Exploratory data Analysis for Machine Learning Assignment

Brief description of the data set and a summary of its attributes

The initial plan consists of the following steps:

1. Clean the data by identifying outliers;
2. Analyse whether the feature engineering is necessary;
3. Formulate several hypothesis about the data;
4. Test the hypothesis;
5. Review the results;

Actions taken for data cleaning and feature engineering

First of all, we identified the outliers in order to remove them from the set and make sure - they will not affect the prediction. The feature engineering part is easier, because all our values are numerical and therefore - there is no need in any sort of transformation. We have not removed any values, because all columns are relevant.

In [1]:
```
import pandas as pd     # Data Wrangling & Preprocessing
import numpy as np      # Data Wrangling & Preprocessing
import seaborn as sns   # Plotting charts
import matplotlib.pyplot as plt    # Plotting charts
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.model_selection import train_test_split    #Splitting the data into training & testing set
from sklearn.preprocessing import OneHotEncoder    #Encoding categorical variables
from sklearn.pipeline import Pipeline    # To create pipelines for preprocessing steps
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression    # Linear Regression Model
from sklearn.ensemble import RandomForestRegressor   # RandomForest Regressor Model
from sklearn.metrics import mean_squared_error    # RMSE Evaluation Metric for Regression
from sklearn.model_selection import cross_val_score    # To Compute validation score
from sklearn.base import BaseEstimator, TransformerMixin
```

```python
from sklearn.compose import ColumnTransformer
import pickle    # To export the trained model
```

In [2]:
```python
data=pd.read_csv(r"D:\Certificate\Coursera Explotory data analysis\Assignments_V2\housing.csv")
```

In [3]:
```python
data.head()
```

Out[3]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_prox
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR

In [4]:
```python
data.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  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object 
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

In [5]:
```python
data['ocean_proximity'].value_counts()
```

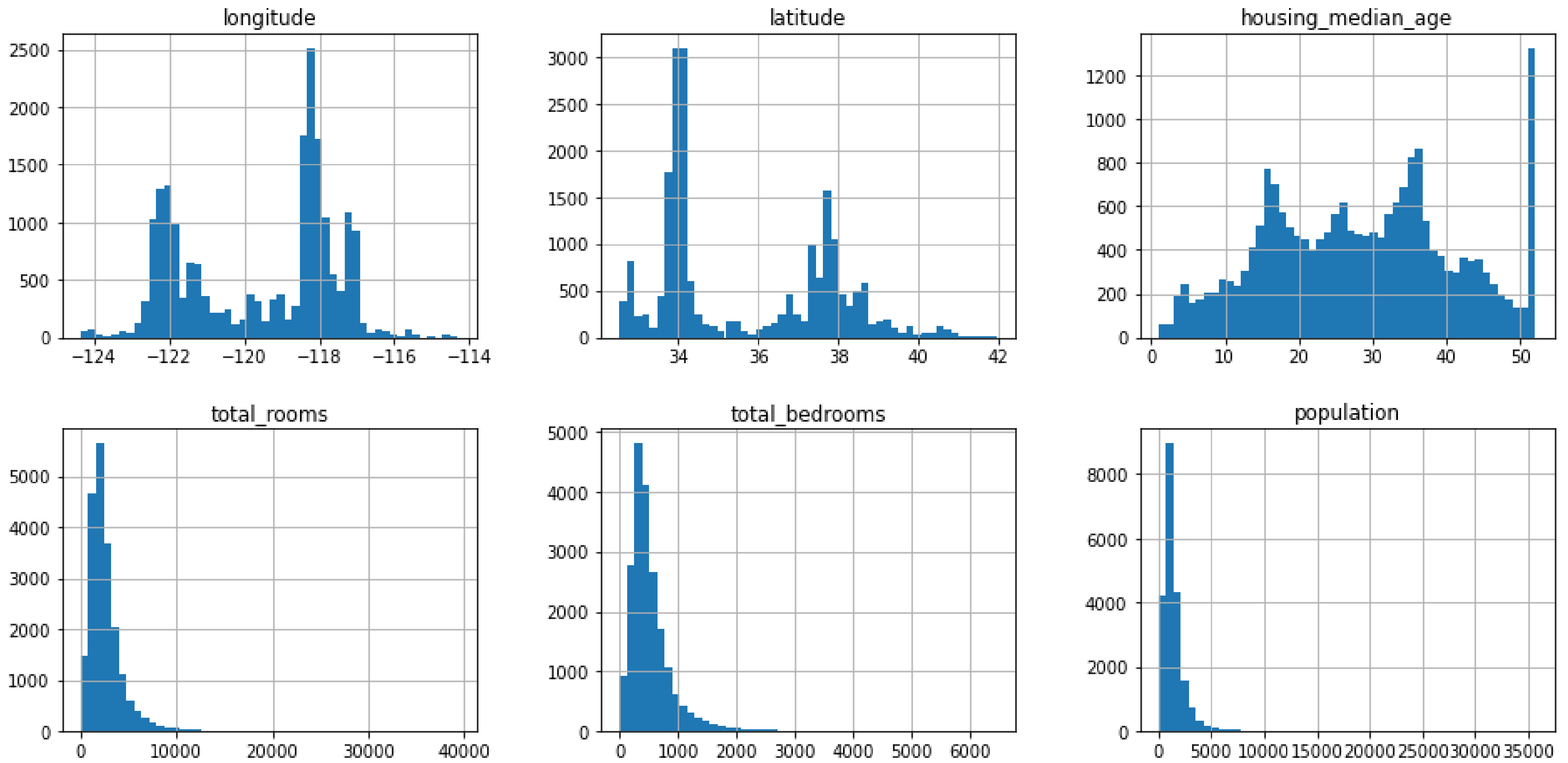
Out[5]:
```
<1H OCEAN     9136
```

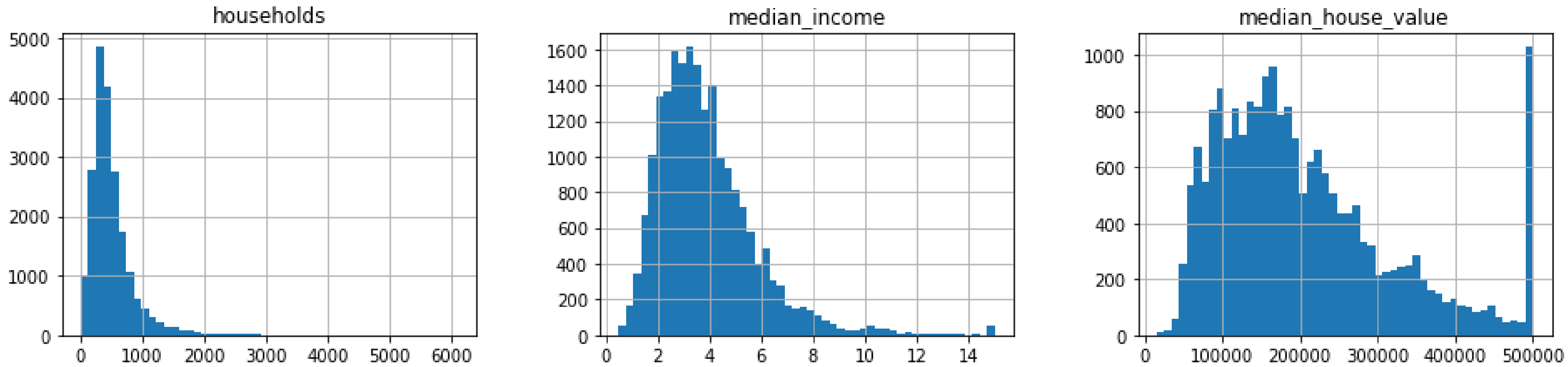
```
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

Key Findings and Insights, which synthesizes the results of Exploratory Data Analysis in an insightful and actionable manner

In [6]:

```
data.hist(bins=50, figsize=(16,12))
plt.show()
```



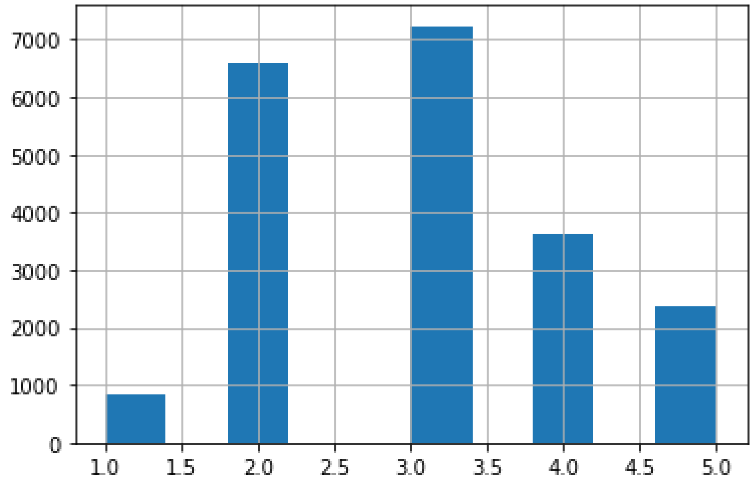


Formulating at least 3 hypothesis about this data

From the above data we can make several assumptions: the house price are not equal for all; there are more attributes i.e lognitudes , latitude, house_median_age etc.

In [9]:
```
train_set, test_set = train_test_split(data, test_size=0.2, random_state=42)
```

In [10]:
```
data['income_cat'] = pd.cut(data['median_income'], bins=[0., 1.5, 3.0, 4.5, 6., np.inf], labels=[1, 2, 3, 4, 5])
data['income_cat'].hist()
plt.show()
```



In [11]:

```
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(data, data["income_cat"]):
    strat_train_set = data.loc[train_index]
    strat_test_set = data.loc[test_index]
print(strat_test_set['income_cat'].value_counts() / len(strat_test_set))
```

```
3    0.350533
2    0.318798
4    0.176357
5    0.114583
1    0.039729
Name: income_cat, dtype: float64
```

Suggestions for next steps in analyzing this data

The results indicate that a larger sample of house has been consider , even we can suggest to broaded the anaysis in the more broader way.

In [12]:

```
#Now you need to remove the Income_cat attribute added by us to get the data back to its form:
for set_ in (strat_train_set, strat_test_set):
    set_.drop('income_cat', axis=1, inplace=True)
data = strat_train_set.copy()
```

In [13]:

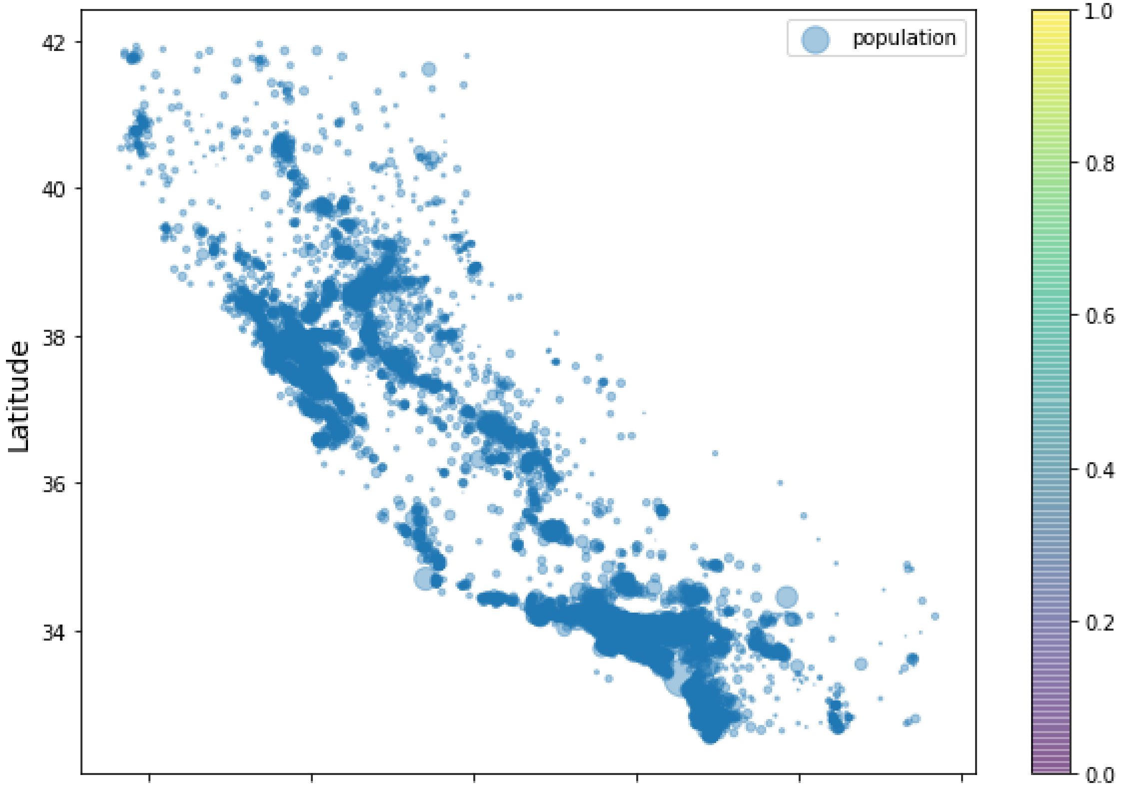
```
data.head()
```

Out[13]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_
17606	-121.89	37.29	38.0	1568.0	351.0	710.0	339.0	2.7042	286600.0	<1
18632	-121.93	37.05	14.0	679.0	108.0	306.0	113.0	6.4214	340600.0	<1
14650	-117.20	32.77	31.0	1952.0	471.0	936.0	462.0	2.8621	196900.0	NEA
3230	-119.61	36.31	25.0	1847.0	371.0	1460.0	353.0	1.8839	46300.0	
3555	-118.59	34.23	17.0	6592.0	1525.0	4459.0	1463.0	3.0347	254500.0	<1

In [14]:

```
#Now before creating a machine learning model for house price prediction with Python let’s visualize the data in tern
data.plot(kind='scatter', x='longitude', y='latitude', alpha=0.4,
                s=data['population']/100, label='population', figsize=(10,7),
                cmap=plt.get_cmap('jet'), colorbar=True)

plt.ylabel("Latitude", fontsize=14)
plt.xlabel("Longitude", fontsize=14)
plt.legend()
plt.show()
```



In [15]:
```
corr_matrix = data.corr()
print(corr_matrix.median_house_value.sort_values(ascending=False))
```

```
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
```

In [16]:
```
data["rooms_per_household"] = data["total_rooms"]/data["households"]
data["bedrooms_per_room"] = data["total_bedrooms"]/data["total_rooms"]
```

```
data["population_per_household"] = data["population"]/data["households"]

corr_matrix = data.corr()
print(corr_matrix["median_house_value"].sort_values(ascending=False))
```

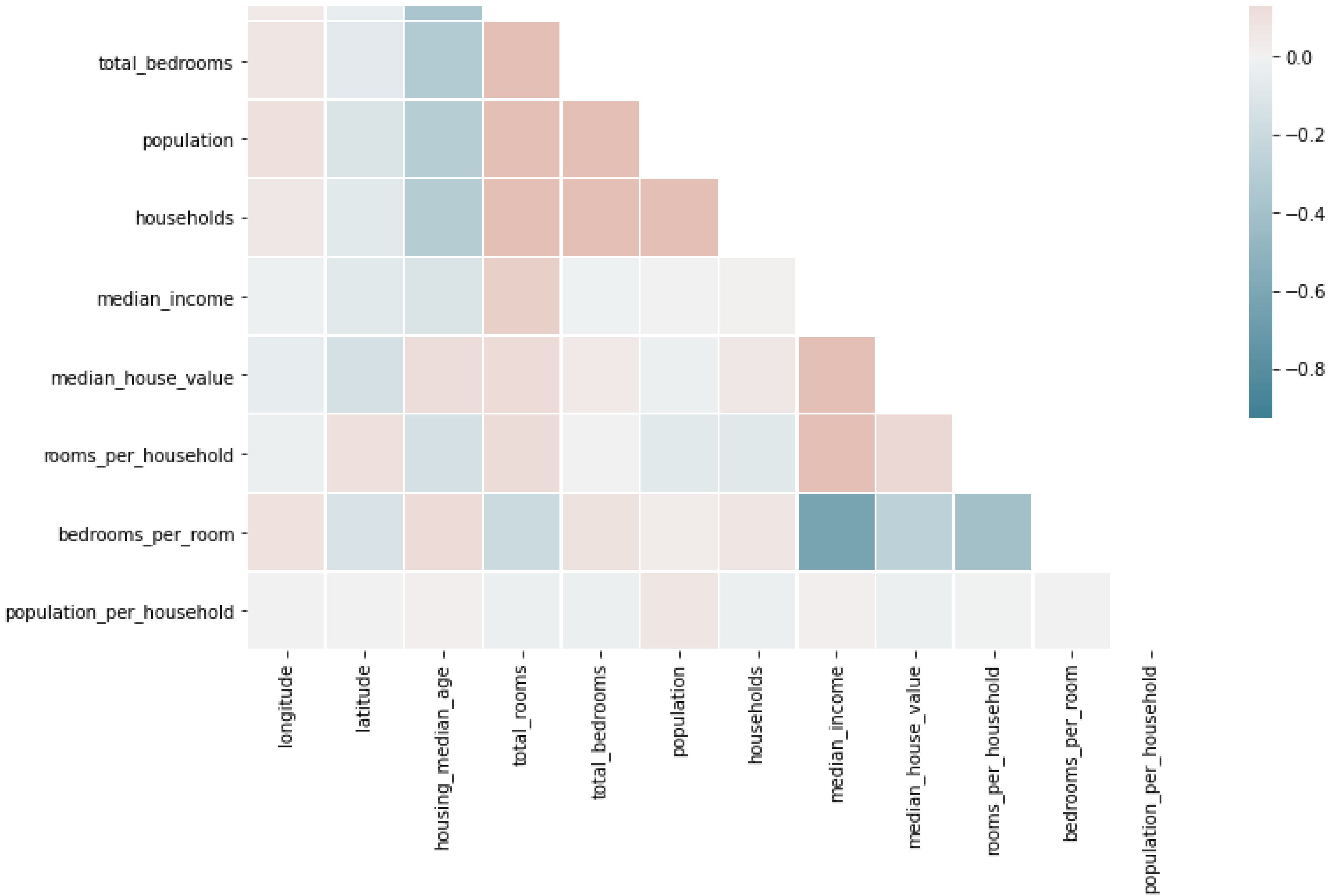
```
median_house_value          1.000000
median_income               0.687160
rooms_per_household         0.146285
total_rooms                 0.135097
housing_median_age          0.114110
households                  0.064506
total_bedrooms              0.047689
population_per_household   -0.021985
population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

In [17]:

```
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(12, 10))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr_matrix, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[17]:

```
<AxesSubplot:>
```



In [18]:

```
# Data Preparation
housing = strat_train_set.drop("median_house_value", axis=1)
housing_labels = strat_train_set["median_house_value"].copy()

median = housing["total_bedrooms"].median()
housing["total_bedrooms"].fillna(median, inplace=True)

housing_num = housing.drop("ocean_proximity", axis=1)
```

```
# column index
rooms_ix, bedrooms_ix, population_ix, households_ix = 3, 4, 5, 6

class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room=True): # no *args or **kargs
        self.add_bedrooms_per_room = add_bedrooms_per_room
    def fit(self, X, y=None):
        return self  # nothing else to do
    def transform(self, X):
        rooms_per_household = X[:, rooms_ix] / X[:, households_ix]
        population_per_household = X[:, population_ix] / X[:, households_ix]
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, bedrooms_ix] / X[:, rooms_ix]
            return np.c_[X, rooms_per_household, population_per_household,
                         bedrooms_per_room]
        else:
            return np.c_[X, rooms_per_household, population_per_household]
```

In [19]:

```
num_pipeline = Pipeline([
    ('imputer',SimpleImputer(strategy="median")),
    ('attribs_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler()),
])
```

In [20]:

```
housing_num_tr = num_pipeline.fit_transform(housing_num)

num_attribs = list(housing_num)
cat_attribs = ["ocean_proximity"]
full_pipeline = ColumnTransformer([
    ("num", num_pipeline, num_attribs),
    ("cat", OneHotEncoder(), cat_attribs),
])
housing_prepared = full_pipeline.fit_transform(housing)
```

In [21]:

```
# function to display scores
def display_scores(scores):
    print("Scores: ", scores)
    print("Mean: ", scores.mean())
    print("Standard Deviation: ", scores.std())
```

In [22]:
```
# Model Training - LR
lin_reg_model = LinearRegression()
lin_reg_model.fit(housing_prepared, housing_labels)

data = housing.iloc[:5]
labels = housing_labels.iloc[:5]
data_preparation = full_pipeline.transform(data)
```

In [23]:
```
# Predictions and RMSE
housing_predictions = lin_reg_model.predict(housing_prepared)
lin_mse = mean_squared_error(housing_labels, housing_predictions)
lin_rmse = np.sqrt(lin_mse)
print('RMSE value for Linear Regression: ', lin_rmse)
```

```
RMSE value for Linear Regression:  68628.19819848923
```

In [24]:
```
#Cross Validation
scores = cross_val_score(lin_reg_model, housing_prepared, housing_labels, scoring="neg_mean_squared_error", cv=10)
pd.Series(np.sqrt(-scores)).describe()
display_scores(scores)
```

```
Scores:  [-4.45993415e+09 -4.48365741e+09 -4.94883441e+09 -5.58600340e+09
 -4.62823518e+09 -5.06856312e+09 -4.22105290e+09 -4.66237845e+09
 -5.11981974e+09 -4.57856587e+09]
Mean:  -4775704463.202972
Standard Deviation:  381684974.0456828
```

In [25]:
```
# Model Training - RFR
forest_reg = RandomForestRegressor(n_estimators=100, random_state=42)
forest_reg.fit(housing_prepared, housing_labels)
```

Out[25]:
```
RandomForestRegressor(random_state=42)
```

In [26]:
```
# Predictions and RMSE
housing_predictions = forest_reg.predict(housing_prepared)
forest_mse = mean_squared_error(housing_labels, housing_predictions)
forest_rmse = np.sqrt(forest_mse)
print('RMSE value for Random Forest Regressor: ', forest_rmse)
```

```
RMSE value for Random Forest Regressor:  18603.515021376355
```

In [27]:
```
# Conducted the Cross Validation on the dataset , outcome we can see Mean=50182.3031 & standard deviation=2097.081
```

```
forest_scores = cross_val_score(forest_reg, housing_prepared, housing_labels,
                                scoring="neg_mean_squared_error", cv=10)
forest_rmse_scores = np.sqrt(-forest_scores)
display_scores(forest_rmse_scores)
```

```
Scores:  [49519.80364233 47461.9115823  50029.02762854 52325.28068953
 49308.39426421 53446.37892622 48634.8036574  47585.73832311
 53490.10699751 50021.5852922 ]
Mean:  50182.303100336096
Standard Deviation:  2097.0810550985693
```

A paragraph that summarizes the quality of this data set and a request for additional data if needed

This investigation could demonstrate the the performance of the data , how we could provide based on the different attributes , we can take bigger data & thier attributes to have better & more accurate results.

In [ ]: