```
from google.colab import drive

drive.mount('/content/gdrive')

    Mounted at /content/gdrive

import numpy as np
import pandas as pd

df = pd.read_csv('/content/gdrive/MyDrive/data.csv')

#task 1--
df.head()
```

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_above	sqft_basemen
0	2014-05-02 00:00:00	313000.0	3.0	1.50	1340	7912	1.5	0	0	3	1340	
1	2014-05-02 00:00:00	2384000.0	5.0	2.50	3650	9050	2.0	0	4	5	3370	28
2	2014-05-02 00:00:00	342000.0	3.0	2.00	1930	11947	1.0	0	0	4	1930	
3	2014-05-02 00:00:00	420000.0	3.0	2.25	2000	8030	1.0	0	0	4	1000	100
4	2014-05-02 00:00:00	550000.0	4.0	2.50	1940	10500	1.0	0	0	4	1140	80

```
#task2--
df.info()
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 4600 entries, 0 to 4599
    Data columns (total 18 columns):
     # Column
                   Non-Null Count Dtype
    ---
     0 date
                      4600 non-null object
                     4600 non-null float64
         price
         bedrooms
                      4600 non-null
                                      float64
         bathrooms
                      4600 non-null
                                     float64
         sqft_living 4600 non-null int64
         sqft_lot
                       4600 non-null
                                      int64
                       4600 non-null
         floors
                                      float64
         waterfront
                       4600 non-null
                                      int64
         view
                       4600 non-null
                                      int64
         condition
                       4600 non-null
                                      int64
                       4600 non-null
     10 sqft_above
                                      int64
     11 sqft_basement 4600 non-null
                                      int64
                       4600 non-null
     12 yr_built
                                     int64
     13 yr_renovated
                       4600 non-null
                                     int64
     14 street
                       4600 non-null
                                      object
     15 city
                       4600 non-null
                                      object
                       4600 non-null
     16 statezip
                                      object
     17 country
                       4600 non-null
                                      object
    dtypes: float64(4), int64(9), object(5)
    memory usage: 647.0+ KB
#task 3--
df.describe(include='all')
```

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	s
count	4600	4.600000e+03	4600.000000	4600.000000	4600.000000	4.600000e+03	4600.000000	4600.000000	4600.000000	4600.000000	46
unique	70	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
top	2014-06- 23 00:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
freq	142	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
mean	NaN	5.519630e+05	3.400870	2.160815	2139.346957	1.485252e+04	1.512065	0.007174	0.240652	3.451739	18
std	NaN	5.638347e+05	0.908848	0.783781	963.206916	3.588444e+04	0.538288	0.084404	0.778405	0.677230	8
min	NaN	0.000000e+00	0.000000	0.000000	370.000000	6.380000e+02	1.000000	0.000000	0.000000	1.000000	3
25%	NaN	3.228750e+05	3.000000	1.750000	1460.000000	5.000750e+03	1.000000	0.000000	0.000000	3.000000	11
50%	NaN	4.609435e+05	3.000000	2.250000	1980.000000	7.683000e+03	1.500000	0.000000	0.000000	3.000000	15
75%	NaN	6.549625e+05	4.000000	2.500000	2620.000000	1.100125e+04	2.000000	0.000000	0.000000	4.000000	23
max	NaN	2.659000e+07	9.000000	8.000000	13540.000000	1.074218e+06	3.500000	1.000000	4.000000	5.000000	94

#task 4--(Find the Null values)
df.isnull()

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_above	sqft_basement	yr_built
0	False	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False	False
4595	False	False	False	False	False	False	False	False	False	False	False	False	False
4596	False	False	False	False	False	False	False	False	False	False	False	False	False
4597	False	False	False	False	False	False	False	False	False	False	False	False	False
4598	False	False	False	False	False	False	False	False	False	False	False	False	False
4599	False	False	False	False	False	False	False	False	False	False	False	False	False

4600 rows × 18 columns

#finding null values
df.isnull().any()

date	False
price	False
bedrooms	False
bathrooms	False
sqft_living	False
sqft_lot	False
floors	False
waterfront	False
view	False
condition	False
sqft_above	False
sqft_basement	False
yr_built	False
yr_renovated	False
street	False
city	False
statezip	False
country	False
dtype: bool	

#finding null valus in numerical
df.isnull().sum()

date 0 price 0 bedrooms 0 bathrooms 0 sqft\_living 0 sqft\_lot 0 floors 0 waterfront 0 view 0 condition sqft\_above 0 sqft\_basement 0 yr\_built \_ yr\_renovated 0 street 0 city 0 statezip 0 country 0 dtype: int64

#selecting a specific data type
df.select\_dtypes(exclude='object')

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_above	sqft_basement	yr_built
0	3.130000e+05	3.0	1.50	1340	7912	1.5	0	0	3	1340	0	1955
1	2.384000e+06	5.0	2.50	3650	9050	2.0	0	4	5	3370	280	1921
2	3.420000e+05	3.0	2.00	1930	11947	1.0	0	0	4	1930	0	1966
3	4.200000e+05	3.0	2.25	2000	8030	1.0	0	0	4	1000	1000	1963
4	5.500000e+05	4.0	2.50	1940	10500	1.0	0	0	4	1140	800	1976
4595	3.081667e+05	3.0	1.75	1510	6360	1.0	0	0	4	1510	0	1954
4596	5.343333e+05	3.0	2.50	1460	7573	2.0	0	0	3	1460	0	1983
4597	4.169042e+05	3.0	2.50	3010	7014	2.0	0	0	3	3010	0	2009
4598	2.034000e+05	4.0	2.00	2090	6630	1.0	0	0	3	1070	1020	1974
4599	2.206000e+05	3.0	2.50	1490	8102	2.0	0	0	4	1490	0	1990

4600 rows × 13 columns

#selecting a specific data types
df.select\_dtypes(include='object')

05-02 00:00:00 05-02 00:00:00 05-02 00:00:00 05-02 00:00:00   	18810 Densmore Ave N 709 W Blaine St 26206-26214 143rd Ave SE 857 170th PI NE 9105 170th Ave NE  501 N 143rd St	Shoreline Seattle Kent Bellevue Redmond Seattle	WA 98133 WA 98119 WA 98042 WA 98008 WA 98052  WA 98133	USA USA USA USA 
	26206-26214 143rd Ave SE 857 170th PI NE 9105 170th Ave NE 	Kent Bellevue Redmond 	WA 98042 WA 98008 WA 98052	USA USA USA
	857 170th PI NE 9105 170th Ave NE 	Bellevue Redmond	WA 98008 WA 98052	USA USA 
	9105 170th Ave NE	Redmond	WA 98052	USA 
 -07-09 00:00:00				
-07-09 00:00:00				
	501 N 143rd St	Seattle	WA 98133	USA
.07_00 00·00·00				
-07-03 00.00.00	14855 SE 10th PI	Bellevue	WA 98007	USA
-07-09 00:00:00	759 Ilwaco Pl NE	Renton	WA 98059	USA
-07-10 00:00:00	5148 S Creston St	Seattle	WA 98178	USA
-07-10 00:00:00	18717 SE 258th St	Covington	WA 98042	USA
columns				
	07-10 00:00:00	07-10 00:00:00 18717 SE 258th St	07-10 00:00:00 18717 SE 258th St Covington	07-10 00:00:00 18717 SE 258th St Covington WA 98042

```
https://colab.research.google.com/drive/1jdWH\_w7SHFsZVL\_WxqY1jk0bHg6dmmZo\#scrollTo=8obZaj4K2Z9n\&printMode=true
```

```
'Auburn', 'Des Moines', 'Bothell', 'Federal Way', 'Kirkland', 'Issaquah', 'Woodinville', 'Normandy Park', 'Fall City', 'Renton', 'Carnation', 'Snoqualmie', 'Duvall', 'Burien', 'Covington', 'Inglewood-Finn Hill', 'Kenmore', 'Newcastle', 'Mercer Island', 'Black Diamond', 'Ravensdale', 'Clyde Hill', 'Algona', 'Skykomish', 'Tukwila', 'Vashon', 'Yarrow Point', 'SeaTac', 'Medina', 'Enumclaw', 'Snoqualmie Pass', 'Pacific', 'Beaux Arts Village', 'Preston', 'Milton'], dtype=object)
df['city'].value_counts()
       Seattle
                                          1573
       Renton
                                          293
       Bellevue
                                           286
       Redmond
                                           235
       Issaquah
                                           187
       Kirkland
                                           187
       Kent
                                          185
       Auburn
                                          176
       Sammamish
                                           175
       Federal Way
                                          148
       Shoreline
                                          123
       Woodinville
                                           115
       Maple Vallev
                                            96
       Mercer Island
                                            86
       Burien
                                            74
       Snoqualmie
                                            71
       Kenmore
                                            66
       Des Moines
                                            58
       North Bend
       Covington
                                            43
       Duvall
                                            42
       Lake Forest Park
       Bothell
                                            33
       Newcastle
                                            33
       SeaTac
                                            29
       Tukwila
                                            29
       Vashon
                                            29
       Enumclaw
                                            28
       Carnation
                                            22
       Normandy Park
                                            18
       Clyde Hill
                                            11
       Medina
                                            11
       Fall City
                                            11
       Black Diamond
                                             9
       Ravensdale
                                             7
       Pacific
       Algona
                                             5
       Yarrow Point
                                             4
       Skykomish
       Preston
       Milton
       Inglewood-Finn Hill
       Snoqualmie Pass
                                              1
       Beaux Arts Village
       Name: city, dtype: int64
df['statezip'].value_counts()
       WA 98103
       WA 98052
                         135
       WA 98117
                         132
       WA 98115
                         130
       WA 98006
                         110
       WA 98047
                            6
       WA 98288
                            3
       WA 98050
                            2
       WA 98354
                            2
       Name: statezip, Length: 77, dtype: int64
df.head()
```

https://colab.research.google.com/drive/1jdWH\_w7SHFsZVL\_WxqY1jk0bHg6dmmZo#scrollTo=8obZaj4K2Z9n&printMode=true

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_above	sqft_basemen
0	2014-05-02 00:00:00	313000.0	3.0	1.50	1340	7912	1.5	0	0	3	1340	
1	2014-05-02 00:00:00	2384000.0	5.0	2.50	3650	9050	2.0	0	4	5	3370	28
2	2014-05-02 00:00:00	342000.0	3.0	2.00	1930	11947	1.0	0	0	4	1930	
3	2014-05-02 00:00:00	420000.0	3.0	2.25	2000	8030	1.0	0	0	4	1000	100
4	2014-05-02 00:00:00	550000.0	4.0	2.50	1940	10500	1.0	0	0	4	1140	80

# Removing the unwanted columns
df = df.drop('date',axis=1)
df.head()

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_above	sqft_basement	yr_built	yr_ren
0	313000.0	3.0	1.50	1340	7912	1.5	0	0	3	1340	0	1955	
1	2384000.0	5.0	2.50	3650	9050	2.0	0	4	5	3370	280	1921	
2	342000.0	3.0	2.00	1930	11947	1.0	0	0	4	1930	0	1966	
3	420000.0	3.0	2.25	2000	8030	1.0	0	0	4	1000	1000	1963	
4	550000.0	4.0	2.50	1940	10500	1.0	0	0	4	1140	800	1976	

pd.get\_dummies(df['city'])

	Algona	Auburn	Beaux Arts Village	Bellevue	Black Diamond	Bothell	Burien	Carnation	Clyde Hill	Covington	 SeaTac	Seattle	Shı
0	0	0	0	0	0	0	0	0	0	0	 0	0	
1	0	0	0	0	0	0	0	0	0	0	 0	1	
2	0	0	0	0	0	0	0	0	0	0	 0	0	
3	0	0	0	1	0	0	0	0	0	0	 0	0	
4	0	0	0	0	0	0	0	0	0	0	 0	0	
459	<b>5</b> 0	0	0	0	0	0	0	0	0	0	 0	1	
4596	6 0	0	0	1	0	0	0	0	0	0	 0	0	
4597	7 0	0	0	0	0	0	0	0	0	0	 0	0	
4598	<b>8</b> 0	0	0	0	0	0	0	0	0	0	 0	1	
4599	9 0	0	0	0	0	0	0	0	0	1	 0	0	

4600 rows × 44 columns

from sklearn.preprocessing import LabelEncoder

le=LabelEncoder()

df['city']=le.fit\_transform(df['city'])

df.head()

```
le2=LabelEncoder()

df['street']=le2.fit_transform(df['street'])

le3=LabelEncoder()

df['statezip']=le3.fit_transform(df['statezip'])
```

price bedrooms bathrooms sqft\_living sqft\_lot floors waterfront view condition sqft\_above sqft\_basement yr\_built yr\_ren **0** 313000.0 0 3.0 1.50 1340 7912 0 3 1340 0 1955 1.5 1 2384000.0 3650 9050 5 280 5.0 2.50 2.0 0 3370 1921 4 **2** 342000.0 3.0 2.00 1930 11947 0 0 4 1930 0 1966 1.0 420000.0 2.25 8030 1000 1000 3.0 2000 1.0 0 0 4 1963 550000.0 4.0 2.50 1940 10500 1.0 0 0 1140 800 1976

df['country']=df['country'].replace({'USA':1})
df.head()

	price	bedrooms	bathrooms	<pre>sqft_living</pre>	sqft_lot	floors	waterfront	view	condition	sqft_above	sqft_basement	yr_built	yr_ren
0	313000.0	3.0	1.50	1340	7912	1.5	0	0	3	1340	0	1955	
1	2384000.0	5.0	2.50	3650	9050	2.0	0	4	5	3370	280	1921	
2	342000.0	3.0	2.00	1930	11947	1.0	0	0	4	1930	0	1966	
3	420000.0	3.0	2.25	2000	8030	1.0	0	0	4	1000	1000	1963	
4	550000.0	4.0	2.50	1940	10500	1.0	0	0	4	1140	800	1976	

x= df.drop('price',axis=1)
y=df['price']

 $from \ sklearn.model\_selection \ import \ train\_test\_split$ 

x\_train,x\_test,y\_train,y\_test=train\_test\_split( x,y,test\_size=0.2)

 $x\_train.shape, x\_test.shape$ 

((3680, 16), (920, 16))

x\_train.head()

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_above	sqft_basement	yr_built	yr_renovated
2143	4.0	1.75	1300	21000	1.0	0	0	4	1300	0	1969	0
4138	5.0	4.00	7320	217800	2.0	0	0	3	7320	0	1992	0
1753	4.0	3.75	2930	3200	1.5	0	0	5	2130	800	1925	0
435	5.0	1.75	2320	8100	1.0	0	0	4	1160	1160	1956	0
3772	2.0	1.00	910	2002	1.5	0	0	3	910	0	1900	2005

 $from \ sklearn.preprocessing \ import \ MinMaxScaler, \ StandardScaler$ 

```
S = StandardScaler()
```

```
xtrainscaled = S.fit_transform(x_train)
```

## xtrainscaled

```
array([[ 0.6639069 , -0.51343648, -0.86674453, ..., -0.96851074, -1.8537657 , 0. ],
        [ 1.76741972 , 2.36097463 , 5.37226467 , ..., 0.53297898, -0.13204052, 0. ],
        [ 0.6639069 , 2.04159561 , 0.8225553 , ..., 0.78322727 , 0.92012487 , 0. ],
        ...,
        [ -0.43960592 , 1.7222166 , 2.61549316 , ..., 0.78322727 , 0.34621648 , 0. ],
        [ 0.6639069 , 2.36097463 , 1.5998405 , ..., 0.61639508 , 0.15491368 , 0. ],
        [ -0.43960592 , 0.12532155 , -0.56619425 , ..., -0.96851074 , -1.75811431 , 0. ]])
```

xtestscaled = S.transform(x\_test)

## xtestscaled

```
array([[ 0.6639069 , 0.76407957, 0.58418784, ..., 0.78322727, 0.77664777, 0. ], [ 0.6639069 , 0.44470056, 0.96764854, ..., 0.53297898, -0.27551762, 0. ], [-1.54311874, -1.47157351, -1.03256537, ..., 0.78322727, 1.11142767, 0. ], ..., [-1.54311874, -1.47157351, -1.42638987, ..., 0.78322727, 1.44620757, 0. ], [-1.54311874, 0.44470056, -0.3641001 , ..., -1.88608779, -1.71028861, 0. ], [-0.43960592, 0.12532155, 0.05563391, ..., 0.53297898, -0.22769192, 0. ]])
```

#Task5-Build ML model with linear regression(Target column is price)

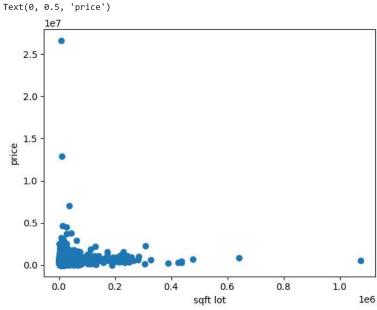
```
df=df[['price','sqft_lot']]
```

df

		price	sqft_lot	
	0	3.130000e+05	7912	ılı
	1	2.384000e+06	9050	
	2	3.420000e+05	11947	
	3	4.200000e+05	8030	
	4	5.500000e+05	10500	
	4595	3.081667e+05	6360	
	4596	5.343333e+05	7573	
	4597	4.169042e+05	7014	
	4598	2.034000e+05	6630	
	4599	2.206000e+05	8102	
4	600 rc	ows × 2 columns		

```
x=df['sqft_lot']
y=df['price']
import matplotlib.pyplot as plt

plt.scatter(x,y)
plt.xlabel('sqft lot')
plt.ylabel('price')
```



from sklearn.model\_selection import train\_test\_split

```
x\_train, x\_test, y\_train, y\_test = train\_test\_split(x,y,test\_size=0.4, random\_state=23)
```

 $from \ sklearn.linear\_model \ import \ LinearRegression$ 

lr=LinearRegression()

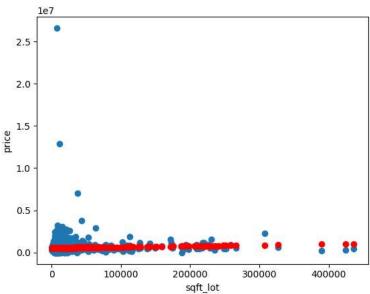
```
lr.fit(x_train,
       y_train)
      ▼ LinearRegression
     LinearRegression()
c=lr.intercept_
     536155.0620619762
m=lr.coef_
m
     array([1.14128005])
y_pred_train=m*x_train+c
y_pred_train.flatten()
     array([594353.49699467, 542558.78442946, 598297.76085174, ...,
            548309.69460763, 547981.00595288, 547111.35055383])
y_pred_train1=lr.predict(x_train)
y_pred_train1
     array([594353.49699467, 542558.78442946, 598297.76085174, ...,
            548309.69460763, 547981.00595288, 547111.35055383])
plt.scatter(x_train,y_train)
plt.scatter(x_train,y_pred_train1,color='red')
plt.xlabel('sqft_lot')
plt.ylabel('price')
     Text(0, 0.5, 'price')
             1e7
         2.5
         2.0
         1.5
         1.0
         0.5
         0.0
                                                      300000
                          100000
                                        200000
                                                                    400000
                                          sqft_lot
plt.scatter(x_train,y_train)
plt.scatter(x_train,y_pred_train1,color='red')
plt.xlabel('sqft_lot')
plt.ylabel('price')
```

```
Text(0, 0.5, 'price')
              1e7
         2.5
         2.0
         1.5
         1.0
         0.5
lr.fit(x_test,y_test)
      ▼ LinearRegression
     LinearRegression()
y_pred_test=m*x_test+c
y_pred_test.flatten()
     array([550633.34079195, 543203.60765841, 541861.46231815, ...,
            556926.35899446, 543205.89021851, 537618.18308766])
y_pred_test1=lr.predict(x_test)
y_pred_test
     array([[550633.34079195],
            [543203.60765841],
            [541861.46231815],
            [556926.35899446],
            [543205.89021851],
            [537618.18308766]])
plt.scatter(x_train,y_train)
plt.scatter(x_train,y_pred_train1,color='red')
plt.xlabel('sqft_lot')
plt.ylabel('price')
     Text(0, 0.5, 'price')
              1e7
         2.0
         1.5
         1.0
         0.5
         0.0
                           100000
                                        200000
                                                      300000
                                                                    400000
                                           sqft_lot
```

```
plt.scatter(x_train,y_train)
plt.scatter(x_train,y_pred_train1,color='red')
```

plt.xlabel('sqft\_lot')
plt.ylabel('price')

Text(0, 0.5, 'price')



"Therefore the linear model is satisfied for both train and test date"

'Therefore the linear model is satisfied for both train and test date'