

NB Week 1 EDA

May 23, 2019

1 House Prices: Advanced Regression Techniques

1.1 Introduction:

This project and the data can be found in <https://www.kaggle.com/c/house-prices-advanced-regression-techniques>.

Ask a home buyer to describe their dream house, and they probably won't begin with the height of the basement ceiling or the proximity to an east-west railroad. But this playground competition's dataset proves that much more influences price negotiations than the number of bedrooms or a white-picket fence.

With 79 explanatory variables describing (almost) every aspect of residential homes in Ames, Iowa, this competition challenges you to predict the final price of each home.

We will start first with EDA to check the dataset, available rows, the distribution of the sale price (target).

1.2 EDA

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
import sys
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
%matplotlib inline
```

```
In [2]: # Read the data
data = pd.read_csv('../train.csv', index_col=0)
data.head()
```

```
Out[2]:
```

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

	LandContour	Utilities	LotConfig	...	PoolArea	PoolQC	Fence	\
Id				...				
1	Lvl	AllPub	Inside	...	0	NaN	NaN	
2	Lvl	AllPub	FR2	...	0	NaN	NaN	
3	Lvl	AllPub	Inside	...	0	NaN	NaN	
4	Lvl	AllPub	Corner	...	0	NaN	NaN	
5	Lvl	AllPub	FR2	...	0	NaN	NaN	

	MiscFeature	MiscVal	MoSold	YrSold	SaleType	SaleCondition	SalePrice
Id							
1	NaN	0	2	2008	WD	Normal	208500
2	NaN	0	5	2007	WD	Normal	181500
3	NaN	0	9	2008	WD	Normal	223500
4	NaN	0	2	2006	WD	Abnorml	140000
5	NaN	0	12	2008	WD	Normal	250000

[5 rows x 80 columns]

```
In [3]: # Read the description of the file
with open('../data_description.txt', 'r') as fi:
    print(fi.read())
```

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
RR Ae	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	Minimum 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	Unfinished
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	Unfinished
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
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

GarageYrBltd: 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 w
Family	Sale between family members
Partial	Home was not completed when last assessed (associated with New Homes)

In [4]: data.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 1 to 1460
Data columns (total 80 columns):
MSSubClass      1460 non-null int64
MSZoning        1460 non-null object
LotFrontage     1201 non-null float64
LotArea         1460 non-null int64
Street          1460 non-null object
Alley           91 non-null object
LotShape        1460 non-null object
LandContour     1460 non-null object
Utilities       1460 non-null object
LotConfig       1460 non-null object
LandSlope       1460 non-null object
Neighborhood    1460 non-null object
Condition1      1460 non-null object
Condition2      1460 non-null object
BldgType        1460 non-null object
HouseStyle      1460 non-null object
OverallQual     1460 non-null int64
OverallCond     1460 non-null int64
YearBuilt       1460 non-null int64
YearRemodAdd    1460 non-null int64
RoofStyle       1460 non-null object
RoofMatl        1460 non-null object
Exterior1st     1460 non-null object
```

Exterior2nd	1460	non-null	object
MasVnrType	1452	non-null	object
MasVnrArea	1452	non-null	float64
ExterQual	1460	non-null	object
ExterCond	1460	non-null	object
Foundation	1460	non-null	object
BsmtQual	1423	non-null	object
BsmtCond	1423	non-null	object
BsmtExposure	1422	non-null	object
BsmtFinType1	1423	non-null	object
BsmtFinSF1	1460	non-null	int64
BsmtFinType2	1422	non-null	object
BsmtFinSF2	1460	non-null	int64
BsmtUnfSF	1460	non-null	int64
TotalBsmtSF	1460	non-null	int64
Heating	1460	non-null	object
HeatingQC	1460	non-null	object
CentralAir	1460	non-null	object
Electrical	1459	non-null	object
1stFlrSF	1460	non-null	int64
2ndFlrSF	1460	non-null	int64
LowQualFinSF	1460	non-null	int64
GrLivArea	1460	non-null	int64
BsmtFullBath	1460	non-null	int64
BsmtHalfBath	1460	non-null	int64
FullBath	1460	non-null	int64
HalfBath	1460	non-null	int64
BedroomAbvGr	1460	non-null	int64
KitchenAbvGr	1460	non-null	int64
KitchenQual	1460	non-null	object
TotRmsAbvGrd	1460	non-null	int64
Functional	1460	non-null	object
Fireplaces	1460	non-null	int64
FireplaceQu	770	non-null	object
GarageType	1379	non-null	object
GarageYrBltd	1379	non-null	float64
GarageFinish	1379	non-null	object
GarageCars	1460	non-null	int64
GarageArea	1460	non-null	int64
GarageQual	1379	non-null	object
GarageCond	1379	non-null	object
PavedDrive	1460	non-null	object
WoodDeckSF	1460	non-null	int64
OpenPorchSF	1460	non-null	int64
EnclosedPorch	1460	non-null	int64
3SsnPorch	1460	non-null	int64
ScreenPorch	1460	non-null	int64
PoolArea	1460	non-null	int64

```

PoolQC          7 non-null object
Fence           281 non-null object
MiscFeature     54 non-null object
MiscVal         1460 non-null int64
MoSold          1460 non-null int64
YrSold          1460 non-null int64
SaleType        1460 non-null object
SaleCondition   1460 non-null object
SalePrice       1460 non-null int64
dtypes: float64(3), int64(34), object(43)
memory usage: 923.9+ KB

```

1.2.1 Notes on the feature columns:

The following columns have NA, but NA here indicate something: * Alley column => NA means "No alley access". * BsmtQual, BsmtCond, BsmtExposure, BsmtFinType1, BsmtFinType2, BsmtFinSF1 columns => NA means "No Basement" * FireplaceQu column => NA means "No fireplace" * GarageType, GarageCond, GarageFinish columns => NA means "No Garage" * PoolQC column => No Pool * Fence column => No fence * MiscFeature column => None

So be careful with dropping NA values. Next cell, I will fillna as if I didn't pandas will ignore NA values.

```

In [5]: data.Alley = data.Alley.fillna(value = 'NoAlley')
        data.BsmtCond = data.BsmtCond.fillna(value = 'NoBsmt')
        data.BsmtQual = data.BsmtQual.fillna(value = 'NoBsmt')
        data.BsmtExposure = data.BsmtExposure.fillna(value= 'NoBsmt')
        data.BsmtFinType1 = data.BsmtFinType1.fillna(value= 'NoBsmt')
        data.BsmtFinType2 = data.BsmtFinType2.fillna(value= 'NoBsmt')
        data.LotFrontage = data.LotFrontage.fillna(value = 0)
        data.FireplaceQu = data.FireplaceQu.fillna(value = 'NoFireplace')
        data.GarageType = data.GarageType.fillna(value = 'NoGarage')
        data.GarageCond = data.GarageCond.fillna(value = 'NoGarage')
        data.GarageFinish = data.GarageFinish.fillna(value = 'NoGarage')
        data.GarageYrBlt = data.GarageYrBlt.fillna(value = 0)
        data.GarageQual = data.GarageQual.fillna(value = 'NoGarage')

        data.PoolQC = data.PoolQC.fillna(value = 'NoPool')
        data.Fence = data.Fence.fillna(value = 'NoFence')
        data.MiscFeature = data.MiscFeature.fillna(value = 'NoMisc')
        data.MasVnrType = data.MasVnrType.fillna(value = 'noMas')
        data.MasVnrArea = data.MasVnrArea.fillna(value = 'noMas')

        data.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 1 to 1460

```

Data columns (total 80 columns):

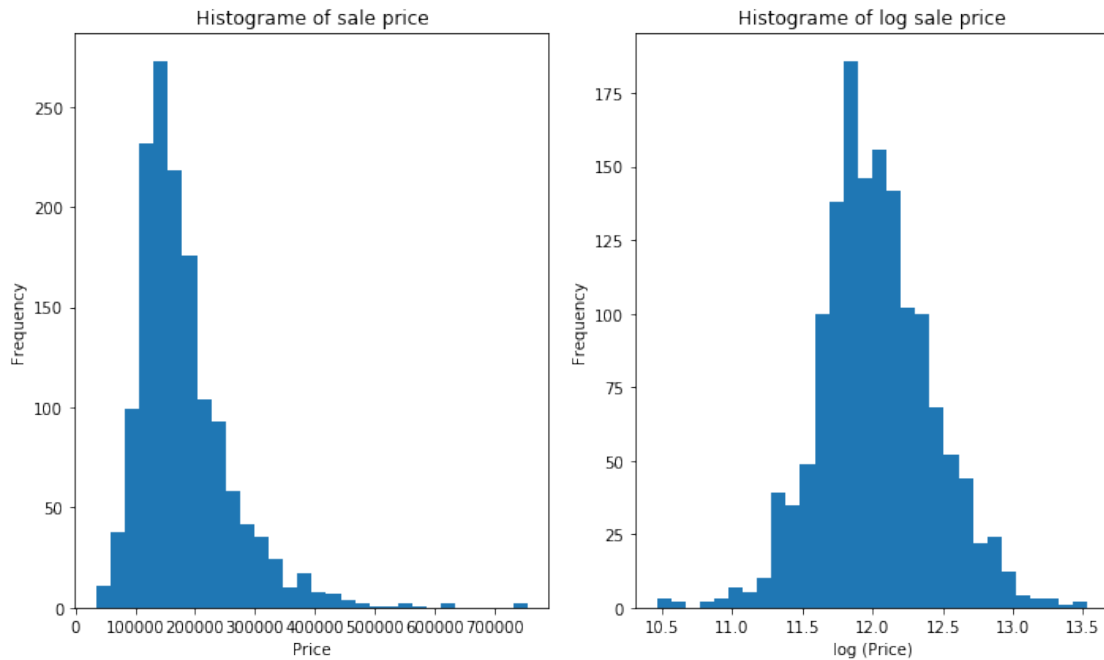
MSSubClass	1460	non-null	int64
MSZoning	1460	non-null	object
LotFrontage	1460	non-null	float64
LotArea	1460	non-null	int64
Street	1460	non-null	object
Alley	1460	non-null	object
LotShape	1460	non-null	object
LandContour	1460	non-null	object
Utilities	1460	non-null	object
LotConfig	1460	non-null	object
LandSlope	1460	non-null	object
Neighborhood	1460	non-null	object
Condition1	1460	non-null	object
Condition2	1460	non-null	object
BldgType	1460	non-null	object
HouseStyle	1460	non-null	object
OverallQual	1460	non-null	int64
OverallCond	1460	non-null	int64
YearBuilt	1460	non-null	int64
YearRemodAdd	1460	non-null	int64
RoofStyle	1460	non-null	object
RoofMatl	1460	non-null	object
Exterior1st	1460	non-null	object
Exterior2nd	1460	non-null	object
MasVnrType	1460	non-null	object
MasVnrArea	1460	non-null	object
ExterQual	1460	non-null	object
ExterCond	1460	non-null	object
Foundation	1460	non-null	object
BsmtQual	1460	non-null	object
BsmtCond	1460	non-null	object
BsmtExposure	1460	non-null	object
BsmtFinType1	1460	non-null	object
BsmtFinSF1	1460	non-null	int64
BsmtFinType2	1460	non-null	object
BsmtFinSF2	1460	non-null	int64
BsmtUnfSF	1460	non-null	int64
TotalBsmtSF	1460	non-null	int64
Heating	1460	non-null	object
HeatingQC	1460	non-null	object
CentralAir	1460	non-null	object
Electrical	1459	non-null	object
1stFlrSF	1460	non-null	int64
2ndFlrSF	1460	non-null	int64
LowQualFinSF	1460	non-null	int64
GrLivArea	1460	non-null	int64
BsmtFullBath	1460	non-null	int64

BsmtHalfBath	1460	non-null	int64
FullBath	1460	non-null	int64
HalfBath	1460	non-null	int64
BedroomAbvGr	1460	non-null	int64
KitchenAbvGr	1460	non-null	int64
KitchenQual	1460	non-null	object
TotRmsAbvGrd	1460	non-null	int64
Functional	1460	non-null	object
Fireplaces	1460	non-null	int64
FireplaceQu	1460	non-null	object
GarageType	1460	non-null	object
GarageYrBlt	1460	non-null	float64
GarageFinish	1460	non-null	object
GarageCars	1460	non-null	int64
GarageArea	1460	non-null	int64
GarageQual	1460	non-null	object
GarageCond	1460	non-null	object
PavedDrive	1460	non-null	object
WoodDeckSF	1460	non-null	int64
OpenPorchSF	1460	non-null	int64
EnclosedPorch	1460	non-null	int64
3SsnPorch	1460	non-null	int64
ScreenPorch	1460	non-null	int64
PoolArea	1460	non-null	int64
PoolQC	1460	non-null	object
Fence	1460	non-null	object
MiscFeature	1460	non-null	object
MiscVal	1460	non-null	int64
MoSold	1460	non-null	int64
YrSold	1460	non-null	int64
SaleType	1460	non-null	object
SaleCondition	1460	non-null	object
SalePrice	1460	non-null	int64

dtypes: float64(2), int64(34), object(44)
memory usage: 923.9+ KB

```
In [9]: fig = plt.figure(figsize=(10,6))
plt.subplot(121)
plt.hist(data.SalePrice, bins=30)
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.title('Histogram of sale price');
plt.subplot(122)
plt.hist(np.log(data.SalePrice), bins=30)
plt.xlabel('log (Price)')
plt.ylabel('Frequency')
plt.title('Histogram of log sale price')
```

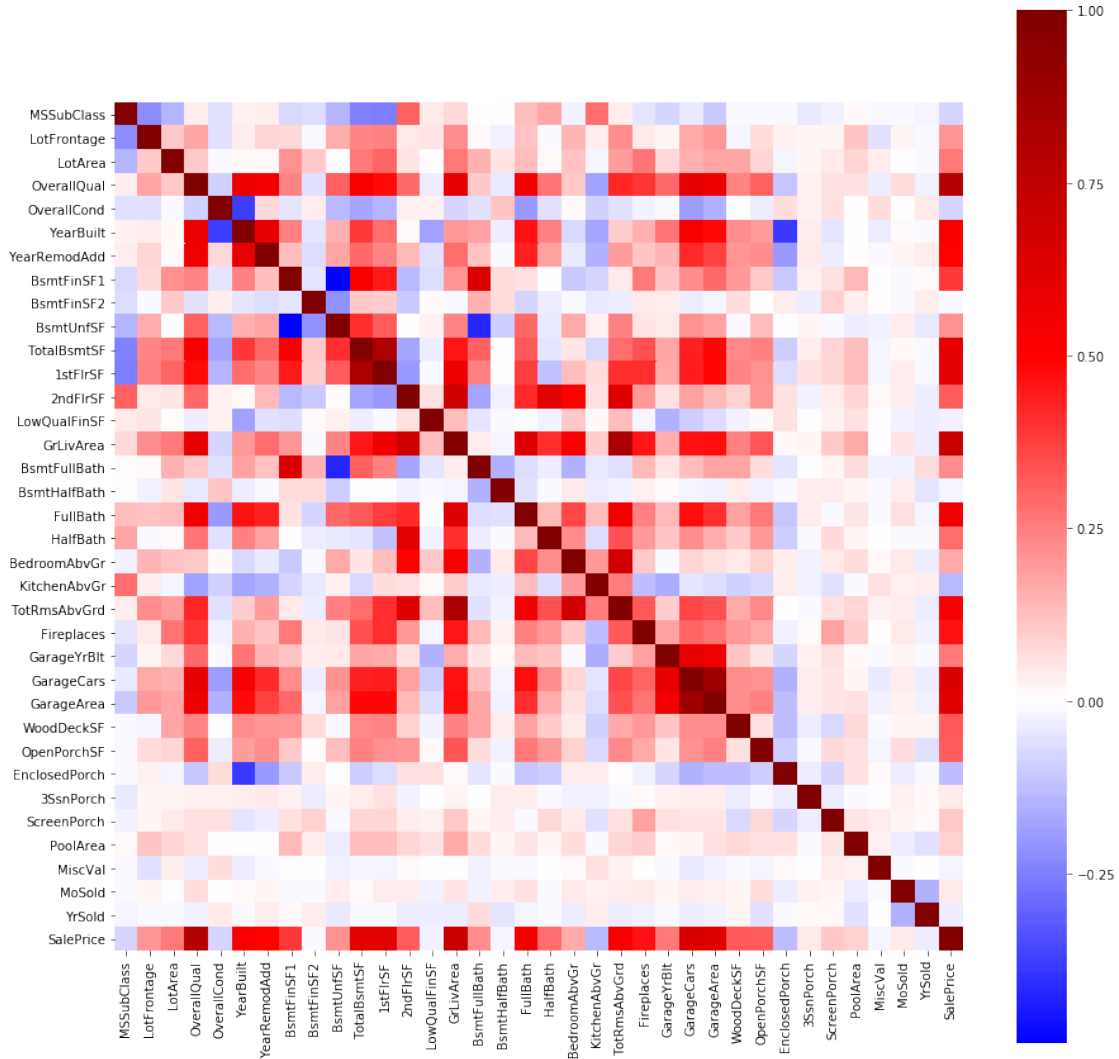
```
plt.tight_layout()
```



The plot of $\log(\text{sale price})$ looks normal without any outliers.

1.3 EDA for Numerical Columns:

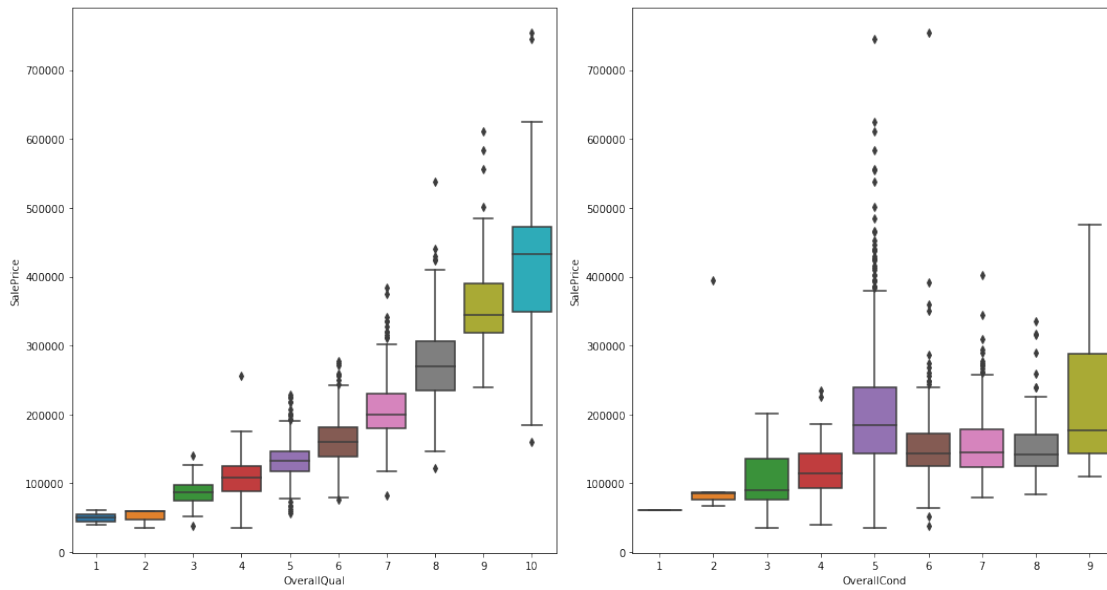
```
In [7]: # heatmap of the Sale price, with the numerical columns
corr = data.corr()
fig, ax = plt.subplots(figsize=(15,15))
sns.heatmap(corr, square=True, ax=ax, cmap='seismic', center= 0.0)
plt.xticks(fontsize=10);
plt.yticks(fontsize=10);
```



- From the above figure, there are some features which have high correlation with the "Sale price" column, most of them with positive correlation.
- It is interesting to find that OverallQual has high correlation with the Sale price, on the otherhand OverallCond has a small correlation factor with sale price.

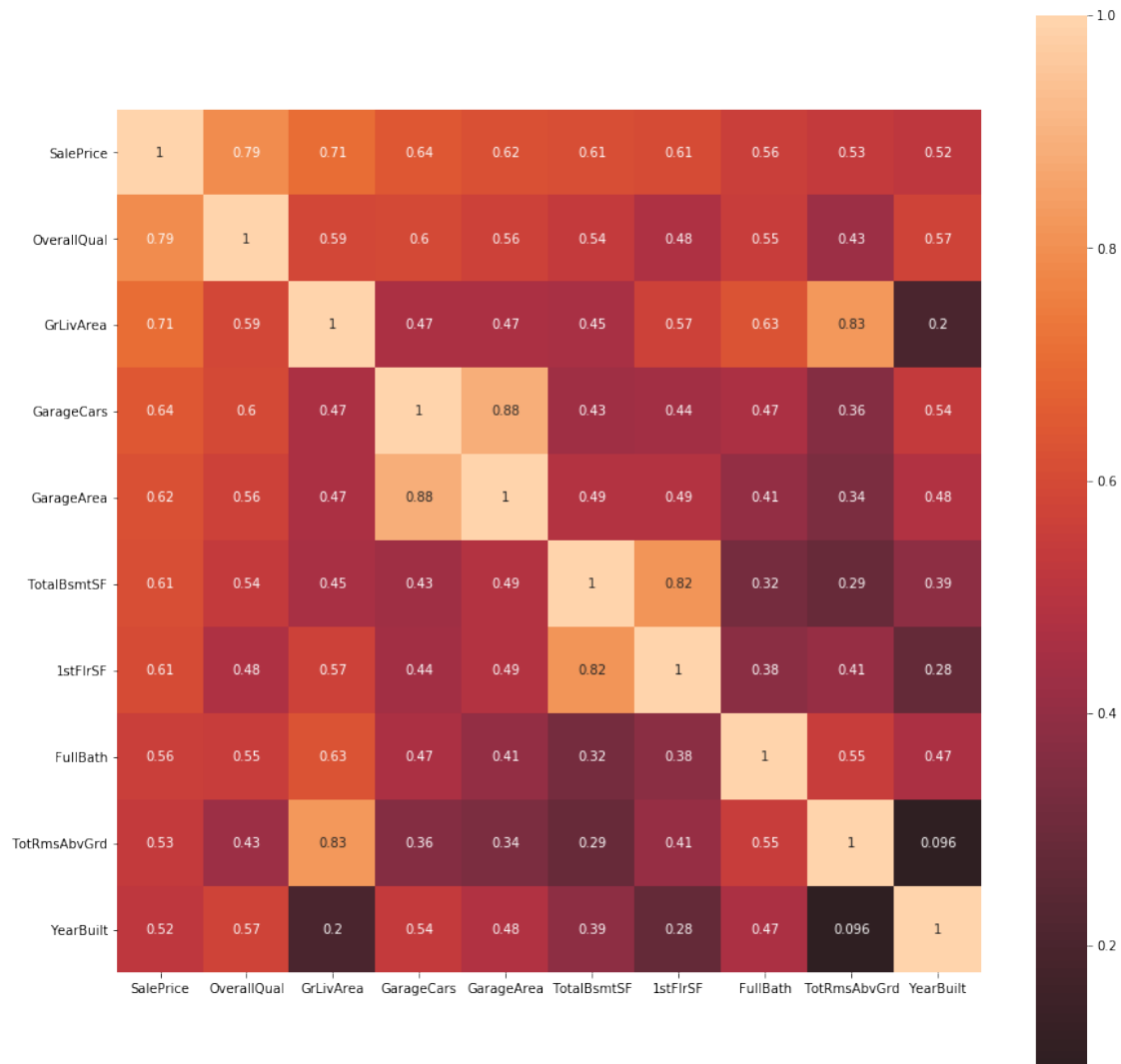
```
In [8]: # Check OverallQual and OverallCond columns
fig = plt.figure(figsize=(15,8))
ax = fig.add_subplot(121)
g = sns.catplot(x="OverallQual", y="SalePrice", kind="box", data=data, ax = ax)
plt.close(g.fig)
ax = fig.add_subplot(122)
g = sns.catplot(x="OverallCond", y="SalePrice", kind="box", data=data, ax = ax)
plt.close(g.fig)

plt.tight_layout()
```



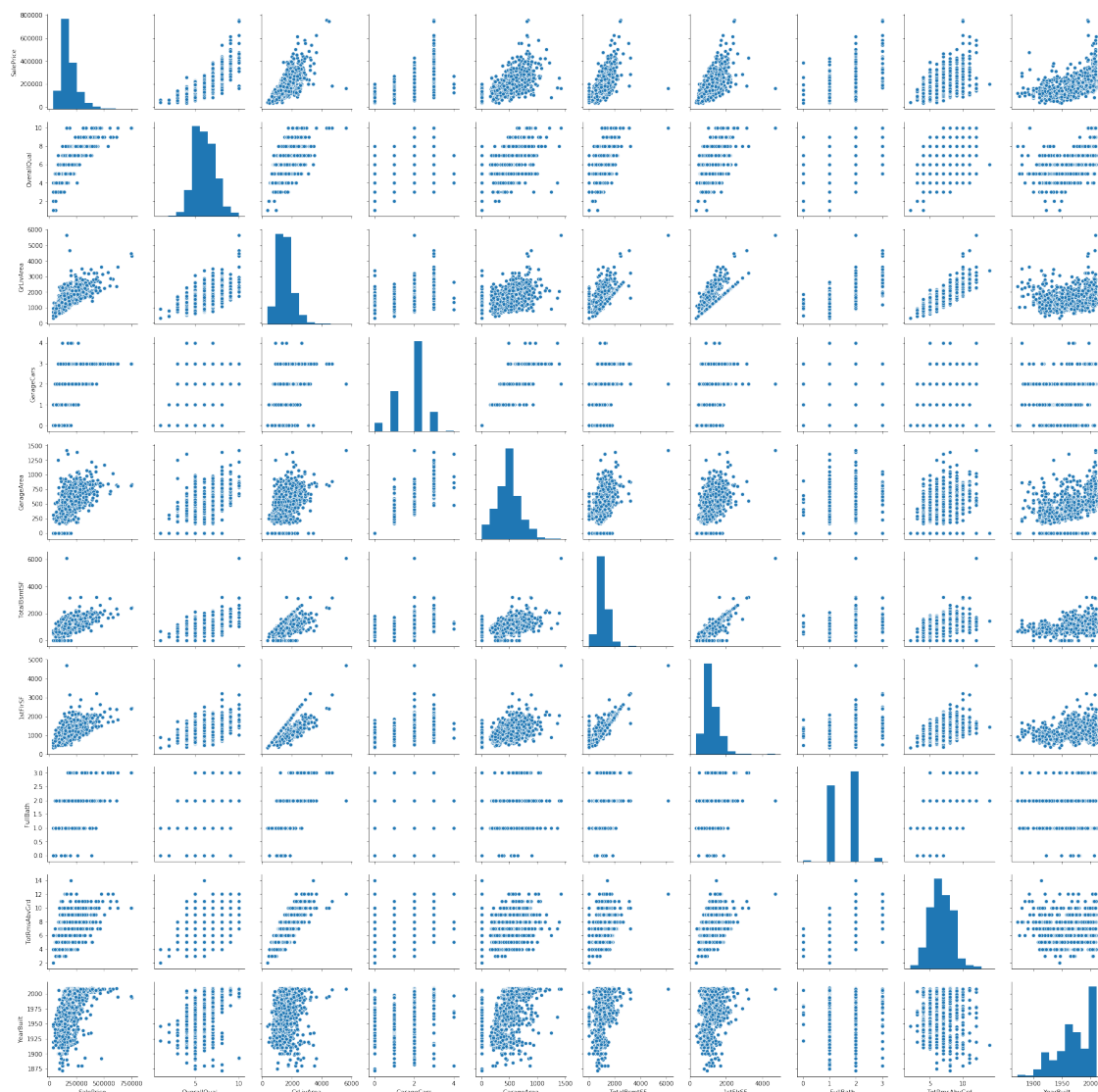
- It make sense now why OverallQual gives high corrolation with saleprice than OverallCond

```
In [9]: corr = data.corr()
        cols = corr.nlargest(10, 'SalePrice')['SalePrice'].index    # Take the max 10
        corr = data[cols].corr()
        fig, ax = plt.subplots(figsize=(15,15))
        sns.heatmap(corr, square=True, ax=ax, center= 0.0, xticklabels=cols, yticklabels=cols,
        plt.xticks(fontsize=10);
        plt.yticks(fontsize=10);
```



- Numerical columns with high correlation with Sale price are: ['SalePrice', 'OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'TotalBsmntSF', '1stFlrSF', 'FullBath', 'TotRmsAbvGrd', 'YearBuilt']

In [10]: sns.pairplot(data[cols]);



The following columns are integer and they give different correlation with sale price: * GarageCars: Size of garage in car capacity, * FullBath: Full bathrooms above grade, and * TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)

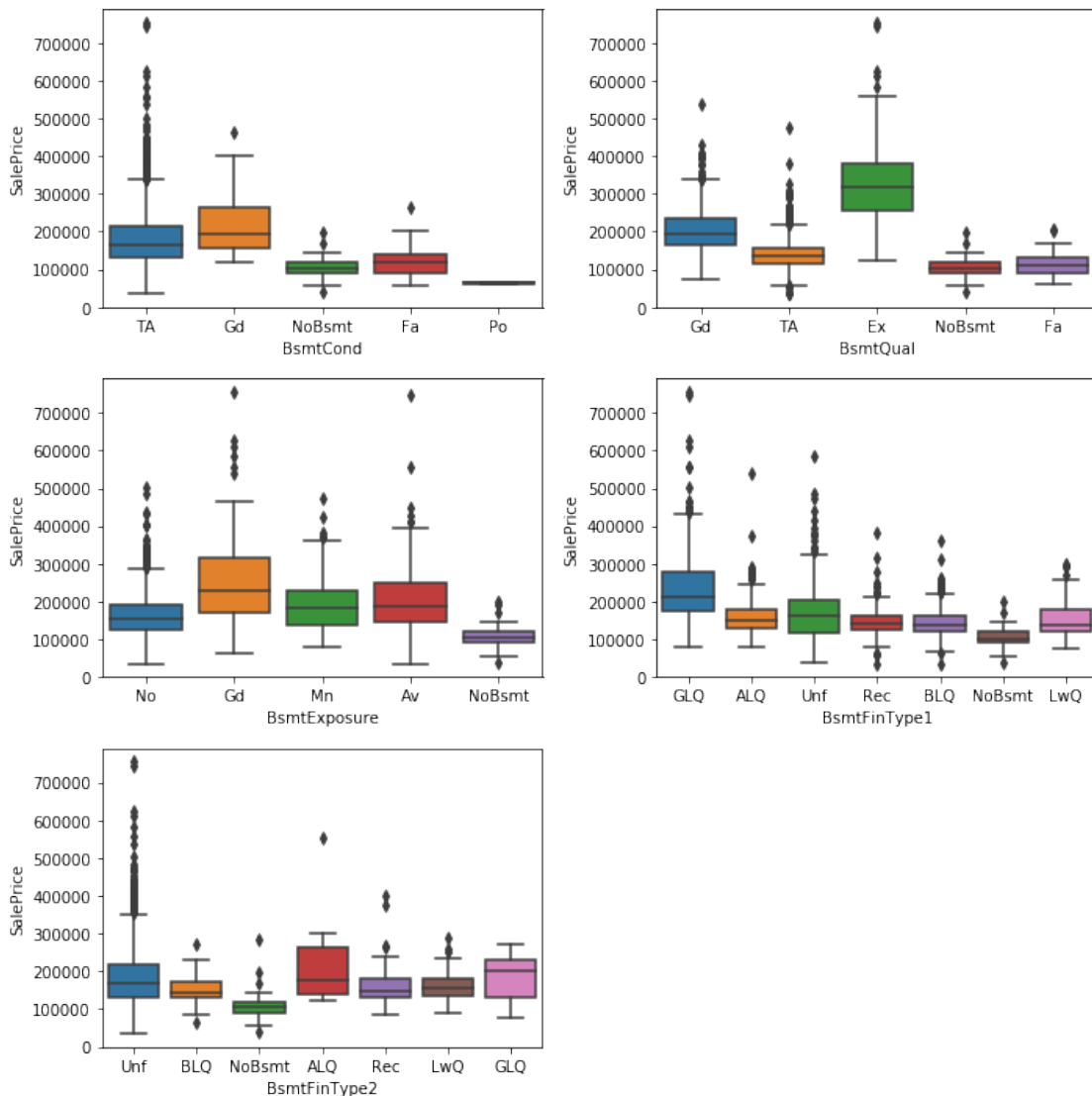
1.4 EDA for Categorical columns

```
In [11]: # Columns related to Basement
fig = plt.figure(figsize=(10,10))
ax = fig.add_subplot(321)
g = sns.catplot(x="BsmtCond", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(322)
g = sns.catplot(x="BsmtQual", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
```

```

ax = fig.add_subplot(323)
g = sns.catplot(x="BsmtExposure", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(324)
g = sns.catplot(x="BsmtFinType1", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(325)
g = sns.catplot(x="BsmtFinType2", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
plt.tight_layout()

```



In [12]: # I will use only BsmtCond and BsmtQual and drop the rest
It is better to use label encoder for these columns than one-hot code:

```

data.BsmtCond = data.BsmtCond.map({'Ex':5 , 'Gd':4 , 'TA':3 , 'Fa':2 , 'Po':1 , 'NoBsmt' :0})
data.BsmtQual = data.BsmtQual.map({'Ex':5 , 'Gd':4 , 'TA':3 , 'Fa':2 , 'Po':1 , 'NoBsmt' :0})
data.BsmtExposure = data.BsmtExposure.map({'Gd':4, 'Av':3, 'Mn':2, 'No':1, 'NoBsmt':0})
data.BsmtFinType1 = data.BsmtFinType1.map({'GLQ':6, 'ALQ':5, 'BLQ':4, 'Rec':3, 'LwQ':2, 'Unf':1})
data.BsmtFinType2 = data.BsmtFinType2.map({'GLQ':6, 'ALQ':5, 'BLQ':4, 'Rec':3, 'LwQ':2, 'Unf':1})

```

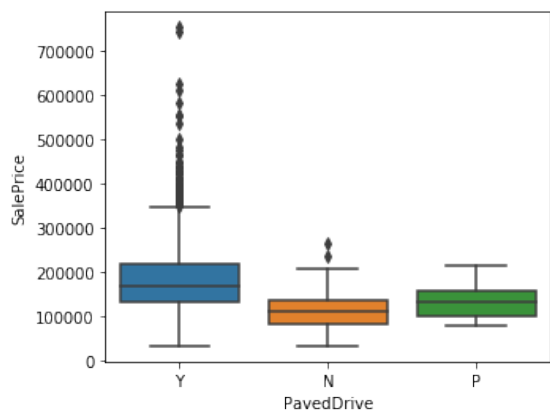
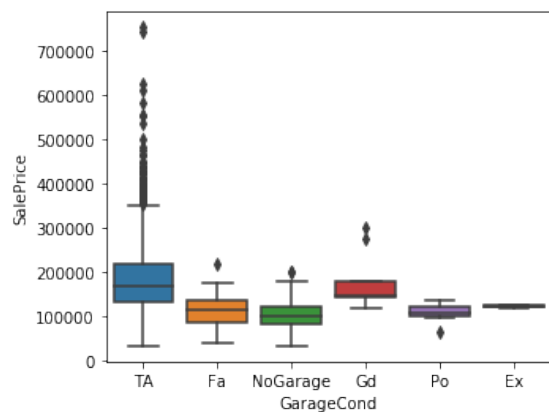
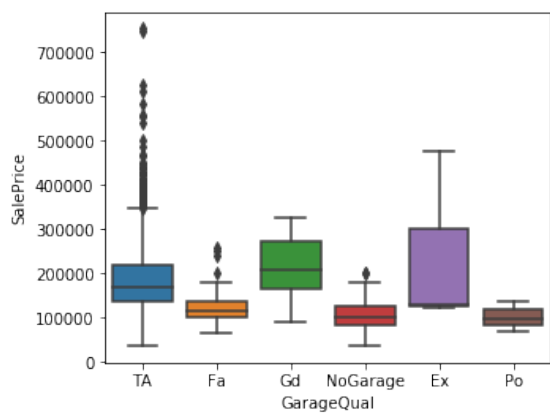
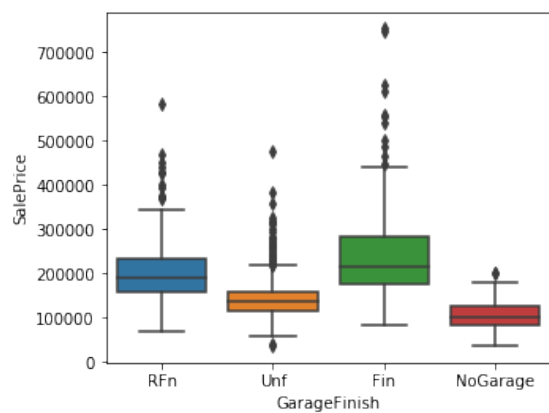
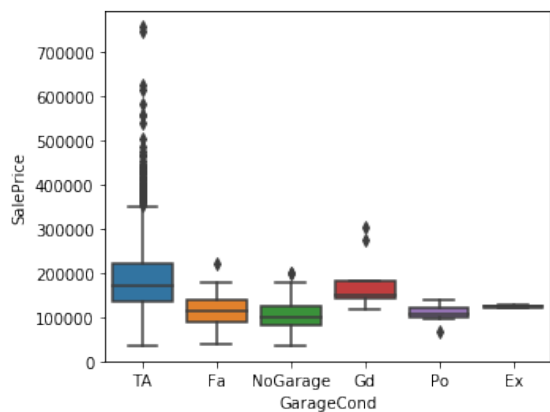
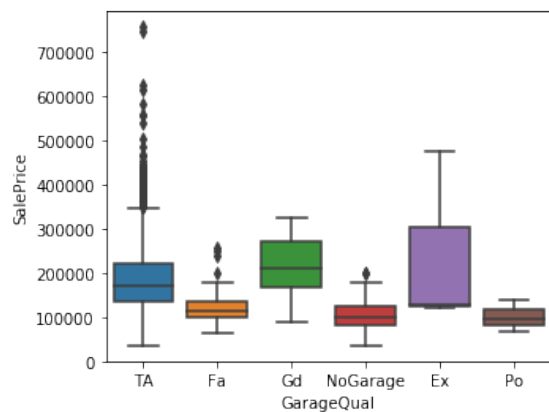
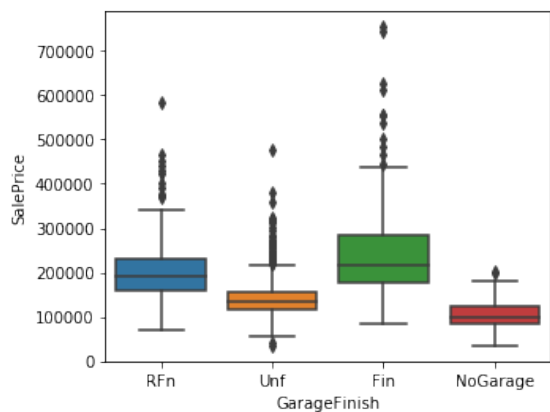
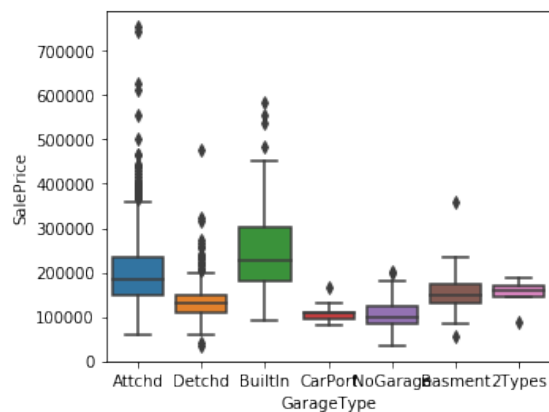
In [13]: *# Columns related to Garage*

```

fig = plt.figure(figsize=(10,15))
ax = fig.add_subplot(421)
g = sns.catplot(x="GarageType", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(422)
g = sns.catplot(x="GarageFinish", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(423)
g = sns.catplot(x="GarageQual", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(424)
g = sns.catplot(x="GarageCond", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(425)
g = sns.catplot(x="GarageFinish", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(426)
g = sns.catplot(x="GarageQual", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(427)
g = sns.catplot(x="GarageCond", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(428)
g = sns.catplot(x="PavedDrive", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)

plt.tight_layout()

```

```

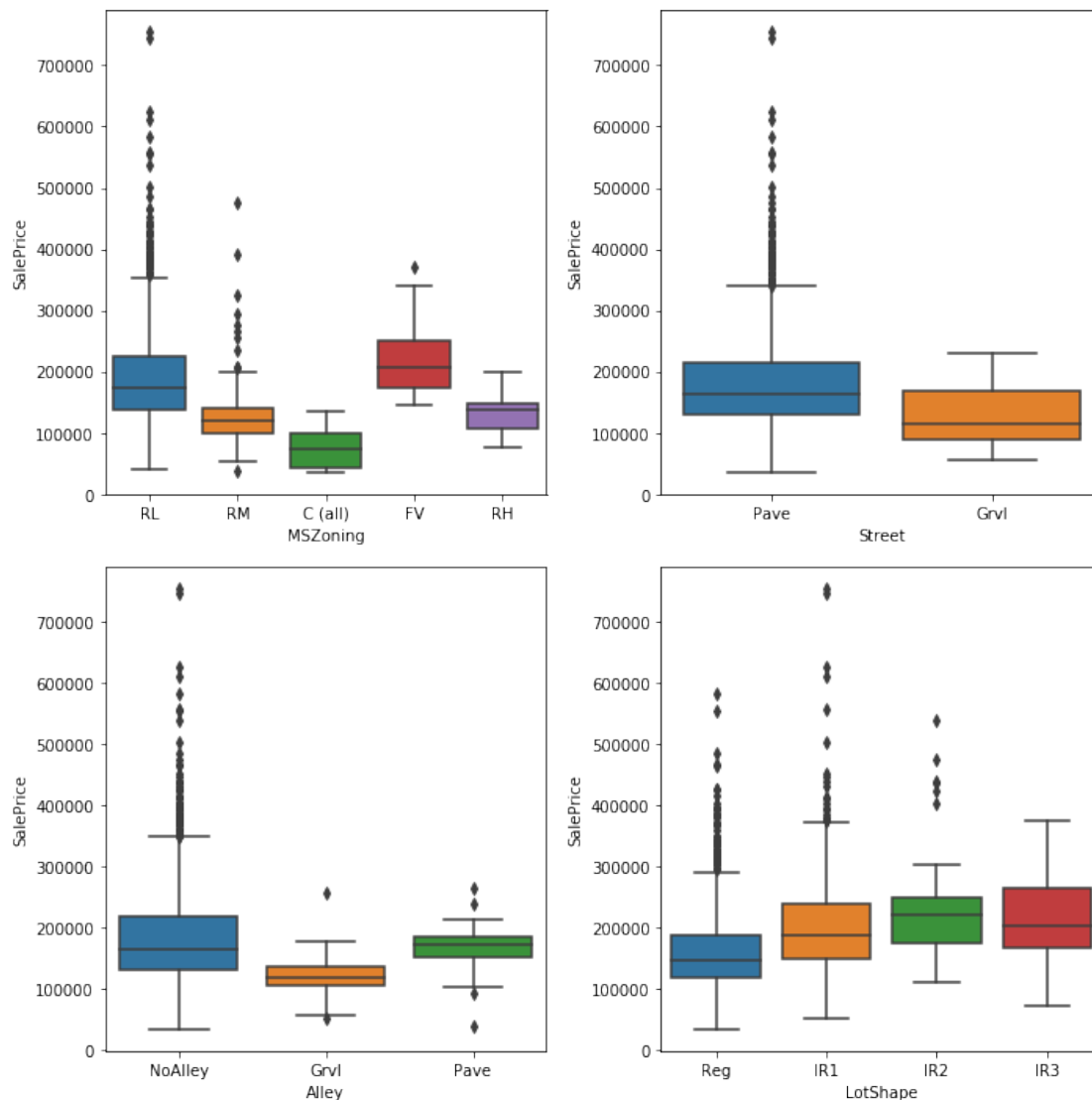
In [14]: data.GarageType = data.GarageType.map({'2Types':4 , 'Attchd': 5, 'Basment':3 , 'BuiltIn':4,
                                                'CarPort' :1, 'Detchd':2 , 'NoGarage': 0})

data.GarageCond = data.GarageCond.map({'NoGarage':0, 'Po':1, 'Fa':2, 'TA':3, 'Gd':4,
data.GarageQual = data.GarageQual.map({'NoGarage':0, 'Po':1, 'Fa':2, 'TA':3, 'Gd':4,
data.GarageFinish = data.GarageFinish.map({'Fin':3, 'RFn':2, 'Unf':1, 'NoGarage':0})
data.PavedDrive = data.PavedDrive.map({'Y':2, 'P':1, 'N':0 })

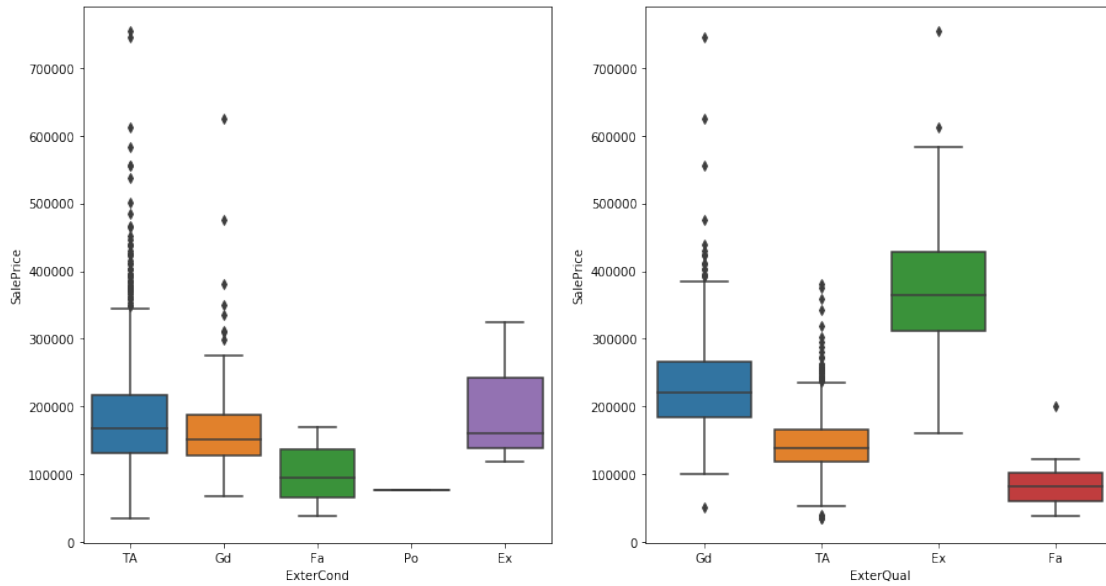
In [15]: # Columns related to surrounding condition
fig = plt.figure(figsize=(10,10))
ax = fig.add_subplot(221)
g = sns.catplot(x="MSZoning", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(222)
g = sns.catplot(x="Street", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(223)
g = sns.catplot(x="Alley", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(224)
g = sns.catplot(x="LotShape", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)

plt.tight_layout()

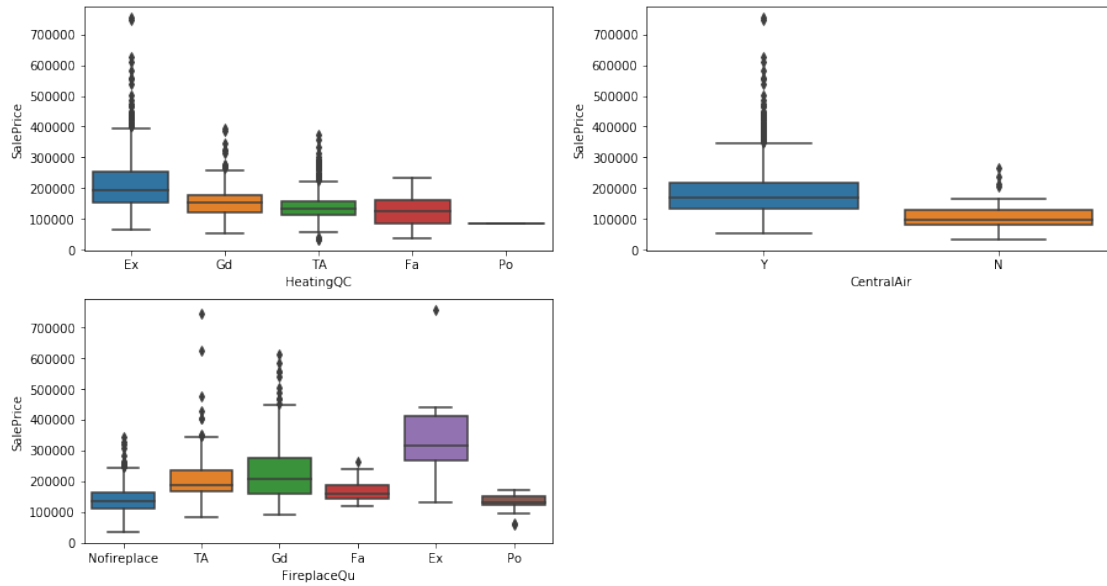
```



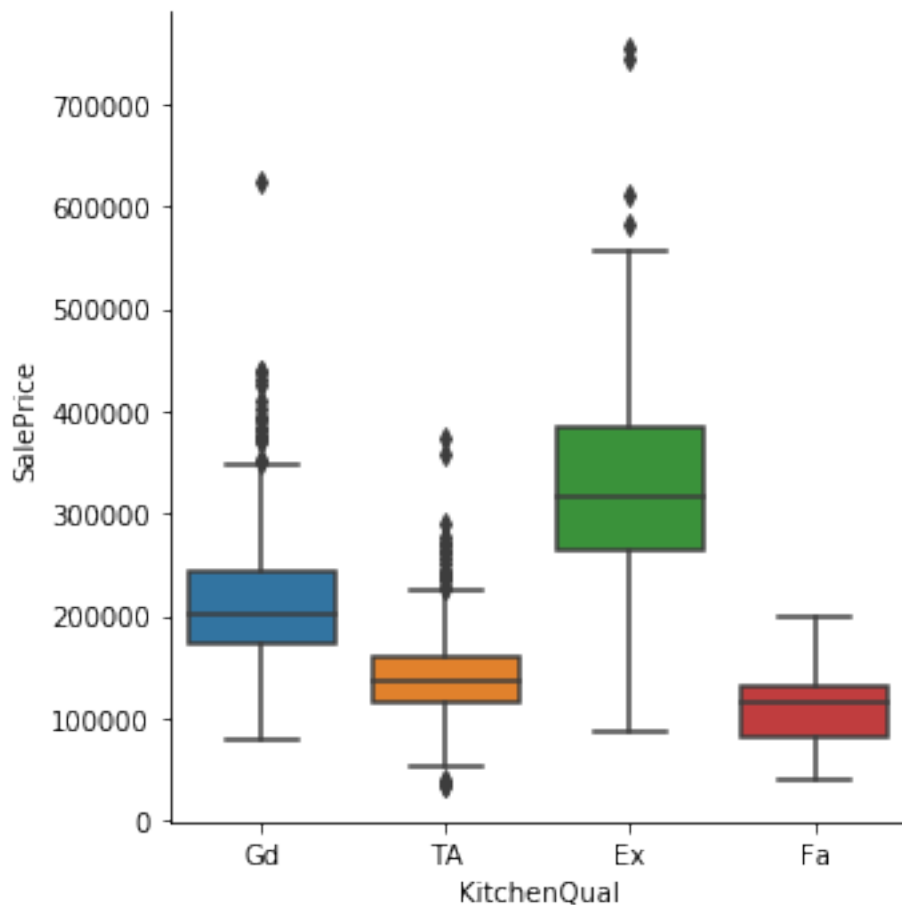
```
In [16]: # Columns related to surrounding condition
fig = plt.figure(figsize=(15,8))
ax = fig.add_subplot(121)
g = sns.catplot(x="ExterCond", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(122)
g = sns.catplot(x="ExterQual", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
data.ExterCond = data.ExterCond.map({"Ex":4, 'Gd':3, 'TA':2, 'Fa':1, 'Po':0})
data.ExterQual = data.ExterQual.map({"Ex":4, 'Gd':3, 'TA':2, 'Fa':1, 'Po':0})
```



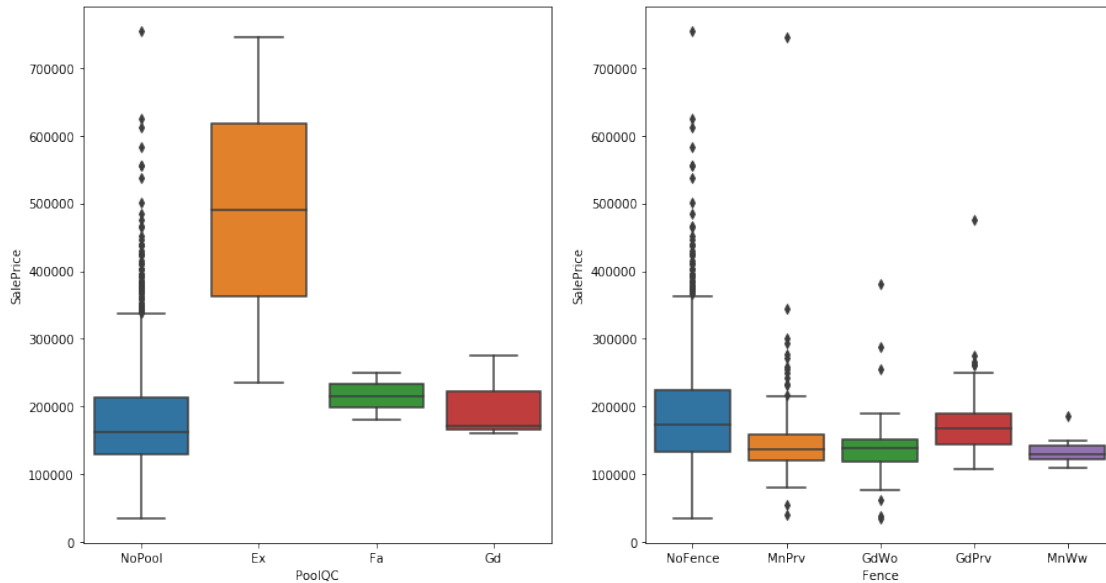
```
In [17]: fig = plt.figure(figsize=(15,8))
ax = fig.add_subplot(221)
g = sns.catplot(x="HeatingQC", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(222)
g = sns.catplot(x="CentralAir", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(223)
g = sns.catplot(x="FireplaceQu", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
data.CentralAir = data.CentralAir.map({'Y':1, 'N':0})
data.HeatingQC = data.HeatingQC.map({'Ex':4, 'Gd':3, 'TA':2, 'Fa':1, 'Po':0})
data.FireplaceQu = data.FireplaceQu.map({'Ex':5, 'Gd':4, 'TA':3, 'Fa':2, 'Po':1, 'Nofirep':0})
```



```
In [18]: sns.catplot(x="KitchenQual", y="SalePrice", kind="box", data=data)
         data.KitchenQual = data.KitchenQual.map({"Ex":4, 'Gd':3, 'TA':2, 'Fa':1, 'Po':0})
```



```
In [19]: fig = plt.figure(figsize=(15,8))
ax = fig.add_subplot(121)
g = sns.catplot(x="PoolQC", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
ax = fig.add_subplot(122)
g = sns.catplot(x="Fence", y="SalePrice", kind="box", data=data, ax=ax)
plt.close(g.fig)
data.PoolQC = data.PoolQC.map({"Ex":4, 'Gd':3, 'TA':2, 'Fa':1, 'NoPool':0})
data.Fence = data.Fence.map({'GdPrv':4 , 'MnPrv':3 , 'GdWo':2 , 'MnWw':1 , 'NoFence':0})
```



1.5 Converting categorical columns

- The task now is to convert the rest of the categorical columns into one-hot code.

In [20]: `data.info()`

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 1 to 1460
Data columns (total 80 columns):
MSSubClass    1460 non-null int64
MSZoning      1460 non-null object
LotFrontage   1460 non-null float64
LotArea       1460 non-null int64
Street        1460 non-null object
Alley         1460 non-null object
LotShape      1460 non-null object
LandContour   1460 non-null object
Utilities     1460 non-null object
LotConfig     1460 non-null object
LandSlope     1460 non-null object
Neighborhood  1460 non-null object
Condition1    1460 non-null object
Condition2    1460 non-null object
BldgType      1460 non-null object
HouseStyle    1460 non-null object
OverallQual   1460 non-null int64
OverallCond   1460 non-null int64
YearBuilt     1460 non-null int64
```

YearRemodAdd	1460 non-null int64
RoofStyle	1460 non-null object
RoofMatl	1460 non-null object
Exterior1st	1460 non-null object
Exterior2nd	1460 non-null object
MasVnrType	1460 non-null object
MasVnrArea	1460 non-null object
ExterQual	1460 non-null int64
ExterCond	1460 non-null int64
Foundation	1460 non-null object
BsmtQual	1460 non-null int64
BsmtCond	1460 non-null int64
BsmtExposure	1460 non-null int64
BsmtFinType1	1460 non-null int64
BsmtFinSF1	1460 non-null int64
BsmtFinType2	1460 non-null int64
BsmtFinSF2	1460 non-null int64
BsmtUnfSF	1460 non-null int64
TotalBsmtSF	1460 non-null int64
Heating	1460 non-null object
HeatingQC	1460 non-null int64
CentralAir	1460 non-null int64
Electrical	1459 non-null object
1stFlrSF	1460 non-null int64
2ndFlrSF	1460 non-null int64
LowQualFinSF	1460 non-null int64
GrLivArea	1460 non-null int64
BsmtFullBath	1460 non-null int64
BsmtHalfBath	1460 non-null int64
FullBath	1460 non-null int64
HalfBath	1460 non-null int64
BedroomAbvGr	1460 non-null int64
KitchenAbvGr	1460 non-null int64
KitchenQual	1460 non-null int64
TotRmsAbvGrd	1460 non-null int64
Functional	1460 non-null object
Fireplaces	1460 non-null int64
FireplaceQu	1460 non-null int64
GarageType	1460 non-null int64
GarageYrBltd	1460 non-null float64
GarageFinish	1460 non-null int64
GarageCars	1460 non-null int64
GarageArea	1460 non-null int64
GarageQual	1460 non-null int64
GarageCond	1460 non-null int64
PavedDrive	1460 non-null int64
WoodDeckSF	1460 non-null int64
OpenPorchSF	1460 non-null int64


```

EnclosedPorch    1460 non-null int64
3SsnPorch        1460 non-null int64
ScreenPorch      1460 non-null int64
PoolArea         1460 non-null int64
PoolQC           1460 non-null int64
Fence            1460 non-null int64
MiscFeature      1460 non-null object
MiscVal          1460 non-null int64
MoSold           1460 non-null int64
YrSold           1460 non-null int64
SaleType         1460 non-null object
SaleCondition    1460 non-null object
SalePrice        1460 non-null int64
dtypes: float64(2), int64(52), object(26)
memory usage: 963.9+ KB

```

```
In [21]: data.Electrical.unique() # One missing value in this column
```

```
Out[21]: array(['SBrkr', 'FuseF', 'FuseA', 'FuseP', 'Mix', nan], dtype=object)
```

We have only one missing observation, I will drop it.

```
In [22]: data.dropna(inplace=True)
```

```
In [27]: data.info()
```

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 1459 entries, 1 to 1460
Data columns (total 80 columns):
MSSubClass      1459 non-null int64
MSZoning        1459 non-null object
LotFrontage     1459 non-null float64
LotArea         1459 non-null int64
Street          1459 non-null object
Alley           1459 non-null object
LotShape        1459 non-null object
LandContour     1459 non-null object
Utilities       1459 non-null object
LotConfig       1459 non-null object
LandSlope       1459 non-null object
Neighborhood    1459 non-null object
Condition1      1459 non-null object
Condition2      1459 non-null object
BldgType        1459 non-null object
HouseStyle      1459 non-null object
OverallQual     1459 non-null int64
OverallCond     1459 non-null int64
YearBuilt       1459 non-null int64

```

YearRemodAdd	1459	non-null	int64
RoofStyle	1459	non-null	object
RoofMatl	1459	non-null	object
Exterior1st	1459	non-null	object
Exterior2nd	1459	non-null	object
MasVnrType	1459	non-null	object
MasVnrArea	1459	non-null	object
ExterQual	1459	non-null	int64
ExterCond	1459	non-null	int64
Foundation	1459	non-null	object
BsmtQual	1459	non-null	int64
BsmtCond	1459	non-null	int64
BsmtExposure	1459	non-null	int64
BsmtFinType1	1459	non-null	int64
BsmtFinSF1	1459	non-null	int64
BsmtFinType2	1459	non-null	int64
BsmtFinSF2	1459	non-null	int64
BsmtUnfSF	1459	non-null	int64
TotalBsmtSF	1459	non-null	int64
Heating	1459	non-null	object
HeatingQC	1459	non-null	int64
CentralAir	1459	non-null	int64
Electrical	1459	non-null	object
1stFlrSF	1459	non-null	int64
2ndFlrSF	1459	non-null	int64
LowQualFinSF	1459	non-null	int64
GrLivArea	1459	non-null	int64
BsmtFullBath	1459	non-null	int64
BsmtHalfBath	1459	non-null	int64
FullBath	1459	non-null	int64
HalfBath	1459	non-null	int64
BedroomAbvGr	1459	non-null	int64
KitchenAbvGr	1459	non-null	int64
KitchenQual	1459	non-null	int64
TotRmsAbvGrd	1459	non-null	int64
Functional	1459	non-null	object
Fireplaces	1459	non-null	int64
FireplaceQu	1459	non-null	int64
GarageType	1459	non-null	int64
GarageYrBltd	1459	non-null	float64
GarageFinish	1459	non-null	int64
GarageCars	1459	non-null	int64
GarageArea	1459	non-null	int64
GarageQual	1459	non-null	int64
GarageCond	1459	non-null	int64
PavedDrive	1459	non-null	int64
WoodDeckSF	1459	non-null	int64
OpenPorchSF	1459	non-null	int64

```

EnclosedPorch    1459 non-null int64
3SsnPorch        1459 non-null int64
ScreenPorch      1459 non-null int64
PoolArea         1459 non-null int64
PoolQC           1459 non-null int64
Fence            1459 non-null int64
MiscFeature      1459 non-null object
MiscVal          1459 non-null int64
MoSold           1459 non-null int64
YrSold           1459 non-null int64
SaleType         1459 non-null object
SaleCondition    1459 non-null object
SalePrice        1459 non-null int64
dtypes: float64(2), int64(52), object(26)
memory usage: 923.3+ KB

```

```
In [23]: n_data = pd.get_dummies(data, drop_first= True)
```

```
In [24]: n_data.info()
```

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 1459 entries, 1 to 1460
Columns: 533 entries, MSSubClass to SaleCondition_Partial
dtypes: float64(2), int64(52), uint8(479)
memory usage: 1.3 MB

```

```
In [25]: n_data.head()
```

```

Out[25]:
   MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond  YearBuilt  \
Id
1           60         65.0    8450             7             5        2003
2           20         80.0    9600             6             8        1976
3           60         68.0   11250             7             5        2001
4           70         60.0    9550             7             5        1915
5           60         84.0   14260             8             5        2000

   YearRemodAdd  ExterQual  ExterCond  BsmtQual  ...  \
Id
1           2003          3          2          4  ...
2           1976          2          2          4  ...
3           2002          3          2          4  ...
4           1970          2          2          3  ...
5           2000          3          2          4  ...

   SaleType_ConLI  SaleType_ConLw  SaleType_New  SaleType_Oth  SaleType_WD  \
Id
1                0                0                0                0        1

```

2	0	0	0	0	1
3	0	0	0	0	1
4	0	0	0	0	1
5	0	0	0	0	1

	SaleCondition_AdjLand	SaleCondition_Alloca	SaleCondition_Family	\
Id				
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
5	0	0	0	

	SaleCondition_Normal	SaleCondition_Partial
Id		
1	1	0
2	1	0
3	1	0
4	0	0
5	1	0

[5 rows x 533 columns]

In [28]: n_data.to_csv('../clean_data.csv')

In [29]: data.to_csv('../semi_clean_data.csv')