2203a51536-ml-assign-1

March 5, 2024

1 2203A51536 ML ASSIGNMENT

[1]:
```
import pandas as pd
import seaborn as sns
import os
import numpy as np
import matplotlib.pyplot as plt
```

[2]:
```
housing_df = pd.read_csv('/content/housing.csv')

# Use .info() to show the features (i.e. columns) in your dataset along with a␣
↪count and datatype
housing_df.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
```

[3]:
```
housing_df.shape
```

[3]: (20640, 10)

[4]:
```
housing_df.head()
```

[4]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms
0	-122.23	37.88	41.0	880.0	129.0
1	-122.22	37.86	21.0	7099.0	1106.0
2	-122.24	37.85	52.0	1467.0	190.0
3	-122.25	37.85	52.0	1274.0	235.0
4	-122.25	37.85	52.0	1627.0	280.0

	population	households	median_income	median_house_value	ocean_proximity
0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	496.0	177.0	7.2574	352100.0	NEAR BAY
3	558.0	219.0	5.6431	341300.0	NEAR BAY
4	565.0	259.0	3.8462	342200.0	NEAR BAY

[5]:
```
housing_df.tail()
```

[5]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms
20635	-121.09	39.48	25.0	1665.0	374.0
20636	-121.21	39.49	18.0	697.0	150.0
20637	-121.22	39.43	17.0	2254.0	485.0
20638	-121.32	39.43	18.0	1860.0	409.0
20639	-121.24	39.37	16.0	2785.0	616.0

	population	households	median_income	median_house_value
20635	845.0	330.0	1.5603	78100.0
20636	356.0	114.0	2.5568	77100.0
20637	1007.0	433.0	1.7000	92300.0
20638	741.0	349.0	1.8672	84700.0
20639	1387.0	530.0	2.3886	89400.0

	ocean_proximity
20635	INLAND
20636	INLAND
20637	INLAND
20638	INLAND
20639	INLAND

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

[6]:

	longitude	latitude	housing_median_age	total_rooms
count	20640.000000	20640.000000	20640.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081
std	2.003532	2.135952	12.585558	2181.615252
min	-124.350000	32.540000	1.000000	2.000000
25%	-121.800000	33.930000	18.000000	1447.750000
50%	-118.490000	34.260000	29.000000	2127.000000
75%	-118.010000	37.710000	37.000000	3148.000000

```
max     -114.310000     41.950000           52.000000  39320.000000

       total_bedrooms    population    households  median_income  \
count    20433.000000  20640.000000  20640.000000   20640.000000
mean       537.870553   1425.476744    499.539680       3.870671
std        421.385070   1132.462122    382.329753       1.899822
min          1.000000      3.000000      1.000000       0.499900
25%        296.000000    787.000000    280.000000       2.563400
50%        435.000000   1166.000000    409.000000       3.534800
75%        647.000000   1725.000000    605.000000       4.743250
max       6445.000000  35682.000000   6082.000000      15.000100

       median_house_value
count        20640.000000
mean        206855.816909
std         115395.615874
min          14999.000000
25%         119600.000000
50%         179700.000000
75%         264725.000000
max         500001.000000
```

[7]:
```python
housing_df.isnull().sum()
```

[7]:
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
median_house_value      0
ocean_proximity         0
dtype: int64
```

[8]:
```python
# Calculate the % of missing data
housing_df['total_bedrooms'].isnull().sum()/housing_df.shape[0] * 100
```

[8]:
```
1.002906976744186
```

[9]:
```python
from sklearn.impute import KNNImputer

# create a temporary copy of the dataset
housing_df_temp = housing_df.copy()
```

```
# retrieve columns with numerical data; will exclude the ocean_proximity column␣
↪since the datatype is object; other columns are float64
columns_list = [col for col in housing_df_temp.columns if housing_df_temp[col].
↪dtype != 'object']

# extract columns that contain at least one missing value
new_column_list = [col for col in housing_df_temp.loc[:, housing_df_temp.
↪isnull().any()]]

# update temp dataframe with numeric columns that have empty values
housing_df_temp = housing_df_temp[new_column_list]
```

[10]:
```
# initialize KNNImputer to impute missing data using machine learning
knn = KNNImputer(n_neighbors = 3)

# fit function trains the model
knn.fit(housing_df_temp)

# transform the data using the model
# applies the transformation model (ie knn) to data
array_Values = knn.transform(housing_df_temp)

# convert the array values to a dataframe with the appropriate column names
housing_df_temp = pd.DataFrame(array_Values, columns = new_column_list)
```

[11]:
```
# confirm there are no columns with missing values
housing_df_temp.isnull().sum()
```

[11]:
```
total_bedroooms    0
dtype: int64
```

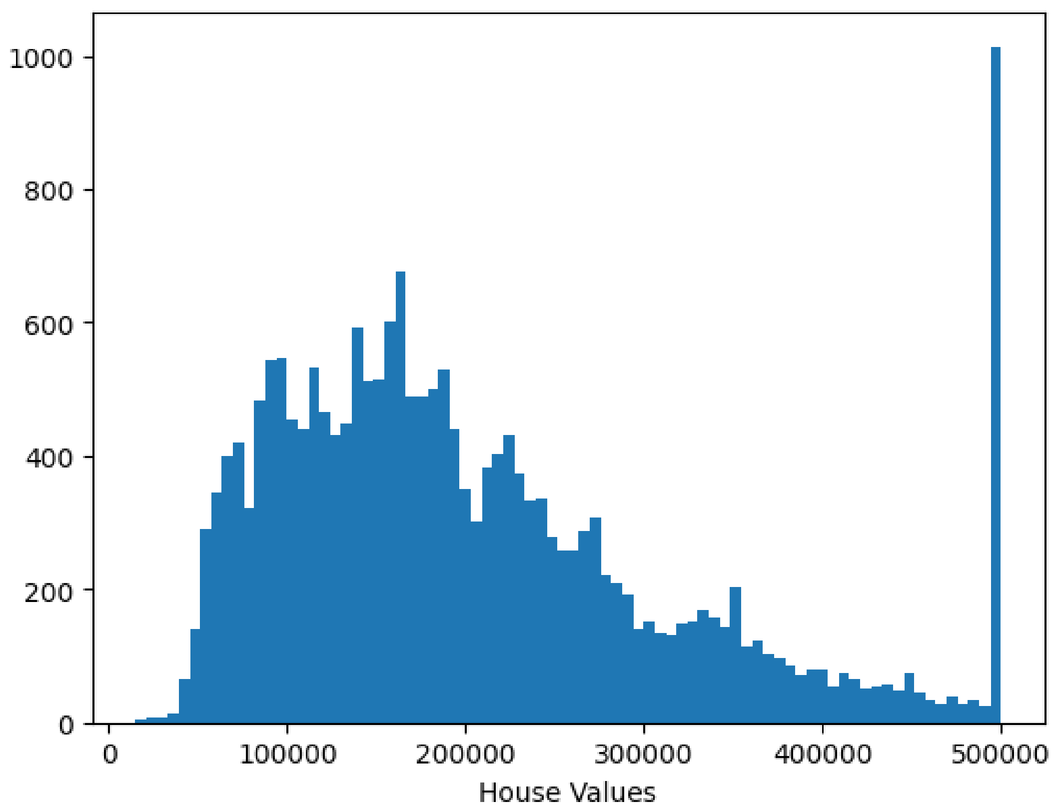
[12]:
```
# overlay the imputed column over the old column with missing values

# loop through the list of columns and overlay each one
for column_name in new_column_list:
    housing_df[column_name] = housing_df_temp.
↪replace(housing_df[column_name],housing_df[column_name])

# confirm columns no longer contain null data
housing_df.isnull().sum()
```

[12]:
```
longitude             0
latitude              0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
```

```
households            0
median_income         0
median_house_value    0
ocean_proximity       0
dtype: int64
```

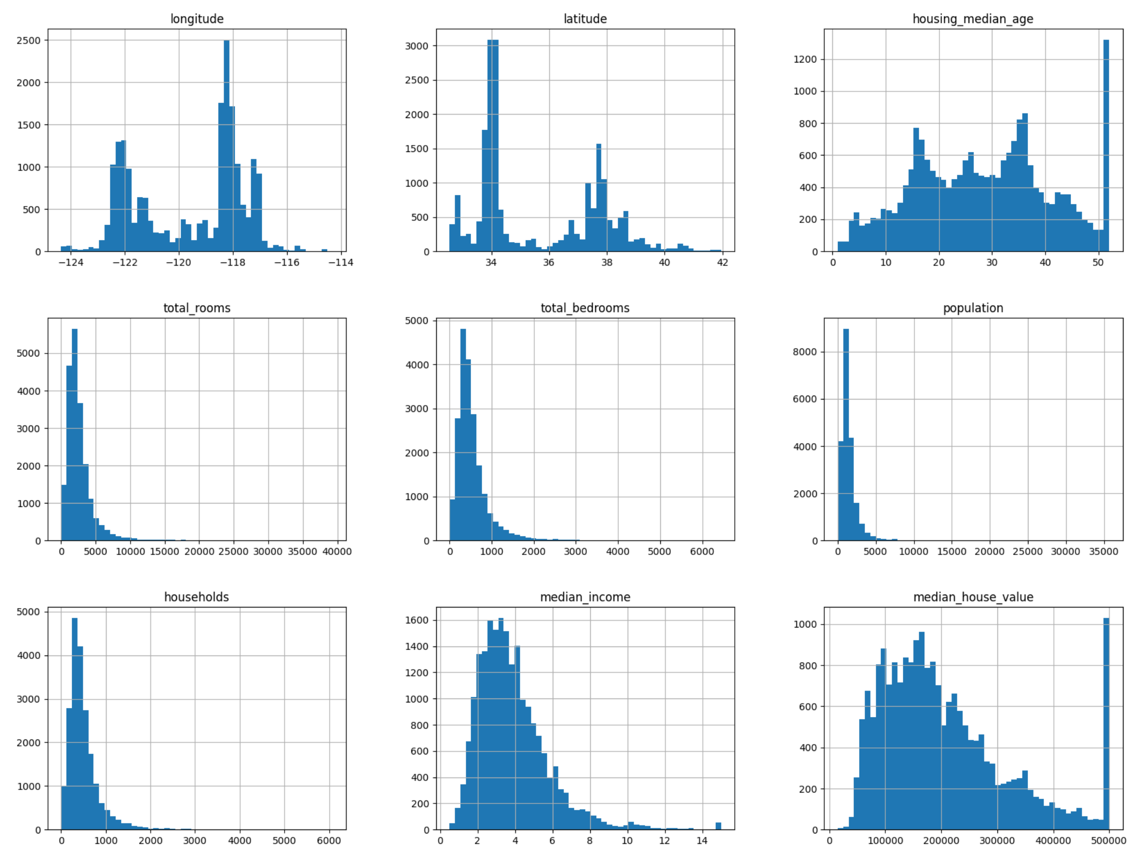
[13]:
```
# Plot the distribution of the target variable (median_house_value) using a␣
 ↪histogram

# bins->amount of columns
plt.hist(housing_df['median_house_value'], bins=80)
plt.xlabel("House Values")


# We can see from the plot that the values of Median House Value are␣
 ↪distributed normally with few outliers.
# Most of the house are around 100,000-200,000 range
```

[13]:
```
Text(0.5, 0, 'House Values')
```



[14]:
```
# let's do histograms for the all the features to understand the data␣
↪distributions
# using housing_df as to not plot the encoded values for OCEAN_PROXIMITY
housing_df.hist(bins=50, figsize=(20,15))
```

[14]:
```
array([[<Axes: title={'center': 'longitude'}>,
        <Axes: title={'center': 'latitude'}>,
        <Axes: title={'center': 'housing_median_age'}>],
       [<Axes: title={'center': 'total_rooms'}>,
        <Axes: title={'center': 'total_bedrooms'}>,
        <Axes: title={'center': 'population'}>],
       [<Axes: title={'center': 'households'}>,
        <Axes: title={'center': 'median_income'}>,
        <Axes: title={'center': 'median_house_value'}>]], dtype=object)
```



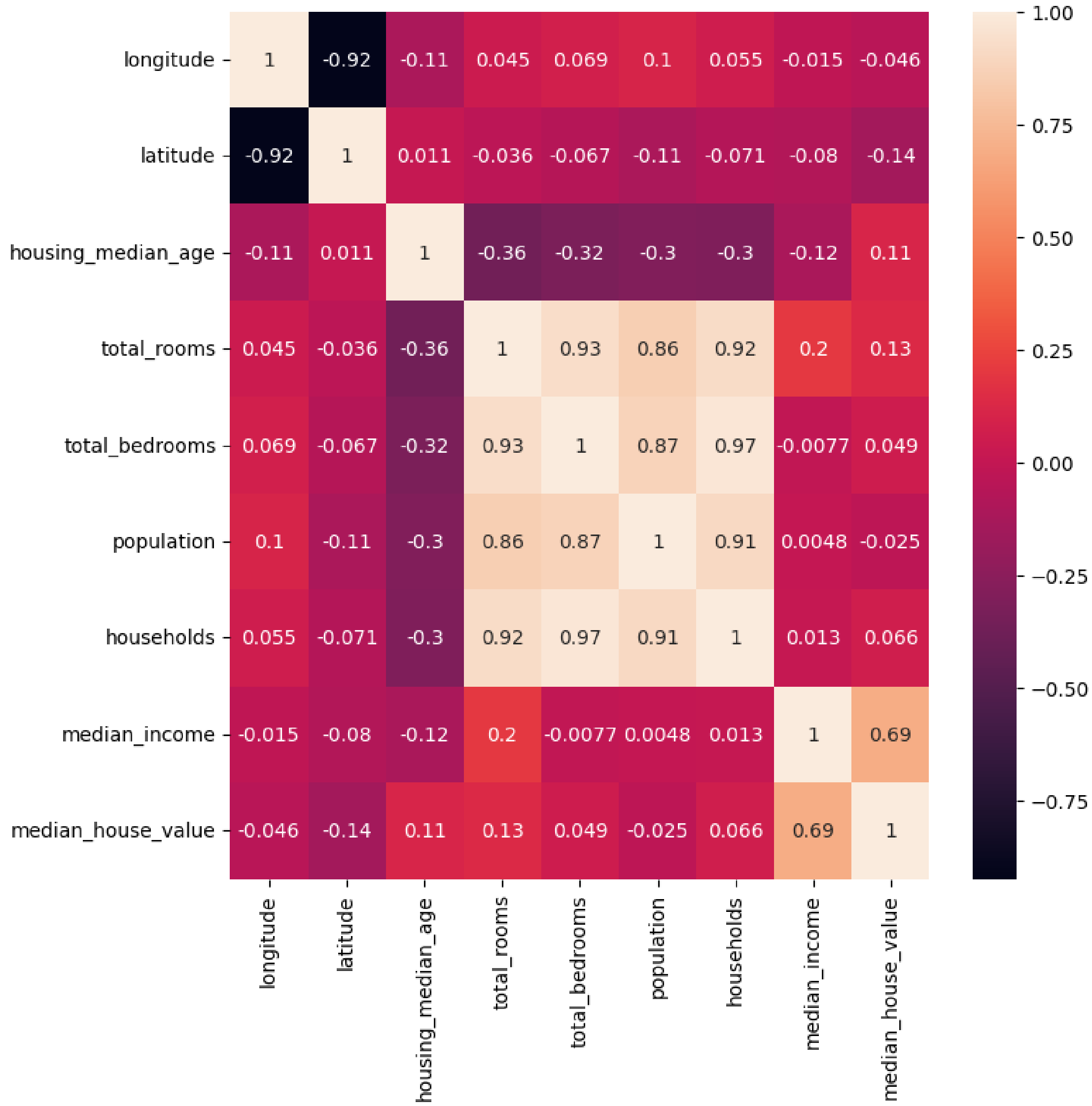
[15]:
```
# Plot a graphical correlation matrix for each pair of columns in the dataframe
corr = housing_df.corr() # data frame correlation function
print(corr)
```

```
                    longitude  latitude  housing_median_age  total_rooms  \
longitude            1.000000 -0.924664           -0.108197     0.044568
```

```
latitude            -0.924664  1.000000            0.011173    -0.036100
housing_median_age  -0.108197  0.011173            1.000000    -0.361262
total_rooms          0.044568 -0.036100           -0.361262     1.000000
total_bedrooms       0.069260 -0.066658           -0.318998     0.927253
population           0.099773 -0.108785           -0.296244     0.857126
households           0.055310 -0.071035           -0.302916     0.918484
median_income       -0.015176 -0.079809           -0.119034     0.198050
median_house_value  -0.045967 -0.144160            0.105623     0.134153

                    total_bedrooms  population  households  median_income  \
longitude                 0.069260    0.099773    0.055310      -0.015176
latitude                 -0.066658   -0.108785   -0.071035      -0.079809
housing_median_age       -0.318998   -0.296244   -0.302916      -0.119034
total_rooms               0.927253    0.857126    0.918484       0.198050
total_bedrooms            1.000000    0.873910    0.974725      -0.007682
population                0.873910    1.000000    0.907222       0.004834
households                0.974725    0.907222    1.000000       0.013033
median_income            -0.007682    0.004834    0.013033       1.000000
median_house_value        0.049454   -0.024650    0.065843       0.688075

                    median_house_value
longitude                    -0.045967
latitude                     -0.144160
housing_median_age            0.105623
total_rooms                   0.134153
total_bedrooms                0.049454
population                   -0.024650
households                    0.065843
median_income                 0.688075
median_house_value            1.000000

<ipython-input-15-3abd71ce2464>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  corr = housing_df.corr() # data frame correlation function
```

[16]:

```python
# make the heatmap larger in size
plt.figure(figsize = (8,8))

sns.heatmap(corr, annot=True)
plt.show()
```



[17]:
```
# Additionally we noted that several features␣
↪(total_rooms,total_bedrooms,population,households) have very high␣
↪correlation to one another,
# so it's interesting to find out if a removal of a few of them would have any␣
↪affect on the model performance

#  a new feature that is a ratio of the total rooms to households
housing_df['rooms_per_household'] = housing_df['total_rooms']/
↪housing_df['households']

# a new feature that is a ratio of the total bedrooms to the total rooms
```

```
housing_df['bedrooms_per_room'] = housing_df['total_bedrooms']/
 ↪housing_df['total_rooms']

# a new feature that is a ratio of the population to the households
housing_df['population_per_household']= housing_df['population']/
 ↪housing_df['households']

# let's combine the latitude and longitude into 1
housing_df['coords'] = housing_df['longitude']/housing_df['latitude']

housing_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 14 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            20640 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
 10  rooms_per_household       20640 non-null  float64
 11  bedrooms_per_room         20640 non-null  float64
 12  population_per_household  20640 non-null  float64
 13  coords                    20640 non-null  float64
dtypes: float64(13), object(1)
memory usage: 2.2+ MB
```

[18]:
```
# remove total_rooms, households, total bedrooms, popluation, longitude,␣
 ↪latitude
housing_df = housing_df.drop('total_rooms', axis=1)
housing_df = housing_df.drop('households', axis=1)
housing_df = housing_df.drop('total_bedrooms', axis=1)
housing_df = housing_df.drop('population', axis=1)
housing_df = housing_df.drop('longitude', axis=1)
housing_df = housing_df.drop('latitude', axis=1)

housing_df.info()
```

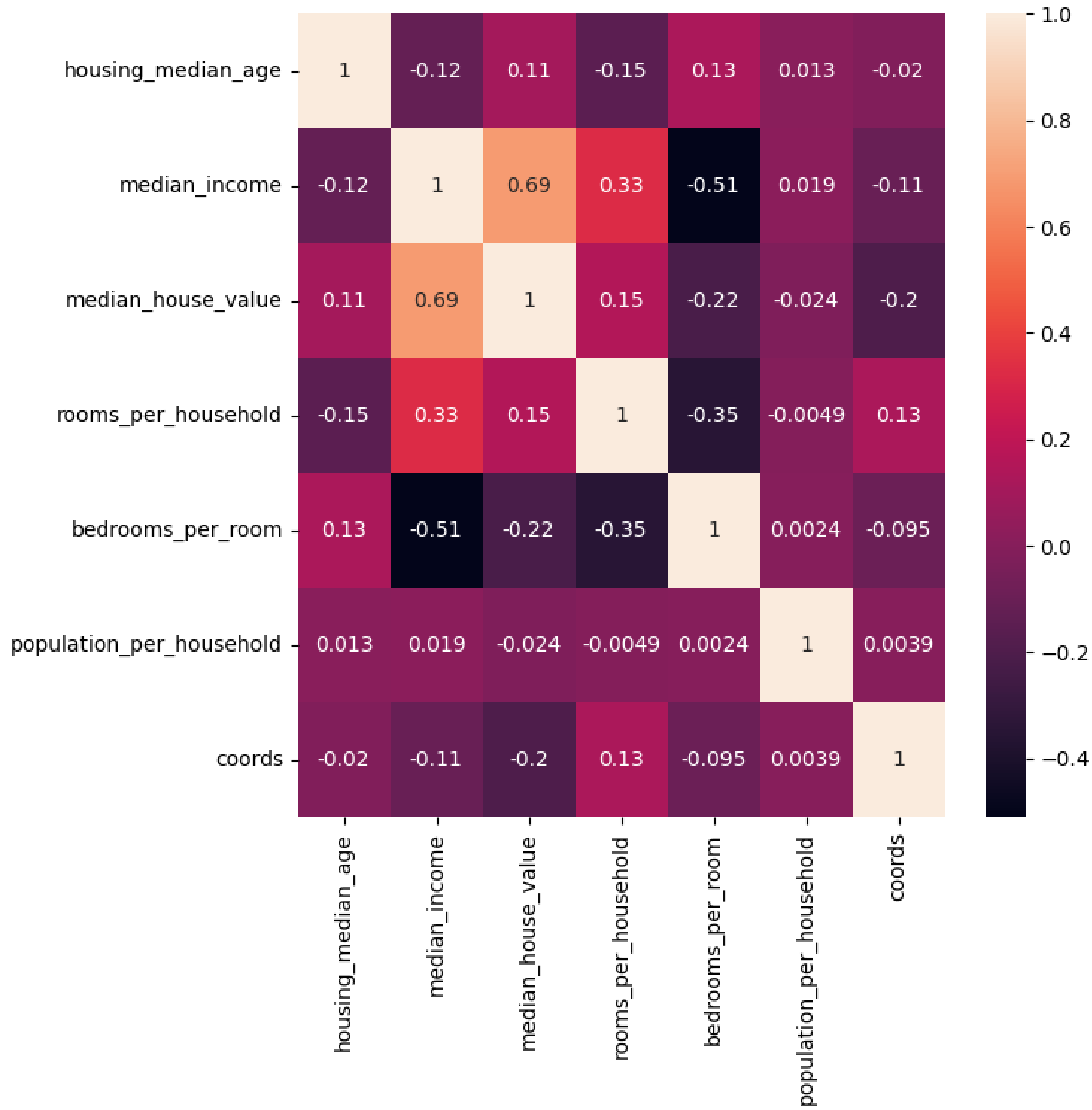
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
```

```
Data columns (total 8 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   housing_median_age        20640 non-null  float64
 1   median_income             20640 non-null  float64
 2   median_house_value        20640 non-null  float64
 3   ocean_proximity           20640 non-null  object
 4   rooms_per_household       20640 non-null  float64
 5   bedrooms_per_room         20640 non-null  float64
 6   population_per_household  20640 non-null  float64
 7   coords                    20640 non-null  float64
dtypes: float64(7), object(1)
memory usage: 1.3+ MB
```

[19]:

```
#Heatmap after removing correlation

corr = housing_df.corr()

#make the heatmap larger in size
plt.figure(figsize = (7,7))

sns.heatmap(corr, annot=True)
plt.show()
```

```
<ipython-input-19-1264607259b1>:3: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  corr = housing_df.corr()
```



[20]:
```
#Encoding categorical data
# Most ML algorithms can only learn from numeric data (it's all Math) so␣
↪categorical data must be encoded (i.e. converted) to numeric data

# Let's review our data types again; showing that ocean_proximity is the only␣
↪categorical data
housing_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 8 columns):
 #   Column                    Non-Null Count  Dtype
```

```
---  ------                    --------------  -----
 0   housing_median_age        20640 non-null  float64
 1   median_income             20640 non-null  float64
 2   median_house_value        20640 non-null  float64
 3   ocean_proximity           20640 non-null  object
 4   rooms_per_household       20640 non-null  float64
 5   bedrooms_per_room         20640 non-null  float64
 6   population_per_household  20640 non-null  float64
 7   coords                    20640 non-null  float64
dtypes: float64(7), object(1)
memory usage: 1.3+ MB
```

[21]:
```
# let's see the unique categories for OCEAN_PROXIMITY
housing_df.ocean_proximity.unique()
```

[21]:
```
array(['NEAR BAY', '<1H OCEAN', 'INLAND', 'NEAR OCEAN', 'ISLAND'],
      dtype=object)
```

[22]:
```
# let's count
housing_df["ocean_proximity"].value_counts()
```

[22]:
```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

[23]:
```
# Let's see how the Panda's get_dummies() function works (generates new columns␣
↪based on the possible options)
print(pd.get_dummies(housing_df['ocean_proximity']))
```

```
       <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]
```

[24]:
```
# let's replace the OCEAN_PROXIMITY column using get_dummies()
housing_df_encoded = pd.get_dummies(data=housing_df,␣
↪columns=['ocean_proximity'])

# print the first few observations; notice the old OCEAN_PROXIMITY column is␣
↪gone
housing_df_encoded.head()
```

[24]:
```
   housing_median_age  median_income  median_house_value  rooms_per_household  \
0                41.0         8.3252            452600.0             6.984127
1                21.0         8.3014            358500.0             6.238137
2                52.0         7.2574            352100.0             8.288136
3                52.0         5.6431            341300.0             5.817352
4                52.0         3.8462            342200.0             6.281853

   bedrooms_per_room  population_per_household    coords  \
0           0.146591                  2.555556 -3.226769
1           0.155797                  2.109842 -3.228209
2           0.129516                  2.802260 -3.229590
3           0.184458                  2.547945 -3.229855
4           0.172096                  2.181467 -3.229855

   ocean_proximity_<1H OCEAN  ocean_proximity_INLAND  ocean_proximity_ISLAND  \
0                         0                       0                       0
1                         0                       0                       0
2                         0                       0                       0
3                         0                       0                       0
4                         0                       0                       0

   ocean_proximity_NEAR BAY  ocean_proximity_NEAR OCEAN
0                        1                           0
1                        1                           0
2                        1                           0
3                        1                           0
4                        1                           0
```

[25]:
```
#Train the model
import sklearn
from sklearn.model_selection import train_test_split

# remove spaces from column names and convert all to lowercase and remove␣
↪special characters as it could cause issues in the future
housing_df_encoded.columns = [c.lower().replace(' ', '_').replace('<', '_') for␣
↪c in housing_df_encoded.columns]

# Split target variable and feature variables
```

```
X = housing_df_encoded[['housing_median_age',␣
↪'median_income','bedrooms_per_room','population_per_household','coords','ocean_proximity__1
␣
↪'ocean_proximity_inland','ocean_proximity_island','ocean_proximity_near_bay','ocean_proximi
y = housing_df_encoded['median_house_value']

print(X)
```

```
       housing_median_age  median_income  bedrooms_per_room  \
0                    41.0         8.3252           0.146591
1                    21.0         8.3014           0.155797
2                    52.0         7.2574           0.129516
3                    52.0         5.6431           0.184458
4                    52.0         3.8462           0.172096
…                     …            …                  …
20635                25.0         1.5603           0.224625
20636                18.0         2.5568           0.215208
20637                17.0         1.7000           0.215173
20638                18.0         1.8672           0.219892
20639                16.0         2.3886           0.221185

       population_per_household    coords  ocean_proximity__1h_ocean  \
0                      2.555556 -3.226769                          0
1                      2.109842 -3.228209                          0
2                      2.802260 -3.229590                          0
3                      2.547945 -3.229855                          0
4                      2.181467 -3.229855                          0
…                         …         …                         …
20635                  2.560606 -3.067123                          0
20636                  3.122807 -3.069385                          0
20637                  2.325635 -3.074309                          0
20638                  2.123209 -3.076845                          0
20639                  2.616981 -3.079502                          0

       ocean_proximity_inland  ocean_proximity_island  \
0                           0                       0
1                           0                       0
2                           0                       0
3                           0                       0
4                           0                       0
…                       …                       …
20635                       1                       0
20636                       1                       0
20637                       1                       0
20638                       1                       0
20639                       1                       0
```

```
       ocean_proximity_near_bay  ocean_proximity_near_ocean
0                             1                           0
1                             1                           0
2                             1                           0
3                             1                           0
4                             1                           0
…                           …                          …
20635                         0                           0
20636                         0                           0
20637                         0                           0
20638                         0                           0
20639                         0                           0

[20640 rows x 10 columns]
```

[26]:
```python
# Split training & test data¶
# Splitting the data into training and testing sets in numpy arrays
# We train the model with 70% of the samples and test with the remaining 30%
# X -> array with the inputs; y -> array of the outputs
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42,␣
 ↪shuffle=True, test_size=0.3)

# Confirm how the data was split
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(14448, 10)
(6192, 10)
(14448,)
(6192,)
```

[27]:
```python
#Linear Regression - Model Training¶
# Use scikit-learn's LinearRegression to train the model on both the training␣
 ↪and evaluate it on the test sets
from sklearn.linear_model import LinearRegression

# Create a Linear regressor using all the feature variables
reg_model = LinearRegression()

# Train the model using the training sets
reg_model.fit(X_train, y_train)
```

[27]: LinearRegression()

[28]:
```
#run the predictions on the training and testing data
y_pred_test = reg_model.predict(X_test)
```

[29]:
```
#compare the actual values (ie, target) with the values predicted by the model
pred_test_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_test})

pred_test_df
```

[29]:

	Actual	Predicted
20046	47700.0	103743.050896
3024	45800.0	92451.250932
15663	500001.0	219490.963844
20484	218600.0	283292.425471
9814	278000.0	244228.861575
…	…	…
17505	237500.0	210121.340663
13512	67300.0	74907.098235
10842	218400.0	216609.962950
16559	119400.0	127975.072923
5786	209800.0	202803.254310

[6192 rows x 2 columns]

[30]:
```
# Determine accuracy uisng  ^2
#  ^2 : R squared is another way to evaluate the performance of a regression␣
 ↪model.
# 1, means that the model is perfect and 0 means the the model will perform␣
 ↪poorly.
r2_reg_model_test = round(reg_model.score(X_test, y_test),2)

print("R^2 Test: {}".format(r2_reg_model_test))
```

```
R^2 Test: 0.56
```

[31]:
```
# try another machine learning algorithm : Randorm Forest
# Use scikit-learn’s Randorm Forest to train the model on both the training and␣
 ↪evaluate it on the test sets
from sklearn.ensemble import RandomForestRegressor

# Create a  regressor using all the feature variables
rf_model = RandomForestRegressor(n_estimators=10,random_state=10)

# Train the model using the training sets
rf_model.fit(X_train, y_train)
```

[31]: RandomForestRegressor(n_estimators=10, random_state=10)

[32]:
```
#run the predictions on the training and testing data
y_rf_pred_test = rf_model.predict(X_test)
```

[33]:
```
#compare the actual values (ie, target) with the values predicted by the model
rf_pred_test_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_rf_pred_test})

rf_pred_test_df
```

[33]:

	Actual	Predicted
20046	47700.0	47840.0
3024	45800.0	92680.0
15663	500001.0	446000.5
20484	218600.0	265320.0
9814	278000.0	240800.0
…	…	…
17505	237500.0	231680.1
13512	67300.0	69680.0
10842	218400.0	203930.0
16559	119400.0	126170.0
5786	209800.0	198160.0

[6192 rows x 2 columns]

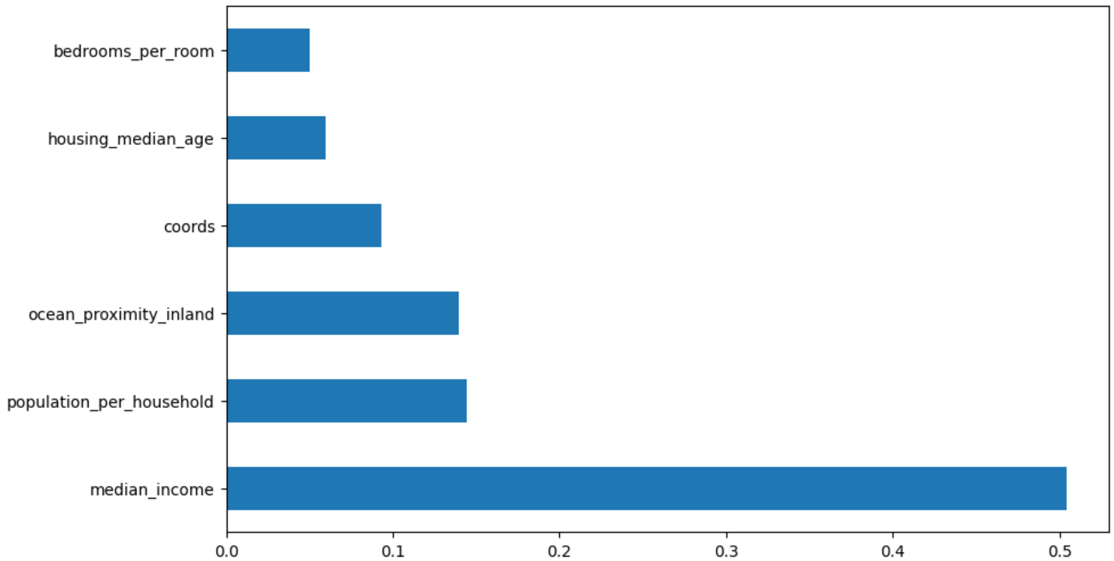
[34]:
```
# Determine accuracy uisng  ^2
from sklearn.metrics import r2_score, mean_squared_error

score = r2_score(y_test, y_rf_pred_test)

print("R^2 - {}%".format(round(score, 2) *100))
```

```
R^2 - 75.0%
```

[35]:
```
# Determine RMSE - Root Mean Squared Error on the test data
print('RMSE on test data: ',  mean_squared_error(y_test, y_rf_pred_test)**(0.5))
```

```
RMSE on test data:  57289.11495447338
```

[36]:
```
# Determine feature importance - random forest algorithm is that it gives you␣
↪the ‘feature importance’ for all the variables in the data
# plot the 6 most important features
plt.figure(figsize=(10,6))
feat_importances = pd.Series(rf_model.feature_importances_, index = X_train.
↪columns)
feat_importances.nlargest(6).plot(kind='barh');
```



[37]:
```
# training data with 5 most important features
train_x_if = X_train[['bedrooms_per_room', 'housing_median_age', 'coords',␣
↪'ocean_proximity_inland','population_per_household','median_income']]
test_x_if = X_test[['bedrooms_per_room', 'housing_median_age', 'coords',␣
↪'ocean_proximity_inland','population_per_household','median_income']]

# create an object of the RandfomForestRegressor Model
rf_model_if = RandomForestRegressor(n_estimators=10,random_state=10)

# fit the model with the training data
rf_model_if.fit(train_x_if, y_train)

# predict the target on the test data
predict_test_with_if = rf_model_if.predict(test_x_if)
```

[38]:
```
# Root Mean Squared Error on the train and test data
print('RMSE on test data: ',  mean_squared_error(y_test,␣
↪predict_test_with_if)**(0.5))
```

```
RMSE on test data:  57366.910692045196
```

[39]:
```
pip install xgboost
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.10/dist-
packages (2.0.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from xgboost) (1.25.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
```

```
(from xgboost) (1.11.4)
```

[40]:
```python
# Extreme Gradient Boosting (XGBoost) is an open-source library that provides␣
↪an efficient and effective implementation of the gradient boosting algorithm.
# Use the scikit-learn wrapper classes: XGBRegressor and XGBClassifier.

# try another machine learning algorithm : XGBoost
from xgboost import XGBRegressor

xgb_model = XGBRegressor()
```

[41]:
```python
# Train the model using the training sets
xgb_model.fit(X_train, y_train)
```

[41]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=None, n_jobs=None,
             num_parallel_tree=None, random_state=None, …)
```

[42]:
```python
#run the predictions on the training and testing data
y_xgb_pred_test = xgb_model.predict(X_test)
```

[43]:
```python
#compare the actual values (ie, target) with the values predicted by the model
xgb_pred_test_df = pd.DataFrame({'Actual': y_test, 'Predicted':␣
↪y_xgb_pred_test})

xgb_pred_test_df
```

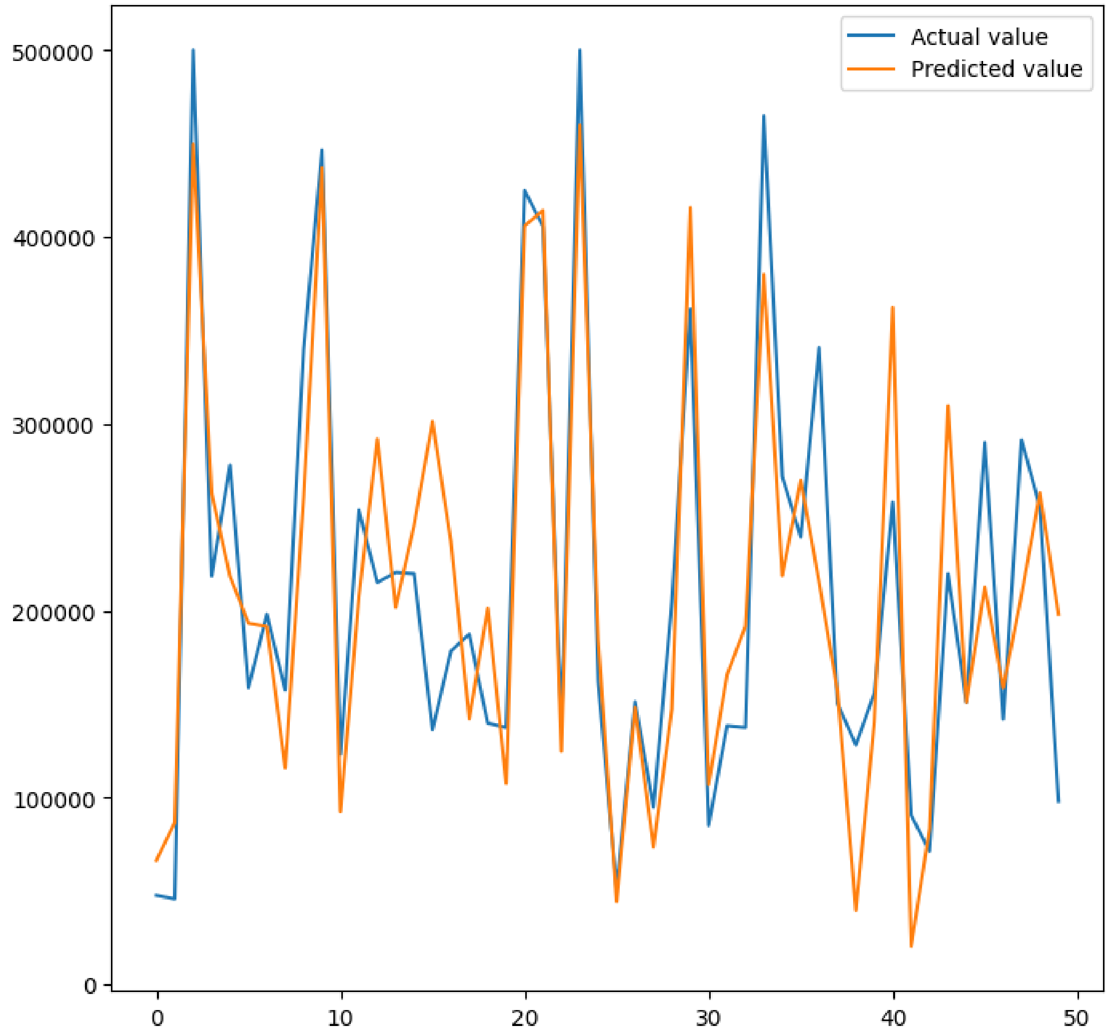
[43]:

	Actual	Predicted
20046	47700.0	66404.914062
3024	45800.0	86681.765625
15663	500001.0	449666.093750
20484	218600.0	262887.281250
9814	278000.0	218322.796875
…	…	…
17505	237500.0	227466.500000
13512	67300.0	64712.433594
10842	218400.0	218226.109375
16559	119400.0	123181.968750
5786	209800.0	227016.828125

[6192 rows x 2 columns]

[44]:
```
fig= plt.figure(figsize=(8,8))
xgb_pred_test_df = xgb_pred_test_df.reset_index()
xgb_pred_test_df = xgb_pred_test_df.drop(['index'],axis=1)
plt.plot(xgb_pred_test_df[:50])
plt.legend(['Actual value','Predicted value'])
```

[44]: <matplotlib.legend.Legend at 0x78b3029be8c0>



[45]:
```
from sklearn.metrics import r2_score

score = r2_score(y_test, y_xgb_pred_test)
```

```
print("R^2 - {}%".format(round(score, 2) *100))
```

```
R^2 - 78.0%
```

[46]:
```
# Determine mean square error and root mean square error
from sklearn.metrics import mean_squared_error
import math

mse = mean_squared_error(y_test, y_xgb_pred_test)
rmse = math.sqrt(mean_squared_error(y_test, y_xgb_pred_test))

print(mse)
print(rmse)
```

```
2939759040.9080276
54219.5448238735
```

[47]:
```
# Calculate mean absolute error(any large error)
from sklearn.metrics import mean_absolute_error

print(mean_absolute_error(y_test, y_xgb_pred_test))
```

```
36285.050324826894
```

[48]:
```
# We can build and score a model on multiple folds using cross-validation
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import cross_val_score


# define model evaluation method
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)

scores = cross_val_score(xgb_model, X, y, scoring='r2', error_score='raise',␣
 ↪cv=cv, n_jobs=-1, verbose=1)

#average of all the r2 scores across runs
print(scores.mean())
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
```

```
0.7850403811484551
```

```
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:    7.0s finished
```

[49]:
```
# determine hyperparameter available for tuning
xgb_model.get_params()
```

[49]: {'objective': 'reg:squarederror',
 'base_score': None,
 'booster': None,
 'callbacks': None,
 'colsample_bylevel': None,
 'colsample_bynode': None,
 'colsample_bytree': None,
 'device': None,
 'early_stopping_rounds': None,
 'enable_categorical': False,
 'eval_metric': None,
 'feature_types': None,
 'gamma': None,
 'grow_policy': None,
 'importance_type': None,
 'interaction_constraints': None,
 'learning_rate': None,
 'max_bin': None,
 'max_cat_threshold': None,
 'max_cat_to_onehot': None,
 'max_delta_step': None,
 'max_depth': None,
 'max_leaves': None,
 'min_child_weight': None,
 'missing': nan,
 'monotone_constraints': None,
 'multi_strategy': None,
 'n_estimators': None,
 'n_jobs': None,
 'num_parallel_tree': None,
 'random_state': None,
 'reg_alpha': None,
 'reg_lambda': None,
 'sampling_method': None,
 'scale_pos_weight': None,
 'subsample': None,
 'tree_method': None,
 'validate_parameters': None,
 'verbosity': None}

[50]:
```
xgb_model_2 = XGBRegressor(
    gamma=0.05,
    learning_rate=0.01,
    max_depth=6,
    n_estimators=1000,
    n_jobs=16,
    objective='reg:squarederror',
```

```
    subsample=0.8,
    scale_pos_weight=0,
    reg_alpha=0,
    reg_lambda=1,
    verbosity=1)

xgb_model_2.fit(X_train, y_train)


#run the predictions on the training and testing data
y_xgb_2_pred_test = xgb_model_2.predict(X_test)
```

[51]:
```
# compare the actual values (ie, target) with the values predicted by the model
xgb_2_pred_test_df = pd.DataFrame({'Actual': y_test, 'Predicted':␣
↪y_xgb_2_pred_test})

xgb_2_pred_test_df
```

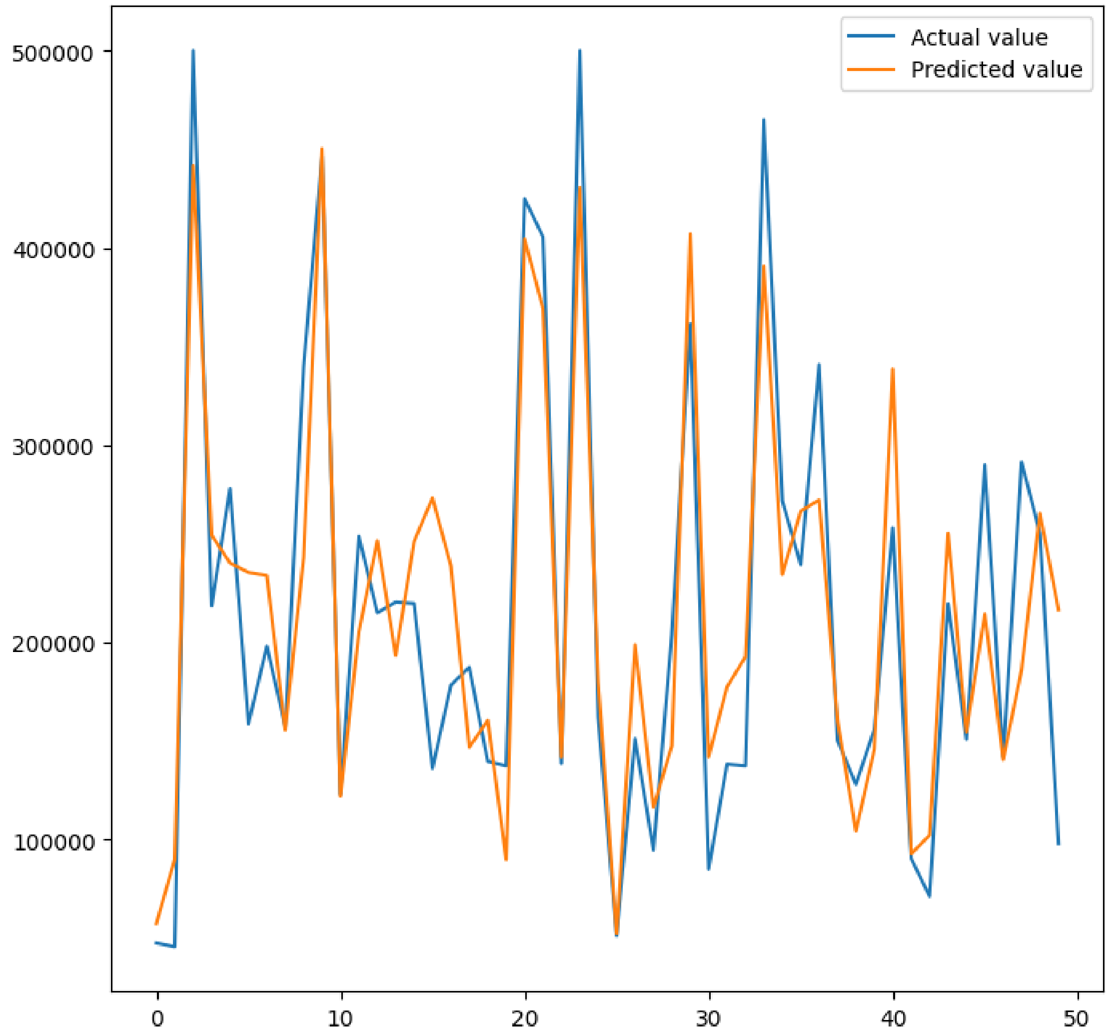
[51]:

	Actual	Predicted
20046	47700.0	57542.468750
3024	45800.0	90140.296875
15663	500001.0	441852.906250
20484	218600.0	254412.796875
9814	278000.0	240307.781250
…	…	…
17505	237500.0	234835.000000
13512	67300.0	64357.855469
10842	218400.0	220460.828125
16559	119400.0	125676.593750
5786	209800.0	208793.187500

[6192 rows x 2 columns]

[52]:
```
fig= plt.figure(figsize=(8,8))
xgb_2_pred_test_df = xgb_2_pred_test_df.reset_index()
xgb_2_pred_test_df = xgb_2_pred_test_df.drop(['index'],axis=1)
plt.plot(xgb_2_pred_test_df[:50])
plt.legend(['Actual value','Predicted value'])
```

[52]: <matplotlib.legend.Legend at 0x78b3029bf0d0>



[53]:
```
from sklearn.metrics import mean_squared_error

mse = np.sqrt(mean_squared_error(y_test, y_xgb_2_pred_test))
print("RMSE: %.2f" % (mse**(1/2.0)))
```

```
RMSE: 230.63
```

[54]:
```
# Determine accuracy uisng ^2
r2_xgb_model_2_test = round(xgb_model_2.score(X_test, y_test),2)

print("R^2 Test: {}".format(r2_xgb_model_2_test))
```

```
R^2 Test: 0.78
```