Project4_905727807

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0.1 Project 4 - Regression Analysis

Reema Kumari (905727807)

In this part of the project, we train and compare multiple regression models across 2 datasets - `diamonds` and `pollution`

Readme: Install the necessary modules using the following commands in a anaconda environment. Run the script to get the regression results

%pip install pandas %pip install matplotlib %pip install seaborn %pip install pandas-profiling %pip install scikit-learn %pip install lightgbm %pip install catboost %pip install scikit-optimize %pip install ipywidgets

[1]:
```
## import basic libraries
import pandas as pd
import numpy as np
import time
import random
import sys
import os


## visualization
import matplotlib.pyplot as plt
import seaborn as sns
import pandas_profiling
from math import log10
%matplotlib inline

## modeling
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

from sklearn.feature_selection import f_regression, mutual_info_regression
from sklearn.model_selection import cross_validate, GridSearchCV

from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.metrics import mean_squared_error, make_scorer
```

```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.neural_network import MLPRegressor
from sklearn.ensemble import RandomForestRegressor

from sklearn import tree

sns.set_style("whitegrid")
sns.color_palette("mako", as_cmap=True)

import lightgbm as lgb
from lightgbm import LGBMRegressor

import catboost
from catboost import CatBoostRegressor
from skopt import BayesSearchCV

import warnings
warnings.simplefilter("ignore")
warnings.filterwarnings('ignore')
if not sys.warnoptions:
    warnings.simplefilter("ignore")
    os.environ["PYTHONWARNINGS"] = "ignore"

# warnings.filterwarnings(action='ignore', category=ConvergenceWarning)
# warnings.filterwarnings(action='ignore', category=UserWarning)
```

[2]:
```
np.random.seed(42)
random.seed(42)
```

[3]:
```
## Load diamonds data
diamonds_df = pd.read_csv('./data/diamonds.csv')
```

[4]:
```
##### Load pollution data
years = [2011, 2012, 2013, 2014, 2015]
path = './data/pp_gas_emission/'

pollution_df = pd.DataFrame()
for year in years:
    tmp = pd.read_csv(path+'gt_'+str(year)+'.csv')
    tmp['year'] = year
    tmp['hour_index'] = range(0, len(tmp))
    print(tmp.shape)
    pollution_df = pd.concat([pollution_df, tmp])

pollution_df = pollution_df.drop(['NOX'], axis = 1)
pollution_df['index'] = range(0, len(pollution_df))
```

```
(7411, 13)
```

```
(7628, 13)
(7152, 13)
(7158, 13)
(7384, 13)
```

Data Exploration

For diamonds dataset

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

[5]:
```
   Unnamed: 0  carat      cut color clarity  depth  table  price     x     y  \
0           1   0.23    Ideal     E     SI2   61.5   55.0    330  3.95  3.98
1           2   0.21  Premium     E     SI1   59.8   61.0    327  3.89  3.84
2           3   0.23     Good     E     VS1   56.9   65.0    328  4.05  4.07
3           4   0.29  Premium     I     VS2   62.4   58.0    337  4.20  4.23
4           5   0.31     Good     J     SI2   63.3   58.0    338  4.34  4.35

      z
0  2.43
1  2.31
2  2.31
3  2.63
4  2.75
```

[6]:
```
diamonds_df.describe()
```

[6]:
```
         Unnamed: 0         carat         depth         table         price  \
count  53940.000000  53940.000000  53940.000000  53940.000000  53940.000000
mean   26970.500000      0.797940     61.749405     57.457184   3934.801557
std    15571.281097      0.474011      1.432621      2.234491   3989.442321
min        1.000000      0.200000     43.000000     43.000000    327.000000
25%    13485.750000      0.400000     61.000000     56.000000    952.000000
50%    26970.500000      0.700000     61.800000     57.000000   2403.000000
75%    40455.250000      1.040000     62.500000     59.000000   5327.250000
max    53940.000000      5.010000     79.000000     95.000000  18823.000000

                  x             y             z
count  53940.000000  53940.000000  53940.000000
mean       5.731157      5.734526      3.538734
std        1.121761      1.142135      0.705699
min        0.000000      0.000000      0.000000
25%        4.710000      4.720000      2.910000
50%        5.700000      5.710000      3.530000
75%        6.540000      6.540000      4.040000
max       10.740000     58.900000     31.800000
```

[7]:
```
diamonds_df[diamonds_df['price']> 15000].shape
```

[7]: (1657, 11)

[8]:
```
diamonds_df.profile_report()
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

[8]:

From the above profiling, we observe that there are no missing values for any of the variables. Using pearson's r correlation, we see high correlation with variables `carat`, `x`, `y` and `z`. Categorical variables - `color`, `clarity` and `cut` are not included. Using interactions pairwise plots, we observe a linear relationship between `carat` and `price` (turns quadratic for high `price` values). Almost no relationship between `depth` and `price`; `table` and `price`. Quadratic relationship with `x` and steep quadratic relationship with `y` and `z`. Again, categorical variables are not incorporated.

Alerts suggest that `carat` is highly correlated with `price` and predictor variables `x`, `y` and `z` suggesting multicollinearity in the predictor variables.It makes sense because, the dimensions of the diamond would affect the weight of the diamond. `cut` is correlated with `depth`.

[9]:
```
diamonds_df.columns
```

[9]:
```
Index(['Unnamed: 0', 'carat', 'cut', 'color', 'clarity', 'depth', 'table',
       'price', 'x', 'y', 'z'],
      dtype='object')
```

[10]:
```
diamonds_df.color.unique()
```

[10]:
```
array(['E', 'I', 'J', 'H', 'F', 'G', 'D'], dtype=object)
```

[11]:
```
diamonds_df.clarity.unique()
```

[11]:
```
array(['SI2', 'SI1', 'VS1', 'VS2', 'VVS2', 'VVS1', 'I1', 'IF'],
      dtype=object)
```

[12]:
```
diamonds_df.cut.unique()
```

[12]:
```
array(['Ideal', 'Premium', 'Good', 'Very Good', 'Fair'], dtype=object)
```

For pollution dataset

[13]:
```
pollution_df.head()
```

[13]:
```
       AT      AP      AH    AFDP    GTEP     TIT     TAT     TEY     CDP  \
0  4.5878  1018.7  83.675  3.5758  23.979  1086.2  549.83  134.67  11.898
1  4.2932  1018.3  84.235  3.5709  23.951  1086.1  550.05  134.67  11.892
2  3.9045  1018.4  84.858  3.5828  23.990  1086.5  550.19  135.10  12.042
```

```
3  3.7436  1018.3  85.434  3.5808  23.911  1086.5  550.17  135.03  11.990
4  3.7516  1017.8  85.182  3.5781  23.917  1085.9  550.00  134.67  11.910

        CO  year  hour_index  index
0  0.32663  2011           0      0
1  0.44784  2011           1      1
2  0.45144  2011           2      2
3  0.23107  2011           3      3
4  0.26747  2011           4      4
```

[14]:
```python
pollution_df.describe()
```

[14]:
```
                 AT            AP            AH          AFDP          GTEP  \
count  36733.000000  36733.000000  36733.000000  36733.000000  36733.000000
mean      17.712726   1013.070165     77.867015      3.925518     25.563801
std        7.447451      6.463346     14.461355      0.773936      4.195957
min       -6.234800    985.850000     24.085000      2.087400     17.698000
25%       11.781000   1008.800000     68.188000      3.355600     23.129000
50%       17.801000   1012.600000     80.470000      3.937700     25.104000
75%       23.665000   1017.000000     89.376000      4.376900     29.061000
max       37.103000   1036.600000    100.200000      7.610600     40.716000

                TIT           TAT           TEY           CDP            CO  \
count  36733.000000  36733.000000  36733.000000  36733.000000  36733.000000
mean    1081.428084    546.158517    133.506404     12.060525      2.372468
std       17.536373      6.842360     15.618634      1.088795      2.262672
min     1000.800000    511.040000    100.020000      9.851800      0.000388
25%     1071.800000    544.720000    124.450000     11.435000      1.182400
50%     1085.900000    549.880000    133.730000     11.965000      1.713500
75%     1097.000000    550.040000    144.080000     12.855000      2.842900
max     1100.900000    550.610000    179.500000     15.159000     44.103000

               year    hour_index         index
count  36733.000000  36733.000000  36733.000000
mean    2012.985735   3674.952985  18366.000000
std        1.418965   2124.552565  10604.048056
min     2011.000000      0.000000      0.000000
25%     2012.000000   1836.000000   9183.000000
50%     2013.000000   3673.000000  18366.000000
75%     2014.000000   5509.000000  27549.000000
max     2015.000000   7627.000000  36732.000000
```

[15]:
```python
pollution_df.profile_report(minimal = True)
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
```

<IPython.core.display.HTML object>

[15]:

[16]:
```
pollution_df.columns
```

[16]:
```
Index(['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'TEY', 'CDP', 'CO',
       'year', 'hour_index', 'index'],
      dtype='object')
```

0.1.1 QUESTION 1

We use standardized dataset because standard input features improves the convergence of descent algorithms as it is not scale invariant for linear models. Also, different scales might lead to some features dominating the objective function. In neural networks, the gradients explode if we have large loss values (resulting from unscaled target variable), which makes the weight values change dramatically leading to unstable learning process. Hence, we scale target variable as well.

[17]:
```
def standardize (data: pd.DataFrame(), features: list):
    '''
    To standardise a list of features given by `features` in the dataset `data`
    Returns standardised data
    '''
    results = data.copy()
    scaler = StandardScaler()
    scaler.fit(results[features])
    results[features] = scaler.transform(results[features])
    return results
```

For diamonds dataset

[18]:
```
print("Preparing diamonds dataset for modeling..")

print("Creating new columns to encode categorical variables to numeric..")
cut_map = {'Ideal' : 1, 'Premium' : 2, 'Very Good' : 3, 'Good' : 4, 'Fair': 5}
clarity_map = {'I1' : 1, 'SI2' : 2, 'SI1' : 3, 'VS2' : 4, 'VS1': 5, 'VVS2':6,␣
 ↪'VVS1':7, 'IF':8}
color_map = {'J' : 1, 'I' : 2, 'H' : 3, 'G' : 4, 'F': 5, 'E': 6, 'D': 7}

diamonds_df['cut_num']= diamonds_df['cut'].map(cut_map)
diamonds_df['clarity_num']= diamonds_df['clarity'].map(clarity_map)
diamonds_df['color_num']= diamonds_df['color'].map(color_map)

print("Standardizing features and target..")
features_to_scale = ['carat', 'cut_num', 'color_num', 'clarity_num', 'depth',␣
 ↪'table',\
        'x', 'y', 'z', 'price']
diamonds_df_scaled = standardize(diamonds_df,features_to_scale)
```

```
# merging back the unscaled price values for evaluation
print("Merging scaled and unscaled target in the datasets (used for␣
 ↪visualization)..")
tmp = diamonds_df[['Unnamed: 0', 'price']]
tmp.columns = ['Unnamed: 0', 'price_unscaled']
diamonds_df_scaled = pd.merge(diamonds_df_scaled, tmp, how = 'left', on =␣
 ↪'Unnamed: 0')

tmp = diamonds_df_scaled[['Unnamed: 0', 'price']]
tmp.columns = ['Unnamed: 0', 'price_scaled']
diamonds_df = pd.merge(diamonds_df, tmp, how = 'left', on = 'Unnamed: 0')
```

```
Preparing diamonds dataset for modeling..
Creating new columns to encode categorical variables to numeric..
Standardizing features and target..
Merging scaled and unscaled target in the datasets (used for visualization)..
```

For pollution dataset

[19]:
```
print("Preparing diamonds dataset for modeling..")

print("Creating new columns to encode categorical variables to numeric..")
year_map = {2011 : 1, 2012 : 2, 2013 : 3, 2014 : 4, 2015: 5}
pollution_df['year_num']= pollution_df['year'].map(year_map)

print("Standardizing features and target..")
features_to_scale = ['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'TEY',␣
 ↪'CDP', 'year_num', 'CO']
pollution_df_scaled = standardize(pollution_df,features_to_scale)

# merging back the unscaled values for evaluation
print("Merging scaled and unscaled target in the datasets (used for␣
 ↪visualization)..")
tmp = pollution_df[['index', 'CO']]
tmp.columns = ['index', 'CO_unscaled']
pollution_df_scaled = pd.merge(pollution_df_scaled, tmp, how = 'left', on =␣
 ↪'index')

tmp = pollution_df_scaled[['index', 'CO']]
tmp.columns = ['index', 'CO_scaled']
pollution_df = pd.merge(pollution_df, tmp, how = 'left', on = 'index')
```

```
Preparing diamonds dataset for modeling..
Creating new columns to encode categorical variables to numeric..
Standardizing features and target..
Merging scaled and unscaled target in the datasets (used for visualization)..
```

0.1.2 QUESTION 2

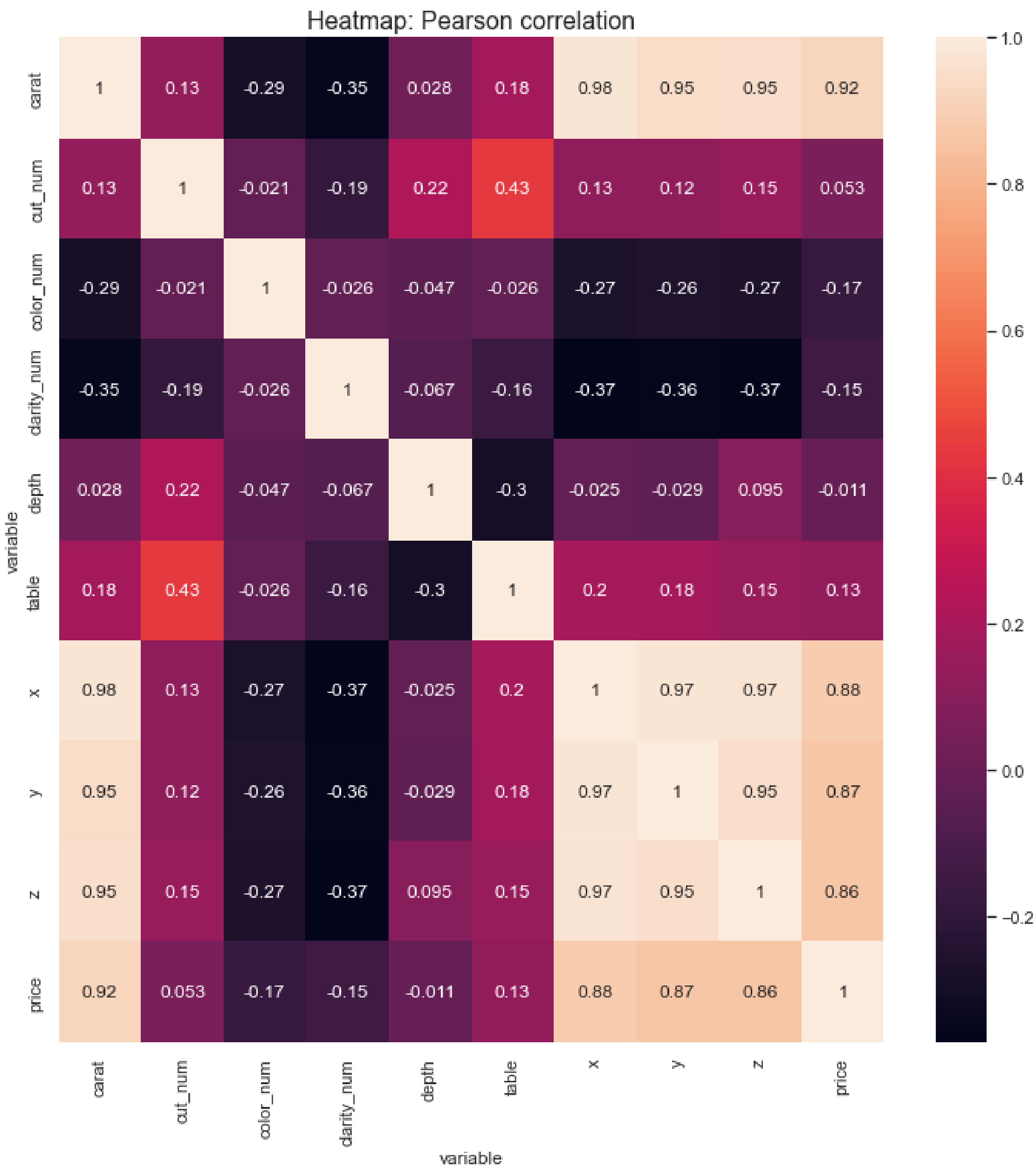
Low correlation means there's no linear relationship, it doesn't mean there's no information in the feature that predicts the target. Also, pearson correlation is a bivariate analysis, the features might become important when interacting with other features.

[20]:
```
def pearson_plot (data: pd.DataFrame(), columns: list):
    '''
    For a list of variables given by `columns` in the dataset `data`,
    plot the heatmap for their pearson correlation
    '''
    tmp = data[columns]
    sns.set(rc={"figure.figsize":(12, 12)})
    dataplot = sns.heatmap(tmp.corr(method='pearson'), annot=True)
    plt.title("Heatmap: Pearson correlation", fontsize = 16)
    plt.xlabel('variable')
    plt.ylabel('variable')
    plt.show()
```

For diamonds dataset

[21]:
```
print("Plotting pearson correlation heatmap for diamonds dataset..")
cols = ['carat', 'cut_num', 'color_num', 'clarity_num', 'depth', 'table',\
        'x', 'y', 'z', 'price']
pearson_plot(diamonds_df_scaled, cols)
```

```
Plotting pearson correlation heatmap for diamonds dataset..
```



The variables - `carat`, `x`, `y`, `z` have high correlation with the target variable `price`. It suggests that the `price` of a diamond is highly correlated to the size of the diamond (determined by `x`, `y`, and `z`) and weight of the diamond (determined by `carat`). The bigger the diamond, costlier it is. Also, the heavier the diamond, costlier it is. Low correlation with `depth`, `table`, `color`, `clarity` and `cut` suggests that the prices are not heavily dependent on these features for a diamond.

For pollution dataset

[22]:
```
print("Plotting pearson correlation heatmap for pollution dataset..")
```

```
cols = ['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'TEY', 'CDP', 'year',␣
↪'CO']
pearson_plot(pollution_df_scaled, cols)
```

```
Plotting pearson correlation heatmap for pollution dataset..
```

The variables - `AFDP`, `GTEP`, `TIT`, `TEY` and `CDP` have high negative correlation with the target variable `CO`. It suggests that as the values for these variables increase, the value for `CO` decreases.

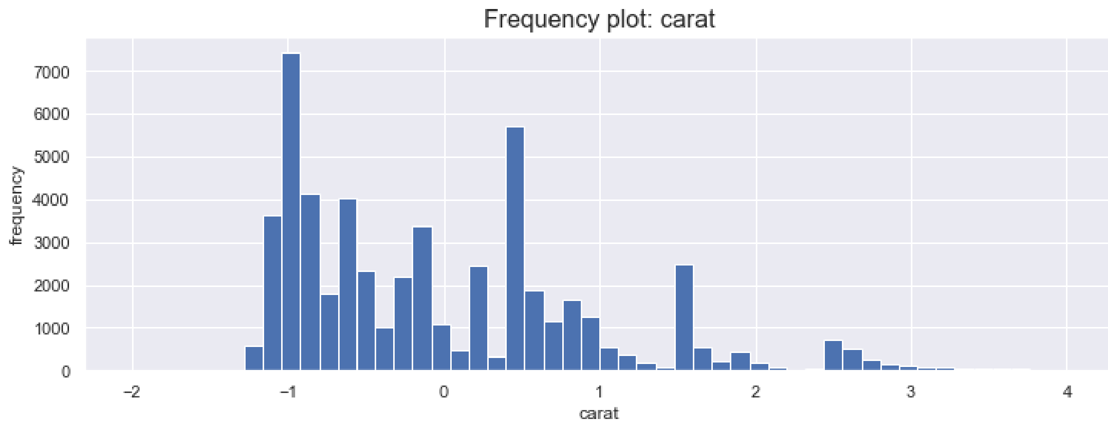
0.1.3 QUESTION 3

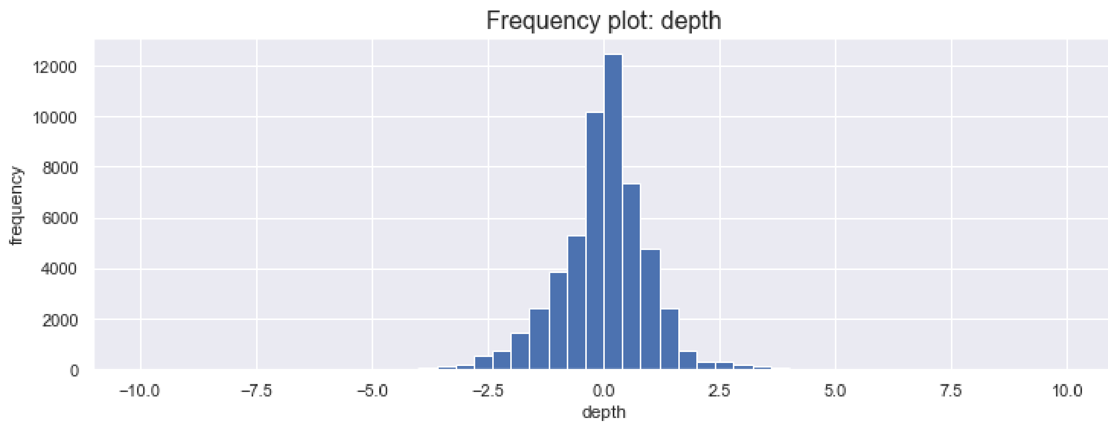
[23]:
```
def plot_histogram(data: pd.DataFrame(), feature: str, range_val = None, bins =␣
↪50):
    '''
    For a given feature in the dataset, plot histogram
    '''
    plt.figure(figsize=(12,4))
    plt.hist(data[feature], bins = bins, range= range_val)
    plt.title('Frequency plot: '+ feature, fontsize = 16)
    plt.xlabel(feature)
    plt.ylabel('frequency')
    plt.show()
```

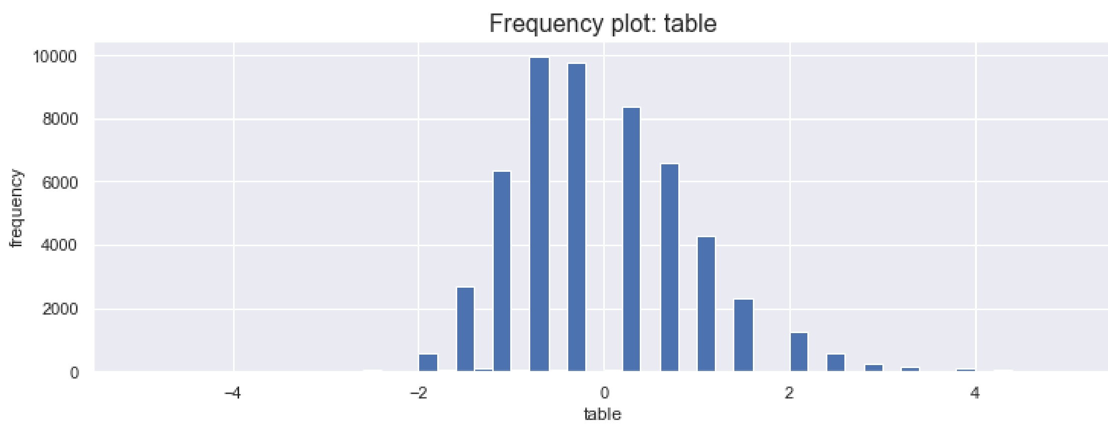
For diamonds dataset

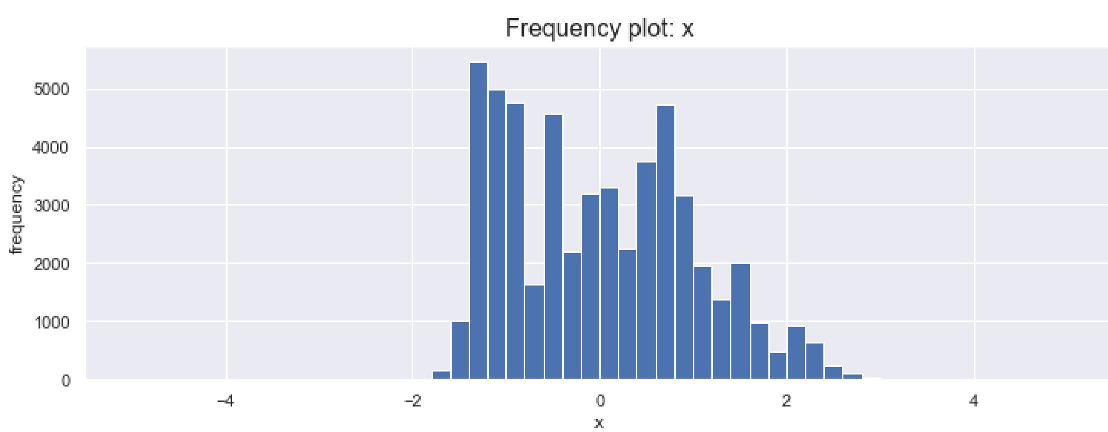
[24]:
```
print("Plotting histograms for continuous variables in diamonds dataset..")
numeric_features = ['carat', 'depth', 'table', 'x', 'y', 'z']
range_map = {'carat' : [-2, 4], 'depth' : [-10, 10], 'table' : [-5,5], \
             'x' : [-5,5], 'y': [-5,5], 'z': [-5,5]}

for feature in numeric_features:
    plot_histogram(diamonds_df_scaled, feature, range_map[feature])
```

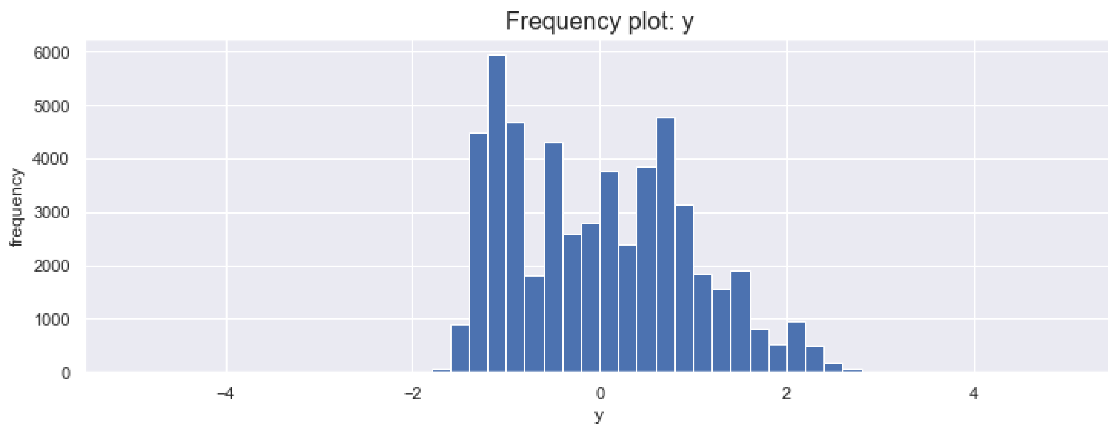
```
Plotting histograms for continuous variables in diamonds dataset..
```

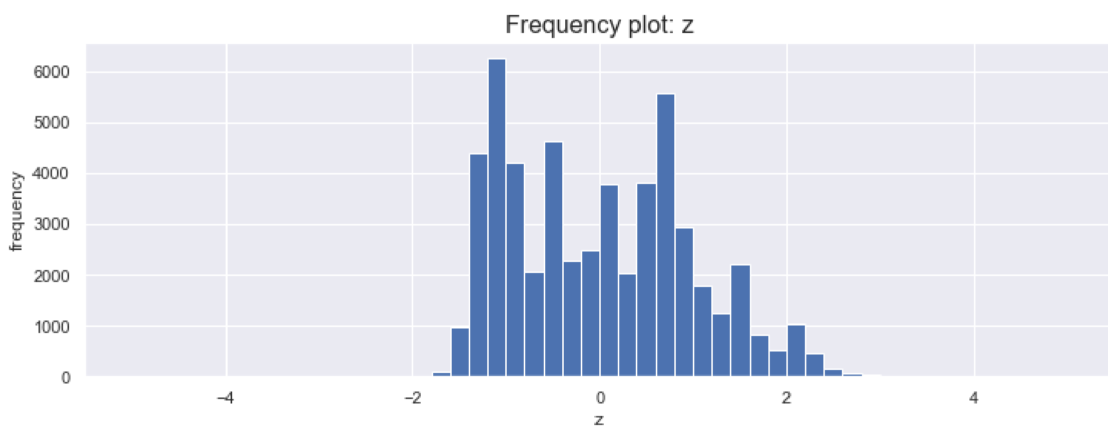



Frequency plot: depth
frequency
12000
10000
8000
6000
4000
2000
0
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
depth

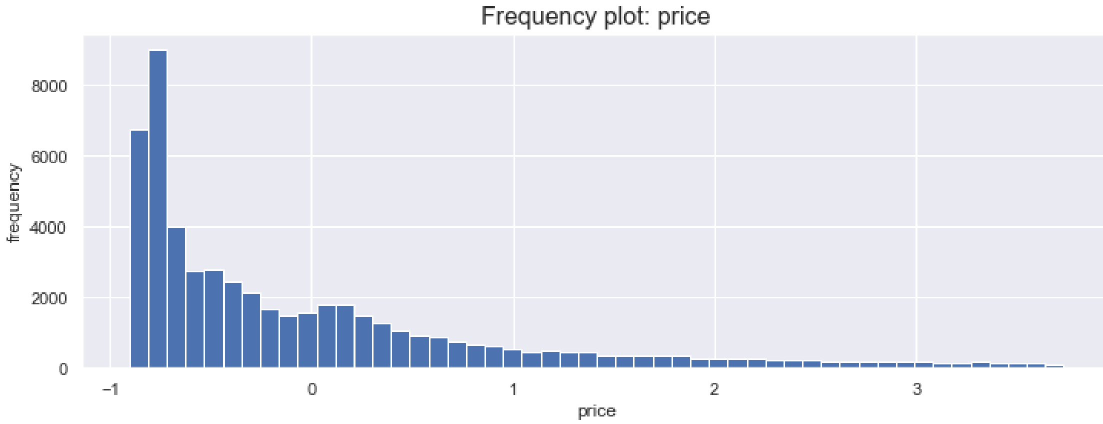

Frequency plot: table
frequency
10000
8000
6000
4000
2000
0
−4
−2
0
2
4
table


Frequency plot: x
frequency
5000
4000
3000
2000
1000
0
−4
−2
0
2
4
x





[25]:
```
plt.figure(figsize=(12,4))
plt.hist(diamonds_df_scaled['price'], bins = 50)
plt.title('Frequency plot: price', fontsize = 16)
plt.xlabel('price')
plt.ylabel('frequency')
plt.show()
```

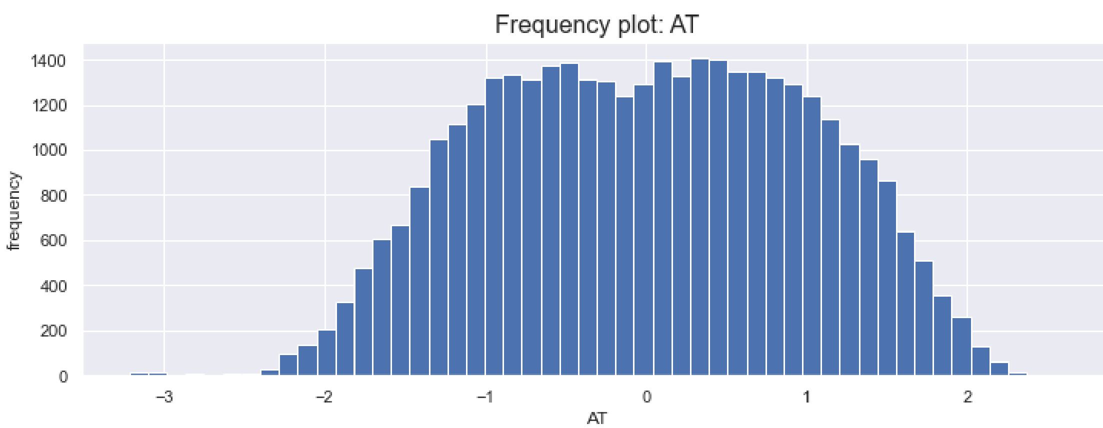


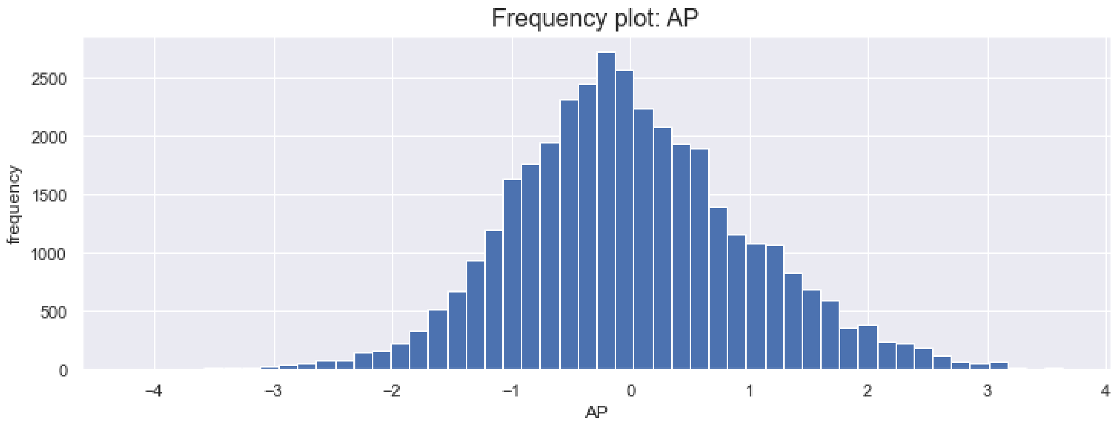
Target variable `price` has a long right tail.

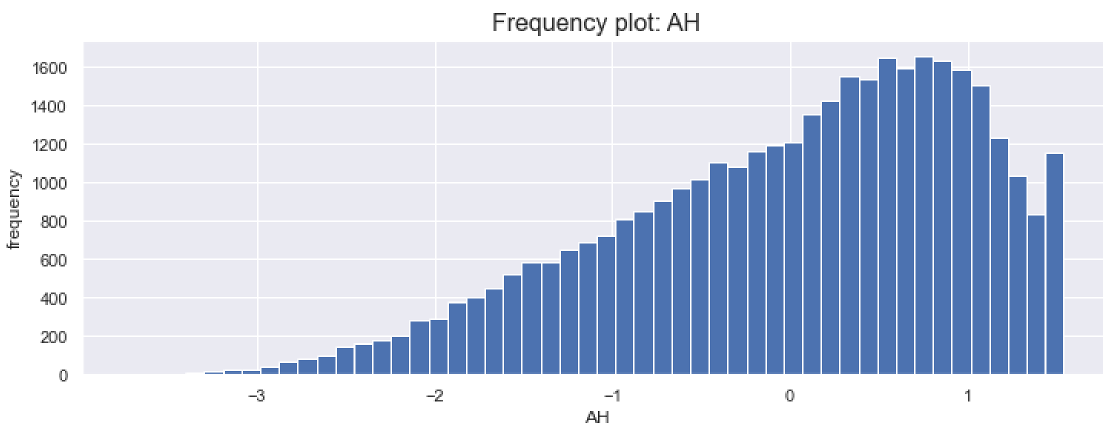
For pollution dataset

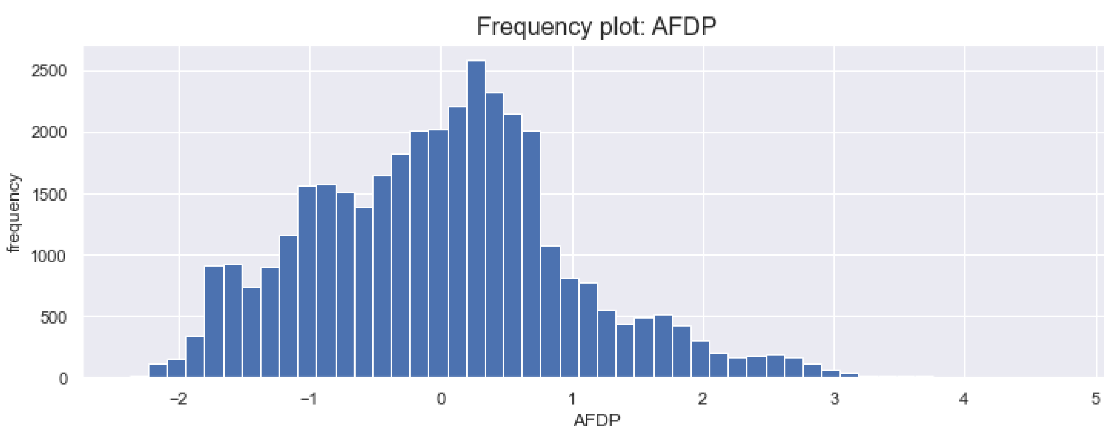
[26]:
```
print("Plotting histograms for continuous variables in pollution dataset..")
numeric_features = ['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'TEY',␣
 ↪'CDP', \
        'year_num']

for feature in numeric_features:
    plot_histogram(pollution_df_scaled, feature)
```

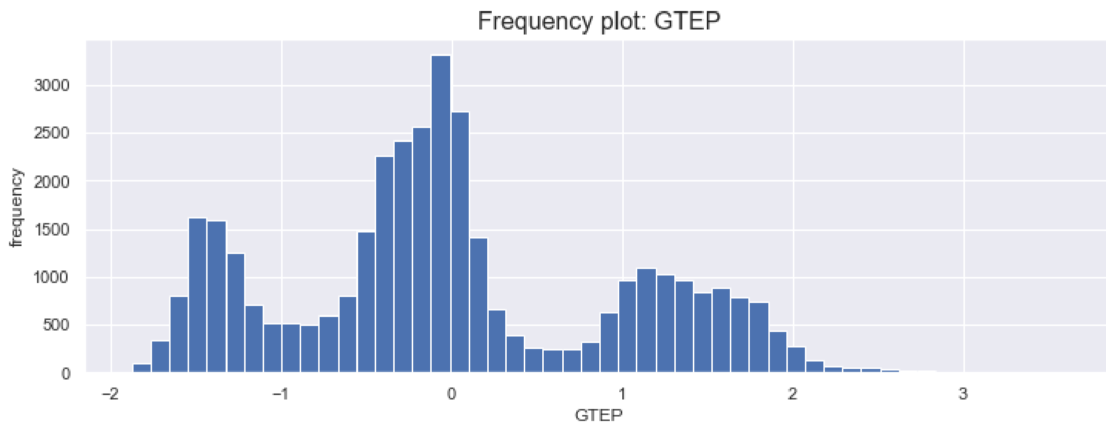
```
Plotting histograms for continuous variables in pollution dataset..
```

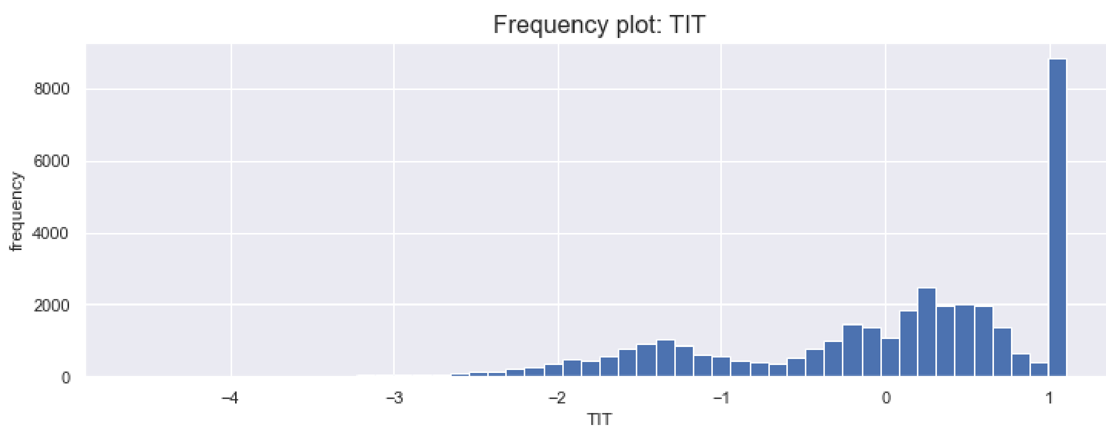


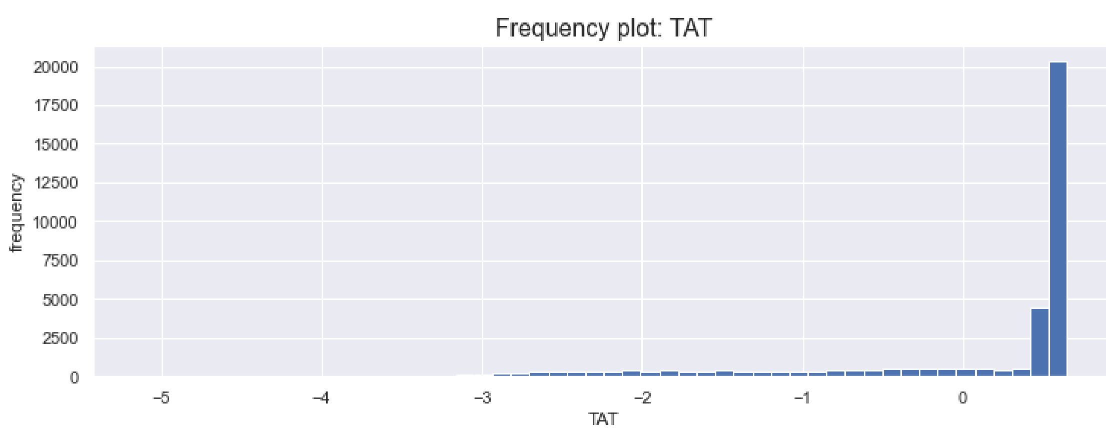

Frequency plot: AP
frequency
2500
2000
1500
1000
500
0
−4
−3
−2
−1
0
1
2
3
4
AP

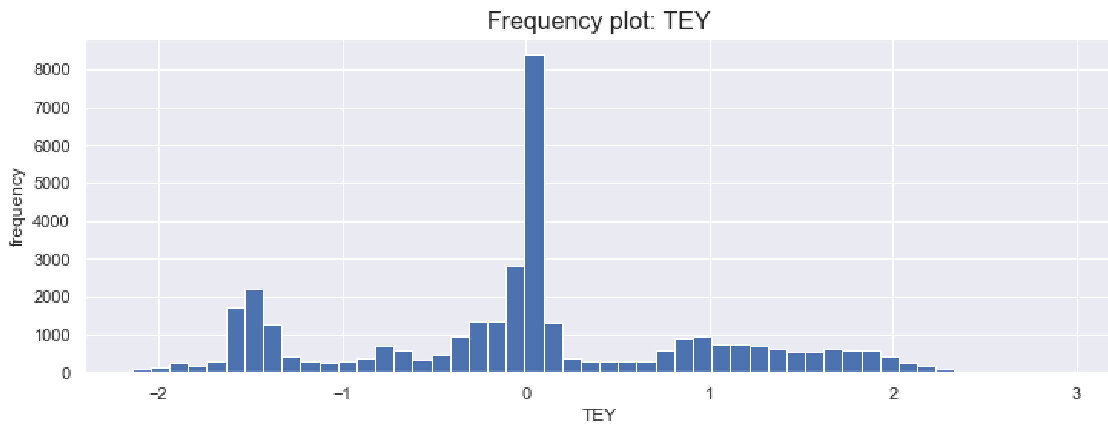

Frequency plot: AH
frequency
1600
1400
1200
1000
800
600
400
200
0
−3
−2
−1
0
1
AH

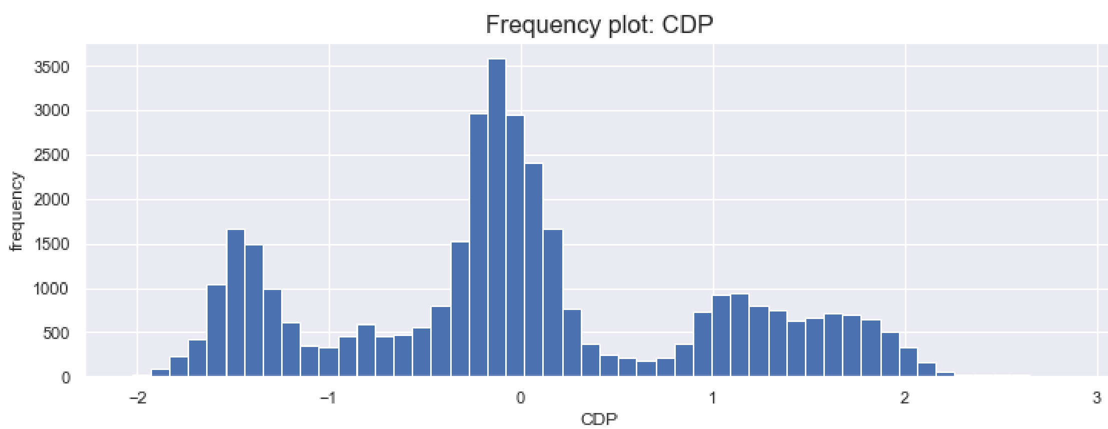

Frequency plot: AFDP
frequency
2500
2000
1500
1000
500
0
−2
−1
0
1
2
3
4
5
AFDP

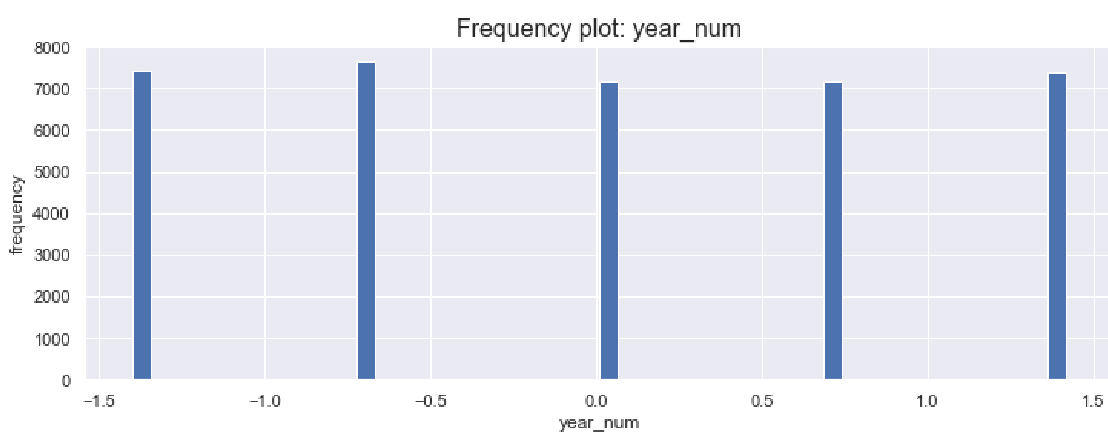

Frequency plot: GTEP
frequency
GTEP
0
500
1000
1500
2000
2500
3000
−2
−1
0
1
2
3


Frequency plot: TIT
frequency
TIT
0
2000
4000
6000
8000
−4
−3
−2
−1
0
1

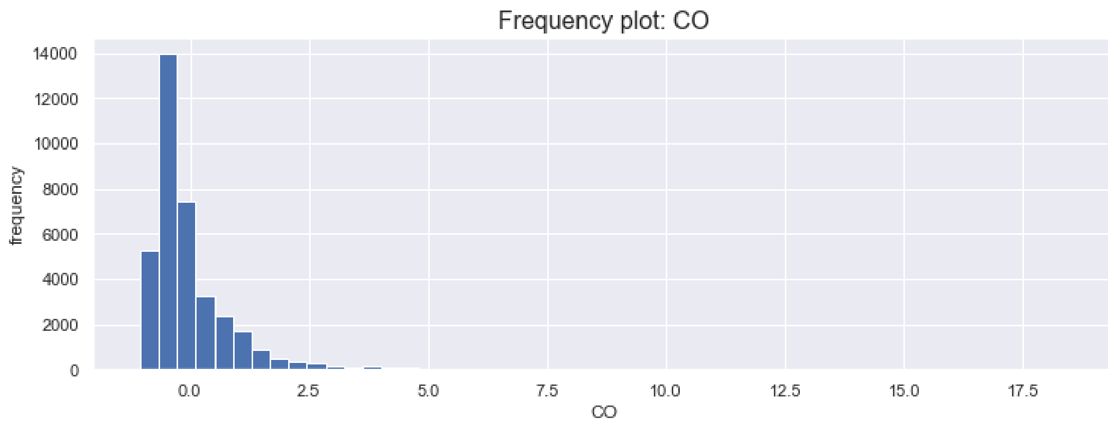

Frequency plot: TAT
frequency
TAT
0
2500
5000
7500
10000
12500
15000
17500
20000
−5
−4
−3
−2
−1
0


Frequency plot: TEY
frequency
TEY
0
1000
2000
3000
4000
5000
6000
7000
8000
−2
−1
0
1
2
3


Frequency plot: CDP
frequency
CDP
0
500
1000
1500
2000
2500
3000
3500
−2
−1
0
1
2
3


Frequency plot: year_num
frequency
year_num
0
1000
2000
3000
4000
5000
6000
7000
8000
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

[27]:
```
plt.figure(figsize=(12,4))
plt.hist(pollution_df_scaled['CO'], bins = 50)
plt.title('Frequency plot: CO', fontsize = 16)
plt.xlabel('CO')
plt.ylabel('frequency')
plt.show()
```



In order to handle skewness of a feature, we can apply a transformation on the feature which leads to the transformed feature being closer to normal distribution. Most popular transformations to handle skewness are - log transform, square root transform and box cox transform.

0.1.4 QUESTION 4

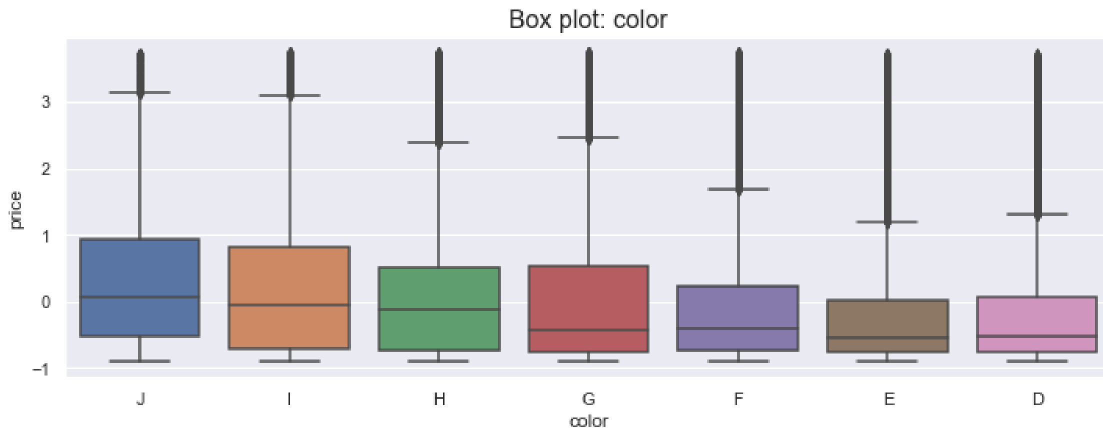
[28]:
```
def plot_boxplot(data: pd.DataFrame(), feature: str, target: str, sort_val :␣
↪str):
    '''
    For a given categorical feature in the dataset, plot box plot
    '''
    plt.figure(figsize=(12,4))
    data = data.sort_values(sort_val)
    sns.boxplot(y = data[target], x = data[feature])

    plt.title('Box plot: '+ feature, fontsize = 16)
    plt.xlabel(feature)
    plt.ylabel(target)
    plt.show()
```

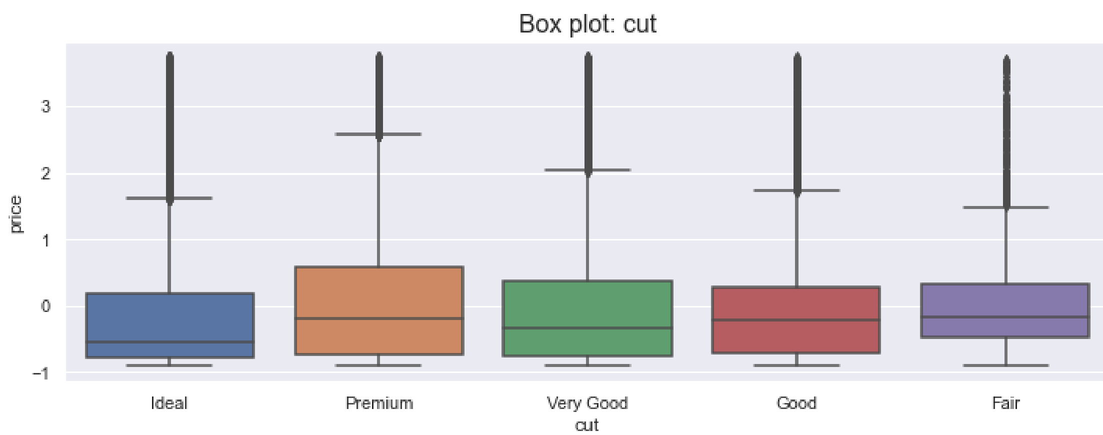
For diamonds dataset

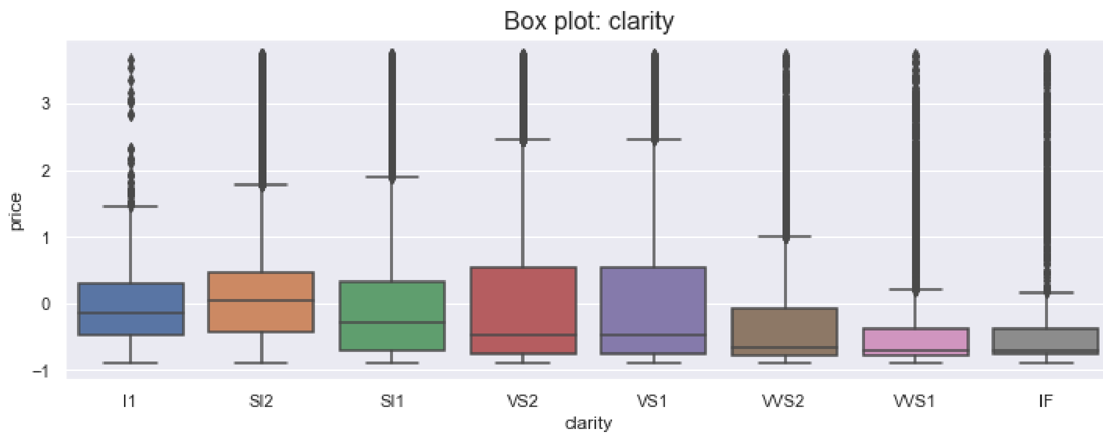
[29]:
```
print("Plotting box plots for categorical features in diamonds dataset..")
cat_features = ['color', 'cut', 'clarity']
features_num = ['color_num', 'cut_num', 'clarity_num']
```

```
target = 'price'

for i in range(len(cat_features)):
    plot_boxplot(diamonds_df_scaled, cat_features[i], target, features_num[i])
```

```
Plotting box plots for categorical features in diamonds dataset..
```







From the above box plots we observe that prices within each category in `color`, `cut`, `clarity` have high `price` outlier diamonds. Within each category, most of the diamonds have low prices given by lower median bars. The large top bar suggests that there are some stones with high prices and there is more variation in price for some high priced stones. There are diamonds with outlier(exceptionally high) prices as well (values beyond Q3+1.5* IQR). Q3 is the 75th percentile and IQR is the difference between Q3 and Q2. Q2 is the 25th percentile.

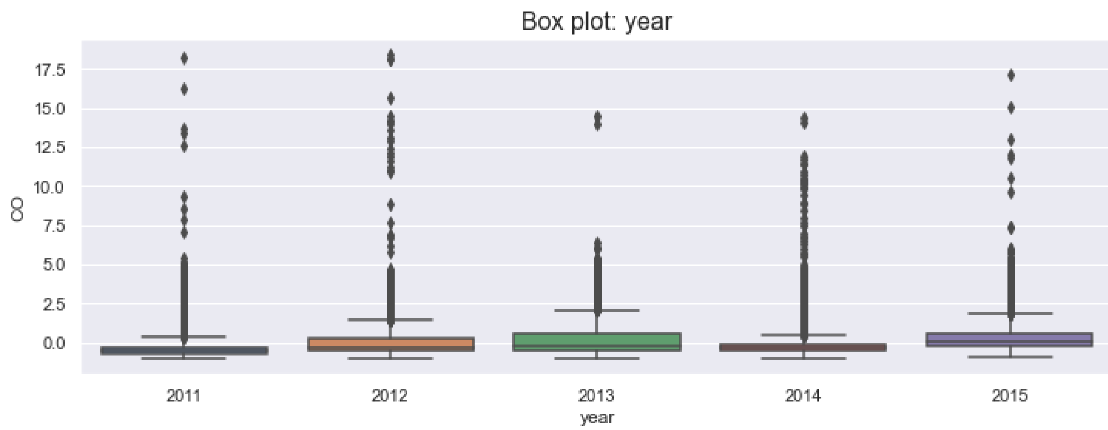
The color box plot suggests that the median price is lower for better colored diamonds. But there are many high priced outliers. For worse color diamonds, the median price is higher but there are few outliers.

For cut, we see the premium quality has relatively higher median price. For clarity as well we see higher median price for I1 compared to IF which is counter-intuitive. We have larger spread for VS2 and VS1 diamonds. We might be observing these trends because of data frequency and confounding effects with other variables such as carat.

For pollution dataset

[30]:
```
print("Plotting box plots for categorical features in pollution dataset..")
cat_features = ['year']
target = 'CO'

print("Plotting box plots..")
for i in range(len(cat_features)):
    plot_boxplot(pollution_df_scaled, cat_features[i], target, cat_features[i])
```

```
Plotting box plots for categorical features in pollution dataset..
Plotting box plots..
```



From the above box plots we observe that for each year we have very less variation in the CO emission measurements. However, some sensor aggregations indicate high CO emissions evident from the outlier values. The outliers deviate in large magnitude from the general distribution across years.

0.1.5 QUESTION 5

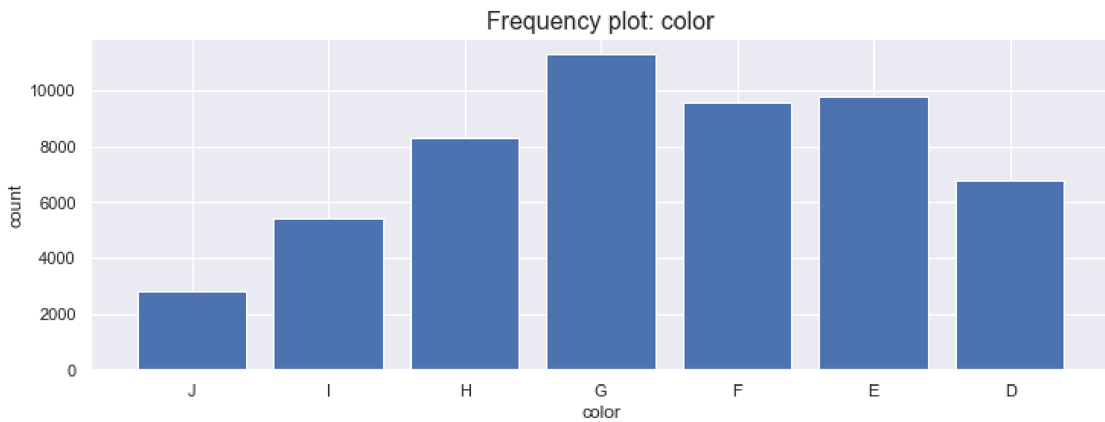
[31]:
```
def plot_freq(data: pd.DataFrame(), feature: str, feature_order: dict):
    '''
    For a given feature in the dataset, plot histogram
    '''
    tmp = data[feature].value_counts().reset_index()
    tmp['order']= tmp['index'].map(feature_order)
    tmp = tmp.sort_values(by=['order'])
    a = tmp['index']
    b = tmp[feature]
    plt.figure(figsize=(12,4))
    plt.bar(a, b)
    plt.title('Frequency plot: '+ feature, fontsize = 16)
    plt.xlabel(feature)
    plt.ylabel('count')
    plt.show()
```

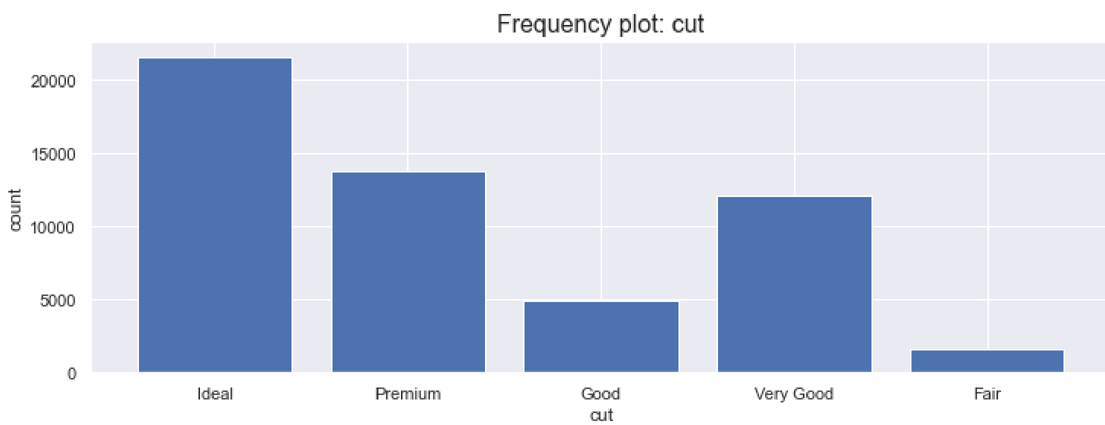
For diamonds dataset

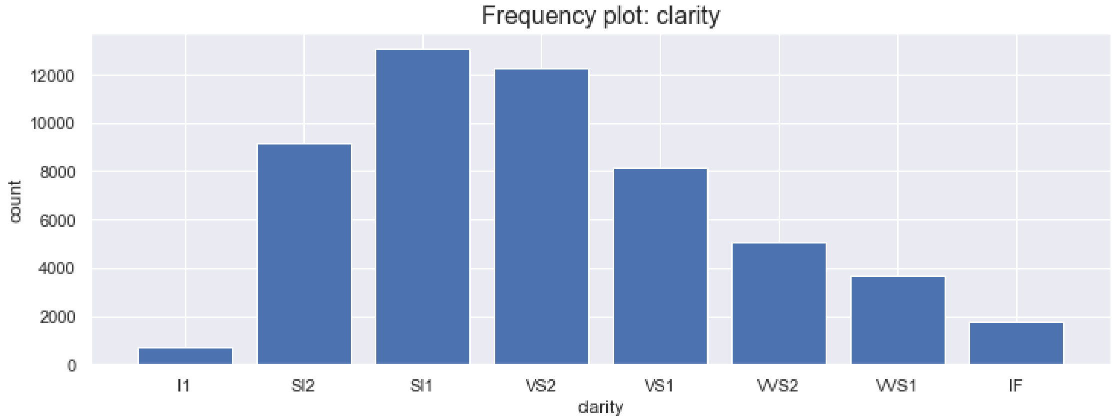
[32]:
```
print("Plotting frequency for categorical features in diamonds dataset..")
cat_features = ['color', 'cut', 'clarity']

feature_order_map = {'cut': {'Ideal' : 1, 'Premium' : 2, 'Good' : 3, 'Very Good'␣
 ↪: 4, 'Fair': 5}, \
                     'clarity' : {'I1' : 1, 'SI2' : 2, 'SI1' : 3, 'VS2' : 4,␣
 ↪'VS1': 5, 'VVS2':6, 'VVS1':7, 'IF':8}, \
```

```
                    'color' : {'J' : 1, 'I' : 2, 'H' : 3, 'G' : 4, 'F': 5, 'E':␣
↪6, 'D': 7}}

for feature in cat_features:
    plot_freq(diamonds_df_scaled, feature, feature_order_map[feature])
```

```
Plotting frequency for categorical features in diamonds dataset..
```



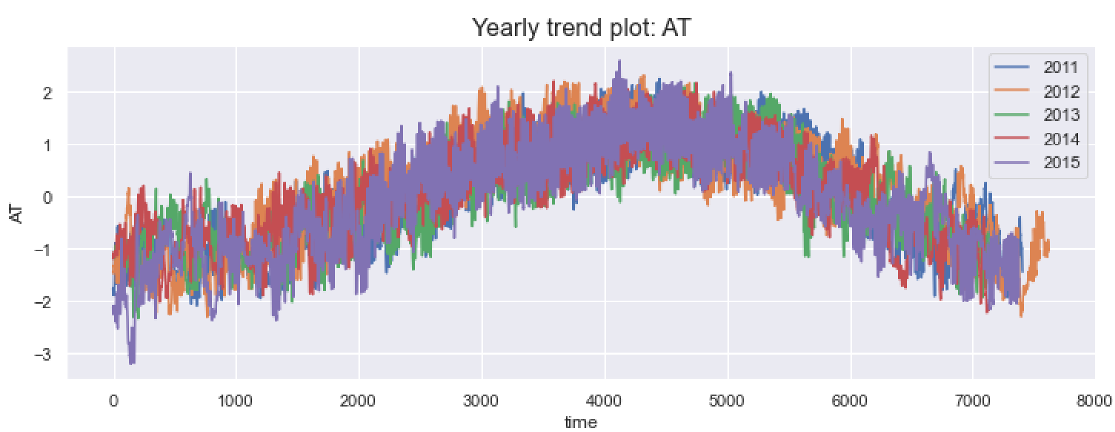


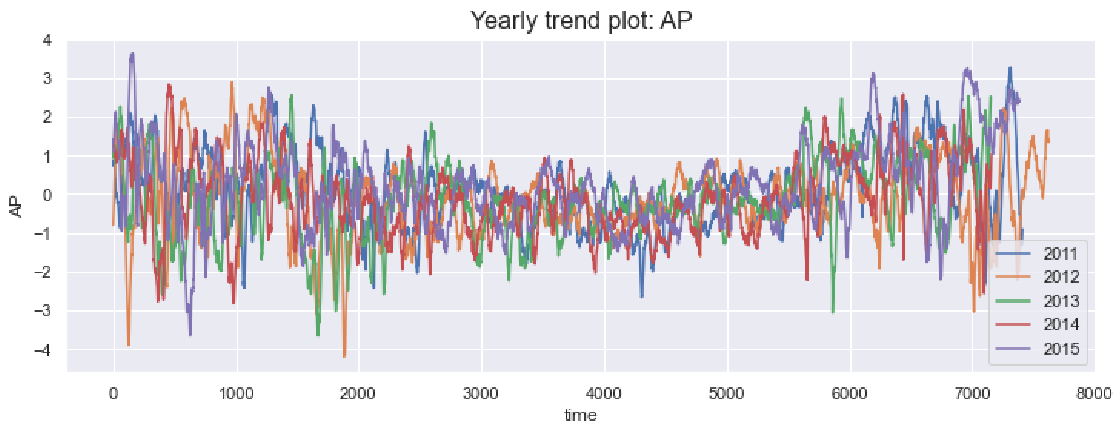


0.1.6 QUESTION 6

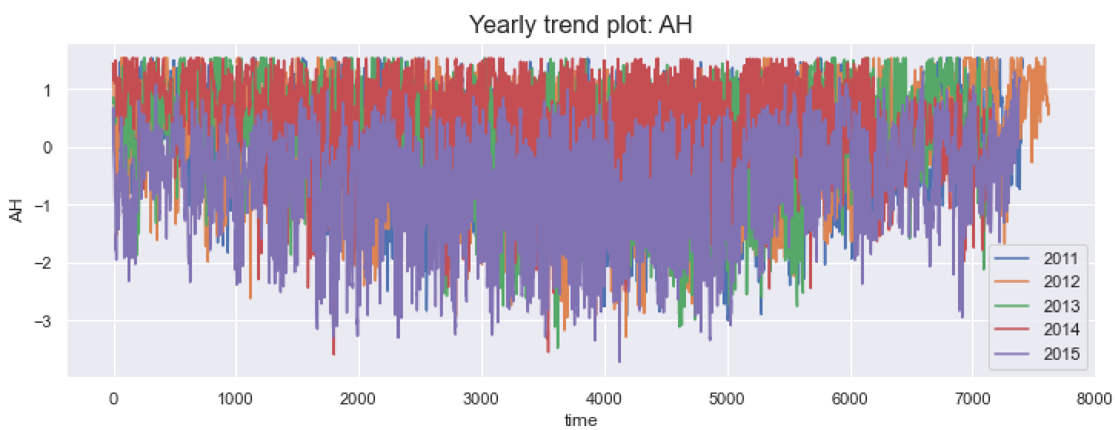
[33]:
```
def plot_yearly_trend(data, feature, years):
    plt.figure(figsize=(12,4))
    for year in years:
        plt.plot(data[data['year'] == year]['hour_index'], data[data['year'] ==␣
↪year][feature], label = year)
    plt.title('Yearly trend plot: '+ feature, fontsize = 16)
    plt.xlabel('time')
    plt.ylabel(feature)
    plt.legend()
    plt.show()
```

[34]:
```
years = list(set(pollution_df_scaled['year']))
features = ['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'TEY', 'CDP']

for feature in features:
    plot_yearly_trend(pollution_df_scaled, feature, years)
```

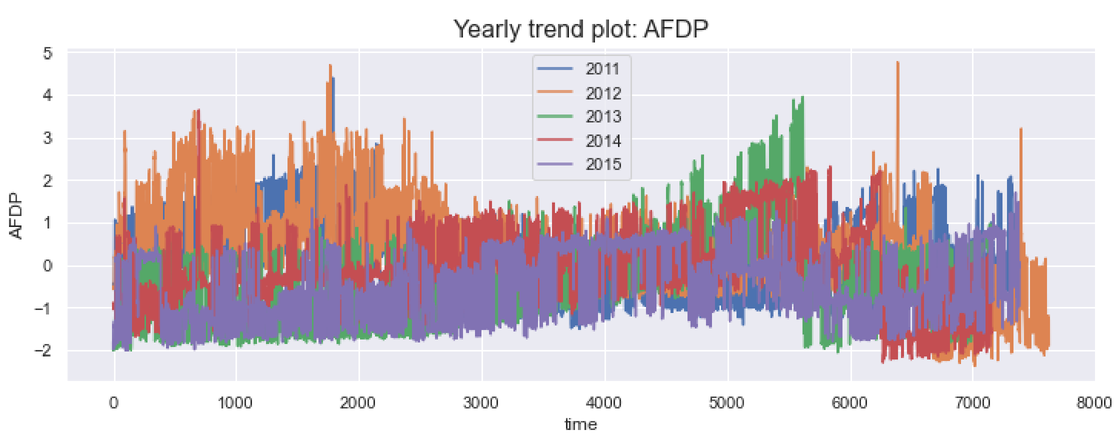




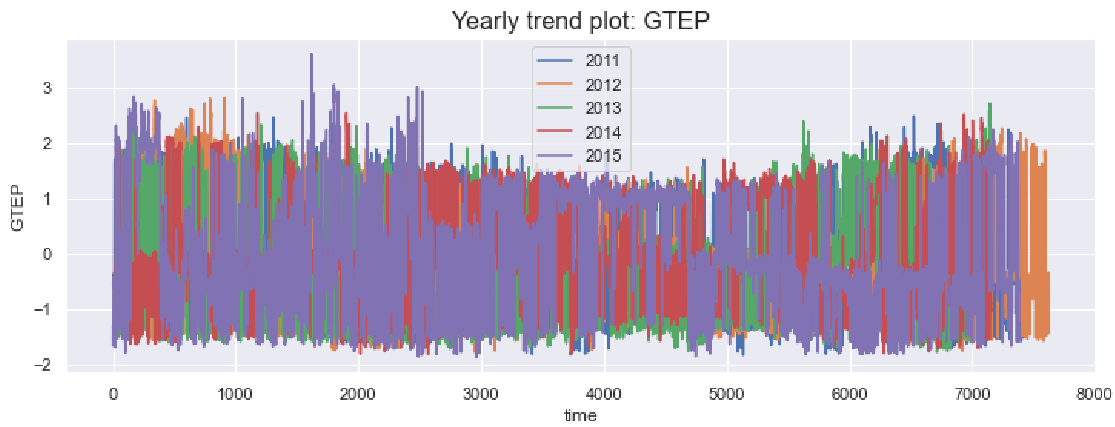
Yearly trend plot: AP
AP
time
2011
2012
2013
2014
2015



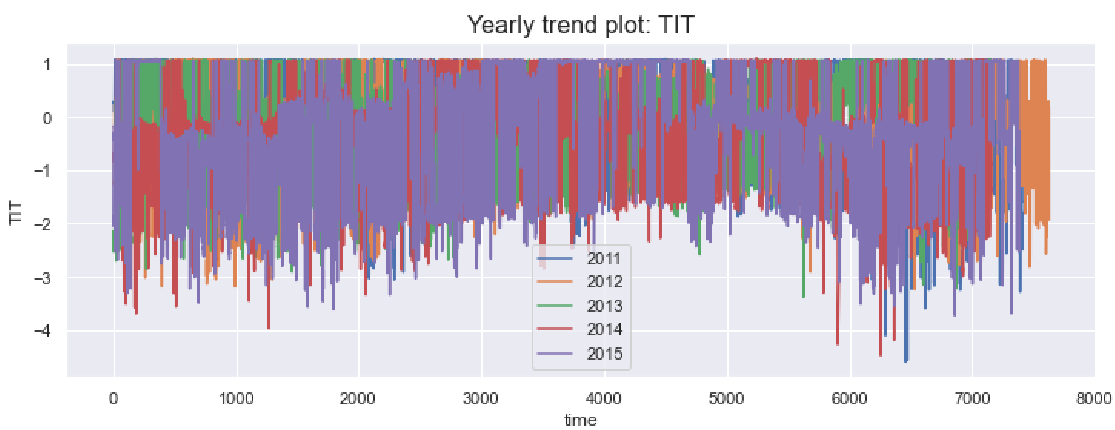
Yearly trend plot: AH
AH
time
2011
2012
2013
2014
2015



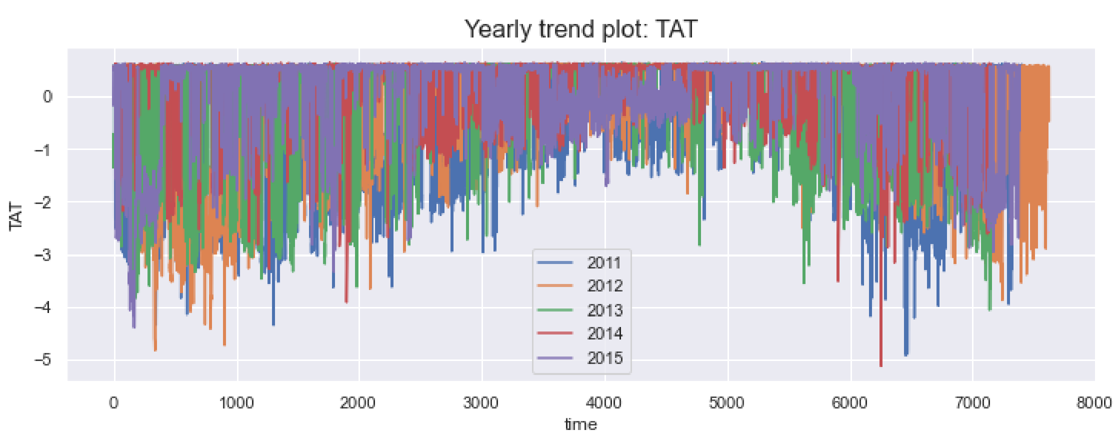
Yearly trend plot: AFDP
AFDP
time
2011
2012
2013
2014
2015



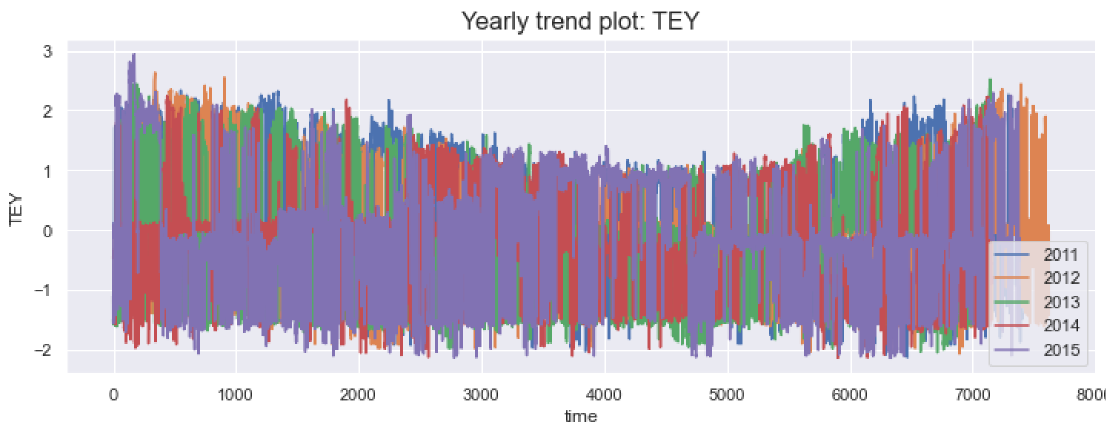
Yearly trend plot: GTEP
GTEP
time
2011
2012
2013
2014
2015

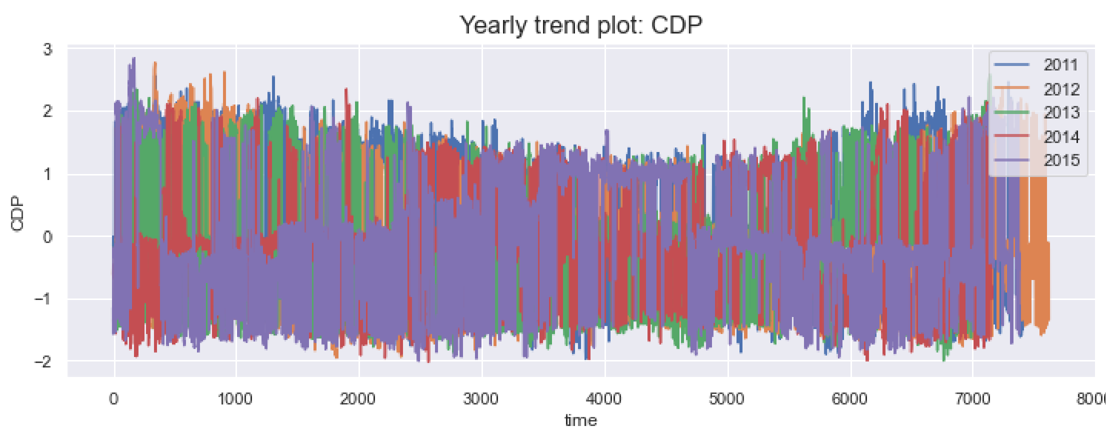


Yearly trend plot: TIT
TIT
time
2011
2012
2013
2014
2015



Yearly trend plot: TAT
TAT
time
2011
2012
2013
2014
2015





For `AT` across the years, the value peaks at around middle of the year and has an inverted U curve with a lot of variance in daily values. We see slightly distinct peaks for `AFDP` across the years. For other variables, the pattern seem quite noisy. For `TAT`, there are some extreme low values in year 2011 compared to the rest.

0.1.7 QUESTION 7

The methods based on F-test estimates the degree of linear dependency between two random variables. On the other hand, mutual information methods can capture any kind of statistical dependency, but being nonparametric, they require more samples for accurate estimation.

[35]:
```
def get_mutual_info_df (data: pd.DataFrame(), target: str, features: list):
    '''
    returns a dataframe with feature name and mutual information
    '''
    y = np.array(data[target])
    mi = mutual_info_regression(data[features], y.ravel(),\
```

```
                                     random_state=42, n_neighbors = 5)
    tmp = pd.DataFrame({'feature': features, 'mutual_info': mi})
    return tmp
```

[36]:
```
def get_f_statistic_df (data: pd.DataFrame(), target: str, features: list):
    '''
    returns a dataframe with feature name and f statistic along with p value
    '''
    y = np.array(data[target])
    f_stat, p_val = f_regression(data[features], y.ravel())
    tmp = pd.DataFrame({'feature': features, 'f_stat': f_stat, 'p_val': p_val})
    return tmp
```

For diamonds dataset

[37]:
```
print("Feature selection for diamonds dataset..")
all_features_diamond = ['carat', 'cut_num', 'color_num', 'clarity_num', 'depth',␣
 ↪'table',\
         'x', 'y', 'z']
target_diamond = 'price'
mi = get_mutual_info_df(diamonds_df_scaled, target_diamond, all_features_diamond)
f_stat = get_f_statistic_df(diamonds_df_scaled, target_diamond,␣
 ↪all_features_diamond)

feat_sel = pd.merge(mi, f_stat, how = 'left', on = 'feature')
feat_sel
```

```
Feature selection for diamonds dataset..
```

[37]:

	feature	mutual_info	f_stat	p_val
0	carat	1.621646	304051.486619	0.000000e+00
1	cut_num	0.054738	154.784468	1.746019e-35
2	color_num	0.133398	1654.401244	0.000000e+00
3	clarity_num	0.212236	1188.007065	1.571721e-257
4	depth	0.027190	6.115863	1.340045e-02
5	table	0.033055	886.119363	3.769963e-193
6	x	1.393433	193741.523066	0.000000e+00
7	y	1.395241	160915.662263	0.000000e+00
8	z	1.346187	154923.266553	0.000000e+00

Low mutual information score and F-statistic suggest weaker relationship or random relationship between the variable and the target variable. Variables with weaker relationship with the target variable are: `cut_num`, `depth` and `table`. Removing these variables should reduce the noise in the predictions and lead to better generalization. Hence, the RMSE on the test set should reduce if we perform feature selection and keep only appropriate features which have strong relationship with the target variable.

`carat`, `x`, `y` , `z` have strong relationship with the target variable where as `color` and `clarity` have moderate relationship.

[38]:
```
selected_features_diamond = ['carat', 'x', 'y', 'z', 'color_num', 'clarity_num']
```

For pollution dataset

[39]:
```
print("Feature selection for pollution dataset..")
all_features_pollution = ['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'TEY',␣
 ↪'CDP', 'year_num']
target_pollution = 'CO'
mi = get_mutual_info_df(pollution_df_scaled, target_pollution,␣
 ↪all_features_pollution)
f_stat = get_f_statistic_df(pollution_df_scaled, target_pollution,␣
 ↪all_features_pollution)

feat_sel = pd.merge(mi, f_stat, how = 'left', on = 'feature')
feat_sel
```

```
Feature selection for pollution dataset..
```

[39]:

	feature	mutual_info	f_stat	p_val
0	AT	0.100237	1151.220905	1.701222e-248
1	AP	0.044572	165.877529	7.106951e-38
2	AH	0.022060	422.080131	2.882457e-93
3	AFDP	0.275695	9245.083774	0.000000e+00
4	GTEP	0.444751	13534.970544	0.000000e+00
5	TIT	0.540375	36558.688346	0.000000e+00
6	TAT	0.161008	125.500842	4.408086e-29
7	TEY	0.497194	17660.022764	0.000000e+00
8	CDP	0.471864	16015.416774	0.000000e+00
9	year_num	0.126037	1208.144337	1.755865e-260

`AP` and `AH` have very low mutual information score and `TAT` has a low F statistic. We will exclude these features from model training.

[40]:
```
selected_features_pollution = ['AT', 'AFDP', 'GTEP', 'TIT', 'TEY', 'CDP',␣
 ↪'year_num']
```

0.1.8 QUESTION 8

Linear regression tries to minimize the residual sum of squares between the observed targets in the dataset and the targets predicted by the linear regression model. The objective function is given by: $\sum_{i=1}^{n}(Y_i - (WX_i + b))^2$ where, n is the total number of records, Y_i is the target value for record i, W are the set of weights assigned to each independent variable from the model, X_i are the set of independent variable values for the i^th record and b is the intercept term. Together, $WX_i + b$ is the prediction for the target from the linear regression model.

For lasso regression, we add an L1 penalty to the above objective function and for ridge regression, we add an L2 penalty to the weights.

[41]:
```
def rmse(y_true, y_pred):
    '''
    rmse scorer for cross validation
    '''
    error = np.linalg.norm(y_pred - y_true) / np.sqrt(len(y_true))
    return error

rmse_scorer = make_scorer(rmse)
```

[42]:
```
def train_model(model, data: pd.DataFrame(), features: list, target: str,\
                        model_name: str, params = 'NA', cv = 10):
    '''
    Given a model and dataset, train the model on 10 fold cross validation with␣
 ↪rmse score
    '''
    results = {}
    X = data[features]
    y = data[target]
    cv_results = cross_validate(model, X, y, cv=cv, scoring=rmse_scorer,\
                                return_train_score=True, n_jobs = -1)
    rmse_test = np.sum(cv_results['test_score'])/cv
    rmse_train = np.sum(cv_results['train_score'])/cv
    results['model'] = model_name
    results['params'] = params
    results['avg_train_rmse'] = rmse_train
    results['avg_test_rmse'] = rmse_test
    return results
```

[43]:
```
def compare_train_test(train_error: dict, test_error : dict, title : str):
    '''
    visualize train and test error for various regularisation parameters for L1␣
 ↪and L2 reg models
    '''
    plt.figure(figsize=(12,4))
    plt.plot( [ log10(i) for i in list(train_error.keys())], list(train_error.
 ↪values()), label = 'train')
    plt.plot( [ log10(i) for i in list(test_error.keys())], list(test_error.
 ↪values()), label = 'test')
    plt.xlabel('log10(reg_parameter)')
    plt.ylabel('rmse')
    plt.title(title, fontsize = 14)
    plt.grid('True')
    plt.legend()
    plt.show()
```

[44]:
```
def get_results(model, X, y, cv):
    cv_results = cross_validate(model, X, y, cv=cv, scoring=rmse_scorer,\
```

```
                                    return_train_score=True, n_jobs = -1)
    rmse_test = np.sum(cv_results['test_score'])/cv
    rmse_train = np.sum(cv_results['train_score'])/cv
    model.fit(X, y)
    return rmse_test, rmse_train, model.coef_


def train_regModel_wCoef(model_name, data: pd.DataFrame(), features: list,␣
↪target: str, grid_params : dict, cv = 10):

    results_test = {}
    results_train = {}
    results_coef = {}

    X = data[features]
    y = data[target]

    for alpha in grid_params['alpha']:
        if(model_name == 'Lasso'):
            model = Lasso(alpha = alpha, random_state = 42)
        elif(model_name == 'Ridge'):
            model = Ridge(alpha = alpha, random_state = 42)
        rmse_test, rmse_train, coef = get_results(model, X, y, cv)
        results_test[alpha] = rmse_test
        results_train[alpha] = rmse_train
        results_coef[alpha] = coef

    return results_test, results_train, results_coef

def generate_reg_report (model_name, data, features, target, grid_params, cv):
    reg = 'L1' if model_name == 'Lasso' else 'L2'
    results_test, results_train, results_coeff =␣
↪train_regModel_wCoef(model_name,\
                                                                    data, \
                                                                    features,␣
↪target, \
                                                                    grid_params,␣
↪10)
    print("Plotting train and test rmse across regularisation parameters for␣
↪"+reg+" regularisation..")
    compare_train_test(results_train,results_test, "Compare train and test rmse␣
↪for "+reg+" regularisation")

    print("Table showing various coefficients(in columns) for different alpha␣
↪values(in rows) for "+reg+" regularisation..")
    print(pd.DataFrame.from_dict(results_coeff, orient = 'index'))
```

```
    best_alpha = min(results_test, key=results_test.get)
    best_params = {'alpha': best_alpha}
    if(model_name == 'Lasso'):
        model = Lasso(**best_params, random_state = 42)
    else:
        model = Ridge(**best_params, random_state = 42)
    result = train_model(model, data, features,\
                         target, str(model_name)+' Regression', best_params)
    return result
```

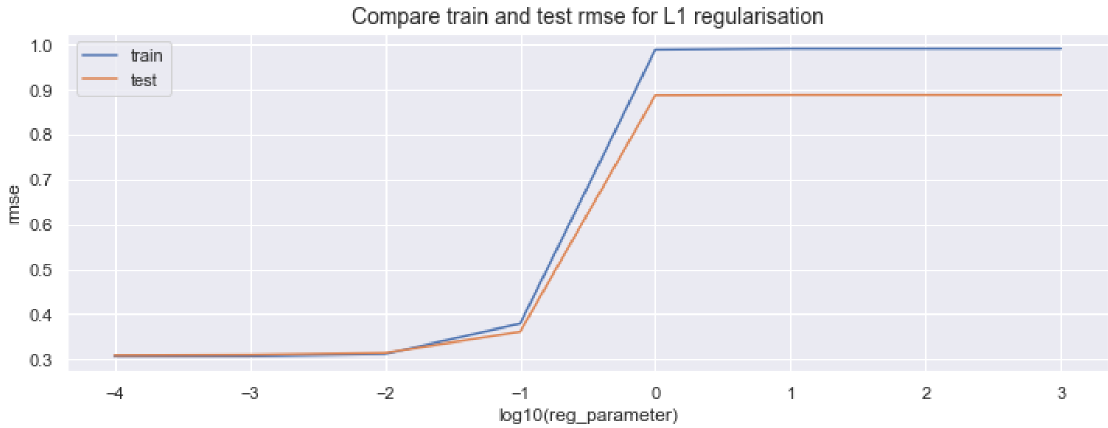
[45]:
```
all_model_results_diamond = []
all_model_results_pollution = []
```

For diamonds dataset

[46]:
```
print("Training baseline regression model for diamonds dataset with selected␣
 ↪features..")
model = LinearRegression(n_jobs = -1)
result = train_model(model, diamonds_df_scaled, selected_features_diamond,␣
 ↪target_diamond, 'Linear Regression')
all_model_results_diamond.append(result)

print("Creating results to analyze the effect of regularisation parameter for L1␣
 ↪regularisation..")
grid_params = {
        'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}
result = generate_reg_report('Lasso',\
                                                                              ␣
 ↪diamonds_df_scaled, \
                                                                              ␣
 ↪selected_features_diamond, target_diamond, \
                                                                   grid_params,␣
 ↪10)
all_model_results_diamond.append(result)

print("Creating results to analyze the effect of regularisation parameter for L2␣
 ↪regularisation..")
grid_params = {
        'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}
result = generate_reg_report('Ridge',\
                                                                              ␣
 ↪diamonds_df_scaled, \
                                                                              ␣
 ↪selected_features_diamond, target_diamond, \
                                                                   grid_params,␣
 ↪10)
```

```
all_model_results_diamond.append(result)
```

```
Training baseline regression model for diamonds dataset with selected features..
Creating results to analyze the effect of regularisation parameter for L1
regularisation..
Plotting train and test rmse across regularisation parameters for L1
regularisation..
```




```
Table showing various coefficients(in columns) for different alpha values(in
rows) for L1 regularisation..
                  0         1         2         3         4         5
0.0001     1.242308 -0.164872  0.021041 -0.066405  0.138174  0.216819
0.0010     1.205831 -0.116586  0.000000 -0.058208  0.136337  0.216429
0.0100     1.019122 -0.000000  0.000000 -0.000000  0.119776  0.205856
0.1000     0.838953  0.000000  0.000000  0.000000  0.000000  0.049215
1.0000     0.000000  0.000000  0.000000  0.000000 -0.000000 -0.000000
10.0000    0.000000  0.000000  0.000000  0.000000 -0.000000 -0.000000
100.0000   0.000000  0.000000  0.000000  0.000000 -0.000000 -0.000000
1000.0000  0.000000  0.000000  0.000000  0.000000 -0.000000 -0.000000
Creating results to analyze the effect of regularisation parameter for L2
regularisation..
Plotting train and test rmse across regularisation parameters for L2
regularisation..
```


```
Table showing various coefficients(in columns) for different alpha values(in
rows) for L2 regularisation..
                  0         1         2         3         4         5
0.0001     1.246584 -0.172075  0.025014 -0.067305  0.138380  0.216846
0.0010     1.246583 -0.172074  0.025014 -0.067305  0.138380  0.216846
0.0100     1.246578 -0.172069  0.025013 -0.067305  0.138379  0.216846
0.1000     1.246529 -0.172019  0.025008 -0.067301  0.138378  0.216846
1.0000     1.246037 -0.171519  0.024952 -0.067268  0.138362  0.216847
10.0000    1.241155 -0.166580  0.024416 -0.066927  0.138201  0.216855
100.0000   1.195544 -0.122596  0.020613 -0.062823  0.136667  0.216865
1000.0000  0.913708  0.073584  0.038931 -0.006099  0.125451  0.213930
```

[47]:
```
pd.DataFrame.from_dict(all_model_results_diamond)
```

[47]:

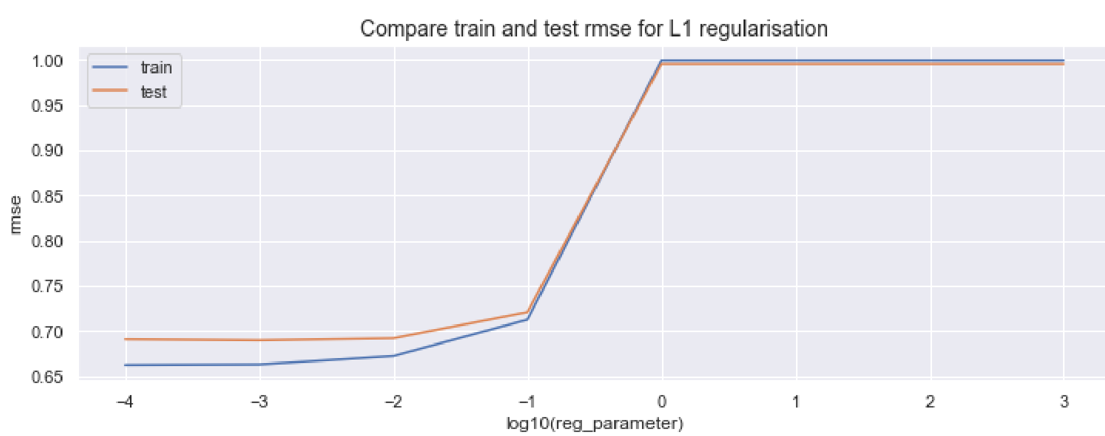
	model	params	avg_train_rmse	avg_test_rmse
0	Linear Regression	NA	0.306212	0.307871
1	Lasso Regression	{'alpha': 0.0001}	0.306215	0.307962
2	Ridge Regression	{'alpha': 0.0001}	0.306212	0.307871

For pollution dataset

[48]:
```
print("Training baseline regression model for pollution dataset with selected␣
 ↪features..")
model = LinearRegression(n_jobs = -1)
result = train_model(model, pollution_df_scaled, selected_features_pollution,␣
 ↪target_pollution, 'Linear Regression')
all_model_results_pollution.append(result)

print("Creating results to analyze the effect of regularisation parameter for L1␣
 ↪regularisation..")
grid_params = {
        'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}
result = generate_reg_report('Lasso',\
```

```
                                                                       ␣
 ↪pollution_df_scaled, \
                                                                       ␣
 ↪selected_features_pollution, target_pollution, \
                                                                        grid_params,␣
 ↪10)
all_model_results_pollution.append(result)

print("Creating results to analyze the effect of regularisation parameter for L2␣
 ↪regularisation..")
grid_params = {
        'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}
result = generate_reg_report('Ridge',\
                                                                       ␣
 ↪pollution_df_scaled, \
                                                                       ␣
 ↪selected_features_pollution, target_pollution, \
                                                                        grid_params,␣
 ↪10)
all_model_results_pollution.append(result)
```

```
Training baseline regression model for pollution dataset with selected
features..
Creating results to analyze the effect of regularisation parameter for L1
regularisation..
Plotting train and test rmse across regularisation parameters for L1
regularisation..
```




```
Table showing various coefficients(in columns) for different alpha values(in
rows) for L1 regularisation..
                  0          1          2          3          4          5  \
0.0001    -0.183258   0.000597   0.082464  -0.850480  -1.497331   1.625373
```

0.0010	-0.131312	0.000879	0.056860	-0.920918	-1.136598	1.355722
0.0100	0.000000	0.004088	0.030332	-1.040039	-0.000000	0.352438
0.1000	-0.000000	-0.000000	0.000000	-0.605992	-0.000000	-0.000000
1.0000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000
10.0000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000
100.0000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000
1000.0000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000	-0.000000

	6
0.0001	0.064690
0.0010	0.060047
0.0100	0.046133
0.1000	0.002250
1.0000	0.000000
10.0000	0.000000
100.0000	0.000000
1000.0000	0.000000

Creating results to analyze the effect of regularisation parameter for L2 regularisation..
Plotting train and test rmse across regularisation parameters for L2 regularisation..

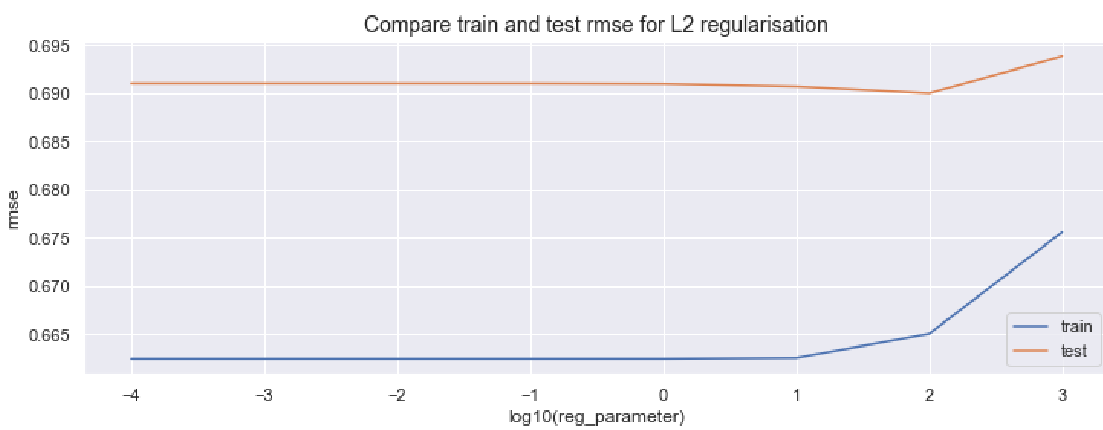


Table showing various coefficients(in columns) for different alpha values(in rows) for L2 regularisation..

	0	1	2	3	4	5 \
0.0001	-0.190271	0.000529	0.086165	-0.840659	-1.545671	1.660898
0.0010	-0.190269	0.000529	0.086165	-0.840662	-1.545656	1.660886
0.0100	-0.190248	0.000530	0.086165	-0.840690	-1.545508	1.660764
0.1000	-0.190047	0.000546	0.086165	-0.840970	-1.544034	1.659542
1.0000	-0.188057	0.000696	0.086165	-0.843739	-1.529440	1.647447
10.0000	-0.170094	0.002079	0.086434	-0.868532	-1.397303	1.537389
100.0000	-0.085372	0.009865	0.099718	-0.975583	-0.751882	0.974273
1000.0000	-0.043248	0.024379	0.153701	-0.898842	-0.193884	0.284272

```
                  6
0.0001     0.065303
0.0010     0.065302
0.0100     0.065301
0.1000     0.065281
1.0000     0.065091
10.0000    0.063382
100.0000   0.055748
1000.0000  0.063641
```

[49]:
```
pd.DataFrame.from_dict(all_model_results_pollution)
```

[49]:

	model	params	avg_train_rmse	avg_test_rmse
0	Linear Regression	NA	0.662448	0.690991
1	Lasso Regression	{'alpha': 0.001}	0.663014	0.689782
2	Ridge Regression	{'alpha': 100}	0.665031	0.689959

Lasso and ridge regression are regularization methods, which are used to put constraints on the weights of the model. Regularisation is used to penalise complex models.

Lasso regression applies an L1 penalisation on the weights, so that the loss function is : $\sum_{i=1}^{n}(Y_i - (WX_i + b))^2 + \alpha\sum_{j=1}^{k}|W_j|$ We observe that, as the regularisation parameter is increased, some of the coefficients become 0 for the lasso regression. This implies that lasso regression can also be used for feature selection. We also, observe an increase in train and test rmse with increase in regularisation parameter, meaning that the less complex model is not predictive enough.

Ridge regression applies an L2 penalisation on the weights, so that the loss function is : $\sum_{i=1}^{n}(Y_i - (WX_i + b))^2 + \alpha\sum_{j=1}^{k}||W_j||$ We observe that, as the regularisation parameter is increased, the coefficient values start to decrease and come closer to zero. We also, observe an increase in train and test rmse. However, the increase is less compared to the lasso regression.

0.1.9 QUESTION 9

For diamonds dataset

[50]:
```
pd.DataFrame.from_dict(all_model_results_diamond)
```

[50]:

	model	params	avg_train_rmse	avg_test_rmse
0	Linear Regression	NA	0.306212	0.307871
1	Lasso Regression	{'alpha': 0.0001}	0.306215	0.307962
2	Ridge Regression	{'alpha': 0.0001}	0.306212	0.307871

For the diamonds dataset, with pre-selected features, the linear regression model and ridge regression model with very low regularisation perform better comared to the Lasso regression. However, the difference in performance is very small. The best regularisation scheme can be determined by first performing cross validation on a grid of alpha values to select best regularisation value for each of the Lasso and ridge regression. The best value is determined by average performance on the cross validation set. Then we can compare which regression scheme works best by comparing the performance of the 3 models. We can also incorporate some measure of generalisation by looking at the gap between train and validation error to choose the best set of hyper parameter.

For pollution dataset

[51]:
```
pd.DataFrame.from_dict(all_model_results_pollution)
```

[51]:

	model	params	avg_train_rmse	avg_test_rmse
0	Linear Regression	NA	0.662448	0.690991
1	Lasso Regression	{'alpha': 0.001}	0.663014	0.689782
2	Ridge Regression	{'alpha': 100}	0.665031	0.689959

For the pollution dataset, lasso regression with penalty = 0.001 performs best in terms of validation error.

0.1.10 QUESTION 10

[52]:
```
def generate_feature_scaling_table (data_scaled, data_unscaled, features,␣
↪target_scaled, target_unscaled,\
                                    alpha_ls, cv):
    all_results_scaled = []
    all_results_unscaled = []

    # Linear regression
    model = LinearRegression(n_jobs = -1)
    result = train_model(model, data_scaled, features, target_scaled, 'Linear␣
↪Regression')
    all_results_scaled.append(result)

    result = train_model(model, data_unscaled, features, target_unscaled,␣
↪'Linear Regression')
    all_results_unscaled.append(result)

    # Lasso and ridge regularisation
    for alpha in alpha_ls:
        models =  [Lasso(alpha=alpha, random_state = 42), Ridge(alpha=alpha,␣
↪random_state = 42)]
        model_names = ['Lasso', 'Ridge']
        for i in range(len(model_names)):
            params = {'alpha': alpha}
            result = train_model(models[i], data_scaled, features,␣
↪target_scaled,\
                                 model_names[i]+' Regression', params)
            all_results_scaled.append(result)
            result = train_model(models[i], data_unscaled, features,␣
↪target_unscaled,\
                                 model_names[i]+' Regression', params)
            all_results_unscaled.append(result)

    results_scaled = pd.DataFrame.from_dict(all_results_scaled)
    results_scaled['params'] = results_scaled['params'].astype(str)
```

```
    results_scaled.columns = ['model', 'params', 'avg_train_rmse_scaled',␣
↪'avg_test_rmse_scaled']
    results_unscaled = pd.DataFrame.from_dict(all_results_unscaled)
    results_unscaled.columns = ['model', 'params', 'avg_train_rmse_unscaled',␣
↪'avg_test_rmse_unscaled']
    results_unscaled['params'] = results_unscaled['params'].astype(str)

    all_results = pd.merge(results_scaled, results_unscaled, how = 'left', on =␣
↪['model', 'params'])
    return all_results
```

For diamonds dataset

[53]:
```
print("Compare results for scaled vs unscaled features for diamonds dataset ..")
target_diamond_unscaled = 'price_scaled'
alpha_ls = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
feat_scaling_results = generate_feature_scaling_table(diamonds_df_scaled,␣
↪diamonds_df, \
                                                      selected_features_diamond,␣
↪target_diamond, \
                                                      target_diamond_unscaled,␣
↪alpha_ls, 10)
feat_scaling_results
```

```
Compare results for scaled vs unscaled features for diamonds dataset ..
```

[53]:
```
               model             params  avg_train_rmse_scaled  \
0  Linear Regression                 NA               0.306212
1   Lasso Regression  {'alpha': 0.0001}               0.306215
2   Ridge Regression  {'alpha': 0.0001}               0.306212
3   Lasso Regression   {'alpha': 0.001}               0.306411
4   Ridge Regression   {'alpha': 0.001}               0.306212
5   Lasso Regression    {'alpha': 0.01}               0.310805
6   Ridge Regression    {'alpha': 0.01}               0.306212
7   Lasso Regression     {'alpha': 0.1}               0.378893
8   Ridge Regression     {'alpha': 0.1}               0.306212
9   Lasso Regression       {'alpha': 1}               0.989606
10  Ridge Regression       {'alpha': 1}               0.306212
11  Lasso Regression      {'alpha': 10}               0.991918
12  Ridge Regression      {'alpha': 10}               0.306215
13  Lasso Regression     {'alpha': 100}               0.991918
14  Ridge Regression     {'alpha': 100}               0.306471
15  Lasso Regression    {'alpha': 1000}               0.991918
16  Ridge Regression    {'alpha': 1000}               0.316016

    avg_test_rmse_scaled  avg_train_rmse_unscaled  avg_test_rmse_unscaled
0               0.307871                 0.306212                0.307871
```

```
1              0.307962            0.306217           0.308023
2              0.307871            0.306212           0.307871
3              0.309042            0.306617           0.309886
4              0.307871            0.306212           0.307871
5              0.313313            0.313118           0.321569
6              0.307871            0.306212           0.307871
7              0.360896            0.439756           0.444732
8              0.307872            0.306212           0.307878
9              0.887510            0.962337           0.872642
10             0.307885            0.306213           0.307942
11             0.888362            0.991918           0.888362
12             0.308020            0.306259           0.308624
13             0.888362            0.991918           0.888362
14             0.309544            0.309413           0.317223
15             0.888362            0.991918           0.888362
16             0.326647            0.350177           0.370561
```

For pollution dataset

[54]:
```
print("Compare results for scaled vs unscaled features for pollution dataset ..")
target_pollution_unscaled = 'CO_scaled'
alpha_ls = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
feat_scaling_results = generate_feature_scaling_table(pollution_df_scaled,␣
 ↪pollution_df, \
                                                                      ␣
 ↪selected_features_pollution, target_pollution, \
                                                      target_pollution_unscaled,␣
 ↪alpha_ls, 10)
feat_scaling_results
```

```
Compare results for scaled vs unscaled features for pollution dataset ..
```

[54]:
```
                model              params  avg_train_rmse_scaled  \
0   Linear Regression                  NA               0.662448
1    Lasso Regression  {'alpha': 0.0001}               0.662456
2    Ridge Regression  {'alpha': 0.0001}               0.662448
3    Lasso Regression   {'alpha': 0.001}               0.663014
4    Ridge Regression   {'alpha': 0.001}               0.662448
5    Lasso Regression    {'alpha': 0.01}               0.672341
6    Ridge Regression    {'alpha': 0.01}               0.662448
7    Lasso Regression     {'alpha': 0.1}               0.712646
8    Ridge Regression     {'alpha': 0.1}               0.662448
9    Lasso Regression       {'alpha': 1}               0.999401
10   Ridge Regression       {'alpha': 1}               0.662449
11   Lasso Regression      {'alpha': 10}               0.999401
12   Ridge Regression      {'alpha': 10}               0.662540
13   Lasso Regression     {'alpha': 100}               0.999401
14   Ridge Regression     {'alpha': 100}               0.665031
```

```
15   Lasso Regression    {'alpha': 1000}              0.999401
16   Ridge Regression    {'alpha': 1000}              0.675577

    avg_test_rmse_scaled  avg_train_rmse_unscaled  avg_test_rmse_unscaled
0               0.690991                 0.662448                0.690991
1               0.690909                 0.662450                0.690934
2               0.690991                 0.662448                0.690991
3               0.689782                 0.662580                0.689483
4               0.690991                 0.662448                0.690991
5               0.692061                 0.672026                0.694967
6               0.690991                 0.662448                0.690991
7               0.720887                 0.680102                0.694806
8               0.690987                 0.662448                0.690985
9               0.995404                 0.709619                0.714026
10              0.690952                 0.662448                0.690930
11              0.995404                 0.908761                0.909022
12              0.690662                 0.662469                0.690430
13              0.995404                 0.999401                0.995404
14              0.689959                 0.663567                0.688602
15              0.995404                 0.999401                0.995404
16              0.693806                 0.670857                0.693372
```

Feature scaling changes the weights of the model. Feature scaling do not play any role in model performance for base linear regression without regularisation. This is because any scaling effect in the features should be captured by the change in weights and the intercept keeping the loss constant. However, if using gradient descent, the scaling would play a role as the gradients change. Since regularisation has a penalty on high weight values, we see that the regularised models perform worse without feature scaling.

0.1.11 QUESTION 11

p-value is a statistic which is used to infer whether a particular independent variable impacts the dependent variable statstically significantly. It describes how likely it is to observe the given set of data if the null hypothesis were true, where the null hypothesis is that the independent variable does not affect the dependent variable. If the value is small, then we reject the null hypothesis that the independent variable does not affect dependent variable.

A p-value of 0.001 indicates that if the null hypothesis tested were indeed true, there would be a one in 1,000 chance of observing the data.

0.1.12 QUESTION 12

[55]:
```
def get_data_columns_polynomial (data, features, target, degree):
    '''
    get dataset and feature list given a polynomial order on a dataset
    '''
    X = data[features]
    y = data[target]
```

```
    poly_reg=PolynomialFeatures(degree=degree)
    X_poly=poly_reg.fit_transform(X)
    columns = poly_reg.get_feature_names_out()

    poly_df = pd.DataFrame(data = X_poly,
                      columns = columns)
    poly_df = poly_df.drop(['1'], axis = 1)
    columns = poly_df.columns
    poly_df[target] = y

    return poly_df, columns
```

For diamonds dataset

[56]:
```
degree = 2
poly_df_2, columns_2 = get_data_columns_polynomial(diamonds_df_scaled,␣
↪selected_features_diamond, \
                                                    target_diamond, degree)

mi = get_mutual_info_df(poly_df_2, target_diamond, columns_2)
f_stat = get_f_statistic_df(poly_df_2, target_diamond, columns_2)

feat_sel = pd.merge(mi, f_stat, how = 'left', on = 'feature')
feat_sel.sort_values(['mutual_info', 'f_stat'], ascending = [False,False]).
↪head(25)
```

[56]:

	feature	mutual_info	f_stat	p_val
11	carat clarity_num	1.707993	909.274840	4.217023e-198
0	carat	1.620390	304051.486619	0.000000e+00
6	carat^2	1.445774	30676.068058	0.000000e+00
2	y	1.394307	160915.662263	0.000000e+00
10	carat color_num	1.393466	4185.168229	0.000000e+00
1	x	1.392225	193741.523066	0.000000e+00
3	z	1.345392	154923.266553	0.000000e+00
8	carat y	1.050298	26021.887415	0.000000e+00
9	carat z	1.047803	28182.113655	0.000000e+00
7	carat x	1.046077	31023.831176	0.000000e+00
16	x clarity_num	1.022089	76.951445	1.802115e-18
20	y clarity_num	1.010153	78.680166	7.520312e-19
23	z clarity_num	1.008889	67.747333	1.899589e-16
12	x^2	1.000665	23089.361534	0.000000e+00
18	y z	0.962432	7893.265942	0.000000e+00
14	x z	0.953520	21472.932371	0.000000e+00
21	z^2	0.929704	401.266660	6.156320e-89
17	y^2	0.923085	276.755648	5.462270e-62
13	x y	0.910399	19947.339234	0.000000e+00
22	z color_num	0.712120	2271.706841	0.000000e+00
15	x color_num	0.710723	2426.794265	0.000000e+00

```
19              y color_num     0.704023    2356.043537    0.000000e+00
25    color_num clarity_num     0.568494     538.685017   1.392890e-118
26            clarity_num^2     0.212435     184.895217    4.853690e-42
5               clarity_num     0.212230    1188.007065   1.571721e-257
```

From the degree 2 polynomial features, the most salient features are [carat* clarity], suggesting that for different clarity categories, weight of the diamond has different effects on the price. We have [carat* carat], suggesting that as weight increases, prices increase in square root fashion. We have [carat* color] again suggesting weight having different effect on price for color categories. We also have features like [x* y] or, length * width suggesting that area across dimensions have an effect.

For pollution dataset

[57]:
```python
degree = 2
poly_df_2, columns_2 = get_data_columns_polynomial(pollution_df_scaled,␣
 ↪selected_features_pollution, \
                                                   target_pollution, degree)

mi = get_mutual_info_df(poly_df_2, target_pollution, columns_2)
f_stat = get_f_statistic_df(poly_df_2, target_pollution, columns_2)

feat_sel = pd.merge(mi, f_stat, how = 'left', on = 'feature')
feat_sel.sort_values(['mutual_info', 'f_stat'], ascending = [False,False]).
 ↪head(25)
```

[57]:

	feature	mutual_info	f_stat	p_val
3	TIT	0.541354	36558.688346	0.000000e+00
28	TIT year_num	0.524304	99.966894	1.660770e-23
4	TEY	0.497038	17660.022764	0.000000e+00
5	CDP	0.472097	16015.416774	0.000000e+00
2	GTEP	0.444826	13534.970544	0.000000e+00
25	TIT^2	0.437256	35467.569005	0.000000e+00
33	CDP year_num	0.398241	9.744380	1.800113e-03
24	GTEP year_num	0.381877	4.362006	3.675587e-02
31	TEY year_num	0.377105	6.060219	1.383061e-02
26	TIT TEY	0.345556	17737.416514	0.000000e+00
21	GTEP TIT	0.327712	13664.127495	0.000000e+00
27	TIT CDP	0.322628	14995.119418	0.000000e+00
1	AFDP	0.275683	9245.083774	0.000000e+00
22	GTEP TEY	0.274420	2530.799627	0.000000e+00
30	TEY CDP	0.271340	2852.148910	0.000000e+00
29	TEY^2	0.270099	3501.495834	0.000000e+00
23	GTEP CDP	0.248508	1922.456204	0.000000e+00
17	AFDP TEY	0.244152	2015.553040	0.000000e+00
19	AFDP year_num	0.240119	193.073426	8.758621e-44
32	CDP^2	0.235175	2227.720087	0.000000e+00
16	AFDP TIT	0.214483	7742.131942	0.000000e+00
20	GTEP^2	0.213729	1724.118919	0.000000e+00

```
18      AFDP CDP    0.211540   1587.575142   0.000000e+00
11        AT TEY    0.200771   2342.102411   0.000000e+00
15     AFDP GTEP    0.194266   1275.325737  1.324128e-274
```

Some of the salient features in the pollution dataset are - [TIT* TIT], interaction of features with the year, [TIT * TEY].

0.1.13 QUESTION 13

For diamonds dataset

[58]:

```
start_time = time.time()
degree_range = [2,3,4]
all_results_polynomial = []
alpha_ls = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]

for degree in degree_range:
    # generate polynomial feature data
    poly_df, columns = get_data_columns_polynomial(diamonds_df_scaled,␣
 ↪selected_features_diamond,\
                                                    target_diamond, degree)

    # Linear regression
    model = LinearRegression(n_jobs = -1)
    result = train_model(model, poly_df, columns, target_diamond, 'Linear(poly␣
 ↪degree='+str(degree)+')')
    all_results_polynomial.append(result)

    # Regularised regression
    for alpha in alpha_ls:
        models =  [Lasso(alpha=alpha, random_state = 42), Ridge(alpha=alpha,␣
 ↪random_state = 42)]
        model_names = ['Lasso', 'Ridge']
        params = {'alpha': alpha}
        for i in range(len(model_names)):
            result = train_model(models[i], poly_df, columns, target_diamond,\
                                 model_names[i]+' (poly␣
 ↪degree='+str(degree)+')', params)
            all_results_polynomial.append(result)
print("done in %0.3fs." % (time.time() - start_time))
```

```
done in 412.480s.
```

[59]:

```
print("Results for polynomial regression..")
result = pd.DataFrame.from_dict(all_results_polynomial)
result
```

```
Results for polynomial regression..
```

[59]:

	model	params	avg_train_rmse	avg_test_rmse
0	Linear(poly degree=2)	NA	0.195480	0.368182
1	Lasso (poly degree=2)	{'alpha': 0.0001}	0.196586	0.370314
2	Ridge (poly degree=2)	{'alpha': 0.0001}	0.195480	0.368181
3	Lasso (poly degree=2)	{'alpha': 0.001}	0.199914	0.308961
4	Ridge (poly degree=2)	{'alpha': 0.001}	0.195480	0.368172
5	Lasso (poly degree=2)	{'alpha': 0.01}	0.210834	0.209531
6	Ridge (poly degree=2)	{'alpha': 0.01}	0.195480	0.368077
7	Lasso (poly degree=2)	{'alpha': 0.1}	0.373516	0.354643
8	Ridge (poly degree=2)	{'alpha': 0.1}	0.195480	0.367159
9	Lasso (poly degree=2)	{'alpha': 1}	0.945338	0.879766
10	Ridge (poly degree=2)	{'alpha': 1}	0.195490	0.360282
11	Lasso (poly degree=2)	{'alpha': 10}	0.991918	0.888362
12	Ridge (poly degree=2)	{'alpha': 10}	0.195762	0.370499
13	Lasso (poly degree=2)	{'alpha': 100}	0.991918	0.888362
14	Ridge (poly degree=2)	{'alpha': 100}	0.198648	0.421677
15	Lasso (poly degree=2)	{'alpha': 1000}	0.991918	0.888362
16	Ridge (poly degree=2)	{'alpha': 1000}	0.205844	0.386712
17	Linear(poly degree=3)	NA	0.154887	2.245337
18	Lasso (poly degree=3)	{'alpha': 0.0001}	0.159847	3.231779
19	Ridge (poly degree=3)	{'alpha': 0.0001}	0.154887	2.243605
20	Lasso (poly degree=3)	{'alpha': 0.001}	0.162392	0.626049
21	Ridge (poly degree=3)	{'alpha': 0.001}	0.154887	2.228819
22	Lasso (poly degree=3)	{'alpha': 0.01}	0.178440	0.713341
23	Ridge (poly degree=3)	{'alpha': 0.01}	0.154890	2.140575
24	Lasso (poly degree=3)	{'alpha': 0.1}	0.354059	0.964755
25	Ridge (poly degree=3)	{'alpha': 0.1}	0.154965	2.566908
26	Lasso (poly degree=3)	{'alpha': 1}	0.747936	0.726628
27	Ridge (poly degree=3)	{'alpha': 1}	0.155422	4.564262
28	Lasso (poly degree=3)	{'alpha': 10}	0.991918	0.888362
29	Ridge (poly degree=3)	{'alpha': 10}	0.157111	4.414137
30	Lasso (poly degree=3)	{'alpha': 100}	0.991918	0.888362
31	Ridge (poly degree=3)	{'alpha': 100}	0.159701	3.522626
32	Lasso (poly degree=3)	{'alpha': 1000}	0.991918	0.888362
33	Ridge (poly degree=3)	{'alpha': 1000}	0.164078	1.610792
34	Linear(poly degree=4)	NA	0.143802	590.768460
35	Lasso (poly degree=4)	{'alpha': 0.0001}	0.151265	16.576379
36	Ridge (poly degree=4)	{'alpha': 0.0001}	0.143812	432.750603
37	Lasso (poly degree=4)	{'alpha': 0.001}	0.154089	4.263657
38	Ridge (poly degree=4)	{'alpha': 0.001}	0.143898	180.991893
39	Lasso (poly degree=4)	{'alpha': 0.01}	0.175049	4.883092
40	Ridge (poly degree=4)	{'alpha': 0.01}	0.144069	147.046978
41	Lasso (poly degree=4)	{'alpha': 0.1}	0.333422	2.427153
42	Ridge (poly degree=4)	{'alpha': 0.1}	0.144351	193.724110
43	Lasso (poly degree=4)	{'alpha': 1}	0.725787	0.719326
44	Ridge (poly degree=4)	{'alpha': 1}	0.144921	123.836108
45	Lasso (poly degree=4)	{'alpha': 10}	0.987422	0.887602

```
46  Ridge (poly degree=4)      {'alpha': 10}        0.146086      41.692268
47  Lasso (poly degree=4)     {'alpha': 100}        0.991889       0.888356
48  Ridge (poly degree=4)     {'alpha': 100}        0.148088      44.433064
49  Lasso (poly degree=4)    {'alpha': 1000}        0.991918       0.888362
50  Ridge (poly degree=4)    {'alpha': 1000}        0.152846      39.636498
```

[60]:
```
print("Best polynomial model with regularisation for diamonds dataset..")
print(result[result['avg_test_rmse'] == min(result['avg_test_rmse'])])
```

```
Best polynomial model with regularisation for diamonds dataset..
                    model           params  avg_train_rmse  avg_test_rmse
5  Lasso (poly degree=2)  {'alpha': 0.01}        0.210834       0.209531
```

[61]:
```
model = list(result[(result['avg_test_rmse'] ==␣
↪min(result['avg_test_rmse']))]['model'])[0]
params = list(result[(result['avg_test_rmse'] ==␣
↪min(result['avg_test_rmse']))]['params'])[0]
best_result = [i for i in all_results_polynomial if (i['model'] == model and␣
↪i['params'] == params)]
all_model_results_diamond.append(best_result[0])
```

Degree 2 polynomial features work best for the given dataset with L1 regularisation and alpha = 0.01. Introducing new features improved the validation rmse from ~0.3 to ~0.2. A high order polynomial would have more degree of freedom to fit (overfit) the training data and start learning noise from the data. The fit improves on the training dataset. However, it performs poorly on the validation set. The larger the degree more overfitting the model is. Degree of the polynomial is a hyper parameter and should be chosen using performance on a validation set.

For pollution dataset

[62]:
```
start_time = time.time()
degree_range = [2,3,4]
all_results_polynomial = []
alpha_ls = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]

for degree in degree_range:
    # generate polynomial feature data
    poly_df, columns = get_data_columns_polynomial(pollution_df_scaled,␣
↪selected_features_pollution,\
                                                    target_pollution, degree)

    # Linear regression
    model = LinearRegression(n_jobs = -1)
    result = train_model(model, poly_df, columns, target_pollution, 'Linear(poly␣
↪degree='+str(degree)+')')
    all_results_polynomial.append(result)

    # Regularised regression
```

```
    for alpha in alpha_ls:
        models =  [Lasso(alpha=alpha, random_state = 42), Ridge(alpha=alpha,␣
↪random_state = 42)]
        model_names = ['Lasso', 'Ridge']
        params = {'alpha': alpha}
        for i in range(len(model_names)):
            result = train_model(models[i], poly_df, columns, target_pollution,\
                                 model_names[i]+' (poly␣
↪degree='+str(degree)+')', params)
            all_results_polynomial.append(result)
print("done in %0.3fs." % (time.time() - start_time))
```

done in 269.950s.

[63]:
```
print("Results for polynomial regression..")
result = pd.DataFrame.from_dict(all_results_polynomial)
result
```

Results for polynomial regression..

[63]:

	model	params	avg_train_rmse	avg_test_rmse
0	Linear(poly degree=2)	NA	0.573496	0.682291
1	Lasso (poly degree=2)	{'alpha': 0.0001}	0.575407	0.694491
2	Ridge (poly degree=2)	{'alpha': 0.0001}	0.573496	0.682292
3	Lasso (poly degree=2)	{'alpha': 0.001}	0.577786	0.677124
4	Ridge (poly degree=2)	{'alpha': 0.001}	0.573496	0.682294
5	Lasso (poly degree=2)	{'alpha': 0.01}	0.597452	0.645245
6	Ridge (poly degree=2)	{'alpha': 0.01}	0.573496	0.682319
7	Lasso (poly degree=2)	{'alpha': 0.1}	0.633304	0.641899
8	Ridge (poly degree=2)	{'alpha': 0.1}	0.573510	0.682541
9	Lasso (poly degree=2)	{'alpha': 1}	0.993957	0.992652
10	Ridge (poly degree=2)	{'alpha': 1}	0.573685	0.683624
11	Lasso (poly degree=2)	{'alpha': 10}	0.999401	0.995404
12	Ridge (poly degree=2)	{'alpha': 10}	0.574567	0.684477
13	Lasso (poly degree=2)	{'alpha': 100}	0.999401	0.995404
14	Ridge (poly degree=2)	{'alpha': 100}	0.578641	0.670846
15	Lasso (poly degree=2)	{'alpha': 1000}	0.999401	0.995404
16	Ridge (poly degree=2)	{'alpha': 1000}	0.590752	0.651532
17	Linear(poly degree=3)	NA	0.514856	0.681238
18	Lasso (poly degree=3)	{'alpha': 0.0001}	0.525281	0.675889
19	Ridge (poly degree=3)	{'alpha': 0.0001}	0.514857	0.680941
20	Lasso (poly degree=3)	{'alpha': 0.001}	0.534283	0.666167
21	Ridge (poly degree=3)	{'alpha': 0.001}	0.514863	0.678809
22	Lasso (poly degree=3)	{'alpha': 0.01}	0.575006	0.629554
23	Ridge (poly degree=3)	{'alpha': 0.01}	0.514903	0.670116
24	Lasso (poly degree=3)	{'alpha': 0.1}	0.630178	0.650169
25	Ridge (poly degree=3)	{'alpha': 0.1}	0.515132	0.662299
26	Lasso (poly degree=3)	{'alpha': 1}	0.715179	0.712668

```
27  Ridge (poly degree=3)        {'alpha': 1}        0.516296        0.666756
28  Lasso (poly degree=3)       {'alpha': 10}        0.999401        0.995404
29  Ridge (poly degree=3)       {'alpha': 10}        0.520142        0.671482
30  Lasso (poly degree=3)      {'alpha': 100}        0.999401        0.995404
31  Ridge (poly degree=3)      {'alpha': 100}        0.533127        0.663267
32  Lasso (poly degree=3)     {'alpha': 1000}        0.999401        0.995404
33  Ridge (poly degree=3)     {'alpha': 1000}        0.554611        0.645807
34  Linear(poly degree=4)                  NA        0.466000        0.751629
35  Lasso (poly degree=4)   {'alpha': 0.0001}        0.488993        0.616899
36  Ridge (poly degree=4)   {'alpha': 0.0001}        0.466053        0.721933
37  Lasso (poly degree=4)    {'alpha': 0.001}        0.499656        0.602067
38  Ridge (poly degree=4)    {'alpha': 0.001}        0.466361        0.735268
39  Lasso (poly degree=4)     {'alpha': 0.01}        0.546234        0.620142
40  Ridge (poly degree=4)     {'alpha': 0.01}        0.467204        0.690300
41  Lasso (poly degree=4)      {'alpha': 0.1}        0.618315        0.665187
42  Ridge (poly degree=4)      {'alpha': 0.1}        0.469161        0.676355
43  Lasso (poly degree=4)        {'alpha': 1}        0.784761        0.783787
44  Ridge (poly degree=4)        {'alpha': 1}        0.472831        0.642927
45  Lasso (poly degree=4)       {'alpha': 10}        0.999401        0.995404
46  Ridge (poly degree=4)       {'alpha': 10}        0.479339        0.625295
47  Lasso (poly degree=4)      {'alpha': 100}        0.999401        0.995404
48  Ridge (poly degree=4)      {'alpha': 100}        0.492688        0.617190
49  Lasso (poly degree=4)     {'alpha': 1000}        0.999401        0.995404
50  Ridge (poly degree=4)     {'alpha': 1000}        0.515169        0.612512
```

[64]:
```
print("Best polynomial model with regularisation for pollution dataset..")
print(result[result['avg_test_rmse'] == min(result['avg_test_rmse'])])
```

```
Best polynomial model with regularisation for pollution dataset..
                    model            params  avg_train_rmse  avg_test_rmse
37  Lasso (poly degree=4)  {'alpha': 0.001}        0.499656       0.602067
```

[65]:
```
model = list(result[(result['avg_test_rmse'] ==␣
 ↪min(result['avg_test_rmse']))]['model'])[0]
params = list(result[(result['avg_test_rmse'] ==␣
 ↪min(result['avg_test_rmse']))]['params'])[0]
best_result = [i for i in all_results_polynomial if (i['model'] == model and␣
 ↪i['params'] == params)]
all_model_results_pollution.append(best_result[0])
```

Degree 4 polynomial with Lasso regression (alpha = 0.001) gives the best validation rmse for the pollution dataset.

0.1.14 QUESTION 14

For the diamonds dataset, it might make sense to include base area or volume of the diamond as a feature. We explore performance using these 2 new features.

[66]:
```
df_tmp = diamonds_df.copy()

df_tmp['base_area_1'] = df_tmp.apply(lambda row: row['x']*row['y'], axis = 1)
df_tmp['base_area_2'] = df_tmp.apply(lambda row: row['y']*row['z'], axis = 1)
df_tmp['base_area_3'] = df_tmp.apply(lambda row: row['z']*row['x'], axis = 1)

df_tmp['vol'] = df_tmp.apply(lambda row: row['x']*row['y']*row['z'], axis = 1)

df_tmp['perimeter_1'] = df_tmp.apply(lambda row: 2 *(row['x'] + row['y']), axis␣
↪= 1)
df_tmp['perimeter_2'] = df_tmp.apply(lambda row: 2 *(row['y'] + row['z']), axis␣
↪= 1)
df_tmp['perimeter_3'] = df_tmp.apply(lambda row: 2 *(row['z'] + row['x']), axis␣
↪= 1)



cols_to_scale = ['carat', 'cut_num', 'color_num', 'clarity_num', 'depth',␣
↪'table',\
        'x', 'y', 'z', 'base_area_1','base_area_2','base_area_3', \
                 'vol', 'price', 'perimeter_1', 'perimeter_2', 'perimeter_3']

standard_df2 = standardize(df_tmp,cols_to_scale)

features = ['carat', 'cut_num', 'color_num', 'clarity_num', 'depth', 'table',\
        'x', 'y', 'z', 'base_area_1','base_area_2','base_area_3', \
                 'vol',  'perimeter_1', 'perimeter_2', 'perimeter_3']

a = get_mutual_info_df(standard_df2, target_diamond, features)
b = get_f_statistic_df(standard_df2, target_diamond, features)
feat_selection = pd.merge(a,b, how = 'left', on = 'feature')
print(feat_selection)
```

```
        feature  mutual_info          f_stat          p_val
0         carat     1.621981   304051.486619   0.000000e+00
1       cut_num     0.055538      154.784468   1.746019e-35
2     color_num     0.134170     1654.401244   0.000000e+00
3   clarity_num     0.212332     1188.007065  1.571721e-257
4         depth     0.027534        6.115863   1.340045e-02
5         table     0.032167      886.119363  3.769963e-193
6             x     1.391760   193741.523066   0.000000e+00
7             y     1.395283   160915.662263   0.000000e+00
8             z     1.347702   154923.266553   0.000000e+00
9   base_area_1     1.378795   233082.111625   0.000000e+00
10  base_area_2     1.400420   184885.352841   0.000000e+00
11  base_area_3     1.391617   239704.780820   0.000000e+00
12          vol     1.418778   236517.164583   0.000000e+00
13  perimeter_1     1.377420   185951.626153   0.000000e+00
```

```
14  perimeter_2     1.424142  174129.251036   0.000000e+00
15  perimeter_3     1.417691  188196.234065   0.000000e+00
```

[67]:
```
print("Base linear regression results with new features..")
features = ['carat', 'cut_num', 'color_num', 'clarity_num', \
        'x', 'y', 'z', 'base_area_1','base_area_2','base_area_3', \
                 'vol',  'perimeter_1', 'perimeter_2', 'perimeter_3']

target = 'price'
model = LinearRegression(n_jobs = -1)
result = train_model(model, standard_df2, features, target, 'Linear Regression␣
 ↪(feature engineering)')
print(result)
```

```
Base linear regression results with new features..
{'model': 'Linear Regression (feature engineering)', 'params': 'NA',
'avg_train_rmse': 0.29492529172667237, 'avg_test_rmse': 0.31767751896968294}
```

We tried to incorporate features related to the dimensions of the diamond. The perimeter or size of the diamond and area of the diamond might impact the price of the diamond. However, we observe that feature engineering although improving the performance on the train set, does not improve the performance on the test set suggesting overfitting. Running regularisation models might help improve the performance in test set. We observe in Q13 above, some interaction features were selected in the Lasso regression and it improved the performance on validation set.

0.1.15 QUESTION 15

Neural Networks Introduction of hidden layers and activation functions incorporates non-linearity in the feature relationships with the target. It allows for training more complex functions. Because of this increase in hypothesis space of functions that can be modeled, multi-layer perceptron or fully connected neural network performs better than the linear regression.

0.1.16 QUESTION 16

[68]:
```
def perform_gridsearch(model, data: pd.DataFrame(), features: list, target: str,␣
 ↪grid_params : dict, cv = 10):
    '''
    Given a model and a grid perform grid search on the given dataset.
    Returns best parameters and cross validation results
    '''
    X = data[features]
    y = data[target]

    grid = GridSearchCV(model, grid_params,␣
 ↪scoring='neg_root_mean_squared_error', cv = cv,\
                                   return_train_score=True, n_jobs = -1)
    grid.fit(X, y)
    tmp = pd.DataFrame.from_dict(grid.cv_results_)
```

```
    tmp = tmp[['params', 'mean_train_score', 'mean_test_score',␣
↪'rank_test_score']]
    tmp['mean_train_score'] = tmp['mean_train_score'].apply(lambda x: -x)
    tmp['mean_test_score'] = tmp['mean_test_score'].apply(lambda x: -x)
    return grid.best_params_ , tmp
```

For diamonds dataset

[69]:
```
start_time = time.time()

model = MLPRegressor(random_state=42, max_iter=200, batch_size = 64, tol = 1e-4,␣
↪early_stopping = True)
grid_params = {'hidden_layer_sizes': [(50), (100), (150), (250), (500), \
                                      (50, 20), (100, 30), (150, 40), (250, 50)],
        'activation': ['identity', 'relu'],
        'learning_rate_init' : [0.001, 0.1],
        'learning_rate' : ['constant', 'adaptive'],
        'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}

best_params, cv_results = perform_gridsearch(model, diamonds_df_scaled,␣
↪selected_features_diamond,\
                                                         target_diamond,␣
↪grid_params, 5)
print("done in %0.3fs." % (time.time() - start_time))
```

```
done in 4822.923s.
```

[70]:
```
cv_results.sort_values('rank_test_score').head(5)
```

[70]:
```
                                                params  mean_train_score  \
336  {'activation': 'relu', 'alpha': 0.001, 'hidden...          0.145987
338  {'activation': 'relu', 'alpha': 0.001, 'hidden...          0.145987
306  {'activation': 'relu', 'alpha': 0.0001, 'hidde...          0.143125
304  {'activation': 'relu', 'alpha': 0.0001, 'hidde...          0.143125
400  {'activation': 'relu', 'alpha': 0.1, 'hidden_l...          0.156420

     mean_test_score  rank_test_score
336         0.243483                1
338         0.243483                1
306         0.244036                3
304         0.244036                3
400         0.244445                5
```

[71]:
```
print("Best results for MLP regression for diamonds dataset is...")
print(cv_results[cv_results['params'] == best_params])
```

```
Best results for MLP regression for diamonds dataset is...
                                                params  mean_train_score  \
336  {'activation': 'relu', 'alpha': 0.001, 'hidden...          0.145987
```

```
     mean_test_score  rank_test_score
336         0.243483                1
```

[72]:
```
model = MLPRegressor(**best_params, random_state=42, max_iter=200, batch_size =␣
↪64, tol = 1e-4, early_stopping = True)
result = train_model(model, diamonds_df_scaled, selected_features_diamond,␣
↪target_diamond, 'MLPRegressor', best_params, 10)
all_model_results_diamond.append(result)
```

For pollution dataset

[73]:
```
start_time = time.time()

model = MLPRegressor(random_state=42, max_iter=200, batch_size = 64, tol = 1e-4,␣
↪early_stopping = True)
grid_params = {'hidden_layer_sizes': [(50), (100), (150), (250), (500), \
                                      (50, 20), (100, 30), (150, 40), (250, 50),␣
↪(500, 50)],
        'activation': ['identity', 'relu'],
        'learning_rate_init' : [0.001, 0.1],
        'learning_rate' : ['constant', 'adaptive'],
        'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}

best_params, cv_results = perform_gridsearch(model, pollution_df_scaled,␣
↪selected_features_pollution,\
                                                           target_pollution,␣
↪grid_params, 5)
print("done in %0.3fs." % (time.time() - start_time))
```

```
done in 5349.791s.
```

[74]:
```
cv_results.sort_values('rank_test_score').head(5)
```

[74]:
```
                                                 params  mean_train_score  \
489  {'activation': 'relu', 'alpha': 1, 'hidden_lay...          0.625726
491  {'activation': 'relu', 'alpha': 1, 'hidden_lay...          0.625726
507  {'activation': 'relu', 'alpha': 1, 'hidden_lay...          0.621622
505  {'activation': 'relu', 'alpha': 1, 'hidden_lay...          0.621622
485  {'activation': 'relu', 'alpha': 1, 'hidden_lay...          0.623740

     mean_test_score  rank_test_score
489         0.678532                1
491         0.678532                1
507         0.680333                3
505         0.680333                3
485         0.685200                5
```

```
[75]: print("Best results for MLP regression for diamonds dataset is...")
print(cv_results[cv_results['params'] == best_params])
```

```
Best results for MLP regression for diamonds dataset is...
                                               params  mean_train_score  \
489  {'activation': 'relu', 'alpha': 1, 'hidden_lay...          0.625726

     mean_test_score  rank_test_score
489         0.678532                1
```

```
[76]: model = MLPRegressor(**best_params, random_state=42, max_iter=200, batch_size =␣
 ↪64, tol = 1e-4, early_stopping = True)
result = train_model(model, pollution_df_scaled, selected_features_pollution,␣
 ↪target_pollution, 'MLPRegressor', best_params, 10)
all_model_results_pollution.append(result)
```

0.1.17 QUESTION 17

Diamonds dataset: Since the price of the diamond is a positive real number, we can use `relu` as the activation function for which the range is the set of positive real numbers. Or we can use the identity, which keeps the output as it. We cannot use tanh or sigmoid(logistic) as the activation function as these functions restrict the output value to be between [0,1], in line with predicting probabilities.

Using relu allows for non-linearity and performs better as can be inferred from the grid results.

Similarly, for CO emissions, relu activation function gives the best results.

0.1.18 QUESTION 18

Increasing the depth of the network too far introduces too many parameters to be trained and increases the complexity of the functions leading to potential overfitting of the train data and poor generalization to validation set or test set.

Moreover, there are many other technical complications with deeper neural networks, for example, problems such as the vanishing (and exploding) gradient problem which leads the gradients to be too small or too large leading to unstable results or no learning at all.

0.1.19 QUESTION 19

For diamonds dataset

```
[77]: start_time = time.time()

model = RandomForestRegressor(n_jobs = -1, random_state = 42)
grid_params = {'max_features': [1,2,3,4,5,6],
        'n_estimators': [20, 50, 100, 200],
        'max_depth': [2, 3, 4, 5, 6]}

best_params, cv_results = perform_gridsearch(model, diamonds_df_scaled,␣
 ↪selected_features_diamond,\
```

```
                                                        target_diamond,␣
↪grid_params, 10)
print("done in %0.3fs." % (time.time() - start_time))  # 403 sec
```

```
done in 410.252s.
```

[78]:
```
cv_results['max_depth'] = cv_results['params'].apply(lambda x: x['max_depth'])
cv_results['max_features'] = cv_results['params'].apply(lambda x:␣
↪x['max_features'])
cv_results['n_estimators'] = cv_results['params'].apply(lambda x:␣
↪x['n_estimators'])
```

[79]:
```
print("Understanding the effect of maximum number of features")
cv_results[(cv_results['max_depth'] == 6) & (cv_results['n_estimators'] == 100)]
```

```
Understanding the effect of maximum number of features
```

[79]:
```
                                                params  mean_train_score  \
98   {'max_depth': 6, 'max_features': 1, 'n_estimat...          0.225418
102  {'max_depth': 6, 'max_features': 2, 'n_estimat...          0.209781
106  {'max_depth': 6, 'max_features': 3, 'n_estimat...          0.192532
110  {'max_depth': 6, 'max_features': 4, 'n_estimat...          0.185120
114  {'max_depth': 6, 'max_features': 5, 'n_estimat...          0.185352
118  {'max_depth': 6, 'max_features': 6, 'n_estimat...          0.190722

     mean_test_score  rank_test_score  max_depth  max_features  n_estimators
98          0.263225               18          6             1           100
102         0.264888               22          6             2           100
106         0.255865               10          6             3           100
110         0.250303                3          6             4           100
114         0.250931                4          6             5           100
118         0.260169               14          6             6           100
```

As maximum number of features increase, the model performance first improves as the model learns from the extra information from the new features in any given tree. However, increasing number of features beyond a certain point starts having an adverse effect.

[80]:
```
print("Understanding the effect of number of trees")
cv_results[(cv_results['max_depth'] == 6) & (cv_results['max_features'] == 5)]
```

```
Understanding the effect of number of trees
```

[80]:
```
                                                params  mean_train_score  \
112  {'max_depth': 6, 'max_features': 5, 'n_estimat...          0.187326
113  {'max_depth': 6, 'max_features': 5, 'n_estimat...          0.185998
114  {'max_depth': 6, 'max_features': 5, 'n_estimat...          0.185352
115  {'max_depth': 6, 'max_features': 5, 'n_estimat...          0.185407

     mean_test_score  rank_test_score  max_depth  max_features  n_estimators
```

```
112         0.253709                8          6           5            20
113         0.251789                6          6           5            50
114         0.250931                4          6           5           100
115         0.250973                5          6           5           200
```

[81]:
```
print("Understanding the effect of max_depth")
cv_results[(cv_results['n_estimators'] == 100) & (cv_results['max_features'] ==␣
↪5)]
```

```
Understanding the effect of max_depth
```

[81]:
```
                                                  params  mean_train_score  \
18   {'max_depth': 2, 'max_features': 5, 'n_estimat...          0.396361
42   {'max_depth': 3, 'max_features': 5, 'n_estimat...          0.317748
66   {'max_depth': 4, 'max_features': 5, 'n_estimat...          0.260142
90   {'max_depth': 5, 'max_features': 5, 'n_estimat...          0.216146
114  {'max_depth': 6, 'max_features': 5, 'n_estimat...          0.185352

     mean_test_score  rank_test_score  max_depth  max_features  n_estimators
18          0.470263              109          2             5           100
42          0.374171               87          3             5           100
66          0.324633               61          4             5           100
90          0.278558               29          5             5           100
114         0.250931                4          6             5           100
```

[82]:
```
cv_results[cv_results['params'] == best_params]
```

[82]:
```
                                                  params  mean_train_score  \
111  {'max_depth': 6, 'max_features': 4, 'n_estimat...           0.18517

     mean_test_score  rank_test_score  max_depth  max_features  n_estimators
111         0.249404                1          6             4           200
```

[83]:
```
model = RandomForestRegressor(**best_params, random_state=42, n_jobs=-1)
result = train_model(model, diamonds_df_scaled, selected_features_diamond,␣
↪target_diamond, 'RandomForest', best_params, 10)
all_model_results_diamond.append(result)
```

For pollution dataset

[84]:
```
start_time = time.time()

model = RandomForestRegressor(n_jobs = -1, random_state = 42)
grid_params = {'max_features': [1,2,3,4,5,6,7],
        'n_estimators': [20, 50, 100, 200],
        'max_depth': [2, 3, 4, 5, 6]}

best_params, cv_results = perform_gridsearch(model, pollution_df_scaled,␣
↪selected_features_pollution,\
```

```
                                                              target_pollution,␣
 ↪grid_params, 10)
print("done in %0.3fs." % (time.time() - start_time))
```

```
done in 665.226s.
```

[85]:
```
cv_results[cv_results['params'] == best_params]
```

[85]:
```
                                                params  mean_train_score  \
128  {'max_depth': 6, 'max_features': 5, 'n_estimat...          0.473607

     mean_test_score  rank_test_score
128         0.600993                1
```

[86]:
```
model = RandomForestRegressor(**best_params, random_state=42, n_jobs=-1)
result = train_model(model, pollution_df_scaled, selected_features_pollution,␣
 ↪target_pollution, 'RandomForest', best_params, 10)
all_model_results_pollution.append(result)
```

Depth of tree has a regularization effect in the sense that it restricts the tree to be smaller and hence, splitting too much or learning noise from the training set is less likely. Maximum number of features used in a tree also has a regularisation effect as it only trains on selected features similar to Lasso regularisation.

0.1.20 QUESTION 20

Random forest performs well because it aggregates output from multiple decision trees to make a prediction. It is able to capture non-linearity in the features by doing sequential splitting. And by aggregating the results from multiple such decision tree (regressors), it is able to make a robust prediction.

0.1.21 QUESTION 21

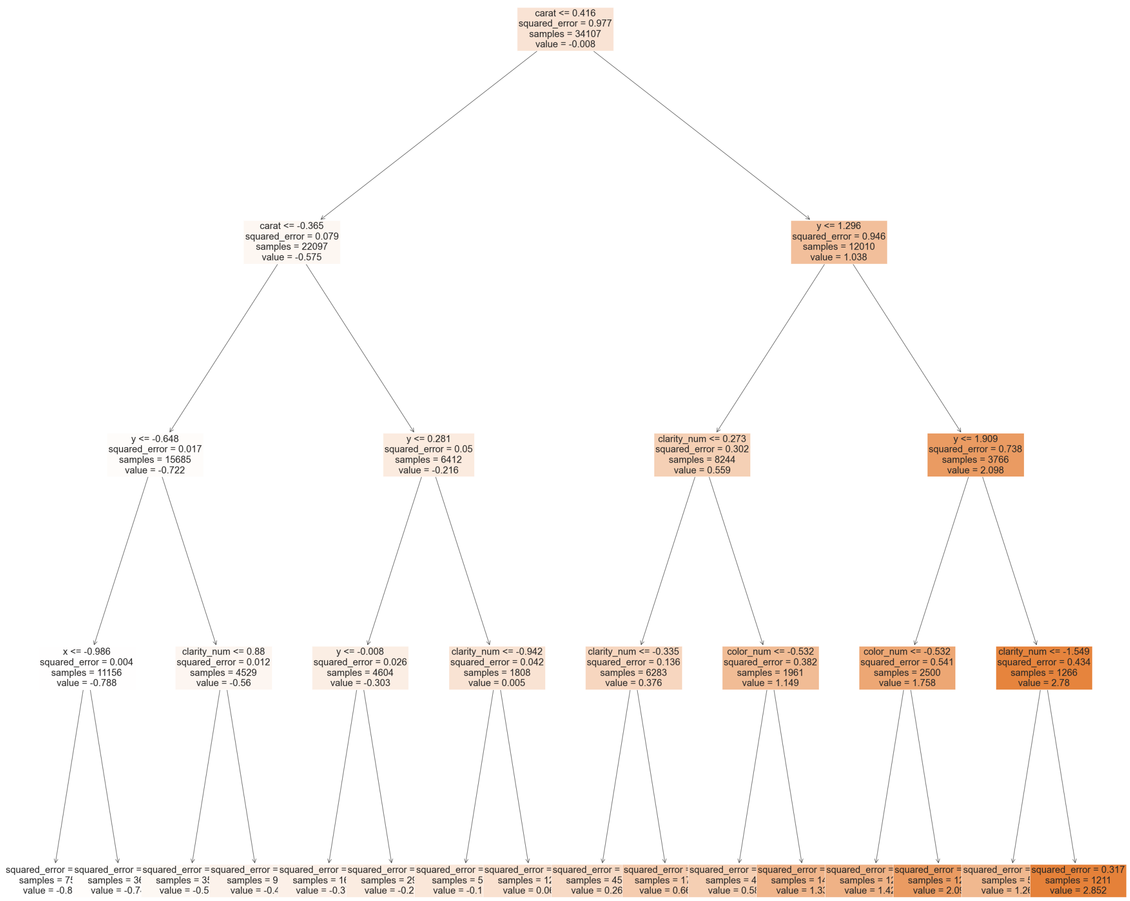
For diamonds dataset

[87]:
```
model = RandomForestRegressor(max_features = 5, n_estimators = 20, max_depth =␣
 ↪4, random_state=42, n_jobs=-1)
X = diamonds_df_scaled[selected_features_diamond]
y = diamonds_df_scaled[target_diamond]
model.fit(X,y)
```

[87]:
```
RandomForestRegressor(max_depth=4, max_features=5, n_estimators=20, n_jobs=-1,
                      random_state=42)
```

[88]:
```
n_estimators = 20
for i in range(n_estimators):
    if( model.estimators_[i].tree_.max_depth == 4):
        plt.figure(figsize=(50,50))
        _ = tree.plot_tree(model.estimators_[i], feature_names=X.columns,␣
 ↪filled=True, fontsize=24)
```

```
        break
```



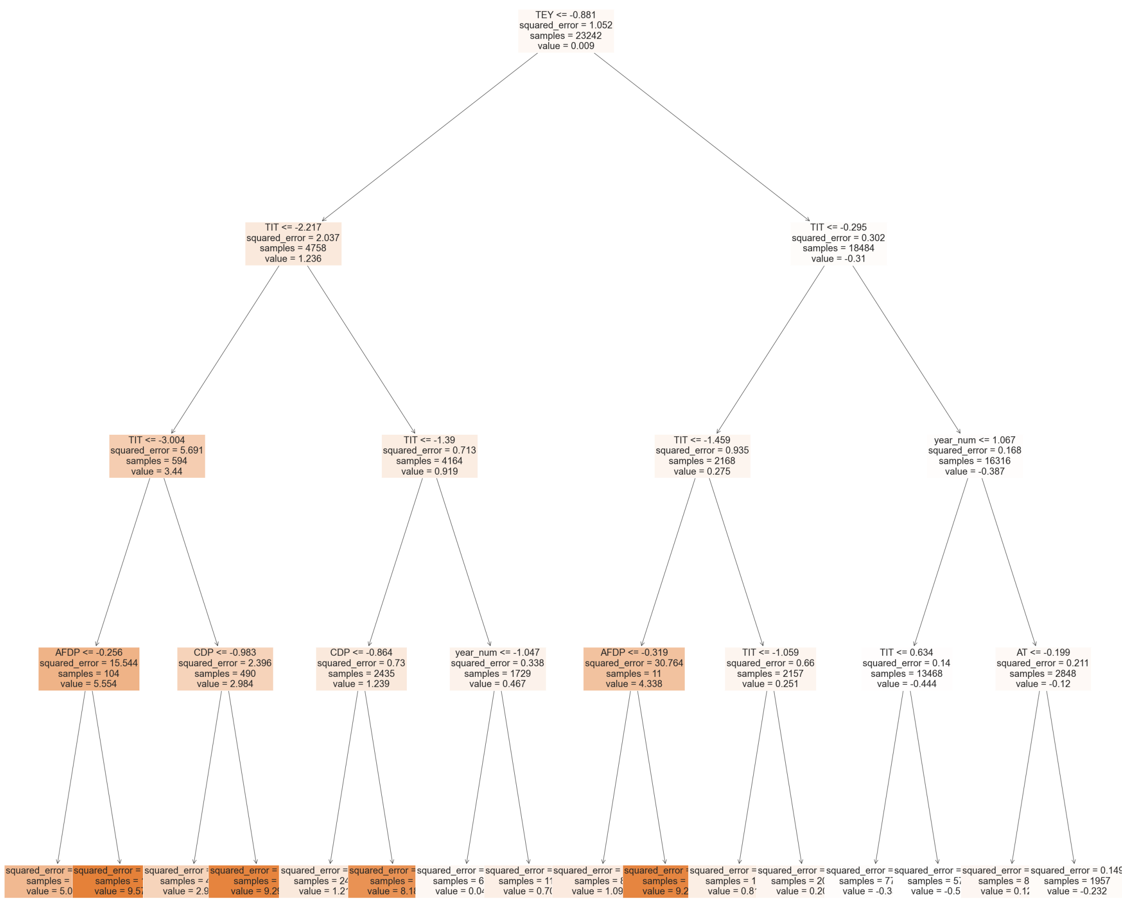
The feature `carat` or weight of the diamond is chosen as the root node feature. Followed by dimension features `x` and `y` in the 2nd and 3rd layers. The splits sequence do match the feature importance observed using MI and F-statistic.

For pollution dataset

[89]:
```
model = RandomForestRegressor(max_features = 5, n_estimators = 20, max_depth =
↪4, random_state=42, n_jobs=-1)
X = pollution_df_scaled[selected_features_pollution]
y = pollution_df_scaled[target_pollution]
model.fit(X,y)
```

```
[89]: RandomForestRegressor(max_depth=4, max_features=5, n_estimators=20, n_jobs=-1,
                            random_state=42)
```

```
[90]: n_estimators = 20
      for i in range(n_estimators):
          if( model.estimators_[i].tree_.max_depth == 4):
              plt.figure(figsize=(50,50))
              _ = tree.plot_tree(model.estimators_[i], feature_names=X.columns,␣
       ↪filled=True, fontsize=24)
              break
```



Here also, we observe that the important features TEY and TIT are among the first features to be used for split. TEY is used as a feature at root node split in line with MI and F-stat scores.

0.2 LightGBM, CatBoost

0.2.1 QUESTION 22

Light GBM Light GBM uses leaf wise tree growth algorithm, while many other popular tools use depth-wise tree growth. Compared with depth-wise growth, the leaf-wise algorithm can converge much faster. However, the leaf-wise growth may be over-fitting if not used with the appropriate parameters.

Parameters for LightGBM: 1. num_leaves: controls complexity of tree model. num_leaves = 2^(max_depth), gives same leaves as depth based algorithms.leaf-wise tree is typically much deeper than a depth-wise tree for a fixed number of leaves. 2. min_data_in_leaf: minimum number of samples in leaf nodes. prevents overfitting. depends on num_leaves and training sample. 3. max_depth: to limit tree depth

For better accuracy use small learning rate and large num_iterations

Catboost GBM **Parameters for CatBoostGBM:**

1. number of trees (num_trees)
2. learning rate (learning_rate) : affects the overall time of training
3. tree depth (depth)
4. L2 regularisation (l2_leaf_reg)
5. min_data_in_leaf

For diamonds dataset

[91]:
```
start_time = time.time()

model = LGBMRegressor(seed = 42)
grid_params = {'n_estimators': [20, 50, 100, 200],
        'num_leaves': [30, 40, 50, 60, 80],
        'max_depth': [2, 4, 6, 8, 10],
        'min_data_in_leaf': [5, 10, 20, 30]}

# best_params, cv_results = perform_gridsearch(model, diamonds_df_scaled,␣
 ↪selected_features_diamond,\
#                                                             target_diamond,␣
 ↪grid_params, 10)
# print("done in %0.3fs." % (time.time() - start_time))  ## 180 sec
```

[92]:
```
start_time = time.time()

model = CatBoostRegressor(loss_function = 'RMSE', random_seed = 42, grow_policy␣
 ↪= 'Lossguide')
grid_params = {'num_trees': [50, 100, 150, 200],
        'depth': [2, 4, 6, 8, 10],
        'l2_leaf_reg': [0.01, 0.1, 0.2, 0.5, 1, 10, 20],
        'min_data_in_leaf': [5, 10, 20, 30],
       'learning_rate': [0.001, 0.01, 0.1, 0.5]}
```

```
# best_params, cv_results = perform_gridsearch(model, diamonds_df_scaled,␣
↪selected_features_diamond,\
#                                                               target_diamond,␣
↪grid_params, 10)
# print("done in %0.3fs." % (time.time() - start_time))
```

0.2.2 QUESTION 23

[110]:
```
def perform_bayes_gridsearch(model, data: pd.DataFrame(), features: list, target:
↪ str, grid_params : dict, cv = 10):
    '''
    Given a model and a grid perform grid search on the given dataset.
    Returns best parameters and cross validation results
    '''
    X = data[features]
    y = data[target]

    grid = BayesSearchCV(model, grid_params,␣
↪scoring='neg_root_mean_squared_error', cv = cv,\
                                   return_train_score=True, n_jobs = -1, verbose␣
↪= False)
    grid.fit(X, y)
    tmp = pd.DataFrame.from_dict(grid.cv_results_)
    tmp = tmp[['params', 'mean_train_score', 'mean_test_score',␣
↪'rank_test_score', 'mean_fit_time']]
    tmp['mean_train_score'] = tmp['mean_train_score'].apply(lambda x: -x)
    tmp['mean_test_score'] = tmp['mean_test_score'].apply(lambda x: -x)
    return grid.best_params_ , tmp
```

For diamonds dataset

[111]:
```
start_time = time.time()

model = LGBMRegressor(seed = 42)
grid_params = {'n_estimators': [20, 50, 100, 200],
        'num_leaves': [30, 40, 50, 60, 80],
        'max_depth': [2, 4, 6, 8, 10],
        'min_data_in_leaf': [5, 10, 20, 30]}

best_params_lgbm, cv_results_lgbm = perform_bayes_gridsearch(model,␣
↪diamonds_df_scaled, selected_features_diamond,\
                                                       target_diamond,␣
↪grid_params, 10)
print("done in %0.3fs." % (time.time() - start_time))
```

```
done in 134.506s.
```

[112]:
```
print("Best parameters for Light GBM on diamonds dataset is..")
best_params_lgbm
```

```
Best parameters for Light GBM on diamonds dataset is..
```

[112]:
```
OrderedDict([('max_depth', 4),
             ('min_data_in_leaf', 5),
             ('n_estimators', 200),
             ('num_leaves', 40)])
```

[113]:
```
cv_results_lgbm[cv_results_lgbm['params'] == best_params_lgbm][:1]
```

[113]:
```
                                                params  mean_train_score  \
30  {'max_depth': 4, 'min_data_in_leaf': 5, 'n_est...          0.126345

    mean_test_score  rank_test_score  mean_fit_time
30         0.157522                1       0.552465
```

[114]:
```
model = LGBMRegressor(**best_params_lgbm, seed = 42)
result = train_model(model, diamonds_df_scaled, selected_features_diamond,␣
 ↪target_diamond, 'LightGBM', best_params_lgbm, 10)
all_model_results_diamond.append(result)
```

[115]:
```
start_time = time.time()

model = CatBoostRegressor(loss_function = 'RMSE', random_seed = 42, grow_policy␣
 ↪= 'Lossguide', verbose = False)
grid_params = {'num_trees': [50, 100, 150, 200],
        'depth': [2, 4, 6, 8, 10],
        'l2_leaf_reg': [0.01, 0.1, 0.2, 0.5, 1, 10, 20],
        'min_data_in_leaf': [5, 10, 20, 30],
       'learning_rate': [0.001, 0.01, 0.1, 0.5]}

best_params_catb, cv_results_catb = perform_bayes_gridsearch(model,␣
 ↪diamonds_df_scaled, selected_features_diamond,\
                                                         target_diamond,␣
 ↪grid_params, 10)
print("done in %0.3fs." % (time.time() - start_time))
```

```
done in 351.188s.
```

[116]:
```
print("Best parameters for Catboost on diamonds dataset is..")
best_params_catb
```

```
Best parameters for Catboost on diamonds dataset is..
```

[116]:
```
OrderedDict([('depth', 4),
             ('l2_leaf_reg', 0.01),
             ('learning_rate', 0.1),
```

```
             ('min_data_in_leaf', 5),
             ('num_trees', 200)])
```

[117]:
```
cv_results_catb[cv_results_catb['params'] == best_params_catb][:1]
```

[117]:
```
                                               params  mean_train_score  \
42  {'depth': 4, 'l2_leaf_reg': 0.01, 'learning_ra...          0.128398

    mean_test_score  rank_test_score  mean_fit_time
42         0.155931                1       5.113333
```

[118]:
```
model = CatBoostRegressor(**best_params_catb, loss_function = 'RMSE',␣
 ↪random_seed = 42, grow_policy = 'Lossguide')
result = train_model(model, diamonds_df_scaled, selected_features_diamond,␣
 ↪target_diamond, 'CatBoost', best_params_catb, 10)
all_model_results_diamond.append(result)
```

```
Learning rate set to 0.279804
```

0.2.3 QUESTION 24

For Light GBM

[119]:
```
cv_results_lgbm['max_depth'] = cv_results_lgbm['params'].apply(lambda x:␣
 ↪x['max_depth'])
cv_results_lgbm['num_leaves'] = cv_results_lgbm['params'].apply(lambda x:␣
 ↪x['num_leaves'])
cv_results_lgbm['n_estimators'] = cv_results_lgbm['params'].apply(lambda x:␣
 ↪x['n_estimators'])
cv_results_lgbm['min_data_in_leaf'] = cv_results_lgbm['params'].apply(lambda x:␣
 ↪x['min_data_in_leaf'])
cv_results_lgbm['gap'] = cv_results_lgbm.apply(lambda row:␣
 ↪(row['mean_test_score'] - row['mean_train_score']), axis = 1)
```

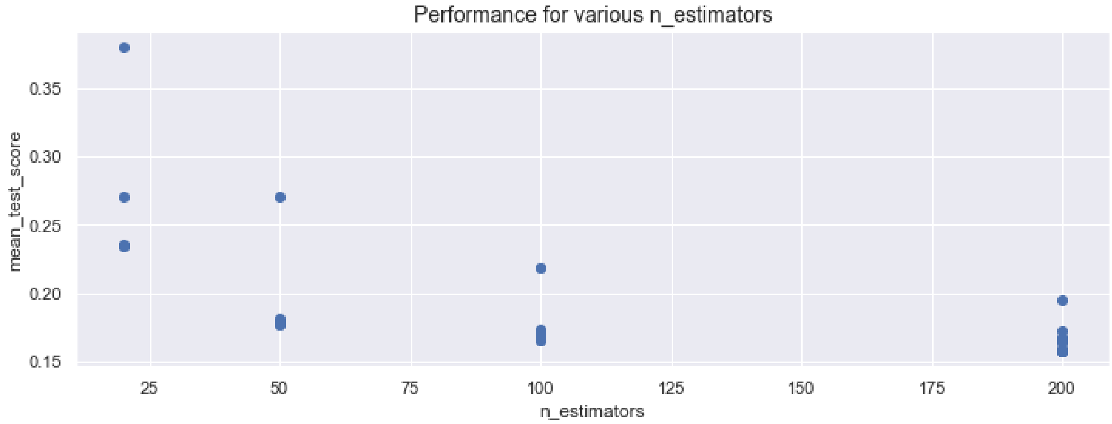
[120]:
```
parameters = ['n_estimators', 'max_depth', 'min_data_in_leaf', 'num_leaves']
for param in parameters:
    cv_results_lgbm[param] = cv_results_lgbm['params'].apply(lambda x: x[param])
cv_results_lgbm['gap'] = cv_results_lgbm.apply(lambda row:␣
 ↪(row['mean_test_score'] - row['mean_train_score']), axis = 1)
```

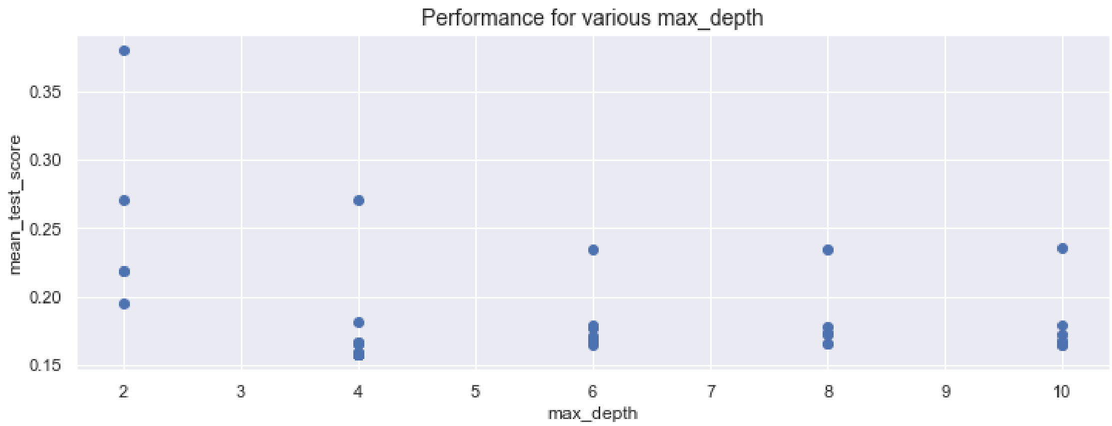
[121]:
```
def plot_metrics(data, parameter, metric, title):
    data = data.drop(['params'], axis = 1)
    data = data.drop_duplicates()
    plt.figure(figsize=(12,4))
    plt.scatter(data[parameter], data['mean_test_score'])
    plt.xlabel(parameter)
    plt.ylabel(metric)
    plt.title(title, fontsize = 14)
```

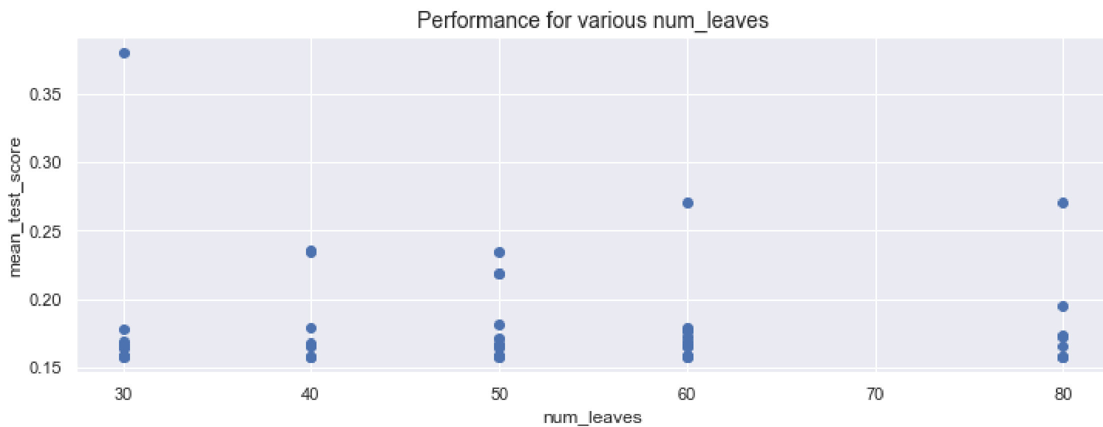
```
    plt.grid('True')
    plt.show()
```

[122]:
```
print("Print performance plots...")
for parameter in parameters:
    plot_metrics(cv_results_lgbm, parameter, 'mean_test_score', "Performance for␣
↪various "+parameter)
```

```
Print performance plots...
```

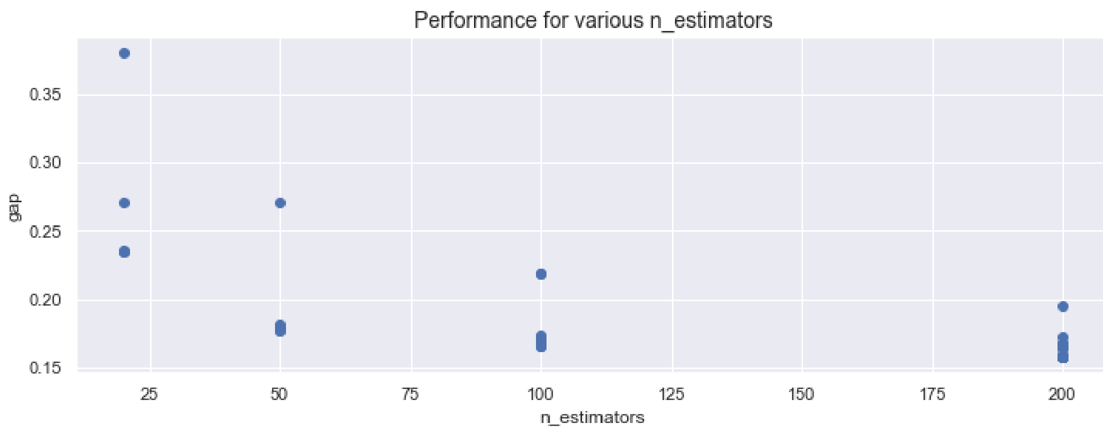


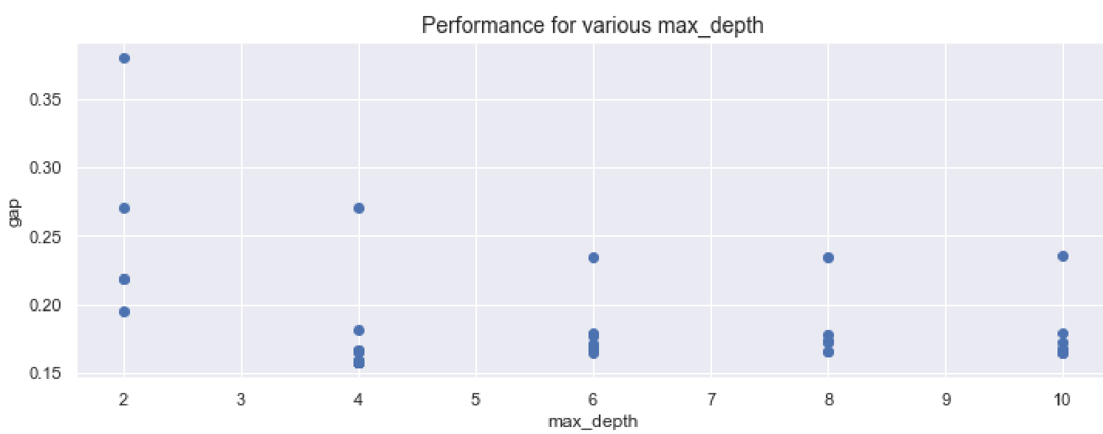


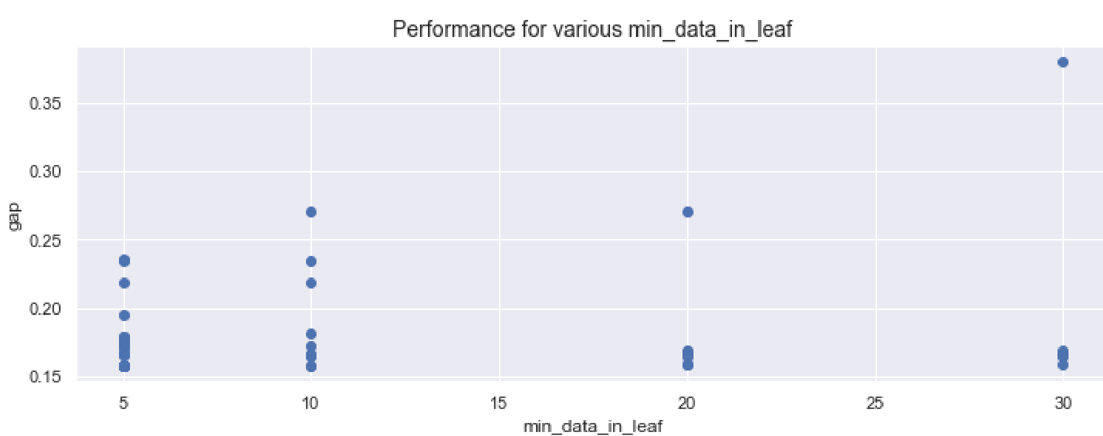


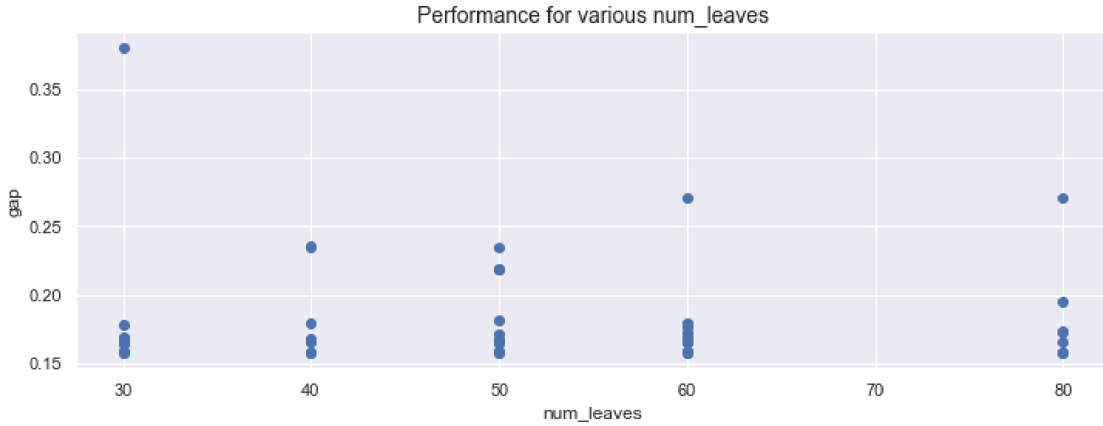
[123]:
```
print("Print performance gap plots...")
for parameter in parameters:
    plot_metrics(cv_results_lgbm, parameter, 'gap', "Performance for various␣
↪"+parameter)
```

```
Print performance gap plots...
```


Performance for various n_estimators
gap
0.35
0.30
0.25
0.20
0.15
25
50
75
100
125
150
175
200
n_estimators

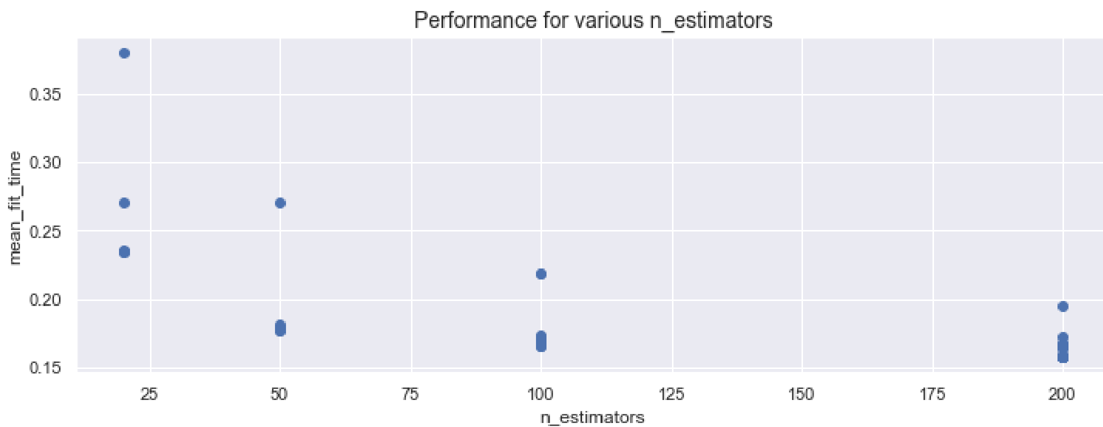

Performance for various max_depth
gap
0.35
0.30
0.25
0.20
0.15
2
3
4
5
6
7
8
9
10
max_depth

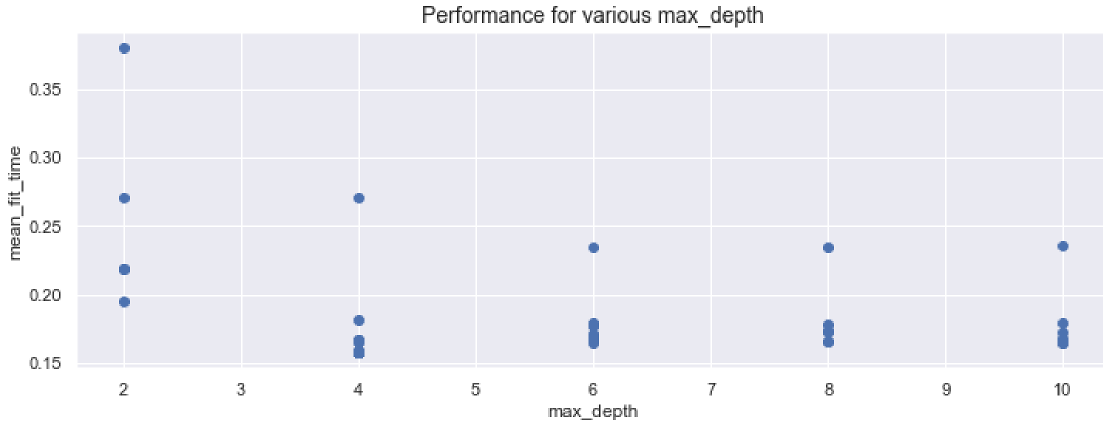

Performance for various min_data_in_leaf
gap
0.35
0.30
0.25
0.20
0.15
5
10
15
20
25
30
min_data_in_leaf

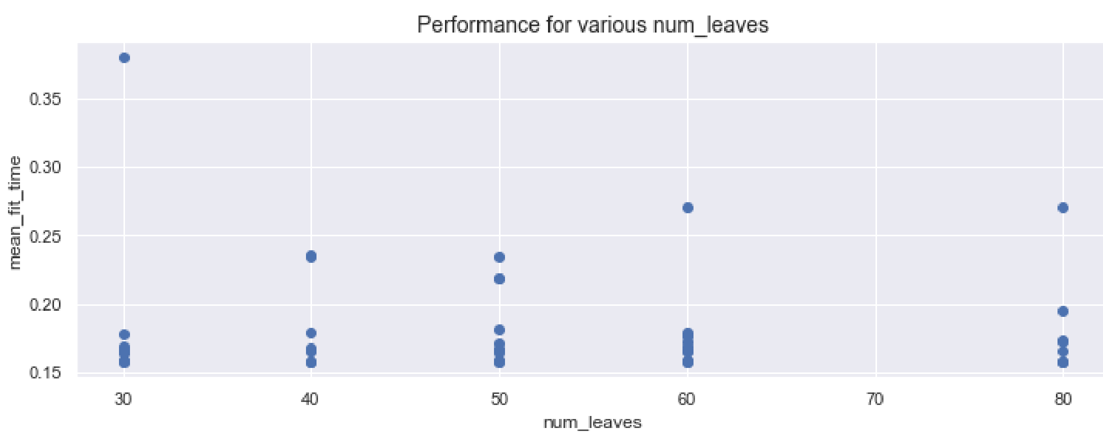


[124]:
```
print("Print fit efficienct plots...")

for parameter in parameters:
    plot_metrics(cv_results_lgbm, parameter, 'mean_fit_time', "Performance for␣
↪various "+parameter)
```

```
Print fit efficienct plots...
```







We observe that `n_estimators` and `max_depth` helps improve the model performance in LightGBM. `max_depth`, `num_leaves` and `num_iterations` affect the fit efficiency of the model.

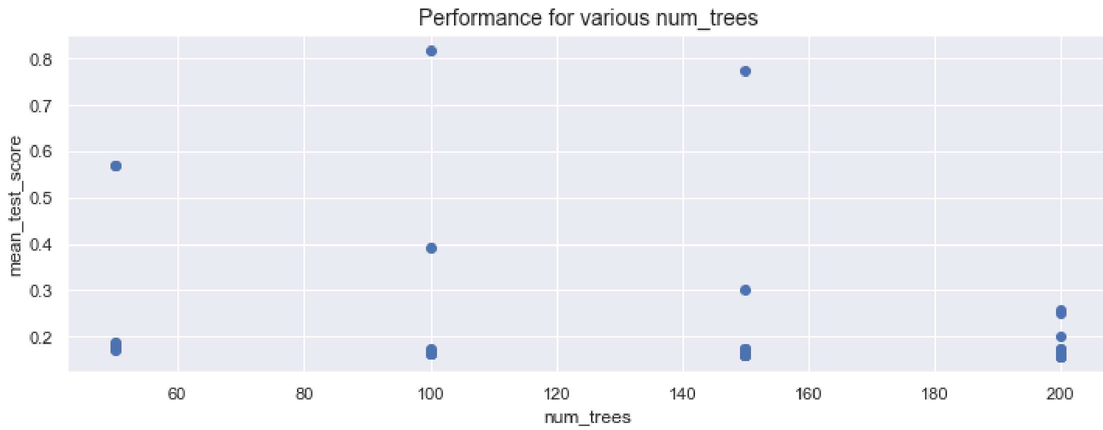
For Catboost regressor

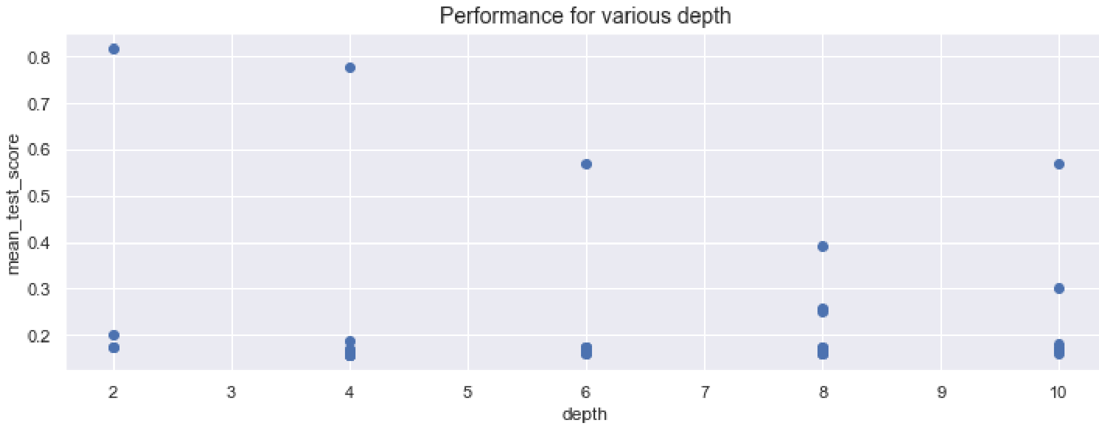
[125]:
```
cat_params = ['num_trees', 'learning_rate', 'depth', 'l2_leaf_reg',␣
↪'min_data_in_leaf']
```

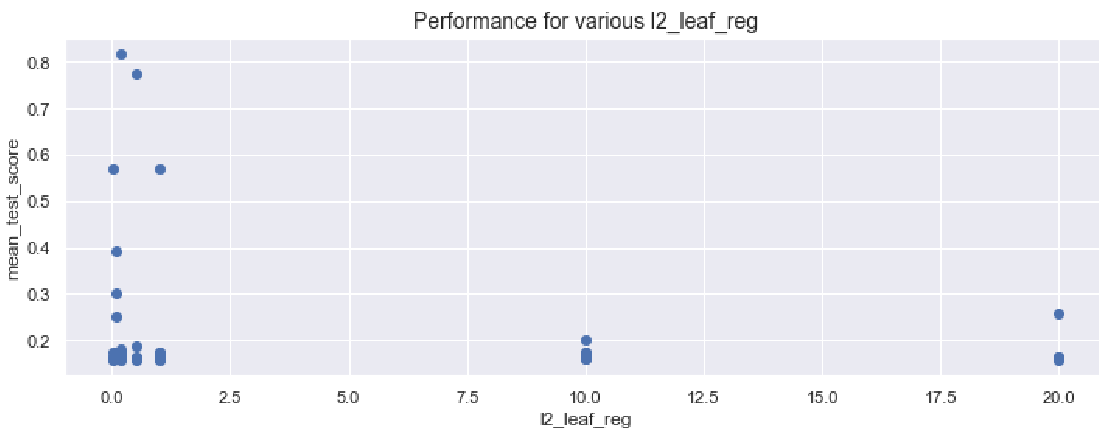
[126]:
```
for param in cat_params:
    cv_results_catb[param] = cv_results_catb['params'].apply(lambda x: x[param])

cv_results_catb['gap'] = cv_results_catb.apply(lambda row:␣
↪(row['mean_test_score'] - row['mean_train_score']), axis = 1)
```

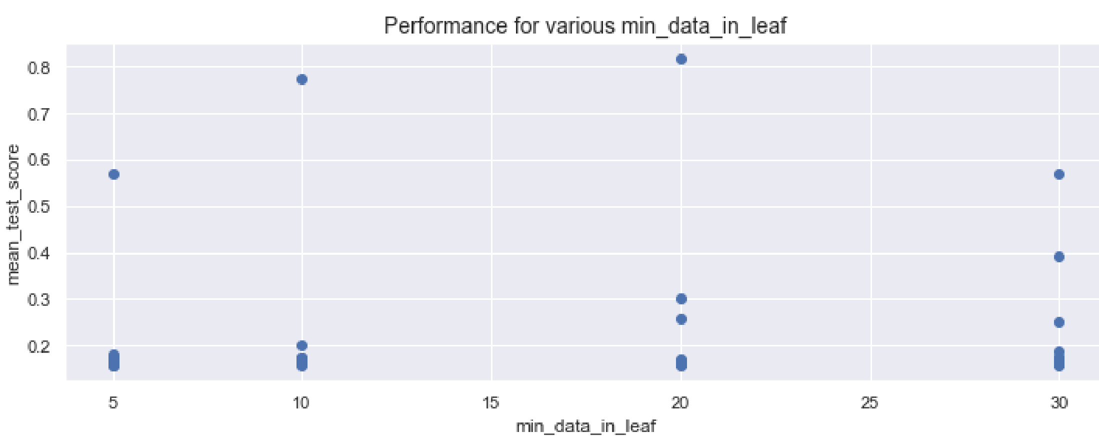
[127]:
```
print("Print performance plots...")
for parameter in cat_params:
    plot_metrics(cv_results_catb, parameter, 'mean_test_score', "Performance for␣
↪various "+parameter)
```

```
Print performance plots...
```



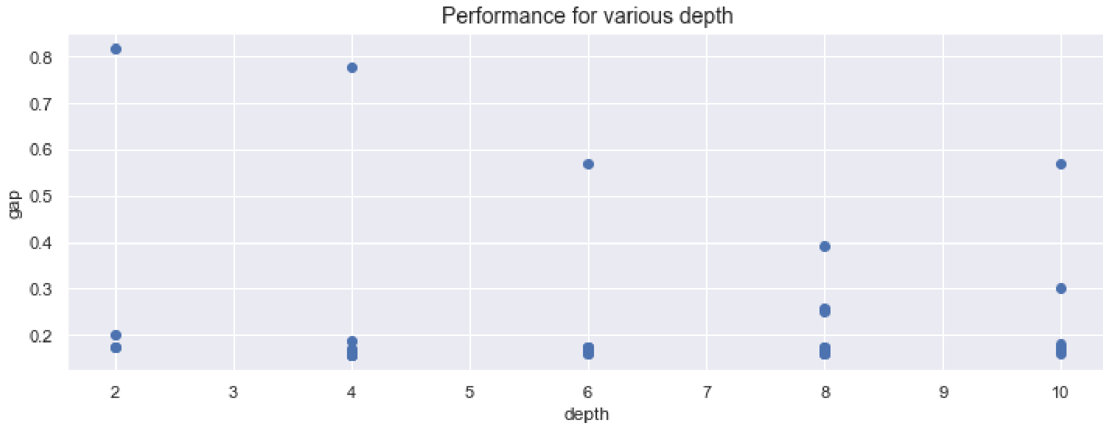

Performance for various depth
mean_test_score
0.8
0.7
0.6
0.5
0.4
0.3
0.2
2
3
4
5
6
7
8
9
10
depth


Performance for various l2_leaf_reg
mean_test_score
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
l2_leaf_reg

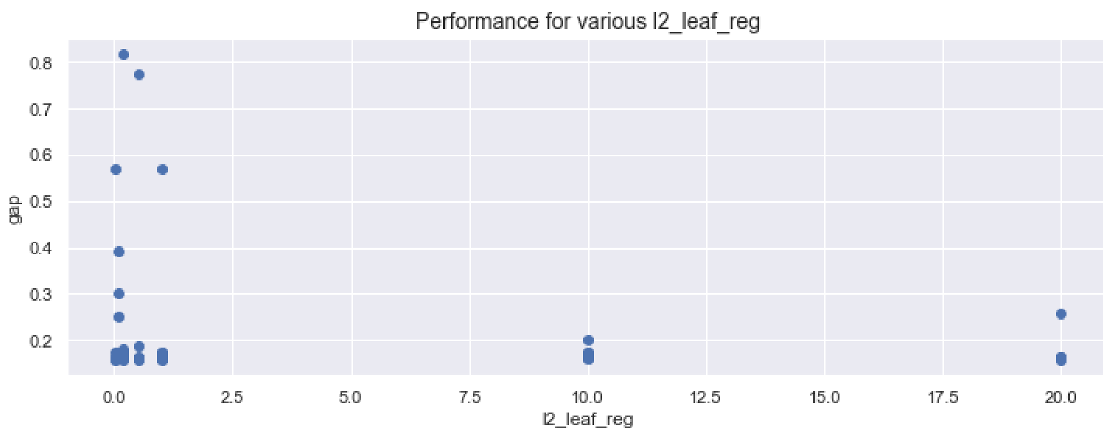

Performance for various min_data_in_leaf
mean_test_score
0.8
0.7
0.6
0.5
0.4
0.3
0.2
5
10
15
20
25
30
min_data_in_leaf

[128]:
```
print("Print performance gap plots...")
for parameter in cat_params:
    plot_metrics(cv_results_catb, parameter, 'gap', "Performance for various␣
 ↪"+parameter)
```

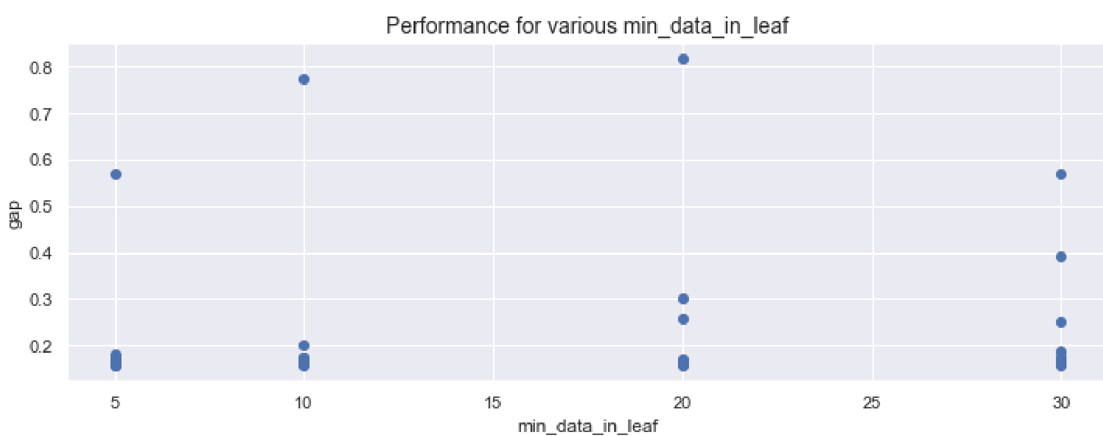
```
Print performance gap plots...
```



Performance for various depth
gap
0.8
0.7
0.6
0.5
0.4
0.3
0.2
2
3
4
5
6
7
8
9
10
depth



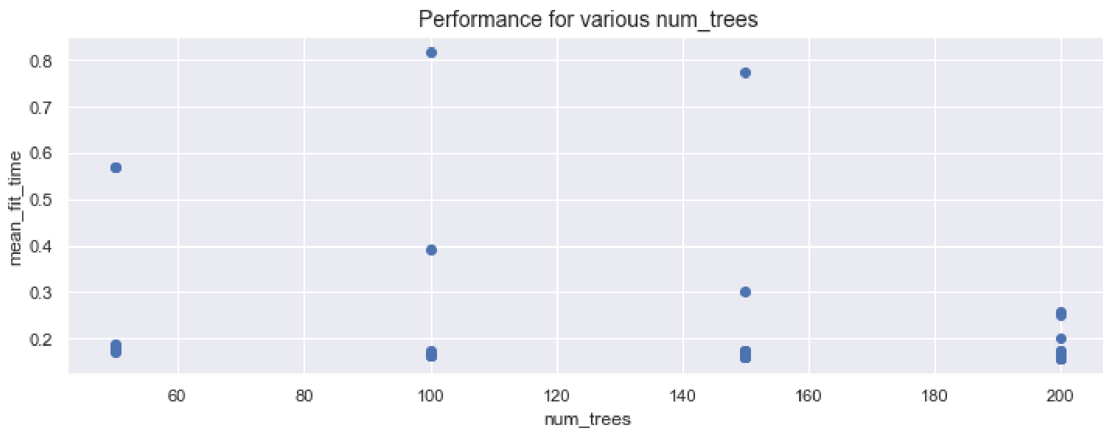
Performance for various l2_leaf_reg
gap
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
l2_leaf_reg

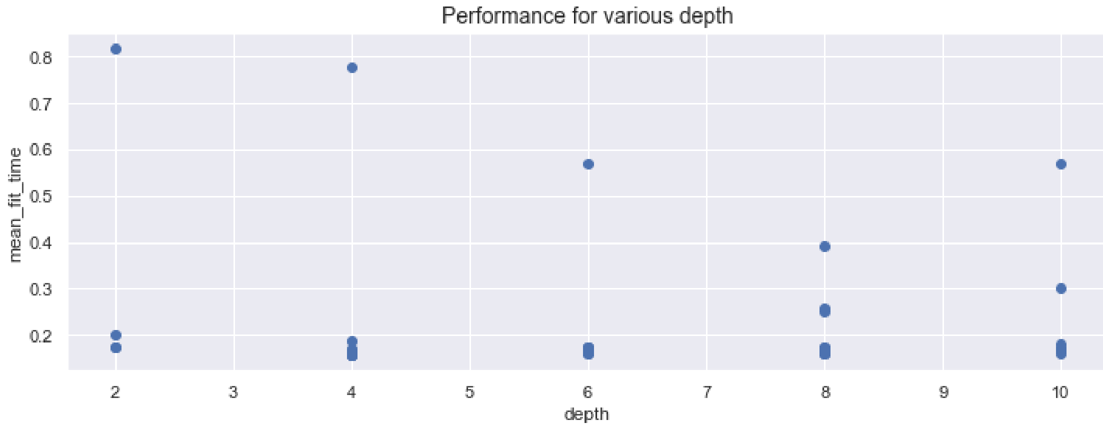


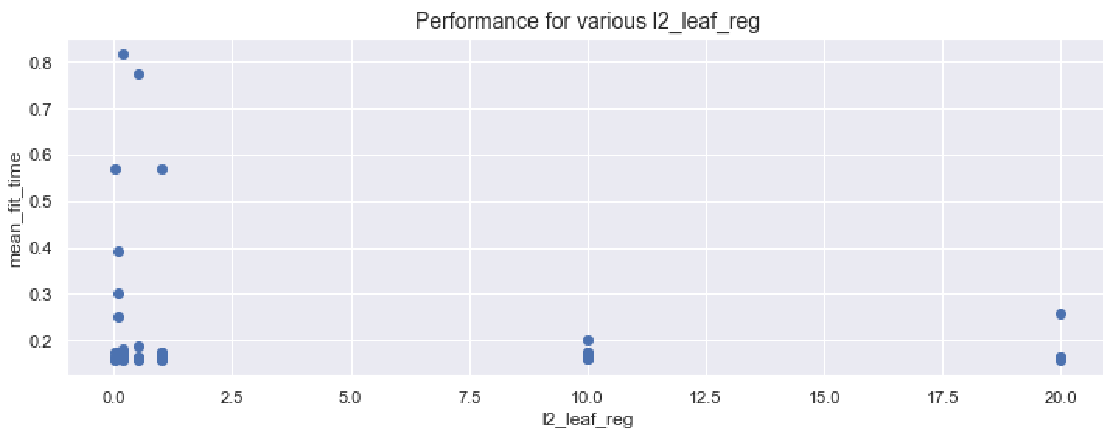
Performance for various min_data_in_leaf
gap
0.8
0.7
0.6
0.5
0.4
0.3
0.2
5
10
15
20
25
30
min_data_in_leaf

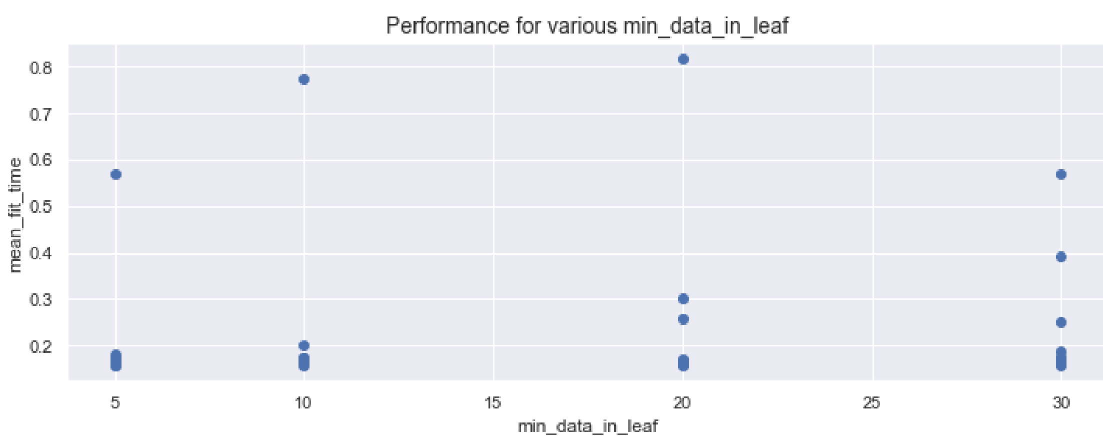
[129]:
```
print("Print fit efficienct plots...")

for parameter in cat_params:
    plot_metrics(cv_results_catb, parameter, 'mean_fit_time', "Performance for␣
↪various "+parameter)
```

```
Print fit efficienct plots...
```









`n_estimators` or `num_trees` and `learning_rate` affects the fit efficiency. `l2_leaf_reg` helps with the regularisation. `num_trees` and `depth` affect the performance of the model

0.2.4 QUESTION 25

For diamonds dataset

[130]:
```
pd.DataFrame.from_dict(all_model_results_diamond)
```

[130]:
```
                   model                                             params  \
0      Linear Regression                                                 NA
1       Lasso Regression                                  {'alpha': 0.0001}
2       Ridge Regression                                  {'alpha': 0.0001}
3  Lasso (poly degree=2)                                    {'alpha': 0.01}
4           MLPRegressor  {'activation': 'relu', 'alpha': 0.001, 'hidden...
5           RandomForest  {'max_depth': 6, 'max_features': 4, 'n_estimat...
6               LightGBM  {'max_depth': 4, 'min_data_in_leaf': 10, 'n_es...
7               CatBoost  {'max_depth': 4, 'min_data_in_leaf': 10, 'n_es...
8               LightGBM  {'max_depth': 4, 'min_data_in_leaf': 5, 'n_est...
9               CatBoost  {'depth': 4, 'l2_leaf_reg': 0.01, 'learning_ra...

   avg_train_rmse  avg_test_rmse
0        0.306212       0.307871
1        0.306215       0.307962
2        0.306212       0.307871
3        0.210834       0.209531
4        0.152632       0.156963
5        0.185170       0.249404
6        0.127457       0.158015
7        0.120934       0.154430
8        0.126345       0.157522
9        0.128398       0.155931
```

For pollution dataset

[131]:
```
pd.DataFrame.from_dict(all_model_results_pollution)
```

[131]:
```
                   model                                             params  \
0      Linear Regression                                                 NA
1       Lasso Regression                                   {'alpha': 0.001}
2       Ridge Regression                                     {'alpha': 100}
3  Lasso (poly degree=4)                                   {'alpha': 0.001}
4           MLPRegressor  {'activation': 'relu', 'alpha': 1, 'hidden_lay...
5           RandomForest  {'max_depth': 6, 'max_features': 5, 'n_estimat...

   avg_train_rmse  avg_test_rmse
0        0.662448       0.690991
1        0.663014       0.689782
2        0.665031       0.689959
3        0.499656       0.602067
4        0.630128       0.655230
5        0.473607       0.600993
```

Training RMSE indicates the error on the dataset using which the model was trained to get the parameters. Since, this is the dataset the model parameters are learnt on, the model performs well on this dataset compared to the validation set, which is the dataset on which the model is scored. The loss minimization happens using the training sample. Hence, the train and validation RMSE values are different.

0.2.5 QUESTION 26

For diamonds dataset

[137]:
```
a = pd.DataFrame.from_dict(all_model_results_diamond)
params = list(a[a['model'] == 'RandomForest']['params'])[0]
```

[138]:
```
start_time = time.time()

model = RandomForestRegressor(**params, n_jobs = -1, oob_score=True,␣
 ↪random_state = 42)
X = diamonds_df_scaled[selected_features_diamond]
y = diamonds_df_scaled[target_diamond]
model.fit(X,y)
print("OOB error is: ", (1-model.oob_score_))



print("done in %0.3fs." % (time.time() - start_time))
```

```
OOB error is:  0.03732291704030033
done in 0.993s.
```

For pollution dataset

[135]:
```
a = pd.DataFrame.from_dict(all_model_results_pollution)
params = list(a[a['model'] == 'RandomForest']['params'])[0]
```

[136]:
```
start_time = time.time()

model = RandomForestRegressor(**params, n_jobs = -1, oob_score=True,␣
 ↪random_state = 42)
X = pollution_df_scaled[selected_features_pollution]
y = pollution_df_scaled[target_pollution]
model.fit(X,y)
print("OOB error is: ", (1-model.oob_score_))



print("done in %0.3fs." % (time.time() - start_time))
```

```
OOB error is:  0.28851981528348747
done in 0.174s.
```

In random forest, each tree is trained on a subset sample obtained by bootstrapping the training data. So each tree is not built using the entire training sample. Out of bag error for a sample is the error obtained using prediction from the trees which did not use this sample to train the splits/model. An aggregate of this error for each sample is the out of bag error for the random forest model. It can be used to estimate validation or test error.

R_squared is the coefficient of correlation which is the proportion of the variation in the dependent variable that is predictable from the independent variable(s). It is given by 1- (residual sum of squares/ total sum of squares). Similar to OOB RMSE (error) value, R_squared can be calculated using the out of bag samples only.

0.3 EXTRAS

https://towardsdatascience.com/top-3-methods-for-handling-skewed-data-1334e0debf45 https://quantifyinghealth.com/f-statistic-in-linear-regression/ https://towardsdatascience.com/select-features-for-machine-learning-model-with-mutual-information-534fe387d5c8

Data Scaling:

Normalizing all the variables to be in the same range (between 0 to 1) improves ML performance, especially for models which use a weighted sum of input such as linear models and neural networks as well as models that use distance measures such as support vector machines and k-nearest neighbor.

Good practice to scale data and perhaps even make the data more normal (fit a Gaussian probability distribution) using a power transform. By default, the PowerTransformer also performs a standardization of each variable after performing the transform.

For regression problems it is often desirable to scale or transform both input and target variables.

Feature scaling improves the convergence of steepest descent algorithms, which do not possess the property of scale invariance. A step through one weight update of size γwill yield much better reduction in the error in the properly scaled case than the improperly scaled case. Normalizing the output will not affect shape of function, so it's generally not necessary.

A target variable with a large spread of values, in turn, may result in large error gradient values causing weight values to change dramatically, making the learning process unstable. This is best modeled with a linear activation function. If the distribution of the value is normal, then you can standardize the output variable. Otherwise, the output variable can be normalized.

there's also a demonstration on code where the model weights exploded during training given the very large errors and, in turn, error gradients calculated for weight updates also exploded. In short, if you don't scale the data and you have very large values, make sure to use very small learning rate values. - more relevant to neural networks

One reason for normalising the inputs is to make gradient descent more stable, as gradients spend more time in a comfortable region with meaningful updates and less neurons 'die' during trainings - getting stuck at one of the tails of e.g. the sigmoid non-linearity.

Normalising the output distribution is perhaps not the best idea, as you are by definition altering the definition of the target. This means you are essentially predicting a distribution that doesn't mirror your real-world target (at least without some reverse non-linear transforms later on).

On this you could do would be to scale the target, instead of normalising. The shape of the distribution should remain almost identical (thinking about the shape of the distribution), but the values themselves might be more easily attainable and therefore faster to optimise for; they are all closer in magnitude to the gradients that are being computed.

Links used to study: https://machinelearningmastery.com/how-to-transform-target-variables-for-regression-with-scikit-learn/ https://stats.stackexchange.com/questions/111467/is-it-necessary-to-scale-the-target-value-in-addition-to-scaling-features-for-re https://stackoverflow.com/questions/57583657/benefits-of-transforming-scaling-target-variable-in-supervised-learning https://machinelearningmastery.com/how-to-improve-neural-network-stability-and-modeling-performance-with-data-scaling/

Unbiased vs biased standard scalar

Review OLS assumptions on data for linear regression

Pearson correlation cutoff: We generally consider correlations above 0.4 to be relatively strong; correlations between 0.2 and 0.4 are moderate, and those below 0.2 are considered weak.

https://askinglot.com/what-is-a-good-pearson-correlation

Mutual Information works similar to information gain in decision tree classifiers. It measures the entropy drop under the condition of target variable. Keep features with MI > 0.2

Lasso - Least absolute shrinkage and selection operator

https://stats.stackexchange.com/questions/174897/choosing-the-range-and-grid-density-for-regularization-parameter-in-lasso

https://ai.stackexchange.com/questions/20680/should-neural-nets-be-deeper-the-more-complex-the-learning-problem-is https://datascience.stackexchange.com/questions/23287/why-large-weights-are-prohibited-in-neural-networks

[ ]:
```
def lasso_regression(data: pd.DataFrame(), features: list, target: str,
 ↪grid_params : dict, cv = 10):

    X = data[features]
    y = data[target]

    reg = Lasso(random_state = 42)
    grid = GridSearchCV(reg, grid_params, scoring='neg_root_mean_squared_error',
 ↪cv = cv,\
                                    return_train_score=True, n_jobs = -1)
    grid.fit(X, y)
    return grid.best_params_ , grid.cv_results_, grid.best_score_
```

M1_Project4_TwitterData

March 18, 2022

This is M1 of 3 modules for the twitter dataset. In this module, we cover question 27 and 28 for exploring twitter data.

[1]:
```
import numpy as np
import random
import pandas as pd
import json
import time
from datetime import datetime
from matplotlib import pyplot as plt
```

[2]:
```
## Load data
start_time = time.time()
files_tag = ['gohawks', 'gopatriots', 'nfl', 'patriots', 'sb49', 'superbowl']

tweet_id_ls = []
file_tag_ls = []
date_ls = []
num_followers_ls = []
retweets_ls = []

for file in files_tag:
    myJSON = []
    print("Reading file : "+file)
    for line in open('./data/ECE219_tweet_data/tweets_#'+file+'.txt','r'):
        data = json.loads(line)

        tweet_id_ls.append(data['tweet']['id_str'])
        file_tag_ls.append(file)
        date_ls.append(data['citation_date'])
        num_followers_ls.append(data['author']['followers'])
        retweets_ls.append(data['metrics']['citations']['total'])

df = pd.DataFrame({'tweet_id': tweet_id_ls, 'file_tag': file_tag_ls,\
                          'citation_datetime': date_ls, 'num_followers':␣
↪num_followers_ls, \
                  'num_retweets': retweets_ls})
```

```
print("done in %0.3fs." % (time.time() - start_time))
```

```
Reading file : gohawks
Reading file : gopatriots
Reading file : nfl
Reading file : patriots
Reading file : sb49
Reading file : superbowl
done in 122.139s.
```

QUESTION 27

[3]:
```
def report_statistics(data):

    ## Avg tweets per hour
    num_hours = (max(data['citation_datetime']) - min(data['citation_datetime']))
 ↪)/3600
    avg_tweets_per_hour = data.shape[0]/num_hours
    print("Average number of tweets per hour is: ", avg_tweets_per_hour)

    ## Avg number of followers
    avg_followers = sum(data['num_followers'])/data.shape[0]
    print("Average number of followers of users is: ", avg_followers)

    ## Avg number of retweets
    avg_retweets = sum(data['num_retweets'])/data.shape[0]
    print("Average number of retweets per tweet is: ", avg_retweets)
```

[4]:
```
for tag in files_tag:
    print("Printing statistics for hashtag: ", tag)
    tmp = df[df['file_tag'] == tag]
    report_statistics(tmp)
    print('')
```

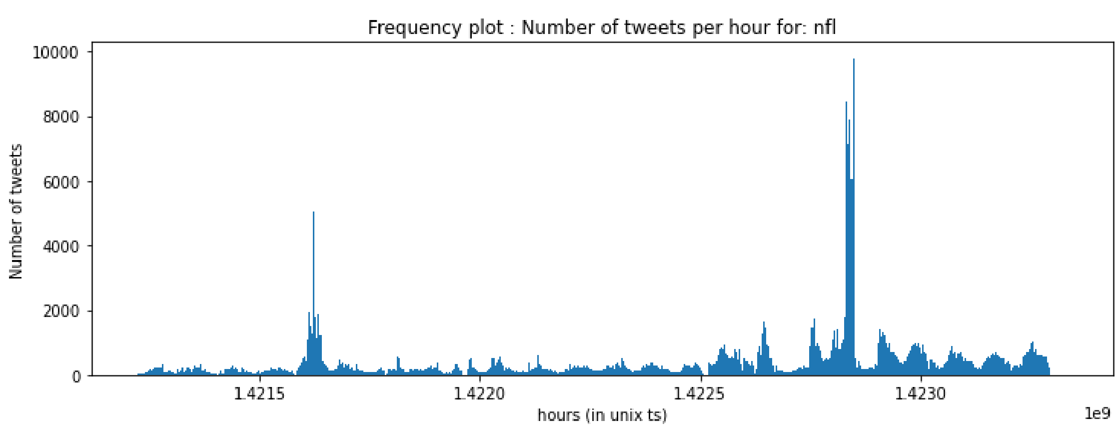
```
Printing statistics for hashtag:  gohawks
Average number of tweets per hour is:  292.48785062173687
Average number of followers of users is:  2217.9237355281984
Average number of retweets per tweet is:  2.0132093991319877

Printing statistics for hashtag:  gopatriots
Average number of tweets per hour is:  40.95469800606194
Average number of followers of users is:  1427.2526051635405
Average number of retweets per tweet is:  1.4081919101697078

Printing statistics for hashtag:  nfl
Average number of tweets per hour is:  397.0213901819841
Average number of followers of users is:  4662.37544523693
Average number of retweets per tweet is:  1.5344602655543254
```

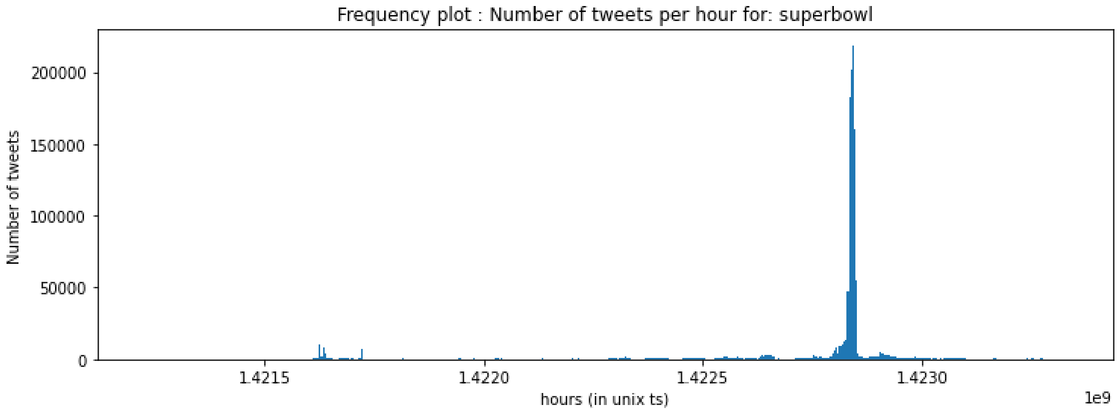
```
Printing statistics for hashtag:  patriots
Average number of tweets per hour is:  750.89426460689
Average number of followers of users is:  3280.4635616550277
Average number of retweets per tweet is:  1.7852871288476946

Printing statistics for hashtag:  sb49
Average number of tweets per hour is:  1276.8570598680474
Average number of followers of users is:  10374.160292019487
Average number of retweets per tweet is:  2.52713444111402

Printing statistics for hashtag:  superbowl
Average number of tweets per hour is:  2072.11840170408
Average number of followers of users is:  8814.96799424623
Average number of retweets per tweet is:  2.3911895819207736
```

QUESTION 28

[37]:
```
def plot_tweets_per_hour (data, tag):
    bins = np.arange(min(data['citation_datetime']),␣
 ↪max(data['citation_datetime'])+1, 3600)
    plt.figure(figsize=(12,4))
    plt.hist(data['citation_datetime'], bins = bins)
    plt.xlabel('hours (in unix ts)')
    plt.ylabel('Number of tweets')
    plt.title("Frequency plot : Number of tweets per hour for: "+ tag)
```

[38]:
```
tags = [ 'nfl', 'superbowl']

for tag in tags:

    tmp = df[df['file_tag'] == tag]
    plot_tweets_per_hour(tmp, tag)
```




Frequency plot : Number of tweets per hour for: superbowl
Number of tweets
200000
150000
100000
50000
0
1.4215
1.4220
1.4225
1.4230
1e9
hours (in unix ts)

```
[ ]:
```

M2_Project4_TwitterData

March 18, 2022

0.0.1 Module 2 - Twitter data

This is M2 of 3 modules for the twitter dataset. In this module, we cover the training parts to be used in M3 for prediction and inference for Q29. We extract the phrases, generate entities and finally create the dataset used for prediction.

[1]:
```
import numpy as np
import random
import pandas as pd
import orjson as json
import time
from datetime import datetime

import regex as re
import spacy
import pytextrank
import multiprocessing as mp
from multiprocessing import Pool
import pickle
from fuzzywuzzy import fuzz

from nltk.corpus import stopwords
stopwords = stopwords.words('english')

num_cores = 4 #number of cores on your machine
num_partitions = 16 #number of partitions to split dataframe

nlp = spacy.load("en_core_web_sm")
nlp.add_pipe("textrank")
```

[1]:
```
<pytextrank.base.BaseTextRankFactory at 0x7f9016fd1040>
```

[2]:
```
## Load data
start_time = time.time()
files_tag = ['gohawks', 'gopatriots', 'nfl', 'patriots', 'sb49', 'superbowl']

df = pd.DataFrame()
tweet_id_ls = []
file_tag_ls = []
```

```
tweet_text_ls = []
tweet_time_ls = []

for file in files_tag:
    myJSON = []
    print("Reading file : "+file)
    for line in open('./data/ECE219_tweet_data/tweets_#'+file+'.txt','r'):
        data = json.loads(line)
        tweet_id_ls.append(data['tweet']['id_str'])
        file_tag_ls.append(file)
        tweet_text_ls.append(data['tweet']['text'])
        tweet_time_ls.append(data['citation_date'])

tweet_txt = pd.DataFrame({'tweet_id': tweet_id_ls, 'file': file_tag_ls,\
                          'text': tweet_text_ls, 'citation_datetime':␣
 ↪tweet_time_ls})

print("done in %0.3fs." % (time.time() - start_time))
```

```
Reading file : gohawks
Reading file : gopatriots
Reading file : nfl
Reading file : patriots
Reading file : sb49
Reading file : superbowl
done in 90.407s.
```

[3]:
```
def clean(text):
    '''
    Helps remove many HTML artefacts from the crawler's output.
    '''
    text = re.sub(r'^https?:\/\/.*[\r\n]*', '', text, flags=re.MULTILINE)
    text = re.sub(r'^http?:\/\/.*[\r\n]*', '', text, flags=re.MULTILINE)
    texter = re.sub(r"<br />", " ", text)
    texter = re.sub(r"&quot;", "\"",texter)
    texter = re.sub('&#39;', "\"", texter)
    texter = re.sub('\n', " ", texter)
    texter = re.sub(' u '," you ", texter)
    texter = re.sub('`',"", texter)
    texter = re.sub(' +', ' ', texter)
    texter = re.sub(r"(!)\1+", r"!", texter)
    texter = re.sub(r"(\?)\1+", r"?", texter)
    texter = re.sub('&amp;', 'and', texter)
    texter = re.sub('\r', ' ',texter)
    clean = re.compile('<.*?>')
    texter = texter.encode('ascii', 'ignore').decode('ascii')
    texter = re.sub(clean, '', texter)
```

```
    if texter == "":
        texter = ""
    return texter

def text_preprocessing (text: str):
    text = text.lower()
    text = clean(text)
    return text
```

0.0.2 Phrase extraction

In this part, we extract top 3 phrases from each tweet text using text rank after applying basic text cleaning

[4]:
```
start_time = time.time()
print("Pre-processing tweet text for phrase extraction..")
tweet_txt['clean_text'] = tweet_txt['text'].apply(lambda x:␣
↪text_preprocessing(x))
print("done in %0.3fs." % (time.time() - start_time))
```

```
Pre-processing tweet text for phrase extraction..
done in 108.820s.
```

[5]:
```
def get_phrases (text: str, tweet_id : str, top_n = 3):
    '''
    Given a tweet id and text, returns top 3 phrases
    '''
    try:
        doc = nlp(text)
        phrases_dict = {}
        for phrase in doc._.phrases:
            phrases_dict[(tweet_id, phrase.text)] = phrase.rank

        a = dict(sorted(phrases_dict.items(), key=lambda x: x[1], reverse=True)[:
↪top_n])
        return a



    except:
        print('Error for Tweet ID %s' % tweet_id)
```

[6]:
```
phrase_extraction_df = tweet_txt[['tweet_id', 'clean_text']].drop_duplicates()
```

[7]:
```
start_time = time.time()
final_dict = {}
for index, row in phrase_extraction_df.iterrows():
    tmp_dict = get_phrases(row['clean_text'], row['tweet_id'])
    final_dict.update(tmp_dict)
```

```
    if(index % 10000 == 0):
        print(index)
        print("done in %0.3fs." % (time.time() - start_time))
        output = open('./twitter_files_v3/textrank_phrases_v2.pkl', 'wb')
        pickle.dump(final_dict, output)
```

```
done in 15497.447s.
```

[12]:
```
output = open('./twitter_files_v3/textrank_phrases_v2.pkl', 'wb')
pickle.dump(final_dict, output)
```

0.0.3 Phrase post-processing

In this part, we process the extracted phrases and do some cleaning on extracted phrases for subsequent tasks

[13]:
```
txtrank_phrase_file = open('./twitter_files_v3/textrank_phrases_v2.pkl', "rb")
txtrank_phrases = pickle.load(txtrank_phrase_file)
```

[14]:
```
#### Drop if all numeric
def all_numeric(number_sequence: str):
     return all(var.isdigit() for var in number_sequence.split())

def drop_allNumeric (data):
    data['allNumeric'] = data['clean_phrase'].apply(lambda x:␣
 ↪all_numeric(str(x)))
    data = data[data['allNumeric'] == False]
    data = data.drop(['allNumeric'], axis=1)
    return data
```

[15]:
```
def clean(text: str):

    # remove punctuation
    text = re.sub('[!"#$%&()*+-/:;<=>?@[\\]^_`{|}~]', '', text)

    # remove the from beginning
    if (text.startswith("the")):
        text = text.replace("the", '', 1)

    # remove http tokens
    tokens = text.split(' ')
    tokens_filt = [i for i in tokens if not i.startswith('http')]
    text = ' '.join(tokens_filt)

    # remove trailing spaces
    text = text.rstrip()
    text = text.lstrip()
```

```python
    return text

def remove_stopwords(data):
    phrase_counts = data.groupby(['clean_phrase']).size().reset_index(name =␣
↪'count')
    phrase_counts = phrase_counts.sort_values('count', ascending = False)
    phrase_counts['len'] = phrase_counts['clean_phrase'].apply(lambda x: len(x.
↪split(' ')))
    phrase_counts['single_stopword_tag'] = phrase_counts.apply(lambda row:␣
↪int(row['clean_phrase'] in stopwords) \
                                                            if (row['len'] == 1)␣
↪else 0, axis = 1)
    data = pd.merge(data, phrase_counts[['clean_phrase',␣
↪'single_stopword_tag']], how = 'left', on = 'clean_phrase')
    data = data[data['single_stopword_tag'] == 0]
    data = data.drop(['single_stopword_tag'], axis = 1)
    return data


def clean_phrases (txtrank_phrases):
    '''
    Given the dictionary of textrank, tweet phrases; clean the phrases to get␣
↪better entities.
    Returns a dataframe `txtrank_dt` with columns - tweet_id, ranking score,␣
↪phrase and other tweet info
    '''

    ## Read phrases
    txtrank_df = pd.DataFrame.from_dict(txtrank_phrases, orient = 'index').
↪reset_index()
    txtrank_df[['tweet_id', 'phrase']] = pd.DataFrame(txtrank_df['index'].
↪tolist(),\
                                                      index=txtrank_df.index)
    txtrank_df = txtrank_df.drop_duplicates()

    ## clean phrase
    txtrank_df['clean_phrase'] = txtrank_df['phrase'].apply(lambda x: clean(x))

    ##drop single word stopword phrases
    txtrank_df = remove_stopwords(txtrank_df)

    ## remove if length of phrase < 2
    txtrank_df['len'] = txtrank_df['clean_phrase'].apply(lambda x: len(x))
    txtrank_df = txtrank_df[txtrank_df['len'] > 2]
    txtrank_df = txtrank_df.drop(['len'], axis=1)
```

```
    ## get count of phrases and drop if count == 1
    phrase_counts = txtrank_df.groupby(['clean_phrase']).size().reset_index(name␣
↪= 'count')
    phrase_counts = phrase_counts.sort_values('count', ascending = False)
    txtrank_df = pd.merge(txtrank_df, phrase_counts, how = 'left', on =␣
↪'clean_phrase')
    txtrank_df = txtrank_df[txtrank_df['count'] > 1]
    txtrank_df = txtrank_df.drop(['count'], axis=1)

    return txtrank_df
```

[16]:
```
start_time = time.time()
print("Post-processing extracted phrases...")
txtrank_df = clean_phrases(txtrank_phrases)
txtrank_df = drop_allNumeric(txtrank_df)
print("done in %0.3fs." % (time.time() - start_time))
```

```
Post-processing extracted phrases...
done in 76.439s.
```

0.0.4 Entity extraction

In this part, we process the phrases to determine whether they are a valid entity

[17]:
```
def get_phrase_counts_overall (txtrank_df):
    '''
    Given the text rank dataframe with clean tweet phrases; get the frequency of␣
↪how many times a phrase was
    used in the entire tweet dataset to assess popular phrases/entities.
    Returns a dataframe `phrase_counts` with columns - `clean_phrase` (the␣
↪phrase) and `count` (num of occurences)
    '''

    phrase_counts = txtrank_df.groupby(['clean_phrase']).size().reset_index(name␣
↪= 'count')
    phrase_counts = phrase_counts.sort_values('count', ascending = False)

    return phrase_counts

def get_close_entities(allphrases : list, entity : str, threshold = 10):
    '''
    Given a phrase, map other phrases to this phrase using fuzzy text matching
    '''
    close_entities = []
    for phrase in allphrases:
        val = fuzz.ratio(phrase, entity)
        if(val > 85):
            close_entities.append(phrase)
```

```
    if(len(close_entities) > threshold):
        return close_entities
    else:
        return "Not an entity"
```

[18]:
```
phrase_counts = get_phrase_counts_overall(txtrank_df)
phrase_counts = phrase_counts.sort_values('count', ascending = False)
phrase_counts['entity'] = 'NA'
```

[19]:
```
phrase_counts.head()
```

[19]:

	clean_phrase	count	entity
154665	sb49	528347	NA
173591	superbowl	318933	NA
123949	nfl	235215	NA
176634	superbowlxlix	185221	NA
136621	patriots	176941	NA

[20]:
```
start_time = time.time()

tmp = phrase_counts[phrase_counts['count'] > 20]
tmp = tmp.sort_values('count', ascending = False)
prospect_entities = list(tmp['clean_phrase'])

entity_dict = {}
entity_key = 1
counter = 0
ind = 0
for phrase in prospect_entities:
    counter +=1
    if(counter % 1000 == 0):
        counter = 0
        ind += 1
        print("Completed for: ", ind)
        print("done in %0.3fs." % (time.time() - start_time))

    entity_val = list(phrase_counts[phrase_counts['clean_phrase'] ==␣
 ↪phrase]['entity'])[0]

    if(entity_val == 'NA'):
        allphrases = list(phrase_counts[phrase_counts['entity'] ==␣
 ↪'NA']['clean_phrase'])
        close_entities = get_close_entities(allphrases, phrase)
        if(close_entities == 'Not an entity'):
            phrase_counts.loc[ (phrase_counts['clean_phrase'] == phrase),␣
 ↪'entity'] = 'Not an entity'
```

```
        else:
            phrase_counts.loc[ (phrase_counts['clean_phrase'].
↪isin(close_entities)), 'entity'] = phrase
            entity_dict[entity_key] = phrase
            entity_key = entity_key+1
```

done in 7280.914s.

[21]:
```
output = open('./twitter_files_v3/entities_v2.pkl', 'wb')
pickle.dump(entity_dict, output)
output.close()
```

[22]:
```
output = open('./twitter_files_v3/clean_phrase_to_entity_v2.pkl', 'wb')
pickle.dump(phrase_counts, output)
output.close()
```

0.0.5 Get data for prediction tasks

[23]:
```
data = pd.merge(txtrank_df, phrase_counts, how = 'left', on = 'clean_phrase')
## merge tweet text and time
data = pd.merge(data, tweet_txt, how = 'left', on = 'tweet_id')
output = open('./twitter_files_v3/prediction_data_v2.pkl', 'wb')
pickle.dump(data, output)
output.close()
```

[24]:
```
entity_dict
```

[24]:
```
Showing top 100 entities:
{1: 'superbowl',
 2: 'superbowlxlix',
 3: 'patriots',
 4: 'seahawks',
 5: 'gohawks',
 6: 'patriotswin nfl',
 7: 'katyperry',
 8: 'tom brady',
 9: 'seattle',
 10: 'halftime',
 11: 'football',
 12: 'pats',
 13: 'superbowlcommercials',
 14: 'gopats',
 15: 'superbowlsunday',
 16: 'seattleseahawks',
 17: 'touchdown',
 18: 'commercials',
 19: 'new england',
 20: 'superbowl2015',
```

```
21: 'marshawn lynch',
22: 'katy',
23: 'patsnation',
24: 'new england patriots',
25: 'missyelliott',
26: 'budweiser',
27: 'this game',
28: 'sb49 superbowl',
29: 'patriotsnation',
30: 'russell wilson',
31: 'katyperry superbowl',
32: 'packers',
33: 'wilson',
34: 'people',
35: 'halftime show',
36: 'pete carroll',
37: 'america',
38: 'chris matthews',
39: 'beastmode',
40: 'dangerusswilson',
41: 'allyouneedisecuador',
42: 'nflplayoffs',
43: 'lenny kravitz',
44: 'bill belichick',
45: 'last year',
46: 'next year',
47: 'los',
48: 'tom',
49: 'national anthem',
50: 'belichick',
51: 'interception',
52: 'edelman',
53: 'seahawkswin',
54: 'our 2015 super bowl commercial',
55: 'this superbowl',
56: 'man',
57: 'seahawks superbowl',
58: 'gohawks sb49',
59: 'richard sherman',
60: 'sports',
61: 'a game',
62: 'mcdonalds',
63: 'win',
64: 'afcchampionship',
65: 'day',
66: 'idinamenzel',
67: 'john legend',
```

```
 68: 'defense',
 69: 'champions',
 70: 'touchdown patriots',
 71: 'malcolm butler',
 72: 'sherman',
 73: 'superbowl halftime show',
 74: 'deflategate',
 75: 'great game',
 76: 'matthews',
 77: 'nationwide',
 78: 'liam neeson',
 79: 'seahawks fans',
 80: 'nfl superbowl',
 81: 'greenbay',
 82: 'patriotsvsseahawks',
 83: 'espntemsuperbowl49',
 84: 'superbowl ads',
 85: 'robgronkowski',
 86: 'things',
 87: 'touchdown seahawks',
 88: 'sea',
 89: 'patriots fans',
 90: 'deflated balls',
 91: 'julian edelman',
 92: 'congratulations',
 93: 'seahawks sb49',
 94: 'halftimeshowkatyperry',
 95: 'los patriots',
 96: 'lol superbowl',
 97: 'robert kraft',
 98: 'sb49 seahawks',
 99: 'patriotsvscolts',
 100: 'american football',
}
```

```
[ ]:
```

M3_Project4_TwitterData

March 18, 2022

0.1 Module-3 Twitter Data

This is M3 of 3 modules for the twitter dataset. In this module, we cover the prediction and inference part of Q29

0.1.1 QUESTION 29

Describe task

Given a set of tweets text data, we try to find out the entities present in dataset using tweet text using a text rank phrase extraction algorithm along with fuzzy matching. The control parameters are - 'number of top phrases per tweet'; 'minimum frequency of phrase' for it to be considered as an entity; 'minimum number of other close phrases present'. After identifying the entities, we further extract closest keywords to the entity to understand the reference in which it is being talked about. We find the set of tweets talking about this entity and further rank them using a page rank algorithm to generate a tweet summary consisting of 4 top tweets.

We predict the closest key phrases, summary and sentiment for entities in each day/ every 10 min on game day (1st Feb) in the dataset. For the game day of 1st Feb, we predict key phrases in each 10 min interval.

To run the script, you will need the following: 1. './twitter_files_v3/entities.pkl' - Dictionary of entities generated in module 2, also provided in the zip file 2. './twitter_files_v3/prediction_data.pkl' - Prediction data generated in module 2, also provided in the zip file 3. './glove/glove.6B.100d.txt' - Glove embeddings

For each task - **you need to provide 4 inputs** - 1. **entity** (from the list of entities), 2. **pred_type** (game_day (predicts in last 10 min), reg_day (predicts for entire day)) 3. **task_type** (from "sentiment", "summary", "keywords") 3. **date** (format %Y-%m-%d for reg_day; %Y-%m-%d %H:%M:%S for game day)

The 3 task types are: 1. 'sentiment': returns the sentiment of the set of tweets for a given entity for the given day or in last 10 min if prediction type is game_day. 2. 'summary': returns list of 4 tweets which summarize the tweets for a given entity for the given day or in last 10 min if prediction type is game_day. 3. 'keywords': returns list of 10 key phrases that appear in context of a given entity for the given day or in last 10 min if prediction type is game_day.

[1]:
```
import numpy as np
import random
import pandas as pd
import orjson as json
```

```
import time
from datetime import datetime,timedelta

import regex as re
import spacy
import pytextrank
import multiprocessing as mp
from multiprocessing import Pool
import pickle

from fuzzywuzzy import fuzz
import textblob

import matplotlib.pyplot as plt
import warnings
warnings.simplefilter("ignore")
num_cores = 4 #number of cores on your machine
num_partitions = 16 #number of partitions to split dataframe

from nltk.corpus import stopwords
stop_words = stopwords.words('english')
from sklearn.metrics.pairwise import cosine_similarity
import networkx as nx

# nltk.download('stopwords')

import pytz
pst_tz = pytz.timezone('America/Los_Angeles')
utc_tz = pytz.utc
```

[2]:

```
## Load extracted files from M2

## list of entities extracted
entities = open('./twitter_files_v3/entities_v2.pkl', 'rb')
entities_dict = pickle.load(entities)
entities = list(entities_dict.values())

## prediction data
df_file = open('./twitter_files_v3/prediction_data_v2.pkl', 'rb')
prediction_df = pickle.load(df_file)

## datetime conversions
prediction_df['citation_dt_trans'] = prediction_df['citation_datetime'].
 ↪apply(lambda x: datetime.fromtimestamp(x, pst_tz))
prediction_df['utc_datetime'] = prediction_df['citation_datetime'].apply(lambda␣
 ↪x: datetime.fromtimestamp(x, utc_tz))
```

```python
prediction_df['date'] = pd.to_datetime(prediction_df['citation_dt_trans']).dt.
 ↪date
prediction_df['datetime'] = prediction_df['citation_dt_trans'].apply(lambda x:␣
 ↪str(x).rsplit('-', 1)[0])
prediction_df['datetime'] = pd.to_datetime(prediction_df['datetime'])
```

[3]:
```python
# prediction_df.head()
```

[3]:
```
                                                  index         0  \
0  (549327579782840320, #gohawks http://t.co/u1pc…  0.215096
1                  (549327579782840320, our defense)  0.117698
2  (549575600210718721, #dogslife http://t.co/gd3…  0.158353
3                      (549575600210718721, twelfth)  0.157154
4                      (549647876406534144, gohawks)  0.196769

             tweet_id                                phrase clean_phrase  count  \
0  549327579782840320   #gohawks http://t.co/u1pcxpesr8      gohawks  67966
1  549327579782840320                       our defense  our defense     51
2  549575600210718721  #dogslife http://t.co/gd3v6vqps5     dogslife      6
3  549575600210718721                           twelfth      twelfth     25
4  549647876406534144                           gohawks      gohawks  67966

         entity     file                                              text  \
0       gohawks  gohawks  I &lt;3 our defense! #GoHawks http://t.co/U1pc…
1  Not an entity  gohawks  I &lt;3 our defense! #GoHawks http://t.co/U1pc…
2            NA  gohawks  twelfth dogs are ready! #gohawks #dogslife htt…
3  Not an entity  gohawks  twelfth dogs are ready! #gohawks #dogslife htt…
4       gohawks  gohawks  "Oh no big deal, just NFC West Champs and the …

  citation_datetime                                    clean_text  \
0        1421518778  i &lt;3 our defense! #gohawks http://t.co/u1pc…
1        1421518778  i &lt;3 our defense! #gohawks http://t.co/u1pc…
2        1421259536  twelfth dogs are ready! #gohawks #dogslife htt…
3        1421259536  twelfth dogs are ready! #gohawks #dogslife htt…
4        1421468519  "oh no big deal, just nfc west champs and the …

          citation_dt_trans              utc_datetime        date  \
0 2015-01-17 10:19:38-08:00 2015-01-17 18:19:38+00:00  2015-01-17
1 2015-01-17 10:19:38-08:00 2015-01-17 18:19:38+00:00  2015-01-17
2 2015-01-14 10:18:56-08:00 2015-01-14 18:18:56+00:00  2015-01-14
3 2015-01-14 10:18:56-08:00 2015-01-14 18:18:56+00:00  2015-01-14
4 2015-01-16 20:21:59-08:00 2015-01-17 04:21:59+00:00  2015-01-16

             datetime
0 2015-01-17 10:19:38
1 2015-01-17 10:19:38
2 2015-01-14 10:18:56
```

```
3 2015-01-14 10:18:56
4 2015-01-16 20:21:59
```

[4]:
```
entities[:50]
```

[4]:
```
['superbowl',
 'superbowlxlix',
 'patriots',
 'seahawks',
 'gohawks',
 'patriotswin nfl',
 'katyperry',
 'tom brady',
 'seattle',
 'halftime',
 'football',
 'pats',
 'superbowlcommercials',
 'gopats',
 'superbowlsunday',
 'seattleseahawks',
 'touchdown',
 'commercials',
 'new england',
 'superbowl2015',
 'marshawn lynch',
 'katy',
 'patsnation',
 'new england patriots',
 'missyelliott',
 'budweiser',
 'this game',
 'sb49 superbowl',
 'patriotsnation',
 'russell wilson',
 'katyperry superbowl',
 'packers',
 'wilson',
 'people',
 'halftime show',
 'pete carroll',
 'america',
 'chris matthews',
 'beastmode',
 'dangerusswilson',
 'allyouneedisecuador',
 'nflplayoffs',
```

```
'lenny kravitz',
'bill belichick',
'last year',
'next year',
'los',
'tom',
'national anthem',
'belichick']
```

0.1.2 TASK 1: Get key phrases for a given entity in each day or last 10 min on game day

[5]:
```
#### For each entity get the top 10 descriptive sentiments around it
def get_n_close_phrases (data: pd.DataFrame(), entity: str, date: str,␣
↪pred_type = 'reg_day', n = 10):
    try:

        # tweets corresponding to the entity
        if(pred_type == 'reg_day'):
            data['date'] = data['date'].astype(str)
            tmp = data[(data['entity'] == entity) & (data['date'] == date)]
            tmp = tmp.drop(['file'], axis =1)
            tmp = tmp.drop_duplicates()

        elif(pred_type == 'game_day'):
            d = datetime.strptime(date, '%Y-%m-%d %H:%M:%S')
            d_prev = d - timedelta(minutes=10)
            tmp = data[(data['entity'] == entity) & (data['datetime'] >=␣
↪d_prev) & \
                    (data['datetime'] <= d)]
            tmp = tmp.drop(['file'], axis =1)
            tmp = tmp.drop_duplicates()

        tweet_ids = list(set(tmp['tweet_id']))

        ## weighted score for other phrases from the tweets
        # get relevant tweet data
        tmp = data[data['tweet_id'].isin(tweet_ids)]

        # remove rows corresponding to the entity itself
        tmp = tmp[tmp['entity'] != entity]

        phrase_counts = tmp.groupby(['clean_phrase']).size().reset_index(name =␣
↪'count')
        tmp = tmp.drop(['count', 'file'], axis = 1)
        tmp = tmp.drop_duplicates()
        tmp = pd.merge(tmp, phrase_counts, how = 'left', on = 'clean_phrase')
```

```
        # get weighted scores
        tmp['weighted_score'] = tmp.apply(lambda row: row[0] * row['count'],␣
↪axis = 1)

        other_phrases = tmp.groupby(['clean_phrase'])['weighted_score'].sum()
        other_phrases = other_phrases.reset_index()
        other_phrases = other_phrases.sort_values('weighted_score', ascending =␣
↪False)
        print(other_phrases[:n])

    except:
        print("Entity not important in the day/interval!")
```

[6]:
```
get_n_close_phrases(prediction_df, 'katyperry', '2015-01-18', 'reg_day')
```

```
     clean_phrase  weighted_score
96  superbowlxlix       60.837808
72       patriots       40.829373
35       halftime       18.224625
87       seahawks       12.932766
93     super bowl       11.643691
95      superbowl        5.264207
39           katy        4.418890
22       el medio        1.691668
57   medio tiempo        1.374621
71   para su show        0.947675
```

[7]:
```
get_n_close_phrases(prediction_df, 'john legend', '2015-02-01 15:20:00',␣
↪'game_day')
```

```
            clean_phrase  weighted_score
558            superbowl    26438.615728
572        superbowlxlix    19883.578545
493                 sb49     4912.672432
57               america     2285.457083
410      national anthem       91.130337
568      superbowlsunday       76.039311
354     love john legend       51.594259
315   john legends voice       49.223582
143               church       32.807374
361                  man       30.259418
```

0.1.3 TASK 2: Get summary for a given entity in each day or last 10 min on game day

[8]:

```
# Extract word vectors
word_embeddings = {}
f = open('./glove/glove.6B.100d.txt', encoding='utf-8')
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    word_embeddings[word] = coefs
f.close()

# function to remove stopwords
def remove_stopwords(sen):
    sen_new = " ".join([i for i in sen if i not in stop_words])
    return sen_new
```

[9]:

```
#### For each entity get data for the entity and date
def get_subset_data (data: pd.DataFrame(), entity: str, date: str, pred_type =␣
↪'reg_day'):
    try:

        # tweets corresponding to the entity
        if(pred_type == 'reg_day'):
            data['date'] = data['date'].astype(str)
            tmp = data[(data['entity'] == entity) & (data['date'] == date)]
            tmp = tmp.drop(['file'], axis =1)
            tmp = tmp.drop_duplicates()

        elif(pred_type == 'game_day'):
            d = datetime.strptime(date, '%Y-%m-%d %H:%M:%S')
            d_prev = d - timedelta(minutes=10)
            tmp = data[(data['entity'] == entity) & (data['datetime'] >=␣
↪d_prev) & \
                  (data['datetime'] <= d)]
            tmp = tmp.drop(['file'], axis =1)
            tmp = tmp.drop_duplicates()

        tweet_ids = list(set(tmp['tweet_id']))

        ## weighted score for other phrases from the tweets
        # get relevant tweet data
        tmp = data[data['tweet_id'].isin(tweet_ids)]
        tmp = tmp.drop(['count', 'file'], axis = 1)
        tmp = tmp.drop_duplicates()
```

```
        # remove rows corresponding to the entity itself
        tmp = tmp[tmp['entity'] != entity]
        phrase_counts = tmp.groupby(['clean_phrase']).size().reset_index(name =␣
↪'count')
        tmp = pd.merge(tmp, phrase_counts, how = 'left', on = 'clean_phrase')

        # get weighted scores
        tmp['weighted_score'] = tmp.apply(lambda row: row[0] * row['count'],␣
↪axis = 1)

        return tmp
    except:
        print("Not enough data")
```

[10]:
```
def get_topn_tweets (data: pd.DataFrame(), entity: str, date: str, pred_type =␣
↪'reg_day', n=4):

    sub_data = get_subset_data(data, entity, date, pred_type)

    ## process top 100 candidates at max according to important phrases
    filter_df = sub_data.groupby(['tweet_id'])['weighted_score'].sum().
↪reset_index()
    if(filter_df.shape[0] > 100):
        filter_df = filter_df.sort_values('weighted_score', ascending = False)[:
↪100]
        tweet_ids = list(set(filter_df['tweet_id']))
        sub_data = sub_data[sub_data['tweet_id'].isin(tweet_ids)]

    sentences = list(set(sub_data['text']))

    # clean sentences
    clean_sentences = pd.Series(sentences).str.replace("[^a-zA-Z]", " ")
    clean_sentences = [s.lower() for s in clean_sentences]
    clean_sentences = [remove_stopwords(r.split()) for r in clean_sentences]

    sentence_vectors = []
    for i in clean_sentences:
        if len(i) != 0:
            v = sum([word_embeddings.get(w, np.zeros((100,))) for w in i.
↪split()])/(len(i.split())+0.001)
        else:
            v = np.zeros((100,))
        sentence_vectors.append(v)
    sim_mat = np.zeros([len(sentences), len(sentences)])
    for i in range(len(sentences)):
        for j in range(len(sentences)):
            if i != j:
```

```
                sim_mat[i][j] = cosine_similarity(sentence_vectors[i].
↪reshape(1,100), sentence_vectors[j].reshape(1,100))[0,0]

    nx_graph = nx.from_numpy_array(sim_mat)
    scores = nx.pagerank(nx_graph)

    ranked_sentences = sorted(((scores[i],s) for i,s in enumerate(sentences)),␣
↪reverse=True)
    results = []
    for i in range(n):
        results.append(ranked_sentences[i][1])
    return results
```

[11]:
```
get_topn_tweets(prediction_df, 'peyton manning', '2015-01-18')
```

[11]:
```
["It's over. Let's see if Tom Brady can play better than Peyton Manning against
the #Seahawks in the #SuperBowl #NFLPlayoffs #INDvsNE",
 "Andrew Luck has taken the torch from Peyton Manning as the next great #Colts
QB that can't get past the #Patriots in the playoffs.",
 'Peyton Manning had his chance last year. Tom Brady gets his chance against the
Seahawks this year. #Brady #Patriots',
 "Real #Patriots fans should be happy Seattle won, now Tom Brady can do what
Peyton Manning couldn't do last year."]
```

[12]:
```
get_topn_tweets(prediction_df, 'john legend', '2015-02-01 15:20:00', 'game_day')
```

[12]:
```
['John legend  #imean #yes #Superbowl #',
 'John Legend was very good! :) #SuperBowl',
 'Love John Legend #SuperBowl',
 'John Legend getting down #SuperBowl']
```

0.1.4 TASK 3: Get sentiment for a given entity in each day or last 10 min on game day

[21]:
```
def get_sentiment (data: pd.DataFrame(), entity: str, date: str, pred_type =␣
↪'reg_day', n=4):

    sub_data = get_subset_data(data, entity, date, pred_type)
    sentences = list(set(sub_data['text']))

    # clean sentences
    clean_sentences = pd.Series(sentences).str.replace("[^a-zA-Z]", " ")
    clean_sentences = [s.lower() for s in clean_sentences]
    clean_sentences = [remove_stopwords(r.split()) for r in clean_sentences]

    polarities_ls = []
    for i in clean_sentences:
```

```
        polarities_ls.append(textblob.TextBlob(i).sentiment.polarity)
    sentiment_score =  sum(polarities_ls)/len(polarities_ls)
    sentiment = 'Neutral'
    if(sentiment_score > 0.05):
        sentiment = 'Positive'
    if(sentiment_score < -0.05):
        sentiment = 'Negative'

    print("Overall sentiment is: ", sentiment,", with score:", sentiment_score)
```

[14]:
```
get_sentiment(prediction_df, 'peyton manning', '2015-01-18')
```

```
Overall sentiment is:  Positive , with score: 0.13933725005153577
```

[15]:
```
get_sentiment(prediction_df, 'john legend', '2015-02-01 15:20:00', 'game_day')
```

```
Overall sentiment is:  Positive , with score: 0.192128009052351
```

0.1.5 PREDICTION

[19]:
```
def validate(datetime_string, pred_type):
    try:
        if(pred_type == 'reg_day'):
            return datetime.strptime(datetime_string,"%Y-%m-%d")
        elif(pred_type == 'game_day'):
            return datetime.strptime(datetime_string,"%Y-%m-%d %H:%M:%S")

    except ValueError:
        return False

def perform_task (entity, date, task, pred_type):
    if(task not in ['sentiment', 'summary', 'keywords'] ):
        print("Task can only be - sentiment, summary or keywords!")
    elif(pred_type not in ['reg_day', 'game_day']):
        print("Prediction type can only be - reg_day or game_day!")
    elif(entity not in entities):
        print("Entity not in data!")
        print("Try entities - katyperry, tom brady, rpeyton manning.. (check␣
↪entities file for more)!")
    elif(validate(date, pred_type) == False):
        print("Date format not valid!")
        print("Try date in format - %Y-%m-%d for reg_day and %Y-%m-%d %H:%M:%S␣
↪for game_day!")
    else:
        if(task == 'keywords'):
            get_n_close_phrases(prediction_df, entity, date, pred_type)
        elif(task == 'sentiment'):
            get_sentiment(prediction_df, entity, date, pred_type)
```

```python
        elif(task == 'summary'):
            results = get_topn_tweets(prediction_df, entity, date, pred_type)
            print(results)
        else:
            print("Unknown error occured! Please check input!")
```

[22]:
```python
task = input('Task to be performed [sentiment, summary, keywords]: ')
entity = input('Entity: ')
pred_type = input('Prediction type [reg_day, game_day]: ')
date = input('Date: ')
perform_task(str(entity), str(date), task, pred_type)
```

```
Task to be performed [sentiment, summary, keywords]: sentiment
Entity: tom brady
Prediction type [reg_day, game_day]: game_day
Date: 2015-02-01 15:20:00
Overall sentiment is:  Positive , with score: 0.09779048814873557
```

[ ]:
```python

```