Assignment: California Housing Price Prediction

The comments/sections provided are your cues to perform the assignment. You don't need to limit yourself to the number of rows/cells provided. You can add additional rows in each section to add more lines of code.

If at any point in time you need help on solving this assignment, view our demo video to understand the different steps of the code.

Happy coding!

California Housing Price Prediction

DESCRIPTION

Background of Problem Statement:

The US Census Bureau has published California Census Data which has 10 types of metrics such as the population, median income, median housing price, and so on for each block group in California. The dataset also serves as an input for project scoping and tries to specify the functional and nonfunctional requirements for it.

Problem Objective :

The project aims at building a model of housing prices to predict median house values in California using the provided dataset. This model should learn from the data and be able to predict the median housing price in any district, given all the other metrics.

Districts or block groups are the smallest geographical units for which the US Census Bureau publishes sample data (a block group typically has a population of 600 to 3,000 people). There are 20,640 districts in the project dataset.

Domain: Finance and Housing

Analysis Tasks to be performed:

1. Build a model of housing prices to predict median house values in California using the provided dataset.

1. Train the model to learn from the data to predict the median housing price in any district, given all the other metrics.

1. Predict housing prices based on median_income and plot the regression chart for it.

Tasks:

1. Load the data :
    - Read the "housing.csv" file from the folder into the program.
    - Print first few rows of this data.
    - Extract input (X) and output (Y) data from the dataset.

1. Handle missing values :
    - Fill the missing values with the mean of the respective column.

1. Encode categorical data :
    - Convert categorical column in the dataset to numerical data.

1. Split the dataset :
    - Split the data into 80% training dataset and 20% test dataset.

1. Standardize data :
    - Standardize training and test datasets.

1. Perform Linear Regression :
    - Perform Linear Regression on training data.
    - Predict output for test dataset using the fitted model.
    - Print root mean squared error (RMSE) from Linear Regression.

    [HINT: Import mean_squared_error from sklearn.metrics]

1. Perform Decision Tree Regression :
    - Perform Decision Tree Regression on training data.
    - Predict output for test dataset using the fitted model.
    - Print root mean squared error from Decision Tree Regression.

1. Perform Random Forest Regression :
    - Perform Random Forest Regression on training data.
    - Predict output for test dataset using the fitted model.
    - Print RMSE (root mean squared error) from Random Forest Regression.

1. Bonus exercise: Perform Linear Regression with one independent variable :
    - Extract just the median_income column from the independent variables (from X_train and X_test).
    - Perform Linear Regression to predict housing values based on median_income.
    - Predict output for test dataset using the fitted model.
    - Plot the fitted model for training data as well as for test data to check if the fitted model satisfies the test data.

Dataset Description :

Field	Description
longitude	(signed numeric - float) : Longitude value for the block in California, USA
latitude	(numeric - float) : Latitude value for the block in California, USA
housing_median_age	(numeric - int) : Median age of the house in the block
total_rooms	(numeric - int) : Count of the total number of rooms (excluding bedrooms) in all houses in the block
total_bedrooms	(numeric - float) : Count of the total number of bedrooms in all houses in the block
population	(numeric - int) : Count of the total number of population in the block
households	(numeric - int) : Count of the total number of households in the block
median_income	(numeric - float) : Median of the total household income of all the houses in the block
ocean_proximity	(numeric - categorical) : Type of the landscape of the block [Unique Values : 'NEAR BAY', '<1H OCEAN', 'INLAND', 'NEAR OCEAN', 'ISLAND']
median_house_value	(numeric - int) : Median of the household prices of all the houses in the block

Load the Dataset

In [1]:
```
#Import required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
#Read the "housing.csv" file from the folder into the program.
data=pd.read_excel('housing.xlsx')
```

In [3]:
```
#Print first few rows of this data
data.head()
```

Out[3]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_inc
0	-122.23	37.88	41	880	129.0	322	126	8.3
1	-122.22	37.86	21	7099	1106.0	2401	1138	8.3
2	-122.24	37.85	52	1467	190.0	496	177	7.2
3	-122.25	37.85	52	1274	235.0	558	219	5.6
4	-122.25	37.85	52	1627	280.0	565	259	3.8

In [4]:
```
data.shape
```

Out[4]: (20640, 10)

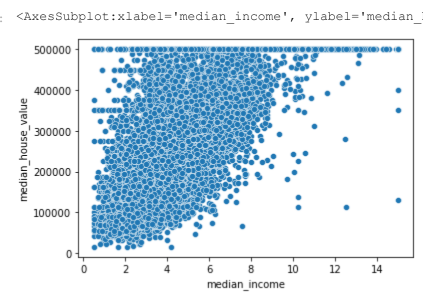
In [5]:
```
data.describe()
```

Out[5]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	househo
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000

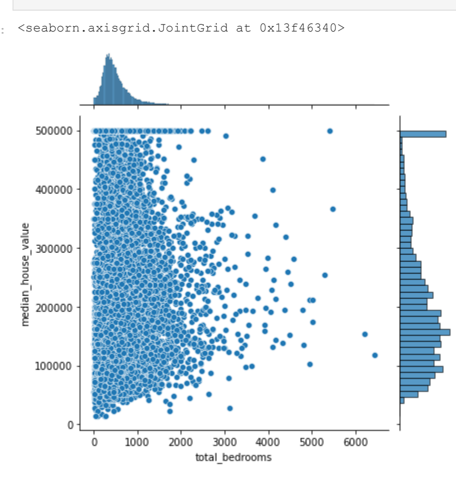
In [6]:
```
sns.scatterplot(data=data, x='median_income', y='median_house_value')
```

Out[6]: <AxesSubplot:xlabel='median_income', ylabel='median_house_value'>



In [7]:
```
sns.jointplot(data=data,  x='total_bedrooms', y='median_house_value')
```

Out[7]: <seaborn.axisgrid.JointGrid at 0x13f46340>



Handle missing values :

In [8]:
```
#Checking the missing values in dataframe
data.isna().sum()
```

Out[8]:
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
ocean_proximity         0
median_house_value      0
dtype: int64
```

In [9]:
```
#Fill the missing values with the mean of the respective column
from sklearn.impute import SimpleImputer

imputer_mean = SimpleImputer(missing_values=np.nan,strategy='mean')
data['total_bedrooms']=imputer_mean.fit_transform(data[['total_bedrooms']])
```

In [10]:
```
data.isnull().sum()
```

Out[10]:
```
longitude             0
latitude              0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
households            0
median_income         0
ocean_proximity       0
median_house_value    0
dtype: int64
```

In [11]:
```
#Extract input/Features (X) and output/label (Y) data from the dataset
X = data.iloc[:,:-1]
Y = data.iloc[:,[-1]]
```

In [12]:
```
X.head()
```

Out[12]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_inc
0	-122.23	37.88	41	880	129.0	322	126	8.3
1	-122.22	37.86	21	7099	1106.0	2401	1138	8.3
2	-122.24	37.85	52	1467	190.0	496	177	7.2
3	-122.25	37.85	52	1274	235.0	558	219	5.6
4	-122.25	37.85	52	1627	280.0	565	259	3.8

In [13]:
```
Y.head()
```

Out[13]:

	median_house_value
0	452600
1	358500
2	352100
3	341300
4	342200

Encode categorical data

In [14]:
```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  int64
 3   total_rooms         20640 non-null  int64
 4   total_bedrooms      20640 non-null  float64
 5   population          20640 non-null  int64
 6   households          20640 non-null  int64
 7   median_income       20640 non-null  float64
 8   ocean_proximity     20640 non-null  object
dtypes: float64(4), int64(4), object(1)
memory usage: 1.3+ MB
```

Ocean Proximity is a categorical variable. Let's see what values it contain.

In [15]:
```
X['ocean_proximity'].value_counts()
```

Out[15]:
```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

In [16]:
```
#Convert categorical column in the dataset to numerical data
X_np =np.array(X)

from sklearn.preprocessing import OneHotEncoder
Ohe = OneHotEncoder(sparse=False)

ohe_ocean_proximity = Ohe.fit_transform(X_np[:,-1].reshape(-1,1))
ohe_ocean_proximity
```

Out[16]:
```
array([[0., 0., 0., 1., 0.],
       [0., 0., 0., 1., 0.],
       [0., 0., 0., 1., 0.],
       ...,
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.]])
```

In [17]:
```
#Concatenating the onehot encoded columns to the remaining feature(X) columns
concat_array=np.concatenate((ohe_ocean_proximity,X_np[:,:-1]),axis=1)
new_columns=np.concatenate((X.ocean_proximity.unique(),X.columns[:-1]),axis=0)
```

In [18]:
```
#Feature dataframe
X_final = pd.DataFrame(concat_array,columns=new_columns)
```

In [19]:
```
X_final.head()
```

Out[19]:

	NEAR BAY	<1H OCEAN	INLAND	NEAR OCEAN	ISLAND	longitude	latitude	housing_median_age	total_rooms	total_bed
0	0.0	0.0	0.0	1.0	0.0	-122.23	37.88	41	880	
1	0.0	0.0	0.0	1.0	0.0	-122.22	37.86	21	7099	
2	0.0	0.0	0.0	1.0	0.0	-122.24	37.85	52	1467	
3	0.0	0.0	0.0	1.0	0.0	-122.25	37.85	52	1274	
4	0.0	0.0	0.0	1.0	0.0	-122.25	37.85	52	1627	

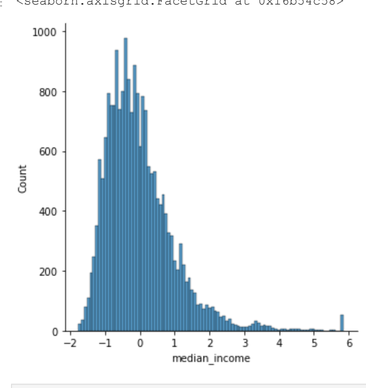
In [20]:
```
X_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 13 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   NEAR BAY            20640 non-null  object
 1   <1H OCEAN           20640 non-null  object
 2   INLAND              20640 non-null  object
 3   NEAR OCEAN          20640 non-null  object
 4   ISLAND              20640 non-null  object
 5   longitude           20640 non-null  object
 6   latitude            20640 non-null  object
 7   housing_median_age  20640 non-null  object
 8   total_rooms         20640 non-null  object
 9   total_bedrooms      20640 non-null  object
 10  population          20640 non-null  object
 11  households          20640 non-null  object
 12  median_income       20640 non-null  object
dtypes: object(13)
memory usage: 1.0+ MB
```

Standardize data

In [21]:
```
#Standardization of features and label
from sklearn import preprocessing
scaler = preprocessing.StandardScaler()

column_names = X_final.columns
scaled_X = scaler.fit_transform(X_final)
scaled_X = pd.DataFrame(scaled_X, columns=column_names)
sns.displot(x=scaled_X['median_income'])
```

Out[21]: <seaborn.axisgrid.FacetGrid at 0x16b54c58>

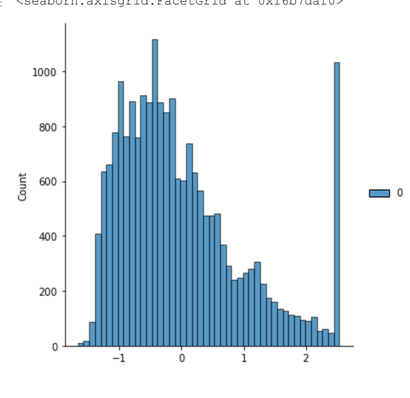


In [22]:
```
scaled_X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 13 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   NEAR BAY            20640 non-null  float64
 1   <1H OCEAN           20640 non-null  float64
 2   INLAND              20640 non-null  float64
 3   NEAR OCEAN          20640 non-null  float64
 4   ISLAND              20640 non-null  float64
 5   longitude           20640 non-null  float64
 6   latitude            20640 non-null  float64
 7   housing_median_age  20640 non-null  float64
 8   total_rooms         20640 non-null  float64
 9   total_bedrooms      20640 non-null  float64
 10  population          20640 non-null  float64
 11  households          20640 non-null  float64
 12  median_income       20640 non-null  float64
dtypes: float64(13)
memory usage: 2.0 MB
```

In [23]:
```
scaled_Y=scaler.fit_transform(Y)
sns.displot(scaled_Y)
```

Out[23]: <seaborn.axisgrid.FacetGrid at 0x16b7daf0>



Split the dataset

In [24]:
```
#Train Test Split in to 80% and 20%
from sklearn.model_selection import train_test_split, cross_val_score
X_train,X_test,y_train,y_test = train_test_split(scaled_X,scaled_Y,test_size=0.3,rand
```

Perform Linear Regression

In [25]:
```
#Perform Linear Regression on training data
from sklearn.linear_model import LinearRegression
model_LR=LinearRegression()

model_LR.fit(X_train,y_train)
train_score=model_LR.score(X_train,y_train)
test_score=model_LR.score(X_test,y_test)
print('Test score is {}, train score is {} '.format(test_score,train_score))
#Predict output for test dataset using the fitted model
predicted_values=model_LR.predict(X_test)
predicted_values
```

```
Test score is 0.6657383389459428, train score is 0.6361722170949844
```

Out[25]:
```
array([[-0.51353846],
       [-0.59916565],
       [-0.54176753],
       ...,
       [ 0.28834806],
       [ 0.31879579],
       [-0.46927475]])
```

In [26]:
```
#Print root mean squared error (RMSE) from Linear Regression
from sklearn.metrics import mean_squared_error
from math import sqrt

rmse = sqrt(mean_squared_error(y_test, model_LR.predict(X_test)))
print(rmse)
```

```
0.5836591471750182
```

Perform Decision Tree Regression

In [27]:
```
#Perform Decision Tree Regression on training data
from sklearn.tree import DecisionTreeRegressor

model_DTR = DecisionTreeRegressor()

#Predict output for test dataset using the fitted model
model_DTR.fit(X_train,y_train.ravel())
predictedvalues=model_DTR.predict(X_test)
predictedvalues
```

Out[27]:
```
array([-0.97281457, -0.94508321, -0.49878161, ...,  0.00644913,
        0.51427968,  0.10264229])
```

In [28]:
```
#Print root mean squared error from Decision Tree Regression
rmse = sqrt(mean_squared_error(y_test, model_DTR.predict(X_test)))
print(rmse)
```

```
0.5760521826736754
```

Perform Random Forest Regression

In [29]:
```
#Perform Random Forest Regression on training data
from sklearn.ensemble import RandomForestRegressor

model_RFR = RandomForestRegressor()

#Predict output for test dataset using the fitted model
model_RFR.fit(X_train,y_train.ravel())
predictedvalues=model_RFR.predict(X_test)
```

In [30]:
```
#Print root mean squared error from Decision Tree Regression
rmse = sqrt(mean_squared_error(y_test, model_RFR.predict(X_test)))
print(rmse)
```

```
0.41919606224545075
```

Bonus exercise: Perform Linear Regression with one independent variable

In [31]:
```
#Extract the median_income column from the independent variables (from X_train and X_
median_income_df = data.iloc[:,[-3]]
column_names = median_income_df.columns
scaled_median_income_df = scaler.fit_transform(median_income_df)
scaled_median_income_df = pd.DataFrame(scaled_median_income_df, columns=column_names)
```

In [32]:
```
#Perform Linear Regression to predict housing values based on median_income
X_train,X_test,y_train,y_test=train_test_split(scaled_median_income_df,scaled_Y,test_s
model=LinearRegression()
model.fit(X_train,y_train)
```

Out[32]: LinearRegression()

In [33]:
```
train_score=model.score(X_train,y_train)
test_score=model.score(X_test,y_test)
print(train_score)
print(test_score)
```

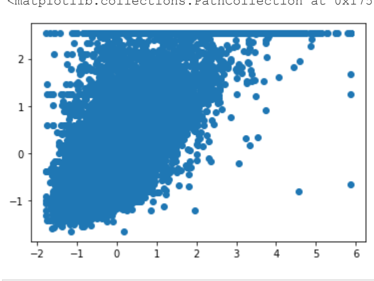
```
0.4767777846183372
0.4656545996086491
```

In [34]:
```
#Predict output for test dataset using the fitted model
y_pred=model.predict(X_test)
y_pred
```

Out[34]:
```
array([[-0.24944527],
       [-0.23602386],
       [ 0.07026422],
       ...,
       [-0.21517402],
       [ 0.33693402],
       [-0.64394144]])
```

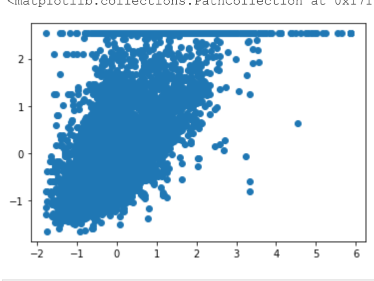
In [35]:
```
#Plot the fitted model for training data as well as for test data
#check if the fitted model satisfies the test data

#scatter plot of known trained feature data and label data
plt.scatter(X_train,y_train)
```

Out[35]: <matplotlib.collections.PathCollection at 0x17557dd8>



In [36]:
```
#scatter plot of known test feature data and label data
plt.scatter(X_test,y_test)
```

Out[36]: <matplotlib.collections.PathCollection at 0x17168310>



In [37]:
```
#Plotting the predicted label for unknown test data
plt.scatter(X_test,y_pred)
```

Out[37]: <matplotlib.collections.PathCollection at 0x171958f8>