```
In [ ]: Sukant Thombare 21102A0037 CMPN A
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         data=pd.read_csv('housing.csv')
               longitude latitude housing_median_age total_rooms total_bedrooms population households median_
            0
                 -122.23
                          37.88
                                              41.0
                                                        0.088
                                                                       129.0
                                                                                 322.0
                                                                                            126.0
                 -122.22
                          37.86
                                              21.0
                                                       7099.0
                                                                      1106.0
                                                                                2401.0
                                                                                           1138.0
            2
                 -122.24
                          37.85
                                              52.0
                                                                                 496.0
                                                                                            177.0
                                                       1467.0
                                                                       190.0
                 -122.25
                          37.85
                                              52.0
                                                       1274.0
                                                                       235.0
                                                                                 558.0
                                                                                            219.0
            4
                 -122.25
                          37.85
                                              52.0
                                                       1627.0
                                                                       280.0
                                                                                 565.0
                                                                                            259.0
         20635
                 -121.09
                          39.48
                                              25.0
                                                       1665.0
                                                                       374.0
                                                                                 845.0
                                                                                            330.0
         20636
                 -121.21
                          39.49
                                              18.0
                                                        697.0
                                                                                            114.0
                                                                       150.0
                                                                                 356.0
         20637
                 -121.22
                          39.43
                                              17.0
                                                       2254.0
                                                                       485.0
                                                                                1007.0
                                                                                            433.0
         20638
                 -121.32
                          39.43
                                              18.0
                                                       1860.0
                                                                       409.0
                                                                                 741.0
                                                                                            349.0
         20639
                 -121.24
                          39.37
                                              16.0
                                                       2785.0
                                                                       616.0
                                                                                1387.0
                                                                                            530.0
        20640 rows × 10 columns
In [6]: data.shape
         (20640, 10)
In [7]: data.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 20640 entries, 0 to 20639
         Data columns (total 10 columns):
          # Column
                                  Non-Null Count Dtype
            longitude
          0
                                   20640 non-null float64
            latitude
          1
                                   20640 non-null float64
          2 housing_median_age 20640 non-null float64
          3
            total_rooms
                                   20640 non-null float64
                                   20433 non-null float64
          4
            total_bedrooms
          5 population
                                  20640 non-null float64
          6
            households
                                   20640 non-null float64
          7
             median_income
                                   20640 non-null float64
            median_house_value 20640 non-null float64
             ocean_proximity 20640 non-null object
         dtypes: float64(9), object(1)
         memory usage: 1.6+ MB
In [8]: data.isnull().sum()
```

```
longitude
                                  0
         latitude
                                  0
         housing_median_age
                                  0
         total_rooms
                                  0
         total_bedrooms
                                207
         population
                                 0
                                  0
         households
         median_income
                                 Ω
         median_house_value
                                 0
         ocean_proximity
                                  0
         dtype: int64
 In [9]: data.dropna(inplace=True)
         data.isnull().sum()
         longitude
                                0
         latitude
                                0
         housing_median_age
                                0
         total_rooms
                                0
         total_bedrooms
                                0
         population
                                0
         households
                                0
         median_income
                                0
         median_house_value
                                0
         ocean_proximity
                                0
         dtype: int64
         data.reset_index(inplace=True, drop=True)
         data['ocean_proximity'].value_counts()
         <1H OCEAN
                      9034
         INLAND
                       6496
         NEAR OCEAN
                       2628
                       2270
         NEAR BAY
         ISLAND
                           5
         Name: ocean_proximity, dtype: int64
In [13]: from sklearn.preprocessing import LabelEncoder
         le=LabelEncoder()
         data['ocean_proximity']=le.fit_transform(data['ocean_proximity'])
In [14]: data["rooms_per_household"] = data["total_rooms"]/data["households"]
         data["bedrooms_per_room"] = data["total_bedrooms"]/data["total_rooms"]
         data["population_per_household"] = data["population"] / data["households"]
         data
```

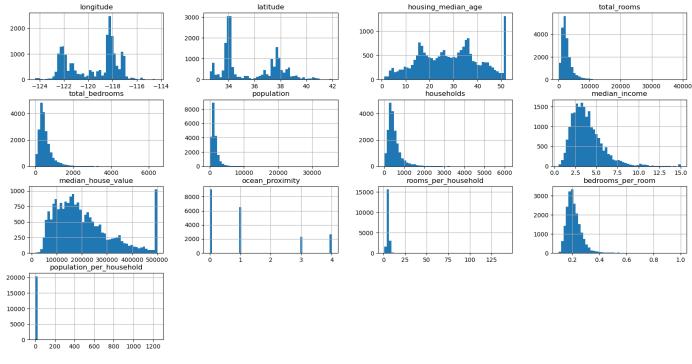
:		longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_
	0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	
	1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	
	2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	
	3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	
	4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	
	20428	-121.09	39.48	25.0	1665.0	374.0	845.0	330.0	
	20429	-121.21	39.49	18.0	697.0	150.0	356.0	114.0	
	20430	-121.22	39.43	17.0	2254.0	485.0	1007.0	433.0	
	20431	-121.32	39.43	18.0	1860.0	409.0	741.0	349.0	
	20432	-121.24	39.37	16.0	2785.0	616.0	1387.0	530.0	

20433 rows × 13 columns

In [16]: data.corr()

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
longitude	1.000000	-0.924616	-0.109357	0.045480	0.069608	0.100270
latitude	-0.924616	1.000000	0.011899	-0.036667	-0.066983	-0.108997
housing_median_age	-0.109357	0.011899	1.000000	-0.360628	-0.320451	-0.295787
total_rooms	0.045480	-0.036667	-0.360628	1.000000	0.930380	0.857281
total_bedrooms	0.069608	-0.066983	-0.320451	0.930380	1.000000	0.877747
population	0.100270	-0.108997	-0.295787	0.857281	0.877747	1.000000
households	0.056513	-0.071774	-0.302768	0.918992	0.979728	0.907186
median_income	-0.015550	-0.079626	-0.118278	0.197882	-0.007723	0.005087
median_house_value	-0.045398	-0.144638	0.106432	0.133294	0.049686	-0.025300
ocean_proximity	-0.289530	0.200801	0.112330	-0.015363	-0.014768	-0.069630
rooms_per_household	-0.027307	0.106423	-0.153031	0.133482	0.001538	-0.071898
bedrooms_per_room	0.092657	-0.113815	0.136089	-0.187900	0.084238	0.035319
population_per_household	0.002304	0.002522	0.013258	-0.024596	-0.028355	0.070062

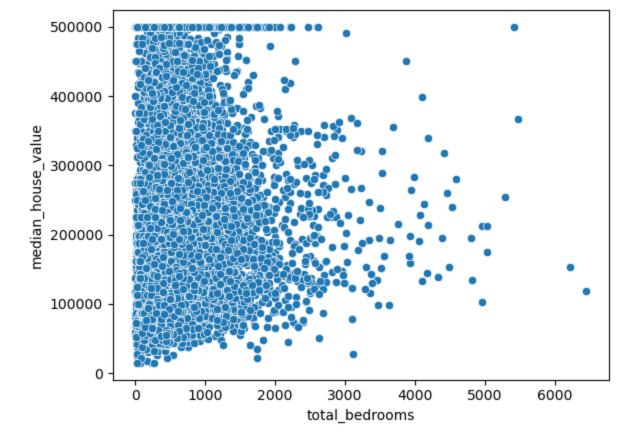
In [17]: data.hist(bins=50, figsize=(20,10));



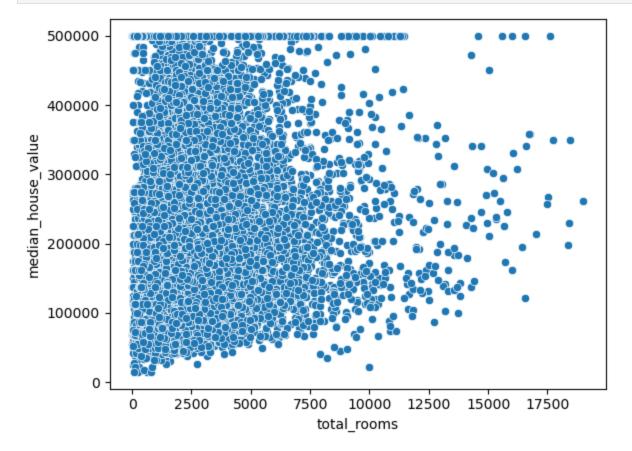
data.plot(kind='box', subplots=True, layout=(4,4), figsize=(15,7)) plt.show() 10000 -115 40 40 20000 -120 20 35 0 longitude latitude O housing median age total rooms 6000 15 6000 30000 0 4000 10 4000 20000 2000 2000 5 10000 0 ٥ 0 median income population households 8 total bedrooms 1.00 400000 0 0.75 100 2 0.50 200000 50 0.25 rooms_per_household bedrooms_per_room median house value ocean_proximity 1000 8 500

```
In [19]: x=data.copy()
In [20]: sns.scatterplot(x=x['total_bedrooms'],y=x['median_house_value'])
    x=x[x['total_bedrooms']<2800]</pre>
```

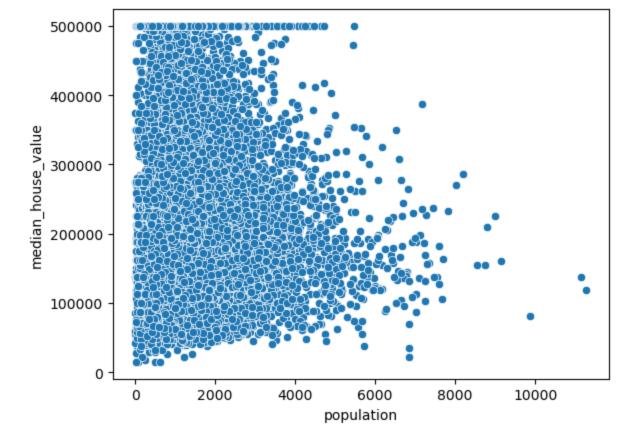
population_per_household



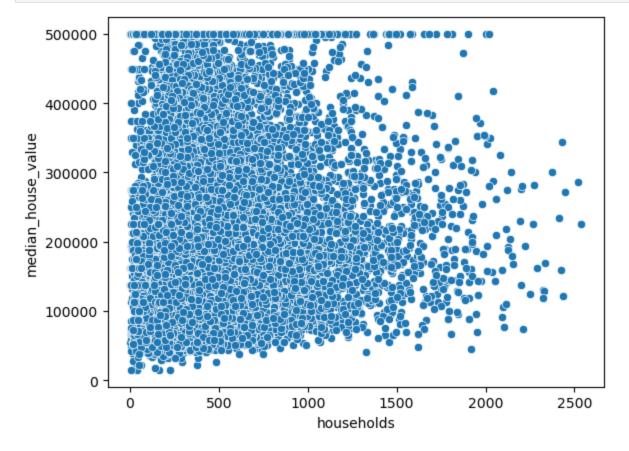
In [21]: sns.scatterplot(x=x['total_rooms'], y=x['median_house_value'])
x=x[x['total_rooms']<15000]</pre>



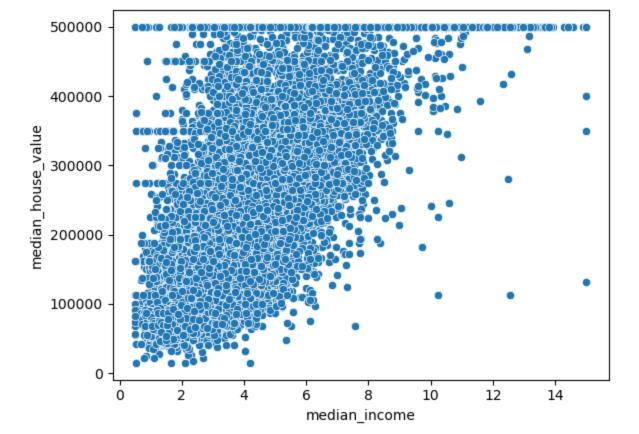
In [22]: sns.scatterplot(x=x['population'],y=x['median_house_value'])
 x=x[x['population']<6500]</pre>



In [23]: sns.scatterplot(x=x['households'],y=x['median_house_value'])
x=x[x['households']<2000]</pre>



```
In [24]: sns.scatterplot(x=x['median_income'],y=x['median_house_value'])
x=x[x['median_income']<9]</pre>
```



```
x.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19805 entries, 0 to 20432
Data columns (total 13 columns):
    Column
                              Non-Null Count Dtype
   longitude
 0
                              19805 non-null float64
 1
   latitude
                              19805 non-null float64
   housing_median_age
                              19805 non-null float64
   total_rooms
                              19805 non-null float64
 3
 4
   total_bedrooms
                              19805 non-null float64
 5
   population
                              19805 non-null float64
   households
                              19805 non-null float64
                              19805 non-null float64
 7
    median_income
   median_house_value
                              19805 non-null float64
 9
   ocean_proximity
                              19805 non-null int32
 10 rooms_per_household
                              19805 non-null float64
 11 bedrooms_per_room
                              19805 non-null float64
 12 population_per_household 19805 non-null float64
dtypes: float64(12), int32(1)
memory usage: 2.0 MB
plt.figure(figsize=(13,13))
sns.heatmap(x.corr(),annot=True)
```

<AxesSubplot:>

																1.00
longitude -	- 1	-0.92	-0.11	0.03	0.061	0.11	0.047	-0.014	-0.046	-0.29	-0.029	0.095	0.028			1.00
latitude -	-0.92	1	0.0066	-0.022	-0.063	-0.12	-0.071	-0.083	-0.15	0.2	0.11	-0.12	-0.014		-	0.75
housing_median_age -	-0.11	0.0066	1	-0.37	-0.31	-0.29	-0.29	-0.15	0.11	0.11	-0.15	0.14	0.0024			
total_rooms -	0.03	-0.022	-0.37	1	0.91	0.82	0.9	0.25	0.15	-0.01	0.15	-0.22	-0.041		-	0.50
total_bedrooms -	0.061	-0.063	-0.31	0.91	1	0.85	0.97	-0.003	0.073	-0.0053	-0.0022	0.11	-0.048			
population -	0.11	-0.12	-0.29	0.82	0.85	1	0.89	0.0085	-0.029	-0.079	-0.1	0.056	0.064		-	0.25
households -	0.047	-0.071	-0.29	0.9	0.97	0.89	1	0.027	0.092	-0.01	-0.1	0.081	-0.044			0.00
median_income -	-0.014	-0.083	-0.15	0.25	-0.003	0.0085	0.027	1	0.65	-0.028	0.29	-0.63	-0.0086			
median_house_value -	-0.046	-0.15	0.11	0.15	0.073	-0.029	0.092	0.65	1	0.08	0.11	-0.21	-0.06		-	-0.25
ocean_proximity -	-0.29	0.2	0.11	-0.01	-0.0053	-0.079	-0.01	-0.028	0.08	1	-0.0049	0.0068	-0.032			
rooms_per_household -	-0.029	0.11	-0.15	0.15	-0.0022	-0.1	-0.1	0.29	0.11	-0.0049	1	-0.4	-0.011		-	-0.50
bedrooms_per_room -	0.095	-0.12	0.14	-0.22	0.11	0.056	0.081	-0.63	-0.21	0.0068	-0.4	1	0.0048			
population_per_household -	0.028	-0.014	0.0024	-0.041	-0.048	0.064	-0.044	-0.0086	-0.06	-0.032	-0.011	0.0048	1		-	-0.75
	longitude -	latitude -	housing_median_age -	total_rooms -	total_bedrooms -	population -	- pouseholds	median_income -	median_house_value -	ocean_proximity -	rooms_per_household -	bedrooms_per_room -	population_per_household -	•		

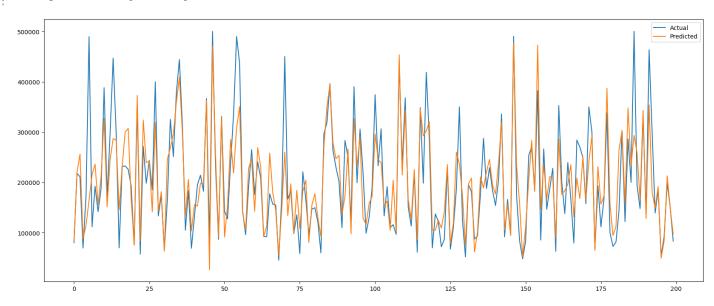
In [27]: x

Out[27]:		longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_			
	0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0				
	1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0				
	2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0				
	3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0				
	4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0				
						•••		•••				
	20428	-121.09	39.48	25.0	1665.0	374.0	845.0	330.0				
	20429	-121.21	39.49	18.0	697.0	150.0	356.0	114.0				
	20430	-121.22	39.43	17.0	2254.0	485.0	1007.0	433.0				
	20431	-121.32	39.43	18.0	1860.0	409.0	741.0	349.0				
	20432	-121.24	39.37	16.0	2785.0	616.0	1387.0	530.0				
	19805 r	rows × 13 c	columns									
In [28]:				dian_house_value" ouse_value"].value		r_household ",'	'bedrooms_	per_room",	'popula			
In [29]:	<pre>from sklearn.preprocessing import PolynomialFeatures feature = PolynomialFeatures(degree=3, include_bias=True, interaction_only=False) x_data = feature.fit_transform(x_data)</pre>											
In [30]:	<pre>from sklearn.preprocessing import StandardScaler scaler = StandardScaler(copy=True, with_mean=True, with_std=True) x_data = scaler.fit_transform(x_data)</pre>											
In [31]:	<pre>from sklearn.model_selection import train_test_split x_train, x_test, y_train , y_test = train_test_split(x_data,y_data, test_size=0.25 , ran</pre>											
In [32]:		sklearn. nearRegre		nodel import Linea	rRegression	n						
In [33]:	lr.fi	t(x_train	n,y_trai	n)								
Out[33]:	Linea	rRegressi	lon()									
In [34]:	lr.sc	ore(x_tra	ain , y_	_train)								
Out[34]:	0.739	235611486	51209									
In [35]:	lr.sc	ore(x_te	st , y_t	cest)								
Out[35]:	0.719	950654175	56351									
In [36]:	y_pre	d = lr.p	redict(x	_test)								

In [37]: df = pd.DataFrame({"Y_test": y_test , "Y_pred" : y_pred})

plt.legend(["Actual" , "Predicted"])

In [38]: plt.figure(figsize=(20,8))
 plt.plot(df[:200])



```
In [39]: from sklearn.metrics import mean_squared_error, r2_score
   mse = mean_squared_error(y_test, y_pred)
   r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error: {mse}')
print(f'R^2 Score: {r2}')
```

Mean Squared Error: 3397195426.647483 R^2 Score: 0.7199506541756351

```
In [43]: input_features = pd.DataFrame({
    'longitude': [-121.09],
    'latitude': [39.48],
    'housing_median_age': [25.0],
    'total_rooms': [1665.0],
    'total_bedrooms': [374.0],
    'population': [845.0],
    'households': [330.0],
    'median_income': [1.5603],
    'ocean_proximity': [1]
})

input_data_poly = feature.transform(input_features)

input_data_scaled = scaler.transform(input_data_poly)

predicted_value = lr.predict(input_data_scaled)
```

C:\Users\saura\anaconda3\lib\site-packages\sklearn\base.py:443: UserWarning: X has featu
re names, but PolynomialFeatures was fitted without feature names
warnings.warn(

```
In [42]: print("Predicted Median House Value:", predicted_value[0])
```

Predicted Median House Value: 72727.9371930804

```
In []:
```