

Project Name: House Prices: Advanced Regression Techniques

Problem Statement

Ask a home buyer to describe their dream house, and they probably won't begin with the height of the basement ceiling or the proximity to an east-west railroad. But this playground competition's dataset proves that much more influences price negotiations than the number of bedrooms or a white-picket fence.

With 79 explanatory variables describing (almost) every aspect of residential homes in Ames, Iowa, this competition challenges you to predict the final price of each home.

The main aim of this project is to predict the house price based on various features which we will discuss as we go ahead

Dataset to download from the below link

<https://www.kaggle.com/c/house-prices-advanced-regression-techniques/data>

##3 Importing libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
pd.pandas.set_option('display.max_columns',None)
```

```
train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")
df_train = pd.concat((train, test))
df_train.head()
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape
0	1	60	RL	65.0	8450	Pave	NaN	Reg
1	2	20	RL	80.0	9600	Pave	NaN	Reg
2	3	60	RL	68.0	11250	Pave	NaN	IR1
3	4	70	RL	60.0	9550	Pave	NaN	IR1
4	5	60	RL	84.0	14260	Pave	NaN	IR1

	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	\
0	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	
1	Lvl	AllPub	FR2	Gtl	Veenker	Feedr	
2	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	
3	Lvl	AllPub	Corner	Gtl	Crawfor	Norm	

4	Lvl	AllPub	FR2	Gtl	NoRidge	Norm
	Condition2	BldgType	HouseStyle	OverallQual	OverallCond	YearBuilt
\						
0	Norm	1Fam	2Story	7	5	2003
1	Norm	1Fam	1Story	6	8	1976
2	Norm	1Fam	2Story	7	5	2001
3	Norm	1Fam	2Story	7	5	1915
4	Norm	1Fam	2Story	8	5	2000

	YearRemodAdd	RoofStyle	RoofMatl	Exterior1st	Exterior2nd	MasVnrType
\						
0	2003	Gable	CompShg	VinylSd	VinylSd	BrkFace
1	1976	Gable	CompShg	MetalSd	MetalSd	None
2	2002	Gable	CompShg	VinylSd	VinylSd	BrkFace
3	1970	Gable	CompShg	Wd Sdng	Wd Shng	None
4	2000	Gable	CompShg	VinylSd	VinylSd	BrkFace

	MasVnrArea	ExterQual	ExterCond	Foundation	BsmtQual	BsmtCond
BsmtExposure	\					
0	196.0	Gd	TA	PConc	Gd	TA
No						
1	0.0	TA	TA	CBlock	Gd	TA
Gd						
2	162.0	Gd	TA	PConc	Gd	TA
Mn						
3	0.0	TA	TA	BrkTil	TA	Gd
No						
4	350.0	Gd	TA	PConc	Gd	TA
Av						

	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	BsmtUnfSF
TotalBsmtSF	\				
0	GLQ	706.0	Unf	0.0	150.0
856.0					
1	ALQ	978.0	Unf	0.0	284.0
1262.0					
2	GLQ	486.0	Unf	0.0	434.0
920.0					

3	ALQ	216.0	Unf	0.0	540.0
756.0					
4	GLQ	655.0	Unf	0.0	490.0
1145.0					

	Heating LowQual	Heating FinSF	QC	CentralAir	Electrical	1stFlrSF	2ndFlrSF
0	GasA		Ex	Y	SBrkr	856	854
0							
1	GasA		Ex	Y	SBrkr	1262	0
0							
2	GasA		Ex	Y	SBrkr	920	866
0							
3	GasA		Gd	Y	SBrkr	961	756
0							
4	GasA		Ex	Y	SBrkr	1145	1053
0							

	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath
Bedroom	AbvGr				
0	1710	1.0	0.0	2	1
3					
1	1262	0.0	1.0	2	0
3					
2	1786	1.0	0.0	2	1
3					
3	1717	1.0	0.0	1	0
3					
4	2198	1.0	0.0	2	1
4					

	Kitchen	AbvGr	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces
Fireplace	Qu					
0	1		Gd	8	Typ	0
NaN						
1	1		TA	6	Typ	1
TA						
2	1		Gd	6	Typ	1
TA						
3	1		Gd	7	Typ	1
Gd						
4	1		Gd	9	Typ	1
TA						

	GarageType	GarageYrBlt	GarageFinish	GarageCars	GarageArea
GarageQual					
0	Attchd	2003.0	RFn	2.0	548.0
TA					
1	Attchd	1976.0	RFn	2.0	460.0
TA					

2	Attchd	2001.0	RFn	2.0	608.0
TA					
3	Detchd	1998.0	Unf	3.0	642.0
TA					
4	Attchd	2000.0	RFn	3.0	836.0
TA					

	GarageCond	PavedDrive	WoodDeckSF	OpenPorchSF	EnclosedPorch
3SsnPorch \					
0	TA	Y	0	61	0
0					
1	TA	Y	298	0	0
0					
2	TA	Y	0	42	0
0					
3	TA	Y	0	35	272
0					
4	TA	Y	192	84	0
0					

	ScreenPorch	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold
YrSold \							
0	0	0	NaN	NaN	NaN	0	2
2008							
1	0	0	NaN	NaN	NaN	0	5
2007							
2	0	0	NaN	NaN	NaN	0	9
2008							
3	0	0	NaN	NaN	NaN	0	2
2006							
4	0	0	NaN	NaN	NaN	0	12
2008							

	SaleType	SaleCondition	SalePrice
0	WD	Normal	208500.0
1	WD	Normal	181500.0
2	WD	Normal	223500.0
3	WD	Abnorml	140000.0
4	WD	Normal	250000.0

df_train.tail()

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley
LotShape \							
1454	2915	160	RM	21.0	1936	Pave	NaN
Reg							
1455	2916	160	RM	21.0	1894	Pave	NaN
Reg							
1456	2917	20	RL	160.0	20000	Pave	NaN
Reg							

1457	2918	85	RL	62.0	10441	Pave	NaN
Reg							
1458	2919	60	RL	74.0	9627	Pave	NaN
Reg							

	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1
\						
1454	Lvl	AllPub	Inside	Gtl	MeadowV	Norm
1455	Lvl	AllPub	Inside	Gtl	MeadowV	Norm
1456	Lvl	AllPub	Inside	Gtl	Mitchel	Norm
1457	Lvl	AllPub	Inside	Gtl	Mitchel	Norm
1458	Lvl	AllPub	Inside	Mod	Mitchel	Norm

	Condition2	BldgType	HouseStyle	OverallQual	OverallCond
YearBuilt	\				
1454	Norm	Twnhs	2Story	4	7
1970					
1455	Norm	TwnhsE	2Story	4	5
1970					
1456	Norm	1Fam	1Story	5	7
1960					
1457	Norm	1Fam	SFoyer	5	5
1992					
1458	Norm	1Fam	2Story	7	5
1993					

	YearRemodAdd	RoofStyle	RoofMatl	Exterior1st	Exterior2nd
MasVnrType	\				
1454	1970	Gable	CompShg	CemntBd	CmentBd
None					
1455	1970	Gable	CompShg	CemntBd	CmentBd
None					
1456	1996	Gable	CompShg	VinylSd	VinylSd
None					
1457	1992	Gable	CompShg	HdBoard	Wd Shng
None					
1458	1994	Gable	CompShg	HdBoard	HdBoard
BrkFace					

	MasVnrArea	ExterQual	ExterCond	Foundation	BsmtQual	BsmtCond	\
1454	0.0	TA	TA	CBlock	TA	TA	
1455	0.0	TA	TA	CBlock	TA	TA	
1456	0.0	TA	TA	CBlock	TA	TA	
1457	0.0	TA	TA	PConc	Gd	TA	

1458	94.0	TA	TA	PConc	Gd	TA
	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	\
1454	No	Unf	0.0	Unf	0.0	
1455	No	Rec	252.0	Unf	0.0	
1456	No	ALQ	1224.0	Unf	0.0	
1457	Av	GLQ	337.0	Unf	0.0	
1458	Av	LwQ	758.0	Unf	0.0	

	BsmtUnfSF	TotalBsmtSF	Heating	HeatingQC	CentralAir	
Electrical	\					
1454	546.0	546.0	GasA	Gd	Y	SBrkr
1455	294.0	546.0	GasA	TA	Y	SBrkr
1456	0.0	1224.0	GasA	Ex	Y	SBrkr
1457	575.0	912.0	GasA	TA	Y	SBrkr
1458	238.0	996.0	GasA	Ex	Y	SBrkr

	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath
BsmtHalfBath	\				
1454	546	546	0	1092	0.0
0.0					
1455	546	546	0	1092	0.0
0.0					
1456	1224	0	0	1224	1.0
0.0					
1457	970	0	0	970	0.0
1.0					
1458	996	1004	0	2000	0.0
0.0					

	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	KitchenQual	\
1454	1	1	3	1	TA	
1455	1	1	3	1	TA	
1456	1	0	4	1	TA	
1457	1	0	3	1	TA	
1458	2	1	3	1	TA	

	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	GarageType
GarageYrBlt	\				
1454	5	Typ	0	NaN	NaN
NaN					
1455	6	Typ	0	NaN	CarPort
1970.0					
1456	7	Typ	1	TA	Detchd

1960.0					
1457	6	Typ	0	NaN	NaN
NaN					
1458	9	Typ	1	TA	Attchd
1993.0					

	GarageFinish	GarageCars	GarageArea	GarageQual	GarageCond
PavedDrive \					
1454	NaN	0.0	0.0	NaN	NaN
Y					
1455	Unf	1.0	286.0	TA	TA
Y					
1456	Unf	2.0	576.0	TA	TA
Y					
1457	NaN	0.0	0.0	NaN	NaN
Y					
1458	Fin	3.0	650.0	TA	TA
Y					

	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	
ScreenPorch \					
1454	0	0	0	0	0
1455	0	24	0	0	0
1456	474	0	0	0	0
1457	80	32	0	0	0
1458	190	48	0	0	0

	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold
SaleType \							
1454	0	NaN	NaN	NaN	0	6	2006
WD							
1455	0	NaN	NaN	NaN	0	4	2006
WD							
1456	0	NaN	NaN	NaN	0	9	2006
WD							
1457	0	NaN	MnPrv	Shed	700	7	2006
WD							
1458	0	NaN	NaN	NaN	0	11	2006
WD							

	SaleCondition	SalePrice
1454	Normal	NaN
1455	Abnorml	NaN
1456	Abnorml	NaN

```
1457      Normal      NaN
1458      Normal      NaN
```

```
df_train.shape
```

```
(2919, 81)
```

```
train.shape
```

```
(1460, 81)
```

```
test.shape
```

```
(1459, 80)
```

```
df_train.tail()
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley
LotShape \							
1454	2915	160	RM	21.0	1936	Pave	NaN
Reg							
1455	2916	160	RM	21.0	1894	Pave	NaN
Reg							
1456	2917	20	RL	160.0	20000	Pave	NaN
Reg							
1457	2918	85	RL	62.0	10441	Pave	NaN
Reg							
1458	2919	60	RL	74.0	9627	Pave	NaN
Reg							

	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1
\						
1454	Lvl	AllPub	Inside	Gtl	MeadowV	Norm
1455	Lvl	AllPub	Inside	Gtl	MeadowV	Norm
1456	Lvl	AllPub	Inside	Gtl	Mitchel	Norm
1457	Lvl	AllPub	Inside	Gtl	Mitchel	Norm
1458	Lvl	AllPub	Inside	Mod	Mitchel	Norm

	Condition2	BldgType	HouseStyle	OverallQual	OverallCond
YearBuilt \					
1454	Norm	Twnhs	2Story	4	7
1970					
1455	Norm	TwnhsE	2Story	4	5
1970					
1456	Norm	1Fam	1Story	5	7
1960					

1457	Norm	1Fam	SFoyer	5	5
1992					
1458	Norm	1Fam	2Story	7	5
1993					

	YearRemodAdd	RoofStyle	RoofMatl	Exterior1st	Exterior2nd
MasVnrType \					
1454	1970	Gable	CompShg	CemntBd	CmentBd
None					
1455	1970	Gable	CompShg	CemntBd	CmentBd
None					
1456	1996	Gable	CompShg	VinylSd	VinylSd
None					
1457	1992	Gable	CompShg	HdBoard	Wd Shng
None					
1458	1994	Gable	CompShg	HdBoard	HdBoard
BrkFace					

	MasVnrArea	ExterQual	ExterCond	Foundation	BsmtQual	BsmtCond	\
1454	0.0	TA	TA	CBlock	TA	TA	
1455	0.0	TA	TA	CBlock	TA	TA	
1456	0.0	TA	TA	CBlock	TA	TA	
1457	0.0	TA	TA	PConc	Gd	TA	
1458	94.0	TA	TA	PConc	Gd	TA	

	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	\
1454	No	Unf	0.0	Unf	0.0	
1455	No	Rec	252.0	Unf	0.0	
1456	No	ALQ	1224.0	Unf	0.0	
1457	Av	GLQ	337.0	Unf	0.0	
1458	Av	LwQ	758.0	Unf	0.0	

	BsmtUnfSF	TotalBsmtSF	Heating	HeatingQC	CentralAir	
Electrical \						
1454	546.0	546.0	GasA	Gd	Y	SBrkr
1455	294.0	546.0	GasA	TA	Y	SBrkr
1456	0.0	1224.0	GasA	Ex	Y	SBrkr
1457	575.0	912.0	GasA	TA	Y	SBrkr
1458	238.0	996.0	GasA	Ex	Y	SBrkr

	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	
BsmtHalfBath \						
1454	546	546	0	1092	0.0	
0.0						

1455	546	546	0	1092	0.0
0.0					
1456	1224	0	0	1224	1.0
0.0					
1457	970	0	0	970	0.0
1.0					
1458	996	1004	0	2000	0.0
0.0					

	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	KitchenQual	\
1454	1	1	3	1	TA	
1455	1	1	3	1	TA	
1456	1	0	4	1	TA	
1457	1	0	3	1	TA	
1458	2	1	3	1	TA	

	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	GarageType
GarageYrBlt \					
1454	5	Typ	0	NaN	NaN
NaN					
1455	6	Typ	0	NaN	CarPort
1970.0					
1456	7	Typ	1	TA	Detchd
1960.0					
1457	6	Typ	0	NaN	NaN
NaN					
1458	9	Typ	1	TA	Attchd
1993.0					

	GarageFinish	GarageCars	GarageArea	GarageQual	GarageCond
PavedDrive \					
1454	NaN	0.0	0.0	NaN	NaN
Y					
1455	Unf	1.0	286.0	TA	TA
Y					
1456	Unf	2.0	576.0	TA	TA
Y					
1457	NaN	0.0	0.0	NaN	NaN
Y					
1458	Fin	3.0	650.0	TA	TA
Y					

	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	
ScreenPorch \					
1454	0	0	0	0	0
1455	0	24	0	0	0
1456	474	0	0	0	0

1457	80	32	0	0	0
1458	190	48	0	0	0

	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold
SaleType \							
1454	0	NaN	NaN	NaN	0	6	2006
WD							
1455	0	NaN	NaN	NaN	0	4	2006
WD							
1456	0	NaN	NaN	NaN	0	9	2006
WD							
1457	0	NaN	MnPrv	Shed	700	7	2006
WD							
1458	0	NaN	NaN	NaN	0	11	2006
WD							

	SaleCondition	SalePrice
1454	Normal	NaN
1455	Abnorml	NaN
1456	Abnorml	NaN
1457	Normal	NaN
1458	Normal	NaN

EDA and Feature Engineering

```
duplicate = df_train[df_train.duplicated()]
print(duplicate)
```

Empty DataFrame

Columns: [Id, MSSubClass, MSZoning, LotFrontage, LotArea, Street, 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]

Index: []

```
df_train.info()
```

<class 'pandas.core.frame.DataFrame'>

Int64Index: 2919 entries, 0 to 1458

Data columns (total 81 columns):

#	Column	Non-Null Count	Dtype
0	Id	2919 non-null	int64
1	MSSubClass	2919 non-null	int64
2	MSZoning	2915 non-null	object
3	LotFrontage	2433 non-null	float64
4	LotArea	2919 non-null	int64
5	Street	2919 non-null	object
6	Alley	198 non-null	object
7	LotShape	2919 non-null	object
8	LandContour	2919 non-null	object
9	Utilities	2917 non-null	object
10	LotConfig	2919 non-null	object
11	LandSlope	2919 non-null	object
12	Neighborhood	2919 non-null	object
13	Condition1	2919 non-null	object
14	Condition2	2919 non-null	object
15	BldgType	2919 non-null	object
16	HouseStyle	2919 non-null	object
17	OverallQual	2919 non-null	int64
18	OverallCond	2919 non-null	int64
19	YearBuilt	2919 non-null	int64
20	YearRemodAdd	2919 non-null	int64
21	RoofStyle	2919 non-null	object
22	RoofMatl	2919 non-null	object
23	Exterior1st	2918 non-null	object
24	Exterior2nd	2918 non-null	object
25	MasVnrType	2895 non-null	object
26	MasVnrArea	2896 non-null	float64
27	ExterQual	2919 non-null	object
28	ExterCond	2919 non-null	object
29	Foundation	2919 non-null	object
30	BsmtQual	2838 non-null	object
31	BsmtCond	2837 non-null	object
32	BsmtExposure	2837 non-null	object
33	BsmtFinType1	2840 non-null	object
34	BsmtFinSF1	2918 non-null	float64
35	BsmtFinType2	2839 non-null	object
36	BsmtFinSF2	2918 non-null	float64
37	BsmtUnfSF	2918 non-null	float64
38	TotalBsmtSF	2918 non-null	float64
39	Heating	2919 non-null	object
40	HeatingQC	2919 non-null	object
41	CentralAir	2919 non-null	object
42	Electrical	2918 non-null	object
43	1stFlrSF	2919 non-null	int64
44	2ndFlrSF	2919 non-null	int64

45	LowQualFinSF	2919	non-null	int64
46	GrLivArea	2919	non-null	int64
47	BsmtFullBath	2917	non-null	float64
48	BsmtHalfBath	2917	non-null	float64
49	FullBath	2919	non-null	int64
50	HalfBath	2919	non-null	int64
51	BedroomAbvGr	2919	non-null	int64
52	KitchenAbvGr	2919	non-null	int64
53	KitchenQual	2918	non-null	object
54	TotRmsAbvGrd	2919	non-null	int64
55	Functional	2917	non-null	object
56	Fireplaces	2919	non-null	int64
57	FireplaceQu	1499	non-null	object
58	GarageType	2762	non-null	object
59	GarageYrBlt	2760	non-null	float64
60	GarageFinish	2760	non-null	object
61	GarageCars	2918	non-null	float64
62	GarageArea	2918	non-null	float64
63	GarageQual	2760	non-null	object
64	GarageCond	2760	non-null	object
65	PavedDrive	2919	non-null	object
66	WoodDeckSF	2919	non-null	int64
67	OpenPorchSF	2919	non-null	int64
68	EnclosedPorch	2919	non-null	int64
69	3SsnPorch	2919	non-null	int64
70	ScreenPorch	2919	non-null	int64
71	PoolArea	2919	non-null	int64
72	PoolQC	10	non-null	object
73	Fence	571	non-null	object
74	MiscFeature	105	non-null	object
75	MiscVal	2919	non-null	int64
76	MoSold	2919	non-null	int64
77	YrSold	2919	non-null	int64
78	SaleType	2918	non-null	object
79	SaleCondition	2919	non-null	object
80	SalePrice	1460	non-null	float64

dtypes: float64(12), int64(26), object(43)

memory usage: 1.8+ MB

df_train.describe()

	Id	MSSubClass	LotFrontage	LotArea
OverallQual \				
count	2919.000000	2919.000000	2433.000000	2919.000000
mean	1460.000000	57.137718	69.305795	10168.114080
std	842.787043	42.517628	23.344905	7886.996359
min	1.000000	20.000000	21.000000	1300.000000

25%	730.500000	20.000000	59.000000	7478.000000
5.000000				
50%	1460.000000	50.000000	68.000000	9453.000000
6.000000				
75%	2189.500000	70.000000	80.000000	11570.000000
7.000000				
max	2919.000000	190.000000	313.000000	215245.000000
10.000000				

	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea
BsmtFinSF1 \				
count	2919.000000	2919.000000	2919.000000	2896.000000
2918.000000				
mean	5.564577	1971.312778	1984.264474	102.201312
441.423235				
std	1.113131	30.291442	20.894344	179.334253
455.610826				
min	1.000000	1872.000000	1950.000000	0.000000
0.000000				
25%	5.000000	1953.500000	1965.000000	0.000000
0.000000				
50%	5.000000	1973.000000	1993.000000	0.000000
368.500000				
75%	6.000000	2001.000000	2004.000000	164.000000
733.000000				
max	9.000000	2010.000000	2010.000000	1600.000000
5644.000000				

	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	1stFlrSF	2ndFlrSF
\					
count	2918.000000	2918.000000	2918.000000	2919.000000	2919.000000
mean	49.582248	560.772104	1051.777587	1159.581706	336.483727
std	169.205611	439.543659	440.766258	392.362079	428.701456
min	0.000000	0.000000	0.000000	334.000000	0.000000
25%	0.000000	220.000000	793.000000	876.000000	0.000000
50%	0.000000	467.000000	989.500000	1082.000000	0.000000
75%	0.000000	805.500000	1302.000000	1387.500000	704.000000
max	1526.000000	2336.000000	6110.000000	5095.000000	2065.000000

	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath
FullBath \				

count	2919.000000	2919.000000	2917.000000	2917.000000
2919.000000				
mean	4.694416	1500.759849	0.429894	0.061364
1.568003				
std	46.396825	506.051045	0.524736	0.245687
0.552969				
min	0.000000	334.000000	0.000000	0.000000
0.000000				
25%	0.000000	1126.000000	0.000000	0.000000
1.000000				
50%	0.000000	1444.000000	0.000000	0.000000
2.000000				
75%	0.000000	1743.500000	1.000000	0.000000
2.000000				
max	1064.000000	5642.000000	3.000000	2.000000
4.000000				

	HalfBath	BedroomAbvGr	KitchenAbvGr	TotRmsAbvGrd
Fireplaces \				
count	2919.000000	2919.000000	2919.000000	2919.000000
2919.000000				
mean	0.380267	2.860226	1.044536	6.451524
0.597122				
std	0.502872	0.822693	0.214462	1.569379
0.646129				
min	0.000000	0.000000	0.000000	2.000000
0.000000				
25%	0.000000	2.000000	1.000000	5.000000
0.000000				
50%	0.000000	3.000000	1.000000	6.000000
1.000000				
75%	1.000000	3.000000	1.000000	7.000000
1.000000				
max	2.000000	8.000000	3.000000	15.000000
4.000000				

	GarageYrBlt	GarageCars	GarageArea	WoodDeckSF	OpenPorchSF
\					
count	2760.000000	2918.000000	2918.000000	2919.000000	2919.000000
mean	1978.113406	1.766621	472.874572	93.709832	47.486811
std	25.574285	0.761624	215.394815	126.526589	67.575493
min	1895.000000	0.000000	0.000000	0.000000	0.000000
25%	1960.000000	1.000000	320.000000	0.000000	0.000000
50%	1979.000000	2.000000	480.000000	0.000000	26.000000

75%	2002.000000	2.000000	576.000000	168.000000	70.000000
max	2207.000000	5.000000	1488.000000	1424.000000	742.000000

	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea
MiscVal \				
count	2919.000000	2919.000000	2919.000000	2919.000000
mean	23.098321	2.602261	16.062350	2.251799
std	64.244246	25.188169	56.184365	35.663946
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1012.000000	508.000000	576.000000	800.000000

	MoSold	YrSold	SalePrice
count	2919.000000	2919.000000	1460.000000
mean	6.213087	2007.792737	180921.195890
std	2.714762	1.314964	79442.502883
min	1.000000	2006.000000	34900.000000
25%	4.000000	2007.000000	129975.000000
50%	6.000000	2008.000000	163000.000000
75%	8.000000	2009.000000	214000.000000
max	12.000000	2010.000000	755000.000000

Handling numerical Missing values

1. For Continious

```
#missing_values_continious = [feature for feature in df_train.columns
if df_train[feature].dtype != "0" and len(df_train[feature].unique())
>20 and df_train[feature].isnull().sum()>0]
#missing_values_continious
```

```
missing_values_continious = []
for feature in df_train.columns:
    if df_train[feature].dtype != "0" and
len(df_train[feature].unique())>20:
        missing_values_continious.append(feature)
missing_values_continious
```



```
['Id',  
 'LotFrontage',  
 'LotArea',  
 'YearBuilt',  
 'YearRemodAdd',  
 'MasVnrArea',  
 'BsmtFinSF1',  
 'BsmtFinSF2',  
 'BsmtUnfSF',  
 'TotalBsmtSF',  
 '1stFlrSF',  
 '2ndFlrSF',  
 'LowQualFinSF',  
 'GrLivArea',  
 'GarageYrBlt',  
 'GarageArea',  
 'WoodDeckSF',  
 'OpenPorchSF',  
 'EnclosedPorch',  
 '3SsnPorch',  
 'ScreenPorch',  
 'MiscVal',  
 'SalePrice']
```

```
for feature in missing_values_continious:  
    print(feature, round(df_train[feature].isnull().mean(),4)*100)
```

```
Id 0.0  
LotFrontage 16.650000000000002  
LotArea 0.0  
YearBuilt 0.0  
YearRemodAdd 0.0  
MasVnrArea 0.79  
BsmtFinSF1 0.03  
BsmtFinSF2 0.03  
BsmtUnfSF 0.03  
TotalBsmtSF 0.03  
1stFlrSF 0.0  
2ndFlrSF 0.0  
LowQualFinSF 0.0  
GrLivArea 0.0  
GarageYrBlt 5.45  
GarageArea 0.03  
WoodDeckSF 0.0  
OpenPorchSF 0.0  
EnclosedPorch 0.0  
3SsnPorch 0.0  
ScreenPorch 0.0  
MiscVal 0.0  
SalePrice 49.980000000000004
```

```
median_value = df_train["LotFrontage"].median()
```

```
median_value
```

```
68.0
```

```
for feature in missing_values_continuous:
```

```
    if feature == "SalePrice":
```

```
        pass
```

```
    else:
```

```
        median_value = df_train[feature].median()
```

```
        df_train[feature].fillna(median_value,inplace=True)
```

```
#
```

```
df_train.drop("Id" , inplace=True , axis = 1)
```

2. For Descrete

```
#missing_values_descrete = [feature for feature in df_train.columns if  
df_train[feature].dtype != "0" and len(df_train[feature].unique()) <20  
and df_train[feature].isnull().sum()>0]
```

```
#missing_values_descrete
```

```
if df_train["Alley"].dtype != "object":
```

```
    print(True)
```

```
else:
```

```
    print(False)
```

```
False
```

```
missing_values_descrete = []
```

```
for feature in df_train.columns:
```

```
    if df_train[feature].dtype != "0" and
```

```
len(df_train[feature].unique()) <=20:
```

```
        missing_values_descrete.append(feature)
```

```
missing_values_descrete
```

```
['MSSubClass',  
'OverallQual',  
'OverallCond',  
'BsmtFullBath',  
'BsmtHalfBath',  
'FullBath',  
'HalfBath',  
'BedroomAbvGr',  
'KitchenAbvGr',  
'TotRmsAbvGrd',  
'Fireplaces',  
'GarageCars',  
'PoolArea',  
'MoSold',  
'YrSold']
```

```

for feature in missing_values_descrete:
    print(feature, round(df_train[feature].isnull().mean(),4)*100)

```

```

MSSubClass 0.0
OverallQual 0.0
OverallCond 0.0
BsmtFullBath 0.06999999999999999
BsmtHalfBath 0.06999999999999999
FullBath 0.0
HalfBath 0.0
BedroomAbvGr 0.0
KitchenAbvGr 0.0
TotRmsAbvGrd 0.0
Fireplaces 0.0
GarageCars 0.03
PoolArea 0.0
MoSold 0.0
YrSold 0.0

```

```
df_train["BsmtFullBath"].mode()[0]
```

```
0.0
```

```
df_train["BsmtFullBath"].unique()
```

```
array([ 1.,  0.,  2.,  3., nan])
```

```

for feature in missing_values_descrete:
    mode_value = df_train[feature].mode()[0]
    df_train[feature].fillna(mode_value,inplace=True)

```

Handling categorical missing values

```

#missing_values_c = [feature for feature in df_train.columns if
df_train[feature].dtype == "O" and df_train[feature].isnull().sum()>0]
#missing_values_c

```

```

missing_values_c = []
for feature in df_train.columns:
    if df_train[feature].dtype == "O" and
df_train[feature].isnull().sum()>0:
        missing_values_c.append(feature)
missing_values_c

```

```

['MSZoning',
'Alley',
'Utilities',
'Exterior1st',
'Exterior2nd',
'MasVnrType',
'BsmtQual',
'BsmtCond',
'BsmtExposure',

```

```
'BsmtFinType1',  
'BsmtFinType2',  
'Electrical',  
'KitchenQual',  
'Functional',  
'FireplaceQu',  
'GarageType',  
'GarageFinish',  
'GarageQual',  
'GarageCond',  
'PoolQC',  
'Fence',  
'MiscFeature',  
'SaleType']
```

```
for feature in missing_values_c:  
    print(feature, round(df_train[feature].isnull().mean(),4)*100)
```

```
MSZoning 0.13999999999999999  
Alley 93.22  
Utilities 0.06999999999999999  
Exterior1st 0.03  
Exterior2nd 0.03  
MasVnrType 0.82000000000000001  
BsmtQual 2.77  
BsmtCond 2.81  
BsmtExposure 2.81  
BsmtFinType1 2.71  
BsmtFinType2 2.74  
Electrical 0.03  
KitchenQual 0.03  
Functional 0.06999999999999999  
FireplaceQu 48.65  
GarageType 5.38  
GarageFinish 5.45  
GarageQual 5.45  
GarageCond 5.45  
PoolQC 99.660000000000001  
Fence 80.44  
MiscFeature 96.39999999999999  
SaleType 0.03
```

```
for feature in missing_values_c:  
    mode_value = df_train[feature].mode()[0]  
    df_train[feature].fillna(mode_value,inplace=True)  
df_train.drop(["Alley" ,"PoolQC", "Fence" , "MiscFeature" ,  
"FireplaceQu" ] , axis = 1 , inplace = True)
```

```
df_train.isnull().sum().sum()
```

```
1459
```

```
df_train.shape
```

```
(2919, 75)
```

Handling year feature

```
#year = [feature for feature in df_train.columns if "Yr" in feature or  
"Year" in feature]  
#year
```

```
year = []  
for feature in df_train.columns:  
    if "Yr" in feature or "Year" in feature:  
        year.append(feature)
```

```
year
```

```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

```
for feature in year:  
    print(feature, len(df_train[feature].unique()) ,  
df_train[feature].dtype)
```

```
YearBuilt 118 int64
```

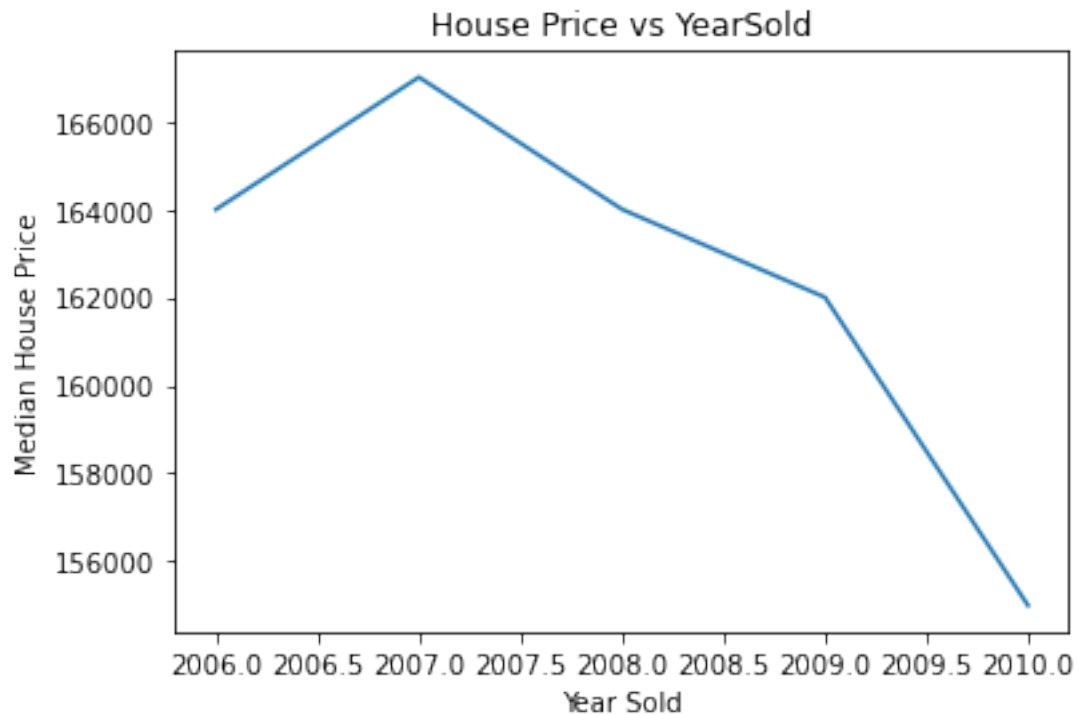
```
YearRemodAdd 61 int64
```

```
GarageYrBlt 103 float64
```

```
YrSold 5 int64
```

```
df_train.groupby('YrSold')['SalePrice'].median().plot()  
plt.xlabel('Year Sold')  
plt.ylabel('Median House Price')  
plt.title("House Price vs YearSold")
```

```
Text(0.5, 1.0, 'House Price vs YearSold')
```



```
for feature in year:
    df_train[feature]=df_train['YrSold']-df_train[feature]
df_train.drop("YrSold", axis = 1 , inplace = True)
```

```
df_train.shape
```

```
(2919, 74)
```

```
df_train.head()
```

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape
LandContour \						
0	60	RL	65.0	8450	Pave	Reg
Lvl						
1	20	RL	80.0	9600	Pave	Reg
Lvl						
2	60	RL	68.0	11250	Pave	IR1
Lvl						
3	70	RL	60.0	9550	Pave	IR1
Lvl						
4	60	RL	84.0	14260	Pave	IR1
Lvl						

	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Condition2
BldgType \						
0	AllPub	Inside	Gtl	CollgCr	Norm	Norm
1Fam						
1	AllPub	FR2	Gtl	Veenker	Feedr	Norm

1Fam						
2	AllPub	Inside	Gtl	CollgCr	Norm	Norm
1Fam						
3	AllPub	Corner	Gtl	Crawfor	Norm	Norm
1Fam						
4	AllPub	FR2	Gtl	NoRidge	Norm	Norm
1Fam						

HouseStyle	OverallQual	OverallCond	YearBuilt	YearRemodAdd
RoofStyle \				
0 2Story	7	5	5	5
Gable				
1 1Story	6	8	31	31
Gable				
2 2Story	7	5	7	6
Gable				
3 2Story	7	5	91	36
Gable				
4 2Story	8	5	8	8
Gable				

RoofMatl	Exterior1st	Exterior2nd	MasVnrType	MasVnrArea	ExterQual
ExterCond \					
0 CompShg	VinylSd	VinylSd	BrkFace	196.0	Gd
TA					
1 CompShg	MetalSd	MetalSd	None	0.0	TA
TA					
2 CompShg	VinylSd	VinylSd	BrkFace	162.0	Gd
TA					
3 CompShg	Wd Sdng	Wd Shng	None	0.0	TA
TA					
4 CompShg	VinylSd	VinylSd	BrkFace	350.0	Gd
TA					

Foundation	BsmtQual	BsmtCond	BsmtExposure	BsmtFinType1
BsmtFinSF1 \				
0 PConc	Gd	TA	No	GLQ
				706.0
1 CBlock	Gd	TA	Gd	ALQ
				978.0
2 PConc	Gd	TA	Mn	GLQ
				486.0
3 BrkTil	TA	Gd	No	ALQ
				216.0
4 PConc	Gd	TA	Av	GLQ
				655.0

BsmtFinType2	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	Heating
HeatingQC \				

0	Unf	0.0	150.0	856.0	GasA	Ex
1	Unf	0.0	284.0	1262.0	GasA	Ex
2	Unf	0.0	434.0	920.0	GasA	Ex
3	Unf	0.0	540.0	756.0	GasA	Gd
4	Unf	0.0	490.0	1145.0	GasA	Ex

	CentralAir	Electrical	1stFlrSF	2ndFlrSF	LowQualFinSF	
GrLivArea	\					
0	Y	SBrkr	856	854	0	1710
1	Y	SBrkr	1262	0	0	1262
2	Y	SBrkr	920	866	0	1786
3	Y	SBrkr	961	756	0	1717
4	Y	SBrkr	1145	1053	0	2198

	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr
KitchenAbvGr	\				
0	1.0	0.0	2	1	3
1					
1	0.0	1.0	2	0	3
1					
2	1.0	0.0	2	1	3
1					
3	1.0	0.0	1	0	3
1					
4	1.0	0.0	2	1	4
1					

	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	GarageType
GarageYrBltd	\				
0	Gd	8	Typ	0	Attchd
5.0					
1	TA	6	Typ	1	Attchd
31.0					
2	Gd	6	Typ	1	Attchd
7.0					
3	Gd	7	Typ	1	Detchd
8.0					
4	Gd	9	Typ	1	Attchd
8.0					

	GarageFinish	GarageCars	GarageArea	GarageQual	GarageCond
0	PavedDrive \				
Y	RFn	2.0	548.0	TA	TA
1	RFn	2.0	460.0	TA	TA
Y					
2	RFn	2.0	608.0	TA	TA
Y					
3	Unf	3.0	642.0	TA	TA
Y					
4	RFn	3.0	836.0	TA	TA
Y					

	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch
0	PoolArea \				
0	0	61	0	0	0
1	298	0	0	0	0
0					
2	0	42	0	0	0
0					
3	0	35	272	0	0
0					
4	192	84	0	0	0
0					

	MiscVal	MoSold	SaleType	SaleCondition	SalePrice
0	0	2	WD	Normal	208500.0
1	0	5	WD	Normal	181500.0
2	0	9	WD	Normal	223500.0
3	0	2	WD	Abnorml	140000.0
4	0	12	WD	Normal	250000.0

Handling continious values

```
#continious = [feature for feature in df_train.columns if
len(df_train[feature].unique())>20 and df_train[feature].dtype != "0"
and feature not in year]
#continious
```

```
continious = []
for feature in df_train.columns:
    if df_train[feature].dtype != "0" and
len(df_train[feature].unique())>20 and feature not in year:
        continious.append(feature)
continious

['LotFrontage',
'LotArea',
'MasVnrArea',
```

```
'BsmtFinSF1',  
'BsmtFinSF2',  
'BsmtUnfSF',  
'TotalBsmtSF',  
'1stFlrSF',  
'2ndFlrSF',  
'LowQualFinSF',  
'GrLivArea',  
'GarageArea',  
'WoodDeckSF',  
'OpenPorchSF',  
'EnclosedPorch',  
'3SsnPorch',  
'ScreenPorch',  
'MiscVal',  
'SalePrice']
```

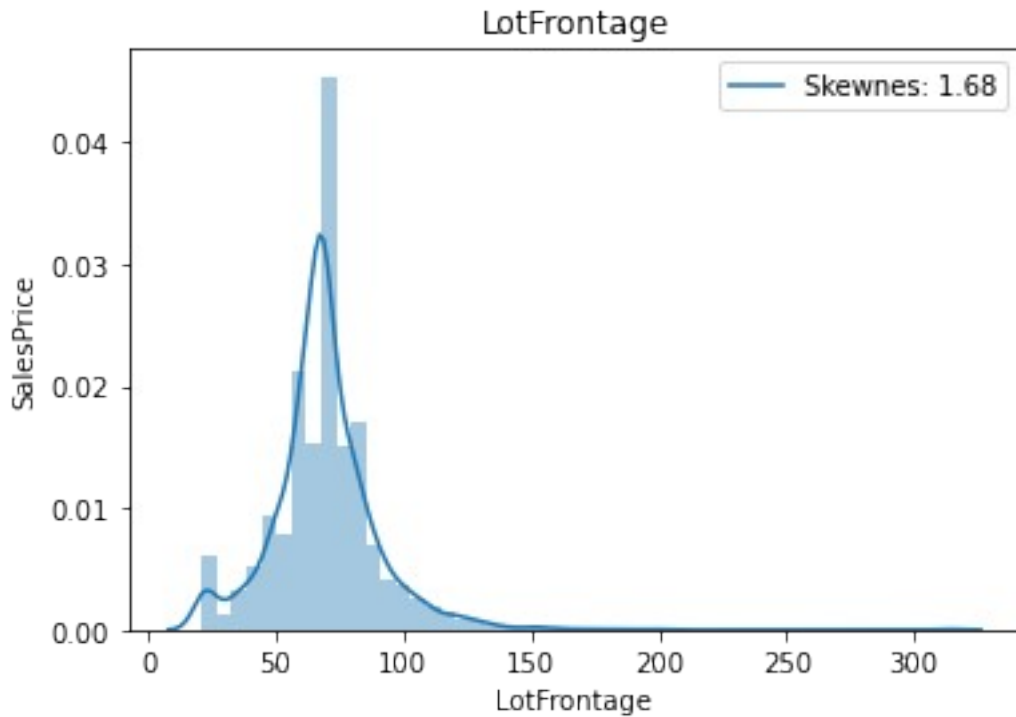
```
data["LotFrontage"].skew()
```

```
-0.9948415692198087
```

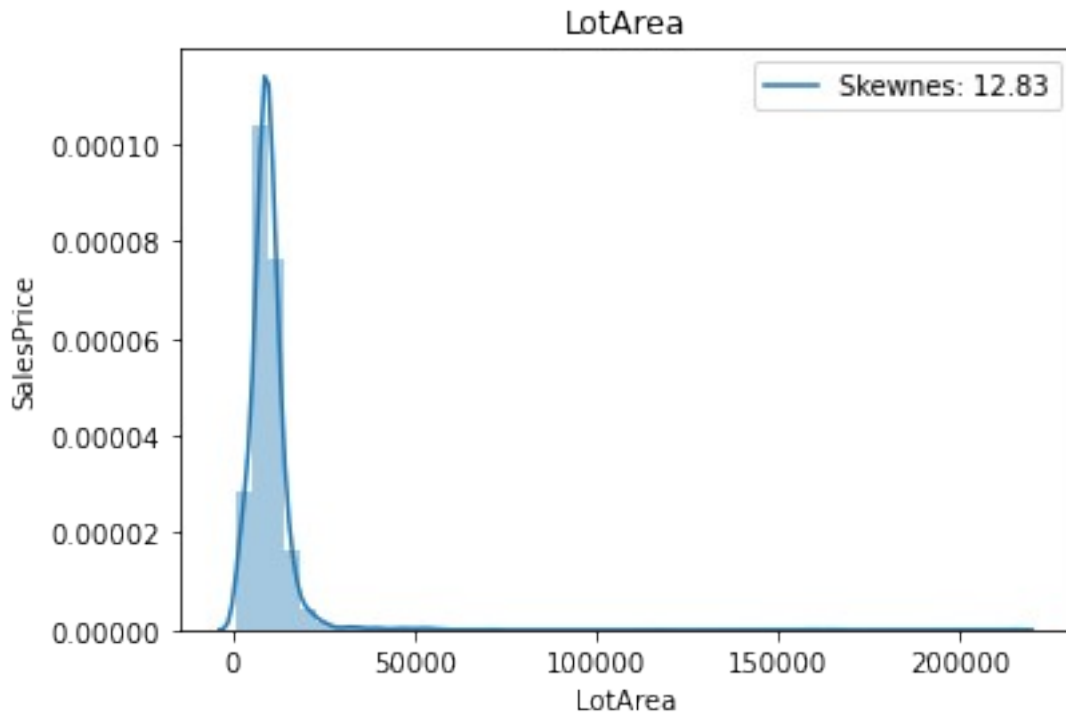
```
## We will be using logarithmic transformation
```

```
for feature in continious:  
    data = df_train.copy()  
    #data[feature]=np.log1p(data[feature])  
    ax = sns.distplot(data[feature])  
    ax.legend(["Skewnes: {:.2f}".format(data[feature].skew())])  
    plt.xlabel(feature)  
    plt.ylabel('SalesPrice')  
    plt.title(feature)  
    plt.show()
```

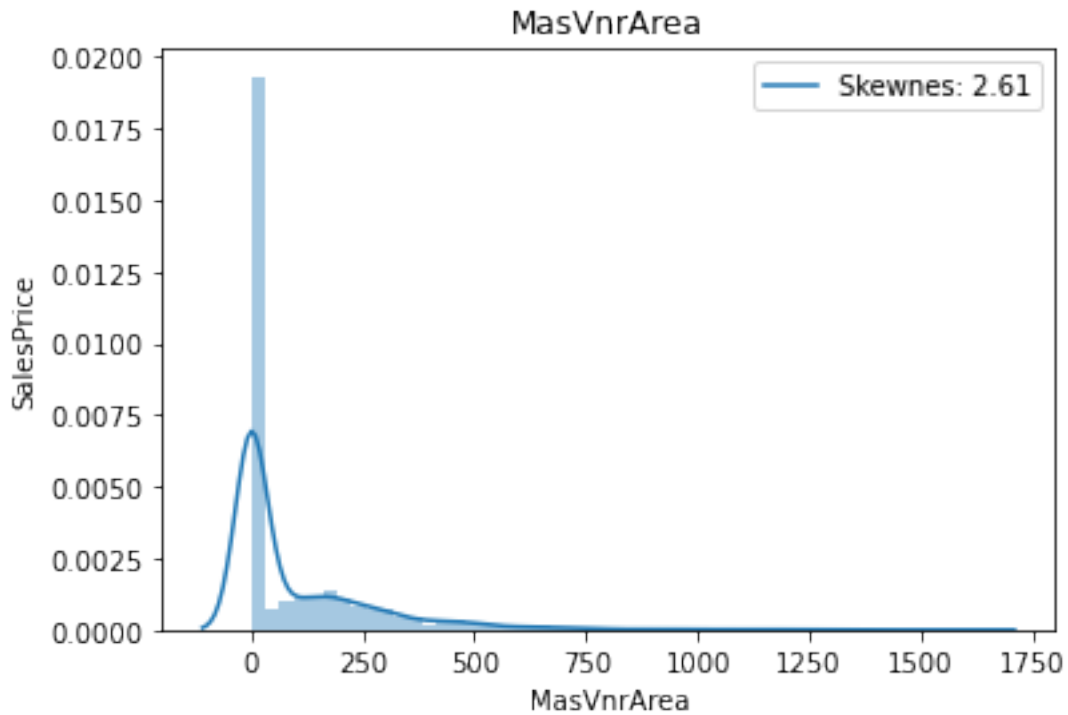
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\  
distributions.py:2557: FutureWarning: `distplot` is a deprecated  
function and will be removed in a future version. Please adapt your  
code to use either `displot` (a figure-level function with similar  
flexibility) or `histplot` (an axes-level function for histograms).  
    warnings.warn(msg, FutureWarning)
```



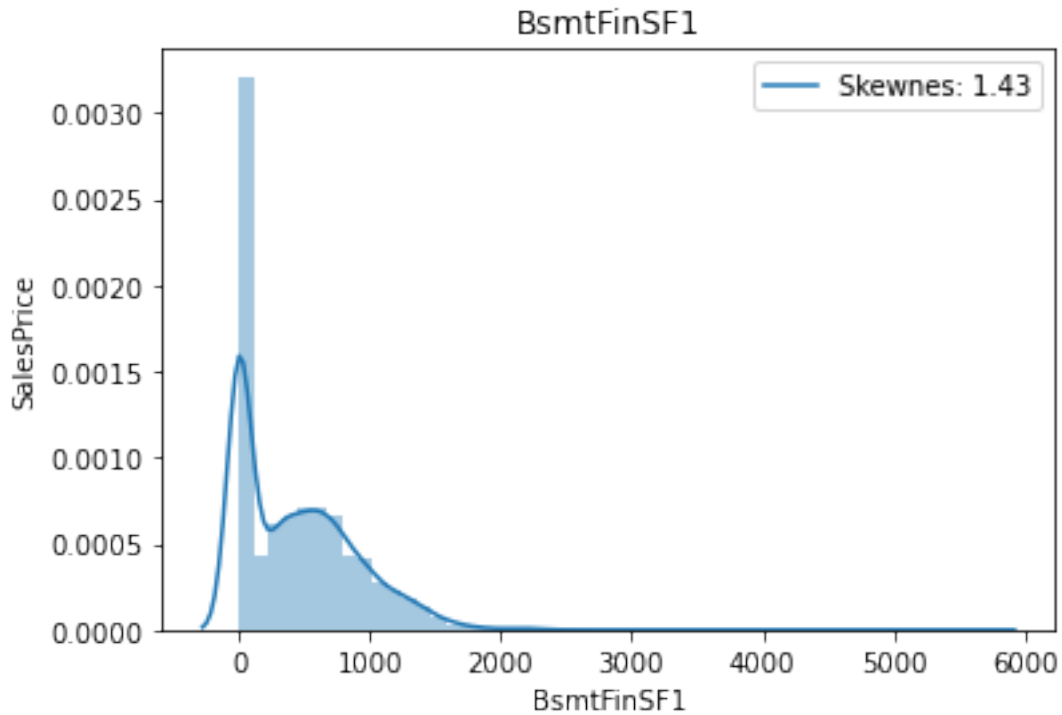
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



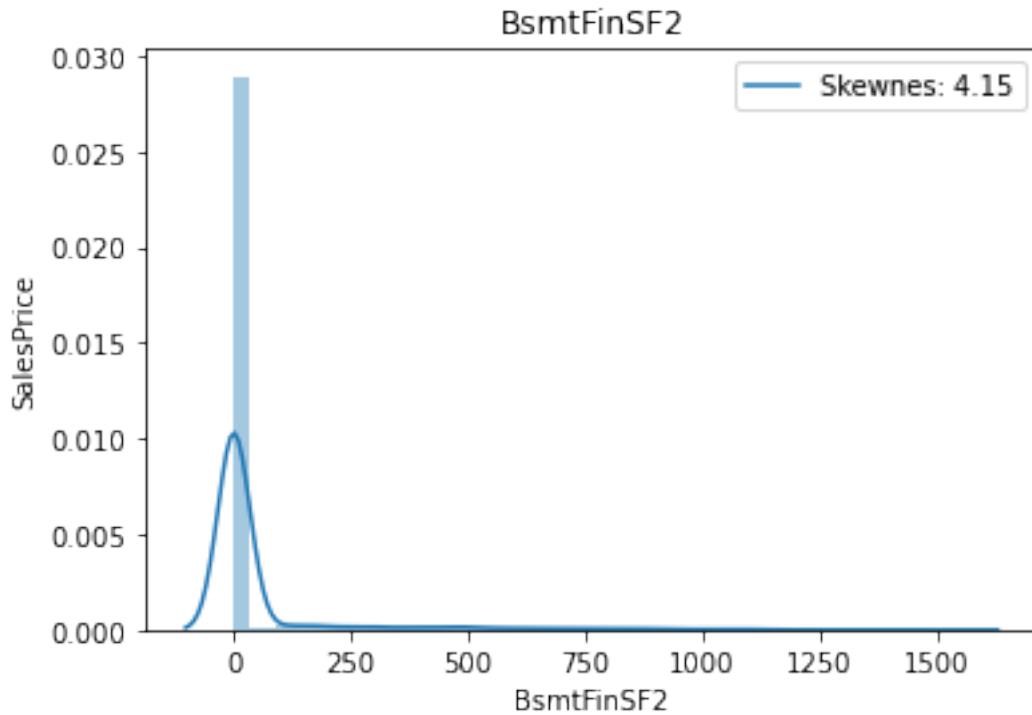
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



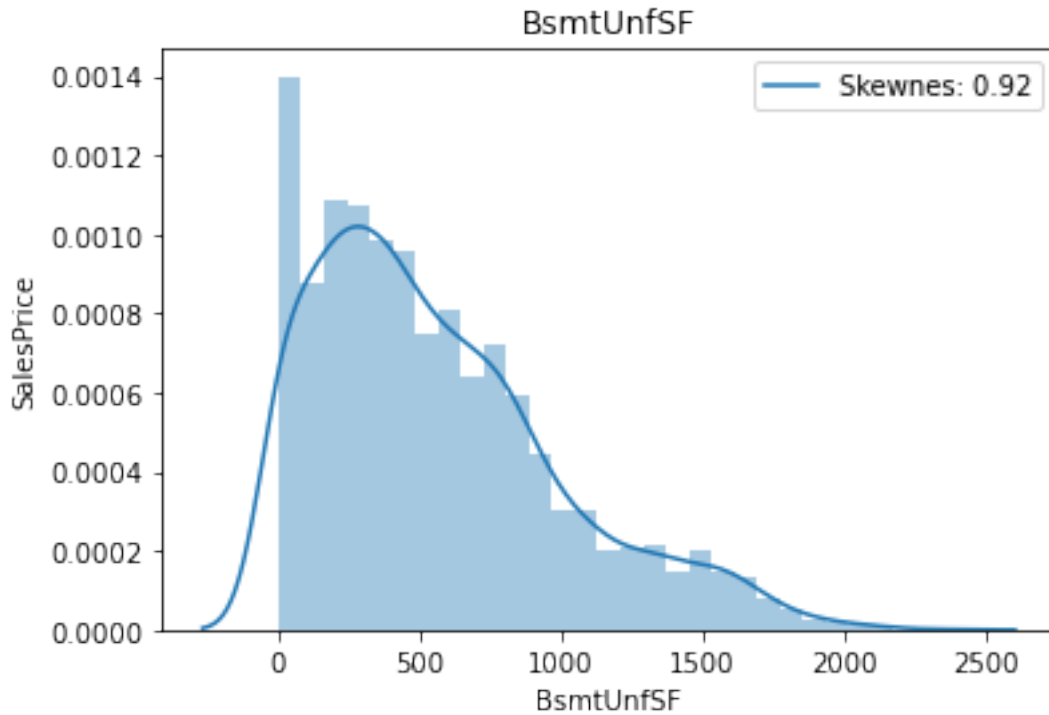
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



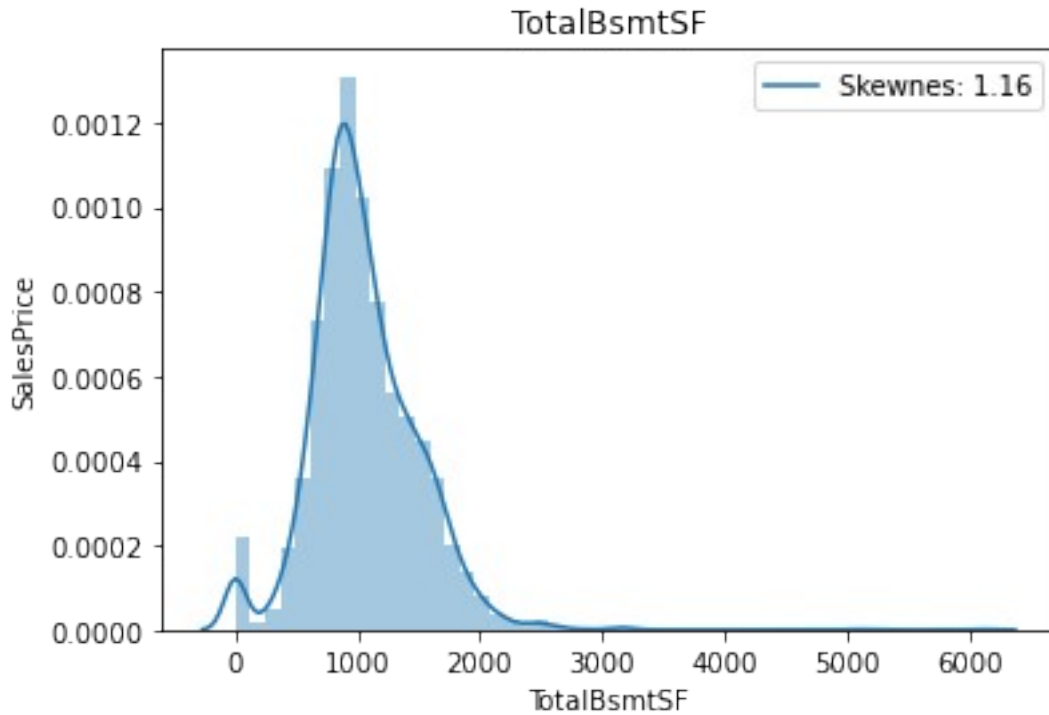
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



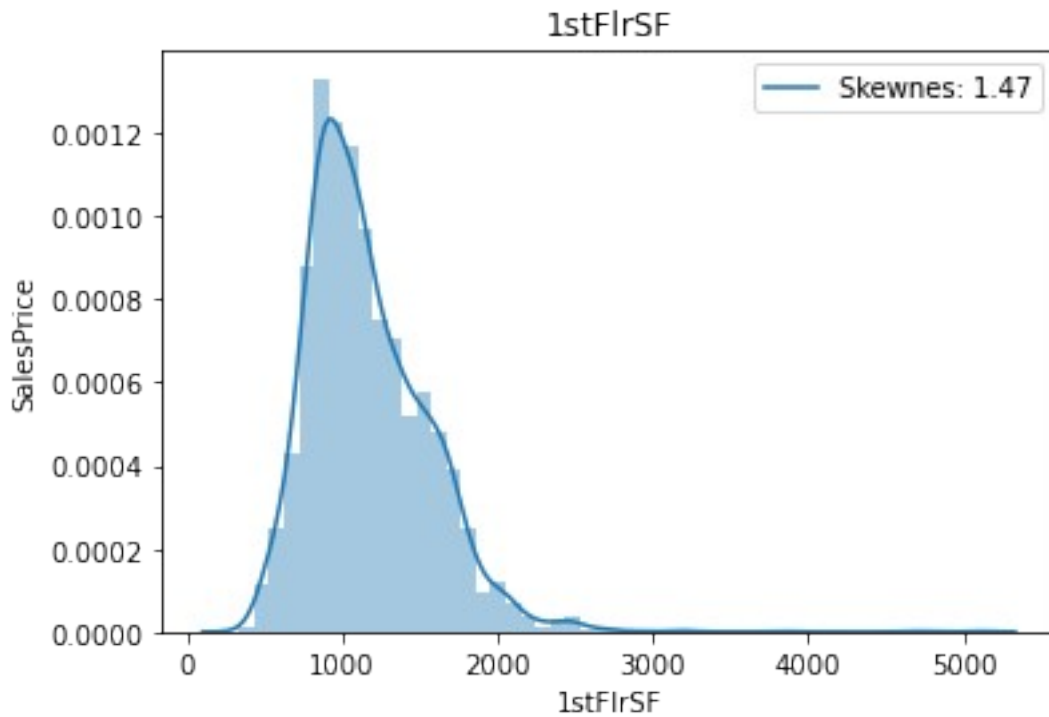
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



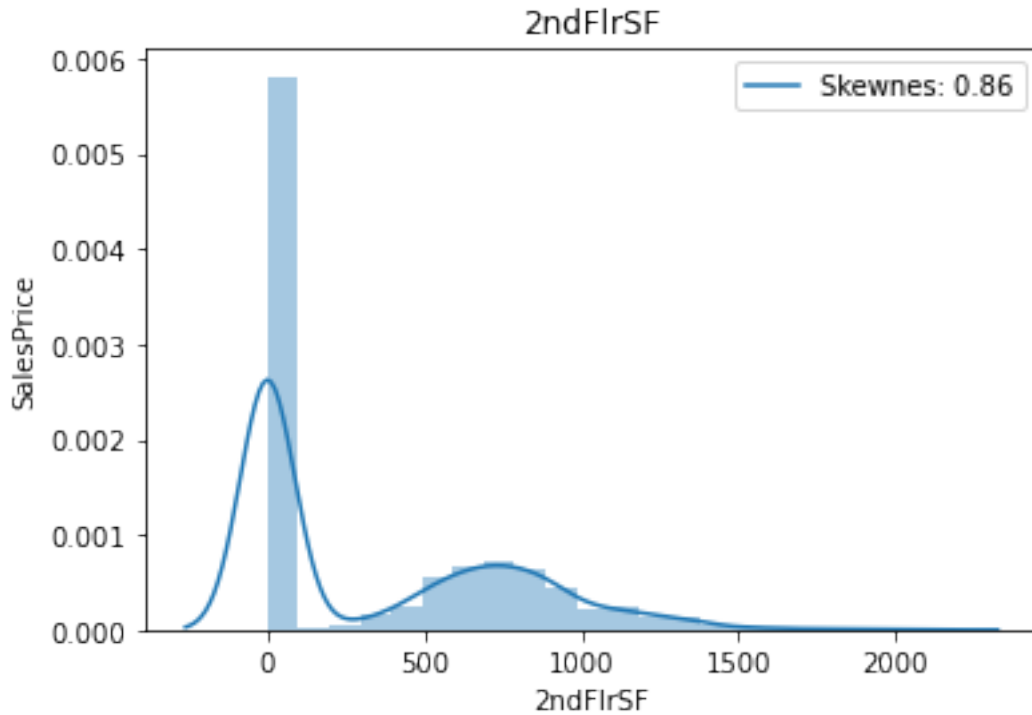
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

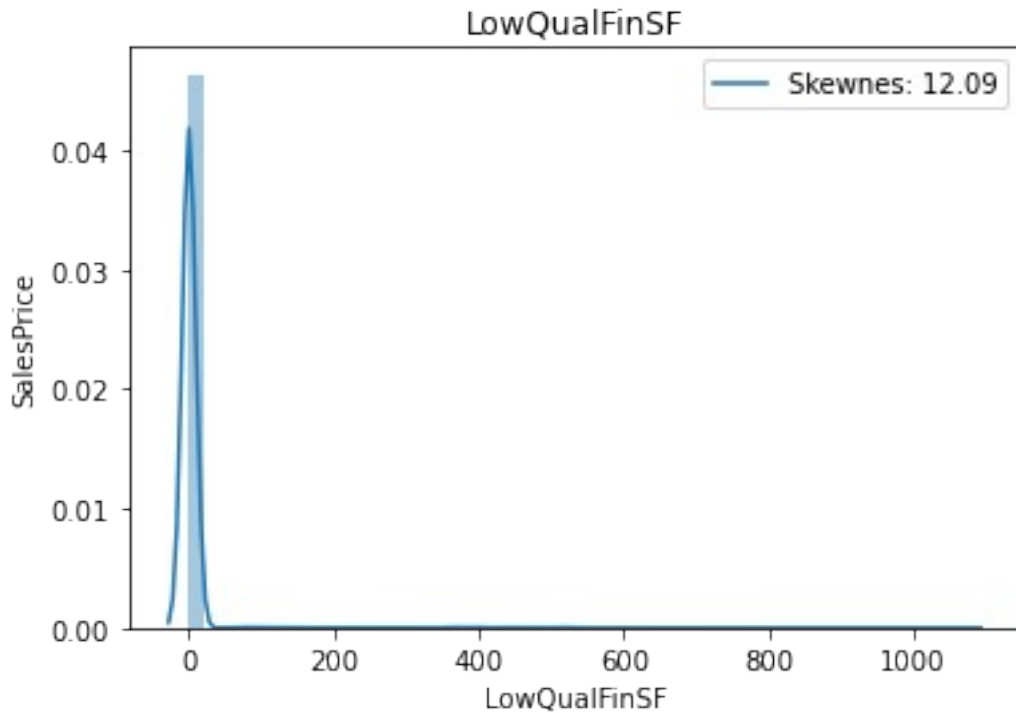
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



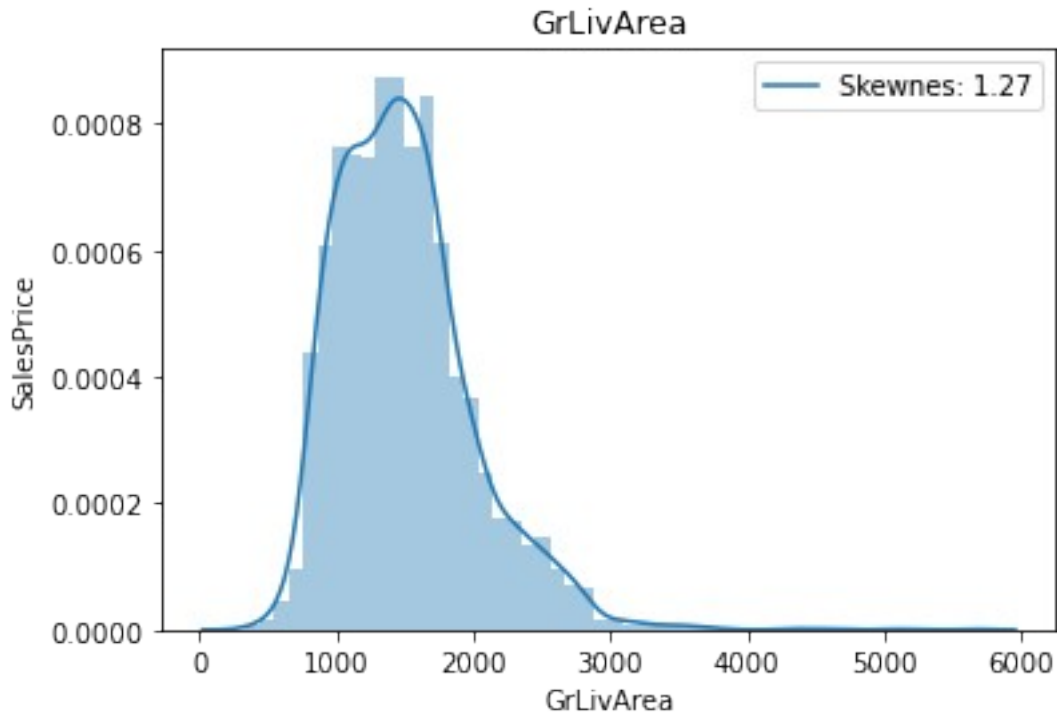
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



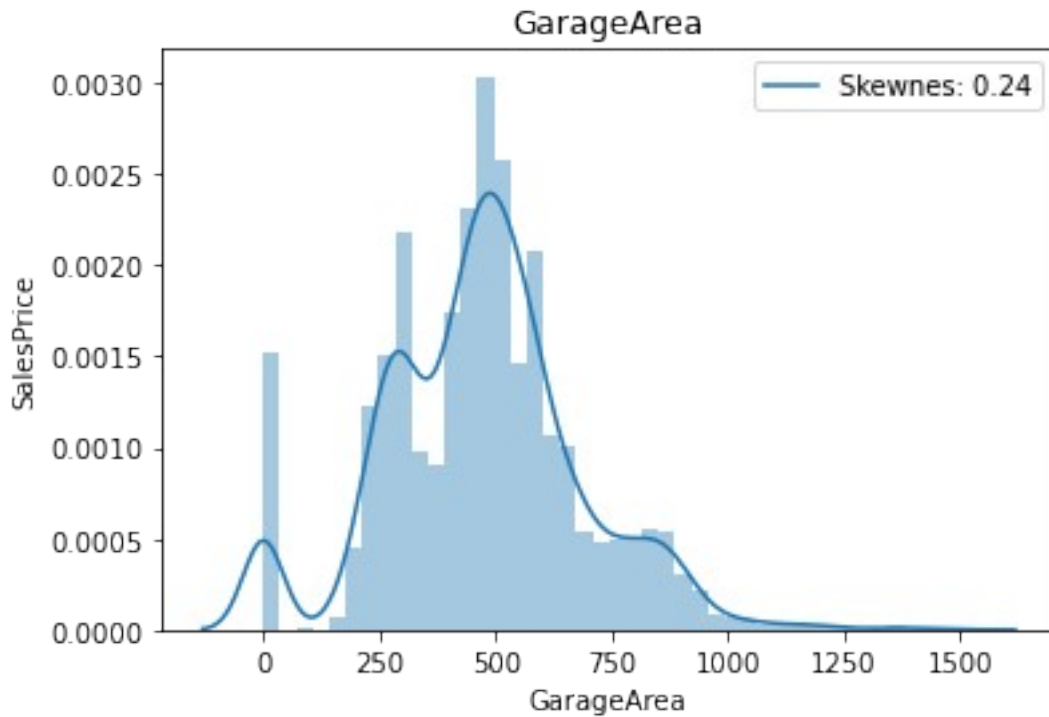
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



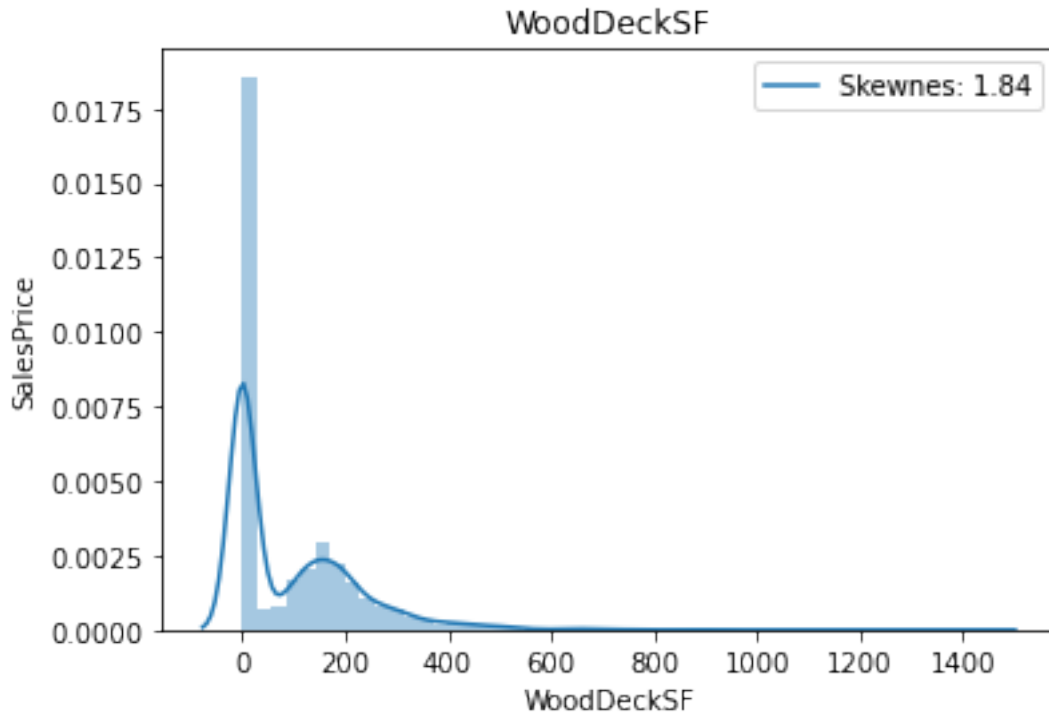
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



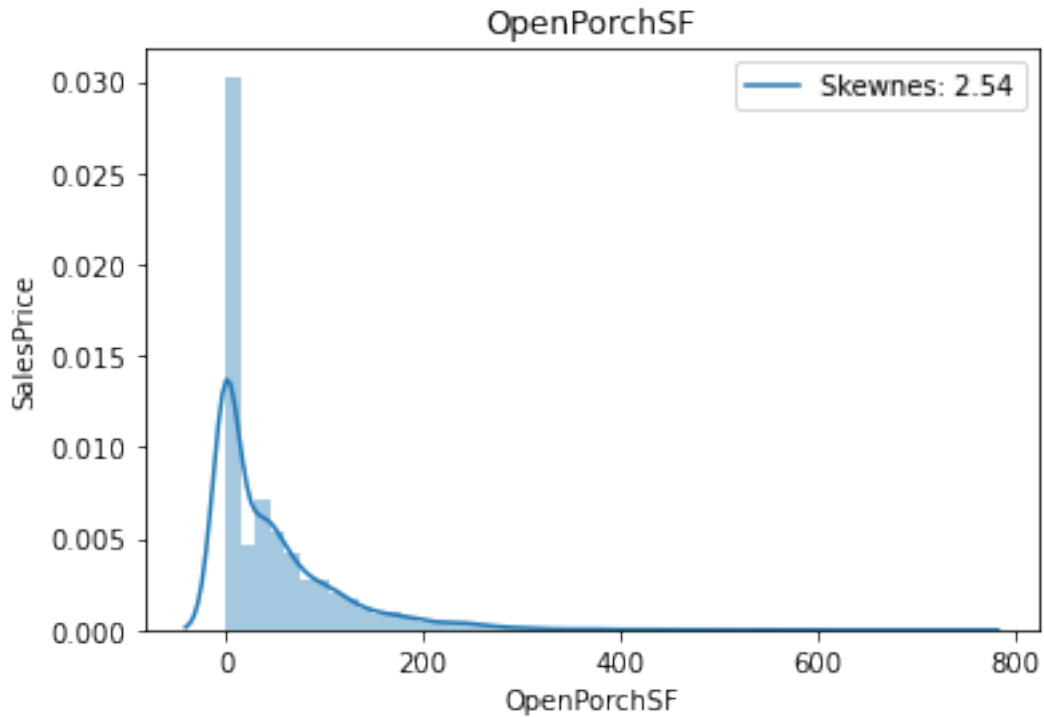
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



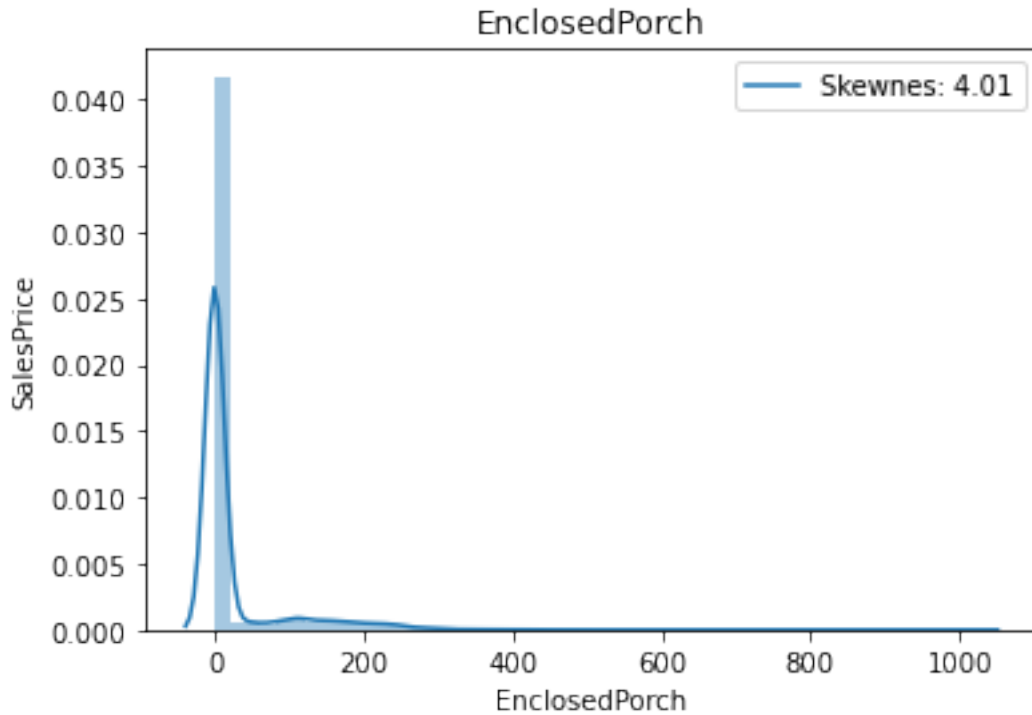
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



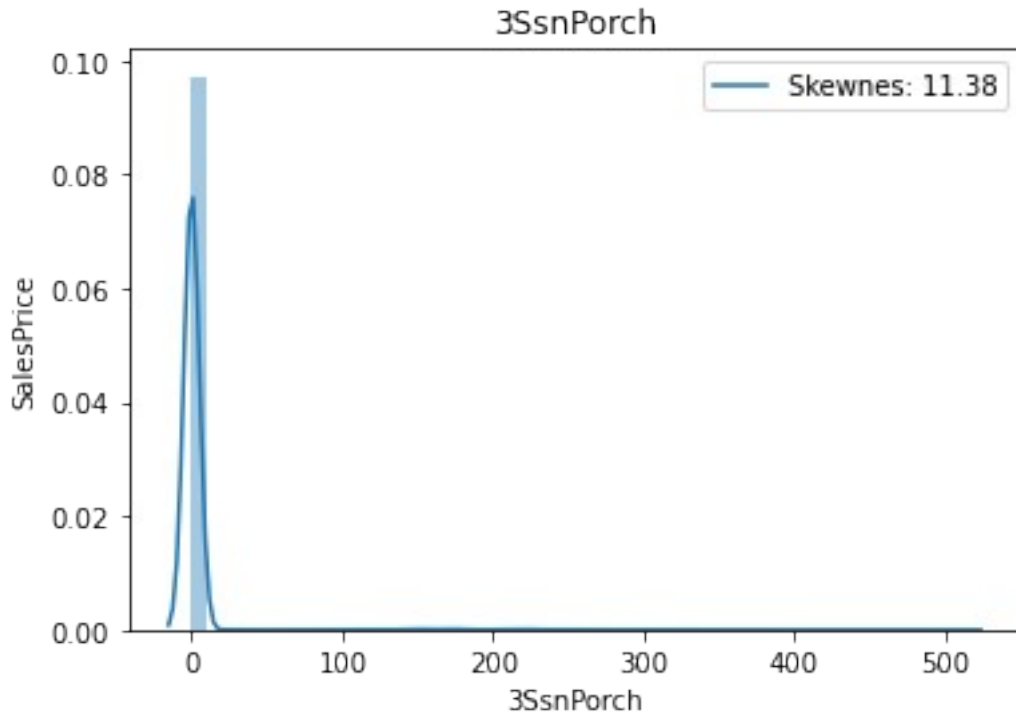
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



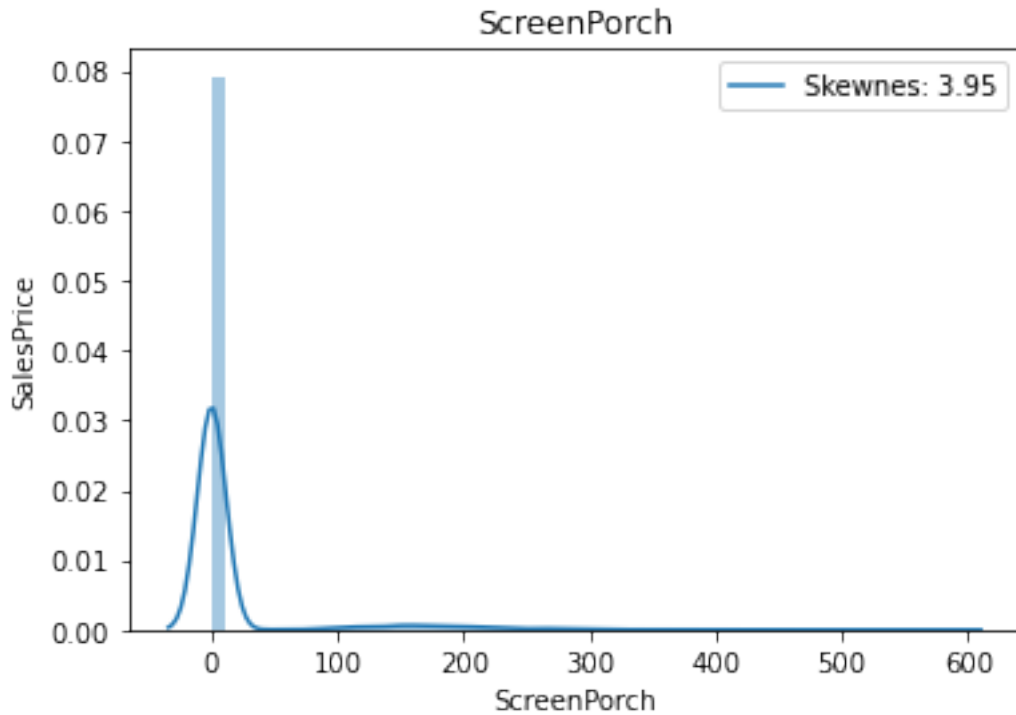
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

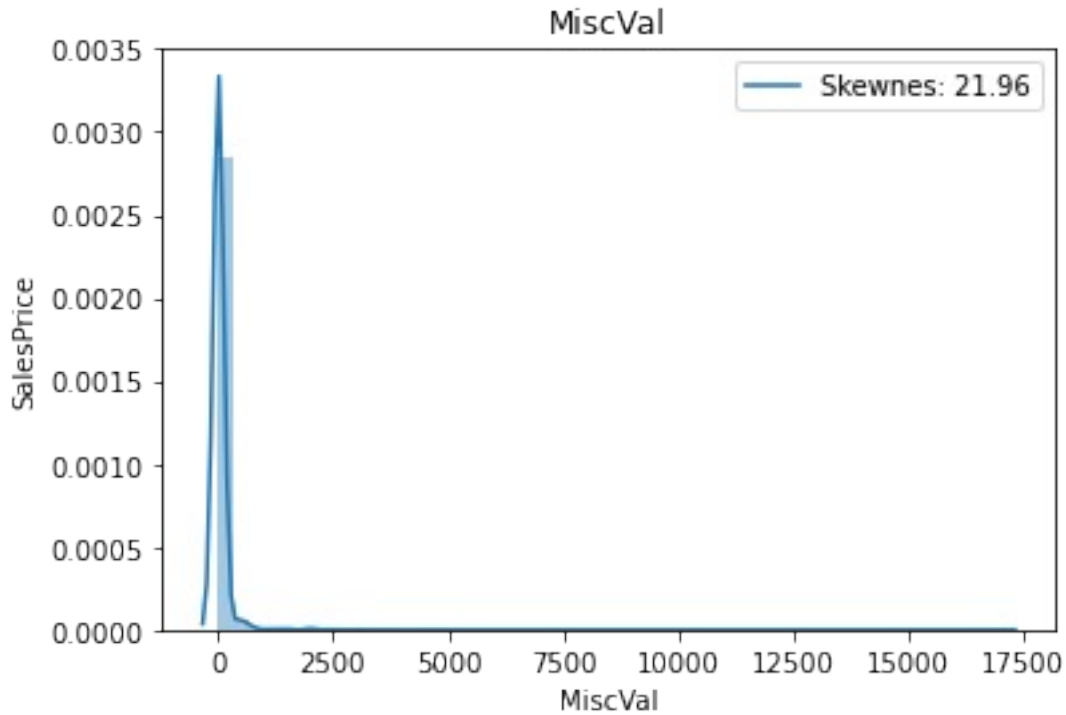
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



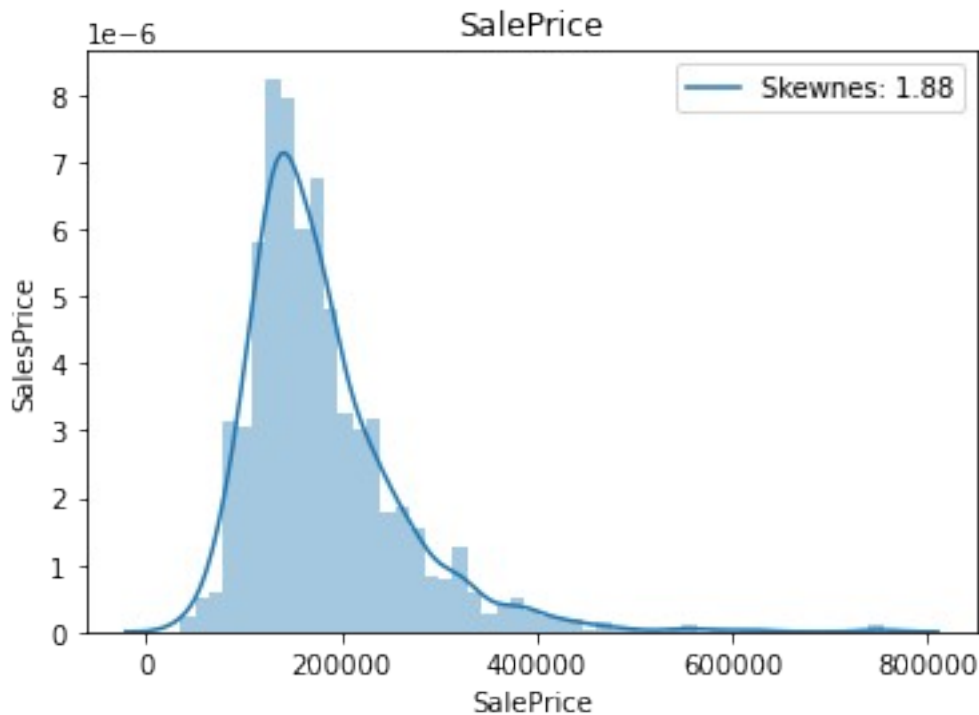
```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



```
C:\Users\Prem\Anaconda3\envs\flight\lib\site-packages\seaborn\
distributions.py:2557: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



```
#skewed = [feature for feature in continious if
data[feature].skew(<1]
#skewed

skewed = []
for feature in continious:
    if abs(df_train[feature].skew())<1:
        skewed.append(feature)
skewed

['BsmtUnfSF', '2ndFlrSF', 'GarageArea']

#for feature in continious:
    #if feature == "SalePrice":
        #pass
    #else:
        # df_train[feature] = np.log1p(df_train[feature])

df_train.shape

(2919, 74)

# correlation heatmap
plt.figure(figsize=(25,25))
ax = sns.heatmap(df_train[continious].corr(), cmap = "coolwarm",
annot=True, linewidth=2)

# to fix the bug "first and last row cut in half of heatmap plot"
```

```

#bottom, top = ax.get_ylim()
#ax.set_ylim(bottom + 0.5, top - 0.5)

# correlation heatmap of highly correlated features with SalePrice
hig_corr = df_train[continious].corr()
hig_corr_features = hig_corr.index[hig_corr["SalePrice"] >= 0.45]
hig_corr_features

abs(-5)

```

Handling categorical variables

```

#categorical = [feature for feature in df_train.columns if
df_train[feature].dtype == "O"]
#len(categorical)

categorical = []
for feature in df_train.columns:
    if df_train[feature].dtype == "O":
        categorical.append(feature)
len(categorical)

for feature in categorical:
    df_train.groupby(feature)['SalePrice'].median().plot.bar()
    plt.xlabel(feature)
    plt.ylabel('SalePrice')
    plt.title(feature)
    plt.show()

```

ORDINAL

```

from pandas.api.types import CategoricalDtype

df_train['BsmtCond'].unique()

df_train['BsmtCond'] =
df_train['BsmtCond'].astype(CategoricalDtype(categories=['NA', 'Po',
'Fa', 'TA', 'Gd', 'Ex'], ordered = True)).cat.codes

df_train['BsmtCond'].unique()

df_train['BsmtExposure'] =
df_train['BsmtExposure'].astype(CategoricalDtype(categories=['NA',
'Mn', 'Av', 'Gd'], ordered = True)).cat.codes
df_train['BsmtFinType1'] =
df_train['BsmtFinType1'].astype(CategoricalDtype(categories=['NA',
'Unf', 'LwQ', 'Rec', 'BLQ', 'ALQ', 'GLQ'], ordered = True)).cat.codes
df_train['BsmtFinType2'] =
df_train['BsmtFinType2'].astype(CategoricalDtype(categories=['NA',
'Unf', 'LwQ', 'Rec', 'BLQ', 'ALQ', 'GLQ'], ordered = True)).cat.codes
df_train['BsmtQual'] =
df_train['BsmtQual'].astype(CategoricalDtype(categories=['NA', 'Po',
'Fa', 'TA', 'Gd', 'Ex'], ordered = True)).cat.codes

```

```

df_train['ExterQual'] =
df_train['ExterQual'].astype(CategoricalDtype(categories=['Po', 'Fa',
'TA', 'Gd', 'Ex'], ordered = True)).cat.codes
df_train['ExterCond'] =
df_train['ExterCond'].astype(CategoricalDtype(categories=['Po', 'Fa',
'TA', 'Gd', 'Ex'], ordered = True)).cat.codes
df_train['Functional'] =
df_train['Functional'].astype(CategoricalDtype(categories=['Sal',
'Sev', 'Maj2', 'Maj1', 'Mod', 'Min2', 'Min1', 'Typ'], ordered =
True)).cat.codes
df_train['GarageCond'] =
df_train['GarageCond'].astype(CategoricalDtype(categories=['NA', 'Po',
'Fa', 'TA', 'Gd', 'Ex'], ordered = True)).cat.codes
df_train['GarageQual'] =
df_train['GarageQual'].astype(CategoricalDtype(categories=['NA', 'Po',
'Fa', 'TA', 'Gd', 'Ex'], ordered = True)).cat.codes
df_train['GarageFinish'] =
df_train['GarageFinish'].astype(CategoricalDtype(categories=['NA',
'Unf', 'RFn', 'Fin'], ordered = True)).cat.codes
df_train['HeatingQC'] =
df_train['HeatingQC'].astype(CategoricalDtype(categories=['Po', 'Fa',
'TA', 'Gd', 'Ex'], ordered = True)).cat.codes
df_train['KitchenQual'] =
df_train['KitchenQual'].astype(CategoricalDtype(categories=['Po',
'Fa', 'TA', 'Gd', 'Ex'], ordered = True)).cat.codes
df_train['PavedDrive'] =
df_train['PavedDrive'].astype(CategoricalDtype(categories=['N', 'P',
'Y'], ordered = True)).cat.codes
df_train['Utilities'] =
df_train['Utilities'].astype(CategoricalDtype(categories=['ELO',
'NASeWa', 'NASeWr', 'AllPub'], ordered = True)).cat.codes

ordinal = ["BsmtCond" , "BsmtExposure" , "BsmtFinType1" ,
"BsmtFinType2" , "BsmtQual" , "ExterQual" , "ExterCond" ,
"Functional",
          "GarageCond" , "GarageQual" , "GarageFinish" , "HeatingQC" ,
"KitchenQual" , "PavedDrive" , "Utilities"]

len(ordinal)

df_train.shape

```

Nominal

- One hot encoding

```
#nominal = [feature for feature in categorical if feature not in
ordinal ]
```

```

nominal = []
for feature in categorical:
    if feature not in ordinal:

```

```

        nominal.append(feature)
nominal

#nominal = [feature for feature in categorical if feature not in ordinal]
for feature in nominal:
    print(feature , len(df_train[feature].unique()))

```

```

new_nominal = ["Neighborhood" , "Exterior1st" , "Exterior2nd"]
#nominal1 = [feature for feature in nominal if feature not in new_nominal]

```

```

nominal1 = []
for feature in nominal:
    if feature not in new_nominal:
        nominal1.append(feature)
nominal1

```

```
len(nominal)
```

```
len(nominal1)
```

```

nominal_variable = pd.get_dummies(columns = nominal1 , data =
df_train, drop_first=True)
nominal_variable.drop(new_nominal , axis = 1 , inplace = True)

nominal_variable.shape

```

- **One hot encoding with many variables**

```
df_train["Neighborhood"].value_counts()
```

```

def top_ten(feature):
    top_ten = []
    for x in feature.value_counts().sort_values(ascending =
False).head(10).index:
        top_ten.append(x)
    return top_ten

```

```
top_10_Neighborhood = top_ten(df_train["Neighborhood"])
```

```
top_10_Exterior1st = top_ten(df_train["Exterior1st"])
```

```
df_train["Exterior1st"].unique()
```

```
df_train["Exterior2nd"].unique()
```

```

#top_10_Neighborhood = [x for x in
df_train.Neighborhood.value_counts().sort_values(ascending=False).head(
10).index]
#top_10_Exterior1st = [x for x in
df_train.Exterior1st.value_counts().sort_values(ascending=False).head(
10).index]

```



```
#top_10_Exterior2nd = [x for x in
df_train.Exterior2nd.value_counts().sort_values(ascending=False).head(
10).index]
```

```
for label in top_10_Neighborhood:
    df_train[label]= np.where(df_train["Neighborhood"]==label,1,0)
```

```
for label in top_10_Exterior1st:
    df_train[label]= np.where(df_train["Exterior1st"]==label,1,0)
```

```
#for label in top_10_Exterior2nd:a
    #df_train[label]= np.where(df_train["Exterior2nd"]==label,1,0)
```

```
#df_train[top_10_Exterior2nd].head()
```

```
df_train[top_10_Exterior1st].head()
```

```
df_train.head()
```

```
df_train.drop(["Neighborhood" , "Exterior1st" , "Exterior2nd"] , axis
= 1 , inplace = True)
```

```
df_train.drop(nominal1 , axis = 1 , inplace = True)
```

```
df_train.head()
```

```
train = pd.concat([nominal_variable , df_train] , axis = 1)
```

```
train.shape
```

```
train.head()
```

```
#preview the df
```

```
train = train.loc[:,~train.columns.duplicated()]
```

```
train.shape
```

```
train.head()
```

```
train.shape
```

```
train.isnull().sum().sum()
```

```
train.var()
```

Feature Selection

```
train_df= train[:1460]
```

```
test1 = train[1460:]
```

```
print(train_df.shape)
```

```
print(test1.shape)
```

```
#print(len(y_train))
```

```

X = train_df.drop("SalePrice" , axis = 1)
y = train_df["SalePrice"]
test = test1.drop("SalePrice" , axis = 1)

X.shape

len(y)

test1.head()

from sklearn.ensemble import ExtraTreesRegressor
model=ExtraTreesRegressor()
model.fit(X,y)

print(model.feature_importances_)

plt.figure(figsize = (20 , 20))
ranked_features=pd.Series(model.feature_importances_,index=X.columns)
ranked_features.nlargest(35).plot(kind='barh')
plt.show()

features = ranked_features.nlargest(23)

X = train_df[features.index]

X.shape

X.head()

```

Model Building

```

# split dataset into train and test
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, random_state= 5)

```

Robust scaler

```

test1 = test1[features.index]

# scaling dataset with robust scaler
from sklearn.preprocessing import RobustScaler
scaler = RobustScaler()
scaler.fit_transform(X_train)
X = scaler.transform(X_test)
test1 = scaler.transform(test1)

```

Linear Regression

```

from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error # for calculating
mean_squared error
from sklearn.metrics import r2_score # for measuring the goodness of
best fit line

```

```

reg = LinearRegression()
reg.fit(X_train , y_train)

y_pred = reg.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test , y_pred))

score=r2_score(y_test,y_pred)
print(f"value of R^2 is {score}")
print(f"rmse value is {rmse}")

```

Random Forest

Random Forest Classifier

```
from sklearn.ensemble import RandomForestRegressor
```

```

rf = RandomForestRegressor()
rf.fit(X_train, y_train)

y_pred_rf = rf.predict(X_test)
score_rf=r2_score(y_test,y_pred_rf)
rmse = np.sqrt(mean_squared_error(y_test , y_pred_rf))

print(f"value of R^2 is {score_rf}")
print(f"rmse value is {rmse}")

```

Xgboost

```

import xgboost
xgb_model = xgboost.XGBRegressor()
xgb_model.fit(X_train,y_train)

y_pred_xg = xgb_model.predict(X_test)
score_xg=r2_score(y_test,y_pred_xg)
rmse = np.sqrt(mean_squared_error(y_test , y_pred_xg))

print(f"value of R^2 is {score_xg}")
print(f"rmse value is {rmse}")

from sklearn.model_selection import cross_val_score
cross_validation = cross_val_score(estimator = xgb_model, X =
X_train,y = y_train, cv = 10)
print("Cross validation accuracy of Xgboost model = ",
cross_validation)
print("\nCross validation mean accuracy of Xgboost model = ",
cross_validation.mean())

y_pred_hyper = rf.predict(test1)
y_pred_hyper

```

```

df = pd.read_csv("test.csv" , usecols = ["Id"])
df.head()

submit_test1 = pd.concat([df["Id"], pd.DataFrame(y_pred_hyper)],
axis=1)
submit_test1.columns=['Id', 'SalePrice']

submit_test1.head(20)

submit_test1 = submit_test1.astype({'Id': 'int', 'SalePrice':
'float'})

submit_test1.to_csv('sample_submission.csv', index=False)

df = pd.read_csv("sample_submission.csv")
df

```

Hyper parameter tuning

Hyperparameter optimization using RandomizedSearchCV

```
from sklearn.model_selection import RandomizedSearchCV
```

#Randomized Search CV

Number of trees in random forest

```
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 1200,
num = 12)]
```

Number of features to consider at every split

```
criterion = ["mse" , "mae"]
```

```
max_features = ['auto', 'sqrt', "log2"]
```

Maximum number of levels in tree

```
max_depth = [int(x) for x in np.linspace(5, 30, num = 6)]
```

Minimum number of samples required to split a node

```
min_samples_split = [2, 5, 10, 15, 100]
```

Minimum number of samples required at each leaf node

```
min_samples_leaf = [1, 2, 5, 10]
```

Create the random grid

```
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf}
```

```
rf_random = RandomizedSearchCV(estimator = rf, param_distributions =
random_grid,scoring='neg_mean_squared_error', n_iter = 10, cv = 5,
verbose=2, random_state=42, n_jobs = -1)
```

```
rf_random.fit(X_train,y_train)
```

```
rf_random.best_params_  
  
prediction = rf_random.predict(X_test)  
score_rf=r2_score(y_test,prediction)  
  
print(f"value of R^2 is {score_rf}")  
print('RMSE:', np.sqrt(mean_squared_error(y_test, prediction)))  
  
y_pred_hyper = rf_random.predict(test1)  
y_pred_hyper  
  
df = pd.read_csv("test.csv" , usecols = ["Id"])  
submit_test1 = pd.concat([df["Id"], pd.DataFrame(y_pred_hyper)],  
axis=1)  
submit_test1.columns=['Id', 'SalePrice']  
  
submit_test1 = submit_test1.astype({'Id': 'int', 'SalePrice':  
'float'})  
submit_test1.to_csv('sample_submission.csv', index=False)  
  
submit_test1
```