```
import pandas as pd
import seaborn as sns
import os
import numpy as np
import matplotlib.pyplot as plt
```

```
housing_df = pd.read_csv("/content/housing.csv")
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
```

```
housing_df.shape
```

```
(20640, 10)
```

```
housing_df.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
0	-122.23	37.88	41.0	880.0	129.0	322.0
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0
2	-122.24	37.85	52.0	1467.0	190.0	496.0
3	-122.25	37.85	52.0	1274.0	235.0	558.0
4	-122.25	37.85	52.0	1627.0	280.0	565.0

```
housing_df.tail()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populat:
20635	-121.09	39.48	25.0	1665.0	374.0	84
20636	-121.21	39.49	18.0	697.0	150.0	35
20637	-121.22	39.43	17.0	2254.0	485.0	100
20638	-121.32	39.43	18.0	1860.0	409.0	74
20639	-121.24	39.37	16.0	2785.0	616.0	138

```
housing_df.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553
std	2.003532	2.135952	12.585558	2181.615252	421.385070
min	-124.350000	32.540000	1.000000	2.000000	1.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000

```
housing_df.isnull().sum()
```

```
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
```

```
housing_df['total_bedrooms'].isnull().sum()/housing_df.shape[0] * 100
```

```
1.002906976744186
```

```
from sklearn.impute import KNNImputer
housing_df_temp = housing_df.copy()
columns_list = [col for col in housing_df_temp.columns if housing_df_temp[col].dtype != 'object']
new_column_list = [col for col in housing_df_temp.loc[:, housing_df_temp.isnull().any()]]
housing_df_temp = housing_df_temp[new_column_list]
```

```
knn = KNNImputer(n_neighbors = 3)
knn.fit(housing_df_temp)
array_Values = knn.transform(housing_df_temp)
housing_df_temp = pd.DataFrame(array_Values, columns = new_column_list)
```

```
housing_df_temp.isnull().sum()
```

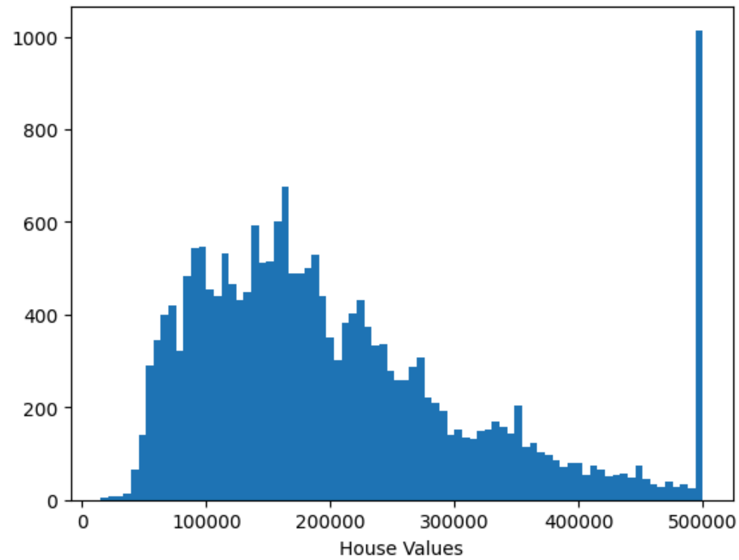
```
total_bedrooms    0
dtype: int64
```

```
for column_name in new_column_list:
    housing_df[column_name] = housing_df_temp.replace(housing_df[column_name],housing_df[column_name])
housing_df.isnull().sum()
```

```
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
```

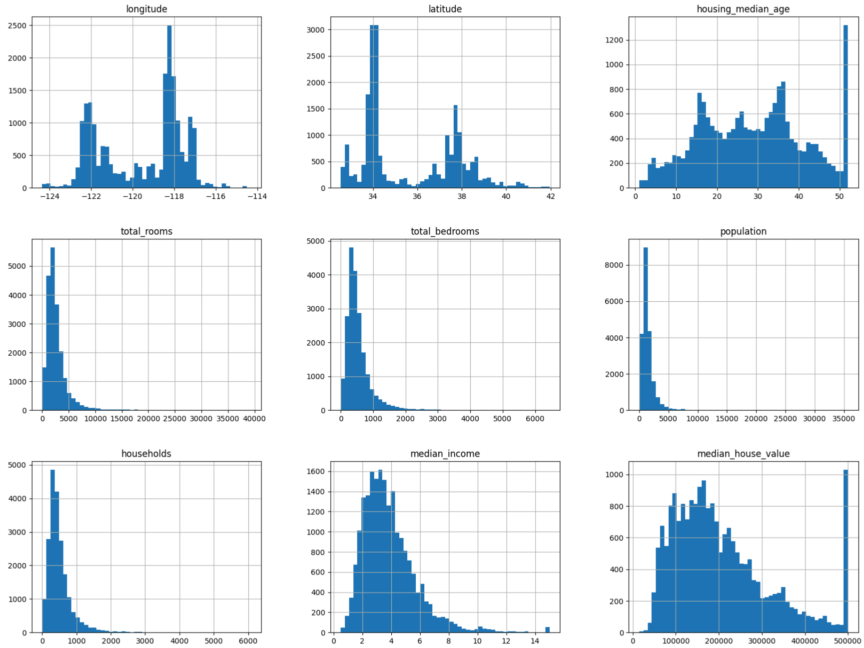
```
plt.hist(housing_df['median_house_value'], bins=80)
plt.xlabel("House Values")
```

```
Text(0.5, 0, 'House Values')
```




```
housing_df.hist(bins=50, figsize=(20,15))
```

```
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)
```

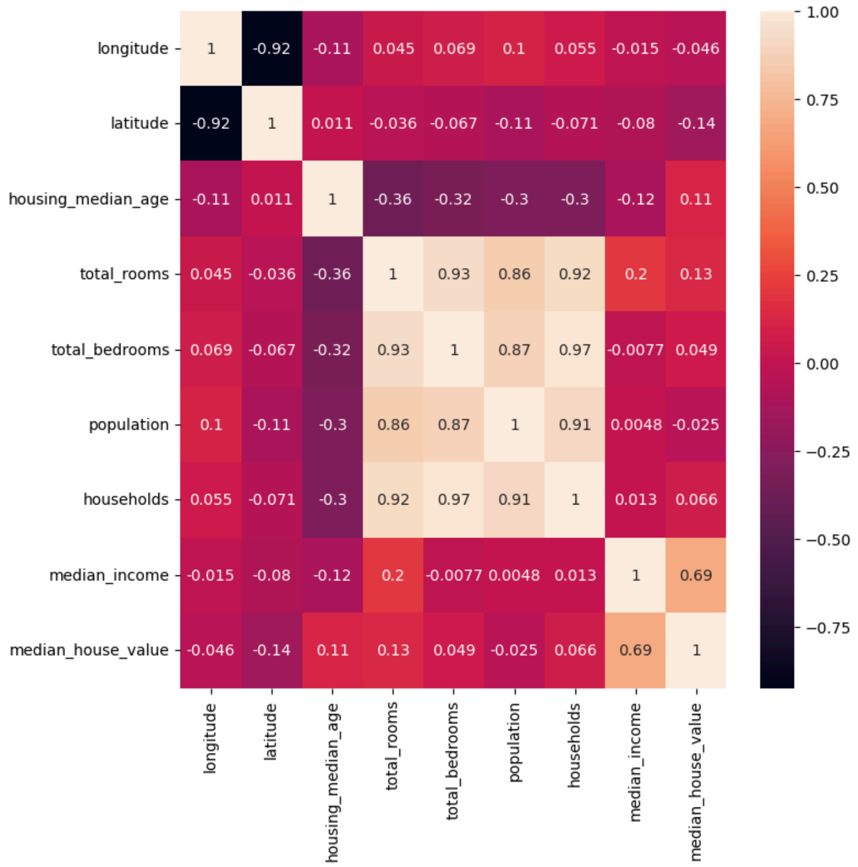



```
corr = housing_df.corr()
print(corr)
```

```
                    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-19-c1cef623e051>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
  corr = housing_df.corr()
```

```
plt.figure(figsize = (8,8))

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




```
housing_df['rooms_per_household'] = housing_df['total_rooms']/housing_df['households']
housing_df['bedrooms_per_room'] = housing_df['total_bedrooms']/housing_df['total_rooms']
housing_df['population_per_household']= housing_df['population']/housing_df['households']
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
```

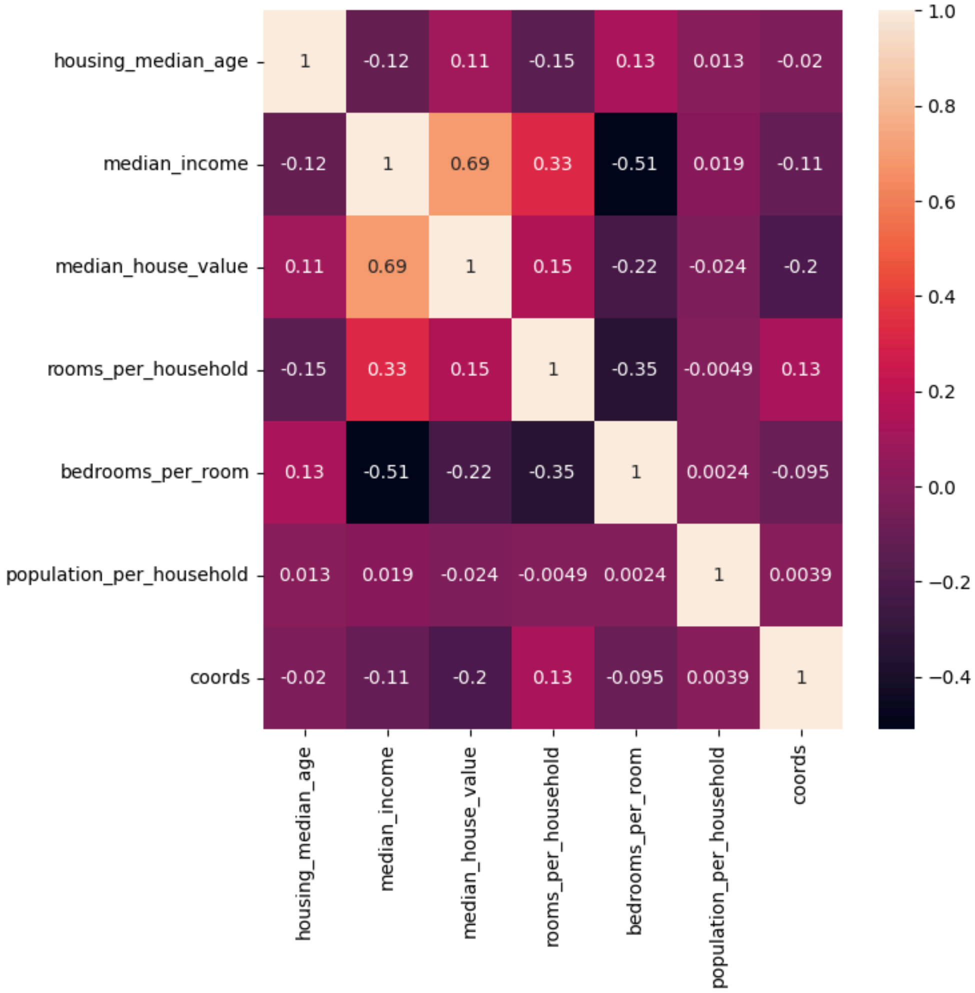
```
dtypes: float64(13), object(1)
memory usage: 2.2+ MB
```

```
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
```

```
corr = housing_df.corr()
plt.figure(figsize = (7,7))

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

```
<ipython-input-23-d23dcbec724f>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
  corr = housing_df.corr()
```




```
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
```

```
housing_df.ocean_proximity.unique()
```

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

```
housing_df["ocean_proximity"].value_counts()
```

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

```
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]
```

```
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()
```

	housing_median_age	median_income	median_house_value	rooms_per_household	bedro
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	

```
#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_
                        'ocean_proximity_inland','ocean_proximity_island','ocean_proximity_near_bay','ocean_proximity_near_ocean']]
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]
```

```
# 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,)
```

```
#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)
```

```
▾ LinearRegression
LinearRegression()
```

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

```
#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
```

	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 × 2 columns

```
# Determine accuracy uisng R^2
# R^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
```

```
# 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)
```

```
▾ RandomForestRegressor
RandomForestRegressor(n_estimators=10, random_state=10)
```

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

```
#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
```

	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 × 2 columns

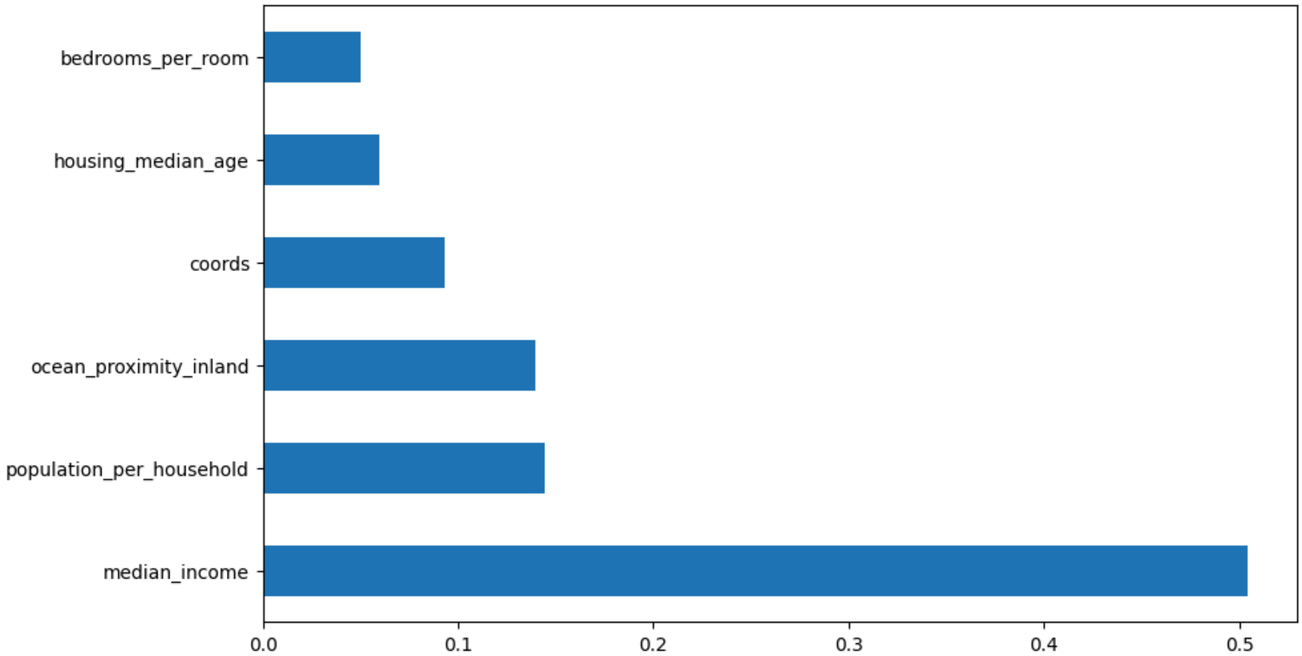
```
# Determine accuracy uisng R^2
from sklearn.metrics import r2_score, mean_squared_error

score = r2_score(y_test, y_rf_pred_test)

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

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

```
# 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
```

```
# Determine feature importance - random forest algorithm is that it gives you the ‘feature importance’ for all the variables in the dat
# 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');
```



```
# 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_
test_x_if = X_test[['bedrooms_per_room', 'housing_median_age', 'coords', 'ocean_proximity_inland','population_per_household','median_in

# 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)


# 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
```

```
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)
```

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

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

xgb_model = XGBRegressor()


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

```
▾                                XGBRegressor
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, ...)
```

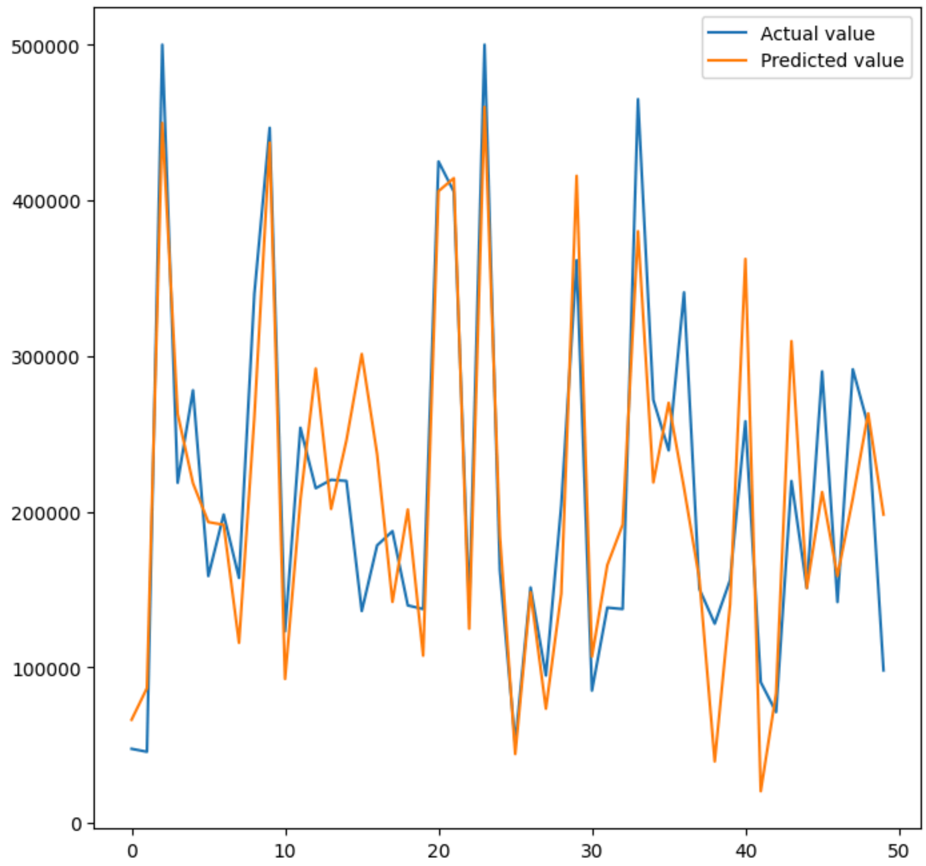
```
#run the predictions on the training and testing data
y_xgb_pred_test = xgb_model.predict(X_test)


#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
```

	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 × 2 columns

```
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'])
```

```
<matplotlib.legend.Legend at 0x783be85fdcf0>
```




```
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%
```

```
# 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
```

```
# 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
```

```
# 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:   12.1s finished
```

```
xgb_model.get_params()
```

```
{'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}
```

```
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)


# 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
```

	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 × 2 columns

```
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'])
```

```
<matplotlib.legend.Legend at 0x783be8693670>
```