In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
%matplotlib inline
```

In [2]:
```
df = pd.read_csv('//Users//omniaelmenshawy//Desktop//machinfy//
df.head(5)
```

Out[2]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	house
0	-122.23	37.88	41.0	880	129.0	322.0	
1	-122.22	37.86	21.0	7099	1106.0	2401.0	
2	-122.24	37.85	52.0	1467	190.0	496.0	
3	-122.25	37.85	52.0	1274	235.0	558.0	
4	-122.25	37.85	NaN	1627	280.0	NaN	

Data Analysis:

In [3]:
```
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  20382 non-null  float64
 3   total_rooms         20640 non-null  int64  
 4   total_bedrooms      15758 non-null  float64
 5   population          20596 non-null  float64
 6   households          19335 non-null  object 
 7   median_income       17873 non-null  float64
 8   median_house_value  20640 non-null  int64  
 9   ocean_proximity     20640 non-null  object 
 10  gender              16620 non-null  object 
dtypes: float64(6), int64(2), object(3)
memory usage: 1.7+ MB
```

In [4]:
```
df = df.drop_duplicates()
```

In [5]:
```
print(df.shape)
```

```
(20640, 11)
```

In [6]:
```
df.describe()
```

Out[6]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	
count	20640.000000	20640.000000	20382.000000	20640.000000	15758.000000	20
mean	-119.569704	35.631861	28.676283	2635.763081	539.920104	1
std	2.003532	2.135952	12.589284	2181.615252	419.834171	1
min	-124.350000	32.540000	1.000000	2.000000	1.000000	
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1
75%	-118.010000	37.710000	37.000000	3148.000000	652.000000	1
max	-114.310000	41.950000	52.000000	39320.000000	6210.000000	35

In [7]:
```
missing_values = df.isnull().sum()
print(missing_values)
```

```
longitude                0
latitude                 0
housing_median_age     258
total_rooms              0
total_bedrooms        4882
population              44
households            1305
median_income         2767
median_house_value       0
ocean_proximity          0
gender                4020
dtype: int64
```

In [8]:
```
#sample of the missing values:
df[df.isnull().any(axis=1)]
```

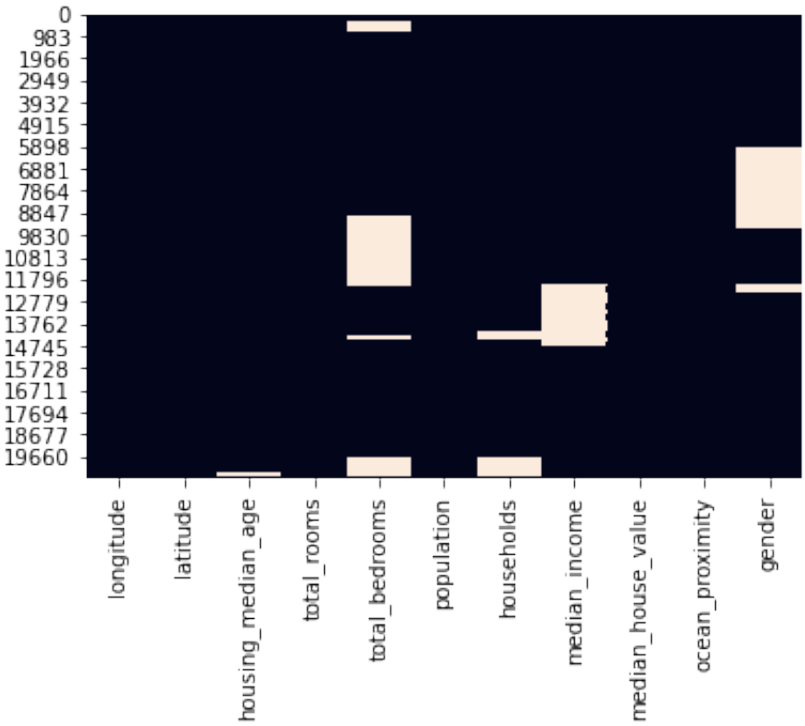
Out[8]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	h
4	-122.25	37.85	NaN	1627	280.0	NaN	
5	-122.25	37.85	NaN	919	213.0	NaN	
6	-122.25	37.84	NaN	2535	NaN	NaN	
7	-122.25	37.84	NaN	3104	NaN	NaN	
8	-122.26	37.84	42.0	2555	NaN	NaN	
...	...	...	...	...	...	...	
20627	-121.32	39.13	NaN	358	NaN	169.0	
20628	-121.48	39.10	NaN	2043	NaN	1018.0	
20629	-121.39	39.12	NaN	10035	NaN	6912.0	
20630	-121.32	39.29	NaN	2640	NaN	1257.0	
20631	-121.40	39.33	15.0	2655	493.0	1200.0	

10463 rows × 11 columns

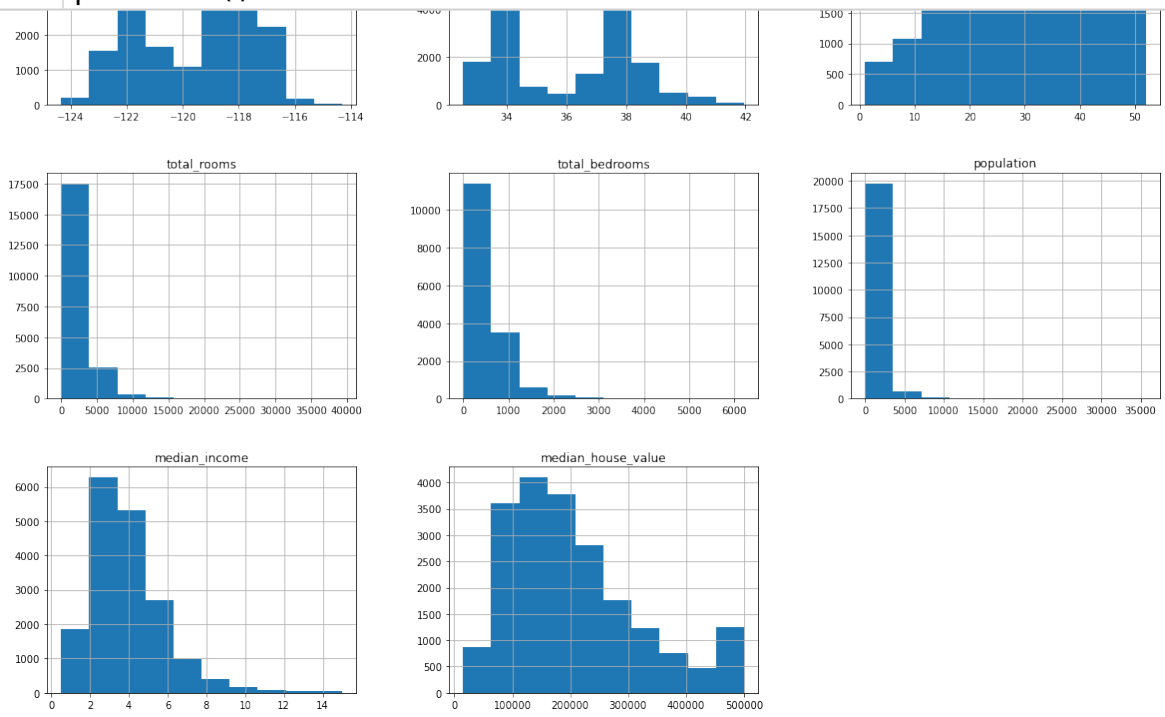
In [9]:
```
sns.heatmap(df.isnull(), cbar=False)
print("Total Missing: ", df.isna().sum().values.sum())
```

```
Total Missing:  13276
```



Data Visualization Before:

In [10]:
```
df.hist(figsize=(20,15))
plt.show()
```

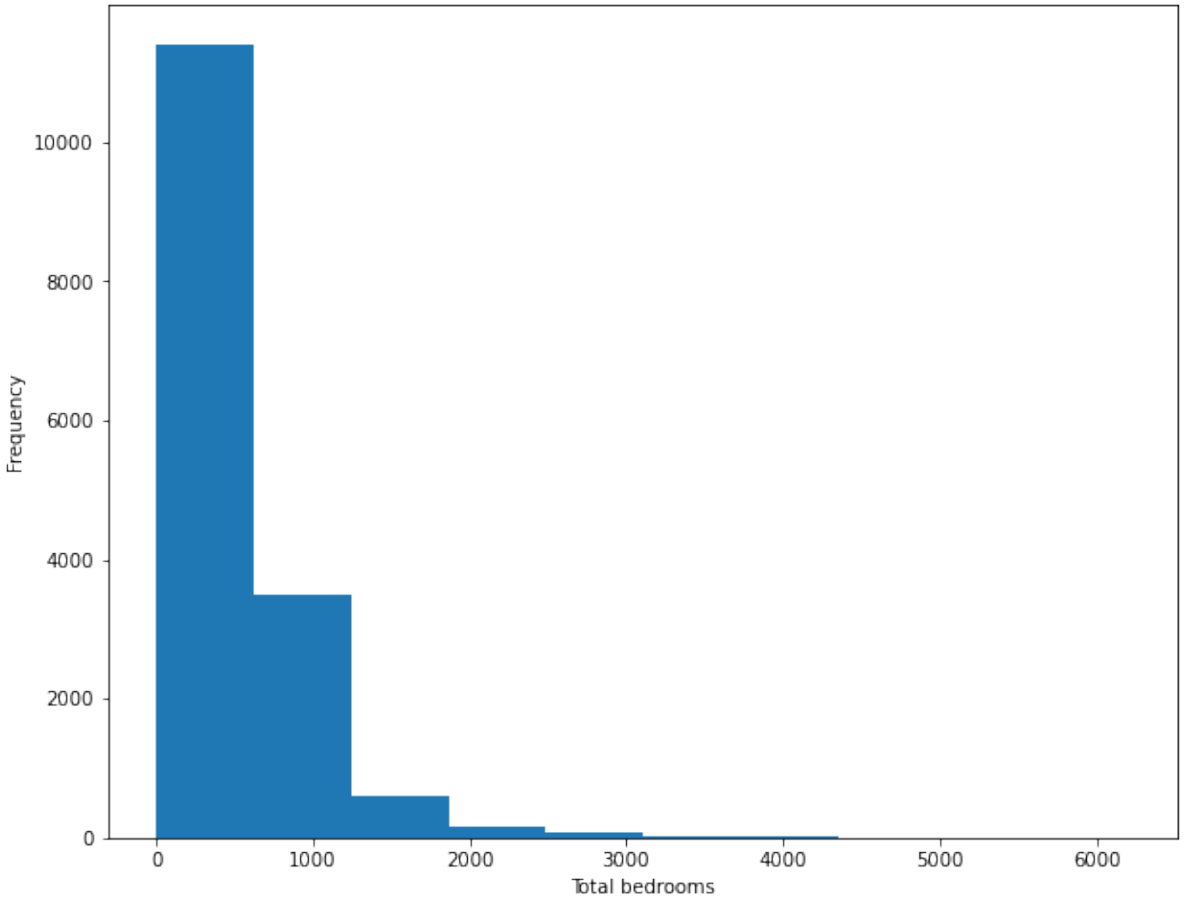


Most houses have bedrooms between 0 to 1000.

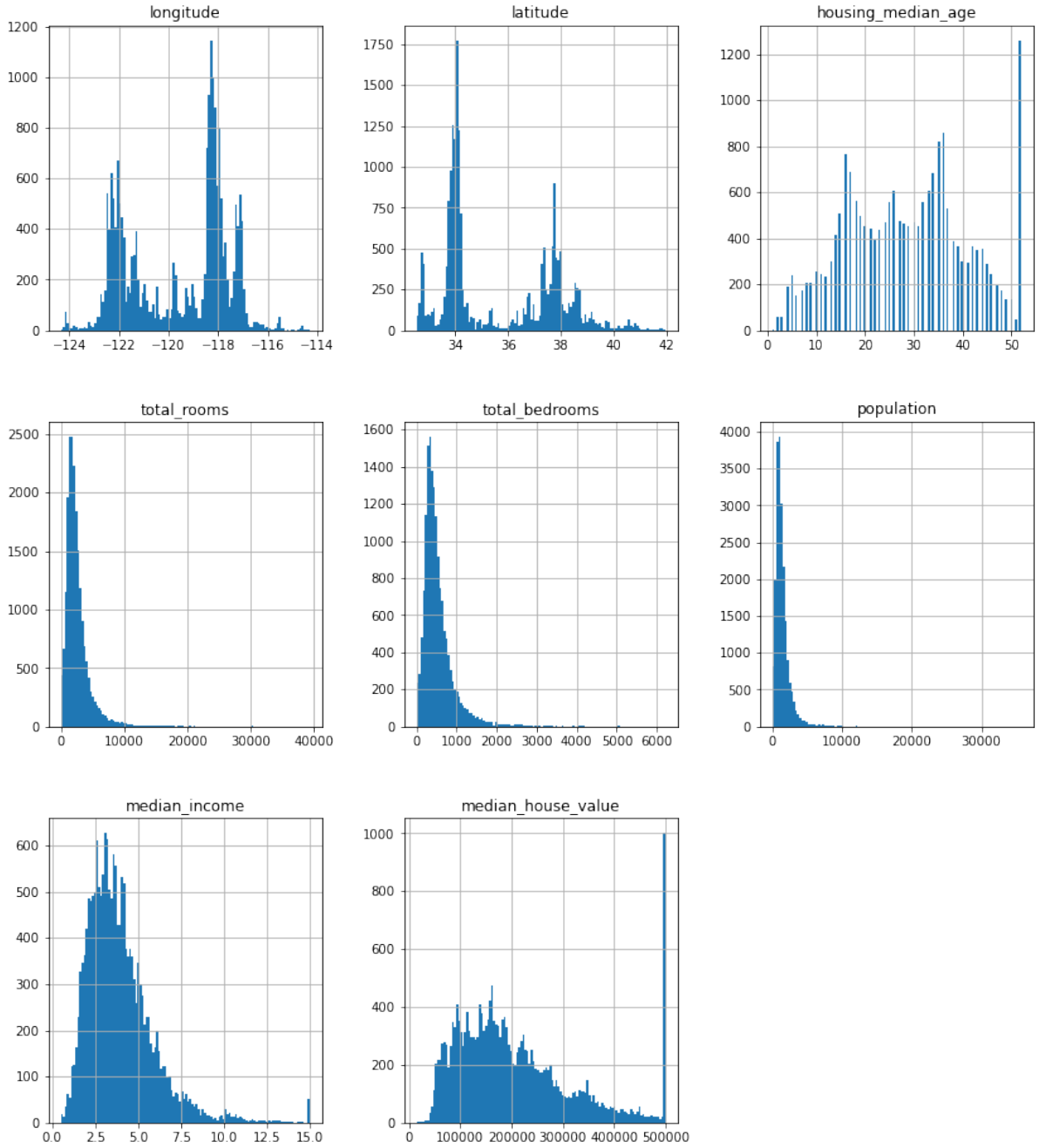
Houses with more than 1000 room are rare.

In [11]:
```
plt.figure(figsize=(10,8))
df['total_bedrooms'].plot(kind='hist')
plt.xlabel('Total bedrooms')
```

Out[11]: Text(0.5, 0, 'Total bedrooms')

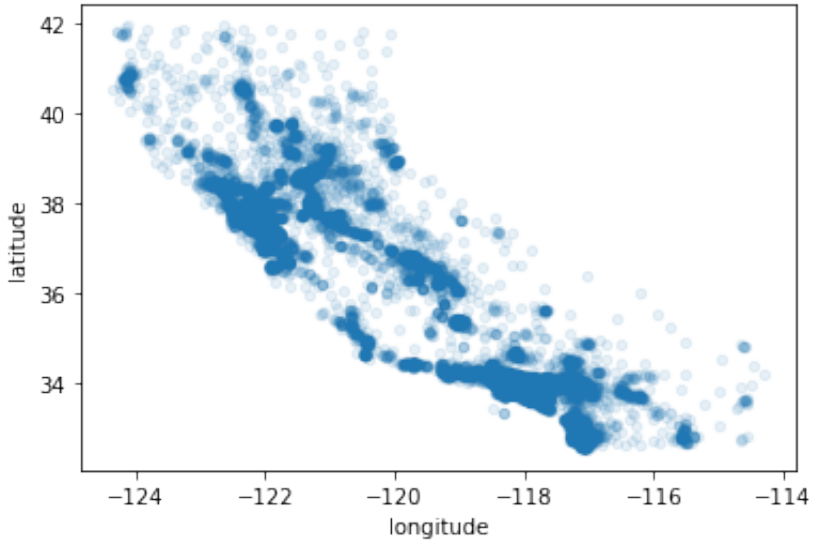


In [12]:
```
df.hist(bins=120, figsize = (14,16))
plt.show()
```



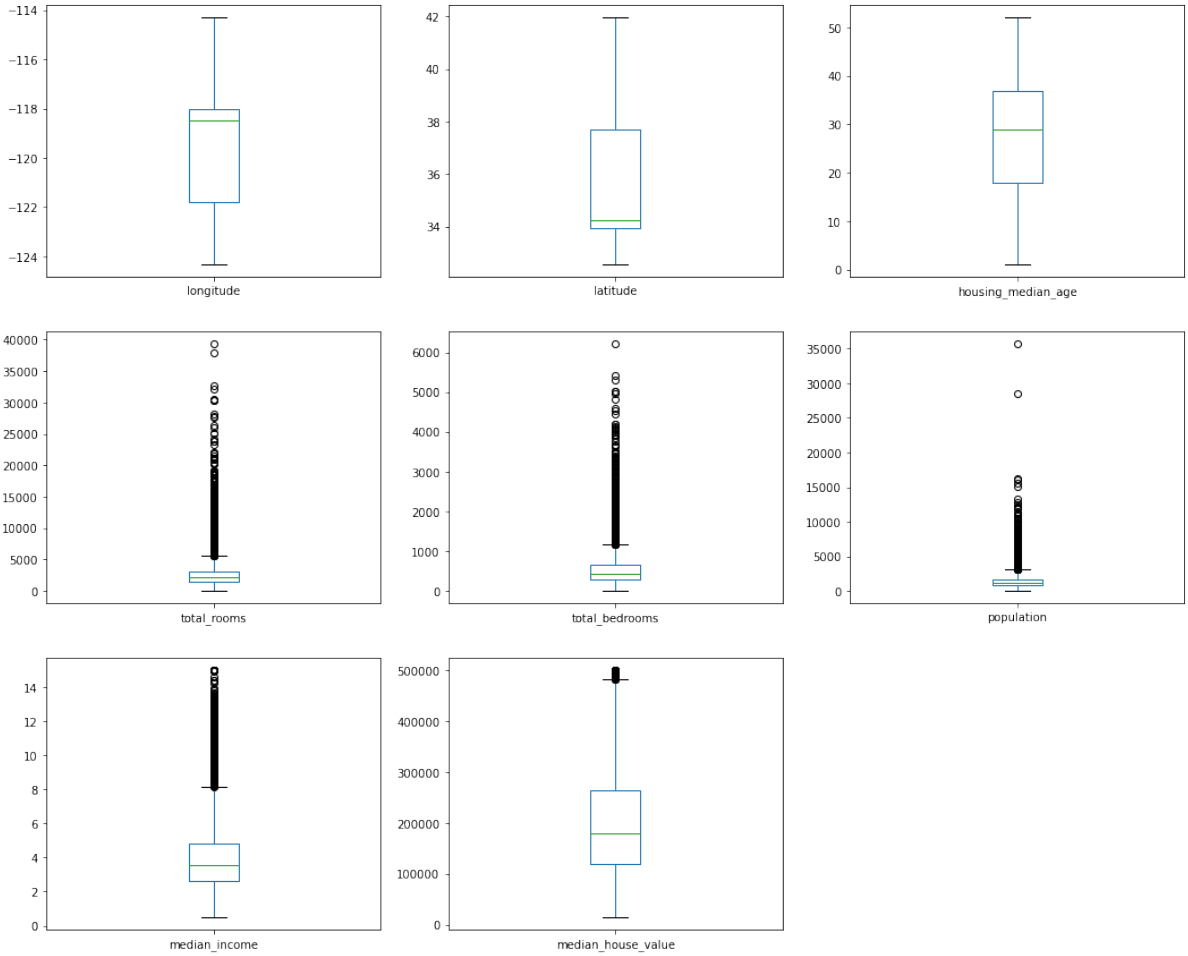
In [13]:
```
df.plot(kind='scatter', x='longitude', y='latitude', alpha = 0.
```

Out[13]: <AxesSubplot:xlabel='longitude', ylabel='latitude'>



Outliers:

In [14]:
```
df.plot(kind='box', subplots = True, figsize=(18,15),layout=(3,
plt.show()
```



Dropping unnecessary data:

In [15]:
```
df.columns
```

Out[15]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms
',
       'total_bedrooms', 'population', 'households', 'median_incom
e',
       'median_house_value', 'ocean_proximity', 'gender'],
      dtype='object')
```

Dropping the gender column:

In [16]:
```
df = df[['longitude', 'latitude', 'housing_median_age', 'total_
       'total_bedrooms', 'population', 'households', 'median_in
       'median_house_value', 'ocean_proximity']]
df.head(1)
```

Out[16]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	house
0	-122.23	37.88	41.0	880	129.0	322.0	

Handelling the missing data:

In [17]:
```
df['total_bedrooms'].mode()
```

Out[17]:
```
0    280.0
dtype: float64
```

In [65]:
```
df.loc[df['total_bedrooms'].isna(),'total_bedrooms']=df['total_
```

In [19]:
```
df.loc[df['median_income'].isna(),'median_income']=df['median_i
```

In [20]:
```
df[(df['population']>4000)]
```

Out[20]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	h
185	-122.23	37.79	43.0	5963	1344.000000	4367.0	
283	-122.16	37.79	22.0	12842	2048.000000	4985.0	
570	-122.24	37.72	5.0	18634	539.920104	7427.0	
576	-122.06	37.77	12.0	14316	539.920104	5781.0	
780	-122.10	37.63	18.0	9963	539.920104	5613.0	
...	...	...	...	...	...	...	...
20530	-121.76	38.57	NaN	15018	539.920104	7984.0	
20539	-121.71	38.56	NaN	8627	539.920104	4071.0	
20544	-121.76	38.55	NaN	8800	539.920104	6330.0	
20563	-121.75	38.67	NaN	12139	539.920104	6837.0	
20629	-121.39	39.12	NaN	10035	539.920104	6912.0	

582 rows × 10 columns

In [29]:
```
df.loc[df['population'].isna(),'population']=df['population'].m
```

In [30]:
```

df.loc[df['housing_median_age'].isna(),'housing_median_age']=df
```

In [31]:
```
df.head(3)
```

Out[31]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	house
0	-122.23	37.88	41.0	880	129.0	322.0	
1	-122.22	37.86	21.0	7099	1106.0	2401.0	
2	-122.24	37.85	52.0	1467	190.0	496.0	

In [40]:
```
df = df[df.isnull().sum(axis=1) < 3]
```

In [41]:
```
df
```

Out[41]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
0	-122.23	37.88	41.000000	880	129.0	322.000000
1	-122.22	37.86	21.000000	7099	1106.0	2401.000000
2	-122.24	37.85	52.000000	1467	190.0	496.000000
3	-122.25	37.85	52.000000	1274	235.0	558.000000
4	-122.25	37.85	28.676283	1627	280.0	1424.928724
...	...	...	...	...	...	...
20635	-121.09	39.48	25.000000	1665	374.0	845.000000
20636	-121.21	39.49	18.000000	697	150.0	356.000000
20637	-121.22	39.43	17.000000	2254	485.0	1007.000000
20638	-121.32	39.43	18.000000	1860	409.0	741.000000
20639	-121.24	39.37	16.000000	2785	616.0	1387.000000

20640 rows × 10 columns

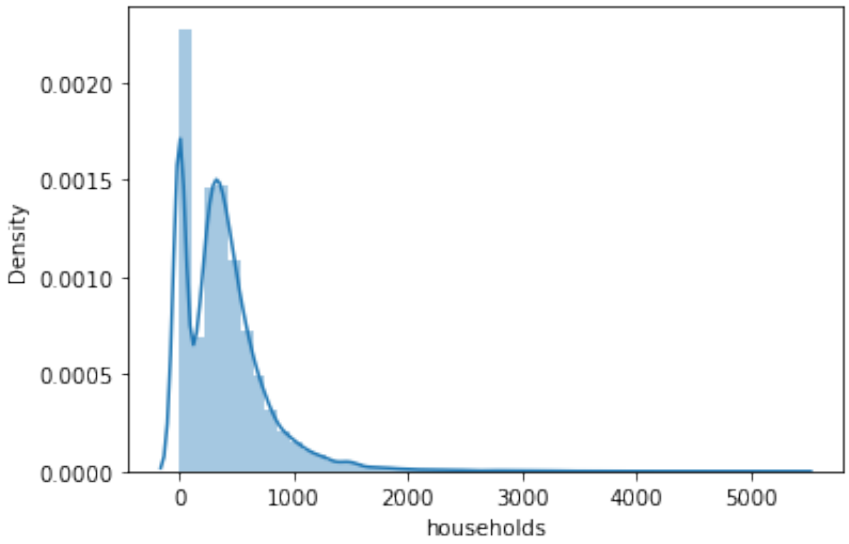
In [42]:
```
df["households"]=df['households'].fillna(df["households"].mode(
```

In [43]:
```
df.replace('no'     ,0,inplace=True)
```

In [44]:
```
1 sns.distplot(df["households"])
```

```
/Users/omniaelmenshawy/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[44]: <AxesSubplot:xlabel='households', ylabel='Density'>

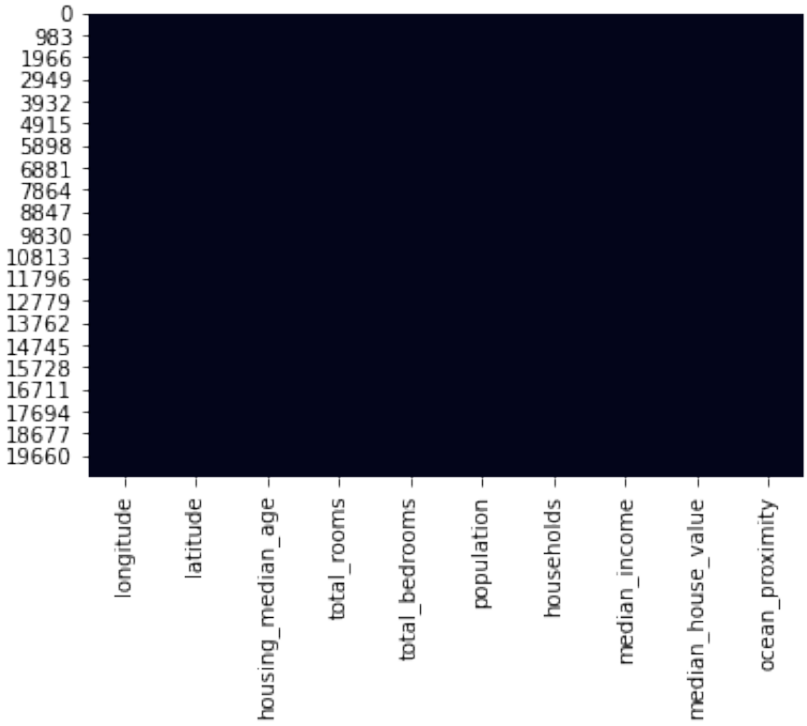


In [45]:
```
1 print(df.isnull().sum())
```

```
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
```

In [46]:
```
sns.heatmap(df.isnull(), cbar=False)
print("Total Missing: ", df.isna().sum().values.sum())
```

```
Total Missing:  0
```



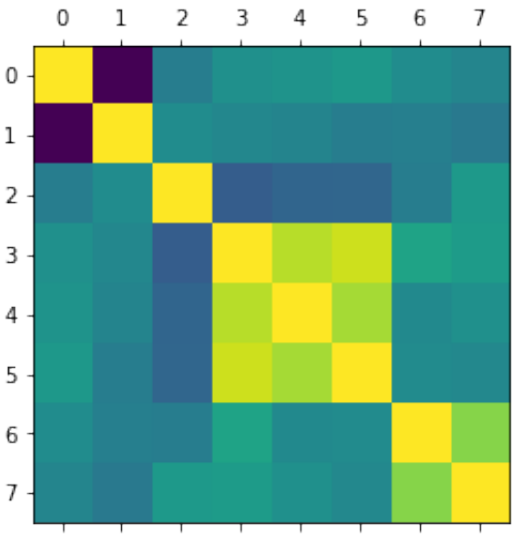
Correlation:

- the median house value is positivily correlated with the median income and has a great impact
- while it is negatively correlated with the:
  - latitude: the value decreases when we go north
  - longitude: the value also decreases when we go west
  - population: the value decreases when the total number of people living in the block increases

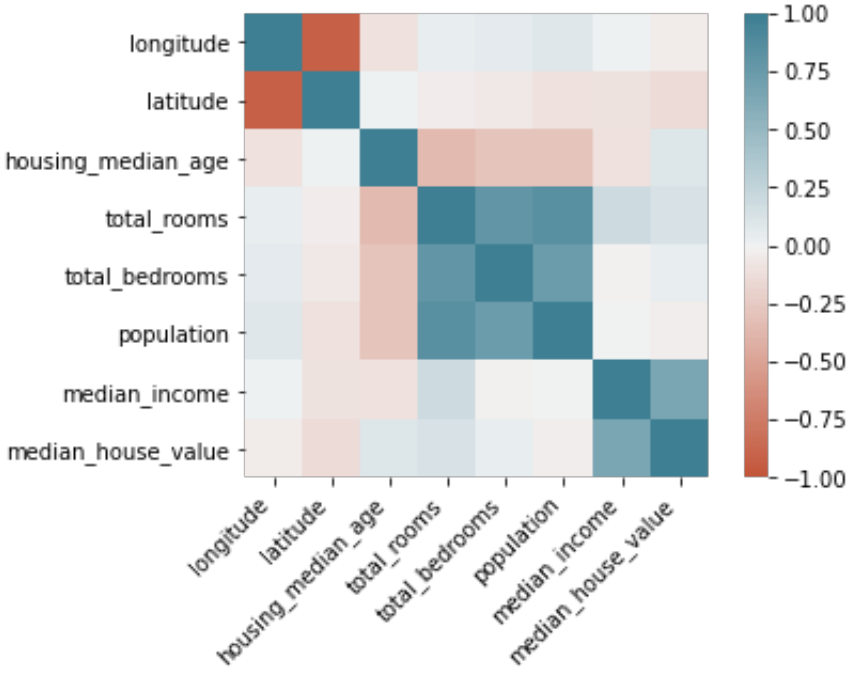
In [49]:
```
corr_matrix = df.corr()
corr_matrix["median_house_value"].sort_values(ascending = False
```

Out[49]:
```
median_house_value    1.000000
median_income         0.650304
total_rooms           0.134153
housing_median_age    0.106648
total_bedrooms        0.044949
population           -0.024351
longitude            -0.045967
latitude             -0.144160
Name: median_house_value, dtype: float64
```

In [51]:
```
plt.matshow(df.corr())
plt.show()
```

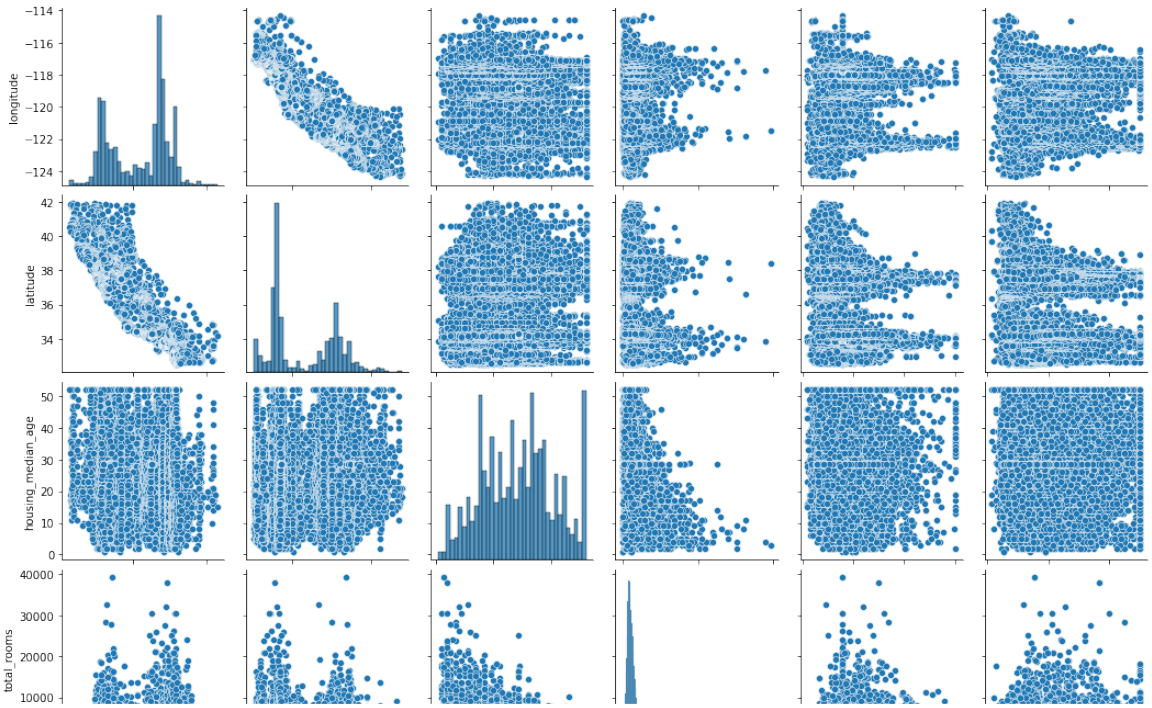


In [53]:
```
corr = df.corr()
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200),
    square=True
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
```



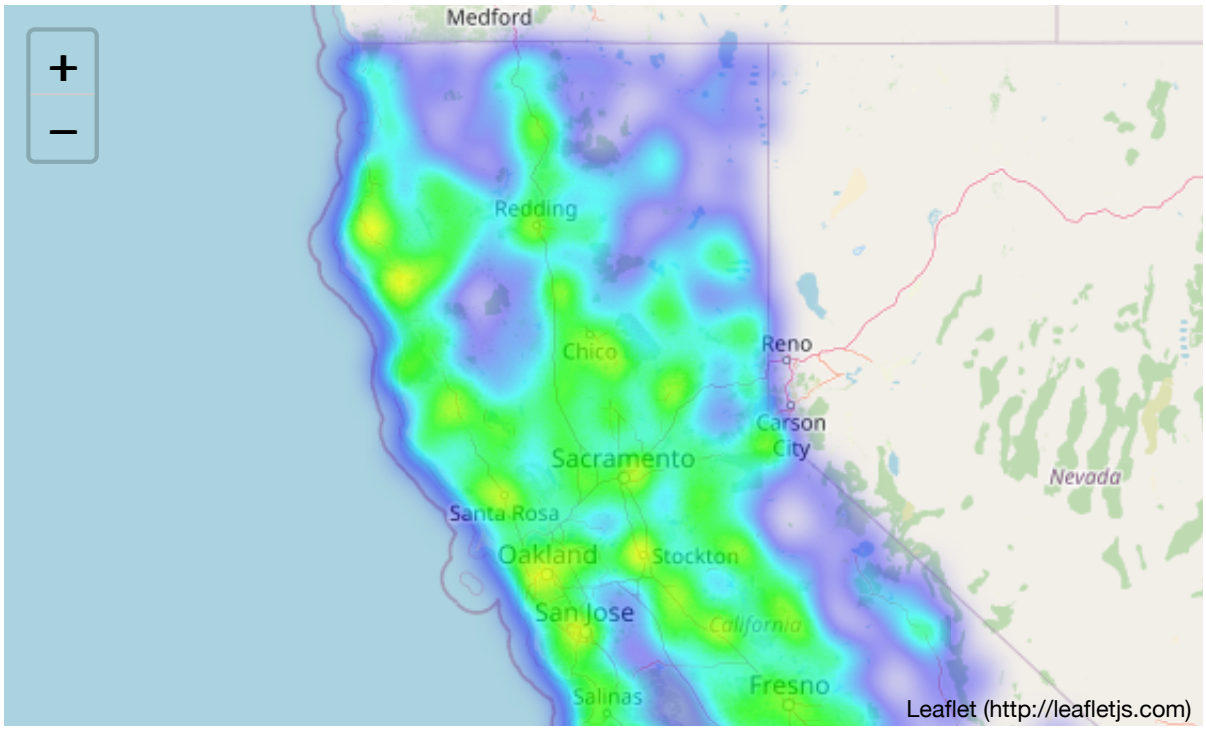
Data Visualization after Handelling it:

In [58]:
```
column_study = ["longitude", "latitude", "housing_median_age",
sns.pairplot(df[column_study], height = 2.5);
plt.show()
```



In [113]:
```
import folium
from folium.plugins import HeatMap, MarkerCluster
from folium import Choropleth, Circle, Marker


cal_map = folium.Map(location=[36.7783,-119.4179], zoom_start =
df_map = df[['latitude', 'longitude']]
data = [[row['latitude'],row['longitude']] for index, row in df
_ = HeatMap(data, radius=10).add_to(cal_map)
cal_map
```

Out[113]:

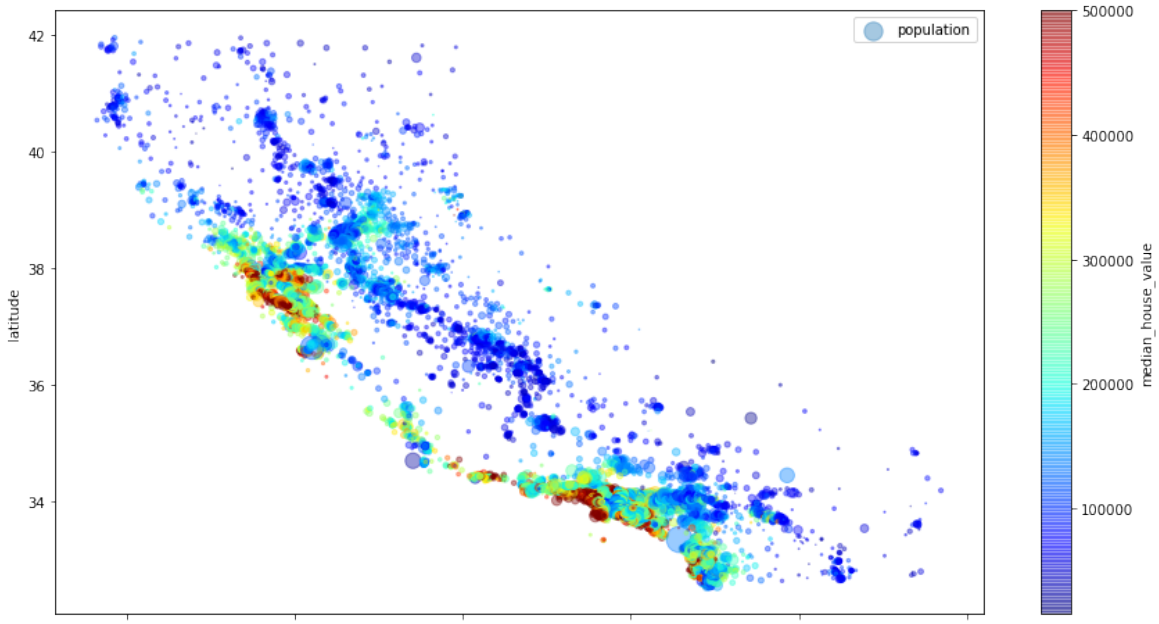


shape of price distribution by the latitude and longitude:

- high-density areas are:
  - the Bay Area
  - around Los Angeles and San Diego
  - plus a long line of fairly high density in the Central Valley, around Sacramento and Fresno.

In [152]:
```
df.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,
 s=df["population"]/100, label="population", figsize=(15,8),
 c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=Tru
)
plt.legend()
```

Out[152]: <matplotlib.legend.Legend at 0x7fbf022ef850>



In [153]:
```
nearbay_df = df.loc[df['ocean_proximity'] == 'NEAR BAY']
nearbay_df.head()
```

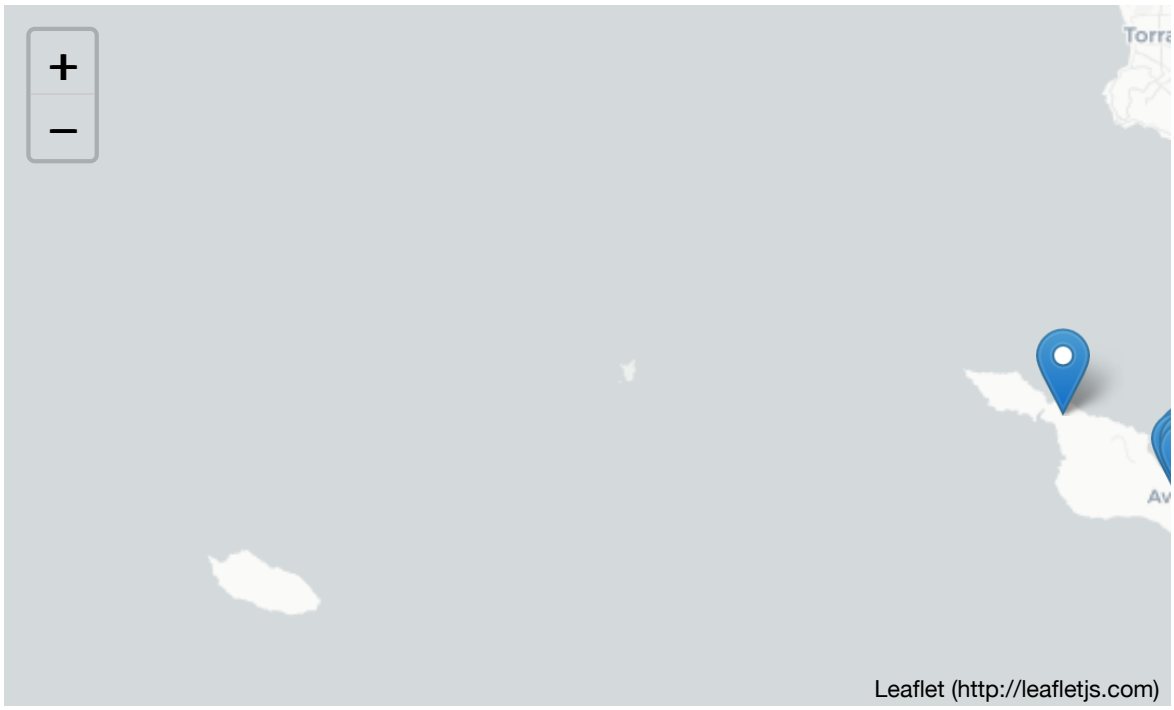
Out[153]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	hous
0	-122.23	37.88	41.000000	880	129.0	322.000000	
1	-122.22	37.86	21.000000	7099	1106.0	2401.000000	
2	-122.24	37.85	52.000000	1467	190.0	496.000000	
3	-122.25	37.85	52.000000	1274	235.0	558.000000	
4	-122.25	37.85	28.676283	1627	280.0	1424.928724	

In [ ]:
```

```

In [108]:
```
latitude = 36.7783
longitude = -119.4179
island_df = df.loc[df['ocean_proximity'] == 'ISLAND']

m = folium.Map(location = [latitude, longitude], tiles='cartodb
for idx, row in island_df.iterrows():
    Marker([row['latitude'], row['longitude']]).add_to(m)
m
```

Out[108]:



Maximum Values around the 500001 Dollar and they are all near the ocean

In [132]:
```
print("House statistics:\n")
print(df['median_house_value'].describe())
```

```
House statistics:

count     20640.000000
mean     206855.816909
std      115395.615874
min       14999.000000
25%      119600.000000
50%      179700.000000
75%      264725.000000
max      500001.000000
Name: median_house_value, dtype: float64
```

Linear Regression and Training:

In [133]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [134]:
```
df.columns
```

Out[134]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms
',
       'total_bedrooms', 'population', 'households', 'median_incom
e',
       'median_house_value', 'ocean_proximity'],
      dtype='object')
```

In [135]:
```
Training = df[['longitude', 'latitude', 'housing_median_age', '
       'total_bedrooms', 'population', 'households', 'median_in
       'median_house_value']]
```

In [136]:
```
x = Training.drop(['median_house_value'],axis = 1).values
y = Training["median_house_value"].values
```

In [137]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_si
```

In [138]:
```
x_train.shape
```

Out[138]:
```
(15480, 8)
```

In [139]:
```
x_test.shape
```

Out[139]:
```
(5160, 8)
```

In [140]:
```
y_train.shape
```

Out[140]:
```
(15480,)
```

In [141]:
```
y_test.shape
```

Out[141]:
```
(5160,)
```

In [142]:
```
100*x_test.shape[0]/x_train.shape[0]
```

Out[142]:
```
33.333333333333336
```

In [143]:
```
lr = LinearRegression()
lr.fit(x_train, y_train)
y_predict = lr.predict(x_test)
```

In [145]:
```
y_predict = lr.predict(x_test)
```

In [146]:
```
lr.score(x_train, y_train)
```

Out[146]:
```
0.5868339060852498
```

In [147]:
```
lr.score(x_test,y_test)
```

Out[147]:
```
0.581149194438561
```

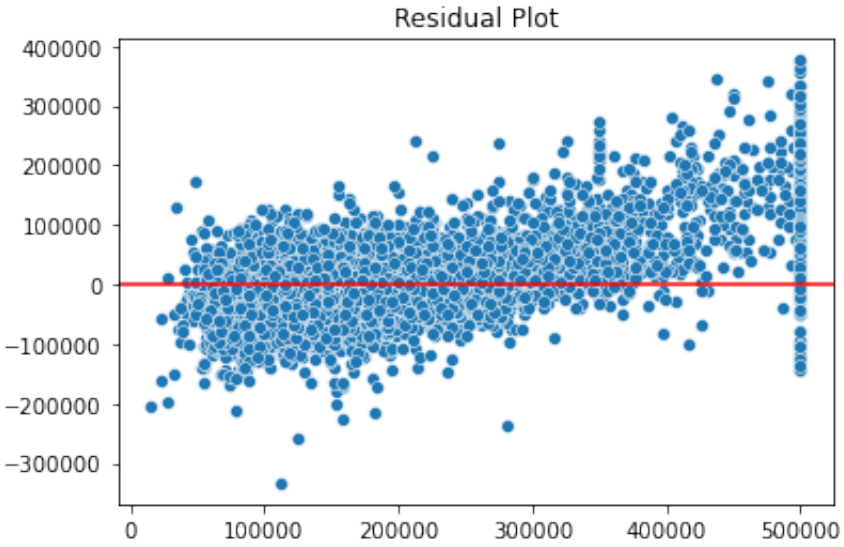
Model Visualization:

Errors are close to normal distribution and also the mean is pretty close to zero

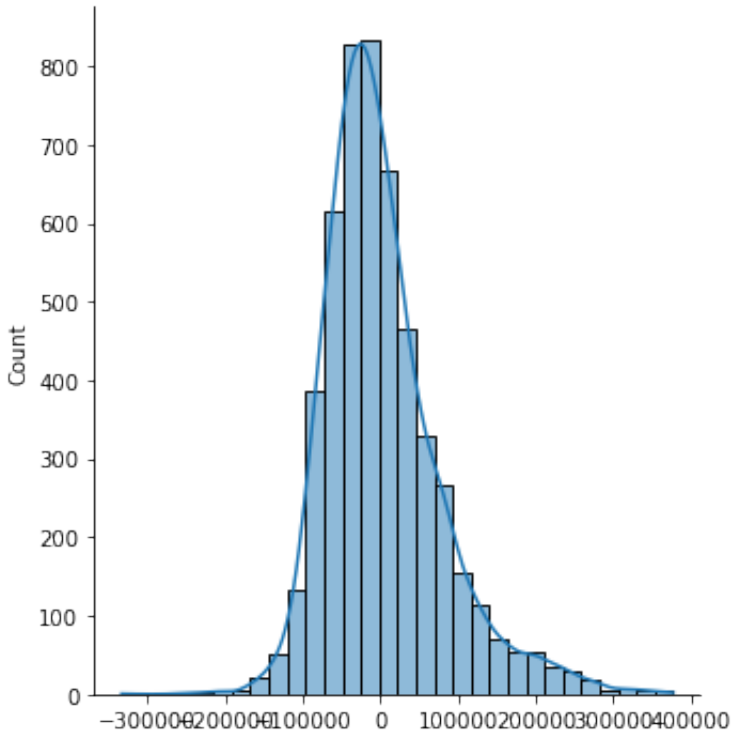
In [116]:
```
test_residuals = y_test - y_predict
test_residuals

```

Out[116]:
```
array([ 11185.38093889, -61306.43844511,  13715.36551086, ...,
       -49592.36875296, -73804.00073398, -84994.9557901 ])
```

In [117]:
```
sns.scatterplot(x=y_test,y=test_residuals)
plt.axhline(y=0,color='red')
plt.title('Residual Plot');
```



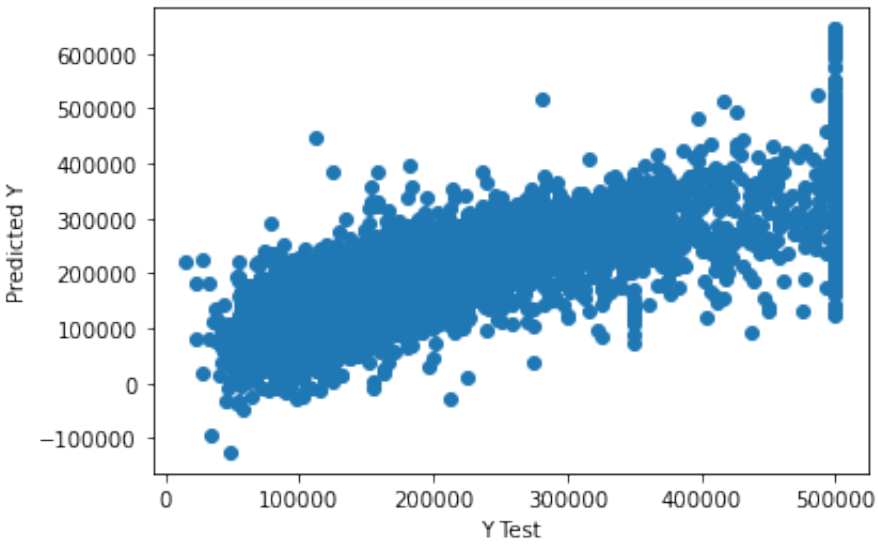
In [148]:
```
sns.displot(test_residuals,bins=30,kde=True);
```



In [149]:
```
predictions = lr.predict(x_test)
```

In [150]:
```
plt.scatter(x = y_test, y = predictions)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

Out[150]: Text(0, 0.5, 'Predicted Y')



In [ ]:
```

```