HOUSING PROJECT CASE STUDY
PROJECT REPORT

SUBMITTED BY: Wesley Sirra

ACKNOWLEDGMENT

I have taken efforts in this project. However, it would not have been possible without the kind support and help of many individuals and organizations. I would like to extend my sincere thanks to all of them.

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I would like to express my special gratitude and thanks to industry persons for giving me such attention and time.

INTRODUCTION

Business Problem Framing

Housing and real estate markets are important contributors to a country's economy. It is a huge market with many firms operating in it. Data Science may assist countries improve their total income, profitability, and marketing strategies by solving challenges in this sector. Machine learning techniques may be utilized to help this housing company achieve its commercial objectives. Our problem is with a housing company based in the United States called Surprise Housing, which wants to enter the Australian market. The company intends to use Data Analytics to buy houses at a discount from their true value and resell them at a profit. The company has compiled a dataset based on house sales in Australia. The firm is looking at potential properties to purchase residences in order to enter the market. We will create a model utilizing Machine Learning to estimate the actual worth of potential properties, which will assist the firm in deciding whether or not to invest in real estate.

Conceptual Background of the Domain Problem

Housing price trends reflect the current economic situation and are a source of concern for both buyers and sellers. House prices are affected by a variety of factors, including the number of bedrooms and bathrooms. The cost of a house is also affected by its location. A house with easy access to roads, schools, malls, and employment possibilities will be more expensive than a house without such connectivity. Predicting home prices manually is a tough process that is typically not very accurate, which is why various methods for house price prediction have been developed.

Review of Literature

The world is evolving away from manual processes and toward automated ones. The goal of our project is to alleviate the customer's issues. In the current circumstance, the consumer goes to a real estate agent so that he or she may recommend acceptable showplaces for his assets. However, the above strategy is risky because the agent may forecast incorrect rates to the customer, resulting in a loss of the customer's investment. This manual approach, which is currently being utilized in the market, is out of date and dangerous. To overcome the disadvantage, an improved and automated system is required.

Machine learning is a type of artificial intelligence that consists of accessible computers with the capability of being learned without being explicitly programmed. Machine learning is focused in the expansions of computer programs that are capable of modifying when exposed to new-fangled data. Machine learning algorithms are divided into three categories: supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning is a type of learning in which we instruct or train the machine using well-labeled data, which implies that part of the data has already been tagged with the correct answer. Following that, the computer is given a fresh collection of samples so that the supervised learning algorithm may analyze the training data and create a proper result from labeled data.

Motivation for the Problem Undertaken

The increasing unaffordability of housing has become a serious problem for governments all around the world. To obtain a better grasp of the commercialized housing market we are presently dealing with, we wish to identify the main influencing elements of home prices. Aside from the more apparent driving causes, such as inflation and land scarcity, there are a number other variables to consider.

Our objective is to explore the key variables that influence house prices and offer accurate predictions. We utilize 80 explanatory variables that cover nearly every element of Australian residential dwellings. Methods from both statistics and regression models, as well as machine learning models, are used and evaluated in order to better predict the ultimate price of each dwelling. The algorithm predicts home prices based on similar comparables of people's ideal homes, allowing both buyers and sellers to better negotiate home pricing based on market trends.

Hardware and Software Requirements

The hardware utilised for this project is a laptop with high-end specifications and a steady internet connection. When it came to the software, I utilised anaconda navigator and Jupyter notebook to conduct my Python programming and analysis.

Microsoft Excel is required to use an excel file. In Jupyter notebook, I utilised several Python libraries to complete this project, which I have listed below with appropriate substantiation:

1. Pandas - It is a library that is used to read data, visualise it, and analyse it.
2. NumPy- utilised for dealing with arrays and different mathematical methods.
3. Seaborn- a visualization tool for plotting many sorts of plots.
4. Matplotlib- It provides an object-oriented API for embedding plots into applications.

Analytical Problem Framing

Data sources and their formats

We are provided two CSV files comprising train and test datasets of house sales in Australia for this project.

The dataset used to train the Machine Learning model has 1168 rows and 81 columns. Using this dataset, we will train the Machine Learning models on 75% of the data and validate the models on 25% of the data. Finally, we will forecast prices for the testing dataset, which has 292 rows and 80 columns.

Below are the descriptions of the features:

MSSubClass: Identifies the type of dwelling involved in the sale.

20	1-STORY 1946 & NEWER ALL STYLES
30	1-STORY 1945 & OLDER
40	1-STORY W/FINISHED ATTIC ALL AGES
45	1-1/2 STORY - UNFINISHED ALL AGES
50	1-1/2 STORY FINISHED ALL AGES
60	2-STORY 1946 & NEWER
70	2-STORY 1945 & OLDER
75	2-1/2 STORY ALL AGES
80	SPLIT OR MULTI-LEVEL
85	SPLIT FOYER
90	DUPLEX - ALL STYLES AND AGES
120	1-STORY PUD (Planned Unit Development) - 1946 & NEWER
150	1-1/2 STORY PUD - ALL AGES
160	2-STORY PUD - 1946 & NEWER

180 PUD - MULTILEVEL - INCL SPLIT LEV/FOYER
190 2 FAMILY CONVERSION - ALL STYLES AND AGES

MSZoning: Identifies the general zoning classification of the sale.

A Agriculture

C Commercial
FV Floating Village Residential
I Industrial
RH Residential High Density
RL Residential Low Density
RP Residential Low Density Park
RM Residential Medium Density

LotFrontage: Linear feet of street connected to property

LotArea: Lot size in square feet

Street: Type of road access to property

Grvl Gravel
Pave Paved

Alley: Type of alley access to property
Grvl Gravel
Pave Paved

NA No alley access

LotShape: General shape of property

Reg Regular
IR1 Slightly irregular

IR2 Moderately Irregular
IR3 Irregular

LandContour: Flatness of the property
Lvl Near Flat/Level
Bnk Banked - Quick and significant rise from street grade to building
HLS Hillside - Significant slope from side to side
Low Depression

Utilities: Type of utilities available

AllPub All public Utilities (E,G,W,& S)
NoSewrElectricity, Gas, and Water (Septic Tank)
NoSeWa Electricity and Gas Only
ELO Electricity only

LotConfig: Lot configuration

Inside Inside lot
Corner Corner lot
CulDSac Cul-de-sac
FR2 Frontage on 2 sides of property
FR3 Frontage on 3 sides of property

LandSlope: Slope of property

Gtl Gentle slope

Mod Moderate Slope

Sev Severe Slope

Neighborhood: Physical locations within Ames city limits

Blmngtn Bloomington Heights
Blueste Bluestem
BrDale Briardale
BrkSide Brookside
ClearCr Clear Creek
CollgCr College Creek
Crawfor Crawford
Edwards Edwards
Gilbert Gilbert
IDOTRR Iowa DOT and Rail Road
MeadowV Meadow Village
Mitchel Mitchell
Names North Ames

NoRidge Northridge
NPkVill Northpark Villa
NridgHtNorthridge Heights
NWAmes Northwest
Ames OldTown Old Town
SWISU South & West of Iowa State University
Sawyer Sawyer
SawyerW Sawyer West
Somerst Somerset
StoneBr Stone Brook
Timber Timberland
Veenker Veenker

Condition1: Proximity to various conditions

Artery Adjacent to arterial street
Feedr Adjacent to feeder street
Norm Normal
RRNn Within 200' of North-South Railroad
RRAn Adjacent to North-South Railroad
PosN Near positive off-site feature--park, greenbelt, etc.
PosA Adjacent to postive off-site feature
RRNe Within 200' of East-West Railroad
RRAe Adjacent to East-West Railroad

Condition2: Proximity to various conditions (if more than one is present)

Artery Adjacent to arterial street
Feedr Adjacent to feeder street
Norm Normal
RRNn Within 200' of North-South Railroad
RRAn Adjacent to North-South Railroad
PosN Near positive off-site feature--park, greenbelt, etc.
PosA Adjacent to postive off-site feature
RRNe Within 200' of East-West Railroad
RRAe Adjacent to East-West Railroad

BldgType: Type of dwelling

1Fam Single-family Detached
2FmCon Two-family Conversion; originally built as one-family dwelling
Duplx Duplex

TwnhsE Townhouse End Unit
TwnhsI Townhouse Inside Unit

HouseStyle: Style of dwelling

1Story One story
1.5Fin One and one-half story: 2nd level finished
1.5Unf One and one-half story: 2nd level unfinished
2Story Two story
2.5Fin Two and one-half story: 2nd level finished
2.5Unf Two and one-half story: 2nd level unfinished
SFoyer Split Foyer
SLvl Split Level

OverallQual: Rates the overall material and finish of the house

10 Very Excellent
9 Excellent
8 Very Good

7 Good

6 Above Average

5 Average
4 Below Average

3 Fair

2 Poor

1 Very Poor

OverallCond: Rates the overall condition of the house

10 Very Excellent
9 Excellent

8 Very Good
7 Good

6 Above Average

5 Average

4 Below Average

3 Fair
2 Poor

1 Very Poor

YearBuilt: Original construction date

YearRemodAdd: Remodel date (same as construction date if no remodeling or additions)

RoofStyle: Type of roof

Flat	Flat
Gable	Gable
Gambrel	Gabrel (Barn)
Hip	Hip
Mansard
Mansard Shed
Shed

RoofMatl: Roof material

ClyTile Clay or Tile
CompShg	Standard (Composite) Shingle
Membran	Membrane
Metal	Metal
Roll	Roll
Tar&Grv	Gravel & Tar
WdShake	Wood Shakes
WdShngl	Wood Shingles

Exterior1st: Exterior covering on house

AsbShng	Asbestos Shingles

AsphShn	Asphalt Shingles
BrkComm	Brick Common
BrkFaceBrick Face
CBlock Cinder Block
CemntBd	Cement Board
HdBoard	Hard Board
ImStuccImitation Stucco
MetalSd	Metal Siding
Other	Other
Plywood
Plywood PreCast
PreCast
Stone	Stone
Stucco Stucco
VinylSd Vinyl Siding
Wd Sdng	Wood Siding
WdShing	Wood Shingles

Exterior2nd: Exterior covering on house (if more than one material)

AsbShng	Asbestos Shingles
AsphShn	Asphalt Shingles
BrkComm	Brick Common
BrkFaceBrick Face
CBlock Cinder Block
CemntBd	Cement Board
HdBoard	Hard Board
ImStuccImitation Stucco
MetalSd	Metal Siding
Other	Other
Plywood
Plywood PreCast
PreCast
Stone	Stone
Stucco Stucco
VinylSd Vinyl Siding
Wd Sdng	Wood Siding

WdShing Wood Shingles

MasVnrType: Masonry veneer type

BrkCmnBrick Common
BrkFaceBrick Face
CBlock Cinder Block
None None
Stone Stone

MasVnrArea: Masonry veneer area in square feet
ExterQual: Evaluates the quality of the material on the exterior
Ex Excellent
Gd Good
TA Average/Typical
Fa Fair

Po Poor

ExterCond: Evaluates the present condition of the material on the exterior
Ex Excellent
Gd Good
TA Average/Typical

Fa Fair

Po Poor
Foundation: Type of foundation
BrkTil Brick & Tile
CBlock Cinder Block
PConc Poured Contrete
Slab Slab
Stone Stone
Wood Wood

BsmtQual: Evaluates the height of the basement

Ex Excellent (100+ inches)
Gd Good (90-99 inches)
TA Typical (80-89 inches)
Fa Fair (70-79 inches)
Po Poor (<70 inches

NA No Basement

BsmtCond: Evaluates the general condition of the basement

Ex Excellent
Gd Good

TA Typical - slight dampness allowed

Fa Fair - dampness or some cracking or settling
Po Poor - Severe cracking, settling, or wetness
NA No Basement

BsmtExposure: Refers to walkout or garden level walls

Gd Good Exposure
Av Average Exposure (split levels or foyers typically score average or above)
Mn Mimimum
Exposure No No Exposure
NA No Basement

BsmtFinType1: Rating of basement finished area

GLQ Good Living Quarters
ALQ Average Living Quarters
BLQ Below Average Living Quarters
Rec Average Rec Room
LwQ Low Quality
Unf Unfinshed
NA No Basement

BsmtFinSF1: Type 1 finished square feet

BsmtFinType2: Rating of basement finished area (if multiple types)

GLQ Good Living Quarters
ALQ Average Living Quarters
BLQ Below Average Living Quarters
Rec Average Rec Room
LwQ Low Quality
Unf Unfinshed
NA No Basement

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of basement area

TotalBsmtSF: Total square feet of basement area

Heating: Type of heating

Floor Floor Furnace
GasA Gas forced warm air furnace
GasW Gas hot water or steam heat
Grav Gravity furnace
OthW Hot water or steam heat other than gas
Wall Wall furnace

HeatingQC: Heating quality and condition

Ex Excellent
Gd Good
TA Average/Typical
Fa Fair
Po Poor

CentralAir: Central air conditioning

N No
Y Yes

Electrical: Electrical system

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

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

LowQualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade

HalfBath: Half baths above grade

Bedroom: Bedrooms above grade (does NOT include basement bedrooms)

Kitchen: Kitchens above grade

KitchenQual: Kitchen quality

Ex Excellent

Gd Good

TA Typical/Average

Fa Fair

Po Poor

TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)

Functional: Home functionality (Assume typical unless deductions are warranted)

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

Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

Ex Excellent - Exceptional Masonry Fireplace

Gd Good - Masonry Fireplace in main level

TA Average - Prefabricated Fireplace in main living area or Masonry Fireplace in basement
Fa Fair - Prefabricated Fireplace in basement
Po Poor - Ben Franklin Stove
NA No Fireplace

GarageType: Garage location

2Types More than one type of garage

Attchd Attached to home
Basment Basement Garage
BuiltIn Built-In (Garage part of house - typically has room above garage)
CarPort Car Port
Detchd Detached from home
NA No Garage

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

Fin Finished
RFn Rough Finished
Unf Unfinished
NA No Garage

GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet

GarageQual: Garage quality

Ex Excellent
Gd Good
TA Typical/Average

Fa Fair

Po Poor
NA No Garage

GarageCond: Garage condition

Ex Excellent
Gd Good
TA Typical/Average

Fa Fair

Po Poor

NA No Garage

PavedDrive: Paved driveway

Y Paved

P Partial Pavement
N Dirt/Gravel

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality

Ex Excellent
Gd Good
TA Average/Typical

Fa Fair
NA No Pool
Fence: Fence quality

GdPrv Good Privacy
MnPrv Minimum Privacy
GdWo Good Wood
MnWw Minimum Wood/Wire
NA No Fence
MiscFeature: Miscellaneous feature not covered in other categories
Elev Elevator
Gar2 2nd Garage (if not described in garage section)
Othr Other
Shed Shed (over 100
SF) TenC Tennis Court
NA None

MiscVal: $Value of miscellaneous feature

MoSold: Month Sold (MM)

YrSold: Year Sold (YYYY)

SaleType: Type of sale

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

SaleCondition: Condition of sale

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)

Mathematical/ Analytical Modeling of the Problem

Let's look at the data now. I've attached a snapshot to give you an idea of what I'm talking about.

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

#Preprocessing,Standardizing
from sklearn.preprocessing import StandardScaler

#For Multicollinearity
from statsmodels.stats.outliers_influence import variance_inflation_factor

#Models
from sklearn.model_selection import train_test_split,RandomizedSearchCV, GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression

#Metrics
from sklearn.metrics import r2_score

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

```
df=pd.read_csv('train.csv')
df.head()
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	Mo
0	127	120	RL	NaN	4928	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	2
1	889	20	RL	95.0	15865	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	10
2	793	60	RL	92.0	9920	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	6
3	110	20	RL	105.0	11751	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0	1
4	422	20	RL	NaN	16635	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	6

5 rows × 81 columns

```
df1=pd.read_csv('test.csv')
df1.head()
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	ScreenPorch	PoolArea	PoolQC	Fence	MiscFeatu
0	337	20	RL	86.0	14157	Pave	NaN	IR1	HLS	AllPub	...	0	0	NaN	NaN	NaN
1	1018	120	RL	NaN	5814	Pave	NaN	IR1	Lvl	AllPub	...	0	0	NaN	NaN	NaN
2	929	20	RL	NaN	11838	Pave	NaN	Reg	Lvl	AllPub	...	0	0	NaN	NaN	NaN
3	1148	70	RL	75.0	12000	Pave	NaN	Reg	Bnk	AllPub	...	0	0	NaN	NaN	NaN
4	1227	60	RL	86.0	14598	Pave	NaN	IR1	Lvl	AllPub	...	0	0	NaN	NaN	NaN

5 rows × 80 columns

Data Analysis

```
df.shape
```

```
(1168, 81)
```

We have 1168 rows and 81 columns in our train dataset.

```
df1.shape
```

```
(292, 80)
```

We have 292 rows and 80 columns in our test dataset.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1168 entries, 0 to 1167
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1168 non-null   int64
 1   MSSubClass     1168 non-null   int64
 2   MSZoning       1168 non-null   object
 3   LotFrontage    954 non-null    float64
 4   LotArea        1168 non-null   int64
 5   Street         1168 non-null   object
 6   Alley          77 non-null     object
 7   LotShape       1168 non-null   object
 8   LandContour    1168 non-null   object
 9   Utilities      1168 non-null   object
 10  LotConfig      1168 non-null   object
 11  LandSlope      1168 non-null   object
 12  Neighborhood   1168 non-null   object
 13  Condition1     1168 non-null   object
 14  Condition2     1168 non-null   object
 15  BldgType       1168 non-null   object
 16  HouseStyle     1168 non-null   object
 17  OverallQual    1168 non-null   int64
 18  OverallCond    1168 non-null   int64
 19  YearBuilt      1168 non-null   int64
 20  YearRemodAdd   1168 non-null   int64
 21  RoofStyle      1168 non-null   object
 22  RoofMatl       1168 non-null   object
 23  Exterior1st    1168 non-null   object
 24  Exterior2nd    1168 non-null   object
 25  MasVnrType     1161 non-null   object
 26  MasVnrArea     1161 non-null   float64
 27  ExterQual      1168 non-null   object
 28  ExterCond      1168 non-null   object
 29  Foundation     1168 non-null   object
 30  BsmtQual       1138 non-null   object
 31  BsmtCond       1138 non-null   object
 32  BsmtExposure   1137 non-null   object
 33  BsmtFinType1   1138 non-null   object
 34  BsmtFinSF1     1168 non-null   int64
 35  BsmtFinType2   1137 non-null   object
 36  BsmtFinSF2     1168 non-null   int64
 37  BsmtUnfSF      1168 non-null   int64
 38  TotalBsmtSF    1168 non-null   int64
 39  Heating        1168 non-null   object
 40  HeatingQC      1168 non-null   object
 41  CentralAir     1168 non-null   object
 42  Electrical     1168 non-null   object
 43  1stFlrSF       1168 non-null   int64
 44  2ndFlrSF       1168 non-null   int64
 45  LowQualFinSF   1168 non-null   int64
 46  GrLivArea      1168 non-null   int64
 47  BsmtFullBath   1168 non-null   int64
 48  BsmtHalfBath   1168 non-null   int64
 49  FullBath       1168 non-null   int64
 50  HalfBath       1168 non-null   int64
 51  BedroomAbvGr   1168 non-null   int64
 52  KitchenAbvGr   1168 non-null   int64
 53  KitchenQual    1168 non-null   object
 54  TotRmsAbvGrd   1168 non-null   int64
 55  Functional     1168 non-null   object
 56  Fireplaces     1168 non-null   int64
 57  FireplaceQu    617 non-null    object
 58  GarageType     1104 non-null   object
 59  GarageYrBlt    1104 non-null   float64
 60  GarageFinish   1104 non-null   object
 61  GarageCars     1168 non-null   int64
 62  GarageArea     1168 non-null   int64
 63  GarageQual     1104 non-null   object
 64  GarageCond     1104 non-null   object
 65  PavedDrive     1168 non-null   object
 66  WoodDeckSF     1168 non-null   int64
 67  OpenPorchSF    1168 non-null   int64
 68  EnclosedPorch  1168 non-null   int64
 69  3SsnPorch      1168 non-null   int64
 70  ScreenPorch    1168 non-null   int64
 71  PoolArea       1168 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          237 non-null    object
 74  MiscFeature    44 non-null     object
 75  MiscVal        1168 non-null   int64
 76  MoSold         1168 non-null   int64
 77  YrSold         1168 non-null   int64
 78  SaleType       1168 non-null   object
 79  SaleCondition  1168 non-null   object
 80  SalePrice      1168 non-null   int64
dtypes: float64(3), int64(35), object(43)
```

```
1 df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 292 entries, 0 to 291
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             292 non-null    int64  
 1   MSSubClass     292 non-null    int64  
 2   MSZoning       292 non-null    object 
 3   LotFrontage    247 non-null    float64
 4   LotArea        292 non-null    int64  
 5   Street         292 non-null    object 
 6   Alley          14 non-null     object 
 7   LotShape       292 non-null    object 
 8   LandContour    292 non-null    object 
 9   Utilities      292 non-null    object 
 10  LotConfig      292 non-null    object 
 11  LandSlope      292 non-null    object 
 12  Neighborhood   292 non-null    object 
 13  Condition1     292 non-null    object 
 14  Condition2     292 non-null    object 
 15  BldgType       292 non-null    object 
 16  HouseStyle     292 non-null    object 
 17  OverallQual    292 non-null    int64  
 18  OverallCond    292 non-null    int64  
 19  YearBuilt      292 non-null    int64  
 20  YearRemodAdd   292 non-null    int64  
 21  RoofStyle      292 non-null    object 
 22  RoofMatl       292 non-null    object 
 23  Exterior1st    292 non-null    object 
 24  Exterior2nd    292 non-null    object 
 25  MasVnrType     291 non-null    object 
 26  MasVnrArea     291 non-null    float64
 27  ExterQual      292 non-null    object 
 28  ExterCond      292 non-null    object 
 29  Foundation     292 non-null    object 
 30  BsmtQual       285 non-null    object 
 31  BsmtCond       285 non-null    object 
 32  BsmtExposure   285 non-null    object 
 33  BsmtFinType1   285 non-null    object 
 34  BsmtFinSF1     292 non-null    int64  
 35  BsmtFinType2   285 non-null    object 
 36  BsmtFinSF2     292 non-null    int64  
 37  BsmtUnfSF      292 non-null    int64  
 38  TotalBsmtSF    292 non-null    int64  
 39  Heating        292 non-null    object 
 40  HeatingQC      292 non-null    object 
 41  CentralAir     292 non-null    object 
 42  Electrical     291 non-null    object 
 43  1stFlrSF       292 non-null    int64  
 44  2ndFlrSF       292 non-null    int64  
 45  LowQualFinSF   292 non-null    int64  
 46  GrLivArea      292 non-null    int64  
 47  BsmtFullBath   292 non-null    int64  
 48  BsmtHalfBath   292 non-null    int64  
 49  FullBath       292 non-null    int64  
 50  HalfBath       292 non-null    int64  
 51  BedroomAbvGr   292 non-null    int64  
 52  KitchenAbvGr   292 non-null    int64  
 53  KitchenQual    292 non-null    object 
 54  TotRmsAbvGrd   292 non-null    int64  
 55  Functional     292 non-null    object 
 56  Fireplaces     292 non-null    int64  
 57  FireplaceQu    153 non-null    object 
 58  GarageType     275 non-null    object 
 59  GarageYrBlt    275 non-null    float64
 60  GarageFinish   275 non-null    object 
```

From the above tables, we can see that we have lot of null values in our train as well as test dataset. Also we have int, float and object datatypes. SalePrice is our target variable.

```
df.describe()
```

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	...	WoodD
count	1168.000000	1168.000000	954.00000	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000	1161.000000	1168.000000	...	1168.0
mean	724.136130	56.767979	70.98847	10484.749144	6.104452	5.595890	1970.930651	1984.758562	102.310078	444.726027	...	96.206
std	416.159877	41.940650	24.82875	8957.442311	1.390153	1.124343	30.145255	20.785185	182.595606	462.664785	...	126.15
min	1.000000	20.000000	21.00000	1300.000000	1.000000	1.000000	1875.000000	1950.000000	0.000000	0.000000	...	0.0000
25%	360.500000	20.000000	60.00000	7621.500000	5.000000	5.000000	1954.000000	1966.000000	0.000000	0.000000	...	0.0000
50%	714.500000	50.000000	70.00000	9522.500000	6.000000	5.000000	1972.000000	1993.000000	0.000000	385.500000	...	0.0000
75%	1079.500000	70.000000	80.00000	11515.500000	7.000000	6.000000	2000.000000	2004.000000	160.000000	714.500000	...	171.00
max	1460.000000	190.000000	313.00000	164660.000000	10.000000	9.000000	2010.000000	2010.000000	1600.000000	5644.000000	...	857.00

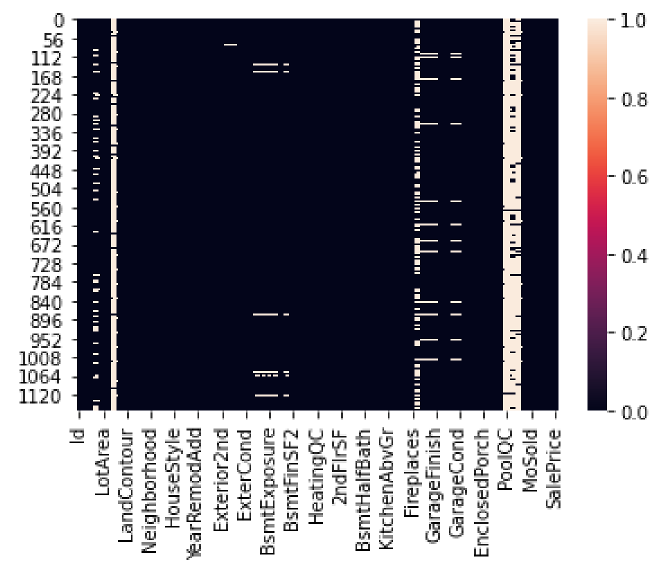
8 rows × 38 columns

As said above, we see some null values in the count row. Also we see some of the features have outliers present in them along with some skewness.

We will now do some visualizations on our train dataset.

```
sns.heatmap(df.isna())
```

<AxesSubplot:>



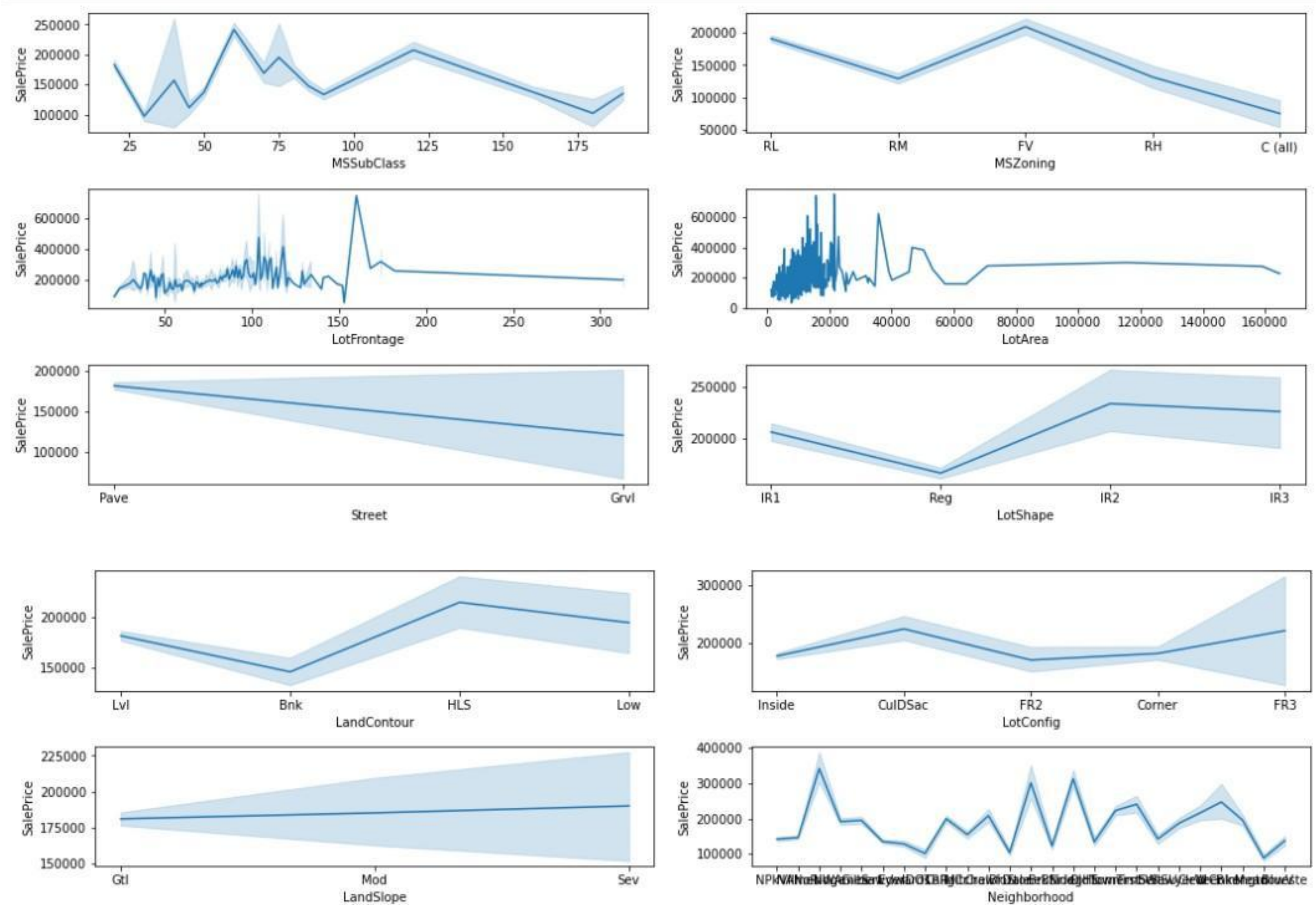
Observation:

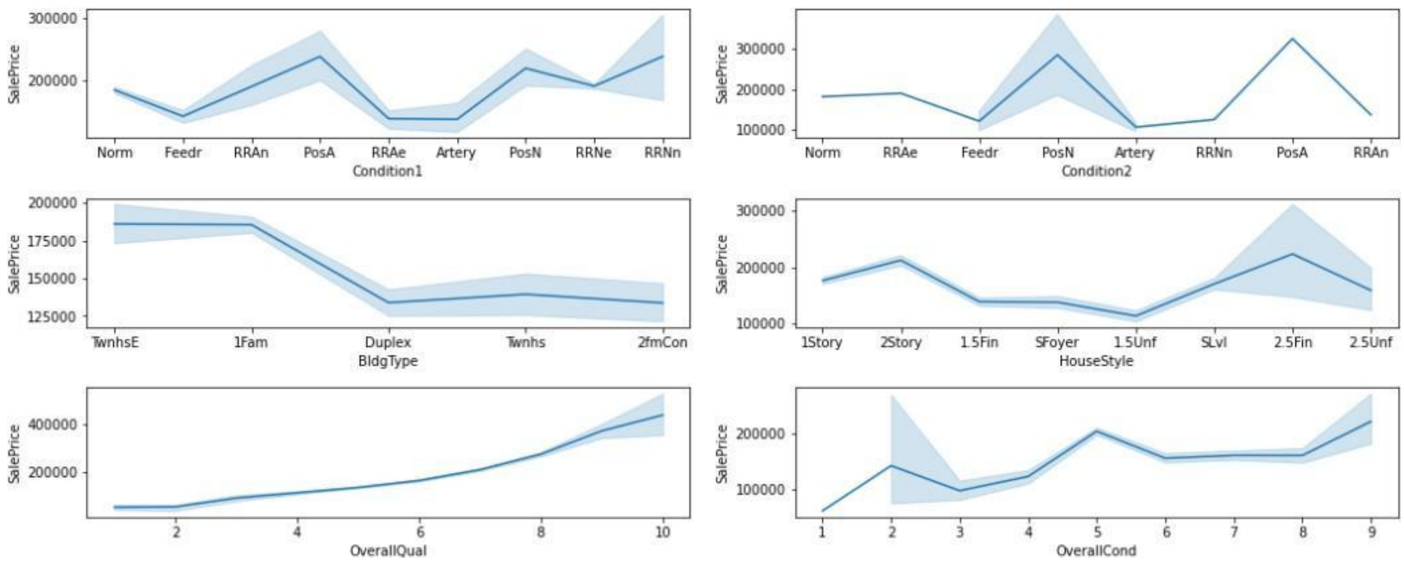
We see null values in a lot of features.

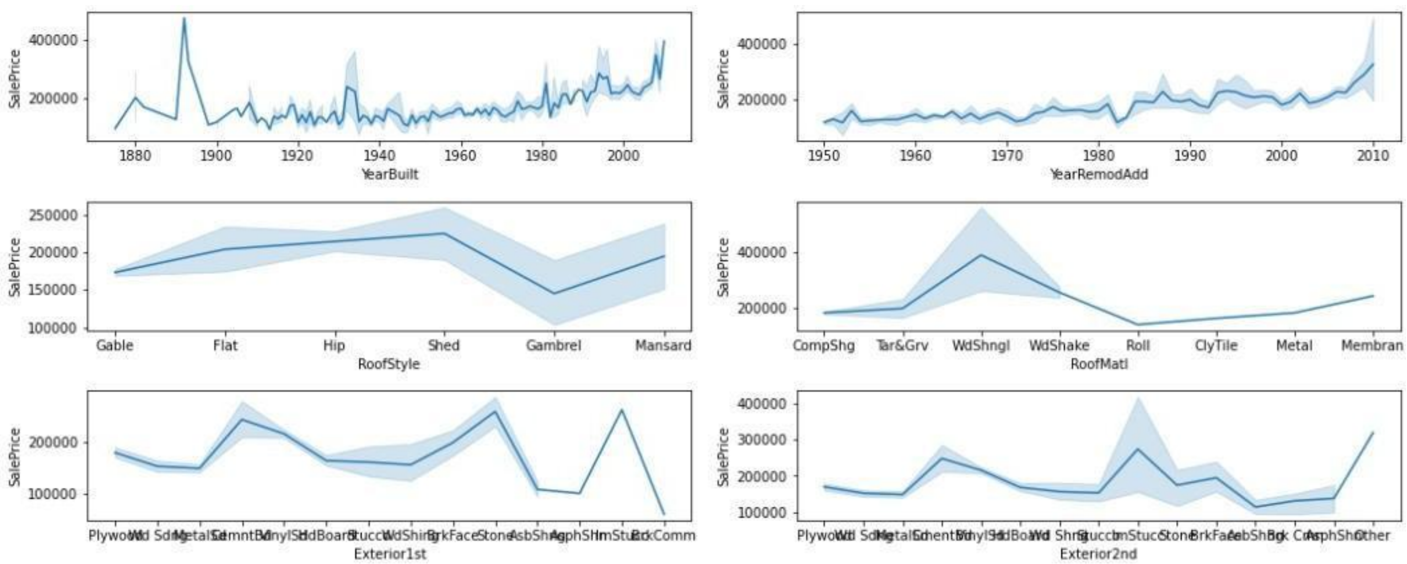
```
y=df['SalePrice']
X=df.drop(columns=['SalePrice'])
```

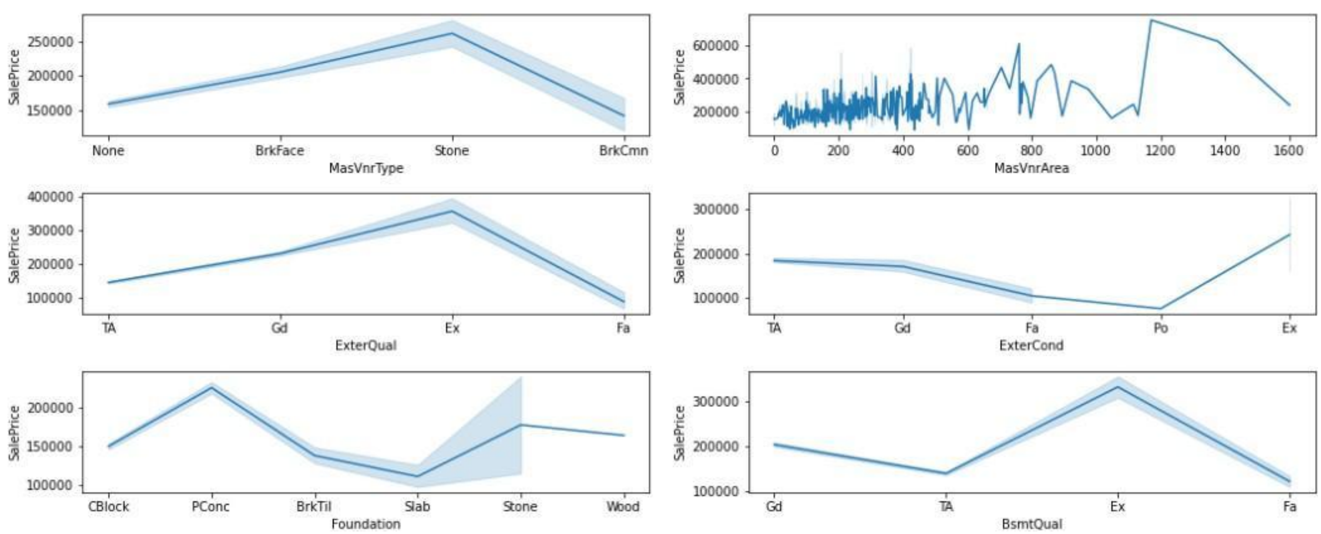
We have separated independent and dependent variables to visualize further with respect to our target variable.

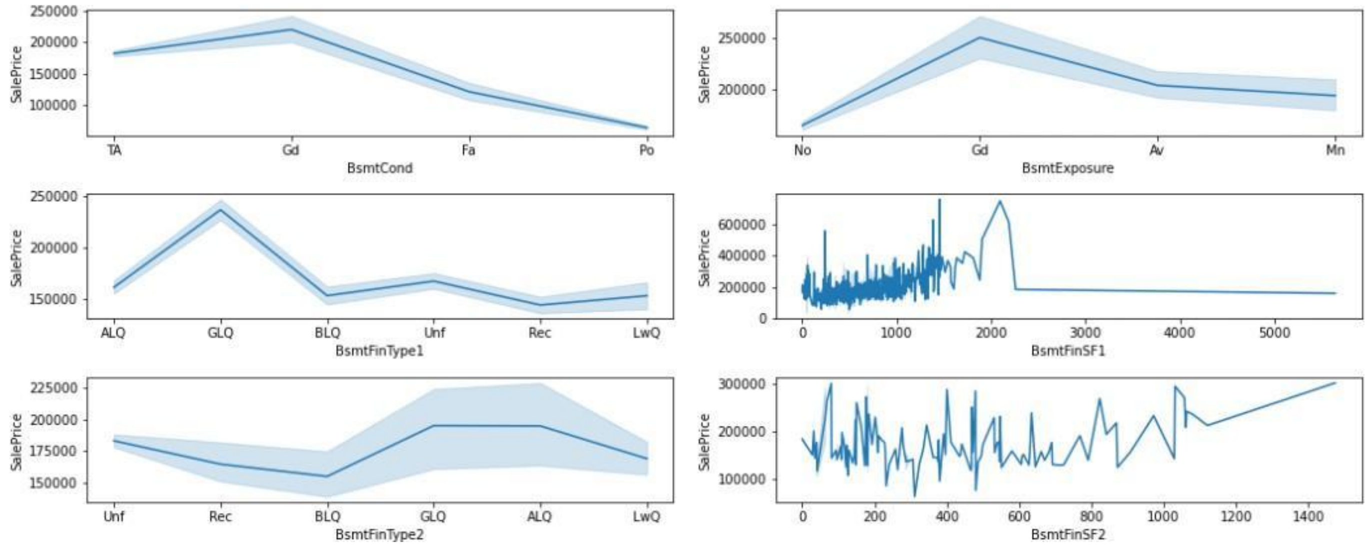
```
plt.figure(figsize=(15,75),facecolor='white')
plotnumber=1

for column in X:
    if plotnumber<=76:
        ax=plt.subplot(38,2,plotnumber)
        sns.lineplot(X[column],y)
        plt.xlabel(column,fontsize=10)
        plt.ylabel('SalePrice',fontsize=10)

    plotnumber+=1
plt.tight_layout()
```

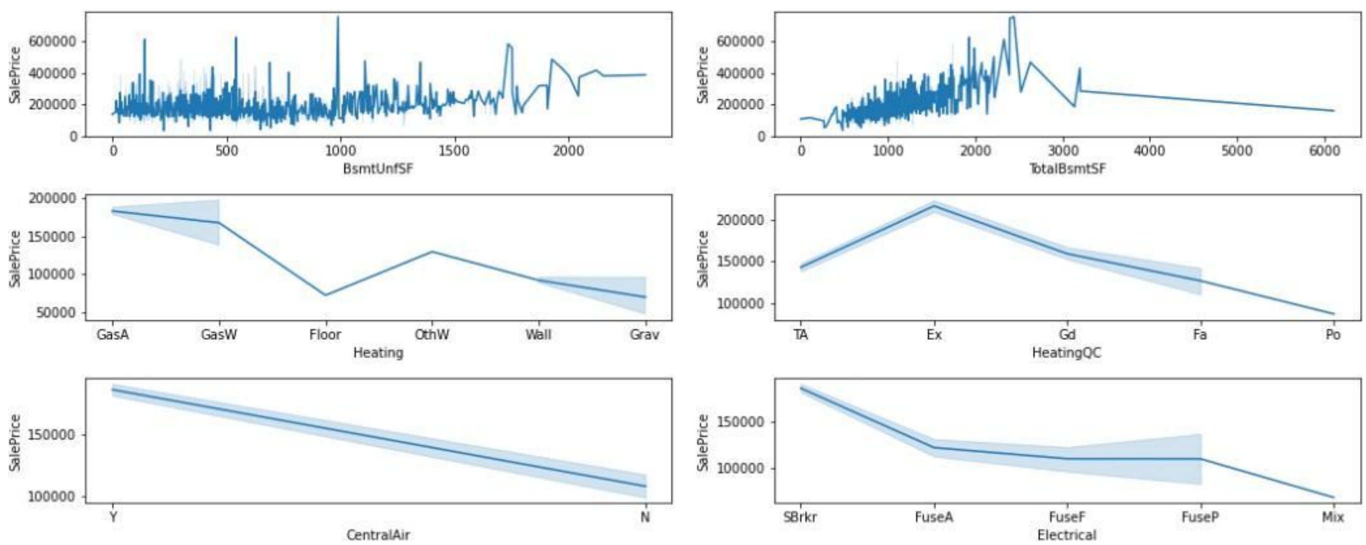


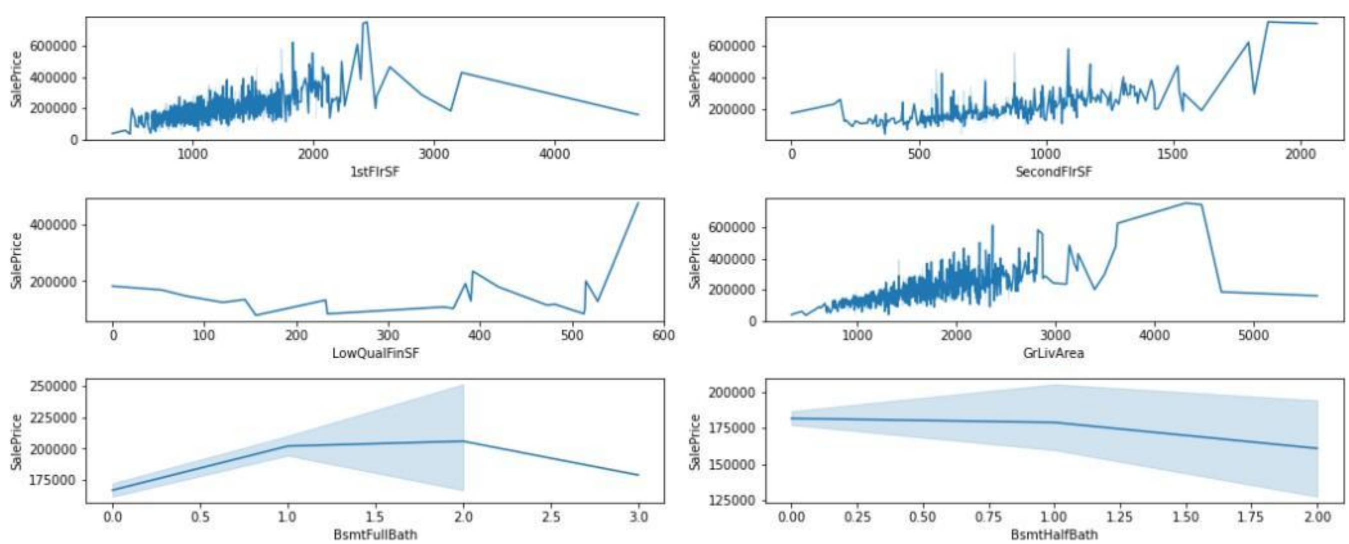

SalePrice
Condition1
Condition2
BldgType
HouseStyle
OverallQual
OverallCond

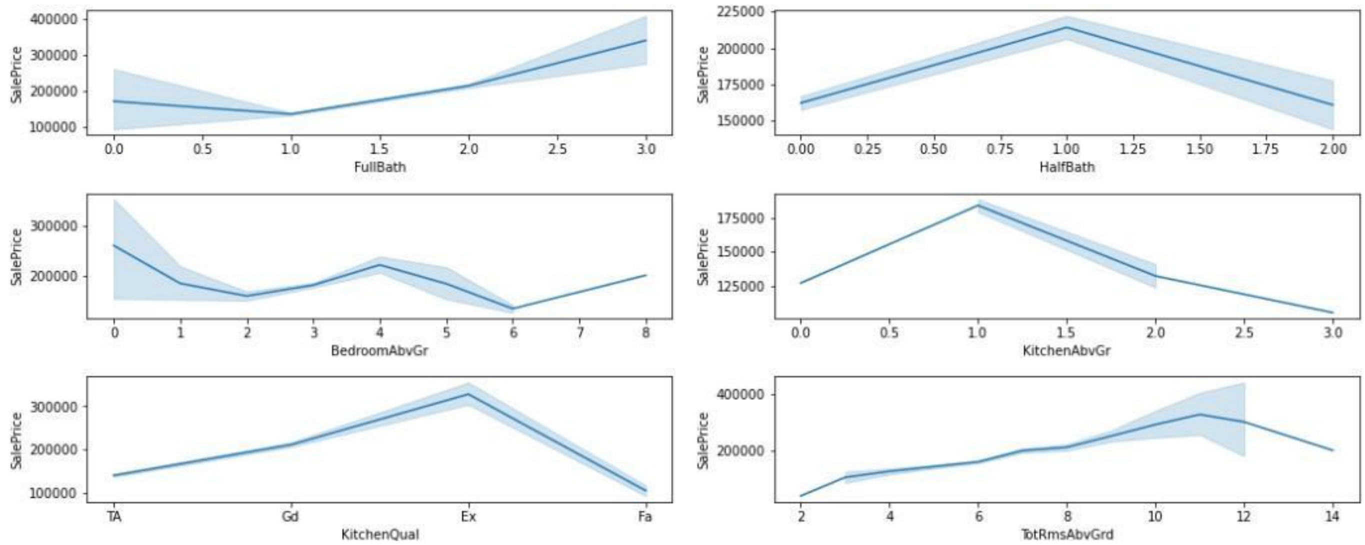

SalePrice
YearBuilt
YearRemodAdd
RoofStyle
RoofMatl
Exterior1st
Exterior2nd

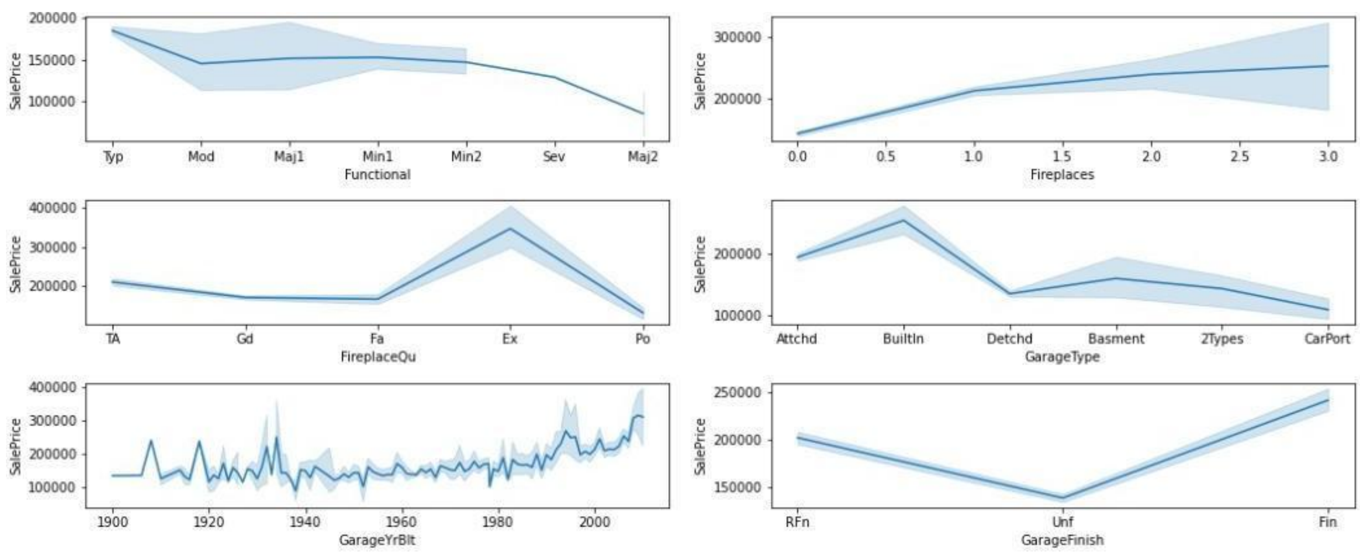

SalePrice
MasVnrType
MasVnrArea
ExterQual
ExterCond
Foundation
BsmtQual

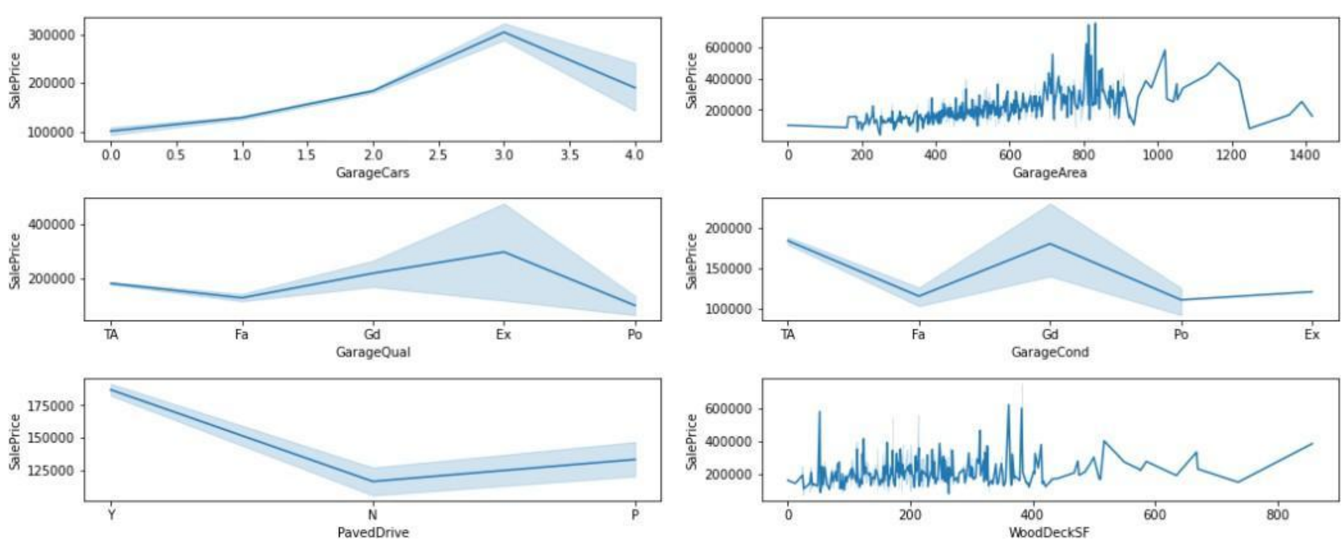

SalePrice
TA Gd Fa Po
BsmtCond
No Gd Av Mn
BsmtExposure
ALQ GLQ BLQ Unf Rec LwQ
BsmtFinType1
BsmtFinSF1
Unf Rec BLQ GLQ ALQ LwQ
BsmtFinType2
BsmtFinSF2

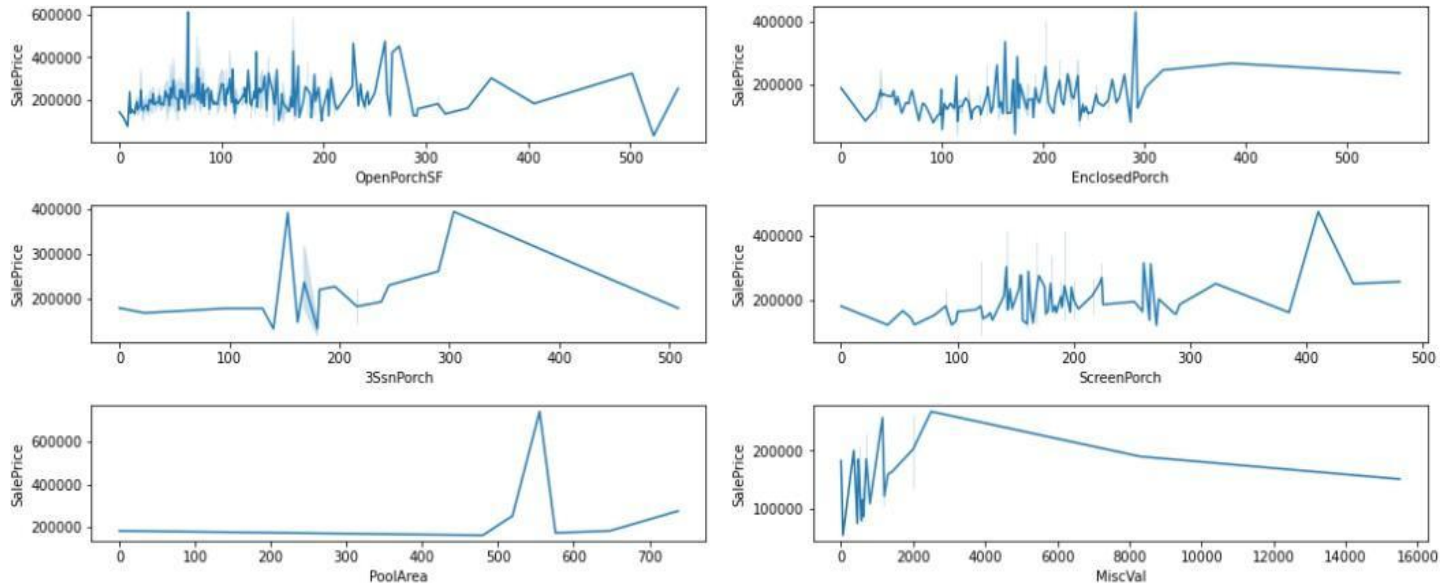

SalePrice
BsmtUnfSF
TotalBsmtSF
GasA GasW Floor OthW Wall Grav
Heating
TA Ex Gd Fa Po
HeatingQC
Y N
CentralAir
SBrkr FuseA FuseF FuseP Mix
Electrical

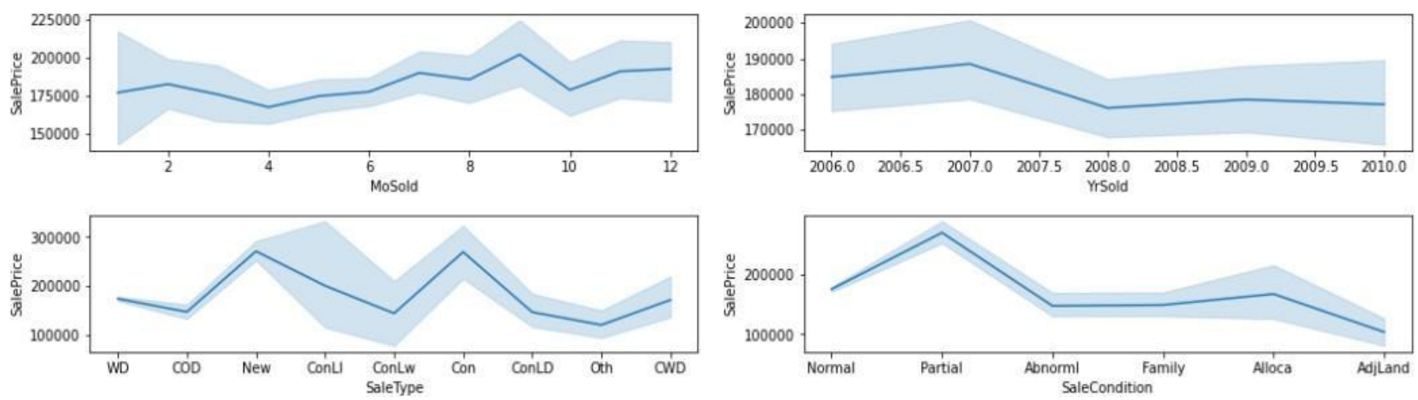

SalePrice
1stFlrSF
SecondFlrSF
LowQualFinSF
GrLivArea
BsmtFullBath
BsmtHalfBath


SalePrice
FullBath
0.0 0.5 1.0 1.5 2.0 2.5 3.0
100000 200000 300000 400000
HalfBath
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
150000 175000 200000 225000
BedroomAbvGr
0 1 2 3 4 5 6 7 8
200000 300000
KitchenAbvGr
0.0 0.5 1.0 1.5 2.0 2.5 3.0
125000 150000 175000
KitchenQual
TA Gd Ex Fa
100000 200000 300000
TotRmsAbvGrd
2 4 6 8 10 12 14
200000 400000


SalePrice
Functional
Typ Mod Maj1 Min1 Min2 Sev Maj2
100000 150000 200000
Fireplaces
0.0 0.5 1.0 1.5 2.0 2.5 3.0
200000 300000
FireplaceQu
TA Gd Fa Ex Po
200000 300000 400000
GarageType
Attchd BuiltIn Detchd Basment 2Types CarPort
100000 200000
GarageYrBlt
1900 1920 1940 1960 1980 2000
100000 200000 300000 400000
GarageFinish
RFn Unf Fin
150000 200000 250000


SalePrice
GarageCars
0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0
100000 200000 300000
GarageArea
0 200 400 600 800 1000 1200 1400
200000 400000 600000
GarageQual
TA Fa Gd Ex Po
200000 400000
GarageCond
TA Fa Gd Po Ex
100000 150000 200000
PavedDrive
Y N P
125000 150000 175000
WoodDeckSF
0 200 400 600 800
200000 400000 600000





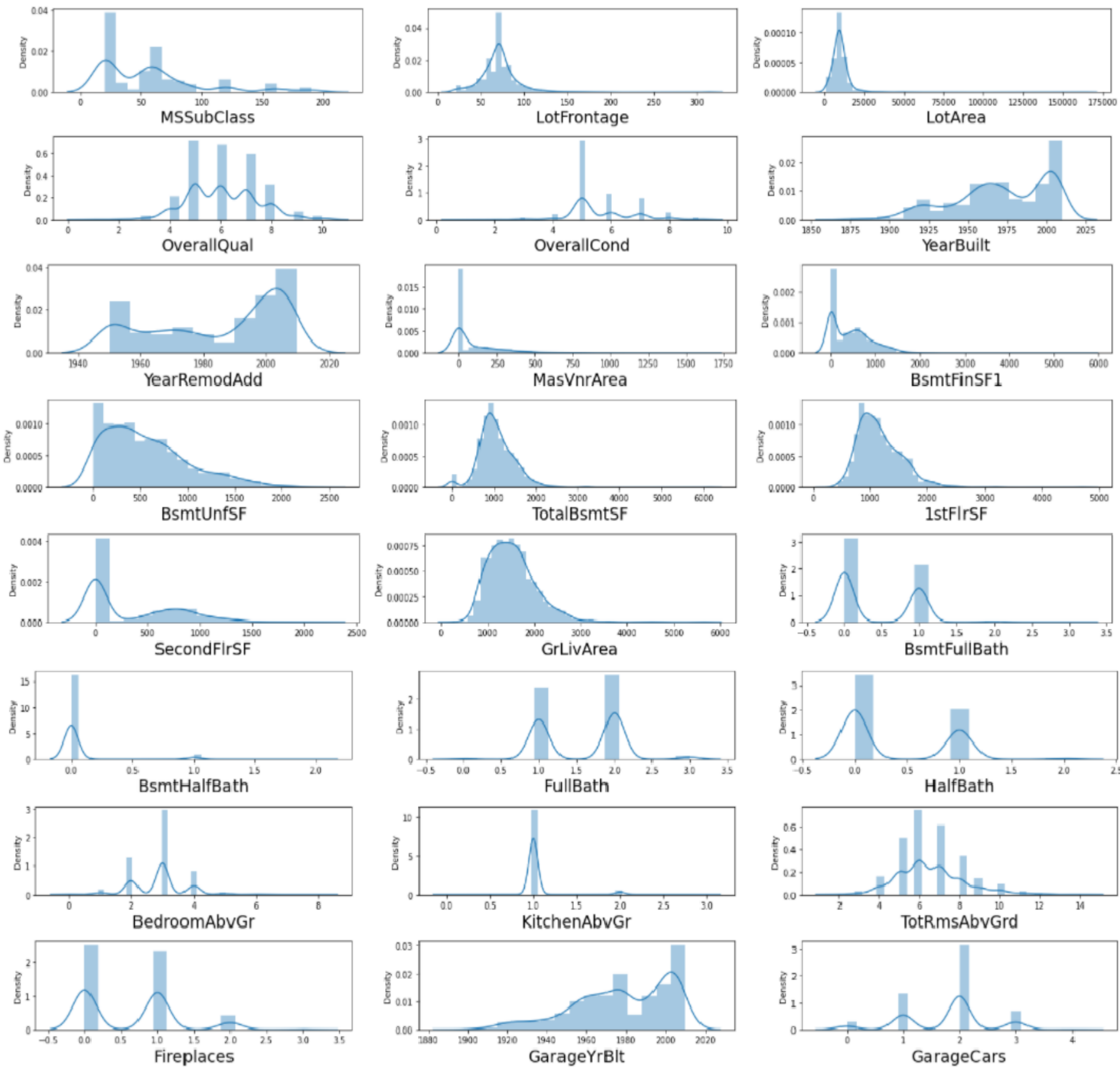
Observations:

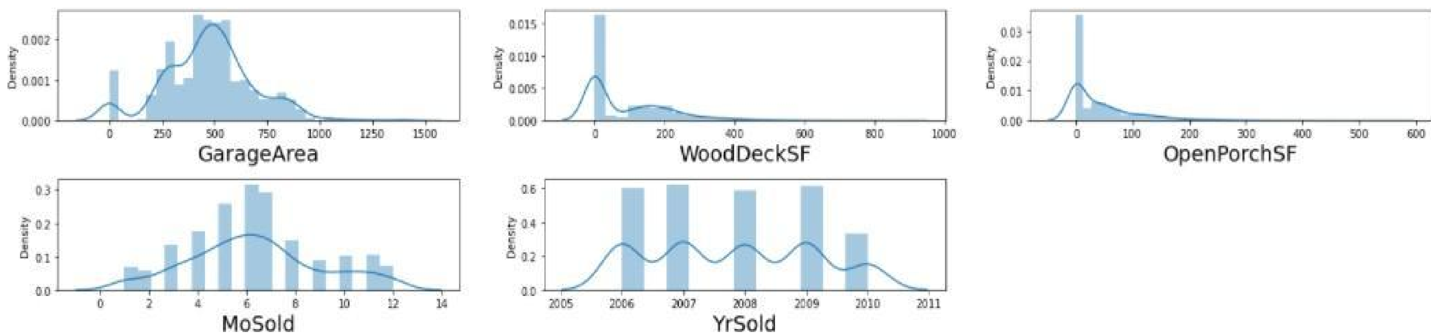
- Sale Price is highest for Floating Residential Village and lowest for Commercial zone.
- Sale Price is highest for Paved Street and lowest for Gravel Street.
- Sale Price is highest for Moderately Irregular shaped property and lowest for Regular shaped property.
- Sale Price increases with Total square feet of basement area but it falls drastically after 2500 square feet area.
- Sale Price is highest on the Hillside flatness whereas lowest in the banked flatness.
- Sale Price doesn't have much of an impact on Type of Land Slope or Neighborhood.

- Better the quality, higher the sale price.
- Although not monotonic, but there's an increase in sale price with better overall condition.
- The sale prices were highest during the late 19th century but fell sharply during the early 20th century and since then the prices have been increasing year by year.
- Also the Sale price increases with every remodeling done.
- Sale price is highest for houses with Shed roofs and lowest for houses with Gambrel roofs.
- Sale price is highest for roofs made with Wood Shingles material and lowest for roofs made with Roll material.
- Houses of Stone Masonry Veneer type have the highest sale price while houses of Brick common masonry veneer type have the lowest sale price.
- Sale price increases with increase in Masonry veneer area but gradually declines after 1200 square feet area.
- Sale price is highest for Poured Concrete foundation and lowest for Slab foundation.
- Sale Price increases with increase in Total square feet of Basement area but gradually declines from 2500 sq. ft. area.
- Sale prices are highest for houses with central air conditioning.
- Prices increase with increase in first floor square feet but there is a gradual decline after 2500 sq. ft.
- Prices increase with increase in Second floor sq. ft although not monotonic.
- Prices increase with increase in Ground living area sq. ft although there is a sharp decline after 4500 sq. ft. area.
- Prices decline with better quality of basement half bathrooms.

```
df_numericals=df[['MSSubClass','LotFrontage','LotArea','OverallQual','OverallCond','YearBuilt','YearRemodAdd','MasVnrArea','BsmtFinSF1','BsmtUnfSF','TotalBsmtSF','1stFlrSF','SecondFlrSF','GrLivArea','BsmtFullBath','BsmtHalfBath','FullBath','HalfBath','BedroomAbvGr','KitchenAbvGr','TotRmsAbvGrd','Fireplaces','GarageYrBlt','GarageCars','GarageArea','WoodDeckSF','OpenPorchSF','MoSold','YrSold']]
```

```
plt.figure(figsize=(20,25),facecolor='white')
plotnumber=1

for column in df_numericals:
    if plotnumber<=36:
        ax=plt.subplot(12,3,plotnumber)
        sns.distplot(df_numericals[column])
        plt.xlabel(column,fontsize=20)

    plotnumber+=1
plt.tight_layout()
```

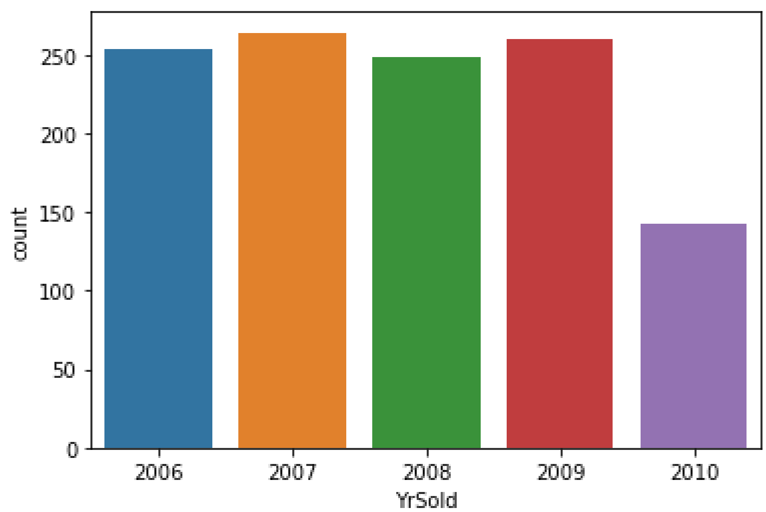




From the above visualizations we notice that most of the variables are not normally distributed and are very much skewed.

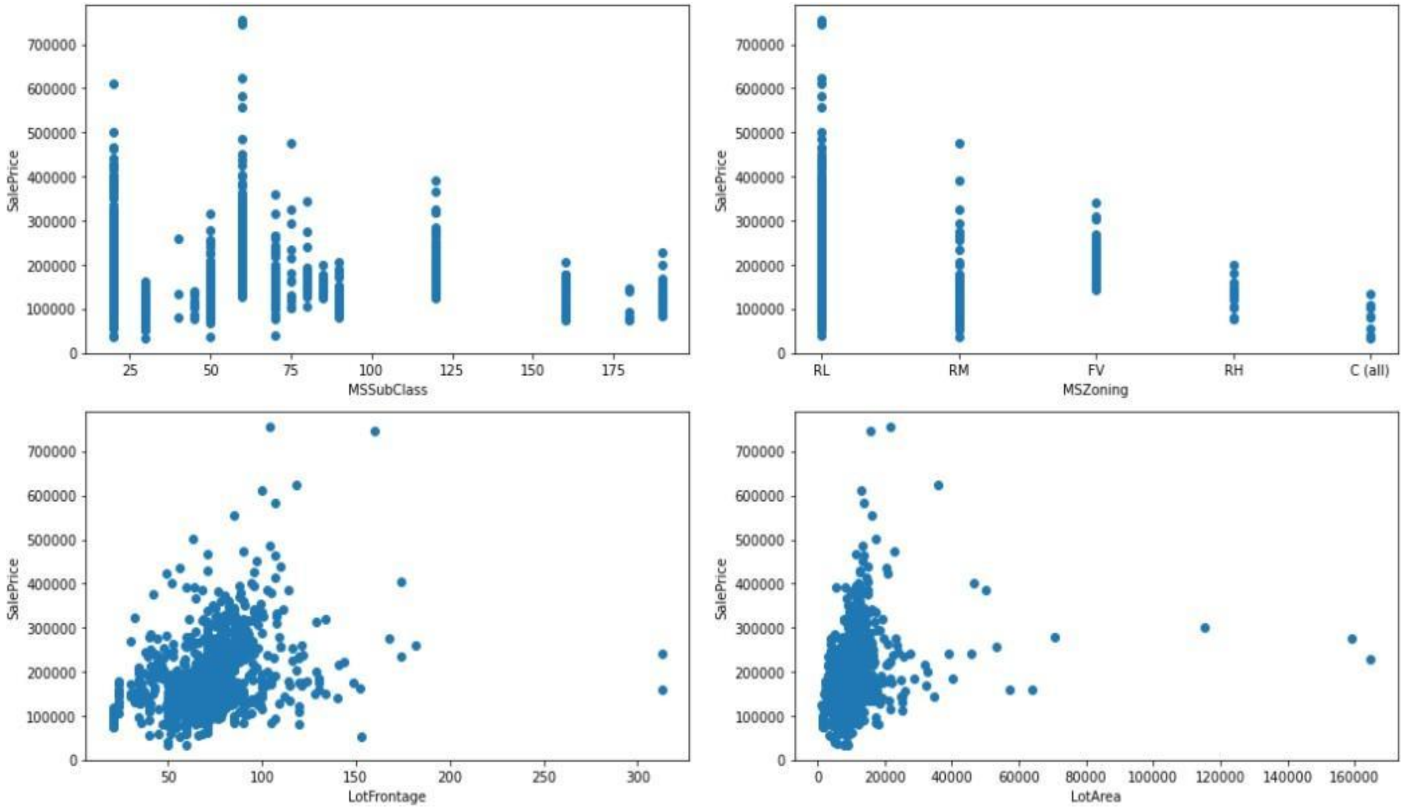
```
sns.countplot(df.YrSold)
```

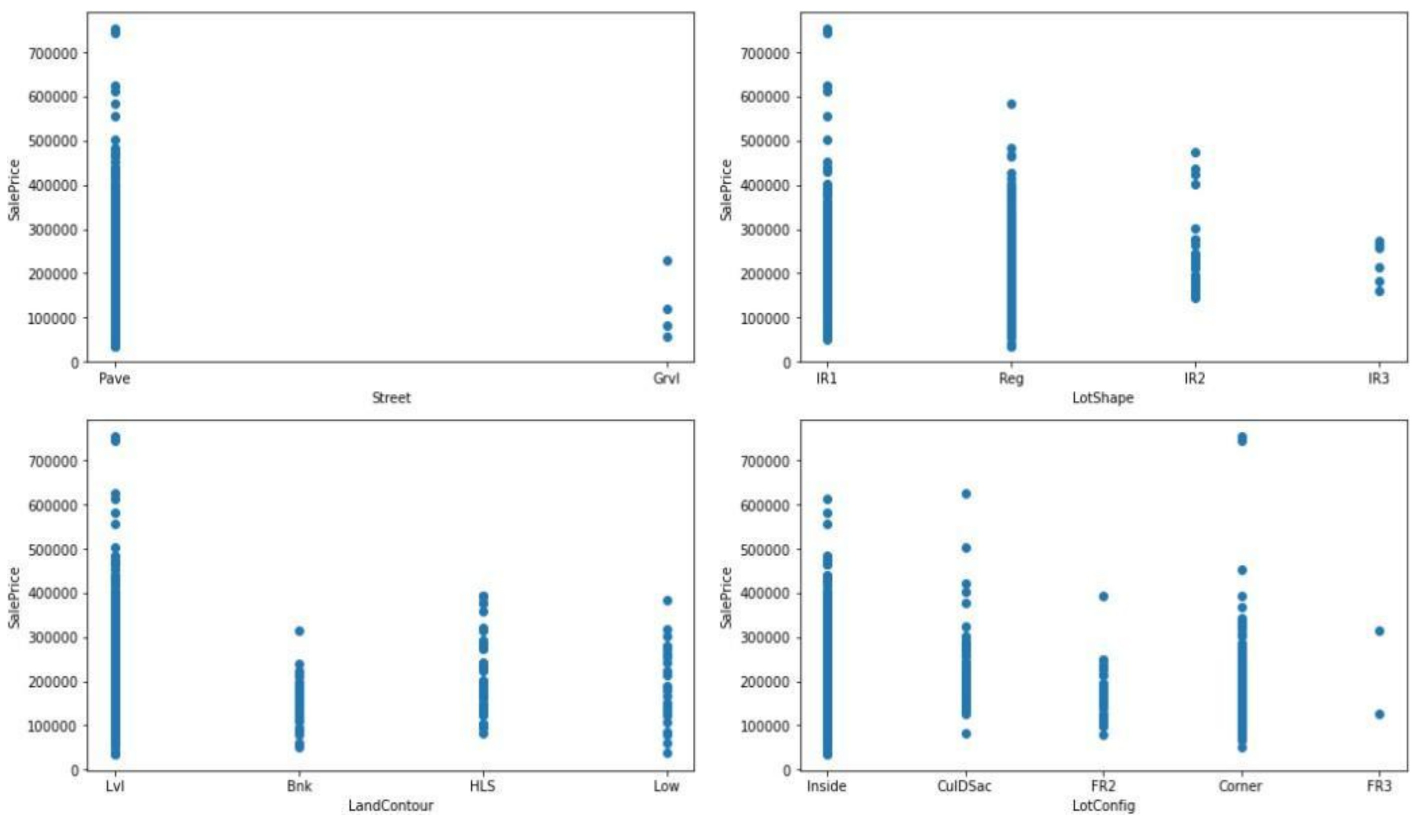
```
<AxesSubplot:xlabel='YrSold', ylabel='count'>
```

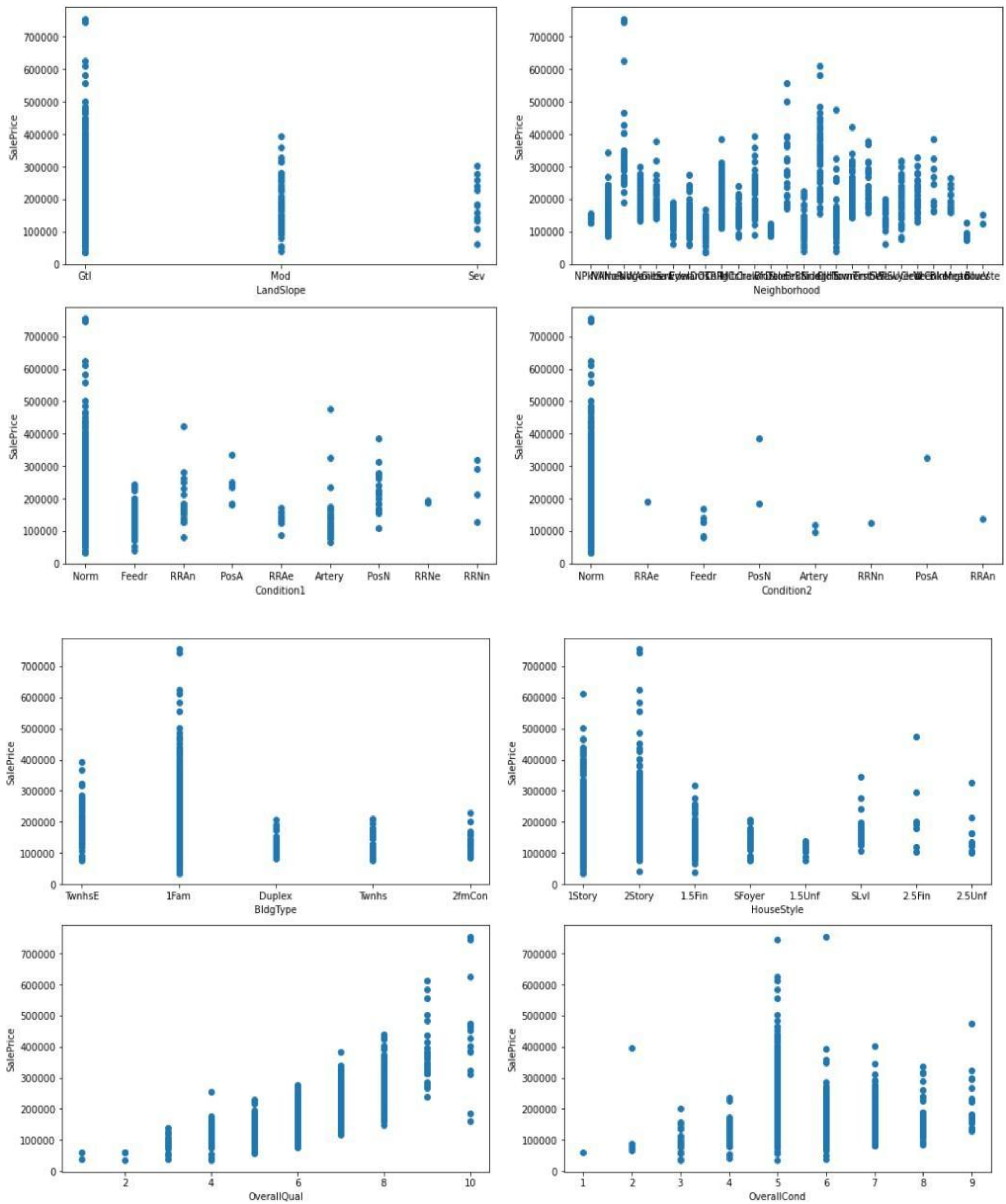


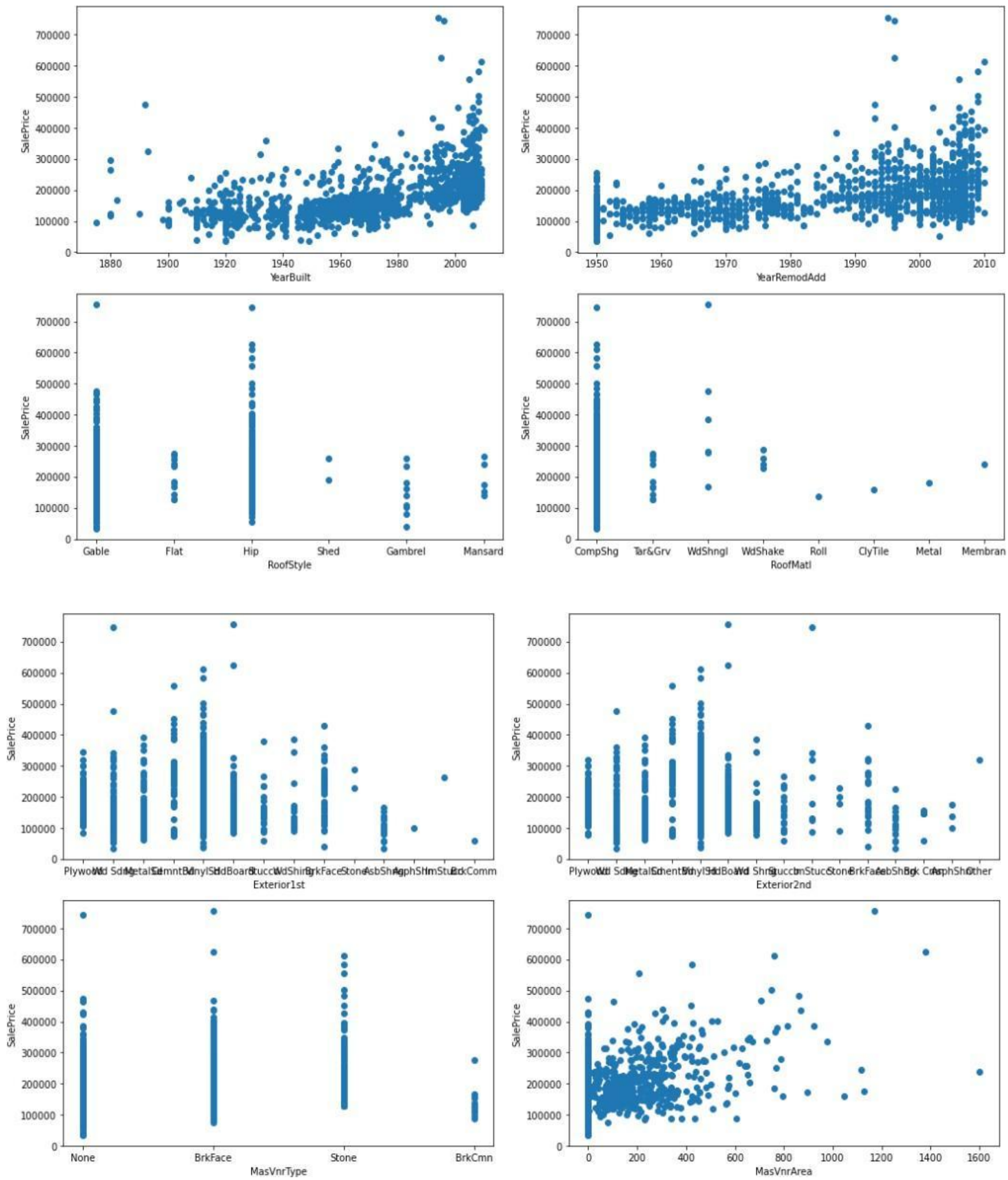
Most number of houses were sold in 2009 and the least in 2010.

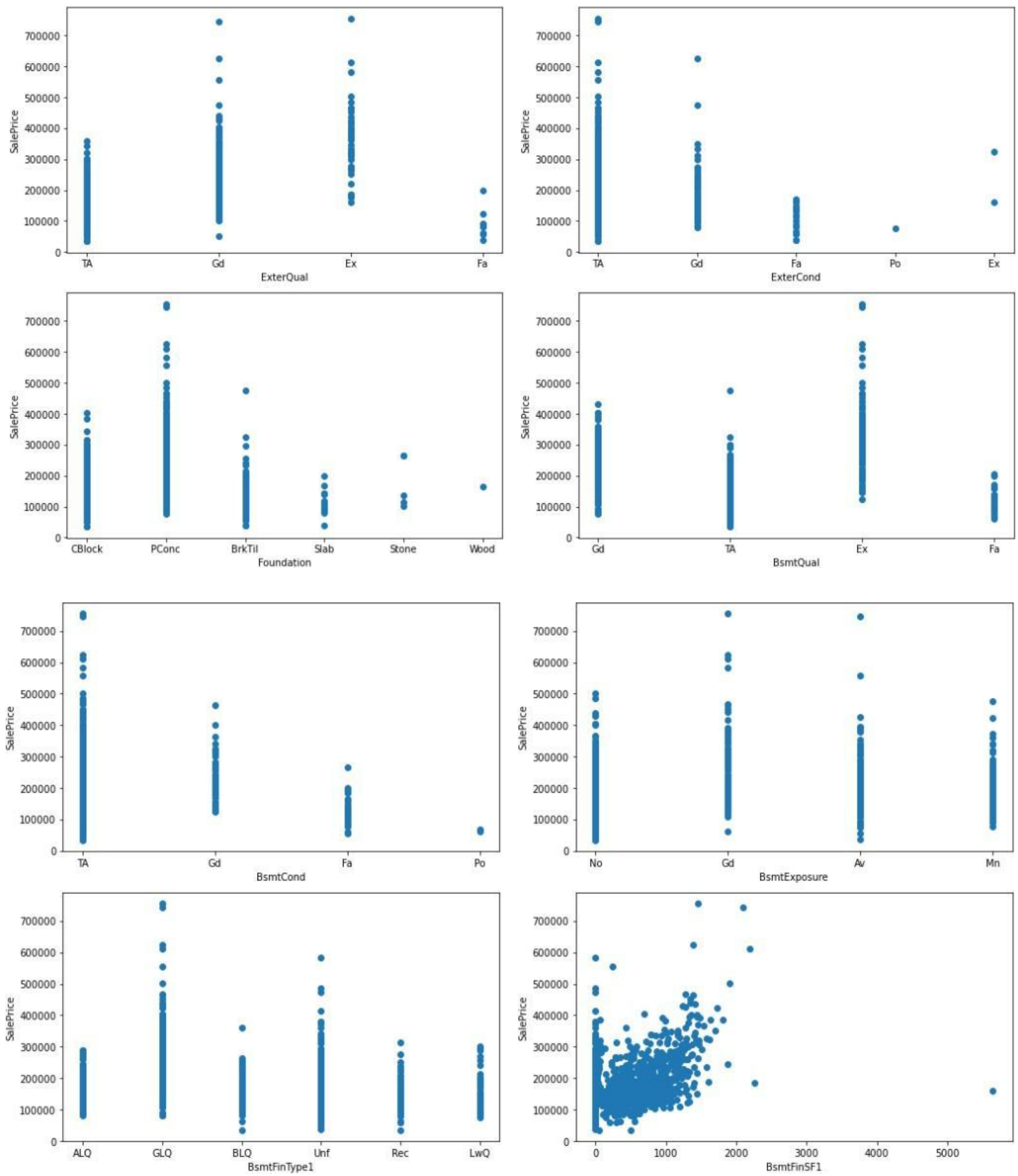
```
plt.figure(figsize=(15,155),facecolor='white')
plotnumber=1

for column in X:
    if plotnumber<=76:
        ax=plt.subplot(38,2,plotnumber)
        plt.scatter(X[column],y)
        plt.xlabel(column,fontsize=10)
        plt.ylabel('SalePrice',fontsize=10)

    plotnumber+=1
plt.tight_layout()
```

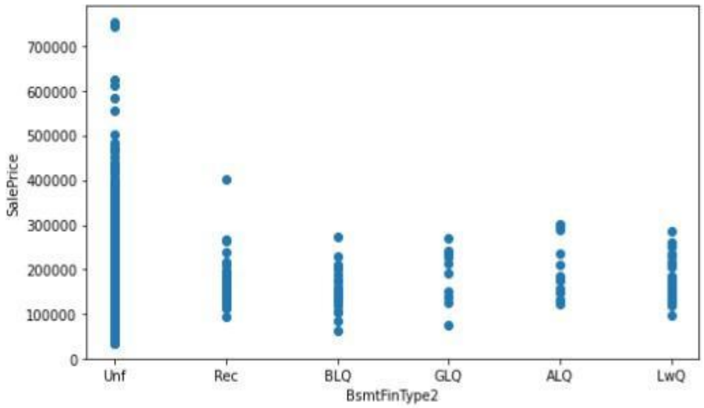

SalePrice
MSSubClass
SalePrice
RL
RM
FV
RH
C (all)
MSZoning
SalePrice
LotFrontage
SalePrice
LotArea

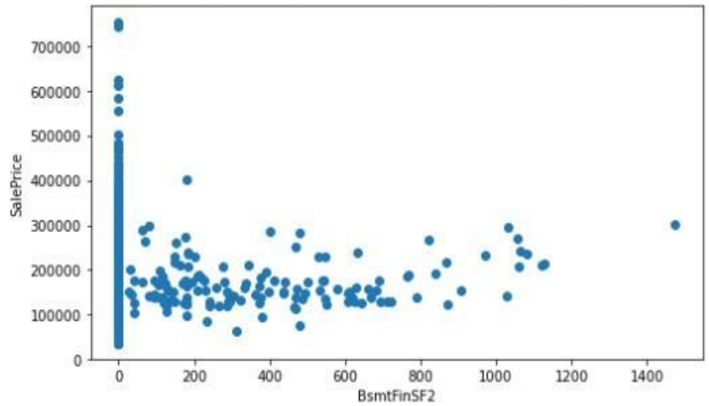

SalePrice
Pave
Grvl
Street
SalePrice
IR1
Reg
IR2
IR3
LotShape
SalePrice
Lvl
Bnk
HLS
Low
LandContour
SalePrice
Inside
CulDSac
FR2
Corner
FR3
LotConfig

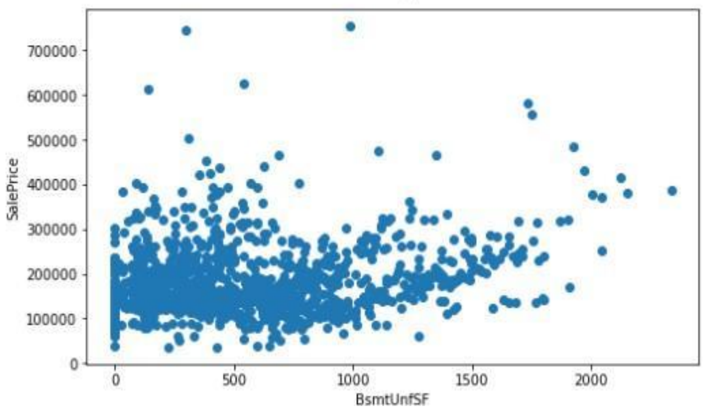

SalePrice
LandSlope
Gtl
Mod
Sev
Neighborhood
Condition1
Norm
Feedr
RRAn
PosA
RRAe
Artery
PosN
RRNe
RRNn
Condition2
BldgType
TwnhsE
1Fam
Duplex
Twnhs
2fmCon
HouseStyle
1Story
2Story
1.5Fin
SFoyer
1.5Unf
SLvl
2.5Fin
2.5Unf
OverallQual
OverallCond

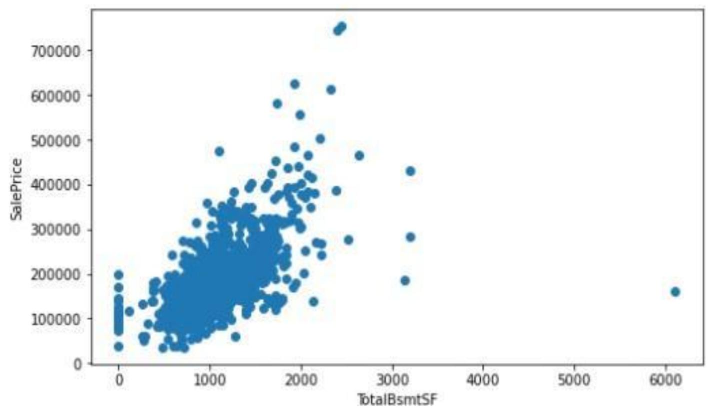

SalePrice
YearBuilt
YearRemodAdd
RoofStyle
Gable
Flat
Hip
Shed
Gambrel
Mansard
RoofMatl
CompShg
Tar&Grv
WdShngl
WdShake
Roll
ClyTile
Metal
Membran
Exterior1st
Exterior2nd
MasVnrType
None
BrkFace
Stone
BrkCmn
MasVnrArea

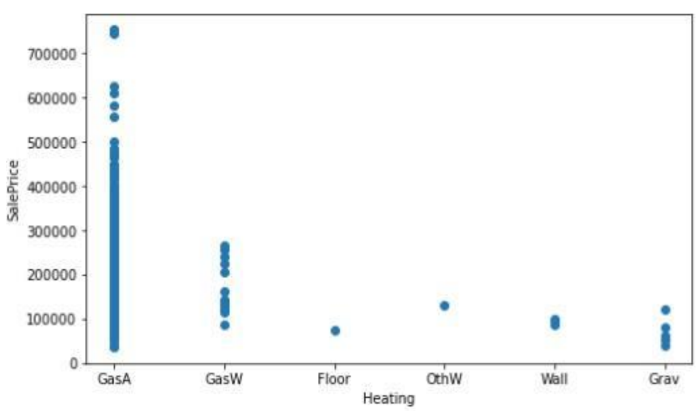

SalePrice
ExterQual
TA Gd Ex Fa
ExterCond
TA Gd Fa Po Ex
Foundation
CBlock PConc BrkTil Slab Stone Wood
BsmtQual
Gd TA Ex Fa
BsmtCond
TA Gd Fa Po
BsmtExposure
No Gd Av Mn
BsmtFinType1
ALQ GLQ BLQ Unf Rec LwQ
BsmtFinSF1
0 1000 2000 3000 4000 5000
0 100000 200000 300000 400000 500000 600000 700000

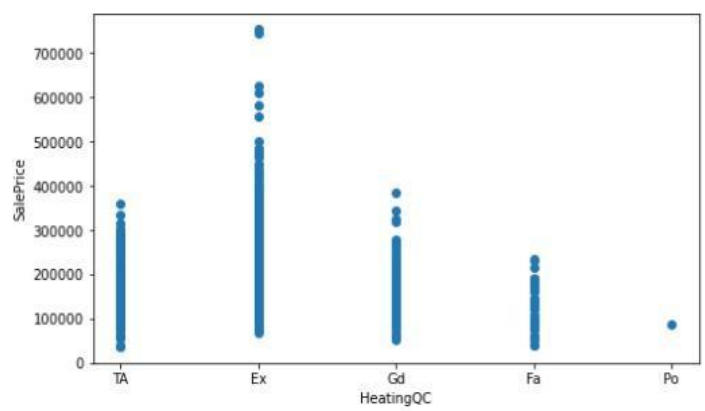

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
Unf
Rec
BLQ
GLQ
ALQ
LwQ
BsmtFinType2

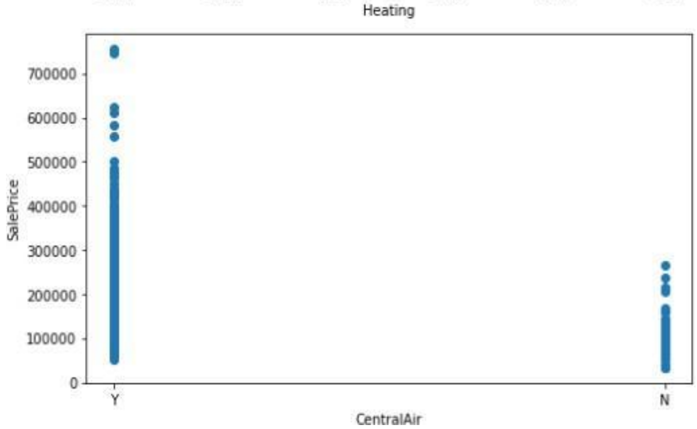

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
0
200
400
600
800
1000
1200
1400
BsmtFinSF2

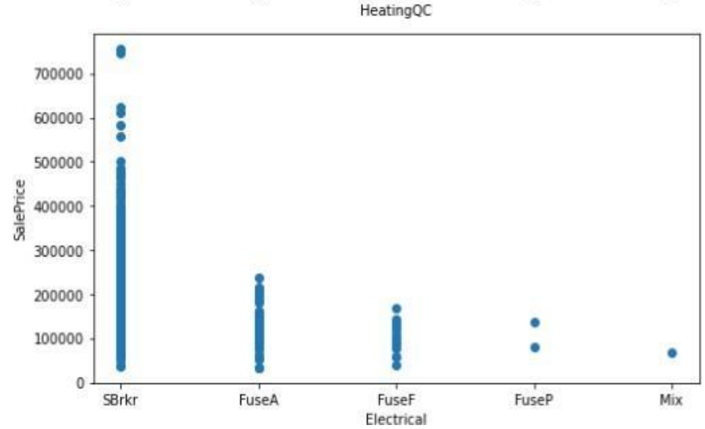

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
0
500
1000
1500
2000
BsmtUnfSF

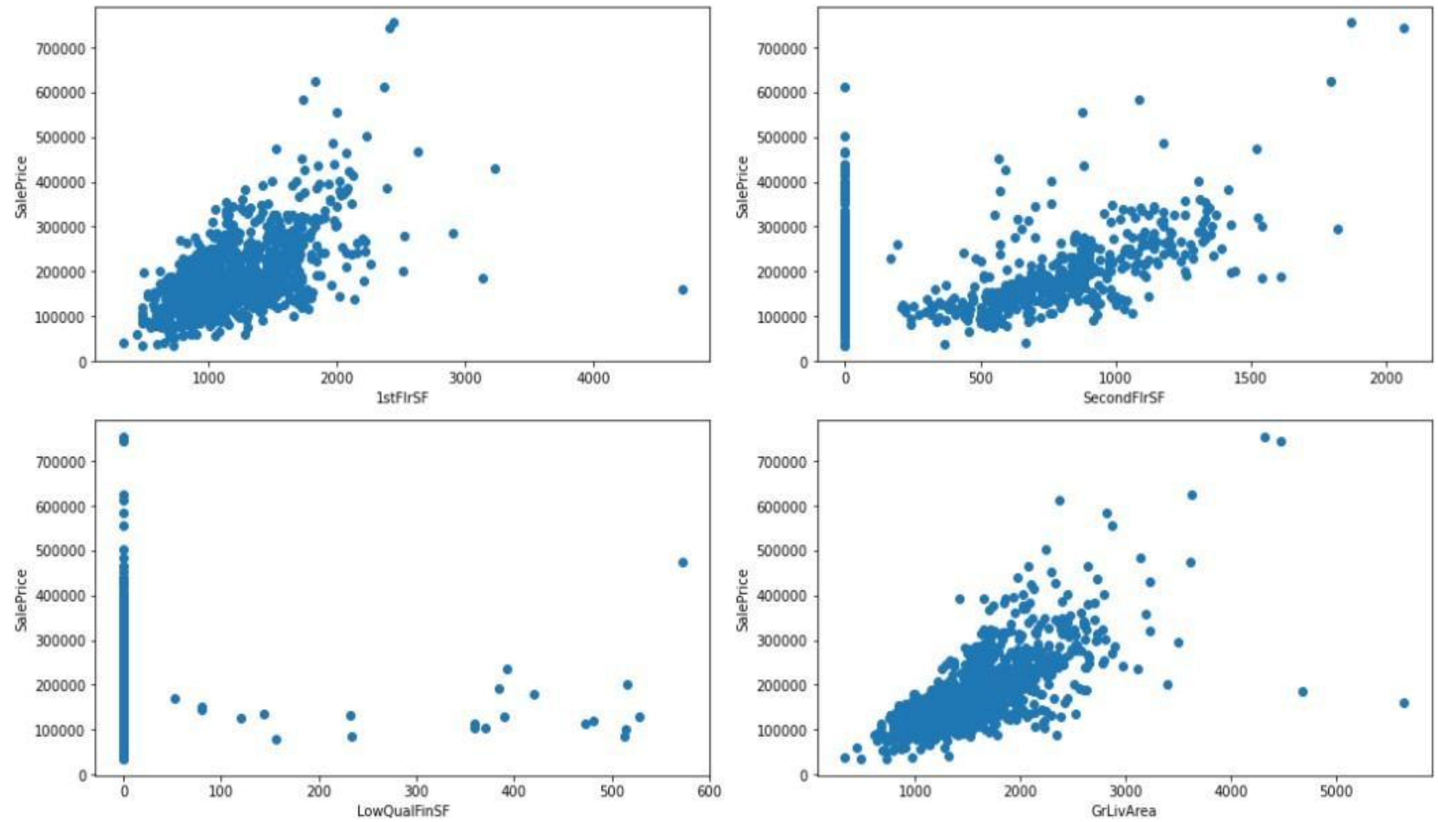

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
0
1000
2000
3000
4000
5000
6000
TotalBsmtSF

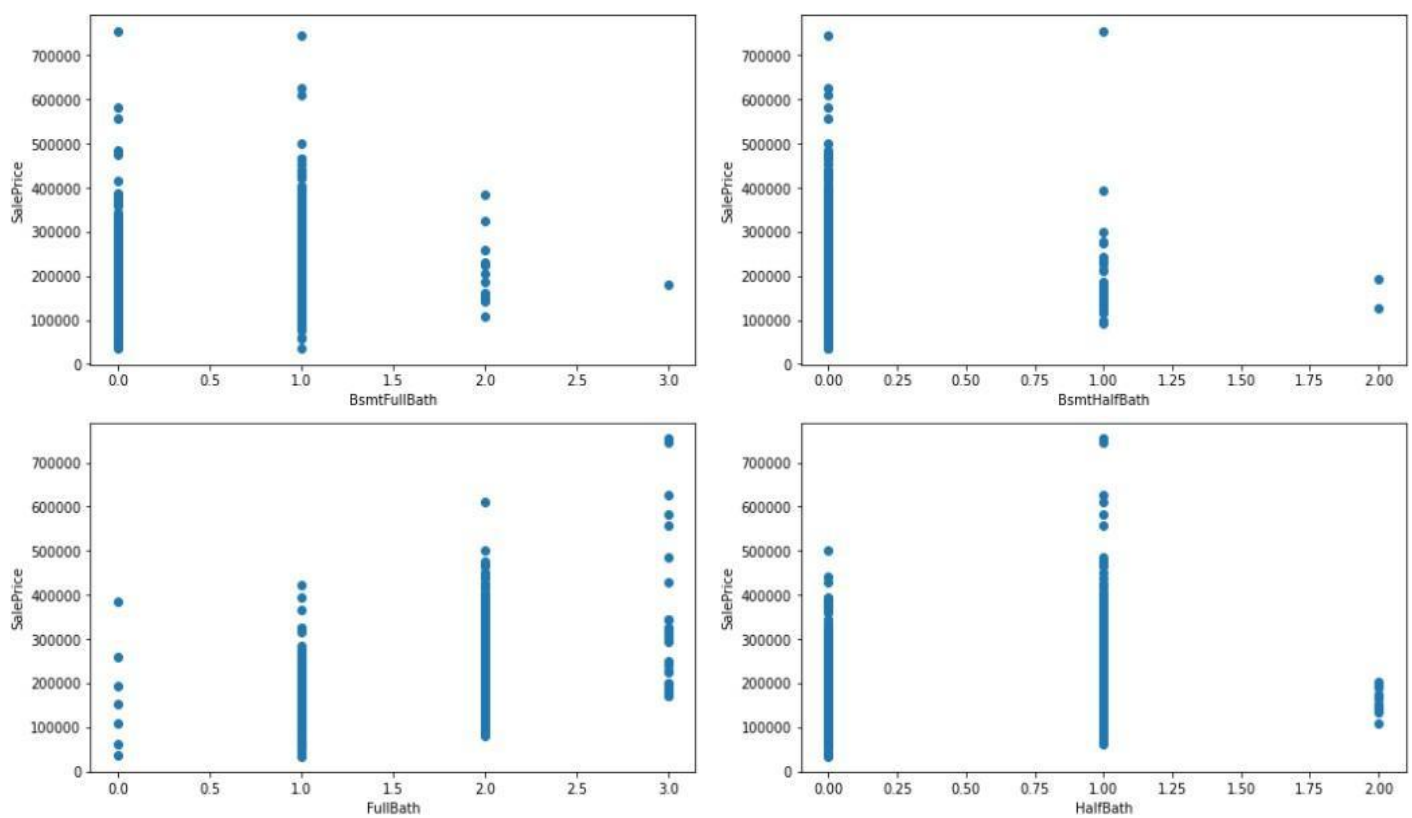

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
GasA
GasW
Floor
OthW
Wall
Grav
Heating

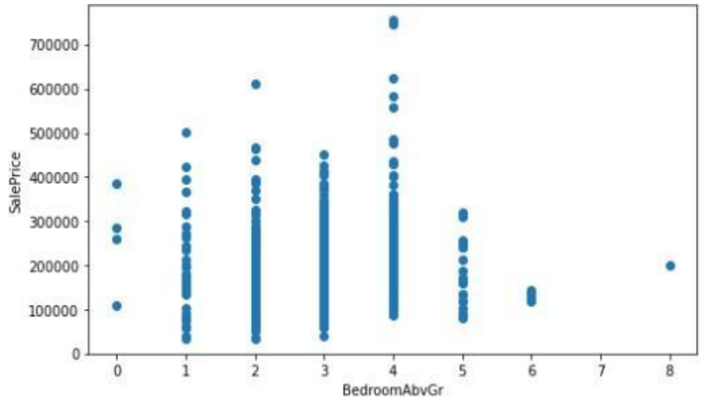

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
TA
Ex
Gd
Fa
Po
HeatingQC

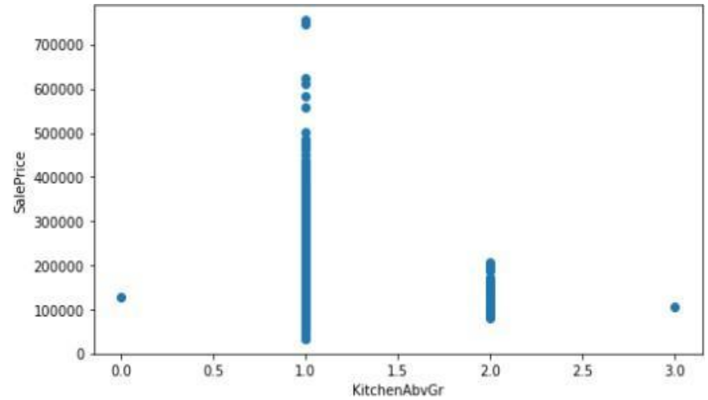

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
Y
N
CentralAir

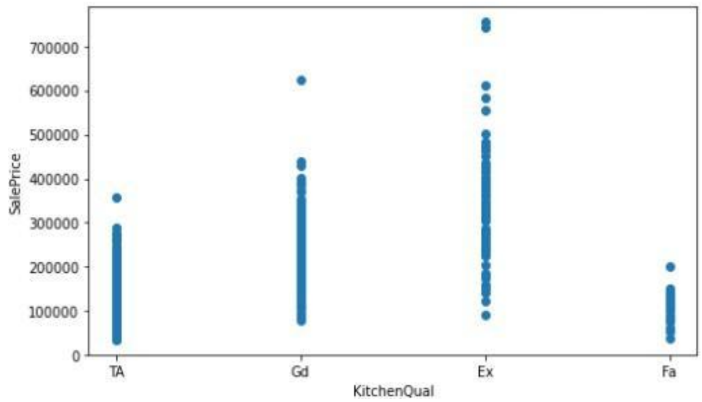

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
SBrkr
FuseA
FuseF
FuseP
Mix
Electrical

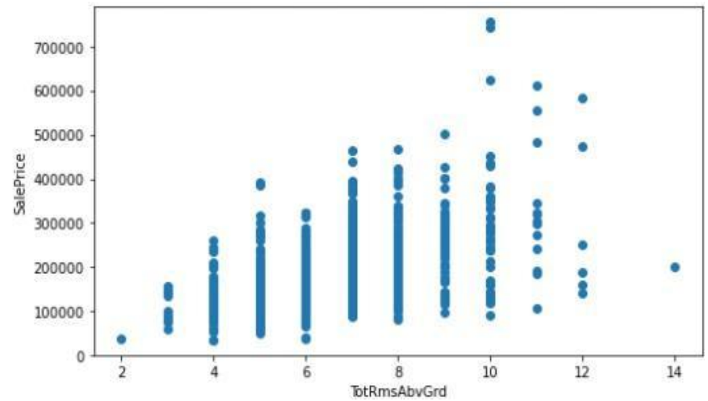

SalePrice
1stFlrSF
SecondFlrSF
LowQualFinSF
GrLivArea

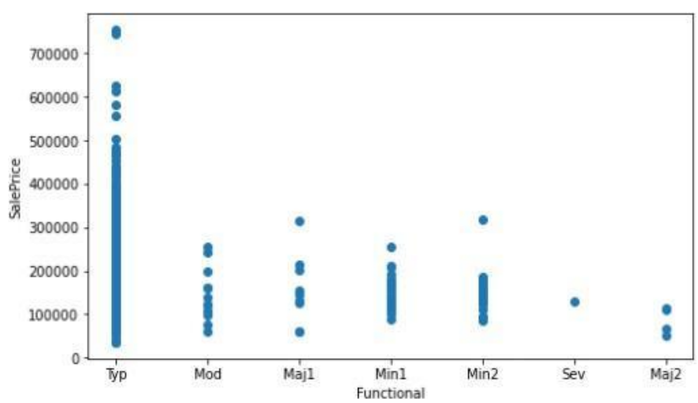

SalePrice
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath

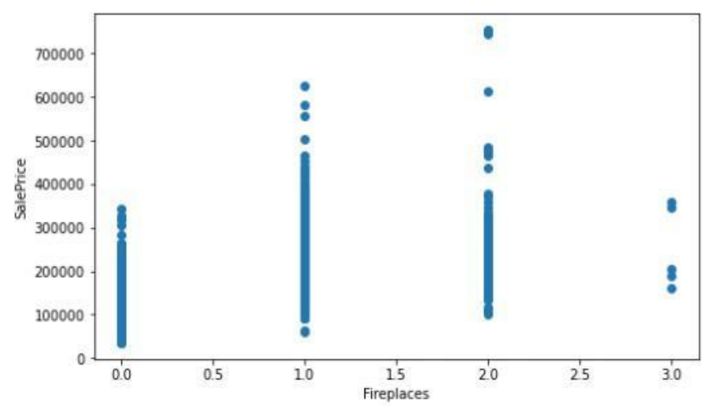

SalePrice
BedroomAbvGr

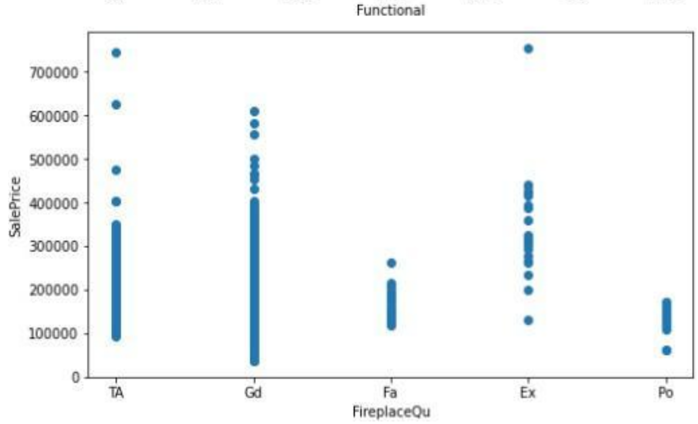

SalePrice
KitchenAbvGr

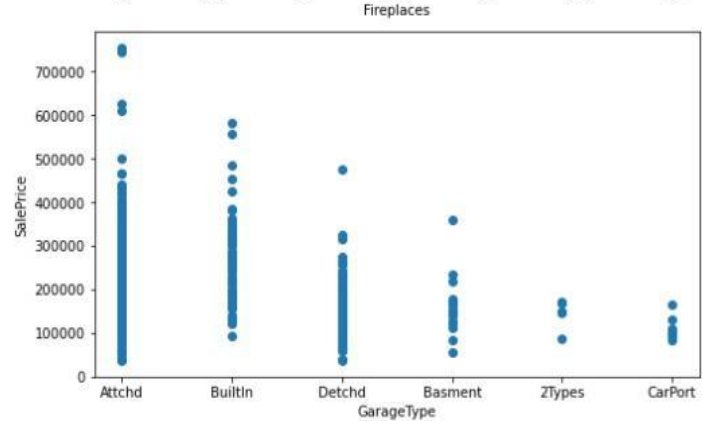

SalePrice
TA
Gd
Ex
Fa
KitchenQual

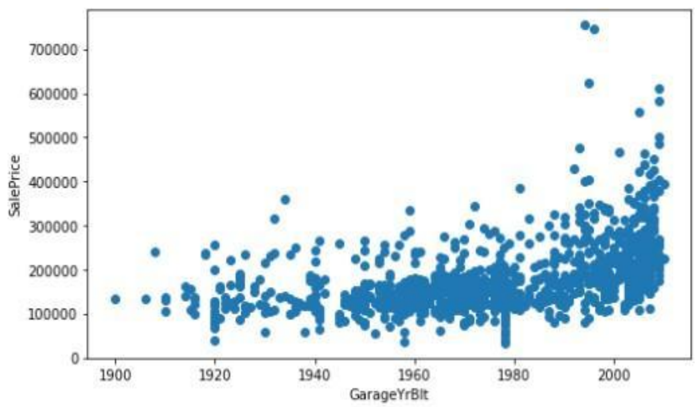

SalePrice
TotRmsAbvGrd

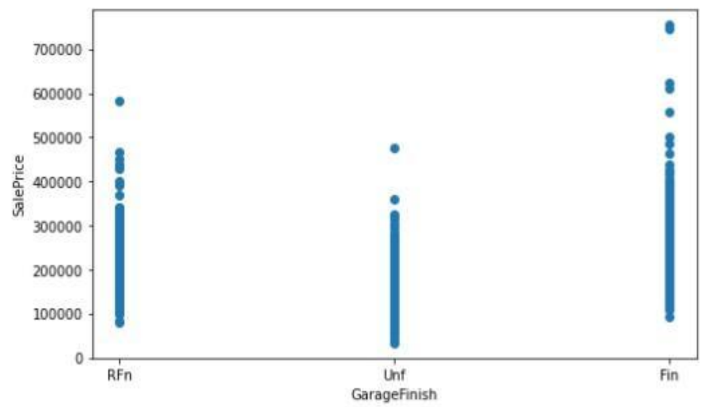

SalePrice
Typ
Mod
Maj1
Min1
Min2
Sev
Maj2
Functional

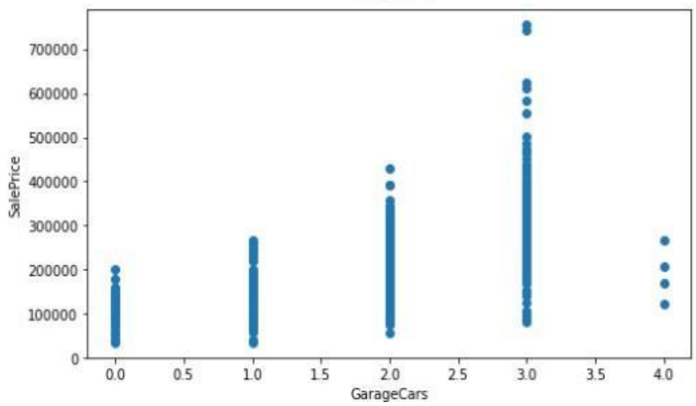

SalePrice
Fireplaces

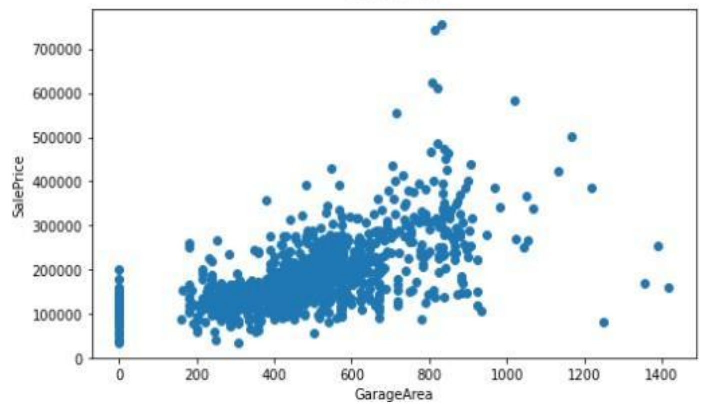

SalePrice
TA
Gd
Fa
Ex
Po
FireplaceQu

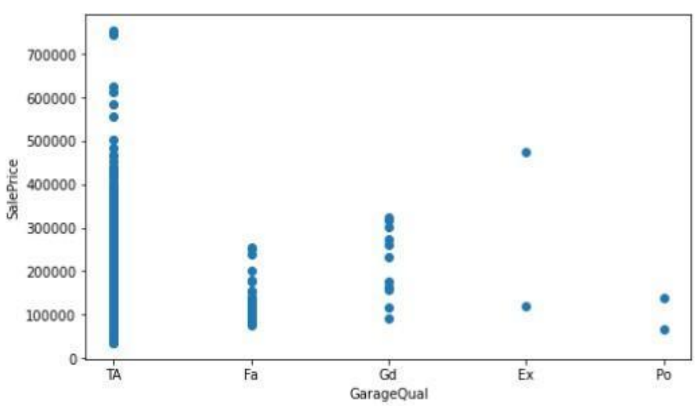

SalePrice
Attchd
BuiltIn
Detchd
Basment
2Types
CarPort
GarageType

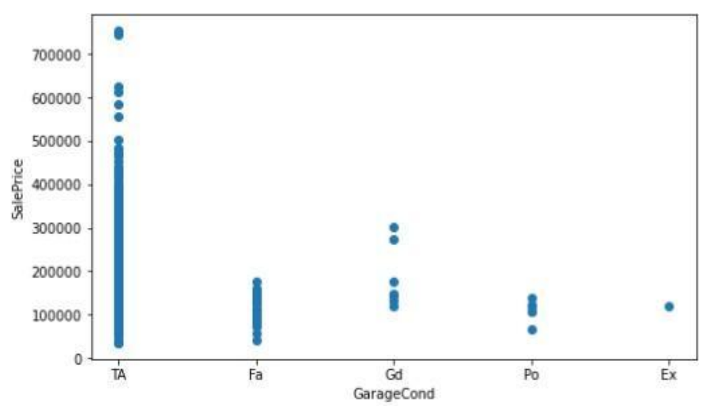

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
1900
1920
1940
1960
1980
2000
GarageYrBlt

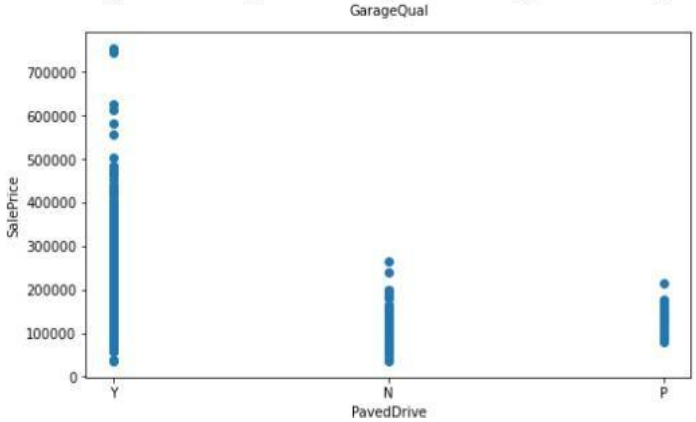

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
RFn
Unf
Fin
GarageFinish

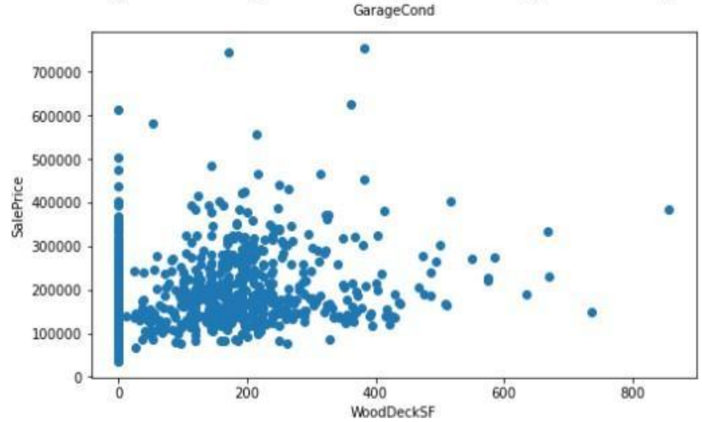

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
GarageCars

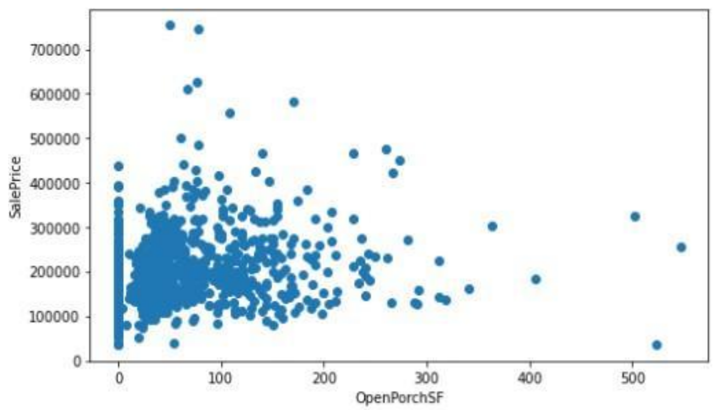

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
0
200
400
600
800
1000
1200
1400
GarageArea

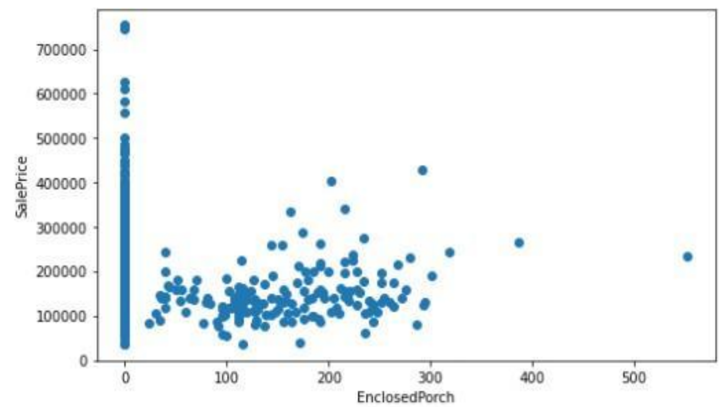

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
TA
Fa
Gd
Ex
Po
GarageQual

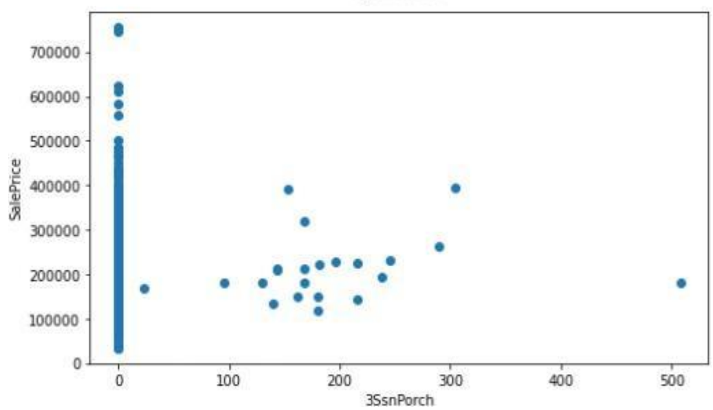

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
TA
Fa
Gd
Po
Ex
GarageCond

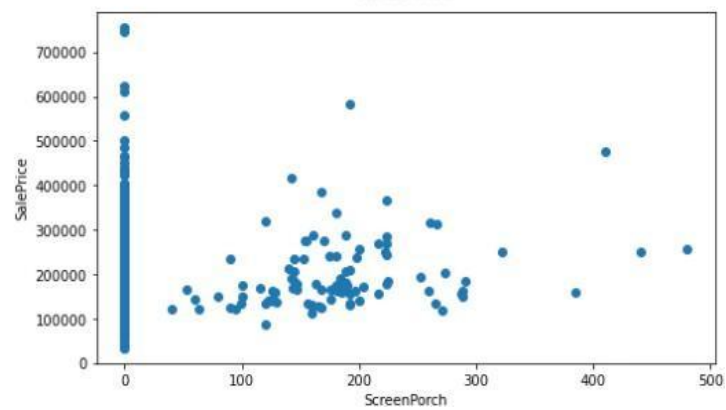

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
Y
N
P
PavedDrive

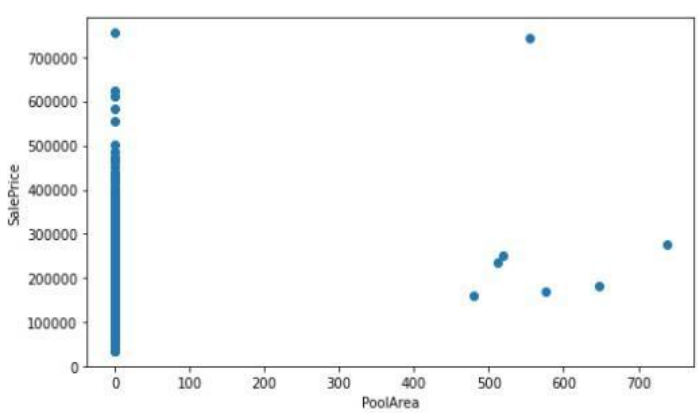

SalePrice
0
100000
200000
300000
400000
500000
600000
700000
0
200
400
600
800
WoodDeckSF

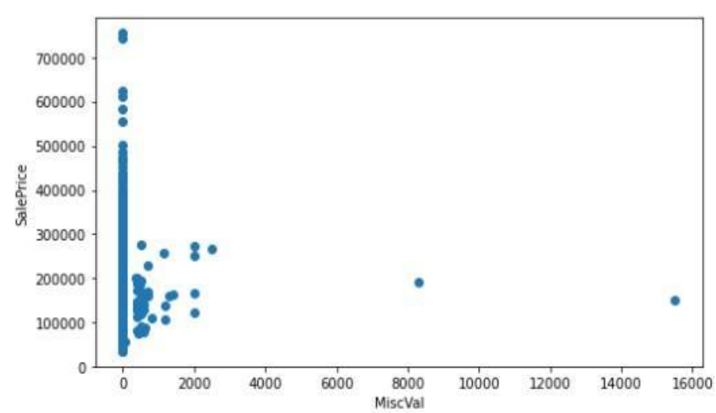

SalePrice
OpenPorchSF

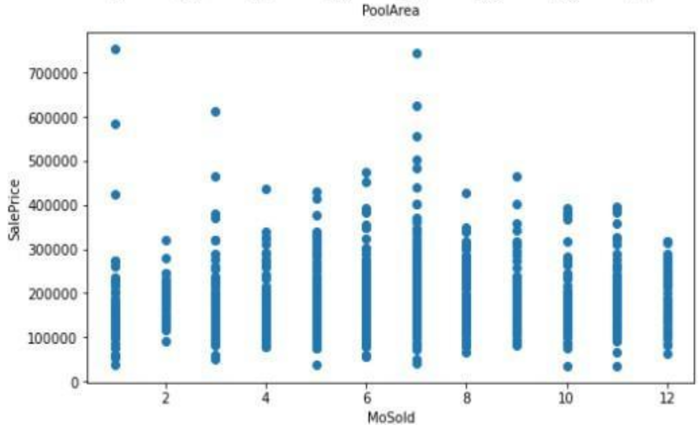

SalePrice
EnclosedPorch

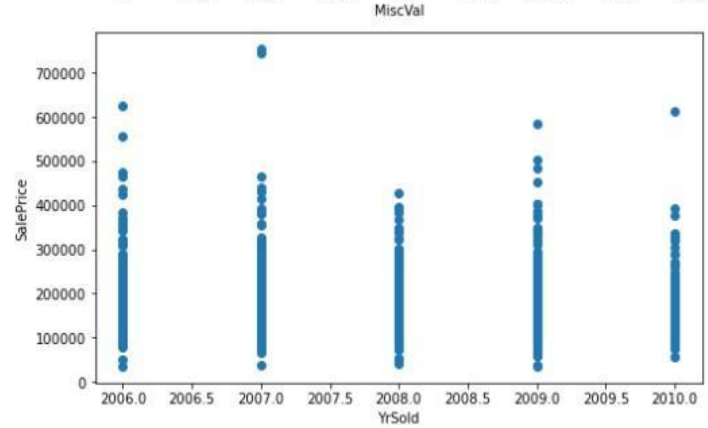

SalePrice
3SsnPorch

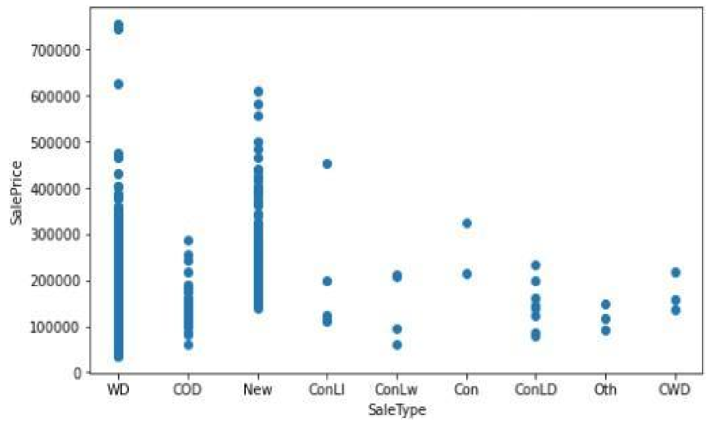

SalePrice
ScreenPorch

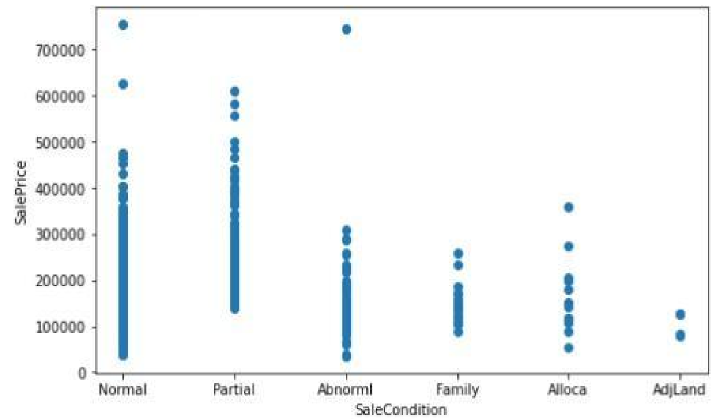

SalePrice
PoolArea


SalePrice
MiscVal


SalePrice
MoSold


SalePrice
YrSold





Observation:

- 'GrLivArea' and 'TotalBsmtSF' appear to be correlated with 'SalePrice' in a linear fashion. Both correlations are positive, which implies that when one variable increases, so does the other. In the instance of 'TotalBsmtSF,' the slope of the linear connection is extremely steep.
- 'OverallQual' and 'YearBuilt' appear to be connected to 'SalePrice' as well. The relationship appears to be greater in the case of 'OverallQual,' where the scatter plot demonstrates how sales prices increase as overall quality improves.

Data Preprocessing

```
df.drop(columns=['Id','Alley','Utilities','PoolQC','Fence','MiscFeature'],axis=1,inplace=True)
```

```
df1.drop(columns=['Id','Alley','Utilities','PoolQC','Fence','MiscFeature'],axis=1,inplace=True)
```

As we have seen earlier, there were number of missing values in our train and test datasets. So we will deal with them now. But we also have features that have more than 80% null values. So it's better we drop them along with unwanted columns.

Next, we will deal with the remaining features that has very less percentage of null values. The numerical columns will be replaced with the mean and the categorical columns will be replaced with the mode of respective features. We will do this in train as well as test dataset.

```
df['LotFrontage']=df['LotFrontage'].fillna(df['LotFrontage'].mean())
df['MasVnrType']=df['MasVnrType'].fillna(df['MasVnrType'].mode()[0])
df['MasVnrArea']=df['MasVnrArea'].fillna(df['MasVnrArea'].mean())
df['BsmtQual']=df['BsmtQual'].fillna(df['BsmtQual'].mode()[0])
df['BsmtCond']=df['BsmtCond'].fillna(df['BsmtCond'].mode()[0])
df['BsmtExposure']=df['BsmtExposure'].fillna(df['BsmtExposure'].mode()[0])
df['BsmtFinType1']=df['BsmtFinType1'].fillna(df['BsmtFinType1'].mode()[0])
df['BsmtFinType2']=df['BsmtFinType2'].fillna(df['BsmtFinType2'].mode()[0])
df['FireplaceQu']=df['FireplaceQu'].fillna(df['FireplaceQu'].mode()[0])
df['GarageType']=df['GarageType'].fillna(df['GarageType'].mode()[0])
df['GarageYrBlt']=df['GarageYrBlt'].fillna(df['GarageYrBlt'].mean())
df['GarageFinish']=df['GarageFinish'].fillna(df['GarageFinish'].mode()[0])
df['GarageQual']=df['GarageQual'].fillna(df['GarageQual'].mode()[0])
df['GarageCond']=df['GarageCond'].fillna(df['GarageCond'].mode()[0])
```

```
df1['LotFrontage']=df1['LotFrontage'].fillna(df1['LotFrontage'].mean())
df1['MasVnrType']=df1['MasVnrType'].fillna(df1['MasVnrType'].mode()[0])
df1['MasVnrArea']=df1['MasVnrArea'].fillna(df1['MasVnrArea'].mean())
df1['BsmtQual']=df1['BsmtQual'].fillna(df1['BsmtQual'].mode()[0])
df1['BsmtCond']=df1['BsmtCond'].fillna(df1['BsmtCond'].mode()[0])
df1['BsmtExposure']=df1['BsmtExposure'].fillna(df1['BsmtExposure'].mode()[0])
df1['BsmtFinType1']=df1['BsmtFinType1'].fillna(df1['BsmtFinType1'].mode()[0])
df1['BsmtFinType2']=df1['BsmtFinType2'].fillna(df1['BsmtFinType2'].mode()[0])
df1['Electrical']=df1['Electrical'].fillna(df1['Electrical'].mode()[0])
df1['FireplaceQu']=df1['FireplaceQu'].fillna(df1['FireplaceQu'].mode()[0])
df1['GarageType']=df1['GarageType'].fillna(df1['GarageType'].mode()[0])
df1['GarageYrBlt']=df1['GarageYrBlt'].fillna(df1['GarageYrBlt'].mean())
df1['GarageFinish']=df1['GarageFinish'].fillna(df1['GarageFinish'].mode()[0])
df1['GarageQual']=df1['GarageQual'].fillna(df1['GarageQual'].mode()[0])
df1['GarageCond']=df1['GarageCond'].fillna(df1['GarageCond'].mode()[0])
```

Now, we will convert all our categorical data into numerical data so that our ML model can understand our data. We will do this in our train as well as test data too.

```
#Converting strings into nu

from sklearn.preprocessing

df['MasVnrType']=df17
df['ExterQual']=df18
df['ExterCond']=df19
df['Foundation']=df20
df['BsmtQual']=df21
df['BsmtCond']=df22
df['BsmtExposure']=df23
df['BsmtFinType1']=df24

df['BsmtFinType2']=df25
df['Heating']=df26
df['HeatingQC']=df27
df['CentralAir']=df28
df['Electrical']=df29
df['KitchenQual']=df30
df['Functional']=df31
df['FireplaceQu']=df32

df['GarageType']=df33
df['GarageFinish']=df34
df['GarageQual']=df35
df['GarageCond']=df36
df['PavedDrive']=df37
df['SaleType']=df38
df['SaleCondition']=df39
```

```
#Converting strings into numberical format

from sklearn.preprocessing import LabelEncoder

lab_enc=LabelEncoder()

df111=lab_enc.fit_transform(df1['MSZoning'])
df2=lab_enc.fit_transform(df1['Street'])
df3=lab_enc.fit_transform(df1['LotShape'])
df4=lab_enc.fit_transform(df1['LandContour'])
df6=lab_enc.fit_transform(df1['LotConfig'])
df7=lab_enc.fit_transform(df1['LandSlope'])
df8=lab_enc.fit_transform(df1['Neighborhood'])

df9=lab_enc.fit_transform(df1['Condition1'])
df10=lab_enc.fit_transform(df1['Condition2'])
df11=lab_enc.fit_transform(df1['BldgType'])
df12=lab_enc.fit_transform(df1['HouseStyle'])
df13=lab_enc.fit_transform(df1['RoofStyle'])
df14=lab_enc.fit_transform(df1['RoofMatl'])
df15=lab_enc.fit_transform(df1['Exterior1st'])
df16=lab_enc.fit_transform(df1['Exterior2nd'])

df17=lab_enc.fit_transform(df1['MasVnrType'])
df18=lab_enc.fit_transform(df1['ExterQual'])
df19=lab_enc.fit_transform(df1['ExterCond'])
df20=lab_enc.fit_transform(df1['Foundation'])
df21=lab_enc.fit_transform(df1['BsmtQual'])
df22=lab_enc.fit_transform(df1['BsmtCond'])
df23=lab_enc.fit_transform(df1['BsmtExposure'])
df24=lab_enc.fit_transform(df1['BsmtFinType1'])
```

```
df25=lab_enc.fit_transform(df['BsmtFinType2'])
(df['Heating'])
(df['HeatingQC'])
(df['CentralAir'])
(df['Electrical'])
(df['KitchenQual'])
(df['Functional'])
(df['FireplaceQu'])

(df['GarageType'])
(df['GarageFinish'])
(df['GarageQual'])
(df['GarageCond'])
(df['PavedDrive'])
(df['SaleType'])
(df['SaleCondition'])
```

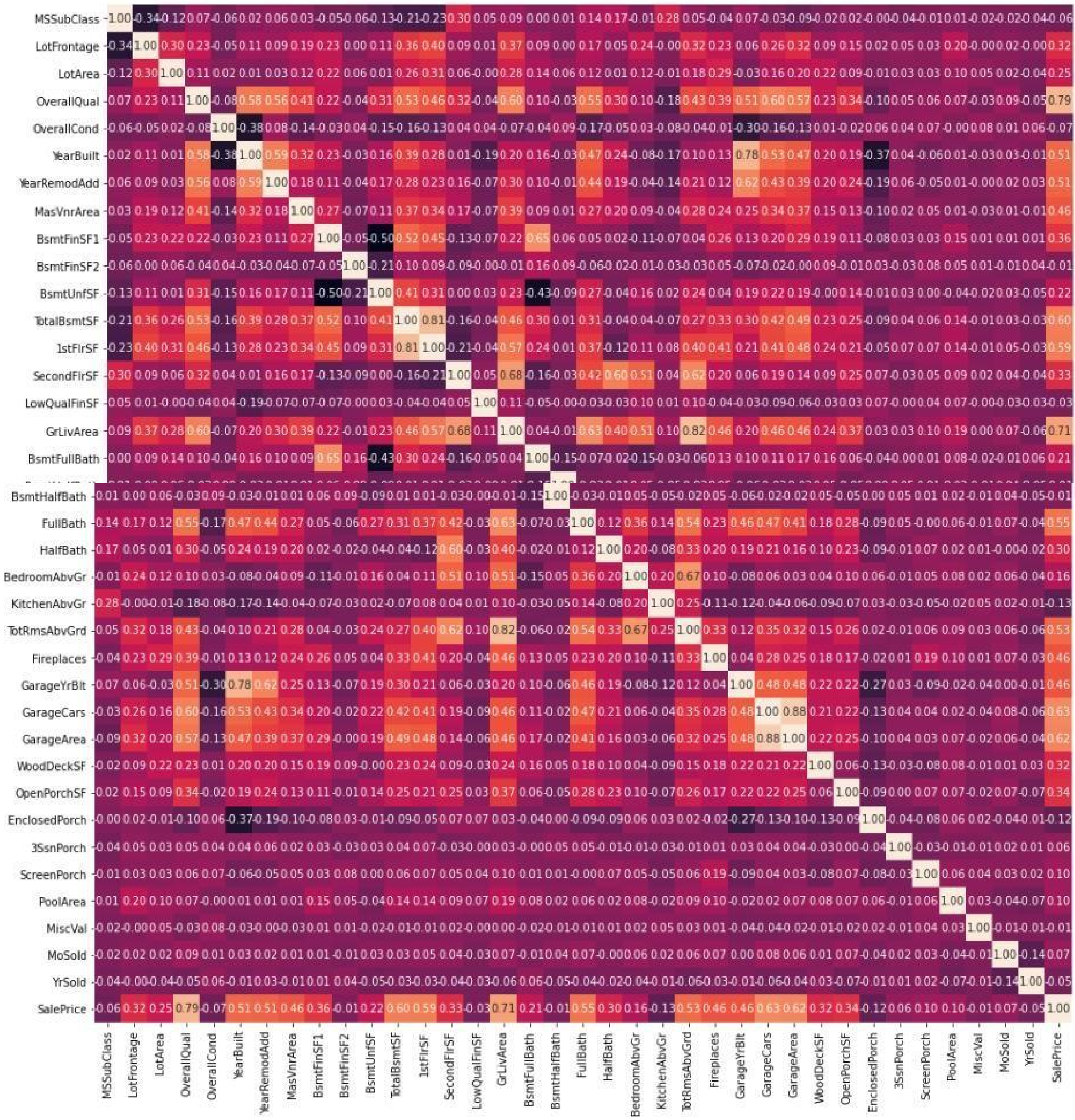
```
df25=lab_enc.fit_transform(df1['BsmtFinType2'])
df26=lab_enc.fit_transform(df1['Heating'])
df27=lab_enc.fit_transform(df1['HeatingQC'])
df28=lab_enc.fit_transform(df1['CentralAir'])
df29=lab_enc.fit_transform(df1['Electrical'])
df30=lab_enc.fit_transform(df1['KitchenQual'])
df31=lab_enc.fit_transform(df1['Functional'])
df32=lab_enc.fit_transform(df1['FireplaceQu'])

df33=lab_enc.fit_transform(df1['GarageType'])
df34=lab_enc.fit_transform(df1['GarageFinish'])
df35=lab_enc.fit_transform(df1['GarageQual'])
df36=lab_enc.fit_transform(df1['GarageCond'])
df37=lab_enc.fit_transform(df1['PavedDrive'])
df38=lab_enc.fit_transform(df1['SaleType'])
df39=lab_enc.fit_transform(df1['SaleCondition'])

df1['MSZoning']=df111
df1['Street']=df2
df1['LotShape']=df3
df1['LandContour']=df4
df1['LotConfig']=df6
df1['LandSlope']=df7
df1['Neighborhood']=df8

df1['Condition1']=df9
df1['Condition2']=df10
df1['BldgType']=df11
df1['HouseStyle']=df12
df1['RoofStyle']=df13
df1['RoofMatl']=df14
df1['Exterior1st']=df15
df1['Exterior2nd']=df16
```

```
df1['MasVnrType']=df17
df1['ExterQual']=df18
df1['ExterCond']=df19
df1['Foundation']=df20
df1['BsmtQual']=df21
df1['BsmtCond']=df22
df1['BsmtExposure']=df23
df1['BsmtFinType1']=df24

df1['BsmtFinType2']=df25
df1['Heating']=df26
df1['HeatingQC']=df27
df1['CentralAir']=df28
df1['Electrical']=df29
df1['KitchenQual']=df30
df1['Functional']=df31
df1['FireplaceQu']=df32

df1['GarageType']=df33
df1['GarageFinish']=df34
df1['GarageQual']=df35
df1['GarageCond']=df36
df1['PavedDrive']=df37
df1['SaleType']=df38
df1['SaleCondition']=df39
```

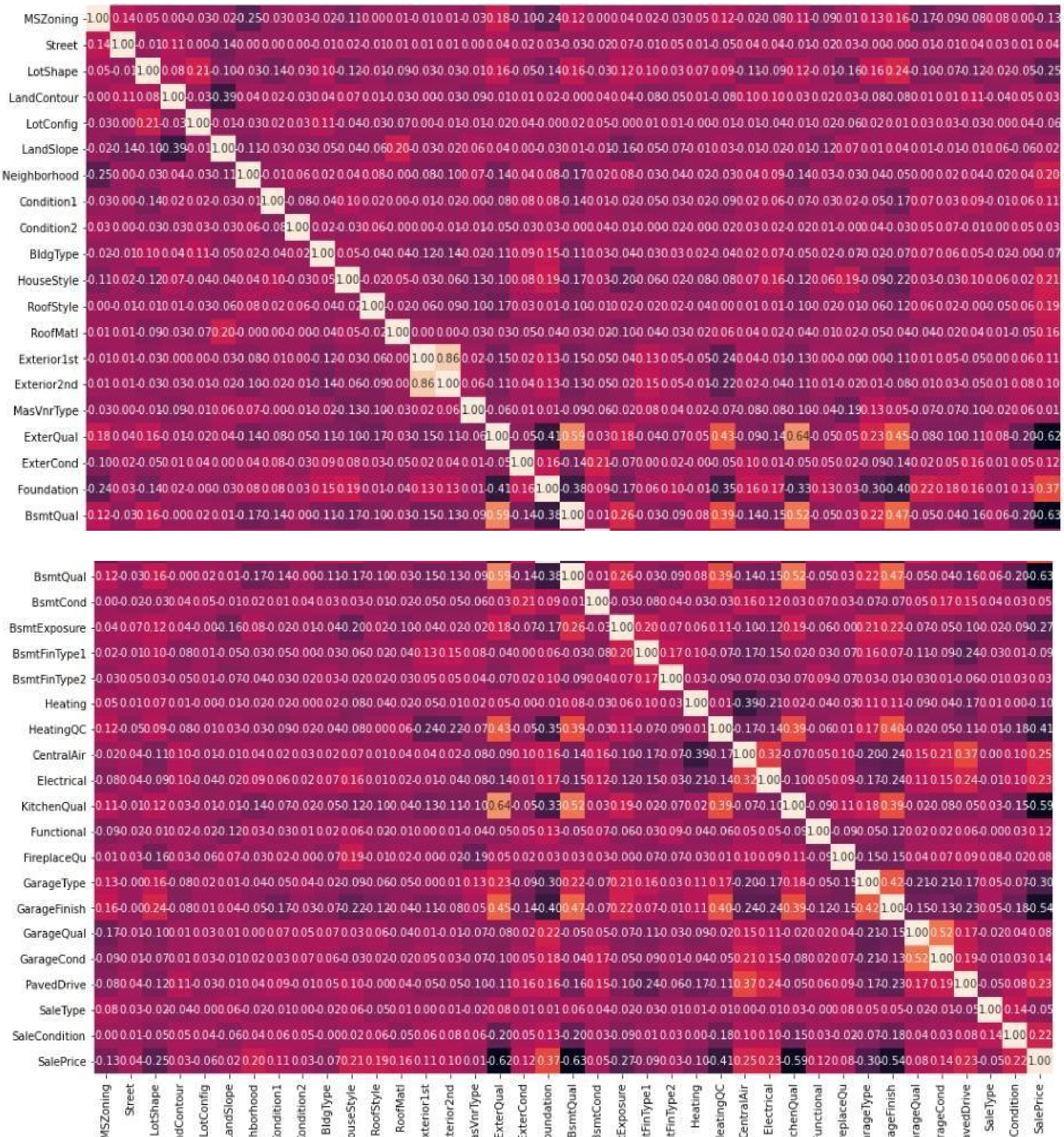
```
YearRemodAdd','MasVnrArea','BsmtFinSF
ullBath','BsmtHalfBath','FullBath','H
eArea','WoodDeckSF','OpenPorchSF','En
```

```
rhood','Condition1','Condition2','Bld
erCond','Foundation','BsmtQual','Bsmt
KitchenQual','Functional','FireplaceQ
lePrice']]
```

```
plt.figure(figsize=(20,20))

sns.heatmap(corr_1,cbar=True,square=True,cbar_kws={'shrink':0.82},fmt='.2f',annot=True,annot_kws={'size':10})
plt.show()
```




```
plt.figure(figsize=(20,20))

sns.heatmap(corr_2,cbar=True,square=True,cbar_kws={'shrink':0.82},fmt='.2f',annot=True,annot_kws={'size':10})
plt.show()
```

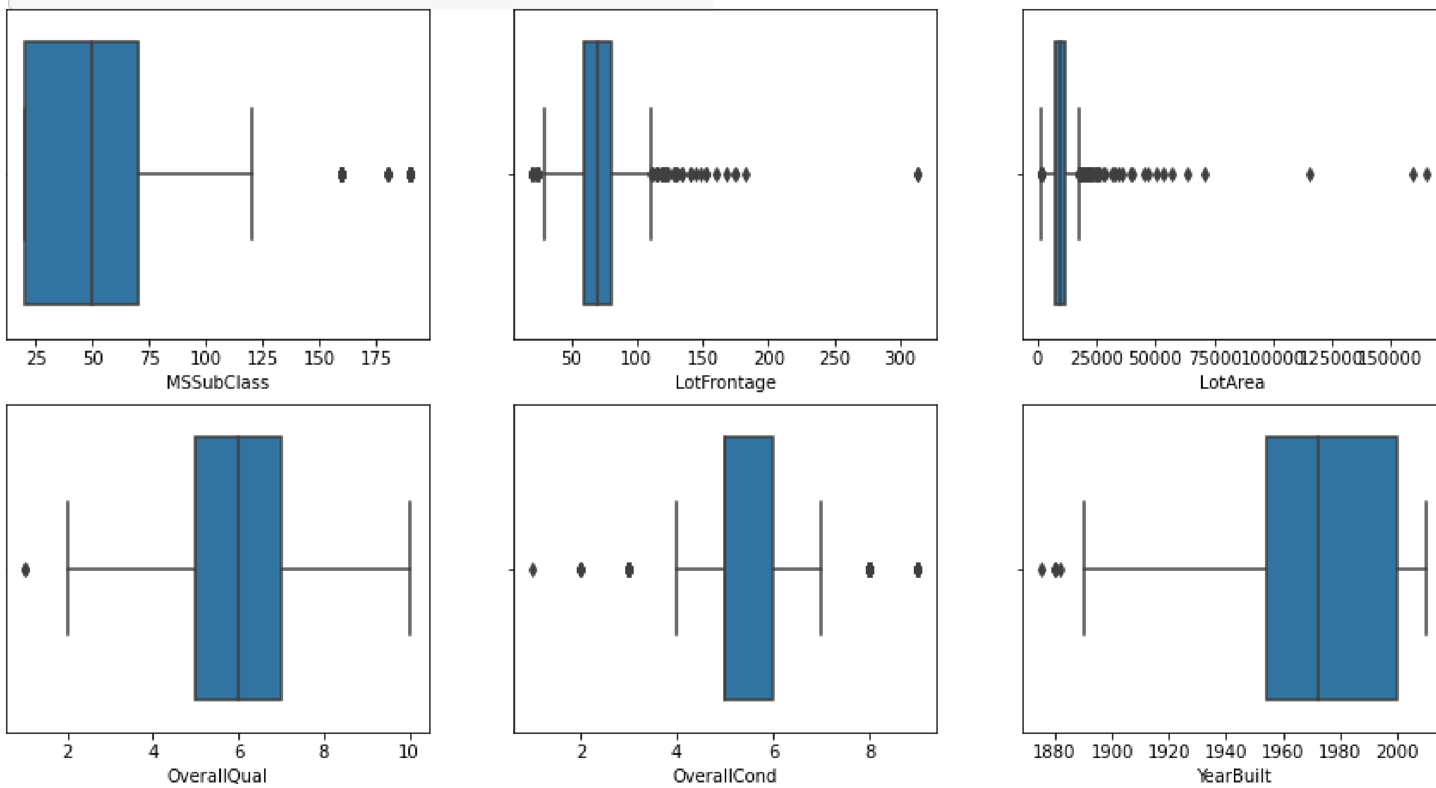


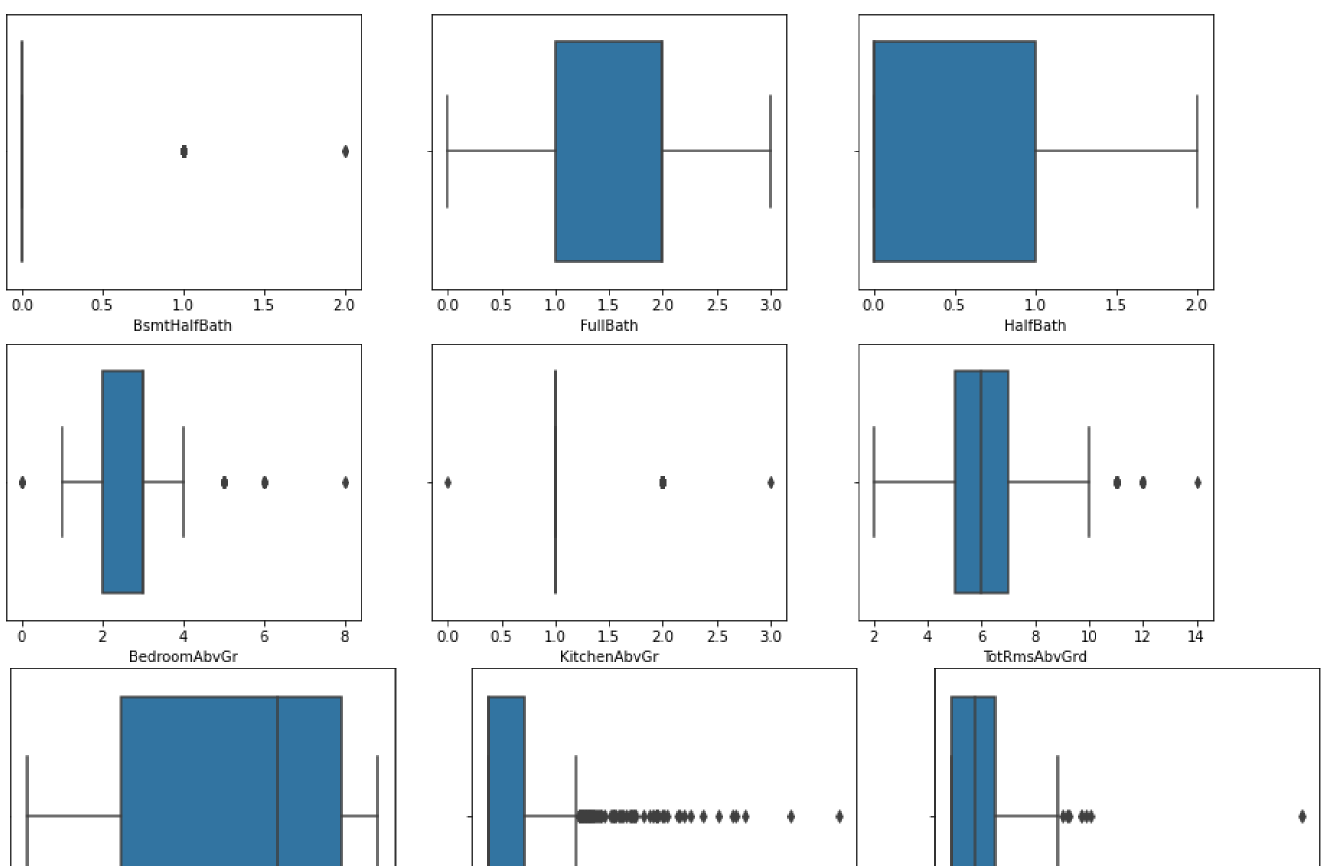
MSZoning
Street
LotShape
LandContour
LotConfig
LandSlope
Neighborhood
Condition1
Condition2
BldgType
HouseStyle
RoofStyle
RoofMatl
Exterior1st
Exterior2nd
MasVnrType
ExterQual
ExterCond
Foundation
BsmtQual
BsmtCond
BsmtExposure
BsmtFinType1
BsmtFinType2
Heating
HeatingQC
CentralAir
Electrical
KitchenQual
Functional
FireplaceQu
GarageType
GarageFinish
GarageQual
GarageCond
PavedDrive
SaleType
SaleCondition
SalePrice

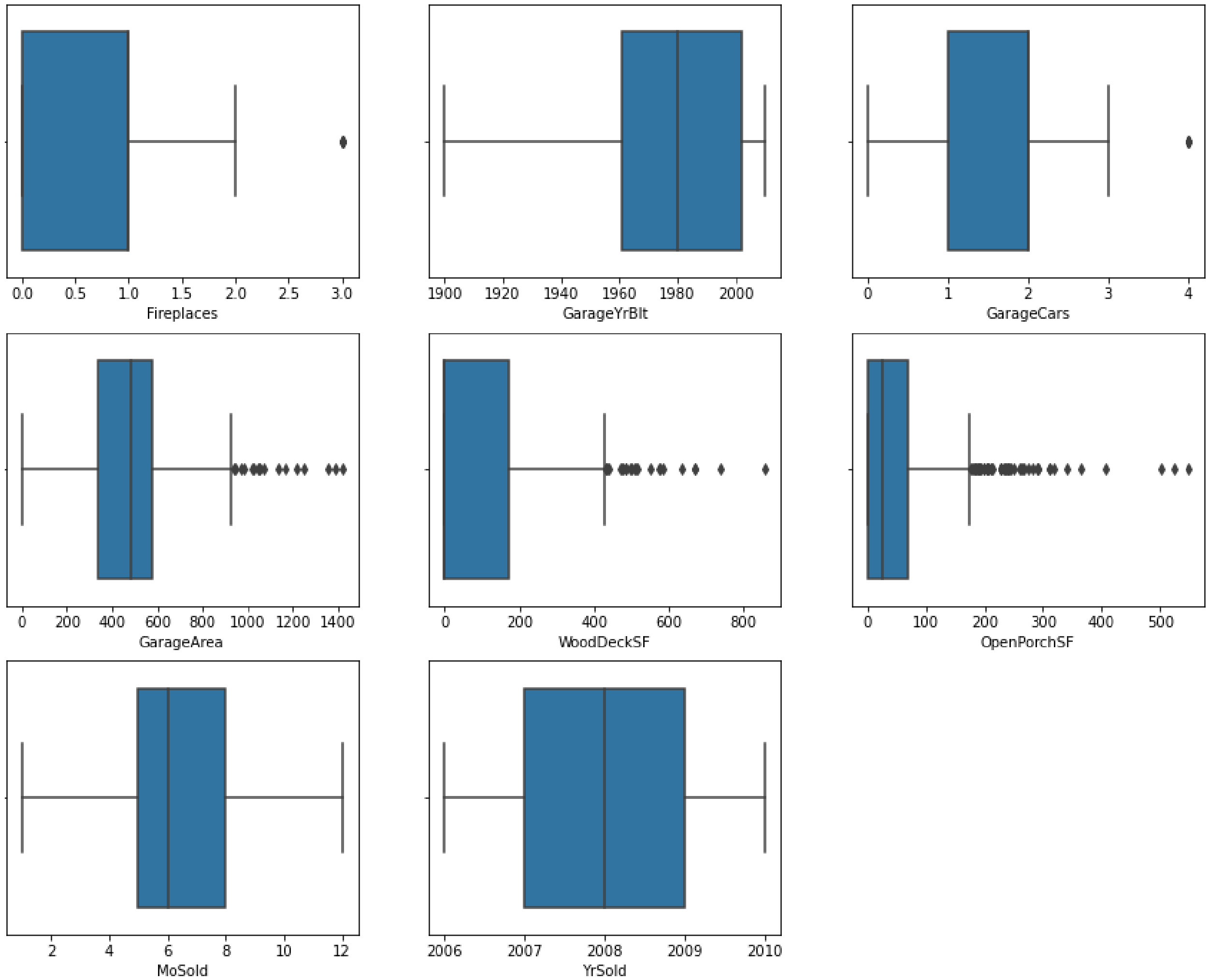
Observations:

- OverallQual has the highest positive correlation with SalePrice followed closely by GrLivarea while OverallCond, KitchenAbvGr, EnclosedPorch have the lowest correlations with SalePrice. (Numerical values)
- GarageCars and GarageArea are also some of the most strongly correlated variables.
- TotalBsmtSF and 1stFlrSF are also strongly correlated variables.
- TotRmsAbvGrd and GrLivArea are also strongly correlated.

```
plt.figure(figsize=(15,50))
graph=1

for column in df_numericals:
    if(graph<=36):
        ax=plt.subplot(12,3,graph)
        sns.boxplot(df_numericals[column],orient='v')
        plt.xlabel(column,fontsize=10)
    graph+=1
plt.show()
```




BsmtHalfBath
FullBath
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd



Removing Ouliers:

```
#Find the IQR (inter quantile range) to identify outliers

q1=df.quantile(0.25) #1st quantile
q3=df.quantile(0.75) #3rd quantile

#IQR
iqr=q3-q1
iqr
```

```
MSSubClass          50.00
MSZoning             0.00
LotFrontage         19.25
LotArea           3894.00
Street               0.00
                    ...
MoSold               3.00
YrSold               2.00
SaleType             0.00
SaleCondition        0.00
SalePrice        84625.00
Length: 75, dtype: float64
```

```
index=np.where(df['BsmtFinSF1']>(q3.BsmtFinSF1)+(1.5*iqr.BsmtFinSF1))
df=df.drop(df.index[index])
print('Shape:',df.shape)
df.reset_index()
```

Shape: (1161, 75)

```
index=np.where(df['TotalBsmtSF']<(q1.TotalBsmtSF)-(1.5*iqr.TotalBsmtSF))
df=df.drop(df.index[index])
print('Shape:',df.shape)
df.reset_index()
```

Shape: (1131, 75)

```
index=np.where(df['LotArea']<(q1.LotArea)-(1.5*iqr.LotArea))
df=df.drop(df.index[index])
print('Shape:',df.shape)
df.reset_index()
```

Shape: (1120, 75)
Shape: (1112, 75)

```
(1168-1112)/1168*100
```

4.794520547945205

Removing Skewness:

```
df_numericals.skew()
```

```
MSSubClass        1.422019
LotFrontage       2.450241
LotArea          10.659285
OverallQual       0.175082
OverallCond       0.580714
YearBuilt        -0.579204
YearRemodAdd     -0.495864
MasVnrArea        2.826173
BsmtFinSF1        1.871606
BsmtUnfSF         0.909057
TotalBsmtSF       1.744591
1stFlrSF          1.513707
SecondFlrSF       0.823479
GrLivArea         1.449952
BsmtFullBath      0.627106
BsmtHalfBath      4.264403
FullBath          0.057809
HalfBath          0.656492
BedroomAbvGr      0.243855
KitchenAbvGr      4.365259
TotRmsAbvGrd      0.644657
Fireplaces        0.671966
GarageYrBlt      -0.644564
GarageCars       -0.358556
GarageArea        0.189665
WoodDeckSF        1.504929
OpenPorchSF       2.410840
MoSold            0.220979
YrSold            0.115765
dtype: float64
```

\ ewness for all those variables that had

s .5 and 0.5.

S

```
tion import SelectKBest, f_classif
```

```
df['LotFrontage']=np.sqrt(df['LotFrontage'])
df['LotArea']=np.sqrt(df['LotArea'])
df['MasVnrArea']=np.sqrt(df['MasVnrArea'])
df['BsmtFinSF1']=np.sqrt(df['BsmtFinSF1'])
df['BsmtFinSF2']=np.sqrt(df['BsmtFinSF2'])
df['BsmtUnfSF']=np.sqrt(df['BsmtUnfSF'])
df['TotalBsmtSF']=np.sqrt(df['TotalBsmtSF'])
df['1stFlrSF']=np.sqrt(df['1stFlrSF'])
df['SecondFlrSF']=np.sqrt(df['SecondFlrSF'])
df['LowQualFinSF']=np.sqrt(df['LowQualFinSF'])
df['GrLivArea']=np.sqrt(df['GrLivArea'])
df['WoodDeckSF']=np.sqrt(df['WoodDeckSF'])
df['OpenPorchSF']=np.sqrt(df['OpenPorchSF'])
df['EnclosedPorch']=np.sqrt(df['EnclosedPorch'])
df['3SsnPorch']=np.sqrt(df['3SsnPorch'])
df['ScreenPorch']=np.sqrt(df['ScreenPorch'])
df['PoolArea']=np.sqrt(df['PoolArea'])
df['MiscVal']=np.sqrt(df['MiscVal'])
```

```
best_features=SelectKBest(score_func=f_classif,k=40)
fit=best_features.fit(X,y)
df_scores=pd.DataFrame(fit.scores_)
df_columns=pd.DataFrame(X.columns)

feature_scores=pd.concat([df_columns,df_scores],axis=1)
feature_scores.columns=['Feature_Name','Score'] #name output columns
print(feature_scores.nlargest(40,'Score')) #print 40 best features
```

	Feature_Name	Score			
14	OverallQual	5.149582	64	OpenPorchSF	1.570705
24	ExterQual	3.572308	3	LotArea	1.543094
43	GrLivArea	3.126663	69	MiscVal	1.490801
27	BsmtQual	2.807488	38	CentralAir	1.451007
50	KitchenQual	2.738808	31	BsmtFinSF1	1.449826
58	GarageCars	2.468362	47	HalfBath	1.351555
46	FullBath	2.432211	5	LotShape	1.343748
59	GarageArea	2.373555	37	HeatingQC	1.318367
40	1stFlrSF	2.268067	36	Heating	1.288921
57	GarageFinish	2.190499	28	BsmtCond	1.268416
16	YearBuilt	2.179121	9	Neighborhood	1.258020
35	TotalBsmtSF	2.123556	63	WoodDeckSF	1.251856
17	YearRemodAdd	1.821069	2	LotFrontage	1.236566
4	Street	1.816640	54	FireplaceQu	1.203226
56	GarageYrBlt	1.751381	55	GarageType	1.194020
1	MSZoning	1.687061	41	SecondFlrSF	1.189878
51	TotRmsAbvGrd	1.629845	29	BsmtExposure	1.183483
26	Foundation	1.585004	22	MasVnrType	1.171093
53	Fireplaces	1.584844	39	Electrical	1.141787
23	MasVnrArea	1.580853	12	BldgType	1.116274

Here we have selected 40 best features with respect to SalePrice among 74 features.

Next, we will do feature scaling and look for correlated features and remove the multicollinearity.

```
#Feature Scaling
scaler=StandardScaler()
X_scaler=scaler.fit_transform(X)

vif=pd.DataFrame()
vif['score']=[variance_inflation_factor(X_scaler,i) for i in range(X_scaler.shape[1])]
vif['Features']=X.columns

vif
```

V … dFlrSF was correlated with
C … nd that would remove the
r …

	score	Features
0	3.411386	OverallQual
1	2.424910	ExterQual
2	43.818682	GrLivArea
3	2.041251	BsmtQual
4	2.046020	KitchenQual
5	5.528327	GarageCars
6	3.070291	FullBath
7	5.342874	GarageArea
8	28.276521	1stFlrSF
9	1.948804	GarageFinish
10	6.024791	YearBuilt
11	4.947137	TotalBsmtSF
12	2.444004	YearRemodAdd
13	1.145724	Street
14	3.557388	GarageYrBlt
15	1.310950	MSZoning
16	3.769092	TotRmsAbvGrd
17	2.220164	Foundation
18	1.757329	Fireplaces
19	1.839734	MasVnrArea
20	1.423990	OpenPorchSF
21	1.775042	LotArea
22	1.058512	MiscVal
23	1.530886	CentralAir
24	1.306240	BsmtFinSF1
25	2.336808	HalfBath
26	1.178640	LotShape
27	1.607399	HeatingQC
28	1.244246	Heating
29	1.082713	BsmtCond
30	1.195169	Neighborhood
31	1.235987	WoodDeckSF
32	1.699123	LotFrontage
33	1.409648	FireplaceQu
34	1.699595	GarageType
35	33.779819	SecondFlrSF
36	1.305831	BsmtExposure
37	1.418914	MasVnrType
38	1.281845	Electrical
39	1.651884	BldgType

Model/s Development and Evaluation

Identification of possible problem-solving approaches (methods)

Given that this is a regression problem with an output of 'Sale Price,' we will employ regression models such as Linear Regression, KNeighbors Regressor, Decision Tree Regressor, Gradient Boosting Regressor, Random Forest Regressor, Ada Boost Regressor, and so on. We will use these algorithms to train our training data, and then we will test on the test data set for final house price prediction. The algorithm with the highest accuracy and the least difference between Cross validation and r2 scores will be chosen as the final model.

Testing of Identified Approaches (Algorithms)

KNeighborsRegressor, Decision Tree Regressor, Gradient Boosting Regressor, Lasso, Random Forest Regressor, Ada Boost Regressor, and Linear Regression methods will be used here.

Run and Evaluate selected models

We will first find the best random state and then predict our test data with the respective algorithms.

```
maxAccu=0
maxRs=0
for i in range(1,200):
    X_train,x_test,Y_train,y_test=train_test_split(X_scaler,y,test_size=0.25,random_state=i)
    mod=DecisionTreeRegressor()
    mod.fit(X_train,Y_train)
    pred=mod.predict(x_test)
    acc=r2_score(y_test,pred)
    if acc>maxAccu:
        maxAccu=acc
        maxRs=i
print("Best accuracy is:",maxAccu,"on Random State",maxRs)
```

```
Best accuracy is: 0.80209554248774 on Random State 185
```

Our best random state is 185 which gives the accuracy of 80.2%. We will use this random state for all the models.

```
X_train,x_test,Y_train,y_test=t e=185)
```

We have different accurac

- Decision Tree Regres

```
DTC=DecisionTreeRegressor()
DTC.fit(X_train,Y_train)
pred=DTC.predict(x_test)
print(r2_score(y_test,pred))
```

```
0.7365631694095114
```

```
lr=LinearRegression()
lr.fit(X_train,Y_train)
pred=lr.predict(x_test)
print(r2_score(y_test,pred))
```

```
0.8838209898296076
```

```
RFR=RandomForestRegressor()
RFR.fit(X_train,Y_train)
pred=RFR.predict(x_test)
print(r2_score(y_test,pred))
```

```
0.8866947818540951
```

```
from sklearn.ensemble import AdaBoostRegressor
ada=AdaBoostRegressor()
ada.fit(X_train,Y_train)
pred=ada.predict(x_test)
print(r2_score(y_test,pred))
```

```
0.85029516538742
```

```
from sklearn.ensemble import GradientBoostingRegressor
gbr=GradientBoostingRegressor()
gbr.fit(X_train,Y_train)
pred=gbr.predict(x_test)
print(r2_score(y_test,pred))
```

```
0.9130577965562511
```

```
from sklearn.neighbors import KNeighborsRegressor
knn=KNeighborsRegressor()
knn.fit(X_train,Y_train)
pred=knn.predict(x_test)
print(r2_score(y_test,pred))
```

```
0.8391263401691001
```

```
import xgboost as xgb
xgb=xgb.XGBRegressor()
xgb.fit(X_train,Y_train)
pred=xgb.predict(x_test)
print(r2_score(y_test,pred))
```

```
0.9008225747150398
```

We will be regularizing our model by Lasso just in case if we have an over fitting model.

```
from sklearn.linear_model import Lasso
```

```
parameters={'alpha':[.0001,.001,.01,.1,1,10],'random_state':list(range(0,10))}
ls=Lasso()
clf=GridSearchCV(ls,parameters)
clf.fit(X_train,Y_train)
print(clf.best_params_)
```

```
{'alpha': 10, 'random_state': 0}
```

```
ls=Lasso(alpha=10,random_state=0)
ls.fit(X_train,Y_train)
ls.score(X_train,Y_train)
pred_ls=ls.predict(x_test)

lss=r2_score(y_test,pred_ls)
lss
```

```
0.8838455350351817
```

We will now be performing cross validation method.

```
from sklearn.model_selection import cross_val_score
```

```
print(cross_val_score(DTC,X_scaler,y,cv=5).mean())
```

```
0.709551159819362
```

```
print(cross_val_score(lr,X_scaler,y,cv=5).mean())
```

```
0.8536637395737239
```

```
print(cross_val_score(RFR,X_scaler,y,cv=5).mean())
```

```
0.8614677527483913
```

```
print(cross_val_score(ada,X_scaler,y,cv=5).mean())
```

```
0.812295753936262
```

```
print(cross_val_score(gbr,X_scaler,y,cv=5).mean())
```

```
0.8773549402659715
```

```
print(cross_val_score(knn,X_scaler,y,cv=5).mean())
```

```
0.7973955361663048
```

```
print(cross_val_score(xgb,X_scaler,y,cv=5).mean())
```

```
0.8591662058575767
```

From the above technique, we can see that Gradient Boosting Regressor has the least difference between cross validation score and r2 score. Therefore, GBR is our best model.

Now we will be performing hyperparameter tuning to our best model just to see if it can increase the accuracy.

```
parameters={'criterion':['friedman_mse','squared_error','mse','mae'],'max_features':['auto','sqrt','log2'],'n_estimators':[40,47,49,5
0],'learning_rate':[0.30,0.40,0.45],'loss':['squared_error','ls','absolute_error','lad','huber','quantile']}
GBR=GradientBoostingRegressor()
clf=RandomizedSearchCV(GBR, cv=5, param_distributions=parameters)
clf.fit(X_train,Y_train)

print(clf.best_params_)
```

```
{'n_estimators': 47, 'max_features': 'auto', 'loss': 'ls', 'learning_rate': 0.3, 'criterion': 'mse'}
```

```
Final_model=GradientBoostingRegressor(max_features='auto',criterion='mse',n_estimators=47,loss='ls',learning_rate=0.3)
Final_model.fit(X_train,Y_train)
pred=Final_model.predict(x_test)
acc=r2_score(y_test,pred)
print('Accuracy:',acc*100)
```

```
Accuracy: 90.51786813222704
```

After hyperparameter also we see the accuracy is around 91% only. So we can conclude that there is no over fitting issue with our model.

We will now save our model and then predict our test dataset.

```
import pickle
filename='FinalisedModel_Housing_Final.pkl'
pickle.dump(gbr,open(filename,'wb'))
```

We will be using the same 40 features used in train dataset to predict our test dataset.

```
df1=df1[['OverallQual','ExterQual','GrLivArea','BsmtQual','KitchenQual','GarageCars','FullBath','GarageArea','1stFlrSF','GarageFinish','Y
earBuilt','TotalBsmtSF','YearRemodAdd','Street','GarageYrBlt','MSZoning','TotRmsAbvGrd','Foundation','Fireplaces','MasVnrArea','OpenPorch
SF','LotArea','MiscVal','CentralAir','BsmtFinSF1','HalfBath','LotShape','HeatingQC','Heating','BsmtCond','Neighborhood','WoodDeckSF','Lot
Frontage','FireplaceQu','GarageType','SecondFlrSF','BsmtExposure','MasVnrType','Electrical','BldgType']]
```

Now we will be performing the same steps that we did for train dataset.

```python
#Feature Scaling
scaler=StandardScaler()
X_scaled=scaler.fit_transform(df1)

vif=pd.DataFrame()
vif['score']=[variance_inflation_factor(X_scaler,i) for i in range(X_scaled.shape[1])]
vif['Features']=df1.columns

vif
```

	score	Features
0	3.411386	OverallQual
1	2.424910	ExterQual
2	43.818682	GrLivArea
3	2.041251	BsmtQual
4	2.046020	KitchenQual
5	5.528327	GarageCars
6	3.070291	FullBath
7	5.342874	GarageArea
8	28.276521	1stFlrSF
9	1.948804	GarageFinish
10	6.024791	YearBuilt
11	4.947137	TotalBsmtSF
12	2.444004	YearRemodAdd
13	1.145724	Street
14	3.557388	GarageYrBlt
15	1.310950	MSZoning
16	3.769092	TotRmsAbvGrd
17	2.220164	Foundation
18	1.757329	Fireplaces
19	1.839734	MasVnrArea
20	1.423990	OpenPorchSF
21	1.775042	LotArea
22	1.058512	MiscVal
23	1.530886	CentralAir
24	1.306240	BsmtFinSF1
25	2.336808	HalfBath
26	1.178640	LotShape
27	1.607399	HeatingQC
28	1.244246	Heating
29	1.082713	BsmtCond
30	1.195169	Neighborhood
31	1.235987	WoodDeckSF
32	1.699123	LotFrontage
33	1.409648	FireplaceQu
34	1.699595	GarageType
35	33.779819	SecondFlrSF
36	1.305831	BsmtExposure
37	1.418914	MasVnrType
38	1.281845	Electrical
39	1.651884	BldgType

```python
df1.drop(columns=['SecondFlrSF'], inplace=True)
```

```python
y_pred=gbr.predict(X_scaled)
```

```
y_pred
```

```
array([383758.40803782, 231557.87362096, 247082.86042353, 184402.15237363,
       226862.74576426,  78557.47047957, 138070.26071821, 368695.88050689,
       229370.63393585, 163182.08564235,  82345.18541002, 142031.13420669,
       138084.79680097, 308889.12586795, 103752.58616021, 120004.26461187,
       125197.64109978, 177762.37198688, 200216.11442486, 153513.37954415,
       141866.11948935, 152752.63872363,  84862.48762455,  98848.17413772,
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       173662.47034021, 118086.02408583, 173079.22834807, 206227.37528479,
       122286.51162894, 164286.64705234, 144697.13848417, 104409.05947711,
       333818.33905954, 209207.31640699, 193085.0412121 , 139973.32163591,
       127098.37122421, 130661.30906766, 105217.62577411, 236513.34390489,
       361953.7391358 , 148851.65606111, 193770.49798553, 100373.29946484,
       105582.64695247, 286675.25098156, 130514.09647305, 151297.90162487,
       192553.51020931, 109291.77190731, 251196.29874042, 108694.52598139,
       182530.87037475, 131914.29563989, 140831.57000582, 202071.91726372,
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       299810.45197256, 141545.19947471, 226917.37420583, 148653.84293245,
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```

```
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118999.92986156, 115538.5008439 , 201097.66158779, 169851.08579319,
146142.05737475, 198433.95081686, 115329.74637619,  93081.17745538,
176475.66047802, 187333.224998  , 136727.12766582, 166459.81362032,
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139229.5451122 , 116263.56862946, 153153.52695155, 164488.99654425,
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 95318.54775105, 150928.75398698,  69760.96850396, 162167.16919692,
199636.4202282 , 149527.86639572, 191213.48651822, 149225.8379538 ,
108051.55650792, 298812.22988223, 346132.62627036, 133371.90954135,
123630.49060797, 265870.40142091, 151265.2698544 , 139473.55701306,
167033.28036958,  97716.99543965, 162349.62585492, 149682.38916514,
179536.58580427,  79498.38289628, 141456.34567729, 146897.31457397,
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210124.71290769, 137528.41795792, 393085.47228527, 191950.88977736,
124069.73300841, 196152.227229  , 182484.46729341, 102967.68516744,
149097.67950707, 215822.23606744, 166207.79151961,  95147.31174199,
178189.14093928, 264908.71534707, 270002.19080601, 166326.42152069,
127760.63069575, 356973.46658465, 263674.79267434, 318460.65250079,
225699.66074802, 178078.78908363, 145959.99167323, 187443.90270853,
127602.28927559, 339982.11733349, 123585.47126877, 313763.59047613,
136516.0882395 , 131454.72129999, 167578.88383783, 242950.24142664,
146753.66361206, 153597.9880393 , 148764.19748938, 110179.06342117])
```

CONCLUSION

Key Findings and Conclusions of the Study

In this we found that Variables like OverallQual (overall material and finish of the house), Year Built, TotRmsAbvGrd (Total rooms above grade (does not include bathrooms), GarageCars (Size of garage in car capacity), GarageArea (Size of garage in square feet), GrLivArea (Above grade (ground) living area square feet), FullBath (Full bathrooms above grade) have positive relationship with the sales Price and they affect the sales price hence these factors should be considered.

Learning Outcomes of the Study in respect of Data Science

The objective is to create a system that will minimize the amount of time it takes to find a property at a fair price. The House Price Prediction model makes an attempt to attain the same result. Using several machine learning approaches, the system focuses on estimating the property price based on the neighborhood and other key factors. The experimental results demonstrate that the approach employed will provide accurate house price forecast.

Limitations of this work and Scope for Future Work

- The amount of data is quite limited; it would be preferable to have more data to more correctly forecast the sale price.
- There are many outliers in the given data, and I was unable to eliminate all of them due to the risk of losing data. With more data, more outliers can be removed from the dataset.