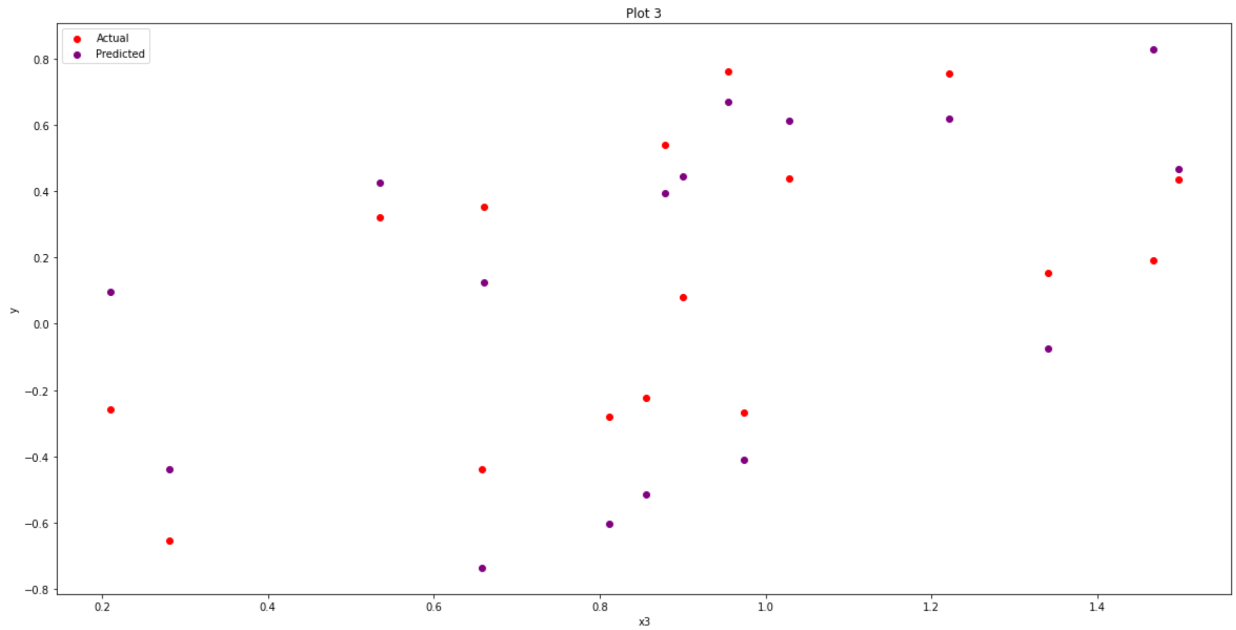


In [505…

```
plt.scatter(x.T[2], pred, c="red")
plt.scatter(x.T[2], y, c="purple")
plt.xlabel("x3")
plt.ylabel("y")
plt.title("Plot 3")
plt.legend(labels = ["Actual", "Predicted"])
```

Out[505]:

```
<matplotlib.legend.Legend at 0x2b6b5df2920>
```

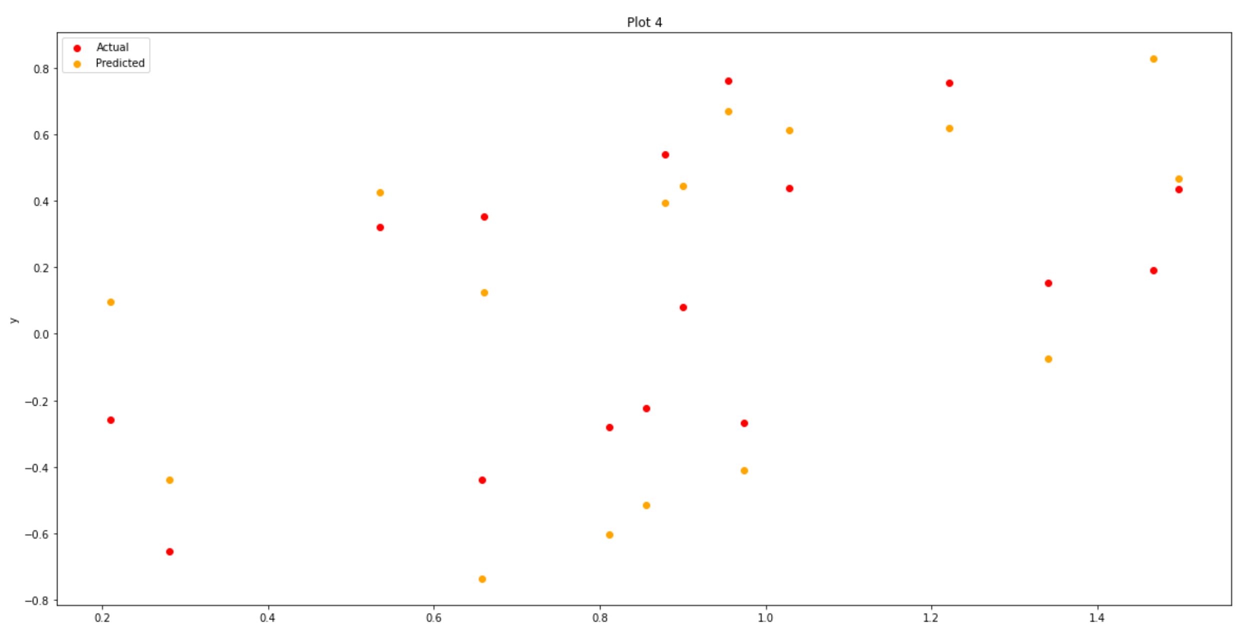


In [506…

```
plt.scatter(x.T[2], pred, c="red")
plt.scatter(x.T[2], y, c="orange")
plt.xlabel("x4")
plt.ylabel("y")
plt.title("Plot 4")
plt.legend(labels = ["Actual", "Predicted"])
```

Out[506]:

```
<matplotlib.legend.Legend at 0x2b6b64c99c0>
```



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 [548…

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

Out[548]:

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

In [543…

```
credit.dtypes
```

Out[543]:

```
Unnamed: 0      int64
Income        float64
Limit           int64
Rating          int64
Cards           int64
Age             int64
Education       int64
Gender         object
Student        object
Married        object
Ethnicity      object
Balance         int64
dtype: object
```

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

In [551…

```
non_numeric = ["Unnamed: 0", "Gender", "Student", "Married", "Ethnicity"]
cred = credit.copy().drop(non_numeric, axis = 1)
cred.head()
```

Out[551]:

	Income	Limit	Rating	Cards	Age	Education	Balance
0	14.891	3606	283	2	34	11	333
1	106.025	6645	483	3	82	15	903
2	104.593	7075	514	4	71	11	580
3	148.924	9504	681	3	36	11	964
4	55.882	4897	357	2	68	16	331

In [552…

```
xC = cred.drop("Rating", axis = 1)
yC = cred["Rating"]
```

In [569…

```
beta = np.linalg.lstsq(xC, yC, rcond=None)[0]
pred = np.dot(xC, beta)
cred["pred"] = pred
cred.head()
```

Out[569]:

	Income	Limit	Rating	Cards	Age	Education	Balance	pred
0	14.891	3606	283	2	34	11	333	268.275784
1	106.025	6645	483	3	82	15	903	486.660454
2	104.593	7075	514	4	71	11	580	518.484791
3	148.924	9504	681	3	36	11	964	671.713620
4	55.882	4897	357	2	68	16	331	363.230731

In [554…

```
beta
```

Out[554]:

```
array([-1.47352977e-02,  6.79727002e-02,  5.99978634e+00,  1.19201683e-01,
        7.49574070e-01, -2.73902251e-03])
```

In [555…

```
from sklearn.metrics import mean_squared_error
y_true = cred["Rating"]
y_pred = cred["pred"]
mean_squared_error(y_true, y_pred)
```

Out[555]:

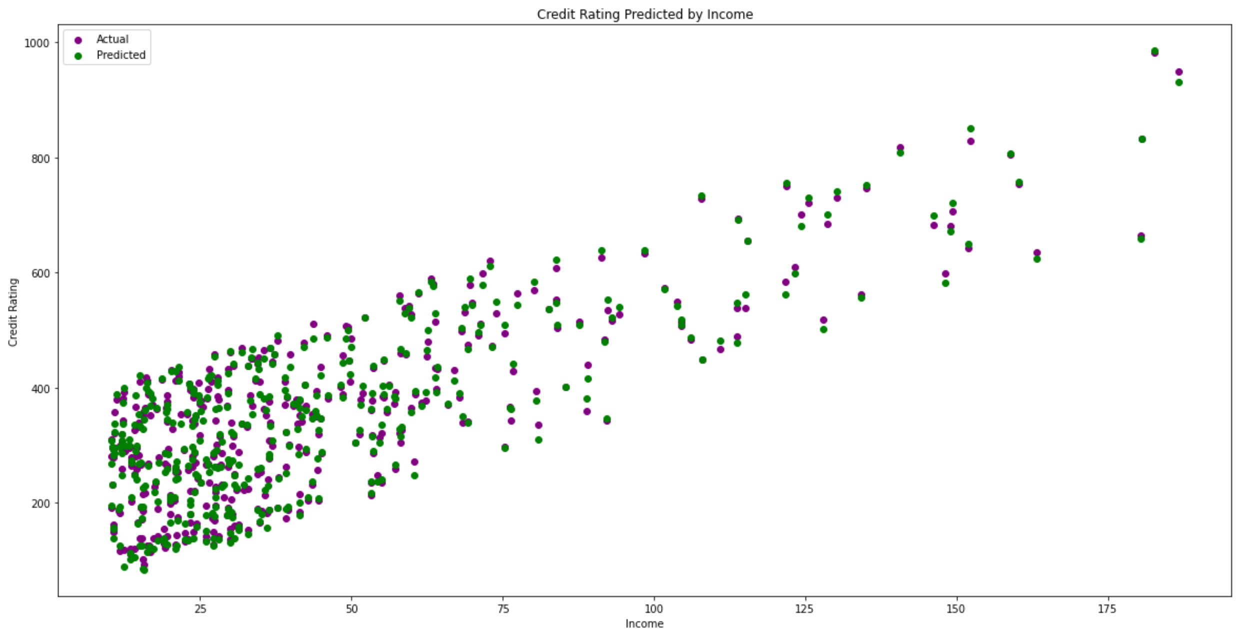
```
122.83382069475256
```

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

In [557…

```
plt.scatter(cred["Income"], cred["Rating"], c = "purple")
plt.scatter(cred["Income"], cred["pred"], c = "green")
plt.xlabel("Income")
plt.ylabel("Credit Rating")
plt.legend(labels = ["Actual", "Predicted"])
plt.title("Credit Rating Predicted by Income")
```

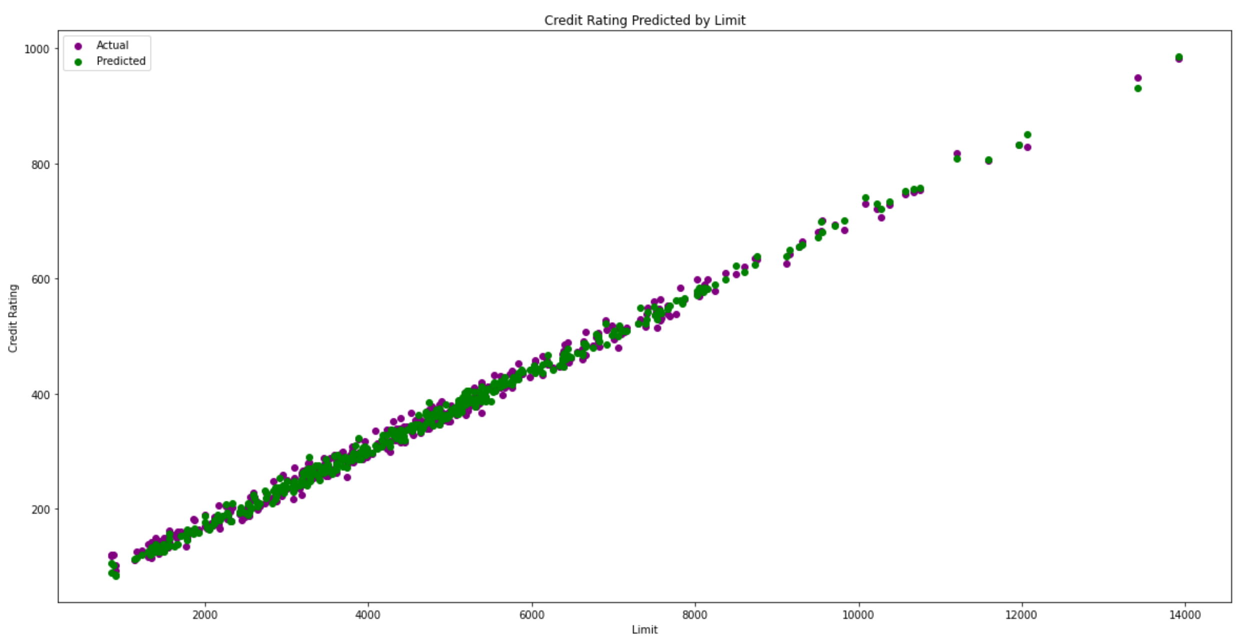
Out[557]: Text(0.5, 1.0, 'Credit Rating Predicted by Income')



In [558…

```
plt.scatter(cred["Limit"], cred["Rating"], c = "purple")
plt.scatter(cred["Limit"], cred["pred"], c = "green")
plt.xlabel("Limit")
plt.ylabel("Credit Rating")
plt.legend(labels = ["Actual", "Predicted"])
plt.title("Credit Rating Predicted by Limit")
```

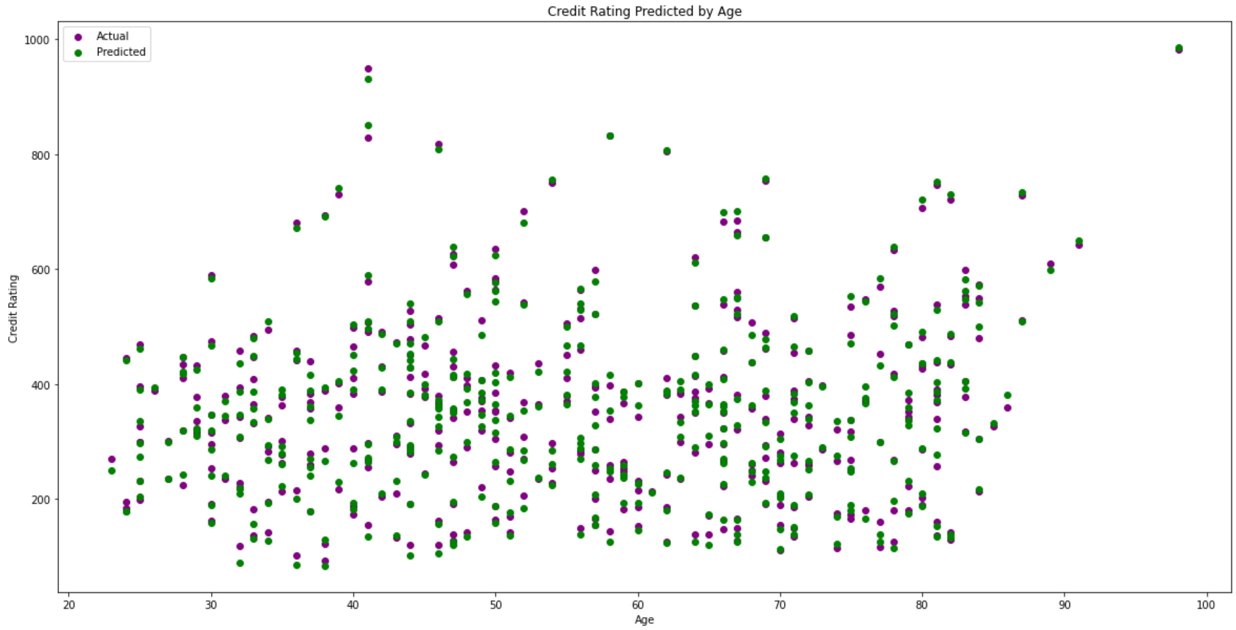
Out[558]: Text(0.5, 1.0, 'Credit Rating Predicted by Limit')



In [559…

```
plt.scatter(cred["Age"], cred["Rating"], c = "purple")
plt.scatter(cred["Age"], cred["pred"], c = "green")
plt.xlabel("Age")
plt.ylabel("Credit Rating")
plt.legend(labels = ["Actual", "Predicted"])
plt.title("Credit Rating Predicted by Age")
```

Out[559]: Text(0.5, 1.0, 'Credit Rating Predicted by Age')



In [560…

```
plt.scatter(cred["Balance"], cred["Rating"], c = "purple")
plt.scatter(cred["Balance"], cred["pred"], c = "green")
plt.xlabel("Balances")
plt.ylabel("Credit Rating")
plt.legend(labels = ["Actual", "Predicted"])
plt.title("Credit Rating Predicted by Balances")
```

Out[560]: Text(0.5, 1.0, 'Credit Rating Predicted by Balances')