Assignment 5

1. Choose a REGRESSION dataset (reusing bikeshare is allowed), perform a test/train split, and build a regression model (just like in assignment 3), and calculate the

```
+ Training Error (MSE, MAE)
+ Testing Error (MSE, MAE)
```

2. Choose a CLASSIFICATION dataset (not the adult.data set, The UCI repository has many datasets as well as Kaggle), perform test/train split and create a classification model (your choice but DecisionTree is fine). Calculate

```
+ Accuracy
+ Confusion Matrix
+ Classifcation Report
```

3. (Bonus) See if you can improve the classification model's performance with any tricks you can think of (modify features, remove features, polynomial features)

In [1]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize'] = (20, 10)
plt.rcParams['font.size'] = 14
import pandas as pd
import numpy as np
from sklearn.metrics import (accuracy_score,
                             classification_report,
                             confusion_matrix, auc, roc_curve
                            )
from sklearn.preprocessing import PolynomialFeatures
from sklearn import linear_model, metrics, svm
from sklearn.model_selection import train_test_split
```

1. Regression Dataset

I used dataset from UCI: Seoul Bike Sharing Demand

- independent variable = temperature
- dependent variable = bike rental per hour

In [2]:
```
#Read the data as 'df1'
df1 = pd.read_csv("SeoulBikeData.csv", encoding='unicode_escape')

df1.head()
```

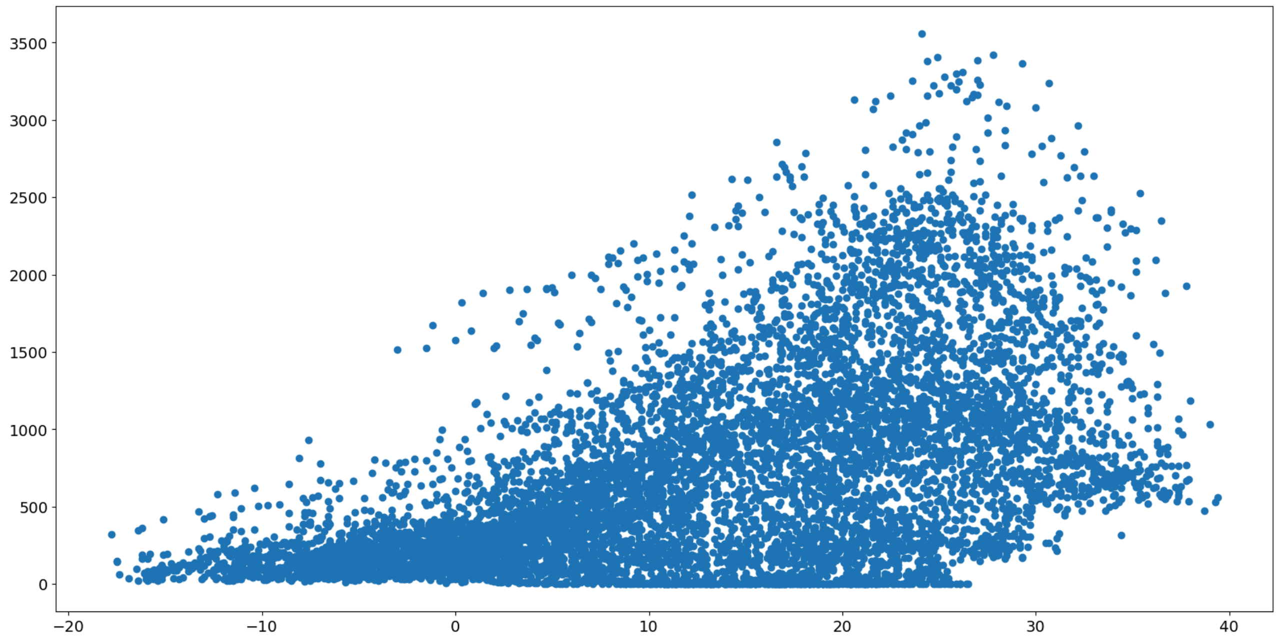
```
Index(['Date', 'Rented Bike Count', 'Hour', 'Temperature(° C)', 'Humidity(%)',
       'Wind speed (m/s)', 'Visibility (10m)', 'Dew point temperature(° C)',
       'Solar Radiation (MJ/m2)', 'Rainfall(mm)', 'Snowfall (cm)', 'Seasons',
       'Holiday', 'Functioning Day'],
      dtype='object')
```

Out[2]:

	Date	Rented Bike Count	Hour	Temperature(°C)	Humidity(%)	Wind speed (m/s)	Visibility (10m)	Dew point temperature(°C)	Solar Radiation (MJ/m2)	Rainfall(mm)	Snowfall (cm)	Seasons	Holid
0	01/12/2017	254	0	-5.2	37	2.2	2000	-17.6	0.0	0.0	0.0	Winter	Holid
1	01/12/2017	204	1	-5.5	38	0.8	2000	-17.6	0.0	0.0	0.0	Winter	Holid
2	01/12/2017	173	2	-6.0	39	1.0	2000	-17.7	0.0	0.0	0.0	Winter	Holid
3	01/12/2017	107	3	-6.2	40	0.9	2000	-17.6	0.0	0.0	0.0	Winter	

In [3]:
```
#Plot the independent and dependent variable
plt.scatter(df1["Temperature(° C)"], df1["Rented Bike Count"])
```

Out[3]: <matplotlib.collections.PathCollection at 0x1a531087150>



In [4]:
```
#transform the variables into numpy array (x1=independent variable, y1=dependent variable)
x1=df1[["Temperature(° C)"]].to_numpy()
y1=df1[["Rented Bike Count"]].to_numpy()

#use train_test_split
x1_train, x1_test, y1_train, y1_test = train_test_split(x1, y1, test_size=0.2)

x1.shape, y1.shape, x1_train.shape, x1_test.shape, y1_train.shape, y1_test.shape
```

Out[4]: ((8760, 1), (8760, 1), (7008, 1), (1752, 1), (7008, 1), (1752, 1))

In [5]:
```
#I will use polynomials 5, 10, 15 and compare the models to find out the best one
poly5 = PolynomialFeatures(degree=5)
poly10 = PolynomialFeatures(degree=10)
poly15 = PolynomialFeatures(degree=15)

#make train and test set for each polynomial
x1_train5 = poly5.fit_transform(x1_train)
x1_train10 = poly10.fit_transform(x1_train)
x1_train15 = poly15.fit_transform(x1_train)

x1_test5 = poly5.fit_transform(x1_test)
x1_test10 = poly10.fit_transform(x1_test)
x1_test15 = poly15.fit_transform(x1_test)

x1_test5.shape, x1_test10.shape, x1_test15.shape
```

Out[5]: ((1752, 6), (1752, 11), (1752, 16))

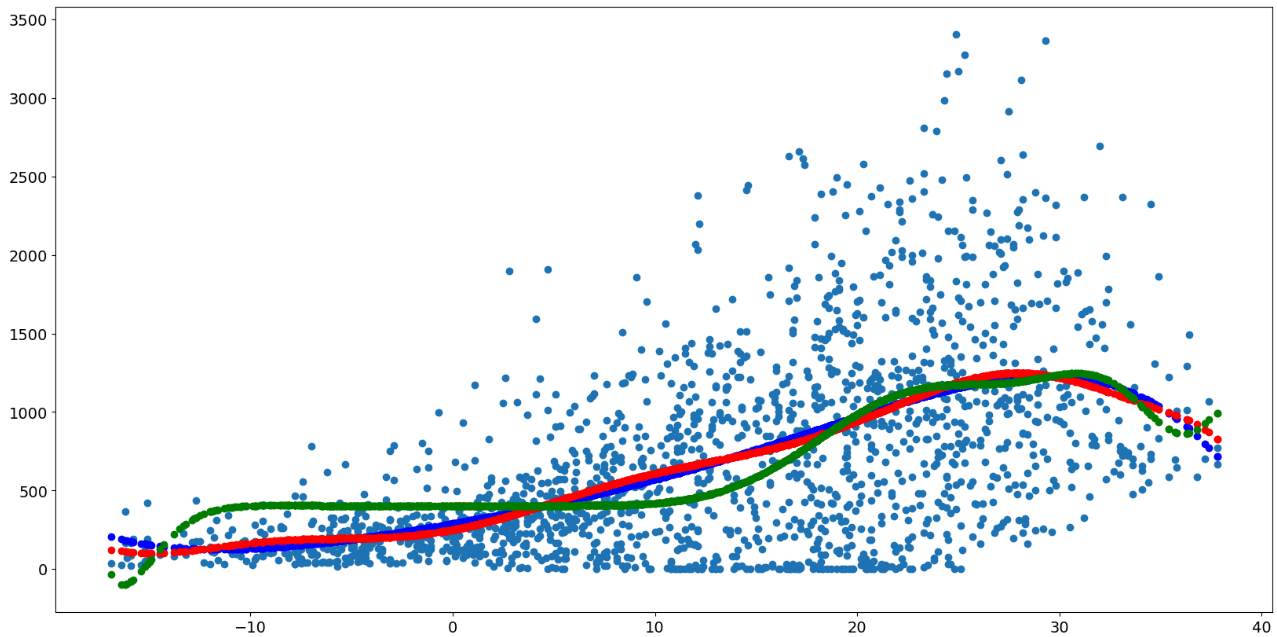
In [6]:
```
#Conduct linear regression for each polynomial model
linear5 = linear_model.LinearRegression()
linear5.fit(x1_train5, y1_train)

linear10 = linear_model.LinearRegression()
linear10.fit(x1_train10, y1_train)

linear15 = linear_model.LinearRegression()
linear15.fit(x1_train15, y1_train)

#Plot prediction values of each model
plt.scatter(x1_test, y1_test)
plt.scatter(x1_test, linear5.predict(x1_test5), c = 'b')
plt.scatter(x1_test, linear10.predict(x1_test10), c = 'r')
plt.scatter(x1_test, linear15.predict(x1_test15), c = 'g')
```

Out[6]: <matplotlib.collections.PathCollection at 0x1a53200f010>



In [7]:
```
#find MSE, MAE for test sets
(
    metrics.mean_squared_error(y1_test, linear5.predict(x1_test5)),
    metrics.mean_squared_error(y1_test, linear10.predict(x1_test10)),
    metrics.mean_squared_error(y1_test, linear15.predict(x1_test15))
)
```

Out[7]: (274179.53590155765, 273626.21288796526, 289169.25050955685)

In [8]:
```
(
    metrics.mean_absolute_error(y1_test, linear5.predict(x1_test5)),
    metrics.mean_absolute_error(y1_test, linear10.predict(x1_test10)),
    metrics.mean_absolute_error(y1_test, linear15.predict(x1_test15))
)
```

Out[8]: (381.0137121814291, 380.8880166212398, 409.43767973719514)

In [9]:
```
#find MSE, MAE for train set
(
    metrics.mean_squared_error(y1_train, linear5.predict(x1_train5)),
    metrics.mean_squared_error(y1_train, linear10.predict(x1_train10)),
    metrics.mean_squared_error(y1_train, linear15.predict(x1_train15))
)
```

Out[9]: (291169.29070432915, 290328.57421383704, 305995.4819886549)

In [10]:
```
(
    metrics.mean_absolute_error(y1_train, linear5.predict(x1_train5)),
    metrics.mean_absolute_error(y1_train, linear10.predict(x1_train10)),
    metrics.mean_absolute_error(y1_train, linear15.predict(x1_train15))
)
```

Out[10]:
```
(395.359640552651, 394.41369836404346, 421.06795381053126)
```

Conclusion: the error of train set is lower than the error of test set

(However, the data is too much scattered and needs to be grouped into daily basis to advance fitting)

2. Classification Dataset

I used a dataset from UCI: Wine Quality

- Classifying good wine (score >= 6) and normal wine (score <5)
- Using Support Vector Machines(SVM) Model

In [11]:
```
# read the dataset as 'df2'
df2 = pd.read_csv("winequality-red.csv")

df2
```

Out[11]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9.8	5
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9.8	5
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9.8	6
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
...	...	...	...	...	...	...	...	...	...	...	...	...
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	5
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	6
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0	6
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	6

1599 rows × 12 columns

In [12]:
```
# transform the values in the column 'quality' into binary values
# quality 6-10 is good wine and quality 1-5 is normal wine

df2['quality'] = df2.quality.between(6,10).astype(int)
df2
```

Out[12]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	0
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9.8	0
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9.8	0
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9.8	1
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	0
...	...	...	...	...	...	...	...	...	...	...	...	...
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	0
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	1
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0	1
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	0
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	1

1599 rows × 12 columns

In [13]:
```
df2.quality.value_counts()
```

Out[13]:
```
quality
1    855
0    744
Name: count, dtype: int64
```

In [14]:
```
#use train_test_split
x2_train, x2_test, y2_train, y2_test = train_test_split(df2.drop(['quality'], axis=1), df2.quality, test_size=.20)

x2_train.shape, x2_test.shape, y2_train.shape, y2_test.shape
```

Out[14]:
```
((1279, 11), (320, 11), (1279,), (320,))
```

In [15]:
```
#define 'model' for SVC

model=svm.SVC()
model.fit(x2_train, y2_train)
```

Out[15]:
```
▾ SVC ⓘ ?
(https://scikit-learn.org/1.4/modules/generated/sklearn.svm.SVC.html)
SVC()
```

In [16]:
```
#define 'predictions' for prediction value
predictions = model.predict(x2_test)
predictions.shape
```

Out[16]:
```
(320,)
```

In [17]:
```
#print accuracy score

print(accuracy_score(y2_test, predictions))
```

```
0.5875
```

In [18]:
```
#print confusion matrix

print(confusion_matrix(y2_test, predictions))
```

```
[[ 48 103]
 [ 29 140]]
```

In [19]:
```
#print classification report
print(classification_report(y2_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.62      0.32      0.42       151
           1       0.58      0.83      0.68       169

    accuracy                           0.59       320
   macro avg       0.60      0.57      0.55       320
weighted avg       0.60      0.59      0.56       320
```

3. Bonus

- As sulphates does not seem much related with quality, removing the feature 'sulphates' may improve the model

In [20]:
```
# use same dataset as Assignment 2 and convert 'quality' column into binary values
df3 = pd.read_csv("winequality-red.csv")

df3['quality'] = df3.quality.between(6,10).astype(int)
df3
```

Out[20]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	0
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9.8	0
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9.8	0
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9.8	1
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	0
...	...	...	...	...	...	...	...	...	...	...	...	...
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	0
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	1
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0	1
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	0
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	1

1599 rows × 12 columns

In [21]:
```
# use train/test split removing 'sulphates'
x3_train, x3_test, y3_train, y3_test = train_test_split(df3.drop(['quality', 'sulphates'], axis=1), df3.quality, test_size=.20)

x3_train.shape, x3_test.shape, y3_train.shape, y3_test.shape
```

Out[21]: ((1279, 10), (320, 10), (1279,), (320,))

In [22]:
```
#define 'model2' for SVC

model2=svm.SVC()
model2.fit(x3_train, y3_train)
```

Out[22]:

```
▾ SVC
(https://scikit-learn.org/1.4/modules/generated/sklearn.svm.SVC.html)
SVC()
```

In [23]:
```
predictions2 = model2.predict(x3_test)
predictions2.shape
```

Out[23]: (320,)

In [24]:
```
#print classification report
print(classification_report(y3_test, predictions2))
```

```
              precision    recall  f1-score   support

           0       0.64      0.38      0.48       142
           1       0.63      0.83      0.71       178

    accuracy                           0.63       320
   macro avg       0.63      0.61      0.60       320
weighted avg       0.63      0.63      0.61       320
```

It worked! all scored went up without the feature 'sulphate'