FLIP ROBO

HOUSING: PRICE PREDICTION

Submitted by:

Gaurav More

ACKNOWLEDGMENT

I express my sincere gratitude to Flip Robo Technologies for giving me the opportunity to work on this project on Housing Price prediction using machine learning algorithms. I would like to express my special thanks to the sources Towards Data Science, Datatrained In which helped me to accomplish this project.

INTRODUCTION

Business Problem Framing

Houses are one of the necessary needs of each and every person around the globe and therefore the housing and real estate market 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 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 a variable?

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

Conceptual Background of the Domain Problem

Predictive modelling, Market mix modelling, recommendation systems are some of the machine learning techniques used for achieving the business goals for housing companies.

Hedonic Characteristics of Housing Price: A Hedonic approach is preferred for predicting the sale prices in the housing market because the market displays resilience, flexibility and spatial fixity.

Housing Attributes: Studying the structural, locational, and economic attributes of housing properties is crucial in understanding their mutually inclusive relationships with their pricing.

Review of Literature

2 research papers, namely: “House Price Prediction using a Machine Learning Model: A Survey of Literature” and “The impact of housing quality on house prices in eight capital cities, Australia” were reviewed and evaluated to gain insights into all the attributes that influence the price of houses.

From studying the papers and analysing the research work it is learnt that locational attributes and structural attributes are prominent factors in predicting house prices. Studies suggest that there exists a close relationship between House pricing and locational attributes such as distance from the closest shopping center, train station, position offering views of hills or shore, the neighborhood in which the property is situated etc.

Structural attributes of the house like lot size, lot shape, quality and condition of the house, garage capacity, rooms, Lot frontage, number of bedrooms, bathrooms, overall finishing of the house etc play a big role in influencing the house price.

Neighbourhood qualities can be included in deciding house price. Factors like efficiency of public education, community social status, and socio-cultural demographics improve the worth of a property.

The demand side of the housing market is also a necessary component. Although population growth is widely known as a driver in housing demand, the key issue lies in the proportion of people with abundant financial resources.

Variables representing land value such as rents and material costs also demonstrate their influence in explaining house prices, which are positively related to housing prices.

Multiple regression analysis models allow us to ascertain price predictions by capturing independent and dependent variable data. In Using multiple regression modelling techniques, we can describe changes brought to a dependent variable with changes in the independent variables.

In this research, various models were built in which the house Sale Price is projected as a separate and dependent variable while locational, structural and various other attributes of housing properties were treated as independent variables. Therefore, the house price is set as a target or dependency variable, while other attributes are set as independent variables to determine the main variables by identifying the correlation coefficient of each attribute.

Motivation for the Problem Undertaken

There is a steady rise in house demand with every passing year, and consequently the house prices are rising every year. The problem arises when there are numerous variables such as location and property demand that influence the pricing. Therefore, buyers, sellers, developers and the real estate industry are keen to know the most important factors influencing the house price to help investors make sound decisions and help house builders set the optimal house price. There are many benefits that home buyers, property investors, and house builders can reap from the house-price model. This model aims to serve as a repository of such information and gainful insights to home buyers, property investors and house builders, that will help them determine best house prices. This model can be useful for potential buyers in deciding the characteristics of a house they want that best fits their budget and will be of tremendous benefit, especially to housing developers and researchers, to ascertain the most significant attributes to determine house prices and to acknowledge the best machine learning model to be used to conduct a study in this field.

Analytical Problem Framing

Mathematical/ Analytical Modelling of the Problem

In this project we have performed various mathematical and statistical analysis such as we checked description or statistical summary of the data using describe, checked correlation using corr() and also visualized it using heatmap. Then we have used z score to plot outliers and remove them

Data Sources and their formats

The data was provided to us by our client who is in the Housing Industry. The data was in the form of a CSV file.

```
In [3]: df
Out[3]:
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Cc
0	127	120	RL	NaN	4928	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	NPkVill	Norm	
1	889	20	RL	95.0	15865	Pave	NaN	IR1	Lvl	AllPub	Inside	Mod	NAmes	Norm	
2	793	60	RL	92.0	9920	Pave	NaN	IR1	Lvl	AllPub	CulDSac	Gtl	NoRidge	Norm	
3	110	20	RL	105.0	11751	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	NWAmes	Norm	
4	422	20	RL	NaN	16635	Pave	NaN	IR1	Lvl	AllPub	FR2	Gtl	NWAmes	Norm	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1163	289	20	RL	NaN	9819	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	Sawyer	Norm	
1164	554	20	RL	67.0	8777	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	Edwards	Feedr	
1165	196	160	RL	24.0	2280	Pave	NaN	Reg	Lvl	AllPub	FR2	Gtl	NPkVill	Norm	
1166	31	70	C (all)	50.0	8500	Pave	Pave	Reg	Lvl	AllPub	Inside	Gtl	IDOTRR	Feedr	
1167	617	60	RL	NaN	7861	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	Gilbert	Norm	

1168 rows × 81 columns

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

```
In [105]: df_1=pd.read_csv('test.csv')
          df_1.head()
```

Out[105]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Con
0	337	20	RL	86.0	14157	Pave	NaN	IR1	HLS	AllPub	Corner	Gtl	StoneBr	Norm	
1	1018	120	RL	NaN	5814	Pave	NaN	IR1	Lvl	AllPub	CulDSac	Gtl	StoneBr	Norm	
2	929	20	RL	NaN	11838	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	
3	1148	70	RL	75.0	12000	Pave	NaN	Reg	Bnk	AllPub	Inside	Gtl	Crawfor	Norm	
4	1227	60	RL	86.0	14598	Pave	NaN	IR1	Lvl	AllPub	CulDSac	Gtl	Somerst	Feedr	

```
In [106]: df_1.shape
```

Out[106]: (292, 80)

Training Dataset contains 1168 entries and 81 variables,

Test Dataset contains 292 entries and 80 variables.

Summary Statistics

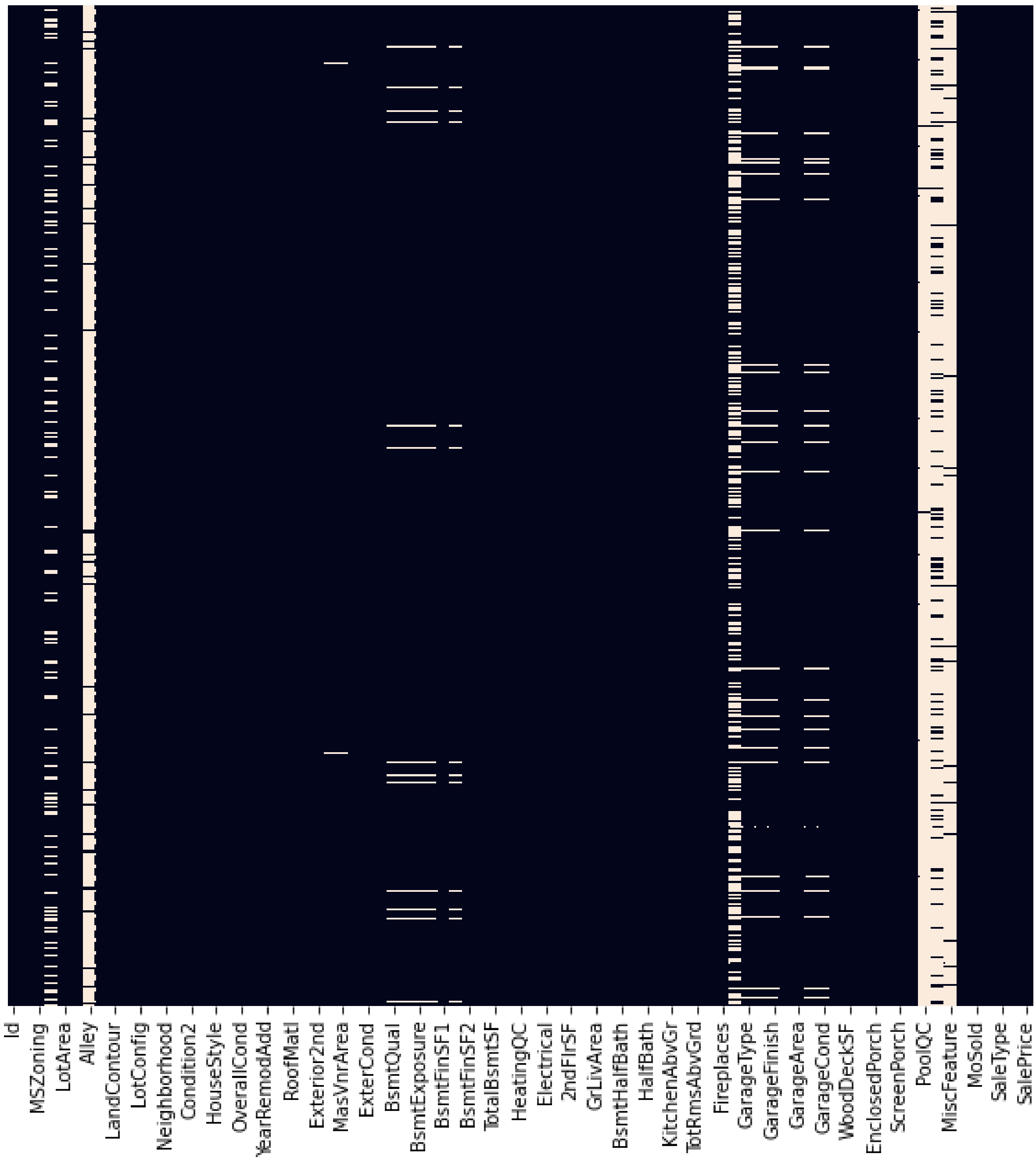
```
In [110]: df_1.describe()
```

Out[110]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2
count	292.000000	292.000000	247.000000	292.000000	292.000000	292.000000	292.000000	292.000000	291.000000	292.000000	292.000000
mean	755.955479	57.414384	66.425101	10645.143836	6.078767	5.493151	1972.616438	1985.294521	109.171821	439.294521	46.157534
std	442.565228	43.780649	21.726343	13330.669795	1.356147	1.063267	30.447016	20.105792	175.030021	429.559675	152.467119
min	6.000000	20.000000	21.000000	1526.000000	3.000000	3.000000	1872.000000	1950.000000	0.000000	0.000000	0.000000
25%	377.750000	20.000000	53.500000	7200.000000	5.000000	5.000000	1954.000000	1968.000000	0.000000	0.000000	0.000000
50%	778.000000	50.000000	65.000000	9200.000000	6.000000	5.000000	1976.000000	1994.000000	0.000000	369.500000	0.000000
75%	1152.250000	70.000000	79.000000	11658.750000	7.000000	6.000000	2001.000000	2003.250000	180.000000	700.500000	0.000000
max	1456.000000	190.000000	150.000000	215245.000000	10.000000	9.000000	2009.000000	2010.000000	1031.000000	1767.000000	1085.000000

Mean is more than median for SalePrice, MoSold, MiscVal, PoolArea, ScreenPorch, 3SsnPorch, EnclosedPorch, OpenPorchSF, WoodDeckSF, BsmtFinSF1, MasVnrArea, YearRemodAdd, OverallCond, OverallQual, LotArea, LotFrontage, MSSubClass and Id Column.

There is large difference between 75% and maximum for Price column.



LotFrontage, Alley, MasVnrType, MasVnrArea, BsmtQual, BsmtCond, BsmtExposure, BsmtFinType1, BsmtFinType2, FireplaceQu, GarageType, GarageYrBlt, GarageFinish, GarageQual, GarageCond, PoolQC, Fence and MiscFeature have null values.

Dataset Description

The Independent Feature columns are:

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

20	1-STORY 1946 & NEWER ALL STYLES
30	1-STORY 1945 & OLDER
40	1-STORY W/FINISHED ATTIC ALL AGES
45	1-1/2 STORY - UNFINISHED ALL AGES
50	1-1/2 STORY FINISHED ALL AGES
60	2-STORY 1946 & NEWER
70	2-STORY 1945 & OLDER
75	2-1/2 STORY ALL AGES
80	SPLIT OR MULTI-LEVEL
85	SPLIT FOYER
90	DUPLEX - ALL STYLES AND AGES
120	1-STORY PUD (Planned Unit Development) - 1946 & NEWER
150	1-1/2 STORY PUD - ALL AGES
160	2-STORY PUD - 1946 & NEWER
180	PUD - MULTILEVEL - INCL SPLIT LEV/FOYER
190	2 FAMILY CONVERSION - ALL STYLES AND AGES

MSZoning: Identifies the general zoning classification of the sale.

A	Agriculture
C	Commercial
FV	Floating Village Residential

I Industrial

RH Residential High Density

RL Residential Low Density

RP Residential Low Density Park

RM Residential Medium Density

LotFrontage: Linear feet of street connected to property

LotArea: Lot size in square feet

Street: Type of road access to property

Grvl Gravel

Pave Paved

Alley: Type of alley access to property

Grvl Gravel

Pave Paved

NA No alley access

LotShape: General shape of property

Reg Regular

IR1 Slightly irregular

IR2 Moderately Irregular

IR3 Irregular

LandContour: Flatness of the property

Lvl Near Flat/Level

Bnk Banked - Quick and significant rise from street grade to building

HLS Hillside - Significant slope from side to side

Low Depression

Utilities: Type of utilities available

AllPub All public Utilities (E,G,W,& S)

NoSewr Electricity, Gas, and Water (Septic Tank)

NoSeWa Electricity and Gas Only

ELO Electricity only

LotConfig: Lot configuration

Inside Inside lot

Corner Corner lot

CulDSac Cul-de-sac

FR2 Frontage on 2 sides of property

FR3 Frontage on 3 sides of property

LandSlope: Slope of property

Gtl Gentle slope

Mod Moderate Slope

Sev Severe Slope

Neighborhood: Physical locations within Ames city limits

Blmngtn Bloomington Heights

Blueste Bluestem

BrDale	**Briardale**
BrkSide	**Brookside**
ClearCr	**Clear Creek**
CollgCr	**College Creek**
Crawfor	**Crawford**
Edwards	**Edwards**
Gilbert	**Gilbert**
IDOTRR	**Iowa DOT and Rail Road**
MeadowV	**Meadow Village**
Mitchel	**Mitchell**
Names	**North Ames**
NoRidge	**Northridge**
NPkVill	**Northpark Villa**
NridgHt	**Northridge Heights**
NWAmes	**Northwest Ames**
OldTown	**Old Town**
SWISU	**South & West of Iowa State University**
Sawyer	**Sawyer**
SawyerW	**Sawyer West**
Somerst	**Somerset**
StoneBr	**Stone Brook**
Timber	**Timberland**
Veenker	**Veenker**

Condition1: Proximity to various conditions

Artery	**Adjacent to arterial street**
Feedr	**Adjacent to feeder street**
Norm	**Normal**
RRNn	**Within 200' of North-South Railroad**

RRAn Adjacent to North-South Railroad

PosN Near positive off-site feature--park, greenbelt, etc.

PosA Adjacent to postive off-site feature

RRNe Within 200' of East-West Railroad

RRAe Adjacent to East-West Railroad

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

Artery Adjacent to arterial street

Feedr Adjacent to feeder street

Norm Normal

RRNn Within 200' of North-South Railroad

RRAn Adjacent to North-South Railroad

PosN Near positive off-site feature--park, greenbelt, etc.

PosA Adjacent to postive off-site feature

RRNe Within 200' of East-West Railroad

RRAe Adjacent to East-West Railroad

BldgType: Type of dwelling

1Fam Single-family Detached

2FmCon Two-family Conversion; originally built as one-family dwelling

Duplx Duplex

TwnhsE Townhouse End Unit

TwnhsI Townhouse Inside Unit

HouseStyle: Style of dwelling

1Story One story

1.5Fin One and one-half story: 2nd level finished

1.5Unf One and one-half story: 2nd level unfinished

2Story Two story

2.5Fin Two and one-half story: 2nd level finished

2.5Unf Two and one-half story: 2nd level unfinished

SFoyer Split Foyer

SLvl Split Level

OverallQual: Rates the overall material and finish of the house

10 Very Excellent

9 Excellent

8 Very Good

7 Good

6 Above Average

5 Average

4 Below Average

3 Fair

2 Poor

1 Very Poor

OverallCond: Rates the overall condition of the house

10 Very Excellent

9 Excellent

8 Very Good

7 Good

6 Above Average

5 Average

4 Below Average

3 Fair

2 Poor

1 Very Poor

YearBuilt: Original construction date

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

RoofStyle: Type of roof

Flat Flat

Gable Gable

Gambrel Gabrel (Barn)

Hip Hip

Mansard Mansard

Shed Shed

RoofMatl: Roof material

ClyTile Clay or Tile

CompShgStandard (Composite) Shingle

Membran Membrane

Metal Metal

Roll Roll

Tar&Grv Gravel & Tar

WdShakeWood Shakes

WdShngl Wood Shingles

Exterior1st: Exterior covering on house

AsbShng Asbestos Shingles

AsphShn Asphalt Shingles

BrkComm Brick Common

BrkFace Brick Face

CBlock Cinder Block

CemntBd Cement Board

HdBoard Hard Board

ImStucc Imitation Stucco

MetalSd Metal Siding

Other Other

Plywood Plywood

PreCast PreCast

Stone Stone

Stucco Stucco

VinylSd Vinyl Siding

Wd Sdng Wood Siding

WdShing Wood Shingles

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

AsbShng Asbestos Shingles

AsphShn Asphalt Shingles

BrkComm Brick Common

BrkFace Brick Face

CBlock Cinder Block

CemntBd Cement Board

HdBoard Hard Board

ImStucc Imitation Stucco

MetalSd Metal Siding

Other Other

Plywood Plywood

PreCast PreCast

Stone Stone

Stucco Stucco

VinylSd Vinyl Siding

Wd Sdng Wood Siding

WdShing Wood Shingles

MasVnrType: Masonry veneer type

BrkCmn Brick Common

BrkFace Brick Face

CBlock Cinder Block

None None

Stone Stone

MasVnrArea: Masonry veneer area in square feet

ExterQual: Evaluates the quality of the material on the exterior

Ex Excellent

Gd Good

TA Average/Typical

Fa Fair

Po Poor

ExterCond: Evaluates the present condition of the material on the exterior

Ex Excellent

Gd Good

**TA		Average/Typical**

**Fa	Fair**

**Po	Poor**

Foundation: Type of foundation

**BrkTil	Brick & Tile**

**CBlock	Cinder Block**

**PConc	Poured Contrete**

**Slab	Slab**

**Stone	Stone**

**Wood	Wood**

BsmtQual: Evaluates the height of the basement

**Ex	Excellent (100+ inches)**

**Gd	Good (90-99 inches)**

**TA	Typical (80-89 inches)**

**Fa	Fair (70-79 inches)**

**Po	Poor (<70 inches**

**NA	No Basement**

BsmtCond: Evaluates the general condition of the basement

**Ex	Excellent**

**Gd	Good**

**TA	Typical - slight dampness allowed**

**Fa	Fair - dampness or some cracking or settling**

**Po	Poor - Severe cracking, settling, or wetness**

**NA	No Basement**

BsmtExposure: Refers to walkout or garden level walls

Gd Good Exposure

Av Average Exposure (split levels or foyers typically score average or above)

Mn Mimimum Exposure

No No Exposure

NA No Basement

BsmtFinType1: Rating of basement finished area

GLQ Good Living Quarters

ALQ Average Living Quarters

BLQ Below Average Living Quarters

Rec Average Rec Room

LwQ Low Quality

Unf Unfinshed

NA No Basement

BsmtFinSF1: Type 1 finished square feet

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

GLQ Good Living Quarters

ALQ Average Living Quarters

BLQ Below Average Living Quarters

Rec Average Rec Room

LwQ Low Quality

Unf Unfinshed

NA No Basement

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of basement area

TotalBsmtSF: Total square feet of basement area

Heating: Type of heating

Floor Floor Furnace

GasA Gas forced warm air furnace

GasW Gas hot water or steam heat

Grav Gravity furnace

OthW Hot water or steam heat other than gas

Wall Wall furnace

HeatingQC: Heating quality and condition

Ex Excellent

Gd Good

TA Average/Typical

Fa Fair

Po Poor

CentralAir: Central air conditioning

N No

Y Yes

Electrical: Electrical system

SBrkr	**Standard Circuit Breakers & Romex**
FuseA	**Fuse Box over 60 AMP and all Romex wiring (Average)**
FuseF	**60 AMP Fuse Box and mostly Romex wiring (Fair)**
FuseP	**60 AMP Fuse Box and mostly knob & tube wiring (poor)**
Mix	**Mixed**

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

LowQualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade

HalfBath: Half baths above grade

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

Kitchen: Kitchens above grade

KitchenQual: Kitchen quality

Ex Excellent

Gd Good

TA Typical/Average

Fa Fair

Po Poor

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

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

Typ Typical Functionality

Min1 Minor Deductions 1

Min2 Minor Deductions 2

Mod Moderate Deductions

Maj1 Major Deductions 1

Maj2 Major Deductions 2

Sev Severely Damaged

Sal Salvage only

Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

Ex Excellent - Exceptional Masonry Fireplace

Gd Good - Masonry Fireplace in main level

TA Average - Prefabricated Fireplace in main living area or Masonry Fireplace in basement

Fa Fair - Prefabricated Fireplace in basement

Po Poor - Ben Franklin Stove

NA No Fireplace

GarageType: Garage location

2Types More than one type of garage

Attchd Attached to home

Basment Basement Garage

BuiltIn Built-In (Garage part of house - typically has room above garage)

CarPort Car Port

Detchd Detached from home

NA No Garage

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

Fin Finished

RFn Rough Finished

Unf Unfinished

NA No Garage

GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet

GarageQual: Garage quality

Ex Excellent

Gd Good

TA Typical/Average

Fa Fair

Po Poor

NA No Garage

GarageCond: Garage condition

Ex Excellent

Gd Good

TA Typical/Average

Fa Fair

Po Poor

NA No Garage

PavedDrive: Paved driveway

Y Paved

P Partial Pavement

N Dirt/Gravel

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality

Ex Excellent

Gd Good

TA Average/Typical

Fa Fair

NA No Pool

Fence: Fence quality

GdPrv Good Privacy

MnPrv Minimum Privacy

GdWo Good Wood

MnWw Minimum Wood/Wire

NA No Fence

MiscFeature: Miscellaneous feature not covered in other categories

Elev Elevator

Gar2 2nd Garage (if not described in garage section)

Othr Other

Shed Shed (over 100 SF)

TenC Tennis Court

NA None

MiscVal: $Value of miscellaneous feature

MoSold: Month Sold (MM)

YrSold: Year Sold (YYYY)

SaleType: Type of sale

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

SaleCondition: Condition of sale

Normal **Normal Sale**

Abnorml **Abnormal Sale - trade, foreclosure, short sale**

AdjLand **Adjoining Land Purchase**

Alloca **Allocation - two linked properties with separate deeds, typically condo with a garage unit**

Family **Sale between family members**

Partial **Home was not completed when last assessed (associated with New Homes)**

Removing the Outliers using Z-score

```
In [44]: from scipy.stats import zscore
         z=np.abs(zscore(df))

In [45]: z

Out[45]: array([[1.50830058, 0.02164599, 0.        , ..., 0.33003329, 0.20793187,
                 0.67631017],
                [0.87704243, 0.02164599, 1.07063136, ..., 0.33003329, 0.20793187,
                 1.09423443],
                [0.07709478, 0.02164599, 0.93686671, ..., 0.33003329, 0.20793187,
                 1.11687211],
                ...,
                [2.46243779, 0.02164599, 2.09513215, ..., 0.33003329, 0.20793187,
                 0.41705186],
                [0.31562908, 4.76211672, 0.93583847, ..., 0.33003329, 0.20793187,
                 1.78922393],
                [0.07709478, 0.02164599, 0.        , ..., 0.33003329, 0.20793187,
                 0.02179027]])

In [46]: threshold=3
         print(np.where(z>3))

         (array([   1,    1,    1, ..., 1166, 1166, 1166], dtype=int64), array([ 8, 19, 33, ..., 38, 60, 61], dtype=int64))

In [47]: df_new=df[(z<3).all(axis=1)]

In [48]: df_new.shape

Out[48]: (482, 74)

In [49]: df.shape

Out[49]: (1168, 74)

In [50]: ((1168-468)/1168)*100

Out[50]: 59.93150684931506

In [51]: Q1=df.quantile(0.25)
         Q3=df.quantile(0.75)
         IQR=Q3-Q1
         df_new1=df[~((df<(Q1-1.5*IQR))|(df<(Q3+1.5*IQR))).any(axis=1)]

In [52]: print("shape before and after")
         print("shape before".ljust(20),":",df.shape)
         print("shape after".ljust(20),":",df_new1.shape)

         shape before and after
         shape before         : (1168, 74)
         shape after          : (0, 74)

In [53]: print("Percentage Loss".ljust(20),":",(df.shape[0]-df_new1.shape[0])/df.shape[0])

         Percentage Loss      : 1.0

In [54]: df=df_new

In [55]: df.shape

Out[55]: (482, 74)
```

JSING PRICE PREDICTION - FLIP ROBO .ipynb#

Data Pre-processing Done

First we will determine whether there are any null values and since there were null values as well as NaN vales present in the dataset we proceeded further by imputing them using Simple Imputer with mean and most frequent as strategies respectively. Next we did Label encoding using label encoder. Then we performed some data visualization in which we observed certain attributes were having skewness and outliers that were plotted using distplot and boxplot. Outliers were removed with the help of Zscore in which 685 rows were removed.

Data Inputs- Logic- Output Relationships

The data consists of 80 inputs and one output-“SalePrice”. MSSubClass,OverallCond,KitchenAbvGr,EnclosedPorch and Yr Sold are the least/negatively correlated column with target('SalePrice') variable. OverallQual is highly correlated column with target variable followed by GrLivArea and other attributes.

Hardware and Software Requirements and Tools Used

In this project we have used HP Pavilion PC with 64-bit operating system and have Windows 10 pro. We have used python to develop this project in which we have used various libraries such as numpy, pandas, matplotlib, seaborn for handling data or arrays and their visualization. For statistical purpose we have used zscore from scipy.stats to remove outliers. Lastly, to develop the model we have used various libraries and metrics from sklearn such as train_test_split, Linear Regression, Lasso, Ridge, Elastic Net, SVR, Decision Tree Regressor, KNeighbors Regressor, Random Forest Regressor, AdaBoost Regressor, Gradient Boosting Regressor, mean_squared_error, mean_absolute_error and r2_score.

Model/s Development and Evaluation

Identification of possible problem-solving approaches (methods)

We have performed various mathematical and statistical analysis such as we checked description or statistical summary of the data using describe, checked correlation using corr and also visualized it using heatmap. Then we have used zscore to plot outliers and remove them. We have used distplot to find the distribution of all attributes.

Testing of Identified Approaches (Algorithms)

We have used following algorithms such as: LinearRegression, Lasso, Ridge, ElasticNet, SVR, DecisionTreeRegressor, KNeighborsRegressor, RandomForestRegressor, AdaBoostRegressor and GradientBoostingRegressor.

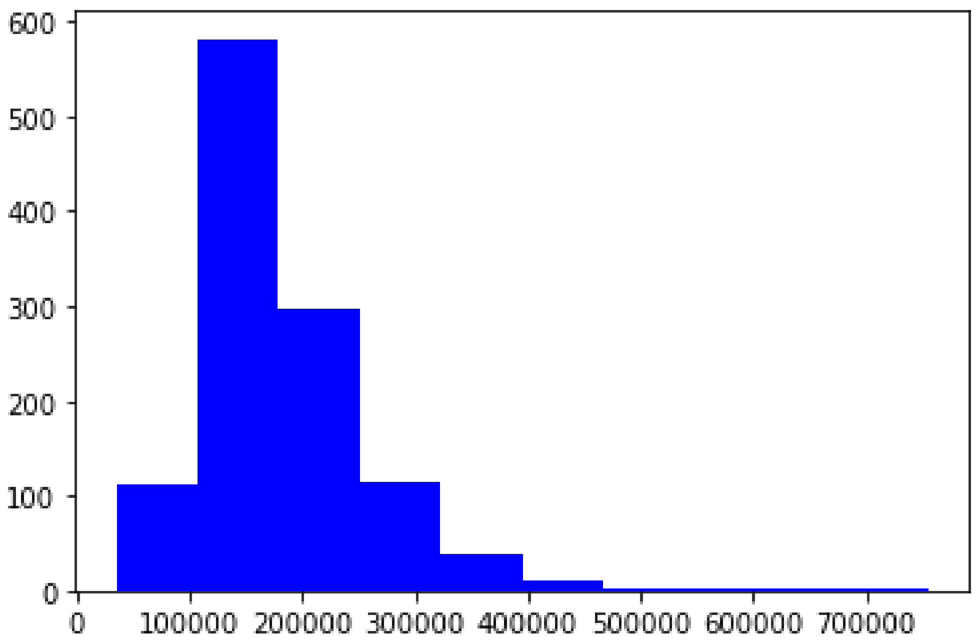
Run and Evaluate selected models

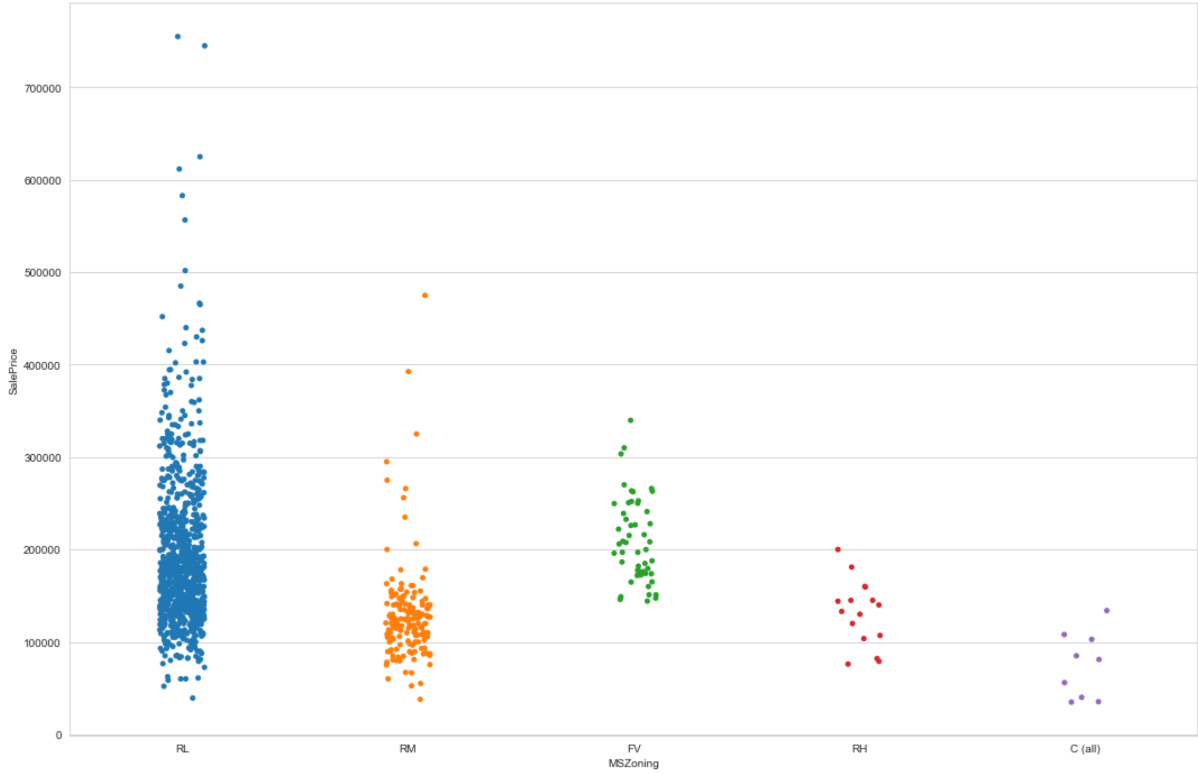
We have formed a loop where all the algorithms will be used one by one and their corresponding Score, Mean Absolute Error, Mean Squared Error, RMSE and r2_score will be evaluated. • I chose GradientBoostingRegressor as our best model since it's giving us best score and it's performing well. It's r2_score is also satisfactory and it shows that our model is neither underfitting/overfitting. Then we performed hyperparamter tuning using GridSearchCV on GradientBoostingRegressor from which got 'learning_rate': 0.1, 'n_estimators': 500 as best parameters. We got score : 0.999517991577412 after performing hyperparameter tuning and earlier it was 0.9846658425719441. Its r2_score is also satisfactory.

Hence we saved GradientBoostingRegressor as our final model using joblib.

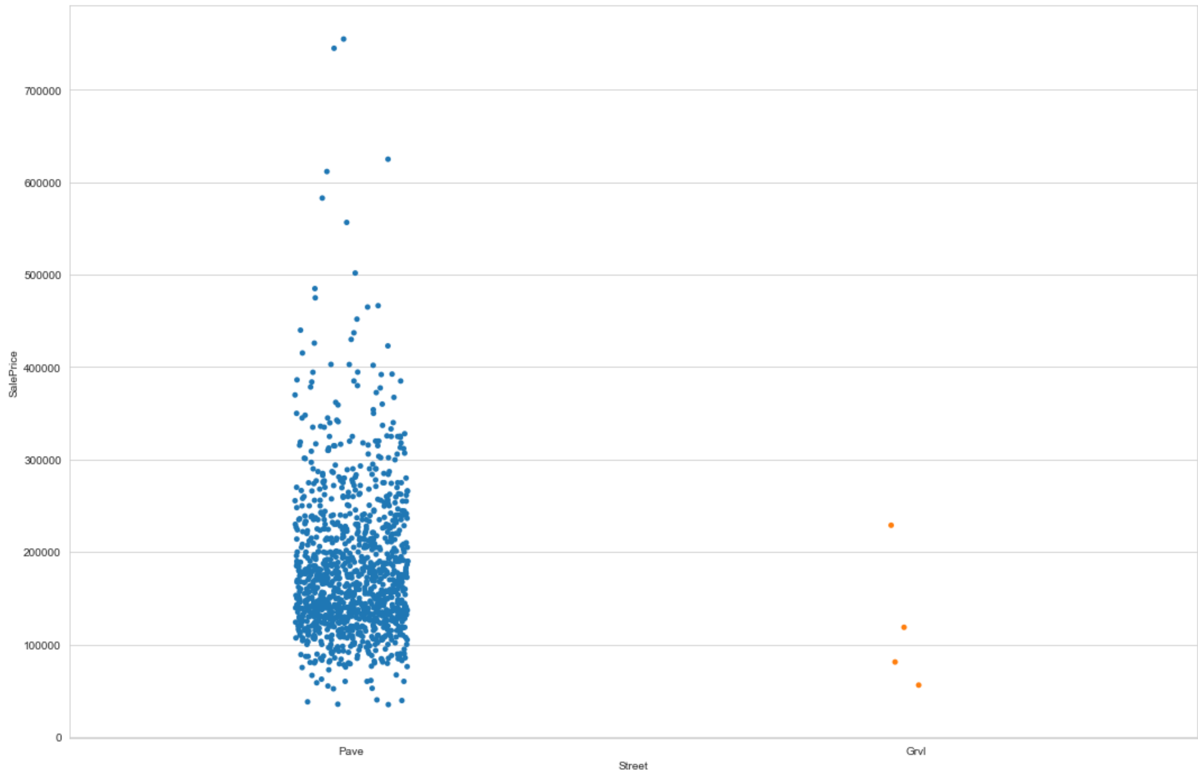
Key Metrics for success in solving problem under consideration

Key metrics used for finalising the model was Score and r2_score. Since in case of GradientBoostingRegressor it's giving us good score among all other models and it's performing well. It's r2_score is also satisfactory and it shows that our model is neither underfitting/overfitting .

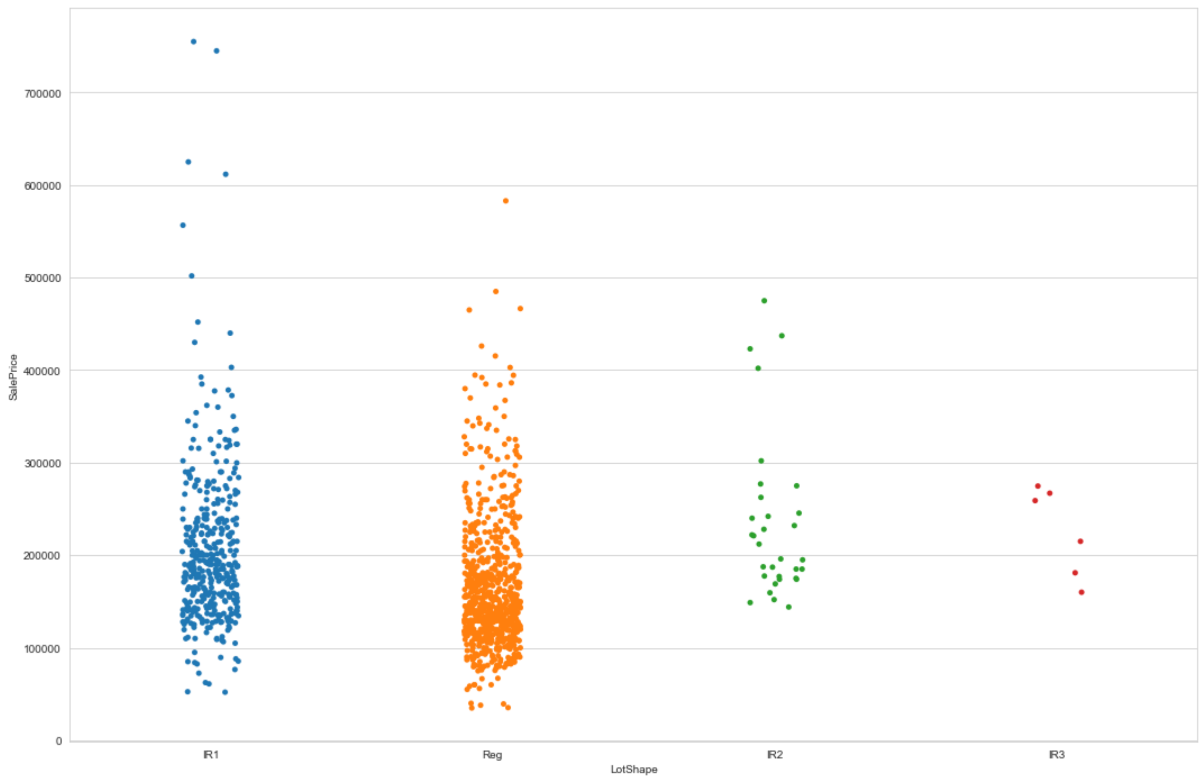




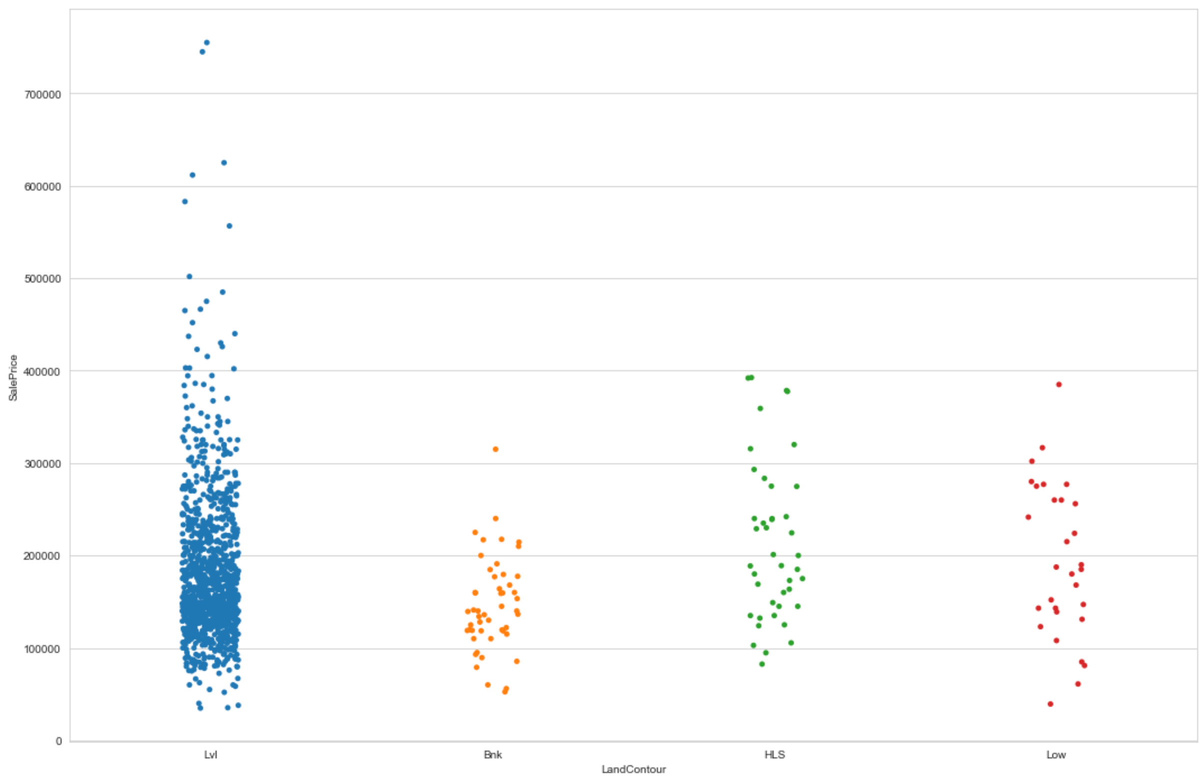
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
RL
RM
FV
RH
C (all)
MSZoning



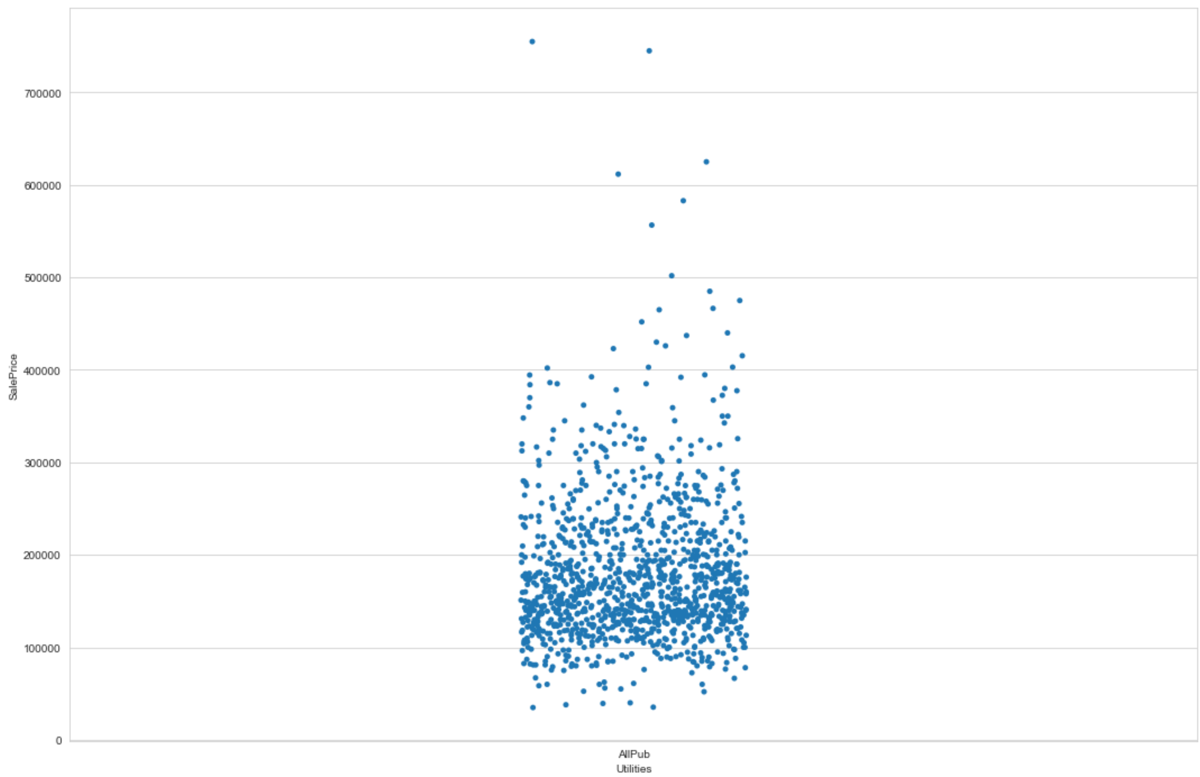
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Pave
Grvl
Street



SalePrice
700000
600000
500000
400000
300000
200000
100000
0
IR1
Reg
IR2
IR3
LotShape

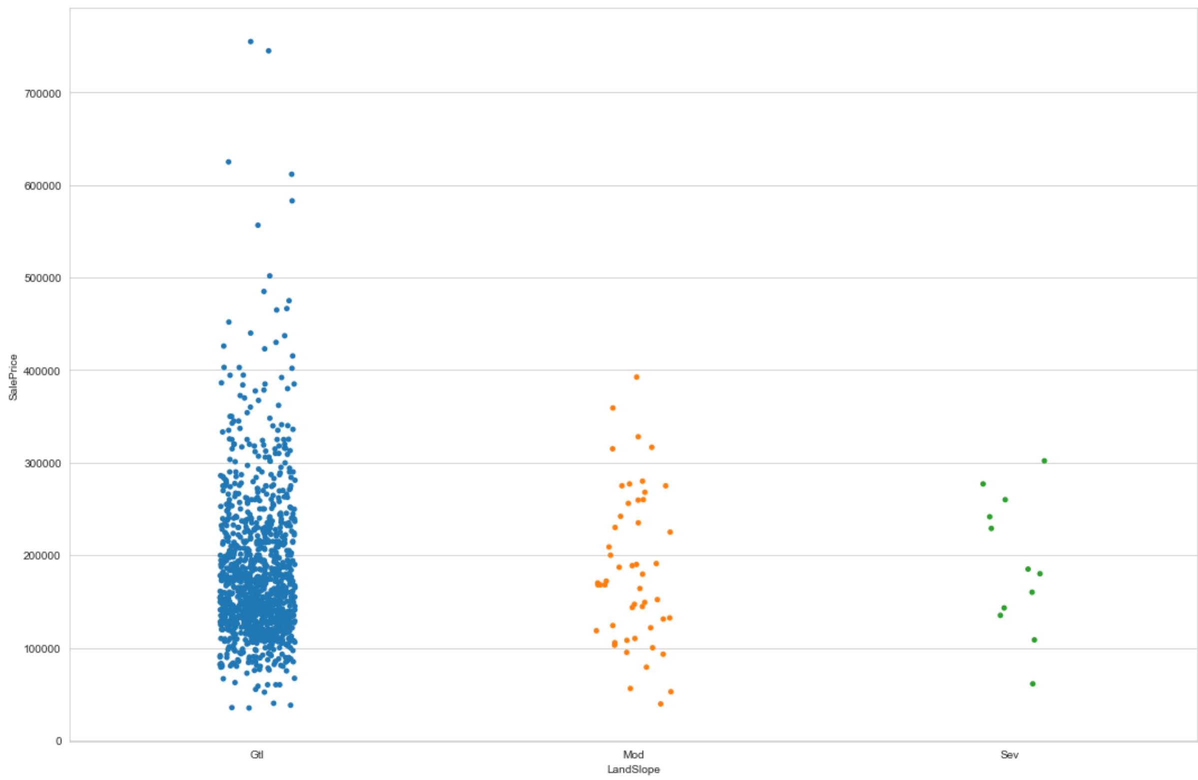


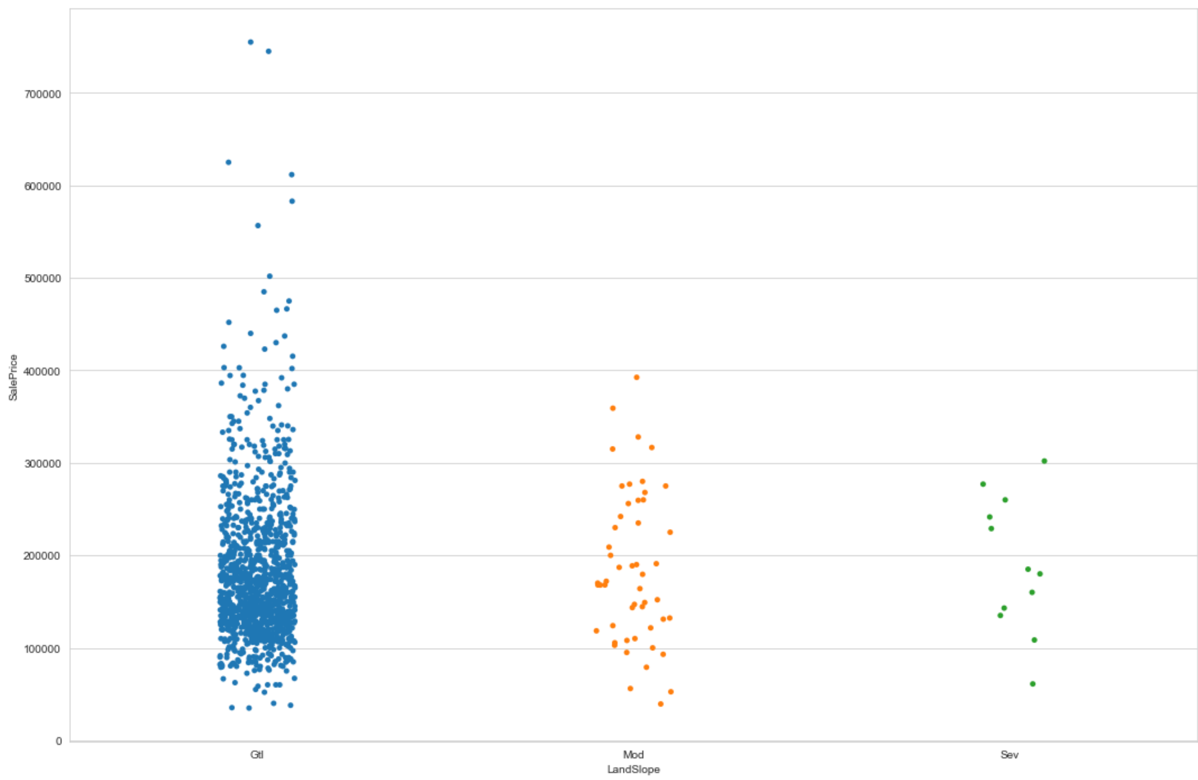
SalePrice
700000
600000
500000
400000
300000
200000
100000
0
Lvl
Bnk
HLS
Low
LandContour

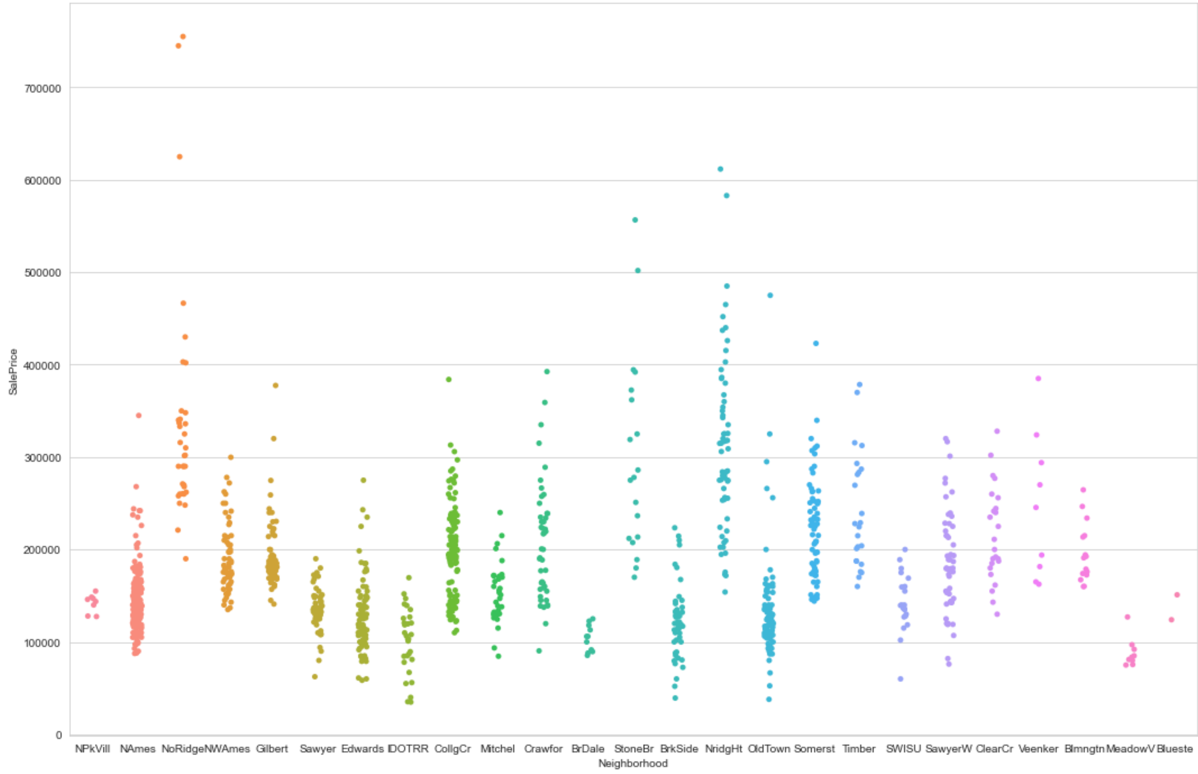


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
AllPub
Utilities

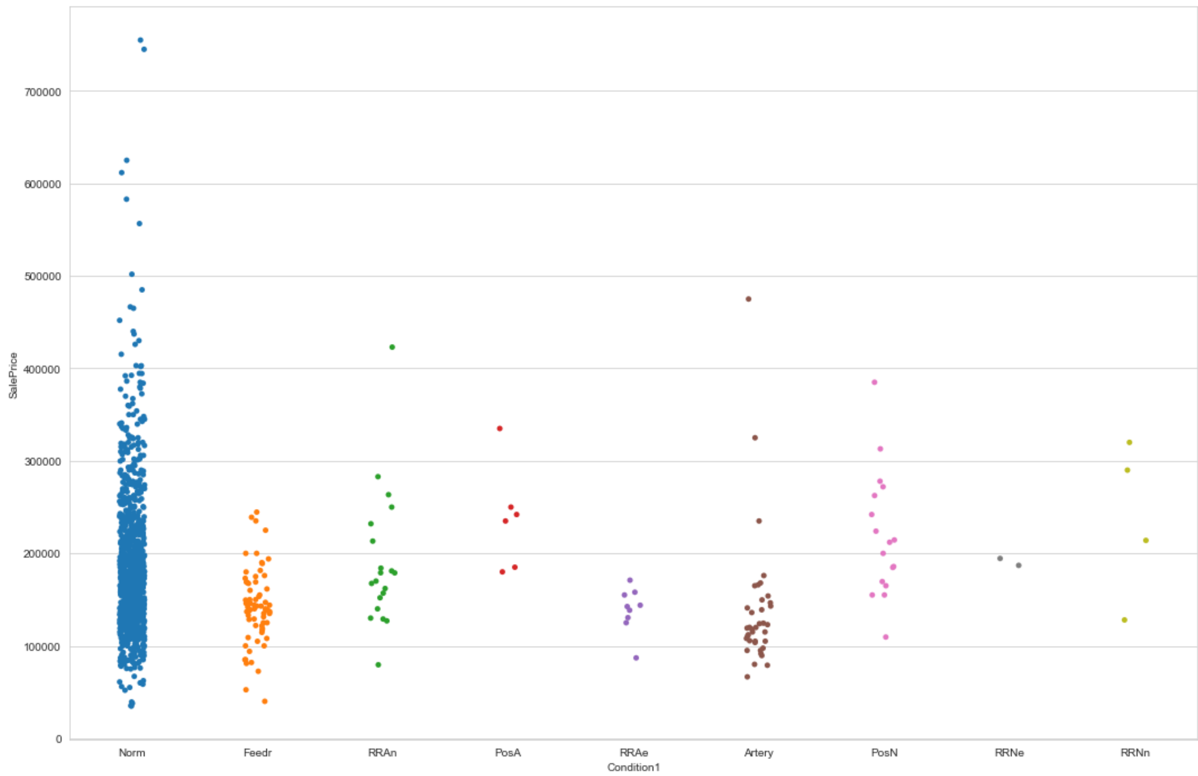
SalePrice
700000
600000
500000
400000
300000
200000
100000
0
Inside
CulDSac
FR2
Corner
FR3
LotConfig


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

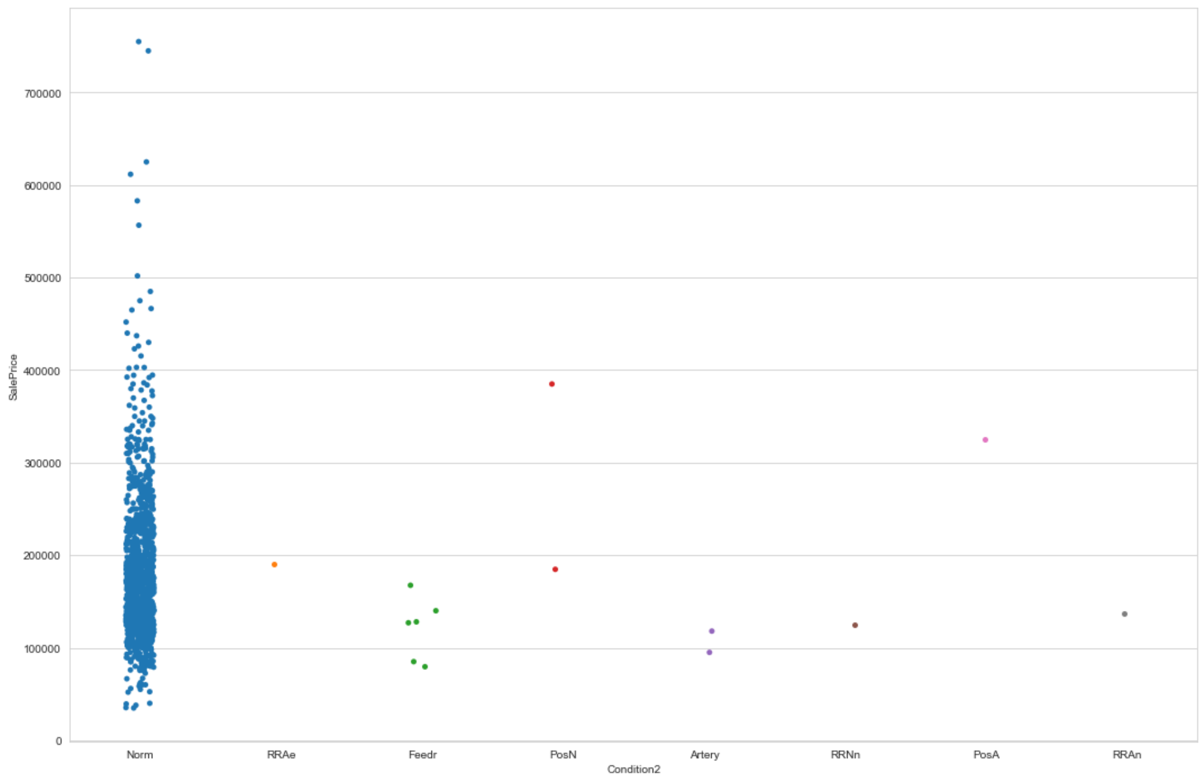

700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Gtl
Mod
Sev
LandSlope



SalePrice
700000
600000
500000
400000
300000
200000
100000
0
NPkVill NAmes NoRidge NWAmes Gilbert Sawyer Edwards IDOTRR CollgCr Mitchel Crawfor BrDale StoneBr BrkSide NridgHt OldTown Somerst Timber SWISU SawyerW ClearCr Veenker Blmngtn MeadowV Blueste
Neighborhood

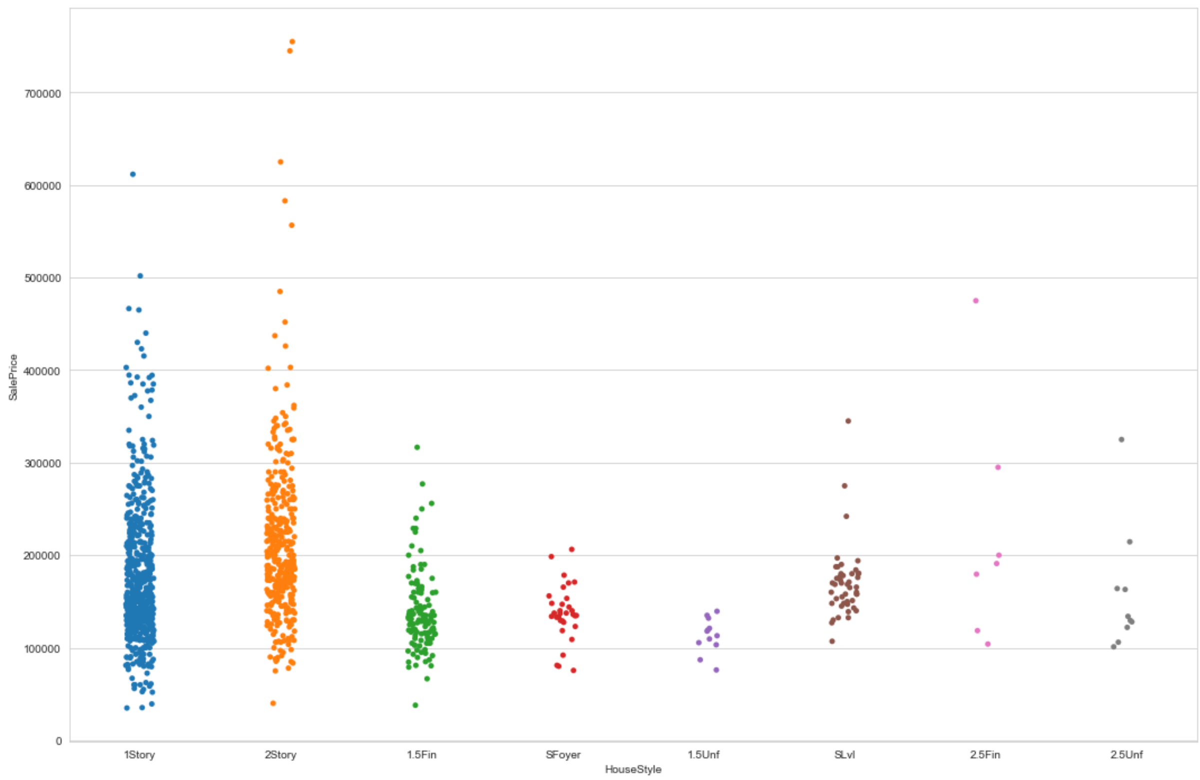


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
Norm Feedr RRAn PosA RRAe Artery PosN RRNe RRNn
Condition1

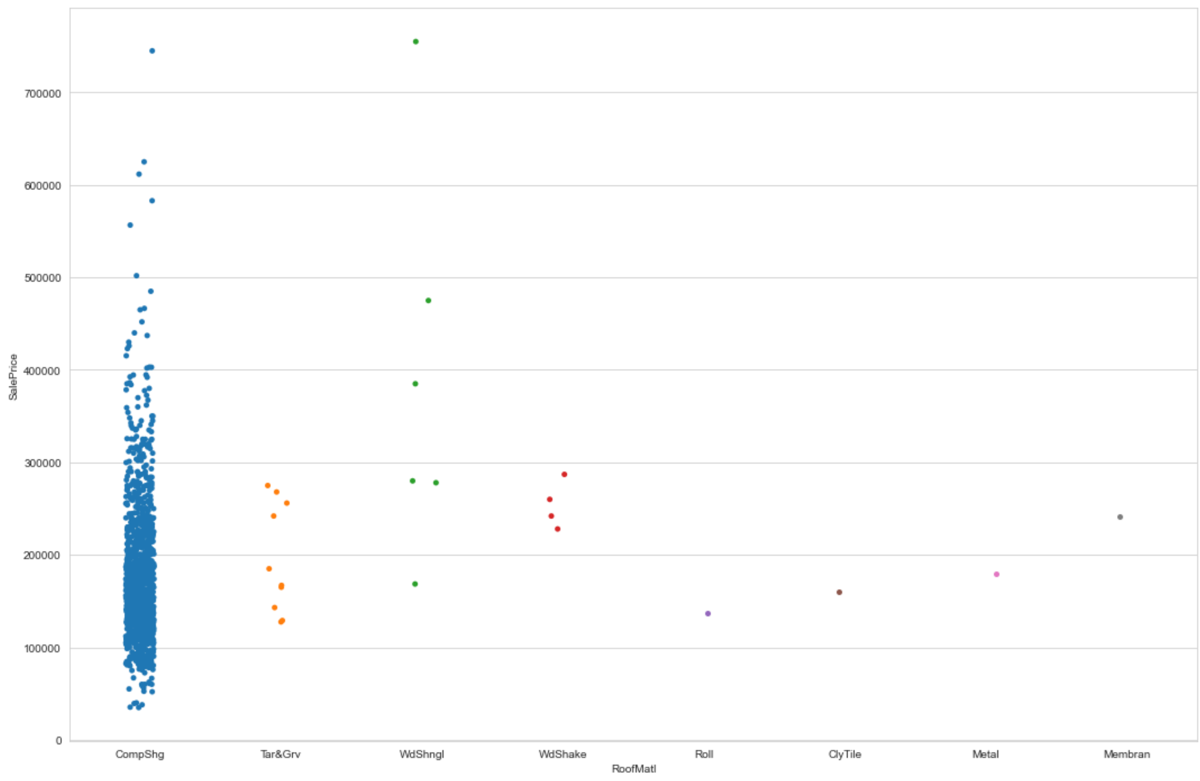


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
Norm
RRAe
Feedr
PosN
Artery
RRNn
PosA
RRAn
Condition2

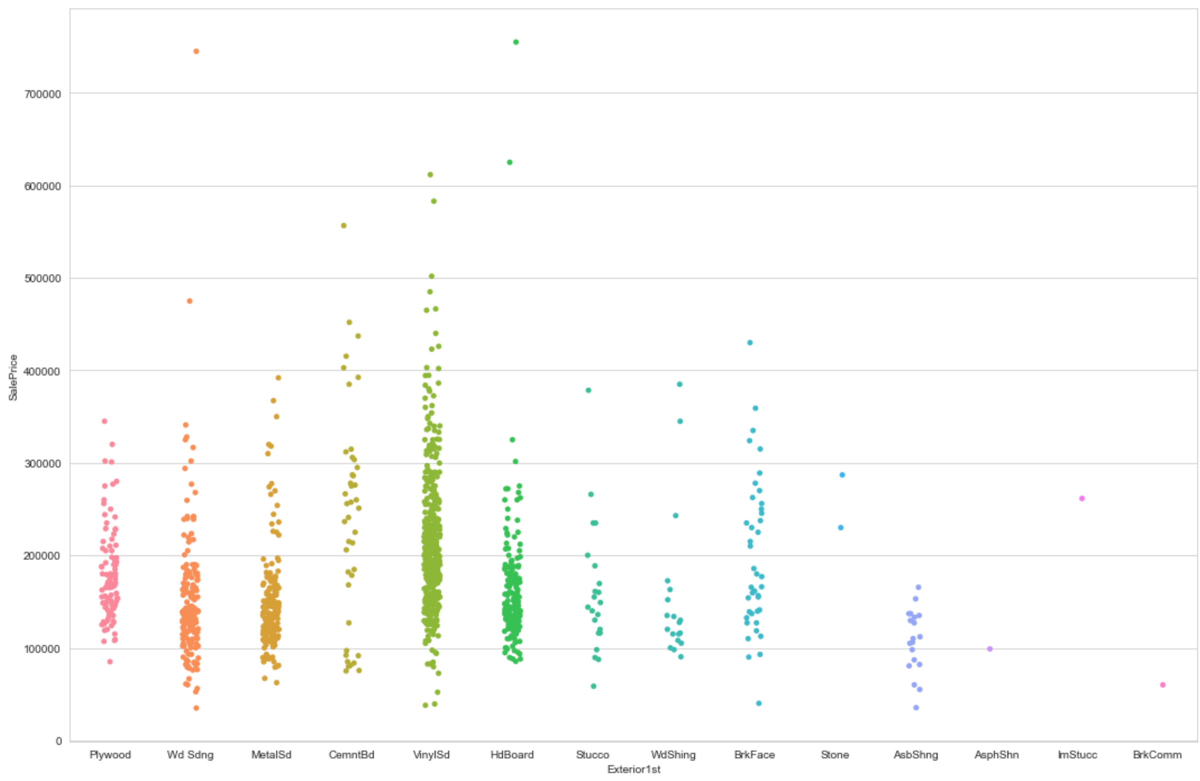
SalePrice
700000
600000
500000
400000
300000
200000
100000
0
TwnhsE
1Fam
Duplex
Twnhs
2fmCon
BldgType


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
1Story
2Story
1.5Fin
SFoyer
1.5Unf
SLvl
2.5Fin
2.5Unf
HouseStyle

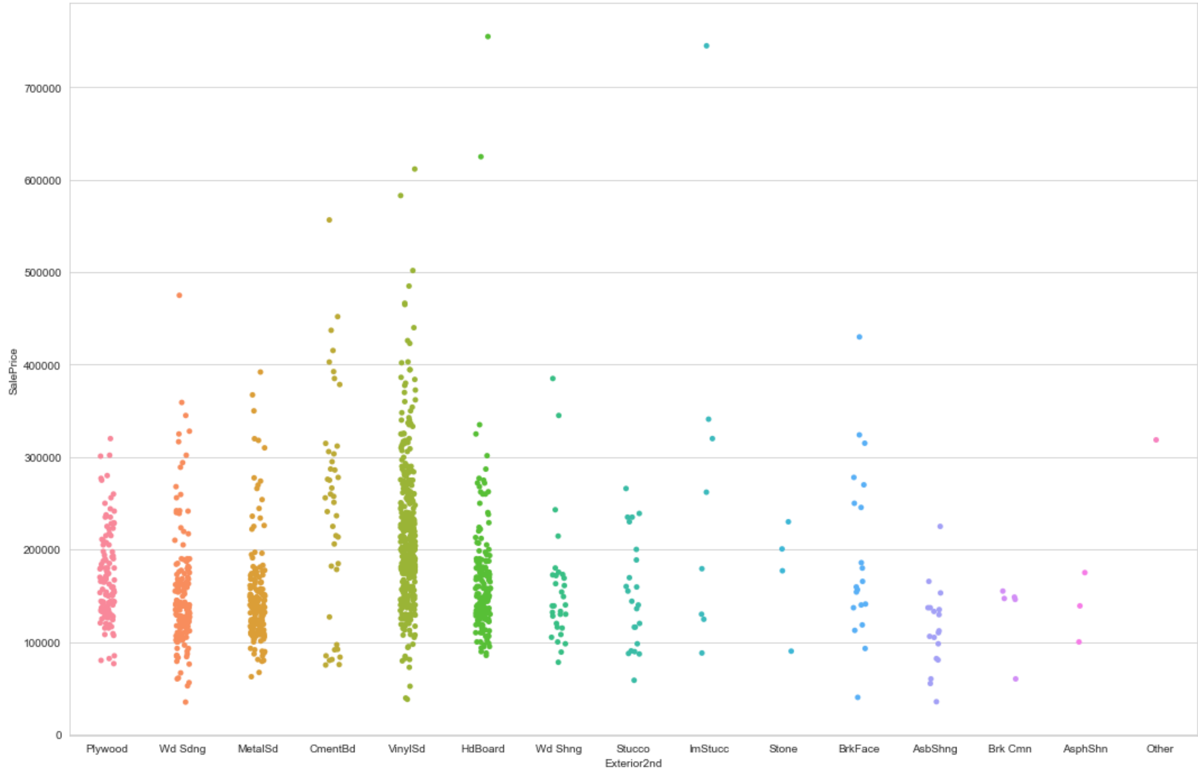

SalePrice
700000
600000
500000
400000
300000
200000
100000
0
Gable
Flat
Hip
Shed
Gambrel
Mansard
RoofStyle

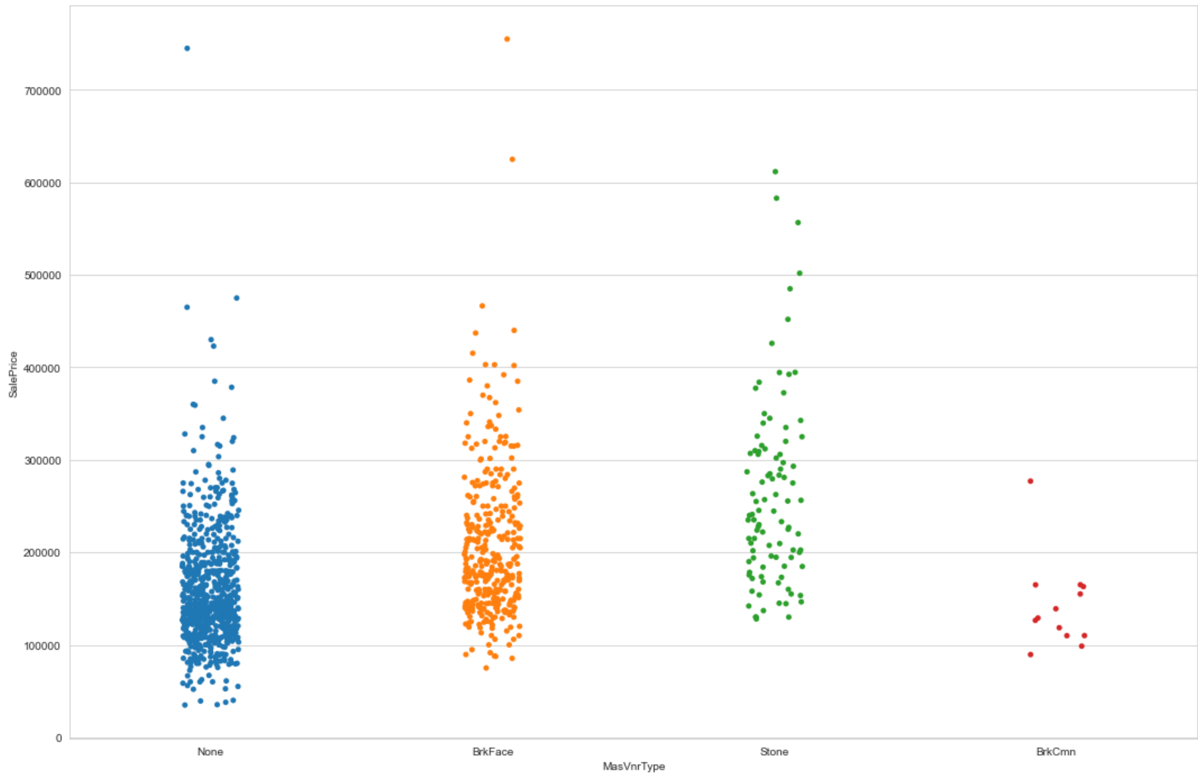


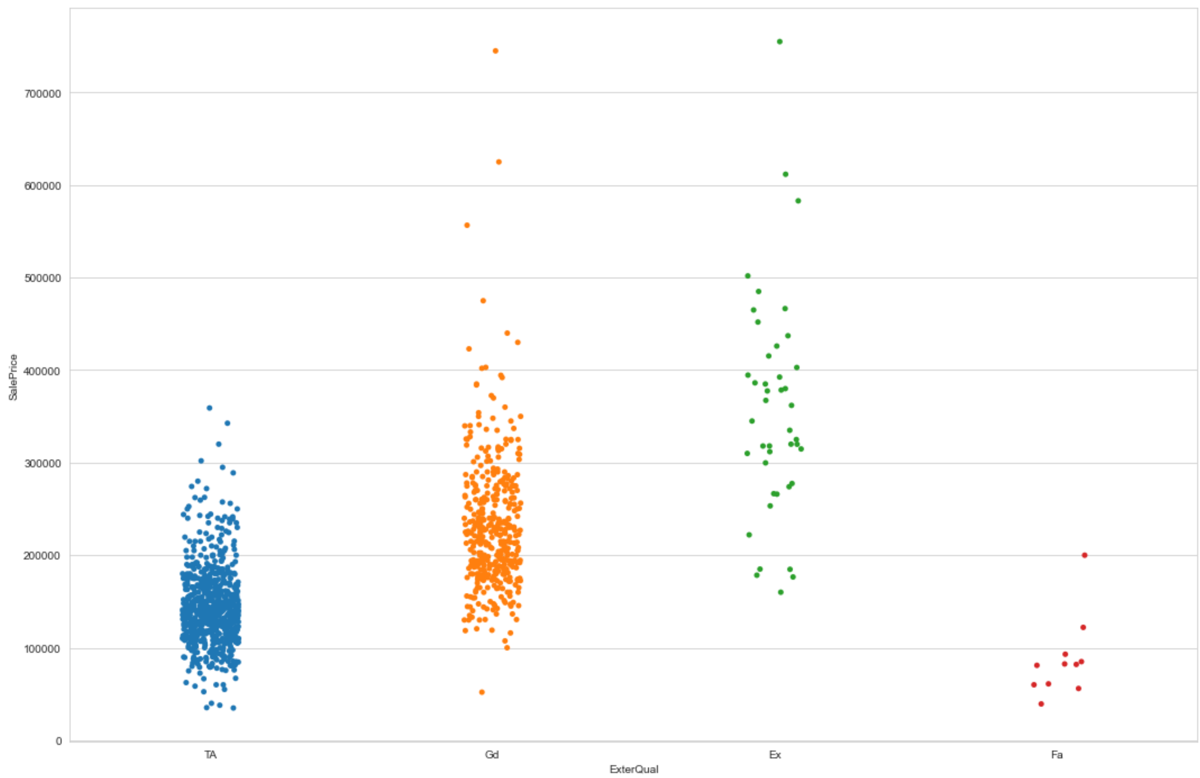
SalePrice
RoofMatl
0
100000
200000
300000
400000
500000
600000
700000
CompShg
Tar&Grv
WdShngl
WdShake
Roll
ClyTile
Metal
Membran



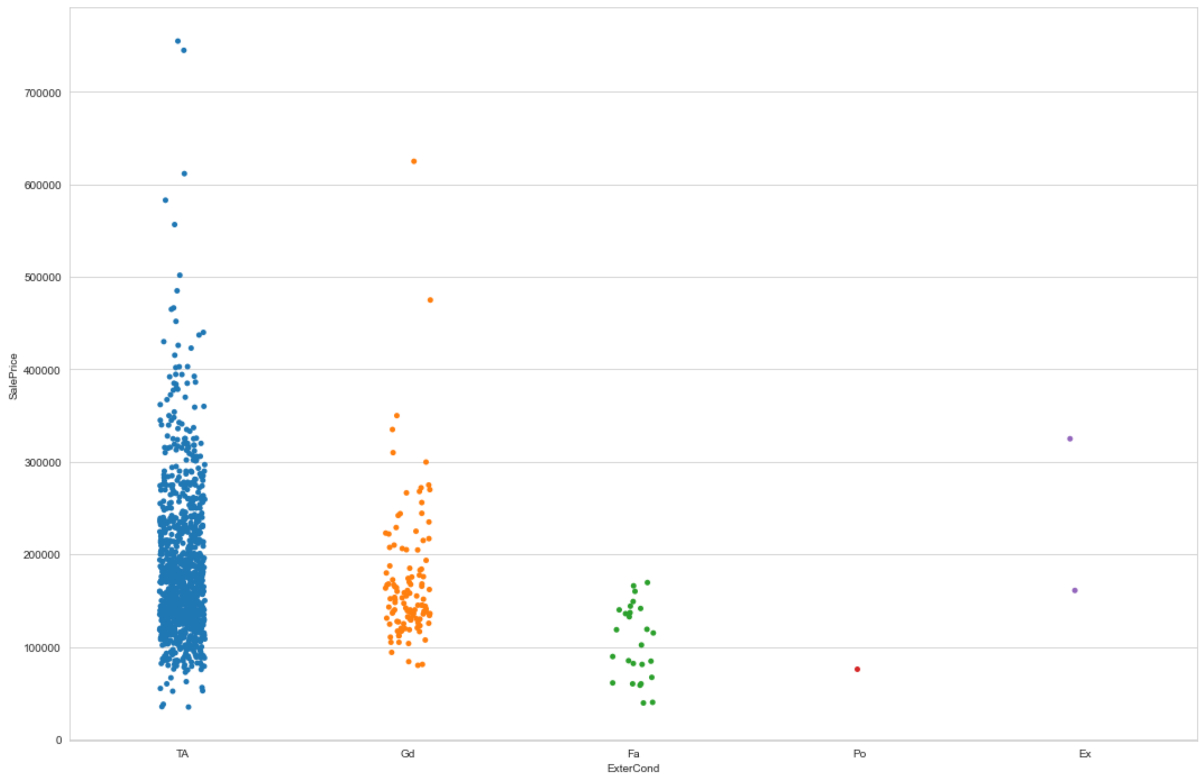
SalePrice
Exterior1st
0
100000
200000
300000
400000
500000
600000
700000
Plywood
Wd Sdng
MetalSd
CemntBd
VinylSd
HdBoard
Stucco
WdShing
BrkFace
Stone
AsbShng
AsphShn
ImStucc
BrkComm


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
Plywood
Wd Sdng
MetalSd
CmentBd
VinylSd
HdBoard
Wd Shng
Stucco
ImStucc
Stone
BrkFace
AsbShng
Brk Cmn
AsphShn
Other
Exterior2nd

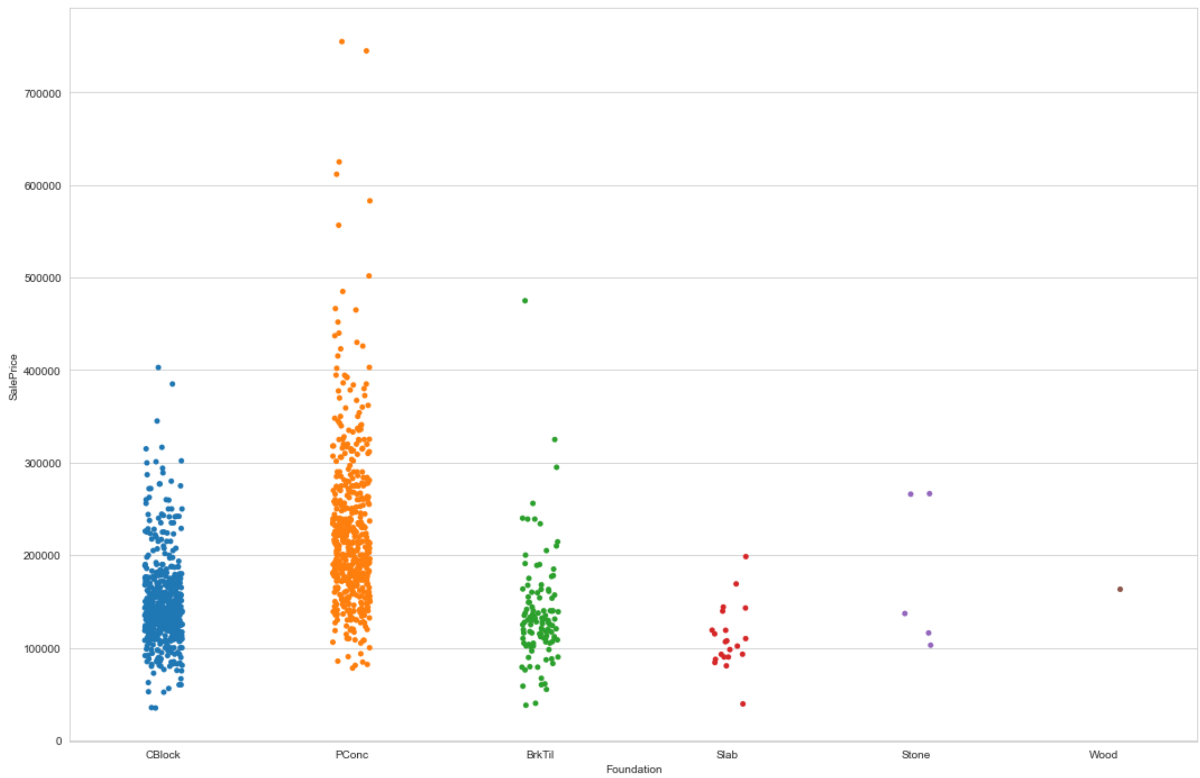

SalePrice
700000
600000
500000
400000
300000
200000
100000
0
None
BrkFace
Stone
BrkCmn
MasVnrType



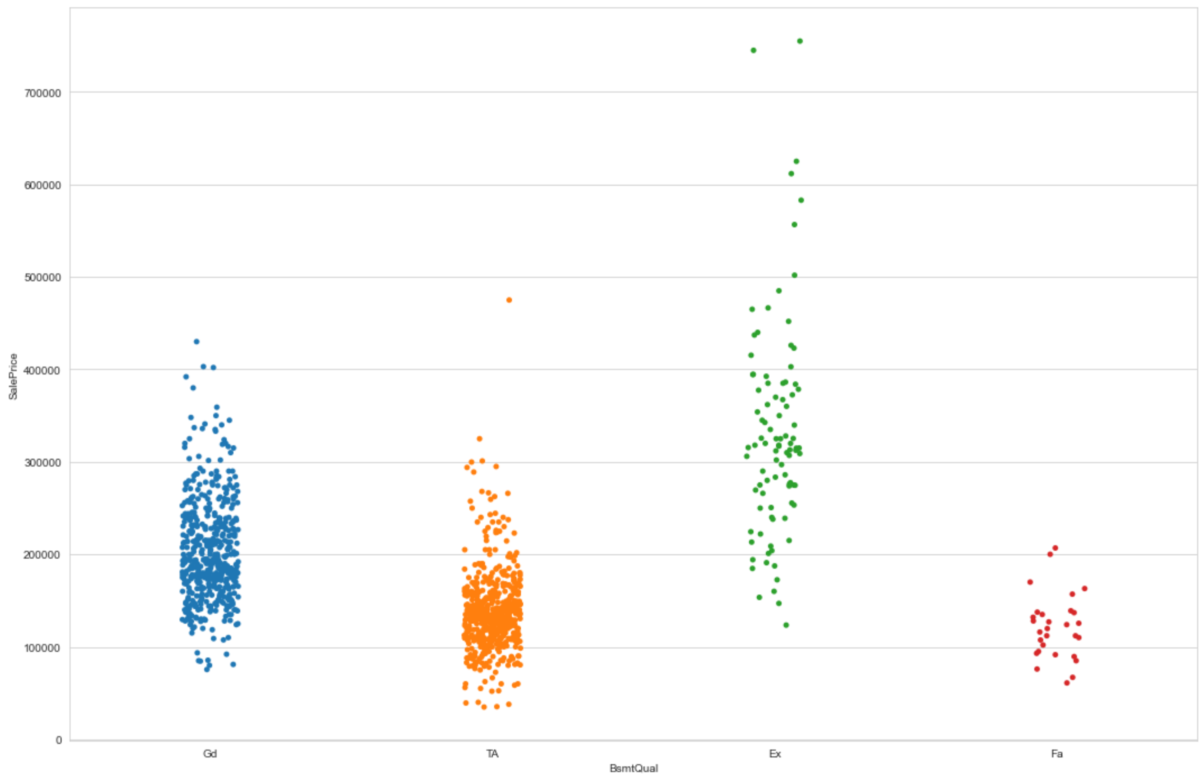
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
TA
Gd
Ex
Fa
ExterQual



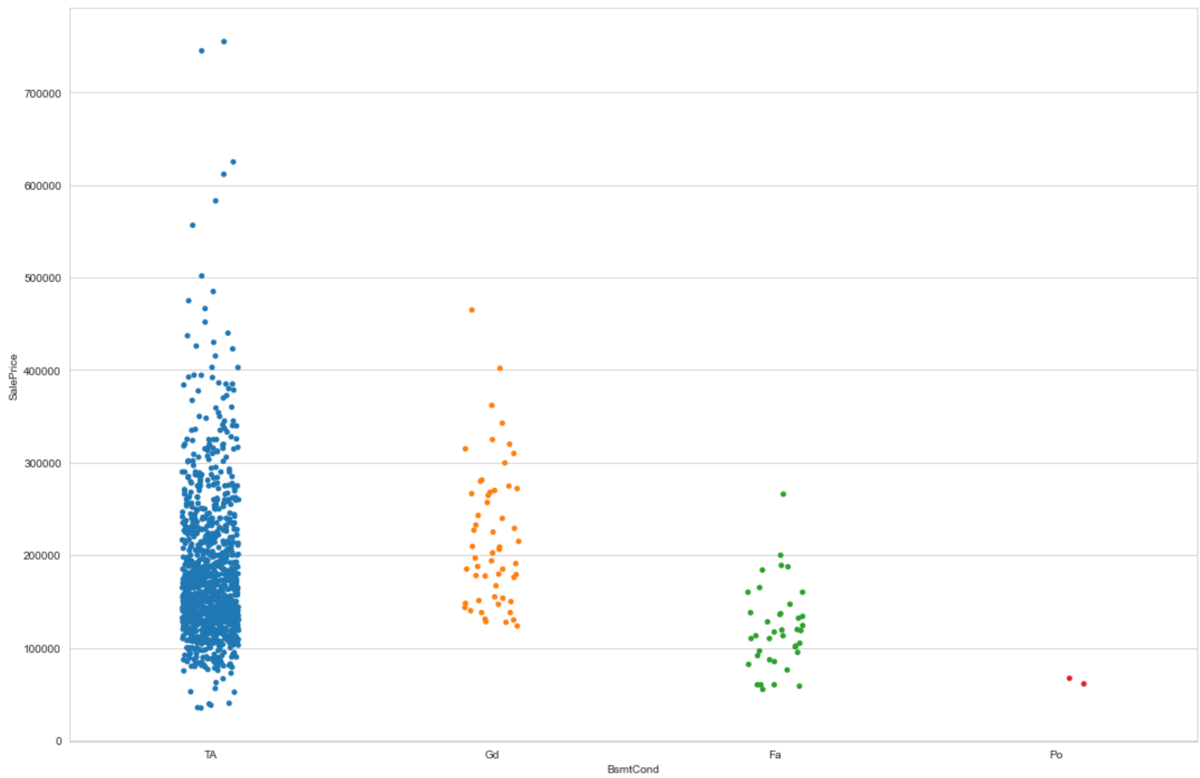
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
TA
Gd
Fa
Po
Ex
ExterCond

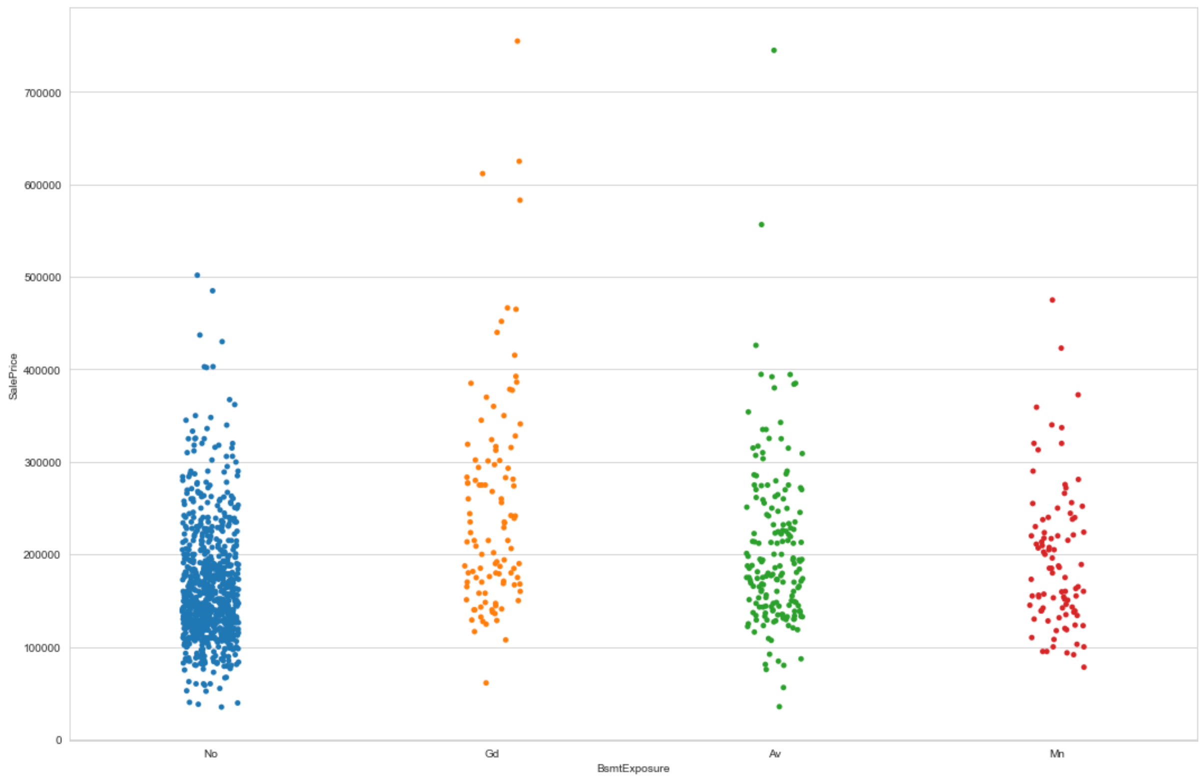


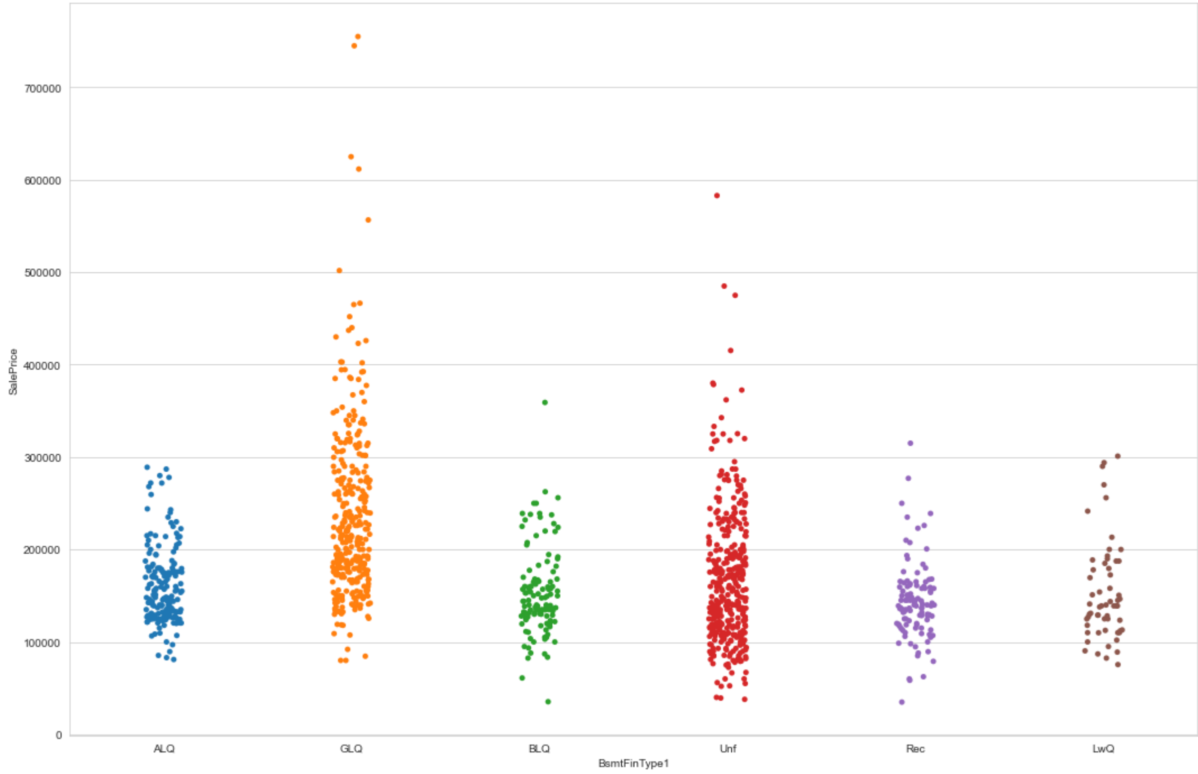
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
CBlock
PConc
BrkTil
Slab
Stone
Wood
Foundation



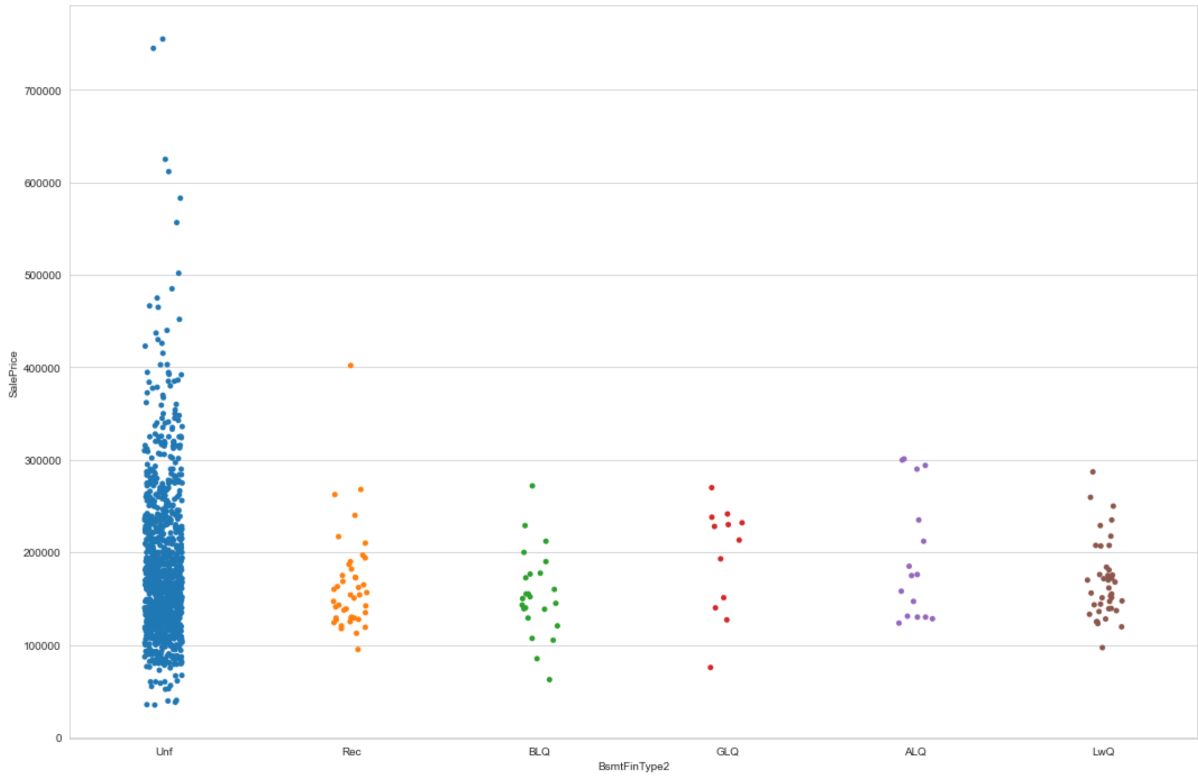
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Gd
TA
Ex
Fa
BsmtQual


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

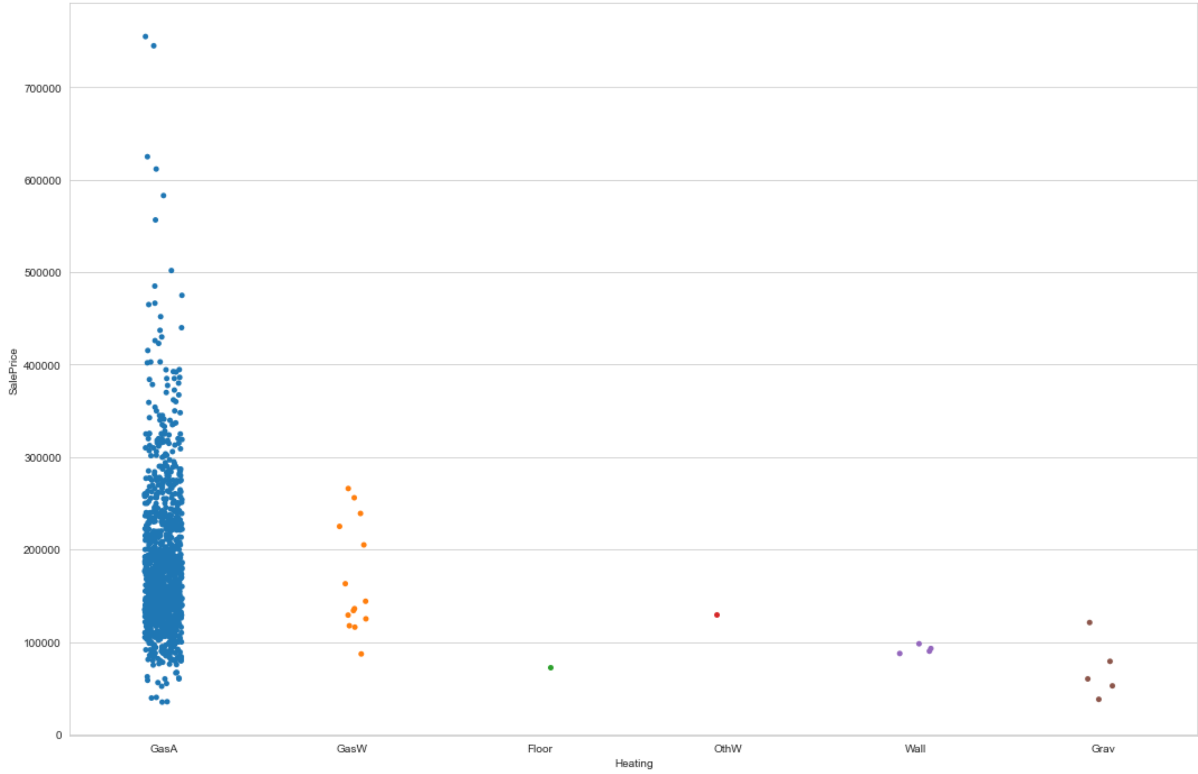

SalePrice
700000
600000
500000
400000
300000
200000
100000
0
No
Gd
Av
Mn
BsmtExposure



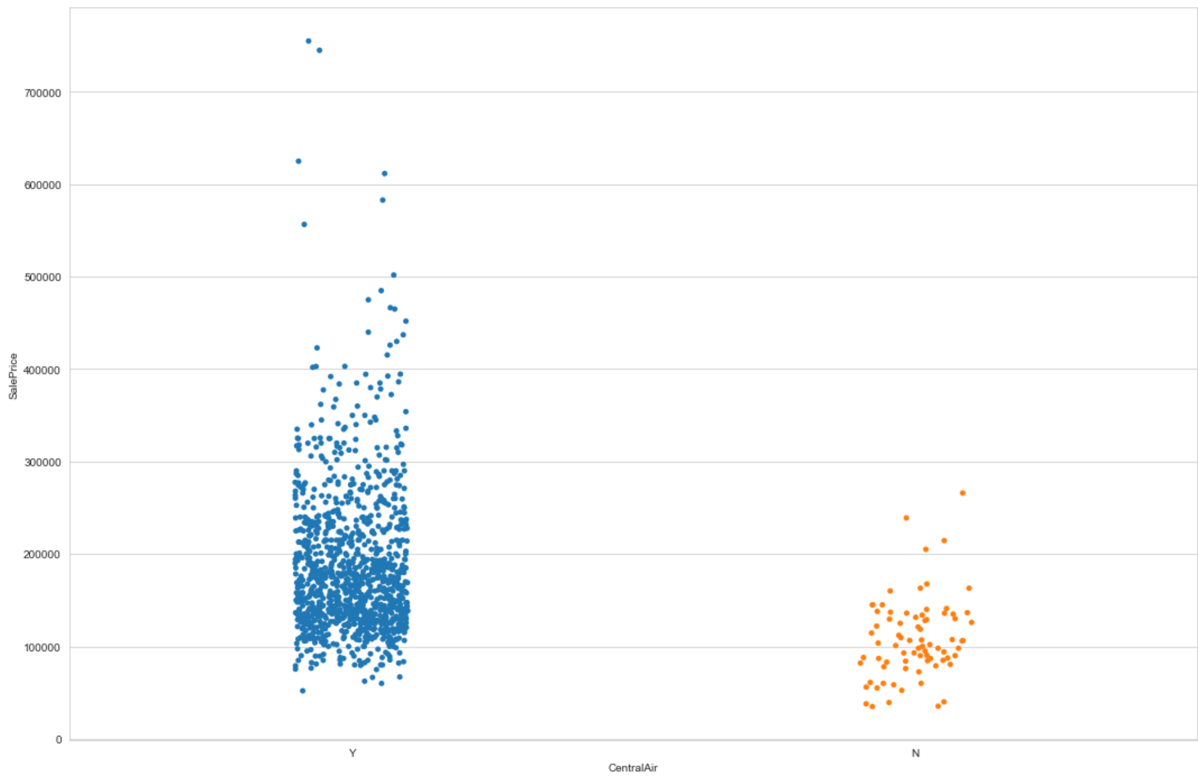
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
ALQ
GLQ
BLQ
Unf
Rec
LwQ
BsmtFinType1



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



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

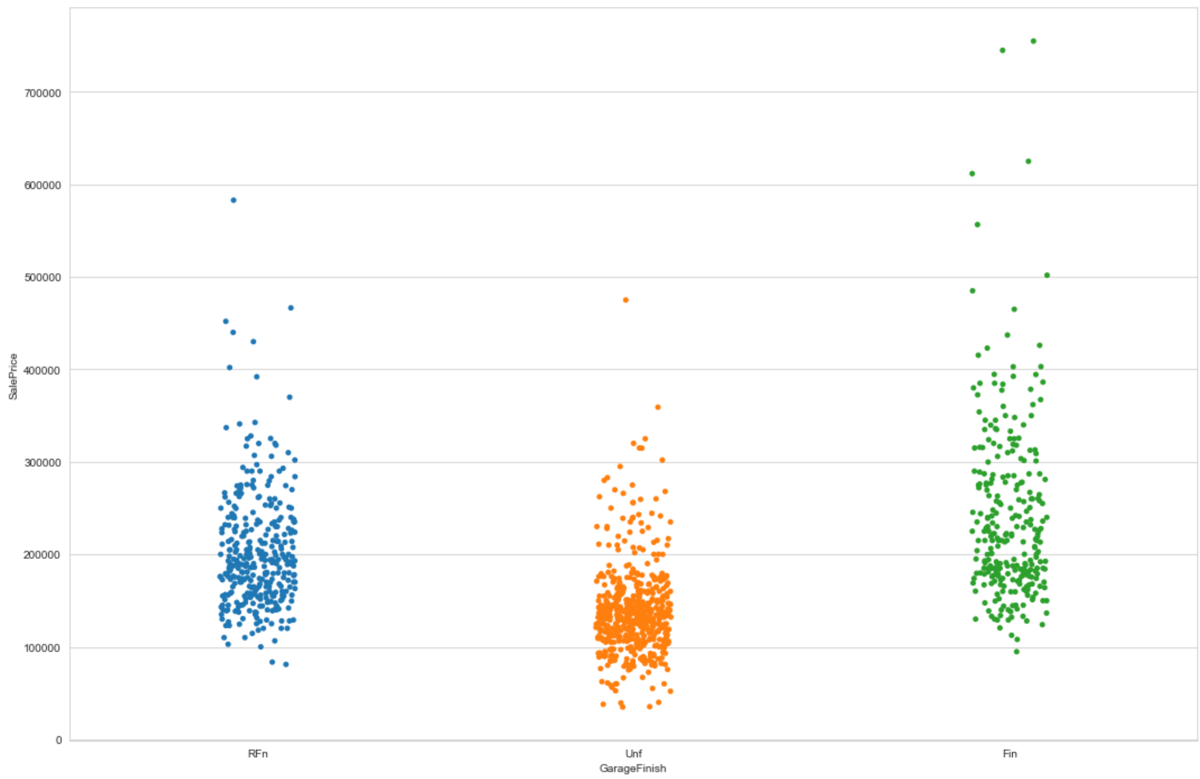


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
Y
N
CentralAir

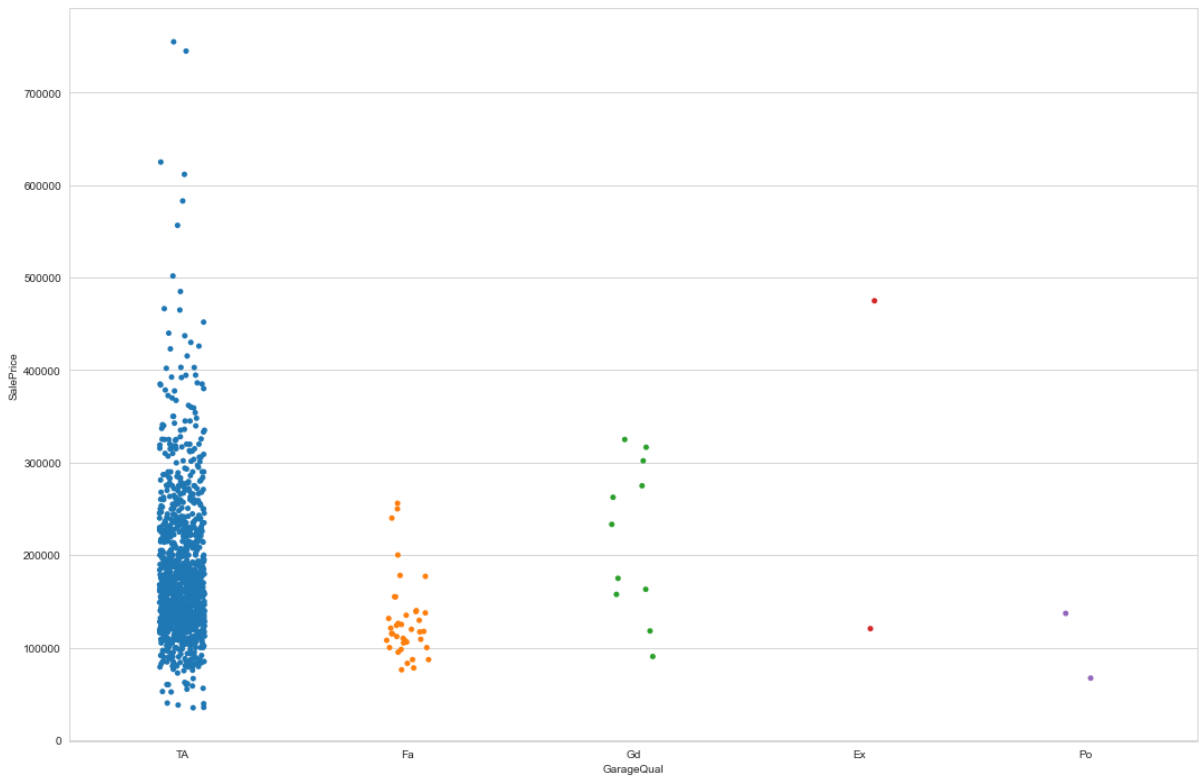
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
TA
Gd
Ex
Fa
KitchenQual

700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Typ
Mod
Maj1
Min1
Min2
Sev
Maj2
Functional

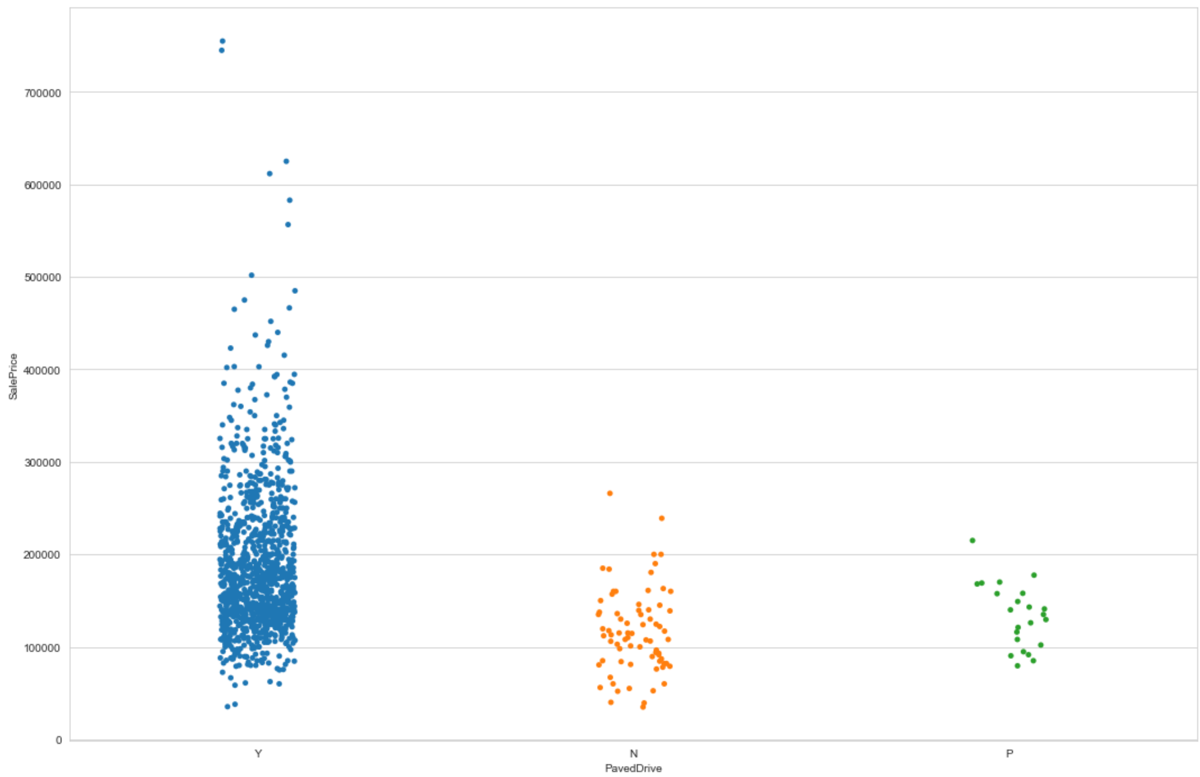
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
TA
Gd
Fa
Ex
Po
FireplaceQu



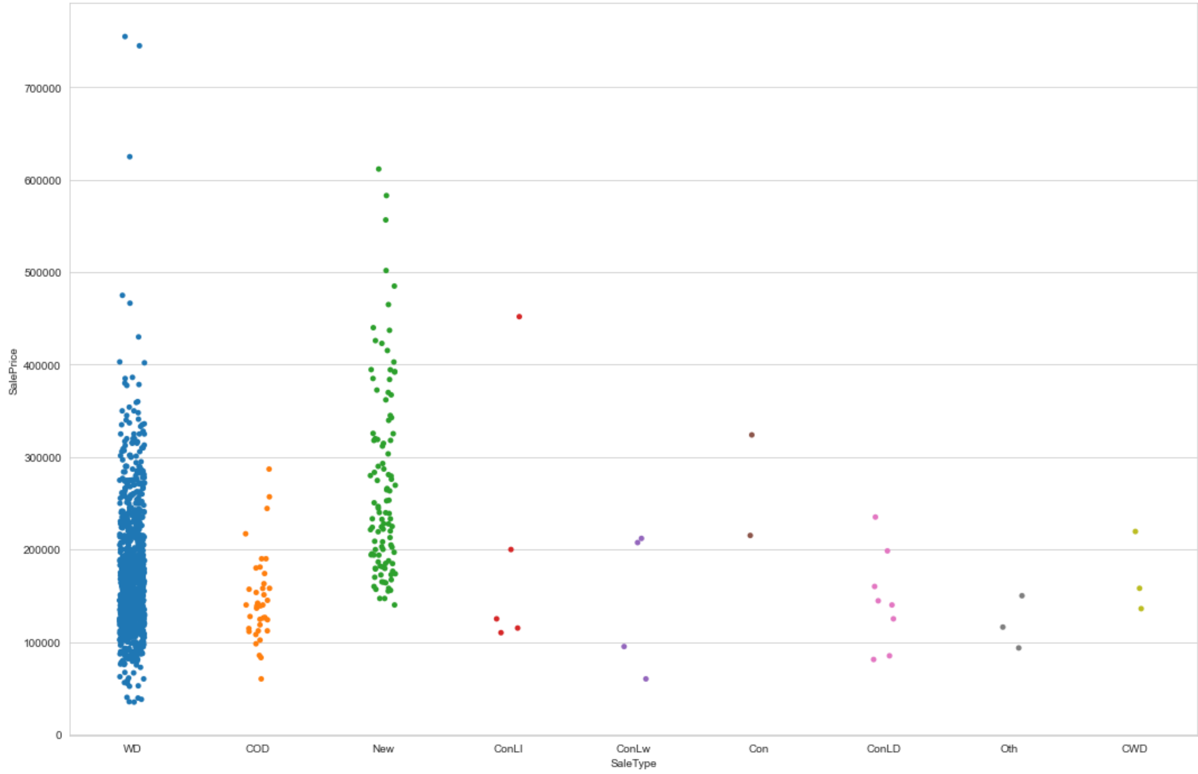
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
RFn
Unf
Fin
GarageFinish



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



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


700000
600000
500000
400000
300000
200000
100000
0
SalePrice
WD
COD
New
ConLI
ConLw
Con
ConLD
Oth
CWD
SaleType


700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Normal
Partial
Abnorml
Family
Alloca
AdjLand
SaleCondition

Interpretation of the Results

·Least SalePrice is for 30:1-STORY 1945 & OLDER and maximum for 60:2-STORY 1946 & NEWER

· In MSZoing maximum is for category 1 i.e, Floating Village Residential

· Lotshape 1 and 2 have almost similar price and 3 has least.

· Landconotur corresponding to 1 i.e, HLS Hillside - Significant slope from side to side has maximum price.

· Lotconfig corresponding to 1 and 3 have similar price.

· Neighborhoot with (15)NPkVill Northpark Villa has maximum sales price and (10)IDOTRR Iowa DOT and Rail Road has least.

· Normal condition houses have highest saleprice

· 1Fam Single-family Detached and TwnhsI Townhouse Inside Unit have maximum saleprice.

· In HouseStyle category 3: 2Story Two story has max sale price.

· In OverallQual: SalePrice increase as Ratings increase.

· Similary for OverallCond 5 and 9 have max sale price

· In RoofStyle 5:Shed has maximum.

· In Exterior1st 6:HardBoard and 9:Other have Saleprice

· In Exterior2nd 8:MetalSd Metal Siding

· In MasVnrType, 3:stone has max saleprice and 0:BrkCmn Brick Common has least

· In ExterQual 0:Excellent has maximum price. Similary for ExterCond

· In Foundation 2:PConc Poured Contrete has max price

· In BsmtQual 0: Ex Excellent (100+ inches), In BsmtCond 1: Gd Good, In BsmtExposure 1: Av Average Exposure (split levels or foyers typically score average or above) have max sale prices

· In BsmtFinType1: Rating of basement finished area - 2:GLQ Good Living Quarters has max price

· In HeatingQC: Heating quality and condition 0:Ex Excellent has max price.

· Houses with CentralAir has higher saleprice

· In FireplaceQu: Fireplace quality 0:Ex Excellent - Exceptional Masonry Fireplace has max saleprice.

· GarageType 3:BuiltIn Built-In (Garage part of house - typically has room above garage) has max saleprice

· Finished Garage has more price

· Paved Driveway has more price

· In 2007 maximum houses are sold followed by 2006

· In saletype category 2 and 6 have max sale price

· Normal sale condition has max price.

CONCLUSION

- ## Key Findings and Conclusions of the Study

  In this project we have tried to show how the house prices vary and what are the factors related to the changing of house prices.The best(minimum) RMSE score was achieved using the best parameters of Ridge Regressor through GridSearchCV though Lasso Regressor model performed well too.

- ## Learning Outcomes of the Study in respect of Data Science

  This project has demonstrated the importance of sampling effectively, modelling and predicting data.

Through different powerful tools of visualization we were able to analyse and interpret different hidden insights about the data.

Through data cleaning we were able to remove unnecessary columns and outliers from our dataset due to which our model would have suffered from overfitting or underfitting.

The few challenges while working on this project where:-

- Improper scaling
- Too many features
- Missing values
- Skewed data due to outliers

The data was improper scaled so we scaled it to a single scale using sklearns's package StandardScaler.

There were too many(256) features present in the data so we applied Principal Component Analysis(PCA) and found out the Eigenvalues and on the basis of number of nodes we were able able to reduce our features upto 90 columns.

There were lot of missing values present in different columns which we imputed on the basis of our understanding.

The columns were skewed due to presence of outliers which we handled through winsorization technique.

• Limitations of this work and Scope for Future Work

While we couldn't reach out goal of minimum RMSE in house price prediction without letting the model to overfit, we did end up creating a system that can with enough time and data get very close to that goal. As with any project there is room for improvement here. The very nature of this project allows for multiple algorithms to be integrated together as modules and their results can be combined to increase the accuracy of the final result. This model can further be improved with the addition of more algorithms into it. However, the output of these algorithms needs to be in the same format as the others. Once that condition is satisfied, the modules are easy to add as done in the code. This provides a great degree of modularity and versatility to the project.