House Sales in King County, USA

This dataset contains house sale prices for King County, which includes Seattle. It includes homes sold between May 2014 and May 2015.

id : A notation for a house

date: Date house was sold

price: Price is prediction target

bedrooms: Number of bedrooms

bathrooms: Number of bathrooms

sqft_living: Square footage of the home

sqft_lot: Square footage of the lot

floors :Total floors (levels) in house

waterfront :House which has a view to a waterfront

view: Has been viewed

condition :How good the condition is overall

grade: overall grade given to the housing unit, based on King County grading system

sqft_above : Square footage of house apart from basement

sqft_basement: Square footage of the basement

yr_built : Built Year

yr_renovated : Year when house was renovated

zipcode: Zip code

lat: Latitude coordinate

long: Longitude coordinate

sqft_living15 : Living room area in 2015(implies-- some renovations) This might or might not have affected the lotsize area

sqft_lot15 : LotSize area in 2015(implies-- some renovations)

You will require the following libraries:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler,PolynomialFeatures
from sklearn.linear_model import LinearRegression
%matplotlib inline
```

Module 1: Importing Data Sets

Load the csv:

```
file_name='https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/D
df=pd.read_csv(file_name)
```

We use the method `head` to display the first 5 columns of the dataframe.

```
df.head()
```

	Unnamed: 0	id	date	price	bedrooms	bathrooms	sqft_living	s
0	0	7129300520	20141013T000000	221900.0	3.0	1.00	1180	
1	1	6414100192	20141209T000000	538000.0	3.0	2.25	2570	
2	2	5631500400	20150225T000000	180000.0	2.0	1.00	770	
3	3	2487200875	20141209T000000	604000.0	4.0	3.00	1960	
4	4	1954400510	20150218T000000	510000.0	3.0	2.00	1680	

Question 1

Display the data types of each column using the attribute dtype, then take a screenshot and submit it, include your code in the image.

```
df.dtypes
```

```
Unnamed: 0        int64
```

```
id                 int64
date              object
price            float64
bedrooms         float64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
grade              int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

We use the method describe to obtain a statistical summary of the dataframe.

```
df.describe()
```

	Unnamed: 0	id	price	bedrooms	bathrooms	sqft_living
count	21613.00000	2.161300e+04	2.161300e+04	21600.000000	21603.000000	21613.000000
mean	10806.00000	4.580302e+09	5.400881e+05	3.372870	2.115736	2079.899736
std	6239.28002	2.876566e+09	3.671272e+05	0.926657	0.768996	918.440897
min	0.00000	1.000102e+06	7.500000e+04	1.000000	0.500000	290.000000
25%	5403.00000	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000
50%	10806.00000	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000
75%	16209.00000	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000
max	21612.00000	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000

Module 2: Data Wrangling

Question 2

Drop the columns `"id"` and `"Unnamed: 0"` from axis 1 using the method `drop()`, then use the method `describe()` to obtain a statistical summary of the data. Take a screenshot and submit it, make sure the `inplace` parameter is set to `True`

```
df.drop(['id', 'Unnamed: 0'], axis = 1, inplace= True)
```

```
df.describe()
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
count	2.161300e+04	21600.000000	21603.000000	21613.000000	2.161300e+04	21613.000000
mean	5.400881e+05	3.372870	2.115736	2079.899736	1.510697e+04	1.494309
std	3.671272e+05	0.926657	0.768996	918.440897	4.142051e+04	0.539989
min	7.500000e+04	1.000000	0.500000	290.000000	5.200000e+02	1.000000
25%	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000

We can see we have missing values for the columns `bedrooms` and `bathrooms`

```
print("number of NaN values for the column bedrooms :", df['bedrooms'].isnull().sum())
print("number of NaN values for the column bathrooms :", df['bathrooms'].isnull().sum())
```

```
number of NaN values for the column bedrooms : 13
number of NaN values for the column bathrooms : 10
```

We can replace the missing values of the column `'bedrooms'` with the mean of the column `'bedrooms'` using the method `replace()`. Don't forget to set the `inplace` parameter to `True`

```
mean=df['bedrooms'].mean()
df['bedrooms'].replace(np.nan,mean, inplace=True)
```

We also replace the missing values of the column `'bathrooms'` with the mean of the column `'bathrooms'` using the method `replace()`. Don't forget to set the `inplace` parameter top `True`

```
mean=df['bathrooms'].mean()
df['bathrooms'].replace(np.nan,mean, inplace=True)
```

```
print("number of NaN values for the column bedrooms :", df['bedrooms'].isnull().sum())
print("number of NaN values for the column bathrooms :", df['bathrooms'].isnull().sum())
```

```
number of NaN values for the column bedrooms : 0
number of NaN values for the column bathrooms : 0
```

Module 3: Exploratory Data Analysis

Question 3

Use the method `value_counts` to count the number of houses with unique floor values, use the method `.to_frame()` to convert it to a dataframe.

```
count_of_each_floor=df['floors'].value_counts()
```

```
count_of_each_floor.to_frame()
```

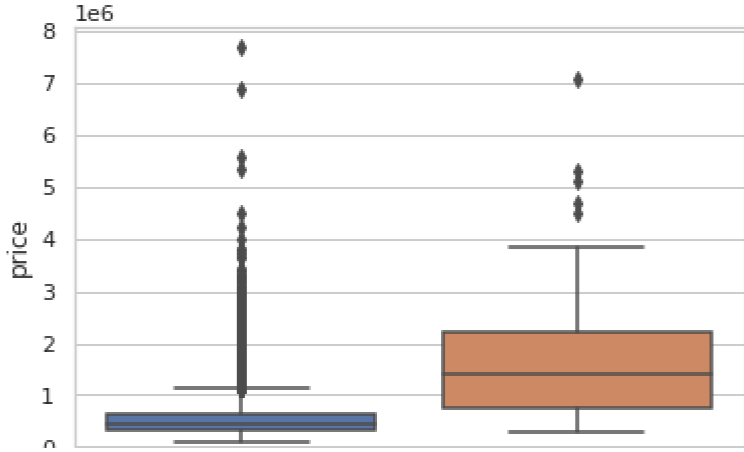
	floors
1.0	10680
2.0	8241
1.5	1910
3.0	613
2.5	161
3.5	8

Question 4

Use the function `boxplot` in the seaborn library to determine whether houses with a waterfront view or without a waterfront view have more price outliers.

```
sns.boxplot(x =df['waterfront'], y =df['price'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff73c55c450>
```

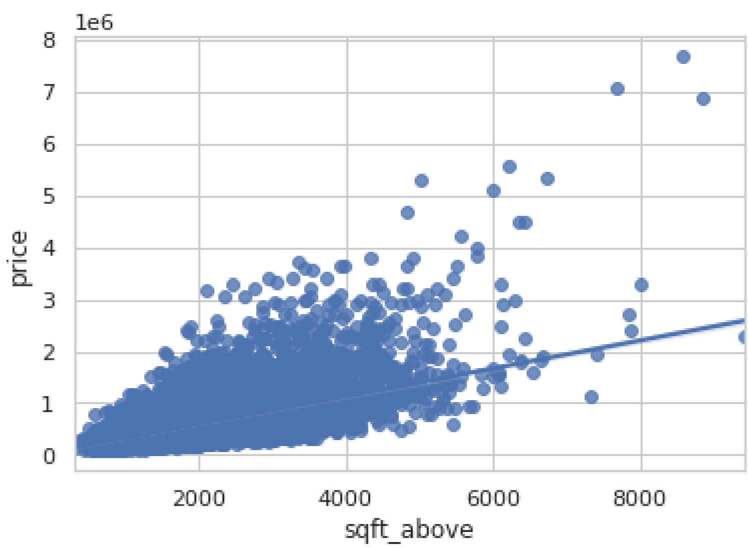


Question 5

Use the function `regplot` in the seaborn library to determine if the feature `sqft_above` is negatively or positively correlated with price.

```
sns.regplot(x=df["sqft_above"],y=df["price"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff73c3f7dd0>
```



We can use the Pandas method `corr()` to find the feature other than price that is most correlated with price.

```
df.corr()['price'].sort_values()
```

```
zipcode        -0.053203
long            0.021626
condition       0.036362
yr_built        0.054012
sqft_lot15      0.082447
```

```
sqft_lot         0.089661
yr_renovated     0.126434
floors           0.256794
waterfront       0.266369
lat              0.307003
bedrooms         0.308797
sqft_basement    0.323816
view             0.397293
bathrooms        0.525738
sqft_living15    0.585379
sqft_above       0.605567
grade            0.667434
sqft_living      0.702035
price            1.000000
Name: price, dtype: float64
```

Module 4: Model Development

We can Fit a linear regression model using the longitude feature `'long'` and caculate the R^2.

```
X = df[['long']]
Y = df['price']
lm = LinearRegression()
lm.fit(X,Y)
lm.score(X, Y)
```

```
0.00046769430149007363
```

Question 6

Fit a linear regression model to predict the `'price'` using the feature `'sqft_living'` then calculate the R^2. Take a screenshot of your code and the value of the R^2.

```
X = df[['sqft_living']]
Y = df['price']
lm = LinearRegression()
lm.fit(X,Y)
lm.score(X, Y)
```

```
0.49285321790379316
```

Question 7

Fit a linear regression model to predict the `'price'` using the list of features:

```
features =["floors", "waterfront","lat" ,"bedrooms" ,"sqft_basement" ,"view" ,"bathrooms","sq
```

Then calculate the R^2. Take a screenshot of your code.

```
X = df[features]
Y = df['price']
lm = LinearRegression()
lm.fit(X,Y)
lm.score(X, Y)
```

```
0.6576581908525534
```

This will help with Question 8

Create a list of tuples, the first element in the tuple contains the name of the estimator:

`'scale'`

`'polynomial'`

`'model'`

The second element in the tuple contains the model constructor

`StandardScaler()`

`PolynomialFeatures(include_bias=False)`

`LinearRegression()`

```
Input=[('scale',StandardScaler()),('polynomial', PolynomialFeatures(include_bias=False)),('mo
```

Question 8

Use the list to create a pipeline object to predict the 'price', fit the object using the features in the list `features`, and calculate the R^2.

```
X = df[features]
Y = df['price']
pipe=Pipeline(Input)
pipe.fit(X,Y)
pipe.score(X, Y)
```

```
0.7513410482623407
```

Module 5: Model Evaluation and Refinement

Import the necessary modules:

```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
print("done")
```

```
done
```

We will split the data into training and testing sets:

```
features =["floors", "waterfront","lat" ,"bedrooms" ,"sqft_basement" ,"view" ,"bathrooms","sq
X = df[features]
Y = df['price']

x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.15, random_state=1)


print("number of test samples:", x_test.shape[0])
print("number of training samples:",x_train.shape[0])
```

```
number of test samples: 3242
number of training samples: 18371
```

Question 9

Create and fit a Ridge regression object using the training data, set the regularization parameter to 0.1, and calculate the R^2 using the test data.

```
from sklearn.linear_model import Ridge


rm=Ridge(alpha=0.1)
rm.fit(x_train,y_train)
rm.score(x_test,y_test)
```

```
0.6478759163939117
```

Question 10

Perform a second order polynomial transform on both the training data and testing data. Create and fit a Ridge regression object using the training data, set the regularisation parameter to 0.1, and calculate the R^2 utilising the test data provided. Take a screenshot of your code and the R^2.

```
pr= PolynomialFeatures(degree=2)
X_train_pr = pr.fit_transform(x_train)
X_test_pr =pr.fit_transform(x_test)
rr = Ridge(alpha=0.1)
rr.fit(X_train_pr,y_train)
rr.score(X_test_pr,y_test)
```

```
0.7002744277220405
```