```
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')

# 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
```

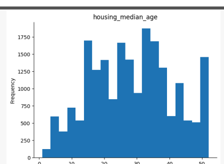
```
housing_df.shape
```

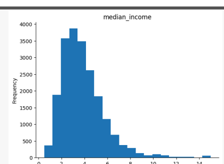
```
(20640, 10)
```

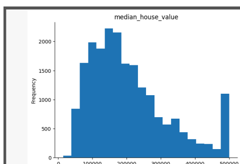
```
housing_df.head()
```

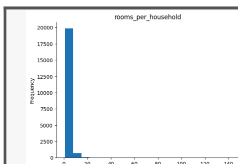
	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	hou
0	-122.23	37.88	41.0	880.0	129.0	322.0	
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	
2	-122.24	37.85	52.0	1467.0	190.0	496.0	
3	-122.25	37.85	52.0	1274.0	235.0	558.0	
4	-122.25	37.85	52.0	1627.0	280.0	565.0	

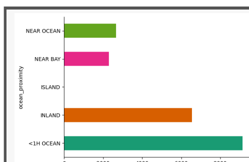
Next steps: View recommended plots

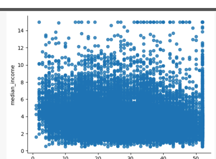

housing_median_age

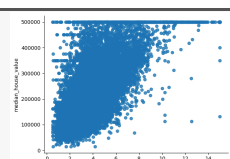

median_income

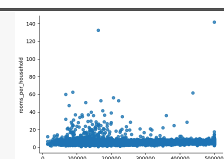

median_house_value

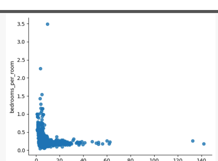

rooms_per_household

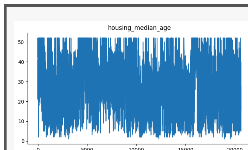

ocean_proximity

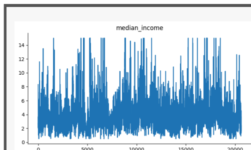

housing_median_age vs median_income

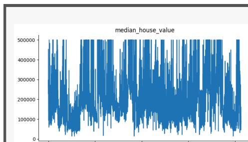

median_income vs median_house_value

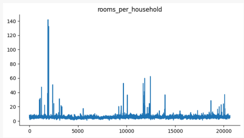

median_house_value vs rooms_per_household


rooms_per_household vs bedrooms_per_room

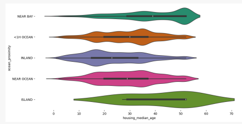

housing_median_age

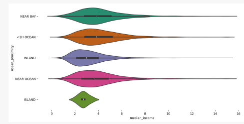

median_income

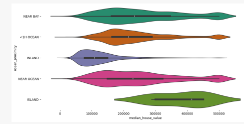

median_house_value

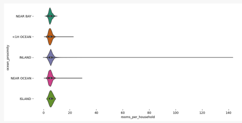


rooms_per_household


ocean_proximity vs housing_median_age


ocean_proximity vs median_income


ocean_proximity vs median_house_value


ocean_proximity vs rooms_per_household

```
housing_df.tail()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
20635	-121.09	39.48	25.0	1665.0	374.0	845.0
20636	-121.21	39.49	18.0	697.0	150.0	356.0
20637	-121.22	39.43	17.0	2254.0	485.0	1007.0
20638	-121.32	39.43	18.0	1860.0	409.0	741.0
20639	-121.24	39.37	16.0	2785.0	616.0	1387.0

```
housing_df.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	pc
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	206
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	14
std	2.003532	2.135952	12.585558	2181.615252	421.385070	11
min	-124.350000	32.540000	1.000000	2.000000	1.000000	
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	7
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	11
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	17
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	356

```
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
```

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

```
1.002906976744186
```

```
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]
```

```
# 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)
```

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

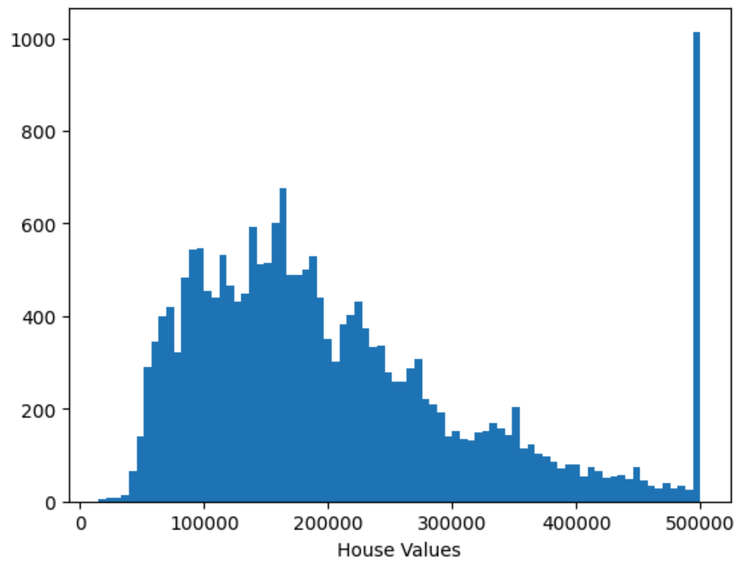
```
total_bedrooms    0
dtype: int64
```

```
# 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()
```

```
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
```

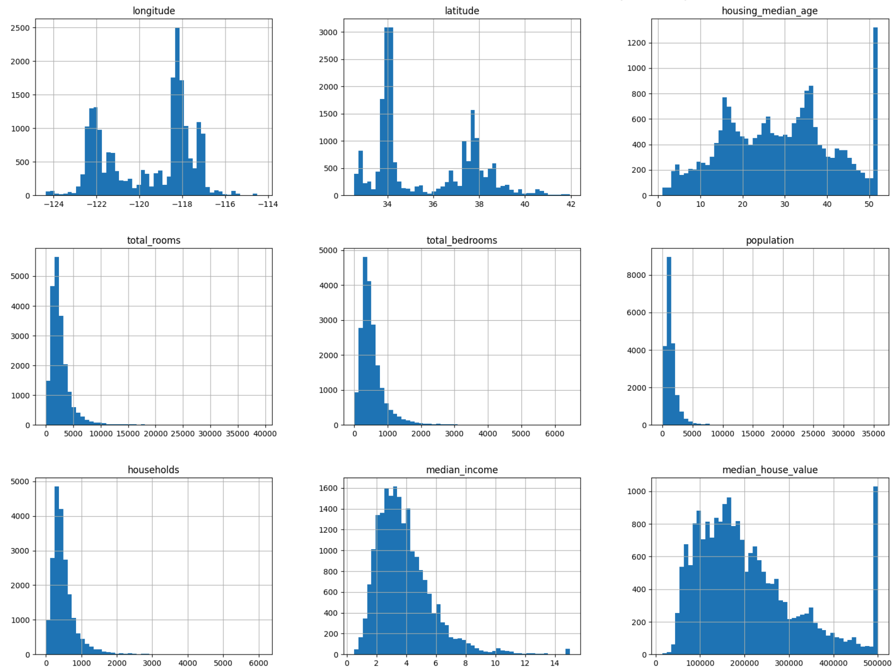
```
# Plot the distribution of the target variable (median_house_value) using a histogram

# 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
```

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




```
# 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))
```

```
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)
```

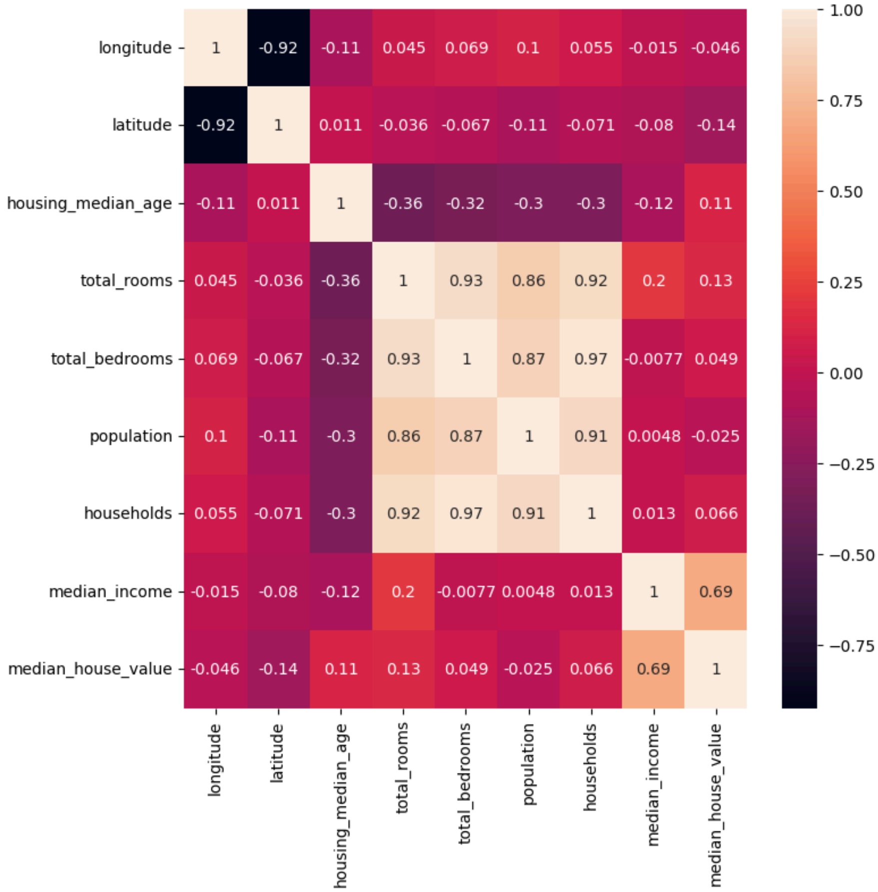



```
# Plot a graphical correlation matrix for each pair of columns in the dataframe
corr = housing_df.corr() # data frame correlation function
print(corr)
```

```
                    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-69-3abd71ce2464>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future versio
  corr = housing_df.corr() # data frame correlation function
```

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

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



```
# 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()
```

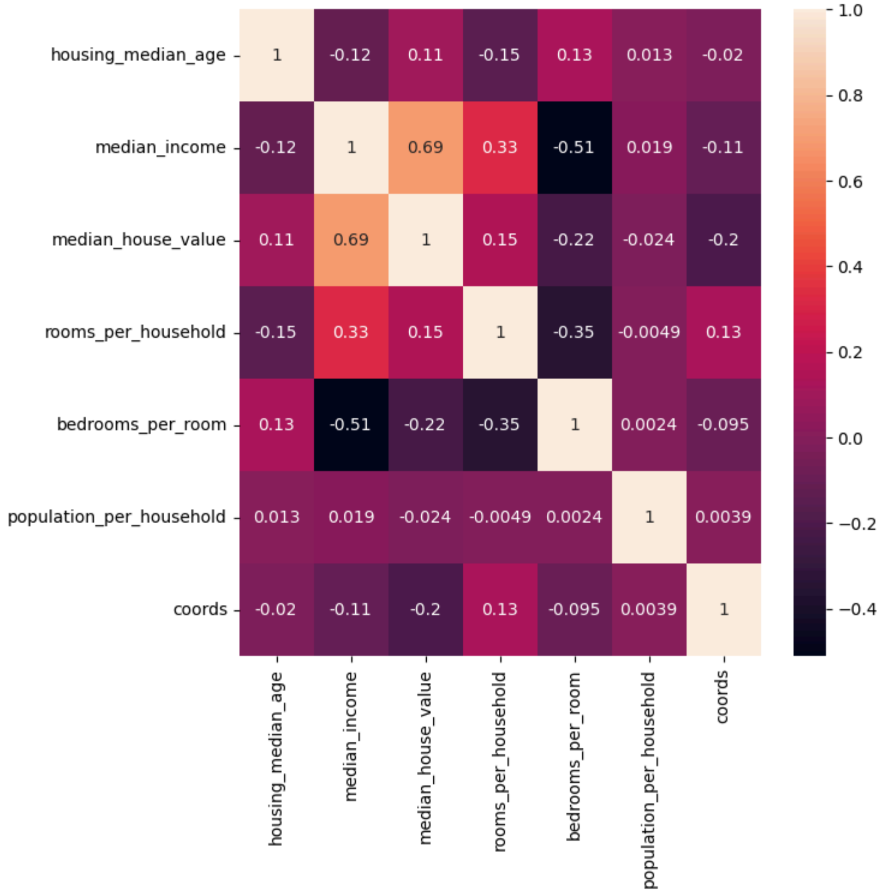
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 14 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   longitude                 20640 non-null  float64
 1   latitude                  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
```

```
# 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
```

```
#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-73-1264607259b1>:3: FutureWarning: The default value of numeric_only in
  corr = housing_df.corr()
```




```
#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
```

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

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

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

```
<1H OCEAN     9136
INLAND        6551
```

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

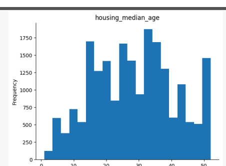
```
# Let's see how the Panda's get_dummies() function works (generates new columns based on the possible options)
print(pd.get_dummies(housing_df['ocean_proximity']))
```

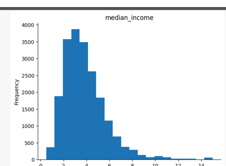
```
       <1H OCEAN  INLAND  ISLAND  NEAR BAY  NEAR OCEAN
0              0       0       0         1           0
1              0       0       0         1           0
2              0       0       0         1           0
3              0       0       0         1           0
4              0       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]
```

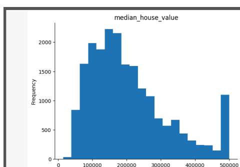
```
# let's replace the OCEAN_PROXIMITY column using get_dummies()
housing_df_encoded = pd.get_dummies(data=housing_df, columns=['ocean_proximity'])

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

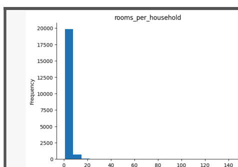
	housing_median_age	median_income	median_house_value	rooms_per_household	bedrooms
0	41.0	8.3252	452600.0	6.984127	
1	21.0	8.3014	358500.0	6.238137	
2	52.0	7.2574	352100.0	8.288136	
3	52.0	5.6431	341300.0	5.817352	
4	52.0	3.8462	342200.0	6.281853	

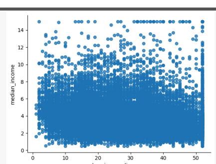
Next steps: View recommended plots

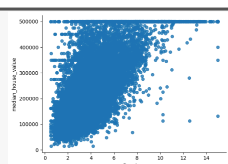

housing_median_age

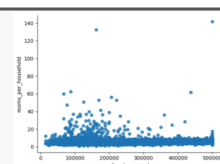

median_income

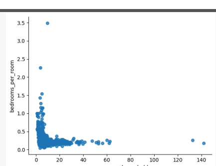

median_house_value

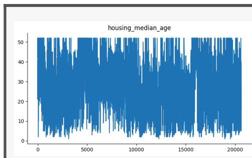

rooms_per_household

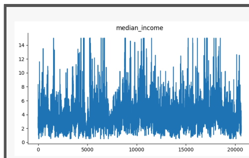

housing_median_age vs median_income

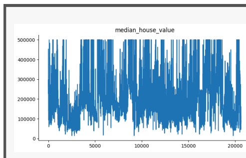

median_income vs median_house_value

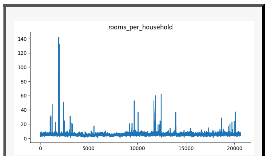

median_house_value vs rooms_per_household


rooms_per_household vs bedrooms_per_room


housing_median_age


median_income


median_house_value


rooms_per_household

```
#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__1h_
                        '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()
```

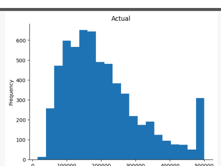
```
#run the predictions on the training and testing data
y_pred_test = reg_model.predict(X_test)
```

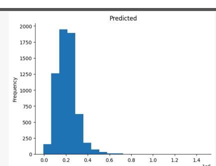
```
#compare the actual values (ie, target) with the values predicted by the model
pred_test_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_test})

pred_test_df
```

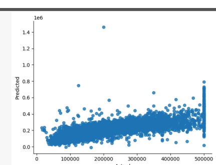
	Actual	Predicted
20046	47700.0	103743.050896
3024	45800.0	92451.250932
15663	500001.0	219490.963844
20484	218600.0	283292.425471
9814	278000.0	244228.861575
...	...	...
17505	237500.0	210121.340663
13512	67300.0	74907.098235
10842	218400.0	216609.962950
16559	119400.0	127975.072923
5786	209800.0	202803.254310

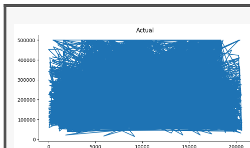
6192 rows × 2 columns

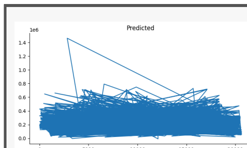
Next steps: View recommended plots


Actual


Predicted


Actual vs Predicted


Actual


Predicted

```
# 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)
```

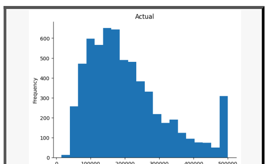
```
#run the predictions on the training and testing data
y_rf_pred_test = rf_model.predict(X_test)
```

```
#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
```

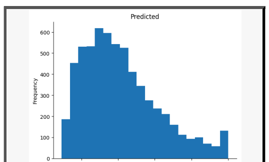
	Actual	Predicted
20046	47700.0	47840.0
3024	45800.0	92680.0
15663	500001.0	446000.5
20484	218600.0	265320.0
9814	278000.0	240800.0
...	...	...
17505	237500.0	231680.1
13512	67300.0	69680.0
10842	218400.0	203930.0
16559	119400.0	126170.0
5786	209800.0	198160.0

6192 rows × 2 columns

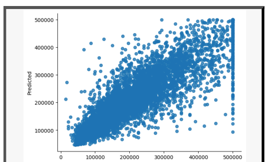
Next steps: View recommended plots



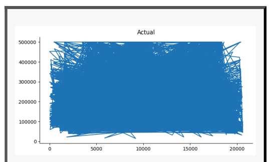
Actual



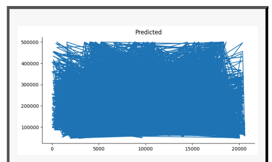
Predicted



Actual vs Predicted



Actual



Predicted

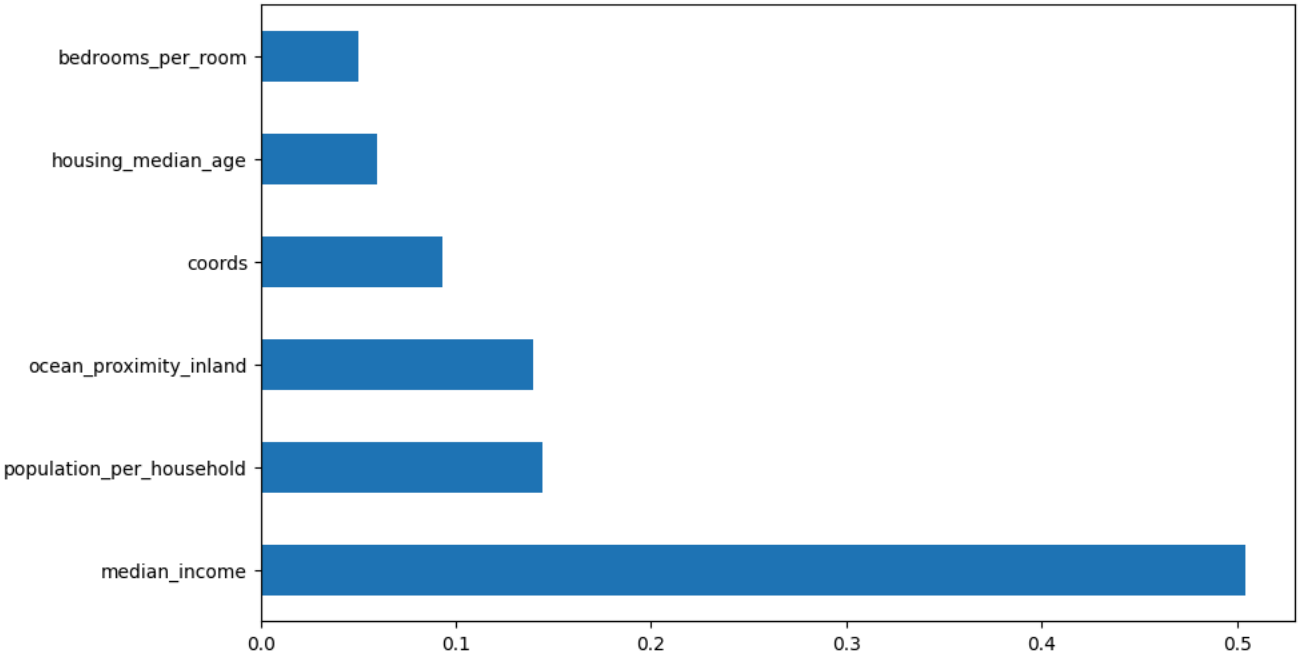
```
# Determine accuracy uisng R^2
from sklearn.metrics import r2_score, mean_squared_error

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 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');
```




```
# 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_inco
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)
```

```
# 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 boo
# 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, ...)
```

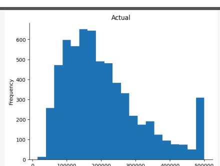
```
#run the predictions on the training and testing data
y_xgb_pred_test = xgb_model.predict(X_test)
```

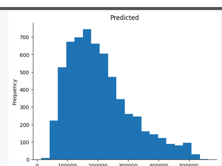
```
#compare the actual values (ie, target) with the values predicted by the model
xgb_pred_test_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_xgb_pred_test})

xgb_pred_test_df
```

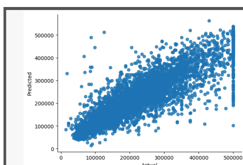
	Actual	Predicted
20046	47700.0	66404.914062
3024	45800.0	86681.765625
15663	500001.0	449666.093750
20484	218600.0	262887.281250
9814	278000.0	218322.796875
...	...	...
17505	237500.0	227466.500000
13512	67300.0	64712.433594
10842	218400.0	218226.109375
16559	119400.0	123181.968750
5786	209800.0	227016.828125

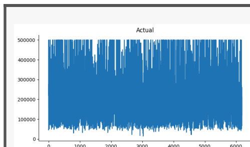
6192 rows × 2 columns

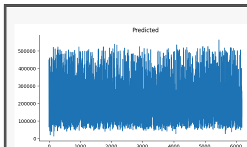
Next steps: View recommended plots


Actual


Predicted

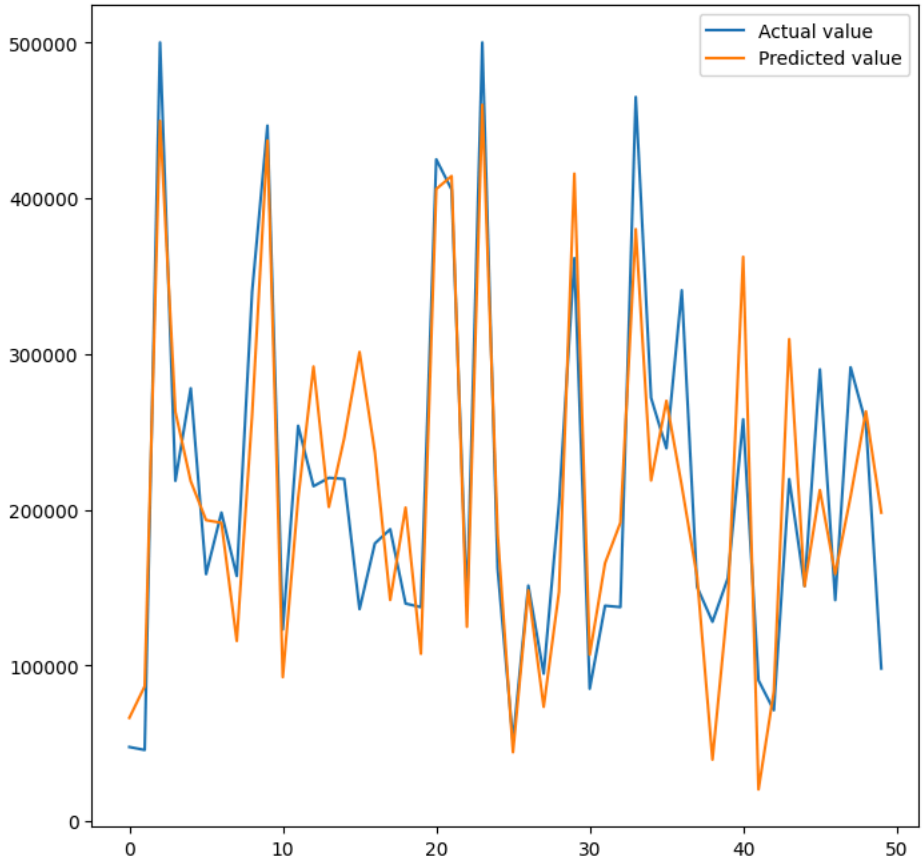

Actual vs Predicted


Actual


Predicted

```
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 0x7ebf5c5bece0>
```




```
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
```

```
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)
```

```
# determine hyperparameter available for tuning
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)
```