In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [5]:
```
train=pd.read_excel(r"C:\Users\Rakesh Lodem\Downloads\train.xlsx","train")
```

In [6]:
```
train.head()
```

Out[6]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeatu
0	127	120	RL	NaN	4928	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	N
1	889	20	RL	95.0	15865	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	N
2	793	60	RL	92.0	9920	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	N
3	110	20	RL	105.0	11751	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	MnPrv	N
4	422	20	RL	NaN	16635	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	N

5 rows × 81 columns

In [7]:
```
test=pd.read_excel(r"C:\Users\Rakesh Lodem\Downloads\test.xlsx","test")
```

In [8]:
```
test.head()
```

Out[8]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	ScreenPorch	PoolArea	PoolQC	Fe
0	337	20	RL	86.0	14157	Pave	NaN	IR1	HLS	AllPub	...	0	0	NaN	
1	1018	120	RL	NaN	5814	Pave	NaN	IR1	Lvl	AllPub	...	0	0	NaN	
2	929	20	RL	NaN	11838	Pave	NaN	Reg	Lvl	AllPub	...	0	0	NaN	
3	1148	70	RL	75.0	12000	Pave	NaN	Reg	Bnk	AllPub	...	0	0	NaN	
4	1227	60	RL	86.0	14598	Pave	NaN	IR1	Lvl	AllPub	...	0	0	NaN	

5 rows × 80 columns

In [9]:
```
print(train.shape)
print(test.shape)
```

```
(1168, 81)
(292, 80)
```

In [10]:
```
## DATA CLEANING
```

In [11]:
```
train.isnull().sum().sum()
```

Out[11]:
```
5558
```

In [12]:
```
train.isnull().sum()[0:40]
```

Out[12]:
```
Id                0
MSSubClass        0
MSZoning          0
LotFrontage     214
LotArea           0
Street            0
Alley          1091
LotShape          0
LandContour       0
Utilities         0
LotConfig         0
```

```
LandSlope          0
Neighborhood       0
Condition1         0
Condition2         0
BldgType           0
HouseStyle         0
OverallQual        0
OverallCond        0
YearBuilt          0
YearRemodAdd       0
RoofStyle          0
RoofMatl           0
Exterior1st        0
Exterior2nd        0
MasVnrType         7
MasVnrArea         7
ExterQual          0
ExterCond          0
Foundation         0
BsmtQual          30
BsmtCond          30
BsmtExposure      31
BsmtFinType1      30
BsmtFinSF1         0
BsmtFinType2      31
BsmtFinSF2         0
BsmtUnfSF          0
TotalBsmtSF        0
Heating            0
dtype: int64
```

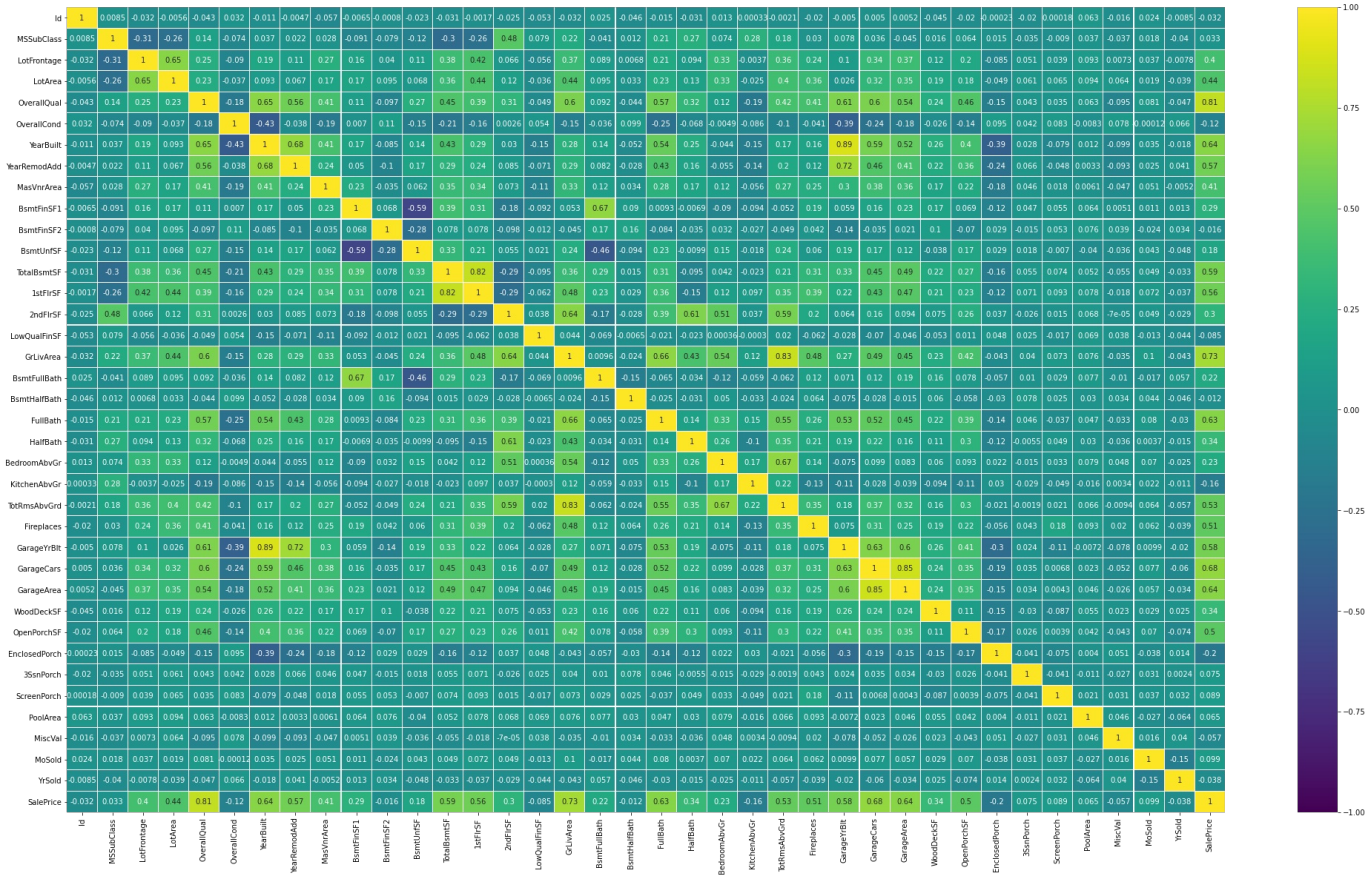
In [13]:
```
train.isnull().sum()[40:81]
```

Out[13]:
```
HeatingQC          0
CentralAir         0
Electrical         0
1stFlrSF           0
2ndFlrSF           0
LowQualFinSF       0
GrLivArea          0
BsmtFullBath       0
BsmtHalfBath       0
FullBath           0
HalfBath           0
BedroomAbvGr       0
KitchenAbvGr       0
KitchenQual        0
TotRmsAbvGrd       0
Functional         0
Fireplaces         0
FireplaceQu      551
GarageType        64
GarageYrBlt       64
GarageFinish      64
GarageCars         0
GarageArea         0
GarageQual        64
GarageCond        64
PavedDrive         0
WoodDeckSF         0
OpenPorchSF        0
EnclosedPorch      0
3SsnPorch          0
ScreenPorch        0
PoolArea           0
PoolQC          1161
Fence            931
MiscFeature     1124
MiscVal            0
MoSold             0
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
dtype: int64
```

In [14]:
```
# Checking correlation between columns
```

```
train_corr = train.corr(method="spearman")
plt.figure(figsize=(35,20))
sns.heatmap(train_corr, vmin=-1, vmax=1, cmap="viridis", annot=True, linewidth=0.1)
```

Out[14]: <AxesSubplot:>



In [15]:
```
# Selecting features with correlation above 50% with target variable
main_features = ['OverallQual','YearBuilt','YearRemodAdd','TotalBsmtSF','1stFlrSF','GrLivArea','FullBath','TotRms
```

In [16]:
```
train_new = train[main_features]
```

In [17]:
```
train_new.isnull().sum().sum()
```

Out[17]: 0

In [18]:
```
test_new = test[main_features]
```

In [19]:
```
test_new.isnull().sum()
```

Out[19]:
```
OverallQual     0
YearBuilt       0
YearRemodAdd    0
TotalBsmtSF     0
1stFlrSF        0
GrLivArea       0
FullBath        0
TotRmsAbvGrd    0
Fireplaces      0
GarageCars      0
GarageArea      0
dtype: int64
```

In [20]:
```
test_new["TotalBsmtSF"].fillna(value=test_new["TotalBsmtSF"].mean(), axis=0, inplace=True )
test_new["GarageCars"].fillna(value=test_new["GarageCars"].mean(), axis=0, inplace = True)
test_new["GarageArea"].fillna(value=test_new["GarageArea"].mean(), axis=0, inplace = True)
```

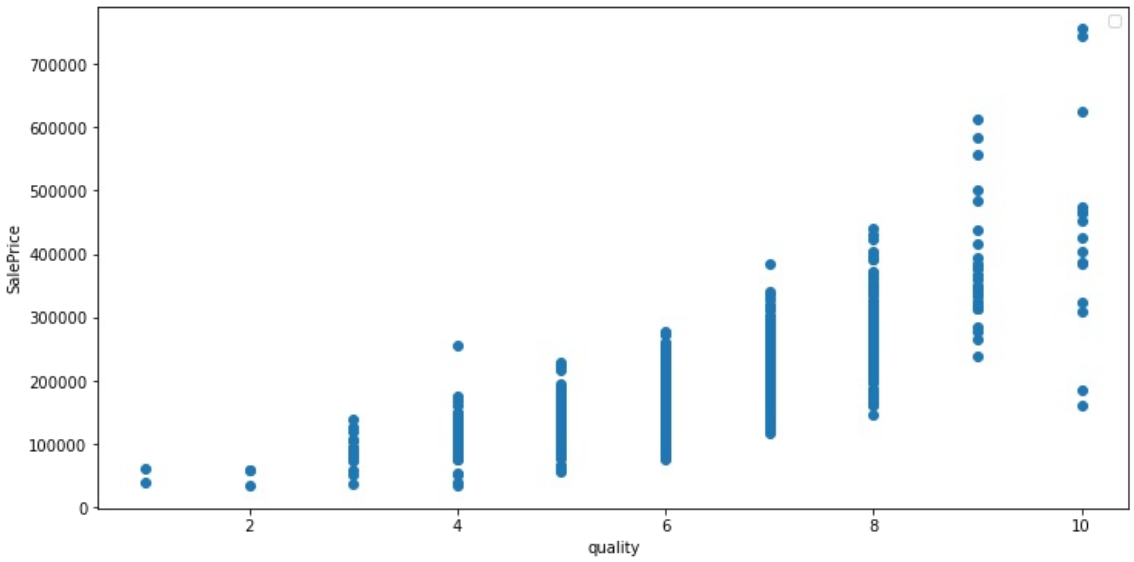
In [21]:
```
test_new.isnull().sum().sum()
```

Out[21]: 0

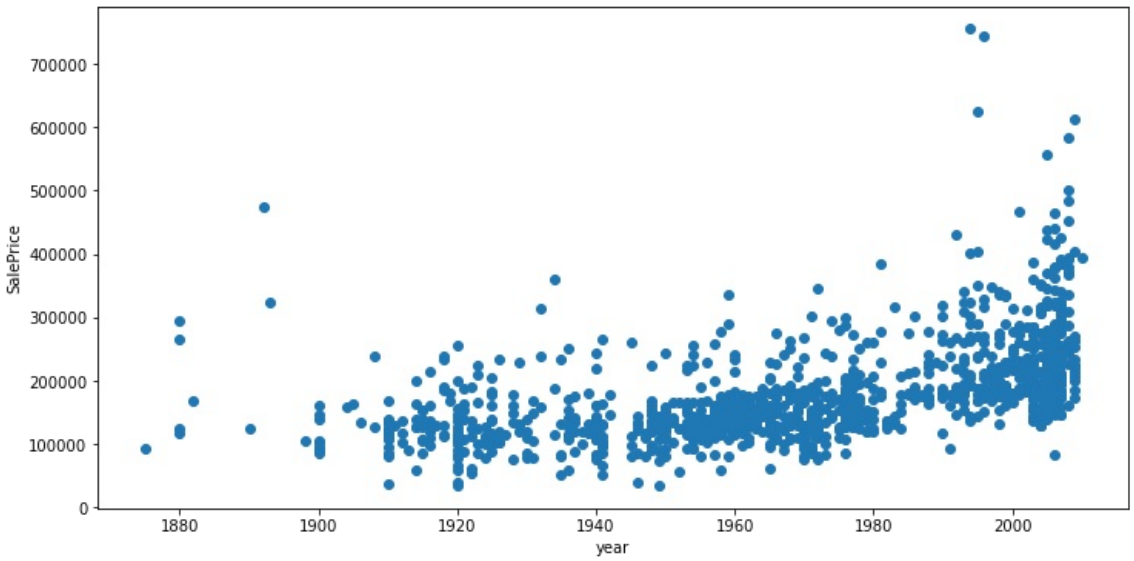
In [22]:
```
## DATA VISULAIZATION
```

In [23]:
```
# Scatter plot b/w OverallQual and SalePrice
plt.figure(figsize=(12,6))
plt.scatter(train["OverallQual"] ,train["SalePrice"])
plt.xlabel("quality")
plt.ylabel("SalePrice")
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```

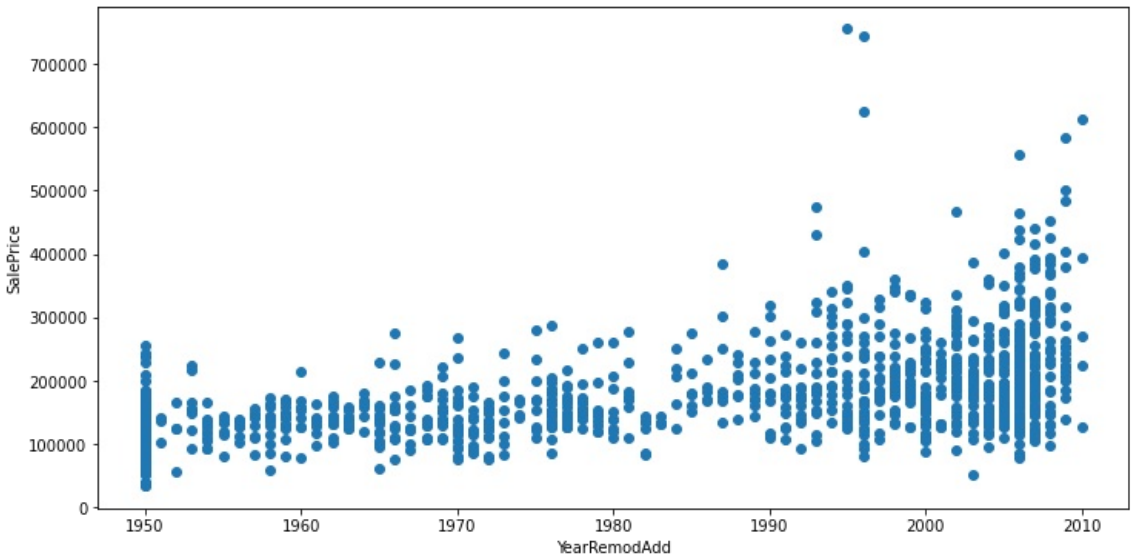


In [24]:
```
# Scatter plot b/w YearBuilt and SalePrice
plt.figure(figsize=(12,6))
plt.scatter(train["YearBuilt"] ,train["SalePrice"])
plt.xlabel("year")
plt.ylabel("SalePrice")
plt.show()
```



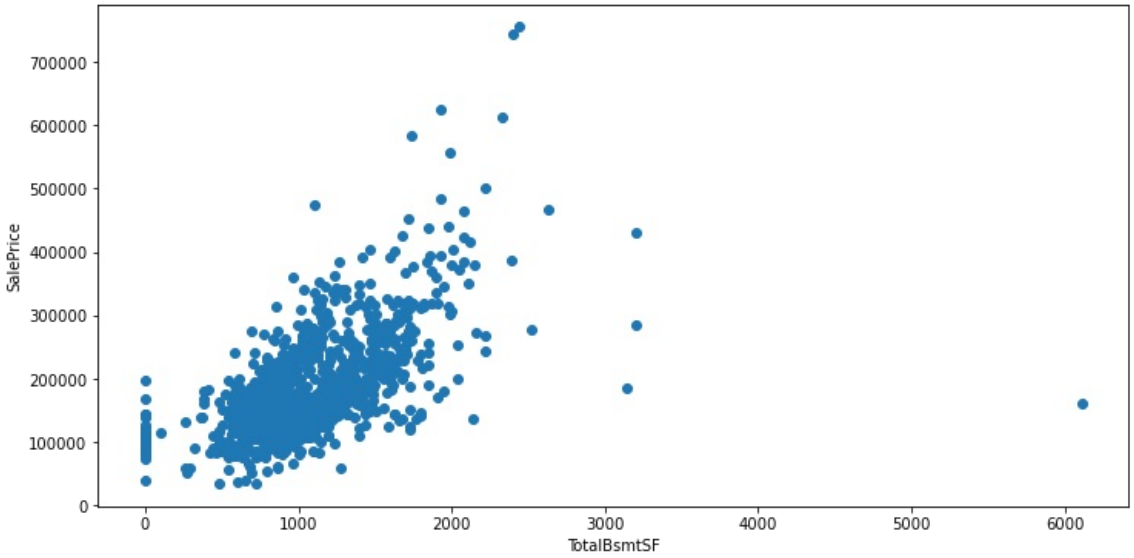
In [25]:
```
# Scatter plot b/w YearRemodAdd and SalePrice
plt.figure(figsize=(12,6))
plt.scatter(train["YearRemodAdd"] ,train["SalePrice"])
plt.xlabel("YearRemodAdd")
plt.ylabel("SalePrice")
```

```
plt.show()
```



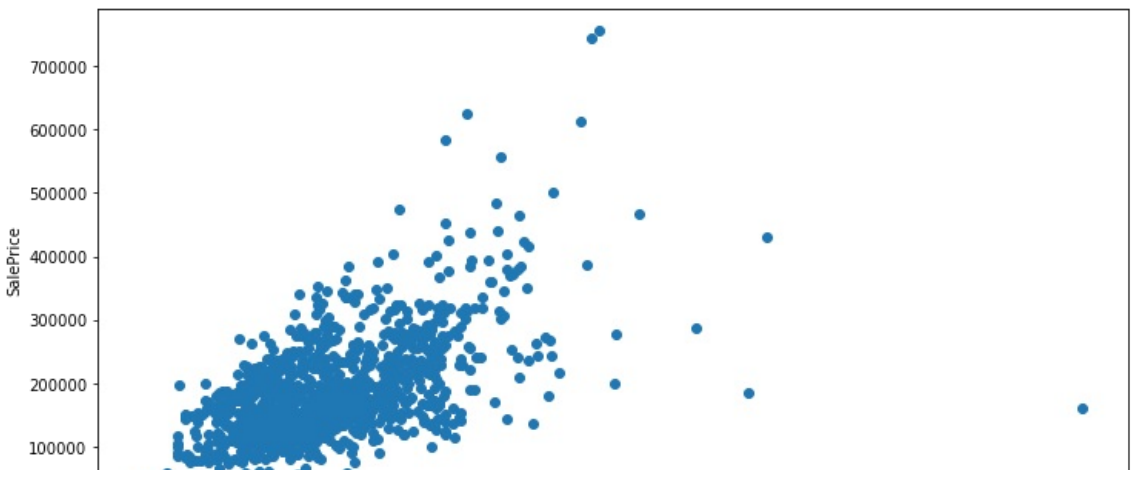
In [26]:

```
# Scatter plot b/w TotalBsmtSF and SalePrice
plt.figure(figsize=(12,6))
plt.scatter(train["TotalBsmtSF"] ,train["SalePrice"])
plt.xlabel("TotalBsmtSF")
plt.ylabel("SalePrice")
plt.show()
```



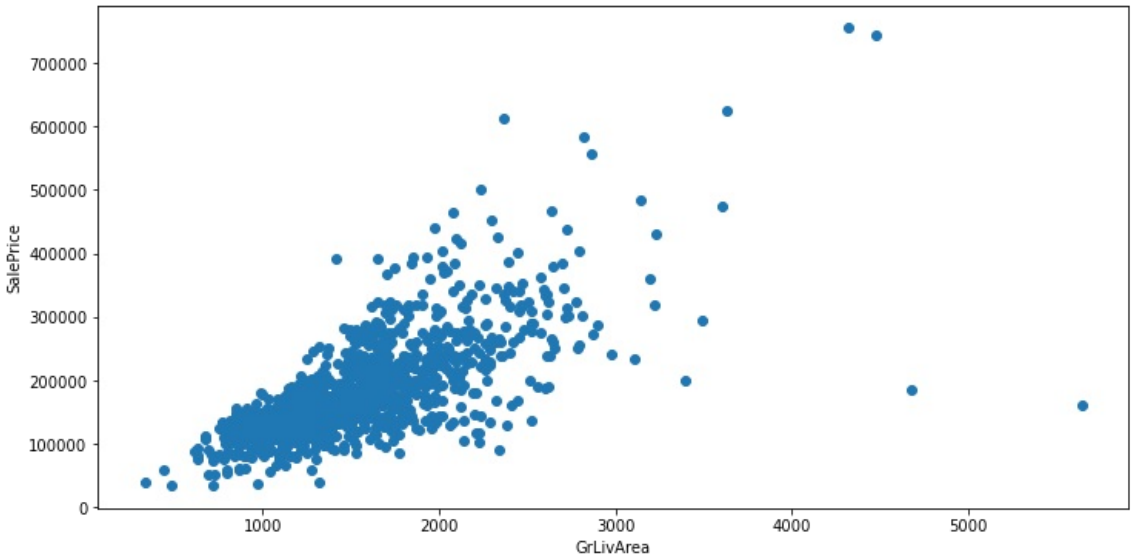
In [27]:

```
# Scatter plot b/w 1stFlrSF and SalePrice
plt.figure(figsize=(12,6))
plt.scatter(train["1stFlrSF"] ,train["SalePrice"])
plt.xlabel("1stFlrSF")
plt.ylabel("SalePrice")
plt.show()
```



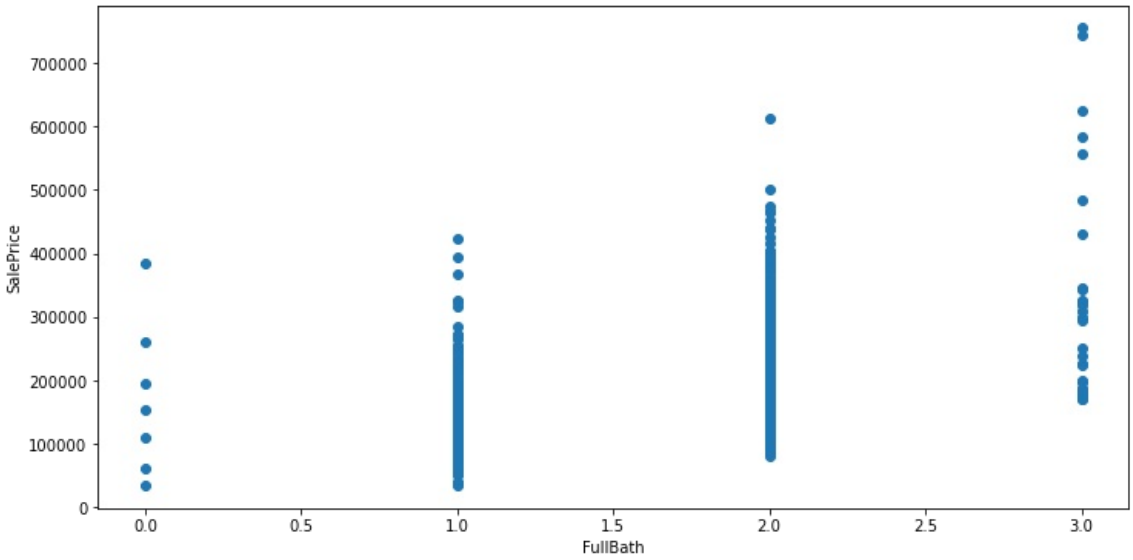
In [28]:

```
# Scatter plot b/w GrLivArea and SalePrice
plt.figure(figsize=(12,6))
plt.scatter(train["GrLivArea"] ,train["SalePrice"])
plt.xlabel("GrLivArea")
plt.ylabel("SalePrice")
plt.show()
```



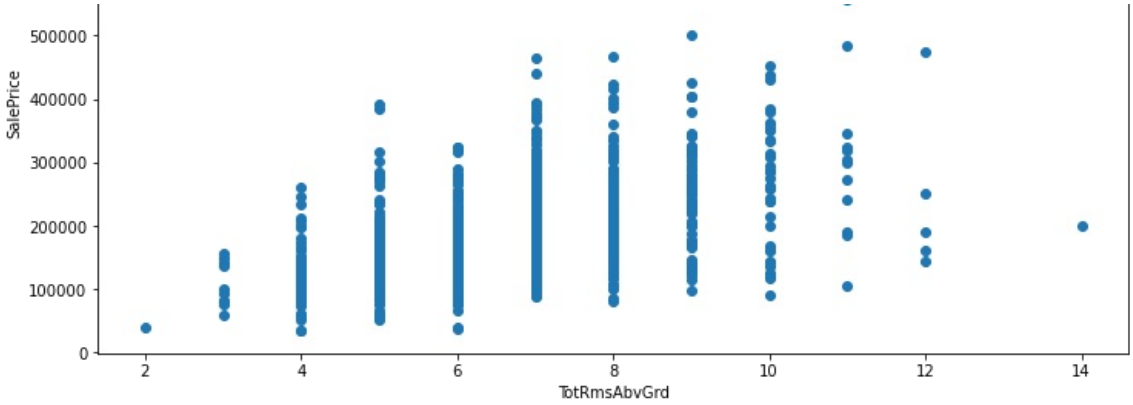
In [29]:

```
# Scatter plot b/w FullBath and SalePrice
plt.figure(figsize=(12,6))
plt.scatter(train["FullBath"] ,train["SalePrice"])
plt.xlabel("FullBath")
plt.ylabel("SalePrice")
plt.show()
```



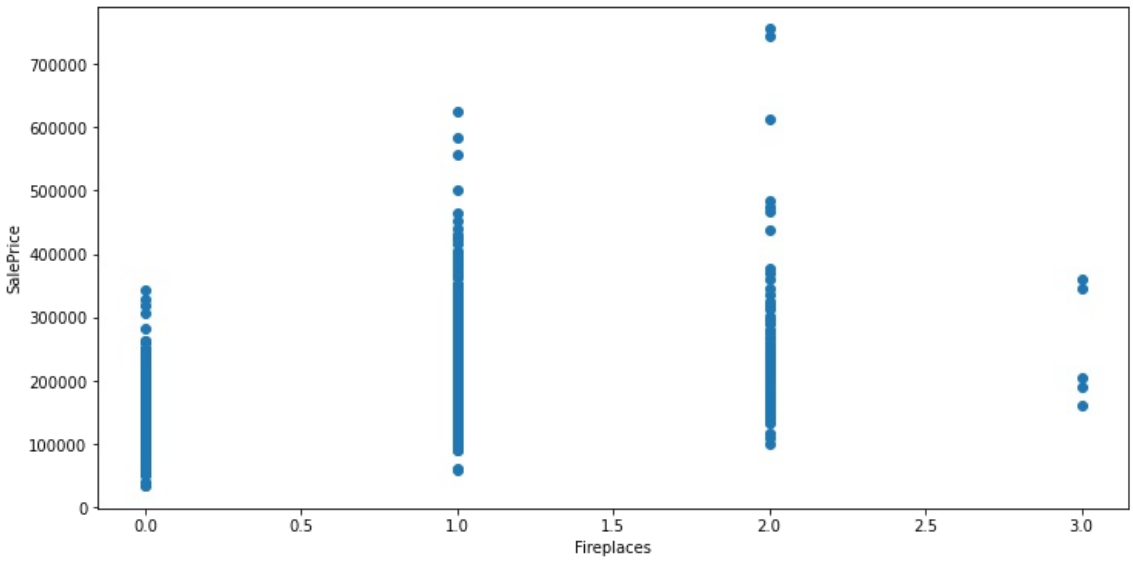
In [30]:

```
# Scatter plot b/w TotRmsAbvGrd and SalePrice
plt.figure(figsize=(12,6))
plt.scatter(train["TotRmsAbvGrd"] ,train["SalePrice"])
plt.xlabel("TotRmsAbvGrd")
plt.ylabel("SalePrice")
plt.show()
```



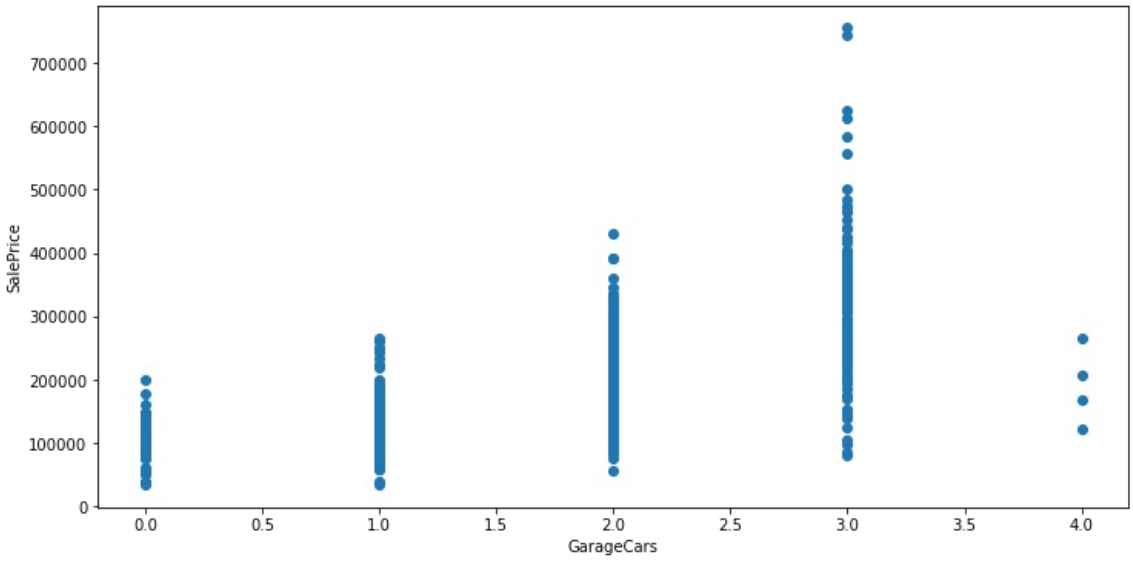
In [31]:

```
# Scatter plot b/w Fireplaces and SalePrice
plt.figure(figsize=(12,6))
plt.scatter(train["Fireplaces"] ,train["SalePrice"])
plt.xlabel("Fireplaces")
plt.ylabel("SalePrice")
plt.show()
```



In [32]:

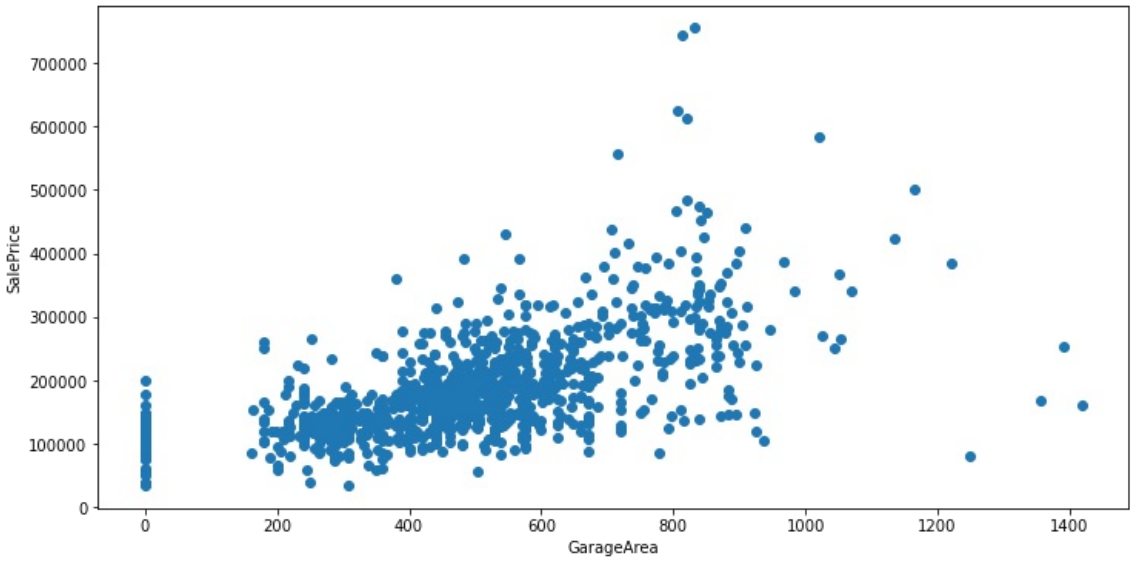
```
# Scatter plot b/w GarageCars and SalePrice
plt.figure(figsize=(12,6))
plt.scatter(train["GarageCars"] ,train["SalePrice"])
plt.xlabel("GarageCars")
plt.ylabel("SalePrice")
plt.show()
```



In [33]:

```
# Scatter plot b/w GarageArea and SalePrice
```

```
plt.figure(figsize=(12,6))
plt.scatter(train["GarageArea"] ,train["SalePrice"])
plt.xlabel("GarageArea")
plt.ylabel("SalePrice")
plt.show()
```



In [34]:
```
## MODELING
```

In [35]:
```
X=train_new
y=train['SalePrice']
```

In [36]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=42)
print(len(X_train),len(X_test),len(y_train),len(y_test))
```

```
817 351 817 351
```

In [37]:
```
## LINEAR REGRESSION
```

In [38]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

In [39]:
```
model.fit(X_train,y_train)
```

Out[39]:
```
LinearRegression()
```

In [40]:
```
predictions = model.predict(X_test)
model.score(X_test,y_test)
```

Out[40]:
```
0.754262299547903
```

In [ ]:
```
## RANDOMFOREST REGRESSOR
```

In [41]:
```
from sklearn.ensemble import RandomForestRegressor
model1 = RandomForestRegressor()
model1.fit(X_train,y_train)
RandomForestRegressor()
prediction1 = model1.predict(X_test)
model1.score(X_test,y_test)
```

Out[41]:
```
0.7821293094419525
```

In [43]:
```
## DECISION TREE REGRESSOR
```

In [44]:
```
from sklearn.tree import DecisionTreeRegressor
model2 = DecisionTreeRegressor()
model2.fit(X_train,y_train)
DecisionTreeRegressor()
prediction2 = model2.predict(X_test)
model2.score(X_test,y_test)
```

Out[44]:
```
0.6426899880475724
```

In [45]:
```
## KNEIGHBORS REGRESSOR
```

In [46]:
```
from sklearn.neighbors import KNeighborsRegressor
model3 = KNeighborsRegressor()
model3.fit(X_train,y_train)
KNeighborsRegressor()
prediction3 = model3.predict(X_test)
model3.score(X_test, y_test)
```

Out[46]:
```
0.689453219430473
```

In [47]:
```
from sklearn.model_selection import RandomizedSearchCV
```

In [48]:
```
## HYPER PARAMETER TUNING
```

In [49]:
```
params={'n_estimators':[100, 300, 500, 700],
        'min_samples_split':[1,2,3,4],
        'min_samples_leaf':[1,2,3,4],
        'max_depth':[None,1,2,3,4,5,6,7,8,9,10,15,20,25,30,35,40]}
```

In [51]:
```
g=RandomizedSearchCV(RandomForestRegressor(),params,cv=10)
```

In [53]:
```
g.fit(X_train,y_train)
```

Out[53]:
```
RandomizedSearchCV(cv=10, estimator=RandomForestRegressor(),
                   param_distributions={'max_depth': [None, 1, 2, 3, 4, 5, 6, 7,
                                                      8, 9, 10, 15, 20, 25, 30,
                                                      35, 40],
                                        'min_samples_leaf': [1, 2, 3, 4],
                                        'min_samples_split': [1, 2, 3, 4],
                                        'n_estimators': [100, 300, 500, 700]})
```

In [54]:
```
print(g.best_estimator_)
print(g.best_params_)
print(g.best_score_)
```

```
RandomForestRegressor(max_depth=40, min_samples_leaf=3)
{'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf': 3, 'max_depth': 40}
0.8124369104270379
```

In [56]:
```
from sklearn.model_selection import cross_val_score
```

In [59]:
```
m=RandomForestRegressor(max_depth=40, min_samples_leaf=3, min_samples_split=2,n_estimators=100)
m.fit(X_train,y_train)
p=m.predict(X_test)
score=cross_val_score(m,X,y,cv=10)
```

In [64]:
```
from sklearn.metrics import r2_score,mean_squared_error
```

In [67]:
```
m.score(X_test,y_test)
```

```
model(X_test,y_test)
```

Out[67]: 0.8007393698118116

In [ ]: