California Housing Price Prediction

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Simplilearn Post Graduate Program - Data Science - In Partnership With Purdue University

Project Report - California Housing Price Prediction

Organization: Simplilearn - Purdue University Batch: PGP DS Mar 2022 COHORT 2 Course: PG -DS - Data Science with Python Project: California Housing Price Prediction Programming Language: Python Submitted by: Lavkush Singh

0.1 Dataset Description

Dataset has the following fields:

- **longitude** (signed numeric - float) : Longitude value for the block in California, USA
- **latitude** (numeric - float) : Latitude value for the block in California, USA
- **housing_median_age** (numeric - int) : Median age of the house in the block
- **total_rooms** (numeric - int) : Count of the total number of rooms (excluding bedrooms) in all houses in the block
- **total_bedrooms** (numeric - float) : Count of the total number of bedrooms in all houses in the block
- **population** (numeric - int) : Count of the total number of population in the block
- **households** (numeric - int) : Count of the total number of households in the block
- **median_incom**e (numeric - float) : Median of the total household income of all the houses in the block
- **ocean_proximity** (numeric - categorical) : Type of the landscape of the block [Unique Values : 'NEAR BAY', '<1H OCEAN', 'INLAND', 'NEAR OCEAN', 'ISLAND']
- **median_house_value** (numeric - int) : Median of the household prices of all the houses in the block

0.2 Problem Statement

The project aims at building a model of housing prices to predict median house values in California using the provided dataset. This model should learn from the data and be able to predict the median housing price in any district, given all the other metrics. There are 20,640 districts in the project dataset.

Analysis Tasks to be performed

- Build a model of housing prices to predict median house values in California using the provided dataset.
- Train the model to learn from the data to predict the median housing price in any district, given all the other metrics.
- Predict housing prices based on median_income and plot the regression chart for it.

0.2.1 1. Load the data

[1]:
```
# importing necessary libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import RobustScaler
from sklearn.linear_model import LinearRegression
from statsmodels.formula.api import ols
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
↪mean_absolute_percentage_error, r2_score
%matplotlib inline
```

[2]:
```
housedata = pd.read_excel('Datasets/1553768847_housing.xlsx') # reading the␣
↪dataset
```

[3]:
```
housedata.head() #viewing first few records
```

[3]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                  41          880           129.0
1    -122.22     37.86                  21         7099          1106.0
2    -122.24     37.85                  52         1467           190.0
3    -122.25     37.85                  52         1274           235.0
4    -122.25     37.85                  52         1627           280.0

   population  households  median_income ocean_proximity  median_house_value
0         322         126         8.3252        NEAR BAY              452600
1        2401        1138         8.3014        NEAR BAY              358500
2         496         177         7.2574        NEAR BAY              352100
3         558         219         5.6431        NEAR BAY              341300
4         565         259         3.8462        NEAR BAY              342200
```

[4]:
```
housedata.info()   # viewing basic info about the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
```

```
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  int64
 3   total_rooms         20640 non-null  int64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  int64
 6   households          20640 non-null  int64
 7   median_income       20640 non-null  float64
 8   ocean_proximity     20640 non-null  object
 9   median_house_value  20640 non-null  int64
dtypes: float64(4), int64(5), object(1)
memory usage: 1.6+ MB
```

[5]:
```
housedata.duplicated().sum() # checking if the dataframe has any duplicate␣
↪entries
```

[5]:
```
0
```

0.2.2 2. Handling Missing Values

[6]:
```
# checking how many total null values we have
nulls = housedata.isnull().sum()
print(nulls)
```

```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
ocean_proximity         0
median_house_value      0
dtype: int64
```

[7]:
```
# checking the percent of null values present in dataset (only null values␣
↪greater then 0 will be displayd)

(nulls[nulls > 0]/housedata.shape[0])*100
```

[7]:
```
total_bedrooms    1.002907
dtype: float64
```

[8]:
```python
housedata['total_bedrooms'].skew().round(2) # checking the magnitude of the␣
↪skewness
```

[8]: 3.46

[9]:
```python
# imputing missing values with median of 'total_bedrooms' column since it is␣
↪highly skewed

housedata['total_bedrooms'].fillna(value=housedata['total_bedrooms'].median(),␣
↪inplace = True)
```

[10]:
```python
housedata.isnull().sum() # checking if all the missing values are now removed
```

[10]:
```
longitude             0
latitude              0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
households            0
median_income         0
ocean_proximity       0
median_house_value    0
dtype: int64
```

0.2.3 Understanding Data and Feature Engineering

[11]:
```python
housedata.describe().round(2) # getting basic descriptive statistics of␣
↪numerical columns
```

[11]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
count   20640.00  20640.00            20640.00     20640.00        20640.00
mean     -119.57     35.63               28.64      2635.76          536.84
std         2.00      2.14               12.59      2181.62          419.39
min      -124.35     32.54                1.00         2.00            1.00
25%      -121.80     33.93               18.00      1447.75          297.00
50%      -118.49     34.26               29.00      2127.00          435.00
75%      -118.01     37.71               37.00      3148.00          643.25
max      -114.31     41.95               52.00     39320.00         6445.00

       population  households  median_income  median_house_value
count    20640.00    20640.00       20640.00            20640.00
mean      1425.48      499.54           3.87           206855.82
std       1132.46      382.33           1.90           115395.62
min          3.00        1.00           0.50            14999.00
25%        787.00      280.00           2.56           119600.00
```

```
50%       1166.00      409.00          3.53          179700.00
75%       1725.00      605.00          4.74          264725.00
max      35682.00     6082.00         15.00          500001.00
```

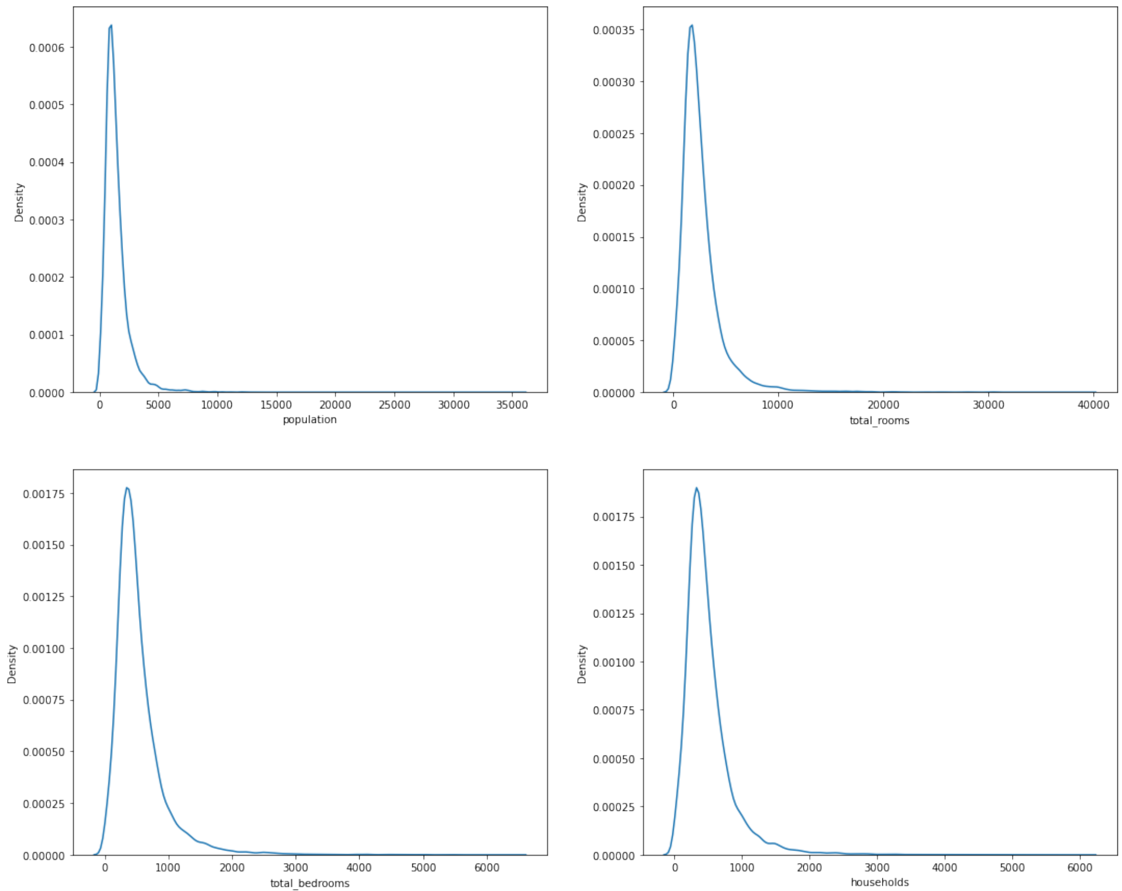
[12]:
```
housedata['ocean_proximity'].value_counts() # ocean_proximity is categorical␣
↪column, so getting its value counts
```

[12]:
```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

[13]:
```
# converting columns into array to traverse through it and plotting graph as␣
↪sub-plots

arr_cols = np.array(['population', 'total_rooms', 'total_bedrooms',␣
↪'households']).reshape(2,2)
arr_cols
```

[13]:
```
array([['population', 'total_rooms'],
       ['total_bedrooms', 'households']], dtype='<U14')
```

[14]:
```
# plotting KDE plot to view how the data is distributed

fig, axes = plt.subplots(2, 2, figsize=(18, 15))

for i in range(2):
    for j in range(2):
            sns.kdeplot(ax=axes[i, j], data = housedata, x = arr_cols[i,j])
```

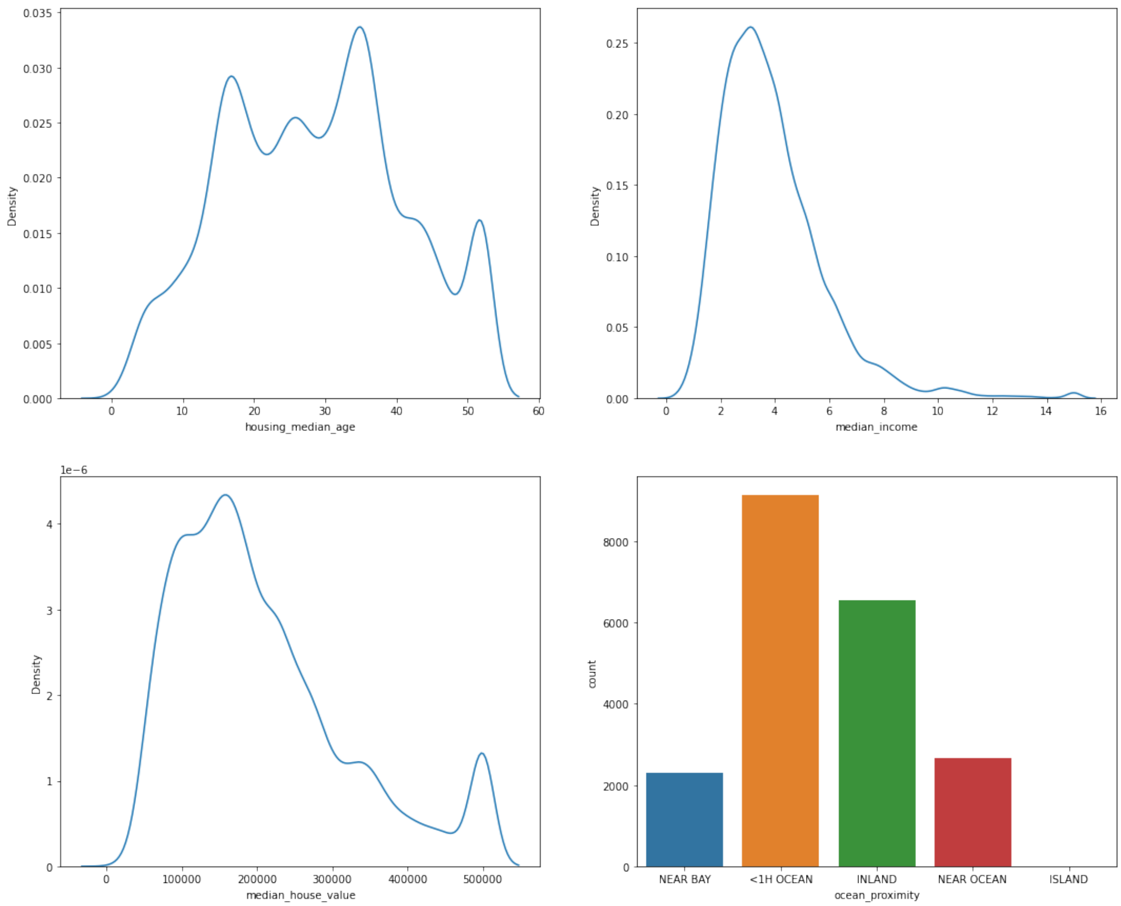


[15]:
```python
# converting columns into array to traverse through it and plotting graph as sub-plots

arr_cols_2 = np.array(['housing_median_age', 'median_income', 'median_house_value', 'ocean_proximity']).reshape(2,2)
arr_cols_2
```

[15]:
```
array([['housing_median_age', 'median_income'],
       ['median_house_value', 'ocean_proximity']], dtype='<U18')
```

[16]:
```python
# KDE plots for all columns except the categorical column for which we have plotted Bar-plot

fig, axes = plt.subplots(2, 2, figsize=(18, 15))

for i in range(2):
    for j in range(2):
        if(i == 1 & j == 1):
            sns.countplot(ax=axes[i, j], data = housedata, x = arr_cols_2[i,j])
```

```
        else:
            sns.kdeplot(ax=axes[i, j], data = housedata, x = arr_cols_2[i,j])
```



[17]:

```
# below is the function which take latitude and longitue as input and returns city, state and country as output
# this function is made with an objective to extract information out of latitude and longitude columns present in the data

from geopy.geocoders import Nominatim

def get_city(lat, long):

    if (type(lat) != str) | (type(long) != str):
        lat = str(lat)
        long = str(long)

    geolocator = Nominatim(user_agent="geoapiExercises")
    location = geolocator.reverse(lat+","+long)
    address = location.raw['address']
```

```
    city = address.get('city', '')
    state = address.get('state', '')
    country = address.get('country', '')
    return city, state, country
```

[18]:
```
# below is the function which take latitude and longitue as input and returns␣
 ↪city, state and country as output
# this function is adjusted to make api calls with pauses to accomodate the␣
 ↪limitations of 1 request per second

from geopy.geocoders import Nominatim
from random import randint
from time import sleep
def get_city_2(lat, long):
    sleep_sec = 1
    if (type(lat) != str) | (type(long) != str):
        lat = str(lat)
        long = str(long)
    sleep(randint(1*100,sleep_sec*100)/100)
    user_agent = 'user_me_{}'.format(randint(10000,99999))
    geolocator = Nominatim(user_agent=user_agent)
    location = geolocator.reverse(lat+","+long)
    address = location.raw['address']
    city = address.get('city', '')
    state = address.get('state', '')
    country = address.get('country', '')
    return city, state, country
```

[19]:
```
get_city(37.86, -122.22) # testing of the get_city() function
```

[19]: ('', 'California', 'United States')

[20]:
```
# testing the code with few values of latitude and longitude

temp = housedata[["latitude", "longitude"]].head()
temp['Lat-Long-to-Info'] = temp.apply(lambda row: get_city(row['latitude'],␣
 ↪row['longitude']), axis = 1)
temp
```

[20]:

	latitude	longitude	Lat-Long-to-Info
0	37.88	-122.23	(Oakland, California, United States)
1	37.86	-122.22	(, California, United States)
2	37.85	-122.24	(Oakland, California, United States)
3	37.85	-122.25	(Oakland, California, United States)
4	37.85	-122.25	(Oakland, California, United States)

[21]:
```
# splitting up the 'Lat-Long-to-Info' column into individual columns

new_col_list = ['city','state','country']
for n,col in enumerate(new_col_list):
    temp[col] = temp['Lat-Long-to-Info'].apply(lambda location: location[n])

temp = temp.drop('Lat-Long-to-Info',axis=1)
temp
```

[21]:

	latitude	longitude	city	state	country
0	37.88	-122.23	Oakland	California	United States
1	37.86	-122.22		California	United States
2	37.85	-122.24	Oakland	California	United States
3	37.85	-122.25	Oakland	California	United States
4	37.85	-122.25	Oakland	California	United States

[22]:
```
housedata[["latitude", "longitude"]].drop_duplicates().head(10)  # This is a␣
↪test sample to check if get_city_2() works
```

[22]:

	latitude	longitude
0	37.88	-122.23
1	37.86	-122.22
2	37.85	-122.24
3	37.85	-122.25
6	37.84	-122.25
8	37.84	-122.26
10	37.85	-122.26
16	37.85	-122.27
19	37.84	-122.27
25	37.85	-122.28

[23]:
```
# This peice of code would pass unique values of latitude and longitudes to␣
↪get_city_2() function and
# would fetch respective city, state and country

housedata_unique_lat_long = housedata[["latitude", "longitude"]].
↪drop_duplicates().head(10)
scraped_data = housedata_unique_lat_long.apply(lambda row:␣
↪get_city_2(row['latitude'], row['longitude']),
                                                                  axis = 1)
```

[24]:
```
scraped_data
```

[24]:
```
0      (Oakland, California, United States)
1             (, California, United States)
2      (Oakland, California, United States)
3      (Oakland, California, United States)
```

```
6      (Oakland, California, United States)
8      (Oakland, California, United States)
10     (Oakland, California, United States)
16    (Berkeley, California, United States)
19     (Oakland, California, United States)
25    (Berkeley, California, United States)
dtype: object
```

Since we have limitations of fetching location from coordinates, a better approch is to cluster the given coordinates and based on that we can put them in groups. This way, we will get rid of two features (latitude and longitue), and instead will have a single feature (cluster or group in which given latitude and longitude belongs to)

[25]:
```python
housedata.head()
```

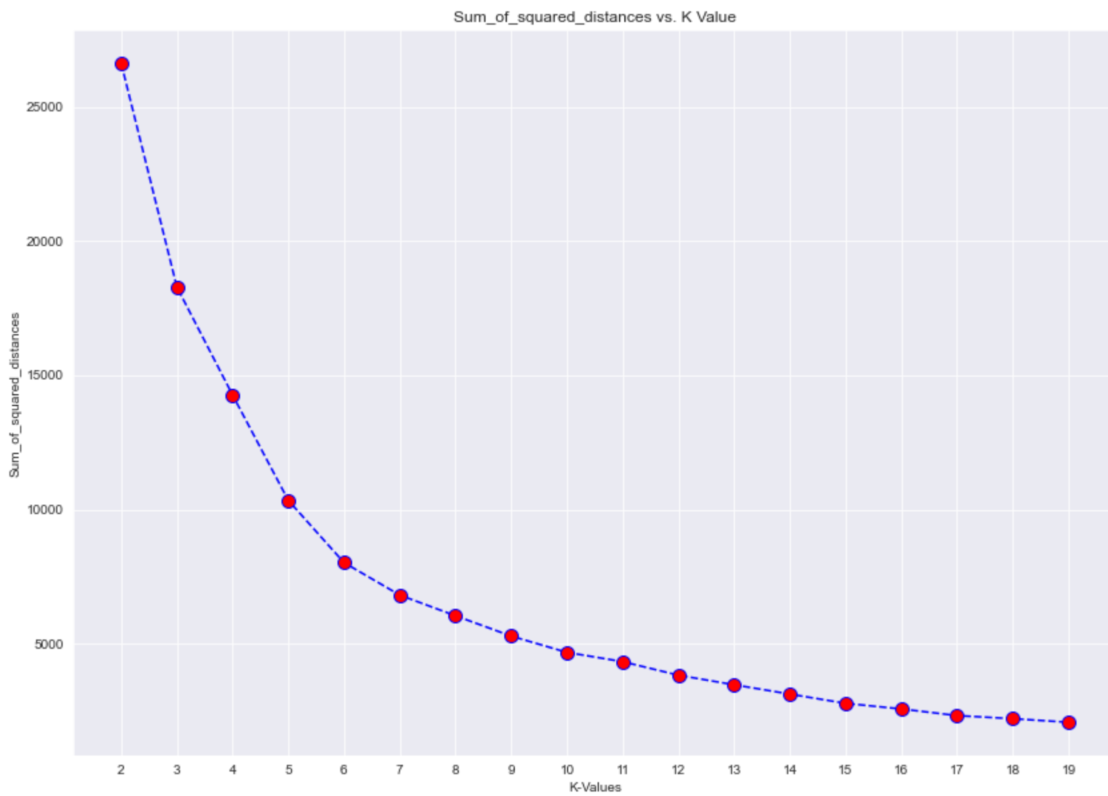
[25]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                  41          880           129.0
1    -122.22     37.86                  21         7099          1106.0
2    -122.24     37.85                  52         1467           190.0
3    -122.25     37.85                  52         1274           235.0
4    -122.25     37.85                  52         1627           280.0

   population  households  median_income ocean_proximity  median_house_value
0         322         126         8.3252        NEAR BAY              452600
1        2401        1138         8.3014        NEAR BAY              358500
2         496         177         7.2574        NEAR BAY              352100
3         558         219         5.6431        NEAR BAY              341300
4         565         259         3.8462        NEAR BAY              342200
```

[26]:
```python
lat_long_data = housedata[["latitude", "longitude"]] # extracting only latitude␣
 ↪and longitude
```

[27]:
```python
# fitting K-Means clustering algorithm for multiple K values and storing the␣
 ↪metric 'sum of squared distances'

sum_of_squared_distances = []
k_values = range(2,20)

for k in k_values:
    kmeans_model = KMeans(n_clusters=k)
    kmeans_model.fit(lat_long_data)
    sum_of_squared_distances.append(kmeans_model.inertia_)
```

[28]:
```python
# plotting the k values versus the 'sum of squared distances'

sns.set_style('darkgrid')
```

```
plt.figure(figsize=(14,10))
plt.plot(k_values,sum_of_squared_distances, color='blue', linestyle='dashed',␣
↪marker='o',
         markerfacecolor='red', markersize=10)
plt.title('Sum_of_squared_distances vs. K Value')
plt.xticks(range(2,20))
plt.xlabel('K-Values')
plt.ylabel('Sum_of_squared_distances');
```



From the above graph, we see that the elbow point is somewhere between 5 to 7. Hence, we will select k = 6 for our analysis

[29]:
```
# Fitting the data with k = 6

kmeans_model = KMeans(n_clusters=6)
kmeans_model.fit(lat_long_data)
```

[29]: KMeans(n_clusters=6)

[30]:
```
# Printing out cluster centers, just in case if required

kmeans_model.cluster_centers_
```

[30]:
```
array([[  40.17953556, -122.75143687],
       [  34.01332397, -118.11814873],
       [  38.39667957, -121.13467957],
       [  37.66910899, -122.17297969],
       [  35.95939794, -119.68459289],
       [  33.05233055, -116.93609099]])
```

[31]:
```
# model labels can be accessed using .labels_ attribute

kmeans_model.labels_
```

[31]:
```
array([3, 3, 3, …, 2, 2, 2])
```

[32]:
```
lat_long_data.shape # checking shape of data we used in clustering (having␣
 ↪latitude and longitude)
```

[32]:
```
(20640, 2)
```

[33]:
```
# creating respective clusters using the KMeans model built

clusters = pd.DataFrame(kmeans_model.labels_, columns=['lat_long_cluster'])
clusters.shape
```

[33]:
```
(20640, 1)
```

Below are the ways with which we can combine the data frame

- pd.concat([lat_long_data, clusters], axis=1)
- lat_long_data = lat_long_data.join(clusters)
- pd.merge(housedata, clusters, left_index=True, right_index=True)

[34]:
```
# Here I have used merge function to combine the clusters to main dataframe and

housedata_processed = pd.merge(housedata, clusters, left_index=True,␣
 ↪right_index=True)

# left_index and right_index is True, because we do not have anything in common␣
 ↪except the index values in both tables
```

[35]:
```
# removed the original columns latitude and longitude

housedata_processed.drop(['latitude', 'longitude'], axis=1, inplace=True)  #␣
 ↪dropping latitude and longitude columns
housedata_processed.head()
```

[35]:
```
   housing_median_age  total_rooms  total_bedrooms  population  households  \
0                  41          880           129.0         322         126
1                  21         7099          1106.0        2401        1138
```

```
2                    52         1467          190.0         496          177
3                    52         1274          235.0         558          219
4                    52         1627          280.0         565          259

   median_income  ocean_proximity  median_house_value  lat_long_cluster
0         8.3252         NEAR BAY              452600                 3
1         8.3014         NEAR BAY              358500                 3
2         7.2574         NEAR BAY              352100                 3
3         5.6431         NEAR BAY              341300                 3
4         3.8462         NEAR BAY              342200                 3
```

0.2.4 3. Encoding of the Categorical variables

[36]:
```
encoded_ocean_proximity = pd.get_dummies(data =␣
 ↪housedata_processed['ocean_proximity'])
encoded_ocean_proximity
```

[36]:
```
       <1H OCEAN  INLAND  ISLAND  NEAR BAY  NEAR OCEAN
0              0       0       0         1           0
1              0       0       0         1           0
2              0       0       0         1           0
3              0       0       0         1           0
4              0       0       0         1           0
…            …     …     …       …         …
20635          0       1       0         0           0
20636          0       1       0         0           0
20637          0       1       0         0           0
20638          0       1       0         0           0
20639          0       1       0         0           0

[20640 rows x 5 columns]
```

[37]:
```
housedata_processed.head()
```

[37]:
```
   housing_median_age  total_rooms  total_bedrooms  population  households  \
0                  41          880           129.0         322         126
1                  21         7099          1106.0        2401        1138
2                  52         1467           190.0         496         177
3                  52         1274           235.0         558         219
4                  52         1627           280.0         565         259

   median_income  ocean_proximity  median_house_value  lat_long_cluster
0         8.3252         NEAR BAY              452600                 3
1         8.3014         NEAR BAY              358500                 3
2         7.2574         NEAR BAY              352100                 3
3         5.6431         NEAR BAY              341300                 3
```

```
4        3.8462        NEAR BAY            342200                3
```

[38]:
```
# I wanted to insert the categoical columns at a specific location and hence I␣
↪used concat method as follows:

housedata_processed = pd.concat((housedata_processed['lat_long_cluster'],
                                 housedata_processed.iloc[:,:6],
                                 encoded_ocean_proximity,
                                 housedata.iloc[:,-1]), axis = 1)
housedata_processed.head()
```

[38]:
```
   lat_long_cluster  housing_median_age  total_rooms  total_bedrooms  \
0                 3                  41          880           129.0
1                 3                  21         7099          1106.0
2                 3                  52         1467           190.0
3                 3                  52         1274           235.0
4                 3                  52         1627           280.0

   population  households  median_income  <1H OCEAN  INLAND  ISLAND  NEAR BAY  \
0         322         126         8.3252          0       0       0         1
1        2401        1138         8.3014          0       0       0         1
2         496         177         7.2574          0       0       0         1
3         558         219         5.6431          0       0       0         1
4         565         259         3.8462          0       0       0         1

   NEAR OCEAN  median_house_value
0           0              452600
1           0              358500
2           0              352100
3           0              341300
4           0              342200
```

[39]:
```
housedata_processed.columns # viewing column names
```

[39]:
```
Index(['lat_long_cluster', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       '<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN',
       'median_house_value'],
      dtype='object')
```

Since one of the categorical column name (<1H OCEAN) has space which will be problematic later on in ols regression model building, therefore, I am renaming this column, and as well as other categorical columns, just to maintain uniform naming convention of all columns

[40]:
```
housedata_processed.rename(columns = {'<1H OCEAN': 'less_1h_ocean',
                                      'INLAND': 'inland',
                                      'ISLAND': 'island',
```

```
                                            'NEAR BAY':'near_bay',
                                            'NEAR OCEAN':'near_ocean'}, inplace =␣
↪True)
```

[41]:
```
# As we have 4 categories, and we are representing them with 0 and 1, three␣
↪columns are enough to serve the purpose.
# Therefore, dropping off 'island' column

housedata_processed.drop('island', axis = 1, inplace = True)
housedata_processed.columns
```

[41]:
```
Index(['lat_long_cluster', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'less_1h_ocean', 'inland', 'near_bay', 'near_ocean',
       'median_house_value'],
      dtype='object')
```

0.2.5 Visualization, Correlation and Pre-Processing of Data

[42]:
```
housedata_processed['lat_long_cluster'].value_counts() # checking the counts of␣
↪the latitude longitude clusters
```

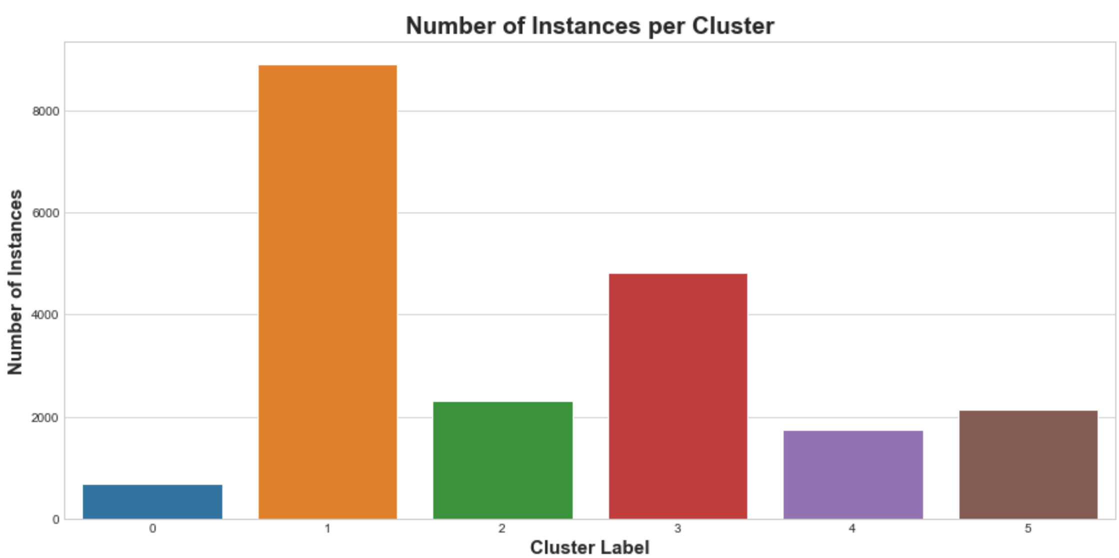
[42]:
```
1    8902
3    4826
2    2325
5    2154
4    1744
0     689
Name: lat_long_cluster, dtype: int64
```

[43]:
```
plt.style.available
```

[43]:
```
['Solarize_Light2',
 '_classic_test_patch',
 'bmh',
 'classic',
 'dark_background',
 'fast',
 'fivethirtyeight',
 'ggplot',
 'grayscale',
 'seaborn',
 'seaborn-bright',
 'seaborn-colorblind',
 'seaborn-dark',
 'seaborn-dark-palette',
```

```
 'seaborn-darkgrid',
 'seaborn-deep',
 'seaborn-muted',
 'seaborn-notebook',
 'seaborn-paper',
 'seaborn-pastel',
 'seaborn-poster',
 'seaborn-talk',
 'seaborn-ticks',
 'seaborn-white',
 'seaborn-whitegrid',
 'tableau-colorblind10']
```

[44]:
```
# Plotting bar graph to visualize the results
plt.style.use('seaborn-whitegrid')

plt.figure(figsize=(15,7))
sns.barplot(x = housedata_processed['lat_long_cluster'].value_counts().index,
            y = housedata_processed['lat_long_cluster'].value_counts().values)
plt.title("Number of Instances per Cluster", fontweight="bold", fontdict =␣
 ↪{'fontsize' : 19})
plt.xlabel("Cluster Label", fontweight="bold", fontdict = {'fontsize' : 15})
plt.ylabel("Number of Instances", fontweight="bold", fontdict = {'fontsize' :␣
 ↪15});
```



[45]:
```
# Checking the distribution of sum of median_house_value prices as per the␣
 ↪latitude-longitude-cluster
```

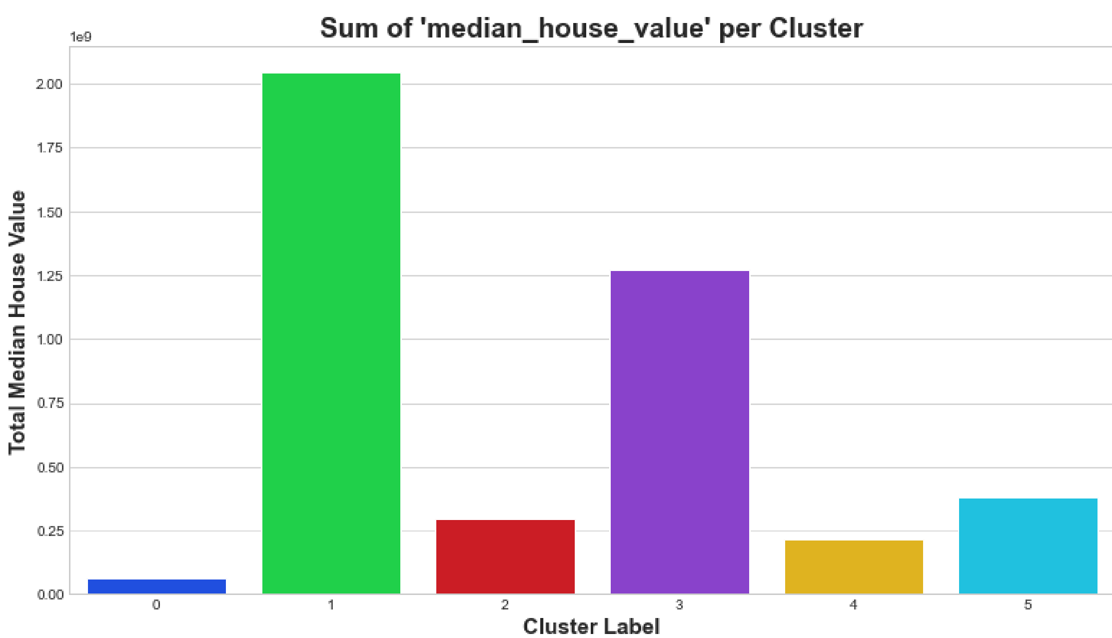
```
cluster_wise_total_house_price = housedata_processed.
→groupby('lat_long_cluster').sum()['median_house_value']
cluster_wise_total_house_price
```

[45]:

```
lat_long_cluster
0      63549998
1    2046839444
2     292577501
3    1269773346
4     213879822
5     382883950
Name: median_house_value, dtype: int64
```

[46]:

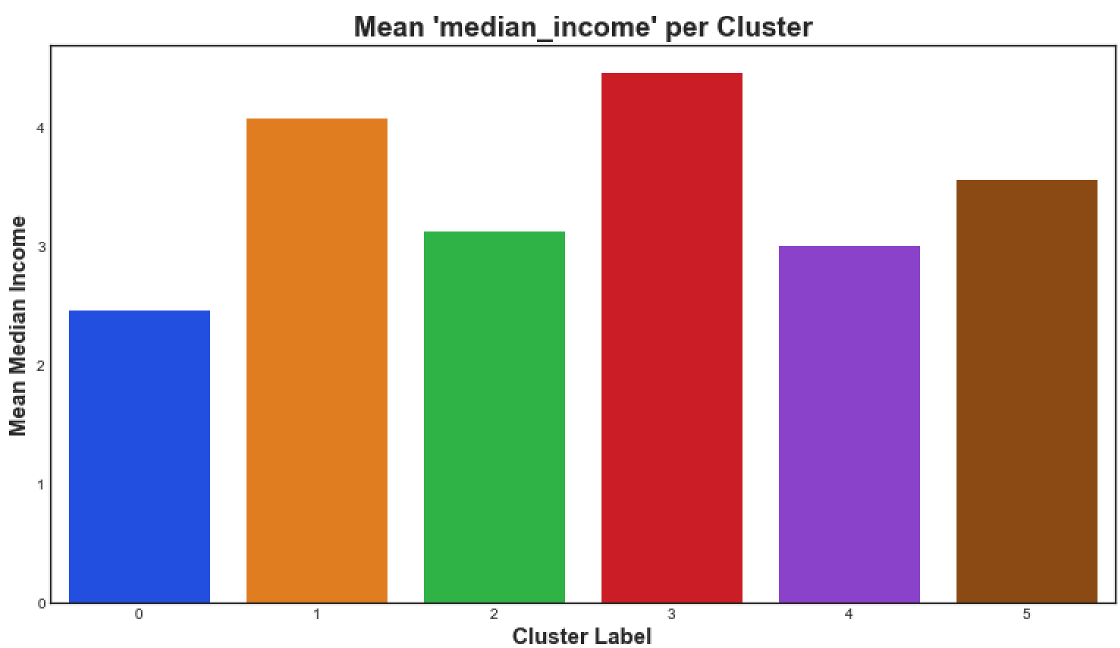
```
# Plotting bar graph to visualize the results
plt.style.use('seaborn-bright')

plt.figure(figsize=(13,7))
sns.barplot(x = cluster_wise_total_house_price.index, y =␣
→cluster_wise_total_house_price.values)
plt.title("Sum of 'median_house_value' per Cluster", fontweight="bold",␣
→fontdict = {'fontsize' : 19})
plt.xlabel("Cluster Label", fontweight="bold", fontdict = {'fontsize' : 15})
plt.ylabel("Total Median House Value", fontweight="bold", fontdict =␣
→{'fontsize' : 15});
```



[47]:
```
# Checking the distribution of mean of median_income prices as per the
↪latitude-longitude-cluster

cluster_wise_avg_of_median_income = housedata_processed.
↪groupby('lat_long_cluster').mean()['median_income'].round(2)
cluster_wise_avg_of_median_income
```

[47]:
```
lat_long_cluster
0    2.47
1    4.09
2    3.14
3    4.47
4    3.01
5    3.57
Name: median_income, dtype: float64
```

[48]:
```
# Plotting bar graph to visualize the results
plt.style.use('seaborn-white')

plt.figure(figsize=(13,7))
sns.barplot(x = cluster_wise_avg_of_median_income.index,
            y = cluster_wise_avg_of_median_income.values,
            palette=sns.color_palette("bright", 6))
plt.title("Mean 'median_income' per Cluster", fontweight="bold", fontdict =
↪{'fontsize' : 19})
plt.xlabel("Cluster Label", fontweight="bold", fontdict = {'fontsize' : 15})
plt.ylabel("Mean Median Income", fontweight="bold", fontdict = {'fontsize' :
↪15});
```



[49]:
```
# Checking the distribution of mean of housing_median_age as per the␣
↪latitude-longitude-cluster

cluster_wise_avg_house_age = housedata_processed.groupby('lat_long_cluster').
↪mean()['housing_median_age'].round(2)
cluster_wise_avg_house_age
```

[49]:
```
lat_long_cluster
0    24.61
1    30.24
2    25.05
3    32.15
4    25.11
5    22.19
Name: housing_median_age, dtype: float64
```

[50]:
```
# Plotting bar graph to visualize the results
plt.style.use('bmh')
plt.figure(figsize=(13,7))
sns.barplot(x = cluster_wise_avg_house_age.index,
            y = cluster_wise_avg_house_age.values,
           palette=sns.color_palette("bright", 6))
plt.title("Mean 'house_median_age' per Cluster", fontweight="bold", fontdict =␣
↪{'fontsize' : 19})
plt.xlabel("Cluster Label", fontweight="bold", fontdict = {'fontsize' : 15})
plt.ylabel("Mean of House_Median_Age", fontweight="bold", fontdict =␣
↪{'fontsize' : 15});
```

Below I am checking if the data has multicolonieartity and if we have redundant features

[51]:
```
# Making correlation plot

corr = housedata_processed.corr()

mask = np.zeros_like(corr, dtype=bool)
mask[np.triu_indices_from(mask)] = True
corr[mask] = np.nan
(corr
 .style
 .background_gradient(cmap='coolwarm', axis=None, vmin=-1, vmax=1)
 .highlight_null(null_color='#f1f1f1')  # Color NaNs grey
 .set_precision(2))
```

[51]: <pandas.io.formats.style.Styler at 0x1c6eeab3f08>

[52]:
```
# This is how original correlation matrix looks like

corr
```

[52]:
```
                    lat_long_cluster  housing_median_age  total_rooms  \
lat_long_cluster                 NaN                 NaN          NaN
housing_median_age         -0.123634                 NaN          NaN
total_rooms                 0.041557           -0.361262          NaN
total_bedrooms              0.024481           -0.319026     0.927058
```

```
population                -0.019781          -0.296244     0.857126
households                 0.008030          -0.302916     0.918484
median_income             -0.037191          -0.119034     0.198050
less_1h_ocean             -0.363544           0.045300    -0.003031
inland                     0.043997          -0.236645     0.025624
near_bay                   0.194009           0.255172    -0.023022
near_ocean                 0.296659           0.021622    -0.009175
median_house_value        -0.075994           0.105623     0.134153

                    total_bedrooms  population  households  median_income  \
lat_long_cluster               NaN         NaN         NaN            NaN
housing_median_age             NaN         NaN         NaN            NaN
total_rooms                    NaN         NaN         NaN            NaN
total_bedrooms                 NaN         NaN         NaN            NaN
population                0.873535         NaN         NaN            NaN
households                0.974366    0.907222         NaN            NaN
median_income            -0.007617    0.004834    0.013033            NaN
less_1h_ocean             0.017966    0.074613    0.042435       0.168876
inland                   -0.006158   -0.020732   -0.039402      -0.237496
near_bay                 -0.019667   -0.060880   -0.010093       0.056197
near_ocean                0.000557   -0.024264    0.001714       0.027344
median_house_value        0.049457   -0.024650    0.065843       0.688075

                    less_1h_ocean    inland  near_bay  near_ocean  \
lat_long_cluster              NaN       NaN       NaN         NaN
housing_median_age            NaN       NaN       NaN         NaN
total_rooms                   NaN       NaN       NaN         NaN
total_bedrooms                NaN       NaN       NaN         NaN
population                    NaN       NaN       NaN         NaN
households                    NaN       NaN       NaN         NaN
median_income                 NaN       NaN       NaN         NaN
less_1h_ocean                 NaN       NaN       NaN         NaN
inland                  -0.607669       NaN       NaN         NaN
near_bay                -0.314813 -0.240887       NaN         NaN
near_ocean              -0.342620 -0.262163 -0.135818         NaN
median_house_value       0.256617 -0.484859  0.160284    0.141862

                    median_house_value
lat_long_cluster                   NaN
housing_median_age                 NaN
total_rooms                        NaN
total_bedrooms                     NaN
population                         NaN
households                         NaN
median_income                      NaN
less_1h_ocean                      NaN
inland                             NaN
```

```
near_bay                           NaN
near_ocean                         NaN
median_house_value                 NaN
```

[53]:
```
# Instead of viewing the entire correlation matrix, if I am interested in␣
↪specific correlation values,
# this is how we will get it, along with the column names which are correlated.

for row in corr.columns:
    for col in corr.columns:
        if corr.loc[row, col] >= 0.60 or corr.loc[row, col] < -0.60:
            print(f"{row}    {col}: {corr.loc[row, col]}")
```

```
total_bedrooms    total_rooms: 0.9270581965414207
population    total_rooms: 0.8571259728659829
population    total_bedrooms: 0.8735348611611192
households    total_rooms: 0.9184844926543111
households    total_bedrooms: 0.9743662937706982
households    population: 0.9072222660959659
inland    less_1h_ocean: -0.6076693393596981
median_house_value    median_income: 0.6880752079585577
```

[54]:
```
# This below function calculates the Variance Inflation Factor, which basically␣
↪tells us if the numerical column present in
# our data is adding to the value or not.

def get_VIF(input_df):

    cols = input_df.columns

    for col in cols:
        X = input_df.drop(col, axis = 1)
        y = input_df[col]

        r_sq = ols(formula = 'y ~ X', data = input_df).fit().rsquared
        vif = round( 1/(1-r_sq),2)
        print(f"{col} VIF: {vif}")
```

[55]:
```
housedata_processed.columns
```

[55]:
```
Index(['lat_long_cluster', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'less_1h_ocean', 'inland', 'near_bay', 'near_ocean',
```

```
        'median_house_value'],
       dtype='object')
```

[56]:
```
# excluding the categorical features and the target, below is the data for␣
↪which VIF needs to be calculated

housedata_processed_vifs = housedata_processed[['housing_median_age',␣
↪'total_rooms', 'total_bedrooms',
                                                'population', 'households',␣
↪'median_income']]
```

Now, in order to determine if the column is significant with respect to information it is adding, VIF is checked, iterateively. After each iteration, VIF of column greater than 5 is removed, and the process continues until all columns have VIFs less than or equal to 5.

[57]:
```
housedata_processed_vifs.head()
```

[57]:
```
   housing_median_age  total_rooms  total_bedrooms  population  households  \
0                  41          880           129.0         322         126
1                  21         7099          1106.0        2401        1138
2                  52         1467           190.0         496         177
3                  52         1274           235.0         558         219
4                  52         1627           280.0         565         259

   median_income
0         8.3252
1         8.3014
2         7.2574
3         5.6431
4         3.8462
```

[58]:
```
get_VIF(housedata_processed_vifs)
```

```
housing_median_age VIF: 1.16
total_rooms VIF: 11.32
total_bedrooms VIF: 26.57
population VIF: 6.12
households VIF: 27.19
median_income VIF: 1.47
```

[59]:
```
housedata_processed_vifs = housedata_processed_vifs.drop('households', axis = 1)
```

[60]:
```
get_VIF(housedata_processed_vifs)
```

```
housing_median_age VIF: 1.15
total_rooms VIF: 11.32
```

```
total_bedrooms VIF: 10.69
population VIF: 4.62
median_income VIF: 1.46
```

[61]:
```
housedata_processed_vifs = housedata_processed_vifs.drop('total_rooms', axis =␣
↪1)
```

[62]:
```
get_VIF(housedata_processed_vifs)
```

```
housing_median_age VIF: 1.13
total_bedrooms VIF: 4.3
population VIF: 4.23
median_income VIF: 1.02
```

[63]:
```
housedata_processed_vifs.head()
```

[63]:

	housing_median_age	total_bedrooms	population	median_income
0	41	129.0	322	8.3252
1	21	1106.0	2401	8.3014
2	52	190.0	496	7.2574
3	52	235.0	558	5.6431
4	52	280.0	565	3.8462

Plotting Correlations again, after removing columns based on VIF values

[64]:
```
fig = plt.figure(figsize=(7,5))

corr = housedata_processed_vifs.corr()

mask = np.zeros_like(corr, dtype=bool)
mask[np.triu_indices_from(mask)] = True
corr[mask] = np.nan
(corr
 .style
 .background_gradient(cmap='coolwarm', axis=None, vmin=-1, vmax=1)
 .highlight_null(null_color='#f1f1f1')  # Color NaNs grey
 .set_precision(2))
```

[64]:
```
<pandas.io.formats.style.Styler at 0x1c6ef84e9c8>

<Figure size 504x360 with 0 Axes>
```

[65]:
```
# This code displays the columns which are highly correlated along with the␣
↪magnitude and sign

for row in corr.columns:
    for col in corr.columns:
```

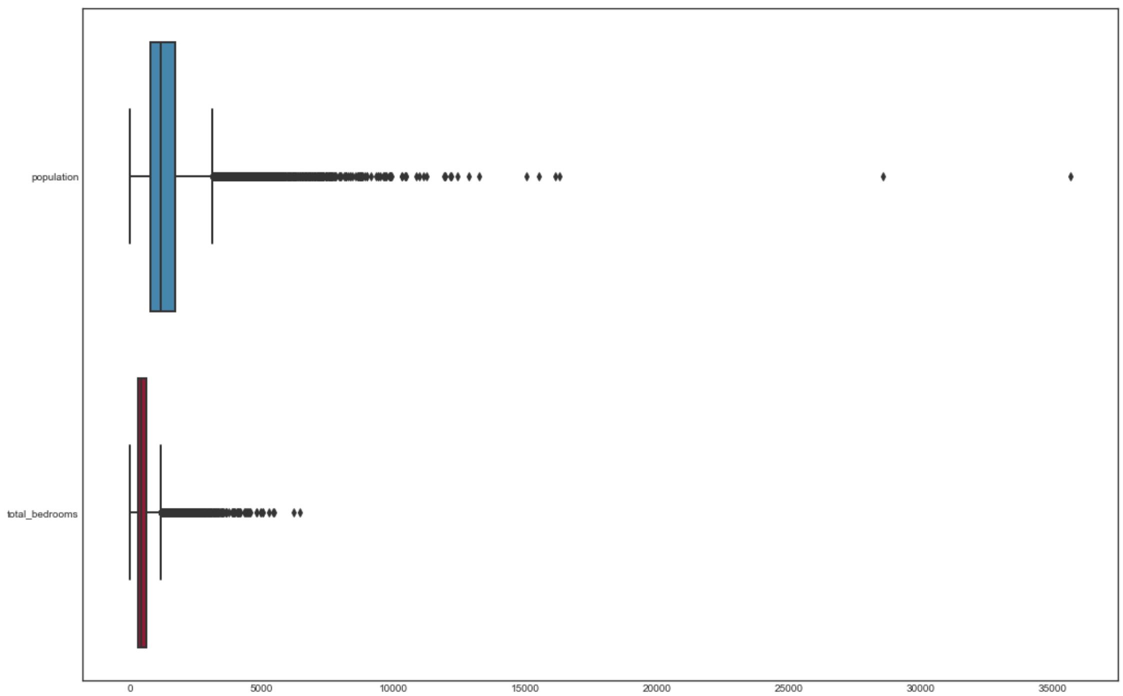
```
        if corr.loc[row, col] >= 0.6 or corr.loc[row, col] < -0.6:
            print(f"{row}    {col}: {corr.loc[row, col]}")
```

```
population    total_bedrooms: 0.8735348611611192
```

Because, 'population' and 'total_bedrooms' are highly correlated, one can be dropped. I have plotted boxplot below to determine which column has higher range of outliars (the one having higher outliars can be dropped)

[66]:
```
plt.style.use('seaborn-white')

plt.figure(figsize = (18,12))
sns.boxplot(data = housedata_processed_vifs[['population', 'total_bedrooms']],␣
 ↪orient='h')
```

[66]:
```
<AxesSubplot:>
```



[67]:
```
housedata_processed_vifs.drop('population', axis = 1, inplace = True) #␣
 ↪dropping population
```

[68]:
```
# combining the entire data after removing non-significant columns

cat_cols_and_target = ['lat_long_cluster', 'less_1h_ocean', 'inland',␣
 ↪'near_bay', 'near_ocean','median_house_value']
```

```
housedata_processed = pd.concat([housedata_processed_vifs,␣
↪housedata_processed[cat_cols_and_target]], axis = 1)
housedata_processed.head()
```

[68]:

```
   housing_median_age  total_bedrooms  median_income  lat_long_cluster  \
0                  41           129.0         8.3252                 3
1                  21          1106.0         8.3014                 3
2                  52           190.0         7.2574                 3
3                  52           235.0         5.6431                 3
4                  52           280.0         3.8462                 3

   less_1h_ocean  inland  near_bay  near_ocean  median_house_value
0              0       0         1           0              452600
1              0       0         1           0              358500
2              0       0         1           0              352100
3              0       0         1           0              341300
4              0       0         1           0              342200
```

0.2.6 4. Splitting of the dataset

[69]:

```
# Splitting the data into features and target seperately

X = housedata_processed.drop('median_house_value', axis = 1)
y = housedata_processed['median_house_value']
```

[70]:

```
# Splitting of training and test set into 80%-20% ratio

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,␣
↪random_state=42)
```

0.2.7 Standardizing the data

[71]:

```
X_train.head(2)
```

[71]:

```
       housing_median_age  total_bedrooms  median_income  lat_long_cluster  \
14196                  33           627.0         3.2596                 5
8267                   49           787.0         3.8125                 1

       less_1h_ocean  inland  near_bay  near_ocean
14196              0       0         0           1
8267               0       0         0           1
```

[72]:

```
X_train.iloc[:, :3].head(2).reset_index(drop = True)
```

[72]:
```
   housing_median_age  total_bedrooms  median_income
0                  33           627.0         3.2596
1                  49           787.0         3.8125
```

[73]:
```
X_train.iloc[:, 3:].head(2).reset_index(drop = True)
```

[73]:
```
   lat_long_cluster  less_1h_ocean  inland  near_bay  near_ocean
0                 5              0       0         0           1
1                 1              0       0         0           1
```

[74]:
```
# scaling input features (except the categorical columns)

robust_scaler = RobustScaler()

X_train_scaled = robust_scaler.fit_transform(X_train.iloc[:, :3])
X_train_scaled = pd.concat([pd.DataFrame(X_train_scaled, columns = X_train.
 ↪iloc[:, :3].columns),
                            X_train.iloc[:, 3:].reset_index(drop=True)], axis =␣
 ↪1)


X_test_scaled  = robust_scaler.transform(X_test.iloc[:, :3])
X_test_scaled = pd.concat([pd.DataFrame(X_test_scaled, columns = X_test.iloc[:,␣
 ↪:3].columns),
                           X_test.iloc[:, 3:].reset_index(drop=True)], axis = 1)
```

[75]:
```
X_train_scaled.head()
```

[75]:
```
   housing_median_age  total_bedrooms  median_income  lat_long_cluster  \
0            0.210526        0.542470      -0.129709                 5
1            1.052632        0.999286       0.120872                 1
2           -1.315789       -0.302641       0.276686                 4
3            0.368421       -0.199857      -0.726634                 5
4            0.736842       -0.017131       0.003807                 4

   less_1h_ocean  inland  near_bay  near_ocean
0              0       0         0           1
1              0       0         0           1
2              0       0         0           1
3              0       0         0           1
4              0       1         0           0
```

[76]:
```
X_test_scaled.head()
```

[76]:
```
   housing_median_age  total_bedrooms  median_income  lat_long_cluster  \
0           -0.210526        -0.00571      -0.845058                 4
1            0.052632        -0.00571      -0.459783                 4
```

```
2            1.210526        -0.00571      -0.029776                 3
3           -0.631579        -0.00571       0.993349                 1
4            0.263158        -0.00571       0.081216                 3

   less_1h_ocean  inland  near_bay  near_ocean
0              0       1         0           0
1              0       1         0           0
2              0       0         1           0
3              1       0         0           0
4              0       0         0           1
```

[77]:
```
# scaling target variables

y_train_scaled = robust_scaler.fit_transform(y_train.values.reshape(-1,1))
y_test_scaled  = robust_scaler.transform(y_test.values.reshape(-1,1))
```

[78]:
```
y_train_scaled
```

[78]:
```
array([[-0.52881473],
       [ 1.39170824],
       [-0.04988818],
       …,
       [ 0.29072768],
       [ 0.71322897],
       [ 0.9987958 ]])
```

[79]:
```
y_test_scaled
```

[79]:
```
array([[-0.90934113],
       [-0.92241528],
       [ 2.20300017],
       …,
       [ 2.20300017],
       [-0.74006537],
       [-0.19507999]])
```

[80]:
```
X_train_scaled.shape, X_test_scaled.shape
```

[80]:
```
((16512, 8), (4128, 8))
```

[81]:
```
y_train_scaled.shape, y_test_scaled.shape
```

[81]:
```
((16512, 1), (4128, 1))
```

0.2.8 6. Building Linear Regression Model

[82]:
```
linear_regression_model = LinearRegression()
```

[83]:
```
linear_regression_model.fit(X_train_scaled, y_train_scaled)
```

[83]:
```
LinearRegression()
```

[84]:
```
y_pred_scaled = linear_regression_model.predict(X_test_scaled) #Predictions␣
↪will be scaled as scaled data was used in training
```

[85]:
```
y_pred = robust_scaler.inverse_transform(y_pred_scaled)   # getting the␣
↪predictions in original scale
y_pred
```

[85]:
```
array([[ 55673.36850733],
       [ 94382.96374567],
       [246529.66541181],
       …,
       [422481.99082252],
       [111999.55434371],
       [200721.73112587]])
```

[86]:
```
pd.DataFrame({'Actual Values': y_test, 'Predicted Values': y_pred.flatten()}).
↪reset_index(drop=True) # just to view and confirm
```

[86]:
```
      Actual Values  Predicted Values
0             47700      55673.368507
1             45800      94382.963746
2            500001     246529.665412
3            218600     284549.983833
4            278000     242164.914452
…               …               …
4123         263300     222325.860267
4124         266800     203906.685581
4125         500001     422481.990823
4126          72300     111999.554344
4127         151500     200721.731126

[4128 rows x 2 columns]
```

[87]:
```
# Defining function to return the MAPE (Mean Absolute Percent Error)

def get_mape(actual, pred):
    actual, pred = np.array(actual), np.array(pred)
    return np.mean(np.abs((actual - pred) / actual)) * 100
```

[88]:
```
# defining a single function to get all required metrics of regression, to
↪avoid writing it again and again

def regression_metrics(actual, predicted):

    mae = mean_absolute_error(actual, predicted)
    mse = mean_squared_error(actual, predicted)
    rmse = np.sqrt(mean_squared_error(actual, predicted))
    mape = get_mape(actual, predicted)
    r_squared = r2_score(actual, predicted)

    return round(mae,2), round(mse,2), round(rmse,2), round(mape,2),
↪round(r_squared, 2)
```

[89]:
```
any(housedata['median_house_value'] == 0) # checking if any of the target is 0,
↪because MAPE will fail otherwise
```

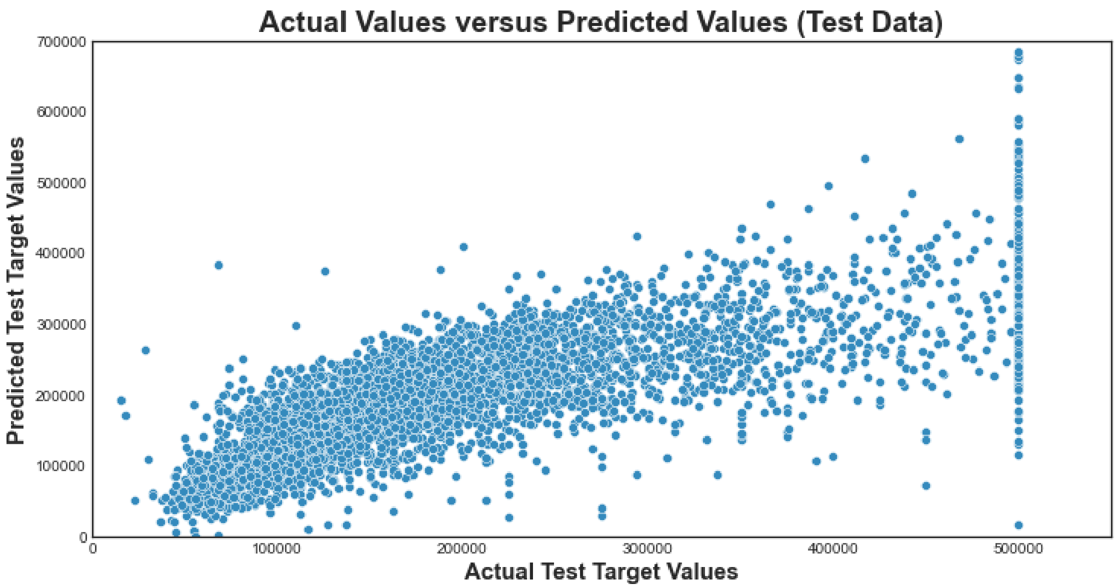
[89]:
```
False
```

[90]:
```
mae, mse, rmse, mape, r_squared = regression_metrics(y_test, y_pred)
```

[91]:
```
print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {rmse}')
print(f'Mean Absolute Percent Error: {mape}%')
print(f'R Squared: {r_squared}')
```

```
Mean Absolute Error: 52622.29
Mean Squared Error: 5304356396.49
Root Mean Squared Error: 72831.01
Mean Absolute Percent Error: 74.73%
R Squared: 0.6
```

[92]:
```
plt.style.use('seaborn-white')

plt.figure(figsize=(12,6))
sns.scatterplot(x=y_test,y=y_pred.ravel())
plt.xlim(0,550000)
plt.ylim(0, 700000)
plt.title("Actual Values versus Predicted Values (Test Data)",
↪fontweight="bold", fontdict = {'fontsize' : 19})
plt.xlabel("Actual Test Target Values", fontweight="bold", fontdict =
↪{'fontsize' : 15})
plt.ylabel("Predicted Test Target Values", fontweight="bold", fontdict =
↪{'fontsize' : 15});
```



0.2.9 7. Bonus Exercise

[93]:
```
linear_regression_model_2 = LinearRegression() # another linear model␣
↪instantiation
```

[94]:
```
y_train_scaled # this is the target variable (scaled by robust scaler)
```

[94]:
```
array([[-0.52881473],
       [ 1.39170824],
       [-0.04988818],
       …,
       [ 0.29072768],
       [ 0.71322897],
       [ 0.9987958 ]])
```

[95]:
```
# training linear regression model with only single feature 'median_income'

linear_regression_model_2.fit(X_train_scaled['median_income'].values.
↪reshape(-1,1), y_train_scaled)
```

[95]:
```
LinearRegression()
```

[96]:
```
# Predicting the target values of Training Data, and getting the original␣
↪scaled values
```

```
y_train_pred = linear_regression_model_2.
↪predict(X_train_scaled['median_income'].values.reshape(-1,1))
y_train_pred = robust_scaler.inverse_transform(y_train_pred)
```

[97]:
```
# Predicted values will also be in scaled format, and getting predicted values␣
↪in original scale

y_pred_scaled_2 = linear_regression_model_2.
↪predict(X_test_scaled['median_income'].values.reshape(-1,1))
y_pred_2 = robust_scaler.inverse_transform(y_pred_scaled_2)
```

[98]:
```
mae, mse, rmse, mape, r_squared = regression_metrics(y_train, y_train_pred) #␣
↪getting required regression performmance metrics
```

[99]:
```
print("Train Data Metrics - Single feature Regression - 'median_income'\n")

print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {rmse}')
print(f'Mean Absolute Percent Error: {mape}%')
print(f'R Squared: {r_squared}')
```

```
Train Data Metrics - Single feature Regression - 'median_income'

Mean Absolute Error: 62495.08
Mean Squared Error: 6991447170.18
Root Mean Squared Error: 83614.87
Mean Absolute Percent Error: 70.06%
R Squared: 0.48
```

[100]:
```
# getting required regression performmance metrics
mae_test, mse_test, rmse_test, mape_test, r_squared_test =␣
↪regression_metrics(y_test, y_pred_2)
```

[101]:
```
print("Test Data Metrics - Single feature Regression - 'median_income'\n")
print(f'Mean Absolute Error: {mae_test}')
print(f'Mean Squared Error: {mse_test}')
print(f'Root Mean Squared Error: {rmse_test}')
print(f'Mean Absolute Percent Error: {mape_test}%')
print(f'R Squared: {r_squared_test}')
```

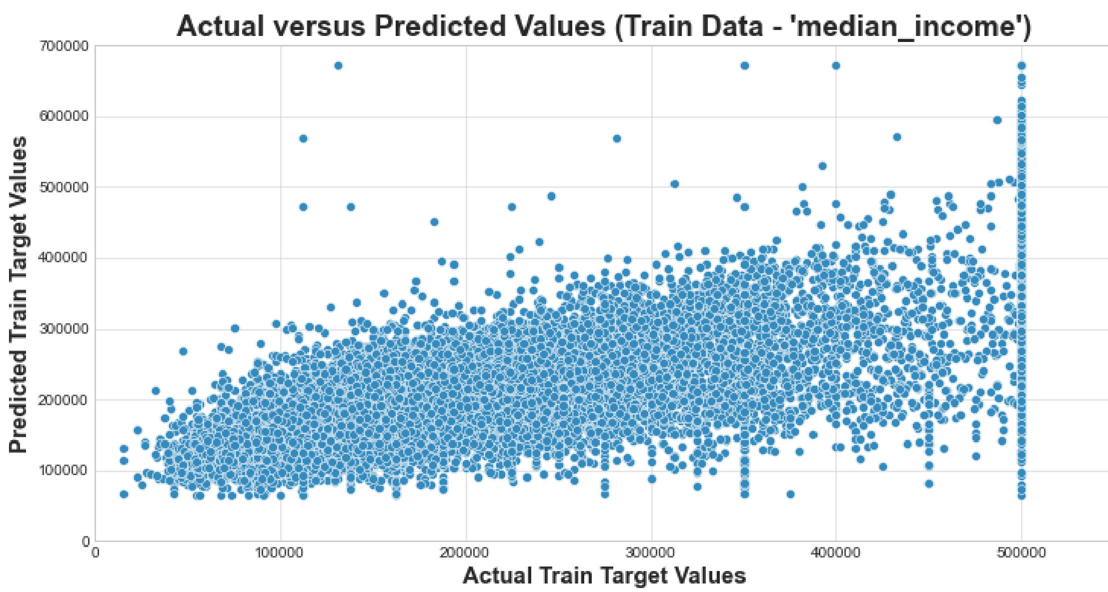
```
Test Data Metrics - Single feature Regression - 'median_income'

Mean Absolute Error: 62990.87
Mean Squared Error: 7091157771.77
Root Mean Squared Error: 84209.01
Mean Absolute Percent Error: 69.95%
```

```
R Squared: 0.46
```

[102]:
```
y_test.shape, y_pred_2.shape
```

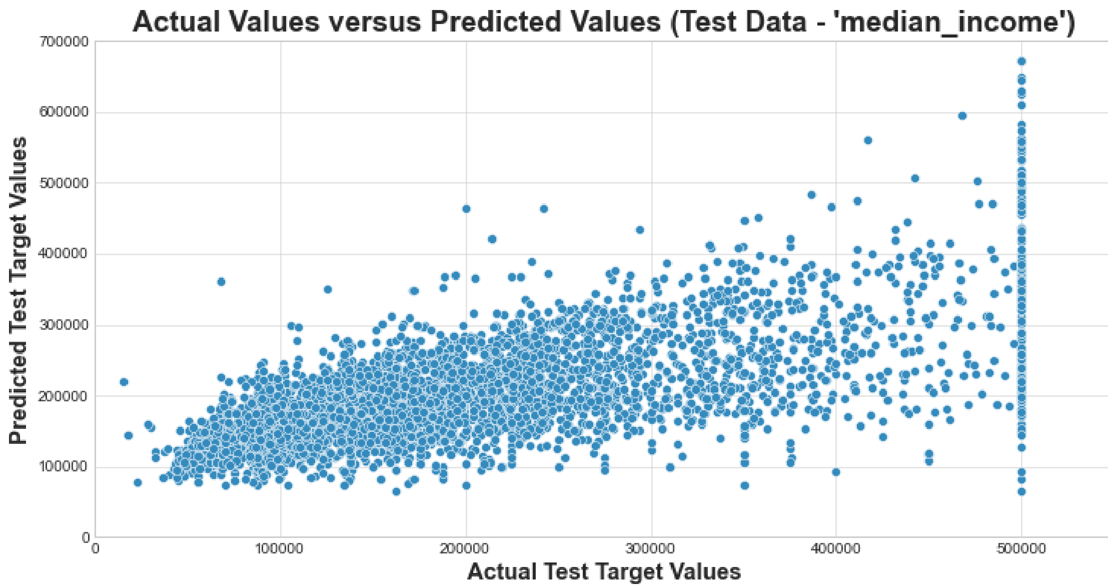
[102]:
```
((4128,), (4128, 1))
```

[103]:
```
plt.style.use('seaborn-whitegrid')

plt.figure(figsize=(12,6))
sns.scatterplot(x=y_train,y=y_train_pred.ravel())
plt.xlim(0,550000)
plt.ylim(0, 700000)
plt.title("Actual versus Predicted Values (Train Data - 'median_income')",␣
↪fontweight="bold", fontdict = {'fontsize' : 19})
plt.xlabel("Actual Train Target Values", fontweight="bold", fontdict =␣
↪{'fontsize' : 15})
plt.ylabel("Predicted Train Target Values", fontweight="bold", fontdict =␣
↪{'fontsize' : 15});
```



[104]:
```
plt.style.use('seaborn-whitegrid')

plt.figure(figsize=(12,6))
sns.scatterplot(x=y_test,y=y_pred_2.ravel())
plt.xlim(0,550000)
plt.ylim(0, 700000)
plt.title("Actual Values versus Predicted Values (Test Data -␣
↪'median_income')", fontweight="bold", fontdict = {'fontsize' : 19})
```

```
plt.xlabel("Actual Test Target Values", fontweight="bold", fontdict =␣
↪{'fontsize' : 15})
plt.ylabel("Predicted Test Target Values", fontweight="bold", fontdict =␣
↪{'fontsize' : 15});
```



0.2.10 Further Analysis: OLS Regression from Statsmodel

Trying to build the linear regression model from OLS Regression (of Statsmodel library)

[105]:
```
# getting all the input column names (features)

features = ' + '.join(X_train_scaled.columns)
features
```

[105]:
```
'housing_median_age + total_bedrooms + median_income + lat_long_cluster +
less_1h_ocean + inland + near_bay + near_ocean'
```

[106]:
```
X_train_scaled.head(3)
```

[106]:
```
   housing_median_age  total_bedrooms  median_income  lat_long_cluster  \
0            0.210526        0.542470      -0.129709                 5
1            1.052632        0.999286       0.120872                 1
2           -1.315789       -0.302641       0.276686                 4

   less_1h_ocean  inland  near_bay  near_ocean
0              0       0         0           1
```

```
1               0       0         0            1
2               0       0         0            1
```

[107]:
```
pd.DataFrame(y_train_scaled, columns=['median_house_value']).head(3)
```

[107]:
```
   median_house_value
0           -0.528815
1            1.391708
2           -0.049888
```

[108]:
```
# Combining training features and input variable to pass it in OLS function to␣
 ↪build the model

ols_scaled_data = pd.concat([X_train_scaled,
                             pd.DataFrame(y_train_scaled,␣
 ↪columns=['median_house_value'])], axis = 1)
ols_scaled_data.head(3)
```

[108]:
```
   housing_median_age  total_bedrooms  median_income  lat_long_cluster  \
0            0.210526        0.542470      -0.129709                 5
1            1.052632        0.999286       0.120872                 1
2           -1.315789       -0.302641       0.276686                 4

   less_1h_ocean  inland  near_bay  near_ocean  median_house_value
0              0       0         0           1           -0.528815
1              0       0         0           1            1.391708
2              0       0         0           1           -0.049888
```

[109]:
```
model = ols(formula = 'median_house_value ~ ' + features, data =␣
 ↪ols_scaled_data).fit() # building the model
```

[110]:
```
model.summary() # viewing the summary
```

[110]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:     median_house_value   R-squared:                       0.611
Model:                            OLS   Adj. R-squared:                  0.611
Method:                 Least Squares   F-statistic:                     3241.
Date:                Tue, 13 Sep 2022   Prob (F-statistic):               0.00
Time:                        23:31:16   Log-Likelihood:                -11857.
No. Observations:               16512   AIC:                         2.373e+04
Df Residuals:                   16503   BIC:                         2.380e+04
Df Model:                           8
Covariance Type:            nonrobust
================================================================================
```

```
======
                         coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------
Intercept              1.4131      0.248      5.693      0.000       0.927
1.900
housing_median_age     0.1520      0.007     22.452      0.000       0.139
0.165
total_bedrooms         0.0640      0.003     18.601      0.000       0.057
0.071
median_income          0.5875      0.005    124.566      0.000       0.578
0.597
lat_long_cluster      -0.0318      0.003    -10.349      0.000      -0.038
-0.026
less_1h_ocean         -1.1481      0.248     -4.625      0.000      -1.635
-0.662
inland                -1.6116      0.248     -6.490      0.000      -2.098
-1.125
near_bay              -1.0251      0.249     -4.125      0.000      -1.512
-0.538
near_ocean            -0.9763      0.249     -3.929      0.000      -1.463
-0.489
==============================================================================
Omnibus:                     3741.006   Durbin-Watson:                   1.965
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            10222.923
Skew:                           1.208   Prob(JB):                         0.00
Kurtosis:                       6.004   Cond. No.                         407.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

Attempting to build Random Forest Regressor Model from Ensemble models library, to see how it performs

[111]:
```
# instantiating and building the random forest regressor

random_forest_regressor = RandomForestRegressor(n_estimators = 150,␣
 ↪random_state = 0)
random_forest_regressor.fit(X_train_scaled, y_train_scaled.ravel())
```

[111]:
```
RandomForestRegressor(n_estimators=150, random_state=0)
```

[112]:
```python
# Getting predicted values (it will be scaled as data fed in was also scaled)

y_predicted_scaled = random_forest_regressor.predict(X_test_scaled)
```

[113]:
```python
# getting predicted values in original scale

y_predicted = robust_scaler.inverse_transform(y_predicted_scaled.reshape(-1,1))
```

[114]:
```python
y_predicted
```

[114]:
```
array([[ 54060.66666667],
       [ 71861.33333333],
       [242491.38      ],
       …,
       [498184.29333333],
       [ 67004.66666667],
       [190369.35333333]])
```

[115]:
```python
mae, mse, rmse, mape, r_squared = regression_metrics(y_test, y_predicted) #␣
↪getting regression performance metrics
```

[116]:
```python
print("Test Data Metrics - Random Forest Regressor\n")

print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {rmse}')
print(f'Mean Absolute Percent Error: {mape}%')
print(f'R Squared: {r_squared}')
```

```
Test Data Metrics - Random Forest Regressor

Mean Absolute Error: 47857.86
Mean Squared Error: 4823567900.96
Root Mean Squared Error: 69451.91
Mean Absolute Percent Error: 76.72%
R Squared: 0.63
```

End of the Project