student

May 24, 2022

0.1 Final Project Submission

- Student name: JASWINDER SINGH
- Student pace: self paced / part time / full time
- Scheduled project review date/time:
- Instructor name: Hardik idnani
- BUSINESS PROBLEM : the stakeholder is expecting a posetive relationship between all the important attributes of the houses and the price.

1 IMPORTING LIBRARIES

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import scipy.stats as st
from scipy import stats
from scipy.stats import skew
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from statsmodels.formula.api import ols
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import StandardScaler
std=StandardScaler()
```

2 IMPORTING DATA

[2]:
```
data=pd.read_csv('kc_house_data.csv')
```

2.1 taking first look at data and understanding

[3]:
```
data.head(10)
```

[3]:
```
           id        date      price  bedrooms  bathrooms  sqft_living  \
0  7129300520  10/13/2014   221900.0         3       1.00         1180
1  6414100192   12/9/2014   538000.0         3       2.25         2570
2  5631500400   2/25/2015   180000.0         2       1.00          770
3  2487200875   12/9/2014   604000.0         4       3.00         1960
4  1954400510   2/18/2015   510000.0         3       2.00         1680
5  7237550310   5/12/2014  1230000.0         4       4.50         5420
6  1321400060   6/27/2014   257500.0         3       2.25         1715
7  2008000270   1/15/2015   291850.0         3       1.50         1060
8  2414600126   4/15/2015   229500.0         3       1.00         1780
9  3793500160   3/12/2015   323000.0         3       2.50         1890

   sqft_lot  floors  waterfront  view  …  grade  sqft_above  sqft_basement  \
0      5650     1.0         NaN   0.0  …      7        1180            0.0
1      7242     2.0         0.0   0.0  …      7        2170          400.0
2     10000     1.0         0.0   0.0  …      6         770            0.0
3      5000     1.0         0.0   0.0  …      7        1050          910.0
4      8080     1.0         0.0   0.0  …      8        1680            0.0
5    101930     1.0         0.0   0.0  …     11        3890         1530.0
6      6819     2.0         0.0   0.0  …      7        1715              ?
7      9711     1.0         0.0   NaN  …      7        1060            0.0
8      7470     1.0         0.0   0.0  …      7        1050          730.0
9      6560     2.0         0.0   0.0  …      7        1890            0.0

  yr_built  yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15
0     1955           0.0    98178  47.5112 -122.257           1340        5650
1     1951        1991.0    98125  47.7210 -122.319           1690        7639
2     1933           NaN    98028  47.7379 -122.233           2720        8062
3     1965           0.0    98136  47.5208 -122.393           1360        5000
4     1987           0.0    98074  47.6168 -122.045           1800        7503
5     2001           0.0    98053  47.6561 -122.005           4760      101930
6     1995           0.0    98003  47.3097 -122.327           2238        6819
7     1963           0.0    98198  47.4095 -122.315           1650        9711
8     1960           0.0    98146  47.5123 -122.337           1780        8113
9     2003           0.0    98038  47.3684 -122.031           2390        7570

[10 rows x 21 columns]
```

[4]:
```python
# cleaning data and dropping unnecessary columns
data.isna().sum()
data=data.drop(['date',
'view',
'sqft_above',
'sqft_basement',
'yr_renovated',
'zipcode',
'lat',
```

```
'long',
'sqft_living15',
'sqft_lot15','waterfront'],axis=1)
```

3 assumptions:

- normality: our data is looking to be normal, but to make sure, we will create visuals of every independent variable.
- linearity: the data is supposed to be linear,though we will remove some outliers if present
- Multicollinearity: as the data set is about the price of houses against the features of house, the Multicollinearity is * not supposed to be present as the dependent variable follows different independent variables
- Autocorrelation: we are assuming the this is not present in the data

[5]:
```
data.head(1)
```

[5]:
```
           id     price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  \
0  7129300520  221900.0         3        1.0         1180      5650     1.0

   condition  grade  yr_built
0          3      7      1955
```

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

[6]:
```
                 id         price      bedrooms     bathrooms   sqft_living  \
count  2.159700e+04  2.159700e+04  21597.000000  21597.000000  21597.000000
mean   4.580474e+09  5.402966e+05      3.373200      2.115826   2080.321850
std    2.876736e+09  3.673681e+05      0.926299      0.768984    918.106125
min    1.000102e+06  7.800000e+04      1.000000      0.500000    370.000000
25%    2.123049e+09  3.220000e+05      3.000000      1.750000   1430.000000
50%    3.904930e+09  4.500000e+05      3.000000      2.250000   1910.000000
75%    7.308900e+09  6.450000e+05      4.000000      2.500000   2550.000000
max    9.900000e+09  7.700000e+06     33.000000      8.000000  13540.000000

           sqft_lot        floors     condition         grade      yr_built
count  2.159700e+04  21597.000000  21597.000000  21597.000000  21597.000000
mean   1.509941e+04      1.494096      3.409825      7.657915   1970.999676
std    4.141264e+04      0.539683      0.650546      1.173200     29.375234
min    5.200000e+02      1.000000      1.000000      3.000000   1900.000000
25%    5.040000e+03      1.000000      3.000000      7.000000   1951.000000
50%    7.618000e+03      1.500000      3.000000      7.000000   1975.000000
75%    1.068500e+04      2.000000      4.000000      8.000000   1997.000000
max    1.651359e+06      3.500000      5.000000     13.000000   2015.000000
```

[7]:
```
# removing outliers, only considering the cases where the price is between␣
↪30000 and 700000 as it falls in the majority of the data
```

```
data = data.astype({'price':'int'})
data=data[(data['price'] >= 300000) & (data['price'] <= 700000)]
```

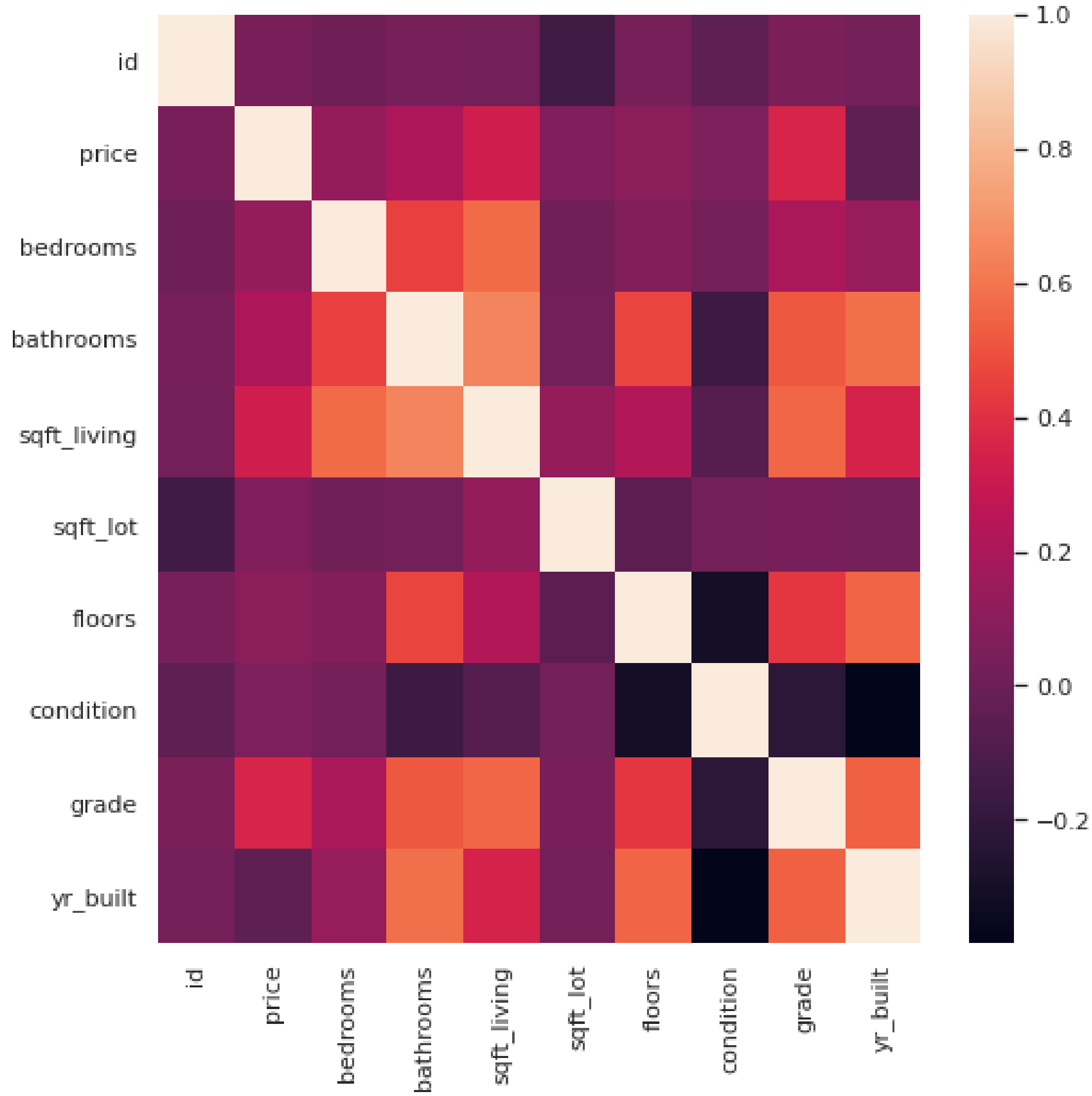
[8]:
```
data.corr()
```

[8]:
```
                   id     price  bedrooms  bathrooms  sqft_living  sqft_lot  \
id           1.000000  0.041012  0.001205   0.038139     0.025295 -0.145108
price        0.041012  1.000000  0.133458   0.210216     0.330074  0.060274
bedrooms     0.001205  0.133458  1.000000   0.446571     0.572897  0.019763
bathrooms    0.038139  0.210216  0.446571   1.000000     0.644385  0.025689
sqft_living  0.025295  0.330074  0.572897   0.644385     1.000000  0.132691
sqft_lot    -0.145108  0.060274  0.019763   0.025689     0.132691  1.000000
floors       0.036880  0.098756  0.073894   0.464352     0.226658 -0.051319
condition   -0.046310  0.059382  0.024514  -0.159436    -0.070331  0.027309
grade        0.050729  0.361308  0.205709   0.517827     0.552788  0.038840
yr_built     0.025829 -0.044638  0.136699   0.582732     0.347224  0.022745

               floors  condition     grade  yr_built
id           0.036880  -0.046310  0.050729  0.025829
price        0.098756   0.059382  0.361308 -0.044638
bedrooms     0.073894   0.024514  0.205709  0.136699
bathrooms    0.464352  -0.159436  0.517827  0.582732
sqft_living  0.226658  -0.070331  0.552788  0.347224
sqft_lot    -0.051319   0.027309  0.038840  0.022745
floors       1.000000  -0.310970  0.419620  0.551684
condition   -0.310970   1.000000 -0.219287 -0.382615
grade        0.419620  -0.219287  1.000000  0.537574
yr_built     0.551684  -0.382615  0.537574  1.000000
```

[9]:
```
sns.set(rc={'figure.figsize':(8, 8)})

# Use the .heatmap method to depict the relationships visually!
sns.heatmap(data.corr());
```



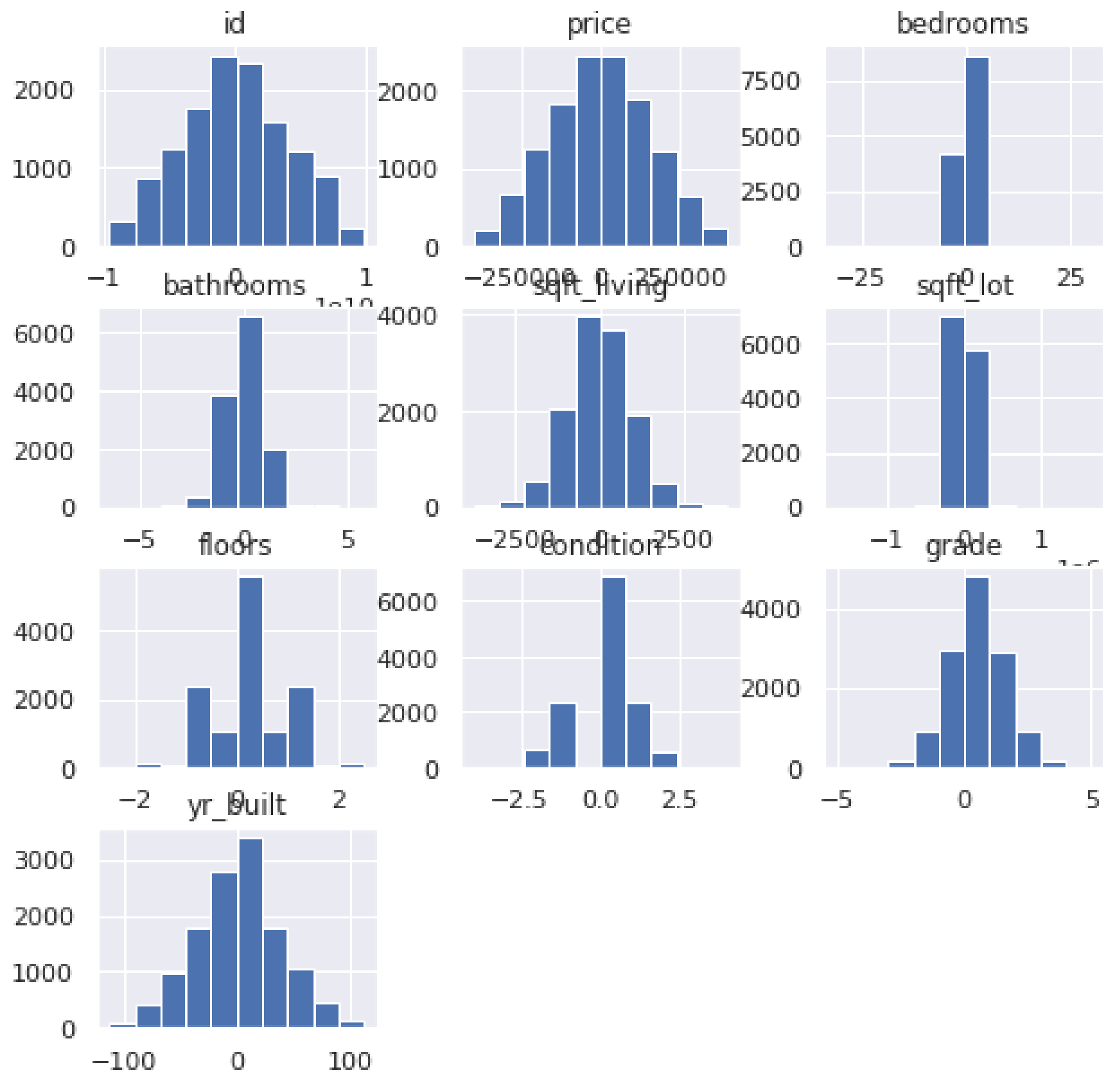
[10]:
```
data_corrs = data.corr()['price'].map(abs).sort_values(ascending=False)
data_corrs
```

[10]:
```
price          1.000000
grade          0.361308
sqft_living    0.330074
bathrooms      0.210216
bedrooms       0.133458
floors         0.098756
sqft_lot       0.060274
condition      0.059382
yr_built       0.044638
id             0.041012
```

```
Name: price, dtype: float64
```

here, we can see that the high correlation is shown by grade, sqft_living. but, to make it warking model for real life, we'll consider number of bedrooms and bathrooms as well

[11]:
```python
data.diff().hist();
```



4 creating first model

[12]:
```
data=pd.read_csv('kc_house_data.csv')
data=data.drop(['id','grade','condition','date',
'view',
'sqft_above',
'sqft_basement',
'yr_renovated',
'zipcode',
'lat',
'long',
'sqft_living15',
'sqft_lot15','waterfront'],axis=1)
data
x=data.drop(['price'],axis=1)
y=data['price']
X = sm.add_constant(x)

model = sm.OLS(y,x)
fitted_model = model.fit()
fitted_model.summary()
```

```
/opt/conda/lib/python3.9/site-packages/statsmodels/tsa/tsatools.py:142:
FutureWarning: In a future version of pandas all arguments of concat except for
the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

[12]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                 OLS Regression Results
================================================================================
=======
Dep. Variable:                  price   R-squared (uncentered):
0.844
Model:                            OLS   Adj. R-squared (uncentered):
0.844
Method:                 Least Squares   F-statistic:
1.952e+04
Date:                Tue, 24 May 2022   Prob (F-statistic):
0.00
Time:                        07:58:46   Log-Likelihood:
-2.9974e+05
No. Observations:               21597   AIC:
5.995e+05
Df Residuals:                   21591   BIC:
5.995e+05
Df Model:                           6
```

```
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
bedrooms     -5.63e+04   2357.316    -23.882      0.000   -6.09e+04   -5.17e+04
bathrooms    6685.3449   3837.541      1.742      0.082    -836.518    1.42e+04
sqft_living   314.0643      3.152     99.628      0.000     307.885     320.243
sqft_lot       -0.3728      0.043     -8.606      0.000      -0.458      -0.288
floors       2234.4329   3817.106      0.585      0.558   -5247.376    9716.242
yr_built       32.4664      4.014      8.088      0.000      24.599      40.334
==============================================================================
Omnibus:                    14201.215   Durbin-Watson:                   1.984
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           468535.936
Skew:                           2.683   Prob(JB):                         0.00
Kurtosis:                      25.178   Cond. No.                     1.13e+05
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[3] The condition number is large, 1.13e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

as we can see that the coef.. are in quite better range as compared to previous models. the r-squared value is great the coef_ for bedroom is in negative, whihc means that it is negatively realted to our target variable. all our coef_ are high, which somewhat validates the model

[13]:
```
y_pred=fitted_model.predict(x)
y_pred
```

[13]:
```
0        271986.897596
1        718404.072377
2        197182.858022
3        474596.574756
4        435837.486860
             …
21592    399844.014079
21593    584698.631150
21594    281953.928160
21595    418963.179223
21596    282023.600537
Length: 21597, dtype: float64
```

[14]:
```
y
```

[14]:
```
0        221900.0
1        538000.0
2        180000.0
3        604000.0
4        510000.0
           …
21592    360000.0
21593    400000.0
21594    402101.0
21595    400000.0
21596    325000.0
Name: price, Length: 21597, dtype: float64
```

5 as the differnce between predicted and actual values are much high, this model is not valid

- also, the coef_ values are not in significant range.
- the p-value score is great, but as the other attributes are not in optimum condition. this model is rejected

5.1 removing another variable from same model

[15]:
```
data=pd.read_csv('kc_house_data.csv')
data=data.drop(['id','grade','condition','date',
'view',
'sqft_above',
'sqft_basement',
'yr_renovated',
'zipcode',
'lat',
'long',
'sqft_living15',
'sqft_lot15','waterfront'],axis=1)
data
x=data.drop(['price','bedrooms'],axis=1)
y=data['price']
X = sm.add_constant(x)

model = sm.OLS(y,x)
fitted_model = model.fit()
fitted_model.summary()
```

```
/opt/conda/lib/python3.9/site-packages/statsmodels/tsa/tsatools.py:142:
FutureWarning: In a future version of pandas all arguments of concat except for
the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

[15]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                 OLS Regression Results
==============================================================================
=======
Dep. Variable:                  price   R-squared (uncentered):
0.840
Model:                            OLS   Adj. R-squared (uncentered):
0.840
Method:                 Least Squares   F-statistic:
2.271e+04
Date:                Tue, 24 May 2022   Prob (F-statistic):
0.00
Time:                        07:58:46   Log-Likelihood:
-3.0002e+05
No. Observations:               21597   AIC:
6.001e+05
Df Residuals:                   21592   BIC:
6.001e+05
Df Model:                           5
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
bathrooms   -7752.5691   3839.263     -2.019      0.043   -1.53e+04    -227.330
sqft_living   288.0573      2.997     96.113      0.000     282.183     293.932
sqft_lot       -0.2875      0.044     -6.575      0.000      -0.373      -0.202
floors        1.24e+04   3842.964      3.228      0.001    4872.210    1.99e+04
yr_built      -29.2667      3.111     -9.407      0.000     -35.365     -23.169
==============================================================================
Omnibus:                    14629.374   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           525382.284
Skew:                           2.777   Prob(JB):                         0.00
Kurtosis:                      26.516   Cond. No.                     1.11e+05
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[3] The condition number is large, 1.11e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[16]:
```
y_pred=fitted_model.predict(x)
y_pred
```

[16]:
```
0        285718.861847
1        688491.830797
2        167008.457931
3        494792.657631
4        420359.708087
             …
21592    399438.440673
21593    610225.873314
21594    253628.533698
21595    406982.652042
21596    253736.584662
Length: 21597, dtype: float64
```

[17]:
```
y
```

[17]:
```
0        221900.0
1        538000.0
2        180000.0
3        604000.0
4        510000.0
           …
21592    360000.0
21593    400000.0
21594    402101.0
21595    400000.0
21596    325000.0
Name: price, Length: 21597, dtype: float64
```

5.1.1 the values are not close to each other.

6 second model

[18]:
```
data=pd.read_csv('kc_house_data.csv')
data.isna().sum()
data=data.drop(['date',
'view',
'sqft_above',
'sqft_basement',
'yr_renovated',
'zipcode',
'lat',
'long',
'sqft_living15',
'sqft_lot15','waterfront'],axis=1)
x=data.drop(['price'],axis=1)
y=data['price']
```

[19]:
```
# removing outliers, only considering the cases where the price is between␣
↪30000 and 700000 as it falls in the majority of the data
data = data.astype({'price':'int'})
data=data[(data['price'] >= 300000) & (data['price'] <= 700000)]
```

[20]:
```
x_train, x_test, y_train, y_test = train_test_split(
                                                x,
                                                y,
                                                test_size=0.33,
                                                random_state=42)
```

[21]:
```
model1=LinearRegression()
model1=model1.fit(x_train,y_train)
```

[22]:
```
model1.coef_
```

[22]:
```
array([-2.29025909e-06, -5.12971820e+04,  5.87523832e+04,  1.83726825e+02,
       -3.27830585e-01,  2.06060871e+04,  2.16935350e+04,  1.33939599e+05,
       -4.09190776e+03])
```

[23]:
```
model1.intercept_
```

[23]:
```
7157370.4574735025
```

[24]:
```
model1.score(x_train,y_train)
```

[24]:
```
0.6235350336580254
```

[25]:
```
model1.score(x_test,y_test)
```

[25]:
```
0.6055665685711678
```

[26]:
```
y_pred=model1.predict(x_test)
y_pred
```

[26]:
```
array([117027.77672846, 305811.84525172, 305228.2752753 , …,
       400013.18535947, 351901.81509789, 702769.86238808])
```

[27]:
```
y_test
```

[27]:
```
3686     132500.0
10247    415000.0
4037     494000.0
3437     355000.0
19291    606000.0
           …
17525    533300.0
```

```
5761     335000.0
18907    410000.0
12348    488500.0
3448     735000.0
Name: price, Length: 7128, dtype: float64
```

[ ]:

```

```

[28]:

```
from sklearn.metrics import mean_absolute_error,r2_score
mean_absolute_error(y_test,y_pred)
```

[28]: 145007.94948066707

7 cross validation

[29]:

```
from sklearn.model_selection import cross_val_score
```

[30]:

```
scores=cross_val_score(model1,x_train,y_train,scoring ='r2',cv=10)
scores
```

[30]:

```
array([0.63328306, 0.6415828 , 0.60126627, 0.61966494, 0.63236141,
       0.62904708, 0.63935869, 0.59642525, 0.61925961, 0.58933415])
```

[31]:

```
np.mean(scores)
```

[31]: 0.6201583256018426

[32]:

```
# getting score for test set
from sklearn.model_selection import cross_val_predict
```

[33]:

```
pred=cross_val_predict(model1,x_test,y_test)
pred
```

[33]:

```
array([128045.3230117 , 306641.00414515, 304155.89227364, …,
       401406.06342291, 359243.52475701, 669289.32982669])
```

[34]:

```
score_test=cross_val_score(model1,x_test,y_test,cv=10)
score_test
```

[34]:

```
array([0.59927559, 0.58805898, 0.59961711, 0.56067266, 0.59306754,
       0.62576355, 0.59992197, 0.60798291, 0.60384164, 0.64213547])
```

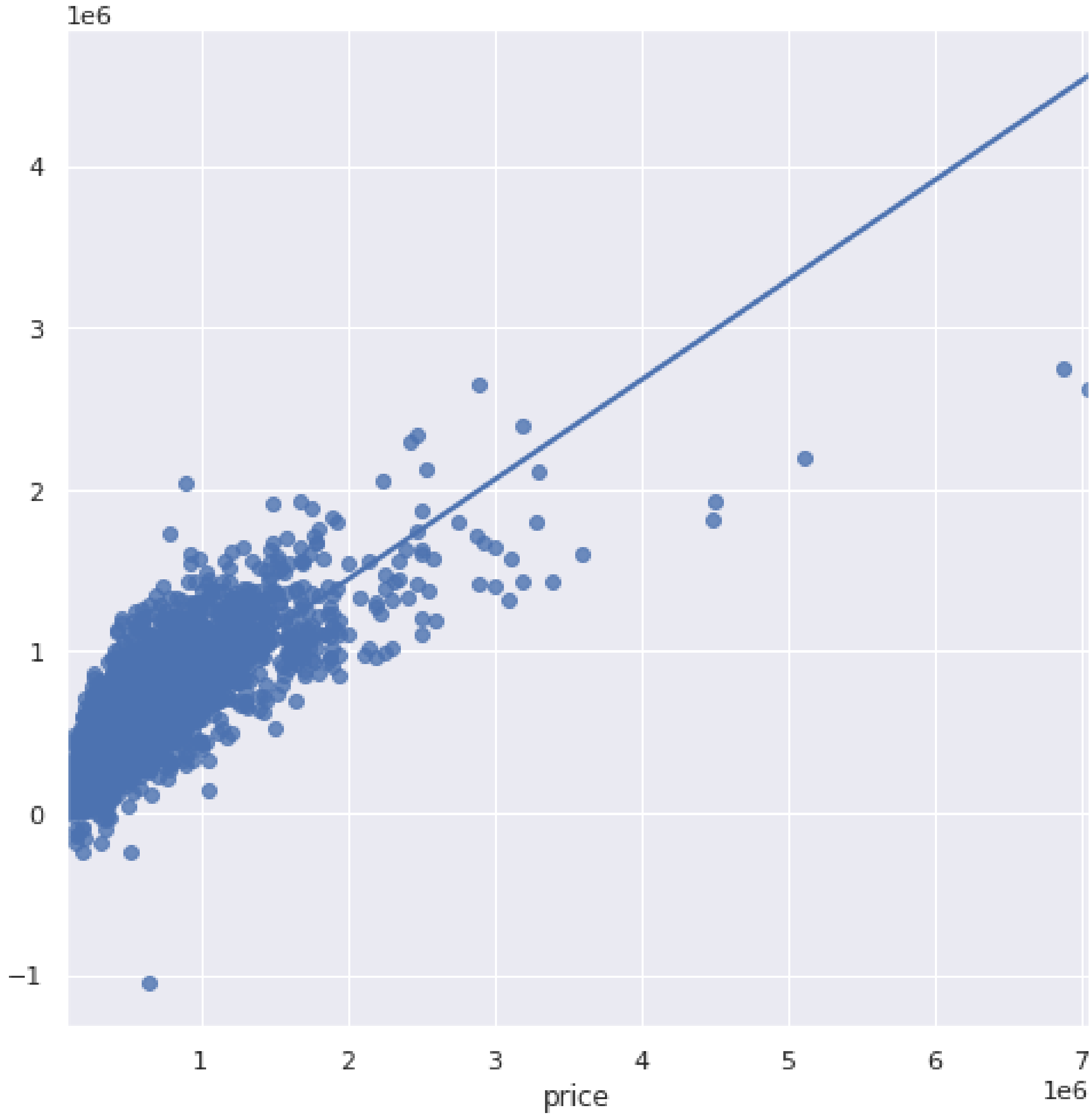
[35]:

```
np.mean(score_test)
```

[35]: 0.6020337410665545

[36]:
```
sns.regplot(x=y_test, y=y_pred, ci=None, color="b")
```

[36]: <AxesSubplot:xlabel='price'>

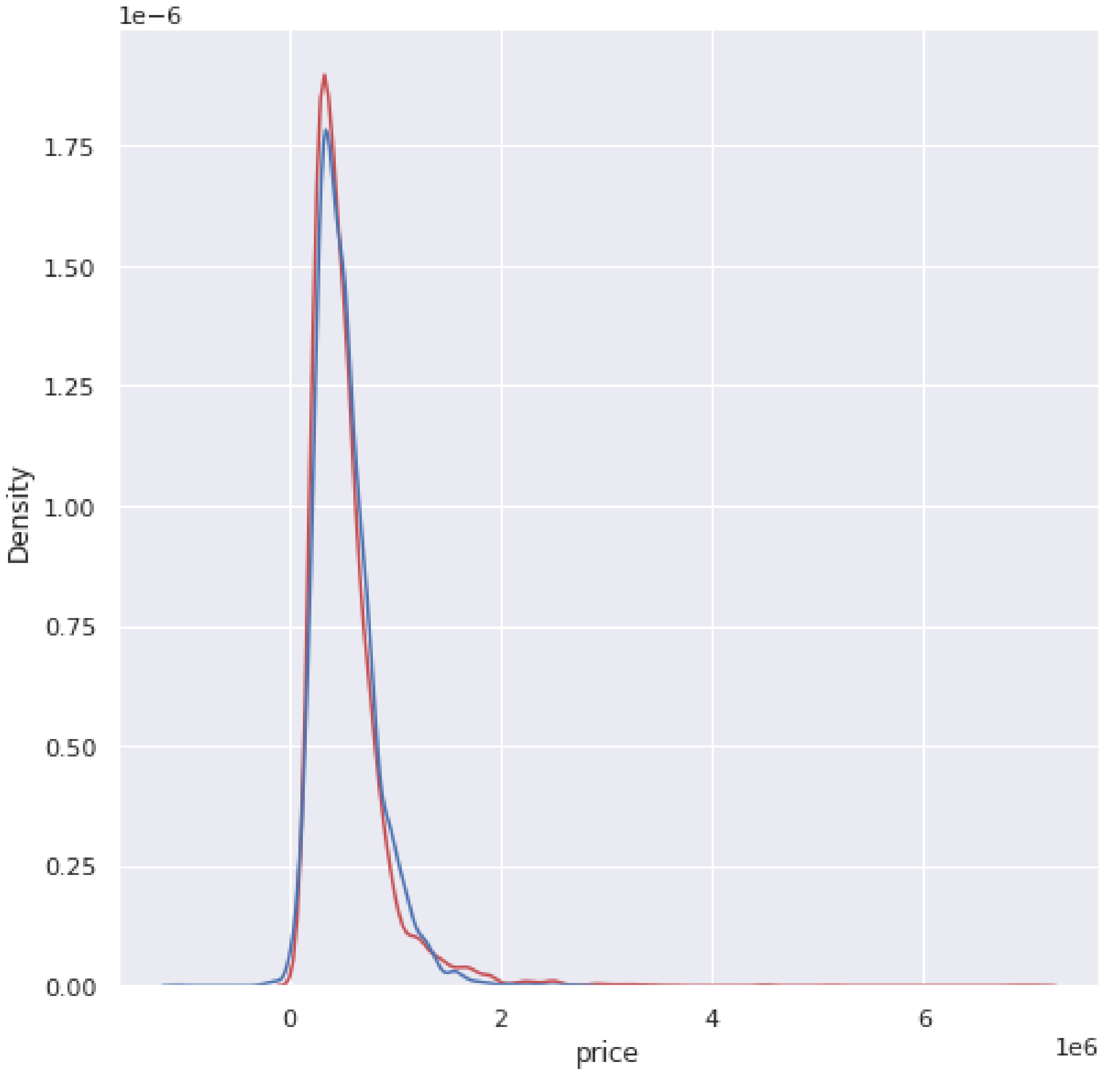


[37]:
```
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred, hist=False, color="b", label="Fitted Values" , ax=ax1)
```

```
/opt/conda/lib/python3.9/site-packages/seaborn/distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
  warnings.warn(msg, FutureWarning)
```

```
/opt/conda/lib/python3.9/site-packages/seaborn/distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
  warnings.warn(msg, FutureWarning)
```

[37]:
```
<AxesSubplot:xlabel='price', ylabel='Density'>
```



7.0.1 this visual is suggesting that this model is fitting properly to the data as most of the values are separted evenly the half data

as the difference between train set score and test set score is very small, this model is neither overfit nor underfit

8 creating another model with different number of variables and normalized dataset

[38]:
```
data.head()
```

[38]:
```
            id   price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  \
1   6414100192  538000         3       2.25         2570      7242     2.0
3   2487200875  604000         4       3.00         1960      5000     1.0
4   1954400510  510000         3       2.00         1680      8080     1.0
9   3793500160  323000         3       2.50         1890      6560     2.0
10  1736800520  662500         3       2.50         3560      9796     1.0

    condition  grade  yr_built
1           3      7      1951
3           5      7      1965
4           3      8      1987
9           3      7      2003
10          3      8      1965
```

[39]:
```
data=data.drop(['id','grade','condition'],axis=1)
```

[40]:
```
# removing outliers, only considering the cases where the price is between␣
↪30000 and 700000 as it falls in the majority of the data
data = data.astype({'price':'int'})
data=data[(data['price'] >= 300000) & (data['price'] <= 700000)]
```

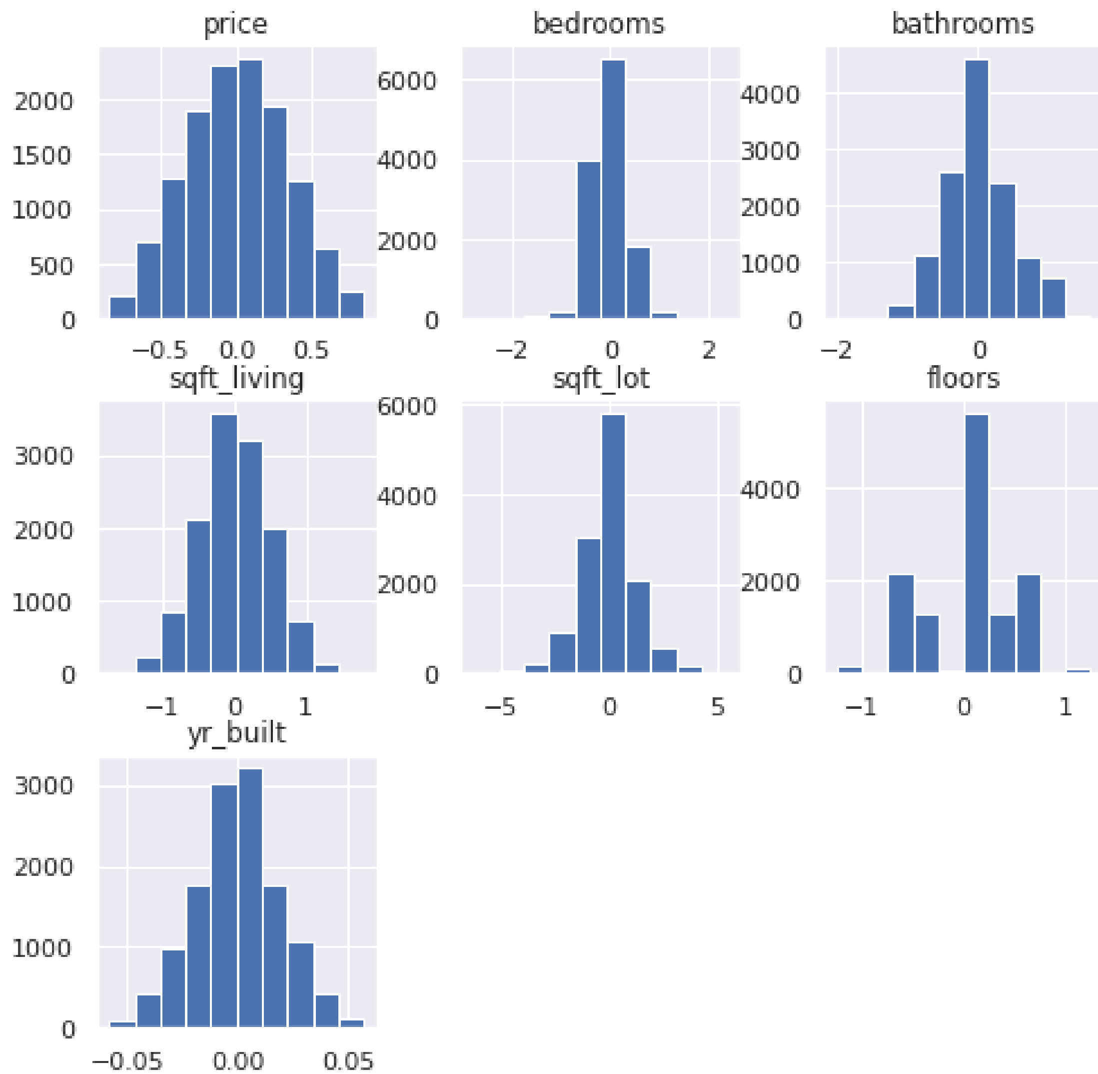
[41]:
```
data=np.log(data)
```

[42]:
```
data.head()
```

[42]:
```
        price  bedrooms  bathrooms  sqft_living  sqft_lot    floors  yr_built
1   13.195614  1.098612   0.810930     7.851661  8.887653  0.693147  7.576097
3   13.311329  1.386294   1.098612     7.580700  8.517193  0.000000  7.583248
4   13.142166  1.098612   0.693147     7.426549  8.997147  0.000000  7.594381
9   12.685408  1.098612   0.916291     7.544332  8.788746  0.693147  7.602401
10  13.403776  1.098612   0.916291     8.177516  9.189729  0.000000  7.583248
```

[43]:
```
data.diff().hist()
```

[43]:
```
array([[<AxesSubplot:title={'center':'price'}>,
        <AxesSubplot:title={'center':'bedrooms'}>,
        <AxesSubplot:title={'center':'bathrooms'}>],
       [<AxesSubplot:title={'center':'sqft_living'}>,
        <AxesSubplot:title={'center':'sqft_lot'}>,
        <AxesSubplot:title={'center':'floors'}>],
       [<AxesSubplot:title={'center':'yr_built'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```



[44]:
```
x=data.drop(['price'],axis=1)
y=data['price']
x_train, x_test, y_train, y_test = train_test_split(
                                                    x,
                                                    y,
                                                    test_size=0.2,
                                                    random_state=42)
```

[45]:
```
model2=LinearRegression()
```

[46]:
```
model2=model2.fit(x_train,y_train)
```

[47]:
```
model2.coef_
```

[47]: array([-0.12238404, 0.08075915, 0.29749955, -0.0121895 , 0.06284265,
        -4.83203963])

9 the coeffecients are much better than the previous model as the negative values are lower

[48]:
```
model2.score(x_train,y_train)
```

[48]: 0.16793183497569197

[49]:
```
model2.score(x_test,y_test)
```

[49]: 0.17295318053883046

[50]:
```
y_pred=model2.predict(x_test)
```

[51]:
```
mean_absolute_error(y_test,y_pred)
```

[51]: 0.17755403514630136

the mean absolute error is even neglegible if considering the price of any random house

10 cross validation

[52]:
```
scores=cross_val_score(model1,x_train,y_train,scoring ='r2',cv=10)
scores
```

[52]: array([0.19543484, 0.14525239, 0.16426408, 0.13535275, 0.17897072,
        0.14924477, 0.19294141, 0.1912632 , 0.15314943, 0.15059297])

[53]:
```
np.mean(scores)
```

[53]: 0.16564665546354077

[54]:
```
pred=cross_val_predict(model1,x_test,y_test)
pred
```

[54]: array([13.02819462, 13.15919555, 12.82802878, …, 12.9904383 ,
        13.1091389 , 13.1777058])

[55]:
```
score_test=cross_val_score(model1,x_test,y_test,cv=10)
score_test
```

[55]: array([0.13453352, 0.18065173, 0.22963364, 0.20270242, 0.17875337,
        0.17701742, 0.11138025, 0.11445984, 0.16417406, 0.17850027])

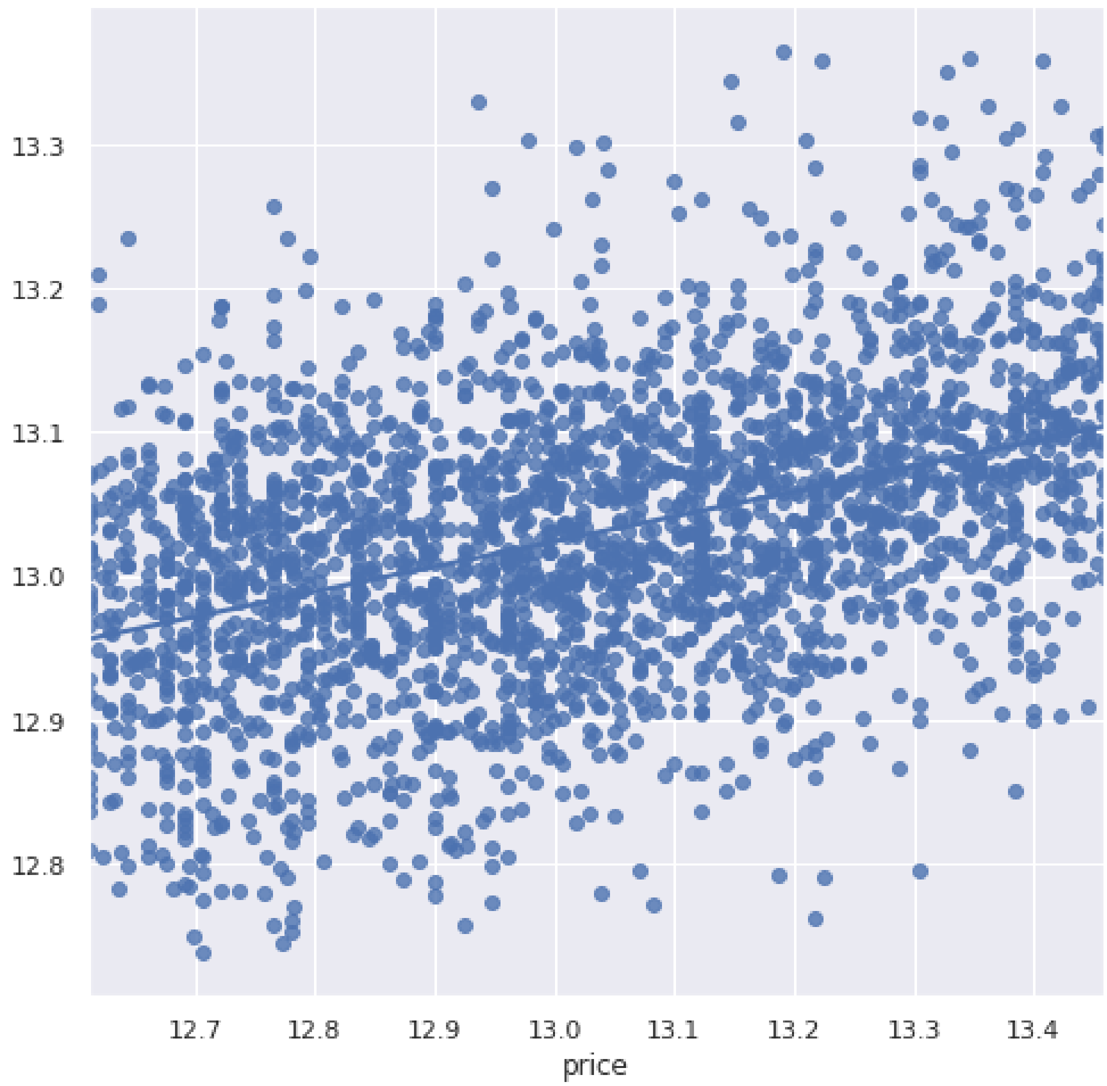
[56]:
```
np.mean(score_test)
```

[56]: 0.16718065156425999

10.0.1 here, again we can see the very small differenc among the scores of training and testing set

[57]:
```
sns.regplot(x=y_test, y=pred, ci=None, color="b")
```

[57]: <AxesSubplot:xlabel='price'>

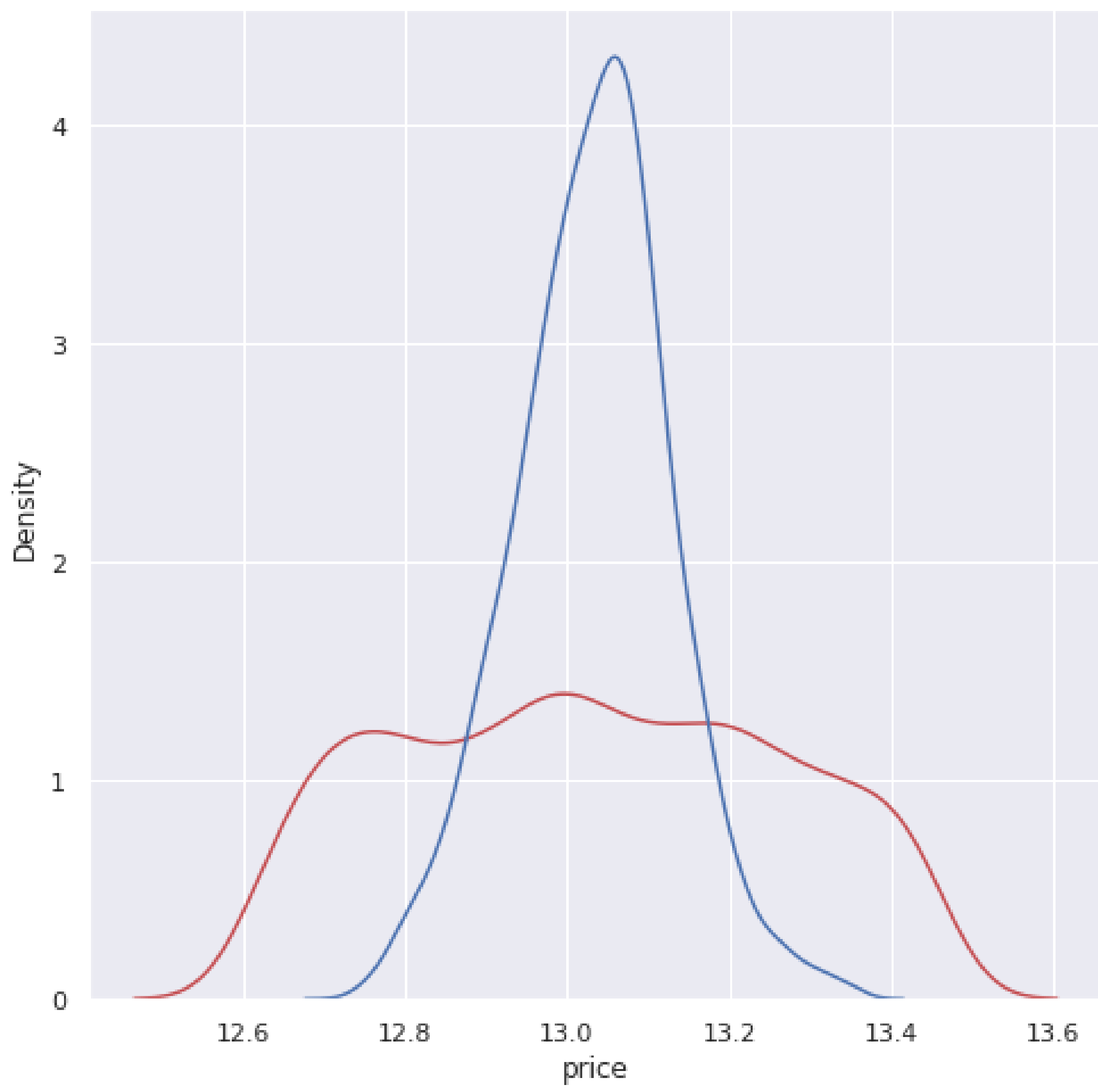


10.1 the visualizations are better in the final model

[58]:
```
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred, hist=False, color="b", label="Fitted Values" , ax=ax1)
```

```
/opt/conda/lib/python3.9/site-packages/seaborn/distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
  warnings.warn(msg, FutureWarning)
/opt/conda/lib/python3.9/site-packages/seaborn/distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
  warnings.warn(msg, FutureWarning)
```

[58]:
```
<AxesSubplot:xlabel='price', ylabel='Density'>
```



[59]:
```
y_pred=model2.predict(x_test)
y_pred
```

[59]:
```
array([13.03444387, 13.16003519, 12.84272585, …, 13.0053775 ,
       13.09497199, 13.19108584])
```

[60]:
```
y_test
```

[60]:
```
17361    13.107250
14       13.180632
14362    13.017003
10316    13.225822
6613     13.151922
```

```
            …
14272    13.122263
5658     12.660328
12622    13.101140
4907     13.215854
3827     12.899095
Name: price, Length: 2570, dtype: float64
```

as we can see that, the difference between predicted and actual value is really low. this model is somewhat valid

11 discussing the second model :

- in the final model, we have the coefficients with high posetive and low negative vlues, which show that the model is promising.
- the visual show the linearity of regression and the worthyness of predicted values.
- the score validaton of the model is better
- and the mean absolute error for train, test and pridcted set is almost same.

12 observatons based on the final model

- the number of bedrooms are not contributing in the price
- the older the house, the more the price
- renovation has posetive impact on the price
- condition of the house is also important factor

[ ]:

```

```