HOUSING PRICE PREDICTION

Platform - ANACONDA
Programming Language – PYTHON

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INDEX

OBJECTIVE

- A Real estate company that runs a website for buying and selling of houses, they would like to give the customers a prediction of the cost of the houses in a few years.
- We have to use the housing data,we have to pre-process it, and have to create a model that will predict the price of the house and will measure the accuracy of the model.

IMPORTING LIBRARIES

Housing Price Prediction

(using LinearRegression Model)

- HARSH YADAV

```
In [ ]:
```

IMPORTING LIBRARIES & DATASET

```
In [1]: import pandas as pd             # to import dataset and create data frames
        import numpy as np              # for solving complex mathematical problems
        import matplotlib.pyplot as plt   # tool for data visualization & representation
        import seaborn as sns # based on matplotlib, but with more colourful themes
        import sklearn


        import statsmodels.api as smapi
        from sklearn.linear_model import LinearRegression
        # NOTE: we can use any of the above library for linear regression model,
        #       but i am using scikit_learn because its best for big data (no. of observations > 1000)
```

```
In [2]: data = pd.read_csv(r"C:\Users\anika\OneDrive\Desktop\data_science\Housing Price Prediction.csv")
```

EXPLORING DATA

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EXPLORING DATA

In [3]: `data.head()`

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_bu
0	9106000005	5/27/2015	1310000.0	4	2.25	3750	5000	2.0	0	0	...	8	2440	1310	19
1	5101400871	5/24/2015	445500.0	2	1.75	1390	6670	1.0	0	0	...	6	720	670	19
2	7923600250	5/15/2015	450000.0	5	2.00	1870	7344	1.5	0	0	...	7	1870	0	19
3	8730000270	5/14/2015	359000.0	2	2.75	1370	1140	2.0	0	0	...	8	1080	290	20
4	9178601660	5/14/2015	1700000.0	5	3.00	3320	5354	2.0	0	0	...	9	3320	0	20

5 rows × 21 columns

In [4]: `data.describe()`

Out[4]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597.000000	21597.000000	21597.000000
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	0.007547	0.234292	3.409825
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	0.086549	0.766390	0.650546
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0.000000	0.000000	1.000000
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	0.000000	0.000000	3.000000
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.000000	3.000000
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	0.000000	0.000000	4.000000
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.000000	5.000000

In [5]: `data.info()`

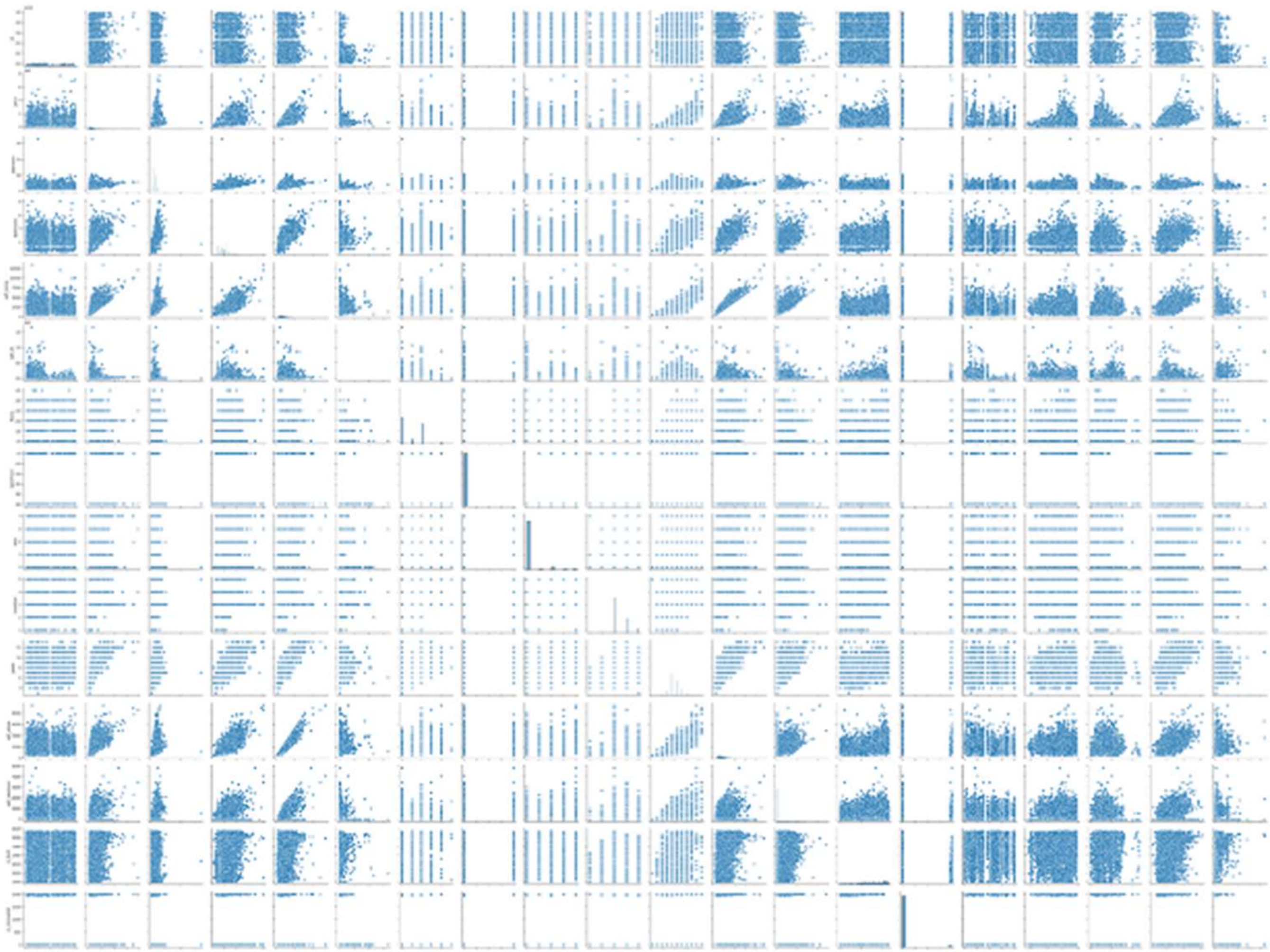
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  object
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     21597 non-null  int64
 9   view           21597 non-null  int64
 10  condition      21597 non-null  int64
 11  grade          21597 non-null  int64
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  int64
 14  yr_built       21597 non-null  int64
 15  yr_renovated   21597 non-null  int64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
```

```
In [6]: data.corr() # TO GET CORELLATION BETWEEN EVERY FEATURE OF DATASET
```

Out[6]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	s
id	1.000000	-0.016772	0.001150	0.005162	-0.012241	-0.131911	0.018608	-0.002727	0.011536	-0.023803	0.008188	-0.010799	
price	-0.016772	1.000000	0.308787	0.525906	0.701917	0.089876	0.256804	0.266398	0.397370	0.036056	0.667951	0.605368	
bedrooms	0.001150	0.308787	1.000000	0.514508	0.578212	0.032471	0.177944	-0.006834	0.080008	0.026496	0.356563	0.479386	
bathrooms	0.005162	0.525906	0.514508	1.000000	0.755758	0.088373	0.502582	0.063744	0.188386	-0.126479	0.665838	0.686668	
sqft_living	-0.012241	0.701917	0.578212	0.755758	1.000000	0.173453	0.353953	0.103854	0.284709	-0.059445	0.762779	0.876448	
sqft_lot	-0.131911	0.089876	0.032471	0.088373	0.173453	1.000000	-0.004814	0.021632	0.074900	-0.008830	0.114731	0.184139	
floors	0.018608	0.256804	0.177944	0.502582	0.353953	-0.004814	1.000000	0.023755	0.028814	-0.264075	0.458794	0.523989	
waterfront	-0.002727	0.266398	-0.006834	0.063744	0.103854	0.021632	0.023755	1.000000	0.401971	0.016611	0.082888	0.072109	
view	0.011536	0.397370	0.080008	0.188386	0.284709	0.074900	0.028814	0.401971	1.000000	0.045999	0.251728	0.167609	
condition	-0.023803	0.036056	0.026496	-0.126479	-0.059445	-0.008830	-0.264075	0.016611	0.045999	1.000000	-0.146896	-0.158904	
grade	0.008188	0.667951	0.356563	0.665838	0.762779	0.114731	0.458794	0.082888	0.251728	-0.146896	1.000000	0.756073	
sqft_above	-0.010799	0.605368	0.479386	0.686668	0.876448	0.184139	0.523989	0.072109	0.167609	-0.158904	0.756073	1.000000	
sqft_basement	-0.005193	0.323799	0.302808	0.283440	0.435130	0.015418	-0.245715	0.080559	0.277078	0.173849	0.168220	-0.052156	
yr_built	0.021617	0.053953	0.155670	0.507173	0.318152	0.052946	0.489193	-0.026153	-0.053636	-0.361592	0.447865	0.424037	
yr_renovated	-0.016925	0.126424	0.018389	0.050544	0.055308	0.007686	0.006427	0.092873	0.103951	-0.060788	0.014261	0.023251	
zipcode	-0.008211	-0.053402	-0.154092	-0.204786	-0.199802	-0.129586	-0.059541	0.030272	0.084622	0.002888	-0.185771	-0.261570	
lat	-0.001798	0.306692	-0.009951	0.024280	0.052155	-0.085514	0.049239	-0.014306	0.005871	-0.015102	0.113575	-0.001199	
long	0.020672	0.022036	0.132054	0.224903	0.241214	0.230227	0.125943	-0.041904	-0.078107	-0.105877	0.200341	0.344842	
sqft_living15	-0.002701	0.585241	0.393406	0.569884	0.756402	0.144763	0.280102	0.086507	0.280681	-0.093072	0.713867	0.731767	
sqft_lot15	-0.138557	0.082845	0.030690	0.088303	0.184342	0.718204	-0.010722	0.030781	0.072904	-0.003126	0.120981	0.195077	

```
In [92]: sns.pairplot(data)
Out[92]: <seaborn.axisgrid.PairGrid at 0x1ef40353850>
```



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checking for missing_values

In [8]:
```
data.isnull().sum()
```

Out[8]:
```
id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
```

In [9]:
```
#no null values are there
```

```
In [10]: #No need to create dummy variables
         #just we have to deal with "date" as it is of data_type = "object"
         #there are a lot ways to perform with "High Cardinallity Variables" like "Date"
         #we can:_
         #1) - Embed with Freq
         #2) - Target Encoding
         #3) - or Simply Drop
         # I am using 3rd technique here,
```

```
In [11]: data.dtypes
```

```
Out[11]: id                 int64
         date              object
         price            float64
         bedrooms           int64
         bathrooms        float64
         sqft_living        int64
         sqft_lot           int64
         floors           float64
         waterfront         int64
         view               int64
         condition          int64
         grade              int64
         sqft_above         int64
         sqft_basement      int64
         yr_built           int64
         yr_renovated       int64
         zipcode            int64
         lat              float64
         long             float64
         sqft_living15      int64
         sqft_lot15         int64
         dtype: object
```

Dropping the date variable, because of its "High Cardinallity"

In [12]:
```
data = data.drop(['date'],axis = 1)
```

In [13]:
```
data.head()
```

Out[13]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built
0	9106000005	1310000.0	4	2.25	3750	5000	2.0	0	0	5	8	2440	1310	1924
1	5101400871	445500.0	2	1.75	1390	6670	1.0	0	0	3	6	720	670	1941
2	7923600250	450000.0	5	2.00	1870	7344	1.5	0	0	3	7	1870	0	1960
3	8730000270	359000.0	2	2.75	1370	1140	2.0	0	0	3	8	1080	290	2009
4	9178601660	1700000.0	5	3.00	3320	5354	2.0	0	0	3	9	3320	0	2004

Removing targetted value"Price" from whole dataset"data

In [14]:
```
y = data.loc[:,"price"]
X = data.drop("price", axis = 1)
```

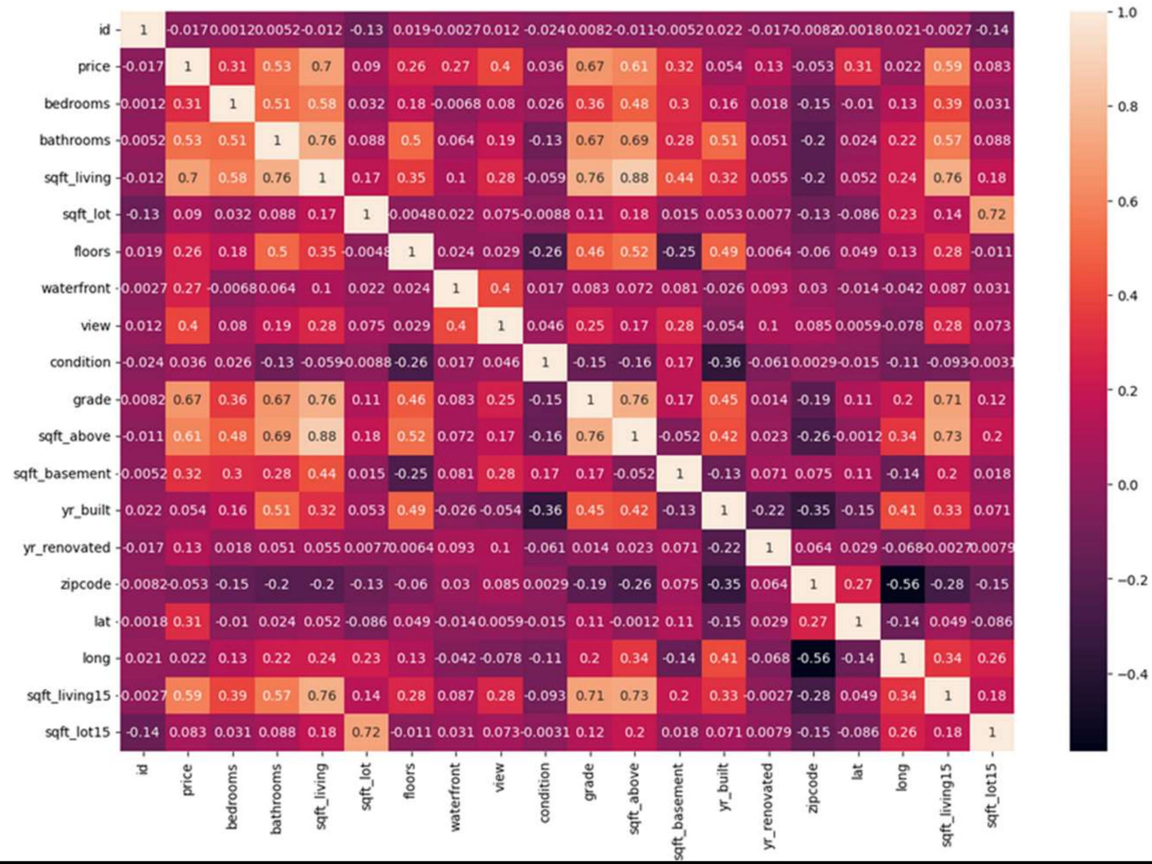
In [15]:
```
X.head()
```

Out[15]:

	id	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovat
0	9106000005	4	2.25	3750	5000	2.0	0	0	5	8	2440	1310	1924	
1	5101400871	2	1.75	1390	6670	1.0	0	0	3	6	720	670	1941	
2	7923600250	5	2.00	1870	7344	1.5	0	0	3	7	1870	0	1960	
3	8730000270	2	2.75	1370	1140	2.0	0	0	3	8	1080	290	2009	
4	9178601660	5	3.00	3320	5354	2.0	0	0	3	9	3320	0	2004	

In [17]:
```python
plt.figure(figsize = (15,10))
sns.heatmap(data.corr(), annot = True)
# HEATMAP SHOWS US THE COLLINEARITY BY VISUALISATION & COLOUR GRADING
# WHICH MAKES IT REALLY EASY TO UNDERSTAND THE RELATION BETWEEN 2 VARIABLES
# HERE, LIGHT COLOURS ARE DEPICTING GREATER CORRELATION VALUE
# & DARK COLOURS ARE DEPICTING LESSER COORELATION VALUE
```

Out[17]: <AxesSubplot:>



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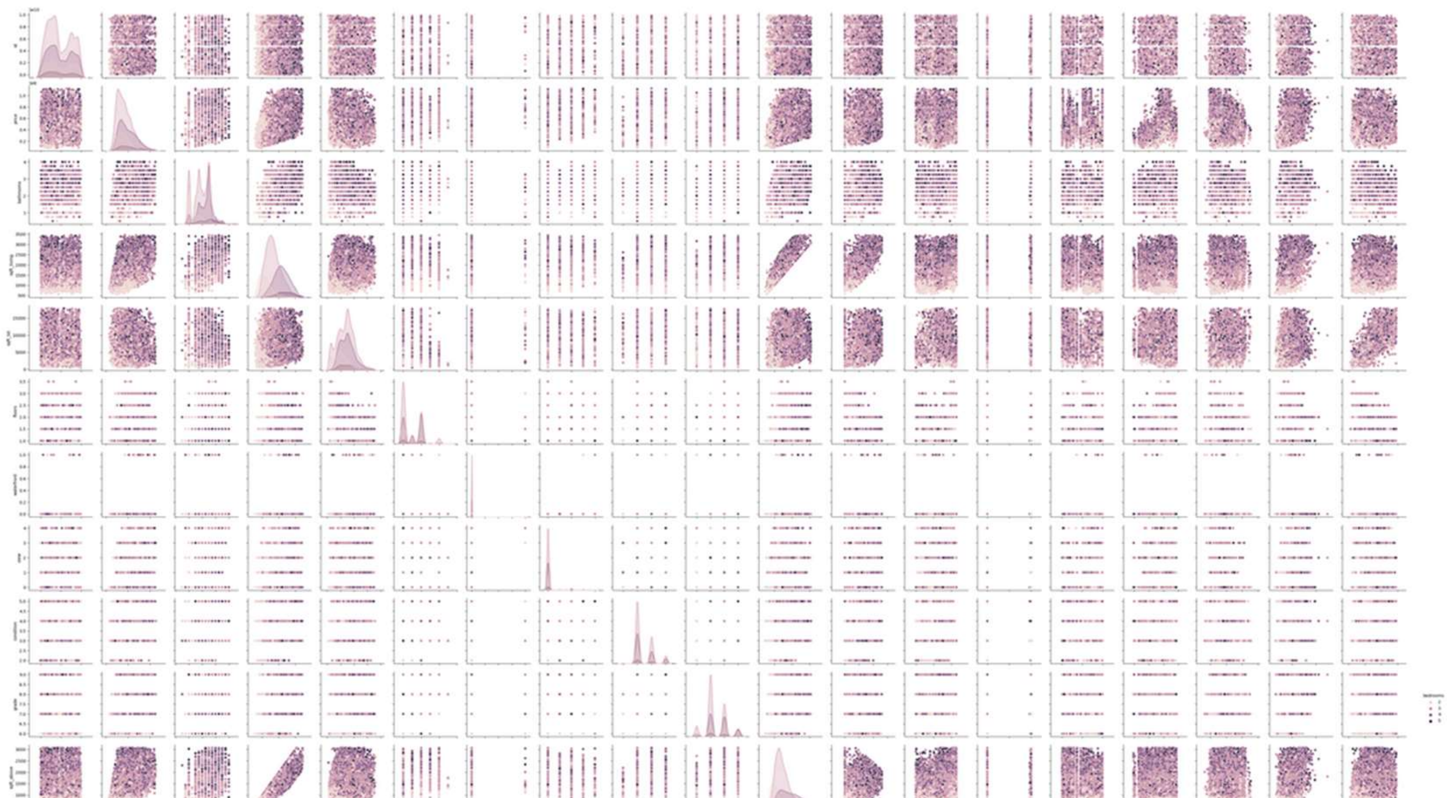
In [89]:
```
#by using 'hue' in pairplot, we can see how no. of bedrooms are corellated with other features of dataset
#we can see the prices are low for light-colored dots, that means
#dark ones are bhks like 33,10 &
#light ones are bhk's like 2,3..
sns.pairplot(df, hue = 'bed,rooms')
plt.savefig("hue")
```



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```
In [90]: # PANDAS PROFILING REPORT WILL GIVE US THE DETAILED INFO ABOUT OUR DATA
         # THIS WILL HELP US UNDERSTAND OUR DATA, FEATURES, RECORDS, CORRELATIONS, MIN, MAX, COUNT AND A LOT MORE...
         from pandas_profiling import ProfileReport
         profile = ProfileReport(data, title="Pandas Profiling Report")

In [91]: profile.to_file("your_report.html")
```

```
Summarize dataset: 100%           323/323 [01:24<00:00, 3.44it/s, Completed]

Generate report structure: 100%   1/1 [00:08<00:00, 8.23s/it]

Render HTML: 100%                 1/1 [00:11<00:00, 11.29s/it]

Export report to file: 100%       1/1 [00:00<00:00, 15.64it/s]
```

Overview

Overview | Alerts 21 | Reproduction

Dataset statistics

Number of variables	20
Number of observations	21597
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	3
Duplicate rows (%)	< 0.1%
Total size in memory	3.3 MiB
Average record size in memory	160.0 B

Variable types

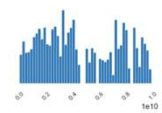
Numeric	17
Categorical	3

Variables

Select Columns

id
Real number ($\mathbb{R}_{\geq 0}$)

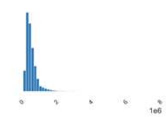
Distinct	21420	Minimum	1000102
Distinct (%)	99.2%	Maximum	9900000190
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	4580474288	Memory size	168.9 KiB



Toggle details

price
Real number ($\mathbb{R}_{\geq 0}$)
HIGH CORRELATION

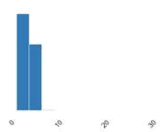
Distinct	3622	Minimum	78000
Distinct (%)	16.8%	Maximum	7700000
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	540296.5735	Memory size	168.9 KiB



Toggle details

bedrooms
Real number ($\mathbb{R}_{\geq 0}$)
HIGH CORRELATION

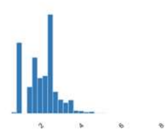
Distinct	12	Minimum	1
Distinct (%)	0.1%	Maximum	33
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	3.373199981	Memory size	168.9 KiB



Toggle details

bathrooms
Real number ($\mathbb{R}_{\geq 0}$)
HIGH CORRELATION

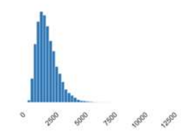
Distinct	29	Minimum	0.5
Distinct (%)	0.1%	Maximum	8
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	2.115826272	Memory size	168.9 KiB



Toggle details

sqft_living
Real number ($\mathbb{R}_{\geq 0}$)
HIGH CORRELATION

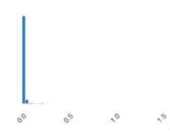
Distinct	1034	Minimum	370
Distinct (%)	4.8%	Maximum	13540
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	2080.32185	Memory size	168.9 KiB



Toggle details

sqft_lot
Real number ($\mathbb{R}_{\geq 0}$)
HIGH CORRELATION

Distinct	9776	Minimum	520
Distinct (%)	45.3%	Maximum	1651359
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	15099.40876	Memory size	168.9 KiB

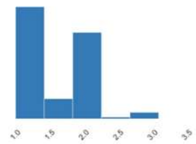


Toggle details

floors
Real number ($\mathbb{R}_{\geq 0}$)

HIGH CORRELATION

Distinct	6	Minimum	1
Distinct (%)	< 0.1%	Maximum	3.5
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	1.494096402	Memory size	168.9 KiB



Toggle details

view
Categorical

HIGH CORRELATION

Distinct	5
Distinct (%)	< 0.1%
Missing	0
Missing (%)	0.0%
Memory size	168.9 KiB

Toggle details

waterfront
Categorical

HIGH CORRELATION

Distinct	2
Distinct (%)	< 0.1%
Missing	0
Missing (%)	0.0%
Memory size	168.9 KiB

Toggle details

condition
Categorical

HIGH CORRELATION

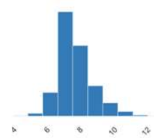
Distinct	5
Distinct (%)	< 0.1%
Missing	0
Missing (%)	0.0%
Memory size	168.9 KiB

Toggle details

grade
Real number ($\mathbb{R}_{\geq 0}$)

HIGH CORRELATION

Distinct	11	Minimum	3
Distinct (%)	0.1%	Maximum	13
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	7.657915451	Memory size	168.9 KiB

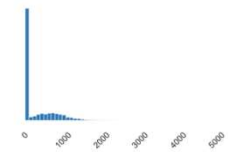


Toggle details

sqft_basement
Real number ($\mathbb{R}_{\geq 0}$)

HIGH CORRELATION
ZEROS

Distinct	306	Minimum	0
Distinct (%)	1.4%	Maximum	4820
Missing	0	Zeros	13110
Missing (%)	0.0%	Zeros (%)	60.7%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	291.7250081	Memory size	168.9 KiB

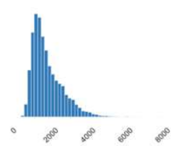


Toggle details

sqft_above
Real number ($\mathbb{R}_{\geq 0}$)

HIGH CORRELATION

Distinct	942	Minimum	370
Distinct (%)	4.4%	Maximum	9410
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	1788.596842	Memory size	168.9 KiB

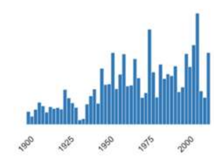


Toggle details

yr_built
Real number ($\mathbb{R}_{\geq 0}$)

HIGH CORRELATION

Distinct	116	Minimum	1900
Distinct (%)	0.5%	Maximum	2015
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	1970.999676	Memory size	168.9 KiB



Toggle details

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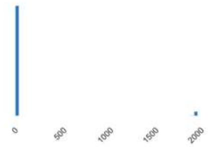
yr_renovated
Real number ($\mathbb{R}_{\geq 0}$)

ZEROS

Distinct	70	**Minimum**	0
Distinct (%)	0.3%	**Maximum**	2015
Missing	0	**Zeros**	20683
Missing (%)	0.0%	**Zeros (%)**	95.8%
Infinite	0	**Negative**	0
Infinite (%)	0.0%	**Negative (%)**	0.0%
Mean	84.46478678	**Memory size**	168.9 KiB

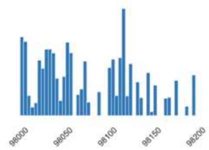


Toggle details

zipcode
Real number ($\mathbb{R}_{\geq 0}$)

HIGH CORRELATION

Distinct	70	**Minimum**	98001
Distinct (%)	0.3%	**Maximum**	98199
Missing	0	**Zeros**	0
Missing (%)	0.0%	**Zeros (%)**	0.0%
Infinite	0	**Negative**	0
Infinite (%)	0.0%	**Negative (%)**	0.0%
Mean	98077.95185	**Memory size**	168.9 KiB

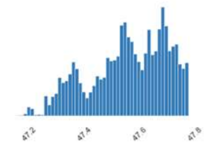


Toggle details

lat
Real number ($\mathbb{R}_{\geq 0}$)

HIGH CORRELATION

Distinct	5033	**Minimum**	47.1559
Distinct (%)	23.3%	**Maximum**	47.7776
Missing	0	**Zeros**	0
Missing (%)	0.0%	**Zeros (%)**	0.0%
Infinite	0	**Negative**	0
Infinite (%)	0.0%	**Negative (%)**	0.0%
Mean	47.56009299	**Memory size**	168.9 KiB

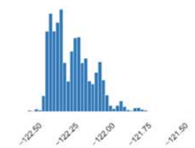


Toggle details

long
Real number ($\mathbb{R}$)

HIGH CORRELATION

Distinct	751	**Minimum**	-122.519
Distinct (%)	3.5%	**Maximum**	-121.315
Missing	0	**Zeros**	0
Missing (%)	0.0%	**Zeros (%)**	0.0%
Infinite	0	**Negative**	21597
Infinite (%)	0.0%	**Negative (%)**	100.0%
Mean	-122.2139825	**Memory size**	168.9 KiB

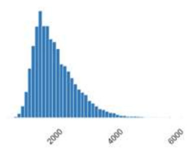


Toggle details

sqft_living15
Real number ($\mathbb{R}_{\geq 0}$)

HIGH CORRELATION

Distinct	777	**Minimum**	399
Distinct (%)	3.6%	**Maximum**	6210
Missing	0	**Zeros**	0
Missing (%)	0.0%	**Zeros (%)**	0.0%
Infinite	0	**Negative**	0
Infinite (%)	0.0%	**Negative (%)**	0.0%
Mean	1986.620318	**Memory size**	168.9 KiB

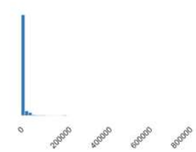


Toggle details

sqft_lot15
Real number ($\mathbb{R}_{\geq 0}$)

HIGH CORRELATION

Distinct	8682	**Minimum**	651
Distinct (%)	40.2%	**Maximum**	871200
Missing	0	**Zeros**	0
Missing (%)	0.0%	**Zeros (%)**	0.0%
Infinite	0	**Negative**	0
Infinite (%)	0.0%	**Negative (%)**	0.0%
Mean	12758.28351	**Memory size**	168.9 KiB



Toggle details

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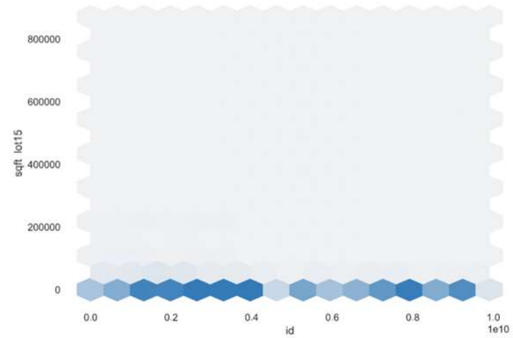
Interactions

- id
- price
- bedrooms
- bathrooms
- sqft_living
- sqft_lot
- floors
- grade
- sqft_above
- sqft_basement
- yr_built
- yr_renovated
- zipcode
- lat
- long
- sqft_living15
- sqft_lot15

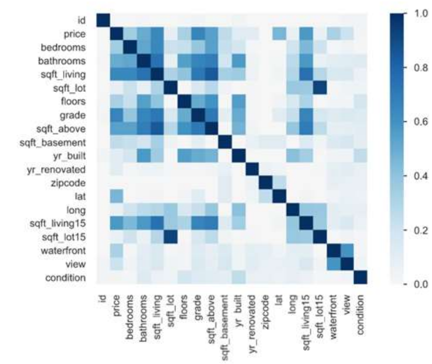
- sqft_lot15
- id
- price
- bedrooms
- bathrooms
- sqft_living
- sqft_lot
- floors
- grade
- sqft_above
- sqft_basement
- yr_built
- yr_renovated
- zipcode
- lat
- long
- sqft_living15



Correlations

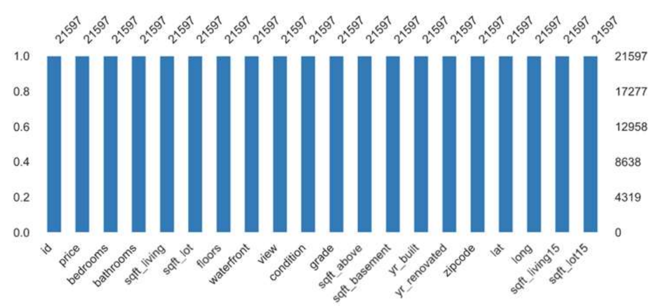
Auto | Spearman's ρ | Pearson's r | Kendall's τ | Cramér's V (φc) | Phik (φk)

Toggle correlation descriptions



Missing values

Count | Matrix



A simple visualization of nullity by column.

Sample

First rows

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built
0	9106000005	1310000.0	4	2.25	3750	5000	2.0	0	0	5	8	2440	1310	1924
1	5101400871	445500.0	2	1.75	1390	6670	1.0	0	0	3	6	720	670	1941
2	7923600250	450000.0	5	2.00	1870	7344	1.5	0	0	3	7	1870	0	1960
3	8730000270	359000.0	2	2.75	1370	1140	2.0	0	0	3	8	1080	290	2009
4	9178601660	1700000.0	5	3.00	3320	5354	2.0	0	0	3	9	3320	0	2004
5	1786200010	456500.0	4	2.50	2580	11780	2.0	0	0	3	9	2580	0	2003
6	1422700040	183000.0	3	1.00	1170	7320	1.0	0	0	3	7	1170	0	1962
7	6752600320	360000.0	4	2.50	2020	7289	2.0	0	0	3	7	2020	0	1994
8	4166600610	335000.0	3	2.00	1410	44866	1.0	0	0	4	7	1410	0	1985
9	7129304540	440000.0	5	2.00	1430	5600	1.5	0	0	3	6	1430	0	1947

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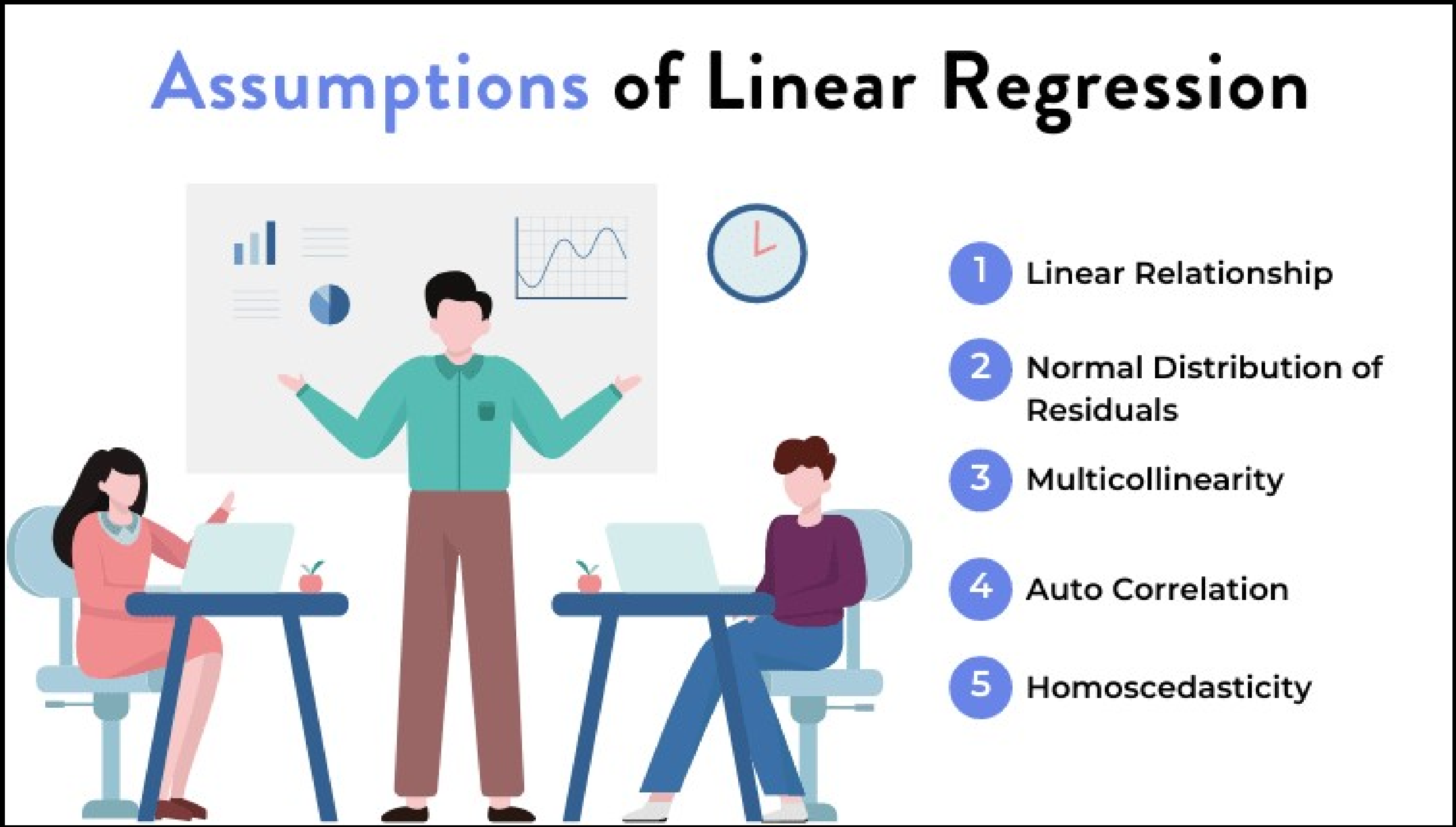
LINEAR REGRESSION (WITHOUT TREATING OUTLIERS)



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Last rows

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_bı
21587	2201501015	430000.0	4	1.50	1920	10000	1.0	0	0	4	7	1070	850	1954
21588	2423600100	491500.0	4	1.75	2190	125452	1.0	0	2	3	9	2190	0	1968
21589	7853220390	785000.0	5	3.25	3660	11995	2.0	0	2	3	10	3660	0	2006
21590	9267200226	436110.0	3	2.50	1770	1235	3.0	0	0	3	8	1600	170	2007
21591	2771102144	385000.0	3	3.25	1320	1327	2.0	0	0	3	8	1040	280	2008
21592	3438501320	295000.0	2	2.50	1630	1368	2.0	0	0	3	7	1280	350	2009
21593	7853361370	555000.0	4	2.50	3310	6500	2.0	0	0	3	8	3310	0	2012
21594	8564860280	459990.0	3	2.50	2680	5539	2.0	0	0	3	8	2680	0	2013
21595	123059127	625000.0	4	3.25	2730	54014	1.0	0	0	3	9	1560	1170	2007
21596	3832050580	300000.0	3	2.50	2540	5050	2.0	0	0	3	7	2540	0	2006

Duplicate rows

Most frequently occurring

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built
0	1825069031	550000.0	4	1.75	2410	8447	2.0	0	3	4	8	2060	350	1936
1	6308000010	585000.0	3	2.50	2290	5089	2.0	0	0	3	9	2290	0	2001
2	8648900110	555000.0	3	2.50	1940	3211	2.0	0	0	3	8	1940	0	2009

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Splitting X into :- Test & Split

In [16]:
```
from sklearn.model_selection import train_test_split
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size = 0.2, random_state = 2)
```

Implementing Linear Regression

In [17]:
```
from sklearn.linear_model import LinearRegression
lin_reg = LinearRegression()
lin_reg.fit(train_X, train_y)
```

Out[17]:
```
LinearRegression()
```

Predicting Results

In [18]:
```
y_pred = lin_reg.predict(test_X)
```

In [19]:
```
y_pred
```

Out[19]:
```
array([287427.00051628, 453058.91054017, 476005.88972716, ...,
       235061.9013533 , 491208.01432038, 396778.71761236])
```

Calculating MAPE(Mean Absolute Percentage Error)

In [20]:
```
from sklearn.metrics import mean_absolute_percentage_error
mean_absolute_percentage_error(test_y, y_pred)*100
```

Out[20]: 25.102180232553984

In [21]:
```
# Pretty Good Scores....That means Our MAPE is 25.10 %
# or we can say that our predicted values are "25.10 % deviated" from our Actual Results
```

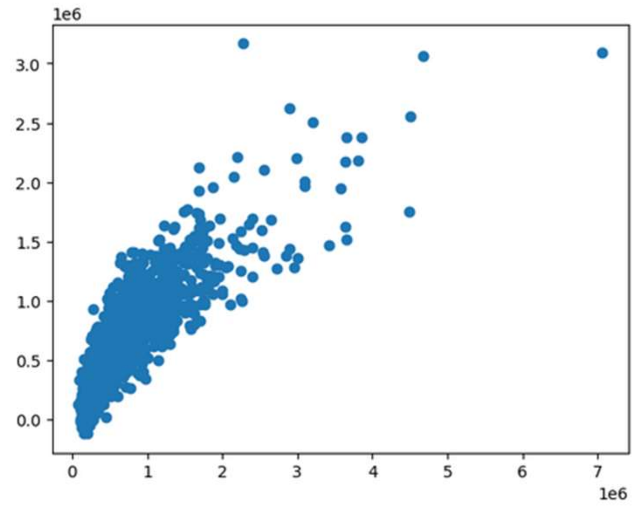
In [22]:
```
# we can easily calculate Accuracy of our Linear Regression Model By Subtracting (100-MAPE)%
```

In [23]:
```
100 - 25.10
```

Out[23]: 74.9

In [24]:
```
plt.scatter(test_y, y_pred)
```

Out[24]: <matplotlib.collections.PathCollection at 0x1eeb7a9bac0>



We Have Got 74.9% of Accuracy

(Using Scikit Learn Library & With Outliers)

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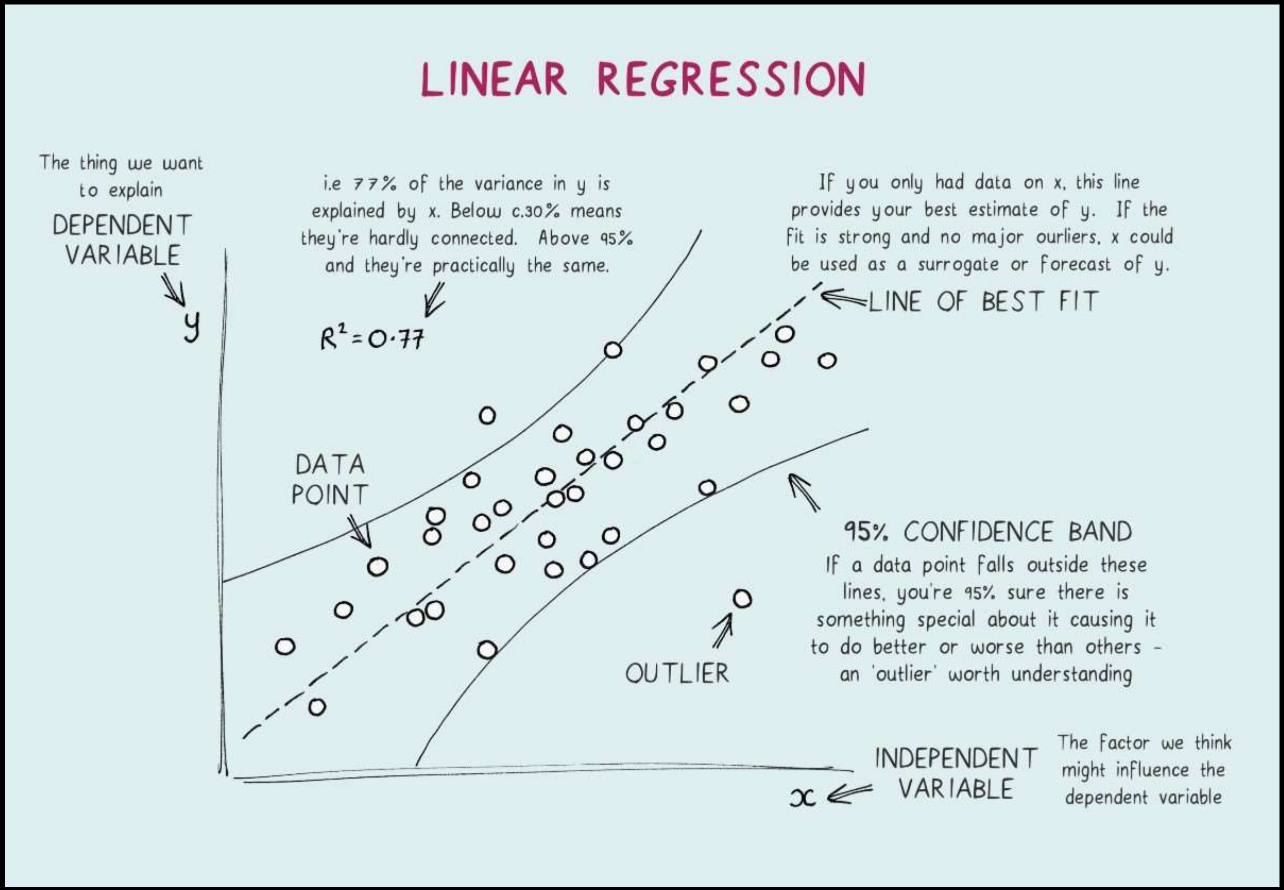
LINEAR REGRESSION (AFTER TREATING OUTLIERS)



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Now Doing it after removing Outliers

In [25]:
```
# we will first create a copy of our dataset-"data", and create a dataFrame-"df"
```

In [26]:
```
df = data.copy()
```

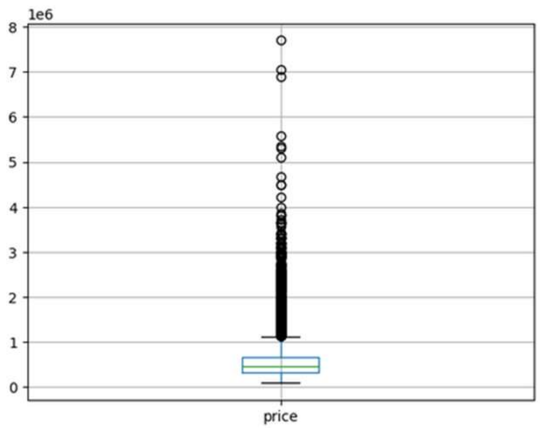
In [27]:
```
df.head()
```

Out[27]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above
0	9106000005	1310000.0	4	2.25	3750	5000	2.0	0	0	5	8	2440
1	5101400871	445500.0	2	1.75	1390	6670	1.0	0	0	3	6	720
2	7923600250	450000.0	5	2.00	1870	7344	1.5	0	0	3	7	1870
3	8730000270	359000.0	2	2.75	1370	1140	2.0	0	0	3	8	1080
4	9178601660	1700000.0	5	3.00	3320	5354	2.0	0	0	3	9	3320

In [28]:
```
#we know that to find Outliers, Boxplot is Best Visualization plot
df.boxplot(column = ['price'])
```

Out[28]: <AxesSubplot:>



In [29]:
```
#there is a significant amount of outliers...so we have to treat them
```

Function to Treat Outliers

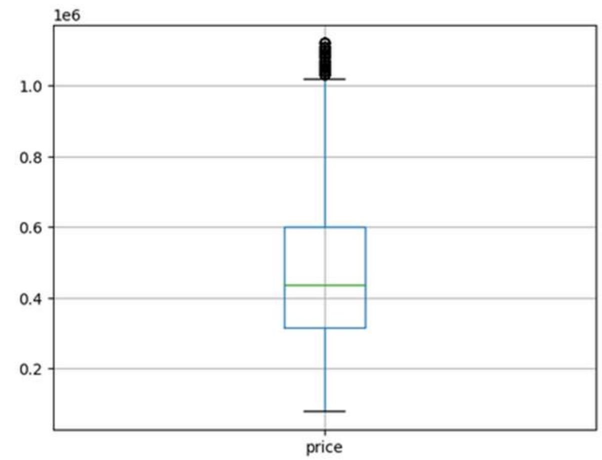
In [30]:
```
def OutRem (data, Var_name):
    Q1 = data[Var_name].quantile(0.25)  #first Quartile
    Q3 = data[Var_name].quantile(0.75)  #third Quartile
    IQR = Q3 - Q1                       #Calculating Inter-Quantile Range
    data = data.loc[~((data[Var_name] < (Q1 - 1.5 * IQR)) | (data[Var_name] > (Q3 + 1.5 * IQR))),]
    return data
```

In [31]:
```
# Treating price's Outliers
df = OutRem(df,"price")
```

In [32]:
```
%matplotlib inline
```

In [33]:
```
#Again checking to Confirm that Outliers have been treated.
df.boxplot(column = ['price'])
```

Out[33]: <AxesSubplot:>



In [34]:
```
# we can see the change clearly, outliers have been treated to an extent.
# we can ignore that small outliers still showing
```

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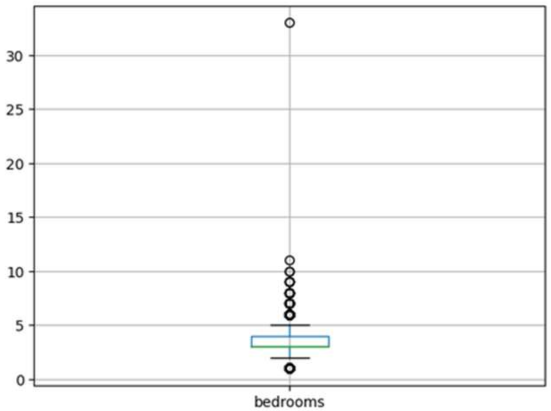
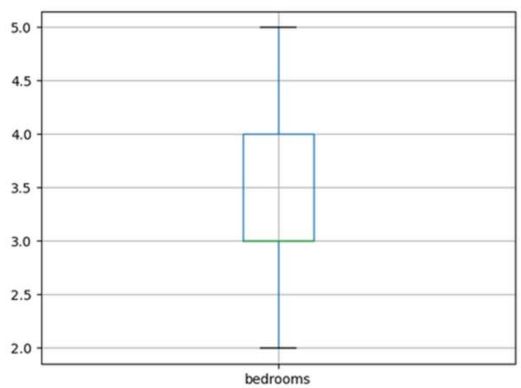
In [37]:
```python
df.boxplot(column = ['bedrooms'])
```
Out[37]: <AxesSubplot:>

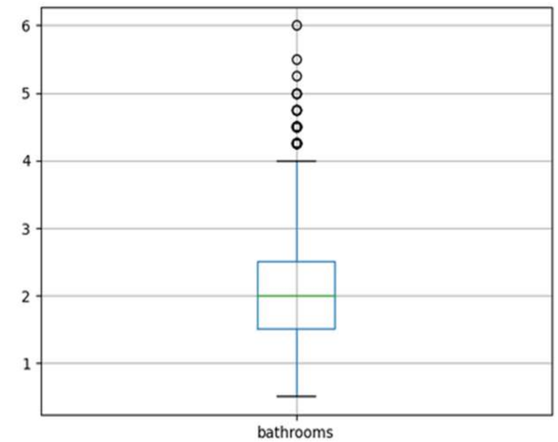


In [38]:
```python
# Treating bedrooms's Outliers
df = OutRem(df,"bedrooms")
```

In [39]:
```python
df.boxplot(column = ['bedrooms'])
```
Out[39]: <AxesSubplot:>

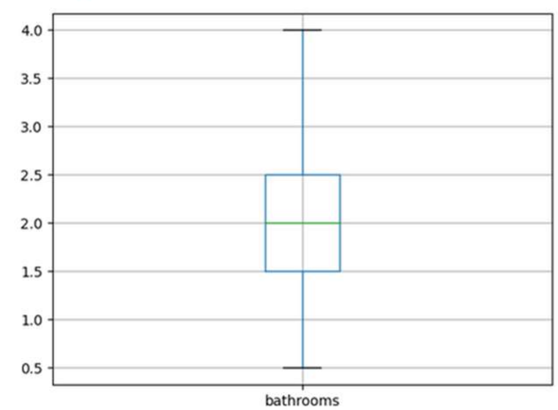


In [40]:
```python
df.boxplot(column = ['bathrooms'])
```
Out[40]: <AxesSubplot:>

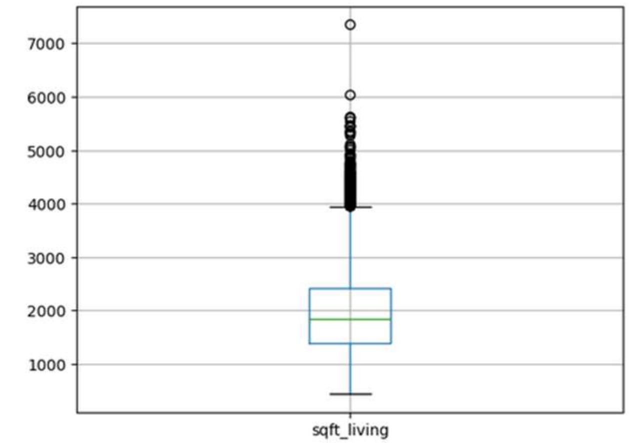


In [41]:
```python
# Treating bathrooms's Outliers
df = OutRem(df,"bathrooms")
```

In [42]:
```python
df.boxplot(column = ['bathrooms'])
```
Out[42]: <AxesSubplot:>

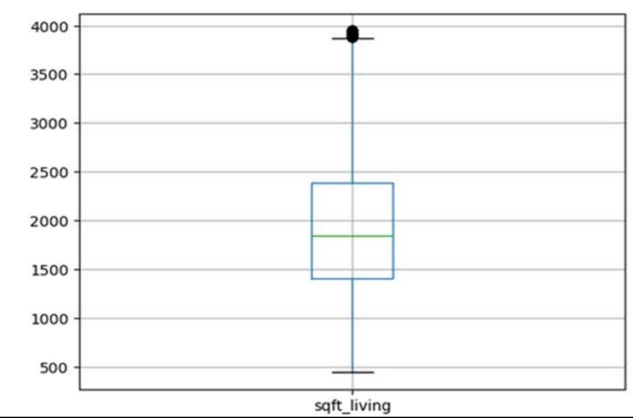


In [43]:
```python
df.boxplot(column = ['sqft_living'])
```
Out[43]: <AxesSubplot:>



In [44]:
```python
# Treating sqft_living's Outliers
df = OutRem(df,"sqft_living")
```

In [45]:
```python
df.boxplot(column = ['sqft_living'])
```
Out[45]: <AxesSubplot:>



```
In [46]: df = OutRem(df,"sqft_lot")

In [47]: df = OutRem(df,"floors")

In [48]: df = OutRem(df,"condition")

In [49]: df = OutRem(df,"grade")

In [50]: df = OutRem(df,"sqft_above")

In [51]: df = OutRem(df,"sqft_basement")

In [52]: df = OutRem(df,"yr_built")

In [53]: df = OutRem(df,"zipcode")
         df = OutRem(df,"lat")
         df = OutRem(df,"long")
         df = OutRem(df,"sqft_living")
         df = OutRem(df,"sqft_lot15")
         # I have not Included certain Variables here, because they were type of binary, like waterfront,view etc.

In [54]: # again doing same steps, as we did with dataset-"data"
         y = df.loc[:,"price"]
         X = df.drop("price", axis = 1)

In [55]: #SPlitting train & test data
         from sklearn.model_selection import train_test_split
         train_X, test_X, train_y, test_y = train_test_split(X, y, test_size = 0.2, random_state = 2)

In [56]: # Again Linear Regression
         from sklearn.linear_model import LinearRegression
         lin_reg = LinearRegression()
         lin_reg.fit(train_X, train_y)

Out[56]: LinearRegression()

In [57]: y_pred_wo = lin_reg.predict(test_X)

In [58]: len(y_pred_wo)

Out[58]: 3092

In [59]: len(test_y)

Out[59]: 3092
```

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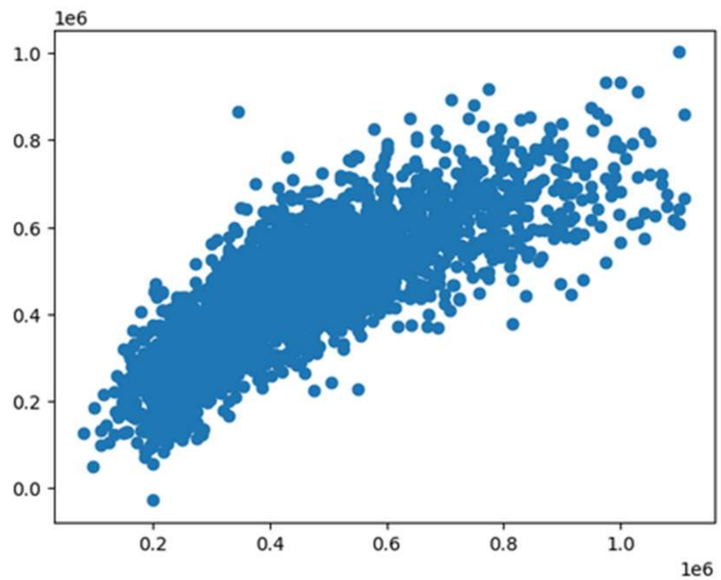
MAPE(Without Outliers)

In [60]:
```
mean_absolute_percentage_error(test_y, y_pred_wo)*100
```
Out[60]: 19.781135275315087

In [61]:
```
# we have improvised the model by removing the outliers and by making it more balanced
```

In [62]:
```
100 - 19.78
```
Out[62]: 80.22

In [63]:
```
plt.scatter(test_y, y_pred_wo)
```
Out[63]: <matplotlib.collections.PathCollection at 0x1eeb7dbca60>



WE HAVE FINALLY ACHIEVED AN ACCURACY OF "80.22%" BY REMOVING OUTLIERS FROM SOME VARIABLES

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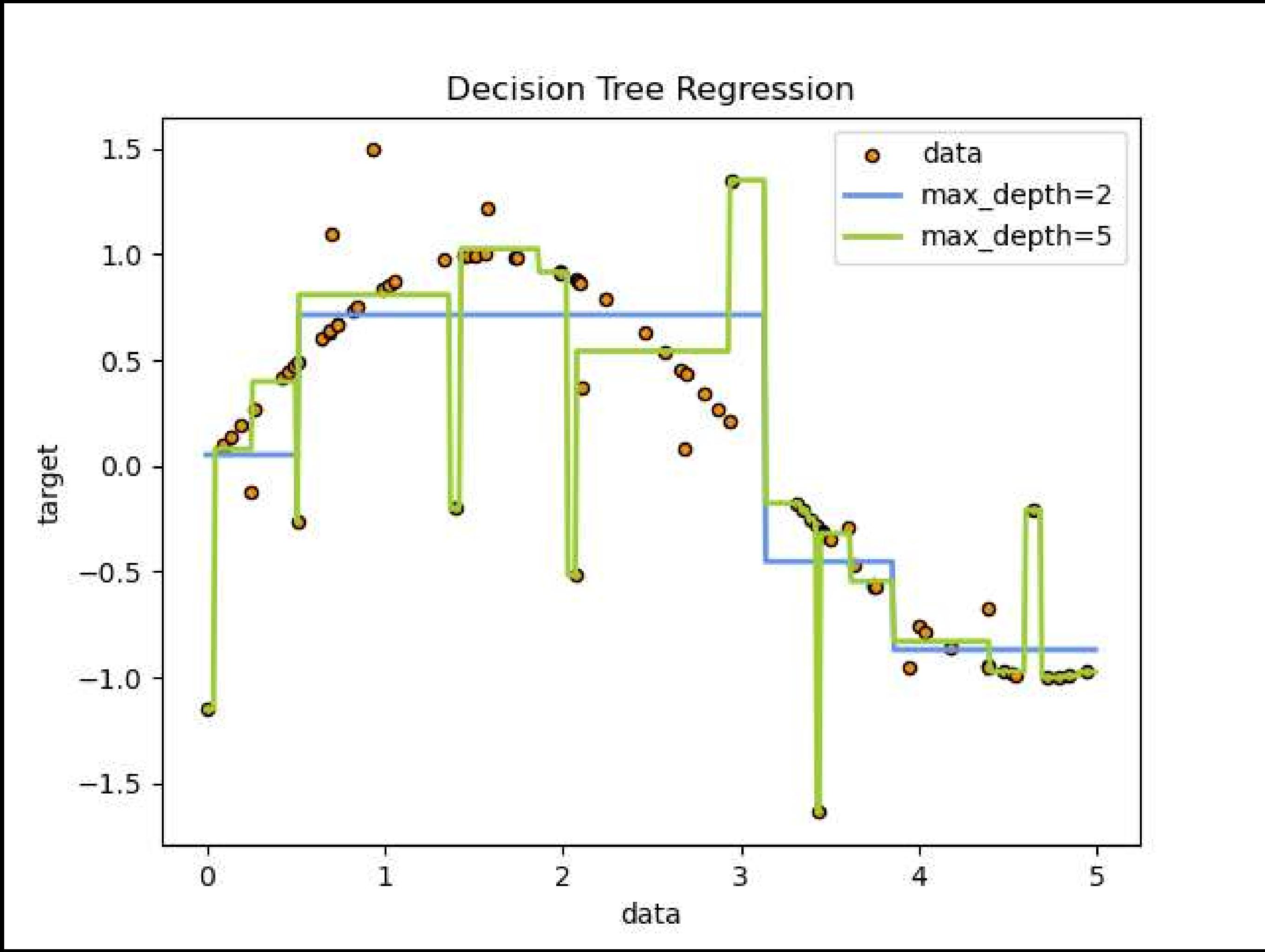
DECISION TREE REGRESSION



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Decision Tree Regression

In [64]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [65]:
```
dt = DecisionTreeRegressor(random_state = 2)
dt.fit(train_X, train_y)
```

Out[65]: DecisionTreeRegressor(random_state=2)

In [66]:
```
y_pred_dt = dt.predict(test_X)
```

In [67]:
```
mean_absolute_percentage_error(test_y, y_pred_dt)
```

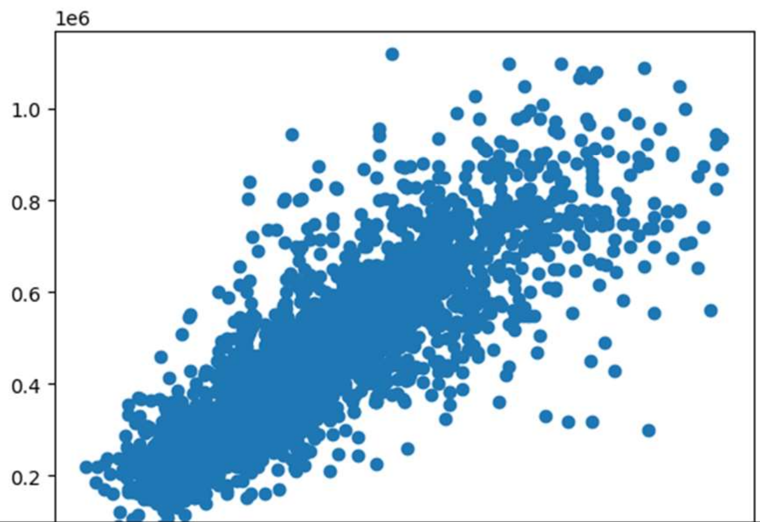
Out[67]: 0.16507669880726836

In [68]:
```
100-16.50
```

Out[68]: 83.5

In [69]:
```
plt.scatter(test_y, y_pred_dt)
```

Out[69]: <matplotlib.collections.PathCollection at 0x1eeb7f0c2e0>



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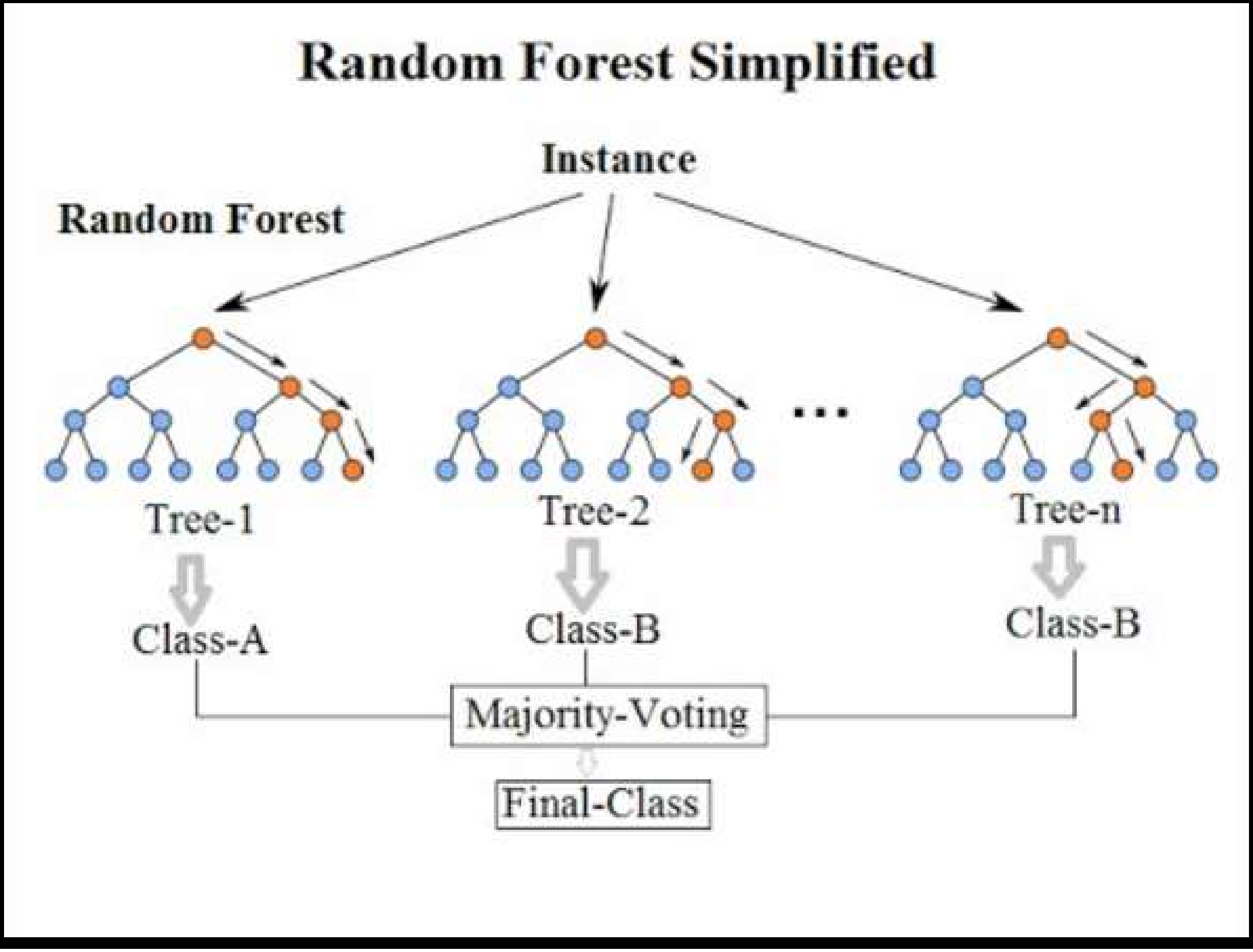
RANDOM FOREST REGRESSION



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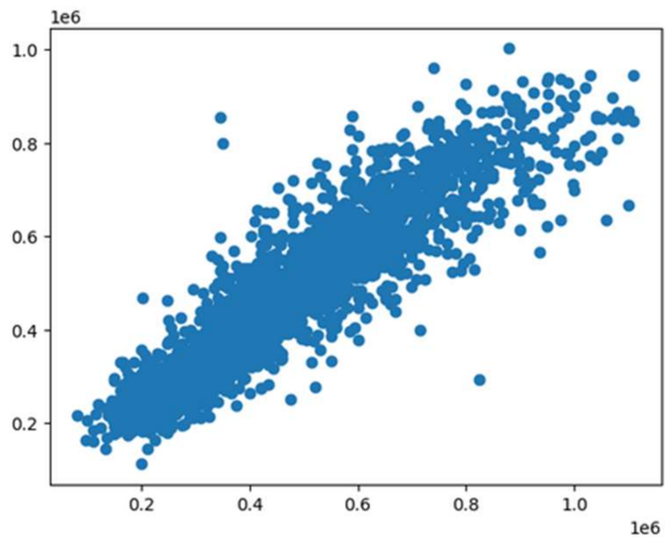
RANDOM FOREST REGRESSOR

```
In [70]: from sklearn.ensemble import RandomForestRegressor

In [71]: rf = RandomForestRegressor(n_estimators = 1000, random_state = 2)
         rf.fit(train_X, train_y)

Out[71]: RandomForestRegressor(n_estimators=1000, random_state=2)

In [72]: y_pred_rf = rf.predict(test_X)

In [73]: mean_absolute_percentage_error(test_y, y_pred_rf)

Out[73]: 0.11566496080803386

In [74]: 100-11.56

Out[74]: 88.44

In [75]: plt.scatter(test_y, y_pred_rf)

Out[75]: <matplotlib.collections.PathCollection at 0x1eebb8ca7f0>
```



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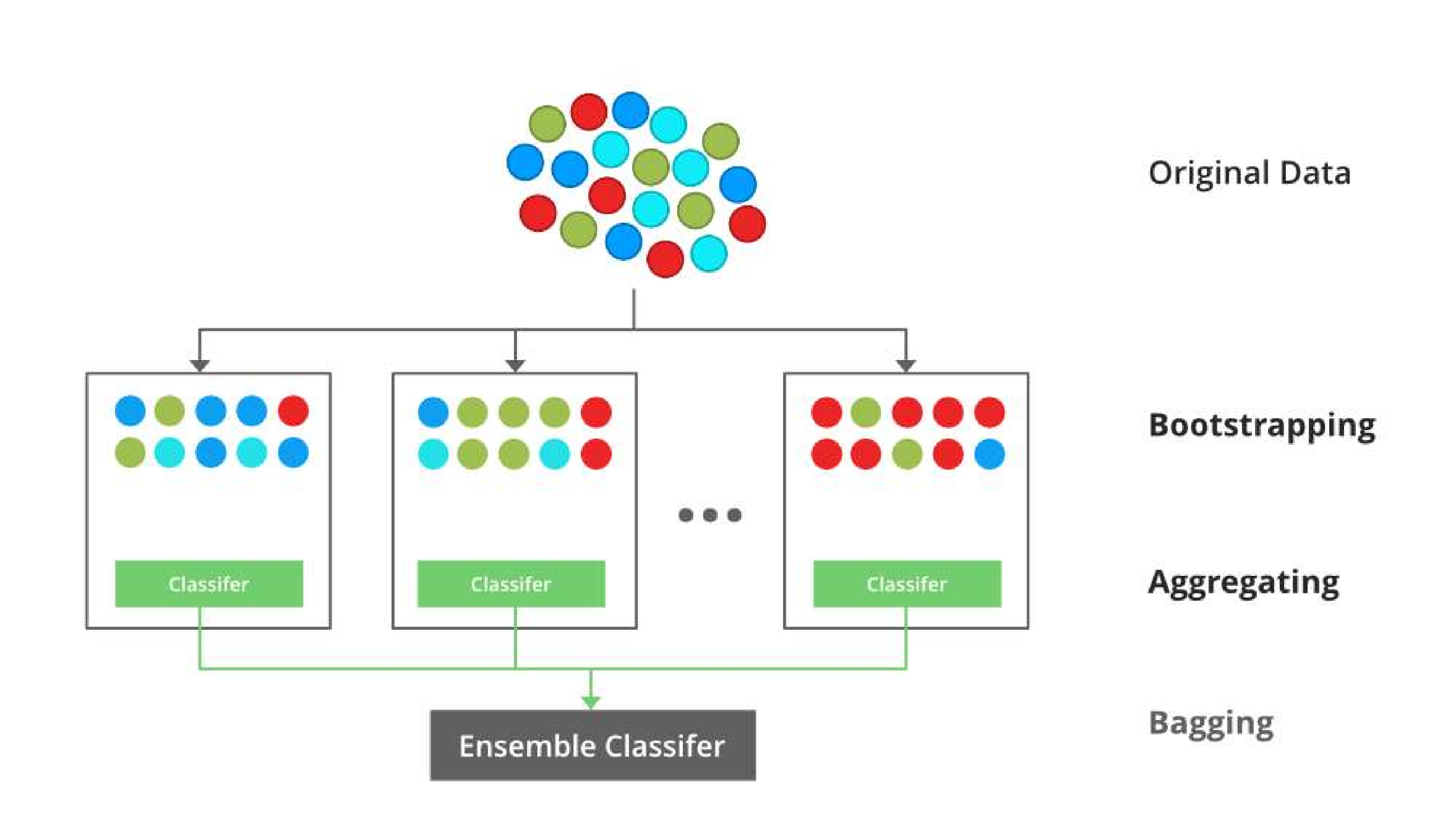
XGBOOST



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XGboost

In [86]:
```
!pip install xgboost
```
```
Requirement already satisfied: xgboost in c:\users\anika\anaconda3\lib\site-packages (1.7.1)
Requirement already satisfied: scipy in c:\users\anika\anaconda3\lib\site-packages (from xgboost) (1.9.1)
Requirement already satisfied: numpy in c:\users\anika\anaconda3\lib\site-packages (from xgboost) (1.21.5)
```

In [87]:
```
import xgboost as xg
```

In [88]:
```
xgb_r = xg.XGBRFRegressor()
xgb_r.fit(train_X, train_y)
```

Out[88]:
```
XGBRFRegressor(base_score=0.5, booster='gbtree', callbacks=None,
               colsample_bylevel=1, colsample_bytree=1,
               early_stopping_rounds=None, enable_categorical=False,
               eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
               grow_policy='depthwise', importance_type=None,
               interaction_constraints='', max_bin=256, max_cat_threshold=64,
               max_cat_to_onehot=4, max_delta_step=0, max_depth=6, max_leaves=0,
               min_child_weight=1, missing=nan, monotone_constraints='()',
               n_estimators=100, n_jobs=0, num_parallel_tree=100,
               objective='reg:squarederror', predictor='auto', random_state=0,
               reg_alpha=0, ...)
```

In [89]:
```
y_pred_x = xgb_r.predict(test_X)
```

In [90]:
```
mean_absolute_percentage_error(test_y, y_pred_x)
```

Out[90]:
```
0.14498487241580113
```

In [91]:
```
100-14.49
```

Out[91]:
```
85.51
```

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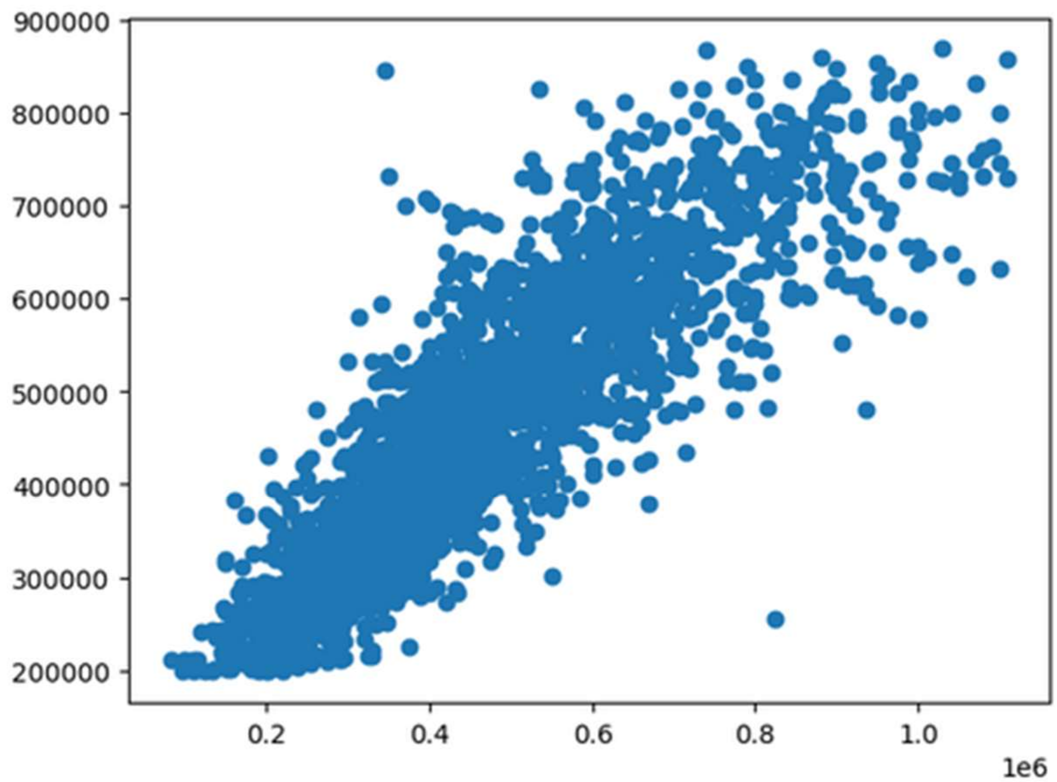
```
In [92]: plt.scatter(test_y, y_pred_x)
Out[92]: <matplotlib.collections.PathCollection at 0x270b18bdc70>
```



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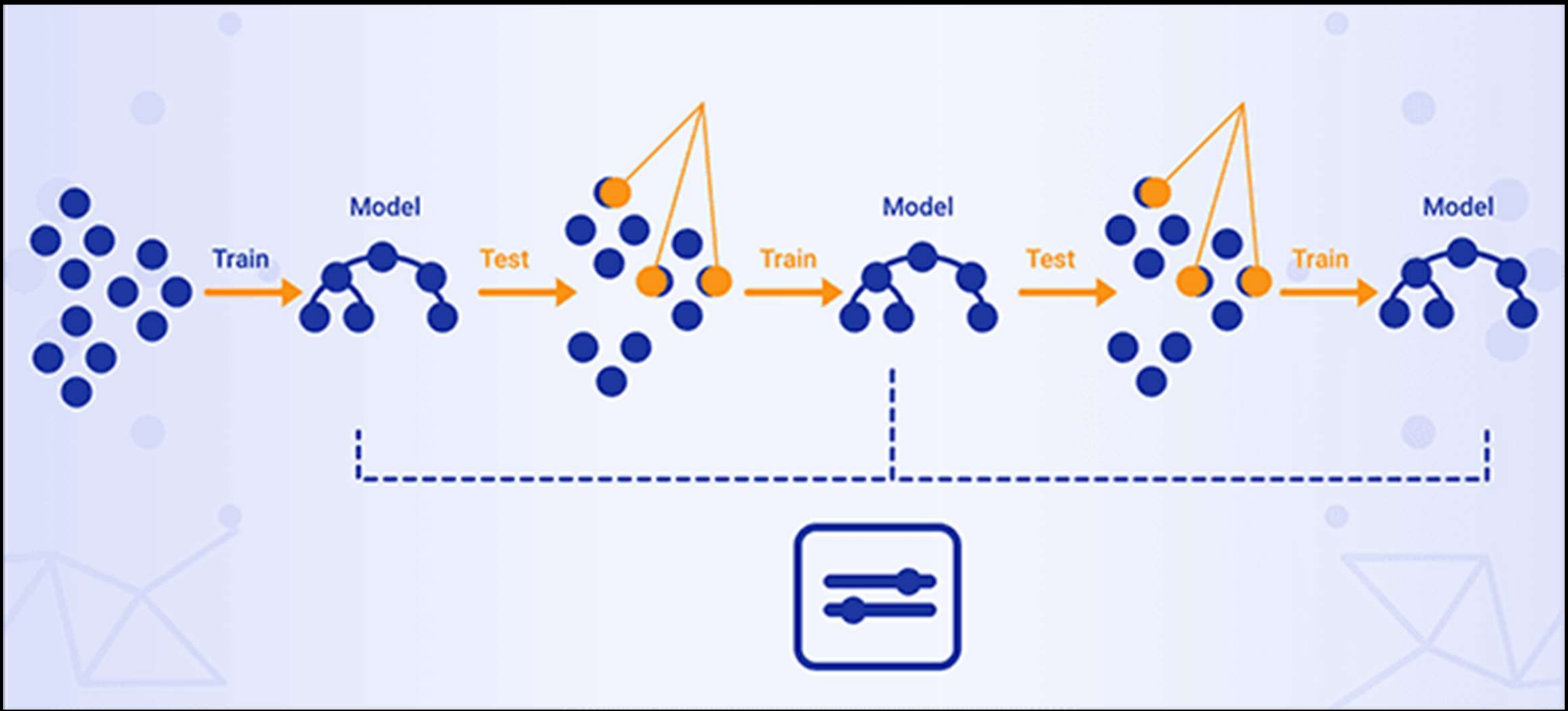
GRADIENT BOOSTING REGRESSION



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GRADIENT BOOSTING REGRESSION

In [77]:
```
from sklearn.ensemble import GradientBoostingRegressor
clf = GradientBoostingRegressor(n_estimators = 400, max_depth = 5, min_samples_split = 2, learning_rate = 0.1, loss =
```

n_estimator — The number of boosting stages to perform. We should not set it too high which would overfit our model

max_depth — The depth of the tree node

learning_rate — Rate of learning the data

loss — loss function

minimum sample split — Number of sample to be split for learning the data

In [78]:
```
clf.fit(train_X, train_y)
```

Out[78]:
```
GradientBoostingRegressor(max_depth=5, n_estimators=400)
```

In [79]:
```
y_pred_clf = clf.predict(test_X)
```

In [80]:
```
mean_absolute_percentage_error(test_y, y_pred_clf)*100
```

Out[80]:
```
10.99443490267817
```

In [81]:
```
#MAPE is 10.99
100-10.99
```

Out[81]:
```
89.01
```

In [82]:
```
# point to be noted : the accuracy is between - ( test"y" & predicted"y" )
```

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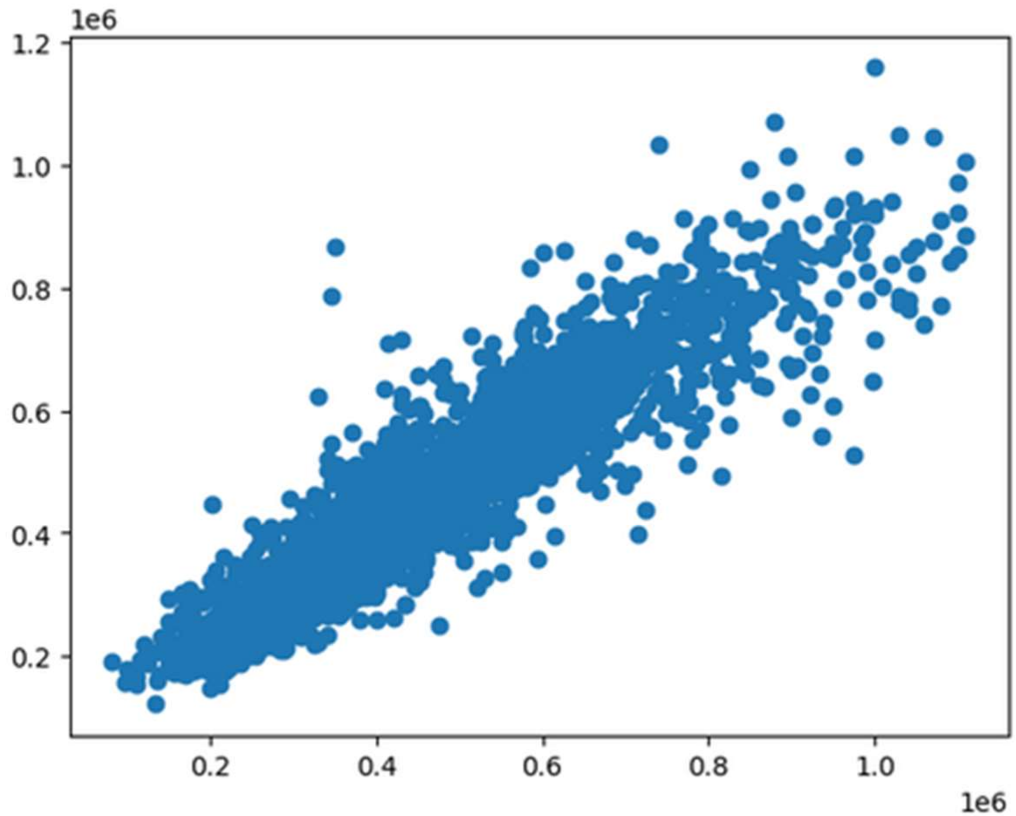
```
In [83]: plt.scatter(test_y, y_pred_clf)
Out[83]: <matplotlib.collections.PathCollection at 0x1eefb3d9460>
```



We Have Achieved the Accuracy of "89.01%" by GRADIENT BOOSTING REGRESSION.

In [100]:
```
# model.score automates the prediction of the data using X_test and compares it with Y_test and by
# default uses the R-squared metric to so (hence don't need to manually derive y_pred).
clf.score(test_X, test_y)
```

Out[100]:
```
0.8659642506327195
```

In [103]:
```
#we can also check this using r2_score
sklearn.metrics.r2_score(test_y, y_pred_clf)
```

Out[103]:
```
0.8659642506327195
```

CROSS-VALIDATION SCORES OF SOME MODELS

In [109]:
```
from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import cross_val_score
```

In [110]:
```
# cv_score of "RandomForestRegressor"
cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
cross_val_score(RandomForestRegressor(), X, y, cv=cv)
```

Out[110]:
```
array([0.85870483, 0.85035836, 0.85279999, 0.83998357, 0.8604371 ])
```

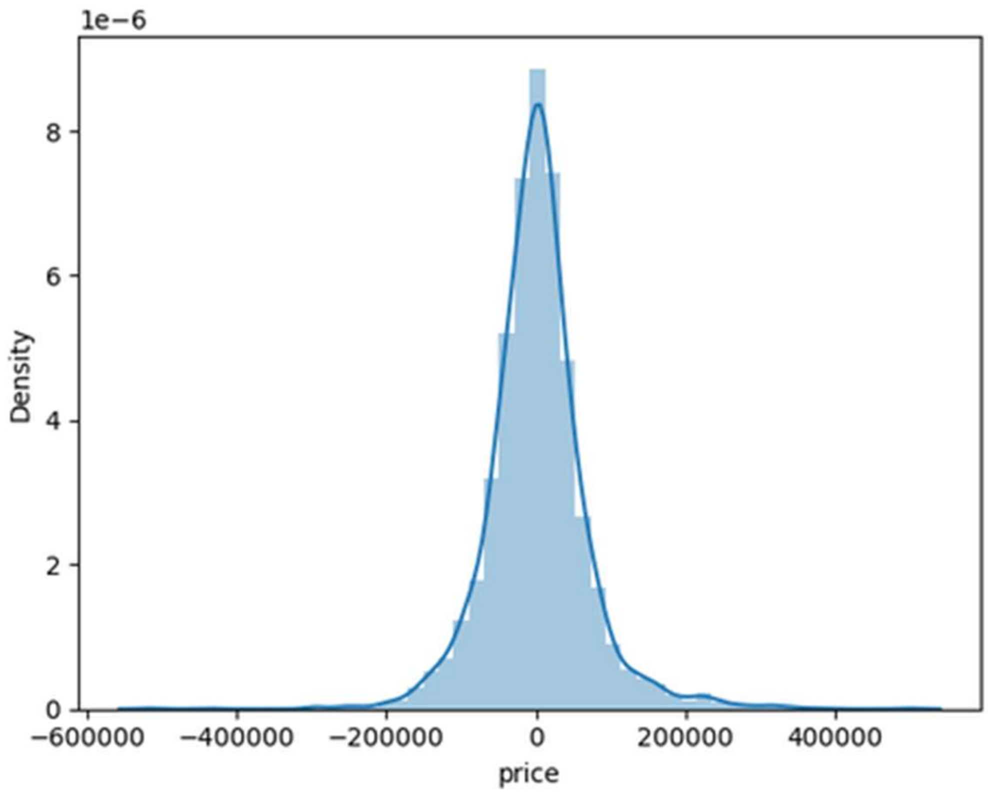
In [ ]:

In [111]:
```
# cv_score of "GradientBoostingRegressor"
cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
cross_val_score(GradientBoostingRegressor(), X, y, cv=cv)
```

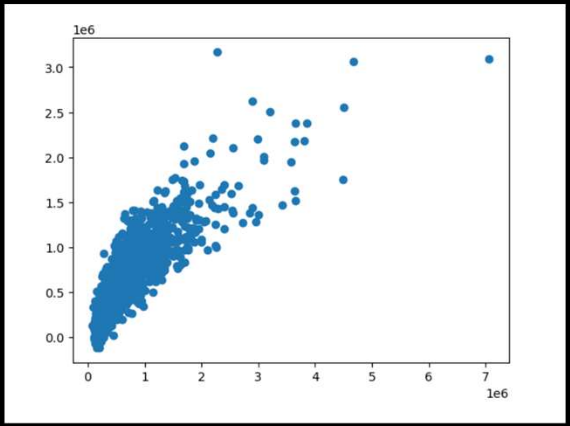
Out[111]:
```
array([0.84148168, 0.83184076, 0.84058511, 0.82753675, 0.84442999])
```

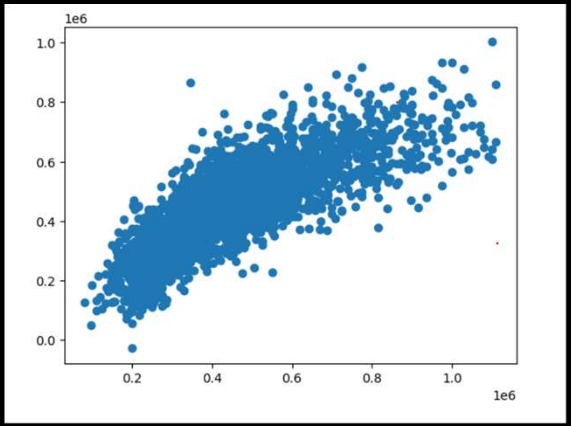
In [120]:
```
sns.distplot((test_y-y_pred_clf),bins=50);# to check that thereis no skewness & our predictions have been computed bal
```

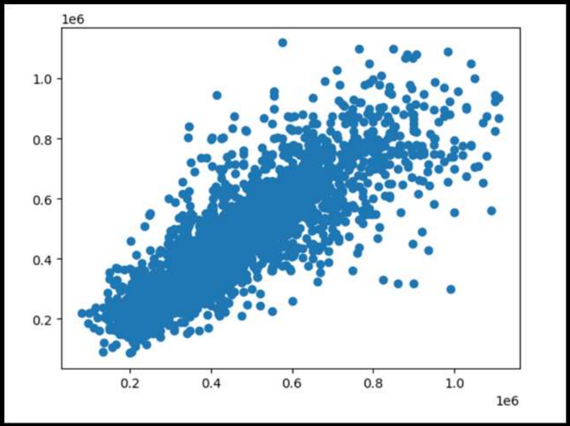
```
C:\Users\anika\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated f
unction and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level funct
ion with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

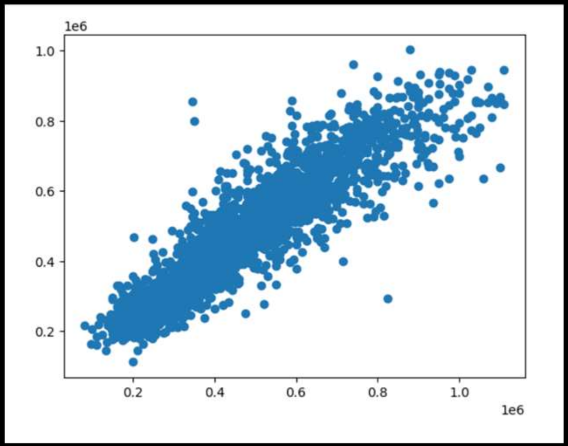


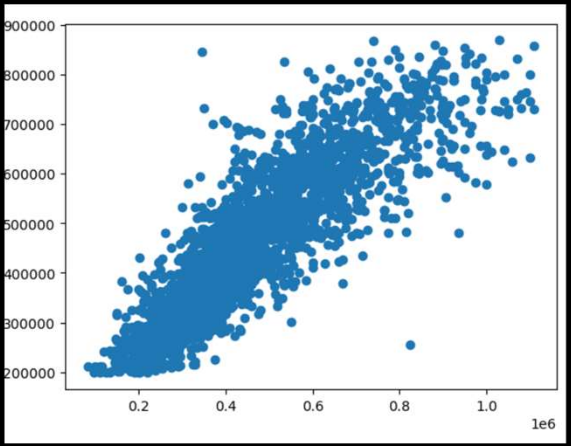
COMPARISON BETWEEN PREDICTED RECORDS AND ORIGINAL RECORDS BY DIFFERENT TECHNIQUES WE'VE USED

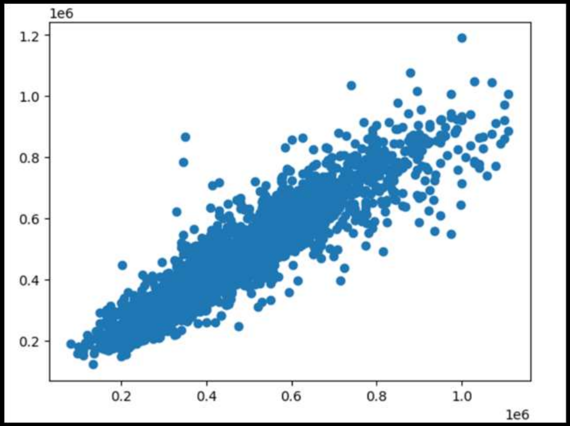












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THE END

THANK YOU

SUBMITTED BY – HARSH YADAV

SUBMITTED TO – DHRUV GOVIL SIR