# Project Report
# on
# California Housing Price Prediction

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# Python execution O/P Screenshots and Interpretation

- I have done this project in two parts:
  - Data analysis and cleaning as explained in **EDA and data cleaning**.
  - Training of machine learning models explained in **Training Machine Learning Algorithms**.

| EDA and Data Cleaning | **Training machine learning algorithms** |
|---|---|
| • Creating new features<br>• Removing outliers<br>• Transforming skewed features<br>• Checking for multicoliniearity | • Linear Regression<br>• Ridge Regression<br>• Support Vector Regression<br>• Gradient Boosting Regression<br>• Stacking of various models |

(Contd.)

# Python execution O/P Screenshots and Interpretation

- **Including library functions of packages**

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
import numpy.random as rnd
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm
```

In [3]:
```
from sklearn.base import BaseEstimator,TransformerMixin,RegressorMixin
```

In [4]:
```
rnd.seed(42)
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

## Load Dataset

In [5]:
```
# Load dataset
housing = pd.read_excel("1553768847_housing.xlsx")
housing
```

Out[5]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households | median_income | ocean_proximity | median_house_value |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | -122.23 | 37.88 | 41 | 880 | 129.0 | 322 | 126 | 8.3252 | NEAR BAY | 452600 |
| **1** | -122.22 | 37.86 | 21 | 7099 | 1106.0 | 2401 | 1138 | 8.3014 | NEAR BAY | 358500 |
| **2** | -122.24 | 37.85 | 52 | 1467 | 190.0 | 496 | 177 | 7.2574 | NEAR BAY | 352100 |
| **3** | -122.25 | 37.85 | 52 | 1274 | 235.0 | 558 | 219 | 5.6431 | NEAR BAY | 341300 |
| **4** | -122.25 | 37.85 | 52 | 1627 | 280.0 | 565 | 259 | 3.8462 | NEAR BAY | 342200 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **20635** | -121.09 | 39.48 | 25 | 1665 | 374.0 | 845 | 330 | 1.5603 | INLAND | 78100 |
| **20636** | -121.21 | 39.49 | 18 | 697 | 150.0 | 356 | 114 | 2.5568 | INLAND | 77100 |
| **20637** | -121.22 | 39.43 | 17 | 2254 | 485.0 | 1007 | 433 | 1.7000 | INLAND | 92300 |
| **20638** | -121.32 | 39.43 | 18 | 1860 | 409.0 | 741 | 349 | 1.8672 | INLAND | 84700 |
| **20639** | -121.24 | 39.37 | 16 | 2785 | 616.0 | 1387 | 530 | 2.3886 | INLAND | 89400 |

20640 rows × 10 columns

**We can see that the dataset contains 20640 rows and 10 columns.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

- **Print first few rows of this data**

```
In [6]: housing.head()
```

Out[6]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households | median_income | ocean_proximity | median_house_value |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | -122.23 | 37.88 | 41 | 880 | 129.0 | 322 | 126 | 8.3252 | NEAR BAY | 452600 |
| **1** | -122.22 | 37.86 | 21 | 7099 | 1106.0 | 2401 | 1138 | 8.3014 | NEAR BAY | 358500 |
| **2** | -122.24 | 37.85 | 52 | 1467 | 190.0 | 496 | 177 | 7.2574 | NEAR BAY | 352100 |
| **3** | -122.25 | 37.85 | 52 | 1274 | 235.0 | 558 | 219 | 5.6431 | NEAR BAY | 341300 |
| **4** | -122.25 | 37.85 | 52 | 1627 | 280.0 | 565 | 259 | 3.8462 | NEAR BAY | 342200 |

**The head() displays the first 5 rows of housing dataset.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

## First Portion: EDA and Data Cleaning

### Getting information of Data Frame

```
In [7]: housing.info()
```

```
<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
```

**The info() gives the information of the "housing" data frame like no. of non-null values, data type and memory usage.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

- **Checking for missing values**

```
In [8]: # checking for missing values
        housing.isnull().sum()
```

```
Out[8]: 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
```

**Here, we can see in the output that, only “total_bedrooms” contains null values and the total number of null values are 207.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

- **Ocean Proximity is a categorical variable. Let's see what values it contains.**

```
In [9]: housing['ocean_proximity'].value_counts()
```

```
Out[9]: <1H OCEAN     9136
        INLAND        6551
        NEAR OCEAN    2658
        NEAR BAY      2290
        ISLAND           5
        Name: ocean_proximity, dtype: int64
```

**The above output shows, ISLAND has only 5 entries. I'll be adding these to other class in subsequent stages (in GetDummies class).**

(Contd.)

# Python execution O/P Screenshots and Interpretation

- **Getting description of Data Frame**

In [10]:
```
housing.describe()
```

Out[10]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households | median_income | median_house_value |
|---|---|---|---|---|---|---|---|---|---|
| count | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 | 20433.000000 | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 |
| mean | -119.569704 | 35.631861 | 28.639486 | 2635.763081 | 537.870553 | 1425.476744 | 499.539680 | 3.870671 | 206855.816909 |
| std | 2.003532 | 2.135952 | 12.585558 | 2181.615252 | 421.385070 | 1132.462122 | 382.329753 | 1.899822 | 115395.615874 |
| min | -124.350000 | 32.540000 | 1.000000 | 2.000000 | 1.000000 | 3.000000 | 1.000000 | 0.499900 | 14999.000000 |
| 25% | -121.800000 | 33.930000 | 18.000000 | 1447.750000 | 296.000000 | 787.000000 | 280.000000 | 2.563400 | 119600.000000 |
| 50% | -118.490000 | 34.260000 | 29.000000 | 2127.000000 | 435.000000 | 1166.000000 | 409.000000 | 3.534800 | 179700.000000 |
| 75% | -118.010000 | 37.710000 | 37.000000 | 3148.000000 | 647.000000 | 1725.000000 | 605.000000 | 4.743250 | 264725.000000 |
| max | -114.310000 | 41.950000 | 52.000000 | 39320.000000 | 6445.000000 | 35682.000000 | 6082.000000 | 15.000100 | 500001.000000 |

**The describe() shows some basic statistical details like count, mean, median, standard deviation, quartile values, percentile, minimum and maximum values of each attributes of the dataset.**

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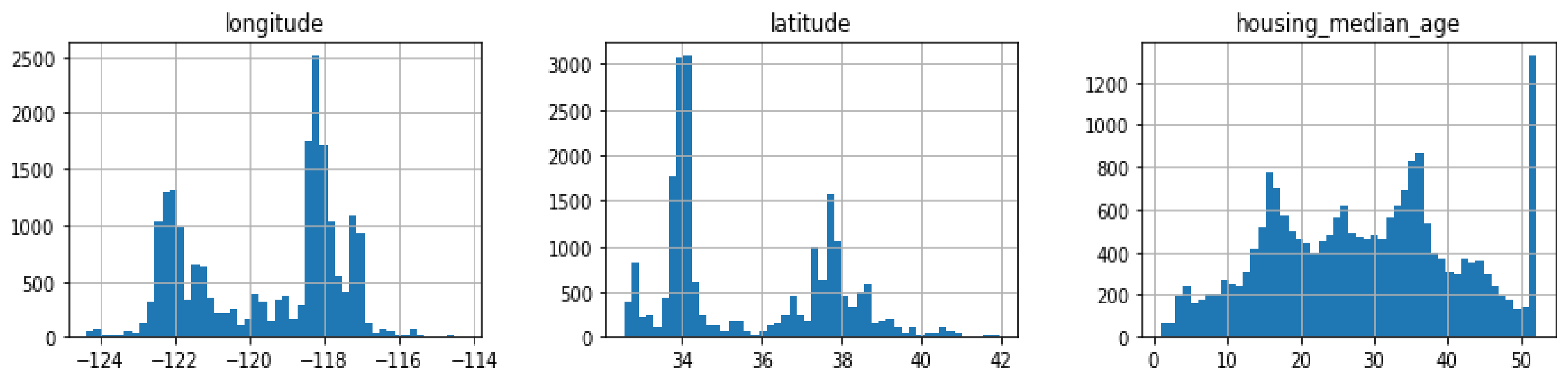
# Python execution O/P Screenshots and Interpretation

- **Histogram of housing Data Frame**

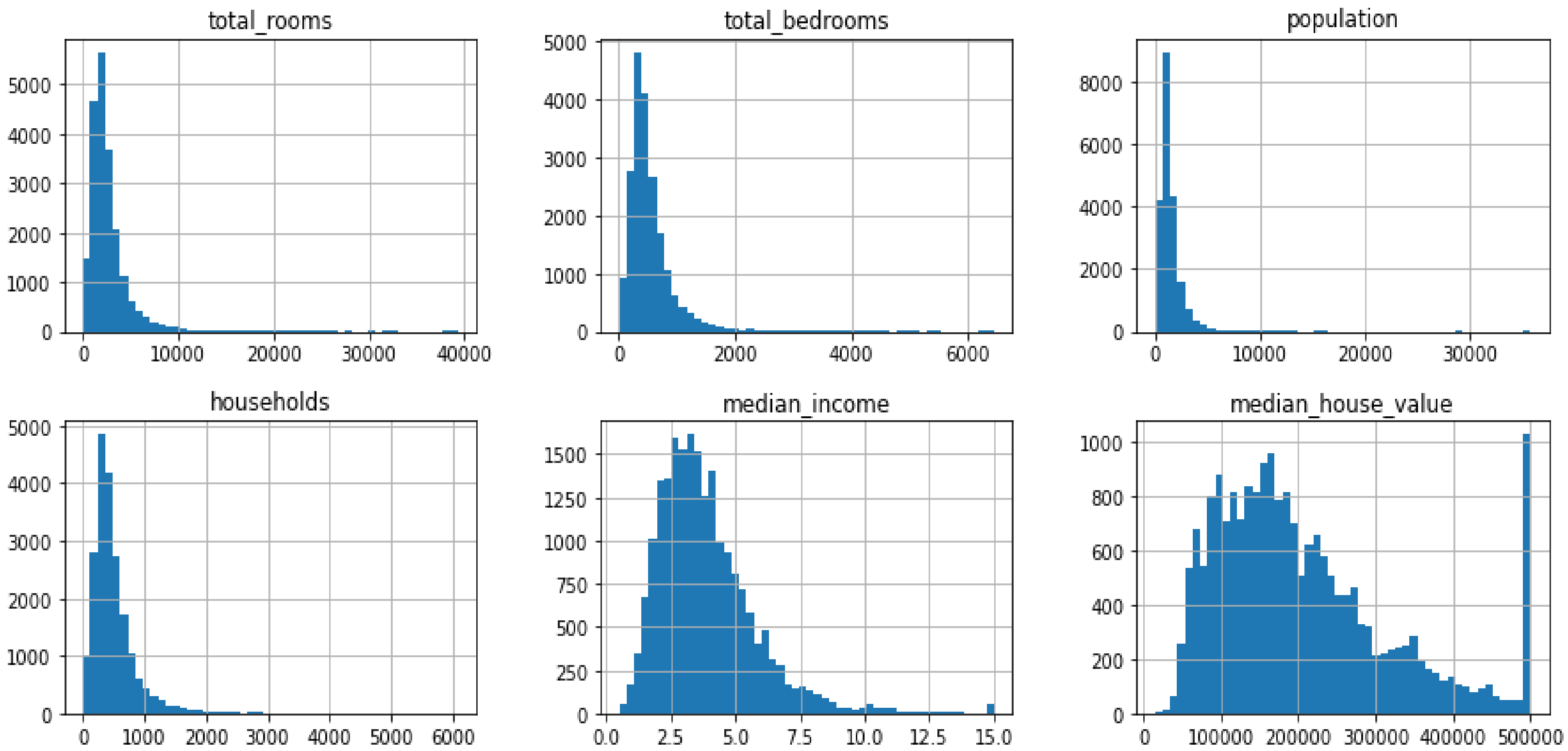
```
In [11]: housing.hist(bins=50,figsize=(15,10))
```

```
Out[11]: array([[<AxesSubplot:title={'center':'longitude'}>,
        <AxesSubplot:title={'center':'latitude'}>,
        <AxesSubplot:title={'center':'housing_median_age'}>],
       [<AxesSubplot:title={'center':'total_rooms'}>,
        <AxesSubplot:title={'center':'total_bedrooms'}>,
        <AxesSubplot:title={'center':'population'}>],
       [<AxesSubplot:title={'center':'households'}>,
        <AxesSubplot:title={'center':'median_income'}>,
        <AxesSubplot:title={'center':'median_house_value'}>]],
      dtype=object)
```




(Contd.)

# Python execution O/P Screenshots and Interpretation




**From above histograms it's clear that most of the features are skewed. It seems that 'housing_median_age' and 'median_house_value' have been capped at the end (Peak at the end).**

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# Python execution O/P Screenshots and Interpretation

- **Getting Test Dataset:**
  - Used Stratified sampling technique.
  - Defined a new feature **income_cat** which is **income category** and used it for sampling.

In [12]:
```
housing['income_cat']=np.ceil(housing['median_income']/1.5)
housing['income_cat'].where(housing['income_cat']<5,5.0,inplace=True)
```

In [13]:
```
from sklearn.model_selection import StratifiedShuffleSplit
```

In [14]:
```
split=StratifiedShuffleSplit(n_splits=1,test_size=0.2,random_state=42)
for train_index,test_index in split.split(housing,housing['income_cat']):
    strat_train_set=housing.loc[train_index]
    strat_test_set=housing.loc[test_index]
```

In [15]:
```
strat_train_set.drop('income_cat',axis=1,inplace=True)
strat_test_set.drop('income_cat',axis=1,inplace=True)
```

In [16]:
```
strat_train_set.to_csv("strat_train_set.csv",index=False)
strat_test_set.to_csv("strat_test_set.csv",index=False)
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

- **Exploratory Data Analysis**

```
In [17]: data=pd.read_csv('strat_train_set.csv')
```

```
In [18]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16512 entries, 0 to 16511
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           16512 non-null  float64
 1   latitude            16512 non-null  float64
 2   housing_median_age  16512 non-null  int64
 3   total_rooms         16512 non-null  int64
 4   total_bedrooms      16354 non-null  float64
 5   population          16512 non-null  int64
 6   households          16512 non-null  int64
 7   median_income       16512 non-null  float64
 8   ocean_proximity     16512 non-null  object
 9   median_house_value  16512 non-null  int64
dtypes: float64(4), int64(5), object(1)
memory usage: 1.3+ MB
```

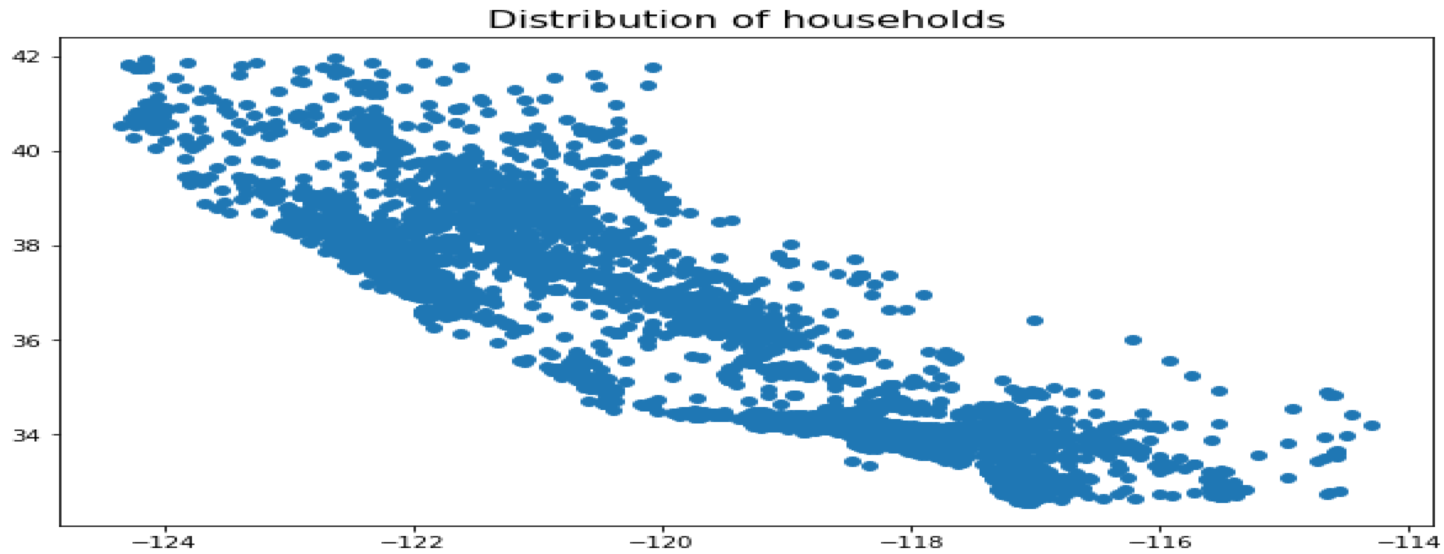
**The info() gives the information of the "data" data frame like no. of non-null values, data type and memory usage.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

In [19]:
```
plt.figure(figsize=(10,6))
plt.scatter(x=data['longitude'],y=data['latitude'])
plt.title("Distribution of households",size=16)
```

Out[19]: Text(0.5, 1.0, 'Distribution of households')




**The above plot showing the distribution of households according to longitude and latitude values in California.**

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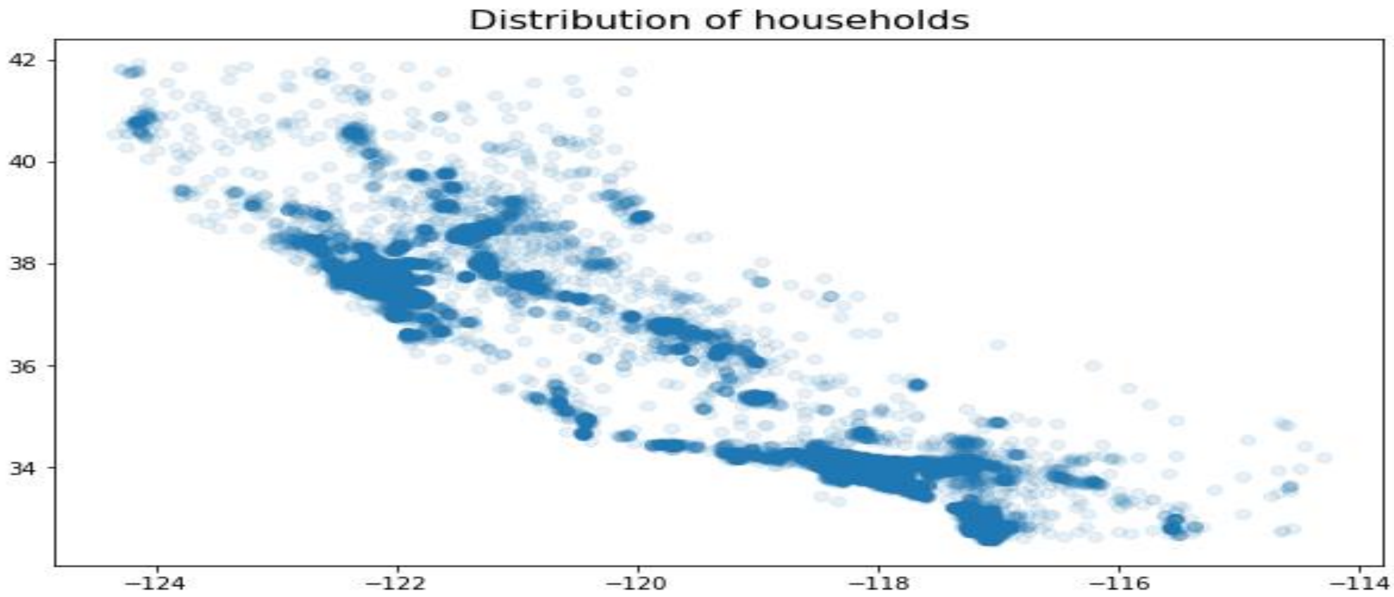
# Python execution O/P Screenshots and Interpretation

In [20]:
```
plt.figure(figsize=(10,6))
plt.scatter(x=data['longitude'],y=data['latitude'],alpha=0.1)
plt.title("Distribution of households",size=16)
```

Out[20]: Text(0.5, 1.0, 'Distribution of households')




**By setting alpha = 0.1, we can see high density areas in the above plot.**

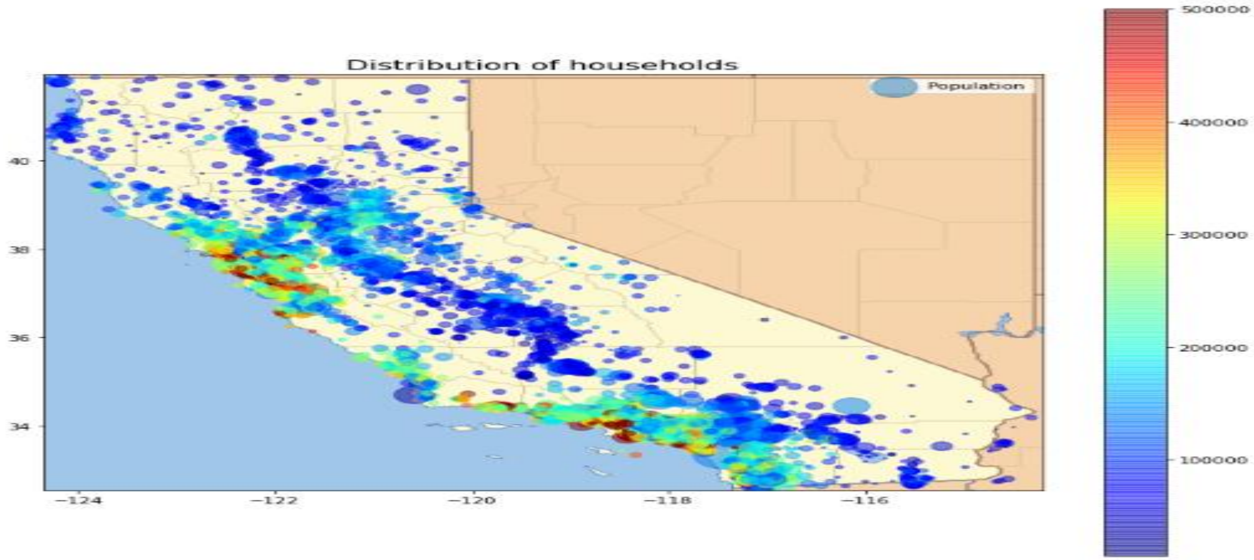
(Contd.)

# Python execution O/P Screenshots and Interpretation

```
In [21]: plt.figure(figsize=(12,12))
         img=plt.imread('california.png')
         plt.imshow(img,zorder=0,extent=[-124.35,-114.2,32.54,41.95])

         plt.scatter(x=data['longitude'],y=data['latitude'],alpha=0.5,s=data['population']/30,c=data['median_house_value'],
                     cmap=plt.get_cmap("jet"),zorder=1,label='Population')
         plt.colorbar()
         plt.title("Distribution of households",size=16)
         plt.legend()
```

```
Out[21]: <matplotlib.legend.Legend at 0xc123d90>
```




**From the above plot we can infer that,**

- Housing prices are much related to location and population density.
- Housing prices near ocean are higher except in northern California.

(Contd.)

# Python execution O/P Screenshots and Interpretation

Now, let's see the correlation of **'median house value'** with other columns. This is **Pearson's correlation coefficient**.

```
In [22]: corr_matrix=data.corr()
```

```
In [23]: corr_matrix['median_house_value'].sort_values(ascending=False)
```

```
Out[23]: median_house_value    1.000000
         median_income         0.687160
         total_rooms           0.135097
         housing_median_age    0.114110
         households            0.064506
         total_bedrooms        0.047689
         population           -0.026920
         longitude            -0.047432
         latitude             -0.142724
         Name: median_house_value, dtype: float64
```

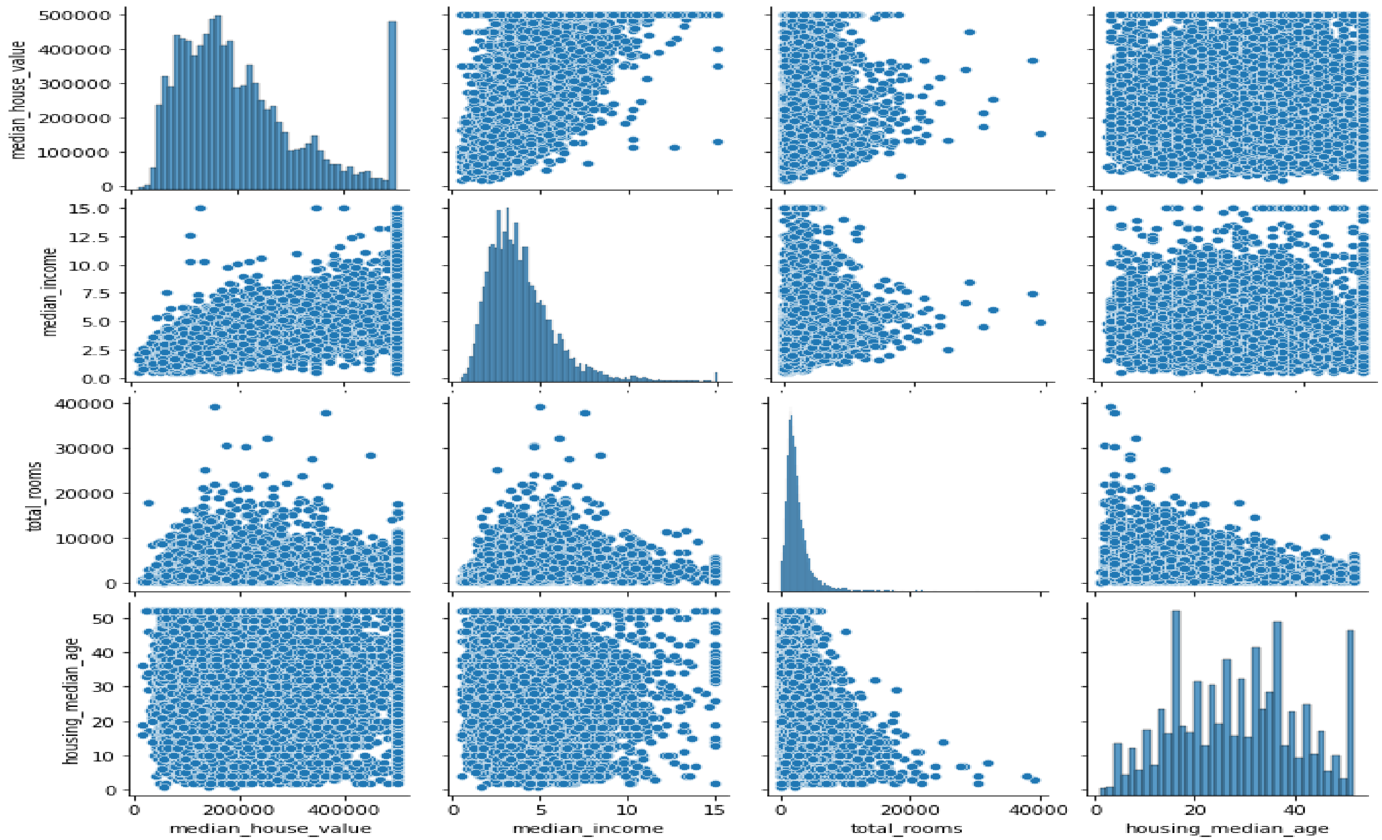
**The above output shows the correlation of median_house_value with other columns.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

```
In [24]: sns.pairplot(data[['median_house_value','median_income','total_rooms','housing_median_age']])

Out[24]: <seaborn.axisgrid.PairGrid at 0xca38640>
```



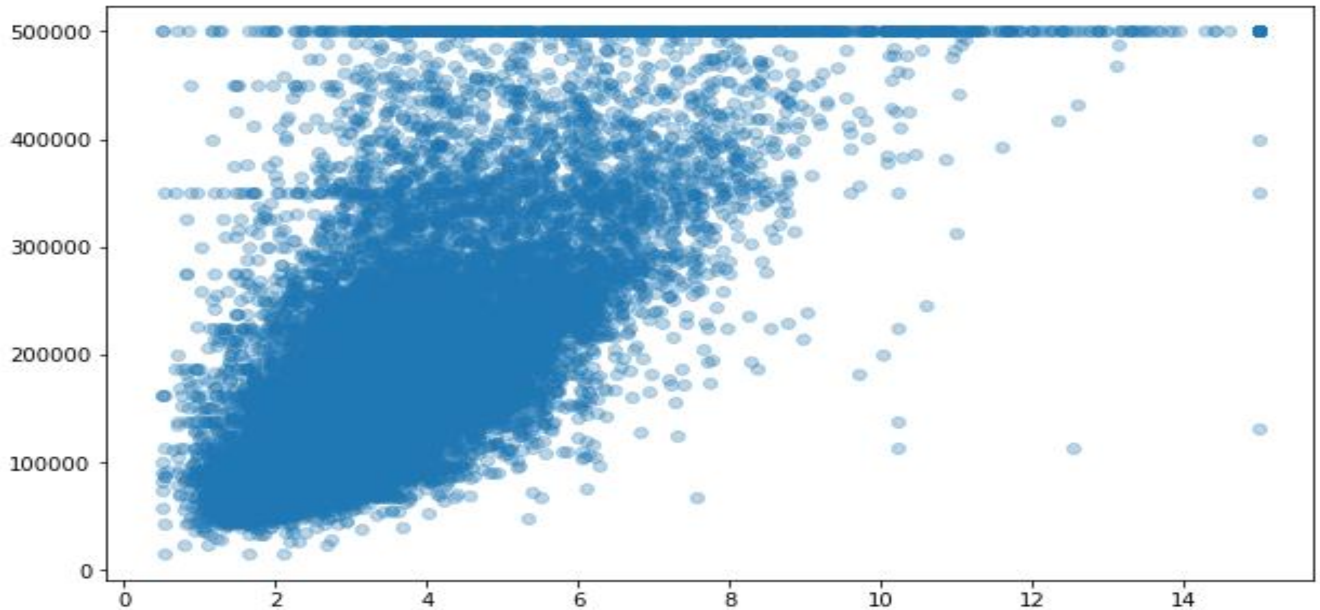

**Median Income is the most promising attribute to get Median Housing Price.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

```
In [25]: plt.figure(figsize=(10,6))
         plt.scatter(y=data['median_house_value'],x=data['median_income'],alpha=0.3)
```

```
Out[25]: <matplotlib.collections.PathCollection at 0xfb605e0>
```




**A clear line can be seen at 500k at which the data is capped. Similar lines can be seen around 450k,350k. This kind of data may degrade the performance of model.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

**Creating new features:**

- rooms per household
- bedrooms per room
- population per household

**Initially creating them on a copy of dataset and checking whether they are making any difference.**

In [26]:
```
data1=data.copy()
```

In [27]:
```
data1['rooms_per_household']=data1['total_rooms']/data1['households']
data1['bedrooms_per_room']=data1['total_bedrooms']/data1['total_rooms']
data1['population_per_household']=data1['population']/data1['households']
```

In [28]:
```
data1.head(1)
```

Out[28]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households | median_income | ocean_proximity | median_house_value | room |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | -121.89 | 37.29 | 38 | 1568 | 351.0 | 710 | 339 | 2.7042 | <1H OCEAN | 286600 | |

**The above output shows the first row of "data1" dataset.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

```
In [29]: corr_matrix=data1.corr()

In [30]: corr_matrix['median_house_value'].sort_values(ascending=False)

Out[30]: median_house_value          1.000000
         median_income               0.687160
         rooms_per_household         0.146285
         total_rooms                 0.135097
         housing_median_age          0.114110
         households                  0.064506
         total_bedrooms              0.047689
         population_per_household   -0.021985
         population                 -0.026920
         longitude                  -0.047432
         latitude                   -0.142724
         bedrooms_per_room          -0.259984
         Name: median_house_value, dtype: float64
```

**It is clear that 'rooms_per_household' and 'bedrooms_per_room' have better correlation with 'median_house_value' than 'total_rooms' and 'total_bedrooms‘.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

**I have created classes for individual data manipulation job, so that I can add them into a pipeline.**

```
In [31]: class FeaturesAdder(BaseEstimator,TransformerMixin):
             """This class adds new features in the dataset.
                Features added are : rooms_per_household, bedrooms_per_room, and population_per_household.
             """
             def fit(self,X,y=None):
                 return self
             def transform(self,X,y=None):
                 X['rooms_per_household']=X['total_rooms']/X['households']
                 X['bedrooms_per_room']=X['total_bedrooms']/X['total_rooms']
                 X['population_per_household']=X['population']/X['households']
                 return X
```

**Null Value Imputation**

```
In [32]: #Get number of Null Values
         def get_null_count(data):
             for i in data.columns:
                 print(i,': ',len(data[data[i].isnull()][i]))
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

```
In [33]: get_null_count(data)
```

```
longitude :  0
latitude :  0
housing_median_age :  0
total_rooms :  0
total_bedrooms :  158
population :  0
households :  0
median_income :  0
ocean_proximity :  0
median_house_value :  0
```

**Here, we can see in the output that, only "total_bedrooms" contains null values and the total number of null values are 158.**

```
In [34]: data_null=data[data['total_bedrooms'].isnull()]
```

**Plotting null values to check for any patterns.**

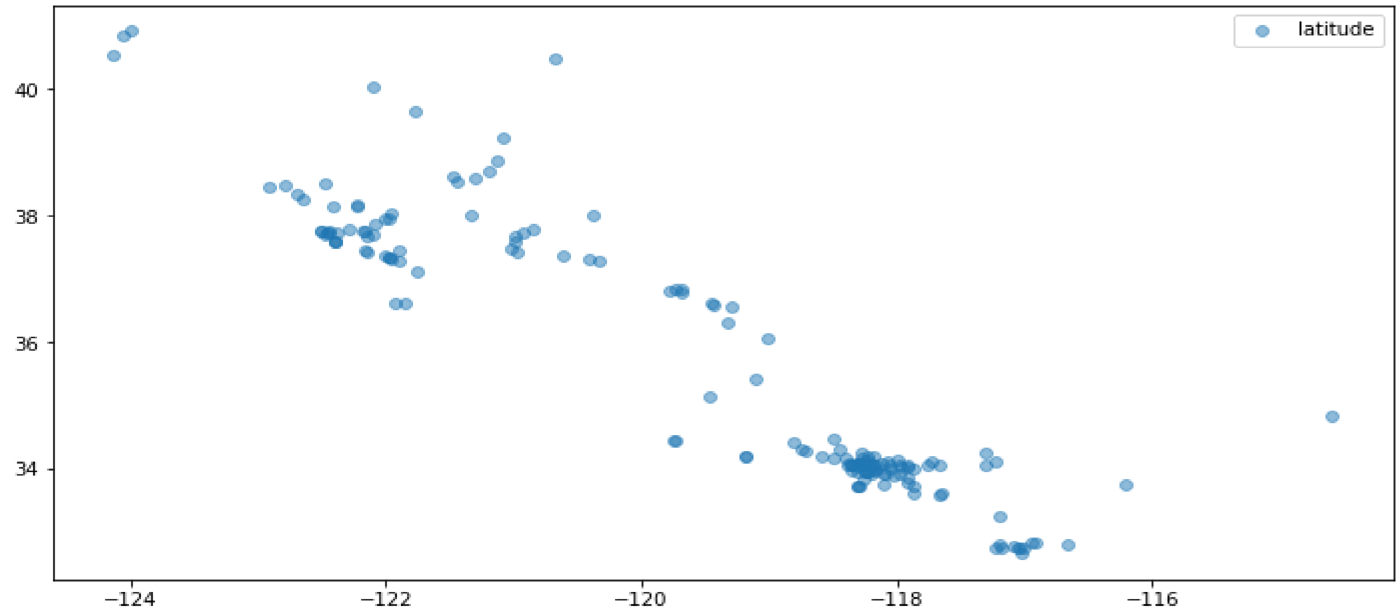
**For example: whether all nulls are concentrated in region or not.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

```
In [35]: plt.figure(figsize=(12,6))
         plt.scatter(x=data_null['longitude'],y=data_null['latitude'],alpha=0.5, label='latitude')
         plt.legend()

Out[35]: <matplotlib.legend.Legend at 0xfb9a790>
```




**We can see from the above plot that, there is not any specific pattern in null values except a dense spot near -118 longitude.**

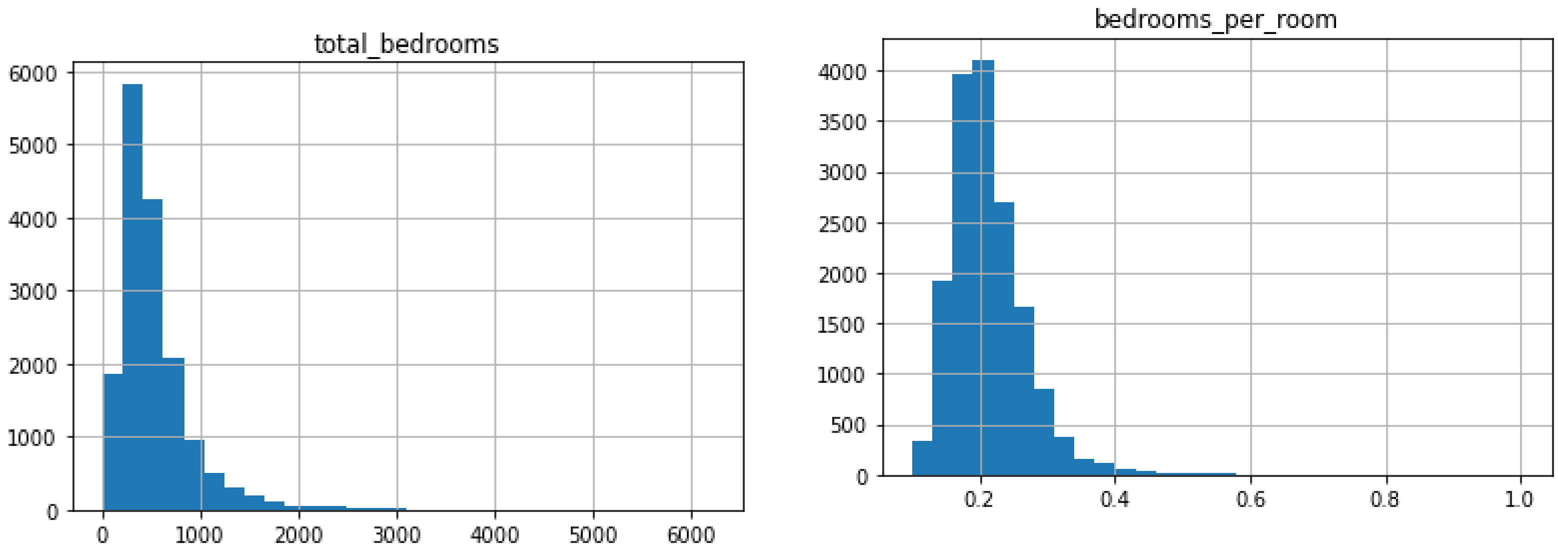
(Contd.)

# Python execution O/P Screenshots and Interpretation

**Let’s plot histograms of columns with null values.**

```
In [36]: data1.hist(column='total_bedrooms',bins=30)
         data1.hist(column='bedrooms_per_room',bins=30)
```

```
Out[36]: array([[<AxesSubplot:title={'center':'bedrooms_per_room'}>]], dtype=object)
```




**As the distributions of 'total_bedrooms' and 'bedrooms_per_room' are skewed, it's better to replace null values by median. I have used sklearn's Imputer to do this job.**

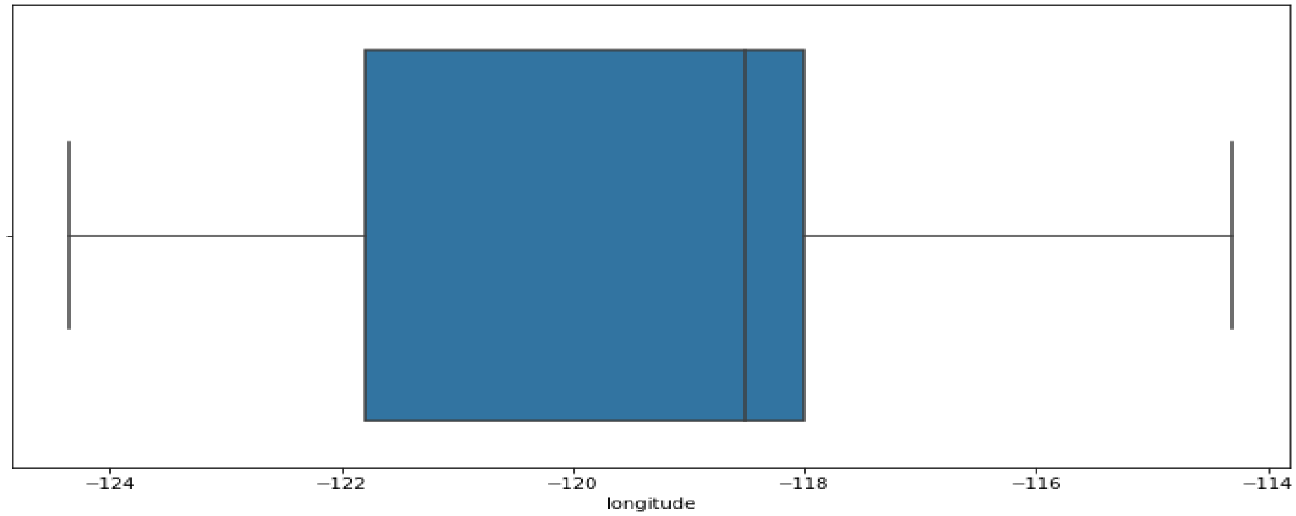
(Contd.)

# Python execution O/P Screenshots and Interpretation

## Removing Outliers

```
In [37]: num_features=['longitude', 'latitude', 'housing_median_age', 'total_rooms',
                'total_bedrooms', 'population', 'households', 'median_income',
                'median_house_value', 'rooms_per_household',
                'bedrooms_per_room', 'population_per_household']
```

```
In [38]: for i in num_features:
             fig, ax = plt.subplots()
             fig.set_size_inches(12,6)
             sns.boxplot(x=i,data=data1,ax=ax)
```

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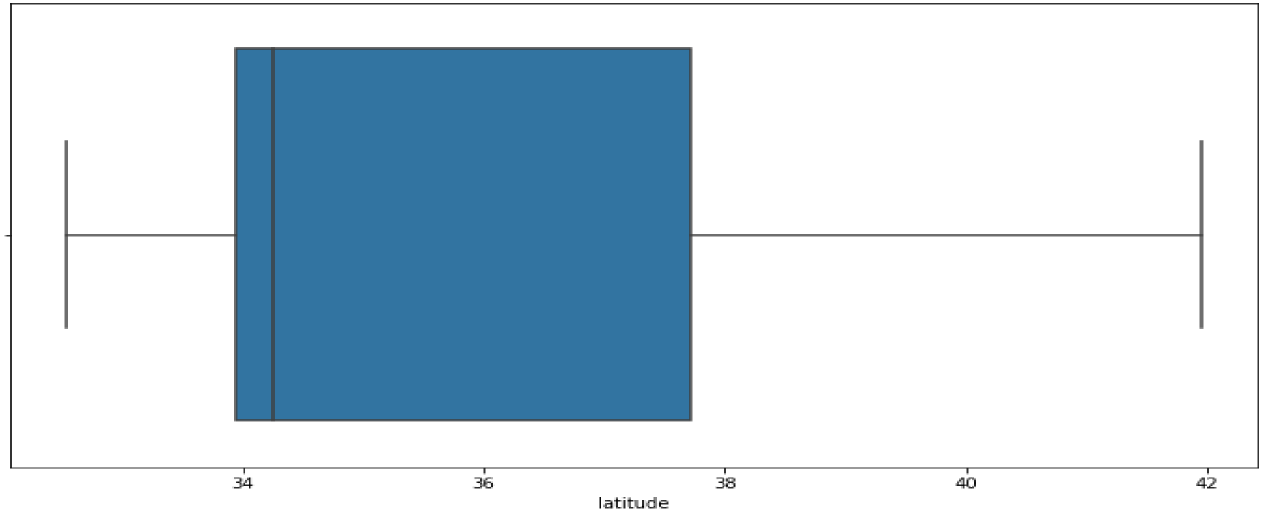
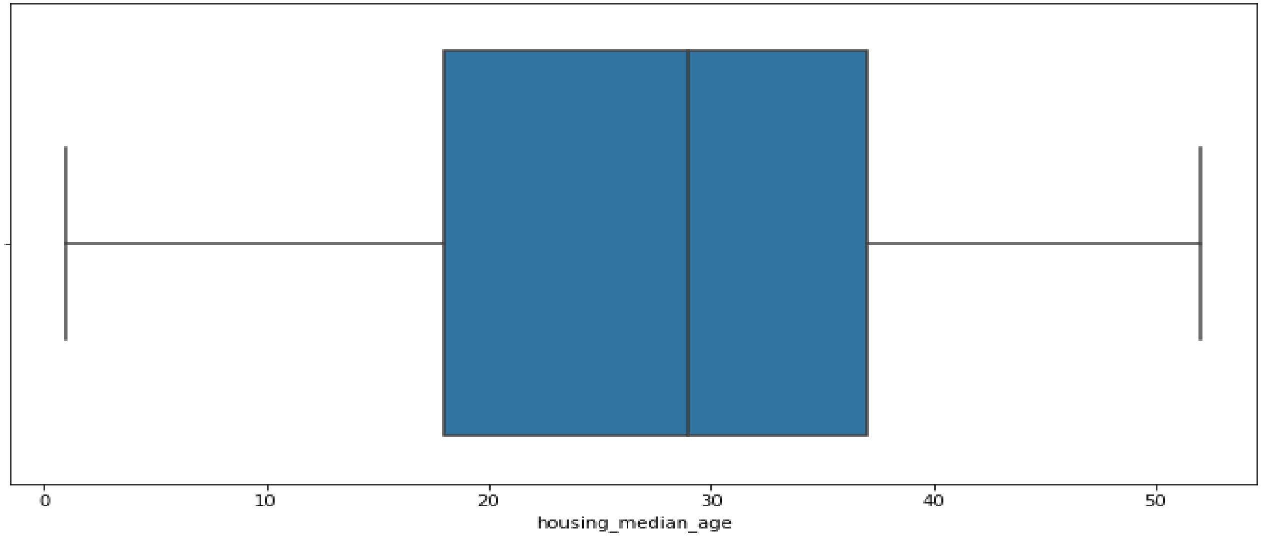
# Python execution O/P Screenshots and Interpretation

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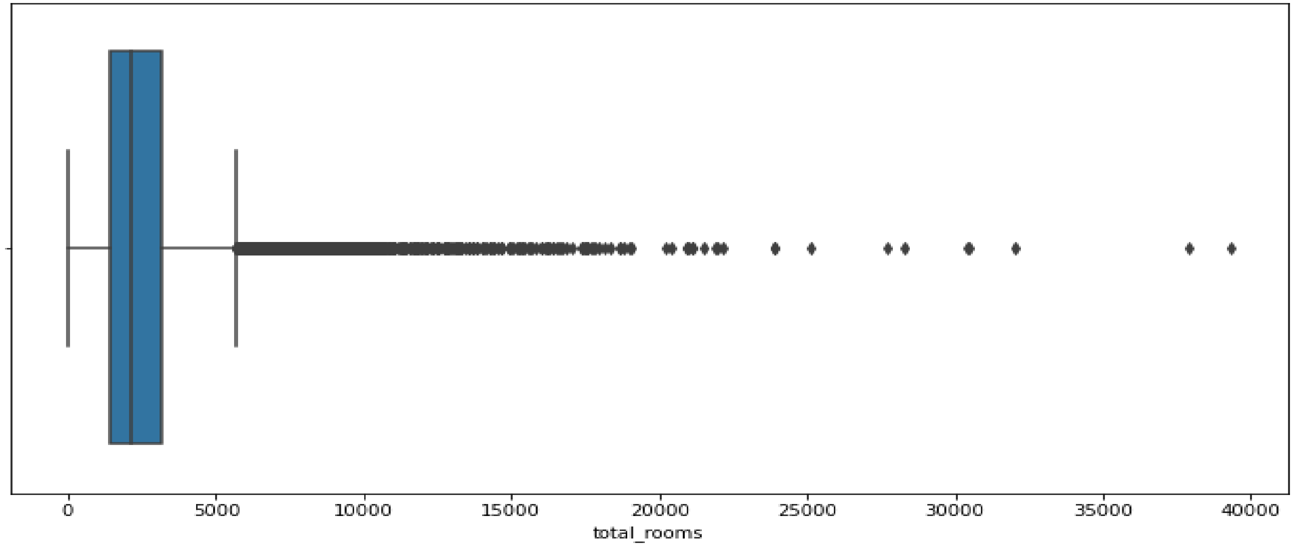
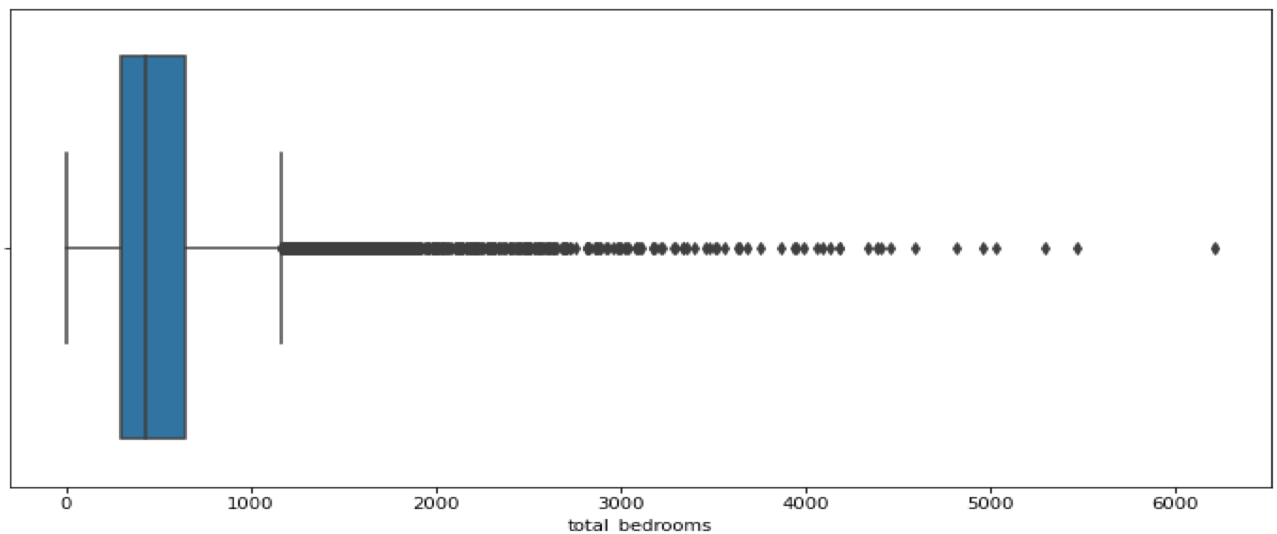
# Python execution O/P Screenshots and Interpretation

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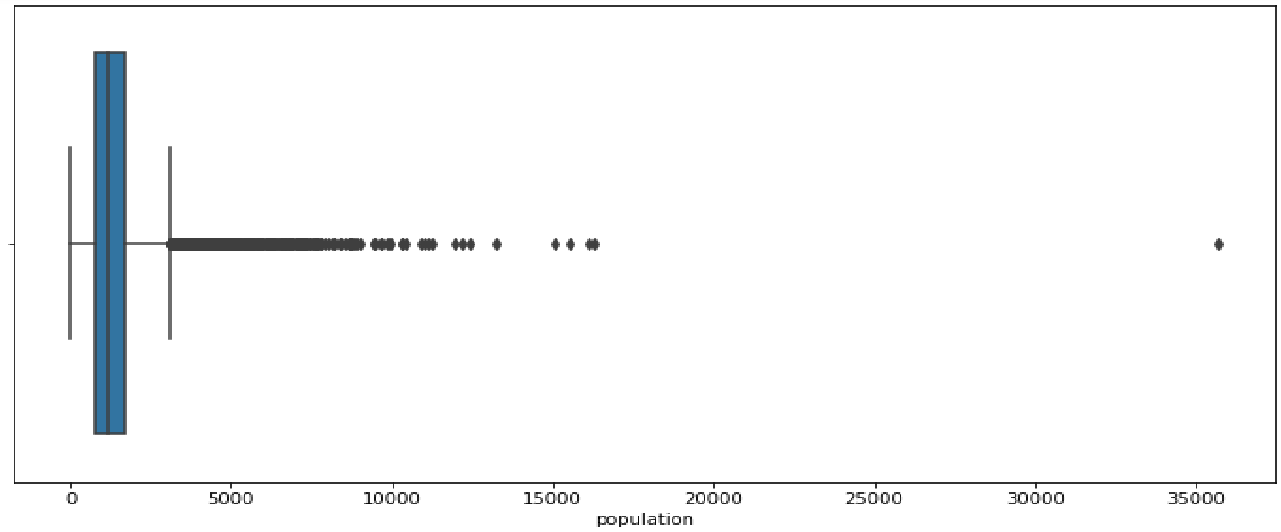
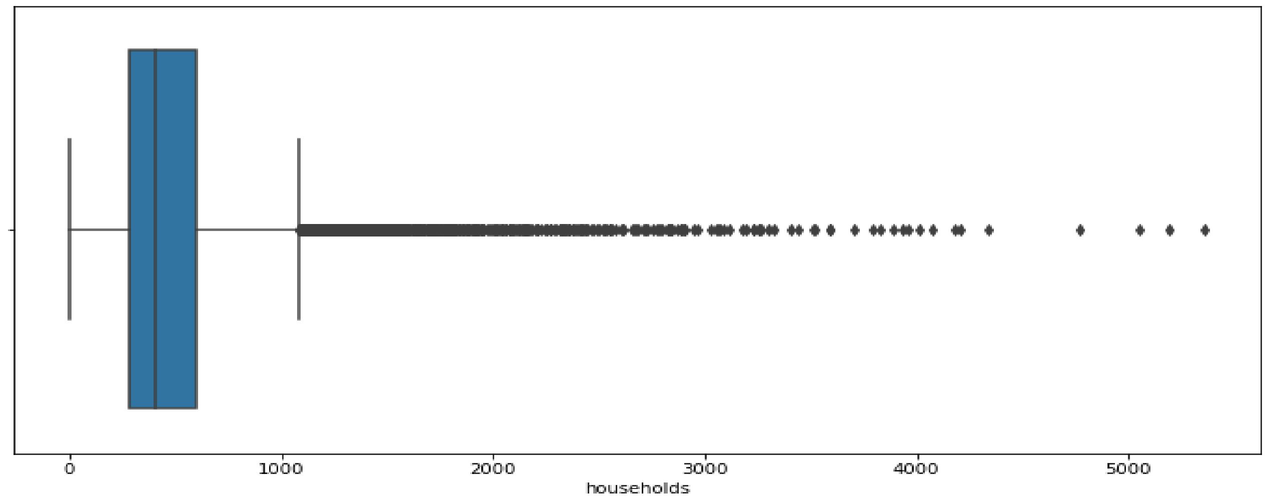
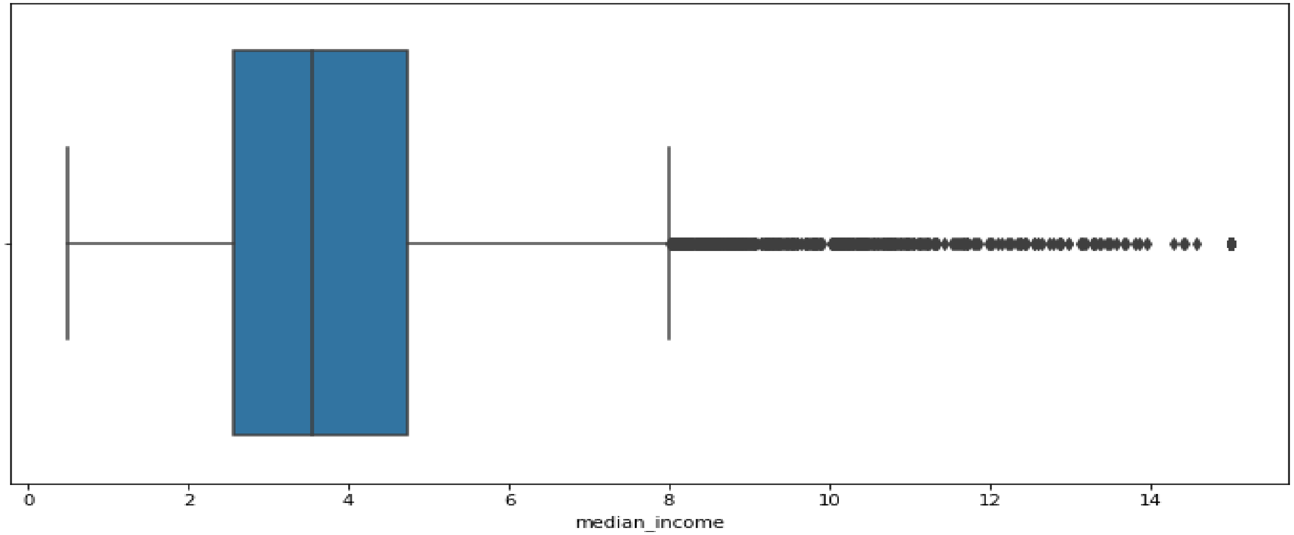
# Python execution O/P Screenshots and Interpretation

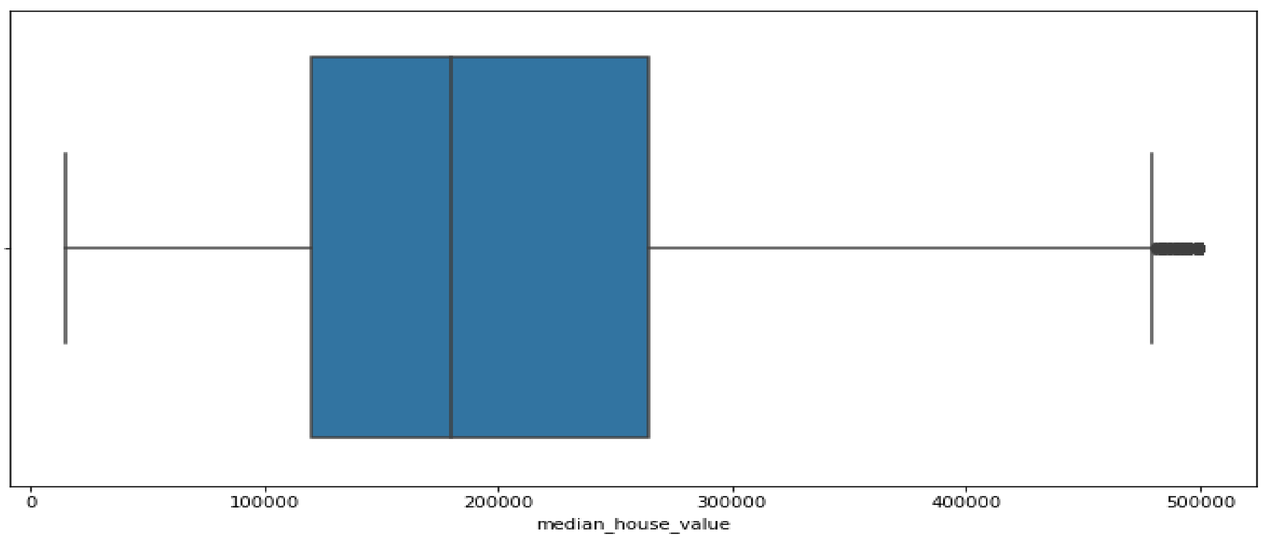



(Contd.)

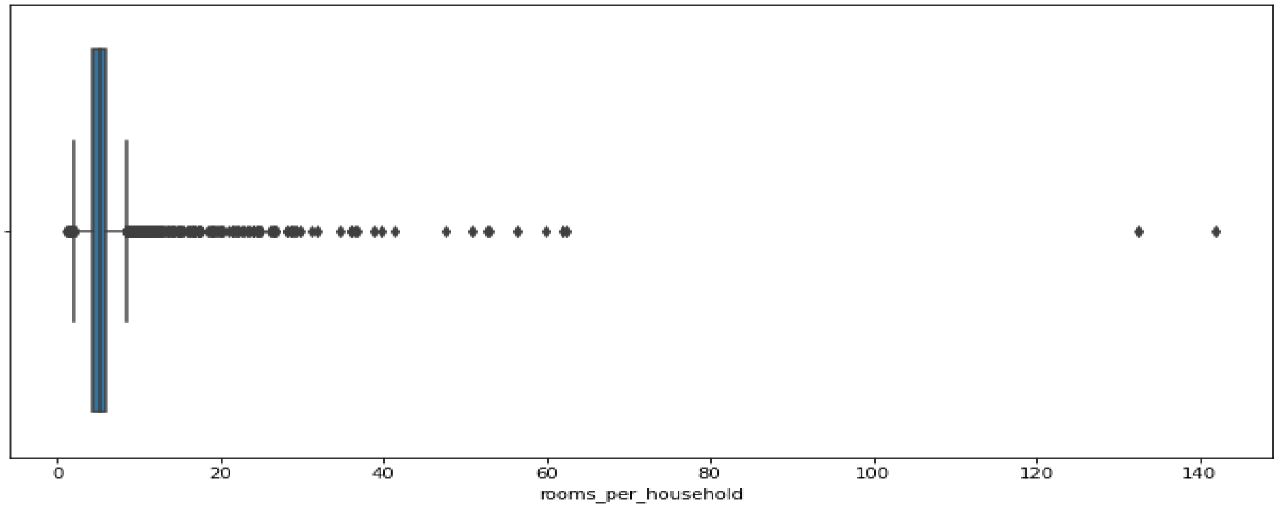
# Python execution O/P Screenshots and Interpretation

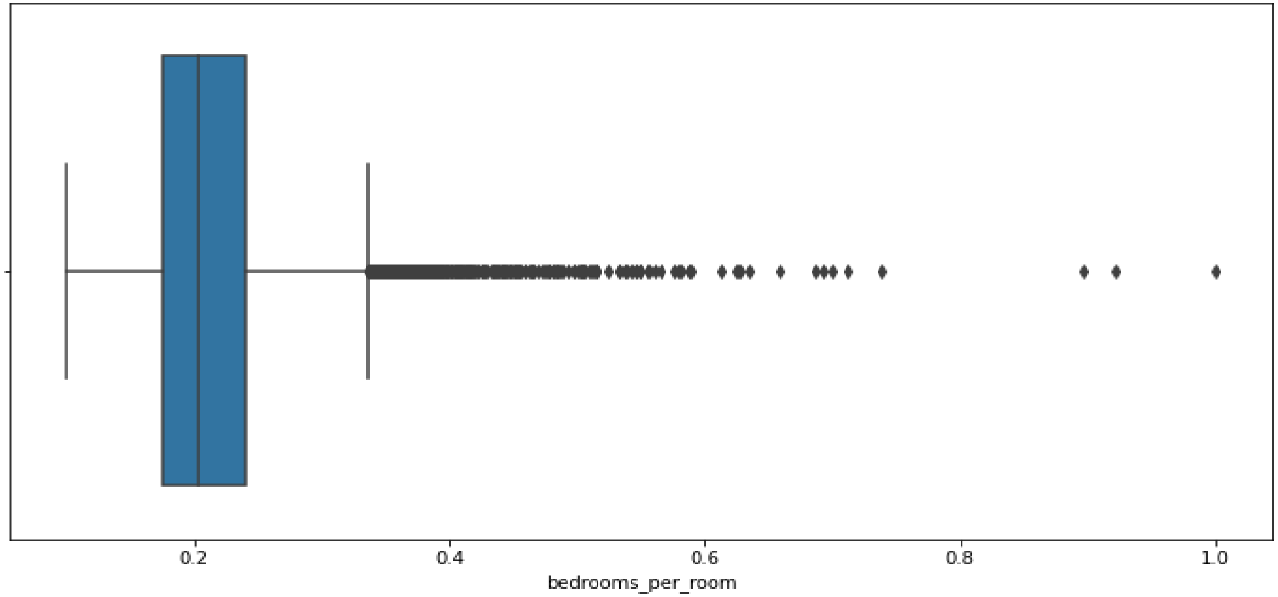



(Contd.)

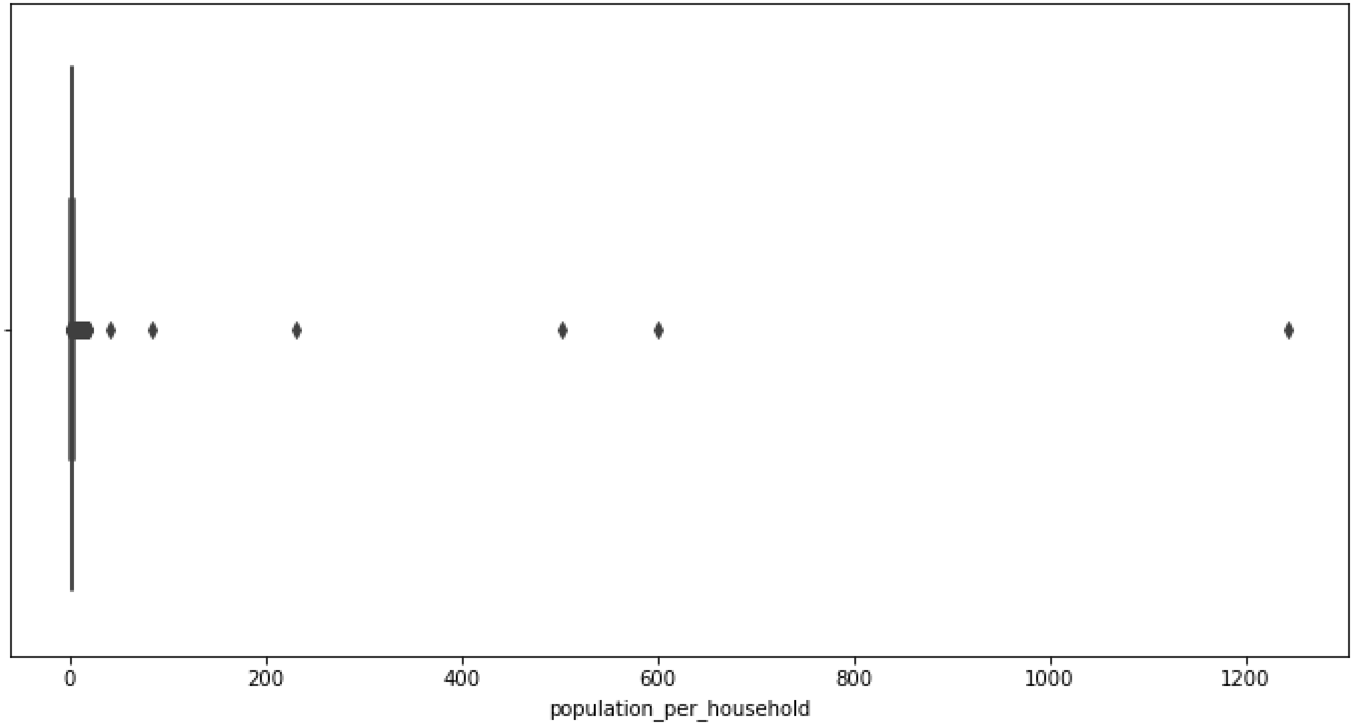
# Python execution O/P Screenshots and Interpretation




(Contd.)

# Python execution O/P Screenshots and Interpretation




**By studying above box plots in details as well as scatter plot of 'Median_House_Value' vs. 'Median_Income', I decided following conditions to remove outliers.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

In [39]:
```
class RemoveOutliers(BaseEstimator,TransformerMixin):
    """This class removes outliers from data.
    Note: Outlier values are hard coded
    """
    def fit (self,X,y=None):
        return self

    def transform(self,X,y=None):
        X=X[(X['median_house_value']!=500001) | (X['median_income']>=2)].reset_index(drop=True)
        X=X[X['median_income']<=11].reset_index(drop=True)
        X=X[(X['median_house_value']!=350000) | (X['median_income']>=1.5)].reset_index(drop=True)
        X=X[(X['median_house_value']!=450000) | (X['median_income']>=2)].reset_index(drop=True)
        X=X[(X['median_house_value']>=350000) | (X['median_income']<=9.5)].reset_index(drop=True)
        X=X[X['population']<=9000]
        X=X[(X['population_per_household']>=1.15) & (X['population_per_household']<=6.5)]
        X=X[X['rooms_per_household']<20]
        X=X[X['bedrooms_per_room']<0.5].reset_index(drop=True)
        return X
```

In [40]:
```
data1=RemoveOutliers().fit_transform(data1)
```

In [41]:
```
data_labels=data1['median_house_value']
data1=data1.drop('median_house_value',axis=1)
```

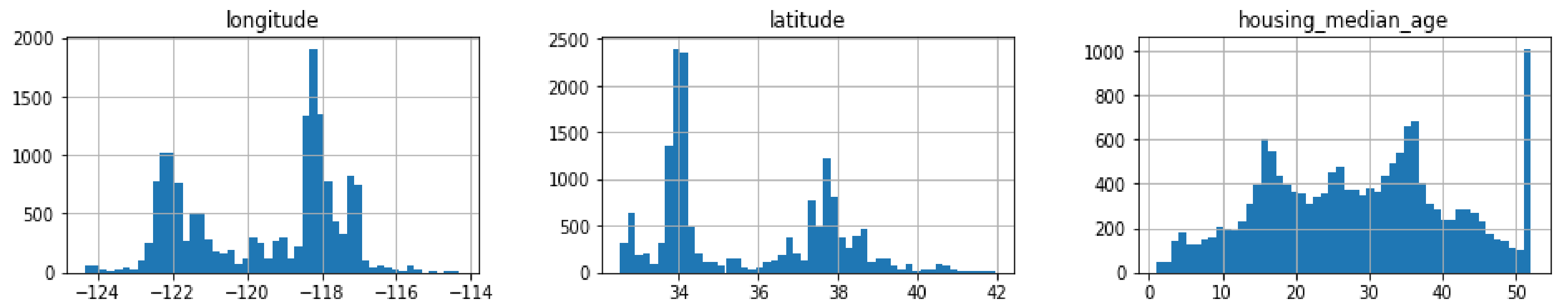
(Contd.)

# Python execution O/P Screenshots and Interpretation

## Transforming skewed features

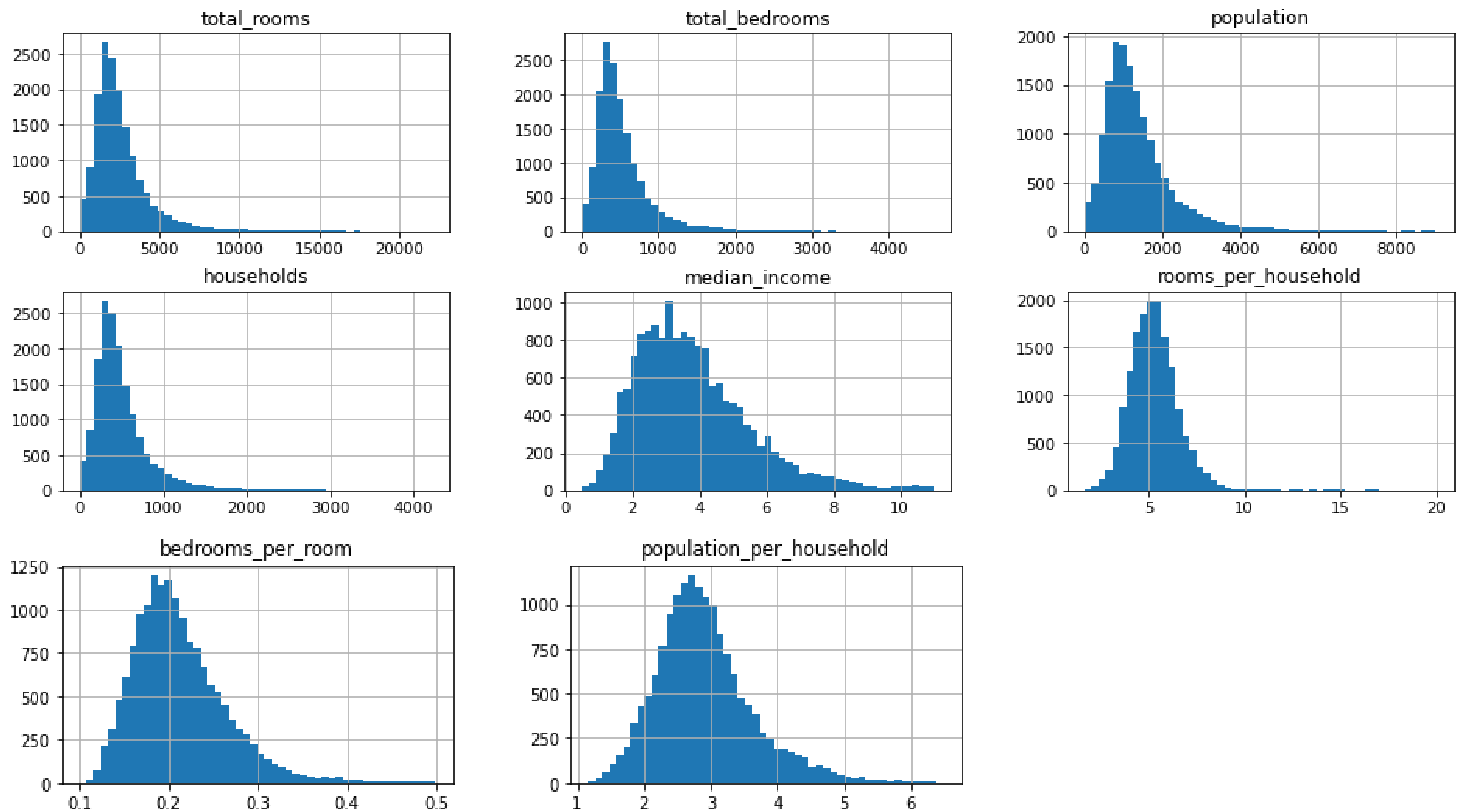
```
In [42]: data1.hist(bins=50,figsize=(16,12))
```

```
Out[42]: array([[<AxesSubplot:title={'center':'longitude'}>,
                 <AxesSubplot:title={'center':'latitude'}>,
                 <AxesSubplot:title={'center':'housing_median_age'}>],
                [<AxesSubplot:title={'center':'total_rooms'}>,
                 <AxesSubplot:title={'center':'total_bedrooms'}>,
                 <AxesSubplot:title={'center':'population'}>],
                [<AxesSubplot:title={'center':'households'}>,
                 <AxesSubplot:title={'center':'median_income'}>,
                 <AxesSubplot:title={'center':'rooms_per_household'}>],
                [<AxesSubplot:title={'center':'bedrooms_per_room'}>,
                 <AxesSubplot:title={'center':'population_per_household'}>,
                 <AxesSubplot:>]], dtype=object)
```




(Contd.)

# Python execution O/P Screenshots and Interpretation




**We can see from the plots that, after removing outliers, the skewness decreased.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

In [43]:
```
num_features=['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'rooms_per_household',
       'bedrooms_per_room', 'population_per_household']
```

**Get skewness of features**

In [44]:
```
skewness=[]
for i in num_features:
    skewness.append(data1[i].skew())
pd.DataFrame(data=skewness,index=num_features,columns=['skewness']).sort_values(by='skewness',ascending=False)
```

Out[44]:

| | skewness |
|---|---|
| total_rooms | 2.902649 |
| total_bedrooms | 2.684070 |
| households | 2.629067 |
| population | 2.453927 |
| rooms_per_household | 2.168956 |
| bedrooms_per_room | 1.158469 |
| median_income | 1.051412 |
| population_per_household | 0.902046 |
| latitude | 0.462198 |
| housing_median_age | 0.061121 |
| longitude | -0.293169 |

**The above output shows the skewness of the attributes.**

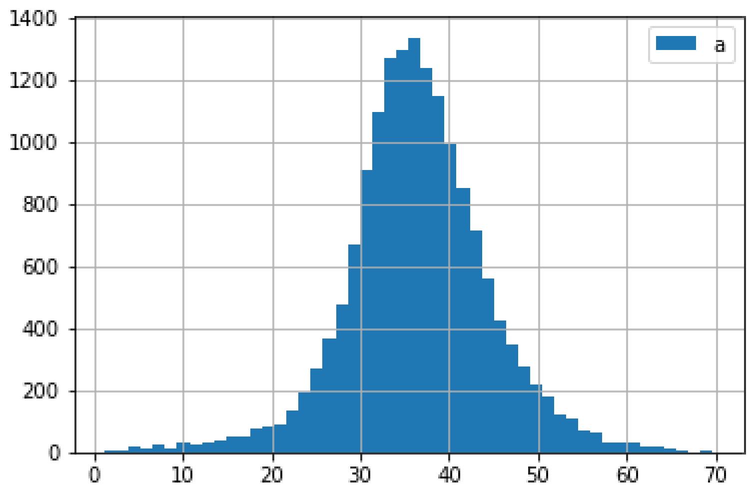
(Contd.)

# Python execution O/P Screenshots and Interpretation

**I transformed features using log1p and boxcox1p functions. boxcox1p is used for highly skewed features.**

```
In [45]: data1['households'].apply(lambda x: np.log1p(x)**2).hist(bins=50,label='a')
         plt.legend()
```

```
Out[45]: <matplotlib.legend.Legend at 0x1254be50>
```




(Contd.)

# Python execution O/P Screenshots and Interpretation

In [46]:
```
class FeaturesTransformer(BaseEstimator,TransformerMixin):
    """This class trnsforms numberical featuress in the dataset.
    Note: Transformations are hard coded.
    """
    def fit(self,X,y=None):
        return self
    def transform(self,X,y=None):
        import numpy as np
        from scipy.special import boxcox1p
        X['total_rooms']=X['total_rooms'].apply(lambda x: boxcox1p(x,0.25))
        X['total_bedrooms']=X['total_bedrooms'].apply(lambda x: boxcox1p(x,0.25))
        X['households']=X['households'].apply(lambda x: boxcox1p(x,0.2))
        X['population']=X['population'].apply(lambda x: boxcox1p(x,0.3))
        X['rooms_per_household']=X['rooms_per_household'].apply(lambda x: np.log1p(x)**0.5)
        X['bedrooms_per_room']=X['bedrooms_per_room'].apply(lambda x: np.log1p(x)**0.25)
        X['median_income']=X['median_income'].apply(lambda x: np.log1p(x)**1.25)
        X['population_per_household']=X['population_per_household'].apply(lambda x: np.log1p(x)**1)
        return X
```

In [47]:
```
data1=FeaturesTransformer().fit_transform(data1)
```

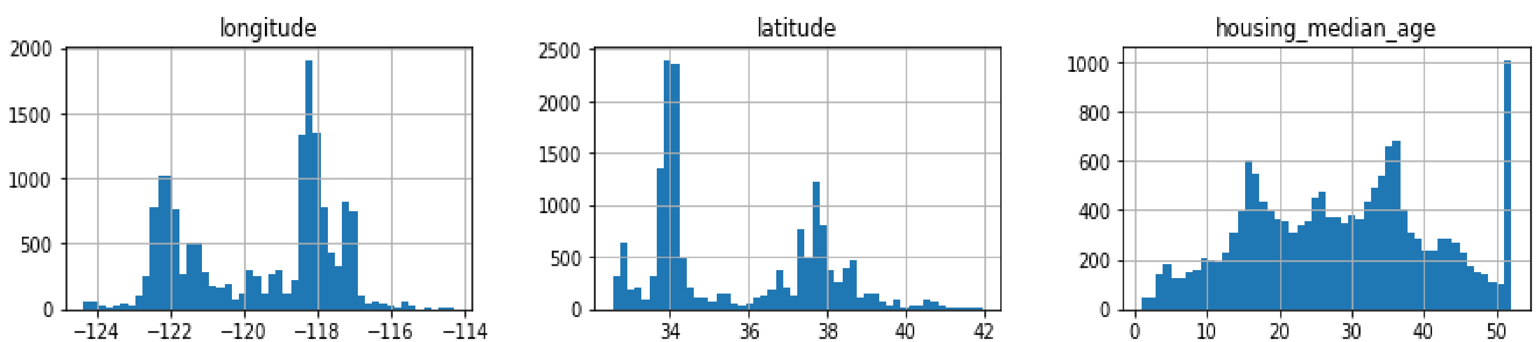
(Contd.)

# Python execution O/P Screenshots and Interpretation

## Transformed features

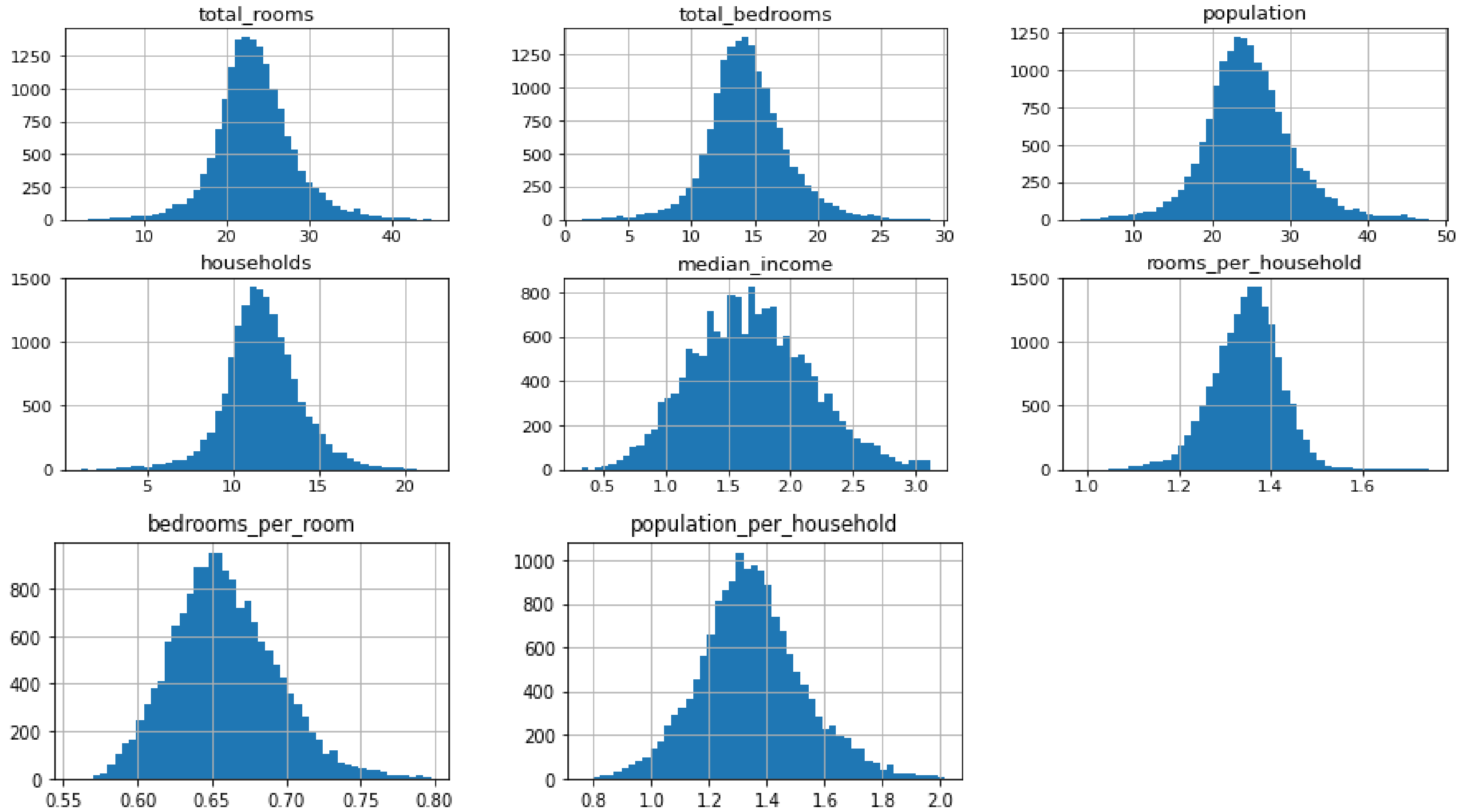
In [48]:
```
data1.hist(bins=50,figsize=(15,12))
```

Out[48]:
```
array([[<AxesSubplot:title={'center':'longitude'}>,
        <AxesSubplot:title={'center':'latitude'}>,
        <AxesSubplot:title={'center':'housing_median_age'}>],
       [<AxesSubplot:title={'center':'total_rooms'}>,
        <AxesSubplot:title={'center':'total_bedrooms'}>,
        <AxesSubplot:title={'center':'population'}>],
       [<AxesSubplot:title={'center':'households'}>,
        <AxesSubplot:title={'center':'median_income'}>,
        <AxesSubplot:title={'center':'rooms_per_household'}>],
       [<AxesSubplot:title={'center':'bedrooms_per_room'}>,
        <AxesSubplot:title={'center':'population_per_household'}>,
        <AxesSubplot:>]], dtype=object)
```




(Contd.)

# Python execution O/P Screenshots and Interpretation




**We can see from the plots that, after feature transform, distribution become normal.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

## Getting dummy variables and Feature Scaling

```
In [49]: from sklearn.pipeline import Pipeline,FeatureUnion
         from sklearn.preprocessing import StandardScaler
         from sklearn.impute import SimpleImputer
```

```
In [50]: imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
```

```
In [51]: class DataFrameSelector(BaseEstimator,TransformerMixin):
             """This class is a dataframe selector.
                Data members:
                    features: A list of column_names you want in output dataframe
             """
             def __init__(self,features):
                 self.features=features
             def fit(self,X,y=None):
                 return self
             def transform(self,X,y=None):
                 return X[self.features]
```

```
In [52]: class GetDummies(BaseEstimator,TransformerMixin):
             """This class is used to get dummy columns from categorical columns."""
             def fit (self,X,y=None):
                 return self
             def transform(self,X,y=None):
                 #change ISLAND to NEAR BAY...as count of ISLAND is very low
                 X[X=='ISLAND']='NEAR BAY'
                 return (pd.get_dummies(X,drop_first=True))
```

```
In [53]: num_features=['longitude', 'latitude', 'housing_median_age', 'total_rooms',
                'total_bedrooms', 'population', 'households', 'median_income',
                'rooms_per_household','bedrooms_per_room', 'population_per_household']
         cat_featues=['ocean_proximity']
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

```
In [54]: num_pipeline=Pipeline([
             ('selector',DataFrameSelector(num_features)),
             ('imputer',SimpleImputer(strategy='mean')),
             ('std_scaler',StandardScaler())
         ])

         #Preparing categorical data
         cat_pipeline=Pipeline([
             ('selector',DataFrameSelector(cat_featues)),
             ('get_dummies',GetDummies())
         ])

         #Combining numerical and categorica data
         data_cleaning_pipeline=FeatureUnion(transformer_list=[
             ('num_pipeline',num_pipeline),
             ('cat_pipeline',cat_pipeline),

         ])
```

```
In [55]: data1=data_cleaning_pipeline.fit_transform(data1)
```

**Above pipeline returned an array. I converted it to data frame again so that we can look at columns easily and do further processing.**

```
In [56]: l=num_features.copy()
         l.extend([0,1,2])
```

```
In [57]: data1=pd.DataFrame(data1,columns=l)
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

```
In [58]: data1.head(2)
```

Out[58]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households | median_income | rooms_per_household | bedrooms_per_room |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | -1.154224 | 0.772567 | 0.746370 | -0.475425 | -0.369225 | -0.743301 | -0.314063 | -0.611150 | -0.449849 | 0.334068 |
| 1 | -1.174180 | 0.660361 | -1.171019 | -1.491029 | -1.797235 | -1.693043 | -1.732155 | 1.464804 | 0.622682 | -1.106072 |

**Scaling labels:**

➢ **This is necessary for some machine learning algorithms**

```
In [59]: y=data_labels.copy()
```

```
In [60]: label_scaler=StandardScaler()
         data_labels=label_scaler.fit_transform(y.values.reshape(-1,1))
```

**Check for multicoliniearity:**

➢ **Here I have removed features having VIF (Variance Inflation Factor) greater than 5 and p-Values greater than 0.05 I have written following functions to do the job.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

```
In [61]: def get_vif(X):
    import statsmodels.api as sm
    from statsmodels.stats.outliers_influence import variance_inflation_factor
    l = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
    return pd.Series(index=X.columns,data=l).sort_values(ascending=False)

def remove_by_pvalue(X,y,pvalue=0.05):
    """Remove features with p-value more than 'pvalue'

    This function uses statsmodels.api.OLS model. Please add intercept to data externally.
    Input:
        X: Array or dataframe excluding predicted variable
        y: Series or list of predicted variable
        pvalue: int or float

    Note:
        X is changed inplace
    """
    import statsmodels.api as sm
    for i in range(len(X.columns)):
        regressor_OLS=sm.OLS(endog=y,exog=X).fit()
        s=regressor_OLS.pvalues.sort_values(ascending=False)
        if s.iloc[0]>pvalue:
            X.drop(s.index[0],axis=1,inplace=True)
            print('Removed: ',s.index[0],'P-value: ',s.iloc[0])

def remove_by_vif(X,vif=5):
    """Remove columns from X whose VIF is greater than supplied 'vif'
    Parameters:
        X:array or dataframe containing data excluding target variable
        vif: int or float of limiting value of VIF
    Note:
        This function changes X inplace
    """
    import statsmodels.api as sm
    from statsmodels.stats.outliers_influence import variance_inflation_factor

    for i in range(len(X.columns)):
        l = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
        s=pd.Series(index=X.columns,data=l).sort_values(ascending=False)
        if s.iloc[0]>vif:
            X.drop(s.index[0],axis=1,inplace=True)
            print('Removed: ',s.index[0],', VIF: ',s.iloc[0])
        else:
            break
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

In [62]:
```
# Get VIFs of all features
get_vif(data1)
```

Out[62]:
```
total_bedrooms              558.923558
households                  389.655010
total_rooms                 287.321351
population                  141.389762
bedrooms_per_room            66.260643
rooms_per_household          50.549888
population_per_household     19.548814
latitude                     18.347840
longitude                    17.347168
median_income                 3.027807
0                             2.022556
1                             1.449785
housing_median_age            1.374288
2                             1.223067
dtype: float64
```

**The above output showing the VIF (Variance Inflation Factor) of attributes of “data1”.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

```
In [63]: remove_by_vif(data1)
```

```
Removed:  total_bedrooms , VIF:  558.9235579608114
Removed:  households , VIF:  228.1741365426593
Removed:  total_rooms , VIF:  108.34813434774779
Removed:  latitude , VIF:  18.337136881413034
Removed:  bedrooms_per_room , VIF:  5.618818797870981
```

**So, above 5 columns were removed because of VIF constraint.**

```
In [64]: remove_by_pvalue(data1,data_labels)
```

**No columns were removed by p-Value constraint.**

**This is all the data manipulation I have done. Following is the summarization:**

- Adding new features
- Removing outliers
- Transforming skewed features
- Null value imputation
- Dummy variables for ocean_proximity
- Check for multicoliniearity
- Standard scaling

(Contd.)

# Python execution O/P Screenshots and Interpretation

## Second Portion : Training machine learning algorithms

I will try to find the best suitable machine learning model to predict house prices.

### Making Train Data ready

```
In [65]: df=pd.read_csv('strat_train_set.csv')
```

```
In [66]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16512 entries, 0 to 16511
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           16512 non-null  float64
 1   latitude            16512 non-null  float64
 2   housing_median_age  16512 non-null  int64
 3   total_rooms         16512 non-null  int64
 4   total_bedrooms      16354 non-null  float64
 5   population          16512 non-null  int64
 6   households          16512 non-null  int64
 7   median_income       16512 non-null  float64
 8   ocean_proximity     16512 non-null  object
 9   median_house_value  16512 non-null  int64
dtypes: float64(4), int64(5), object(1)
memory usage: 1.3+ MB
```

**The info() gives the information of the "strat_train_set" data frame like no. of non-null values, data type and memory usage.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

In [67]:
```
#Adding features
df=FeaturesAdder().fit_transform(df)

num_features=['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', 'rooms_per_household',
       'bedrooms_per_room', 'population_per_household']

#Removing outliers
df=RemoveOutliers().fit_transform(df)

data_labels=df['median_house_value']
df=df.drop('median_house_value',axis=1)

#Transforming features
df=FeaturesTransformer().fit_transform(df)

num_features=['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'rooms_per_household','bedrooms_per_room', 'population_per_household']
cat_featues=['ocean_proximity']

#Mean value imputation, feature scaling, gettin gdummy variables
num_pipeline=Pipeline([
    ('selector',DataFrameSelector(num_features)),
    ('imputer',SimpleImputer(strategy='mean')),
    ('std_scaler',StandardScaler())
])

cat_pipeline=Pipeline([
    ('selector',DataFrameSelector(cat_featues)),
    ('get_dummies',GetDummies())
])

#Combining numerical and categorica data
data_cleaning_pipeline=FeatureUnion(transformer_list=[
    ('num_pipeline',num_pipeline),
    ('cat_pipeline',cat_pipeline),
])

df=data_cleaning_pipeline.fit_transform(df)

l=num_features.copy()
l.extend([0,1,2])
df=pd.DataFrame(df,columns=l)
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

```
#Check for multicoliniearity
remove_by_vif(df)
remove_by_pvalue(df,data_labels)

data_prepared=df
y_train=data_labels.copy()

label_scaler=StandardScaler()
data_labels=label_scaler.fit_transform(y_train.values.reshape(-1,1))
```

```
Removed:  total_bedrooms , VIF:  558.9235579608114
Removed:  households , VIF:  228.1741365426593
Removed:  total_rooms , VIF:  108.34813434774779
Removed:  latitude , VIF:  18.337136881413034
Removed:  bedrooms_per_room , VIF:  5.618818797870981
```

**So, above 5 columns were removed because of VIF constraint.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

In [68]:
```
data_prepared
```

Out[68]:

| | longitude | housing_median_age | population | median_income | rooms_per_household | population_per_household | 0 | 1 | 2 |
|---|---|---|---|---|---|---|---|---|---|
| **0** | -1.154224 | 0.746370 | -0.743301 | -0.611150 | -0.449849 | -1.207634 | 0.0 | 0.0 | 0.0 |
| **1** | -1.174180 | -1.171019 | -1.693043 | 1.464804 | 0.622682 | -0.204224 | 0.0 | 0.0 | 0.0 |
| **2** | 1.185638 | 0.187132 | -0.375164 | -0.492940 | -0.825039 | -1.331664 | 0.0 | 0.0 | 1.0 |
| **3** | -0.016721 | -0.292216 | 0.285178 | -1.299468 | 0.057913 | 1.602935 | 1.0 | 0.0 | 0.0 |
| **4** | 0.492161 | -0.931346 | 2.390008 | -0.368150 | -0.558206 | 0.282264 | 0.0 | 0.0 | 0.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **16000** | 0.721657 | 1.385500 | -1.008524 | 0.771706 | 0.651982 | -0.173482 | 1.0 | 0.0 | 0.0 |
| **16001** | 1.006033 | 0.906153 | -0.210085 | -1.132569 | -0.440662 | 1.539436 | 1.0 | 0.0 | 0.0 |
| **16002** | 1.584762 | -1.570475 | 0.892959 | -0.203348 | 0.844114 | -0.152823 | 1.0 | 0.0 | 0.0 |
| **16003** | 0.781526 | 0.187132 | 0.169212 | 0.294852 | 0.266387 | 1.238031 | 0.0 | 0.0 | 0.0 |
| **16004** | -1.433610 | 1.864848 | 0.067323 | -0.004051 | -0.259595 | -1.405587 | 0.0 | 1.0 | 0.0 |

16005 rows × 9 columns

**The “data_prepared “data frame is created from “df” having 16005 rows and 9 columns.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

In [69]:
```
data_prepared.describe()
```

Out[69]:

| | longitude | housing_median_age | population | median_income | rooms_per_household | population_per_household | 0 | 1 | |
|---|---|---|---|---|---|---|---|---|---|
| count | 1.600500e+04 | 1.600500e+04 | 1.600500e+04 | 1.600500e+04 | 1.600500e+04 | 1.600500e+04 | 16005.000000 | 16005.000000 | 1600ɛ |
| mean | 2.320016e-15 | 1.304382e-16 | 5.637521e-16 | 1.228842e-16 | 5.576989e-16 | -8.838776e-17 | 0.319838 | 0.112277 | ( |
| std | 1.000031e+00 | 1.000031e+00 | 1.000031e+00 | 1.000031e+00 | 1.000031e+00 | 1.000031e+00 | 0.466428 | 0.315717 | ( |
| min | -2.381529e+00 | -2.209605e+00 | -3.858035e+00 | -2.883611e+00 | -4.797942e+00 | -3.198401e+00 | 0.000000 | 0.000000 | ( |
| 25% | -1.109322e+00 | -8.514543e-01 | -6.030186e-01 | -7.133766e-01 | -6.151884e-01 | -6.358845e-01 | 0.000000 | 0.000000 | ( |
| 50% | 5.320735e-01 | 2.734921e-02 | -5.728918e-02 | -2.813425e-02 | 5.124493e-02 | -4.460040e-02 | 0.000000 | 0.000000 | ( |
| 75% | 7.815258e-01 | 6.664790e-01 | 5.488315e-01 | 6.611860e-01 | 6.324853e-01 | 5.870352e-01 | 1.000000 | 0.000000 | ( |
| max | 2.627473e+00 | 1.864848e+00 | 4.123765e+00 | 3.009781e+00 | 5.234390e+00 | 3.701446e+00 | 1.000000 | 1.000000 | 1 |

**The describe() shows some basic statistical details like count, mean, median, standard deviation, quartile values, percentile, minimum and maximum values of each attributes of the dataset.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

In [70]:
```
data_prepared.isnull().sum()
```

Out[70]:
```
longitude                   0
housing_median_age          0
population                  0
median_income               0
rooms_per_household         0
population_per_household    0
0                           0
1                           0
2                           0
dtype: int64
```

**Here, we can see in the output that, no attribute contains null values.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

## Choosing ML Algorithm

In [71]:
```
from sklearn.metrics import mean_squared_error,r2_score
from sklearn.model_selection import learning_curve,cross_val_score,validation_curve,train_test_split
from sklearn.model_selection import GridSearchCV
```

In [72]:
```
def plot_validation_curve(scores,param_range,param_name,scoring='r2'):
    """This function plot validation curve.

    Parameters:
        scores: scores obtained from validation_curve() method
        param_range: list of range of parameters passed as 'param_range' in validation_curve() method
        scoring: str
    """
    n=len(param_range)
    if scoring=='r2':
        train_score=[scores[0][i].mean() for i in range (0,n)]
        test_score=[scores[1][i].mean() for i in range (0,n)]
    elif scoring=='neg_mean_squared_error':
        train_score=[np.sqrt(-scores[0][i].mean()) for i in range (0,n)]
        test_score=[np.sqrt(-scores[1][i].mean()) for i in range (0,n)]

    fig=plt.figure(figsize=(8,6))
    plt.plot(param_range,train_score,label='Train')
    plt.plot(param_range,test_score,label='Test')
    plt.xticks=param_range
    plt.title("Validation curve of {}".format(param_name),size=12)
    plt.legend()
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

## Linear Regression

```
In [73]: from sklearn.linear_model import LinearRegression,Ridge
```

```
In [74]: lr=LinearRegression()
         scores=cross_val_score(lr,data_prepared,data_labels,n_jobs=-1,cv=5,scoring='r2')
         print('R2: ',np.sqrt(scores).mean())
```

```
R2:  0.7991862993882449
```

**To calculate RMSE I have used 'train_y' which are unscaled labels.**

```
In [75]: lr=LinearRegression()
         scores=cross_val_score(lr,data_prepared,y_train,n_jobs=-1,cv=5,scoring='neg_mean_squared_error')
         print('RMSE: ',np.sqrt(-scores).mean())
```

```
RMSE:  67960.78780025143
```

**So with linear regression,**

- R-squared=0.8
- RMSE=67960.78
- RMSE of above model is 67960 which means that there's an average error of $67960 in prediction of house price.

(Contd.)

# Python execution O/P Screenshots and Interpretation

## Ridge Regression

```
In [76]: ridge=Ridge(alpha=0.1,random_state=42)
         scores=cross_val_score(ridge,data_prepared,data_labels,n_jobs=-1,cv=5,scoring='r2')
         print('R2: ',np.sqrt(scores).mean())
```

```
R2:  0.7991863159569764
```

(Contd.)

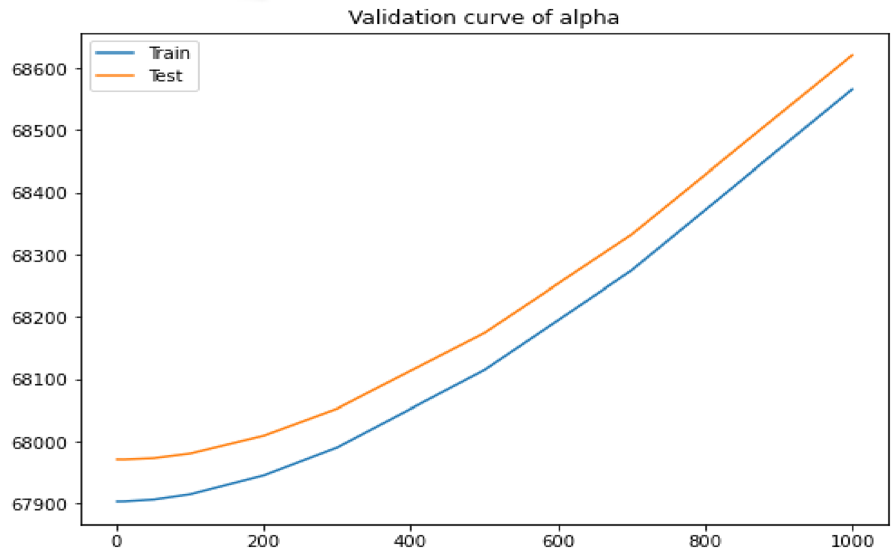
# Python execution O/P Screenshots and Interpretation

In [77]:
```
ridge=Ridge(random_state=42)
param_name='alpha'
param_range = [1,10,50,100,200,300,500,700,1000]

scoring='neg_mean_squared_error'
curve=validation_curve(ridge,data_prepared,y_train,scoring=scoring,cv=5,param_name=param_name,
    param_range=param_range,n_jobs=-1)

n=len(param_range)
'''if scoring=='r2':
    train_score=[curve[0][i].mean() for i in range (0,n)]
    test_score=[curve[1][i].mean() for i in range (0,n)]
elif scoring=='neg_mean_squared_error':
    train_score=[np.sqrt(-curve[0][i].mean()) for i in range (0,n)]
    test_score=[np.sqrt(-curve[1][i].mean()) for i in range (0,n)]
    '''

plot_validation_curve(curve,param_range,param_name,scoring)
```




- **From this plot It can be seen that Train and Test scores are almost after alpha=700.**
- **Even at alpha=0, difference between RMSE is not much, so there is no objectionable over-fitting. As alpha is increased, bias is increasing and so the RMSE.**
- **As linear regression is not over-fitting the model, using Ridge regression is not necessary.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

## Support Vector Regression

```
In [78]: from sklearn.svm import SVR
```

```
In [79]: svr=SVR(degree=2)
         param_grid={
             'C':[1,10,50,100]
         }
         scoring='r2'
         grid=GridSearchCV(svr,param_grid,scoring=scoring,n_jobs=-1,cv=3,verbose=3)
         grid.fit(data_prepared,data_labels)
```

```
Fitting 3 folds for each of 4 candidates, totalling 12 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 out of  12 | elapsed:  4.4min remaining:   53.0s
[Parallel(n_jobs=-1)]: Done  12 out of  12 | elapsed:  5.5min finished
```

```
Out[79]: GridSearchCV(cv=3, estimator=SVR(degree=2), n_jobs=-1,
                      param_grid={'C': [1, 10, 50, 100]}, scoring='r2', verbose=3)
```

```
In [80]: print(grid.best_params_)
```

```
{'C': 10}
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

In [81]:
```
svr=SVR(degree=2,C=10)
scores=cross_val_score(svr,data_prepared,data_labels,n_jobs=-1,cv=5,scoring='r2')
print('R2: ',np.sqrt(scores).mean())
```

```
R2:  0.8787045011060872
```

**So, with support vector machines, R2=0.878.**

**Which is better than Linear Regression model.**

## Decision Tree

In [82]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [83]:
```
dtr=DecisionTreeRegressor(random_state=42)
scores=cross_val_score(dtr,data_prepared,y_train,n_jobs=-1,cv=5,scoring='r2')
print('R2: ',np.sqrt(scores).mean())
```

```
R2:  0.7571871948332872
```

- **So, basic decision tree model is giving R2=0.7571.**
- **Then I did some parameter tuning so get best decision tree model.**

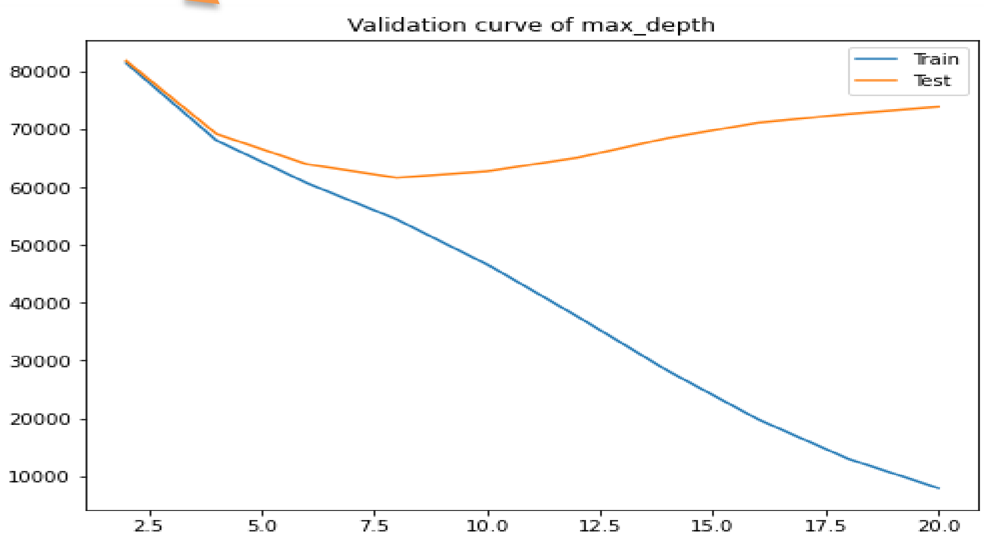
(Contd.)

# Python execution O/P Screenshots and Interpretation

## max_depth

In [84]:
```
dtr=DecisionTreeRegressor(random_state=42)
param_name='max_depth'
param_range = range(2,21,2)
scoring='neg_mean_squared_error'
curve=validation_curve(dtr,data_prepared,y_train,scoring=scoring,cv=5,param_name=param_name,
    param_range=param_range,n_jobs=-1)

plot_validation_curve(curve,param_range,param_name,scoring)
```



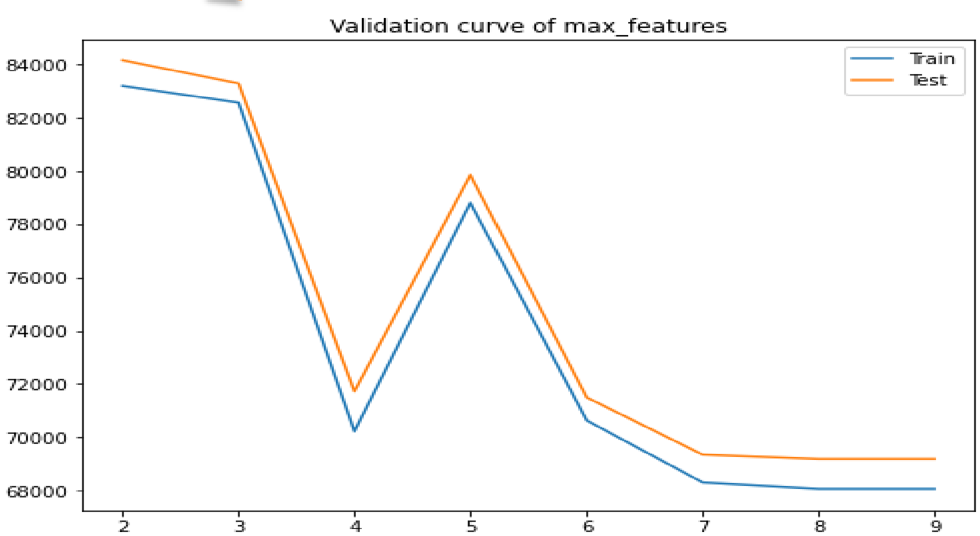

- From above diagram it is clear that model starts overfitting heavily after max_depth=8.
- max_depth: 3 to 8

(Contd.)

# Python execution O/P Screenshots and Interpretation

## max_features

```
In [85]: dtr=DecisionTreeRegressor(max_depth=4,random_state=42)
         param_name='max_features'
         param_range = range(2,10)
         scoring='neg_mean_squared_error'
         curve=validation_curve(dtr,data_prepared,y_train,scoring=scoring,cv=5,param_name=param_name,
             param_range=param_range,n_jobs=-1)
         plot_validation_curve(curve,param_range,param_name,scoring)
```



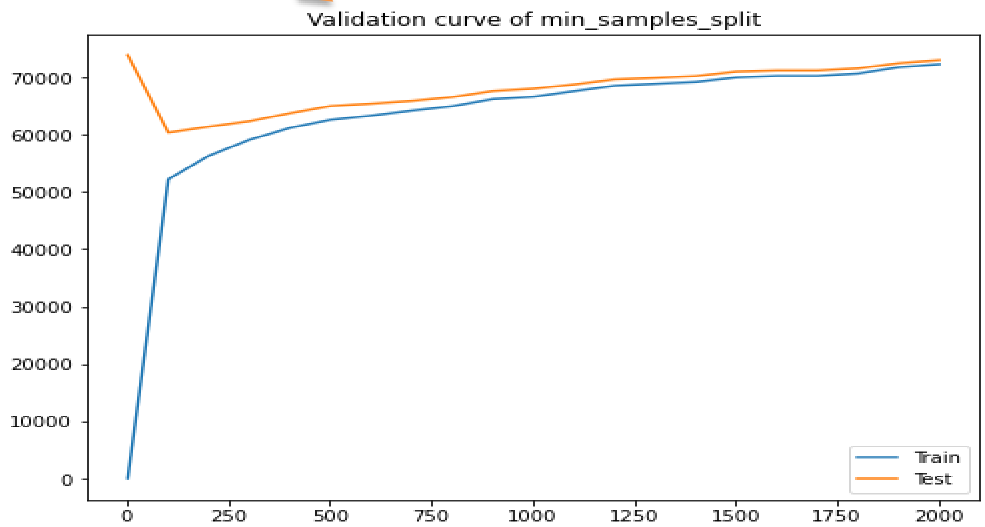

**So, we get the value of max_features: 6 to 9.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

## min_samples_split

```
In [86]: dtr=DecisionTreeRegressor(random_state=42)
         param_name='min_samples_split'
         param_range = range(2,2003,100)
         scoring='neg_mean_squared_error'
         curve=validation_curve(dtr,data_prepared,y_train,scoring=scoring,cv=5,param_name=param_name,
             param_range=param_range,n_jobs=-1)
         plot_validation_curve(curve,param_range,param_name,scoring)
```



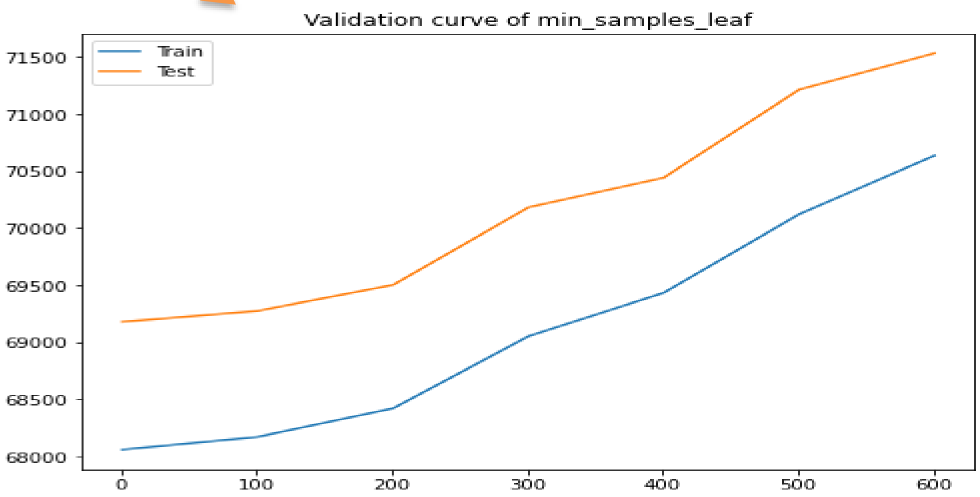

**With increasing min_samples_split after 200, variance is reducing.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

## min_samples_leaf

In [87]:
```
dtr=DecisionTreeRegressor(max_depth=4,random_state=42)
param_name='min_samples_leaf'
param_range = range(1,701,100)
scoring='neg_mean_squared_error'
curve=validation_curve(dtr,data_prepared,y_train,scoring=scoring,cv=5,param_name=param_name,
    param_range=param_range,n_jobs=-1)
plot_validation_curve(curve,param_range,param_name,scoring)
```




**Increasing min_samples_leaf is neither giving good results nor helping to reduce overfitting.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

## Gradient Boosting Regression

I used this ensembling method to get the best model from decision trees.

```
In [88]: from sklearn.ensemble import GradientBoostingRegressor
```

```
In [89]: gbr=GradientBoostingRegressor(random_state=42)
         param_grid={
             'n_estimators':[100,500,1000],
             'max_depth':range(3,9,1),
             'max_features':[6,7,9],
             'min_samples_split':[200,400]
         }
         scoring='r2'
         grid=GridSearchCV(gbr,param_grid,scoring=scoring,n_jobs=-1,cv=3,verbose=1)
         grid.fit(data_prepared,y_train)
         print(grid.best_params_)
```

```
Fitting 3 folds for each of 108 candidates, totalling 324 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 192 tasks      | elapsed: 14.8min
[Parallel(n_jobs=-1)]: Done 324 out of 324 | elapsed: 34.0min finished
```

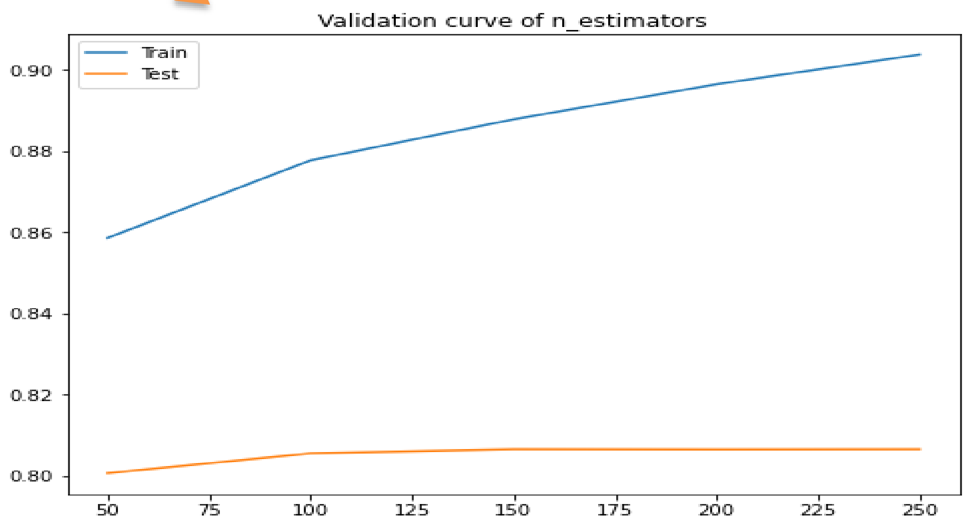
```
{'max_depth': 8, 'max_features': 6, 'min_samples_split': 200, 'n_estimators': 100}
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

## Check for n_estimators

```
In [90]: gbr=GradientBoostingRegressor(max_depth= 8, max_features=6, min_samples_split=200,random_state=42)
param_name='n_estimators'
param_range = range(50,251,50)
scoring='r2'
curve=validation_curve(gbr,data_prepared,y_train,scoring=scoring,cv=5,param_name=param_name,
    param_range=param_range,n_jobs=-1)
plot_validation_curve(curve,param_range,param_name,scoring)
```




- With increasing number of estimators, model is overfitting.
- With lower number of estimators, model is underfitting.

(Contd.)

# Python execution O/P Screenshots and Interpretation

**I chose n_estimators=100**

```
In [91]: gbr=GradientBoostingRegressor(max_depth= 8, max_features=6, min_samples_split=200, n_estimators=100,random_state=42)
         scores=cross_val_score(gbr,data_prepared,y_train,n_jobs=-1,cv=5,scoring='r2')
         print('R2: ',np.sqrt(scores).mean())

R2:  0.8974790145435815
```

- **With above Gradient Boosting model, R2=0.897.**
- **This model is even better than support vector regressor.**

**Stacking**

- This is another ensembling method.
- In this, I have used Linear regression and Gradient boosing regression as base models and Support Vector Regression as meta model.

(Contd.)

# Python execution O/P Screenshots and Interpretation

In [92]:
```
from mlxtend.regressor import StackingRegressor
```

In [93]:
```
lr=LinearRegression()
svr=SVR(degree=2,C=10)
gbr=GradientBoostingRegressor(max_depth= 8, max_features=6, min_samples_split=200, n_estimators=100,random_state=42)
```

In [94]:
```
sr=StackingRegressor([lr,gbr],svr,verbose=3)
scores=cross_val_score(sr,data_prepared,data_labels,n_jobs=-1,cv=3,scoring='r2')
print('R2: ',np.sqrt(scores).mean())
```

```
R2:  0.8920759836217309
```

**For stacking,**

- R2=0.892
- This is less than Gradient Boosting Regressor.

## Final Model:

**I finalized following Gradient Boosing Regressor with following parameters:**

- n_estimators=100
- max_depth=8
- max_features=6
- min_samples_split=200

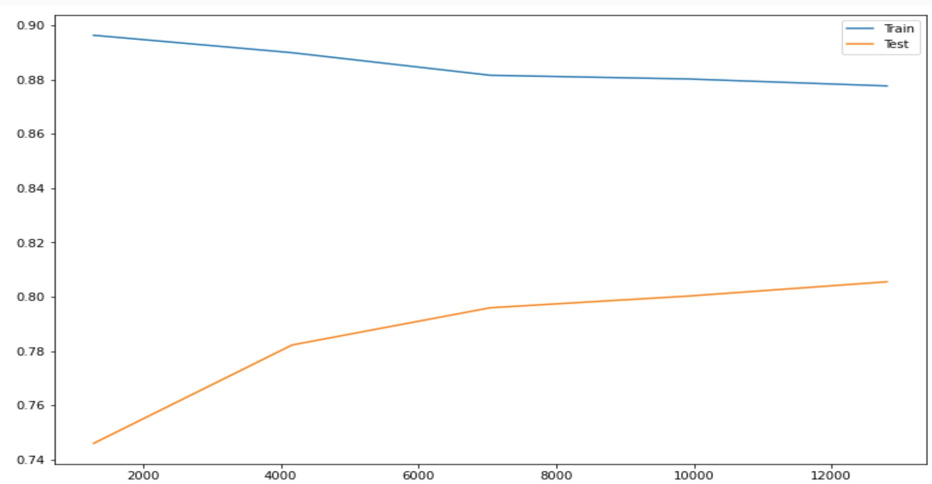
(Contd.)

# Python execution O/P Screenshots and Interpretation

## Learning Curve

In [95]:
```
gbr=GradientBoostingRegressor(max_depth= 8, max_features=6, min_samples_split=200, n_estimators=100,random_state=42)
lc=learning_curve(gbr,data_prepared,y_train,cv=5,n_jobs=-1)
size=lc[0]
train_score=[lc[1][i].mean() for i in range (0,5)]
test_score=[lc[2][i].mean() for i in range (0,5)]
fig=plt.figure(figsize=(12,8))
plt.plot(size,train_score,label='Train')
plt.plot(size,test_score,label="Test")
plt.legend()
```

Out[95]: <matplotlib.legend.Legend at 0x15071400>




- **From learning curve it is clear that this model is still overfitting. But, with the increase in number of samples, variance is decreasing.**
- **So, getting more training data can be a solution for overfitting.**

(Contd.)

# Python execution O/P Screenshots and Interpretation

- **Predicting on Test Data Set**

```
In [96]: test_data=pd.read_csv('strat_test_set.csv')
         test_data_labels=test_data['median_house_value'].copy()
         test_data.drop('median_house_value',axis=1,inplace=True)
```

**I did following data manipulations on test data**

- Adding features
- Transforming skewed features

```
In [97]: fa=FeaturesAdder()
         df_test=fa.fit_transform(test_data)

         df_test=FeaturesTransformer().fit_transform(df_test)

         #used 'transform' method, as I don't want to refit the standard scalar on test data.
         df_test=data_cleaning_pipeline.transform(df_test)

         df_test=pd.DataFrame(df_test,columns=l)
```

(Contd.)

# Python execution O/P Screenshots and Interpretation

- **Scaling test data labels**

```
In [98]: #used 'transform' method, as I don't want to refit the standard scalar on test data.

         y_test=test_data_labels.copy()
         test_data_labels=label_scaler.transform(y_test.values.reshape(-1,1))
```

- **Choosing same columns of test_data as of train_data**

```
In [99]: test_data_prepared=df_test[data_prepared.columns]
```

```
In [100]: gbr=GradientBoostingRegressor(max_depth= 8, max_features=6, min_samples_split=200, n_estimators=100,random_state=42)
          gbr.fit(data_prepared,data_labels)
          train_pred=gbr.predict(data_prepared)
          test_pred=gbr.predict(test_data_prepared)
```

```
In [101]: mse=mean_squared_error(y_train,label_scaler.inverse_transform(train_pred))
          rmse=np.sqrt(mse)
          print('train error:',rmse)
          mse=mean_squared_error(y_test,label_scaler.inverse_transform(test_pred))
          rmse=np.sqrt(mse)
          print('test error:',rmse)
```

```
train error: 39773.94783299169
test error: 49795.96894045239
```

**So, the train error : 39773.94783299169 and test error : 49795.96894045239.**