Exercise

For this exercise, you will be working with the [House Price Dataset (https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/code)](https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/code).

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 (https://gist.github.com/ericmjl/27e50331f24db3e8f957d1fe7bbbe510)](https://gist.github.com/ericmjl/27e50331f24db3e8f957d1fe7bbbe510)

In [15]:

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

In [16]:

```
df = pd.read_csv("train.csv")
df
```

Out[16]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandConto
0	1	60	RL	65.0	8450	Pave	NaN	Reg	L
1	2	20	RL	80.0	9600	Pave	NaN	Reg	L
2	3	60	RL	68.0	11250	Pave	NaN	IR1	L
3	4	70	RL	60.0	9550	Pave	NaN	IR1	L
4	5	60	RL	84.0	14260	Pave	NaN	IR1	L
...	...	...	...	...	...	...	...	...	
1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	L
1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	L
1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	L
1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	L
1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	L

1460 rows × 81 columns

Exploratory Data Analysis

We can see that the dataset consists of 38 numerical columns of 81 all. Morover, some columns contain missing data.

In [27]:

```
print(df.shape)
```

```
(1460, 81)
```

In [28]:

```
print(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_Log  1460 non-null   float64
dtypes: float64(4), int64(34), object(43)
memory usage: 924.0+ KB
None
```

In [29]:

```
df.head()
```

Out[29]:

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

5 rows × 81 columns

In [17]:

```
# Basic summary:
df['SalePrice'].describe()
```

Out[17]:

```
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
```

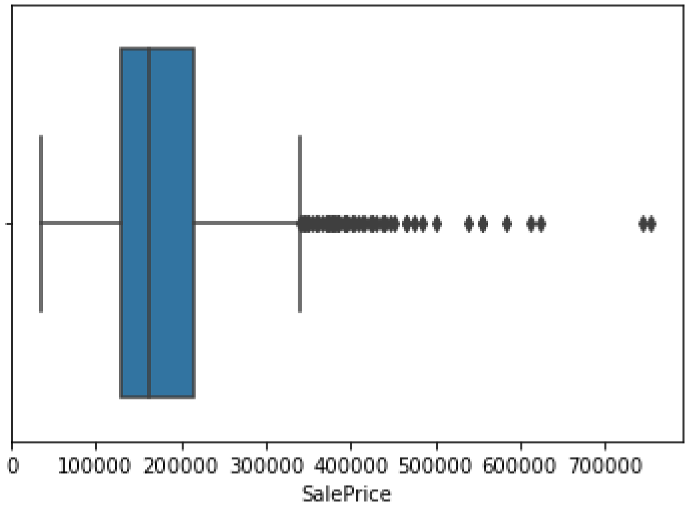
In [18]:

```
sns.boxplot(df['SalePrice'])
```

```
C:\Users\Aarushi\anaconda3\lib\site-packages\seaborn\_decorators.py:36: Futu
reWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretati
on.
  warnings.warn(
```

Out[18]:

```
<AxesSubplot:xlabel='SalePrice'>
```



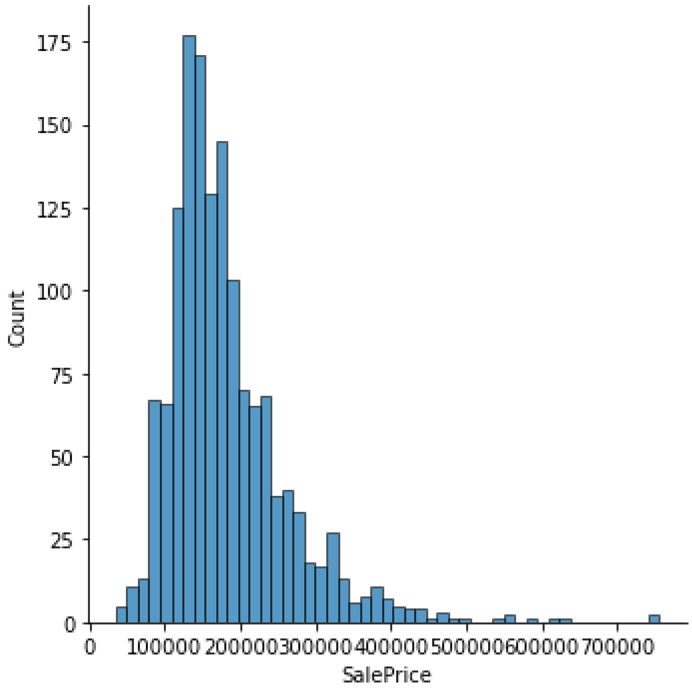
There are two outliers with prices more than 700000.

The target variable : Distribution of SalePrice

In [19]:

```
sns.displot(df['SalePrice']);
#skewness and kurtosis
print("Skewness: %f" % df['SalePrice'].skew())
print("Kurtosis: %f" % df['SalePrice'].kurt())
```

```
Skewness: 1.882876
Kurtosis: 6.536282
```



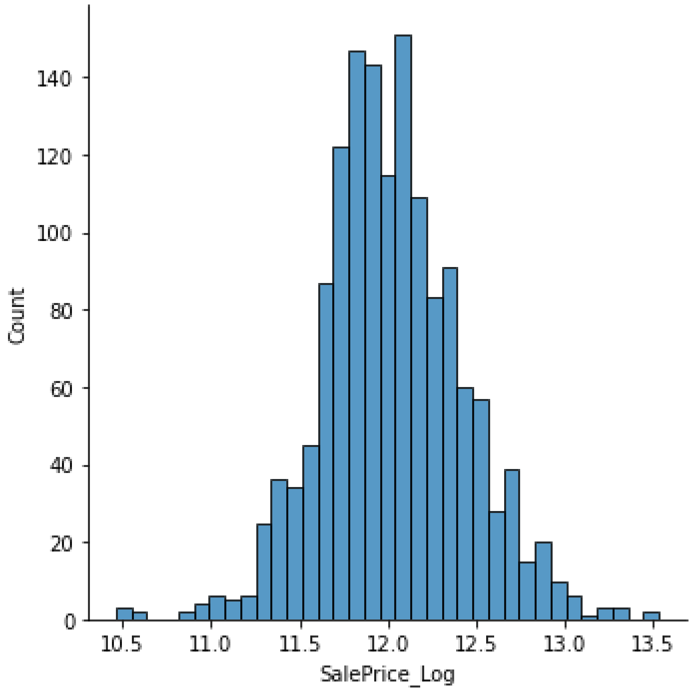

```
As we see, the target variable SalePrice is not normally distributed.
This can reduce the performance of the ML regression models because some assume normal
distribution,
see sklearn info on preprocessing
Therfore we make a log transformation, the resulting distribution looks much better.
```

In [20]:

```
df['SalePrice_Log'] = np.log(df['SalePrice'])

sns.displot(df['SalePrice_Log']);
# skewness and kurtosis
print("Skewness: %f" % df['SalePrice_Log'].skew())
print("Kurtosis: %f" % df['SalePrice_Log'].kurt())
# dropping old column
df.drop('SalePrice', axis= 1, inplace=True)
```

```
Skewness: 0.121335
Kurtosis: 0.809532
```

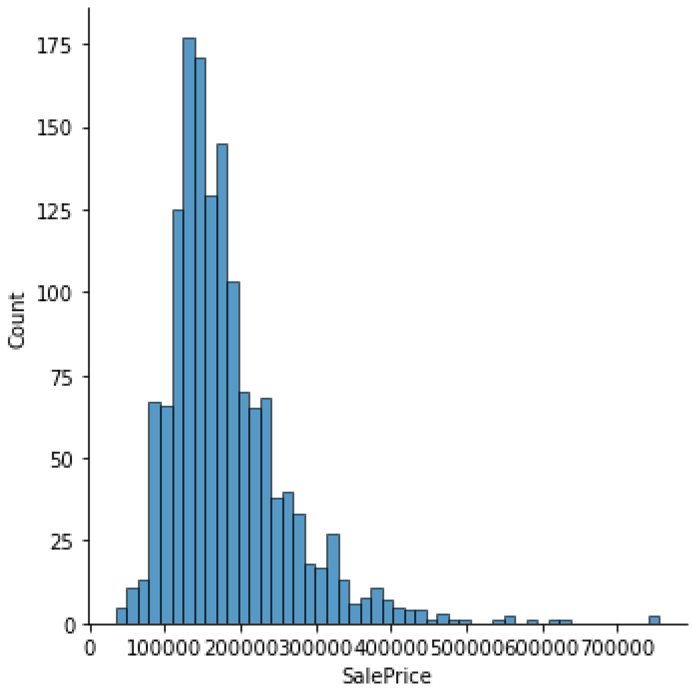


In [8]:

```
# The Density Plot of SalePrice
sns.displot(df['SalePrice'])
```

Out[8]:

```
<seaborn.axisgrid.FacetGrid at 0x21011665520>
```



it is right-skewed distribution with the pick around 160k and quite long tail with maximum about 800k.

In [9]:

```
# Positive Skeweness:
df['SalePrice'].skew()
```

Out[9]:

```
1.8828757597682129
```

In [63]:

```
y_train = df["SalePrice"]
```

Check Missing Data

Columns with Nan values

Columns with Nan values

At first, I am checking the fraction of Nan values in each column.

In [67]:

```
total = df.isnull().sum().sort_values(ascending=False)
percent = (df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)*100
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
missing_data.head(20)
```

Out[67]:

	Total	Percent
PoolQC	1453	99.520548
MiscFeature	1406	96.301370
Alley	1369	93.767123
Fence	1179	80.753425
FireplaceQu	690	47.260274
LotFrontage	259	17.739726
GarageYrBlt	81	5.547945
GarageCond	81	5.547945
GarageType	81	5.547945
GarageFinish	81	5.547945
GarageQual	81	5.547945
BsmtFinType2	38	2.602740
BsmtExposure	38	2.602740
BsmtQual	37	2.534247
BsmtCond	37	2.534247
BsmtFinType1	37	2.534247
MasVnrArea	8	0.547945
MasVnrType	8	0.547945
Electrical	1	0.068493
Id	0	0.000000

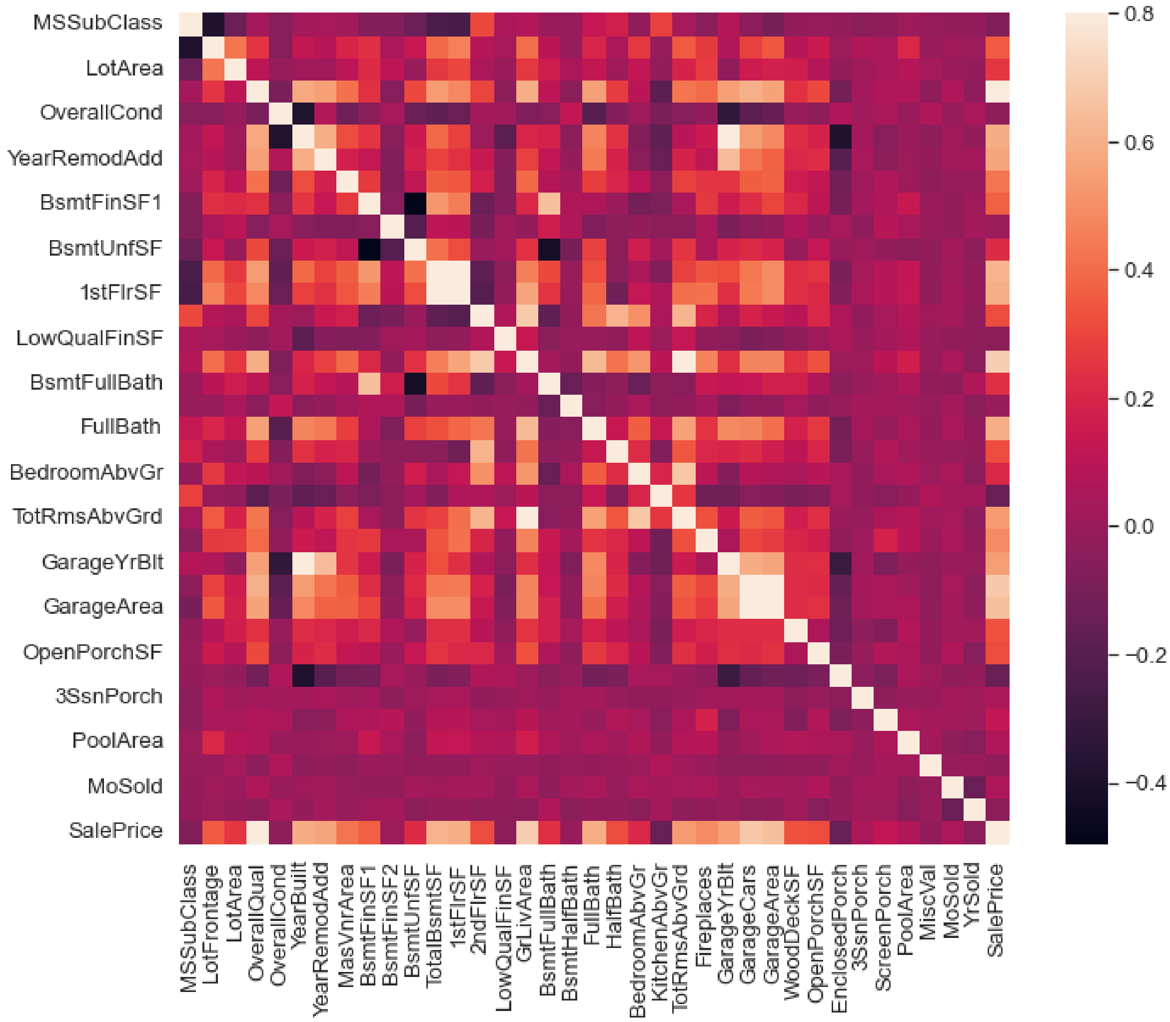
Further narrowing down, we will look for numerical type features with missing values in each of the train data and test data. First, we will search from the train data.

Visualize with a heatmap

Let's visualize the correlation of feature quantities with a heatmap and confirm.

In [69]:

```
#correlation matrix
df=df.drop(['Id'],axis=1).copy()
corrmat = df.corr()
f, ax = plt.subplots(figsize=(12, 9))
sns.heatmap(corrmat, vmax=.8, square=True);
```



We can see that 'OverallQual', 'GrLivArea', 'GarageCars',' GarageArea ',' TotalBsmtSF etc are strongly correlated with 'SalePrice'.

Analyze, identify patterns, and explore the data.

Analyze by pivoting features We will explore the relationship with 'SalePrice' about the feature quantity of the object type which does not include the missing value. From the name of feature quantity we pick up what seems to be strongly related to 'SalePrice' and analyze the mutual relationship with pivot.

Creating new feature extracting from existing

We can convert the categorical titles to ordinal.

In [70]:

```
df[['HouseStyle', 'SalePrice']].groupby(['HouseStyle'], as_index=False).mean().sort_values(
```

Out[70]:

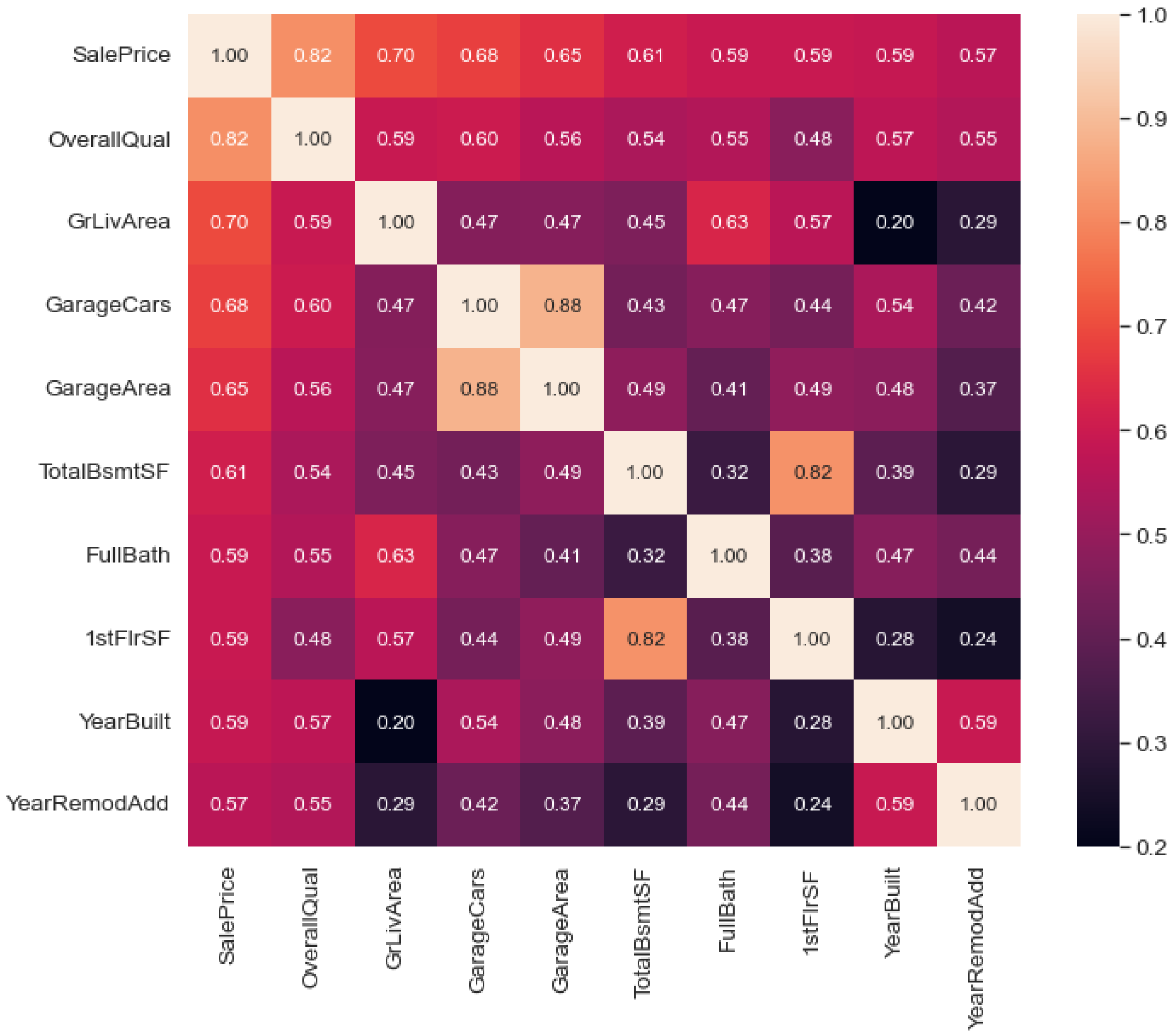
	HouseStyle	SalePrice
3	2.5Fin	2.579223
5	2Story	2.578496
7	SLvl	2.564995
2	1Story	2.563969
4	2.5Unf	2.557606
0	1.5Fin	2.550170
6	SFoyer	2.548212
1	1.5Unf	2.533208

'SalePrice' correlation matrix (zoomed heatmap style)

Select 10 features including 'SalePrice' which has strong correlation with 'SalePrice' and display it with a heat map.

In [71]:

```
#saleprice correlation matrix
k = 10  #number of variables for heatmap
corrmat = df.corr()
cols = corrmat.nlargest(k, '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={'size': 12},
plt.show()
```



'GarageArea' and 'GarageCars' are indicators showing the same thing at different angles, so we can see that the correlation coefficient is close.

Unfortunately, it was confirmed that 'HouseStyle' and 'HeatingQC' are weakly correlated with 'SalePrice'.

Scatter plots between 'SalePrice' and correlated variables

In order to check for outliers, convert the heatmap to a scatter plot with the pairplot method.

In [74]:

```
#scatter plots
sns.set()
sns.pairplot(df[cols], height = 3)
plt.show();
```

Bivariate analysis

When checking the correlation between 'SalePrice' and 'GrLivArea' with a scatter plots, outlier 2 is found at the lower right. Let's delete this.

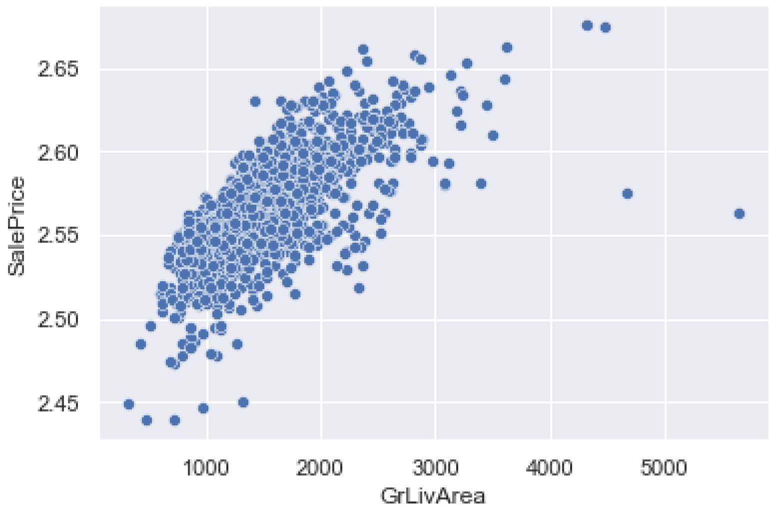
Let's check the result of the operation with the scatter plot of 'SalePrice' and 'GrLivArea'.

In [82]:

```
#  bivariate analysis saleprice/grlivarea
var = 'GrLivArea'
data1 = pd.concat([df['SalePrice'], df[var]], axis=1)
sns.scatterplot(data = data1, x=var, y='SalePrice')
```

Out[82]:

```
<AxesSubplot:xlabel='GrLivArea', ylabel='SalePrice'>
```



In this way the outliers have been properly deleted.

We will look at the heatmap of 'SalePrice' and feature amount best ten 10 again. The correlation coefficient also rises somewhat, which shows that the ranking has changed.

As we see, the target variable SalePrice is not normally distributed. This can reduce the performance of the ML regression models because some assume normal distribution, see sklearn info on preprocessing Therfore we make a log transformation, the resulting distribution looks much better.