ECE 219 Project 4: Regression Analysis and Define Your Own Task!

In [2]:
```
# import all necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# allows matlab plots to be generated in line
%matplotlib inline

from google.colab import drive
drive.mount("/content/drive/")

# add system path to current directory
import sys
sys.path.append('/content/drive/MyDrive/Colab Notebooks/ECE_219/Project4')
```

Dataset 1: Diamond Characteristics

In [3]:
```
# read the csv file and get the shape
file_path = '/content/drive/MyDrive/Colab Notebooks/ECE_219/Project4/dataset/diamond
diamond_df = pd.read_csv(file_path, index_col=0)

rows, columns = diamond_df.shape

print('Total number of rows: {0} and columns: {1}'.format(rows, columns))
diamond_df.head(5)
```

```
Total number of rows: 53940 and columns: 10
```

Out[3]:

	carat	cut	color	clarity	depth	table	price	x	y	z
1	0.23	Ideal	E	SI2	61.5	55.0	330	3.95	3.98	2.43
2	0.21	Premium	E	SI1	59.8	61.0	327	3.89	3.84	2.31
3	0.23	Good	E	VS1	56.9	65.0	328	4.05	4.07	2.31
4	0.29	Premium	I	VS2	62.4	58.0	337	4.20	4.23	2.63
5	0.31	Good	J	SI2	63.3	58.0	338	4.34	4.35	2.75

3 Required Steps

3.1 Before Training

3.1.1 Handling Categorical Features

In [4]:
```
mapping_table = {'cut':{'Fair': 1, 'Good': 2, 'Very Good': 3, 'Premium': 4, 'Ideal':
                 'color':{'J': 1, 'I': 2, 'H': 3, 'G': 4, 'F': 5, 'E': 6, 'D': 7},
                 'clarity':{'I1': 1, 'SI2': 2, 'SI1': 3, 'VS2': 4, 'VS1': 5,
                            'VVS2': 6, 'VVS1': 7, 'IF': 8}
                }
```

```
# convert the categorical features
diamond_df = diamond_df.replace(mapping_table)
diamond_df.head()
```

Out[4]:

	carat	cut	color	clarity	depth	table	price	x	y	z
1	0.23	5	6	2	61.5	55.0	330	3.95	3.98	2.43
2	0.21	4	6	3	59.8	61.0	327	3.89	3.84	2.31
3	0.23	2	6	5	56.9	65.0	328	4.05	4.07	2.31
4	0.29	4	2	4	62.4	58.0	337	4.20	4.23	2.63
5	0.31	2	1	2	63.3	58.0	338	4.34	4.35	2.75

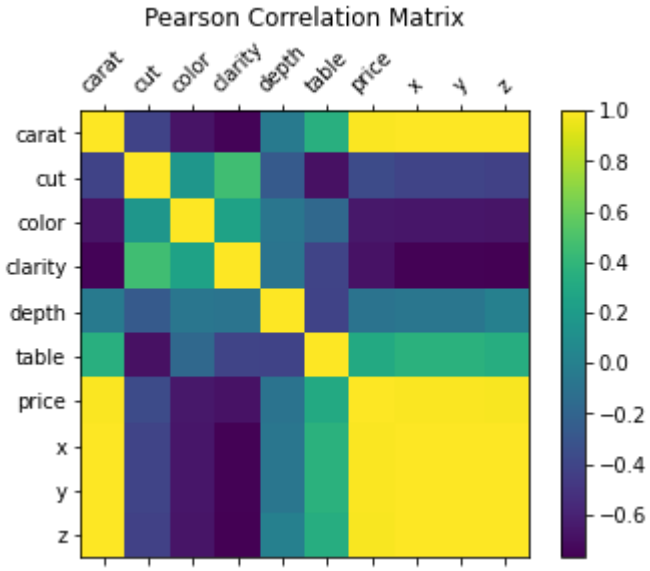
3.1.2 Data Inspection

In [6]:

```
# calculate the pearson correlation
pearson_corr = diamond_df.corr(method='pearson')

# plot
f = plt.figure(figsize=(6, 4))
plt.matshow(pearson_corr.corr(), fignum=f.number)
plt.xticks(range(pearson_corr.select_dtypes(['number']).shape[1]),
           pearson_corr.select_dtypes(['number']).columns, fontsize=10, rotation=45)
plt.yticks(range(pearson_corr.select_dtypes(['number']).shape[1]),
           pearson_corr.select_dtypes(['number']).columns, fontsize=10)
cb = plt.colorbar()
cb.ax.tick_params(labelsize=10)
plt.title('Pearson Correlation Matrix', fontsize=12)

# only look at the price column
pearson_corr['price']
```

Out[6]:

```
carat      0.921591
cut       -0.053493
color     -0.172509
clarity   -0.146802
depth     -0.010648
table      0.127134
price      1.000000
x          0.884436
y          0.865422
z          0.861250
Name: price, dtype: float64
```



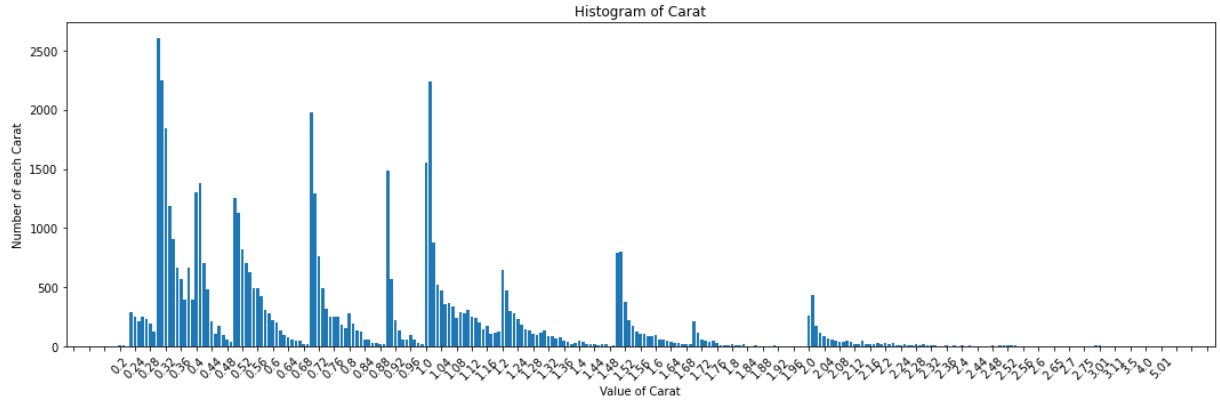
QUESTION 1.1: Plot a heatmap of the Pearson correlation matrix of the dataset columns. Report which features have the highest absolute correlation with the target variable. In the context of either dataset, describe what the correlation patterns suggest.

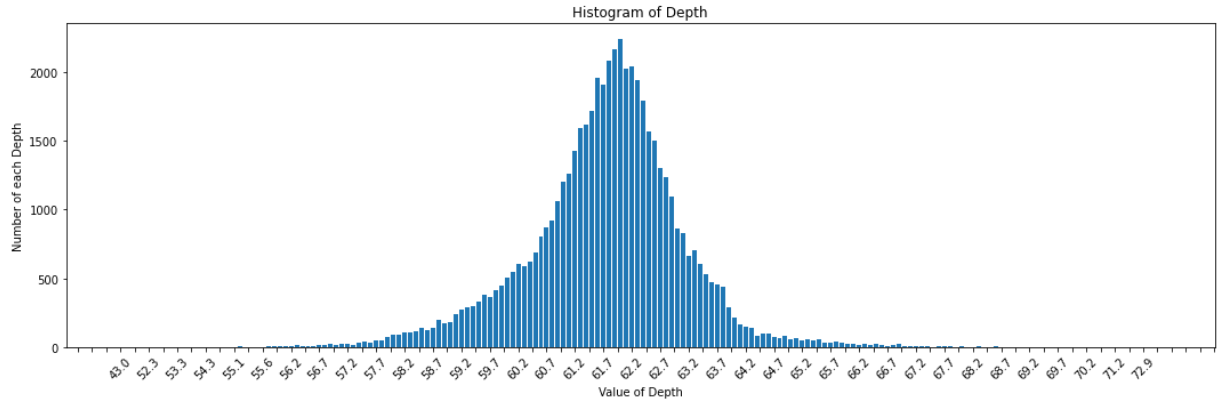
ANSWER 1.1: The plot is shown above. Carat is the feature with the highest absolute correlation with the target variable, price. Based on the pattern of the pearson correlation matrix, one can tell that the features such as carat, x, y and z are highly related to the price and thus are the most important features to utilize to trian the model. The rest of the features, on the other hand, might as well also provide some useful information but not as informative as those four for the purpose of price estimation.

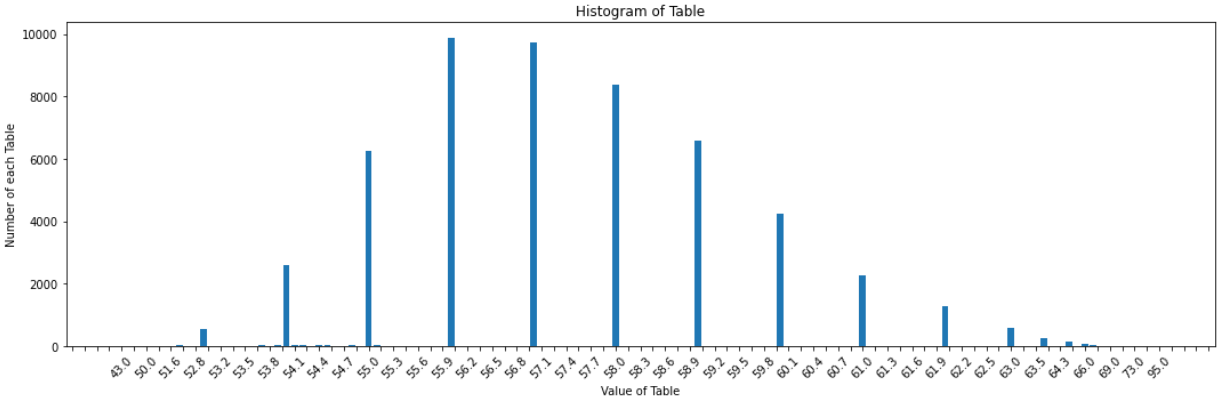
In [ ]:

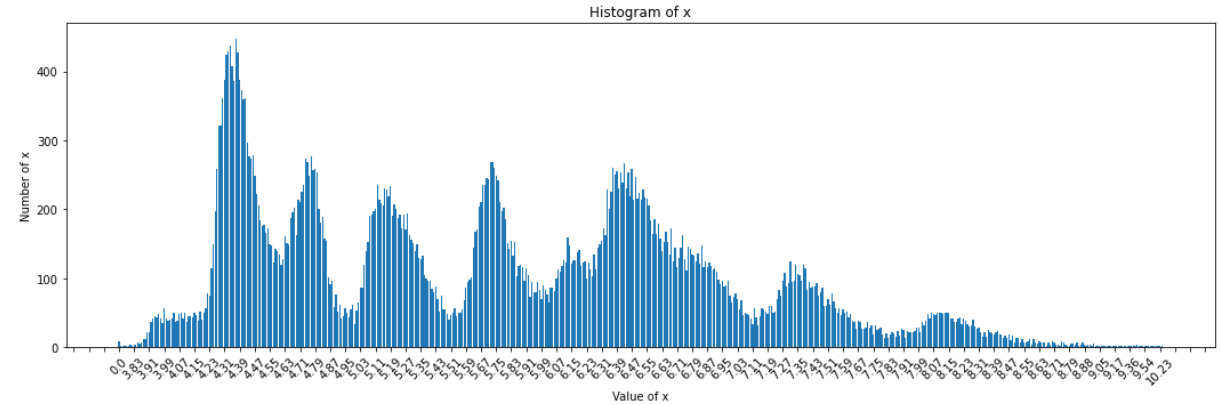
```
# the numerical features are carat, depth, table, x, y, z

# plot
fig, axes = plt.subplots(nrows=6, ncols=1, figsize=(15, 30))

# histogram of 'carat'
unique, counts = np.unique(diamond_df['carat'].to_numpy(), return_counts=True)
axes[0].bar(range(len(unique)), counts)
axes[0].set_xticks(range(len(unique)), unique, rotation=45)
axes[0].xaxis.set_major_locator(plt.MaxNLocator(100))
axes[0].set_xlabel('Value of Carat')
axes[0].set_ylabel('Number of each Carat')
axes[0].set_title('Histogram of Carat')

# histogram of 'depth'
unique, counts = np.unique(diamond_df['depth'].to_numpy(), return_counts=True)
axes[1].bar(range(len(unique)), counts)
axes[1].set_xticks(range(len(unique)), unique, rotation=45)
axes[1].xaxis.set_major_locator(plt.MaxNLocator(100))
axes[1].set_xlabel('Value of Depth')
axes[1].set_ylabel('Number of each Depth')
axes[1].set_title('Histogram of Depth')

# histogram of 'table'
unique, counts = np.unique(diamond_df['table'].to_numpy(), return_counts=True)
axes[2].bar(range(len(unique)), counts)
axes[2].set_xticks(range(len(unique)), unique, rotation=45)
axes[2].xaxis.set_major_locator(plt.MaxNLocator(100))
```

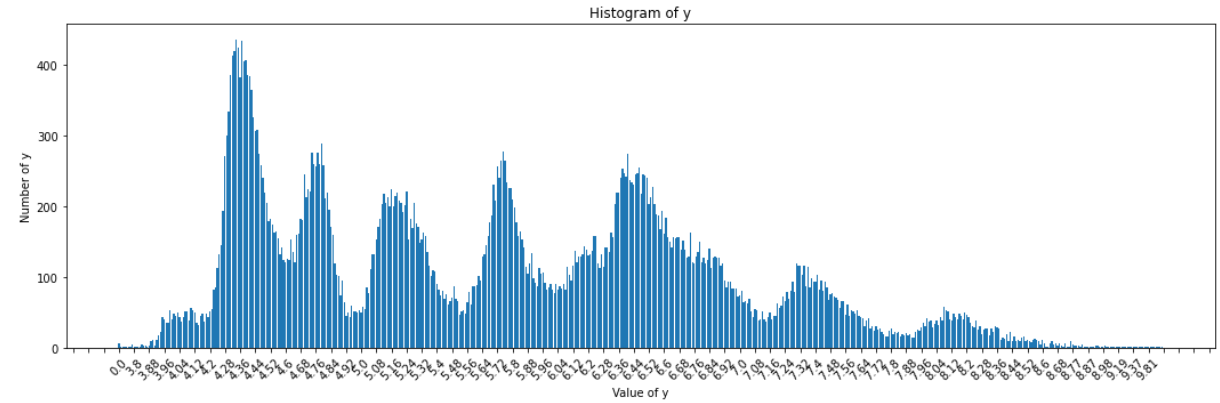
```
axes[2].set_xlabel('Value of Table')
axes[2].set_ylabel('Number of each Table')
axes[2].set_title('Histogram of Table')

# histogram of 'x'
unique, counts = np.unique(diamond_df['x'].to_numpy(), return_counts=True)
axes[3].bar(range(len(unique)), counts)
axes[3].set_xticks(range(len(unique)), unique, rotation=45)
axes[3].xaxis.set_major_locator(plt.MaxNLocator(100))
axes[3].set_xlabel('Value of x')
axes[3].set_ylabel('Number of x')
axes[3].set_title('Histogram of x')

# histogram of 'y'
unique, counts = np.unique(diamond_df['y'].to_numpy(), return_counts=True)
axes[4].bar(range(len(unique)), counts)
axes[4].set_xticks(range(len(unique)), unique, rotation=45)
axes[4].xaxis.set_major_locator(plt.MaxNLocator(100))
axes[4].set_xlabel('Value of y')
axes[4].set_ylabel('Number of y')
axes[4].set_title('Histogram of y')

# histogram of 'z'
unique, counts = np.unique(diamond_df['z'].to_numpy(), return_counts=True)
axes[5].bar(range(len(unique)), counts)
axes[5].set_xticks(range(len(unique)), unique, rotation=45)
axes[5].xaxis.set_major_locator(plt.MaxNLocator(100))
axes[5].set_xlabel('Value of z')
axes[5].set_ylabel('Number of z')
axes[5].set_title('Histogram of z')

fig.tight_layout()
plt.show()
```


Histogram of Carat
Number of each Carat
Value of Carat


Histogram of Depth
Number of each Depth
Value of Depth


Histogram of Table
Number of each Table
Value of Table


Histogram of x
Number of x
Value of x


Histogram of y
Number of y
Value of y

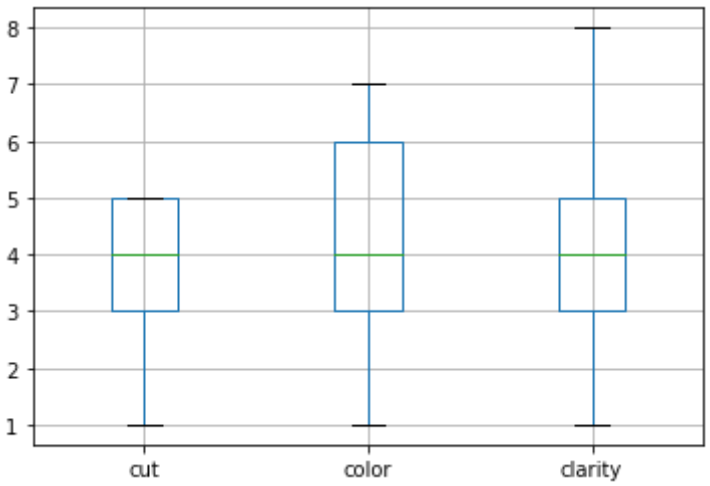

Histogram of z

QUESTION 1.2: Plot the histogram of numerical features. What preprocessing can be done if the distribution of a feature has high skewness?

ANSWER 1.2: The results of the histogram of numerical features are shown above. If the distribution of a certain feature has high skewness, one can apply normalization or standardization techniques to resolve it.

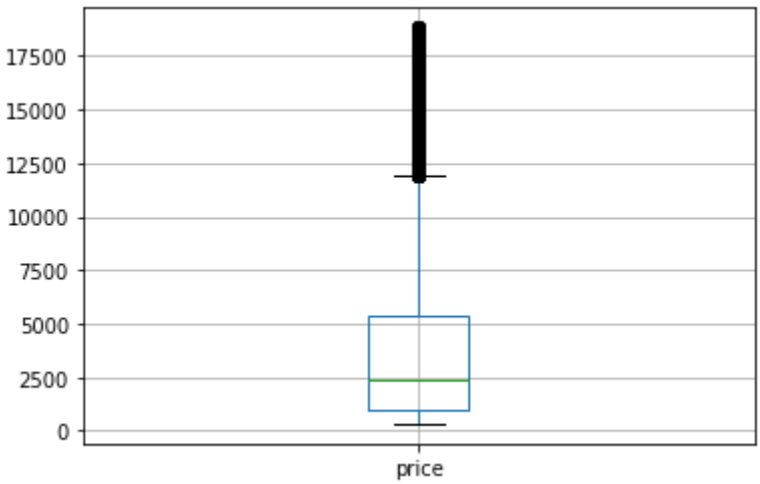
In [ ]:
```
diamond_df.boxplot(column=['cut', 'color', 'clarity'])
```

Out[ ]:
```
<Axes: >
```



In [7]:
```
diamond_df.boxplot(column=['price'])
```

Out[7]:
```
<Axes: >
```

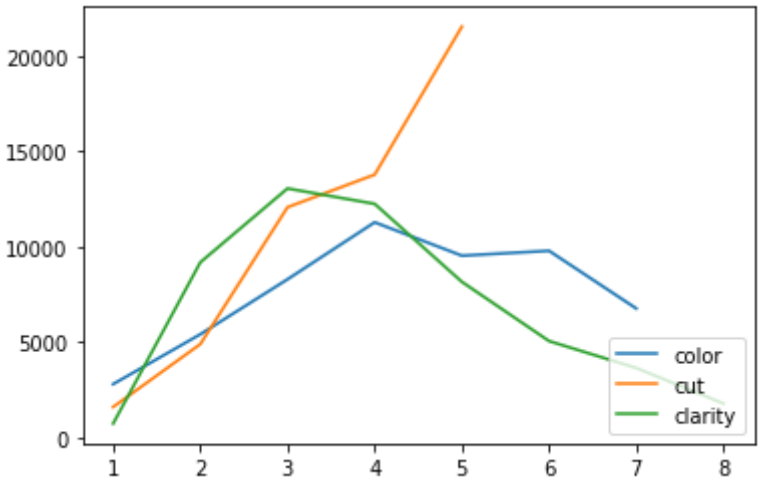


QUESTION 1.3: Construct and inspect the box plot of categorical features vs target variable. What do you find?

ANSWER 1.3: The price of a diamond is affected differently between each categorical feature. It seems not to depend on the quality of the cut since most of the diamond (the upper quartile) have high quality cut but the price is still relative low. Clarity and color, on the other hand, show more correlation with the price. But still, the price of most of the diamond

(the upper quartile)is relative low compared to the highest price, which means there might be other factors that affect more to the price of a diamond.

In [8]:
```
color_unique, color_counts = np.unique(diamond_df['color'].to_numpy(), return_counts
cut_unique, cut_counts = np.unique(diamond_df['cut'].to_numpy(), return_counts=True)
clarity_unique, clarity_counts = np.unique(diamond_df['clarity'].to_numpy(), return_

plt.plot(color_unique, color_counts, label='color')
plt.plot(cut_unique, cut_counts, label='cut')
plt.plot(clarity_unique, clarity_counts, label='clarity')
plt.legend(loc=4)
plt.show()
```



QUESTION 1.4: Plot the counts by color, cut and clarity.

ANSWER 1.4: The plots are shown above.

3.1.3 Standardization

In [9]:
```
from sklearn.preprocessing import StandardScaler
from sklearn_pandas import DataFrameMapper

# split into training features and target
X_df = diamond_df[['carat', 'cut', 'color', 'clarity', 'depth', 'table', 'x', 'y','z
y_df = diamond_df['price']

mapper = DataFrameMapper([(X_df.columns, StandardScaler())])
X_scaled = mapper.fit_transform(X_df.copy(), len(X_df.columns))
X_scaled_df = pd.DataFrame(X_scaled, index=X_df.index, columns=X_df.columns)
X_scaled_df.head(5)
```

Out[9]:

	carat	cut	color	clarity	depth	table	x	y	z
1	-1.198168	0.981473	0.937163	-1.245215	-0.174092	-1.099672	-1.587837	-1.536196	-1.571129
2	-1.240361	0.085889	0.937163	-0.638095	-1.360738	1.585529	-1.641325	-1.658774	-1.741175
3	-1.198168	-1.705279	0.937163	0.576145	-3.385019	3.375663	-1.498691	-1.457395	-1.741175
4	-1.071587	0.085889	-1.414272	-0.030975	0.454133	0.242928	-1.364971	-1.317305	-1.287720
5	-1.029394	-1.705279	-2.002131	-1.245215	1.082358	0.242928	-1.240167	-1.212238	-1.117674

QUESTION 2.1: Standardize feature columns and prepare them for training.

ANSWER 2.1: The standardized results are shown above.

3.1.4 Feature Selection

In [10]:
```
from sklearn.feature_selection import mutual_info_regression, f_regression

# get features and target
X = X_scaled
y = y_df.to_numpy()

# calculate the mutual info and f-score
mi_reg = mutual_info_regression(X, y)
f_reg = f_regression(X, y)
```

In [11]:
```
mi_reg_pd = pd.Series(mi_reg)
mi_reg_pd.index = X_scaled_df.columns
mi_reg_pd.sort_values(ascending=False)
```

Out[11]:
```
carat      1.652971
y          1.420542
x          1.413453
z          1.361221
clarity    0.215971
color      0.137740
cut        0.058884
table      0.035162
depth      0.031628
dtype: float64
```

In [12]:
```
f_reg_pd = pd.DataFrame(f_reg, index=np.array(['F-statistic', 'p-values']),
                        columns=X_scaled_df.columns)
f_reg_pd
```

Out[12]:

	carat	cut	color	clarity	depth	table	
F-statistic	304051.486619	1.547845e+02	1654.401244	1.188007e+03	6.115863	8.861194e+02	193741.52
p-values	0.000000	1.746019e-35	0.000000	1.571721e-257	0.013400	3.769963e-193	0.00

QUESTION 2.2: You **may** use these functions to select features that yield better regression results (especially in the classical models). Describe how this step qualitatively affects the performance of your models in terms of test RMSE. Is it true for all model types? Also list two features for either dataset that has the lowest MI w.r.t to the target.

ANSWER 2.2: Feature selection is an important step in machine learning. A good and strong correlated feature with high MI value can lead to a model with high performance and low test RMSE. A week or uncorrelated feature with low MI value will cause a hard time to train a

good and robust model since such feature is not representative and uninformative enough to the target variable and is like noise to the model. Thus, including such feature, will increase the test RMSE and decrease the model performance. In diamond dataset, 'depth' and 'table' are the features with the lowest MI w.r.t to the target.

3.2 Training + 3.3 Evaluation

QUESTION 3: For random forest model, measure "Out-of-Bag Error" (OOB) as well.Explain what OOB error and R^2 score means given this link.

ANSWER 3: The out-of-bag (OOB) error is the average error on each training sample x_i predicted by the trained models such as random forest that didn't include x_i in their bootstrap sample under the utilization of bootstrap aggregating technique/algorithm. R^2 score is a statistical measure in a regression model that determines the proportion of variance in the dependent variable that can be explained by the independent variable. It explains the goodness of the data fitting in the regression model and the variance of one variable against another.

3.3.1 Linear Regression

In [13]:
```
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import ShuffleSplit, KFold
```

In [34]:
```
'''
Training regression models with standardized features
'''

# get the standardized features and select
# here I choose 'carat', 'cut', 'color', 'clarity', 'x', 'y', 'z' as features to tra
X = X_scaled_df[['carat', 'cut', 'color', 'clarity', 'x', 'y', 'z']].to_numpy()
y = y_df.to_numpy()


# normal linear regression
LR = LinearRegression()
cv = KFold(n_splits=10, shuffle=True, random_state=42)
LR_errors = cross_val_score(LR, X, y , cv=cv, scoring='neg_root_mean_squared_error')
LR_error = LR_errors.mean()*-1
print('Linear Regression - RMSE: {:5.4f}'.format(LR_error))


# lasso regression, alpha: 1e-5 ~ 1e5
l1_best_error = np.inf
LR_l1_error_list = []
for k in range(-5, 5+1):
    # lasso model
    alpha = 10**k
    LR_l1 = Lasso(alpha)
    # train with cross validation
    cv = KFold(n_splits=10, shuffle=True, random_state=42)
    LR_l1_errors = cross_val_score(LR_l1, X, y, cv=cv, scoring='neg_root_mean_square
    cur_error = LR_l1_errors.mean()*-1
```

```
    LR_l1_error_list.append(cur_error)
    # find the best
    if cur_error < l1_best_error:
        l1_best_error = cur_error
        l1_best_alpha = alpha
print('Lasso Regression - RMSE: {:5.4f} with the best alpha: {}'.format(l1_best_erro


# ridge regression, alpha: 1e-5 ~ 1e5
l2_best_error = np.inf
LR_l2_error_list = []
for k in range(-5, 5+1):
    # lasso model
    alpha = 10**k
    LR_l2 = Ridge(alpha)
    # train with cross validation
    cv = KFold(n_splits=10, shuffle=True, random_state=42)
    LR_l2_errors = cross_val_score(LR_l2, X, y, cv=cv, scoring='neg_root_mean_square
    cur_error = LR_l2_errors.mean()*-1
    LR_l2_error_list.append(cur_error)
    # find the best
    if cur_error < l2_best_error:
        l2_best_error = cur_error
        l2_best_alpha = alpha
print('Ridge Regression - RMSE: {:5.4f} with the best alpha: {}'.format(l2_best_erro
```

```
Linear Regression - RMSE: 1222.4796
Lasso Regression - RMSE: 1221.4436 with the best alpha: 1
Ridge Regression - RMSE: 1222.3082 with the best alpha: 10
```

QUESTION 4.1: Explain how each regularization scheme affects the learned parameter set.

ANSWER 4.1: By adding the regularization term, there is a chance that the validation error will reduce due to the reduction of the variance of the model. For lasso regression, an l_1-norm term is added to the objective function which helps to handle the sparsity of the learned coefficients, meaning that it decreases the less important feature's coefficient to zero and inherently performs feature selection. For ridge regression, an l_2-norm term is added to the objective function which provides the ability to avoid overfitting. It adds a penalty to the excessive fluctuation of the learned coefficients and forces weights toward zero.

QUESTION 4.2: Report your choice of the best regularization scheme along with the optimal penalty parameter and explain how you computed it.

ANSWER 4.2: Based on the results shown above, the best regularization model is lasso regression with $\alpha = 1$ as the optimal penalty parameter. I find this by computing each regression model and compare their best achieved error. For each lasso and ridge regression, α is varies in range 10^{-5} to 10^{5}. The errors are then computed and compared to search for the optimal penalty parameter.

In [35]:
```
'''
Training ridge regression with original features (no standardization)
'''


# get the original features and select
# here I choose 'carat', 'cut', 'color', 'clarity', 'x', 'y', 'z' as features to tra
```

```
X_orig = X_df[['carat', 'cut', 'color', 'clarity', 'x', 'y', 'z']].to_numpy()
y = y_df.to_numpy()

# ridge regression, alpha: 1e-5 ~ 1e5
l2_orig_best_error = np.inf
LR_l2_orig_error_list = []
for k in range(-5, 5+1):
    # lasso model
    alpha = 10**k
    LR_l2_orig = Ridge(alpha)
    # train with cross validation
    cv = KFold(n_splits=10, shuffle=True, random_state=42)
    LR_l2_orig_errors = cross_val_score(LR_l2_orig, X_orig, y, cv=cv,
                                        scoring='neg_root_mean_squared_error')
    cur_error = LR_l2_orig_errors.mean()*-1
    LR_l2_orig_error_list.append(cur_error)
    # find the best
    if cur_error < l2_orig_best_error:
        l2_orig_best_error = cur_error
        l2_orig_best_alpha = alpha
print('Ridge Regression with original data '\
      '- RMSE: {:5.4f} with the best alpha: {}'.format(l2_orig_best_error, l2_orig_b
```

```
Ridge Regression with original data - RMSE: 1222.4035 with the best alpha: 10
```

QUESTION 4.3: Does feature standardization play a role in improving the model performance (in the cases with ridge regularization)? Justify your answer.

ANSWER 4.3: Yes. According to the results shown above, a RMSE of 1222.3082 is achieved with standardization and a RMSE of 1222.4035 without standardization. Therefore, we can observe a slight improvement of performance by applying standardization.

In [37]:

```
import statsmodels.api as sm

# get selected features
X = X_scaled_df[['carat', 'cut', 'color', 'clarity', 'x', 'y', 'z']].to_numpy()
y = y_df.to_numpy()

# find p-values
estimator = sm.OLS(y, X)
est_fit = estimator.fit()
print(est_fit.summary2().tables[1]['P>|t|'])
```

```
x1     0.000000e+00
x2     1.486538e-22
x3    4.895631e-189
x4     0.000000e+00
x5     2.786948e-10
x6     2.662459e-01
x7     1.164380e-02
Name: P>|t|, dtype: float64
```

QUESTION 4.4: Some linear regression packages return p-values for different features. What is the meaning of these p-values and how can you infer the most significant features?

ANSWER 4.4: The linear regression p-value for each independent variable tests the null hypothesis that the variable has no correlation with the dependent variable. A low p-value

indicates that the null hypothesis can be rejected (no effect). This means that a predictor is likely to be a meaningful in addition to the model because changes in the predictor's value are related to changes in the response variable. On the other hand, a larger (insignificant) p-value suggests that changes in the predictor are not associated with changes in the response. Therefore, it is typical to use the coefficient p-values to determine which features to keep in the regression model. Features with the lowest value of p-value are the most significant, which are 'carat' and 'clarity' in this dataset.

3.3.2 Polynomial Regression

In [38]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
```

In [42]:
```
'''
Training polynomial regression with multiple features
'''

# get the standardized features, select, and then multiply together
# here I choose 'carat', 'y', 'x' as features to train
X = X_scaled_df[['carat', 'y', 'x']].to_numpy()
X = np.prod(X, axis=1)
y = y_df.to_numpy()

# polynomial regression
PR_best_error = np.inf
PR_error_list = []
degrees = np.arange(1, 6+1)
for i in degrees:
    # preprocessing (max degress = 6)
    poly = PolynomialFeatures(degree=i, include_bias=False)
    poly_features = poly.fit_transform(X.reshape(-1, 1))

    # train polynomial regression with cross validation
    PR = LinearRegression()
    cv = KFold(n_splits=10, shuffle=True, random_state=42)
    PR_errors = cross_val_score(PR, poly_features, y, cv=cv,
                                scoring='neg_root_mean_squared_error')
    PR_cur_error = PR_errors.mean()*-1
    PR_error_list.append(PR_cur_error)

    # find the best
    if PR_cur_error < PR_best_error:
        PR_best_error = PR_cur_error
        PR_best_degree = i
print('Polynomial Regression with multiple features - RMSE: {:5.4f} '\
      'with the best degree: {}'.format(PR_best_error, PR_best_degree))
```

```
Polynomial Regression with multiple features - RMSE: 2753.7405 with the best degree:
2
```

In [44]:
```
'''
Training polynomial regression with single feature
'''

# get the standardized features, select, and then multiply together
# here I choose 'carat' only
X = X_scaled_df[['carat']].to_numpy()
```

```
X = np.prod(X, axis=1)
y = y_df.to_numpy()

# polynomial regression
PR_best_error = np.inf
PR_error_list = []
degrees = np.arange(1, 6+1)
for i in degrees:
    # preprocessing (max degress = 6)
    poly = PolynomialFeatures(degree=i, include_bias=False)
    poly_features = poly.fit_transform(X.reshape(-1, 1))

    # train polynomial regression with cross validation
    PR = LinearRegression()
    cv = KFold(n_splits=10, shuffle=True, random_state=42)
    PR_errors = cross_val_score(PR, poly_features, y, cv=cv,
                                scoring='neg_root_mean_squared_error')
    PR_cur_error = PR_errors.mean()*-1
    PR_error_list.append(PR_cur_error)

    # find the best
    if PR_cur_error < PR_best_error:
        PR_best_error = PR_cur_error
        PR_best_degree = i
print('Polynomial Regression based on carat only - RMSE: {:5.4f} '\
      'with the best degree: {}'.format(PR_best_error, PR_best_degree))


# get the standardized features, select, and then multiply together
# here I choose 'depth' only
X = X_scaled_df[['depth']].to_numpy()
X = np.prod(X, axis=1)
y = y_df.to_numpy()

# polynomial regression
PR_best_error = np.inf
PR_error_list = []
degrees = np.arange(1, 6+1)
for i in degrees:
    # preprocessing (max degress = 6)
    poly = PolynomialFeatures(degree=i, include_bias=False)
    poly_features = poly.fit_transform(X.reshape(-1, 1))

    # train polynomial regression with cross validation
    PR = LinearRegression()
    cv = KFold(n_splits=10, shuffle=True, random_state=42)
    PR_errors = cross_val_score(PR, poly_features, y, cv=cv,
                                scoring='neg_root_mean_squared_error')
    PR_cur_error = PR_errors.mean()*-1
    PR_error_list.append(PR_cur_error)

    # find the best
    if PR_cur_error < PR_best_error:
        PR_best_error = PR_cur_error
        PR_best_degree = i
print('Polynomial Regression based on clarity only - RMSE: {:5.4f} '\
      'with the best degree: {}'.format(PR_best_error, PR_best_degree))
```

```
Polynomial Regression based on carat only - RMSE: 1435.8302 with the best degree: 6
Polynomial Regression based on clarity only - RMSE: 3983.7127 with the best degree:
6
```

QUESTION 5.1: What are the most salient features? Why?

ANSWER 5.1: For training based on single feature, 'carat' is the most salient feature since it achieves the lowest RMSE compared with the others. For training based on multiple features, 'carat', 'y', 'x' are the most salient features. Based on the experients where I test with different combinations, fusing 'carat', 'y', 'x' features achieves the lowest RMSE. Removing any one of them or adding other features will increase the error.

QUESTION 5.2: What degree of polynomial is best? How did you find the optimal degree? What does a very high-order polynomial imply about the fit on the training data? What about its performance on testing data?

ANSWER 5.2: For training based on multiple features, the optimal degree of polynomial is 2. I find this by looping through different degree of polynomial, training the models and comparing the achieved RMSE errors. A very high-order polynomial implies that the fit get wigglier to the training data, meaning it tries to fit the trianing data perfectly. This, however, could lead to overfitting problem and thus cause higher test / validation RMSE, which corresponds to a worse performance.

3.3.3 Neural Network

In [130…

```
from sklearn.neural_network import MLPRegressor
# grid seach related
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
```

In [131…

```
'''
Training neural network with standardized features
'''

# get the standardized features and select
# here I choose 'carat', 'cut', 'color', 'clarity', 'x', 'y', 'z' as features to tra
X = X_scaled_df[['carat', 'cut', 'color', 'clarity', 'x', 'y', 'z']].to_numpy()
y = y_df.to_numpy()

# set up pipeline
pipeline = Pipeline([
    ('nn', MLPRegressor(learning_rate='adaptive')),
])

# parameters
HIDDEN_LAYER_SIZES = [(64, ), (32, ), (16, ), (16, 8), (32, 16), (32, 16, 8)]
ALPHA = [1e-3, 1e-4, 1e-5] # 1e-4, 1e-5

param_grid = [
    {
        'nn__hidden_layer_sizes': HIDDEN_LAYER_SIZES, # 6 choices
        'nn__alpha': ALPHA                            # 3 choices
        # 18 choices in total
    },
]
```

In [136…

```
# start grid search
num_folds = 10
```

```
grid = GridSearchCV(pipeline, param_grid=param_grid, cv=num_folds,
                    scoring='neg_root_mean_squared_error', n_jobs=1)
grid.fit(X, y)
```

In [140…

```
# get all mean test scores on validation (max 20)
best_scores = np.sort(grid.cv_results_['mean_test_score'])[::-1][:20]
# print('The test scores on validation are: {}'.format(best_scores*-1))

# get the corresponding indices
best_scores_idx = np.argsort(grid.cv_results_['mean_test_score'])[::-1][:20]

# print the best combinations in descending order
print('The best combinations from top to bottom are:')
for i in range(len(best_scores_idx)):
    print('{} - RMSE: {}'.format(grid.cv_results_['params'][best_scores_idx[i]], bes
```

```
The best combinations from top to bottom are:
{'nn__alpha': 1e-05, 'nn__hidden_layer_sizes': (32, 16, 8)} - RMSE: 723.629387165280
4
{'nn__alpha': 1e-05, 'nn__hidden_layer_sizes': (16, 8)} - RMSE: 726.3236031015405
{'nn__alpha': 0.001, 'nn__hidden_layer_sizes': (32, 16)} - RMSE: 730.7512714577322
{'nn__alpha': 1e-05, 'nn__hidden_layer_sizes': (32, 16)} - RMSE: 731.9783171963811
{'nn__alpha': 0.0001, 'nn__hidden_layer_sizes': (32, 16)} - RMSE: 770.9000980691015
{'nn__alpha': 0.0001, 'nn__hidden_layer_sizes': (16, 8)} - RMSE: 771.1557310811
{'nn__alpha': 0.0001, 'nn__hidden_layer_sizes': (32, 16, 8)} - RMSE: 777.45033951353
31
{'nn__alpha': 0.0001, 'nn__hidden_layer_sizes': (64,)} - RMSE: 793.8125700290535
{'nn__alpha': 0.001, 'nn__hidden_layer_sizes': (16, 8)} - RMSE: 793.8975042772227
{'nn__alpha': 0.001, 'nn__hidden_layer_sizes': (64,)} - RMSE: 794.4192147904672
{'nn__alpha': 1e-05, 'nn__hidden_layer_sizes': (64,)} - RMSE: 794.9277815467547
{'nn__alpha': 0.001, 'nn__hidden_layer_sizes': (32, 16, 8)} - RMSE: 795.828393922901
5
{'nn__alpha': 0.0001, 'nn__hidden_layer_sizes': (32,)} - RMSE: 884.8374843447084
{'nn__alpha': 0.001, 'nn__hidden_layer_sizes': (32,)} - RMSE: 889.5258217109565
{'nn__alpha': 1e-05, 'nn__hidden_layer_sizes': (32,)} - RMSE: 890.3370440638366
{'nn__alpha': 1e-05, 'nn__hidden_layer_sizes': (16,)} - RMSE: 1002.5854772257222
{'nn__alpha': 0.001, 'nn__hidden_layer_sizes': (16,)} - RMSE: 1003.4286003597821
{'nn__alpha': 0.0001, 'nn__hidden_layer_sizes': (16,)} - RMSE: 1027.6506606248167
```

QUESTION 6.1: Adjust your network size (number of hidden neurons and depth), and weight decay as regularization. Find a good hyper-parameter set systematically (no more than 20 experiments in total).

ANSWER 6.1: To find a good hyper-parameter set systematically, I apply grid search at here and the results are shown above. I set the following values for each hyperparameter:

- 'hidden_layer_sizes': [(64,), (32,), (16,), (16, 8), (32, 16), (32, 16, 8)]
- 'alpha' (weight decay) : $[10^{-3}, 10^{-4}, 10^{-5}]$

QUESTION 6.2: How does the performance generally compare with linear regression? Why?

ANSWER 6.2: Generally, the neural network model performs better than the linear regression model. The worst RMSE score achieved in NN is 1027.65, whereas the best score lasso regressor achieved is 1221.44. The reason why NN performs better is because it introduces non-linearity in training. Since most of the real world data are not fully linearly

seperable, model with the capability of non-linear transformation will yield better performance by fitting the training data better.

QUESTION 6.3: What activation function did you use for the output and why? You may use none

ANSWER 6.3: Since we are doing regression at here and not classification, I didn't use any activation function like sigmoid or so for the output layer. I just let the model predict the regression value.

QUESTION 6.4: What is the risk of increasing the depth of the network too far?

ANSWER 6.4: Overfitting is the risk of increasing the depth of the network too far as the model complexity becomes too high and tries the fit the training data perfectly.

3.3.4 Random Forest

In [46]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import ShuffleSplit, KFold
```

In [72]:
```
'''
Training random forest wih standardized features
'''

# get the standardized features and select
# here I choose 'carat', 'y', 'x', 'z', 'clarity', 'color' as features to train
X = X_scaled_df[['carat', 'cut', 'color', 'clarity', 'x', 'y', 'z']].to_numpy()
y = y_df.to_numpy()

# Random Forest
RFR = RandomForestRegressor(max_features=3, n_estimators=100, max_depth=4, oob_score
# train with cross validation
cv = KFold(n_splits=10, shuffle=True, random_state=42)
RFR_errors = cross_val_score(RFR, X, y, cv=cv, scoring='neg_root_mean_squared_error'
RFR_error = RFR_errors.mean()*-1

print('Random Forest Regression - RMSE: {:5.4f}'.format(RFR_error))
```

```
Random Forest Regression - RMSE: 1101.0223
```

QUESTION 7.1: Explain how these hyper-parameters affect the overall performance. Describe if and how each hyper-parameter results in a regularization effect during training.

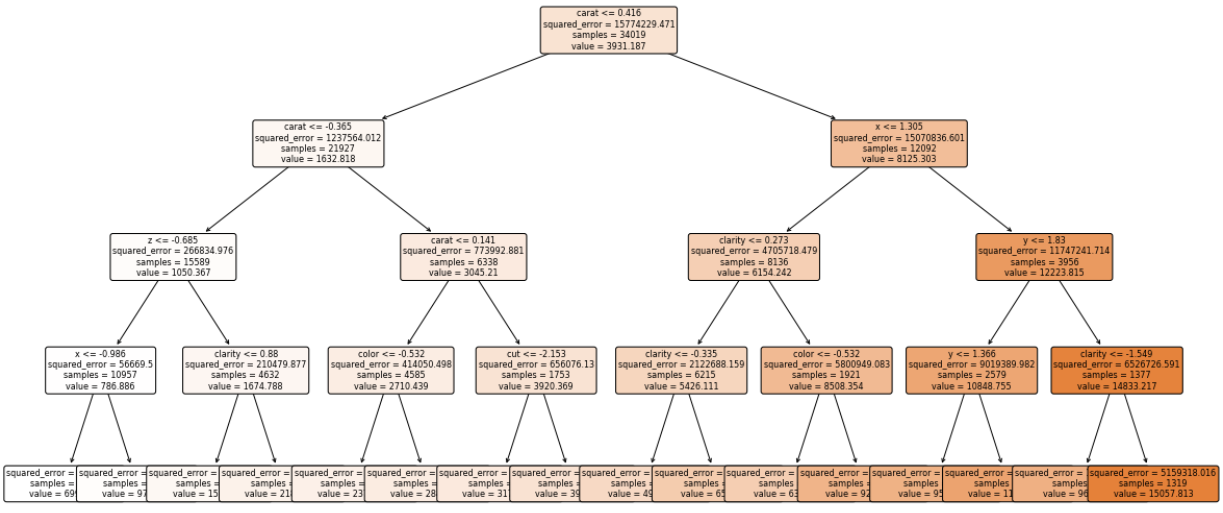
ANSWER 7.1: After testing around with different setting of those hyper-parameters, one can find out that increasing either one of those will result in lower RMSE, meaning a better model performance. However, with such flexibility decision trees provide, the model might also easily overfit the data since they can keep growing until having exactly one leaf node for every single data point and thus perfectly predicting all of them. To avoid this and achieve some regularization effect, one can limit these hyper-parameters. By limiting the maximum

number of features, we reduce the number of features to be considered when looking for the best split, which reduces the chance of overfitting. Limiting the number of trees, can also reduce the overall complexity of the random forest regressor and thus reduce overfitting. Lastly and most importantly, limiting the depth of each tree can avoid the tree keep growing and overfit the training data, which is also a regularization effect.

QUESTION 7.2: How do random forests create a highly non-linear decision boundary despite the fact that all we do at each layer is apply a threshold on a feature?

ANSWER 7.2: Random forests are able to create a highly non-linear decision boundary because they cluster the data based on threshold at each layer and create lots of rectangular-like clusters with such decision boundary (like vertical/horizontal lines). These rectangle cluster of the same class can be far away from each other with other class rectangles in between which is similar to how nonlinear relations are modeled. This is why it can create a highly non-linear decision boundary. Moreover, the final decision is also based on the bootstrap aggregation, which also acts as extra non-linear layer.

In [87]:
```
'''
plot the structure of one of the decision trees
'''

from sklearn.tree import plot_tree

# Train
RFR = RandomForestRegressor(max_features=3, n_estimators=100,
                            max_depth=4, oob_score=True)
RFR.fit(X, y)

fig, axe = plt.subplots(figsize=(20,10))
tree_structure = plot_tree(RFR.estimators_[13],
                           feature_names=['carat', 'cut', 'color', 'clarity', 'x', '
                           class_names=['price'], ax=axe, fontsize=8,
                           filled=True, impurity=True, rounded=True)
```



QUESTION 7.3: Randomly pick a tree in your random forest model (with maximum depth of 4) and plot its structure. Which feature is selected for branching at the root node? What can

you infer about the importance of this feature as opposed to others? Do the important features correspond to what you got in part 3.3.1?

ANSWER 7.3: The example of tree structure is shown above. The feature selected for branching at the root node is 'carat', which means this is the most important feature compared to others as it yields the decision boundary with the lowest error. This result of the most important feature corresponds to the result in part 3.3.1.

In [88]:
```
print('The out-of-bag (OOB) error is: {}'.format(RFR.oob_score_))
```

```
The out-of-bag (OOB) error is: 0.9241314326322944
```

QUESTION 7.4: Measure "Out-of-Bag Error" (OOB). Explain what OOB error and R2 score means.

ANSWER 7.4: The measure of OOB is 0.9241. The out-of-bag (OOB) error is the average error on each training sample x_i predicted by the trained models such as random forest that didn't include x_i in their bootstrap sample under the utilization of bootstrap aggregating technique/algorithm. R^2 score is a statistical measure in a regression model that determines the proportion of variance in the dependent variable that can be explained by the independent variable. It explains the goodness of the data fitting in the regression model and the variance of one variable against another.

3.3.5 LightGBM, CatBoost and Bayesian Optimization

In [68]:
```
# ! pip install scikit-optimize
```

In [124…
```
import lightgbm as lgb
from skopt import BayesSearchCV
```

In [137…
```
# start grid search
opt = BayesSearchCV(
    lgb.LGBMRegressor(task='train', application='regression',
                      objective='root_mean_squared_error',
                      metric='rmse', random_state=42),
    {
        'num_leaves':[7, 15, 31],
        'max_depth' :[4, 8, 10],
        'min_data_in_leaf':[20, 30],
    },
    scoring='neg_root_mean_squared_error',
    n_jobs=1,
    cv=10
)

opt.fit(X, y)
```

In [139…
```
# get all mean test scores on validation (max 20)
best_scores = np.sort(opt.cv_results_['mean_test_score'])[::-1][:20]
```

```
# print('The test scores on validation are: {}'.format(best_scores*-1))

# get the corresponding indices
best_scores_idx = np.argsort(opt.cv_results_['mean_test_score'])[::-1][:20]

# print the best combinations in descending order
print('The best combinations from top to bottom are:')
for i in range(len(best_scores_idx)):
    print('{} - RMSE: {}'.format(opt.cv_results_['params'][best_scores_idx[i]], best
```

```
The best combinations from top to bottom are:
OrderedDict([('max_depth', 8), ('min_data_in_leaf', 29), ('num_leaves', 15)]) - RMS
E: 654.4696527746863
OrderedDict([('max_depth', 8), ('min_data_in_leaf', 29), ('num_leaves', 15)]) - RMS
E: 654.4696527746863
OrderedDict([('max_depth', 8), ('min_data_in_leaf', 29), ('num_leaves', 15)]) - RMS
E: 654.4696527746863
OrderedDict([('max_depth', 8), ('min_data_in_leaf', 29), ('num_leaves', 15)]) - RMS
E: 654.4696527746863
OrderedDict([('max_depth', 8), ('min_data_in_leaf', 29), ('num_leaves', 15)]) - RMS
E: 654.4696527746863
OrderedDict([('max_depth', 8), ('min_data_in_leaf', 29), ('num_leaves', 15)]) - RMS
E: 654.4696527746863
OrderedDict([('max_depth', 8), ('min_data_in_leaf', 29), ('num_leaves', 15)]) - RMS
E: 654.4696527746863
OrderedDict([('max_depth', 8), ('min_data_in_leaf', 29), ('num_leaves', 15)]) - RMS
E: 654.4696527746863
OrderedDict([('max_depth', 8), ('min_data_in_leaf', 29), ('num_leaves', 15)]) - RMS
E: 654.4696527746863
OrderedDict([('max_depth', 4), ('min_data_in_leaf', 21), ('num_leaves', 31)]) - RMS
E: 654.9409653794248
OrderedDict([('max_depth', 10), ('min_data_in_leaf', 30), ('num_leaves', 15)]) - RMS
E: 654.9952707746922
OrderedDict([('max_depth', 10), ('min_data_in_leaf', 30), ('num_leaves', 15)]) - RMS
E: 654.9952707746922
OrderedDict([('max_depth', 10), ('min_data_in_leaf', 30), ('num_leaves', 15)]) - RMS
E: 654.9952707746922
OrderedDict([('max_depth', 10), ('min_data_in_leaf', 30), ('num_leaves', 15)]) - RMS
E: 654.9952707746922
OrderedDict([('max_depth', 10), ('min_data_in_leaf', 30), ('num_leaves', 15)]) - RMS
E: 654.9952707746922
OrderedDict([('max_depth', 10), ('min_data_in_leaf', 30), ('num_leaves', 15)]) - RMS
E: 654.9952707746922
OrderedDict([('max_depth', 10), ('min_data_in_leaf', 30), ('num_leaves', 15)]) - RMS
E: 654.9952707746922
OrderedDict([('max_depth', 10), ('min_data_in_leaf', 28), ('num_leaves', 15)]) - RMS
E: 655.2932160885142
OrderedDict([('max_depth', 10), ('min_data_in_leaf', 29), ('num_leaves', 15)]) - RMS
E: 655.3696989745987
OrderedDict([('max_depth', 8), ('min_data_in_leaf', 25), ('num_leaves', 15)]) - RMS
E: 655.4936394641583
```

QUESTION 8.1: Read the documentation of LightGBM OR CatBoost and determine the important hyperparameters along with a search space for the tuning of these parameters (keep the search space small).

ANSWER 8.1: The important hyperparameters for LightGBM are 'num_leaves', 'max_depth', 'min_data_in_leaf' since they are similar hyperparameters as in random forest regression that also provide the regularization effect during training. For the search space, I set the following values for each hyperparameter:

- 'num_leaves': [7, 15, 31]
- 'max_depth' : [4, 8, 10]
- 'min_data_in_leaf': [20, 30]

QUESTION 8.2: Apply Bayesian optimization using skopt.BayesSearchCV from scikit-optmize to find the ideal hyperparameter combination in your search space. Report the best hyperparameter set found and the corresponding RMSE.

ANSWER 8.2: The results of Bayesian optimization are shown above. The best found hyperparameter set is ('max_depth' = 8, 'min_data_in_leaf' = 29, 'num_leaves' = 15) with the lowest RMSE: 654.47.

QUESTION 8.3: Qualitatively interpret the effect of the hyperparameters using the Bayesian optimization results: Which of them helps with performance? Which helps with regularization (shrinks the generalization gap)? Which affects the fitting efficiency?

ANSWER 8.3: 'num_leaves' controls the complexity of the tree model, which is highly related to the model performance. Higher value of 'num_leaves' will lead to a complex model and thus potentially better model performance. However, one has to aslo be aware of overfitting. 'min_data_in_leaf' prevents overfitting in a leaf-wise tree, which provides regularization effect. Setting it too large can avoid growing too deep tree, but may cause under-fitting. 'max_depth' is also another hyperparameter for regularization as it limit the maximum depth of the tree and avoid the model to be too complex and overfit the training data. As for affecting the fitting efficiency, a low value of 'num_leaves' and 'max_depth' will increase the train efficiency, however, it's a trade-off between training time and model performance.

Show Us Your Skills: Twitter Data

3.4 About the Data

In [49]:
```
# import all necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.metrics import mean_squared_error
import json
import datetime
import pytz


# allows matlab plots to be generated in line
%matplotlib inline
```

In [8]:
```
hashtags = ['tweets_#gohawks.txt', 'tweets_#gopatriots.txt',
            'tweets_#nfl.txt', 'tweets_#patriots.txt',
            'tweets_#sb49.txt', 'tweets_#superbowl.txt']
```

```
# iterate through each file
for tweet_file in hashtags:
    file_path = f'D:\\ECE219\\ECE219_tweet_data\\{tweet_file}'

    # init
    hours, num_followers, num_retweets = [], [], []
    num_tweets = 0

    # read file and store the needed values
    with open(file_path, mode='r', encoding="utf8") as file:
        for line in file:
            tweet = json.loads(line)
            hours.append(tweet['citation_date'])
            num_followers.append(tweet['author']['followers'])
            num_retweets.append(tweet['metrics']['citations']['total'])
            num_tweets += 1

    avg_num_tweet = num_tweets/((max(hours) - min(hours))/3600)
    avg_num_followers = sum(num_followers)/float(num_tweets)
    avg_num_retweets = sum(num_retweets)/float(num_tweets)

    print('Statistics for {}'.format(tweet_file))
    print('- Average number of tweets per hour: {}'.format(avg_num_tweet))
    print('- Average number of followers of users '\
          'posting the tweets per tweet: {}'.format(avg_num_followers))
    print('- Average number of retweets per tweet: {}'.format(avg_num_retweets))
    print('='*80)
```

```
Statistics for tweets_#gohawks.txt
- Average number of tweets per hour: 292.48785062173687
- Average number of followers of users posting the tweets per tweet: 2217.9237355281
984
- Average number of retweets per tweet: 2.0132093991319877
================================================================================
Statistics for tweets_#gopatriots.txt
- Average number of tweets per hour: 40.95469800606194
- Average number of followers of users posting the tweets per tweet: 1427.2526051635
405
- Average number of retweets per tweet: 1.4081919101697078
================================================================================
Statistics for tweets_#nfl.txt
- Average number of tweets per hour: 397.0213901819841
- Average number of followers of users posting the tweets per tweet: 4662.3754452369
3
- Average number of retweets per tweet: 1.5344602655543254
================================================================================
Statistics for tweets_#patriots.txt
- Average number of tweets per hour: 750.89426460689
- Average number of followers of users posting the tweets per tweet: 3280.4635616550
277
- Average number of retweets per tweet: 1.7852871288476946
================================================================================
Statistics for tweets_#sb49.txt
- Average number of tweets per hour: 1276.8570598680474
- Average number of followers of users posting the tweets per tweet: 10374.160292019
487
- Average number of retweets per tweet: 2.52713444111402
================================================================================
Statistics for tweets_#superbowl.txt
- Average number of tweets per hour: 2072.11840170408
- Average number of followers of users posting the tweets per tweet: 8814.9679942462
3
```

```
- Average number of retweets per tweet: 2.3911895819207736
================================================================================
```

QUESTION 9.1: Report the following statistics for each hashtag, i.e. each file has:

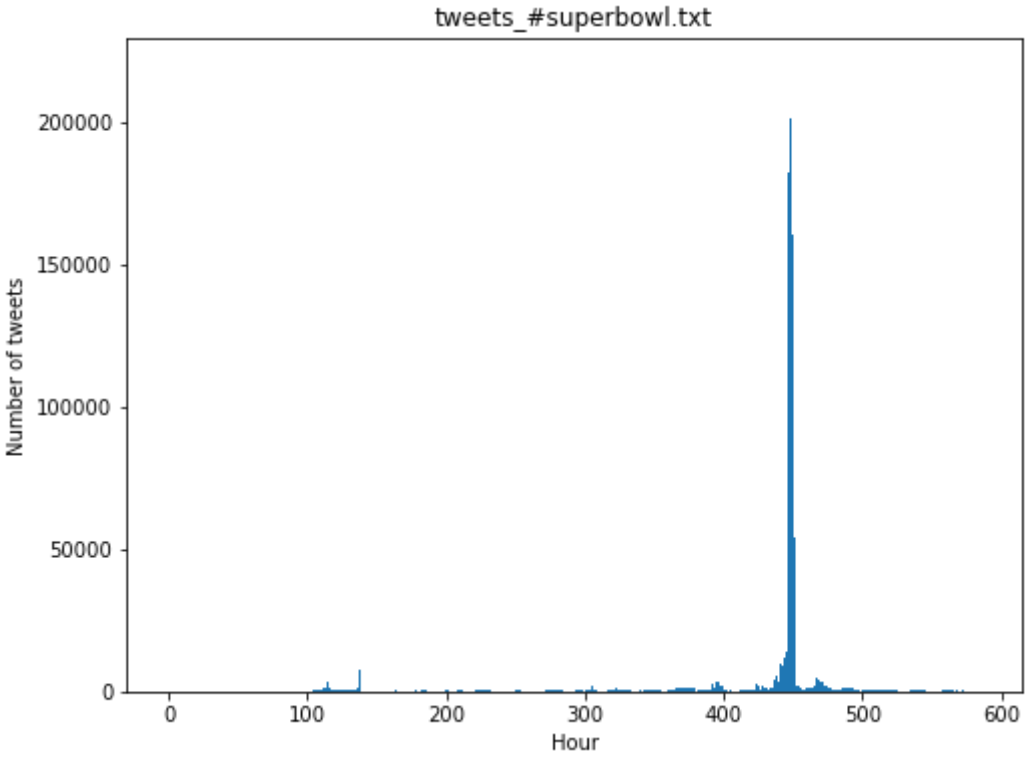
- Average number of tweets per hour
- Average number of followers of users posting the tweets per tweet (to make it simple, we average over the number of tweets; if a users posted twice, we count the user and the user's followers twice as well)
- Average number of retweets per tweet

ANSWER 9.1: The statistics for each hashtag are printed above

Superbowl

In [13]:

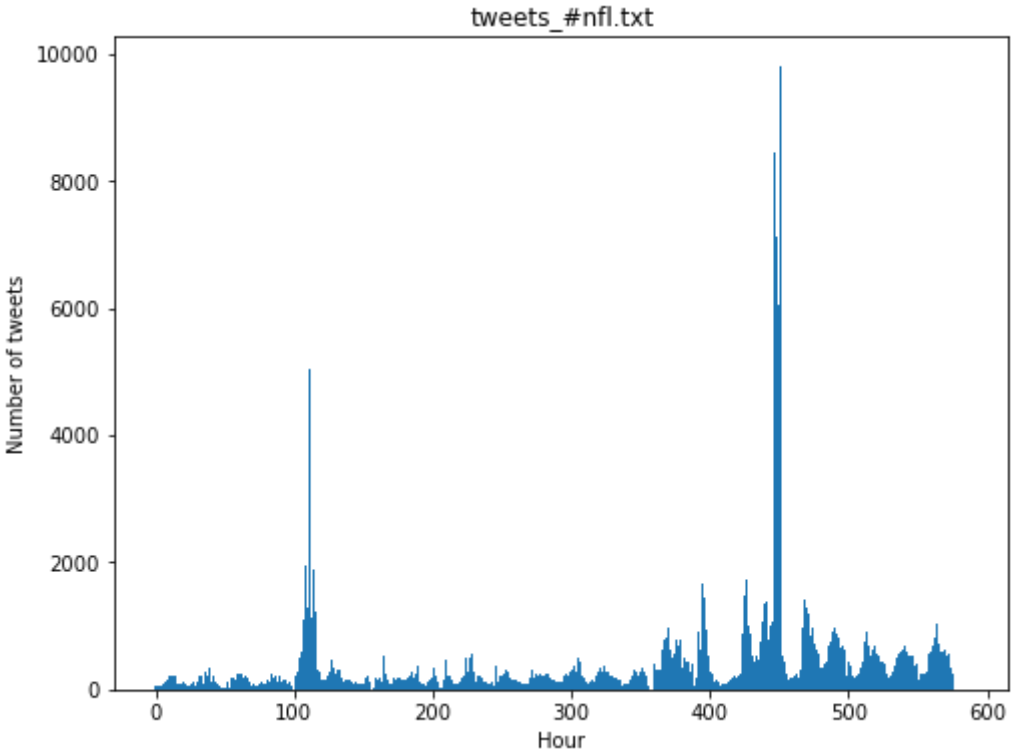
```
# get file path
tweet_file = 'tweets_#superbowl.txt'
file_path = f'D:\\ECE219\\ECE219_tweet_data\\{tweet_file}'

# init
hours = []
num_tweets = 0

# read file and store the needed values
with open(file_path, mode='r', encoding="utf8") as file:
    for line in file:
        tweet = json.loads(line)
        hours.append(tweet['citation_date'])
        num_tweets += 1

# init list of tweet per hour
tweets_hr = [0] * int((max(hours)-min(hours))/3600+1)
start = min(hours)
# start calculating
for i in hours:
    tweets_hr[int((i-start)/3600)] += 1

# plot
f = plt.figure(figsize=(8, 6))
x = [i for i in range(0,len(tweets_hr))]
plt.bar(x, tweets_hr, 1)
plt.xlabel("Hour")
plt.ylabel("Number of tweets")
plt.title(tweet_file)
plt.show()
```



NFL

In [14]:

```
# get file path
tweet_file = 'tweets_#nfl.txt'
file_path = f'D:\\ECE219\\ECE219_tweet_data\\{tweet_file}'

# init
hours = []
num_tweets = 0

# read file and store the needed values
with open(file_path, mode='r', encoding="utf8") as file:
    for line in file:
        tweet = json.loads(line)
        hours.append(tweet['citation_date'])
        num_tweets += 1

# init list of tweet per hour
tweets_hr = [0] * int((max(hours)-min(hours))/3600+1)
start = min(hours)
# start calculating
for i in hours:
    tweets_hr[int((i-start)/3600)] += 1

# plot
f = plt.figure(figsize=(8, 6))
x = [i for i in range(0,len(tweets_hr))]
plt.bar(x, tweets_hr, 1)
plt.xlabel("Hour")
plt.ylabel("Number of tweets")
plt.title(tweet_file)
plt.show()
```



QUESTION 9.2: Plot "number of tweets in hour" over time for **#SuperBowl** and **#NFL** (a bar plot with 1-hour bins). The tweets are stored in separate files for different hashtags and files are named as tweet [#hashtag].txt.

ANSWER 9.2: The plots of "number of tweets in hour" for **#SuperBowl** and **#NFL** are shown above.

QUESTION 10: Follow the steps outlined below:

- Describe your task.
- Explore the data and any metadata (you can even incorporate additional datasets if you choose).
- Describe the feature engineering process. Implement it with reason: Why are you extracting features this way - why not in any other way?
- Generate baselines for your final ML model.
- A thorough evaluation is necessary.
- Be creative in your task design - use things you have learned in other classes too if you are excited about them!

ANSWER 10: Since this tweet dataset contains tweets that were posted before, during, and after the Superbowl, I want to find out the most indicative features at each time period that correlated to the number of tweets in the next next hour or minute. With such information hand, I can then predict the number of the tweets in the future (Part 1). Moreover, one can even consider using this representative features at each time period along with more complex models to do more complex future prediction such as the predicted winning team, the predicted scores, increment of followers, etc (Part 2). However, since I am doing this project alone and considering the work load, I only complete the first part. For feature engineering process, I extract 'date', 'time', 'tweets', 'followers', 'retweets', 'mentions', 'score',

'hashtags' as the features needed for the training and standardize most of them to avoid imbalance scale range across different features and bias.

Get all necessary data and create data frame

In [15]:
```
# get file path
tweet_file = 'tweets_#superbowl.txt'
file_path = f'D:\\ECE219\\ECE219_tweet_data\\{tweet_file}'

# init
date, time, time_5min = [], [], []
num_tweets, num_followers, num_retweets = [], [], []
num_mentions, rank_score, num_hashtags = [], [], []

# parameter
pst_tz = pytz.timezone('America/Los_Angeles')

# read file and store the needed values
with open(file_path, mode='r', encoding="utf8") as file:
    for line in file:
        tweet = json.loads(line)

        # LA time
        timestamp = tweet['citation_date']
        timestamp = str(datetime.datetime.fromtimestamp(int(timestamp), pst_tz))
        time_split = ''.join(timestamp[0:10].split('-'))
        date.append(int(time_split))
        time.append(int(timestamp[11:13]))

        # get time windows
        a, b, c, _ = timestamp.split(':')
        rounded = str(int((int(b)/5))*5).zfill(2)
        time_mins = timestamp[11:13] + rounded
        time_5min.append(int(time_mins))

        num_tweets.append(1)
        num_followers.append(tweet['author']['followers'])
        num_retweets.append(tweet['metrics']['citations']['total'])
        num_mentions.append(len(tweet['tweet']['entities']['user_mentions']))
        rank_score.append(tweet['metrics']['ranking_score'])
        num_hashtags.append(tweet['title'].count('#'))
```

In [92]:
```
columns = ['date', 'time', 'tweets', 'followers',
           'retweets', 'mentions', 'score', 'hashtags']

df1 = pd.DataFrame({'date': date, 'time': time, 'tweets': num_tweets,
                    'followers': num_followers, 'retweets': num_retweets,
                    'mentions': num_mentions, 'score': rank_score,
                    'hashtags': num_hashtags}, columns=columns)

df1 = df1.groupby(['date', 'time']).agg({'time': np.max, 'tweets': np.sum,
                                         'followers': np.sum, 'retweets': np.sum,
                                         'mentions': np.sum, 'score': np.sum,
                                         'hashtags': np.sum})

df_5 = pd.DataFrame({'date': date, 'time': time_5min, 'tweets': num_tweets,
                     'followers': num_followers, 'retweets': num_retweets,
                     'mentions': num_mentions, 'score': rank_score,
                     'hashtags': num_hashtags}, columns=columns)
```

```
df_5 = df_5.groupby(['date', 'time']).agg({'time': np.max, 'tweets': np.sum,
                                           'followers': np.sum, 'retweets': np.sum,
                                           'mentions': np.sum, 'score': np.sum,
                                           'hashtags': np.sum})

time_frame1 = df1.query('date < 20150201 or (date == 20150201 and time < 8)')
time_frame2 = df_5.query('date == 20150201 and (time >= 800 and time <= 2000)')
time_frame3 = df1.query('date > 20150201 or (date == 20150201 and time > 20)')
```

Data inspection

In [93]:
```
time_frame1.head()
```

Out[93]:

		time	tweets	followers	retweets	mentions	score	hashtags
date	**time**							
20150114	**0**	0	8	3181.0	9	10	33.149173	20
	1	1	6	12618.0	8	7	24.862325	17
	2	2	12	1406539.0	75	7	61.154177	22
	3	3	10	3210.0	10	6	41.463227	26
	4	4	11	27896.0	16	7	51.386322	30

In [94]:
```
time_frame2.head()
```

Out[94]:

		time	tweets	followers	retweets	mentions	score	hashtags
date	**time**							
20150201	**800**	800	815	31752316.0	2065	330	3937.105762	1799
	805	805	838	7014228.0	1706	304	3778.794464	2274
	810	810	705	3938937.0	1163	294	3229.159620	1805
	815	815	758	5736082.0	1312	334	3430.129700	1779
	820	820	747	4954814.0	1168	274	3318.970026	2061

In [95]:
```
time_frame3.head()
```

Out[95]:

		time	tweets	followers	retweets	mentions	score	hashtags
date	**time**							
20150201	**21**	21	1771	47501907.0	11006	862	8212.099064	5673
	22	22	2579	15615953.0	10597	1207	11514.393423	8448
	23	23	1546	9276926.0	4444	638	6838.339453	5121
20150202	**0**	0	1097	13775183.0	6362	482	4827.763922	3551
	1	1	890	4621085.0	1506	396	3927.715512	2885

Data preprocessing

In [98]:
```
from sklearn.preprocessing import StandardScaler
from sklearn_pandas import DataFrameMapper

'''
Standardize all data in each time frame
'''
mapper = DataFrameMapper([(time_frame1.iloc[:, 2:].columns, StandardScaler())])

# time frame 1
time_frame1_scaled = mapper.fit_transform(time_frame1.iloc[:, 2:].copy(),
                                          len(time_frame1.iloc[:, 2:].columns))
time_frame1.loc[:, 'followers':] = pd.DataFrame(time_frame1_scaled,
                                                index=time_frame1.iloc[:, 2:].index,
                                                columns=time_frame1.iloc[:, 2:].columns

# time frame 2
time_frame2_scaled = mapper.fit_transform(time_frame2.iloc[:, 2:].copy(),
                                          len(time_frame2.iloc[:, 2:].columns))
time_frame2.loc[:, 'followers':] = pd.DataFrame(time_frame2_scaled,
                                                index=time_frame2.iloc[:, 2:].index,
                                                columns=time_frame2.iloc[:, 2:].columns

# time frame 3
time_frame3_scaled = mapper.fit_transform(time_frame3.iloc[:, 2:].copy(),
                                          len(time_frame3.iloc[:, 2:].columns))
time_frame3.loc[:, 'followers':] = pd.DataFrame(time_frame3_scaled,
                                                index=time_frame3.iloc[:, 2:].index,
                                                columns=time_frame3.iloc[:, 2:].columns
```

Model training and evaluation

In [100…
```
'''
Time frame 1: before Feb. 1, 8:00am - 1 hour window
'''

# get data
X = []
for i in time_frame1.index:
    X.append(time_frame1.loc[i, 'tweets':].values)
X.pop()
X = sm.add_constant(X)
y = time_frame1.loc[time_frame1.index[1]:, 'tweets'].values

# train model and predict
model = sm.OLS(y,X).fit()
pred_y = model.predict(X)

# print
print('MSE for {} for before Feb 1 '\
      '- RMSE: {:5.4f}'.format(tweet_file, np.sqrt(mean_squared_error(y, pred_y))))
print(model.summary())
```

```
MSE for tweets_#superbowl.txt for before Feb 1 - RMSE: 695.9451
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.439
Model:                            OLS   Adj. R-squared:                  0.431
Method:                 Least Squares   F-statistic:                     56.28
Date:                Sun, 19 Mar 2023   Prob (F-statistic):           3.06e-51
Time:                        23:03:01   Log-Likelihood:                -3496.3
No. Observations:                 439   AIC:                             7007.
```

```
Df Residuals:                      432   BIC:                             7035.
Df Model:                            6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -2299.8094    990.478     -2.322      0.021   -4246.564    -353.055
x1             6.2633      2.255      2.778      0.006       1.832      10.695
x2           165.7670     62.156      2.667      0.008      43.602     287.932
x3          -172.2764    146.299     -1.178      0.240    -459.823     115.270
x4           856.1031    215.873      3.966      0.000     431.811    1280.395
x5         -5852.3777   2159.816     -2.710      0.007   -1.01e+04   -1607.323
x6           -99.1736    298.347     -0.332      0.740    -685.567     487.219
==============================================================================
Omnibus:                      627.399   Durbin-Watson:                   1.949
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           121111.266
Skew:                           7.343   Prob(JB):                         0.00
Kurtosis:                      83.034   Cond. No.                     6.89e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 6.89e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [101…

```
'''
Time frame 2: between Feb. 1, 8:00am ~ 8:00pm - 5 minutes window
'''

# get data
X = []
for i in time_frame2.index:
    X.append(time_frame2.loc[i, 'tweets':].values)
X.pop()
X = sm.add_constant(X)
y = time_frame2.loc[time_frame2.index[1]:, 'tweets'].values

# train model and predict
model = sm.OLS(y,X).fit()
pred_y = model.predict(X)

# print
print('MSE for {} for between Feb 1 '\
      '- RMSE: {:5.4f}'.format(tweet_file, np.sqrt(mean_squared_error(y, pred_y))))
print(model.summary())
```

```
MSE for tweets_#superbowl.txt for between Feb 1 - RMSE: 2443.4510
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.904
Model:                            OLS   Adj. R-squared:                  0.900
Method:                 Least Squares   F-statistic:                     215.4
Date:                Sun, 19 Mar 2023   Prob (F-statistic):           3.51e-67
Time:                        23:03:05   Log-Likelihood:                -1327.7
No. Observations:                 144   AIC:                             2669.
Df Residuals:                     137   BIC:                             2690.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       3.422e+04   1.95e+04      1.752      0.082   -4400.376    7.28e+04
```

```
x1            -4.3682      3.064     -1.426      0.156     -10.427       1.690
x2          -410.3663    618.576     -0.663      0.508   -1633.559     812.826
x3          -826.1702    363.202     -2.275      0.024   -1544.377    -107.964
x4          1568.4573   1056.847      1.484      0.140    -521.386    3658.300
x5          4.997e+04   2.12e+04      2.360      0.020    8107.940    9.18e+04
x6         -8623.8371   5057.950     -1.705      0.090   -1.86e+04    1377.912
==============================================================================
Omnibus:                       46.490   Durbin-Watson:                   1.548
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              203.297
Skew:                           1.068   Prob(JB):                     7.16e-45
Kurtosis:                       8.415   Cond. No.                     1.41e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 1.41e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [102…

```
'''
Time frame 3: after Feb. 1, 8:00pm - 1 hour window
'''


# get data
X = []
for i in time_frame3.index:
    X.append(time_frame3.loc[i, 'tweets':].values)
X.pop()
X = sm.add_constant(X)
y = time_frame3.loc[time_frame3.index[1]:, 'tweets'].values

# train model and predict
model = sm.OLS(y,X).fit()
pred_y = model.predict(X)

# print
print('MSE for {} for after Feb 1 '\
      '- MSE: {:5.4f}'.format(tweet_file, mean_squared_error(y, pred_y)))
print(model.summary())
```

```
MSE for tweets_#superbowl.txt for after Feb 1 - MSE: 79534.4816
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.888
Model:                            OLS   Adj. R-squared:                  0.882
Method:                 Least Squares   F-statistic:                     165.9
Date:                Sun, 19 Mar 2023   Prob (F-statistic):           2.54e-57
Time:                        23:03:05   Log-Likelihood:                -939.10
No. Observations:                 133   AIC:                             1892.
Df Residuals:                     126   BIC:                             1912.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       5172.5140   1105.719      4.678      0.000    2984.329    7360.699
x1            -6.5396      1.607     -4.069      0.000      -9.720      -3.359
x2            88.4593     87.418      1.012      0.314     -84.538     261.456
x3           -26.5039     44.618     -0.594      0.554    -114.802      61.794
x4          -100.9199    142.599     -0.708      0.480    -383.119     181.279
x5          5805.1153   1306.620      4.443      0.000    3219.354    8390.877
x6           534.2747    217.892      2.452      0.016     103.073     965.476
==============================================================================
```

```
Omnibus:                      197.984   Durbin-Watson:                   2.135
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            17236.959
Skew:                           5.782   Prob(JB):                         0.00
Kurtosis:                      57.559   Cond. No.                     7.39e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 7.39e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Discussion

Before the superbowl started, one can notice that x1('tweets'), x2('followers'), x4('mentions'), x5('score') are the main features that are most informative for predicting the number of tweets in the future since the p-score is almost 0. During the superbowl, x3('retweets') and x5('score') are the most indicative features and after the superbowl, x1('tweets'), x5('score'), and x6('hashtags') are the best features for the prediction of number of tweets in the near future. By combining all together, one can discover that x5('score') is the sole feature that always shows high correlation to the number of tweets in the near future. Therefore, if we want to build a simple model to predict the number of tweets in the near future, we can just choose 'score' as feature and it might already be able to yield good result. However, for more complexe cases, one can use an ensemble of different models trained on those representative features at each time period to achieve high model performance.

In [ ]: