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)
```

In [111…

```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize'] = 20, 10
import pandas as pd
import numpy as np
credit = pd.read_csv('../data/Credit.csv')
credit.head()
```

Out[111…

	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

In [112…

```
x = credit['Balance'].to_numpy()
y = credit['Rating'].to_numpy()

x= x.reshape(-1, 1)
y = y.reshape(-1, 1)
```

In [113…

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=.40)
```

In [114…

```
from sklearn import linear_model, metrics
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

In [115…

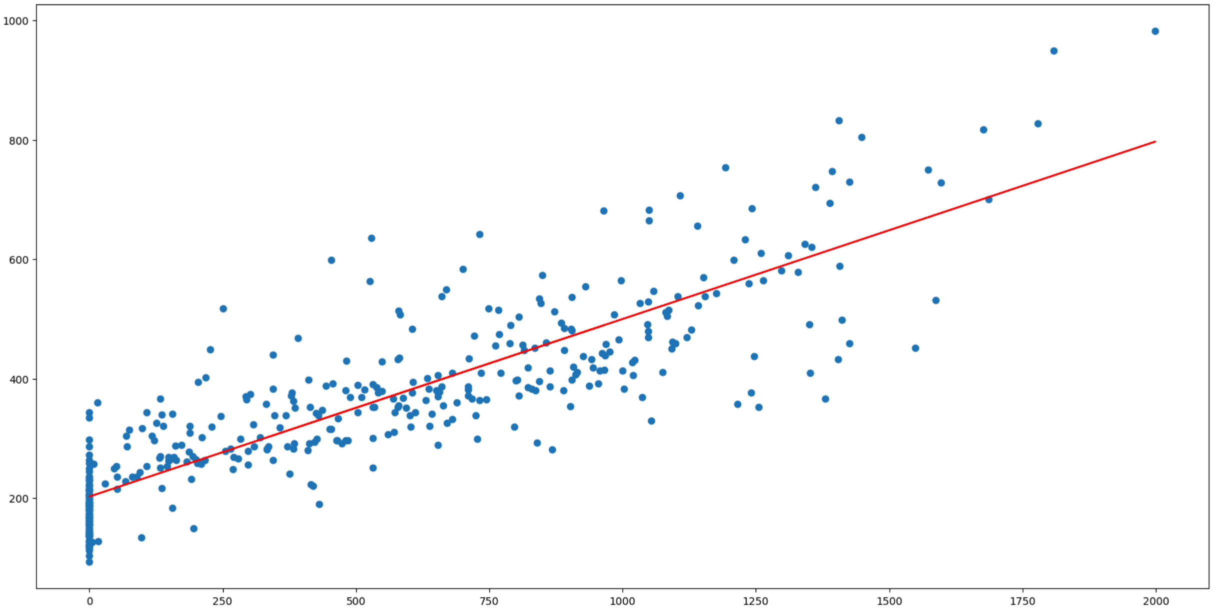
```
model.fit(x_train, y_train)
model.coef_, model.intercept_
```

```
Out[115… (array([[0.29742749]]), array([202.35136259]))
```

Plot of Training Model (Red) versus Actual Data (Blue)

```
In [116… plt.scatter(x, y)
         plt.plot(x, np.dot(x, model.coef_) + model.intercept_, c='r')
```

```
Out[116… [<matplotlib.lines.Line2D at 0x1ba6939e290>]
```



Training Error (MSE, MAE)

```
In [117… (
             metrics.mean_squared_error(y_train, np.dot(x_train, model.coef_) + model.interc
             metrics.mean_absolute_error(y_train, np.dot(x_train, model.coef_) + model.inter
         )
```

```
Out[117… (6435.394001360988, 59.73485084756984)
```

Testing Error (MSE, MAE)

```
In [118… (
             metrics.mean_squared_error(y_test, np.dot(x_test, model.coef_) + model.intercep
             metrics.mean_absolute_error(y_test, np.dot(x_test, model.coef_) + model.interce
         )
```

```
Out[118… (5554.666371103305, 55.07999097492727)
```

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
+ Classification Report
```

In [119…

```
df = pd.read_csv('../data/College.csv', index_col=False)
```

In [120…

```
df.head()
```

Out[120…

	Unnamed: 0	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Underg
0	Abilene Christian University	Yes	1660	1232	721	23	52	2885	
1	Adelphi University	Yes	2186	1924	512	16	29	2683	1
2	Adrian College	Yes	1428	1097	336	22	50	1036	
3	Agnes Scott College	Yes	417	349	137	60	89	510	
4	Alaska Pacific University	Yes	193	146	55	16	44	249	

In [121…

```
df['Private'].unique()
```

Out[121…

```
array(['Yes', 'No'], dtype=object)
```

In [122…

```
df.columns
```

Out[122…

```
Index(['Unnamed: 0', 'Private', 'Apps', 'Accept', 'Enroll', 'Top10perc',
       'Top25perc', 'F.Undergrad', 'P.Undergrad', 'Outstate', 'Room.Board',
       'Books', 'Personal', 'PhD', 'Terminal', 'S.F.Ratio', 'perc.alumni',
       'Expend', 'Grad.Rate'],
      dtype='object')
```

In [123…

```
non_numeric_columns = ['Unnamed: 0']
x1 = df.copy().drop(non_numeric_columns, axis = 1)
x1['Private'] = x1.Private.str.contains('Yes').astype(int)
x1.head()
```

Out[123…

	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outsta
0	1	1660	1232	721	23	52	2885	537	74
1	1	2186	1924	512	16	29	2683	1227	122
2	1	1428	1097	336	22	50	1036	99	112
3	1	417	349	137	60	89	510	63	129
4	1	193	146	55	16	44	249	869	75

In [124…

```
x1.Private.value_counts()
```

Out[124…

```
Private
1    565
0    212
Name: count, dtype: int64
```

In [125…

```
x1_train, x1_test, y1_train, y1_test = train_test_split(x1.drop(['Private'], axis=1
```

In [126…

```
x1.shape, x1_train.shape, x1_test.shape
```

Out[126…

```
((777, 18), (621, 17), (156, 17))
```

In [127…

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import (accuracy_score,
                             classification_report,
                             confusion_matrix, auc, roc_curve
                            )
model1 = DecisionTreeClassifier(criterion='entropy')
```

In [128…

```
model1.fit(x1_train, y1_train)
```

Out[128…

```
▾        DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy')
```

In [129…

```
test_predictions = model1.predict(x1_test)
```

Accuracy Score

In [130…

```
accuracy_score(y1_test, test_predictions)
```

Out[130…

```
0.9230769230769231
```

Confusion Matrix

In [131…

```
confusion_matrix(y1_test, test_predictions)
```

Out[131…

```
array([[ 34,   3],
       [  9, 110]], dtype=int64)
```

Classification Report

In [132…

```
print(classification_report(y1_test, test_predictions))
```

```
              precision    recall  f1-score   support

           0       0.79      0.92      0.85        37
           1       0.97      0.92      0.95       119

    accuracy                           0.92       156
   macro avg       0.88      0.92      0.90       156
weighted avg       0.93      0.92      0.92       156
```

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 [133…

```
list(zip(x1.drop(['Private'], axis=1).columns, model1.feature_importances_))
```

Out[133…

```
[('Apps', 0.007508158360841993),
 ('Accept', 0.007320706919750773 5),
 ('Enroll', 0.05599612007141374 6),
 ('Top10perc', 0.04299202955266883),
 ('Top25perc', 0.0),
 ('F.Undergrad', 0.4019146762155514),
 ('P.Undergrad', 0.04157049674065695),
 ('Outstate', 0.30405059366229037),
 ('Room.Board', 0.018979755625197606),
 ('Books', 0.0),
 ('Personal', 0.017353442174389035),
 ('PhD', 0.039485948188319145),
 ('Terminal', 0.027007203544034727),
 ('S.F.Ratio', 0.012182409266252097),
 ('perc.alumni', 0.015264108687949503),
 ('Expend', 0.008374350990683 76),
 ('Grad.Rate', 0.0)]
```

In [134…

```
x1.columns
```

Out[134…

```
Index(['Private', 'Apps', 'Accept', 'Enroll', 'Top10perc', 'Top25perc',
       'F.Undergrad', 'P.Undergrad', 'Outstate', 'Room.Board', 'Books',
       'Personal', 'PhD', 'Terminal', 'S.F.Ratio', 'perc.alumni', 'Expend',
       'Grad.Rate'],
      dtype='object')
```

In [135…

```
#low importance features
drop_columns = ['Apps', 'Accept', 'Enroll', 'Top25perc','Books',
       'Personal', 'Terminal', 'S.F.Ratio', 'Expend']
```

```
x2 = x1.copy().drop(drop_columns, axis = 1)
x2.head()
```

Out[135…

	Private	Top10perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	PhD	perc.alumni
0	1	23	2885	537	7440	3300	70	12
1	1	16	2683	1227	12280	6450	29	16
2	1	22	1036	99	11250	3750	53	30
3	1	60	510	63	12960	5450	92	37
4	1	16	249	869	7560	4120	76	2

In [136…

```
x2_train, x2_test, y2_train, y2_test = train_test_split(x2.drop(['Private'], axis=1
```

In [137…

```
model2 = DecisionTreeClassifier(criterion='entropy')
model2.fit(x2_train, y2_train)
```

Out[137…

```
▾ DecisionTreeClassifier

DecisionTreeClassifier(criterion='entropy')
```

In [138…

```
test2_predictions = model2.predict(x2_test)
```

Accuracy

In [139…

```
accuracy_score(y2_test, test2_predictions)
```

Out[139…

```
0.9487179487179487
```

Confusion Matrix

In [140…

```
confusion_matrix(y2_test, test2_predictions)
```

Out[140…

```
array([[ 41,   3],
       [  5, 107]], dtype=int64)
```

Classification Report

In [141…

```
print("Test 2", classification_report(y2_test, test2_predictions), "Test 1", classi
Test 2               precision    recall  f1-score   support

           0       0.89      0.93      0.91        44
           1       0.97      0.96      0.96       112

    accuracy                           0.95       156
   macro avg       0.93      0.94      0.94       156
weighted avg       0.95      0.95      0.95       156
 Test 1               precision    recall  f1-score   support

           0       0.79      0.92      0.85        37
           1       0.97      0.92      0.95       119

    accuracy                           0.92       156
   macro avg       0.88      0.92      0.90       156
weighted avg       0.93      0.92      0.92       156
```