TK 18 dec

January 5, 2025

1 Data Mining and Machine Learning Lab

1.1 Experiment 1

1.1.1 Importing the necessary libraries

```
[15]: import pandas as pd import numpy as np import matplotlib.pyplot as plt
```

1.1.2 Load the file to your python program in to a data frame DF1.

[16]: df1 = pd.read_csv(r"D:\study material\VIT_Data_Science\Winter_Sem\Data Mining_

and Machine Learning Lab\Class_notes\18_Dec_ML_exp1\housepricedata.csv")

[17]: df1

LotArea	OverallQual	OverallCond	${\tt TotalBsmtSF}$	FullBath	HalfBath \
8450	7	5	856	2	1
9600	6	8	1262	2	0
11250	7	5	920	2	1
9550	7	5	756	1	0
14260	8	5	1145	2	1
•••	•••	•••		•••	
7917	6	5	953	2	1
13175	6	6	1542	2	0
9042	7	9	1152	2	0
9717	5	6	1078	1	0
9937	5	6	1256	1	1
	8450 9600 11250 9550 14260 7917 13175 9042 9717	8450 7 9600 6 11250 7 9550 7 14260 8 7917 6 13175 6 9042 7 9717 5	8450 7 5 9600 6 8 11250 7 5 9550 7 5 14260 8 5 7917 6 5 13175 6 6 9042 7 9 9717 5 6	8450 7 5 856 9600 6 8 1262 11250 7 5 920 9550 7 5 756 14260 8 5 1145 7917 6 5 953 13175 6 6 1542 9042 7 9 1152 9717 5 6 1078	8450 7 5 856 2 9600 6 8 1262 2 11250 7 5 920 2 9550 7 5 756 1 14260 8 5 1145 2 7917 6 5 953 2 13175 6 6 1542 2 9042 7 9 1152 2 9717 5 6 1078 1

	${\tt BedroomAbvGr}$	${ t TotRmsAbvGrd}$	Fireplaces	${ t GarageArea}$	AboveMedianPrice	
0	3	8	0	548	1	
1	3	6	1	460	1	
2	3	6	1	608	1	
3	3	7	1	642	0	
4	4	9	1	836	1	
•••	•••	•••	•••	•••	•••	
1455	3	7	1	460	1	

1456	3	7	2	500	1
1457	4	9	2	252	1
1458	2	5	0	240	0
1459	3	6	0	276	0

1.1.3 First five observations from your dataset

[18]: df1.head(5)

[18]: LotArea OverallQual OverallCond TotalBsmtSF FullBath HalfBath \

[18]:	LotArea	OverallQual	OverallCond	${\tt TotalBsmtSF}$	FullBath	${\tt HalfBath}$	\
0	8450	7	5	856	2	1	
1	9600	6	8	1262	2	0	
2	11250	7	5	920	2	1	
3	9550	7	5	756	1	0	
4	14260	8	5	1145	2	1	

	BedroomAbvGr	TotRmsAbvGrd	Fireplaces	GarageArea	AboveMedianPrice
0	3	8	0	548	1
1	3	6	1	460	1
2	3	6	1	608	1
3	3	7	1	642	0
4	4	9	1	836	1

1.1.4 Last five observations from our dataset

[19]: df1.tail(5)

[19]:		LotArea	OverallQual	OverallCond	TotalBsmtSF	FullBath	HalfBath	\
	1455	7917	6	5	953	2	1	
	1456	13175	6	6	1542	2	0	
	1457	9042	7	9	1152	2	0	
	1458	9717	5	6	1078	1	0	
	1459	9937	5	6	1256	1	1	

	${\tt BedroomAbvGr}$	${ t TotRmsAbvGrd}$	Fireplaces	${ t GarageArea}$	AboveMedianPrice
1455	3	7	1	460	1
1456	3	7	2	500	1
1457	4	9	2	252	1
1458	2	5	0	240	0
1459	3	6	0	276	0

1.1.5 Shape of your dataset

[20]: df1.shape

```
[20]: (1460, 11)
```

1.1.6 info of your dataset

```
[21]: df1.info()
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 1460 entries, 0 to 1459
     Data columns (total 11 columns):
      #
          Column
                             Non-Null Count
                                             Dtype
                             _____
      0
          LotArea
                             1460 non-null
                                              int64
      1
          OverallQual
                             1460 non-null
                                              int64
      2
          OverallCond
                             1460 non-null
                                             int64
      3
          TotalBsmtSF
                             1460 non-null
                                             int64
          FullBath
      4
                             1460 non-null
                                              int64
      5
          HalfBath
                             1460 non-null
                                              int64
      6
          {\tt BedroomAbvGr}
                             1460 non-null
                                              int64
      7
          TotRmsAbvGrd
                             1460 non-null
                                              int64
          Fireplaces
                             1460 non-null
                                              int64
          GarageArea
                             1460 non-null
                                              int64
      10 AboveMedianPrice 1460 non-null
                                              int64
```

dtypes: int64(11) memory usage: 125.6 KB

1.1.7 Create a new dataframe DF2 with the first 100 observations of your dataset with only the columns LotArea and BedroomAbvGr [Use iloc operator]

```
[22]: df2 = (df1.iloc[0:100])[['LotArea', 'BedroomAbvGr']]

[23]: df2
```

	LotArea	${\tt BedroomAbvGr}$
0	8450	3
1	9600	3
2	11250	3
3	9550	3
4	14260	4
	•••	•••
95	9765	3
96	10264	3
97	10921	3
98	10625	2
99	9320	3
	1 2 3 4 95 96 97	0 8450 1 9600 2 11250 3 9550 4 14260 95 9765 96 10264 97 10921 98 10625

[100 rows x 2 columns]

1.1.8 Write or export your dataset DF2 to a csv file DF11.csv and save it.

```
[24]: df2.to_csv('DF11.csv')
```

1.1.9 Find the maximum and minimum of the LotArea column for your dataset DF1

```
[25]: print("Maximum of LotArea column is:",df1['LotArea'].max())
```

Maximum of LotArea column is: 215245

Minimum of LotArea column is: 1300

1.1.10 Find the observations from your dataset with LotArea > 10650 from your DF1 dataframe.

[27]:	df1[df1['LotArea']>10650]	
-------	---------------------------	--

[27]:		LotArea	OverallQual	OverallCond	${\tt TotalBsmtSF}$	FullBath	HalfBath	\
	2	11250	7	5	920	2	1	
	4	14260	8	5	1145	2	1	
	5	14115	5	5	796	1	1	
	10	11200	5	5	1040	1	0	
	11	11924	9	5	1175	3	0	
		•••	•••	•••		•••		
	1442	11003	10	5	1017	2	1	
	1446	26142	5	7	1188	1	0	
	1448	11767	4	7	560	1	1	
	1453	17217	5	5	1140	1	0	
	1456	13175	6	6	1542	2	0	

	${\tt BedroomAbvGr}$	${\tt TotRmsAbvGrd}$	Fireplaces	${\tt GarageArea}$	a AboveMedianPrice	
2	3	6	1	608	1	
4	4	9	1	836	1	
5	1	5	0	480	0	
10	3	5	0	384	0	
11	4	11	2	736	1	
•••	•••	•••	•••	•••	•••	
1442	3	10	1	812	1	
1446	3	6	0	312	0	
1448	2	6	0	384	0	
1453	3	6	0	0	0	
1456	3	7	2	500	1	

[502 rows x 11 columns]

1.1.11 Find the mean, median of your column TotalBsmtSF and find the unique entries (non-repeated ones)

773 1926 731 1417 1024

712 650

1935 1614 761 1413 956

1649 1568 778 1489 2078 1454 1516 1067 1559 1127 1390 1273 918 1763 1090 1054 1039 1148 1002 1638 105 676 1184 1109 892 2217 1505 1059 951 2330 1670 1623 1017 1105 1001 546 480 1134 1104 1272 1316 1126 1181 1753 964 1466 925 1905 1500 585 1632 819 1616 1161 979 561 696 1330 817 1098 1428 673 1241 944 1225 1266 1128 1930 1396 916 822 750 1700 1007 1187 691 1574 1680 1346 602 1022 1082 810 1504 1220 1132 1565 1338 1654 1620 1055 1475 2524 1992 1193 973 854 662 1103 1154 942 1048 727 690 1096 1459 1251 1247 1074 1271 290 655 1463 1836 803 833 408 533 1012 1552 1005 1530 974 1567 1006 1042 1298 704 932 1219 1296 1198 1261 1598 1683 818 1600 2396 1624 831 1224 663 879 815 1630 2158 931 1660 559 1300 1702 1075 1361 1106 1476 1689 2076 792 2110 1405 746 1986 841 2002 1332 935 1019 661 1309 1328 1085 6110 1246 976 1652 1278 1902 1274 1393 1622 1352 420 1795 544 1510 911 693 1284 1732 2033 570 1980 814 873 757 1108 2633 1571 714 1746 1525 482 1356 862 839 1286 1485 1594 622 791 913 656 1319 1932 539 1221 1542]

1.1.12 Sort the dataset DF1 according to the TotalBsmtSF column of your dataset DF1 in ascending and descending order

[31]: ##sorting in descending order df1.sort_values(by=['TotalBsmtSF'],ascending=False)

	dil.sort_values(by=['lotalBsmtSF'],ascending=ralse)										
[31]:		LotArea	Over	allQual	Overa	llCond	Tota	lBsmtSF	FullBath	HalfBath	\
	1298	63887		10		5		6110	2	1	
	332	10655		8		5		3206	2	0	
	496	12692		8		5		3200	3	0	
	523	40094		10		5		3138	3	1	
	440	15431		10		5		3094	2	0	
		•••		•••	•••		•••	•••	•••		
	1412	7200		4		5		0	2	0	
	1179	8335		5		5		0	1	0	
	102	7018		5		5		0	2	0	
	259	12702		5		5		0	1	0	
	1048	21750		5		4		0	1	0	
		BedroomA	bvGr	TotRmsA		Firepl		_		eMedianPrio	e
	1298		3		12		3	1	418		0
	332		3		7		1		880		1
	496		4		10		1		546		1
	523		3		11		1		884		1
	440		2		10		2		672		1
		•••		•••		•••		•••	•••		
	1412		2		6		0		420		0
	1179		3		5		1		0		0
	102		4		8		0		410		0

259	2	4	0	308	0
1048	3	9	1	336	0

```
[32]: #sorted in ascending order
df1.sort_values(by=['TotalBsmtSF'])
```

	${ t LotArea}$	OverallQual	UverallCond	${ t TotalBsmtSF}$	FullBath	HalfBath	'
646	7200	5	5	0	1	0	
1035	11500	4	3	0	1	0	
392	8339	5	7	0	1	0	
749	8405	4	3	0	2	0	
1011	9825	5	5	0	2	0	
	•••	•••			•••		
440	15431	10	5	3094	2	0	
523	40094	10	5	3138	3	1	
496	12692	8	5	3200	3	0	
332	10655	8	5	3206	2	0	
1298	63887	10	5	6110	2	1	
	1035 392 749 1011 440 523 496 332	646 7200 1035 11500 392 8339 749 8405 1011 9825 440 15431 523 40094 496 12692 332 10655	646 7200 5 1035 11500 4 392 8339 5 749 8405 4 1011 9825 5 440 15431 10 523 40094 10 496 12692 8 332 10655 8	646 7200 5 5 1035 11500 4 3 392 8339 5 7 749 8405 4 3 1011 9825 5 5 440 15431 10 5 523 40094 10 5 496 12692 8 5 332 10655 8 5	646 7200 5 5 0 1035 11500 4 3 0 392 8339 5 7 0 749 8405 4 3 0 1011 9825 5 5 0 440 15431 10 5 3094 523 40094 10 5 3138 496 12692 8 5 3200 332 10655 8 5 3206	646 7200 5 5 0 1 1035 11500 4 3 0 1 392 8339 5 7 0 1 749 8405 4 3 0 2 1011 9825 5 5 0 2 440 15431 10 5 3094 2 523 40094 10 5 3138 3 496 12692 8 5 3200 3 332 10655 8 5 3206 2	646 7200 5 5 0 1 0 1035 11500 4 3 0 1 0 392 8339 5 7 0 1 0 749 8405 4 3 0 2 0 1011 9825 5 5 0 2 0 </td

	${\tt BedroomAbvGr}$	${\tt TotRmsAbvGrd}$	Fireplaces	GarageArea	AboveMedianPrice
646	3	7	0	420	0
1035	3	5	0	290	0
392	3	5	0	294	0
749	4	9	0	240	0
1011	4	8	0	0	0
	•••	•••	•••	•••	•••
440	2	10	2	672	1
523	3	11	1	884	1
496	4	10	1	546	1
332	3	7	1	880	1
1298	3	12	3	1418	0

[1460 rows x 11 columns]

1.1.13 Find the empty cells in 'GarageArea' column of your dataset DF1 and fill it with the average value of the column GarageArea

```
[33]: df1['GarageArea'].isnull().sum()
[33]: 0
```

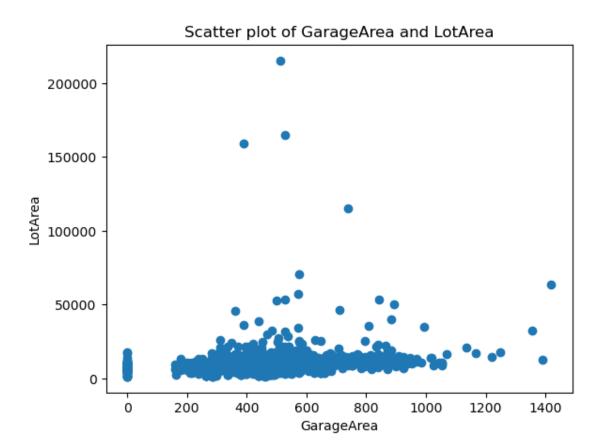
```
[34]: df1['GarageArea'].fillna(df1['GarageArea'].mean(),inplace=True)
```

1.1.14 Replace the column named Above median price in your dataframe with 1's where ever you have Yes and 0 where ever you have No

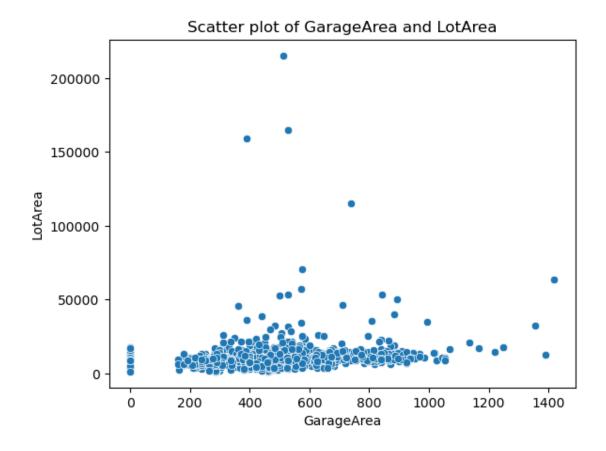
```
[35]: df1['AboveMedianPrice'].replace({'Yes':1, 'no':0}, inplace=True)
[36]: df1['AboveMedianPrice']
[36]: 0
              1
      1
              1
      2
              1
      3
              0
              1
      1455
              1
      1456
              1
      1457
              1
      1458
              0
      1459
              0
      Name: AboveMedianPrice, Length: 1460, dtype: int64
```

1.1.15 Draw a scatterplot with columns 'GarageArea' on x axis and 'LotArea' on y-axis

```
[37]: plt.scatter(df1['GarageArea'],df1['LotArea'])
   plt.title("Scatter plot of GarageArea and LotArea")
   plt.xlabel("GarageArea")
   plt.ylabel("LotArea")
   plt.show()
```



```
[38]: import seaborn as sns
sns.scatterplot(x=df1['GarageArea'],y = df1['LotArea'])
plt.title("Scatter plot of GarageArea and LotArea")
plt.xlabel("GarageArea")
plt.ylabel("LotArea")
plt.show()
```



1.1.16 Drop the column 'GarageArea' from your dataset DF1

: df1.d	lrop(' <mark>Gara</mark>	geArea',axis=	1,inplace=Tru	le)			
: df1							
:	LotArea	OverallQual	OverallCond	TotalBsmtSF	FullBath	HalfBath	\
0	8450	7	5	856	2	1	
1	9600	6	8	1262	2	0	
2	11250	7	5	920	2	1	
3	9550	7	5	756	1	0	
4	14260	8	5	1145	2	1	
•••	•••	•••	•••		•••		
1455	7917	6	5	953	2	1	
1456	13175	6	6	1542	2	0	
1457	9042	7	9	1152	2	0	
1458	9717	5	6	1078	1	0	
1459	9937	5	6	1256	1	1	

BedroomAbvGr TotRmsAbvGrd Fireplaces AboveMedianPrice

0	3	8	0		1
1	3	6	1		1
2	3	6	1		1
3	3	7	1		0
4	4	9	1		1
	•••			•••	
 1455	 3	 7	1	•••	1
		 7 7	1 2	•••	1 1
1455	3	7 7 9	1 2 2	•••	1 1 1
1455 1456	3	7 7	_		1 1 1 0

1.2 Q1. Now, normalize the columns of the dataset1 using the above technique and save it to a new csv file DF3.csv

```
[41]: from sklearn import preprocessing
      min_max_scaler = preprocessing.MinMaxScaler()
      col_name = df1.columns[:]
      x = df1.loc[:, col_name]
      x = pd.DataFrame(data = min_max_scaler.fit_transform(x), columns = col_name)
      print(x)
      x.to_csv('df3.csv')
             LotArea OverallQual
                                    OverallCond
                                                  TotalBsmtSF
                                                               FullBath
                                                                          HalfBath
     0
            0.033420
                         0.666667
                                          0.500
                                                     0.140098
                                                               0.666667
                                                                               0.5
     1
            0.038795
                         0.555556
                                          0.875
                                                     0.206547
                                                               0.666667
                                                                               0.0
     2
           0.046507
                         0.666667
                                          0.500
                                                     0.150573 0.666667
                                                                               0.5
     3
            0.038561
                         0.666667
                                          0.500
                                                     0.123732
                                                               0.333333
                                                                               0.0
     4
            0.060576
                         0.777778
                                          0.500
                                                     0.187398
                                                                               0.5
                                                               0.666667
     1455
           0.030929
                                          0.500
                                                     0.155974
                                                               0.666667
                                                                               0.5
                         0.555556
                                                     0.252373
                                                                               0.0
     1456
           0.055505
                         0.555556
                                          0.625
                                                               0.666667
     1457
           0.036187
                         0.666667
                                          1.000
                                                     0.188543
                                                               0.666667
                                                                               0.0
     1458
           0.039342
                         0.44444
                                          0.625
                                                     0.176432
                                                                               0.0
                                                               0.333333
     1459
           0.040370
                         0.44444
                                          0.625
                                                     0.205565
                                                               0.333333
                                                                               0.5
            BedroomAbvGr
                          {\tt TotRmsAbvGrd}
                                         Fireplaces
                                                      AboveMedianPrice
                                           0.000000
     0
                   0.375
                               0.500000
                                                                    1.0
     1
                   0.375
                               0.333333
                                           0.333333
                                                                    1.0
     2
                   0.375
                               0.333333
                                           0.333333
                                                                    1.0
     3
                   0.375
                               0.416667
                                           0.333333
                                                                    0.0
     4
                   0.500
                               0.583333
                                           0.333333
                                                                    1.0
                   0.375
                               0.416667
                                           0.333333
                                                                    1.0
     1455
                                                                    1.0
     1456
                   0.375
                               0.416667
                                           0.666667
                   0.500
                               0.583333
                                           0.666667
                                                                    1.0
     1457
```

1458	0.250	0.250000	0.000000	0.0
1459	0.375	0.333333	0.00000	0.0

1.2.1 Q2. Now normalize the whole data to the range (2,3) using Min-Max normalization

```
[42]: from sklearn import preprocessing
      min_max_scaler = preprocessing.MinMaxScaler(feature_range=(2,3))
      col name = df1.columns[:]
      x = df1.loc[:, col_name]
      x = pd.DataFrame(data = min max scaler.fit transform(x), columns = col name)
      print(x)
                      OverallQual
                                   OverallCond
                                                 TotalBsmtSF
            LotArea
                                                              FullBath
                                                                        HalfBath
     0
           2.033420
                         2.666667
                                          2.500
                                                    2.140098
                                                              2.666667
                                                                              2.5
     1
                                         2.875
                                                                              2.0
           2.038795
                         2.555556
                                                    2.206547
                                                              2.666667
     2
                                                                              2.5
           2.046507
                         2.666667
                                         2.500
                                                    2.150573
                                                              2.666667
     3
           2.038561
                         2.666667
                                         2.500
                                                    2.123732
                                                              2.333333
                                                                              2.0
     4
                                                                              2.5
           2.060576
                         2.777778
                                         2.500
                                                    2.187398
                                                              2.666667
     1455 2.030929
                         2.555556
                                         2.500
                                                    2.155974
                                                              2.666667
                                                                              2.5
     1456
           2.055505
                         2.555556
                                         2.625
                                                    2.252373
                                                              2.666667
                                                                              2.0
     1457 2.036187
                         2.666667
                                         3.000
                                                    2.188543
                                                              2.666667
                                                                              2.0
     1458 2.039342
                         2.444444
                                         2.625
                                                    2.176432
                                                              2.333333
                                                                              2.0
     1459
           2.040370
                         2.44444
                                          2.625
                                                    2.205565
                                                              2.333333
                                                                              2.5
           BedroomAbvGr
                          TotRmsAbvGrd Fireplaces
                                                     AboveMedianPrice
     0
                   2.375
                              2.500000
                                           2.000000
                                                                   3.0
                   2.375
                                                                   3.0
     1
                              2.333333
                                           2.333333
     2
                   2.375
                                                                   3.0
                              2.333333
                                           2.333333
     3
                   2.375
                                                                   2.0
                              2.416667
                                           2.333333
     4
                   2.500
                              2.583333
                                           2.333333
                                                                   3.0
                                                                   3.0
     1455
                   2.375
                              2.416667
                                           2.333333
     1456
                   2.375
                              2.416667
                                           2.666667
                                                                   3.0
     1457
                   2.500
                              2.583333
                                           2.666667
                                                                   3.0
                                                                   2.0
     1458
                   2.250
                              2.250000
                                           2.000000
     1459
                   2.375
                              2.333333
                                           2.000000
                                                                   2.0
```

[1460 rows x 10 columns]

1.3 Q3. Now do decimal scaling for the original column data of the column LotArea of your initial dataframe and print the results.

```
[43]: max_abs_values = abs(df1.max())
[44]: max_abs_values
[44]: LotArea
                           215245
      OverallQual
                               10
      OverallCond
                                9
      TotalBsmtSF
                             6110
      FullBath
                                3
      HalfBath
                                2
      BedroomAbvGr
                                8
      TotRmsAbvGrd
                               14
      Fireplaces
                                3
      AboveMedianPrice
                                1
      dtype: int64
[45]: df88 = df1['LotArea'].apply(lambda x : x/
       →10**(len(str(max_abs_values['LotArea']))))
[46]: df88
[46]: 0
              0.008450
              0.009600
      1
      2
              0.011250
      3
              0.009550
              0.014260
      1455
              0.007917
      1456
              0.013175
      1457
              0.009042
      1458
              0.009717
      1459
              0.009937
      Name: LotArea, Length: 1460, dtype: float64
```

1.3.1 Q4. Now try to standardize the whole data in the dataframe and print the dataframe.

```
[47]: from sklearn import preprocessing
standard_scaler = preprocessing.StandardScaler()
col_name = df1.columns
x = df1.loc[:, col_name]
x = pd.DataFrame(data = standard_scaler.fit_transform(x), columns = col_name)
print(x)

LotArea OverallQual OverallCond TotalBsmtSF FullBath HalfBath \
```

-0.517200

0

-0.207142

0.651479

-0.459303 0.789741 1.227585

```
-0.091886
                  -0.071836
                                2.179628
                                              0.466465 0.789741 -0.761621
1
2
                   0.651479
                                             -0.313369 0.789741 1.227585
      0.073480
                                -0.517200
3
     -0.096897
                   0.651479
                                -0.517200
                                             -0.687324 -1.026041 -0.761621
4
                                -0.517200
                                              0.199680 0.789741 1.227585
      0.375148
                   1.374795
                                                   •••
1455 -0.260560
                  -0.071836
                                -0.517200
                                             -0.238122
                                                        0.789741 1.227585
1456 0.266407
                  -0.071836
                                 0.381743
                                              1.104925 0.789741 -0.761621
1457 -0.147810
                   0.651479
                                 3.078570
                                              0.215641 0.789741 -0.761621
1458 -0.080160
                  -0.795151
                                 0.381743
                                              0.046905 -1.026041 -0.761621
1459 -0.058112
                  -0.795151
                                              0.452784 -1.026041 1.227585
                                 0.381743
      BedroomAbvGr TotRmsAbvGrd Fireplaces AboveMedianPrice
          0.163779
                                    -0.951226
0
                        0.912210
                                                       1.002743
1
                       -0.318683
                                     0.600495
          0.163779
                                                       1.002743
2
          0.163779
                       -0.318683
                                     0.600495
                                                       1.002743
3
          0.163779
                        0.296763
                                     0.600495
                                                      -0.997264
4
          1.390023
                        1.527656
                                     0.600495
                                                       1.002743
                                     0.600495
1455
          0.163779
                        0.296763
                                                       1.002743
1456
          0.163779
                        0.296763
                                     2.152216
                                                       1.002743
1457
          1.390023
                         1.527656
                                     2.152216
                                                       1.002743
1458
         -1.062465
                       -0.934130
                                    -0.951226
                                                      -0.997264
1459
          0.163779
                       -0.318683
                                    -0.951226
                                                      -0.997264
```

[48]: x

[48]:		LotArea	OverallQual	OverallCor	ıd TotalBsmtSF	' FullBath	HalfBath	$\overline{}$
	0	-0.207142	0.651479	-0.51720	0 -0.459303	0.789741	1.227585	•
	1	-0.091886	-0.071836	2.17962	0.466465	0.789741	-0.761621	
	2	0.073480	0.651479	-0.51720	0 -0.313369	0.789741	1.227585	
	3	-0.096897	0.651479	-0.51720	0 -0.687324	-1.026041	-0.761621	
	4	0.375148	1.374795	-0.51720	0.199680	0.789741	1.227585	
	•••		•••	•••		•••		
	1455	-0.260560	-0.071836	-0.51720	0 -0.238122	0.789741	1.227585	
	1456	0.266407	-0.071836	0.38174	1.104925	0.789741	-0.761621	
	1457	-0.147810	0.651479	3.07857	0.215641	0.789741	-0.761621	
	1458	-0.080160	-0.795151	0.38174	3 0.046905	-1.026041	-0.761621	
	1459	-0.058112	-0.795151	0.38174	3 0.452784	-1.026041	1.227585	
		BedroomAb		-	olaces AboveMe	dianPrice		
	0	0.163	779 0.91	2210 -0.9	51226	1.002743		
	1	0.163	779 -0.31	8683 0.6	00495	1.002743		
	2	0.163	779 -0.31	8683 0.6	00495	1.002743		
	3	0.163	779 0.29	6763 0.6	00495	-0.997264		
	4	1.390	023 1.52	7656 0.6	300495	1.002743		

•••	•••	•••	•••	•••
1455	0.163779	0.296763	0.600495	1.002743
1456	0.163779	0.296763	2.152216	1.002743
1457	1.390023	1.527656	2.152216	1.002743
1458	-1.062465	-0.934130	-0.951226	-0.997264
1459	0.163779	-0.318683	-0.951226	-0.997264

- 1.4 Train Test splitting of data for model training.
- 1.4.1 Now perfrom 70:30 train test split for our dataframe data with the target variable or output variable as LotArea and print the training and testing data which may be we can use for fitting a model for this data. Say like trying to predict the LotArea for a house based on all the other features.

```
[49]: from sklearn.model_selection import train_test_split
    x =df1.drop('LotArea', axis=1)
    y = df1['LotArea']
    #Split the data into training and testing sets (70% train, 30% test)
    x_train,x_test,y_train,y_test = train_test_split(x, y, test_size=0.3,u_arandom_state=42)
    #Print the testing and training data
    print("Training Features:\n", x_train)
    print("Testing Features:\n", x_test)
    print("Training Target:\n", y_train)
    print("Testing Target:\n", y_test)
```

Training Features:

	OverallQual	OverallCond	${\tt TotalBsmtSF}$	FullBath	${\tt HalfBath}$	${\tt BedroomAbvGr}$
\						
135	7	6	1304	2	0	3
1452	5	5	547	1	0	2
762	7	5	756	2	1	3
932	9	5	1905	2	0	3
435	7	6	799	2	1	3
•••	•••	•••		•••	•••	
1095	6	5	1314	2	0	3
1130	4	3	1122	2	0	4
1294	5	7	864	1	0	2
860	7	8	912	1	1	3
1126	7	5	1373	2	0	2

	${ t TotRmsAbvGrd}$	Fireplaces	AboveMedianPrice
135	7	1	1
1452	5	0	0
762	7	0	1
932	8	1	1

435	6	1		1
•••	•••	•••	•••	
1095	6	1		1
1130	7	2		0
1294	5	0		0
860	7	1		1
1126	7	1		1

[1022 rows x 9 columns]

Testing Features:

	OverallQual	OverallCond	TotalBsmtSF	FullBath	HalfBath	${\tt BedroomAbvGr}$
\						
892	6	8	1059	1	0	3
1105	8	5	1463	2	1	3
413	5	6	1008	1	0	2
522	6	7	1004	2	0	3
1036	9	5	1620	2	0	2
•••	•••	•••		•••	•••	
331	5	6	1056	1	0	3
323	3	8	1162	1	0	3
650	7	6	813	2	1	3
439	6	8	684	1	0	3
798	9	5	1926	3	1	4

	${\tt TotRmsAbvGrd}$	Fireplaces	${\tt Above Median Price}$
892	6	0	0
1105	9	2	1
413	5	1	0
522	7	2	0
1036	6	1	1
•••	•••	•••	•••
331	6	0	0
323	6	0	0
650	7	0	1
439	7	0	0
798	11	2	1

[438 rows x 9 columns]

Training Target:

```
860
              7642
     1126
              3684
     Name: LotArea, Length: 1022, dtype: int64
     Testing Target:
      892
               8414
     1105
             12256
     413
              8960
     522
              5000
     1036
             12898
     331
              8176
     323
              5820
     650
              8125
     439
             12354
             13518
     798
     Name: LotArea, Length: 438, dtype: int64
[50]: # Linear Regression model
      from sklearn.linear_model import LinearRegression
      from sklearn.metrics import mean_squared_error, r2_score
      model = LinearRegression()
      model.fit(x_train, y_train)
      # Predicting the LotArea for test data
      y_pred = model.predict(x_test)
      # Evaluating the model's performance
      mse = mean_squared_error(y_test, y_pred)
                                                # Mean Squared Error
      r2 = r2_score(y_test, y_pred)
                                                # R-squared score
      print("Model Coefficients:", model.coef_)
      print("Model Intercept:", model.intercept_)
      print("Mean Squared Error:", mse)
      print("R-squared Score:", r2)
      results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
      print(results)
     Model Coefficients: [-1784.57317854
                                            535.39223068
                                                             6.34890747
                                                                           105.64506875
       -350.6656404
                       499.86480782
                                       514.75964975 3611.59648719
       2444.37464586]
     Model Intercept: 3657.748961708652
     Mean Squared Error: 31147397.821340438
     R-squared Score: 0.03359678635359464
           Actual
                      Predicted
     892
             8414
                    8650.738138
     1105
            12256 17007.199705
     413
             8960 11637.704604
```

522	5000	15609.753689
1036	12898	10914.330395
•••	•••	•••
331	8176	9345.480133
323	5820	14658.395143
650	8125	6947.662984
439	12354	6784.657486
798	13518	19797.199861

[438 rows x 2 columns]