PRCP-1020-House Price Prediction using Advanced Regression

#Problem Statement Task 1:- Prepare a complete data analysis report on the given data. Task 2:-a) Create a robust machine learning algorithm to accurately predict the price of the house given the various factors across the market. b) Determine the relationship between the house features and how the price varies based on this. Task3:- Come up with suggestions for the customer to buy the house according to the area, price and other requirements.

Importing important libraires

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
#%matplotlibinline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
```

Read data set -

n [2]:	<pre>df=pd.read_csv("data.csv")</pre>											
[3]:	df											
[3]:		ld	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut	
	0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	1	
	1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	ļ	
	2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	1	
	3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	ļ	
	4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	1	
	•••											
	1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	Lvl	1	
	1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	Lvl	ļ	
	1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	Lvl	1	
	1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	Lvl	ļ	
	1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	Lvl	1	
	1460 r	460 rows × 81 columns										

In [6]: df.shape # number of columns are 1460 and columns are 81

```
HOUSE PRICE-Copy1
         (1460, 81)
Out[6]:
         df.columns
In [5]:
         Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
Out[5]:
                 'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
                 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
                'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
                 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
                 'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
                'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
                'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
                 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
                'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
                'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
                 'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
                'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
                'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
                 'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
                 'SaleCondition', 'SalePrice'],
               dtype='object')
         df.head() # display first 5 rows
```

Out[7]:		Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
	0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub
	1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub
	2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub
	3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub
	4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub

5 rows × 81 columns

df.info() In [8]:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):

Data	columns (total	81 columns):	
#	Column	Non-Null Count	Dtype
0	Id	1460 non-null	int64
1	MSSubClass	1460 non-null	int64
2	MSZoning	1460 non-null	object
3	LotFrontage	1201 non-null	float64
4	LotArea	1460 non-null	int64
5	Street	1460 non-null	object
6	Alley	91 non-null	object
7	LotShape LandContour	1460 non-null 1460 non-null	object
8			object
9	Utilities	1460 non-null	object
10	LotConfig	1460 non-null	object
11 12	LandSlope Neighborhood	1460 non-null 1460 non-null	object object
13	Condition1	1460 non-null	
14	Condition2	1460 non-null	object object
15		1460 non-null	object
16	BldgType HouseStyle	1460 non-null	object
17	OverallQual	1460 non-null	int64
18	OverallCond	1460 non-null	int64
19	YearBuilt	1460 non-null	int64
20	YearRemodAdd	1460 non-null	int64
21	RoofStyle	1460 non-null	object
22	RoofMatl	1460 non-null	object
23	Exterior1st	1460 non-null	object
24	Exterior2nd	1460 non-null	object
25	MasVnrType	1452 non-null	object
26	MasVnrArea	1452 non-null	float64
27	ExterQual	1460 non-null	object
28	ExterCond	1460 non-null	object
29	Foundation	1460 non-null	object
30	BsmtQual	1423 non-null	object
31	BsmtCond	1423 non-null	object
32	BsmtExposure	1422 non-null	object
33	BsmtFinType1	1423 non-null	object
34	BsmtFinSF1	1460 non-null	int64
35	BsmtFinType2	1422 non-null	object
36	BsmtFinSF2	1460 non-null	int64
37	BsmtUnfSF	1460 non-null	int64
38	TotalBsmtSF	1460 non-null	int64
39	Heating	1460 non-null	object
40	HeatingQC	1460 non-null	object
41	CentralAir	1460 non-null	object
42	Electrical	1459 non-null	object
43	1stFlrSF	1460 non-null	int64
44	2ndFlrSF	1460 non-null	int64
45	LowQualFinSF	1460 non-null	int64
46	GrLivArea	1460 non-null	int64
47	BsmtFullBath	1460 non-null	int64
48	BsmtHalfBath	1460 non-null	int64
49	FullBath	1460 non-null	int64
50	HalfBath	1460 non-null	int64
51	BedroomAbvGr	1460 non-null	int64
52 52	KitchenAbvGr	1460 non-null	int64
53 54	KitchenQual TotRmsAbvGrd	1460 non-null 1460 non-null	object int64
54	I O CNIIISAUVUI'U	THOS HOH-HULL	111104

```
55 Functional
                   1460 non-null
                                   object
 56 Fireplaces
                   1460 non-null
                                   int64
 57 FireplaceQu
                   770 non-null
                                   object
 58 GarageType
                   1379 non-null
                                   object
                                   float64
 59
    GarageYrBlt
                   1379 non-null
 60 GarageFinish
                   1379 non-null
                                   object
 61
    GarageCars
                   1460 non-null
                                   int64
    GarageArea
                   1460 non-null
                                   int64
 62
 63
    GarageQual
                   1379 non-null
                                   object
 64 GarageCond
                   1379 non-null
                                   object
 65
    PavedDrive
                   1460 non-null
                                   object
    WoodDeckSF
                   1460 non-null
                                   int64
    OpenPorchSF
                   1460 non-null
                                   int64
 67
 68 EnclosedPorch 1460 non-null
                                   int64
 69
    3SsnPorch
                   1460 non-null
                                   int64
 70 ScreenPorch
                   1460 non-null
                                   int64
 71 PoolArea
                   1460 non-null
                                   int64
 72 PoolQC
                   7 non-null
                                   object
 73 Fence
                   281 non-null
                                   object
 74 MiscFeature
                   54 non-null
                                   object
 75 MiscVal
                   1460 non-null
                                   int64
 76 MoSold
                   1460 non-null
                                   int64
 77 YrSold
                   1460 non-null
                                   int64
 78 SaleType
                   1460 non-null
                                   object
    SaleCondition 1460 non-null
                                   object
 80 SalePrice
                   1460 non-null
                                   int64
memory usage: 924.0+ KB
```

dtypes: float64(3), int64(35), object(43)

To show the all columns In [9]: pd.set_option("display.max_columns", 2000) pd.set_option("display.max_rows", 85)

df In [10]:

Out[10]:

:		ld	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut
	0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	1
	1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	ļ
	2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	1
	3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	1
	4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	1
	•••										
	1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	Lvl	1
	1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	Lvl	ļ
	1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	Lvl	1
	1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	Lvl	I
	1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	Lvl	1

1460 rows × 81 columns

In [9]:	df	.he	ad(6)										
Out[9]:		Id	MSSubClass	MSZon	ing L	otFrontage	LotArea	Street	Alley	LotShape	LandCont	our	Utilities
	0	1	60		RL	65.0	8450	Pave	NaN	Reg		Lvl	AllPub
	1	2	20		RL	80.0	9600	Pave	NaN	Reg		Lvl	AllPub
	2	3	60		RL	68.0	11250	Pave	NaN	IR1		Lvl	AllPub
	3	4	70		RL	60.0	9550	Pave	NaN	IR1		Lvl	AllPub
	4	5	60		RL	84.0	14260	Pave	NaN	IR1		Lvl	AllPub
	5	6	50		RL	85.0	14115	Pave	NaN	IR1		Lvl	AllPub
4													•
In [10]:	df	.sh	ape										
Out[10]:	(14	460,	, 81)										
In [11]:	df	.de	scribe() #	shows r	numeri	cal featur	es						
Out[11]:			ld	MSSub	Class	LotFrontage	· I	_otArea	Overa	allQual Ov	erallCond	Υ	earBuilt
	cou	unt	1460.000000	1460.00	00000	1201.000000	1460	.000000	1460.0	000000 14	60.000000	1460	0.000000
	me	ean	730.500000	56.89	97260	70.049958	10516	.828082	6.0)99315	5.575342	1971	1.267808
	:	std	421.610009	42.30	00571	24.284752	9981	.264932	1.3	382997	1.112799	30).202904
	n	nin	1.000000	20.00	00000	21.000000	1300	.000000	1.0	000000	1.000000	1872	2.000000
	2	5%	365.750000	20.00	00000	59.000000	7553	.500000	5.0	000000	5.000000	1954	1.000000
	5	0%	730.500000	50.00	00000	69.000000	9478	.500000	6.0	000000	5.000000	1973	3.000000
	7	5%	1095.250000	70.00	00000	80.000000	11601	.500000	7.0	000000	6.000000	2000	0.000000
	n	nax	1460.000000	190.00	00000	313.000000	215245	.000000	10.0	000000	9.000000	2010	0.000000
4													•
In [12]:	df	. de	scribe(incl	ude='0')# cc	ntegorical	columns						
Out[12]:			MSZoning	Street	Alley	LotShape	LandCon	tour U	tilities	LotConfig	LandSlope	e N	eighborh
	co	ount	: 1460	1460	91	1460	1	460	1460	1460	1460)	1
	uni	ique	5	2	2	4		4	2	5	3	3	
		top	RL	Pave	Grvl	Reg		Lvl	AllPub	Inside	Gt	l	NA
		freq	1151	1454	50	925	1	311	1459	1052	1382	2	
4													•
In [13]:	df	.dt	ypes										

Out[13]: Id

Id	int64
MSSubClass	int64
MSZoning	object
LotFrontage	float64
LotArea	int64
Street	object
Alley	object
LotShape	object
LandContour	object
Utilities	object
LotConfig	object
LandSlope	object
Neighborhood	object
Condition1	object
Condition2	object
BldgType	object
HouseStyle	object
OverallQual	int64
OverallCond	int64
YearBuilt	int64
YearRemodAdd	int64
RoofStyle	object
RoofMatl	
Exterior1st	object
	object
Exterior2nd	object
MasVnrType	object
MasVnrArea	float64
ExterQual	object
ExterCond	object
Foundation	object
BsmtQual	object
BsmtCond	object
BsmtExposure	object
BsmtFinType1	object
BsmtFinSF1	int64
BsmtFinType2	object
BsmtFinSF2	int64
BsmtUnfSF	int64
TotalBsmtSF	int64
Heating	object
HeatingQC	object
CentralAir	object
Electrical	object
1stFlrSF	int64
2ndFlrSF	int64
LowQualFinSF	int64
GrLivArea	int64
BsmtFullBath	int64
BsmtHalfBath	int64
FullBath	int64
HalfBath	int64
BedroomAbvGr	int64
KitchenAbvGr	int64
KitchenQual	object
TotRmsAbvGrd	int64
Functional	object
Fireplaces	int64
FireplaceQu	object
GarageType	object
GarageYrBlt	float64

GarageFinish	object
GarageCars	int64
GarageArea	int64
GarageQual	object
GarageCond	object
PavedDrive	object
WoodDeckSF	int64
OpenPorchSF	int64
EnclosedPorch	int64
3SsnPorch	int64
ScreenPorch	int64
PoolArea	int64
Poo1QC	object
Fence	object
MiscFeature	object
MiscVal	int64
MoSold	int64
YrSold	int64
SaleType	object
SaleCondition	object
SalePrice	int64
dtype: object	

#df.describe(include='O').value_counts

```
In [15]: # Set index as Id
df = df.set_index("Id")
```

In [16]:

Out[16]:		MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
	Id									
	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub
	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub
	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub
	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub
	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub
	•••									
	1456	60	RL	62.0	7917	Pave	NaN	Reg	Lvl	AllPub
	1457	20	RL	85.0	13175	Pave	NaN	Reg	Lvl	AllPub
	1458	70	RL	66.0	9042	Pave	NaN	Reg	Lvl	AllPub
	1459	20	RL	68.0	9717	Pave	NaN	Reg	Lvl	AllPub
	1460	20	RL	75.0	9937	Pave	NaN	Reg	Lvl	AllPub

1460 rows × 80 columns

Id column set as index column so no nned to remobve it # not necessary step because we set index as id column in df # drop unimportant column ID : df.drop(df['Id'], axis = 1, inplace = True)

10:03 PM		
Out[18]:	MSSubClass	15
out[10].	MSZoning	5
	LotFrontage	110
	LotArea	1073
	Street	2
	Alley	2
	LotShape	4
	LandContour	4
	Utilities	2
	LotConfig	5
	LandSlope	3
	Neighborhood	25
	Condition1	9
	Condition2	8
	BldgType	5
	HouseStyle	8
	OverallQual	10
	OverallCond	9
	YearBuilt	112
	YearRemodAdd	61
	RoofStyle	6
	RoofMatl	8
	Exterior1st	15
	Exterior2nd	16
	MasVnrType	4
	MasVnrArea	327
	ExterQual	4
	ExterCond	5
	Foundation	6
	BsmtQual	4
	BsmtCond	4
	BsmtExposure	4
	BsmtFinType1	6
	BsmtFinSF1	637
	BsmtFinType2	6
	D 15. CE2	

BsmtFinSF2

TotalBsmtSF Heating

BsmtUnfSF

HeatingQC

CentralAir

Electrical

LowQualFinSF

BsmtFullBath

BsmtHalfBath

BedroomAbvGr KitchenAbvGr

KitchenQual

Functional Fireplaces

FireplaceQu GarageType

GarageYrBlt

GarageFinish

TotRmsAbvGrd

1stFlrSF

2ndFlrSF

GrLivArea

FullBath

HalfBath

144

780 721

6

5

2

5

753

417

861

24

4

3

4

3 8

4

4

12 7

> 4 5

> 6

3

97

GarageCars	5
GarageArea	441
GarageQual	5
GarageCond	5
PavedDrive	3
WoodDeckSF	274
OpenPorchSF	202
EnclosedPorch	120
3SsnPorch	20
ScreenPorch	76
PoolArea	8
PoolQC	3
Fence	4
MiscFeature	4
MiscVal	21
MoSold	12
YrSold	5
SaleType	9
SaleCondition	6
SalePrice	663
dtyne: int64	

dtype: int64

2. EXPLORATORY DATA ANALYSIS -with data analysis

-Using EDA: Visualize fesatures, insight /observation from the data

- Missing Values
- All The Numerical Variables
- Distribution of the Numerical Variables
- Categorical Variables
- Cardinality of Categorical Variables
- Outliers

use automated pandas profiling for EDA - Pandas profiling - goal is to a EDA like df.desribe() function

```
from pandas_profiling import ProfileReport # file import
In [40]: !pip install pandas-profiling
```

```
Collecting pandas-profiling
 Downloading pandas profiling-3.6.6-py2.py3-none-any.whl (324 kB)
     ----- 324.4/324.4 kB 872.6 kB/s eta 0:00:00
Collecting ydata-profiling
 Downloading ydata profiling-4.3.1-py2.py3-none-any.whl (352 kB)
     ----- 353.0/353.0 kB 2.4 MB/s eta 0:00:00
Requirement already satisfied: numpy<1.24,>=1.16.0 in c:\users\vijay shelke\anaconda3
\lib\site-packages (from ydata-profiling->pandas-profiling) (1.21.5)
Requirement already satisfied: jinja2<3.2,>=2.11.1 in c:\users\vijay shelke\anaconda3
\lib\site-packages (from ydata-profiling->pandas-profiling) (2.11.3)
Collecting wordcloud>=1.9.1
 Downloading wordcloud-1.9.2-cp39-cp39-win amd64.whl (153 kB)
     ----- 153.3/153.3 kB 1.3 MB/s eta 0:00:00
Collecting visions[type_image_path]==0.7.5
 Downloading visions-0.7.5-py3-none-any.whl (102 kB)
     ----- 102.7/102.7 kB 211.5 kB/s eta 0:00:00
Requirement already satisfied: scipy<1.11,>=1.4.1 in c:\users\vijay shelke\anaconda3
\lib\site-packages (from ydata-profiling->pandas-profiling) (1.9.1)
Requirement already satisfied: pandas!=1.4.0,<2.1,>1.1 in c:\users\vijay shelke\anaco
nda3\lib\site-packages (from vdata-profiling->pandas-profiling) (1.4.4)
Requirement already satisfied: matplotlib<4,>=3.2 in c:\users\vijay shelke\anaconda3
\lib\site-packages (from ydata-profiling->pandas-profiling) (3.5.2)
Collecting htmlmin==0.1.12
 Downloading htmlmin-0.1.12.tar.gz (19 kB)
 Preparing metadata (setup.py): started
 Preparing metadata (setup.py): finished with status 'done'
Collecting phik<0.13,>=0.11.1
 Downloading phik-0.12.3-cp39-cp39-win amd64.whl (663 kB)
     ----- 663.5/663.5 kB 3.8 MB/s eta 0:00:00
Requirement already satisfied: tqdm<5,>=4.48.2 in c:\users\vijay shelke\anaconda3\lib
\site-packages (from ydata-profiling->pandas-profiling) (4.64.1)
Requirement already satisfied: seaborn<0.13,>=0.10.1 in c:\users\vijay shelke\anacond
a3\lib\site-packages (from ydata-profiling->pandas-profiling) (0.11.2)
Collecting multimethod<2,>=1.4
 Downloading multimethod-1.9.1-py3-none-any.whl (10 kB)
Requirement already satisfied: PyYAML<6.1,>=5.0.0 in c:\users\vijay shelke\anaconda3
\lib\site-packages (from ydata-profiling->pandas-profiling) (6.0)
Collecting pydantic<2,>=1.8.1
 Downloading pydantic-1.10.11-cp39-cp39-win amd64.whl (2.2 MB)
     ----- 2.2/2.2 MB 4.5 MB/s eta 0:00:00
Collecting typeguard<3,>=2.13.2
 Downloading typeguard-2.13.3-py3-none-any.whl (17 kB)
Collecting imagehash==4.3.1
 Downloading ImageHash-4.3.1-py2.py3-none-any.whl (296 kB)
     ------ 296.5/296.5 kB 171.2 kB/s eta 0:00:00
Requirement already satisfied: requests<3,>=2.24.0 in c:\users\vijay shelke\anaconda3
\lib\site-packages (from ydata-profiling->pandas-profiling) (2.28.1)
Collecting dacite>=1.8
 Downloading dacite-1.8.1-py3-none-any.whl (14 kB)
Requirement already satisfied: statsmodels<1,>=0.13.2 in c:\users\vijay shelke\anacon
da3\lib\site-packages (from ydata-profiling->pandas-profiling) (0.13.2)
Requirement already satisfied: pillow in c:\users\vijay shelke\anaconda3\lib\site-pac
kages (from imagehash==4.3.1->ydata-profiling->pandas-profiling) (9.2.0)
Requirement already satisfied: PyWavelets in c:\users\vijay shelke\anaconda3\lib\site
-packages (from imagehash==4.3.1->ydata-profiling->pandas-profiling) (1.3.0)
Collecting tangled-up-in-unicode>=0.0.4
 Downloading tangled up in unicode-0.2.0-py3-none-any.whl (4.7 MB)
     ----- 4.7/4.7 MB 5.7 MB/s eta 0:00:00
Requirement already satisfied: attrs>=19.3.0 in c:\users\vijay shelke\anaconda3\lib\s
ite-packages (from visions[type image path] == 0.7.5->ydata-profiling->pandas-profilin
```

```
HOUSE PRICE-Copy1
g) (21.4.0)
Requirement already satisfied: networkx>=2.4 in c:\users\vijay shelke\anaconda3\lib\s
ite-packages (from visions[type image path] == 0.7.5->ydata-profiling->pandas-profilin
g) (2.8.4)
Requirement already satisfied: MarkupSafe>=0.23 in c:\users\vijay shelke\anaconda3\li
b\site-packages (from jinja2<3.2,>=2.11.1->ydata-profiling->pandas-profiling) (2.0.1)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\vijay shelke\anaconda3\l
ib\site-packages (from matplotlib<4,>=3.2->ydata-profiling->pandas-profiling) (1.4.2)
Requirement already satisfied: packaging>=20.0 in c:\users\vijay shelke\anaconda3\lib
\site-packages (from matplotlib<4,>=3.2->ydata-profiling->pandas-profiling) (21.3)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\vijay shelke\anaconda3\l
ib\site-packages (from matplotlib<4,>=3.2->ydata-profiling->pandas-profiling) (4.25.
Requirement already satisfied: python-dateutil>=2.7 in c:\users\vijay shelke\anaconda
3\lib\site-packages (from matplotlib<4,>=3.2->ydata-profiling->pandas-profiling) (2.
8.2)
Requirement already satisfied: pyparsing>=2.2.1 in c:\users\vijay shelke\anaconda3\li
b\site-packages (from matplotlib<4,>=3.2->ydata-profiling->pandas-profiling) (3.0.9)
Requirement already satisfied: cycler>=0.10 in c:\users\vijay shelke\anaconda3\lib\si
te-packages (from matplotlib<4,>=3.2->ydata-profiling->pandas-profiling) (0.11.0)
Requirement already satisfied: pytz>=2020.1 in c:\users\vijay shelke\anaconda3\lib\si
te-packages (from pandas!=1.4.0,<2.1,>1.1->ydata-profiling->pandas-profiling) (2022.
1)
Requirement already satisfied: joblib>=0.14.1 in c:\users\vijay shelke\anaconda3\lib
\site-packages (from phik<0.13,>=0.11.1->vdata-profiling->pandas-profiling) (1.2.0)
Requirement already satisfied: typing-extensions>=4.2.0 in c:\users\vijay shelke\anac
onda3\lib\site-packages (from pydantic<2,>=1.8.1->ydata-profiling->pandas-profiling)
(4.3.0)
Requirement already satisfied: idna<4,>=2.5 in c:\users\vijay shelke\anaconda3\lib\si
te-packages (from requests<3,>=2.24.0->ydata-profiling->pandas-profiling) (3.3)
```

te-packages (from requests<3,>=2.24.0->ydata-profiling->pandas-profiling) (3.3)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\vijay shelke\anaconda3
\lib\site-packages (from requests<3,>=2.24.0->ydata-profiling->pandas-profiling) (202
2.9.14)

Requirement already satisfied: charset-normalizer<3,>=2 in c:\users\vijay shelke\anac onda3\lib\site-packages (from requests<3,>=2.24.0->ydata-profiling->pandas-profiling) (2.0.4)

Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\users\vijay shelke\anacond a3\lib\site-packages (from requests<3,>=2.24.0->ydata-profiling->pandas-profiling) (1.26.11)

Requirement already satisfied: patsy>=0.5.2 in c:\users\vijay shelke\anaconda3\lib\site-packages (from statsmodels<1,>=0.13.2->ydata-profiling->pandas-profiling) (0.5.2)
Requirement already satisfied: colorama in c:\users\vijay shelke\anaconda3\lib\site-packages (from tqdm<5,>=4.48.2->ydata-profiling->pandas-profiling) (0.4.5)
Requirement already satisfied: six in c:\users\vijay shelke\anaconda3\lib\site packages

Requirement already satisfied: six in c:\users\vijay shelke\anaconda3\lib\site-packag es (from patsy>=0.5.2->statsmodels<1,>=0.13.2->ydata-profiling->pandas-profiling) (1. 16.0)

Building wheels for collected packages: htmlmin

Building wheel for htmlmin (setup.py): started

Building wheel for htmlmin (setup.py): finished with status 'done'

Created wheel for htmlmin: filename=htmlmin-0.1.12-py3-none-any.whl size=27082 sha2 56=9c3ba0be9f45119adaf9bbc0087789278be164ab100e2f538d6a77647431d3e5

Stored in directory: c:\users\vijay shelke\appdata\local\pip\cache\wheels\1d\05\04 \c6d7d3b66539d9e659ac6dfe81e2d0fd4c1a8316cc5a403300

Successfully built htmlmin

Installing collected packages: htmlmin, typeguard, tangled-up-in-unicode, pydantic, m ultimethod, dacite, imagehash, wordcloud, visions, phik, ydata-profiling, pandas-profiling

Successfully installed dacite-1.8.1 htmlmin-0.1.12 imagehash-4.3.1 multimethod-1.9.1 pandas-profiling-3.6.6 phik-0.12.3 pydantic-1.10.11 tangled-up-in-unicode-0.2.0 typeg uard-2.13.3 visions-0.7.5 wordcloud-1.9.2 ydata-profiling-4.3.1

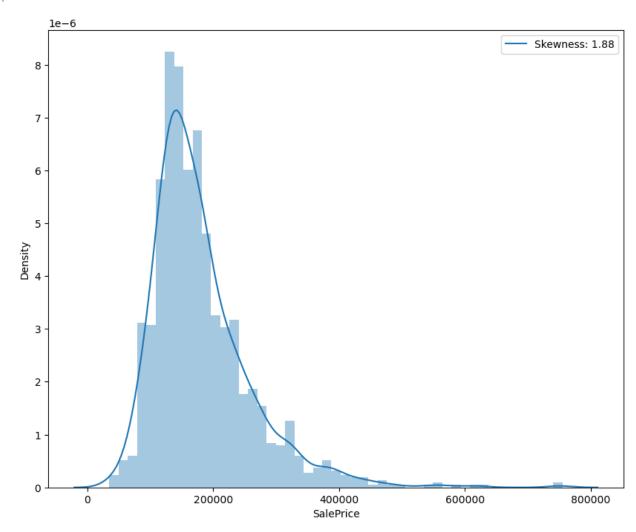
Generate the EDA report profile=ProfileReport(df,explorative=True) # EXPORATIVE TRUE- GIVES ALL INFORMATION FROM YOUR DATASET profile.to_file('house.html')

```
#know the data types of each columns
          obj = (df.dtypes == 'object')
          object cols = list(obj[obj].index)
           print("Categorical variables:",len(object cols))
          Categorical variables: 43
          # most features are categorical varaibles
In [60]:
          df.select_dtypes(include=['int64', 'float64']).columns
In [21]:
          Index(['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
Out[21]:
                   'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
                  'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
                  'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
                  'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
                  'MoSold', 'YrSold', 'SalePrice'],
                 dtvpe='object')
In [23]: # list of all objects column categorical
          df.select_dtypes(include=['object']).columns
          Index(['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities',
                   'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
                  'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
                  'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation',
                  'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2',
                  'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
                  'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual',
                  'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature',
                  'SaleType', 'SaleCondition'],
                 dtype='object')
```

check the distribution of target column - do log transformation due to right positive skewness:

```
# check the distrubution of target varible i.e SalePrcie
In [71]:
          df["SalePrice"].describe()
                     1460.000000
         count
Out[71]:
         mean
                   180921.195890
                   79442.502883
         std
                   34900.000000
         min
         25%
                   129975.000000
         50%
                   163000.000000
         75%
                   214000.000000
                   755000.000000
         max
         Name: SalePrice, dtype: float64
         # Plot the distplot of target
In [24]:
          plt.figure(figsize=(10,8))
          bar = sns.distplot(df["SalePrice"],kde=True)
          bar.legend(["Skewness: {:.2f}".format(df['SalePrice'].skew())])
```

Out[24]: <matplotlib.legend.Legend at 0x2cd1631880>

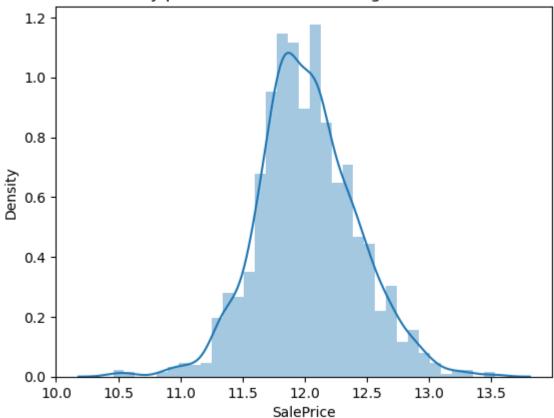


here sales price normaly distrubeted with right skew

log transformation on sale price -right skewness

```
In [31]: # this indicated output variabvle Sale price is right skewed so i applied log trabnsof
In [25]: # Positive Skeweness:
    df['SalePrice'].skew()
Out[25]: 1.8828757597682129
In [26]: df["SalePrice"] = np.log1p(df["SalePrice"])
In [28]: #SalePrice after Log-transformation
    sns.distplot(df["SalePrice"])
    plt.title("Density plot of SalePrice after Log Transformation")
Out[28]: Text(0.5, 1.0, 'Density plot of SalePrice after Log Transformation')
```

Density plot of SalePrice after Log Transformation



```
In [29]: # again check skewness :
    # Positive Skeweness:
    df['SalePrice'].skew()
```

Out[29]: 0.12134661989685333

3. Datapreprocessing

- handling missing values
- handling outliers
- drop duplicates
- scaling

```
In [31]: #sum of missing data
    df.isnull().sum().sort_values(ascending=False)
```

Out[31]:	PoolQC	
our[].	MiccEostupo	

Poo1QC	1453
MiscFeature	1406
Alley	1369
Fence	1179
FireplaceQu	690
LotFrontage	259
GarageYrBlt	81
GarageCond	81
GarageType	81
GarageFinish	81
GarageQual	81
BsmtExposure	38
BsmtFinType2	38
BsmtCond	37
BsmtQual	37
BsmtFinType1	37
MasVnrArea	8
MasVnrType	8
Electrical	1
MSSubClass	0
Fireplaces	0
Functional	0
KitchenQual	0
KitchenAbvGr	0
BedroomAbvGr	0
HalfBath	0
FullBath	0
BsmtHalfBath	0
TotRmsAbvGrd	0
GarageCars	0
GrLivArea	0
GarageArea	0
PavedDrive	0
WoodDeckSF	0
OpenPorchSF	0
EnclosedPorch	0
3SsnPorch	0
ScreenPorch	0
PoolArea	0
MiscVal	0
MoSold	0
YrSold	0
SaleType	0
SaleCondition	0
BsmtFullBath	0
CentralAir	0
LowQualFinSF	0

LotConfig 0 Utilities 0 LandContour 0 LotShape

Neighborhood

OverallCond

OverallQual

HouseStyle

Condition2

Condition1

LandSlope

2ndFlrSF

BldgType

0

0

0

0

0

0

0

0

0

```
Street
                    0
LotArea
                    0
YearBuilt
                    0
YearRemodAdd
                    0
RoofStyle
                    0
RoofMatl
                    0
Exterior1st
                    0
Exterior2nd
                    0
ExterQual
                    0
ExterCond
                    0
Foundation
                    0
BsmtFinSF1
                    0
BsmtFinSF2
                    0
BsmtUnfSF
                    0
TotalBsmtSF
                    0
Heating
                    0
HeatingQC
                    0
MSZoning
                    0
1stFlrSF
                    0
SalePrice
                    0
dtype: int64
```

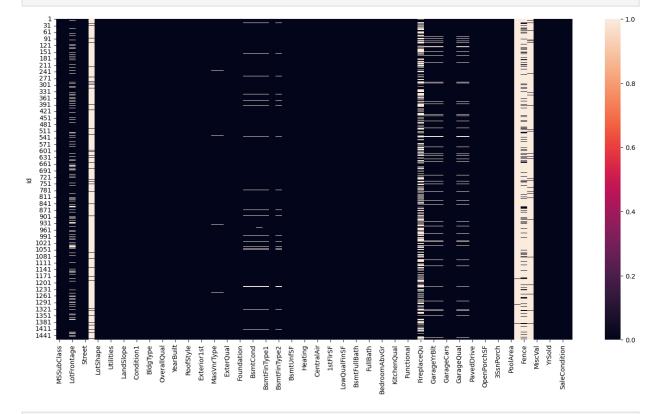
```
In [79]: # Get the percentages of null values of each column
null_percent = df.isnull().sum()/df.shape[0]*100
null_percent
```

Out[79]:

MSSubClass	0.000000
MSZoning	0.000000
LotFrontage	17.739726
LotArea	0.000000
Street	0.000000
Alley	93.767123
LotShape	0.000000
LandContour	0.000000
Utilities	0.000000
LotConfig	0.000000
LandSlope	0.000000
Neighborhood	0.000000
Condition1	0.000000
Condition2	0.000000
BldgType	0.000000
HouseStyle	0.000000
OverallQual	0.000000
OverallCond	0.000000
YearBuilt	0.000000
YearRemodAdd	0.000000
RoofStyle	0.000000
RoofMatl	0.000000
Exterior1st	0.000000
Exterior2nd	0.000000
MasVnrType	0.547945
MasVnrArea	0.547945
	0.000000
ExterQual	
ExterCond	0.000000
Foundation	0.000000
BsmtQual	2.534247
BsmtCond	2.534247
BsmtExposure	2.602740
BsmtFinType1	2.534247
BsmtFinSF1	0.000000
BsmtFinType2	2.602740
BsmtFinSF2	0.000000
BsmtUnfSF	0.000000
TotalBsmtSF	0.000000
Heating	0.000000
HeatingQC	0.000000
CentralAir	
	0.000000
Electrical	0.068493
1stFlrSF	0.000000
2ndFlrSF	0.000000
LowQualFinSF	0.000000
GrLivArea	0.000000
BsmtFullBath	0.000000
BsmtHalfBath	0.000000
FullBath	0.000000
HalfBath	0.000000
BedroomAbvGr	0.000000
KitchenAbvGr	0.000000
KitchenQual	0.000000
TotRmsAbvGrd	0.000000
Functional	0.000000
Fireplaces	0.000000
FireplaceQu	47.260274
GarageType	5.547945
GarageYrBlt	5.547945
GarageFinish	5.547945
-	

```
GarageCars
                  0.000000
GarageArea
                  0.000000
GarageQual
                  5.547945
GarageCond
                  5.547945
PavedDrive
                  0.000000
WoodDeckSF
                  0.000000
OpenPorchSF
                  0.000000
EnclosedPorch
                  0.000000
3SsnPorch
                  0.000000
ScreenPorch
                  0.000000
PoolArea
                  0.000000
PoolQC
                  99.520548
Fence
                  80.753425
MiscFeature
                  96.301370
MiscVal
                  0.000000
MoSold
                  0.000000
YrSold
                  0.000000
SaleType
                  0.000000
SaleCondition
                  0.000000
SalePrice
                  0.000000
dtype: float64
```

```
In [32]: # Show the null values using heatmap
plt.figure(figsize=(18,9))
sns.heatmap(df.isnull())
plt.show()
```



```
In [33]: # We have to drop some columns which contains large number of null values and features
drop_variables = ['Alley', 'FireplaceQu', 'PoolQC', 'Fence', 'MiscFeature']
df = df.drop(drop_variables, axis = 1)
df
```

Out[33]:		MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotCoı
	Id									
	1	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	In
	2	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	
	3	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	In
	4	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Co
	5	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	
	•••					•••				
	1456	60	RL	62.0	7917	Pave	Reg	Lvl	AllPub	In
	1457	20	RL	85.0	13175	Pave	Reg	Lvl	AllPub	In
	1458	70	RL	66.0	9042	Pave	Reg	Lvl	AllPub	In
	1459	20	RL	68.0	9717	Pave	Reg	Lvl	AllPub	In
	1460	20	RL	75.0	9937	Pave	Reg	Lvl	AllPub	In

1460 rows × 75 columns

5 columns get droped # most null values columns are - ALLEY ,PoolQC ,MiscFeature, Fence

In [34]: # some columns aremissing values less ampount of missing values
after some delete missing values columns some columns have missing values
col_nan = df.isna().sum() / df.shape[0]

In [35]: col_nan.sort_values(ascending=False)

Out[35]:

LotFrontage	0.177397
GarageType	0.055479
GarageYrBlt	0.055479
GarageFinish	0.055479
GarageQual	0.055479
GarageCond	0.055479
BsmtFinType2	0.026027
BsmtExposure	0.026027
BsmtQual	0.025342
BsmtCond	0.025342
	0.025342
BsmtFinType1 MasVnrArea	0.005479
MasVnrType	0.005479
Electrical	0.000685
KitchenAbvGr	0.000000
BedroomAbvGr	0.000000
HalfBath	0.000000
FullBath	0.000000
BsmtHalfBath	0.000000
BsmtFullBath	0.000000
KitchenQual	0.000000
GrLivArea	0.000000
TotRmsAbvGrd	0.000000
Functional	0.000000
MSSubClass	0.000000
Fireplaces	0.000000
ScreenPorch	0.000000
SaleCondition	0.000000
SaleType	0.000000
YrSold	0.000000
MoSold	0.000000
MiscVal	0.000000
PoolArea	0.000000
3SsnPorch	0.000000
2ndFlrSF	0.000000
EnclosedPorch	0.000000
OpenPorchSF	0.000000
WoodDeckSF	0.000000
PavedDrive	0.000000
GarageArea	0.000000
GarageCars	0.000000
LowQualFinSF	0.000000
Heating	0.000000
1stFlrSF	0.000000
CentralAir	0.000000
LotArea	0.000000
Street	0.000000
LotShape	0.000000
LandContour	0.000000
Utilities	0.000000
LotConfig	0.000000
LandSlope	0.000000
Neighborhood	0.000000
Neighbornood Condition1	0.000000
Condition1 Condition2	
	0.000000
BldgType	
HouseStyle	0.000000
OverallQual	0.000000
OverallCond	0.000000
YearBuilt	0.000000

```
YearRemodAdd
                 0.000000
RoofStyle
                 0.000000
RoofMat1
                 0.000000
Exterior1st
                 0.000000
Exterior2nd
                 0.000000
                 0.000000
ExterOual
ExterCond
                 0.000000
Foundation
                 0.000000
BsmtFinSF1
                 0.000000
BsmtFinSF2
                 0.000000
BsmtUnfSF
                 0.000000
TotalBsmtSF
                 0.000000
                 0.000000
MSZoning
                 0.000000
HeatingQC
SalePrice
                 0.000000
dtype: float64
```

these columns have missing values: LotFrontage 0.177397 GarageType 0.055479 GarageYrBlt 0.055479 GarageFinish 0.055479 GarageQual 0.055479 GarageCond 0.055479 BsmtFinType2 0.026027 BsmtExposure 0.026027 BsmtQual 0.025342 BsmtCond 0.025342 BsmtFinType1 0.025342 MasVnrArea 0.005479 MasVnrType 0.005479 Electrical 0.000685

#these categorical columns missing values MasVnrType 8 BsmtQual 37 BsmtCond 37 BsmtExposure 38 BsmtFinType1 37 BsmtFinType2 38 GarageType 81 GarageFinish 81 GarageQual 81 GarageCond 81 Electrical 1 # NUMERICAL COLUMNS - MasVnrArea-8 , ' -1 # DATE AND TIME COLUMNS : GarageYrBlt', 81'

```
In [48]: # filling missing value with median and mode of numerical as wlll as categorical varai
df['LotFrontage'] = df['LotFrontage'].fillna(df['LotFrontage'].mean())
```

cat col=['BsmtQual','BsmtCond','BsmtExposure','BsmtFinType1','BsmtFinType2',

'MasVnrType','GarageType','GarageFinish','GarageQual', 'GarageCond'] # these are objectS 10 columns has missing vlaues .

```
# MasVnrType-
In [49]:
         df['MasVnrType'] = df['MasVnrType'].fillna(df['MasVnrType'].mode()[0])
          #MasVnrArea
          df['MasVnrArea'] = df['MasVnrArea'].fillna(df['MasVnrArea'].median())
         # electrical cat features
In [50]:
         df['Electrical'] = df['Electrical'].fillna(df['Electrical'].mode()[0])
         # basement features :
In [51]:
                       BsmtCond
                                   BsmtExposure BsmtFinType1 BsmtFinType2
                                                                               -categorical feat
         df['BsmtQual'] = df['BsmtQual'].fillna(df['BsmtQual'].mode()[0])
          df['BsmtCond'] = df['BsmtCond'].fillna(df['BsmtCond'].mode()[0])
          df['BsmtExposure'] = df['BsmtExposure'].fillna(df['BsmtExposure'].mode()[0])
          df['BsmtFinType1'] = df['BsmtFinType1'].fillna(df['BsmtFinType1'].mode()[0])
         df['BsmtFinType2'] = df['BsmtFinType2'].fillna(df['BsmtFinType2'].mode()[0])
         #All garage features : are categorical -replace with mode
In [52]:
                         GarageFinish GarageQual
                                                    GarageCond
         # GarageType
          print('Fill missing values of Garage features with medain or mode')
         df['GarageType'] = df['GarageType'].fillna(df['GarageType'].mode()[0])
```

In [53]:

In [54]:

df.isnull().sum() # no null is present

```
df['GarageFinish'] = df['GarageFinish'].fillna(df['GarageFinish'].mode()[0])
df['GarageCond'] = df['GarageCond'].fillna(df['GarageCond'].mode()[0])
df['GarageQual'] = df['GarageQual'].fillna(df['GarageQual'].mode()[0])
Fill missing values of Garage features with medain or mode

df['GarageYrBlt'] = df['GarageYrBlt'].fillna(int(0))
```

MSSubClass 0 Out[54]: 0 MSZoning LotFrontage 0 LotArea 0 0 Street LotShape 0 LandContour 0 Utilities 0 LotConfig 0 LandSlope 0 Neighborhood 0 Condition1 0 Condition2 0 BldgType 0 HouseStyle 0 OverallQual 0 OverallCond 0 YearBuilt 0 YearRemodAdd 0 RoofStyle 0 RoofMat1 0 Exterior1st 0 Exterior2nd 0 MasVnrType 0 MasVnrArea 0 ExterQual 0 ExterCond 0 Foundation 0 **BsmtQual** 0 **BsmtCond** 0 BsmtExposure 0 BsmtFinType1 0 BsmtFinSF1 0 BsmtFinType2 0 BsmtFinSF2 0 BsmtUnfSF 0 TotalBsmtSF 0 0 Heating HeatingQC 0 CentralAir 0 Electrical 0 1stFlrSF 0 2ndFlrSF 0 LowQualFinSF 0 GrLivArea 0 **BsmtFullBath** 0 BsmtHalfBath 0 FullBath 0 HalfBath 0 BedroomAbvGr 0 KitchenAbvGr 0 KitchenQual 0 TotRmsAbvGrd 0 Functional 0 Fireplaces 0 GarageType 0 GarageYrBlt 0 GarageFinish 0 GarageCars 0 GarageArea 0

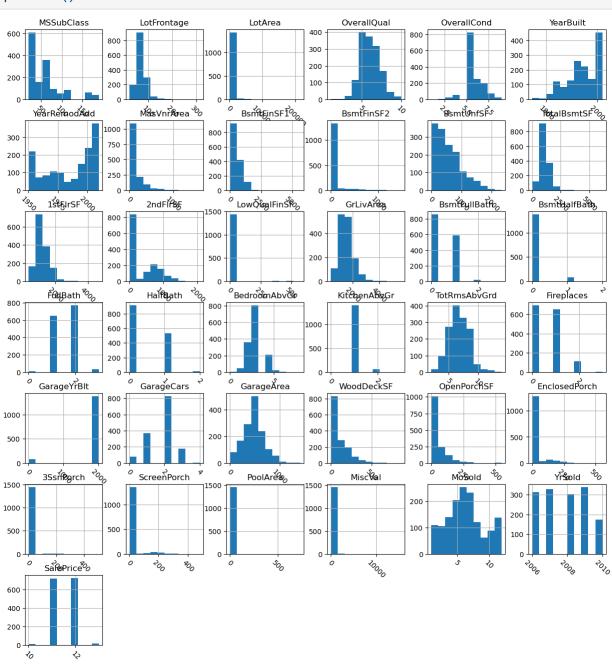
```
GarageQual
                             0
            GarageCond
                             0
            PavedDrive
                             0
            WoodDeckSF
            OpenPorchSF
                             0
            EnclosedPorch
                             0
            3SsnPorch
            ScreenPorch
                             0
            PoolArea
                             0
            MiscVal
                             0
            MoSold
                             0
            YrSold
                             0
            SaleType
            SaleCondition
                             0
            SalePrice
            dtype: int64
  In [55]: # convert year column into another column and float column into int columns :
            # LotFrontage, MasVnrArea - float 64 type into int 64
            df['LotFrontage'] = df['LotFrontage'].astype(np.int64)
            df['MasVnrArea'] = df['MasVnrArea'].astype(np.int64)
            # convert sale price into int 64 -SalePrice
  In [56]:
            df['SalePrice'] = df['SalePrice'].astype(np.int64)
  In [57]: df['GarageYrBlt']=df['GarageYrBlt'].astype(np.int64)
  In [58]: df['Utilities'].value counts()
            # these features totaly nosewa having only one value so it is no use for category
            df.drop(columns='Utilities',inplace=True)
            print('Drop Utilities \n')
            Drop Utilities
  In [59]: # Convert year related columns to number of years, to find how old the house is, or he
            # house was sold.
            # there 4 date time features -YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
            df['YearBuilt'] = 2023 - df['YearBuilt']
            df['YearRemodAdd'] = 2023 - df['YearRemodAdd']
            df['GarageYrBlt'] = 2023 - df['GarageYrBlt']
            df['YrSold'] = 2023 - df['YrSold']
           print(df.isnull().sum().sum()) # no null values are present
            0
# no null values are present
            df['Street'].value counts() # only GRVL VALUE IS 6 PAVE MOST CATEGORY SO WE CAN DROP s
                    1454
            Pave
  Out[61]:
            Grvl
            Name: Street, dtype: int64
   In [ ]:
```

OUTLIER DETECTION AND REMOVAL: MOST IMP

Removing outliers is important step in data analysis. However, while removing outliers in ML we should be careful, because we do not know if there are not any outliers in test set. I used two techniques: The first one was Z-score method. Z-scores are expressed in terms of standard deviations from their means. As a result, these z-scores have a distribution with a mean of 0 and a standard deviation of 1. I set threshold = 3 to identify outliers.

OUTLIER DETECTION AND REMOVAL: MOST IMP STEPS:

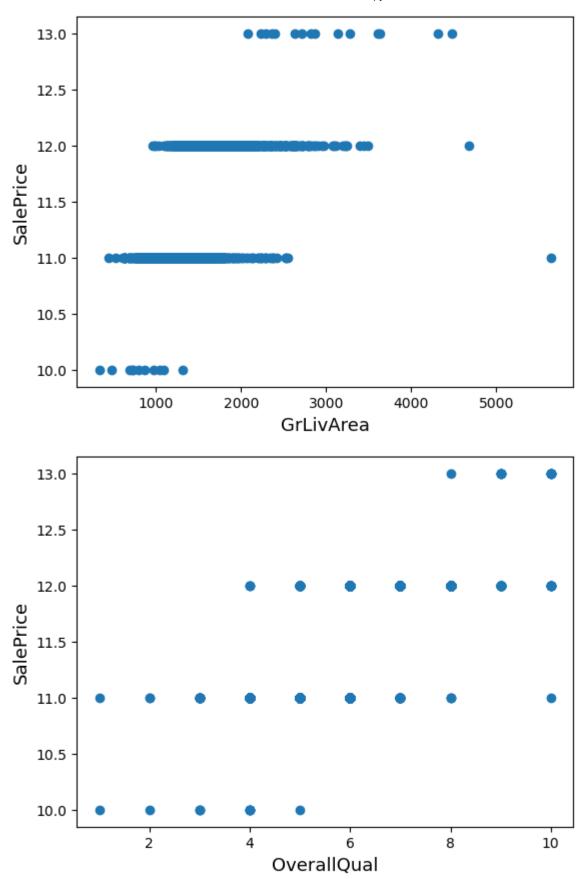


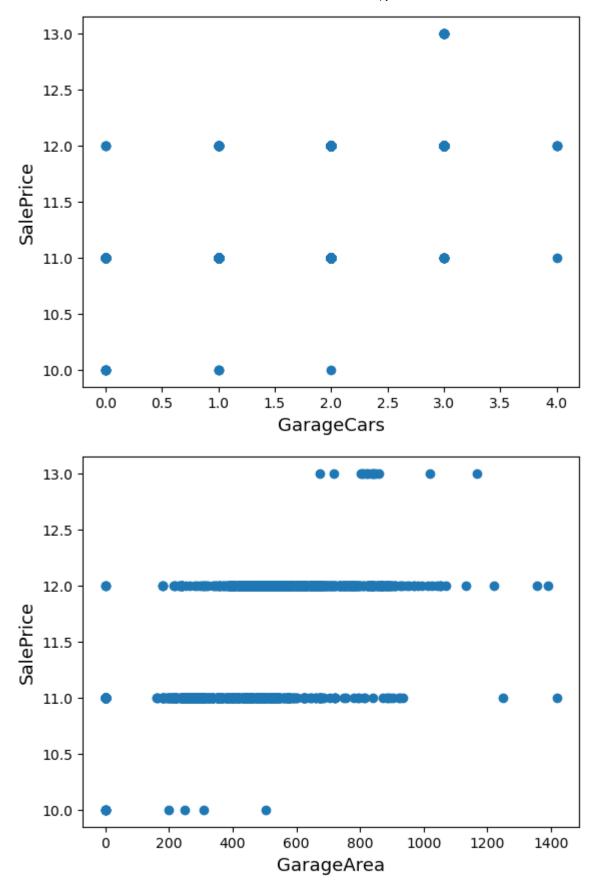


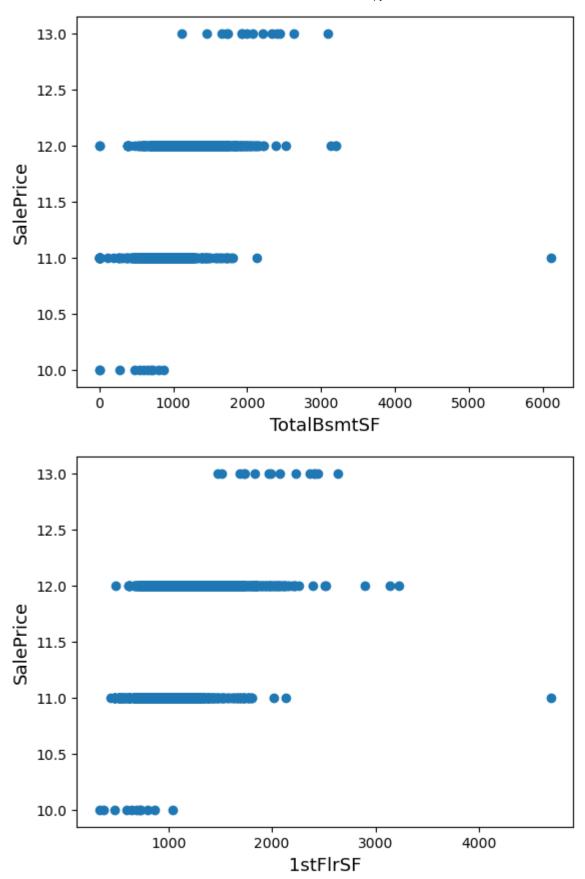
In [126... # MOST COLUMNS ARE RIGHT SKEWED

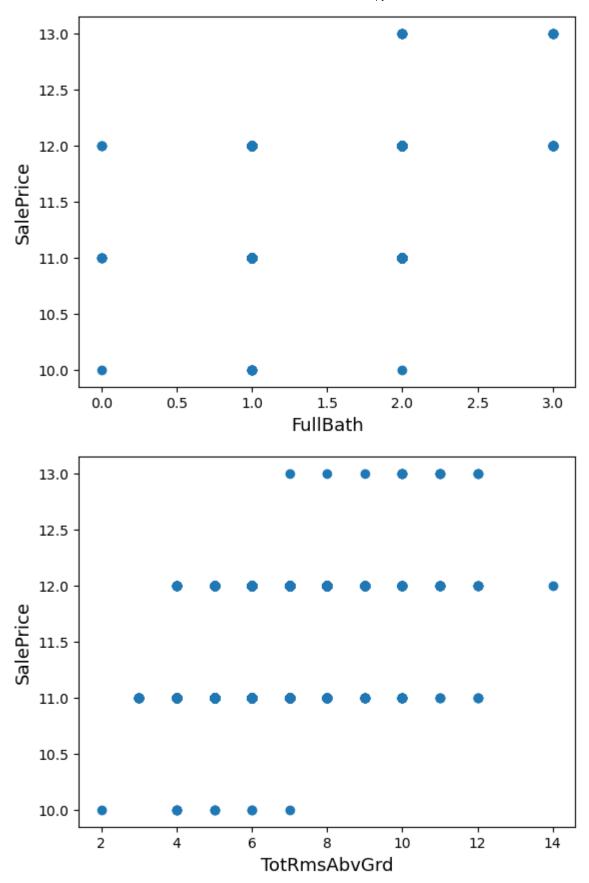
In [69]: # plot outliers of different scatter plot
 #now we are going detect outliers in whole dataset

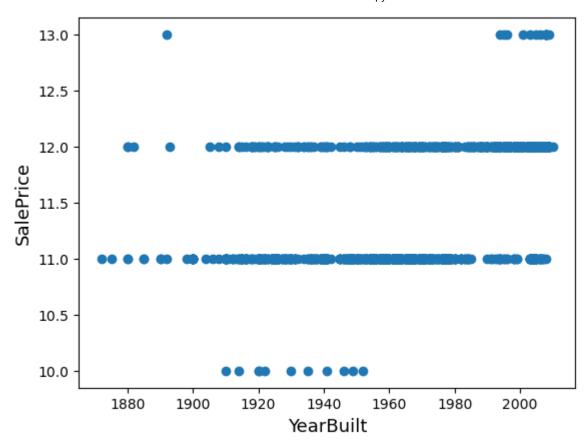
```
fig = plt.subplots()
plt.scatter(x = df['GrLivArea'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GrLivArea', fontsize=13)
plt.show()
fig1= plt.subplots()
plt.scatter(x = df['OverallQual'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('OverallQual', fontsize=13)
plt.show()
fig2= plt.subplots()
plt.scatter(x = df['GarageCars'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GarageCars', fontsize=13)
plt.show()
fig3= plt.subplots()
plt.scatter(x = df['GarageArea'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GarageArea', fontsize=13)
plt.show()
fig4= plt.subplots()
plt.scatter(x = df['TotalBsmtSF'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('TotalBsmtSF', fontsize=13)
plt.show()
fig5= plt.subplots()
plt.scatter(x = df['1stFlrSF'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('1stFlrSF', fontsize=13)
plt.show()
fig6= plt.subplots()
plt.scatter(x = df['FullBath'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('FullBath', fontsize=13)
plt.show()
fig7= plt.subplots()
plt.scatter(x = df['TotRmsAbvGrd'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('TotRmsAbvGrd', fontsize=13)
plt.show()
fig8= plt.subplots()
plt.scatter(x = df['YearBuilt'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('YearBuilt', fontsize=13)
plt.show()
```



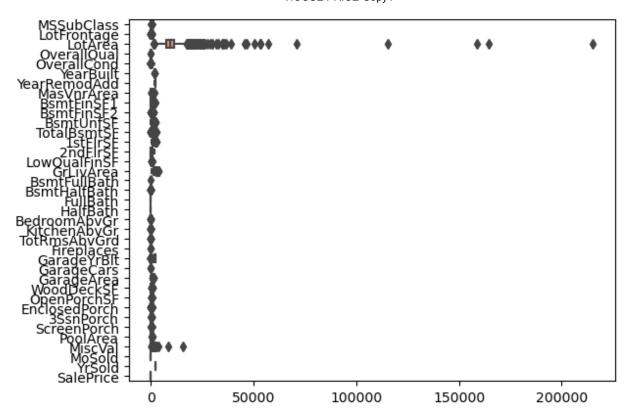






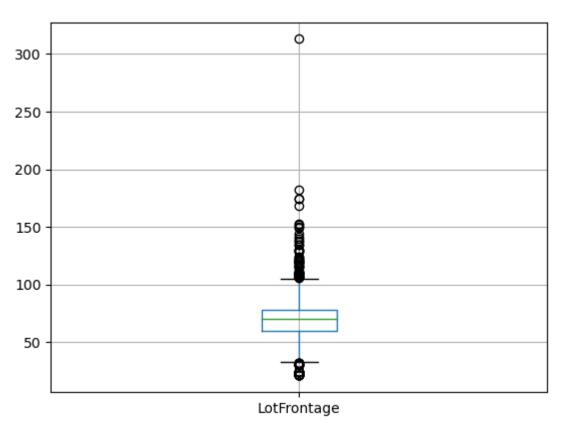


```
In [72]: # above all highly correlated with output so i check thier outliers
    df = df.drop(df[(df['GrLivArea']>4000) & (df['SalePrice']<300000)].index)
    df = df.drop(df[(df['GarageArea']>1200) & (df['SalePrice']<500000)].index)
    df = df.drop(df[(df['TotalBsmtSF']>3000) & (df['SalePrice']<700000)].index)
    df = df.drop(df[(df['1stFlrSF']>2700) & (df['1stFlrSF']<700000)].index)</pre>
In [73]: #check outliers
    sns.boxplot(data=df,orient="h")
Out[73]: <AxesSubplot:>
```



```
In [83]: # box plot of numeric column only
    df.boxplot(column =['LotFrontage'])
```

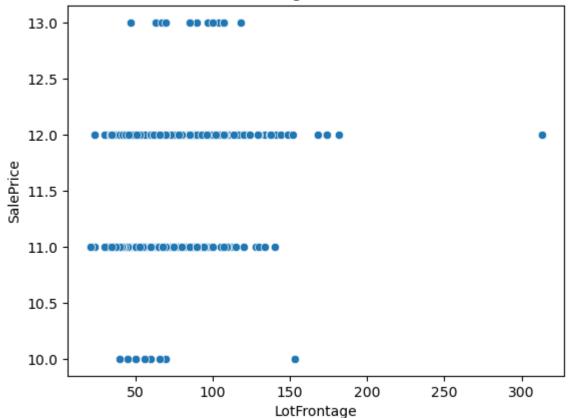
Out[83]: <AxesSubplot:>



not useful boxplot for outllier display sns.set_style("whitegrid") plt.figure(figsize=(20,10)) ax = sns.boxplot(x="LotFrontage", y="SalePrice", hue='MSZoning', data=df, width=0.8) plt.show()

```
In [88]: sns.scatterplot(df['LotFrontage'], df["SalePrice"])
    plt.title("LotFrontage'vs SalePrice")
    plt.show()
```





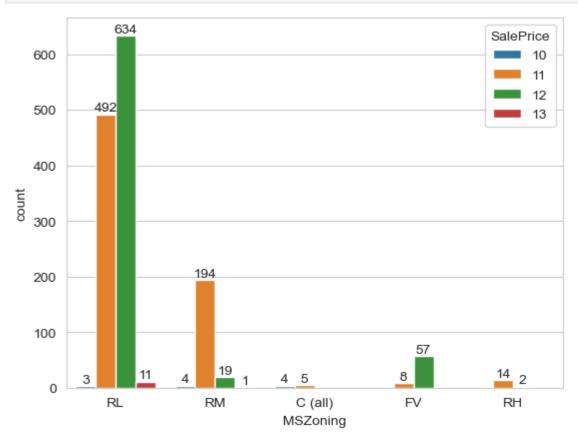
```
In [113... #i decided to replace <code>lLotFrontage</code> house <code>i</code> impute value with median only <code>print('skewness value of : ',df['LotFrontage'].skew())</code> # skew value between -1 to 1 so # LotFrontage area increse sale prize also increase so need to remove LotFrontage outl
```

skewness value of : 1.7045256035173681

3. EDA - DATA VISUALIZATION

```
In [118... # first column msc=subclass vs street
ax = sns.countplot(data = df, x ='MSZoning', hue = 'SalePrice')
```

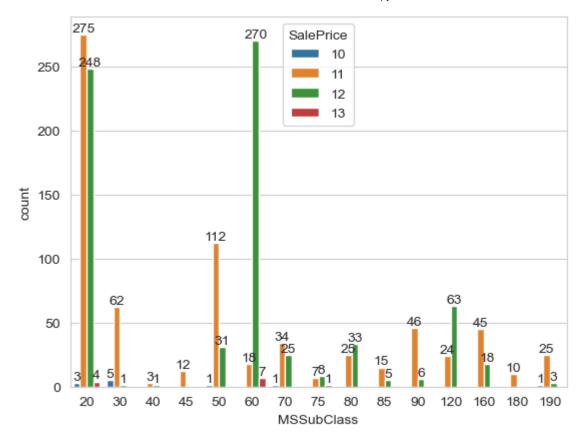
```
for bars in ax.containers:
    ax.bar_label(bars)
```



INSIGHT RL MSZoning have large sale count

```
# first column msc=subclass vs street
ax = sns.countplot(data = df, x = 'MSSubClass', hue = 'SalePrice')

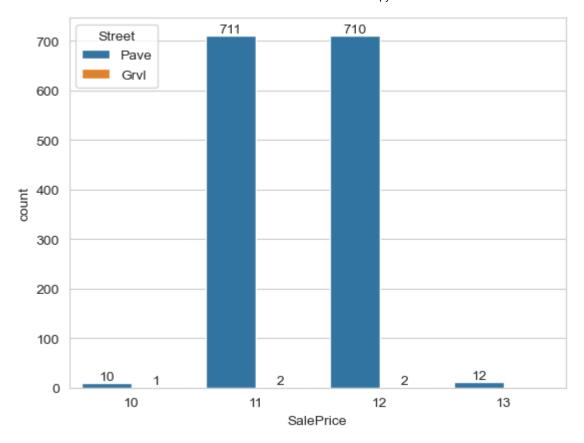
for bars in ax.containers:
    ax.bar_label(bars)
# at pave street more no. of building glass grvl street dont have mssubclass
```



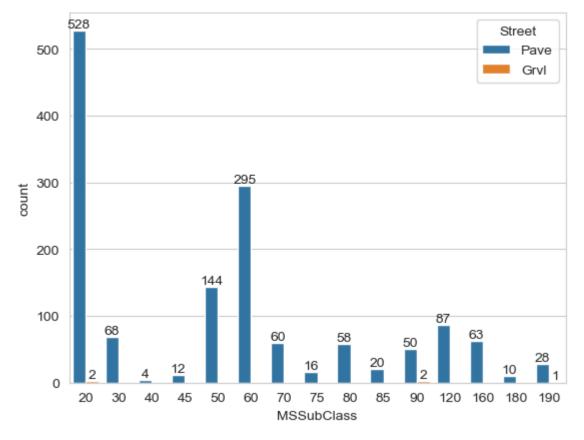
11 and 12 buliding class - have large count sale # 20, 60 number also have more sale

```
In [119... # first column msc=subclass vs street
    ax = sns.countplot(data = df, x = 'SalePrice', hue = 'Street')

for bars in ax.containers:
    ax.bar_label(bars)
# at pave street more no. of building glass grvl street dont have mssubclass
# only pave street have more sales ,Grvi strret no sale at all
# only 11 and 12 large counts.
```







In [133...

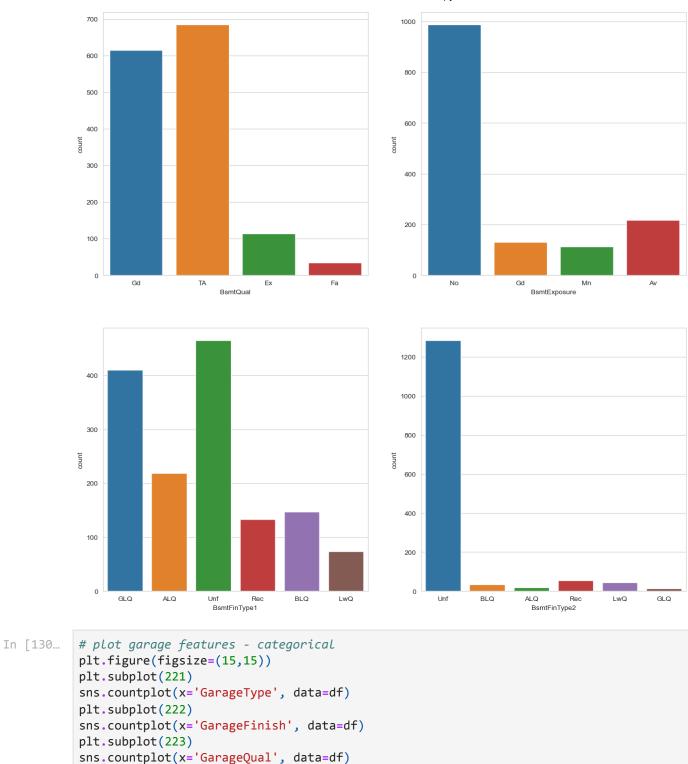
identifying numeric variables

numeric = df.select dtypes(include=['float64','int64'])

```
numeric = numeric.columns
             numeric
 In [134...
            Index(['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
 Out[134]:
                     'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
                     'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
                     'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
                     'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
                     'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
                     'MoSold', 'YrSold', 'SalePrice'],
                   dtype='object')
# taling too much time #sns.pairplot(df, hue ='SalePrice') # plt.show()## making pairplots to identify trends
plt.figure(figsize = (20,50)) i = 1 for x in numeric : plt.subplot(len(numeric)//3+1,3,i)
sns.scatterplot(y='SalePrice', x=x, data=df) plt.xticks(rotation = 'vertical') i = i+1 plt.tight_layout() plt.show()
             plot categorical columns
             # plot categorical columns
 In [131...
             ##identifying categorical variables
             categorical = df.select_dtypes(include=['object'])
             categorical = categorical.columns
             categorical
 In [132...
            Index(['MSZoning', 'Street', 'LotShape', 'LandContour', 'LotConfig',
 Out[132]:
                     'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
                     'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd',
                     'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
                     'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'Heating',
                     'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual', 'Functional',
                     'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond', 'PavedDrive',
                     'SaleType', 'SaleCondition'],
                   dtype='object')
   In [ ]: plt.figure(figsize=(15,15))
             plt.subplot(221)
             sns.countplot(x='MSZoning', data=df)
             plt.subplot(222)
             sns.countplot(x='Street', data=df, hue="SalePrice")
             plt.subplot(223)
             sns.countplot(x='LotShape', data=df)
             plt.subplot(224)
             sns.countplot(x='LandContour', data=df)
             # outside part
 In [128...
             plt.figure(figsize=(15,15))
             plt.subplot(221)
             sns.countplot(x='RoofStyle', data=df)
             plt.subplot(222)
             sns.countplot(x='LotConfig', data=df)
             plt.subplot(223)
             sns.countplot(x='LandSlope', data=df)
             plt.subplot(224)
             sns.countplot(x='Neighborhood', data=df)
```

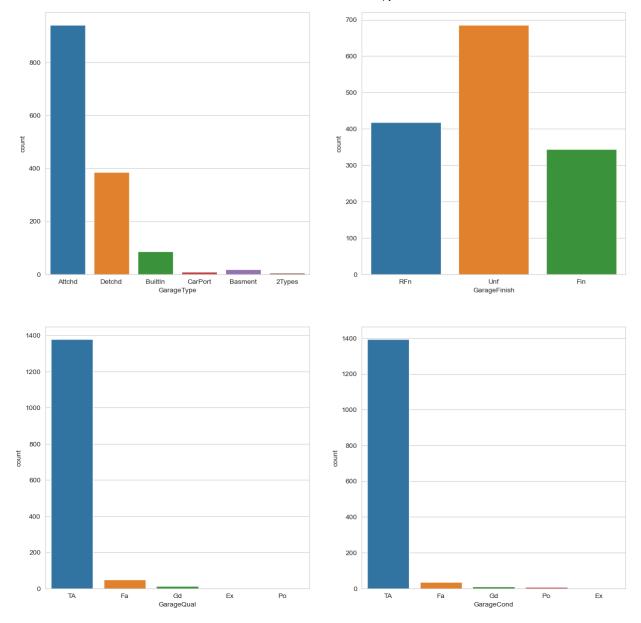
Out[128]: <AxesSubplot:xlabel='Neighborhood', ylabel='count'>





```
sns.countplot(x='GarageCond', data=df)
Out[130]: <AxesSubplot:xlabel='GarageCond', ylabel='count'>
```

plt.subplot(224)



Insights of univariate analysis - - RL MSZoning large amount of sale - write all above insights# GarageQual, GarageCond same values so we can drop any one # i will drop same columns charactersitcs -BldgType: Type of dwelling, HouseStyle: Style of dwelling drop any 1 # df.drop['GarageQual'] df.drop(columns=["Letter", "GDP per capita"], inplace=True) # check on tomarrow do encoding

In []: df.shape