Housing dataset

August 31, 2022

[1]:
```
# 1. Load housing dataset "housing.csv" (find the file on this server) into a␣
↪variable df
import pandas as pd
df = pd.read_csv(r'/home/ishita/Documents/datasets/housing/housing.csv')
```

[3]:
```
# 2. Display the brief information about this dataset.
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
```

[4]:
```
# 3. Display number of rows and features available in this dataset.
print("Number of rows: ",df.shape[0])
print("Number of coloumn: ",df.shape[1])
```

```
Number of rows:  20640
Number of coloumn:  10
```

[5]:
```
# 4. Find the target variable.
target = "median_house_value"
print(df[target])
```

```
0        452600.0
```

```
1         358500.0
2         352100.0
3         341300.0
4         342200.0
            …
20635      78100.0
20636      77100.0
20637      92300.0
20638      84700.0
20639      89400.0
Name: median_house_value, Length: 20640, dtype: float64
```

[6]:
```python
# 5. Show first few rows of the dataset.
df.head()
```

[6]:
```
   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
```

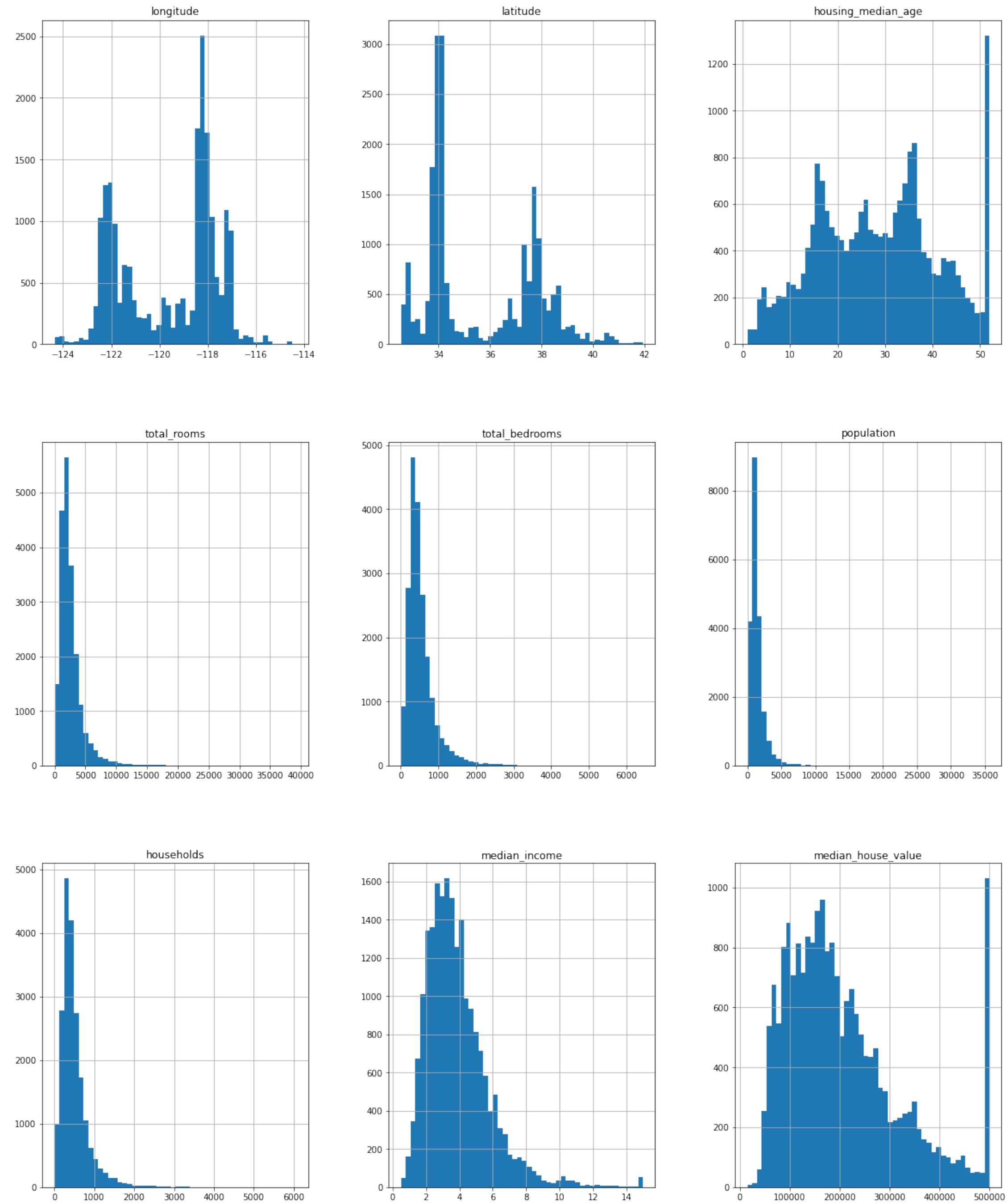
[7]:
```python
# 6. Display the summary statistics about all the features of the dataset.
df.describe()
```

[7]:
```
          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
```

[8]:

```
# 7. Show the histogram plot of each attribute.
%matplotlib inline
import matplotlib.pyplot as plt
df.hist(bins=50, figsize=(20,25))
plt.show()
```



[13]:
```
# 8. Show if there are any missing/Null values in the dataset.
df.isnull().sum()
```

[13]:
```
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
```

[12]:

```
# 9. Show different types of values in categorical attributes along with their␣
 ↪frequencies.
df["ocean_proximity"].value_counts()
```

[12]:

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

[13]:

```
# 10. Fill the missing values with most frequently used value for categorical␣
 ↪attribute and for
# numerical attribute fill median value.
df_num =pd.read_csv(r'/home/ishita/Documents/datasets/housing/housing.csv')
median = df_num["total_bedrooms"].median()
df_num["total_bedrooms"].fillna(median, inplace=True)
mode = df_num["ocean_proximity"].mode()
df_num["ocean_proximity"].fillna(mode, inplace=True)
df_num.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      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
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

[14]:
```
# 11. Display sum of missing values after filling the values.
((df.isnull().sum().sum()) * median)
```

[14]: 90045.0

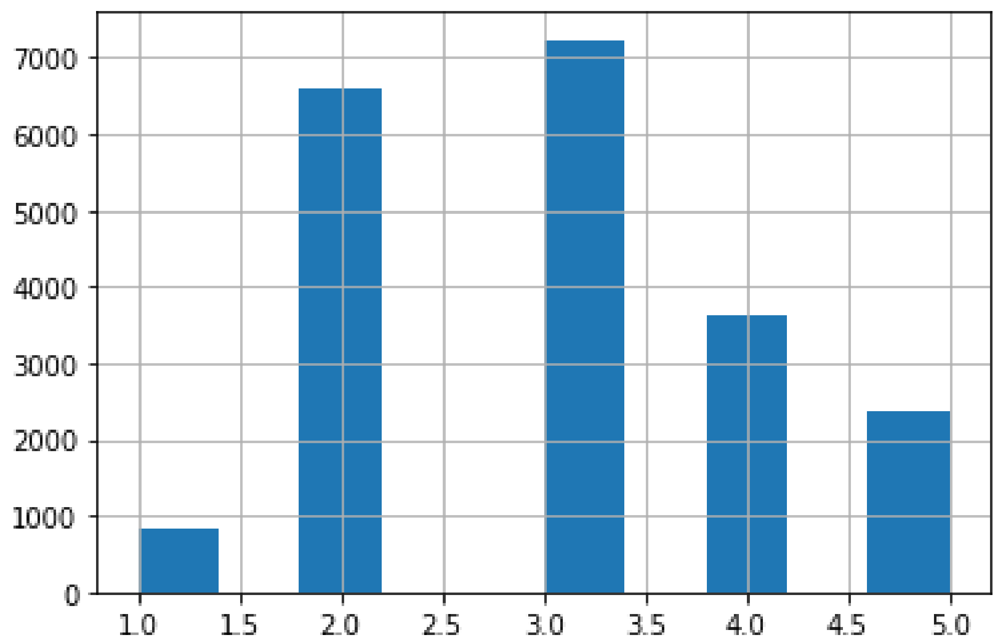
[15]:
```
# 12. Transform "median_income" attribute into a new attribute "income_cat"␣
↪which has 5 levels (1,2,3,4,5) ranging
#from 0-1.5, 1.5-3.0, 3.0-4.5, 4.5-6.0, 6.0-np.inf respectively.
# Use pd.cut(df["median_income"], bins=[0., 1.5, 3.0, 4.5, 6., np.inf],␣
↪labels=[1, 2, 3, 4, 5])
import numpy as np
df["income_cat"] = pd.cut(df["median_income"],
 bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
 labels=[1, 2, 3, 4, 5])
```

[16]:
```
# 13. Find the distribution based on "income_cat" in the entire dataset.
df["income_cat"].value_counts() / len(df)
```

[16]:
```
3    0.350581
2    0.318847
4    0.176308
5    0.114438
1    0.039826
Name: income_cat, dtype: float64
```

[17]:
```
# 14. Plot histogram of "income_cat" attributes. (use df['attribute name'].
↪hist() )
df["income_cat"].hist()
```

[17]: <AxesSubplot:>



[18]:
```python
# 15. Split the dataset 80% of rows for training, and 20% of rows for testing␣
↪purpose. Just for the sake
#of learning take first 80% rows as training and, rest 20% rows as testing␣
↪respectively. Store these
#train and test datasets in temp_train and temp_test variables.
def split_train_test(data, test_ratio):
 shuffled_indices = np.random.permutation(len(data))
 test_set_size = int(len(data) * test_ratio)
 test_indices = shuffled_indices[:test_set_size]
 train_indices = shuffled_indices[test_set_size:]
 return data.iloc[train_indices], data.iloc[test_indices]
temp_train, temp_test = split_train_test(df, 0.2)
print(len(temp_train))
print(len(temp_test))
```

```
16512
4128
```

[19]:
```python
# 16. Check the distribution based on "income_cat" in train and test set that␣
↪you obtained in above step.
df["income_cat"].value_counts() / len(df)
```

[19]:
```
3    0.350581
2    0.318847
4    0.176308
5    0.114438
```

```
1    0.039826
Name: income_cat, dtype: float64
```

[20]:
```
temp_train["income_cat"].value_counts() / len(temp_train)
```

[20]:
```
3    0.349746
2    0.317769
4    0.177386
5    0.115250
1    0.039850
Name: income_cat, dtype: float64
```

[21]:
```
temp_test["income_cat"].value_counts() / len(temp_test)
```

[21]:
```
3    0.353924
2    0.323159
4    0.171996
5    0.111192
1    0.039729
Name: income_cat, dtype: float64
```

[22]:
```
# 17. Reshufle the dataset to have stratified distribution of 'income_cat' and
 ↪then split it into train
#and test. Use following function
from sklearn.model_selection import StratifiedShuffleSplit
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(df, df["income_cat"]):
 train = df.loc[train_index]
 test = df.loc[test_index]
print(len(train))
print(len(test))
```

```
16512
4128
```

[23]:
```
# 18. Check again the distribution based on "income_cat" in train and test set
df["income_cat"].value_counts() / len(df)
```

[23]:
```
3    0.350581
2    0.318847
4    0.176308
5    0.114438
1    0.039826
Name: income_cat, dtype: float64
```

[24]:
```
train["income_cat"].value_counts() / len(train)
```

[24]:
```
3    0.350594
2    0.318859
4    0.176296
5    0.114462
1    0.039789
Name: income_cat, dtype: float64
```

[25]:
```
test["income_cat"].value_counts() / len(test)
```

[25]:
```
3    0.350533
2    0.318798
4    0.176357
5    0.114341
1    0.039971
Name: income_cat, dtype: float64
```

[26]:
```
# 19. Find correlation of target attribute with rest of the attributes. Use␣
↪correlation=df.corr()
# correlation["attribute name"].sort_values()
correlation=df.corr()
correlation["median_house_value"].sort_values()
```

[26]:
```
latitude             -0.144160
longitude            -0.045967
population           -0.024650
total_bedrooms        0.049686
households            0.065843
housing_median_age    0.105623
total_rooms           0.134153
median_income         0.688075
median_house_value    1.000000
Name: median_house_value, dtype: float64
```

[27]:
```
# 20. Convert categorical attribute to numeric using ordinal encoder. Use
from sklearn.preprocessing import OrdinalEncoder
oe=OrdinalEncoder ()
df_cat_oe =oe.fit_transform(df[["ocean_proximity"]])
print(df_cat_oe)
```

```
[[3.]
 [3.]
 [3.]
 …
 [1.]
 [1.]
 [1.]]
```

[28]:
```
# 21. Add the new attribute that you have transformed into numeric into dataset␣
  ↪df.
d = dict(enumerate(df_cat_oe.flatten(), 1))
df["df_cat_oe"]=d.values()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 12 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
 10  income_cat          20640 non-null  category
 11  df_cat_oe           20640 non-null  float64
dtypes: category(1), float64(10), object(1)
memory usage: 1.8+ MB
```

[29]:
```
# 22. Drop the attribute which has categorical values from the dataset.
df=df.drop("ocean_proximity" , axis=1)
```

[30]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 11 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   income_cat          20640 non-null  category
 10  df_cat_oe           20640 non-null  float64
```

```
dtypes: category(1), float64(10)
memory usage: 1.6 MB
```

[54]:
```python
# 23. Split the dataset. use sklearn.model_selection import train_test_split
# train_set, test_set = train_test_split(housing, test_size=0.2,␣
 ↪random_state=42)
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(df, test_size=0.2, random_state=42)
print(len(train_set))
print(len(test_set))
```

```
16512
4128
```

[56]:
```python
# 24. Separate the target attribute and rest of the attributes from train_set␣
 ↪and test_set and store
# them as train_target, and test_target in two separate variables.
train_target = train_set[target]
train_rest=train_set.drop("median_house_value",axis=1)
test_target = test_set[target]
test_rest = test_set.drop("median_house_value",axis=1)
train_target.info()
print("\n")
test_target.info()
```

```
<class 'pandas.core.series.Series'>
Int64Index: 16512 entries, 14196 to 15795
Series name: median_house_value
Non-Null Count  Dtype
--------------  -----
16512 non-null  float64
dtypes: float64(1)
memory usage: 258.0 KB


<class 'pandas.core.series.Series'>
Int64Index: 4128 entries, 20046 to 3665
Series name: median_house_value
Non-Null Count  Dtype
--------------  -----
4128 non-null   float64
dtypes: float64(1)
memory usage: 64.5 KB
```

[70]:
```python
# 25. Take a linear regression mode and train it.
from sklearn.linear_model import LinearRegression
reg = LinearRegression()
```

[71]:
```
# 26. reg.fit(training_dataset_name, training_dataset_target)
reg.fit(train_set, train_target)
reg.intercept_
reg.coef_
```

[71]:
```
array([-5.53030717e-11, -5.81505955e-11,  3.94919286e-14,  2.15175100e-14,
       -9.03183778e-14, -7.23726634e-15,  2.01839413e-14, -1.20954654e-11,
        1.00000000e+00,  5.77589516e-13, -9.05660909e-14])
```

[73]:
```
# 27. Predict few values from the dataset. Use predict method and pass some␣
 ↪rows from dataset.
train_set_rand = train_set.sample(frac=0.50)
reg.predict(train_set_rand)
```

[73]:
```
array([184900., 158200., 328500., …, 262700., 113600., 180100.])
```