House pricing prediction using Regression Analysis

January 12, 2021

1 1- Introduction

A very common use of machine learning regression techniques is predicting prices of goods. Especially prices of real estate due to all the telling features that have influence of the price.

In the following notebook we will make use of the publicaly available housing price data (https://www.kaggle.com/c/house-prices-advanced-regression-techniques).

This is data set is particularly good for exploratory data analysis and feature engineering as it has a whopping 79 variables to analyse. Here is a description of the features:

- SalePrice - the property's sale price in dollars. This is the target variable that you're trying to predict.
- MSSubClass: The building class
- MSZoning: The general zoning classification
- LotFrontage: Linear feet of street connected to property
- LotArea: Lot size in square feet
- Street: Type of road access
- Alley: Type of alley access
- LotShape: General shape of property
- LandContour: Flatness of the property
- Utilities: Type of utilities available
- LotConfig: Lot configuration
- LandSlope: Slope of property
- Neighborhood: Physical locations within Ames city limits
- Condition1: Proximity to main road or railroad
- Condition2: Proximity to main road or railroad (if a second is present)
- BldgType: Type of dwelling
- HouseStyle: Style of dwelling
- OverallQual: Overall material and finish quality
- OverallCond: Overall condition rating
- YearBuilt: Original construction date
- YearRemodAdd: Remodel date
- RoofStyle: Type of roof
- RoofMatl: Roof material
- Exterior1st: Exterior covering on house
- Exterior2nd: Exterior covering on house (if more than one material)
- MasVnrType: Masonry veneer type
- MasVnrArea: Masonry veneer area in square feet

- ExterQual: Exterior material quality
- ExterCond: Present condition of the material on the exterior
- Foundation: Type of foundation
- BsmtQual: Height of the basement
- BsmtCond: General condition of the basement
- BsmtExposure: Walkout or garden level basement walls
- BsmtFinType1: Quality of basement finished area
- BsmtFinSF1: Type 1 finished square feet
- BsmtFinType2: Quality of second finished area (if present)
- BsmtFinSF2: Type 2 finished square feet
- BsmtUnfSF: Unfinished square feet of basement area
- TotalBsmtSF: Total square feet of basement area
- Heating: Type of heating
- HeatingQC: Heating quality and condition
- CentralAir: Central air conditioning
- Electrical: Electrical system
- 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: Number of bedrooms above basement level
- Kitchen: Number of kitchens
- KitchenQual: Kitchen quality
- TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)
- Functional: Home functionality rating
- Fireplaces: Number of fireplaces
- FireplaceQu: Fireplace quality
- GarageType: Garage location
- GarageYrBlt: Year garage was built
- GarageFinish: Interior finish of the garage
- GarageCars: Size of garage in car capacity
- GarageArea: Size of garage in square feet
- GarageQual: Garage quality
- GarageCond: Garage condition
- PavedDrive: Paved driveway
- 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
- Fence: Fence quality
- MiscFeature: Miscellaneous feature not covered in other categories

- MiscVal: $Value of miscellaneous feature
- MoSold: Month Sold
- YrSold: Year Sold
- SaleType: Type of sale
- SaleCondition: Condition of sale

let's ge to it!

Importing the data

[1]:
```
import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import sklearn.linear_model as linear_model
from sklearn.ensemble import GradientBoostingRegressor


pd.options.display.max_rows = 1000
pd.options.display.max_columns = 20
```

[2]:
```
train = pd.read_csv('C:/Users/eliec/house-prices-advanced-regression-techniques/
↪train.csv')
test = pd.read_csv('C:/Users/eliec/house-prices-advanced-regression-techniques/
↪test.csv')
```

[3]:
```
print(train.columns)
train.head()
```

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

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

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

[4]:
```python
print(test.columns)
test.head()
```

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition'],
      dtype='object')
```

[4]:
```
     Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0  1461          20       RH         80.0    11622   Pave   NaN      Reg
1  1462          20       RL         81.0    14267   Pave   NaN      IR1
```

```
2  1463           60        RL          74.0     13830    Pave    NaN       IR1
3  1464           60        RL          78.0      9978    Pave    NaN       IR1
4  1465          120        RL          43.0      5005    Pave    NaN       IR1

  LandContour Utilities  … ScreenPorch PoolArea PoolQC  Fence MiscFeature  \
0         Lvl    AllPub  …         120        0    NaN  MnPrv         NaN
1         Lvl    AllPub  …           0        0    NaN    NaN        Gar2
2         Lvl    AllPub  …           0        0    NaN  MnPrv         NaN
3         Lvl    AllPub  …           0        0    NaN    NaN         NaN
4         HLS    AllPub  …         144        0    NaN    NaN         NaN

  MiscVal MoSold  YrSold  SaleType  SaleCondition
0       0      6    2010        WD         Normal
1   12500      6    2010        WD         Normal
2       0      3    2010        WD         Normal
3       0      6    2010        WD         Normal
4       0      1    2010        WD         Normal

[5 rows x 80 columns]
```

[5]:
```
print ("train shape", train.shape)
print ("test shape", test.shape)
```

```
train shape (1460, 81)
test shape (1459, 80)
```

Splitting and organizing the data Due to the high number of variables and generally a good practice, we will split our variables into 3 main categories. Qualitative/Discrete, Quantitative/Continuous and Datetime. This will help us in the analysis as those 3 categories tend to be analized using different approaches.

[6]:
```
quantitative = [f for f in train.columns if train.dtypes[f] != 'object']
quantitative.remove('SalePrice')
quantitative.remove('Id')
qualitative = [f for f in train.columns if train.dtypes[f] == 'object']
```

[7]:
```
print("quantitative: ", len(quantitative))
print("qualitative: ", len(qualitative))
```

```
quantitative:  36
qualitative:  43
```

eventhough some features are expressed in numbers, it does not mean that they are continous. We will look at the length of the unique values for each quantitative feature to get a hint of whether to treat it as dicrete or continous.

[8]:
```
for f in quantitative:
    print(f, "has", len(train[f].unique()), "values")
```

```
MSSubClass has 15 values
LotFrontage has 111 values
LotArea has 1073 values
OverallQual has 10 values
OverallCond has 9 values
YearBuilt has 112 values
YearRemodAdd has 61 values
MasVnrArea has 328 values
BsmtFinSF1 has 637 values
BsmtFinSF2 has 144 values
BsmtUnfSF has 780 values
TotalBsmtSF has 721 values
1stFlrSF has 753 values
2ndFlrSF has 417 values
LowQualFinSF has 24 values
GrLivArea has 861 values
BsmtFullBath has 4 values
BsmtHalfBath has 3 values
FullBath has 4 values
HalfBath has 3 values
BedroomAbvGr has 8 values
KitchenAbvGr has 4 values
TotRmsAbvGrd has 12 values
Fireplaces has 4 values
GarageYrBlt has 98 values
GarageCars has 5 values
GarageArea has 441 values
WoodDeckSF has 274 values
OpenPorchSF has 202 values
EnclosedPorch has 120 values
3SsnPorch has 20 values
ScreenPorch has 76 values
PoolArea has 8 values
MiscVal has 21 values
MoSold has 12 values
YrSold has 5 values
```

[9]:

```
discrete = ['MSSubClass', 'OverallQual', 'OverallCond',␣
 ↪'LowQualFinSF','BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces', 'GarageCars',␣
 ↪'3SsnPorch','MiscVal', 'MoSold', 'YrSold']
print("discrete", len(discrete))
date = ['YearBuilt','YearRemodAdd', 'GarageYrBlt']
print("date", len(date))
```

```
discrete 17
date 3
```

[10]:
```
qualitative = qualitative+discrete
print("qualtitative", len(qualitative))
```

```
qualtitative 60
```

[11]:
```
quali_date = qualitative+date
```

[12]:
```
quantitative = train.columns.to_list()

for f in quali_date:
    quantitative.remove(f)

quantitative.remove("Id")
quantitative.remove("SalePrice")

print("quantitative", len(quantitative))
quantitative
```

```
quantitative 16
```

[12]:
```
['LotFrontage',
 'LotArea',
 'MasVnrArea',
 'BsmtFinSF1',
 'BsmtFinSF2',
 'BsmtUnfSF',
 'TotalBsmtSF',
 '1stFlrSF',
 '2ndFlrSF',
 'GrLivArea',
 'GarageArea',
 'WoodDeckSF',
 'OpenPorchSF',
 'EnclosedPorch',
 'ScreenPorch',
 'PoolArea']
```

2 2- Exploratory Data Analysis

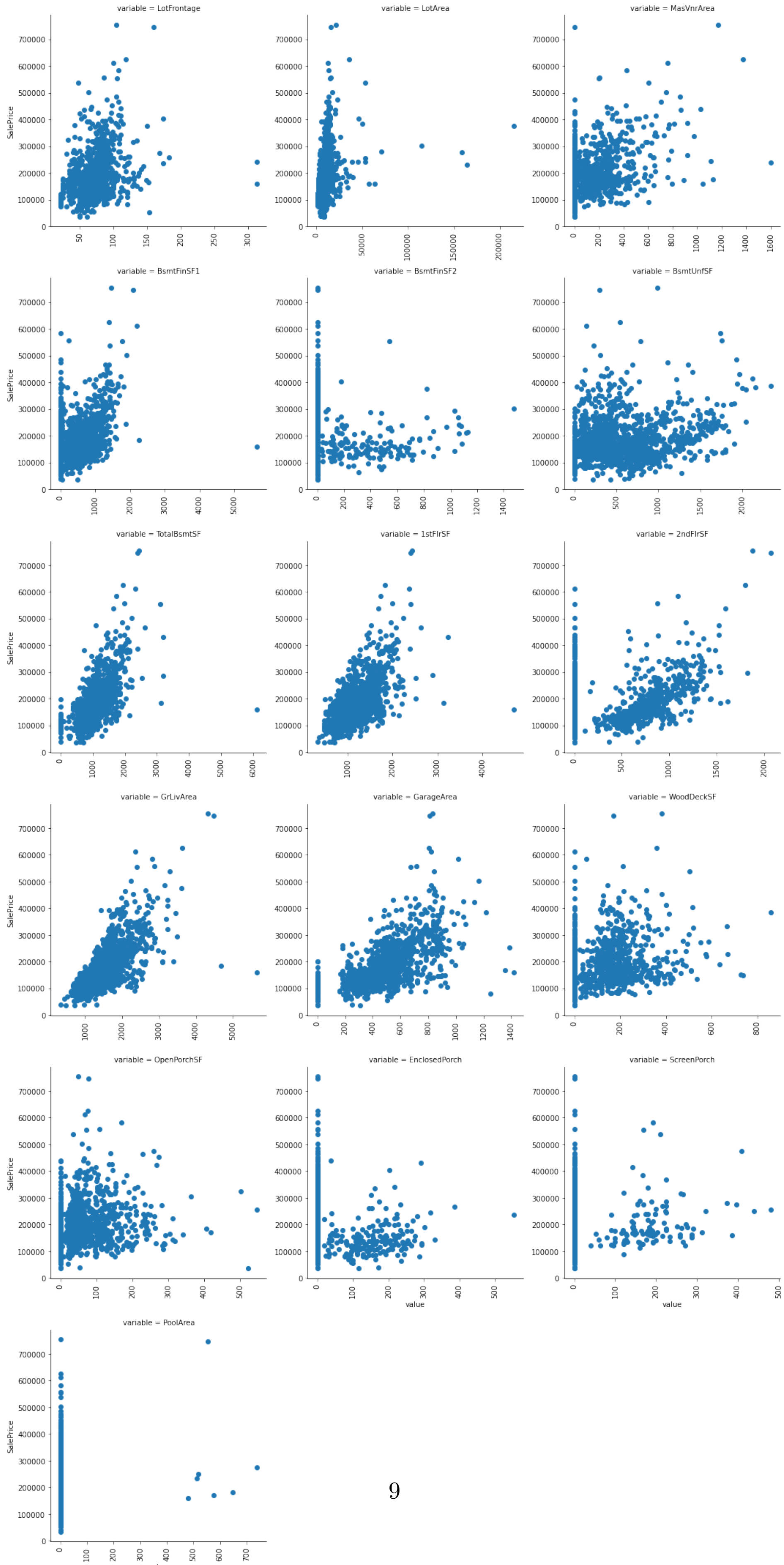
2.1 Continuous Features

2.1.1 Pairplots

It would be useful to see how sale price compares to each continous variable.

[13]:
```
def pairplot(x, y, **kwargs):
    ax = plt.gca()
    ax.scatter(x=x, y=y)
    plt.xticks(rotation=90)
```

```
f_quantitative = pd.melt(train, id_vars=['SalePrice'], value_vars=quantitative)
g = sns.FacetGrid(f_quantitative, col="variable",  col_wrap=3, sharex=False, sharey=False, height=5)
g = g.map(pairplot, "value", "SalePrice")
```


variable = LotFrontage
variable = LotArea
variable = MasVnrArea
variable = BsmtFinSF1
variable = BsmtFinSF2
variable = BsmtUnfSF
variable = TotalBsmtSF
variable = 1stFlrSF
variable = 2ndFlrSF
variable = GrLivArea
variable = GarageArea
variable = WoodDeckSF
variable = OpenPorchSF
variable = EnclosedPorch
variable = ScreenPorch
variable = PoolArea
SalePrice
value

[14]:

```
train[quantitative].corr("pearson")
```

[14]:

	LotFrontage	LotArea	MasVnrArea	BsmtFinSF1	BsmtFinSF2 \
LotFrontage	1.000000	0.426095	0.193458	0.233633	0.049900
LotArea	0.426095	1.000000	0.104160	0.214103	0.111170
MasVnrArea	0.193458	0.104160	1.000000	0.264736	-0.072319
BsmtFinSF1	0.233633	0.214103	0.264736	1.000000	-0.050117
BsmtFinSF2	0.049900	0.111170	-0.072319	-0.050117	1.000000
BsmtUnfSF	0.132644	-0.002618	0.114442	-0.495251	-0.209294
TotalBsmtSF	0.392075	0.260833	0.363936	0.522396	0.104810
1stFlrSF	0.457181	0.299475	0.344501	0.445863	0.097117
2ndFlrSF	0.080177	0.050986	0.174561	-0.137079	-0.099260
GrLivArea	0.402797	0.263116	0.390857	0.208171	-0.009640
GarageArea	0.344997	0.180403	0.373066	0.296970	-0.018227
WoodDeckSF	0.088521	0.171698	0.159718	0.204306	0.067898
OpenPorchSF	0.151972	0.084774	0.125703	0.111761	0.003093
EnclosedPorch	0.010700	-0.018340	-0.110204	-0.102303	0.036543
ScreenPorch	0.041383	0.043160	0.061466	0.062021	0.088871
PoolArea	0.206167	0.077672	0.011723	0.140491	0.041709

	BsmtUnfSF	TotalBsmtSF	1stFlrSF	2ndFlrSF	GrLivArea \
LotFrontage	0.132644	0.392075	0.457181	0.080177	0.402797
LotArea	-0.002618	0.260833	0.299475	0.050986	0.263116
MasVnrArea	0.114442	0.363936	0.344501	0.174561	0.390857
BsmtFinSF1	-0.495251	0.522396	0.445863	-0.137079	0.208171
BsmtFinSF2	-0.209294	0.104810	0.097117	-0.099260	-0.009640
BsmtUnfSF	1.000000	0.415360	0.317987	0.004469	0.240257
TotalBsmtSF	0.415360	1.000000	0.819530	-0.174512	0.454868
1stFlrSF	0.317987	0.819530	1.000000	-0.202646	0.566024
2ndFlrSF	0.004469	-0.174512	-0.202646	1.000000	0.687501
GrLivArea	0.240257	0.454868	0.566024	0.687501	1.000000
GarageArea	0.183303	0.486665	0.489782	0.138347	0.468997
WoodDeckSF	-0.005316	0.232019	0.235459	0.092165	0.247433
OpenPorchSF	0.129005	0.247264	0.211671	0.208026	0.330224
EnclosedPorch	-0.002538	-0.095478	-0.065292	0.061989	0.009113
ScreenPorch	-0.012579	0.084489	0.088758	0.040606	0.101510
PoolArea	-0.035092	0.126053	0.131525	0.081487	0.170205

	GarageArea	WoodDeckSF	OpenPorchSF	EnclosedPorch \
LotFrontage	0.344997	0.088521	0.151972	0.010700
LotArea	0.180403	0.171698	0.084774	-0.018340
MasVnrArea	0.373066	0.159718	0.125703	-0.110204
BsmtFinSF1	0.296970	0.204306	0.111761	-0.102303
BsmtFinSF2	-0.018227	0.067898	0.003093	0.036543

```
BsmtUnfSF        0.183303  -0.005316   0.129005      -0.002538
TotalBsmtSF      0.486665   0.232019   0.247264      -0.095478
1stFlrSF         0.489782   0.235459   0.211671      -0.065292
2ndFlrSF         0.138347   0.092165   0.208026       0.061989
GrLivArea        0.468997   0.247433   0.330224       0.009113
GarageArea       1.000000   0.224666   0.241435      -0.121777
WoodDeckSF       0.224666   1.000000   0.058661      -0.125989
OpenPorchSF      0.241435   0.058661   1.000000      -0.093079
EnclosedPorch   -0.121777  -0.125989  -0.093079       1.000000
ScreenPorch      0.051412  -0.074181   0.074304      -0.082864
PoolArea         0.061047   0.073378   0.060762       0.054203

               ScreenPorch  PoolArea
LotFrontage       0.041383  0.206167
LotArea           0.043160  0.077672
MasVnrArea        0.061466  0.011723
BsmtFinSF1        0.062021  0.140491
BsmtFinSF2        0.088871  0.041709
BsmtUnfSF        -0.012579 -0.035092
TotalBsmtSF       0.084489  0.126053
1stFlrSF          0.088758  0.131525
2ndFlrSF          0.040606  0.081487
GrLivArea         0.101510  0.170205
GarageArea        0.051412  0.061047
WoodDeckSF       -0.074181  0.073378
OpenPorchSF       0.074304  0.060762
EnclosedPorch    -0.082864  0.054203
ScreenPorch       1.000000  0.051307
PoolArea          0.051307  1.000000
```

[15]:
```
train[quantitative+["SalePrice"]].corr("pearson")["SalePrice"]
```

[15]:
```
LotFrontage      0.351799
LotArea          0.263843
MasVnrArea       0.477493
BsmtFinSF1       0.386420
BsmtFinSF2      -0.011378
BsmtUnfSF        0.214479
TotalBsmtSF      0.613581
1stFlrSF         0.605852
2ndFlrSF         0.319334
GrLivArea        0.708624
GarageArea       0.623431
WoodDeckSF       0.324413
OpenPorchSF      0.315856
EnclosedPorch   -0.128578
ScreenPorch      0.111447
```

```
PoolArea         0.092404
SalePrice        1.000000
Name: SalePrice, dtype: float64
```

Most of the features seem to have a certain correlation with the SalePrice but many have a lot of values equal to zero. This is due to the unit not having this particular feature. we need to deal with that by creating new boolean features for all of those features which have a strong correlation with SalePrice

- ScreenPorch = 0 does not have an open porch
- 2ndFlrSF = 0 does not have a 2nd floor
- TotalBsmtSF = 0 does not have a basement
- PoolArea = 0 does not have a pool

[16]:
```
train['Basement'] = train['TotalBsmtSF'].apply(lambda x: 1 if x > 0 else 0)
train['2ndFloor'] = train['2ndFlrSF'].apply(lambda x: 1 if x > 0 else 0)
train['Porch'] = train['ScreenPorch'].apply(lambda x: 1 if x > 0 else 0)
train['Pool'] = train['PoolArea'].apply(lambda x: 1 if x > 0 else 0)
```

[17]:
```
train.drop(columns=["TotalBsmtSF",'2ndFlrSF', 'ScreenPorch', 'PoolArea'],␣
↪inplace=True)
```

We will drop the features that have no impact on sales price and we should be investigating multicollinearity. A lot of the features are correlated so sales price but also to one another which could be problematic for our model. We need to filter our the features that are represented by other more important features and carry no additional information.

[18]:
```
train.drop(columns=["MasVnrArea", "BsmtFinSF1", "BsmtFinSF2", "BsmtUnfSF",␣
↪"GarageArea", "WoodDeckSF",
                    "OpenPorchSF", "EnclosedPorch"], inplace=True)
```

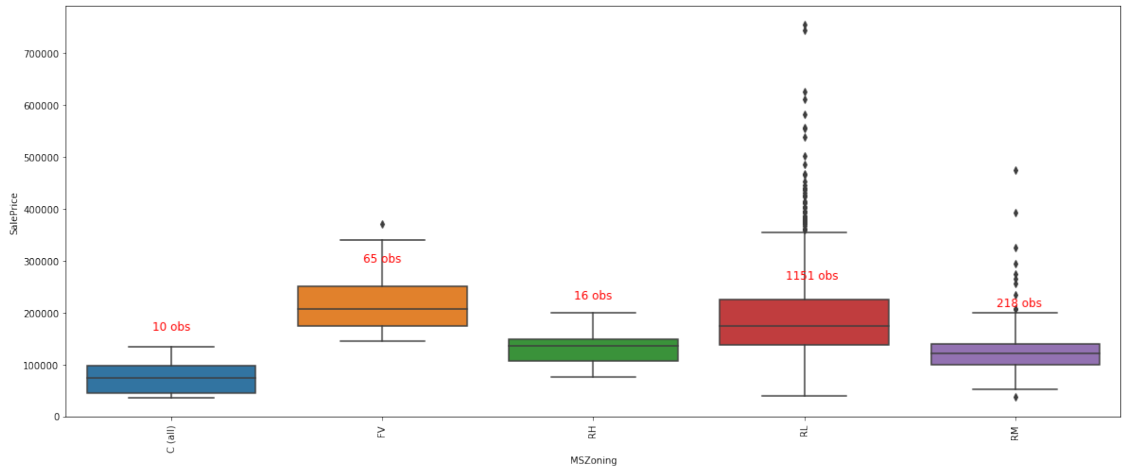
2.2 Discrete Features

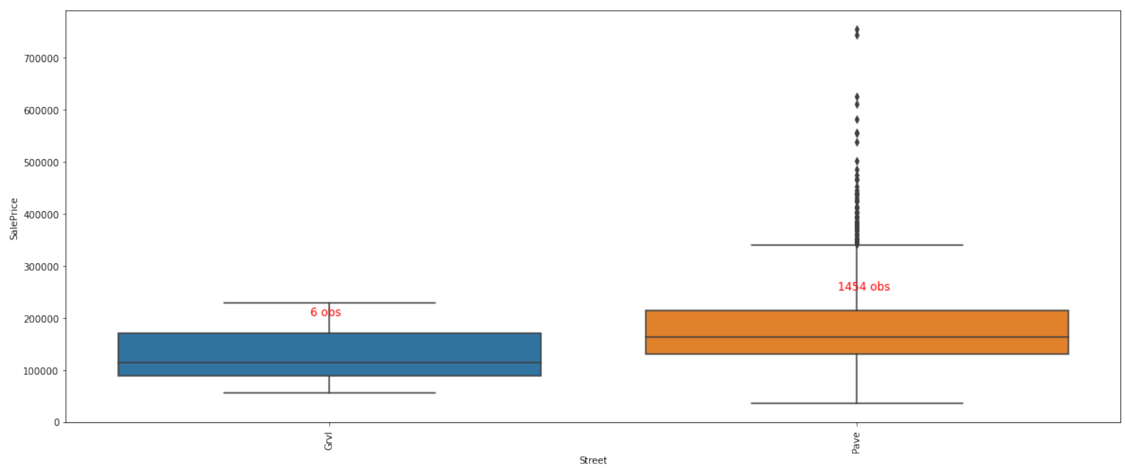
For simplicity we will replace all missing values in the discrete features with “missing” then we will plot a boxplot for each feature detailing the distrícution of that feature and the number of observations for each category. This will alow us to assess the impact of each feature on our target variable SalePrice so that we can decide whether the keep, drop or convert the feature.

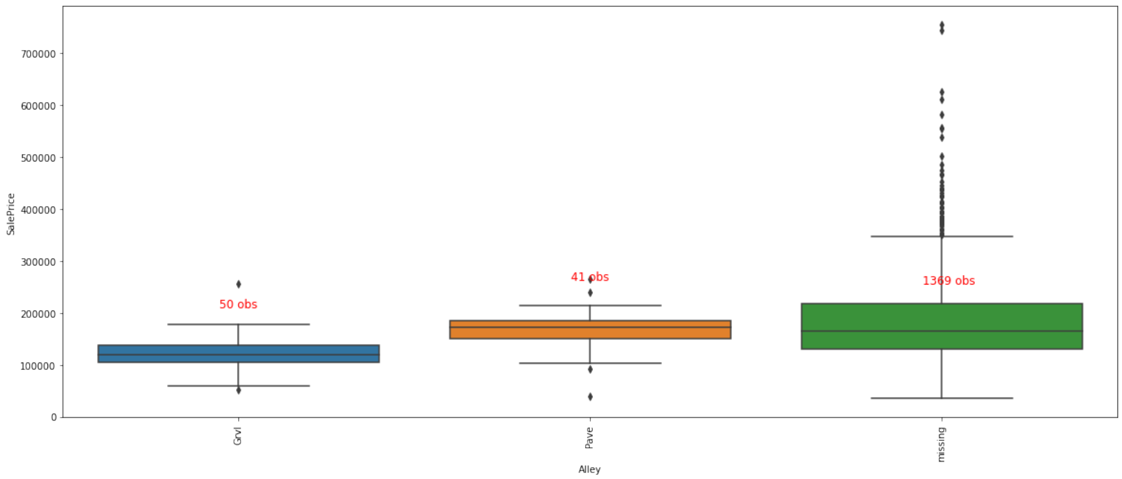
[19]:
```
for c in qualitative:
    train[c] = train[c].astype('category')
    if train[c].isnull().any():
        train[c] = train[c].cat.add_categories(['missing'])
        train[c] = train[c].fillna('missing')
```

[20]:
```
for x in qualitative:
    plt.rcParams.update({'figure.max_open_warning': 0})
    fig = plt.figure(figsize = (20, 8))
    ax = fig.add_subplot()
    ax = sns.boxplot(x=x, y="SalePrice", data=train)
```

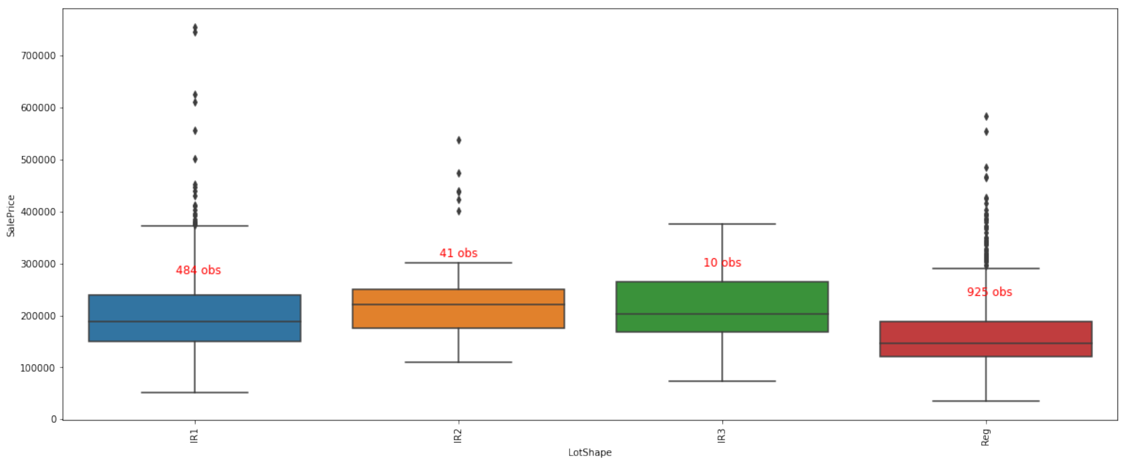
```
    plt.xticks(rotation=90)
    for v, tick in zip(sorted(train[x].unique()),ax.get_xticks()):
        ax.annotate("{} obs".format(len(train[train[x]==v])),
                xy = (tick, train[train[x]==v]["SalePrice"].median()),
                xytext = (-20, 50),
                color="red",
                textcoords = "offset points",
                fontsize = 12)
```



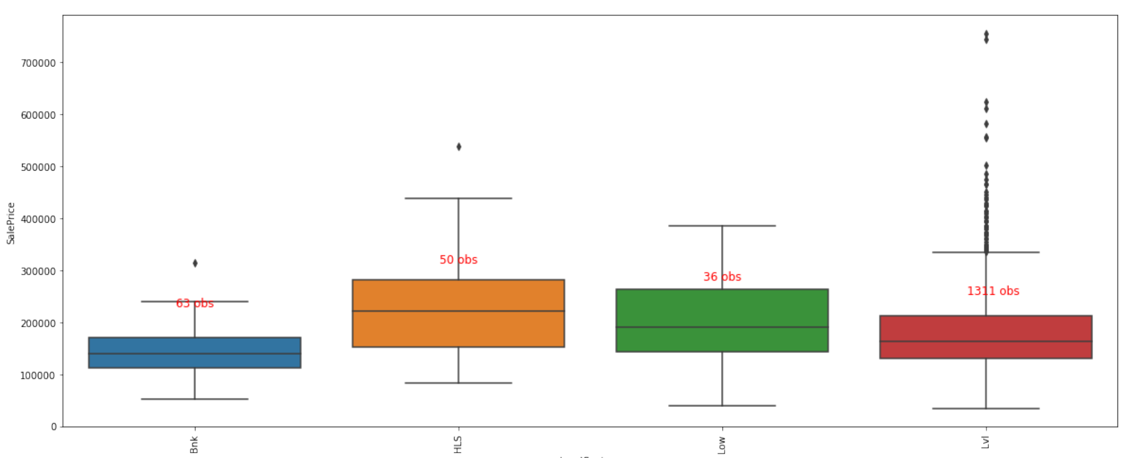




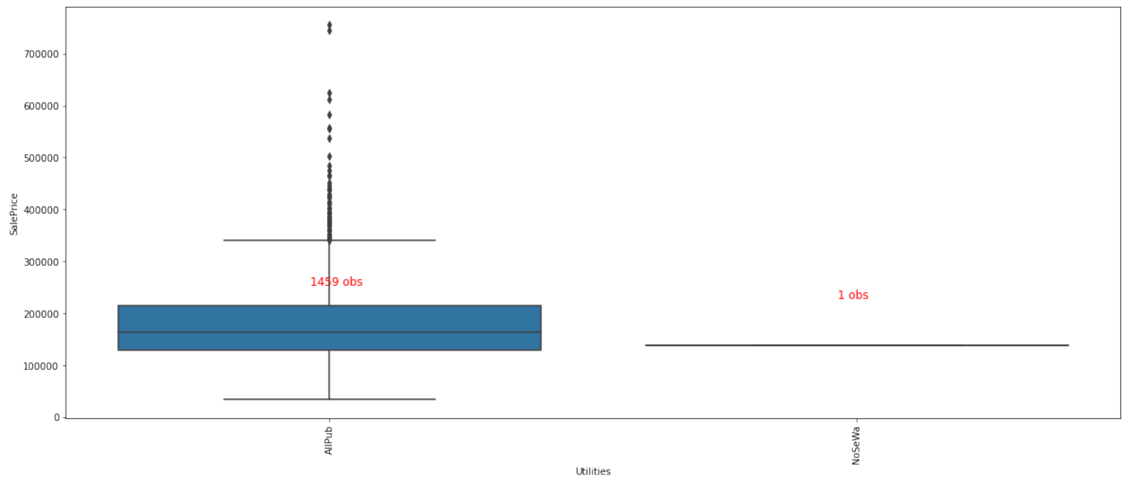
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
50 obs
41 obs
1369 obs
Grvl
Pave
missing
Alley



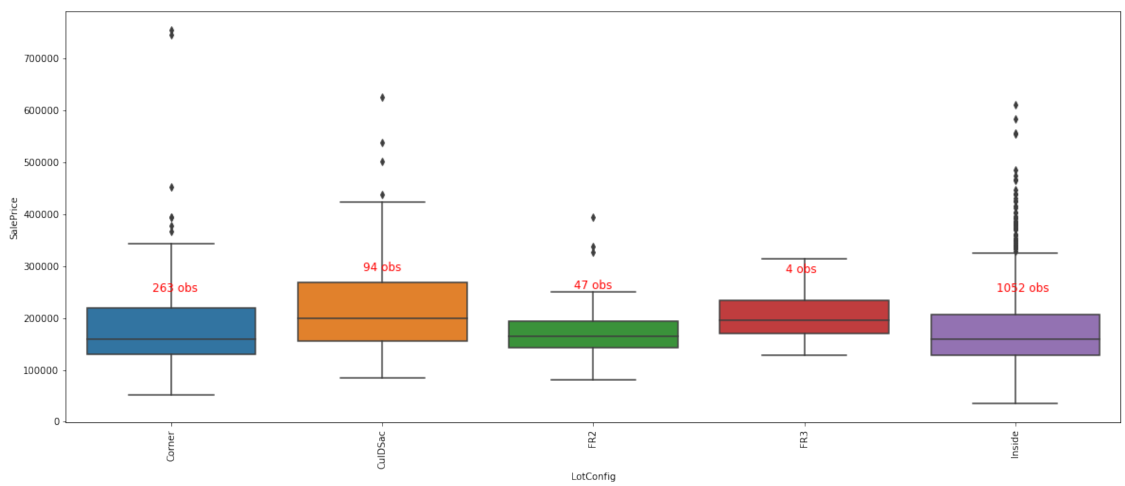
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
484 obs
41 obs
10 obs
925 obs
IR1
IR2
IR3
Reg
LotShape



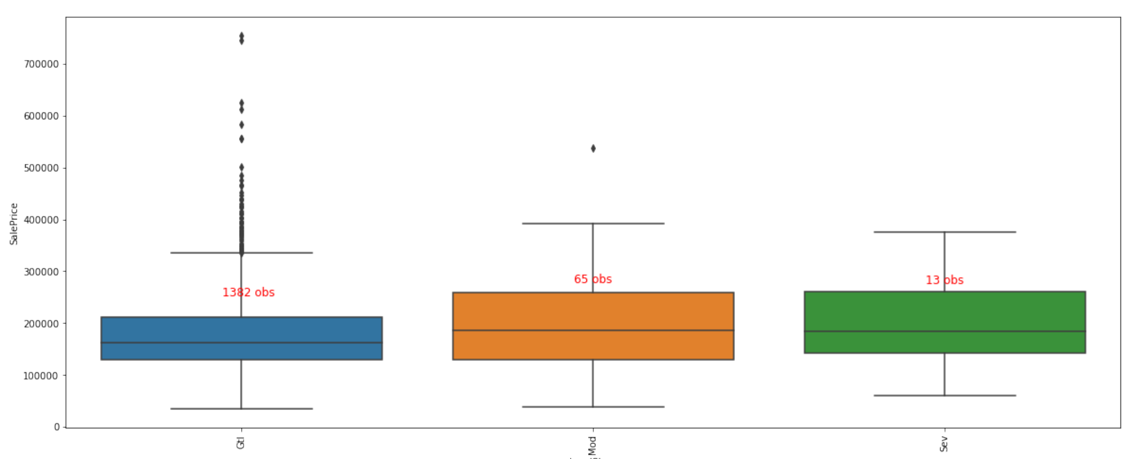
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
63 obs
50 obs
36 obs
1311 obs
Bnk
HLS
Low
Lvl
LandContour



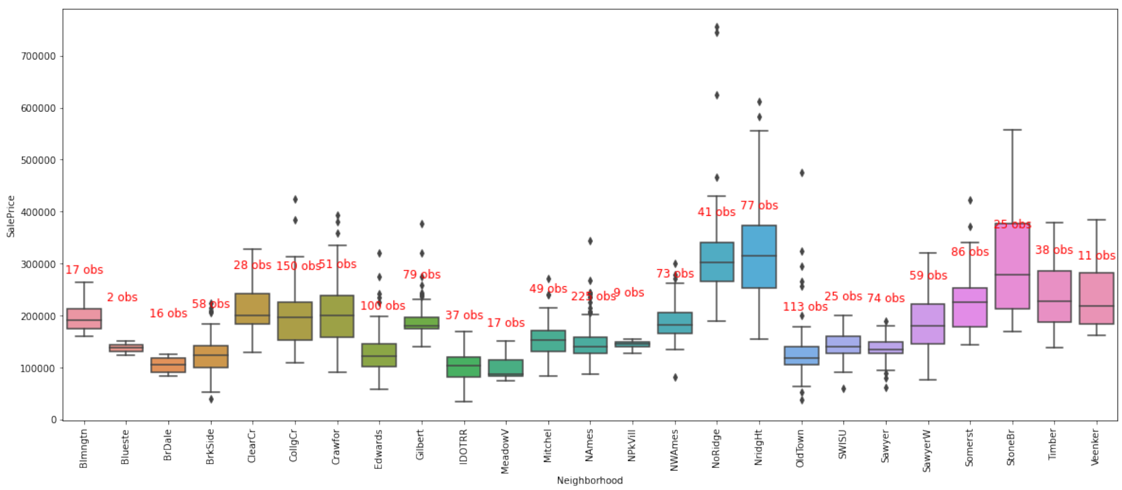
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1459 obs
1 obs
AllPub
NoSeWa
Utilities

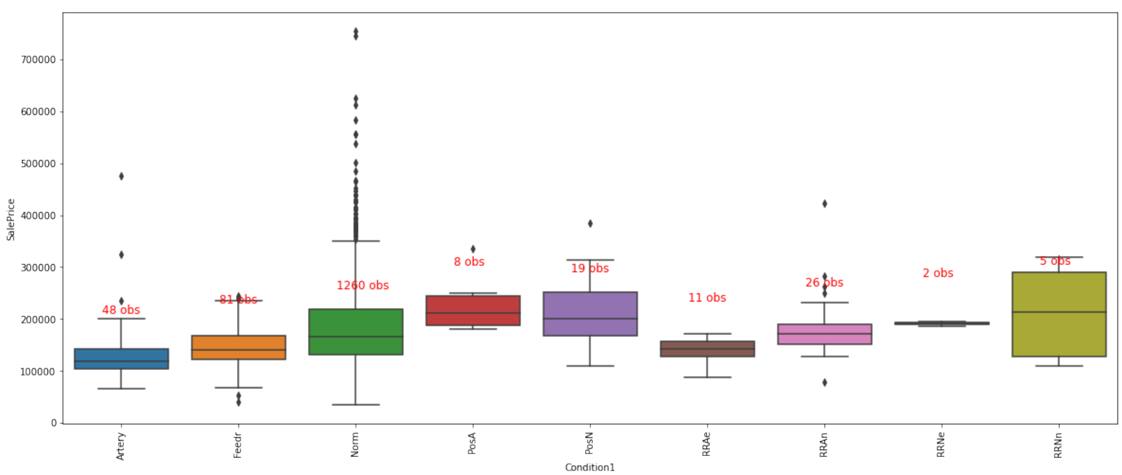


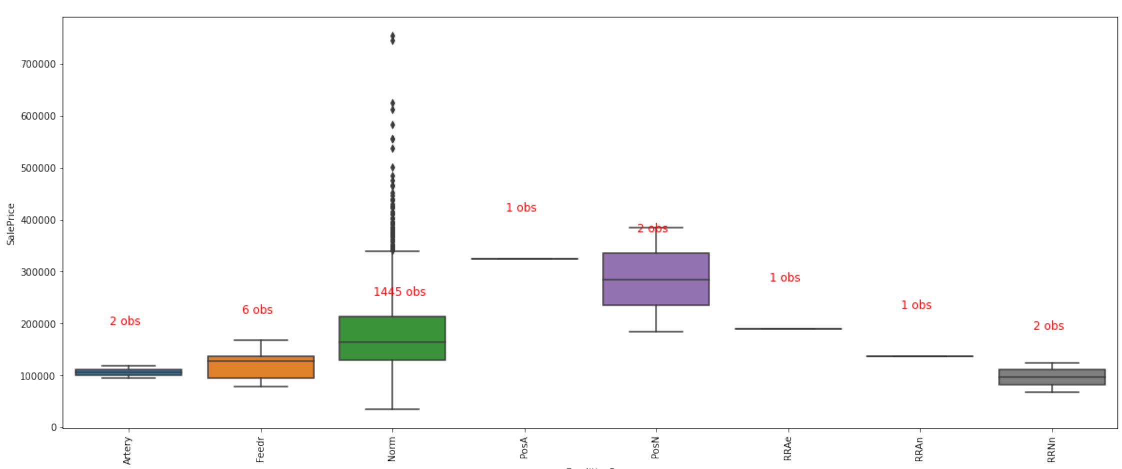
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
263 obs
94 obs
47 obs
4 obs
1052 obs
Corner
CulDSac
FR2
FR3
Inside
LotConfig

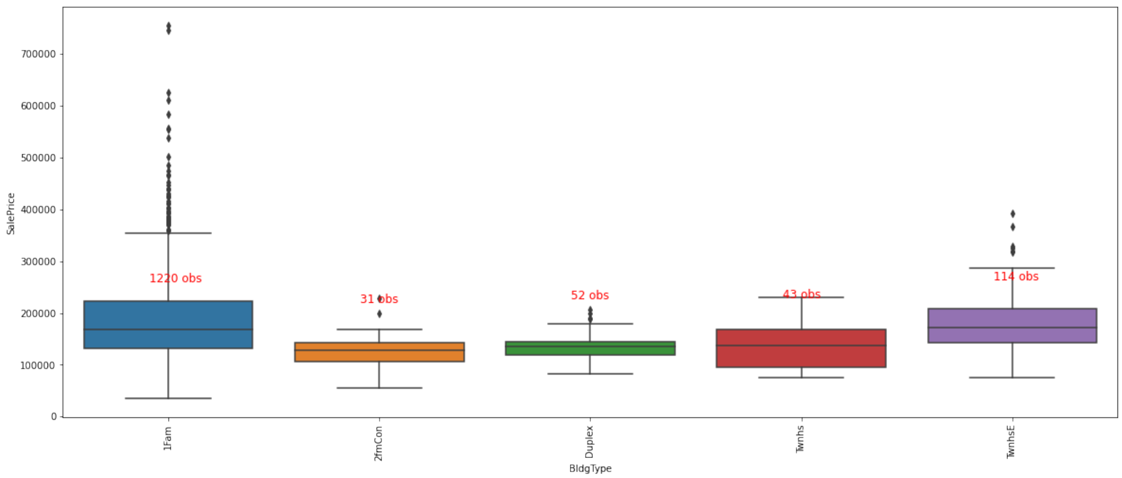


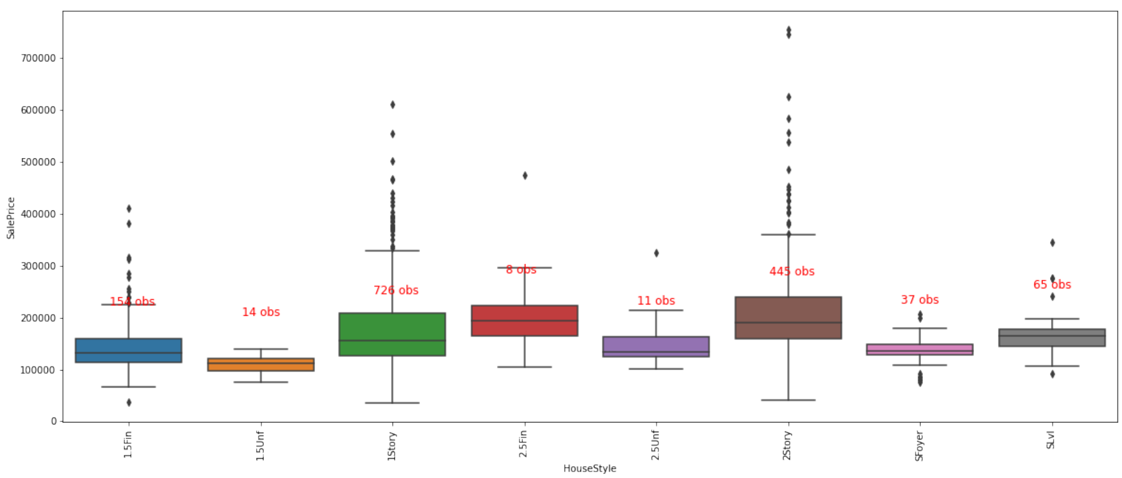
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1382 obs
65 obs
13 obs
Gtl
Mod
Sev
LandSlope

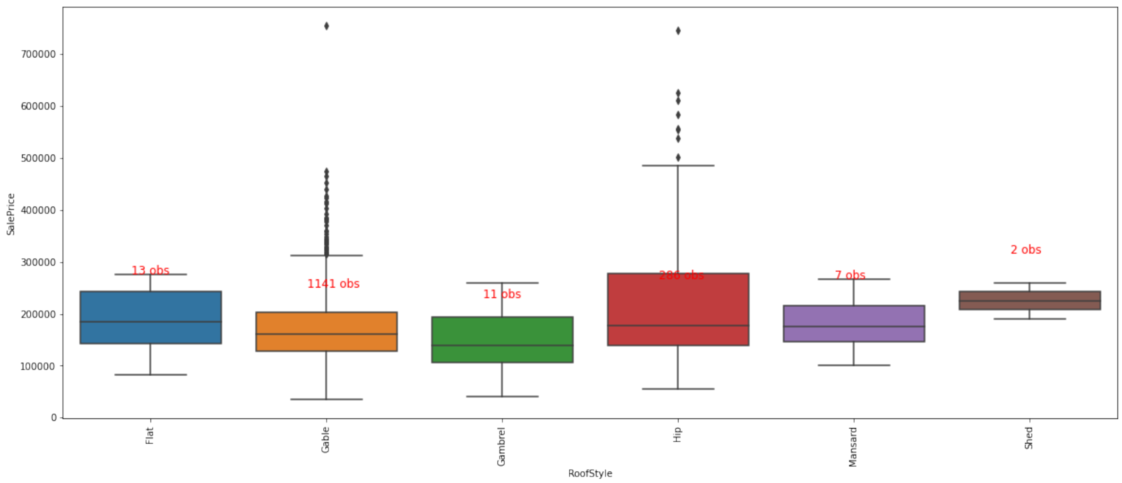

SalePrice
Neighborhood
Blmngtn
Blueste
BrDale
BrkSide
ClearCr
CollgCr
Crawfor
Edwards
Gilbert
IDOTRR
MeadowV
Mitchel
NAmes
NPkVill
NWAmes
NoRidge
NridgHt
OldTown
SWISU
Sawyer
SawyerW
Somerst
StoneBr
Timber
Veenker
17 obs
2 obs
16 obs
58 obs
28 obs
150 obs
51 obs
100 obs
79 obs
37 obs
17 obs
49 obs
225 obs
9 obs
73 obs
41 obs
77 obs
113 obs
25 obs
74 obs
59 obs
86 obs
25 obs
38 obs
11 obs

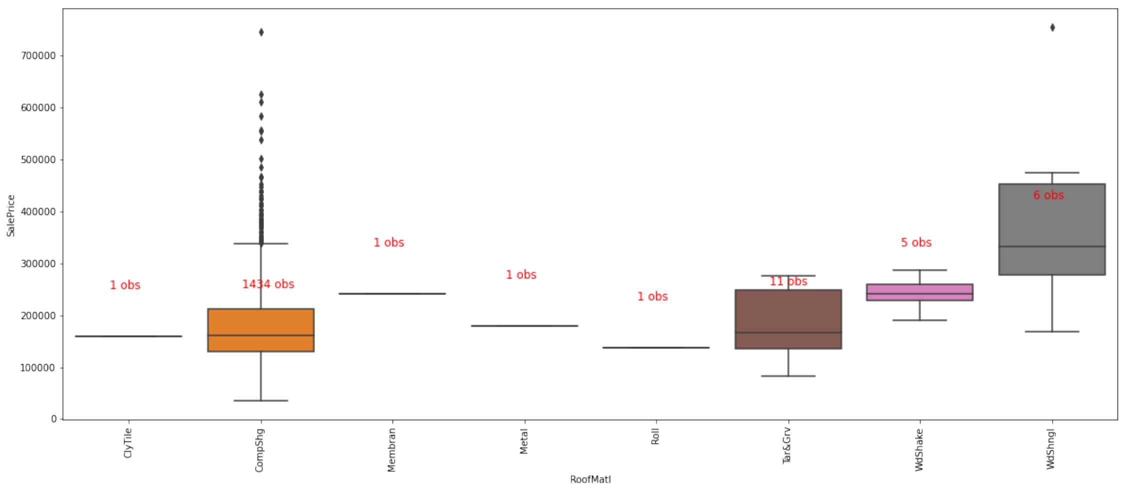

SalePrice
Condition1
Artery
Feedr
Norm
PosA
PosN
RRAe
RRAn
RRNe
RRNn
48 obs
81 obs
1260 obs
8 obs
19 obs
11 obs
26 obs
2 obs
5 obs

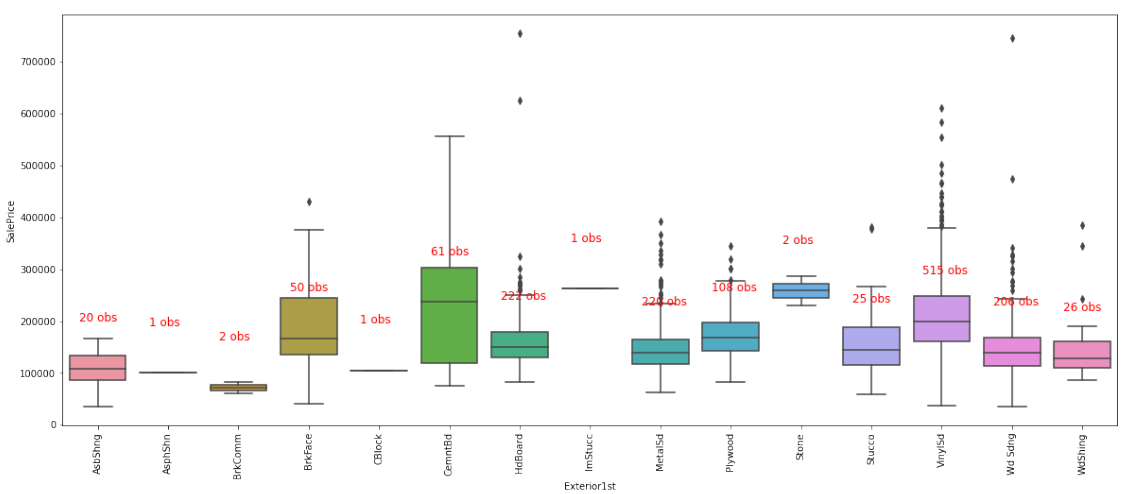

SalePrice
Condition2
Artery
Feedr
Norm
PosA
PosN
RRAe
RRAn
RRNn
2 obs
6 obs
1445 obs
1 obs
2 obs
1 obs
1 obs
2 obs

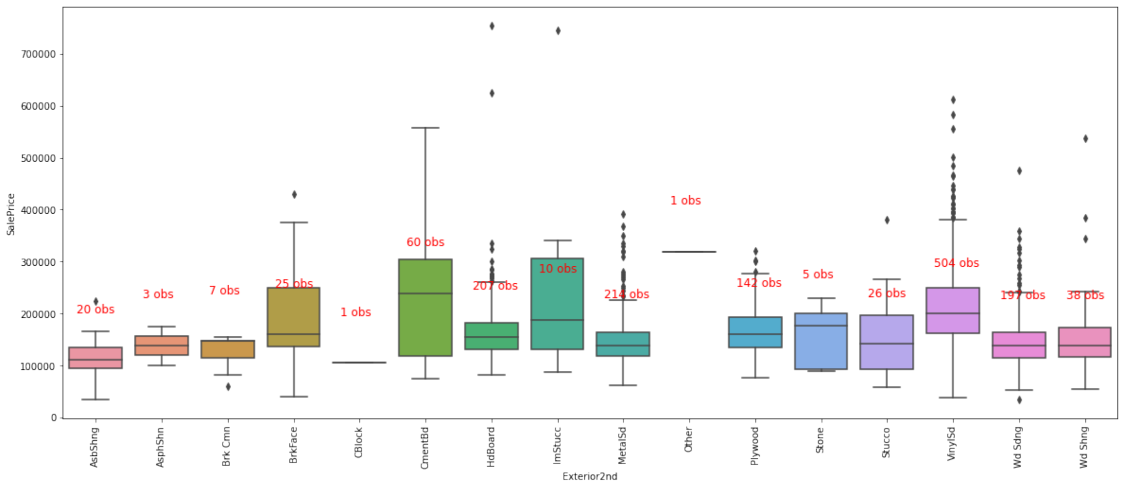

SalePrice
700000
600000
500000
400000
300000
200000
100000
0
1220 obs
31 obs
52 obs
43 obs
114 obs
1Fam
2fmCon
Duplex
Twnhs
TwnhsE
BldgType

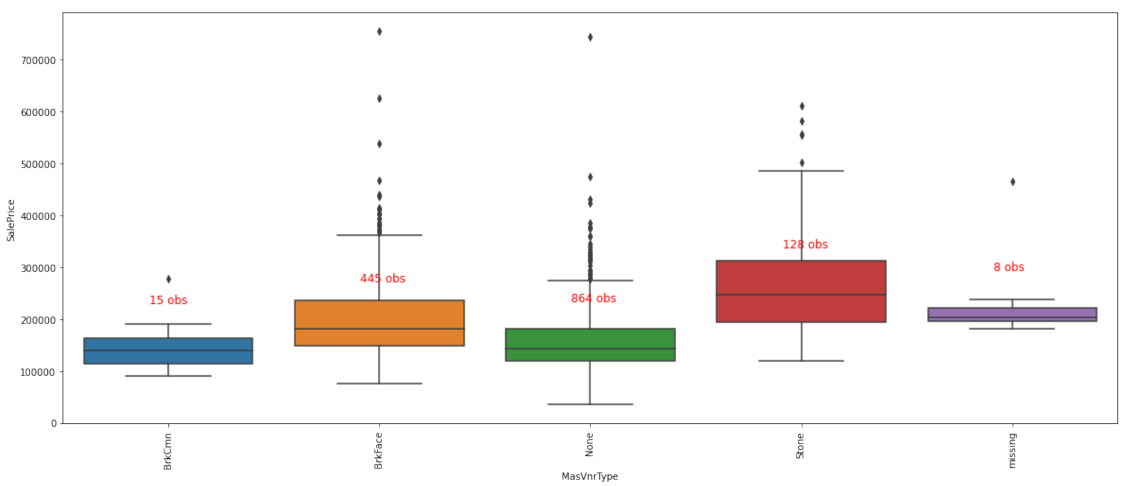

SalePrice
700000
600000
500000
400000
300000
200000
100000
0
154 obs
14 obs
726 obs
8 obs
11 obs
445 obs
37 obs
65 obs
1.5Fin
1.5Unf
1Story
2.5Fin
2.5Unf
2Story
SFoyer
SLvl
HouseStyle

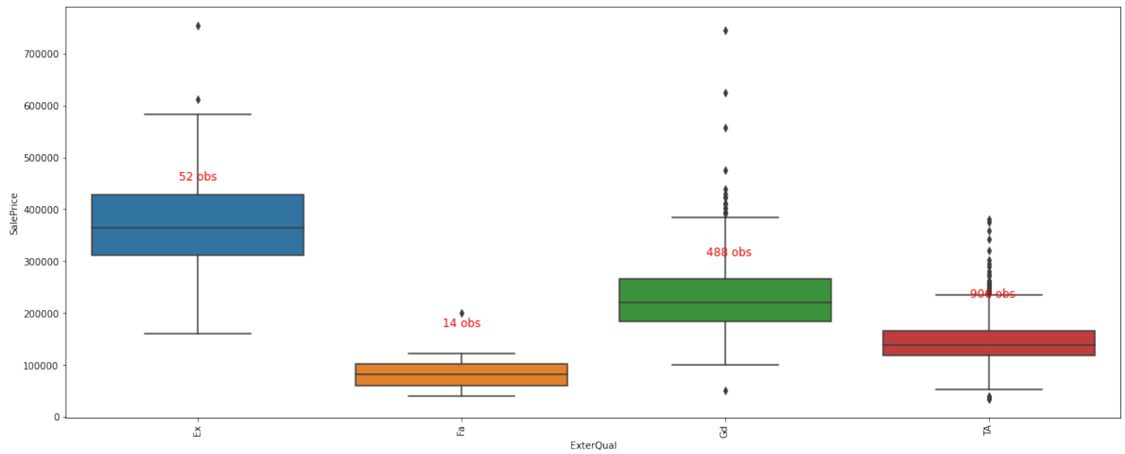

SalePrice
RoofStyle
Flat
Gable
Gambrel
Hip
Mansard
Shed
13 obs
1141 obs
11 obs
7 obs
2 obs

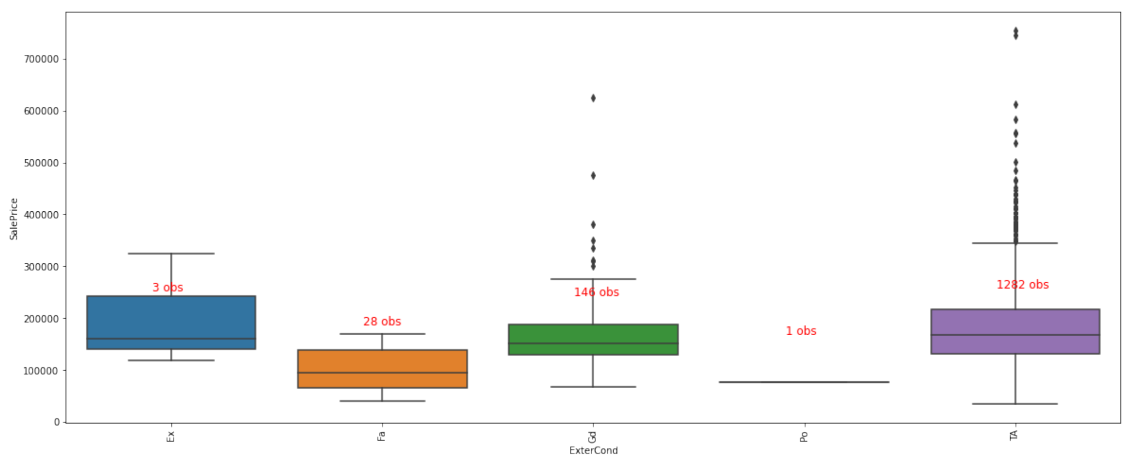

SalePrice
RoofMatl
ClyTile
CompShg
Membran
Metal
Roll
Tar&Grv
WdShake
WdShngl
1 obs
1434 obs
1 obs
1 obs
1 obs
11 obs
5 obs
6 obs

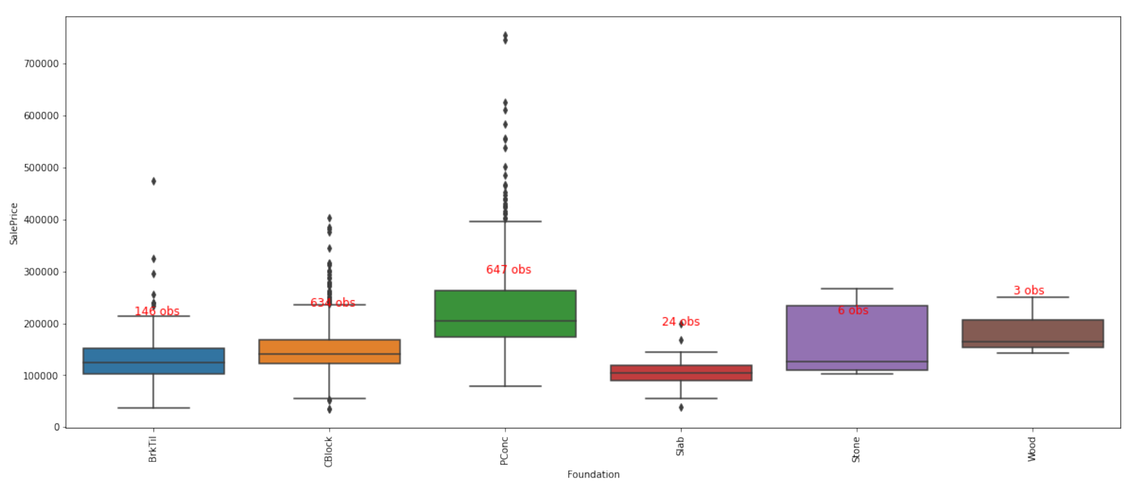

SalePrice
Exterior1st
AsbShng
AsphShn
BrkComm
BrkFace
CBlock
CemntBd
HdBoard
ImStucc
MetalSd
Plywood
Stone
Stucco
VinylSd
Wd Sdng
WdShing
20 obs
1 obs
2 obs
50 obs
1 obs
61 obs
1 obs
108 obs
2 obs
25 obs
515 obs
26 obs

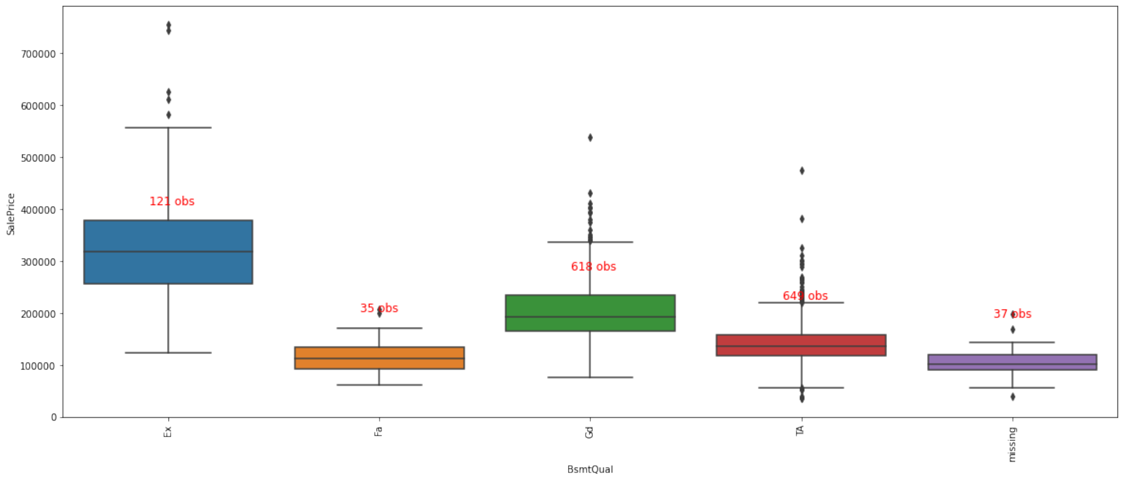

SalePrice
Exterior2nd
20 obs
3 obs
7 obs
25 obs
1 obs
60 obs
207 obs
10 obs
214 obs
1 obs
142 obs
5 obs
26 obs
504 obs
197 obs
38 obs
AsbShng
AsphShn
Brk Cmn
BrkFace
CBlock
CmentBd
HdBoard
ImStucc
MetalSd
Other
Plywood
Stone
Stucco
VinylSd
Wd Sdng
Wd Shng


SalePrice
MasVnrType
15 obs
445 obs
864 obs
128 obs
8 obs
BrkCmn
BrkFace
None
Stone
missing

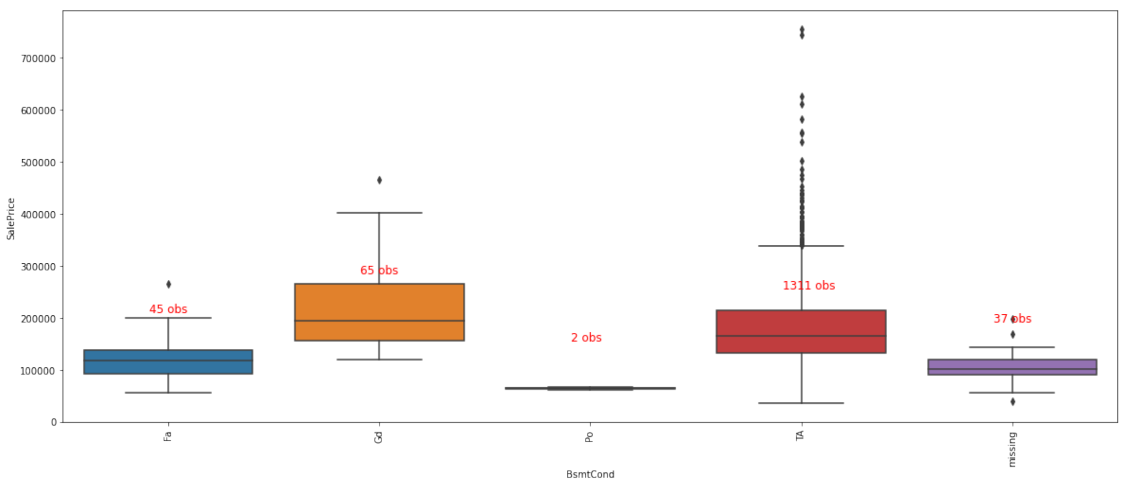

SalePrice
ExterQual
52 obs
14 obs
488 obs
906 obs
Ex
Fa
Gd
TA


SalePrice
ExterCond
3 obs
28 obs
146 obs
1 obs
1282 obs
Ex
Fa
Gd
Po
TA

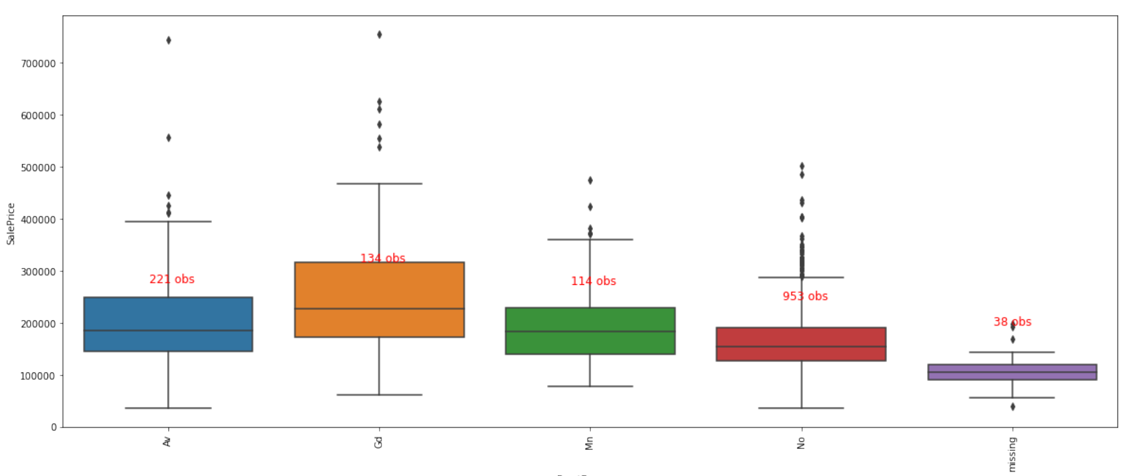

SalePrice
Foundation
146 obs
634 obs
647 obs
24 obs
6 obs
3 obs
BrkTil
CBlock
PConc
Slab
Stone
Wood



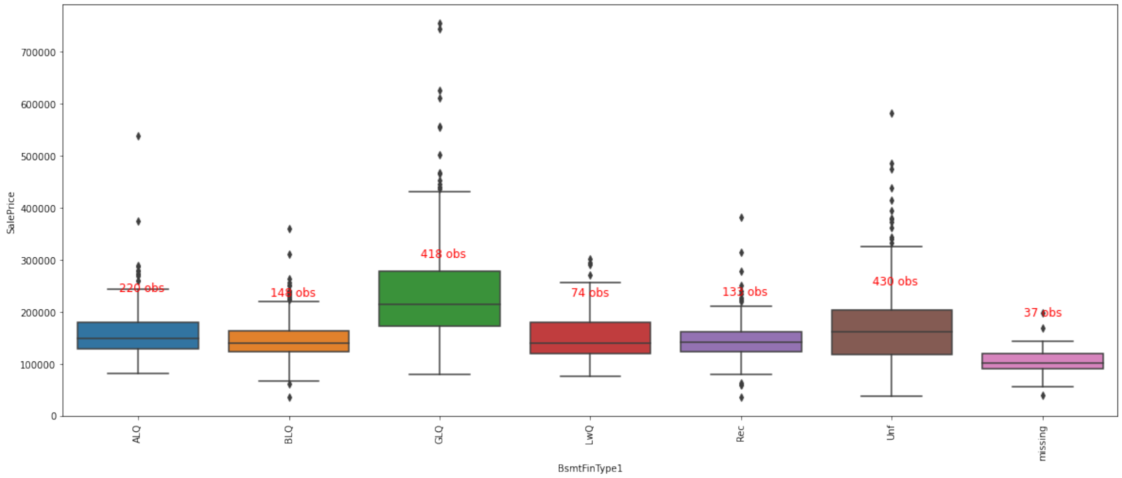
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
121 obs
35 obs
618 obs
649 obs
37 obs
Ex
Fa
Gd
TA
missing
BsmtQual

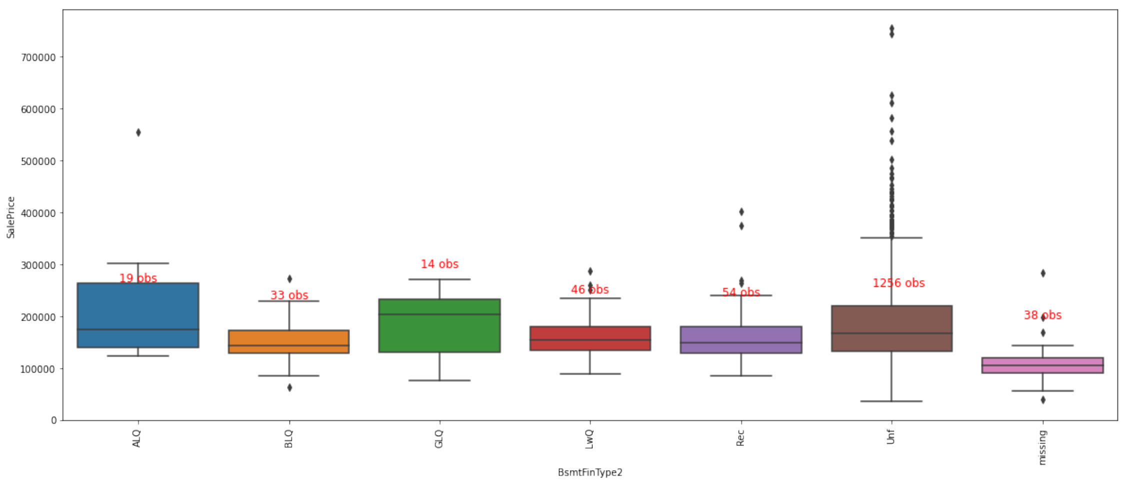


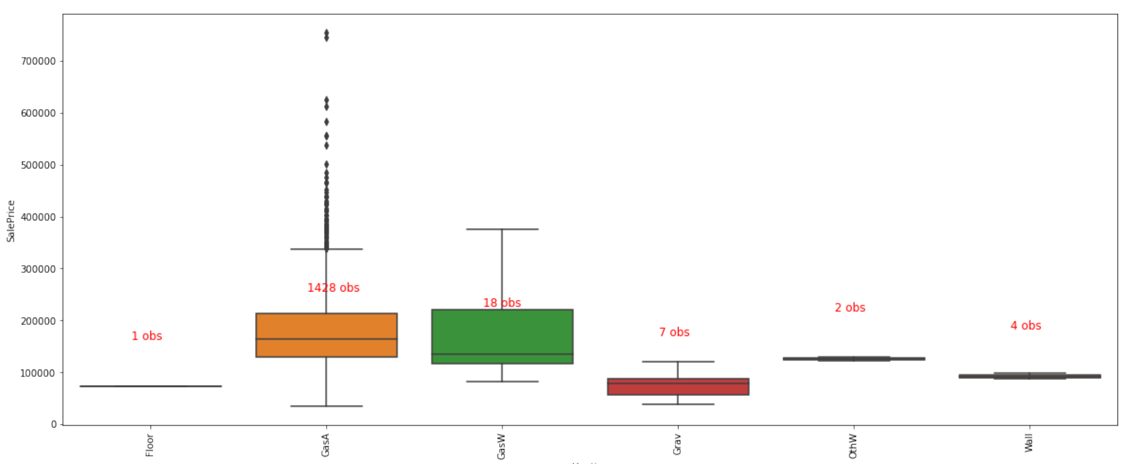
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
45 obs
65 obs
2 obs
1311 obs
37 obs
Fa
Gd
Po
TA
missing
BsmtCond

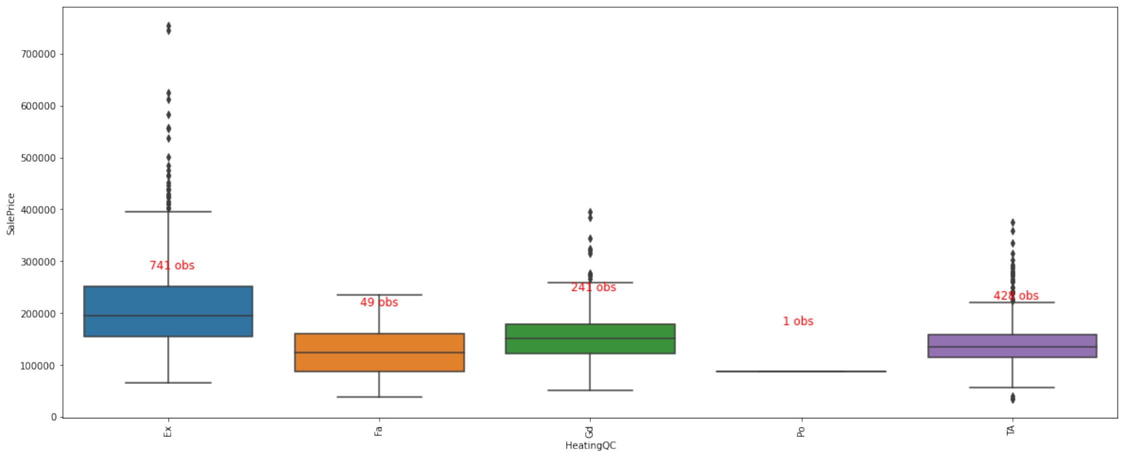


700000
600000
500000
400000
300000
200000
100000
0
SalePrice
221 obs
134 obs
114 obs
953 obs
38 obs
Av
Gd
Mn
No
missing
BsmtExposure

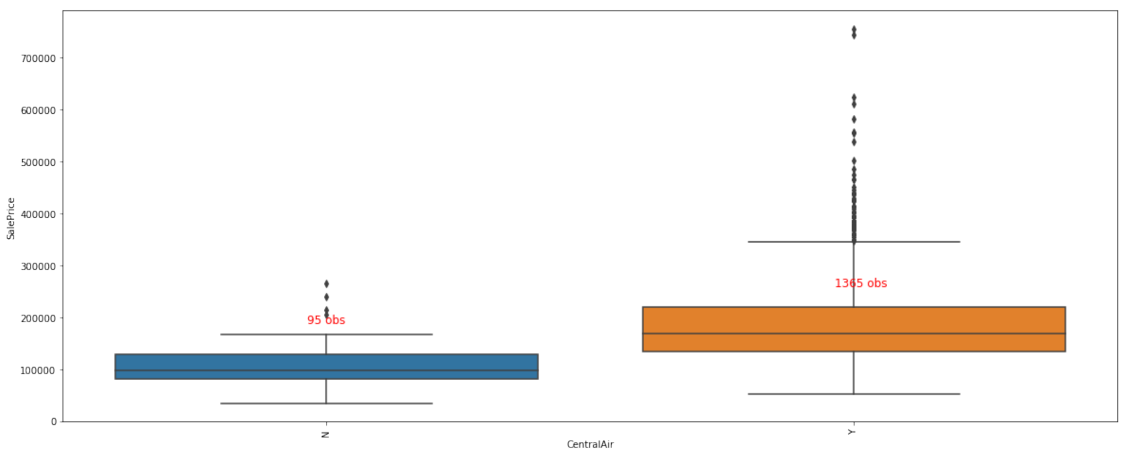

SalePrice
BsmtFinType1
220 obs
148 obs
418 obs
74 obs
133 obs
430 obs
37 obs
ALQ
BLQ
GLQ
LwQ
Rec
Unf
missing


SalePrice
BsmtFinType2
19 obs
33 obs
14 obs
46 obs
54 obs
1256 obs
38 obs
ALQ
BLQ
GLQ
LwQ
Rec
Unf
missing

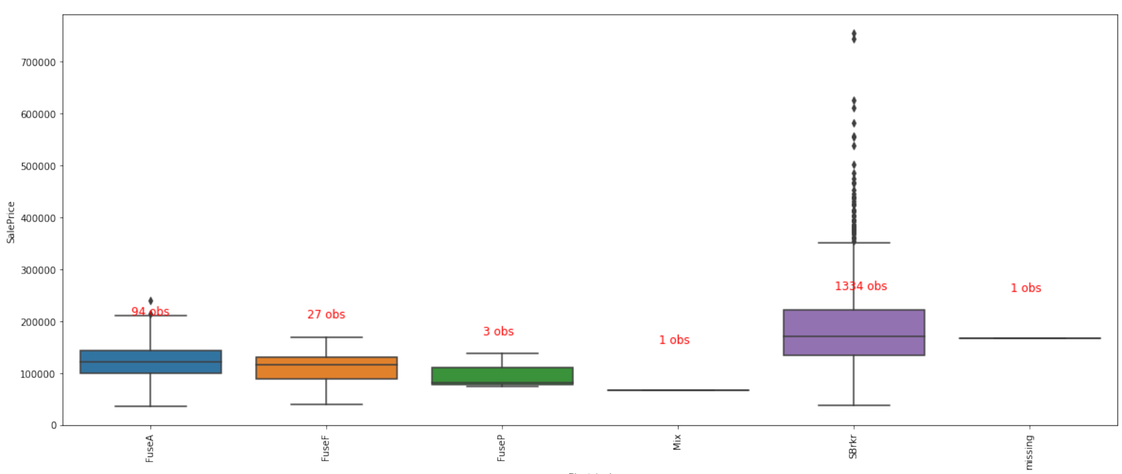

SalePrice
Heating
1 obs
1428 obs
18 obs
7 obs
2 obs
4 obs
Floor
GasA
GasW
Grav
OthW
Wall



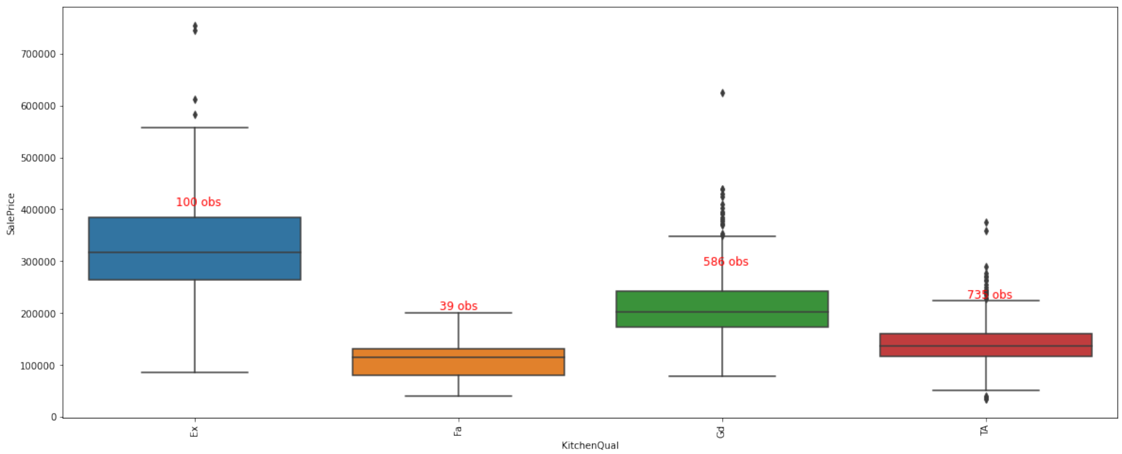
SalePrice
HeatingQC
741 obs
49 obs
241 obs
1 obs
428 obs
Ex
Fa
Gd
Po
TA

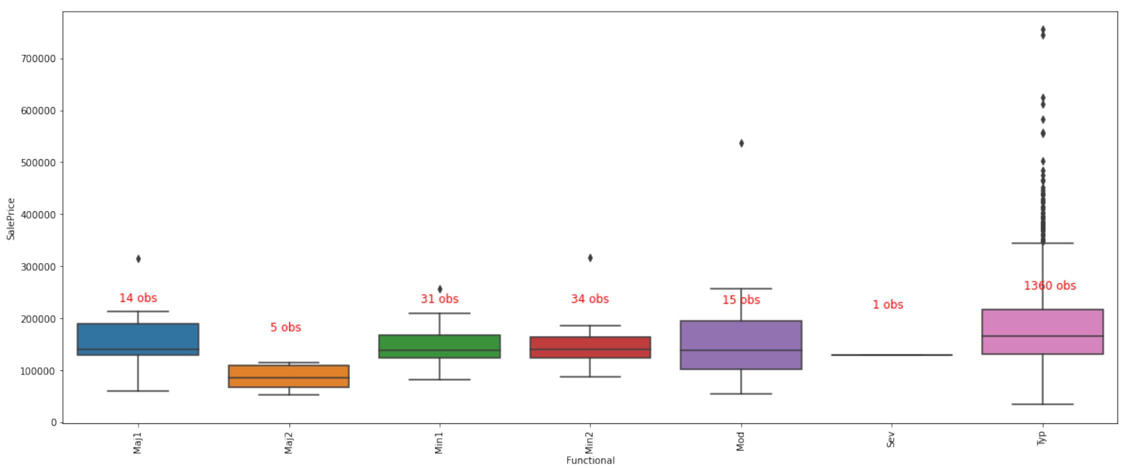


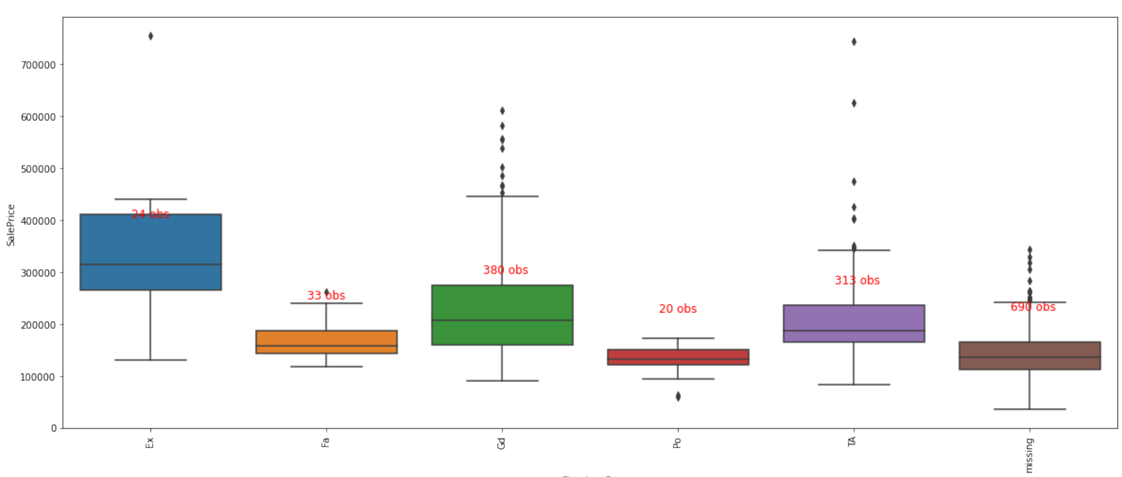
SalePrice
CentralAir
95 obs
1365 obs
N
Y

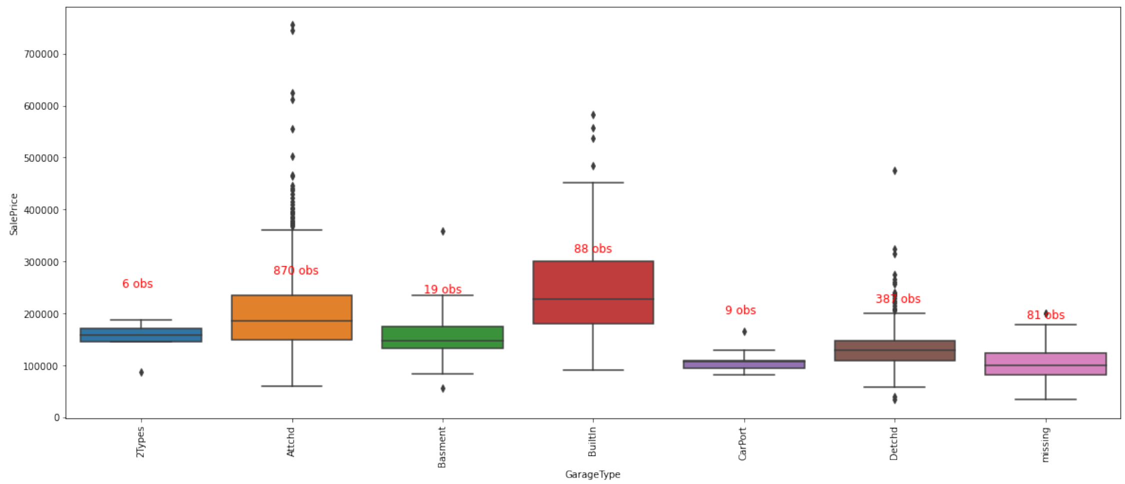


SalePrice
Electrical
94 obs
27 obs
3 obs
1 obs
1334 obs
1 obs
FuseA
FuseF
FuseP
Mix
SBrkr
missing

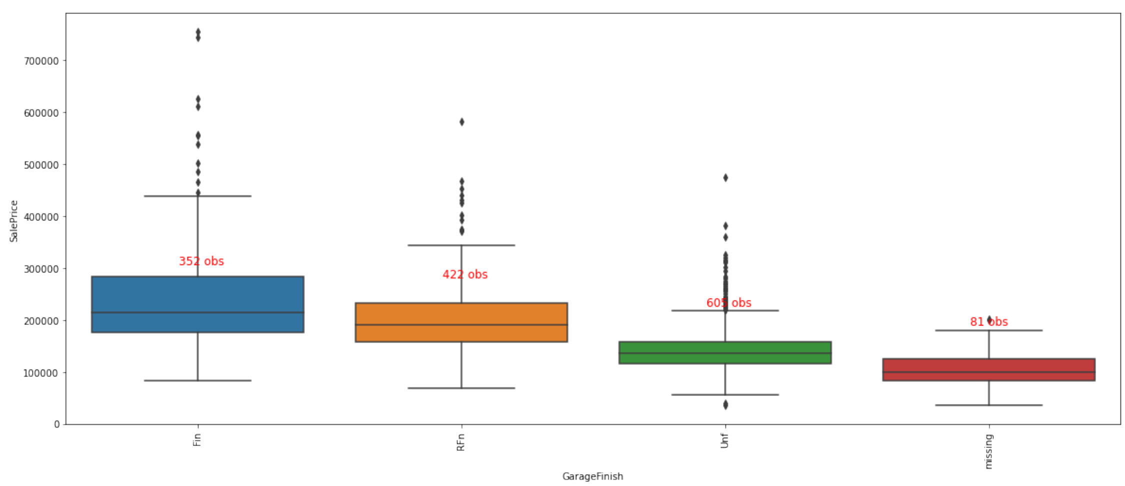

SalePrice
KitchenQual
100 obs
39 obs
586 obs
735 obs
Ex
Fa
Gd
TA


SalePrice
Functional
14 obs
5 obs
31 obs
34 obs
15 obs
1 obs
1360 obs
Maj1
Maj2
Min1
Min2
Mod
Sev
Typ

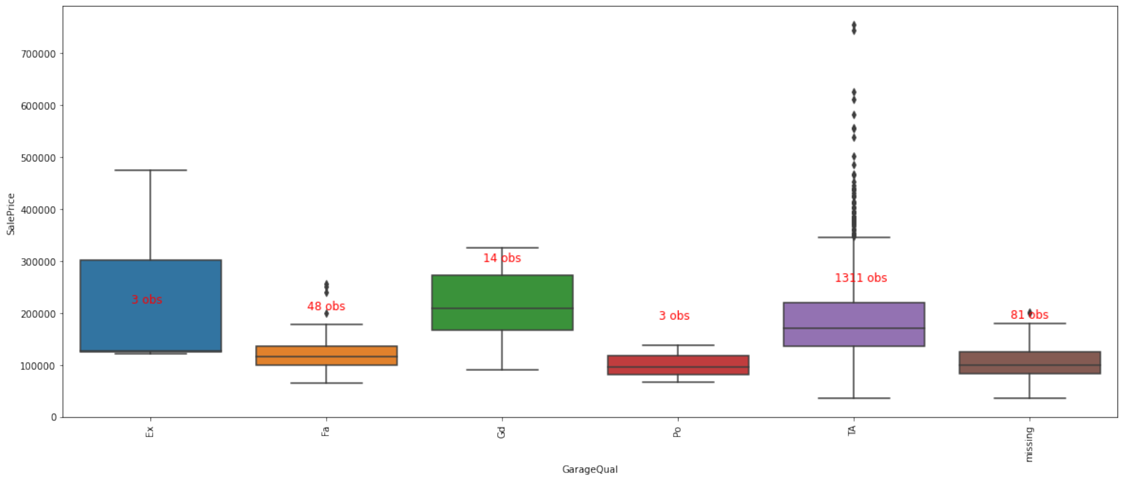

SalePrice
FireplaceQu
24 obs
33 obs
380 obs
20 obs
313 obs
690 obs
Ex
Fa
Gd
Po
TA
missing

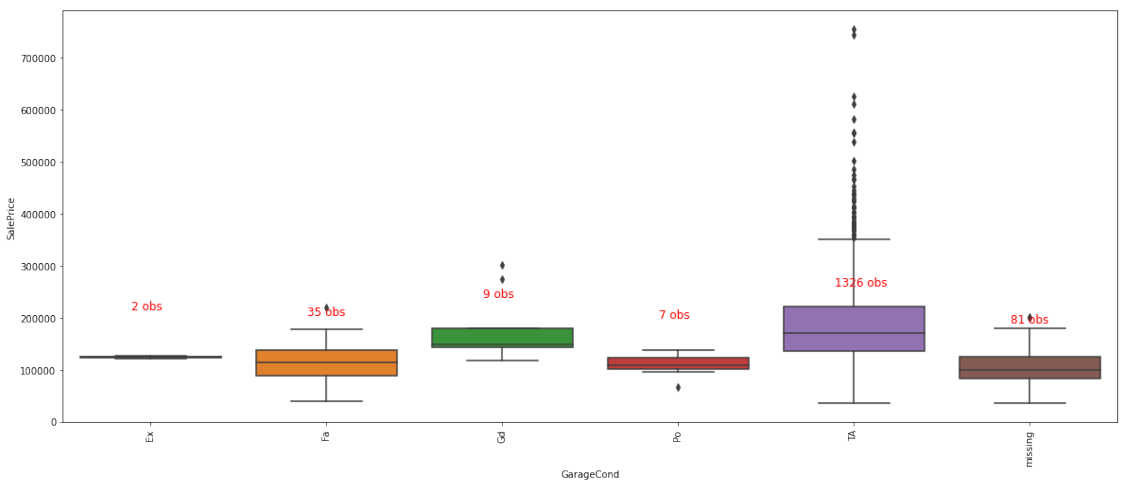


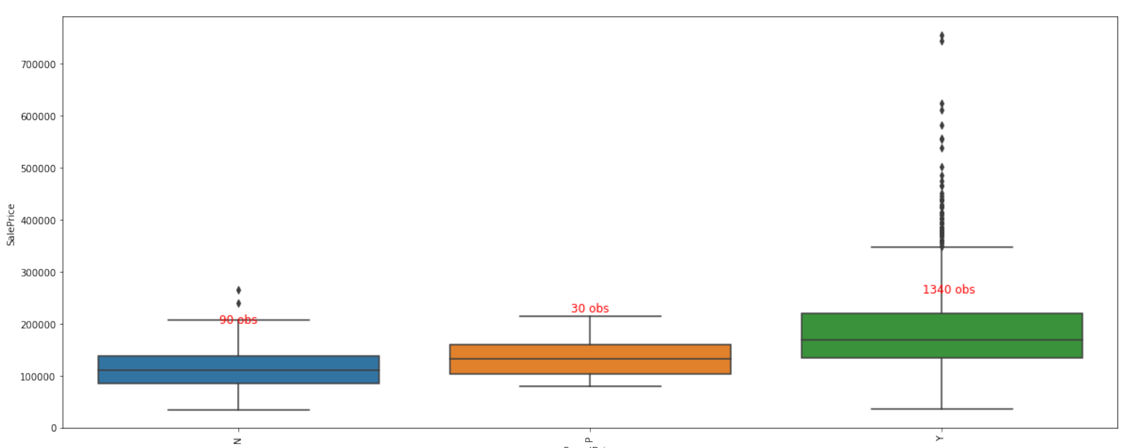
SalePrice
700000
600000
500000
400000
300000
200000
100000
0
6 obs
870 obs
19 obs
88 obs
9 obs
381 obs
81 obs
2Types
Attchd
Basment
BuiltIn
CarPort
Detchd
missing
GarageType

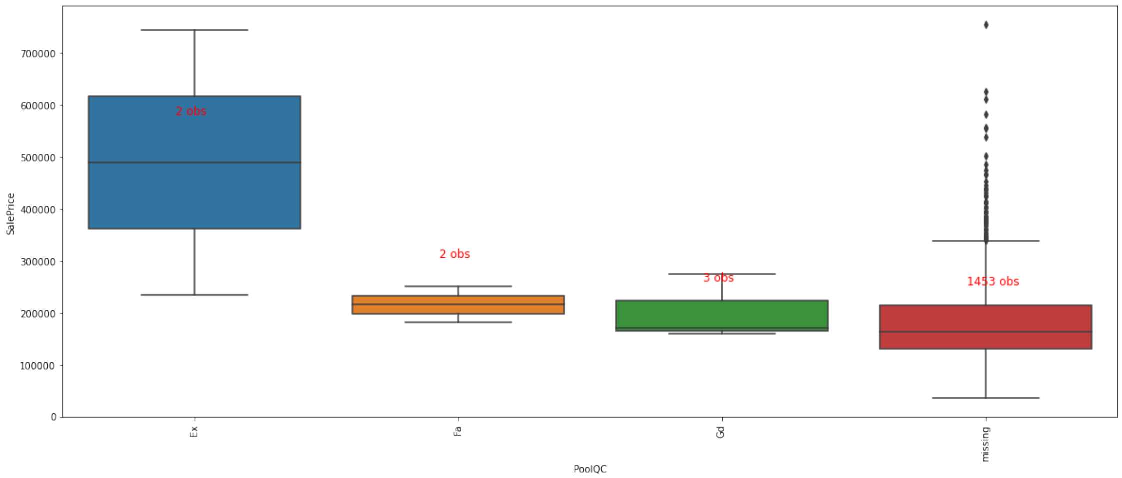


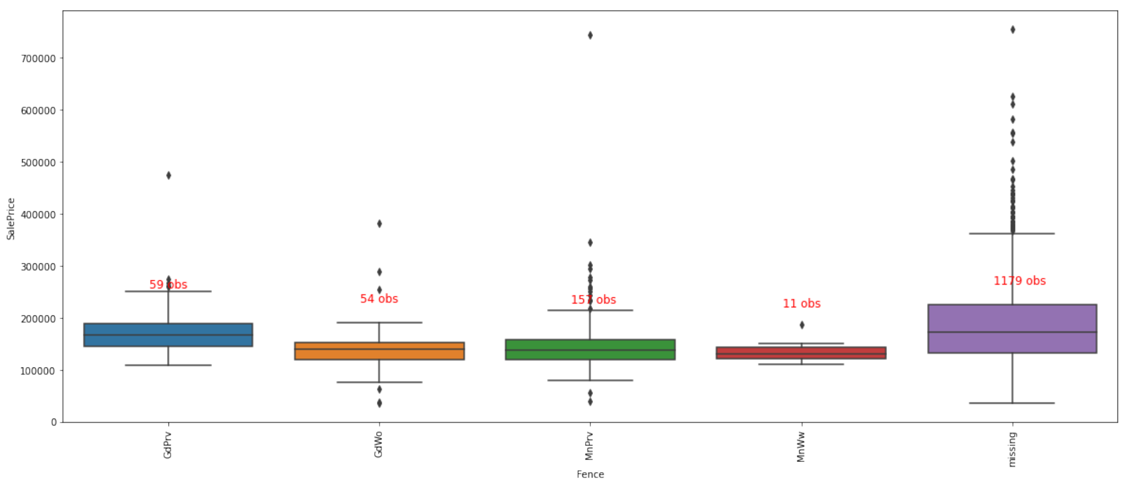
SalePrice
700000
600000
500000
400000
300000
200000
100000
0
352 obs
422 obs
605 obs
81 obs
Fin
RFn
Unf
missing
GarageFinish

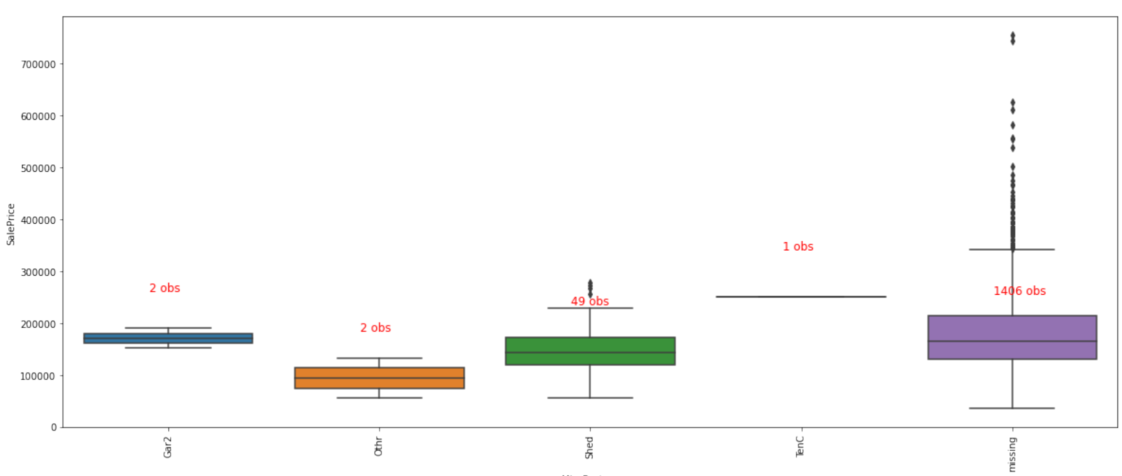

SalePrice
GarageQual
Ex
Fa
Gd
Po
TA
missing
3 obs
48 obs
14 obs
3 obs
1311 obs
81 obs

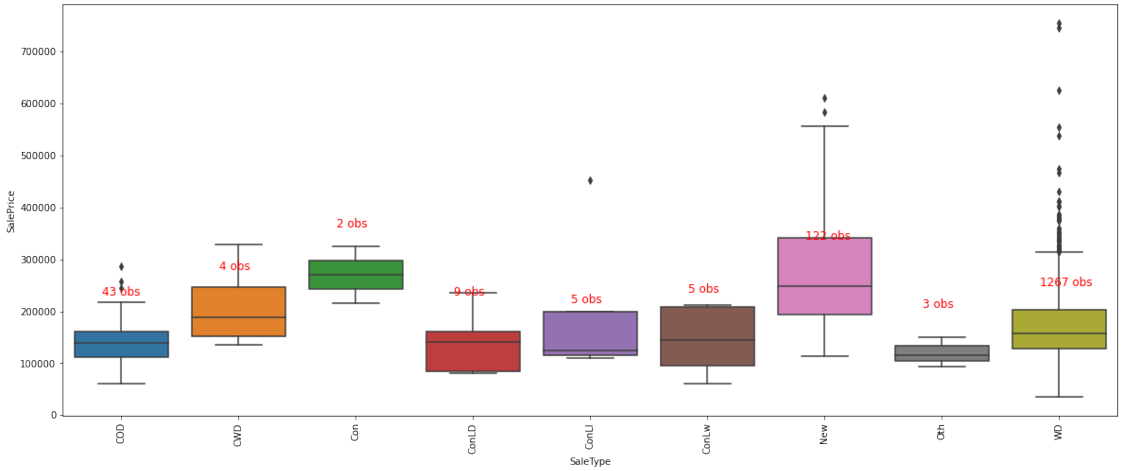

SalePrice
GarageCond
Ex
Fa
Gd
Po
TA
missing
2 obs
35 obs
9 obs
7 obs
1326 obs
81 obs


SalePrice
PavedDrive
N
P
Y
90 obs
30 obs
1340 obs

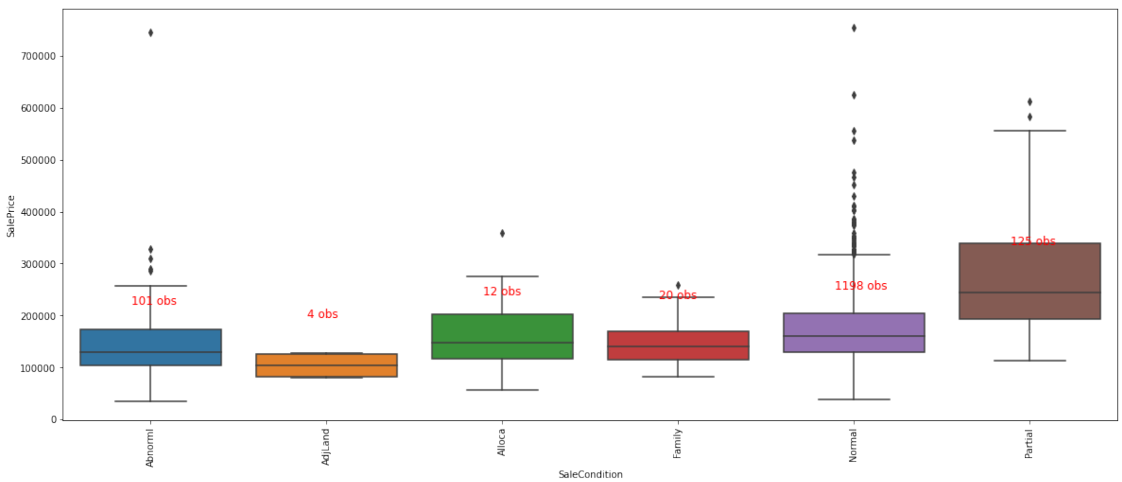

SalePrice
PoolQC
Ex
Fa
Gd
missing
2 obs
2 obs
3 obs
1453 obs
0
100000
200000
300000
400000
500000
600000
700000


SalePrice
Fence
GdPrv
GdWo
MnPrv
MnWw
missing
59 obs
54 obs
157 obs
11 obs
1179 obs
0
100000
200000
300000
400000
500000
600000
700000

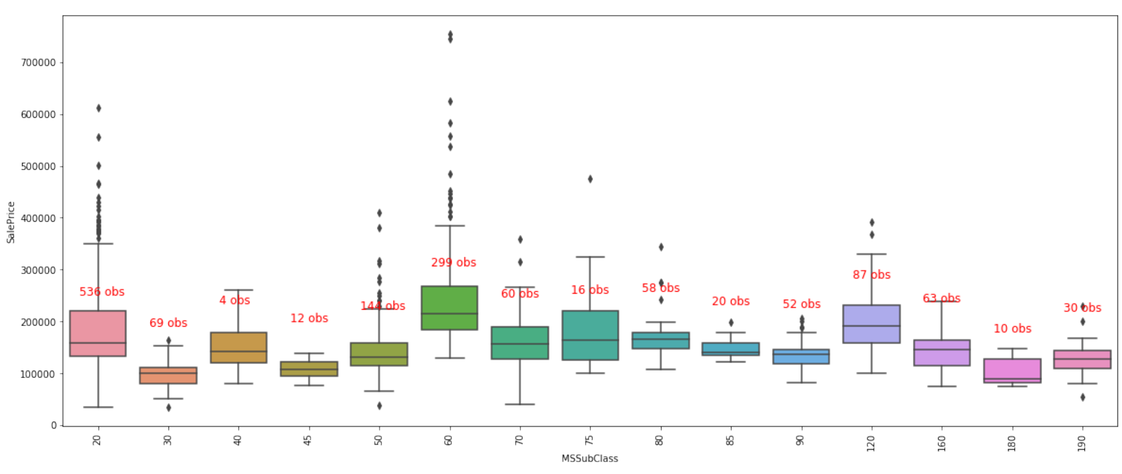

SalePrice
MiscFeature
Gar2
Othr
Shed
TenC
missing
2 obs
2 obs
49 obs
1 obs
1406 obs
0
100000
200000
300000
400000
500000
600000
700000



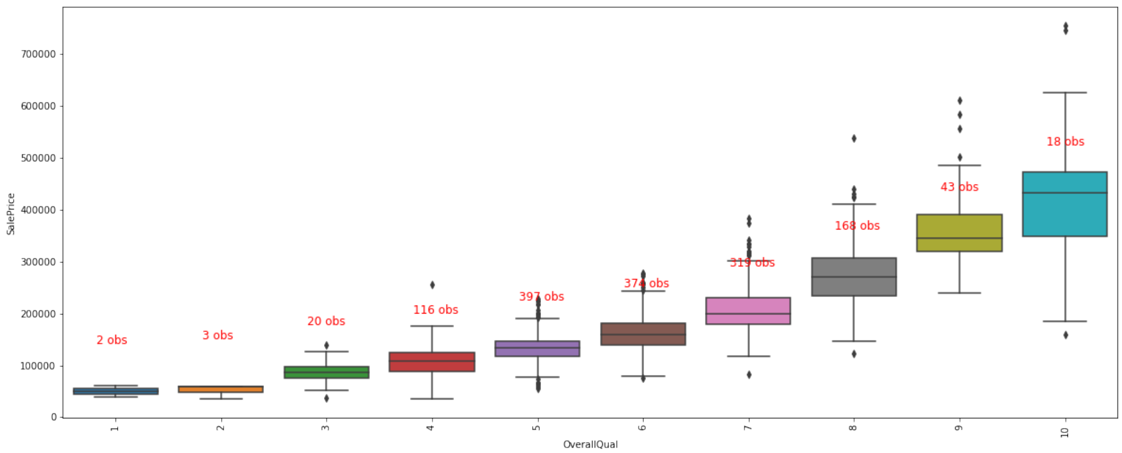
SalePrice
SaleType
COD
CWD
Con
ConLD
ConLI
ConLw
New
Oth
WD
43 obs
4 obs
2 obs
9 obs
5 obs
5 obs
122 obs
3 obs
1267 obs



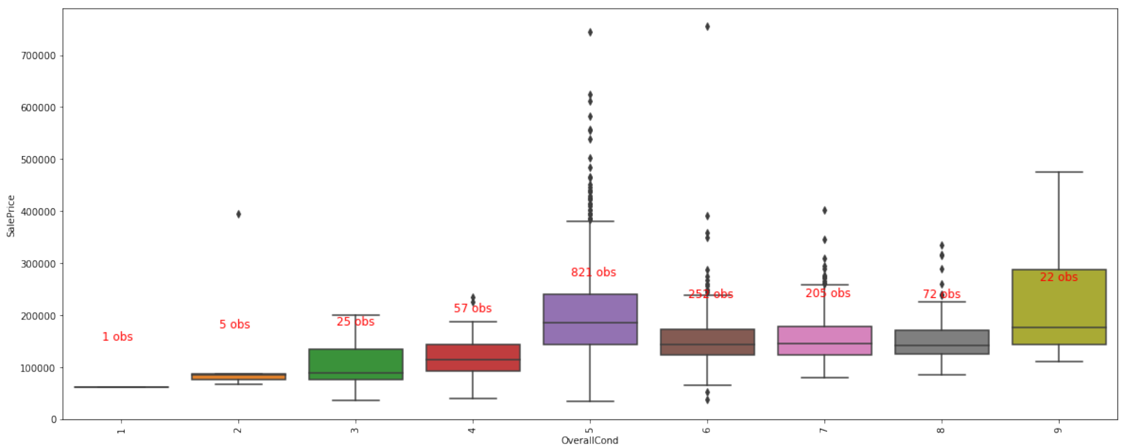
SalePrice
SaleCondition
Abnorml
AdjLand
Alloca
Family
Normal
Partial
101 obs
4 obs
12 obs
20 obs
1198 obs
125 obs



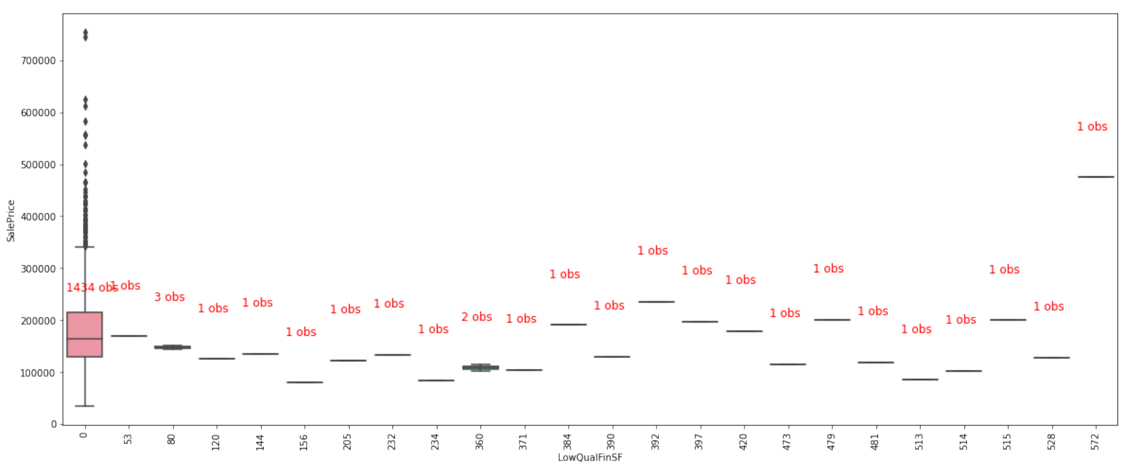
SalePrice
MSSubClass
20
30
40
45
50
60
70
75
80
85
90
120
160
180
190
536 obs
69 obs
4 obs
12 obs
144 obs
299 obs
60 obs
16 obs
58 obs
20 obs
52 obs
87 obs
63 obs
10 obs
30 obs



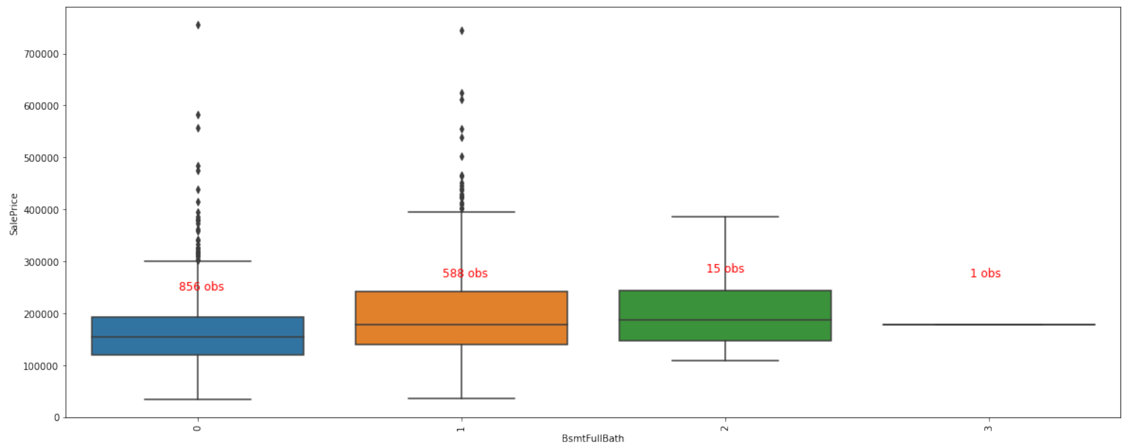
SalePrice
OverallQual
2 obs
3 obs
20 obs
116 obs
397 obs
374 obs
319 obs
168 obs
43 obs
18 obs



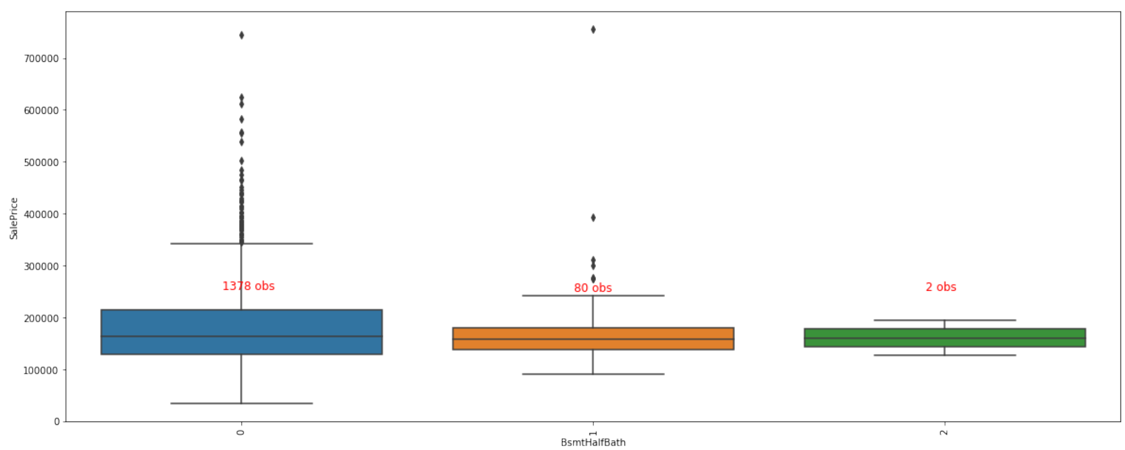
SalePrice
OverallCond
1 obs
5 obs
25 obs
57 obs
821 obs
252 obs
205 obs
72 obs
22 obs



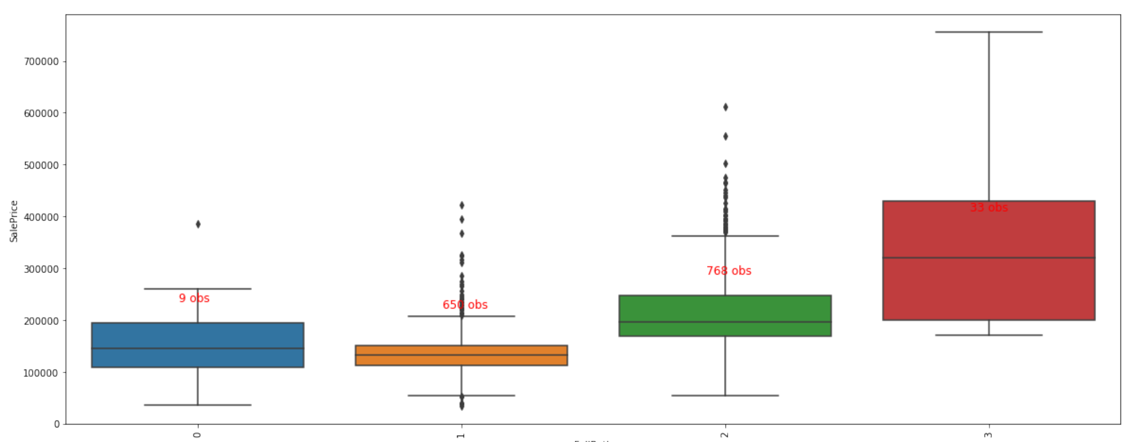
SalePrice
LowQualFinSF
1434 obs
3 obs
2 obs



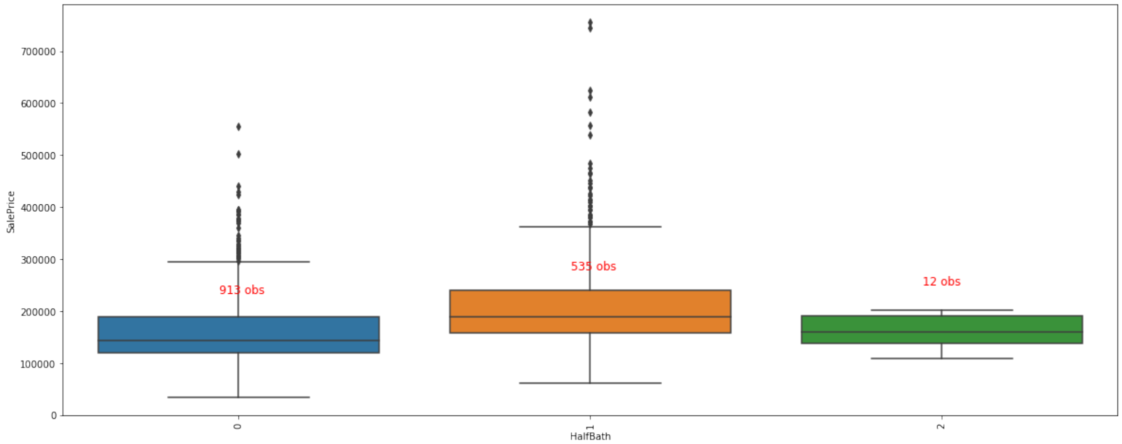
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
856 obs
588 obs
15 obs
1 obs
0
1
2
3
BsmtFullBath

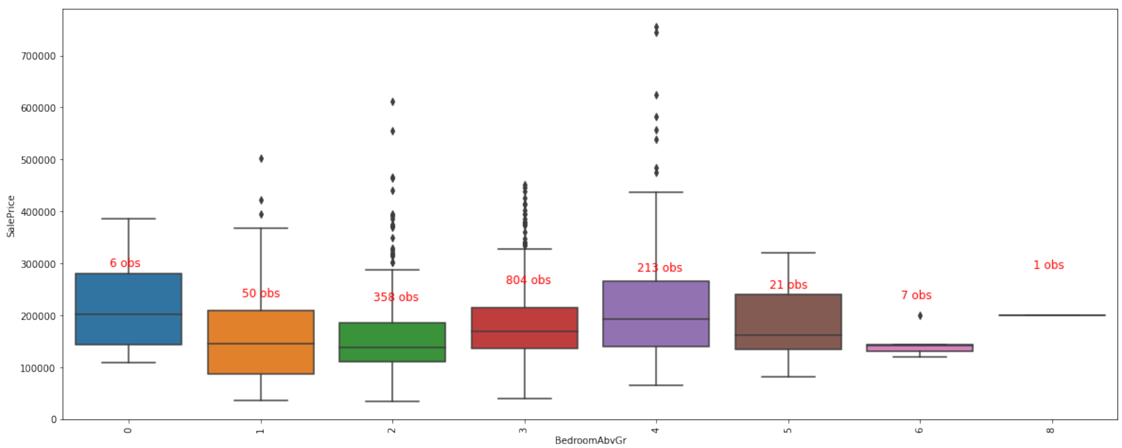


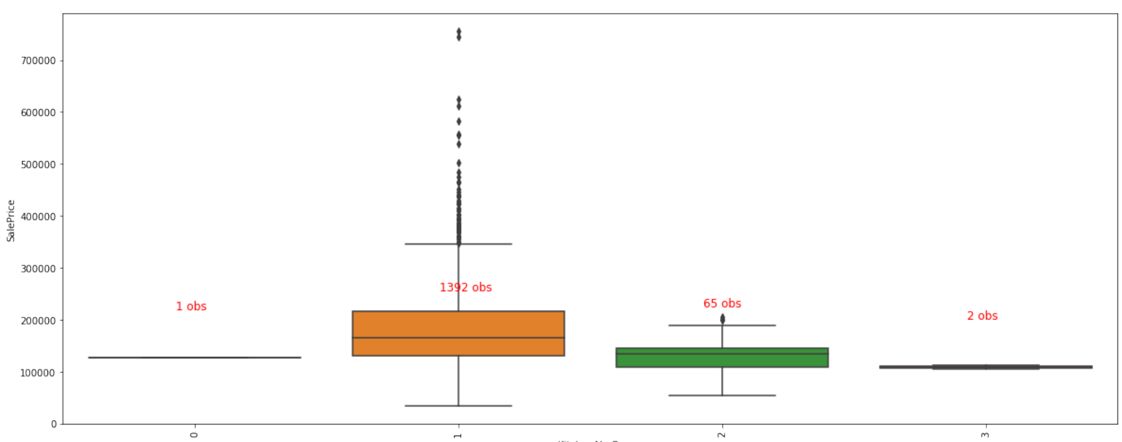
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1378 obs
80 obs
2 obs
0
1
2
BsmtHalfBath

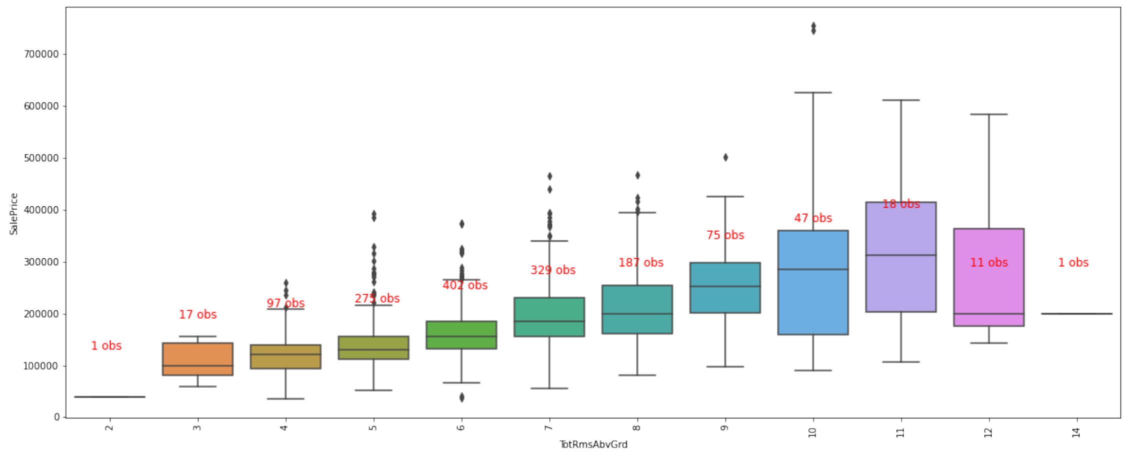


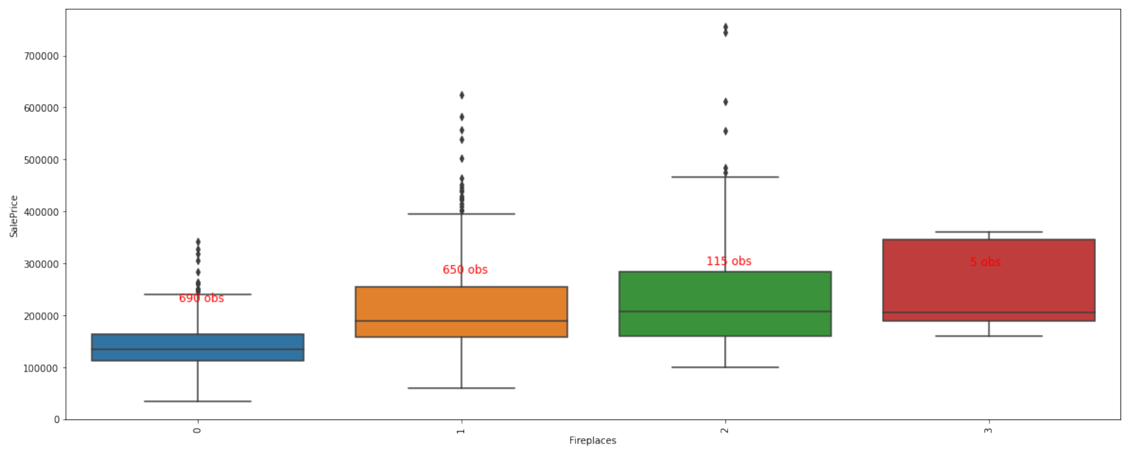
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
9 obs
650 obs
768 obs
33 obs
0
1
2
3
FullBath

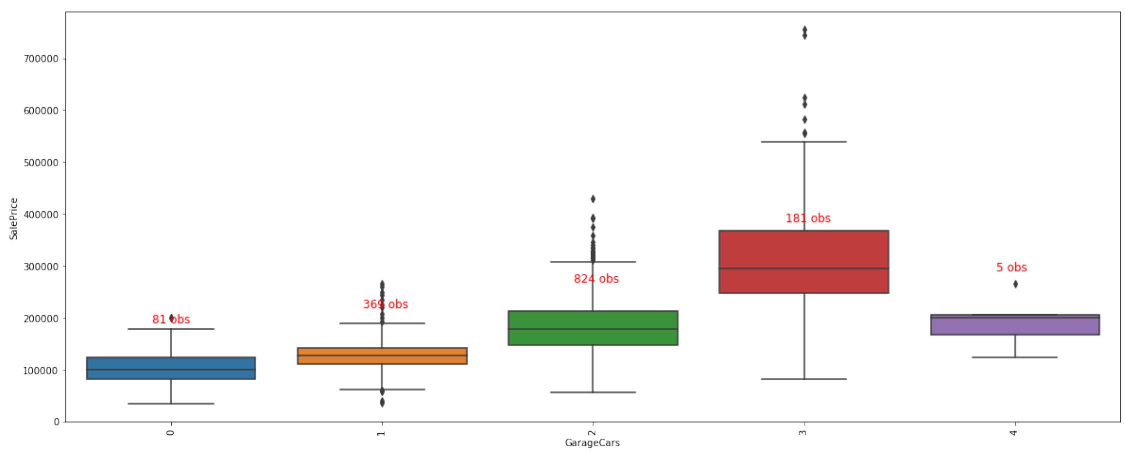

700000
600000
500000
400000
300000
200000
100000
0
SalePrice
913 obs
535 obs
12 obs
0
1
2
HalfBath

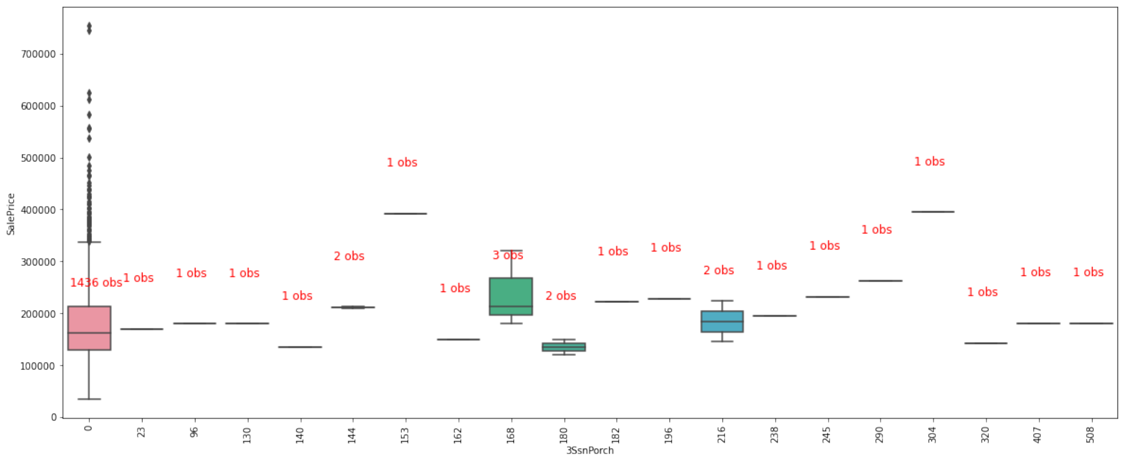

700000
600000
500000
400000
300000
200000
100000
0
SalePrice
6 obs
50 obs
358 obs
804 obs
213 obs
21 obs
7 obs
1 obs
0
1
2
3
4
5
6
8
BedroomAbvGr

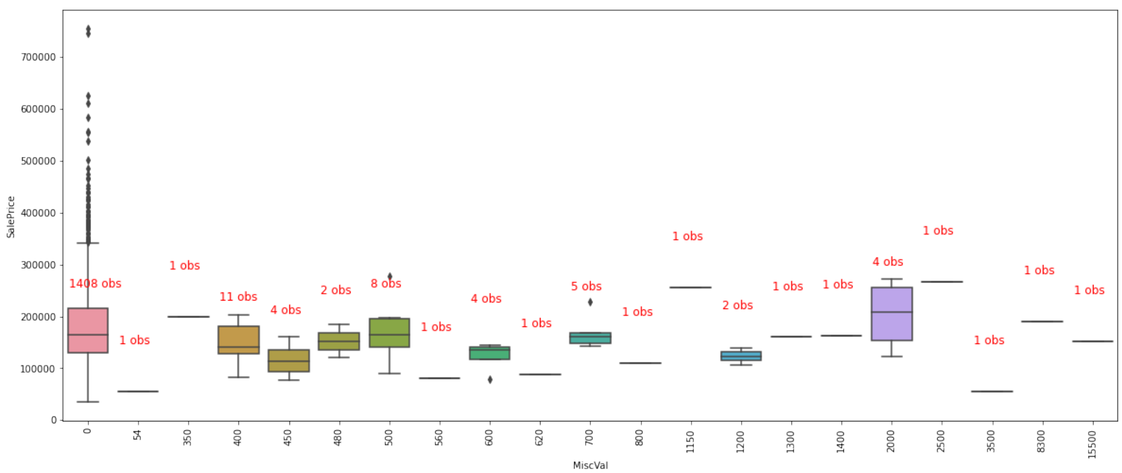

700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1 obs
1392 obs
65 obs
2 obs
0
1
2
3
KitchenAbvGr

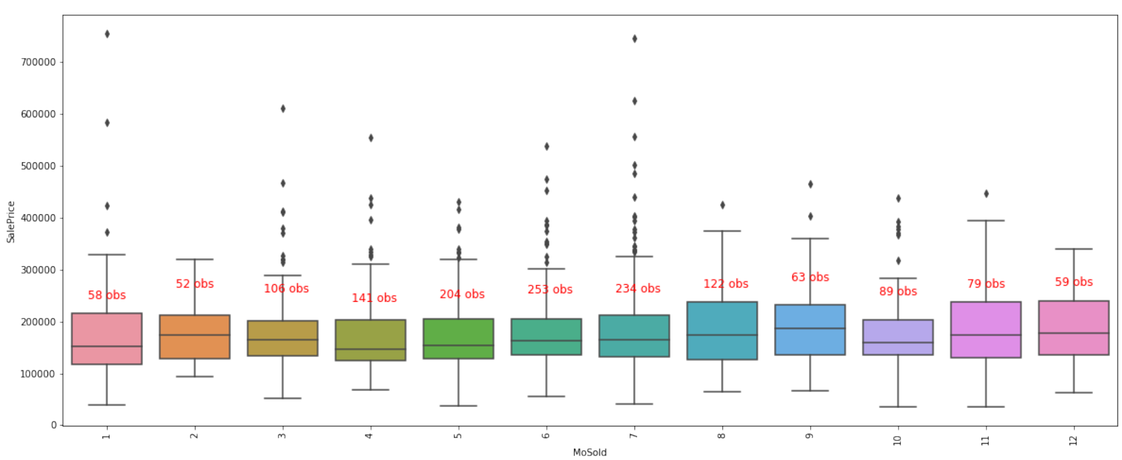

SalePrice
TotRmsAbvGrd
1 obs
17 obs
97 obs
275 obs
402 obs
329 obs
187 obs
75 obs
47 obs
18 obs
11 obs
1 obs

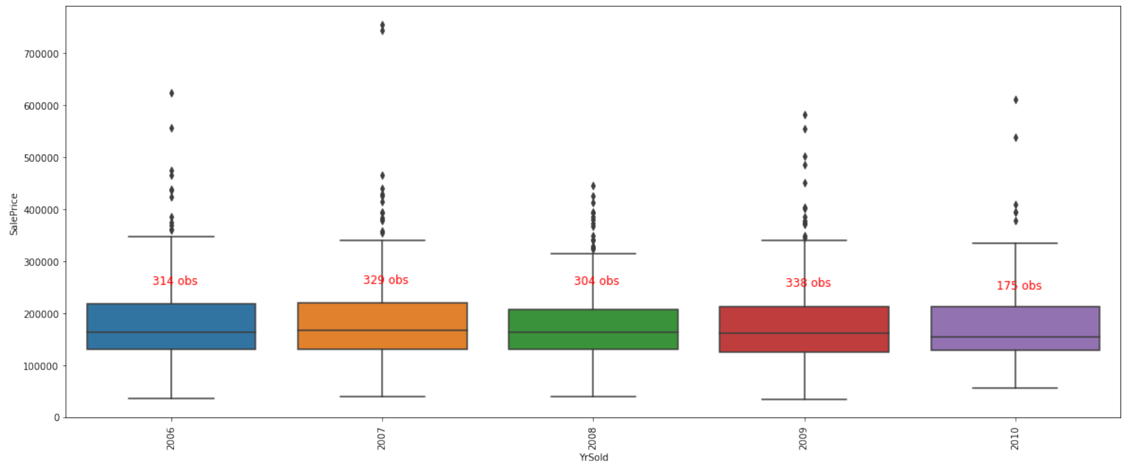

SalePrice
Fireplaces
690 obs
650 obs
115 obs
5 obs


SalePrice
GarageCars
81 obs
369 obs
824 obs
181 obs
5 obs


SalePrice
3SsnPorch
1436 obs
1 obs
2 obs
3 obs
5 obs


SalePrice
MiscVal
1408 obs
11 obs
4 obs
8 obs
5 obs


SalePrice
MoSold
58 obs
52 obs
106 obs
141 obs
204 obs
253 obs
234 obs
122 obs
63 obs
89 obs
79 obs
59 obs



Looking through the boxplots we can drop the following features as they either have very little impact on SalePrice or they are represented by other features.

[21]:
```
train.drop(columns=["LowQualFinSF", "3SsnPorch", "RoofMatl", "Alley",␣
↪"LotShape", "LandContour", "Utilities", "LotConfig", "LandSlope",
                    "Condition2", "RoofStyle", "Exterior2nd", "ExterCond",␣
↪"BsmtCond", "BsmtExposure", "BsmtFinType1", "BsmtFinType2",
                    "Heating", "Electrical", "Functional", "FireplaceQu",␣
↪"GarageType", "GarageQual", "GarageCond", "PoolQC", "Fence",
                    "MiscFeature", "SaleType", "OverallCond", "LowQualFinSF",␣
↪"BsmtHalfBath", "HalfBath", "BedroomAbvGr", "KitchenAbvGr",
                    "MiscVal", "MoSold", "YrSold"], inplace=True)
```

We will also do some feature engineering on GarageCars, Fireplaces, Foundation, SaleCondition, BsmtFullBath, FullBath, BsmtFullBath and TotRmsAbvGrd as following

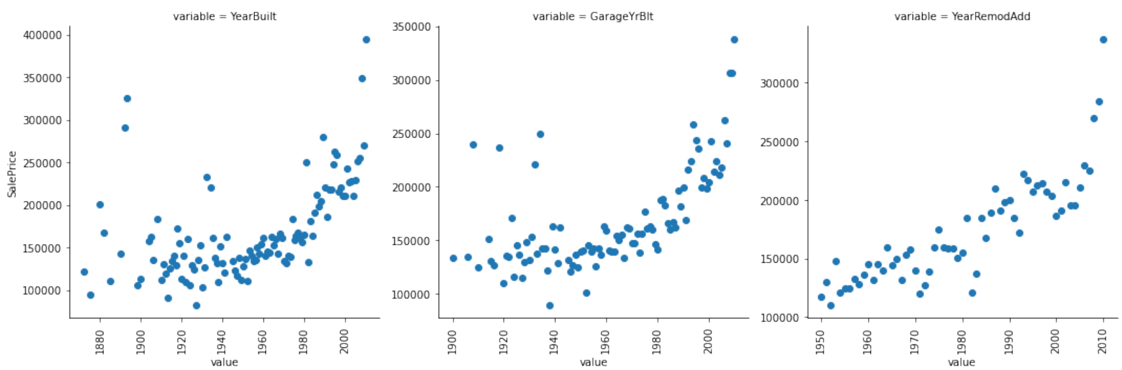
[22]:
```
train['Garage'] = train['GarageCars'].apply(lambda x: 1 if x > 0 else 0)
train['Fireplace'] = train['Fireplaces'].apply(lambda x: 1 if x > 0 else 0)
train['Foundations'] = train['Foundation'].apply(lambda x: 1 if x == "PConc"␣
↪else 0)
train['SaleCond'] = train['SaleCondition'].apply(lambda x: 1 if x == "Partial"␣
↪else 0)
train['BsmtBath'] = train['BsmtFullBath'].apply(lambda x: 1 if x > 0 else 0)
train['Bath'] = train['FullBath'].apply(lambda x: 1 if x > 0 else 0)
train['BsmtBath'] = train['BsmtFullBath'].apply(lambda x: 1 if x > 0 else 0)
train["Rooms"] = train["TotRmsAbvGrd"].apply(lambda x: 3 if x > 8 else(2 if x >␣
↪5 else 0))
```

[23]:
```
train.drop(columns=['GarageCars', 'Fireplaces', 'Foundation', 'SaleCondition',␣
↪'BsmtFullBath',
                     'FullBath', 'BsmtFullBath', "TotRmsAbvGrd"], inplace=True)
```

2.3 Date features

[24]:
```
def pairplot(x, y, **kwargs):
    ax = plt.gca()
    ax.scatter(x,y)
    plt.xticks(rotation=90)

f_date = pd.melt(train, id_vars=['SalePrice'], value_vars=date)
f_date = f_date.groupby(["variable", "value"]).mean().
 ↪sort_values(by="SalePrice", ascending=False).reset_index()
g = sns.FacetGrid(f_date, col="variable",  col_wrap=3, sharex=False,␣
 ↪sharey=False, height=5)
g = g.map(pairplot, "value", "SalePrice")
```



there is a strong positive correlation between YearBuilt, YearRemodAdd and SalePrice. HOwever there is a significant sharp increase for units built after 1990 or remodeled after 2000. Let's create boolean variables to reflect that

[25]:
```
train['After1990'] = train['YearBuilt'].apply(lambda x: 1 if x > 1990 else 0)
train['After2000'] = train['YearRemodAdd'].apply(lambda x: 1 if x > 2000 else 0)
```

[26]:
```
train.drop(columns=['GarageYrBlt'], inplace=True)
```

After dropping and converting some of the features we will now update out feature lists

[27]:
```
qualitative = ['MSSubClass', 'MSZoning', 'Street',
       'Neighborhood', 'Condition1', 'BldgType', 'HouseStyle', 'OverallQual',
       'Exterior1st', 'MasVnrType', 'ExterQual',
       'BsmtQual', 'HeatingQC', 'CentralAir',
       'KitchenQual', 'GarageFinish', 'PavedDrive']
```

[28]:
```
quantitative = ["LotFrontage", 'LotArea','1stFlrSF', 'GrLivArea', 'YearBuilt',␣
 ↪'YearRemodAdd']
```

[29]:
```
boolean = ['Basement', '2ndFloor', 'Porch', 'Garage', 'Pool', 'Fireplace',
       'Foundations', 'SaleCond', 'BsmtBath', 'Bath', 'Rooms', 'After1990',
       'After2000']
```

3 3- Missing Values and Outliers

Missing values

[30]:
```
train.isnull().sum().sort_values(ascending=False)
```

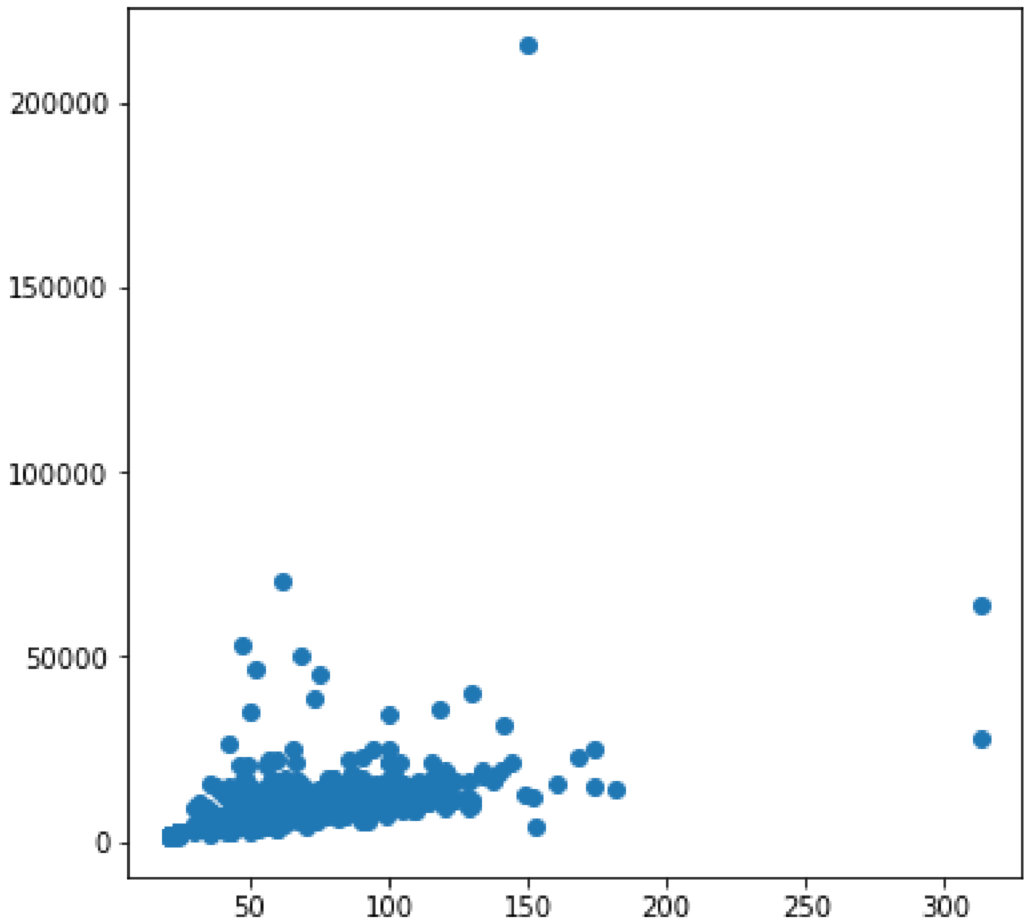
[30]:
```
LotFrontage     259
After2000         0
HouseStyle        0
BsmtQual          0
ExterQual         0
MasVnrType        0
Exterior1st       0
YearRemodAdd      0
YearBuilt         0
OverallQual       0
BldgType          0
After1990         0
Condition1        0
Neighborhood      0
Street            0
LotArea           0
MSZoning          0
MSSubClass        0
HeatingQC         0
CentralAir        0
1stFlrSF          0
GrLivArea         0
Rooms             0
Bath              0
BsmtBath          0
SaleCond          0
Foundations       0
Fireplace         0
Garage            0
Pool              0
Porch             0
2ndFloor          0
Basement          0
SalePrice         0
PavedDrive        0
GarageFinish      0
KitchenQual       0
Id                0
```

```
dtype: int64
```

At this point it seems that only one feature has missing values which is LotFrontage. Since LotFrontage should be linearly dependant on LotArea we will study that relationship and try to fill in the missing values.

[31]:
```
fig = plt.figure(figsize=(6,6))
ax = fig.add_subplot()
ax.scatter(train.LotFrontage, train.LotArea)
```

[31]:
```
<matplotlib.collections.PathCollection at 0x21241222460>
```



Apart from a few outliers the realtionship between the 2 features seems quite linear

[32]:
```
ratio = train[train["LotFrontage"].notnull()]["LotArea"].sum()/
↪train[train["LotFrontage"].notnull()]["LotFrontage"].sum()
ratio
```

[32]:
```
142.0657316058481
```

No all we have to do is divide the LotArea entries by 142,06 to get an estimation of the missing LotFrontage. It might seem as multicollinearity if we can derive one feature from another but remember this is only an estimation to fill in the missing values as best we can. The collinearity between LotFrontage and LotArea is below at 0,4 and there is still a lot of information to be derived from LotFrontage

[33]:
```
train["LotFrontage"].fillna(train[train["LotFrontage"].isnull()]["LotArea"]/
↪ratio, inplace=True)
```

Outliers We will not deal with all of the outliers because it could get very complicated.There is however 2 features where dealing with the outliers is pretty simple so we will do that. If we look back at the pair plots for the countinous features we seethat 1stFlrSF has 1 outlier and LotArea has 4. We will proceed with deleting those observations from the data set.

[34]:
```
train.sort_values(by = 'LotArea', ascending = False)[0:4]
```

[34]:
```
      Id MSSubClass MSZoning  LotFrontage  LotArea Street Neighborhood  \
313  314         20       RL   150.000000   215245   Pave       Timber
335  336        190       RL  1159.040946   164660   Grvl       Timber
249  250         50       RL  1119.200234   159000   Pave      ClearCr
706  707         20       RL   810.533256   115149   Pave      ClearCr

    Condition1 BldgType HouseStyle  … Pool  Garage  Fireplace Foundations  \
313       Norm     1Fam     1Story  …    0       1          1           0
335       Norm   2fmCon     1.5Fin  …    0       1          1           0
249       Norm     1Fam     1.5Fin  …    0       1          1           0
706       Norm     1Fam     1Story  …    0       1          1           0

    SaleCond BsmtBath Bath Rooms After1990  After2000
313        0        1    1     2         0          0
335        0        1    1     2         0          0
249        0        0    1     2         0          1
706        0        1    1     0         0          1

[4 rows x 38 columns]
```

[35]:
```
train = train.drop(train[train['Id'] == 314].index)
train = train.drop(train[train['Id'] == 336].index)
train = train.drop(train[train['Id'] == 250].index)
train = train.drop(train[train['Id'] == 707].index)
```

[36]:
```
train.sort_values(by = '1stFlrSF', ascending = False)[0:1]
```

[36]:
```
        Id MSSubClass MSZoning  LotFrontage  LotArea Street Neighborhood  \
1298  1299         60       RL        313.0    63887   Pave      Edwards
```

```
     Condition1 BldgType HouseStyle  … Pool   Garage  Fireplace Foundations  \
1298      Feedr     1Fam     2Story  …    1       1          1            1

     SaleCond BsmtBath Bath Rooms After1990  After2000
1298        1        1    1     3         1          1

[1 rows x 38 columns]
```

[37]:
```
train = train.drop(train[train['Id'] == 497].index)
```

3.0.1 ANOVA rankings and Categorical feature encoding

In order to rank the influence of the categorical features on our target value "SalePrice" we need to calculate the pvalue for each category using ANOVA approach(see more at https://bit.ly/3nLCiqu). the smaller the pvalue the more influence the corresponding category/feature has on the "SalePrice".

If this method seems representative of the features impact, we will use it later of to encode the catefgorical features based on their influence on SalePrice

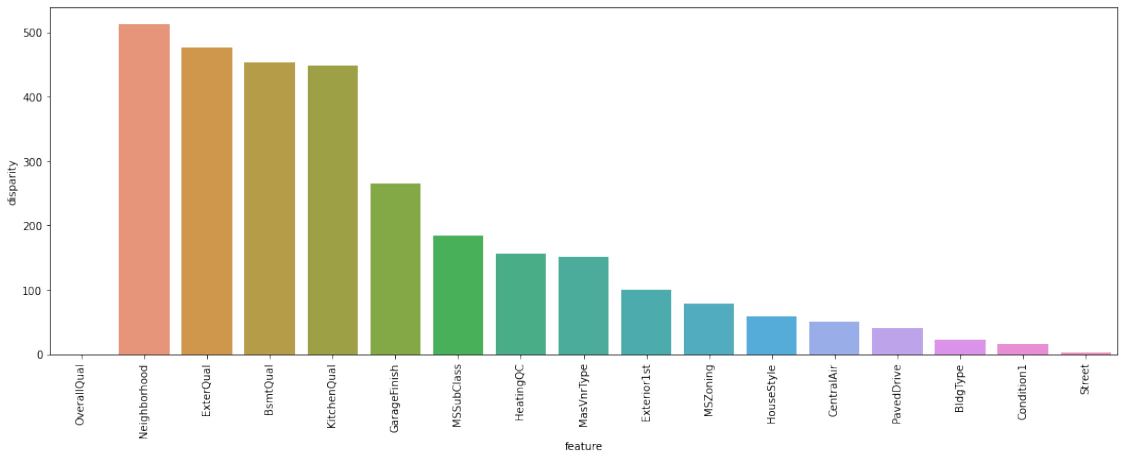
[38]:
```
def anova(frame):
    anv = pd.DataFrame() #instatiates an empty dataframe called "anv"
    anv['feature'] = qualitative #qualitative is a list of qualitative features␣
 ↪instatiated at the beginning of the notebook
    pvals = [] #creates an empty list
    for category in qualitative:
        samples = [] #for category in qualitative create an empty list called␣
 ↪sample
        for value in frame[category].unique():
            s = frame[frame[category] == value]['SalePrice'].values #returns a␣
 ↪list of SalePrice values for each unique value of the category
            samples.append(s) #appends the samples list with the SalesPrice␣
 ↪values iterated in list s
        pval = stats.f_oneway(*samples)[1] #f_oneway gives a list with 2 values␣
 ↪"statistic"[0] and "pvalue"[1]. We are only interested in the pvalue
                                          #this returns a list "pval" with all␣
 ↪the pvalues of the different categories
        pvals.append(pval) #appends the list of pvalues to the empty list␣
 ↪"pvals"
    anv['pval'] = pvals    #adds a column "pval" to the dataframe we are␣
 ↪creating "anv"
    return anv.sort_values('pval')  #finally the returned dataframe will be␣
 ↪sorted by pvalues in ascending order

a = anova(train)
a['disparity'] = np.log(1/a['pval'].values) #the pvalues are to small so␣
 ↪disparity = log(1/pvalues) is better for plotting
```

```
                                                    #the feature with the highest␣
↪disparity is the feature with the most influence on "SalePrice"

plt.figure(figsize=(18, 6))
sns.barplot(data=a, x='feature', y='disparity')
x=plt.xticks(rotation=90)
```

```
<ipython-input-38-a99309fcf53b>:17: RuntimeWarning: divide by zero encountered
in true_divide
  a['disparity'] = np.log(1/a['pval'].values) #the pvalues are to small so
disparity = log(1/pvalues) is better for plotting
```



Here is quick estimation of influence of categorical variable on SalePrice. For each variable SalePrices are partitioned to distinct sets based on category values. Then check with ANOVA test if sets have similar distributions. If variable has minor impact then set means should be equal. Decreasing pval is sign of increasing diversity in partitions.

The ranking seem to be consistent with the boxplot and most importantly common sense.

No we encode the feature categories to numerical based on the degree of influence on the SalePrice. if the feature category increases the price it will have a higher encoding number and vice versa

[39]:
```
def encode(frame, feature):
    ordering = pd.DataFrame() #instatiates an empty dataframe "ordering"
    ordering['val'] = frame[feature].unique()  #creates a column "val" in df␣
↪"ordering" with the feature's unique values
    ordering.index = ordering.val  #make the column "val" the index of df␣
↪"ordering"
    ordering['spmean'] = frame[[feature, 'SalePrice']].groupby(feature).
↪mean()['SalePrice'] #adds a column that lists the mean SalePrice for
                                                                          ␣
↪              #each unique value in each category/feature
```

```
    ordering = ordering.sort_values('spmean') #sorts the df via spmean in␣
 ↪ascending order
    ordering['ordering'] = range(1, ordering.shape[0]+1)  #adds a column␣
 ↪"ordering" to the df where the feature value with the lowest spmean
                                                            #has an ordering␣
 ↪value of 1 and the feature value with the highest spmean has an ordering
                                                            #of "ordering.
 ↪shape[0]+1" which is basically the number of unique values in each feature
    ordering = ordering['ordering'].to_dict()  #intsatiates a Dict where the␣
 ↪key is the unique values of a feature and the value is the order number
                                                 #see above example using feature␣
 ↪"Neighborhood"
    for cat, o in ordering.items():
        frame.loc[frame[feature] == cat, feature+'_E'] = o #adds a column␣
 ↪"feature_E" to the original df "frame" and adds the corresponding
                                                             #ordering number␣
 ↪based on the unique value of that feature
                                                             #for example in the␣
 ↪case on the feature "Neighborhood" the ordering number 2 will be
                                                             #filled when the␣
 ↪value is "IDOTRR" and 13 when the value is "SawyerW" (see example above)

qual_encoded = []
for q in qualitative:
    encode(train, q)
    qual_encoded.append(q+'_E')
print(qual_encoded)
```

```
['MSSubClass_E', 'MSZoning_E', 'Street_E', 'Neighborhood_E', 'Condition1_E',
'BldgType_E', 'HouseStyle_E', 'OverallQual_E', 'Exterior1st_E', 'MasVnrType_E',
'ExterQual_E', 'BsmtQual_E', 'HeatingQC_E', 'CentralAir_E', 'KitchenQual_E',
'GarageFinish_E', 'PavedDrive_E']
```

[40]:
```
train.columns
```

[40]:
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Neighborhood', 'Condition1', 'BldgType', 'HouseStyle', 'OverallQual',
       'YearBuilt', 'YearRemodAdd', 'Exterior1st', 'MasVnrType', 'ExterQual',
       'BsmtQual', 'HeatingQC', 'CentralAir', '1stFlrSF', 'GrLivArea',
       'KitchenQual', 'GarageFinish', 'PavedDrive', 'SalePrice', 'Basement',
       '2ndFloor', 'Porch', 'Pool', 'Garage', 'Fireplace', 'Foundations',
       'SaleCond', 'BsmtBath', 'Bath', 'Rooms', 'After1990', 'After2000',
       'MSSubClass_E', 'MSZoning_E', 'Street_E', 'Neighborhood_E',
       'Condition1_E', 'BldgType_E', 'HouseStyle_E', 'OverallQual_E',
       'Exterior1st_E', 'MasVnrType_E', 'ExterQual_E', 'BsmtQual_E',
       'HeatingQC_E', 'CentralAir_E', 'KitchenQual_E', 'GarageFinish_E',
       'PavedDrive_E'],
```

```
dtype='object')
```

4 4-Model Deployment

We will first split train dataframe between train and test data using the train_test_split method. 10% test data and 90% train data due to the relatively low number of observations (1460).

We will also need to standardize the features using the standardscaler() method before fitting the data.

We will compare the follwing 4 regression models and choose the most accurate:

- Lasso
- Ridge
- SGD Regressor
- Random Forest Regressor
- Gradient Boosting Regressor

[41]:
```
from sklearn.model_selection import train_test_split

X = train[qual_encoded + quantitative + boolean]
y = train["SalePrice"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1,␣
↪random_state=1)
```

[42]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
sc.fit(X_train)
```

[42]:
```
StandardScaler()
```

[43]:
```
sc.transform(X_train)
sc.transform(X_test);
```

[44]:
```
from sklearn import linear_model
lasso = linear_model.Lasso()
from sklearn.linear_model import Ridge
ridge = Ridge()
from sklearn.linear_model import SGDRegressor
sgd = SGDRegressor()
from sklearn.ensemble import RandomForestRegressor
forest = RandomForestRegressor()
from sklearn.ensemble import GradientBoostingRegressor
gbr = GradientBoostingRegressor()
```

[46]:
```
models = [lasso, ridge, sgd, forest, gbr]
```

[47]:
```python
def get_name(list_):
    name =[x for x in globals() if globals()[x] is list_][0]
    return name
```

[48]:
```python
for model in models:
    model.fit(X_train, y_train)
    print(get_name(model), "done")
```

```
lasso done
ridge done
sgd done
forest done
gbr done
```

[49]:
```python
y_hat_sgd = sgd.predict(X_test)
y_hat_lasso = lasso.predict(X_test)
y_hat_ridge = ridge.predict(X_test)
y_hat_forest = forest.predict(X_test)
y_hat_gbr = gbr.predict(X_test)
```

[50]:
```python
predictions = [y_hat_lasso, y_hat_sgd, y_hat_ridge, y_hat_forest, y_hat_gbr]
```

[51]:
```python
from sklearn.metrics import mean_squared_error
for prediction in predictions:
    print (get_name(prediction), "RMSE: ", np.sqrt(mean_squared_error(y_test,␣
 ↪prediction)))
```

```
y_hat_lasso RMSE:  41161.37987970997
y_hat_sgd RMSE:  4.104506981691722e+16
y_hat_ridge RMSE:  40583.53993964646
y_hat_forest RMSE:  31911.262748783924
y_hat_gbr RMSE:  27346.661045860703
```

The Gradient Boosting Regressor yielded the best result. In case you are using this notebook to submit to the kaggle competion, here is how to proceed with getting the test data in shape.

Missing values

[52]:
```python
missing_test = test[qualitative].isnull().sum()
missing_test = missing_test[missing_test > 0]
missing_test.sort_values(ascending=False, inplace=True)
missing_test
```

[52]:
```
GarageFinish    78
BsmtQual        44
MasVnrType      16
MSZoning         4
KitchenQual      1
```

```
Exterior1st      1
dtype: int64
```

the test data has features with missing values that are not present in the train data. We cannot drop thos observations nor the features. We will introduce a corretion and replace every missing value by 999.

[53]:
```
correction = ["MSZoning","Exterior1st", "KitchenQual", "GarageFinish",␣
↪"BsmtQual", "MasVnrType"]
```

[54]:
```
for f in correction:
    test[f].fillna(-999, inplace=True)
```

[55]:
```
missing_test_ = test[quantitative].isnull().sum()
missing_test_ = missing_test_[missing_test_ > 0]
missing_test_.sort_values(ascending=False, inplace=True)
missing_test_
```

[55]:
```
LotFrontage    227
dtype: int64
```

the test data also has a lot of missing values for LotFrontage. we will deal with that by estimating using LotArea just like we did in the train set

[56]:
```
ratio_2 = test[test["LotFrontage"].notnull()]["LotArea"].sum()/
↪test[test["LotFrontage"].notnull()]["LotFrontage"].sum()
test["LotFrontage"].fillna(test[test["LotFrontage"].isnull()]["LotArea"]/
↪ratio_2, inplace=True)
```

Feature engineering the test dataset just like we did for the train dataset

[57]:
```
test['After1990'] = test['YearBuilt'].apply(lambda x: 1 if x > 1990 else 0)
test['After2000'] = test['YearRemodAdd'].apply(lambda x: 1 if x > 2000 else 0)
test.drop(columns=["MasVnrArea", "BsmtFinSF1", "BsmtFinSF2", "BsmtUnfSF",␣
↪"GarageArea", "WoodDeckSF", "OpenPorchSF", "EnclosedPorch",
                  "LowQualFinSF", "3SsnPorch", "RoofMatl", "Alley", "LotShape",␣
↪"LandContour", "Utilities", "LotConfig", "LandSlope",
                   "Condition2", "RoofStyle", "Exterior2nd", "ExterCond",␣
↪"BsmtCond", "BsmtExposure", "BsmtFinType1", "BsmtFinType2",
                   "Heating", "Electrical", "Functional", "FireplaceQu",␣
↪"GarageType", "GarageQual", "GarageCond", "PoolQC", "Fence",
                   "MiscFeature", "SaleType", "OverallCond", "LowQualFinSF",␣
↪"BsmtHalfBath", "HalfBath", "BedroomAbvGr", "KitchenAbvGr",
                   "MiscVal", "MoSold", "YrSold"], inplace=True)
test['Basement'] = test['TotalBsmtSF'].apply(lambda x: 1 if x > 0 else 0)
test['2ndFloor'] = test['2ndFlrSF'].apply(lambda x: 1 if x > 0 else 0)
test['Porch'] = test['ScreenPorch'].apply(lambda x: 1 if x > 0 else 0)
test['Garage'] = test['GarageCars'].apply(lambda x: 1 if x > 0 else 0)
test['Pool'] = test['PoolArea'].apply(lambda x: 1 if x > 0 else 0)
```

```
test['Fireplace'] = test['Fireplaces'].apply(lambda x: 1 if x > 0 else 0)
test['Foundations'] = test['Foundation'].apply(lambda x: 1 if x == "PConc" else␣
↪0)
test['SaleCond'] = test['SaleCondition'].apply(lambda x: 1 if x == "Partial"␣
↪else 0)
test['BsmtBath'] = test['BsmtFullBath'].apply(lambda x: 1 if x > 0 else 0)
test['Bath'] = test['FullBath'].apply(lambda x: 1 if x > 0 else 0)
test['BsmtBath'] = test['BsmtFullBath'].apply(lambda x: 1 if x > 0 else 0)
test["Rooms"] = test["TotRmsAbvGrd"].apply(lambda x: 3 if x > 8 else(2 if x > 5␣
↪else 0))
test.drop(columns=['TotalBsmtSF', '2ndFlrSF', 'ScreenPorch', 'GarageCars',␣
↪'PoolArea', 'Fireplaces', 'Foundation', 'SaleCondition', 'BsmtFullBath',
                    'FullBath', 'BsmtFullBath', "TotRmsAbvGrd"], inplace=True)
test.drop(columns=['GarageYrBlt'], inplace=True)
```

Encoding test categorical features Since the categorical features were encoded in an ordinal way based on their impact on the SalePrice we cannot take the same approach for the test data as SalePrice is missing. Instead we will create a dictionary for those features based on the train set and map it into the test dataset

creating the encoding dictionary

[58]:
```
for q, e in zip(qualitative, qual_encoded):
    print("'",q,"'",":", pd.Series(train[e].values, index=train[q]).
↪to_dict(),",", sep='')
```

```
'MSSubClass':{60: 15.0, 20: 12.0, 70: 10.0, 50: 7.0, 190: 4.0, 45: 3.0, 90: 5.0,
120: 14.0, 30: 1.0, 85: 8.0, 80: 11.0, 160: 6.0, 75: 13.0, 180: 2.0, 40: 9.0},
'MSZoning':{'RL': 4.0, 'RM': 2.0, 'C (all)': 1.0, 'FV': 5.0, 'RH': 3.0},
'Street':{'Pave': 2.0, 'Grvl': 1.0},
'Neighborhood':{'CollgCr': 17.0, 'Veenker': 21.0, 'Crawfor': 19.0, 'NoRidge':
25.0, 'Mitchel': 12.0, 'Somerst': 20.0, 'NWAmes': 14.0, 'OldTown': 6.0,
'BrkSide': 4.0, 'Sawyer': 7.0, 'NridgHt': 24.0, 'NAmes': 11.0, 'SawyerW': 13.0,
'IDOTRR': 2.0, 'MeadowV': 1.0, 'Edwards': 5.0, 'Timber': 22.0, 'Gilbert': 15.0,
'StoneBr': 23.0, 'ClearCr': 18.0, 'NPkVill': 10.0, 'Blmngtn': 16.0, 'BrDale':
3.0, 'SWISU': 9.0, 'Blueste': 8.0},
'Condition1':{'Norm': 4.0, 'Feedr': 3.0, 'PosN': 8.0, 'Artery': 1.0, 'RRAe':
2.0, 'RRNn': 7.0, 'RRAn': 5.0, 'PosA': 9.0, 'RRNe': 6.0},
'BldgType':{'1Fam': 5.0, '2fmCon': 1.0, 'Duplex': 2.0, 'TwnhsE': 4.0, 'Twnhs':
3.0},
'HouseStyle':{'2Story': 7.0, '1Story': 6.0, '1.5Fin': 3.0, '1.5Unf': 1.0,
'SFoyer': 2.0, 'SLvl': 5.0, '2.5Unf': 4.0, '2.5Fin': 8.0},
'OverallQual':{7: 7.0, 6: 6.0, 8: 8.0, 5: 5.0, 9: 9.0, 4: 4.0, 10: 10.0, 3: 3.0,
1: 1.0, 2: 2.0},
'Exterior1st':{'VinylSd': 12.0, 'MetalSd': 6.0, 'Wd Sdng': 5.0, 'HdBoard': 9.0,
'BrkFace': 11.0, 'WdShing': 7.0, 'CemntBd': 13.0, 'Plywood': 10.0, 'AsbShng':
4.0, 'Stucco': 8.0, 'BrkComm': 1.0, 'AsphShn': 2.0, 'Stone': 14.0, 'ImStucc':
15.0, 'CBlock': 3.0},
```

```
'MasVnrType':{'BrkFace': 3.0, 'None': 2.0, 'Stone': 5.0, 'BrkCmn': 1.0,
'missing': 4.0},
'ExterQual':{'Gd': 3.0, 'TA': 2.0, 'Ex': 4.0, 'Fa': 1.0},
'BsmtQual':{'Gd': 4.0, 'TA': 3.0, 'Ex': 5.0, 'missing': 1.0, 'Fa': 2.0},
'HeatingQC':{'Ex': 5.0, 'Gd': 4.0, 'TA': 3.0, 'Fa': 2.0, 'Po': 1.0},
'CentralAir':{'Y': 2.0, 'N': 1.0},
'KitchenQual':{'Gd': 3.0, 'TA': 2.0, 'Ex': 4.0, 'Fa': 1.0},
'GarageFinish':{'RFn': 3.0, 'Unf': 2.0, 'Fin': 4.0, 'missing': 1.0},
'PavedDrive':{'Y': 3.0, 'N': 1.0, 'P': 2.0},
```

[59]:
```python
dict_encoded = {'MSSubClass':{60: 15.0, 20: 12.0, 70: 10.0, 50: 7.0, 190: 4.0, 45: 3.0, 90: 5.0, 120: 14.0, 30: 1.0, 85: 8.0, 80: 11.0, 160: 6.0, 75: 13.0, 180: 2.0, 40: 9.0},
'MSZoning':{'RL': 4.0, 'RM': 2.0, 'C (all)': 1.0, 'FV': 5.0, 'RH': 3.0},
'Street':{'Pave': 2.0, 'Grvl': 1.0},
'Neighborhood':{'CollgCr': 17.0, 'Veenker': 21.0, 'Crawfor': 19.0, 'NoRidge': 25.0, 'Mitchel': 12.0, 'Somerst': 20.0, 'NWAmes': 14.0, 'OldTown': 6.0, 'BrkSide': 4.0, 'Sawyer': 7.0, 'NridgHt': 24.0, 'NAmes': 11.0, 'SawyerW': 13.0, 'IDOTRR': 2.0, 'MeadowV': 1.0, 'Edwards': 5.0, 'Timber': 22.0, 'Gilbert': 15.0, 'StoneBr': 23.0, 'ClearCr': 18.0, 'NPkVill': 10.0, 'Blmngtn': 16.0, 'BrDale': 3.0, 'SWISU': 9.0, 'Blueste': 8.0},
'Condition1':{'Norm': 4.0, 'Feedr': 3.0, 'PosN': 8.0, 'Artery': 1.0, 'RRAe': 2.0, 'RRNn': 7.0, 'RRAn': 5.0, 'PosA': 9.0, 'RRNe': 6.0},
'BldgType':{'1Fam': 5.0, '2fmCon': 1.0, 'Duplex': 2.0, 'TwnhsE': 4.0, 'Twnhs': 3.0},
'HouseStyle':{'2Story': 7.0, '1Story': 6.0, '1.5Fin': 3.0, '1.5Unf': 1.0, 'SFoyer': 2.0, 'SLvl': 5.0, '2.5Unf': 4.0, '2.5Fin': 8.0},
'OverallQual':{7: 7.0, 6: 6.0, 8: 8.0, 5: 5.0, 9: 9.0, 4: 4.0, 10: 10.0, 3: 3.0, 1: 1.0, 2: 2.0},
'Exterior1st':{'VinylSd': 12.0, 'MetalSd': 6.0, 'Wd Sdng': 5.0, 'HdBoard': 8.0, 'BrkFace': 11.0, 'WdShing': 7.0, 'CemntBd': 13.0, 'Plywood': 10.0, 'AsbShng': 4.0, 'Stucco': 9.0, 'BrkComm': 1.0, 'AsphShn': 2.0, 'Stone': 14.0, 'ImStucc': 15.0, 'CBlock': 3.0},
'MasVnrType':{'BrkFace': 3.0, 'None': 2.0, 'Stone': 5.0, 'BrkCmn': 1.0, 'missing': 4.0},
'ExterQual':{'Gd': 3.0, 'TA': 2.0, 'Ex': 4.0, 'Fa': 1.0},
'BsmtQual':{'Gd': 4.0, 'TA': 3.0, 'Ex': 5.0, 'missing': 1.0, 'Fa': 2.0},
'HeatingQC':{'Ex': 5.0, 'Gd': 4.0, 'TA': 3.0, 'Fa': 2.0, 'Po': 1.0},
'CentralAir':{'Y': 2.0, 'N': 1.0},
'KitchenQual':{'Gd': 3.0, 'TA': 2.0, 'Ex': 4.0, 'Fa': 1.0},
'GarageFinish':{'RFn': 3.0, 'Unf': 2.0, 'Fin': 4.0, 'missing': 1.0},
'PavedDrive':{'Y': 3.0, 'N': 1.0, 'P': 2.0}}
```

replacing the qualitative feature values with their corresponding codes

[60]:
```python
for q, k in zip(qualitative, dict_encoded.keys()):
    test = test.replace({q : dict_encoded[k]})
```

now that the features in train and test are matching we can proceed with deploying the model

[61]:
```
X = train[qual_encoded + quantitative + boolean]
y = train["SalePrice"]
```

[62]:
```
X_hat = test[qualitative + quantitative + boolean]
```

[63]:
```
sc.fit(X)
sc.transform(X)
sc.transform(X_hat);
```

[64]:
```
GBR = GradientBoostingRegressor(random_state=0)
```

[65]:
```
GBR.fit(X,y)
```

[65]:
```
GradientBoostingRegressor(random_state=0)
```

[66]:
```
y_hat = GBR.predict(X_hat)
```

[67]:
```
y_hat
```

[67]:
```
array([123638.99910299, 148935.11717237, 178523.65454128, …,
       161386.00447232, 119889.6328585 , 185291.4420935 ])
```

[68]:
```
output = pd.DataFrame({'Id': test.Id,
                       'SalePrice': y_hat})
output.to_csv('submission.csv', index=False)
```

This yields a score of 0,14 on the leaderboard without any hyperparameter tuning