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

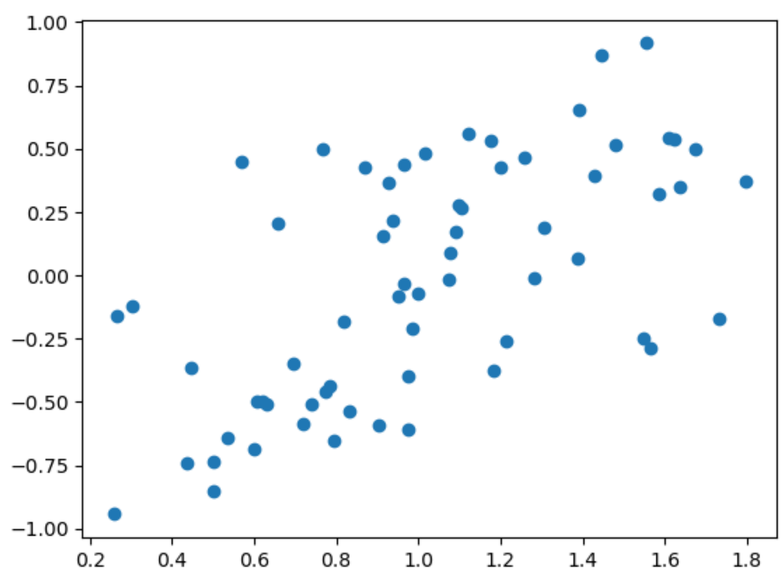
In [62]:
```
import numpy as np
import matplotlib.pylab as plt
%matplotlib inline
```

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 [119…
```
# set seed so that I can actually test things without the randomizer messing things up
np.random.seed(123)
n = 64
x = np.linspace(0,1,n) + np.random.rand(4,n)
# put the ones at the beginning because I like the first coefficient to be beta zero
x = np.vstack([np.ones(len(x.T)), x]).T
y = np.linspace(0,1,n) + np.random.rand(n) - 1
```

In [102…
```
plt.scatter(x.T[1],y)
```

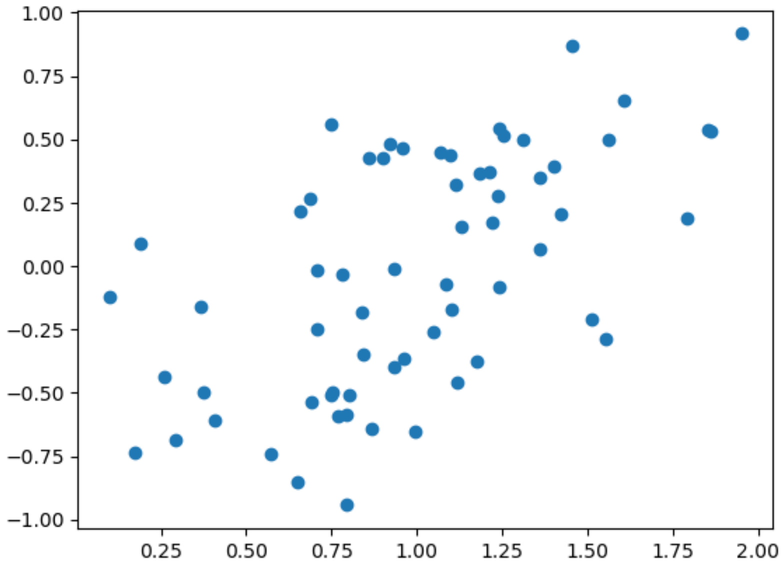
Out[102]:
```
<matplotlib.collections.PathCollection at 0x27cc529f820>
```



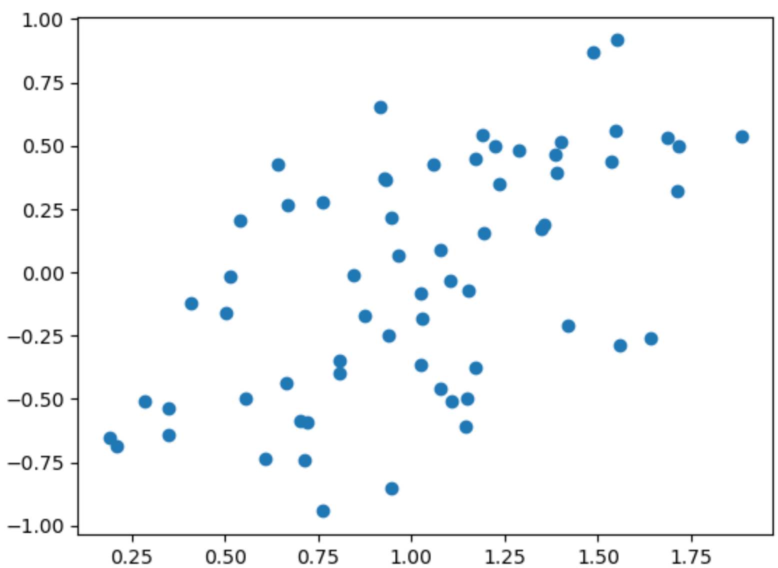
In [103…
```
plt.scatter(x.T[2],y)
```

Out[103]:
```
<matplotlib.collections.PathCollection at 0x27cc54725e0>
```

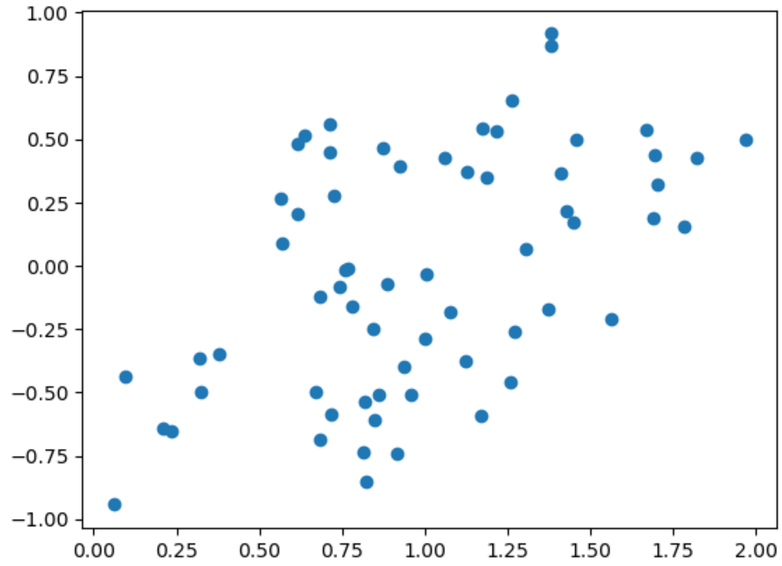
Alt+Q



In [104…
```
plt.scatter(x.T[3],y)
```
Out[104]:
```
<matplotlib.collections.PathCollection at 0x27cc54f45b0>
```



In [105…
```
plt.scatter(x.T[4],y)
```
Out[105]:
```
<matplotlib.collections.PathCollection at 0x27cc6547640>
```



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), calculate a new column $y_p = \Sigma\beta_n \cdot x_n$

$\beta = (X^TX)^{-1}Y^TX$

In [137…
```
beta = np.dot(np.linalg.inv(np.dot(x.T,x)), np.dot(y.T,x))
print(beta)
```
```
[-0.98604904  0.36086932  0.25127869  0.23263096  0.11111903]
```

In [138…
```
#check
beta2 = np.linalg.lstsq(x,y, rcond=-1)[0]
print(beta2)
```
```
[-0.98604904  0.36086932  0.25127869  0.23263096  0.11111903]
```

In [139…
```
p = np.dot(x,beta)
print(p)
```
```
[-0.29321354 -0.68069916 -0.50861392 -0.57221907 -0.47359985 -0.32946556
 -0.2356857  -0.37824818 -0.37355329 -0.47120698 -0.52899059 -0.16857557
 -0.39859234 -0.59450492 -0.3643324  -0.10722987 -0.4174499  -0.31016667
 -0.12119042 -0.33916682 -0.00900048  0.13342781 -0.21666784 -0.17048169
 -0.19776834 -0.2831239  -0.03513668 -0.19721107 -0.16474038  0.18972297
 -0.16029465  0.01894425 -0.10305962 -0.01882585 -0.07287006 -0.1804488
  0.01337558  0.26007485  0.06312323  0.0460841   0.12805678  0.06730944
  0.25272864 -0.02167551  0.4423649   0.18388707  0.23743609  0.27127715
 -0.00764957  0.27302276  0.10396207  0.36517018  0.30752187  0.22563206
  0.11152038  0.43336058  0.43926555  0.45356453  0.30827386  0.40160438
  0.68880911  0.57916359  0.31406806  0.62961459]
```

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 [140…
```
# real values = blue, prediction = red
plt.scatter(x.T[1], y, c='blue')
plt.scatter(x.T[1], p, c='red')
```

Out[140]:
```
<matplotlib.collections.PathCollection at 0x27cc4cf67c0>
```

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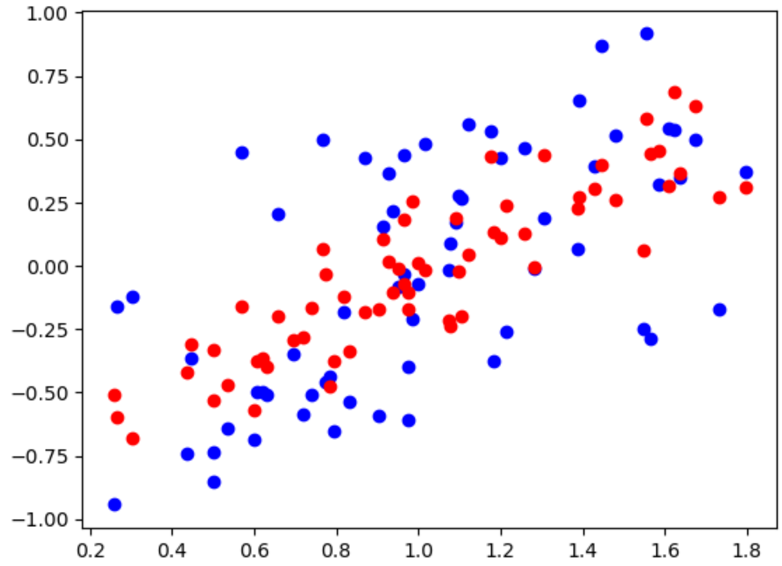
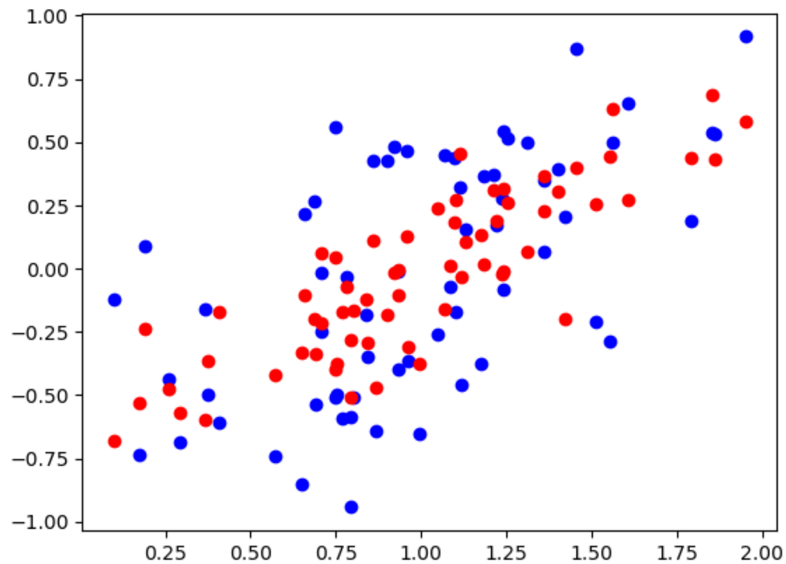


In [141…

```
# real values = blue, prediction = red
plt.scatter(x.T[2], y, c='blue')
plt.scatter(x.T[2], p, c='red')
```

Out[141]: <matplotlib.collections.PathCollection at 0x27cc4d8a880>

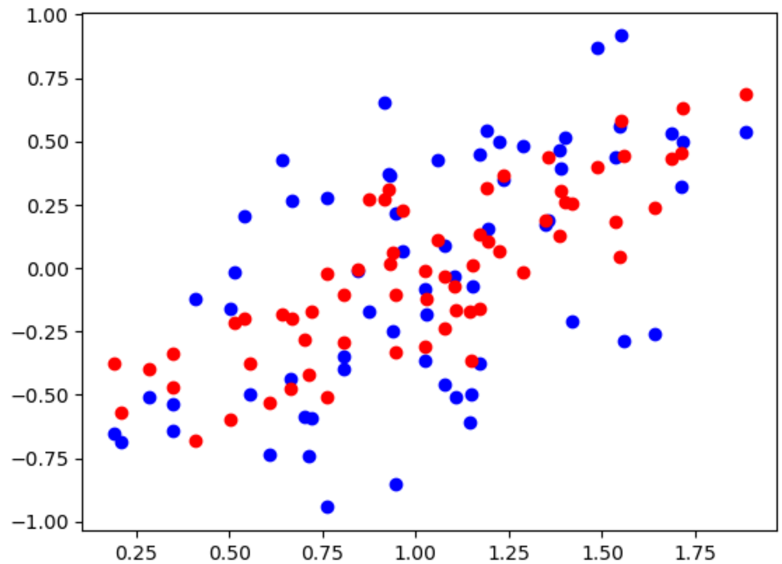


In [142…

```
# real values = blue, prediction = red
plt.scatter(x.T[3], y, c='blue')
plt.scatter(x.T[3], p, c='red')
```

Out[142]: <matplotlib.collections.PathCollection at 0x27cbef53910>

Alt+Q

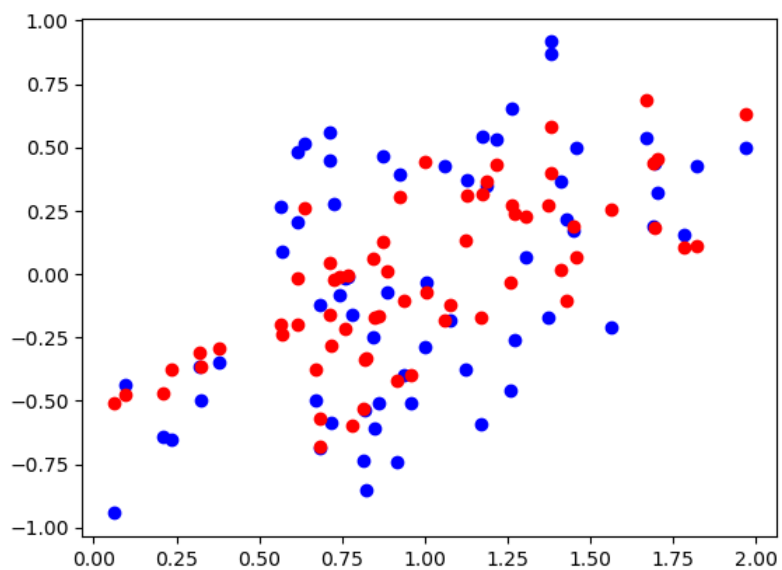


In [143…

```
# real values = blue, prediction = red
plt.scatter(x.T[4], y, c='blue')
plt.scatter(x.T[4], p, c='red')
```

Out[143]:

```
<matplotlib.collections.PathCollection at 0x27cc5315400>
```



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 [144…

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

Out[144]:

	Unnamed: 0	Income	Limit	Rating	Cards	Age	Education	Gender	Student	Married	Ethnicity	Balance
0	1	14.891	3606	283	2	34	11	Male	No	Yes	Caucasian	333
1	2	106.025	6645	483	3	82	15	Female	Yes	Yes	Asian	903
2	3	104.593	7075	514	4	71	11	Male	No	No	Asian	580
3	4	148.924	9504	681	3	36	11	Female	No	No	Asian	964
4	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 [173…

```
columns = ['Income', 'Limit', 'Education', 'Age', 'Balance']
X = credit[columns].values
X = np.vstack([np.ones(len(X)), X.T]).T
X
```

Out[173]:

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

In [174…

```
z = credit['Rating']
z
```

Out[174]:

```
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 [175…

```
beta_credit = np.dot(np.linalg.inv(np.dot(X.T,X)), np.dot(z.T,X))
print(beta_credit)
```

```
[ 4.75140526e+01  1.32064098e-01  6.25891484e-02 -3.44829447e-01
  3.25811876e-02  1.51557697e-02]
```

In [176…

```
#check
beta_credit2 = np.linalg.lstsq(X,z, rcond=-1)[0]
print(beta_credit2)
```

```
[ 4.75140526e+01  1.32064098e-01  6.25891484e-02 -3.44829447e-01
  3.25811876e-02  1.51557697e-02]
```

In [185…

```
p_credit = np.dot(X,beta_credit)
```

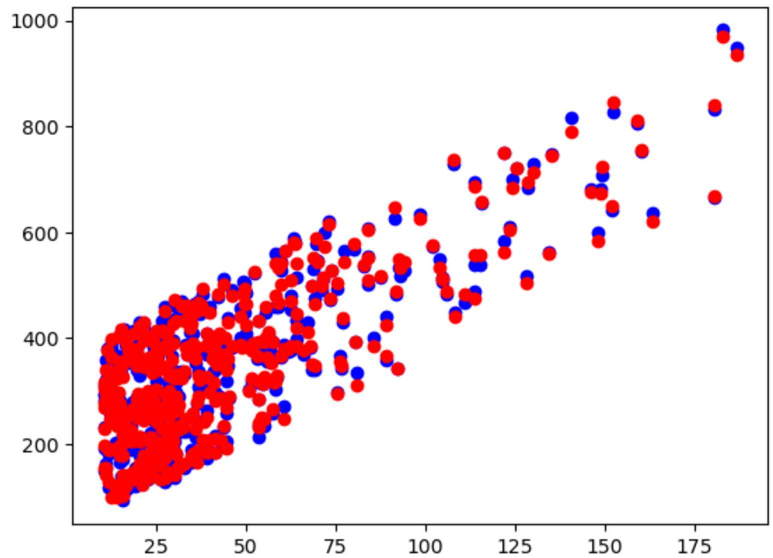
5. Plot your results using scatter plots (just like in class). Show as many of your columns vs. credit rating that you can.

In [184…

```
# real values = blue, prediction = red
plt.scatter(X.T[1], z, c='blue')
plt.scatter(X.T[1], p_credit, c='red')
```

Out[184]:

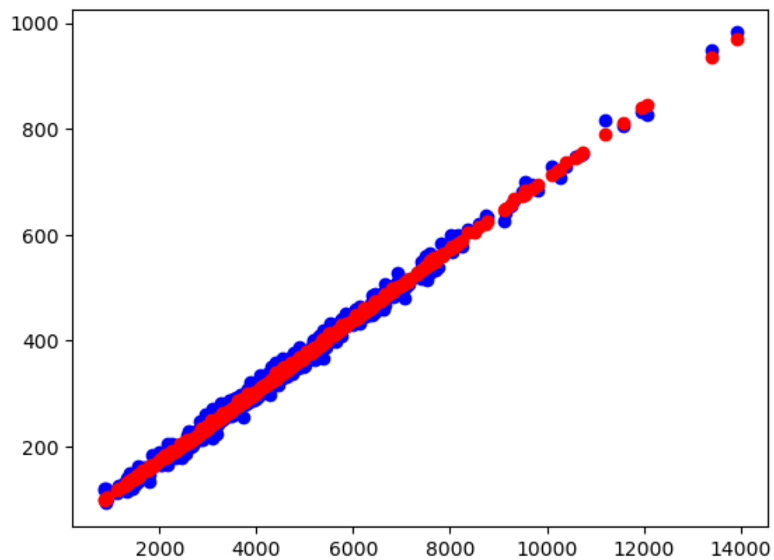
```
<matplotlib.collections.PathCollection at 0x27cc76f1af0>
```



In [179…

```
# real values = blue, prediction = red
plt.scatter(X.T[2], z, c='blue')
plt.scatter(X.T[2], p_credit, c='red')
```

Out[179]: <matplotlib.collections.PathCollection at 0x27cc76243d0>

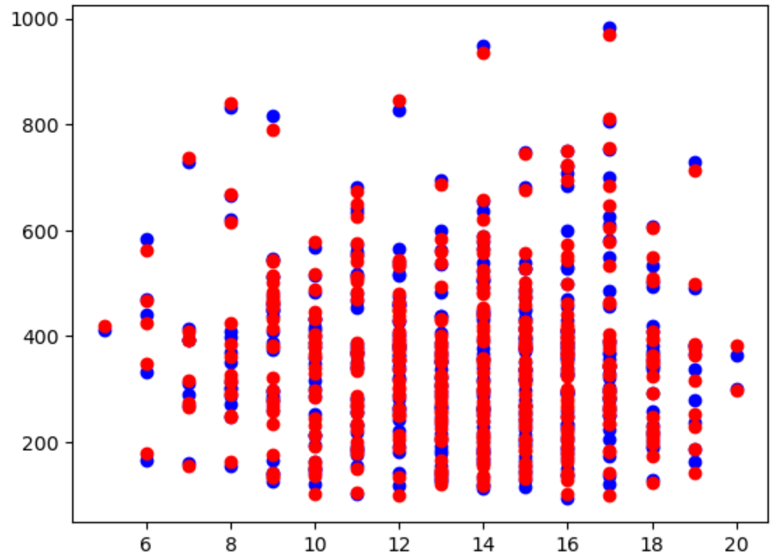


In [180…

```
# real values = blue, prediction = red
plt.scatter(X.T[3], z, c='blue')
plt.scatter(X.T[3], p_credit, c='red')
```

Out[180]: <matplotlib.collections.PathCollection at 0x27cc7584e80>

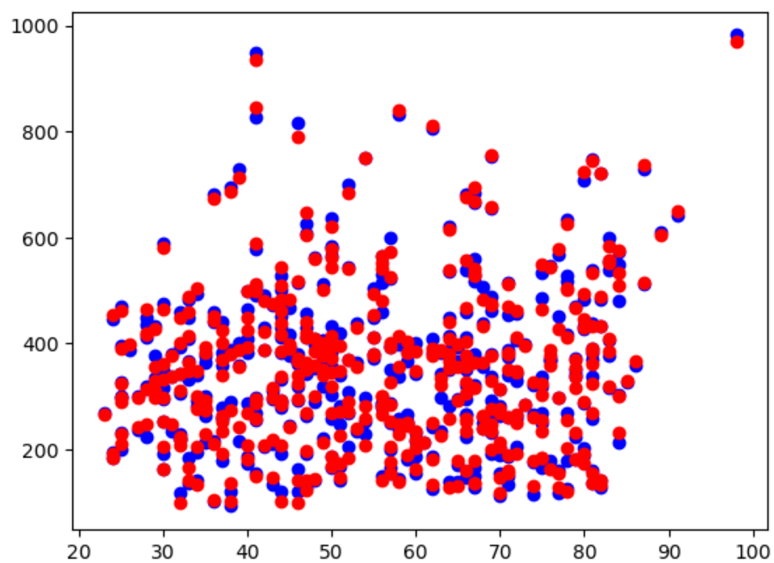
Alt+Q



In [181…

```
# real values = blue, prediction = red
plt.scatter(X.T[4], z, c='blue')
plt.scatter(X.T[4], p_credit, c='red')
```

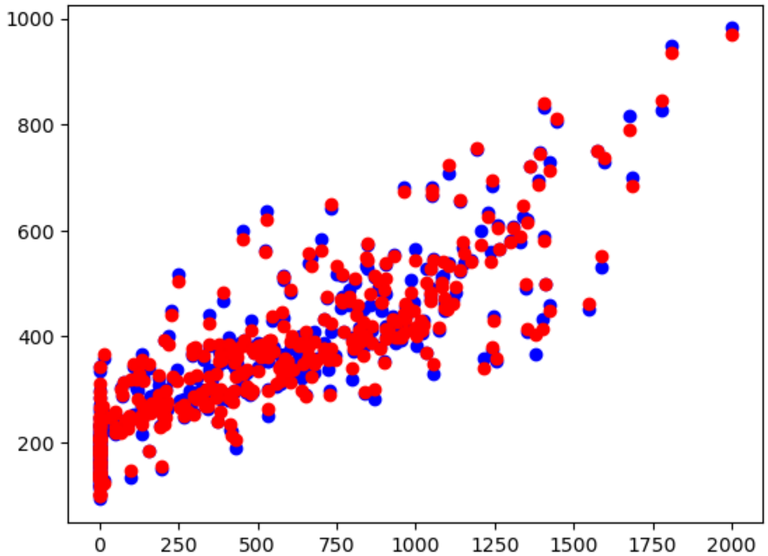
Out[181]: <matplotlib.collections.PathCollection at 0x27cc8790e50>



In [182…

```
# real values = blue, prediction = red
plt.scatter(X.T[5], z, c='blue')
plt.scatter(X.T[5], p_credit, c='red')
```

Out[182]: <matplotlib.collections.PathCollection at 0x27cc7624d60>


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