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', 'Vrijstraat', '5611', '17
```

'FriendlyHousing' - creating the dataframe

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

	TYPE	STREET NAME	POSTCODE	PRICE
0	Kamer	Willem	5611	320
1	Kamer	Willem	5611	310
2	Kamer	Julianastraat	5611	375
3	Kamer	Bennekelstraat	5654	430
4	Kamer	Leenderweg	5615	415
...	...	...	...	...
114	Appartement	Frankrijkstraat	5622	925
115	Appartement	Kerkakkerstraat	5616	950
116	Appartement	Leenderweg	5614	800
117	Appartement	Leostraat	5615	775
118	Appartement	Stratumsedijk	5614	1075

119 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	Vrijstraat	5611	1750	90	2
2	Room	Schootsestraat	5616	445	10	1
3	Apartment	Jeroen	5642	1195	75	3
4	Apartment	De	5612	423	20	2
...	...	...	...	...	...	...
88	House	Grote	5632	1290	115	4
89	Room	Sebastiaan	5622	475	14	1
90	House	van	5612	1500	108	5
91	Room	Aalsterweg	5615	360	16	1
92	House	Landgraaf	5658	1350	113	5

93 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	Willem	5611	320	NaN	NaN
1	Kamer	Willem	5611	310	NaN	NaN
2	Kamer	Julianastraat	5611	375	NaN	NaN
3	Kamer	Bennekelstraat	5654	430	NaN	NaN
4	Kamer	Leenderweg	5615	415	NaN	NaN
...	...	...	...	...	...	...
92	House	Landgraaf	5658	1350	113	5

Data analysis

Checking the dimension of the dataset and the features.

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

```
(212, 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: 212 entries, 0 to 92
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   TYPE         212 non-null    object
 1   STREET NAME  212 non-null    object
 2   POSTCODE     212 non-null    object
 3   PRICE        212 non-null    object
 4   LIVING_AREA  93 non-null     object
 5   ROOMS        93 non-null     object
dtypes: object(6)
memory usage: 11.6+ 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     119
ROOMS           119
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	119	56.13
LIVING_AREA	119	56.13

> 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	212	212	212	212	93	93
unique	6	107	25	123	51	6
top	Apartment	Leenderweg	5611	415	75	2
freq	69	9	47	15	6	30

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

	TYPE	STREET NAME	POSTCODE	PRICE	LIVING_AREA	ROOMS
0	Kamer	Willem	5611	320	NaN	NaN
1	Kamer	Willem	5611	310	NaN	NaN
2	Kamer	Julianastraat	5611	375	NaN	NaN
3	Kamer	Bennekelstraat	5654	430	NaN	NaN
4	Kamer	Leenderweg	5615	415	NaN	NaN

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

	TYPE	STREET NAME	POSTCODE	PRICE	LIVING_AREA	ROOMS
88	House	Grote	5632	1290	115	4
89	Room	Sebastiaan	5622	475	14	1
90	House	van	5612	1500	108	5
91	Room	Aalsterweg	5615	360	16	1
92	House	Landgraaf	5658	1350	113	5

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

```
Apartment      69
Kamer          47
Studio         36
Appartement    36
House          16
Room            8
Name: TYPE, dtype: int64
```

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

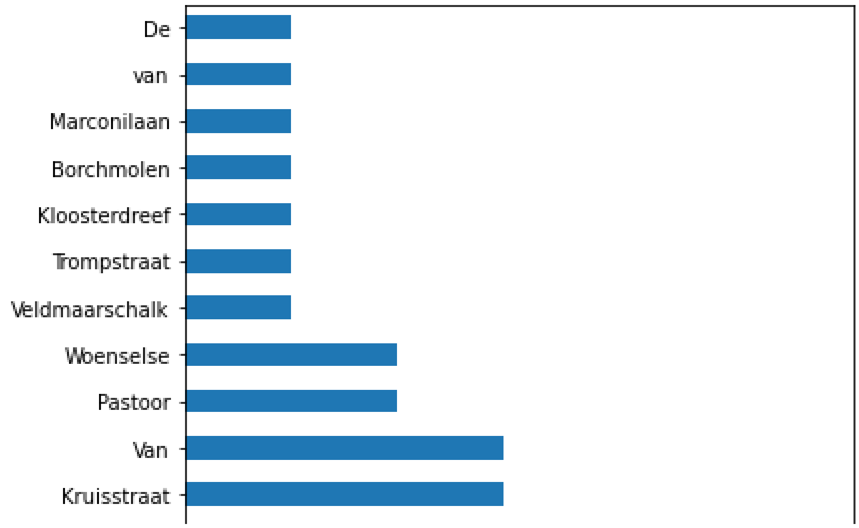
```
TYPE            Kamer
STREET NAME    Willem
POSTCODE         5611
PRICE             320
LIVING_AREA       NaN
ROOMS             NaN
Name: 0, dtype: object
```

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

POSTCODE	TYPE	STREET NAME	PRICE	LIVING_AREA	ROOMS
5503	1	1	1	0	0
5611	47	47	47	30	30
5612	30	30	30	14	14
5613	9	9	9	4	4
5614	13	13	13	2	2
5615	15	15	15	7	7
5616	8	8	8	6	6
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	4	4	4	3	3
5629	1	1	1	1	1
5631	3	3	3	0	0
5632	1	1	1	1	1
5642	7	7	7	2	2
5643	13	13	13	2	2
5644	5	5	5	2	2
5646	2	2	2	2	2
5651	4	4	4	0	0
5652	1	1	1	1	1
5653	5	5	5	1	1
5654	13	13	13	7	7

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff5e45161d0>
```



Sorting the data by `Type`.

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

	TYPE	STREET NAME	POSTCODE	PRICE	LIVING_AREA	ROOMS
29	Apartment	Bomanshof	5611	1385	79	2
34	Apartment	Bomanshof	5611	1100	50	2
35	Apartment	Bomanshof	5611	1260	63	2
36	Apartment	Bomanshof	5611	1460	86	2
37	Apartment	Kruisstraat	5612	950	45	2
...	...	...	...	...	...	...
51	Studio	Van	5612	592	NaN	NaN
50	Studio	Boschdijk	5612	570	NaN	NaN
67	Studio	Zernikestraat	5612	590	NaN	NaN
52	Studio	Aalsterweg	5615	500	NaN	NaN
66	Studio	Kempensebaan	5613	425	NaN	NaN

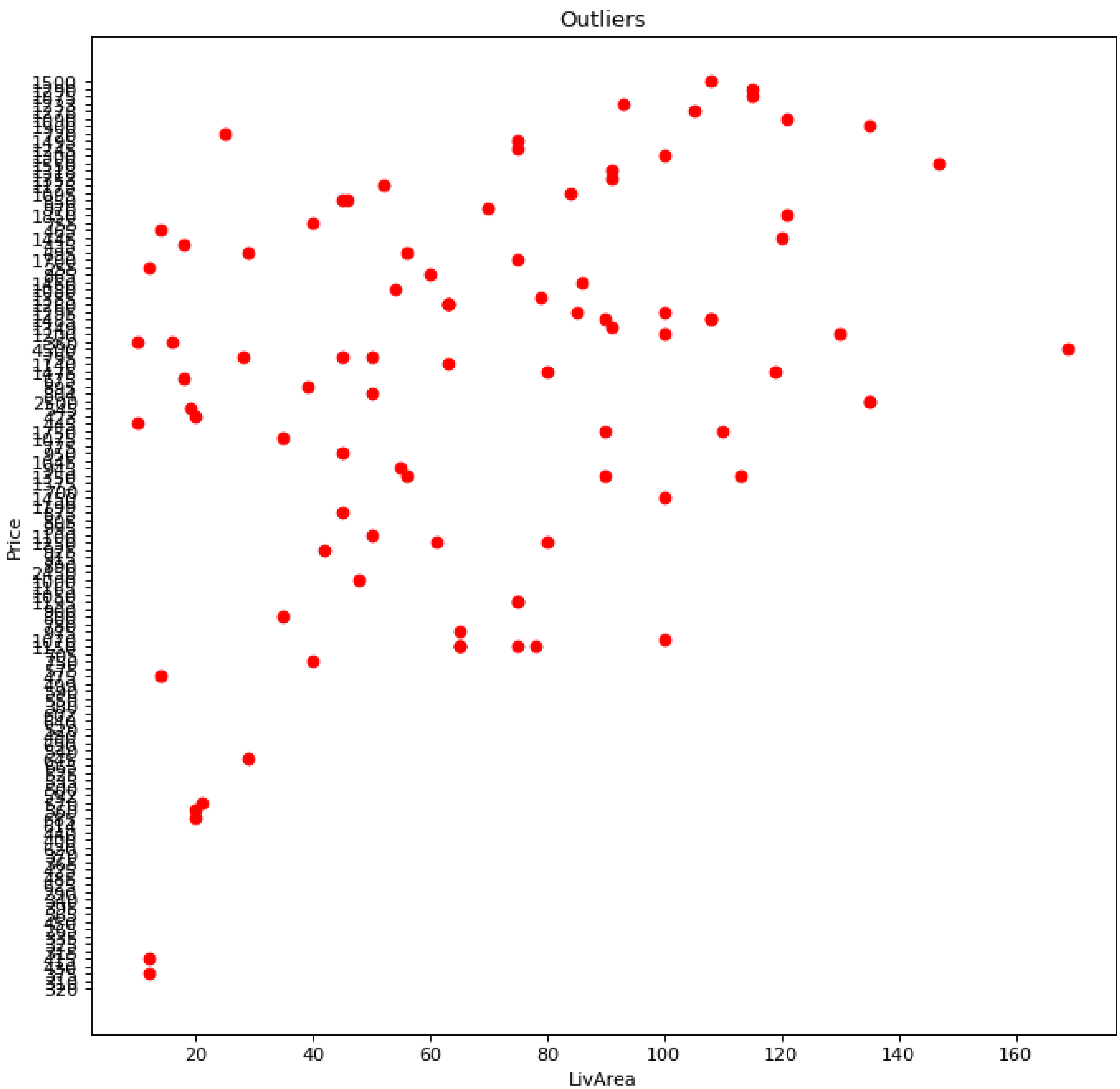
212 rows × 6 columns

Pre Processing

Handling Outlier

> An **outlier** is a data point in a data set that is distant from all other observations (a

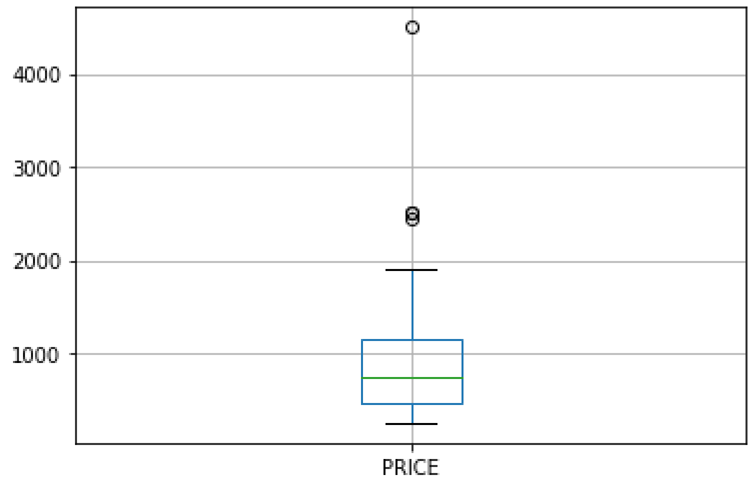
```
plt.figure(figsize=(10, 10), dpi=80)
plt.scatter(df.LIVING_AREA, df.PRICE, c= 'red')
plt.title("Outliers")
plt.xlabel("LivArea")
plt.ylabel("Price")
plt.show()
```




```
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'].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()
```

```
68.27956989247312
```

```
#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        19.25
PRICE          688.75
LIVING_AREA     53.00
ROOMS            1.00
dtype: float64
```

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

```
2.3931092033413135
```

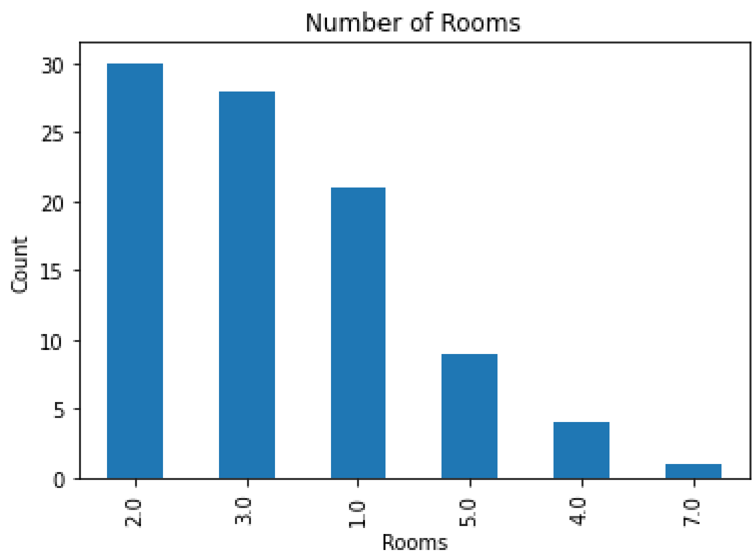
```
count     212.000000
mean      865.136792
std       503.871594
min       255.000000
25%       461.250000
50%       752.500000
75%      1150.000000
max      4500.000000
Name: PRICE, dtype: float64
```

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

```
400.0
1439.0000000000002
```

```
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      320.0
1      310.0
2      375.0
3      430.0
4      415.0
       ...
88    1290.0
89     475.0
90    1500.0
91     360.0
```

```
92    1350.0
Name: PRICE, Length: 212, dtype: float64
```

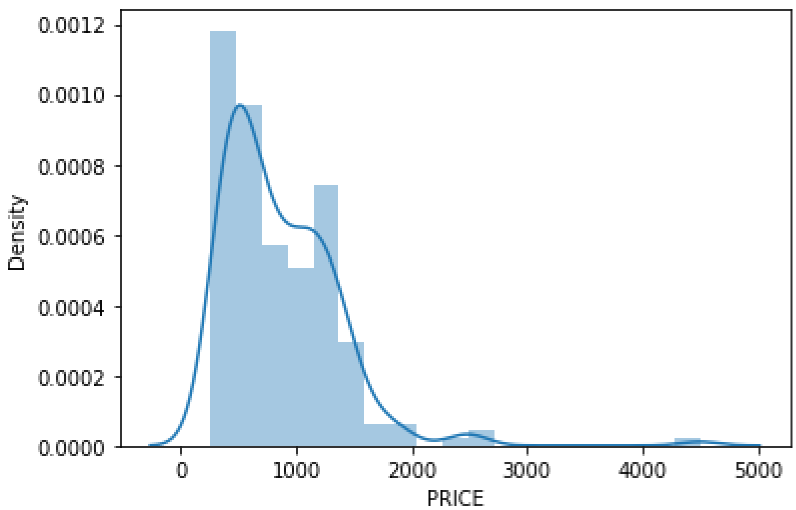
We will analyze the features in their descending of correlation with sales price

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.

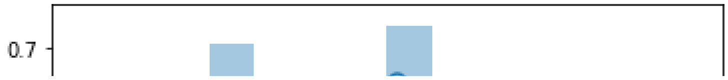
```
sns.distplot(df['PRICE'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7ff5e3cdf910>
```




```
# 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 0x7ff5e3c1a190>
```



> 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)
```

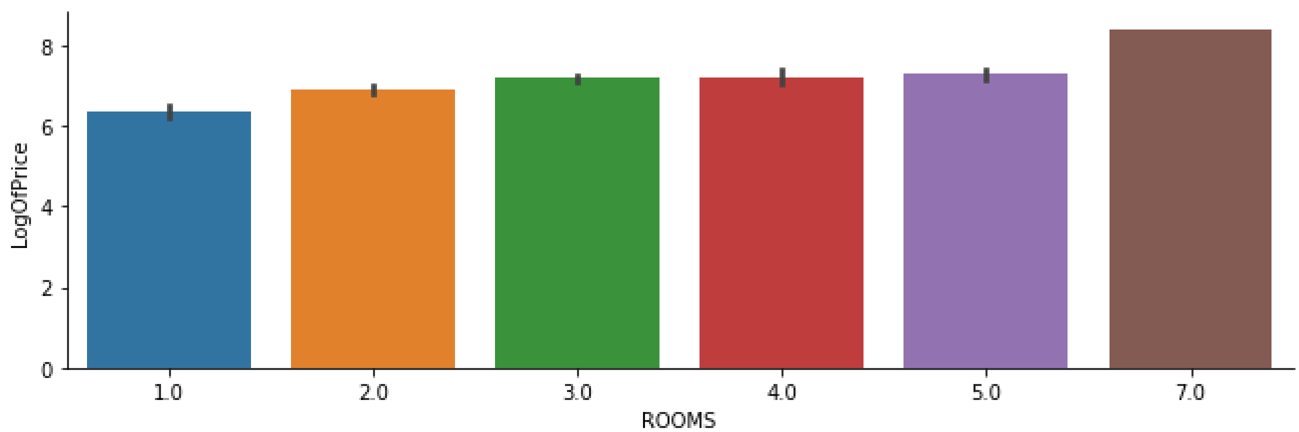
```
ROOMS          0.942239
TYPE           0.331908
LIVING_AREA    0.283844
LogOfPrice     0.170493
POSTCODE      -0.808656
dtype: float64
```

> 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()
```

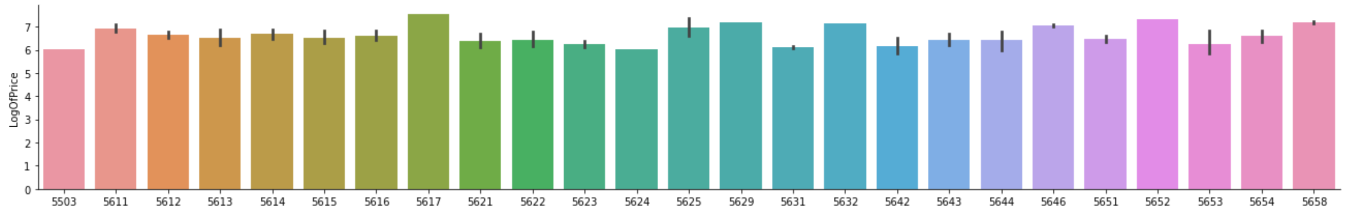
```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:3714: UserWarning: The `fa
  warnings.warn(msg)
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:3720: UserWarning: The `si
  warnings.warn(msg, UserWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass th
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass th
  FutureWarning
6.028279    15
7.047517     7
6.109248     5
6.345636     4
6.380123     4
            ..
7.153052     1
5.899897     1
6.993933     1
7.803843     1
7.210080     1
Name: LogOfPrice, Length: 123, 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 0x7ff5e3b20dd0>
```



> 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: 212 entries, 0 to 92
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   TYPE         212 non-null    float64
 1   STREET NAME  212 non-null    object 
 2   POSTCODE     212 non-null    int64  
 3   LIVING_AREA  93 non-null     float64
 4   ROOMS        93 non-null     float64
 5   LogOfPrice   212 non-null    float64
dtypes: float64(4), int64(1), object(1)
memory usage: 16.6+ KB
```

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

```
TYPE           0
STREET NAME    0
```

```
POSTCODE          0
LIVING_AREA     119
ROOMS           119
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	Willem	5611	0.0	0.0	5.768321
1	5.0	Willem	5611	0.0	0.0	5.736572
2	5.0	Julianastraat	5611	0.0	0.0	5.926926
3	5.0	Bennekelstraat	5654	0.0	0.0	6.063785
4	5.0	Leenderweg	5615	0.0	0.0	6.028279
...	...	...	...	...	...	...
88	3.0	Grote	5632	115.0	4.0	7.162397
89	2.0	Sebastiaan	5622	14.0	1.0	6.163315
90	3.0	van	5612	108.0	5.0	7.313220
91	2.0	Aalsterweg	5615	16.0	1.0	5.886104
92	3.0	Landgraaf	5658	113.0	5.0	7.207860

212 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
...	...	...	...	...	...	...
88	False	False	False	False	False	False
89	False	False	False	False	False	False
90	False	False	False	False	False	False
91	False	False	False	False	False	False
92	False	False	False	False	False	False

93 rows × 6 columns

Modelling

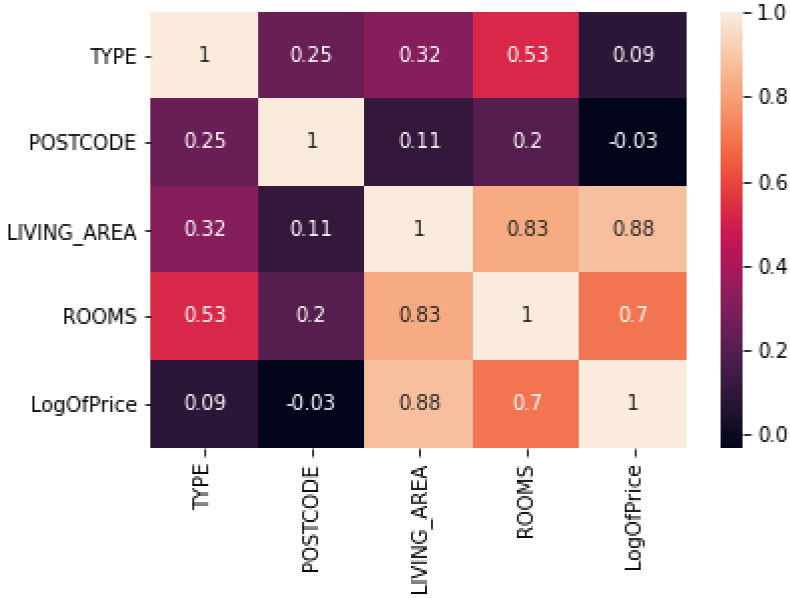
Two models will be built and evaluated by their performances with R-squared metric. Additionally, insights on the features that are strong predictors of house prices, will be analised .

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 0x7ff5d6b11f90>
```




```
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.

> RMSE values between 0.2 and 0.5 shows that the model can relatively predict the data accurately. In this case, it is exactly 0.2, so it is relatively accurate.

```
from sklearn.metrics import mean_squared_error
```

```
# 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 0.20765301137306907
```

```
# 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))
```

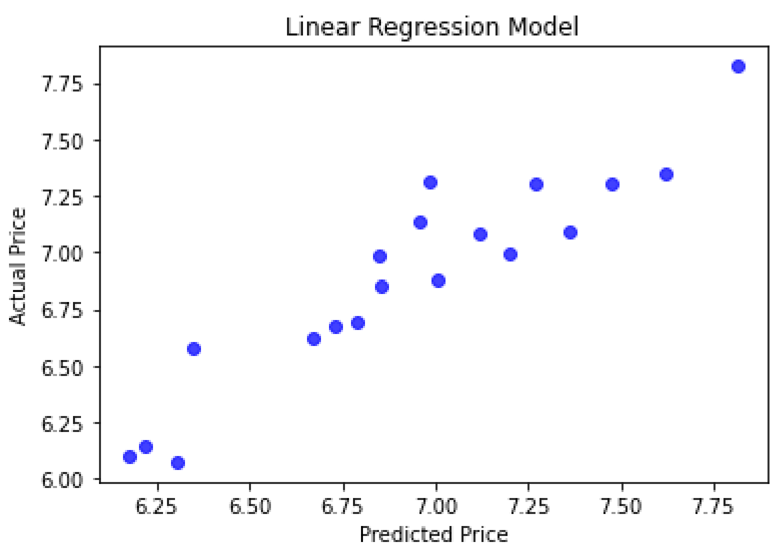
```
The model performance for testing set:
RMSE is 0.1665026490419032
```

```
#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:  0.8635924573514335
```

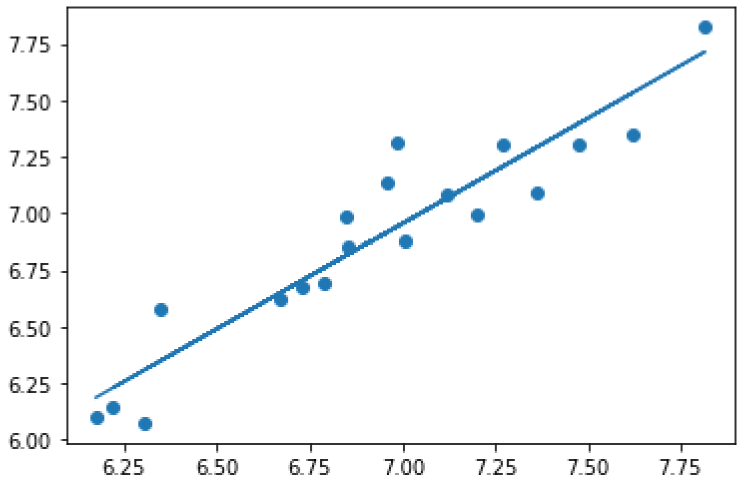
```
actual_values = y_test
plt.scatter(yr_hat, actual_values, alpha=.75,
            color='b') #alpha helps to show overlapping data
plt.xlabel('Predicted Price')
plt.ylabel('Actual Price')
plt.title('Linear Regression Model')
plt.show()
#pltrandom_state=None.show()
```




```
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:  [0.87346696 0.76442401 0.80012497 0.66745531 0.5488312 ]
R2:  0.7308604883584712
```

> 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).

Regularization:

The alpha parameter in ridge and lasso regularizes the regression model. The regression algorithms with regularization differ from linear regression in that they try to penalize those features that are not significant in our prediction. Ridge will try to reduce their effects (i.e., shrink their coeffients) in order to optimize all the input features. Lasso will try to remove the not-significant features by making their coefficients zero. In short, Lasso (L1 regularization) can eliminate the not-significant features, thus performing feature selection while Ridge (L2 regularization) cannot.

Lasso regression

```
lasso = Lasso(alpha = 1)  # sets alpha to almost zero as baseline
lasso.fit(X_train, y_train)
```

```
Lasso(alpha=1, copy_X=True, fit_intercept=True, max_iter=1000, normalize=False,
      positive=False, precompute=False, random_state=None, selection='cyclic',
      tol=0.0001, warm_start=False)
```

RMSE tells you how concentrated the data is around the line of best fit.

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

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

```
The model performance for training set:
RMSE is 0.23581221443279687
```

RMSE values between 0.2 and 0.5 shows that the model can relatively predict the data accurately. In this case, it is 0.5, so it is relatively accurate.

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

```
The model performance for testing set:
RMSE is 0.19371218192805603
```

RMSE values between 0.2 and 0.5 shows that the model can relatively predict the data accurately. In this case, it is 0.5, so it is relatively accurate.

```
#predict y_values using X_test set
yr_lasso = lasso.predict(X_test)
```

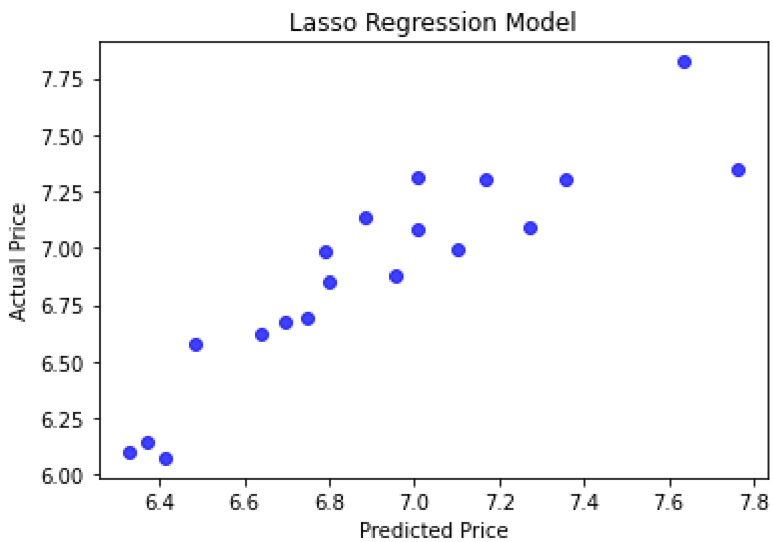
```
lasso_score =lasso.score((X_test),y_test)
print("Accuracy: ", lasso_score)
```

```
Accuracy:  0.8153667322347822
```

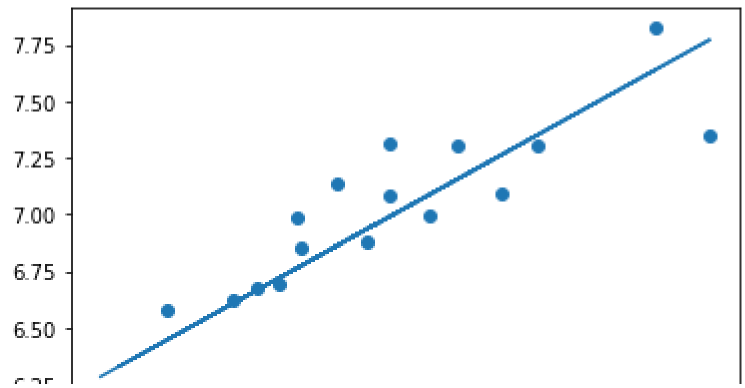
```
lasso_cv = cross_val_score(lasso, X, y, cv = 5, scoring = 'r2')
print ("Cross-validation results: ", lasso_cv)
print ("R2: ", lasso_cv.mean())
```

```
Cross-validation results:  [0.82842652 0.66440621 0.69514684 0.59111828 0.48721021]
R2:  0.6532616143265344
```

```
actual_values = y_test
plt.scatter(yr_lasso, actual_values, alpha=.75,
            color='b') #alpha helps to show overlapping data
plt.xlabel('Predicted Price')
plt.ylabel('Actual Price')
plt.title('Lasso 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_lasso, 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_lasso))
#Draw the scatter plot
plt.scatter(yr_lasso, y_test)
#Draw the line of linear regression
plt.plot(yr_lasso, mymodel)
plt.show()
```



Ridge regression

```
ridge = Ridge(alpha = 1)  # sets alpha to a default value as baseline
ridge.fit(X_train, y_train)
```

```
Ridge(alpha=1, copy_X=True, fit_intercept=True, max_iter=None, normalize=False,
      random_state=None, solver='auto', tol=0.001)
```

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

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

```
The model performance for training set:
RMSE is 0.20767204734215916
```

> RMSE values between 0.2 and 0.5 shows that the model can relatively predict the data accurately. In this case, it is 0.2, so it is relatively accurate.

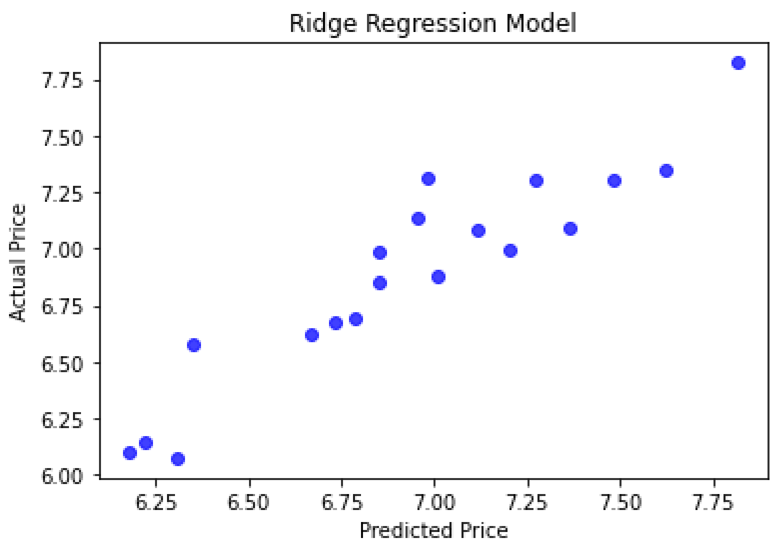
```
# model evaluation for testing set
y_test_r_predict = ridge.predict(X_test)
rmse = (np.sqrt(mean_squared_error(y_test, y_test_r_predict)))
print("The model performance for testing set:")
print('RMSE is {}'.format(rmse))
```

```
The model performance for testing set:
RMSE is 0.16812086580920915
```

> RMSE values between 0.2 and 0.5 shows that the model can relatively predict the data accurately. In this case, it is rounded to 0.2, so it is relatively accurate.

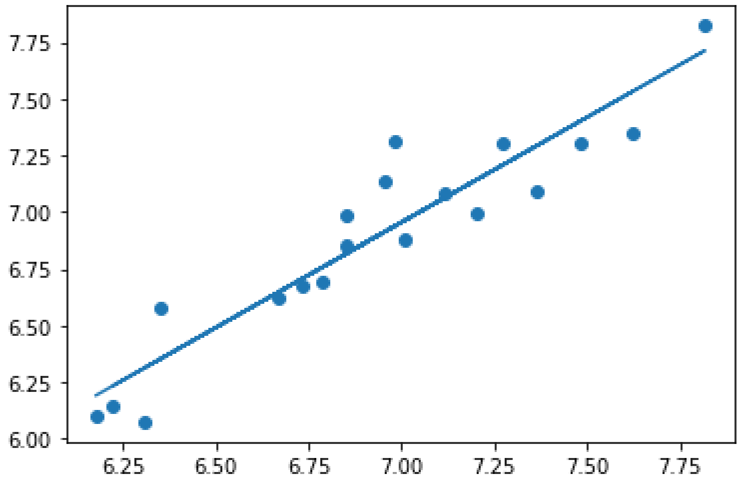
```
#predict y_values using X_test set
```

```
yr_ridge = ridge.predict(X_test)


ridge_score =ridge.score((X_test),y_test)
print("Accuracy: ", ridge_score)

     Accuracy:  0.8609281198121118


ridge_cv = cross_val_score(ridge, X, y, cv = 5, scoring = 'r2')
print ("Cross-validation results: ", ridge_cv)
print ("R2: ", ridge_cv.mean())

     Cross-validation results:  [0.87430768 0.76335975 0.79883498 0.67112458 0.54775124]
     R2:  0.7310756447849953


actual_values = y_test
plt.scatter(yr_ridge, actual_values, alpha=.75,
            color='b') #alpha helps to show overlapping data
plt.xlabel('Predicted Price')
plt.ylabel('Actual Price')
plt.title('Ridge 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_ridge, 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_ridge))
#Draw the scatter plot
plt.scatter(yr_ridge, y_test)
```

```
#Draw the line of linear regression
plt.plot(yr_ridge, mymodel)
plt.show()
```



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: 0.12552548827951324
Mean Squared Error: 0.024254698257395242
Root Mean Squared Error: 0.15573919948874543
```

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: 0.13 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: 98.13 %.
```

> 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())
```

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_
```

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)
```

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.

> 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.

```
# **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 four models to determine the accuracy - Linear Regression, Lasso
Regression and Ridge Regression, Random Forest.

From the exploring of the models RMSE:

* Linear Regression score: 0.2003 (0.1887)

* Lasso score: 0.5 (0.4675)

* Ridge score: 0.2 (0.1877)

* Random forest score: 0.2372

> RMSE values between 0.2 and 0.5 shows that the model can relatively predict
the data accurately. All of the models showed values in this range.
```

```
From the exploring of the models accuracy:

* Linear Regression score:  0.80 (80%)

* Lasso score: 0.82 (82%)

* Ridge score: 0.86 (86%)

* Random forest score: 98.13 %

From the exploring of the models cross-validation:

* Linear Regression score:  R2: 0.7308604883584712

* Lasso score: R2:  0.6532616143265344

* Ridge score: R2:  0.7310756447849953

* Random forest: R2:  0.7742740242196954

Random forest turns out to be the more accurate model for predicting the house
price.

All of the models showed RMSE values between 0.2 and 0.5 so that they show
relatively accurate predictions of the data.

I evaluated the models performances with R-squared metric and the one that is
overfitting the least is the Linear Regression.
```

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