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 [223…

```
#### Regression
# Re-Import
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize'] = 20, 10
import pandas as pd
import numpy as np


day_hour_count = pd.read_csv("../data/bikeshare_hour_count.csv")
day_hour_count
```

Out[223]:

	hour	monday	tuesday	wednesday	thursday	friday	saturday	sunday
0	0.0	21.0	34.0	43.0	47.0	51.0	89.0	106.0
1	0.1	39.0	22.0	27.0	37.0	56.0	87.0	100.0
2	0.2	31.0	24.0	26.0	42.0	50.0	98.0	77.0
3	0.3	26.0	27.0	25.0	29.0	52.0	99.0	87.0
4	0.4	19.0	24.0	29.0	29.0	50.0	98.0	69.0
...	...	...	...	...	...	...	...	...
235	23.5	36.0	65.0	60.0	94.0	80.0	93.0	28.0
236	23.6	37.0	61.0	66.0	100.0	81.0	95.0	28.0
237	23.7	30.0	42.0	49.0	80.0	101.0	105.0	27.0
238	23.8	33.0	52.0	47.0	79.0	91.0	93.0	24.0
239	23.9	34.0	33.0	48.0	65.0	105.0	111.0	23.0

240 rows × 8 columns

In [224…
```
def shuffle(a, b):
    assert len(a) == len(b)
    p = np.random.permutation(len(a))
    return p
```

In [225…
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(day_hour_count, day_hour_count, te
```

In [226…
```
(
x_train.shape,
x_test.shape,
y_train.shape,
y_test.shape
)
```

Out[226]:
```
((192, 8), (48, 8), (192, 8), (48, 8))
```

In [227…
```
y_train
```

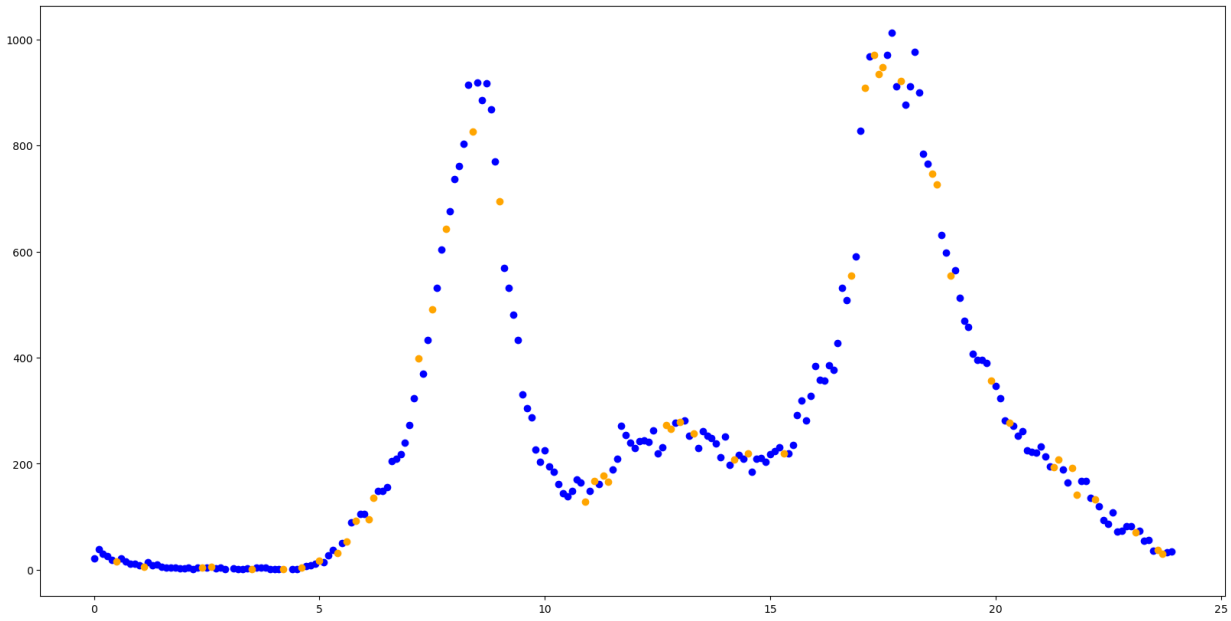
Out[227]:

	hour	monday	tuesday	wednesday	thursday	friday	saturday	sunday
177	17.7	1012.0	1063.0	1110.0	1148.0	861.0	351.0	329.0
209	20.9	221.0	284.0	293.0	304.0	167.0	143.0	128.0
149	14.9	203.0	223.0	242.0	229.0	303.0	402.0	439.0
115	11.5	189.0	163.0	204.0	237.0	231.0	382.0	359.0
225	22.5	87.0	132.0	152.0	158.0	137.0	114.0	99.0
...	...	...	...	...	...	...	...	...
6	0.6	21.0	14.0	22.0	25.0	42.0	58.0	83.0
48	4.8	9.0	11.0	14.0	8.0	10.0	5.0	2.0
33	3.3	2.0	1.0	3.0	2.0	9.0	16.0	17.0
94	9.4	433.0	387.0	436.0	492.0	486.0	308.0	189.0
129	12.9	277.0	247.0	297.0	311.0	340.0	478.0	420.0

192 rows × 8 columns

In [228...
```
plt.scatter(x_train["hour"],x_train["monday"], c='b')
plt.scatter(x_test["hour"],x_test["monday"], c='orange')
```

Out[228]:
```
<matplotlib.collections.PathCollection at 0x2871e604970>
```



In [229...
```
x_train
```

Out[229]:

	hour	monday	tuesday	wednesday	thursday	friday	saturday	sunday
177	17.7	1012.0	1063.0	1110.0	1148.0	861.0	351.0	329.0
209	20.9	221.0	284.0	293.0	304.0	167.0	143.0	128.0
149	14.9	203.0	223.0	242.0	229.0	303.0	402.0	439.0
115	11.5	189.0	163.0	204.0	237.0	231.0	382.0	359.0
225	22.5	87.0	132.0	152.0	158.0	137.0	114.0	99.0
...	...	...	...	...	...	...	...	...
6	0.6	21.0	14.0	22.0	25.0	42.0	58.0	83.0
48	4.8	9.0	11.0	14.0	8.0	10.0	5.0	2.0
33	3.3	2.0	1.0	3.0	2.0	9.0	16.0	17.0
94	9.4	433.0	387.0	436.0	492.0	486.0	308.0	189.0
129	12.9	277.0	247.0	297.0	311.0	340.0	478.0	420.0

192 rows × 8 columns

In [230…

```
from sklearn.preprocessing import PolynomialFeatures
from sklearn import linear_model, metrics
linear = linear_model.LinearRegression()

x = x_train['hour']
y = x_train['monday']

x = np.asarray(x)
y = np.asarray(y)

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

x = np.nan_to_num(x, nan=0.0) # A NaN is throwing off my models
y = np.nan_to_num(y, nan=0.0)
```

In [231…

```
linear_monday = linear_model.LinearRegression().fit(x, y)
```

In [232…

```
x_test_val = x_test['hour']
y_test_val = x_test['monday']

x_test_val = np.asarray(x)
y_test_val = np.asarray(y)

x_test_val = x.reshape(-1,1)
y_test_val = y.reshape(-1,1)

x_test_val = np.nan_to_num(x, nan=0.0) # A NaN is throwing off my models
y_test_val = np.nan_to_num(y, nan=0.0)

linear_monday
linear_monday.fit(x,y) # Built off Training Split
```

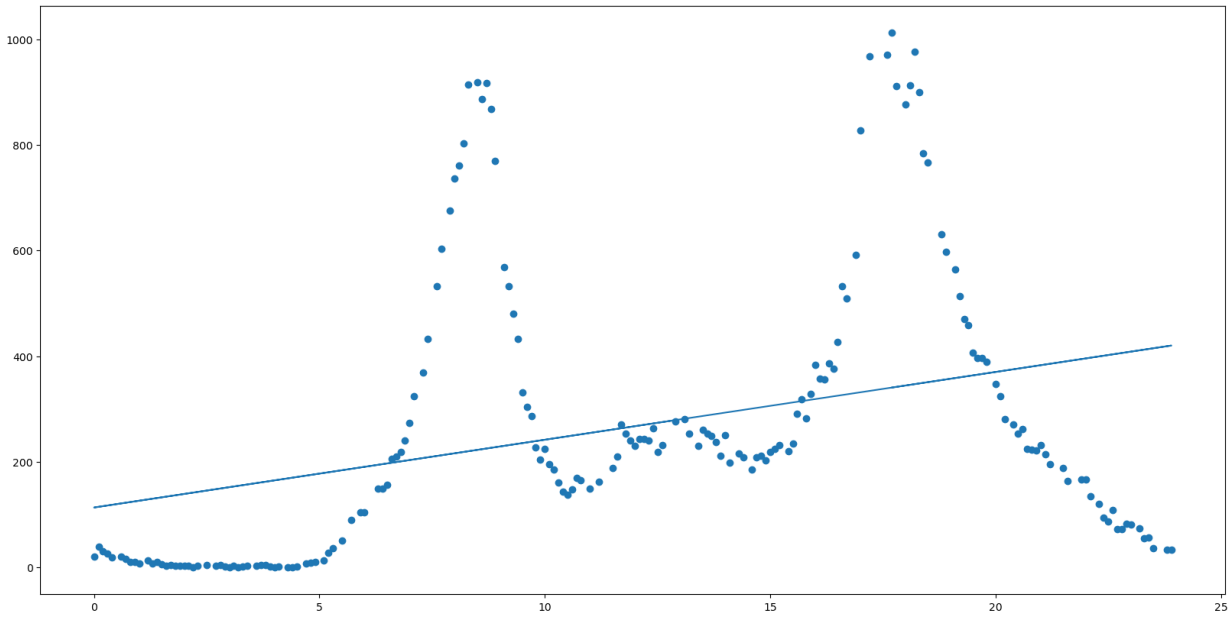
Out[232]:
```
LinearRegression
LinearRegression()
```

In [233…
```
linear_monday.coef_,linear_monday.intercept_
```

Out[233]:
```
(array([[12.82560919]]), array([113.59064369]))
```

In [234…
```
plt.scatter(x,y)
plt.plot(x_test_val, np.dot(x_test_val, linear_monday.coef_) + linear_monday.intercept
```

Out[234]:
```
[<matplotlib.lines.Line2D at 0x2871e653e50>]
```



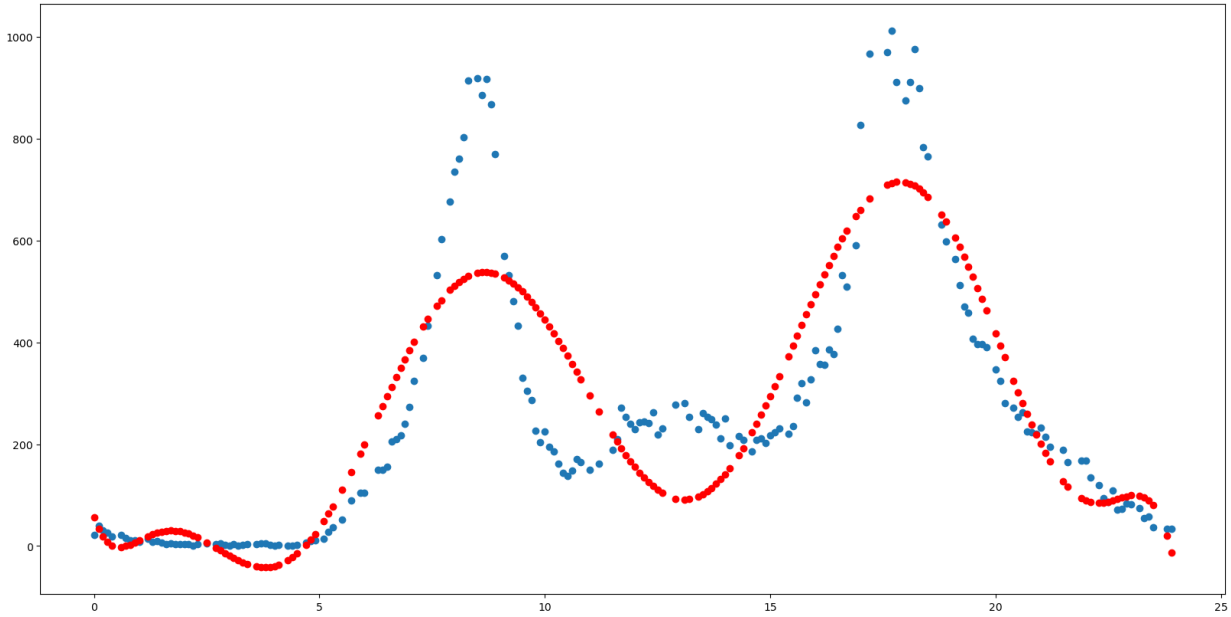
In [235…
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.metrics import mean_absolute_error

(
mean_squared_error(x_test_val, np.dot(x_test_val, linear_monday.coef_) + linear_monday
mean_absolute_error(x_test_val, np.dot(x_test_val, linear_monday.coef_) + linear_monda
    )
```

Out[235]:
```
(70480.30079583293, 252.4984375)
```

In [236…
```
# BONUS: Using a Polynomial Model to increase accuracy and lower errors
poly = PolynomialFeatures(degree=10)
x_10 = poly.fit_transform(x)
linear10_monday = linear_model.LinearRegression()
linear10_monday.fit(x_10, y)
plt.scatter(x,y)
plt.scatter(x, linear10_monday.predict(x_10), c='r')
```

Out[236]:
```
<matplotlib.collections.PathCollection at 0x2871ebd7af0>
```



In [237…
```
# linear10_monday.predict(x_10)
```

In [238…
```
(
mean_squared_error(x_test_val, linear10_monday.predict(x_10)),
mean_absolute_error(x_test_val, linear10_monday.predict(x_10))
    )

# Conclusion: the polynomial model did not produce an error less than the one produced
    # based on the visuals, this seems incorrect, but it may be that the model is more
    # results in a higher mean squared error while leaving the absolute error much clo
```

Out[238]:
```
(114130.80252191091, 258.5721558049679)
```

In [239…
```
#### Classification
resume = pd.read_csv("../data/resume.csv")
# Source: https://www.kaggle.com/datasets/utkarshx27/which-resume-attributes-drive-job
```

In [240…
```
resume
```

Out[240]:

	job_ad_id	job_city	job_industry	job_type	job_fed_contractor	job_equal_opp_em
0	384	Chicago	manufacturing	supervisor	NaN	
1	384	Chicago	manufacturing	supervisor	NaN	
2	384	Chicago	manufacturing	supervisor	NaN	
3	384	Chicago	manufacturing	supervisor	NaN	
4	385	Chicago	other_service	secretary	0.0	
...	...	...	...	...	...	
4865	1344	Boston	finance_insurance_real_estate	secretary	0.0	
4866	382	Boston	other_service	manager	NaN	
4867	382	Boston	other_service	manager	NaN	
4868	382	Boston	other_service	manager	NaN	
4869	382	Boston	other_service	manager	NaN	

4870 rows × 30 columns

In [241…

```
# Removing String Columns - Causing Issues With Decision Tree
resume_no_strings = resume.select_dtypes(exclude = ['object']).dropna(axis=1) # NaN Al
resume_no_strings
# resume.shape
```

Out[241]:

	job_ad_id	job_equal_opp_employer	job_req_any	job_req_communication	job_req_education	job
0	384	1	1	0	0	
1	384	1	1	0	0	
2	384	1	1	0	0	
3	384	1	1	0	0	
4	385	1	1	0	0	
...	...	...	...	...	...	
4865	1344	0	1	0	0	
4866	382	0	0	0	0	
4867	382	0	0	0	0	
4868	382	0	0	0	0	
4869	382	0	0	0	0	

4870 rows × 19 columns

In [242…

```
resume_no_strings.columns
```

Out[242]:
```
Index(['job_ad_id', 'job_equal_opp_employer', 'job_req_any',
       'job_req_communication', 'job_req_education', 'job_req_computer',
       'job_req_organization', 'received_callback', 'years_college',
       'college_degree', 'honors', 'worked_during_school', 'years_experience',
       'computer_skills', 'special_skills', 'volunteer', 'military',
       'employment_holes', 'has_email_address'],
      dtype='object')
```

In [243…
```
# Random Sampling
w_train, w_test, z_train, z_test = train_test_split(resume_no_strings, resume_no_strir
```

In [244…
```
(
w_train.shape,
w_test.shape,
z_train.shape,
z_test.shape
)
```

Out[244]:
```
((3896, 19), (974, 19), (3896, 19), (974, 19))
```

In [245…
```
# from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

In [246…
```
dt_model = DecisionTreeClassifier(criterion='entropy')
```

In [247…
```
w_inputs = w_train.drop('received_callback', axis = 1) # Building model off training s
w_output = w_train['received_callback'] # had some issues with making these subsectior
dt_model.fit(w_inputs, w_output)
```

Out[247]:
```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy')
```

In [248…
```
from sklearn.metrics import (accuracy_score,
                             classification_report,
                             confusion_matrix, auc, roc_curve
                            )
```

In [249…
```
# Predictions
w_test_inputs = w_test.drop('received_callback', axis = 1)
w_test_output = w_test['received_callback'] # Building predictions off testing split

dt_predictions = dt_model.predict(w_test_inputs)

# Accuracy
resume_accuracy_score = accuracy_score(w_test_output, dt_predictions)
# Confusion Matrix
resume_confusion_matrix = confusion_matrix(w_test_output, dt_predictions)
# Classifcation Report
resume_classification_report = classification_report(w_test_output, dt_predictions)
```

In [250…
```
(
print(resume_accuracy_score),
print(resume_confusion_matrix),
```

```
print(resume_classification_report)
)
```

```
0.8921971252566735
[[855  44]
 [ 61  14]]
              precision    recall  f1-score   support

           0       0.93      0.95      0.94       899
           1       0.24      0.19      0.21        75

    accuracy                           0.89       974
   macro avg       0.59      0.57      0.58       974
weighted avg       0.88      0.89      0.89       974
```

Out[250]:
```
(None, None, None)
```

In [251…
```
## (BONUS) Attempt to Improve Model
resume_new = resume_no_strings
resume_new["years_college_squared"] = resume_new["years_college"]^2 # Squaring Feature
resume_new["years_experience_squared"] = resume_new["years_experience"]^2
resume_new
```

Out[251]:

	job_ad_id	job_equal_opp_employer	job_req_any	job_req_communication	job_req_education	job
0	384	1	1	0	0	
1	384	1	1	0	0	
2	384	1	1	0	0	
3	384	1	1	0	0	
4	385	1	1	0	0	
…	…	…	…	…	…	
4865	1344	0	1	0	0	
4866	382	0	0	0	0	
4867	382	0	0	0	0	
4868	382	0	0	0	0	
4869	382	0	0	0	0	

4870 rows × 21 columns

In [252…
```
# Random Sampling for New Model
# Random Sampling; N for 'New Model'
n_train, n_test, m_train, m_test = train_test_split(resume_new, resume_new, test_size=
#w_train.drop('received_callback', axis = 1)
```

In [253…
```
dt_model_new = DecisionTreeClassifier(criterion='entropy')

n_inputs = n_train.drop('received_callback', axis = 1)
n_output = n_train['received_callback'] # had some issues with making these subsectior
```

```
dt_model_new.fit(n_inputs, n_output)
# dt_new_predictions = dt_model_new.predict(n_inputs, n_output)
# dt_new_predictions
# dt_predictions = dt_model.predict(w_test_inputs)
```

Out[253]:

DecisionTreeClassifier

DecisionTreeClassifier(criterion='entropy')

In [254…

```
# Predictions
n_test_inputs = n_test.drop('received_callback', axis = 1)
n_test_output = n_test['received_callback']

dt_new_predictions = dt_model_new.predict(n_test_inputs)

# Accuracy
resume_accuracy_score_new = accuracy_score(n_test_output, dt_new_predictions)
# Confusion Matrix
resume_confusion_matrix_new = confusion_matrix(n_test_output, dt_new_predictions)
# Classifcation Report
resume_classification_report_new = classification_report(n_test_output, dt_new_predict
```

In [255…

```
(
print(resume_accuracy_score_new),
print(resume_confusion_matrix_new),
print(resume_classification_report_new)
)
```

```
0.9024640657084189
[[859  53]
 [ 42  20]]
              precision    recall  f1-score   support

           0       0.95      0.94      0.95       912
           1       0.27      0.32      0.30        62

    accuracy                           0.90       974
   macro avg       0.61      0.63      0.62       974
weighted avg       0.91      0.90      0.91       974
```

Out[255]:

```
(None, None, None)
```

In [ ]:

```
# Conclusion: Squaring certain featured increased precision and accuracy by a small am
```