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

%matplotlib inline
sns.set(rc = {'figure.figsize':[10, 10]}, font_scale = 1.2)
```

```
# I'll import all csv files
df_train = pd.read_csv("/content/drive/MyDrive/House price prediction/train.csv")
df_test = pd.read_csv("/content/drive/MyDrive/House price prediction/test.csv")
```

```
df_train.head()
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	Pool
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	N
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	N
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	N
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	N
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	N

5 rows × 81 columns

From describtion we can see that

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
CompShg    Standard (Composite) Shingle
Membran    Membrane
Metal    Metal
Roll    Roll
Tar&Grv    Gravel & Tar
WdShake    Wood Shakes
WdShngl    Wood Shingles
```

Exterior1st: Exterior covering on house

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

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

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

MasVnrType: Masonry veneer type

```
BrkCmn    Brick Common
BrkFace    Brick Face
CBlock    Cinder Block
None    None
Stone    Stone
```

MasVnrArea: Masonry veneer area in square feet

ExterQual: Evaluates the quality of the material on the exterior

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

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

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

Foundation: Type of foundation

```
BrkTil    Brick & Tile
CBlock    Cinder Block
PConc    Poured Contrete
Slab    Slab
Stone    Stone
Wood    Wood
```

BsmtQual: Evaluates the height of the basement

```
Ex    Excellent (100+ inches)
Gd    Good (90-99 inches)
TA    Typical (80-89 inches)
Fa    Fair (70-79 inches)
Po    Poor (<70 inches
NA    No Basement
```

BsmtCond: Evaluates the general condition of the basement

```
Ex    Excellent
Gd    Good
TA    Typical - slight dampness allowed
Fa    Fair - dampness or some cracking or settling
Po    Poor - Severe cracking, settling, or wetness
NA    No Basement
```

BsmtExposure: Refers to walkout or garden level walls

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

BsmtFinType1: Rating of basement finished area

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

BsmtFinSF1: Type 1 finished square feet

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

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

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of basement area

TotalBsmtSF: Total square feet of basement area

Heating: Type of heating

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

HeatingQC: Heating quality and condition

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

CentralAir: Central air conditioning

```
N    No
Y    Yes
```

Electrical: Electrical system

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

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

LowQualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade

HalfBath: Half baths above grade

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

Kitchen: Kitchens above grade

KitchenQual: Kitchen quality

```
Ex    Excellent
Gd    Good
TA    Typical/Average
```

```
Fa    Fair
Po    Poor
```

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

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

```
Typ    Typical Functionality
Min1    Minor Deductions 1
Min2    Minor Deductions 2
Mod    Moderate Deductions
Maj1    Major Deductions 1
Maj2    Major Deductions 2
Sev    Severely Damaged
Sal    Salvage only
```

Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

```
Ex    Excellent - Exceptional Masonry Fireplace
Gd    Good - Masonry Fireplace in main level
TA    Average - Prefabricated Fireplace in main living area or Masonry Fireplace in basement
Fa    Fair - Prefabricated Fireplace in basement
Po    Poor - Ben Franklin Stove
NA    No Fireplace
```

GarageType: Garage location

```
2Types    More than one type of garage
Attchd    Attached to home
Basment    Basement Garage
```

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

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

```
Fin    Finished
RFn    Rough Finished
Unf    Unfinished
NA    No Garage
```

GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet

GarageQual: Garage quality

```
Ex    Excellent
Gd    Good
TA    Typical/Average
Fa    Fair
Po    Poor
NA    No Garage
```

GarageCond: Garage condition

```
Ex    Excellent
Gd    Good
TA    Typical/Average
Fa    Fair
```

```
Po    Poor
NA    No Garage
```

PavedDrive: Paved driveway

```
Y    Paved
P    Partial Pavement
N    Dirt/Gravel
```

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality

```
Ex    Excellent
Gd    Good
TA    Average/Typical
Fa    Fair
NA    No Pool
```

Fence: Fence quality

```
GdPrv    Good Privacy
MnPrv    Minimum Privacy
GdWo    Good Wood
```

```
MnWw    Minimum Wood/Wire
NA    No Fence
```

MiscFeature: Miscellaneous feature not covered in other categories

```
Elev    Elevator
Gar2    2nd Garage (if not described in garage section)
Othr    Other
Shed    Shed (over 100 SF)
TenC    Tennis Court
NA    None
```

MiscVal: $Value of miscellaneous feature

MoSold: Month Sold (MM)

YrSold: Year Sold (YYYY)

SaleType: Type of sale

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

SaleCondition: Condition of sale

```
   Normal    Normal Sale
   Abnorml    Abnormal Sale -  trade, foreclosure, short sale
   AdjLand    Adjoining Land Purchase
   Alloca    Allocation - two linked properties with separate deeds, typically condo with a garage unit
   Family    Sale between family members
   Partial    Home was not completed when last assessed (associated with New Homes)
```

```
df_train.describe().T # T for transform as we have like 81 column
# from describtion we should see if there were any outliers
```

	count	mean	std	min	25%	50%	75%	max
Id	1460.0	730.500000	421.610009	1.0	365.75	730.5	1095.25	1460.0
MSSubClass	1460.0	56.897260	42.300571	20.0	20.00	50.0	70.00	190.0
LotFrontage	1201.0	70.049958	24.284752	21.0	59.00	69.0	80.00	313.0
LotArea	1460.0	10516.828082	9981.264932	1300.0	7553.50	9478.5	11601.50	215245.0
OverallQual	1460.0	6.099315	1.382997	1.0	5.00	6.0	7.00	10.0
OverallCond	1460.0	5.575342	1.112799	1.0	5.00	5.0	6.00	9.0
YearBuilt	1460.0	1971.267808	30.202904	1872.0	1954.00	1973.0	2000.00	2010.0
YearRemodAdd	1460.0	1984.865753	20.645407	1950.0	1967.00	1994.0	2004.00	2010.0
MasVnrArea	1452.0	103.685262	181.066207	0.0	0.00	0.0	166.00	1600.0
BsmtFinSF1	1460.0	443.639726	456.098091	0.0	0.00	383.5	712.25	5644.0
BsmtFinSF2	1460.0	46.549315	161.319273	0.0	0.00	0.0	0.00	1474.0
BsmtUnfSF	1460.0	567.240411	441.866955	0.0	223.00	477.5	808.00	2336.0
TotalBsmtSF	1460.0	1057.429452	438.705324	0.0	795.75	991.5	1298.25	6110.0
1stFlrSF	1460.0	1162.626712	386.587738	334.0	882.00	1087.0	1391.25	4692.0
2ndFlrSF	1460.0	346.992466	436.528436	0.0	0.00	0.0	728.00	2065.0
LowQualFinSF	1460.0	5.844521	48.623081	0.0	0.00	0.0	0.00	572.0
GrLivArea	1460.0	1515.463699	525.480383	334.0	1129.50	1464.0	1776.75	5642.0
BsmtFullBath	1460.0	0.425342	0.518911	0.0	0.00	0.0	1.00	3.0
BsmtHalfBath	1460.0	0.057534	0.238753	0.0	0.00	0.0	0.00	2.0
FullBath	1460.0	1.565068	0.550916	0.0	1.00	2.0	2.00	3.0
HalfBath	1460.0	0.382877	0.502885	0.0	0.00	0.0	1.00	2.0
BedroomAbvGr	1460.0	2.866438	0.815778	0.0	2.00	3.0	3.00	8.0
KitchenAbvGr	1460.0	1.046575	0.220338	0.0	1.00	1.0	1.00	3.0

TotRmsAbvGrd	1460.0	6.517808	1.625393	2.0	5.00	6.0	7.00	14.0

```
df_train.info()
```

```
 25  MasVnrType     1452 non-null   object
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object
 28  ExterCond      1460 non-null   object
 29  Foundation     1460 non-null   object
 30  BsmtQual       1423 non-null   object
 31  BsmtCond       1423 non-null   object
 32  BsmtExposure   1422 non-null   object
 33  BsmtFinType1   1423 non-null   object
 34  BsmtFinSF1     1460 non-null   int64
 35  BsmtFinType2   1422 non-null   object
 36  BsmtFinSF2     1460 non-null   int64
 37  BsmtUnfSF      1460 non-null   int64
 38  TotalBsmtSF    1460 non-null   int64
 39  Heating        1460 non-null   object
 40  HeatingQC      1460 non-null   object
 41  CentralAir     1460 non-null   object
 42  Electrical     1459 non-null   object
 43  1stFlrSF       1460 non-null   int64
 44  2ndFlrSF       1460 non-null   int64
 45  LowQualFinSF   1460 non-null   int64
 46  GrLivArea      1460 non-null   int64
 47  BsmtFullBath   1460 non-null   int64
 48  BsmtHalfBath   1460 non-null   int64
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
```

```
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
```

```
df_train.shape
```

```
(1460, 81)
```

```
## by looking to 81 columns we could see our first insights
null_percentage = df_train.isnull().sum() * 100 / len(df_train)
null_percentage = pd.DataFrame(data=null_percentage)
pd.set_option('display.max_rows', 81)
null_percentage
```

	0
Id	0.000000
MSSubClass	0.000000
MSZoning	0.000000
LotFrontage	17.739726
LotArea	0.000000
Street	0.000000
Alley	93.767123
LotShape	0.000000
LandContour	0.000000
Utilities	0.000000
LotConfig	0.000000
LandSlope	0.000000
Neighborhood	0.000000
Condition1	0.000000
Condition2	0.000000
BldgType	0.000000
HouseStyle	0.000000
OverallQual	0.000000
OverallCond	0.000000
YearBuilt	0.000000
YearRemodAdd	0.000000
RoofStyle	0.000000
RoofMatl	0.000000

Exterior1st	0.000000
Exterior2nd	0.000000
MasVnrType	0.547945
MasVnrArea	0.547945
ExterQual	0.000000
ExterCond	0.000000
Foundation	0.000000
BsmtQual	2.534247
BsmtCond	2.534247
BsmtExposure	2.602740
BsmtFinType1	2.534247
BsmtFinSF1	0.000000
BsmtFinType2	2.602740
BsmtFinSF2	0.000000
BsmtUnfSF	0.000000
TotalBsmtSF	0.000000
Heating	0.000000
HeatingQC	0.000000
CentralAir	0.000000
Electrical	0.068493
1stFlrSF	0.000000
2ndFlrSF	0.000000
LowQualFinSF	0.000000

GrLivArea	0.000000
BsmtFullBath	0.000000
BsmtHalfBath	0.000000
FullBath	0.000000
HalfBath	0.000000
BedroomAbvGr	0.000000
KitchenAbvGr	0.000000
KitchenQual	0.000000
TotRmsAbvGrd	0.000000
Functional	0.000000
Fireplaces	0.000000
FireplaceQu	47.260274
GarageType	5.547945
GarageYrBlt	5.547945
GarageFinish	5.547945
GarageCars	0.000000
GarageArea	0.000000
GarageQual	5.547945
GarageCond	5.547945
PavedDrive	0.000000
WoodDeckSF	0.000000
OpenPorchSF	0.000000
EnclosedPorch	0.000000
3SsnPorch	0.000000

ScreenPorch	0.000000
PoolArea	0.000000
PoolQC	99.520548
Fence	80.753425
MiscFeature	96.301370
MiscVal	0.000000
MoSold	0.000000

As a first insight more than 50% of data we should drop columns from it

- PoolQC is 99% null
- MiscFeature is 96% null
- Fence is 80.7% null
- Alley 93.767123% null

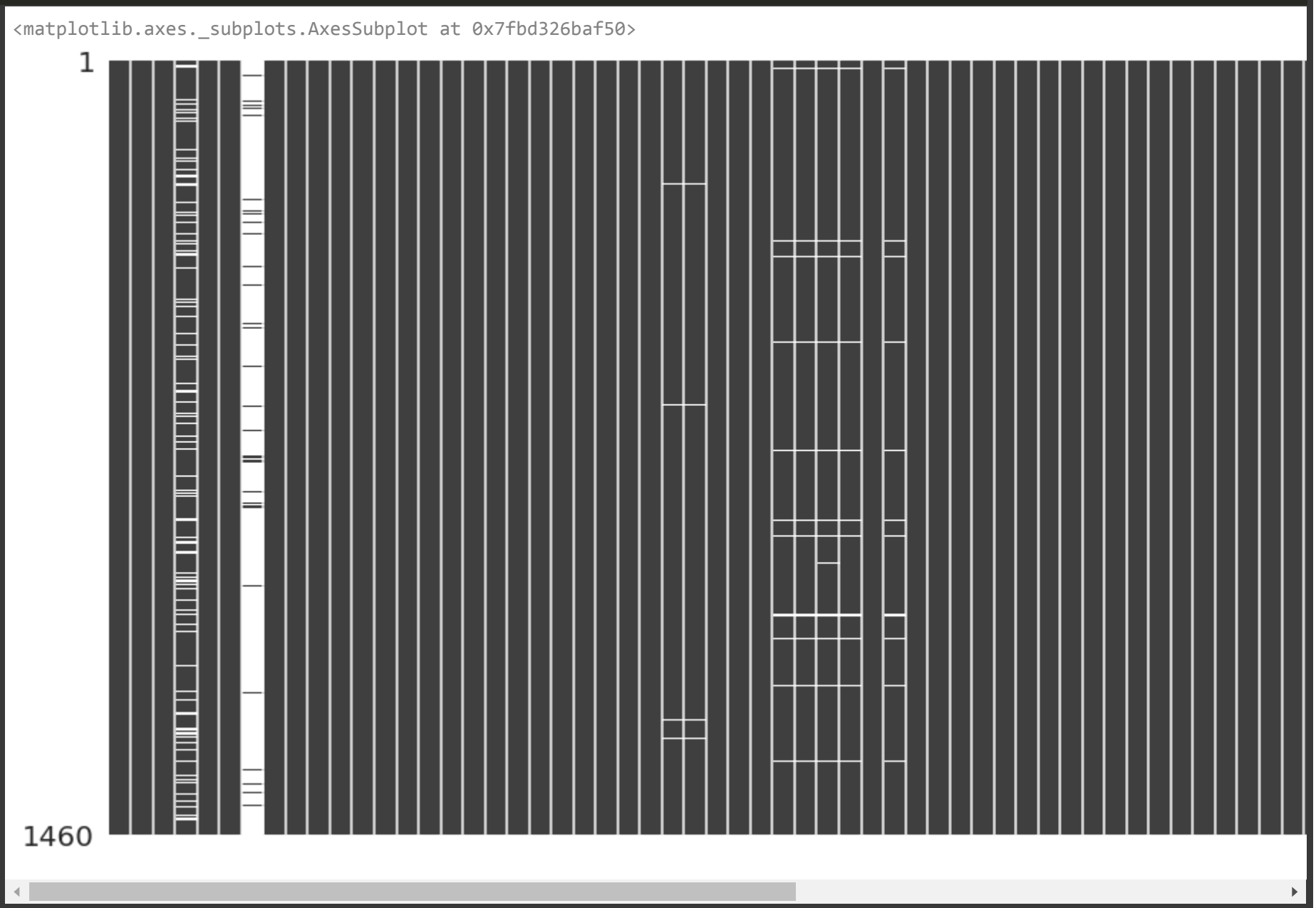
```
## here we will try to visualize our missing data
!pip install missingno
```

```
Requirement already satisfied: missingno in /usr/local/lib/python3.7/dist-packages (0.5.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-packages (from missingno) (3.2.2)
Requirement already satisfied: seaborn in /usr/local/lib/python3.7/dist-packages (from missingno) (0.11.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from missingno) (1.21.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from missingno) (1.4.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib->missingno) (0.
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->missingno
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (fro
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->missin
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from kiwisolver>=1.0.1->ma
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.1->matplotl
Requirement already satisfied: pandas>=0.23 in /usr/local/lib/python3.7/dist-packages (from seaborn->missingno) (1.3.5
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.23->seaborn->mis
```

```
import missingno as msno
```

```
## In depth info about missing data
msno.matrix(df_train)
```

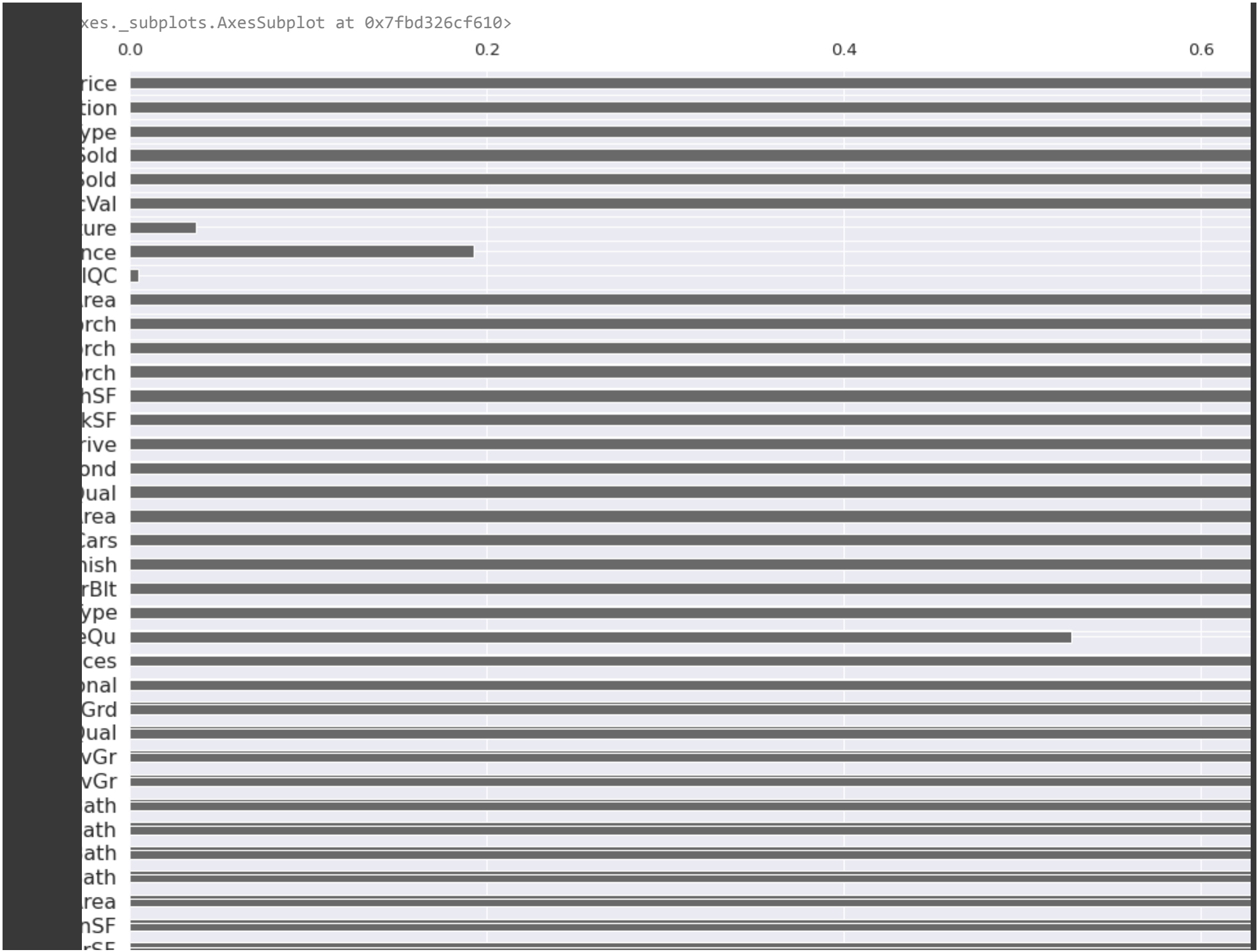
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd326baf50>
```



On the right side of the plot is a sparkline that ranges from 0 on the left to the total number of columns in the dataframe on the right.

When a row has a value in each column, the line will be at the maximum right position. As missing values start to increase within that row the line will move towards the left.

```
# general info
msno.bar(df_train)
```


xes._subplots.AxesSubplot at 0x7fbd326cf610>
0.0
0.2
0.4
0.6

```
df_train_copy = df_train.copy()
```

```
df_train_copy.drop(['PoolQC', 'MiscFeature', 'Fence', 'Alley'], axis=1, inplace = True)
```

```
df_train_copy.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Id	1460.0	730.500000	421.610009	1.0	365.75	730.5	1095.25	1460.0
MSSubClass	1460.0	56.897260	42.300571	20.0	20.00	50.0	70.00	190.0
LotFrontage	1201.0	70.049958	24.284752	21.0	59.00	69.0	80.00	313.0
LotArea	1460.0	10516.828082	9981.264932	1300.0	7553.50	9478.5	11601.50	215245.0
OverallQual	1460.0	6.099315	1.382997	1.0	5.00	6.0	7.00	10.0
OverallCond	1460.0	5.575342	1.112799	1.0	5.00	5.0	6.00	9.0
YearBuilt	1460.0	1971.267808	30.202904	1872.0	1954.00	1973.0	2000.00	2010.0
YearRemodAdd	1460.0	1984.865753	20.645407	1950.0	1967.00	1994.0	2004.00	2010.0
MasVnrArea	1452.0	103.685262	181.066207	0.0	0.00	0.0	166.00	1600.0
BsmtFinSF1	1460.0	443.639726	456.098091	0.0	0.00	383.5	712.25	5644.0
BsmtFinSF2	1460.0	46.549315	161.319273	0.0	0.00	0.0	0.00	1474.0
BsmtUnfSF	1460.0	567.240411	441.866955	0.0	223.00	477.5	808.00	2336.0
TotalBsmtSF	1460.0	1057.429452	438.705324	0.0	795.75	991.5	1298.25	6110.0
1stFlrSF	1460.0	1162.626712	386.587738	334.0	882.00	1087.0	1391.25	4692.0
2ndFlrSF	1460.0	346.992466	436.528436	0.0	0.00	0.0	728.00	2065.0
LowQualFinSF	1460.0	5.844521	48.623081	0.0	0.00	0.0	0.00	572.0
GrLivArea	1460.0	1515.463699	525.480383	334.0	1129.50	1464.0	1776.75	5642.0
BsmtFullBath	1460.0	0.425342	0.518911	0.0	0.00	0.0	1.00	3.0
BsmtHalfBath	1460.0	0.057534	0.238753	0.0	0.00	0.0	0.00	2.0
FullBath	1460.0	1.565068	0.550916	0.0	1.00	2.0	2.00	3.0
HalfBath	1460.0	0.382877	0.502885	0.0	0.00	0.0	1.00	2.0
BedroomAbvGr	1460.0	2.866438	0.815778	0.0	2.00	3.0	3.00	8.0
KitchenAbvGr	1460.0	1.046575	0.220338	0.0	1.00	1.0	1.00	3.0

TotRmsAbvGrd	1460.0	6.517808	1.625393	2.0	5.00	6.0	7.00	14.0
Fireplaces	1460.0	0.613014	0.644666	0.0	0.00	1.0	1.00	3.0
GarageYrBlt	1379.0	1978.506164	24.689725	1900.0	1961.00	1980.0	2002.00	2010.0
GarageCars	1460.0	1.767123	0.747315	0.0	1.00	2.0	2.00	4.0
GarageArea	1460.0	472.980137	213.804841	0.0	334.50	480.0	576.00	1418.0
WoodDeckSF	1460.0	94.244521	125.338794	0.0	0.00	0.0	168.00	857.0
OpenPorchSF	1460.0	46.660274	66.256028	0.0	0.00	25.0	68.00	547.0

```
pd.set_option('display.max_columns', 77)
```

3SsnPorch	1460.0	3.409589	29.317331	0.0	0.00	0.0	0.00	508.0

```
df_train_copy.head()
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neig
0	1	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl	
1	2	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl	
2	3	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl	
3	4	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl	
4	5	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl	

```
## So our final goal is to predict price column depending on various inputs
## So we should tune values and going through each column
df_train_copy['MSZoning'].value_counts()
```

```
RL         1151
RM          218
```

```
FV          65
RH          16
C (all)     10
Name: MSZoning, dtype: int64
```

```
df_train_copy['Street'].value_counts()
```

```
Pave    1454
Grvl       6
Name: Street, dtype: int64
```

```
df_train_copy['LotShape'].value_counts()
```

```
Reg    925
IR1    484
IR2     41
IR3     10
Name: LotShape, dtype: int64
```

```
df_train_copy['LandContour'].value_counts()
```

```
Lvl    1311
Bnk      63
HLS      50
Low      36
Name: LandContour, dtype: int64
```

```
df_train_copy['Utilities'].value_counts()
```

```
AllPub    1459
NoSeWa       1
Name: Utilities, dtype: int64
```

```
df_train_copy['LotConfig'].value_counts()
```

```
Inside     1052
Corner      263
```

```
CulDSac      94
FR2          47
FR3           4
Name: LotConfig, dtype: int64
```

```
df_train_copy['LandSlope'].value_counts()
```

```
Gtl    1382
Mod      65
Sev      13
Name: LandSlope, dtype: int64
```

```
df_train_copy['Neighborhood'].value_counts()
```

```
NAmes      225
CollgCr    150
OldTown    113
Edwards    100
Somerst     86
Gilbert     79
NridgHt     77
Sawyer      74
NWAmes      73
SawyerW     59
BrkSide     58
Crawfor     51
Mitchel     49
NoRidge     41
Timber      38
IDOTRR      37
ClearCr     28
StoneBr     25
SWISU       25
MeadowV     17
Blmngtn     17
BrDale      16
Veenker     11
NPkVill      9
Blueste      2
Name: Neighborhood, dtype: int64
```

```
df_train_copy['Condition1'].value_counts()
```

```
Norm      1260
Feedr       81
Artery      48
RRAn        26
PosN        19
RRAe        11
PosA         8
RRNn         5
RRNe         2
Name: Condition1, dtype: int64
```

```
df_train_copy['BldgType'].value_counts()
```

```
1Fam      1220
TwnhsE     114
Duplex      52
Twnhs       43
2fmCon      31
Name: BldgType, dtype: int64
```

```
df_train_copy['HouseStyle'].value_counts()
```

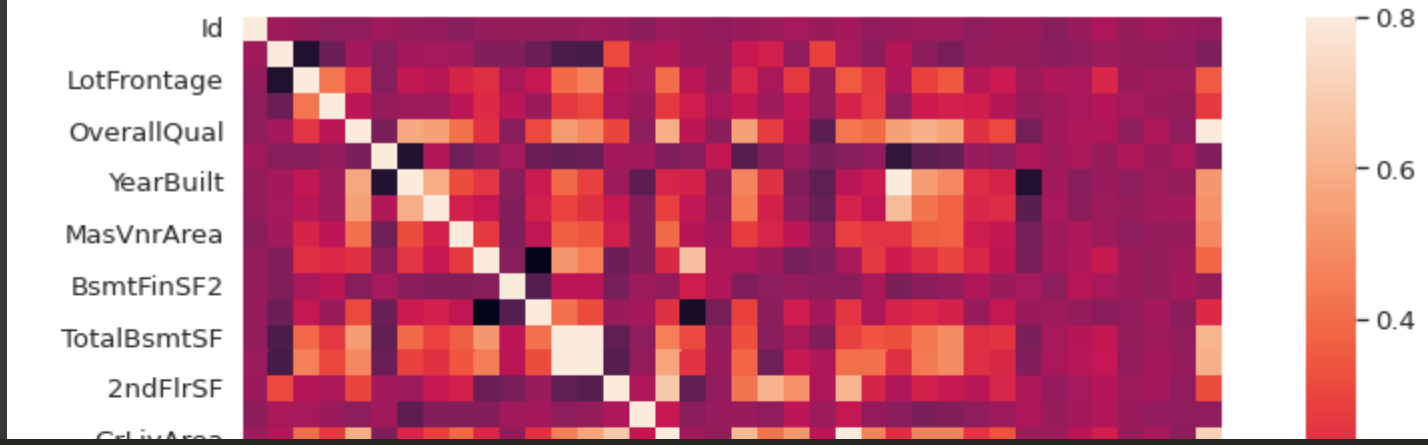
```
1Story    726
2Story    445
1.5Fin    154
SLvl       65
SFoyer     37
1.5Unf     14
2.5Unf     11
2.5Fin      8
Name: HouseStyle, dtype: int64
```

```
df_train_copy.shape
```

```
(1460, 77)
```

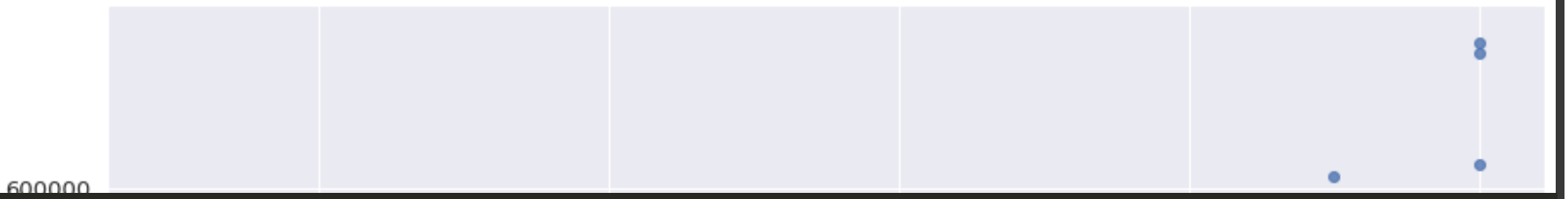
- MSZoning: Identifies the general zoning classification of the sale.
- Street: Type of road access to property
- LotShape: General shape of property
- LandContour: Flatness of the property
- Utilities: Type of utilities available
- LandSlope: Slope of property
- Neighborhood: Physical locations within Ames city limits
- Condition1: Proximity to various conditions

```
plt.rcParams['figure.figsize'] = (15.0, 9.0)
train_corr = df_train_copy.corr()
sns.heatmap(train_corr, vmax=.8, square=True);
```




```
## We will be getting correlation between price and overall quality, condition quality
sns.regplot(x=df_train_copy["OverallQual"], y=df_train_copy["SalePrice"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd2f56af10>
```




```
sns.regplot(x=df_train_copy["OverallCond"], y=df_train_copy["SalePrice"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd2f598090>
```

- lotFrontage and LotArea in square feet so we will convert it into meters
  - square feet * 0.092903 = 1 meter
- LotArea is feet length So to convert from feet length into meter length
  - feet length * 0.3048 = 1 meter
- Is there like a relation between LotFrontage and LotArea
- OverallQual and condition is categorical values Like from bad to excellent
- Is there any changing happend? YearRemodAdd - YearBuilt = if 0 = No if else = yes
- Is there any specific physical location that make our saleprice high

conditions 1 & 2 are conditions that may exist Norm or not

- We can make a new column that have 3 types of conditions
  - if condition 1 = condition 2 return norm elif condition 1 = norm and condition 2 != norm return half norm if condition 1 != condition 2 return not norm

Exterior 1st & 2nd: Exterior covering on house

Masonry veneer type and ExterQual and ExterCond

- Evaluates the quality of the material on the exterior relation and will keep ExterQual
- ExterCond: Evaluates the present condition of the material on the exterior Masonry veneer area in square feet

BsmtQual in inches --> height of 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

1 inch * 0.0254 = 1 meter

BsmtFin

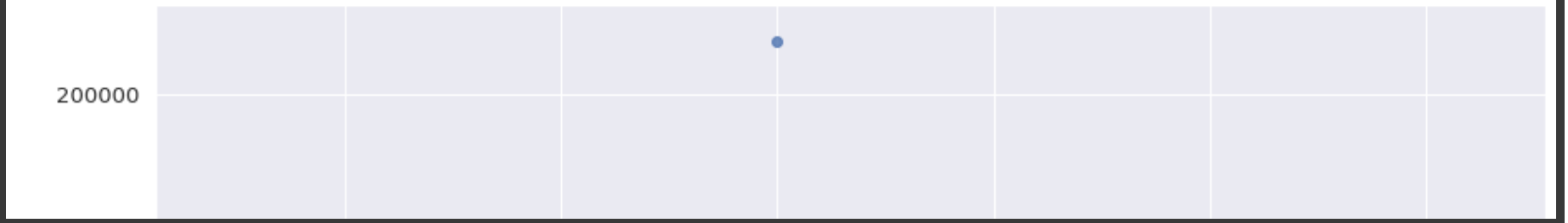
BsmtCond general condition

BldgType: Type of dwellingType get_dummies

Is there like a relation between LotFrontage and LotArea?

```
# Is there like a relation between LotFrontage and LotArea
sns.regplot(x=df_train_copy["LotFrontage"], y=df_train_copy["LotArea"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd2dc9ab90>
```



We can see like there's an outlier in LotArea

```
## remove outliers
q1 = df_train_copy["LotArea"].quantile(0.25)
q3 = df_train_copy["LotArea"].quantile(0.75)
iqr = q3-q1
min_wisk = q1 - 1.5 * iqr
max_wisk = q3 + 1.5 * iqr
```

```
clean_train = df_train_copy[  df_train_copy['LotArea'].between(min_wisk, max_wisk)  ]
clean_train
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope
0	1	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl
1	2	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl
2	3	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl
3	4	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl
4	5	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl

```
# after removing outliers
sns.regplot(x=clean_train["LotFrontage"], y=clean_train["LotArea"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd2f61e990>
```


```
## No duplicates
df_train_copy[  df_train_copy.duplicated()  ]
```

Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neigh

```
df_train_copy.groupby('YearBuilt').sum()
```

YearRemodAdd	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	MasVnrArea	BsmtFinSF1	Bsm
YearBuilt									
1872	1350	70	50.0	5250	8	5	0.0	259	

```
df_train_copy.groupby('YearRemodAdd').sum()
```

YearRemodAdd	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	MasVnrArea	BsmtFinSF1	Bs
1950	138589	9870	9878.0	1582031	894	984	343594	3349.0	31781	
1951	3415	80	356.0	46045	18	20	7804	44.0	2564	
1952	3161	200	328.0	41454	23	24	9760	360.0	717	
1953	5248	410	712.0	114691	54	48	19503	892.0	5286	
1954	11092	505	878.0	146056	69	73	27356	777.0	5032	
1955	5246	590	507.0	114802	40	49	17580	421.0	2878	
1956	6142	225	490.0	100921	48	54	19560	194.0	3732	
1957	6615	180	579.0	88731	46	47	17613	387.0	5127	
1958	11794	730	947.0	150570	79	83	29315	1483.0	5455	
1959	12051	450	1198.0	187173	93	97	35262	1242.0	9134	
1960	6785	420	704.0	150114	63	62	23471	1280.0	6214	
1961	5100	230	466.0	70089	39	39	15688	1079.0	5037	
1962	10298	685	826.0	161477	73	76	27468	1996.0	5406	
1963	10680	505	861.0	155837	68	69	25519	1979.0	8475	
1964	8867	510	583.0	137140	62	62	21604	2662.0	6066	
1965	12113	965	1315.0	544798	98	103	37188	539.0	11478	
1966	11865	735	780.0	148502	79	82	29464	2559.0	5379	
1967	8614	615	515.0	142829	60	60	23604	362.0	4687	
1968	14388	620	1064.0	172267	94	92	33409	2275.0	6867	
1969	13117	690	743.0	175337	76	75	27537	1678.0	7812	
1970	20854	2435	1138.0	208276	138	143	50919	2098.0	11396	
1971	12026	1370	704.0	129629	92	93	35478	2303.0	6336	

1972	12859	1465	966.0	156412	102	119	39387	1631.0	8322
1973	7659	1200	478.0	64036	63	58	21678	3090.0	6621
1974	6708	455	525.0	72463	40	36	13799	525.0	2652
1975	6018	480	545.0	208763	55	53	19702	399.0	7532
1976	21564	2420	1071.0	284073	177	171	59210	2991.0	15293
1977	20750	1470	1440.0	251230	142	139	49425	3032.0	15536
1978	13532	1180	582.0	157150	94	90	31616	1758.0	7707
1979	8206	750	466.0	107860	55	52	19760	535.0	4336
1980	8126	1010	590.0	96526	71	70	23682	840.0	6435
1981	4920	325	365.0	96178	50	48	15751	1303.0	4360
1982	3610	530	375.0	55900	34	37	13686	0.0	2972
1983	3625	165	151.0	46755	26	28	9868	0.0	2435
1984	4470	630	162.0	61262	46	40	13828	220.0	4995
1985	7157	450	340.0	79235	55	49	17791	421.0	5166
1986	3786	400	288.0	52782	35	31	9775	132.0	3322
1987	6061	550	533.0	149513	65	60	19539	329.0	5377
1988	6764	410	565.0	102390	58	52	17760	912.0	7018
1989	5795	690	446.0	125657	69	61	21758	1457.0	7119
1990	11179	745	1042.0	177638	97	85	29406	1712.0	9218
1991	10245	840	879.0	155973	88	83	27528	1001.0	7706
1992	13380	1005	973.0	199900	107	96	33643	1073.0	6140
1993	9362	1165	847.0	195381	125	114	37427	921.0	9991
1994	19574	1215	1331.0	291724	138	132	43390	3026.0	11109

Is there any changing happend through years??

- YearRemodAdd - YearBuilt = if 0 = No if else = yes

Why this we want to know if there was any change or not and we will drop 2 year columns

```
# clean_train
clean_train['year_diff'] = clean_train['YearRemodAdd']- clean_train['YearBuilt']
clean_train['year_diff']
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-

0        0
1        0
2        1
3       55
4        0
       ..
1455     1
1456    10
1457    65
1458    46
1459     0
Name: year_diff, Length: 1391, dtype: int64
```

```
clean_train['Is_diff'] = clean_train['year_diff'].apply(lambda x: 0 if x == 0 else 1)
clean_train['Is_diff']
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-

0       0
1       0
2       1
3       1
4       0
       ..
1455    1
1456    1
1457    1
1458    1
1459    0
Name: Is_diff, Length: 1391, dtype: int64
```

```
clean_train.loc[clean_train['SalePrice'] == clean_train['SalePrice'].max()]
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope
1182	1183	60	RL	160.0	15623	Pave	IR1	Lvl	AllPub	Corner	Gtl

1 rows × 79 columns

```
clean_train.loc[clean_train['SalePrice'] == clean_train['SalePrice'].min()]
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	
495	496	30	C (all)	60.0	7879	Pave	Reg	Lvl	AllPub	Inside	Gtl	

1 rows × 79 columns

- 1996 Year built without any modification and sold on 2007 but 745000 SalePrice
- While 1920 and modified on 1950 and sold on 2009 is the minimum with 34900 SalePrice
- So let's check the relation between year sold and SalePrice

```
sns.regplot(x=clean_train["YrSold"], y=clean_train["SalePrice"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd2db8e0d0>
```

As we can see There's an outlier in SalePrice

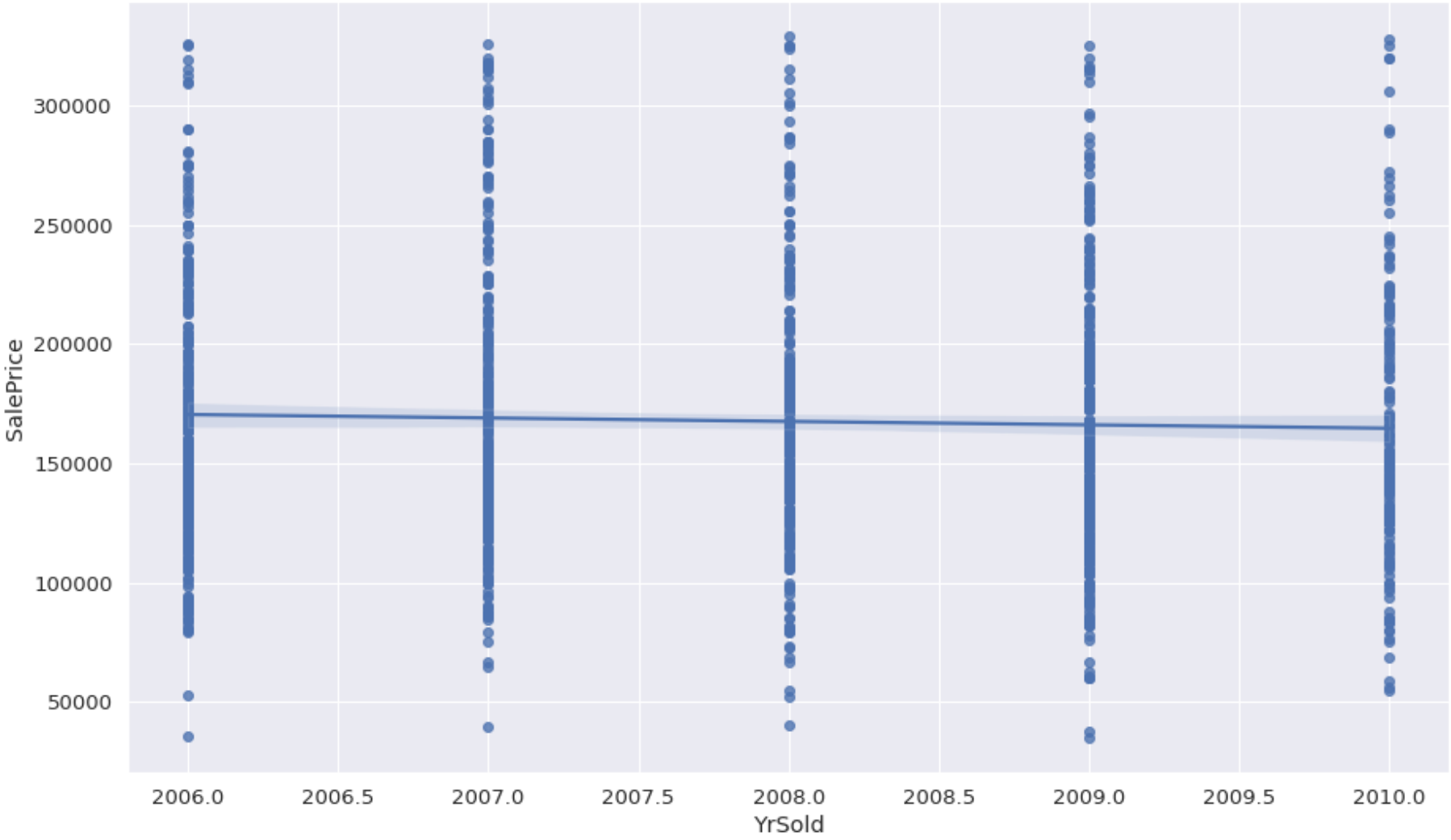
```
## remove outliers
q1 = clean_train["SalePrice"].quantile(0.25)
q3 = clean_train["SalePrice"].quantile(0.75)
iqr = q3-q1
min_wisk = q1 - 1.5 * iqr
max_wisk = q3 + 1.5 * iqr
```

```
clean_train = clean_train[  clean_train['SalePrice'].between(min_wisk, max_wisk)  ]
clean_train
```

Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope

```
sns.regplot(x=clean_train["YrSold"], y=clean_train["SalePrice"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd2daeba10>
```




```
clean_train['Condition1'].value_counts()
```

```
Norm      1147
```

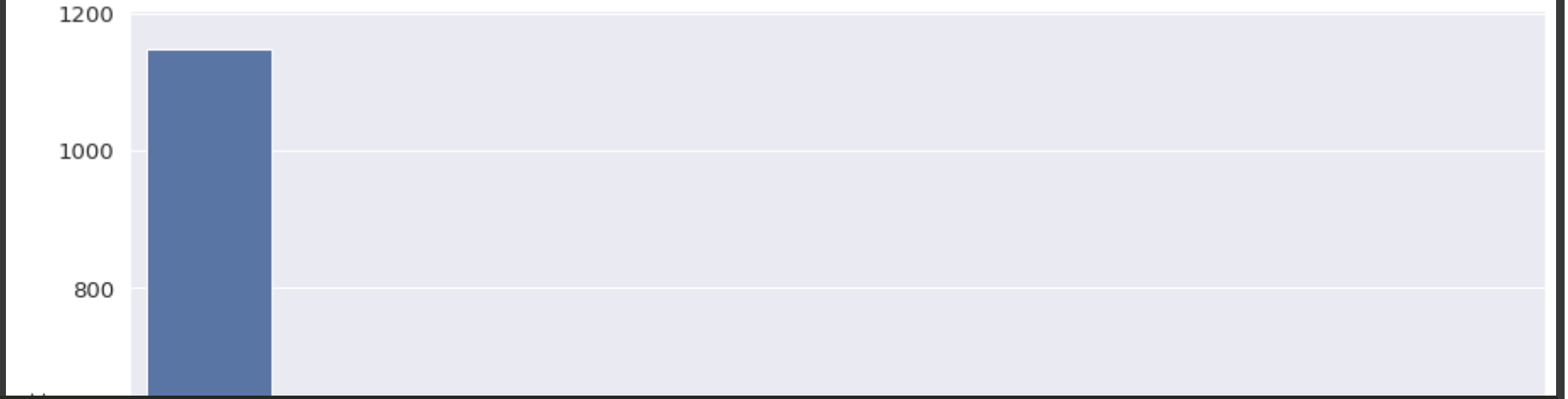
```
Feedr       77
Artery      44
RRAn        23
PosN        16
RRAe        11
RRNn         5
PosA         5
RRNe         2
Name: Condition1, dtype: int64
```

```
clean_train['Condition2'].value_counts()
```

```
Norm      1318
Feedr        6
Artery       2
RRNn         2
PosA         1
RRAn         1
Name: Condition2, dtype: int64
```

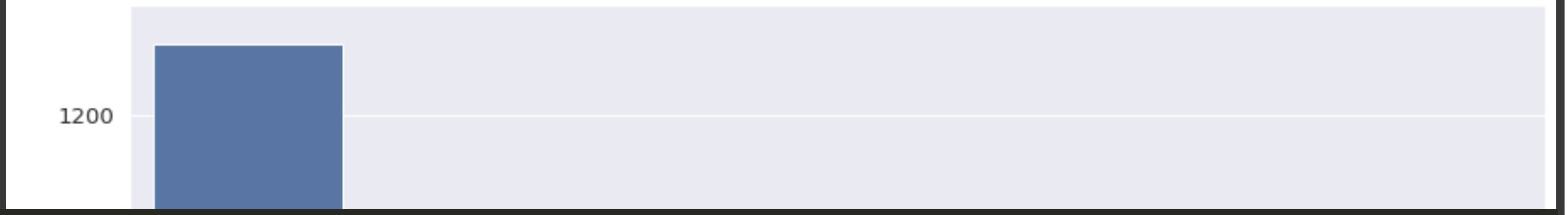
```
sns.countplot(x = "Condition1", data = clean_train)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd2da54a10>
```



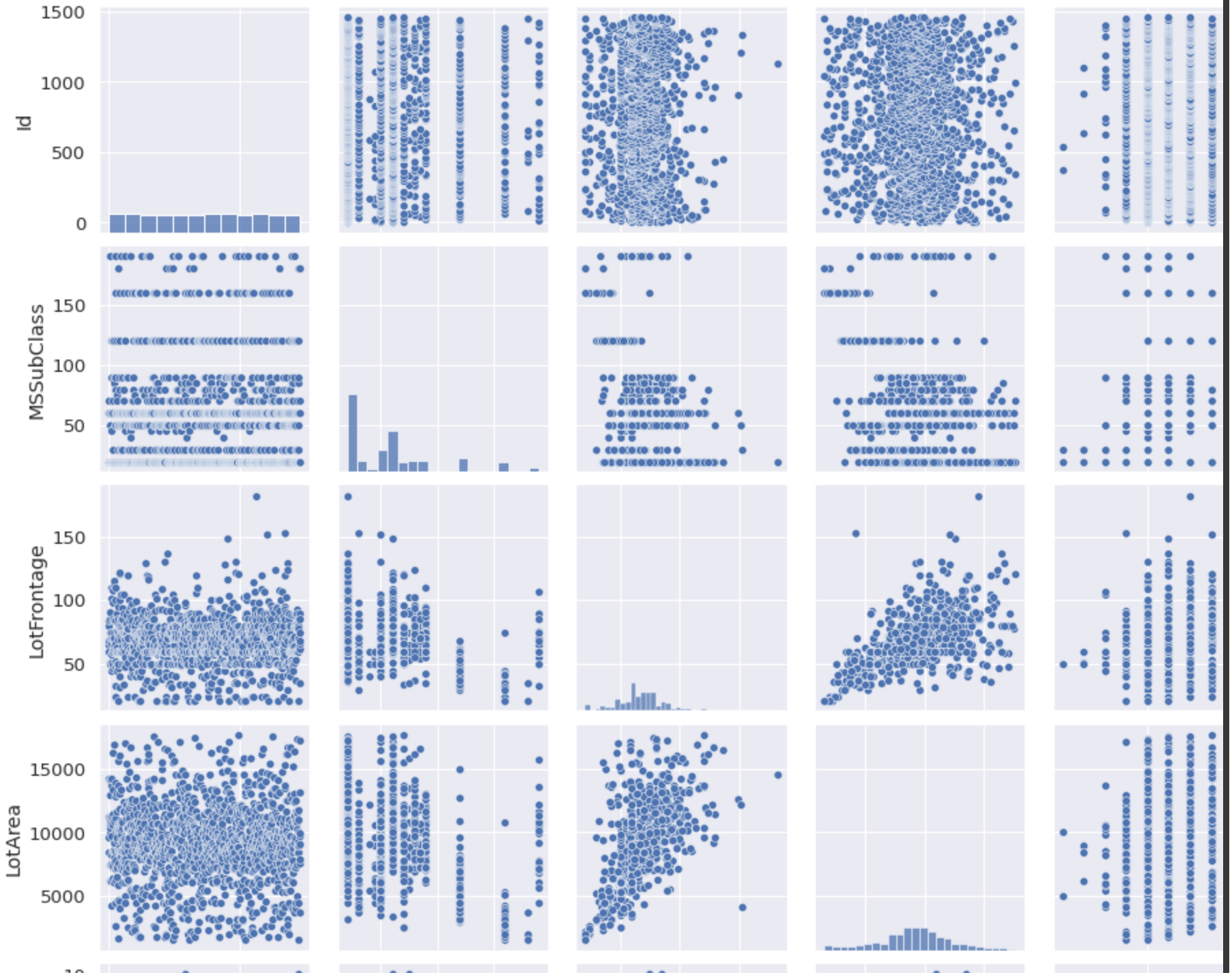

```
sns.countplot(x = "Condition2", data = clean_train)
```

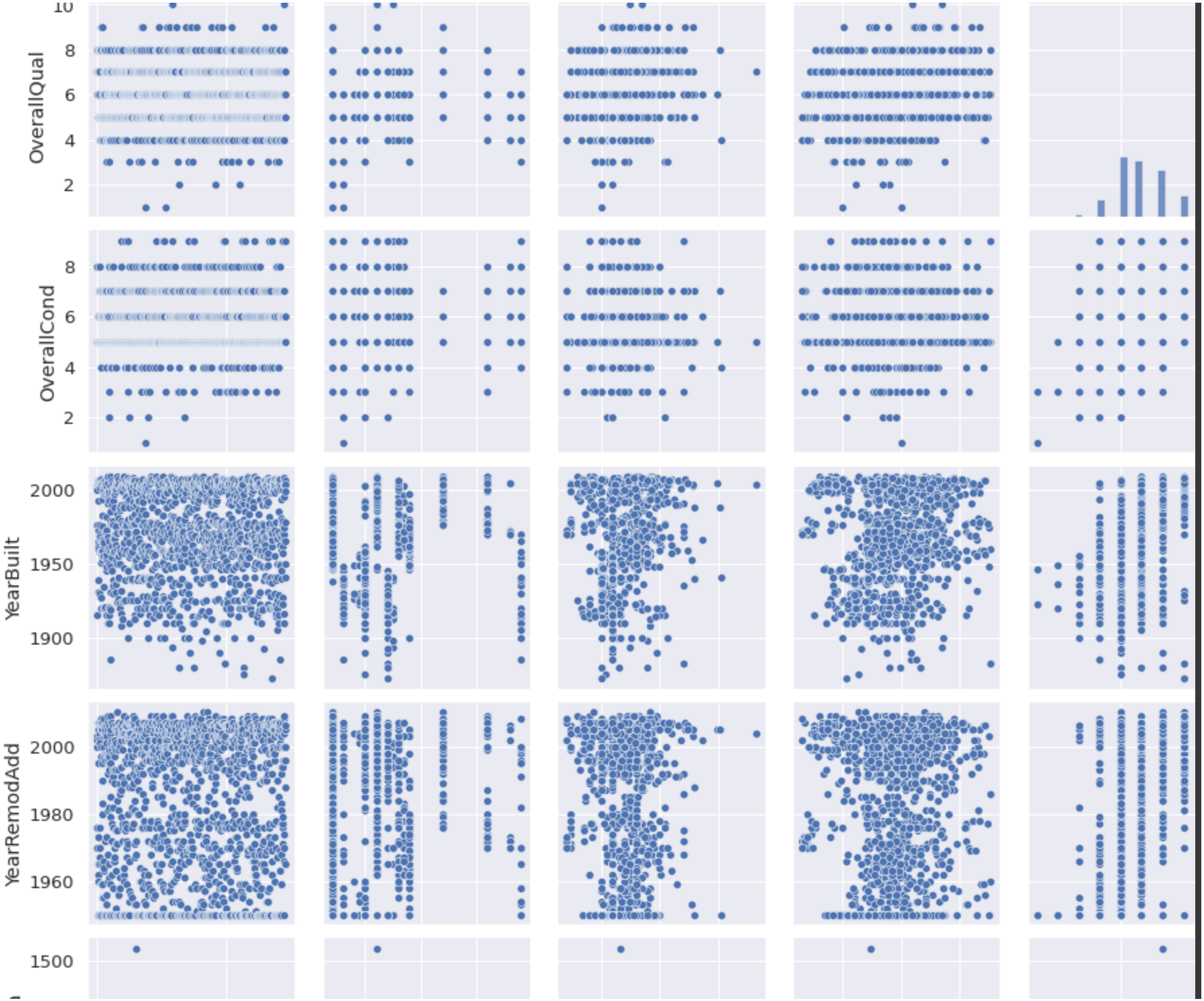
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd2d9cd210>
```

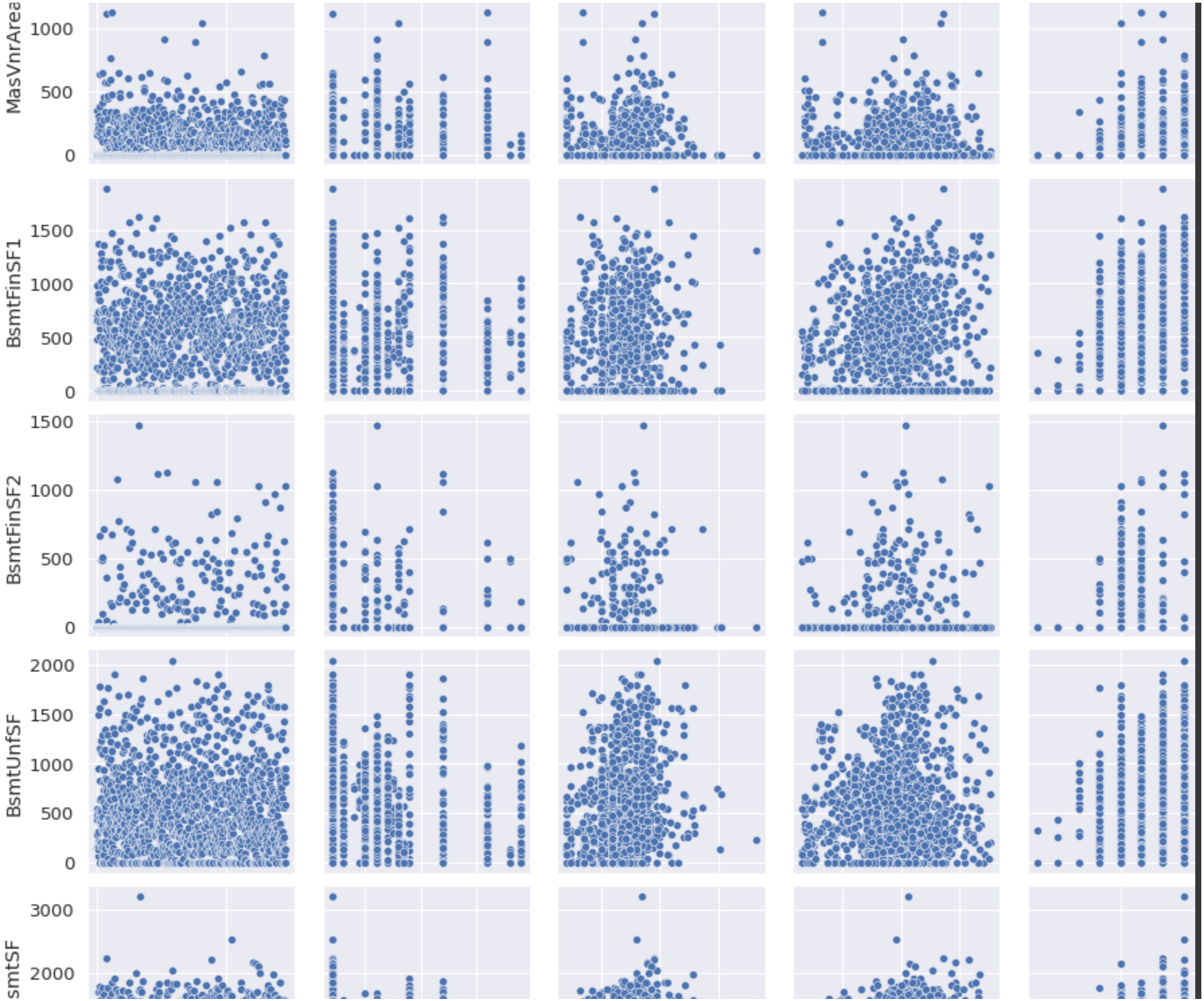


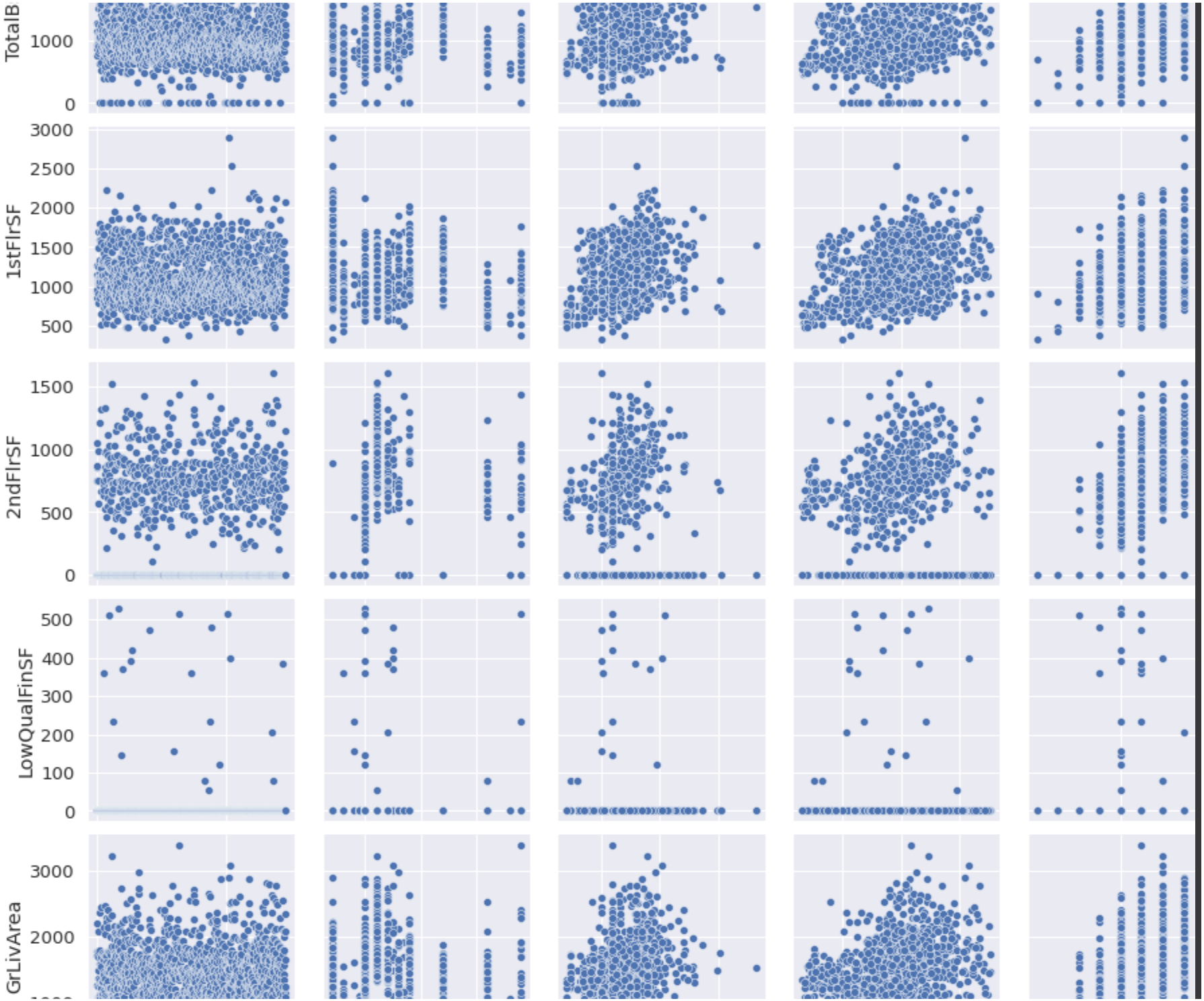

```
sns.pairplot(clean_train)
```

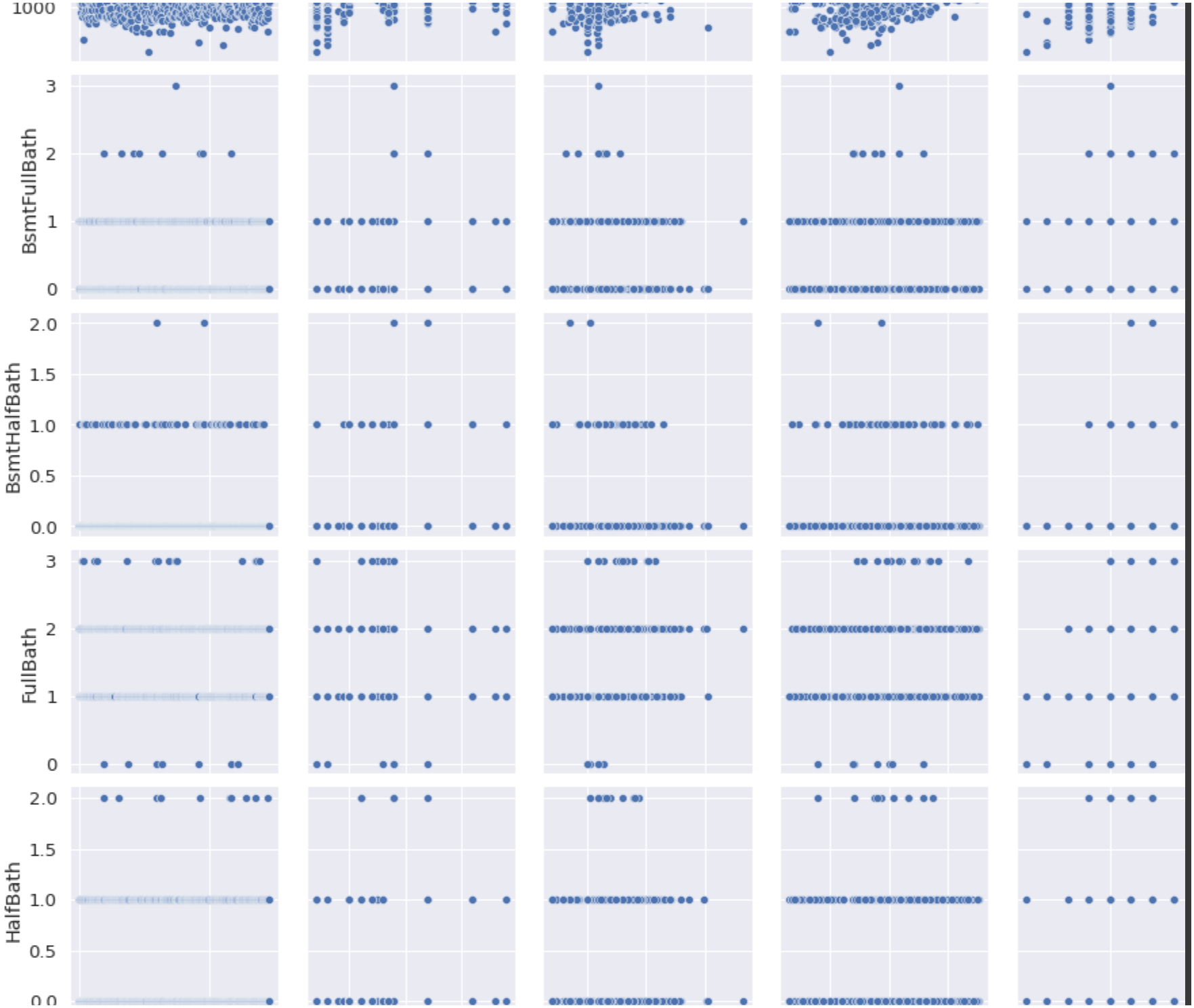
```
<seaborn.axisgrid.PairGrid at 0x7fbd2da3a450>
```



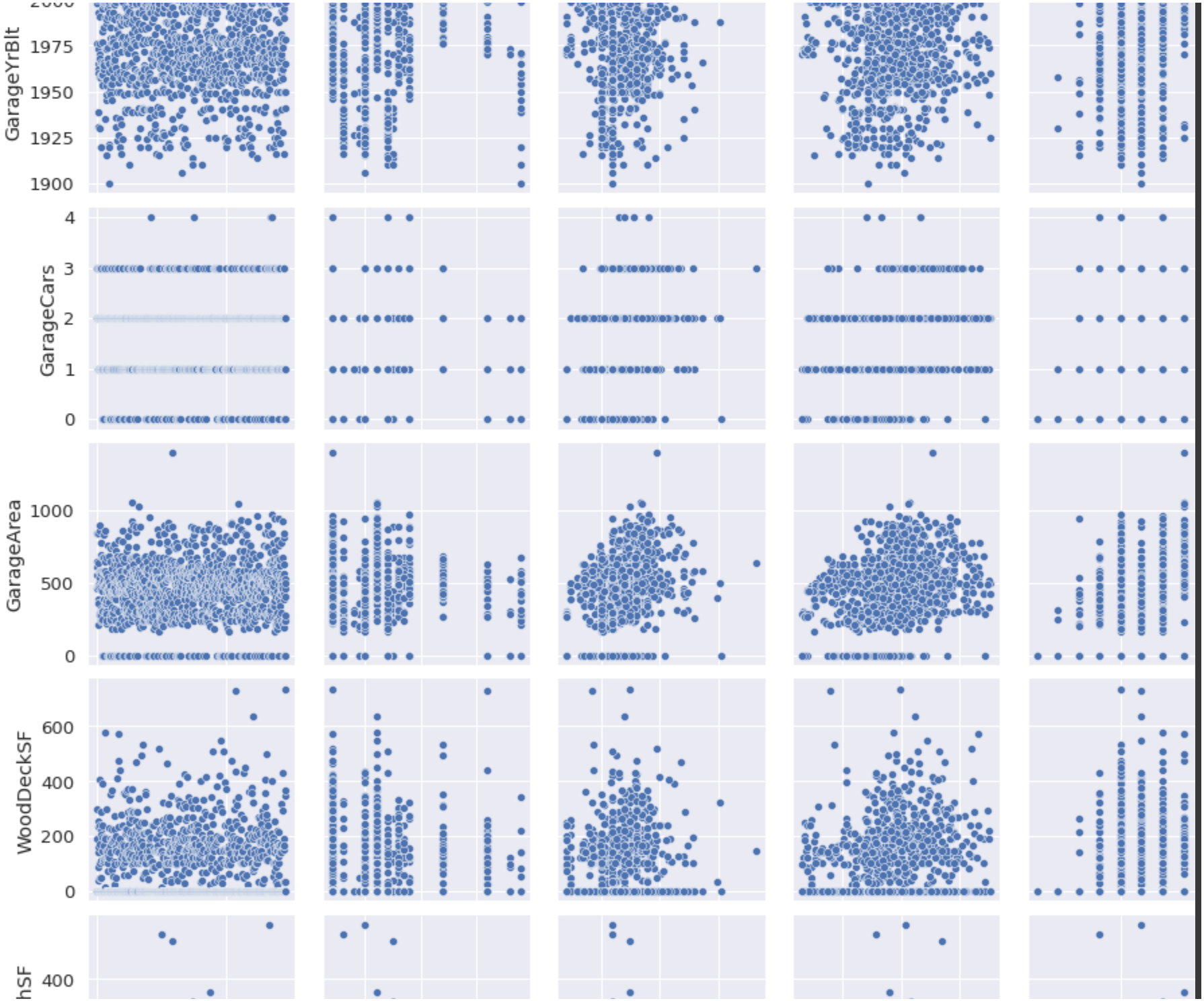

OverallQual
OverallCond
YearBuilt
YearRemodAdd
10
8
6
4
2
2000
1950
1900
2000
1980
1960
1500

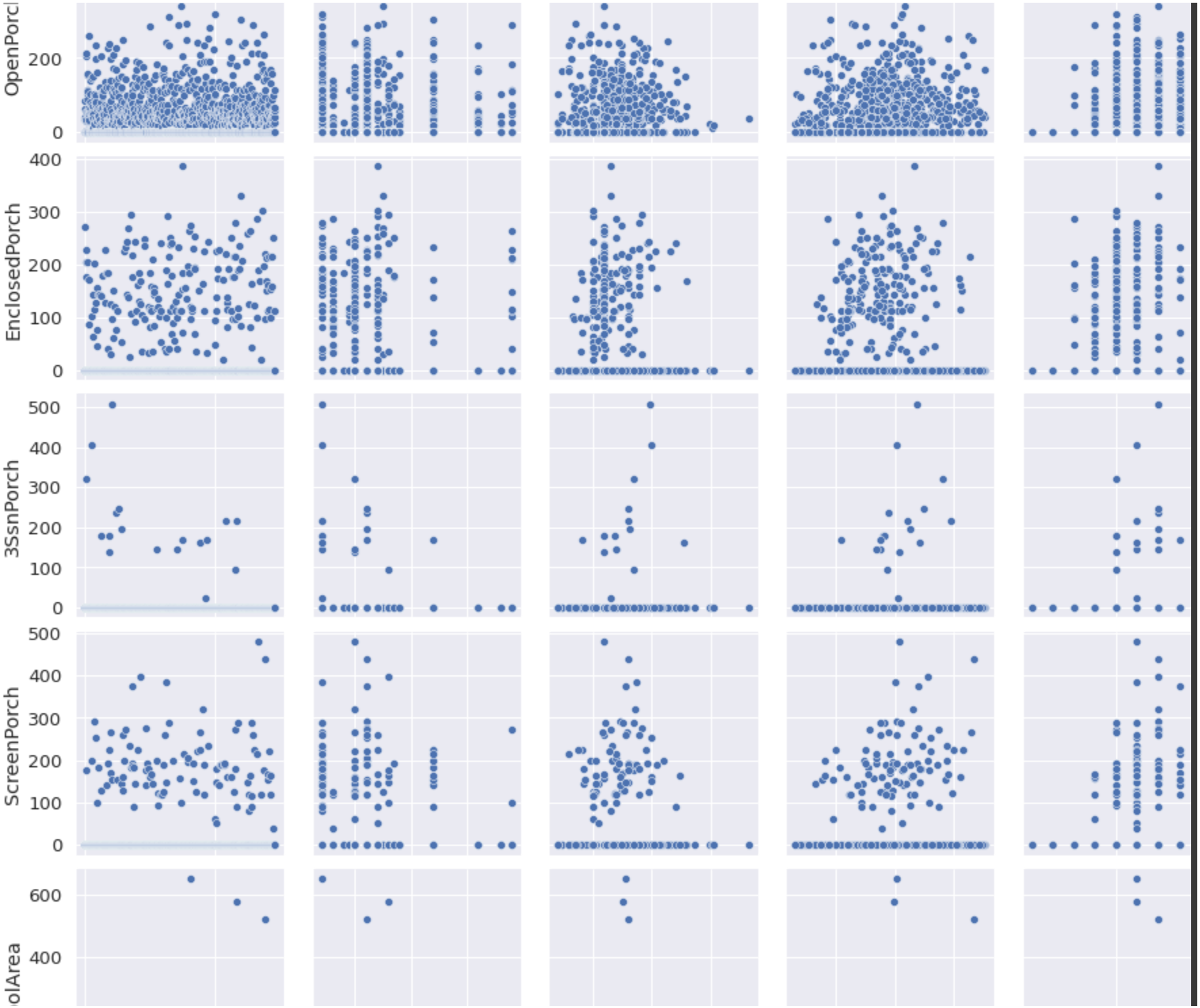

MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
smtSF
0
500
1000
1500
2000
3000

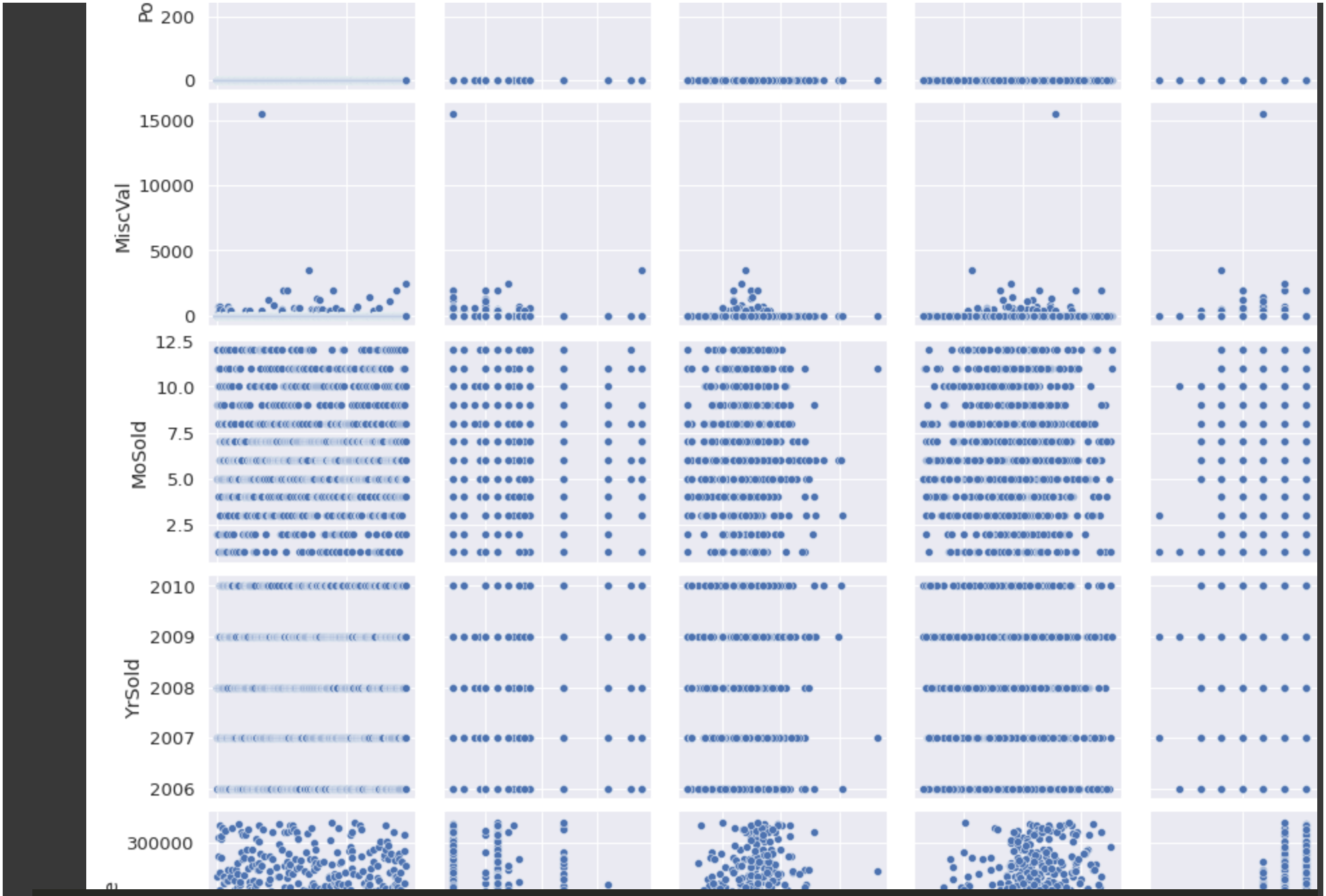

TotalB
1000
0
3000
2500
2000
1stFlrSF
1500
1000
500
1500
1000
2ndFlrSF
500
0
500
400
300
LowQualFinSF
200
100
0
3000
2000
GrLivArea


1000
BsmtFullBath
3
2
1
0
BsmtHalfBath
2.0
1.5
1.0
0.5
0.0
FullBath
3
2
1
0
HalfBath
2.0
1.5
1.0
0.5
0.0

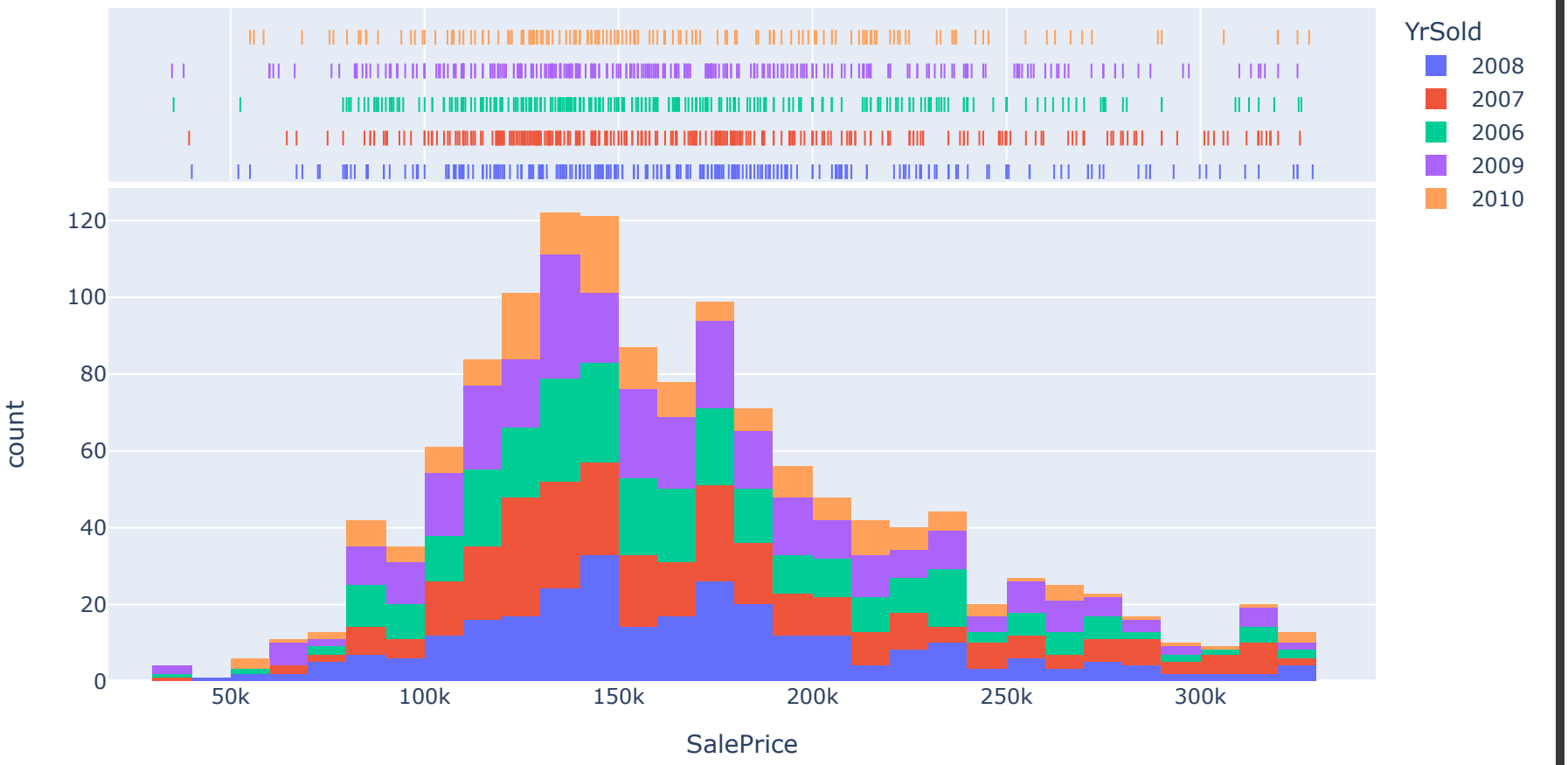

BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces


GarageYrBlt
1975
1950
1925
1900
GarageCars
4
3
2
1
0
GarageArea
1000
500
0
WoodDeckSF
600
400
200
0
400

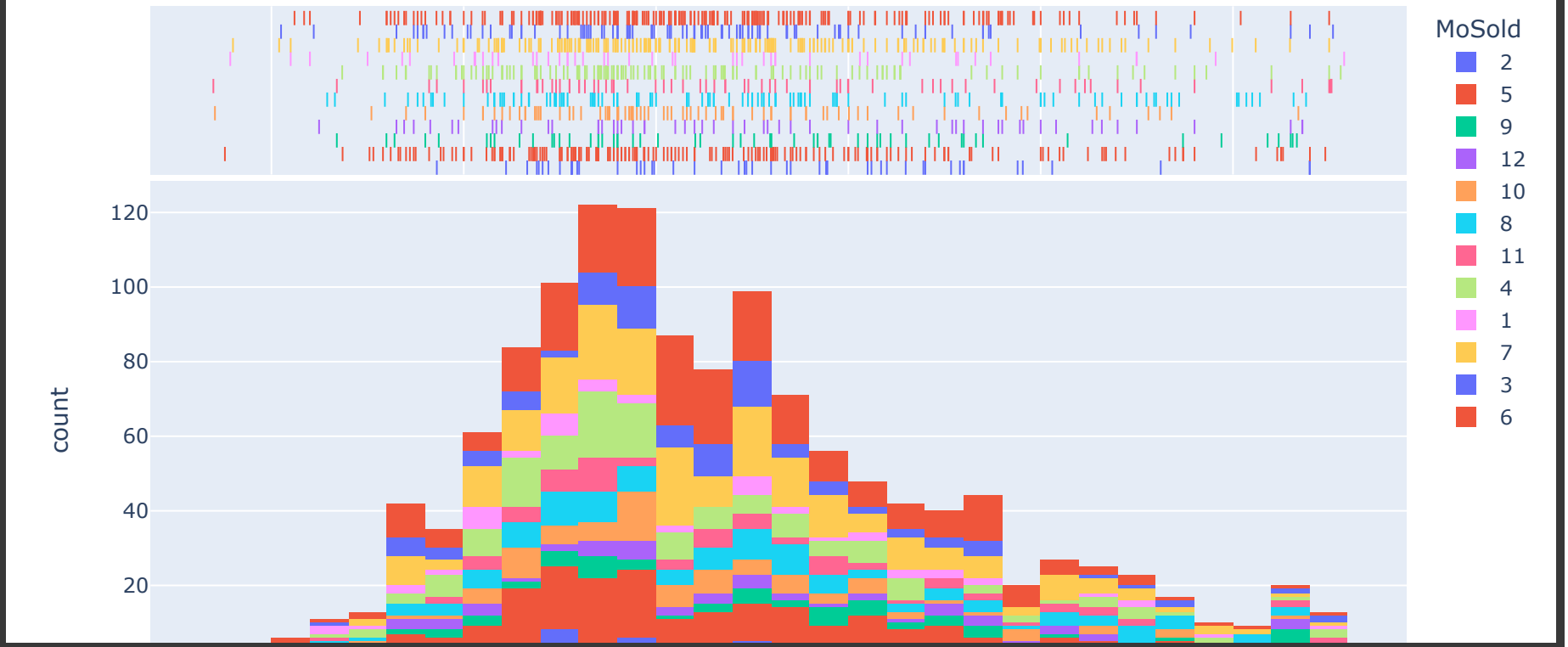

OpenPorch
EnclosedPorch
3SsnPorch
ScreenPorch
olArea




```
import plotly.express as px
fig = px.histogram(clean_train, x="SalePrice", color="YrSold", marginal='rug',hover_data=clean_train.columns)
fig.show()
```




```
# import plotly.express as px
fig = px.histogram(clean_train, x="SalePrice", color="MoSold", marginal='rug',hover_data=clean_train.columns)
fig.show()
```



We can see that the count of houses sold was on Month 6 and the most year houses sold was on 2010

```
clean_train.columns
```

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
       'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle',
       'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle',
       'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
       'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
       'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQC',
       'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd',
```

```
       'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'GarageYrBlt',
       'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond',
       'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
       'ScreenPorch', 'PoolArea', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice', 'year_diff'],
      dtype='object')
```

```
# Now let's drop YearBuilt and YearRemodAdd since we got a column to express if they remod or not
clean_train.drop(['YearBuilt', 'YearRemodAdd'], axis=1, inplace = True)
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/frame.py:4913: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-
```

```
## After that we can calculate the percentage of Bsmt Finished
clean_train['finish_percentage_of_Bsmt'] = (clean_train['BsmtFinSF1'] + clean_train['BsmtFinSF2'])/ clean_train['TotalBsmtSF
clean_train['Unfinished_percentage_of_Bsmt'] = clean_train['BsmtUnfSF']/clean_train['TotalBsmtSF']
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-
```

```
clean_train.drop(['BsmtUnfSF', 'BsmtFinSF1', 'BsmtUnfSF'], axis=1, inplace = True)
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/frame.py:4913: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-
```

```
clean_train.columns
```

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

```
clean_train.shape
```

```
(1330, 77)
```

Is there's any relation between those two categorical values and which affects on SalePrice (condqual and overallqual)?

- **Does it really mean overall quality have an overall good condition?**

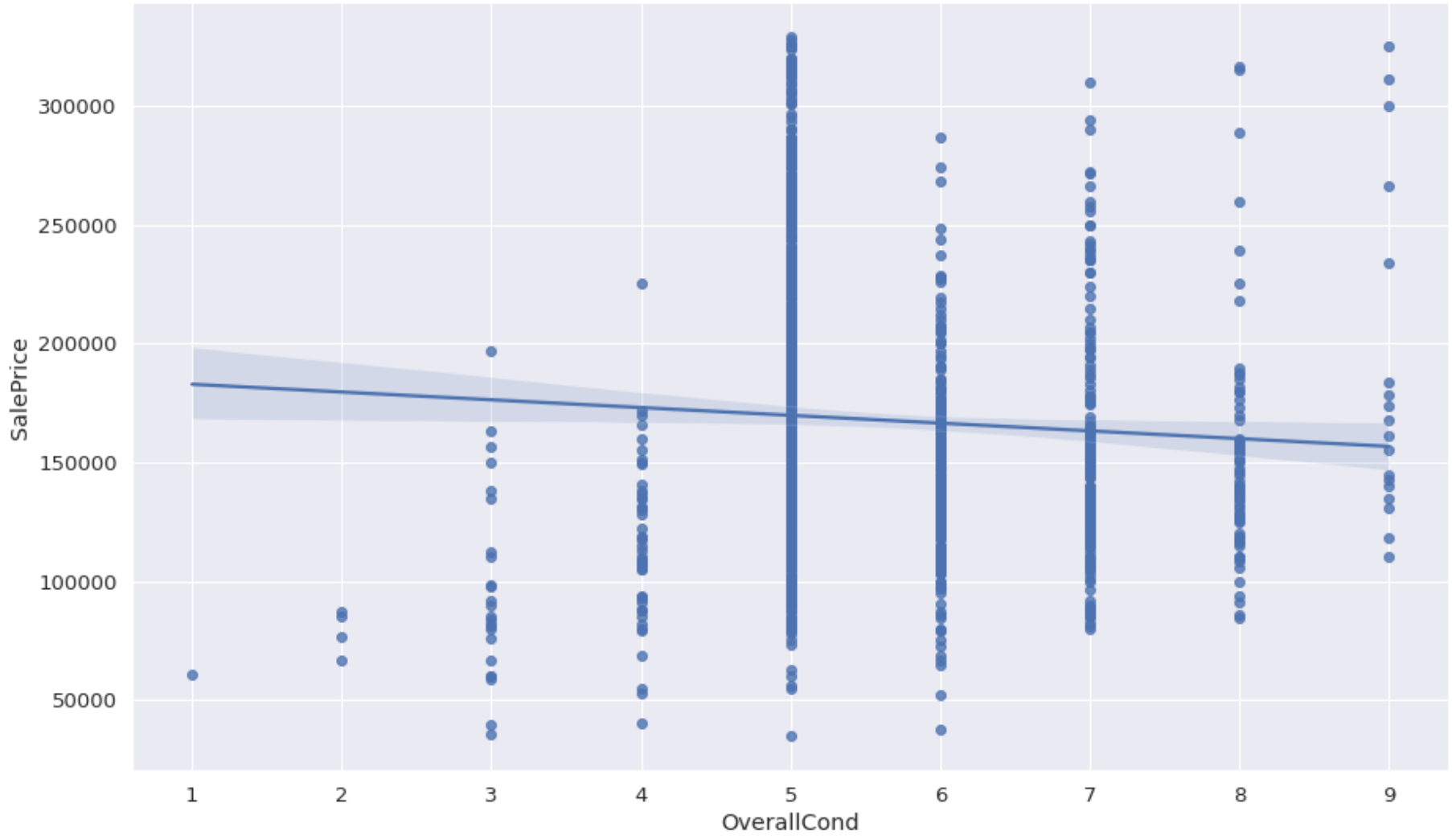
```
sns.regplot(x=clean_train["OverallQual"], y=clean_train["OverallCond"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd2d9ac490>
```

- Does it really mean that have an overall very good condition will have most sales?

```
sns.regplot(x=clean_train["OverallCond"], y=clean_train["SalePrice"])
```

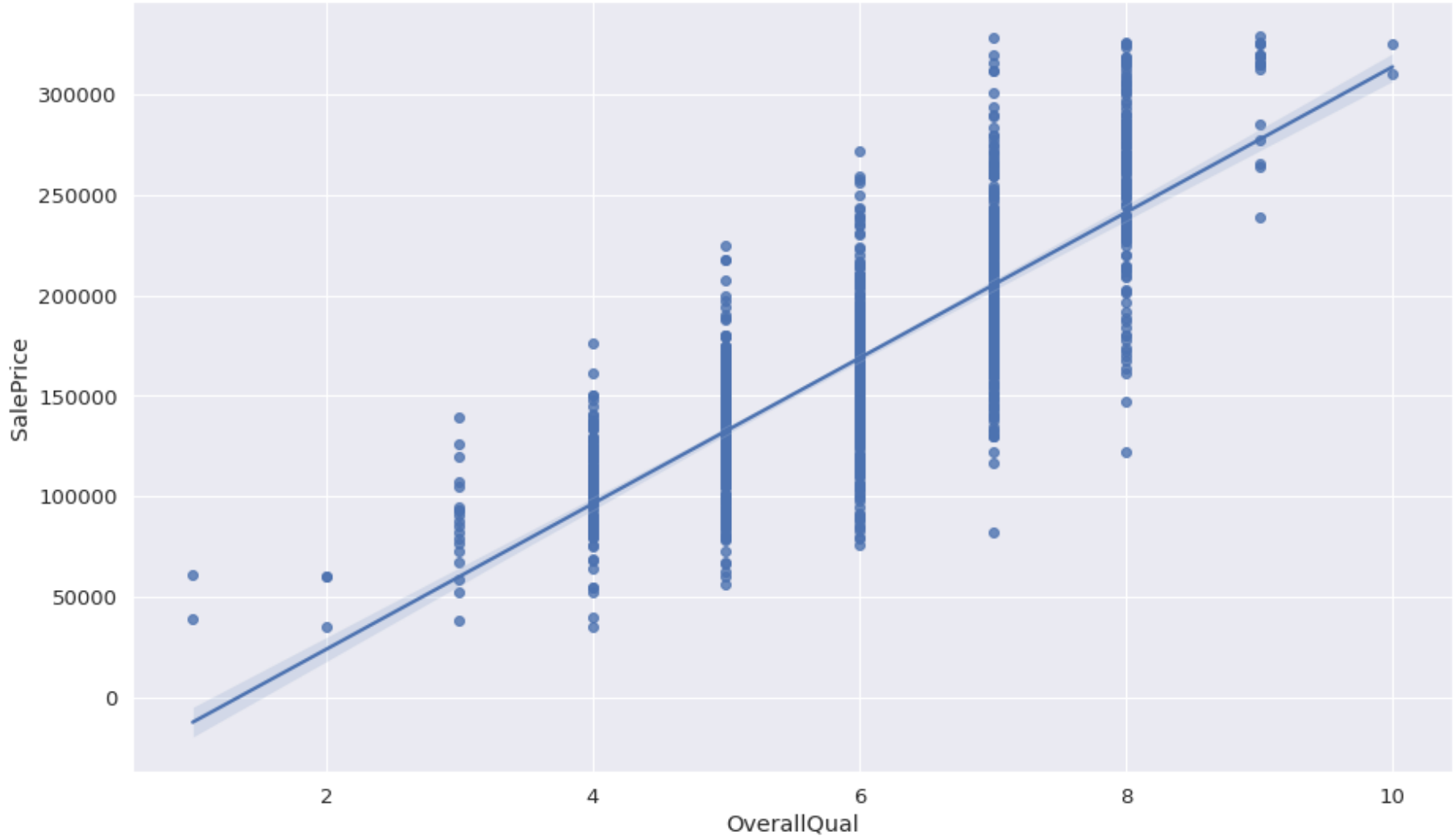
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd09613dd0>
```



- Does it really Saleprice will be sold at high prices depending on an overallquality?

```
sns.regplot(x=clean_train["OverallQual"], y=clean_train["SalePrice"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd096397d0>
```



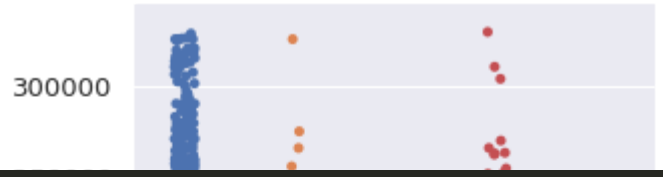

```
clean_train.columns
```

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

Is there any specific physical location that make our saleprice high?

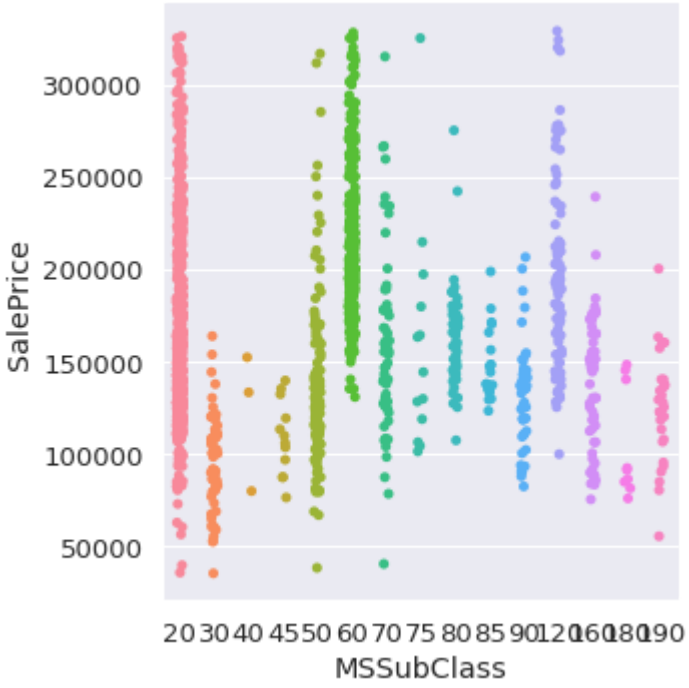
```
sns.catplot(x="MSZoning", y="SalePrice", data=clean_train)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fbd092ce090>
```



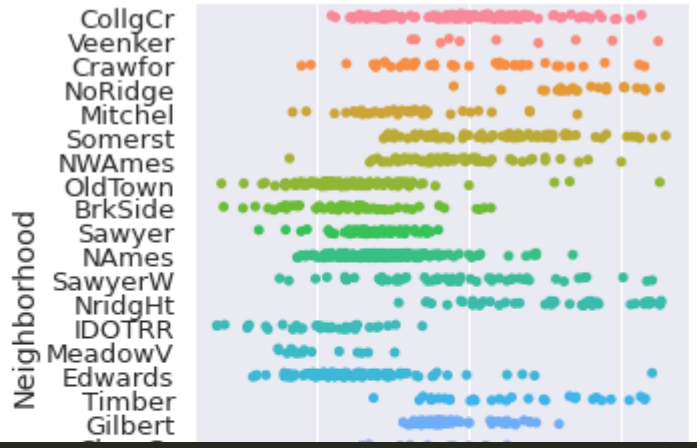

```
sns.catplot(x="MSSubClass", y="SalePrice", data=clean_train)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fbd0967d0d0>
```



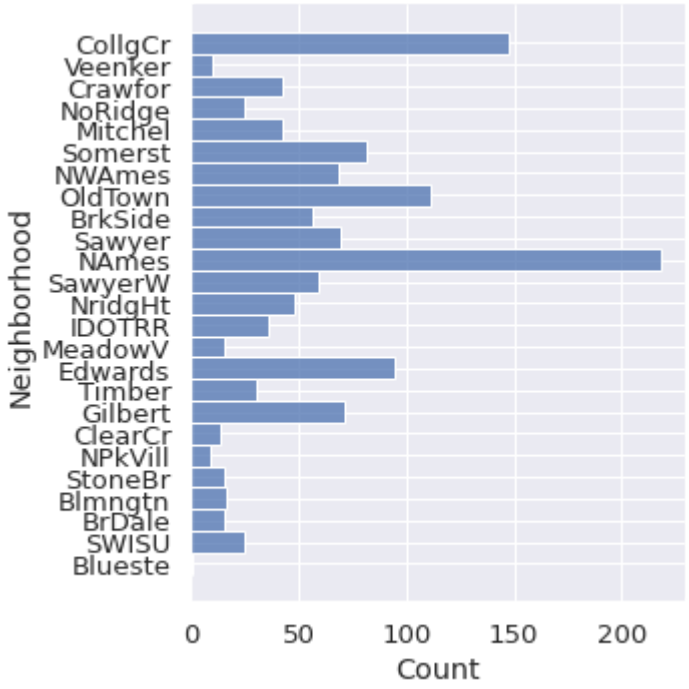

```
sns.catplot(x="SalePrice", y="Neighborhood", data=clean_train)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fbd095c7a90>
```



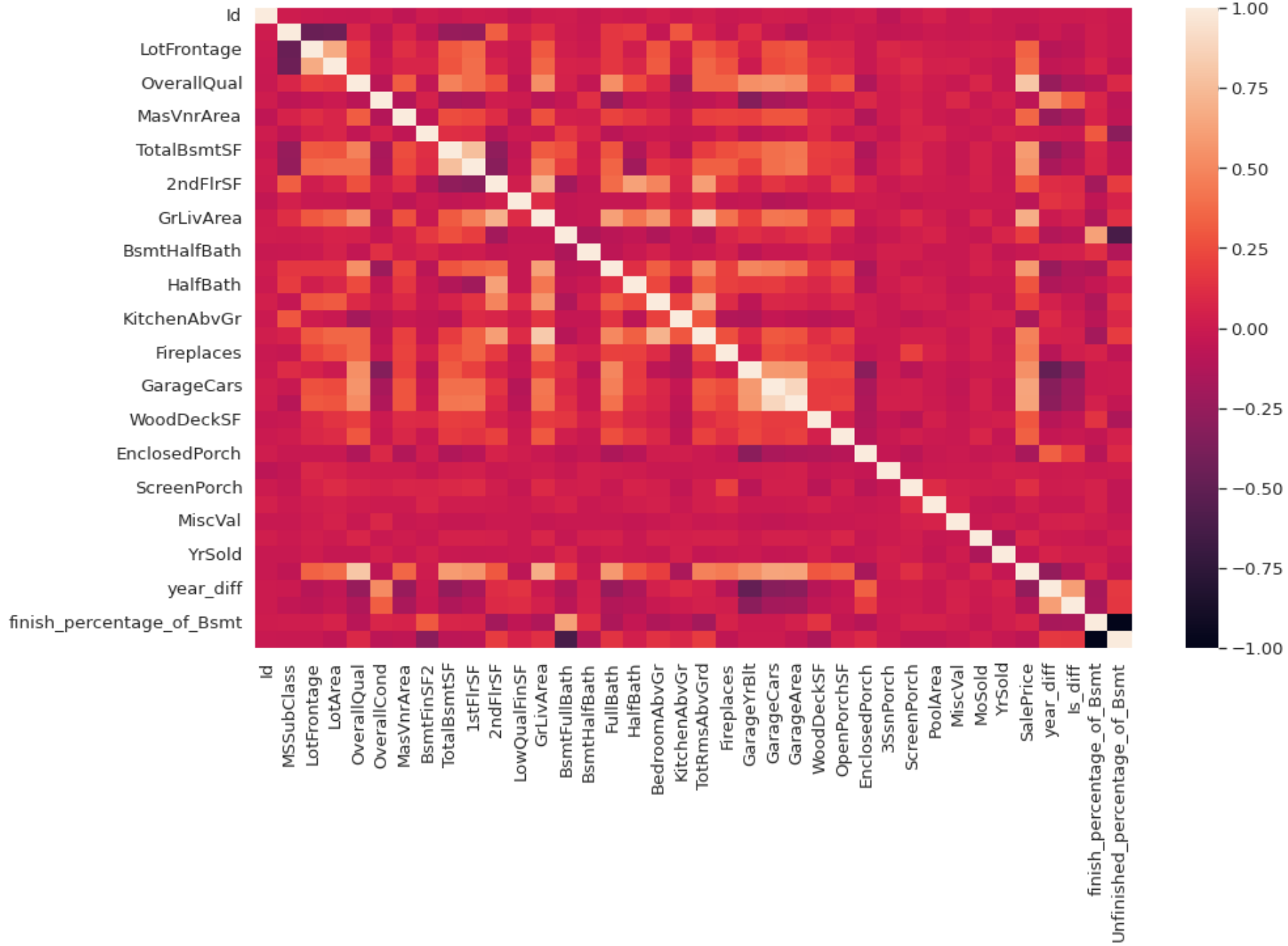

```
sns.displot(y = 'Neighborhood', data = clean_train)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fbd09561d10>
```




```
sns.heatmap(clean_train.corr())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd095032d0>
```



```
clean_train.groupby('Neighborhood').describe()['SalePrice']
```

Neighborhood	count	mean	std	min	25%	50%	75%	max
Blmngtn	17.0	194870.882353	30393.229219	159895.0	174000.0	191000.0	213490.0	264561.0
Blueste	1.0	151000.000000	NaN	151000.0	151000.0	151000.0	151000.0	151000.0
BrDale	16.0	104493.750000	14330.176493	83000.0	91000.0	106000.0	118000.0	125000.0

```
clean_train.groupby('MSSubClass').describe()['SalePrice']
```

	count	mean	std	min	25%	50%	75%	max

```
clean_train.groupby('MSZoning').describe()['SalePrice']
```

	count	mean	std	min	25%	50%	75%	max
MSZoning								
C (all)	9.0	73808.888889	35759.614502	34900.0	40000.00	68400.0	102776.0	133900.0
FV	62.0	207423.967742	43709.982987	144152.0	173799.75	198450.0	240500.0	328900.0
RH	16.0	131558.375000	35714.118435	76000.0	106150.00	136500.0	148608.5	200000.0
RL	1030.0	176102.956311	56346.606483	39300.0	135000.00	167500.0	210000.0	328000.0
RM	213.0	122866.521127	36685.889631	37900.0	100000.00	120000.0	140000.0	325000.0

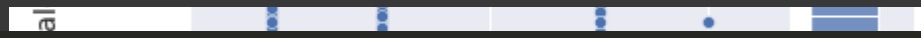
```
sns.jointplot(x= 'MSZoning', y = 'SalePrice', data = clean_train)
```

```
<seaborn.axisgrid.JointGrid at 0x7fbd0912b090>
```

- RL is the safest place where we can find all types of saleprice from low to high
- FV is a bit more risky with highest SalePrice

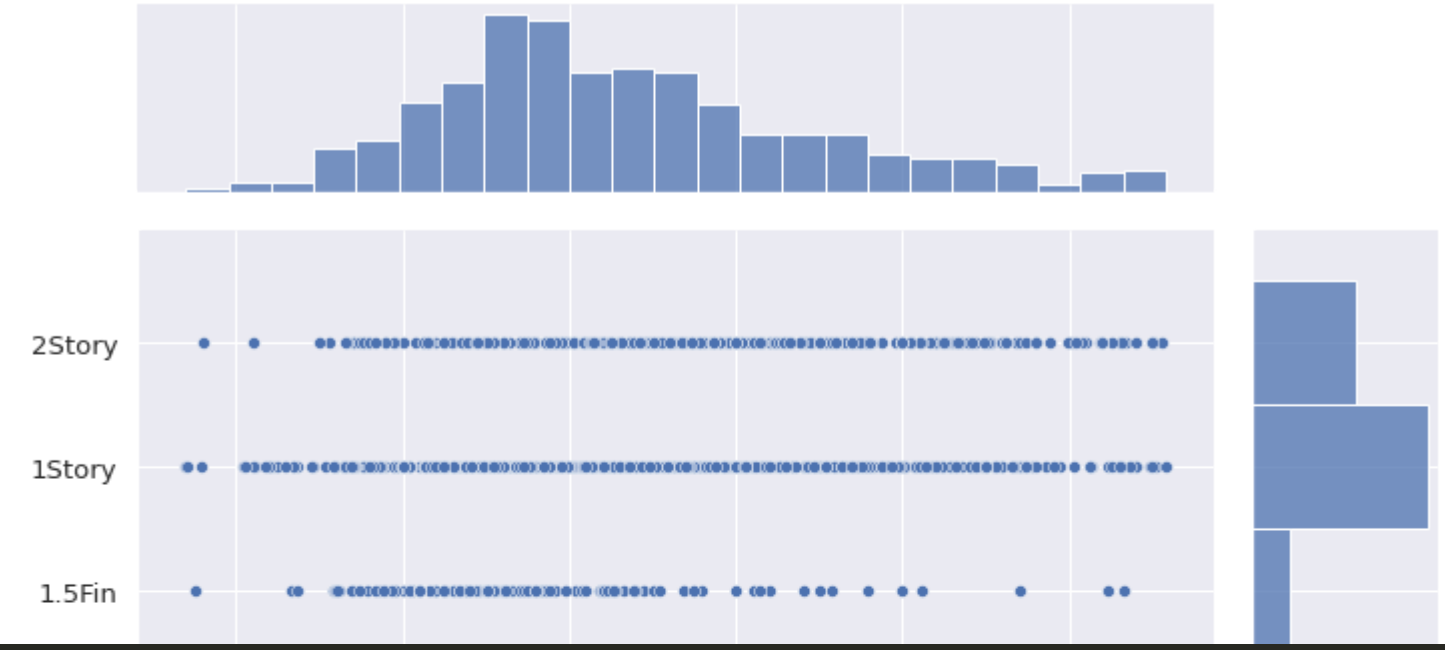
BUT

What's my insight? We have like +1k row that containing RL so we have a good info about all the prices included in that place While we have much more less data in FV... So Is that insight for real we may need more data



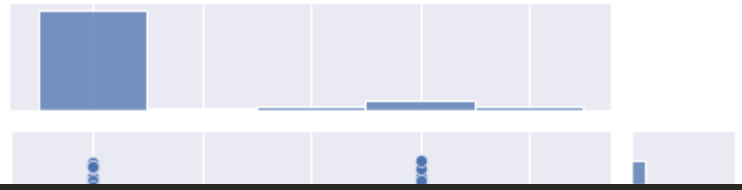
```
# fig, ax = plt.figure(figsize=(20, 10))
sns.jointplot(x= 'SalePrice', y = 'HouseStyle', data = clean_train, height = 10)
```

```
<seaborn.axisgrid.JointGrid at 0x7fbd0916b3d0>
```



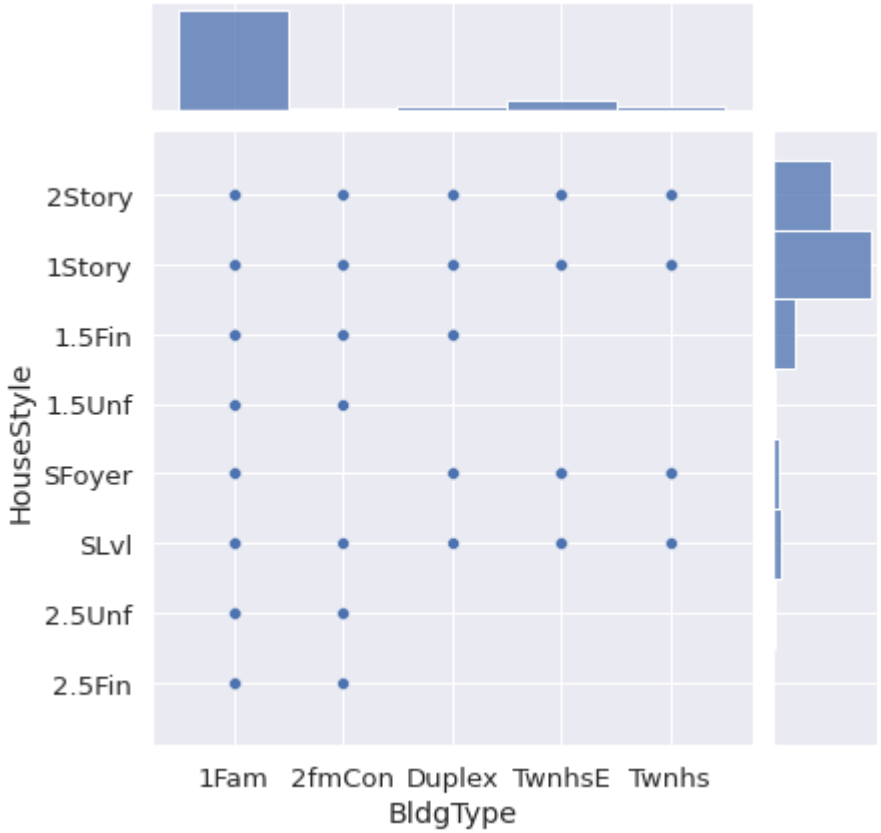

```
sns.jointplot(x= 'BldgType', y = 'SalePrice', data = clean_train)
```

```
<seaborn.axisgrid.JointGrid at 0x7fbd09083790>
```



```
sns.jointplot(x= 'BldgType', y = 'HouseStyle', data = clean_train)
```

```
<seaborn.axisgrid.JointGrid at 0x7fbd08d1ead0>
```




```
clean_train['Condition1'].value_counts()
```

```
Norm      1147
Feedr       77
Artery      44
```

```
RRAn        23
PosN        16
RRAe        11
RRNn         5
PosA         5
RRNe         2
Name: Condition1, dtype: int64
```

```
clean_train['Condition2'].value_counts()
```

```
Norm      1318
Feedr        6
Artery       2
RRNn         2
PosA         1
RRAn         1
Name: Condition2, dtype: int64
```

```
clean_train['BldgType'].value_counts()
```

```
1Fam      1099
TwnhsE     110
Duplex      50
Twnhs       43
2fmCon      28
Name: BldgType, dtype: int64
```

```
clean_train['Utilities'].value_counts()
```

```
AllPub    1329
NoSeWa       1
Name: Utilities, dtype: int64
```

```
clean_train['LotShape'].value_counts()
```

```
Reg    870
IR1    429
IR2     26
```

```
IR3      5
Name: LotShape, dtype: int64
```

```
clean_train['LotConfig'].value_counts()
```

```
Inside     970
Corner     242
CulDSac     72
FR2         42
FR3          4
Name: LotConfig, dtype: int64
```

```
clean_train['LandContour'].value_counts()
```

```
Lvl    1220
Bnk      56
HLS      34
Low      20
Name: LandContour, dtype: int64
```

```
clean_train['LandSlope'].value_counts()
```

```
Gtl    1276
Mod      51
Sev       3
Name: LandSlope, dtype: int64
```

```
clean_train['PoolArea'].value_counts()
```

```
0      1327
648       1
576       1
519       1
Name: PoolArea, dtype: int64
```

```
clean_train.columns
```

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

```
clean_train['MSZoning'] = clean_train['MSZoning'].apply(lambda x: x if ((x== 'RL') | (x == 'RM')) else 'Other')
clean_train['Condition1'] = clean_train['Condition1'].apply(lambda x:"Norm" if x== 'Norm' else "Other")
clean_train['Condition2'] = clean_train['Condition1'].apply(lambda x:"Norm" if x== 'Norm' else "Other")
clean_train['BldgType'] = clean_train['BldgType'].apply(lambda x:"1Fam" if x== '1Fam' else "Other")
clean_train['LotShape'] = clean_train['LotShape'].apply(lambda x: x if ((x== 'Reg') | (x == 'IR1')) else 'Other')
clean_train['LotConfig'] = clean_train['LotConfig'].apply(lambda x: x if ((x== 'Inside') | (x == 'corner')) else 'Other')
clean_train['LandContour'] = clean_train['LandContour'].apply(lambda x:"Lvl" if x== 'Lvl' else "Other")
clean_train['LandSlope'] = clean_train['LandSlope'].apply(lambda x:"Gtl" if x== 'Gtl' else "Other")
clean_train['PoolArea'] = clean_train['PoolArea'].apply(lambda x:0 if x== 0 else 1)
```

```
      See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin

      /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: SettingWithCopyWarning:


      A value is trying to be set on a copy of a slice from a DataFrame.
      Try using .loc[row_indexer,col_indexer] = value instead

      See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin

      /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead


See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:8: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:9: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin
```

```
clean_train['RoofStyle'].value_counts()
```

```
Gable      1076
Hip         231
Gambrel      11
Mansard       7
Flat          5
Name: RoofStyle, dtype: int64
```

```
clean_train['ExterQual'].value_counts()
```

```
TA    857
Gd    440
Ex     20
Fa     13
Name: ExterQual, dtype: int64
```

```
clean_train['BsmtCond'].value_counts()
```

```
TA    1190
Gd      57
Fa      45
Po       2
Name: BsmtCond, dtype: int64
```

```
clean_train['BsmtQual'].value_counts()
```

```
TA    618
Gd    571
Ex     70
Fa     35
Name: BsmtQual, dtype: int64
```

```
clean_train['SaleType'].value_counts()
```

```
WD       1177
New        86
COD        41
ConLD       8
ConLw       5
ConLI       4
CWD         4
Oth         3
Con         2
Name: SaleType, dtype: int64
```

```
clean_train['RoofStyle'] = clean_train['RoofStyle'].apply(lambda x: x if ((x== 'Gable') | (x == 'Hip')) else "Other")
clean_train['ExterQual'] = clean_train['ExterQual'].apply(lambda x: x if ((x== 'TA') | (x == 'Gd')) else "Other")
clean_train['BsmtCond'] = clean_train['BsmtCond'].apply(lambda x:"TA" if x== 'TA' else "Other")
clean_train['BsmtQual'] = clean_train['BsmtQual'].apply(lambda x: x if ((x== 'TA') | (x == 'Gd')) else "Other")
clean_train['SaleType'] = clean_train['SaleType'].apply(lambda x:"WD" if x== 'WD' else "Other")
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-
```

```
clean_train['SaleCondition'].value_counts()
```

```
Normal     1114
Abnorml      95
Partial      88
Family       20
Alloca        9
AdjLand       4
Name: SaleCondition, dtype: int64
```

```
clean_train['FireplaceQu'].value_counts()
```

```
Gd    310
TA    279
Fa     32
Po     19
Ex     12
Name: FireplaceQu, dtype: int64
```

```
clean_train['SaleCondition'] = clean_train['SaleCondition'].apply(lambda x:"Normal" if x== 'Normal' else "Other")
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-
```

```
clean_train.drop(['FireplaceQu'], axis=1, inplace = True)
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/frame.py:4913: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-
```

```
clean_train.info()
```

```
 19  KitchenAbvGr                1330 non-null   object
 20  Exterior1st                 1330 non-null   object
 21  Exterior2nd                 1330 non-null   object
 22  MasVnrType                  1324 non-null   object
 23  MasVnrArea                  1324 non-null   float64
 24  ExterQual                   1330 non-null   object
 25  ExterCond                   1330 non-null   object
 26  Foundation                  1330 non-null   object
 27  BsmtQual                    1330 non-null   object
 28  BsmtCond                    1330 non-null   object
 29  BsmtExposure                1293 non-null   object
 30  BsmtFinType1                1294 non-null   object
 31  BsmtFinType2                1293 non-null   object
 32  BsmtFinSF2                  1330 non-null   int64
 33  TotalBsmtSF                 1330 non-null   int64
 34  Heating                     1330 non-null   object
 35  HeatingQC                   1330 non-null   object
 36  CentralAir                  1330 non-null   object
 37  Electrical                  1330 non-null   object
```

```
 37  Electrical                  1329 non-null   object
 38  1stFlrSF                    1330 non-null   int64
 39  2ndFlrSF                    1330 non-null   int64
 40  LowQualFinSF                1330 non-null   int64
 41  GrLivArea                   1330 non-null   int64
 42  BsmtFullBath                1330 non-null   int64
 43  BsmtHalfBath                1330 non-null   int64
 44  FullBath                    1330 non-null   int64
 45  HalfBath                    1330 non-null   int64
 46  BedroomAbvGr                1330 non-null   int64
 47  KitchenAbvGr                1330 non-null   int64
 48  KitchenQual                 1330 non-null   object
 49  TotRmsAbvGrd                1330 non-null   int64
 50  Functional                  1330 non-null   object
 51  Fireplaces                  1330 non-null   int64
 52  GarageType                  1250 non-null   object
 53  GarageYrBlt                 1250 non-null   float64
 54  GarageFinish                1250 non-null   object
 55  GarageCars                  1330 non-null   int64
 56  GarageArea                  1330 non-null   int64
 57  GarageQual                  1250 non-null   object
 58  GarageCond                  1250 non-null   object
 59  PavedDrive                  1330 non-null   object
 60  WoodDeckSF                  1330 non-null   int64
 61  OpenPorchSF                 1330 non-null   int64
 62  EnclosedPorch               1330 non-null   int64
 63  3SsnPorch                   1330 non-null   int64
 64  ScreenPorch                 1330 non-null   int64
 65  PoolArea                    1330 non-null   int64
 66  MiscVal                     1330 non-null   int64
 67  MoSold                      1330 non-null   int64
 68  YrSold                      1330 non-null   int64
 69  SaleType                    1330 non-null   object
 70  SaleCondition               1330 non-null   object
 71  SalePrice                   1330 non-null   int64
 72  year_diff                   1330 non-null   int64
 73  Is_diff                     1330 non-null   int64
 74  finish_percentage_of_Bsmt   1294 non-null   float64
 75  Unfinished_percentage_of_Bsmt  1294 non-null   float64
dtypes: float64(5), int64(33), object(38)
memory usage: 832.4+ KB
```

```
clean_train['LotFrontage'].dtypes
```

```
dtype('float64')
```

```
from sklearn.impute import KNNImputer
imputer = KNNImputer(n_neighbors = 2)
df_filled = imputer.fit_transform(clean_train[['LotFrontage']])
df_filled
```

```
array([[65.],
       [80.],
       [68.],
       ...,
       [66.],
       [68.],
       [75.]])
```

```
df_filled.shape
```

```
(1330, 1)
```

```
df_filled= pd.DataFrame(df_filled)
```

```
df_filled.head()
```

	0
0	65.0
1	80.0
2	68.0
3	60.0
4	84.0

```
df_filled[0]
```

```
0       65.0
1       80.0
2       68.0
3       60.0
4       84.0
        ...
1325    62.0
1326    85.0
1327    66.0
1328    68.0
1329    75.0
Name: 0, Length: 1330, dtype: float64
```

```
# entry = df_filled[0]
combined_clean_train = pd.concat([clean_train, df_filled], axis=1)
combined_clean_train.head()
```

rchSF	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea	MiscVal	MoSold	YrSold	SaleType	SaleCondition	SalePrice	yea
61.0	0.0	0.0	0.0	0.0	0.0	2.0	2008.0	WD	Normal	208500.0	
0.0	0.0	0.0	0.0	0.0	0.0	5.0	2007.0	WD	Normal	181500.0	
42.0	0.0	0.0	0.0	0.0	0.0	9.0	2008.0	WD	Normal	223500.0	
35.0	272.0	0.0	0.0	0.0	0.0	2.0	2006.0	WD	Other	140000.0	
84.0	0.0	0.0	0.0	0.0	0.0	12.0	2008.0	WD	Normal	250000.0	

```
## now we will rename 0 column into LotFrontage and drop old one
combined_clean_train.drop(['LotFrontage'], axis=1, inplace = True)
```

```
combined_clean_train.rename(columns={0: 'LotFrontage'}, inplace = True)
```

```
combined_clean_train['LotFrontage'].isna().sum()
```

```
118
```

```
combined_clean_train.dropna(inplace=True)
```

```
combined_clean_train['LotFrontage'].isna().sum()
```

```
0
```

```
combined_clean_train.shape
```

```
(1102, 76)
```

```
combined_clean_train.info()
```

```
 20  Exterior2nd                  1102 non-null   object
 21  MasVnrType                   1102 non-null   object
 22  MasVnrArea                   1102 non-null   float64
 23  ExterQual                    1102 non-null   object
 24  ExterCond                    1102 non-null   object
 25  Foundation                   1102 non-null   object
 26  BsmtQual                     1102 non-null   object
 27  BsmtCond                     1102 non-null   object
 28  BsmtExposure                 1102 non-null   object
 29  BsmtFinType1                 1102 non-null   object
 30  BsmtFinType2                 1102 non-null   object
 31  BsmtFinSF2                   1102 non-null   float64
 32  TotalBsmtSF                  1102 non-null   float64
 33  Heating                      1102 non-null   object
 34  HeatingQC                    1102 non-null   object
 35  CentralAir                   1102 non-null   object
 36  Electrical                   1102 non-null   object
 37  1stFlrSF                     1102 non-null   float64
 38  2ndFlrSF                     1102 non-null   float64
 39  LowQualFinSF                 1102 non-null   float64
 40  GrLivArea                    1102 non-null   float64
 41  BsmtFullBath                 1102 non-null   float64
```

```
 42  BsmtHalfBath                  1102 non-null   float64
 43  FullBath                      1102 non-null   float64
 44  HalfBath                      1102 non-null   float64
 45  BedroomAbvGr                  1102 non-null   float64
 46  KitchenAbvGr                  1102 non-null   float64
 47  KitchenQual                   1102 non-null   object
 48  TotRmsAbvGrd                  1102 non-null   float64
 49  Functional                    1102 non-null   object
 50  Fireplaces                    1102 non-null   float64
 51  GarageType                    1102 non-null   object
 52  GarageYrBlt                   1102 non-null   float64
 53  GarageFinish                  1102 non-null   object
 54  GarageCars                    1102 non-null   float64
 55  GarageArea                    1102 non-null   float64
 56  GarageQual                    1102 non-null   object
 57  GarageCond                    1102 non-null   object
 58  PavedDrive                    1102 non-null   object
 59  WoodDeckSF                    1102 non-null   float64
 60  OpenPorchSF                   1102 non-null   float64
 61  EnclosedPorch                 1102 non-null   float64
 62  3SsnPorch                     1102 non-null   float64
 63  ScreenPorch                   1102 non-null   float64
 64  PoolArea                      1102 non-null   float64
 65  MiscVal                       1102 non-null   float64
 66  MoSold                        1102 non-null   float64
 67  YrSold                        1102 non-null   float64
 68  SaleType                      1102 non-null   object
 69  SaleCondition                 1102 non-null   object
 70  SalePrice                     1102 non-null   float64
 71  year_diff                     1102 non-null   float64
 72  Is_diff                       1102 non-null   float64
 73  finish_percentage_of_Bsmt     1102 non-null   float64
 74  Unfinished_percentage_of_Bsmt 1102 non-null   float64
 75  LotFrontage                   1102 non-null   float64
dtypes: float64(38), object(38)
memory usage: 662.9+ KB
```

```
combined_clean_train["Condition_all"]= combined_clean_train[["Condition1","Condition2"]].apply(lambda x: "Norm" if (x.Condit
combined_clean_train["Condition_all"]
```

```
0        Norm
1       Other
```

```
2        Norm
3        Norm
4        Norm
        ...
1322     Norm
1324     Norm
1327     Norm
1328     Norm
1329     Norm
Name: Condition_all, Length: 1102, dtype: object
```

```
combined_clean_train[(combined_clean_train.Condition1 == 'Norm') & (combined_clean_train.Condition2 != 'Norm')]
```

Id	MSSubClass	MSZoning	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Cond

```
combined_clean_train[(combined_clean_train.Condition1 != 'Norm') & (combined_clean_train.Condition2 == 'Norm')]
```

Id	MSSubClass	MSZoning	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Cond

```
combined_clean_train["Condition_all"].value_counts()
```

```
Norm     955
Other    147
Name: Condition_all, dtype: int64
```

```
combined_clean_train.drop(['Condition1', 'Condition2'], axis=1, inplace = True)
combined_clean_train.columns
```

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotArea', 'Street', 'LotShape',
```

```
       'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood',
       'BldgType', 'HouseStyle', 'OverallQual', 'OverallCond', 'RoofStyle',
       'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
       'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
       'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'BsmtFinSF2',
       'TotalBsmtSF', 'Heating', 'HeatingQC', 'CentralAir', 'Electrical',
       '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath',
       'BsmtHalfBath', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr',
       'KitchenQual', 'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
       'MoSold', 'YrSold', 'SaleType', 'SaleCondition', 'SalePrice',
       'year_diff', 'Is_diff', 'finish_percentage_of_Bsmt',
       'Unfinished_percentage_of_Bsmt', 'LotFrontage', 'Condition_all'],
      dtype='object')
```

```
combined_clean_train.shape
```

```
(1102, 75)
```

What we are doing is trying to minimize categorical values for each column and replace values then we will apply get_dummies on dataset and then apply train test split and see what's coming after that

We won't use imblearn as we are predicting price not categorical value we won't also stratify y as we said we are not predicting categorical values as y is SalePrice

```
combined_clean_train["LandContour"].value_counts()
```

```
Lvl      1019
Other      83
Name: LandContour, dtype: int64
```

```
combined_clean_train["Utilities"].value_counts()
```

```
AllPub    1101
NoSeWa       1
```

```
Name: Utilities, dtype: int64
```

```
combined_clean_train["LotConfig"].value_counts()
```

```
Inside    792
Other     310
Name: LotConfig, dtype: int64
```

```
combined_clean_train["LotShape"].value_counts()
```

```
Reg      697
IR1      377
Other     28
Name: LotShape, dtype: int64
```

```
combined_clean_train["Street"].value_counts()
```

```
Pave    1100
Grvl       2
Name: Street, dtype: int64
```

```
combined_clean_train["LandSlope"].value_counts()
```

```
Gtl      1058
Other      44
Name: LandSlope, dtype: int64
```

```
combined_clean_train["RoofStyle"].value_counts()
```

```
Gable    881
Hip      203
Other     18
Name: RoofStyle, dtype: int64
```

```
combined_clean_train["RoofMatl"].value_counts()
```

```
CompShg    1092
WdShake       4
Tar&Grv       3
WdShngl       2
Roll          1
Name: RoofMatl, dtype: int64
```

```
combined_clean_train["Exterior1st"].value_counts()
```

```
VinylSd    396
HdBoard    186
MetalSd    173
Wd Sdng    153
Plywood     78
BrkFace     35
CemntBd     33
Stucco      15
WdShing     15
AsbShng     14
Stone        2
BrkComm      1
ImStucc      1
Name: Exterior1st, dtype: int64
```

```
combined_clean_train["Exterior2nd"].value_counts()
```

```
VinylSd    387
HdBoard    172
MetalSd    171
Wd Sdng    148
Plywood     99
CmentBd     32
Wd Shng     25
BrkFace     19
Stucco      17
AsbShng     14
ImStucc      8
Brk Cmn      6
AsphShn      2
Other        1
```

```
Stone        1
Name: Exterior2nd, dtype: int64
```

```
combined_clean_train["MasVnrType"].value_counts()
```

```
None       646
BrkFace    358
Stone       86
BrkCmn      12
Name: MasVnrType, dtype: int64
```

```
combined_clean_train["BldgType"].value_counts()
```

```
1Fam     930
Other    172
Name: BldgType, dtype: int64
```

```
combined_clean_train["HouseStyle"].value_counts()
```

```
1Story    550
2Story    341
1.5Fin    108
SLvl       54
SFoyer     26
1.5Unf     10
2.5Unf     10
2.5Fin      3
Name: HouseStyle, dtype: int64
```

```
combined_clean_train["ExterQual"].value_counts()
```

```
TA       688
Gd       391
Other     23
Name: ExterQual, dtype: int64
```

```
combined_clean_train["ExterCond"].value_counts()
```

```
TA    974
Gd    111
Fa     15
Ex      2
Name: ExterCond, dtype: int64
```

```
combined_clean_train["Foundation"].value_counts()
```

```
PConc     495
CBlock    495
BrkTil    104
Stone       5
Wood        3
Name: Foundation, dtype: int64
```

```
combined_clean_train["BsmtQual"].value_counts()
```

```
TA       508
Gd       502
Other     92
Name: BsmtQual, dtype: int64
```

```
combined_clean_train["BsmtCond"].value_counts()
```

```
TA       1018
Other      84
Name: BsmtCond, dtype: int64
```

```
combined_clean_train["BsmtExposure"].value_counts()
```

```
No    774
Av    168
Mn     89
Gd     71
Name: BsmtExposure, dtype: int64
```

```
combined_clean_train["BsmtFinType1"].value_counts()
```

```
Unf    329
GLQ    301
ALQ    183
BLQ    120
Rec    109
LwQ     60
Name: BsmtFinType1, dtype: int64
```

```
combined_clean_train["BsmtFinType2"].value_counts()
```

```
Unf    968
LwQ     42
Rec     37
BLQ     29
ALQ     16
GLQ     10
Name: BsmtFinType2, dtype: int64
```

```
combined_clean_train["Heating"].value_counts()
```

```
GasA    1086
GasW      13
Grav       2
OthW       1
Name: Heating, dtype: int64
```

```
combined_clean_train["HeatingQC"].value_counts()
```

```
Ex    556
TA    324
Gd    191
Fa     30
Po      1
Name: HeatingQC, dtype: int64
```

```
combined_clean_train["CentralAir"].value_counts()
```

```
Y    1049
```

```
N      53
Name: CentralAir, dtype: int64
```

```
combined_clean_train["Electrical"].value_counts()
```

```
SBrkr    1015
FuseA      69
FuseF      15
FuseP       2
Mix         1
Name: Electrical, dtype: int64
```

```
combined_clean_train["KitchenQual"].value_counts()
```

```
TA    558
Gd    474
Ex     50
Fa     20
Name: KitchenQual, dtype: int64
```

```
combined_clean_train["Functional"].value_counts()
```

```
Typ     1034
Min2      26
Min1      20
Maj1      10
Mod        8
Maj2       4
Name: Functional, dtype: int64
```

```
combined_clean_train["GarageType"].value_counts()
```

```
Attchd     699
Detchd     320
BuiltIn     57
Basment     16
CarPort      6
```

```
2Types       4
Name: GarageType, dtype: int64
```

```
# def Ext_condition(x, y):
#   if x == y

# BsmtFinType2, BsmtFinType1
# combined_clean_train["Exterior_Cond"]= combined_clean_train[["Exterior1st","Exterior2nd"]].apply(lambda x: "VinylSd" if (x
```

```
combined_clean_train["GarageFinish"].value_counts()
```

```
Unf    505
RFn    349
Fin    248
Name: GarageFinish, dtype: int64
```

```
combined_clean_train["GarageQual"].value_counts()
```

```
TA    1047
Fa      39
Gd      11
Po       3
Ex       2
Name: GarageQual, dtype: int64
```

```
combined_clean_train["GarageCond"].value_counts()
```

```
TA    1058
Fa      28
Gd       8
Po       6
Ex       2
Name: GarageCond, dtype: int64
```

```
combined_clean_train["PavedDrive"].value_counts()
```

```
Y    1040
```

```
N      41
P      21
Name: PavedDrive, dtype: int64
```

```
combined_clean_train["SaleType"].value_counts()
```

```
WD       972
Other    130
Name: SaleType, dtype: int64
```

```
combined_clean_train["SaleCondition"].value_counts()
```

```
Normal    926
Other     176
Name: SaleCondition, dtype: int64
```

```
combined_clean_train["RoofMatl"] = combined_clean_train["RoofMatl"].apply(lambda x:"CompShg" if x== 'CompShg' else "Other")
combined_clean_train["Exterior1st"] = combined_clean_train["Exterior1st"].apply(lambda x: x if ((x== 'VinylSd') | (x == 'HdB
combined_clean_train["Exterior2nd"] = combined_clean_train["Exterior2nd"].apply(lambda x: x if ((x== 'VinylSd') | (x == 'HdB
combined_clean_train["MasVnrType"] = combined_clean_train["MasVnrType"].apply(lambda x: x if ((x== 'None') | (x == 'BrkFace'
combined_clean_train["HouseStyle"] = combined_clean_train["HouseStyle"].apply(lambda x: x if ((x== '1Story') | (x == '2Story
combined_clean_train["ExterCond"] = combined_clean_train["ExterCond"].apply(lambda x: x if ((x== 'TA') | (x == 'Gd')) else "
combined_clean_train["Foundation"] = combined_clean_train["ExterCond"].apply(lambda x: x if ((x== 'PConc') | (x == 'CBlock')
combined_clean_train["Bsmt Exposure"] = combined_clean_train["BsmtExposure"].apply(lambda x: x if ((x== 'No') | (x == 'Av'))
combined_clean_train["Heating"] = combined_clean_train["Heating"].apply(lambda x: x if ((x== 'GasA')) else "Other")
combined_clean_train["HeatingQC"] = combined_clean_train["HeatingQC"].apply(lambda x: x if (( x== 'Ex')|(x == 'TA')| (x == '
combined_clean_train["Electrical"] = combined_clean_train["Electrical"].apply(lambda x: x if ((x== 'SBrkr')) else "Other")
combined_clean_train["KitchenQual"] = combined_clean_train["KitchenQual"].apply(lambda x: x if (( x== 'TA')|(x == 'Gd')) els
combined_clean_train["Functional"] = combined_clean_train["Functional"].apply(lambda x: x if (( x== 'Typ')) else "Other")
combined_clean_train["GarageType"] = combined_clean_train["GarageType"].apply(lambda x: x if (( x== 'Attchd')|(x == 'Detchd'
combined_clean_train["GarageQual"] = combined_clean_train["GarageQual"].apply(lambda x: x if (( x== 'TA')) else "Other")
combined_clean_train["GarageCond"] = combined_clean_train["GarageCond"].apply(lambda x: x if (( x== 'TA')) else "Other")
```

```
combined_clean_train["Neighborhood"].value_counts()
```

```
NAmes      183
CollgCr    126
```

```
OldTown     87
Somerst     70
Gilbert     65
Sawyer      64
NWAmes      61
Edwards     58
SawyerW     50
NridgHt     46
BrkSide     40
Crawfor     38
Mitchel     36
Timber      27
IDOTRR      26
NoRidge     24
SWISU       17
StoneBr     15
Blmngtn     15
ClearCr     13
BrDale      13
Veenker     10
MeadowV     10
NPkVill      7
Blueste      1
Name: Neighborhood, dtype: int64
```

```
combined_clean_train.head()
```

```
Id  MSSubClass  MSZoning  LotArea  Street  LotShape  LandContour  Utilities  LotConfig  LandSlope  Neighborhood  Bl
```

We also need to rename columns to more identifying name

```
combined_clean_train.columns
```

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

```
combined_clean_train.rename({'MSSubClass':'dwelling_involved_type',
                             'MSZoning':'general_zoning_classification',
                             'LotArea' : 'Total_area',
                             'Street':'type_of_road',
                             'LotShape':'property_general_shape',
                             'LandContour':'property_Flatness',
                             'Utilities':'utilities_types',
                             'BldgType':'dwelling_type',
                             'RoofMatl':'roof_material',
                             'Exterior1st':'exterior_covering_1',
                             'Exterior2nd':'exterior_covering_2',
                             'MasVnrType':'masonry_veneer_type',
                             'Electrical':'electrical_system',
```

```
                            'TotRmsAbvGrd':'total_rooms_above_grade',
                            'GarageFinish':'interior_finish_garage',
                            'GarageCars':'garage_car_capacity',
                            '3SsnPorch':'three_season_porch_area',
                            'MiscFeature':'other_features',
                            'MiscVal':'other_features_values'
                            }, axis='columns', inplace = True)
```

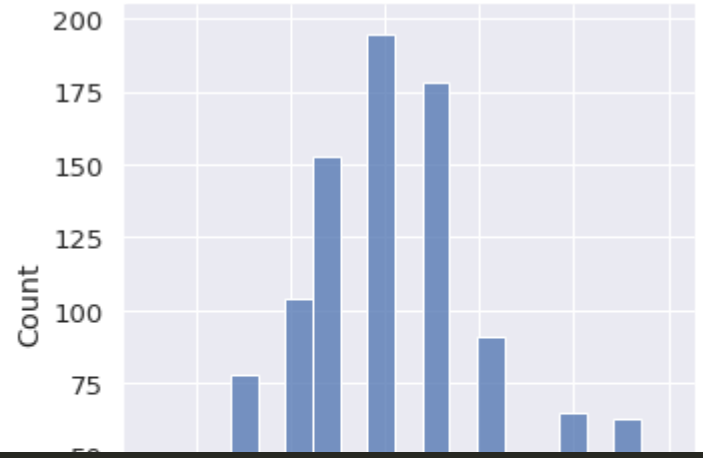
```
combined_clean_train.head()
```

	Id	dwelling_involved_type	general_zoning_classification	Total_area	type_of_road	property_general_shape	proper
0	1.0	60.0	RL	8450.0	Pave	Reg	
1	2.0	20.0	RL	9600.0	Pave	Reg	
2	3.0	60.0	RL	11250.0	Pave	IR1	
3	4.0	70.0	RL	9550.0	Pave	IR1	
4	5.0	60.0	RL	14260.0	Pave	IR1	

```
combined_clean_train.drop(['Id'], axis=1, inplace = True)
```

```
sns.displot(x = 'MoSold', data = combined_clean_train)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fbd07ec9a50>
```

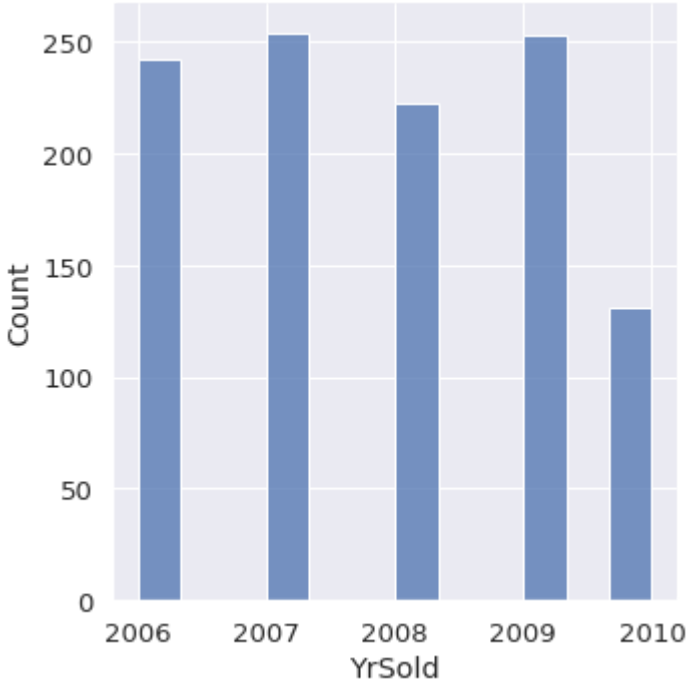



```
sns.jointplot(x= 'MoSold', y = 'SalePrice', data = combined_clean_train)
```

```
<seaborn.axisgrid.JointGrid at 0x7fbd07e6c190>
```

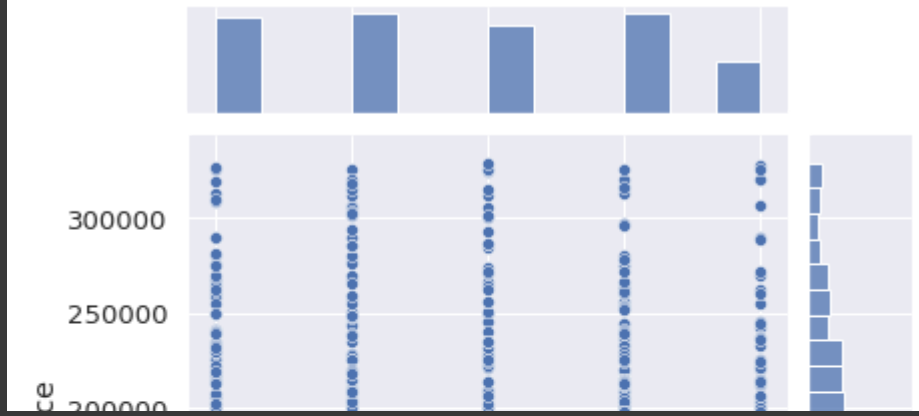
```
sns.displot(x = 'YrSold', data = combined_clean_train)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fbd07daadd0>
```




```
sns.jointplot(x= 'YrSold', y = 'SalePrice', data = combined_clean_train)
```

```
<seaborn.axisgrid.JointGrid at 0x7fbd07cf7310>
```



What are we getting from this Plots?!

- Which year/month sold with most profits
- Which year/month sold most in count
- Does it really mean year that selling less isn't reaching high prices?
- In 2010 Was least year to sell houses but yet we could found that we could still sell with high prices


```
# combined_clean_train.to_csv('final_mod_house_price.csv', encoding = "UTF-8")
combined_clean_train.to_csv('final_mod_house_price.csv', encoding = "UTF-8")
```

```
## Now let's make get_dummies for categorical value
```

```
# !pip install datasist
# from datasist.structdata import detect_outliers
# ## Not needed since we got 0 outliers
# # idx = detect_outliers(df, 0,['charges'])
# # df = df.drop(idx, axis = 0, inplace=True)
# # df
```

```
## We can check where is the most of companies are depending on employee residence
# city_count = clean['employee_residence'].value_counts()
```

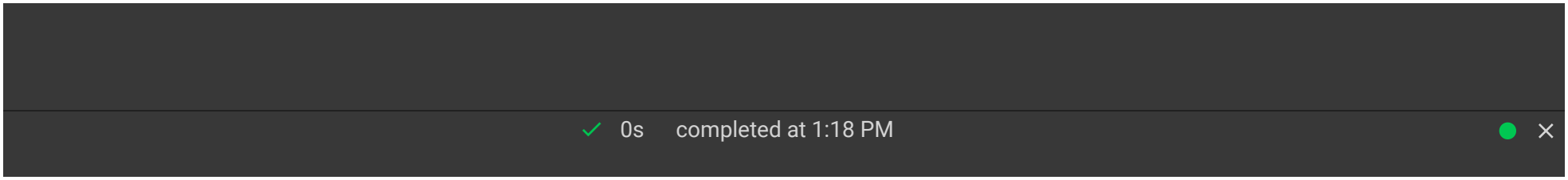
```
# cities = city_count[city_count > 10].index
# cities
# sns.countplot(y = 'Neighborhood', data = clean[clean['Neighborhood'].isin(cities)])
```

```
# conditions 1 & 2 are conditions that may exist Norm or not
# - We can make a new column that have 3 types of conditions
#     - if condition 1 = condition 2 return norm elif condition 1 = norm and condition 2 != norm return half norm if conditi

# Exterior 1st & 2nd: Exterior covering on house
```

```
# di = {"L": 0, "M": 1, "H": 2 }
# df.replace({"Type": di}, inplace=True)
```

```
# clean = pd.get_dummies(clean, columns = ['job_title', 'employee_residence','company_location'], drop_first=True)
```


0s completed at 1:18 PM