

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
```

```
data = pd.read_csv('/content/housing.csv')
print("Description of the data:")
print(data.describe())
```

Description of the data:

	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

```
# b) Find data type and shape of each column
print("\nData types of each column:")
print(data.dtypes)
print("\nShape of the data:")
print(data.shape)
```

Data types of each column:

longitude	float64
latitude	float64
housing_median_age	float64

```
total_rooms      float64
total_bedrooms   float64
population        float64
households        float64
median_income     float64
median_house_value float64
ocean_proximity   object
dtype: object
```

Shape of the data:
(20640, 10)

c) Find the null values (if yes fill the null values with '0' or mean of that column)

```
null_values = data.isnull().sum()
print("\nNull values in the data:")
print(null_values)
```

Null values in the data:

```
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
```

d) find features and target variables

Assuming the target variable is in the last column

```
features = data.iloc[:, :-1]
target = data.iloc[:, -1]
print(features)
print(target)
```

	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
...
...
20635 -121.09 39.48 25.0 1665.0
374.0
20636 -121.21 39.49 18.0 697.0
150.0
20637 -121.22 39.43 17.0 2254.0
485.0
20638 -121.32 39.43 18.0 1860.0
409.0
20639 -121.24 39.37 16.0 2785.0
616.0

```

	population	households	median_income	median_house_value
0	322.0	126.0	8.3252	452600.0
1	2401.0	1138.0	8.3014	358500.0
2	496.0	177.0	7.2574	352100.0
3	558.0	219.0	5.6431	341300.0
4	565.0	259.0	3.8462	342200.0
...
20635	845.0	330.0	1.5603	78100.0
20636	356.0	114.0	2.5568	77100.0
20637	1007.0	433.0	1.7000	92300.0
20638	741.0	349.0	1.8672	84700.0
20639	1387.0	530.0	2.3886	89400.0

```
[20640 rows x 9 columns]
```

```

0 NEAR BAY
1 NEAR BAY
2 NEAR BAY
3 NEAR BAY
4 NEAR BAY

```

```

...
20635 INLAND
20636 INLAND
20637 INLAND
20638 INLAND
20639 INLAND

```

```
Name: ocean_proximity, Length: 20640, dtype: object
```

```
# e) Split the data into train and test
```

```
X_train, X_test, y_train, y_test = train_test_split(features, target,
test_size=0.2, random_state=42)
```

```
print(X_train,y_train)
```

```
print(X_test,y_test)
```

	longitude	latitude	housing_median_age	total_rooms
total_bedrooms \				
14196	-117.03	32.71	33.0	3126.0

```

627.0
8267      -118.16      33.77      49.0      3382.0
787.0
17445     -120.48      34.66      4.0      1897.0
331.0
14265     -117.11      32.69      36.0      1421.0
367.0
2271      -119.80      36.78      43.0      2382.0
431.0
...      ...      ...      ...      ...
...
11284     -117.96      33.78      35.0      1330.0
201.0
11964     -117.43      34.02      33.0      3084.0
570.0
5390      -118.38      34.03      36.0      2101.0
569.0
860       -121.96      37.58      15.0      3575.0
597.0
15795     -122.42      37.77      52.0      4226.0
1315.0

```

```

      population  households  median_income  median_house_value
14196      2300.0      623.0      3.2596      103000.0
8267      1314.0      756.0      3.8125      382100.0
17445      915.0      336.0      4.1563      172600.0
14265     1418.0      355.0      1.9425      93400.0
2271      874.0      380.0      3.5542      96500.0
...      ...      ...      ...      ...
11284      658.0      217.0      6.3700      229200.0
11964     1753.0      449.0      3.0500      97800.0
5390      1756.0      527.0      2.9344      222100.0
860       1777.0      559.0      5.7192      283500.0
15795     2619.0     1242.0      2.5755      325000.0

```

```
[16512 rows x 9 columns] 14196      NEAR OCEAN
```

```

8267      NEAR OCEAN
17445     NEAR OCEAN
14265     NEAR OCEAN
2271      INLAND

```

```

...
11284     <1H OCEAN
11964     INLAND
5390      <1H OCEAN
860       <1H OCEAN
15795     NEAR BAY

```

```
Name: ocean_proximity, Length: 16512, dtype: object
```

```

      longitude  latitude  housing_median_age  total_rooms
total_bedrooms \

```

```

20046      -119.01      36.06              25.0      1505.0
NaN
3024       -119.46      35.14              30.0      2943.0
NaN
15663      -122.44      37.80              52.0      3830.0
NaN
20484      -118.72      34.28              17.0      3051.0
NaN
9814       -121.93      36.62              34.0      2351.0
NaN
...
...
15362      -117.22      33.36              16.0      3165.0
482.0
16623      -120.83      35.36              28.0      4323.0
886.0
18086      -122.05      37.31              25.0      4111.0
538.0
2144       -119.76      36.77              36.0      2507.0
466.0
3665       -118.37      34.22              17.0      1787.0
463.0

      population  households  median_income  median_house_value
20046      1392.0      359.0      1.6812      47700.0
3024      1565.0      584.0      2.5313      45800.0
15663      1310.0      963.0      3.4801      500001.0
20484      1705.0      495.0      5.7376      218600.0
9814      1063.0      428.0      3.7250      278000.0
...
15362      1351.0      452.0      4.6050      263300.0
16623      1650.0      705.0      2.7266      266800.0
18086      1585.0      568.0      9.2298      500001.0
2144      1227.0      474.0      2.7850      72300.0
3665      1671.0      448.0      3.5521      151500.0

[4128 rows x 9 columns] 20046      INLAND
3024      INLAND
15663      NEAR BAY
20484      <1H OCEAN
9814      NEAR OCEAN
...
15362      <1H OCEAN
16623      NEAR OCEAN
18086      <1H OCEAN
2144      INLAND
3665      <1H OCEAN
Name: ocean_proximity, Length: 4128, dtype: object

```

```

# f) Normalize the data with min-max scaling
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
print(X_train_scaled)
print(X_test_scaled)

[[0.72908367 0.01702128 0.62745098 ... 0.10228581 0.19032151
0.18144461]
 [0.61653386 0.12978723 0.94117647 ... 0.12415721 0.22845202
0.75690616]
 [0.38545817 0.22446809 0.05882353 ... 0.05508962 0.25216204
0.32494918]
 ...
 [0.59462151 0.15744681 0.68627451 ... 0.08649893 0.16789424
0.42701061]
 [0.23804781 0.53510638 0.2745098 ... 0.09176122 0.35994676
0.55360803]
 [0.19223108 0.55531915 1. ... 0.20407828 0.14314285
0.63917468]]
[[0.53187251 0.37340426 0.47058824 ... 0.0588719 0.08146784
0.06742446]
 [0.48705179 0.27553191 0.56862745 ... 0.09587239 0.14009462
0.06350695]
 [0.19023904 0.55851064 1. ... 0.15819766 0.2055282 1.
]
 ...
 [0.22908367 0.50638298 0.47058824 ... 0.09324124 0.60205376 1.
]
 [0.45717131 0.44893617 0.68627451 ... 0.07778326 0.15759093 0.1181459
]
 [0.59561753 0.17765957 0.31372549 ... 0.07350765 0.21049365 0.2814442
]]

```