In [1]:

```
##importing the necessary libraries

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:

```
##reading in the csv file

df = pd.read_csv('train (1).csv')
```

In [3]:

```
##The first five rows of the dataset

df.head()
```

Out[3]:

	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 [4]:

```
##the shape of the dataset

df.shape
```

Out[4]:

```
(1460, 81)
```

In [5]:

```
##getting the names of the columns in the dataset

df.columns.to_list()
```

Out[5]:

```
['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']
```

In [6]:

```
##Separating the features into categorical and numerical features

num_feats = df.dtypes[df.dtypes != "object"].index
cat_feats = df.dtypes[df.dtypes == "object"].index
print(df[num_feats].columns)
print("-"*100)
print(df[cat_feats].columns)
```

```
Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
       'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF
1',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBat
h',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd',
       'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckS
F',
       'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolAre
a',
       'MiscVal', 'MoSold', 'YrSold', 'SalePrice'],
      dtype='object')
----------------------------------------------------------------------------
------------------------
Index(['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilitie
s',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType
2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
       'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQua
l',
       'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature',
       'SaleType', 'SaleCondition'],
      dtype='object')
```

In [7]:

```
#lets see if there are any columns with missing values
nullvalues = df.columns[df.isnull().any()]
df[nullvalues].isnull().sum()
```

Out[7]:

```
LotFrontage      259
Alley           1369
MasVnrType         8
MasVnrArea         8
BsmtQual          37
BsmtCond          37
BsmtExposure      38
BsmtFinType1      37
BsmtFinType2      38
Electrical         1
FireplaceQu      690
GarageType        81
GarageYrBlt       81
GarageFinish      81
GarageQual        81
GarageCond        81
PoolQC          1453
Fence           1179
MiscFeature     1406
dtype: int64
```

In [8]:

```
# Grouping by neighborhood and filling missing value by the median LotFrontage of all the n
df['LotFrontage'] = df.groupby('Neighborhood')['LotFrontage'].transform(
    lambda x: x.fillna(x.median()))
```

In [9]:

```
df['Alley'] = df['Alley'].fillna('None')
```

In [10]:

```
df['MasVnrType'] = df['MasVnrType'].fillna('None')
df['MasVnrArea'] = df['MasVnrArea'].fillna(0)
```

In [11]:

```
##BsmtQual, BsmtCond, BsmtExposure, BsmtFinType1 and BsmtFinType2 are all categorical basem
##NaN means that there is no basement.
```

In [12]:

```
for col in ('BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2'):
    df[col] = df[col].fillna('None')
```

In [13]:

```
##Electrical : It has one NA value. Since this feature has mostly 'SBrkr', we can set that
```

In [14]:

```
df['Electrical'] = df['Electrical'].fillna(df['Electrical'].mode()[0])
```

In [15]:

```
##FireplaceQu : data description says NA means "no fireplace"
```

In [16]:

```
df['FireplaceQu'] = df['FireplaceQu'].fillna('None')
```

In [17]:

```
##GarageType, GarageFinish, GarageQual and GarageCond : Replacing missing data with None

for col in ('GarageType', 'GarageFinish', 'GarageQual', 'GarageCond'):
    df[col] = df[col].fillna('None')
```

In [18]:

```
##GarageYrBlt: Replacing missing data with 0 (Since No garage = no cars in such garage.)
df['GarageYrBlt'] = df['GarageYrBlt'].fillna(0)
```

In [19]:

```
##PoolQC: data description says NA means "No Pool".
##That make sense, given the huge ratio of missing value (+99%) and majority of houses have

df['PoolQC'] = df['PoolQC'].fillna('None')
```

In [20]:

```
##Fence : data description says NA means "no fence"

df['Fence'] = df['Fence'].fillna('None')
```

In [21]:

```
##MiscFeature : data description says NA means "no misc feature"

df['MiscFeature'] = df['MiscFeature'].fillna('None')
```

In [22]:

```
df.get_dtype_counts()
```

Out[22]:

```
float64     3
int64      35
object     43
dtype: int64
```

In [23]:

```
df.isnull().sum()
```

Out[23]:

```
Id               0
MSSubClass       0
MSZoning         0
LotFrontage      0
LotArea          0
Street           0
Alley            0
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       0
MasVnrArea       0
ExterQual        0
ExterCond        0
Foundation       0
                ..
BedroomAbvGr     0
KitchenAbvGr     0
KitchenQual      0
TotRmsAbvGrd     0
Functional       0
Fireplaces       0
FireplaceQu      0
GarageType       0
GarageYrBlt      0
GarageFinish     0
GarageCars       0
GarageArea       0
GarageQual       0
GarageCond       0
PavedDrive       0
WoodDeckSF       0
OpenPorchSF      0
EnclosedPorch    0
3SsnPorch        0
ScreenPorch      0
PoolArea         0
PoolQC           0
Fence            0
MiscFeature      0
```

```
MiscVal          0
MoSold           0
YrSold           0
SaleType         0
SaleCondition    0
SalePrice        0
Length: 81, dtype: int64
```

In [24]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
Id                1460 non-null int64
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 float64
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        1460 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(3), int64(35), object(43)
memory usage: 924.0+ KB
```

In [25]:

```
df.describe()
```

Out[25]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	Ye
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.(
mean	730.500000	56.897260	70.199658	10516.828082	6.099315	5.575342	1971.:
std	421.610009	42.300571	22.431902	9981.264932	1.382997	1.112799	30.:
min	1.000000	20.000000	21.000000	1300.000000	1.000000	1.000000	1872.(
25%	365.750000	20.000000	60.000000	7553.500000	5.000000	5.000000	1954.(
50%	730.500000	50.000000	70.000000	9478.500000	6.000000	5.000000	1973.(
75%	1095.250000	70.000000	80.000000	11601.500000	7.000000	6.000000	2000.(
max	1460.000000	190.000000	313.000000	215245.000000	10.000000	9.000000	2010.(

8 rows × 38 columns

In [26]:

```
corr = df.corr()
corr.sort_values(["SalePrice"], ascending = False, inplace = True)
corr = corr.SalePrice
corr
```

Out[26]:

```
SalePrice        1.000000
OverallQual      0.790982
GrLivArea        0.708624
GarageCars       0.640409
GarageArea       0.623431
TotalBsmtSF      0.613581
1stFlrSF         0.605852
FullBath         0.560664
TotRmsAbvGrd     0.533723
YearBuilt        0.522897
YearRemodAdd     0.507101
MasVnrArea       0.472614
Fireplaces       0.466929
BsmtFinSF1       0.386420
LotFrontage      0.349876
WoodDeckSF       0.324413
2ndFlrSF         0.319334
OpenPorchSF      0.315856
HalfBath         0.284108
LotArea          0.263843
GarageYrBlt      0.261366
BsmtFullBath     0.227122
BsmtUnfSF        0.214479
BedroomAbvGr     0.168213
ScreenPorch      0.111447
PoolArea         0.092404
MoSold           0.046432
3SsnPorch        0.044584
BsmtFinSF2      -0.011378
BsmtHalfBath    -0.016844
MiscVal         -0.021190
Id              -0.021917
LowQualFinSF    -0.025606
YrSold          -0.028923
OverallCond     -0.077856
MSSubClass      -0.084284
EnclosedPorch   -0.128578
KitchenAbvGr    -0.135907
Name: SalePrice, dtype: float64
```

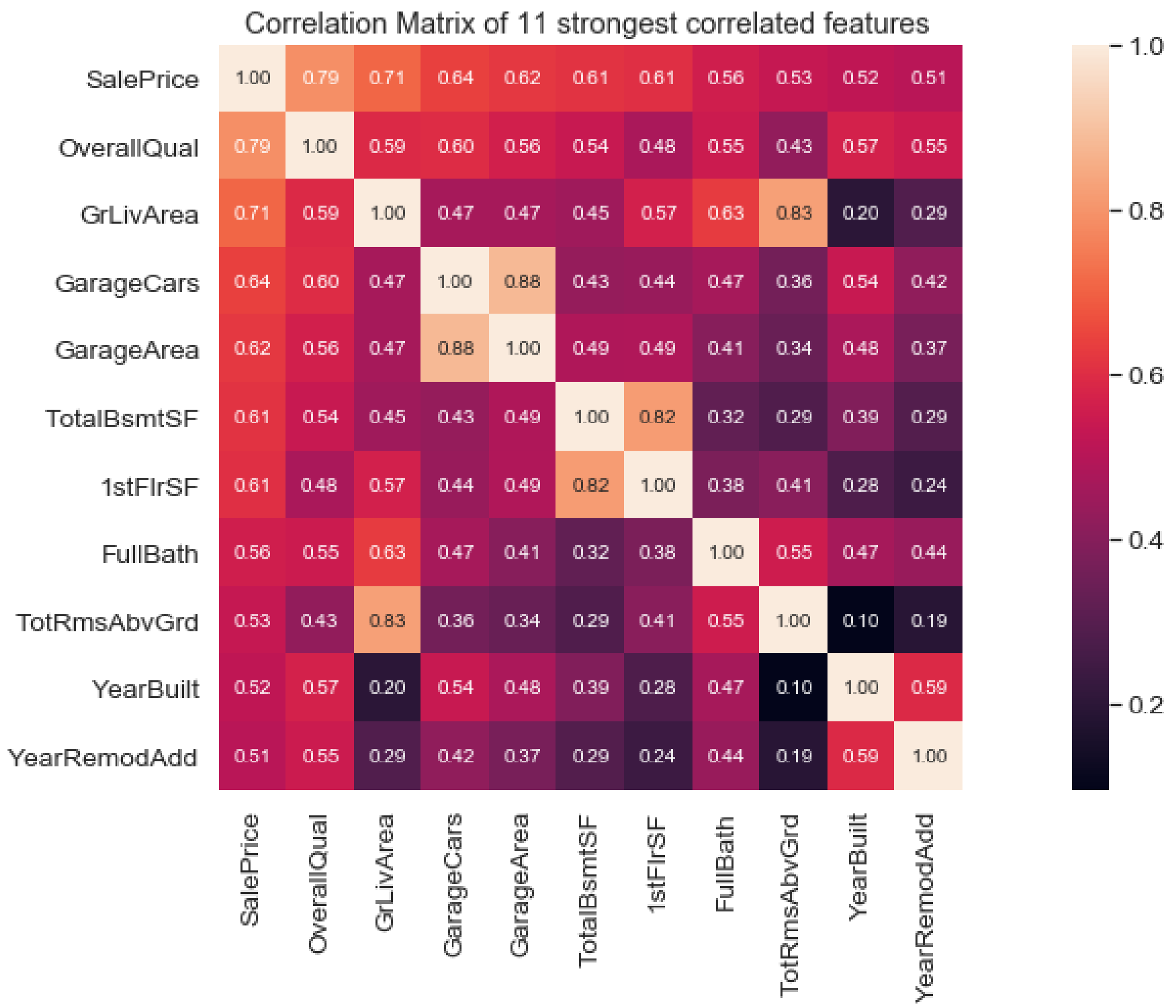
In [27]:

```
corr_matrix = df.corr()
plt.figure(figsize=(20,7))
k = 11 #number of variables for heatmap (including SalePrice)
cols_positive = corr_matrix.nlargest(k, 'SalePrice')['SalePrice'].index
cm = np.corrcoef(df[cols_positive].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size': 10},
                 xticklabels=cols_positive.values)

plt.title('Correlation Matrix of 11 strongest correlated features ')
```

Out[27]:

```
Text(0.5, 1.0, 'Correlation Matrix of 11 strongest correlated features ')
```



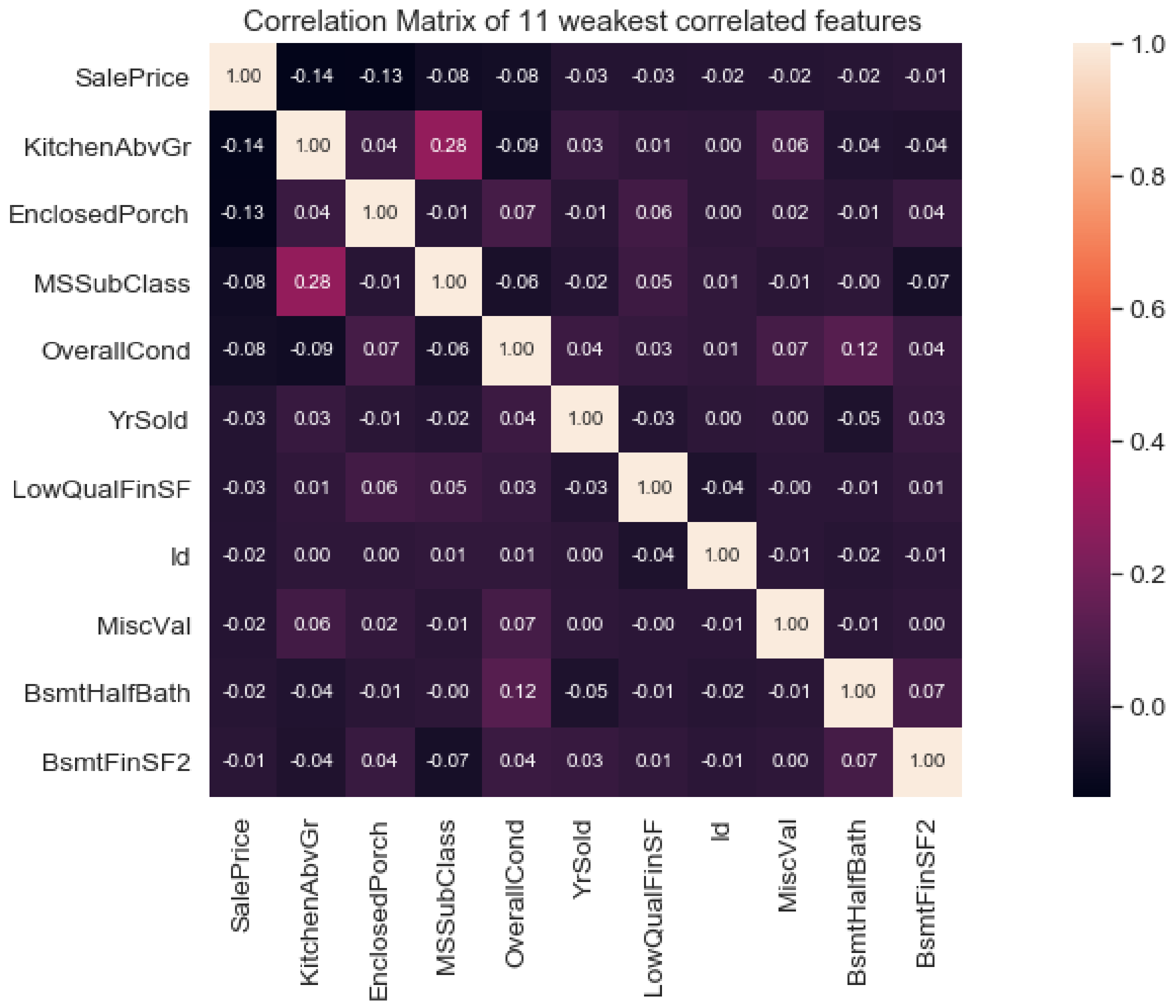
As we can see from the heatmap above, some of the Independent variables are correlated with each other. One of the basic assumptions of Linear regression is that the independent variables are not correlated with each other, if they are then we will not know which of the two variables is imparting the correct information about the Dependent variable

In [28]:

```
plt.figure(figsize=(20,7))
k = 10 #number of variables for heatmap
cols_negative = np.append(['SalePrice'], corr_matrix.nsmallest(k, 'SalePrice')['SalePrice']
cm = np.corrcoef(df[cols_negative].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size': 10},
                 xticklabels=cols_negative)
plt.title('Correlation Matrix of 11 weakest correlated features ')
```

Out[28]:

```
Text(0.5, 1.0, 'Correlation Matrix of 11 weakest correlated features ')
```



	SalePrice	KitchenAbvGr	EnclosedPorch	MSSubClass	OverallCond	YrSold	LowQualFinSF	Id	MiscVal	BsmtHalfBath	BsmtFinSF2
SalePrice	1.00	-0.14	-0.13	-0.08	-0.08	-0.03	-0.03	-0.02	-0.02	-0.02	-0.01
KitchenAbvGr	-0.14	1.00	0.04	0.28	-0.09	0.03	0.01	0.00	0.06	-0.04	-0.04
EnclosedPorch	-0.13	0.04	1.00	-0.01	0.07	-0.01	0.06	0.00	0.02	-0.01	0.04
MSSubClass	-0.08	0.28	-0.01	1.00	-0.06	-0.02	0.05	0.01	-0.01	-0.00	-0.07
OverallCond	-0.08	-0.09	0.07	-0.06	1.00	0.04	0.03	0.01	0.07	0.12	0.04
YrSold	-0.03	0.03	-0.01	-0.02	0.04	1.00	-0.03	0.00	0.00	-0.05	0.03
LowQualFinSF	-0.03	0.01	0.06	0.05	0.03	-0.03	1.00	-0.04	-0.00	-0.01	0.01
Id	-0.02	0.00	0.00	0.01	0.01	0.00	-0.04	1.00	-0.01	-0.02	-0.01
MiscVal	-0.02	0.06	0.02	-0.01	0.07	0.00	-0.00	-0.01	1.00	-0.01	0.00
BsmtHalfBath	-0.02	-0.04	-0.01	-0.00	0.12	-0.05	-0.01	-0.02	-0.01	1.00	0.07
BsmtFinSF2	-0.01	-0.04	0.04	-0.07	0.04	0.03	0.01	-0.01	0.00	0.07	1.00

In [29]:

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

Out[29]:

	OverallQual	SalePrice
9	10	438588.388889
8	9	367513.023256
7	8	274735.535714
6	7	207716.423197
5	6	161603.034759
4	5	133523.347607
3	4	108420.655172
2	3	87473.750000
1	2	51770.333333
0	1	50150.000000

In [30]:

```
##The first feature which has the maximum correlation with the Sale Price is OverallQual. A
#that when the OverallQual is increasing, the average Sale Price for each OverallQual is in
plt.style.use('seaborn-dark-palette')
plot = plt.subplot()
plot.scatter(x = df['OverallQual'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('OverallQual', fontsize=13)
plt.title(' Sale Price vs Overall quality')
```

Out[30]:

```
Text(0.5, 1.0, ' Sale Price vs Overall quality')
```

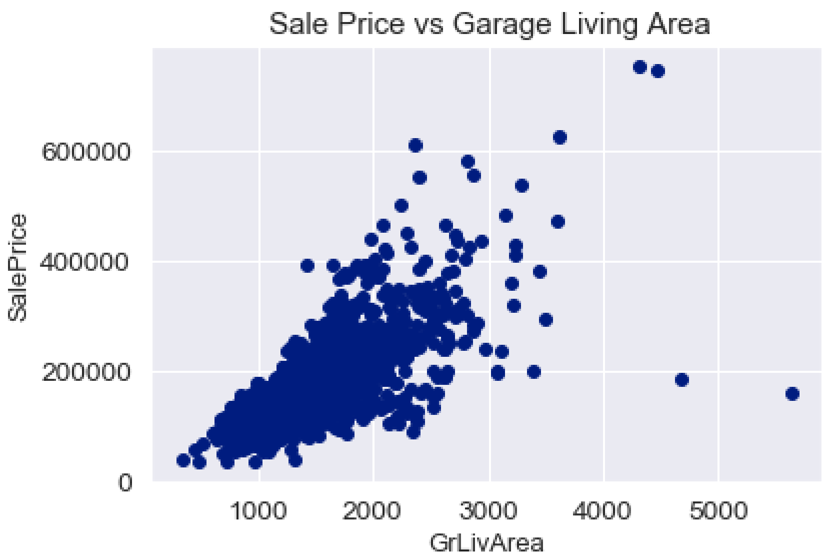
In [31]:

```
##Now, the second most important feature is the GrLivArea.
#We can see in the graph that as the living area increases there is an increase in the Sale
##But we can also see that there are couple of outliers where GrLivArea>4500 but Sale Price

plt.style.use('seaborn-dark-palette')
plot = plt.subplot()
plot.scatter(x = df['GrLivArea'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GrLivArea', fontsize=13)
plt.title(' Sale Price vs Garage Living Area')
```

Out[31]:

```
Text(0.5, 1.0, ' Sale Price vs Garage Living Area')
```



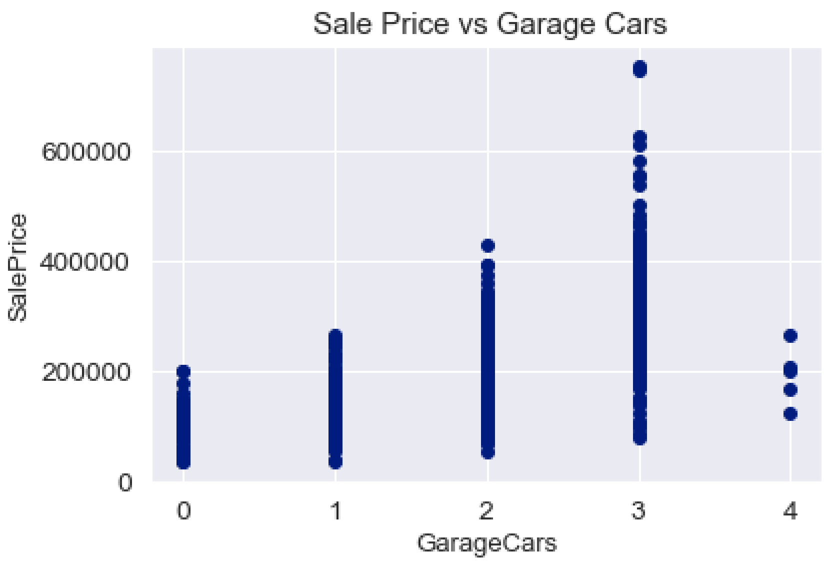
In [32]:

```
##Now, the third most important feature is the GarageCars.
#We can see in the graph that as the GarageCars increases there is an increase in the SaleP
##But we can also see that there are couple of outliers where GarageCars >3  but Sale Price

plt.style.use('seaborn-dark-palette')
plot = plt.subplot()
plot.scatter(x = df['GarageCars'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GarageCars', fontsize=13)
plt.title(' Sale Price vs Garage Cars')
```

Out[32]:

```
Text(0.5, 1.0, ' Sale Price vs Garage Cars')
```



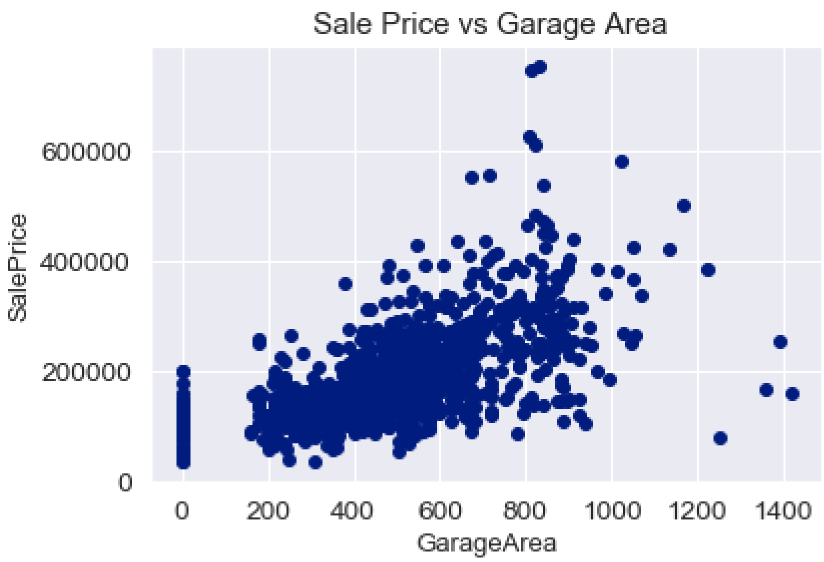
In [33]:

```
#Now, the fourth most important feature is the GarageArea.
#We can see in the graph that as the GarageArea increases there is an increase in the SaleP
##But we can also see that there are couple of outliers where GarageArea >1200  but Sale Pr

plt.style.use('seaborn-dark-palette')
plot = plt.subplot()
plot.scatter(x = df['GarageArea'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GarageArea', fontsize=13)
plt.title(' Sale Price vs Garage Area')
```

Out[33]:

```
Text(0.5, 1.0, ' Sale Price vs Garage Area')
```



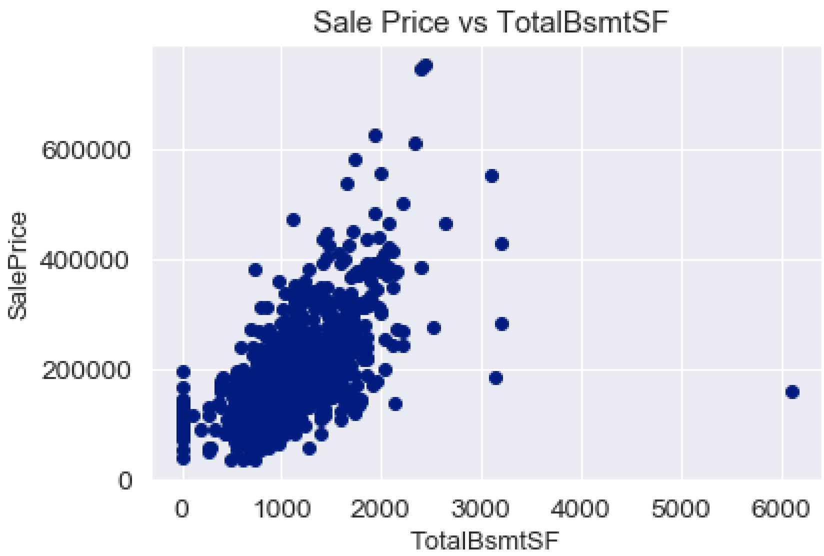
In [34]:

```
#Now, the fifth most important feature is the TotalBsmtSF.
#We can see in the graph that as the TotalBsmtSF increases there is an increase in the Sale
##But we can also see that there are couple of outliers where TotalBsmtSF >6000  but Sale P

plt.style.use('seaborn-dark-palette')
plot = plt.subplot()
plot.scatter(x = df['TotalBsmtSF'], y = df['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('TotalBsmtSF', fontsize=13)
plt.title(' Sale Price vs TotalBsmtSF')
```

Out[34]:

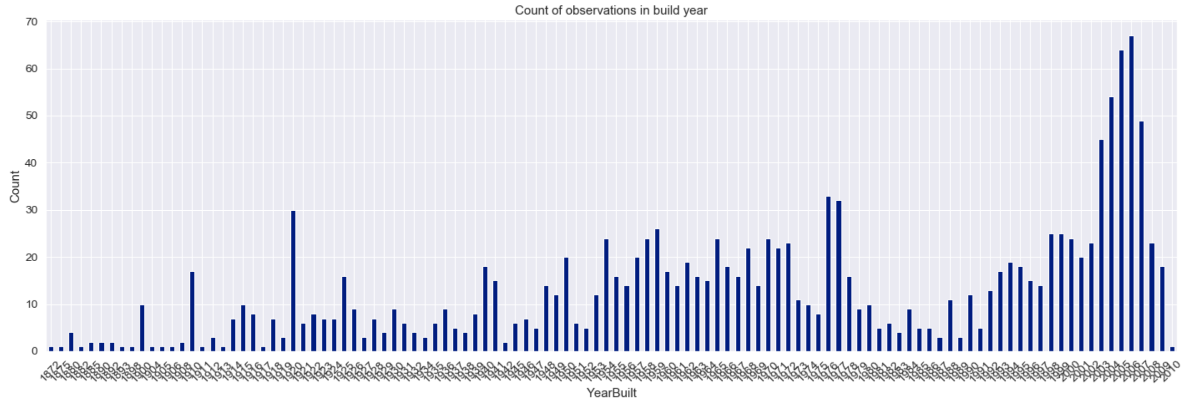
```
Text(0.5, 1.0, ' Sale Price vs TotalBsmtSF')
```



Another point to be noted here is that GarageCars and GarageArea are correlated with each other in a sense that, larger the area, larger is the number of cars that can be accomodated. This should be investigated in the correlation matrix.

In [35]:

```
plt.style.use('seaborn-dark-palette')
plt.figure(figsize=(20,7));
df.groupby("YearBuilt").SalePrice.count().plot(kind="bar")
plt.title("Count of observations in build year")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Houses that were built recently have higher prices as compared to others

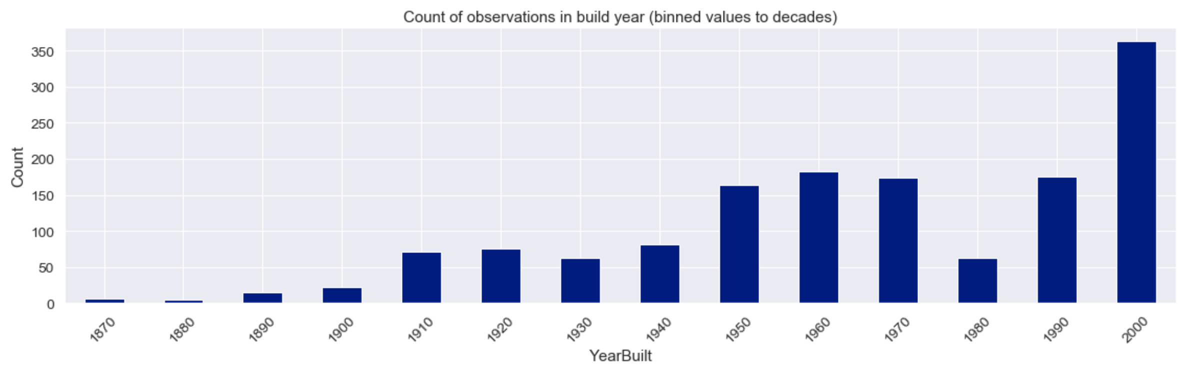
In [36]:

```
#bin years to decades since plotting every single year would clutter the plot
decades = np.arange(1870, 2015, 10)
df_cut = pd.cut(df.YearBuilt, bins=decades, labels=decades[:-1])
df_comb = pd.concat([df_cut, df.SalePrice], axis=1)

plt.figure(figsize=(16,5));
df_comb.groupby("YearBuilt").SalePrice.count().plot(kind="bar")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.title("Count of observations in build year (binned values to decades)")
```

Out[36]:

```
Text(0.5, 1.0, 'Count of observations in build year (binned values to decade
s)')
```



We observe that:

Most of the house were built after 1950.

A good third of all properties was built 1990 and later.

Newer houses tend to yield a little higher mean of sale price.

In [37]:

```
df['YearBuilt'].value_counts(dropna=False).sort_values(ascending=False).head()
```

Out[37]:

```
2006    67
2005    64
2004    54
2007    49
2003    45
Name: YearBuilt, dtype: int64
```

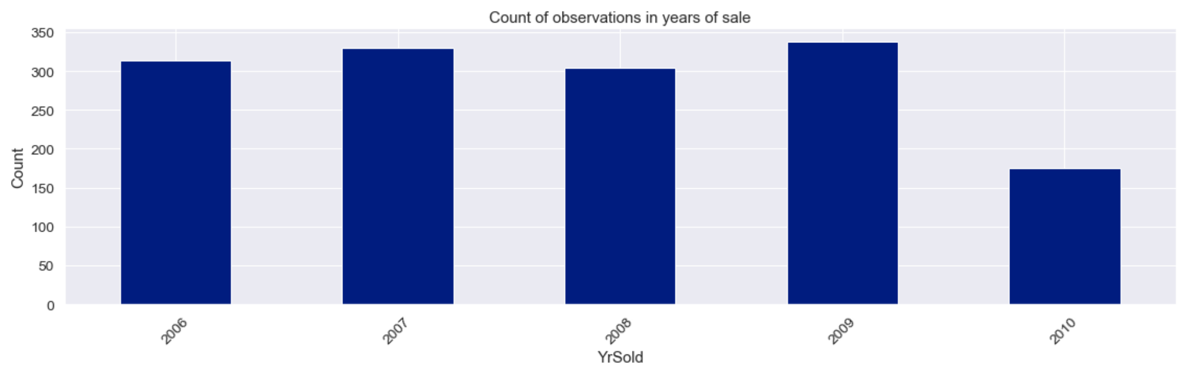
Many houses were built in 2005 and 2006 as compared to other years.

In [38]:

```
plt.figure(figsize=(16,5));
df.groupby("YrSold").SalePrice.count().plot(kind="bar")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.title("Count of observations in years of sale")
```

Out[38]:

```
Text(0.5, 1.0, 'Count of observations in years of sale')
```

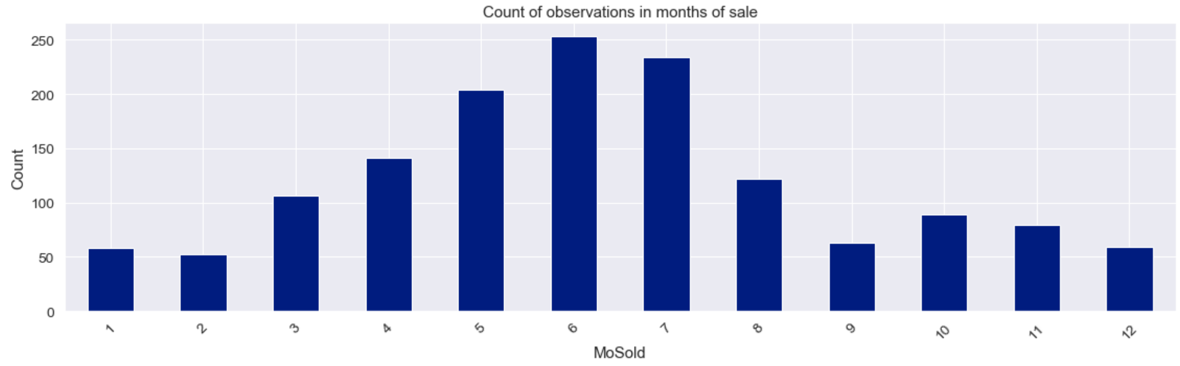


In [39]:

```
plt.figure(figsize=(16,5));
df.groupby("MoSold").SalePrice.count().plot(kind="bar")
plt.ylabel("Count")
plt.xticks(ticks=np.arange(0, 12), rotation=45)
plt.tight_layout()
plt.title("Count of observations in months of sale")
```

Out[39]:

```
Text(0.5, 1.0, 'Count of observations in months of sale')
```



Observations:

Fewer sales in 2010. Could be either because less samples were collected. Or the financial crisis of 2009 hit the market.

Most sales in summer months.

In [40]:

```
df["Age"] = df.YrSold - df.YearBuilt
print(df.Age.describe())
```

```
count    1460.000000
mean       36.547945
std        30.250152
min         0.000000
25%         8.000000
50%        35.000000
75%        54.000000
max       136.000000
Name: Age, dtype: float64
```

On average the properties were 37 years old at the time of sale (with a mean of 35 very close to that).

On average houses can be +/- 30 years older or younger than that at time of sale.

The oldest house was 136 years old and we have sales of house that were built in the year of sale.

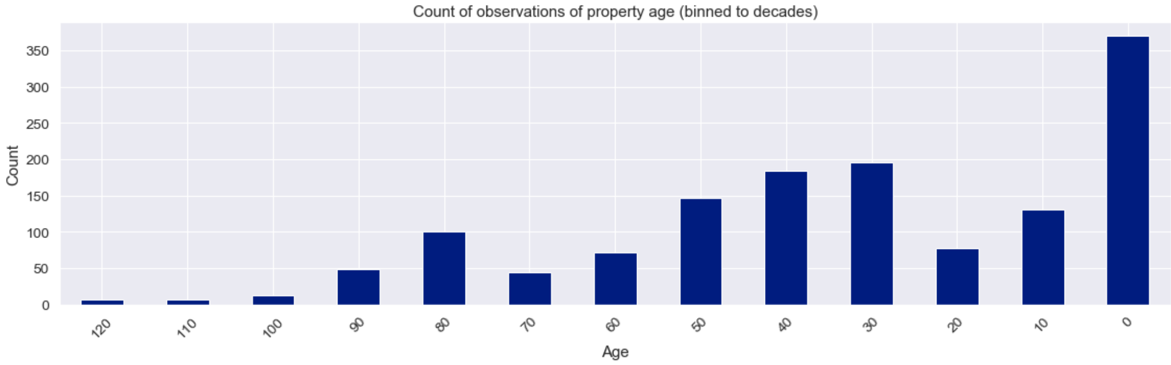
In [41]:

```
decades = np.arange(0, 136, 10)
df_cut = pd.cut(df.Age, bins=decades, labels=decades[:-1])
df_comb = pd.concat([df_cut, df.SalePrice], axis=1)

plt.figure(figsize=(16,5));
df_comb.groupby("Age").SalePrice.count().plot(kind="bar")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.gca().invert_xaxis()
plt.tight_layout()
plt.title("Count of observations of property age (binned to decades)")
```

Out[41]:

```
Text(0.5, 1.0, 'Count of observations of property age (binned to decades)')
```



We only observe a notable difference for newer houses. E.g. the median of price for houses between 0 and 19 years of age is almost the same now.

In [42]:

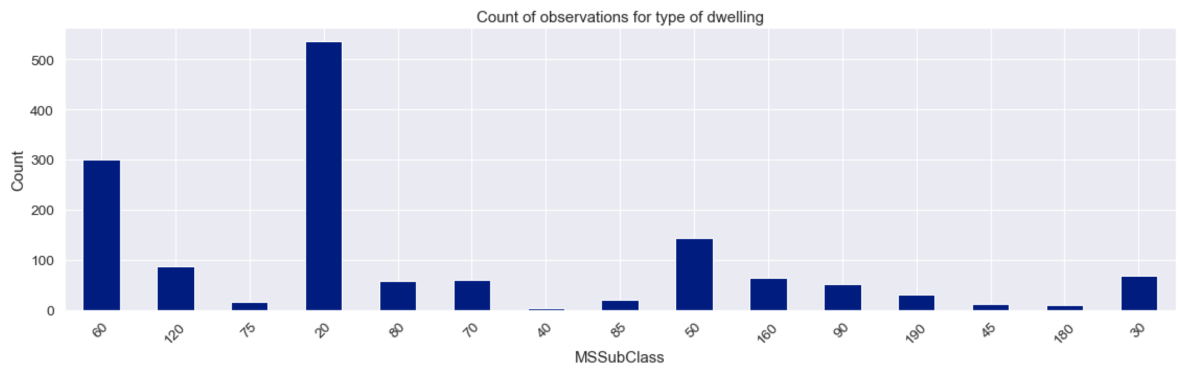
```
# MSSubClass: Identifies the type of dwelling involved in the sale.
order = df.groupby("MSSubClass").SalePrice.mean().sort_values(ascending=False).index
```

In [43]:

```
plt.figure(figsize=(16,5));
df_g = df.groupby("MSSubClass").SalePrice.count()
df_g = df_g.reindex(order)
df_g.plot(kind="bar")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.title("Count of observations for type of dwelling")
```

Out[43]:

```
Text(0.5, 1.0, 'Count of observations for type of dwelling')
```

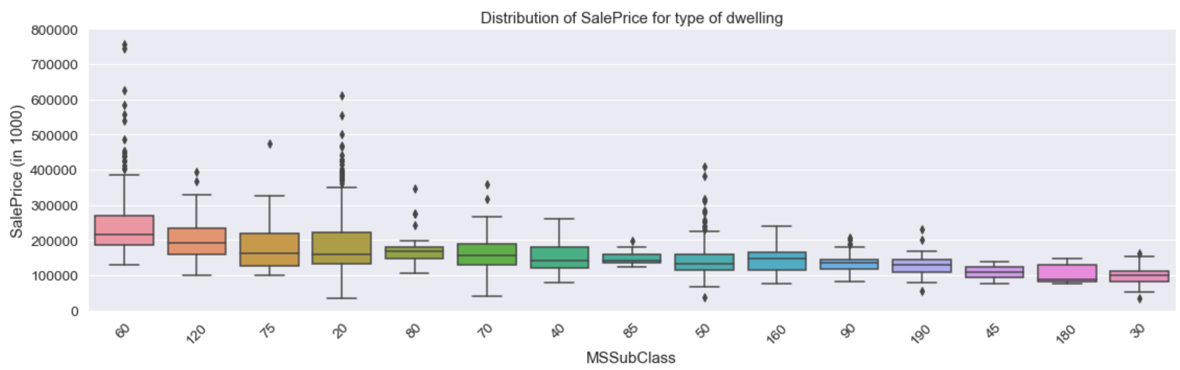


In [44]:

```
plt.figure(figsize=(16,5));
ax = sns.boxplot(x="MSSubClass", y="SalePrice", data=df, order=order)
plt.axis(ymin=0, ymax=800000)
plt.ylabel("SalePrice (in 1000)")
plt.xticks(rotation=45)
plt.tight_layout()
plt.title("Distribution of SalePrice for type of dwelling")
```

Out[44]:

```
Text(0.5, 1.0, 'Distribution of SalePrice for type of dwelling')
```



In [45]:

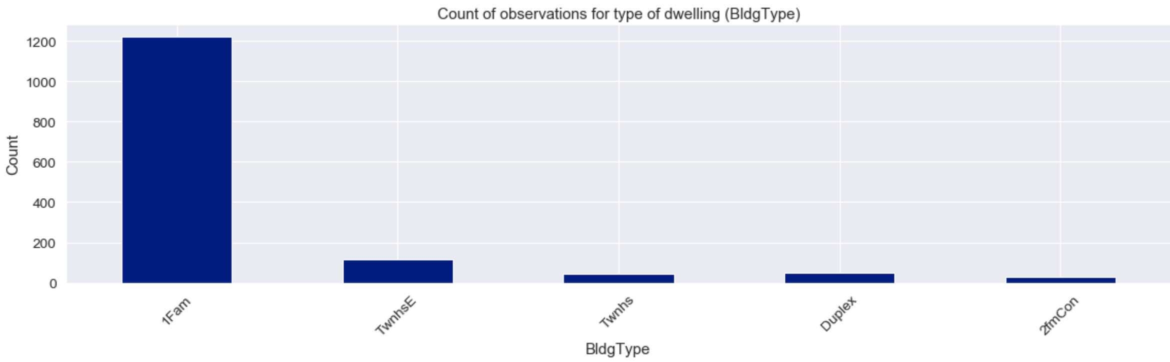
```
##BldgType: Type of dwelling
order = df.groupby("BldgType").SalePrice.mean().sort_values(ascending=False).index
```

In [46]:

```
plt.figure(figsize=(16,5));
df_g = df.groupby("BldgType").SalePrice.count()
df_g = df_g.reindex(order)
df_g.plot(kind="bar")
plt.xticks(rotation=45)
plt.tight_layout()
plt.ylabel("Count")
plt.title("Count of observations for type of dwelling (BldgType)")
```

Out[46]:

```
Text(0.5, 1.0, 'Count of observations for type of dwelling (BldgType)')
```

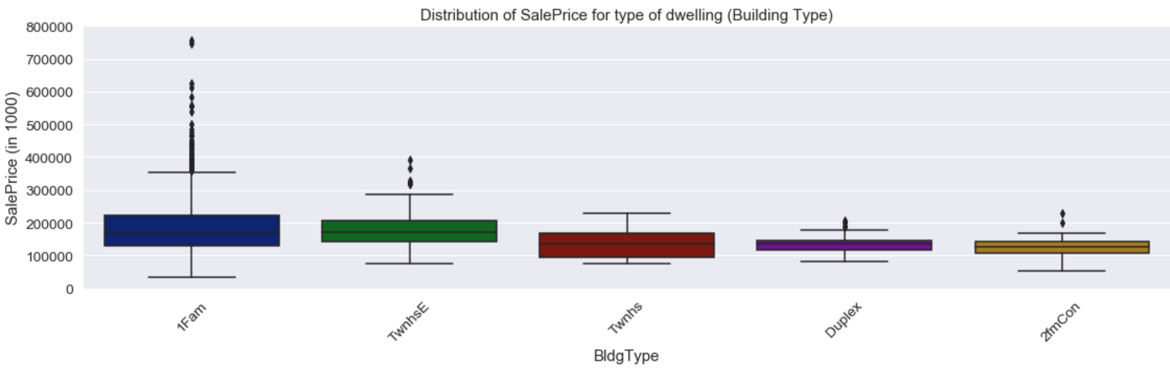


In [47]:

```
plt.figure(figsize=(16,5));
ax = sns.boxplot(x="BldgType", y="SalePrice", data=df, order=order)
plt.axis(ymin=0, ymax=800000)
plt.ylabel("SalePrice (in 1000)")
plt.xticks(rotation=45)
plt.tight_layout()
plt.title("Distribution of SalePrice for type of dwelling (Building Type)")
```

Out[47]:

```
Text(0.5, 1.0, 'Distribution of SalePrice for type of dwelling (Building Typ
e)')
```



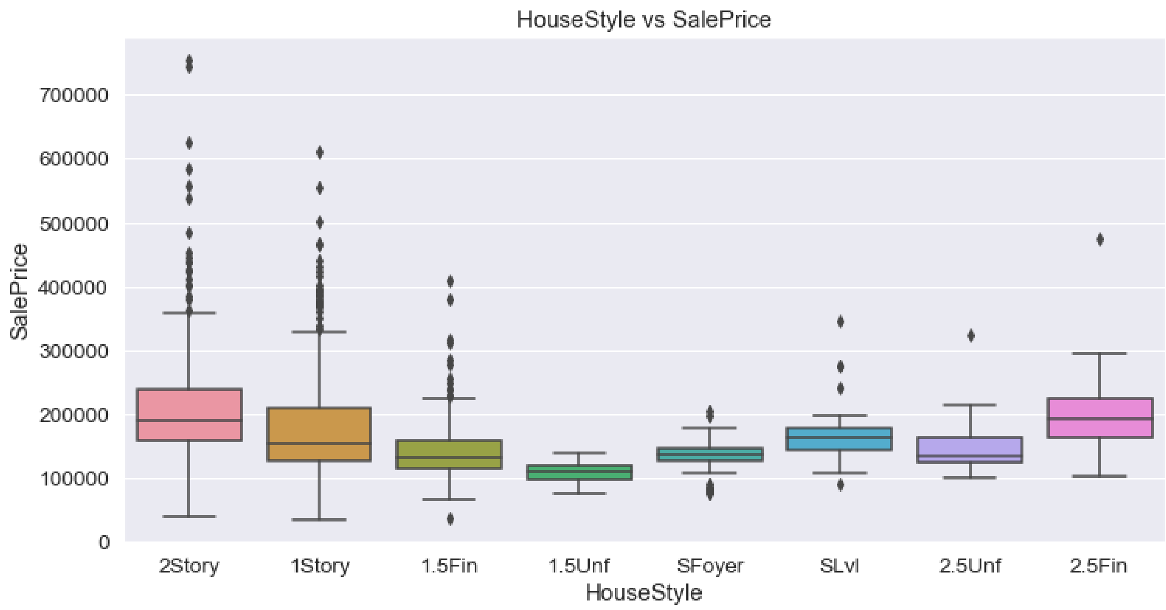
In [48]:

```
plt.figure(figsize=(12,6))

sns.boxplot(data=df,x='HouseStyle',y='SalePrice')
plt.title('HouseStyle vs SalePrice')
```

Out[48]:

```
Text(0.5, 1.0, 'HouseStyle vs SalePrice')
```



Most of the houses are 1Story/2Story. Some of the houses have One and Half story with 2nd level unfinished etc.

The wide mayority of properties are Single-family Detached.

Townhouse End Units (TwhnsE) come second pricewise and are more expensive than Inside Units (Twhns). Makes sense...

Two-family Conversions, originally built as one-family dwelling are the least expensives properties on average.

In [49]:

```
###we can see that as the amount of fireplaces increases, sale price also increases

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

Out[49]:

	Fireplaces	SalePrice
3	3	252000.000000
2	2	240588.539130
1	1	211843.909231
0	0	141331.482609

In [50]:

```
#histogram
plt.figure(figsize=(10, 7))
sns.distplot(df['SalePrice'])
plt.title('Sale Price')
```

Out[50]:

```
Text(0.5, 1.0, 'Sale Price')
```

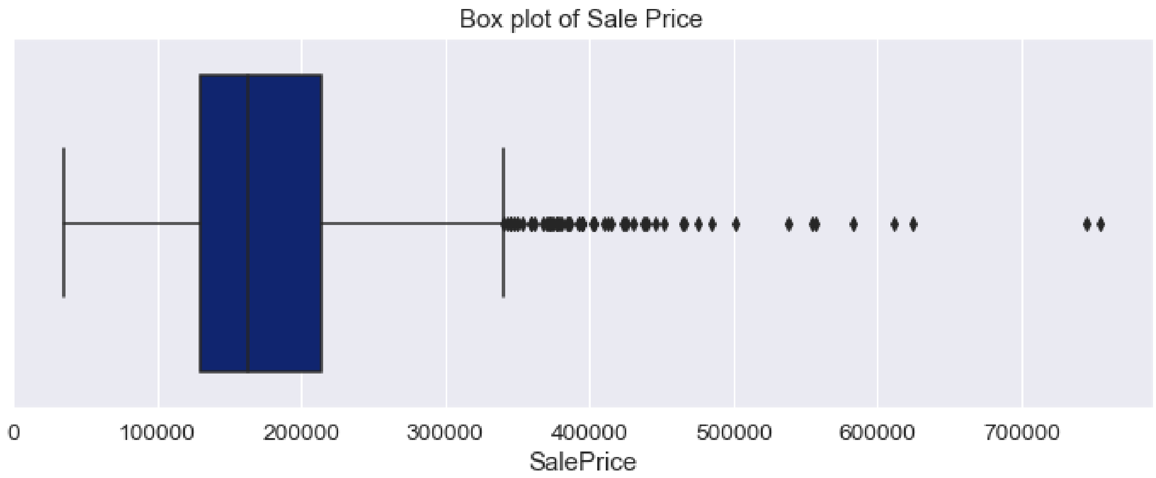
The distribution does not look normal, it is positively skewed, some outliers can also be seen. Simple log transformation might change the distribution to normal.

In [51]:

```
plt.figure(figsize=(12, 4))
sns.boxplot(df['SalePrice'])
plt.title('Box plot of Sale Price')
```

Out[51]:

```
Text(0.5, 1.0, 'Box plot of Sale Price')
```



In [52]:

```
df['SalePrice'].skew()
```

Out[52]:

```
1.8828757597682129
```

In [53]:

```
df['SalePrice'].kurt()
```

Out[53]:

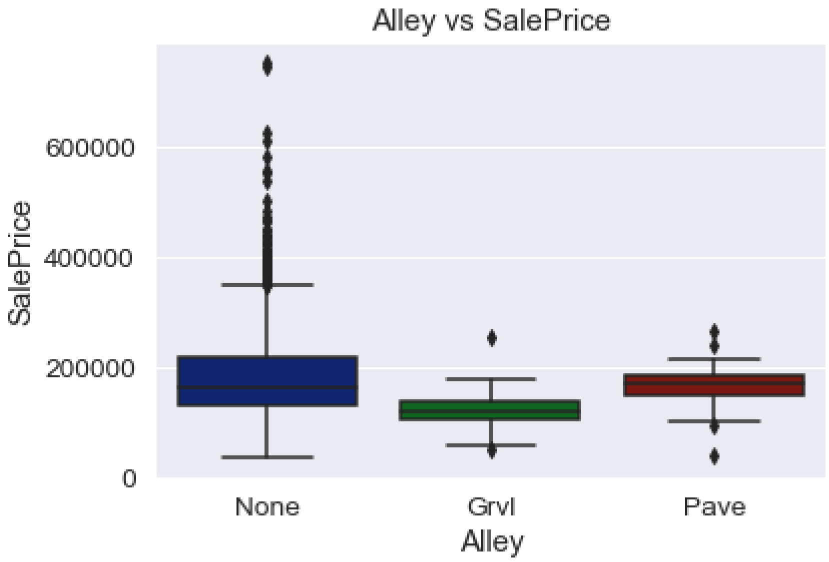
```
6.536281860064529
```

In [54]:

```
sns.boxplot(data=df,x='Alley',y='SalePrice')
plt.title('Alley vs SalePrice')
```

Out[54]:

```
Text(0.5, 1.0, 'Alley vs SalePrice')
```



In [55]:

```
sns.stripplot(x=df["Street"], y=df["SalePrice"],jitter=True)
plt.title("Sale Price vs Streets")
```

Out[55]:

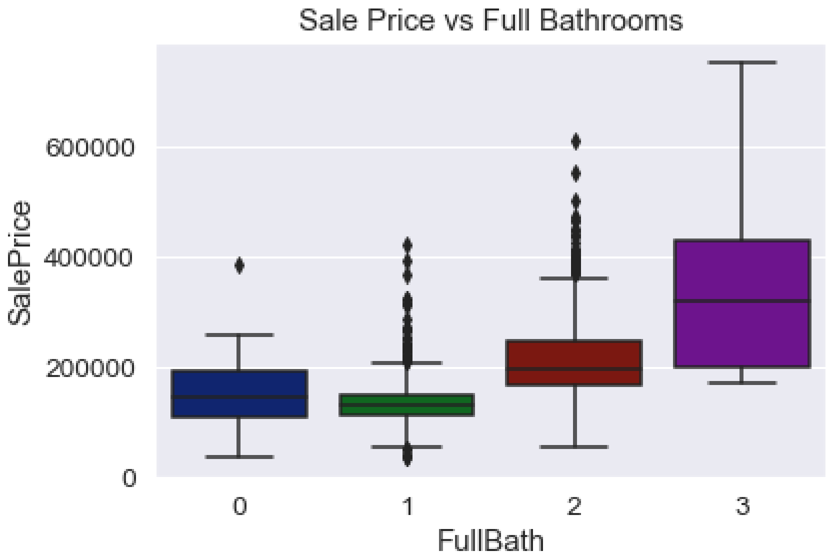
```
Text(0.5, 1.0, 'Sale Price vs Streets')
```

In [56]:

```
sns.boxplot(df["FullBath"], df["SalePrice"])
plt.title("Sale Price vs Full Bathrooms")
```

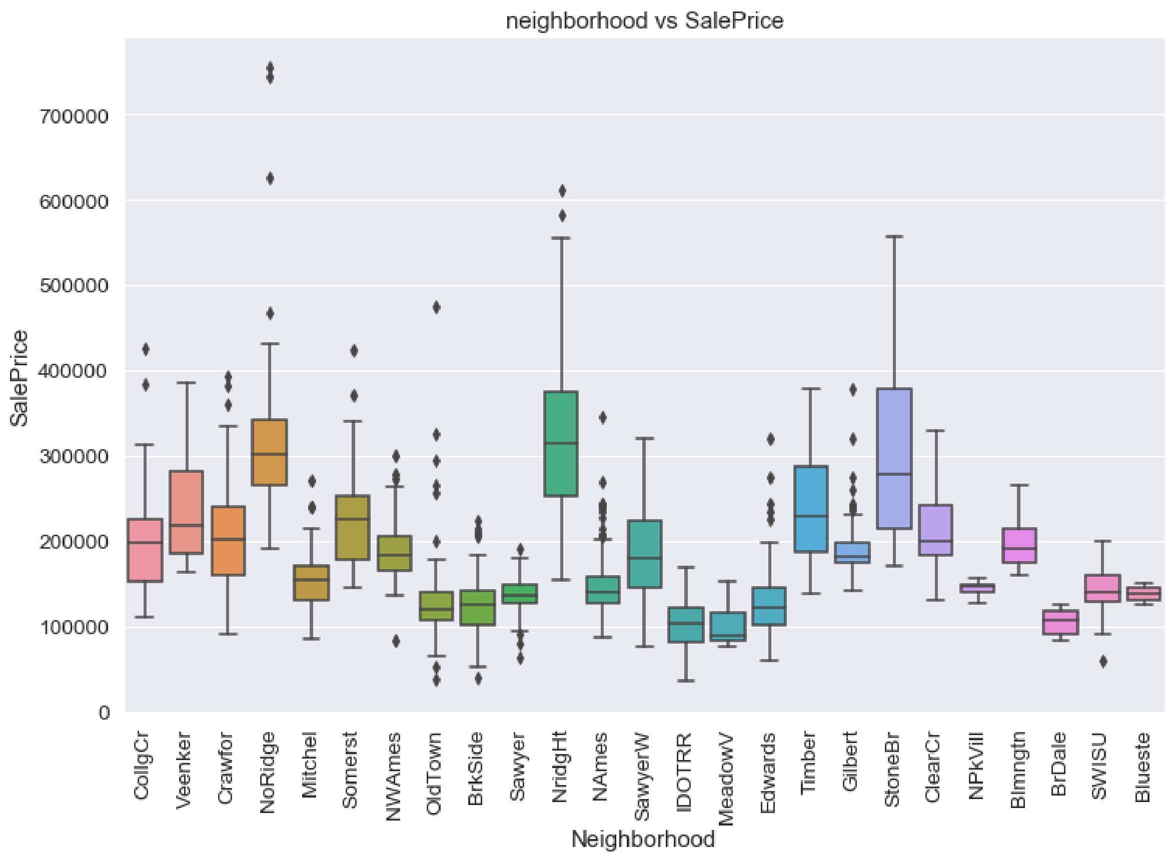
Out[56]:

```
Text(0.5, 1.0, 'Sale Price vs Full Bathrooms')
```



In [57]:

```
fig,ax = plt.subplots(figsize=(12,8))
sns.boxplot(x = 'Neighborhood', y = 'SalePrice',  data = df,ax=ax)
plt.title('neighborhood vs SalePrice')
ticks = plt.setp(ax.get_xticklabels(),rotation=90)
```

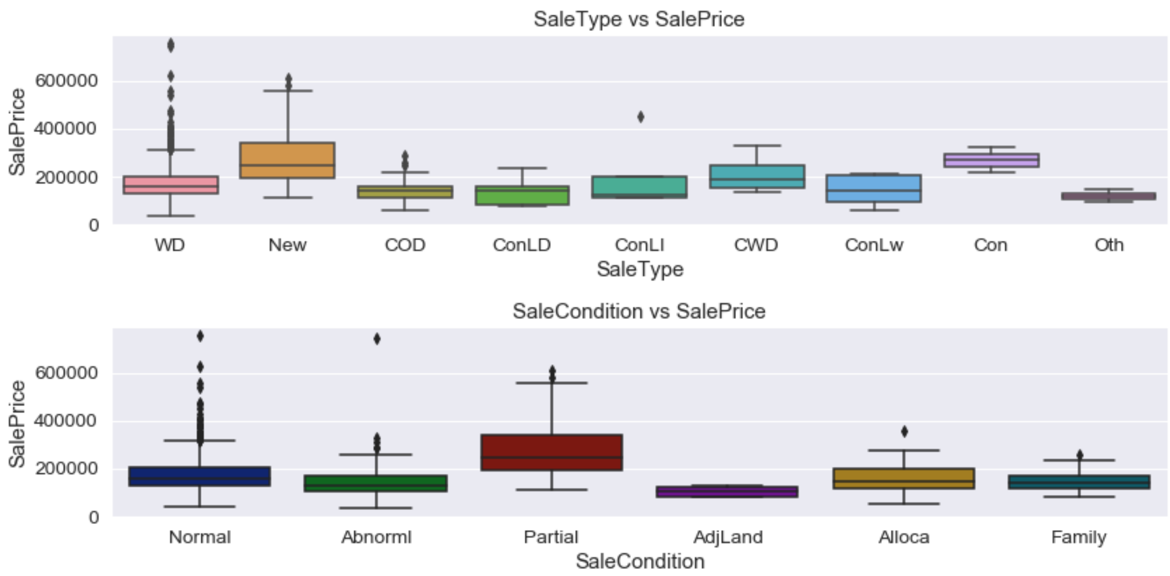


In [58]:

```
fig = plt.figure(2,figsize=(12,6))
plt.subplot(211)
sns.boxplot(data=df,x='SaleType',y='SalePrice')
plt.title('SaleType vs SalePrice')

plt.subplot(212)
sns.boxplot(data = df,x='SaleCondition',y='SalePrice')
plt.title('SaleCondition vs SalePrice')

plt.tight_layout()
```

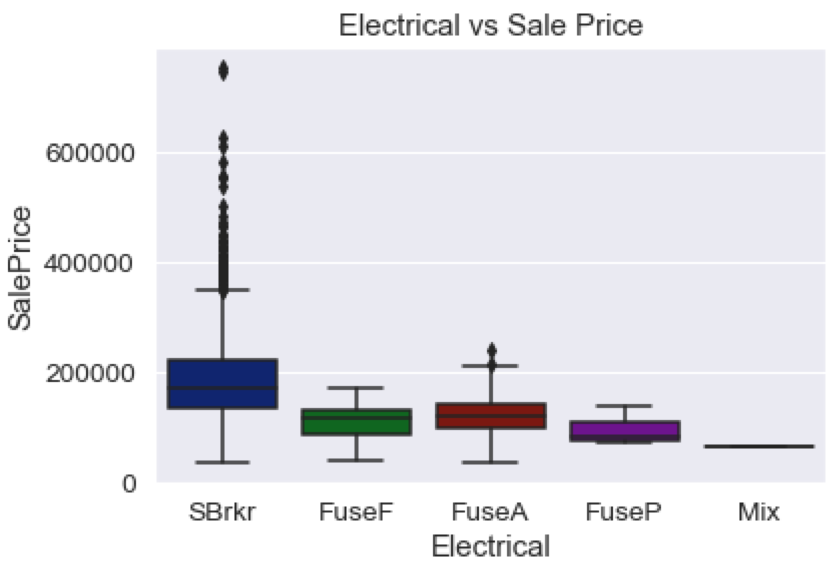


In [59]:

```
sns.boxplot(data=df,x='Electrical',y='SalePrice')
plt.title('Electrical vs Sale Price')
```

Out[59]:

```
Text(0.5, 1.0, 'Electrical vs Sale Price')
```

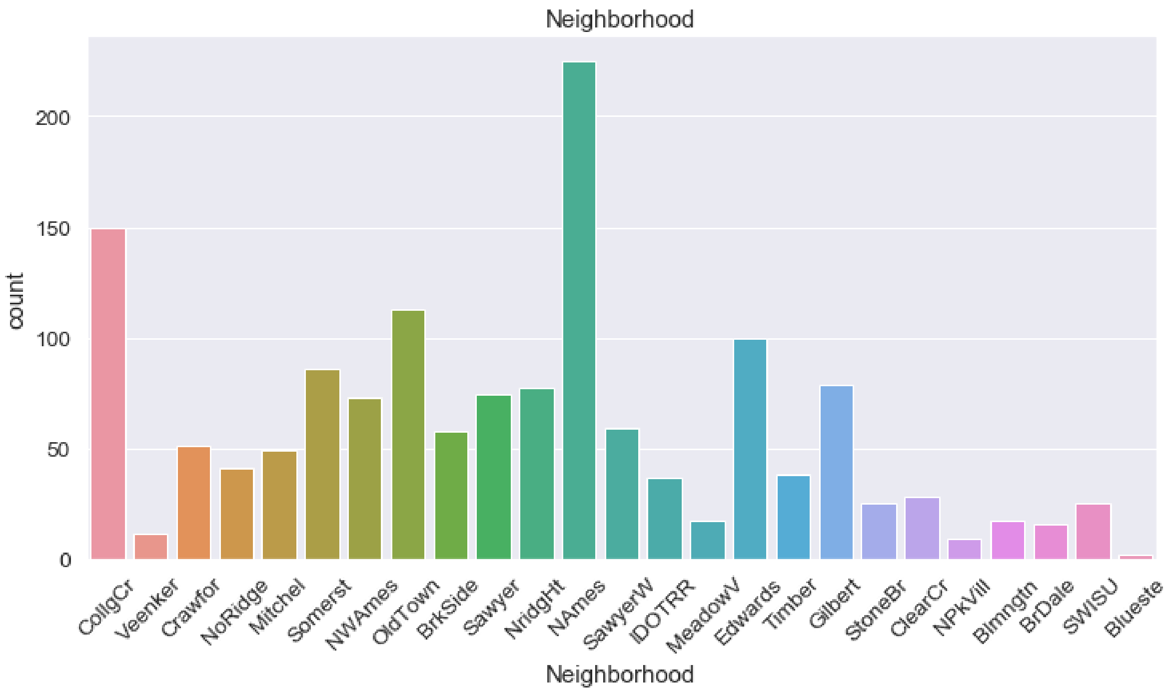


In [60]:

```
plt.figure(figsize = (12, 6))
sns.countplot(x = 'Neighborhood', data = df)
xt = plt.xticks(rotation=45)
plt.title('Neighborhood')
```

Out[60]:

```
Text(0.5, 1.0, 'Neighborhood')
```

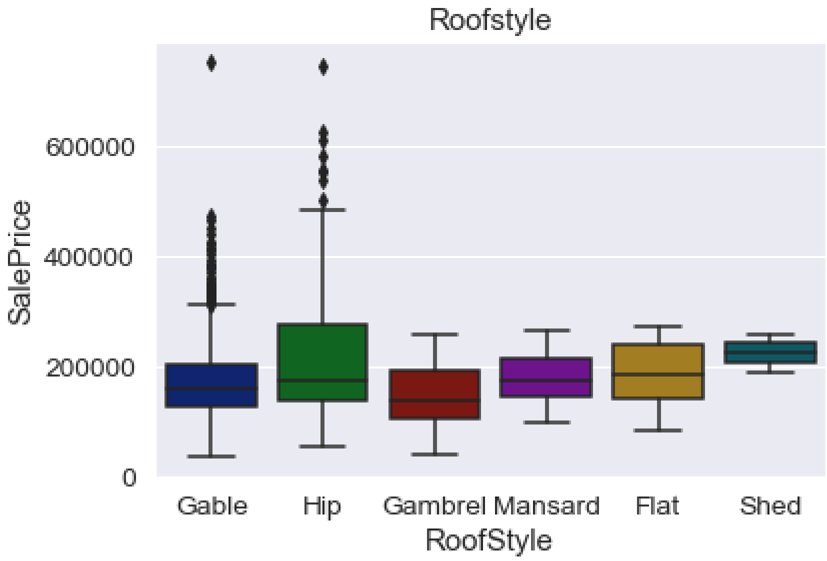


In [61]:

```
sns.boxplot(df['RoofStyle'], df['SalePrice'])
plt.title('Roofstyle vs Sale Price')
plt.title('Roofstyle')
```

Out[61]:

```
Text(0.5, 1.0, 'Roofstyle')
```

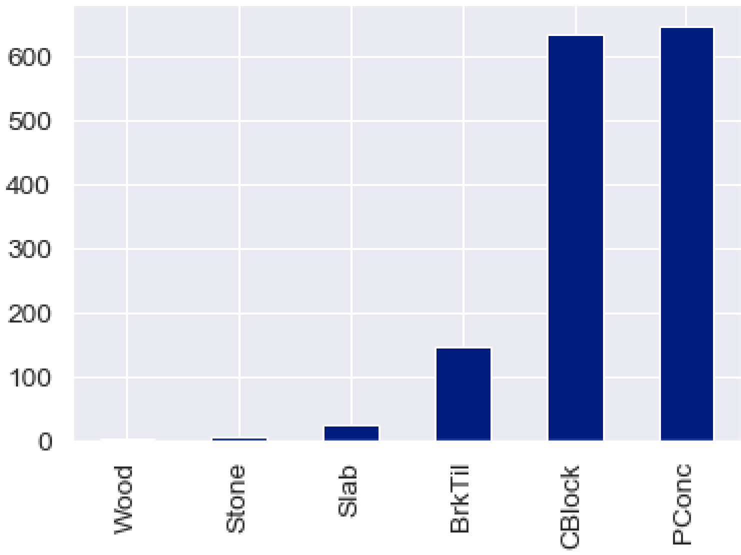


In [62]:

```
df['Foundation'].value_counts(dropna=False).sort_values().plot(kind='bar')
```

Out[62]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fb9a81f0b8>
```



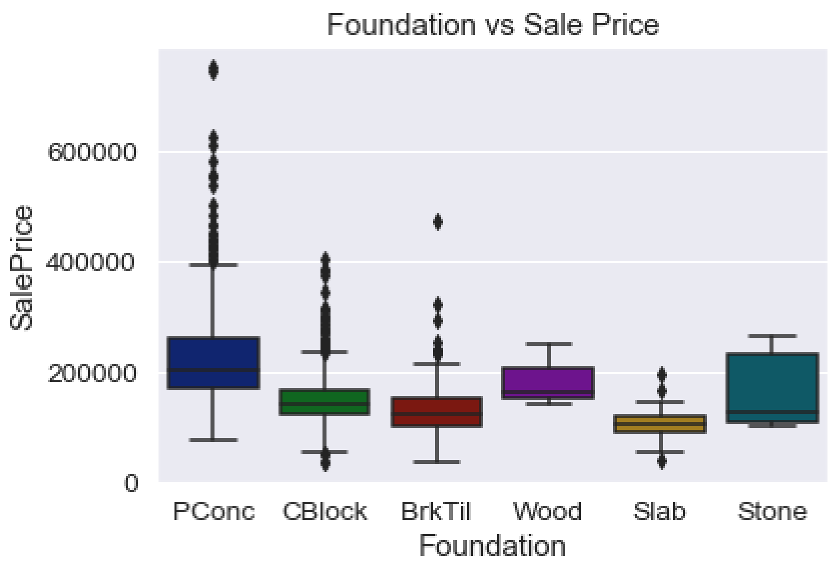
Most houses have Poured Concrete or Concrete Block as their Foundation.

In [63]:

```
sns.boxplot(df['Foundation'], df['SalePrice'])
plt.title('Foundation vs Sale Price')
```

Out[63]:

```
Text(0.5, 1.0, 'Foundation vs Sale Price')
```



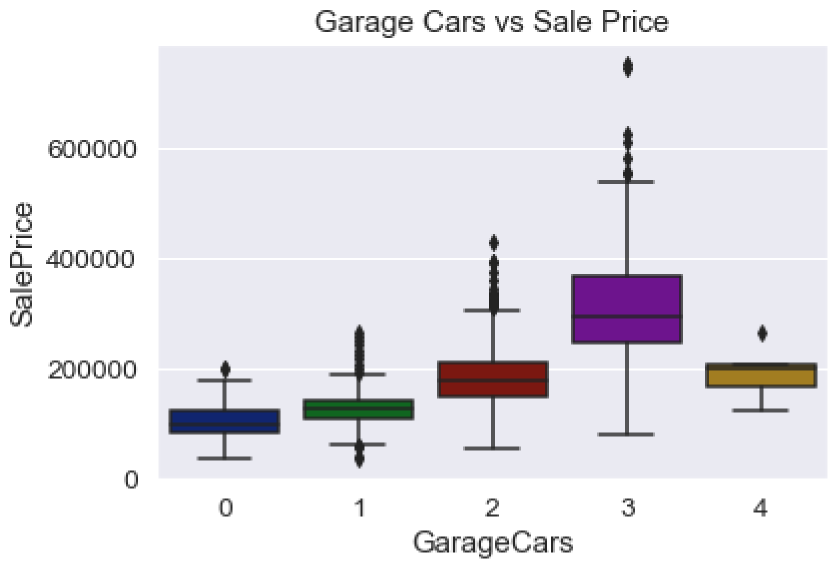
Poured Concrete has higher values of Sale Prices.

In [64]:

```
###Price increases with increase in accomodating capacity of the cars in the garage
sns.boxplot(df['GarageCars'],df['SalePrice'])
plt.title('Garage Cars vs Sale Price')
```

Out[64]:

```
Text(0.5, 1.0, 'Garage Cars vs Sale Price')
```

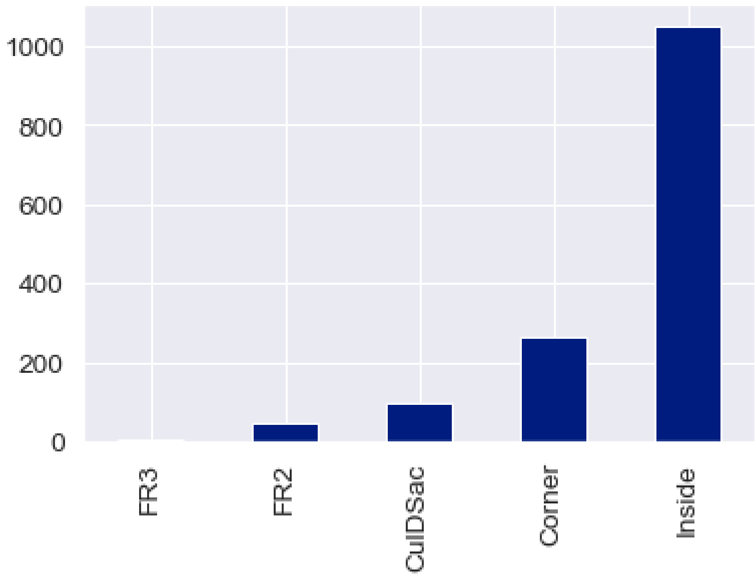


In [65]:

```
df['LotConfig'].value_counts().sort_values().plot(kind='bar')
```

Out[65]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fb9ab0c160>
```



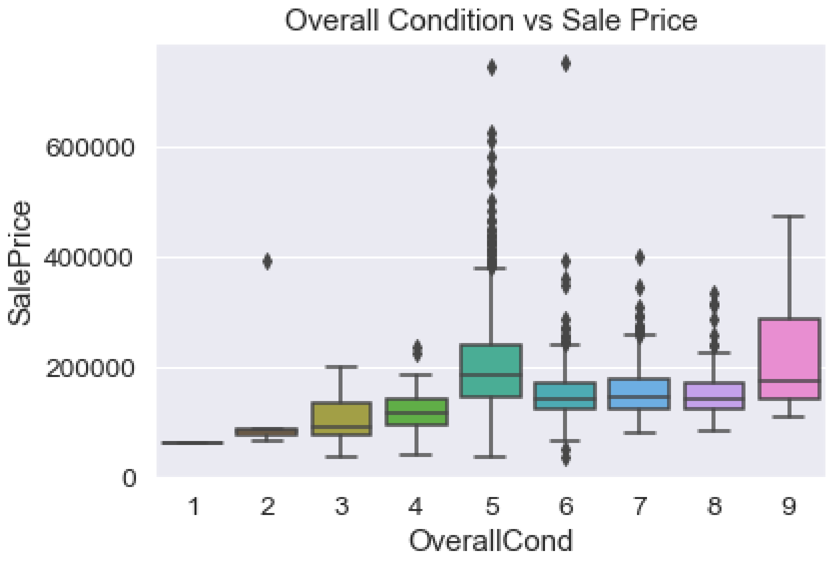
Most of the houses are are Inside Lot type followed by Corner plot.

In [66]:

```
sns.boxplot(df['OverallCond'],df['SalePrice'])
plt.title('Overall Condition vs Sale Price')
```

Out[66]:

```
Text(0.5, 1.0, 'Overall Condition vs Sale Price')
```

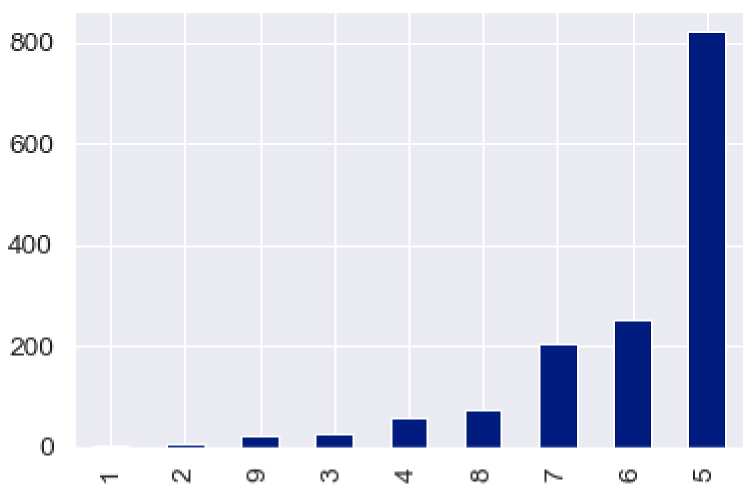


In [67]:

```
df['OverallCond'].value_counts().sort_values(ascending = True).plot(kind='bar')
```

Out[67]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fb9ada4748>
```



More than 50% of the houses have average (rating of 5) overall condition of the house.

There is no house with a rating of 10.

Very few have a rating of 9.

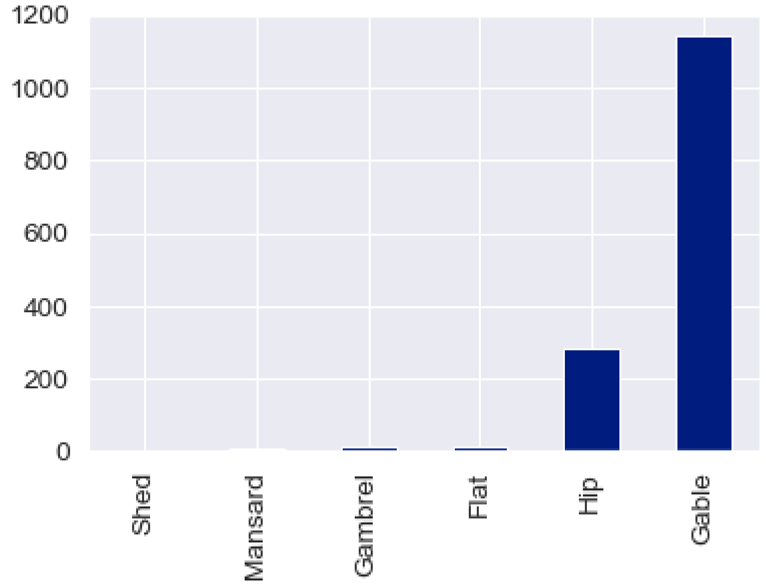
OverallCond does not have the same affect as that of OverallQual towards SalePrice variable.

In [68]:

```
df['RoofStyle'].value_counts(dropna=False).sort_values().plot(kind='bar')
```

Out[68]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fb98571e10>
```



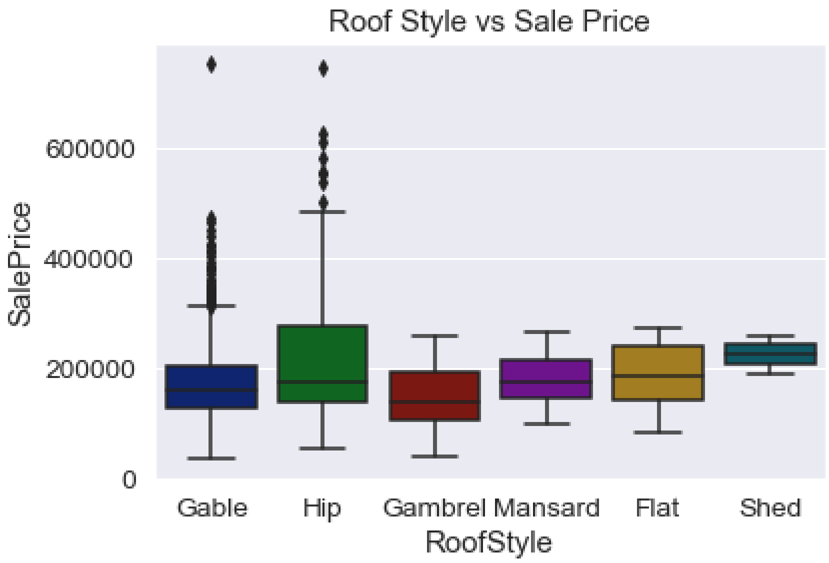
Most of the houses have Gable type of roof followed by Hip type.

In [69]:

```
sns.boxplot(df['RoofStyle'], df['SalePrice'])
plt.title('Roof Style vs Sale Price')
```

Out[69]:

```
Text(0.5, 1.0, 'Roof Style vs Sale Price')
```



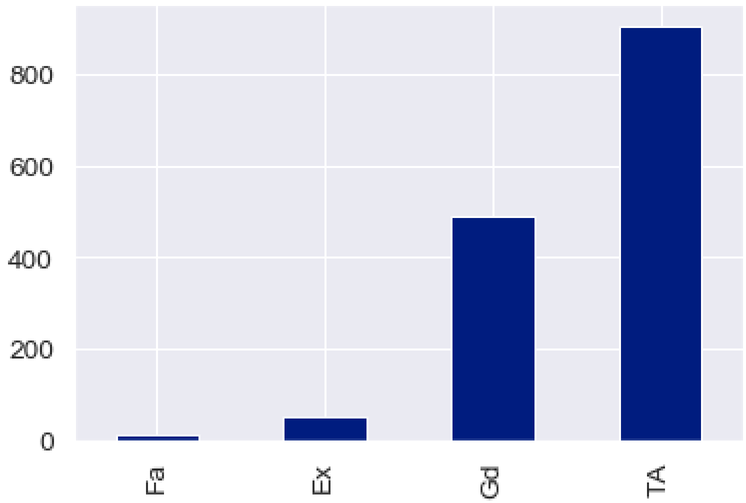
Houses with Gable type of roof also have the highest sale price. This tells us that there is a relationship between roof type and sale price

In [70]:

```
df['ExterQual'].value_counts(dropna=False).sort_values().plot(kind='bar')
```

Out[70]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fb9aeeb4a8>
```



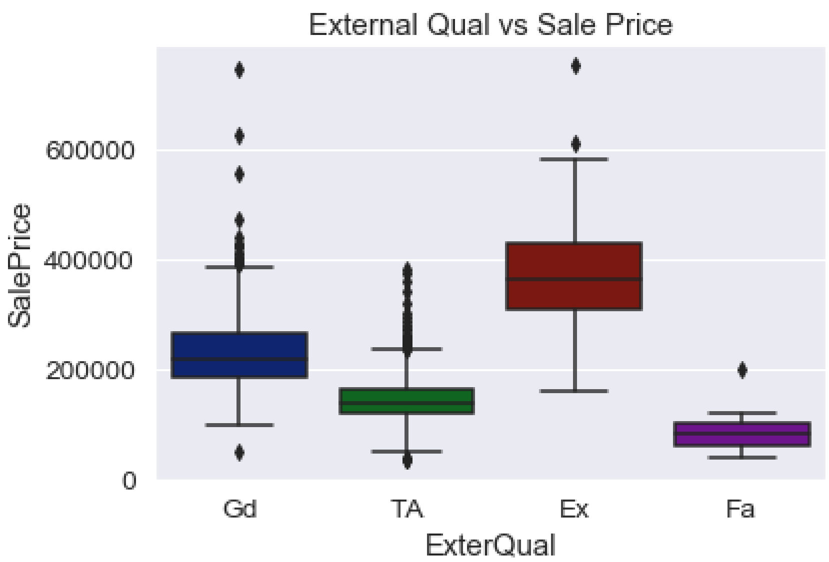
Most of the houses have Average / Typical external quality of the house, this is followed by houses that are rated Good. No Missing values here.

In [71]:

```
sns.boxplot(df['ExterQual'], df['SalePrice'])
plt.title('External Qual vs Sale Price')
```

Out[71]:

```
Text(0.5, 1.0, 'External Qual vs Sale Price')
```



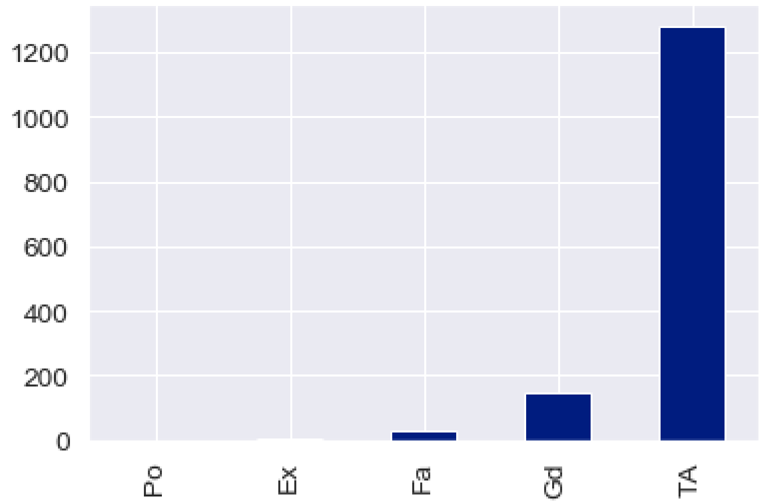
The price of houses that have Excellent external quality rating are much higher as compared to others.

In [72]:

```
df['ExterCond'].value_counts(dropna=False).sort_values().plot(kind='bar')
```

Out[72]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fb9afcd668>
```



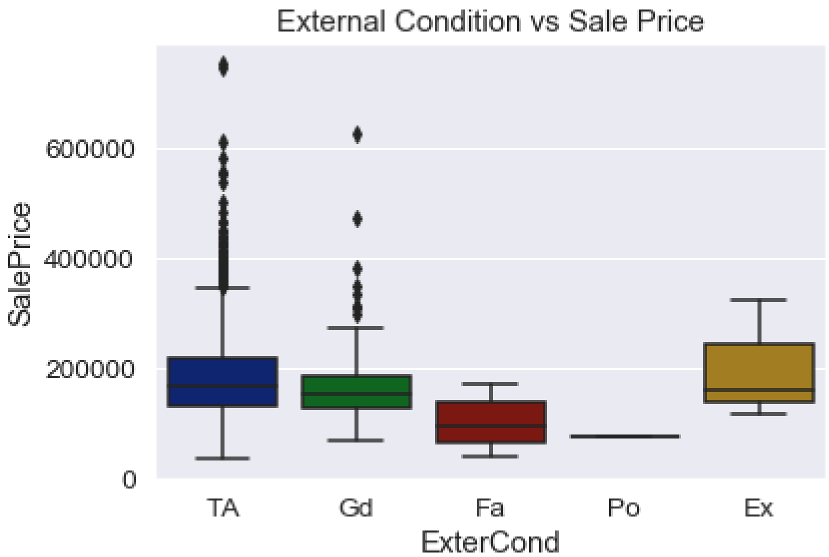
Most of the houses have either Typical or Good condition of the material on the exterior.

In [73]:

```
sns.boxplot(df['ExterCond'],df['SalePrice'])
plt.title('External Condition vs Sale Price')
```

Out[73]:

```
Text(0.5, 1.0, 'External Condition vs Sale Price')
```



In [ ]: