In [78]:
```
from wordcount import nb_word_count

filename = "MSIN0143_2020_GROUP_E2.ipynb"
nb_word_count(filename)
```
Out[78]: 1998

Report Structure:

1. Introduction
2. Data Preparation
3. Exploratory and Descriptive Analysis
4. Predictive Analysis
5. Limitations
6. Conclusion

1. Introduction

Problem Statement

London housing is famously known for its extremely high price tag. Besides it being the capital, thereby contributing to house price, we would like to know what other influencing factors exist. Currently, there is no such platform/dataset offering transparent details on housing and related factors.

We aim to investigate how to gather insights from multiple datasets about the boroughs in London and how we can use predictive models to derive which factors are most important in influencing housing prices in London's 33 boroughs.

With this project, we support the government in helping first-time home buyers find their ideal house, by increasing their understanding of trends in different Boroughs.

Objective

Using historical data on house prices in London, we want to build a large dataset including various attributes influencing value and build a customisable search engine.

Based on our initial research, we have gathered a shortlist of variables that may contribute towards housing prices (Mason, 2017). We will then research the relevant dataset at Borough level to compile our dataset.

Our goal is to create a model transparently predicting house prices in different boroughs, whilst controlling for certain area characteristics and time. Different factors that influence the price shall be taken into consideration and analysed with regards to their influence on price.

In [1]:
```
#Import necessary modules and codes
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

import faculty.datasets as datasets
import pandas as pd
from pandas import DataFrame
from functools import reduce
import numpy as np
from scipy.stats import skew
import matplotlib.pyplot as plt
import math
import seaborn as sn
from functools import reduce
from scipy.stats import skew
from sklearn import linear_model
import statsmodels.api as sm
from linearmodels import PanelOLS
from linearmodels import PooledOLS
from linearmodels.panel import compare
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split, cross_val_score, GridSearch
CV, StratifiedKFold
import xgboost as xgb
import lightgbm as lgb
from sklearn.linear_model import LinearRegression,LogisticRegression, SGDRegresso
r, RidgeCV
from sklearn.ensemble import RandomForestRegressor
import sklearn.model_selection
from sklearn import metrics
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn import preprocessing
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
<ipython-input-1-eb4abfac22d0> in <module>
     16 from sklearn import linear_model
     17 import statsmodels.api as sm
---> 18 from linearmodels import PanelOLS
     19 from linearmodels import PooledOLS
     20 from linearmodels.panel import compare

ModuleNotFoundError: No module named 'linearmodels'
```

2. Data Preparation

This report will be based on 9 different datasets.

Datasets 1 to 7 contain information on each of London's 33 boroughs for a variable of interest, across different time periods. Whereas datasets 8 and 9 contain information on a variable of interest at one single point in time.

Upon completion of prepping the 9 datasets, 3 seperate merges will carried out:

1. Panel Data Merge - Datasets 1 to 7 will be merged on the Area Code and Year Column
2. First Year Data Merge (2011) - Datasets 1 to 7 with 8 and 9 will be merged on the Area Code Column
3. Last Year Data Merge (2017) - Datasets 1 to 7 with , 8 and 9 will be merged on the Area Code Column

All 3 merged datasets will be used for Exploratory and Descriptive Analysis, and the merged panel dataset will be used for Predictive Analysis.

Data Prep

Dataset

Source of main dataset (Housing in London):

https://www.kaggle.com/justinas/housing-in-london?select=housing_in_london_yearly_variables.csv (https://www.kaggle.com/justinas/housing-in-london?select=housing_in_london_yearly_variables.csv)

House Prices

- Source - **Kaggle**
- Variable of Interest - **House Prices**

In [2]:
```
# Importing the House Price Dataset
house_price_df= pd.read_csv("01. Monthly House Price Data.csv",usecols=[0,1,2,3])
house_price_df=house_price_df.sort_values(by=["date","code"])
house_price_df["date"]=house_price_df["date"].astype(str)

# Filtering for relevant years (2011 to 2017)
house_price_df=house_price_df[8644:12424]

# Calculating the yearly average price
house_price_df["year"]=house_price_df["date"].str[0:4]
house_price_df=house_price_df.groupby(["code","area","year"]).mean()
house_price_df["average_price"]=house_price_df["average_price"].astype(int)

# Filtering for relevant area codes (London Borough Codes)
house_price_df=house_price_df.sort_values(by=["code","year"])
house_price_df=house_price_df[:231]

# Renaming and coverting column types in preparation of merge
house_price_df=house_price_df.reset_index(inplace=False)
house_price_df = house_price_df.rename(columns={'area': 'Area','code': 'Code',
                                                'year': "Year",'average_price':
'House Price'})
house_price_df["Year"]=house_price_df["Year"].astype(int)
```

In [3]:
```
# Checking first 5 rows of dataset
house_price_df.head()
```

Out[3]:

	Code	Area	Year	House Price
0	E09000001	city of london	2011	463930
1	E09000001	city of london	2012	525327
2	E09000001	city of london	2013	570008
3	E09000001	city of london	2014	709385
4	E09000001	city of london	2015	760253

Crime

- Source - **Metropolitan Police**
- Variable of Interest - **Recorded Offences**

In [4]:
```
# Importing the Crime dataset
crime_df = pd.read_excel('01 New Crime data .xlsx',
                            usecols=[0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,
18,19,20],
                            header = 1,
                            index_col=0,
                            sheet_name="Crime Rates")

# Dropping NAs and irrelevant columns
crime_df = crime_df.dropna()
crime_df = crime_df.drop(labels = ['Borough','1999-00','2000-01','2001-02','2002-
03','2003-04','2004-05',
                                         '2005-06','2006-07','2007-08','2008-09',
'2009-10','2010-11'],axis = 1)

# Renaming the columns name and dropping irrelevant areas (Codes outside of Londo
n)
crime_df = crime_df.rename(index=str,columns={'2011-12':'2011','2012-13':'2012',
'2013-14':'2013'
                           ,'2014-15':'2014','2015-16':'2015','2016-17':'2016','2
017-18':'2017'})
crime_df = crime_df.drop(['E12000007','E13000001','E13000002'],axis = 0)
crime_df = crime_df.sort_values(by='Code')

# Converting table into panel data format
crime_2011 = crime_df["2011"]
crime_2012 = crime_df["2012"]
crime_2013 = crime_df["2013"]
crime_2014 = crime_df["2014"]
crime_2015 = crime_df["2015"]
crime_2016 = crime_df["2016"]
crime_2017 = crime_df["2017"]
crime_df2 = pd.concat([crime_2011,crime_2012,crime_2013,crime_2014,crime_2015,cri
me_2016,crime_2017]
                       ,axis = 0)
crime_df2 = pd.DataFrame(crime_df2,columns = ['Crime Rates'])

# Creating lists of Borough Codes and Years for crime_df2
codes = []
for i in crime_df.columns:
    for j in range(33):
        codes.append(i)
years = []
for j in range(7):
    for i in crime_df.index:
        years.append(i)

# Adding Borough codes to Borough Codes to crime_df2
years_df = pd.DataFrame(codes,columns = ['Year'],index = years)
crime_df2 = pd.concat([years_df,crime_df2],axis = 1)
crime_df2 = crime_df2.sort_values(by = ['Code','Year'])

# Resetting the index and converting year values in preperation of merge
crime_df2.reset_index(inplace=True)
crime_df2["Year"] = crime_df2["Year"].astype(int)
```

In [5]:
```
# Checking first 5 rows of dataset
crime_df2.head()
```

Out[5]:

	Code	Year	Crime Rates
0	E09000001	2011	90.6
1	E09000001	2012	85.8
2	E09000001	2013	77.9
3	E09000001	2014	85.5
4	E09000001	2015	82.4

Education

- Source - **London Datastore**
- Variable of Interest - **Schools**

In [6]:
```
# Each years data is held on a different worksheet in the excel file
# Defining functions that will automatically clean a worksheet
# For years 2011-2015
def education_cleaning1(year):
    education_df = pd.read_excel("01. Education Data.xls", header=1,
                                 usecols=[0,1,18],
                                 skiprows=[2,3,4,38,39,40,41,42,43,44,45,46,47,48
,49,50,51,52,53,54],
                                 sheet_name=year)
    education_df = education_df.dropna()
    education_df = education_df.rename(columns={'All schools': 'Schools'})
    education_df["Schools"]=education_df["Schools"].astype(int) # change from flo
at to int
    education_df.insert(2,"Year",year)
    return education_df

# Function for years 2016-2017, as "total" are in different columns in dataset
def education_cleaning2(year):
    education_df = pd.read_excel("01. Education Data.xls", header=1,
                             usecols=[0,1,16],
                             skiprows=[2,3,4,38,39,40,41,42,43,44,45,46,47,48,49,
50,51,52,53,54],
                             sheet_name=year)
    education_df = education_df.dropna()
    education_df = education_df.rename(columns={'All schools': 'Schools'})
    education_df["Schools"]=education_df["Schools"].astype(int)
    education_df.insert(2,"Year",year)
    return education_df

# Grouping all the dataframes together
edu_2011 = education_cleaning1("2011")
edu_2012 = education_cleaning1("2012")
edu_2013 = education_cleaning1("2013")
edu_2014 = education_cleaning1("2014")
edu_2015 = education_cleaning1("2015")
edu_2016 = education_cleaning2("2016")
edu_2017 = education_cleaning2("2017")

edu_dataset = [edu_2011, edu_2012, edu_2013, edu_2014,edu_2015,edu_2016,
               edu_2017]
edu_df = pd.concat(edu_dataset)

# Transforming dataframe into panel data format by ordering and renaming columns
edu_df = edu_df.sort_values(by=["LA Code","Year"])
edu_df=edu_df.rename(columns={"LA Code": 'Code'})

# Converting year values and keeping relevant columns in preperation of merge
edu_df["Year"]=edu_df["Year"].astype(int)
edu_df = edu_df[["Code", "Year", "Schools"]]
```

In [7]:
```
# Checking first 5 rows of dataset
edu_df.head()
```

Out[7]:

	Code	Year	Schools
0	E09000001	2011	5
0	E09000001	2012	5
0	E09000001	2013	5
0	E09000001	2014	5
0	E09000001	2015	5

Employment Opportunity

- Source - **London Datastore**
- Variable of Interest - **Job Density**

In [8]:
```
# Importing the Employment Opportunity Dataset
employment_opps_df = pd.read_excel("01. Employment Opportuntiy Data.xlsx", index_
col=0, sheet_name="Jobs Density")

# Dropping NAs, irrelevant areas (Codes outside of London) and years
employment_opps_df = employment_opps_df.dropna()
employment_opps_df = employment_opps_df[0:33]
employment_opps_df = employment_opps_df[[2011,2012,2013, 2014, 2015, 2016, 2017]]

# Converting the dataframe into panel data format
employment_df = employment_opps_df.stack()
employment_df = pd.DataFrame(employment_df)

# Renaming the Years and Job Density Columns
employment_df = employment_df.reset_index()
employment_df.rename(index=str, columns={"level_1": "Year", 0: "Job Density"}, in
place = True)
```

In [9]:
```
# Checking first 5 rows of dataset
employment_df.head()
```

Out[9]:

	Code	Year	Job Density
0	E09000001	2011	75.79
1	E09000001	2012	92.41
2	E09000001	2013	110.98
3	E09000001	2014	121.23
4	E09000001	2015	121.73

Wages

- Source - **London Datastore**
- Variable of Interest - **Full-Time Annual Salary**

In [10]:
```
# Importing the Wages, Area Codes dataset
wages_df = pd.read_excel("01. Wage Dataset.xlsx", index_col=0, sheet_name="Full-t
ime, Weekly")
area_codes_df = pd.read_csv("01. Area Codes.csv")

# Removing NAs and filtering for relevant areas
wages_df = wages_df.dropna()
wages_df = wages_df[0:33]

# Merging Wages and London Area Codes Dataset (this adds the area codes for each
 borough)
wages_df = wages_df.rename(columns={"Area": "Borough"})
m_wages_df = pd.merge(wages_df, area_codes_df, on = 'Borough')
m_wages_df = m_wages_df.drop(["Borough"], axis = 1)

#Select the year ranging from 2011 to 2017, whilst dropping any duplicated row
m_wages_df = m_wages_df[["Area Code",2011,2012,2013, 2014, 2015, 2016, 2017]]
m_wages_df = m_wages_df.set_index("Area Code")
m_wages_df = m_wages_df.drop_duplicates()
m_wages_df = m_wages_df.replace("#",0)

#Since we used the weekly wage sheet, to get the annual salary we times weekly wa
ges by 52
m_wages_df[[2011,2012,2013, 2014, 2015, 2016, 2017]] = m_wages_df[[2011,2012,2013
, 2014, 2015, 2016, 2017]]*52
f_wages_df = m_wages_df[[2011,2012,2013, 2014, 2015, 2016, 2017]]

#using the stack function we will transform the dataframe into a panel data
f_wages_df = f_wages_df.stack()
f_wages_df = f_wages_df.reset_index()
f_wages_df.rename(index=str, columns={"Area Code": "Code","level_1": "Year", 0:
"Annual Salary"}, inplace = True)
```

In [11]:
```
# Checking first 5 rows of dataset
f_wages_df.head()
```

Out[11]:

	Code	Year	Annual Salary
0	E09000001	2011	52358.800000
1	E09000001	2012	52379.993605
2	E09000001	2013	55510.309047
3	E09000001	2014	55514.808380
4	E09000001	2015	55889.369644

Leisure & Entertainment

- Source - **London Datastore**
- Variable of Interest - **Number of Pubs and Restaurants**

In [12]:
```
#importing the pubs (p) and restaurants (r) datasets
leisure_p_df = pd.read_excel("01. Leisure & Entertainment Data (Pubs).xls", sheet
_name="Pubs units", header = 3, skiprows = [4,5])
leisure_r_df = pd.read_excel("01. Leisure & Entertainment Data (Restaurants).xls"
, sheet_name="Restaurants units", header = 3,skiprows = [4,5])

# Dropping NAs
leisure_p_df = leisure_p_df.dropna()
leisure_r_df = leisure_r_df.dropna()

# Renaming columns manually
leisure_p_df = leisure_p_df.rename(columns={"Unnamed: 0":"Area Code", "Unnamed:
 1": "Area Name"})
leisure_p_df = leisure_p_df.set_index("Area Code")
leisure_r_df = leisure_r_df.rename(columns={"Unnamed: 0":"Area Code","Unnamed: 1"
: "Area Name"})
leisure_r_df = leisure_r_df.set_index("Area Code")

# Excluding years outside of 2011 - 2017
leisure_p_df_selected = leisure_p_df[[2011, 2012,2013,2014,2015,2016,2017]]
leisure_r_df_selected = leisure_r_df[[2011, 2012,2013,2014,2015,2016,2017]]

# Converting to panel data format
panel_leisure_p_df_selected = leisure_p_df_selected.stack()
panel_leisure_p_df_selected = pd.DataFrame(panel_leisure_p_df_selected)
panel_leisure_r_df_selected = leisure_r_df_selected.stack()
panel_leisure_r_df_selected = pd.DataFrame(panel_leisure_r_df_selected)

# Renaming columns years and No. of Pubs/Restaurants
panel_leisure_p_df_selected = panel_leisure_p_df_selected.reset_index()
panel_leisure_p_df_selected.rename(index=str, columns={"level_1": "Year", 0: "Num
ber of Facilities"}, inplace = True)
panel_leisure_r_df_selected = panel_leisure_r_df_selected.reset_index()
panel_leisure_r_df_selected.rename(index=str, columns={"level_1": "Year", 0: "Num
ber of Facilities"}, inplace = True)

# Merging Pubs and Restaurants into one Dataframe
leisure_df = pd.merge(panel_leisure_p_df_selected, panel_leisure_r_df_selected, l
eft_index=True, right_index=True, how='outer')
leisure_df = leisure_df.drop(['Area Code_y', 'Year_y'], axis=1)
leisure_df = leisure_df.rename(index=str, columns={"Area Code_x":"Area Code", "Ye
ar_x": "Year", "Number of Facilities_x": "Number of Pubs","Number of Facilities_
y":"Number of Restaurants"})

# Combining Bars and Restuarants Values and renaming Area Code Column in preparat
ion of merge
leisure_df["Bars and Restaurants"] = leisure_df['Number of Pubs'] + leisure_df['N
umber of Restaurants']
leisure_df = leisure_df.drop(['Number of Restaurants', 'Number of Pubs'], axis=1)
leisure_df = leisure_df.rename(columns={"Area Code":"Code"})
```

In [13]:
```
# Checking first 5 rows of dataset
leisure_df.head()
```

Out[13]:

	Code	Year	Bars and Restaurants
0	E09000001	2011	365.0
1	E09000001	2012	370.0
2	E09000001	2013	385.0
3	E09000001	2014	415.0
4	E09000001	2015	420.0

Healthcare

- Source - **NHS**
- Variable of Interest - **Number of GP Practices**

In [14]:
```
# Importing the healthcare, mappings and area codes datasets
healthcare_df = pd.read_csv("01. Healthcare Data.csv", names=["Practice Name", "P
ostcode"], usecols= [1, 9])
mappings_df = pd.read_csv('01. Postcodes to Borough Mappings.csv', usecols=[0,8])
area_codes_df = pd.read_csv("01. Area Codes.csv")

# Dropping NAs from dataset
healthcare_df = healthcare_df.dropna()

# Merging Healthcare and Mappings Dataset
mappings_df = mappings_df.rename(columns = {"District": "Borough"})
m_healthcare_df = pd.merge(healthcare_df, mappings_df,on = ['Postcode'],how = 'in
ner')
m_healthcare_df = m_healthcare_df[["Practice Name", "Borough"]]

# Aggregating Dataframe by the number of Practices per Borough
m_healthcare_df = m_healthcare_df['Borough'].value_counts().rename_axis('Borough'
).reset_index(name='Healthcare Practices')

# Merging Healthcare and London Area Codes Dataset (this drops practices out of L
ondon)
f_healthcare_df = pd.merge(m_healthcare_df, area_codes_df, on="Borough")
f_healthcare_df = f_healthcare_df.set_index("Area Code").sort_values("Area Code")

# Resetting index, renaming and dropping unneeded columns in preparation of merge
f_healthcare_df=f_healthcare_df.reset_index(inplace=False)
f_healthcare_df.rename(columns={"Area Code":"Code"}, inplace = True)
f_healthcare_df=f_healthcare_df.drop(columns="Borough")
```

In [15]:
```
# Checking first 5 rows of dataset
f_healthcare_df.head()
```

Out[15]:

	Code	Healthcare Practices
0	E09000001	2
1	E09000002	65
2	E09000003	98
3	E09000004	46
4	E09000005	95

Transport

- Source - **Doogal**
- Variable of Interest - **Number of TfL Transport Stations and Average of TfL Transport Zones (in Borough)**

In [16]:
```
# Importing the transport, mappings and area codes datasets
transport_df = pd.read_csv("01. Transport Data.csv")
mappings_df = pd.read_csv('01. Postcodes to Borough Mappings.csv', usecols=[0,8])
area_codes_df = pd.read_csv("01. Area Codes.csv")

# Dropping NAs and keeping columns of interest
transport_df = transport_df[["Station", "Zone", "Postcode"]]
transport_df = transport_df.dropna()

# Creating a Zone Column representing the most central transport zone
zones = transport_df["Zone"].str.split(",", expand = True)
transport_df["Zone"] = zones[0]

# Merging Transport and Mappings Datasets
mappings_df = mappings_df.rename(columns = {"District": "Borough"})
m_transport_df = pd.merge(transport_df, mappings_df,on = ['Postcode'],how = 'inne
r')
m_transport_df = m_transport_df[["Station", "Zone", "Borough"]]

# Aggregating Dataframe by the number of Stations per Borough
f_transport_df = m_transport_df['Borough'].value_counts().rename_axis('Borough').
reset_index(name='Transport Stations')

# Creating a Zones dataset with a mean transport zone for each borough
zones_df = m_transport_df[["Zone", "Borough"]].set_index('Borough')
zones_df["Zone"] = zones_df["Zone"].astype(int)
zones_df = zones_df.mean(level="Borough")

# Merging the merged transport dataset with Zones dataset
f_transport_df = pd.merge(f_transport_df, zones_df, on = ['Borough'])
f_transport_df.rename(columns={'Zone': 'Average of Transport Zones'}, inplace = T
rue)

# Merging Transport and London Area Codes Dataset (this drops practices out of Lo
ndon)
f_transport_df = pd.merge(f_transport_df, area_codes_df, on="Borough")
f_transport_df = f_transport_df.set_index("Area Code").sort_values("Area Code")

# Resetting index, renaming and dropping unneeded columns in preparation of merge
f_transport_df = f_transport_df.reset_index(inplace=False)
f_transport_df.rename(columns={"Area Code":"Code"}, inplace = True)
f_transport_df = f_transport_df.drop(columns="Borough")
```

In [17]:
```
# Checking first 5 rows of dataset
f_transport_df.head()
```

Out[17]:

	Code	Transport Stations	Average of Transport Zones
0	E09000001	13	1.000000
1	E09000002	7	4.714286
2	E09000003	18	3.833333
3	E09000004	12	5.166667
4	E09000005	27	3.148148

Data Merge

Panel Data

In [18]:
```
# Merging the indidviual panel dataframes
sources_df = [house_price_df, crime_df2, edu_df, employment_df, f_wages_df, leisu
re_df]

final_dataset = reduce(lambda  left, right: pd.merge(left,right,on=("Code","Year"
),
                                             how='inner'), sources_df)

# Capitalising Area Column
final_dataset["Area"] = final_dataset["Area"].apply(lambda x: x.upper())
```

In [19]:
```
# Checking first 5 rows of dataset
final_dataset.head()
```

Out[19]:

	Code	Area	Year	House Price	Crime Rates	Schools	Job Density	Annual Salary	Bars and Restaurants
0	E09000001	CITY OF LONDON	2011	463930	90.6	5	75.79	52358.800000	365.0
1	E09000001	CITY OF LONDON	2012	525327	85.8	5	92.41	52379.993605	370.0
2	E09000001	CITY OF LONDON	2013	570008	77.9	5	110.98	55510.309047	385.0
3	E09000001	CITY OF LONDON	2014	709385	85.5	5	121.23	55514.808380	415.0
4	E09000001	CITY OF LONDON	2015	760253	82.4	5	121.73	55889.369644	420.0

First Year Data

In [20]:
```
# Filtering Final Dataset for the first year (2011)
firstyr_dataset = final_dataset[final_dataset["Year"]==2011].drop(columns="Year")

# Merging Filtered Final Dataset with Transport and Healthcare Dataset
firstyr_dataset = pd.merge(firstyr_dataset, f_healthcare_df,on=("Code"))
firstyr_dataset = pd.merge(firstyr_dataset, f_transport_df,on=("Code"))
```

In [21]:
```
# Checking first 5 rows of dataset
firstyr_dataset.head()
```

Out[21]:

	Code	Area	House Price	Crime Rates	Schools	Job Density	Annual Salary	Bars and Restaurants	Healthcare Practices
0	E09000001	CITY OF LONDON	463930	90.600000	5	75.79	52358.8	365.0	2
1	E09000002	BARKING AND DAGENHAM	163465	100.652840	59	0.45	26041.6	55.0	65
2	E09000003	BARNET	338978	73.505474	154	0.62	32312.8	300.0	98
3	E09000004	BEXLEY	200672	52.273879	83	0.53	31668.0	190.0	46
4	E09000005	BRENT	298964	101.176960	103	0.53	25911.6	250.0	95

Last Year Data

In [22]:
```
# Filtering Final Dataset for the last year (2017)
lastyr_dataset = final_dataset[final_dataset["Year"]==2017].drop(columns="Year")

# Merging Filtered Final Dataset with Transport and Healthcare Dataset
lastyr_dataset = pd.merge(lastyr_dataset, f_healthcare_df,on=("Code"))
lastyr_dataset = pd.merge(lastyr_dataset, f_transport_df,on=("Code"))
```

In [23]:
```
# Checking first 5 rows of dataset
lastyr_dataset.head()
```

Out[23]:

	Code	Area	House Price	Crime Rates	Schools	Job Density	Annual Salary	Bars and Restaurants	Health Pract
0	E09000001	CITY OF LONDON	849790	92.200000	5	124.78	57328.122094	455.0	2
1	E09000002	BARKING AND DAGENHAM	287734	78.794325	64	0.49	28906.800000	55.0	65
2	E09000003	BARNET	538280	54.429232	161	0.70	35880.000000	350.0	98
3	E09000004	BEXLEY	335694	39.765179	84	0.59	32479.200000	205.0	46
4	E09000005	BRENT	487703	69.910019	98	0.71	29302.000000	260.0	95

3. Descriptive and Exploratory Analysis

Data type and Borough

Here, we introduce the datatypes of all variables and list all boroughs in London.

In [24]:
```
final_dataset.dtypes
```

Out[24]:
```
Code                        object
Area                        object
Year                         int64
House Price                  int64
Crime Rates                float64
Schools                      int64
Job Density                float64
Annual Salary              float64
Bars and Restaurants       float64
dtype: object
```

In [25]:
```
table_borough = final_dataset[["Code","Area"]].drop_duplicates()
table_borough.set_index("Code")
```

Out[25]:

	Area
Code	
E09000001	CITY OF LONDON
E09000002	BARKING AND DAGENHAM
E09000003	BARNET
E09000004	BEXLEY
E09000005	BRENT
E09000006	BROMLEY
E09000007	CAMDEN
E09000008	CROYDON
E09000009	EALING
E09000010	ENFIELD
E09000011	GREENWICH
E09000012	HACKNEY
E09000013	HAMMERSMITH AND FULHAM
E09000014	HARINGEY
E09000015	HARROW
E09000016	HAVERING
E09000017	HILLINGDON
E09000018	HOUNSLOW
E09000019	ISLINGTON
E09000020	KENSINGTON AND CHELSEA
E09000021	KINGSTON UPON THAMES
E09000022	LAMBETH
E09000023	LEWISHAM
E09000024	MERTON
E09000025	NEWHAM
E09000026	REDBRIDGE
E09000027	RICHMOND UPON THAMES
E09000028	SOUTHWARK
E09000029	SUTTON
E09000030	TOWER HAMLETS
E09000031	WALTHAM FOREST
E09000032	WANDSWORTH
E09000033	WESTMINSTER

Statistical Description of Data

We create a summary statistics table for our dataset:

In [26]:
```
descriptive_table = final_dataset.describe()
descriptive_table
```

Out[26]:

	Year	House Price	Crime Rates	Schools	Job Density	Annual Salary	Bars and Restaurants
count	231.000000	2.310000e+02	231.000000	231.000000	231.000000	231.000000	231.000000
mean	2014.000000	4.357631e+05	84.779510	93.536797	4.194805	33529.633135	326.645022
std	2.004343	2.126523e+05	34.024164	26.678557	18.972746	5366.229929	270.522240
min	2011.000000	1.634650e+05	39.765179	5.000000	0.390000	25906.400000	55.000000
25%	2012.000000	2.979545e+05	64.265730	78.500000	0.540000	30209.400000	187.500000
50%	2014.000000	3.769240e+05	77.847006	96.000000	0.650000	32219.200000	255.000000
75%	2016.000000	5.035330e+05	96.723957	108.000000	1.100000	35648.600000	370.000000
max	2017.000000	1.344539e+06	302.005629	164.000000	124.780000	57328.122094	1700.000000

We have 231 observations. Now we provide a snapshot of 2017’s summary statistics:

In [27]:
```
#Using describe to generate mean for all the variable in 2011 and create a Datafr
ame
last = lastyr_dataset.describe()
lastyr_describe = pd.DataFrame(last)

#Using describe to generate mean for all the variable in 2017 and create a Datafr
ame
first = firstyr_dataset.describe()
firstyr_describe = pd.DataFrame(first)

#using the following formula we can generate the percentage different over the 6
 years.
ptc_df = round(((lastyr_describe - firstyr_describe)/(firstyr_describe))*100,2)
#Dropping any non-relevant variable, since Healthcare Practice, Transport station
and average transport zone didn't change between 2011 and 2017.
ptc_df = ptc_df.drop(["Healthcare Practices", "Transport Stations", "Average of T
ransport Zones"], axis = 1)
#Dropping other non-relevant rows provided by the describe function
ptc_df = ptc_df[1:2]
#Adding percentage sign onto the values
ptc_df.astype(str).add("%").T
```

Out[27]:

	mean
House Price	62.59%
Crime Rates	-28.21%
Schools	4.14%
Job Density	51.12%
Annual Salary	7.3%
Bars and Restaurants	15.27%

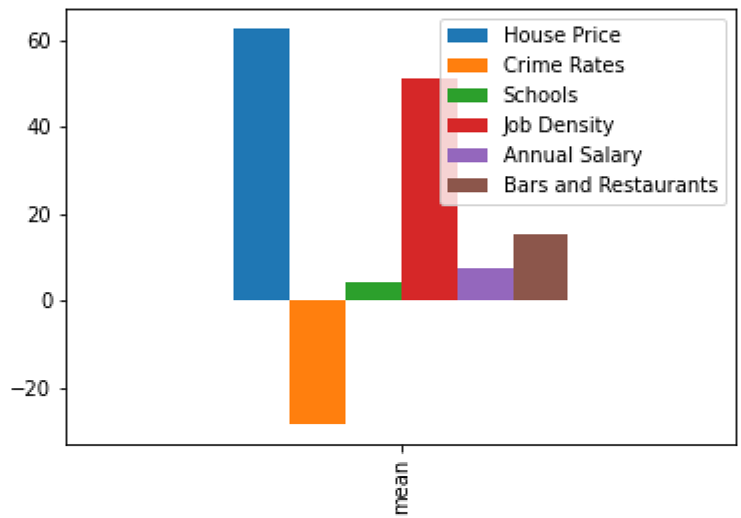
Next, we vissualize the percentage change in summary statistics from 2011 to 2017.

In [28]:
```
%matplotlib inline
plt.figure(figsize=(16, 8))
ptc_df.plot.bar()
```

Out[28]: <Figure size 1152x576 with 0 Axes>

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb920d2d4f0>

<Figure size 1152x576 with 0 Axes>



Exploratory Analysis

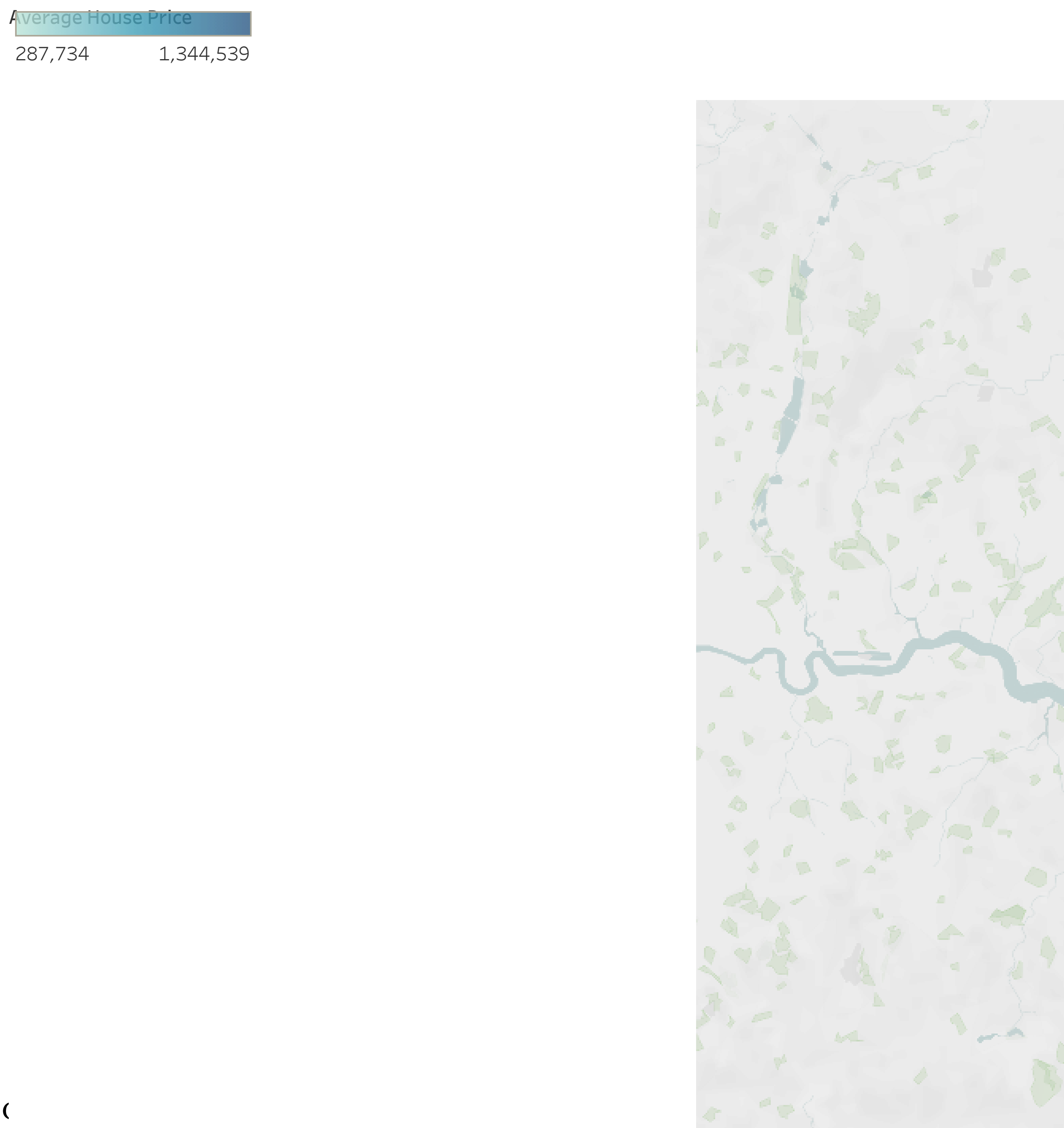
Dependent Variable - House Price

We will now review house prices in detail, as it is our dependent variable in Section 4.

House Price Heatmap

In [1]:
```
%%HTML
# we didn't run the output because it cannot show correctly in PDF. However we to
ok a screenshot to show what does it looks like. People can run it on faculty.
<div class='tableauPlaceholder' id='viz1607777849491' style='position: relative'>
<noscript><a href='#'><img alt=' ' src='https:&#47;&#47;public.tableau.com&#47;st
atic&#47;images&#47;SM&#47;SMX2P7QYY&#47;1_rss.png' style='border: none' /></a></
noscript><object class='tableauViz'  style='display:none;'><param name='host_url'
value='https%3A%2F%2Fpublic.tableau.com%2F' /> <param name='embed_code_version' v
alue='3' /> <param name='path' value='shared&#47;SMX2P7QYY' /> <param name='toolb
ar' value='yes' /><param name='static_image' value='https:&#47;&#47;public.tablea
u.com&#47;static&#47;images&#47;SM&#47;SMX2P7QYY&#47;1.png' /> <param name='anima
te_transition' value='yes' /><param name='display_static_image' value='yes' /><pa
ram name='display_spinner' value='yes' /><param name='display_overlay' value='ye
s' /><param name='display_count' value='yes' /><param name='language' value='en'
 /><param name='filter' value='publish=yes' /></object></div>                <scr
ipt type='text/javascript'>                    var divElement = document.getEleme
ntById('viz1607777849491');                    var vizElement = divElement.getEle
mentsByTagName('object')[0];                    vizElement.style.width='100%';viz
Element.style.height=(divElement.offsetWidth*0.75)+'px';                    var s
criptElement = document.createElement('script');                    scriptElemen
t.src = 'https://public.tableau.com/javascripts/api/viz_v1.js';
vizElement.parentNode.insertBefore(scriptElement, vizElement);                </s
cript>
```

we didn't run the output because it cannot show correctly in PDF. However we took a screenshot to show what does it looks like. People can run it on faculty.



Annual Salary and House Price Plot

Given high property prices in London, we compare the percentage change in Londoners' salaries and house prices.

Annual%20Salary%20V%20House%20Price%20Plot.JPG

Between 2013 and 2014, the percentage change in house prices increased by 8.11%, attributed to record low interest rates, driving up demand (Osborne, 2014). However, from 2016 to 2017 the percentage change in prices decreased by 3.19%, as uncertainty over Brexit take effect (Collinson, 2017).

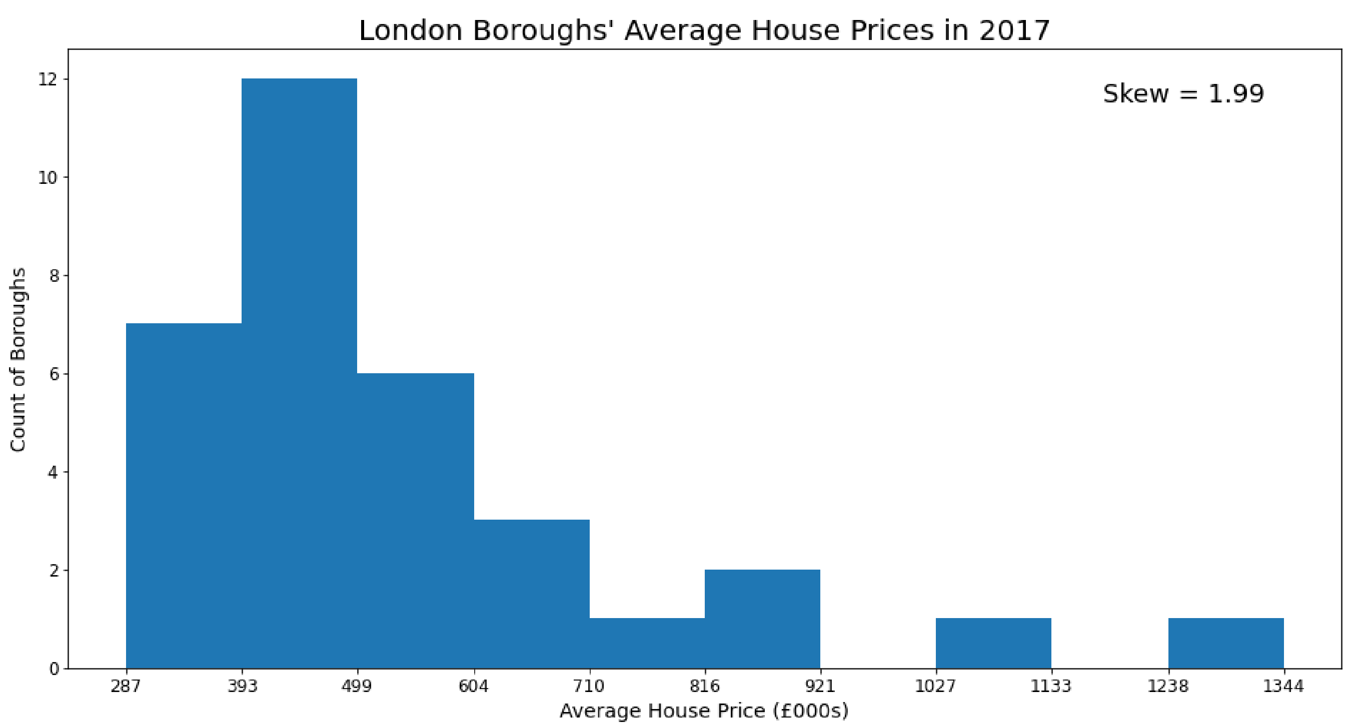
London's problem of affordability is visualised above, by the disproportionate increases in house prices relative to annual salary. New home buyers face challenging times ahead.

Histogram

In [29]:

```
#Selecting House Price to be plotted on the histogram
house_price =lastyr_dataset["House Price"]

# Creating a histogram based on 10 bins
hist, bin_edges = np.histogram(house_price)

# Dividing bin edges by 1000 and rounding for ease of reading on histogram
tick_labels = bin_edges/1000
tick_labels = [int(label) for label in tick_labels]

# Calculating the skewness of the histogram
skew_value = round(skew(house_price), 2)
skew_text = "Skew = " + str(skew_value)

# Plotting the histogram and adding text on it's skewness

plt.figure(figsize=(16, 8))
plt.hist(house_price, bins=10)
plt.title("London Boroughs' Average House Prices in 2017", fontsize = 20)
plt.xticks(bin_edges, tick_labels, fontsize = 12)
plt.yticks(fontsize = 12)
plt.xlabel("Average House Price (£000s)", fontsize = 14)
plt.ylabel("Count of Boroughs", fontsize = 14)
plt.text(1180000, 11.5, skew_text, fontsize = 18)
plt.show()
```

```
Out[29]: <Figure size 1152x576 with 0 Axes>

Out[29]: (array([ 7., 12.,  6.,  3.,  1.,  2.,  0.,  1.,  0.,  1.]),
          array([ 287734. ,  393414.5,  499095. ,  604775.5,  710456. ,  816136.5,
                  921817. , 1027497.5, 1133178. , 1238858.5, 1344539. ]),
          <a list of 10 Patch objects>)

Out[29]: Text(0.5, 1.0, "London Boroughs' Average House Prices in 2017")

Out[29]: ([<matplotlib.axis.XTick at 0x7f058a3e5130>,
           <matplotlib.axis.XTick at 0x7f058a3e5100>,
           <matplotlib.axis.XTick at 0x7f05873b36d0>,
           <matplotlib.axis.XTick at 0x7f058aa84490>,
           <matplotlib.axis.XTick at 0x7f058aa84ca0>,
           <matplotlib.axis.XTick at 0x7f058aa84520>,
           <matplotlib.axis.XTick at 0x7f058aa5d430>,
           <matplotlib.axis.XTick at 0x7f058aa5d8e0>,
           <matplotlib.axis.XTick at 0x7f058aa5de50>,
           <matplotlib.axis.XTick at 0x7f058aac43a0>,
           <matplotlib.axis.XTick at 0x7f058aa35f10>],
          [Text(0, 0, '287'),
           Text(0, 0, '393'),
           Text(0, 0, '499'),
           Text(0, 0, '604'),
           Text(0, 0, '710'),
           Text(0, 0, '816'),
           Text(0, 0, '921'),
           Text(0, 0, '1027'),
           Text(0, 0, '1133'),
           Text(0, 0, '1238'),
           Text(0, 0, '1344')])

Out[29]: (array([ 0.,  2.,  4.,  6.,  8., 10., 12., 14.]),
          <a list of 8 Text major ticklabel objects>)

Out[29]: Text(0.5, 0, 'Average House Price (£000s)')

Out[29]: Text(0, 0.5, 'Count of Boroughs')

Out[29]: Text(1180000, 11.5, 'Skew = 1.99')
```



The House Prices histogram illustrates a positively skewed distribution, indicating that many boroughs average house prices are below London’s total mean. This is an indication of London’s high upper bound of house prices.

Independent Variables

Seaborn Heatmap

In [30]:
```
%%capture
# Creating a Seaborn Heatmap visualising the Density of Schools per Borough
last = lastyr_dataset
last_df = pd.DataFrame(last)
school_df = last_df.drop(["Code","House Price","Bars and Restaurants","Crime Rate
s","Job Density","Annual Salary","Healthcare Practices", "Transport Stations", "A
verage of Transport Zones"], axis = 1)
school_df['Area'] = school_df['Area'].apply(lambda x: x.capitalize())
school_df = school_df.set_index("Area")
fig, ax = plt.subplots(figsize=(20,20))
heatmap_school = sn.heatmap(school_df,linewidth=1,square=True,vmin=5, vmax=175, c
map="Blues",annot = True, fmt='.0f', yticklabels = False)

# Creating a Seaborn Heatmap visualising the avg. Annual Salary per Borough
last = lastyr_dataset
last_df = pd.DataFrame(last)
salary_df= last_df.drop(["Code","House Price","Schools","Bars and Restaurants","C
rime Rates","Transport Stations","Job Density", "Healthcare Practices", "Average
 of Transport Zones"], axis = 1)
salary_df['Area'] = salary_df['Area'].apply(lambda x: x.capitalize())
salary_df = salary_df.set_index("Area")
fig, ax = plt.subplots(figsize=(20,20))
heatmap_salary = sn.heatmap(salary_df,linewidth=1,square=True,vmin=20000, vmax=60
000, cmap="winter_r",annot = True, fmt='.0f', yticklabels = False)
# Extreme outlier: City of London

# Creating a Seaborn Heatmap visualising the Density of Leisure Opportunities per
Borough
last = lastyr_dataset
last_df = pd.DataFrame(last)
bars_rests_df = last_df.drop(["Code","House Price","Schools","Crime Rates","Job D
ensity","Annual Salary","Healthcare Practices", "Transport Stations", "Average of
Transport Zones"], axis = 1)
bars_rests_df['Area'] = bars_rests_df['Area'].apply(lambda x: x.capitalize())
bars_rests_df = bars_rests_df.set_index("Area")
fig, ax = plt.subplots(figsize=(20,20))
heatmap_leisure = sn.heatmap(bars_rests_df,linewidth=1,square=True,vmin=55, vmax=
1000, cmap="Reds",annot = True, fmt='.0f', yticklabels = False)
# extreme outlier: Westminster

# Creating a Seaborn Heatmap visualising the Number of Tube Stations per Borough
last = lastyr_dataset
last_df = pd.DataFrame(last)
tfl_stations_df= last_df.drop(["Code","House Price","Schools","Bars and Restauran
ts","Crime Rates","Annual Salary","Job Density", "Healthcare Practices", "Average
of Transport Zones"], axis = 1)
tfl_stations_df['Area'] = tfl_stations_df['Area'].apply(lambda x: x.capitalize())
tfl_stations_df = tfl_stations_df.set_index("Area")
fig, ax = plt.subplots(figsize=(20,20))
heatmap_tfl_stations = sn.heatmap(tfl_stations_df,linewidth=1,square=True,vmin=5,
vmax=40, cmap="YlOrBr",annot = True, fmt='.0f', yticklabels = False)
# Extreme outlier: Croydon

# Creating a Seaborn Heatmap visualising the Density of Healthcare Practices per
 Borough
last = lastyr_dataset
last_df = pd.DataFrame(last)
healthcare_df= last_df.drop(["Code","House Price","Schools","Bars and Restaurant
s","Crime Rates","Annual Salary","Job Density", "Transport Stations", "Average of
Transport Zones"], axis = 1)
healthcare_df['Area'] = healthcare_df['Area'].apply(lambda x: x.capitalize())
```

```
healthcare_df = healthcare_df.set_index("Area")
fig, ax = plt.subplots(figsize=(20,20))
heatmap_health = sn.heatmap(healthcare_df,linewidth=1,square=True,vmin=2, vmax=9
5, cmap="autumn",annot = True, fmt='.0f', yticklabels = False)
# Extreme outlier: Croydon

# Creating a Seaborn Heatmap visualising the Density of Jobs per Borough
last = lastyr_dataset
last_df = pd.DataFrame(last)
job_density_df= last_df.drop(["Code","House Price","Schools","Bars and Restaurant
s","Crime Rates","Annual Salary","Healthcare Practices", "Transport Stations", "A
verage of Transport Zones"], axis = 1)
job_density_df['Area'] = job_density_df['Area'].apply(lambda x: x.capitalize())
job_density_df = job_density_df.set_index("Area")
fig, ax = plt.subplots(figsize=(20,20))
heatmap_density = sn.heatmap(job_density_df,linewidth=1,square=True,vmin=0, vmax=
1.5, cmap="Purples",annot = True, fmt='.0f', yticklabels = False)
# extreme outlier: City of London

# Creating a Seaborn Heatmap visualising the Density of Crime Rate per Borough
last = lastyr_dataset
last_df = pd.DataFrame(last)
crime_df = last_df.drop(["Code","House Price","Schools","Bars and Restaurants","J
ob Density","Annual Salary","Healthcare Practices", "Transport Stations", "Averag
e of Transport Zones"], axis = 1)
crime_df['Area'] = crime_df['Area'].apply(lambda x: x.capitalize())
crime_df = crime_df.set_index("Area")
fig, ax = plt.subplots(figsize=(20,20))
heatmap_crime = sn.heatmap(crime_df,linewidth=1,square=True,vmin=35, vmax=100, cm
ap="Greens",annot = True, fmt='.0f', yticklabels = False )
# extreme outlier: Westminster

# The 7 heatmaps were merged externally.
```

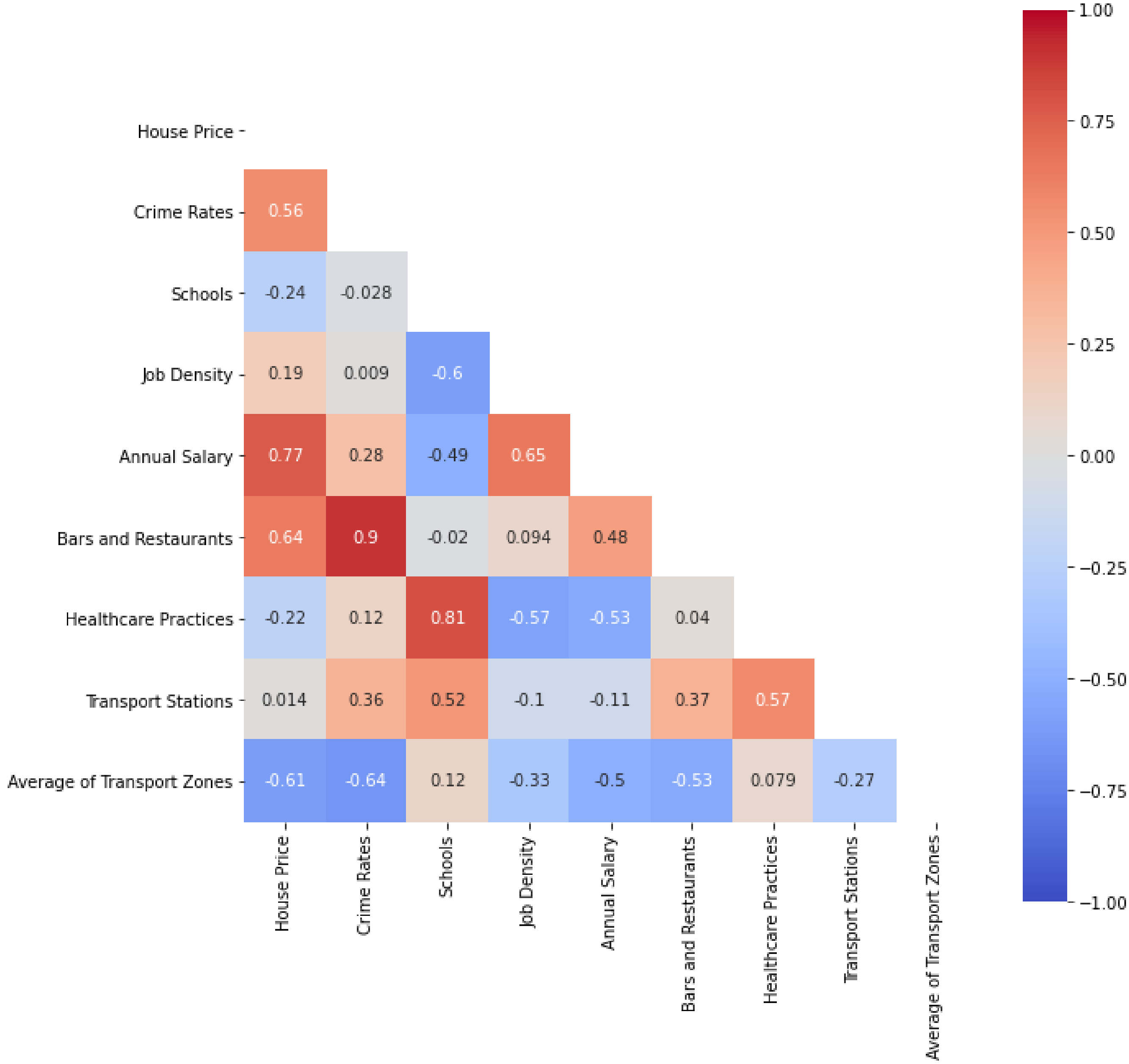
The merged heatmap provides us with a snapshot of borough performance per variable in the final year. Central boroughs, e.g. City of London, Camden and Westminster, generally perform strongest.

Correlation Matrix

Using a correlation matrix enables us to see closely how variables interact with each other

In [31]:
```
#first we set a size of this correlation matrix so that values are visible
fig, ax = plt.subplots(figsize=(10,10))

#using the .corr() calculates the correlation matrix
corr_table_firstyr = (firstyr_dataset.corr())

#using np.triu() can help use get a triangle matrix so that the top half of the d
uplicated matrix is deleted
matrix = np.triu(firstyr_dataset.corr())

#print Matrix
sn.heatmap(corr_table_firstyr, annot = True, vmin=-1, vmax=1, center= 0, cmap =
"coolwarm",square = True, mask = matrix, ax=ax)
plt.show()
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0586ceeb50>



We identify that Crime Rate and Bars & Restaurants, are positively correlated with house prices.

Surprisingly, the number of Schools in a borough decreases, the higher the house price.

Oddly, the average transport zone variable is negatively correlated with house prices. As zones range from 1 to 6, we gather that more central boroughs closer have higher house prices.

We observe that the number of Schools in a borough is correlated with the amount of Healthcare Practices(0.81). An increase in Bars & Restaurants is correlated with a higher crime rate (0.9). Individuals living closer towards Central London (Zone 1), tend to have a higher salary (-0.61).

Some of the information may sound intuitive, yet demonstrating the correlations add to the general understanding of how the variables interact.

Scenario

One particular struggle, when looking for the right house, is finding the ideal area within a suitable range price. However, using the following function helps new home buyers understand borough traits.

House Price Finder

To use this function, users must simply input the letter corresponding to their ideal price range. As a result, borough code, name and prices within the range are presented.

In [32]:
```
def house_price_finder():
    desired_price=input("""Please indicate your desired house price range:
    A: £280,000-£380,000.
    B: £380,000-£480,000
    C: £480,000-£750,000.
    D: £750,000-£1,000,000.
    E: more than £1,000,000.
    """) # Ask for customers' input as a letter option.
    # in case customers enter lower-case letter.
    desired_price=desired_price.upper()
    # Below are the five scenarios and their output as a data frame
    if desired_price=="A":
        print ("These are the suitable boroughs.")
        return lastyr_dataset.loc[lastyr_dataset["House Price"].between(280000,38
0000),["Code","Area","House Price"]]
    elif desired_price=="B":
        print ("These are the suitable boroughs.")
        return lastyr_dataset.loc[lastyr_dataset["House Price"].between(380000,48
0000),["Code","Area","House Price"]]
    elif desired_price=="C":
        print ("These are the suitable boroughs.")
        return lastyr_dataset.loc[lastyr_dataset["House Price"].between(480000,75
0000),["Code","Area","House Price"]]
    elif desired_price=="D":
        print ("These are the suitable boroughs.")
        return lastyr_dataset.loc[lastyr_dataset["House Price"].between(750000,10
00000),["Code","Area","House Price"]]
    elif desired_price=="E":
        print ("These are the suitable boroughs.")
        return lastyr_dataset.loc[lastyr_dataset["House Price"].between(1000000,1
500000),["Code","Area","House Price"]]
    else: # if customers enter other letters or words
        print("Please enter a valid option.")

house_price_finder()  # run the function
```

```
Please indicate your desired house price range:
    A: £280,000-£380,000.
    B: £380,000-£480,000
    C: £480,000-£750,000.
    D: £750,000-£1,000,000.
    E: more than £1,000,000.
    A
These are the suitable boroughs.
```

Out[32]:

	Code	Area	House Price
1	E09000002	BARKING AND DAGENHAM	287734
3	E09000004	BEXLEY	335694
7	E09000008	CROYDON	372554
15	E09000016	HAVERING	360479
24	E09000025	NEWHAM	362131
28	E09000029	SUTTON	376924

From this list of house prices, users can choose their ideal orough and proceed.

Borough Information Finder

Having narrowed it down to boroughs of interest, we take a closer look by entering the corresponding borough code illustrated above.

In [33]:
```
def borough_information_finder():
    prompt = input("Please Enter Borough Name: ") #asking for user's input
    prompt=prompt.upper() # Change all input to upper case letter, because the ar
ea in final-year dataset are all in capital letter
    # Change the area name into lower case letter and check if the input is in.
    if prompt in str(lastyr_dataset["Area"]):
        # return the borough as a transposed data frame so it is easier for custo
mer to view
        return lastyr_dataset.loc[lastyr_dataset["Area"]==prompt].T
    else: # If customers enter other letters or words
        print ("Please enter a valid area name from the house price finder.")
borough_information_finder()
```

```
Please Enter Borough Name: city of london
```

Out[33]:

	0
Code	E09000001
Area	CITY OF LONDON
House Price	849790
Crime Rates	92.2
Schools	5
Job Density	124.78
Annual Salary	57328.1
Bars and Restaurants	455
Healthcare Practices	2
Transport Stations	13
Average of Transport Zones	1

As a result, users may use the customized table to check whether the borough satisfies their requirements.

Now that our users established the key attributes their dream borough should have, they want to know more about future prices in the area and which attributes are the most important in determining that price. Let us have a look.

4. Predictive Analysis

Regression Analysis

Pooled-OLS model, one-way fixed-effect model (with entity-effect) and two-way fixed effects model (with both entity and time effects) are generated for our dataset. The dependent variable of the regression model is house price, and the independent variables are all time-variant variables.

Since house prices take large values, a log dependent variable is created. We will use both house price and log house price as dependent variable for each model. Hence, six models will be generated.

In [34]:
```
#  Set code and year as index, prepared for regression analysis
regression_df=final_dataset.set_index(["Code","Year"])

#log(House Price) is created
regression_df["log_HousePrice"]=np.log(regression_df["House Price"])
regression_df.head()

# Prepare Independent Variables for convenience and add a constant
x=regression_df[["Schools","Bars and Restaurants","Crime Rates","Job Density","An
nual Salary"]]
x=sm.add_constant(x)
```

Out[34]:

		Area	House Price	Crime Rates	Schools	Job Density	Annual Salary	Bars and Restaurants	log_House
Code	**Year**								
E09000001	**2011**	CITY OF LONDON	463930	90.6	5	75.79	52358.800000	365.0	13.047489
	2012	CITY OF LONDON	525327	85.8	5	92.41	52379.993605	370.0	13.171776
	2013	CITY OF LONDON	570008	77.9	5	110.98	55510.309047	385.0	13.253406
	2014	CITY OF LONDON	709385	85.5	5	121.23	55514.808380	415.0	13.472154
	2015	CITY OF LONDON	760253	82.4	5	121.73	55889.369644	420.0	13.541407

In [35]:
```
# 1 Pooled OLS
  # 1.1 linear OLS
OLS_1 = PooledOLS(regression_df["House Price"], x)
OLS_linear=OLS_1.fit()
  # 1.2 log-lin OLS
OLS_2 = PooledOLS(regression_df["log_HousePrice"], x)
OLS_log=OLS_2.fit()

# 2 Area-FE model (include only entity effect)
  # 2.1 Linear Area-FE
FE_area1 = PanelOLS(regression_df["House Price"],x,entity_effects=True,time_effec
ts=False)
FE_area_linear = FE_area1.fit(cov_type="robust")
  # 2.2 log Area-FE
FE_area2 = PanelOLS(regression_df["log_HousePrice"],x,entity_effects=True,time_ef
fects=False)
FE_area_log = FE_area2.fit(cov_type="robust")

# 3 Two way fixed effects
 # 3.1 Linear Version
FE2_1 = PanelOLS(regression_df["House Price"],x,entity_effects=True,time_effects=
True)
FE_2way_linear = FE2_1.fit(cov_type="robust")
 #3.2 Log version FE-two way
FE2_1 = PanelOLS(regression_df["log_HousePrice"],x,entity_effects=True,time_effec
ts=True)
FE_2way_log = FE2_1.fit(cov_type="robust")
```

In [36]:
```python
# linear model comparision
print(compare({'OLS-linear':OLS_linear,'FE-oneway':FE_area_linear,'FE-twoway':FE_2way_linear}))
```

```
                             Model Comparison
========================================================================
                                OLS-linear       FE-oneway       FE-twoway
------------------------------------------------------------------------
Dep. Variable                  House Price     House Price     House Price
Estimator                        PooledOLS        PanelOLS        PanelOLS
No. Observations                       231             231             231
Cov. Est.                       Unadjusted          Robust          Robust
R-squared                           0.6439          0.7169          0.4448
R-Squared (Within)                  0.1612          0.7169          0.3235
R-Squared (Between)                 0.7303         -0.5251          0.0461
R-Squared (Overall)                 0.6439         -0.3364          0.0883
F-statistic                         81.353          97.747          29.962
P-value (F-stat)                    0.0000          0.0000          0.0000
======================     =============   =============   =============
const                           -6.851e+05      -6.253e+05       7.082e+05
                                 (-5.6243)       (-2.1926)        (3.0933)
Schools                            -307.63          7229.5          216.77
                                 (-0.7463)        (4.3389)        (0.2269)
Bars and Restaurants                204.30          884.35          320.61
                                  (2.9920)        (3.7813)        (3.3282)
Crime Rates                         321.28         -2759.9         -1381.5
                                  (0.6997)       (-5.9658)       (-5.5374)
Job Density                        -4488.8          5037.3          4525.3
                                 (-6.0549)        (4.5186)        (7.8500)
Annual Salary                       32.047          9.2113         -8.9268
                                  (10.477)        (1.2750)       (-1.7111)
======================= =============== =============== ===============
Effects                                             Entity          Entity
                                                                      Time
------------------------------------------------------------------------

T-stats reported in parentheses
```

In [37]:

```
# log-lin model comparision
print(compare({'OLS-log':OLS_log,'FE-oneway-log':FE_area_log,'FE-twoway-log':FE_2way_log}))
```

Model Comparison

	OLS-log	FE-oneway-log	FE-twoway-log
Dep. Variable	log_HousePrice	log_HousePrice	log_HousePrice
Estimator	PooledOLS	PanelOLS	PanelOLS
No. Observations	231	231	231
Cov. Est.	Unadjusted	Robust	Robust
R-squared	0.6533	0.6334	0.0386
R-Squared (Within)	0.3410	0.6334	-0.0129
R-Squared (Between)	0.7365	-1.0353	0.1065
R-Squared (Overall)	0.6533	-0.6839	0.0814
F-statistic	84.778	66.682	1.5011
P-value (F-stat)	0.0000	0.0000	0.1914
const	10.614	9.2613	12.885
	(45.046)	(15.399)	(62.649)
Schools	0.0003	0.0198	-0.0007
	(0.4265)	(4.4236)	(-0.4665)
Bars and Restaurants	0.0005	0.0014	1.125e-06
	(3.6189)	(2.6563)	(0.0059)
Crime Rates	-0.0005	-0.0046	0.0003
	(-0.5399)	(-3.5800)	(0.6073)
Job Density	-0.0081	0.0047	0.0020
	(-5.6618)	(2.9301)	(3.0169)
Annual Salary	6.455e-05	5.009e-05	1.221e-06
	(10.912)	(3.9229)	(0.2872)
Effects		Entity	Entity Time

```
T-stats reported in parentheses
```

The first table shows the linear function form models, while the second table shows the log-log models. It does not become clear which dependent variable we shall use, as most of them are statistically significant with similar R2. A Pearson's coefficient is calculated to check the skewness of the house price.

In [38]:
```
# calculate Pearson's coefficient for House price, to determine if we should use
 the log-version or not
house_price_skewness=regression_df["House Price"].describe().astype(int)
Persons_coefficient=3*(house_price_skewness["mean"]+house_price_skewness["50%"])/
house_price_skewness["std"]
Persons_coefficient
```

Out[38]:
```
11.465027368658653
```

Results suggest "House Price" is positively skewed. We shall use the log dependent variable. FE-twoway-log has an insignificant F-value, implying the model is insignificant overall, potentially because OLS contains insignificant variables.

Our best model is the one-way FE.

In [39]:
```
print(FE_area_log)
```

```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:          log_HousePrice   R-squared:                        0.6334
Estimator:                    PanelOLS   R-squared (Between):             -1.0353
No. Observations:                  231   R-squared (Within):               0.6334
Date:                 Mon, Dec 14 2020   R-squared (Overall):             -0.6839
Time:                         23:37:24   Log-likelihood                    170.70
Cov. Estimator:                 Robust
                                         F-statistic:                      66.682
Entities:                           33   P-value                           0.0000
Avg Obs:                        7.0000   Distribution:                   F(5,193)
Min Obs:                        7.0000
Max Obs:                        7.0000   F-statistic (robust):             101.41
                                         P-value                           0.0000
Time periods:                        7   Distribution:                   F(5,193)
Avg Obs:                        33.000
Min Obs:                        33.000
Max Obs:                        33.000

                               Parameter Estimates
================================================================================
========
                      Parameter  Std. Err.     T-stat    P-value    Lower CI
Upper CI
--------------------------------------------------------------------------------
--------
const                    9.2613     0.6014     15.399     0.0000      8.0751
10.447
Schools                  0.0198     0.0045     4.4236     0.0000      0.0110
0.0287
Bars and Restaurants     0.0014     0.0005     2.6563     0.0086      0.0004
0.0025
Crime Rates             -0.0046     0.0013    -3.5800     0.0004     -0.0072
-0.0021
Job Density              0.0047     0.0016     2.9301     0.0038      0.0015
0.0078
Annual Salary         5.009e-05  1.277e-05     3.9229     0.0001   2.491e-05
7.528e-05
================================================================================
========

F-test for Poolability: 21.058
P-value: 0.0000
Distribution: F(32,193)

Included effects: Entity
```

This model captures 63.34% of the dependent variable's variation.

If number of schools and number of leisure places increases by 1, house prices increase by 1.98% and 0.14% respectively. If crime rates (%) increase by 1%, house prices decrease by 0.46%. A 1 unit increase in job density (job availability/population), results in a 0.47% increase in prices. If a borough's average annual salary increases by £1,000, the borough's house prices increase by 5.009%.

The coefficients are statistically significant and signs are consistent with expectations and economic theories. The magnitude of change shows that annual salary (in £1,000) is the most important factor influencing house price.

Machine Learning Analysis

We would now like to use some our data to train and test the following models:

1. XGBoost
2. LightGBM
3. Random forest

By comparing the models we hope to find the model making the most accurate predictions. When training the model, we assign and modify the parameters of various models repeatedly to achieve greater accuracy, Overall, we aim to derive the following results: A comparison of all feature importance diagrams including a ranking on the average of importance in predicting house prices Three trained models including descriptive information (r2_score, mean_absolute_error, mean_squared_error). An overall comparison of different models and their respective outcomes. House price predictions

In [40]:
```
# read the final dataset and drop the 'Area' and 'Code' columns because it is 'st
ring' data
Final_dataset_df = pd.DataFrame(final_dataset)
Final_dataset_df.drop(['Area','Code'],axis = 1,inplace = True)
# show the first five rows to check results we get.
Final_dataset_df.head()
```

Out[40]:

	Year	House Price	Crime Rates	Schools	Job Density	Annual Salary	Bars and Restaurants
0	2011	463930	90.6	5	75.79	52358.800000	365.0
1	2012	525327	85.8	5	92.41	52379.993605	370.0
2	2013	570008	77.9	5	110.98	55510.309047	385.0
3	2014	709385	85.5	5	121.23	55514.808380	415.0
4	2015	760253	82.4	5	121.73	55889.369644	420.0

Retrieve Variable Importance

Now, we randomly assign our data to two parts, a training and a testing dataset, using train_test_split. We exclude 'House Price' in the train set, while the target set includes 'House Price'.

In [41]:

```
train_fe = Final_dataset_df.copy()
target_fe = train_fe['House Price']
del train_fe['House Price']
train_fe.head()
X = train_fe
z = target_fe

# in train_test_split function, first parameter is your train dataset, the second
one is your target dataset.
# test_size means the proportion of test dataset
# random_state is a random seed to ensure we can get the same dataset by splitin
g.
Xtrain, Xval, Ztrain, Zval = train_test_split(X, z, test_size=0.2, random_state=0
)

# lgb.Dataset() is to specific feature names and categorical features:
# Note: we should convert your categorical features to 'int' type before we const
ruct Dataset.

train_set = lgb.Dataset(Xtrain, Ztrain, silent=False)
valid_set = lgb.Dataset(Xval, Zval, silent=False)
```

Out[41]:

	Year	Crime Rates	Schools	Job Density	Annual Salary	Bars and Restaurants
0	2011	90.6	5	75.79	52358.800000	365.0
1	2012	85.8	5	92.41	52379.993605	370.0
2	2013	77.9	5	110.98	55510.309047	385.0
3	2014	85.5	5	121.23	55514.808380	415.0
4	2015	82.4	5	121.73	55889.369644	420.0

Next, we will use LightGBM to get the importance of each variable for our House Price. LightGBM is a gradient boosting framework that uses tree based learning algorithms, greatly reducing the time complexity of processing samples, without losing accuracy.

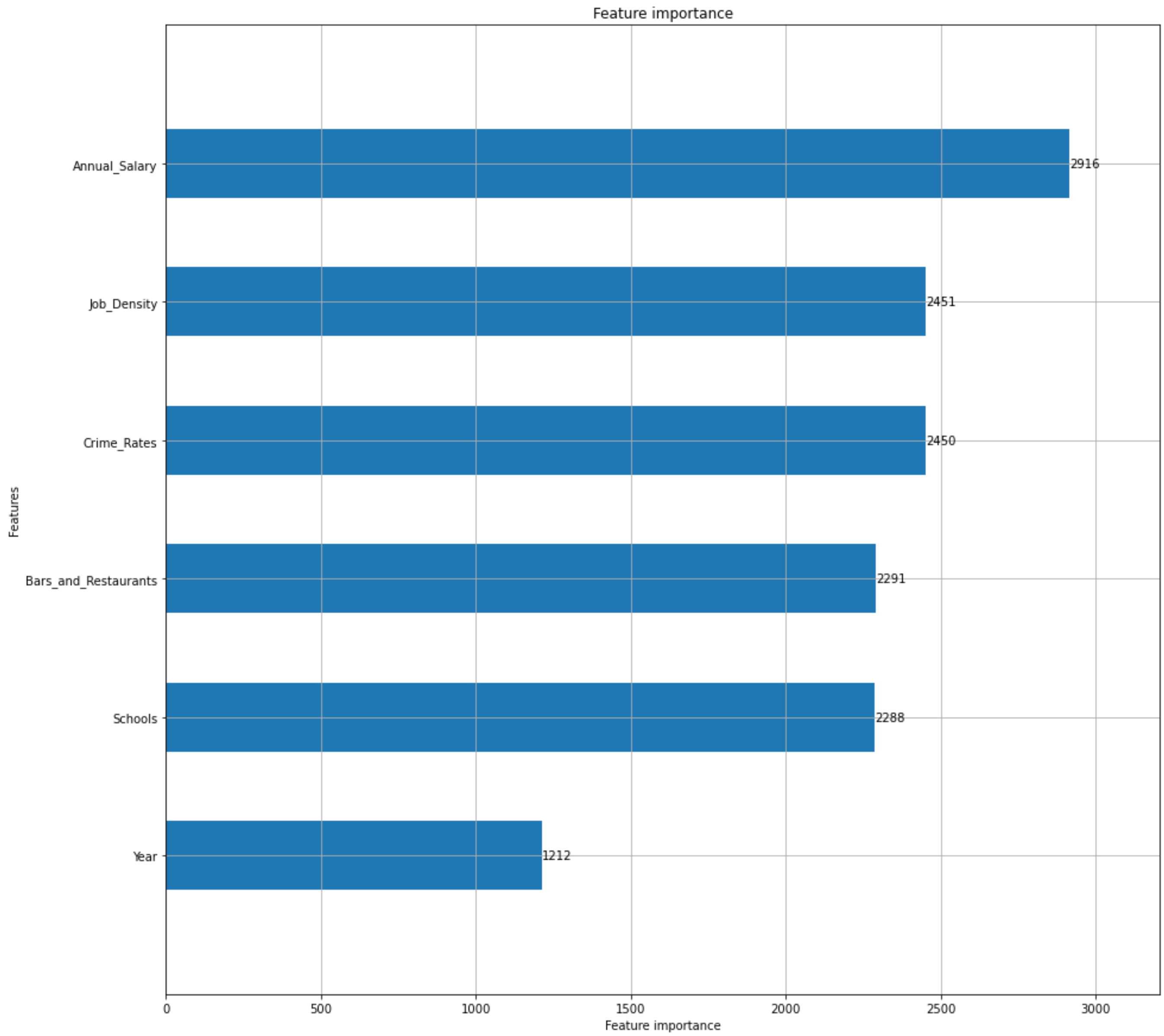
Parameters retrieved here: https://lightgbm.readthedocs.io/en/latest/pythonapi/lightgbm.LGBMRegressor.html (https://lightgbm.readthedocs.io/en/latest/pythonapi/lightgbm.LGBMRegressor.html)

In [42]:

```
%%capture
# hide the process of running because there will be too wordy and lengthy if we s
how it.
params = {
        'boosting_type':'gbdt',  # Gradient Boosting Decision Tree
        'objective': 'regression',# regression , if we want to make classificatio
n we need to use 'binary'
        'num_leaves': 31, # number of leaves for one tree
        'learning_rate': 0.05, # learning rate in machine learning, like a speed!
        'max_depth': -1, # default to '-1' which means that we do not limit its d
epth, the greater the depth, the possible overfitting
        'subsample': 0.8, # sample size
        'bagging_fraction' : 1, # if our data is small, 1 will be better!
        'max_bin' : 5000 , #Feature maximum segmentation
        'bagging_freq': 20, # it is default to '0',It means bagging once every 20
iterations
        'colsample_bytree': 0.6,
        'metric': 'rmse',
        'min_split_gain': 0.5,
        'min_child_weight': 1, # Minimum sum of hessians in one leaf to allow a s
plit. Higher values potentially decrease overfitting
        'min_child_samples': 10,#Setting it larger can avoid generating a tree th
at is too deep, but it may cause underfitting
        'scale_pos_weight':1,
        'zero_as_missing': True,
        'seed':0,
    }

modelL = lgb.train(params, train_set = train_set, num_boost_round=1000,
                   early_stopping_rounds=50,verbose_eval=100, valid_sets=valid_se
t)
```

In [43]:
```
# use matplotlib and plot with lgb to show their importance by bar chart.
fig =  plt.figure(figsize = (15,15))
axes = fig.add_subplot(111)
lgb.plot_importance(modelL,ax = axes,height = 0.5)
plt.show();plt.close()
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x7f05898f8610>



The graph above implies, according to the LightGBM model, annual salary is the most important varibale in determining House Price, while 'Year' and 'Bars and Restaurants' are least important.

In [44]:
```
# create a dataframe to save our outcome in one column named 'score_lgb'.
feature_score = pd.DataFrame(train_fe.columns, columns = ['feature'])
feature_score['score_lgb'] = modelL.feature_importance()
```

XGBoost is an implementation of the Gradient Boosting Decision Tree (GBDT).

Continuously add trees, and perform feature splitting to grow our tree. Each time we add a tree, we are actually learning a new function f(x) to fit the residual of the last prediction. Once finished, we must predict the score of a sample.

In fact, according to the characteristics of this sample, each tree will fall to a corresponding leaf node, which corresponds to a score.

In the end, we add up the scores corresponding to each tree to retrieve the predicted value of the sample.

Parameters retrieved here: https://xgboost.readthedocs.io/en/latest/python/index.html (https://xgboost.readthedocs.io/en/latest/python/index.html)

In [45]:

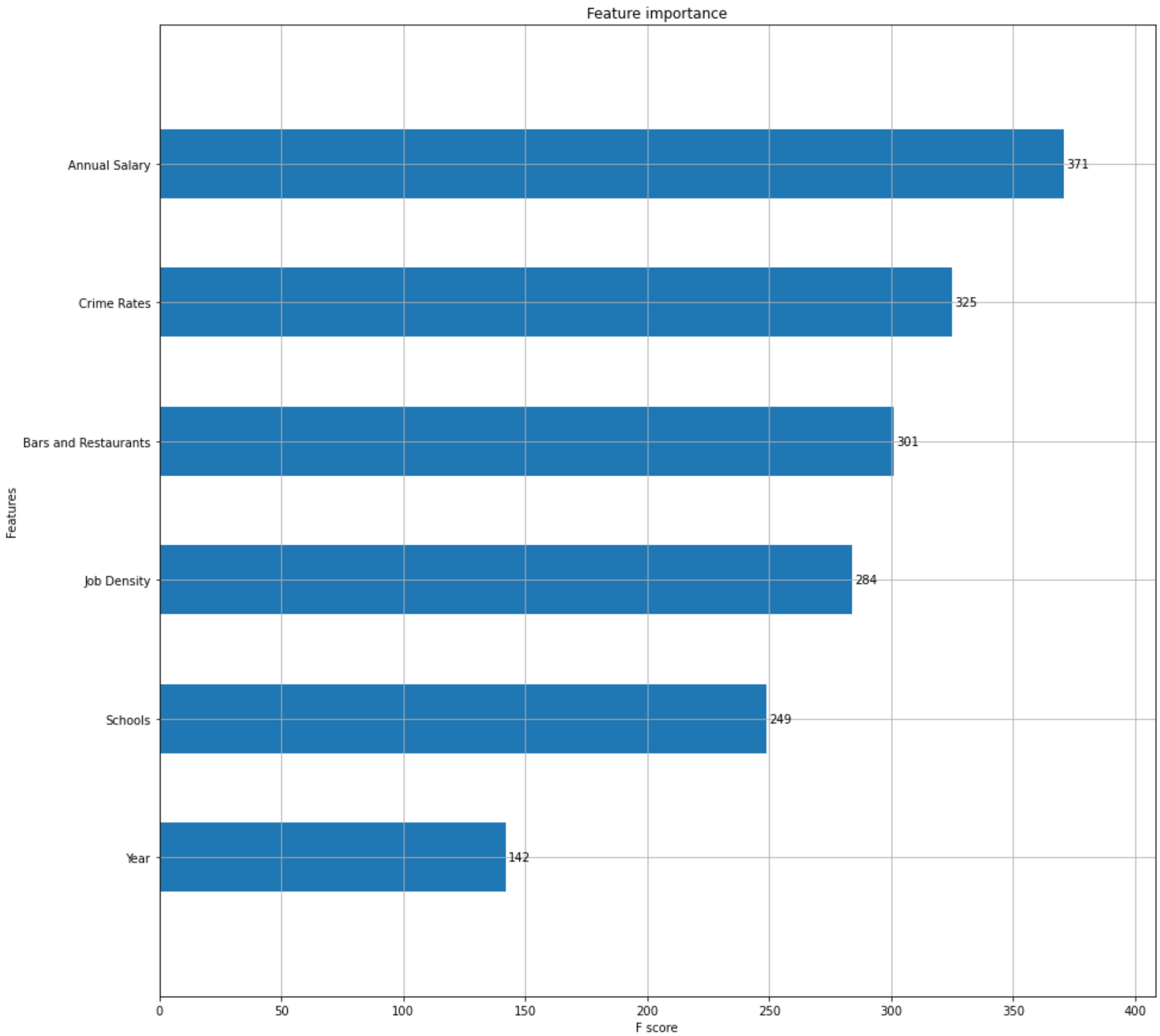
```
# split training set to validation set
# assgin our data to the xgb matirx because xgboost requrie the input is a matrix
type.
data_tr  = xgb.DMatrix(Xtrain, label=Ztrain)
data_cv  = xgb.DMatrix(Xval , label=Zval)
evallist = [(data_tr, 'train'), (data_cv, 'valid')]
```

In [46]:

```
%%capture
parms = {'max_depth':8, #maximum depth of a tree
         'objective':'reg:squarederror', # regression type
         'eta'      :0.3,
         'subsample':0.8,#SGD will use this percentage of data
         'lambda '  :4, #L2 regularization term,>1 more conservative
         'colsample_bytree ':0.9,
         'colsample_bylevel':1,
         'min_child_weight': 10}
modelx = xgb.train(parms, data_tr, num_boost_round=200, evals = evallist,
                  early_stopping_rounds=30, maximize=False,
                  verbose_eval=10)

print('score = %1.5f, n_boost_round =%d.'%(modelx.best_score,modelx.best_iteratio
n))
```

In [47]:
```
# use matplotlib and plot with xgb to show their importance by bar chart.
fig =  plt.figure(figsize = (15,15))
axes = fig.add_subplot(111)
xgb.plot_importance(modelx,ax = axes,height = 0.5)
plt.show();plt.close()
```

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0589a0d6d0>



The graph illustrates that annually salary remains the most important variable, while ‘Schools’ has lost in importance. Additionally, the importance of 'Job Density' and 'Bars and Restaurants' increased greatly due to the different gradient method in different models.

In [48]:
```
# create a dataframe to save our outcome in one column named 'score_xgb'.
feature_score['score_xgb'] = feature_score['feature'].map(modelx.get_score(import
ance_type='weight'))
```

Next, we will run a logistic regression, analysing the variables’ coefficients to derive importance. However, we must retrieve results after standardizing, due to the variables differing scales.

In [49]:
```
# Standardization for regression model and generate a dataframe for our logistic
 regression
train_fe = pd.DataFrame(
    preprocessing.MinMaxScaler().fit_transform(train_fe),
    columns=train_fe.columns,
    index=train_fe.index)
```

In [50]:
```
# Logistic Regression
logreg = LogisticRegression()
logreg.fit(train_fe, target_fe)
coeff_logreg = pd.DataFrame(train_fe.columns.delete(0))
coeff_logreg.columns = ['feature']
coeff_logreg["score_logreg"] = pd.Series(logreg.coef_[0])
coeff_logreg.sort_values(by='score_logreg', ascending=False)
```

Out[50]: LogisticRegression()

Out[50]:

	feature	score_logreg
1	Schools	0.058646
3	Annual Salary	-0.026421
2	Job Density	-0.214256
4	Bars and Restaurants	-0.228347
0	Crime Rates	-0.447357

In [51]:
```
# the level of importance of features is not associated with the sign
# create a dataframe to save our outcome in one column named 'score_logreg'.
coeff_logreg["score_logreg"] = coeff_logreg["score_logreg"].abs()
feature_score = pd.merge(feature_score, coeff_logreg, on='feature')
```

Lastly, we run a linear regression, using 'preprocessing.MinMaxScaler().fit_transform' to transform the variables' scale with different weights to (0,1).

In [52]:
```
# Linear Regression
linreg = LinearRegression()
linreg.fit(train_fe, target_fe) #fit the regression model
coeff_linreg = pd.DataFrame(train_fe.columns.delete(0))
coeff_linreg.columns = ['feature'] # change the column name
coeff_linreg["score_linreg"] = pd.Series(linreg.coef_)
coeff_linreg.sort_values(by='score_linreg', ascending=False)
```

Out[52]: LinearRegression()

Out[52]:

	feature	score_linreg
4	Bars and Restaurants	1.013117e+06
1	Schools	6.123616e+05
0	Crime Rates	2.319551e+05
2	Job Density	-4.870303e+04
3	Annual Salary	-5.571588e+05

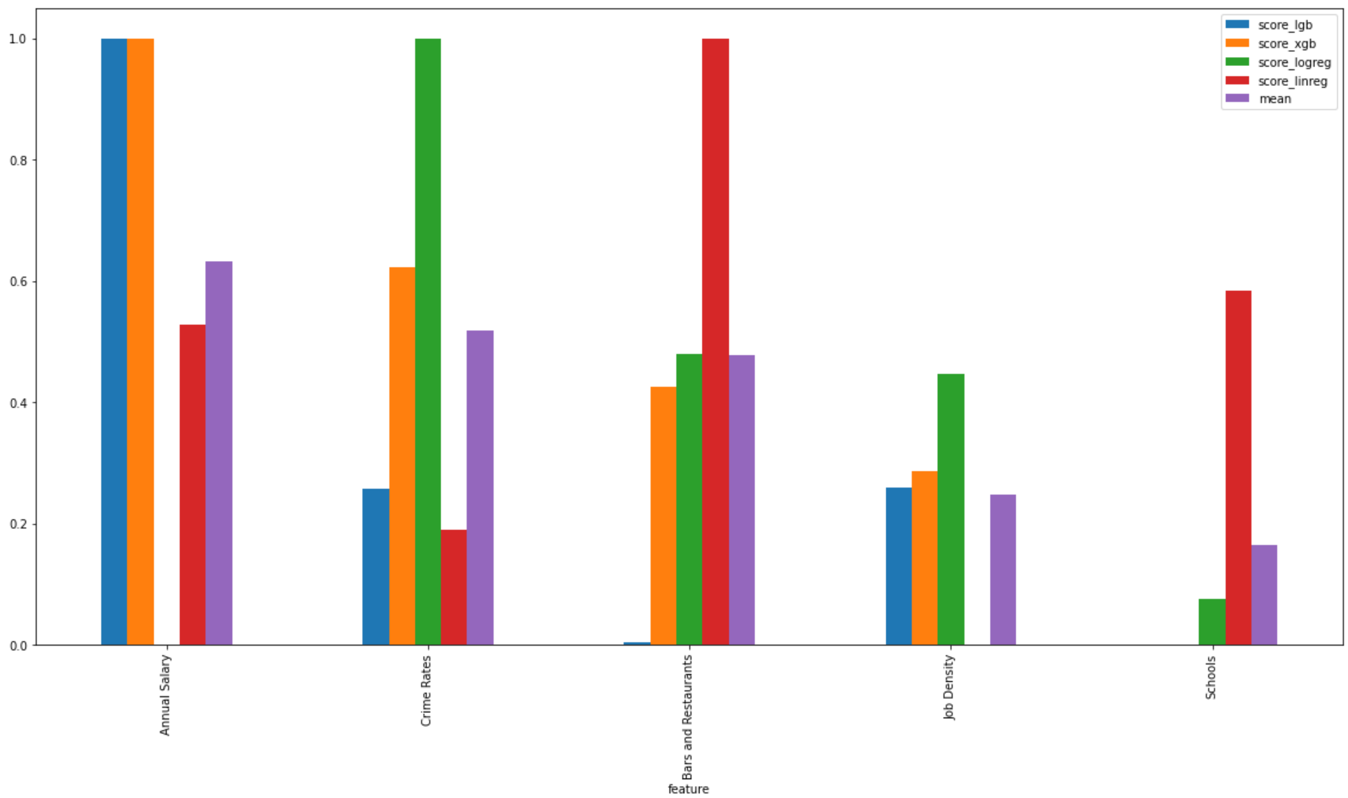
In [53]:
```
# To compare the different models, we merge the outcomes row by row.
# The level of importance of features is not associated with the sign
# Create a dataframe to save our outcome in one column named 'score_linreg'.
coeff_linreg["score_linreg"] = coeff_linreg["score_linreg"].abs()

# merge those 4 columns to a new dataframe named feature_score
feature_score = pd.merge(feature_score, coeff_linreg, on='feature')
feature_score = feature_score.fillna(0)
feature_score = feature_score.set_index('feature')
feature_score
```

Out[53]:

	score_lgb	score_xgb	score_logreg	score_linreg
feature				
Crime Rates	2450	325	0.447357	2.319551e+05
Schools	2288	249	0.058646	6.123616e+05
Job Density	2451	284	0.214256	4.870303e+04
Annual Salary	2916	371	0.026421	5.571588e+05
Bars and Restaurants	2291	301	0.228347	1.013117e+06

In [54]:
```python
# use matplotlib to plot their importance variable by variable in bar chat.
feature_score = pd.DataFrame(
    preprocessing.MinMaxScaler().fit_transform(feature_score),
    columns=feature_score.columns,
    index=feature_score.index
)

# Create mean column
feature_score['mean'] = feature_score.mean(axis=1)

# Plot the feature importances
feature_score.sort_values('mean', ascending=False).plot(kind='bar', figsize=(20, 10))
```

Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7f058ab9aa30>



In [55]:
```python
# sort them by the means of importance
feature_score.sort_values('mean', ascending=False)
```

Out[55]:

	score_lgb	score_xgb	score_logreg	score_linreg	mean
feature					
Annual Salary	1.000000	1.000000	0.000000	0.527217	0.631804
Crime Rates	0.257962	0.622951	1.000000	0.190014	0.517732
Bars and Restaurants	0.004777	0.426230	0.479708	1.000000	0.477679
Job Density	0.259554	0.286885	0.446233	0.000000	0.248168
Schools	0.000000	0.000000	0.076556	0.584457	0.165253

The illustration above shows the impact of each variable on House Price ranked by 'mean'. Annual salary consistently ranks as greatest influencer of house prices, while number of Bars or Restaurants hold the weakest influence.

Train and Test our Model

Next, we use three models for training and testing:

1. Random Forest: Training the model and checking the accuracy ratee.
2. XGboost: Training our dataset with XGBoost model, returning its score and rmse.
3. LightGBM: Lastly, we importing LightGBM model and report its outcome.

In [56]:
```
target_name = 'House Price'
train_target0 = Final_dataset_df[target_name]
train0 = Final_dataset_df.drop([target_name], axis=1)
```

In [57]:
```
# Synthesis test0 from train0
train0, test0, train_target0, test_target0 = train_test_split(
    train0, train_target0, test_size=0.2, random_state=0)
```

In [58]:
```
# For boosting model
train0b = train0
train_target0b = train_target0
# Synthesis valid as test for selection models
trainb, testb, targetb, target_testb = train_test_split(train0b, train_target0b,
test_size=0.3, random_state=0)
```

In [59]:
```
#For models from Sklearn, data normalization and standardization
scaler = StandardScaler()
train0 = pd.DataFrame(scaler.fit_transform(train0), columns = train0.columns)
```

In [60]:
```
# Synthesis test0 from train0
train0, test0, train_target0, test_target0 = train_test_split(
    train0, train_target0, test_size=0.2, random_state=0)
```

In [61]:
```
# For boosting model
train0b = train0
train_target0b = train_target0
# Synthesis valid as test for selection models
trainb, testb, targetb, target_testb = train_test_split(train0b, train_target0b,
test_size=0.3, random_state=0)
```

In [62]:
```
#For models from Sklearn, data normalization and standardization
scaler = StandardScaler()
train0 = pd.DataFrame(scaler.fit_transform(train0), columns = train0.columns)
```

In [63]:
```
# Synthesis valid as test for selection models
train, test, target, target_test = train_test_split(train0, train_target0, test_s
ize=0.3, random_state=0)
```

To calculate the r2 and rmse of each model, we must define new functions:

In [64]:
```python
# create four empty list to store the outcome.
acc_train_r2 = []
acc_test_r2 = []
acc_train_rmse = []
acc_test_rmse = []
```

In [65]:
```python
# RMSE between predicted y_pred and measured y_meas values
def acc_rmse(y_meas, y_pred):
    return (mean_squared_error(y_meas, y_pred))**0.5
```

In [66]:
```python
# Calculation of accuracy of boosting model by different metrics
def acc_boosting_model(num,model,train,test,num_iteration=0):
    global acc_train_r2, acc_test_r2,acc_train_rmse, acc_test_rmse

    if num_iteration > 0:
        ytrain = model.predict(train, num_iteration = num_iteration)
        ytest = model.predict(test, num_iteration = num_iteration)
    else:
        ytrain = model.predict(train)
        ytest = model.predict(test)

    print('target = ', targetb[:5].values)
    print('ytrain = ', ytrain[:5])

    acc_train_r2_num = round(r2_score(targetb, ytrain) * 100, 2)
    print('acc(r2_score) for train =', acc_train_r2_num)
    acc_train_r2.insert(num, acc_train_r2_num)

    acc_train_rmse_num = round(acc_rmse(targetb, ytrain) * 100, 2)
    print('acc(rmse) for train =', acc_train_rmse_num)
    acc_train_rmse.insert(num, acc_train_rmse_num)

    print('target_test =', target_testb[:5].values)
    print('ytest =', ytest[:5])

    acc_test_r2_num = round(r2_score(target_testb, ytest) * 100, 2)
    print('acc(r2_score) for test =', acc_test_r2_num)
    acc_test_r2.insert(num, acc_test_r2_num)

    acc_test_rmse_num = round(acc_rmse(target_testb, ytest) * 100, 2)
    print('acc(rmse) for test =', acc_test_rmse_num)
    acc_test_rmse.insert(num, acc_test_rmse_num)
```

In [67]:
```
# Calculation of accuracy of model from Sklearn by different metrics
def acc_model(num,model,train,test):
    global acc_train_r2, acc_test_r2,acc_train_rmse, acc_test_rmse

    ytrain = model.predict(train)
    ytest = model.predict(test)

    print('target = ', target[:5].values)
    print('ytrain = ', ytrain[:5])

    acc_train_r2_num = round(r2_score(target, ytrain) * 100, 2)
    print('acc(r2_score) for train =', acc_train_r2_num)
    acc_train_r2.insert(num, acc_train_r2_num)

    acc_train_rmse_num = round(acc_rmse(target, ytrain) * 100, 2)
    print('acc(rmse) for train =', acc_train_rmse_num)
    acc_train_rmse.insert(num, acc_train_rmse_num)

    print('target_test =', target_test[:5].values)
    print('ytest =', ytest[:5])

    acc_test_r2_num = round(r2_score(target_test, ytest) * 100, 2)
    print('acc(r2_score) for test =', acc_test_r2_num)
    acc_test_r2.insert(num, acc_test_r2_num)

    acc_test_rmse_num = round(acc_rmse(target_test, ytest) * 100, 2)
    print('acc(rmse) for test =', acc_test_rmse_num)
    acc_test_rmse.insert(num, acc_test_rmse_num)
```

Now, we use random forest to train the model and check its accuracy rate.

In [68]:
```
random_forest = RandomForestRegressor() # create a randomforest function
random_forest.fit(train, target) # train the model
acc_model(1,random_forest,train,test) # return the outcome by the function we def
ined
```

Out[68]:
```
RandomForestRegressor()

target =  [435807 386200 506799 484592 260476]
ytrain =  [404287.98 416220.69 482675.55 468705.57 269181.67]
acc(r2_score) for train = 96.22
acc(rmse) for train = 3630269.8
target_test = [339685 760833 964643 995543 570008]
ytest = [281733.34 599055.65 807129.19 848916.73 773846.1 ]
acc(r2_score) for test = 68.77
acc(rmse) for test = 12350697.68
```

XGboost: Next, we train our dataset with XGBoost model, returning its score and rmse.

In [69]:
```
xgb_clf = xgb.XGBRegressor(objective = 'reg:squarederror')  # set our regression
 type as squarderror
parameters = {'n_estimators': [60, 100, 120, 140],
              'learning_rate': [0.01, 0.1],
              'max_depth': [5, 7],
              'reg_lambda': [0.5]}
xgb_reg = GridSearchCV(estimator=xgb_clf, param_grid=parameters, cv=5, n_jobs=-1)
.fit(trainb, targetb) # train the model
print("Best score: %0.3f" % xgb_reg.best_score_)
print("Best parameters set:", xgb_reg.best_params_)
acc_boosting_model(2,xgb_reg,trainb,testb)# print the outcome with the function t
hat we have defined
```

```
Best score: 0.634
Best parameters set: {'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 60,
'reg_lambda': 0.5}
target =  [435807 386200 506799 484592 260476]
ytrain =  [426647.7  391055.7  499246.7  478518.25 260945.62]
acc(r2_score) for train = 99.8
acc(rmse) for train = 840657.73
target_test = [339685 760833 964643 995543 570008]
ytest = [294219.62 642578.5  793559.44 794539.06 691809.4 ]
acc(r2_score) for test = 67.81
acc(rmse) for test = 12539875.87
```

In [70]:
```
Xtrain, Xval, Ztrain, Zval = train_test_split(trainb, targetb, test_size=0.2, ran
dom_state=0)
train_set = lgb.Dataset(Xtrain, Ztrain, silent=False)
valid_set = lgb.Dataset(Xval, Zval, silent=False)
```

In [71]:
```
%%capture
# hide the process of running because there will be too wordy and lengthy if we s
how it.
# adjusting the parameter of lgb to make it more proper
params = {
        'boosting_type':'gbdt',
        'objective': 'regression',
        'num_leaves': 31,
        'learning_rate': 0.01,
        'max_depth': -1,
        'subsample': 0.8,
        'bagging_fraction' : 1,
        'max_bin' : 5000 ,
        'bagging_freq': 20,
        'colsample_bytree': 0.6,
        'metric': 'rmse',
        'min_split_gain': 0.5,
        'min_child_weight': 1,
        'min_child_samples': 10,
        'scale_pos_weight':1,
        'zero_as_missing': False,
        'seed':0,
    }
modelL = lgb.train(params, train_set = train_set, num_boost_round=10000,
                   early_stopping_rounds=50,verbose_eval=10, valid_sets=valid_se
t)
# train the lightgbm model again for better result
```

In [72]:
```
acc_boosting_model(3,modelL,trainb,testb,modelL.best_iteration) # return the scor
e and rmse.
```

```
target =  [435807 386200 506799 484592 260476]
ytrain =  [385530.92304794 398470.15594588 476353.19240978 447017.2865607
 320626.91197774]
acc(r2_score) for train = 74.22
acc(rmse) for train = 9477831.12
target_test = [339685 760833 964643 995543 570008]
ytest = [300064.63911308 500472.0031412  734720.37246198 735886.96038568
 702907.46033295]
acc(r2_score) for test = 60.51
acc(rmse) for test = 13889036.42
```

In [73]:
```
# generate a dataframe that we can compare the scroe and rmse
models = pd.DataFrame({
    'Model': ['Random Forest', 'XGB', 'LGBM'],
    'r2_train': acc_train_r2,
    'r2_test': acc_test_r2,
    'rmse_train': acc_train_rmse,
    'rmse_test': acc_test_rmse
                    })
```

In [74]:
```
pd.options.display.float_format = '{:,.2f}'.format
models
```

Out[74]:

	Model	r2_train	r2_test	rmse_train	rmse_test
0	Random Forest	96.22	68.77	3,630,269.80	12,350,697.68
1	XGB	99.80	67.81	840,657.73	12,539,875.87
2	LGBM	74.22	60.51	9,477,831.12	13,889,036.42

In [75]:
```
testn = pd.DataFrame(scaler.transform(test0), columns = test0.columns)
```

In [76]:

```
lgb_predict = modelL.predict(test0)# predict the house price in the test dataset
final_df = test_target0.values # find the target value
final_df = pd.DataFrame(final_df,columns=['Real_price'])
final_df['predicted_prices'] = lgb_predict.astype(int) # change it type to 'int'
final_df['difference'] = abs(final_df['Real_price'] - final_df['predicted_prices'
]).astype(int) # change it type to 'int'
final_df.head(20)# show prediction of the first 10 rows.
```

Out[76]:

	Real_price	predicted_prices	difference
0	577055	635447	58392
1	696926	731601	34675
2	314934	351254	36320
3	331124	382673	51549
4	787440	732357	55083
5	642137	587634	54503
6	315812	358908	43096
7	467867	488478	20611
8	424103	441490	17387
9	436116	378441	57675
10	362131	394518	32387
11	586166	548315	37851
12	362965	378845	15880
13	408604	342740	65864
14	261965	290757	28792
15	314112	318924	4812
16	760253	734720	25533
17	240572	296134	55562
18	922702	734720	187982
19	347956	398372	50416

As LGBM has the highest test score, 85.46, we select LGBM as our prediction model; although it is not very accurate.

5. Limitations

Our dataset only covers 2011 to 2017, a longer historical time frame can generate more up-to-date results and better predictions. Also, the prediction of house price in the future should consider unforeseen events, such as financial crisis.

As for regression analyses, multicollinearity, shown by the correlation matrix, may bias results. Omitted variables that affect both house price and independent variables -- such as inflation, may further bias the result. Therefore, the regression analysis does not necessarily imply casual inference between the factors and the house price. Further empirical research is necessary. The accuracy of machine learning analysis can be increased, if with more data points for training and testing.

6. Conclusion

A finder gathering boroughs based on different traits has been developed to aid buyers in their search and to support the government in analysing the state of boroughs and highlighting developments over the years.

Both the regressions and machine learning methods illustrate that average annual salary (in £1,000) is the most important factor affecting house prices.