House Price Prediction with Linear Regression and Random Forest

The aim of this project is to predict real-estate prices using the machine learning algorithm, Linear Regression, Random Forest. Both will show different results for the accuracy. Also, I will use regression with regularization such as Ridge and Lasso to try to improve the prediction accuracy.

Imports

```
from bs4 import BeautifulSoup as bs4
from requests import get
import json
import pandas as pd
import requests
import matplotlib.pyplot as plt
import seaborn as sns
import mpl_toolkits
import numpy as np
%matplotlib inline
#from fake_useragent import UserAgent
```

Data preparation (Web scraping)

Scraping data from the first website - 'FriendlyHousing'

```
url_1 = 'https://www.friendlyhousing.nl/nl/aanbod/kamer'
url_2 = 'https://www.friendlyhousing.nl/nl/aanbod/studio'
url_3 = 'https://www.friendlyhousing.nl/nl/aanbod/appartement'
urls= [url_1, url_2, url_3]
```

Scraping data from the second website - 'Pararius'

```
url_1p = 'https://www.pararius.com/apartments/eindhoven'
url_2p = 'https://www.pararius.com/apartments/eindhoven/page-2'
url_3p = 'https://www.pararius.com/apartments/eindhoven/page-3'
urls_p= [url_1p, url_2p, url_3p]
```

'FriendlyHousing'

```
#user_agent = UserAgent()
#headers={"user-agent": user_agent.chrome}
soup_array=[]
for url in urls:
    ## getting the reponse from the page using get method of requests module
    page = get(url)

    ## storing the content of the page in a variable
    html = page.content

    ## creating BeautifulSoup object
    soup = bs4(html, "html.parser")
    soup_array.append(soup)
```

'Pararius'

```
soup_array_p=[]
for url in urls_p:
    ## getting the reponse from the page using get method of requests module
    page = get(url)

    ## storing the content of the page in a variable
    html = page.content

    ## creating BeautifulSoup object
    soup = bs4(html, "html.parser")
    soup_array_p.append(soup)
```

'FriendlyHousing' - finding the elements from the html file

```
houses=[]
for s in soup_array:
    allHouses = s.find("ul", {"class": "list list-unstyled row equal-row"})
    #print(len(allHouses))
    for h in allHouses.find_all("li", {"class": "col-xs-12 col-sm-6 col-md-4 equal-col"}):
     # print(h)

      houses.append(h)
     # print(h.findAll("li", {"class": "search-list__item search-list__item--listing"}))
```

```
catalog=[]
for h in houses:
```

```
  #data['houses'].append({
      type__= h.find('div', class_= 'specs').text
      t = type__.split()
      type_=t[0]
      street_ = h.find('h3').text
      s = street_.split()
      street = s[0]
      address = h.find('p').text
      a = address.split()
      postcode = a[0]
      #city = a[2]
      price = h.find('div', class_= 'price').text
      vars = type_,street, postcode, price
      catalog.append(vars)
      #print(city)
```

'Pararius' - finding the elements from the html file

```
houses_p=[]
for s in soup_array_p:
    allHouses = s.find("ul", {"class": "search-list"})
    #print(len(allHouses))
    for h in allHouses.find_all("li", {"class": "search-list__item search-list__item--listing
     # print(h)

      houses_p.append(h)
     # print(h.findAll("li", {"class": "search-list__item search-list__item--listing"}))



catalog_p=[]
for h in houses_p:
  #data['houses'].append({
        name = h.find('a',class_='listing-search-item__link listing-search-item__link--title'
        _name = name.split()
        house_type = _name[0]
        street = _name[1]
        _address= h.findAll('div', class_='listing-search-item__location')[0].text
        #String manipulation to remove the unwanted signs from the address
        __address = _address.replace("\nnew\n ", "")
        address = __address.replace("\n ", "")   #actual address after string manipulation -
        new_address = address.split()
        postcode = new_address[0]
        price_ = h.findAll('span', class_='listing-search-item__price')[0].text
        #splitting the string to find the price
        p=price_.split()
        _price = p[0] #actual price before string manipulation
        __price = _price.replace("€", "")  #actual price before full string manipulation
        price = __price.replace(",", "")   #actual price after string manipulation - ready to

        #finding the whole element from the web page
```

```
        #finding the whole element from the web page
        ylr= h.findAll('section', class_= 'illustrated-features illustrated-features--vertica

        #splitting the string to find the living are, rooms and year
        lry= ylr.split()

        #living_area after taking the indexes that define it
        living_area = lry[0]

        #rooms after taking the index that defines the variable
        rooms = lry[4]

        vars = house_type, street, postcode,price,living_area,rooms
        catalog_p.append(vars)

print(catalog_p)
```

```
[('House', 'Nieuwe', '5612', '1150', '65', '3'), ('Apartment', 'Nicolaas', '5615', '115(
```

'FriendlyHousing' - creating the dataframe

```
dataframe = pd.DataFrame(catalog)
dataframe.columns=['TYPE', 'STREET NAME', 'POSTCODE', 'PRICE']
dataframe
```

	TYPE	STREET NAME	POSTCODE	PRICE
0	Kamer	Julianastraat	5611	375
1	Kamer	Bennekelstraat	5654	430
2	Kamer	Leenderweg	5615	415
3	Kamer	Bennekelstraat	5654	315
4	Kamer	Willem	5611	320
...	...	...	...	...
118	Appartement	Frankrijkstraat	5622	925
119	Appartement	Kerkakkerstraat	5616	950
120	Appartement	Leenderweg	5614	800
121	Appartement	Leostraat	5615	775
122	Appartement	Stratumsedijk	5614	1075

123 rows × 4 columns

'Pararius'- creating the dataframe

```
df_ = pd.DataFrame(catalog_p)
df_.columns=['TYPE', 'STREET NAME', 'POSTCODE', 'PRICE','LIVING_AREA', 'ROOMS']
df_
```

	TYPE	STREET NAME	POSTCODE	PRICE	LIVING_AREA	ROOMS
0	House	Nieuwe	5612	1150	65	3
1	Apartment	Nicolaas	5615	1150	72	3
2	Apartment	Aalsterweg	5615	795	45	2
3	House	Jacob	5611	4500	169	7
4	Room	Eckartseweg	5623	360	10	1
...	...	...	...	...	...	...
91	Apartment	Peperstraat	5612	710	20	1
92	Apartment	Hermanus	5611	675	20	1
93	Apartment	Genovevalaan	5625	1050	54	2
94	Apartment	St	5611	1250	75	3
95	House	Primulastraat	5644	2250	162	7

96 rows × 6 columns

Data integration

> Using concat to create a `Union` between the two datasets and then, integrate them into one dataset.

```
frames = [dataframe, df_]
```

```
df = pd.concat(frames)
df
```

	TYPE	STREET NAME	POSTCODE	PRICE	LIVING_AREA	ROOMS
0	Kamer	Julianastraat	5611	375	NaN	NaN
1	Kamer	Bennekelstraat	5654	430	NaN	NaN
2	Kamer	Leenderweg	5615	415	NaN	NaN
3	Kamer	Bennekelstraat	5654	315	NaN	NaN
4	Kamer	Willem	5611	320	NaN	NaN
...	...	...	...	...	...	...
95	House	Primulastraat	5644	2250	162	7

Data analysis

Checking the dimension of the dataset and the features.

```
# Check the dimension of the dataset
df.shape
```

```
(219, 6)
```

> The dataset has 219 observations and 6 features, but the observations(rows) will change with time because the data is scraped and this means it is up to date. Whenever there is a change on the websites, there is a change in the dataset.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 219 entries, 0 to 95
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   TYPE         219 non-null    object
 1   STREET NAME  219 non-null    object
 2   POSTCODE     219 non-null    object
 3   PRICE        219 non-null    object
 4   LIVING_AREA  96 non-null     object
 5   ROOMS        96 non-null     object
dtypes: object(6)
memory usage: 12.0+ KB
```

> It can be seen that none features are numeric, but objects. Later, they will have to be converted into either float or int in order to be plotted and then used for the trainig of the models. There are also missing values in the dataset.

There are missing values in the dataset, which appeared after the data integration of the two datasets. This will be fixed later before the training of the models.

```
df.isnull().sum()
```

```
TYPE              0
STREET NAME       0
POSTCODE          0
PRICE             0
LIVING_AREA     123
ROOMS           123
dtype: int64
```

```
# Find columns with missing values and their percent missing
df.isnull().sum()
miss_val = df.isnull().sum().sort_values(ascending=False)
miss_val = pd.DataFrame(data=df.isnull().sum().sort_values(ascending=False), columns=['Missva

# Add a new column to the dataframe and fill it with the percentage of missing values
miss_val['Percent'] = miss_val.MissvalCount.apply(lambda x : '{:.2f}'.format(float(x)/df.shap
miss_val = miss_val[miss_val.MissvalCount > 0].style.background_gradient(cmap='Reds')
miss_val
```

	MissvalCount	Percent
ROOMS	123	56.16
LIVING_AREA	123	56.16

> The light red color shows the small amount of NaN values. If the features were with a high percent of missing values, they would have to be removed. Yet, in this case, they have relatively low percentage so they can be used in future. Then, the NaN values will be replaced.

```
#Description of the dataset
df.describe()
```

	TYPE	STREET NAME	POSTCODE	PRICE	LIVING_AREA	ROOMS
count	219	219	219	219	96	96
unique	6	109	27	122	54	6
top	Apartment	Leenderweg	5611	415	100	2
freq	71	11	45	15	5	29

```
#First 5 rows of our dataset
df.head()
```

	TYPE	STREET NAME	POSTCODE	PRICE	LIVING_AREA	ROOMS
0	Kamer	Julianastraat	5611	375	NaN	NaN
1	Kamer	Bennekelstraat	5654	430	NaN	NaN
2	Kamer	Leenderweg	5615	415	NaN	NaN
3	Kamer	Bennekelstraat	5654	315	NaN	NaN
4	Kamer	Willem	5611	320	NaN	NaN

```
#Last 5 rows of our dataset
df.tail()
```

	TYPE	STREET NAME	POSTCODE	PRICE	LIVING_AREA	ROOMS
91	Apartment	Peperstraat	5612	710	20	1
92	Apartment	Hermanus	5611	675	20	1
93	Apartment	Genovevalaan	5625	1050	54	2
94	Apartment	St	5611	1250	75	3
95	House	Primulastraat	5644	2250	162	7

```
df['TYPE'].value_counts()
```

```
Apartment      71
Kamer          49
Appartement    38
Studio         36
House          18
Room            7
Name: TYPE, dtype: int64
```

```
df.iloc[0]
```

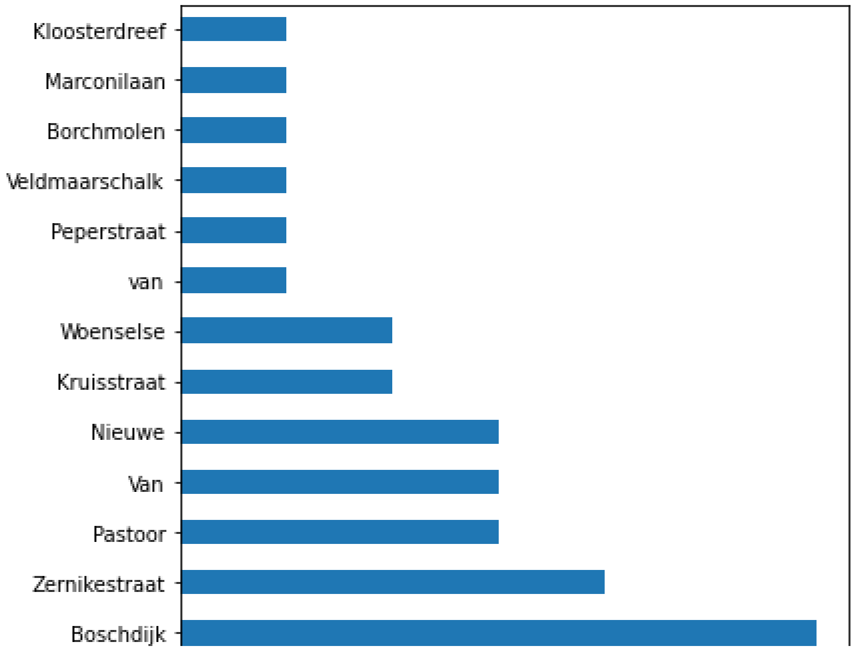
```
TYPE                   Kamer
STREET NAME    Julianastraat
POSTCODE                5611
PRICE                    375
LIVING_AREA              NaN
ROOMS                    NaN
Name: 0, dtype: object
```

```
df.groupby('POSTCODE').count()
```

POSTCODE	TYPE	STREET NAME	PRICE	LIVING_AREA	ROOMS
5503	1	1	1	0	0
5611	45	45	45	28	28
5612	29	29	29	12	12
5613	9	9	9	4	4
5614	15	15	15	4	4
5615	16	16	16	8	8
5616	8	8	8	5	5
5617	1	1	1	1	1
5621	8	8	8	1	1
5622	8	8	8	3	3
5623	10	10	10	1	1
5624	1	1	1	0	0
5625	5	5	5	4	4
5627	1	1	1	1	1
5628	1	1	1	1	1
5629	1	1	1	1	1
5631	3	3	3	0	0
5632	1	1	1	1	1
5642	6	6	6	1	1
5643	14	14	14	2	2
5644	6	6	6	3	3
5646	2	2	2	2	2
5651	4	4	4	0	0
5652	1	1	1	1	1
5653	6	6	6	1	1
5654	15	15	15	9	9

```
df[(df['POSTCODE'] == '5612')]['STREET NAME'].value_counts().plot(kind='barh', figsize=(6, 6)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5bbebc7b90>
```



Sorting the data by `Type`.

```
df.sort_values('TYPE', ascending = True)
```

	TYPE	STREET NAME	POSTCODE	PRICE	LIVING_AREA	ROOMS
29	Apartment	Geldropseweg	5611	645	29	1
30	Apartment	Geldropseweg	5611	695	29	1
31	Apartment	Jan	5642	435	18	1
33	Apartment	Heezerweg	5614	1150	83	2
36	Apartment	Stevinstraat	5621	795	28	1
...	...	...	...	...	...	...
64	Studio	Van	5612	614	NaN	NaN
65	Studio	Van	5612	602	NaN	NaN
66	Studio	Leenderweg	5643	380	NaN	NaN
58	Studio	Woenselsestraat	5623	540	NaN	NaN
84	Studio	Kleine	5611	705	NaN	NaN

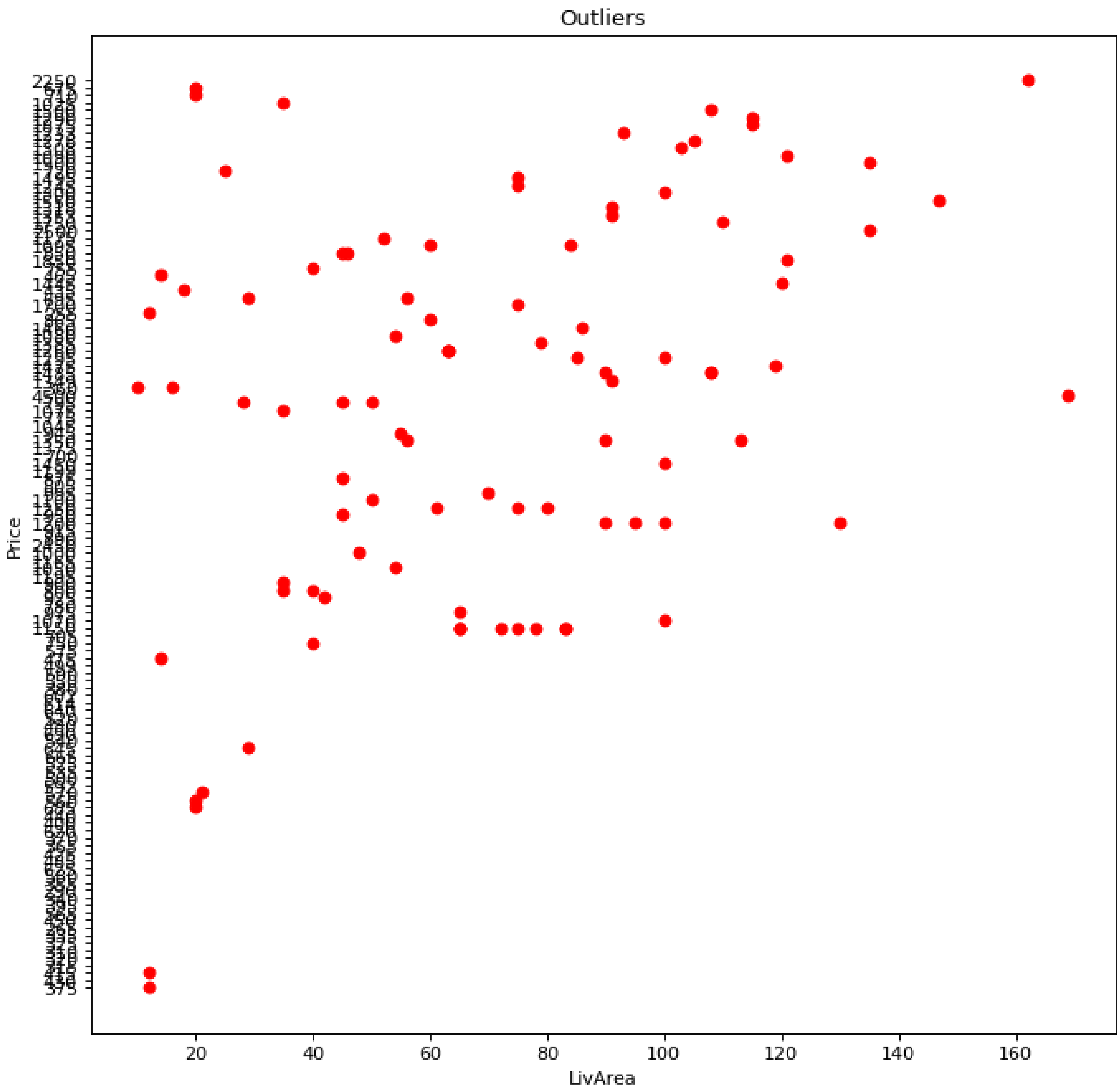
219 rows × 6 columns

Pre Processing

Handling Outlier

> An **outlier** is a data point in a data set that is distant from all other observations (a data point that lies outside the overall distribution of the dataset.)

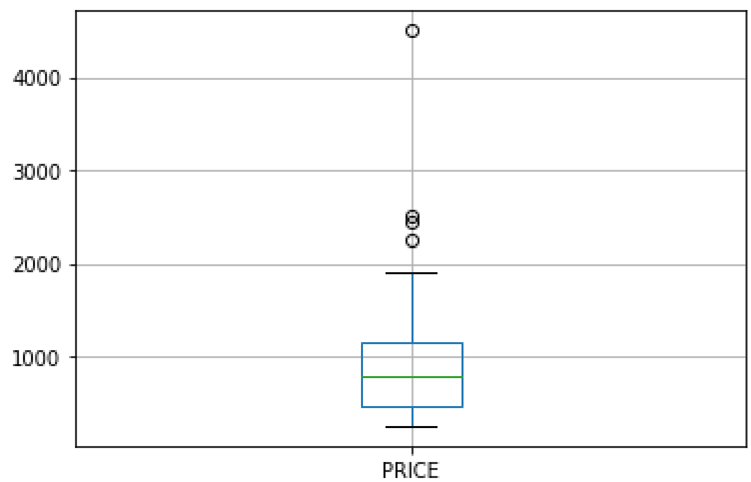
```
plt.figure(figsize=(10, 10), dpi=80)
plt.scatter(df.LIVING_AREA, df.PRICE, c= 'red')
plt.title("Outliers")
plt.xlabel("LivArea")
plt.ylabel("Price")
plt.show()
```




```
df['PRICE'] =df['PRICE'].astype(float)
df['POSTCODE'] =df['POSTCODE'].astype(int)
```

```
df['LIVING_AREA'] =df['LIVING_AREA'].astype(float)
df['ROOMS'] =df['ROOMS'].astype(float)
code_numeric = {'Kamer': 5,'Apartment': 1, 'Appartement': 1, 'Room': 2, 'Studio': 4, 'House':
df ['TYPE'] = df['TYPE'].map(code_numeric)
df['TYPE'] =df['TYPE'].astype(float)


df['PRICE'] =df['PRICE'].astype(float)


df.boxplot(column=['PRICE'])
plt.show
```

```
<function matplotlib.pyplot.show>
```




```
#Check the mean values
df['LIVING_AREA'].mean()
```

```
69.82291666666667
```

```
#Check the median
df['LIVING_AREA'].median()
```

```
65.0
```

```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
print(IQR)
```

```
TYPE             3.00
POSTCODE        30.00
PRICE          672.50
LIVING_AREA     54.75
ROOMS            1.00
dtype: float64
```

```
print(df['PRICE'].skew())
```

```
print(df['PRICE'].skew())
df['PRICE'].describe()
```

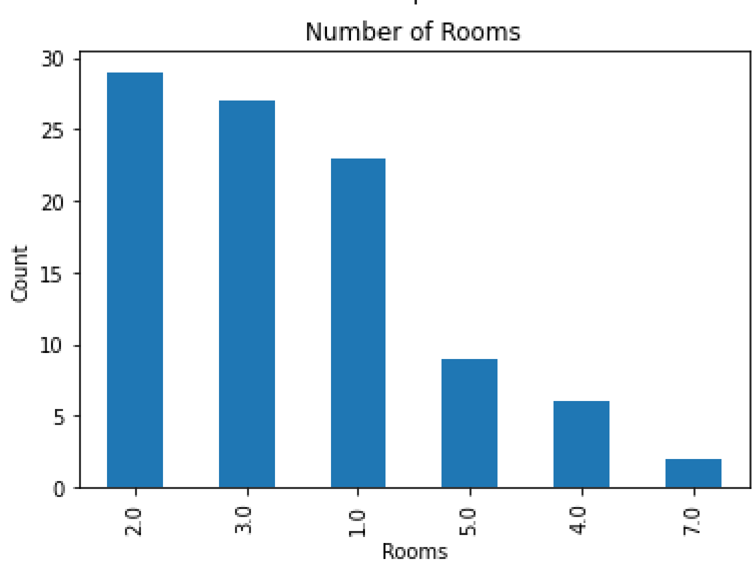
```
2.402139256066373
count     219.000000
mean      869.360731
std       489.826886
min       255.000000
25%       477.500000
50%       795.000000
75%      1150.000000
max      4500.000000
Name: PRICE, dtype: float64
```

```
print(df['PRICE'].quantile(0.10))
print(df['PRICE'].quantile(0.90))
```

```
399.0
1357.4000000000003
```

```
df['ROOMS'].value_counts().plot(kind='bar')
plt.title('Number of Rooms')
plt.xlabel('Rooms')
plt.ylabel('Count')
sns.despine
```

```
<function seaborn.utils.despine>
```




```
print(df['PRICE'])
```

```
0      375.0
1      430.0
2      415.0
3      315.0
4      320.0
       ...
91     710.0
```

```
92     675.0
93    1050.0
94    1250.0
95    2250.0
Name: PRICE, Length: 219, dtype: float64
```

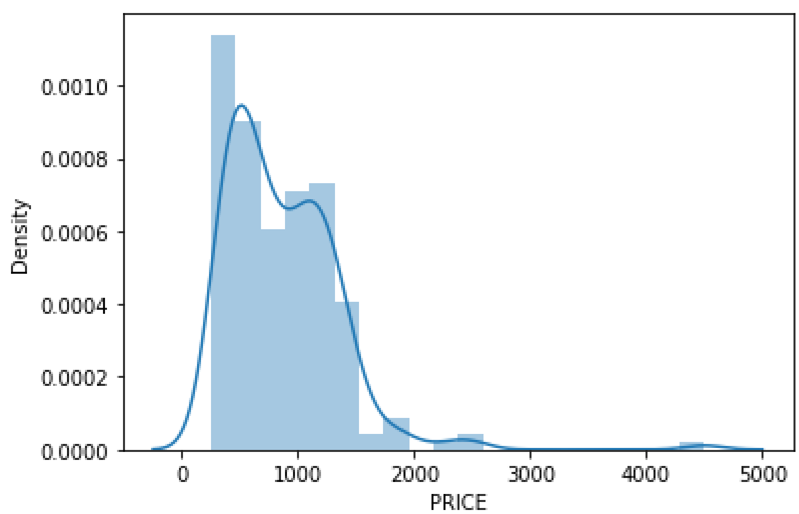
We will analyze the features in their descending of correlation with sales price

Examining the data distributions of the features. We will start with the target variable, `PRICE`, to make sure it's normally distributed.

This is important because most machine learning algorithms make the assumption that the data is normally distributed. When data fits a normal distribution, statements about the price using analytical techniques will be made.

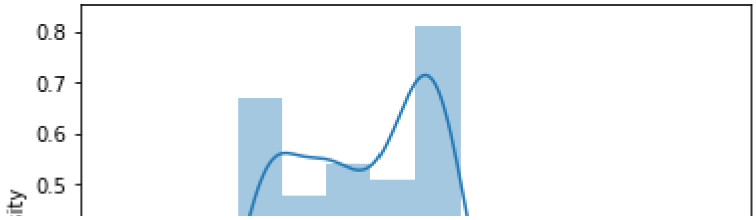
```
sns.distplot(df['PRICE'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7f5bcf797310>
```




```
# Transform the target variable
sns.distplot(np.log(df.PRICE))
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7f5bceb77150>
```



> We can see that the `PRICE` distribution is not skewed after the transformation, but normally distributed. The transformed data will be used in in the dataframe and remove the skewed distribution:

> **Normally distributed** means that the data is symmetric about the mean, showing that data near the mean are more frequent in occurrence than data far from the mean.

```
df['LogOfPrice'] = np.log(df.PRICE)
df.drop(["PRICE"], axis=1, inplace=True)
```

Reviewing the skewness of each feature

```
df.skew().sort_values(ascending=False)
```

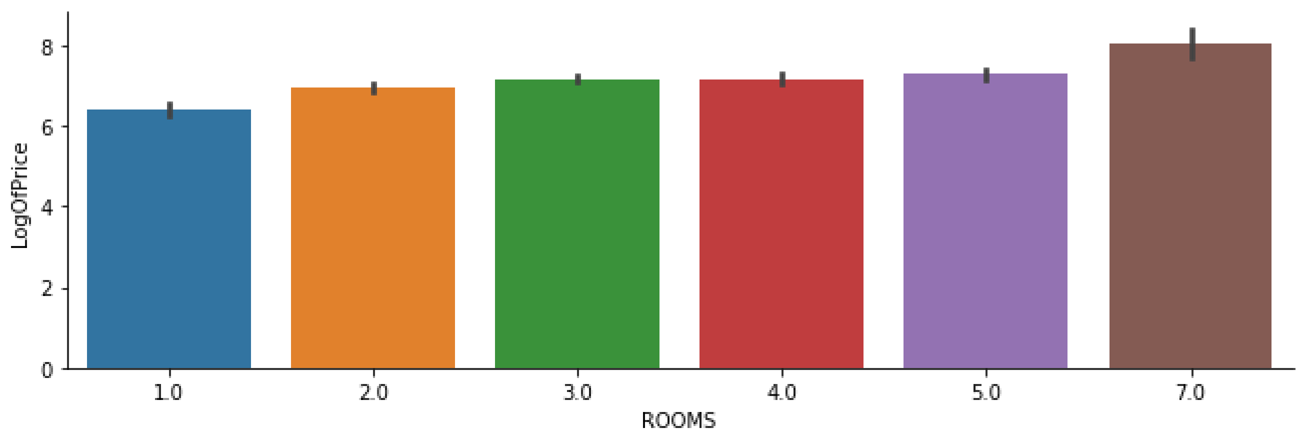
```
ROOMS           1.015947
LIVING_AREA     0.334395
TYPE            0.332601
LogOfPrice      0.085555
POSTCODE       -0.781026
dtype: float64
```

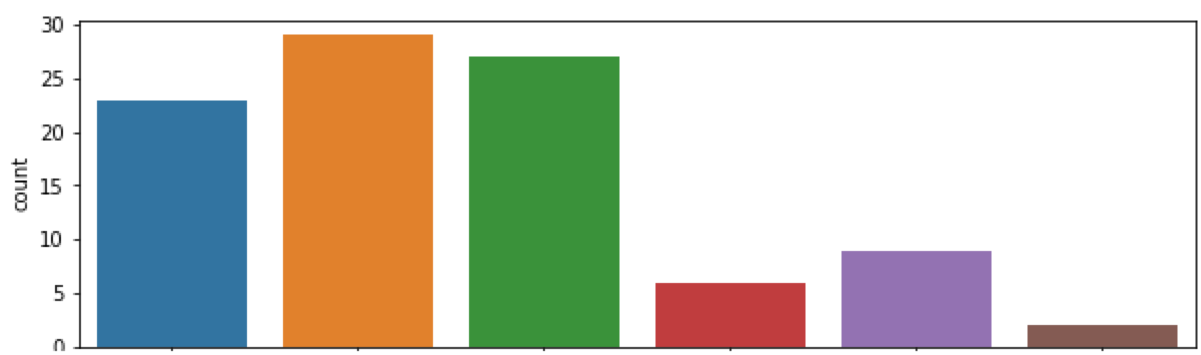
> Values closer to zero are less skewed. The results show some features having a positive (right-tailed) or negative (left-tailed) skew.

Factor plot is informative when we have multiple groups to compare.

```
sns.factorplot('ROOMS', 'LogOfPrice', data=df,kind='bar',size=3,aspect=3)
fig, (axis1) = plt.subplots(1,1,figsize=(10,3))
sns.countplot('ROOMS', data=df)
df['LogOfPrice'].value_counts()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:3714: UserWarning: The `fa
  warnings.warn(msg)
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:3720: UserWarning: The `si
  warnings.warn(msg, UserWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass th
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass th
  FutureWarning
6.028279    15
7.047517    10
6.109248     5
7.090077     5
7.207860     4
            ..
7.153052     1
5.899897     1
5.872118     1
7.803843     1
7.210080     1
Name: LogOfPrice, Length: 122, dtype: int64
```

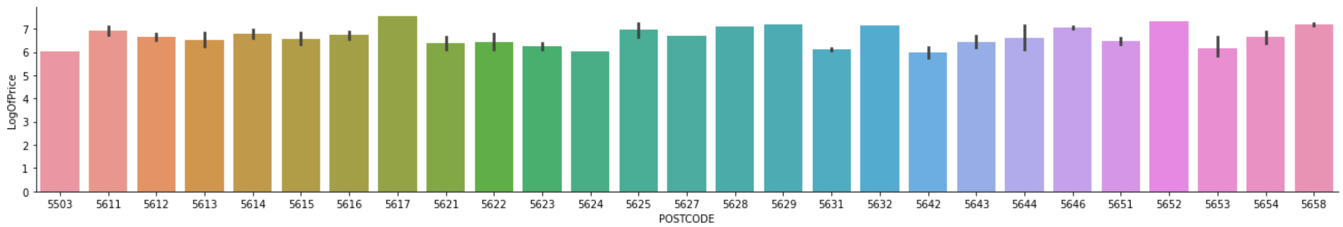




> Real estate with 5 rooms has the highest `Price` while the sales of others with rooms of 2 is the most sold ones.

```
#g = sns.factorplot(x='POSTCODE', y='Skewed_SP', col='PRICE', data=df, kind='bar', col_wrap=4
sns.factorplot('POSTCODE', 'LogOfPrice', data=df,kind='bar',size=3,aspect=6)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:3714: UserWarning: The `fa
  warnings.warn(msg)
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:3720: UserWarning: The `si
  warnings.warn(msg, UserWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass th
  FutureWarning
<seaborn.axisgrid.FacetGrid at 0x7f5bceb89d50>
```



> The diagram represents the `price` of a rpoperty, depending on its `postcode`.

Preparing the data for training the models

Train-Test Split dataset

> Necessary imports

```
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import cross_val_score, train_test_split, GridSearchCV
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 219 entries, 0 to 95
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   TYPE          219 non-null    float64
 1   STREET NAME   219 non-null    object
 2   POSTCODE      219 non-null    int64
 3   LIVING_AREA   96 non-null     float64
 4   ROOMS         96 non-null     float64
 5   LogOfPrice    219 non-null    float64
dtypes: float64(4), int64(1), object(1)
memory usage: 17.0+ KB
```

```
df.isnull().sum()
```

```
df.isnull().sum()
```

```
TYPE              0
STREET NAME       0
POSTCODE          0
LIVING_AREA     123
ROOMS           123
LogOfPrice        0
dtype: int64
```

Analyzing the numeric features.

```
numeric_features = df.select_dtypes(include=[np.number])
```

```
numeric_features.columns
```

```
Index(['TYPE', 'POSTCODE', 'LIVING_AREA', 'ROOMS', 'LogOfPrice'], dtype='object')
```

Filling up the null values in order to train the model.

```
df.fillna(0)
```

	TYPE	STREET NAME	POSTCODE	LIVING_AREA	ROOMS	LogOfPrice
0	5.0	Julianastraat	5611	0.0	0.0	5.926926
1	5.0	Bennekelstraat	5654	0.0	0.0	6.063785
2	5.0	Leenderweg	5615	0.0	0.0	6.028279
3	5.0	Bennekelstraat	5654	0.0	0.0	5.752573
4	5.0	Willem	5611	0.0	0.0	5.768321
...	...	...	...	...	...	...
91	1.0	Peperstraat	5612	20.0	1.0	6.565265
92	1.0	Hermanus	5611	20.0	1.0	6.514713
93	1.0	Genovevalaan	5625	54.0	2.0	6.956545
94	1.0	St	5611	75.0	3.0	7.130899
95	3.0	Primulastraat	5644	162.0	7.0	7.718685

219 rows × 6 columns

```
df.dropna(inplace=True)
```

```
# set the target and predictors
y = df.LogOfPrice  # target
```

```
# use only those input features with numeric data type
df_temp = df.select_dtypes(include=["int64","float64"])

X = df_temp.drop(["LogOfPrice"],axis=1)  # predictors
```

To split the dataset, I will use random sampling with 80/20 train-test split; that is, 80% of the dataset will be used for training and set aside 20% for testing:

```
# split the dataset into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=0)
```

```
df.isnull()
```

	TYPE	STREET NAME	POSTCODE	LIVING_AREA	ROOMS	LogOfPrice
0	False	False	False	False	False	False
1	False	False	False	False	False	False
2	False	False	False	False	False	False
3	False	False	False	False	False	False
4	False	False	False	False	False	False
...	...	...	...	...	...	...
91	False	False	False	False	False	False
92	False	False	False	False	False	False
93	False	False	False	False	False	False
94	False	False	False	False	False	False
95	False	False	False	False	False	False

96 rows × 6 columns

Modelling

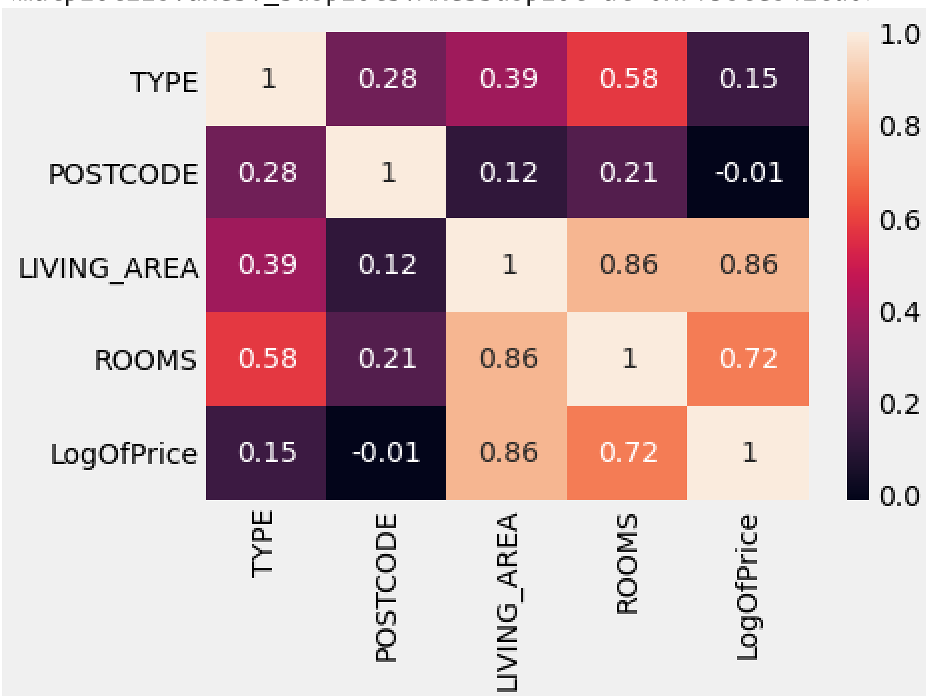
Two models will be built and evaluated by their performances with R-squared metric. Additionally, insights on the features that are strong predictors of house prices, will be analised .

Linear Regression

To fit a linear regression model, the features which have a high correlation with the target variable PRICE are selected. By looking at the correlation matrix, it is noticable that the rooms and the living area have a strong correlation with the price ('Log of price').

```
correlation_matrix = df.corr().round(2)
# annot = True to print the values inside the square
sns.heatmap(data=correlation_matrix, annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5bceb42cd0>
```




```
lr = LinearRegression()
# fit optimal linear regression line on training data
lr.fit((X_train),y_train)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Root Mean Square Error (RMSE) is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are. In other words, it tells you how concentrated the data is around the line of best fit.

```
# model evaluation for training set
y_train_predict = lr.predict(X_train)
rmse = (np.sqrt(mean_squared_error(y_train, y_train_predict)))

print("The model performance for training set:")
print('RMSE is {}'.format(rmse))
```

```
The model performance for training set:
RMSE is 0.20287534346276573
```

```
# model evaluation for testing set
y_test_predict = lr.predict(X_test)
rmse = (np.sqrt(mean_squared_error(y_test, y_test_predict)))
print("The model performance for testing set:")
print('RMSE is {}'.format(rmse))
```

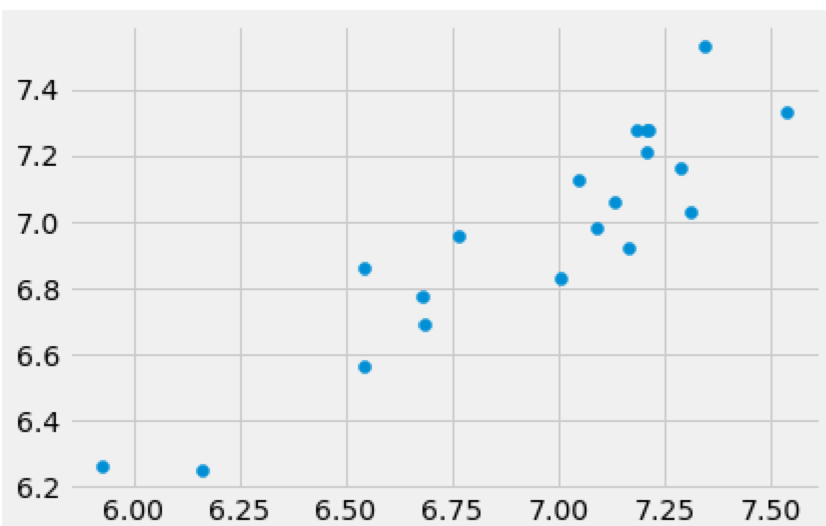
```
The model performance for testing set:
RMSE is 0.16870032503507307
```

```
#predict y_values using X_test set
yr_hat = lr.predict(X_test)
```

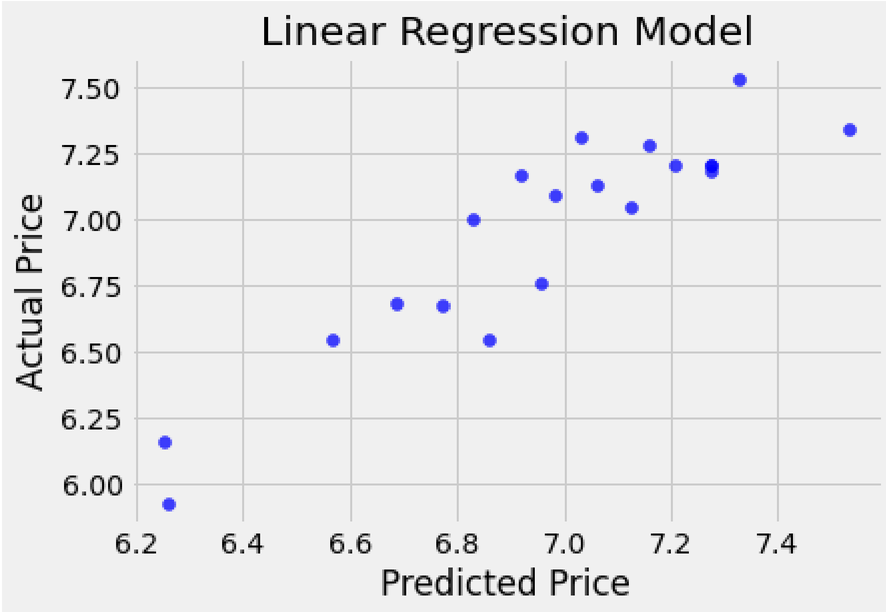
```
lr_score =lr.score((X_test),y_test)
print("Accuracy: ", lr_score)
```

```
Accuracy:  0.8266862395629924
```

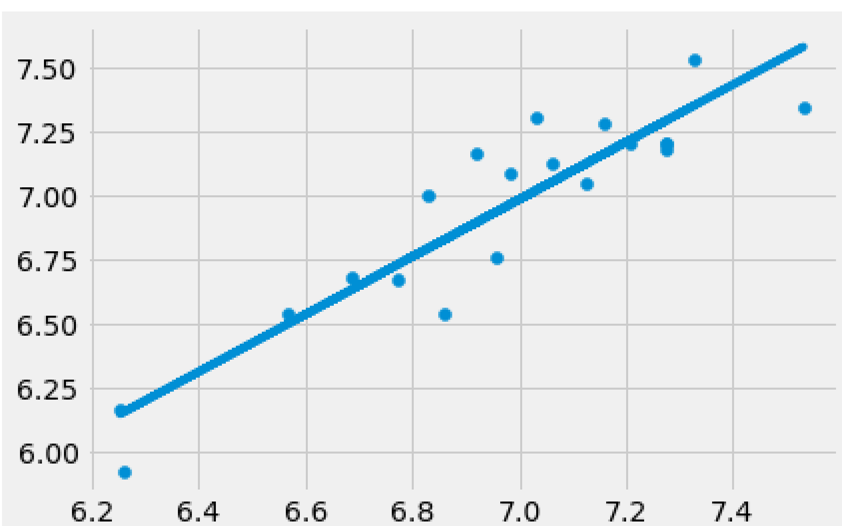
```
# plotting the y_test vs y_pred
# ideally should have been a straight line
plt.scatter(y_test, y_test_predict)
plt.show()
```




```
actual_values = y_test
plt.scatter(yr_hat, actual_values, alpha=.75,
            color='b') #alpha helps to show overlapping data
plt.xlabel('Predicted Price')
plt.ylabel('Actual Price')
plt.title('Linear Regression Model')
plt.show()
#pltrandom_state=None.show()
```




```
from scipy import stats

#Execute a method that returns the important key values of Linear Regression
slope, intercept, r, p, std_err = stats.linregress(yr_hat, y_test)
#Create a function that uses the slope and intercept values to return a new value. This new v
def myfunc(x):
  return slope * x + intercept

mymodel = list(map(myfunc, yr_hat))
#Draw the scatter plot
plt.scatter(yr_hat, y_test)
#Draw the line of linear regression
plt.plot(yr_hat, mymodel)
plt.show()
```



Using cross-validation to see whether the model is over-fitting the data.

```
# cross validation to find 'validate' score across multiple samples, automatically does Kfold
lr_cv = cross_val_score(lr, X, y, cv = 5, scoring= 'r2')
print("Cross-validation results: ", lr_cv)
print("R2: ", lr_cv.mean())
```

```
Cross-validation results:  [ 0.83877029  0.74146093  0.87064014 -0.24180301  0.80738371]
R2:  0.6032904102490614
```

> It doesn't appear that for this train-test dataset the model is over-fitting the data (the cross-validation performance is very close in value).

Random Forest

The library sklearn.ensemble is used to solve regression problems via Random forest. The most important parameter is the n_estimators parameter. This parameter defines the number of trees in the random forest.

```
# Feature Scaling
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

```
regressor = RandomForestRegressor(n_estimators=20, random_state=0)
regressor.fit(X_train, y_train)
y_pred = regressor.predict(X_test)
```

Evaluating the Algorithm: The last and final step of solving a machine learning problem is to evaluate the performance of the algorithm. For regression problems the metrics used to evaluate an algorithm are mean absolute error, mean squared error, and root mean squared error.

```
from sklearn import metrics

print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Mean Absolute Error: 0.12371824248046574
Mean Squared Error: 0.029054637154100033
Root Mean Squared Error: 0.17045420837896622
```

Training the model

```
# Import the model we are using
from sklearn.ensemble import RandomForestRegressor
# Instantiate model with 1000 decision trees
rf = RandomForestRegressor(n_estimators = 1000, random_state = 42)
# Train the model on training data
rf.fit(X_train, y_train)
```

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=1000, n_jobs=None, oob_score=False,
                      random_state=42, verbose=0, warm_start=False)
```

Making predictions on the test set:

When performing regression, the absolute error should be used.It needs to be checked how far away the average prediction is from the actual value so the absolute value has to be calculated.

```
# Use the forest's predict method on the test data
predictions = rf.predict(X_test)
# Calculate the absolute errors
errors = abs(predictions - y_test)
# Print out the mean absolute error (mae)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
```

```
Mean Absolute Error: 0.12 degrees.
```

> There is a 0.12 improvement.

Determine performance metrics:

To put the predictions in perspective, accuracy can be calculated by using the mean average percentage error subtracted from 100 %.

```
# Calculate mean absolute percentage error (MAPE)
mape = 100 * (errors /y_test)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

```
Accuracy: 98.32 %.
```

> The model has learned how to predict the price with 98% accuracy.

```
rfr = RandomForestRegressor()
rfr.fit(X_train, y_train) # gets the parameters for the rfr model
rfr_cv = cross_val_score(rfr,X, y, cv = 5, scoring = 'r2')
print("R2: ", rfr_cv.mean())
```

```
R2:  0.7341382477629055
```

The performance of Random forest is slightly better than the Linear regression. The model parameters can be optimised for better performance using gridsearch.

```
#Random forest determined feature importances
rfr.feature_importances_
```

```
array([0.02024793, 0.04472535, 0.89850892, 0.0365178 ])
```

Plotting the Feature Importance

Finding the features that are the most promising predictors:

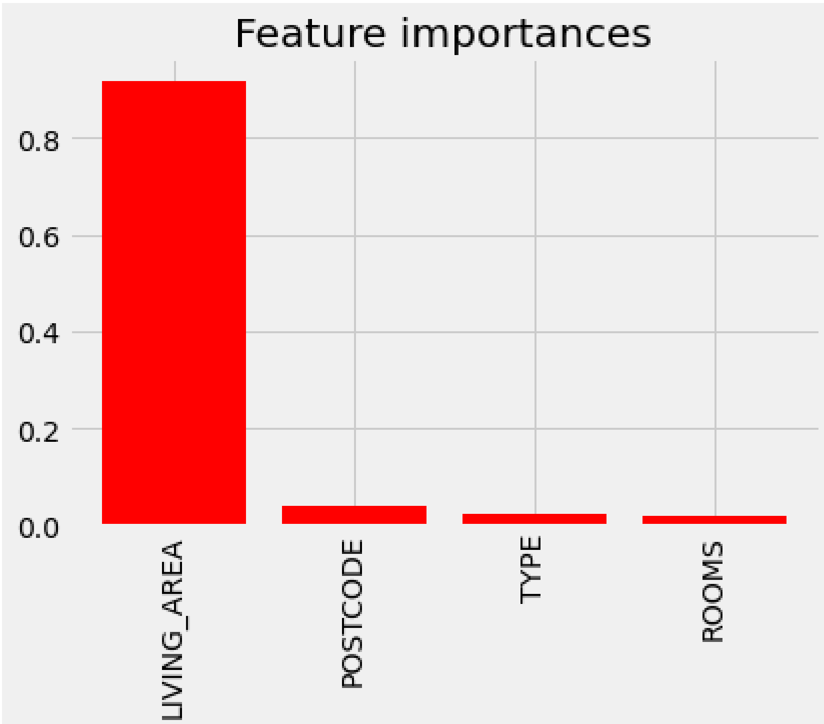
```
importance = rfr.feature_importances_

# map feature importance values to the features
feature_importances = zip(importance, X.columns)

#list(feature_importances)
sorted_feature_importances = sorted(feature_importances, reverse = True)

#print(sorted_feature_importances)
top_15_predictors = sorted_feature_importances[0:15]
values = [value for value, predictors in top_15_predictors]
predictors = [predictors for value, predictors in top_15_predictors]
print(predictors)
```

```
['LIVING_AREA', 'POSTCODE', 'TYPE', 'ROOMS']
```

Plotting the feauture importance of the Random forest.

Plotting the feature importances to illustrate the disparities in the relative significance of the variables.

```
plt.figure()
plt.title( "Feature importances")
plt.bar(range(len(predictors)), values,color="r", align="center");
plt.xticks(range(len(predictors)), predictors, rotation=90);
```



The idea behind the plotting of feauture importance is that after evaluating the performance of the model, the values of a feature of interest must be permuted and reevaluate model performance. The feature importance (variable importance) describes which features are relevant.

Conclusion

Data collection:

For the data collection part, I decided to use `web scraping` as e technique because it gives the opportunity to work with a data set that is up to date and therefore, makes more accurate summaries.

Data preprocessing:

I tried different types of data transforms to expose the data structure better, so we may be able to improve model accuracy later.

- `Standardizing` was made to the data set so as to reduce the effects of differing distributions.
- `The skewness` of the features was checked in order to see how distorted a data sample is from the normal distribution.

- `Rescaling (normalizing)` the dataset was also included to reduce the effects of differing scales

Modelling:

I used two models to determine the accuracy - Linear Regression and Random Forest.

Linear Regression turns out to be the more accurate model for predicting the house price. It scored an estimated accuracy of 68%, out performing the Random Forest - 66%. Random Forest determined that overall the living area of a home is by far the most important predictor. Following are the sizes of above rooms and postcode.

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