Exploratory Data Analysis and Supervised Machine Learning (Regression)

Summary

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Objective:

The main objective of this data analysis is to predict the price of houses based on numerous characteristics. The dataset used is the Ames housing dataset. It examines features of houses sold in Ames (a small city in the state of Iowa in the United States) during the 2006–2010 timeframe.

Dataset description:

The dataset is composed of 2931 rows and 81 columns. 'SalePrice' is our target or response variable and the rest of the characteristics are our predictor features. We also have a mix of numeric data types (28 int64 and 11 float64) and 43 objects. Among the numeric variables, there are continuous (ex: Lot Frontage, Lot Area) and discrete (ex: OverallQual, OverallCond, Bsmt Full Bath). Nominal (ex: BsmtQual, Foundation), ordinal (ex: PoolQC) and binary (ex: CentralAir) qualitative variables. There are also time variables such as Yr Sold.All the characteristics are detailed in the Feature description section.

Data Cleaning:

Regarding data cleaning, duplicates were searched for and deleted.

27 features had missing values with a number ranging from 1 to 2917. According to the description of the data, NA is used as qualifiers for many features to mean that there is no pool or basement for example. Or NA or NaN means a missing value for python. Therefore, for these features, we will replace the NA with another qualifier such as No Pool for example to mean that the house does not have a swimming pool. Depending on the study of each variable, the missing values were replaced and some features have been removed. indeed, Regarding 'Garage Cars' and 'Garage Area', it is possible that the data does not exist because the property does not have a garage or the property has a garage but the data is truly missing. Therefore we will proceed as follows: if there is no garage then 'Garage Cars' and 'Garage Area' equal to zero.

According to the graphical visualizations, some variables presented outliers (Gr Liv Area, Lot Area, Low Qual Fin SF). For some of them, the Z-score method was used. Most outliers have been removed. Others were kept because they reflected a reality on the ground.

Some numerical features are actually really categorial features as MSSubClass and MoSold. We choose to transform them into nominal qualitative variables, as follows.

Data Exploratory Analysis:

After cleaning the data, a visual exploration of the numerical and categorical data was carried out using pair plot and box plot. These visualizations allowed on the one hand, the validation of data cleaning. On the other hand, they made it possible to highlight polynomial relationships between certain features such as SalePrice and Overall Qual or Year Built for example.

A correlation study was carried out on the numerical features. Disregarding the target, we see that the features are not too correlated with each other, which is a good thing. However, we note that 3 pairs of variables are strongly correlated with each other: 1st Flr SF/Total Bsmt SF, Giv Liv Area/TotsRms AbvGr and Garage Area/Garage cars.

We will study the relationships between the qualitative features and the target using box plot, in order to carry out some hypothesis testing. The results of these tests showed significant differences between certain categories of characteristics and average house prices, such as MS Zoning and Central Air for example.

Feature Engineering:

It was also studied the representation of the different modalities of the features. As a result, the 'Neighborhoods' variable has been modified for better representativeness of its modalities.

In some characteristics like 'Overall Qual' and 'Gr Liv Qual', we noticed an upward curved relationship rather than a simple linear correspondence. Polynomial features were created for these characteristics.

In addition, interaction features have also been created for certain features such as 'Overall Qual' et 'Year Built' or 'Lot Area'.

Then, a One Hot encoding was performed on the categorical variables using Pandas one-hot encoder (get_dummies).

Modelisation:

The dataset was split into train set and test set, with a test size of 0.25%.

4 algorithms were tested on the dataset with a cross validation of 4 splits.

A simple linear regression was performed with GridSearchCV. Regularized linear regressions were also performed with RidgeCV, LassoCv and ElasticNetCV. For the latter 3, the numerical data was scaled using the StandardScaler transformer. The metrics studied during these modelings were the Pearson coefficient (r2) and the root mean squared error (RMSE).

For these 4 regressions, very good results were obtained with r2 of 0.924 (simple linear regression) and 0.93 for the others. However, the lowest RMSE was obtained with LassoCV for a value of 22095. The best performing model on this dataset is LassoCV with 4-split cross-validation and standardization using StandardScaler.

Improvement:

In order to improve the performance of these models:

- a further analysis of the functionalities could be considered, with hypothesis tests carried out on all the modalities of the categorical features for an optimized selection of the features, and with the establishment of other interactions of the features.
- The more in-depth study of the hyper-parameters could also contribute to the improvement of the model.

A) Import the required libraries

In [1]:

```
# Managing data
import pandas as pd

# Mathematical operations
import numpy as np

# For visualizing data
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px

# For statistical analysis
from scipy import stats
from statsmodels.formula.api import ols
from statsmodels.stats.anova import anova_lm

# For splitting data
from sklearn.model_selection import train_test_split, KFold

# For scaling data
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler

# For modelisation
from sklearn.linear_model import LinearRegression, LassoCV, RidgeCV, ElasticNetCV
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
```

B) Dataset description and understanding data

The Ames housing dataset examines features of houses sold in Ames (a small city in the state of Iowa in the United States) during the 2006–2010 timeframe.

Import dataset

In [2]:

```
data = pd.read_csv("https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-ML0232EN-SkillsNetwo
data.head(5)
```

Out[2]:

	Order	PID	MS SubClass	MS Zoning	Lot Frontage	Lot Area	Street	Alley	Lot Shape	Land Contour	...	Pool Area	Pool QC	Fence	Misc Feature	Misc Val	Mo Sold	Yr Sold
0	1	526301100	20	RL	141.0	31770	Pave	NaN	IR1	Lvl	...	0	NaN	NaN	NaN	0	5	2010
1	1	526301100	20	RL	141.0	31770	Pave	NaN	IR1	Lvl	...	0	NaN	NaN	NaN	0	5	2010
2	2	526350040	20	RH	80.0	11622	Pave	NaN	Reg	Lvl	...	0	NaN	MnPrv	NaN	0	6	2010
3	3	526351010	20	RL	81.0	14267	Pave	NaN	IR1	Lvl	...	0	NaN	NaN	Gar2	12500	6	2010
4	4	526353030	20	RL	93.0	11160	Pave	NaN	Reg	Lvl	...	0	NaN	NaN	NaN	0	4	2010

5 rows × 82 columns

In [3]:

```
data.tail(5)
```

Out[3]:

	Order	PID	MS SubClass	MS Zoning	Lot Frontage	Lot Area	Street	Alley	Lot Shape	Land Contour	...	Pool Area	Pool QC	Fence	Misc Feature	Misc Val	Mo Sold	Y Sol
2926	2926	923275080	80	RL	37.0	7937	Pave	NaN	IR1	Lvl	...	0	NaN	GdPrv	NaN	0	3	200
2927	2927	923276100	20	RL	NaN	8885	Pave	NaN	IR1	Low	...	0	NaN	MnPrv	NaN	0	6	200
2928	2928	923400125	85	RL	62.0	10441	Pave	NaN	Reg	Lvl	...	0	NaN	MnPrv	Shed	700	7	200
2929	2929	924100070	20	RL	77.0	10010	Pave	NaN	Reg	Lvl	...	0	NaN	NaN	NaN	0	4	200
2930	2930	924151050	60	RL	74.0	9627	Pave	NaN	Reg	Lvl	...	0	NaN	NaN	NaN	0	11	200

5 rows × 82 columns

Feature description

In [4]:

```
data_description = pd.read_csv('data_description.txt', sep="_")
data_description
for k in data_description['MSSubClass: Identifies the type of dwelling involved in the sale.\t']:
    print(k)
```

```
        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)
       NoSewr   Electricity, 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
       NridgHt  Northridge 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
       BrkFace  Brick Face
       CBlock   Cinder Block
       CemntBd  Cement Board
       HdBoard  Hard Board
       ImStucc  Imitation 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
       BrkFace  Brick Face
       CBlock   Cinder Block
       CemntBd  Cement Board
       HdBoard  Hard Board
       ImStucc  Imitation 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
       BrkCmn   Brick Common
       BrkFace  Brick 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)
```

Dataset information

In [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2931 entries, 0 to 2930
Data columns (total 82 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Order            2931 non-null   int64
 1   PID              2931 non-null   int64
 2   MS SubClass      2931 non-null   int64
 3   MS Zoning        2931 non-null   object
 4   Lot Frontage     2441 non-null   float64
 5   Lot Area         2931 non-null   int64
 6   Street           2931 non-null   object
 7   Alley            198 non-null    object
 8   Lot Shape        2931 non-null   object
 9   Land Contour     2931 non-null   object
 10  Utilities        2931 non-null   object
 11  Lot Config       2931 non-null   object
 12  Land Slope       2931 non-null   object
 13  Neighborhood     2931 non-null   object
 14  Condition 1      2931 non-null   object
 15  Condition 2      2931 non-null   object
 16  Bldg Type        2931 non-null   object
 17  House Style      2931 non-null   object
 18  Overall Qual     2931 non-null   int64
 19  Overall Cond     2931 non-null   int64
 20  Year Built       2931 non-null   int64
 21  Year Remod/Add   2931 non-null   int64
 22  Roof Style       2931 non-null   object
 23  Roof Matl        2931 non-null   object
 24  Exterior 1st     2931 non-null   object
 25  Exterior 2nd     2931 non-null   object
 26  Mas Vnr Type     2908 non-null   object
 27  Mas Vnr Area     2908 non-null   float64
 28  Exter Qual       2931 non-null   object
 29  Exter Cond       2931 non-null   object
 30  Foundation       2931 non-null   object
 31  Bsmt Qual        2851 non-null   object
 32  Bsmt Cond        2851 non-null   object
 33  Bsmt Exposure    2848 non-null   object
 34  BsmtFin Type 1   2851 non-null   object
 35  BsmtFin SF 1     2930 non-null   float64
 36  BsmtFin Type 2   2850 non-null   object
 37  BsmtFin SF 2     2930 non-null   float64
 38  Bsmt Unf SF      2930 non-null   float64
 39  Total Bsmt SF    2930 non-null   float64
 40  Heating          2931 non-null   object
 41  Heating QC       2931 non-null   object
 42  Central Air      2931 non-null   object
 43  Electrical       2930 non-null   object
 44  1st Flr SF       2931 non-null   int64
 45  2nd Flr SF       2931 non-null   int64
 46  Low Qual Fin SF  2931 non-null   int64
 47  Gr Liv Area      2931 non-null   int64
 48  Bsmt Full Bath   2929 non-null   float64
 49  Bsmt Half Bath   2929 non-null   float64
 50  Full Bath        2931 non-null   int64
 51  Half Bath        2931 non-null   int64
 52  Bedroom AbvGr    2931 non-null   int64
 53  Kitchen AbvGr    2931 non-null   int64
 54  Kitchen Qual     2931 non-null   object
 55  TotRms AbvGrd    2931 non-null   int64
 56  Functional       2931 non-null   object
 57  Fireplaces       2931 non-null   int64
 58  Fireplace Qu     1509 non-null   object
 59  Garage Type      2774 non-null   object
 60  Garage Yr Blt    2772 non-null   float64
 61  Garage Finish    2772 non-null   object
 62  Garage Cars      2930 non-null   float64
 63  Garage Area      2930 non-null   float64
 64  Garage Qual      2772 non-null   object
 65  Garage Cond      2772 non-null   object
 66  Paved Drive      2931 non-null   object
 67  Wood Deck SF     2931 non-null   int64
 68  Open Porch SF    2931 non-null   int64
 69  Enclosed Porch   2931 non-null   int64
 70  3Ssn Porch       2931 non-null   int64
 71  Screen Porch     2931 non-null   int64
 72  Pool Area        2931 non-null   int64
 73  Pool QC          13 non-null     object
 74  Fence            572 non-null    object
 75  Misc Feature     106 non-null    object
 76  Misc Val         2931 non-null   int64
 77  Mo Sold          2931 non-null   int64
 78  Yr Sold          2931 non-null   int64
 79  Sale Type        2931 non-null   object
 80  Sale Condition   2931 non-null   object
 81  SalePrice        2931 non-null   int64
dtypes: float64(11), int64(28), object(43)
memory usage: 1.8+ MB
```

- According to the output above, we have 2931 entries, from 0 to 2930, along with 81 features.
- We notice that there are missing values for some features.
- 'SalePrice' is our target or response variable and the rest of the characteristics are our predictor variables.
- We also have a mix of numeric data types (28 int64 and 11 float64) and 43 objects.
- Among the numeric variables, there are continuous (ex: Lot Frontage, Lot Area) and discrete (ex: OverallQual, OverallCond, Bsmt Full Bath). Nominal (ex: BsmtQual, Foundation), ordinal (ex: PoolQC) and binary (ex: CentralAir) qualitative variables. There are also time variables such as Yr Sold.

Analysis og response variable

In [6]:

```
data['SalePrice'].describe().T
```

Out[6]:

```
count      2931.000000
mean     180807.729785
std       79875.557267
min       12789.000000
25%      129500.000000
50%      160000.000000
75%      213500.000000
max      755000.000000
Name: SalePrice, dtype: float64
```

From the above analysis, it is important to note that the minimum value is greater than 0. Also, there is a large difference between the minimum value and the 25th percentile. It is greater than the 75th percentile and the maximum value. This means that our data may not be normally distributed (an important assumption for linear regression analysis), so will check for normality in the Log Transform section.

Looking for Correlations

Before proceeding with data cleaning, it is useful to establish a correlation between the target variable (SalePrice) and other predictor variables, since some of them might not have a major impact in determining the price of the house and not to be used in the analysis. There are many ways to discover the correlation between the target variable and the rest of the characteristics. Pair plots, scatter plots, heat maps and correlation matrices are the most common. Below, we'll use the corr() function to list the top features based on Pearson's correlation coefficient (a measure of how closely two number sequences are correlated). Correlation coefficient can only be calculated on numeric attributes (float and integer), therefore only numeric attributes will be selected.

We will select correlations greater than 0.5.

In [7]:

```
data_num = data.select_dtypes(include = ['float64', 'int64'])
data_num_corr = data_num.corr()['SalePrice'][:-1]
best_num_corr = data_num_corr[abs(data_num_corr)>0.5].sort_values(ascending=False)
print(f'The {len(best_num_corr)} most highly correlated variables with SalePrice:')
best_num_corr
```

Out[7]:

```
The 11 most highly correlated variables with SalePrice:
Overall Qual      0.799226
Gr Liv Area       0.706791
Garage Cars       0.647891
Garage Area       0.640411
Total Bsmt SF     0.632270
1st Flr SF        0.621672
Year Built        0.558340
Full Bath         0.545339
Year Remod/Add    0.532664
Garage Yr Blt     0.526808
Mas Vnr Area      0.508277
Name: SalePrice, dtype: float64
```

Next, let's generate a few per plot to visually inspect the correlation between some of these features and the target variable. We will use the seaborns sns.pairplot() function for this analysis. Also, constructing pair plots is one of the possible ways to spot outliers that might be present in the data.

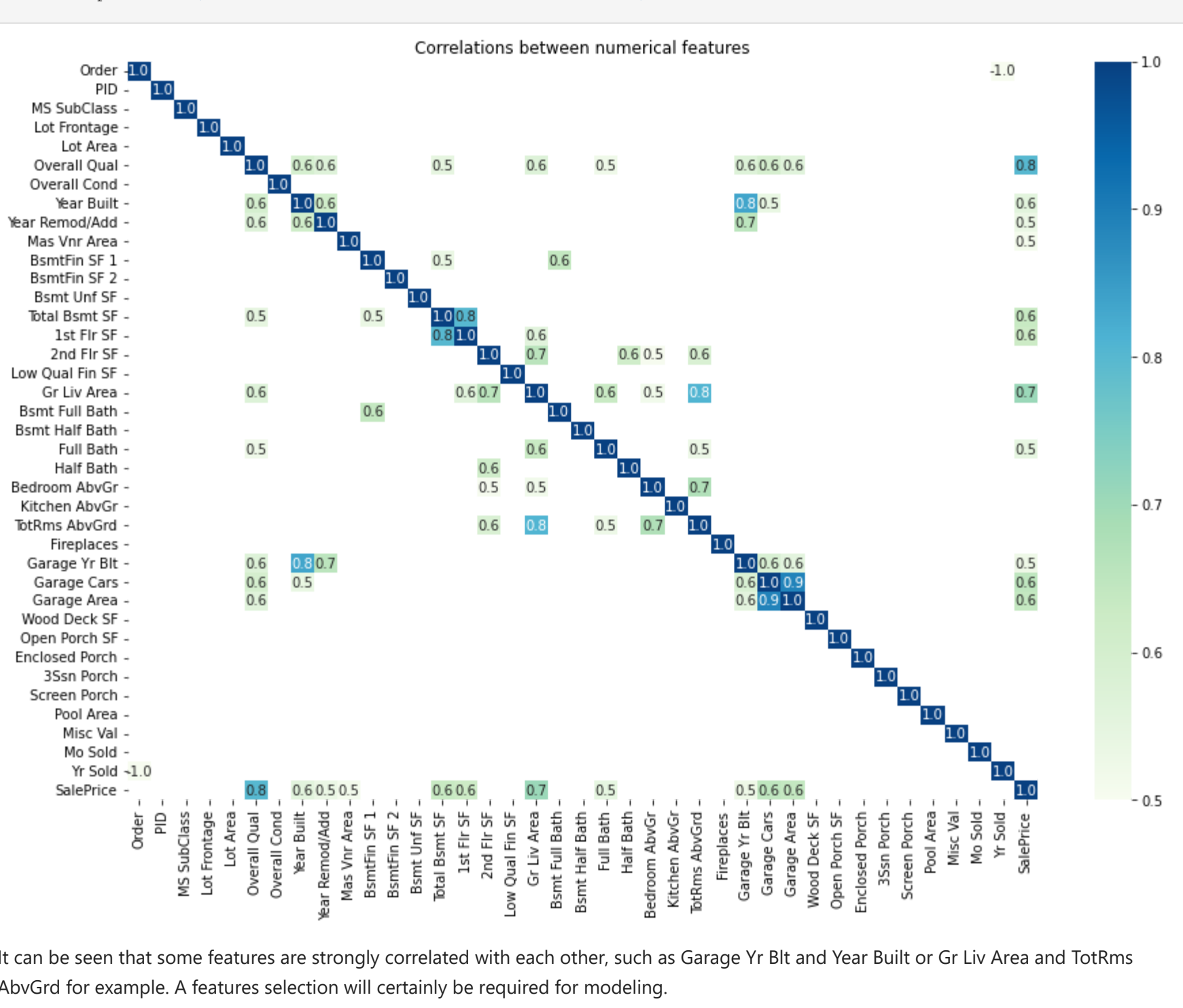
In [8]:

```
for i in range(0, len(data_num.columns), 5):
    sns.pairplot(data = data_num, x_vars = data_num.columns[i:i+5], y_vars = ['SalePrice'])
```

Visually, we notice that Overall Qual, Gr Liv Area, Garage Cars, Garage Area and more features are correlated to the target 'SalePrice'. We also see that there are possibly outliers for some features like Lot Area, 1st Flr SF and Gr Liv Area.

The heat maps method also makes it possible to check whether certain features are not correlated with each other, which could bias the model.

In [9]:
```
data_num_corr = data_num.corr()
heatmap_num_corr = data_num_corr[abs(data_num_corr)>=0.5]
plt.figure(figsize=(15, 10))
sns.heatmap(heatmap_num_corr,
            annot=True,
            fmt='.1f',
            cmap='GnBu',
            vmin=0.5,
            vmax=1)
title = plt.title('Correlations between numerical features')
```



It can be seen that some features are strongly correlated with each other, such as Garage Yr Blt and Year Built or Gr Liv Area and TotRms AbvGrd for example. A features selection will certainly be required for modeling.

Feature distribution

The normal distribution assumption must be satisfied in order to perform any type of regression analysis. There are several ways to verify this assumption. Here, we can simply use the skew() function to calculate our level of feature skewness. We consider that the distribution is not normally distributed if the level of asymmetry is less than 0.5 or greater than 0.5.

In [10]:
```
for i in data_num.columns:
    if (data[i].skew() < -0.5 or data[i].skew() > 0.5):
        print(f'Skewness for {i}: {data[i].skew()}')
```

```
Skewness for MS SubClass: 1.3579444255012858
Skewness for Lot Frontage: 1.4987745667871724
Skewness for Lot Area: 12.778040640965061
Skewness for Overall Cond: 0.5749264559629781
Skewness for Year Built: -0.6041550817882403
Skewness for Mas Vnr Area: 2.6073702204244156
Skewness for BsmtFin SF 1: 1.4158746240905902
Skewness for BsmtFin SF 2: 4.140793742804169
Skewness for Bsmt Unf SF: 0.9234449946334007
Skewness for Total Bsmt SF: 1.1563330901082214
Skewness for 1st Flr SF: 1.467869250067155
Skewness for 2nd Flr SF: 0.8669705520684831
Skewness for Low Qual Fin SF: 12.120267034881609
Skewness for Gr Liv Area: 1.273957871771539
Skewness for Bsmt Full Bath: 0.615697638287629
Skewness for Bsmt Half Bath: 3.941592438497531
Skewness for Half Bath: 0.6982547390083218
Skewness for Kitchen AbvGr: 4.314674320298005
Skewness for TotRms AbvGrd: 0.75327505916172
Skewness for Fireplaces: 0.7388070196848527
Skewness for Wood Deck SF: 1.841517608437007
Skewness for Open Porch SF: 2.5355422026364764
Skewness for Enclosed Porch: 4.0152171477751555
Skewness for 3Ssn Porch: 11.40578191460577
Skewness for Screen Porch: 3.9582613014724886
Skewness for Pool Area: 16.94205995438875
Skewness for Misc Val: 22.003538980504583
Skewness for SalePrice: 1.743221853159165
```

Most of the numerical features do not satisfy the assumption of a normal distribution. Therefore, a log transformation will need to be applied.

C) Data Cleaning

1. Handling the Duplicates

Duplicate values can affect analysis, so it's good to check if there are duplicates in our data. We will use the pandas duplicated() function and search by the 'PID' column, which contains a unique index number for each entry.

In [11]:
```
# Let's check that there are duplicates for the PID variable
data.PID.is_unique
```

Out[11]: False

There is indeed one or more duplicate(s) for the PID variable.

In [12]:
```
# Search for duplicates
duplicate = data[data.duplicated(['PID'])]
duplicate
```

Out[12]:

	Order	PID	MS SubClass	MS Zoning	Lot Frontage	Lot Area	Street	Alley	Lot Shape	Land Contour	...	Pool Area	Pool QC	Fence	Misc Feature	Misc Val	Mo Sold	Yr Sold
1	1	526301100	20	RL	141.0	31770	Pave	NaN	IR1	Lvl	...	0	NaN	NaN	NaN	0	5	2010

1 rows × 82 columns

There is a duplicate for this variable.

In [13]:
```
# Remove duplicate and verification
data = data.drop_duplicates(subset=['PID'])
data.PID.is_unique
```

Out[13]: True

2. Handling the Missing Values

Missing values research

Missing data can significantly bias modeling. We create a function to determine the percentage of missing values according to the different predictive variables.

In [14]:
```
def missing_data(data):
    missing_data_count = data.isna().sum()
    missing_data_percent = data.isna().sum() / len(data) * 100

    missing_data = pd.DataFrame({
        'Number_NaN': missing_data_count,
        '%_NaN': missing_data_percent
        })
    missing_data = missing_data[missing_data.Number_NaN > 0]
    missing_data.sort_values(by='Number_NaN', ascending=False, inplace=True)

    print(f"There are {missing_data.shape[0]} features with missing values.\n")
    return missing_data
```

In [15]:
```
missing_data(data)
```

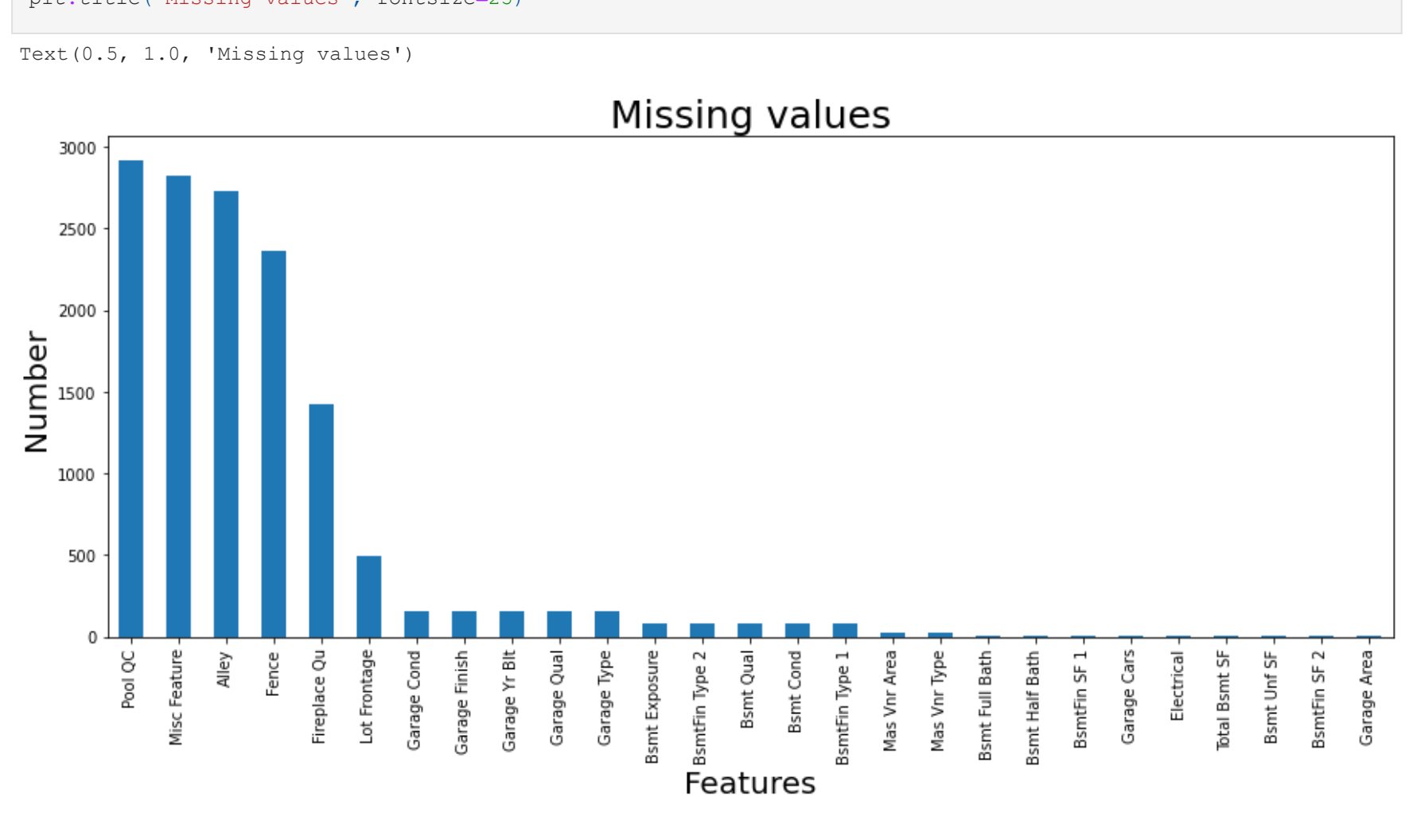
```
There are 27 features with missing values.
```

Out[15]:

	Number_NaN	%_NaN
Pool QC	2917	99.556314
Misc Feature	2824	96.382253
Alley	2732	93.242321
Fence	2358	80.477816
Fireplace Qu	1422	48.532423
Lot Frontage	490	16.723549
Garage Cond	159	5.426621
Garage Qual	159	5.426621
Garage Finish	159	5.426621
Garage Yr Blt	159	5.426621
Garage Type	157	5.358362
Bsmt Exposure	83	2.832765
BsmtFin Type 2	81	2.764505
BsmtFin Type 1	80	2.730375
Bsmt Qual	80	2.730375
Bsmt Cond	80	2.730375
Mas Vnr Area	23	0.784983
Mas Vnr Type	23	0.784983
Bsmt Half Bath	2	0.068259
Bsmt Full Bath	2	0.068259
Total Bsmt SF	1	0.034130
Bsmt Unf SF	1	0.034130
Garage Cars	1	0.034130
Garage Area	1	0.034130
BsmtFin SF 2	1	0.034130
BsmtFin SF 1	1	0.034130
Electrical	1	0.034130

In [16]:
```
missing_values = data.isnull().sum().sort_values(ascending=False)
missing_values = missing_values.head(27)
missing_values.plot(kind='bar', figsize=(15,6), fontsize=10)
plt.xlabel('Features', fontsize=20)
plt.ylabel('Number', fontsize=20)
plt.title('Missing values', fontsize=25)
```

Out[16]: Text(0.5, 1.0, 'Missing values')



Replacement of missing values and deletion of variables

According to the description of the data, NA is used as qualifiers for many features to mean that there is no pool or basement for example. Or NA or NaN means a missing value for python. Therefore, for these features, we will replace the NA with another qualifier such as No Pool for example to mean that the house does not have a swimming pool.

In [17]:
```
data['Pool QC'] = data['Pool QC'].replace(np.nan, 'No Pool')
data['Misc Feature'] = data['Misc Feature'].replace(np.nan, 'None')
data['Alley'] = data['Alley'].replace(np.nan, 'No Alley')
data['Fence'] = data['Fence'].replace(np.nan, 'No Fence')
data['Fireplace Qu'] = data['Fireplace Qu'].replace(np.nan, 'No Fireplace')
data['Garage Cond'] = data['Garage Cond'].replace(np.nan, 'No Garage')
data['Garage Finish'] = data['Garage Finish'].replace(np.nan, 'No Garage')
data['Garage Qual'] = data['Garage Qual'].replace(np.nan, 'No Garage')
data['Garage Type'] = data['Garage Type'].replace(np.nan, 'No Garage')
data['Bsmt Exposure'] = data['Bsmt Exposure'].replace(np.nan, 'No Basement')
data['BsmtFin Type 2'] = data['BsmtFin Type 2'].replace(np.nan, 'No Basement')
data['Bsmt Qual'] = data['Bsmt Qual'].replace(np.nan, 'No Basement')
data['Bsmt Cond'] = data['Bsmt Cond'].replace(np.nan, 'No Basement')
data['BsmtFin Type 1'] = data['BsmtFin Type 1'].replace(np.nan, 'No Basement')
data['Mas Vnr Type'] = data['Mas Vnr Type'].replace(np.nan, 'None')
```

In [18]:
```
missing_data(data)
```

```
There are 12 features with missing values.
```

Out[18]:

	Number_NaN	%_NaN
Lot Frontage	490	16.723549
Garage Yr Blt	159	5.426621
Mas Vnr Area	23	0.784983
Bsmt Full Bath	2	0.068259
Bsmt Half Bath	2	0.068259
BsmtFin SF 1	1	0.034130
BsmtFin SF 2	1	0.034130
Bsmt Unf SF	1	0.034130
Total Bsmt SF	1	0.034130
Electrical	1	0.034130
Garage Cars	1	0.034130
Garage Area	1	0.034130

Regarding 'Garage Cars' and 'Garage Area', it is possible that the data does not exist because the property does not have a garage or the property has a garage but the data is truly missing. Therefore we will proceed as follows: if there is no garage then 'Garage Cars' and 'Garage Area' equal to zero.

In [19]:
```
data['Garage Cars'] = np.where(data['Garage Cond']=='No Garage', 0, data['Garage Cars'])
data['Garage Area'] = np.where(data['Garage Cond']=='No Garage', 0, data['Garage Area'])
```

Regarding 'Garage Yr Blt', we choose to delete the entire column, because this variable is strongly correlated to x and cannot be replaced by any date.

In [20]:
```
data = data.drop('Garage Yr Blt', axis=1)
```

Similarly, if the house has no basement, we will set the following variables to zero.

In [21]:
```
data['Bsmt Full Bath'].unique().tolist()
```

Out[21]: [1.0, 0.0, 2.0, 3.0, nan]

In [22]:
```
data['BsmtFin SF 1'] = np.where(data['Bsmt Qual']=='No Basement', 0, data['BsmtFin SF 1'])
data['BsmtFin SF 2'] = np.where(data['Bsmt Qual']=='No Basement', 0, data['BsmtFin SF 2'])
data['Bsmt Unf SF'] = np.where(data['Bsmt Qual']=='No Basement', 0, data['Bsmt Unf SF'])
data['Total Bsmt SF'] = np.where(data['Bsmt Qual']=='No Basement', 0, data['Total Bsmt SF'])
data['Bsmt Full Bath'] = np.where(data['Bsmt Qual']=='No Basement', 0, data['Bsmt Full Bath'])
data['Bsmt Half Bath'] = np.where(data['Bsmt Qual']=='No Basement', 0, data['Bsmt Half Bath'])
```

In [23]:
```
# Verification
data['Bsmt Full Bath'].unique().tolist()
```

Out[23]: [1.0, 0.0, 2.0, 3.0]

Similarly, if the property does not have a type of masonry veneer, the Masonry veneer area is considered equal zero square feet.

In [24]:
```
data['Mas Vnr Area'] = np.where(data['Mas Vnr Type']=='None', 0, data['Mas Vnr Area'])
```

For electricity, we choose to replace the missing value with the most frequent value in the data, which is Standard Circuit Breakers & Romex.

In [25]:
```
data['Electrical'].value_counts()
```

Out[25]:
```
SBrkr    2682
FuseA     188
FuseF      50
FuseP       8
Mix         1
Name: Electrical, dtype: int64
```

In [26]:
```
data['Electrical'].fillna('SBrkr', inplace = True)
```

Regarding the Linear feet of street connected to property, we replace missing values by 0.

In [27]:
```
data['Lot Frontage'] = data['Lot Frontage'].fillna(0)
```

Verification of missing values

In [28]:
```
missing_data(data)
```

```
There are 0 features with missing values.
```

Out[28]:

Number_NaN	%_NaN

We can remove the Order and PID columns which will bring nothing to our predictions.

In [29]:
```
data.drop(['PID', 'Order'], axis=1, inplace=True)
```

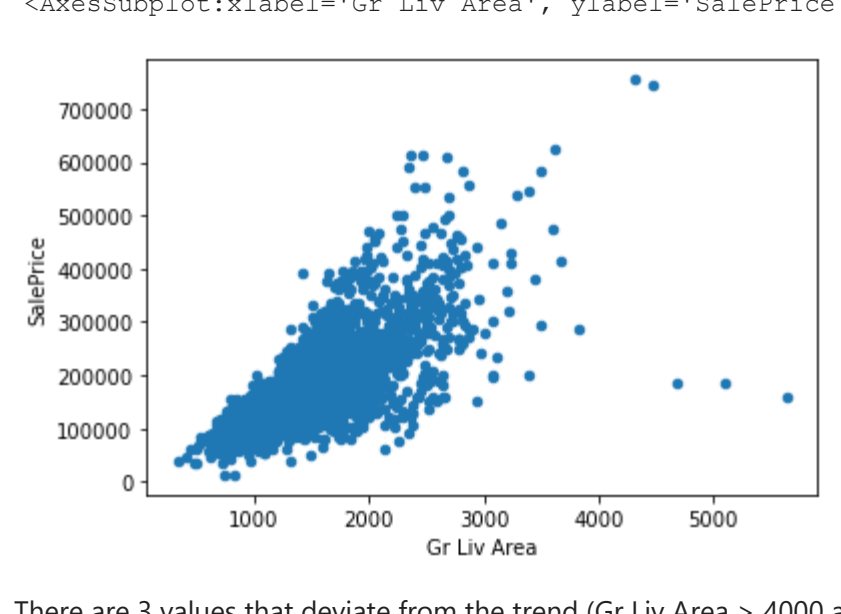
3. Handling the Outliers

According to the graphical analyzes carried out in "looking correlation" part, there are some outliers. Outliers can significantly affect our models and can be a valuable source of information, providing us with insights into specific behaviors.

Gr Liv Area

In [30]:
```
data.plot.scatter(x = 'Gr Liv Area', y = 'SalePrice')
```

Out[30]: <AxesSubplot:xlabel='Gr Liv Area', ylabel='SalePrice'>



There are 3 values that deviate from the trend (Gr Liv Area > 4000 and SalePrice < 300000). We will delete them.

In [31]:
```
GrLivArea_outlier = data[(data['Gr Liv Area'] > 4000) & (data['SalePrice'] < 300000)]
GrLivArea_outlier
```

Out[31]:

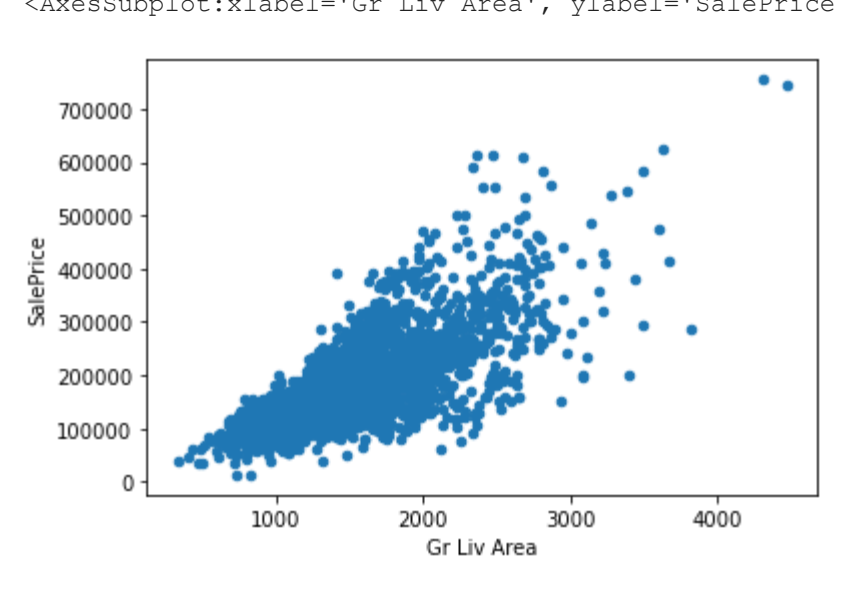
	MS SubClass	MS Zoning	Lot Frontage	Lot Area	Street	Alley	Lot Shape	Land Contour	Utilities	Lot Config	...	Pool Area	Pool QC	Fence	Misc Feature	Misc Val	Mo Sold	Yr Sold
1499	60	RL	313.0	63887	Pave	No Alley	IR3	Bnk	AllPub	Corner	...	480	Gd	No Fence	None	0	1	2008
2181	20	RL	128.0	39290	Pave	No Alley	IR1	Bnk	AllPub	Inside	...	0	No Pool	No Fence	Elev	17000	10	2007
2182	60	RL	130.0	40094	Pave	No Alley	IR1	Bnk	AllPub	Inside	...	0	No Pool	No Fence	None	0	10	2007

3 rows × 79 columns

In [32]:
```
data = data.drop(GrLivArea_outlier.index)
```

In [33]:
```
# Verification
data.plot.scatter(x = 'Gr Liv Area', y = 'SalePrice')
```

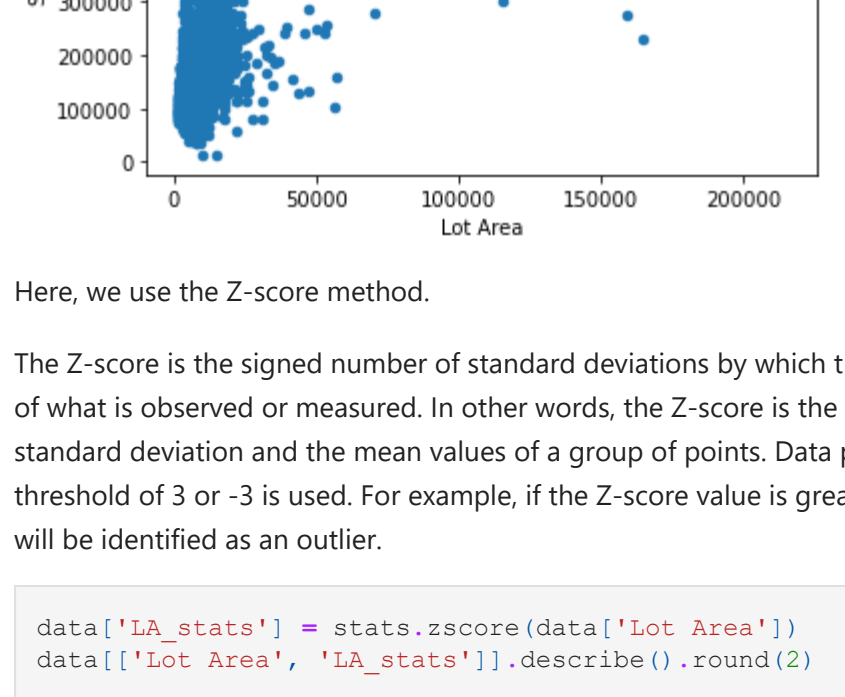
Out[33]: <AxesSubplot:xlabel='Gr Liv Area', ylabel='SalePrice'>



Lot Area

In [34]:
```
data.plot.scatter(x = 'Lot Area', y = 'SalePrice')
```

Out[34]: <AxesSubplot:xlabel='Lot Area', ylabel='SalePrice'>



Here, we use the Z-score method.

The Z-score is the signed number of standard deviations by which the value of an observation or data point is greater than the mean value of what is observed or measured. In other words, the Z-score is the value that quantifies the relationship between a data point and a standard deviation and the mean values of a group of points. Data points too far from zero will be treated as outliers. In most cases, a threshold of 3 or -3 is used. For example, if the Z-score value is greater or less than 3 or -3 standard deviations respectively, that data point will be identified as an outlier.

In [35]:
```
data['LA_stats'] = stats.zscore(data['Lot Area'])
data[['Lot Area', 'LA_stats']].describe().round(2)
```

Out[35]:

	Lot Area	LA_stats
count	2927.00	2927.00
mean	10109.37	0.00
std	7782.88	1.00
min	1300.00	-1.13
25%	7439.00	-0.34
50%	9430.00	-0.09
75%	11523.00	0.18
max	215245.00	26.36

The scaled results show a mean of 0.000 and a standard deviation of 1.000, indicating that the transformed values fit the z-scale model. The maximum value of 26.36 is further evidence of the presence of outliers, as it is well above the z-score limit of +3.

We choose to delete the 4 points whose Lot Area is greater than 100000.

In [36]:
```
LA_outlier = data.sort_values(by = 'Lot Area', ascending=False)[:4]
LA_outlier
```

Out[36]:

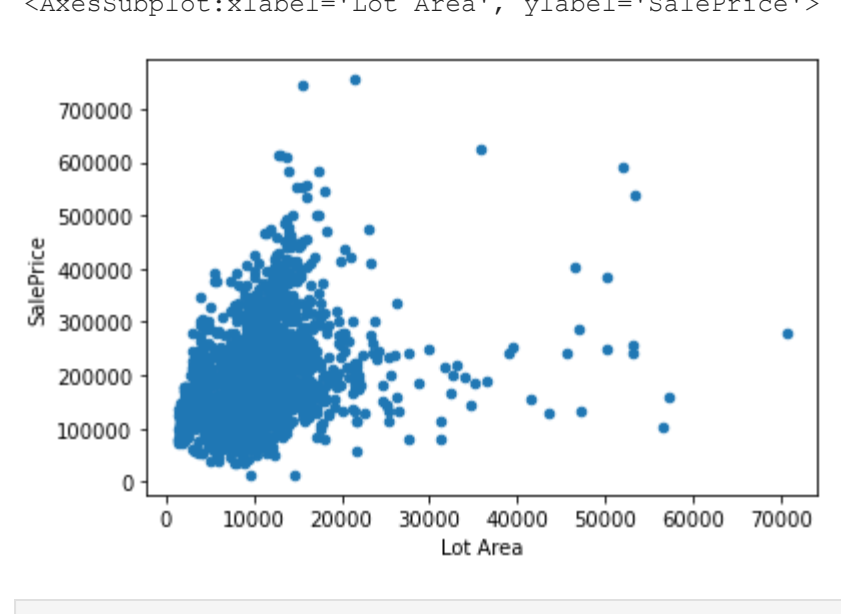
	MS SubClass	MS Zoning	Lot Frontage	Lot Area	Street	Alley	Lot Shape	Land Contour	Utilities	Lot Config	...	Pool QC	Fence	Misc Feature	Misc Val	Mo Sold	Yr Sold	Sale Type
957	20	RL	150.0	215245	Pave	No Alley	IR3	Low	AllPub	Inside	...	No Pool	No Fence	None	0	6	2009	WD
1571	190	RL	0.0	164660	Grvl	No Alley	IR1	HLS	AllPub	Corner	...	No Pool	No Fence	Shed	700	8	2008	WD
2116	50	RL	0.0	159000	Pave	No Alley	IR2	Low	AllPub	CulDSac	...	No Pool	No Fence	Shed	500	6	2007	WD
2072	20	RL	0.0	115149	Pave	No Alley	IR2	Low	AllPub	CulDSac	...	No Pool	No Fence	None	0	6	2007	WD

4 rows × 80 columns

In [37]:
```
data = data.drop(LA_outlier.index)
```

In [38]:
```
# Verification
data.plot.scatter(x = 'Lot Area', y = 'SalePrice')
```

Out[38]: <AxesSubplot:xlabel='Lot Area', ylabel='SalePrice'>



In [39]:
```
data['LA_stats'] = stats.zscore(data['Lot Area'])
data[['Lot Area', 'LA_stats']].describe().round(2)
```

Out[39]:

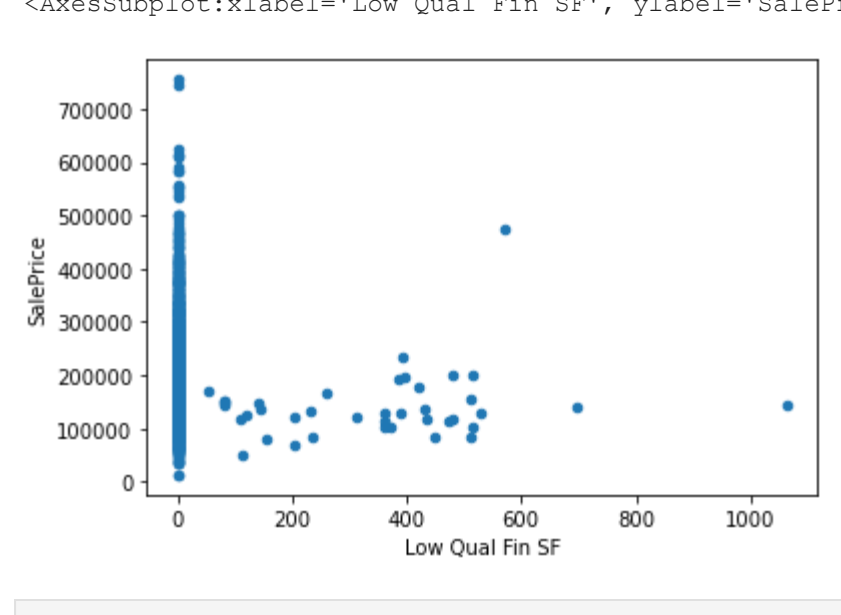
	Lot Area	LA_stats
count	2923.00	2923.00
mean	9899.45	0.00
std	5164.64	1.00
min	1300.00	-1.67
25%	7437.00	-0.48
50%	9416.00	-0.09
75%	11506.00	0.31
max	70761.00	11.79

According to the Z-score method, there are still outliers but we consider that these remaining values reflect a reality on the ground.

Low Qual Fin SF

In [40]:
```
data.plot.scatter(x = 'Low Qual Fin SF', y = 'SalePrice')
```

Out[40]: <AxesSubplot:xlabel='Low Qual Fin SF', ylabel='SalePrice'>



In [41]:
```
data['LQFSF_Stats'] = stats.zscore(data['Low Qual Fin SF'])
data[['Low Qual Fin SF','LQFSF_Stats']].describe().round(2)
```

Out[41]:

	Low Qual Fin SF	LQFSF_Stats
count	2923.00	2923.00
mean	4.69	0.00
std	46.37	1.00
min	0.00	-0.10
25%	0.00	-0.10
50%	0.00	-0.10
75%	0.00	-0.10
max	1064.00	22.85

The result shows the presence of outliers. Here, we choose to delete the last value, namely the largest.

In [42]:
```
LQFSF_outlier = data.sort_values(by = 'Low Qual Fin SF', ascending=False)[:1]
LQFSF_outlier
```

Out[42]:

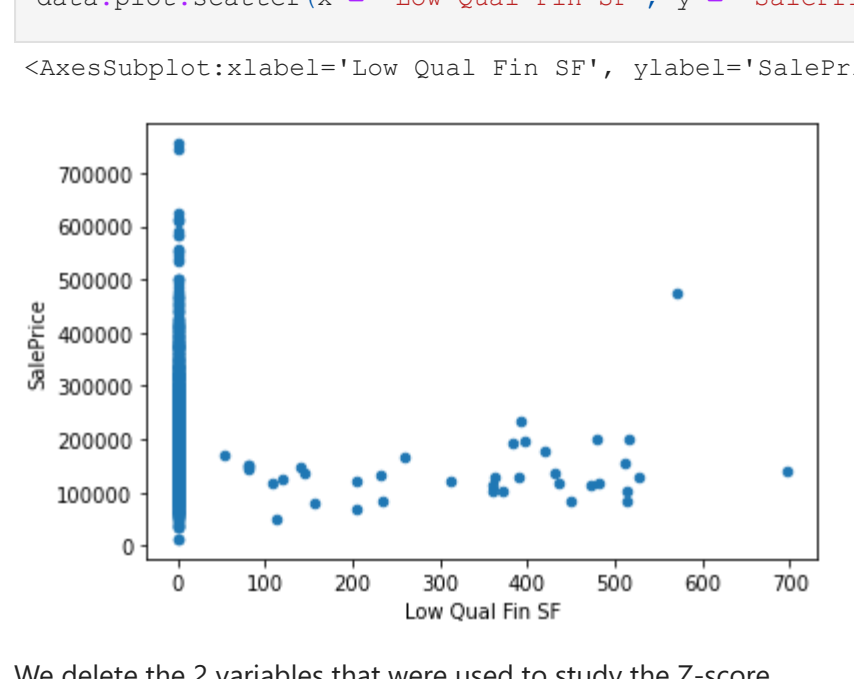
	MS SubClass	MS Zoning	Lot Frontage	Lot Area	Street	Alley	Lot Shape	Land Contour	Utilities	Lot Config	...	Fence	Misc Feature	Misc Val	Mo Sold	Yr Sold	Sale Type	S Conditi
661	50	RL	60.0	10410	Pave	Grvl	Reg	Lvl	AllPub	Inside	...	No Fence	None	0	6	2009	WD	Norr

1 rows × 81 columns

In [43]:
```
data = data.drop(LQFSF_outlier.index)
```

In [44]:
```
# Verification
data.plot.scatter(x = 'Low Qual Fin SF', y = 'SalePrice')
```

Out[44]: <AxesSubplot:xlabel='Low Qual Fin SF', ylabel='SalePrice'>



We delete the 2 variables that were used to study the Z-score.

In [45]:
```
data.drop(['LQFSF_Stats', 'LA_stats'], axis=1, inplace=True)
```

4. Feature modification

Some numerical features are actually really categorial features as MSSubClass and MoSold. We choose to transform them into nominal qualitative variables, as follows.

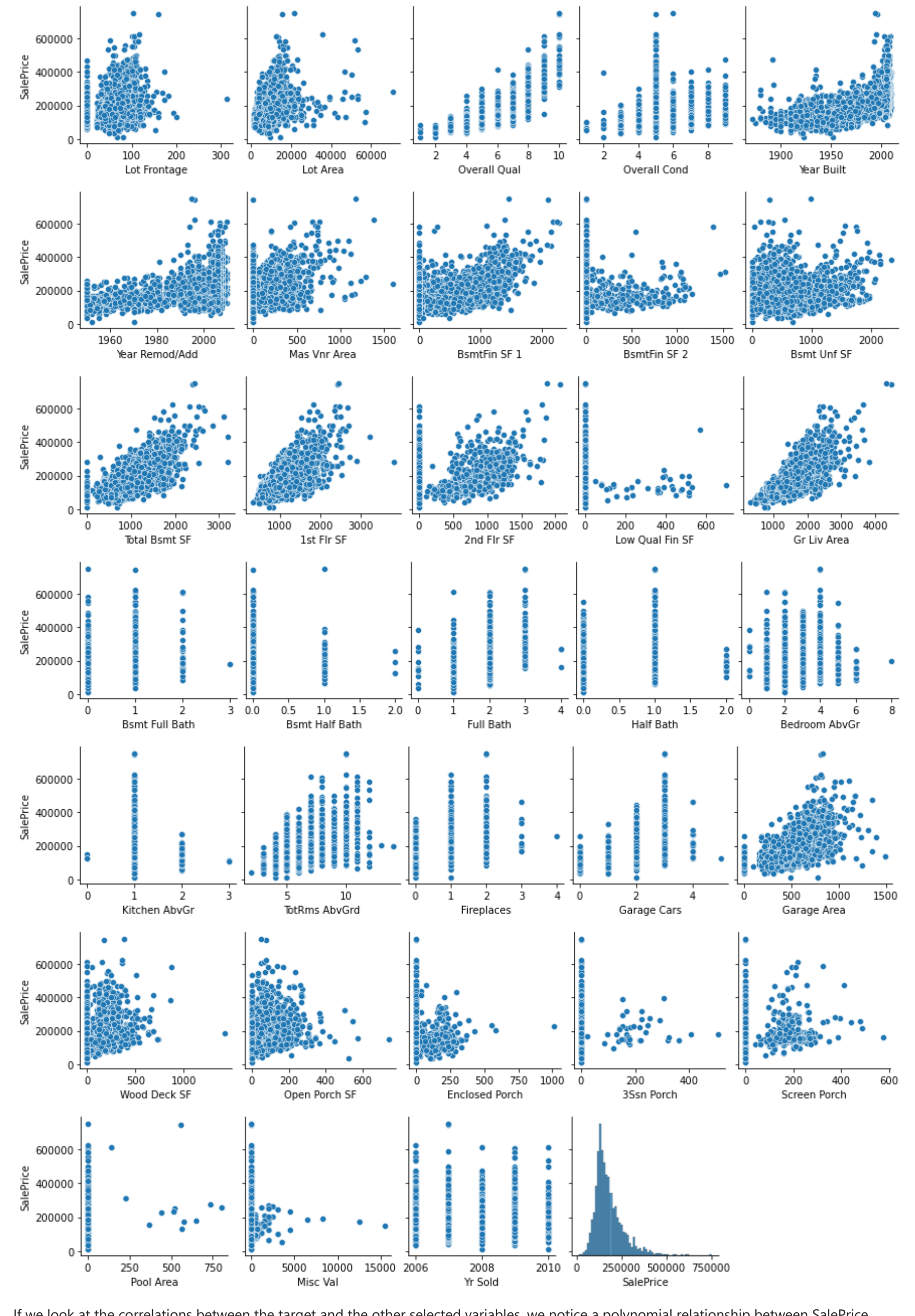
In [46]:
```
data = data.replace({"MS SubClass" : {20 : "SC20", 30 : "SC30", 40 : "SC40", 45 : "SC45",
                                      50 : "SC50", 60 : "SC60", 70 : "SC70", 75 : "SC75",
                                      80 : "SC80", 85 : "SC85", 90 : "SC90", 120 : "SC120",
                                      150 : "SC150", 160 : "SC160", 180 : "SC180", 190 : "SC190"},
                     "Mo Sold" : {1 : "Jan", 2 : "Feb", 3 : "Mar", 4 : "Apr", 5 : "May", 6 : "Jun",
                                  7 : "Jul", 8 : "Aug", 9 : "Sep", 10 : "Oct", 11 : "Nov", 12 : "Dec"}
                    })
```

D) Exploratory data vizualization

Numerical features

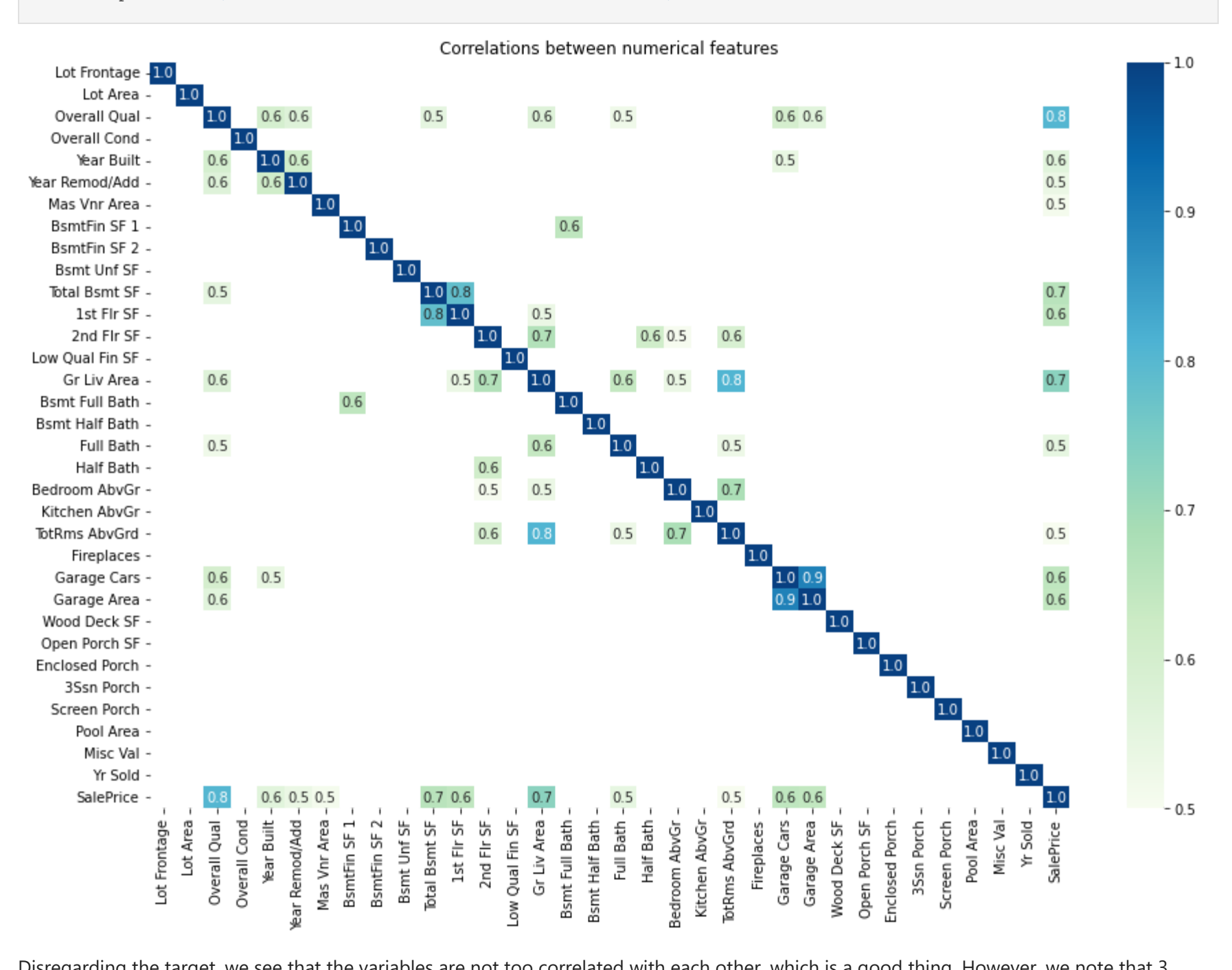
After cleaning the data, we proceed again to a graphical study and correlation analysis of the different numerical features. This allows the verification of the removal of outliers and the search for a link between the predictive features and the target.

In [47]:
```
data_num = data.select_dtypes(include = ['float64', 'int64'])
for i in range(0, len(data_num.columns), 5):
    sns.pairplot(data = data_num, x_vars = data_num.columns[i:i+5], y_vars = ['SalePrice'])
```



If we look at the correlations between the target and the other selected variables, we notice a polynomial relationship between SalePrice and Overall Qual or Year Built for example. We will proceed to the creation of polynomials later.

In [48]:
```
data_num_corr = data_num.corr()
heatmap_num_corr = data_num_corr[abs(data_num_corr)>=0.5]
plt.figure(figsize=(15, 10))
sns.heatmap(heatmap_num_corr,
            annot=True,
            fmt='.1f',
            cmap='GnBu',
            vmin=0.5,
            vmax=1)
title = plt.title('Correlations between numerical features')
```



Disregarding the target, we see that the variables are not too correlated with each other, which is a good thing. However, we note that 3 pairs of variables are strongly correlated with each other: 1st Flr SF/Total Bsmt SF, Giv Liv Area/TotsRms AbvGr and Garage Area/Garage cars.

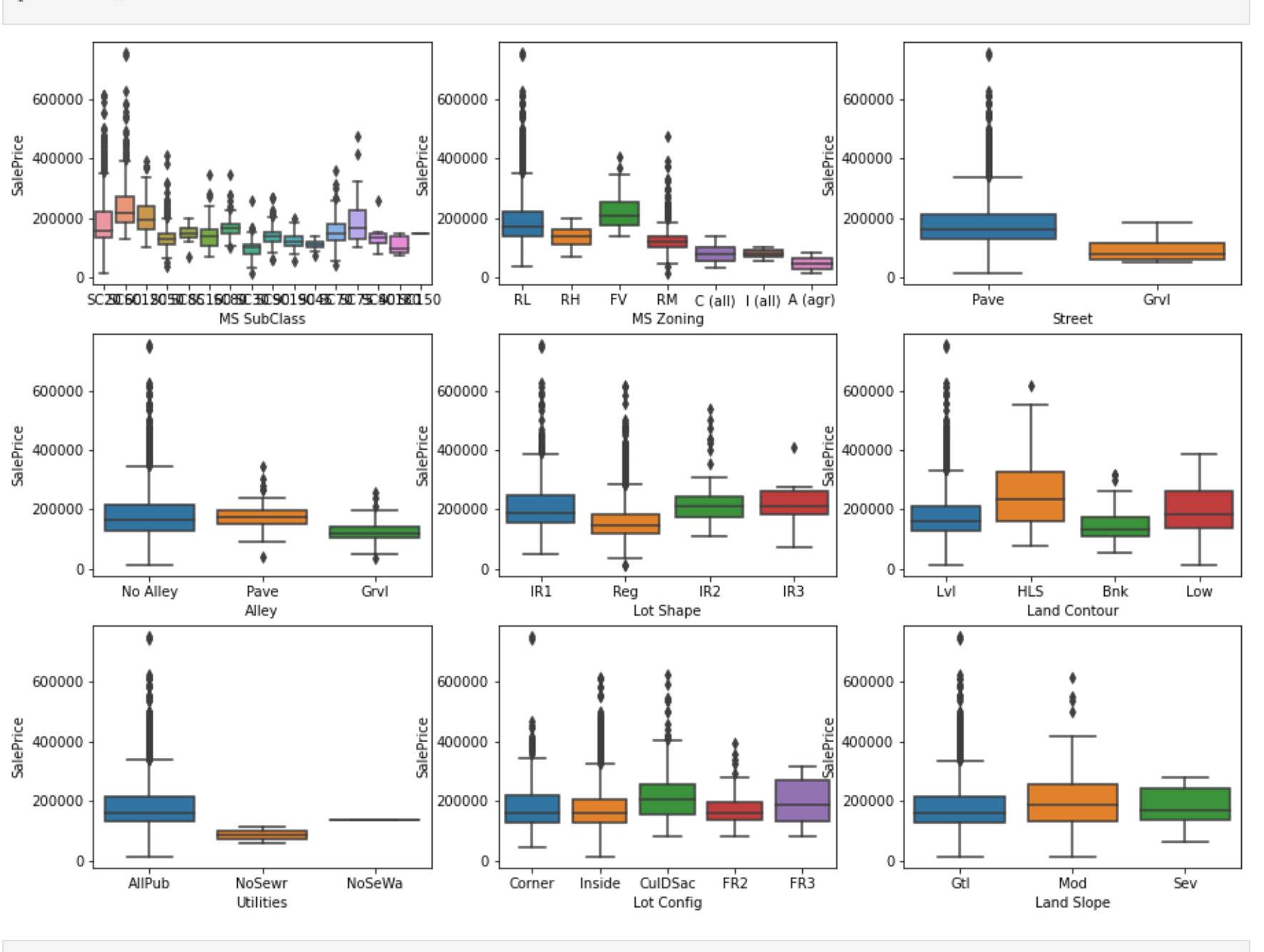
Categorial features

We will study the relationships between the qualitative features and the target using box plot.

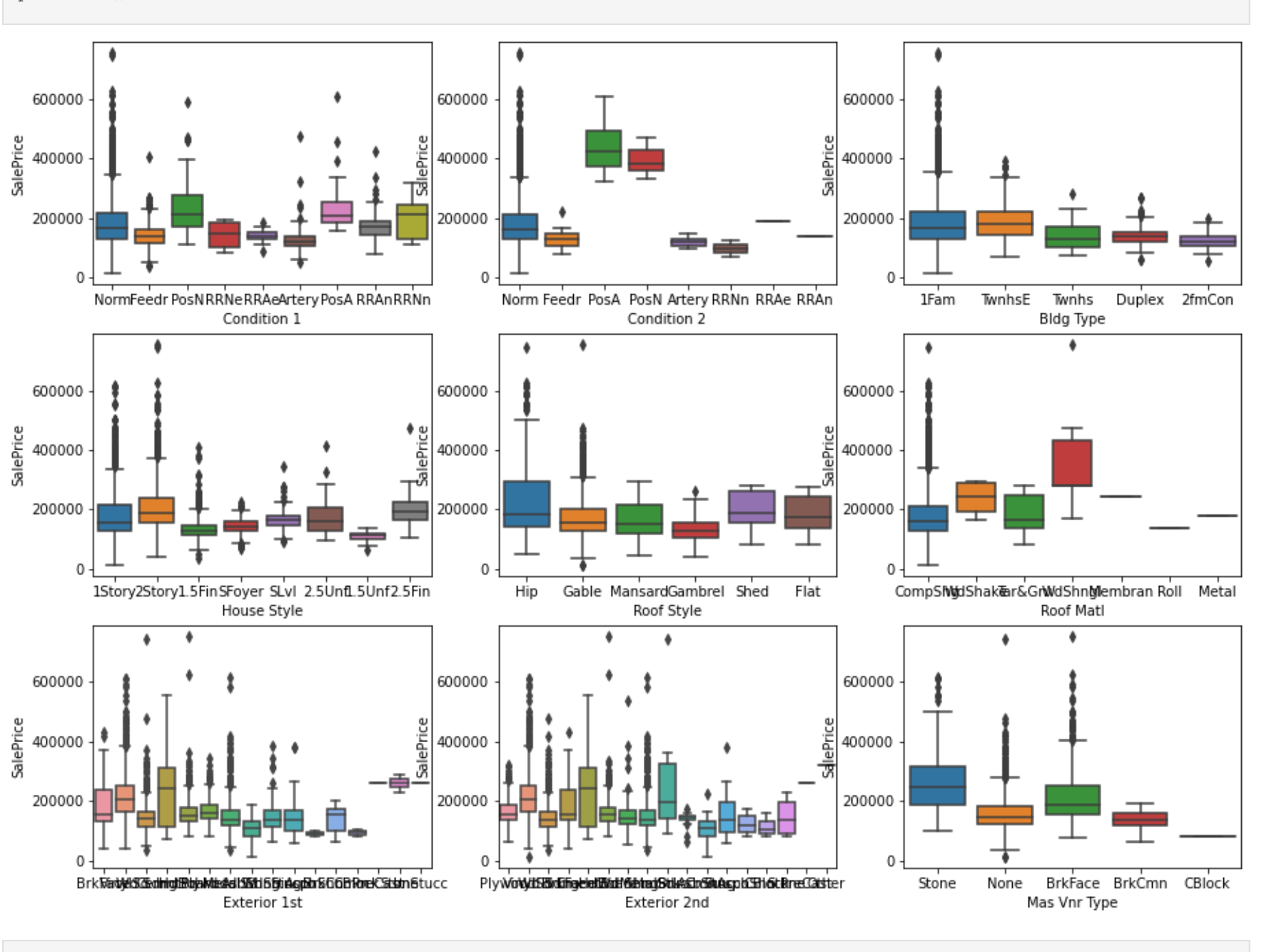
In [49]:
```
data_cat = data.select_dtypes(include = ['object'])
print(f'Thera are {len(data_cat.columns)} features object type')
print(data_cat.columns)
```

```
Thera are 45 features object type
Index(['MS SubClass', 'MS Zoning', 'Street', 'Alley', 'Lot Shape',
       'Land Contour', 'Utilities', 'Lot Config', 'Land Slope', 'Neighborhood',
       'Condition 1', 'Condition 2', 'Bldg Type', 'House Style', 'Roof Style',
       'Roof Matl', 'Exterior 1st', 'Exterior 2nd', 'Mas Vnr Type',
       'Exter Qual', 'Exter Cond', 'Foundation', 'Bsmt Qual', 'Bsmt Cond',
       'Bsmt Exposure', 'BsmtFin Type 1', 'BsmtFin Type 2', 'Heating',
       'Heating QC', 'Central Air', 'Electrical', 'Kitchen Qual', 'Functional',
       'Fireplace Qu', 'Garage Type', 'Garage Finish', 'Garage Qual',
       'Garage Cond', 'Paved Drive', 'Pool QC', 'Fence', 'Misc Feature',
       'Mo Sold', 'Sale Type', 'Sale Condition'],
      dtype='object')
```

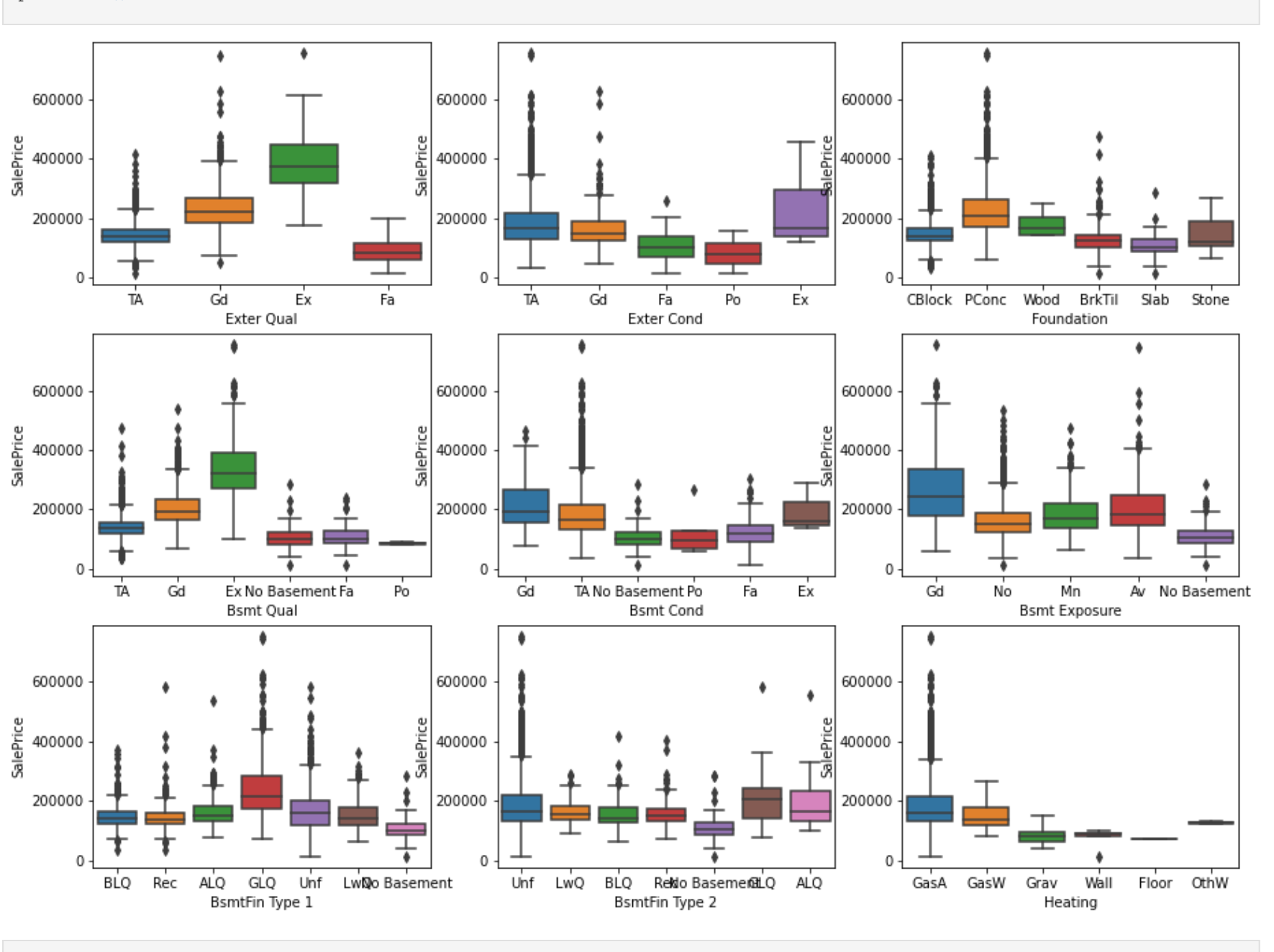
In [50]:
```
fig = plt.figure(figsize=(15,15))
y="SalePrice"
plt.subplot(431)
ax1 = sns.boxplot(x="MS SubClass", y=y, data=data)
plt.subplot(432)
ax2 = sns.boxplot(x="MS Zoning", y=y, data=data)
plt.subplot(433)
ax3 = sns.boxplot(x="Street", y=y, data=data)
plt.subplot(434)
ax4 = sns.boxplot(x="Alley", y=y, data=data)
plt.subplot(435)
ax5 = sns.boxplot(x="Lot Shape", y=y, data=data)
plt.subplot(436)
ax6 = sns.boxplot(x="Land Contour", y=y, data=data)
plt.subplot(437)
ax7 = sns.boxplot(x="Utilities", y=y, data=data)
plt.subplot(438)
ax8 = sns.boxplot(x="Lot Config", y=y, data=data)
plt.subplot(439)
ax9 = sns.boxplot(x="Land Slope", y=y, data=data)
plt.show()
```



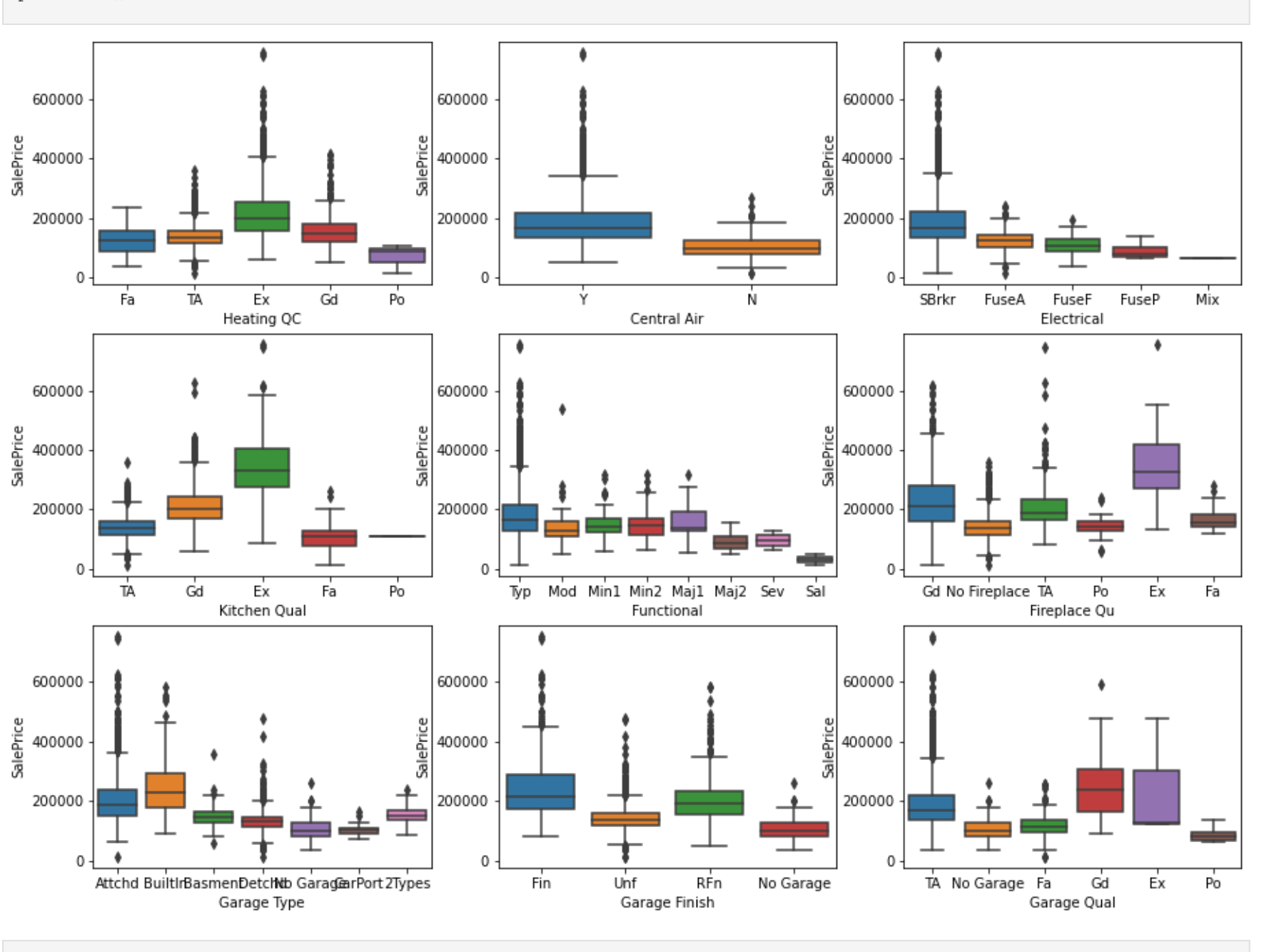
In [51]:
```
fig = plt.figure(figsize=(15,15))
y="SalePrice"
plt.subplot(431)
ax1 = sns.boxplot(x="Condition 1", y=y, data=data)
plt.subplot(432)
ax2 = sns.boxplot(x="Condition 2", y=y, data=data)
plt.subplot(433)
ax3 = sns.boxplot(x="Bldg Type", y=y, data=data)
plt.subplot(434)
ax4 = sns.boxplot(x="House Style", y=y, data=data)
plt.subplot(435)
ax5 = sns.boxplot(x="Roof Style", y=y, data=data)
plt.subplot(436)
ax6 = sns.boxplot(x="Roof Matl", y=y, data=data)
plt.subplot(437)
ax7 = sns.boxplot(x="Exterior 1st", y=y, data=data)
plt.subplot(438)
ax8 = sns.boxplot(x="Exterior 2nd", y=y, data=data)
plt.subplot(439)
ax9 = sns.boxplot(x="Mas Vnr Type", y=y, data=data)
plt.show()
```



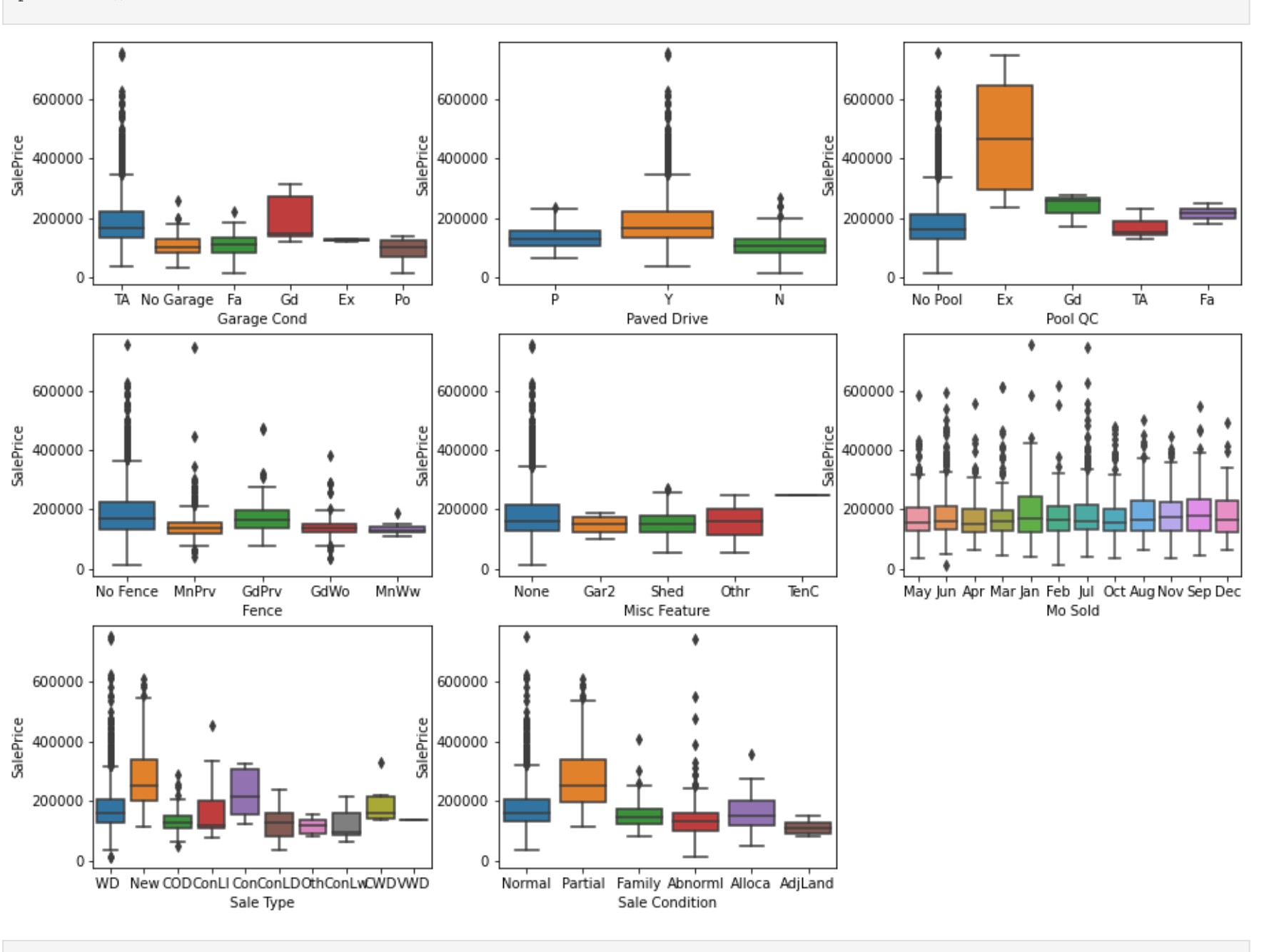
In [52]:
```
fig = plt.figure(figsize=(15,15))
y="SalePrice"
plt.subplot(431)
ax1 = sns.boxplot(x="Exter Qual", y=y, data=data)
plt.subplot(432)
ax2 = sns.boxplot(x="Exter Cond", y=y, data=data)
plt.subplot(433)
ax3 = sns.boxplot(x="Foundation", y=y, data=data)
plt.subplot(434)
ax4 = sns.boxplot(x="Bsmt Qual", y=y, data=data)
plt.subplot(435)
ax5 = sns.boxplot(x="Bsmt Cond", y=y, data=data)
plt.subplot(436)
ax6 = sns.boxplot(x="Bsmt Exposure", y=y, data=data)
plt.subplot(437)
ax7 = sns.boxplot(x="BsmtFin Type 1", y=y, data=data)
plt.subplot(438)
ax8 = sns.boxplot(x="BsmtFin Type 2", y=y, data=data)
plt.subplot(439)
ax9 = sns.boxplot(x="Heating", y=y, data=data)
plt.show()
```



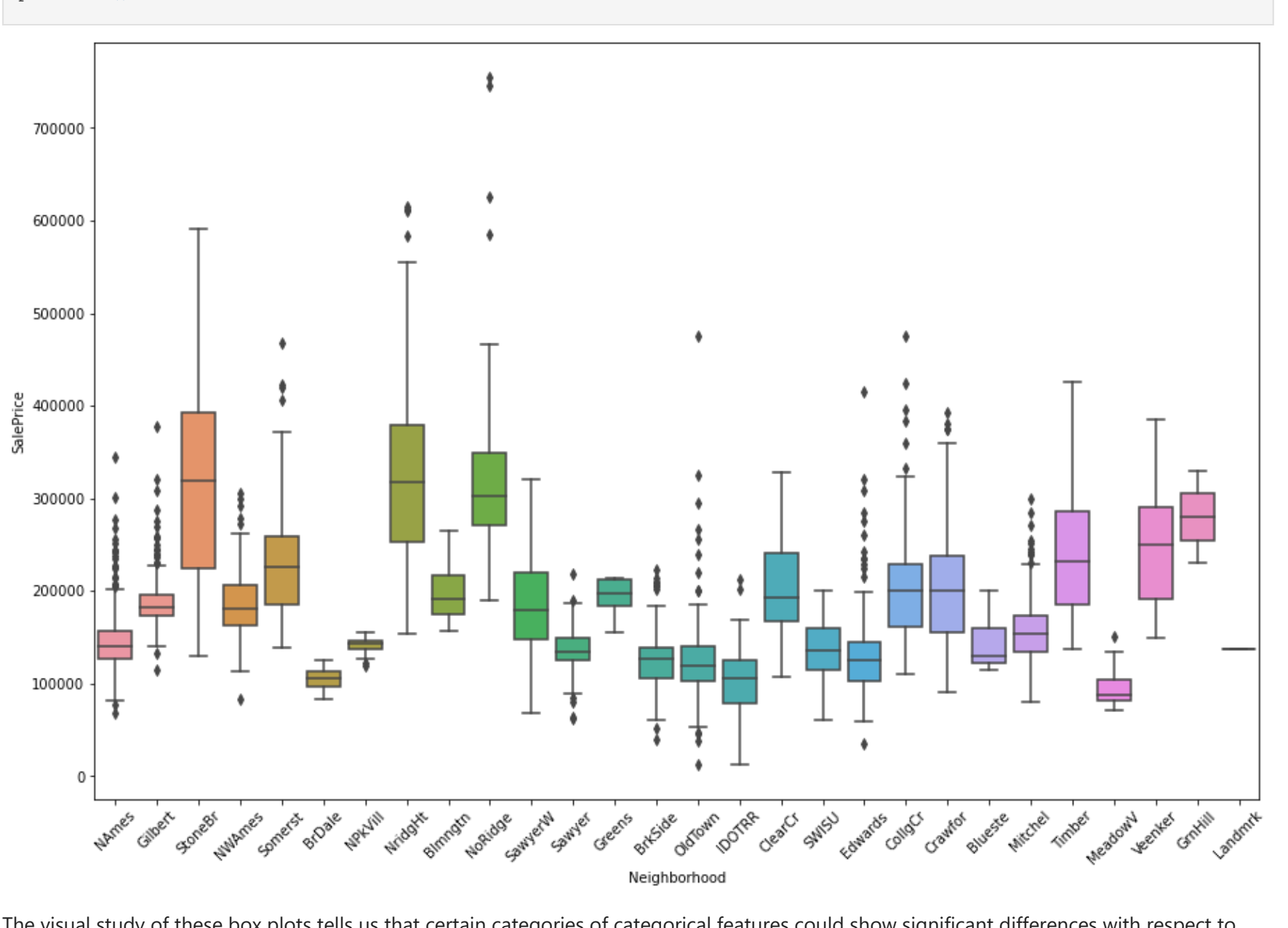
In [53]:
```
fig = plt.figure(figsize=(15,15))
y="SalePrice"
plt.subplot(431)
ax1 = sns.boxplot(x="Heating QC", y=y, data=data)
plt.subplot(432)
ax2 = sns.boxplot(x="Central Air", y=y, data=data)
plt.subplot(433)
ax3 = sns.boxplot(x="Electrical", y=y, data=data)
plt.subplot(434)
ax4 = sns.boxplot(x="Kitchen Qual", y=y, data=data)
plt.subplot(435)
ax5 = sns.boxplot(x="Functional", y=y, data=data)
plt.subplot(436)
ax6 = sns.boxplot(x="Fireplace Qu", y=y, data=data)
plt.subplot(437)
ax7 = sns.boxplot(x="Garage Type", y=y, data=data)
plt.subplot(438)
ax8 = sns.boxplot(x="Garage Finish", y=y, data=data)
plt.subplot(439)
ax9 = sns.boxplot(x="Garage Qual", y=y, data=data)
plt.show()
```



In [54]:
```
fig = plt.figure(figsize=(15,15))
y="SalePrice"
plt.subplot(431)
ax1 = sns.boxplot(x="Garage Cond", y=y, data=data)
plt.subplot(432)
ax2 = sns.boxplot(x="Paved Drive", y=y, data=data)
plt.subplot(433)
ax3 = sns.boxplot(x="Pool QC", y=y, data=data)
plt.subplot(434)
ax4 = sns.boxplot(x="Fence", y=y, data=data)
plt.subplot(435)
ax5 = sns.boxplot(x="Misc Feature", y=y, data=data)
plt.subplot(436)
ax6 = sns.boxplot(x="Mo Sold", y=y, data=data)
plt.subplot(437)
ax7 = sns.boxplot(x="Sale Type", y=y, data=data)
plt.subplot(438)
ax8 = sns.boxplot(x="Sale Condition", y=y, data=data)
# plt.subplot(439)
# ax9 = sns.boxplot(x="Garage Qual", y=y, data=data)
plt.show()
```



In [55]:
```
fig = plt.figure(figsize=(15,10))
ax10 = sns.boxplot(x="Neighborhood", y="SalePrice", data=data)
plt.setp(ax10.get_xticklabels(), rotation=45)
plt.show()
```



The visual study of these box plots tells us that certain categories of categorical features could show significant differences with respect to the target. As a result, we will subsequently formulate hypothesis tests for each of these categorical features.

E) Hypothesis testing

We are going to use the hypothesis tests to show if there are significant differences in the sale prices of the houses between the different modalities of certain qualitative variables such as central air or not, or the land slope (gentle, moderate, severe) for example.

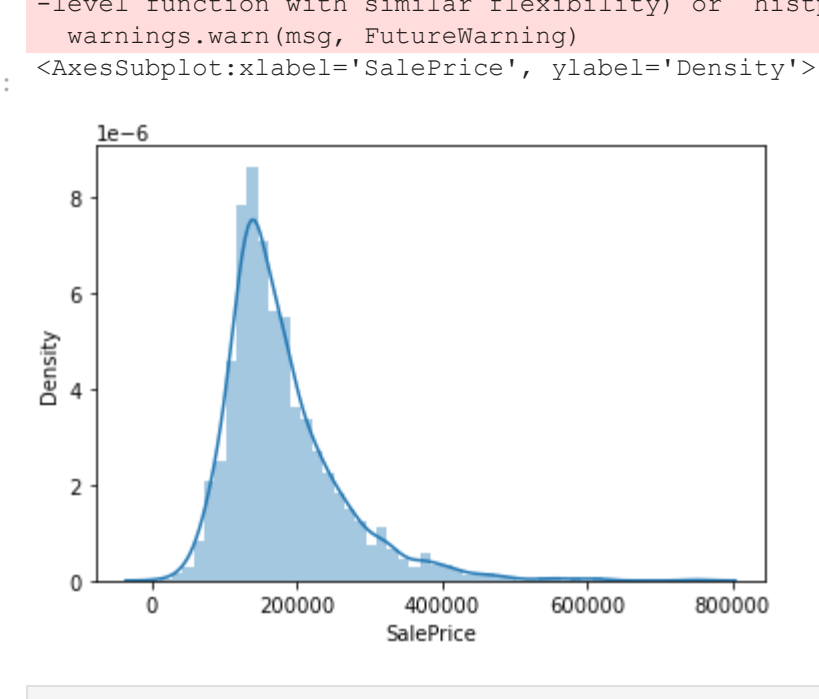
We have seen previously that a large number of features were not normally distributed. Before proceeding to the hypothesis test, we will first apply a log transformation for the sale price. Indeed, we assume that the distribution follows a normal law.

Log transformation of sale price

In [56]:
```
sns.distplot(data['SalePrice'])
```

```
C:\Users\godet\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[56]: `<AxesSubplot:xlabel='SalePrice', ylabel='Density'>`



In [57]:
```
print('Skewness: %f' % data['SalePrice'].skew())
```

```
Skewness: 1.748866
```

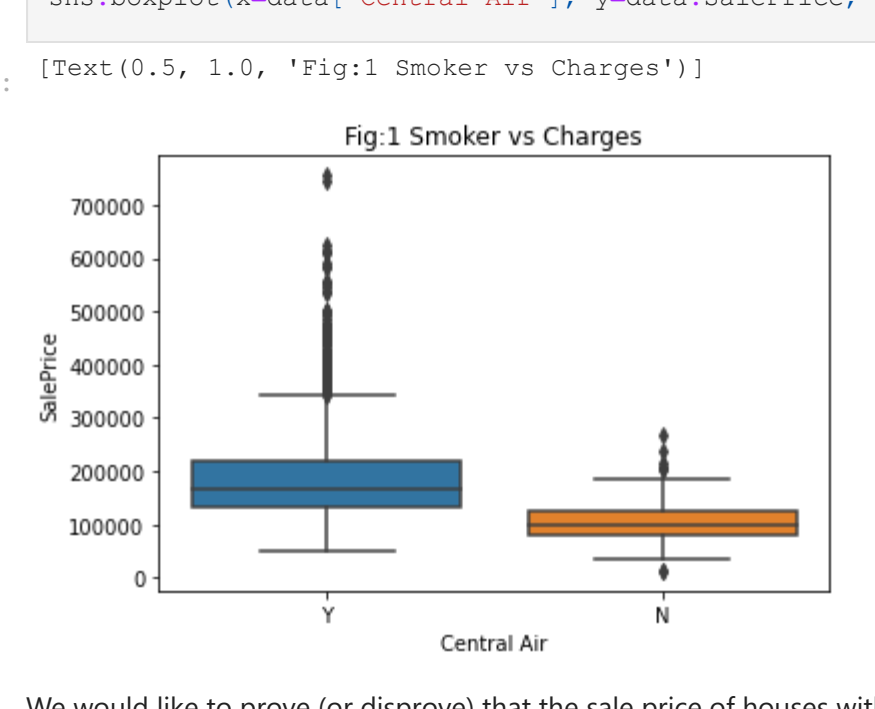
In [58]:
```
#Log transformation
# data['SalePrice'] = np.log(data['SalePrice'])
# sns.distplot(data['SalePrice'])
# print('Skewness: %f' % data['SalePrice'].skew())
```

As we can see, the logarithmic method has transformed the "SalePrice" distribution into a more symmetrical bell curve and the skewness level is now -0.01 instead of 1.74.

Central Air

In [59]:
```
sns.boxplot(x=data['Central Air'], y=data.SalePrice, data=data).set(title="Fig:1 Smoker vs Charges")
```

Out[59]: `[Text(0.5, 1.0, 'Fig:1 Smoker vs Charges')]`



We would like to prove (or disprove) that the sale price of houses with central air is more important than the sale price of houses without central air. We compare the average values (μ) of houses with or without central air.

In [60]:
```
central_air = data.loc[data['Central Air'] == 'Y']
central_air_price = central_air.SalePrice
cap_mean = central_air_price.mean()
cap_mean
```

Out[60]: `186319.6889214967`

In [61]:
```
no_central_air = data.loc[data['Central Air'] == 'N']
no_central_air_price = no_central_air.SalePrice
ncap_mean = no_central_air_price.mean()
ncap_mean
```

Out[61]: `101890.47959183673`

We define the null and alternative hypothesis:

- $H\_0 : \mu\_1 <= \mu\_2$ The average prices of houses with central air are less than or equal to or equal to those without central air.
- $H\_A : \mu\_1 > \mu\_2$ The average prices of houses with central air are higher than those without central air.

The '>' sign in the alternative hypothesis indicates that the test is right-tailed. To compare the average values of the populations of smokers and non-smokers, we will use a t-test. If the z-values (calculated from a t-test) fall in the area on the right side of a distribution curve, this would cause us to reject the null hypothesis.

Calculation of the value of t and p for the sales price of houses with and without central air:

In [62]:
```
alpha=0.05
t_val2, p_value2 = stats.ttest_ind(central_air_price, no_central_air_price)
p_value_onetail = p_value2/2
print("t_value = {} , p_value ={} , p_value_onetail = {}".format(t_val2, p_value2, p_value_onetail))
```

```
t_value = 14.82249153829442 , p_value =5.56900766468521e-48 , p_value_onetail = 2.784503832342605e-48
```

In [63]:
```
if p_value2 <alpha :
    print("Conclusion:Since p_value {} is less than alpha {} ".format (p_value_onetail,alpha) )
    print("Reject null hypothesis that average SalePrice for central air houses are less than or equal to house


else:
    print("Conclusion:Since p value {} is greater than alpha {} ".format (p_value_onetail,alpha))
    print("Failed to reject null hypothesis that average SalePrice for central air houses are less than or equa
```

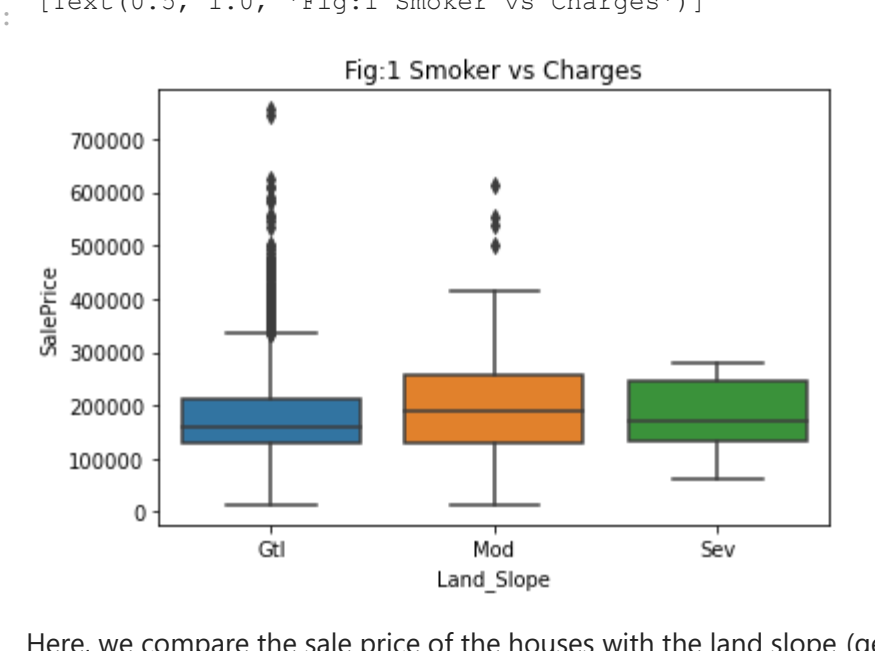
```
Conclusion:Since p_value 2.784503832342605e-48 is less than alpha 0.05
Reject null hypothesis that average SalePrice for central air houses are less than or equal to houses without c
entral air.
```

Land Slope

In [64]:
```
data.rename(columns={'Land Slope': 'Land_Slope'}, inplace=True)
```

In [65]:
```
sns.boxplot(x=data['Land_Slope'], y=data.SalePrice, data=data).set(title="Fig:1 Smoker vs Charges")
```

Out[65]: `[Text(0.5, 1.0, 'Fig:1 Smoker vs Charges')]`



Here, we compare the sale price of the houses with the land slope (gentle, moderate, severe).

The null and alternative hypotheses are defined:

- $H\_0 : \mu\_1 = \mu\_2 = \mu\_3$ The average sale prices of houses are identical regardless of the slope of the land . \
- H_A : At least one of the sale price averages is not the same.

For this example, we will use a one-way ANOVA statistic and an f-score to assess the variances of these three different populations. We will set the alpha value to 0.05.

In [66]:
```
data['SalePrice'].groupby([data['Land_Slope']]).mean()
```

Out[66]:
```
Land_Slope
Gtl    179582.155476
Mod    204853.784000
Sev    177915.000000
Name: SalePrice, dtype: float64
```

Now we will build the ANOVA table and check for each group (gentle, moderate, severe) against the sale price values. We will use the ols (ordinary least squares) model for the estimation of the unknown parameters.

In [67]:
```
formula = 'SalePrice ~ C(Land_Slope)'
model = ols(formula, data).fit()
aov_table = anova_lm(model)
aov_table
```

Out[67]:

	df	sum_sq	mean_sq	F	PR(>F)
C(Land_Slope)	2.0	7.649325e+10	3.824663e+10	6.018394	0.002464
Residual	2919.0	1.855011e+13	6.354955e+09	NaN	NaN

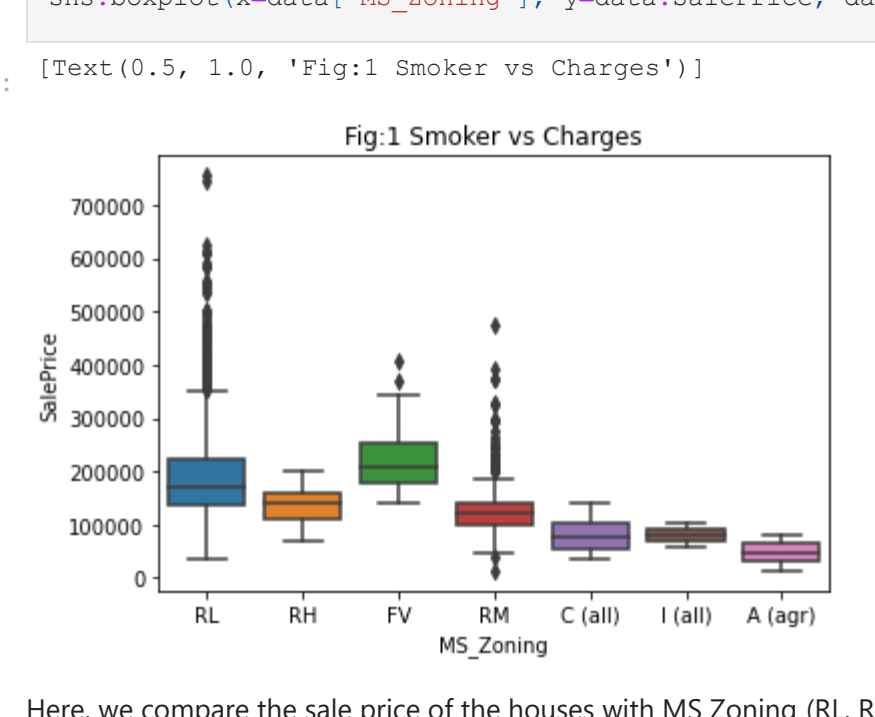
The p value is 0.002464 and it is smaller than alpha(0.05). Therefore, we do not reject the null hypothesis and conclude that at least one average sale price is different depending on land slope.

MS Zoning

In [68]:
```
data.rename(columns={'MS Zoning': 'MS_Zoning'}, inplace=True)
```

In [69]:
```
sns.boxplot(x=data['MS_Zoning'], y=data.SalePrice, data=data).set(title="Fig:1 Smoker vs Charges")
```

Out[69]: `[Text(0.5, 1.0, 'Fig:1 Smoker vs Charges')]`



Here, we compare the sale price of the houses with MS Zoning (RL, RH, FV, RM, C (all), I (all), A (agr)).

The null and alternative hypotheses are defined:

- $H\_0 : \mu\_1 = \mu\_2 = \mu\_3 = \mu\_4 = \mu\_5 = \mu\_6 = \mu\_7$ The average sale prices of houses are identical regardless of the MS Zoning . \
- H_A : At least one of the sale price averages is not the same.

For this example, we will use a one-way ANOVA statistic and an f-score to assess the variances of these three different populations. We will set the alpha value to 0.05.

In [70]:
```
data['SalePrice'].groupby([data['MS_Zoning']]).mean()
```

Out[70]:
```
MS_Zoning
A (agr)     47300.000000
C (all)     79795.040000
FV         218986.949640
I (all)     80312.500000
RH         136419.777778
RL         191140.124062
RM         126781.393939
Name: SalePrice, dtype: float64
```

Now we will build the ANOVA table and check for each group (gentle, moderate, severe) against the sale price values. We will use the ols (ordinary least squares) model for the estimation of the unknown parameters.

In [71]:
```
formula = 'SalePrice ~ C(MS_Zoning)'
model = ols(formula, data).fit()
aov_table = anova_lm(model)
aov_table
```

Out[71]:

	df	sum_sq	mean_sq	F	PR(>F)
C(MS_Zoning)	6.0	2.156995e+12	3.594992e+11	63.628706	1.799378e-74
Residual	2915.0	1.646961e+13	5.649953e+09	NaN	NaN

The p value is 6.122206e-130 and it is smaller than alpha(0.05). Therefore, we reject the null hypothesis and conclude that at least one average sale price is different depending on MS Zoning.

Summary

Hypothesis tests revealed significant differences in sales prices between houses with or without central air, and according to the general zoning classification of sale. In addition, no significant difference in sales prices was shown between houses with a gentle, moderate or severe land slope. Therefore, the 'Land Slope' feauture could be removed for the linear regression analysis. It would be interesting to perform hypothesis tests on all 45 qualitative variables.

F) Feature Engineering

1. Log transforming skew variables

A log transformation was performed on the target (SalePrice) so that these data follow a normal distribution law (see hypothesis test section). Concerning the predictive features, the study of the asymmetry was carried out in section B shows that most of the numerical variables do not follow a normal distribution. Therefore, a standardization of these data will be applied later during the linear regression after the data set is divided into a train set and a test set.

2. Basic feature engineering: adding polynomial and interaction terms

Feature representation

Before jumping straight to the dummy variables, it's a good idea to check the number of categories to make sure that all categories have a reasonable representation.

For this we will study the representation of the modalities of the categorical variable 'Neighborhood'.

In [72]:
```
nbh_counts = data.Neighborhood.value_counts()
nbh_counts
```

Out[72]:
```
NAmes      443
CollgCr    267
OldTown    238
Edwards    191
Somerst    182
NridgHt    166
Gilbert    165
Sawyer     151
NWAmes     131
SawyerW    125
Mitchel    114
BrkSide    108
Crawfor    103
IDOTRR      93
NoRidge     71
Timber      70
StoneBr     51
SWISU       48
ClearCr     42
MeadowV     37
BrDale      30
Blmngtn     28
Veenker     24
NPkVill     23
Blueste     10
Greens       8
GrnHill      2
Landmrk      1
Name: Neighborhood, dtype: int64
```

We note that some neighborhoods are poorly represented as 'Greens', 'GrnHill' or 'Landmrk'. We are therefore going to group these neighborhoods in the same modality called 'Others'.

In [73]:
```
other_nbhs = list(nbh_counts[nbh_counts <= 8].index)
other_nbhs
```

Out[73]: `['Greens', 'GrnHill', 'Landmrk']`

In [74]:
```
data['Neighborhood'] = data['Neighborhood'].replace(other_nbhs, 'Other')
```

Polynomial Features

One of the first things we looked for in the pairplot was evidence of the relationship between each feature and the target. In some characteristics like *'Overall Qual'* and *'Gr Liv Qual'*, we notice an upward curved relationship rather than a simple linear correspondence. This suggests that we should add quadratic **polynomial terms or transformations** for these features, which allows us to express this nonlinear relationship while using linear regression as a model.

In [75]:
```
data['OQ2'] = data['Overall Qual'] ** 2
data['GLA2'] = data['Gr Liv Area'] ** 2
```

Interaction terms

As is, each feature is treated as an independent quantity. However, there may be **interaction effects**, in which the impact of one feature may dependent on the current value of a different feature.

For example, there may be a higher premium for increasing *'Overall Qual'* for houses that were built more recently. If such a premium or a similar effect exists, a feature that multiplies *'Overall Qual'* by *'Year Built'* can help us capture it.

Another style of interaction term involves feature proprtions: for example, to get at something like quality per square foot we could divide *'Overall Qual'* by *'Lot Area'*.

In [76]:
```
data['OQ_x_YB'] = data['Overall Qual'] * data['Year Built']
data['OQ_/_LA'] = data['Overall Qual'] / data['Lot Area']
```

3. Feature Scaling

A transformer such as StandarScaler() , MinMaxScaler() or RobustScaler() will be used later on the train and test set in order to scale the numerical features.

4. One-hot encoding for dummy variables

A significant challenge, especially when dealing with data with many columns, is ensuring that each column is correctly encoded.

This is especially true with columns of data that are ordered categories (ordinals) versus unordered categories. Unordered categories should be one-hot encoded, but this can greatly increase the number of features and create features that are highly correlated with each other, which is not necessarily the case here.

The Pandas one-hot encoder (get_dummies) works well with data defined as categorical. By default it only converts object columns. We will also delete the 1st column.

However, one-hot encoding can overfit data with much higher mean squared errors on test data than no encoding.

In [77]:
```
cat_cols = data.select_dtypes(include = ['object']).columns

print(f'There are {len(cat_cols.tolist())} object variables to encode')

cat_cols.tolist()
```

Out[77]:
```
There are 45 object variables to encode
['MS SubClass',
 'MS_Zoning',
 'Street',
 'Alley',
 'Lot Shape',
 'Land Contour',
 'Utilities',
 'Lot Config',
 'Land_Slope',
 'Neighborhood',
 'Condition 1',
 'Condition 2',
 'Bldg Type',
 'House Style',
 'Roof Style',
 'Roof Matl',
 'Exterior 1st',
 'Exterior 2nd',
 'Mas Vnr Type',
 'Exter Qual',
 'Exter Cond',
 'Foundation',
 'Bsmt Qual',
 'Bsmt Cond',
 'Bsmt Exposure',
 'BsmtFin Type 1',
 'BsmtFin Type 2',
 'Heating',
 'Heating QC',
 'Central Air',
 'Electrical',
 'Kitchen Qual',
 'Functional',
 'Fireplace Qu',
 'Garage Type',
 'Garage Finish',
 'Garage Qual',
 'Garage Cond',
 'Paved Drive',
 'Pool QC',
 'Fence',
 'Misc Feature',
 'Mo Sold',
 'Sale Type',
 'Sale Condition']
```

In [78]:
```
data[cat_cols].apply(lambda x: x.nunique()).sort_values(ascending=False)
```

Out[78]:
```
Neighborhood      26
Exterior 2nd      17
MS SubClass       16
Exterior 1st      16
Mo Sold           12
Sale Type         10
Condition 1        9
Functional         8
Condition 2        8
House Style        8
Garage Type        7
BsmtFin Type 2     7
Roof Matl          7
BsmtFin Type 1     7
MS_Zoning          7
Fireplace Qu       6
Foundation         6
Heating            6
Garage Qual        6
Garage Cond        6
Bsmt Cond          6
Bsmt Qual          6
Sale Condition     6
Roof Style         6
Electrical         5
Misc Feature       5
Fence              5
Pool QC            5
Kitchen Qual       5
Exter Cond         5
Heating QC         5
Bldg Type          5
Mas Vnr Type       5
Bsmt Exposure      5
Lot Config         5
Exter Qual         4
Garage Finish      4
Land Contour       4
Lot Shape          4
Land_Slope         3
Utilities          3
Paved Drive        3
Alley              3
Central Air        2
Street             2
dtype: int64
```

In [79]:
```
data[cat_cols].apply(lambda x: x.nunique()).sort_values(ascending=False).sum()
```

Out[79]:
```
306
```

No categorical variable has only one value. We can therefore encode them all. The 45 object columns will become 306 columns in total.

We'll use the Pandas One Hot Encoder (get_dummies), which by default only converts object columns.

In [80]:
```
#data.info()
```

In [81]:
```
data = pd.get_dummies(data)
```

In [82]:
```
data.shape
```

Out[82]:
```
(2922, 344)
```

Summary EDA

After all the processing provided, the dataset now has 2922 rows and 344 columns.

- Duplicates have been removed.
- Outliers were removed.
- Missing values have been processed.
- The distribution of variables has been studied and corrected.
- Hypothesis tests were carried out.
- New features such as polynomials have been created and others have been modified.
- All the categorical features were encoded.

G) Modelisation

1. Train test split

In [83]:
```
print('data shape: ', data.shape)

X = data.drop('SalePrice', axis = 1)
y = data['SalePrice']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 5)

print('X_train shape: ', X_train.shape)
print('y_train shape: ', y_train.shape)
print('X_test shape: ', X_test.shape)
print('y_test shape: ', y_test.shape)
```

```
data shape:  (2922, 344)
X_train shape:  (2191, 343)
y_train shape:  (2191,)
X_test shape:  (731, 343)
y_test shape:  (731,)
```

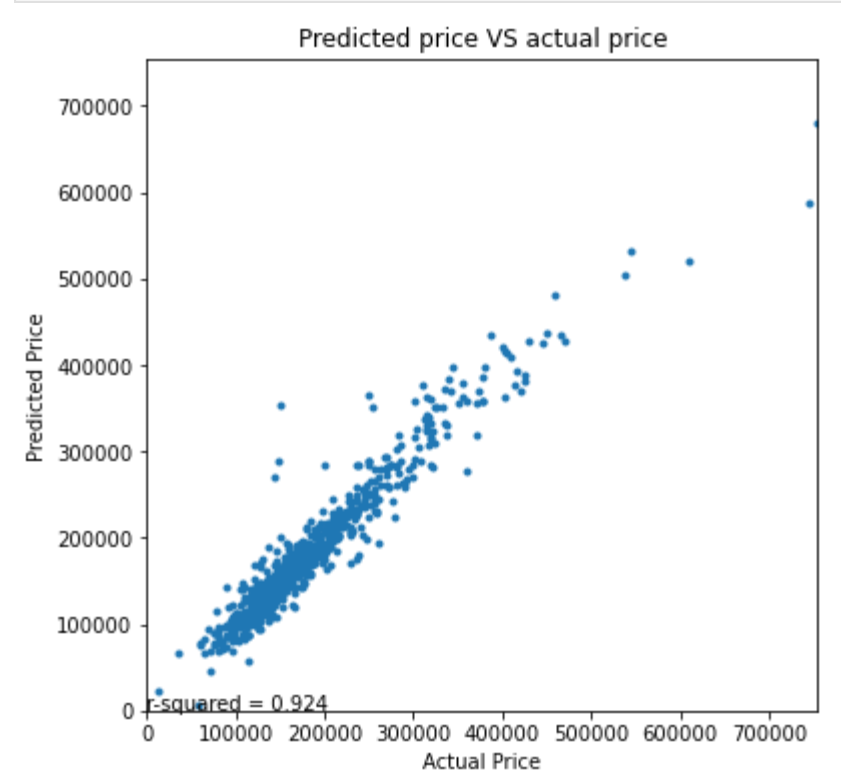
2. Simple linear regression with GridSearchCV

In [84]:
```
param_grid = {'fit_intercept': ['bool', 'True'],
              'n_jobs': np.arange(1,21)}

grid = GridSearchCV(LinearRegression(), param_grid, cv=4, scoring='r2')

grid.fit(X_train, y_train)

print(grid.best_score_)
print(grid.best_params_)
print(grid.best_estimator_)

model_lr = grid.best_estimator_

y_pred = model_lr.predict(X_test)

r2_lr = model_lr.score(X_test, y_test).round(3)
rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred)).round(0)
print('RMSE_Linear_Regression:',rmse_lr)
print('r2 :', r2_lr)
```

```
0.9229727482155242
{'fit_intercept': 'bool', 'n_jobs': 1}
LinearRegression(fit_intercept='bool', n_jobs=1)
RMSE_Linear_Regression: 23050.0
r2 : 0.924
```

In [85]:
```
def Plot(y_test, y_pred):
    f = plt.figure(figsize=(6,6))
    ax = plt.axes()
    ax.plot(y_test, y_pred, marker='o', ls='', ms=3.0)
    ax.annotate("r-squared = {:.3f}".format(r2_score(y_test, y_pred)), (0,1))
    lim = (0, y_test.max())
    ax.set(xlabel='Actual Price',
           ylabel='Predicted Price',
           xlim=lim,
           ylim=lim,
           title='Predicted price VS actual price', );
```

In [86]:
```
Plot(y_test, y_pred)
```



3. Scaling numerical features

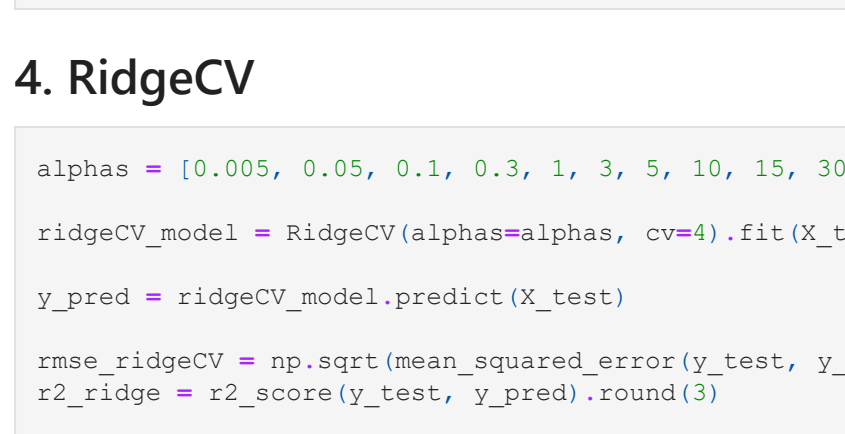
In [87]:
```
scaler = StandardScaler()
num_col = X_train.select_dtypes(include = ['float64', 'int64']).columns
X_train[num_col] = scaler.fit_transform(X_train[num_col])
X_test[num_col] = scaler.transform(X_test[num_col])
```

4. RidgeCV

In [88]:
```
alphas = [0.005, 0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 80]

ridgeCV_model = RidgeCV(alphas=alphas, cv=4).fit(X_train, y_train)

y_pred = ridgeCV_model.predict(X_test)

rmse_ridgeCV = np.sqrt(mean_squared_error(y_test, y_pred)).round(0)
r2_ridge = r2_score(y_test, y_pred).round(3)

print('Alpha_best',ridgeCV_model.alpha_)
print('RMSE_RidgeCV',rmse_ridgeCV)
print('r2 :', r2_ridge)
```

```
Alpha_best 10.0
RMSE_RidgeCV 22149.0
r2 : 0.93
```

In [89]:
```
Plot(y_test, y_pred)
```



5. LassoCV

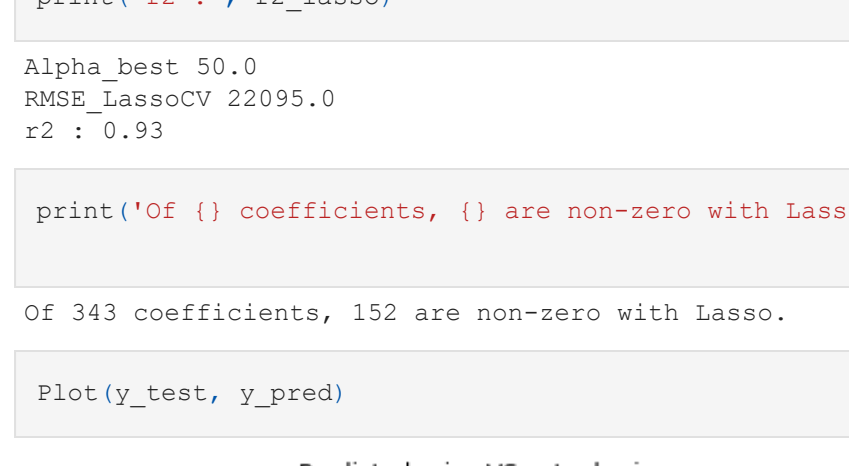
In [90]:
```
alphas2 = np.array([1e-5, 5e-5, 0.0001, 0.0005, 0.05, 0.1, 1, 5, 20, 50, 80, 100, 120, 140])

lassoCV_model = LassoCV(alphas=alphas2, max_iter=5e5, cv=4).fit(X_train, y_train)

y_pred = lassoCV_model.predict(X_test)

rmse_lassoCV = np.sqrt(mean_squared_error(y_test, y_pred)).round(0)
r2_lasso = r2_score(y_test, y_pred).round(3)

print('Alpha_best',lassoCV_model.alpha_)
print('RMSE_LassoCV',rmse_lassoCV)
print('r2 :', r2_lasso)
```

```
Alpha_best 50.0
RMSE_LassoCV 22095.0
r2 : 0.93
```

In [91]:
```
print('Of {} coefficients, {} are non-zero with Lasso.'.format(len(lassoCV_model.coef_),
                                                              len(lassoCV_model.coef_.nonzero()[0])))
```

```
Of 343 coefficients, 152 are non-zero with Lasso.
```

In [92]:
```
Plot(y_test, y_pred)
```



6. ElasticNetCV

In [93]:
```
l1_ratios = np.linspace(0.1, 0.9, 9)

elasticNetCV_model = ElasticNetCV(alphas=alphas2,
                                  l1_ratio=l1_ratios,
                                  max_iter=15e5).fit(X_train, y_train)

y_pred = elasticNetCV_model.predict(X_test)

rmse_elasticNetCV = np.sqrt(mean_squared_error(y_test, y_pred)).round(0)

r2_elasticNetCV = r2_score(y_test, y_pred).round(3)

print('Alpha_best',elasticNetCV_model.alpha_)
print('RMSE_elasticNetCV',rmse_elasticNetCV)
print('r2 :', r2_elasticNetCV)
```

```
C:\Users\godet\anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:633: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations. Duality gap: 8033072842.539062
5, tolerance: 1093400454.5755181
  model = cd_fast.enet_coordinate_descent_gram(
C:\Users\godet\anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:633: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations. Duality gap: 2991554944.078613
3, tolerance: 1079843679.0488164
  model = cd_fast.enet_coordinate_descent_gram(
C:\Users\godet\anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:633: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations. Duality gap: 2627979628.62359
6, tolerance: 1118839322.64557
  model = cd_fast.enet_coordinate_descent_gram(
C:\Users\godet\anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:633: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations. Duality gap: 1424847463.729980
5, tolerance: 1047134139.775393
  model = cd_fast.enet_coordinate_descent_gram(
Alpha_best 0.05
RMSE_elasticNetCV 22150.0
r2 : 0.93
```

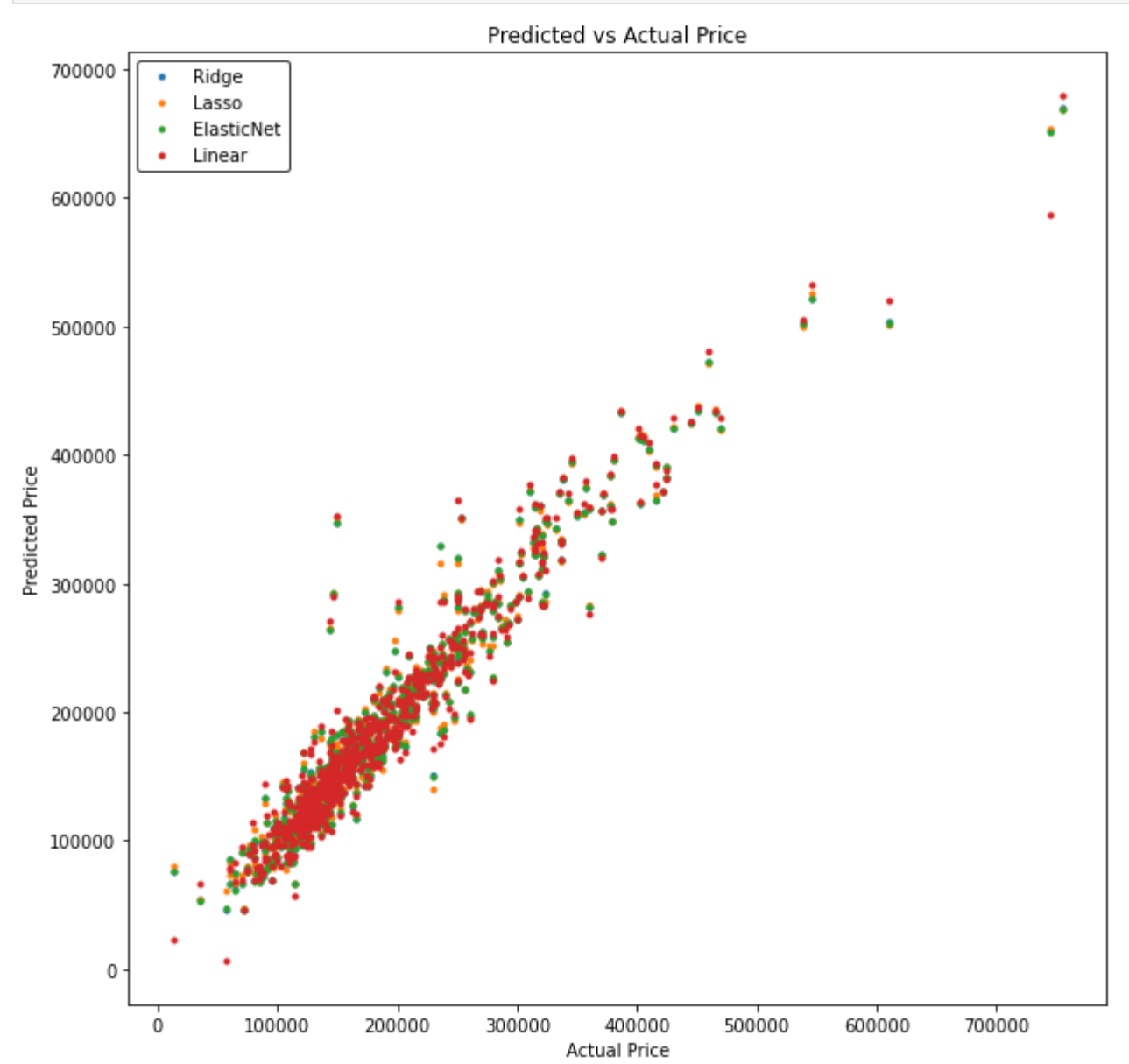
7. Result and discussion

In [94]:
```
rmse_vals = [rmse_lr, rmse_ridgeCV, rmse_lassoCV, rmse_elasticNetCV]
r2_vals = [r2_lr, r2_ridge, r2_lasso, r2_elasticNetCV]
labels = ['Linear', 'Ridge', 'Lasso', 'ElasticNet']

df = pd.Series(rmse_vals, index=labels).to_frame()
df.rename(columns={0: 'RMSE'}, inplace=1)
df['R2'] = pd.Series(r2_vals, index=labels).to_frame()
df
```

Out[94]:

	RMSE	R2
Linear	23050.0	0.924
Ridge	22149.0	0.930
Lasso	22095.0	0.930
ElasticNet	22150.0	0.930

In [95]:
```
f = plt.figure(figsize=(10,10))
ax = plt.axes()

labels = ['Ridge', 'Lasso', 'ElasticNet']

models = [ridgeCV_model, lassoCV_model, elasticNetCV_model]

for mod, lab in zip(models, labels):
    ax.plot(y_test, mod.predict(X_test),
             marker='o', ls='', ms=3.0, label=lab)

X = data.drop('SalePrice', axis = 1)
y = data['SalePrice']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 5)
ax.plot(y_test, model_lr.predict(X_test),
             marker='o', ls='', ms=3.0, label='Linear')

leg = plt.legend(frameon=True)
leg.get_frame().set_edgecolor('black')
leg.get_frame().set_linewidth(1.0)

ax.set(xlabel='Actual Price',
       ylabel='Predicted Price',
       title='Predicted vs Actual Price');
```



For these 4 regressions, very good results were obtained with r2 of 0.924 (simple linear regression) and 0.93 for the others. However, the lowest RMSE was obtained with LassoCV for a value of 22095. The best performing model on this dataset is LassoCV with 4 splits cross-validation and standardization using StandardScaler.

In [ ]: