final assinment coding

May 2, 2020

[2]:
```
House Sales in King County, USA

id :a notation for a house

date: Date house was sold

price: Price is prediction target

bedrooms: Number of Bedrooms/House

bathrooms: Number of bathrooms/bedrooms

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
%matplotlib inline
```

[3]:
```
file_name='https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/
 ↪CognitiveClass/DA0101EN/coursera/project/kc_house_data_NaN.csv'
df=pd.read_csv(file_name)
```

[4]:
```
df.head()
```

[4]:

	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]
```

[5]:
```
print(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
```

[6]:
```
df.describe()
```

[6]:
```
        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]
```

[7]:
```
df.drop(['id', 'Unnamed: 0'], axis=1, inplace=True)
df.describe()
```

[7]:
```
              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
```

[8]:
```
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
```

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

[10]:
```
mean=df['bathrooms'].mean()
df['bathrooms'].replace(np.nan,mean, inplace=True)
```

[11]:
```
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
```

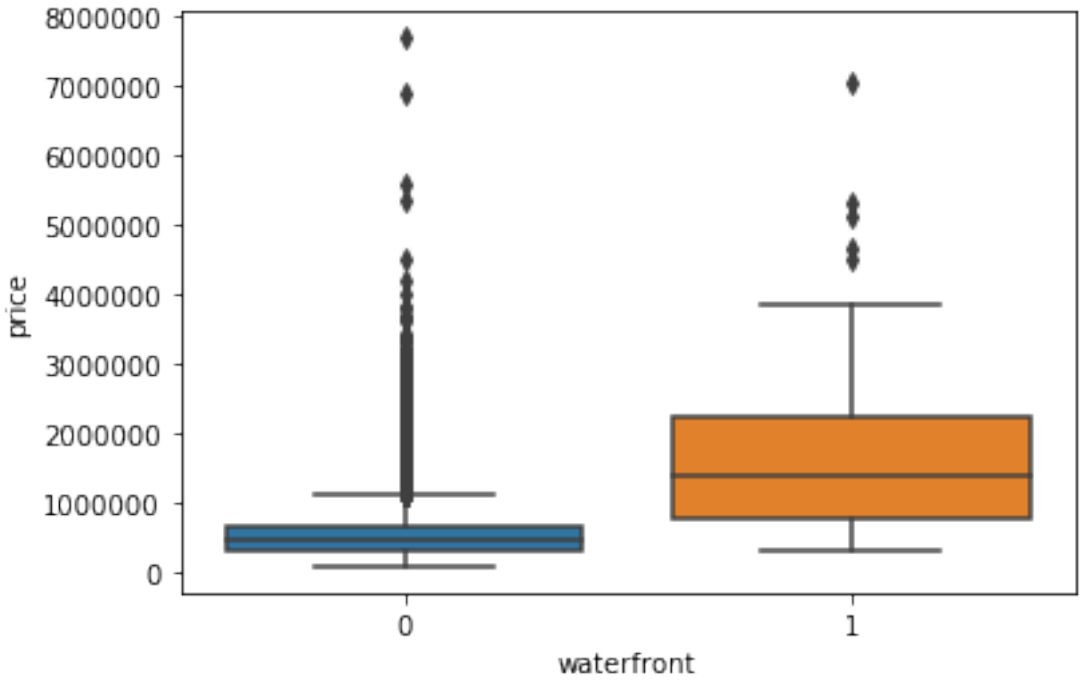
[12]:
```
df['floors'].value_counts().to_frame()
```

[12]:

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

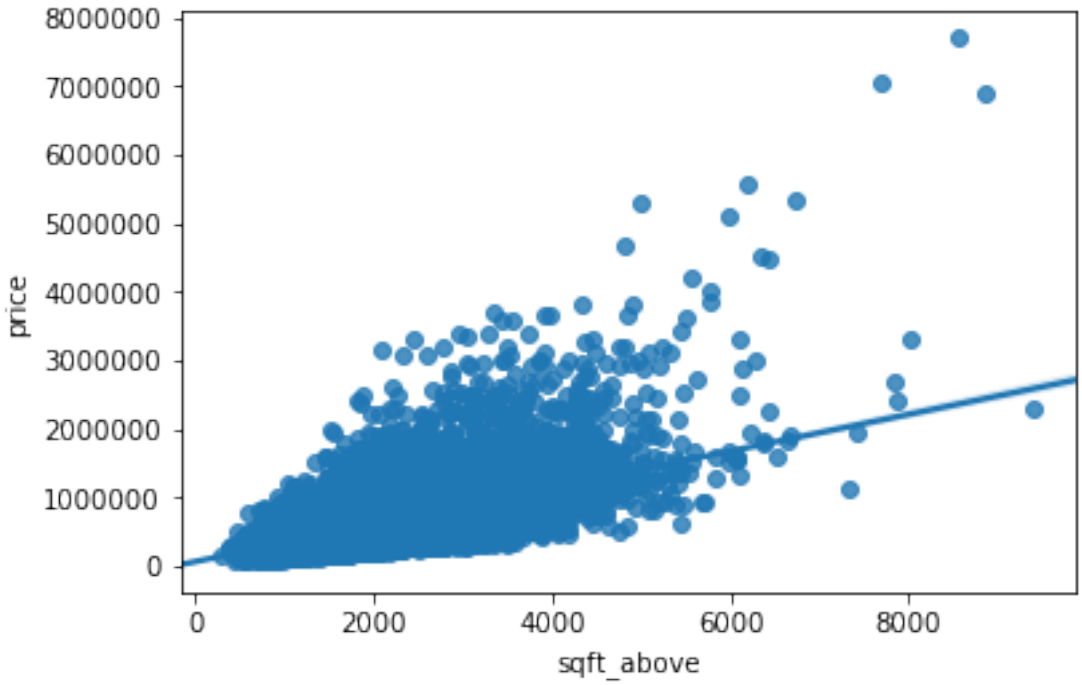
[15]:
```
sns.boxplot(x='waterfront', y='price', data=df)
```

[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3cad5a4400>
```



[16]:
```
sns.regplot(x='sqft_above', y='price', data=df)
```

[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3cad522588>
```



[17]:
```
df.corr()['price'].sort_values()
```

[17]:
```
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
```

[18]:
```
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
```

[19]:
```
X = df[['long']]
Y = df['price']
lm = LinearRegression()
lm
lm.fit(X,Y)
lm.score(X, Y)
```

[19]:
```
0.00046769430149007363
```

[20]:
```
X = df[['sqft_living']]
Y = df['price']
lm = LinearRegression()
lm.fit(X, Y)
lm.score(X, Y)
```

[20]:
```
0.49285321790379316
```

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

[22]:
```
X = df[features]
Y= df['price']
lm = LinearRegression()
lm.fit(X, Y)
lm.score(X, Y)
```

[22]:
```
0.6576527411217378
```

[36]:
```
'scale'

'polynomial'

'model'

'The second element in the tuple contains the model constructor'

StandardScaler()

PolynomialFeatures(include_bias=False)

LinearRegression()
```

[36]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

[37]:
```
Input=[('scale',StandardScaler()),('polynomial',␣
↪PolynomialFeatures(include_bias=False)),('model',LinearRegression())]
```

[ ]:
```
pipe=Pipeline(Input)
pipe
```

[39]:
```
pipe.fit(X,Y)
```

```
/home/jupyterlab/conda/envs/python/lib/python3.6/site-
packages/sklearn/preprocessing/data.py:625: DataConversionWarning: Data with
input dtype int64, float64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
/home/jupyterlab/conda/envs/python/lib/python3.6/site-
packages/sklearn/base.py:465: DataConversionWarning: Data with input dtype
int64, float64 were all converted to float64 by StandardScaler.
  return self.fit(X, y, **fit_params).transform(X)
```

[39]:
```
Pipeline(memory=None,
     steps=[('scale', StandardScaler(copy=True, with_mean=True, with_std=True)),
('polynomial', PolynomialFeatures(degree=2, include_bias=False,
interaction_only=False)), ('model', LinearRegression(copy_X=True,
fit_intercept=True, n_jobs=None,
         normalize=False))])
```

[40]:
```
pipe.score(X,Y)
```

```
/home/jupyterlab/conda/envs/python/lib/python3.6/site-
packages/sklearn/pipeline.py:511: DataConversionWarning: Data with input dtype
int64, float64 were all converted to float64 by StandardScaler.
  Xt = transform.transform(Xt)
```

[40]:
```
0.7513406368483374
```

[41]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
print("done")
```

```
done
```

[42]:
```
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
```

[43]:
```
from sklearn.linear_model import Ridge
```

[44]:
```
RidgeModel = Ridge(alpha = 0.1)
RidgeModel.fit(x_train, y_train)
RidgeModel.score(x_test, y_test)
```

[44]:
```
0.6478759163939115
```

[45]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import Ridge
pr = PolynomialFeatures(degree=2)
x_train_pr = pr.fit_transform(x_train)
x_test_pr = pr.fit_transform(x_test)
poly = Ridge(alpha=0.1)
poly.fit(x_train_pr, y_train)
poly.score(x_test_pr, y_test)
```

[45]:
```
0.7002744288456159
```

[ ]:
```

```