FINAL PROJECT - House_Sales_in_King_Count_USA

May 27, 2025

1 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:

[15]:
```
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
```

2 Module 1: Importing Data Sets

Load the csv:

[16]:
```
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.

[17]:
```
df.head()
```

[17]:
```
   Unnamed: 0          id             date     price  bedrooms  bathrooms  \
0           0  7129300520  20141013T000000  221900.0       3.0       1.00
1           1  6414100192  20141209T000000  538000.0       3.0       2.25
2           2  5631500400  20150225T000000  180000.0       2.0       1.00
3           3  2487200875  20141209T000000  604000.0       4.0       3.00
4           4  1954400510  20150218T000000  510000.0       3.0       2.00

   sqft_living  sqft_lot  floors  waterfront  …  grade  sqft_above  \
0         1180      5650     1.0           0  …      7        1180
1         2570      7242     2.0           0  …      7        2170
2          770     10000     1.0           0  …      6         770
3         1960      5000     1.0           0  …      7        1050
4         1680      8080     1.0           0  …      8        1680

   sqft_basement  yr_built  yr_renovated  zipcode      lat     long  \
0              0      1955             0    98178  47.5112 -122.257
1            400      1951          1991    98125  47.7210 -122.319
2              0      1933             0    98028  47.7379 -122.233
3            910      1965             0    98136  47.5208 -122.393
4              0      1987             0    98074  47.6168 -122.045

   sqft_living15  sqft_lot15
0           1340        5650
1           1690        7639
2           2720        8062
3           1360        5000
4           1800        7503

[5 rows x 22 columns]
```

2.0.1 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.

[18]:
```
df.dtypes
```

[18]:
```
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.

[19]:
```
df.describe()
```

[19]:

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

	sqft_living	sqft_lot	floors	waterfront	view	\
count	21613.000000	2.161300e+04	21613.000000	21613.000000	21613.000000	
mean	2079.899736	1.510697e+04	1.494309	0.007542	0.234303	
std	918.440897	4.142051e+04	0.539989	0.086517	0.766318	

```
min      290.000000  5.200000e+02      1.000000      0.000000      0.000000
25%     1427.000000  5.040000e+03      1.000000      0.000000      0.000000
50%     1910.000000  7.618000e+03      1.500000      0.000000      0.000000
75%     2550.000000  1.068800e+04      2.000000      0.000000      0.000000
max    13540.000000  1.651359e+06      3.500000      1.000000      4.000000

       …         grade    sqft_above  sqft_basement      yr_built  \
count  …  21613.000000  21613.000000   21613.000000  21613.000000
mean   …      7.656873   1788.390691     291.509045   1971.005136
std    …      1.175459    828.090978     442.575043     29.373411
min    …      1.000000    290.000000       0.000000   1900.000000
25%    …      7.000000   1190.000000       0.000000   1951.000000
50%    …      7.000000   1560.000000       0.000000   1975.000000
75%    …      8.000000   2210.000000     560.000000   1997.000000
max    …     13.000000   9410.000000    4820.000000   2015.000000

       yr_renovated       zipcode           lat          long  sqft_living15  \
count  21613.000000  21613.000000  21613.000000  21613.000000   21613.000000
mean      84.402258  98077.939805     47.560053   -122.213896    1986.552492
std      401.679240     53.505026      0.138564      0.140828     685.391304
min        0.000000  98001.000000     47.155900   -122.519000     399.000000
25%        0.000000  98033.000000     47.471000   -122.328000    1490.000000
50%        0.000000  98065.000000     47.571800   -122.230000    1840.000000
75%        0.000000  98118.000000     47.678000   -122.125000    2360.000000
max     2015.000000  98199.000000     47.777600   -121.315000    6210.000000

          sqft_lot15
count   21613.000000
mean    12768.455652
std     27304.179631
min       651.000000
25%      5100.000000
50%      7620.000000
75%     10083.000000
max    871200.000000

[8 rows x 21 columns]
```

3 Module 2: Data Wrangling

3.0.1 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

[20]:
```
df.drop("id", axis = 1, inplace = True)
df.drop("Unnamed: 0", axis = 1, inplace = True)
df.describe()
```

[20]:

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

	floors	waterfront	view	condition	grade
count	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000
mean	1.494309	0.007542	0.234303	3.409430	7.656873
std	0.539989	0.086517	0.766318	0.650743	1.175459
min	1.000000	0.000000	0.000000	1.000000	1.000000
25%	1.000000	0.000000	0.000000	3.000000	7.000000
50%	1.500000	0.000000	0.000000	3.000000	7.000000
75%	2.000000	0.000000	0.000000	4.000000	8.000000
max	3.500000	1.000000	4.000000	5.000000	13.000000

	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode
count	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000
mean	1788.390691	291.509045	1971.005136	84.402258	98077.939805
std	828.090978	442.575043	29.373411	401.679240	53.505026
min	290.000000	0.000000	1900.000000	0.000000	98001.000000
25%	1190.000000	0.000000	1951.000000	0.000000	98033.000000
50%	1560.000000	0.000000	1975.000000	0.000000	98065.000000
75%	2210.000000	560.000000	1997.000000	0.000000	98118.000000
max	9410.000000	4820.000000	2015.000000	2015.000000	98199.000000

	lat	long	sqft_living15	sqft_lot15
count	21613.000000	21613.000000	21613.000000	21613.000000
mean	47.560053	-122.213896	1986.552492	12768.455652
std	0.138564	0.140828	685.391304	27304.179631
min	47.155900	-122.519000	399.000000	651.000000
25%	47.471000	-122.328000	1490.000000	5100.000000
50%	47.571800	-122.230000	1840.000000	7620.000000
75%	47.678000	-122.125000	2360.000000	10083.000000
max	47.777600	-121.315000	6210.000000	871200.000000

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

```
[21]: 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

```
[22]: 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

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

```
[24]: 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
```

4 Module 3: Exploratory Data Analysis

4.0.1 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.

```
[25]: df["floors"].value_counts().to_frame()
```

[25]:

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

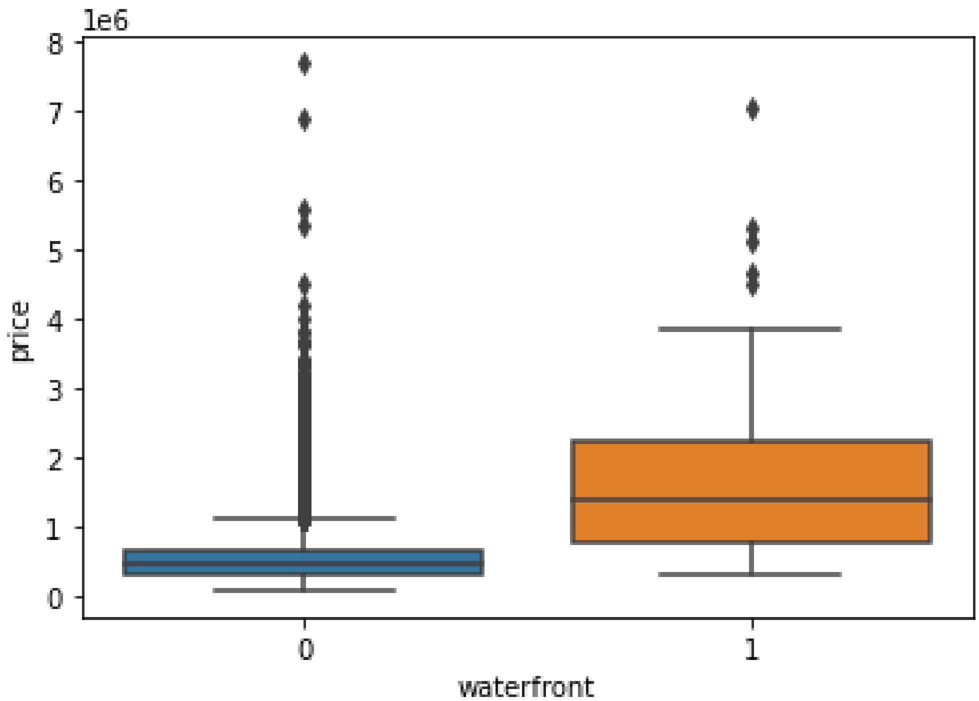
4.0.2 Question 4

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.

[26]:
```
sns.boxplot(x = 'waterfront', y= 'price', data = df)

#The Boxplot for houses without a waterfront view has many more outlier points
#beyond its upper extremes than the boxplot for houses with a waterfront view.
```

[26]: <AxesSubplot:xlabel='waterfront', ylabel='price'>



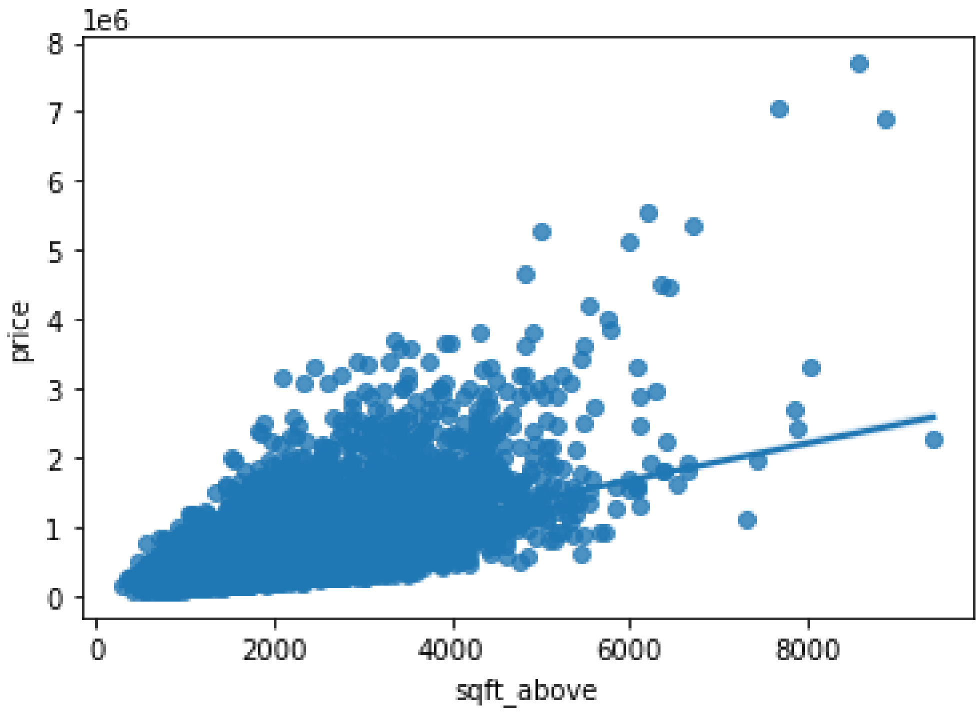
4.0.3 Question 5

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

[27]:
```
sns.regplot(x = 'sqft_above', y = 'price', data = df)

#Sqft_above is postiviely correlated with price based on the graph. The
↪regression line has a positive slope.
```

[27]: <AxesSubplot:xlabel='sqft_above', ylabel='price'>



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

[28]:
```
df.corr()['price'].sort_values()
```

[28]:
```
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
```

5 Module 4: Model Development

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

[29]:
```
X = df[['long']]
Y = df['price']
lm = LinearRegression()
lm.fit(X,Y)
r_squared = lm.score(X, Y)

print("r-squared is: ", r_squared)
```

```
r-squared is:  0.00046769430149029567
```

5.0.1 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.

[30]:
```
lm = LinearRegression()
X = df[['sqft_living']]
Y = df['price']
lm.fit(X,Y)
yhat = lm.predict(X)
r_squared = lm.score(X,Y)

print("r-squared is: ", r_squared)
print("First few predicted y values: ",  yhat[0:5])
```

```
r-squared is:  0.4928532179037931
First few predicted y values:  [287555.06702452 677621.82640197 172499.40418656
506441.44998452
 427866.85097324]
```

5.0.2 Question 7

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

[31]:
```
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.

[32]:
```
lm = LinearRegression()
X = df[features]
Y = df['price']
```

```
lm.fit(X, Y)
yhat = lm.predict(X)
r_squared = lm.score(X, Y)

print("r-squared is: ",  r_squared)
print("First few predicted y values: ",  yhat[0:5])
```

```
r-squared is:  0.6576951666037495
First few predicted y values:  [283270.39007439 662572.30128733 306267.58455133
408476.54986727
 532313.80775074]
```

5.0.3 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()

[33]:
```
Input=[('scale',StandardScaler()),('polynomial',␣
↪PolynomialFeatures(include_bias=False)),('model',LinearRegression())]
```

5.0.4 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.

[34]:
```
pipe = Pipeline(Input)          #Pass inputs into piepline constructor
Z = df[features].astype(float) #Z contains all of our needed features in float␣
↪form to avoid problems
pipe.fit(Z, Y)                  #fit (and normalize & transform) the model

yhat = pipe.predict(Z)          #Get predicted price values
r_squared = pipe.score(Z,Y)     #Calculate the r-squared

print("r-squared is: ", r_squared)
print("First few predicted y values: ",  yhat[0:5])
```

```
r-squared is:  0.751340143833189
First few predicted y values:  [349644.125 559088.125 449488.125 393224.125
521702.125]
```

6 Module 5: Model Evaluation and Refinement

Import the necessary modules:

[36]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
```

We will split the data into training and testing sets:

[37]:
```
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
```

6.0.1 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.

[38]:
```
from sklearn.linear_model import Ridge
```

[39]:
```
RidgeModel = Ridge(alpha = 0.1)
RidgeModel.fit(x_train, y_train )
r_squared = RidgeModel.score(x_test, y_test)

print("r-squared is: ", r_squared)
```

```
r-squared is:  0.6478759163939116
```

6.0.2 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.

[40]:
```
#Do a degree 2 polynomial transformation on training & testing data:

pt = PolynomialFeatures(degree = 2)
x_train_pt = pt.fit_transform(x_train) #Polynomial transform the training data
x_test_pt = pt.fit_transform(x_test)   #Polynomial transform the testing data
```

```
#Create & fit a ridge regression object. Find r-squared.

RidgeModel = Ridge(alpha = 0.1)
RidgeModel.fit(x_train_pt, y_train)
r_squared = RidgeModel.score(x_test_pt, y_test)

print("r-squared is: ", r_squared)
```

```
r-squared is:  0.700274426746305
```