# STAT724_Sherien_Hassan_Exam_

December 17, 2020

Importing Required Libraries

[33]:
```
import pandas
import pandas as pd
import numpy as np
import datetime as dt

import seaborn as sns
import matplotlib.pyplot as plt

%matplotlib inline

from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn import preprocessing

from sklearn.linear_model import LinearRegression, Ridge
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR

#import pandas as pd
#import numpy as np
#import matplotlib.pyplot as plt
#from sklearn.linear_model import LinearRegression, Ridge, Lasso
#from sklearn.model_selection import train_test_split, cross_val_score
#from statistics import mean

#import matplotlib.pyplot as plt
#import pandas as pd
#import numpy as np
```

Loading and Cleaning Data

[34]:
```
data = pd.read_csv('kc_house_data.csv')
```

Data Analysis

[35]:
```
format(data.shape)
```

[35]:
```
'(21613, 21)'
```

[36]:
```
data.dtypes
```

[36]:
```
id                  int64
date               object
price             float64
bedrooms            int64
bathrooms         float64
sqft_living         int64
sqft_lot            int64
floors            float64
waterfront          int64
view                int64
condition           int64
grade               int64
sqft_above        float64
sqft_basement       int64
yr_built            int64
yr_renovated        int64
zipcode             int64
lat               float64
long              float64
sqft_living15       int64
sqft_lot15          int64
dtype: object
```

[37]:
```
data.hist(figsize=(30,20))
plt.show()
```


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

[38]:

| | id | price | bedrooms | bathrooms | sqft_living |
|---|---|---|---|---|---|
| count | 2.161300e+04 | 2.161300e+04 | 21613.000000 | 21613.000000 | 21613.000000 |
| mean | 4.580302e+09 | 5.400881e+05 | 3.370842 | 2.114757 | 2079.899736 |
| std | 2.876566e+09 | 3.671272e+05 | 0.930062 | 0.770163 | 918.440897 |
| min | 1.000102e+06 | 7.500000e+04 | 0.000000 | 0.000000 | 290.000000 |
| 25% | 2.123049e+09 | 3.219500e+05 | 3.000000 | 1.750000 | 1427.000000 |
| 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 | waterfront | view | condition |
|---|---|---|---|---|---|
| count | 2.161300e+04 | 21613.000000 | 21613.000000 | 21613.000000 | 21613.000000 |
| mean | 1.510697e+04 | 1.494309 | 0.007542 | 0.234303 | 3.409430 |
| std | 4.142051e+04 | 0.539989 | 0.086517 | 0.766318 | 0.650743 |
| min | 5.200000e+02 | 1.000000 | 0.000000 | 0.000000 | 1.000000 |
| 25% | 5.040000e+03 | 1.000000 | 0.000000 | 0.000000 | 3.000000 |
| 50% | 7.618000e+03 | 1.500000 | 0.000000 | 0.000000 | 3.000000 |
| 75% | 1.068800e+04 | 2.000000 | 0.000000 | 0.000000 | 4.000000 |
| max | 1.651359e+06 | 3.500000 | 1.000000 | 4.000000 | 5.000000 |

| | grade | sqft_above | sqft_basement | yr_built | yr_renovated |
|---|---|---|---|---|---|
| count | 21613.000000 | 21611.000000 | 21613.000000 | 21613.000000 | 21613.000000 |

```
mean      7.656873   1788.396095    291.509045   1971.005136     84.402258
std       1.175459    828.128162    442.575043     29.373411    401.679240
min       1.000000    290.000000      0.000000   1900.000000      0.000000
25%       7.000000   1190.000000      0.000000   1951.000000      0.000000
50%       7.000000   1560.000000      0.000000   1975.000000      0.000000
75%       8.000000   2210.000000    560.000000   1997.000000      0.000000
max      13.000000   9410.000000   4820.000000   2015.000000   2015.000000

            zipcode           lat          long  sqft_living15     sqft_lot15
count  21613.000000  21613.000000  21613.000000   21613.000000   21613.000000
mean   98077.939805     47.560053   -122.213896    1986.552492   12768.455652
std       53.505026      0.138564      0.140828     685.391304   27304.179631
min    98001.000000     47.155900   -122.519000     399.000000     651.000000
25%    98033.000000     47.471000   -122.328000    1490.000000    5100.000000
50%    98065.000000     47.571800   -122.230000    1840.000000    7620.000000
75%    98118.000000     47.678000   -122.125000    2360.000000   10083.000000
max    98199.000000     47.777600   -121.315000    6210.000000  871200.000000
```

[39]:

```
#Reference 1
data[["price","bedrooms","bathrooms","sqft_living","sqft_lot","sqft_above","yr_built","sqft_li
↪describe()
```

[39]:

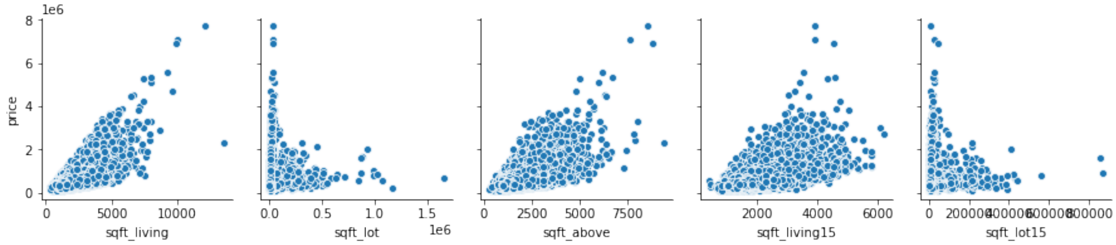
```
              price      bedrooms     bathrooms   sqft_living      sqft_lot  \
count  2.161300e+04  21613.000000  21613.000000  21613.000000  2.161300e+04
mean   5.400881e+05      3.370842      2.114757   2079.899736  1.510697e+04
std    3.671272e+05      0.930062      0.770163    918.440897  4.142051e+04
min    7.500000e+04      0.000000      0.000000    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

         sqft_above      yr_built  sqft_living15     sqft_lot15
count  21611.000000  21613.000000   21613.000000   21613.000000
mean    1788.396095   1971.005136    1986.552492   12768.455652
std      828.128162     29.373411     685.391304   27304.179631
min      290.000000   1900.000000     399.000000     651.000000
25%     1190.000000   1951.000000    1490.000000    5100.000000
50%     1560.000000   1975.000000    1840.000000    7620.000000
75%     2210.000000   1997.000000    2360.000000   10083.000000
max     9410.000000   2015.000000    6210.000000  871200.000000
```

[40]:

```
sns.pairplot(data=data,␣
↪x_vars=['sqft_living','sqft_lot','sqft_above','sqft_living15','sqft_lot15'],␣
↪y_vars=["price"])
```

[40]: <seaborn.axisgrid.PairGrid at 0x7feec1d928b0>



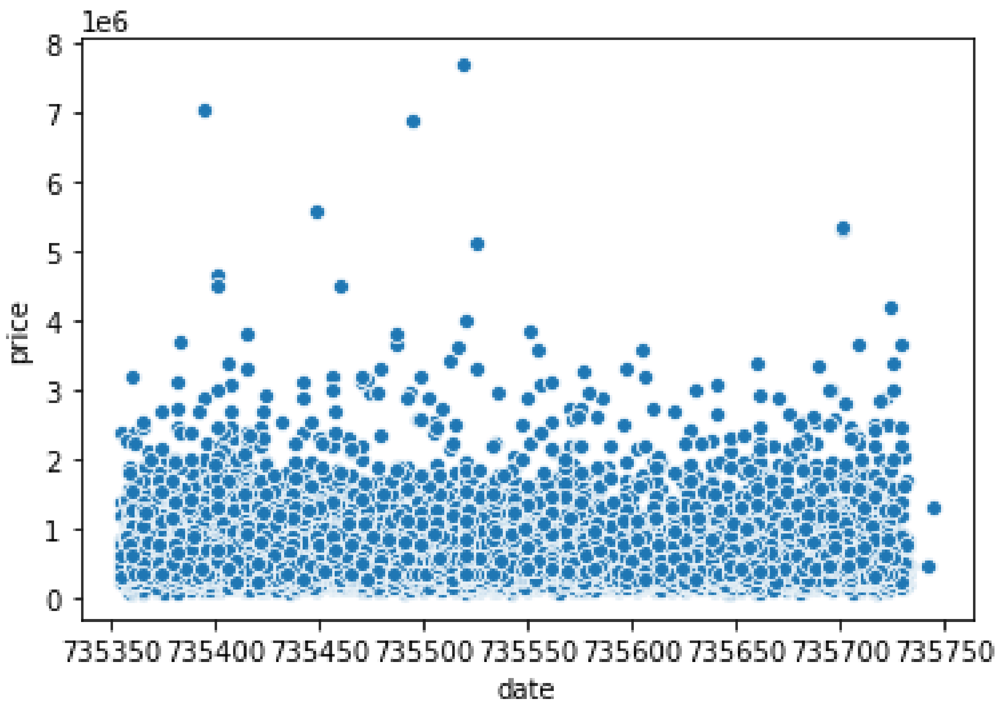

We will check to see which columns we should drop by testing everything against the column price

[41]:
```
dateObj = dt.datetime.strptime('20140623T000000', '%Y%m%dT%H%M%S')

data['date'] = data['date'].apply(lambda x: dt.datetime.strptime(x,␣
 ↪'%Y%m%dT%H%M%S'))
data['date']=data['date'].map(dt.datetime.toordinal)
```

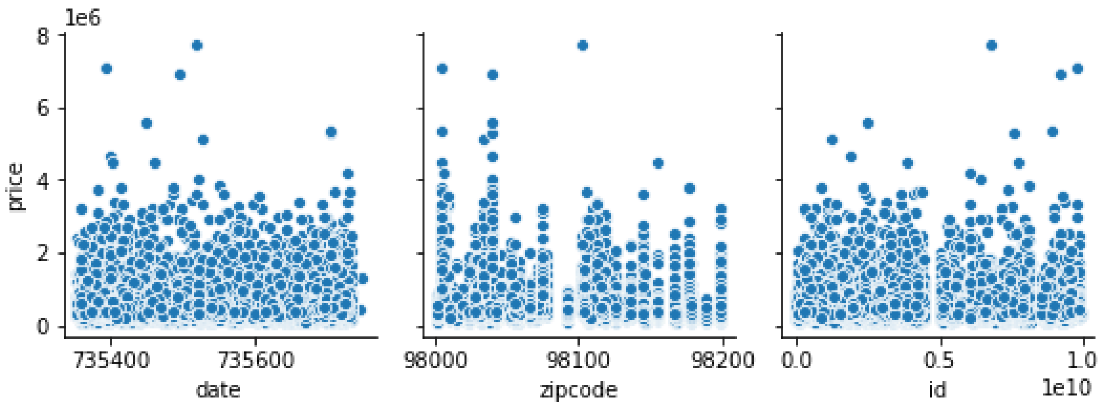
[42]:
```
sns.scatterplot(data=data, x="date", y="price")
```

[42]: <matplotlib.axes._subplots.AxesSubplot at 0x7feec2200430>




[43]:
```
sns.pairplot(data=data, x_vars=['date','zipcode','id'], y_vars=["price"])
```

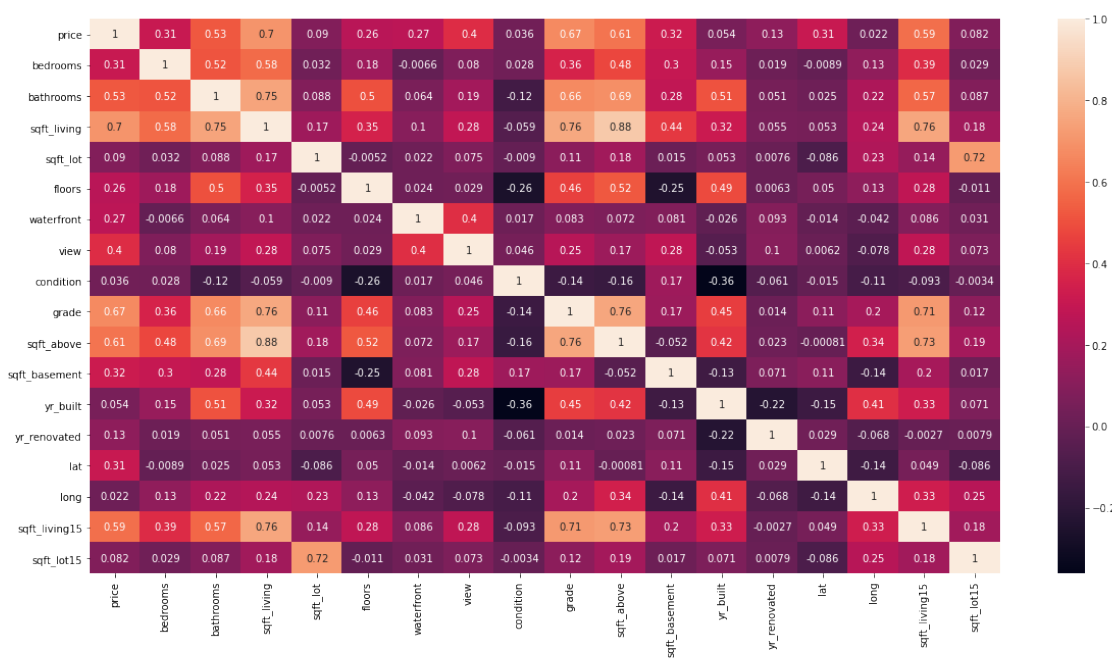
[43]: <seaborn.axisgrid.PairGrid at 0x7feec0e8b2b0>




[44]:
```
#We could conclude that columns: id, date, and zipcode will not benefit us here␣
↪so we will drop them
dropColumns = ['id', 'date', 'zipcode']
data = data.drop(dropColumns, axis = 1)
```

[45]:
```
plt.figure(figsize=(20,10))
sns.heatmap(data.corr(), annot=True)
```

[45]: <matplotlib.axes._subplots.AxesSubplot at 0x7feec211cb20>



[46]:

```
#From this, we see that columns:'sqft_living', 'grade', 'sqft_above',␣
↪'sqft_living15', 'sqft_lot15', 'yr_built' are all highly correlated
def remove_collinear_features(x, threshold):

    # Create correlation matrix:
    corr_matrix = x.corr()
    iters = range(len(corr_matrix.columns) - 1)
    drop_cols = []

    # Work through the iterations setup:
    for i in iters:
        for j in range(i+1):
            items = corr_matrix.iloc[j:(j+1), (i+1):(i+2)]
            col = items.columns
            row = items.index
            val = abs(items.values)

            # Compare against threshold:
            if val >= threshold:
                print(col.values[0], "|", row.values[0], "|", round(val[0][0],␣
↪2))
                drop_cols.append(col.values[0])

    cols_to_drop = set(drop_cols)
    x = x.drop(columns = cols_to_drop, axis=1)

    return x
features = data.drop('price', axis=1)
remove_collinear_features(features, 0.7)
features = features.drop(columns = ['sqft_living', 'grade', 'sqft_above',␣
↪'sqft_living15', 'sqft_lot15', 'yr_built'], axis=1)
```

```
sqft_living | bathrooms | 0.75
grade | sqft_living | 0.76
sqft_above | sqft_living | 0.88
sqft_above | grade | 0.76
sqft_living15 | sqft_living | 0.76
sqft_living15 | grade | 0.71
sqft_living15 | sqft_above | 0.73
sqft_lot15 | sqft_lot | 0.72
```

[47]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from pandas.plotting import scatter_matrix
from sklearn import preprocessing
```

```python
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler
import numpy as np
import statsmodels.api as sm
x = pd.DataFrame({
    'sqft_living': data.sqft_living,
    'grade': data.grade,
    'sqft_above': data.sqft_above,
    'sqft_living15' : data.sqft_living15,
    'bathrooms': data.bathrooms,
    'lat' : data.lat,
    'waterfront': data.waterfront,
    'floors': data.floors,
    'yr_renovated':data.yr_renovated,
    'sqft_lot':data.sqft_lot,
    'sqft_lot15':data.sqft_lot15,
    'yr_built':data.yr_built,
    'condition':data.condition,
    'long':data.long,


})

scaler = preprocessing.MinMaxScaler()
minmax_scaled_data = scaler.fit_transform(x)
minmax_scaled_data = pd.DataFrame(minmax_scaled_data, columns=['sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms', 'lat','waterfront', 'floors', 'yr_renovated', 'sqft_lot', 'sqft_lot15','yr_built','condition', 'long' ])

scaler = preprocessing.StandardScaler()
scaled_data = scaler.fit_transform(x)
scaled_data = pd.DataFrame(scaled_data, columns=['sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms', 'lat','waterfront', 'floors', 'yr_renovated', 'sqft_lot', 'sqft_lot15','yr_built','condition', 'long'])

scaler = preprocessing.RobustScaler()
robust_scaled_data = scaler.fit_transform(x)
robust_scaled_data = pd.DataFrame(robust_scaled_data, columns=['sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms', 'lat','waterfront', 'floors', 'yr_renovated', 'sqft_lot', 'sqft_lot15','yr_built','condition', 'long'])



fig, (ax1, ax2, ax3, ax4) = plt.subplots(ncols=4, figsize=(9, 5))
```

```
ax1.set_title('Before Scaling')
sns.kdeplot(x['sqft_living'], ax=ax1)
sns.kdeplot(x['sqft_above'], ax=ax1)
sns.kdeplot(x['sqft_living15'], ax=ax1)
sns.kdeplot(x['bathrooms'], ax=ax1)
sns.kdeplot(x['lat'], ax=ax1)
sns.kdeplot(x['waterfront'], ax=ax1)
sns.kdeplot(x['floors'], ax=ax1)
sns.kdeplot(x['yr_renovated'], ax=ax1)
sns.kdeplot(x['sqft_lot15'], ax=ax1)
sns.kdeplot(x['yr_built'], ax=ax1)
sns.kdeplot(x['sqft_lot'], ax=ax1)
sns.kdeplot(x['condition'], ax=ax1)
sns.kdeplot(x['long'], ax=ax1)


ax2.set_title('After Min-Max Scaling')
sns.kdeplot(minmax_scaled_data['sqft_living'], ax=ax2)
sns.kdeplot(minmax_scaled_data['sqft_above'], ax=ax2)
sns.kdeplot(minmax_scaled_data['sqft_living15'], ax=ax2)
sns.kdeplot(minmax_scaled_data['bathrooms'], ax=ax2)
sns.kdeplot(minmax_scaled_data['lat'], ax=ax2)
sns.kdeplot(minmax_scaled_data['waterfront'], ax=ax2)
sns.kdeplot(minmax_scaled_data['floors'], ax=ax2)
sns.kdeplot(minmax_scaled_data['yr_renovated'], ax=ax2)
sns.kdeplot(minmax_scaled_data['sqft_lot15'], ax=ax2)
sns.kdeplot(minmax_scaled_data['yr_built'], ax=ax2)
sns.kdeplot(minmax_scaled_data['sqft_lot'], ax=ax2)
sns.kdeplot(minmax_scaled_data['condition'], ax=ax2)
sns.kdeplot(minmax_scaled_data['long'], ax=ax2)

ax3.set_title('After Standard Scaler')
sns.kdeplot(scaled_data['sqft_living'], ax=ax3)
sns.kdeplot(scaled_data['sqft_above'], ax=ax3)
sns.kdeplot(scaled_data['sqft_living15'], ax=ax3)
sns.kdeplot(scaled_data['bathrooms'], ax=ax3)
sns.kdeplot(scaled_data['lat'], ax=ax3)
sns.kdeplot(scaled_data['waterfront'], ax=ax3)
sns.kdeplot(scaled_data['floors'], ax=ax3)
sns.kdeplot(scaled_data['yr_renovated'], ax=ax3)
sns.kdeplot(scaled_data['sqft_lot15'], ax=ax3)
sns.kdeplot(scaled_data['yr_built'], ax=ax3)
sns.kdeplot(scaled_data['sqft_lot'], ax=ax3)
sns.kdeplot(scaled_data['condition'], ax=ax3)
sns.kdeplot(scaled_data['long'], ax=ax3)

ax4.set_title('After Robust Scaling')
```

```
sns.kdeplot(robust_scaled_data['sqft_living'], ax=ax4)
sns.kdeplot(robust_scaled_data['sqft_above'], ax=ax4)
sns.kdeplot(robust_scaled_data['sqft_living15'], ax=ax4)
sns.kdeplot(robust_scaled_data['bathrooms'], ax=ax4)
sns.kdeplot(robust_scaled_data['lat'], ax=ax4)
sns.kdeplot(robust_scaled_data['waterfront'], ax=ax4)
sns.kdeplot(robust_scaled_data['floors'], ax=ax4)
sns.kdeplot(robust_scaled_data['yr_renovated'], ax=ax4)
sns.kdeplot(robust_scaled_data['sqft_lot15'], ax=ax4)
sns.kdeplot(robust_scaled_data['yr_built'], ax=ax4)
sns.kdeplot(robust_scaled_data['sqft_lot'], ax=ax4)
sns.kdeplot(robust_scaled_data['condition'], ax=ax4)
sns.kdeplot(robust_scaled_data['long'], ax=ax4)

plt.show()
```

```
/Users/SherienHassan/opt/anaconda3/lib/python3.8/site-
packages/seaborn/distributions.py:369: UserWarning: Default bandwidth for data
is 0; skipping density estimation.
  warnings.warn(msg, UserWarning)
/Users/SherienHassan/opt/anaconda3/lib/python3.8/site-
packages/seaborn/distributions.py:369: UserWarning: Default bandwidth for data
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/Users/SherienHassan/opt/anaconda3/lib/python3.8/site-
packages/seaborn/distributions.py:369: UserWarning: Default bandwidth for data
is 0; skipping density estimation.
```
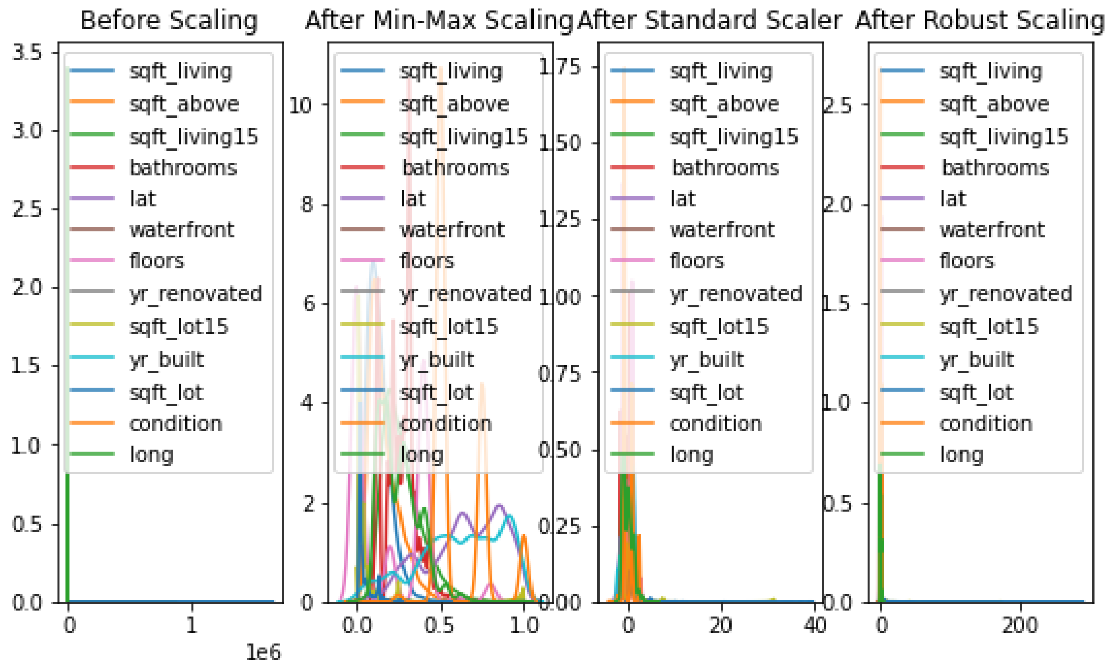

```
warnings.warn(msg, UserWarning)
```




[20]:
```
# Normalization
#'waterfront', 'floors', 'yr_renovated', 'sqft_lot',␣
↪'sqft_lot15','yr_built','condition', 'long'
x_array = np.array(data['sqft_living'])
normalized_sqft_living = preprocessing.normalize([x_array])

x_array = np.array(data['grade'])
normalized_grade = preprocessing.normalize([x_array])

x_array = np.array(data['sqft_above'])
normalized_sqft_above = preprocessing.normalize([x_array])

x_array = np.array(data['sqft_living15'])
normalized_sqft_living15 = preprocessing.normalize([x_array])

x_array = np.array(data['bathrooms'])
normalized_bathrooms = preprocessing.normalize([x_array])

x_array = np.array(data['lat'])
normalized_lat = preprocessing.normalize([x_array])

x_array = np.array(data['waterfront'])
normalized_waterfront = preprocessing.normalize([x_array])
```

```
x_array = np.array(data['floors'])
normalized_floors = preprocessing.normalize([x_array])

x_array = np.array(data['yr_renovated'])
normalized_yr_renovated = preprocessing.normalize([x_array])

x_array = np.array(data['sqft_lot'])
normalized_sqft_lot = preprocessing.normalize([x_array])

x_array = np.array(data['sqft_lot15'])
normalized_sqft_lot15 = preprocessing.normalize([x_array])

x_array = np.array(data['yr_built'])
normalized_yr_built = preprocessing.normalize([x_array])

x_array = np.array(data['condition'])
normalized_condition = preprocessing.normalize([x_array])

x_array = np.array(data['long'])
normalized_long = preprocessing.normalize([x_array])
```

```
      ␣
↪---------------------------------------------------------------------------

       ValueError                                Traceback (most recent call␣
↪last)

       <ipython-input-20-b9333458e3cf> in <module>
         8
         9 x_array = np.array(data['sqft_above'])
   ---> 10 normalized_sqft_above = preprocessing.normalize([x_array])
        11
        12 x_array = np.array(data['sqft_living15'])


       ~/opt/anaconda3/lib/python3.8/site-packages/sklearn/utils/validation.py␣
↪in inner_f(*args, **kwargs)
        71                           FutureWarning)
        72         kwargs.update({k: arg for k, arg in zip(sig.parameters,␣
↪args)})
   ---> 73         return f(**kwargs)
        74     return inner_f
        75
```

```
~/opt/anaconda3/lib/python3.8/site-packages/sklearn/preprocessing/_data.
↪py in normalize(X, norm, axis, copy, return_norm)
   1708         raise ValueError("'%d' is not a supported axis" % axis)
   1709
-> 1710     X = check_array(X, accept_sparse=sparse_format, copy=copy,
   1711                     estimator='the normalize function',␣
↪dtype=FLOAT_DTYPES)
   1712     if axis == 0:


~/opt/anaconda3/lib/python3.8/site-packages/sklearn/utils/validation.py␣
↪in inner_f(*args, **kwargs)
     71                           FutureWarning)
     72         kwargs.update({k: arg for k, arg in zip(sig.parameters,␣
↪args)})
---> 73         return f(**kwargs)
     74     return inner_f
     75


~/opt/anaconda3/lib/python3.8/site-packages/sklearn/utils/validation.py␣
↪in check_array(array, accept_sparse, accept_large_sparse, dtype, order, copy,␣
↪force_all_finite, ensure_2d, allow_nd, ensure_min_samples,␣
↪ensure_min_features, estimator)
    643
    644         if force_all_finite:
--> 645             _assert_all_finite(array,
    646                                allow_nan=force_all_finite ==␣
↪'allow-nan')
    647


~/opt/anaconda3/lib/python3.8/site-packages/sklearn/utils/validation.py␣
↪in _assert_all_finite(X, allow_nan, msg_dtype)
     95                 not allow_nan and not np.isfinite(X).all()):
     96             type_err = 'infinity' if allow_nan else 'NaN, infinity'
---> 97             raise ValueError(
     98                     msg_err.format
     99                     (type_err,


ValueError: Input contains NaN, infinity or a value too large for␣
↪dtype('float64').
```

[48]:
```
#There is an issue with this:Input contains NaN, infinity or a value too large␣
↪for dtype('float64') So we will fix this here
#x_array = np.array(df1['sqft_above'])
#normalized_sqft_above = preprocessing.normalize([x_array])

#Lets check for null values!
data['sqft_above'].isnull().values.any()
```

[48]:
```
True
```

[49]:
```
#There are various ways we can go about this, but because the data is so large,␣
↪I do not think it would matter which approach we take
#I decided to fill it in with the random number: 1200
data['sqft_above'] = data['sqft_above'].fillna(1200)
data['sqft_above'].isnull().values.any()
```

[49]:
```
False
```

[53]:
```
# Normalization
#'waterfront', 'floors', 'yr_renovated', 'sqft_lot',␣
↪'sqft_lot15','yr_built','condition', 'long'
x_array = np.array(data['sqft_living'])
normalized_sqft_living = preprocessing.normalize([x_array])

x_array = np.array(data['grade'])
normalized_grade = preprocessing.normalize([x_array])

x_array = np.array(data['sqft_above'])
normalized_sqft_above = preprocessing.normalize([x_array])

x_array = np.array(data['sqft_living15'])
normalized_sqft_living15 = preprocessing.normalize([x_array])

x_array = np.array(data['bathrooms'])
normalized_bathrooms = preprocessing.normalize([x_array])

x_array = np.array(data['lat'])
normalized_lat = preprocessing.normalize([x_array])

x_array = np.array(data['waterfront'])
normalized_waterfront = preprocessing.normalize([x_array])

x_array = np.array(data['floors'])
normalized_floors = preprocessing.normalize([x_array])

x_array = np.array(data['yr_renovated'])
normalized_yr_renovated = preprocessing.normalize([x_array])
```

```
x_array = np.array(data['sqft_lot'])
normalized_sqft_lot = preprocessing.normalize([x_array])

x_array = np.array(data['sqft_lot15'])
normalized_sqft_lot15 = preprocessing.normalize([x_array])

x_array = np.array(data['yr_built'])
normalized_yr_built = preprocessing.normalize([x_array])

x_array = np.array(data['condition'])
normalized_condition = preprocessing.normalize([x_array])

x_array = np.array(data['long'])
normalized_long = preprocessing.normalize([x_array])

#No errors this time!
```

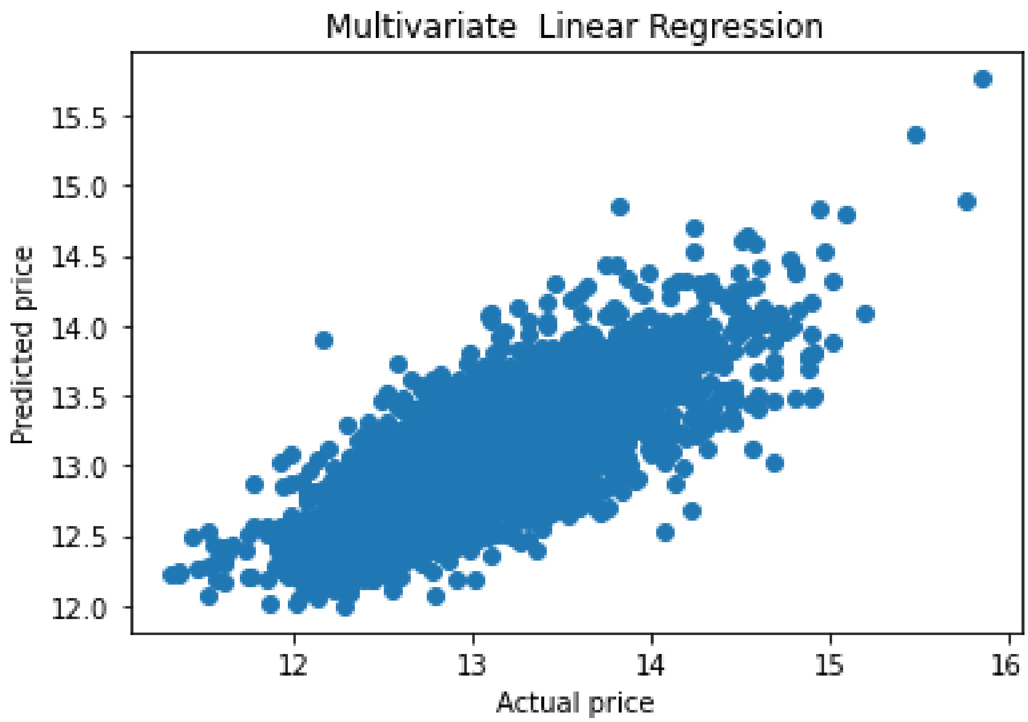
[54]:
```
# Dividing the data into training and testing set
X = features
y=data['price']
y=np.log(y)

#note, normalization and standarization were both attempted, but no effects␣
↪were seen on improving the model more than it is now

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)
```

[55]:
```
#Multivariate Linear Regresion Model
Linear_Regression = LinearRegression()
Linear_Regression_Model = Linear_Regression.fit(X_train, y_train)

Linear_Regression_preds = Linear_Regression_Model.predict(X_test)

rmse1 = np.sqrt(mean_squared_error(y_test, Linear_Regression_preds))
print('RMSE: ', rmse1)
rsq1 = r2_score(y_test, Linear_Regression_preds)
print('R2 Score: ', rsq1)
mae1 = mean_absolute_error(y_test, Linear_Regression_preds)
print('MAE: ', mae1)
plt.scatter(y_test, Linear_Regression_preds)
plt.xlabel("Actual price")
plt.ylabel("Predicted price")
plt.title("Multivariate  Linear Regression")
```

```
RMSE:  0.3361510551443762
R2 Score:  0.596933551393023
```

```
MAE:  0.25891335450495595
```

[55]:
```
Text(0.5, 1.0, 'Multivariate  Linear Regression')
```




[80]:
```
#Ridge Regression Model(alpha 2.0)
Ridge_Regression = Ridge(alpha=2.0)
Ridge_Regression_model = Ridge_Regression.fit(X_train, y_train)

Ridge_Regression_preds = Ridge_Regression_model.predict(X_test)

rmse2 = np.sqrt(mean_squared_error(y_test, Ridge_Regression_preds))
print('RMSE: ', rmse2)
rsq2 = r2_score(y_test, Ridge_Regression_preds)
print('R2 Score: ', rsq2)
mae2 = mean_absolute_error(y_test, Ridge_Regression_preds)
print('MAE: ', mae2)

#Ridge Regression Model(alpha 1.0)
Ridge_Regression = Ridge(alpha=1.0)
Ridge_Regression_model = Ridge_Regression.fit(X_train, y_train)

Ridge_Regression_preds = Ridge_Regression_model.predict(X_test)

rmse21 = np.sqrt(mean_squared_error(y_test, Ridge_Regression_preds))
```

```
print('RMSE: ', rmse21)
rsq21 = r2_score(y_test, Ridge_Regression_preds)
print('R2 Score: ', rsq21)
mae21 = mean_absolute_error(y_test, Ridge_Regression_preds)
print('MAE: ', mae21)

#Ridge Regression Model(alpha 0.5)
Ridge_Regression = Ridge(alpha=0.5)
Ridge_Regression_model = Ridge_Regression.fit(X_train, y_train)

Ridge_Regression_preds = Ridge_Regression_model.predict(X_test)

rmse22 = np.sqrt(mean_squared_error(y_test, Ridge_Regression_preds))
print('RMSE: ', rmse22)
rsq22 = r2_score(y_test, Ridge_Regression_preds)
print('R2 Score: ', rsq22)
mae22 = mean_absolute_error(y_test, Ridge_Regression_preds)
print('MAE: ', mae22)

scores = {
         'Alpha': ['2', '1', '.5'],

         'RMSE': [rmse2,rmse21,rmse22],

         'R2 Score': [rsq2,rsq21,rsq22],

        'MAE': [mae2,mae21, mae22]
            }

col = ['Alpha', 'RMSE', 'R2 Score', 'MAE']

error_matrix = pd.DataFrame(data=scores, columns=col).sort_values(by='MAE',␣
 ↪ascending=True).reset_index()
error_matrix.drop(columns=['index'], inplace=True)

error_matrix
```

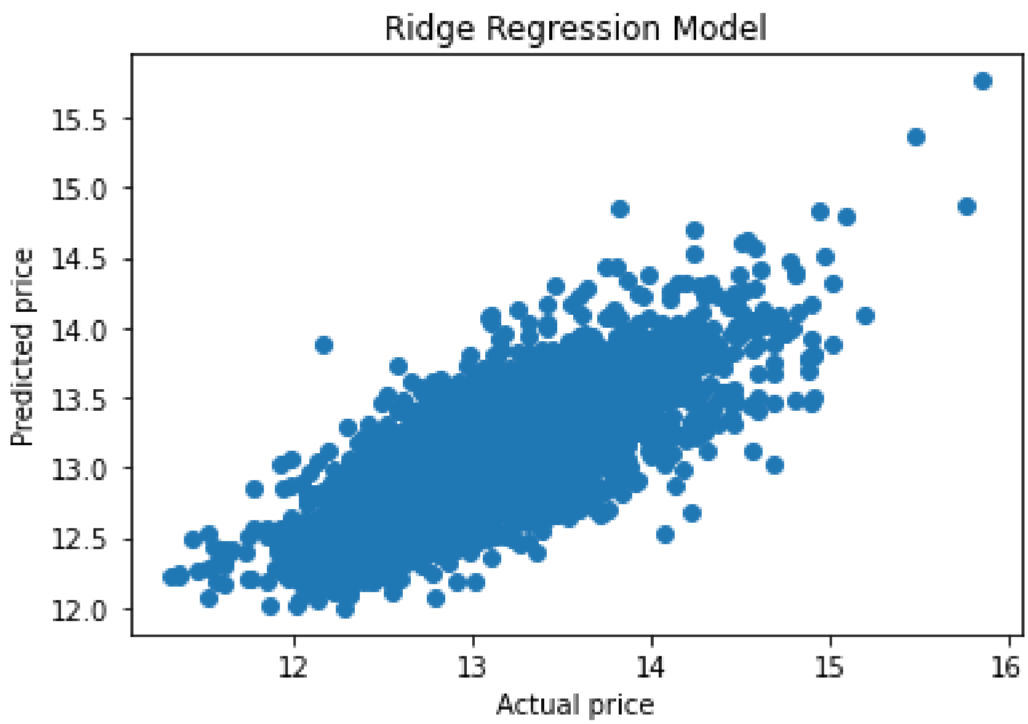
```
RMSE:  0.3347906397773514
R2 Score:  0.5950868383734451
MAE:  0.2578837705528117
RMSE:  0.33476958567120185
R2 Score:  0.5951377646277263
MAE:  0.25783359787683474
RMSE:  0.33475963841424705
R2 Score:  0.5951618242139389
MAE:  0.2578086387946662
```

[80]:

| | Alpha | RMSE | R2 Score | MAE |
|---|---|---|---|---|
| 0 | .5 | 0.334760 | 0.595162 | 0.257809 |
| 1 | 1 | 0.334770 | 0.595138 | 0.257834 |
| 2 | 2 | 0.334791 | 0.595087 | 0.257884 |

[57]:
```
plt.scatter(y_test, Ridge_Regression_preds)
plt.xlabel("Actual price")
plt.ylabel("Predicted price")
plt.title("Ridge Regression Model")
```

[57]: Text(0.5, 1.0, 'Ridge Regression Model')

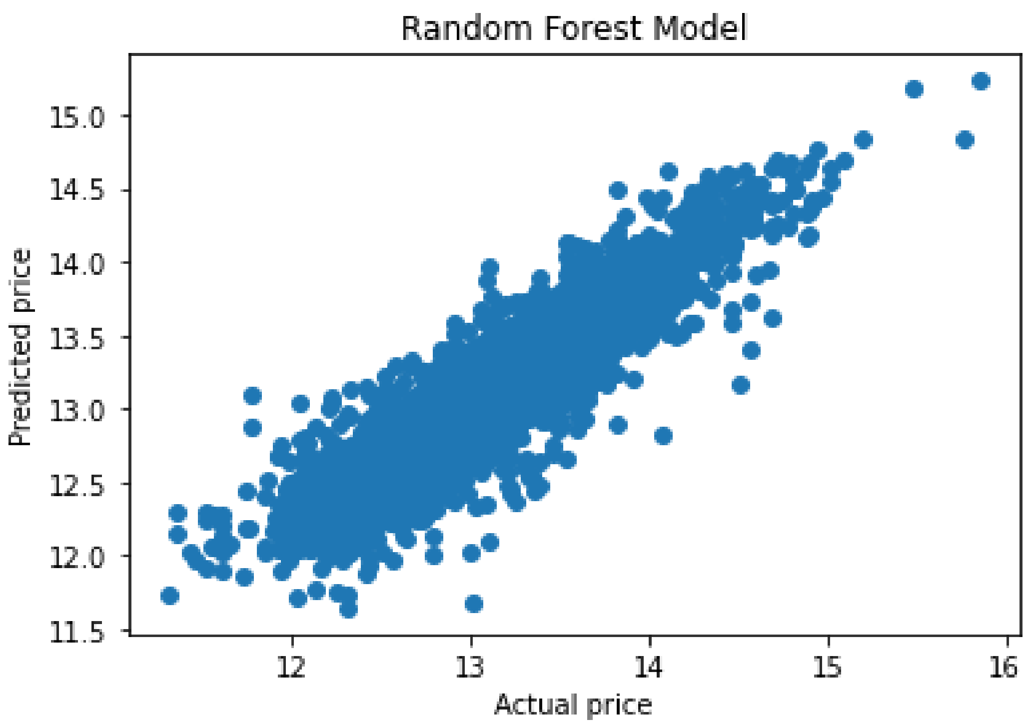



[58]:
```
#Random Forest Model
Random_Forest = RandomForestRegressor(max_depth=None, min_samples_split=2,␣
 ↪min_samples_leaf=1)
Random_Forest_Model = Random_Forest.fit(X_train, y_train)

Random_Forest_preds = Random_Forest_Model.predict(X_test)

rmse3 = np.sqrt(mean_squared_error(y_test, Random_Forest_preds))
print('RMSE: ', rmse3)
rsq3 = r2_score(y_test, Random_Forest_preds)
print('R2 Score: ', rsq3)
```

```
mae3 = mean_absolute_error(y_test, Random_Forest_preds)
print('MAE: ', mae3)
plt.scatter(y_test, Random_Forest_preds)
plt.xlabel("Actual price")
plt.ylabel("Predicted price")
plt.title("Random Forest Model")
#changing the parameters in this case did not change the accuracy. It might␣
↪have to do with the actual data before being put into this model
```

```
RMSE:  0.21147053870365048
R2 Score:  0.8404828306363288
MAE:  0.153169285871099
```

[58]: Text(0.5, 1.0, 'Random Forest Model')

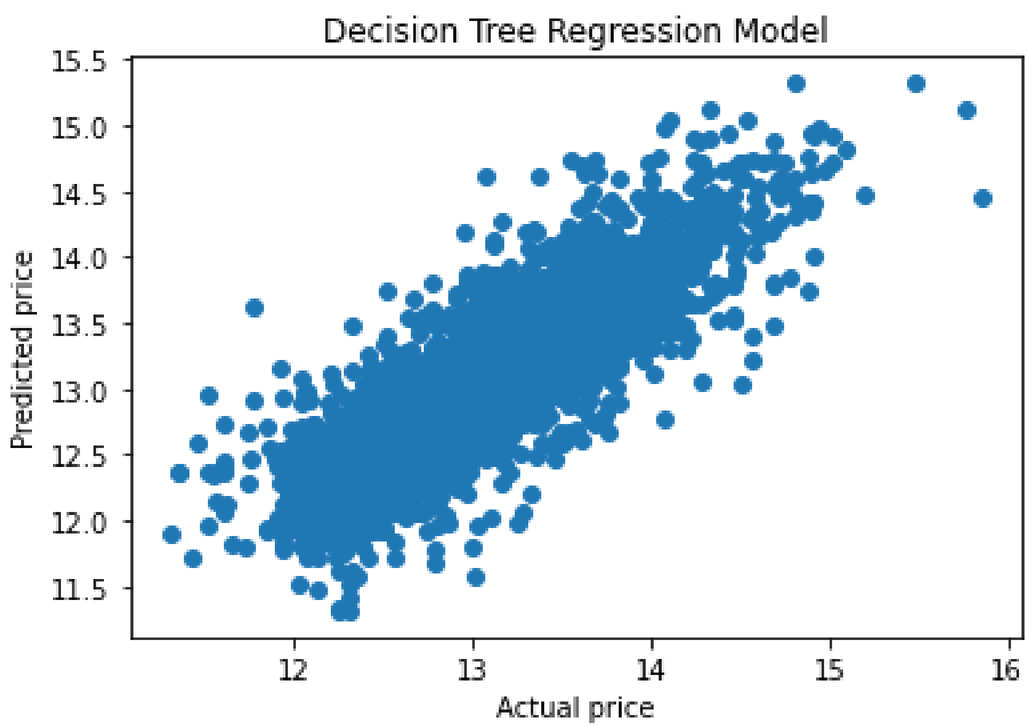



[59]:
```
#Decision Tree Regression Model
Decision_Tree = DecisionTreeRegressor(criterion='mse', splitter='best',␣
↪max_depth=None, min_samples_split=2, min_samples_leaf=1,)
Decision_Tree_Model = Decision_Tree.fit(X_train, y_train)

Decision_Tree_Model_preds = Decision_Tree_Model.predict(X_test)

rmse4 = np.sqrt(mean_squared_error(y_test, Decision_Tree_Model_preds))
```

```
print('RMSE: ', rmse4)
rsq4 = r2_score(y_test, Decision_Tree_Model_preds)
print('R2 Score: ', rsq4)
mae4 = mean_absolute_error(y_test, Decision_Tree_Model_preds)
print('MAE: ', mae4)
plt.scatter(y_test, Decision_Tree_Model_preds)
plt.xlabel("Actual price")
plt.ylabel("Predicted price")
plt.title("Decision Tree Regression Model")
#changing the parameters in this case did not change the accuracy. It might␣
↪have to do with the actual data before being put into this model
```

```
RMSE:  0.28883817062338357
R2 Score:  0.7024110078106671
MAE:  0.20902646373030037
```

[59]: Text(0.5, 1.0, 'Decision Tree Regression Model')




[69]:
```
#Support Vector Regression Model(c=1.0)
Support_Vector_Regression = SVR(gamma=1, C=.001)
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
↪y_train)
```

```
Support_Vector_Regression_preds = Support_Vector_Regression_Model.
↪predict(X_test)

rmse5 = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse5)
rsq5 = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq5)
mae5 = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae5)

#Support Vector Regression Model(c=1)
Support_Vector_Regression = SVR(gamma=1.0, C=.01)
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
↪y_train)

Support_Vector_Regression_preds = Support_Vector_Regression_Model.
↪predict(X_test)

rmse51 = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse51)
rsq51 = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq51)
mae51 = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae51)

#Support Vector Regression Model(c=1)
Support_Vector_Regression = SVR(gamma=1, C=10.0)
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
↪y_train)

Support_Vector_Regression_preds = Support_Vector_Regression_Model.
↪predict(X_test)

rmse52 = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse52)
rsq52 = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq52)
mae52 = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae52)

#Support Vector Regression Model(c=10)
Support_Vector_Regression = SVR(gamma=1.0, C=1.0)
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
↪y_train)
```

```
Support_Vector_Regression_preds = Support_Vector_Regression_Model.
 ↪predict(X_test)

rmse53 = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse53)
rsq53 = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq53)
mae53 = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae53)
```

```
RMSE:  366124.3075860474
R2 Score:  -0.06144156011328139
MAE:  220129.51848259591
RMSE:  366124.3053745621
R2 Score:  -0.06144154729051965
MAE:  220129.5162806445
RMSE:  366121.64338307123
R2 Score:  -0.06142611243381335
MAE:  220127.10056806626
RMSE:  366124.0462249328
R2 Score:  -0.061440044674702765
MAE:  220129.27679016447
```

[70]:
```
scores = {
         'C': ['.001', '.01', '10.0','1.0'],

         'RMSE': [rmse5,rmse51,rmse52,rmse53],

         'R2 Score': [rsq5,rsq51,rsq52, rsq53],

        'MAE': [mae5,mae51, mae52, mae53]
            }

col = ['C', 'RMSE', 'R2 Score', 'MAE']

error_matrix = pd.DataFrame(data=scores, columns=col).sort_values(by='MAE',␣
 ↪ascending=True).reset_index()
error_matrix.drop(columns=['index'], inplace=True)

error_matrix
```

[70]:

| | C | RMSE | R2 Score | MAE |
|---|---|---|---|---|
| 0 | 10.0 | 366121.643383 | -0.061426 | 220127.100568 |
| 1 | 1.0 | 366124.046225 | -0.061440 | 220129.276790 |
| 2 | .01 | 366124.305375 | -0.061442 | 220129.516281 |
| 3 | .001 | 366124.307586 | -0.061442 | 220129.518483 |

[71]:
```
#Support Vector Regression Model(gamma=1)
Support_Vector_Regression = SVR(gamma=1, C=1.0)
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
↪y_train)

Support_Vector_Regression_preds = Support_Vector_Regression_Model.
↪predict(X_test)

rmse5 = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse5)
rsq5 = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq5)
mae5 = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae5)

#Support Vector Regression Model(gamma=10.)
Support_Vector_Regression = SVR(gamma=10.0, C=1)
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
↪y_train)

Support_Vector_Regression_preds = Support_Vector_Regression_Model.
↪predict(X_test)

rmse51 = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse51)
rsq51 = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq51)
mae51 = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae51)

#Support Vector Regression Model(gamma=.01)
Support_Vector_Regression = SVR(gamma=.01, C=1.0)
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
↪y_train)

Support_Vector_Regression_preds = Support_Vector_Regression_Model.
↪predict(X_test)

rmse52 = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse52)
rsq52 = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq52)
mae52 = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae52)

#Support Vector Regression Model(gamma=.001)
Support_Vector_Regression = SVR(gamma=.001, C=1.0)
```

```
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
↪y_train)

Support_Vector_Regression_preds = Support_Vector_Regression_Model.
↪predict(X_test)

rmse53 = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse53)
rsq53 = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq53)
mae53 = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae53)
```

```
RMSE:  366124.0462249328
R2 Score:  -0.061440044674702765
MAE:  220129.27679016447
RMSE:  366124.1522482343
R2 Score:  -0.061440659424786936
MAE:  220129.4328591825
RMSE:  366123.761244609
R2 Score:  -0.06143839228714154
MAE:  220128.4425958709
RMSE:  366122.8481854245
R2 Score:  -0.0614330981491098
MAE:  220127.26865998548
```

[81]:
```
scores = {
         'Gamma': ['1.0', '10.0', '.01','.001'],

         'RMSE': [rmse5,rmse51,rmse52,rmse53],

         'R2 Score': [rsq5,rsq51,rsq52, rsq53],

        'MAE': [mae5,mae51, mae52, mae53]
            }

col = ['Gamma', 'RMSE', 'R2 Score', 'MAE']

error_matrix = pd.DataFrame(data=scores, columns=col).sort_values(by='MAE',␣
↪ascending=True).reset_index()
error_matrix.drop(columns=['index'], inplace=True)

error_matrix
```

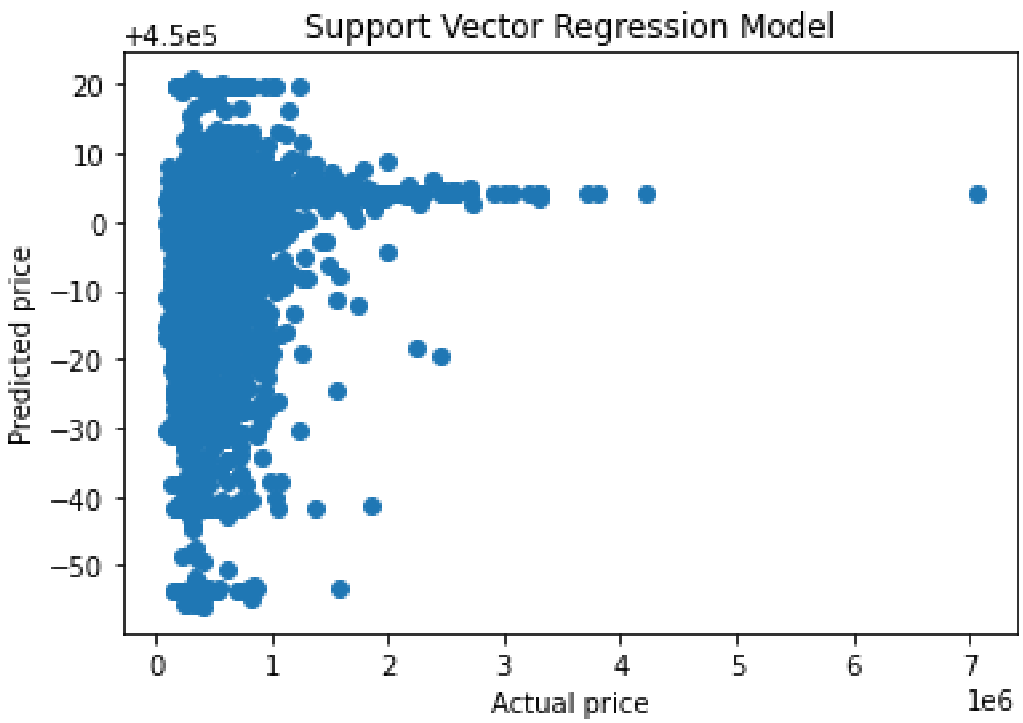
[81]:

| | Gamma | RMSE | R2 Score | MAE |
|---|---|---|---|---|
| 0 | 1.0 | 0.512341 | 0.051726 | 0.399704 |
| 1 | .001 | 366122.848185 | -0.061433 | 220127.268660 |

```
2   .01  366123.761245 -0.061438  220128.442596
3  10.0  366124.152248 -0.061441  220129.432859
```

[73]:
```
plt.scatter(y_test, Support_Vector_Regression_preds)
plt.xlabel("Actual price")
plt.ylabel("Predicted price")
plt.title("Support Vector Regression Model")
```

[73]:
```
Text(0.5, 1.0, 'Support Vector Regression Model')
```

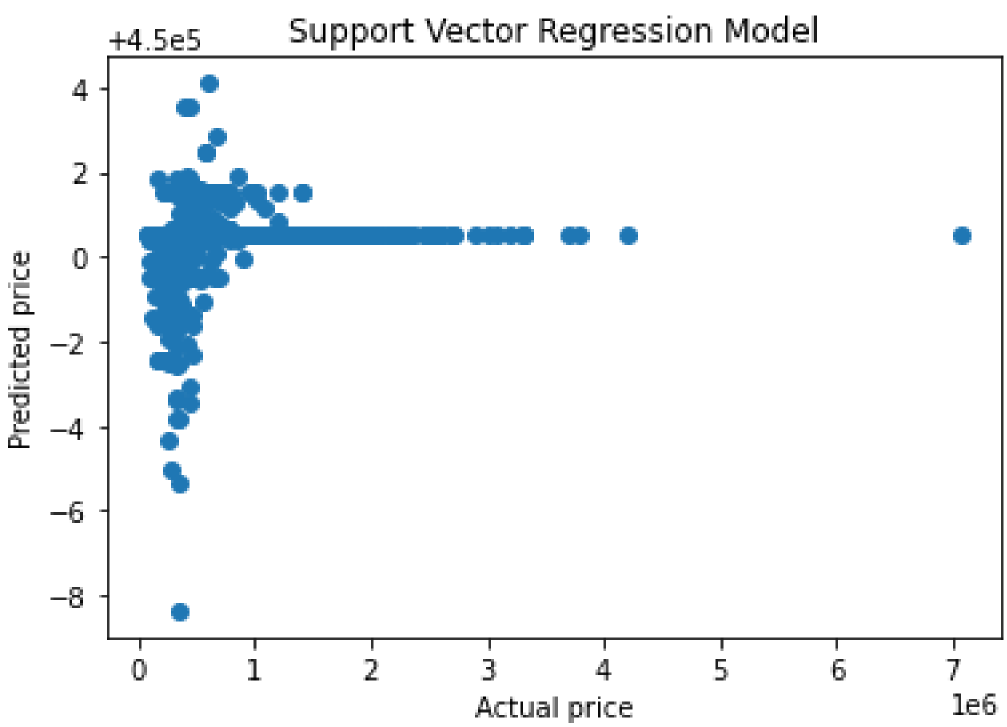



[66]:
```
#Trying without log(Y)
# Dividing the data into training and testing set
X = features
y=data['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)

#Support Vector Regression Model
Support_Vector_Regression = SVR(gamma=100.00)
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
 ↪y_train)

Support_Vector_Regression_preds = Support_Vector_Regression_Model.
 ↪predict(X_test)
```

```
rmse = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse)
rsq = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq)
mae = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae)
plt.scatter(y_test, Support_Vector_Regression_preds)
plt.xlabel("Actual price")
plt.ylabel("Predicted price")
plt.title("Support Vector Regression Model")
```

```
RMSE:  366124.17310173565
R2 Score:  -0.06144078033871603
MAE:  220129.46686048718
```

[66]:
```
Text(0.5, 1.0, 'Support Vector Regression Model')
```

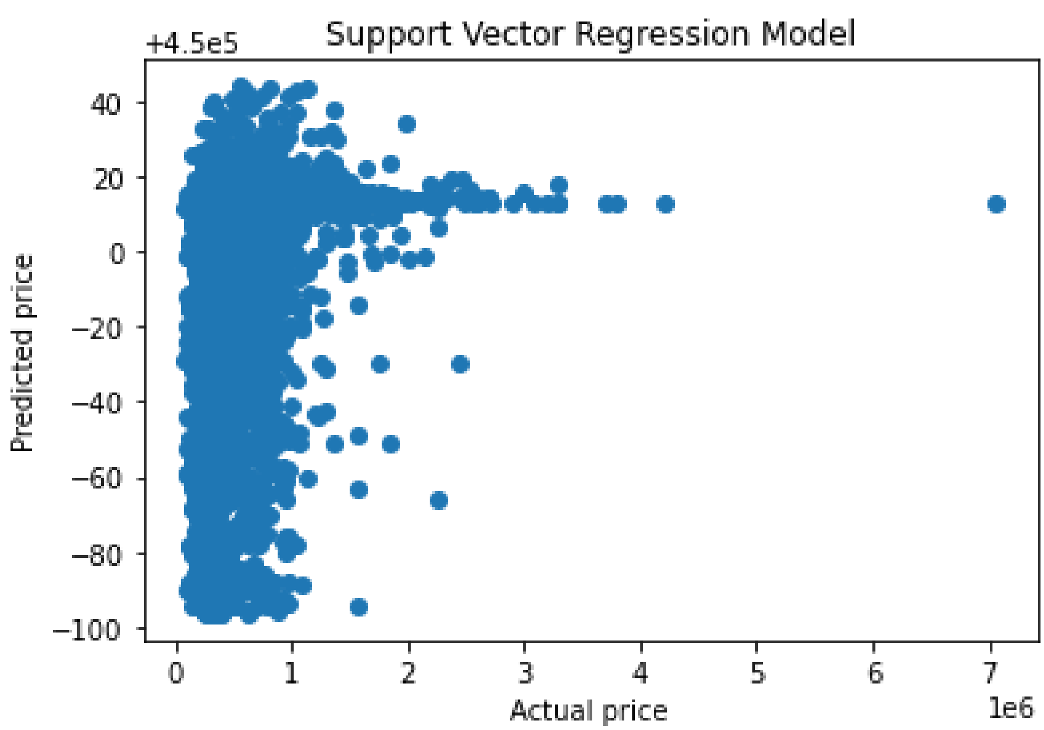



[67]:
```
#Support Vector Regression Model
Support_Vector_Regression = SVR(gamma=.0001)
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
↪y_train)
```

```
Support_Vector_Regression_preds = Support_Vector_Regression_Model.
 ↪predict(X_test)

rmse = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse)
rsq = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq)
mae = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae)
plt.scatter(y_test, Support_Vector_Regression_preds)
plt.xlabel("Actual price")
plt.ylabel("Predicted price")
plt.title("Support Vector Regression Model")
```

```
RMSE:  366119.64435764274
R2 Score:  -0.06141452168502837
MAE:  220123.24505602836
```

[67]: Text(0.5, 1.0, 'Support Vector Regression Model')




[77]:
```
data = pd.read_csv('kc_house_data.csv')
X = features
y=data['price']
```

```
y=np.log(y)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)
Support_Vector_Regression = SVR(gamma=10.0, C=1.0)
Support_Vector_Regression_Model = Support_Vector_Regression.fit(X_train,␣
 ↪y_train)

Support_Vector_Regression_preds = Support_Vector_Regression_Model.
 ↪predict(X_test)

rmse5 = np.sqrt(mean_squared_error(y_test, Support_Vector_Regression_preds))
print('RMSE: ', rmse5)
rsq5 = r2_score(y_test, Support_Vector_Regression_preds)
print('R2 Score: ', rsq5)
mae5 = mean_absolute_error(y_test, Support_Vector_Regression_preds)
print('MAE: ', mae5)
```

```
RMSE:  0.5123413269941175
R2 Score:  0.051725533801635803
MAE:  0.39970412487460555
```

[78]:

```
scores = {
        'Model': ['Linear Regression', 'Ridge Regression', 'Random Forest␣
 ↪Regression','Decision Tree Regression',
                    'SVR'],

        'RMSE': [rmse1,rmse2,rmse3,rmse4,rmse5],

        'R2 Score': [rsq1,rsq2,rsq3,rsq4,rsq5],

       'MAE': [mae1,mae2, mae3,mae4,mae4]
            }

col = ['Model', 'RMSE', 'R2 Score', 'MAE']

error_matrix = pd.DataFrame(data=scores, columns=col).sort_values(by='MAE',␣
 ↪ascending=True).reset_index()
error_matrix.drop(columns=['index'], inplace=True)

error_matrix
```

[78]:

| | Model | RMSE | R2 Score | MAE |
|---|---|---|---|---|
| 0 | Random Forest Regression | 0.211471 | 0.840483 | 0.153169 |
| 1 | Decision Tree Regression | 0.288838 | 0.702411 | 0.209026 |
| 2 | SVR | 0.512341 | 0.051726 | 0.209026 |
| 3 | Linear Regression | 0.336151 | 0.596934 | 0.258913 |
| 4 | Ridge Regression | 0.336177 | 0.596872 | 0.258999 |

[ ]:

```

```