Exercise

For this exercise, you will be working with the House Price Dataset.

Please grab the train.csv file from Kaggle and explore this dataset. You need to perform explroatory data analysis and see if there is any correlation between the variables and analyze the distribution of the dataset. The question is open-ended and basically you're asked to perform EDA.

1- Write a summary of your findings in one page (e.g., summary statistics, plots) and submit the pdf file. Therefore, for part 3 of your assignment, you need to submit at least one jupyter notebook file and one pdf file.

2- Push your code and project to github and provide the link to your code here. Ensure that your github project is organized to at least couple of main folders, ensure that you have the README file as well:

- Src
- Data
- Docs
- Results

Read this link for further info:
https://gist.github.com/ericmjl/27e50331f24db3e8f957d1fe7bbbe510

In [4]:
```
import pandas as pd
import numpy as np
import seaborn as sns

df = pd.read_csv('train.csv')
df.columns
```

Out[4]:
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1460 non-null   int64  
 1   MSSubClass     1460 non-null   int64  
 2   MSZoning       1460 non-null   object 
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64  
 5   Street         1460 non-null   object 
 6   Alley          91 non-null     object 
 7   LotShape       1460 non-null   object 
 8   LandContour    1460 non-null   object 
 9   Utilities      1460 non-null   object 
 10  LotConfig      1460 non-null   object 
 11  LandSlope      1460 non-null   object 
 12  Neighborhood   1460 non-null   object 
 13  Condition1     1460 non-null   object 
 14  Condition2     1460 non-null   object 
 15  BldgType       1460 non-null   object 
 16  HouseStyle     1460 non-null   object 
 17  OverallQual    1460 non-null   int64  
 18  OverallCond    1460 non-null   int64  
 19  YearBuilt      1460 non-null   int64  
 20  YearRemodAdd   1460 non-null   int64  
 21  RoofStyle      1460 non-null   object 
 22  RoofMatl       1460 non-null   object 
 23  Exterior1st    1460 non-null   object 
 24  Exterior2nd    1460 non-null   object 
 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)
memory usage: 924.0+ KB
```

Summary of SalePrice

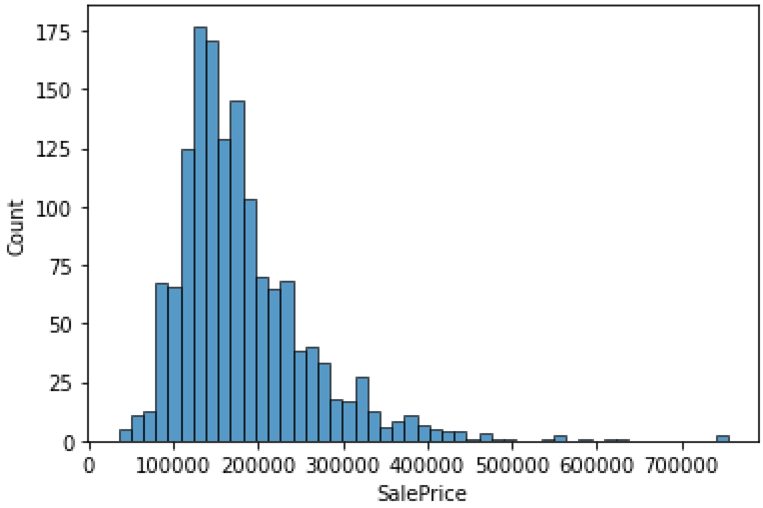
In [23]:
```
df.describe()['SalePrice']
#describe(df['SalePrice'])
```

Out[23]:
```
count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
50%      163000.000000
75%      214000.000000
max      755000.000000
Name: SalePrice, dtype: float64
```

The average Sale price for the house is 163k.The maximum price is 755k and the minimum price is 34k

In [6]:
```
sns.histplot(df['SalePrice'])
```

Out[6]:
```
<AxesSubplot:xlabel='SalePrice', ylabel='Count'>
```



From the histogram above, the distribution of our variable-- SalePrice is skewed to right. Thus, a log term of SalePrice should be generated for linear regression.

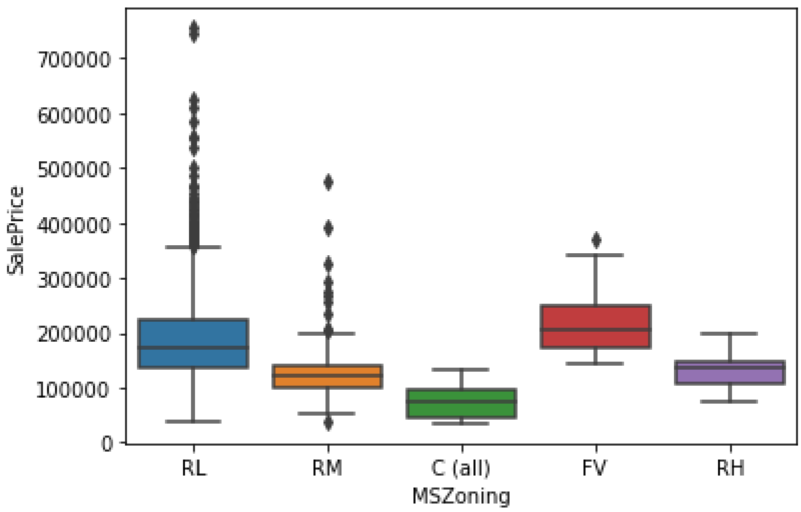
Distribution of SalePrice by MSZoning

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

comparing Salesprice with MSZoning

In [14]:
```
from matplotlib import pyplot as plt
%matplotlib inline
sns.boxplot(x="MSZoning",y ="SalePrice",data=df)
```

Out[14]:
```
<AxesSubplot:xlabel='MSZoning', ylabel='SalePrice'>
```



The graph above shows the distribution of SalePrice by MSZoning. The sales in "Floating Village Residential" area have the highest average sale price, and then "Residential Low Density". While "Commercial" sales have the lowest average sale price.

It is surprising that commercial area has the lowest average Sale Price while village area has the highest. One possible explanation could be SalePrice is also related to the size of houses.

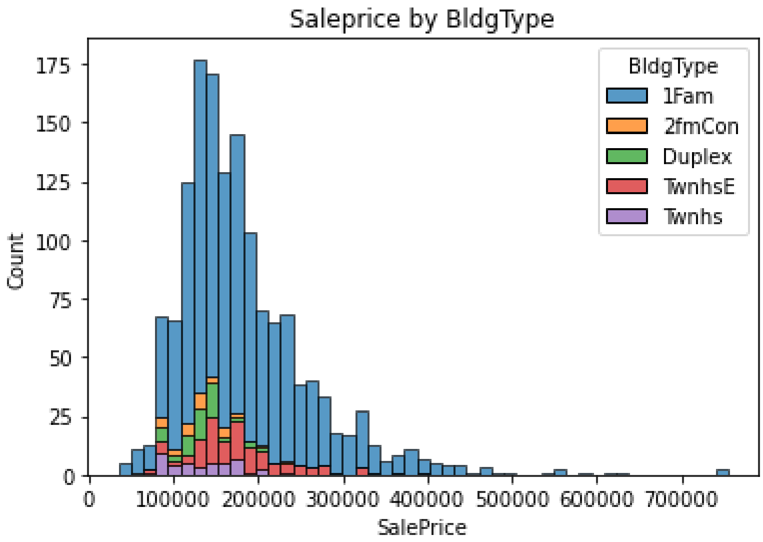
Distribution of SalePrice by BldgType

Describing SalePrice by different cateogries of BldfType.

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

In [43]:
```
#sns.jointplot(x = 'BLdgType',y = 'SalePrice', data = df, color = 'red')
sns.histplot(data=df,x='SalePrice',hue='BldgType',multiple="stack").set_title('Sal
```

Out[43]:
```
Text(0.5, 1.0, 'Saleprice by BldgType')
```



For houses with type of Single-family, most of their prices are within the range from 50000 to 300000 For Two-family Conversion, Duplex, Townhouse End Unit and Townhouse Inside Unit, most of house prices are ranging from 75000 to 210000 The highest and lowest house price both come to Single-family house type

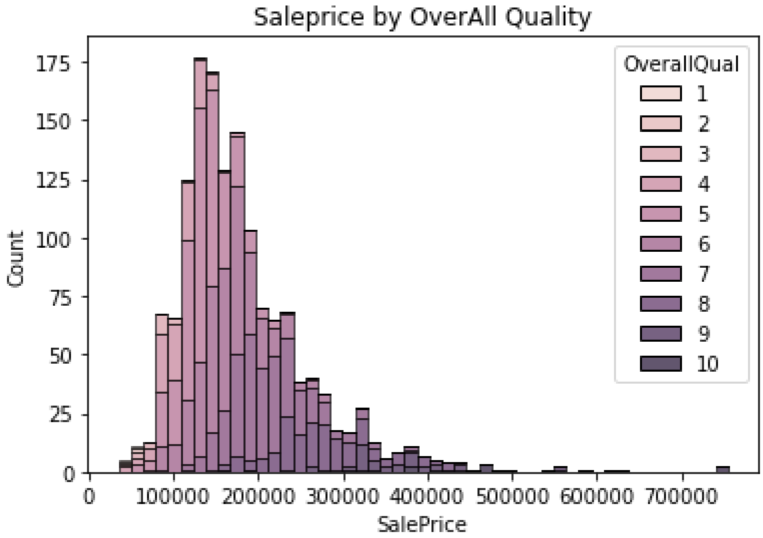
Distribution of SalePrice by OverallQuality

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

In [45]:
```
sns.histplot(data=df,x='SalePrice',hue='OverallQual',multiple="stack").set_title('S
```

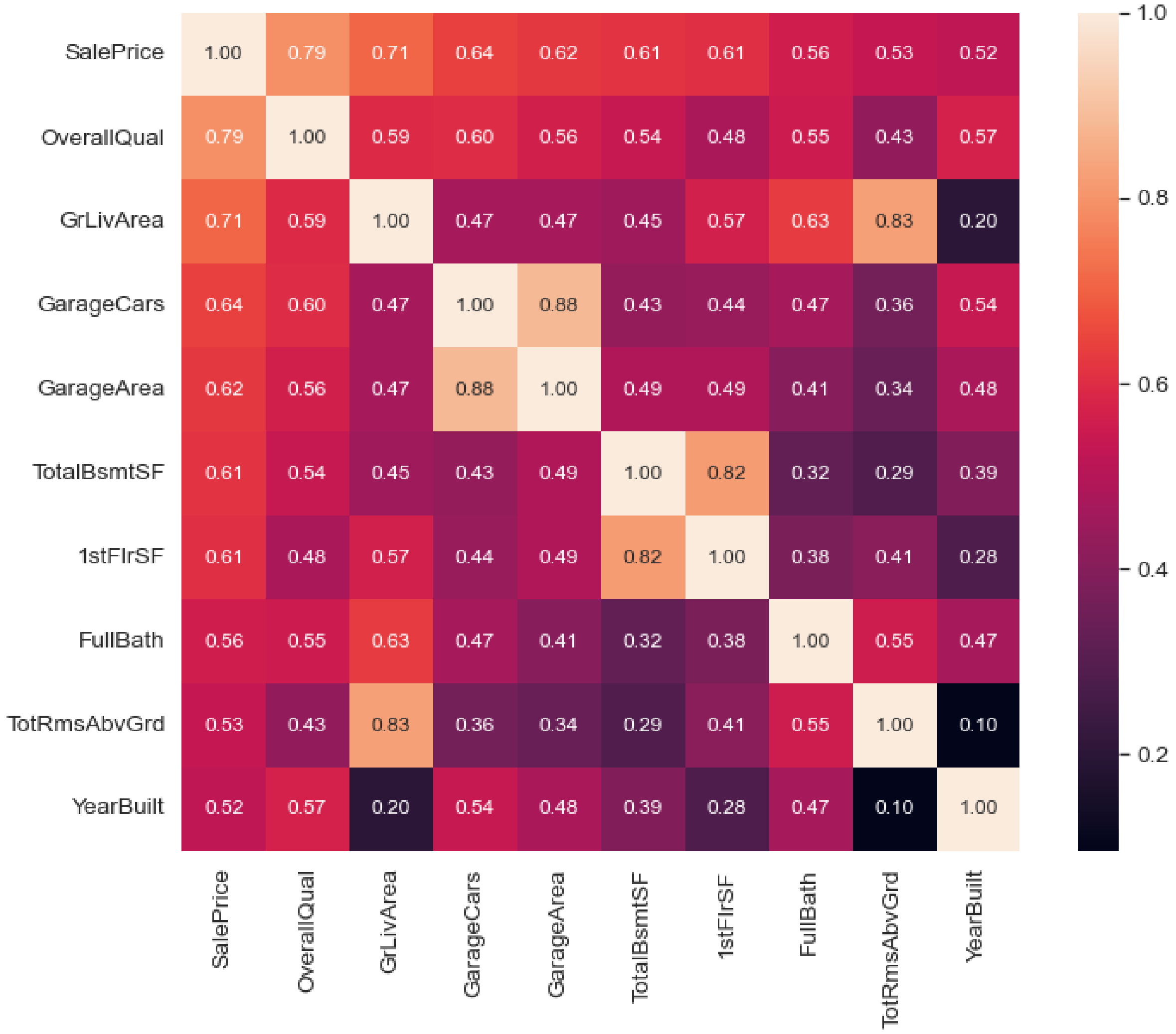
Out[45]:
```
Text(0.5, 1.0, 'Saleprice by OverAll Quality')
```



Most houses fall in the categories 4,5,6,7 i.e "Below Average", "Average", "Above Average" and "Good". The higher rate of overall quality,higher its sale price For each rate level of overall quality, the distribution of house price is almost symmetric

Heatmap based on SalePrice

In [59]:
```
corrm = df.corr()
cols = corrm.nlargest(10, 'SalePrice')['SalePrice'].index
cm = np.corrcoef(df[cols].values.T)
sns.set(font_scale=1.25)
f,ax=plt.subplots(figsize=(12,9))
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'si
plt.show()
```

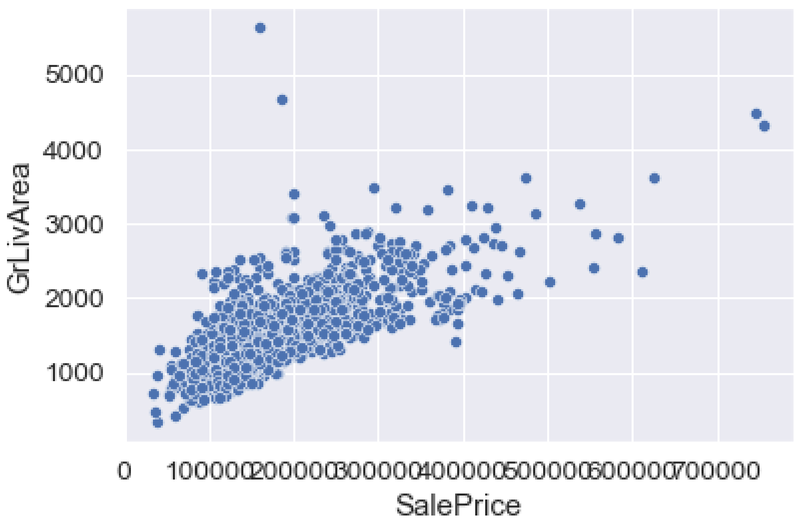


Correlation between SalePrice and some numeric variables

Scatterplot of SalePrice and GrLivArea

In [66]:
```
sns.scatterplot(data=df, x="SalePrice", y="GrLivArea")
```

Out[66]: <AxesSubplot:xlabel='SalePrice', ylabel='GrLivArea'>

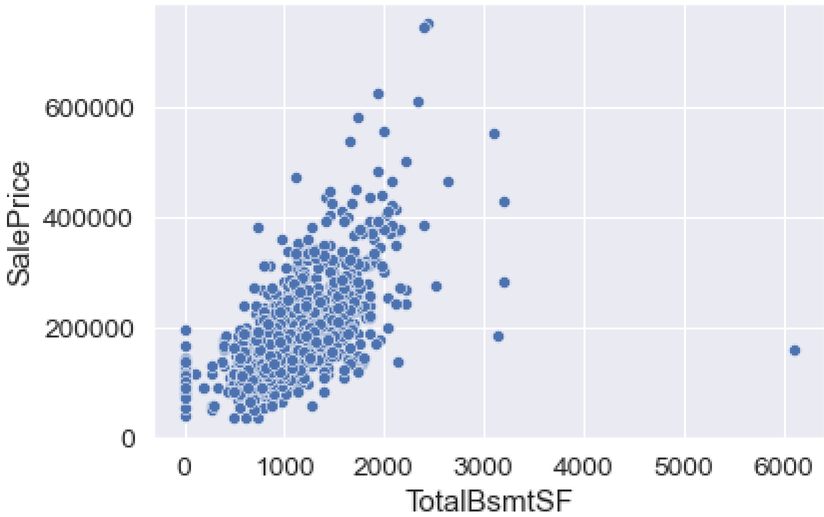


SalePrice is positively correlated with GrLivArea(Above grade (ground) living area square feet) . There are few outliers on the top left and right corner

Scatterplot of SalePrice and TotalBsmtSF

In [71]:
```
sns.scatterplot(data=df, y="SalePrice", x="TotalBsmtSF")
```

Out[71]: <AxesSubplot:xlabel='TotalBsmtSF', ylabel='SalePrice'>

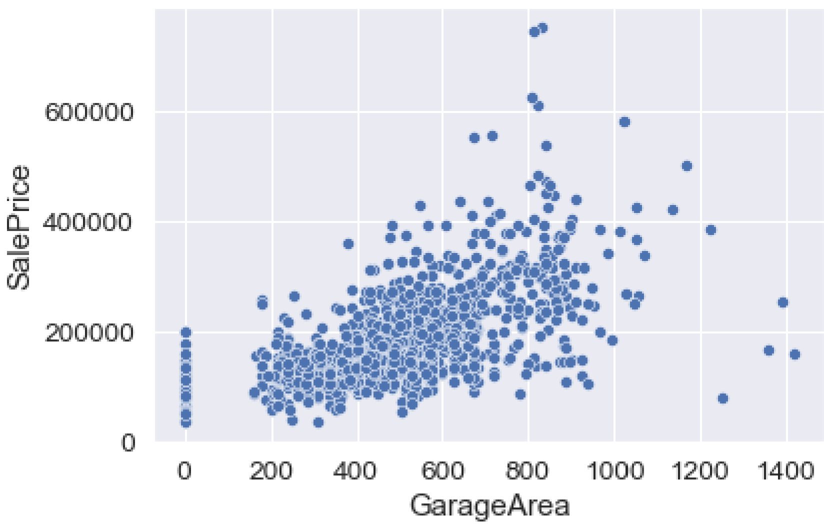


SalePrice is positively correlated with TotalBsmtSF(Total square feet of basement area). There is one outlier in the right corner.

Scatterplot of SalePrice and GarageArea

In [70]:
```
sns.scatterplot(data=df, y="SalePrice", x="GarageArea")
```

Out[70]: <AxesSubplot:xlabel='GarageArea', ylabel='SalePrice'>

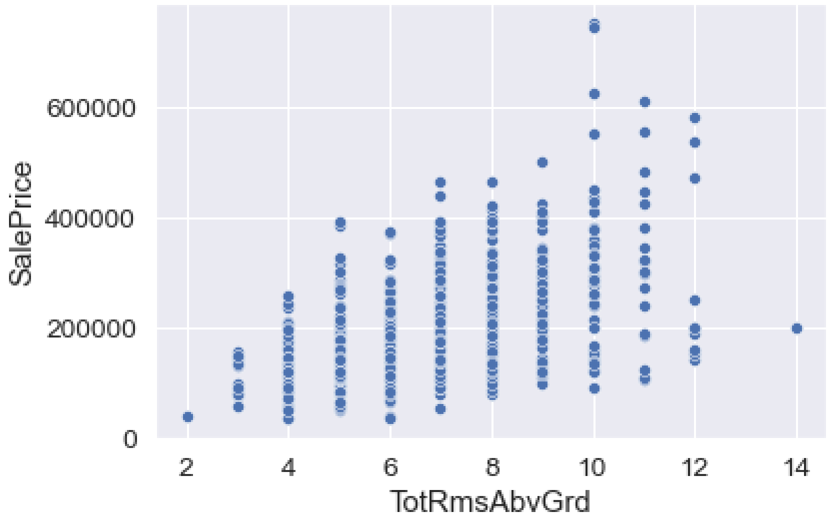


SalePrice is positively correlated with GarageArea(Size of garage in square feet). There is are few outliers on the top and the right.

Scatterplot of SalePrice and TotRmsAbvGrd

In [72]:
```
sns.scatterplot(data=df, y="SalePrice", x="TotRmsAbvGrd")
```

Out[72]: <AxesSubplot:xlabel='TotRmsAbvGrd', ylabel='SalePrice'>



SalePrice is positively correlated with TotRmsAbvGrd(Total rooms above grade (does not include bathrooms)). We can see increase in Saleprice with increase in TotRmsAbvGrd.

Please find the code pushed to GIT in the below given URL
https://github.com/sameekshamendon/Python_Assignment3_Part3.git