

housing-price-prediction

May 30, 2024

1 ABSTRACT

The “House Price Prediction” project aims to develop a machine learning model to predict housing prices based on various features such as lot size, building type, and neighborhood. Utilizing a dataset from a reputable source, the project involves data cleaning, exploratory data analysis (EDA), and the application of regression models. The model’s performance is evaluated to ensure accurate and reliable predictions. The outcome of this project can assist stakeholders in making informed decisions in the real estate market.

2 OBJECTIVE

The primary objective of this project is to develop a machine learning model that can predict house prices based on various features of the properties. Specific objectives include:

- 1). Cleaning and preprocessing the dataset to ensure high-quality data.
- 2). Conducting exploratory data analysis (EDA) to understand the relationships between features and house prices.
- 3). Implementing and evaluating multiple regression models to determine the most accurate predictor.
- 4). Providing insights and recommendations based on the model’s predictions to assist in real estate decision-making.

3 INTRODUCTION

The real estate market is a significant component of the global economy, where accurate price predictions can lead to better investment decisions and market understanding. This project focuses on predicting house prices using a dataset containing various features related to property characteristics. By leveraging machine learning techniques, the project aims to build a robust predictive model that can provide accurate price estimates, thereby benefiting buyers, sellers, and investors in making informed decisions.

4 METHODOLOGY

1). Importing Dataset and Data Inception:

With the help of Pandas library of python we had extracted the data from the CSV file named 'housing_price_prediction.csv' which was prepared by Kaggle Community.

Here data is also checked that how many null values are present in each columns. So that further while analysis and also while making models, we can't find difficulty.

2). Data Cleaning:

The main purpose of Data Cleaning is to fill the null values. We can also say that to handle the null value because if the data remain unclean then EDA can't be accurate.

Converting categorical variables into numerical formats using techniques like one-hot encoding.

If the dtypes of columns holding data, is non numeric, then fill it with 'None' rather than to keep it null because in Analysis, "None" is not count as null.

So for this we had filled the numeric values [Float64, int64, etc. dtypes], with either mean or mode as per need.

3). EDA:

We had done two types of EDA .. for better understanding of our data set.

a): Univariate Analysis:

Analyzing the distribution and statistics of individual features.

b): Bivariate and Multivariate Analysis:

Exploring relationships between features and the target variable (house prices), using visualizations like scatter plots, histograms, and correlation matrices.

4). Data Preparation:

For Data Preparation, we had divide the whole in 'numeric' and 'non-numeric' values. Where later with the help of 'dummies' module of pandas, we had converted non_numeric terms to numeric too, and later we concat them so that we not get the clear from of Data.

For model, we divided the whole into 4 parts. Suppose X is input and Y is output then, we split X as per train and test and similar with Y too. So in total we split whole data set with 4 parts. which can be X_train, X_test, y_train, y_test.

Scaling and normalizing the data to ensure that all features contribute equally to the model.

For splitting and scaling and normalizing we used Sklearn library

5). ML Model:

While preparing ML model we had split with two processes:

a). Model Implementation:

Here with the help of Sklearn, we make sure to apply 'Linear Regression', 'Ridge', 'Lasso'. Each will do analysis first and then each will give output as per the working of the algorithms.

b). Model Evaluation:

Evaluating the models using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared score. This will help to conclude that which model is best to use and which is not healthy for data.

5 CODE

```
[1]: import warnings
warnings.filterwarnings('ignore')
```

```
[2]: import numpy as np
import pandas as pd
```

```
[3]: pd.set_option("display.max_columns",None)
pd.set_option("display.max_rows",None)
```

5.1 Importing Dataset & Data Inception

```
[4]: housing = pd.read_csv('housing_price_prediction.csv')
```

```
[5]: housing.head(5)
```

```
[5]:
```

	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	NaN	
2	2002	Gable	CompShg	VinylSd	VinylSd	BrkFace	
3	1970	Gable	CompShg	Wd Sdng	Wd Shng	NaN	
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	Unf	0	150	856	
1	ALQ	978	Unf	0	284	1262	
2	GLQ	486	Unf	0	434	920	
3	ALQ	216	Unf	0	540	756	
4	GLQ	655	Unf	0	490	1145	

	Heating	HeatingQC	CentralAir	Electrical	1stFlrSF	2ndFlrSF	LowQualFinSF	\
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	BedroomAbvGr	\
0	1710	1	0	2	1	3	
1	1262	0	1	2	0	3	
2	1786	1	0	2	1	3	
3	1717	1	0	1	0	3	
4	2198	1	0	2	1	4	

	KitchenAbvGr	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	\
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	548	TA	

1	Attchd	1976.0	RFn	2	460	TA
2	Attchd	2001.0	RFn	2	608	TA
3	Detchd	1998.0	Unf	3	642	TA
4	Attchd	2000.0	RFn	3	836	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
1	WD	Normal	181500
2	WD	Normal	223500
3	WD	Abnorml	140000
4	WD	Normal	250000

```
[ ]:
```

```
[6]: housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
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        1460 non-null  object
8   LandContour     1460 non-null  object
9   Utilities       1460 non-null  object
10  LotConfig       1460 non-null  object
11  LandSlope       1460 non-null  object
```

12	Neighborhood	1460	non-null	object
13	Condition1	1460	non-null	object
14	Condition2	1460	non-null	object
15	BldgType	1460	non-null	object
16	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	588	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	KitchenAbvGr	1460	non-null	int64
53	KitchenQual	1460	non-null	object
54	TotRmsAbvGrd	1460	non-null	int64
55	Functional	1460	non-null	object
56	Fireplaces	1460	non-null	int64
57	FireplaceQu	770	non-null	object
58	GarageType	1379	non-null	object
59	GarageYrBlt	1379	non-null	float64

```

60 GarageFinish    1379 non-null    object
61 GarageCars      1460 non-null    int64
62 GarageArea      1460 non-null    int64
63 GarageQual      1379 non-null    object
64 GarageCond      1379 non-null    object
65 PavedDrive      1460 non-null    object
66 WoodDeckSF      1460 non-null    int64
67 OpenPorchSF     1460 non-null    int64
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
79 SaleCondition   1460 non-null    object
80 SalePrice       1460 non-null    int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB

```

```
[ ]:
```

```
[7]: housing.isnull().sum()/housing.shape[0]*100
```

```

[7]: Id                0.000000
    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	59.726027
MasVnrArea	0.547945
ExterQual	0.000000
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

```

5.2 Data Cleaning

```
[ ]:
```

```
[8]: na_col = [col for col in housing.columns if housing[col].isnull().any() and
↳housing[col].dtype == 'object']
```

```
[9]: na_col
```

```
[9]: ['Alley',
'MasVnrType',
'BsmtQual',
'BsmtCond',
'BsmtExposure',
'BsmtFinType1',
'BsmtFinType2',
'Electrical',
'FireplaceQu',
'GarageType',
'GarageFinish',
'GarageQual',
'GarageCond',
'PoolQC',
'Fence',
'MiscFeature']
```

```
[10]: for feature in na_col:
housing[feature].fillna('None',inplace=True)
```

```
[11]: housing.isnull().sum()/housing.shape[0]*100
```

```

[11]: Id                0.000000
      MSSubClass         0.000000
      MSZoning           0.000000
      LotFrontage       17.739726
      LotArea           0.000000
      Street            0.000000
      Alley             0.000000
      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       0.000000
      MasVnrArea       0.547945
      ExterQual        0.000000
      ExterCond        0.000000
      Foundation       0.000000
      BsmtQual         0.000000
      BsmtCond         0.000000
      BsmtExposure     0.000000
      BsmtFinType1     0.000000
      BsmtFinSF1       0.000000
      BsmtFinType2     0.000000
      BsmtFinSF2       0.000000
      BsmtUnfSF        0.000000
      TotalBsmtSF      0.000000
      Heating          0.000000
      HeatingQC        0.000000
      CentralAir       0.000000
      Electrical       0.000000
      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       0.000000
GarageType        0.000000
GarageYrBlt       5.547945
GarageFinish      0.000000
GarageCars        0.000000
GarageArea        0.000000
GarageQual        0.000000
GarageCond        0.000000
PavedDrive        0.000000
WoodDeckSF        0.000000
OpenPorchSF       0.000000
EnclosedPorch     0.000000
3SsnPorch         0.000000
ScreenPorch       0.000000
PoolArea          0.000000
PoolQC            0.000000
Fence             0.000000
MiscFeature       0.000000
MiscVal           0.000000
MoSold            0.000000
YrSold            0.000000
SaleType          0.000000
SaleCondition     0.000000
SalePrice         0.000000
dtype: float64

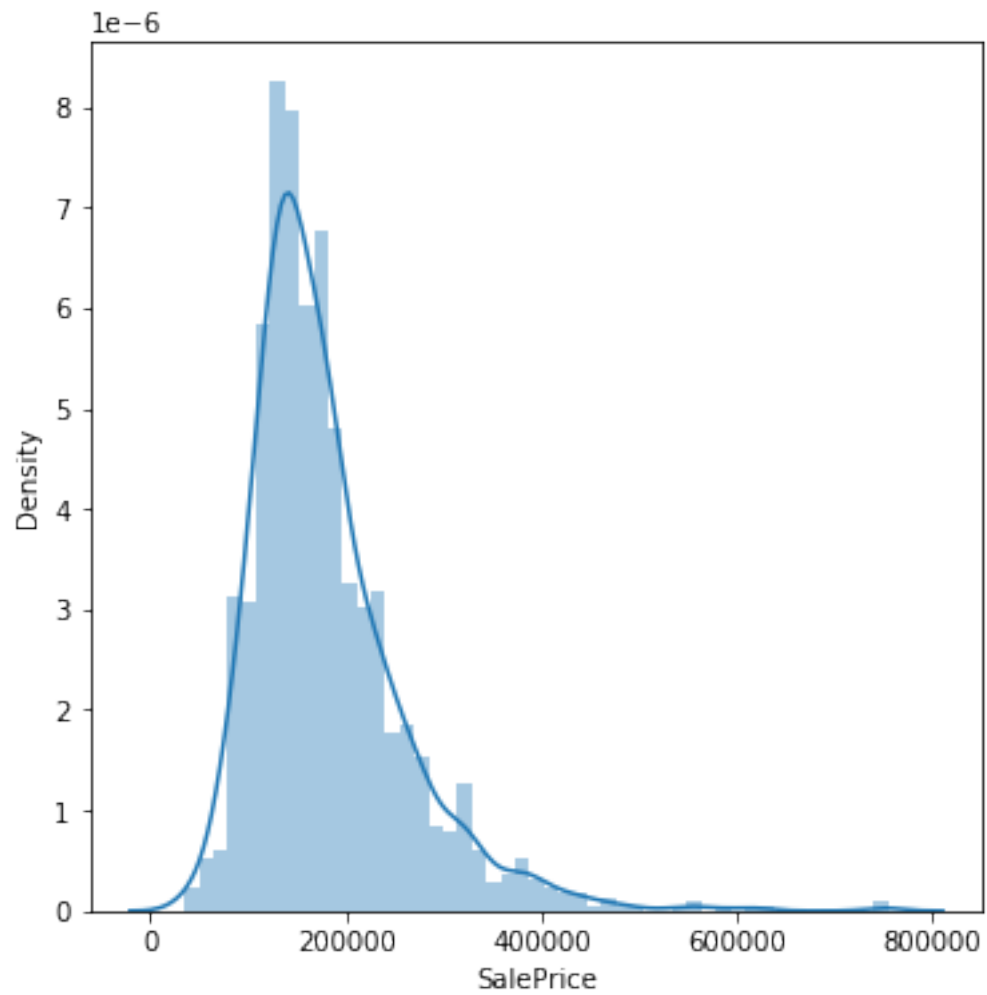
```

```
[ ]:
```

```
[12]: import seaborn as sns
import matplotlib.pyplot as plt
```

```
[13]: plt.figure(figsize=(6,6))
sns.distplot(housing['SalePrice'])
```

```
[13]: <Axes: xlabel='SalePrice', ylabel='Density'>
```



[]:

[14]: housing['SalePrice'].skew()

[14]: 1.8828757597682129

[]:

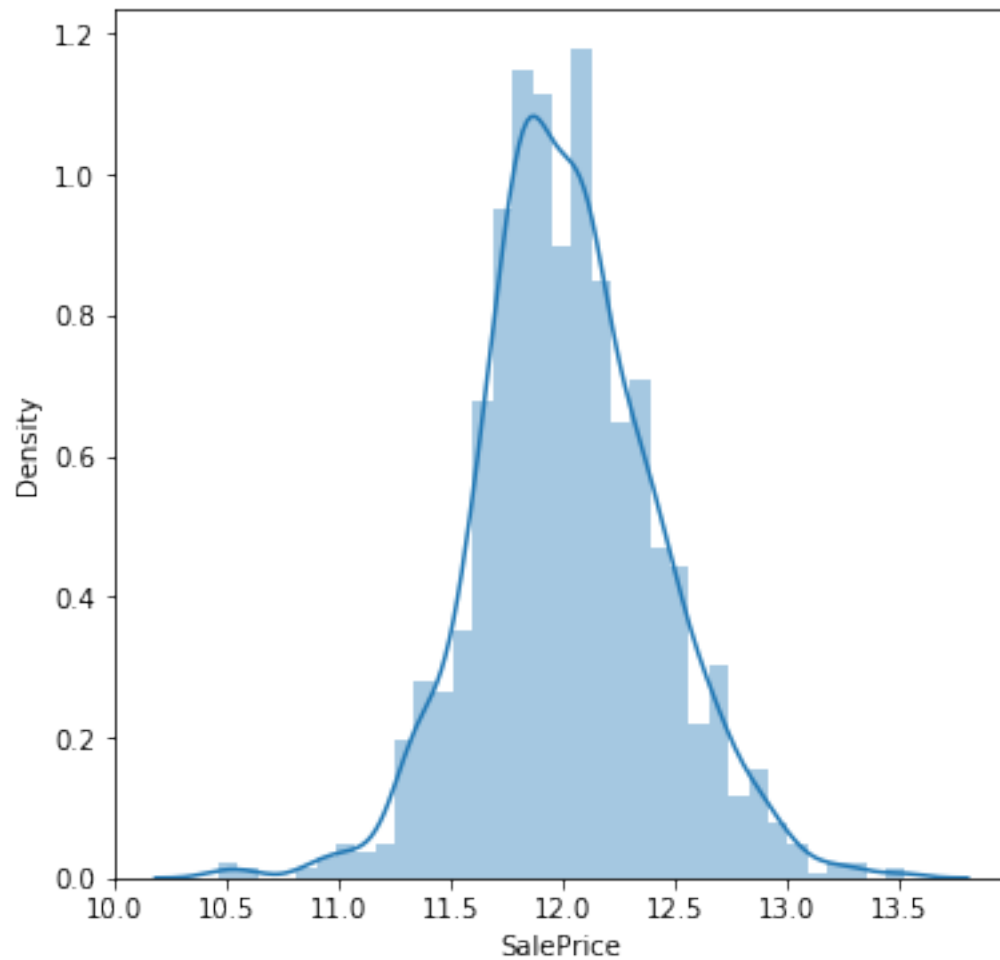
[15]: housing['SalePrice'].kurt()

[15]: 6.536281860064529

[]:

```
[16]: housing['SalePrice'] = np.log(housing['SalePrice'])  
plt.figure(figsize=(6,6))  
sns.distplot(housing['SalePrice'])
```

```
[16]: <Axes: xlabel='SalePrice', ylabel='Density'>
```



```
[ ]:
```

```
[17]: housing['SalePrice'].skew()
```

```
[17]: 0.12133506220520406
```

```
[ ]:
```

```
[18]: housing['SalePrice'].kurt()
```

```
[18]: 0.8095319958036296
```

```
[ ]:
```

```
[19]: housing.drop('Id',axis=1,inplace=True)
```

```
[ ]:
```

```
[20]: housing[['MSSubClass', 'OverallQual', 'OverallCond']] =
↳housing[['MSSubClass', 'OverallQual', 'OverallCond']].astype('object')
```

```
[21]: housing['LotFrontage'] = pd.to_numeric(housing['LotFrontage'], errors='coerce')
housing['MasVnrArea'] = pd.to_numeric(housing['MasVnrArea'], errors='coerce')
```

```
[22]: null_cols = housing.columns[housing.isnull().any()]
null_cols
```

```
[22]: Index(['LotFrontage', 'MasVnrArea', 'GarageYrBlt'], dtype='object')
```

```
[ ]:
```

```
[23]: for feature in null_cols:
    if housing[feature].dtype == np.float64 or housing[feature].dtype == np.
↳int64:
        housing[feature].fillna(housing[feature].mean(), inplace=True)
    else:
        housing[feature].fillna(housing[feature].mode()[0], inplace=True)
```

```
[24]: housing.isnull().sum()
```

```
[24]: MSSubClass      0
      MSZoning      0
      LotFrontage   0
      LotArea       0
      Street        0
      Alley         0
      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
RoofMatl	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
Heating	0
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
FireplaceQu	0
GarageType	0
GarageYrBlt	0
GarageFinish	0
GarageCars	0
GarageArea	0
GarageQual	0
GarageCond	0
PavedDrive	0
WoodDeckSF	0

```

OpenPorchSF      0
EnclosedPorch    0
3SsnPorch        0
ScreenPorch      0
PoolArea         0
PoolQC           0
Fence            0
MiscFeature      0
MiscVal          0
MoSold           0
YrSold           0
SaleType         0
SaleCondition    0
SalePrice        0
dtype: int64

```

```
[ ]:
```

5.3 EDA

```
[25]: cat_cols = housing.select_dtypes(include='object').columns
cat_cols
```

```
[25]: Index(['MSSubClass', 'MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour',
            'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1',
            'Condition2', 'BldgType', 'HouseStyle', 'OverallQual', 'OverallCond',
            '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')
```

```
[ ]:
```

```
[26]: num_cols = housing.select_dtypes(include=['float64', 'int64']).columns
num_cols
```

```
[26]: Index(['LotFrontage', 'LotArea', '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')
```

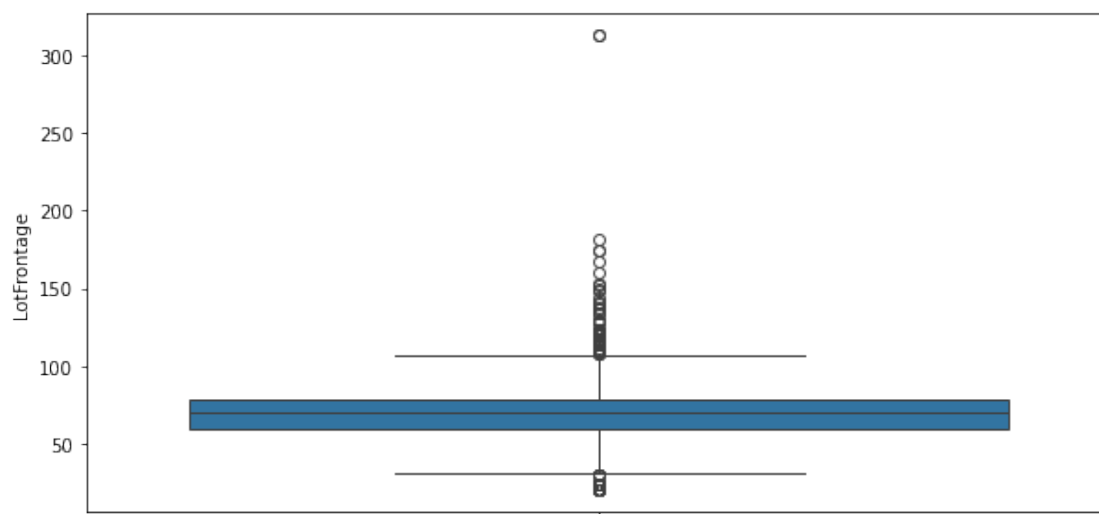


```
[ ]:
```

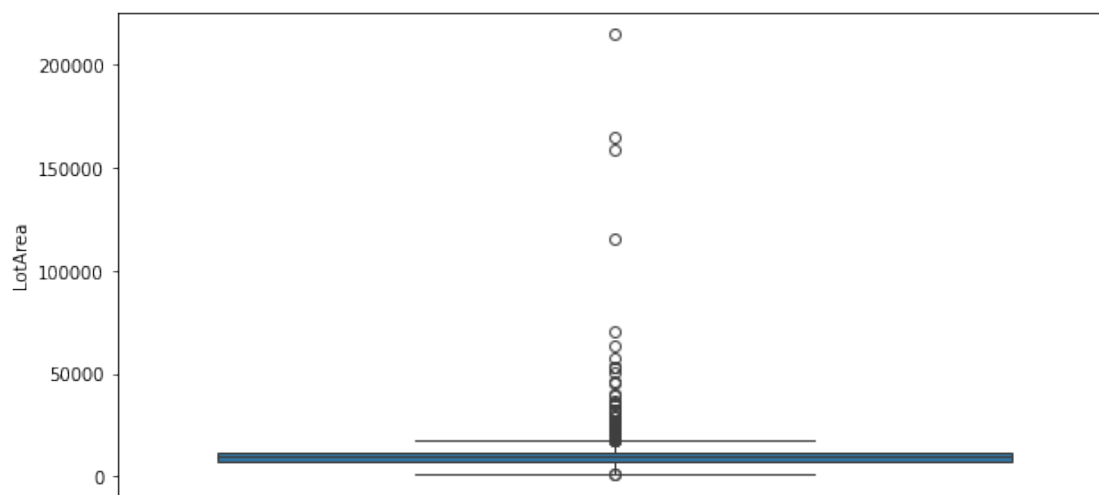
5.3.1 Univariate Analysis

```
[27]: for col in num_cols:
      plt.figure(figsize=(10,5))
      print(col)
      sns.boxplot(housing[col])
      plt.show()
```

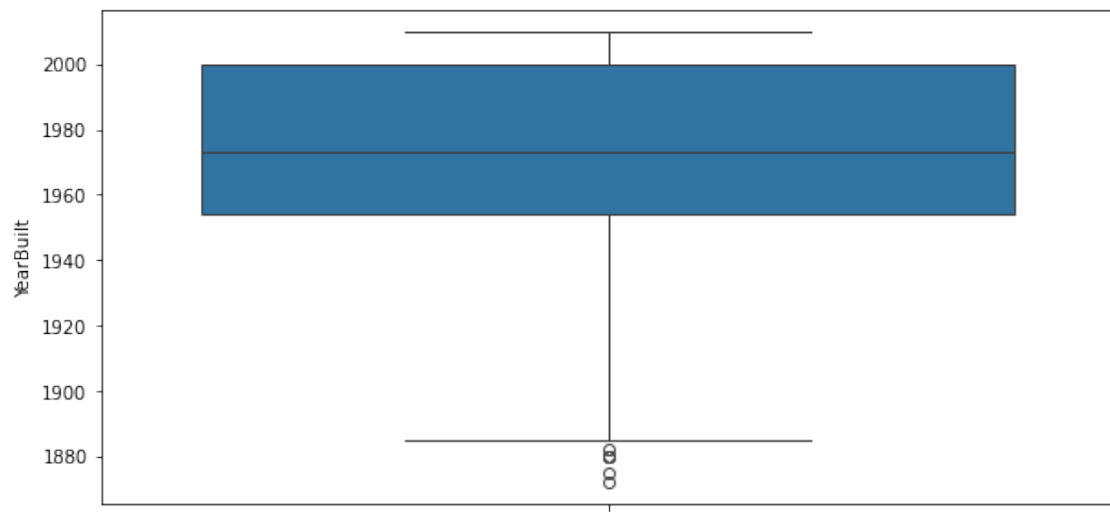
LotFrontage



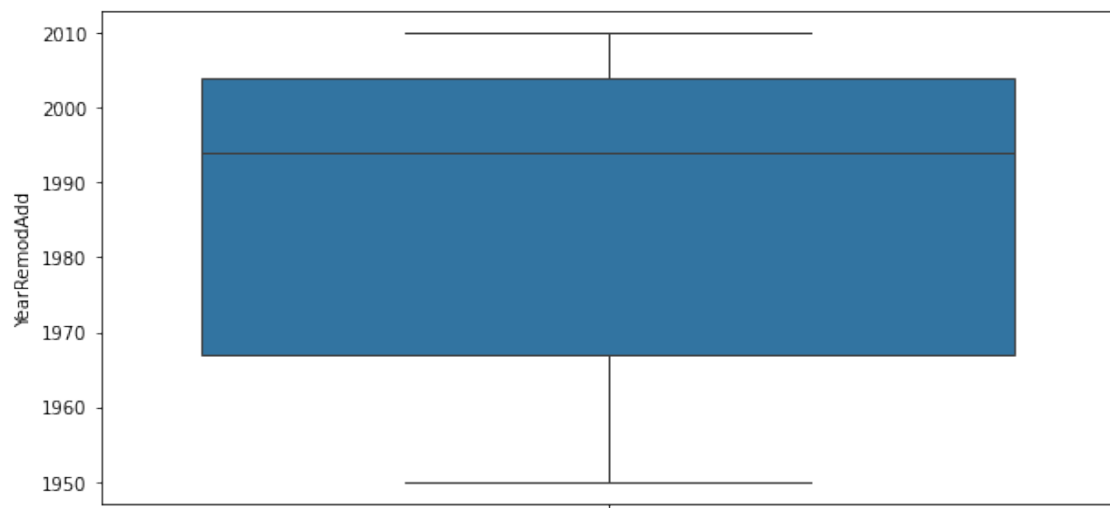
LotArea



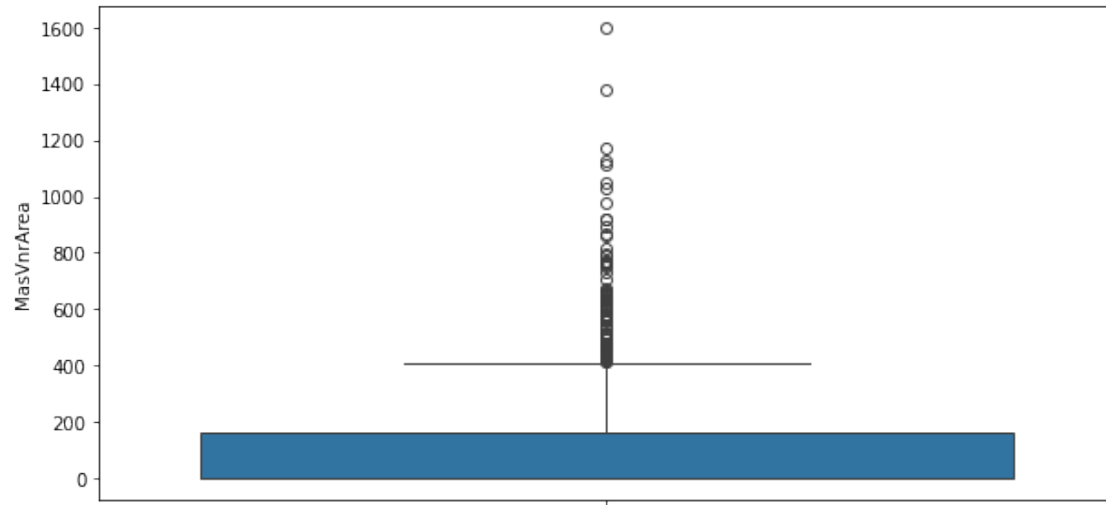
YearBuilt



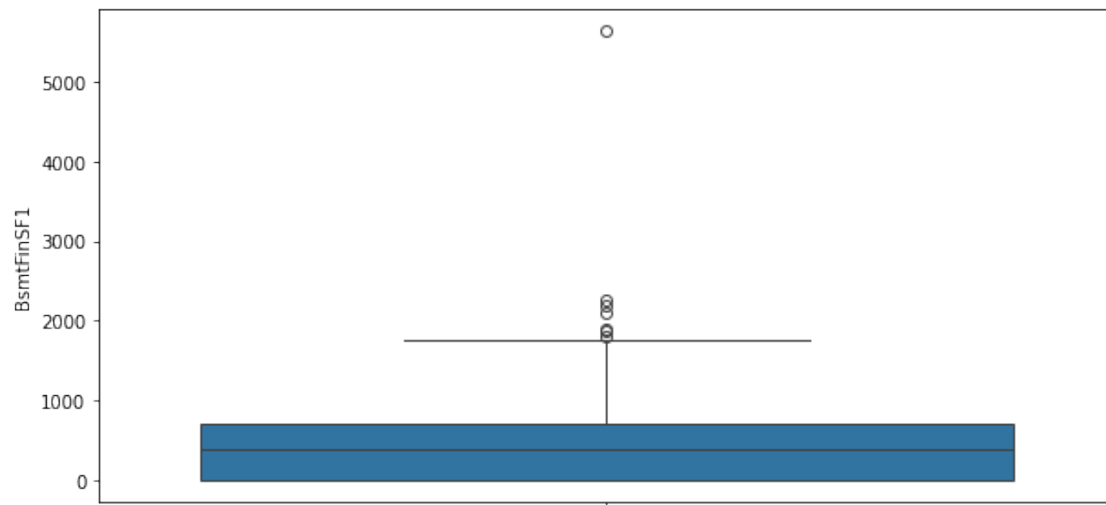
YearRemodAdd



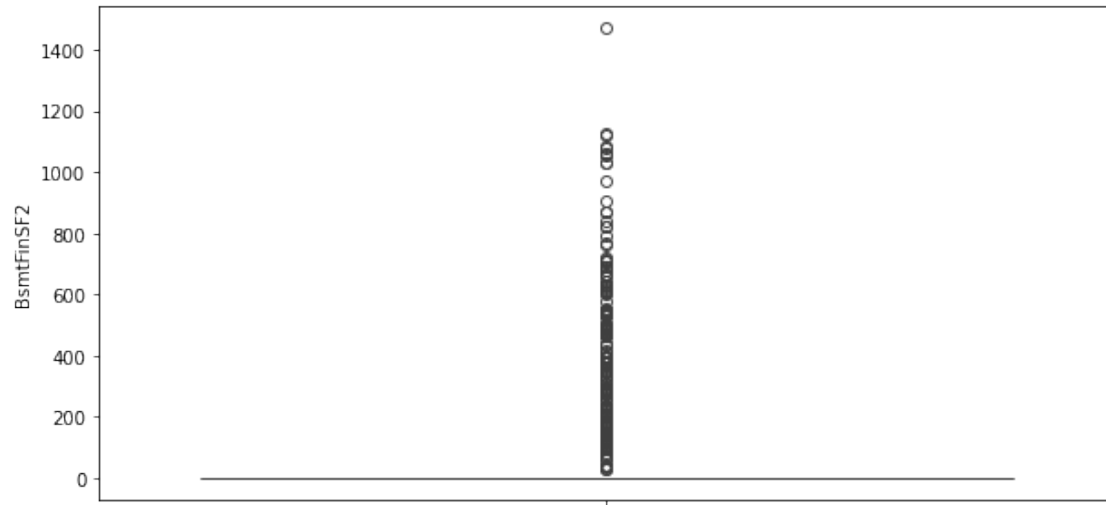
MasVnrArea



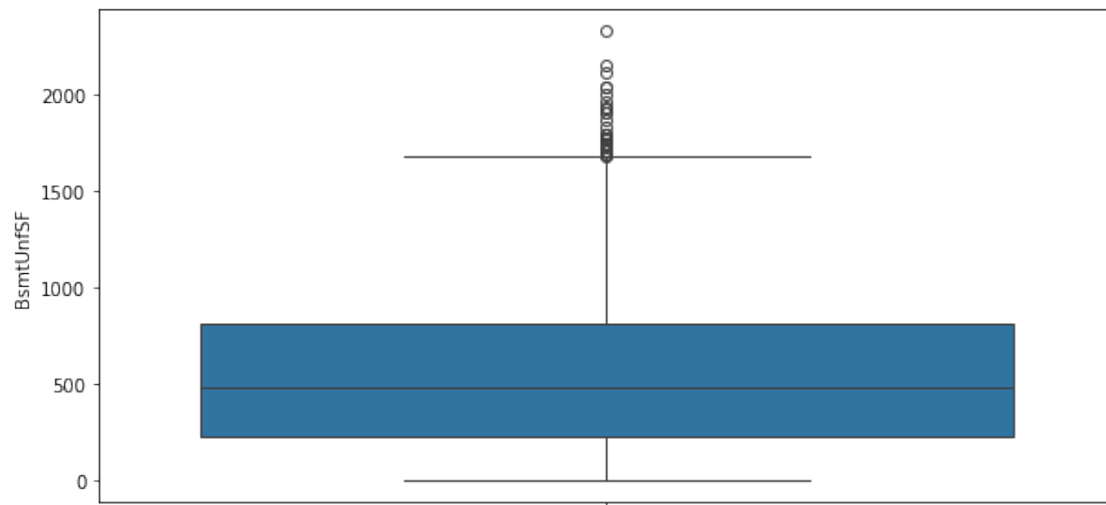
BsmtFinSF1



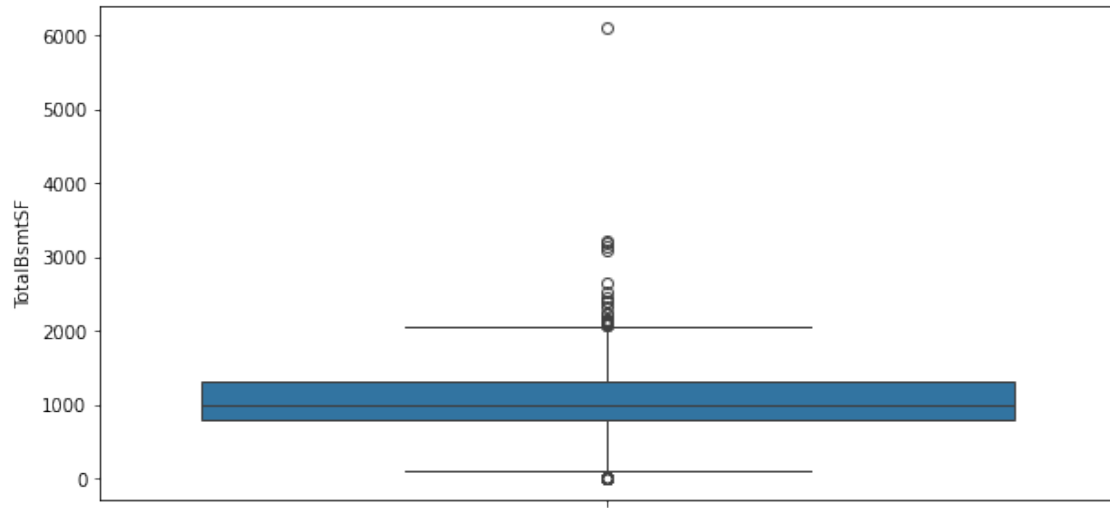
BsmtFinSF2



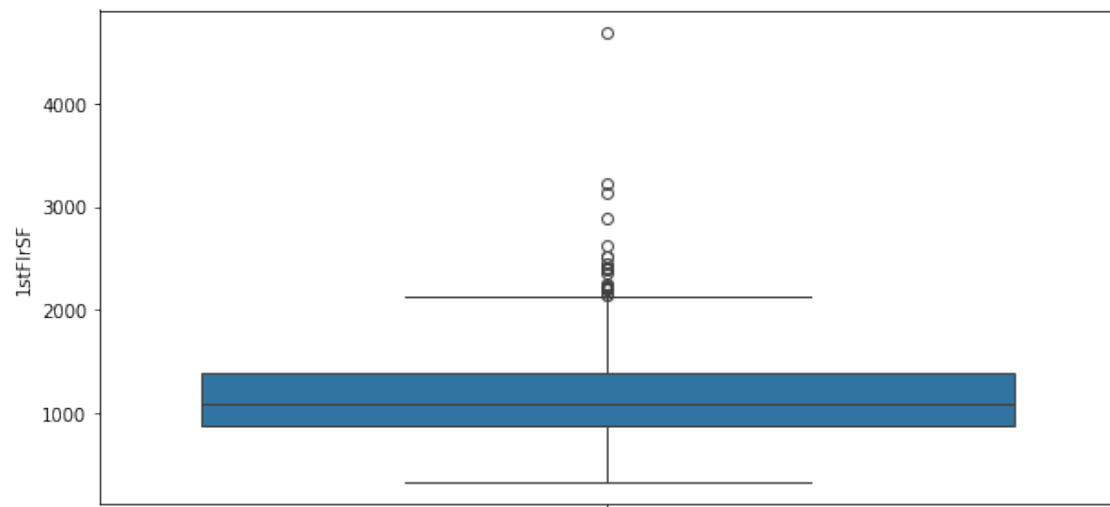
BsmtUnfSF



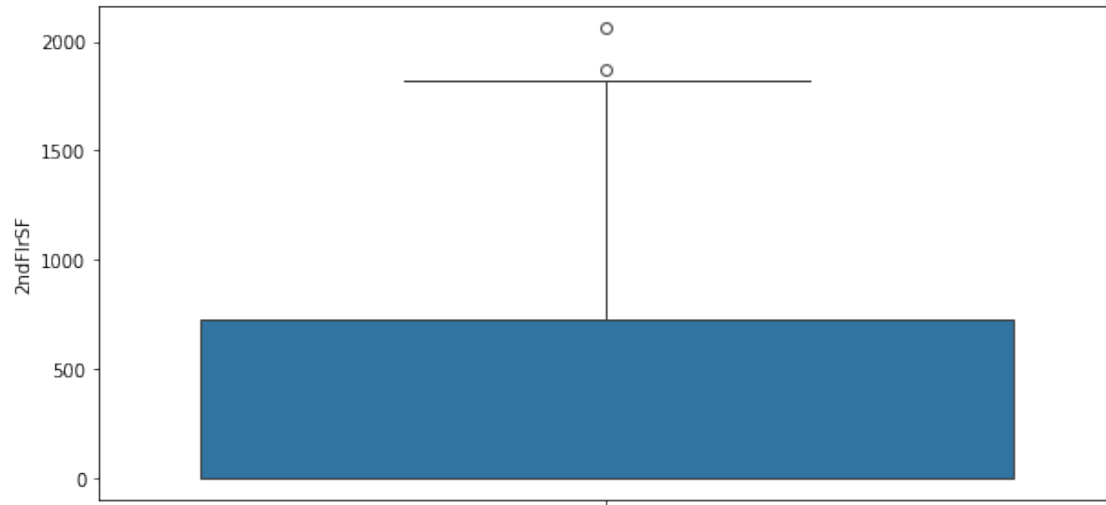
TotalBsmtSF



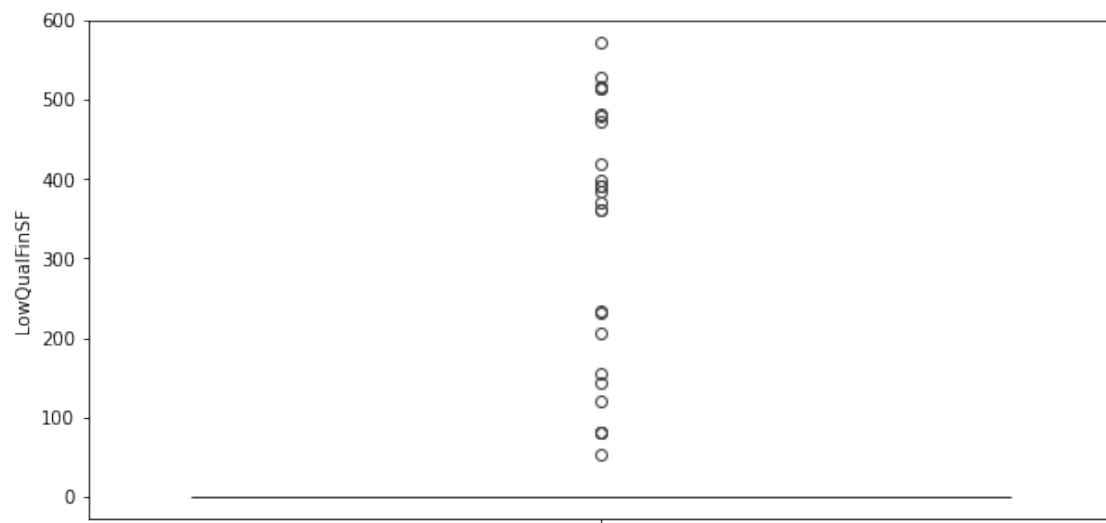
1stFlrSF



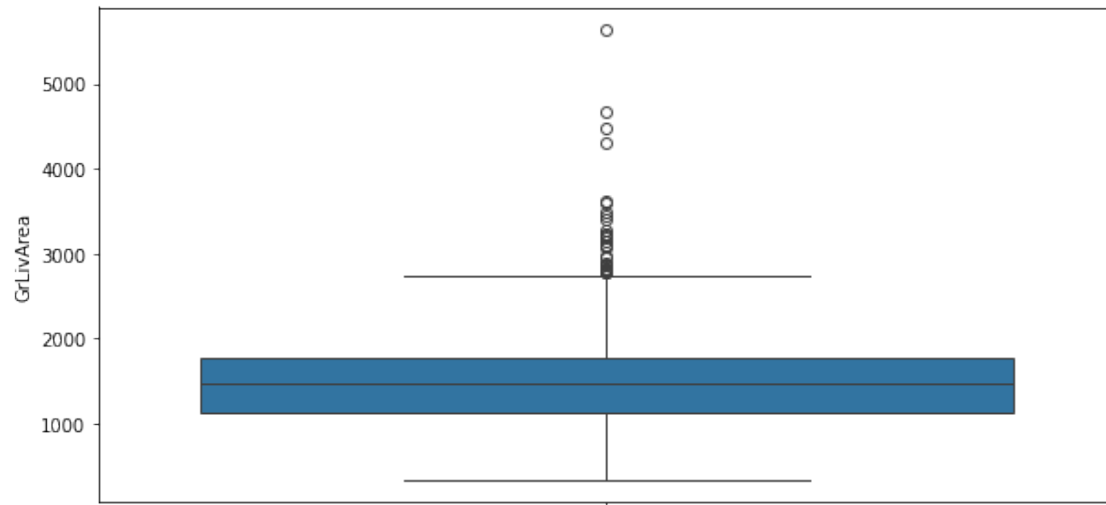
2ndFlrSF



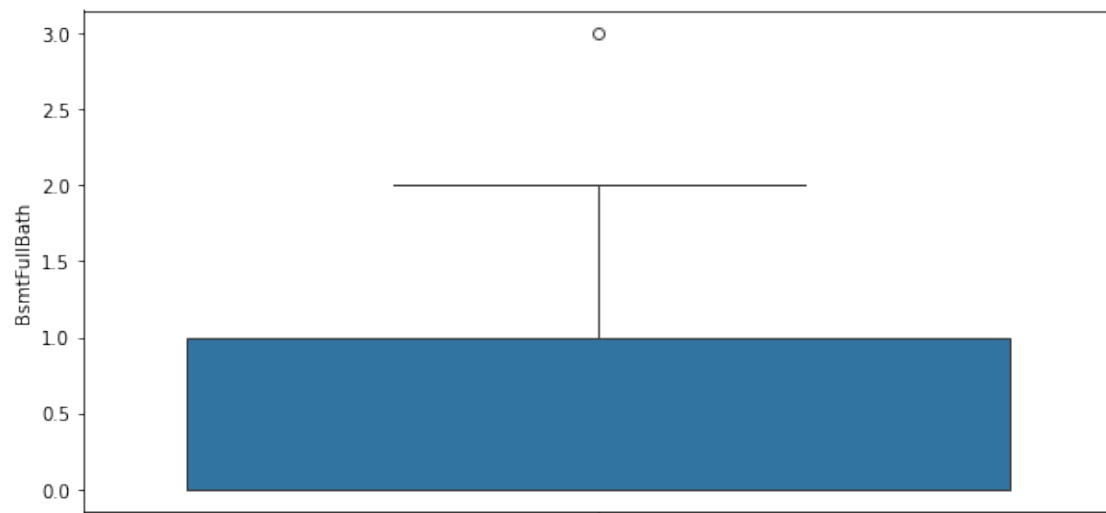
LowQualFinSF



GrLivArea



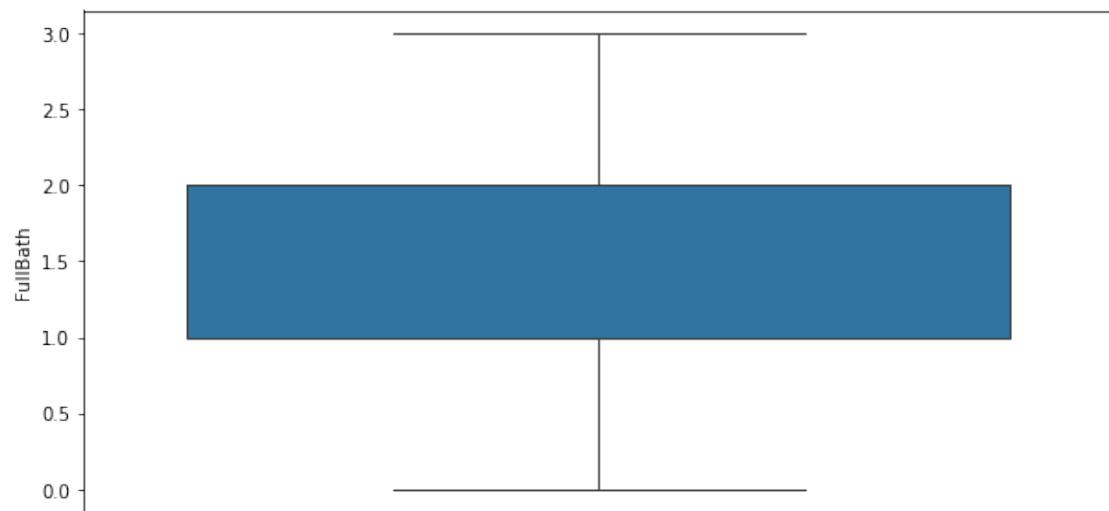
BsmtFullBath



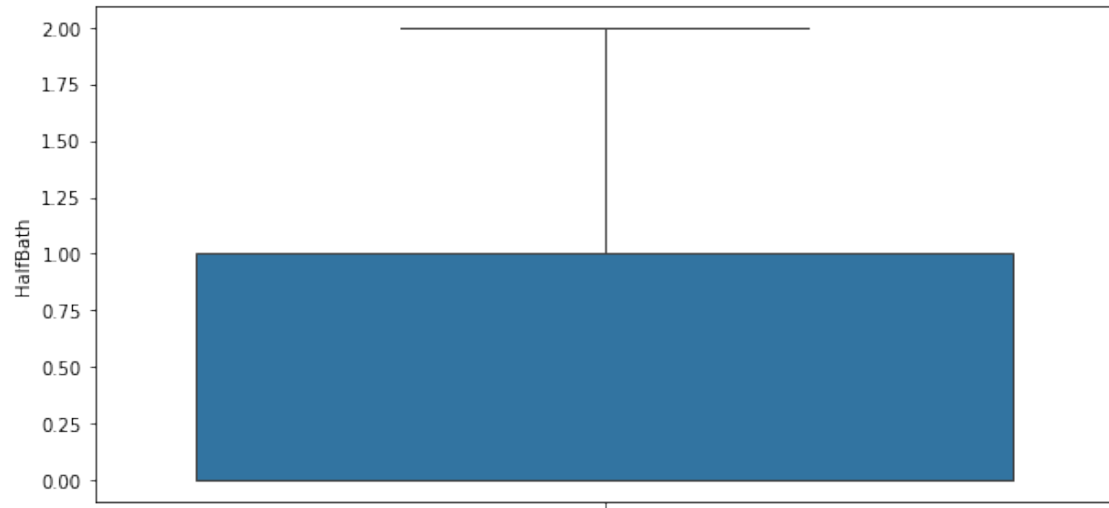
BsmtHalfBath



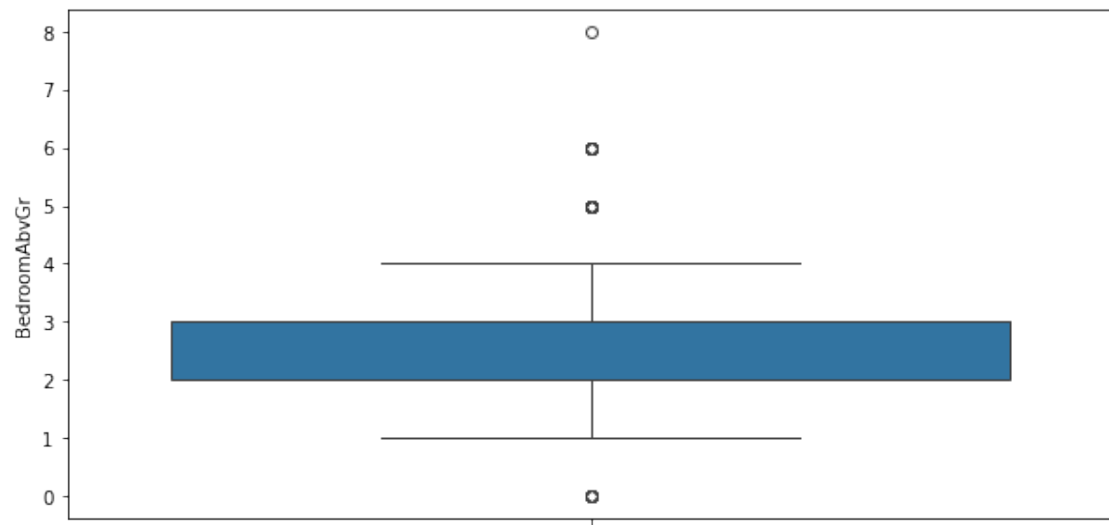
FullBath



HalfBath



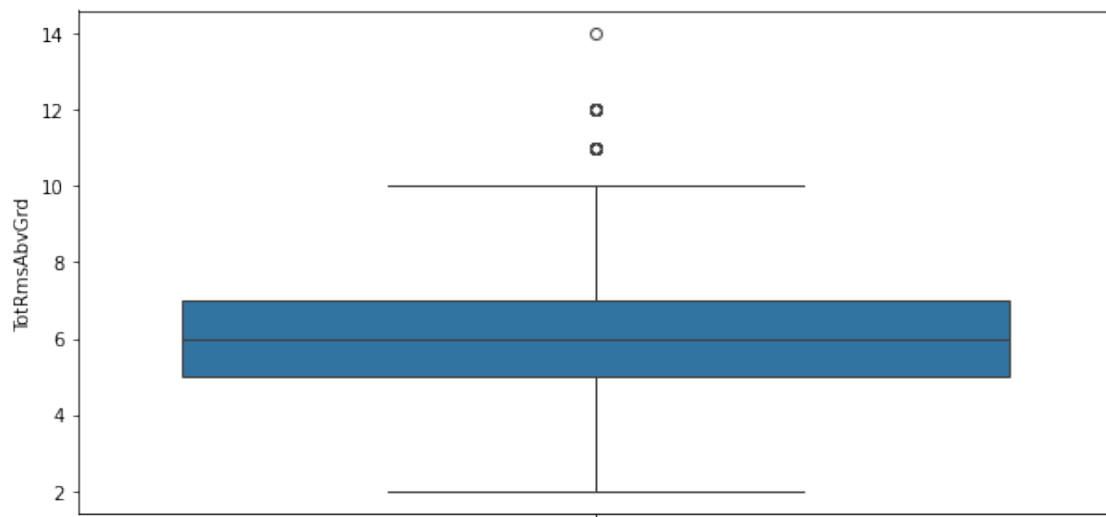
BedroomAbvGr



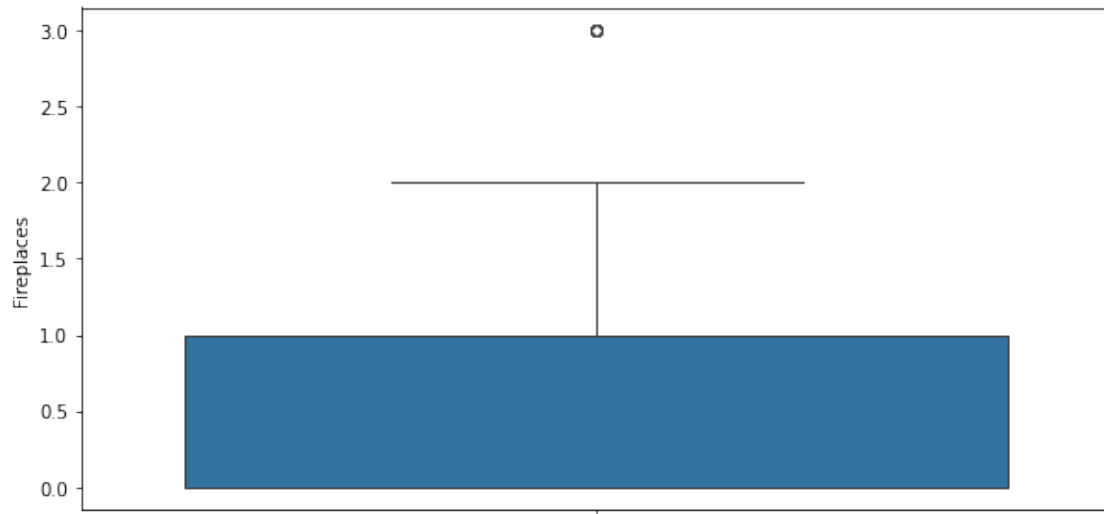
KitchenAbvGr



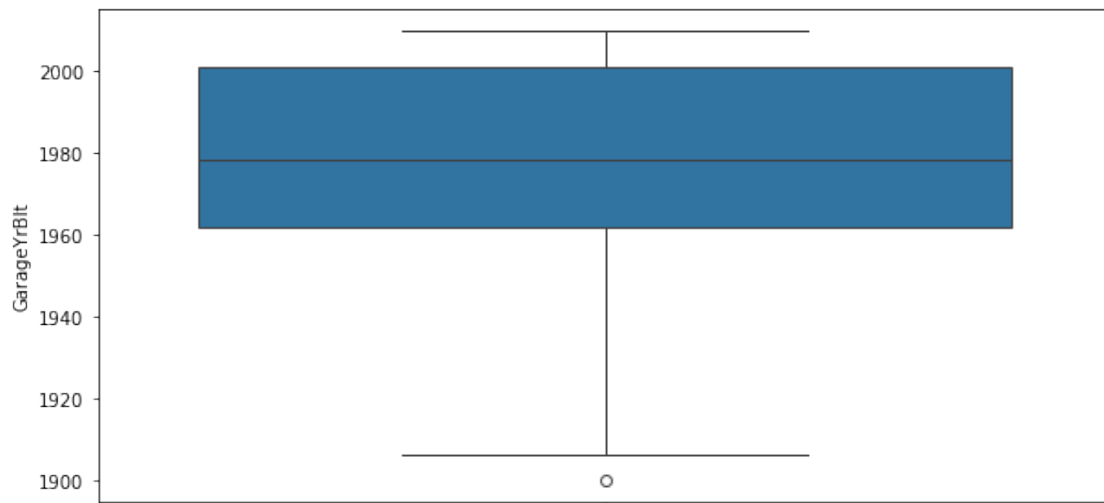
TotRmsAbvGrd



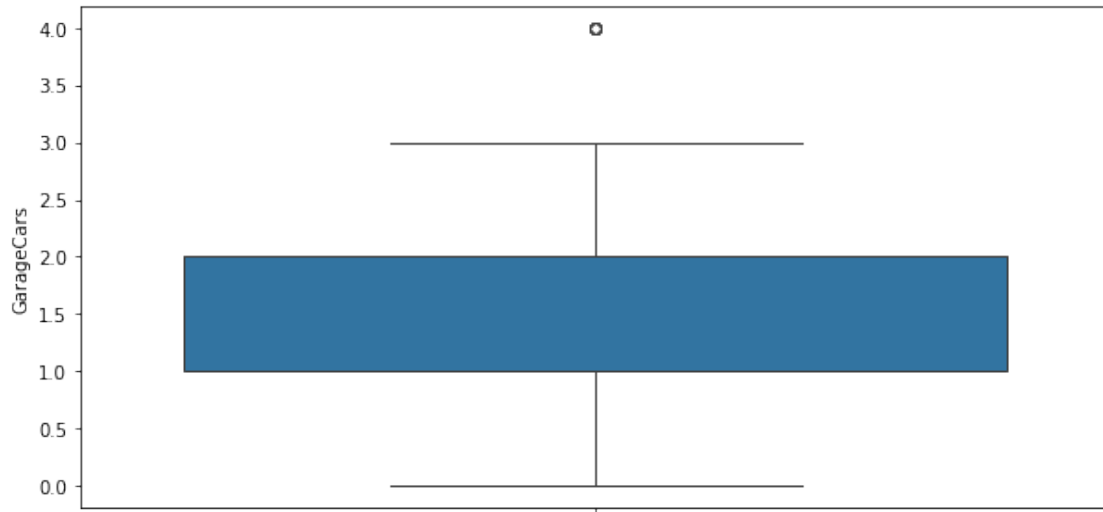
Fireplaces



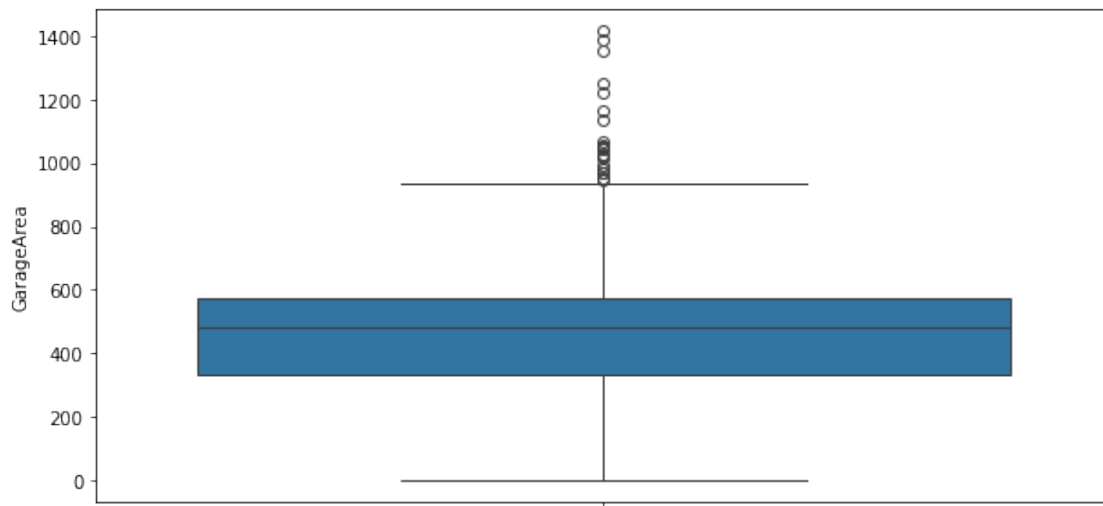
GarageYrBlt



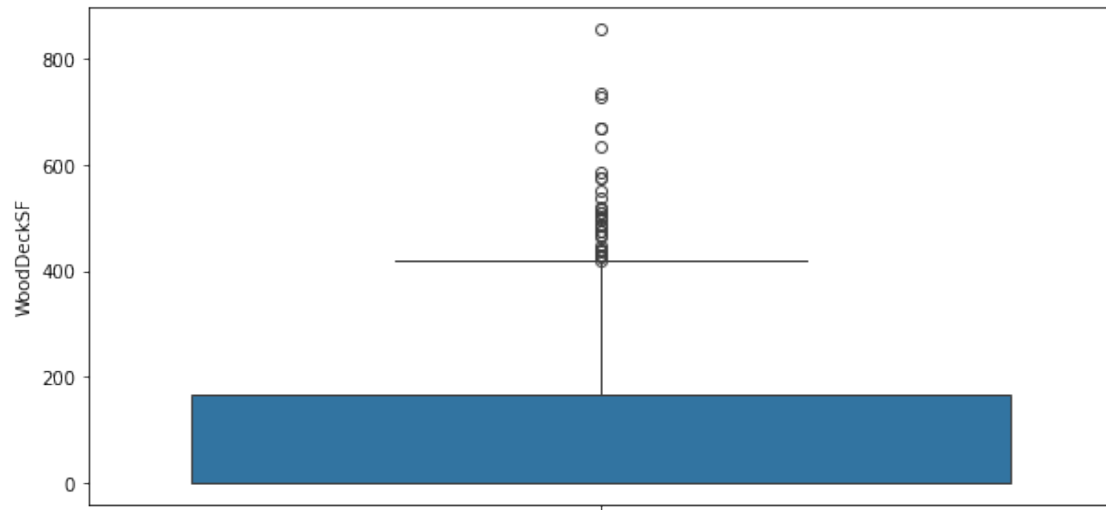
GarageCars



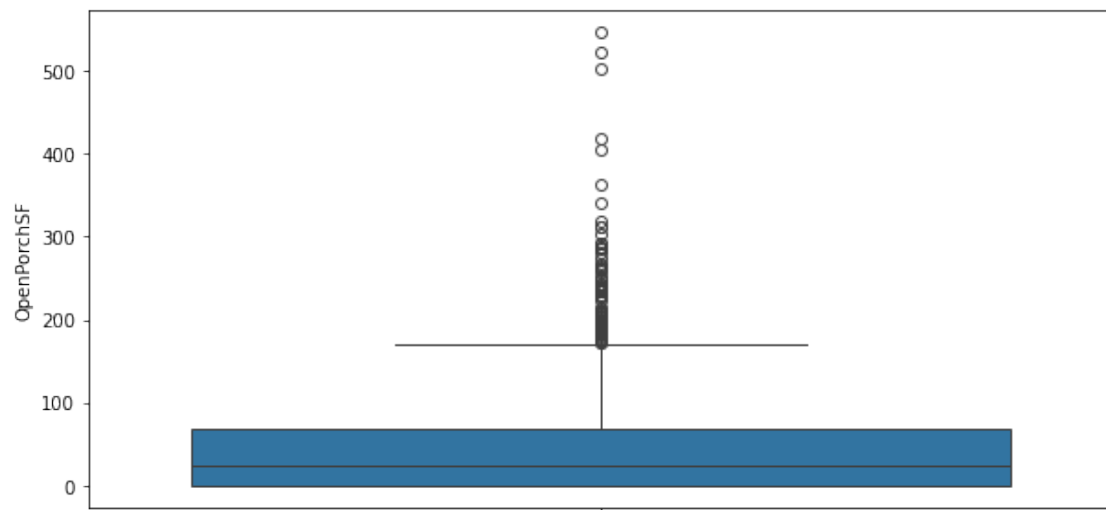
GarageArea



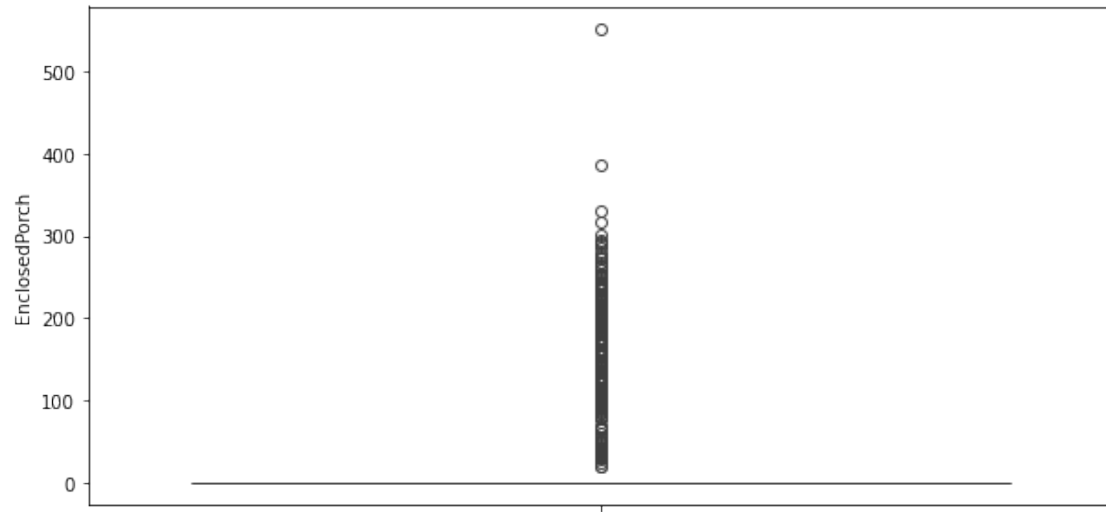
WoodDeckSF



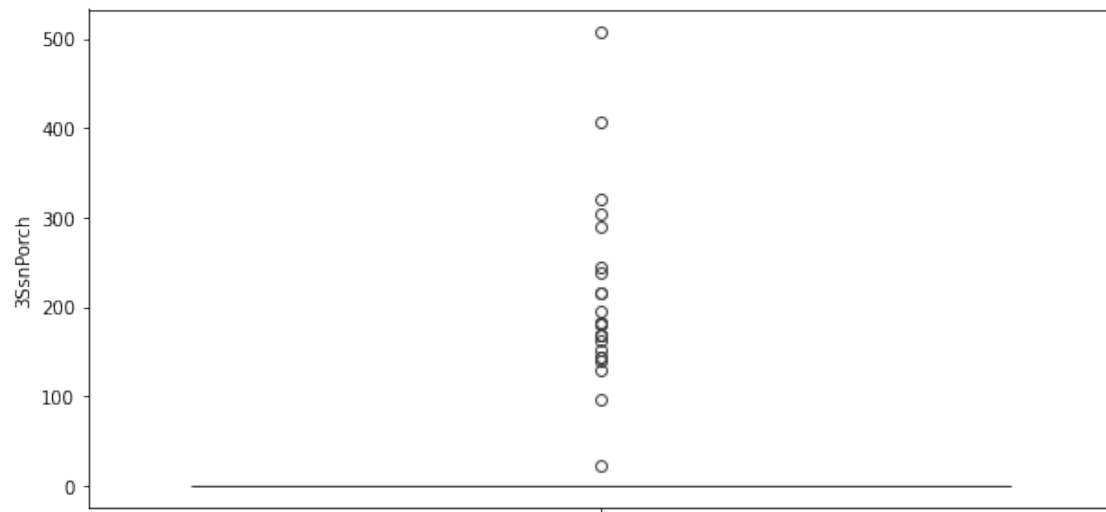
OpenPorchSF



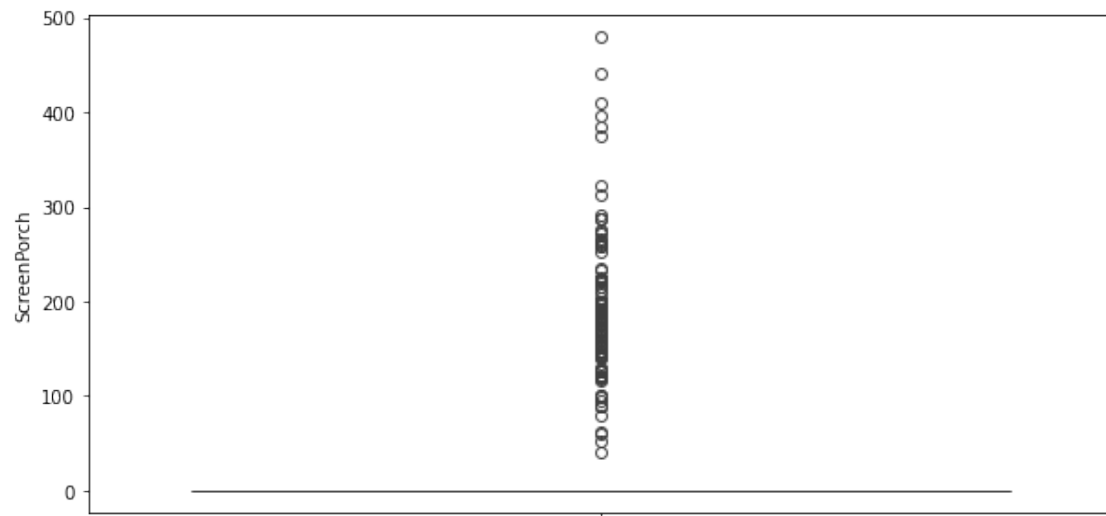
EnclosedPorch



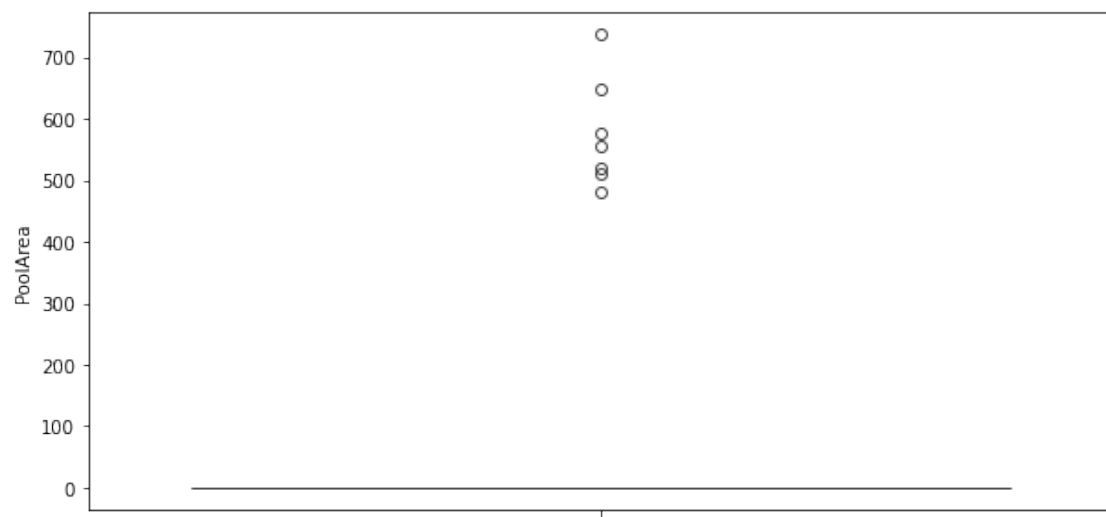
3SsnPorch



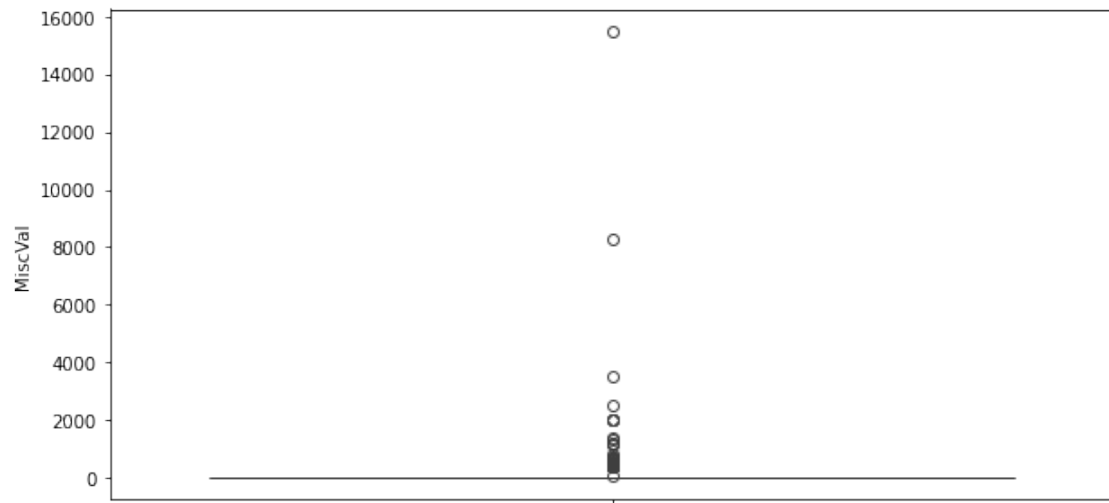
ScreenPorch



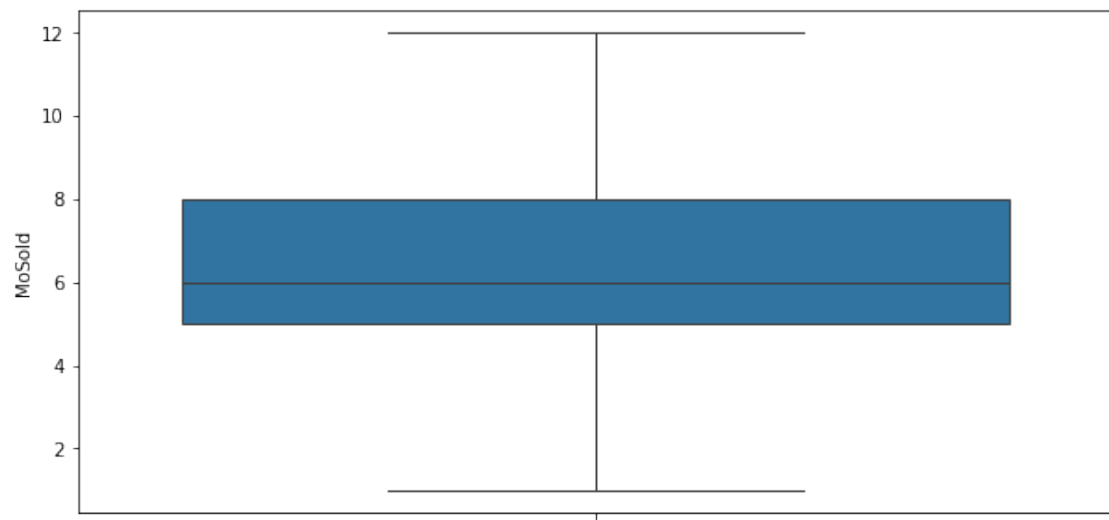
PoolArea



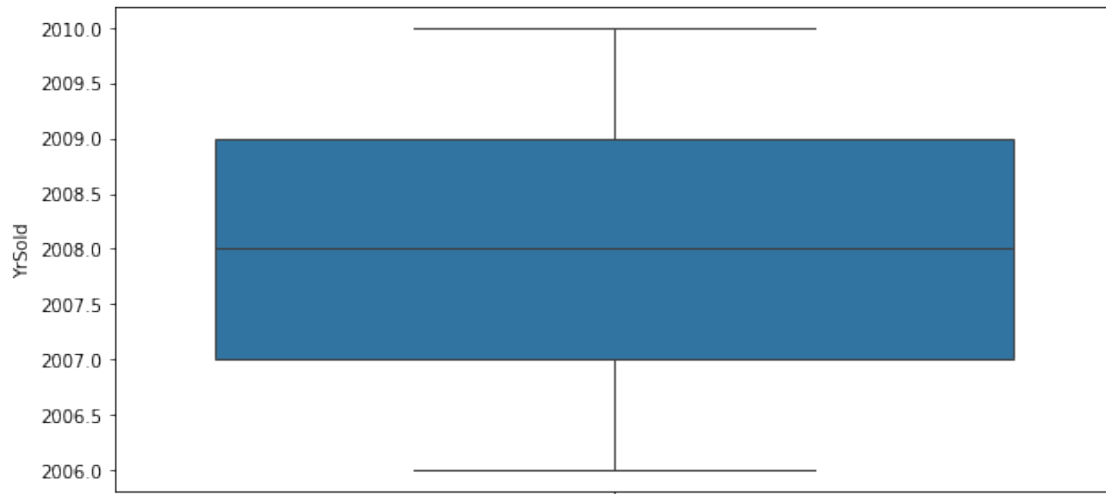
MiscVal



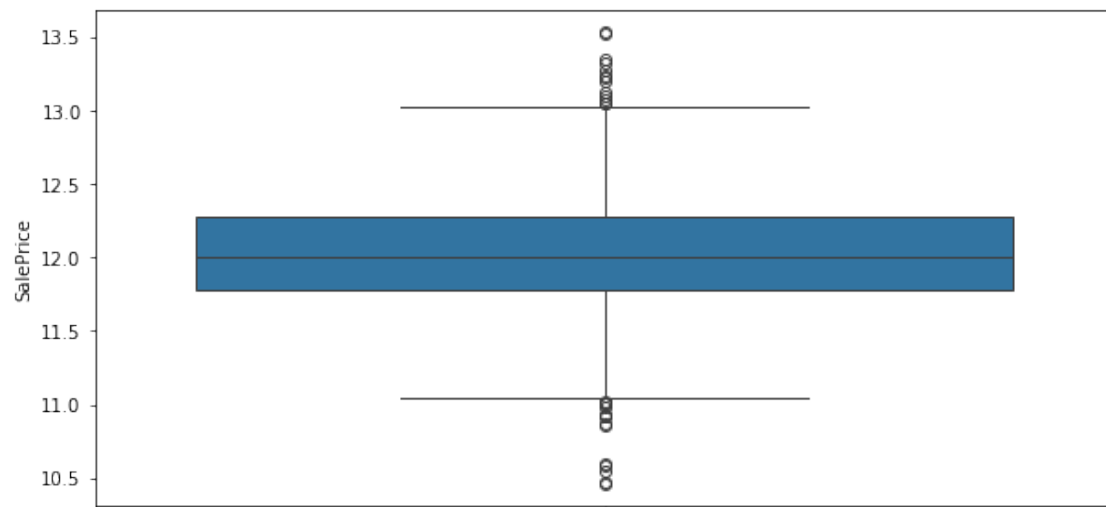
MoSold



YrSold



SalePrice



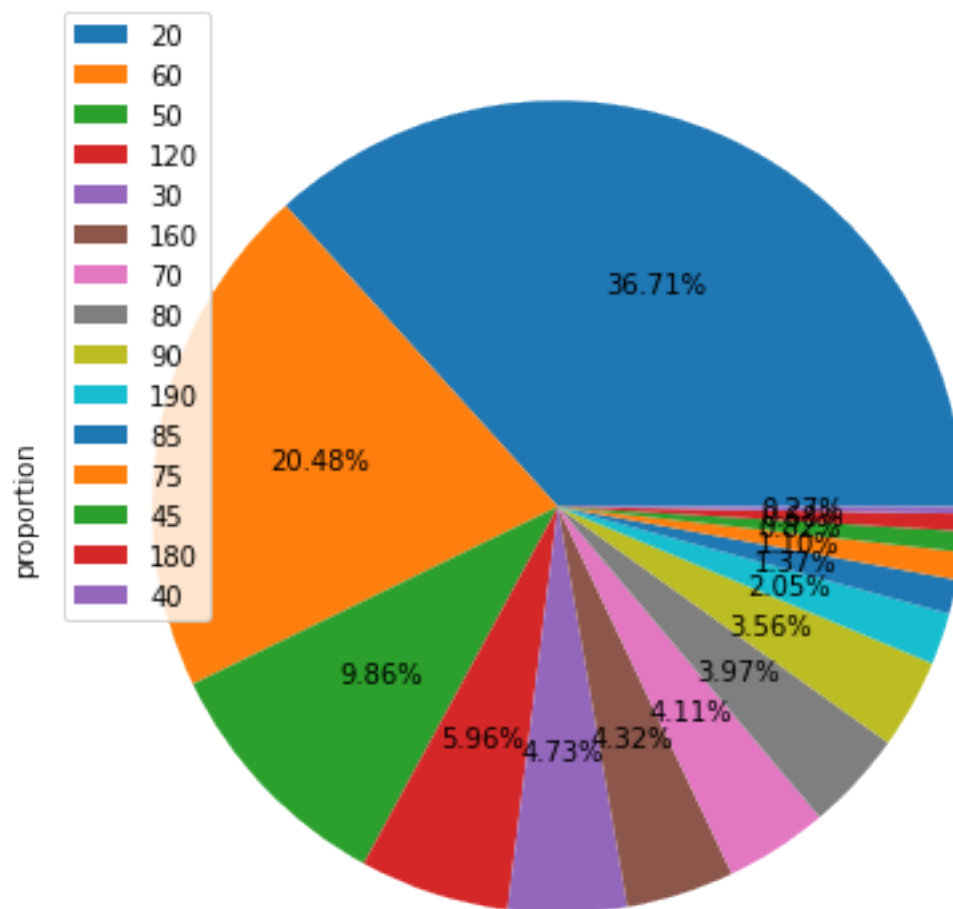
[]:

```
[28]: for col in cat_cols:
        print(housing[col].value_counts(normalize=True))
        plt.figure(figsize=(7,7))
        housing[col].value_counts(normalize=True).plot.pie(labeldistance=None,
        ↪ autopct='%1.2f%%')
        plt.legend()
        plt.show()
```

MSSubClass

20	0.367123
60	0.204795
50	0.098630
120	0.059589
30	0.047260
160	0.043151
70	0.041096
80	0.039726
90	0.035616
190	0.020548
85	0.013699
75	0.010959
45	0.008219
180	0.006849
40	0.002740

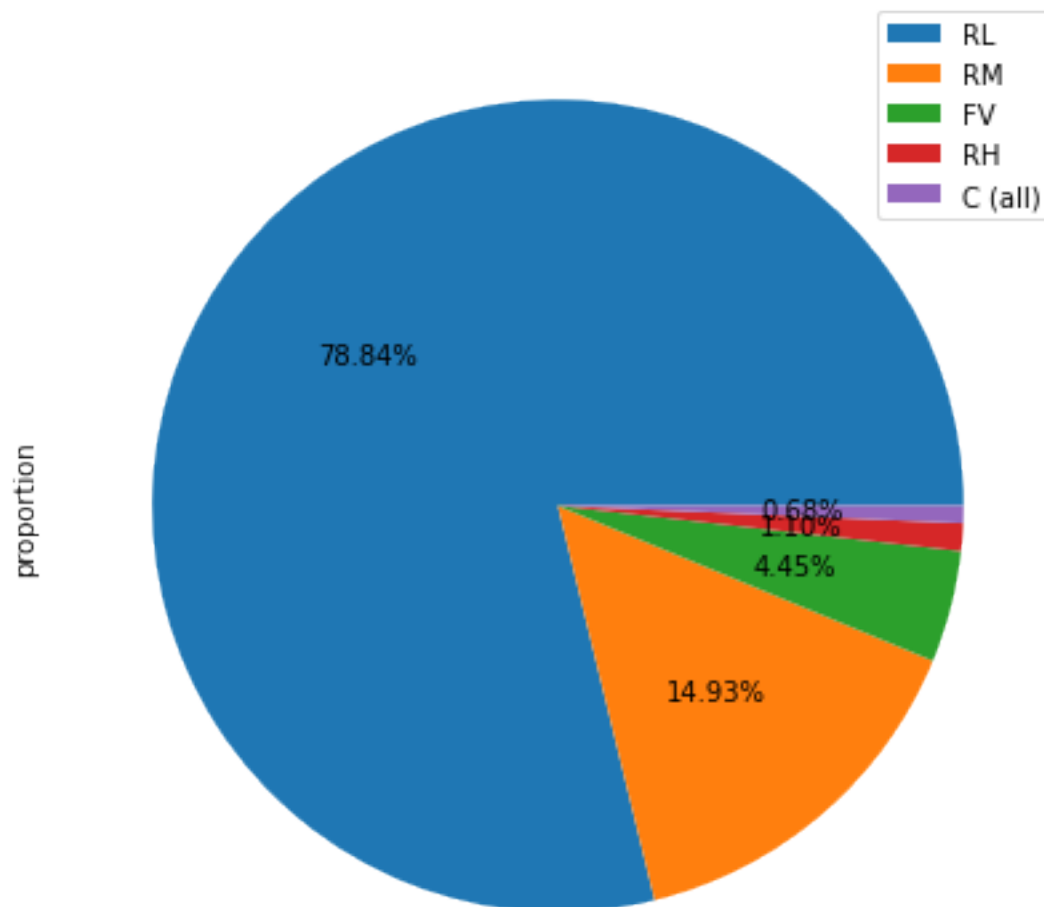
Name: proportion, dtype: float64



```

MSZoning
RL      0.788356
RM      0.149315
FV      0.044521
RH      0.010959
C (all) 0.006849
Name: proportion, dtype: float64

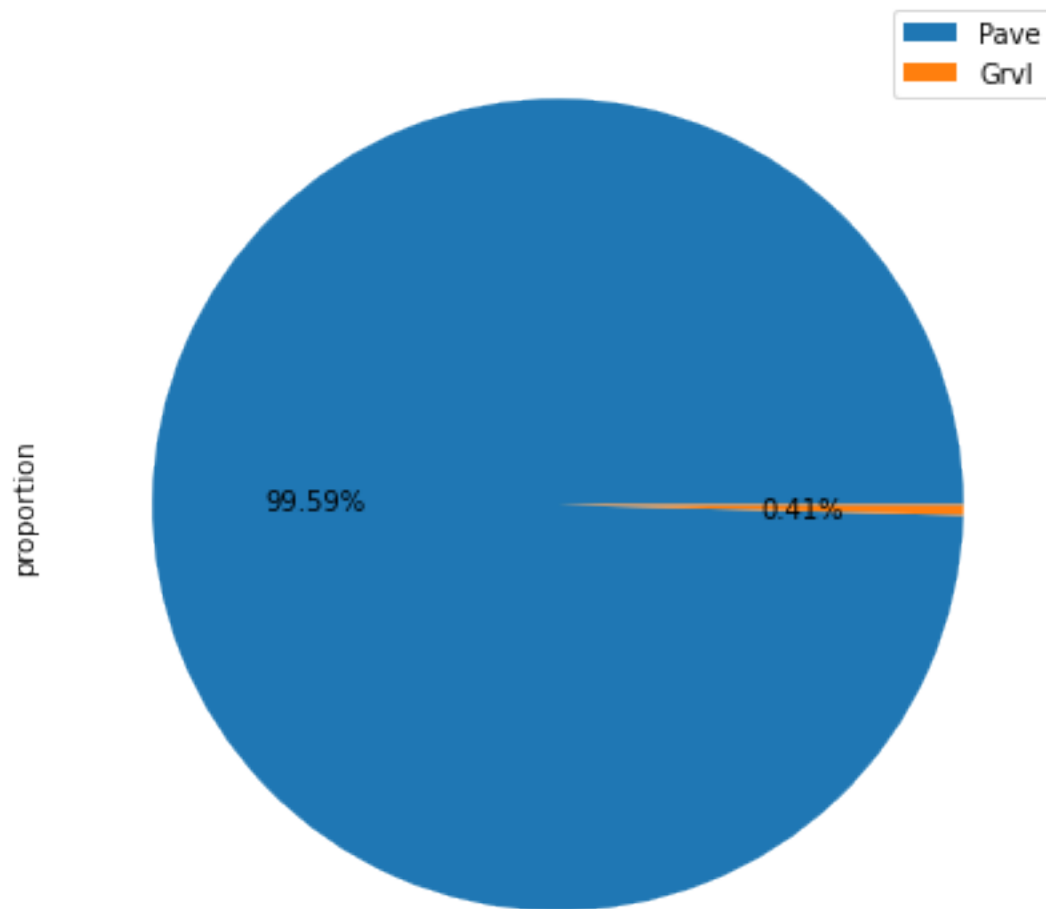
```



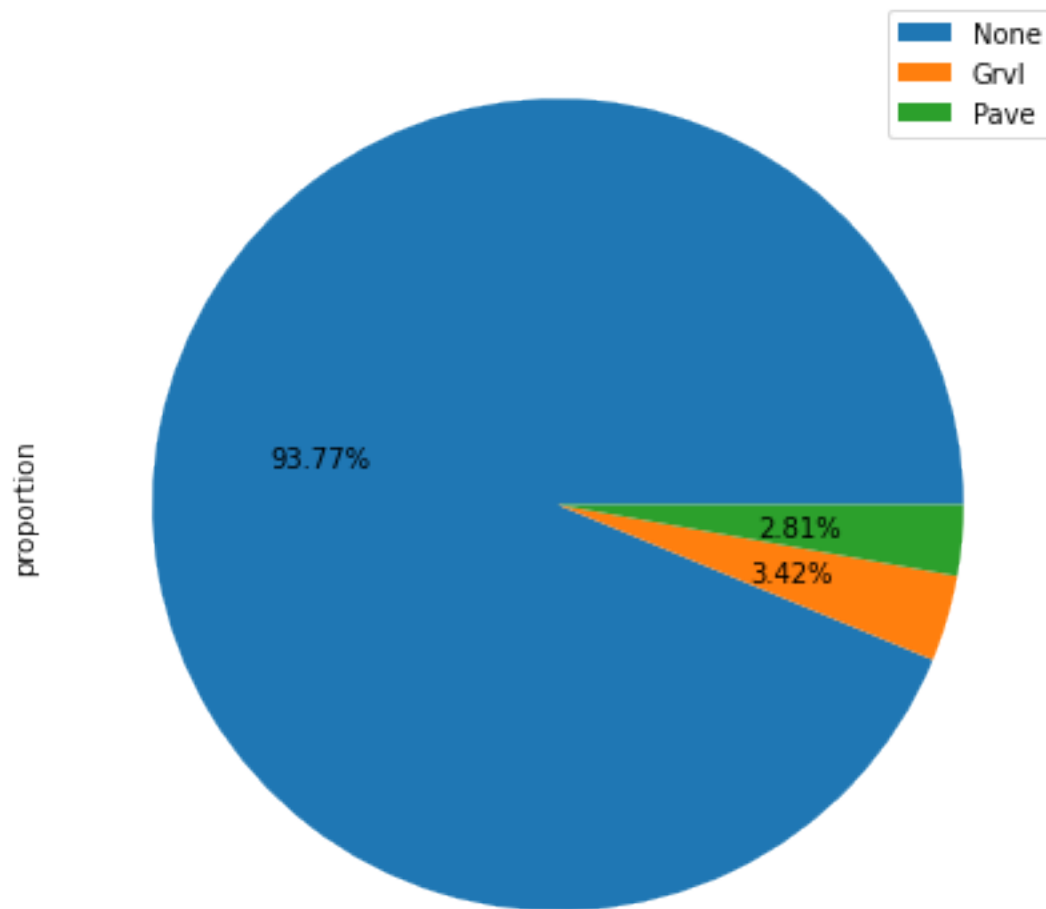
```

Street
Pave    0.99589
Grvl    0.00411
Name: proportion, dtype: float64

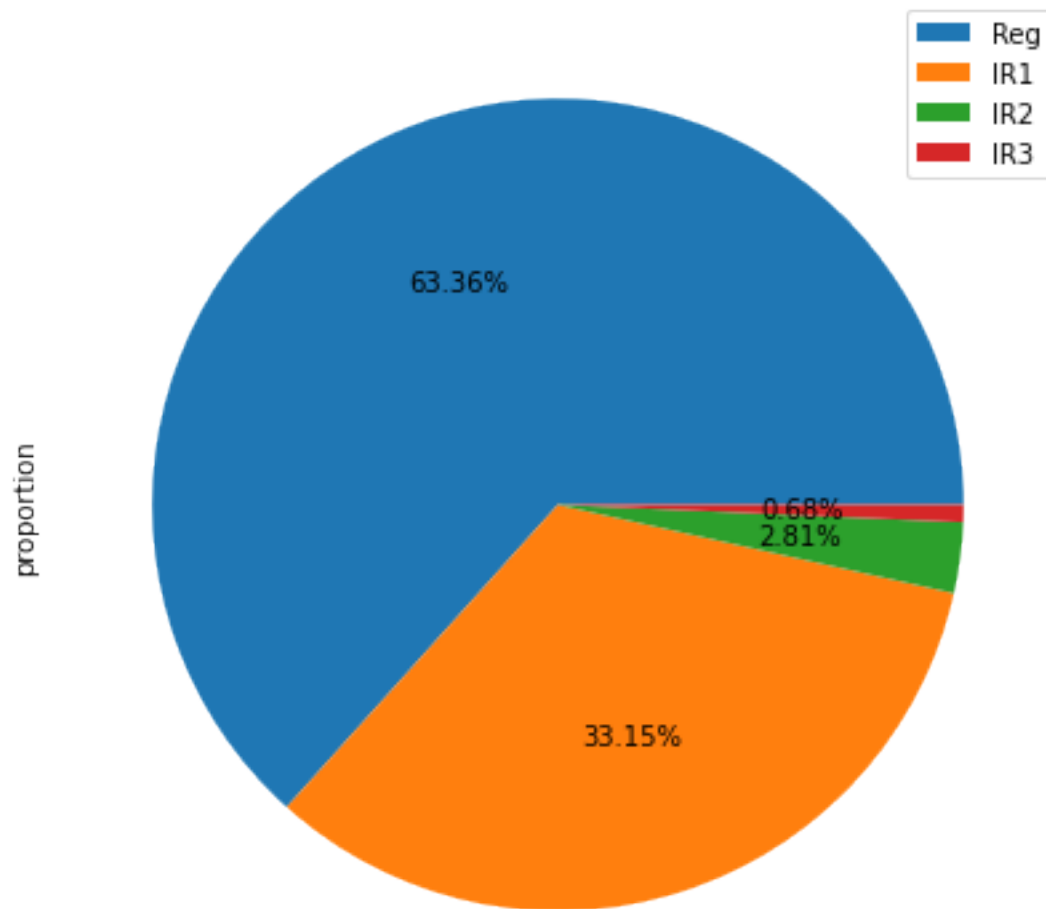
```



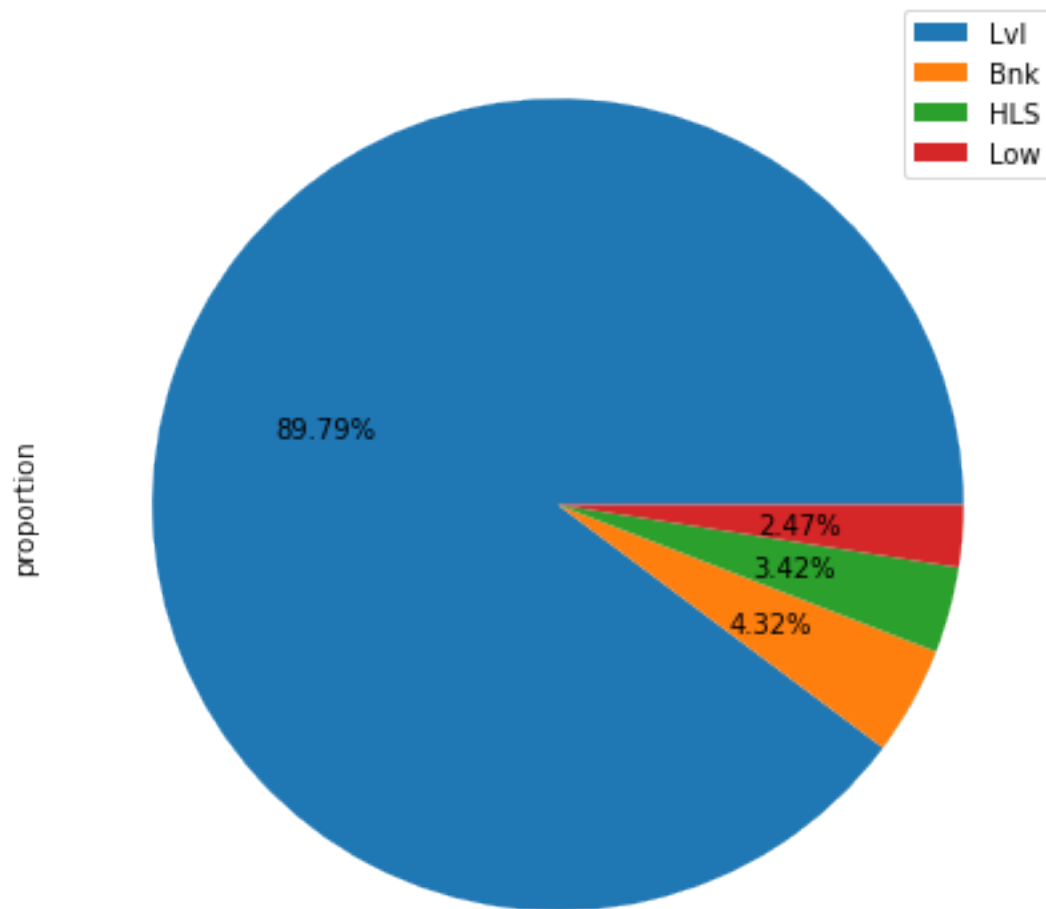
```
Alley
None    0.937671
Grvl     0.034247
Pave     0.028082
Name: proportion, dtype: float64
```



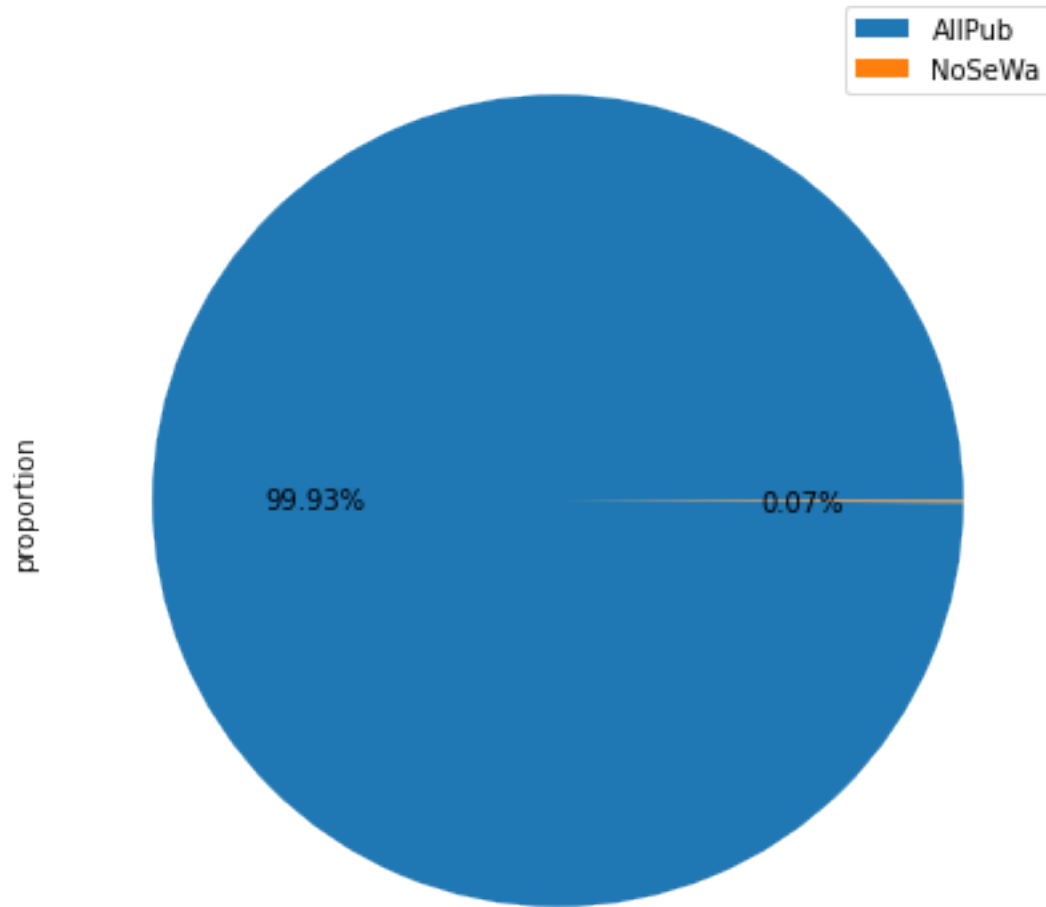
```
LotShape
Reg      0.633562
IR1      0.331507
IR2      0.028082
IR3      0.006849
Name: proportion, dtype: float64
```



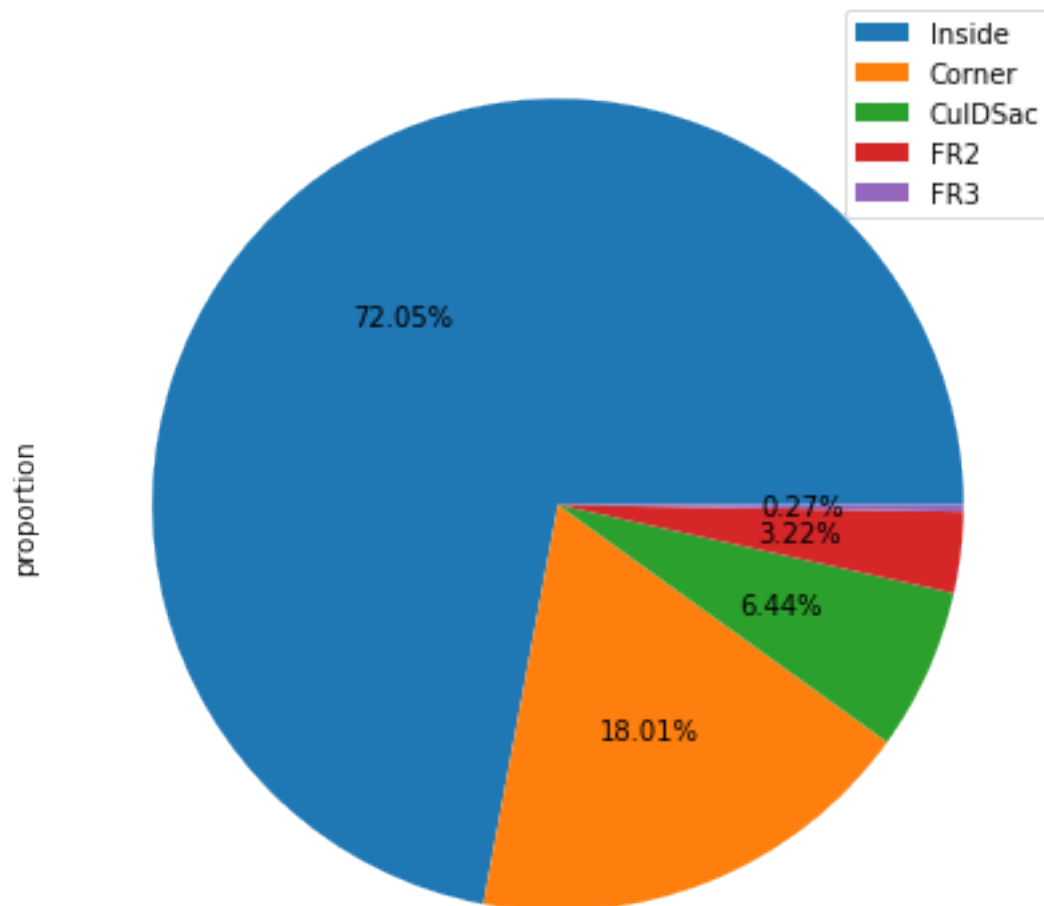
```
LandContour
Lvl      0.897945
Bnk      0.043151
HLS      0.034247
Low      0.024658
Name: proportion, dtype: float64
```



```
Utilities
AllPub    0.999315
NoSeWa    0.000685
Name: proportion, dtype: float64
```



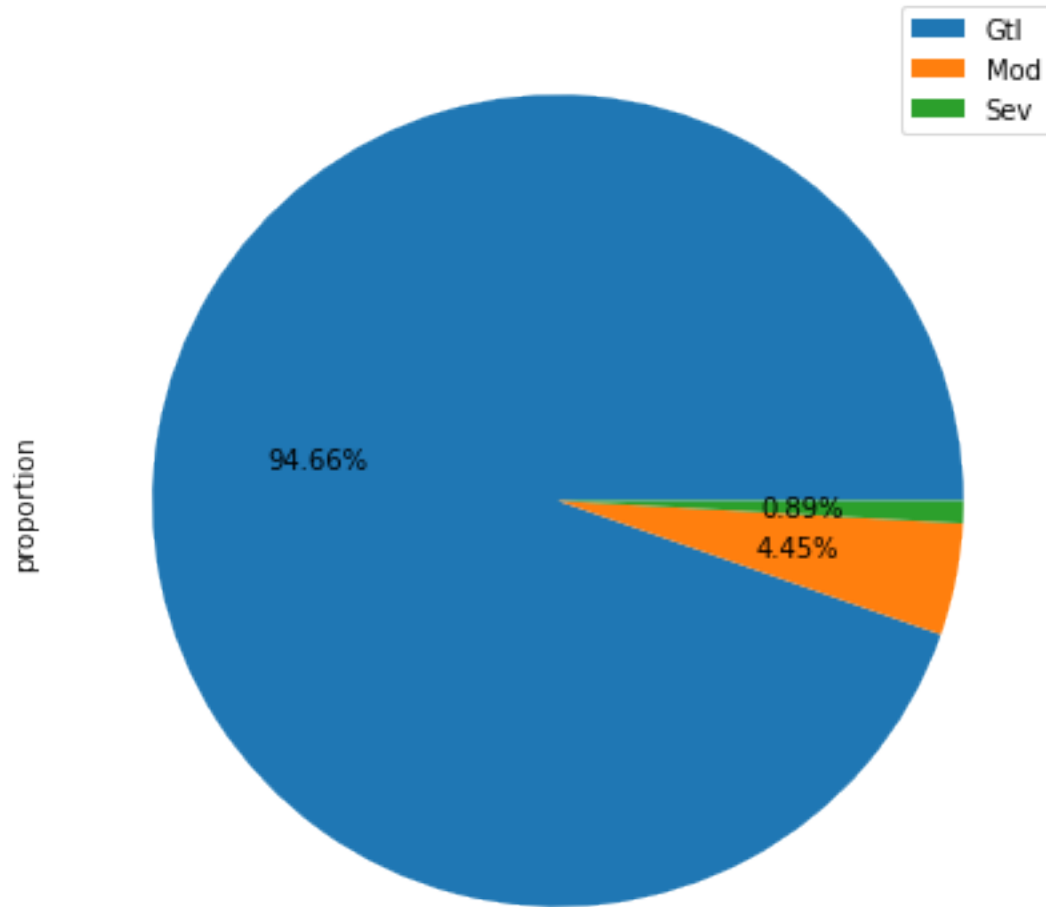
```
LotConfig
Inside    0.720548
Corner    0.180137
CulDSac   0.064384
FR2       0.032192
FR3       0.002740
Name: proportion, dtype: float64
```

```

LandSlope
Gtl    0.946575
Mod    0.044521
Sev    0.008904
Name: proportion, dtype: float64

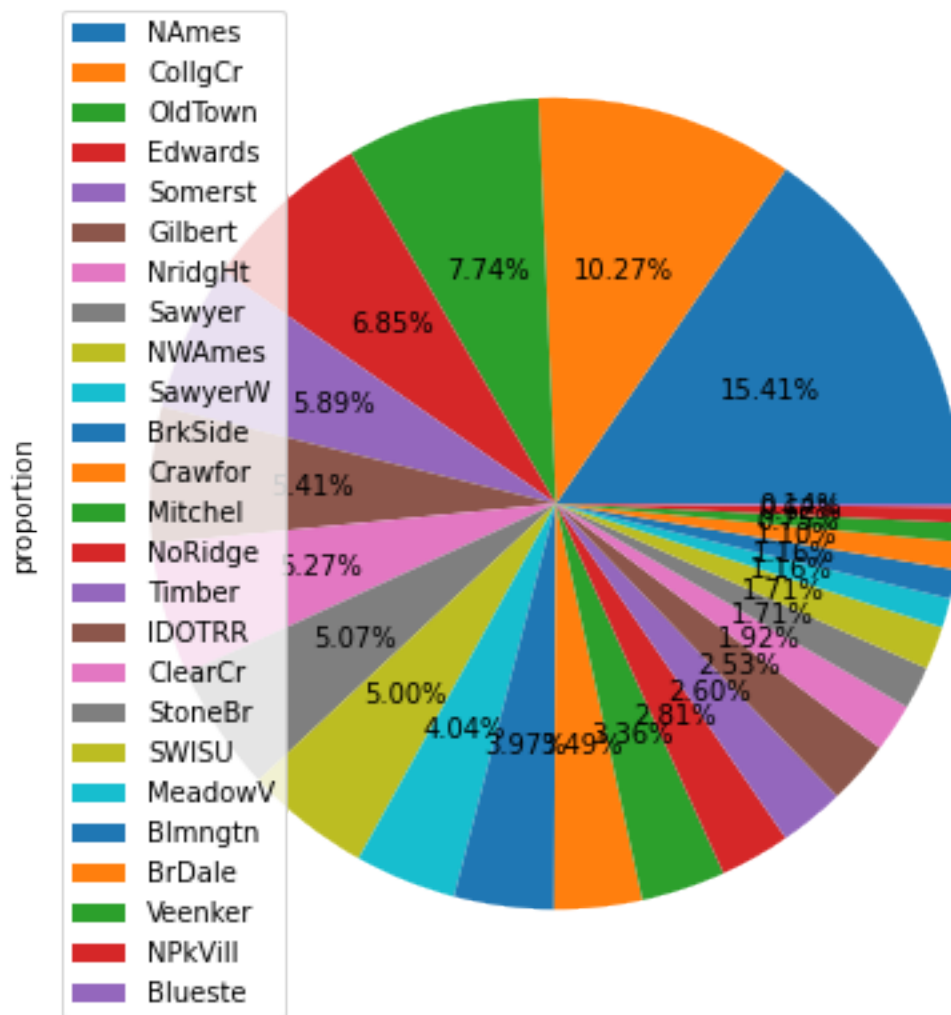
```



Neighborhood	
NAmes	0.154110
CollgCr	0.102740
OldTown	0.077397
Edwards	0.068493
Somerst	0.058904
Gilbert	0.054110
NridgHt	0.052740
Sawyer	0.050685
NWAmes	0.050000
SawyerW	0.040411
BrkSide	0.039726
Crawfor	0.034932
Mitchel	0.033562
NoRidge	0.028082

Timber	0.026027
IDOTRR	0.025342
ClearCr	0.019178
StoneBr	0.017123
SWISU	0.017123
MeadowV	0.011644
Blmngtn	0.011644
BrDale	0.010959
Veenker	0.007534
NPkVill	0.006164
Blueste	0.001370

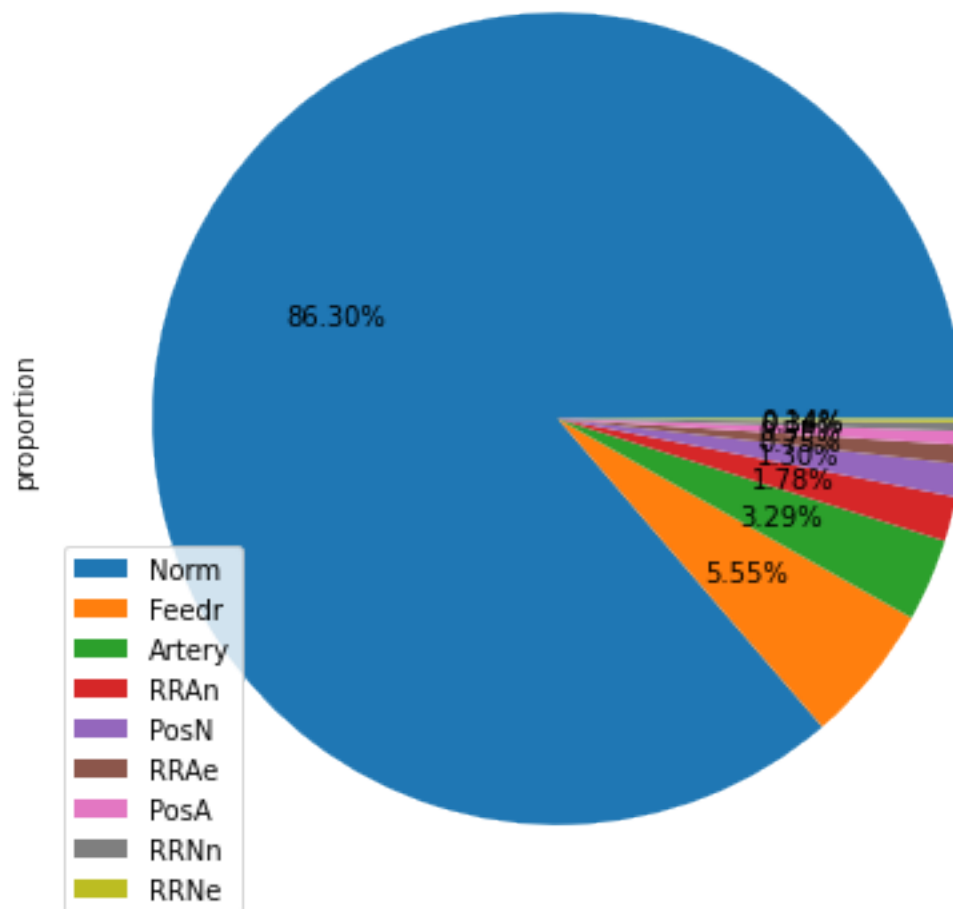
Name: proportion, dtype: float64



Condition1
Norm 0.863014

Feedr	0.055479
Artery	0.032877
RRAn	0.017808
PosN	0.013014
RR Ae	0.007534
PosA	0.005479
RRNn	0.003425
RRNe	0.001370

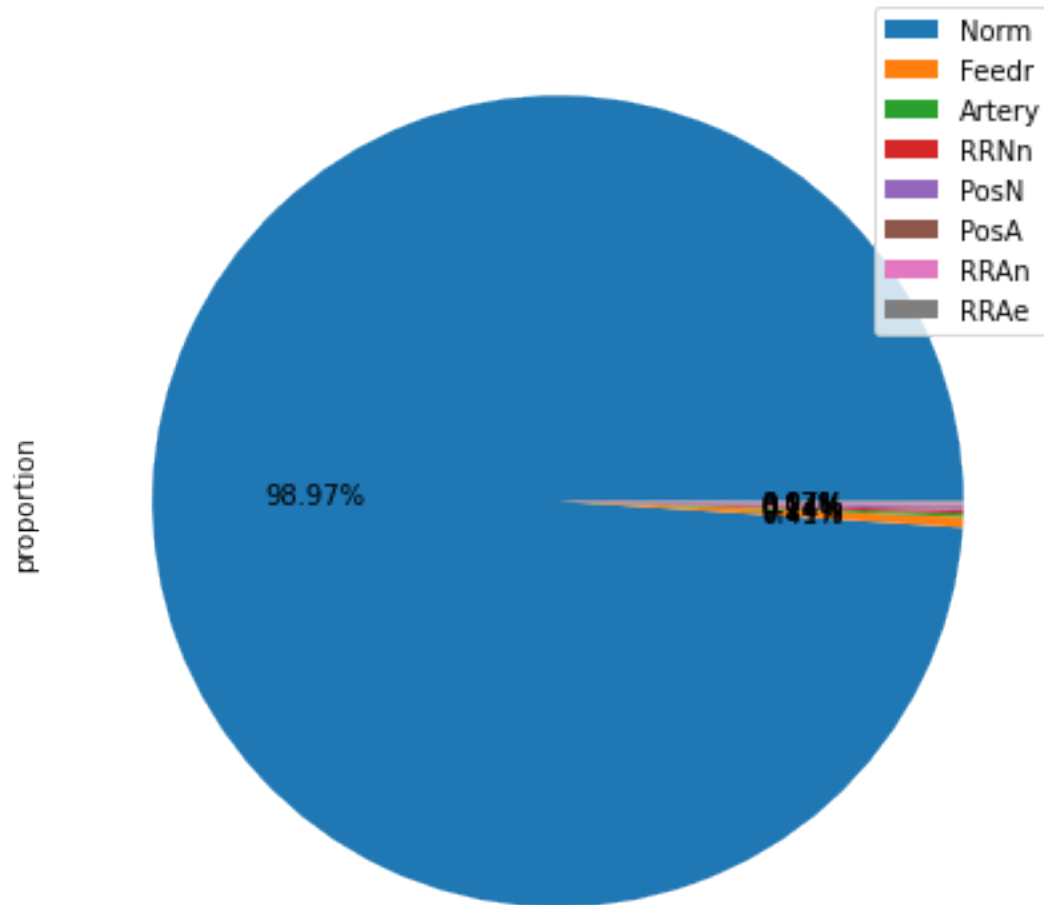
Name: proportion, dtype: float64



Condition2	
Norm	0.989726
Feedr	0.004110
Artery	0.001370
RRNn	0.001370
PosN	0.001370

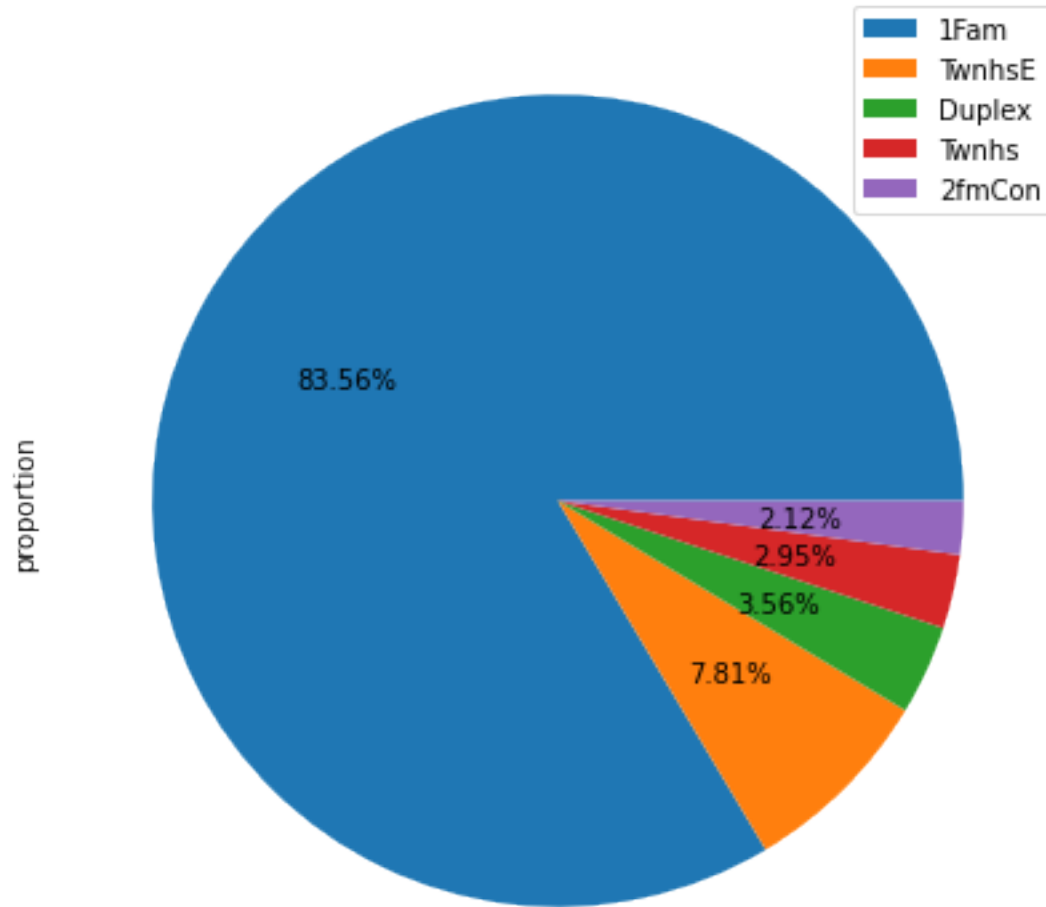
PosA	0.000685
RRAn	0.000685
RR Ae	0.000685

Name: proportion, dtype: float64

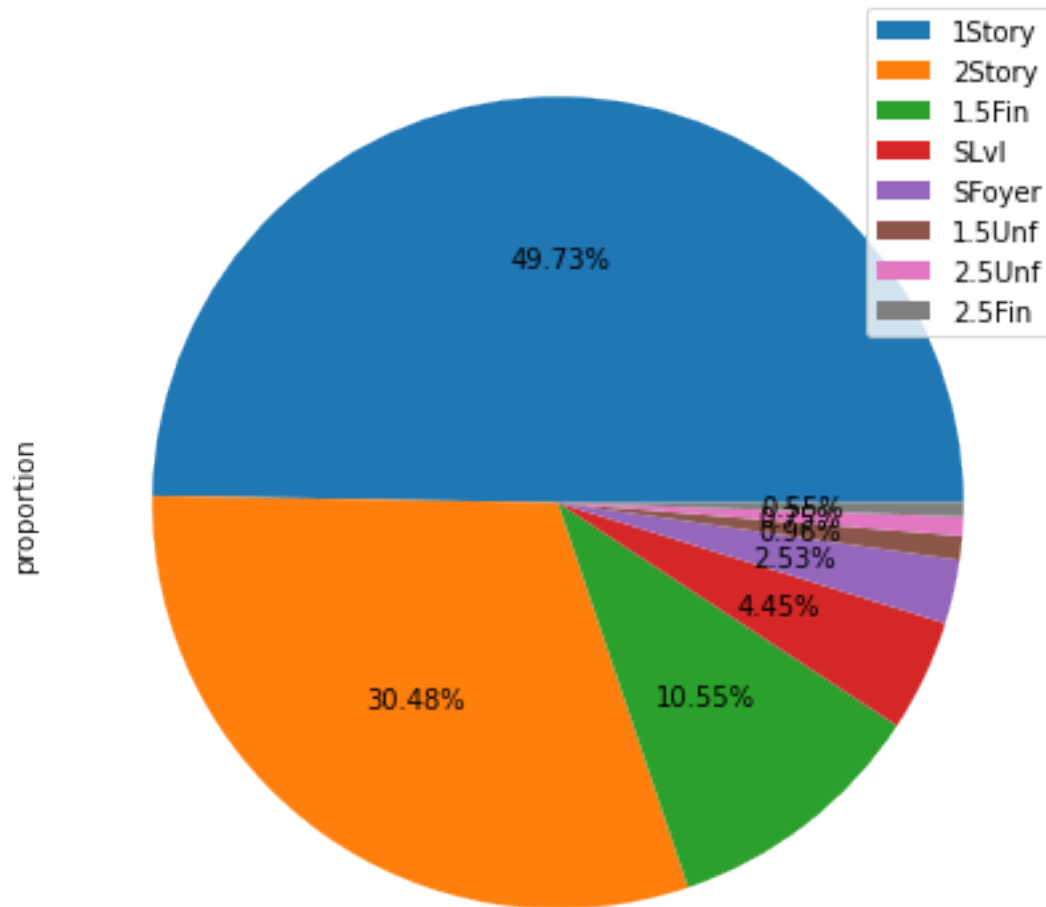


BldgType	
1Fam	0.835616
TwnhsE	0.078082
Duplex	0.035616
Twnhs	0.029452
2fmCon	0.021233

Name: proportion, dtype: float64

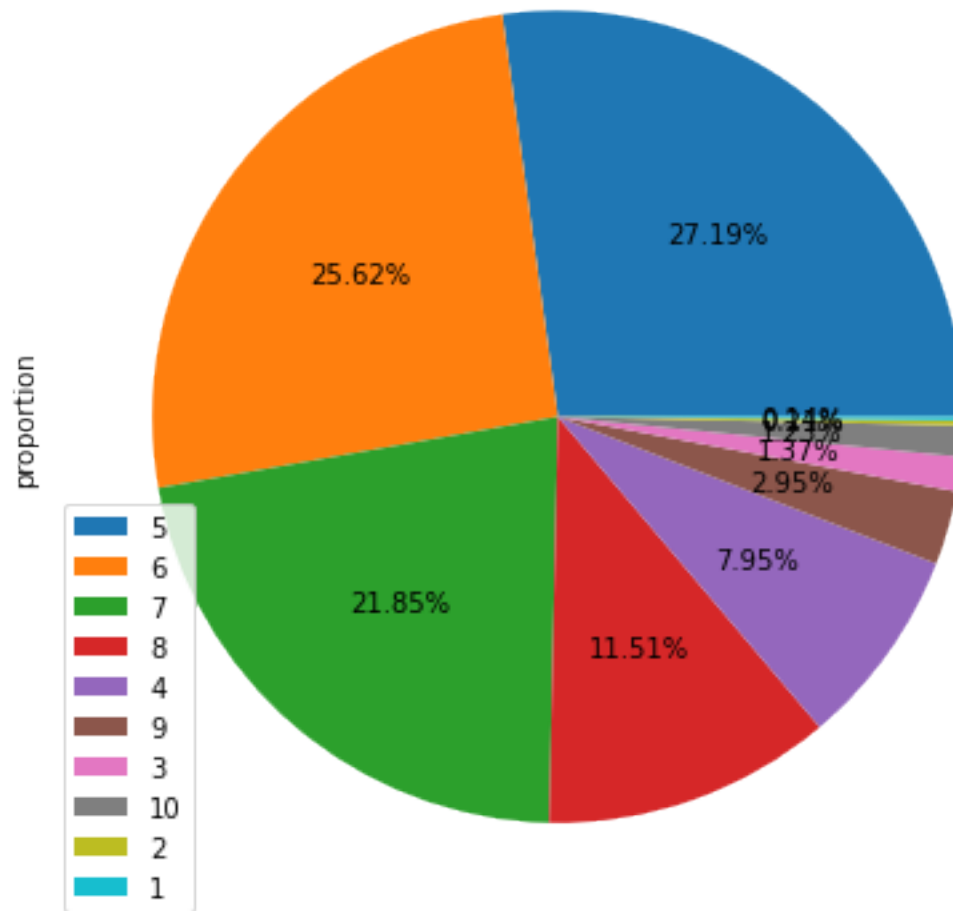


```
HouseStyle
1Story    0.497260
2Story    0.304795
1.5Fin    0.105479
SLvl      0.044521
SFoyer    0.025342
1.5Unf    0.009589
2.5Unf    0.007534
2.5Fin    0.005479
Name: proportion, dtype: float64
```

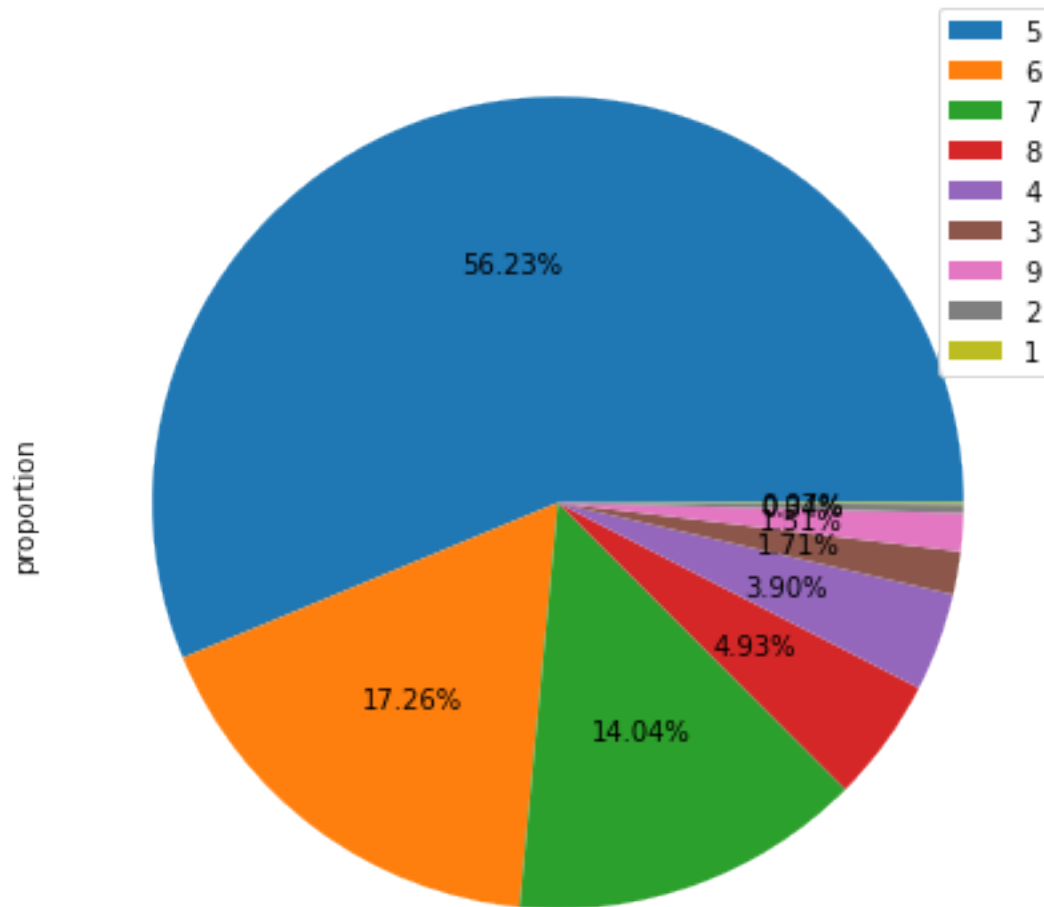


```
OverallQual
5      0.271918
6      0.256164
7      0.218493
8      0.115068
4      0.079452
9      0.029452
3      0.013699
10     0.012329
2      0.002055
1      0.001370
```

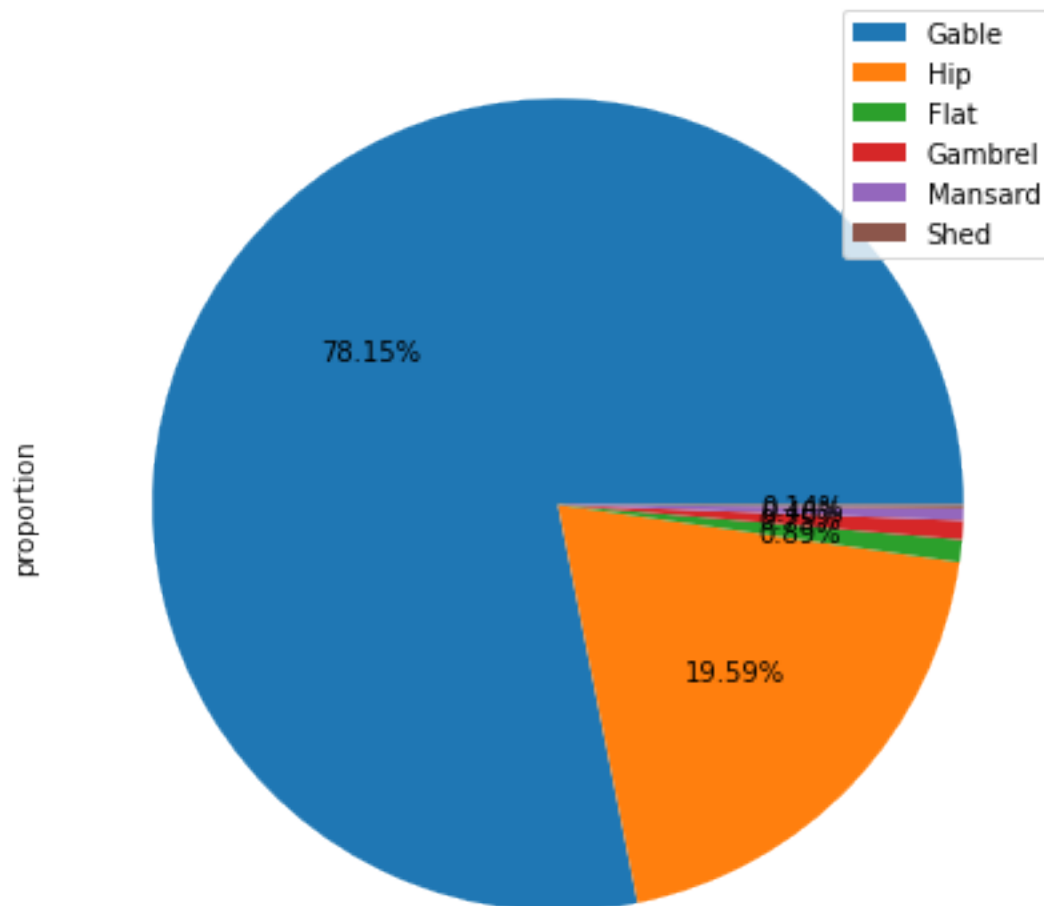
Name: proportion, dtype: float64



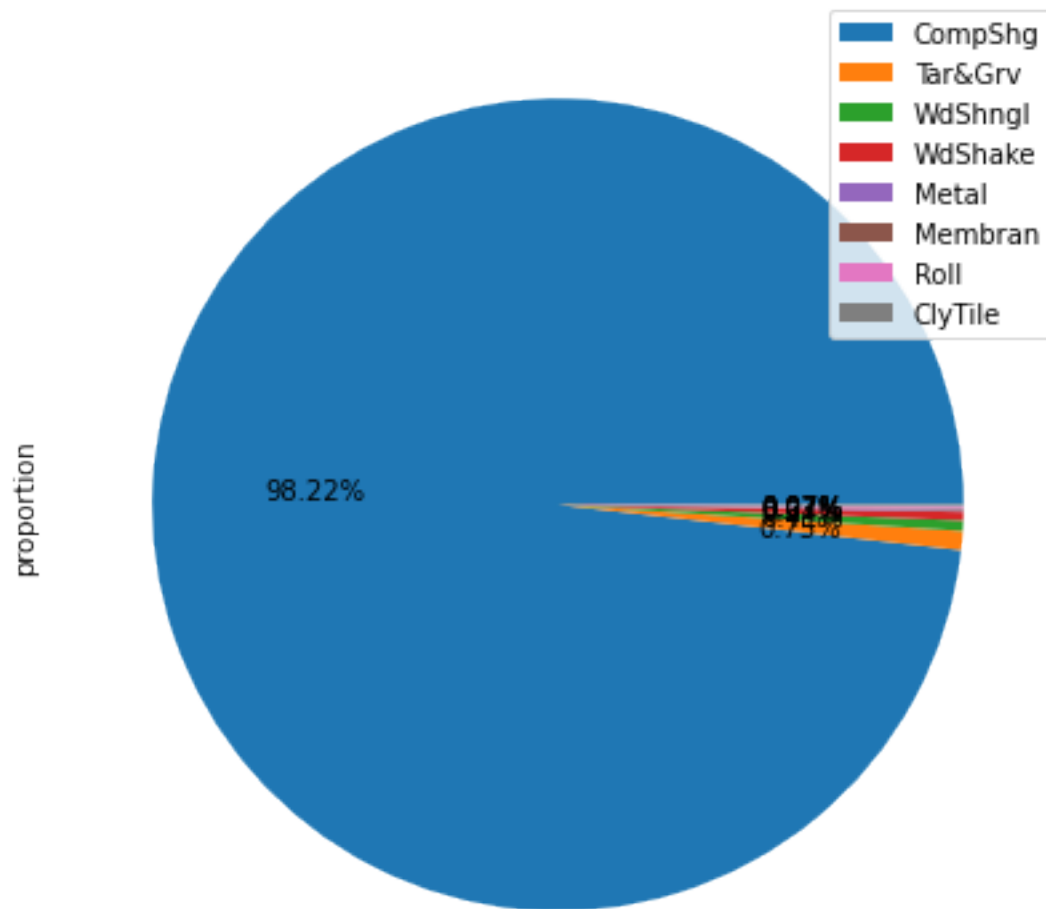
```
OverallCond
5      0.562329
6      0.172603
7      0.140411
8      0.049315
4      0.039041
3      0.017123
9      0.015068
2      0.003425
1      0.000685
Name: proportion, dtype: float64
```

```
RoofStyle
Gable      0.781507
Hip        0.195890
Flat       0.008904
Gambrel    0.007534
Mansard    0.004795
Shed       0.001370
Name: proportion, dtype: float64
```



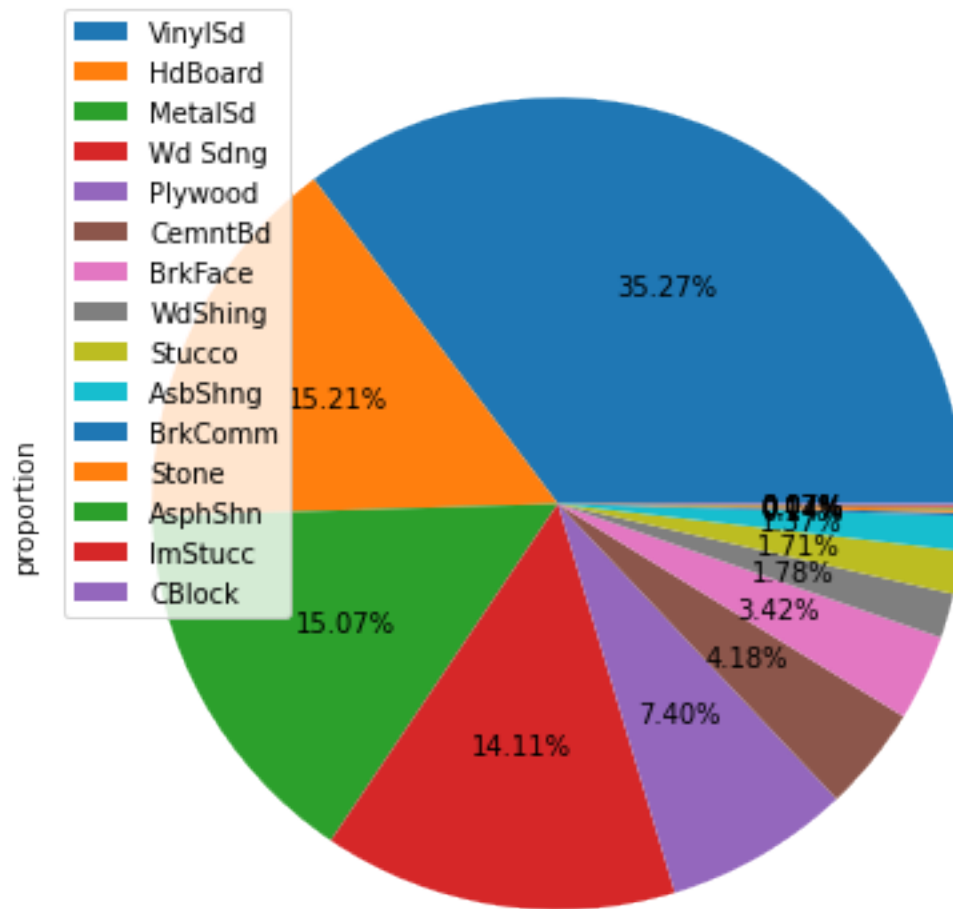
```
RoofMatl
CompShg    0.982192
Tar&Grv    0.007534
WdShngl    0.004110
WdShake    0.003425
Metal       0.000685
Membran     0.000685
Roll        0.000685
ClyTile     0.000685
Name: proportion, dtype: float64
```



Exterior1st

VinylSd	0.352740
HdBoard	0.152055
MetalSd	0.150685
Wd Sdng	0.141096
Plywood	0.073973
CemntBd	0.041781
BrkFace	0.034247
WdShing	0.017808
Stucco	0.017123
AsbShng	0.013699
BrkComm	0.001370
Stone	0.001370
AsphShn	0.000685
ImStucc	0.000685

CBlock 0.000685
 Name: proportion, dtype: float64

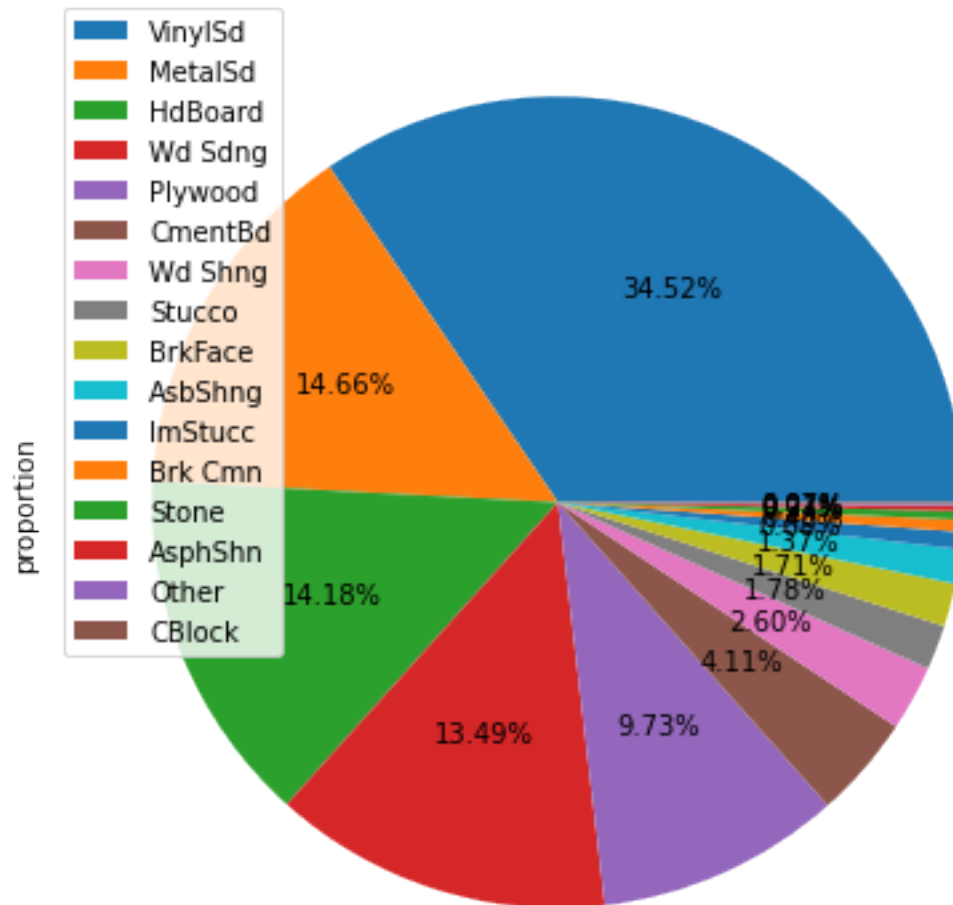


Exterior2nd

VinylSd	0.345205
MetalSd	0.146575
HdBoard	0.141781
Wd Sdng	0.134932
Plywood	0.097260
CmentBd	0.041096
Wd Shng	0.026027
Stucco	0.017808
BrkFace	0.017123
AsbShng	0.013699
ImStucc	0.006849
Brk Cmn	0.004795

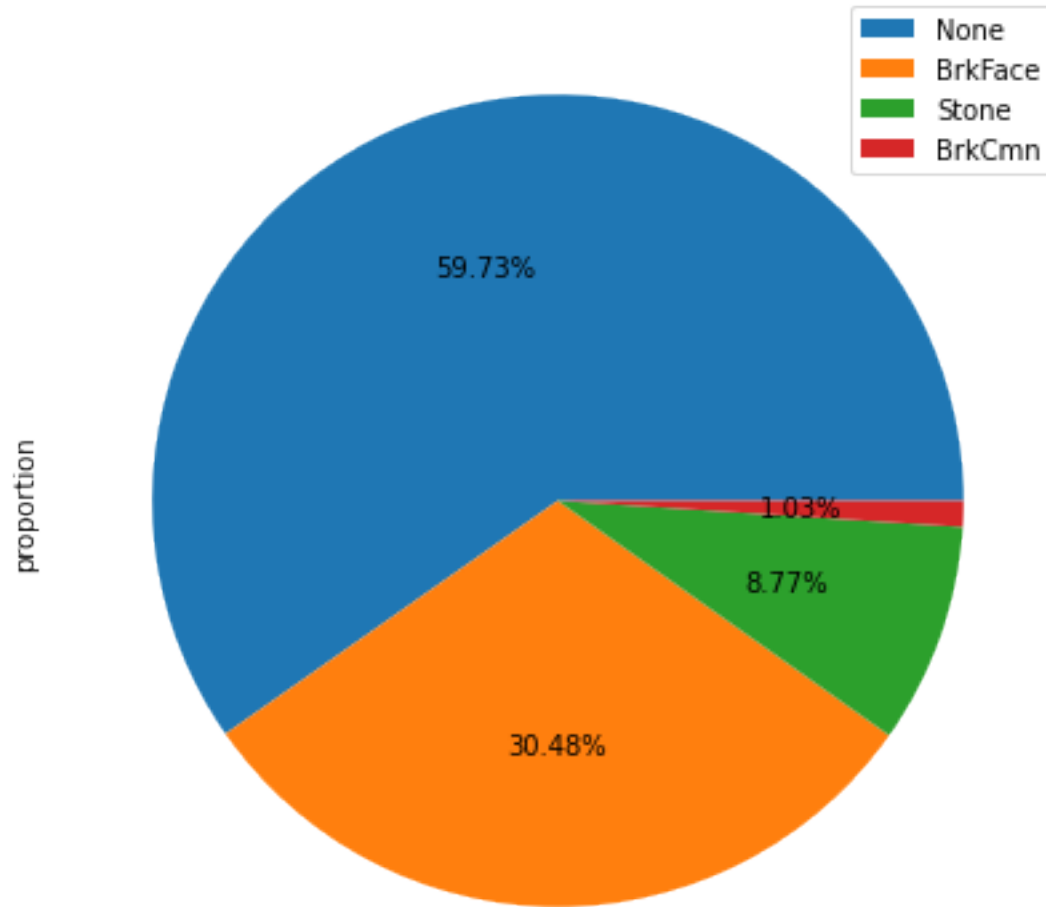
Stone	0.003425
AsphShn	0.002055
Other	0.000685
CBlock	0.000685

Name: proportion, dtype: float64

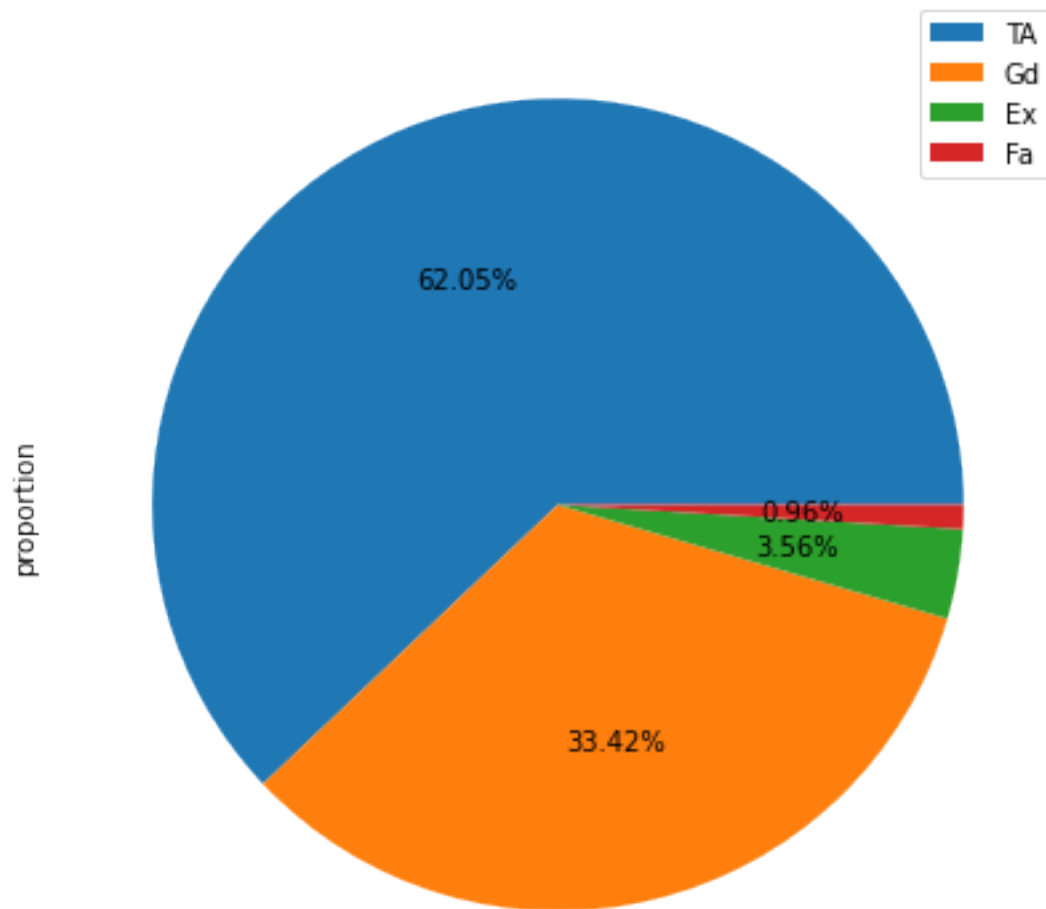


MasVnrType	
None	0.597260
BrkFace	0.304795
Stone	0.087671
BrkCmn	0.010274

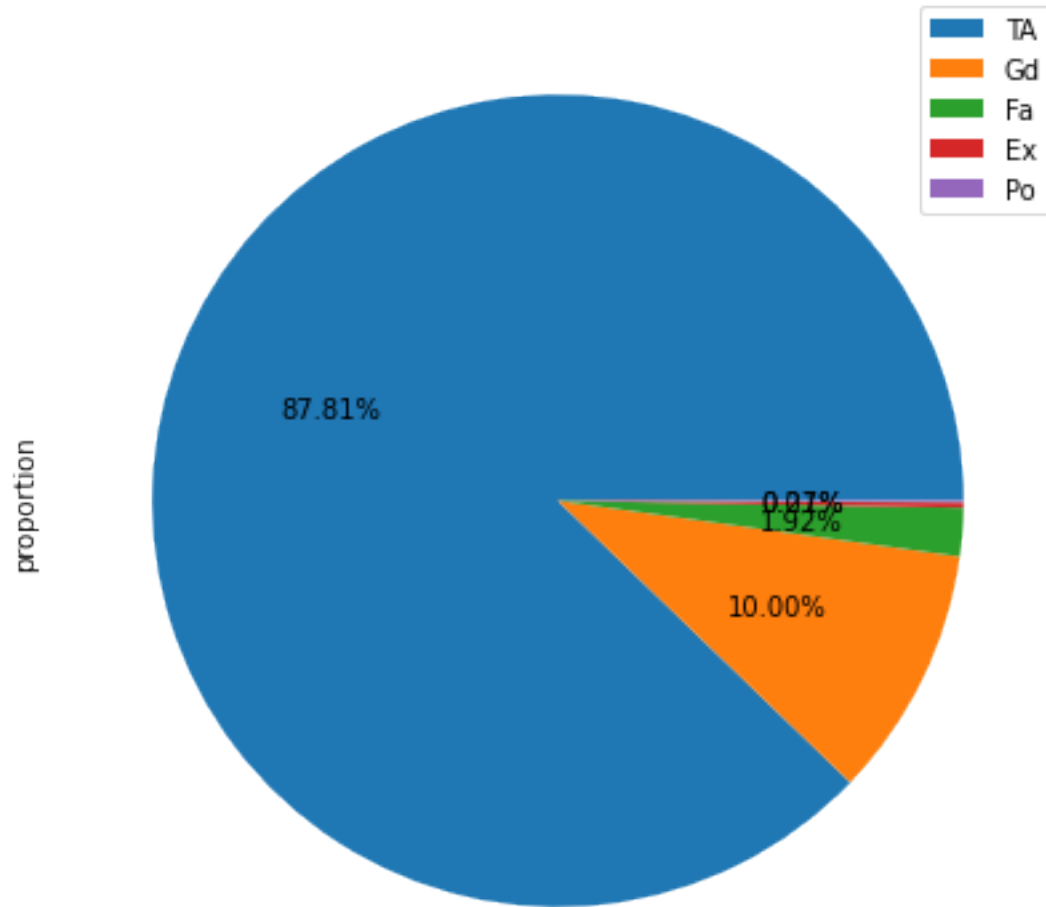
Name: proportion, dtype: float64



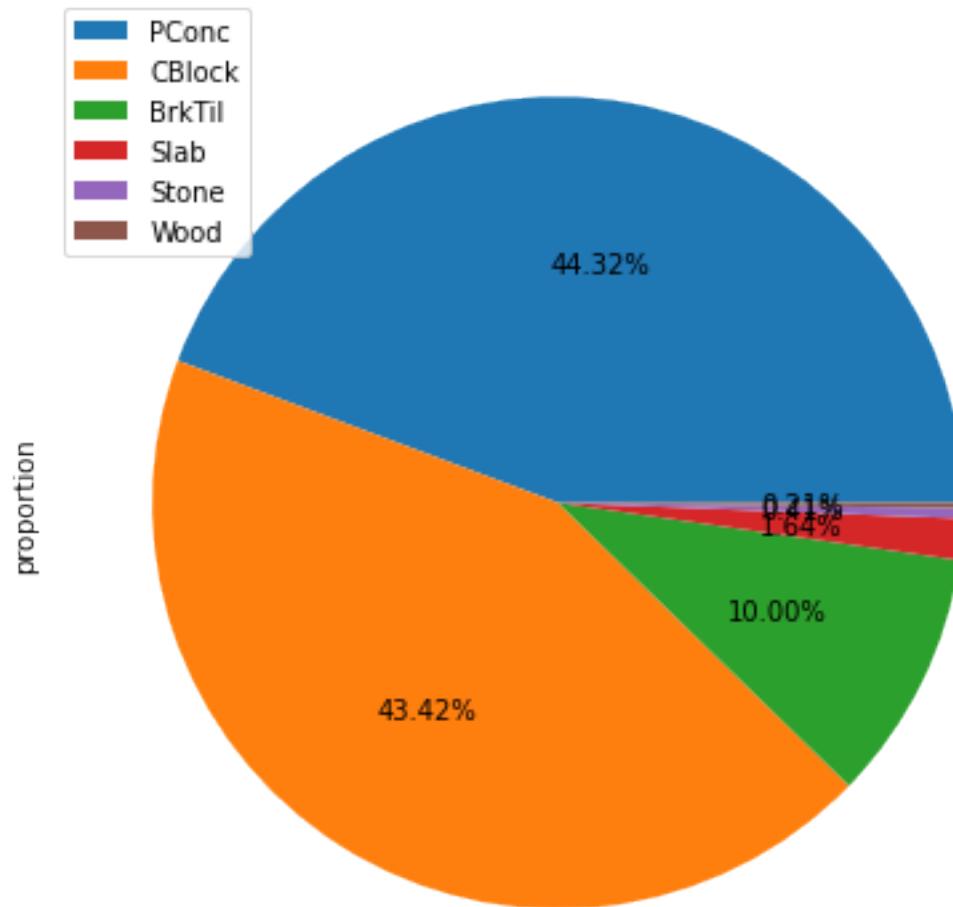
```
ExterQual
TA    0.620548
Gd    0.334247
Ex    0.035616
Fa    0.009589
Name: proportion, dtype: float64
```



```
ExterCond
TA      0.878082
Gd      0.100000
Fa      0.019178
Ex      0.002055
Po      0.000685
Name: proportion, dtype: float64
```



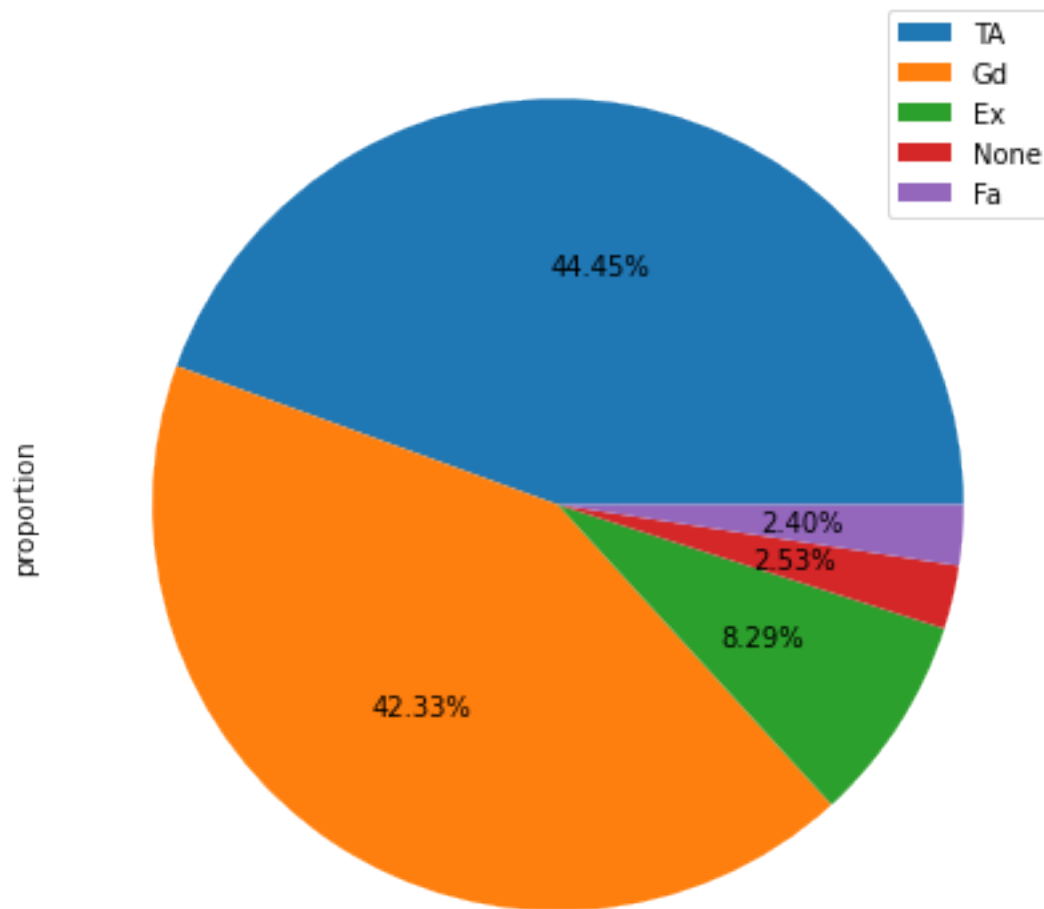
```
Foundation
PConc      0.443151
CBlock     0.434247
BrkTil     0.100000
Slab       0.016438
Stone      0.004110
Wood       0.002055
Name: proportion, dtype: float64
```

```

BsmtQual
TA      0.444521
Gd      0.423288
Ex      0.082877
None    0.025342
Fa      0.023973
Name: proportion, dtype: float64

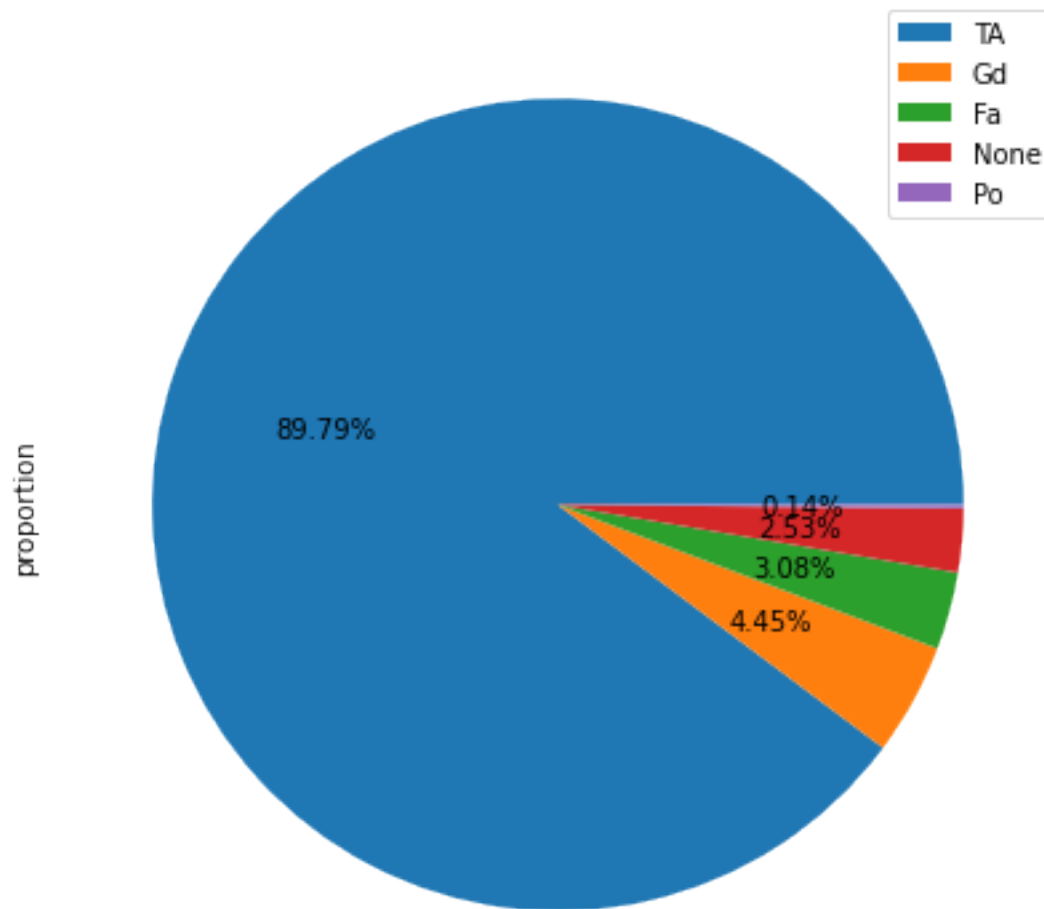
```



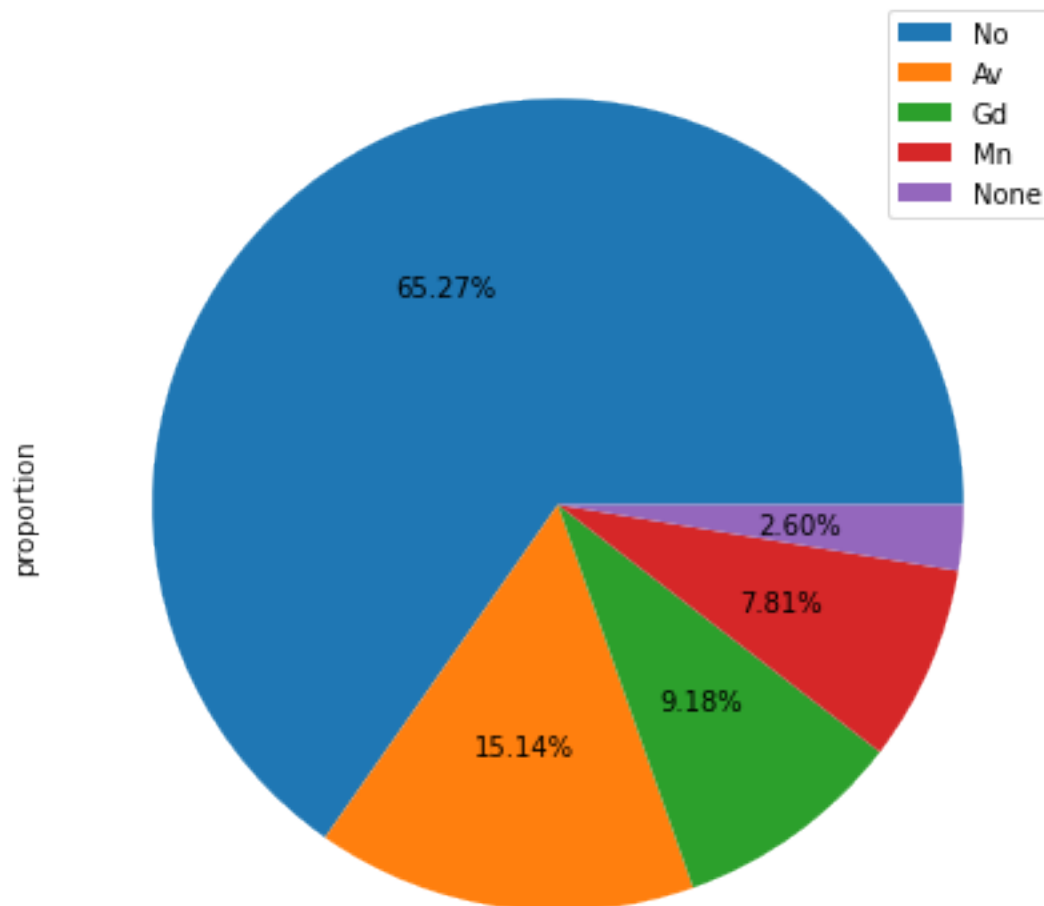
```

BsmtCond
TA      0.897945
Gd      0.044521
Fa      0.030822
None    0.025342
Po      0.001370
Name: proportion, dtype: float64

```



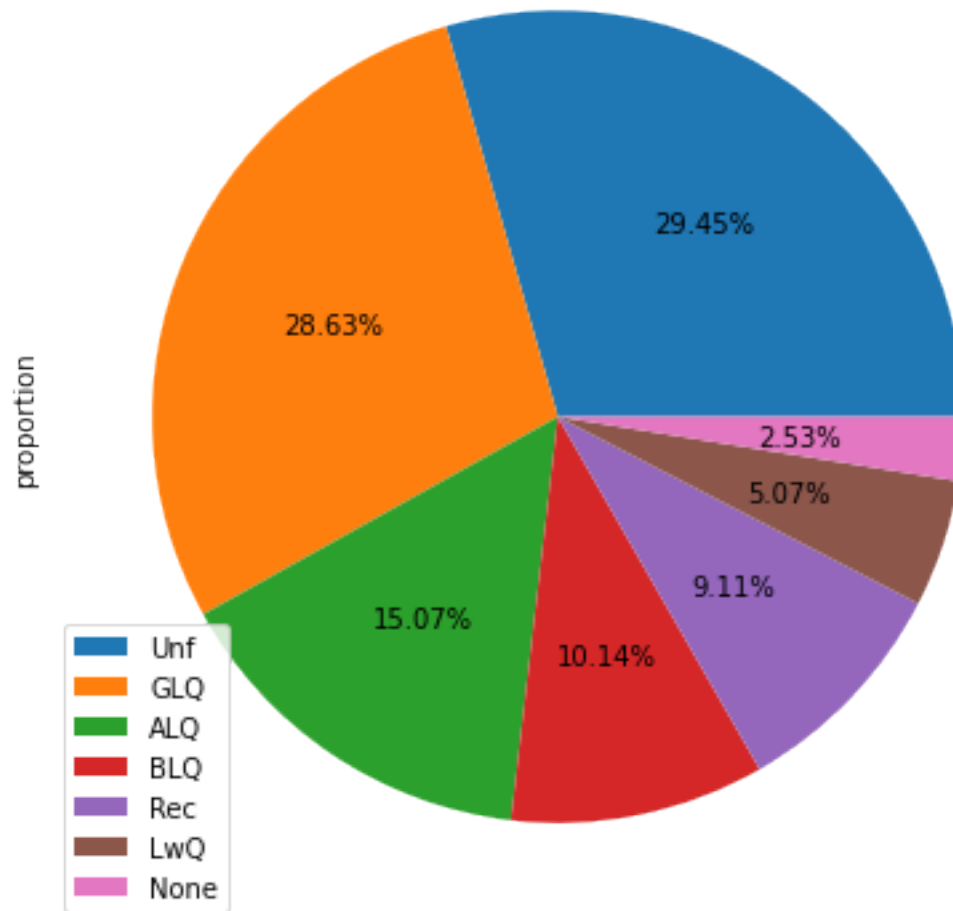
```
BsmtExposure
No      0.652740
Av      0.151370
Gd      0.091781
Mn      0.078082
None    0.026027
Name: proportion, dtype: float64
```



```

BsmtFinType1
Unf      0.294521
GLQ      0.286301
ALQ      0.150685
BLQ      0.101370
Rec       0.091096
LwQ      0.050685
None     0.025342
Name: proportion, dtype: float64

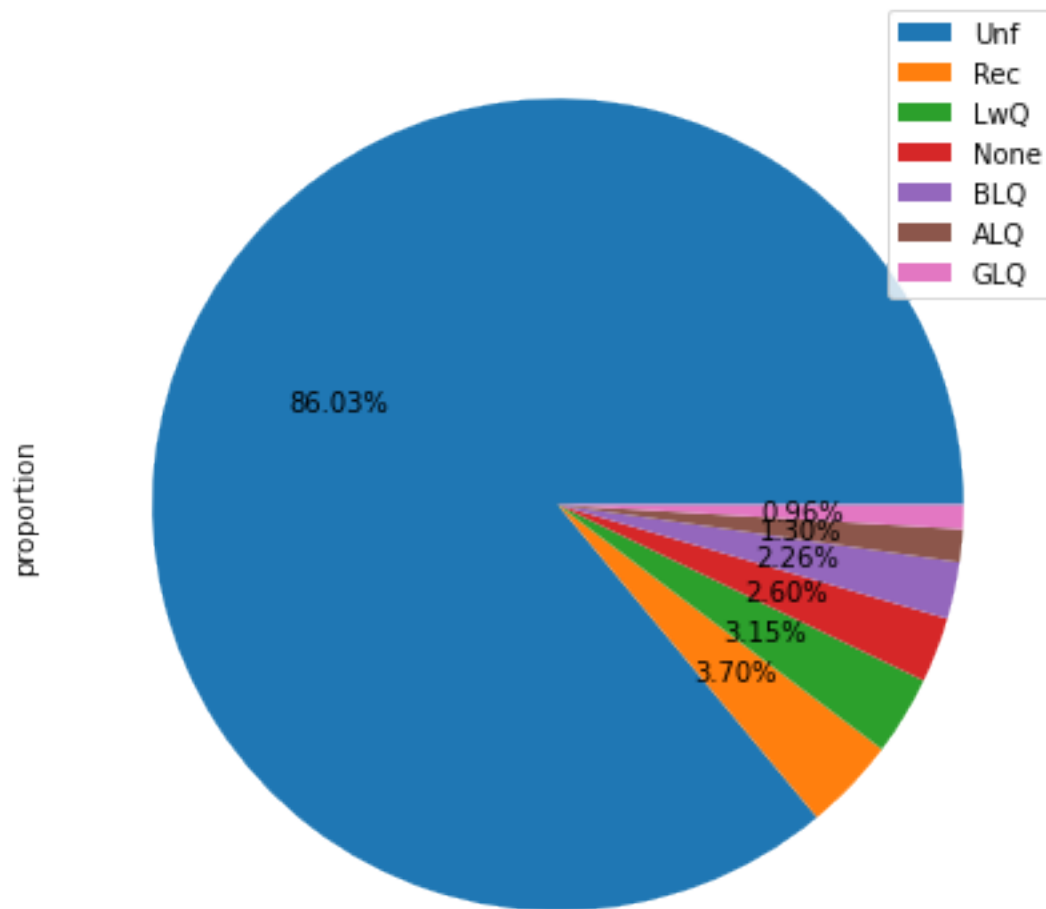
```



```

BsmtFinType2
Unf      0.860274
Rec      0.036986
LwQ      0.031507
None     0.026027
BLQ      0.022603
ALQ      0.013014
GLQ      0.009589
Name: proportion, dtype: float64

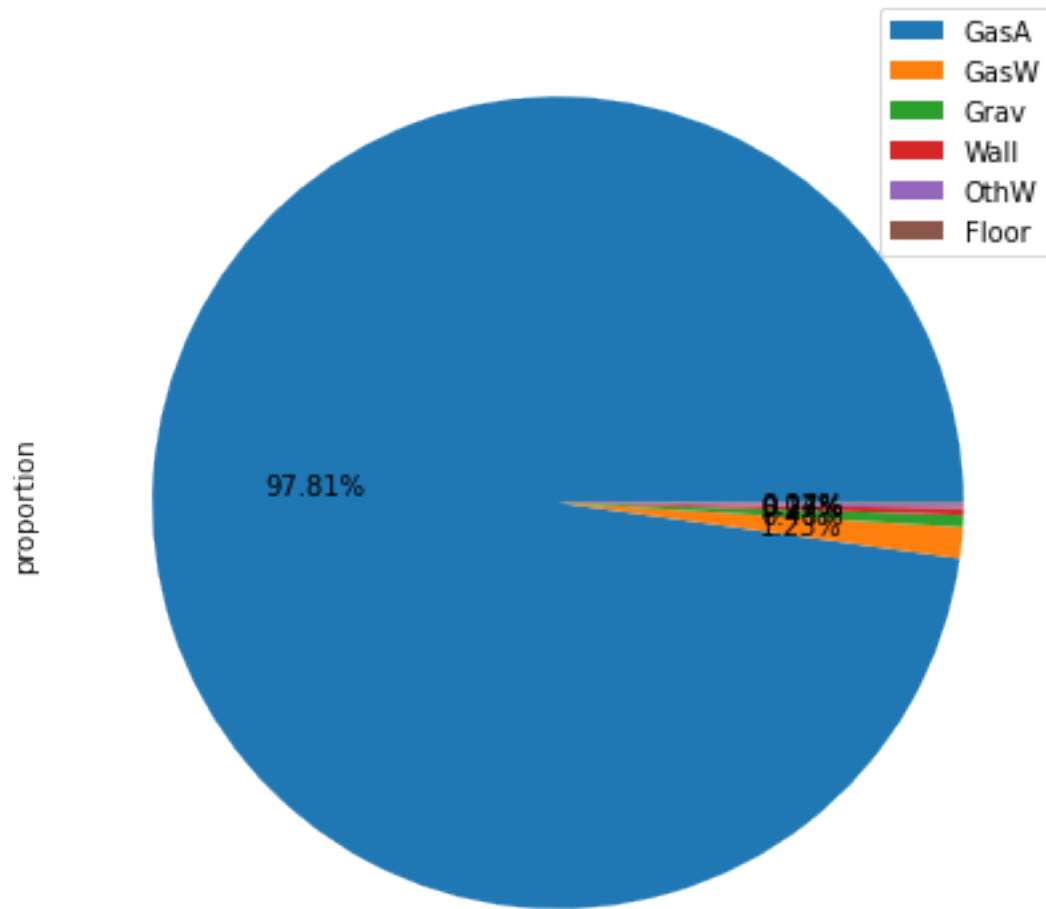
```



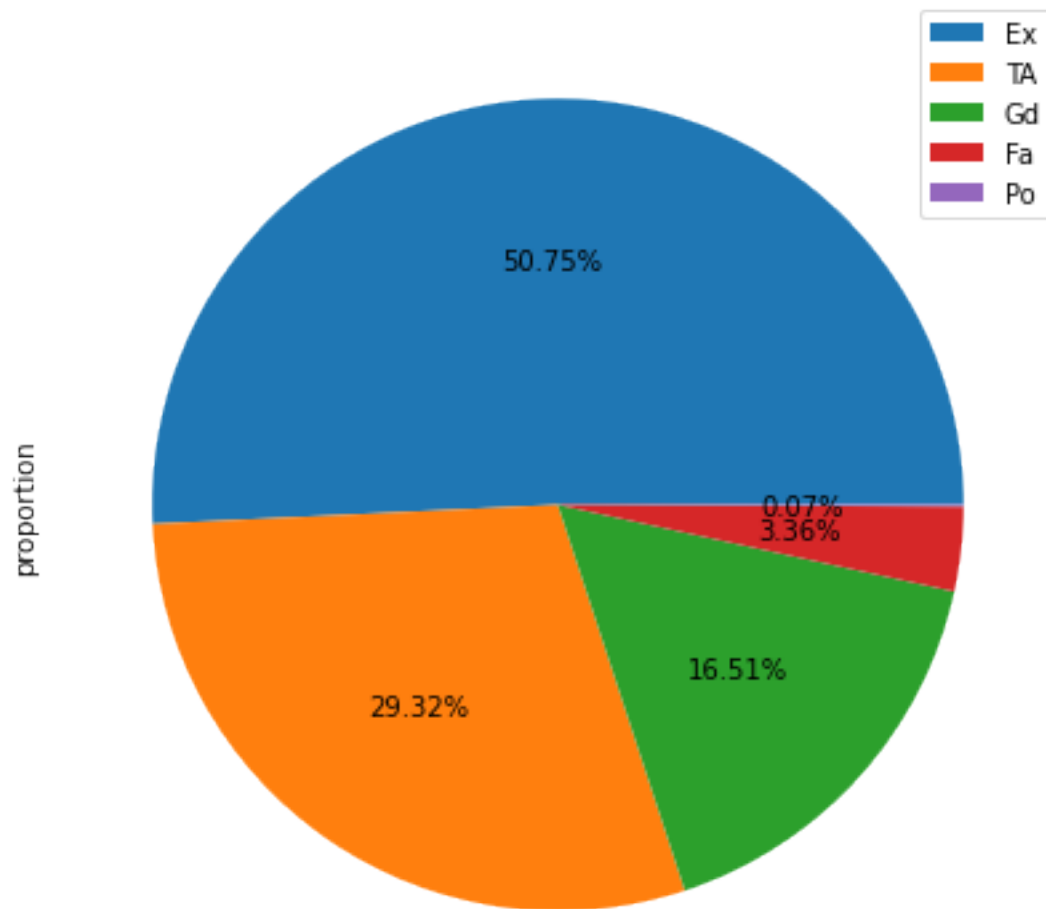
```

Heating
GasA      0.978082
GasW      0.012329
Grav      0.004795
Wall      0.002740
OthW      0.001370
Floor     0.000685
Name: proportion, dtype: float64

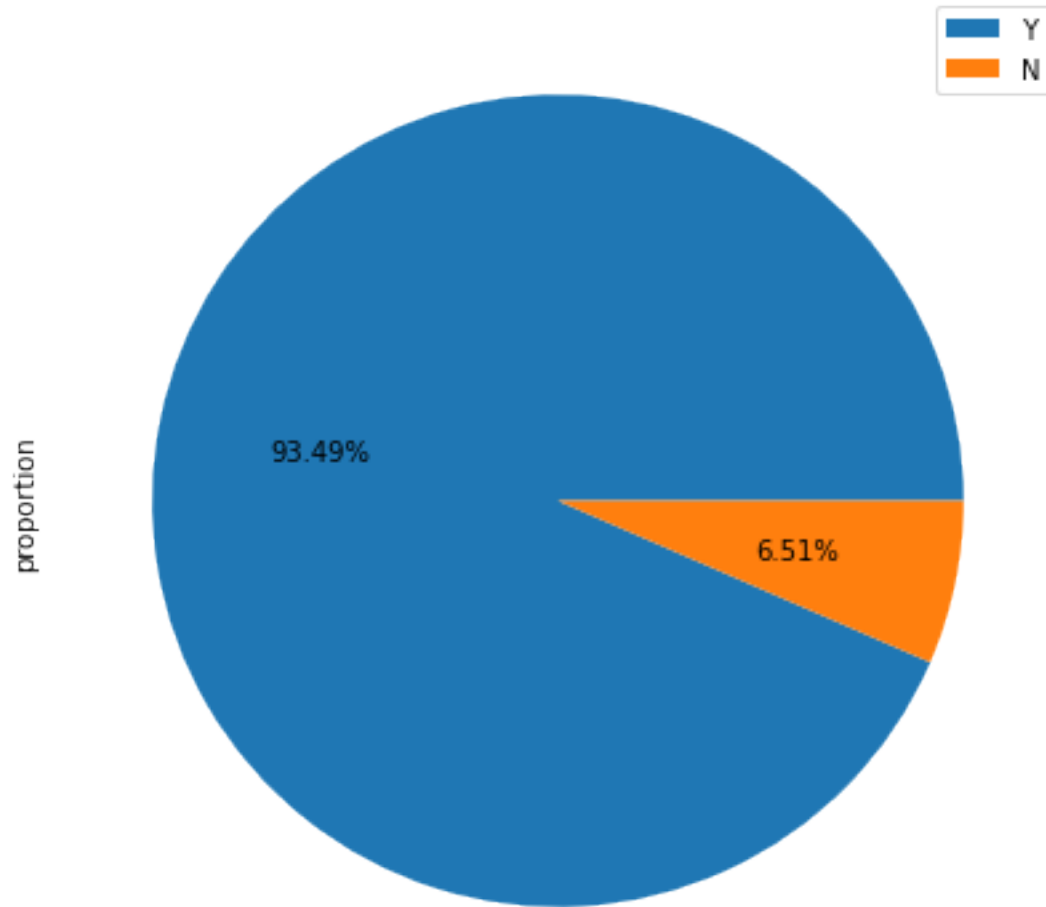
```



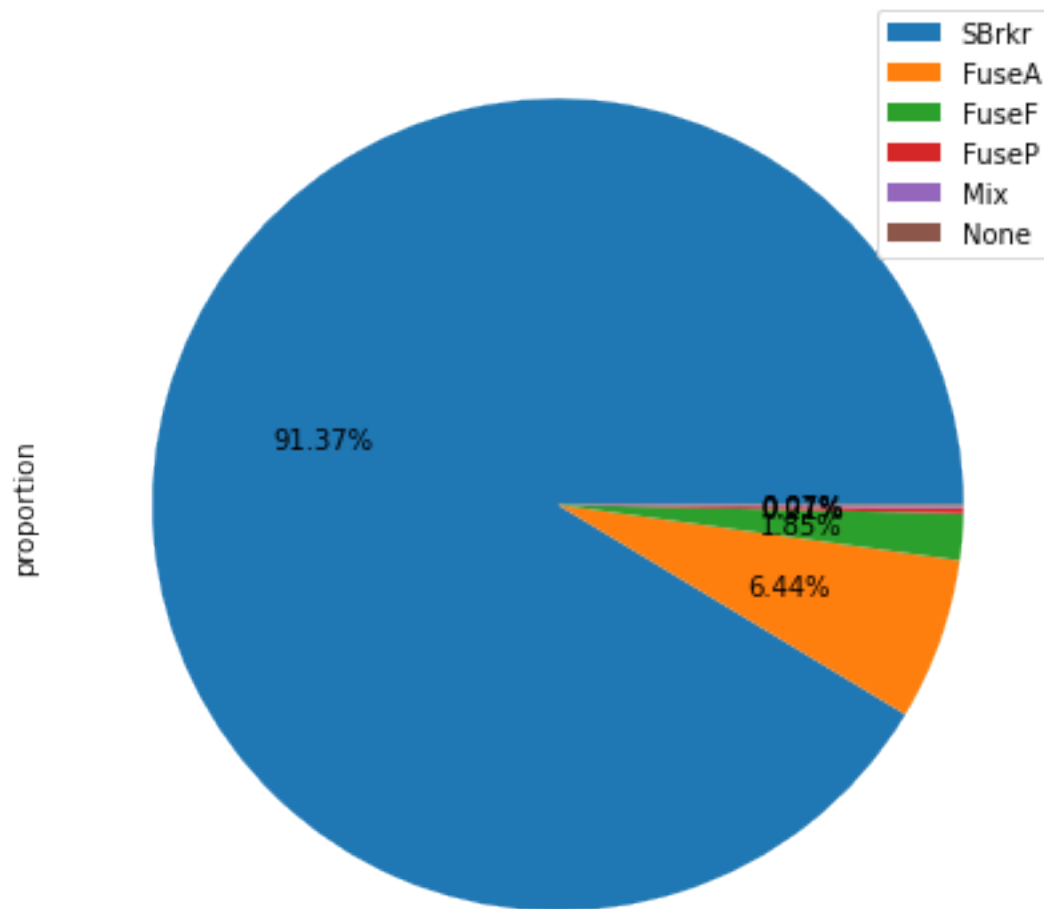
```
HeatingQC
Ex      0.507534
TA      0.293151
Gd      0.165068
Fa      0.033562
Po      0.000685
Name: proportion, dtype: float64
```



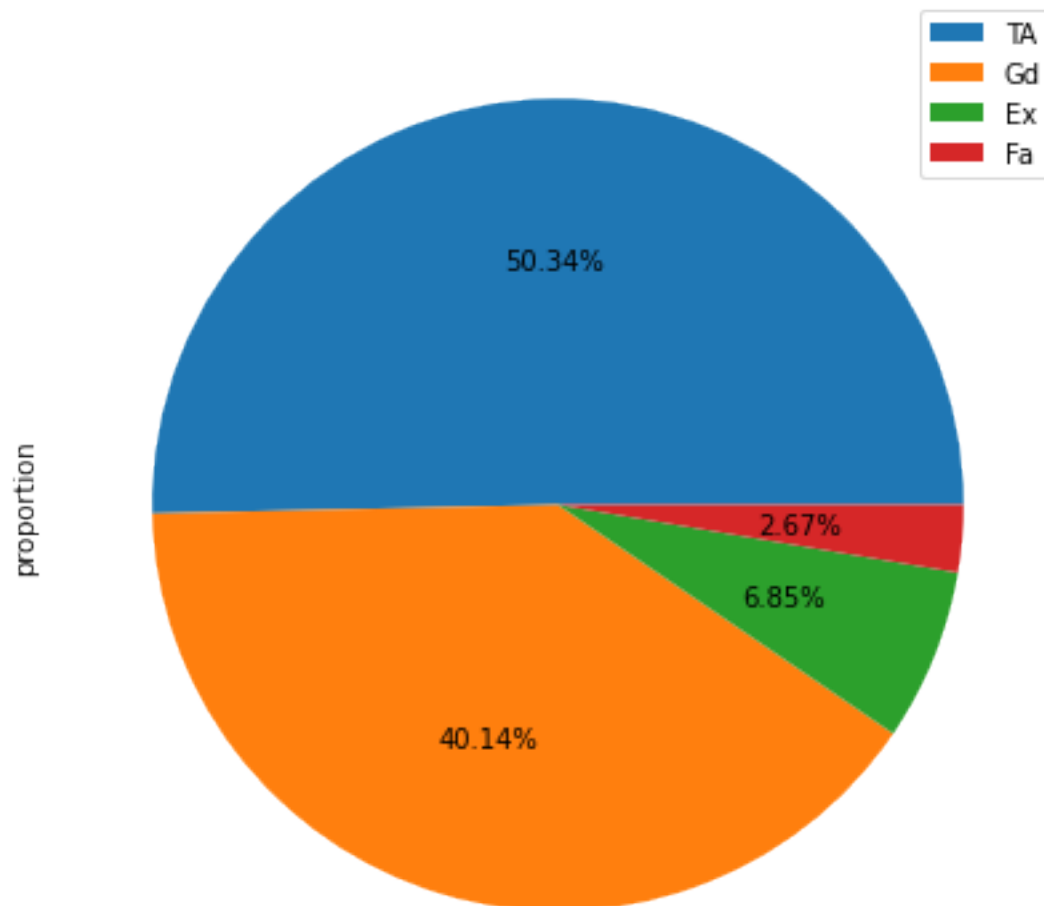
```
CentralAir
Y    0.934932
N    0.065068
Name: proportion, dtype: float64
```

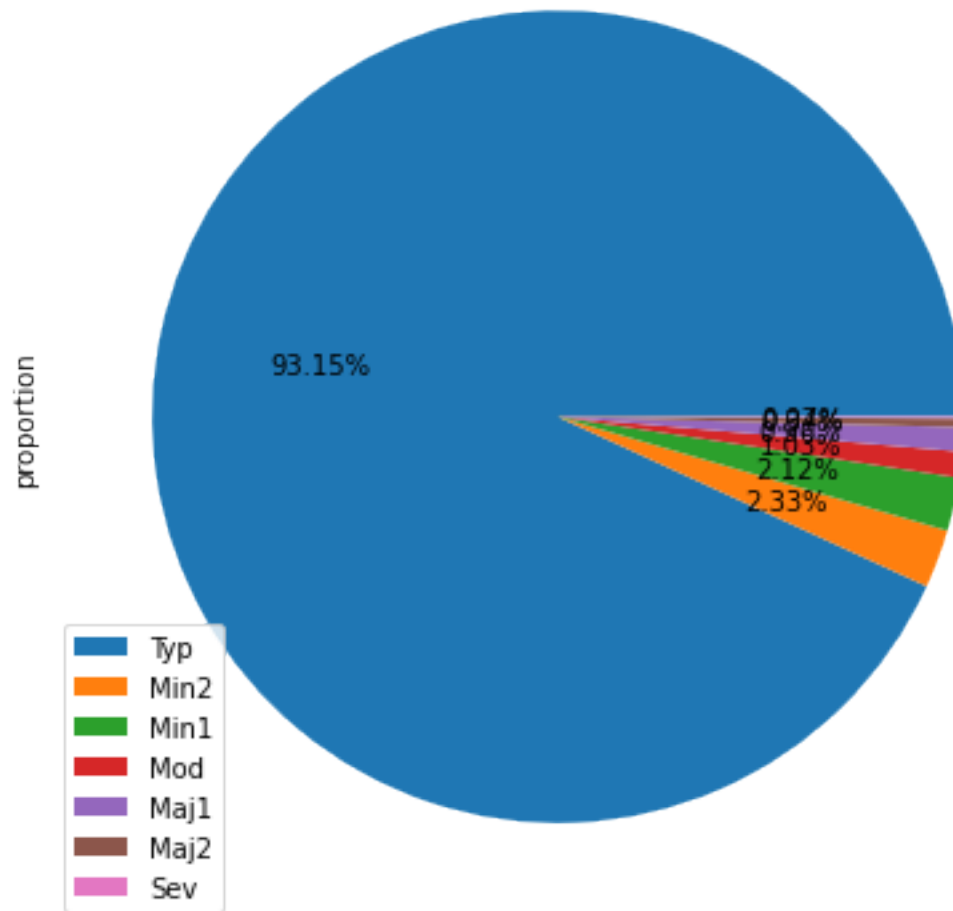
```
Electrical
SBrkr    0.913699
FuseA    0.064384
FuseF    0.018493
FuseP    0.002055
Mix      0.000685
None     0.000685
Name: proportion, dtype: float64
```



```
KitchenQual
TA    0.503425
Gd    0.401370
Ex    0.068493
Fa    0.026712
Name: proportion, dtype: float64
```



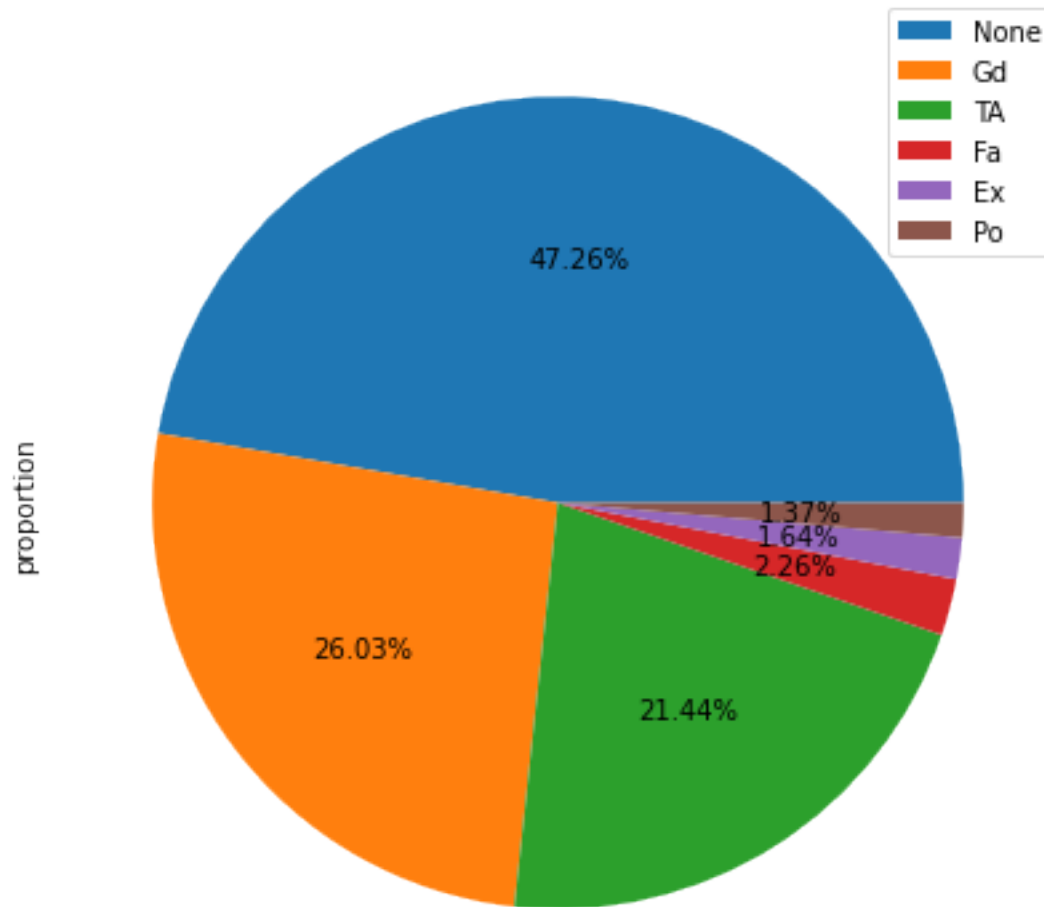
```
Functional
Typ      0.931507
Min2     0.023288
Min1     0.021233
Mod       0.010274
Maj1     0.009589
Maj2     0.003425
Sev       0.000685
Name: proportion, dtype: float64
```



```

FireplaceQu
None      0.472603
Gd        0.260274
TA        0.214384
Fa        0.022603
Ex        0.016438
Po        0.013699
Name: proportion, dtype: float64

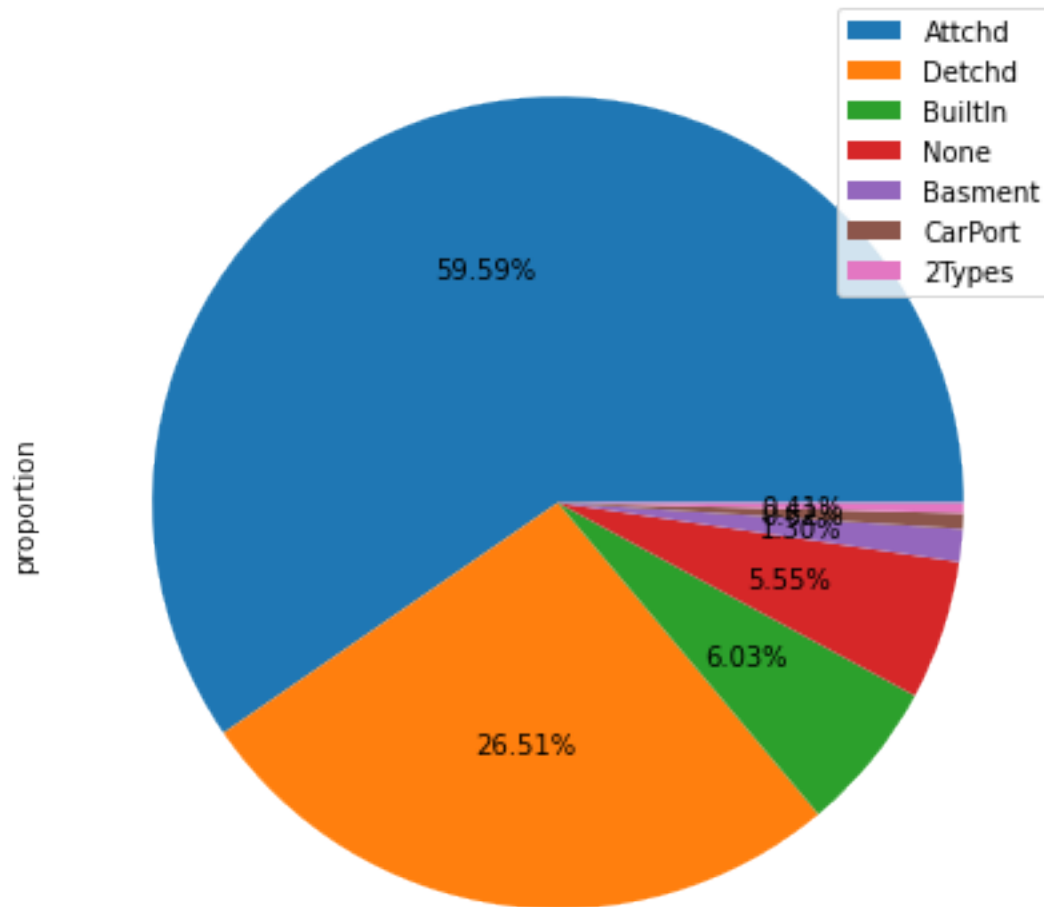
```



```

GarageType
Attchd      0.595890
Detchd      0.265068
BuiltIn     0.060274
None        0.055479
Basement    0.013014
CarPort     0.006164
2Types      0.004110
Name: proportion, dtype: float64

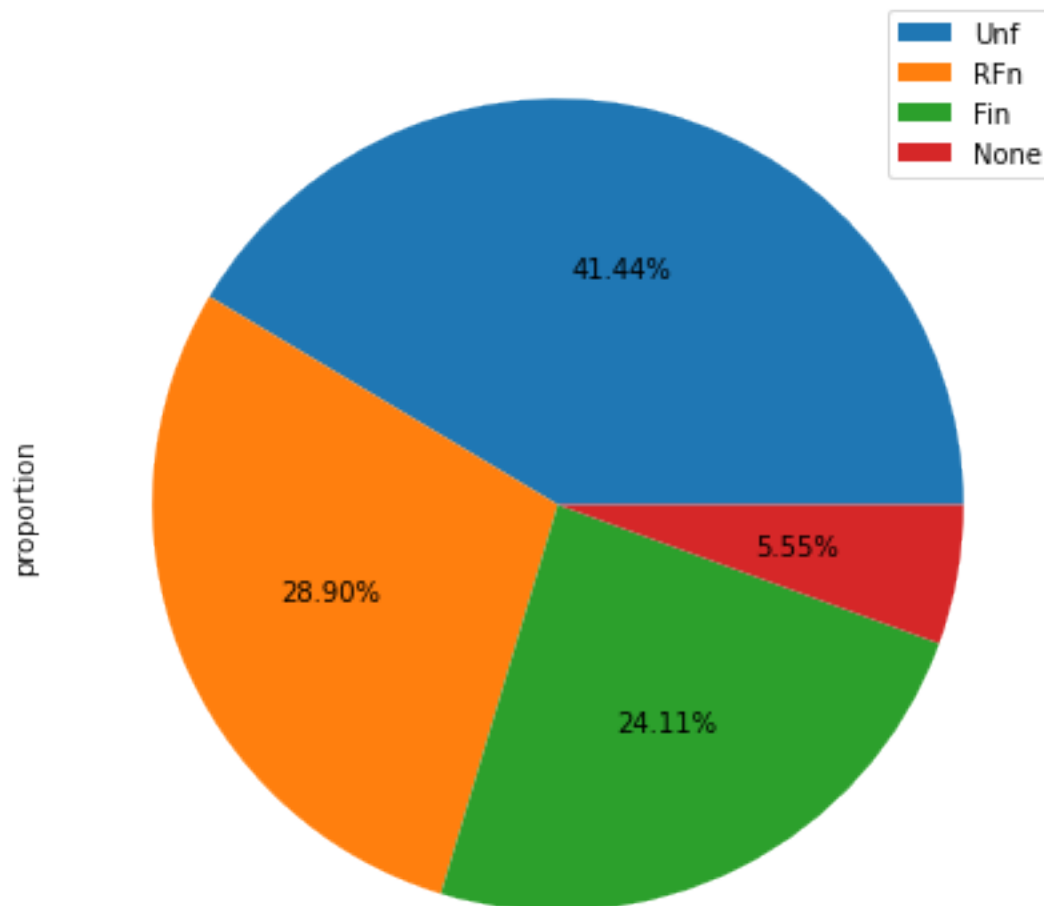
```



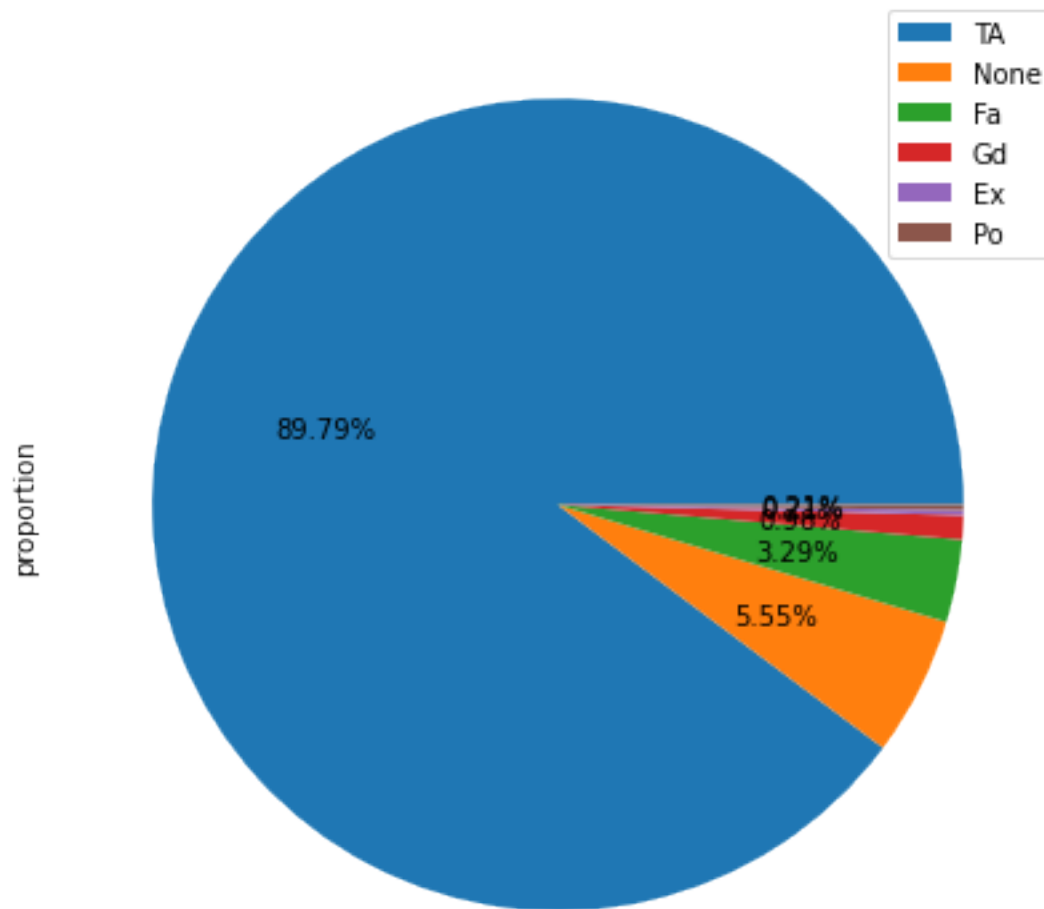
```

GarageFinish
Unf      0.414384
RFn      0.289041
Fin      0.241096
None     0.055479
Name: proportion, dtype: float64

```



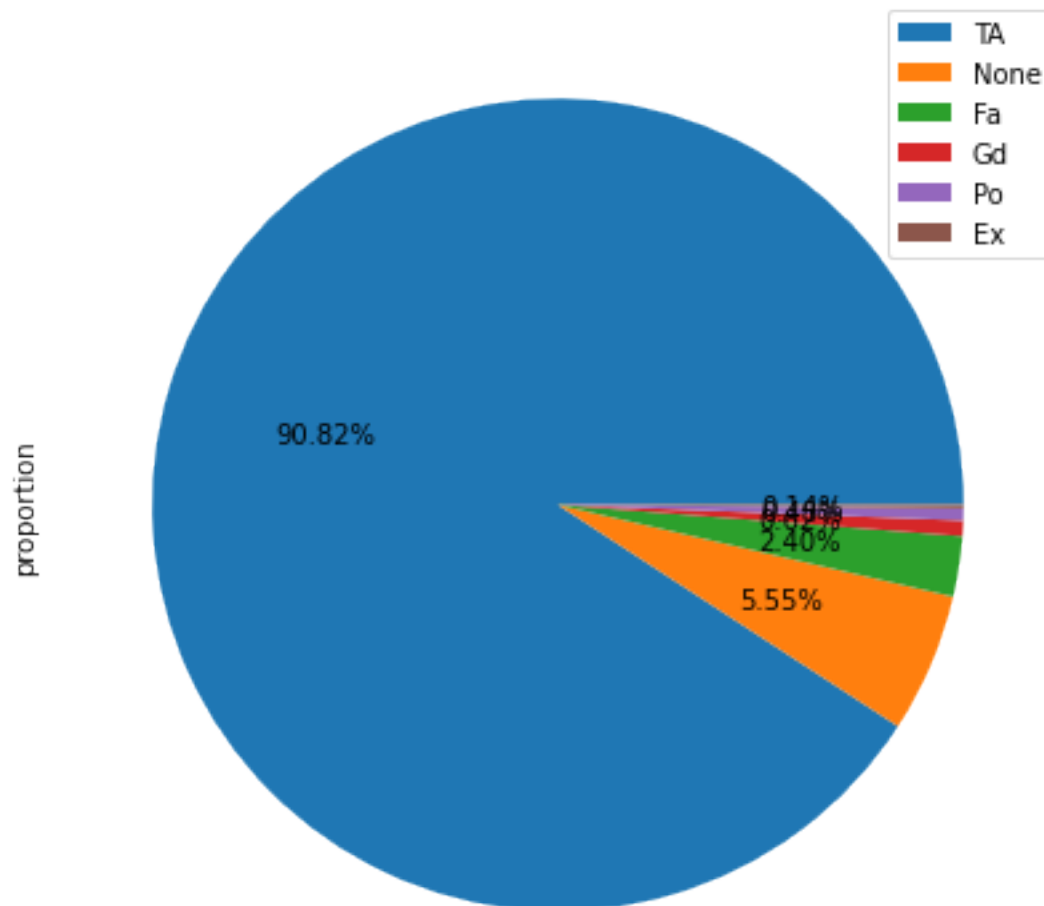
```
GarageQual
TA      0.897945
None    0.055479
Fa      0.032877
Gd      0.009589
Ex      0.002055
Po      0.002055
Name: proportion, dtype: float64
```



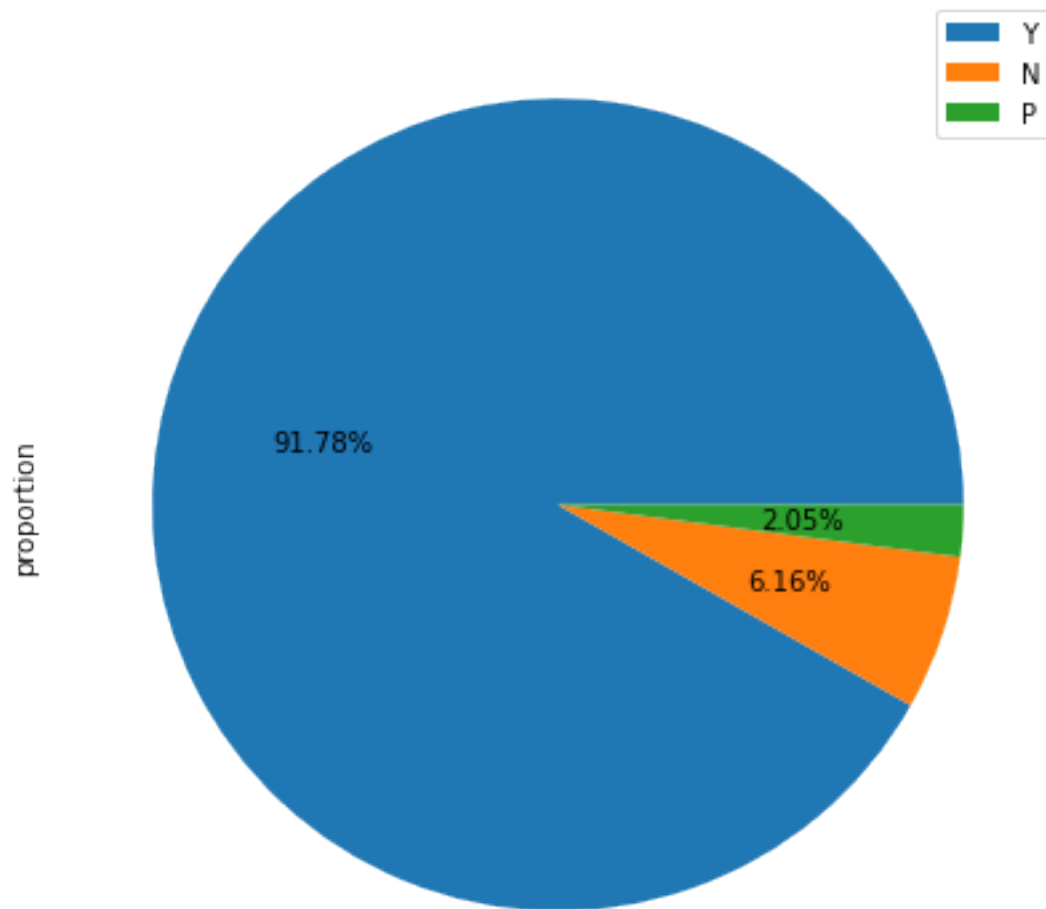
```

GarageCond
TA      0.908219
None    0.055479
Fa      0.023973
Gd      0.006164
Po      0.004795
Ex      0.001370
Name: proportion, dtype: float64

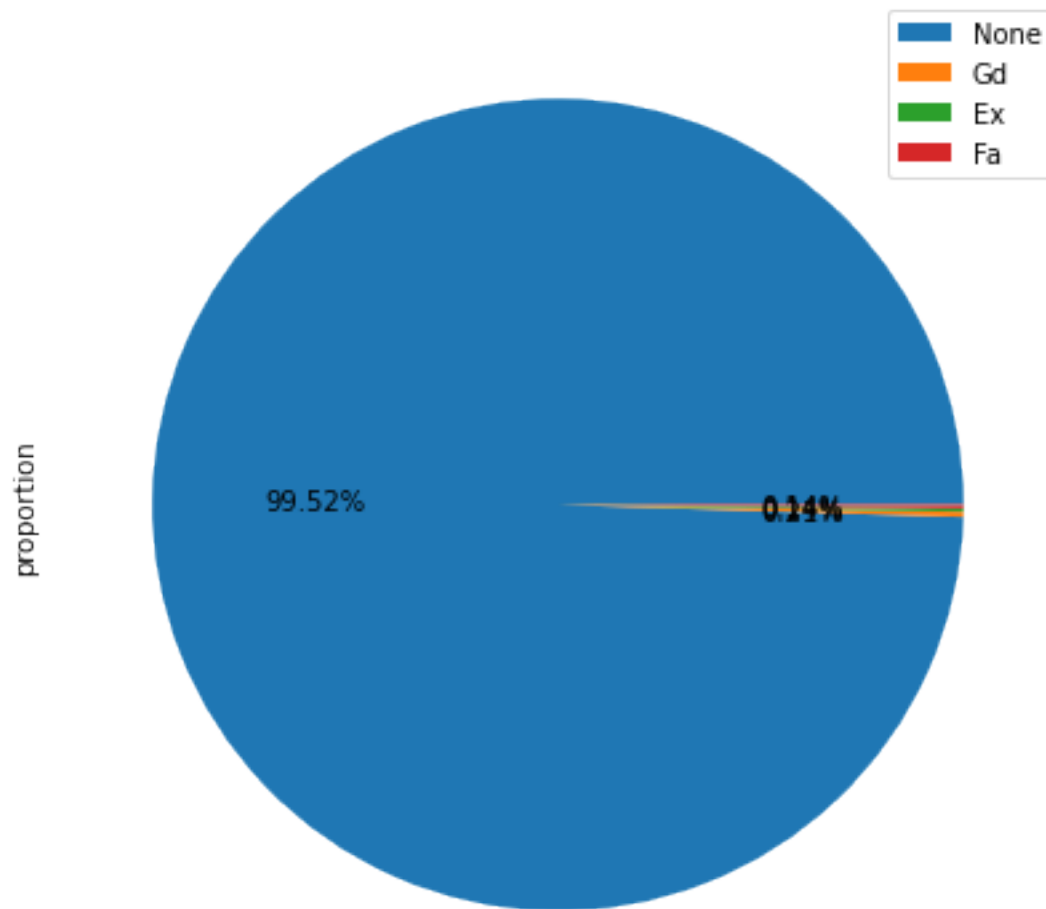
```

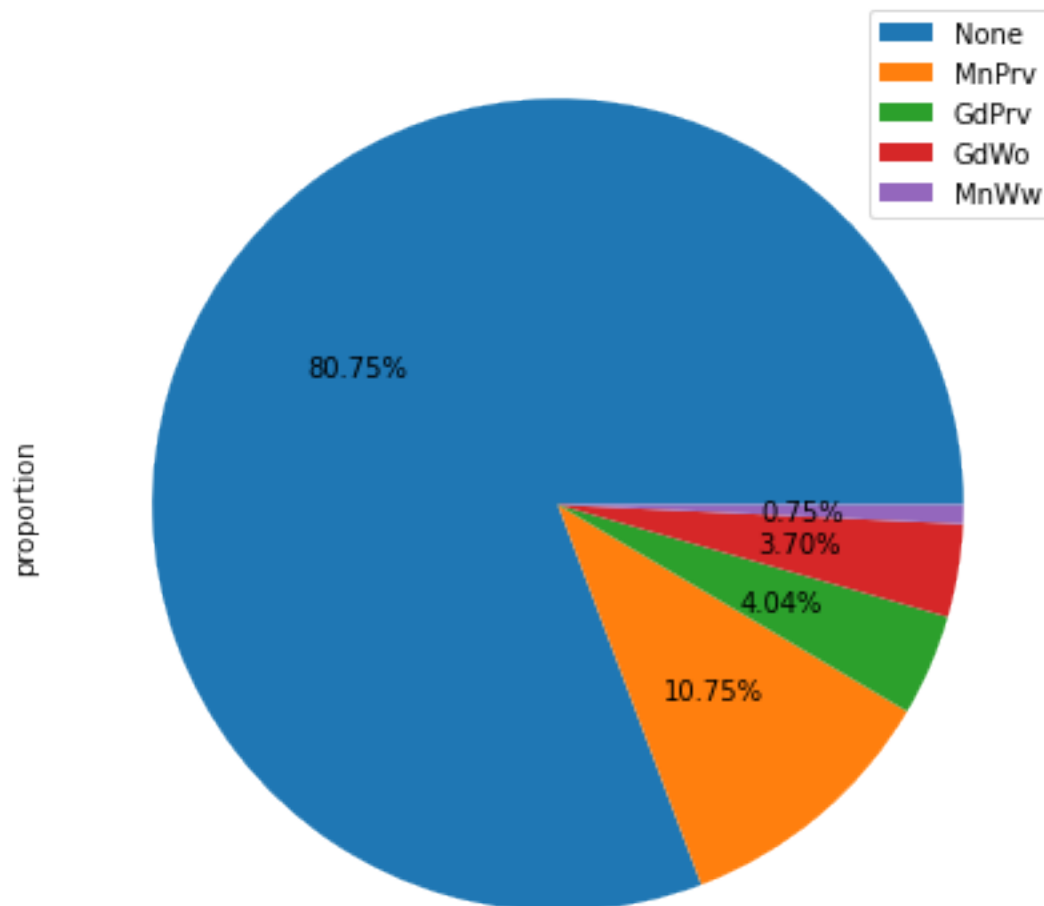
```
PavedDrive
Y    0.917808
N    0.061644
P    0.020548
Name: proportion, dtype: float64
```



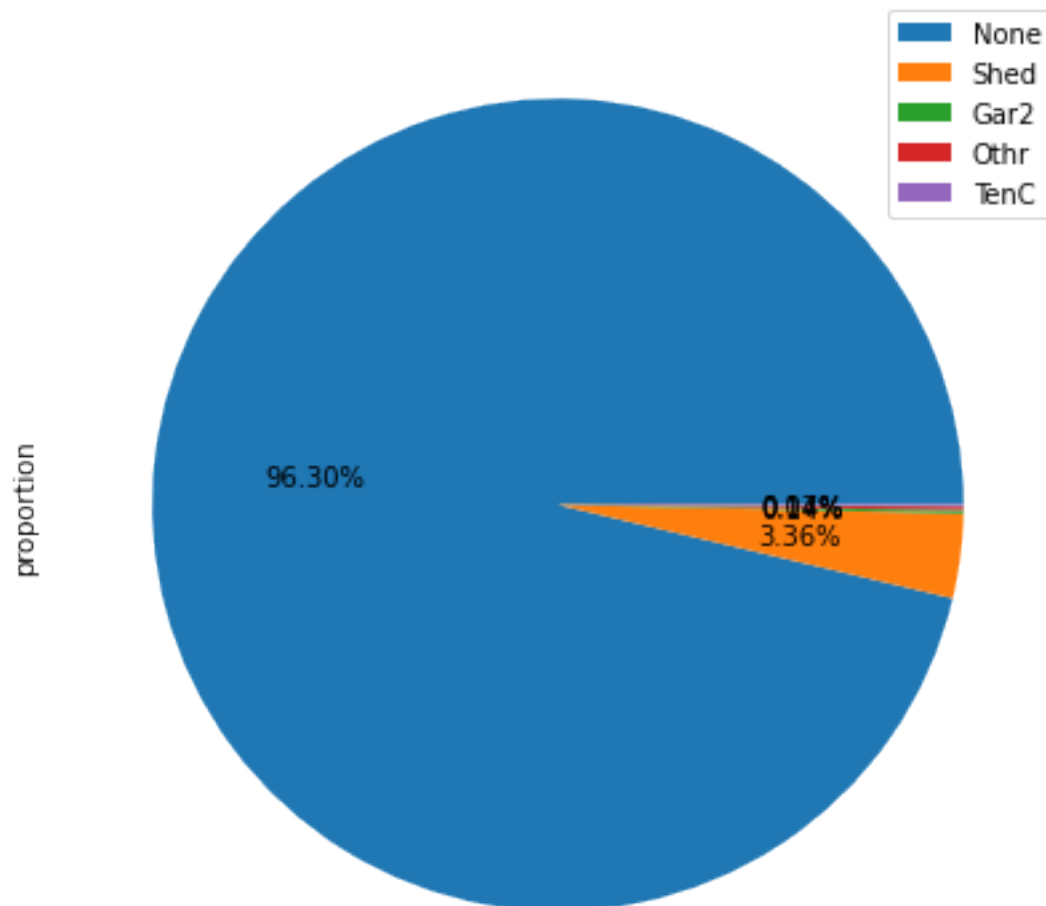
```
PoolQC
None    0.995205
Gd      0.002055
Ex      0.001370
Fa      0.001370
Name: proportion, dtype: float64
```



```
Fence
None      0.807534
MnPrv     0.107534
GdPrv     0.040411
GdWo      0.036986
MnWw      0.007534
Name: proportion, dtype: float64
```



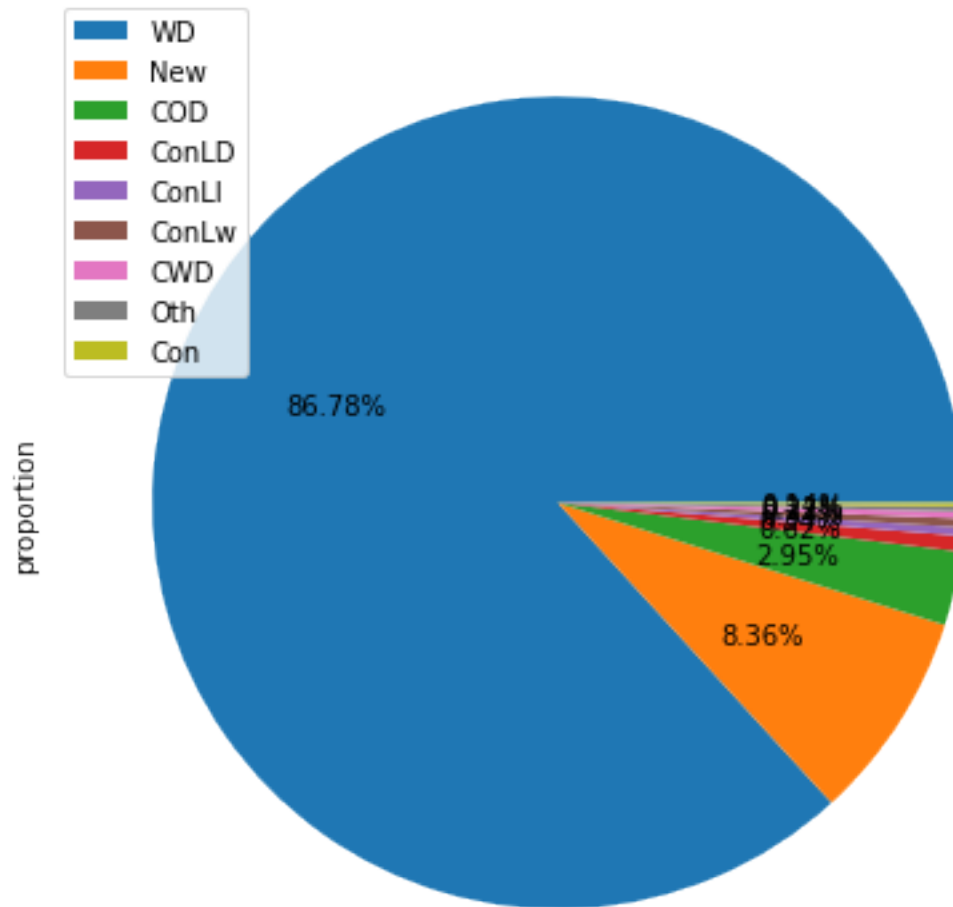
```
MiscFeature
None      0.963014
Shed      0.033562
Gar2      0.001370
Othr      0.001370
TenC      0.000685
Name: proportion, dtype: float64
```



```

SaleType
WD      0.867808
New     0.083562
COD     0.029452
ConLD   0.006164
ConLI   0.003425
ConLw   0.003425
CWD     0.002740
Oth     0.002055
Con     0.001370
Name: proportion, dtype: float64

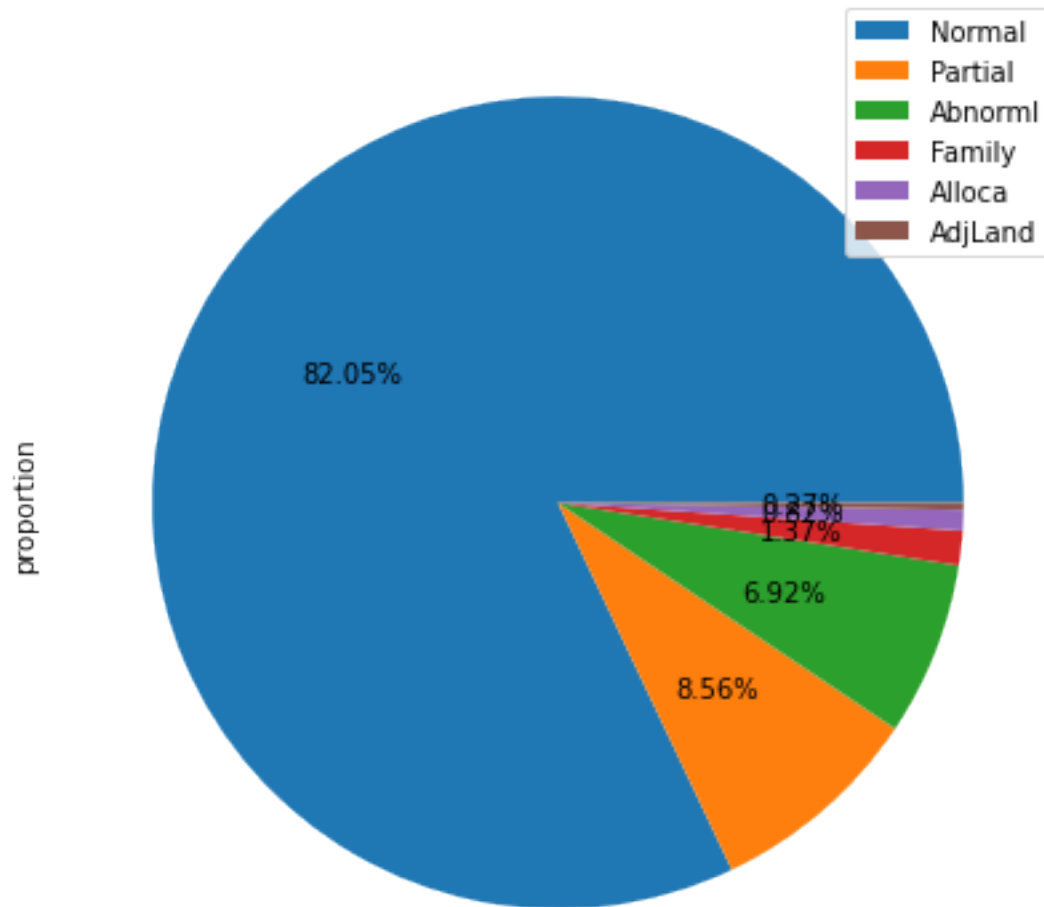
```



```

SaleCondition
Normal      0.820548
Partial     0.085616
Abnorml     0.069178
Family      0.013699
Alloca      0.008219
AdjLand     0.002740
Name: proportion, dtype: float64

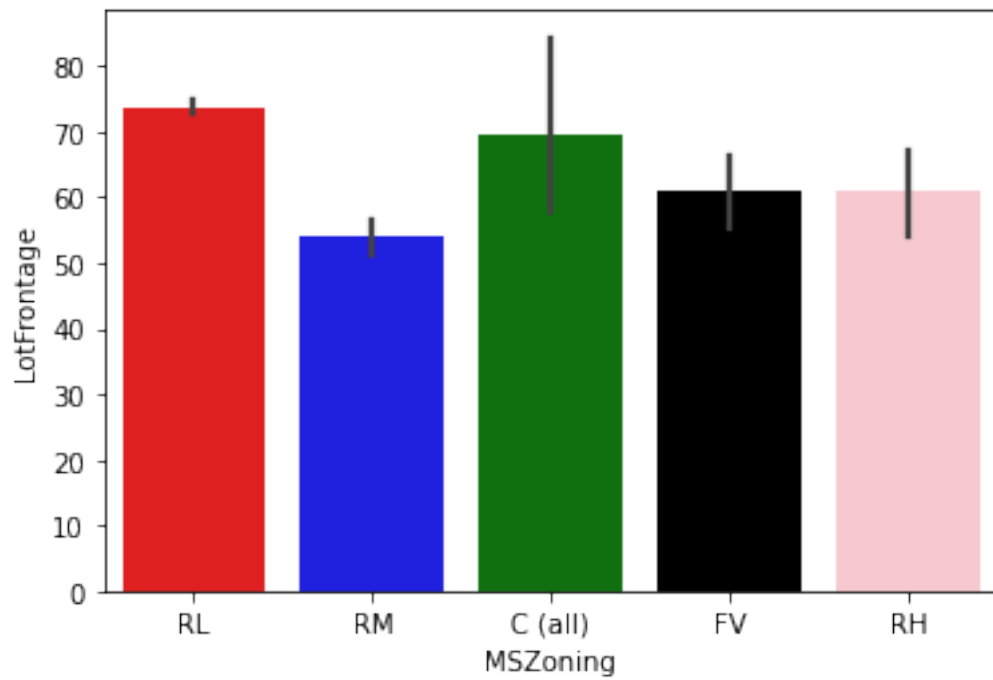
```



[]:

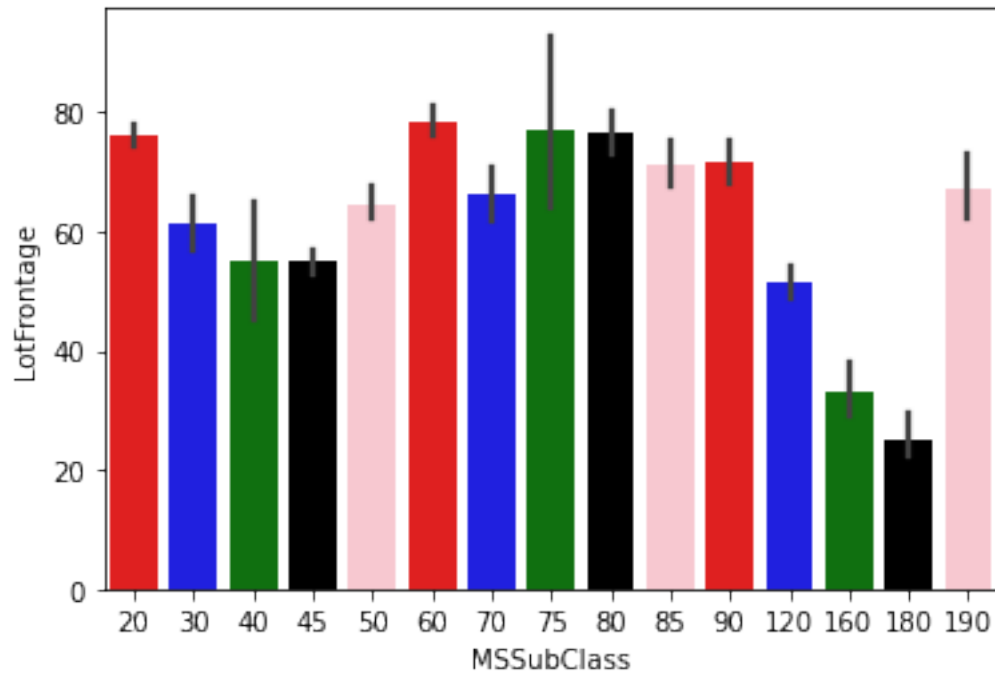
5.3.2 Bivariate / Multivariate Analysis

```
[29]: sns.barplot(x='MSZoning', y='LotFrontage', data=housing,
               palette=['red', 'blue', 'green', 'black', 'pink'])
plt.show()
```



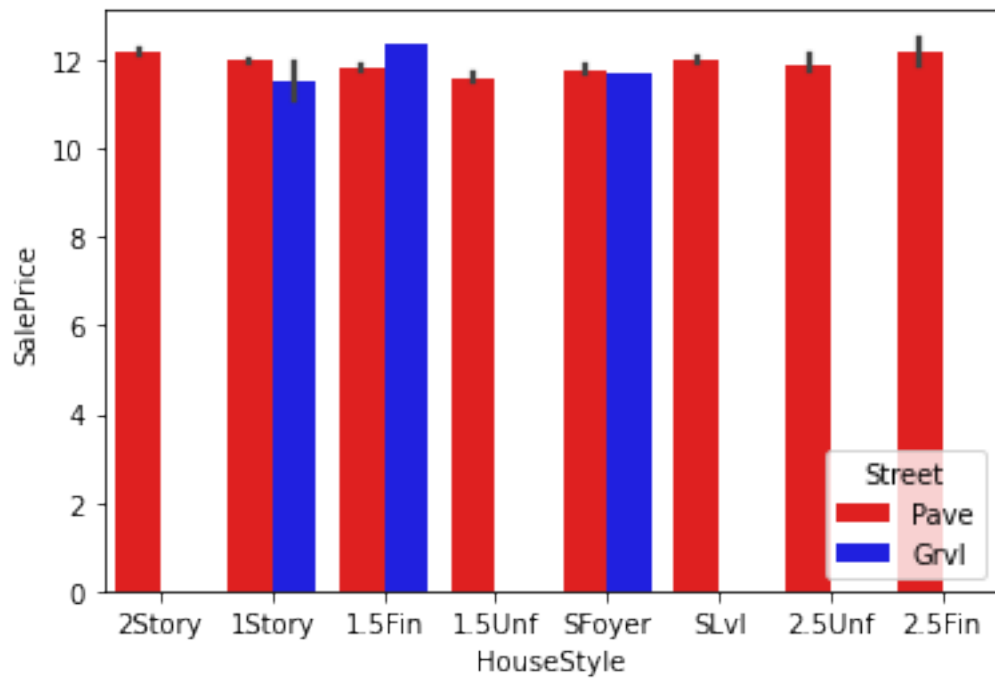
[]:

```
[30]: sns.barplot(x='MSSubClass', y='LotFrontage',data=housing,palette=['red','blue','green','black','pink'])  
plt.show()
```

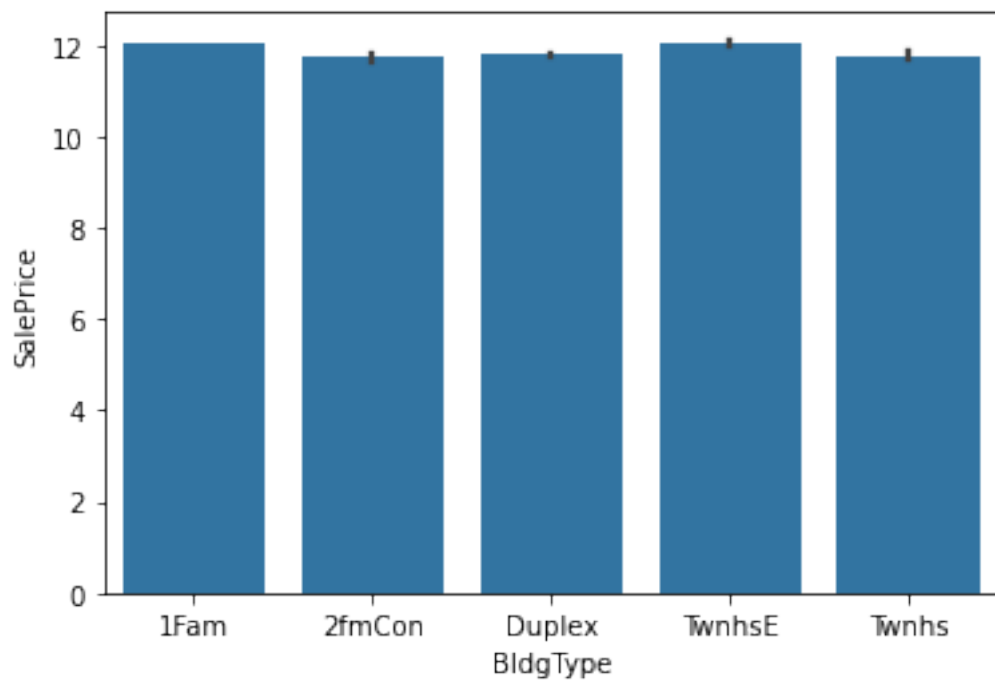
[]:

```
[31]: sns.barplot(x='HouseStyle', y='SalePrice', hue='Street', data=housing,
    palette=['red', 'blue', 'green', 'black', 'pink'])
plt.show()
```



[]:

```
[32]: sns.barplot(x="BldgType",y="SalePrice",data=housing)
plt.show()
```



```
[ ]:
```

Conclusion

We can see that RL(Residential Low Density) has highest lot frontage and RM (Residential Medium Density) has least

We can see that 2-story 1946 & Newer has highest lot frontGE and PUD-MULTILEVEL-INCL SPLIT LEV/FOYER has least

The SalesPrice is not showing much variance with respect to the Style of dwelling (1 story / 2 story)

The SalesPrice is almost same for all the Building Type (Type of Dwelling) and the basement quality so there is no significant pattern

```
[33]: housing['Age'] = housing['YrSold'] - housing['YearBuilt']
```

```
[34]: housing['Age'].head()
```

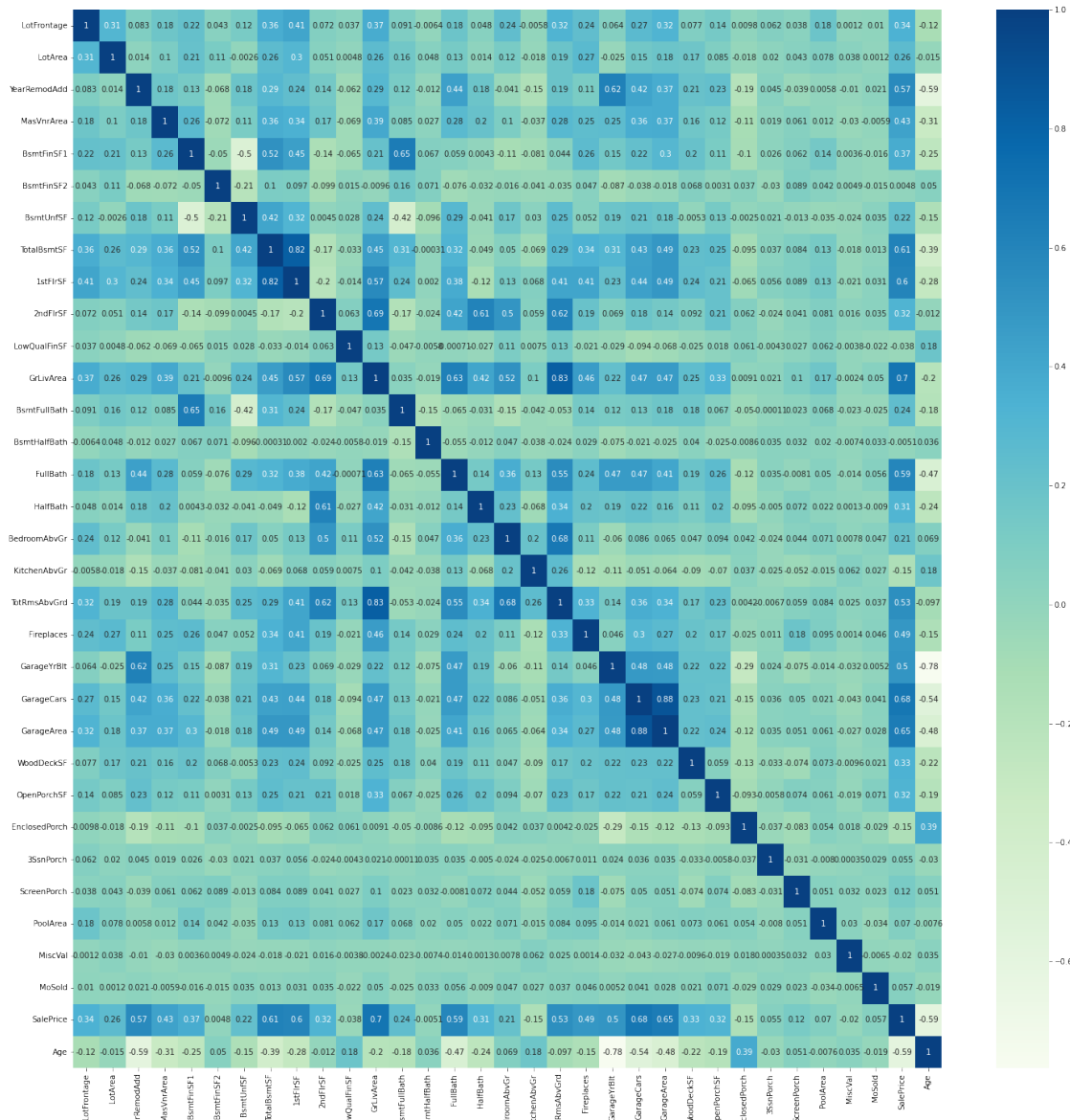
```
[34]: 0      5
      1     31
      2      7
      3     91
      4      8
      Name: Age, dtype: int64
```

```
[ ]:
```

```
[35]: housing.drop(columns=['YearBuilt','YrSold'],axis=1, inplace=True)
```

```
[36]: plt.figure(figsize=(25,25))
      sns.heatmap(housing.corr(numeric_only=True), annot=True, cmap = 'GnBu')
```

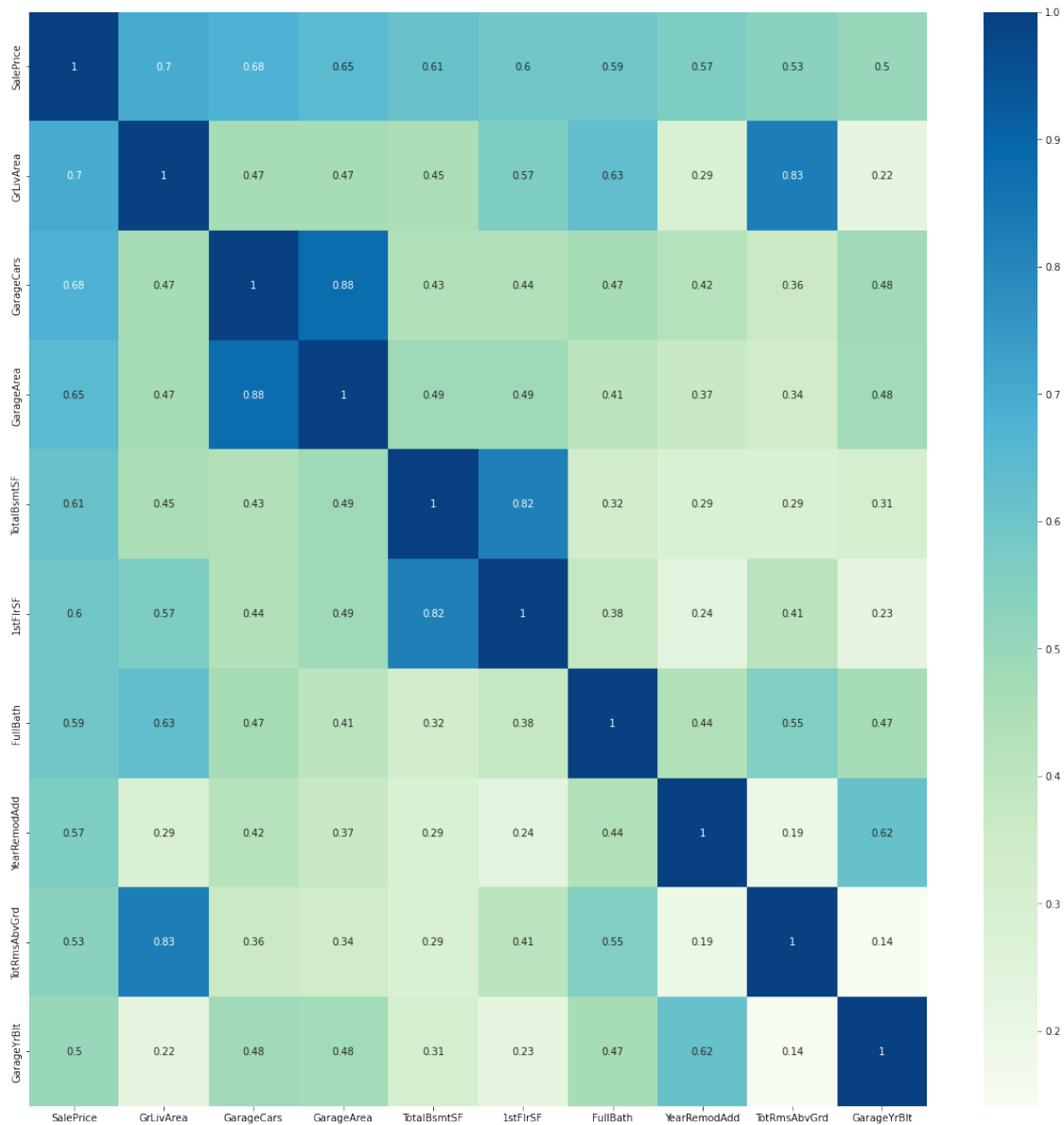
```
[36]: <Axes: >
```



[]:

```
[37]: cols = housing.corr(numeric_only=True).nlargest(10,'SalePrice').index
cm=np.corrcoef(housing[cols].values.T)
plt.figure(figsize=(20,20))
sns.heatmap(cm, annot=True, cmap = 'GnBu', yticklabels=cols.values ,
xticklabels=cols.values)
```

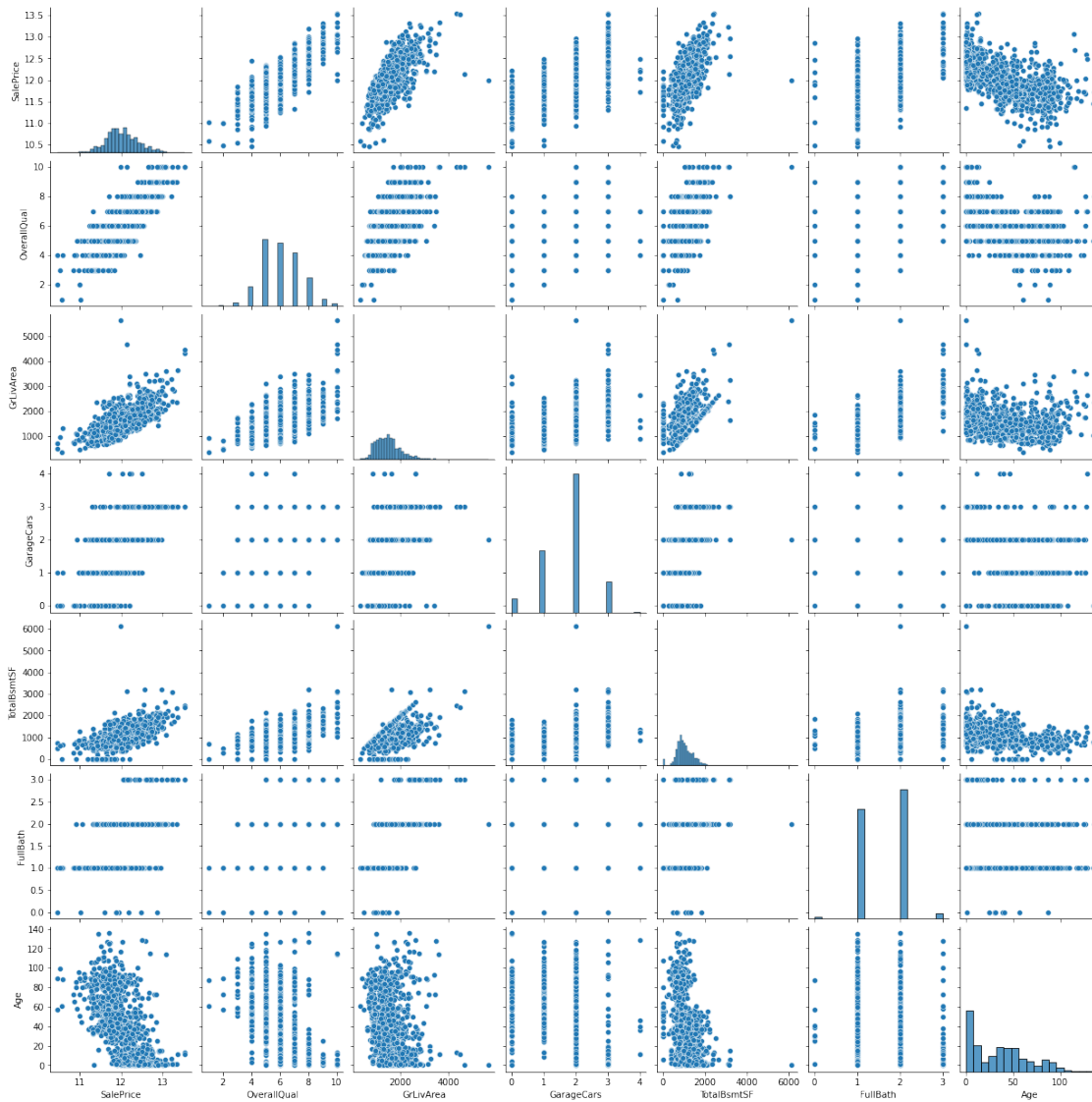
[37]: <Axes: >



```
[ ]:
```

```
[38]: cols = ['SalePrice', 'OverallQual', 'GrLivArea', 'GarageCars', 'TotalBsmtSF', 'FullBath', 'Age']
plt.figure(figsize=(20,20))
sns.pairplot(housing[cols])
plt.show()
```

<Figure size 1440x1440 with 0 Axes>



[]:

5.4 Data Preparation

```
[39]: housing_num = housing.select_dtypes(include=['int64','float64'])
housing_cat = housing.select_dtypes(include='object')
housing_cat.head()
```

```
[39]: MSSubClass MSZoning Street Alley LotShape LandContour Utilities LotConfig \
0          60      RL   Pave   None      Reg        Lvl    AllPub   Inside
1          20      RL   Pave   None      Reg        Lvl    AllPub    FR2
2          60      RL   Pave   None      IR1        Lvl    AllPub   Inside
```

3	70	RL	Pave	None	IR1	Lvl	AllPub	Corner
4	60	RL	Pave	None	IR1	Lvl	AllPub	FR2

	LandSlope	Neighborhood	Condition1	Condition2	BldgType	HouseStyle	\
0	Gtl	CollgCr	Norm	Norm	1Fam	2Story	
1	Gtl	Veenker	Feedr	Norm	1Fam	1Story	
2	Gtl	CollgCr	Norm	Norm	1Fam	2Story	
3	Gtl	Crawfor	Norm	Norm	1Fam	2Story	
4	Gtl	NoRidge	Norm	Norm	1Fam	2Story	

	OverallQual	OverallCond	RoofStyle	RoofMatl	Exterior1st	Exterior2nd	\
0	7	5	Gable	CompShg	VinylSd	VinylSd	
1	6	8	Gable	CompShg	MetalSd	MetalSd	
2	7	5	Gable	CompShg	VinylSd	VinylSd	
3	7	5	Gable	CompShg	Wd Sdng	Wd Shng	
4	8	5	Gable	CompShg	VinylSd	VinylSd	

	MasVnrType	ExterQual	ExterCond	Foundation	BsmtQual	BsmtCond	BsmtExposure	\
0	BrkFace	Gd	TA	PConc	Gd	TA	No	
1	None	TA	TA	CBlock	Gd	TA	Gd	
2	BrkFace	Gd	TA	PConc	Gd	TA	Mn	
3	None	TA	TA	BrkTil	TA	Gd	No	
4	BrkFace	Gd	TA	PConc	Gd	TA	Av	

	BsmtFinType1	BsmtFinType2	Heating	HeatingQC	CentralAir	Electrical	\
0	GLQ	Unf	GasA	Ex	Y	SBrkr	
1	ALQ	Unf	GasA	Ex	Y	SBrkr	
2	GLQ	Unf	GasA	Ex	Y	SBrkr	
3	ALQ	Unf	GasA	Gd	Y	SBrkr	
4	GLQ	Unf	GasA	Ex	Y	SBrkr	

	KitchenQual	Functional	FireplaceQu	GarageType	GarageFinish	GarageQual	\
0	Gd	Typ	None	Attchd	RFn	TA	
1	TA	Typ	TA	Attchd	RFn	TA	
2	Gd	Typ	TA	Attchd	RFn	TA	
3	Gd	Typ	Gd	Detchd	Unf	TA	
4	Gd	Typ	TA	Attchd	RFn	TA	

	GarageCond	PavedDrive	PoolQC	Fence	MiscFeature	SaleType	SaleCondition
0	TA	Y	None	None	None	WD	Normal
1	TA	Y	None	None	None	WD	Normal
2	TA	Y	None	None	None	WD	Normal
3	TA	Y	None	None	None	WD	Abnorml
4	TA	Y	None	None	None	WD	Normal

[]:

```
[40]: housing_cat_dn = pd.get_dummies(housing_cat, drop_first=True, dtype=int)
housing_cat_dn.head()
```

```
[40]: MSSubClass_30 MSSubClass_40 MSSubClass_45 MSSubClass_50 MSSubClass_60 \
0          0          0          0          0          1
1          0          0          0          0          0
2          0          0          0          0          1
3          0          0          0          0          0
4          0          0          0          0          1

MSSubClass_70 MSSubClass_75 MSSubClass_80 MSSubClass_85 MSSubClass_90 \
0          0          0          0          0          0
1          0          0          0          0          0
2          0          0          0          0          0
3          1          0          0          0          0
4          0          0          0          0          0

MSSubClass_120 MSSubClass_160 MSSubClass_180 MSSubClass_190 \
0          0          0          0          0
1          0          0          0          0
2          0          0          0          0
3          0          0          0          0
4          0          0          0          0

MSZoning_FV MSZoning_RH MSZoning_RL MSZoning_RM Street_Pave \
0          0          0          1          0          1
1          0          0          1          0          1
2          0          0          1          0          1
3          0          0          1          0          1
4          0          0          1          0          1

Alley_None Alley_Pave LotShape_IR2 LotShape_IR3 LotShape_Reg \
0          1          0          0          0          1
1          1          0          0          0          1
2          1          0          0          0          0
3          1          0          0          0          0
4          1          0          0          0          0

LandContour_HLS LandContour_Low LandContour_Lvl Utilities_NoSeWa \
0          0          0          1          0
1          0          0          1          0
2          0          0          1          0
3          0          0          1          0
4          0          0          1          0

LotConfig_CulDSac LotConfig_FR2 LotConfig_FR3 LotConfig_Inside \
0          0          0          0          1
```


1	0	1	0	0
2	0	0	0	1
3	0	0	0	0
4	0	1	0	0

	LandSlope_Mod	LandSlope_Sev	Neighborhood_Blueste	Neighborhood_BrDale	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Neighborhood_BrkSide	Neighborhood_ClearCr	Neighborhood_CollgCr	\
0	0	0	1	
1	0	0	0	
2	0	0	1	
3	0	0	0	
4	0	0	0	

	Neighborhood_Crawfor	Neighborhood_Edwards	Neighborhood_Gilbert	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	1	0	0	
4	0	0	0	

	Neighborhood_IDOTRR	Neighborhood_MeadowV	Neighborhood_Mitchel	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Neighborhood_NAmes	Neighborhood_NPkVill	Neighborhood_NWAmes	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Neighborhood_NoRidge	Neighborhood_NridgHt	Neighborhood_OldTown	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	1	0	0	

	Neighborhood_SWISU	Neighborhood_Sawyer	Neighborhood_SawyerW	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Neighborhood_Somerst	Neighborhood_StoneBr	Neighborhood_Timber	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Neighborhood_Veenker	Condition1_Feedr	Condition1_Norm	Condition1_PosA	\
0	0	0	1	0	
1	1	1	0	0	
2	0	0	1	0	
3	0	0	1	0	
4	0	0	1	0	

	Condition1_PosN	Condition1_RRAe	Condition1_RRAn	Condition1_RRNe	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Condition1_RRNn	Condition2_Feedr	Condition2_Norm	Condition2_PosA	\
0	0	0	1	0	
1	0	0	1	0	
2	0	0	1	0	
3	0	0	1	0	
4	0	0	1	0	

	Condition2_PosN	Condition2_RRAe	Condition2_RRAn	Condition2_RRNn	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	BldgType_2fmCon	BldgType_Duplex	BldgType_Twnhs	BldgType_TwnhsE	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	

4	0	0	0	0
---	---	---	---	---

	HouseStyle_1.5Unf	HouseStyle_1Story	HouseStyle_2.5Fin	HouseStyle_2.5Unf	\
0	0	0	0	0	
1	0	1	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	HouseStyle_2Story	HouseStyle_SFoyer	HouseStyle_SLv1	OverallQual_2	\
0	1	0	0	0	
1	0	0	0	0	
2	1	0	0	0	
3	1	0	0	0	
4	1	0	0	0	

	OverallQual_3	OverallQual_4	OverallQual_5	OverallQual_6	OverallQual_7	\
0	0	0	0	0	1	
1	0	0	0	1	0	
2	0	0	0	0	1	
3	0	0	0	0	1	
4	0	0	0	0	0	

	OverallQual_8	OverallQual_9	OverallQual_10	OverallCond_2	OverallCond_3	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	1	0	0	0	0	

	OverallCond_4	OverallCond_5	OverallCond_6	OverallCond_7	OverallCond_8	\
0	0	1	0	0	0	
1	0	0	0	0	1	
2	0	1	0	0	0	
3	0	1	0	0	0	
4	0	1	0	0	0	

	OverallCond_9	RoofStyle_Gable	RoofStyle_Gambrel	RoofStyle_Hip	\
0	0	1	0	0	
1	0	1	0	0	
2	0	1	0	0	
3	0	1	0	0	
4	0	1	0	0	

	RoofStyle_Mansard	RoofStyle_Shed	RoofMatl_CompShg	RoofMatl_Membran	\
0	0	0	1	0	
1	0	0	1	0	

2	0	0	1	0
3	0	0	1	0
4	0	0	1	0

	RoofMatl_Metal	RoofMatl_Roll	RoofMatl_Tar&Grv	RoofMatl_WdShake	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	RoofMatl_WdShngl	Exterior1st_AsphShn	Exterior1st_BrkComm	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior1st_BrkFace	Exterior1st_CBlock	Exterior1st_CemntBd	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior1st_HdBoard	Exterior1st_ImStucc	Exterior1st_MetalSd	\
0	0	0	0	
1	0	0	1	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior1st_Plywood	Exterior1st_Stone	Exterior1st_Stucco	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior1st_VinylSd	Exterior1st_Wd Sdng	Exterior1st_WdShing	\
0	1	0	0	
1	0	0	0	
2	1	0	0	
3	0	1	0	
4	1	0	0	

	Exterior2nd_AsphShn	Exterior2nd_Brk Cmn	Exterior2nd_BrkFace	\
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0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Exterior2nd_CBlock	Exterior2nd_CmentBd	Exterior2nd_HdBoard	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior2nd_ImStucc	Exterior2nd_MetalSd	Exterior2nd_Other	\
0	0	0	0	
1	0	1	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior2nd_Plywood	Exterior2nd_Stone	Exterior2nd_Stucco	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior2nd_VinylSd	Exterior2nd_Wd Sdng	Exterior2nd_Wd Shng	\
0	1	0	0	
1	0	0	0	
2	1	0	0	
3	0	0	1	
4	1	0	0	

	MasVnrType_BrkFace	MasVnrType_None	MasVnrType_Stone	ExterQual_Fa	\
0	1	0	0	0	
1	0	1	0	0	
2	1	0	0	0	
3	0	1	0	0	
4	1	0	0	0	

	ExterQual_Gd	ExterQual_TA	ExterCond_Fa	ExterCond_Gd	ExterCond_Po	\
0	1	0	0	0	0	
1	0	1	0	0	0	
2	1	0	0	0	0	
3	0	1	0	0	0	
4	1	0	0	0	0	

	ExterCond_TA	Foundation_CBlock	Foundation_PConc	Foundation_Slab	\
0	1	0	1	0	
1	1	1	0	0	
2	1	0	1	0	
3	1	0	0	0	
4	1	0	1	0	

	Foundation_Stone	Foundation_Wood	BsmtQual_Fa	BsmtQual_Gd	BsmtQual_None	\
0	0	0	0	1	0	
1	0	0	0	1	0	
2	0	0	0	1	0	
3	0	0	0	0	0	
4	0	0	0	1	0	

	BsmtQual_TA	BsmtCond_Gd	BsmtCond_None	BsmtCond_Po	BsmtCond_TA	\
0	0	0	0	0	1	
1	0	0	0	0	1	
2	0	0	0	0	1	
3	1	1	0	0	0	
4	0	0	0	0	1	

	BsmtExposure_Gd	BsmtExposure_Mn	BsmtExposure_No	BsmtExposure_None	\
0	0	0	1	0	
1	1	0	0	0	
2	0	1	0	0	
3	0	0	1	0	
4	0	0	0	0	

	BsmtFinType1_BLQ	BsmtFinType1_GLQ	BsmtFinType1_LwQ	BsmtFinType1_None	\
0	0	1	0	0	
1	0	0	0	0	
2	0	1	0	0	
3	0	0	0	0	
4	0	1	0	0	

	BsmtFinType1_Rec	BsmtFinType1_Unf	BsmtFinType2_BLQ	BsmtFinType2_GLQ	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	BsmtFinType2_LwQ	BsmtFinType2_None	BsmtFinType2_Rec	BsmtFinType2_Unf	\
0	0	0	0	1	
1	0	0	0	1	
2	0	0	0	1	

3	0	0	0	1
4	0	0	0	1

	Heating_GasA	Heating_GasW	Heating_Grav	Heating_OthW	Heating_Wall	\
0	1	0	0	0	0	
1	1	0	0	0	0	
2	1	0	0	0	0	
3	1	0	0	0	0	
4	1	0	0	0	0	

	HeatingQC_Fa	HeatingQC_Gd	HeatingQC_Po	HeatingQC_TA	CentralAir_Y	\
0	0	0	0	0	1	
1	0	0	0	0	1	
2	0	0	0	0	1	
3	0	1	0	0	1	
4	0	0	0	0	1	

	Electrical_FuseF	Electrical_FuseP	Electrical_Mix	Electrical_None	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Electrical_SBrkr	KitchenQual_Fa	KitchenQual_Gd	KitchenQual_TA	\
0	1	0	1	0	
1	1	0	0	1	
2	1	0	1	0	
3	1	0	1	0	
4	1	0	1	0	

	Functional_Maj2	Functional_Min1	Functional_Min2	Functional_Mod	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Functional_Sev	Functional_Typ	FireplaceQu_Fa	FireplaceQu_Gd	\
0	0	1	0	0	
1	0	1	0	0	
2	0	1	0	0	
3	0	1	0	1	
4	0	1	0	0	

	FireplaceQu_None	FireplaceQu_Po	FireplaceQu_TA	GarageType_Attchd	\
0	1	0	0	1	

1	0	0	1	1
2	0	0	1	1
3	0	0	0	0
4	0	0	1	1

	GarageType_Basment	GarageType_BuiltIn	GarageType_CarPort	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	GarageType_Detachd	GarageType_None	GarageFinish_None	GarageFinish_RFn	\
0	0	0	0	1	
1	0	0	0	1	
2	0	0	0	1	
3	1	0	0	0	
4	0	0	0	1	

	GarageFinish_Unf	GarageQual_Fa	GarageQual_Gd	GarageQual_None	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	1	0	0	0	
4	0	0	0	0	

	GarageQual_Po	GarageQual_TA	GarageCond_Fa	GarageCond_Gd	\
0	0	1	0	0	
1	0	1	0	0	
2	0	1	0	0	
3	0	1	0	0	
4	0	1	0	0	

	GarageCond_None	GarageCond_Po	GarageCond_TA	PavedDrive_P	PavedDrive_Y	\
0	0	0	1	0	1	
1	0	0	1	0	1	
2	0	0	1	0	1	
3	0	0	1	0	1	
4	0	0	1	0	1	

	PoolQC_Fa	PoolQC_Gd	PoolQC_None	Fence_GdWo	Fence_MnPrv	Fence_MnWw	\
0	0	0	1	0	0	0	
1	0	0	1	0	0	0	
2	0	0	1	0	0	0	
3	0	0	1	0	0	0	
4	0	0	1	0	0	0	

	Fence_None	MiscFeature_None	MiscFeature_Othr	MiscFeature_Shed	\
0	1	1	0	0	
1	1	1	0	0	
2	1	1	0	0	
3	1	1	0	0	
4	1	1	0	0	

	MiscFeature_TenC	SaleType_CWD	SaleType_Con	SaleType_ConLD	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	SaleType_ConLI	SaleType_ConLw	SaleType_New	SaleType_Oth	SaleType_WD	\
0	0	0	0	0	1	
1	0	0	0	0	1	
2	0	0	0	0	1	
3	0	0	0	0	1	
4	0	0	0	0	1	

	SaleCondition_AdjLand	SaleCondition_Alloca	SaleCondition_Family	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	SaleCondition_Normal	SaleCondition_Partial
0	1	0
1	1	0
2	1	0
3	0	0
4	1	0

```
[ ]:
```

```
[41]: house = pd.concat([housing_num, housing_cat_dn], axis=1)
```

```
[42]: house.shape
```

```
[42]: (1460, 288)
```

```
[ ]:
```

```
[43]: x = house.drop(['SalePrice'], axis=1).copy()
      y = house['SalePrice'].copy()
```

```
[44]: x.head()
```

```
[44]:
```

	LotFrontage	LotArea	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	\
0	65.0	8450	2003	196.0	706	0	
1	80.0	9600	1976	0.0	978	0	
2	68.0	11250	2002	162.0	486	0	
3	60.0	9550	1970	0.0	216	0	
4	84.0	14260	2000	350.0	655	0	

	BsmtUnfSF	TotalBsmtSF	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	\
0	150	856	856	854	0	1710	
1	284	1262	1262	0	0	1262	
2	434	920	920	866	0	1786	
3	540	756	961	756	0	1717	
4	490	1145	1145	1053	0	2198	

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

	TotRmsAbvGrd	Fireplaces	GarageYrBlt	GarageCars	GarageArea	WoodDeckSF	\
0	8	0	2003.0	2	548	0	
1	6	1	1976.0	2	460	298	
2	6	1	2001.0	2	608	0	
3	7	1	1998.0	3	642	0	
4	9	1	2000.0	3	836	192	

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

	MoSold	Age	MSSubClass_30	MSSubClass_40	MSSubClass_45	MSSubClass_50	\
0	2	5	0	0	0	0	
1	5	31	0	0	0	0	
2	9	7	0	0	0	0	
3	2	91	0	0	0	0	
4	12	8	0	0	0	0	

	MSSubClass_60	MSSubClass_70	MSSubClass_75	MSSubClass_80	MSSubClass_85	\
0	1	0	0	0	0	
1	0	0	0	0	0	

2	1	0	0	0	0
3	0	1	0	0	0
4	1	0	0	0	0

	MSSubClass_90	MSSubClass_120	MSSubClass_160	MSSubClass_180	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	MSSubClass_190	MSZoning_FV	MSZoning_RH	MSZoning_RL	MSZoning_RM	\
0	0	0	0	1	0	
1	0	0	0	1	0	
2	0	0	0	1	0	
3	0	0	0	1	0	
4	0	0	0	1	0	

	Street_Pave	Alley_None	Alley_Pave	LotShape_IR2	LotShape_IR3	\
0	1	1	0	0	0	
1	1	1	0	0	0	
2	1	1	0	0	0	
3	1	1	0	0	0	
4	1	1	0	0	0	

	LotShape_Reg	LandContour_HLS	LandContour_Low	LandContour_Lvl	\
0	1	0	0	1	
1	1	0	0	1	
2	0	0	0	1	
3	0	0	0	1	
4	0	0	0	1	

	Utilities_NoSeWa	LotConfig_CulDSac	LotConfig_FR2	LotConfig_FR3	\
0	0	0	0	0	
1	0	0	1	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	1	0	

	LotConfig_Inside	LandSlope_Mod	LandSlope_Sev	Neighborhood_Blueste	\
0	1	0	0	0	
1	0	0	0	0	
2	1	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Neighborhood_BrDale	Neighborhood_BrkSide	Neighborhood_ClearCr	\
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0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Neighborhood_CollgCr	Neighborhood_Crawfor	Neighborhood_Edwards	\
0	1	0	0	
1	0	0	0	
2	1	0	0	
3	0	1	0	
4	0	0	0	

	Neighborhood_Gilbert	Neighborhood_IDOTRR	Neighborhood_MeadowV	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Neighborhood_Mitchel	Neighborhood_NAmes	Neighborhood_NPkVill	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Neighborhood_NWAmes	Neighborhood_NoRidge	Neighborhood_NridgHt	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	1	0	

	Neighborhood_OldTown	Neighborhood_SWISU	Neighborhood_Sawyer	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Neighborhood_SawyerW	Neighborhood_Somerst	Neighborhood_StoneBr	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Neighborhood_Timber	Neighborhood_Veenker	Condition1_Feedr	\
0	0	0	0	
1	0	1	1	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Condition1_Norm	Condition1_PosA	Condition1_PosN	Condition1_RRAe	\
0	1	0	0	0	
1	0	0	0	0	
2	1	0	0	0	
3	1	0	0	0	
4	1	0	0	0	

	Condition1_RRAn	Condition1_RRNe	Condition1_RRNn	Condition2_Feedr	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Condition2_Norm	Condition2_PosA	Condition2_PosN	Condition2_RRAe	\
0	1	0	0	0	
1	1	0	0	0	
2	1	0	0	0	
3	1	0	0	0	
4	1	0	0	0	

	Condition2_RRAn	Condition2_RRNn	BldgType_2fmCon	BldgType_Duplex	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	BldgType_Twnhs	BldgType_TwnhsE	HouseStyle_1.5Unf	HouseStyle_1Story	\
0	0	0	0	0	
1	0	0	0	1	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	HouseStyle_2.5Fin	HouseStyle_2.5Unf	HouseStyle_2Story	HouseStyle_SFoyer	\
0	0	0	1	0	
1	0	0	0	0	
2	0	0	1	0	

3	0	0	1	0
4	0	0	1	0

	HouseStyle_SLvl	OverallQual_2	OverallQual_3	OverallQual_4	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	OverallQual_5	OverallQual_6	OverallQual_7	OverallQual_8	OverallQual_9	\
0	0	0	1	0	0	
1	0	1	0	0	0	
2	0	0	1	0	0	
3	0	0	1	0	0	
4	0	0	0	1	0	

	OverallQual_10	OverallCond_2	OverallCond_3	OverallCond_4	OverallCond_5	\
0	0	0	0	0	1	
1	0	0	0	0	0	
2	0	0	0	0	1	
3	0	0	0	0	1	
4	0	0	0	0	1	

	OverallCond_6	OverallCond_7	OverallCond_8	OverallCond_9	\
0	0	0	0	0	
1	0	0	1	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	RoofStyle_Gable	RoofStyle_Gambrel	RoofStyle_Hip	RoofStyle_Mansard	\
0	1	0	0	0	
1	1	0	0	0	
2	1	0	0	0	
3	1	0	0	0	
4	1	0	0	0	

	RoofStyle_Shed	RoofMatl_CompShg	RoofMatl_Membran	RoofMatl_Metal	\
0	0	1	0	0	
1	0	1	0	0	
2	0	1	0	0	
3	0	1	0	0	
4	0	1	0	0	

	RoofMatl_Roll	RoofMatl_Tar&Grv	RoofMatl_WdShake	RoofMatl_WdShngl	\
0	0	0	0	0	

1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Exterior1st_AsphShn	Exterior1st_BrkComm	Exterior1st_BrkFace	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior1st_CBlock	Exterior1st_CemntBd	Exterior1st_HdBoard	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior1st_ImStucc	Exterior1st_MetalSd	Exterior1st_Plywood	\
0	0	0	0	
1	0	1	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior1st_Stone	Exterior1st_Stucco	Exterior1st_VinylSd	\
0	0	0	1	
1	0	0	0	
2	0	0	1	
3	0	0	0	
4	0	0	1	

	Exterior1st_Wd Sdng	Exterior1st_WdShing	Exterior2nd_AsphShn	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	1	0	0	
4	0	0	0	

	Exterior2nd_Brk Cmn	Exterior2nd_BrkFace	Exterior2nd_CBlock	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior2nd_CmentBd	Exterior2nd_HdBoard	Exterior2nd_ImStucc	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior2nd_MetalSd	Exterior2nd_Other	Exterior2nd_Plywood	\
0	0	0	0	
1	1	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Exterior2nd_Stone	Exterior2nd_Stucco	Exterior2nd_VinylSd	\
0	0	0	1	
1	0	0	0	
2	0	0	1	
3	0	0	0	
4	0	0	1	

	Exterior2nd_Wd Sdng	Exterior2nd_Wd Shng	MasVnrType_BrkFace	\
0	0	0	1	
1	0	0	0	
2	0	0	1	
3	0	1	0	
4	0	0	1	

	MasVnrType_None	MasVnrType_Stone	ExterQual_Fa	ExterQual_Gd	\
0	0	0	0	1	
1	1	0	0	0	
2	0	0	0	1	
3	1	0	0	0	
4	0	0	0	1	

	ExterQual_TA	ExterCond_Fa	ExterCond_Gd	ExterCond_Po	ExterCond_TA	\
0	0	0	0	0	1	
1	1	0	0	0	1	
2	0	0	0	0	1	
3	1	0	0	0	1	
4	0	0	0	0	1	

	Foundation_CBlock	Foundation_PConc	Foundation_Slab	Foundation_Stone	\
0	0	1	0	0	
1	1	0	0	0	
2	0	1	0	0	
3	0	0	0	0	

4	0	1	0	0
---	---	---	---	---

	Foundation_Wood	BsmtQual_Fa	BsmtQual_Gd	BsmtQual_None	BsmtQual_TA	\
0	0	0	1	0	0	
1	0	0	1	0	0	
2	0	0	1	0	0	
3	0	0	0	0	1	
4	0	0	1	0	0	

	BsmtCond_Gd	BsmtCond_None	BsmtCond_Po	BsmtCond_TA	BsmtExposure_Gd	\
0	0	0	0	1	0	
1	0	0	0	1	1	
2	0	0	0	1	0	
3	1	0	0	0	0	
4	0	0	0	1	0	

	BsmtExposure_Mn	BsmtExposure_No	BsmtExposure_None	BsmtFinType1_BLQ	\
0	0	1	0	0	
1	0	0	0	0	
2	1	0	0	0	
3	0	1	0	0	
4	0	0	0	0	

	BsmtFinType1_GLQ	BsmtFinType1_LwQ	BsmtFinType1_None	BsmtFinType1_Rec	\
0	1	0	0	0	
1	0	0	0	0	
2	1	0	0	0	
3	0	0	0	0	
4	1	0	0	0	

	BsmtFinType1_Unf	BsmtFinType2_BLQ	BsmtFinType2_GLQ	BsmtFinType2_LwQ	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	BsmtFinType2_None	BsmtFinType2_Rec	BsmtFinType2_Unf	Heating_GasA	\
0	0	0	1	1	
1	0	0	1	1	
2	0	0	1	1	
3	0	0	1	1	
4	0	0	1	1	

	Heating_GasW	Heating_Grav	Heating_OthW	Heating_Wall	HeatingQC_Fa	\
0	0	0	0	0	0	
1	0	0	0	0	0	

2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	HeatingQC_Gd	HeatingQC_Po	HeatingQC_TA	CentralAir_Y	Electrical_FuseF	\
0	0	0	0	1	0	
1	0	0	0	1	0	
2	0	0	0	1	0	
3	1	0	0	1	0	
4	0	0	0	1	0	

	Electrical_FuseP	Electrical_Mix	Electrical_None	Electrical_SBrkr	\
0	0	0	0	1	
1	0	0	0	1	
2	0	0	0	1	
3	0	0	0	1	
4	0	0	0	1	

	KitchenQual_Fa	KitchenQual_Gd	KitchenQual_TA	Functional_Maj2	\
0	0	1	0	0	
1	0	0	1	0	
2	0	1	0	0	
3	0	1	0	0	
4	0	1	0	0	

	Functional_Min1	Functional_Min2	Functional_Mod	Functional_Sev	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Functional_Typ	FireplaceQu_Fa	FireplaceQu_Gd	FireplaceQu_None	\
0	1	0	0	1	
1	1	0	0	0	
2	1	0	0	0	
3	1	0	1	0	
4	1	0	0	0	

	FireplaceQu_Po	FireplaceQu_TA	GarageType_Attchd	GarageType_Basment	\
0	0	0	1	0	
1	0	1	1	0	
2	0	1	1	0	
3	0	0	0	0	
4	0	1	1	0	

	GarageType_BuiltIn	GarageType_CarPort	GarageType_Detchd	GarageType_None	\
--	--------------------	--------------------	-------------------	-----------------	---

0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	1	0
4	0	0	0	0

	GarageFinish_None	GarageFinish_RFn	GarageFinish_Unf	GarageQual_Fa	\
0	0	1	0	0	
1	0	1	0	0	
2	0	1	0	0	
3	0	0	1	0	
4	0	1	0	0	

	GarageQual_Gd	GarageQual_None	GarageQual_Po	GarageQual_TA	\
0	0	0	0	1	
1	0	0	0	1	
2	0	0	0	1	
3	0	0	0	1	
4	0	0	0	1	

	GarageCond_Fa	GarageCond_Gd	GarageCond_None	GarageCond_Po	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	GarageCond_TA	PavedDrive_P	PavedDrive_Y	PoolQC_Fa	PoolQC_Gd	\
0	1	0	1	0	0	
1	1	0	1	0	0	
2	1	0	1	0	0	
3	1	0	1	0	0	
4	1	0	1	0	0	

	PoolQC_None	Fence_GdWo	Fence_MnPrv	Fence_MnWw	Fence_None	\
0	1	0	0	0	1	
1	1	0	0	0	1	
2	1	0	0	0	1	
3	1	0	0	0	1	
4	1	0	0	0	1	

	MiscFeature_None	MiscFeature_Othr	MiscFeature_Shed	MiscFeature_TenC	\
0	1	0	0	0	
1	1	0	0	0	
2	1	0	0	0	
3	1	0	0	0	
4	1	0	0	0	

	SaleType_CWD	SaleType_Con	SaleType_ConLD	SaleType_ConLI	SaleType_ConLw	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	SaleType_New	SaleType_Oth	SaleType_WD	SaleCondition_AdjLand	\
0	0	0	1	0	
1	0	0	1	0	
2	0	0	1	0	
3	0	0	1	0	
4	0	0	1	0	

	SaleCondition_Alloca	SaleCondition_Family	SaleCondition_Normal	\
0	0	0	1	
1	0	0	1	
2	0	0	1	
3	0	0	0	
4	0	0	1	

	SaleCondition_Partial
0	0
1	0
2	0
3	0
4	0

```
[ ]:
```

Data Split

```
[45]: from sklearn.model_selection import train_test_split
      from sklearn.preprocessing import StandardScaler
```

```
[46]: X_train ,X_test, y_train, y_test = train_test_split(x,y,test_size = 0.33,
      ↪random_state=42)
```

```
[47]: num_cols = list(X_train.select_dtypes(include=['int64', 'float64']).columns)
```

```
[48]: num_cols
```

```
[48]: ['LotFrontage',
      'LotArea',
      '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',
'Age',
'MSSubClass_30',
'MSSubClass_40',
'MSSubClass_45',
'MSSubClass_50',
'MSSubClass_60',
'MSSubClass_70',
'MSSubClass_75',
'MSSubClass_80',
'MSSubClass_85',
'MSSubClass_90',
'MSSubClass_120',
'MSSubClass_160',
'MSSubClass_180',
'MSSubClass_190',
'MSZoning_FV',
'MSZoning_RH',
'MSZoning_RL',
'MSZoning_RM',
'Street_Pave',

'Alley_None',
'Alley_Pave',
'LotShape_IR2',
'LotShape_IR3',
'LotShape_Reg',
'LandContour_HLS',
'LandContour_Low',
'LandContour_Lvl',
'Utilities_NoSeWa',
'LotConfig_CulDSac',
'LotConfig_FR2',
'LotConfig_FR3',
'LotConfig_Inside',
'LandSlope_Mod',
'LandSlope_Sev',
'Neighborhood_Blueste',
'Neighborhood_BrDale',
'Neighborhood_BrkSide',
'Neighborhood_ClearCr',
'Neighborhood_CollgCr',
'Neighborhood_Crawfor',
'Neighborhood_Edwards',
'Neighborhood_Gilbert',
'Neighborhood_IDOTRR',
'Neighborhood_MeadowV',
'Neighborhood_Mitchel',
'Neighborhood_NAmes',
'Neighborhood_NPkVill',
'Neighborhood_NWAmes',
'Neighborhood_NoRidge',
'Neighborhood_NridgHt',
'Neighborhood_OldTown',
'Neighborhood_SWISU',
'Neighborhood_Sawyer',
'Neighborhood_SawyerW',
'Neighborhood_Somerst',
'Neighborhood_StoneBr',
'Neighborhood_Timber',
'Neighborhood_Veenker',
'Condition1_Feedr',
'Condition1_Norm',
'Condition1_PosA',
'Condition1_PosN',
'Condition1_RRAe',
'Condition1_RRAn',
'Condition1_RRNe',
'Condition1_RRNn',

'Condition2_Feedr',
'Condition2_Norm',
'Condition2_PosA',
'Condition2_PosN',
'Condition2_RRAe',
'Condition2_RRAn',
'Condition2_RRNn',
'BldgType_2fmCon',
'BldgType_Duplex',
'BldgType_Twnhs',
'BldgType_TwnhsE',
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'HouseStyle_2.5Fin',
'HouseStyle_2.5Unf',
'HouseStyle_2Story',
'HouseStyle_SFoyer',
'HouseStyle_SLvl',
'OverallQual_2',
'OverallQual_3',
'OverallQual_4',
'OverallQual_5',
'OverallQual_6',
'OverallQual_7',
'OverallQual_8',
'OverallQual_9',
'OverallQual_10',
'OverallCond_2',
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'OverallCond_4',
'OverallCond_5',
'OverallCond_6',
'OverallCond_7',
'OverallCond_8',
'OverallCond_9',
'RoofStyle_Gable',
'RoofStyle_Gambrel',
'RoofStyle_Hip',
'RoofStyle_Mansard',
'RoofStyle_Shed',
'RoofMatl_CompShg',
'RoofMatl_Membran',
'RoofMatl_Metal',
'RoofMatl_Roll',
'RoofMatl_Tar&Grv',
'RoofMatl_WdShake',
'RoofMatl_WdShngl',

'Exterior1st_AsphShn',
'Exterior1st_BrkComm',
'Exterior1st_BrkFace',
'Exterior1st_CBlock',
'Exterior1st_CemntBd',
'Exterior1st_HdBoard',
'Exterior1st_ImStucc',
'Exterior1st_MetalSd',
'Exterior1st_Plywood',
'Exterior1st_Stone',
'Exterior1st_Stucco',
'Exterior1st_VinylSd',
'Exterior1st_Wd Sdng',
'Exterior1st_WdShing',
'Exterior2nd_AsphShn',
'Exterior2nd_Brk Cmn',
'Exterior2nd_BrkFace',
'Exterior2nd_CBlock',
'Exterior2nd_CmentBd',
'Exterior2nd_HdBoard',
'Exterior2nd_ImStucc',
'Exterior2nd_MetalSd',
'Exterior2nd_Other',
'Exterior2nd_Plywood',
'Exterior2nd_Stone',
'Exterior2nd_Stucco',
'Exterior2nd_VinylSd',
'Exterior2nd_Wd Sdng',
'Exterior2nd_Wd Shng',
'MasVnrType_BrkFace',
'MasVnrType_None',
'MasVnrType_Stone',
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'ExterQual_Gd',
'ExterQual_TA',
'ExterCond_Fa',
'ExterCond_Gd',
'ExterCond_Po',
'ExterCond_TA',
'Foundation_CBlock',
'Foundation_PConc',
'Foundation_Slab',
'Foundation_Stone',
'Foundation_Wood',
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'BsmtQual_Gd',
'BsmtQual_None',

'BsmtQual_TA',
'BsmtCond_Gd',
'BsmtCond_None',
'BsmtCond_Po',
'BsmtCond_TA',
'BsmtExposure_Gd',
'BsmtExposure_Mn',
'BsmtExposure_No',
'BsmtExposure_None',
'BsmtFinType1_BLQ',
'BsmtFinType1_GLQ',
'BsmtFinType1_LwQ',
'BsmtFinType1_None',
'BsmtFinType1_Rec',
'BsmtFinType1_Unf',
'BsmtFinType2_BLQ',
'BsmtFinType2_GLQ',
'BsmtFinType2_LwQ',
'BsmtFinType2_None',
'BsmtFinType2_Rec',
'BsmtFinType2_Unf',
'Heating_GasA',
'Heating_GasW',
'Heating_Grav',
'Heating_OthW',
'Heating_Wall',
'HeatingQC_Fa',
'HeatingQC_Gd',
'HeatingQC_Po',
'HeatingQC_TA',
'CentralAir_Y',
'Electrical_FuseF',
'Electrical_FuseP',
'Electrical_Mix',
'Electrical_None',
'Electrical_SBrkr',
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'KitchenQual_Gd',
'KitchenQual_TA',
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'Functional_Min1',
'Functional_Min2',
'Functional_Mod',
'Functional_Sev',
'Functional_Typ',
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'FireplaceQu_Gd',

'FireplaceQu_None',
'FireplaceQu_Po',
'FireplaceQu_TA',
'GarageType_Attchd',
'GarageType_Basment',
'GarageType_BuiltIn',
'GarageType_CarPort',
'GarageType_Detchd',
'GarageType_None',
'GarageFinish_None',
'GarageFinish_RFn',
'GarageFinish_Unf',
'GarageQual_Fa',
'GarageQual_Gd',
'GarageQual_None',
'GarageQual_Po',
'GarageQual_TA',
'GarageCond_Fa',
'GarageCond_Gd',
'GarageCond_None',
'GarageCond_Po',
'GarageCond_TA',
'PavedDrive_P',
'PavedDrive_Y',
'PoolQC_Fa',
'PoolQC_Gd',
'PoolQC_None',
'Fence_GdWo',
'Fence_MnPrv',
'Fence_MnWw',
'Fence_None',
'MiscFeature_None',
'MiscFeature_Othr',
'MiscFeature_Shed',
'MiscFeature_TenC',
'SaleType_CWD',
'SaleType_Con',
'SaleType_ConLD',
'SaleType_ConLI',
'SaleType_ConLw',
'SaleType_New',
'SaleType_Oth',
'SaleType_WD',
'SaleCondition_AdjLand',
'SaleCondition_Alloca',
'SaleCondition_Family',
'SaleCondition_Normal',

```
'SaleCondition_Partial']
```

```
[ ]:
```

```
[49]: scaler = StandardScaler()
X_train[num_cols] = scaler.fit_transform(X_train[num_cols])
X_test[num_cols] = scaler.fit_transform(X_test[num_cols])
```

```
[50]: def eval_metrics(y_train, y_train_pred, y_test, y_test_pred):

    # r2 values for train and test
    print('r2 score (train) - ', '%.2f' % r2_score(y_train,y_train_pred))
    print('r2 score (test) - ', '%.2f' % r2_score(y_test,y_test_pred))

    ## RMSE for train and test data
    mse_train = mean_squared_error(y_train,y_train_pred)
    mse_test = mean_squared_error(y_test,y_test_pred)
    rmse_train = mse_train**0.5
    rmse_test = mse_test**0.5

    print("RMSE(TRAIN) - ", '%.2f' % rmse_train)
    print("RMSE(TEST) - ", '%.2f' % rmse_test)
```

5.5 ML MODEL

```
[51]: import sklearn
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.linear_model import Ridge, Lasso
from sklearn.model_selection import GridSearchCV
```

```
[52]: from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV

params = {'alpha':
          [0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.
↪9, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 25, 50, 75, 100, 250, 500, 750, 1000]
          }

ridge = Ridge()
ridgeCV = GridSearchCV(estimator=ridge, param_grid=params,
↪scoring='neg_mean_absolute_error', cv=5, return_train_score=True, verbose=1,
↪n_jobs=1)
ridgeCV.fit(X_train, y_train)
```

Fitting 5 folds for each of 32 candidates, totalling 160 fits

```
[52]: GridSearchCV(cv=5, estimator=Ridge(), n_jobs=1,
                param_grid={'alpha': [0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3,
                                       0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 2, 3, 4, 5,
                                       6, 7, 8, 9, 10, 20, 25, 50, 75, 100, 250,
                                       500, ...]},
                return_train_score=True, scoring='neg_mean_absolute_error',
                verbose=1)
```

```
[ ]:
```

```
[53]: ridgeCV.best_params_
```

```
[53]: {'alpha': 250}
```

```
[ ]:
```

```
[54]: ridgeCV.cv_results_
```

```
[54]: {'mean_fit_time': array([0.0879035 , 0.08687029, 0.07577825, 0.0755312 ,
                                0.07479348,
                                0.07905078, 0.08429389, 0.08706932, 0.08368921, 0.08998322,
                                0.07541676, 0.08752074, 0.08594232, 0.08607178, 0.08531208,
                                0.0811583 , 0.06979175, 0.07075171, 0.07719626, 0.08130217,
                                0.07936773, 0.06606183, 0.08393402, 0.05928211, 0.06819053,
                                0.0789144 , 0.06750736, 0.08448939, 0.08441358, 0.08480988,
                                0.08471651, 0.08316207]),
        'std_fit_time': array([0.04597761, 0.01236269, 0.00977123, 0.03088432,
                                0.01295795,
                                0.00880811, 0.00137102, 0.0021064 , 0.00235141, 0.01406186,
                                0.01399517, 0.00514582, 0.0018703 , 0.00281302, 0.00130704,
                                0.01623709, 0.01463442, 0.01444202, 0.01270581, 0.00381954,
                                0.01332118, 0.02274605, 0.01595511, 0.02505871, 0.01572118,
                                0.01566747, 0.006522 , 0.01161833, 0.00090567, 0.00057201,
                                0.00065993, 0.00379906]),
        'mean_score_time': array([0.05911541, 0.08071237, 0.05309186, 0.02615752,
                                0.04332337,
                                0.06106305, 0.04901495, 0.04834385, 0.04917574, 0.04904785,
                                0.05622959, 0.04826484, 0.04835591, 0.04808297, 0.04816327,
                                0.03980894, 0.02977624, 0.03468914, 0.03964577, 0.0496047 ,
                                0.10831199, 0.03609529, 0.05374885, 0.06438694, 0.02742629,
                                0.04867282, 0.05029893, 0.04822898, 0.04802637, 0.04747496,
                                0.04781432, 0.04311996]),
        'std_score_time': array([2.40487824e-02, 1.79224577e-02, 9.59164610e-03,
                                2.02028572e-04,
                                1.13811726e-02, 2.21855676e-02, 2.96565749e-04, 2.06031095e-03,
                                2.99653098e-04, 3.53858622e-04, 9.86223932e-03, 2.62163864e-04,
                                3.51321716e-04, 1.44432204e-04, 1.41744335e-04, 1.26344061e-02,
```

```

1.03717908e-02, 1.21697034e-02, 1.24327482e-02, 1.83345650e-03,
1.24486535e-01, 1.34331295e-02, 1.21108773e-02, 1.01273043e-02,
7.51217231e-04, 1.73447043e-02, 8.72465619e-03, 6.28183678e-03,
4.29587288e-04, 9.51426480e-05, 4.47419876e-04, 9.14309221e-03]),
'param_alpha': masked_array(data=[0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3,
0.4, 0.5,
                                0.6, 0.7, 0.8, 0.9, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20,
                                25, 50, 75, 100, 250, 500, 750, 1000],
                                mask=[False, False, False, False, False, False, False, False,
                                False, False, False, False, False, False, False, False, False, False, False,
                                False, False, False, False, False, False, False, False, False,
                                False, False, False, False, False, False, False, False, False],
                                fill_value='?',
                                dtype=object),
'params': [{'alpha': 0.0001},
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{'alpha': 25},
{'alpha': 50},
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{'alpha': 250},
{'alpha': 500},
{'alpha': 750},
{'alpha': 1000}],
'split0_test_score': array([-0.1081354 , -0.10813011, -0.10807762, -0.10785282,

```

```

-0.10759944,
    -0.10714982, -0.10675376, -0.10639564, -0.1060812 , -0.10579298,
    -0.10552539, -0.10527524, -0.10503998, -0.10481904, -0.10347827,
    -0.1026274 , -0.10199151, -0.10146577, -0.1010282 , -0.10064712,
    -0.10032384, -0.10002332, -0.09974587, -0.09785385, -0.09719699,
    -0.09517043, -0.09402131, -0.0933147 , -0.09222951, -0.09415239,
    -0.09694953, -0.09975034]],
'split1_test_score': array([-0.11704567, -0.11704724, -0.11706208, -0.11711289,
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    -0.11755135, -0.11771725, -0.1177954 , -0.11782005, -0.11780789,
    -0.11776994, -0.11771376, -0.11764443, -0.11757196, -0.11667041,
    -0.11573994, -0.11492204, -0.11424224, -0.11365868, -0.11312632,
    -0.11265518, -0.11223772, -0.11184761, -0.1090066 , -0.10801746,
    -0.10502548, -0.10362202, -0.10264378, -0.10026259, -0.1002254 ,
    -0.10135933, -0.10325652]],
'split2_test_score': array([-0.11390045, -0.11386392, -0.11351017, -0.11215609,
-0.11084421,
    -0.10902431, -0.10816938, -0.10755279, -0.10707397, -0.10668746,
    -0.10638972, -0.1062716 , -0.1062677 , -0.1062628 , -0.10642655,
    -0.1063922 , -0.10635415, -0.10627525, -0.10618395, -0.10613879,
    -0.10609011, -0.10603696, -0.10598997, -0.10543159, -0.10512938,
    -0.10377669, -0.10269111, -0.10184112, -0.09981971, -0.10151928,
    -0.10543341, -0.10951323]],
'split3_test_score': array([-0.10861138, -0.1086083 , -0.10857759, -0.10844477,
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    -0.10817885, -0.10807806, -0.10796697, -0.10785795, -0.10774713,
    -0.10763376, -0.10751916, -0.10740416, -0.1072906 , -0.1064039 ,
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    -0.09489088, -0.09739477]],
'split4_test_score': array([-0.10267967, -0.10265759, -0.10244313, -0.1016464 ,
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    -0.09709478, -0.09688106, -0.09688386, -0.09684008, -0.0968561 ,
    -0.09687889, -0.09690954, -0.09692111, -0.0964555 , -0.09605839,
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    -0.09594534, -0.09823913]],
'mean_test_score': array([-0.11007452, -0.11006143, -0.10993412, -0.10944259,
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    -0.10392589, -0.10370867, -0.10350049, -0.1017938 , -0.10110287,
    -0.09872197, -0.0973427 , -0.09642978, -0.09489977, -0.09633076,
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'std_test_score': array([0.00497633, 0.00497833, 0.00499995, 0.00510882,
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    0.00466024, 0.00476857, 0.00477489, 0.0042496 , 0.00378724,
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'rank_test_score': array([32, 31, 30, 29, 28, 27, 26, 25, 24, 23, 22, 21, 20,
19, 18, 17, 16,
    15, 14, 13, 12, 11, 10,  9,  7,  5,  4,  3,  1,  2,  6,  8],
    dtype=int32),
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'split1_train_score': array([-0.05522149, -0.05522186, -0.05522615,
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```

```

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0.00196384, 0.00196262, 0.00196006, 0.00195728, 0.0018978 ,
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0.00169938, 0.00169912, 0.00170314, 0.0018761 , 0.00198219,
0.00228688, 0.00241602, 0.00246153, 0.00246651, 0.00234205,
0.0022209 , 0.0021689 ]))}

```

[]:

```

[55]: y_train_pred = ridgeCV.predict(X_train)
      y_test_pred = ridgeCV.predict(X_test)

```

```

[56]: eval_metrics(y_train, y_train_pred, y_test, y_test_pred)

```

```

r2 score (train) - 0.93
r2 score (test) - 0.88
RMSE(TRAIN) - 0.10
RMSE(TEST) - 0.14

```

[]:

```

[57]: ridgeCV_res = pd.DataFrame(ridgeCV.cv_results_)
      ridgeCV_res.head()

```

```

[57]:   mean_fit_time  std_fit_time  mean_score_time  std_score_time  param_alpha  \
0      0.087903    0.045978      0.059115      0.024049      0.0001
1      0.086870    0.012363      0.080712      0.017922      0.001
2      0.075778    0.009771      0.053092      0.009592      0.01
3      0.075531    0.030884      0.026158      0.000202      0.05
4      0.074793    0.012958      0.043323      0.011381      0.1

      params  split0_test_score  split1_test_score  split2_test_score  \

```


0	{'alpha': 0.0001}	-0.108135	-0.117046	-0.113900
1	{'alpha': 0.001}	-0.108130	-0.117047	-0.113864
2	{'alpha': 0.01}	-0.108078	-0.117062	-0.113510
3	{'alpha': 0.05}	-0.107853	-0.117113	-0.112156
4	{'alpha': 0.1}	-0.107599	-0.117246	-0.110844

	split3_test_score	split4_test_score	mean_test_score	std_test_score \
0	-0.108611	-0.102680	-0.110075	0.004976
1	-0.108608	-0.102658	-0.110061	0.004978
2	-0.108578	-0.102443	-0.109934	0.005000
3	-0.108445	-0.101646	-0.109443	0.005109
4	-0.108307	-0.100937	-0.108987	0.005270

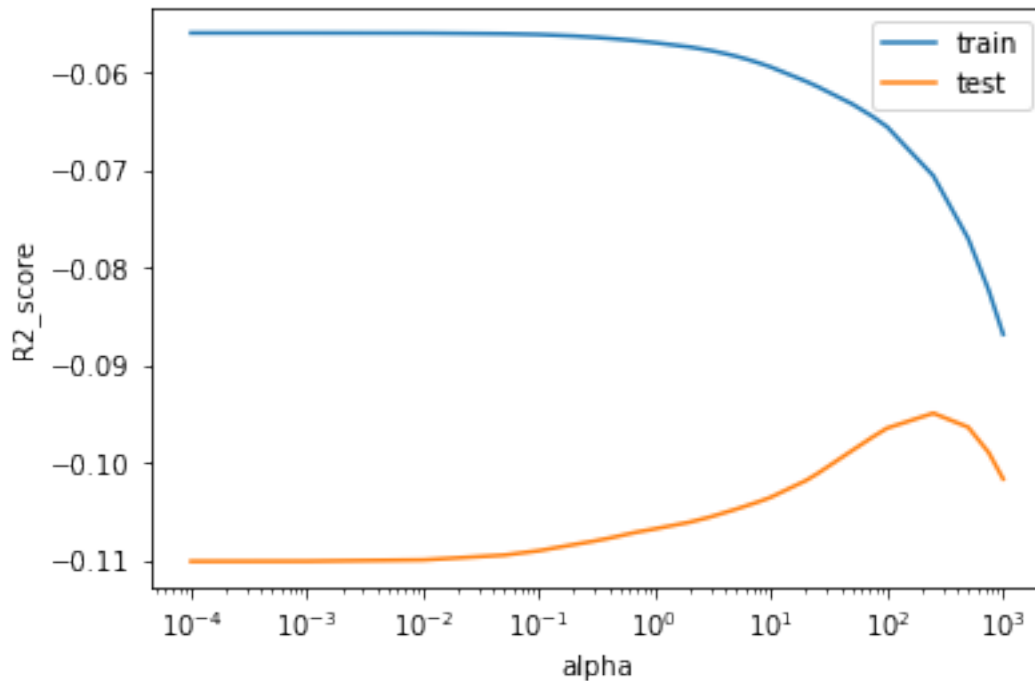
	rank_test_score	split0_train_score	split1_train_score \
0	32	-0.056046	-0.055221
1	31	-0.056046	-0.055222
2	30	-0.056047	-0.055226
3	29	-0.056052	-0.055270
4	28	-0.056058	-0.055333

	split2_train_score	split3_train_score	split4_train_score \
0	-0.052882	-0.056983	-0.058567
1	-0.052883	-0.056985	-0.058570
2	-0.052899	-0.057003	-0.058603
3	-0.052973	-0.057086	-0.058733
4	-0.053055	-0.057182	-0.058869

	mean_train_score	std_train_score
0	-0.055940	0.001891
1	-0.055941	0.001891
2	-0.055955	0.001897
3	-0.056023	0.001915
4	-0.056099	0.001934

```
[ ]:
```

```
[58]: plt.plot(ridgeCV_res['param_alpha'], ridgeCV_res['mean_train_score'],
        label='train')
plt.plot(ridgeCV_res['param_alpha'], ridgeCV_res['mean_test_score'],
        label='test')
plt.xlabel('alpha')
plt.ylabel('R2_score')
plt.xscale('log')
plt.legend()
plt.show()
```



```
[ ]:
```

```
[59]: params = {'alpha':
               [0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.
↪ 9, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 25, 50, 75, 100, 250, 500, 750, 1000]
               }

lasso = Lasso()
lassoCV = GridSearchCV(estimator=ridge, param_grid=params,
↪ scoring='neg_mean_absolute_error', cv=5, return_train_score=True, verbose=1,
↪ n_jobs=1)
lassoCV.fit(X_train, y_train)
print(lassoCV.best_params_)
print(lassoCV.cv_results_)
y_train_pred = lassoCV.predict(X_train)
y_test_pred = lassoCV.predict(X_test)
eval_metrics(y_train, y_train_pred, y_test, y_test_pred)
lassoCV_res = pd.DataFrame(lassoCV.cv_results_)
lassoCV_res.head()

plt.plot(lassoCV_res['param_alpha'], lassoCV_res['mean_train_score'],
↪ label='train')
plt.plot(lassoCV_res['param_alpha'], lassoCV_res['mean_test_score'],
↪ label='test')
```

```
plt.xlabel('alpha')
plt.ylabel('R2_score')
plt.xscale('log')
plt.legend()
plt.show()
```

```
Fitting 5 folds for each of 32 candidates, totalling 160 fits
{'alpha': 250}
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    0.08318243, 0.08238325, 0.08292017, 0.07448511, 0.07552218,
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    0.07209482, 0.07375689]), 'std_fit_time': array([0.0323913 , 0.05701231,
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    0.00117132, 0.00105149, 0.005543 , 0.01673155, 0.0113798 ,
    0.01948068, 0.01387246, 0.01211616, 0.01070922, 0.01240012,
    0.05722614, 0.01093784, 0.01907057, 0.01115639, 0.01614332,
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    0.03578176, 0.04128637, 0.03998618, 0.04616222, 0.04819326,
    0.0333878 , 0.05015965, 0.03741269, 0.03891168, 0.04537034,
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    0.03962684, 0.04614716]), 'std_score_time': array([0.02625963,
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    0.00043343, 0.00027015, 0.00047912, 0.01124513, 0.01320565,
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    0.01342693, 0.01355588, 0.01216865, 0.01084769, 0.00803358,
    0.0109085 , 0.00169772, 0.01535118, 0.01474108, 0.01095801,
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```

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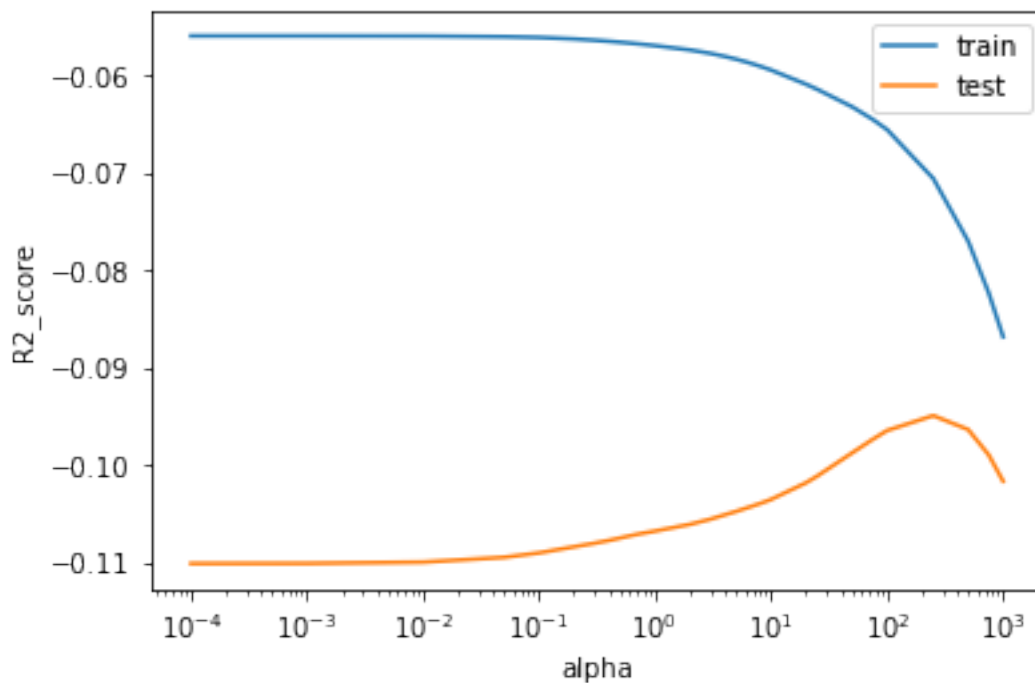
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    -0.07840056, -0.08300725]), 'split2_train_score': array([-0.05288177,
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    -0.05393063, -0.05402774, -0.05411551, -0.05419607, -0.05485804,
    -0.05536962, -0.05581957, -0.05624029, -0.05664021, -0.05699387,
    -0.057309 , -0.05759683, -0.05786219, -0.05982506, -0.06049684,
    -0.06285908, -0.06442276, -0.06561875, -0.07055981, -0.0767388 ,
    -0.08192475, -0.08644165]), 'split3_train_score': array([-0.05698323,
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    -0.05739032, -0.05755677, -0.05769975, -0.05782252, -0.05792931,
    -0.05802561, -0.05811086, -0.05818776, -0.05825859, -0.05880115,
    -0.05921657, -0.05962349, -0.05998159, -0.06030275, -0.06059372,
    -0.06087841, -0.06114802, -0.06139866, -0.06333139, -0.06401018,
    -0.06610777, -0.06747705, -0.0685724 , -0.07373494, -0.08004127,
    -0.08517634, -0.08953242]), 'split4_train_score': array([-0.05856724,
-0.05857043, -0.05860275, -0.05873269, -0.05886917,
    -0.05909703, -0.05926421, -0.05940031, -0.05951565, -0.05961009,
    -0.05969648, -0.05977023, -0.05983365, -0.05989034, -0.06022812,
    -0.06044907, -0.06063053, -0.06078009, -0.06091134, -0.06103048,
    -0.06113999, -0.06124085, -0.06133682, -0.06208958, -0.06238183,
    -0.06355209, -0.0645493 , -0.06549444, -0.07060602, -0.07766581,
    -0.08325636, -0.08801752]), 'mean_train_score': array([-0.05593995,
-0.05594134, -0.05595547, -0.05602258, -0.05609942,
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    -0.05675095, -0.05681967, -0.05688284, -0.05694112, -0.05738502,

```

```

-0.05773559, -0.05805062, -0.05833048, -0.05858913, -0.05882641,
-0.05904915, -0.05925461, -0.05944599, -0.06089827, -0.06142337,
-0.063218 , -0.06449776, -0.06555672, -0.07056906, -0.07700579,
-0.08228344, -0.08680844]), 'std_train_score': array([0.00189055,
0.00189109, 0.00189678, 0.00191543, 0.00193396,
0.00195525, 0.0019588 , 0.00196221, 0.00196467, 0.00196377,
0.00196384, 0.00196262, 0.00196006, 0.00195728, 0.0018978 ,
0.00184055, 0.00179968, 0.00176273, 0.00172998, 0.00170819,
0.00169938, 0.00169912, 0.00170314, 0.0018761 , 0.00198219,
0.00228688, 0.00241602, 0.00246153, 0.00246651, 0.00234205,
0.0022209 , 0.0021689 ])}
r2 score (train) - 0.93
r2 score (test) - 0.88
RMSE(TRAIN) - 0.10
RMSE(TEST) - 0.14

```



[]:

```

[60]: best_ridge = ridgeCV.best_estimator_
best_lasso = lassoCV.best_estimator_

beats = pd.DataFrame(index = x.columns)
beats.rows = x.columns
beats['Ridge'] = best_ridge.coef_

```

```
beats['Lasso'] = best_lasso.coef_  
beats
```

```
[60]:
```

	Ridge	Lasso
LotFrontage	0.000827	0.000827
LotArea	0.013938	0.013938
YearRemodAdd	0.019722	0.019722
MasVnrArea	0.009757	0.009757
BsmtFinSF1	0.009438	0.009438
BsmtFinSF2	0.005310	0.005310
BsmtUnfSF	0.003365	0.003365
TotalBsmtSF	0.014836	0.014836
1stFlrSF	0.023885	0.023885
2ndFlrSF	0.016167	0.016167
LowQualFinSF	0.005832	0.005832
GrLivArea	0.031856	0.031856
BsmtFullBath	0.013907	0.013907
BsmtHalfBath	-0.002217	-0.002217
FullBath	0.019654	0.019654
HalfBath	0.016722	0.016722
BedroomAbvGr	0.010503	0.010503
KitchenAbvGr	-0.010644	-0.010644
TotRmsAbvGrd	0.022304	0.022304
Fireplaces	0.014674	0.014674
GarageYrBlt	0.004733	0.004733
GarageCars	0.023721	0.023721
GarageArea	0.018956	0.018956
WoodDeckSF	0.011385	0.011385
OpenPorchSF	0.001850	0.001850
EnclosedPorch	0.003743	0.003743
3SsnPorch	0.006549	0.006549
ScreenPorch	0.012044	0.012044
PoolArea	0.005551	0.005551
MiscVal	0.000246	0.000246
MoSold	0.003180	0.003180
Age	-0.016451	-0.016451
MSSubClass_30	-0.017343	-0.017343
MSSubClass_40	0.002550	0.002550
MSSubClass_45	-0.000851	-0.000851
MSSubClass_50	0.001294	0.001294
MSSubClass_60	0.002010	0.002010
MSSubClass_70	0.006207	0.006207
MSSubClass_75	0.006207	0.006207
MSSubClass_80	-0.002916	-0.002916
MSSubClass_85	-0.001198	-0.001198
MSSubClass_90	-0.004598	-0.004598
MSSubClass_120	-0.004561	-0.004561

MSSubClass_160	-0.015000	-0.015000
MSSubClass_180	-0.005280	-0.005280
MSSubClass_190	-0.001294	-0.001294
MSZoning_FV	0.007578	0.007578
MSZoning_RH	0.001448	0.001448
MSZoning_RL	0.009843	0.009843
MSZoning_RM	-0.006350	-0.006350
Street_Pave	0.004067	0.004067
Alley_None	-0.001902	-0.001902
Alley_Pave	0.008105	0.008105
LotShape_IR2	0.004953	0.004953
LotShape_IR3	-0.005358	-0.005358
LotShape_Reg	-0.002022	-0.002022
LandContour_HLS	0.010439	0.010439
LandContour_Low	-0.000337	-0.000337
LandContour_Lvl	0.010855	0.010855
Utilities_NoSeWa	-0.006878	-0.006878
LotConfig_CulDSac	0.009609	0.009609
LotConfig_FR2	-0.006253	-0.006253
LotConfig_FR3	-0.003128	-0.003128
LotConfig_Inside	-0.003404	-0.003404
LandSlope_Mod	-0.000496	-0.000496
LandSlope_Sev	0.000460	0.000460
Neighborhood_Blueste	-0.001436	-0.001436
Neighborhood_BrDale	-0.002165	-0.002165
Neighborhood_BrkSide	0.001524	0.001524
Neighborhood_ClearCr	0.007937	0.007937
Neighborhood_CollgCr	-0.001761	-0.001761
Neighborhood_Crawfor	0.018133	0.018133
Neighborhood_Edwards	-0.012329	-0.012329
Neighborhood_Gilbert	-0.004123	-0.004123
Neighborhood_IDOTRR	-0.008007	-0.008007
Neighborhood_MeadowV	-0.015515	-0.015515
Neighborhood_Mitchel	-0.000396	-0.000396
Neighborhood_NAmes	-0.010222	-0.010222
Neighborhood_NPkVill	0.001245	0.001245
Neighborhood_NWAmes	-0.002998	-0.002998
Neighborhood_NoRidge	0.011335	0.011335
Neighborhood_NridgHt	0.021087	0.021087
Neighborhood_OldTown	-0.009498	-0.009498
Neighborhood_SWISU	-0.000127	-0.000127
Neighborhood_Sawyer	-0.002855	-0.002855
Neighborhood_SawyerW	-0.001036	-0.001036
Neighborhood_Somerst	0.006152	0.006152
Neighborhood_StoneBr	0.017797	0.017797
Neighborhood_Timber	0.004006	0.004006
Neighborhood_Veenker	0.005511	0.005511

Condition1_Feedr	-0.002697	-0.002697
Condition1_Norm	0.011905	0.011905
Condition1_PosA	-0.001591	-0.001591
Condition1_PosN	0.001633	0.001633
Condition1_RRAe	-0.004991	-0.004991
Condition1_RRAn	0.003093	0.003093
Condition1_RRNe	0.000471	0.000471
Condition1_RRNn	0.001554	0.001554
Condition2_Feedr	0.004647	0.004647
Condition2_Norm	0.007151	0.007151
Condition2_PosA	0.000000	0.000000
Condition2_PosN	-0.016772	-0.016772
Condition2_RRAe	-0.001379	-0.001379
Condition2_RRAn	0.001915	0.001915
Condition2_RRNn	0.000000	0.000000
BldgType_2fmCon	-0.001403	-0.001403
BldgType_Duplex	-0.004598	-0.004598
BldgType_Twnhs	-0.009058	-0.009058
BldgType_TwnhsE	-0.011362	-0.011362
HouseStyle_1.5Unf	0.001856	0.001856
HouseStyle_1Story	0.002458	0.002458
HouseStyle_2.5Fin	0.000725	0.000725
HouseStyle_2.5Unf	0.001742	0.001742
HouseStyle_2Story	-0.002399	-0.002399
HouseStyle_SFoyer	-0.005053	-0.005053
HouseStyle_SLvl	-0.001892	-0.001892
OverallQual_2	-0.007130	-0.007130
OverallQual_3	-0.018202	-0.018202
OverallQual_4	-0.016084	-0.016084
OverallQual_5	-0.013436	-0.013436
OverallQual_6	-0.003148	-0.003148
OverallQual_7	0.007517	0.007517
OverallQual_8	0.022802	0.022802
OverallQual_9	0.026090	0.026090
OverallQual_10	0.009309	0.009309
OverallCond_2	-0.002750	-0.002750
OverallCond_3	-0.019080	-0.019080
OverallCond_4	-0.006153	-0.006153
OverallCond_5	-0.008644	-0.008644
OverallCond_6	0.003820	0.003820
OverallCond_7	0.011804	0.011804
OverallCond_8	0.006735	0.006735
OverallCond_9	0.010137	0.010137
RoofStyle_Gable	-0.006769	-0.006769
RoofStyle_Gambrel	0.001195	0.001195
RoofStyle_Hip	0.001288	0.001288
RoofStyle_Mansard	0.007167	0.007167

RoofStyle_Shed	0.003399	0.003399
RoofMatl_CompShg	0.008265	0.008265
RoofMatl_Membran	0.000000	0.000000
RoofMatl_Metal	0.002475	0.002475
RoofMatl_Roll	0.003351	0.003351
RoofMatl_Tar&Grv	0.012191	0.012191
RoofMatl_WdShake	0.003126	0.003126
RoofMatl_WdShngl	0.010667	0.010667
Exterior1st_AsphShn	0.000526	0.000526
Exterior1st_BrkComm	0.001828	0.001828
Exterior1st_BrkFace	0.016004	0.016004
Exterior1st_CBlock	-0.001623	-0.001623
Exterior1st_CemntBd	0.004500	0.004500
Exterior1st_HdBoard	-0.004880	-0.004880
Exterior1st_ImStucc	0.000000	0.000000
Exterior1st_MetalSd	0.001587	0.001587
Exterior1st_Plywood	0.002476	0.002476
Exterior1st_Stone	0.002644	0.002644
Exterior1st_Stucco	-0.000170	-0.000170
Exterior1st_VinylSd	-0.001591	-0.001591
Exterior1st_Wd Sdng	-0.005965	-0.005965
Exterior1st_WdShing	-0.001805	-0.001805
Exterior2nd_AsphShn	0.003451	0.003451
Exterior2nd_Brk Cmn	0.000319	0.000319
Exterior2nd_BrkFace	0.000071	0.000071
Exterior2nd_CBlock	-0.001623	-0.001623
Exterior2nd_CmentBd	0.006787	0.006787
Exterior2nd_HdBoard	-0.001579	-0.001579
Exterior2nd_ImStucc	-0.001555	-0.001555
Exterior2nd_MetalSd	-0.001154	-0.001154
Exterior2nd_Other	-0.002004	-0.002004
Exterior2nd_Plywood	-0.004631	-0.004631
Exterior2nd_Stone	-0.000743	-0.000743
Exterior2nd_Stucco	-0.000578	-0.000578
Exterior2nd_VinylSd	-0.000480	-0.000480
Exterior2nd_Wd Sdng	0.005775	0.005775
Exterior2nd_Wd Shng	-0.004316	-0.004316
MasVnrType_BrkFace	0.001981	0.001981
MasVnrType_None	-0.000848	-0.000848
MasVnrType_Stone	0.003939	0.003939
ExterQual_Fa	-0.004032	-0.004032
ExterQual_Gd	0.001332	0.001332
ExterQual_TA	-0.010062	-0.010062
ExterCond_Fa	-0.003273	-0.003273
ExterCond_Gd	-0.001920	-0.001920
ExterCond_Po	-0.002386	-0.002386
ExterCond_TA	0.002399	0.002399

Foundation_CBlock	-0.000390	-0.000390
Foundation_PConc	0.010176	0.010176
Foundation_Slab	-0.002964	-0.002964
Foundation_Stone	-0.000747	-0.000747
Foundation_Wood	-0.002588	-0.002588
BsmtQual_Fa	-0.003668	-0.003668
BsmtQual_Gd	-0.005848	-0.005848
BsmtQual_None	-0.003221	-0.003221
BsmtQual_TA	-0.017634	-0.017634
BsmtCond_Gd	0.005172	0.005172
BsmtCond_None	-0.003221	-0.003221
BsmtCond_Po	-0.007162	-0.007162
BsmtCond_TA	0.011528	0.011528
BsmtExposure_Gd	0.014506	0.014506
BsmtExposure_Mn	-0.003033	-0.003033
BsmtExposure_No	-0.008891	-0.008891
BsmtExposure_None	-0.003221	-0.003221
BsmtFinType1_BLQ	-0.003942	-0.003942
BsmtFinType1_GLQ	0.012488	0.012488
BsmtFinType1_LwQ	-0.002830	-0.002830
BsmtFinType1_None	-0.003221	-0.003221
BsmtFinType1_Rec	-0.001242	-0.001242
BsmtFinType1_Unf	-0.011330	-0.011330
BsmtFinType2_BLQ	-0.003457	-0.003457
BsmtFinType2_GLQ	0.002535	0.002535
BsmtFinType2_LwQ	0.000849	0.000849
BsmtFinType2_None	-0.003221	-0.003221
BsmtFinType2_Rec	-0.001004	-0.001004
BsmtFinType2_Unf	-0.001489	-0.001489
Heating_GasA	0.002615	0.002615
Heating_GasW	0.004539	0.004539
Heating_Grav	-0.012122	-0.012122
Heating_OthW	-0.001409	-0.001409
Heating_Wall	0.003066	0.003066
HeatingQC_Fa	-0.005973	-0.005973
HeatingQC_Gd	-0.008056	-0.008056
HeatingQC_Po	-0.002708	-0.002708
HeatingQC_TA	-0.010667	-0.010667
CentralAir_Y	0.017404	0.017404
Electrical_FuseF	-0.001586	-0.001586
Electrical_FuseP	-0.001371	-0.001371
Electrical_Mix	0.000000	0.000000
Electrical_None	0.001087	0.001087
Electrical_SBrkr	-0.001681	-0.001681
KitchenQual_Fa	-0.000545	-0.000545
KitchenQual_Gd	-0.004383	-0.004383
KitchenQual_TA	-0.014860	-0.014860

Functional_Maj2	-0.010894	-0.010894
Functional_Min1	-0.001818	-0.001818
Functional_Min2	-0.003580	-0.003580
Functional_Mod	0.004222	0.004222
Functional_Sev	-0.007892	-0.007892
Functional_Typ	0.006004	0.006004
FireplaceQu_Fa	-0.002237	-0.002237
FireplaceQu_Gd	0.004236	0.004236
FireplaceQu_None	-0.013861	-0.013861
FireplaceQu_Po	-0.002776	-0.002776
FireplaceQu_TA	0.005399	0.005399
GarageType_Attchd	0.004507	0.004507
GarageType_Basment	0.000489	0.000489
GarageType_BuiltIn	0.003887	0.003887
GarageType_CarPort	-0.002485	-0.002485
GarageType_Detchd	-0.001534	-0.001534
GarageType_None	-0.004899	-0.004899
GarageFinish_None	-0.004899	-0.004899
GarageFinish_RFn	0.002608	0.002608
GarageFinish_Unf	-0.004731	-0.004731
GarageQual_Fa	-0.003499	-0.003499
GarageQual_Gd	0.008161	0.008161
GarageQual_None	-0.004899	-0.004899
GarageQual_Po	-0.000116	-0.000116
GarageQual_TA	-0.001406	-0.001406
GarageCond_Fa	-0.004160	-0.004160
GarageCond_Gd	0.001492	0.001492
GarageCond_None	-0.004899	-0.004899
GarageCond_Po	0.009000	0.009000
GarageCond_TA	0.002031	0.002031
PavedDrive_P	0.003722	0.003722
PavedDrive_Y	0.007823	0.007823
PoolQC_Fa	-0.000039	-0.000039
PoolQC_Gd	-0.023152	-0.023152
PoolQC_None	0.011530	0.011530
Fence_GdWo	-0.007762	-0.007762
Fence_MnPrv	-0.003277	-0.003277
Fence_MnWw	-0.001894	-0.001894
Fence_None	-0.001657	-0.001657
MiscFeature_None	0.001654	0.001654
MiscFeature_Othr	-0.005092	-0.005092
MiscFeature_Shed	-0.000614	-0.000614
MiscFeature_TenC	-0.000039	-0.000039
SaleType_CWD	0.004342	0.004342
SaleType_Con	0.002921	0.002921
SaleType_ConLD	0.006036	0.006036
SaleType_ConLI	-0.001578	-0.001578

SaleType_ConLw	0.000532	0.000532
SaleType_New	0.008830	0.008830
SaleType_Oth	0.007225	0.007225
SaleType_WD	-0.003668	-0.003668
SaleCondition_AdjLand	0.003461	0.003461
SaleCondition_Alloca	0.017280	0.017280
SaleCondition_Family	-0.002218	-0.002218
SaleCondition_Normal	0.010352	0.010352
SaleCondition_Partial	0.009449	0.009449

```
[ ]:
```

```
[61]: lasso_cols_removed = list(beats[beats['Lasso']==0].index)
      print(lasso_cols_removed)
```

```
['Condition2_PosA', 'Condition2_RRNn', 'RoofMatl_Membran',
'Exterior1st_ImStucc', 'Electrical_Mix']
```

```
[ ]:
```

```
[62]: lasso_cols_selected = list(beats[beats['Lasso']!=0].index)
      print(lasso_cols_selected)
      print(len(lasso_cols_selected))
```

```
['LotFrontage', 'LotArea', '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',
'Age', 'MSSubClass_30', 'MSSubClass_40', 'MSSubClass_45', 'MSSubClass_50',
'MSSubClass_60', 'MSSubClass_70', 'MSSubClass_75', 'MSSubClass_80',
'MSSubClass_85', 'MSSubClass_90', 'MSSubClass_120', 'MSSubClass_160',
'MSSubClass_180', 'MSSubClass_190', 'MSZoning_FV', 'MSZoning_RH', 'MSZoning_RL',
'MSZoning_RM', 'StreetPave', 'Alley_None', 'Alley_Pave', 'LotShape_IR2',
'LotShape_IR3', 'LotShape_Reg', 'LandContour_HLS', 'LandContour_Low',
'LandContour_Lvl', 'Utilities_NoSeWa', 'LotConfig_CulDSac', 'LotConfig_FR2',
'LotConfig_FR3', 'LotConfig_Inside', 'LandSlope_Mod', 'LandSlope_Sev',
'Neighborhood_Blueste', 'Neighborhood_BrDale', 'Neighborhood_BrkSide',
'Neighborhood_ClearCr', 'Neighborhood_CollgCr', 'Neighborhood_Crawfor',
'Neighborhood_Edwards', 'Neighborhood_Gilbert', 'Neighborhood_IDOTRR',
'Neighborhood_MeadowV', 'Neighborhood_Mitchel', 'Neighborhood_Names',
'Neighborhood_NPkVill', 'Neighborhood_NWAmes', 'Neighborhood_NoRidge',
'Neighborhood_NridgHt', 'Neighborhood_OldTown', 'Neighborhood_SWISU',
'Neighborhood_Sawyer', 'Neighborhood_SawyerW', 'Neighborhood_Somerst',
'Neighborhood_StoneBr', 'Neighborhood_Timber', 'Neighborhood_Veenker',
'Condition1_Feedr', 'Condition1_Norm', 'Condition1_PosA', 'Condition1_PosN',
```

'Condition1_RRAe', 'Condition1_RRAAn', 'Condition1_RRNe', 'Condition1_RRNn',
 'Condition2_Feendr', 'Condition2_Norm', 'Condition2_PosN', 'Condition2_RRAe',
 'Condition2_RRAAn', 'BldgType_2fmCon', 'BldgType_Duplex', 'BldgType_Twnhs',
 'BldgType_TwnhsE', 'HouseStyle_1.5Unf', 'HouseStyle_1Story',
 'HouseStyle_2.5Fin', 'HouseStyle_2.5Unf', 'HouseStyle_2Story',
 'HouseStyle_SFoyer', 'HouseStyle_SLvl', 'OverallQual_2', 'OverallQual_3',
 'OverallQual_4', 'OverallQual_5', 'OverallQual_6', 'OverallQual_7',
 'OverallQual_8', 'OverallQual_9', 'OverallQual_10', 'OverallCond_2',
 'OverallCond_3', 'OverallCond_4', 'OverallCond_5', 'OverallCond_6',
 'OverallCond_7', 'OverallCond_8', 'OverallCond_9', 'RoofStyle_Gable',
 'RoofStyle_Gambrel', 'RoofStyle_Hip', 'RoofStyle_Mansard', 'RoofStyle_Shed',
 'RoofMatl_CompShg', 'RoofMatl_Metal', 'RoofMatl_Roll', 'RoofMatl_Tar&Grv',
 'RoofMatl_WdShake', 'RoofMatl_WdShngl', 'Exterior1st_AsphShn',
 'Exterior1st_BrkComm', 'Exterior1st_BrkFace', 'Exterior1st_CBlock',
 'Exterior1st_CemntBd', 'Exterior1st_HdBoard', 'Exterior1st_MetalSd',
 'Exterior1st_Plywood', 'Exterior1st_Stone', 'Exterior1st_Stucco',
 'Exterior1st_VinylSd', 'Exterior1st_Wd Sdng', 'Exterior1st_WdShng',
 'Exterior2nd_AsphShn', 'Exterior2nd_Brk Cmn', 'Exterior2nd_BrkFace',
 'Exterior2nd_CBlock', 'Exterior2nd_CmentBd', 'Exterior2nd_HdBoard',
 'Exterior2nd_ImStucc', 'Exterior2nd_MetalSd', 'Exterior2nd_Other',
 'Exterior2nd_Plywood', 'Exterior2nd_Stone', 'Exterior2nd_Stucco',
 'Exterior2nd_VinylSd', 'Exterior2nd_Wd Sdng', 'Exterior2nd_Wd Shng',
 'MasVnrType_BrkFace', 'MasVnrType_None', 'MasVnrType_Stone', 'ExterQual_Fa',
 'ExterQual_Gd', 'ExterQual_TA', 'ExterCond_Fa', 'ExterCond_Gd', 'ExterCond_Po',
 'ExterCond_TA', 'Foundation_CBlock', 'Foundation_PConc', 'Foundation_Slab',
 'Foundation_Stone', 'Foundation_Wood', 'BsmtQual_Fa', 'BsmtQual_Gd',
 'BsmtQual_None', 'BsmtQual_TA', 'BsmtCond_Gd', 'BsmtCond_None', 'BsmtCond_Po',
 'BsmtCond_TA', 'BsmtExposure_Gd', 'BsmtExposure_Mn', 'BsmtExposure_No',
 'BsmtExposure_None', 'BsmtFinType1_BLQ', 'BsmtFinType1_GLQ', 'BsmtFinType1_LwQ',
 'BsmtFinType1_None', 'BsmtFinType1_Rec', 'BsmtFinType1_Unf', 'BsmtFinType2_BLQ',
 'BsmtFinType2_GLQ', 'BsmtFinType2_LwQ', 'BsmtFinType2_None', 'BsmtFinType2_Rec',
 'BsmtFinType2_Unf', 'Heating_GasA', 'Heating_GasW', 'Heating_Grav',
 'Heating_OthW', 'Heating_Wall', 'HeatingQC_Fa', 'HeatingQC_Gd', 'HeatingQC_Po',
 'HeatingQC_TA', 'CentralAir_Y', 'Electrical_FuseF', 'Electrical_FuseP',
 'Electrical_None', 'Electrical_SBrkr', 'KitchenQual_Fa', 'KitchenQual_Gd',
 'KitchenQual_TA', 'Functional_Maj2', 'Functional_Min1', 'Functional_Min2',
 'Functional_Mod', 'Functional_Sev', 'Functional_Typ', 'FireplaceQu_Fa',
 'FireplaceQu_Gd', 'FireplaceQu_None', 'FireplaceQu_Po', 'FireplaceQu_TA',
 'GarageType_Attchd', 'GarageType_Basment', 'GarageType_BuiltIn',
 'GarageType_CarPort', 'GarageType_Detchd', 'GarageType_None',
 'GarageFinish_None', 'GarageFinish_RFn', 'GarageFinish_Unf', 'GarageQual_Fa',
 'GarageQual_Gd', 'GarageQual_None', 'GarageQual_Po', 'GarageQual_TA',
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 'GarageCond_TA', 'PavedDrive_P', 'PavedDrive_Y', 'PoolQC_Fa', 'PoolQC_Gd',
 'PoolQC_None', 'Fence_GdWo', 'Fence_MnPrv', 'Fence_MnWw', 'Fence_None',
 'MiscFeature_None', 'MiscFeature_Othr', 'MiscFeature_Shed', 'MiscFeature_TenC',
 'SaleType_CWD', 'SaleType_Con', 'SaleType_ConLD', 'SaleType_ConLI',
 'SaleType_ConLw', 'SaleType_New', 'SaleType_Oth', 'SaleType_WD',

```
'SaleCondition_AdjLand', 'SaleCondition_Alloca', 'SaleCondition_Family',
'SaleCondition_Normal', 'SaleCondition_Partial']
```

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[ ]:
```

```
[63]: beats["Ridge"].sort_values(ascending=False)[:10]
```

```
[63]: GrLivArea          0.031856
      OverallQual_9      0.026090
      1stFlrSF           0.023885
      GarageCars         0.023721
      OverallQual_8      0.022802
      TotRmsAbvGrd       0.022304
      Neighborhood_NridgHt 0.021087
      YearRemodAdd       0.019722
      FullBath           0.019654
      GarageArea         0.018956
      Name: Ridge, dtype: float64
```

```
[ ]:
```

```
[64]: ridge_coeffs = np.exp(beats['Ridge'])
      ridge_coeffs.sort_values(ascending=False)[:10]
```

```
[64]: GrLivArea          1.032369
      OverallQual_9      1.026433
      1stFlrSF           1.024172
      GarageCars         1.024005
      OverallQual_8      1.023064
      TotRmsAbvGrd       1.022555
      Neighborhood_NridgHt 1.021311
      YearRemodAdd       1.019918
      FullBath           1.019848
      GarageArea         1.019137
      Name: Ridge, dtype: float64
```

```
[ ]:
```

```
[65]: beats["Lasso"].sort_values(ascending=False)[:10]
      lasso_coeffs = np.exp(beats['Lasso'])
      lasso_coeffs.sort_values(ascending=False)[:10]
```

```
[65]: GrLivArea          1.032369
      OverallQual_9      1.026433
      1stFlrSF           1.024172
      GarageCars         1.024005
```

```
OverallQual_8          1.023064
TotRmsAbvGrd          1.022555
Neighborhood_NridgHt   1.021311
YearRemodAdd           1.019918
FullBath               1.019848
GarageArea             1.019137
Name: Lasso, dtype: float64
```

[]:

6 CONCLUSION:

6.0.1 Below are the top 10 features with corresponding coefficients according to Ridge model:

- 1). GrLivArea 1.032369
- 2). OverallQual_9 1.026433
- 3). 1stFlrSF 1.024172
- 4). GarageCars 1.024005
- 5). OverallQual_8 1.023064
- 6). TotRmsAbvGrd 1.022555
- 7). Neighborhood_NridgHt 1.021311
- 8). YearRemodAdd 1.019918
- 9). FullBath 1.019848
- 10). GarageArea 1.019137

6.0.2 Below are the top 10 features with corresponding coefficients according to Lasso model:

- 1). GrLivArea 1.032369
- 2). OverallQual_9 1.026433
- 3). 1stFlrSF 1.024172
- 4). GarageCars 1.024005
- 5). OverallQual_8 1.023064
- 6). TotRmsAbvGrd 1.022555
- 7). Neighborhood_NridgHt 1.021311
- 8). YearRemodAdd 1.019918
- 9). FullBath 1.019848

10).GarageArea 1.019137

So here to highlight that both Ridge and Lasso algorithms will give us appropriate results only.

6.0.3 The list of features and their respective importance values indicates which attributes of a house have the most significant impact on predicting its price. Here's a detailed interpretation:

1) GrLivArea:

Gross Living Area is the most influential feature in predicting house prices. This makes sense as larger living spaces typically command higher prices due to the increased usable area. Which means that if GrLivArea increases then price will increase 1.032369 times.

2) OverallQual_9:

Overall Quality of house with Quality rating of 9, will increase the price of house 1.026433 times.

3) 1stFlrSF:

First Floor Square Footage is another critical feature. Larger first-floor areas are desirable and add significant value to a house. This means if Larger first floor areas, price increase 1.024172 times.

4) GarageCars:

The number of Garage Spaces impacts house prices notably. More garage spaces are often associated with larger, more valuable properties. Which means that if Garage cars space increase then price hike will be 1.024005 times.

5) OverallQual_8:

Overall Quality of house with Quality rating of 8, will increase the price of house 1.023065 times.

6) TotRmsAbvGrd:

The total number of Rooms Above Ground affects the price. More rooms typically mean a larger and potentially more versatile living space, which buyers value. Means price will hike 1.022555 times

7) Neighborhood_NridgHt:

The house being located in the Neighborhood of NridgHt (Northridge Heights) is a significant predictor. This suggests that houses in this neighborhood are generally priced higher, possibly due to better amenities, location, or reputation. Means hike of 1.021311 times.

8) YearRemodAdd :

The Year the House was Remodeled or Added to impacts its value. More recent renovations usually mean the house is more up-to-date and potentially more appealing to buyers. Means price will hike 1.019918 times.

9) FullBath:

The number of Full Bathrooms is an important feature. More full bathrooms increase the convenience and utility of the property, thereby increasing its value. Means if number of full bathrooms increases, price will rise with 1.019848 times.

10) GarageArea:

The Area of the Garage also influences house prices. Larger garages provide more storage and utility space, which can be attractive features for buyers. Means Area increases then price will hike 1.019137 times.

6.0.4 Overall Insights:

Living Space and Quality:

The size of the living area (GrLivArea, 1stFlrSF) and overall quality ratings (OverallQual) are the most critical factors in determining house prices. Larger and higher-quality homes naturally fetch higher prices.

Garage and Bathrooms:

The presence and size of garages (GarageCars, GarageArea) and the number of full bathrooms significantly contribute to the house price, highlighting the importance of these features in buyer decisions.

Neighborhood Influence:

Location remains a crucial factor, as indicated by the importance of the Neighborhood feature (NridgHt). This aligns with real estate trends where location often dictates property values.

Recent Renovations:

The recency of renovations (YearRemodAdd) affects house prices, emphasizing the value of updated and modernized homes.

These insights can help real estate professionals, buyers, and sellers understand which features are most valued in the market, thereby informing decisions related to property improvements, pricing strategies, and purchase considerations.

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