Assignment

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1 TensorGo Assignment

dataset: California Housing Price

dataset_url: https://www.kaggle.com/datasets/camnugent/california-housing-prices/data?select=housing.csv

[7]:
```
from langchain_community.llms import Ollama
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
```

[8]:
```
df = pd.read_csv("housing.csv")
```

[9]:
```
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
```

[10]:
```
df.dropna(inplace=True)
```

[11]:
```
df.ocean_proximity.unique()
```

[11]:
```
array(['NEAR BAY', '<1H OCEAN', 'INLAND', 'NEAR OCEAN', 'ISLAND'],
      dtype=object)
```

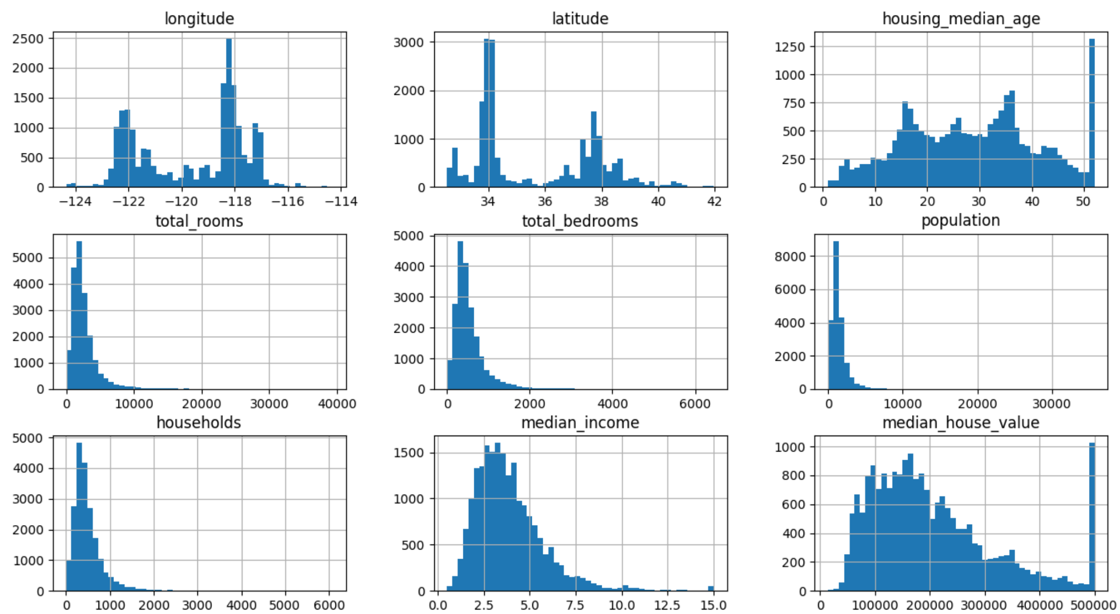
1.1 graphs

1.1.1 Histogram

The following graphs are histograms, they are used here to show the distribution of the data

[12]:
```python
df.hist(figsize=(15, 8), bins=50)
```

[12]:
```
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)
```



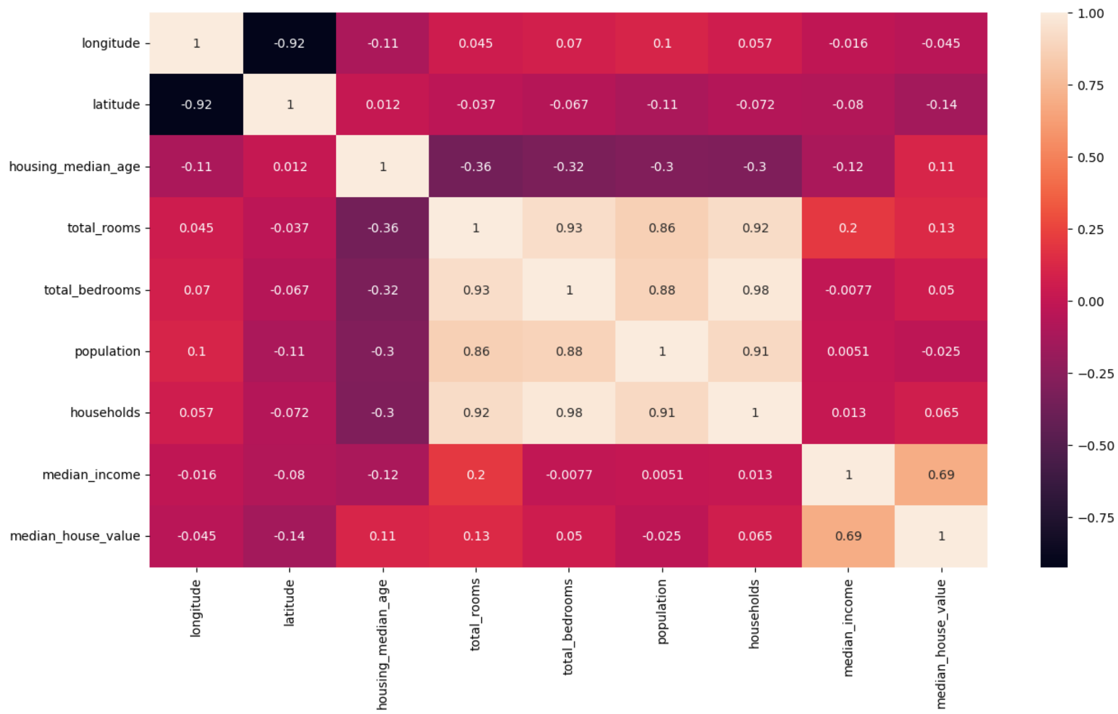
1.1.2 Heatmap

The following is a heatmap, it is used here to show the correlation of attributes with respect to each other

[13]:
```python
ndf = df.select_dtypes(include=[np.number])
plt.figure(figsize=(15, 8))
```

```python
sns.heatmap(ndf.corr(), annot=True)
```

[13]: <Axes: >



1.2 llm

As median_house_value is the only value that is of important to us, we are only generating the correlations with respect to that particual value

[14]:
```python
corr = ndf.drop(['median_house_value'], axis=1).corrwith(df.median_house_value)
print(corr)
```

```
longitude            -0.045398
latitude             -0.144638
housing_median_age    0.106432
total_rooms           0.133294
total_bedrooms        0.049686
population           -0.025300
households            0.064894
median_income         0.688355
dtype: float64
```

We are doing the same with the ocean proximity values, as the values are strings we have to use special functions

[16]:
```python
ocorr = df.ocean_proximity.str.get_dummies().corrwith(df.median_house_value)
print(ocorr)
```

```
<1H OCEAN     0.257614
INLAND       -0.484787
ISLAND        0.023525
NEAR BAY      0.160526
NEAR OCEAN    0.140378
dtype: float64
```

[21]:
```python
description = df.describe()
print(description)
```

```
          longitude      latitude  housing_median_age   total_rooms  \
count  20433.000000  20433.000000        20433.000000  20433.000000
mean    -119.570689     35.633221           28.633094   2636.504233
std        2.003578      2.136348           12.591805   2185.269567
min     -124.350000     32.540000            1.000000      2.000000
25%     -121.800000     33.930000           18.000000   1450.000000
50%     -118.490000     34.260000           29.000000   2127.000000
75%     -118.010000     37.720000           37.000000   3143.000000
max     -114.310000     41.950000           52.000000  39320.000000

       total_bedrooms    population    households  median_income  \
count    20433.000000  20433.000000  20433.000000   20433.000000
mean       537.870553   1424.946949    499.433465       3.871162
std        421.385070   1133.208490    382.299226       1.899291
min          1.000000      3.000000      1.000000       0.499900
25%        296.000000    787.000000    280.000000       2.563700
50%        435.000000   1166.000000    409.000000       3.536500
75%        647.000000   1722.000000    604.000000       4.744000
max       6445.000000  35682.000000   6082.000000      15.000100

       median_house_value
count        20433.000000
mean        206864.413155
std         115435.667099
min          14999.000000
25%         119500.000000
50%         179700.000000
75%         264700.000000
max         500001.000000
```

Here we are injecting the desciption of the data and the correlation values calculated above into the llm

[17]:
```python
system_message = f"""
you are currently working on the calafornia housing price dataset
some key indication in the dataset are as follows
```

```
{description}
the correlation of median house values with respect to give paramters are as␣
 ↪follows
{corr}
and the correlation of median house values with respect to proximity of ocean is␣
 ↪as follows
{ocorr}
"""
```

[18]:
```
llm = Ollama(model="mistral", system=system_message)
for s in llm.stream("what are some characteristics of the give dataset"):
    print(s, end="")
```

```
 Based on the provided information, here are some characteristics of the
California housing price dataset:

1. The dataset contains information about 20,433 houses or housing units in
California.
2. The longitude and latitude coordinates provide the geographical location of
each house.
3. Housing-related features include median age (in years), total rooms, total
bedrooms, and household size.
4. Demographic features include population and median income for the
neighborhood or area where each house is located.
5. The dataset also includes a categorical variable "proximity of ocean," which
indicates whether a house is located near the ocean (INLAND, NEAR BAY, NEAR
OCEAN, <1H OCEAN, or ISLAND).
6. The primary outcome variable is the median housing value or price for each
house.
7. The mean median housing age is 28.6 years with a standard deviation of 12.59
years.
8. The mean total rooms and total bedrooms are 2,636.5 and 537.9, respectively.
9. The mean population size for the neighborhood or area is 1,424.9 persons with
a standard deviation of 1,133.2.
10. The mean median income for the area is $3,871.
11. The correlation between median housing values and most features (longitude,
latitude, housing_median_age, total_rooms, population, and households) are weak
to moderate. However, median housing values have a strong positive correlation
with median income and proximity to the ocean (INLAND, NEAR BAY, NEAR OCEAN, <1H
OCEAN, or ISLAND).
12. The median housing price is $206,864.41, but it ranges from a minimum of
$14,999 to a maximum of $500,001.
```

[19]:
```
for s in llm.stream("which condition affect the median house price the most"):
    print(s, end="")
```

```
 Based on the correlation values provided, it appears that the proximity of a
housing unit to the ocean or a body of water (as represented by the variables
```

"<1H OCEAN," INLAND," ISLAND," NEAR BAY," and NEAR OCEAN) has a stronger relationship with median house prices than other features such as longitude, latitude, housing age, total rooms, total bedrooms, population, households, or median income. Specifically, houses near the ocean or bodies of water tend to have higher median house prices (as indicated by a positive correlation), while houses inland tend to have lower median house prices (as indicated by a negative correlation). However, it's important to keep in mind that correlation does not imply causation, and there may be other factors at play that are influencing housing prices in these areas. It would be useful to explore additional data and perform further analysis to better understand the relationship between housing prices and these variables.

[ ]:

```

```