HOUSING PROJECT

BY CHARITHA LANKA

ACKNOWLEDGMENT

In this project different libraries and methods are used that are available in python which helped in completion of the project:

https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

http://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.PowerTransformer.html

http://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html

http://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html

http://scikit-learn.org/stable/modules/model_evaluation.html

http://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html

http://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html

https://seaborn.pydata.org/generated/seaborn.countplot.html

https://www.analyticsvidhya.com/blog/2020/06/auc-roc-curve-machine-learning/

https://www.analyticsvidhya.com/blog/2020/10/how-to-choose-evaluation-metrics-for-classification-model/

https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/

INTRODUCTION

- Business Problem Framing

Houses are one of the necessary need of each and every person around the globe and therefore housing and real estate

market is one of the markets which is one of the major contributors in the world's economy. It is a very large market

and there are various companies working in the domain. Data science comes as a very important tool to solve problems

in the domain to help the companies increase their overall revenue, profits, improving their marketing strategies and

focusing on changing trends in house sales and purchases. Predictive modelling, Market mix modelling,

recommendation systems are some of the machine learning techniques used for achieving the business goals for housing

companies. Our problem is related to one such housing company.

A US-based housing company named Surprise Housing has decided to enter the Australian market. The company uses

data analytics to purchase houses at a price below their actual values and flip them at a higher price. For the same

purpose, the company has collected a data set from the sale of houses in Australia. The data is provided in the CSV file

below.

The company is looking at prospective properties to buy houses to enter the market. You are required to build a model

using Machine Learning in order to predict the actual value of the prospective properties and decide whether to invest

in them or not. For this company wants to know:

•Which variables are important to predict the price of variable?

•How do these variables describe the price of the house?

- ## Conceptual Background of the Domain Problem

The project will require knowledge and practice in building Graphs /Plots and analyzing them to get the relationship between dataset, Knowledge of Different Learning Models to build and predict the required output. Basic Data science concepts to increase the quality of the dataset and Python Knowledge (Coding Language) which will be used to solve the complete Micro Credit Defaulter project. Understanding of calculating F2 score, accuracy, skewness and basic mathematics/statistical approaches will help to build an accurate model for this project.

- ## Review of Literature

Market price is what a willing, ready and bank-qualified buyer will pay for a property and what the seller will accept for it. The transaction that takes place determines the market price, which will then influence the market value of future sales. Price is determined by local supply and demand, the property's condition and what other similar properties have sold for without adding in the value component.

Market value is an opinion of what a property would sell for in a competitive market based on the features and benefits of that property (the value), the overall real estate market, supply and demand, and what other similar properties have sold for in the same condition.

The major difference between market value and market price is that the market value, in the eyes of the seller, might be much more than what a buyer will pay for the property or it's true market price. Value can create demand, which can influence price. But, without the demand function, value alone cannot influence price. As supply increases and demand decreases, price goes down, and value is not influential. As supply decreases and demand increases, the price will rise, and value will influence price. Market value and market price can be equal in a balanced market.

However, buyers and sellers can view value differently. A seller might feel that their in-ground pool is a benefit, but the buyer could see it as a negative and place less value on the property. Or the seller could feel the new roof they put on the house has great value; however, the buyer places no value on this because they expect the property to have a roof in good condition. Or a builder might feel he has superior quality and demand a higher price, but the buyer places less value on quality and more value on the lot, neighborhood and floor plan of the property.

- Motivation for the Problem Undertaken

  I wanted to solve the real-life problem using the technical skills gathered during the course of being a Data Analyst and improving the skill set.

Analytical Problem Framing

- Mathematical/ Analytical Modelling of the Problem----

  Regression Models->

  Regression analysis is a form of predictive modelling technique which investigates the relationship between a dependent (target) and independent variable (s) (predictor). This technique is used for forecasting, time series modelling and finding the causal effect relationship between the variables. For example, relationship between rash driving and number of road accidents by a driver is best studied through regression.

  Decision Tree –

  It is a decision-making tool that uses a flowchart-like tree structure or is a model of decisions and all of their possible results, including outcomes, input costs and utility.

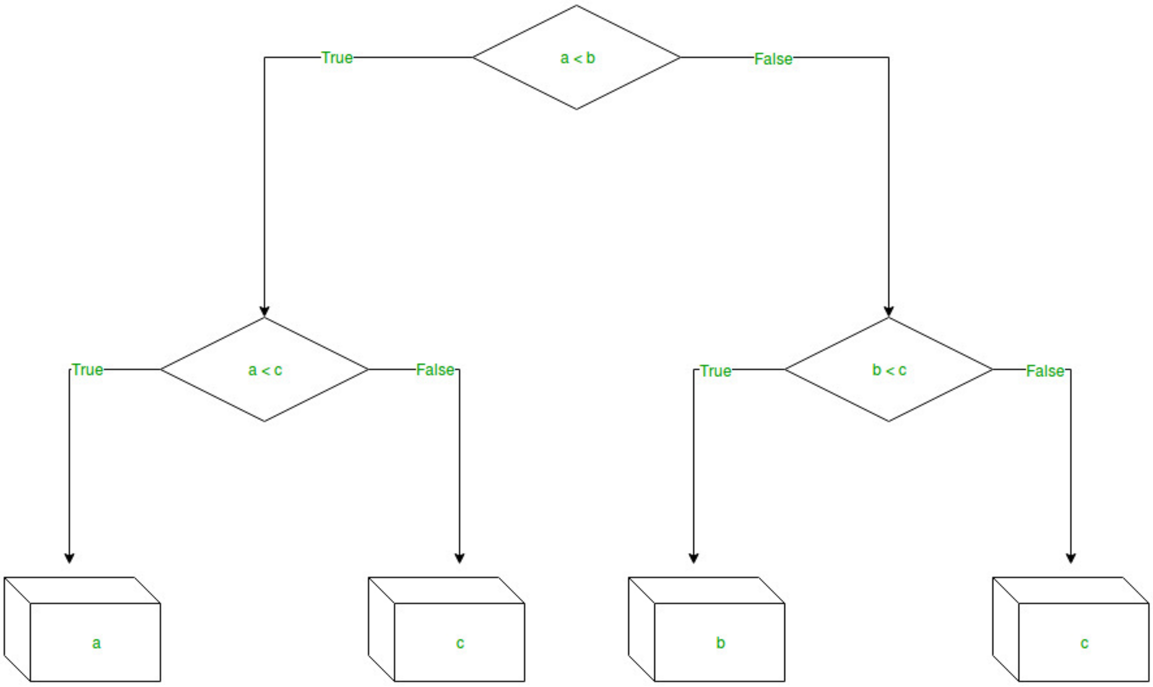
  Decision-tree algorithm falls under the category of supervised learning algorithms. It works for both continuous as well as categorical output variables.

  The branches/edges represent the result of the node and the nodes have either:

  Conditions [Decision Nodes]

  Result [End Nodes]

  The branches/edges represent the truth/falsity of the statement and takes makes a decision based on that in the example below which shows a decision tree that evaluates the smallest of three numbers:



Random Forest –

Random forest is a supervised learning algorithm which is used for both classification as well as regression. But however, it is mainly used for classification problems. As we know that a forest is made up of trees and more trees means more robust forest. Similarly, random forest algorithm creates decision trees on data samples and then gets the prediction from each of them and finally selects the best solution by means of voting. It is an ensemble method which is better than a single decision tree because it reduces the over-fitting by averaging the result.

Naive Bayes –

Naive Bayes classifiers are a collection of classification algorithms based on Bayes' Theorem. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other.

Linear Regression –

Linear regression is a linear model, e.g. a model that assumes a linear relationship between the input variables (x) and the single output variable (y). More specifically, that y can be calculated from a linear combination of the input variables (x).

When there is a single input variable (x), the method is referred to as simple linear regression. When there are multiple input variables, literature from statistics often refers to the method as multiple linear regression.

SVM –

Supervised Machine Learning Algorithm used for classification and/or regression. It is more preferred for classification but is sometimes very useful for regression as well. Basically, SVM finds a hyper-plane that creates a boundary between the types of data. In 2-dimensional space, this hyper-plane is nothing but a line.

We used different Plots/ graphs to perform EDA on the dataset->

1) Box Plot**:** It is a type of chart that depicts a group of numerical data through their quartiles. It is a simple way to visualize the shape of our data. It makes comparing characteristics of data between categories very easy.
2) Count Plot: IT is kind of like a histogram or a bar graph for some categorical area. It simply shows the number of occurrences of an item based on a certain type of category
3) Heat Map: It contains values representing various shades of the same color for each value to be plotted. Usually, the darker shades of the chart represent higher values than the lighter shade. For a very different value a completely different color can also be used.

4) Scatter Plot: A scatter plot is a diagram where each value in the data set is represented by a dot. The Matplotlib module has a method for drawing scatter plots

- ## Data Sources and their formats

Below are the fields present in our dataset with the information what these fields describe

MS Subclass: Identifies the type of dwelling involved in the sale.

20 1-STORY 1946 & NEWER ALL STYLES

30 1-STORY 1945 & OLDER

40 1-STORY W/FINISHED ATTIC ALL AGES

45 1-1/2 STORY - UNFINISHED ALL AGES

50 1-1/2 STORY FINISHED ALL AGES

60 2-STORY 1946 & NEWER

70 2-STORY 1945 & OLDER

75 2-1/2 STORY ALL AGES

80 SPLIT OR MULTI-LEVEL

85 SPLIT FOYER

90 DUPLEX - ALL STYLES AND AGES

120 1-STORY PUD (Planned Unit Development) - 1946 & NEWER

150 1-1/2 STORY PUD - ALL AGES

160 2-STORY PUD - 1946 & NEWER

180 PUD - MULTILEVEL - INCL SPLIT LEV/FOYER

190 2 FAMILY CONVERSION - ALL STYLES AND AGES

MS Zoning: 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

Lot Frontage: Linear feet of street connected to

property Lot Area: 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 GilbertGilbert
IDOTRR Iowa DOT and Rail Road

MeadowV Meadow Village

Mitchel Mitchell

NamesNorth 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

TwnhsITownhouse 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

2TypesMore 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)

Data types of the fields:

Below is the information of all the attributes with their respective datatypes:

Column name	datatype
Id	int64
MSSubClass	int64
MSZoning	object
LotFrontage	float64
LotArea	int64
Street	object
Alley	object
LotShape	object
LandContour	object
Utilities	object
LotConfig	object
LandSlope	object
Neighborhood	object
Condition1	object
Condition2	object
BldgType	object
HouseStyle	object
OverallQual	int64
OverallCond	int64
YearBuilt	int64
YearRemodAdd	int64
RoofStyle	object

RoofMatl	object
Exterior1st	object
Exterior2nd	object
MasVnrType	object
MasVnrArea	float64
ExterQual	object
ExterCond	object
Foundation	object
BsmtQual	object
BsmtCond	object
BsmtExposure	object
BsmtFinType1	object
BsmtFinSF1	int64
BsmtFinType2	object
BsmtFinSF2	int64
BsmtUnfSF	int64
TotalBsmtSF	int64
Heating	object
HeatingQC	object
CentralAir	object
Electrical	object
1stFlrSF	int64
2ndFlrSF	int64
LowQualFinSF	int64
GrLivArea	int64

BsmtFullBath	int64
BsmtHalfBath	int64
FullBath	int64
HalfBath	int64
BedroomAbvGr	int64
KitchenAbvGr	int64
KitchenQual	object
TotRmsAbvGrd	int64
Functional	object
Fireplaces	int64
FireplaceQu	object
GarageType	object
GarageYrBlt	float64
GarageFinish	object
GarageCars	int64
GarageArea	int64
GarageQual	object
GarageCond	object
PavedDrive	object
WoodDeckSF	int64
OpenPorchSF	int64
EnclosedPorch	int64
3SsnPorch	int64
ScreenPorch	int64
PoolArea	int64

PoolQC	object
Fence	object
MiscFeature	object
MiscVal	int64
MoSold	int64
YrSold	int64
SaleType	object
SaleCondition	object
SalePrice	int64

- Data Pre-processing Done

    1) First we checked the data set dimensions

```
In [4]: df.shape
Out[4]: (1168, 81)
```

    We have 1168 rows and 81 columns

    2) Then we checked whether there is any repeating data available

```
duplicate = df.duplicated()
print(duplicate.sum())
df[duplicate]
```

```
0
```

    3) We checked the outliers using the Box Plot and replaced the outliers with more appropriate values. Removal of outliers can also be done but taking the Data Loss percentage into consideration It is better to replace the outlier

- Hardware and Software Requirements and Tools Used

1) Software: Jupyter Notebook - To code and build the project in python
2) Libraries:
    a) numpy - To perform basic math operations
    b) pandas - To perform basic File operations
    c) Matplotlib - To plot Different Graphs/ Plots
    d) Seaborn - Advance library to enhance the quality of graphs/plots
    e) warnings - To ignore the unwanted warnings raised while interpreting the code
    f) sklearn - To build the Prediction models
    g) imblearn - To balance our dataset distribution

Model/s Development and Evaluation

- ## Identification of possible problem-solving approaches (methods)

  We used different approaches from checking the dataset quality to building the model. We checked the null values and repeated rows in the dataset. For checking the Outliers, we used Box Plot and to remove the outliers we used IQR method. Then we moved to next step of checking data distribution and skewness. To scale the data, we used MinMax Scaler method and to remove the skewness we first checked the log and square root method but skewness of the dataset was not getting removed from it so we performed the Power transform to remove skewness.. We started building different models and checked their R2 score and selected the best suited model to perform Hyper tuning on. We got Random Forest Algo with the best result and after performing Hyper tuning we finalized the model.

- ## Testing of Identified Approaches (Algorithms)

  1) Linear Regression
  2) Decision Tree
  3) Elastic Net
  4) Lasso
  5) Random Forest
  6) Ridge

- Run and Evaluate selected models

```
In [36]: from sklearn import metrics
         regr = LinearRegression()
         regr.fit(x_train, y_train)
         pred=regr.predict(x_test)
         print('R2 score',r2_score(y_test, pred))
         print('MAE:', metrics.mean_absolute_error(y_test, pred))
         print('MSE:', metrics.mean_squared_error(y_test, pred))
         print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, pred)))

         R2 score 0.9122522295050699
         MAE: 14889.955766381772
         MSE: 371736028.1239309
         RMSE: 19280.45715547043
```

```
In [37]: rr = Ridge(alpha=0.01)
         rr.fit(x_train, y_train)
         pred=rr.predict(x_test)
         print('R2 score',r2_score(y_test, pred))
         print('MAE:', metrics.mean_absolute_error(y_test, pred))
         print('MSE:', metrics.mean_squared_error(y_test, pred))
         print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, pred)))

         R2 score 0.911823459114965
         MAE: 14934.890606094272
         MSE: 373552477.7145672
         RMSE: 19327.505729259716
```

```
In [38]: model_lasso = Lasso(alpha=0.01)
         model_lasso.fit(x_train, y_train)
         pred=model_lasso.predict(x_test)
         print('R2 score',r2_score(y_test, pred))
         print('MAE:', metrics.mean_absolute_error(y_test, pred))
         print('MSE:', metrics.mean_squared_error(y_test, pred))
         print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, pred)))

         R2 score 0.9118234658159894
         MAE: 14935.104867786691
         MSE: 373552449.3262428
         RMSE: 19327.504994857532
```

In [39]:

```
mode1_enet = E1ast1c Net (alpha = fi .81)
mode1_enet .f16(x_tra1n, y_6ra1n)
pred     dei_enet .pred1ct(x_6est)
pr1nt ( ' R2  score,'   r2_score(y_test    pred))
pr1nt('UAE: "    metric s. atean_abso1ute_error(y_test, pred) )
pr1nt('NSE: "    metr1c s. atean_squared_error(y_tes6, pred))
pr1nt ( ' RNSE : ' , np . sqrt(rne6r1cs .mean_squared_error(y_6est, pred) ) )
```

```
R2  score0.9119966779517421
HAf: 14928.821981156287
MSE:  372818650.7236752B
RNSE: 193€l8.51239£tZ3fi255
```

In [4B]:

```
from sklearn.free 1rspor-I Dec1s lonTreeRegressor
-from sklearn Jzapot-I: metr1c s
dtr A ec1s1onTreeRegressor ( )
dtr .f16(x_tra1n,y_6ra1n)
pred—dtr.pred1ct(x_6est)
pr1nt('R2  score,'    r2_score(y_tes6, pred))
pr1nt('PIAE: "    metr1c s. atean_abso1ute_error(y_test, pred) )
pr1nt('NSE: "    metr1c s. atean_squared_error(y_tes6, pred))
pr1nt ( ' RNSE : ' , np . sqrt(metrics .mean_squared_error(y_6est, pred) ) )
```

```
R2 score‹B.77238316G82535
HAS: 2M81.713d7B213676
HSE: 964618430.767B94
BMSE: 91f158.3B69526B927
```

In [41.]:

```
from  sklearn. ensemble  Mg  sr•t   RandonForest:Regressor
rdr = RandomF orest Regres sor ( )
rdr.fit(x_train,y_train)
predl=rdr.predict(x_test)
print('R2  score',r2_score(y_test, predl))
print('PIAE:"    metrics.atean_abso1ute_error(y_test,  pred1))
print('NSE:"    metrics.atean_squared_error(y_tes6,  pred1))
print ( ' RfñSE : ' , np . sqrt(metrics .mean_ squared_error ( y_6es,t     pred1) ) )
```

```
R2  score0.887077749951416#

HSE: 478385589.8121692
BMSE: 21872.B275654BJ875
```

- Key Metrics for success in solving problem under consideration

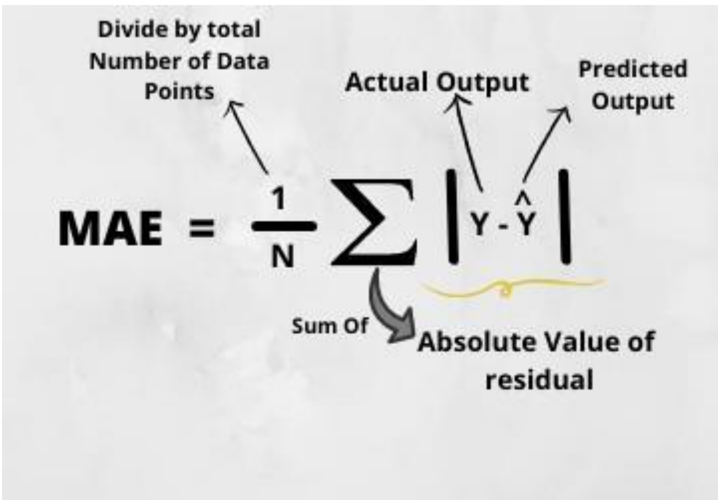
1) Mean Absolute Error(MAE)

MAE is a very simple metric which calculates the absolute difference between actual and predicted values.

To better understand, let's take an example you have input data and output data and use Linear Regression, which draws a best-fit line.

Now you have to find the MAE of your model which is basically a mistake made by the model known as an error. Now find the difference between the actual value and predicted value that is an absolute error but we have to find the mean absolute of the complete dataset.

so, sum all the errors and divide them by a total number of observations And this is MAE. And we aim to get a minimum MAE because this is a loss.



Advantages of MAE

The MAE you get is in the same unit as the output variable.

It is most Robust to outliers.

Disadvantages of MAE

The graph of MAE is not differentiable so we have to apply various optimizers like Gradient descent which can be differentiable.

from sklearn.metrics import mean_absolute_error

print("MAE",mean_absolute_error(y_test,y_pred))

Now to overcome the disadvantage of MAE next metric came as MSE.

2) Mean Squared Error(MSE)

MSE is a most used and very simple metric with a little bit of change in mean absolute error. Mean squared error states that finding the squared difference between actual and predicted value.

So, above we are finding the absolute difference and here we are finding the squared difference.

What actually the MSE represents? It represents the squared distance between actual and predicted values. we perform squared to avoid the cancellation of negative terms and it is the benefit of MSE.

$$MSE = \frac{1}{n} \Sigma \underbrace{\left(y - \widehat{y} \right)}_{\text{The square of the difference between actual and predicted}}{}^2$$

Advantages of MSE

The graph of MSE is differentiable, so you can easily use it as a loss function.

Disadvantages of MSE

The value you get after calculating MSE is a squared unit of output. for example, the output variable is in meter(m) then after calculating MSE the output we get is in meter squared.

If you have outliers in the dataset then it penalizes the outliers most and the calculated MSE is bigger. So, in short, It is not Robust to outliers which were an advantage in MAE.

from sklearn.metrics import mean_squared_error

print("MSE",mean_squared_error(y_test,y_pred))

3) Root Mean Squared Error(RMSE)

As RMSE is clear by the name itself, that it is a simple square root of mean squared error.

$$\text{RMSE} = \sqrt{\text{MSE}}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)}$$

Advantages of RMSE

The output value you get is in the same unit as the required output variable which makes interpretation of loss easy.

Disadvantages of RMSE

It is not that robust to outliers as compared to MAE.

for performing RMSE we have to NumPy NumPy square root function over MSE.

print("RMSE",np.sqrt(mean_squared_error(y_test,y_pred)))

Most of the time people use RMSE as an evaluation metric and mostly when you are working with deep learning techniques the most preferred metric is RMSE.

4) Root Mean Squared Log Error(RMSLE)

Taking the log of the RMSE metric slows down the scale of error. The metric is very helpful when you are developing a model without calling the inputs. In that case, the output will vary on a large scale.

To control this situation of RMSE we take the log of calculated RMSE error and resultant we get as RMSLE.

To perform RMSLE we have to use the NumPy log function over RMSE.

```
print("RMSE",np.log(np.sqrt(mean_squared_error(y_test,y_pred))))
```

It is a very simple metric that is used by most of the datasets hosted for Machine Learning competitions.

5) R Squared (R2)

R2 score is a metric that tells the performance of your model, not the loss in an absolute sense that how many wells did your model perform.

In contrast, MAE and MSE depend on the context as we have seen whereas the R2 score is independent of context.

So, with help of R squared we have a baseline model to compare a model which none of the other metrics provides. The same we have in classification problems which we call a threshold which is fixed at 0.5. So basically R2 squared calculates how must regression line is better than a mean line.

Hence, R2 squared is also known as Coefficient of Determination or sometimes also known as Goodness of fit.

$$\textbf{R2 Squared} = 1 - \frac{SSr}{SSm}$$

SSr = Squared sum error of regression line

SSm = Squared sum error of mean line

R2 Squared

Now, how will you interpret the R2 score? suppose If the R2 score is zero then the above regression line by mean line is equal means 1 so 1-1 is zero. So, in this case, both lines are overlapping means model performance is worst, It is not capable to take advantage of the output column.

Now the second case is when the R2 score is 1, it means when the division term is zero and it will happen when the regression line does not make any mistake, it is perfect. In the real world, it is not possible.

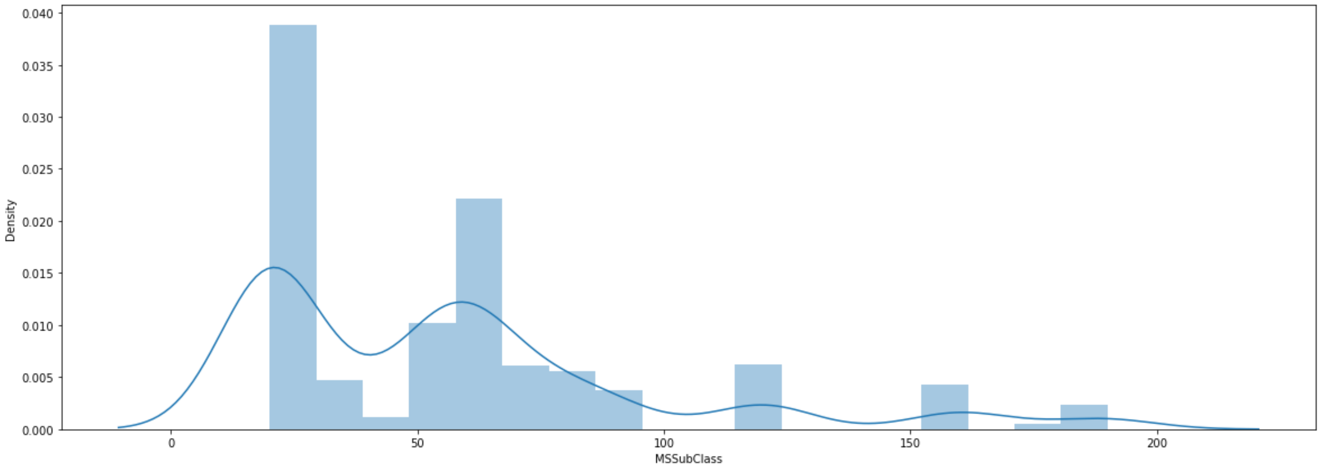
So we can conclude that as our regression line moves towards perfection, R2 score move towards one. And the model performance improves.

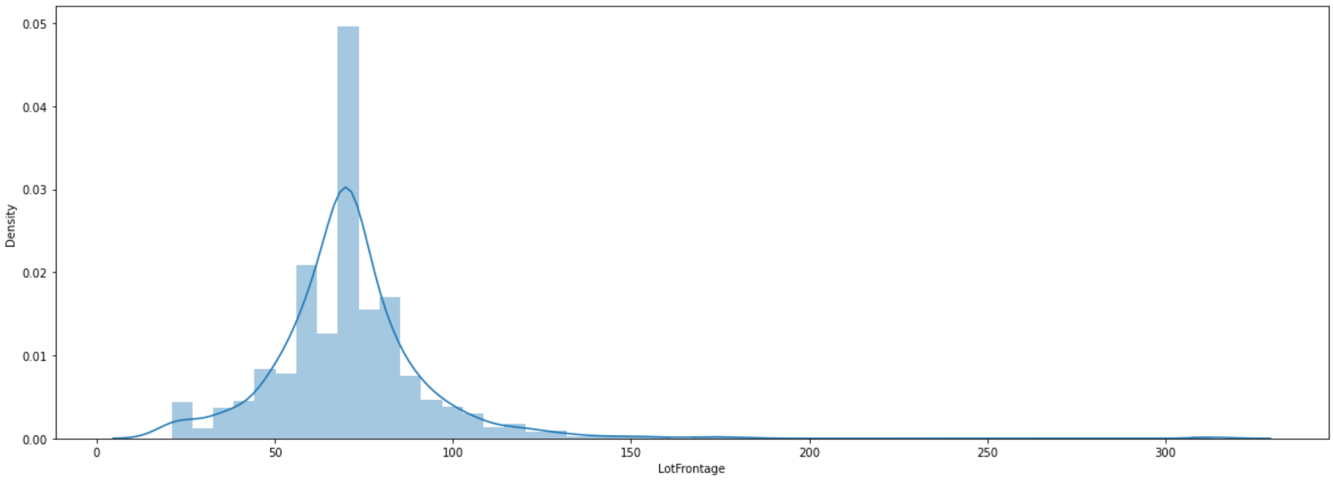
The normal case is when the R2 score is between zero and one like 0.8 which means your model is capable to explain 80 per cent of the variance of data.

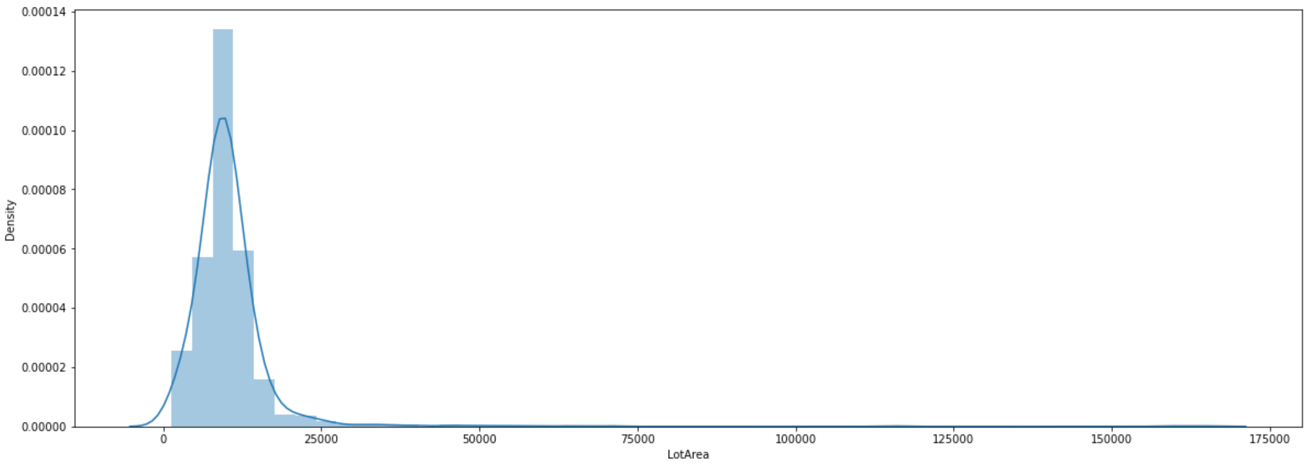
```
from sklearn.metrics import r2_score

r2 = r2_score(y_test,y_pred)

print(r2)
```

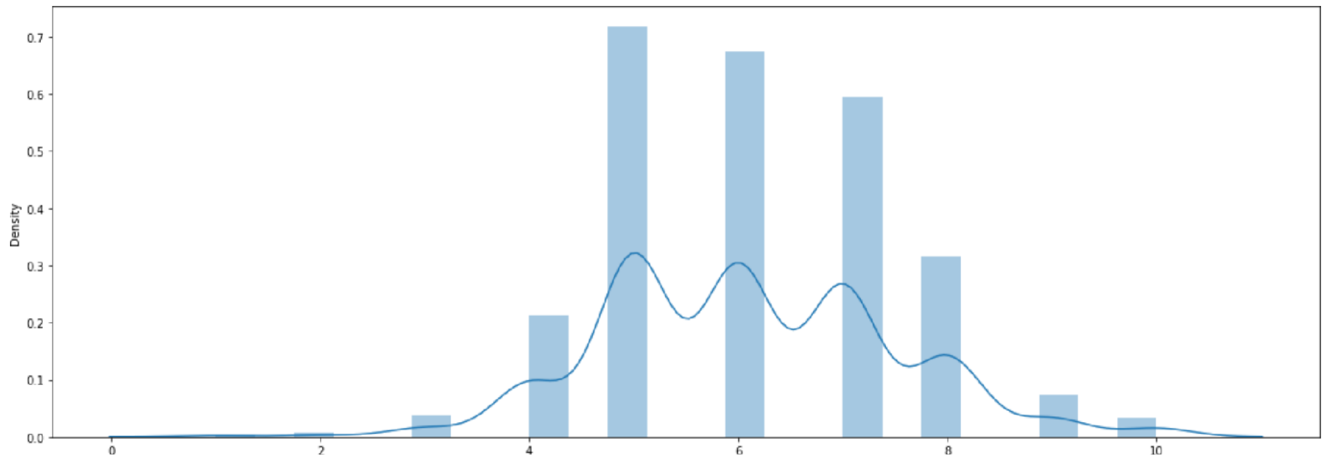
- Visualizations

In [14]:
```
counter=1;
for i in range(0,len(continous_columns)):
        plt.figure(figsize=(20,500))
        plt.subplot(60,1,counter)
        counter=counter+1
        sns.distplot(df[continous_columns[i]])
        plt.show()
```





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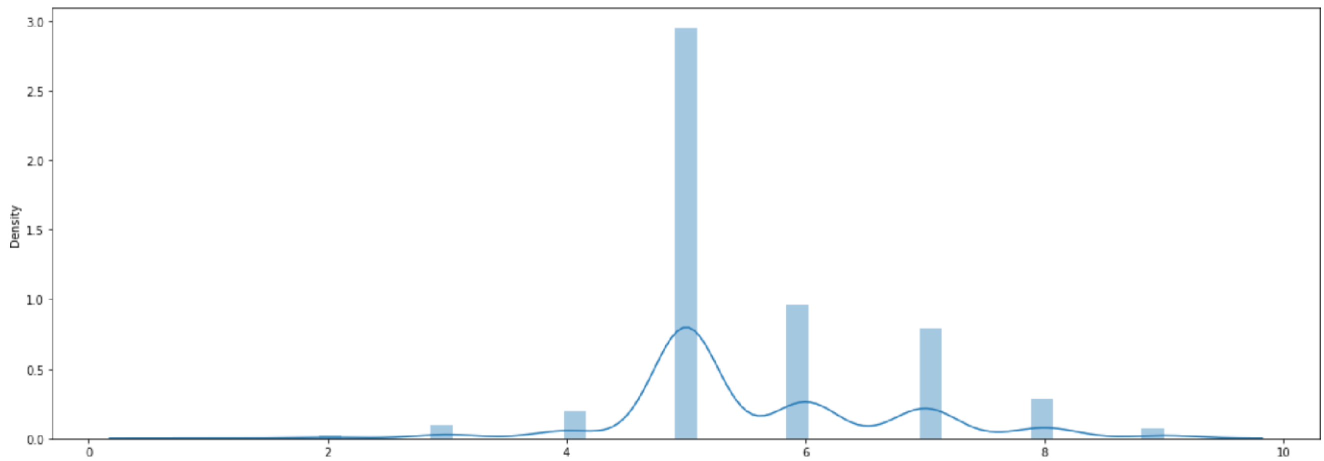
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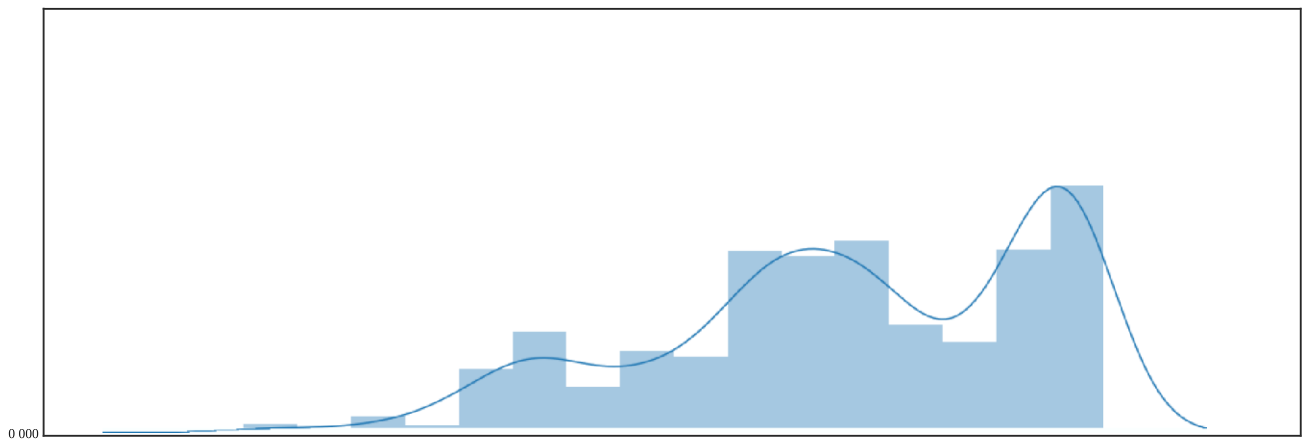
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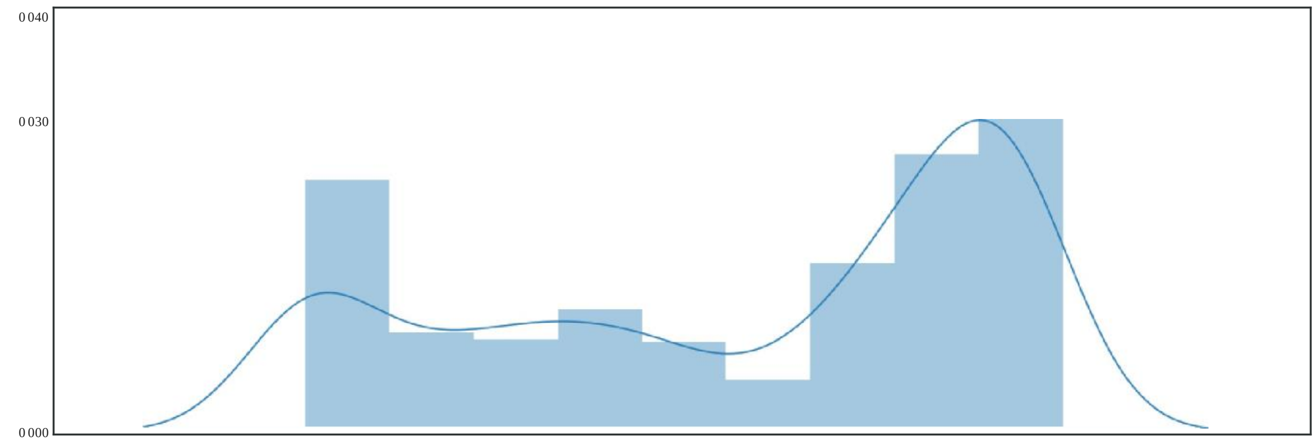
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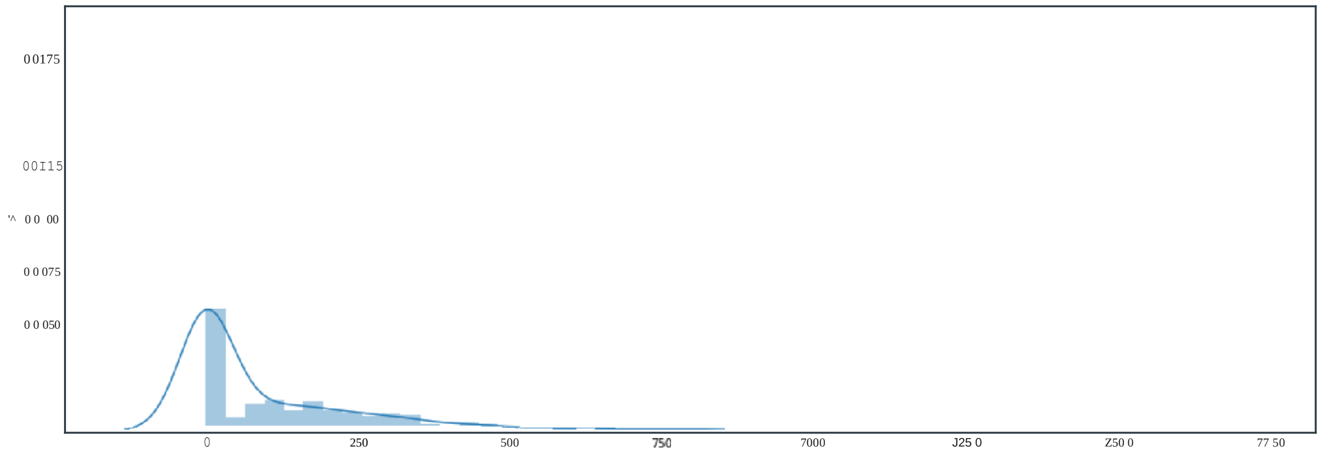
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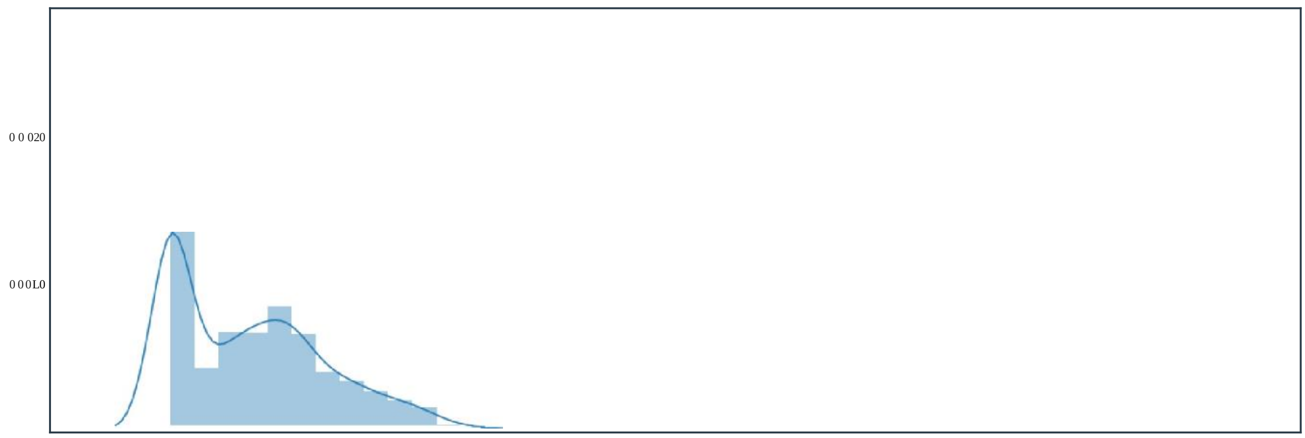
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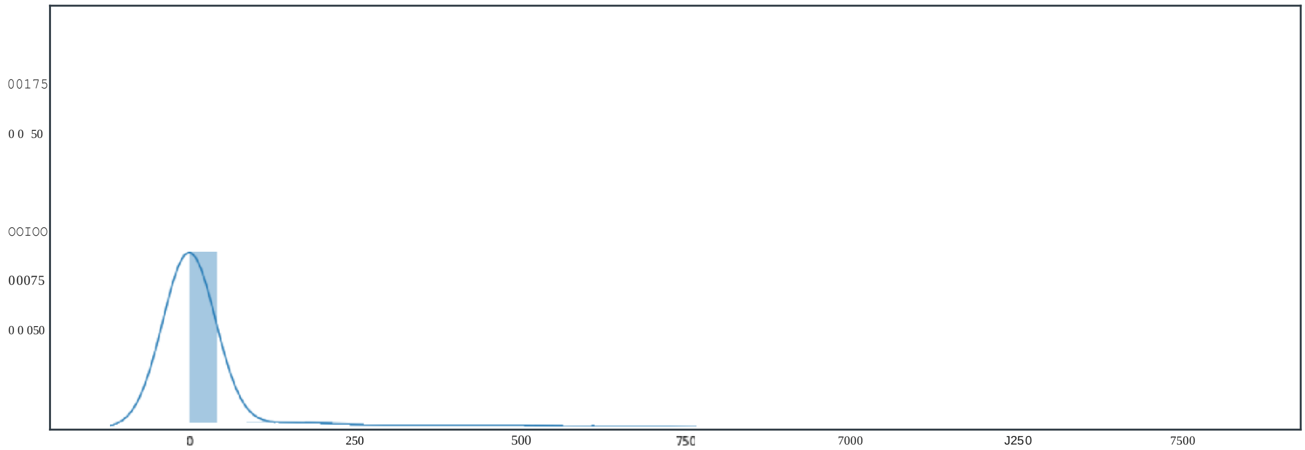
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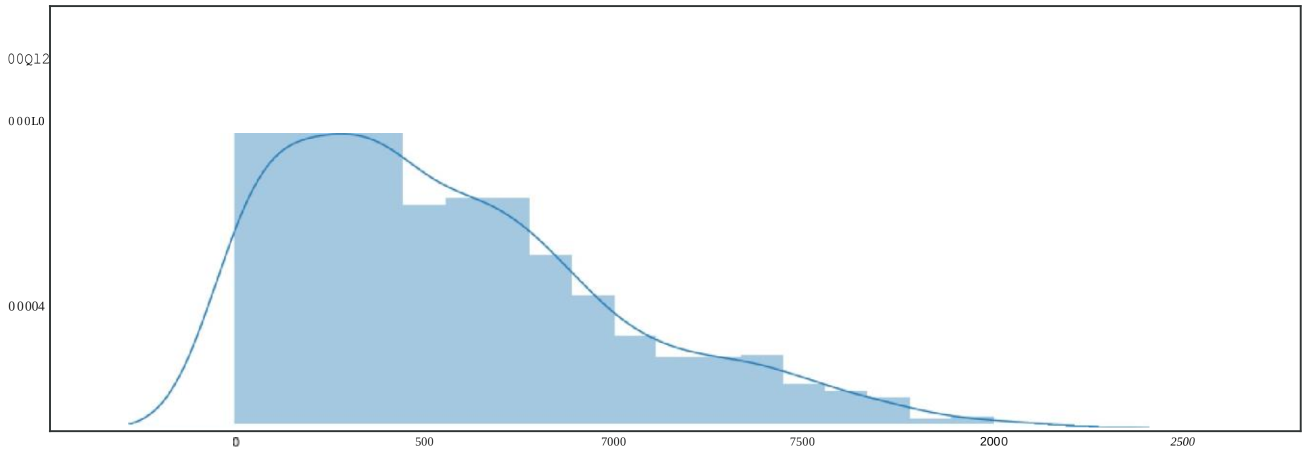
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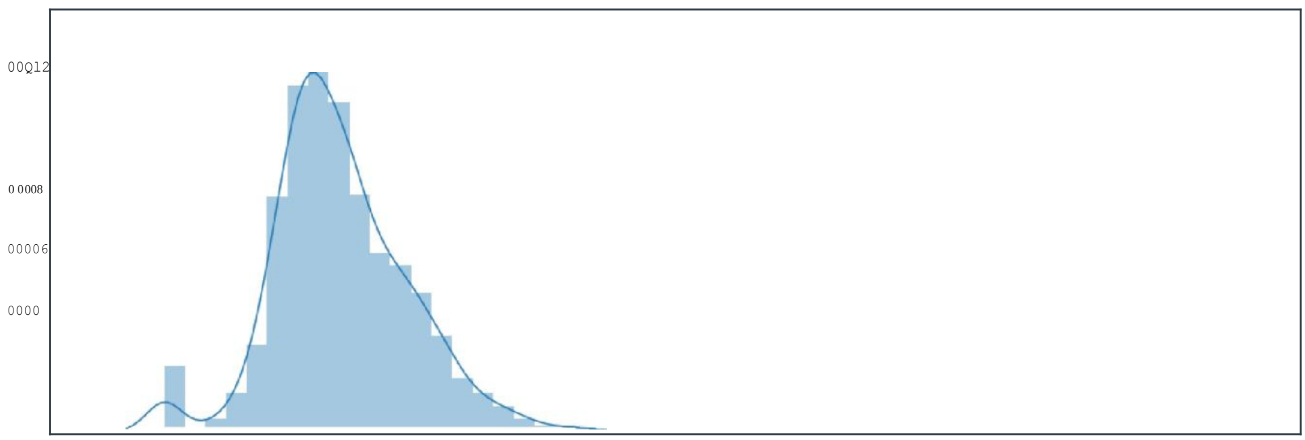
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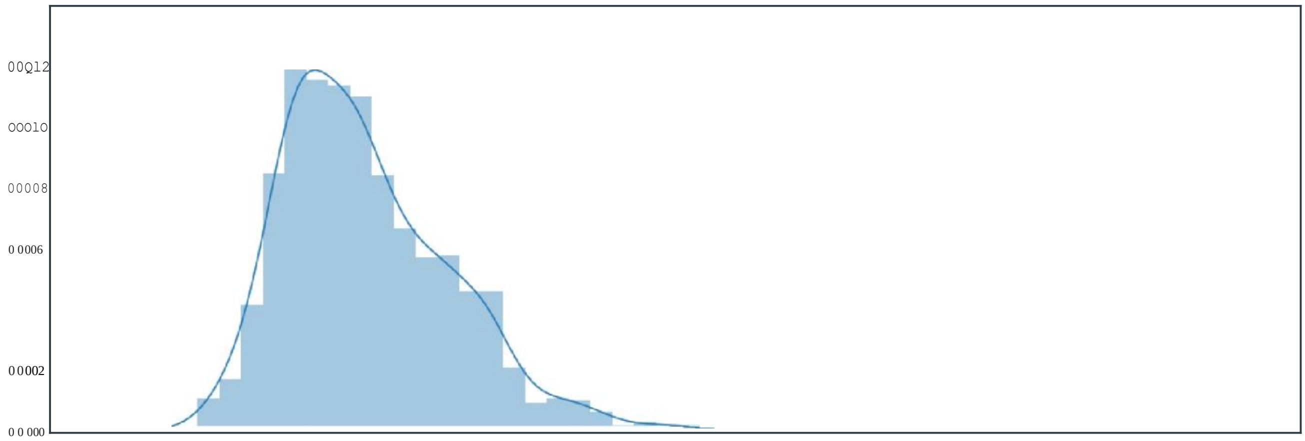
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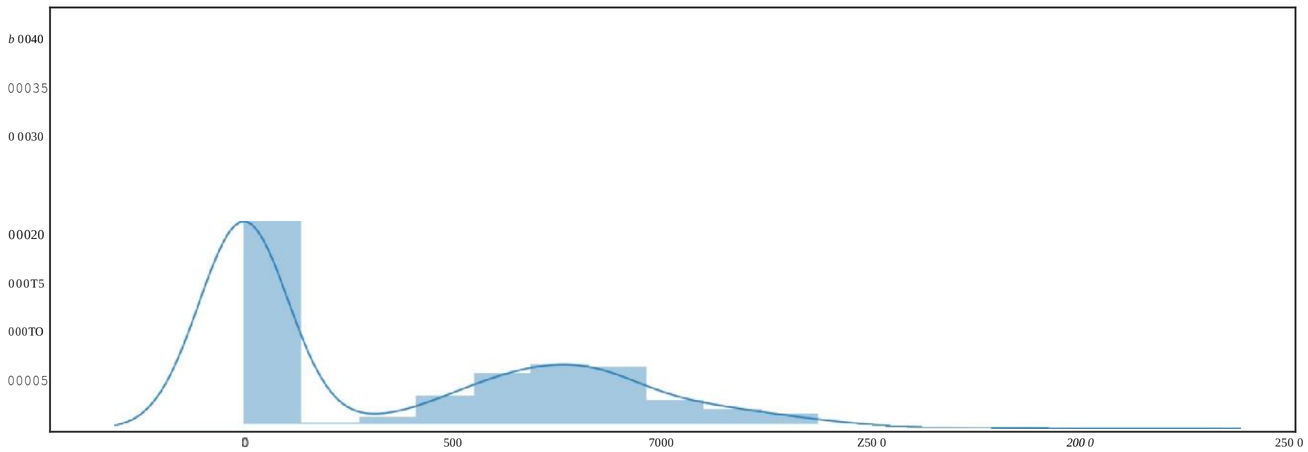
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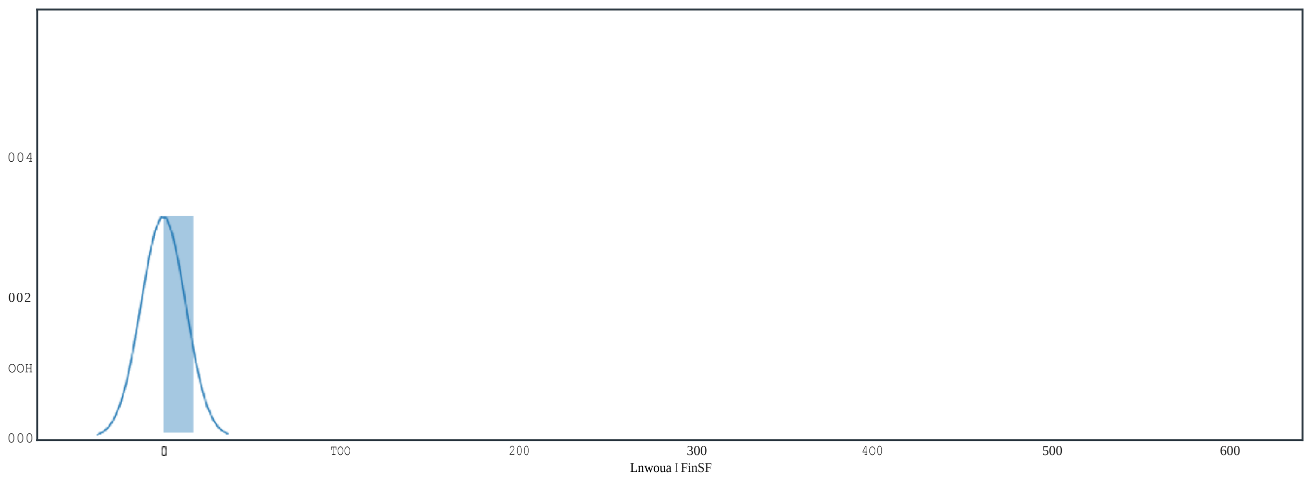
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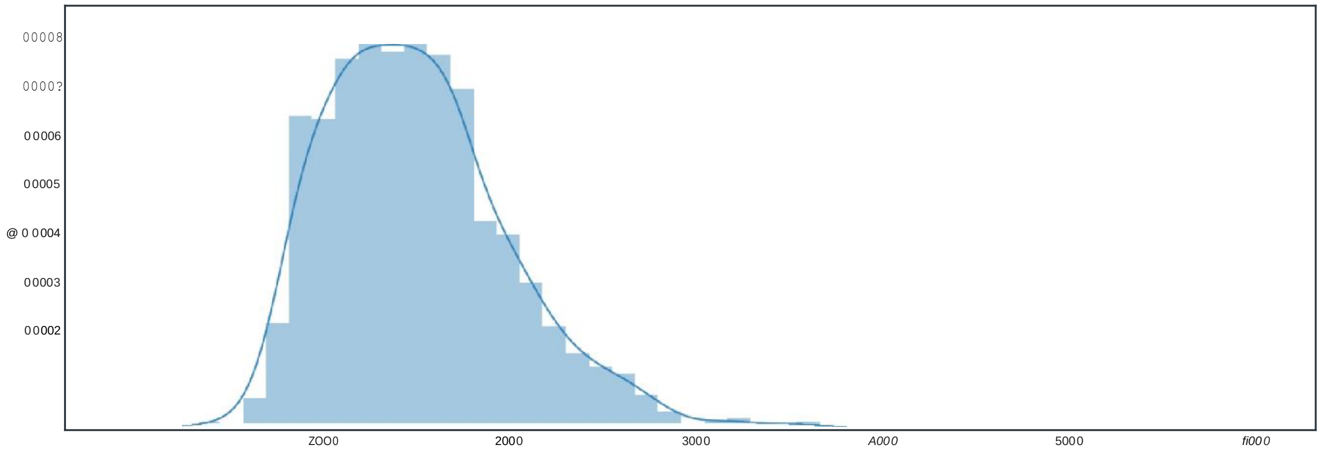
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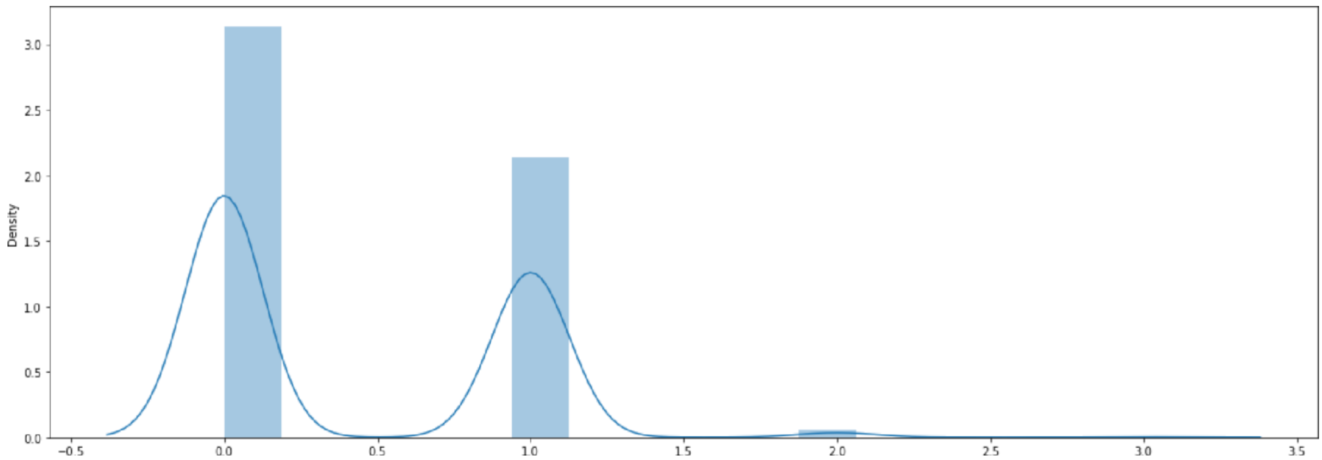
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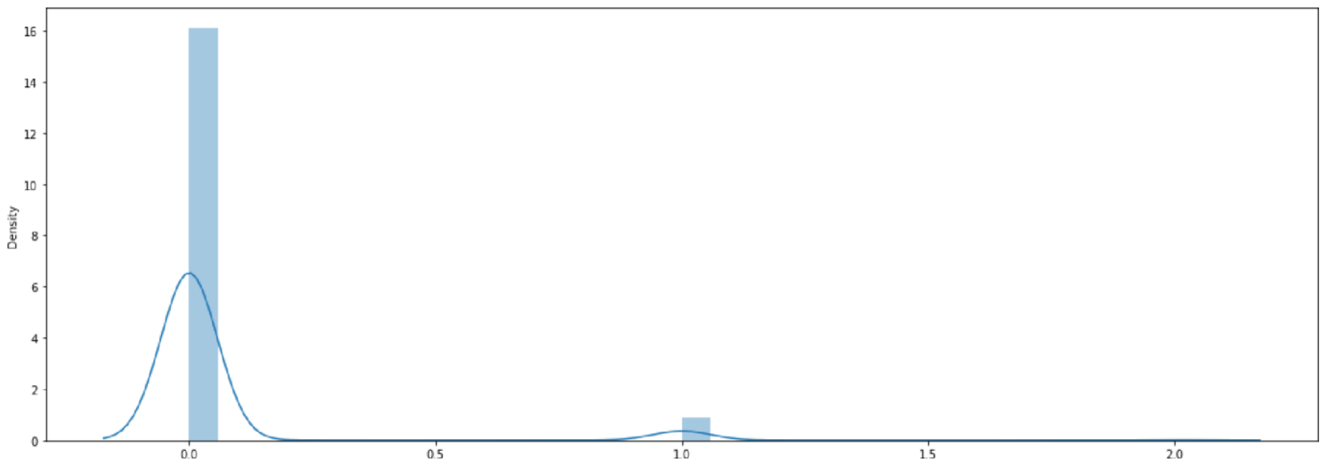
Density
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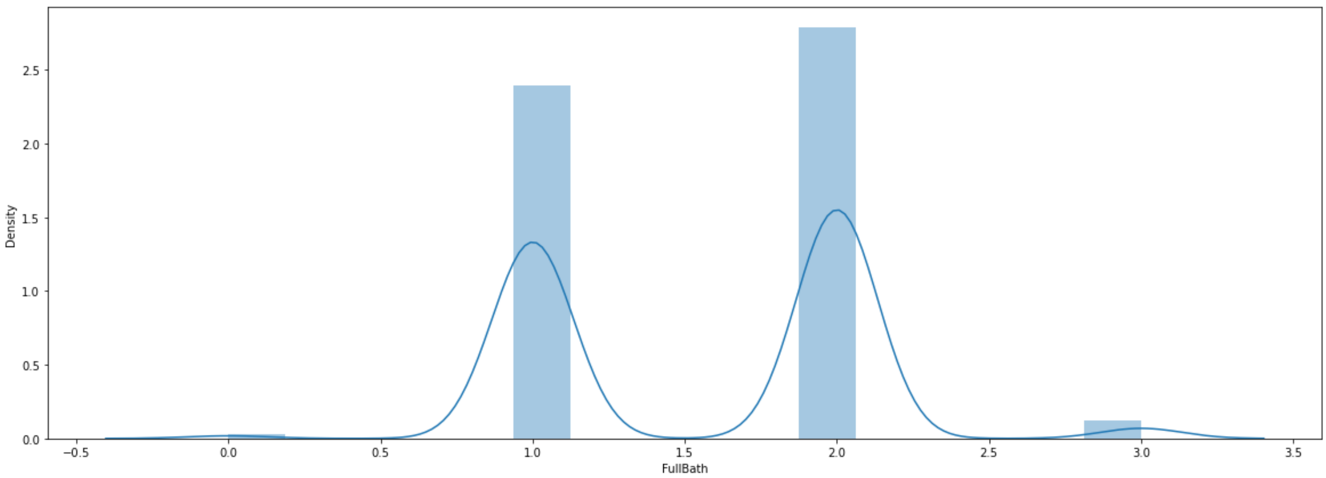

Density
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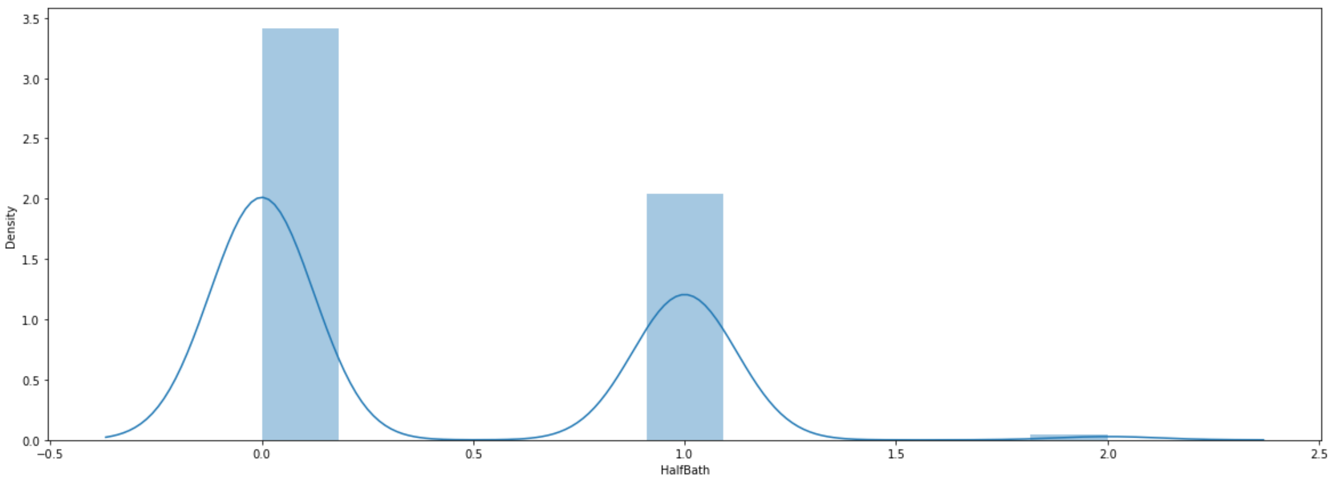

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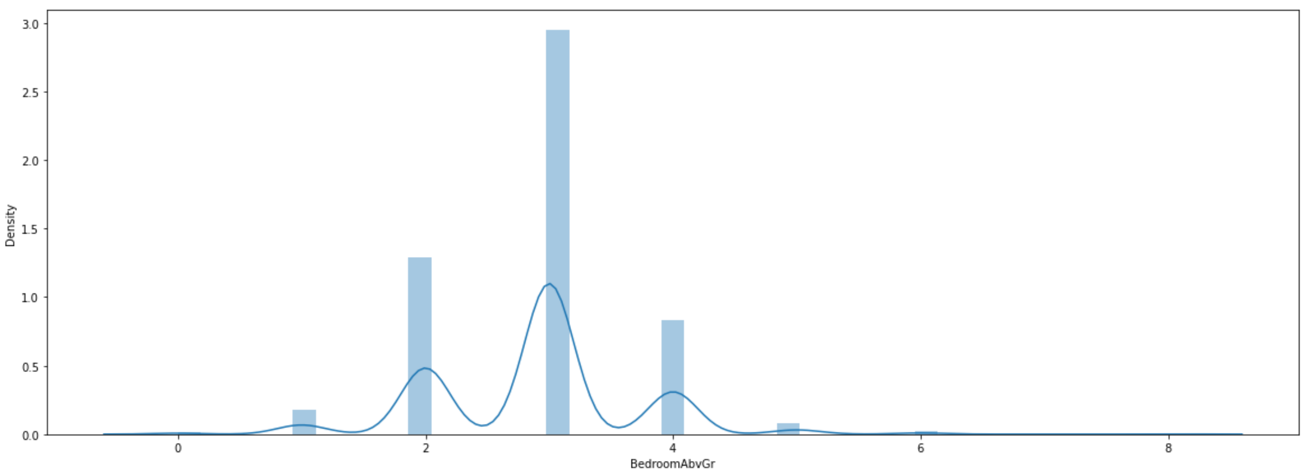

Density
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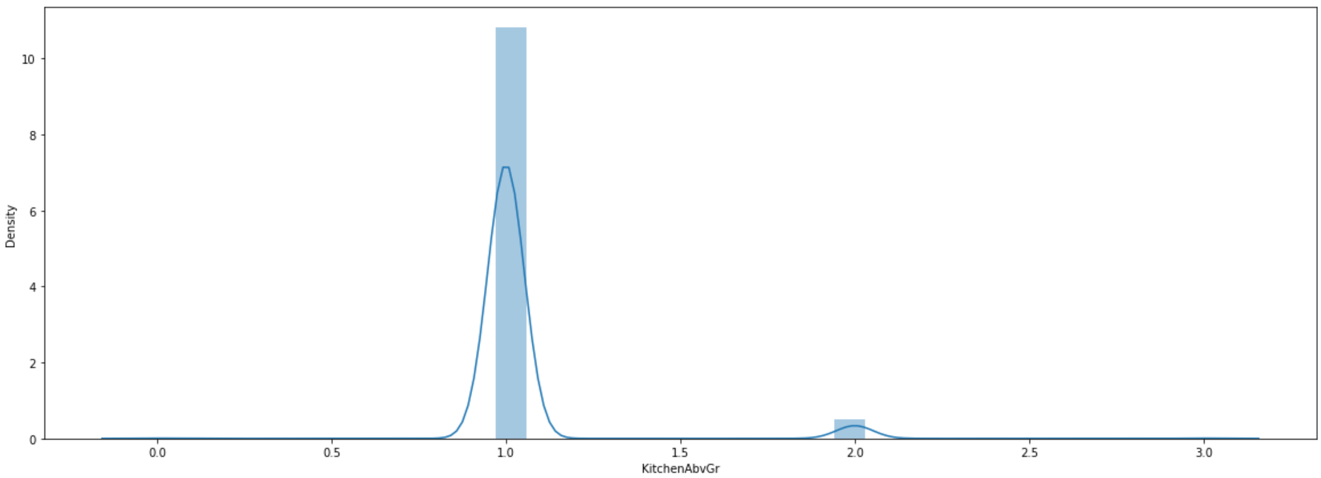
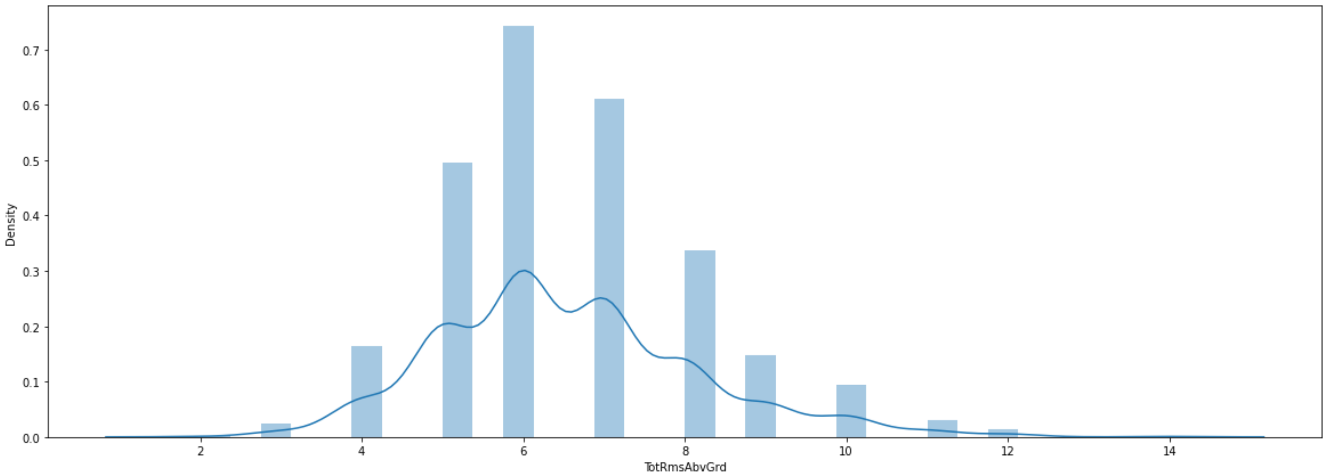
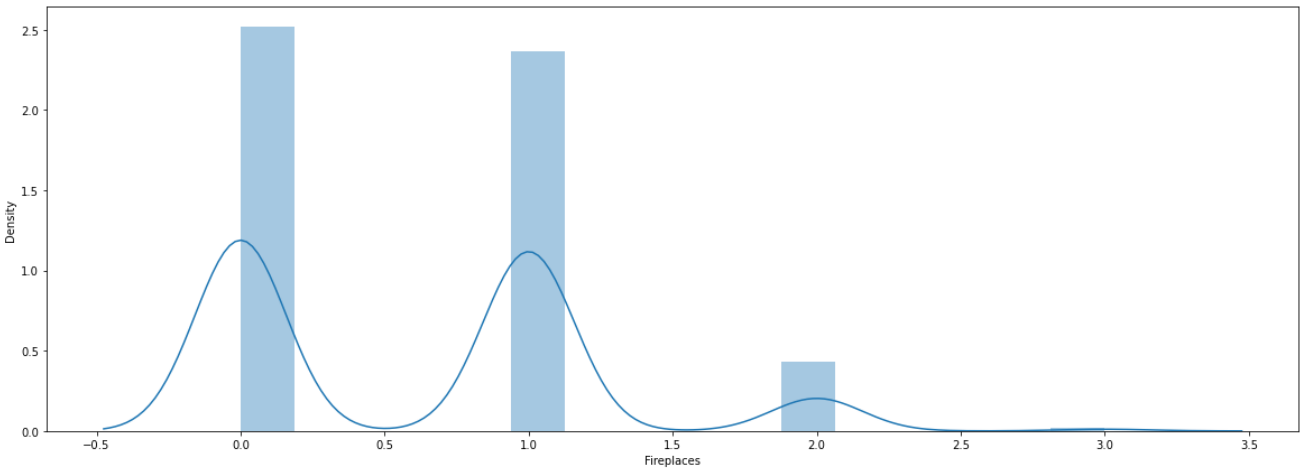


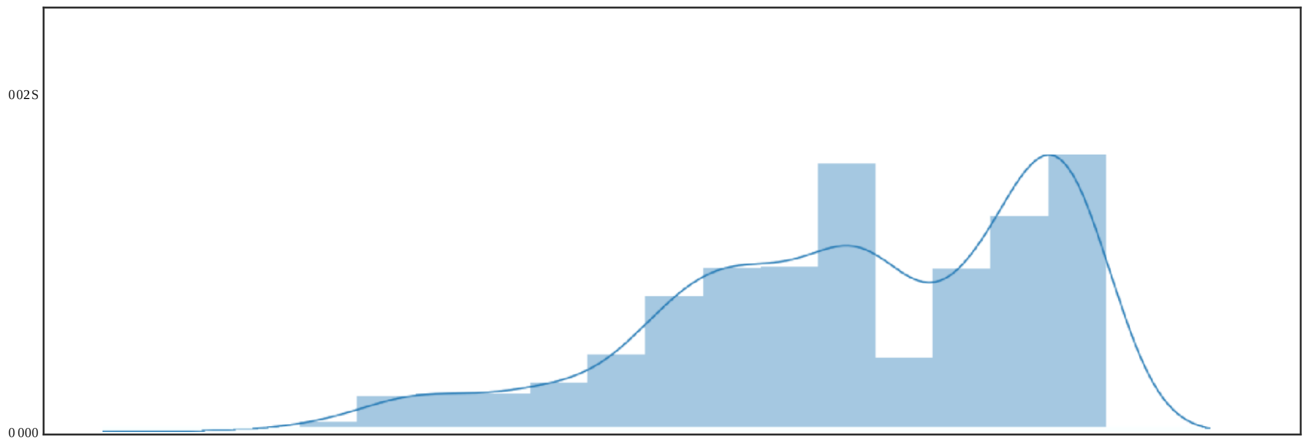
Density
KitchenAbvGr



Density
TotRmsAbvGrd



Density
Fireplaces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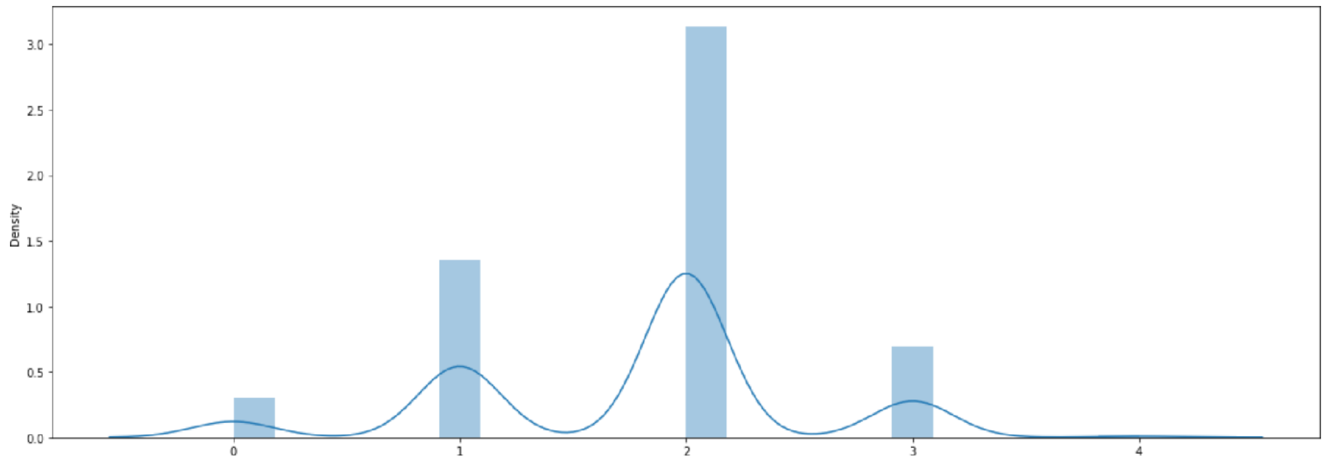
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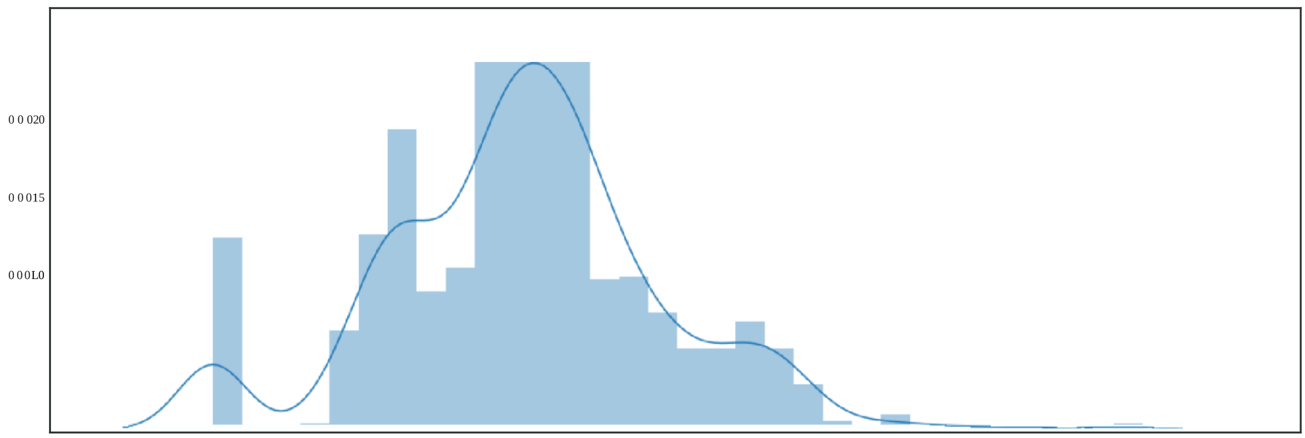
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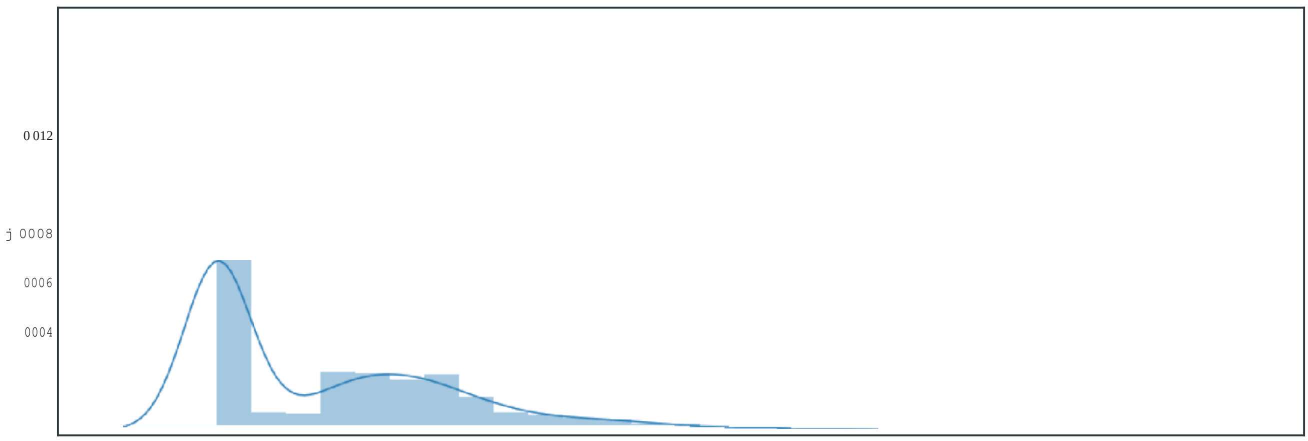
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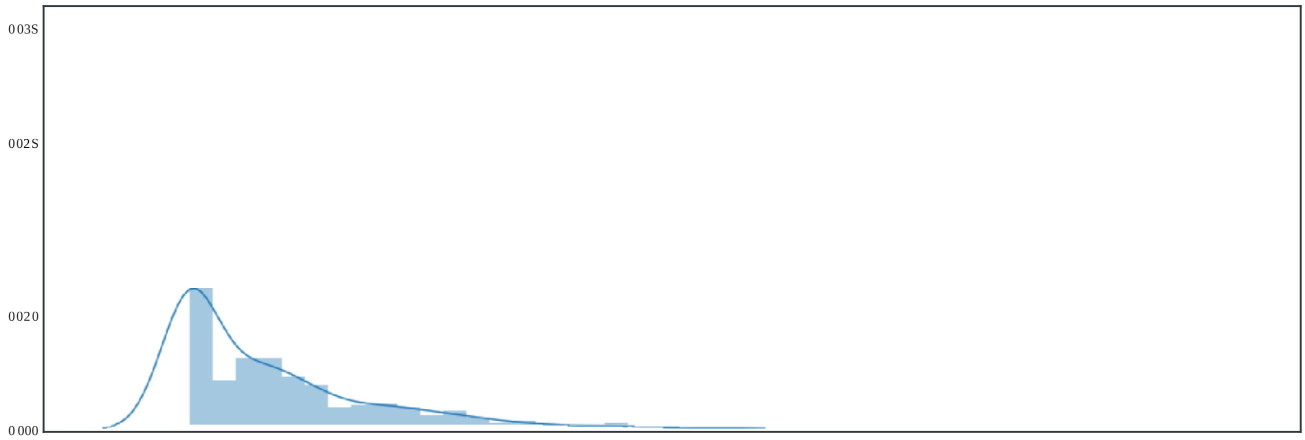
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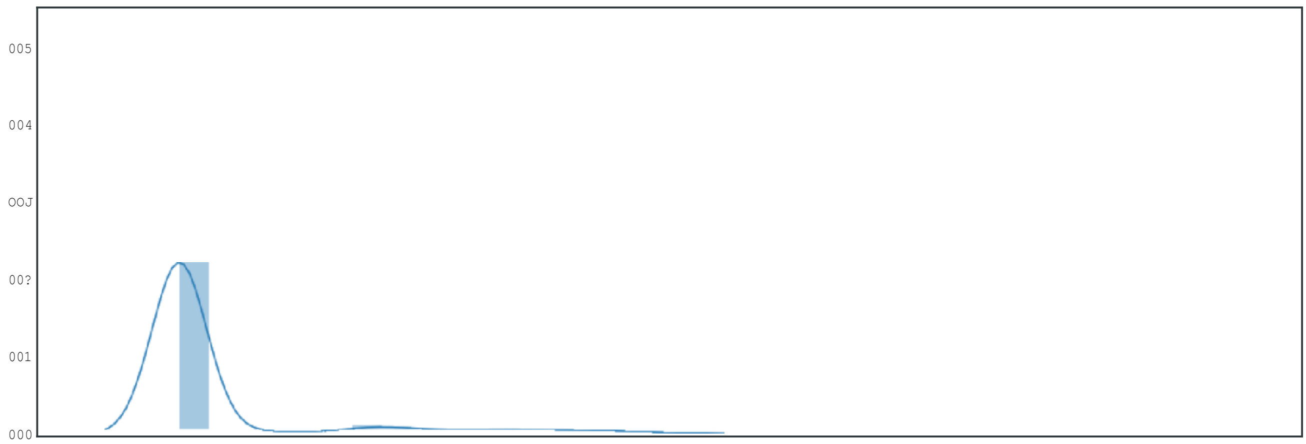
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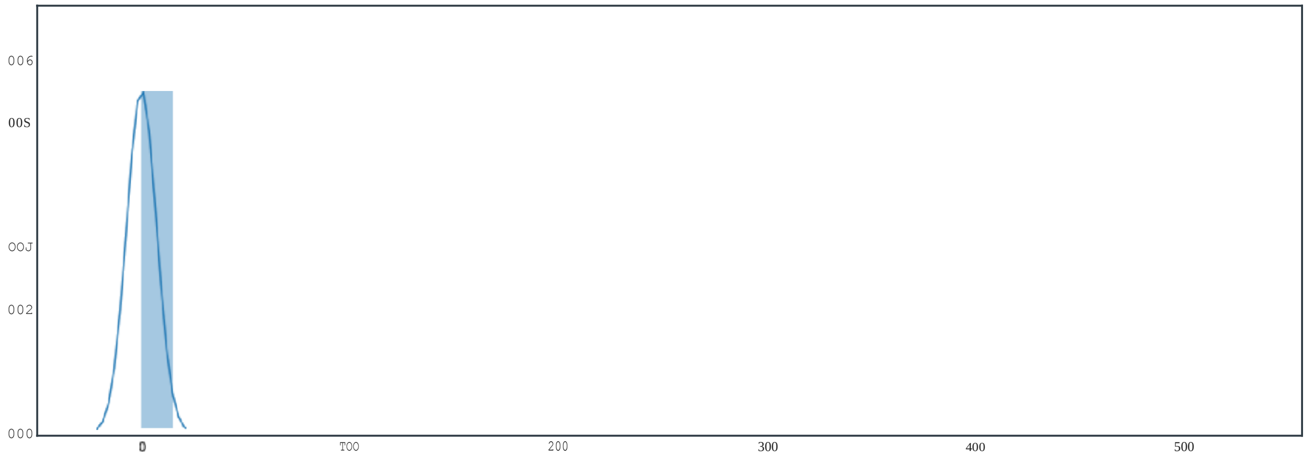

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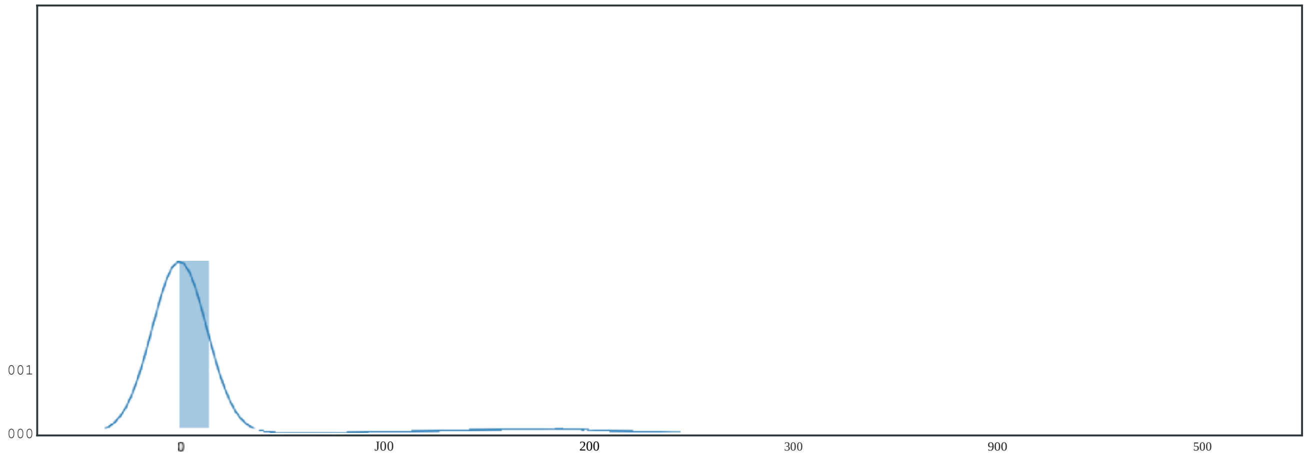

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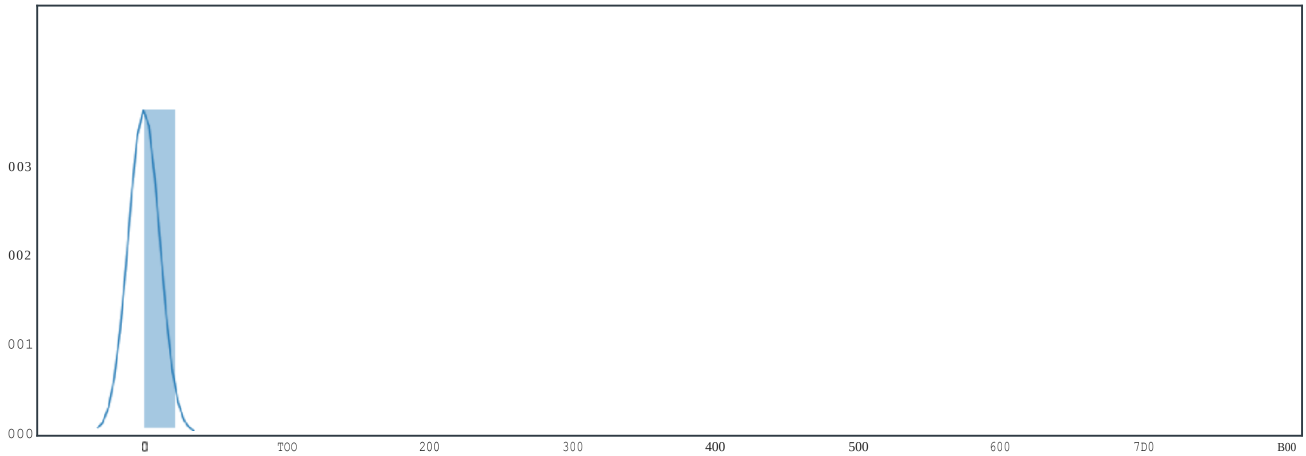

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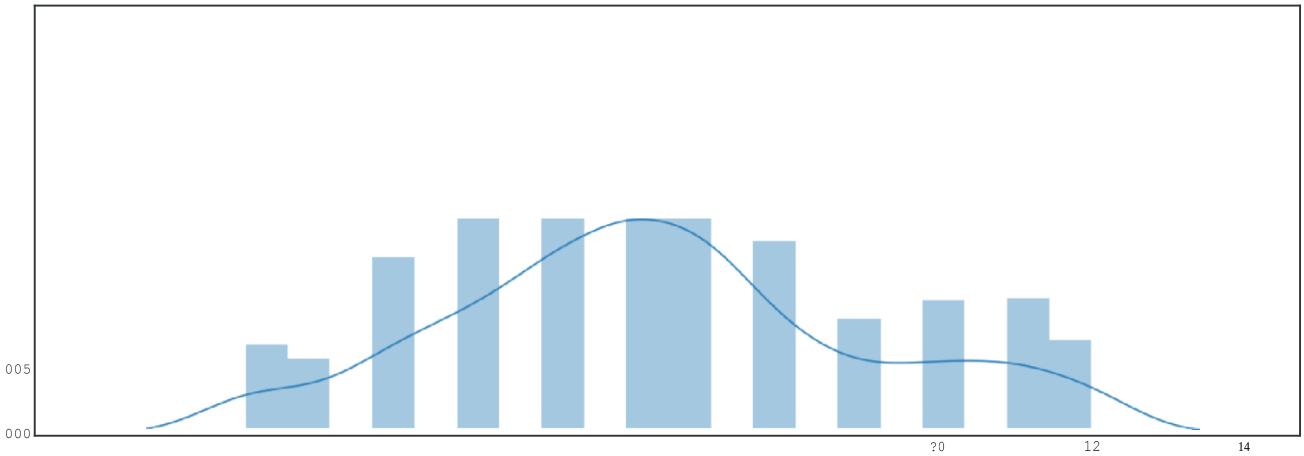
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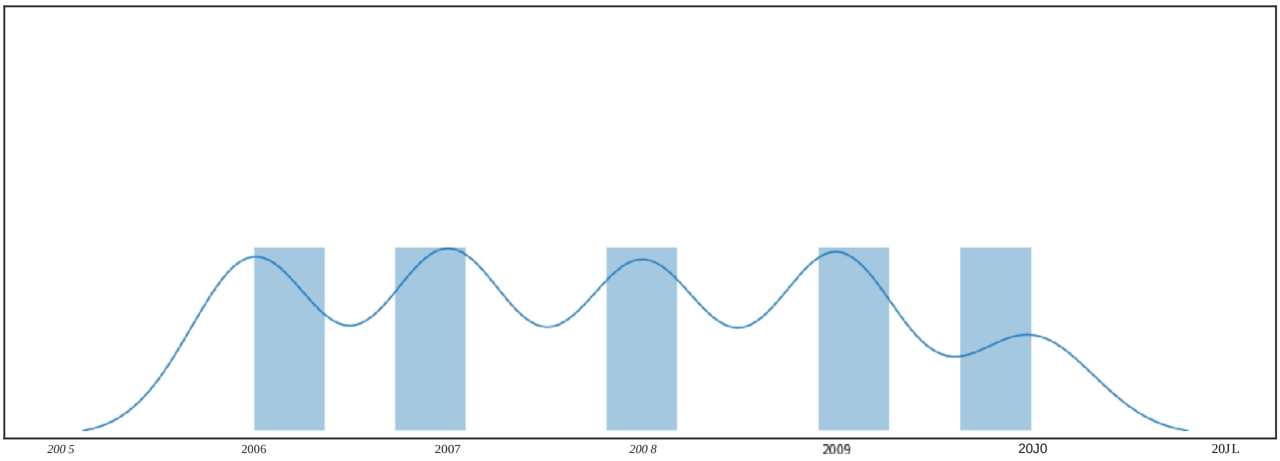
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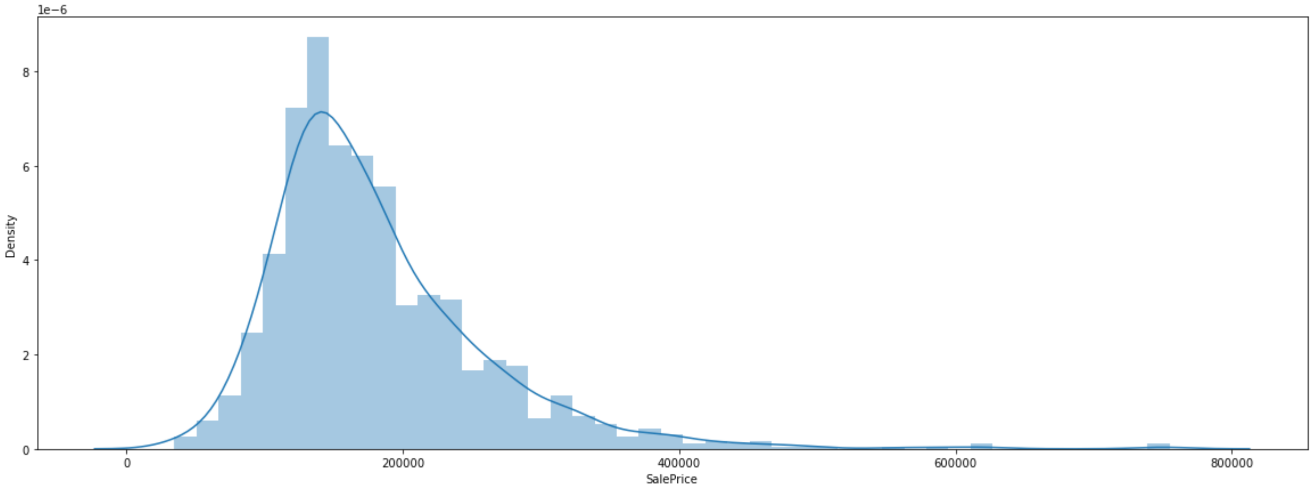


Findings:

MSSubClass -> not normally distributed

LotFrontage -> normally distributed

LotArea -> Normally distributed

OverallQual-> Not normally distributed

Overall cond-> Not normally distributed

Year Built -> Not normally distributed

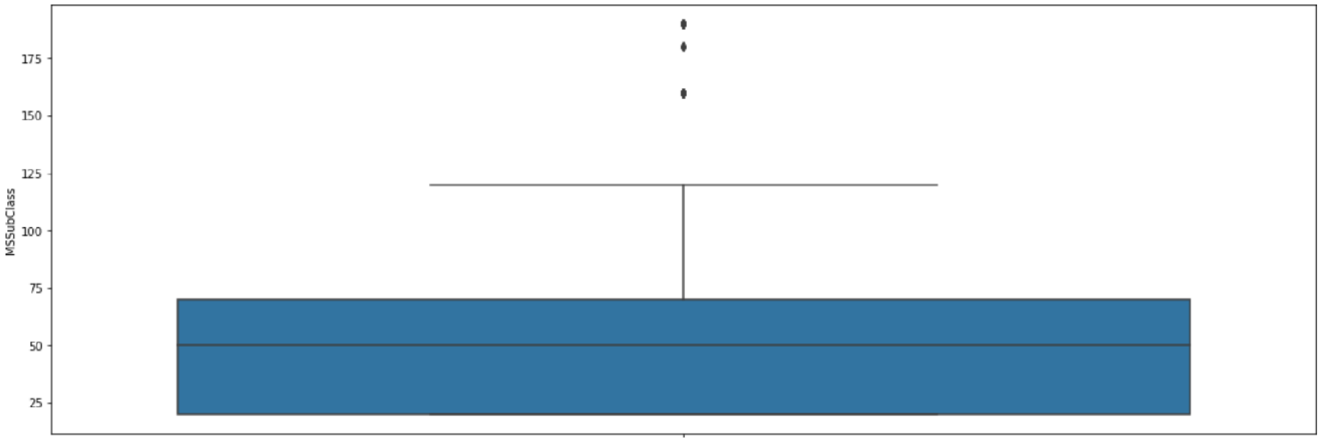
Year remod add->not normally distributed

BsmtFinSF1 ->not normally distributed

GaragerBlt ->not normally distributed

Garage Area -> not normally distributed

```
In [15]:  counter=1;
          for i in range(0,len(continous_columns)):
                  plt.figure(figsize=(20,500))
                  plt.subplot(60,1,counter)
                  counter=counter+1
                  sns.boxplot(y=continous_columns[i],hue = continous_columns[i],data=df)
                  #sns.boxplot(df[columns[i]])
                  plt.show()
```


MSSubClass
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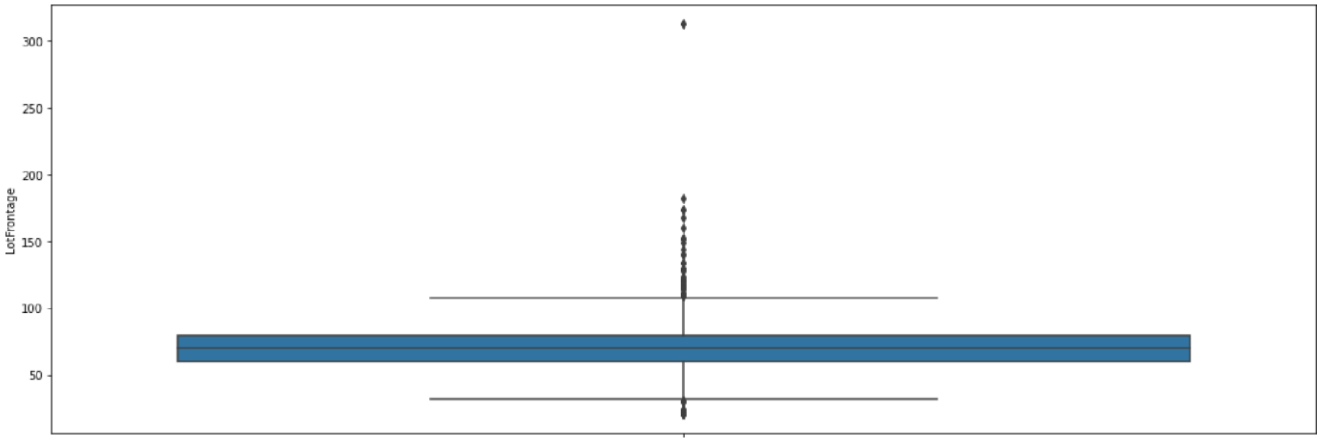
75
50
25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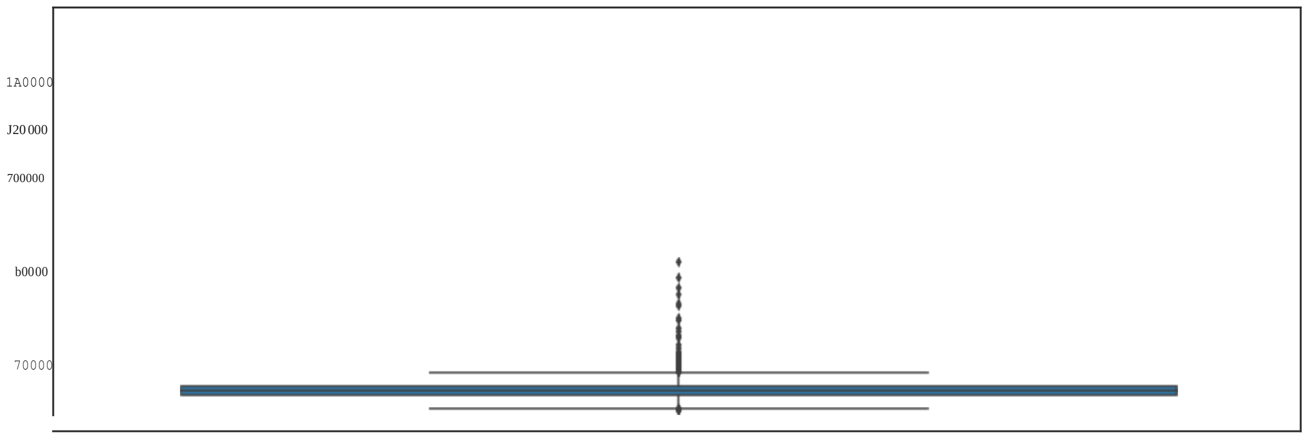
100
50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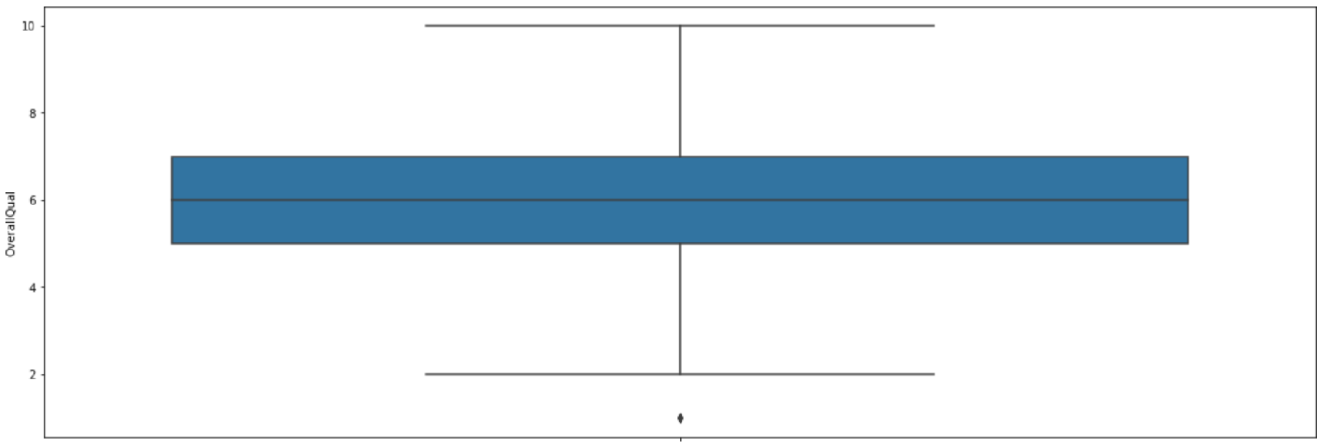
OverallQual
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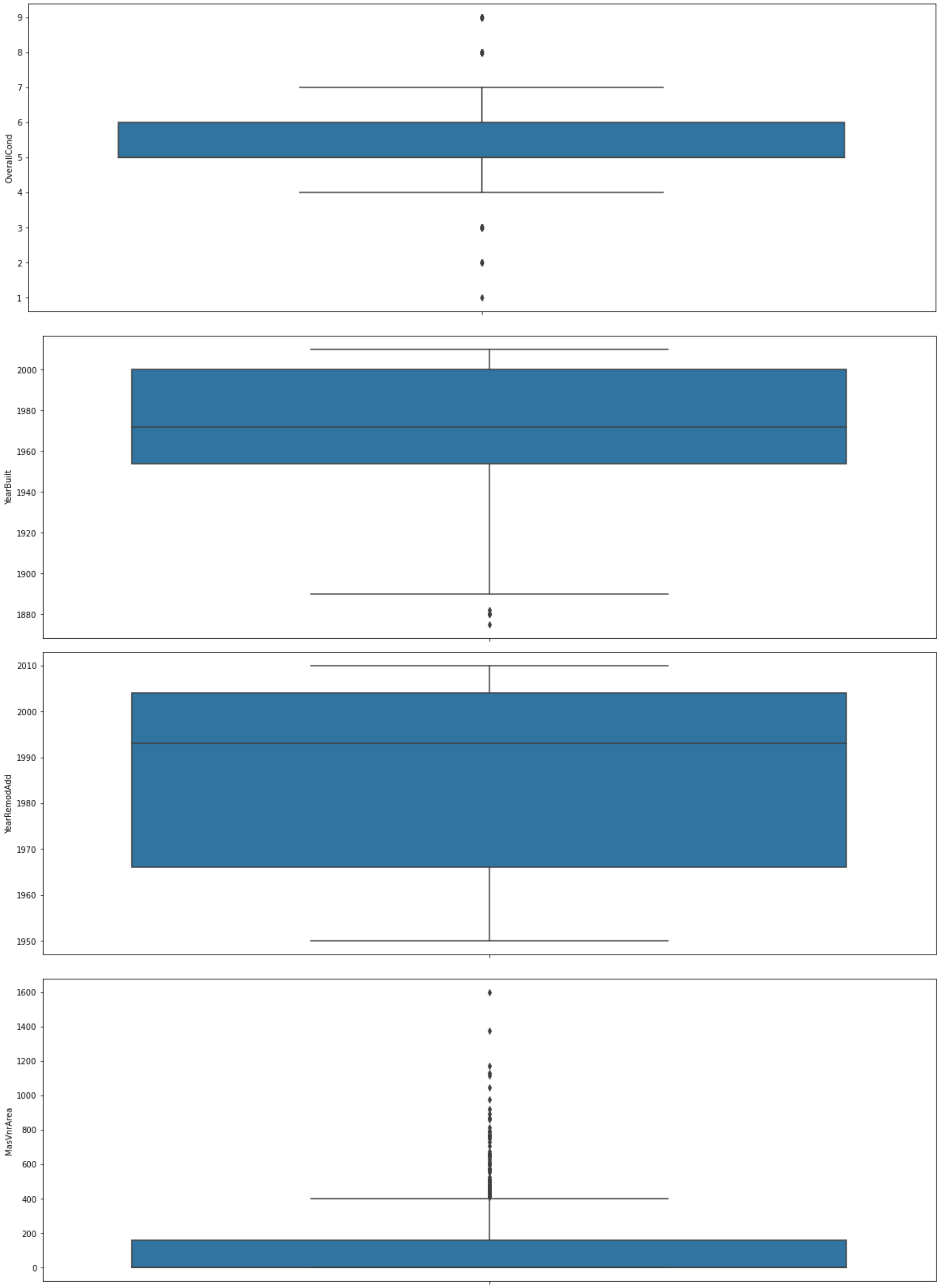
2


OverallCond
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9
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1900
1920
1940
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1980
2000
YearRemodAdd
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1970
1980
1990
2000
2010
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400
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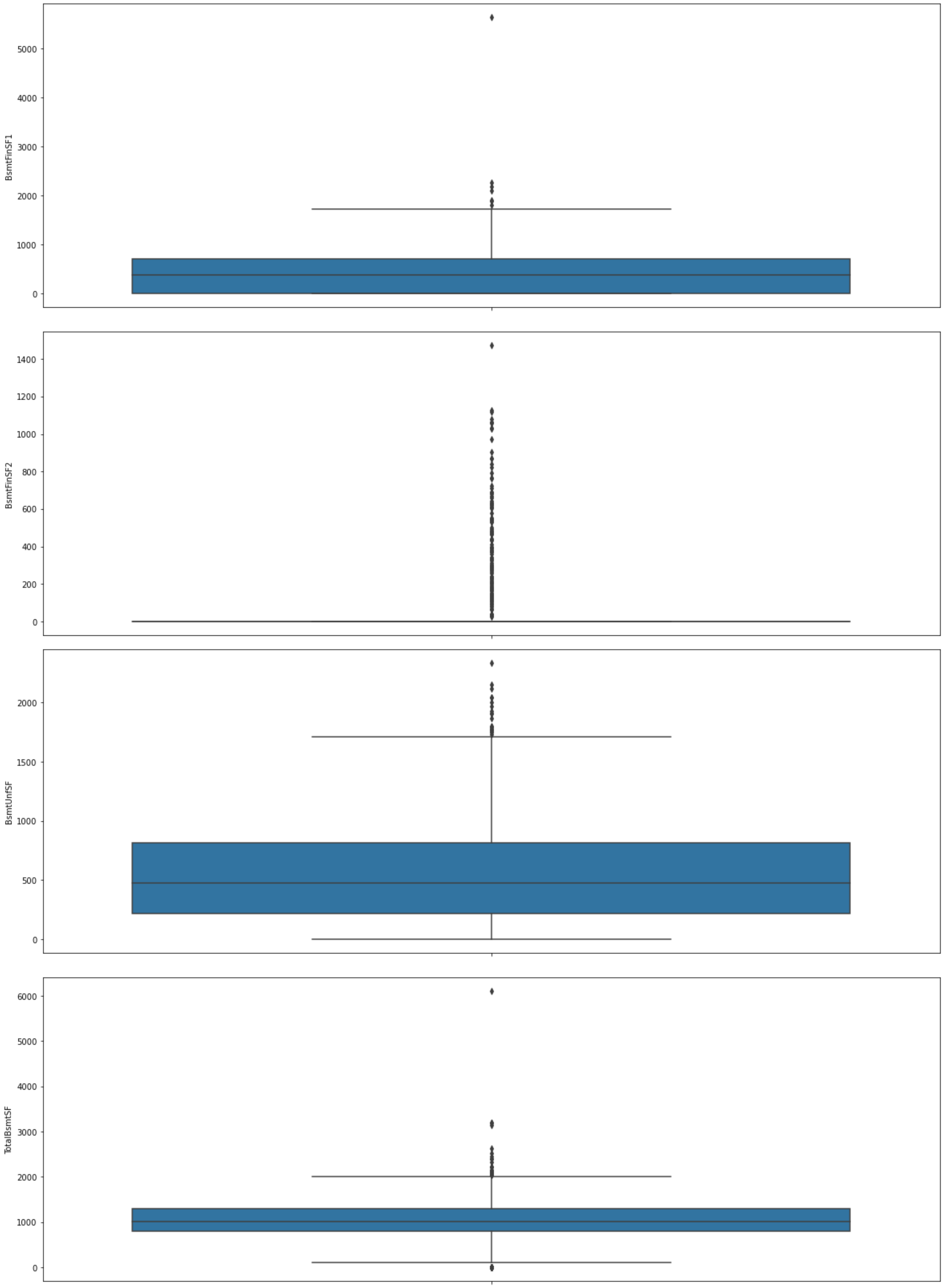
1000
1200
1400
1600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3000
4000
5000
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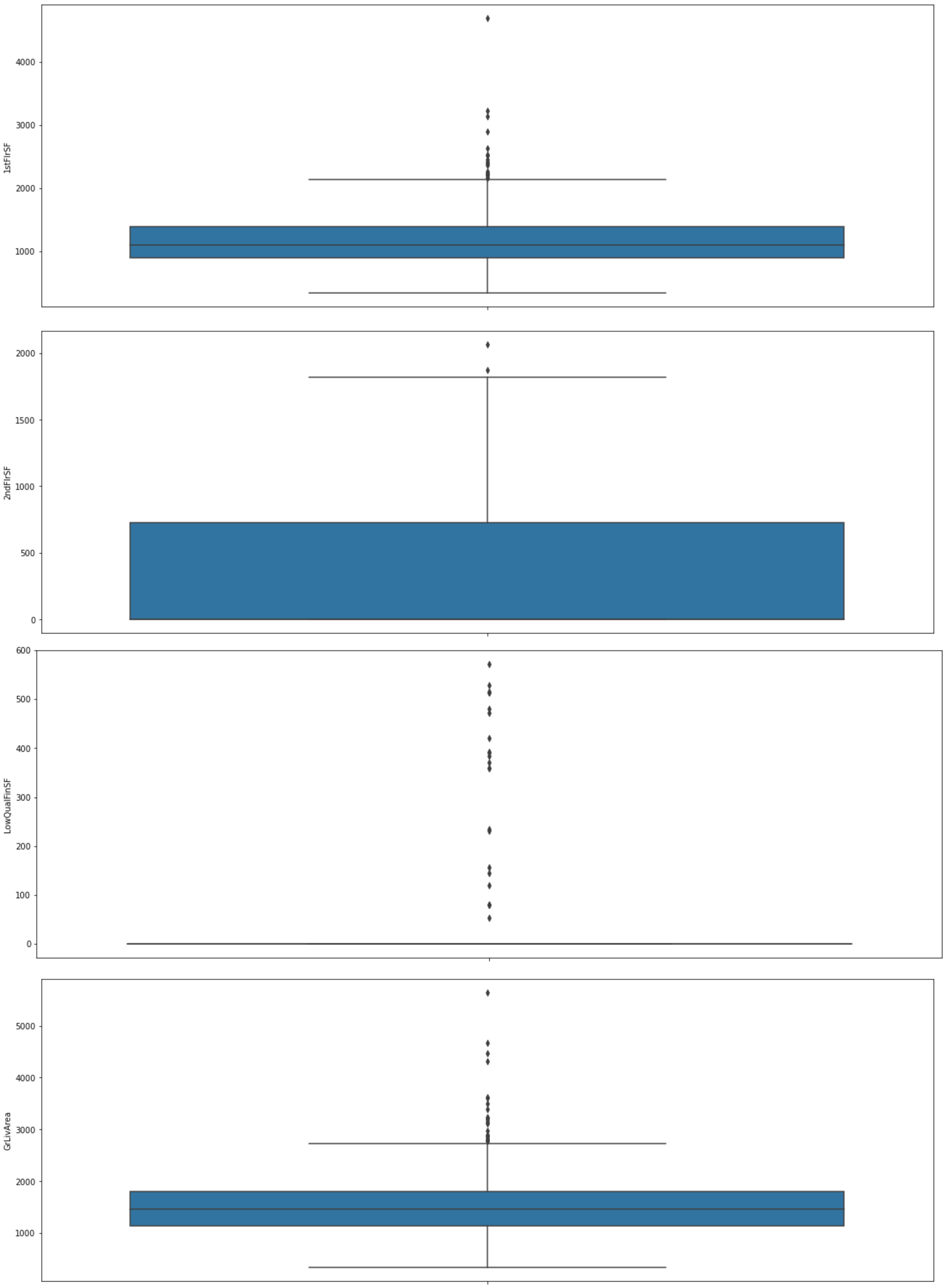
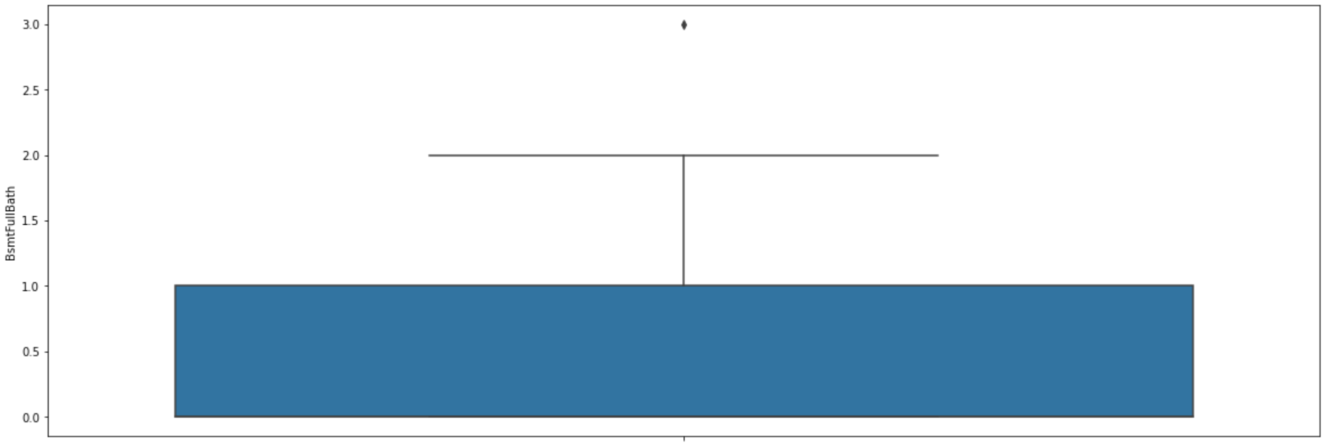
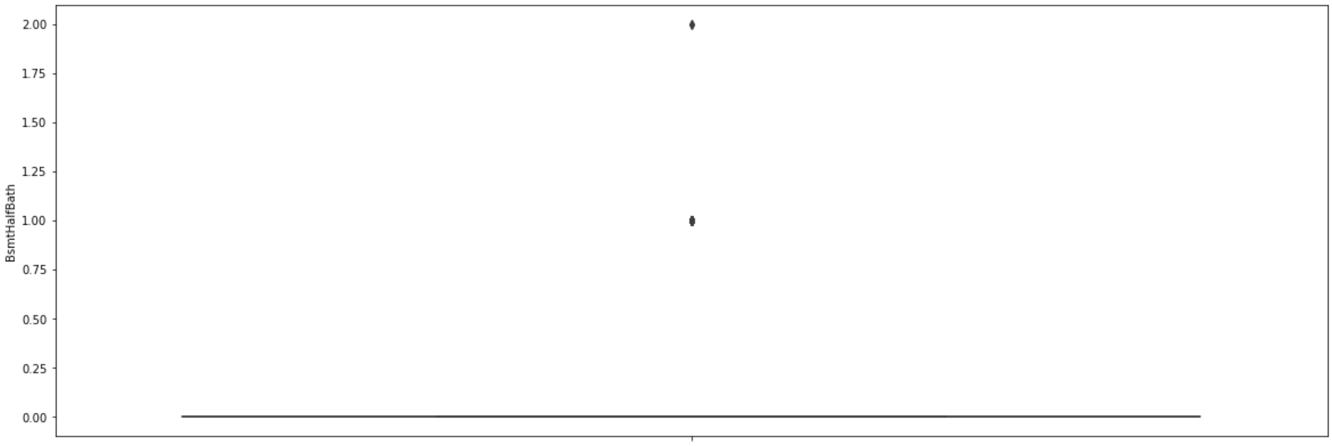
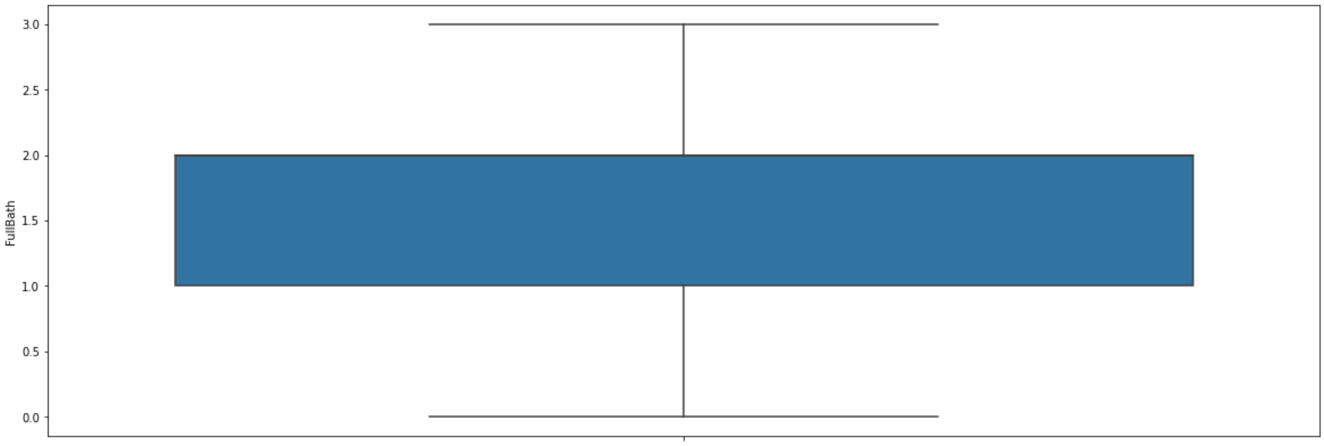
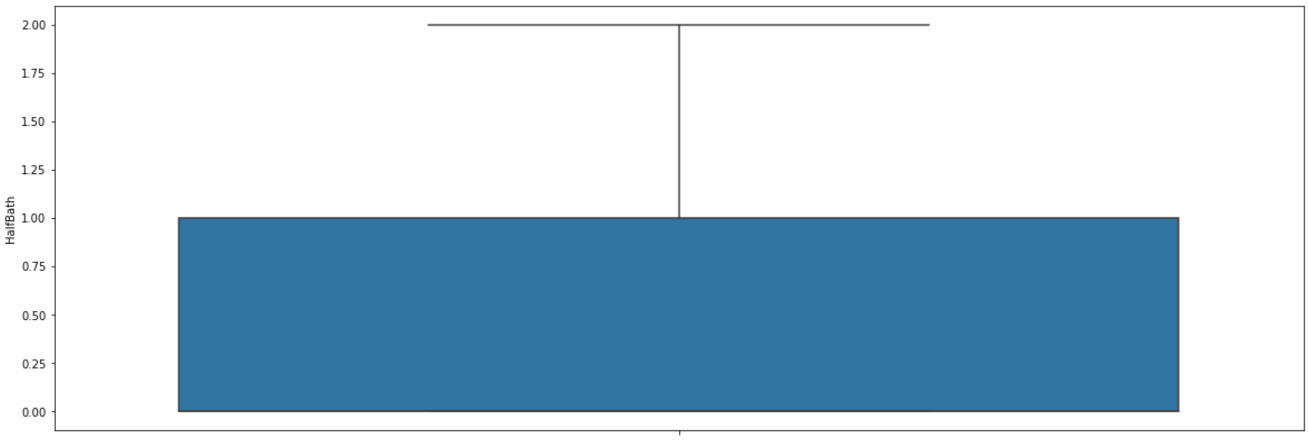
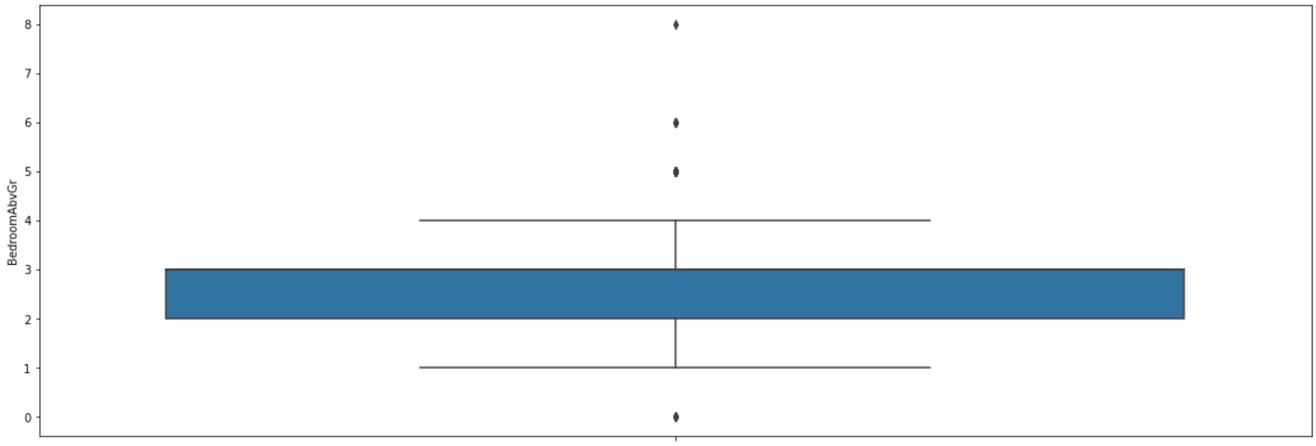
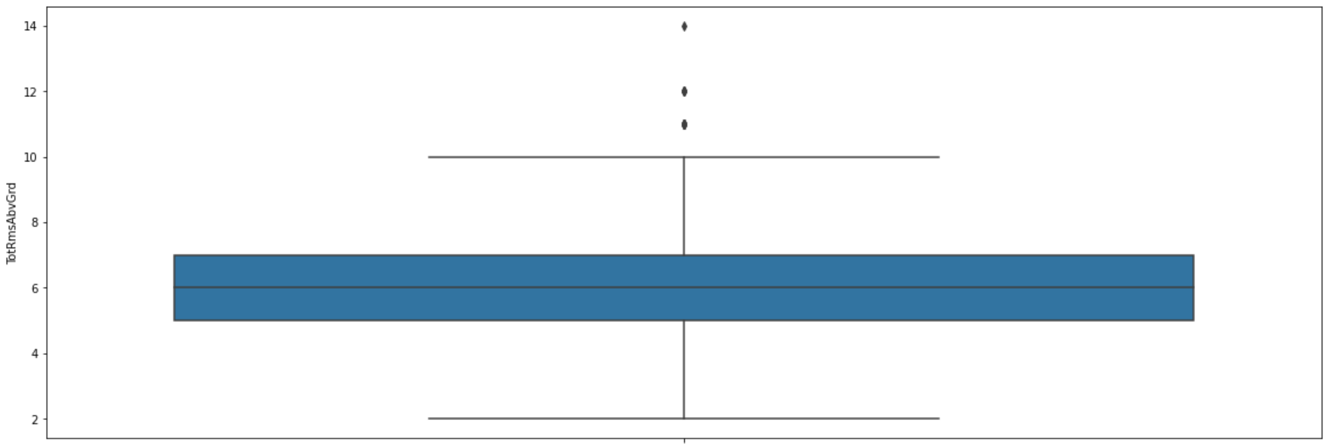
0
200
400
600
800
1000
1200
1400
BsmtUnfSF
0
500
1000
1500
2000
TotalBsmtSF
0
1000
2000
3000
4000
5000
6000

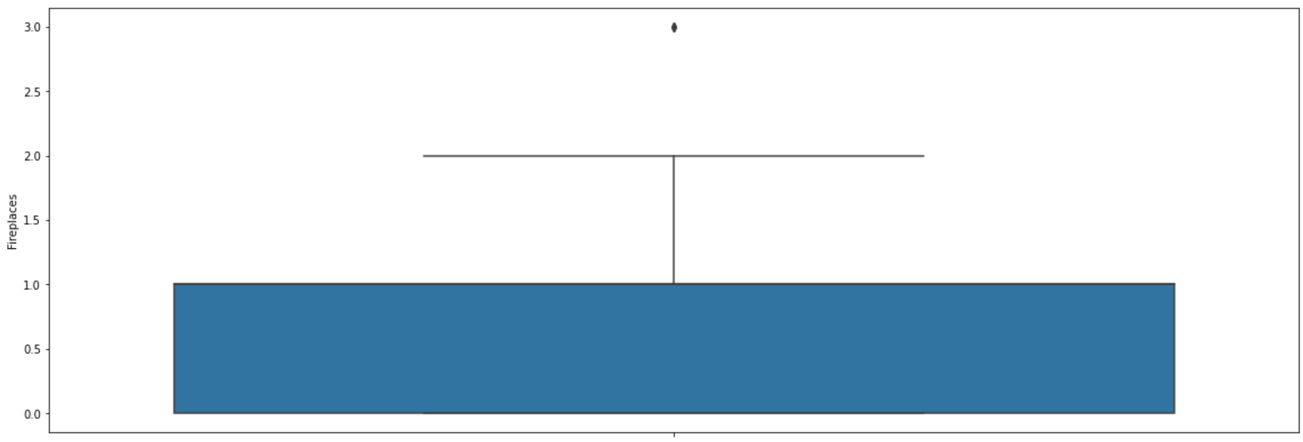

1stFlrSF
1000
2000
3000
4000
2ndFlrSF
0
500
1000
1500
2000
LowQualFinSF
0
100
200
300
400
500
600
GrLivArea
1000
2000
3000
4000
5000

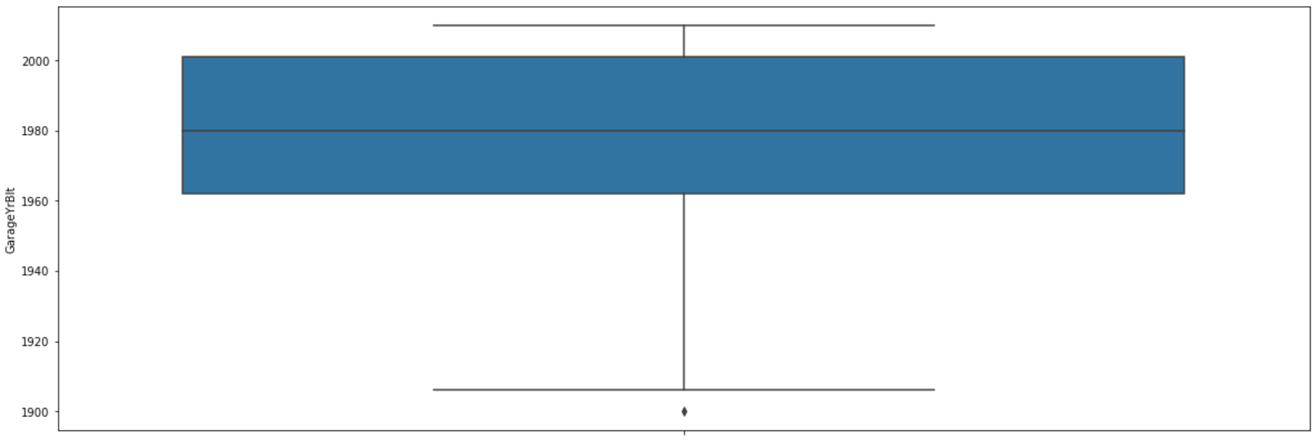

BsmtFullBath
0.0
0.5
1.0
1.5
2.0
2.5
3.0

BsmtHalfBath
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

FullBath
0.0
0.5
1.0
1.5
2.0
2.5
3.0

HalfBath
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

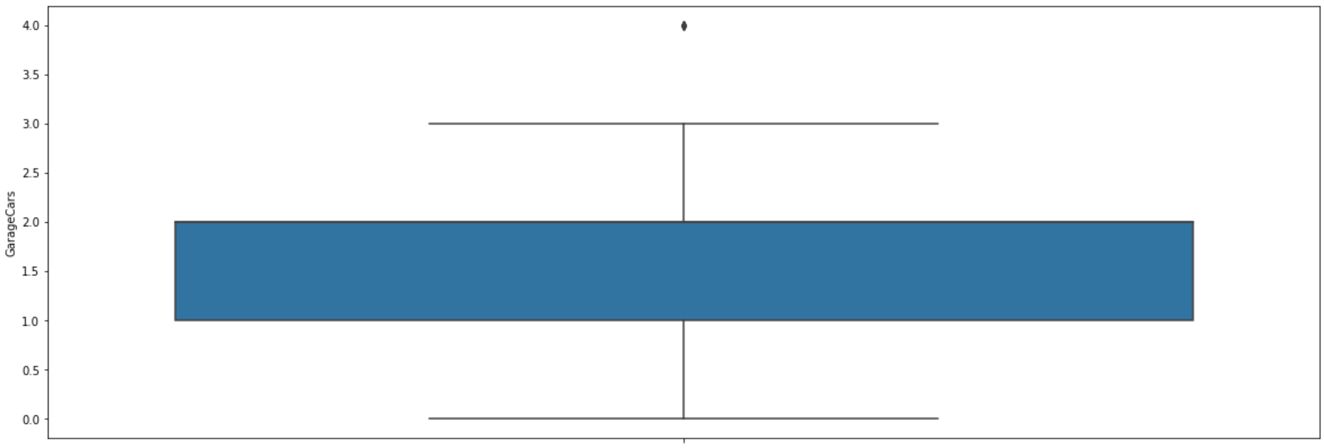

BedroomAbvGr
0
1
2
3
4
5
6
7
8

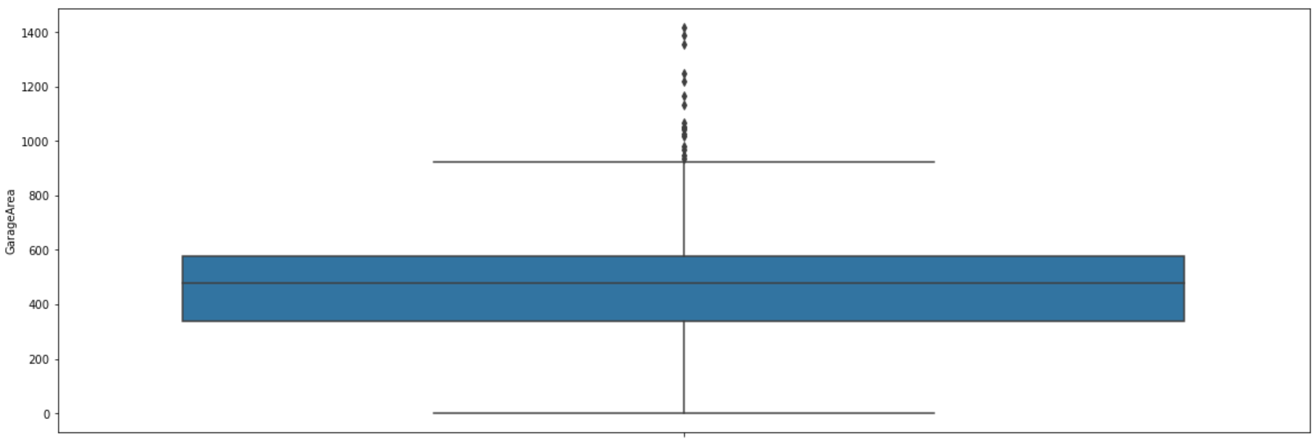

KitchenAbvGr
0.0
0.5
1.0
1.5
2.0
2.5
3.0

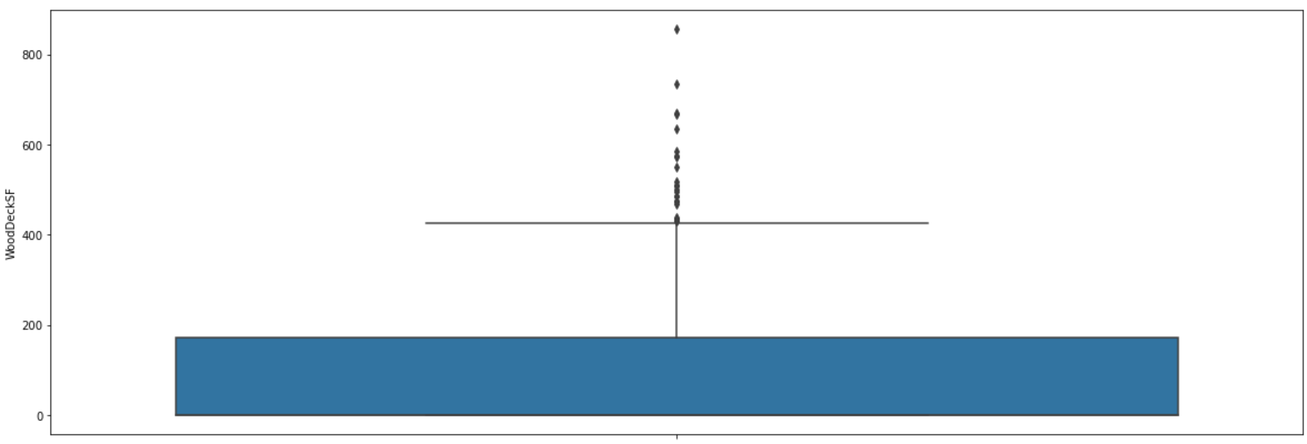

TotRmsAbvGrd
2
4
6
8
10
12
14

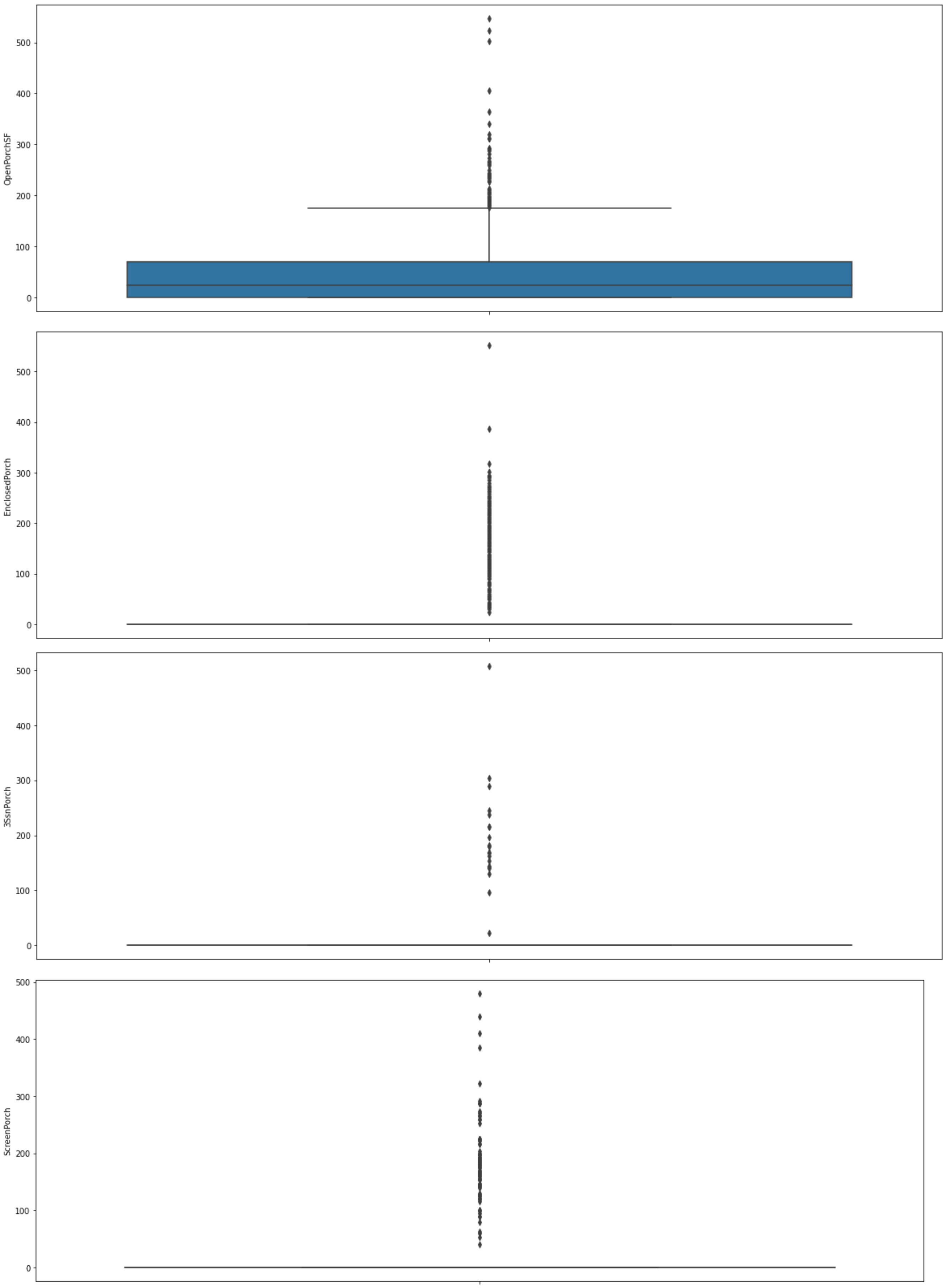

Fireplaces
0.0
0.5
1.0
1.5
2.0
2.5
3.0

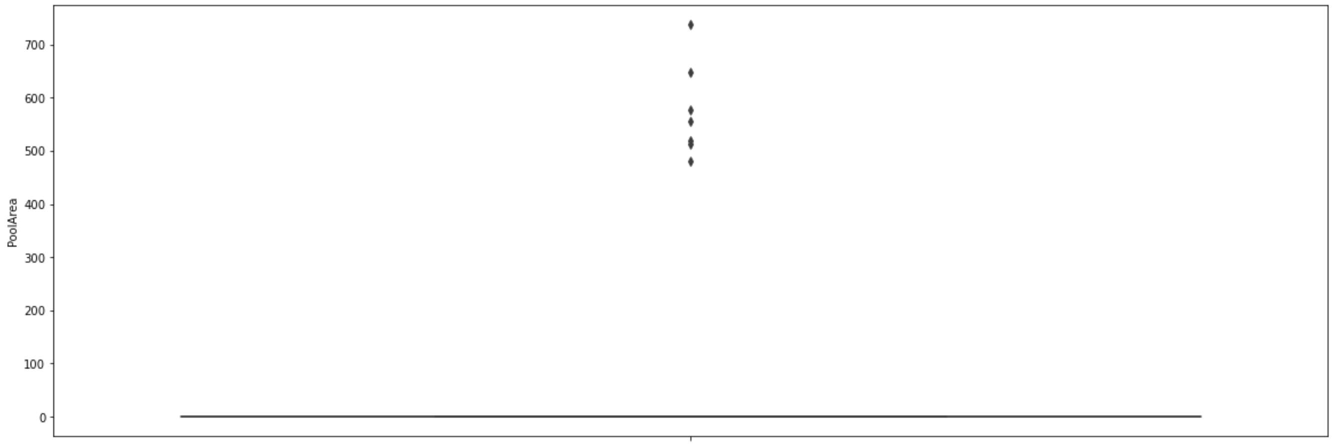

GarageYrBlt
2000
1980
1960
1940
1920
1900

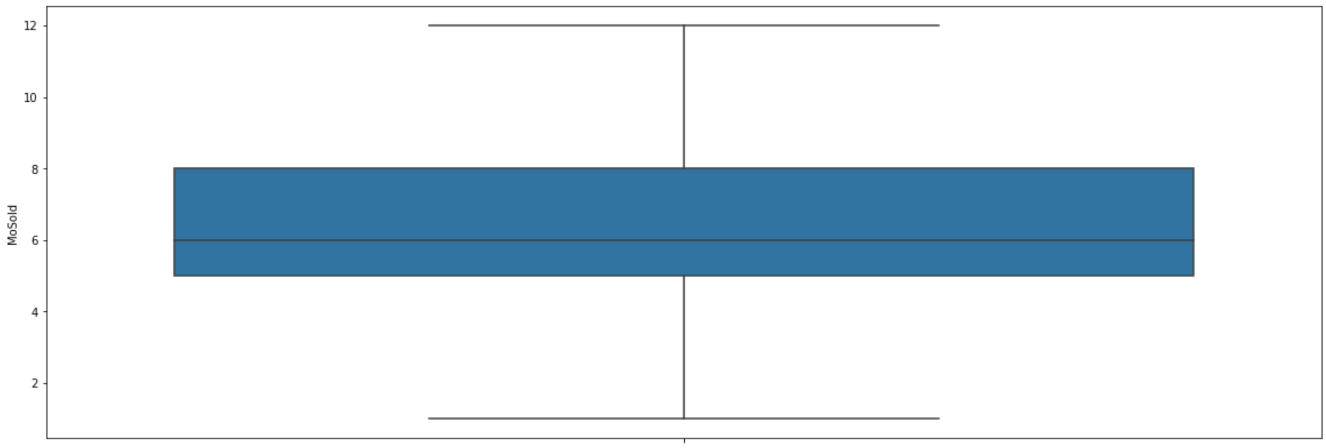

GarageCars
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0

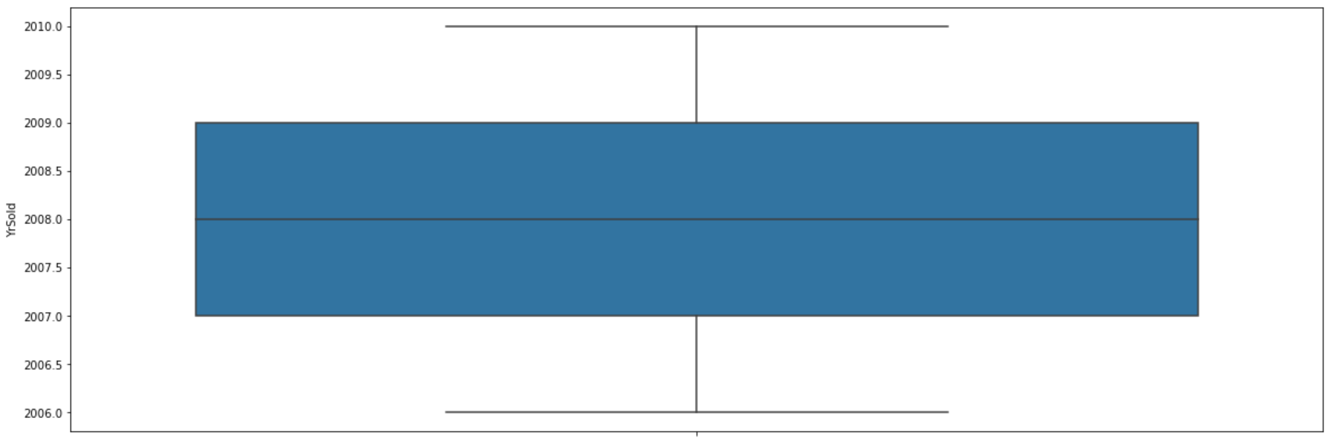

GarageArea
1400
1200
1000
800
600
400
200
0


WoodDeckSF
800
600
400
200
0


OpenPorchSF
0
100
200
300
400
500
EnclosedPorch
0
100
200
300
400
500
3SsnPorch
0
100
200
300
400
500
ScreenPorch
0
100
200
300
400
500



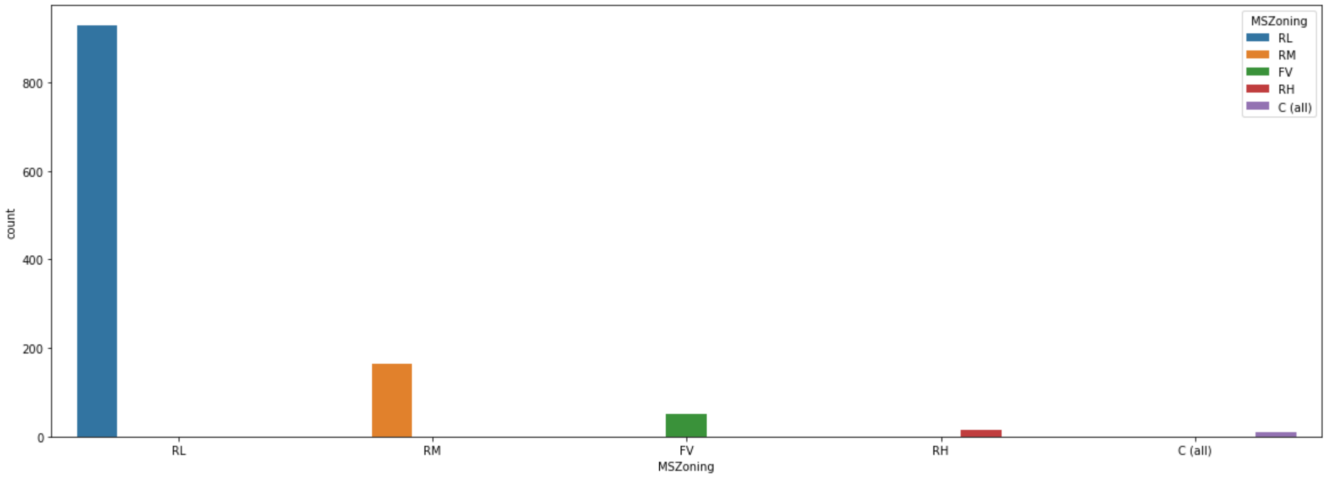


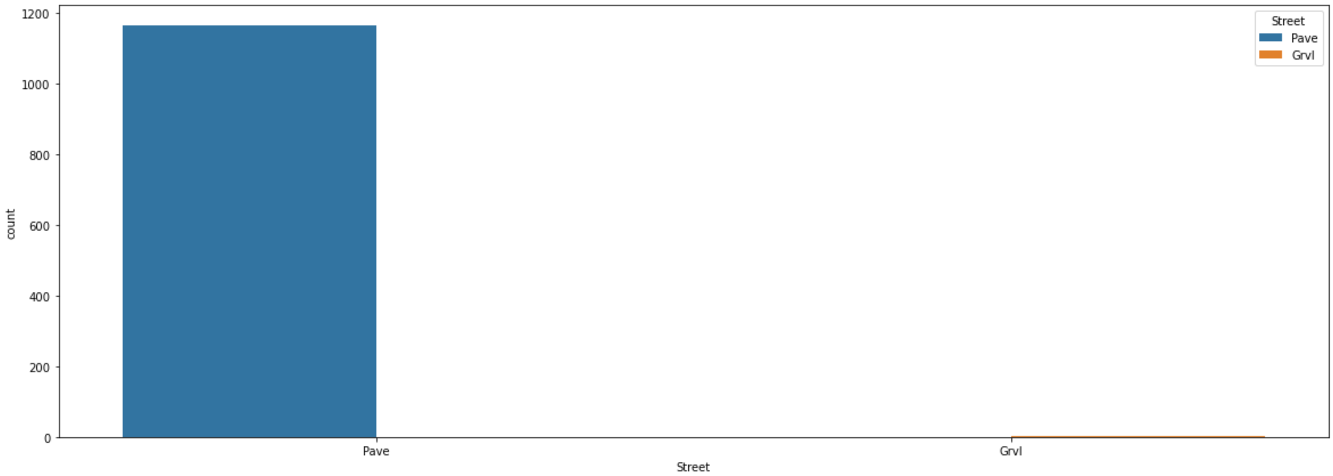


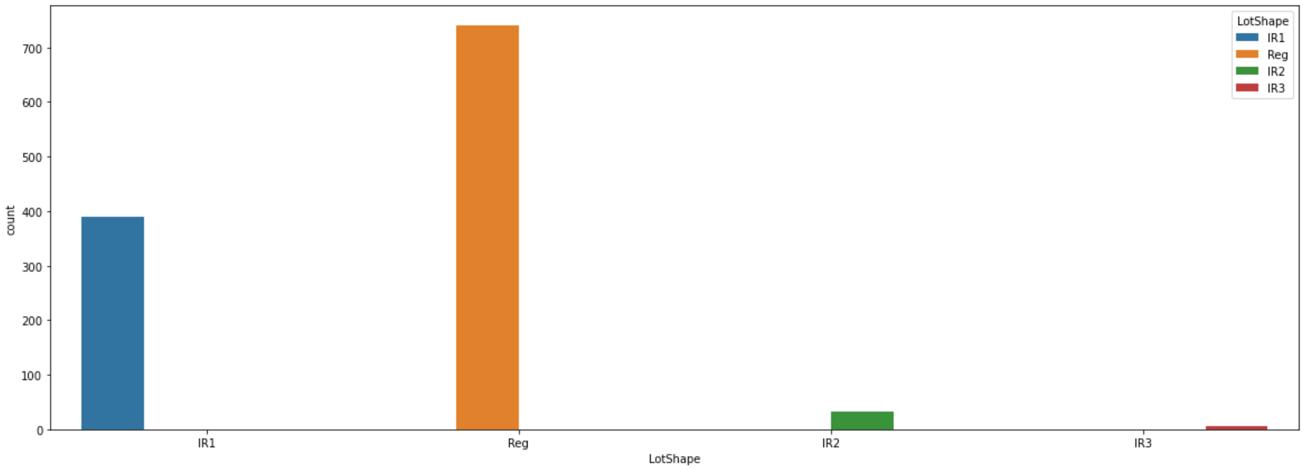
Findings:
columns { 'MSSubClass', 'LotFrontage', 'LotArea', 'Alley', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF',

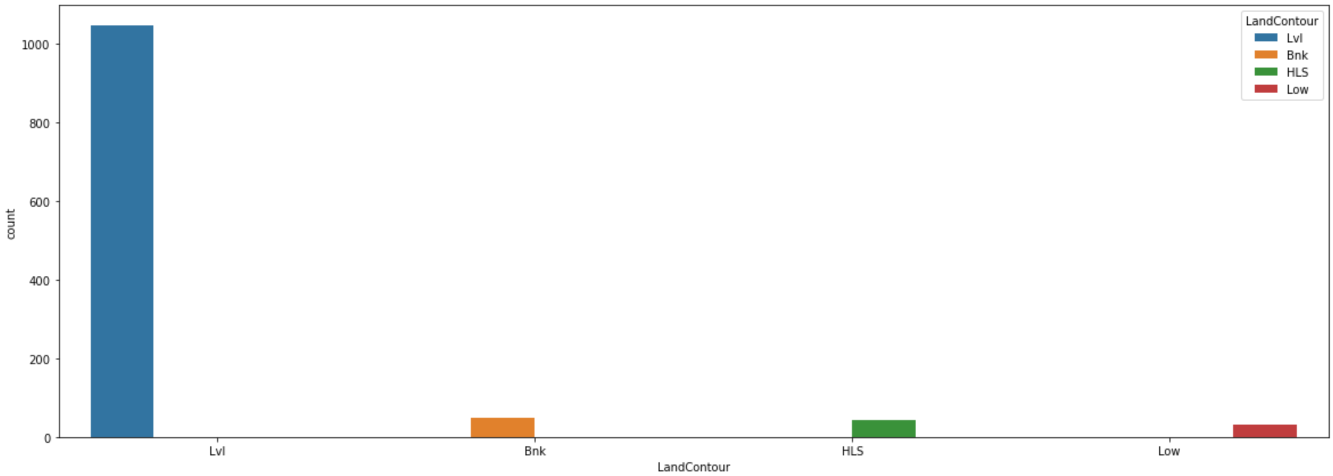
'2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces', 'FireplaceQu', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature', 'MiscVal', 'SalePrice' } in the dataset have outliers present in them.

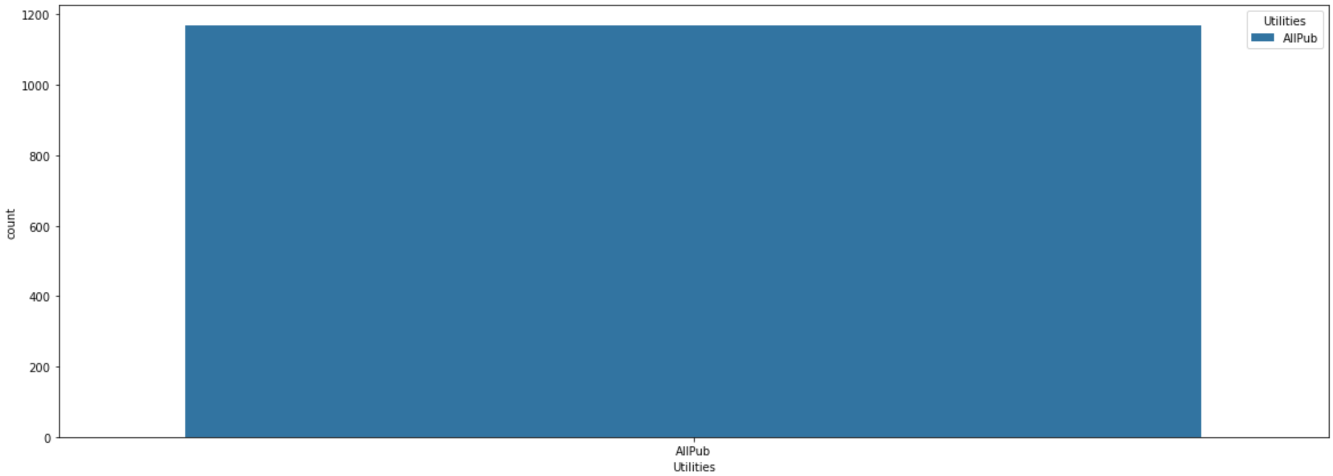
In [18]:
```
counter=1;

for column in categorical_columns:
        plt.figure(figsize=(20,500))
        plt.subplot(60,1,counter)
        counter=counter+1
        sns.countplot(x=column,hue=column,data=df)
        plt.show()
```

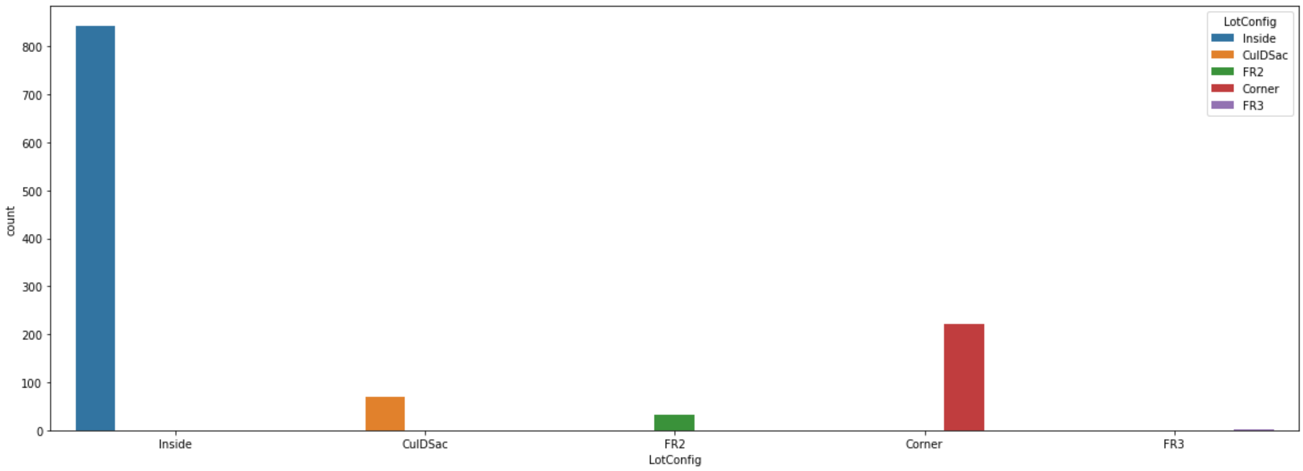


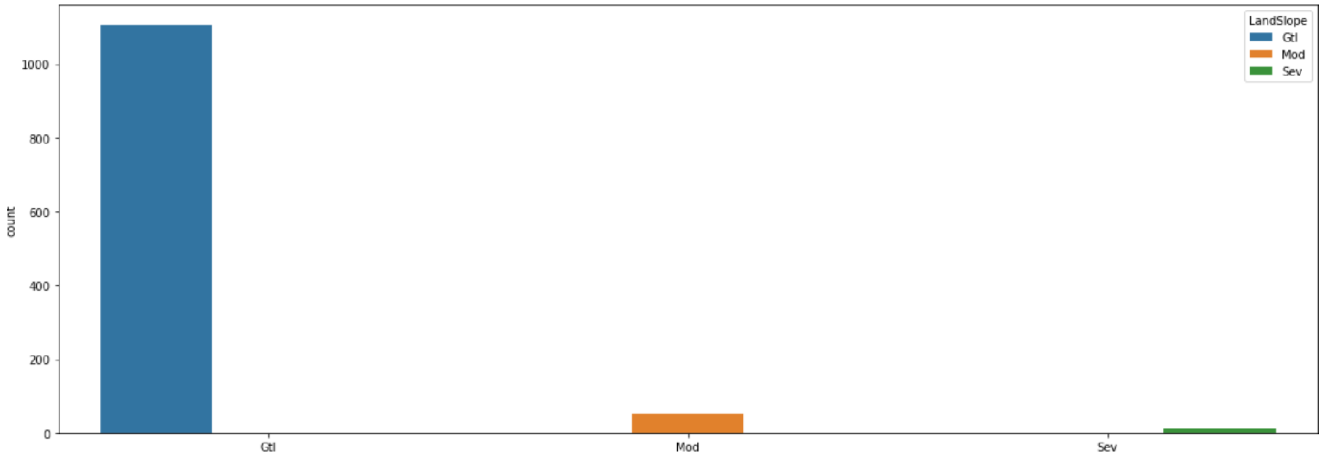


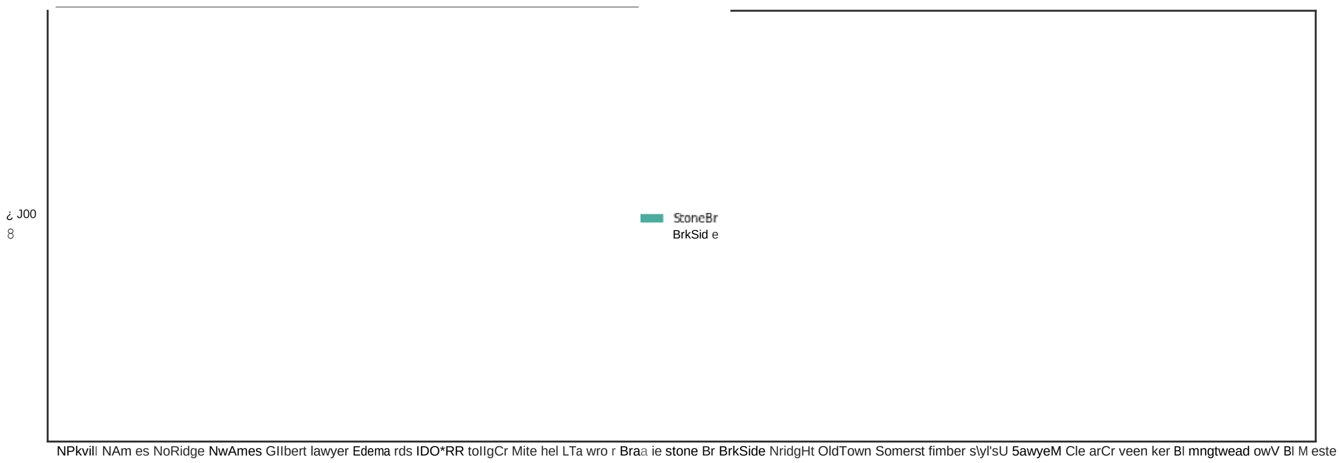


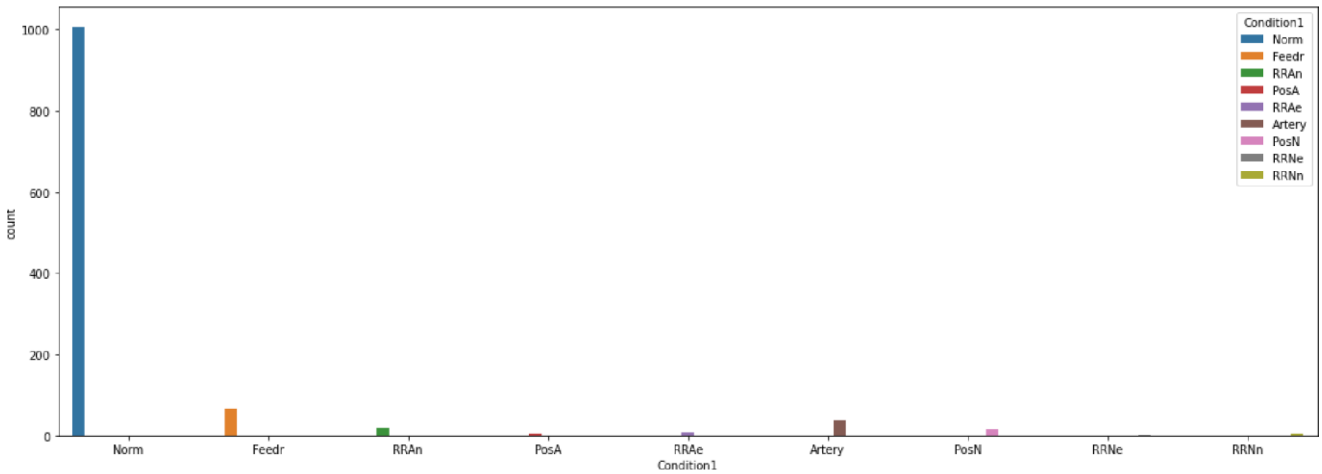

LandContour
Lvl
Bnk
HLS
Low
count
1000
800
600
400
200
0
Lvl
Bnk
HLS
Low
LandContour

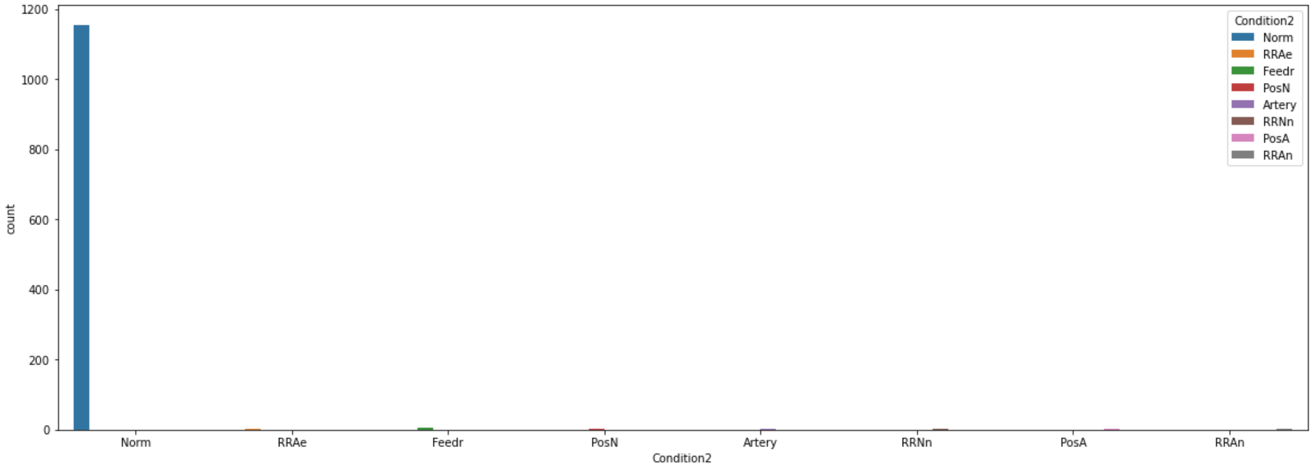

Utilities
AllPub
count
1200
1000
800
600
400
200
0
AllPub
Utilities


LotConfig
Inside
CulDSac
FR2
Corner
FR3
count
800
700
600
500
400
300
200
100
0
Inside
CulDSac
FR2
Corner
FR3
LotConfig

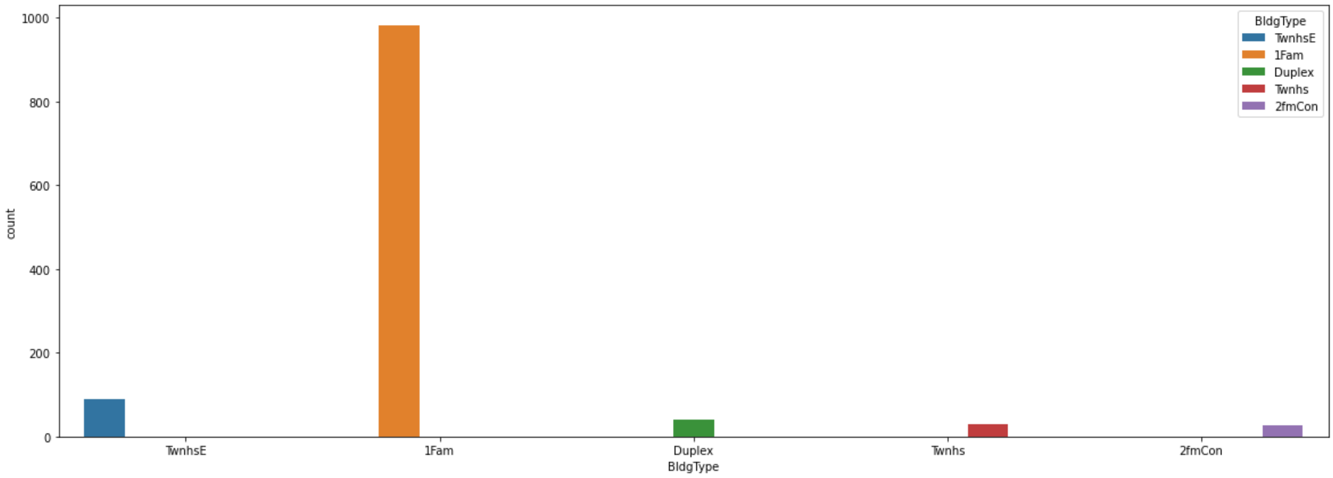

LandSlope
Gtl
Mod
Sev
count
1000
800
600
400
200
0
Gtl
Mod
Sev


¿ J00
8
StoneBr
BrkSid e
NPkvill NAm es NoRidge NwAmes GIlbert lawyer Edema rds IDO*RR tolIgCr Mite hel LTa wro r Braa ie stone Br BrkSide NridgHt OldTown Somerst fimber s\yl'sU 5awyeM Cle arCr veen ker Bl mngtwead owV Bl M este

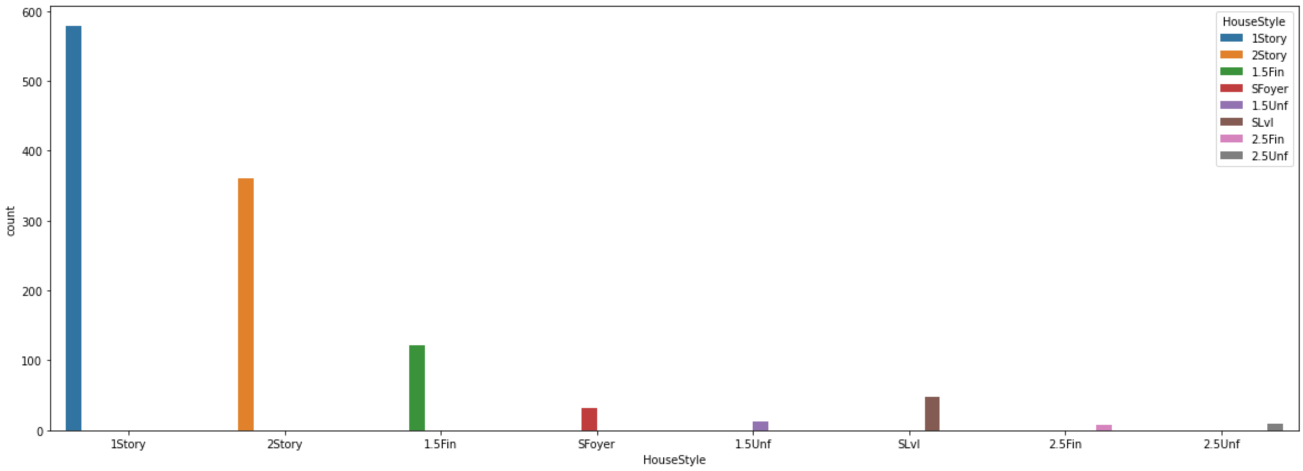

Condition1
Norm
Feedr
RRAn
PosA
RRAe
Artery
PosN
RRNe
RRNn
count
1000
800
600
400
200
0
Norm
Feedr
RRAn
PosA
RRAe
Artery
PosN
RRNe
RRNn
Condition1



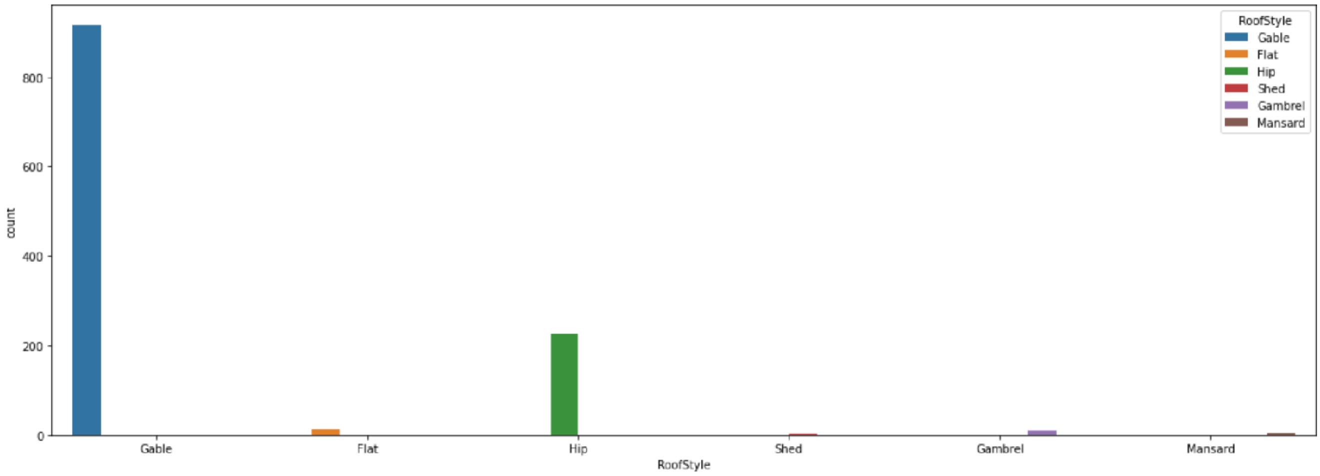
Condition2
Norm
RRAe
Feedr
PosN
Artery
RRNn
PosA
RRAn
count
1200
1000
800
600
400
200
0
Norm
RRAe
Feedr
PosN
Artery
RRNn
PosA
RRAn
Condition2

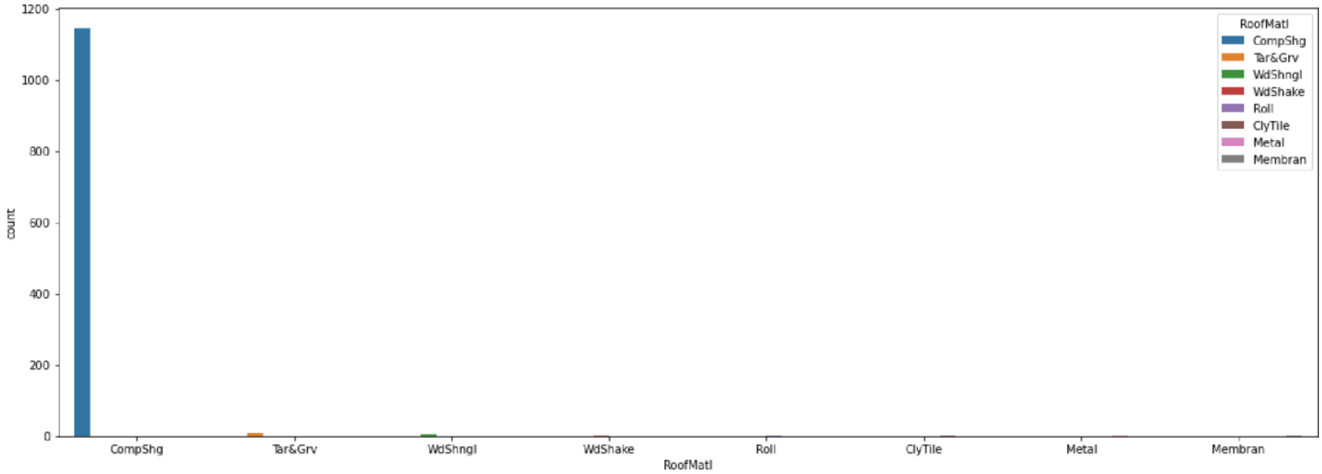


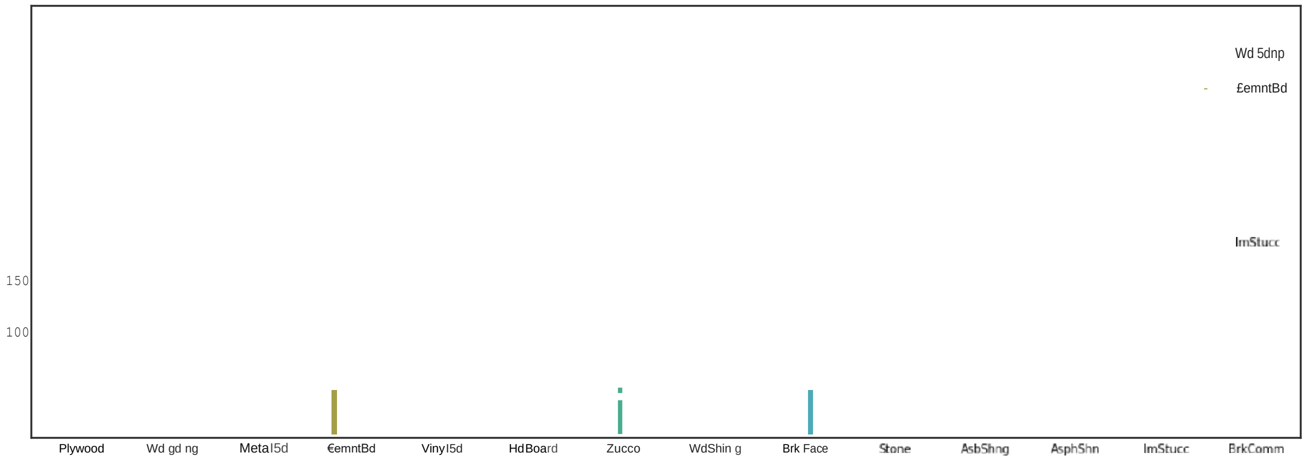
BldgType
TwnhsE
1Fam
Duplex
Twnhs
2fmCon
count
1000
800
600
400
200
0
TwnhsE
1Fam
Duplex
Twnhs
2fmCon
BldgType

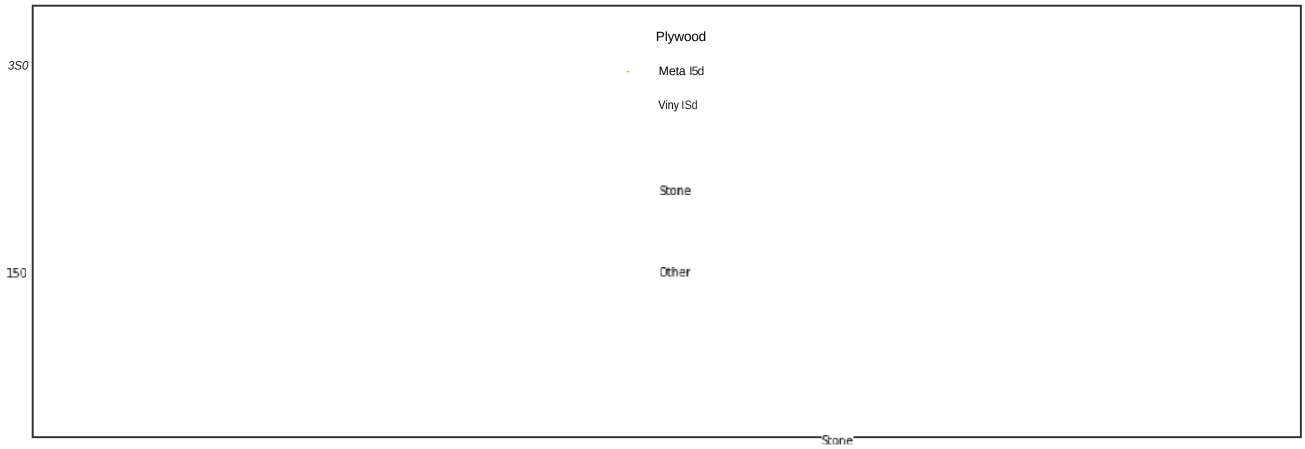


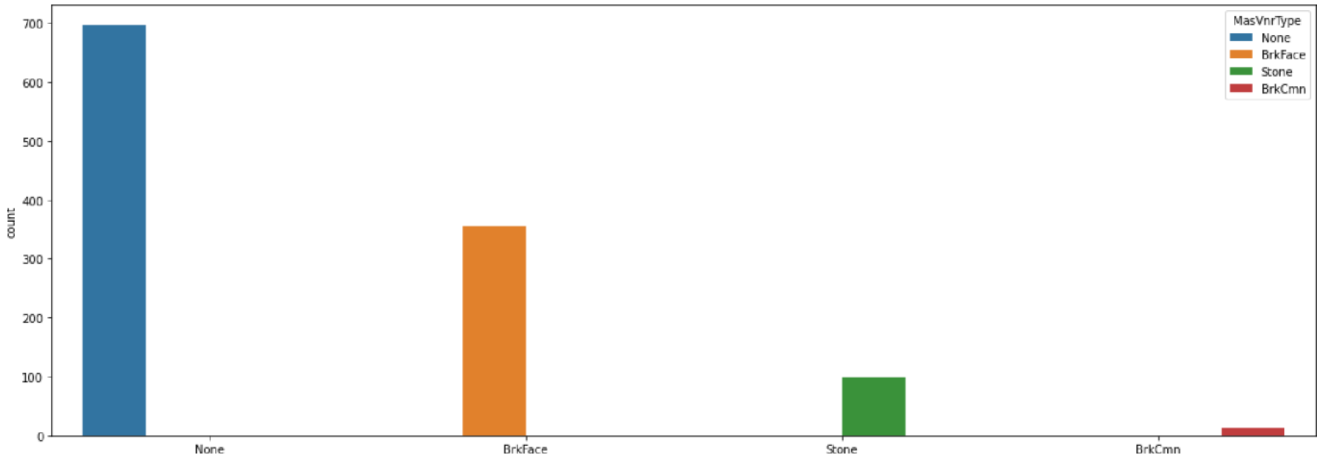
HouseStyle
1Story
2Story
1.5Fin
SFoyer
1.5Unf
SLvl
2.5Fin
2.5Unf
count
600
500
400
300
200
100
0
1Story
2Story
1.5Fin
SFoyer
1.5Unf
SLvl
2.5Fin
2.5Unf
HouseStyle

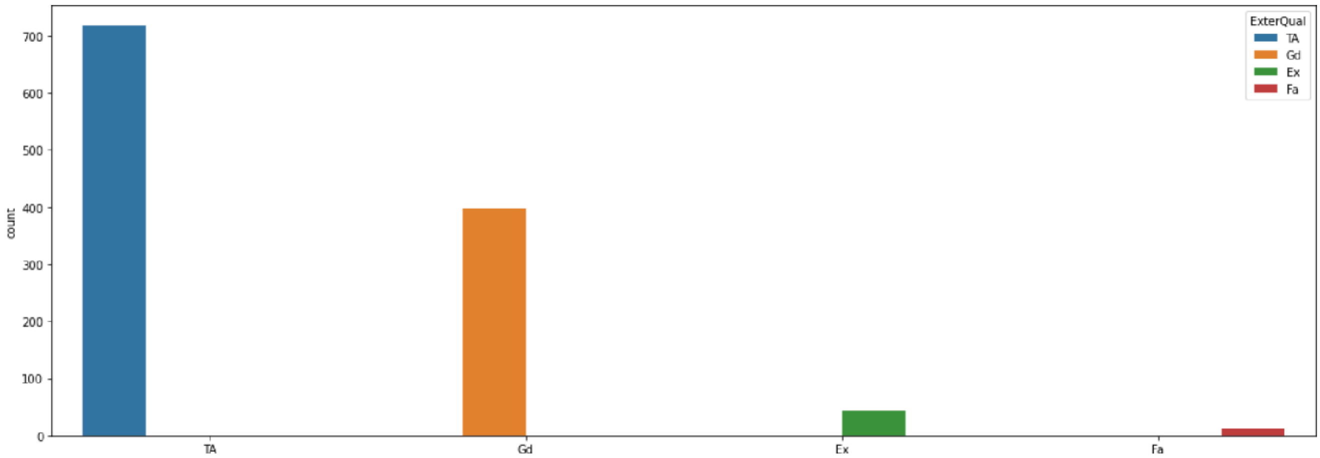

RoofStyle
Gable
Flat
Hip
Shed
Gambrel
Mansard
count
800
600
400
200
0
Gable
Flat
Hip
Shed
Gambrel
Mansard
RoofStyle

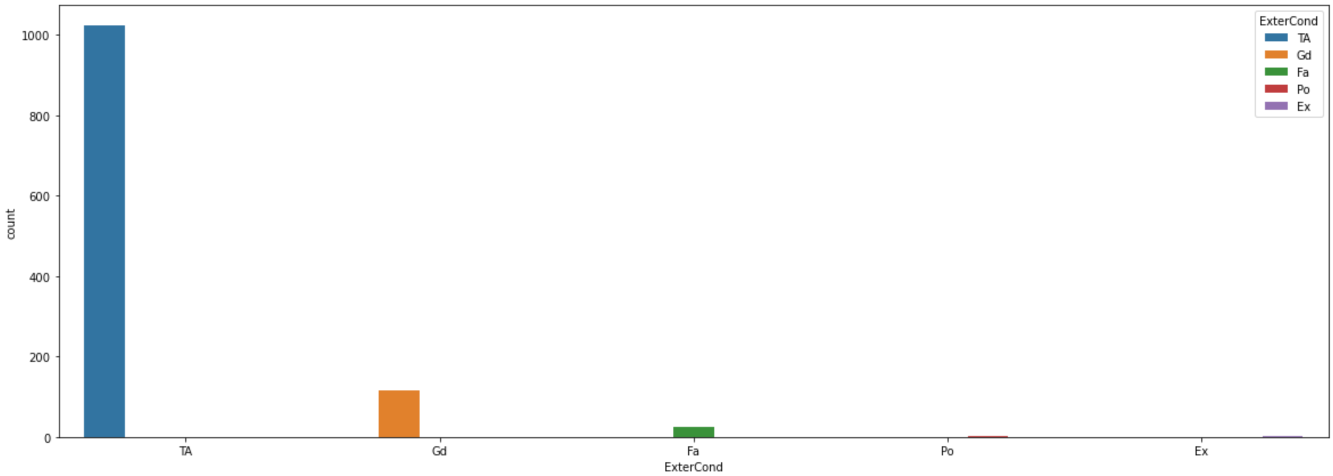

RoofMatl
CompShg
Tar&Grv
WdShngl
WdShake
Roll
ClyTile
Metal
Membran
count
1200
1000
800
600
400
200
0
CompShg
Tar&Grv
WdShngl
WdShake
Roll
ClyTile
Metal
Membran
RoofMatl


Wd 5dnp
£emntBd
ImStucc
150
100
Plywood
Wd gd ng
Metal5d
€emntBd
Vinyl5d
HdBoard
Zucco
WdShin g
Brk Face
Stone
AsbShng
AsphShn
ImStucc
BrkComm

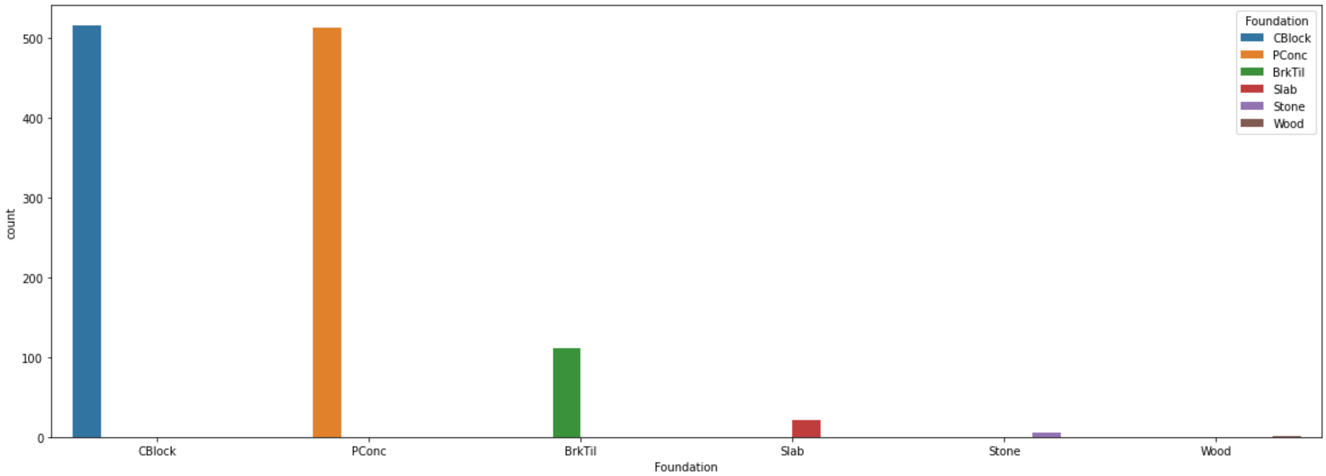

Plywood
Meta l5d
Viny lSd
Stone
Other
3S0
150
Stone


MasVnrType
None
BrkFace
Stone
BrkCmn
count
700
600
500
400
300
200
100
0
None
BrkFace
Stone
BrkCmn

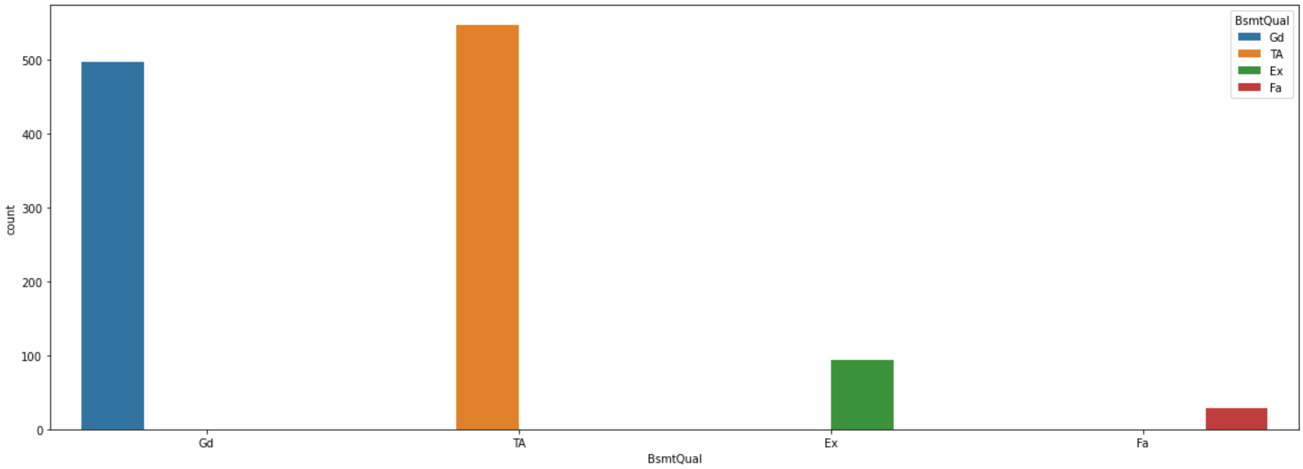

ExterQual
TA
Gd
Ex
Fa
count
700
600
500
400
300
200
100
0
TA
Gd
Ex
Fa



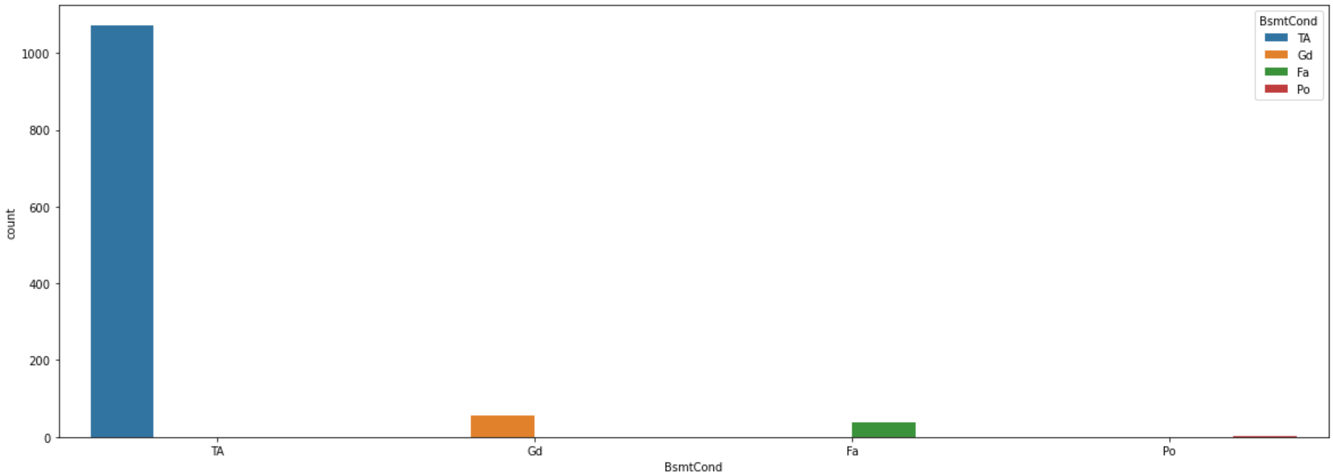
ExterCond
TA
Gd
Fa
Po
Ex
count
0
200
400
600
800
1000
ExterCond

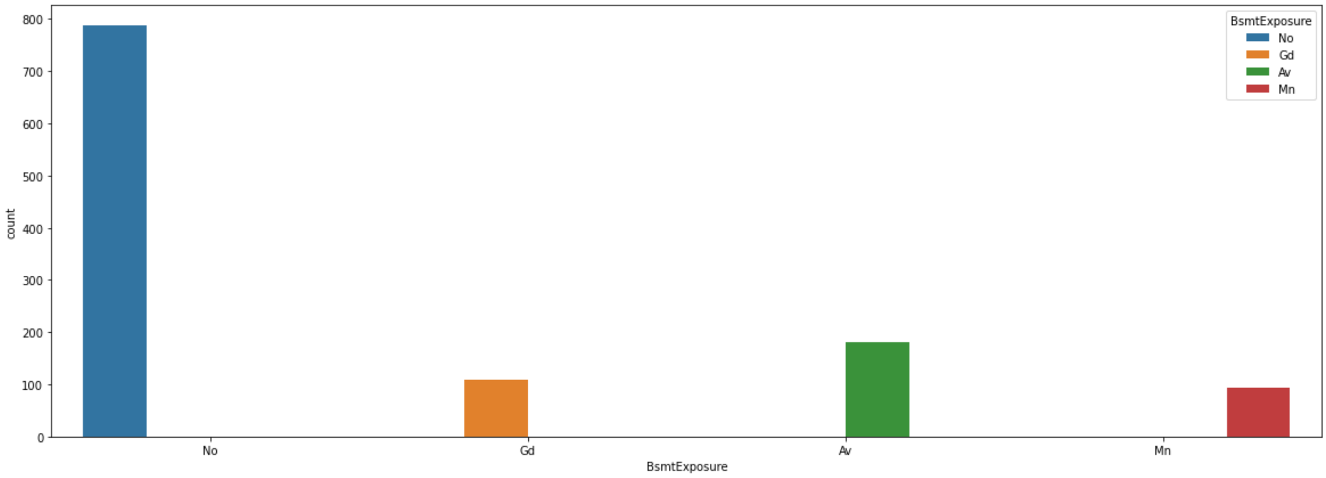


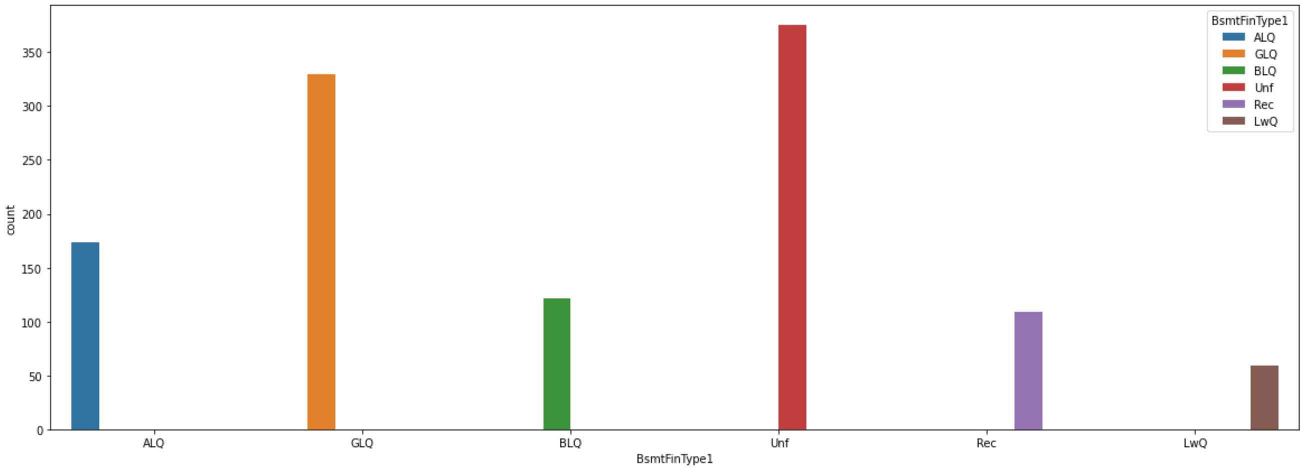
Foundation
CBlock
PConc
BrkTil
Slab
Stone
Wood
count
0
100
200
300
400
500
Foundation

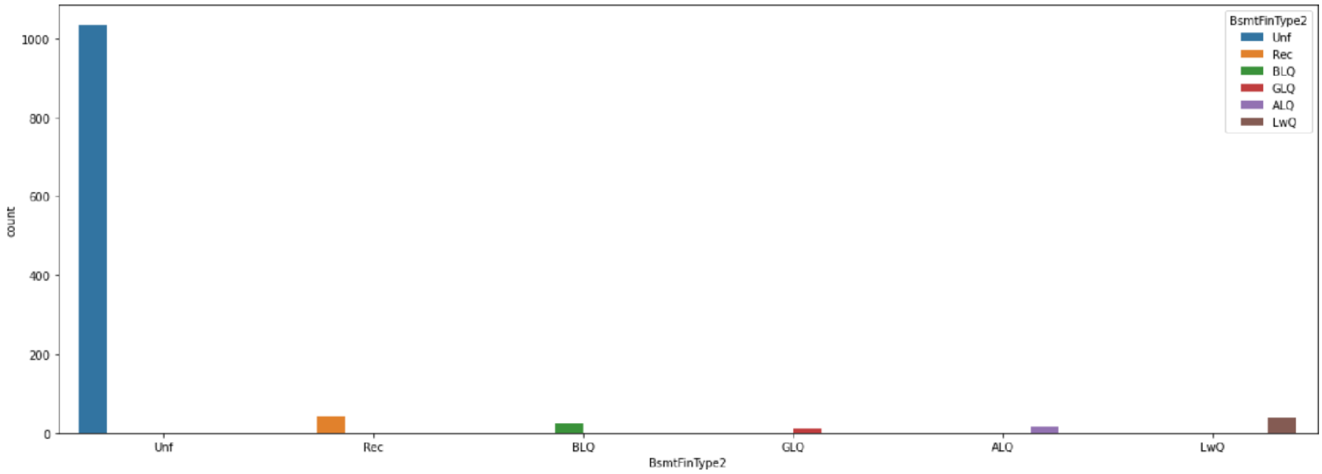


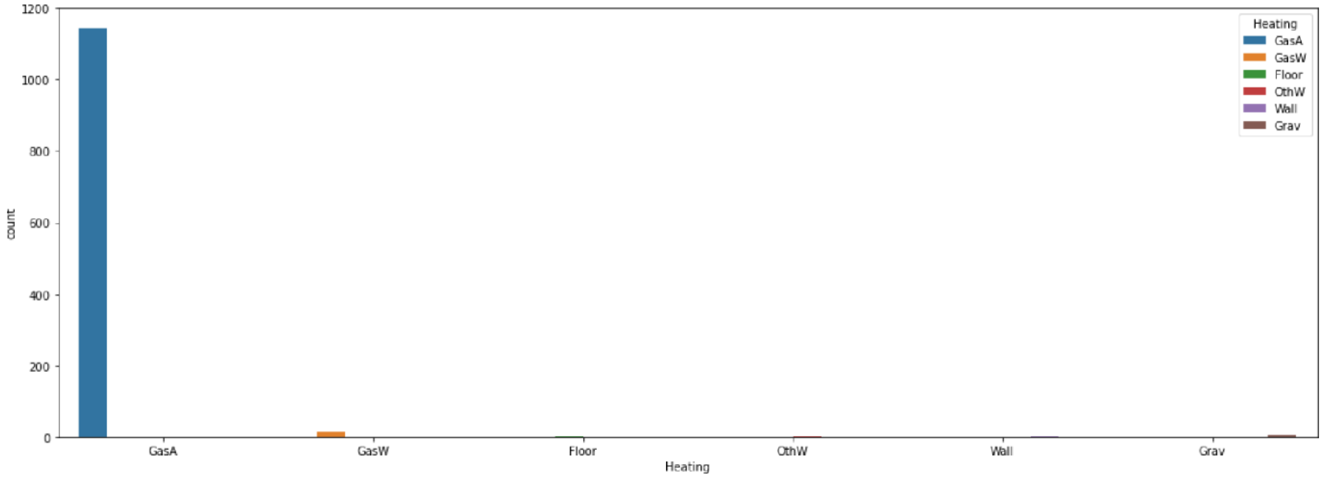
BsmtQual
Gd
TA
Ex
Fa
count
0
100
200
300
400
500
BsmtQual

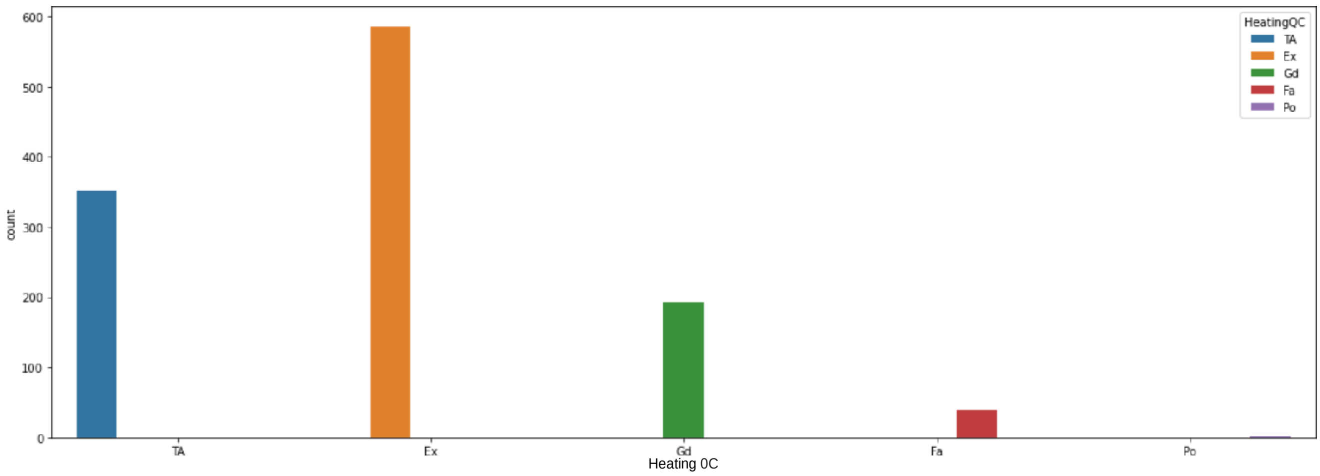

BsmtCond
TA
Gd
Fa
Po
count
0
200
400
600
800
1000
TA
Gd
Fa
Po
BsmtCond

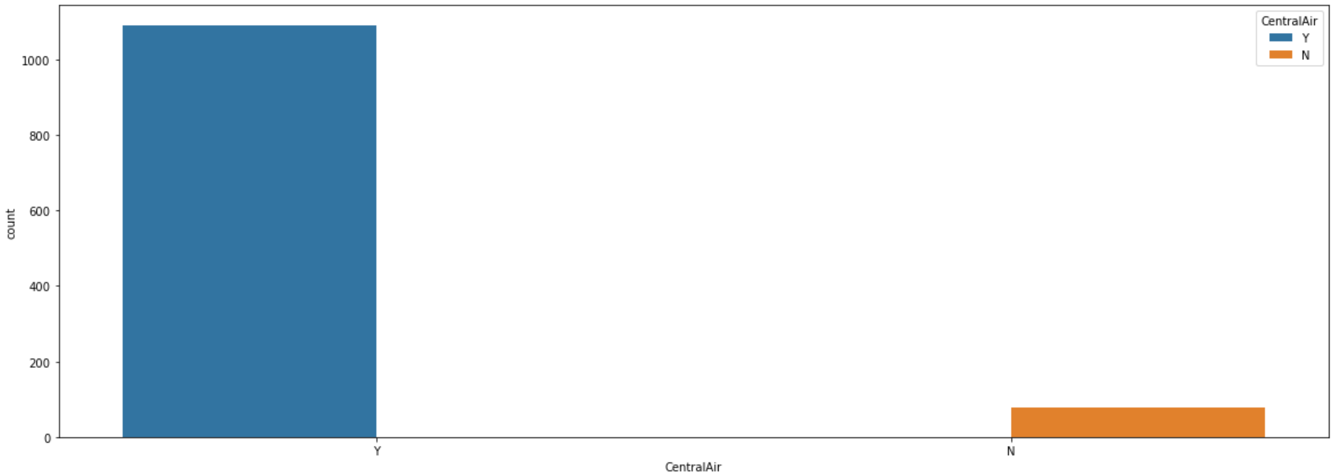

BsmtExposure
No
Gd
Av
Mn
count
0
100
200
300
400
500
600
700
800
No
Gd
Av
Mn
BsmtExposure

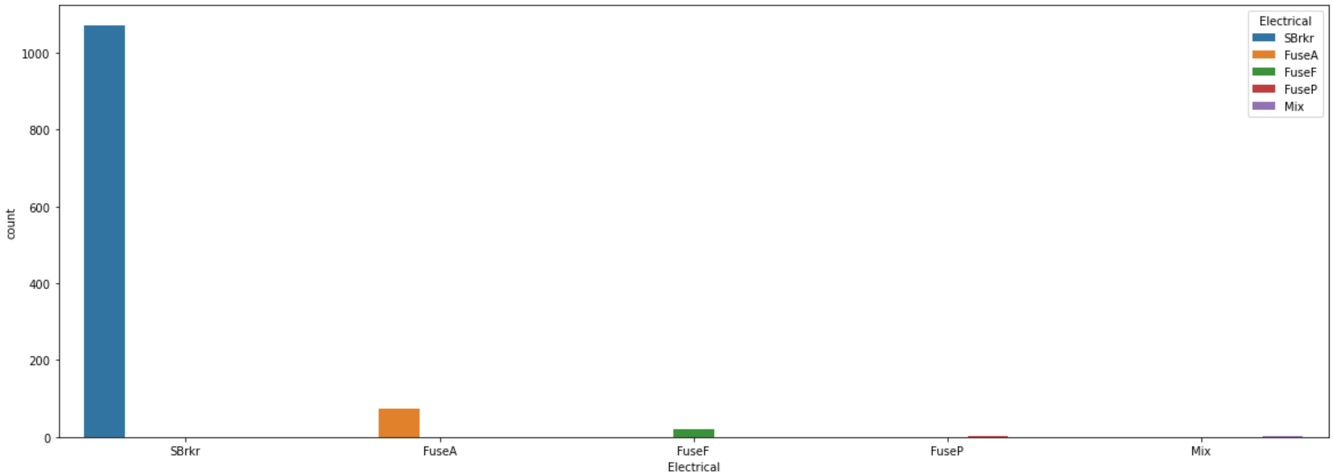

BsmtFinType1
ALQ
GLQ
BLQ
Unf
Rec
LwQ
count
0
50
100
150
200
250
300
350
ALQ
GLQ
BLQ
Unf
Rec
LwQ
BsmtFinType1

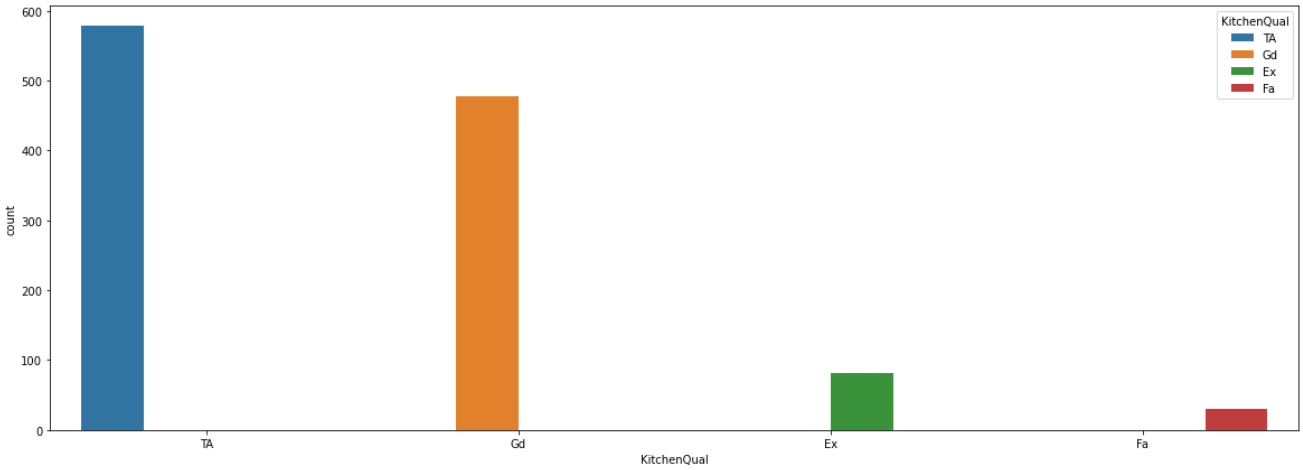

BsmtFinType2
Unf
Rec
BLQ
GLQ
ALQ
LwQ
count
1000
800
600
400
200
0
BsmtFinType2

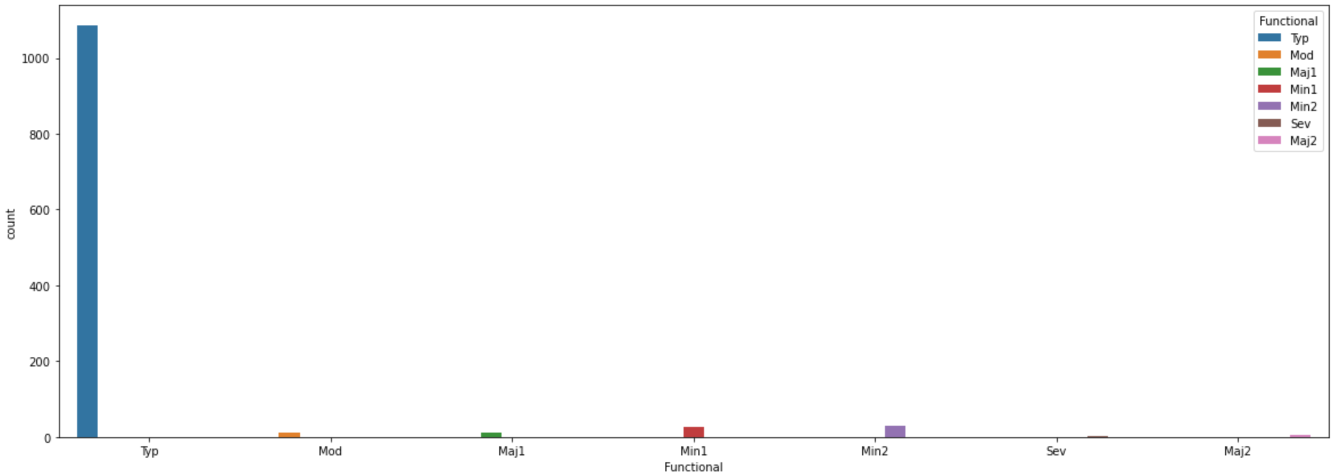

Heating
GasA
GasW
Floor
OthW
Wall
Grav
count
1200
1000
800
600
400
200
0
Heating

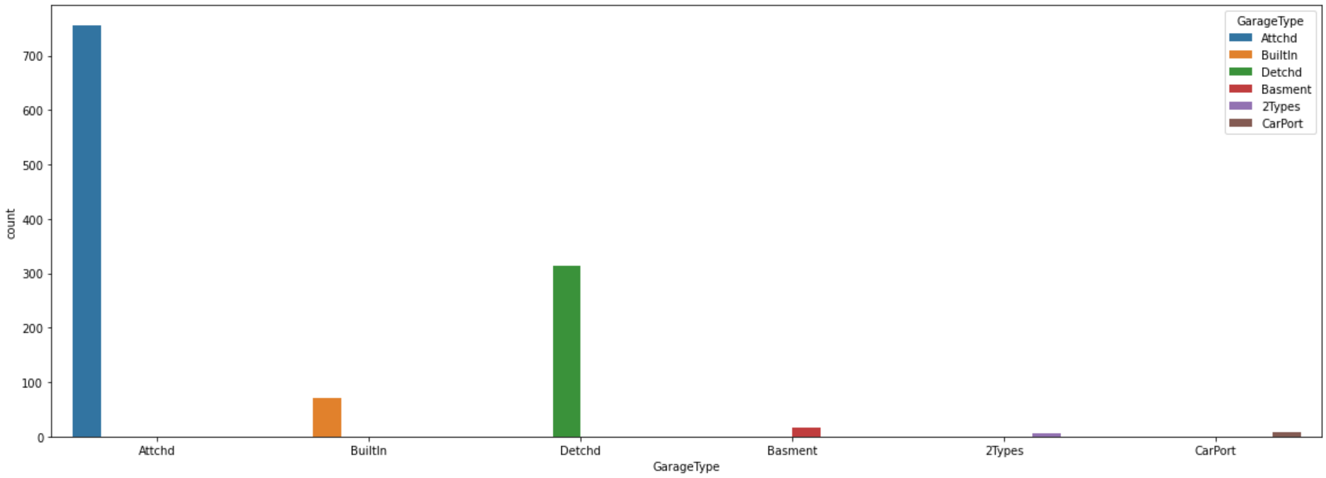

HeatingQC
TA
Ex
Gd
Fa
Po
count
600
500
400
300
200
100
0
Heating 0C

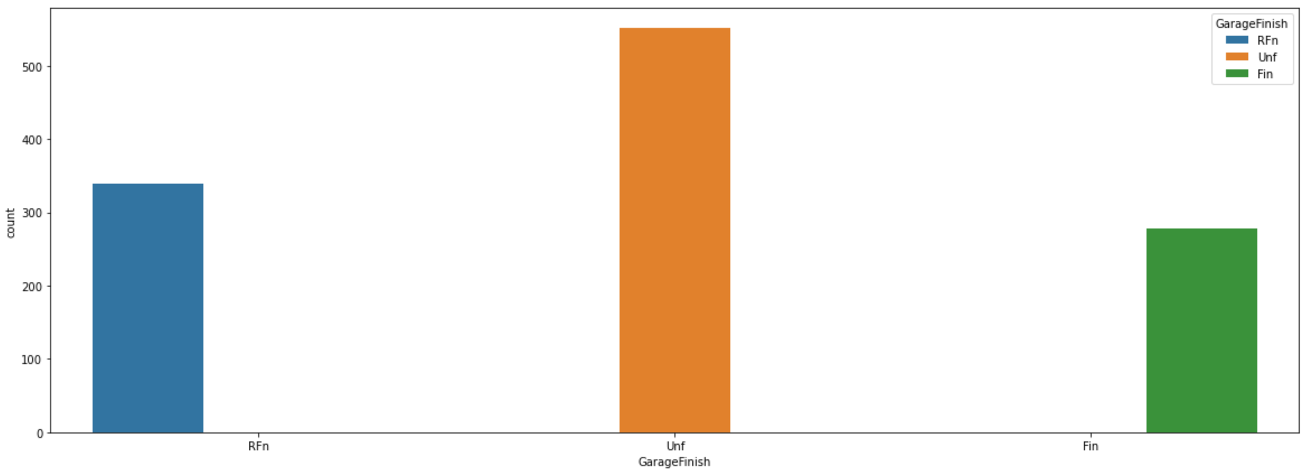

CentralAir
Y
N
count
1000
800
600
400
200
0
Y
N
CentralAir

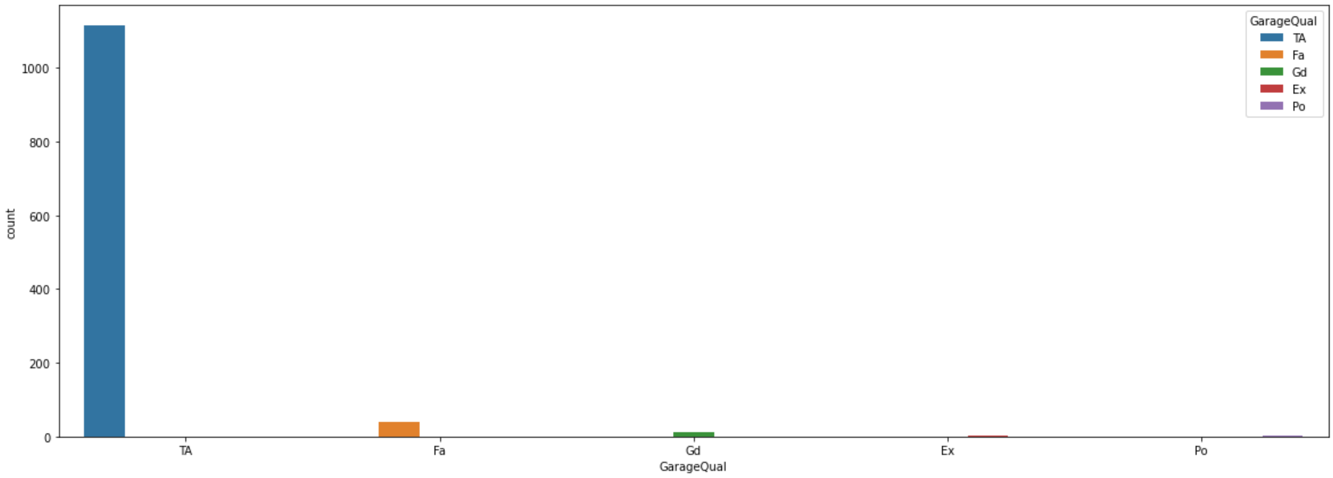

Electrical
SBrkr
FuseA
FuseF
FuseP
Mix
count
1000
800
600
400
200
0
SBrkr
FuseA
FuseF
FuseP
Mix
Electrical

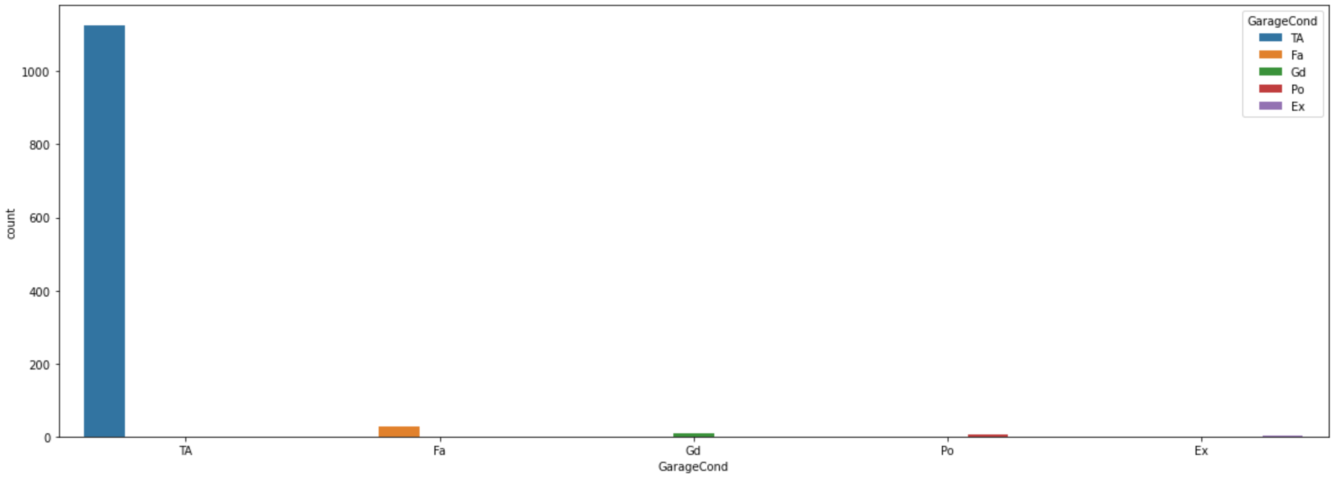

KitchenQual
TA
Gd
Ex
Fa
count
600
500
400
300
200
100
0
TA
Gd
Ex
Fa
KitchenQual

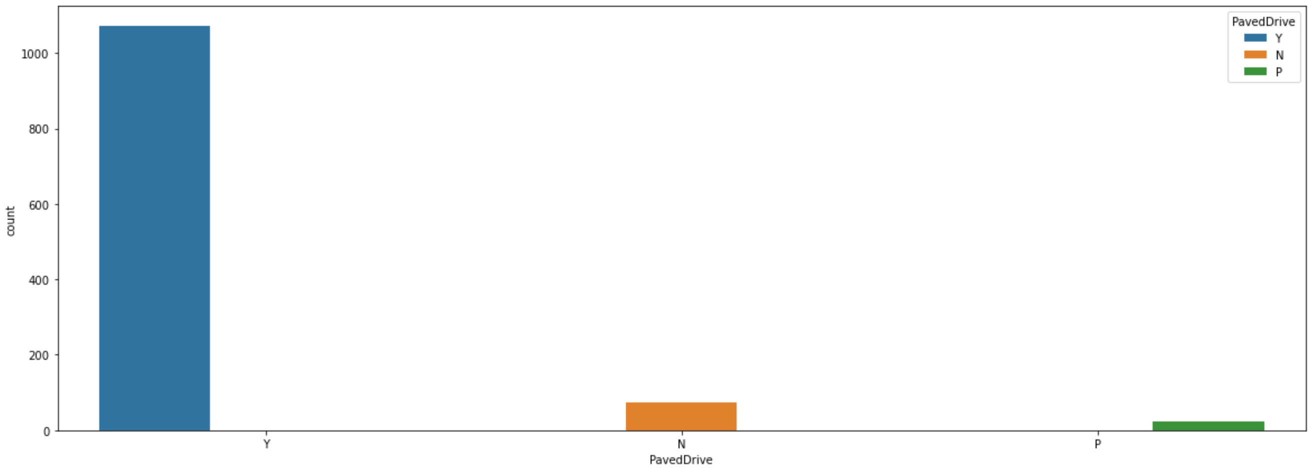

Functional
Typ
Mod
Maj1
Min1
Min2
Sev
Maj2
count
0
200
400
600
800
1000
Typ
Mod
Maj1
Min1
Min2
Sev
Maj2
Functional

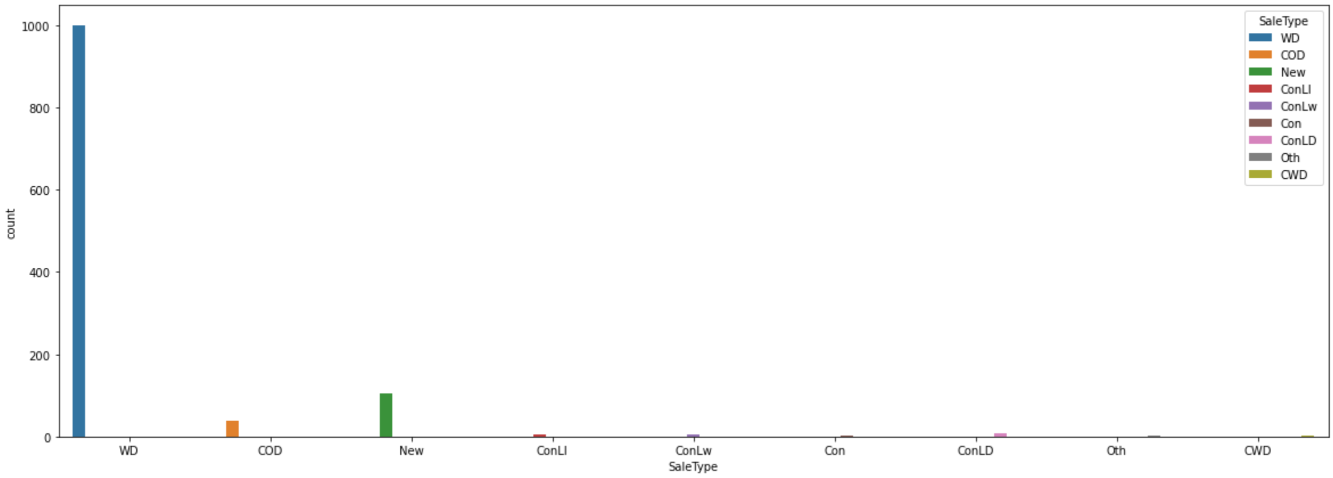

GarageType
Attchd
BuiltIn
Detchd
Basment
2Types
CarPort
count
0
100
200
300
400
500
600
700
Attchd
BuiltIn
Detchd
Basment
2Types
CarPort
GarageType

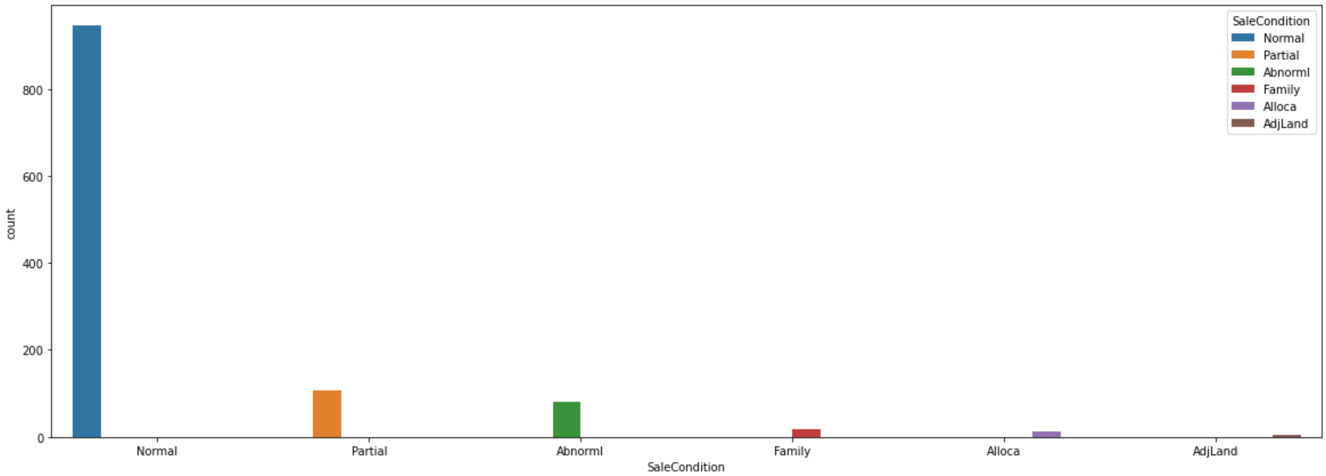

GarageFinish
RFn
Unf
Fin
count
0
100
200
300
400
500
RFn
Unf
Fin
GarageFinish


GarageQual
TA
Fa
Gd
Ex
Po
count
0
200
400
600
800
1000
TA
Fa
Gd
Ex
Po
GarageQual


GarageCond
TA
Fa
Gd
Po
Ex
count
0
200
400
600
800
1000
TA
Fa
Gd
Po
Ex
GarageCond


PavedDrive
Y
N
P
count
0
200
400
600
800
1000
Y
N
P
PavedDrive



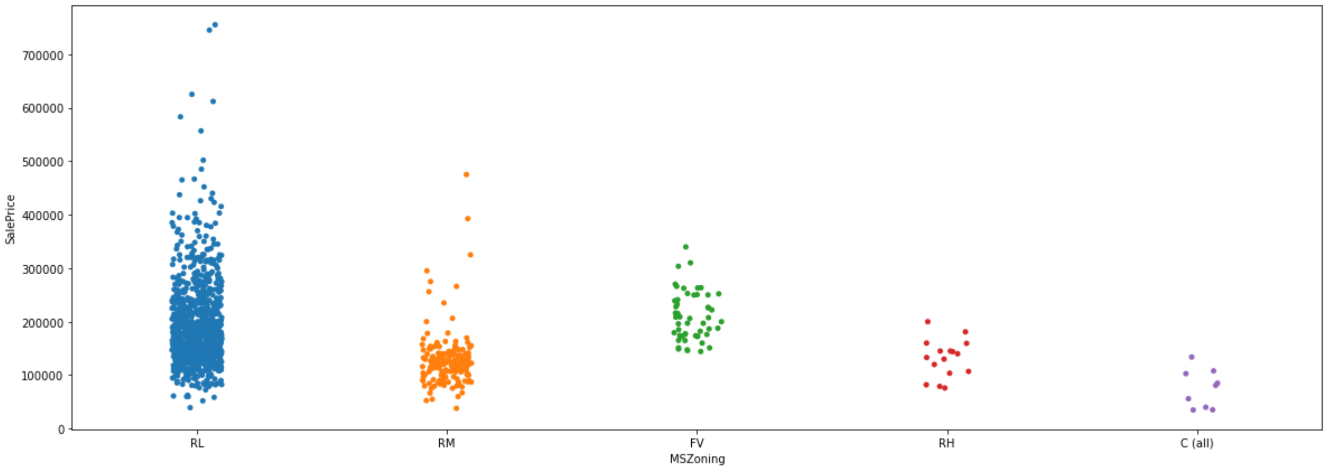


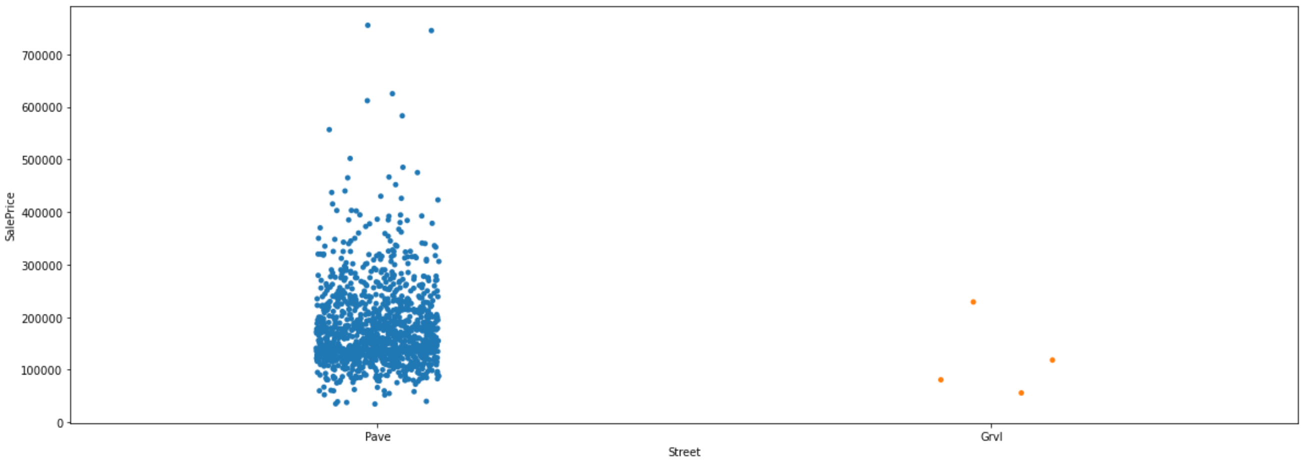
Findings:

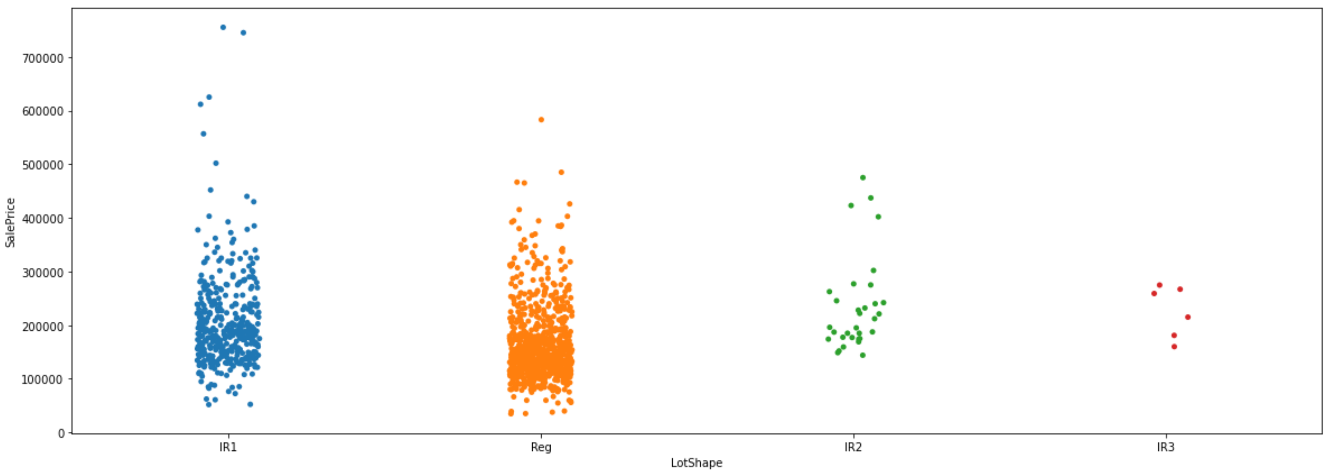
MSZoning -> majority are RL
Street-> majority streets are Pave style
LotShape-> majority are Reg shape
LandContour -> LVL have the highest count in the dataset
Utilities -> All values are AllPub
LotConfig -> We have very few FR3 and majority are Inside
LandSlope -> Landslope is Gentle for majority of houses
Neighborhood -> their are many differnt neighborhood present
Condition1 ->Majority of the houses are norm
Condition2 -> Majority of the houses are norm
BldgType -> Maajority of the houses are 1Fam
HouseStyle -> We have very few 2.5fin houses
RoofStyle -> We have very few houses with shed
RoofMatl -> Most of the houses have Compshg
Exterior1st -> Most of the houses have VinylSd
Exterior2nd -> Most of the houses have VinylSd
MasVnrType -> Most of the houses dont have this
Foundation -> Their are 0 houses with wood foundation
BsmtQual -> Very few houses have Fa quality
BsmtCond -> Most of the houses have TA
BsmtExposure -> Most of the houses dont have exposure
BsmtFinType1 -> Very few houses have LwQ
BsmtFinType2 -> Most of the houses have Unf
Heating -> Almost all the houses have GasA type
HeatingQC -> Most of the houses have Ex

CentralAir -> Very houses doesnot have central air facility
Electrical -> Their are no houses with FuseP and Mix
KitchenQual -> Most of the houses have TA quality
GarageType -> Very few houses have Basement, 2types and CarPort
GarageFinish -> Majority of the houses have GarageFinish
PavedDrive -> Most of the houses have Paved drive
SaleType -> Almost all the houses have WD salestype
SaleCondition -> Most of the houses have normal sales condition

In [24]:
```
counter=1;


for column in categorical_columns:
        plt.figure(figsize=(20,500))
        plt.subplot(60,1,counter)
        counter=counter+1
        sns.stripplot(x=column, y="SalePrice", data=df)
        plt.show()
```



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300000
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500000
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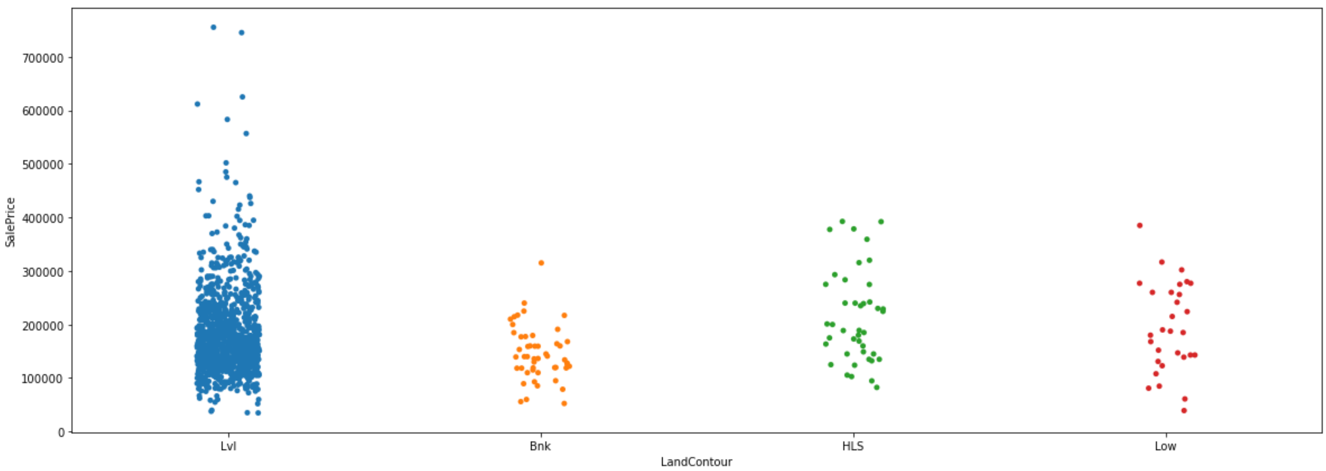
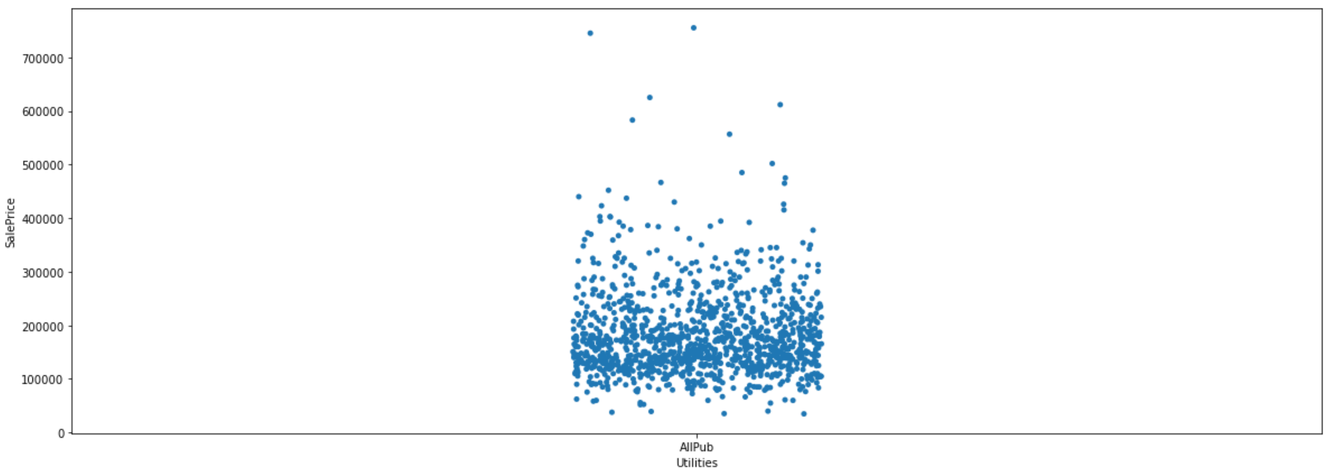
700000
IR1
Reg
IR2
IR3
LotShape


SalePrice
0
100000
200000
300000
400000
500000
600000
700000
Lvl
Bnk
HLS
Low
LandContour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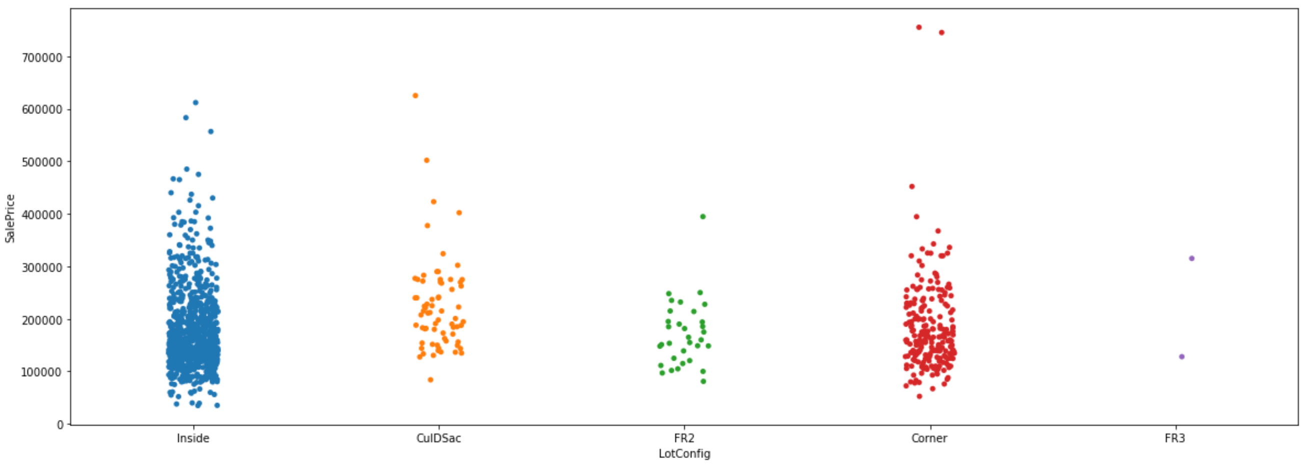
600000
700000
AllPub
Utilities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0
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300000
400000
500000
600000
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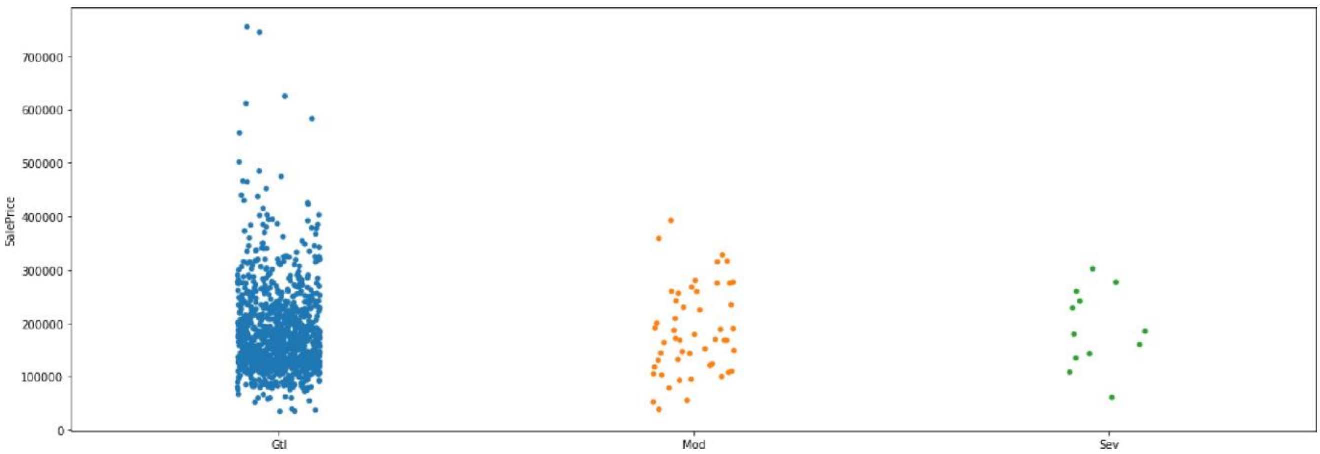
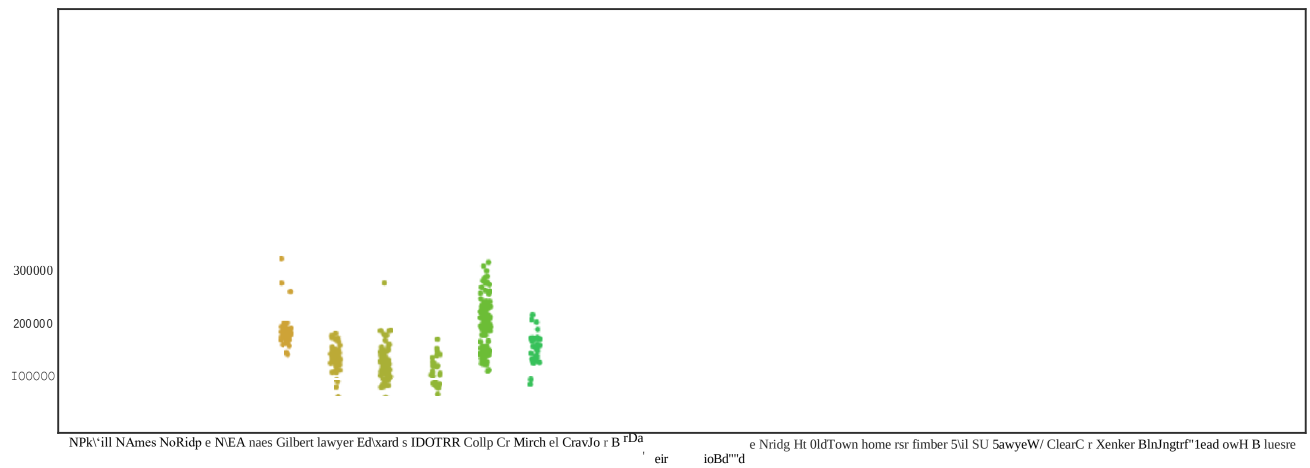
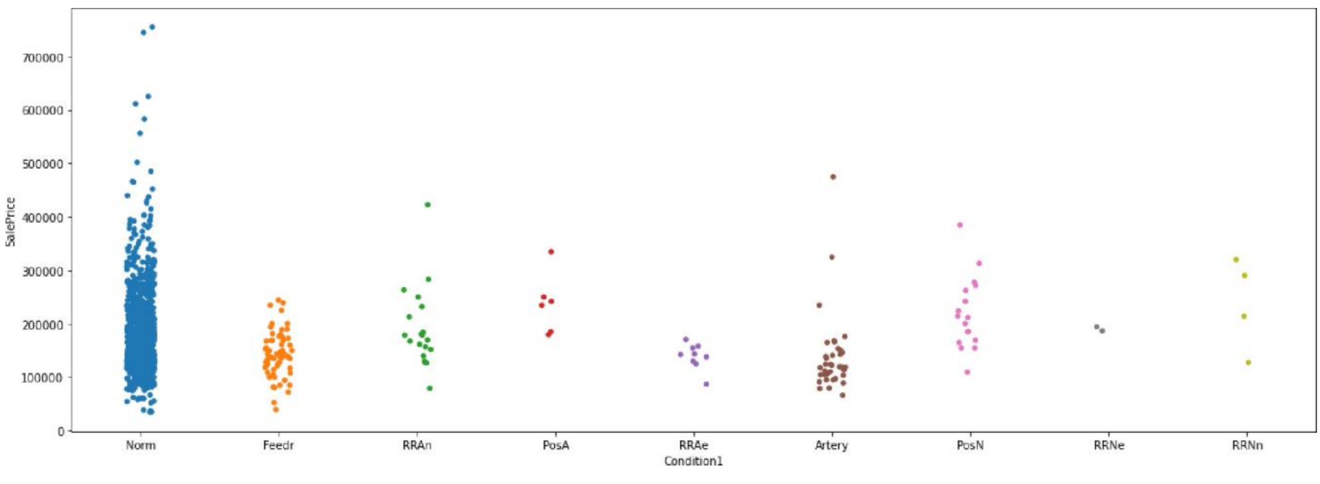
Inside
CulDSac
FR2
Corner
FR3
LotConfig


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
Gtl
Mod
Sev


300000
200000
I00000
NPk\'ill NAmes NoRidp e N\EA naes Gilbert lawyer Ed\xard s IDOTRR Collp Cr Mirch el CravJo r B rDa
eir ioBd""d
e Nridg Ht 0ldTown home rsr fimber 5\il SU 5awyeW/ ClearC r Xenker BlnJngtrf"1ead owH B luesre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600000
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300000
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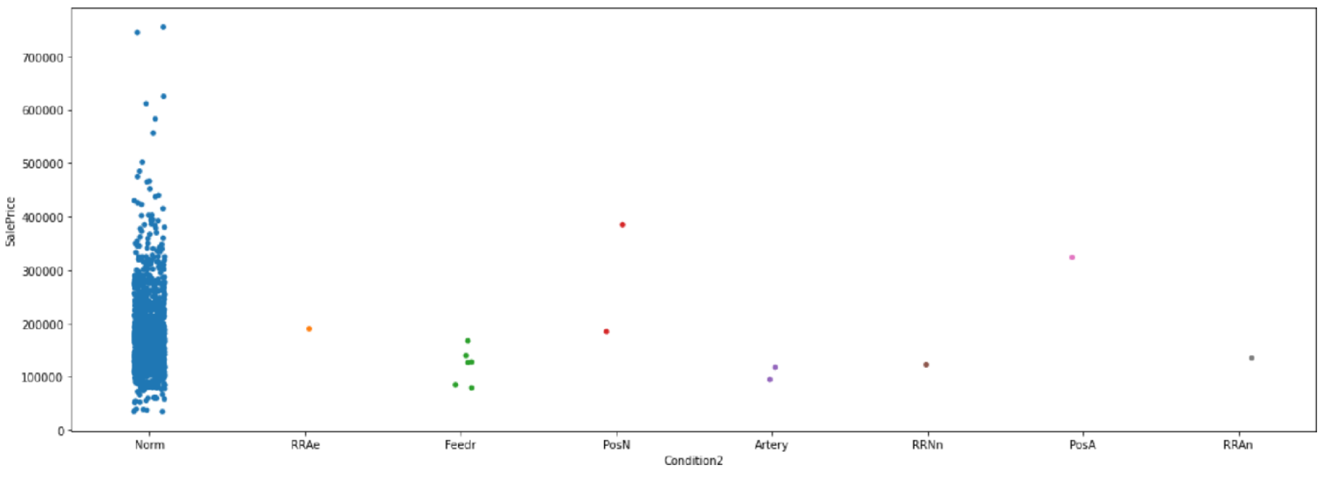
100000
0
Norm
Feedr
RRAn
PosA
RRAe
Artery
PosN
RRNe
RRNn
Condition1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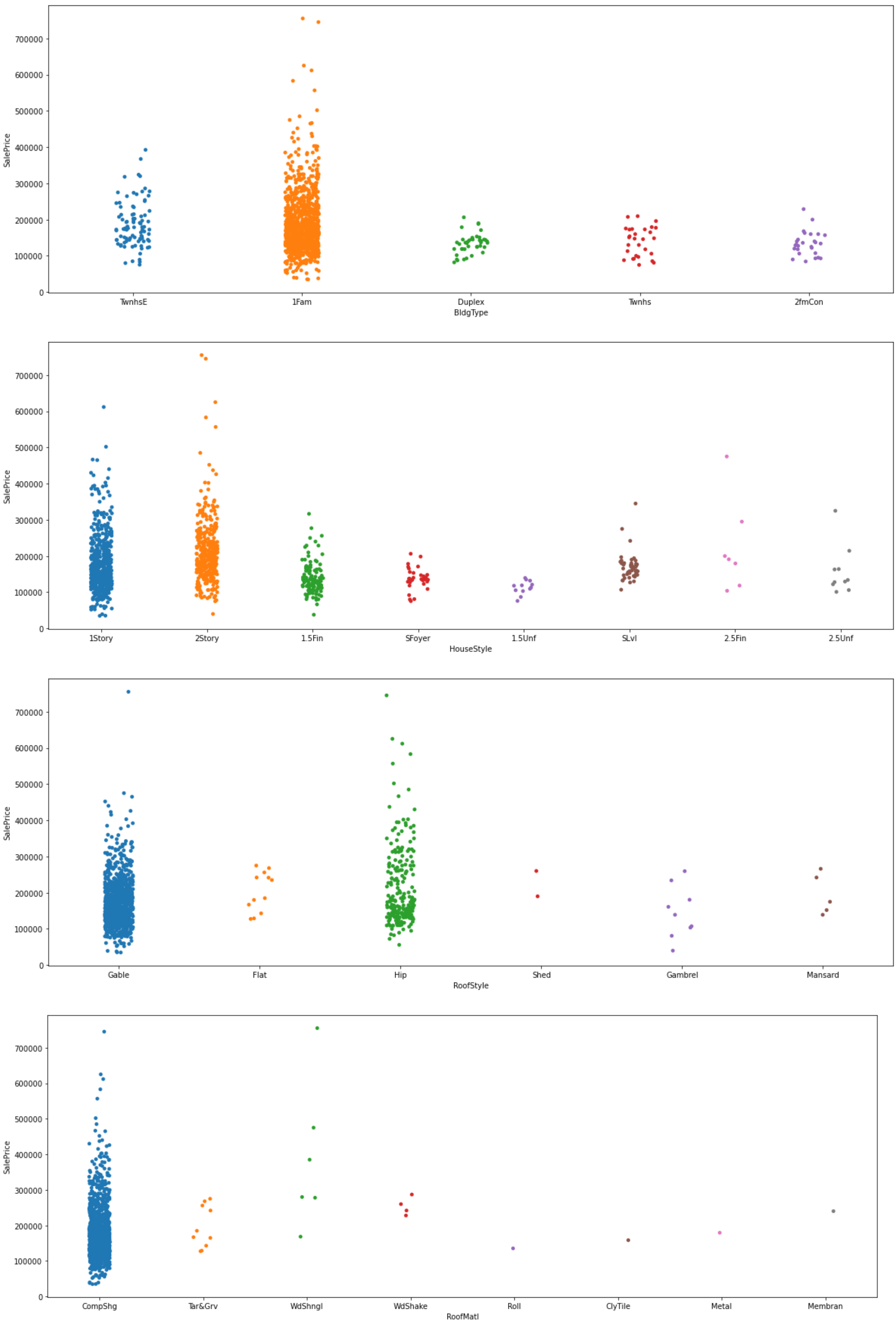
Norm
RRAe
Feedr
PosN
Artery
RRNn
PosA
RRAn
Condition2


SalePrice
0
100000
200000
300000
400000
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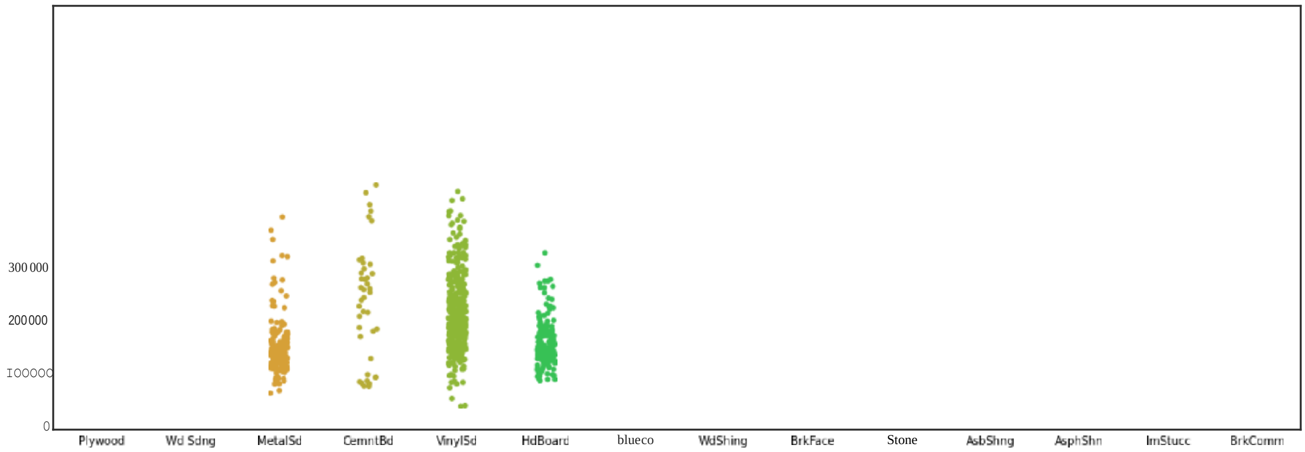
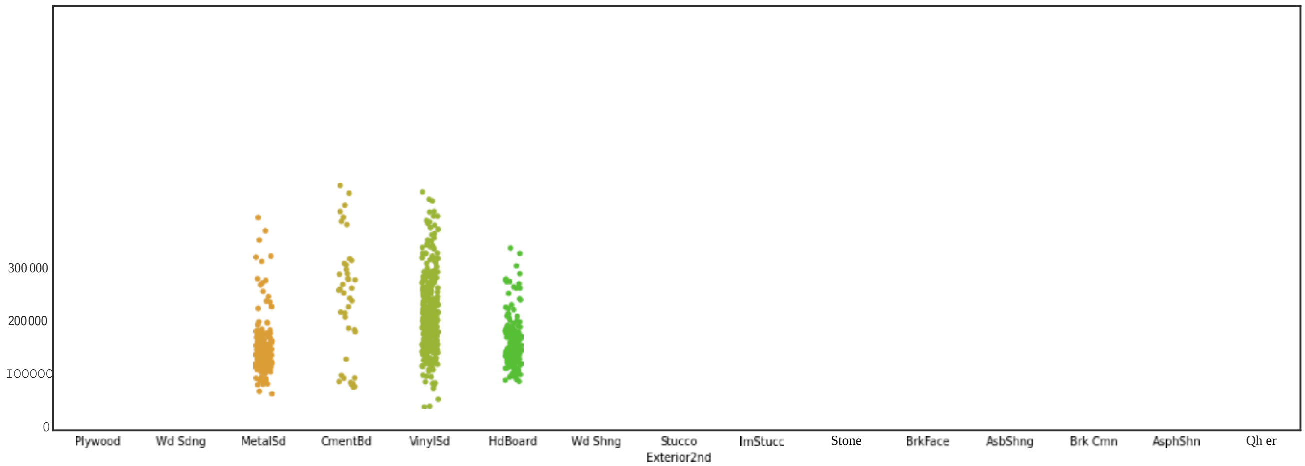
600000
700000
TwnhsE
1Fam
Duplex
Twnhs
2fmCon
BldgType
1Story
2Story
1.5Fin
SFoyer
1.5Unf
SLvl
2.5Fin
2.5Unf
HouseStyle
Gable
Flat
Hip
Shed
Gambrel
Mansard
RoofStyle
CompShg
Tar&Grv
WdShngl
WdShake
Roll
ClyTile
Metal
Membran
RoofMatl


300 000
200 000
IOOOOO
0
Plywood
Wd Sdng
MetalSd
CemntBd
VinylSd
HdBoard
blueco
WdShing
BrkFace
Stone
AsbShng
AsphShn
ImStucc
BrkComm


300 000
200 000
IOOOOO
0
Plywood
Wd Sdng
MetalSd
CmentBd
VinylSd
HdBoard
Wd Shng
Stucco
ImStucc
Stone
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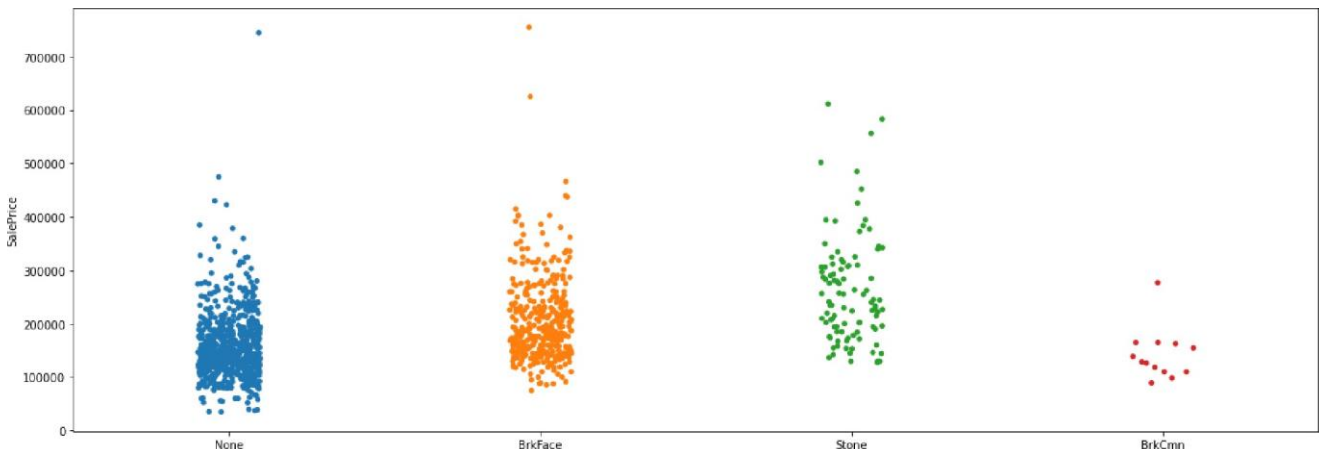
AsbShng
Brk Cmn
AsphShn
Qh er
Exterior2nd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SalePrice
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Stone
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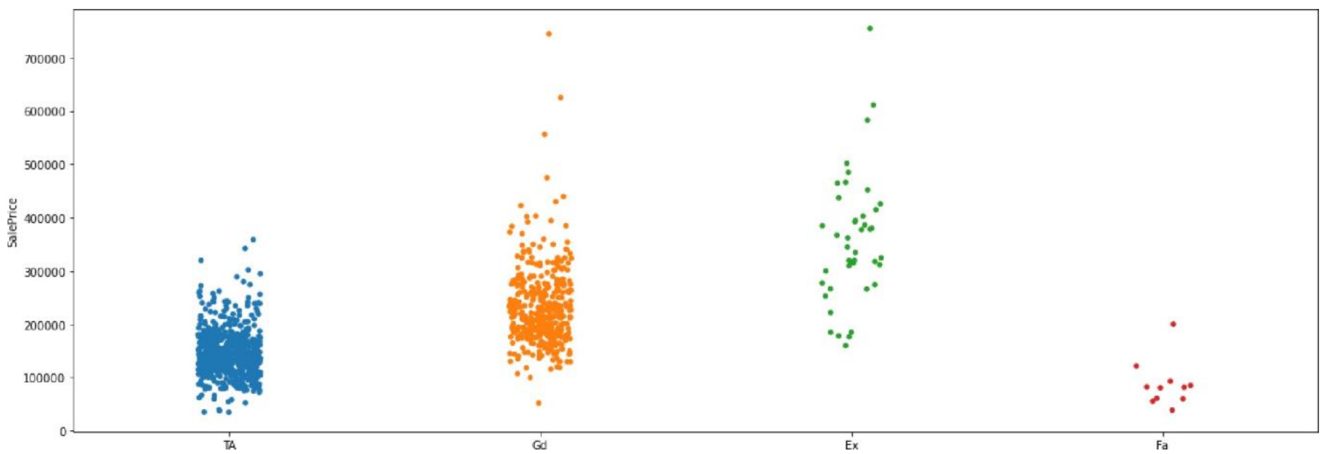
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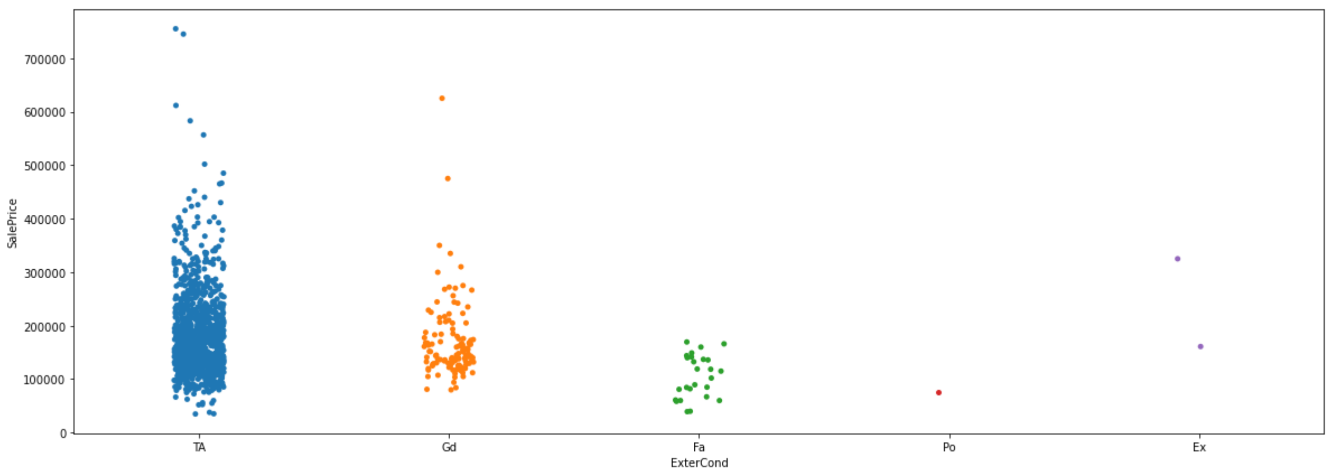
SalePrice
TA
Gd
Ex
Fa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200000
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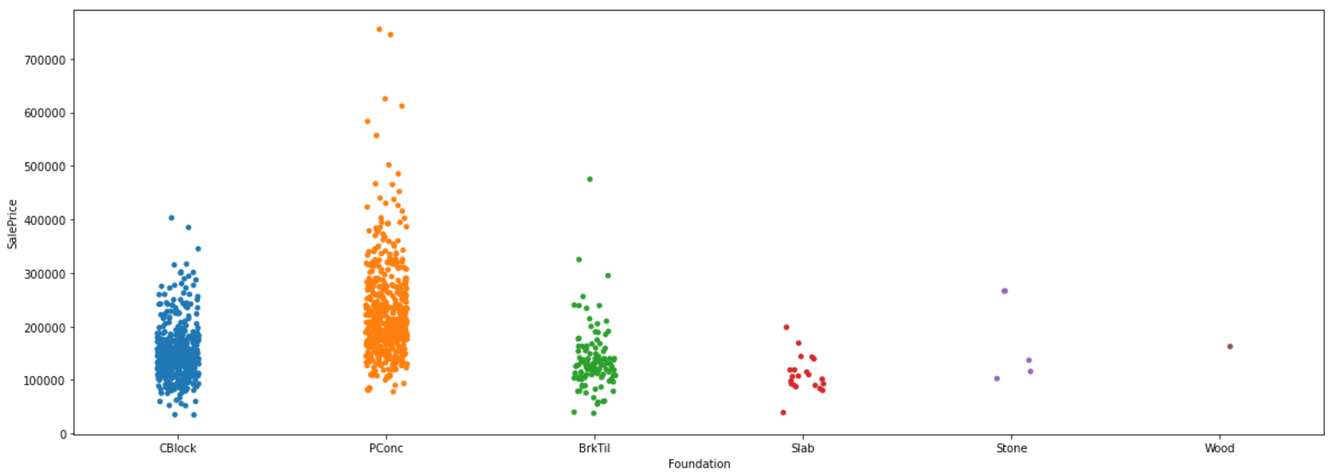
600000
700000
TA
Gd
Fa
Po
Ex
ExterCond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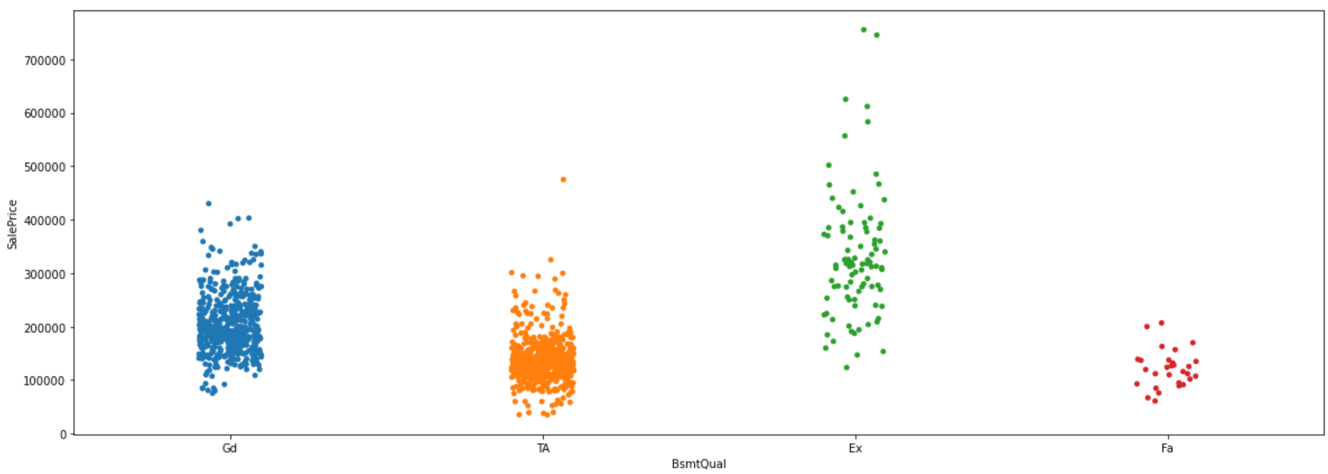
PConc
BrkTil
Slab
Stone
Wood
Foundation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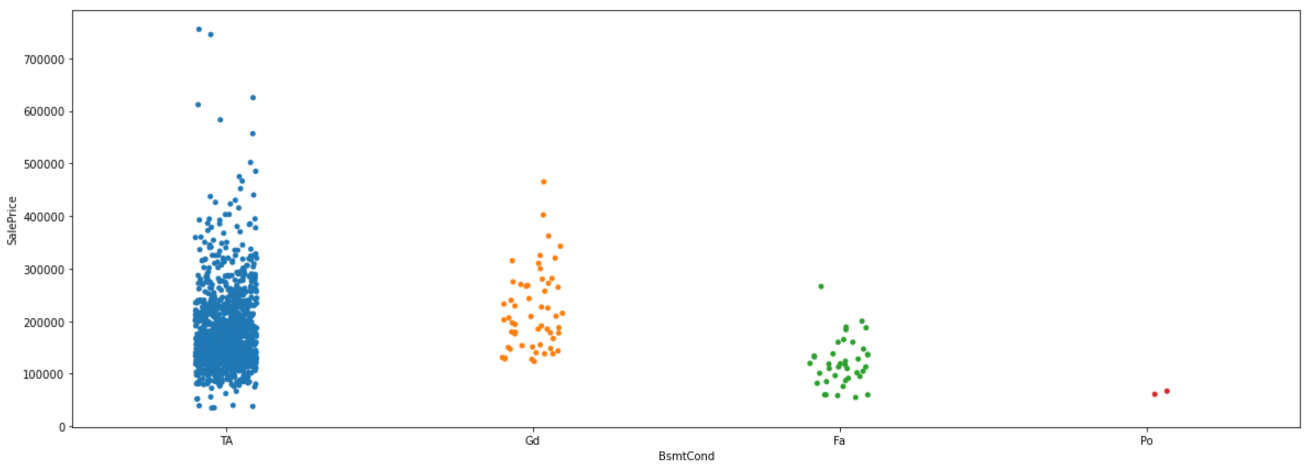
Gd
TA
Ex
Fa
BsmtQual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700000
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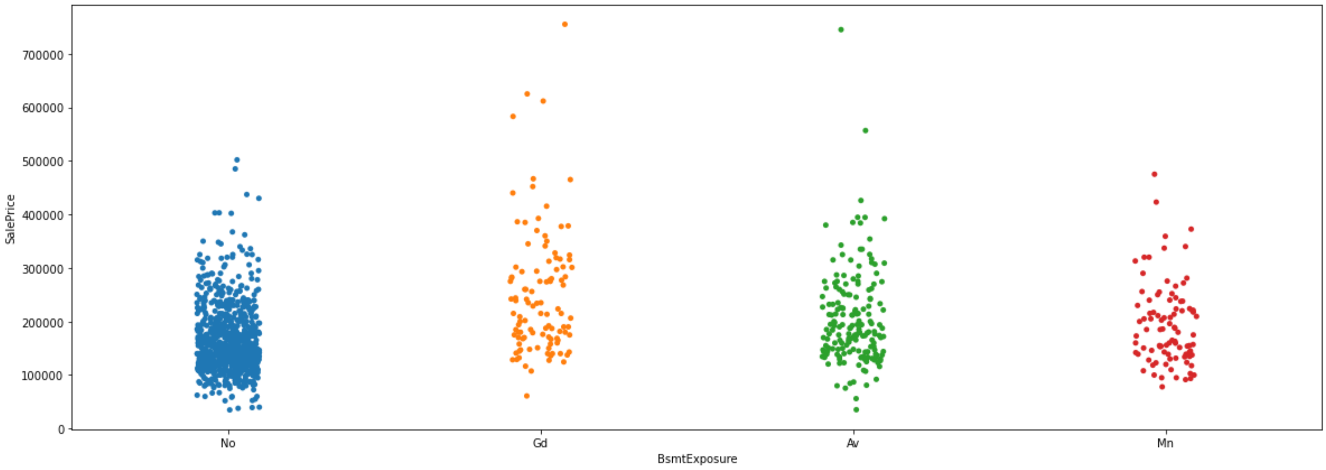
Gd
Fa
Po
BsmtCond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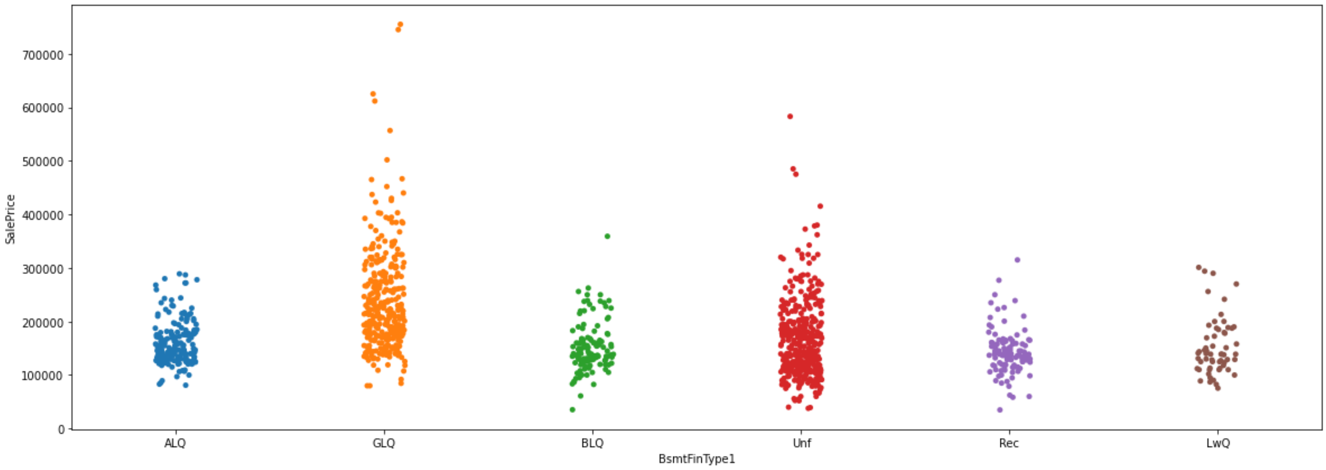
700000
No
Gd
Av
Mn
BsmtExposure


SalePrice
0
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400000
500000
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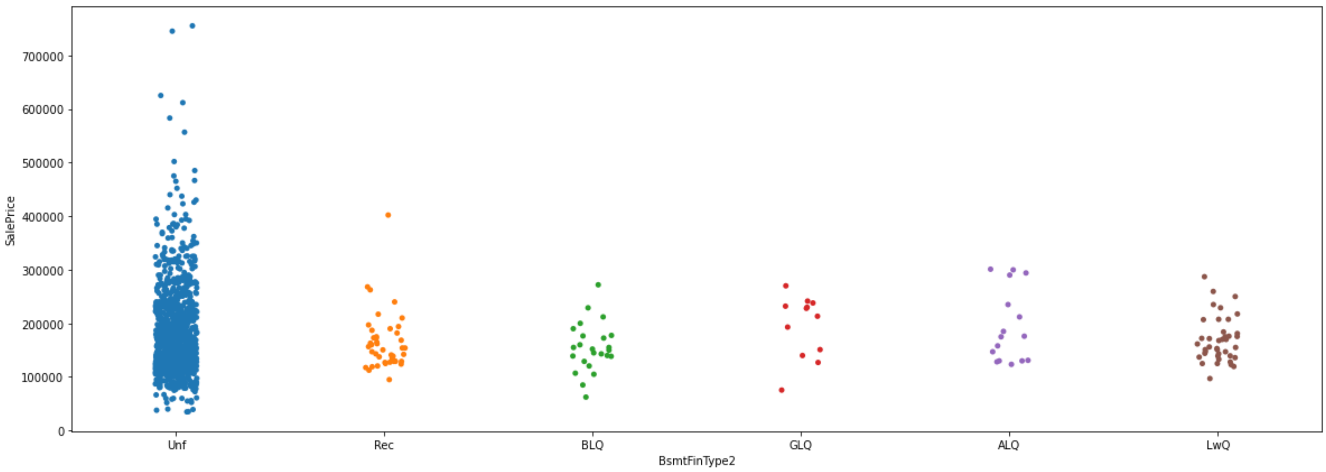
ALQ
GLQ
BLQ
Unf
Rec
LwQ
BsmtFinType1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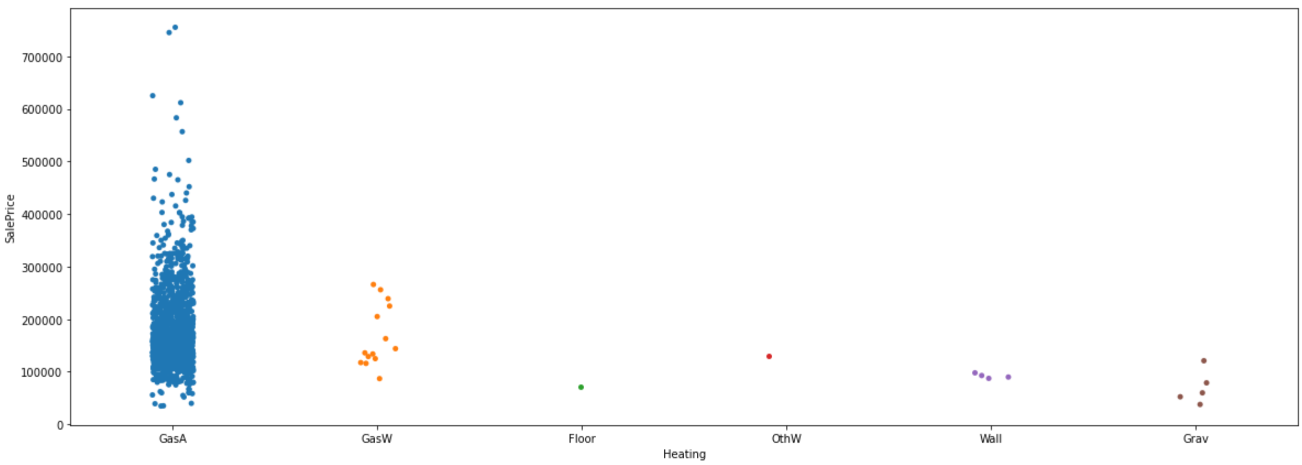
Unf
Rec
BLQ
GLQ
ALQ
LwQ
BsmtFinType2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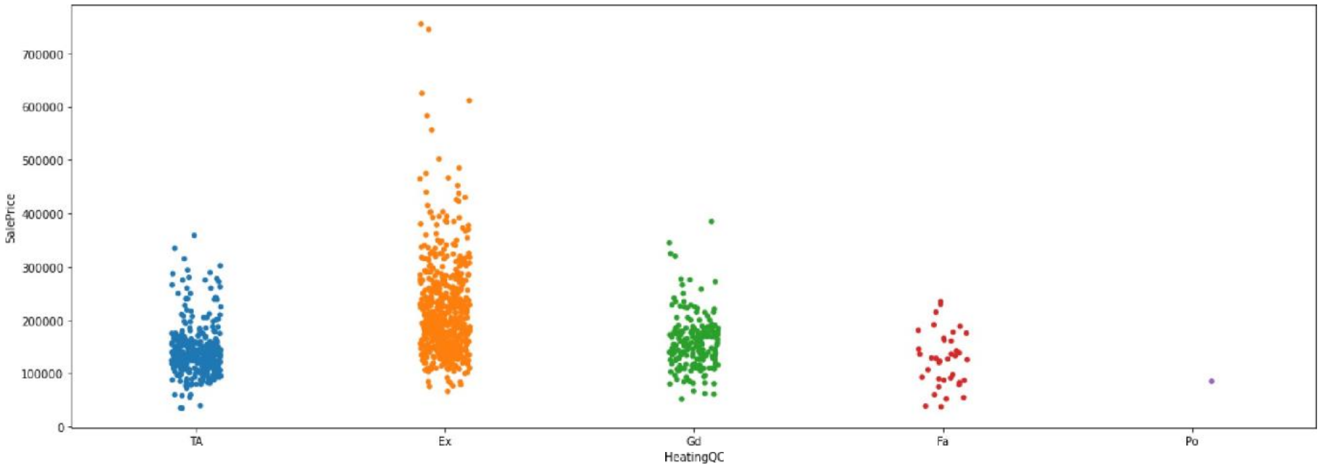
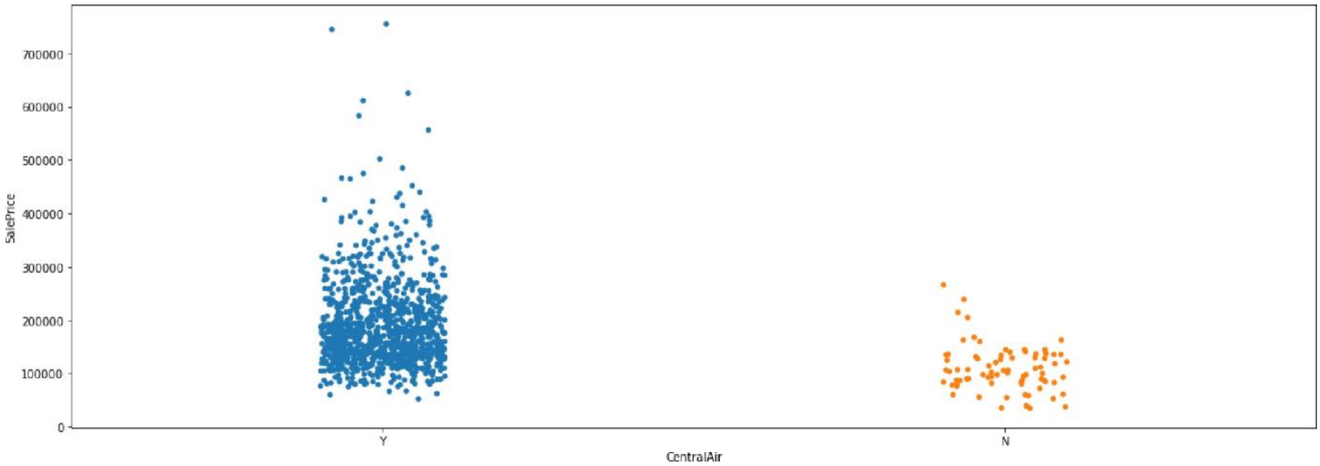
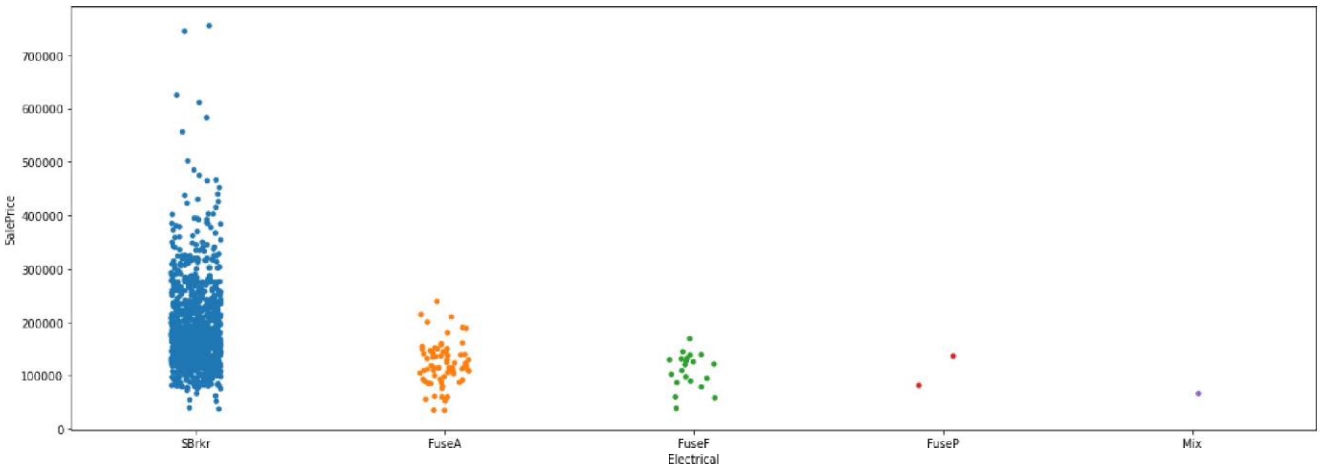
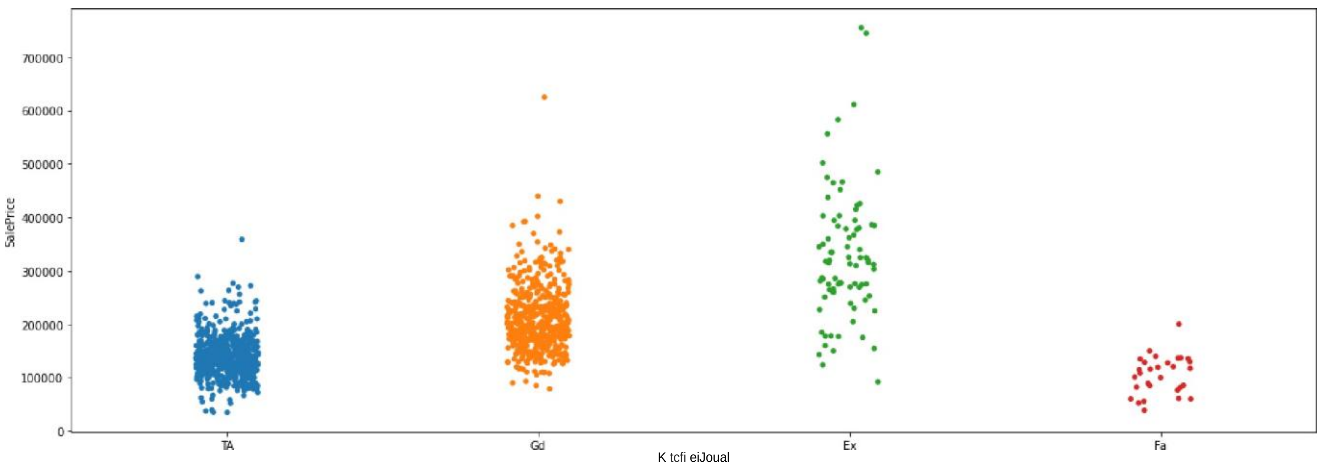
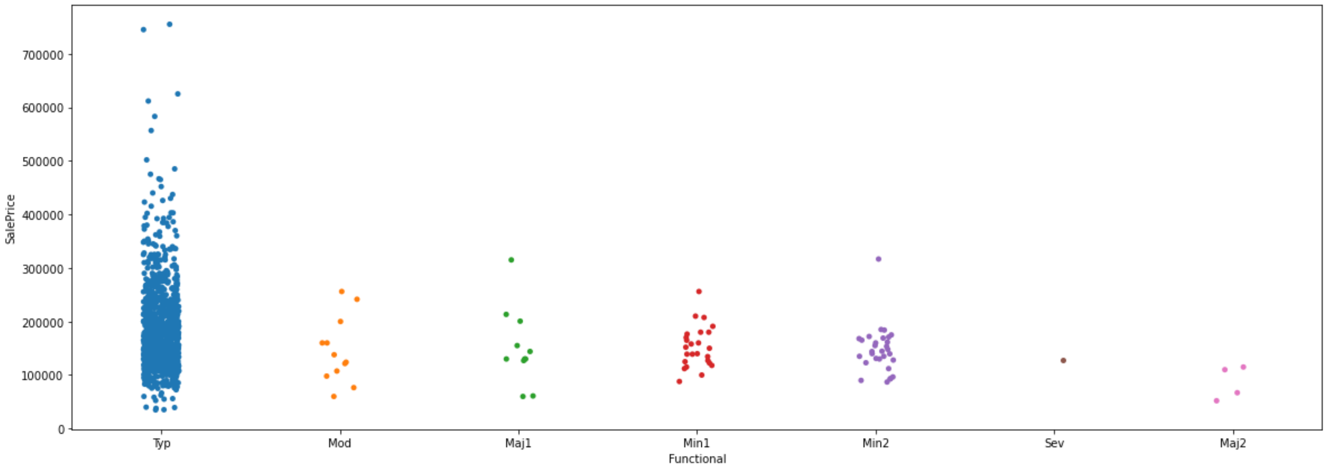
600000
700000
GasA
GasW
Floor
OthW
Wall
Grav
Heating


SalePrice
HeatingQC
TA
Ex
Gd
Fa
Po


SalePrice
CentralAir
Y
N


SalePrice
Electrical
SBrkr
FuseA
FuseF
FuseP
Mix


SalePrice
TA
Gd
Ex
Fa
K tcfi eiJoual



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200000
100000
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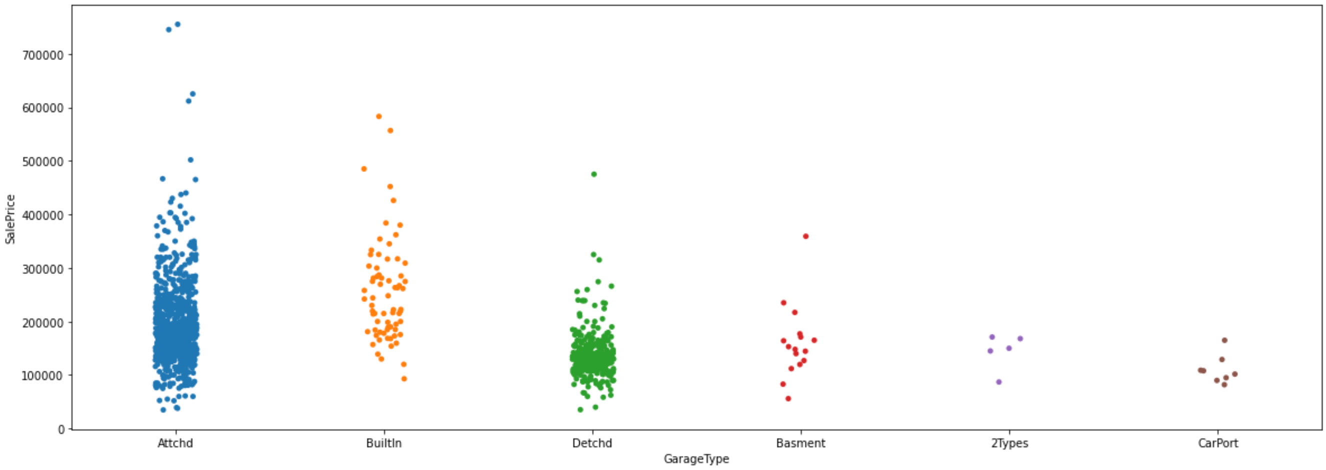
SalePrice
Typ
Mod
Maj1
Min1
Min2
Sev
Maj2
Functional



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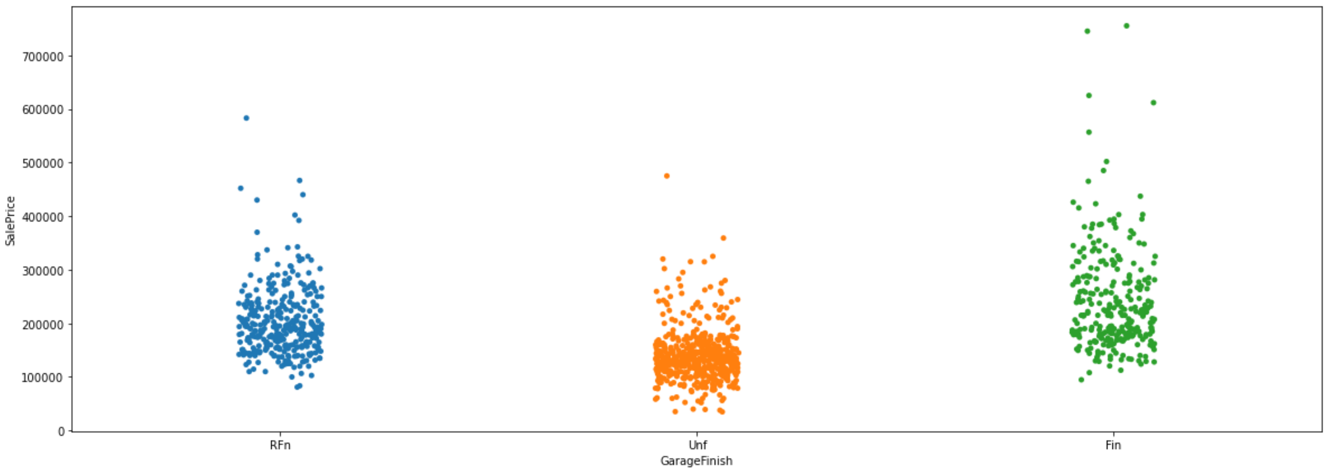
BuiltIn
Detchd
Basment
2Types
CarPort
GarageType



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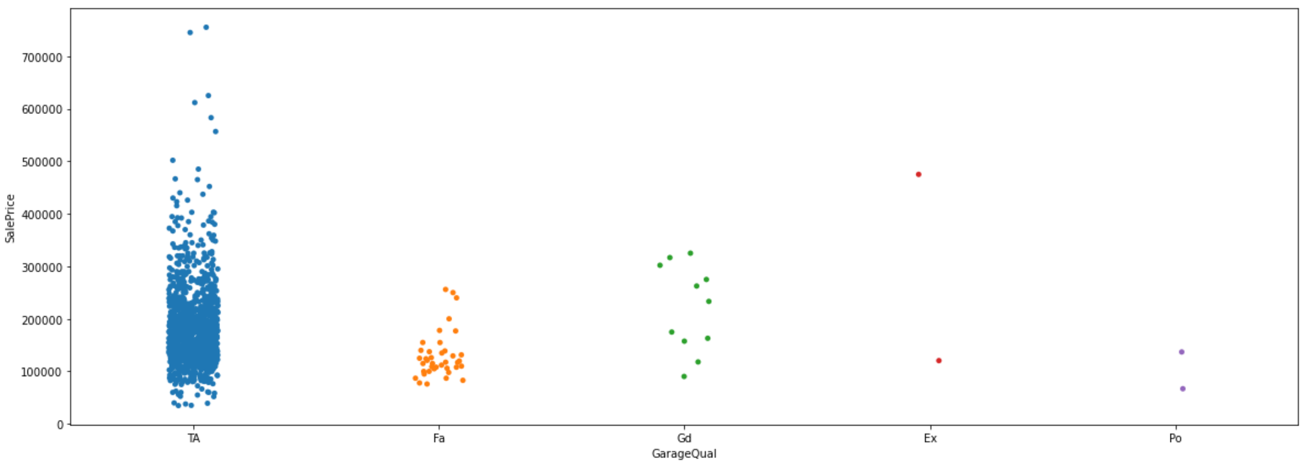
Unf
Fin
GarageFinish



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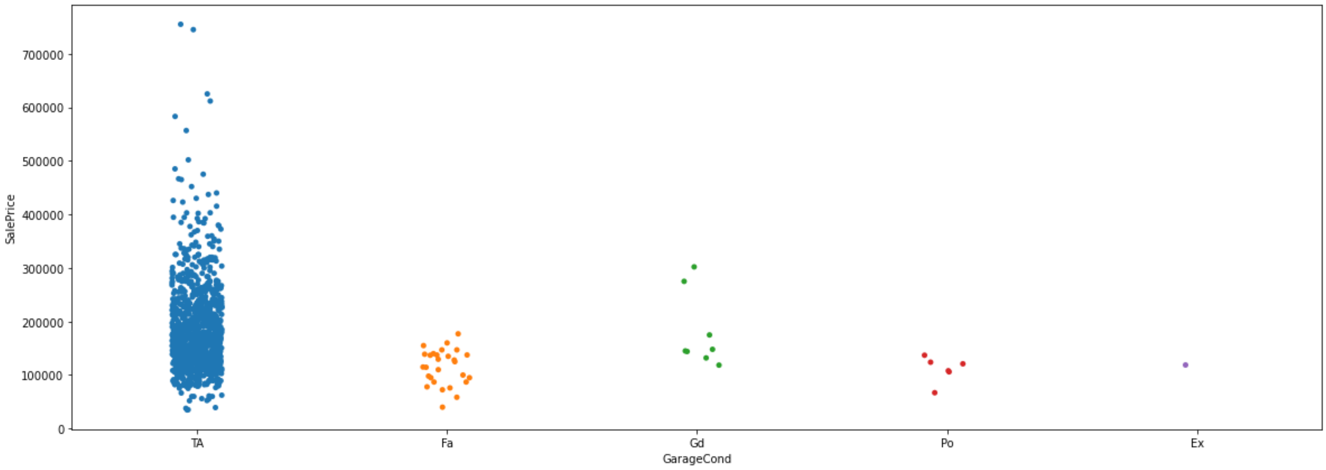
TA
Fa
Gd
Ex
Po
GarageQual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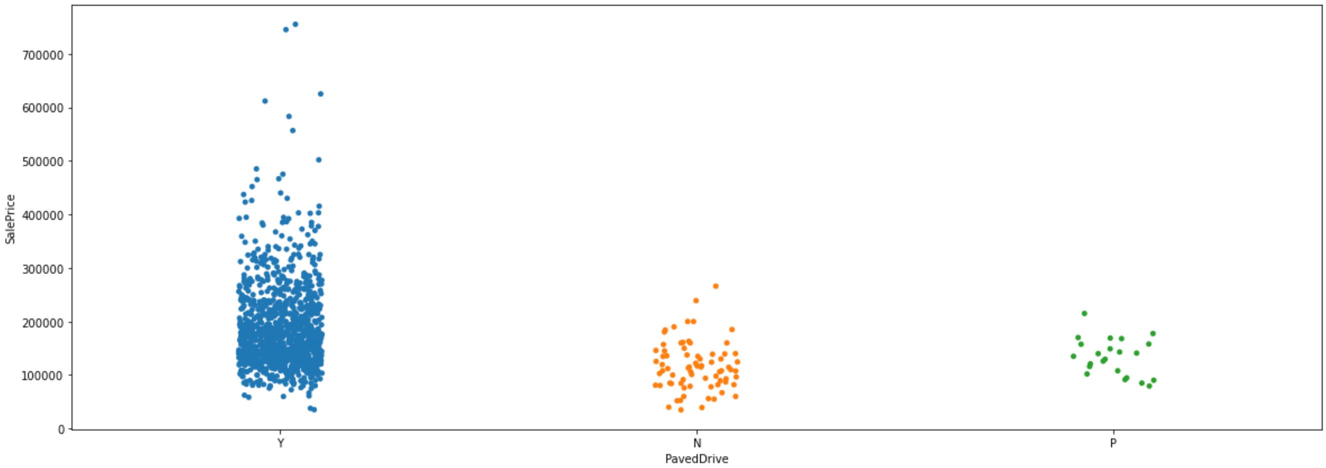
TA
Fa
Gd
Po
Ex
GarageCond


700000
600000
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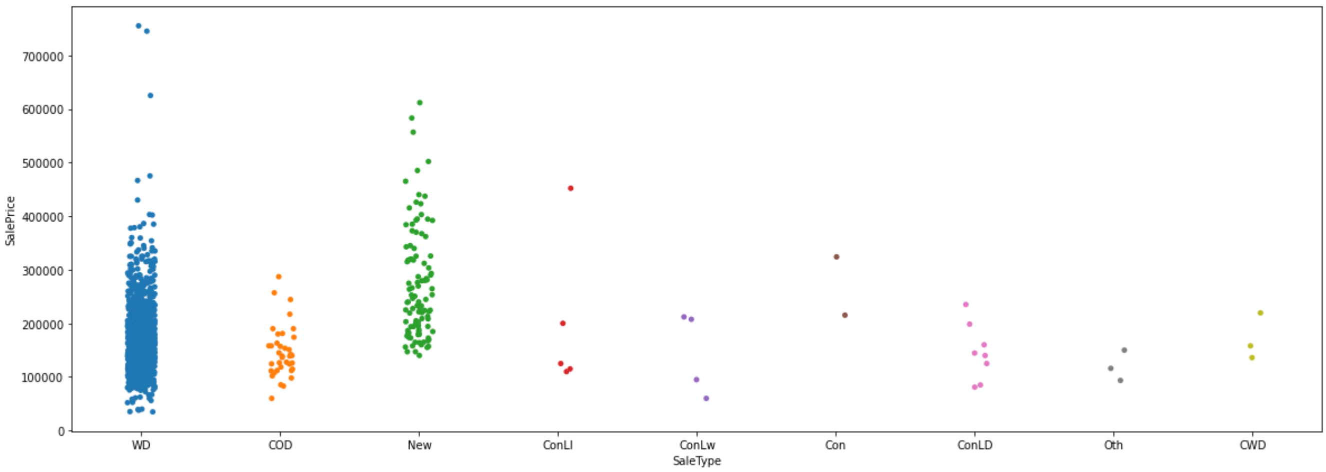
100000
0
SalePrice
Y
N
P
PavedDrive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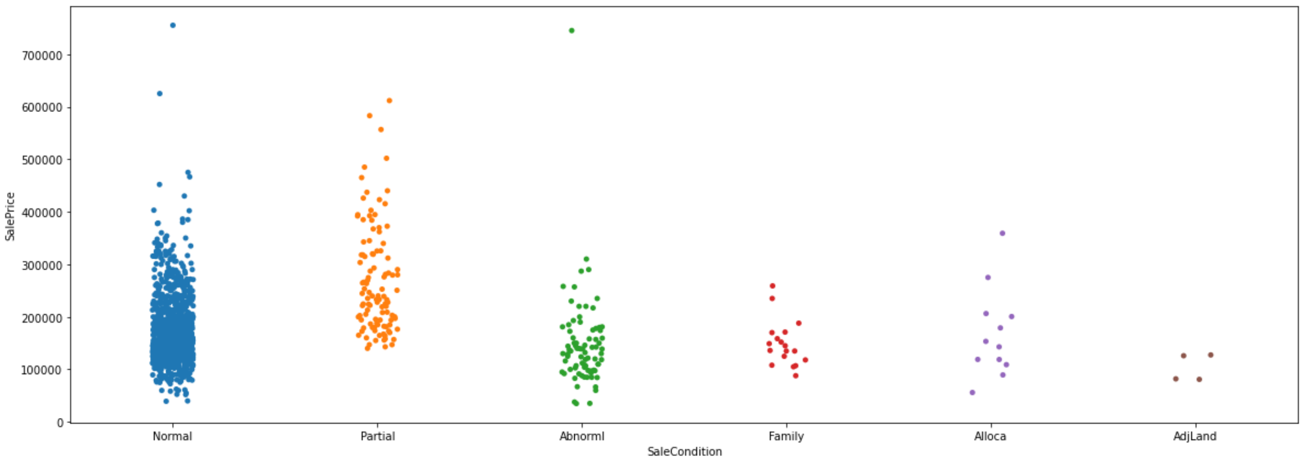
WD
COD
New
ConLI
ConLw
Con
ConLD
Oth
CWD
SaleType


700000
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400000
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200000
100000
0
SalePrice
Normal
Partial
Abnorml
Family
Alloca
AdjLand
SaleCondition

Findings:

MSZoning -> With RL zoning the property have higher value
Street-> with Pave stype property have higher value
LotShape-> IR1 shape property have higher value
LandContour -> LVL property have higher value
LotConfig -> Corner property have higher value
LandSlope -> Gentle slope property have higher value
Neighborhood -> NoRidge property have higher value
Condition1 ->norm property have higher value
Condition2 ->norm property have higher value
BldgType -> 1Fam property have higher value
HouseStyle -> 2 story property have higher value
RoofStyle -> Gable and Hip stype property have higher value
RoofMatl -> Compshg and WdShngle type property have higher value
Exterior1st -> Brkcomm, Aspshnn style decreases the property value
Exterior2nd -> Hd board type property have higher value
MasVnrType -> BrkCmn type decreases the property value
ExterQual -> Gd and Ex quality have higher property value
Foundation -> Pconc foundation property have higher value
BsmtQual -> Ex quality property have higher value
BsmtCond -> Po quality property have low price
BsmtFinType1 -> GLQ type have higher property prices
BsmtFinType2 -> Unf type have higher price
Heating -> GasA heating system have higher property price
HeatingQC -> Houses with Fa HeatingQc price is low
CentralAir -> Houses with central air have higher cost
Electrical -> houses with FuseP and Mix have lower property value
KitchenQual -> Excelent kitchen quality can increase the Property value
GarageType -> Attached garage have higher property value
GarageQual -> Poor garage quality decreases the price of property
PavedDrive -> Paved drive hiuses have higher price
SaleType -> WD and New sale type can get higher price
SaleCondition -> having AdjLand have lower price

Interpretation of the Results

Results:

1) Large amount of null values are present in the dataset
2) Data Set is not normally distributed
3) Dataset have outliers in most of the variables
4) Dataset is not normalized
5) Dataset is highly skewed
6) Random Forest Algorithm is best suited for the current dataset

CONCLUSION

- Key Findings and Conclusions of the Study

  We found that to predict the House price using Data Science the best way after performing Data Cleaning is to use Random Forest Algorithm it provides 88% accuracy which is better than other Regression algorithms.

- Learning Outcomes of the Study in respect of Data Science

  In data science, there are various steps involved during Data analysis and cleaning. With the help of various Visualization tools like plots, Graphs we were able to perform the actions and observe different things. Like for finding the outliers we used Box Plot visualization, for finding the skewness and normalization we used Count Plot visualization, for finding skewness we visualized the skewness using Heat Map for the clear picture of how the variables are co-related to each other in the dataset. We used different metrics to check which model best fits the prediction for the dataset.

- Limitations of this work and Scope for Future Work

  Data was unbalanced if data was balanced more accurate and clear picture of the output -> result is dependent on the data

  Neural network classifier which are still unexplored & can be taken for future consideration