

2203a51521-ml1

March 4, 2024

```
[2]: import pandas as pd
housing=pd.read_csv('/content/housing.csv')
print(housing)
```

	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	

	ocean_proximity
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

```

```
[20640 rows x 10 columns]
```

```
[4]: housing.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

```

```
[5]: housing.describe()
```

```

[5]:      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

```

```
[6]: housing['households'].shape
```

```
[6]: (20640,)
```

```
[22]: z=housing.drop('ocean_proximity',axis=1)
print(z)
```

	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]
```

```
[24]: print(housing.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
```

```
[12]: housing['total_bedrooms'].isnull().sum()/housing.shape[0]
```

```
[12]: 0.01002906976744186
```

```
[25]: y=housing['median_house_value']
x=housing.drop('median_house_value',axis=1)

print(x)
```

	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	ocean_proximity
0	322.0	126.0	8.3252	NEAR BAY
1	2401.0	1138.0	8.3014	NEAR BAY
2	496.0	177.0	7.2574	NEAR BAY
3	558.0	219.0	5.6431	NEAR BAY
4	565.0	259.0	3.8462	NEAR BAY
...	...	...	...	...
20635	845.0	330.0	1.5603	INLAND
20636	356.0	114.0	2.5568	INLAND
20637	1007.0	433.0	1.7000	INLAND
20638	741.0	349.0	1.8672	INLAND
20639	1387.0	530.0	2.3886	INLAND

[20640 rows x 9 columns]

```
[15]: print(x.shape)
      print(y.shape)
```

```
(20640, 9)
(20640,)
```

```
[16]: from sklearn.model_selection import train_test_split
      x_train,y_train,x_test,y_test=train_test_split(x,y,test_size=0.
      ↪30,random_state=40)
      print(x_train)
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	\
14827	-117.09	32.66	37.0	1232.0	330.0	
12640	-121.45	38.53	34.0	1893.0	415.0	
6016	-117.78	34.06	33.0	1056.0	272.0	
13650	-117.31	34.08	37.0	953.0	231.0	
13275	-117.63	34.10	15.0	4799.0	1209.0	
...	...	...	...	...	...	
11532	-118.09	33.77	26.0	5359.0	1508.0	
16065	-122.48	37.75	49.0	2203.0	407.0	
14501	-117.23	32.86	16.0	1200.0	468.0	
14555	-117.13	32.96	15.0	2267.0	292.0	
11590	-118.01	33.78	26.0	2343.0	377.0	

	population	households	median_income	ocean_proximity
14827	1086.0	330.0	1.6389	NEAR OCEAN
12640	884.0	395.0	2.1679	INLAND
6016	964.0	300.0	2.4464	INLAND
13650	611.0	230.0	1.9926	INLAND
13275	2554.0	1057.0	2.6582	INLAND
...	...	...	...	...
11532	1829.0	1393.0	1.7675	<1H OCEAN
16065	1052.0	405.0	4.4375	NEAR BAY
14501	648.0	443.0	3.0450	NEAR OCEAN
14555	1180.0	289.0	6.7120	<1H OCEAN
11590	1166.0	373.0	6.0000	<1H OCEAN

[14448 rows x 9 columns]

```
[17]: print(x_test)
```

```
14827    114300.0
12640     75400.0
6016     128700.0
13650     81500.0
```

```

13275    122800.0
...
11532    61300.0
16065    329200.0
14501    100000.0
14555    240200.0
11590    233100.0

```

Name: median\_house\_value, Length: 14448, dtype: float64

```
[18]: print(y_train)
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	\
6607	-118.14	34.18	47.0	3457.0	622.0	
884	-121.97	37.54	31.0	1949.0	344.0	
9457	-123.84	39.83	19.0	1461.0	340.0	
18681	-121.82	36.86	17.0	1573.0	272.0	
4654	-118.33	34.05	48.0	2405.0	527.0	
...	...	...	...	...	...	
3606	-118.48	34.23	29.0	3354.0	707.0	
11607	-118.01	33.80	16.0	4021.0	701.0	
12610	-121.51	38.54	34.0	2815.0	479.0	
8561	-118.41	33.93	22.0	2514.0	605.0	
203	-122.23	37.78	52.0	986.0	258.0	

	population	households	median_income	ocean_proximity
6607	1700.0	579.0	3.5164	<1H OCEAN
884	986.0	322.0	4.6349	<1H OCEAN
9457	515.0	227.0	1.5278	NEAR OCEAN
18681	142.0	55.0	2.1719	NEAR OCEAN
4654	1868.0	502.0	3.3750	<1H OCEAN
...	...	...	...	...
3606	1752.0	650.0	4.5484	<1H OCEAN
11607	1488.0	650.0	5.3200	<1H OCEAN
12610	1075.0	471.0	3.9792	INLAND
8561	1225.0	568.0	4.1818	<1H OCEAN
203	1008.0	255.0	1.4844	NEAR BAY

[6192 rows x 9 columns]

```
[19]: print(y_test)
```

```

6607    226500.0
884     196200.0
9457    145800.0
18681   420000.0
4654    257800.0
...
3606    239900.0

```

```
11607    219500.0
12610    164800.0
8561     339700.0
203      119400.0
Name: median_house_value, Length: 6192, dtype: float64
```

```
[20]: print(x_train.shape)
      print(y_train.shape)
      print(x_test.shape)
      print(y_test.shape)
```

```
(14448, 9)
(6192, 9)
(14448,)
(6192,)
```

```
[23]: from sklearn.preprocessing import MinMaxScaler
      d=MinMaxScaler()
      dd=d.fit_transform(z)
      print(dd)
```

```
[[0.21115538 0.5674814  0.78431373 ... 0.02055583 0.53966842 0.90226638]
 [0.21215139 0.565356   0.39215686 ... 0.18697583 0.53802706 0.70824656]
 [0.21015936 0.5642933  1.          ... 0.02894261 0.46602805 0.69505074]
 ...
 [0.31175299 0.73219979 0.31372549 ... 0.07104095 0.08276438 0.15938285]
 [0.30179283 0.73219979 0.33333333 ... 0.05722743 0.09429525 0.14371281]
 [0.30976096 0.72582359 0.29411765 ... 0.08699227 0.13025338 0.15340349]]
```