Data Analysis with Python

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.

Variable	Description
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:

In [1]:
```
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:

In [2]:
```
file_name='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/FinalModule_Coursera/data/kc_house_data_NaN.csv'
df=pd.read_csv(file_name)
```

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

In [3]:
```python
df.head()
```

Out[3]:

	Unnamed: 0	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	...	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	long	sqft_living15	sqft_lot15
0	0	7129300520	20141013T000000	221900.0	3.0	1.00	1180	5650	1.0	0	...	7	1180	0	1955	0	98178	47.5112	-122.257	1340	5650
1	1	6414100192	20141209T000000	538000.0	3.0	2.25	2570	7242	2.0	0	...	7	2170	400	1951	1991	98125	47.7210	-122.319	1690	7639
2	2	5631500400	20150225T000000	180000.0	2.0	1.00	770	10000	1.0	0	...	6	770	0	1933	0	98028	47.7379	-122.233	2720	8062
3	3	2487200875	20141209T000000	604000.0	4.0	3.00	1960	5000	1.0	0	...	7	1050	910	1965	0	98136	47.5208	-122.393	1360	5000
4	4	1954400510	20150218T000000	510000.0	3.0	2.00	1680	8080	1.0	0	...	8	1680	0	1987	0	98074	47.6168	-122.045	1800	7503

5 rows × 22 columns

Question 1

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

In [4]:
```python
df.dtypes
```

Out[4]:
```
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.

In [5]:
```python
df.describe()
```

Out[5]:

	Unnamed: 0	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	long	sqft_living15	sqft_lot15
count	21613.00000	2.161300e+04	2.161300e+04	21600.000000	21603.000000	21613.000000	2.161300e+04	21613.000000	21613.000000	21613.000000	...	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000
mean	10806.00000	4.580302e+09	5.400881e+05	3.372870	2.115736	2079.899736	1.510697e+04	1.494309	0.007542	0.234303	...	7.656873	1788.390691	291.509045	1971.005136	84.402258	98077.939805	47.560053	-122.213896	1986.552492	12768.455652
std	6239.28002	2.876566e+09	3.671272e+05	0.926657	0.768996	918.440897	4.142051e+04	0.539989	0.086517	0.766318	...	1.175459	828.090978	442.575043	29.373411	401.679240	53.505026	0.138564	0.140828	685.391304	27304.179631
min	0.00000	1.000102e+06	7.500000e+04	1.000000	0.500000	290.000000	5.200000e+02	1.000000	0.000000	0.000000	...	1.000000	290.000000	0.000000	1900.000000	0.000000	98001.000000	47.155900	-122.519000	399.000000	651.000000
25%	5403.00000	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	0.000000	0.000000	...	7.000000	1190.000000	0.000000	1951.000000	0.000000	98033.000000	47.471000	-122.328000	1490.000000	5100.000000
50%	10806.00000	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.000000	...	7.000000	1560.000000	0.000000	1975.000000	0.000000	98065.000000	47.571800	-122.230000	1840.000000	7620.000000
75%	16209.00000	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	0.000000	0.000000	...	8.000000	2210.000000	560.000000	1997.000000	0.000000	98118.000000	47.678000	-122.125000	2360.000000	10083.000000
max	21612.00000	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.000000	...	13.000000	9410.000000	4820.000000	2015.000000	2015.000000	98199.000000	47.777600	-121.315000	6210.000000	871200.000000

8 rows × 21 columns

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`

In [6]:
```python
df.drop(['id','Unnamed: 0'],axis=1,inplace=True)
df.describe()
```

Out[6]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	long	sqft_living15	sqft_lot15
count	2.161300e+04	21600.000000	21603.000000	21613.000000	2.161300e+04	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000
mean	5.400881e+05	3.372870	2.115736	2079.899736	1.510697e+04	1.494309	0.007542	0.234303	3.409430	7.656873	1788.390691	291.509045	1971.005136	84.402258	98077.939805	47.560053	-122.213896	1986.552492	12768.455652
std	3.671272e+05	0.926657	0.768996	918.440897	4.142051e+04	0.539989	0.086517	0.766318	0.650743	1.175459	828.090978	442.575043	29.373411	401.679240	53.505026	0.138564	0.140828	685.391304	27304.179631
min	7.500000e+04	1.000000	0.500000	290.000000	5.200000e+02	1.000000	0.000000	0.000000	1.000000	1.000000	290.000000	0.000000	1900.000000	0.000000	98001.000000	47.155900	-122.519000	399.000000	651.000000
25%	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	0.000000	0.000000	3.000000	7.000000	1190.000000	0.000000	1951.000000	0.000000	98033.000000	47.471000	-122.328000	1490.000000	5100.000000
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.000000	3.000000	7.000000	1560.000000	0.000000	1975.000000	0.000000	98065.000000	47.571800	-122.230000	1840.000000	7620.000000
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	0.000000	0.000000	4.000000	8.000000	2210.000000	560.000000	1997.000000	0.000000	98118.000000	47.678000	-122.125000	2360.000000	10083.000000
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.000000	5.000000	13.000000	9410.000000	4820.000000	2015.000000	2015.000000	98199.000000	47.777600	-121.315000	6210.000000	871200.000000

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

In [7]:
```
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`

In [8]:
```
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`

In [9]:
```
mean=df['bathrooms'].mean()
df['bathrooms'].replace(np.nan,mean, inplace=True)
```

In [10]:
```
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.

In [11]:
```
df['floors'].value_counts().to_frame()
```

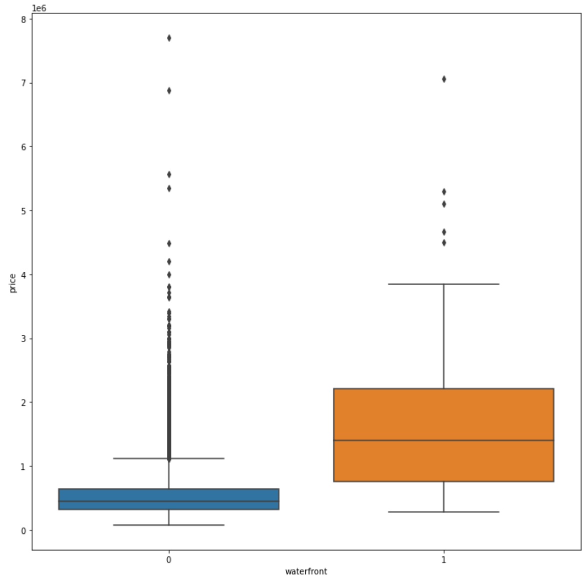
Out[11]:

	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.

In [12]:
```
width, height=12,12
wf=df[['waterfront','price']]
plt.figure(figsize=(width,height))
ax = sns.boxplot(x='waterfront',y='price',data=wf)

## Will change the labels to be more defined.
    # xticks = ["Without \n Waterfront","With \n Waterfront"]
    # ax.set_xticklabels(xticks)


## Useful in other contexts, just not in this one
    # wf=pd.get_dummies(wf,columns=['waterfront'])
```

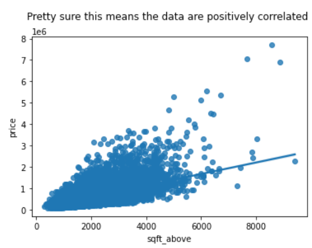


Question 5

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

In [13]:
```
# sns.set_theme(color_codes=True)
sns.regplot(x="sqft_above",y="price",data=df).set(title="Pretty sure this means the data are positively correlated \n")
```

Out[13]: [Text(0.5, 1.0, 'Pretty sure this means the data are positively correlated \n')]



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

In [14]:
```
df.corr()['price'].sort_values(ascending=False)
```

Out[14]:
```
price            1.000000
sqft_living      0.702035
grade            0.667434
sqft_above       0.605567
sqft_living15    0.585379
bathrooms        0.525738
view             0.397293
sqft_basement    0.323816
bedrooms         0.308797
lat              0.307003
waterfront       0.266369
floors           0.256794
yr_renovated     0.126434
sqft_lot         0.089661
sqft_lot15       0.082447
yr_built         0.054012
condition        0.036362
long             0.021626
zipcode         -0.053203
Name: price, dtype: float64
```

Module 4: Model Development

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

In [15]:
```
X = df[['long']]
Y = df['price']
lm = LinearRegression()
lm.fit(X,Y)
lm.score(X, Y)
```

Out[15]:
```
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.

written by the student

Recall the form of a simple linear regression for a single variable is of the form

$$\hat{Y} = a_0 + a_1 X$$

In [16]:
```
X = df[['sqft_living']]
Y = df['price']
lm = LinearRegression()
lm.fit(X,Y)

##predicted price
Yhat=lm.predict(X)
##intercept
a1=lm.coef_
##slope
a2=lm.intercept_
##correlation of 'sqft_living' and 'price'
R=df['sqft_living'].corr(df['price'])
print("Here is a list of linear regression statistics:")
print("Slope: ",a1)
print("Intercept: ", a2)
print("Coefficient of correlation of sqft_living and price: ",R)
print("Coefficient of determination:",lm.score(X, Y))
```

```
Here is a list of linear regression statistics:
Slope:  [280.6235679]
Intercept:  -43580.743094473146
Coefficient of correlation of sqft_living and price:  0.7020350546117996
Coefficient of determination: 0.4928532179037931
```

Question 7

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

In [17]:
```
features = ["floors", "waterfront","lat" ,"bedrooms" ,"sqft_basement" ,"view" ,"bathrooms","sqft_living15","sqft_above","grade","sqft_living"]
```

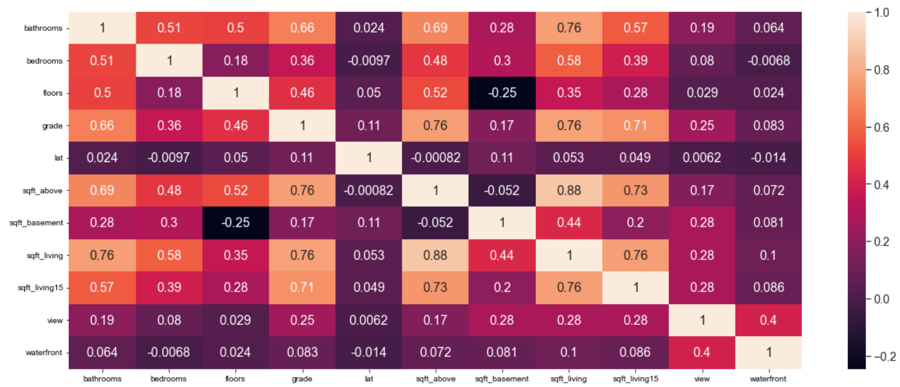
Then calculate the R^2. Take a screenshot of your code.

In [18]:
```python
X = df[features]
Y = df['price']
lm = LinearRegression()
lm.fit(X,Y)
##predicted price
Yhat=lm.predict(X)
##intercept
a1=lm.coef_
##slope
a2=lm.intercept_
##correlation of featires and price
R=np.sqrt(lm.score(X,Y))
print("Here is a list of linear regression statistics:")
print("Slope: ",a1)
print("Intercept: ", a2)
print("correlation of features and price: ",R)
print("coefficient of determination:",lm.score(X, Y))

# sns.pairplot(df[features],kind='reg')
```

```
Here is a list of linear regression statistics:
Slope:  [-2.75903200e+04  6.08735587e+05  6.73727152e+05 -2.55611780e+04
 -3.15550843e+15  6.71159510e+04 -1.20458167e+03  7.41464758e+00
 -3.15550843e+15  8.20123187e+04  3.15550843e+15]
Intercept:  -32428996.244040627
correlation of features and price:  0.810948393594544
coefficient of determination: 0.6576372970735713
```

In [19]:
```python
#Individual correlation for each feature with respect to every other feature.
mydf=df[sorted(features)]    # to show the fields alphabetically.
fig, ax = plt.subplots(figsize=(20, 8))
sns.set(font_scale=1.3)
sns.heatmap(mydf.corr(),annot=True)
```

Out[19]: <AxesSubplot:>



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()`

In [20]:
```python
Input=[('scale',StandardScaler()),('polynomial', PolynomialFeatures(include_bias=False)),('model',LinearRegression())]
```

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.

In [21]:
```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

In [22]:
```
features = ["floors", "waterfront","lat" ,"bedrooms" ,
            "sqft_basement" ,"view" ,"bathrooms","sqft_living15",
            "sqft_above","grade","sqft_living"]

Input=[('scale',StandardScaler()),
       ('polynomial', PolynomialFeatures(include_bias=False)),
       ('model',LinearRegression())]
pipe=Pipeline(Input)

df_features=df[features]
df_price=df['price']
# lm.fit(df_features, df_price)
# lm.intercept_
# lm.coef_
# lm.predict(df_features)
pipe.fit(df_features,df_price)
pipe.predict(df_features)
```

Out[22]:
```
array([351376., 562952., 450802., ..., 418916., 461724., 418820.])
```

In [23]:
```
from sklearn.metrics import r2_score
print("The correlation coefficient R^2 for this pipeline is:",r2_score(pipe.predict(df_features),df_price))
```

```
The correlation coefficient R^2 for this pipeline is: 0.6641557176322042
```

Module 5: Model Evaluation and Refinement

Import the necessary modules:

In [24]:
```
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:

In [25]:
```
features =["floors", "waterfront","lat" ,"bedrooms" ,"sqft_basement" ,"view" ,"bathrooms","sqft_living15","sqft_above","grade","sqft_living"]
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.

In [26]:
```
from sklearn.linear_model import Ridge
```

In [27]:
```
# Create and fit a Ridge regression object using the training data
    # set the regularization parameter to 0.1
RR_train=Ridge(alpha=0.1)
RR_train.fit(x_train, y_train)

# calculate the R^2 using the test data
print("R^2 for the training model on the testing data is: ",RR_train.score(x_test,y_test))
```

```
R^2 for the training model on the testing data is:  0.6478759163939116
```

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.

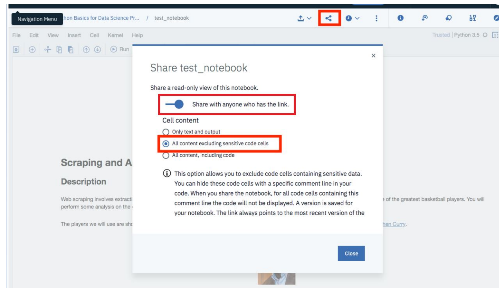
Added By Student

Hidden old code that I didn't end up using but don't want to delete and hid so you don't get confused

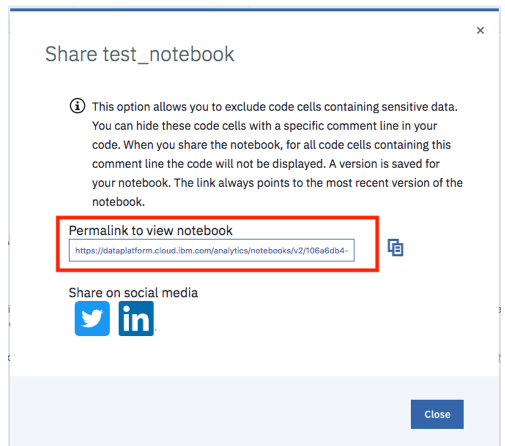
```python
## Perform a second order polynomial transform on both the training data and testing data.
pr=PolynomialFeatures(degree=2)
x_train_pr=pr.fit_transform(x_train)
x_test_pr=pr.fit_transform(x_test)

## Create and fit a Ridge regression object using the training data
RR1_train=Ridge(alpha=0.1)
RR1_train.fit(x_train_pr, y_train)
yhat_train_pr = RR1_train.predict(x_train_pr)

## Calculate the R^2 utilising the test data provided
print("The Training model applied to the test data has an R^2 of: ",RR1_train.score(x_test_pr,y_test))
```

```
The Training model applied to the test data has an R^2 of:  0.700274426566343
```

Once you complete your notebook you will have to share it. Select the icon on the top right a marked in red in the image below, a dialogue box should open, and select the option all content excluding sensitive code cells.



You can then share the notebook via a URL by scrolling down as shown in the following image:



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Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2020-12-01	2.2	Aije Egwaikhide	Coverted Data describtion from text to table
2020-10-06	2.1	Lakshmi Holla	Changed markdown instruction of Question1
2020-08-27	2.0	Malika Singla	Added lab to GitLab