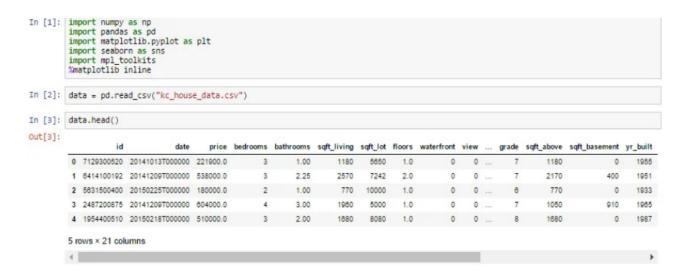
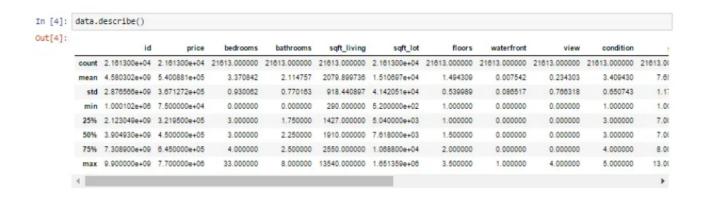
First thing first, we import our libraries and dataset and then we see the head of the data to know how the data looks like and use describe function to see the percentile's and other key statistics.





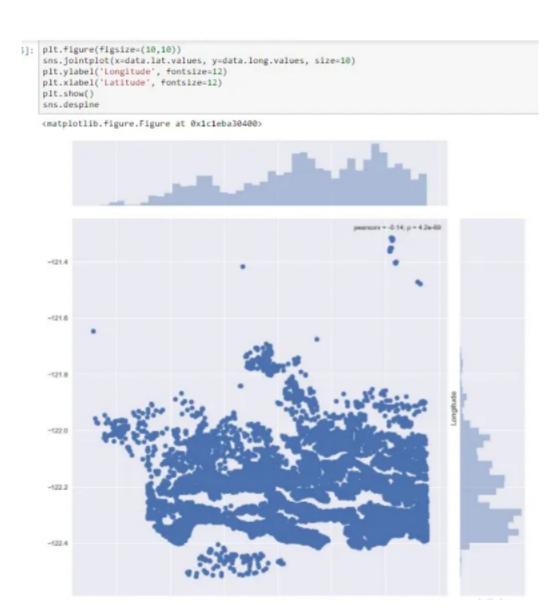
Look at the bedroom columns, the dataset has a house where the house has 33 bedrooms, seems to be a massive house and would be interesting to know more about it as we progress.

- 1.Maximum square feet is 13,450 where as the minimum is 290. we can see that the data is distributed.
- 2.Now, we are going to see some visualization and also going to see how and what can we infer from visualization.
- 3.Let's see which is most common bedroom number. You may wonder why is it important? Let's look at this problem from a builder's perspective, sometimes it's important for a builder to see which is the highest selling house type which enables the builder to make house based on that. Here in India, for a good locality a builder

opts to make houses which are more than 3 bedrooms which attracts the higher middle class and upper class section of the society.



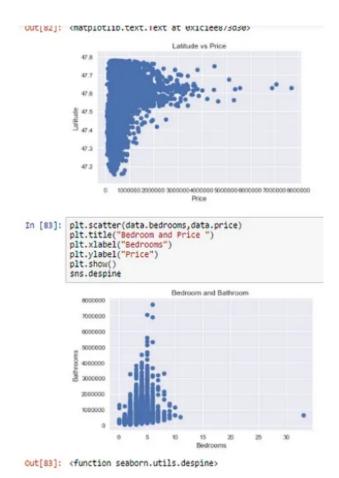
So according to the dataset , we have latitude and longitude on the dataset for each house. We are going to see the common location and how the houses are placed.



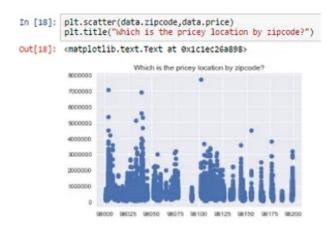
We saw the common locations and now we're going to see few common factors affecting the prices of the house and if so? then by how much?

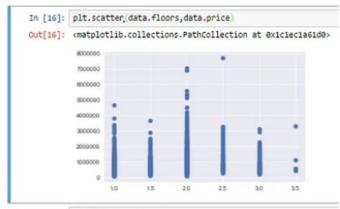


The plot that we used above is called scatter plot, scatter plot helps us to see how our data points are scattered and are usually used for two variables. From the first figure we can see that more the living area, more the price though data is concentrated towards a particular price zone, but from the figure we can see that the data points seem to be in linear direction. Thanks to scatter plot we can also see some irregularities that the house with the highest square feet was sold for very less, maybe there is another factor or probably the data must be wrong. The second figure tells us about the location of the houses in terms of longitude and it gives us quite an interesting observation that -122.2 to -122.4 sells houses at much higher amount.



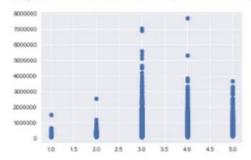
We can see more factors affecting the price





In [17]: plt.scatter(data.condition,data.price)

Out[17]: cmatplotlib.collections.PathCollection at 0x1c1ec214630>



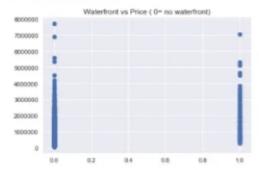
In [84]: plt.scatter((data['sqft_living']+data['sqft_basement']),data['price'])

Out[84]: <matplotlib.collections.PathCollection at 0x1c1edfea160>



In [12]: plt.scatter(data.waterfront,data.price)
plt.title("Waterfront vs Price (0= no waterfront)")

Out[12]: <matplotlib.text.Text at 0x1c1eb8a87f0>



ex.no-4
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go

data = pd.read_csv("House_Rent_Dataset.csv")
print(data.head())

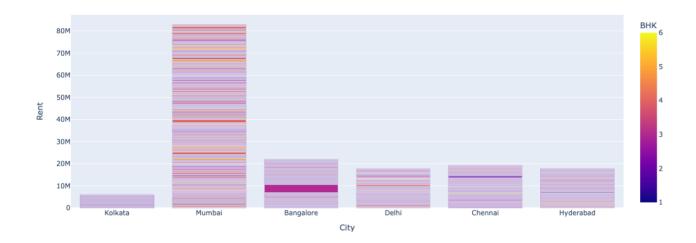
```
Posted On
               BHK
                     Rent
                           Size
                                            Floor
                                                     Area Type \
 2022-05-18
                 2
                   10000
                           1100
                                 Ground out of 2
                                                    Super Area
1 2022-05-13
                 2
                    20000
                                      1 out of 3
                            800
                                                    Super Area
                                      1 out of 3
2 2022-05-16
                 2
                    17000
                           1000
                                                    Super Area
 2022-07-04
                 2
                                      1 out of 2
                                                    Super Area
3
                    10000
                            800
  2022-05-09
                                      1 out of 2 Carpet Area
                 2
                     7500
                            850
              Area Locality
                                City Furnishing Status Tenant Preferred
0
                     Bandel
                             Kolkata
                                            Unfurnished
                                                         Bachelors/Family
1
   Phool Bagan, Kankurgachi
                             Kolkata
                                         Semi-Furnished Bachelors/Family
2
    Salt Lake City Sector 2
                             Kolkata
                                         Semi-Furnished Bachelors/Family
                                            Unfurnished Bachelors/Family
3
                Dumdum Park
                             Kolkata
4
              South Dum Dum Kolkata
                                            Unfurnished
                                                                Bachelors
   Bathroom Point of Contact
0
          2
               Contact Owner
          1
1
               Contact Owner
2
          1
               Contact Owner
               Contact Owner
3
          1
          1
               Contact Owner
4
```

print(data.isnull().sum())

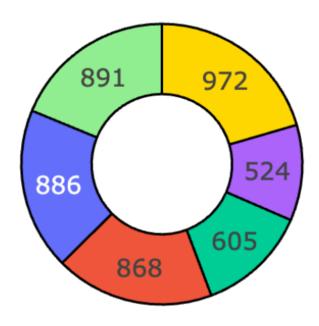
Posted On	0
ВНК	0
Rent	0
Size	0
Floor	0
Area Type	0
Area Locality	0
City	0
Furnishing Status	0
Tenant Preferred	0
Bathroom	0
Point of Contact	0
dtype: int64	

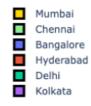
print(data.describe())

	ВНК	Rent	Size	Bathroom
count	4746.000000	4.746000e+03	4746.000000	4746.000000
mean	2.083860	3.499345e+04	967.490729	1.965866
std	0.832256	7.810641e+04	634.202328	0.884532
min	1.000000	1.200000e+03	10.000000	1.000000
25%	2.000000	1.000000e+04	550.000000	1.000000
50%	2.000000	1.600000e+04	850.000000	2.000000
75%	3.000000	3.300000e+04	1200.000000	2.000000
max	6.000000	3.500000e+06	8000.000000	10.000000



cities = data["City"].value_counts()
label = cities.index
counts = cities.values
colors = ['gold','lightgreen']





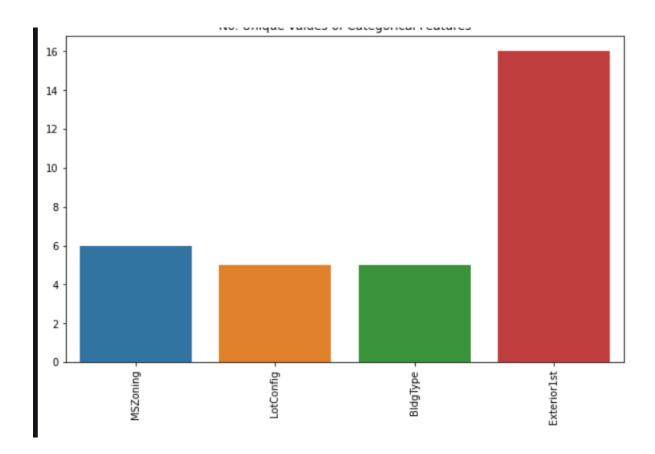
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
dataset = pd.read_excel("HousePricePrediction.csv")
print(dataset.head(5))

	MSSubClass M	SZoning	LotArea	LotConfig	BldgType	OverallCond	YearBuilt
0	60	RL	8450	Inside	1Fam	5	2003
1	20	RL	9600	FR2	1Fam	8	1976
2	60	RL	11250	Inside	1Fam	5	2001
3	70	RL	9550	Corner	1Fam	5	1915
4	60	RL	14260	FR2	1Fam	5	2000
	YearRemodAdd			ntFinSF2	TotalBsmtSF	SalePrice	
0	2003	Viny	/lSd	0.0	856.6	208500.0	
1	1976	Meta	alSd	0.0	1262.6	181500.0	
2	2002	Viny	/lSd	0.0	920.6	223500.0	
3	1970	Wd S	dng	0.0	756.6	140000.0	
4	2000	Viny	/lSd	0.0	1145.6	250000.0	

```
plt.figure(figsize=(12, 6))
sns.heatmap(dataset.corr(),
cmap = 'BrBG',
fmt = '.2f',
linewidths = 2,
annot = True)
```

											-1.0
ld -	1.00	0.01	-0.04	-0.00	-0.02	-0.05	0.02	-0.02	-0.02		
MSSubClass -	0.01	1.00	-0.20	-0.07	0.03	0.04	-0.07	-0.22	-0.08		- 0.8
LotArea -	-0.04	-0.20	1.00	-0.04	0.02	0.02	0.08	0.25	0.26		- 0.6
OverallCond -	-0.00	-0.07	-0.04	1.00	-0.37	0.05	0.04	-0.17	-0.08		- 0.4
YearBuilt -	-0.02	0.03	0.02	-0.37	1.00	0.61	-0.03	0.41	0.52		0.4
YearRemodAdd -	-0.05	0.04	0.02	0.05	0.61	1.00	-0.06	0.30	0.51		- 0.2
BsmtFinSF2 -	0.02	-0.07	0.08	0.04	-0.03	-0.06	1.00	0.09	-0.01		- 0.0
TotalBsmtSF -	-0.02	-0.22	0.25	-0.17	0.41	0.30	0.09	1.00	0.61		0.2
SalePrice -	-0.02	-0.08	0.26	-0.08	0.52	0.51	-0.01	0.61	1.00		
	- pl	MSSubClass -	LotArea -	OverallCond -	YearBuilt -	NearRemodAdd -	BsmtFinSF2 -	TotalBsmtSF -	SalePrice -	'	

unique_values = []
for col in object_cols:
 unique_values.append(dataset[col].unique().size)
plt.figure(figsize=(10,6))
plt.title('No. Unique values of Categorical Features')
plt.xticks(rotation=90)
sns.barplot(x=object_cols,y=unique_values)



Ex.6:

import sklearn
from sklearn.datasets import load_diabetes
import pandas as pd
import matplotlib.pyplot as plt

diabetics = load_diabetes()
column_name = diabetics.feature_names
df_diabetics = pd.DataFrame(diabetics.data)
df_diabetics.columns = column_name
df_diabetics.head()

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.019907	-0.017646
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.068332	-0.092204
2	0.085299	0.050680	0.044451	-0.005670	-0.045599	-0.034194	-0.032356	-0.002592	0.002861	-0.025930
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.022688	-0.009362
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.031988	-0.046641

fig, ax = plt.subplots(figsize = (6,4))
ax.scatter(df_diabetics['bmi'],df_diabetics['bp'])

x-axis label
ax.set_xlabel('(body mass index of people)')

y-axis label
ax.set_ylabel('(bp of the people)')
plt.show()

