FLIP ROBO

HOUSING PRICE PREDICTION PROJECT

Prepared by:

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ACKNOWLEDGMENT

Firstly, I would like to thank FlipRobo Technologies for giving me the opportunity to work on this project. Also, I would like to thank the DataTrained team, especially Khushboo Garg Ma'am for providing me the guidance which helped me a lot to work on the project.

References:

https://stackoverflow.com/

https://scikit-learn.org/stable/

https://seaborn.pydata.org/

INTRODUCTION

- Business Problem Framing

  The main objective of this project is to model the price of houses with the available independent variables. This model will then be used by the management to understand how exactly the prices vary with the variables. They can accordingly manipulate the strategy of the firm and concentrate on areas that will yield high returns. Further, the model will be a good way for the management to understand the pricing dynamics of a new market.

- Conceptual Background of the Domain Problem

  Houses are one of the necessary need of each and every person around the globe and therefore housing and real estate market is one of the markets which is one of the major contributors in the world's economy. It is a very large market and there are various companies working in the domain. Data science comes as a very important tool to solve problems in the domain to help the companies increase their overall revenue, profits, improving their marketing strategies and focusing on changing trends in house sales and purchases. Predictive modelling, Market mix modelling, recommendation systems are some of the machine learning techniques used for achieving the business goals for housing companies. Our problem is related to one such housing company.

- Technical Requirements

  - Data contains 1460 entries each having 81 variables.
  - Data contains Null values. We need to treat them using the domain knowledge and your own understanding.
  - Extensive EDA has to be performed to gain relationships of variable and price.

- Data contains numerical as well as categorical variable. We need to handle them accordingly.
- We have to build Machine Learning methods, apply regularization and determine the optimal values for HyperParameters.
- We need to find important features which affect the price positively or negatively.
- Two datasets are being provided to us (test.csv, train.csv).

- ADVANTAGES:

  1. The objective behind to take this project is to implement therequired data science skills.
  2. Improve the analytical thinking.
  3. Get into the real world problem solving mechanics.

Analytical Problem Framing

- Mathematical Modeling of the Problem:

  This is a Regression problem, where our end goal is to predict the Prices of House, based on given data provided in the dataset. We have divided the provided dataset into Training and Testing phases.

  A Regression Model will be built and trained using the Training data and the Test data is used to predict the outcomes. This will be compared with available test results to find how our model has performed.

  We are using Mean Absolute Error, Root Mean Square Error, and 'R2_Score' to determine the best model among,

  - ❖ Linear Regression
  - ❖ Decision Tree Regression
  - ❖ Random Forest Regression
  - ❖ K Neighbors Regression
  - ❖ Lasso Regression

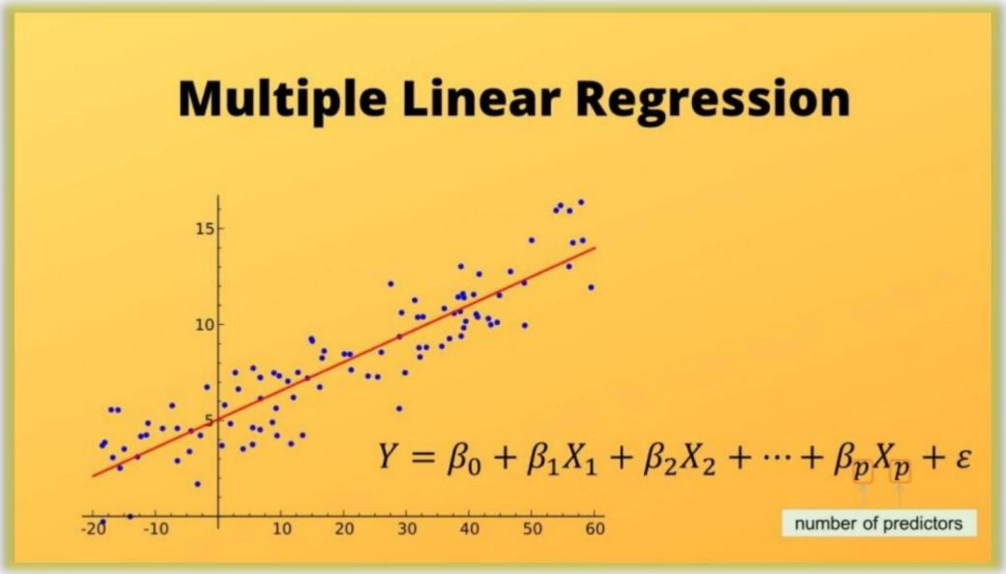
The best results were obtained using Lasso Regression. So, let's discuss a little bit about it. In a simple regression problem (a single xand a single y), the form of the model would be:

y = B0 + B1*x

where **B0** —intercept, **B1** —coefficient, **x** —independent variable **y** — output or the dependent variable.

In higher dimensions when we have more than one input (x), The General equation for a Multiple linear regression with p — independent variables:

Y=B0 + B1 * X1 + B2 * X2 +…………+ Bp * Xp + E(Random Error or Noise)



Let's consider a regression scenario where 'y' is the predicted vector and 'x' is the feature matrix. Basically in any regression problem, we try to minimize the squared error. Let 'β' be the vector of parameters (weights of importance of features) and 'p' be the number of features.

Now, let's discuss the case of lasso regression, which is also called L1 regression since it uses the L1 norm for regularization. In lasso regression, we try to solve the below minimization problem:

$$Min_{\beta}\ L_1 = (y - x\beta)^2 + \lambda \sum_{i=1}^{p} |\beta_i|$$

To simplify, suppose p =1, βi = β. Then,

$$\begin{aligned} L_1 &= (y - x\beta)^2 + \lambda|\beta| \\ &= \mathrm{y}^2 - 2\mathrm{xy}\beta + x^2\beta^2 + \lambda|\beta| \end{aligned}$$

In Lasso Regression, the L1 penalty will look like,

L1p = |β1| + |β2|

Shrinking β1 to 8 and β2 to 100 would minimize the penalty to 108 from 1010, which means in this case the change is not so significant just by shrinking the larger quantity. So, in the case of the L1 penalty, both the coefficients have to be shrunk to extremely small values, in order to achieve regularization. And in this whole process, some coefficients may shrink to zero.

(Reference: https://www.analyticsvidhya.com/blog/2020/11/lasso-regression-causes-sparsity-while-ridge-regression-doesnt-unfolding-the-math/)

Assumptions:

I. **Linearity:** The relationship between X & mean of Y is linear.

II. **Homoscedasticity:** The variance of residual is the same for any value of X.

III. **Independence:** Observations are independent of each other.

IV. **Normality:** For any fixed value of X, Y is normally distributed.

- Data Sources and their formats

A US-based housing company named Surprise Housing has decided to enter the Australian market. The company uses data analytic to purchase houses at a price below their actual values and flip them at a higher price. For the same purpose, the company has collected a data set from the sale of houses in Australia. The data is provided in the CSV file below.

The dataset contains 1460 rows and 81 columns (including the train dataset and test dataset).

The top 5 rows of the dataset are:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1
0	127	120	RL	NaN	4928	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	NPkVill	Norm
1	889	20	RL	95.0	15865	Pave	NaN	IR1	Lvl	AllPub	Inside	Mod	NAmes	Norm
2	793	60	RL	92.0	9920	Pave	NaN	IR1	Lvl	AllPub	CulDSac	Gtl	NoRidge	Norm
3	110	20	RL	105.0	11751	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	NWAmes	Norm
4	422	20	RL	NaN	16635	Pave	NaN	IR1	Lvl	AllPub	FR2	Gtl	NWAmes	Norm

Condition2	BldgType	HouseStyle	OverallQual	OverallCond	YearBuilt	YearRemodAdd	RoofStyle	RoofMatl	Exterior1st	Exterior2nd	MasVnrType	MasVnrArea
Norm	TwnhsE	1Story	6	5	1976	1976	Gable	CompShg	Plywood	Plywood	None	0.0
Norm	1Fam	1Story	8	6	1970	1970	Flat	Tar&Grv	Wd Sdng	Wd Sdng	None	0.0
Norm	1Fam	2Story	7	5	1996	1997	Gable	CompShg	MetalSd	MetalSd	None	0.0
Norm	1Fam	1Story	6	6	1977	1977	Hip	CompShg	Plywood	Plywood	BrkFace	480.0
Norm	1Fam	1Story	6	7	1977	2000	Gable	CompShg	CemntBd	CmentBd	Stone	126.0

ExterQual	ExterCond	Foundation	BsmtQual	BsmtCond	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF
TA	TA	CBlock	Gd	TA	No	ALQ	120	Unf	0	958	1078
Gd	Gd	PConc	TA	Gd	Gd	ALQ	351	Rec	823	1043	2217
Gd	TA	PConc	Gd	TA	Av	GLQ	862	Unf	0	255	1117
TA	TA	CBlock	Gd	TA	No	BLQ	705	Unf	0	1139	1844
Gd	TA	CBlock	Gd	TA	No	ALQ	1246	Unf	0	356	1602

Heating	HeatingQC	CentralAir	Electrical	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr
GasA	TA	Y	SBrkr	958	0	0	958	0	0	2	0	2
GasA	Ex	Y	SBrkr	2217	0	0	2217	1	0	2	0	4
GasA	Ex	Y	SBrkr	1127	886	0	2013	1	0	2	1	3
GasA	Ex	Y	SBrkr	1844	0	0	1844	0	0	2	0	3
GasA	Gd	Y	SBrkr	1602	0	0	1602	0	1	2	0	3

KitchenAbvGr	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	GarageType	GarageYrBlt	GarageFinish	GarageCars	GarageArea	GarageQual
1	TA	5	Typ	1	TA	Attchd	1977.0	RFn	2	440	TA
1	Gd	8	Typ	1	TA	Attchd	1970.0	Unf	2	621	TA
1	TA	8	Typ	1	TA	Attchd	1997.0	Unf	2	455	TA
1	TA	7	Typ	1	TA	Attchd	1977.0	RFn	2	546	TA
1	Gd	8	Typ	1	TA	Attchd	1977.0	Fin	2	529	TA

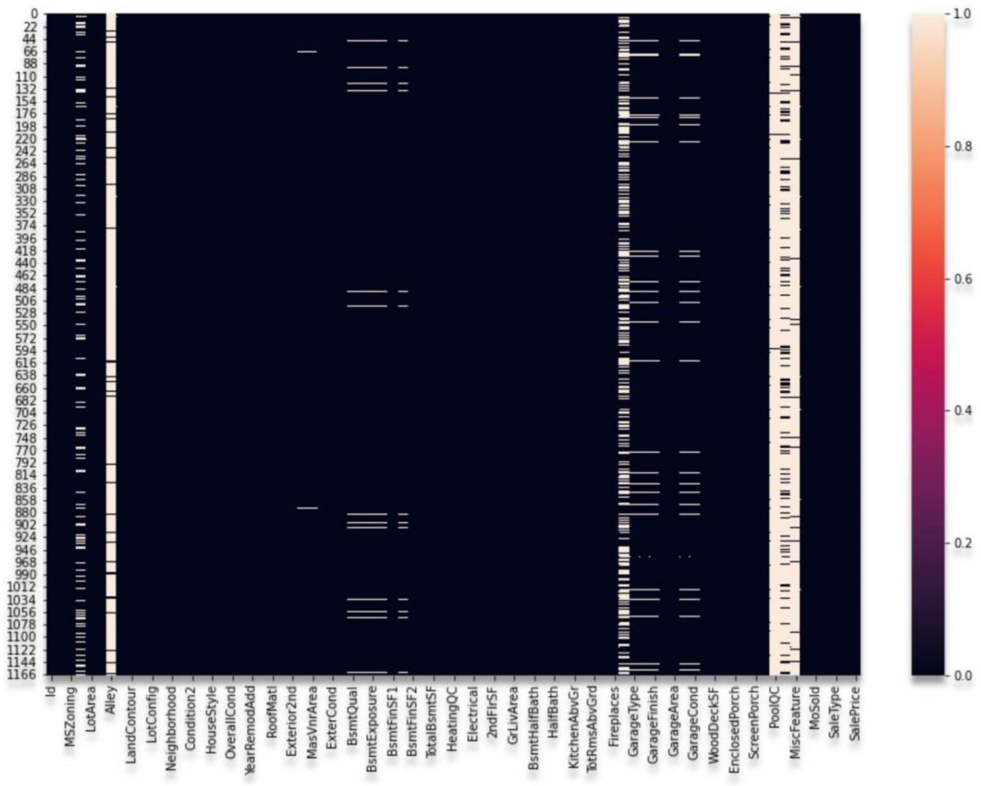
GarageCond	PavedDrive	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold
TA	Y	0	205	0	0	0	0	NaN	NaN	NaN	0	2
TA	Y	81	207	0	0	224	0	NaN	NaN	NaN	0	10
TA	Y	180	130	0	0	0	0	NaN	NaN	NaN	0	6
TA	Y	0	122	0	0	0	0	NaN	MnPrv	NaN	0	1
TA	Y	240	0	0	0	0	0	NaN	NaN	NaN	0	6

YrSold	SaleType	SaleCondition	SalePrice
2007	WD	Normal	128000
2007	WD	Normal	268000
2007	WD	Normal	269790
2010	COD	Normal	190000
2009	WD	Normal	215000

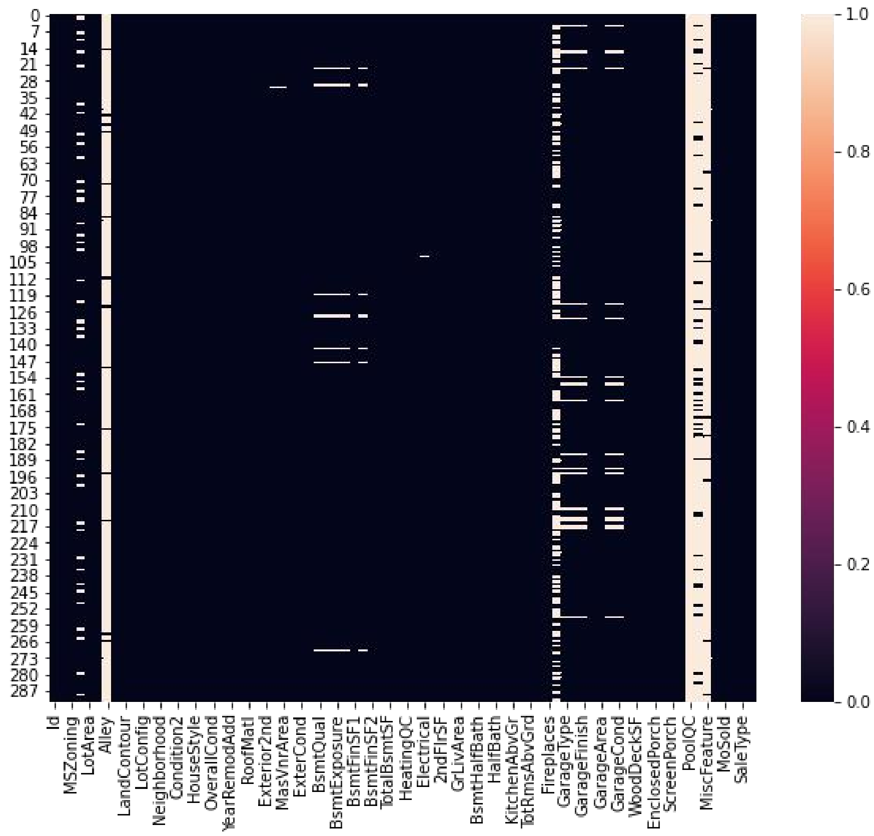
- The column **'SalePrice'** is the target column. We need to predict the sale price of the houses.

- Data Preprocessing Done

As our dataset contains null values (missing values) so we have replace the missing values with the required values. Details are mentioned below:



Heatmap to show the null values of Train Dataset



Heatmap to show the null values of Test Dataset.

1. PoolQC (Pool Quality)

We can see that most of the rows of the column "PoolQC" is empty so we're considering the empty values as there is no pool available in the house. So, we're filling the null values with 'NA'

```
# Checking for the values counts of the column "PoolQC"

df['PoolQC'].value_counts()
```

```
Gd    3
Fa    2
Ex    2
Name: PoolQC, dtype: int64
```

```
# Replacing the null values with 'NA'

df['PoolQC'].fillna('NA', inplace=True)
```

2. MiscFeature (Miscellaneous feature not covered in other categories)

We can see that most of the rows of the column "MiscFeature" is empty so considering it as None we are replacing the missing values with 'NA'

```
# Checking for the value counts of the column "MiscFeature"

df['MiscFeature'].value_counts()
```

```
Shed    49
Othr     2
Gar2     2
TenC     1
Name: MiscFeature, dtype: int64
```

```
# Replacing the null values with 'NA'

df['MiscFeature'].fillna('NA', inplace=True)
```

3. Alley (Type of alley access to property)

We can see that in the case of alley column also most of the rows are empty. So considering it as no alley option was avaiable we're replacing the missing values with 'NA'

```
# Checking for the values counts of the column "Alley"

df['Alley'].value_counts()
```

```
Grvl    50
Pave    41
Name: Alley, dtype: int64
```

```
# Replacing the null values with 'NA'

df['Alley'].fillna('NA', inplace=True)
```

4. Fence (Fence quality)

From our observation we found that most of the rows are empty of Fence column also. So, we're replacing the missing values with 'NA' to show that no fence was available.

```
# Checking for the value counts

df['Fence'].value_counts()
```

```
MnPrv    157
GdPrv     59
GdWo      54
MnWw      11
Name: Fence, dtype: int64
```

```
# Replacing the empty rows with 'NA'

df['Fence'].fillna('NA', inplace=True)
```

5. FireplaceQu (Fireplace quality)

```
# Checking for the values counts

df['FireplaceQu'].value_counts()
```

```
Gd     380
TA     313
Fa      33
Ex      24
Po      20
Name: FireplaceQu, dtype: int64
```

We're considering the empty values as no fireplace is avaiable & replacing the empty values with 'NA'.

```
# Replacing the empty values with NA

df['FireplaceQu'].fillna('NA', inplace=True)
```

6. LotFrontage (Linear feet of street connected to property):

We'll replace the missing values of this column with the mean value.

```
# Checking for the mean value of the column 'LotFrontage'

df['LotFrontage'].mean()
```

```
70.04995836802665
```

```
# Replacing the missing values with the mean of the column.

df['LotFrontage'].fillna(df['LotFrontage'].mean(), inplace=True)
```

7. GarageType (Garage location)

```
# Checking for the value counts:

df['GarageType'].value_counts()
```

```
Attchd     870
Detchd     387
BuiltIn     88
Basment     19
CarPort      9
2Types       6
Name: GarageType, dtype: int64
```

Considering the Garage option is not avaiable for the houses that have empty rows for 'GarageType' column. So, we're replcing it with 'NA'

```
# Replacing the missing values with 'NA'

df['GarageType'].fillna('NA', inplace=True)
```

8. GarageYrBlt (Year garage was built)

```
# Replacing the missing values with 'NA' to show that Garage is not avaiable

df['GarageYrBlt'].fillna('NA', inplace = True)
```

9. GarageFinish (Interior finish of the garage)

```
# Checking for the value counts

df['GarageFinish'].value_counts()
```

```
Unf    605
RFn    422
Fin    352
Name: GarageFinish, dtype: int64
```

```
# Replacing the missing values with 'NA'  to show garage option is not available

df['GarageFinish'].fillna('NA', inplace=True)
```

10. GarageQual (Garage quality)

```
# Replacing the missing values with 'NA' to show Garage is not available

df['GarageQual'].fillna('NA', inplace=True)
```

11. GarageCond (Garage condition)

```
# Replacing the missing values with 'NA'

df['GarageCond'].fillna('NA', inplace=True)
```

12. BsmtFinType2 (Rating of basement finished area (if multiple types))

```
# Replacing the missing values with NA
df['BsmtFinType2'].fillna('NA', inplace=True)
```

13. BsmtExposure (Refers to walkout or garden level walls)

```
# Replacing the missing values with 'NA'
df['BsmtExposure'].fillna('NA', inplace=True)
```

14. BsmtQual (Evaluates the height of the basement)

```
# Replacing the missing values with 'NA'
df['BsmtQual'].fillna('NA', inplace=True)
```

15. BsmtCond (Evaluates the general condition of the basement)

```
# Replacing the missing  values with 'NA'
df['BsmtCond'].fillna('NA', inplace=True)
```

16. BsmtFinType1 (Rating of basement finished area)

```
# Replacing the missing values with 'NA'
df['BsmtFinType1'].fillna('NA', inplace=True)
```

17. MasVnrType (Masonry veneer type)

```
# Checking for the value counts
df['MasVnrType'].value_counts()
```

```
None       864
BrkFace    445
Stone      128
BrkCmn      15
Name: MasVnrType, dtype: int64
```

- As the most occuring masonary venner type is None so, we are replacing the missing values with 'None'

```
# Replacing the missing values with 'None'
df['MasVnrType'].fillna('None', inplace=True)
```

18. MasVnrArea (Masonry veneer area in square feet)

```
# Calculating the mean value

df['MasVnrArea'].mean()
```

```
103.68526170798899
```

```
# Replacing the missing values with the mean value

df['MasVnrArea'].fillna(df['MasVnrArea'].mean(), inplace=True)
```

19. Electrical (Electrical system)

```
# Checking for the value counts

df['Electrical'].value_counts()
```

```
SBrkr    1334
FuseA      94
FuseF      27
FuseP       3
Mix         1
Name: Electrical, dtype: int64
```

- Circuit Breakers & Romex electrical system is mostly used so we are replacing the missing value with SBrkr

```
The numerical features are:
  Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
       'OverallCond', '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')
 --------------------------------------------------------------------------------
 The categorical features are:
  Index(['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
       'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual',
       'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature',
       'SaleType', 'SaleCondition', 'Source'],
      dtype='object')
```

- Data Inputs- Logic- Output Relationships

  EDA was performed by creating valuable insights using various visualization libraries.

Importing the required libraries:

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

from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split

import warnings
warnings.filterwarnings("ignore")
```

Software & Tools:

a) Jupyter Notebook

b) Python

c) Pandas

d) Numpy

e) Matplotlib (used for visualization)

f) Seaborn (used for visualization)

g) Scikit-learn (used as algorithmic libraries)

Development and Evaluation

- Methods:
  - ✓ Performed EDA (Exploratory Data Analysis).
  - ✓ Data Cleaning and dropping the columns which were not contributing to the dataset.
  - ✓ Handled the missing values.
  - ✓ Checked for the outliers and tried to remove the outliers of the dataset.
  - ✓ Checked for the skewness in the dataset and removed the skewness for better model building.
  - ✓ Train- Test the dataset into independent and dependent variables.
  - ✓ Model Building.
- Testing of Identified Approaches (Algorithms)

  Below are the algorithms used for the training and testing:

  1) Linear Regression.
  2) Lasso
  3) Decision Tree Regression.
  4) K Neighbour Regression.
  5) Random Forest Regression.

- Evaluating selected models:

1. LinearRegression: ¶

```
from sklearn.linear_model import LinearRegression
LR = LinearRegression( fit_intercept = True)

LR.fit(x_train, y_train)
print(f"Linear coefficients : {LR.coef_}")
print(f"Intercept : {LR.intercept_}")
```

```
Linear coefficients : [ 8.03328015e+02 -1.19340146e+02 -4.37179268e+02 -4.82330058e+02
  5.33507676e+03  1.45874067e+03  1.07144277e+03  2.81630650e+03
 -1.00174878e+03  1.46346716e+03  1.56220891e+03 -2.44967596e+02
 -1.56530022e+03 -4.76366819e+03 -1.56558207e+03  1.62527912e+04
  5.34617811e+03 -1.52133719e+03  2.03824578e+02  6.36276198e+03
  1.29204204e+04 -3.31310097e+02 -2.05575965e+03  8.89946375e+02
  1.59810157e+02 -4.86914853e+03  8.81079125e+02  1.72894848e+03
 -5.18318324e+03 -3.38694984e+02 -4.62829878e+03  1.16696580e+03
  6.45614865e+03 -9.19678376e+03 -9.52719330e+03 -4.00054986e+03
  1.41440436e+04 -1.11943311e+03 -2.24885057e+03  7.81524720e+02
 -1.71043063e+03 -1.30389313e+03 -1.49218814e+02 -2.30666691e+03
  1.71694947e+04  1.62517313e+03 -1.68605436e+03  3.25099799e+03
  5.01700714e+03 -1.63394307e+03 -1.76613177e+03 -5.88504560e+03
  3.37937524e+03  3.24367604e+03  4.17102505e+03 -3.15206622e+03
  2.47775321e+03  3.21989047e+03 -2.70524274e+03  8.83444623e+03
  3.75437007e+02 -2.88203704e+03  3.16546924e+03  1.03268148e+03
  1.23663546e+03 -4.34562341e+02 -1.98628237e+02 -2.56343863e+02
  7.22343174e+02 -6.92337710e+15 -6.92337710e+15  5.87022656e+02
  5.40287087e+02  7.55021211e+00 -1.06136434e+03 -2.31728522e+02
 -1.41132880e+03  1.86576023e+03]
Intercept : 180956.48107936294
```

```python
# Predicting the new result

LR_pred = LR.predict(x_test)
LR_pred
```

```
array([256716.48107936, 204204.23107936, 109856.16857936, 246401.29357936,
       107879.79357936, 184986.35607936, 337696.35607936, 139660.85607936,
       167618.41857936, 225302.10607936, 186906.79357936, 313815.98107936,
       140021.73107936, 199287.60607936, 195260.48107936,  78335.54357936,
       126657.10607936, 140280.60607936, 317595.85607936, 140201.79357936,
        83317.41857936, 195316.48107936, 168171.04357936, 198882.10607936,
       202724.48107936, 299457.85607936, 117977.48107936, 106937.54357936,
       139954.79357936, 165186.60607936, 228213.16857936,  94140.60607936,
       248583.66857936, 232501.48107936, 196442.85607936, 175321.66857936,
       176085.48107936, 146047.85607936, 242080.48107936, 144043.41857936,
       115072.23107936, 104007.04357936, 266917.35607936, 129103.85607936,
       150529.54357936,  58012.41857936, 329317.73107936, 218173.79357936,
       152245.98107936, 189484.91857936, 238531.54357936, 215465.10607936,
       286204.23107936, 343814.29357936, 113150.48107936, 254671.04357936,
       144170.10607936, 162390.48107936, 165479.60607936,  89990.98107936,
       104649.23107936, 370119.35607936, 205967.54357936, 179662.98107936,
       240843.85607936, 163529.04357936, 186592.29357936,  97815.41857936,
       241524.98107936, 141450.91857936,  86540.60607936, 295013.29357936,
       206109.79357936,  58300.35607936, 373636.79357936, 177345.29357936,
       217945.23107936, 234856.29357936, 163416.16857936, 372280.10607936,
       125680.98107936, 162036.85607936, 218271.29357936, 102870.79357936,
        42980.79357936,  75225.91857936, 120956.60607936, 129975.91857936,
       143231.16857936,  94655.79357936, 217569.79357936,  53121.16857936,
       138960.66857936, 149665.54357936, 105651.04357936, 124832.60607936,
       169725.16857936, 130298.91857936, 252270.85607936, 217928.98107936,
       112547.98107936, 265156.41857936, 206056.10607936,  92962.23107936,
```

2. Lasso

```
from sklearn.linear_model import Lasso

ls = Lasso()
ls.fit(x_train, y_train)

# Predicting the new results

ls_pred = ls.predict(x_test)
ls_pred
```

```
array([256688.08817155, 204223.08659   , 109890.38811304, 246407.94173583,
       107883.22300311, 184983.46133061, 337732.2089803 , 139640.78262227,
       167653.44223094, 225273.71254572, 186903.86792293, 313805.20605809,
       140009.71288715, 199305.45289377, 195258.14272947,  78345.80172911,
       126658.7024441 , 140330.61824404, 317592.78030951, 140199.07543347,
        83326.89017777, 195280.652163  , 168188.21786071, 198854.3630583 ,
       202780.11892162, 299447.88839209, 117983.21397872, 106944.83319864,
       139959.51467239, 165210.80449453, 228238.55930373,  94138.70949859,
       248577.59114329, 232522.80439988, 196442.51447149, 175344.92434395,
       176073.21292545, 146084.07640641, 242039.31062706, 144058.34493572,
       115106.14068428, 104041.26742747, 266912.54877247, 129155.99982369,
       150512.22586034,  58026.86336072, 329300.00986379, 218165.85571348,
       152259.36794295, 189455.87647037, 238506.76817475, 215455.34542988,
       286183.53435009, 343797.48648858, 113115.08282487, 254682.9277769 ,
       144167.96286903, 162388.29327192, 165453.58851096,  90055.68654516,
       104648.76273926, 370135.94190307, 205968.0474855 , 179681.52820127,
       240855.42411666, 163532.67998818, 186609.47911161,  97820.99467318,
       241557.27096387, 141484.78249687,  86550.93215834, 295047.97918466,
       206117.62526479,  58308.35501493, 373599.51825468, 177342.50179593,
       217949.75045909, 234843.20172002, 163441.23378364, 372324.60782701,
       125628.17797224, 161980.34758642, 218305.97587601, 102898.58767191,
        42974.38036831,  75238.22184147, 120981.61655061, 129930.88694625,
       143254.03176356,  94639.19237423, 217531.92854144,  53096.92017722,
       138954.28729472, 149714.38014656, 105642.49533234, 124838.71934031,
       169727.88566236, 130319.23048415, 252267.60817386, 217916.3889303 ,
       112542.45552326, 265171.79589115, 206046.18977574,  92911.10781167,
```

3. DecisionTreeRegressor:

```
from sklearn.tree import DecisionTreeRegressor #Importing the library

DT = DecisionTreeRegressor()
DT.fit(x_train, y_train)

# Predicting the new result

DT_pred = DT.predict(x_test)
DT_pred
```

```
array([175000., 173000., 140000., 203000., 135900., 155000., 246578.,
        89471., 215000., 205000., 206900., 317000., 120500., 201000.,
       138800., 129000., 133000., 123000., 281000., 108000.,  98600.,
       202900., 140000., 172500., 235000., 317000., 135000., 140000.,
       115000., 181000., 227000.,  78000., 236500., 194000., 181000.,
       192000., 172500., 167900., 262280., 133900., 128000., 102000.,
       250000., 141000., 139000.,  92000., 325624., 176000., 136500.,
       200100., 222500., 250580., 311872., 306000., 116050., 236500.,
       139000., 154000., 124900., 120500., 128500., 611657., 185000.,
       167500., 226000., 175000., 132000., 109500., 224000., 155000.,
       123000., 235000., 240000., 108000., 611657., 125000., 260000.,
       154000., 137900., 437154.,  89471.,  82500., 272000., 121600.,
        94000., 128000., 149000., 125000., 175000., 100000., 268000.,
        85400., 142500., 168000., 116500., 129500., 169000., 142500.,
       383970., 227000., 139000., 249700., 226000., 109900., 282922.,
       278000., 192500., 190000.,  72500., 144000., 205000., 188000.,
       325300., 175500.,  79500., 275000., 176432., 159000., 192500.,
       191000., 140000., 192500., 191000., 169000., 201000., 250000.,
       124500., 171750., 277500., 135000., 238000., 119500., 202500.,
       140000., 203000., 120500.,  93000., 147400., 402000., 192000.,
       133000., 127000., 130000., 148000., 117000., 191000., 127000.,
       237000., 230000., 150500., 302000., 132000., 160000., 200500.,
       175000., 103000.,  83500., 135500., 128000., 257000., 230000.,
       211000., 191000., 171750., 415298., 325000., 213500., 165500.,
       145000., 129000., 172500.,  89471., 132500., 114500., 134500.,
```

4. KNeighborsRegressor:

```
from sklearn.neighbors import KNeighborsRegressor

KNN = KNeighborsRegressor(n_neighbors=2)
KNN.fit(x_train, y_train)

# Predicting the new result

KNN_pred = KNN.predict(x_test)
KNN_pred
```

```
array([497500. , 190637.5, 128500. , 185850. , 108500. , 135250. ,
       332500. , 112950. , 155450. , 196200. , 185250. , 299875. ,
       147250. , 208000. , 509985. , 104500. , 144600. ,  95691.5,
       262050. , 112000. , 103000. , 273900. , 151750. , 254500. ,
       196250. , 305000. , 142000. , 114250. , 113000. , 196000. ,
       293375. , 123500. , 225000. , 238250. , 146950. , 222250. ,
       158500. , 142950. , 145000. , 144750. , 115000. , 135950. ,
       301000. , 133500. , 144250. ,  86000. , 307000. , 210000. ,
       143450. , 146250. , 238250. , 237790. , 214000. , 191495. ,
        95000. , 221500. , 125250. , 155000. , 145000. , 117750. ,
       144450. , 431966.5, 205700. , 165750. , 234750. , 157475. ,
       193125. , 111250. , 218500. , 165500. , 117750. , 331875. ,
       231500. ,  86000. , 503044.5, 118954. , 174700. , 167975. ,
       174000. , 380500. , 126700. , 126450. , 189700. , 153500. ,
        98600. ,  86750. , 160250. , 110750. , 118000. , 100600. ,
       179950. ,  97000. , 155250. , 150125. , 136750. , 161500. ,
       178750. , 137450. , 282875. , 204725. ,  93691.5, 261000. ,
       192500. ,  97200. , 230425. , 270000. , 190450. , 113950. ,
        60500. , 145000. , 183950. , 166550. , 293500. , 205250. ,
       138750. , 248946.5, 109000. , 230750. , 187600. , 228350. ,
       119450. , 230500. , 159250. , 114000. , 254038.5, 209800. ,
       127750. , 189000. , 318980.5, 109500. , 252000. , 151125. ,
       198600. , 138250. , 179500. , 130750. , 109000. , 145776. ,
       274950. , 177216. , 118504. , 122004. , 124750. , 148250. ,
       109000. , 133475. , 175100. , 255750. , 233500. , 145000. ,
       231250. , 148750. , 149950. , 192950. , 222250. , 119950. ,
```

5. RandomForestRegressor:

```
from sklearn.ensemble import RandomForestRegressor
RF = RandomForestRegressor(max_depth=2, random_state=42)

RF.fit(x_train,y_train)

# Predicting the new result

RF_pred = RF.predict(x_test)
RF_pred
```

```
array([152018.811756  , 203612.72279716, 143205.2902323 , 205982.26328349,
       143763.05656626, 209563.64111188, 205502.72175165, 150485.11194221,
       163303.81032812, 209537.30656935, 163303.81032812, 274393.6371864 ,
       148900.23334221, 206605.90343334, 150437.75412853, 128827.01487053,
       129961.13870096, 150081.71498632, 280165.71772777, 130411.89347053,
       130764.11164022, 264053.32885347, 133416.24018354, 164774.45722734,
       207448.12727862, 269602.50783888, 141930.58497411, 132727.20324515,
       162003.80344578, 164774.45722734, 262705.55632178, 129230.41182642,
       263860.1437495 , 210773.39263101, 164774.45722734, 205982.26328349,
       164774.45722734, 152800.42171683, 211870.96106693, 144582.71351743,
       162003.80344578, 144535.35570375, 273214.57011654, 129629.98780979,
       131125.93633315, 128827.01487053, 286416.32538585, 206605.90343334,
       148900.23334221, 204198.72499706, 207448.12727862, 205982.26328349,
       212920.09530163, 280966.7469931 , 150081.71498632, 263860.1437495 ,
       131546.01730096, 130764.11164022, 143763.05656626, 129629.98780979,
       128827.01487053, 333541.59011704, 206605.90343334, 152018.811756  ,
       211397.03278086, 151619.23577264, 205502.72175165, 129646.67182171,
       165790.05581954, 131142.62034507, 129961.13870096, 278634.30287429,
       165790.05581954, 128827.01487053, 327258.96545754, 150884.68792557,
       209724.63907297, 152393.24151634, 145716.83734786, 316248.10545572,
       130811.4694539 , 150485.11194221, 165790.05581954, 129961.13870096,
       128827.01487053, 128827.01487053, 202509.54111547, 130411.89347053,
       131882.54036975, 128827.01487053, 209537.30656935, 130364.53565685,
       134933.06936497, 143112.06661822, 128827.01487053, 141538.62653175,
       165790.05581954, 130008.49651464, 216662.09041445, 262705.55632178,
       130364.53565685, 267496.6856693 , 205982.26328349, 129188.83956347,
```

- Key Metrics for success in solving problem under consideration

Calculating Mean Absolute Error:

```
from sklearn.metrics import mean_absolute_error

print(' Mean Absolute Error for LinearRegression is ', mean_absolute_error(y_test, LR_pred),
      '\n Mean Absolute Error for the Lasso is ', mean_absolute_error(y_test, ls_pred),
     '\n Mean Absolute Error for DecisionTreeRegressor is ', mean_absolute_error(y_test, DT_pred),
     '\n Mean Absolute Error for KNeighborsRegressor is ', mean_absolute_error(y_test, KNN_pred),
      '\n Mean Absolute Error for RandomForestRegressor is ', mean_absolute_error(y_test, RF_pred))
```

```
 Mean Absolute Error for LinearRegression is  22158.142691832993
 Mean Absolute Error for the Lasso is  22154.59984041892
 Mean Absolute Error for DecisionTreeRegressor is  25394.410256410258
 Mean Absolute Error for KNeighborsRegressor is  29492.096153846152
 Mean Absolute Error for RandomForestRegressor is  30094.539950999737
```

- We can see that the Mean Absilute error is least for Lasso (22154.599), so this can be considered as good model.
- Also the Mean Absolute Error for LinearRegression is (22158.14), which is almost equal to the Lasso. So, let's check for Root Mean Squared Error and R2_Score to decide the best model.

Root Mean Square Error:

```
from sklearn import metrics

rmse_LR = np.sqrt(metrics.mean_squared_error(y_test, LR_pred))
rmse_ls = np.sqrt(metrics.mean_squared_error(y_test, ls_pred))
rmse_DT = np.sqrt(metrics.mean_squared_error(y_test, DT_pred))
rmse_KNN = np.sqrt(metrics.mean_squared_error(y_test, KNN_pred))
rmse_RF = np.sqrt(metrics.mean_squared_error(y_test, RF_pred))

print('Root Mean Squared Error for LinearRegression is ', rmse_LR)
print('Root Mean Squared Error for Lasso is ', rmse_ls)
print('Root Mean Squared Error for DecisionTreeRegressor is ', rmse_DT)
print('Root Mean Squared Error for KNeighborsRegressor is ', rmse_KNN)
print('Root Mean Squared Error for RandomForestRegressor is ', rmse_RF)
```

```
Root Mean Squared Error for LinearRegression is  32900.06525455999
Root Mean Squared Error for Lasso is  32896.55457436603
Root Mean Squared Error for DecisionTreeRegressor is  38982.791146512965
Root Mean Squared Error for KNeighborsRegressor is  54358.71132123481
Root Mean Squared Error for RandomForestRegressor is  44644.049167381185
```

- We can see that the root mean square error is minimum for Lasso. So, we can say that Lasso is the best fit model. Let's check r2 score for more accurate decision.

R-Squared:

```
from sklearn.metrics import r2_score

print(' R2_Score for LinearRegression is ', r2_score(y_test, LR_pred),
      '\n R2_Score for the Lasso is', r2_score(y_test, ls_pred),
      '\n R2_Score for DecisionTreeRegressor is ', r2_score(y_test, DT_pred),
      '\n R2_Score for KNeighborsRegressor is ', r2_score(y_test, KNN_pred),
      '\n R2_Score for RandomForestRegressor is ', r2_score(y_test, RF_pred))
```

```
 R2_Score for LinearRegression is  0.8419165475343597
 R2_Score for the Lasso is 0.8419502830805364
 R2_Score for DecisionTreeRegressor is  0.7780583779481173
 R2_Score for KNeighborsRegressor is  0.5684499232056501
 R2_Score for RandomForestRegressor is  0.7089148507145988
```

-
  - R2_Score closest to 1.0 is considered as best. From the above observations we can see that the best R2_Score is for LinearRegression and Lasso (0.84).
- So, as per our observations we can say that the best fit model for our dataset is Lasso.

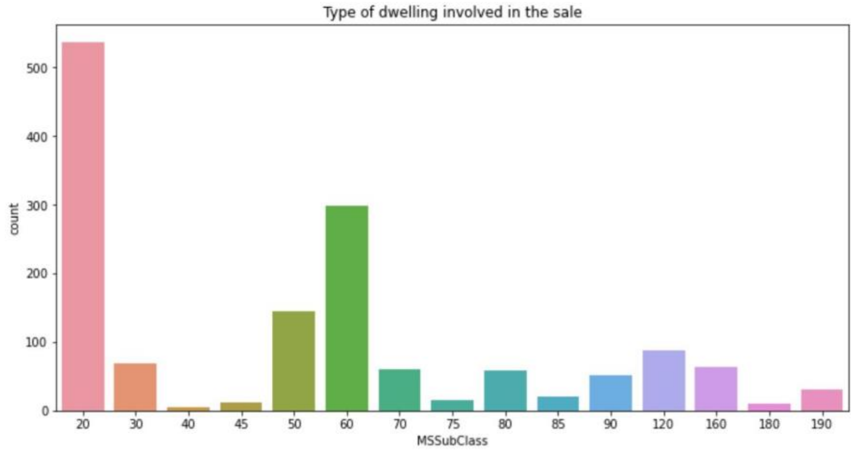
- # Visualizations

Data Visualization:

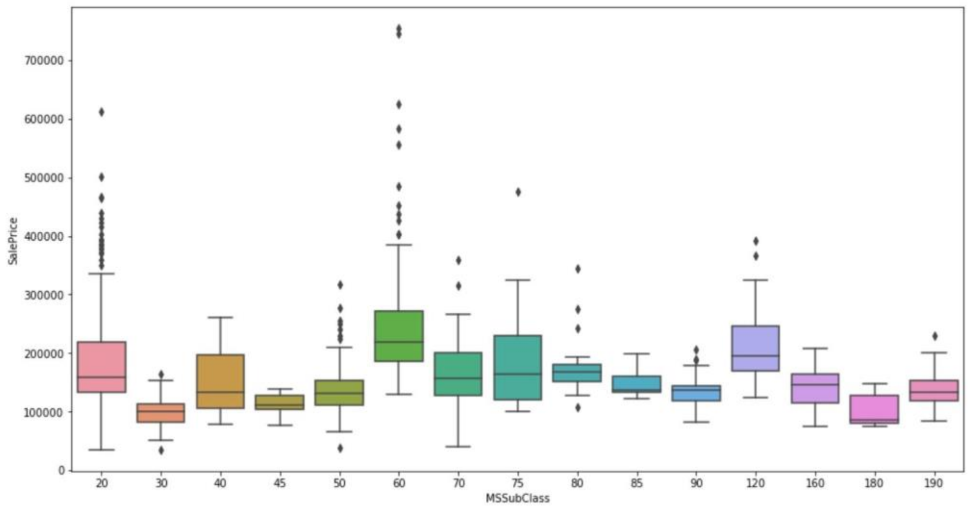
```
# Checking for the value counts of column 'MSSubClass'

df['MSSubClass'].value_counts()
```

```
20     536
60     299
50     144
120     87
30      69
160     63
70      60
80      58
90      52
190     30
85      20
75      16
45      12
180     10
40       4
Name: MSSubClass, dtype: int64
```

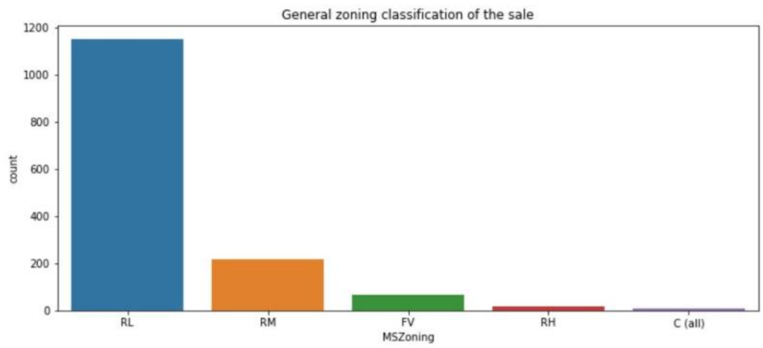
```
# Visualizing the value counts of the column 'MSSubClass'

plt.figure(figsize=[12,6])
sns.countplot(df.MSSubClass)
plt.title('Type of dwelling involved in the sale')
plt.show()
```




```
plt.figure(figsize=(15,8))
sns.boxplot(x='MSSubClass',y='SalePrice',data=df.sort_values('SalePrice',ascending=False))
plt.show()
```



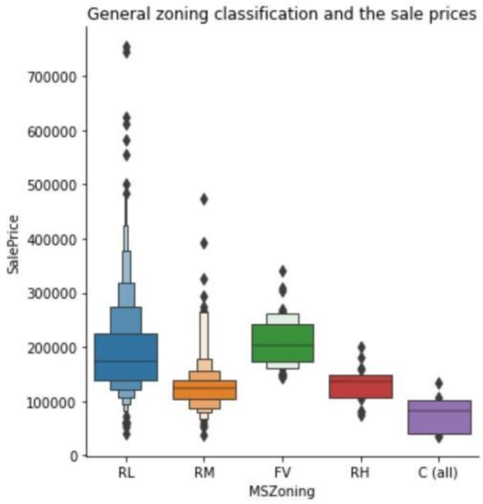

```
# Checking for the value counts of the column 'MSZoning'(Identifies the general zoning classification of the sale)

plt.figure(figsize=[12,5])
sns.countplot(df.MSZoning)
plt.title('General zoning classification of the sale')
plt.show()
```



- We can see that the maximum number of general zoning classification of the sale is Residential Low Density (RL) and the minimum is for the commercial.

```python
# Let's check the effect of zoning classification on the sale price.

plt.figure(figsize=[12,8])
sns.catplot(x='MSZoning', y='SalePrice',data=df.sort_values('SalePrice',ascending=False), kind='boxen')
plt.title('General zoning classification and the sale prices')
plt.show()
```

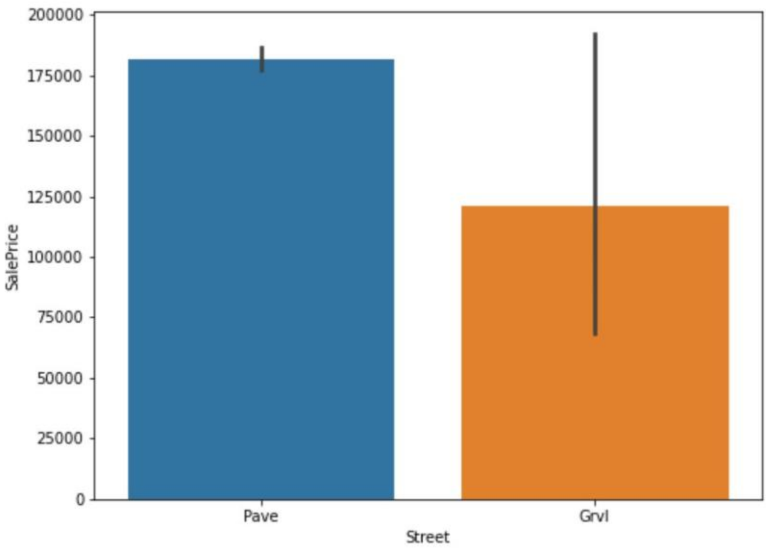
```
<Figure size 864x576 with 0 Axes>
```



Observations:

- For Residential Low Density (RL), the maximum prices are ranging between 50,000 to 4,00,000.
- For Floating Village Residential (FV), the maximum prices are ranging between 150000 to 250000.

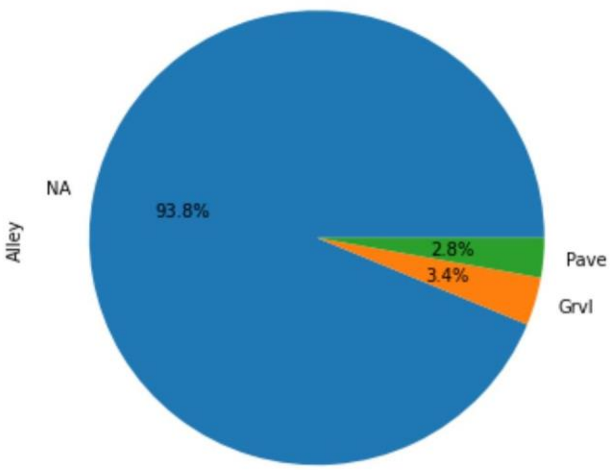
```python
# Checking for the sale price on the basis of road access to the property

plt.figure(figsize=[8,6])
sns.barplot(x='Street', y='SalePrice', data = df.sort_values('SalePrice', ascending=False))

plt.show()
```



- we can observe that the property with the road access of Pave is in more demand and so its price is also high.

```python
# Let's check for the alley access to property

plt.figure(figsize=[6,6])
df['Alley'].value_counts().plot.pie(autopct='%0.1f%%')
```

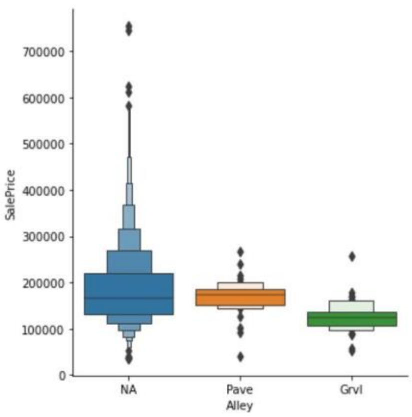
<AxesSubplot:ylabel='Alley'>



- We can see that approx 94% property have no alley access.

```python
# Let's check the effect of alley access on the sale price.

plt.figure(figsize=[8,6])
sns.catplot(x='Alley', y='SalePrice', data=df.sort_values('SalePrice', ascending=False), kind = 'boxen')
plt.show()
```

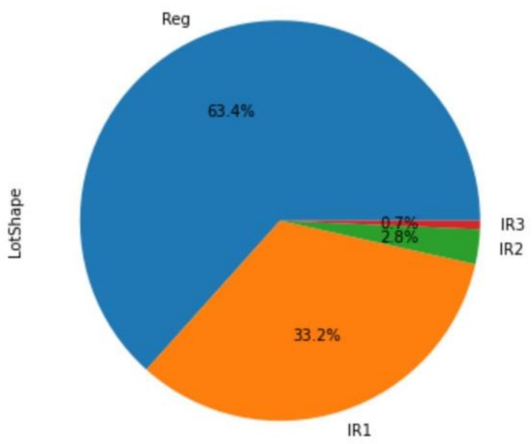
<Figure size 576x432 with 0 Axes>



We can observe that the effect of alley access to the properties is very less. So, it is better to remove this column as approx 94% of properties has no alley access.

```python
# Let's check for the General shape of property

plt.figure(figsize=[6,6])
df['LotShape'].value_counts().plot.pie(autopct='%0.1f%%')
```

```
<AxesSubplot:ylabel='LotShape'>
```

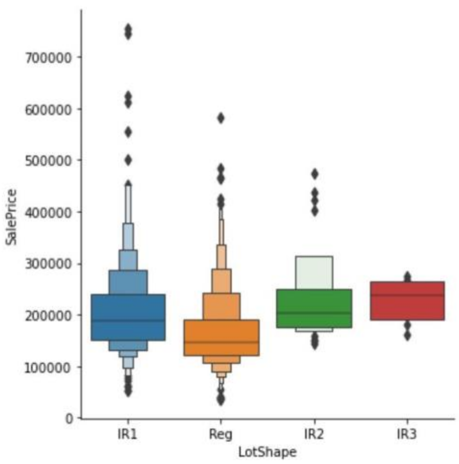


Observations:

- We can see that most of the properties are of regular shape (approx 63%).
- Approx 33% properties are of slightly irregular shape.

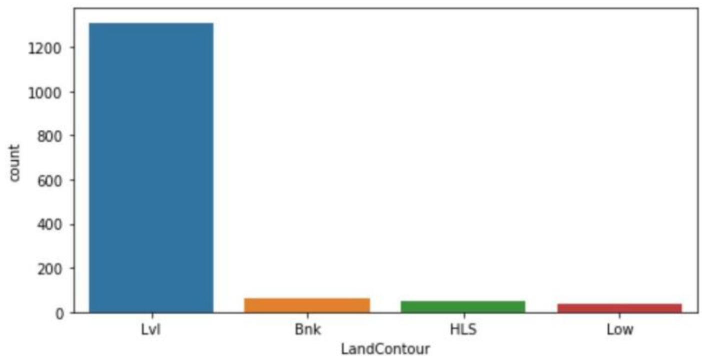
```python
# Checking the relation of property shape on the sale price

plt.figure(figsize=[8,4])
sns.catplot(x='LotShape', y='SalePrice', data=df.sort_values('SalePrice', ascending=False), kind = 'boxen')
plt.show()
```

```
<Figure size 576x288 with 0 Axes>
```



```python
# Let's check for the Flatness of the property

plt.figure(figsize=[8,4])
sns.countplot(df['LandContour'])
```

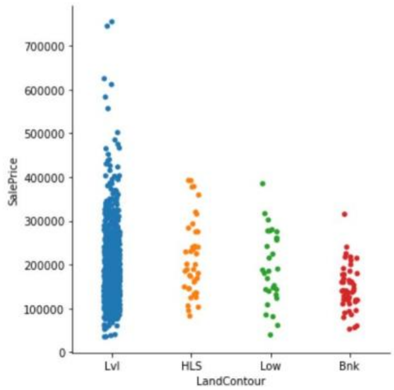
```
<AxesSubplot:xlabel='LandContour', ylabel='count'>
```



- Most of the properties are of near flat level

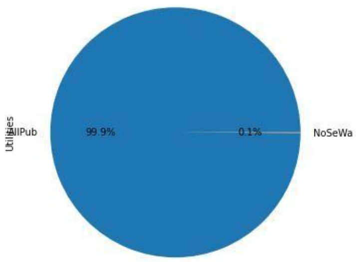
```python
# Let's check for the effect of flatness of the property on the sale price

plt.figure(figsize=[8,4])
sns.catplot(x='LandContour', y='SalePrice', data=df.sort_values('SalePrice', ascending=False))
```

```
<seaborn.axisgrid.FacetGrid at 0x189ce7a8730>

<Figure size 576x288 with 0 Axes>
```




```python
# Let's check for the type of utilities available in the property

plt.figure(figsize=[6,6])
df['Utilities'].value_counts().plot.pie(autopct='%0.1f%%')
```

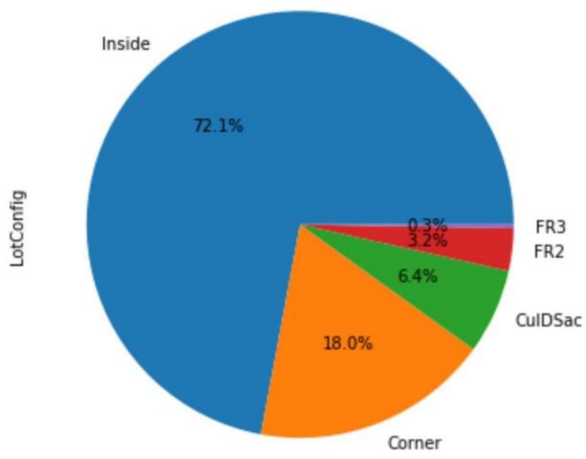
```
<AxesSubplot:ylabel='Utilities'>
```



- We can see that approx 100% properties have all public Utilities (E,G,W,& S). So, we can drop this column as this will not contribute to the dataset in the model building.

```python
# Let's check for the lot configuration

plt.figure(figsize=[6,6])
df['LotConfig'].value_counts().plot.pie(autopct='%0.1f%%')
```

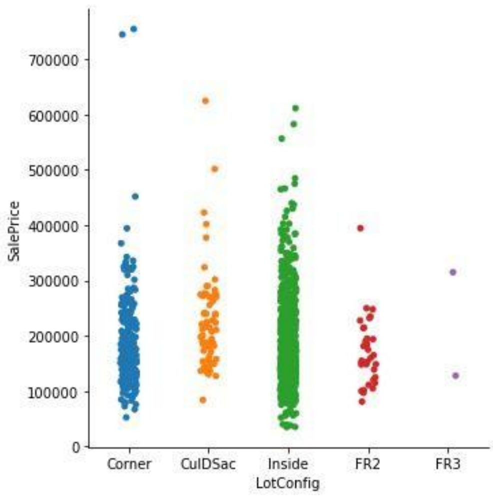
```
<AxesSubplot:ylabel='LotConfig'>
```



- Approx 72% properties have inside lot configuration.
- 18% properties have corner lot.
- Only 0.3% properties have frontage on 3 sides of property.

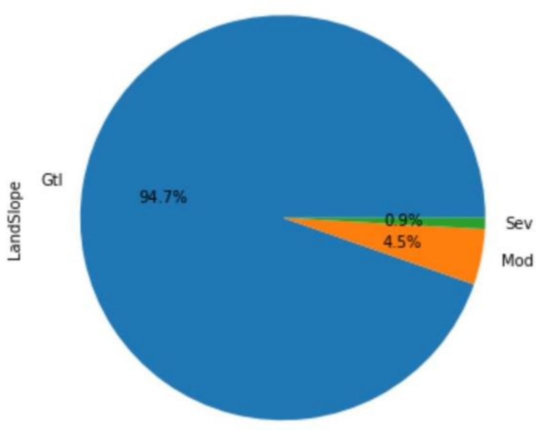
```python
# Checking for the lot configuration and its effect on the sale pricing.

plt.figure(figsize=[6,4])
sns.catplot(x='LotConfig', y='SalePrice', data=df.sort_values('SalePrice', ascending=False))
```

```
<seaborn.axisgrid.FacetGrid at 0x189ce3c6640>

<Figure size 432x288 with 0 Axes>
```



```python
# Let's check for the slope of the property

plt.figure(figsize=[6,6])
df['LandSlope'].value_counts().plot.pie(autopct='%0.1f%%')
```

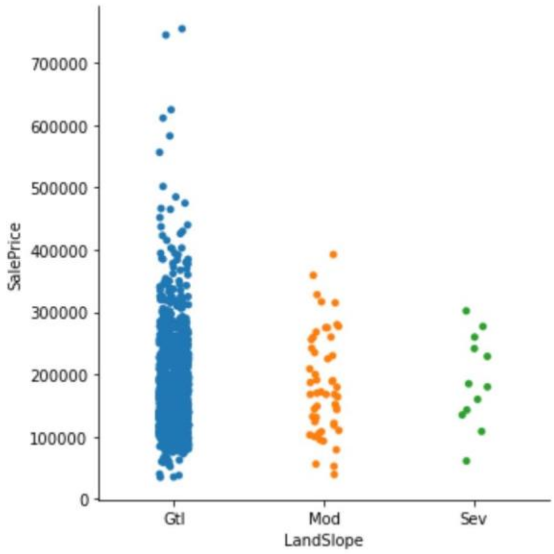
```
<AxesSubplot:ylabel='LandSlope'>
```



- Approx 95% properties having gentle slope.
- Only approx 1% properties having severe Slope and 4.5% properites having moderate slope.

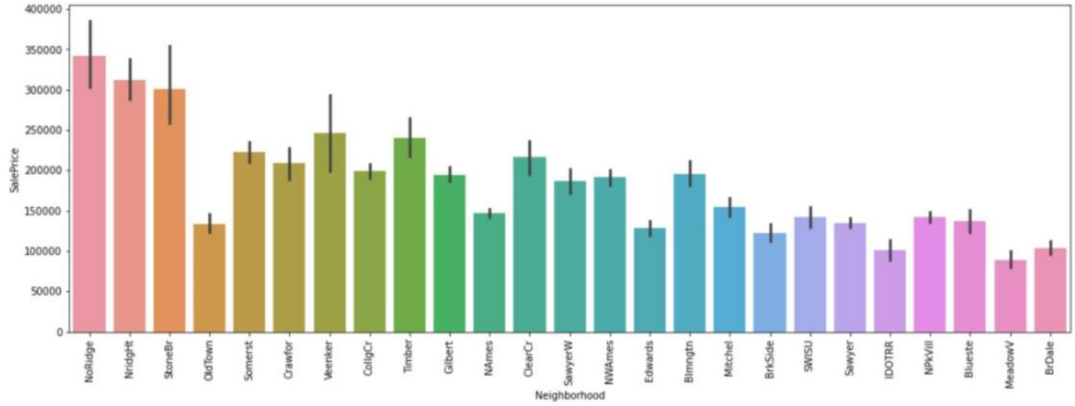
```python
# Cheecking for the slope wise sale pricing of the properties

plt.figure(figsize=[8,6])
sns.catplot(x='LandSlope', y='SalePrice', data=df.sort_values('SalePrice', ascending=False))
```

```
<seaborn.axisgrid.FacetGrid at 0x189ce282c10>

<Figure size 576x432 with 0 Axes>
```



- The maximum gentle slope type properties having the sale price ranging between 100000 to 300000.

```python
# Checking for the effect of physical locations within Ames city limits on the sale price

plt.figure(figsize=[18,6])
sns.barplot(x='Neighborhood', y='SalePrice', data= df.sort_values('SalePrice', ascending=False))
plt.xticks(rotation=90)
plt.show()
```




```python
# Checking for the value counts of type of dwelling

df['BldgType'].value_counts()
```

```
1Fam      1220
TwnhsE     114
Duplex      52
Twnhs       43
2fmCon      31
Name: BldgType, dtype: int64
```

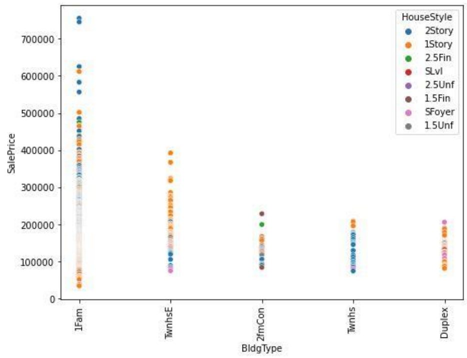
- Single-family Detached dewlling is most popular.
- Two-family Conversion; originally built as one-family dwelling is least popular.

```python
# Checking for the value counts of the style of dwelling

df['HouseStyle'].value_counts()
```

```
1Story    726
2Story    445
1.5Fin    154
SLvl       65
SFoyer     37
1.5Unf     14
2.5Unf     11
2.5Fin      8
Name: HouseStyle, dtype: int64
```

- One story style of houses are most popular.
- Two and one-half story: 2nd level finished style of house is least popular.

```python
# Let's check for the type & style of dwelling

plt.figure(figsize=[8,6])
sns.scatterplot(x= 'BldgType', y='SalePrice', hue = 'HouseStyle', data = df.sort_values('SalePrice', ascending=False))
plt.xticks(rotation = 90)
plt.show()
```



```
# Checking for the value counts of the Rates the overall material and finish of the house

df['OverallQual'].value_counts()
```

```
5     397
6     374
7     319
8     168
4     116
9      43
3      20
10     18
2       3
1       2
Name: OverallQual, dtype: int64
```

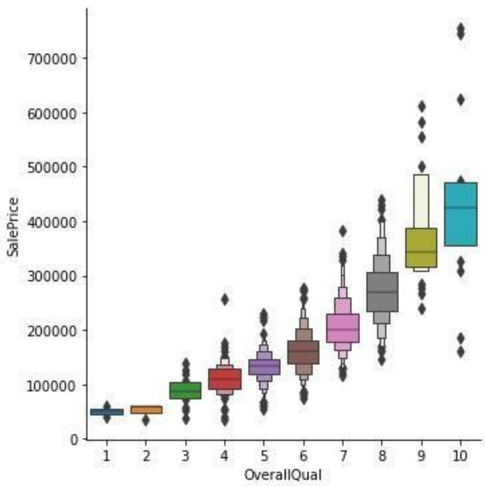
- Most of the houses are rated 5 which means the overall material and finish of the houses are average and above average.
- Very few houses was rated 1 which says the overall material and finish of very few houses are very poor.

```
# Checking for the value counts of the rates the overall condition of the house

df['OverallCond'].value_counts()
```

```
5    821
6    252
7    205
8     72
4     57
3     25
9     22
2      5
1      1
Name: OverallCond, dtype: int64
```

- Most of the houses are rated average and above average for the overall condition of the house.
- None of the houses got the ratings of very excellent.

```
<Figure size 576x432 with 0 Axes>
```



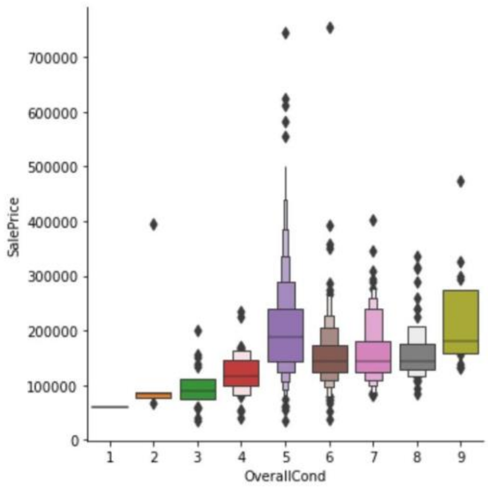
Notations:

- 1: Very Poor
- 2: Poor
- 3: Fair
- 4: Below Average
- 5: Average
- 6: Above Average
- 7: Good
- 8: Very Good
- 9: Excellent
- 10: Very Excellent

- We can see that as the ratings are increasing the price of the property is also increasing.

```python
# Let's check for the saleprices based on the ratings of overall condition of the house

plt.figure(figsize=[8,6])
sns.catplot(x='OverallCond', y='SalePrice', data = df.sort_values('SalePrice', ascending=False), kind = 'boxen')

plt.show()
```

```
<Figure size 576x432 with 0 Axes>
```



- We can see that the price of the house is highest for the house which got 9 ratings (Excellent)

```python
# Let's check for the value counts of type of roof of the houses

df['RoofStyle'].value_counts()
```

```
Gable      1141
Hip         286
Flat         13
Gambrel      11
Mansard       7
Shed          2
Name: RoofStyle, dtype: int64
```

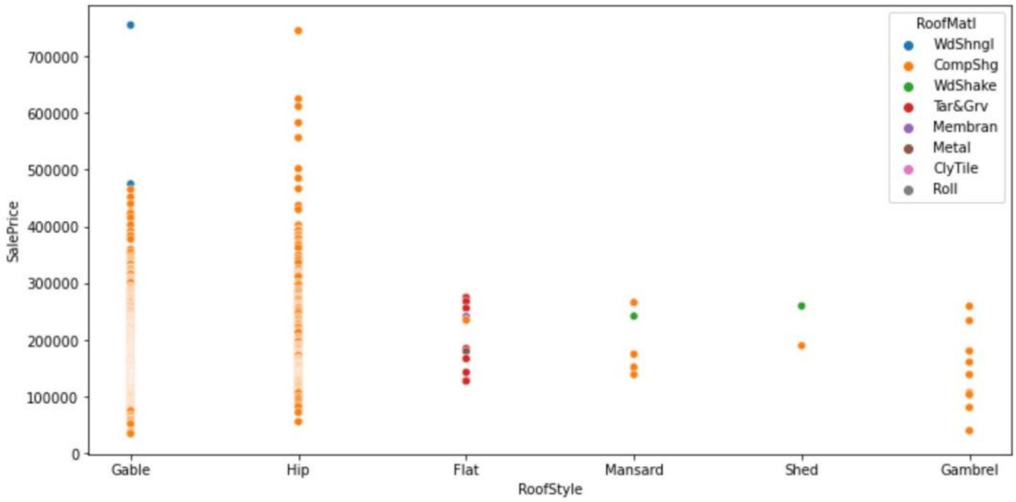
- Maximum houses having Gable type of roof.

```python
# Checking for the value counts of the material used for the roof.

df['RoofMatl'].value_counts()
```

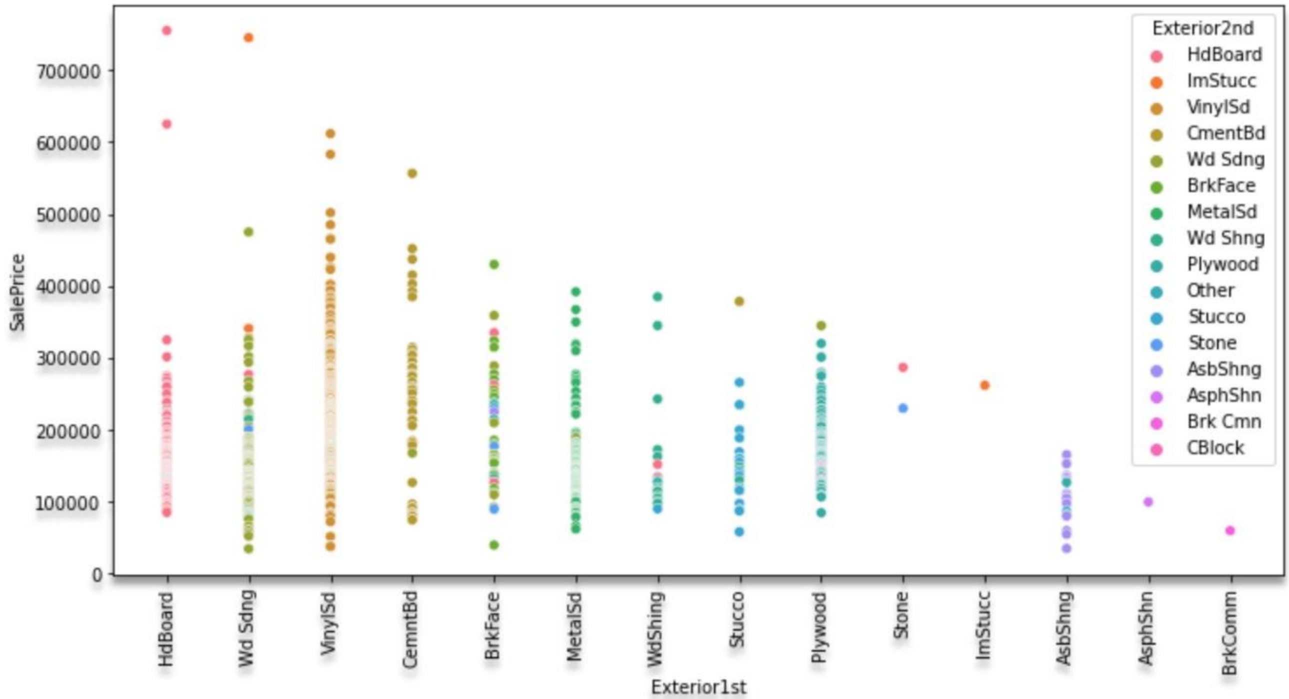
```
CompShg    1434
Tar&Grv      11
WdShngl       6
WdShake       5
ClyTile       1
Roll          1
Metal         1
Membran       1
Name: RoofMatl, dtype: int64
```

- Maximum houses having the roof which is made up of Standard (Composite) Shingle

```
# Let's check for the effect of roof on the sale price

plt.figure(figsize=[12,6])
sns.scatterplot(x='RoofStyle', y='SalePrice', hue = 'RoofMatl', data = df.sort_values('SalePrice', ascending=False))

plt.show()
```



- We can see that the most of the roof are made up of Standard (Composite) Shingle.
- The highest price of the house having Gable roof type and the material of the roof is Wood Shingles.



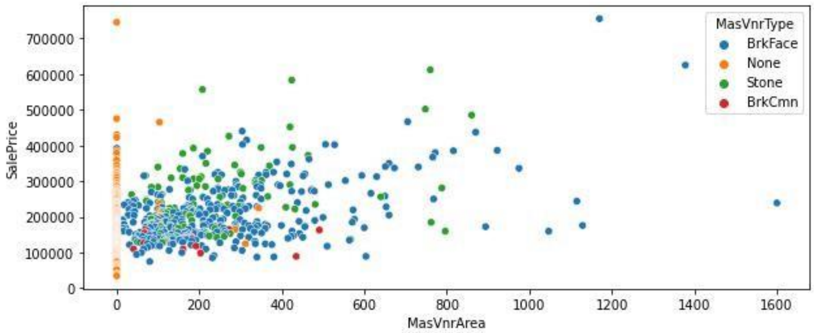
```python
# Let's check for the value counts of the masonry veneer type

df['MasVnrType'].value_counts()
```

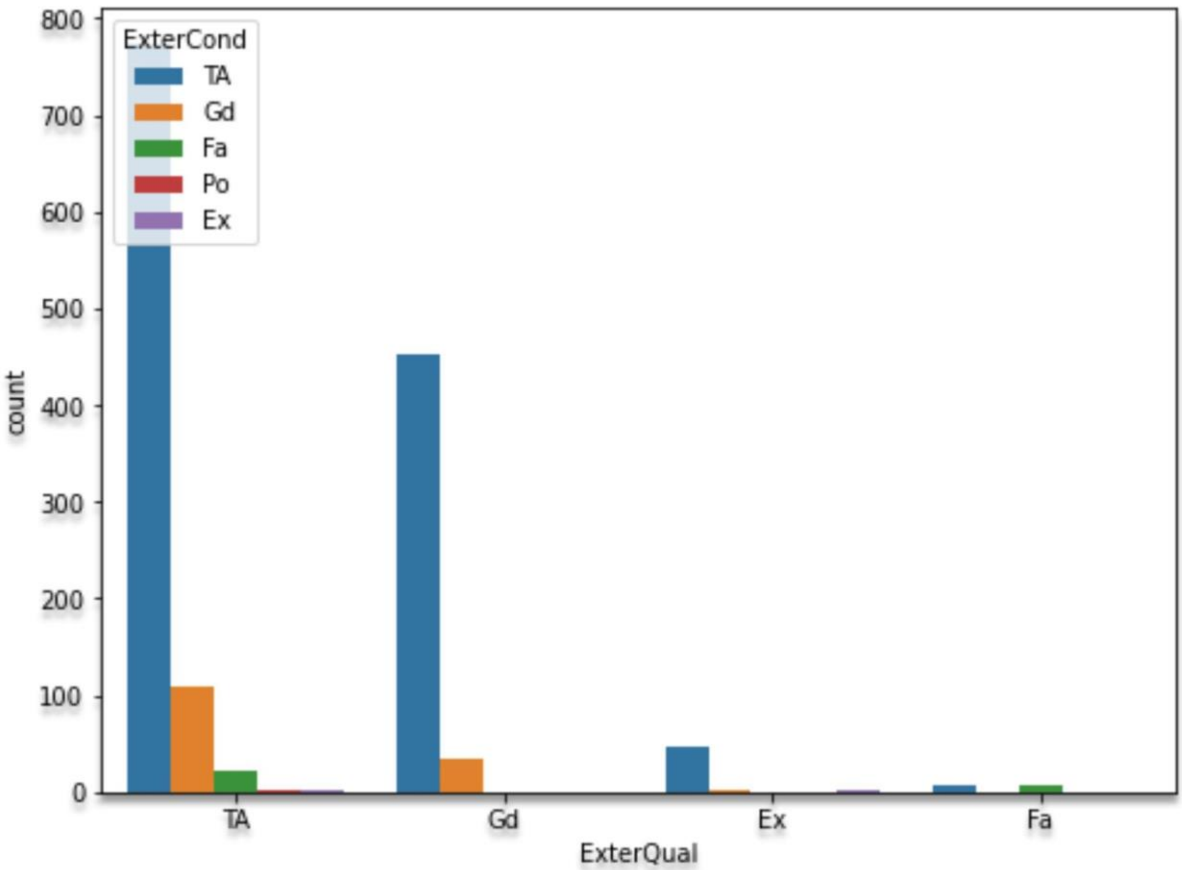
```
None       872
BrkFace    445
Stone      128
BrkCmn      15
Name: MasVnrType, dtype: int64
```

- Most of the houses have no masonry veneer.

```python
# Let's check for the sale price based on the masonry veneer

plt.figure(figsize=[10,4])
sns.scatterplot(x='MasVnrArea', y='SalePrice', hue = 'MasVnrType', data = df.sort_values('SalePrice', ascending=False))
```

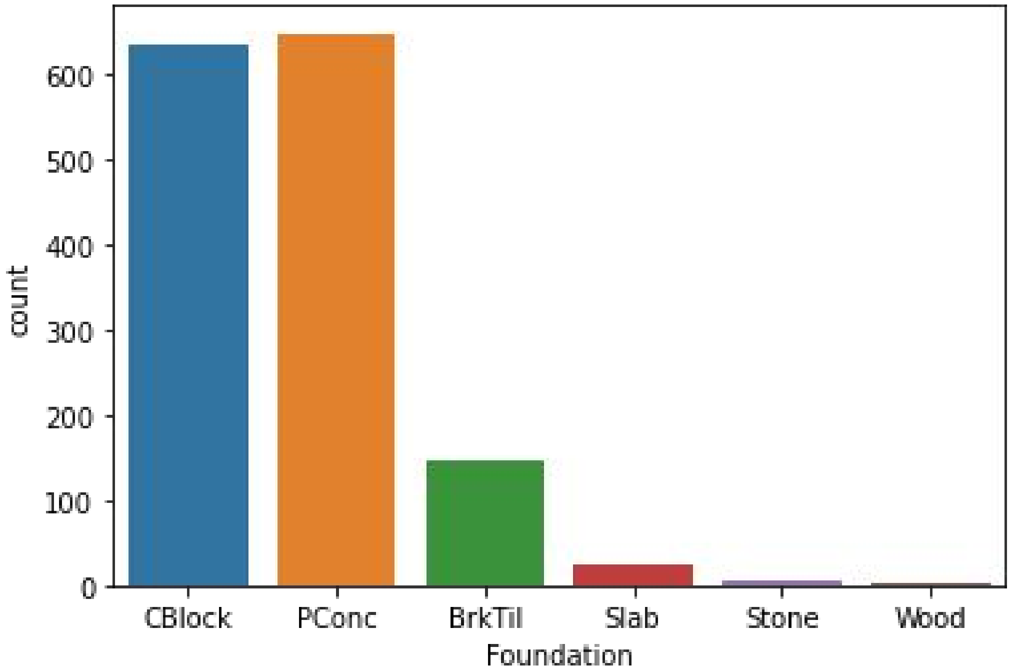
```
<AxesSubplot:xlabel='MasVnrArea', ylabel='SalePrice'>
```

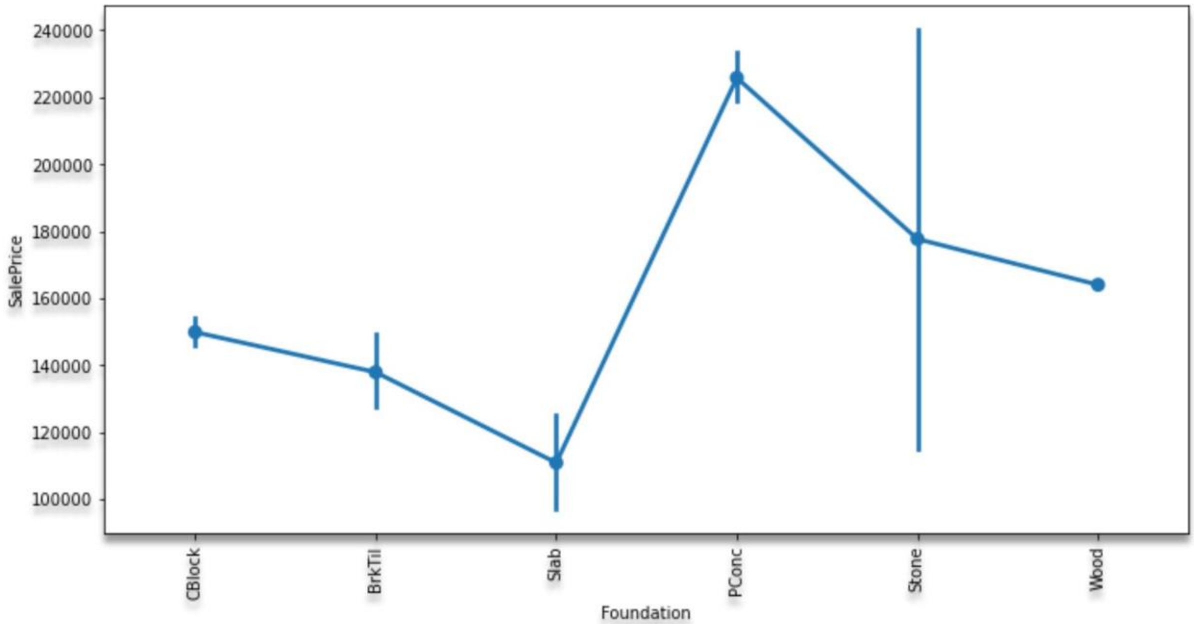




Notations:

- Ex Excellent
- Gd Good
- TA Average/Typical
- Fa Fair
- Po Poor
    - Most of the houses are of average/typical quality of the material on the exterior.
    - None houses have poor quality of material on the exterior.



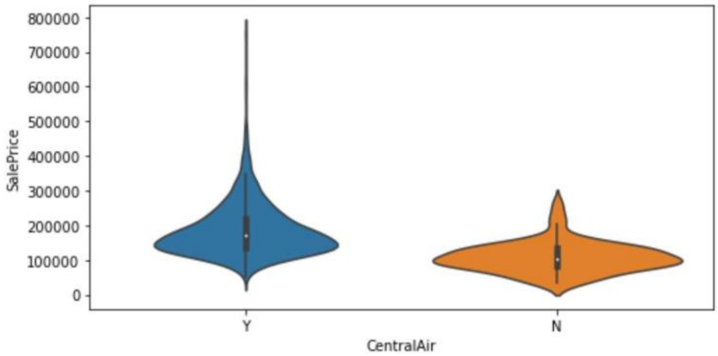


```python
# Let's check for the central air conditioning

df['CentralAir'].value_counts()
```

```
Y    1365
N      95
Name: CentralAir, dtype: int64
```

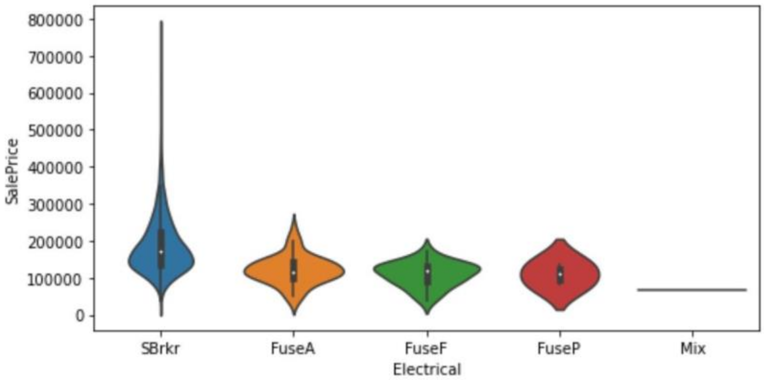
- Most of the houses having central air conditioning

```python
# Checking for the price of the houses on the basis of air conditioning

plt.figure(figsize=[8,4])
sns.violinplot(x='CentralAir', y='SalePrice', data=df.sort_values('SalePrice', ascending=False))

plt.show()
```



- Houses having the option of central air conditioning have more price.

```python
# Let's check for the electrical system of the house

plt.figure(figsize=[8,4])
sns.violinplot(x='Electrical', y='SalePrice', data=df.sort_values('SalePrice', ascending=False))

plt.show()
```



Notation:

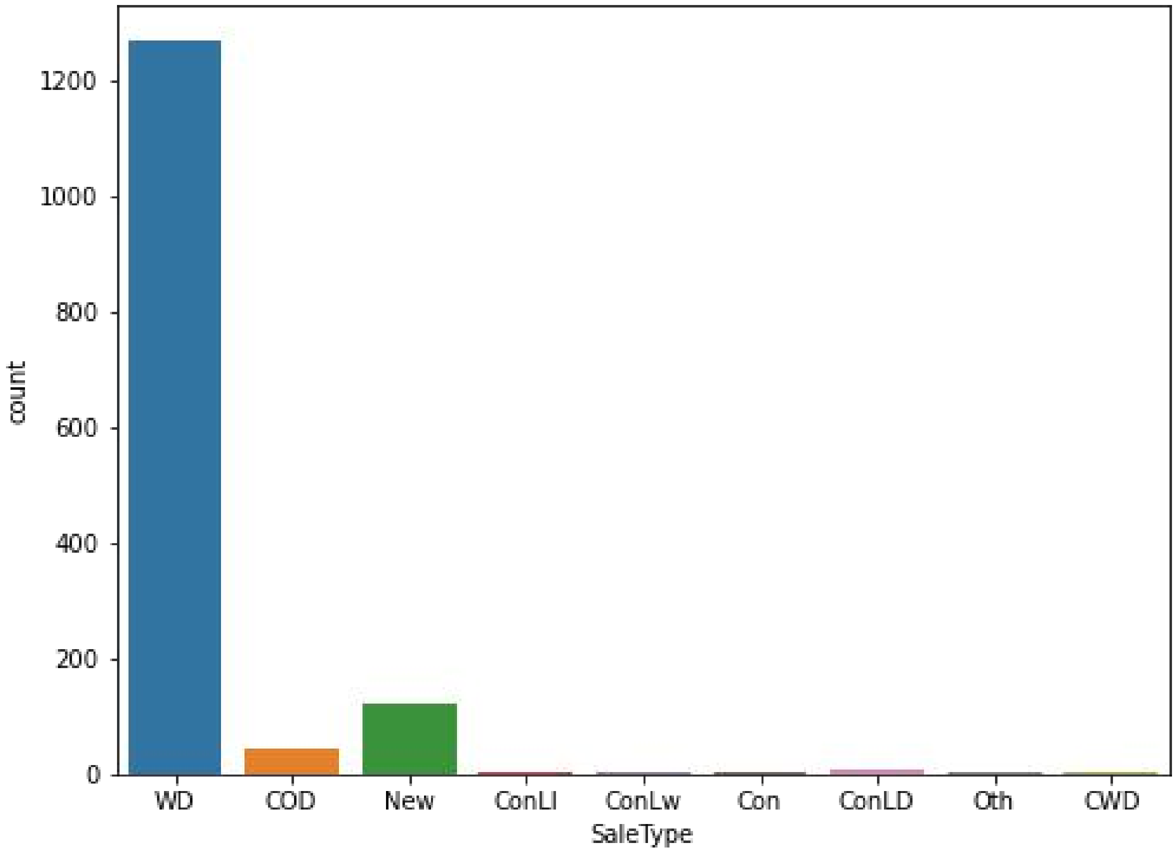
- SBrkr Standard Circuit Breakers & Romex
- FuseA Fuse Box over 60 AMP and all Romex wiring (Average)
- FuseF 60 AMP Fuse Box and mostly Romex wiring (Fair)
- FuseP 60 AMP Fuse Box and mostly knob & tube wiring (poor)
- Mix Mixed
  - Most of the houses are having the electrical system of standard circuit breakers and romex.

```python
# Let's check value count for the home functionality (Assume typical unless deductions are warranted)

df['Functional'].value_counts()
```

```
Typ     1360
Min2      34
Min1      31
Mod       15
Maj1      14
Maj2       5
Sev        1
Name: Functional, dtype: int64
```

Notations:

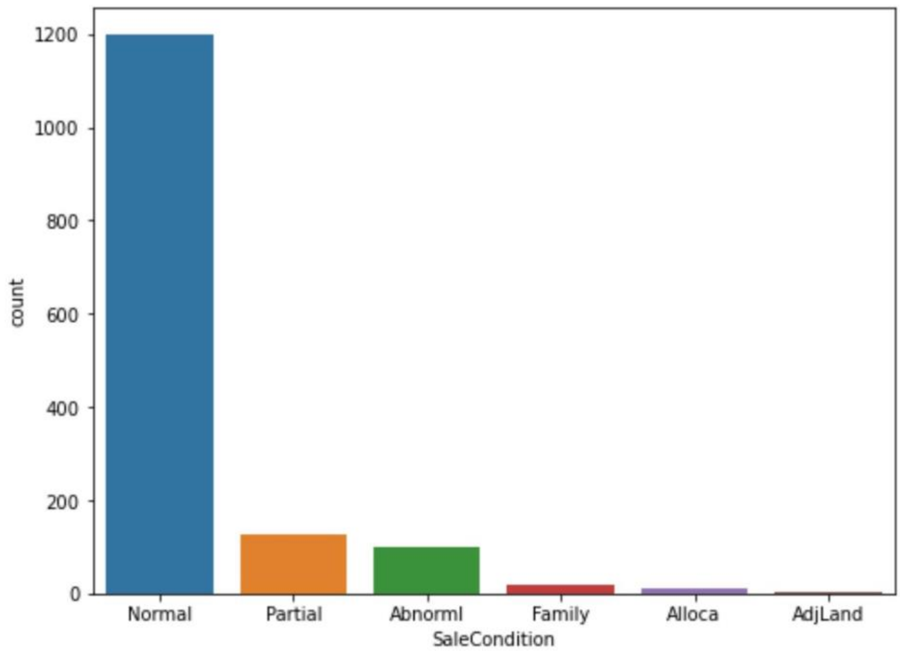
- Typ Typical Functionality
- Min1 Minor Deductions 1
- Min2 Minor Deductions 2
- Mod Moderate Deductions
- Maj1 Major Deductions 1
- Maj2 Major Deductions 2
- Sev Severely Damaged
- Sal Salvage only
    - Maximum home have typical functionality.



Notation:

- WD Warranty Deed - Conventional
- CWD Warranty Deed - Cash
- VWD Warranty Deed - VA Loan
- New Home just constructed and sold
- COD Court Officer Deed/Estate
- Con Contract 15% Down payment regular terms
- ConLw Contract Low Down payment and low interest
- ConLI Contract Low Interest
- ConLD Contract Low Down
- Oth Other
    - Most of the sale type are Warranty Deed - Conventional.

```
plt.figure(figsize=[8,6])
sns.countplot(df['SaleCondition'])
plt.show()
```



Notation:

- Normal Normal Sale
- Abnorml Abnormal Sale - trade, foreclosure, short sale
- AdjLand Adjoining Land Purchase
- Alloca Allocation - two linked properties with separate deeds, typically condo with a garage unit
- Family Sale between family members
- Partial Home was not completed when last assessed (associated with New Homes)
    - Most of the sale are normal sale.

CONCLUSION

- Key Findings and Conclusions of the given dataset:
  - ✓ MS Sub Class seems to have the biggest impact on House Prices, followed by Basement Full Bath and Basement Half Bath.
  - ✓ Other than the Basement related features, Condition 2, Exterior Quality and Lot Area are some of the other important features.