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November 10, 2021

1 Assignment 4,

1.1 Part 1:

1.1.1 Data Exploration

```
1) Read in bike_share_hour.csv as a pandas dataframe. The columns are
described in the bike_share_readme.txt if you need more information
about them.
2) Look at the dataset, and convert the columns that are categorical to a
pandas "category" type.
3) Look for non-null values in the dataset.
4) Do a descriptive analysis of the numeric columns.=
5) Implement a bar plot of cnt versus season. Document which season has
the most bike rides and which season has the least.
6) Implement a bar chart for working day versus count. Document how bike
rides are distributed across these two classes.
7) Implement a bar chart for month versus count. Document which months
have the most bike rides.
8) Implement code to figure out which months belong to which seasons.
9) Implement a bar plot of weathersit versus cnt. Document which weather
situation has less bike rentals.
10) Implement a point plot of weathersit on the x-axis, count on the y-axis, and
the season as the hue. Document how season and weathersit are related.
11) Implement a bar plot of hour versus count. Are there any specific hours
that are busier than others?
12) Implement a bar plot of hour versus count on weekends and holidays
(when workingday = 0). Does the hourly trend change on weekends?
```

1.2 Part 2:

1.2.1 Data Preparation

```
1) Implement and graph a correlation matrix with the remaining numeric
features. Any interesting relationships?
2) Scale the numerical features using StandardScaler(), and replace the
original columns in your dataframe.
3) Drop the following columns from your dataset: casual, registered, dteday,
instant.
4) Implement a histogram of the count column. What can be said based on
```

the resulting distribution?
5) Implement a train/test split with a test size of 33%.
6) Implement a baseline linear regression algorithm. Use cross-validation to output r2 and mse. Calculate RMSE base on mse. Document your scores.

1.3 Part 3:

1.3.1 Model Training (Hint: trained all of these with a for loop and added my results to a PrettyTable.)

1)Create one-hot-encoded values for your categorical columns using get_dummies and add them to your source dataset.
2) Drop the original categorical columns from your source dataset.
3) Do a test/train split based on your new source dataset. Implement and fit a new linear model on your new training set.
4) What are the new values for r2, mse, and rmse?
5) Implement and score a decision tree regressor with random_state=0.
6) Implement and score a RandomForestRegressor with random_state=0 and n_esitmators=30.
7) Implement and score an SGDRegressor with max_iter=1000 and tol=1e3).
8) Implement and score a Lasso Regressor with alpha=0.1.
9) Implement and score an ElasticNet Regressor with random_state=0.
10) Implement and score a Ridge Regressor with alpha=0.5.
11) Implement and score a BaggingRegressor.

1.4 Part 4:

1.4.1 Model Tuning

1) Take the top three performing models and implement cross-validation on them. Hint: They should be Decision Tree Regressor, RandomForestRegressor, and BaggingRegress
2) Take your top performing model (mine was the RandomForestRegressor) and do a randomize search cv with 20 iterations and three folds.
I found it is best to set your n_jobs = (# of cpu's you have - 1). This took about 10 minutes on my MacBook with 4 CPUs and 8 GB of memory.
Your param distributions should include the following:
3) Bootstrap: true, false
4) Max_depth: 10-110, number of bins 11
5) Max_features: auto, sqrt
6) Min_samples_split: 2,5,10
7) Min_samples_leaf: 1,2,4
8) 200 - 2000, number of bins 10
9) Take your best_estimator_ and see how it compares by doing cross_vals for r2, mse, and calculating rmse.
Finally, run predictions on your test set with this model, and see how your r2 score and RMSE look.

1.5 Part 1:

1.5.1 Data Exploration

1) Read in bike_share_hour.csv as a pandas dataframe. The columns are described in the bike_share_readme.txt if you need more information about them.
2) Look at the dataset, and convert the columns that are categorical to a pandas "category" type.
3) Look for non-null values in the dataset.
4) Do a descriptive analysis of the numeric columns.=
5) Implement a bar plot of cnt versus season. Document which season has the most bike rides and which season has the least.
6) Implement a bar chart for working day versus count. Document how bike rides are distributed across these two classes.
7) Implement a bar chart for month versus count. Document which months have the most bike rides.
8) Implement code to figure out which months belong to which seasons.
9) Implement a bar plot of weathersit versus cnt. Document which weather situation has less bike rentals.
10) Implement a point plot of weathersit on the x-axis, count on the y-axis, and the season as the hue. Document how season and weathersit are related.
11) Implement a bar plot of hour versus count. Are there any specific hours that are busier than others?
12) Implement a bar plot of hour versus count on weekends and holidays (when workingday = 0). Does the hourly trend change on weekends?

[ ]:
```
import pandas as pd
import numpy as np
import sweetviz
import matplotlib.pyplot as plt
from seaborn import pointplot, heatmap
from sklearn import preprocessing, model_selection, linear_model, metrics,␣
 ↪tree, ensemble
```

[ ]:
```
bike_share_data = pd.read_csv("bike_share_hour.csv", index_col = [0])
```

To begin we are going to be performing exploratory data analysis:

Categorical:

- dteday: the date of the rental
- season: season of the rental
- yr: year of the rental
- mnth: month of the rental
- hr: which hour of the day
- holiday: whether it is a holiday or not
- weekday: which day of the week
- workingday: if it's a working day
- weathersit: the weather out

Numerical:

- temp : Normalized temperature in Celsius. The values are divided to 41 (max)
- atemp: Normalized feeling temperature in Celsius. The values are divided to 50 (max)
- hum: Normalized humidity. The values are divided to 100 (max)
- windspeed: Normalized wind speed. The values are divided to 67 (max)
- casual: count of casual users
- registered: count of registered users
- cnt: count of total rental bikes including both casual and registered

[ ]:
```
bike_share_data.sample(10)
```

[ ]:
```
             dteday  season  yr  mnth  hr  holiday  weekday  workingday  \
instant
7588     2011-11-17       4   0    11  18        0        4           1
14330    2012-08-25       3   1     8   6        0        6           0
10609    2012-03-23       2   1     3   3        0        5           1
14362    2012-08-26       3   1     8  14        0        0           0
3397     2011-05-26       2   0     5  10        0        4           1
11020    2012-04-09       2   1     4   7        0        1           1
8733     2012-01-04       1   1     1  16        0        3           1
1315     2011-02-27       1   0     2  23        0        0           0
16139    2012-11-10       4   1    11   4        0        6           0
1151     2011-02-20       1   0     2  17        0        0           0

         weathersit  temp   atemp   hum  windspeed  casual  registered  cnt
instant
7588              1  0.32  0.3182  0.39     0.1940       9         298  307
14330             2  0.64  0.5909  0.78     0.1642       5          25   30
10609             1  0.52  0.5000  0.88     0.1045       4           6   10
14362             1  0.64  0.5758  0.89     0.1045     125         252  377
3397              1  0.70  0.6667  0.74     0.2836      49          94  143
11020             1  0.42  0.4242  0.28     0.1940      11         320  331
8733              2  0.18  0.1667  0.40     0.2836       8         123  131
1315              2  0.36  0.3485  0.62     0.1642       6          53   59
16139             1  0.26  0.2727  0.87     0.1045       2           4    6
1151              1  0.34  0.3485  0.33     0.1642      60          86  146
```

[ ]:
```
feature_names = bike_share_data.columns
feature_names
```

[ ]:
```
Index(['dteday', 'season', 'yr', 'mnth', 'hr', 'holiday', 'weekday',
       'workingday', 'weathersit', 'temp', 'atemp', 'hum', 'windspeed',
       'casual', 'registered', 'cnt'],
      dtype='object')
```

[ ]:
```
categorical_feature_names = feature_names[:8]
categorical_feature_names
```

[ ]:
```
Index(['dteday', 'season', 'yr', 'mnth', 'hr', 'holiday', 'weekday',
       'workingday'],
      dtype='object')
```

[ ]:
```
for name in categorical_feature_names:
    bike_share_data[name] = pd.Categorical(bike_share_data[name])
```

[ ]:
```
bike_share_data.yr.head(10)
```

[ ]:
```
instant
1     0
2     0
3     0
4     0
5     0
6     0
7     0
8     0
9     0
10    0
Name: yr, dtype: category
Categories (2, int64): [0, 1]
```

[ ]:
```
for feature_name in feature_names:
    print(feature_name, sum(bike_share_data[feature_name].isna()))
```

```
dteday 0
season 0
yr 0
mnth 0
hr 0
holiday 0
weekday 0
workingday 0
weathersit 0
temp 0
atemp 0
hum 0
windspeed 0
casual 0
registered 0
cnt 0
```

[ ]:
```
exploratory_analysis = sweetviz.analyze(bike_share_data)
```

```
Done! Use 'show' commands to display/save.   |      | [100%]   00:00 ->
(00:00 left)
```

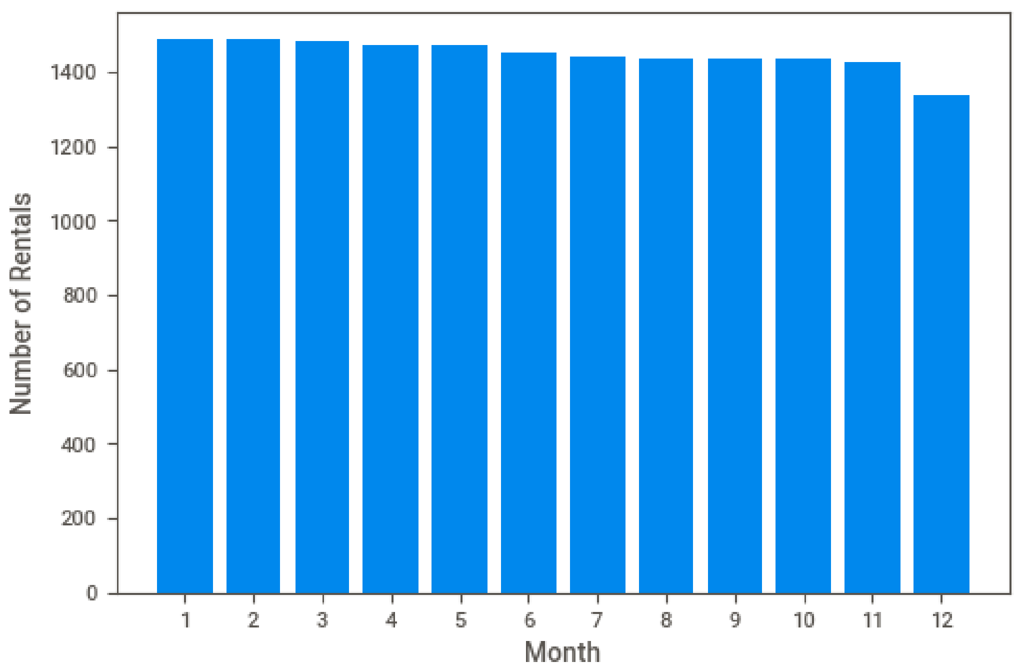
[ ]:
```
exploratory_analysis.show_notebook()
```

```
&lt;IPython.core.display.HTML object&gt;
```

[ ]:
```
months = bike_share_data.mnth
months.describe()
```

[ ]:
```
count     17379
unique       12
top           5
freq       1488
Name: mnth, dtype: int64
```

[ ]:
```
x = [i for i in range(1,13)]
x_str = [str(i) for i in x]
months.value_counts()
plt.bar(x, months.value_counts())
plt.xlabel("Month")
plt.ylabel("Number of Rentals")
plt.xticks(ticks = x, labels = x_str)
plt.show()
```



[ ]:
```
months.unique()
```

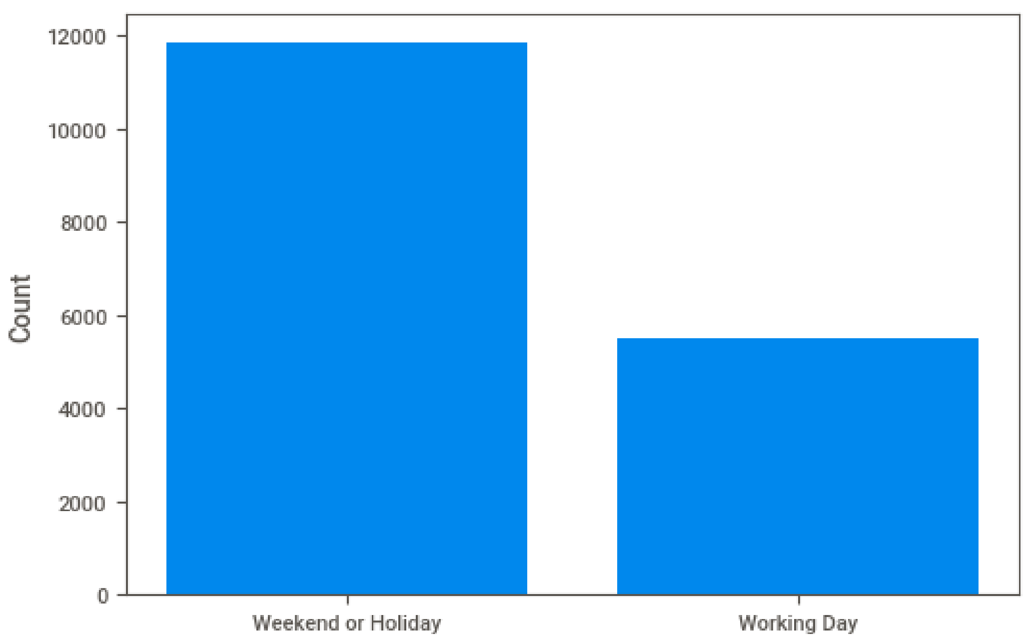
[ ]:
```
[1, 2, 3, 4, 5, …, 8, 9, 10, 11, 12]
Length: 12
Categories (12, int64): [1, 2, 3, 4, …, 9, 10, 11, 12]
```

[ ]:
```
def months_in_seasons(data_set):
    months_in_season = []
    for season in data_set["season"].unique():
        seasonal_data_set = data_set[data_set["season"] == season]
        months_in_season.append(list(seasonal_data_set["mnth"].unique()))
    return months_in_season
```

[ ]:
```
months_in_seasons(bike_share_data)
```

[ ]:
```
[[1, 2, 3, 12], [3, 4, 5, 6], [6, 7, 8, 9], [9, 10, 11, 12]]
```

[ ]:
```
plt.bar(x = [0,1], height = bike_share_data.workingday.value_counts())
plt.ylabel("Count")
plt.xticks(ticks = [0,1], labels = ["Weekend or Holiday","Working Day"])
plt.show()
```



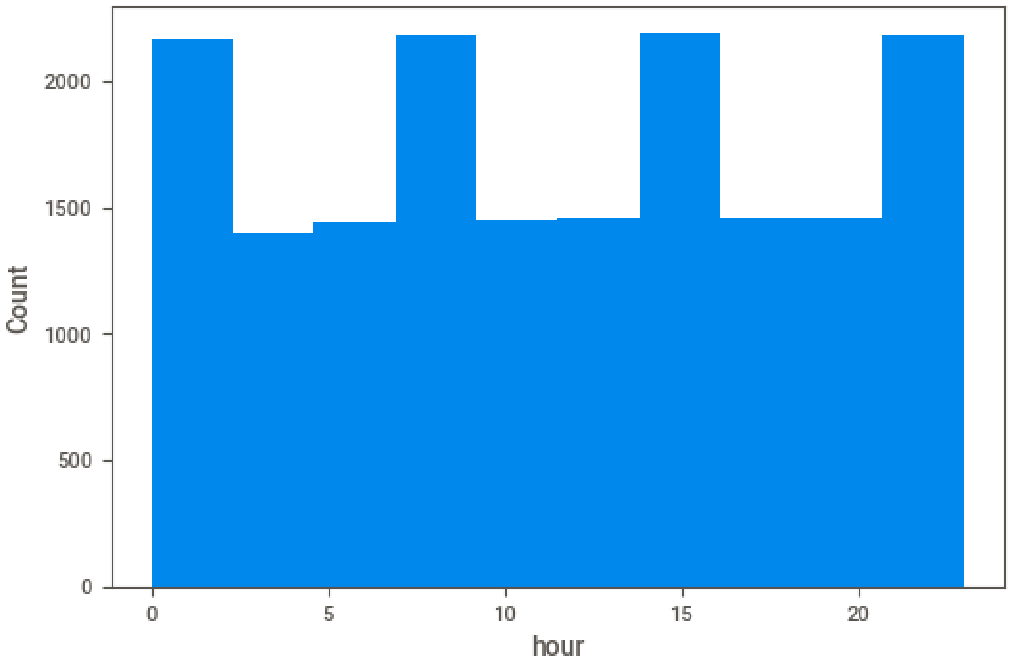
[ ]:
```
x = [i for i in range(0, len(bike_share_data.weathersit.unique()))]

# plt.scatter()
# plt.xticks(ticks = x, labels = ["clear", "mist", "light snow / raing", "heavy␣
↪snow / rain"], rotation = 60)
# plt.ylabel("Count")
```

```
# plt.show()
```

[ ]:
```
list(bike_share_data.weathersit.value_counts())
```

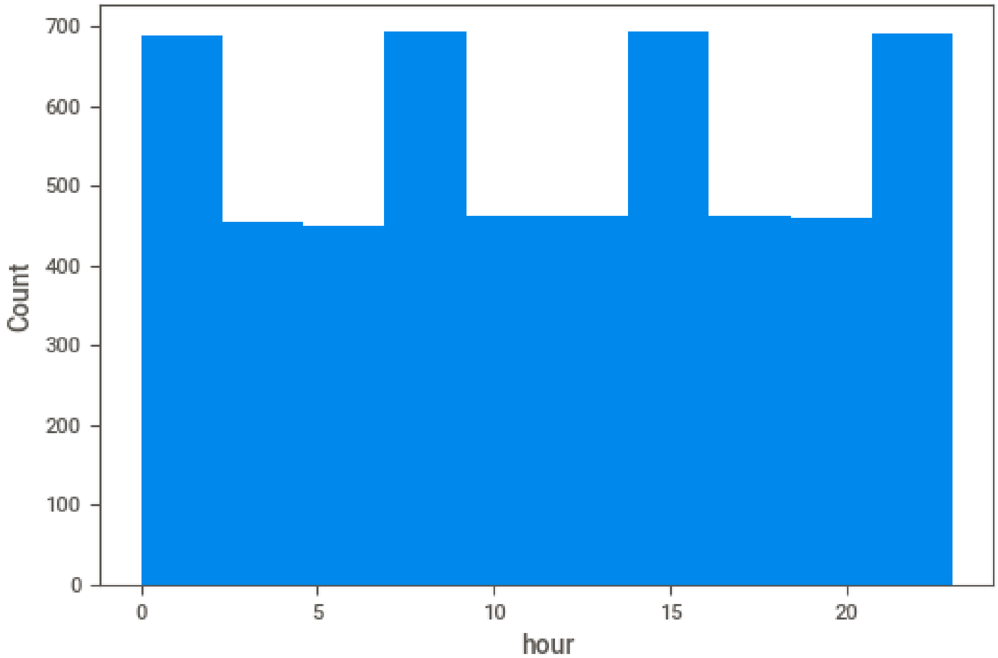
[ ]:
```
[11413, 4544, 1419, 3]
```

[ ]:
```
plt.hist(bike_share_data.hr)
plt.xlabel("hour")
plt.ylabel("Count")
plt.show()
```



[ ]:
```
bike_share_weekend_holiday_data = bike_share_data[bike_share_data.workingday ==␣
↪0]
```

[ ]:
```
plt.hist(bike_share_weekend_holiday_data.hr)
plt.xlabel("hour")
plt.ylabel("Count")
plt.show()
```



1.6 Part 2:

1.6.1 Data Preparation

```
1) Implement and graph a correlation matrix with the remaining numeric
features. Any interesting relationships?
2) Scale the numerical features using StandardScaler(), and replace the
original columns in your dataframe.
3) Drop the following columns from your dataset: casual, registered, dteday,
instant.
4) Implement a histogram of the count column. What can be said based on
the resulting distribution?
5) Implement a train/test split with a test size of 33%.
6) Implement a baseline linear regression algorithm. Use cross-validation to
output r2 and mse. Calculate RMSE base on mse. Document your scores.
```

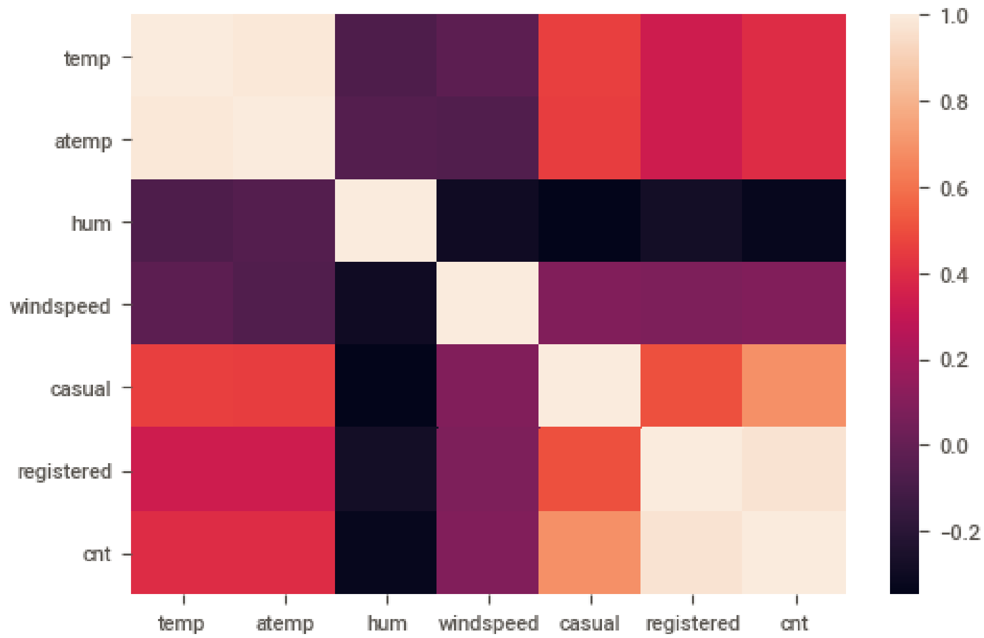
[ ]:
```python
x = [i for i in range(9, 16)]
```

[ ]:
```python
bike_share_numeric_data = bike_share_data.iloc[:,x]
bike_share_numeric_feature_names = bike_share_numeric_data.columns
bike_share_numeric_feature_names
```

[ ]:
```
Index(['temp', 'atemp', 'hum', 'windspeed', 'casual', 'registered', 'cnt'],
dtype='object')
```

[ ]:
```python
heatmap(bike_share_numeric_data.corr())
```

[ ]:
```
<AxesSubplot:>
```



[ ]:
```python
scalar = preprocessing.StandardScaler()

scalar.fit_transform(bike_share_numeric_data)

# for feature_name in bike_share_numeric_feature_names:
#     scalar.fit(bike_share_data[feature_name].values.ravel())
#     bike_share_data[feature_name] = scalar.
 ↪transform(bike_share_data[feature_name])


bike_share_numeric_data.head(10)
```

[ ]:

	temp	atemp	hum	windspeed	casual	registered	cnt
instant							
1	0.24	0.2879	0.81	0.0000	3	13	16
2	0.22	0.2727	0.80	0.0000	8	32	40
3	0.22	0.2727	0.80	0.0000	5	27	32
4	0.24	0.2879	0.75	0.0000	3	10	13
5	0.24	0.2879	0.75	0.0000	0	1	1
6	0.24	0.2576	0.75	0.0896	0	1	1
7	0.22	0.2727	0.80	0.0000	2	0	2
8	0.20	0.2576	0.86	0.0000	1	2	3
9	0.24	0.2879	0.75	0.0000	1	7	8

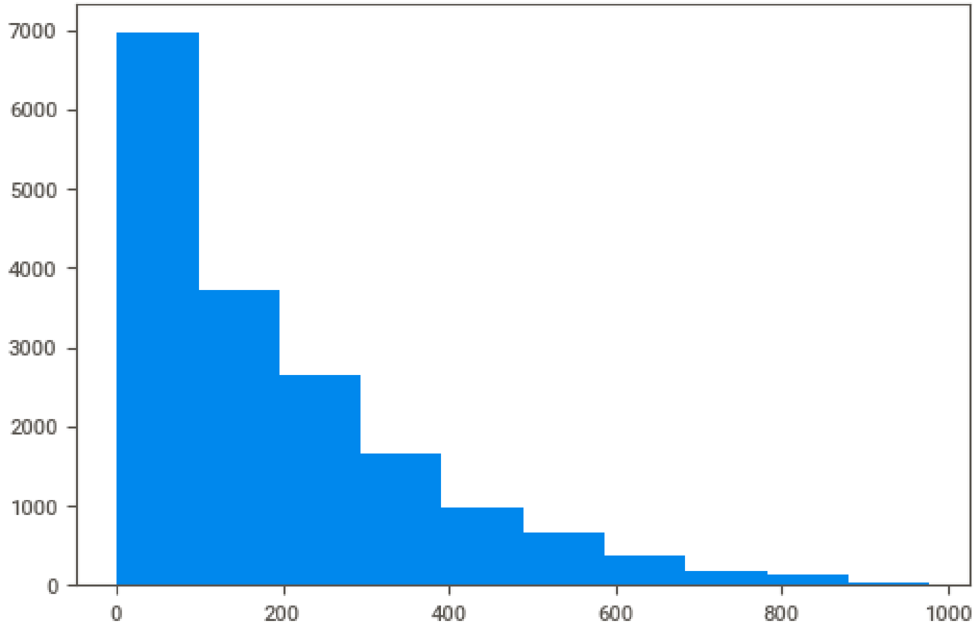
```
10          0.32  0.3485  0.76     0.0000       8            6   14
```

```
[ ]: columns_to_drop = ["casual", "registered", "dteday"]
```

```
[ ]: bike_share_data = bike_share_data.drop(columns = columns_to_drop)
     bike_share_data.head(10)
```

```
[ ]:         season yr mnth hr holiday weekday workingday  weathersit  temp  \
instant
1             1  0    1  0       0       6          0           1  0.24
2             1  0    1  1       0       6          0           1  0.22
3             1  0    1  2       0       6          0           1  0.22
4             1  0    1  3       0       6          0           1  0.24
5             1  0    1  4       0       6          0           1  0.24
6             1  0    1  5       0       6          0           2  0.24
7             1  0    1  6       0       6          0           1  0.22
8             1  0    1  7       0       6          0           1  0.20
9             1  0    1  8       0       6          0           1  0.24
10            1  0    1  9       0       6          0           1  0.32

          atemp   hum  windspeed  cnt
instant
1        0.2879  0.81     0.0000   16
2        0.2727  0.80     0.0000   40
3        0.2727  0.80     0.0000   32
4        0.2879  0.75     0.0000   13
5        0.2879  0.75     0.0000    1
6        0.2576  0.75     0.0896    1
7        0.2727  0.80     0.0000    2
8        0.2576  0.86     0.0000    3
9        0.2879  0.75     0.0000    8
10       0.3485  0.76     0.0000   14
```

```
[ ]: plt.hist(bike_share_data.cnt)
     plt.show()
```



[ ]:
```
bike_share_train, bike_share_test = model_selection.
 ↪train_test_split(bike_share_data, test_size = .33)
```

[ ]:
```
bike_share_train.head(5)
```

[ ]:
```
         season  yr  mnth  hr  holiday  weekday  workingday  weathersit  temp  \
instant
3943          2   0     6   4        0        6           0           1  0.60
17352         1   1    12  20        0        0           0           1  0.22
6801          4   0    10  22        0        6           0           1  0.50
12325         2   1     6  17        0        6           0           1  0.64
15151         4   1     9  11        0        5           1           2  0.66

          atemp   hum  windspeed  cnt
instant
3943     0.5455  0.88     0.0896    5
17352    0.1970  0.47     0.3284   72
6801     0.4848  0.36     0.1343  166
12325    0.6212  0.36     0.0000  586
15151    0.6212  0.69     0.0000  361
```

[ ]:
```
bike_share_test.head(5)
```

[ ]:
```
         season  yr  mnth  hr  holiday  weekday  workingday  weathersit  temp  \
instant
11125         2   1     4  17        0        5           1           1  0.56
```

```
8155          4  0   12  10        0        0           0            1  0.24
6935          4  0   10  13        0        5           1            1  0.48
5145          3  0    8   6        0        0           0            1  0.70
4500          3  0    7   9        0        1           1            1  0.78

          atemp   hum  windspeed  cnt
instant
11125    0.5303  0.24     0.1642  738
8155     0.2879  0.44     0.0000  194
6935     0.4697  0.48     0.3284  206
5145     0.6667  0.89     0.1642   13
4500     0.7424  0.59     0.2985  208
```

[ ]:
```python
bike_share_target_train = bike_share_train["cnt"]
bike_share_target_test = bike_share_test["cnt"]

bike_share_train = bike_share_train.drop(columns = ["cnt"])
bike_share_test = bike_share_test.drop(columns = ["cnt"])
```

[ ]:
```python
linear_regressor = linear_model.LinearRegression()
```

[ ]:
```python
#linear_model = linear_regressor.fit(bike_share_train, bike_share_target_train)
```

[ ]:
```python
#linear_predictions = linear_model.predict(bike_share_test)
```

[ ]:
```python
linear_cross_validated = model_selection.cross_validate(linear_regressor,␣
 ↪bike_share_train, bike_share_target_train, return_estimator = True)
```

[ ]:
```python
print(linear_cross_validated)
```

```
{'fit_time': array([0.00600004, 0.00500011, 0.00500083, 0.00600147,
0.00500107]), 'score_time': array([0.00199866, 0.00300097, 0.0030005 , 0.0040009
, 0.00300074]), 'estimator': [LinearRegression(), LinearRegression(),
LinearRegression(), LinearRegression(), LinearRegression()], 'test_score':
array([0.36844688, 0.39820529, 0.4027645 , 0.39036941, 0.36895054])}
```

[ ]:
```python
linear_model_optimized = linear_cross_validated["estimator"][4]
```

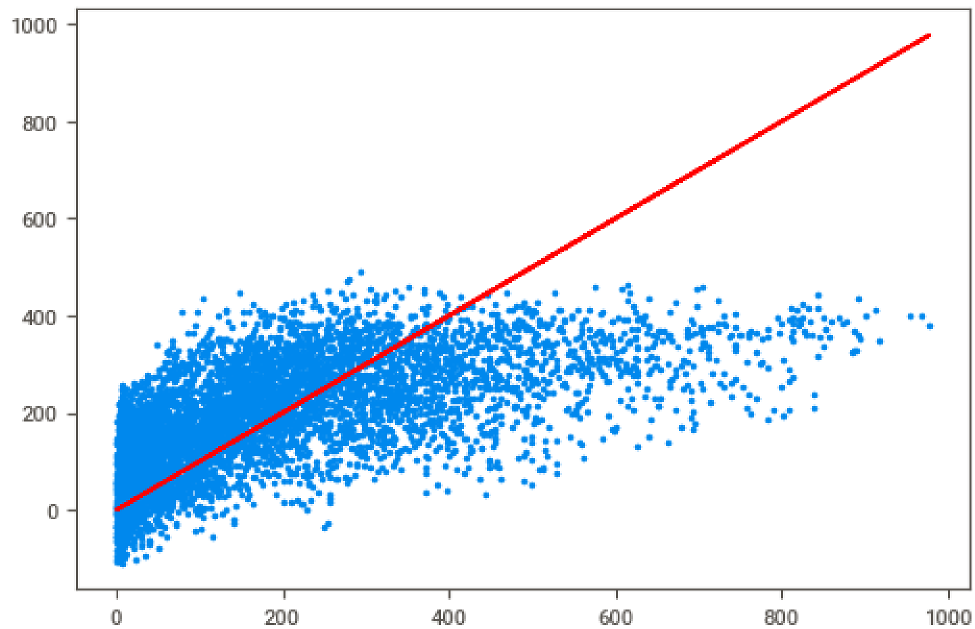
[ ]:
```python
linear_optimized_predictions = linear_model_optimized.predict(bike_share_test)
```

[ ]:
```python
r_squared = metrics.r2_score(bike_share_target_test,␣
 ↪linear_optimized_predictions)
linear_mse = metrics.mean_squared_error(bike_share_target_test,␣
 ↪linear_optimized_predictions)
linear_rmse = np.sqrt(linear_mse)
print(r_squared)
print(linear_rmse)
```

```
0.39186466949444654
142.43285542243592
```

[ ]:
```
plt.figure(1)
plt.plot(bike_share_target_test, linear_optimized_predictions, '.')
plt.plot(bike_share_target_test, bike_share_target_test, 'r-')
```

[ ]:
```
[<matplotlib.lines.Line2D at 0x1af4655de80>]
```



1.7 Part 3:

1.7.1 Model Training (Hint: trained all of these with a for loop and added my results to a PrettyTable.)

```
1)Create one-hot-encoded values for your categorical columns using
get_dummies and add them to your source dataset.
2) Drop the original categorical columns from your source dataset.
3) Do a test/train split based on your new source dataset. Implement and fit a
new linear model on your new training set.
4) What are the new values for r2, mse, and rmse?
5) Implement and score a decision tree regressor with random_state=0.
6) Implement and score a RandomForestRegressor with random_state=0
and n_esitmators=30.
7) Implement and score an SGDRegressor with max_iter=1000 and tol=1e3).
8) Implement and score a Lasso Regressor with alpha=0.1.
9) Implement and score an ElasticNet Regressor with random_state=0.
10) Implement and score a Ridge Regressor with alpha=0.5.
```

11) Implement and score a BaggingRegressor.

[ ]:
```
x = [i for i in range(0,9)]

categorical_data_set = bike_share_numeric_data = bike_share_data.iloc[:,x]
categorical_feature_names = categorical_data_set.columns
categorical_feature_names
```

[ ]:
```
Index(['season', 'yr', 'mnth', 'hr', 'holiday', 'weekday', 'workingday',
       'weathersit', 'temp'],
      dtype='object')
```

[ ]:
```
def rename_dummy_column(data_set, col_name):
    for col in data_set.columns:
        replace_string = col_name + "_" + str(col)
        data_set = data_set.rename(columns = {col : replace_string})
    return data_set
```

[ ]:
```
print(categorical_feature_names)
categorical_feature_names = categorical_feature_names.drop("temp")
```

```
Index(['season', 'yr', 'mnth', 'hr', 'holiday', 'weekday', 'workingday',
       'weathersit', 'temp'],
      dtype='object')
```

[ ]:
```
for feature in categorical_feature_names:
    dummy_data = pd.get_dummies(bike_share_data[feature])
    dummy_data = rename_dummy_column(dummy_data, feature)
    bike_share_data = bike_share_data.join(dummy_data)
```

[ ]:
```
bike_share_data.columns
```

[ ]:
```
Index(['season', 'yr', 'mnth', 'hr', 'holiday', 'weekday', 'workingday',
       'weathersit', 'temp', 'atemp', 'hum', 'windspeed', 'cnt', 'season_1',
       'season_2', 'season_3', 'season_4', 'yr_0', 'yr_1', 'mnth_1', 'mnth_2',
       'mnth_3', 'mnth_4', 'mnth_5', 'mnth_6', 'mnth_7', 'mnth_8', 'mnth_9',
       'mnth_10', 'mnth_11', 'mnth_12', 'hr_0', 'hr_1', 'hr_2', 'hr_3', 'hr_4',
       'hr_5', 'hr_6', 'hr_7', 'hr_8', 'hr_9', 'hr_10', 'hr_11', 'hr_12',
       'hr_13', 'hr_14', 'hr_15', 'hr_16', 'hr_17', 'hr_18', 'hr_19', 'hr_20',
       'hr_21', 'hr_22', 'hr_23', 'holiday_0', 'holiday_1', 'weekday_0',
       'weekday_1', 'weekday_2', 'weekday_3', 'weekday_4', 'weekday_5',
       'weekday_6', 'workingday_0', 'workingday_1', 'weathersit_1',
       'weathersit_2', 'weathersit_3', 'weathersit_4'],
      dtype='object')
```

[ ]:
```
bike_share_data = bike_share_data.drop(columns = categorical_feature_names)
```

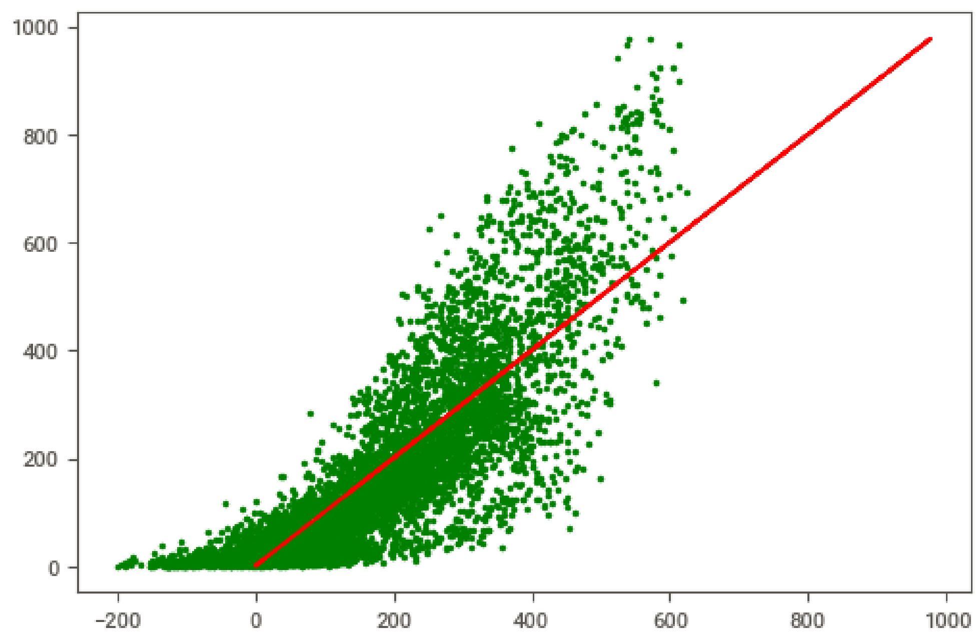
[ ]:
```
bike_share_train, bike_share_test = model_selection.
↪train_test_split(bike_share_data, test_size = .33)
```

[ ]:
```
bike_share_target_train = bike_share_train["cnt"]
bike_share_target_test = bike_share_test["cnt"]

bike_share_train = bike_share_train.drop(columns = ["cnt"])
bike_share_test = bike_share_test.drop(columns = ["cnt"])
```

[ ]:
```
bike_linear_model = linear_regressor.
↪fit(bike_share_train,bike_share_target_train)
```

[ ]:
```
linear_predictions = bike_linear_model.predict(bike_share_test)
```

[ ]:
```
plt.figure()
plt.plot(linear_predictions, bike_share_target_test, 'g.')
plt.plot(bike_share_target_test, bike_share_target_test, 'r-')
plt.show()
```



[ ]:
```
r_squared = metrics.r2_score(bike_share_target_test, linear_predictions)
linear_mse = metrics.mean_squared_error(bike_share_target_test,␣
↪linear_predictions)
linear_rsme = np.sqrt(linear_mse)

print("rsquared", r_squared)
print("linear_mse", linear_mse)
```

```
print("linear rmse", linear_rsme)
```

```
rsquared 0.681858881776355
linear_mse 10250.576897827319
linear rmse 101.24513271178678
```

Here we see that we have a higher r squared value and a lower root mean squared error. Categorizing all of the data gave us a better fit. One point to bring up is that at values larger than the mean, the lack of categorization led to underestimating the number of rentals and adding categorization to the variables led to over estimation

```
[ ]: def plot_predictions(true_values, predicted_values, title = ""):
         plt.figure()
         plt.plot(true_values, predicted_values,'.')
         plt.plot(true_values, true_values, 'r-')
         plt.xlabel("True Values")
         plt.ylabel("Predicted Values")
         plt.title(title)
         plt.show()
```

```
[ ]: def score_model(true_values, predicted_values):

         model_score = {
             "rsquared" : metrics.r2_score(true_values, predicted_values),
             "mse" : metrics.mean_squared_error(true_values, predicted_values),
             "rmse" : np.sqrt(metrics.mean_squared_error(true_values,␣
     ↪predicted_values))
             }

         return model_score
```

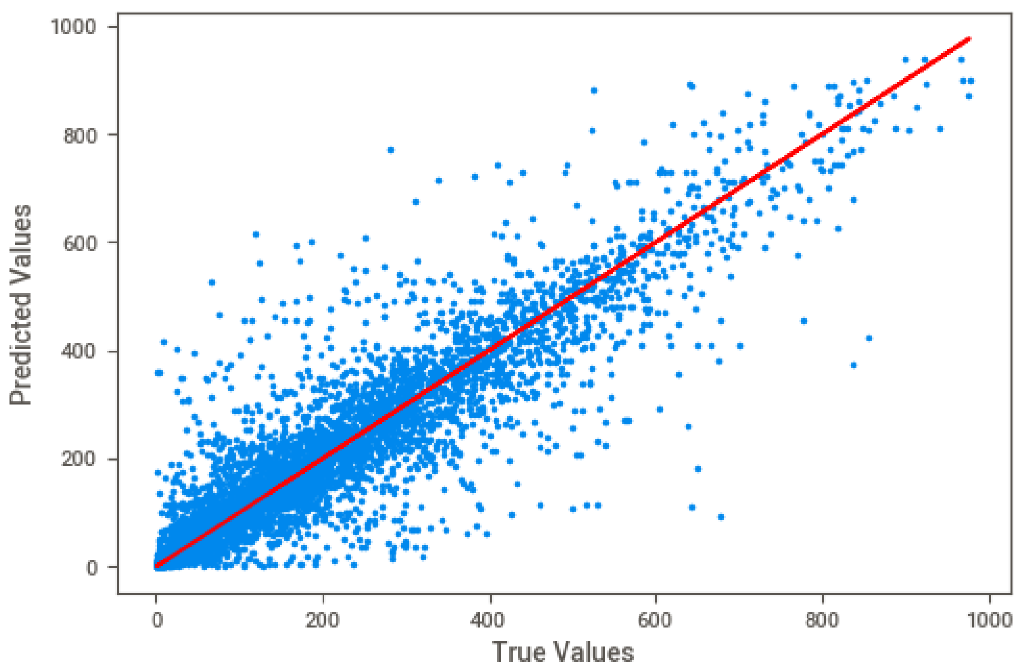
```
[ ]: def fit_and_score(regressor, train, target_train, test, target_test, title =␣
     ↪""):

         print(title)

         ## fitting the data and predicting:
         model = regressor.fit(train, target_train)
         predictions = model.predict(test)

         ## plotting the predictions by the true values
         plot_predictions(target_test, predictions)

         ## scoring and printing
         model_scores = score_model(target_test, predictions)
         for score in model_scores:
             print(score, model_scores[score])
```

```
    print("\n\n---------------------")
```

[ ]:
```
regressors = {

    "Decision Tree" : tree.DecisionTreeRegressor(random_state=0),
    "Random Forest" : ensemble.RandomForestRegressor(random_state=0,␣
 ↪n_estimators=30),
    "Stochastic Gradient Decent" : linear_model.SGDRegressor(max_iter=1000,␣
 ↪tol=1e3),
    "Lasso Regression" : linear_model.Lasso(alpha=.1),
    "Ridge Regression": linear_model.Ridge(alpha=.5),
    "Elastic Net": linear_model.ElasticNet(random_state=0),
    "Bagging" : ensemble.BaggingRegressor()

}
```

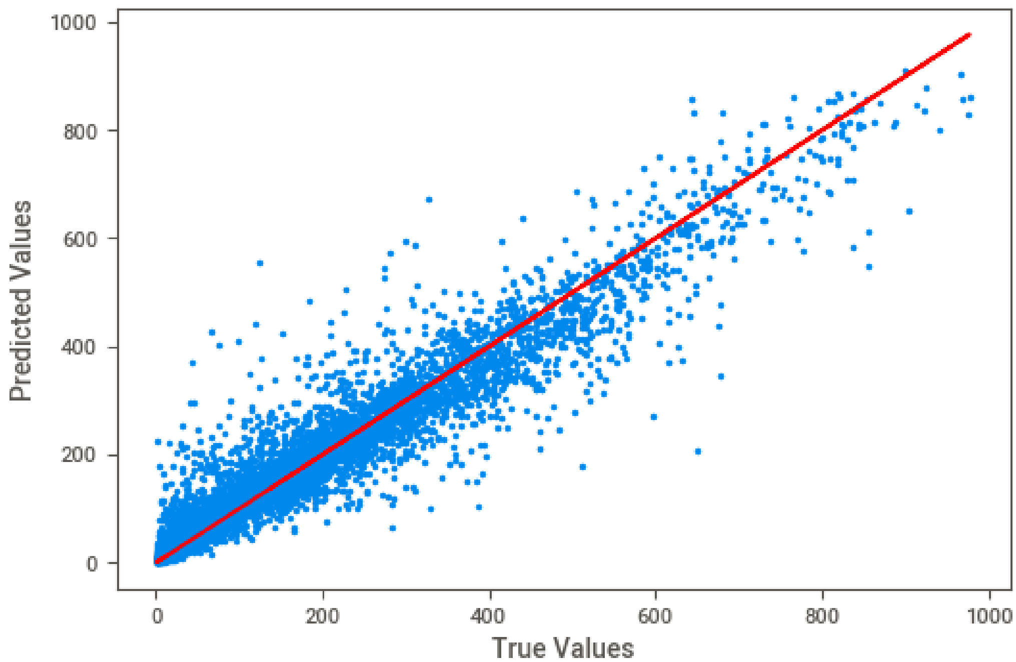
[ ]:
```
for regressor in regressors:
    fit_and_score(regressors[regressor], bike_share_train,␣
 ↪bike_share_target_train, bike_share_test, bike_share_target_test, regressor)
```

```
Decision Tree
```



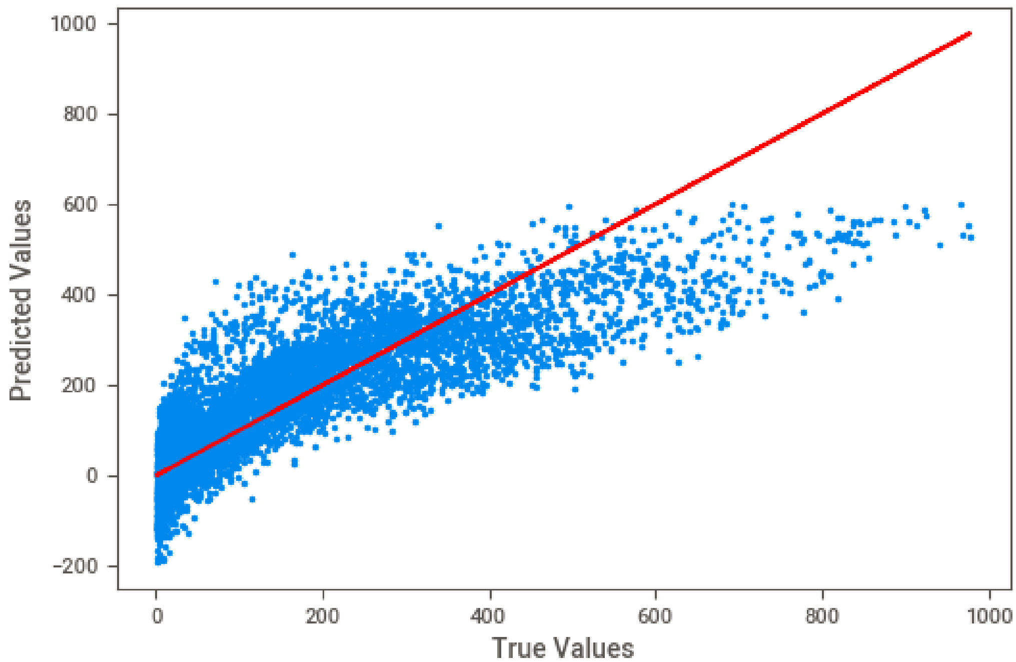

```
rsquared 0.8316652915565048
mse 5423.781380753138
rmse 73.64632632218078
```

```
---------------------
Random Forest
```

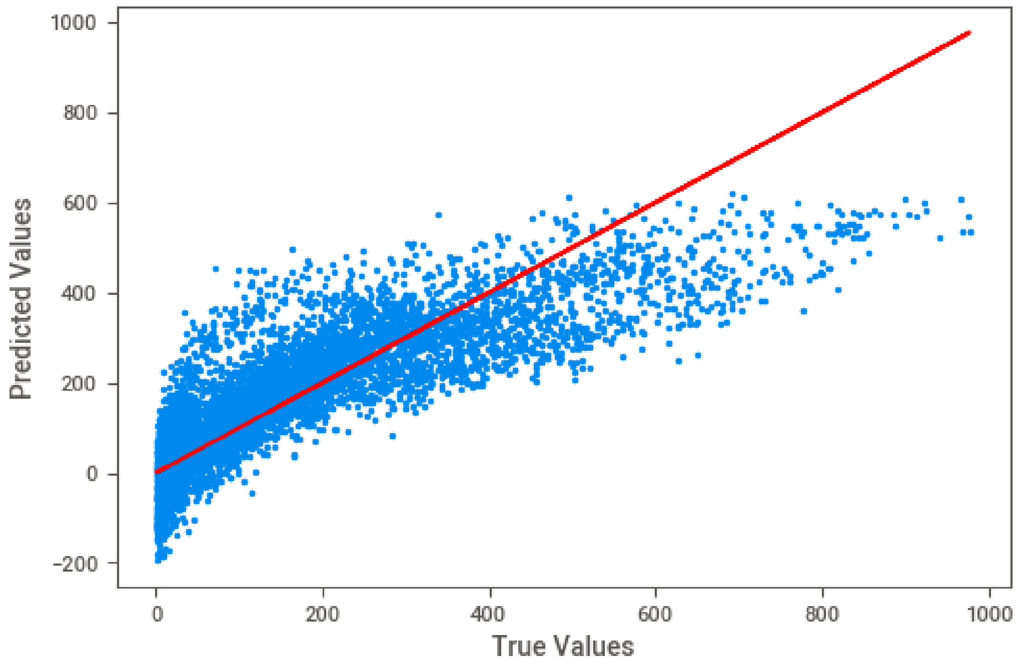



```
rsquared 0.9110772758920012
mse 2865.1097554531057
rmse 53.52672001396224
```

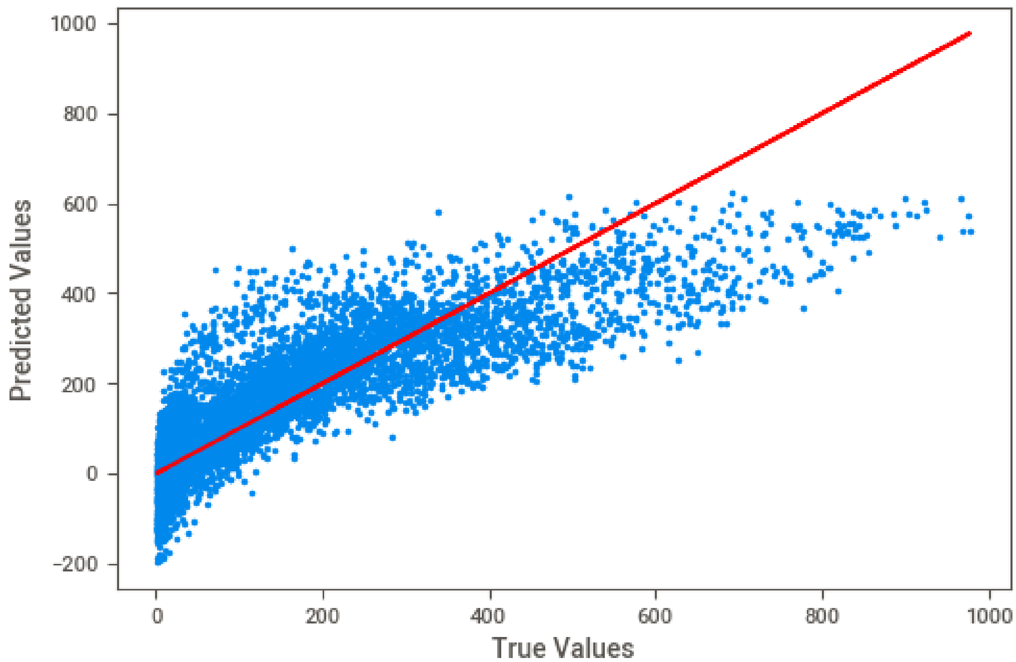
```
---------------------
Stochastic Gradient Decent
```



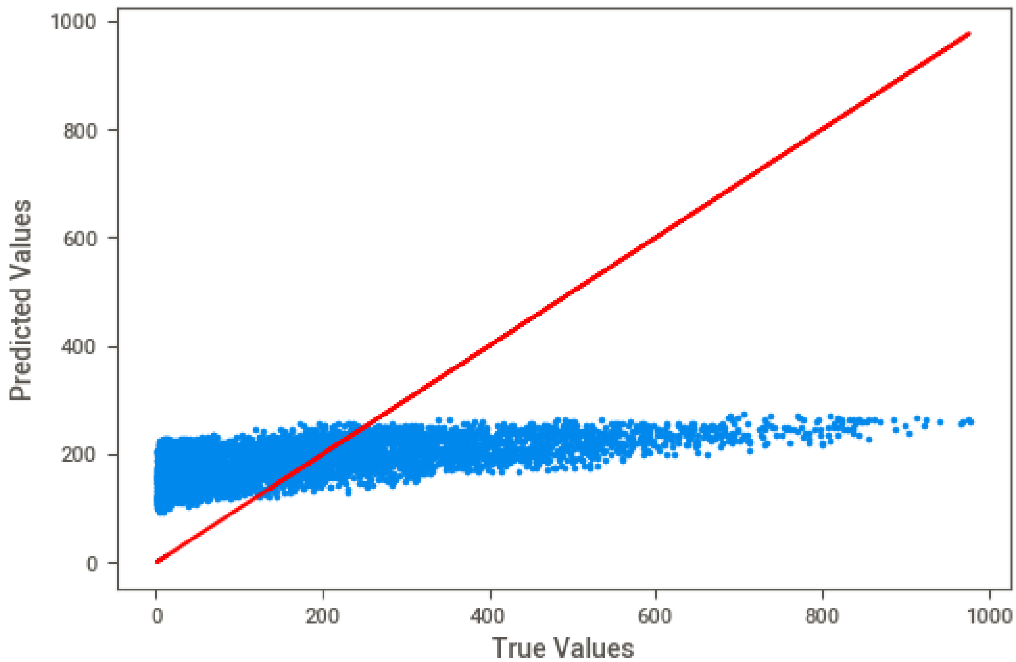

```
rsquared 0.6792376056020615
mse 10335.034993483316
rmse 101.66137414713278


---------------------
Lasso Regression
```



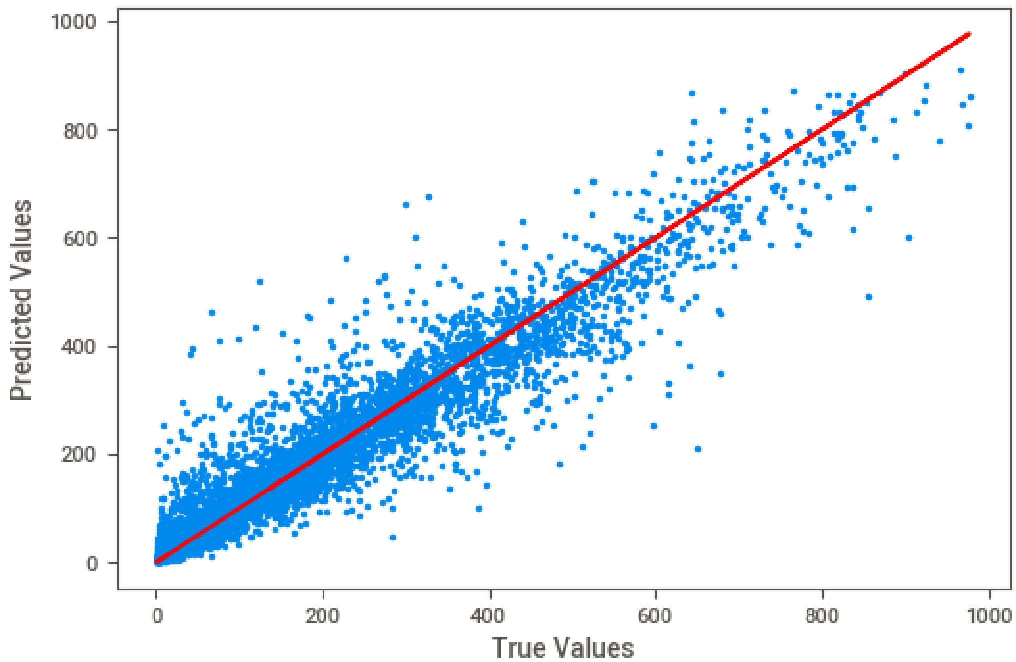

```
rsquared 0.6821760246728652
mse 10240.358483852953
rmse 101.19465639969806


---------------------
Ridge Regression
```




```
rsquared 0.6819070741255705
mse 10249.02412972152
rmse 101.23746406208286


---------------------
Elastic Net
```




```
rsquared 0.19518293000647968
mse 25931.38325129425
rmse 161.03224289344743


---------------------
Bagging
```




```
rsquared 0.9000254741102476
mse 3221.2012429538586
rmse 56.75562741221225
```

1.8 Part 4:

1.8.1 Model Tuning

1) Take the top three performing models and implement cross-validation on them. Hint: They should be Decision Tree Regressor, RandomForestRegressor, and BaggingRegressor.
2) Take your top performing model (mine was the RandomForestRegressor) and do a randomize search cv with 20 iterations and three folds. I found it is best to set your n_jobs = (# of cpu's you have – 1). This took about 10 minutes on my MacBook with 4 CPUs and 8 GB of memory. Your param distributions should include the following:
   1) Bootstrap: true, false
   2) Max_depth: 10-110
   3) number of bins: 11
   4) Max_features: auto, sqrt
   5) Min_samples_split: 2,5,10
   6) Min_samples_leaf: 1,2,4
   7) 200 – 2000, number of bins 10
3) Take your best_estimator_ and see how it compares by doing cross_vals for r2, mse, and calculating rmse.

4) Finally, run predictions on your test set with this model, and see how your r2 score and RMSE look.

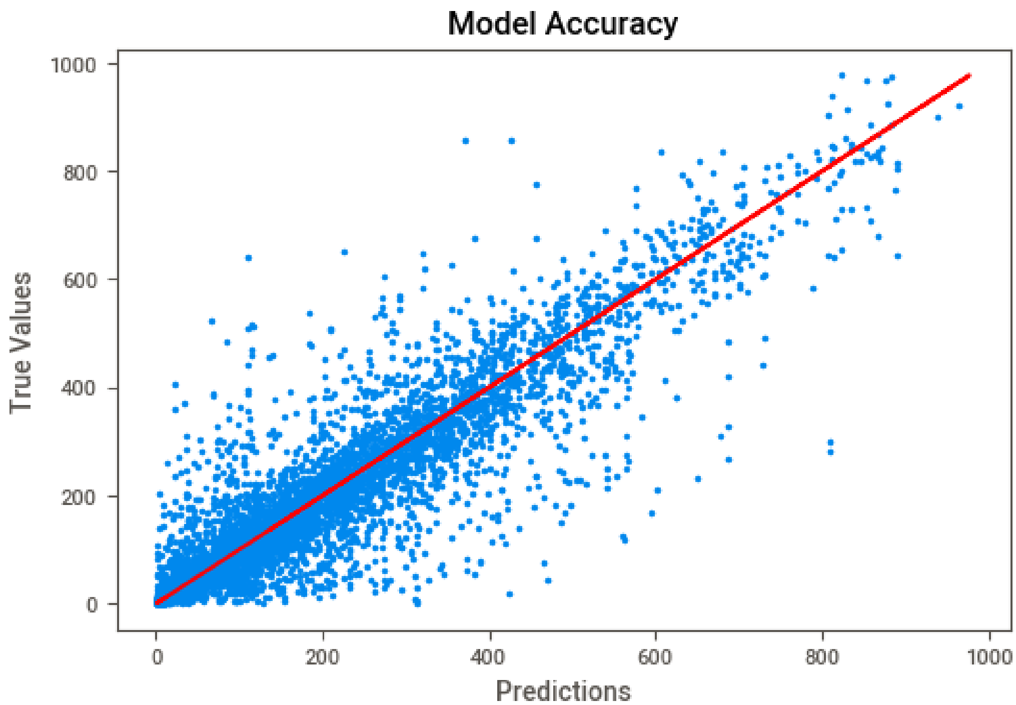
```
[ ]: class CrossValidatedModel:

         def __init__(self, regressor, train_data, target, test_data, target_test):
             self.model = self._cross_validate(regressor, train_data, target)
             self.predictions = self._predict(test_data)
             self.mse = metrics.mean_squared_error(self.predictions, target_test)
             self.rmse = np.sqrt(self.mse)
             self._target_test = target_test


         def _cross_validate(self, regressor, train_data, target):
             cross_validation = model_selection.cross_validate(regressor,␣
      ↪train_data, target, return_estimator = True)
             max_score = max(cross_validation["test_score"])
             max_score_index = list(cross_validation["test_score"]).index(max_score)
             best_model = cross_validation["estimator"][max_score_index]
             return best_model

         def _predict(self, test_data):
             return self.model.predict(test_data)

         def _plot(self):
             plt.figure()
             plt.plot(self.predictions, self._target_test,'.')
             plt.plot(self._target_test, self._target_test,'r-')
             plt.title("Model Accuracy")
             plt.ylabel("True Values")
             plt.xlabel("Predictions")
             plt.show()

         def display_results(self):
             print("rmse", self.rmse)
             self._plot()
```

```
[ ]: best_models = {
         "tree" : tree.DecisionTreeRegressor(),
         "random_forest" : ensemble.RandomForestRegressor(),
         "bagging" : ensemble.BaggingRegressor()
     }
```

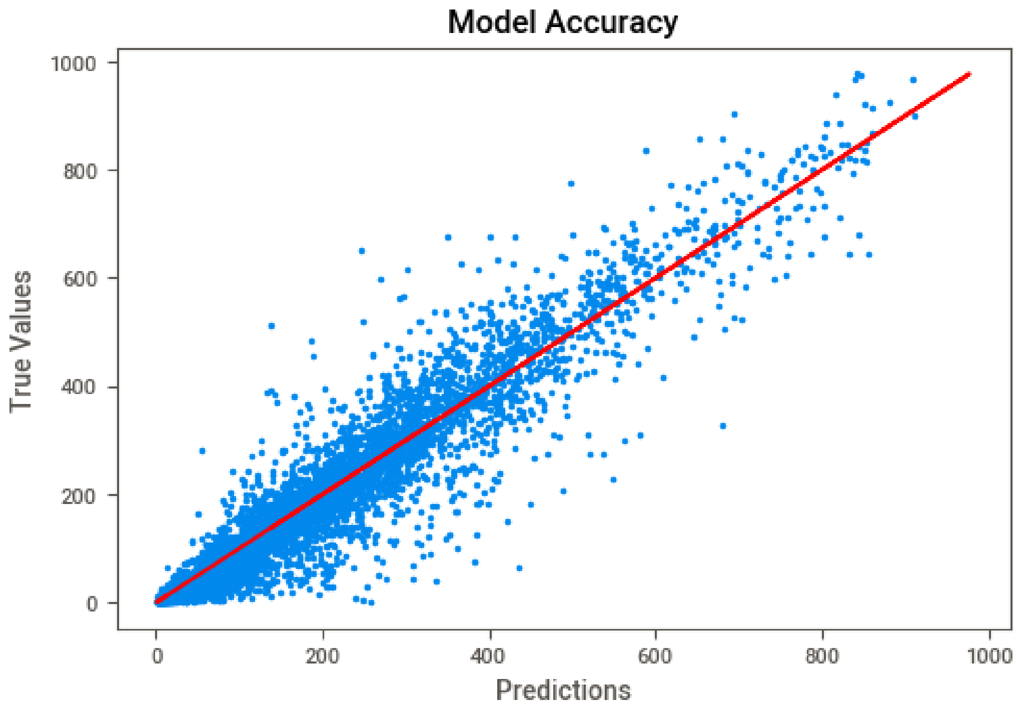
```
[ ]: for regressor in best_models:
         print(regressor)
```

```
    cross_validated = CrossValidatedModel(best_models[regressor],
 ↪bike_share_train, bike_share_target_train, bike_share_test,
 ↪bike_share_target_test)
    cross_validated.display_results()
```

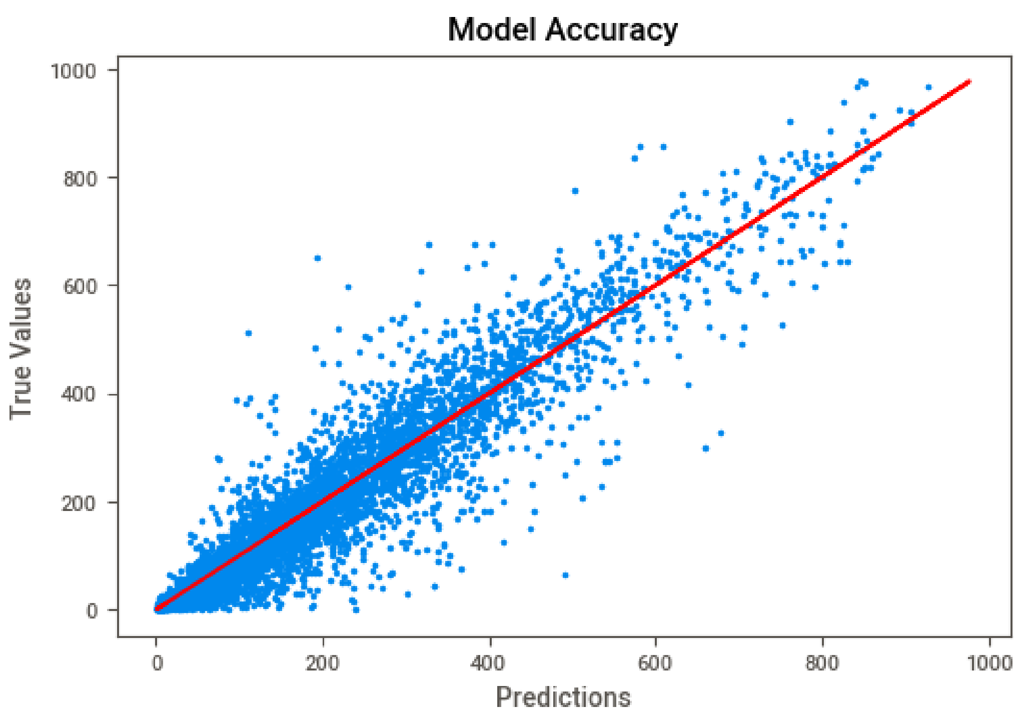
```
tree
rmse 75.1218361860686
```




```
random_forest
rmse 54.7726618841057
```




```
bagging
rmse 58.399783708385364
```



[ ]:
```
hyperparameters = {
    "bootstrap": [True, False],
    "max_depth": [i for i in range(10,110,10)],
    "max_features": ["auto", "sqrt"],
    "min_samples_split": [2,5,10],
    "min_samples_leaf": [1,2,4]
}
```

[ ]:
```
###Just checking to see what the parameters are for a random forest regressor␣
↪to create the hyper parameter dict.
random_forrest_regressor = ensemble.RandomForestRegressor(random_state=0)
random_forrest_regressor.get_params()
```

[ ]:
```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'criterion': 'mse',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 0,
 'verbose': 0,
 'warm_start': False}
```

[ ]:
```
random_search_cv = model_selection.RandomizedSearchCV(random_forrest_regressor,␣
↪hyperparameters, n_jobs = 11)
```

[ ]:
```
forrest_random_search_model = random_search_cv.fit(bike_share_train,␣
↪bike_share_target_train)
```

[ ]:
```
forrest_random_search_model_params = forrest_random_search_model.best_params_
forrest_random_search_model_params
```

[ ]:
```
{'min_samples_split': 2,
 'min_samples_leaf': 2,
 'max_features': 'auto',
 'max_depth': 30,
```

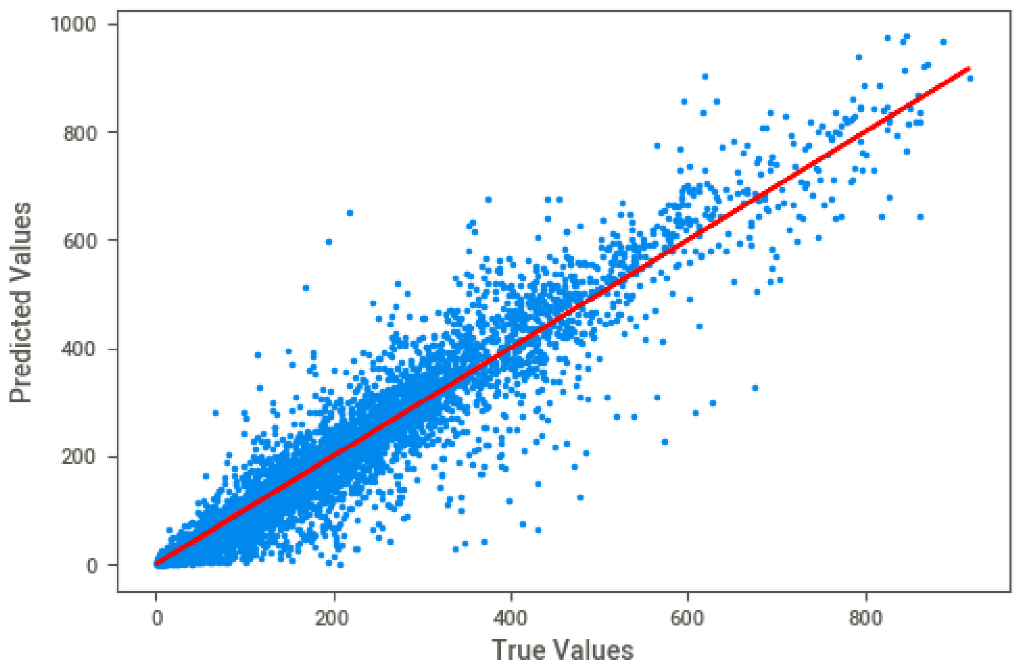
```
'bootstrap': True}
```

```
[ ]: forrest_random_search_predictions = forrest_random_search_model.
      ↪predict(bike_share_test)
```

```
[ ]: forrest_optimized_mse = metrics.
      ↪mean_squared_error(forrest_random_search_predictions, bike_share_target_test)
     forrest_optimized_rmse = np.sqrt(forrest_optimized_mse)
     forrest_optimized_rsquared = metrics.
      ↪r2_score(forrest_random_search_predictions, bike_share_target_test)
```

```
[ ]: print("optimized rmse: ", forrest_optimized_rmse)
     print("optimized rsquared: ", forrest_optimized_rsquared)

     plot_predictions(forrest_random_search_predictions, bike_share_target_test)
```

```
optimized rmse:  54.076789933816016
optimized rsquared:  0.8957180668266025
```



2 Conclusions:

In conclusion, if we observe our random forrest model, the initial random forest model has a rmse of ~51, while the cross validated model has a worse rmse of ~53, and the random search validation has a rmse of ~50. Our random search cv of the random forest gave us the best results.