MODULE 2: HOUSING PRICES ASSIGNMENT

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Introduction

Factors influencing home prices can be understood through the use of statistical methods such as regression analysis. Selecting the appropriate methodology to fit data to a regression model is influenced by factors such as prior research, the shape of the data, and avoiding violations of model assumptions. Developing a well-tuned predictive model can provide accurate, precise estimates of home prices, which may be helpful to stakeholders (e.g., buyers, sellers, those in real-estate industries). To that end, a predictive model was built to identify drivers, or predictors, of home prices.

Method

Data about home sale prices in Ames, Iowa, were downloaded from Kaggle and analyzed using Jupyter Notebooks (Montoya, 2016). An exploratory data analysis was conducted to understand feature characteristics (associations, distributions, missingness, and outliers). This included employing bivariate (Pearson correlations, t-tests, ANOVAs, simple linear regressions) and multivariate analyses (e.g., OLS and Ridge regression). Multivariate analyses were also conducted using a *k*-fold cross-validation design (James et al. 2021), training/validation sets, and certain model components (polynomial, indicator, and dichotomous predictors). Underlying model assumptions and metrics were examined in analyses.

Results and Insights

The outcome variable of interest, Sale Price, was first visually inspected by constructing histograms and boxplots, then examined by calculating summary statistics. Sale price was skewed right, ranged from \$34,900 to \$755,000 (M=\$180,921), and included outliers. A log transformation of the home sale price variable improved the normality of the outcome variable ahead of subsequent analyses.

After appropriately addressing missing data and outliers, features were examined to determine which were significantly, strongly associated with Sale Price. Additionally, one aim was to identify and include predictors that had polynomial, indicator, dichotomous, & piecewise model components. The following features were selected for the model because bivariate analyses suggested a strong relationship with Sale Price: central air ($t(1458) = 17.26$, $p < .001$), exterior quality ($F(3, 1456) = 443.33$, $p < .001$), and total square footage (TotalSF, a linear combination of GrLivArea and TotalBsmtSF; $r = .82$, $p < .001$).

Then, we conducted two simple OLS regressions to examine associations with Sale Price. Sale Price and log of Sale Price were regressed on TotalSF. The regression analysis between TotalSF and Sale Price violated the linearity, homoscedasticity, and the independence of errors assumptions. The analysis between TotalSF and the log of Sale Price met the linearity assumption and better met the homoscedasticity and independence of errors assumptions than the model predicting the untransformed Sales Price. The latter model explained about two-thirds of the variance ($R^2 = .67$, $R^2_{adj} = .67$), a moderate goodness of fit.

Next, we fitted a third-order polynomial regression to examine the association between TotalSF and Sale Price. It explained about 2/3 of the variance but inspection of the residuals showed that the residuals were scattered across Sales Prices. We added a new feature, YrSinceRemod, as a predictor to create a multiple linear regression (MLR) model due to its weak association with the predictor, TotalSF ($r = -.35$). This MLR model explained over 3/4 of the variance ($R^2 = .76$, $R^2_{adj} = .76$), and the residuals were more randomly scattered across values of the log transformed Sales Price. This MLR model meets the homoscedasticity and

the independence of errors assumptions better than the model with the untransformed Sales Price. However, the high omnibus value indicated that the distribution of the residuals were not normally distributed.

Then, we created and evaluated a piecewise regression model regressing TotalSF and Sale Price. The model's metrics (root mean squared error, RMSE) suggested that a piecewise approach may be able to accurately predict Sale Prices (RMSE = .23) and account for over 3/4 of the variance (R^2 = .82). An inspection of a residual and a Q-Q plot showed that the values were scattered and deviated from normality.

We regressed Sale Price on the principal components of original numerical variables (excluding our engineered features and encoded categorical variables). Principal components are sensitive to scale, so we scaled x in addition to y. The initial regression had an average R^2 over 10 folds of cross-validation of .87, a curvilinear shape of y vs. predicted values, and displayed an apparent quadratic relationship. The plot of the residuals had a corresponding inverted U-shape. The same regression of the scaled log of sale price had a more linear shape, with an out-of-sample R^2 or 0.88.

Then a quadratic transformation of the principal components to fit a quadratic trend was explored. A regression of standard scaled sale price on a second degree polynomial transformation of the principal component matrix had an out-of-sample (10-fold cross-validation) R^2 of .90 with a standard deviation (SD) of .23. This transformation added features to the x-matrix, increasing the number of variables from 8 to 45. However, the in-sample R^2_{adj} was identical to the R^2, at 0.914 vs 0.911. The plot of y vs. y-predicted appeared linear and the residuals after this transformation appeared random, though there were outliers at values of sale price beyond 4.5 SDs from the mean. We may consider omitting these points in subsequent analyses. While squared principal components have a complex conceptual interpretation, the robustness of the model and improvement in predictive power indicate that this transformation has merit.

Next, we considered regularization techniques (Ridge regression, Elastic Net) and applied them across all numerical variables, not including our new or encoded variables. The five features returned with meaningful coefficients by ElasticNet (OverallQual, TotalBsmtSF, GrLivArea, GarageCars, and GarageArea) correspond with variables we noted in our previous analysis as good predictors. A multilinear regression based on these five predictors had a high goodness of fit (R^2= .83). Interestingly, the Ridge regression based on the original set of numerical variables (which focused on the five aforementioned features) had an R^2 of .36, but after adding the constructed and encoded variables, the R^2 increased to 0.78. This finding indicated that the original data contained multicollinearity, and that these modifications resulted in a powerful model.

Lastly, we used our Polynomial PCA regression to predict Sales Price for the test data set. We also tested a Ridge PCA regression model. Principal components had no collinearity by definition, but we explored this concept and created a more robust PCA, informed by Ledoit's method and others (see the appendix for more comments about insights from this analysis). We submitted those predictions to Kaggle and these predictions achieved RMSE scores of 0.169 and 0.163, respectively.

This analysis provided insights about factors that predict the Sale Price of homes in Ames. It successfully explored methods to accurately predict Sale Price using regression techniques (e.g., simple linear, MLR, Piecewise, PCA, and polynomial regression). This model prototype has practical implications for Ames real estate market stakeholders who could benefit from a tool to accurately predict home sale prices.

References

James, Gareth, Daniela Witten, Trevor Hastie, and Robert Tibshirani. 2021. *An Introduction to Statistical Learning*. Springer. https://www.statlearning.com/

Montoya, Anna. 2016. “House Prices - Advanced Regression Techniques.” *Kaggle*. https://www.kaggle.com/c/house-prices-advanced-regression-techniques

Appendix - Python Code and Outputs

Data Preparation

First, we will set up this notebook so that it will display multiple outputs for each cell if needed.

In [1]:
```
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

Second, we will import the data. We will view the first five rows of data and the shape of the dataframe to confirm that the data imported correctly.

In [2]:
```
import pandas as pd
housing_training_data = pd.read_csv('train.csv')

# show first five rows of the data
housing_training_data.head()
# show number of columns and rows
housing_training_data.shape
```

Out[2]:

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

5 rows × 81 columns

Out[2]:
```
(1460, 81)
```

Distribution of the Dependent Variable

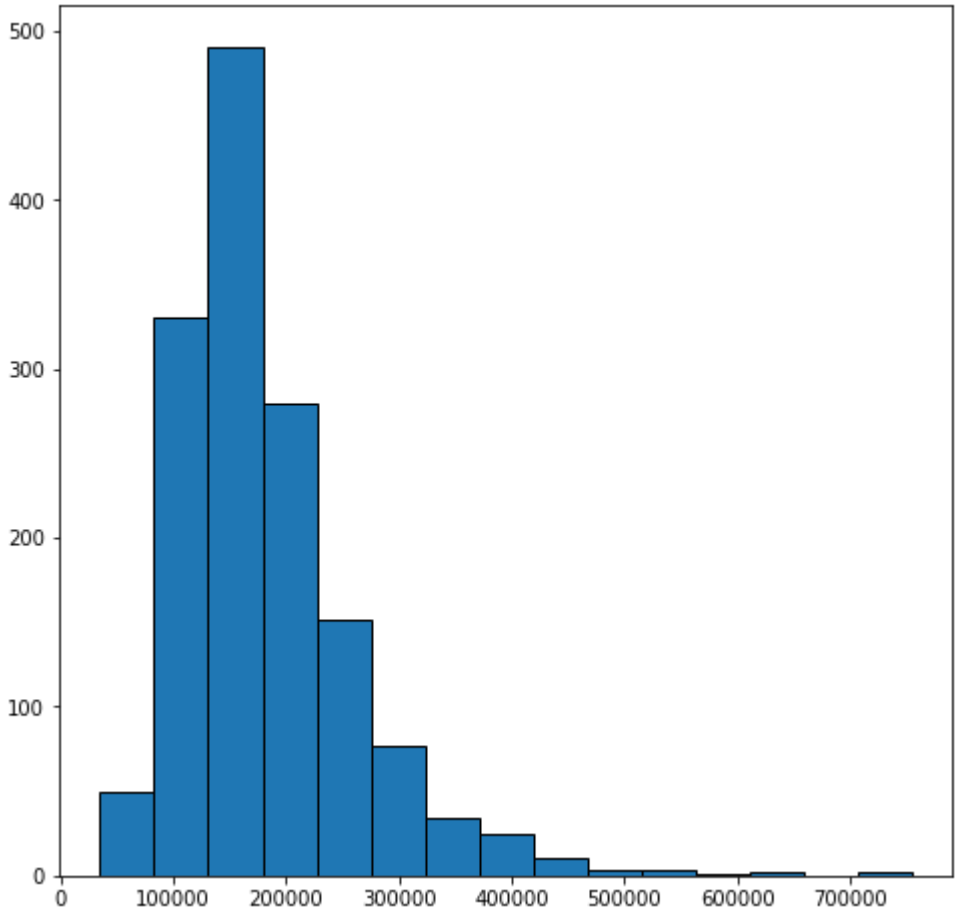
We can begin examining the distribution of this dataset's dependent variable, sale price, by generating summary statistics for this variable.

In [3]:
```
housing_training_data['SalePrice'].describe()
```

Out[3]:
```
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
```

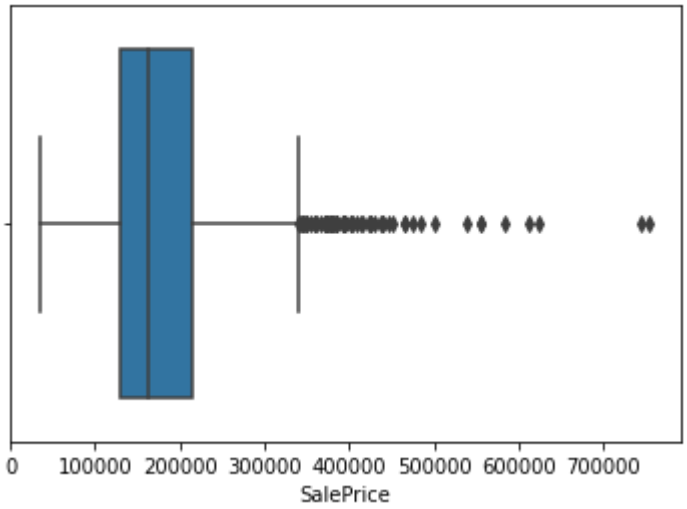
We can also construct a histogram and a boxplot to visualize the distribution of the sale price variable in this dataframe.

In [4]:
```
import seaborn as sns
import matplotlib.pyplot as plt

histogram = housing_training_data['SalePrice'].hist(edgecolor = 'black', bins = 15, fi
```



In [5]:
```
sns.boxplot(x=housing_training_data["SalePrice"])
```

Out[5]:
```
<AxesSubplot:xlabel='SalePrice'>
```



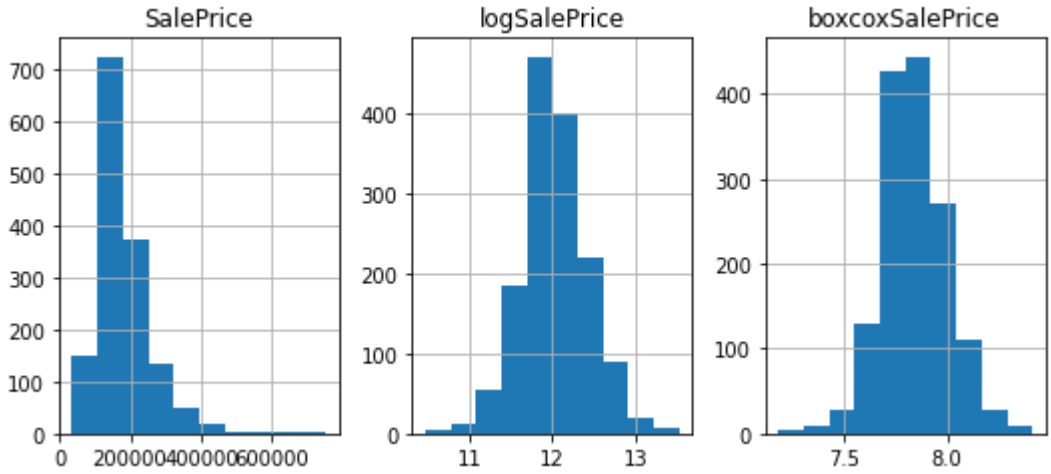
In [6]:
```
import numpy as np
from scipy import stats
from scipy.stats import norm, kurtosis
df = []
raw_data = housing_training_data['SalePrice']
transform_data = np.log(housing_training_data['SalePrice'])
transform_data2, best_lambda = stats.boxcox(housing_training_data['SalePrice'])


print("homeprice kurtosis:", kurtosis(raw_data))
print("log of homeprice kurtosis:", kurtosis(transform_data))
print("boxcox transform of homeprice kurtosis:", kurtosis(transform_data2))


plt.rcParams["figure.figsize"] = [7.50, 3.50]
plt.rcParams["figure.autolayout"] = True

s1 = pd.DataFrame(raw_data)
s2 = pd.DataFrame(np.array(transform_data).tolist(), columns = ['logSalePrice'])
s3 = pd.DataFrame(np.array(transform_data2).tolist(), columns = ['boxcoxSalePrice'])

fig, axes = plt.subplots(1, 3)

s1.hist('SalePrice', ax=axes[0])
s2.hist('logSalePrice', ax=axes[1])
s3.hist('boxcoxSalePrice', ax=axes[2])
plt.show()
```

```
homeprice kurtosis: 6.509812011089439
log of homeprice kurtosis: 0.8026555069117713
boxcox transform of homeprice kurtosis: 0.870759906431624
```

Out[6]:
```
array([<AxesSubplot:title={'center':'SalePrice'}>], dtype=object)
```

Out[6]:
```
array([<AxesSubplot:title={'center':'logSalePrice'}>], dtype=object)
```

Out[6]:
```
array([<AxesSubplot:title={'center':'boxcoxSalePrice'}>], dtype=object)
```



Shapiro Wilk test for normality

In [7]:
```
print("Shapiro Wilk test for normality: ", stats.shapiro(raw_data))
print("Shapiro Wilk test for normality: ", stats.shapiro(transform_data))
print("Shapiro Wilk test for normality: ", stats.shapiro(transform_data2))
```

```
Shapiro Wilk test for normality:  (0.869671642780304, 3.206247534576162e-33)
Shapiro Wilk test for normality:  (0.9912067651748657, 1.1490678986092462e-07)
Shapiro Wilk test for normality:  (0.9915341138839722, 1.906367685933219e-07)
```

The Shapiro Wilk test for normality (H0: normal, Ha: not-normal) suggests a departure from normality for both the raw and transformed data.

Investigation of Missing Data and Outliers

We can take a look at the counts of reported values in each column to determine the number of missing values for each variable in the dataframe.

In [8]:
```
# find null counts, percentage of null values, and column type
null_count = housing_training_data.isnull().sum()
null_percentage = housing_training_data.isnull().sum() * 100 / len(housing_training_da
column_type = housing_training_data.dtypes

# show null counts, percentage of null values, and column type for columns with more t
null_summary = pd.concat([null_count, null_percentage, column_type], axis=1, keys=['Mi
null_summary_only_missing = null_summary[null_count != 0].sort_values('Percentage Miss
null_summary_only_missing
```

Out[8]:

	Missing Count	Percentage Missing	Column Type
PoolQC	1453	99.520548	object
MiscFeature	1406	96.301370	object
Alley	1369	93.767123	object
Fence	1179	80.753425	object
FireplaceQu	690	47.260274	object
LotFrontage	259	17.739726	float64
GarageType	81	5.547945	object
GarageYrBlt	81	5.547945	float64
GarageFinish	81	5.547945	object
GarageQual	81	5.547945	object
GarageCond	81	5.547945	object
BsmtExposure	38	2.602740	object
BsmtFinType2	38	2.602740	object
BsmtFinType1	37	2.534247	object
BsmtCond	37	2.534247	object
BsmtQual	37	2.534247	object
MasVnrArea	8	0.547945	float64
MasVnrType	8	0.547945	object
Electrical	1	0.068493	object

We will deal with columns that contain missing values. For the purpose of this exploratory data analysis, we will use the percentage of nulls missing, the column type, and the other columns present in the data that may provide information that can be used to fill in the missing values.

We will remove columns with over 50% Null values.

In [9]:
```
# PoolQC, MiscFeature, Alley, Fence all have over 50% of missing values, we will remov
housing_training_data.drop(['Alley','PoolQC','Fence','MiscFeature'],axis=1,inplace=Tru

# show new shape
housing_training_data.shape
```

Out[9]:
```
(1460, 77)
```

We will set Null values in columns that are non-numeric to None.

In [10]:
```
# select non-numeric columns that contain more than 1 Null value
columns_None = ['BsmtQual','BsmtCond','BsmtExposure','BsmtFinType1','BsmtFinType2','Ga
# set Nulls in non-numeric columns to 'None'
housing_training_data[columns_None] = housing_training_data[columns_None].fillna('None
```

We determine the best way to handle nulls for each numeric column. We replace nulls in Masonry veneer area with 0, nulls in Lot Frontage with the median, and nulls in Year Garage was built with the average between the year the garage was built and year house was built .

In [11]:
```
# change Null values to 0 for Masonry veneer area
housing_training_data['MasVnrArea'].fillna(0, inplace=True)

# show distribution stats for Lot Frontage
housing_training_data['LotFrontage'].describe()
# fill Nulls for Lot Frontage with median value
housing_training_data['LotFrontage'].fillna(housing_training_data['LotFrontage'].media

# average years between garage being built and years built
avg_years = round((housing_training_data['GarageYrBlt'] - housing_training_data['YearB
# fill Nulls with avg bet year garage was built and year house was built
housing_training_data['GarageYrBlt'].fillna(housing_training_data['YearBuilt']+avg_yea
```

Out[11]:
```
count    1201.000000
mean       70.049958
std        24.284752
min        21.000000
25%        59.000000
50%        69.000000
75%        80.000000
max       313.000000
Name: LotFrontage, dtype: float64
```

We can see there are no more missing values in our original dataframe.

In [12]:
```
# check that there are no more missing values in the dataframe
null_count = housing_training_data.isnull().sum()
null_count[null_count != 0]
```

Out[12]:
```
Series([], dtype: int64)
```

We can also create boxplots for each of the continuous variables in the dataframe to analyze whether outliers exist for each of those variables.

In [13]:
```
numerical_vars = ['LotFrontage', 'LotArea', 'OverallQual', 'OverallCond', 'YearBuilt',
                  'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF',
                  'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
                  'TotRmsAbvGrd', 'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageAre
                  'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',

fig, ax = plt.subplots(17, 2, figsize = (10, 20))

for var, subplot in zip(numerical_vars, ax.flatten()):
    sns.boxplot(x=housing_training_data[var], ax = subplot)

fig.tight_layout()
```

Out[13]:
```
<AxesSubplot:xlabel='LotFrontage'>
```

Out[13]:
```
<AxesSubplot:xlabel='LotArea'>
```

Out[13]:
```
<AxesSubplot:xlabel='OverallQual'>
```

Out[13]: <AxesSubplot:xlabel='OverallCond'>

Out[13]: <AxesSubplot:xlabel='YearBuilt'>

Out[13]: <AxesSubplot:xlabel='YearRemodAdd'>

Out[13]: <AxesSubplot:xlabel='MasVnrArea'>

Out[13]: <AxesSubplot:xlabel='BsmtFinSF1'>

Out[13]: <AxesSubplot:xlabel='BsmtFinSF2'>

Out[13]: <AxesSubplot:xlabel='BsmtUnfSF'>

Out[13]: <AxesSubplot:xlabel='TotalBsmtSF'>

Out[13]: <AxesSubplot:xlabel='1stFlrSF'>

Out[13]: <AxesSubplot:xlabel='2ndFlrSF'>

Out[13]: <AxesSubplot:xlabel='LowQualFinSF'>

Out[13]: <AxesSubplot:xlabel='GrLivArea'>

Out[13]: <AxesSubplot:xlabel='BsmtFullBath'>

Out[13]: <AxesSubplot:xlabel='BsmtHalfBath'>

Out[13]: <AxesSubplot:xlabel='FullBath'>

Out[13]: <AxesSubplot:xlabel='HalfBath'>

Out[13]: <AxesSubplot:xlabel='BedroomAbvGr'>

Out[13]: <AxesSubplot:xlabel='KitchenAbvGr'>

Out[13]: <AxesSubplot:xlabel='TotRmsAbvGrd'>

Out[13]: <AxesSubplot:xlabel='Fireplaces'>

Out[13]: <AxesSubplot:xlabel='GarageYrBlt'>

Out[13]: <AxesSubplot:xlabel='GarageCars'>

Out[13]: <AxesSubplot:xlabel='GarageArea'>

Out[13]: <AxesSubplot:xlabel='WoodDeckSF'>

Out[13]: <AxesSubplot:xlabel='OpenPorchSF'>

Out[13]: <AxesSubplot:xlabel='EnclosedPorch'>

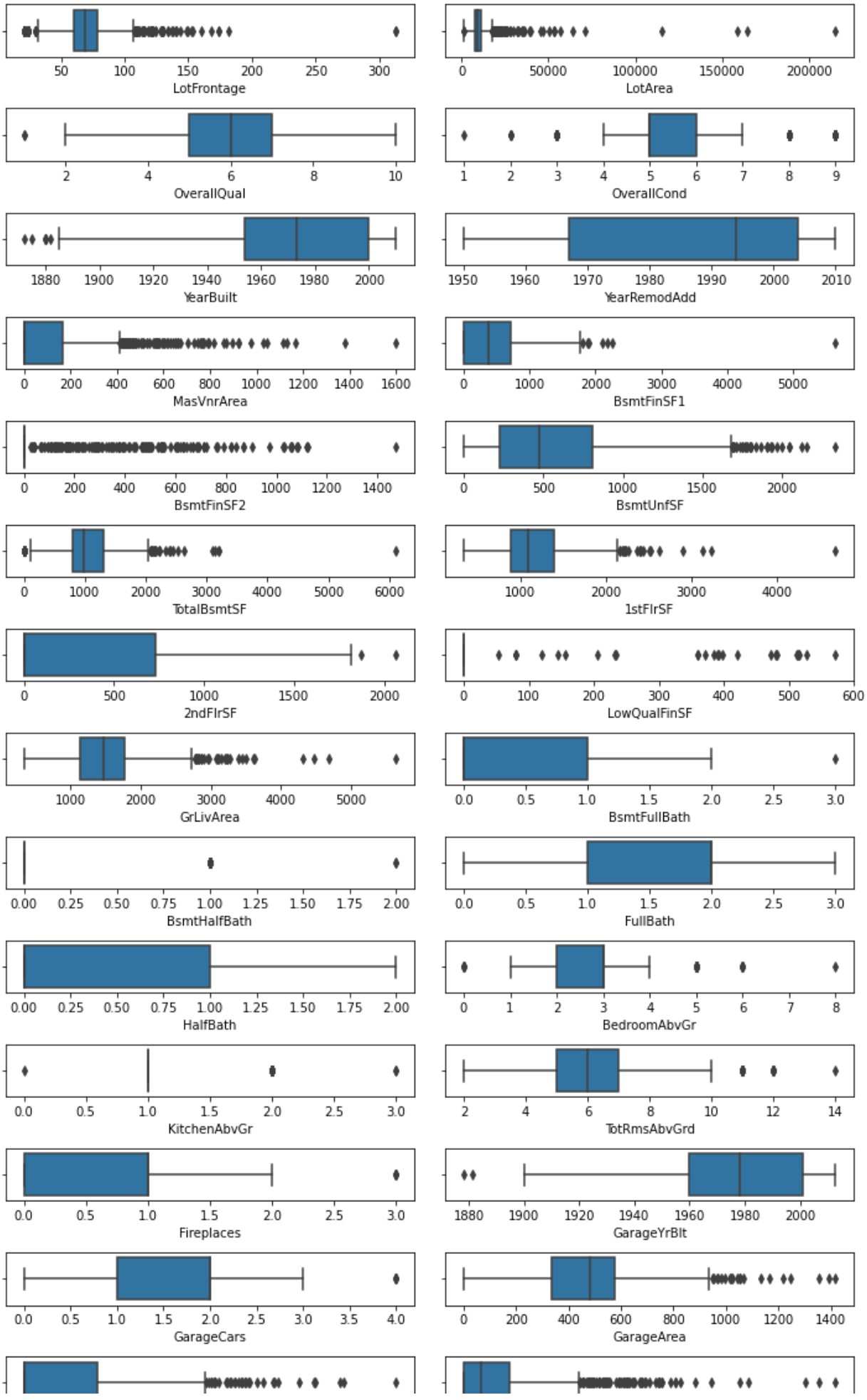
Out[13]: <AxesSubplot:xlabel='3SsnPorch'>

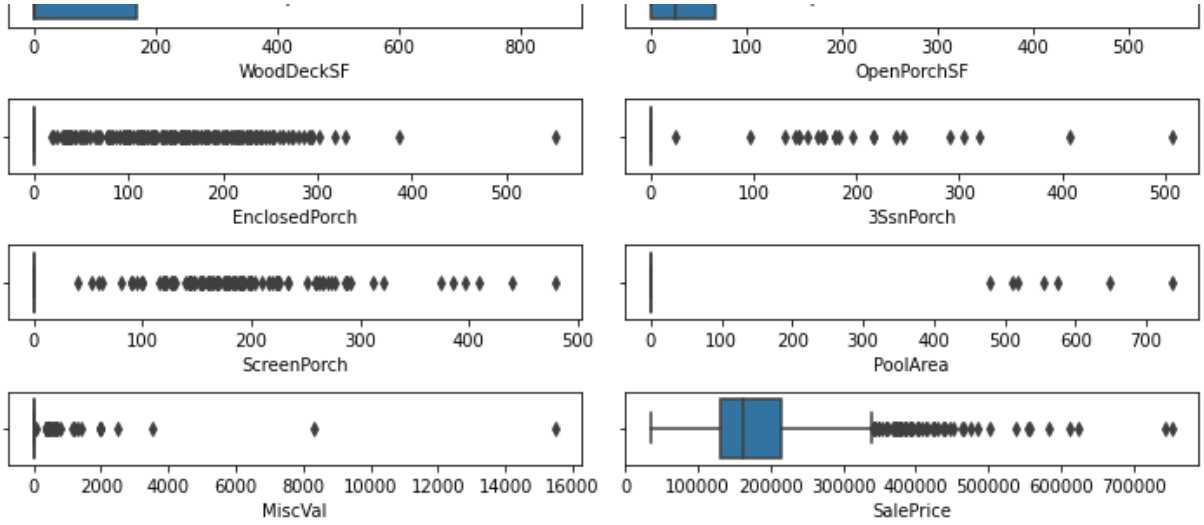
Out[13]: <AxesSubplot:xlabel='ScreenPorch'>

Out[13]: <AxesSubplot:xlabel='PoolArea'>

Out[13]: <AxesSubplot:xlabel='MiscVal'>

Out[13]: <AxesSubplot:xlabel='SalePrice'>


LotFrontage
LotArea
OverallQual
OverallCond
YearBuilt
YearRemodAdd
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
LowQualFinSF
GrLivArea
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces
GarageYrBlt
GarageCars
GarageArea

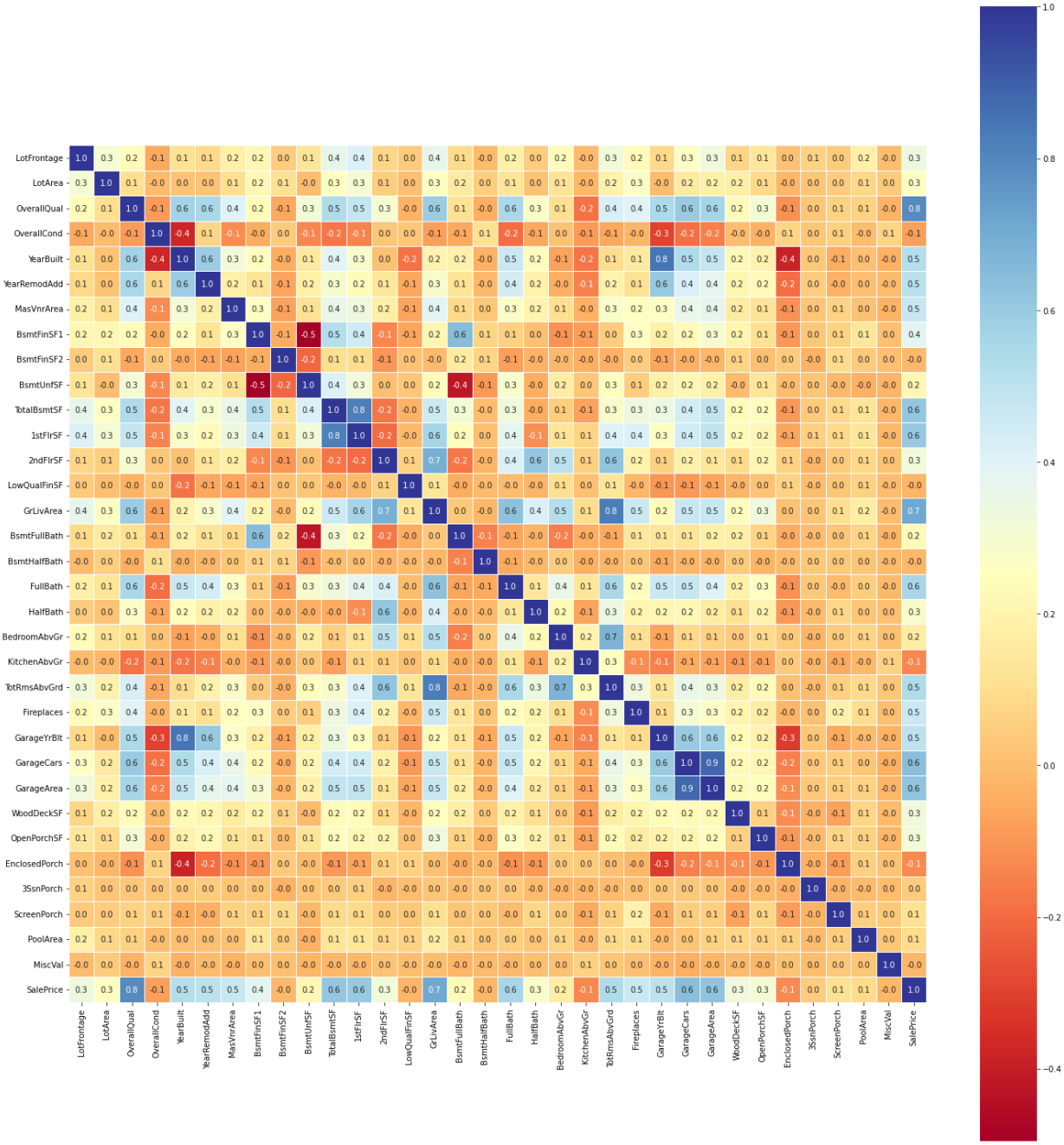


Examination of the Relationship between the Dependent Variable and Potential Predictors

We can use a correlation heatmap to quantify the correlation between the dependent variable, sale price, and the potential continuous predictor variables.

In [14]:
```
df_corr_housing_training = housing_training_data[numerical_vars]
corrmat_housing_training = df_corr_housing_training.corr()

f, ax = plt.subplots(figsize = (20, 20))
sns.heatmap(corrmat_housing_training, vmax = 1, square = True, annot = True,
            cmap = 'RdYlBu', linewidths = 0.5, fmt=".1f")
```

Out[14]:
```
<AxesSubplot:>
```



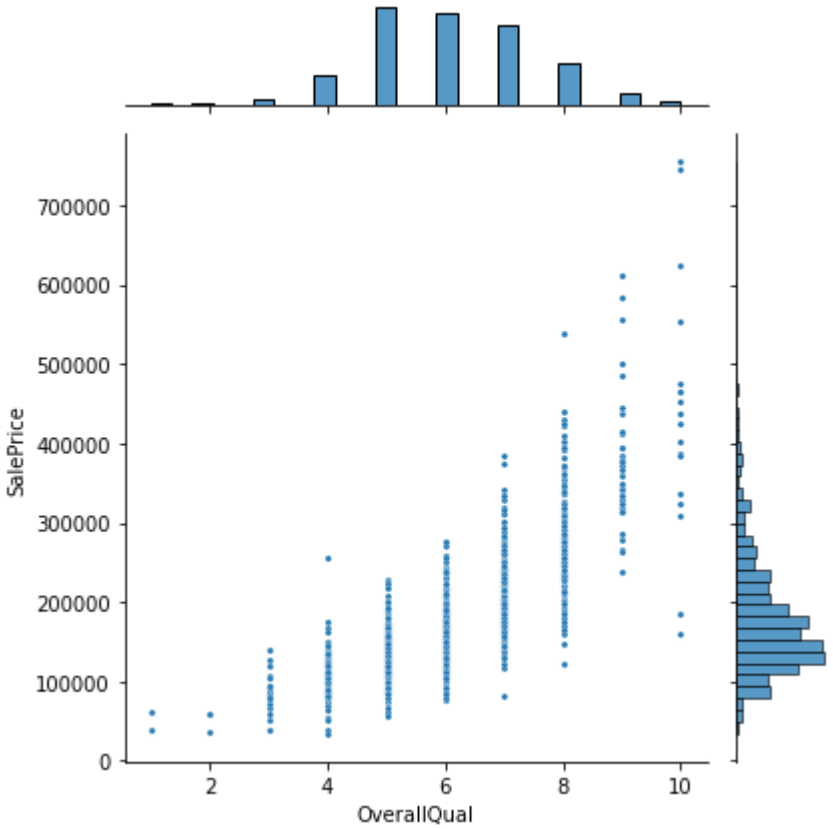
In [15]:
```
#Correlation with output variable
cor_target = abs(corrmat_housing_training["SalePrice"])
#Selecting highly correlated features
relevant_features = cor_target[cor_target>0.5]
relevant_features.sort_values(ascending=False)
```

Out[15]:
```
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
GarageYrBlt     0.503288
Name: SalePrice, dtype: float64
```

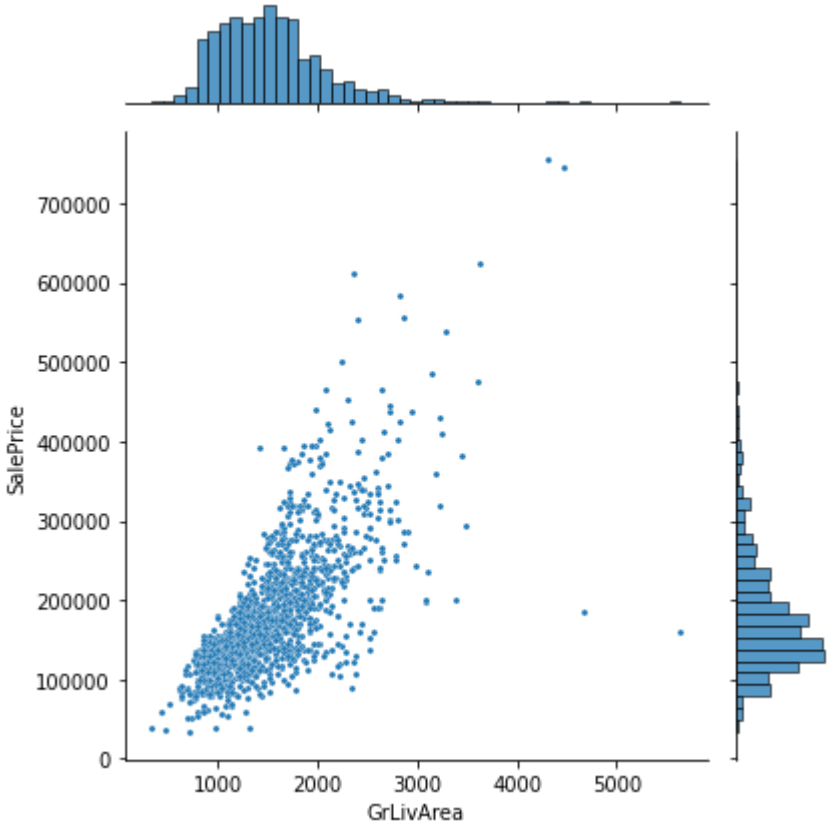
We can use jointplots to take a closer look at the relationship between sale price and five of the continuous variables with which sale price has a strong or moderate association: OverallQual, GrLivArea, GarageArea, Fullbath, and TotalBsmntSF.

Below are plots that examine the relationship between variables of interest and sale price

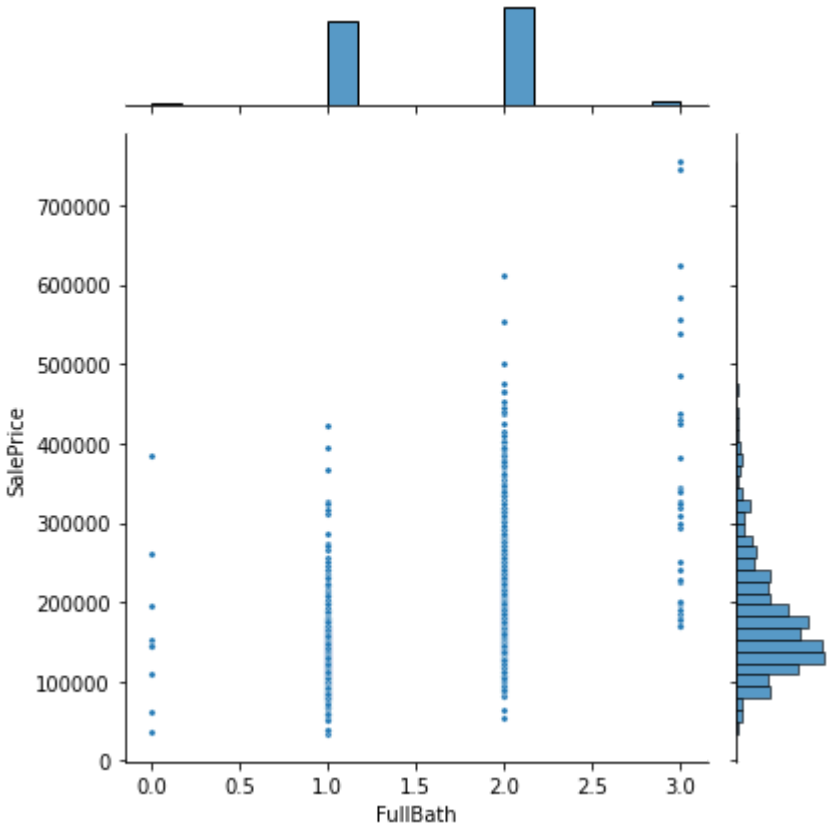
In [16]:
```
sns.jointplot(x='OverallQual', y='SalePrice', data = housing_training_data, joint_kws=
```



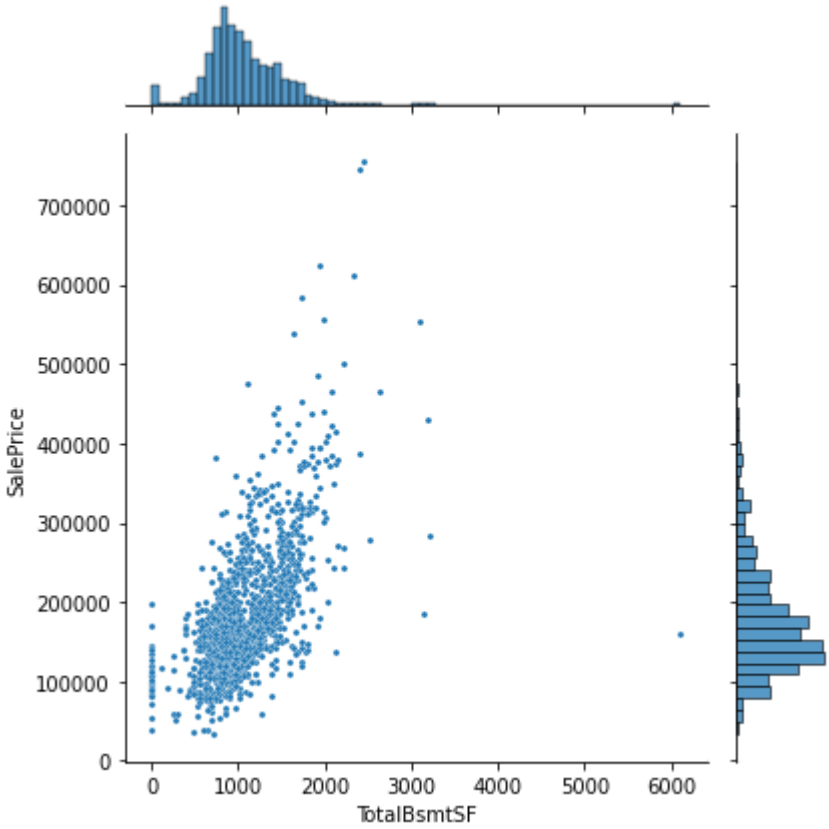
In [17]:
```
sns.jointplot(x='GrLivArea', y='SalePrice', data = housing_training_data, joint_kws={'
```



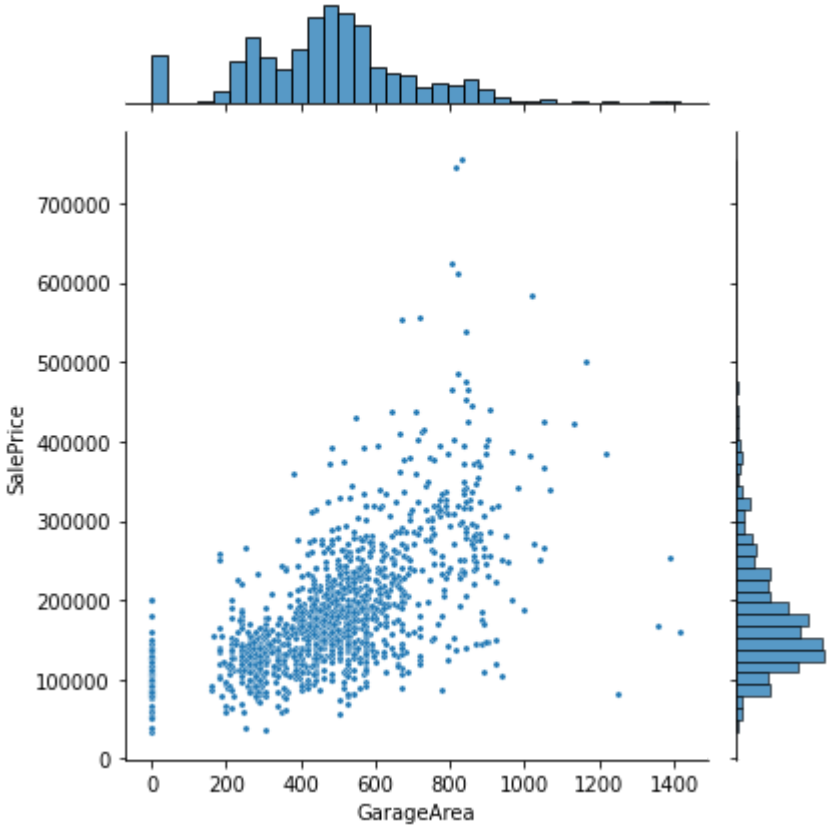
In [18]:
```
sns.jointplot(x='FullBath', y='SalePrice', data = housing_training_data, joint_kws={"s
```



In [19]:
```
sns.jointplot(x='TotalBsmtSF', y='SalePrice', data = housing_training_data, joint_kws=
```



In [20]:
```
sns.jointplot(x='GarageArea', y='SalePrice', data = housing_training_data, joint_kws={
```



To determine which binary categorical variables might serve as the best predictors in a regression model, we can create boxplots and run t-tests to help decipher which binary indicator variables may have the strongest relationship with home sale prices.

In [21]:
```
categorical_variables = ['MSZoning', 'Street', 'LotShape', 'LandContour', 'Utilities',
                         'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'House
                         'Exterior1st', 'Exterior2nd', 'MasVnrType', 'ExterQual', 'Exte
                         'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtF
                         'CentralAir', 'Electrical', 'KitchenQual', 'Functional', 'Fire
                         'GarageQual', 'GarageCond', 'PavedDrive',  'SaleType', 'SaleCo

category_counts = []

for var in categorical_variables:
    category_counts.append(len(housing_training_data[var].unique()))



categorical_variable_dictionary = {'Categorical Predictor':categorical_variables,'Numb
categorical_var_df = pd.DataFrame(categorical_variable_dictionary)
categorical_var_df


# Identify the Indicator Variables
indicator_variables_df = categorical_var_df[categorical_var_df['Number of Categories']
indicator_variables_df

# Identify the Non-Indicator Categorical Variables
non_indicator_categorial_vars_df = categorical_var_df[categorical_var_df['Number of Ca
non_indicator_categorial_vars_df
```

Out[21]:

	Categorical Predictor	Number of Categories
0	MSZoning	5
1	Street	2
2	LotShape	4
3	LandContour	4
4	Utilities	2
5	LotConfig	5
6	LandSlope	3
7	Neighborhood	25
8	Condition1	9
9	Condition2	8
10	BldgType	5
11	HouseStyle	8
12	RoofStyle	6
13	RoofMatl	8
14	Exterior1st	15
15	Exterior2nd	16
16	MasVnrType	4
17	ExterQual	4
18	ExterCond	5
19	Foundation	6
20	BsmtQual	5
21	BsmtCond	5
22	BsmtExposure	5
23	BsmtFinType1	7
24	BsmtFinType2	7
25	Heating	6
26	HeatingQC	5
27	CentralAir	2
28	Electrical	6
29	KitchenQual	4
30	Functional	7
31	FireplaceQu	6
32	GarageType	7

	Categorical Predictor	Number of Categories
33	GarageQual	6
34	GarageCond	6
35	PavedDrive	3
36	SaleType	9
37	SaleCondition	6

Out[21]:

	Categorical Predictor	Number of Categories
1	Street	2
4	Utilities	2
27	CentralAir	2

Out[21]:

	Categorical Predictor	Number of Categories
0	MSZoning	5
2	LotShape	4
3	LandContour	4
5	LotConfig	5
6	LandSlope	3
7	Neighborhood	25
8	Condition1	9
9	Condition2	8
10	BldgType	5
11	HouseStyle	8
12	RoofStyle	6
13	RoofMatl	8
14	Exterior1st	15
15	Exterior2nd	16
16	MasVnrType	4
17	ExterQual	4
18	ExterCond	5
19	Foundation	6
20	BsmtQual	5
21	BsmtCond	5
22	BsmtExposure	5
23	BsmtFinType1	7
24	BsmtFinType2	7
25	Heating	6
26	HeatingQC	5
28	Electrical	6
29	KitchenQual	4
30	Functional	7
31	FireplaceQu	6
32	GarageType	7
33	GarageQual	6
34	GarageCond	6
35	PavedDrive	3

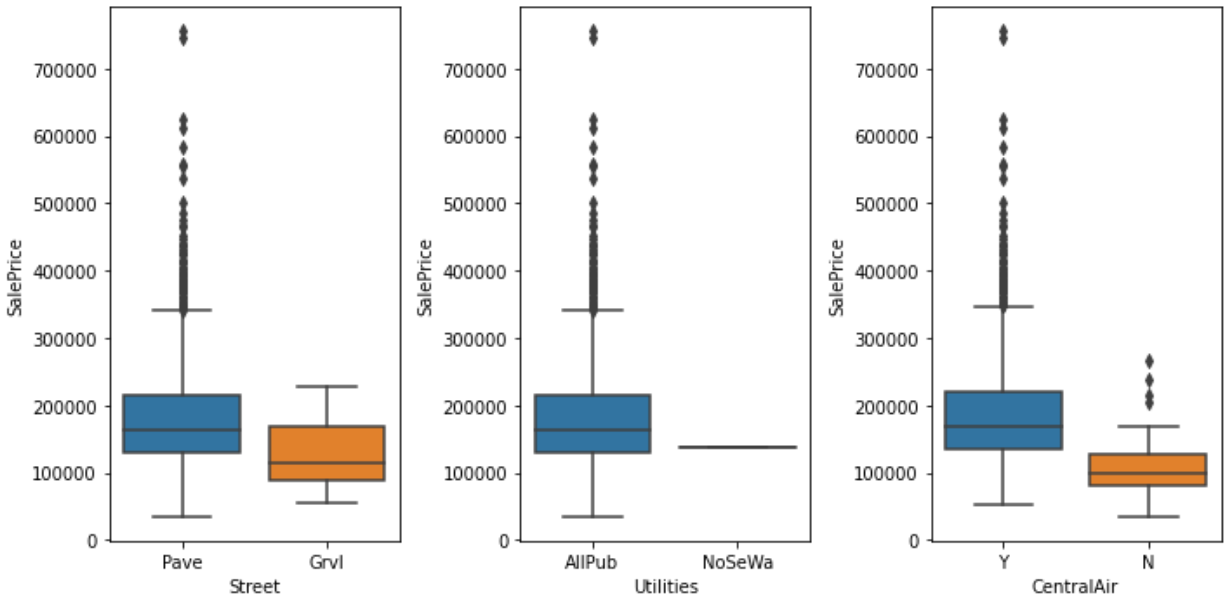
	Categorical Predictor	Number of Categories
36	SaleType	9
37	SaleCondition	6

In [22]:
```
indicator_vars = ['Street', 'Utilities', 'CentralAir']

fig, ax = plt.subplots(1, 3, figsize=(10, 5))

for var, subplot in zip(indicator_vars, ax.flatten()):
        sns.boxplot(x = var, y = 'SalePrice', data=housing_training_data, ax=subplot)

fig.tight_layout()
```

Out[22]: <AxesSubplot:xlabel='Street', ylabel='SalePrice'>

Out[22]: <AxesSubplot:xlabel='Utilities', ylabel='SalePrice'>

Out[22]: <AxesSubplot:xlabel='CentralAir', ylabel='SalePrice'>



In [23]:
```
# Run T-Tests To Determine Which Indicator Variables Might Have the Strongest Associat
from scipy.stats import ttest_ind

Street_t_test = ttest_ind(housing_training_data['SalePrice'][housing_training_data['St
          housing_training_data['SalePrice'][housing_training_data['Street'] == 'Grvl'
          equal_var=False)

Utilities_t_test = ttest_ind(housing_training_data['SalePrice'][housing_training_data[
          housing_training_data['SalePrice'][housing_training_data['Utilities'] == 'No
          equal_var=False)

Central_Air_t_test = ttest_ind(housing_training_data['SalePrice'][housing_training_dat
          housing_training_data['SalePrice'][housing_training_data['CentralAir'] == 'N
          equal_var=False)



Indicator_Variable_t_test_statistics = [Street_t_test[0], Utilities_t_test[0], Central
```

```
Indicator_Variable_t_test_p_values = [Street_t_test[1], Utilities_t_test[1], Central_A

indicator_var_t_tests = {'Indicator Variable':indicator_vars,'T-Test Statistic':Indica
                         'P-Values':Indicator_Variable_t_test_p_values}
Indicator_var_t_test_df = pd.DataFrame(indicator_var_t_tests)
Indicator_var_t_test_df.style.background_gradient(cmap = 'Greens')
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/numpy/c
ore/fromnumeric.py:3724: RuntimeWarning: Degrees of freedom <= 0 for slice
  **kwargs)
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/numpy/c
ore/_methods.py:254: RuntimeWarning: invalid value encountered in double_scalars
  ret = ret.dtype.type(ret / rcount)
```

Out[23]:

	Indicator Variable	T-Test Statistic	P-Values
0	Street	1.900788	0.115048
1	Utilities	nan	nan
2	CentralAir	17.267773	0.000000

To determine which categorical variables might be most useful for inclusion in a regression model (in the form of a dichotomous variable), we can create boxplots and run analyses of variance (ANOVA) to determine which non-binary categorical variables may have the strongest relationship with home sale prices.

We can create boxplots to visually display the distribution of sale prices disaggregated by the categories associated with each of the non-indicator categorical variables as well.

In [24]:
```
fig, ax = plt.subplots(35, 1, figsize=(15, 200))

for var, subplot in zip(non_indicator_categorial_vars_df['Categorical Predictor'], ax.
         sns.boxplot(x = var, y = 'SalePrice', data=housing_training_data, ax=subplot)

fig.tight_layout()
```

Out[24]: <AxesSubplot:xlabel='MSZoning', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='LotShape', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='LandContour', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='LotConfig', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='LandSlope', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='Neighborhood', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='Condition1', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='Condition2', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='BldgType', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='HouseStyle', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='RoofStyle', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='RoofMatl', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='Exterior1st', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='Exterior2nd', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='MasVnrType', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='ExterQual', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='ExterCond', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='Foundation', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='BsmtQual', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='BsmtCond', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='BsmtExposure', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='BsmtFinType1', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='BsmtFinType2', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='Heating', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='HeatingQC', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='Electrical', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='KitchenQual', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='Functional', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='FireplaceQu', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='GarageType', ylabel='SalePrice'>

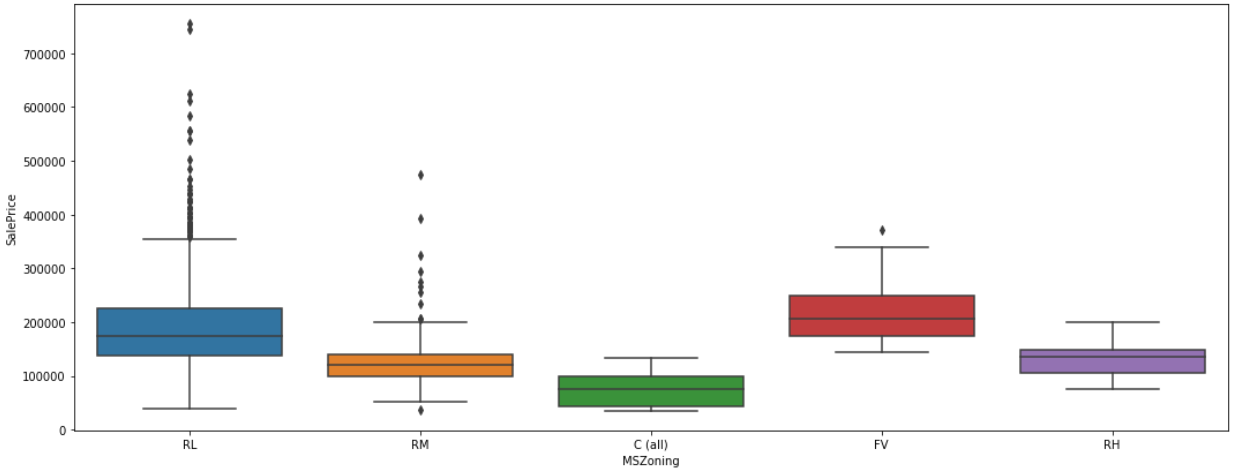
Out[24]: <AxesSubplot:xlabel='GarageQual', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='GarageCond', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='PavedDrive', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='SaleType', ylabel='SalePrice'>

Out[24]: <AxesSubplot:xlabel='SaleCondition', ylabel='SalePrice'>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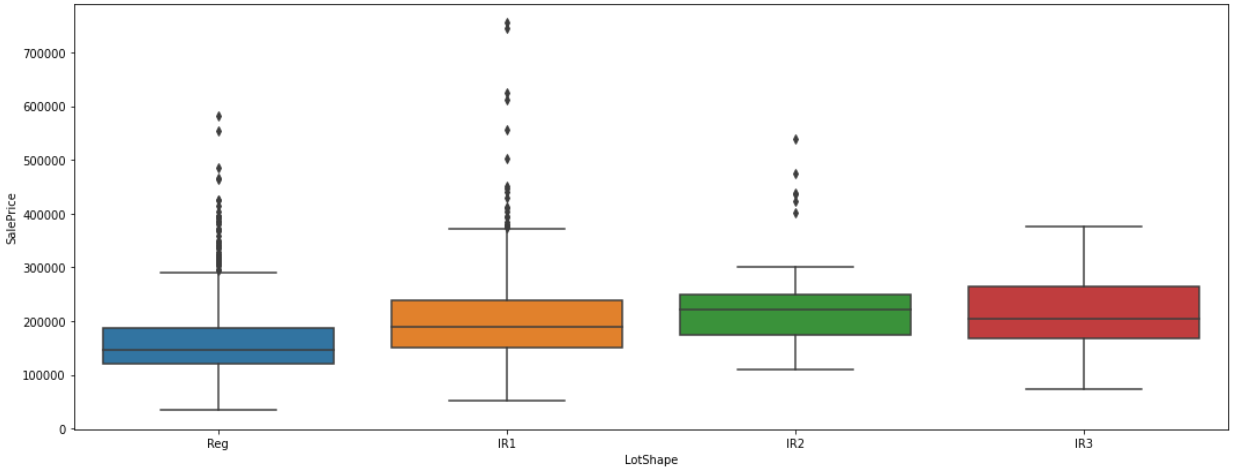
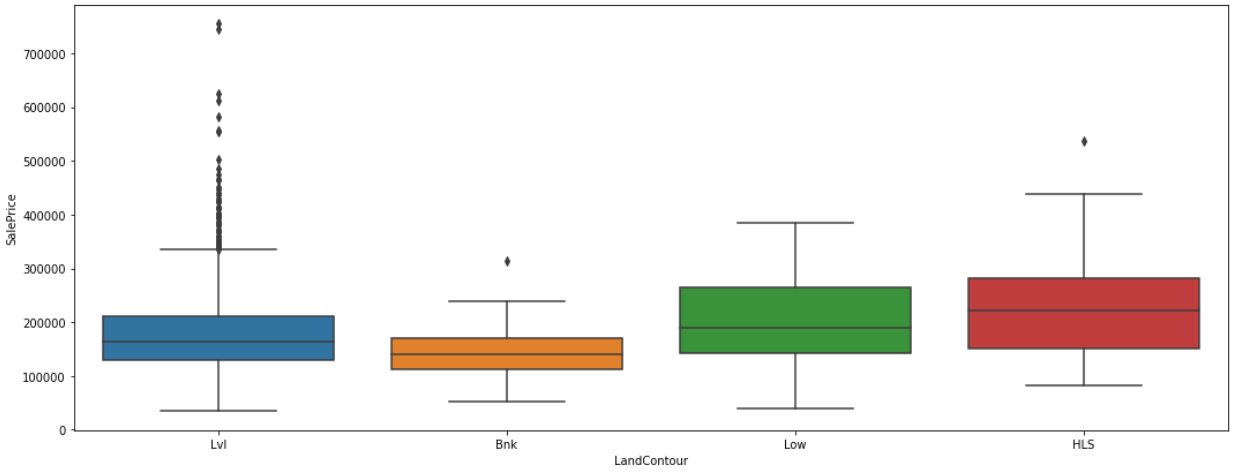
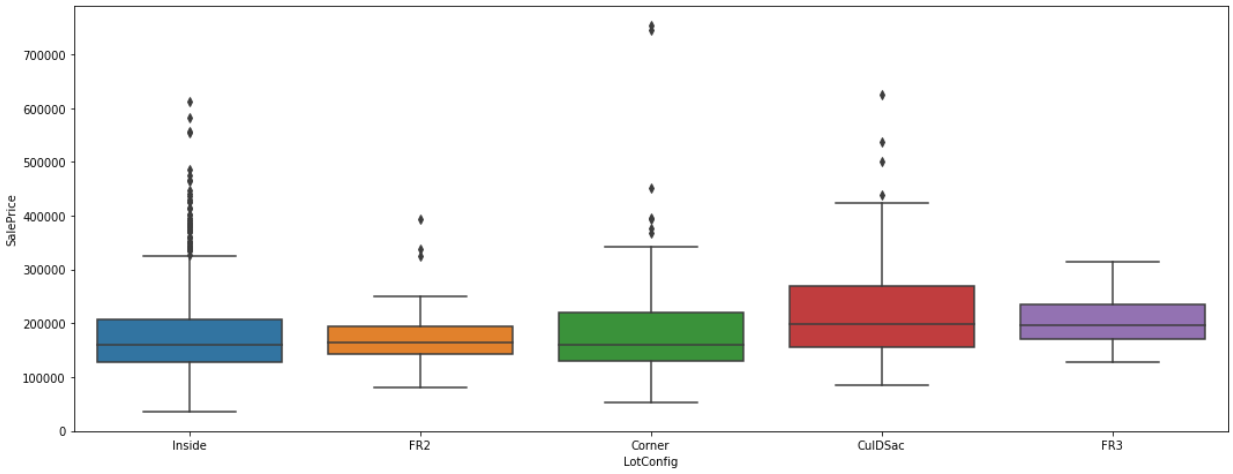
100000
200000
300000
400000
500000
600000
700000
RL
RM
C (all)
FV
RH
MSZoning


SalePrice
0
100000
200000
300000
400000
500000
600000
700000
Reg
IR1
IR2
IR3
LotShape


SalePrice
0
100000
200000
300000
400000
500000
600000
700000
Lvl
Bnk
Low
HLS
LandContour


SalePrice
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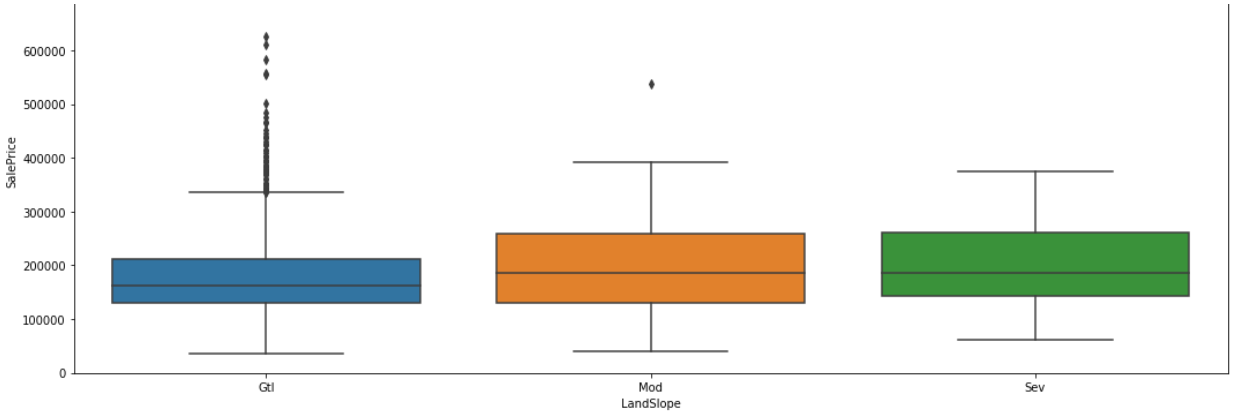
300000
400000
500000
600000
700000
Inside
FR2
Corner
CulDSac
FR3
LotConfig


700000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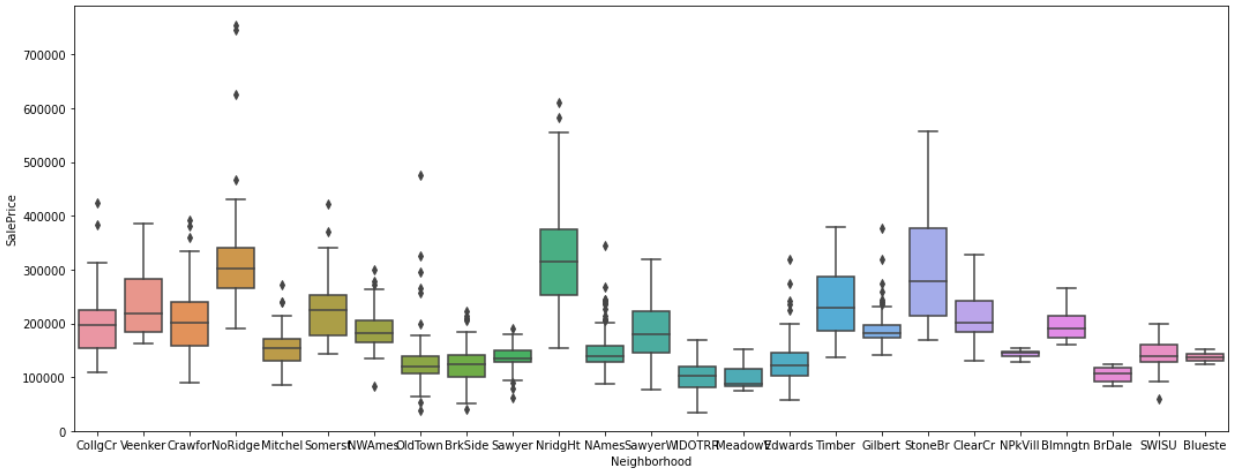
0
100000
200000
300000
400000
500000
600000
Gtl
Mod
Sev
LandSlope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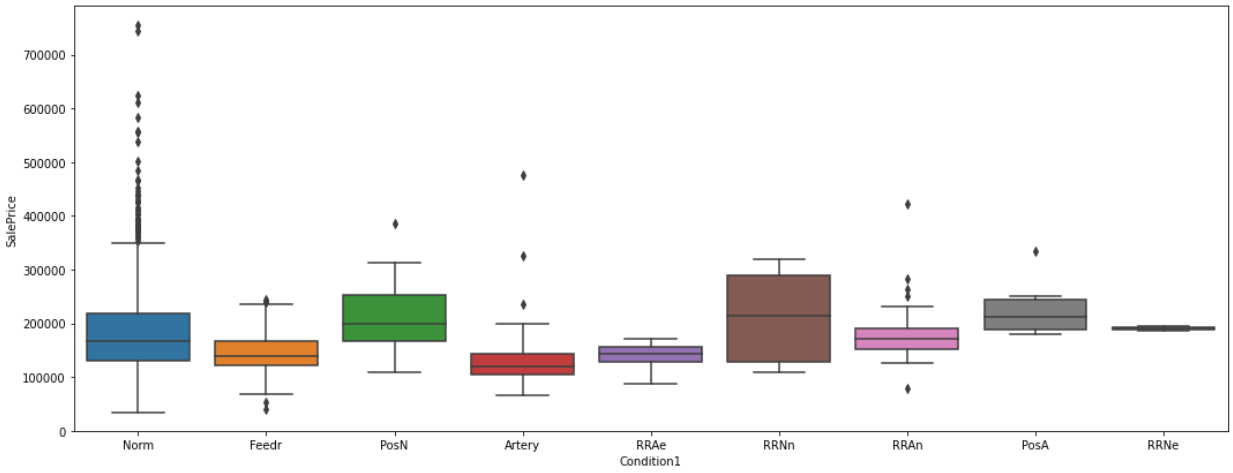
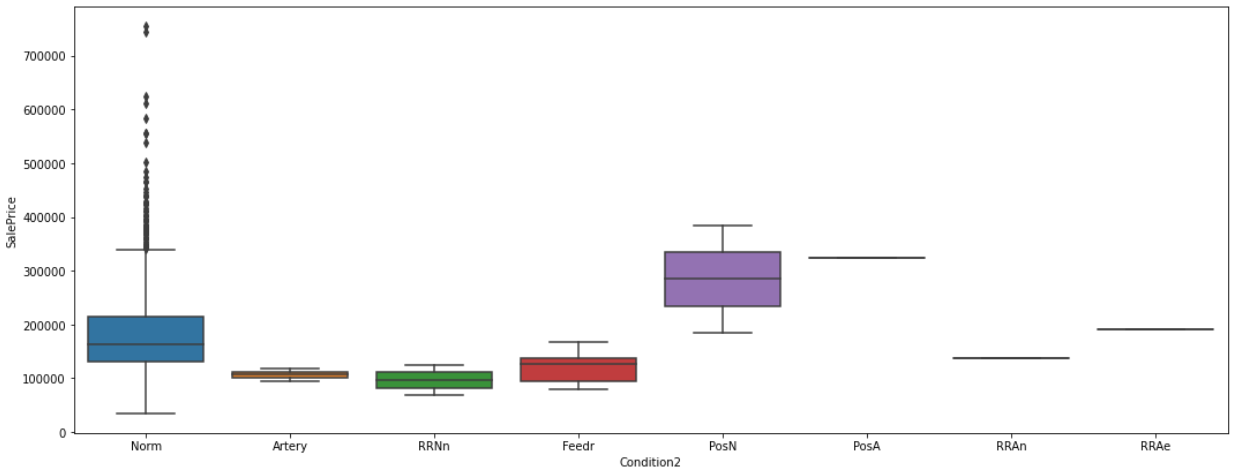
0
100000
200000
300000
400000
500000
600000
700000
CollgCr
Veenker
Crawfor
NoRidge
Mitchel
Somerst
NWAmes
OldTown
BrkSide
Sawyer
NridgHt
NAmes
SawyerW
IDOTRR
Meadow
Edwards
Timber
Gilbert
StoneBr
ClearCr
NPkVill
Blmngtn
BrDale
SWISU
Blueste
Neighborhood


SalePrice
0
100000
200000
300000
400000
500000
600000
700000
Norm
Feedr
PosN
Artery
RRAe
RRNn
RRAn
PosA
RRNe
Condition1


SalePrice
0
100000
200000
300000
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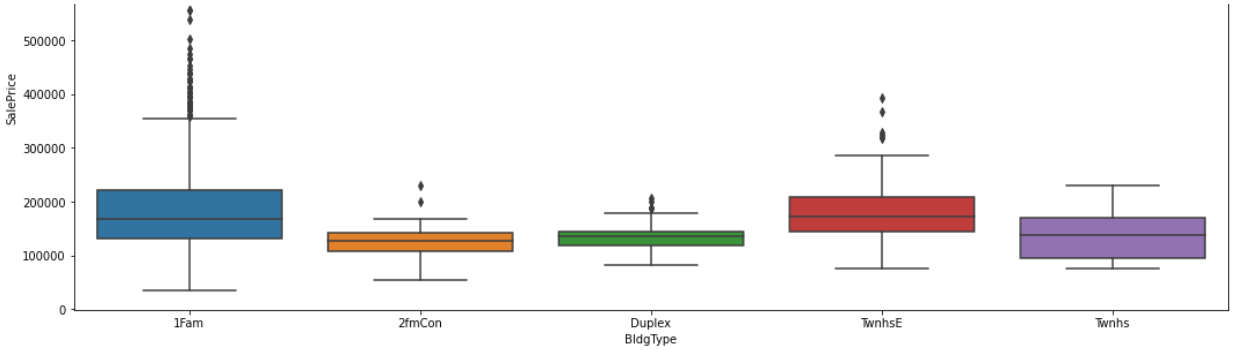
700000
Norm
Artery
RRNn
Feedr
PosN
PosA
RRAn
RRAe
Condition2


700000
600000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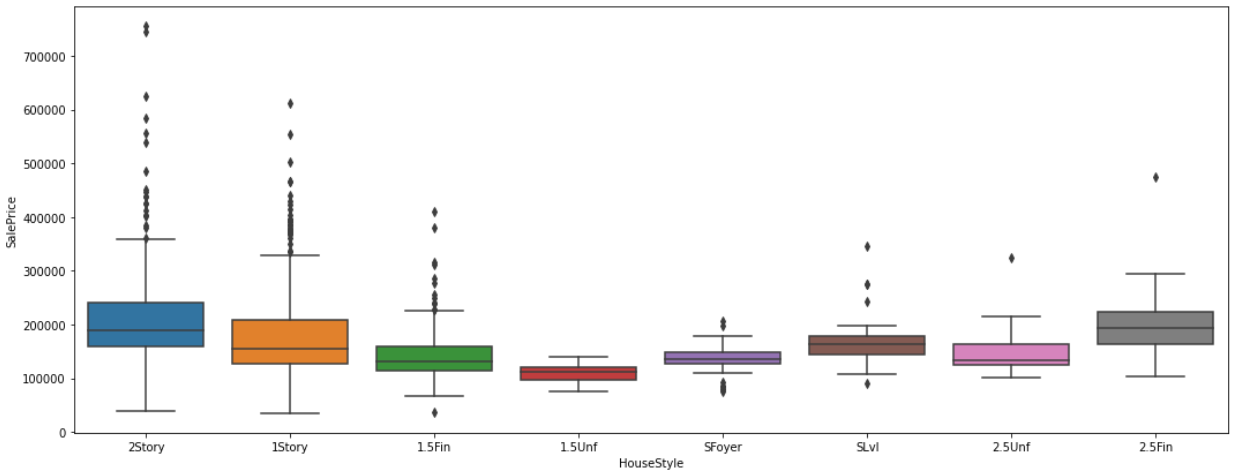
1Fam
2fmCon
Duplex
TwnhsE
Twnhs
BldgType


SalePrice
0
100000
200000
300000
400000
500000
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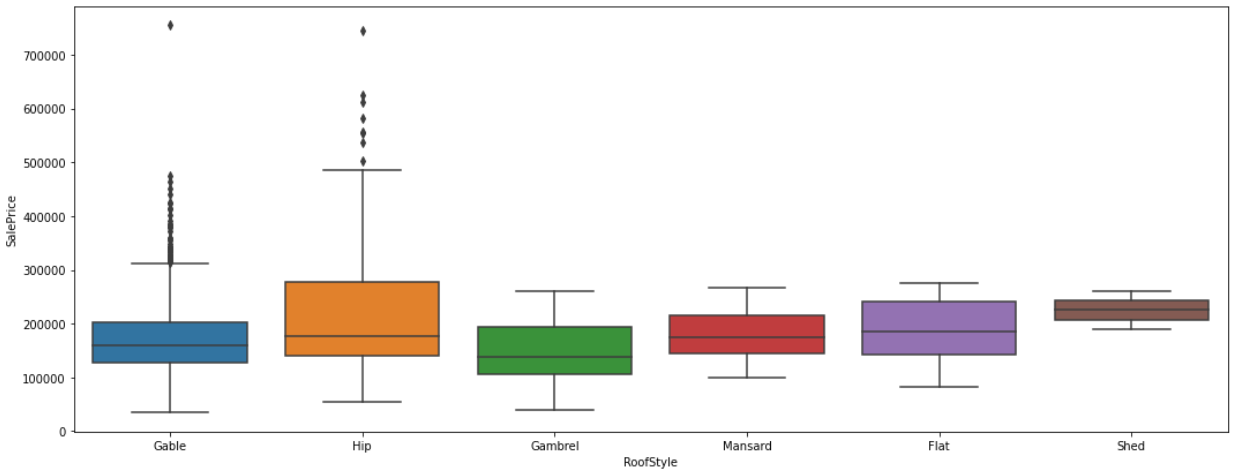
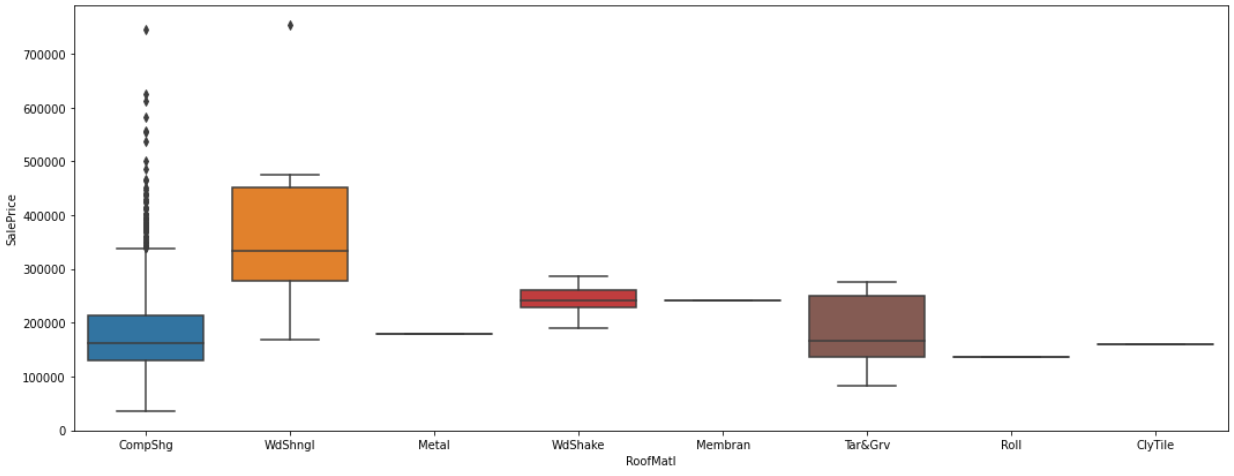
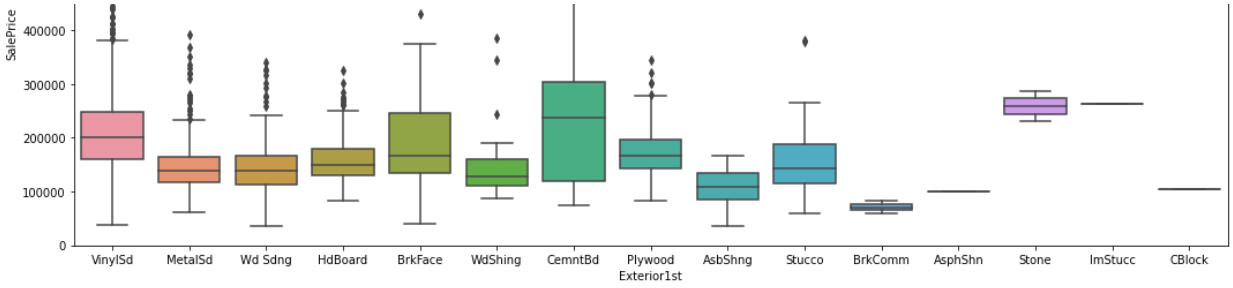
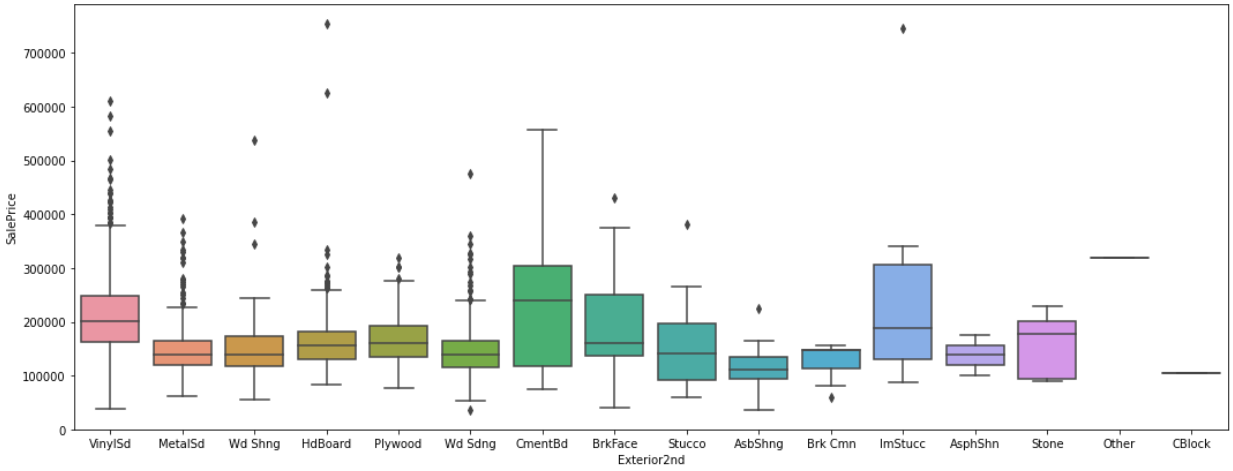
700000
2Story
1Story
1.5Fin
1.5Unf
SFoyer
SLvl
2.5Unf
2.5Fin
HouseStyle


SalePrice
0
100000
200000
300000
400000
500000
600000
700000
Gable
Hip
Gambrel
Mansard
Flat
Shed
RoofStyle


SalePrice
0
100000
200000
300000
400000
500000
600000
700000
CompShg
WdShngl
Metal
WdShake
Membran
Tar&Grv
Roll
ClyTile
RoofMatl


700000
600000
500000


SalePrice
0
100000
200000
300000
400000
VinylSd
MetalSd
Wd Sdng
HdBoard
BrkFace
WdShing
CemntBd
Plywood
AsbShng
Stucco
BrkComm
AsphShn
Stone
ImStucc
CBlock
Exterior1st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0
100000
200000
300000
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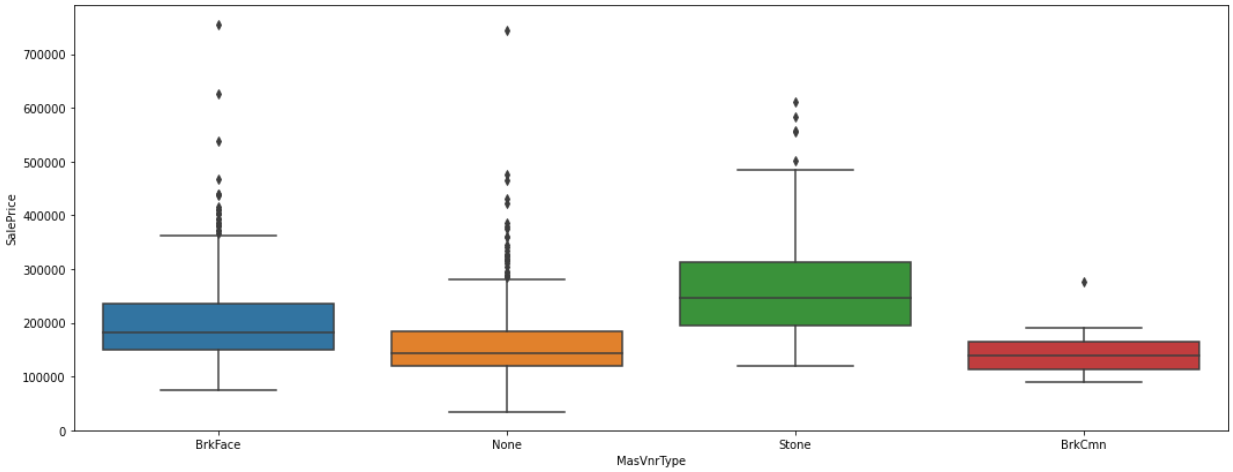
500000
600000
700000
VinylSd
MetalSd
Wd Shng
HdBoard
Plywood
Wd Sdng
CmentBd
BrkFace
Stucco
AsbShng
Brk Cmn
ImStucc
AsphShn
Stone
Other
CBlock
Exterior2nd


SalePrice
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100000
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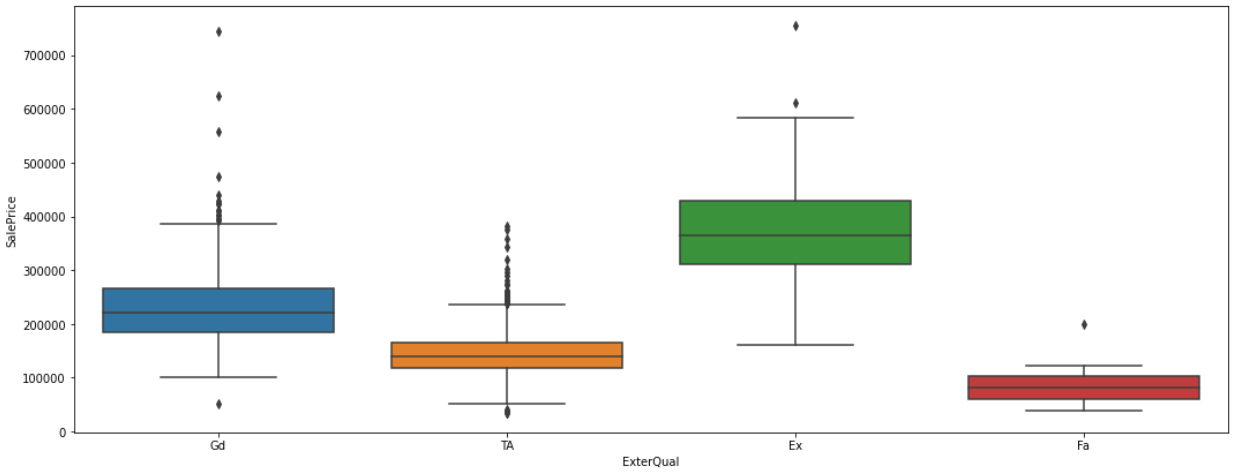
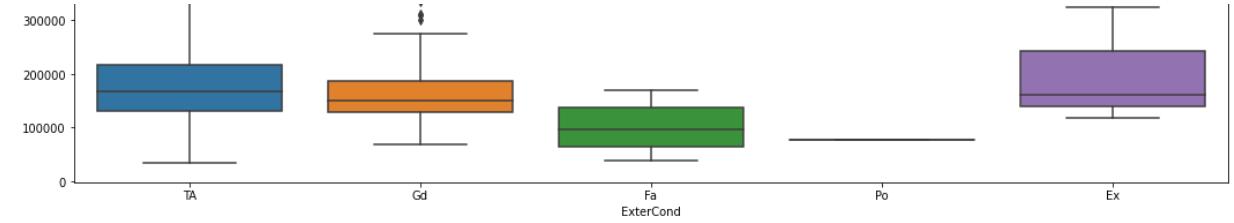
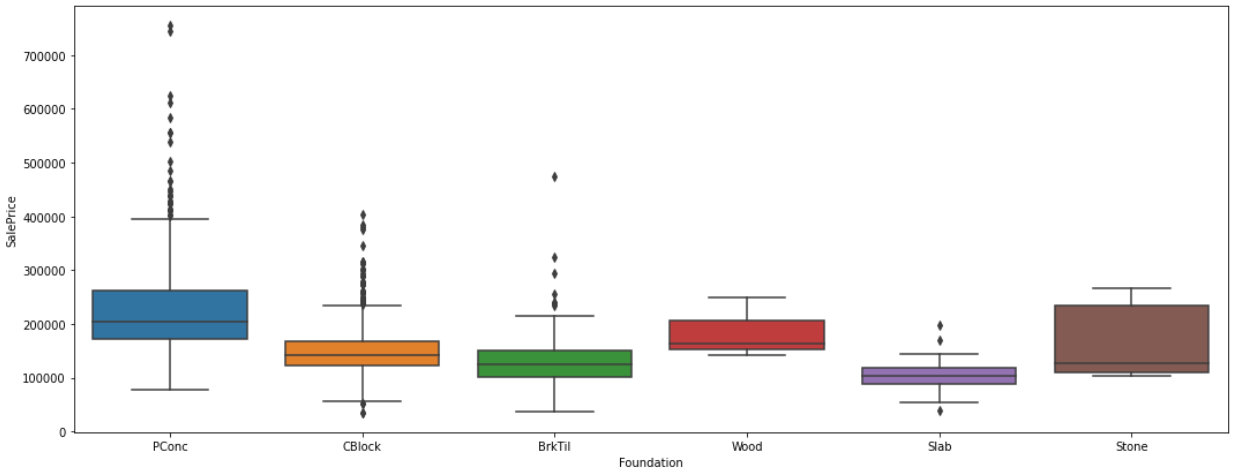
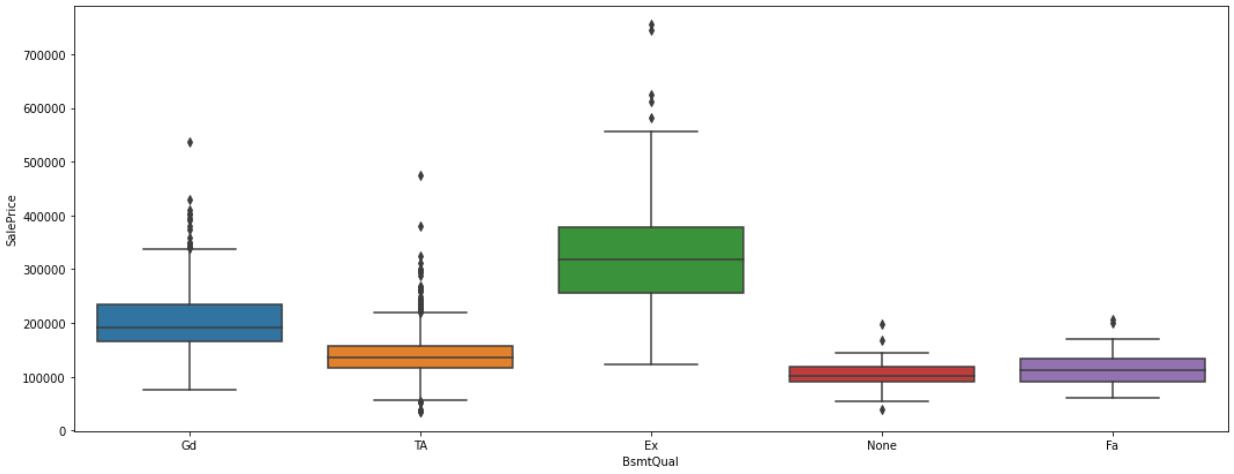
700000
BrkFace
None
Stone
BrkCmn
MasVnrType


SalePrice
0
100000
200000
300000
400000
500000
600000
700000
Gd
TA
Ex
Fa
ExterQual


SalePrice
400000
500000
600000
700000


300000
200000
100000
0
TA
Gd
Fa
Po
Ex
ExterCond


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
PConc
CBlock
BrkTil
Wood
Slab
Stone
Foundation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600000
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300000
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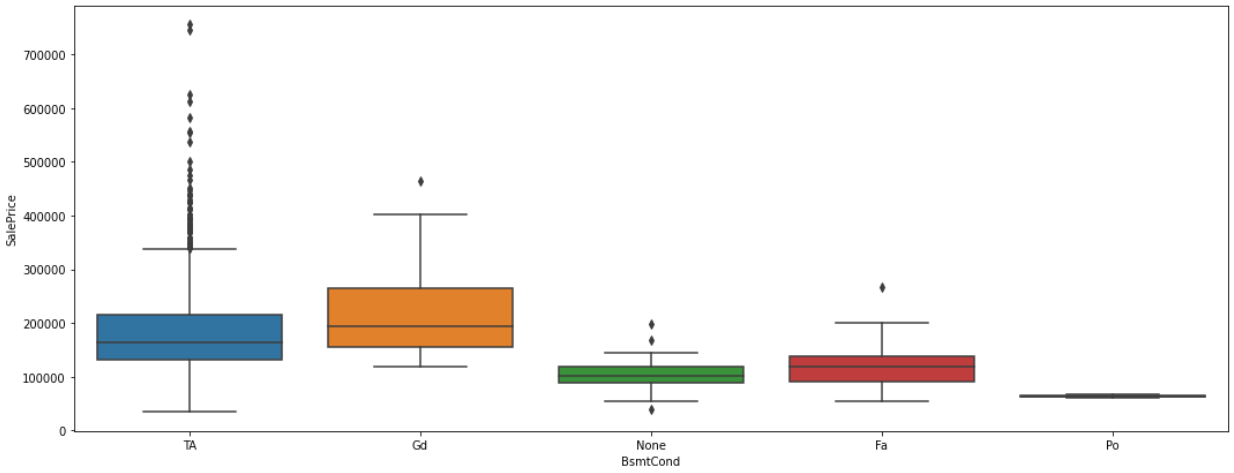
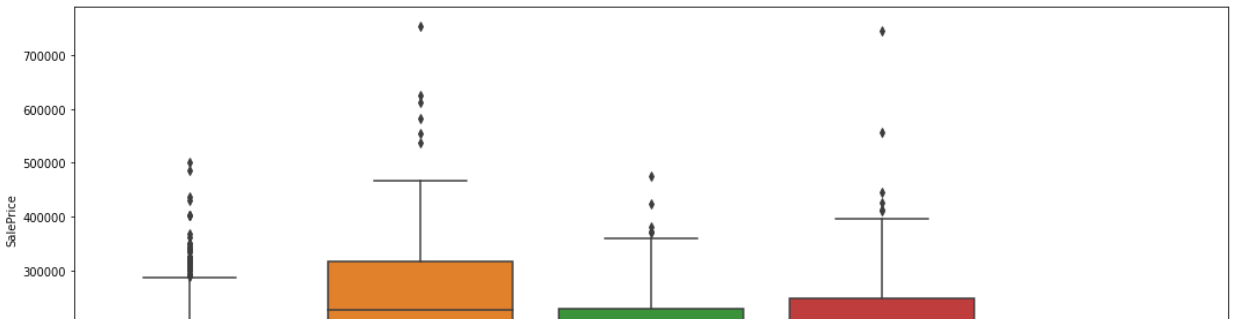
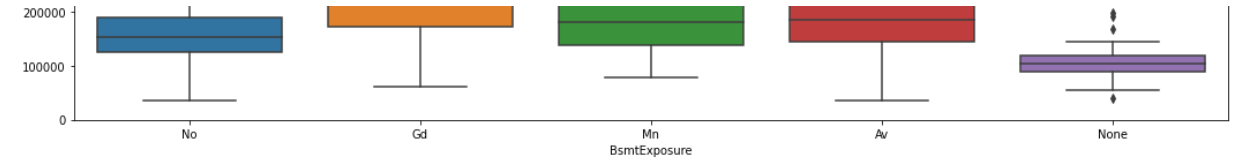
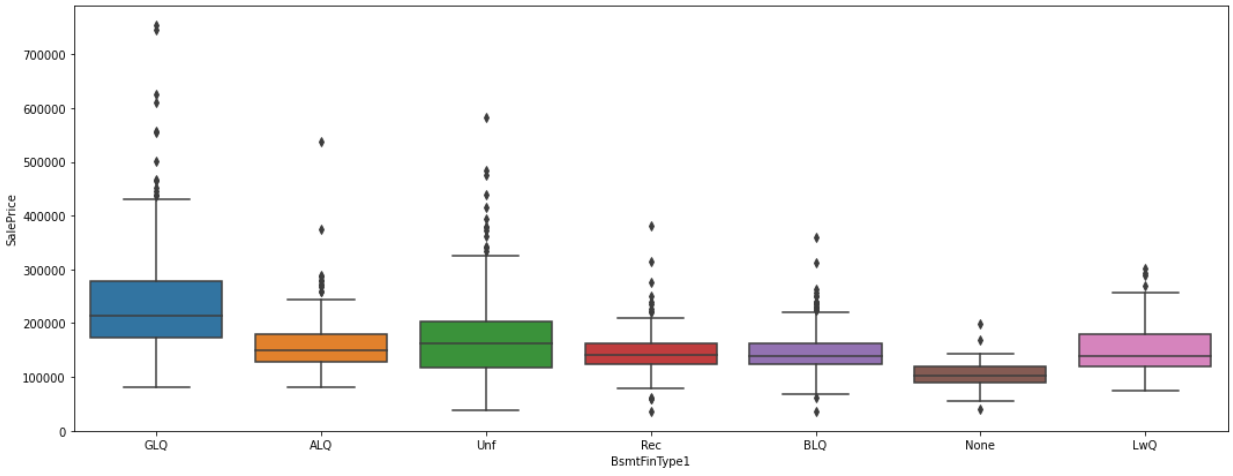
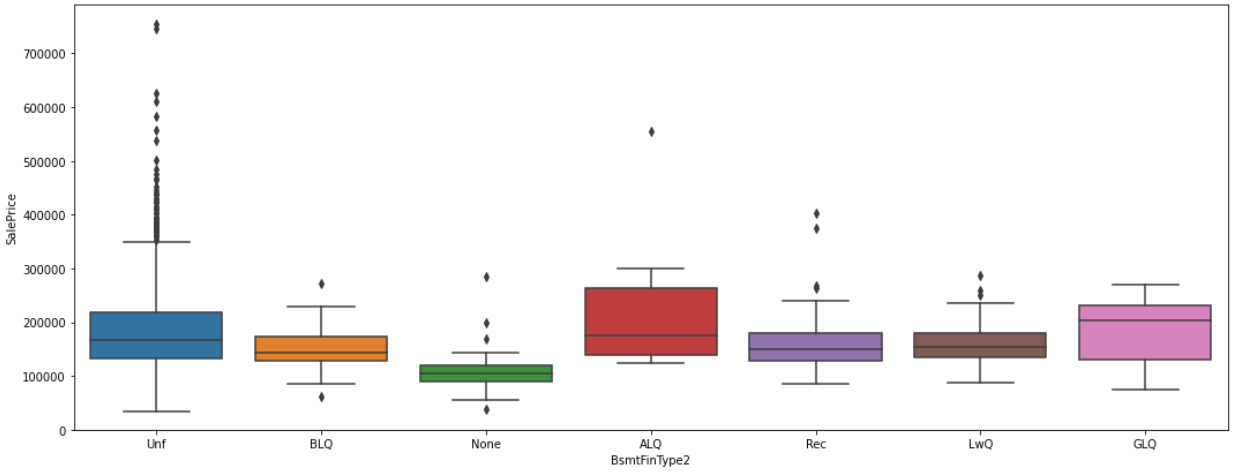
100000
0
Gd
TA
Ex
None
Fa
BsmtQual

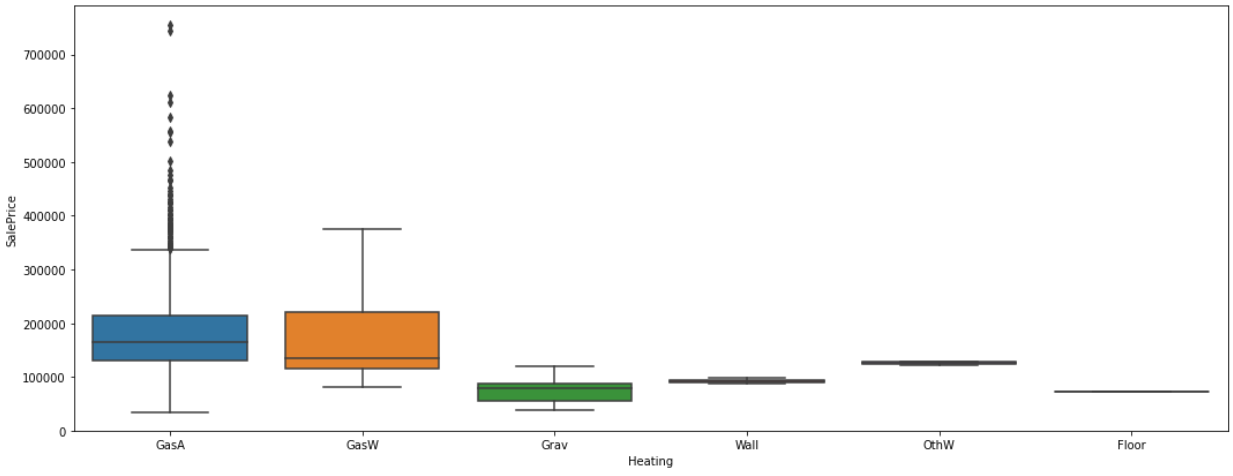

SalePrice
700000
600000
500000
400000
300000
200000
100000
0
TA
Gd
None
Fa
Po
BsmtCond

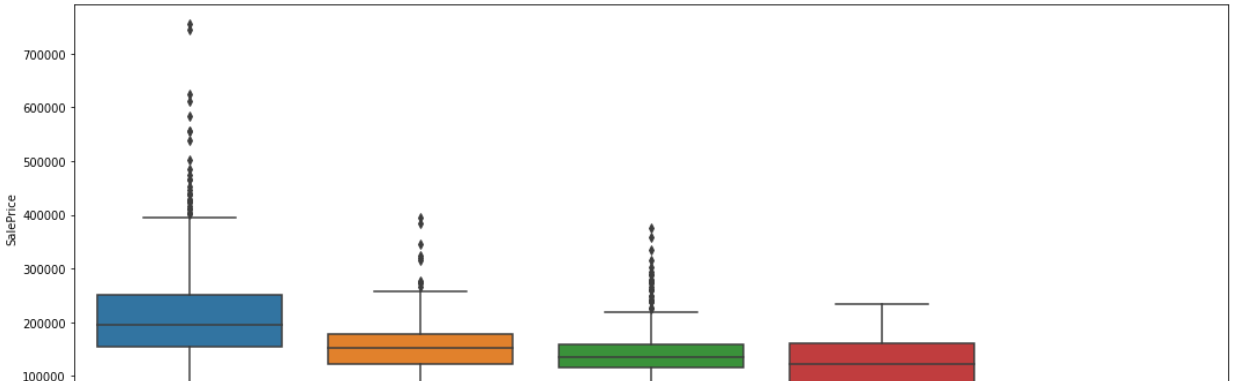

SalePrice
700000
600000
500000
400000
300000


200000
100000
0
No
Gd
Mn
Av
None
BsmtExposure


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
GLQ
ALQ
Unf
Rec
BLQ
None
LwQ
BsmtFinType1


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
Unf
BLQ
None
ALQ
Rec
LwQ
GLQ
BsmtFinType2


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
GasA
GasW
Grav
Wall
OthW
Floor
Heating


SalePrice
700000
600000
500000
400000
300000
200000
100000

Visual inspection of the boxplots above suggests that the variables for exterior quality, basement quality, fireplace quality, and kitchen quality may provide the most promise in our search for helpful categorical predictors that may be transformed into dichotomous variables. Conducting ANOVAs can shed more light on the relationship between these four variables and home sale prices.

In [25]:
```
ANOVA_variables = ['ExterQual', 'BsmtQual', 'FireplaceQu', 'KitchenQual']

from scipy.stats import f_oneway

# ExterQual ANOVA
ExterQual_Gd = housing_training_data['SalePrice'][housing_training_data['ExterQual'] =
ExterQual_TA = housing_training_data['SalePrice'][housing_training_data['ExterQual'] =
ExterQual_Ex = housing_training_data['SalePrice'][housing_training_data['ExterQual'] =
ExterQual_Fa = housing_training_data['SalePrice'][housing_training_data['ExterQual'] =

ANOVA_ExterQual = f_oneway(ExterQual_Gd, ExterQual_TA, ExterQual_Ex, ExterQual_Fa)

# BsmtQual ANOVA
BsmtQual_Gd = housing_training_data['SalePrice'][housing_training_data['BsmtQual'] ==
BsmtQual_TA = housing_training_data['SalePrice'][housing_training_data['BsmtQual'] ==
BsmtQual_Ex = housing_training_data['SalePrice'][housing_training_data['BsmtQual'] ==
BsmtQual_None = housing_training_data['SalePrice'][housing_training_data['BsmtQual'] =
BsmtQual_Fa = housing_training_data['SalePrice'][housing_training_data['BsmtQual'] ==

ANOVA_BsmtQual = f_oneway(BsmtQual_Gd, BsmtQual_TA, BsmtQual_Ex, BsmtQual_None, BsmtQu

# FireplaceQu ANOVA
FireplaceQu_None = housing_training_data['SalePrice'][housing_training_data['Fireplace
```

```
FireplaceQu_TA = housing_training_data['SalePrice'][housing_training_data['FireplaceQu
FireplaceQu_Gd = housing_training_data['SalePrice'][housing_training_data['FireplaceQu
FireplaceQu_Fa = housing_training_data['SalePrice'][housing_training_data['FireplaceQu
FireplaceQu_Ex = housing_training_data['SalePrice'][housing_training_data['FireplaceQu
FireplaceQu_Po = housing_training_data['SalePrice'][housing_training_data['FireplaceQu

ANOVA_FireplaceQu = f_oneway(FireplaceQu_None, FireplaceQu_TA, FireplaceQu_Gd, Firepla
                             FireplaceQu_Ex, FireplaceQu_Po)

# KitchenQual ANOVA
KitchenQual_Gd = housing_training_data['SalePrice'][housing_training_data['KitchenQual
KitchenQual_TA = housing_training_data['SalePrice'][housing_training_data['KitchenQual
KitchenQual_Ex = housing_training_data['SalePrice'][housing_training_data['KitchenQual
KitchenQual_Fa = housing_training_data['SalePrice'][housing_training_data['KitchenQual

ANOVA_KitchenQual = f_oneway(KitchenQual_Gd, KitchenQual_TA, KitchenQual_Ex, KitchenQu

# Compile Outputs

ANOVA_statistics = [ANOVA_ExterQual[0], ANOVA_BsmtQual[0], ANOVA_FireplaceQu[0], ANOVA

ANOVA_p_values = [ANOVA_ExterQual[1], ANOVA_BsmtQual[1], ANOVA_FireplaceQu[1], ANOVA_K

ANOVA_outputs = {'Categorical Variable': ANOVA_variables ,'Test Statistic': ANOVA_stat
                 'P-Values': ANOVA_p_values}
ANOVA_df = pd.DataFrame(ANOVA_outputs)
ANOVA_df.style.background_gradient(cmap = 'Greens')
```

Out[25]:

	Categorical Variable	Test Statistic	P-Values
0	ExterQual	443.334831	0.000000
1	BsmtQual	316.148635	0.000000
2	FireplaceQu	121.075121	0.000000
3	KitchenQual	407.806352	0.000000

Based on the analysis above, the variable for exterior quality seems to provide the most promise for the creation of a dichotomous variable for a regression model. We will use the Tukey-Cramer Multiple Comparison Test to confirm whether there are statistically significant differences in means when considering pairwise comparisons of categorical variable values.

In [26]:

```
from statsmodels.stats.multicomp import pairwise_tukeyhsd

tukey_cramer_result = pairwise_tukeyhsd(endog=housing_training_data['SalePrice'],
                                        groups=housing_training_data['ExterQual'],
                                        alpha=0.05)
print(tukey_cramer_result)
```

```
      Multiple Comparison of Means - Tukey HSD, FWER=0.05
=================================================================
group1 group2   meandiff   p-adj     lower        upper     reject
-----------------------------------------------------------------
    Ex     Fa -279375.7473  0.001 -323897.1579 -234854.3366   True
    Ex     Gd -135727.4513  0.001 -157297.3415 -114157.5611   True
    Ex     TA -223019.6481  0.001 -244104.9402  -201934.356   True
    Fa     Gd   143648.296  0.001  103567.1096  183729.4823   True
    Fa     TA   56356.0992 0.0016    16533.607   96178.5913   True
    Gd     TA  -87292.1968  0.001  -95594.9096   -78989.484   True
-----------------------------------------------------------------
```

Given that the ANOVA and Tukey-Cramer tests suggested that excellent home exterior quality could be a good predictor of sale price, We can create a dichotomous variable to reflect whether the exterior quality of a home is excellent.

In [27]:
```
housing_training_data['Excellent_Exterior_Quality'] = np.where(housing_training_data['

housing_training_data.head()
```

Out[27]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotCo
0	1	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	In
1	2	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	
2	3	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	In
3	4	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Co
4	5	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	

5 rows × 78 columns

Encode important categorical variables

In [28]:
```
from sklearn.preprocessing import LabelEncoder
important_categorical = ['ExterQual', 'BsmtQual', 'FireplaceQu', 'KitchenQual','Centra

# process columns, apply LabelEncoder to categorical features
for i in important_categorical:
    lbl = LabelEncoder()
    lbl.fit(list(housing_training_data[i].values))
    housing_training_data[i] = lbl.transform(list(housing_training_data[i].values))

# shape
print('Shape all_data: {}'.format(housing_training_data.shape))
```

Out[28]:
```
LabelEncoder()
```

Out[28]:
```
LabelEncoder()
```

Out[28]:
```
LabelEncoder()
```

Out[28]:
```
LabelEncoder()
```

Out[28]:
```
LabelEncoder()
```

```
Shape all_data: (1460, 78)
```

Feature Creation

New features may enable us to create more accurate prediction models for home sale prices. Accordingly, we will create a feature to reflect the number of years since a home has been remodeled.

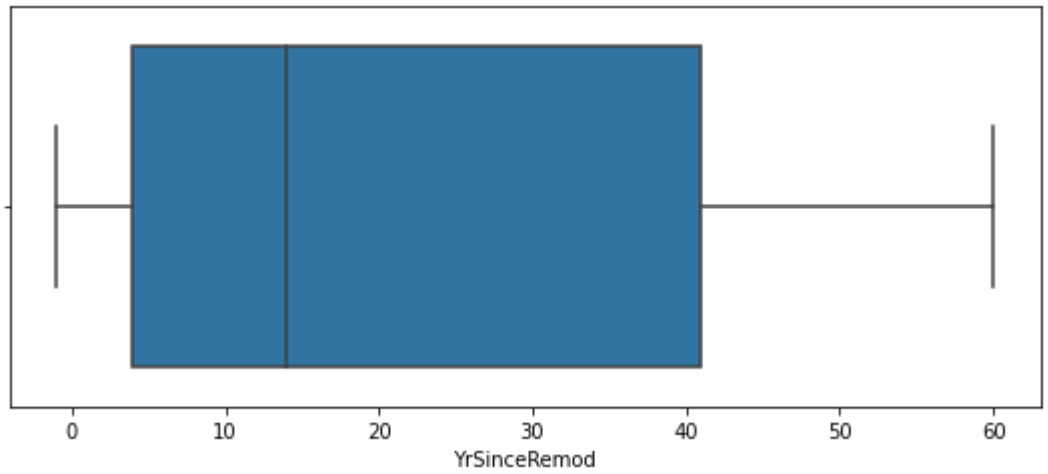
In [29]:
```
# create new variable, years since the house has been remodeled from selling date (use
housing_training_data['YrSinceRemod'] = housing_training_data['YrSold'] - housing_trai
housing_training_data['YrSinceRemod'].describe()
# create boxplot of YrSinceRemod
sns.boxplot(x = 'YrSinceRemod', data=housing_training_data)

#Pearson correlation coefficient and p value for sale price and GarageArea (Size of ga
res6 = stats.pearsonr(housing_training_data.YrSinceRemod, housing_training_data.SalePr
print("Pearson correlation coefficient and p value for sale price and Years since Hous
res6
```

Out[29]:
```
count    1460.000000
mean       22.950000
std        20.640653
min        -1.000000
25%         4.000000
50%        14.000000
75%        41.000000
max        60.000000
Name: YrSinceRemod, dtype: float64
```

Out[29]:
```
<AxesSubplot:xlabel='YrSinceRemod'>
```

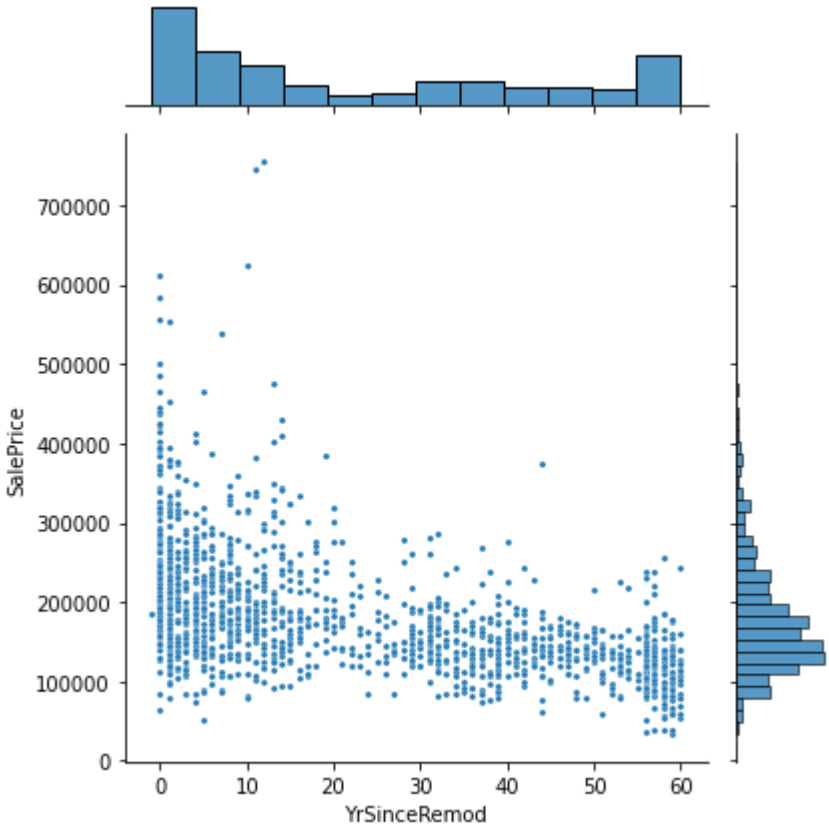
```
Pearson correlation coefficient and p value for sale price and Years since House was
remodeled/built:
```

Out[29]:
```
(-0.509078738015629, 4.3748554463775595e-97)
```



We can create a scatterplot to visualize the relationship between years since remodel and sale price.

In [30]:
```
sns.jointplot(x='YrSinceRemod', y='SalePrice', data = housing_training_data, joint_kws
```

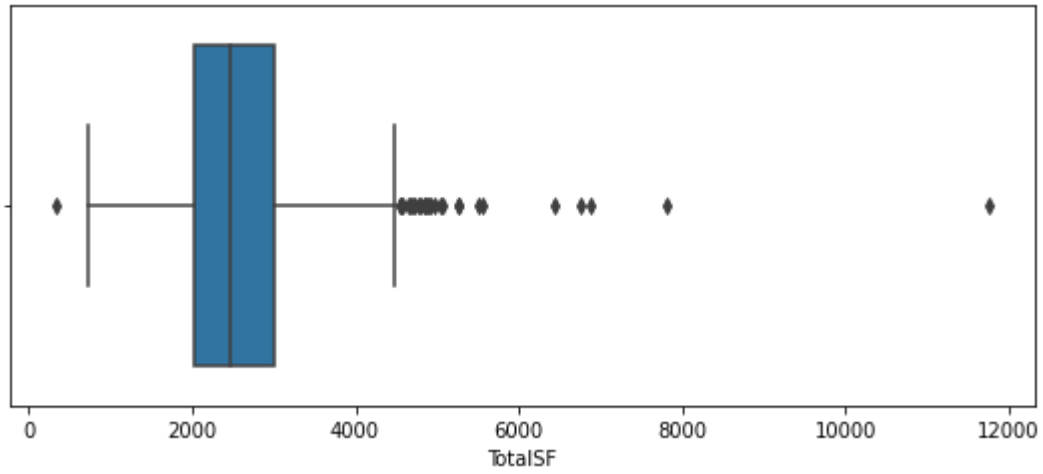


We will also create a feature to reflect the number of total square feet in a home.

In [31]:
```
# create new variable TotalSF
housing_training_data['TotalSF'] = housing_training_data['TotalBsmtSF'] + housing_trai
housing_training_data['TotalSF'].describe()
# create boxplot of TotalSF
sns.boxplot(x = 'TotalSF', data=housing_training_data)
```

Out[31]:
```
count     1460.000000
mean      2572.893151
std        823.598492
min        334.000000
25%       2014.000000
50%       2479.000000
75%       3008.500000
max      11752.000000
Name: TotalSF, dtype: float64
<AxesSubplot:xlabel='TotalSF'>
```

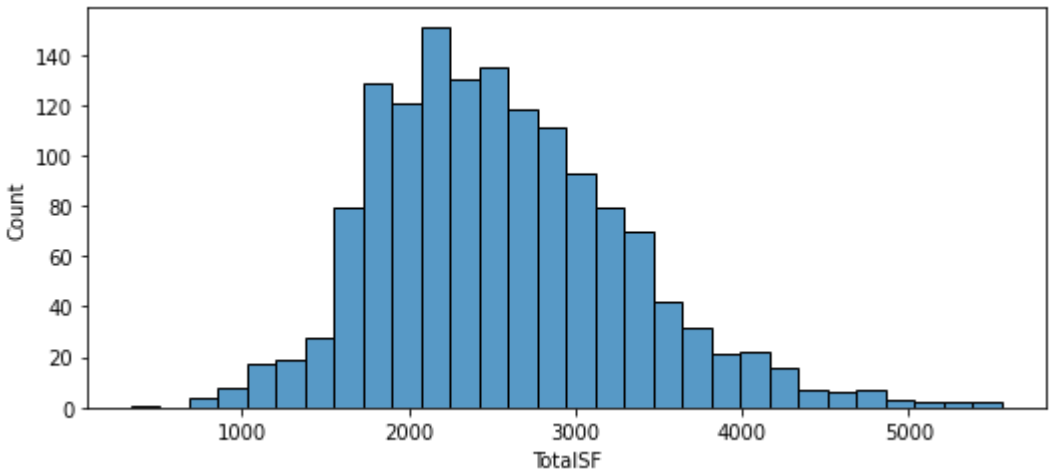
Out[31]:



In [32]:
```
# drop large outlier from the dataframe
housing_training_data.drop(housing_training_data[housing_training_data['TotalSF'] > 60
# visualize distribution without extreme outliers
sns.histplot(data=housing_training_data, x="TotalSF")

#Pearson correlation coefficient and p value for sale price and TotalSF):
res7 = stats.pearsonr(housing_training_data.TotalSF, housing_training_data.SalePrice)
print("Pearson correlation coefficient and p value for sale price and TotalSF (Total s
res7
```

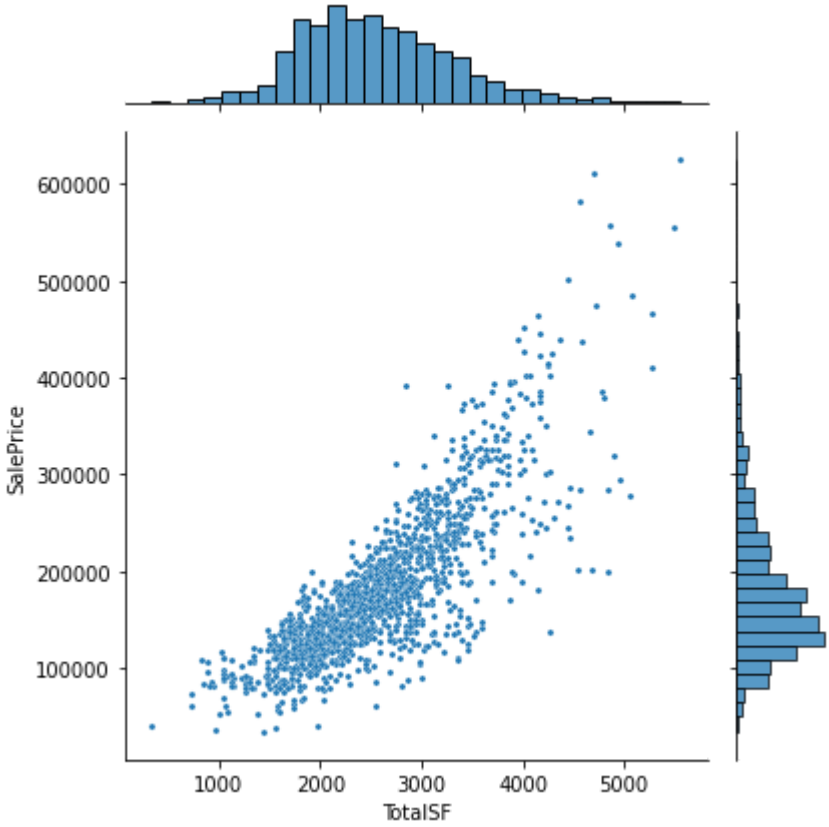
Out[32]:
```
<AxesSubplot:xlabel='TotalSF', ylabel='Count'>
```

Out[32]:
```
Pearson correlation coefficient and p value for sale price and TotalSF (Total square
feet - includes basement):
(0.81999629129728, 0.0)
```



We can create a scatterplot to examine the relationship between total square feet and sale price.

In [33]:
```
sns.jointplot(x='TotalSF', y='SalePrice', data = housing_training_data, joint_kws={"s'
```



Model Assumptions

1. Linearity
2. Homoscedasticity
3. Independence of Errors
4. Multivariate Normality
5. No or little Multicollinearity

Constructing Models to Predict Home Prices

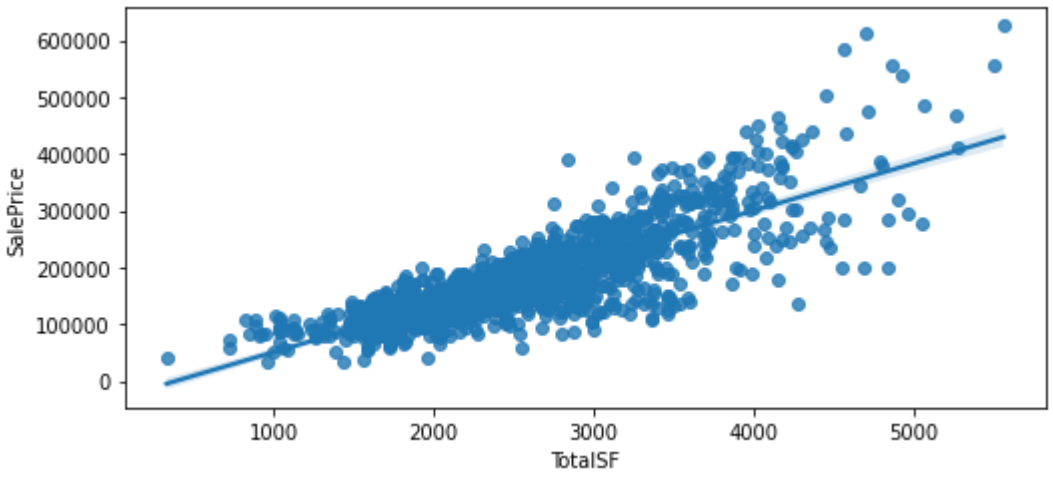
Below are simple and multiple regressions that examine the associations between variables of interest and sale price.

In [34]:
```
import numpy as np
import statsmodels.api as sm
# New feature is highly correlated, lets try a simple linear regression
x = housing_training_data['TotalSF']
y = housing_training_data['SalePrice']

#add constant to predictor variables
X = sm.add_constant(x)

#fit linear regression model
model = sm.OLS(y, X).fit()

#view model summary
print(model.summary())
```

```
# plot the regression model
sns.regplot(x=x, y=y)
```

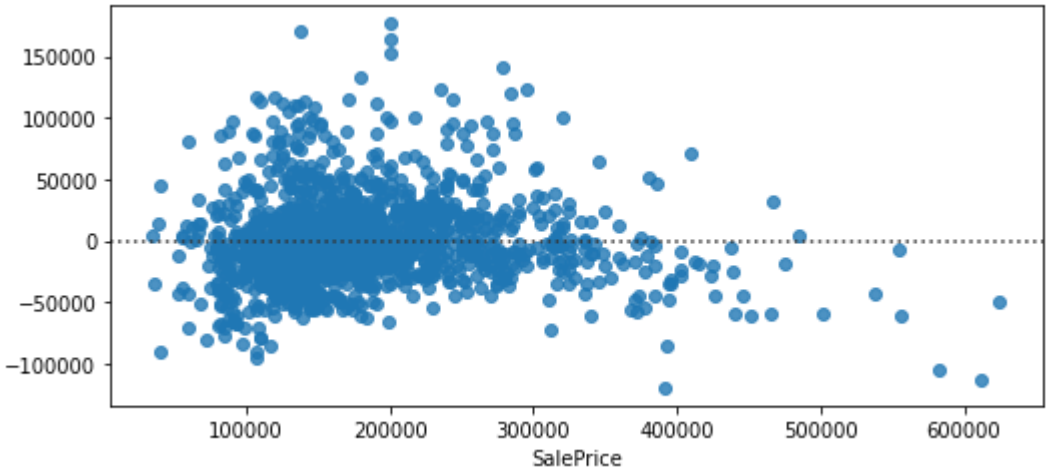
```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.672
Model:                            OLS   Adj. R-squared:                  0.672
Method:                 Least Squares   F-statistic:                     2982.
Date:                Sun, 09 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:59:50   Log-Likelihood:                -17613.
No. Observations:                1455   AIC:                         3.523e+04
Df Residuals:                    1453   BIC:                         3.524e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -3.239e+04   4054.647     -7.989      0.000   -4.03e+04   -2.44e+04
TotalSF       83.1361      1.522     54.610      0.000      80.150      86.122
==============================================================================
Omnibus:                      125.366   Durbin-Watson:                   1.967
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              649.680
Skew:                           0.197   Prob(JB):                    8.39e-142
Kurtosis:                       6.250   Cond. No.                     9.41e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 9.41e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Out[34]: <AxesSubplot:xlabel='TotalSF', ylabel='SalePrice'>



In [35]:
```
# plot the residuals
y_pred=model.predict(X)
sns.residplot(x=y, y=y_pred)
```

Out[35]: <AxesSubplot:xlabel='SalePrice'>



The residual plot shows evidence of Heteroscedasticity since the residuals are not evenly scattered. For higher Sales Prices, the residuals are negative indicating that the model is over estimating homes with higher Sales Prices. There is evidence that this model violates the linearity assumption, Homoscedasticity assumption and the Independence of Errors assumption.

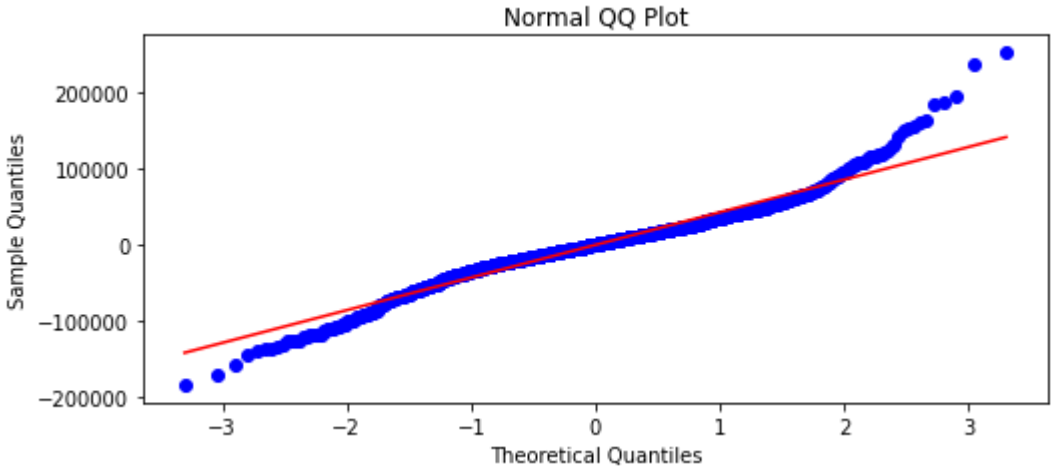
In [36]:
```
# qqplot
import matplotlib.pyplot as plt
stats.probplot(y-y_pred, dist="norm", plot=plt)
plt.title("Normal QQ Plot")
plt.xlabel("Theoretical Quantiles")
plt.ylabel("Sample Quantiles")
plt.show()
```

Out[36]:
```
((array([-3.30417817, -3.04690148, -2.90382339, ...,  2.90382339,
          3.04690148,  3.30417817]),
  array([-184865.74057368, -169571.36528068, -156517.81407152, ...,
          195404.36999739,  236556.60682101,  253807.82492125])),
 (42839.88750440423, 1.5086045390486717e-10, 0.9775030165443651))
```

Out[36]:
```
Text(0.5, 1.0, 'Normal QQ Plot')
```

Out[36]:
```
Text(0.5, 0, 'Theoretical Quantiles')
```

Out[36]:
```
Text(0, 0.5, 'Sample Quantiles')
```



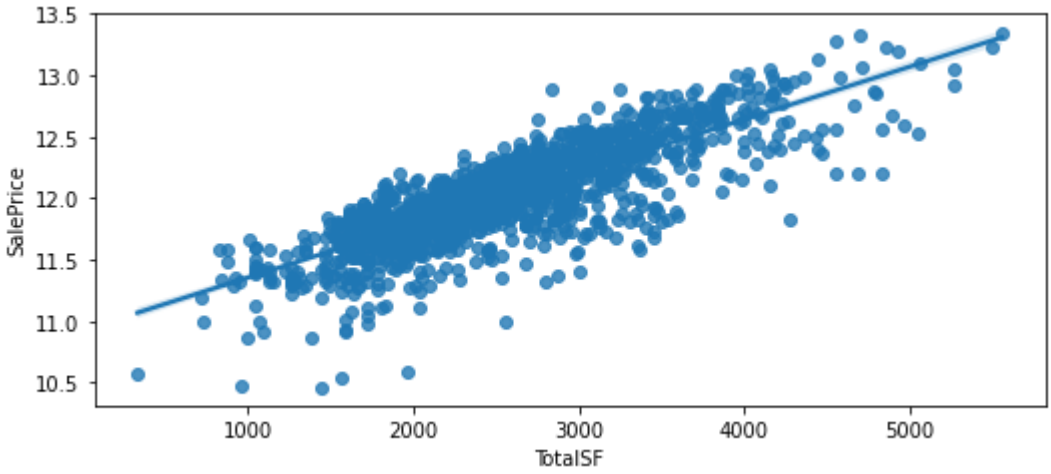
The tails of the distribution deviate from the qqline indicating that the errors are not Normally distributed.

Let's try transforming the independent variable, Sales Price since we saw earlier in this analysis that this helped to Normalize its distribution.

In [37]:
```
# log transform Sales Price variable
y_log = np.log(housing_training_data['SalePrice'])

#add constant to predictor variables
X = sm.add_constant(x)

#fit linear regression model
model = sm.OLS(y_log, X).fit()

#view model summary
print(model.summary())

# plot the regression model
sns.regplot(x=x, y=y_log)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.669
Model:                            OLS   Adj. R-squared:                  0.669
Method:                 Least Squares   F-statistic:                     2934.
Date:                Sun, 09 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:59:51   Log-Likelihood:                 89.766
No. Observations:                1455   AIC:                            -175.5
Df Residuals:                    1453   BIC:                            -165.0
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         10.9256      0.021    518.068      0.000      10.884      10.967
TotalSF        0.0004   7.92e-06     54.167      0.000       0.000       0.000
==============================================================================
Omnibus:                      274.748   Durbin-Watson:                   1.937
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              567.536
Skew:                          -1.090   Prob(JB):                    5.77e-124
Kurtosis:                       5.147   Cond. No.                     9.41e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 9.41e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Out[37]:
```
<AxesSubplot:xlabel='TotalSF', ylabel='SalePrice'>
```

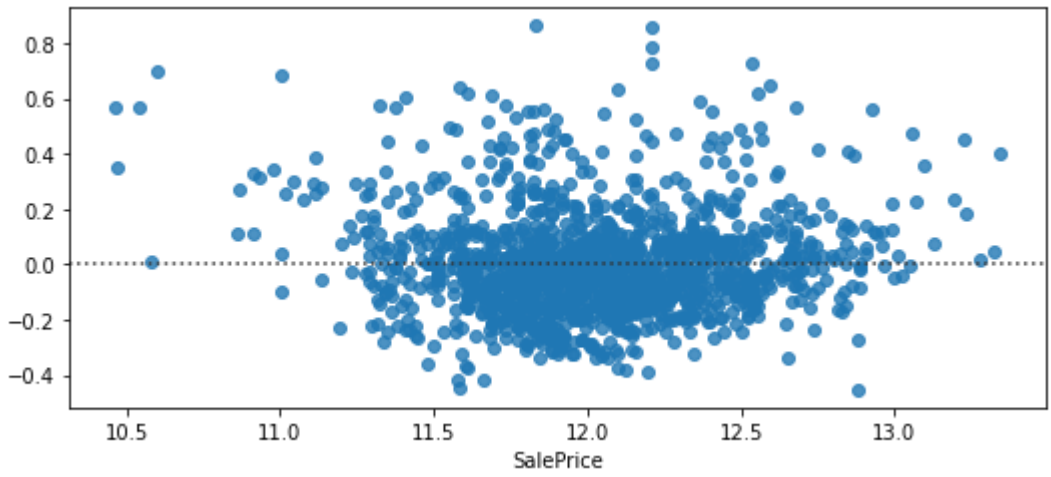


The relationship between log(Sale Price) and TotalSF appears to be linear. This meets the Linearity assumption.

An r-squared value of 0.669 means that the model explains 66.9 percent of the variance in the dependent variable. The omnibus test, however, indicates that residuals are not normally distributed and the high kurtosis value indicates that the distribution of the residuals are more peaked than a normal distribution. The condition number is 1.12e+04, which is quite high and suggests that there may be multicollinearity in the model.

In [38]:
```
# plot the residuals
y_pred=model.predict(X)
sns.residplot(x=y_log, y=y_pred)
```

Out[38]:
```
<AxesSubplot:xlabel='SalePrice'>
```



The residuals appear to be more randomly scattered across values of Sales Price. This appears to better meet the Homoscedasticity assumption and the Independence of Errors assumptions than the model with the untransformed Sales Price.

In [39]:
```
# qqplot
stats.probplot(y_log-y_pred, dist="norm", plot=plt)
plt.title("Normal QQ Plot")
plt.xlabel("Theoretical Quantiles")
```

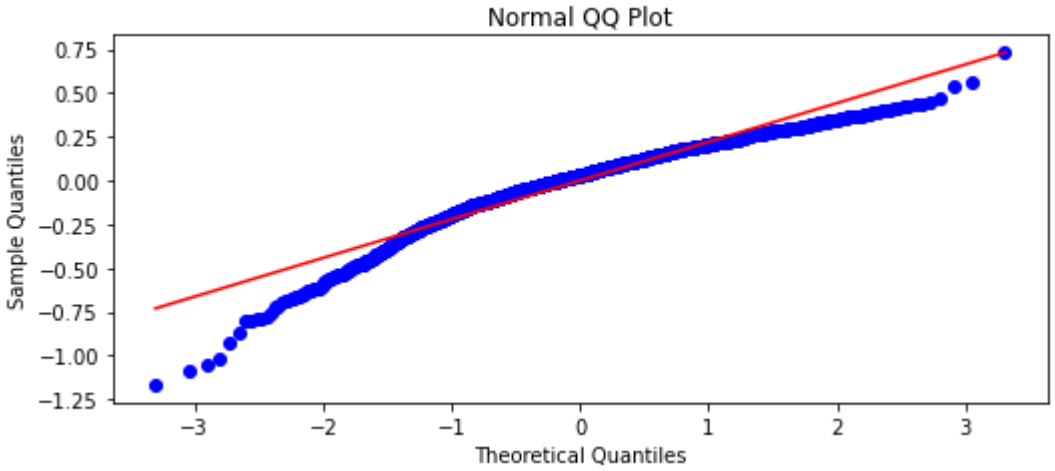
```
plt.ylabel("Sample Quantiles")
plt.show()
```

Out[39]:
```
((array([-3.30417817, -3.04690148, -2.90382339, ...,  2.90382339,
          3.04690148,  3.30417817]),
  array([-1.17224411, -1.08303201, -1.05546774, ...,  0.54315541,
          0.55983944,  0.73613196])),
 (0.22111127940895553, 6.253817917920981e-15, 0.9700026442288759))
```

Out[39]:
```
Text(0.5, 1.0, 'Normal QQ Plot')
```

Out[39]:
```
Text(0.5, 0, 'Theoretical Quantiles')
```

Out[39]:
```
Text(0, 0.5, 'Sample Quantiles')
```



The tails of the distribution still stray from the qqline, indicating the distribution of the errors is not Normal.

We can see the assumptions of a linear model are still not met by transforming Sales Price, lets try building a polynomial model.

Polynomial Regression

Third Order Polynomial Regression with Total SF as a predictor of Sales Price

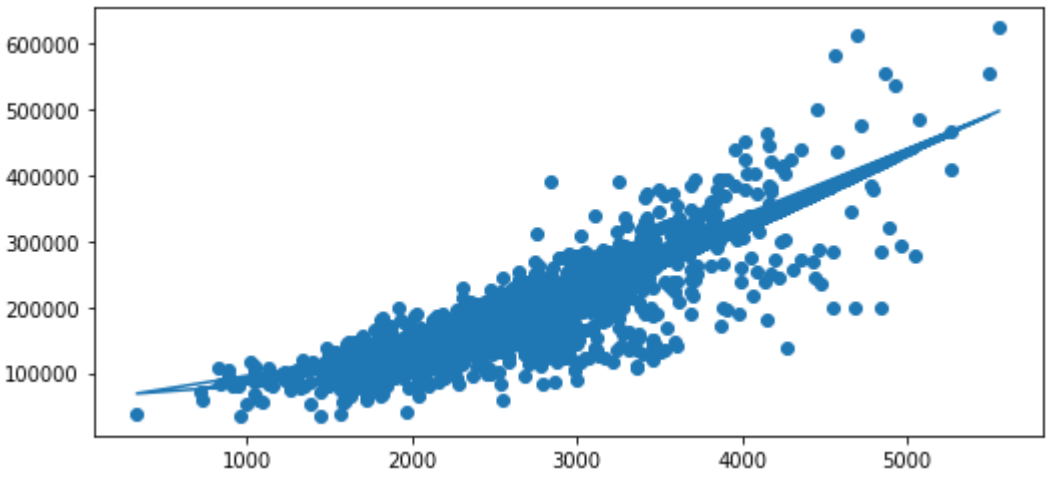
In [40]:
```
from sklearn.preprocessing import PolynomialFeatures
x = housing_training_data[['TotalSF']]
y = housing_training_data['SalePrice']

polynomial_features= PolynomialFeatures(degree=3)
xp = polynomial_features.fit_transform(x)
xp.shape

model = sm.OLS(y, xp).fit()

#view model summary
print(model.summary())
# predicted sales price
y_pred = model.predict(xp)

# plot model against data
plt.scatter(x,y)
plt.plot(x,y_pred)
```

Out[40]:
```
(1455, 4)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.689
Model:                            OLS   Adj. R-squared:                  0.688
Method:                 Least Squares   F-statistic:                     1070.
Date:                Sun, 09 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:59:52   Log-Likelihood:                -17576.
No. Observations:                1455   AIC:                         3.516e+04
Df Residuals:                    1451   BIC:                         3.518e+04
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       6.831e+04   2.17e+04      3.146      0.002    2.57e+04    1.11e+05
x1            -4.1538     24.479     -0.170      0.865     -52.171      43.864
x2             0.0203      0.009      2.311      0.021       0.003       0.037
x3         -1.007e-06   9.93e-07     -1.015      0.310   -2.95e-06     9.4e-07
==============================================================================
Omnibus:                      126.279   Durbin-Watson:                   1.954
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              633.593
Skew:                          -0.222   Prob(JB):                    2.61e-138
Kurtosis:                       6.202   Cond. No.                     5.70e+11
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 5.7e+11. This might indicate that there are
strong multicollinearity or other numerical problems.
```

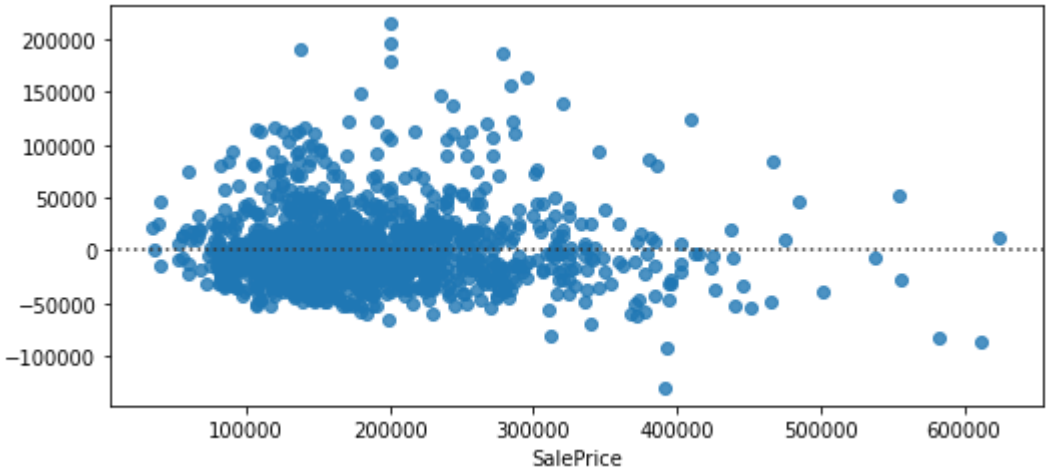
Out[40]:
```
<matplotlib.collections.PathCollection at 0x7fc197a41210>
```

Out[40]:
```
[<matplotlib.lines.Line2D at 0x7fc197bbd1d0>]
```



In [41]:
```
# plot the residuals
sns.residplot(x=y, y=y_pred)
```

Out[41]:
```
<AxesSubplot:xlabel='SalePrice'>
```



The residuals are fairly scattered across Sales Prices. Let's try adding more predictors to a linear regression model.

Multiple Linear Regression

Check the correlation between the two new variables. If they are highly correlated we won't construct a mutliple linear regression model with the both of those variables as predictors.

In [42]:
```
df_corr_mult_lreg = housing_training_data[['TotalSF','YrSinceRemod']]
df_corr_mult_lreg.corr()
```

Out[42]:

	TotalSF	YrSinceRemod
TotalSF	1.000000	-0.352279
YrSinceRemod	-0.352279	1.000000

TotalSF and YrSinceRemod are not highly correlated so we will construct a multiple linear regression model using the two variables as predictors of the log transformed Sales Price.

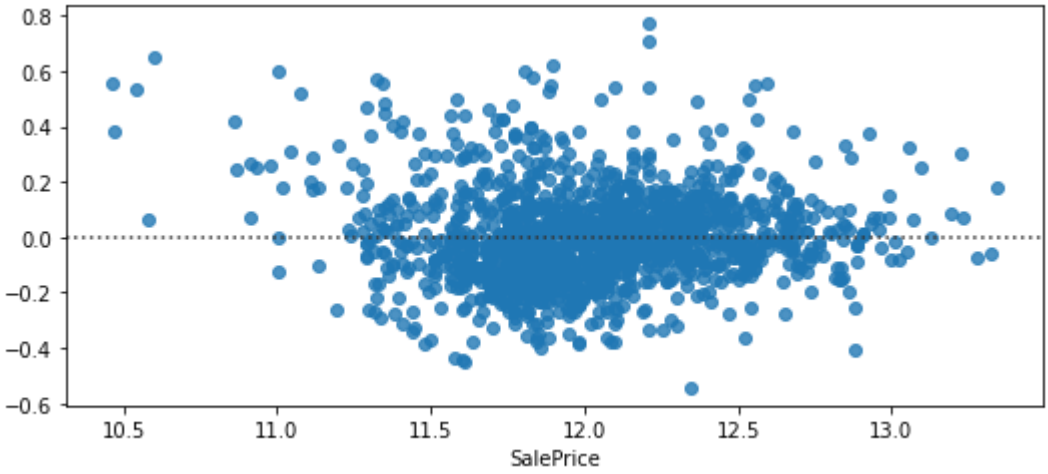
In [43]:
```
x = housing_training_data[['TotalSF','YrSinceRemod']]
y_log = np.log(housing_training_data['SalePrice'])

#add constant to predictor variables
X = sm.add_constant(x)

#fit linear regression model
model = sm.OLS(y_log, X).fit()

#view model summary
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.761
Model:                            OLS   Adj. R-squared:                  0.760
Method:                 Least Squares   F-statistic:                     2308.
Date:                Sun, 09 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:59:53   Log-Likelihood:                326.20
No. Observations:                1455   AIC:                            -646.4
Df Residuals:                    1452   BIC:                            -630.6
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          11.2212      0.022    513.127      0.000      11.178      11.264
TotalSF         0.0004   7.19e-06     51.300      0.000       0.000       0.000
YrSinceRemod   -0.0062      0.000    -23.614      0.000      -0.007      -0.006
==============================================================================
Omnibus:                      279.765   Durbin-Watson:                   1.927
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              639.242
Skew:                          -1.065   Prob(JB):                    1.55e-139
Kurtosis:                       5.450   Cond. No.                     1.15e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 1.15e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

An r-squared value of 0.765 means that the model explains 76.5 percent of the variance in the dependent variable. The adjusted R-squared value is about the same as the r-squared value, indicating that we aren't overfitting the model by addding multiple variables. The omnibus test, however, indicates that residuals are not normally distributed and the high kurtosis value indicates that the distribution of the residuals are more peaked than a normal distribution. The condition number is 1.12e+04, which is quite high and suggests that there may be multicollinearity in the model.

In [44]:
```
# plot the residuals
y_pred=model.predict(X)
sns.residplot(x=y_log, y=y_pred)
```

Out[44]:
```
<AxesSubplot:xlabel='SalePrice'>
```



The residuals appear to be more randomly scattered across values of Sales Price. This appears to better meet the Homoscedasticity assumption and the Independence of Errors assumptions than the model with the untransformed Sales Price. But as we mentioned above, the high omnibus value indicates the distribution of the residuals is not normally distributed.

Piecewise Regression

We can try fitting a linear regression model of sale price using a piecewise regression model.

In [45]:
```
import pwlf

x = np.array(housing_training_data['TotalSF'])
y = np.array(np.log(housing_training_data['SalePrice']))

# initialize piecewise linear fit with your x and y data
my_pwlf = pwlf.PiecewiseLinFit(x, y)

# fit the data for four line segments
res = my_pwlf.fit(3)

# predict for the determined points
xHat = np.array(housing_training_data['TotalSF'])
yHat = my_pwlf.predict(xHat)

piecewise_regression_output = housing_training_data[["TotalSF"]]
piecewise_regression_output['Log Sale Price'] = y.tolist()
piecewise_regression_output['Predicted Log Sale Price'] = yHat.tolist()
piecewise_regression_output['residual'] = piecewise_regression_output['Log Sale Price'
piecewise_regression_output['squared residuals'] = piecewise_regression_output['residu

RMSE = (piecewise_regression_output['squared residuals'].sum() / len(piecewise_regress
print(f"The Root Mean Squared Error of this piecewise regression model is {RMSE}.")

correlation = piecewise_regression_output['Log Sale Price'].corr(piecewise_regression_
print(f"The correlation of this piecewise regreession model is {correlation}.")
```

```
The Root Mean Squared Error of this piecewise regression model is 0.2253870306616782.
The correlation of this piecewise regreession model is 0.8215249613160736.
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/ipykern
el_launcher.py:17: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/ipykern
el_launcher.py:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/ipykern
el_launcher.py:19: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/ipykern
el_launcher.py:20: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
```

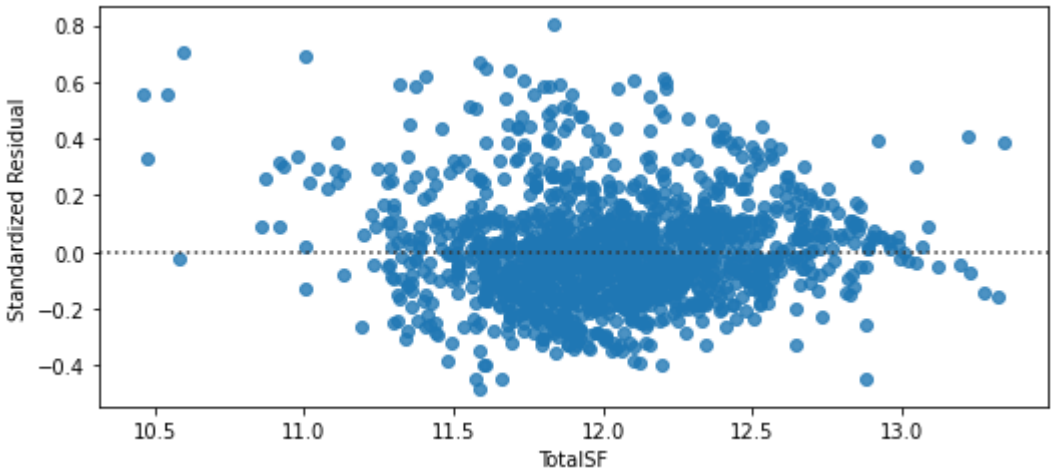
We can visualize the residuals plot to examine whether the regression model may violate any of the regression assumptions.

In [46]:
```
sns.residplot(x=y, y=yHat)
plt.ylabel('Standardized Residual')
plt.xlabel('TotalSF')
```

Out[46]:
```
<AxesSubplot:>
```

Out[46]:
```
Text(0, 0.5, 'Standardized Residual')
```

Out[46]:
```
Text(0.5, 0, 'TotalSF')
```



We can visualize a Q-Q plot to determine whether this regression model violates the linear regression assumption that residuals are noramlly distributed.

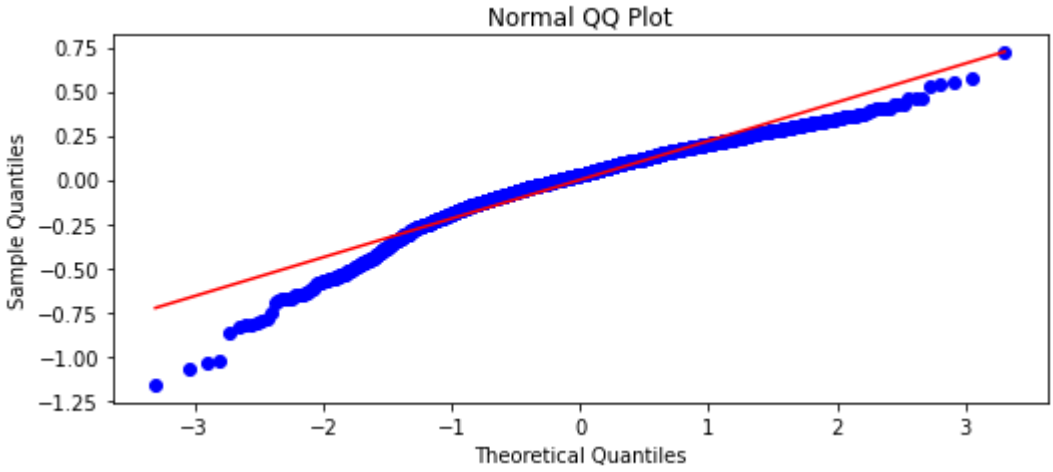
In [47]:
```
# qqplot
stats.probplot(y - yHat, dist="norm", plot=plt)
plt.title("Normal QQ Plot")
plt.xlabel("Theoretical Quantiles")
plt.ylabel("Sample Quantiles")
plt.show()
```

Out[47]:
```
((array([-3.30417817, -3.04690148, -2.90382339, ...,  2.90382339,
          3.04690148,  3.30417817]),
  array([-1.16507054, -1.06389866, -1.03924475, ...,  0.54759817,
          0.57974149,  0.72347869])),
 (0.21935094918618248, 7.904013153481133e-15, 0.9712739756549295))
```

Out[47]:
```
Text(0.5, 1.0, 'Normal QQ Plot')
```

Out[47]:
```
Text(0.5, 0, 'Theoretical Quantiles')
```

Out[47]:
```
Text(0, 0.5, 'Sample Quantiles')
```



We will try and add more predictors to our model. First, lets observe any multicollinearity.

Inspection of multicollinearity: VIF, correlations

The correlation between garage cars and total square feet is moderately high. We will take that into consideration when analyzing the output of the model.

In [48]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

# the independent variables set
x = housing_training_data[['TotalSF','YrSinceRemod','GarageCars','ExterQual','CentralA

# VIF dataframe
vif_data = pd.DataFrame()
vif_data["feature"] = x.columns

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(x.values, i)
                          for i in range(len(x.columns))]
```

```
print(vif_data)
x.corr()
```

```
        feature         VIF
0       TotalSF   14.662165
1  YrSinceRemod    3.243161
2    GarageCars   10.247820
3     ExterQual   12.812931
4    CentralAir   14.699583
```

Out[48]:

	TotalSF	YrSinceRemod	GarageCars	ExterQual	CentralAir
TotalSF	1.000000	-0.352279	0.556693	-0.483450	0.180174
YrSinceRemod	-0.352279	1.000000	-0.422033	0.480107	-0.299245
GarageCars	0.556693	-0.422033	1.000000	-0.447523	0.233414
ExterQual	-0.483450	0.480107	-0.447523	1.000000	-0.085933
CentralAir	0.180174	-0.299245	0.233414	-0.085933	1.000000

These VIF values suggests that our model contains some multicollinearity across all features. Some resources stated that greater than 10 suggests multicollinearity, while others used a cut-off of 5.0 or 1.0. This may not be an issue for a predictive model, but could have implications for an inferential model.

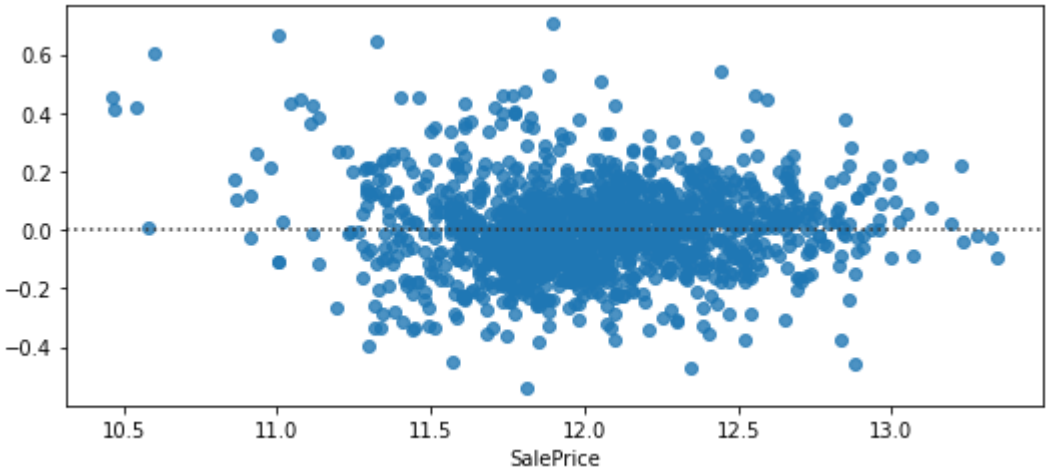
In [49]:
```
x = housing_training_data[['TotalSF','YrSinceRemod','GarageCars','Excellent_Exterior_(
y_log = np.log(housing_training_data['SalePrice'])


polynomial_features= PolynomialFeatures(degree=2)
xp = polynomial_features.fit_transform(x)
xp.shape

#add constant to predictor variables
x = sm.add_constant(xp)

#fit polynomial regression model
model = sm.OLS(y_log, x).fit()

#view model summary
print(model.summary())
```

Out[49]:
```
(1455, 21)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.830
Model:                            OLS   Adj. R-squared:                  0.828
Method:                 Least Squares   F-statistic:                     412.1
Date:                Sun, 09 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:59:54   Log-Likelihood:                574.02
No. Observations:                1455   AIC:                            -1112.
Df Residuals:                    1437   BIC:                            -1017.
Df Model:                          17
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         10.6513      0.090    118.095      0.000      10.474      10.828
x1             0.0005   4.39e-05     10.571      0.000       0.000       0.001
x2             0.0015      0.002      0.866      0.386      -0.002       0.005
x3             0.2298      0.038      6.127      0.000       0.156       0.303
x4             0.0807      0.059      1.366      0.172      -0.035       0.197
x5             0.0742      0.038      1.949      0.052      -0.000       0.149
x6         -2.638e-08      7e-09     -3.766      0.000   -4.01e-08   -1.26e-08
x7         -1.842e-06   4.28e-07     -4.307      0.000   -2.68e-06      -1e-06
x8          1.834e-05   1.06e-05      1.730      0.084   -2.46e-06    3.91e-05
x9         -9.317e-06   4.14e-05     -0.225      0.822   -9.05e-05    7.18e-05
x10        -1.168e-05   2.66e-05     -0.439      0.661   -6.39e-05    4.05e-05
x11        -6.093e-06   1.64e-05     -0.371      0.711   -3.83e-05    2.61e-05
x12           -0.0018      0.000     -4.510      0.000      -0.003      -0.001
x13           -0.0053      0.008     -0.644      0.520      -0.022       0.011
x14            0.0018      0.001      1.827      0.068      -0.000       0.004
x15           -0.0377      0.007     -5.325      0.000      -0.052      -0.024
x16           -0.0211      0.064     -0.331      0.741      -0.146       0.104
x17           -0.0026      0.023     -0.112      0.911      -0.048       0.043
x18            0.0807      0.059      1.366      0.172      -0.035       0.197
x19            0.0807      0.059      1.366      0.172      -0.035       0.197
x20            0.0742      0.038      1.949      0.052      -0.000       0.149
==============================================================================
Omnibus:                      248.722   Durbin-Watson:                   2.001
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              691.756
Skew:                          -0.888   Prob(JB):                    6.13e-151
Kurtosis:                       5.873   Cond. No.                     7.81e+23
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The smallest eigenvalue is 1.63e-31. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

In [50]:
```
# plot the residuals
y_pred=model.predict(x)
sns.residplot(x=y_log, y=y_pred)
```

Out[50]:
```
<AxesSubplot:xlabel='SalePrice'>
```



The adjusted r-squared value is high for the 2nd order polynomial model, but the residuals are not randomly scattered. The plot indicates that the model is underestimating the value of homes with actual low sales prices and overestimating the value of homes with actual high sales prices.

In [51]:
```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression
from numpy import mean
from numpy import absolute
from numpy import sqrt
from sklearn.linear_model import Ridge
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.metrics import mean_squared_error
```

Let's use PCA to find some more important predictors to add to our models

Regress on principal components

In [52]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import scale
from sklearn.linear_model import LinearRegression
import os
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score

scaler = StandardScaler()

pca = PCA(n_components=8)


## independent variables ###

x_raw = housing_training_data.select_dtypes(exclude=['object']).drop(columns = ['SaleP
x_scale = scaler.fit_transform(x_raw)

x_pca_raw = pca.fit_transform(x_raw)
x_pca_scale = pca.fit_transform(x_scale) # PCA is affected by scale. We use the scaled
```

```
## importance scores of the principal components ##
# show loadings for features
loadings = pd.DataFrame(pca.components_.T, columns=['PC1','PC2','PC3','PC4','PC5','PC6
loadings


## dependent variable ##

y_trans = scaler.fit_transform(housing_training_data[['SalePrice']])

y_raw = np.array(housing_training_data[['SalePrice']]).reshape(-1,1)
y_scale = np.array(y_trans).reshape(-1,1)

## train linear model ##

regr = LinearRegression()

regr.fit(x_pca_scale, y_scale)

y_pred = regr.predict(x_pca_scale)


plt.subplot(1, 2, 1)

plt.scatter(y_scale, y_pred)
plt.xlabel('Log Sale Price (Standard Scaled)')
plt.ylabel('Predicted Log Sale Price')
plt.title('Log Sale Price vs Predicted Log Sale Price')

# Residuals
plt.subplot(1, 2, 2)
sns.residplot(x=y_scale, y=y_pred)
plt.xlabel('Log Sale Price')
plt.ylabel('Residual')
plt.title('Residual Plot')
## calculate RMSE ##

# Mean Squared Error
MSE = np.square(np.subtract(y_scale,y_pred)).mean()
print("MSE:",MSE)

r2 = r2_score(y_scale, y_pred)
print("R_sq:",r2)
```

Out[52]:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Id	-0.005909	0.014958	-0.011284	-0.002488	-0.017369	-0.046538	0.023226
MSSubClass	-0.012204	0.080370	-0.278781	-0.188115	0.352751	-0.064781	0.127411
LotFrontage	0.110586	0.087468	0.234430	0.071633	-0.176092	-0.024338	-0.022364
LotArea	0.068160	0.064595	0.246330	-0.094678	-0.100251	0.002935	0.066998
OverallQual	0.270606	-0.015069	-0.061261	0.021368	0.002469	0.114572	-0.060625
OverallCond	-0.066550	0.038027	0.025912	-0.089610	-0.225601	0.484802	0.247949
YearBuilt	0.220423	-0.226182	-0.176541	-0.059718	-0.084121	-0.227579	-0.054445
YearRemodAdd	0.208273	-0.151206	-0.229276	-0.019507	-0.147906	0.168903	0.337900
MasVnrArea	0.159272	0.016322	0.044181	-0.040351	0.125622	-0.028650	-0.270203
ExterQual	-0.228220	0.087863	0.081144	-0.147353	-0.243604	-0.215199	0.089686
BsmtQual	-0.219829	0.130985	0.138871	-0.023364	-0.134766	0.031318	0.029809
BsmtFinSF1	0.103026	-0.192765	0.276793	-0.351708	0.199497	-0.011733	0.055276
BsmtFinSF2	-0.012580	-0.013898	0.171931	-0.123403	-0.100072	0.053389	0.081221
BsmtUnfSF	0.108751	0.103963	-0.059932	0.525342	-0.169299	-0.069499	-0.046130
TotalBsmtSF	0.220842	-0.096189	0.294678	0.147989	-0.012329	-0.066241	0.040526
CentralAir	0.099816	-0.126076	-0.014168	-0.157113	-0.393092	0.046199	-0.034015
1stFlrSF	0.211012	-0.019393	0.342101	0.149386	0.005848	-0.092907	0.127883
2ndFlrSF	0.094109	0.371667	-0.250042	-0.223730	0.026304	0.098780	-0.080109
LowQualFinSF	-0.011885	0.126397	0.034499	0.046686	0.018942	0.142844	0.142806
GrLivArea	0.236690	0.322217	0.037937	-0.080205	0.029119	0.031599	0.038617
BsmtFullBath	0.061454	-0.198900	0.226250	-0.349448	0.221375	-0.031221	0.163678
BsmtHalfBath	-0.015208	0.006571	0.043610	-0.064613	-0.161716	0.111057	0.003411
FullBath	0.220107	0.143708	-0.123609	0.033677	0.005401	-0.161334	0.181291
HalfBath	0.098551	0.170704	-0.215595	-0.284626	-0.035484	0.063907	-0.283824
BedroomAbvGr	0.067452	0.386726	0.027506	-0.034120	-0.128606	-0.092693	0.098861
KitchenAbvGr	-0.027788	0.185163	0.011982	0.061468	0.306613	-0.297263	0.355353
KitchenQual	-0.196267	0.067382	0.048271	-0.119037	-0.197604	-0.277948	-0.014291
TotRmsAbvGrd	0.184433	0.366822	0.023261	-0.020446	0.030855	-0.017921	0.109010
Fireplaces	0.143169	0.089855	0.178284	-0.149139	-0.052180	0.110715	-0.192757
FireplaceQu	-0.018131	0.062374	-0.037372	-0.229227	-0.168201	-0.234631	-0.072221
GarageYrBlt	0.219956	-0.201918	-0.204100	-0.029754	-0.092822	-0.203107	-0.003064
GarageCars	0.244464	-0.038202	-0.004957	-0.021550	-0.058291	-0.160894	-0.097534
GarageArea	0.234732	-0.051260	0.048832	-0.014471	-0.053761	-0.138547	-0.095358

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
WoodDeckSF	0.110453	-0.034947	0.052802	-0.163807	-0.055213	0.014857	0.137923
OpenPorchSF	0.119585	0.054719	-0.031005	-0.027478	-0.009899	0.081208	-0.115460
EnclosedPorch	-0.070058	0.133110	0.087786	0.073877	0.096926	0.149705	0.069250
3SsnPorch	0.016533	-0.023000	0.020275	0.035695	-0.076007	0.033130	0.021411
ScreenPorch	0.024889	0.049290	0.109448	-0.077957	-0.014445	0.163102	-0.297296
PoolArea	0.008125	0.044174	0.053416	-0.056422	-0.020419	0.077381	0.085210
MiscVal	-0.009671	0.026936	0.013262	-0.028261	-0.032558	0.044838	0.089291
MoSold	0.021600	0.029270	0.003346	0.032774	-0.065029	0.003351	-0.069938
YrSold	-0.006417	-0.031656	0.015663	-0.022014	0.097061	0.050843	0.132271
Excellent_Exterior_Quality	0.142836	-0.052664	0.037904	0.142745	0.309003	0.309049	-0.176091
YrSinceRemod	-0.208747	0.149212	0.230352	0.018095	0.154199	-0.165680	-0.329483
TotalSF	0.274999	0.159407	0.184528	0.027516	0.012436	-0.015140	0.047302

Out[52]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Out[52]:
```
<AxesSubplot:>
```

Out[52]:
```
<matplotlib.collections.PathCollection at 0x7fc18ac7d4d0>
```

Out[52]:
```
Text(0.5, 0, 'Log Sale Price (Standard Scaled)')
```

Out[52]:
```
Text(0, 0.5, 'Predicted Log Sale Price')
```

Out[52]:
```
Text(0.5, 1.0, 'Log Sale Price vs Predicted Log Sale Price')
```

Out[52]:
```
<AxesSubplot:>
```

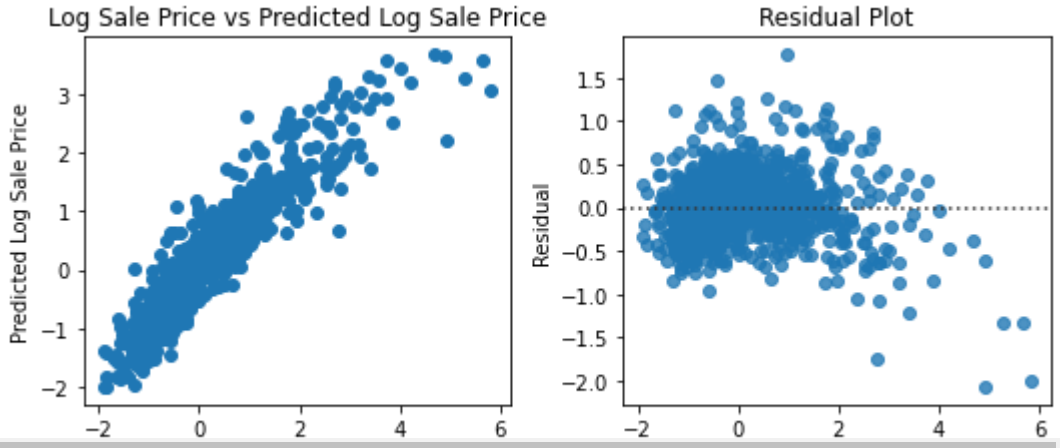
Out[52]:
```
<AxesSubplot:>
```

Out[52]:
```
Text(0.5, 0, 'Log Sale Price')
```

Out[52]:
```
Text(0, 0.5, 'Residual')
```

Out[52]:
```
Text(0.5, 1.0, 'Residual Plot')
```

```
MSE: 0.12963226774939893
R_sq: 0.870367732250601
```



In [79]:
```
x_raw.columns
```

Out[79]:
```
Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
       'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'ExterQual',
       'BsmtQual', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF',
       'CentralAir', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea',
       'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath', 'BedroomAbvGr',
       'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd', 'Fireplaces',
       'FireplaceQu', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF',
       'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea',
       'MiscVal', 'MoSold', 'YrSold', 'Excellent_Exterior_Quality',
       'YrSinceRemod', 'TotalSF'],
      dtype='object')
```

In [80]:
```
#define cross-validation method to use

cv = KFold(n_splits=10, random_state=1, shuffle=True)

#build multiple linear regression model
model = LinearRegression()

#use k-fold CV to evaluate model
scores_mse = cross_val_score(model, x_pca_scale, y_scale, scoring='neg_mean_absolute_e
                             cv=cv, n_jobs=-1)
print("Over 10 folds: %0.2f MSE with a standard deviation of %0.2f" % (scores_mse.mean


#use k-fold CV to evaluate model R2
scores_r2 = cross_val_score(model, x_pca_scale, y_scale, scoring='r2',
                             cv=cv, n_jobs=-1)
print("Over 10 folds: %0.2f r2 with a standard deviation of %0.2f" % (scores_r2.mean()
```

```
Over 10 folds: -0.25 MSE with a standard deviation of 0.03
Over 10 folds: 0.87 r2 with a standard deviation of 0.02
```

There appears to be a lot of large negative residuals for higher Sales Prices indicating that the model is overestimating the price of homes with large sales prices.

In [81]:
```
# Try log of Y

y_log_scale = scaler.fit_transform(np.array(np.log(housing_training_data['SalePrice']))

## train linear model ##

regr2 = LinearRegression()

regr2.fit(x_pca_scale, y_log_scale)

y_pred = regr2.predict(x_pca_scale)

plt.subplot(1, 2, 1)

plt.scatter(y_log_scale, y_pred)
plt.xlabel('Log Sale Price (Standard Scaled)')
plt.ylabel('Predicted Log Sale Price')
plt.title('Log Sale Price vs Predicted Log Sale Price')

# Residuals
plt.subplot(1, 2, 2)
```

```
sns.residplot(x=y_log_scale, y=y_pred)
plt.xlabel('Log Sale Price')
plt.ylabel('Residual')
plt.title('Residual Plot')

##RMSE
# Mean Squared Error

MSE = np.square(np.subtract(y_scale,y_pred)).mean()
print("MSE:",MSE)

r2 = r2_score(y_log_scale, y_pred)
print("R_sq:",r2)
```

Out[81]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Out[81]:
```
<AxesSubplot:>
```

Out[81]:
```
<matplotlib.collections.PathCollection at 0x7fc18c5eb890>
```

Out[81]:
```
Text(0.5, 0, 'Log Sale Price (Standard Scaled)')
```

Out[81]:
```
Text(0, 0.5, 'Predicted Log Sale Price')
```

Out[81]:
```
Text(0.5, 1.0, 'Log Sale Price vs Predicted Log Sale Price')
```

Out[81]:
```
<AxesSubplot:>
```

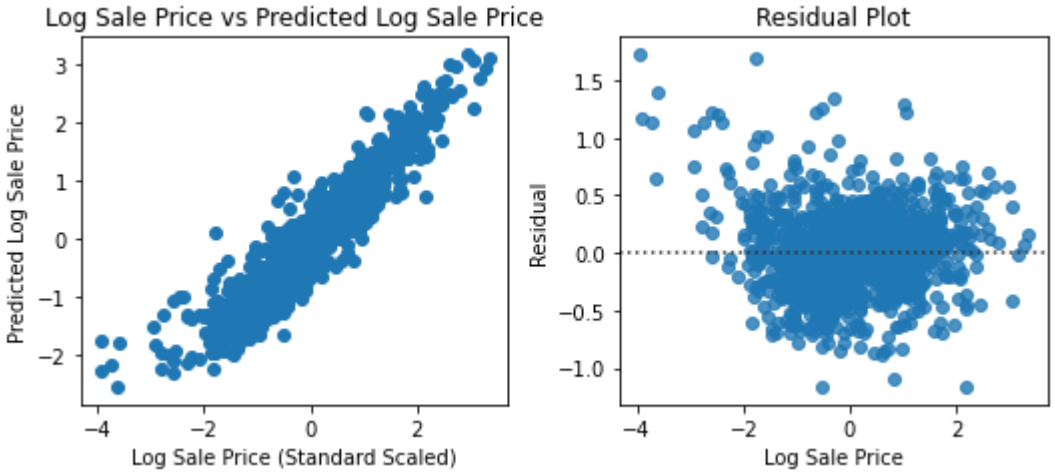
Out[81]:
```
<AxesSubplot:>
```

Out[81]:
```
Text(0.5, 0, 'Log Sale Price')
```

Out[81]:
```
Text(0, 0.5, 'Residual')
```

Out[81]:
```
Text(0.5, 1.0, 'Residual Plot')
```

```
MSE: 0.15526016516119903
R_sq: 0.8789054567599288
```



In [82]:
```
#define cross-validation method to use

cv = KFold(n_splits=10, random_state=1, shuffle=True)

#build multiple linear regression model
model = LinearRegression()

#use k-fold CV to evaluate model
```

```
scores_mse = cross_val_score(model, x_pca_scale, y_log_scale, scoring='neg_mean_absolu
                             cv=cv, n_jobs=-1)
print("Over 10 folds: %0.2f MSE with a standard deviation of %0.2f" % (scores_mse.mean


#use k-fold CV to evaluate model R2
scores_r2 = cross_val_score(model, x_pca_scale, y_log_scale, scoring='r2',
                             cv=cv, n_jobs=-1)
print("Over 10 folds: %0.2f r2 with a standard deviation of %0.2f" % (scores_r2.mean()
```

```
Over 10 folds: -0.25 MSE with a standard deviation of 0.02
Over 10 folds: 0.88 r2 with a standard deviation of 0.02
```

There are a lot of positive residuals for lower sales prices indicating that the model is underestimating the value of homes with lower sales prices.

In [83]:

```
### FROM PCA ON SALE PRICE WE SEE QUADRATIC PATTERN -- TRY DEGREE 2 POLYNOMIAL

from sklearn.preprocessing import PolynomialFeatures

#define our polynomial model, degree 2

degree=2

# PolynomialFeatures will create a new matrix consisting of all polynomial combinatior
# of the features with a degree less than or equal to the degree we just gave the mode
poly_model = PolynomialFeatures(degree=degree)

# transform out polynomial features
poly_x_values = poly_model.fit_transform(x_pca_scale)

regression_model = LinearRegression()
regression_model.fit(poly_x_values, y_scale)
y_pred = regression_model.predict(poly_x_values)

plt.subplot(1, 2, 1)
plt.scatter(y_scale, y_pred)
plt.xlabel('Sale Price (Standard Scaled)')
plt.ylabel('Predicted Sale Price')
plt.title('Sale Price vs Predicted Sale Price')

# Residuals

plt.subplot(1, 2, 2)
sns.residplot(x=y_scale, y=y_pred)
plt.xlabel('Sale Price')
plt.ylabel('Residual')
plt.title('Residual Plot')


# SCORES

SS_Residual = sum((y_scale-y_pred)**2)
SS_Total = sum((y_scale-np.mean(y_scale))**2)
r_squared = 1 - (float(SS_Residual))/SS_Total
adjusted_r_squared = 1 - (1-r_squared)*(len(y_scale)-1)/(len(y)-poly_x_values.shape[1]

print('x_shape_transformed',poly_x_values.shape)
print('x_shape_original',x_pca_scale.shape)
```

```
MSE = np.square(np.subtract(y_scale,y_pred)).mean()
print("MSE:",MSE)

r2 = r2_score(y_scale, y_pred)
print("R_sq:",r_squared[0])

print("R_sq_adjusted:", 1 - (1-r_squared[0])*(len(y_scale)-1)/(len(y_scale)-poly_x_val
```

Out[83]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Out[83]:
```
<AxesSubplot:>
```

Out[83]:
```
<matplotlib.collections.PathCollection at 0x7fc18d25f850>
```

Out[83]:
```
Text(0.5, 0, 'Sale Price (Standard Scaled)')
```

Out[83]:
```
Text(0, 0.5, 'Predicted Sale Price')
```

Out[83]:
```
Text(0.5, 1.0, 'Sale Price vs Predicted Sale Price')
```

Out[83]:
```
<AxesSubplot:>
```

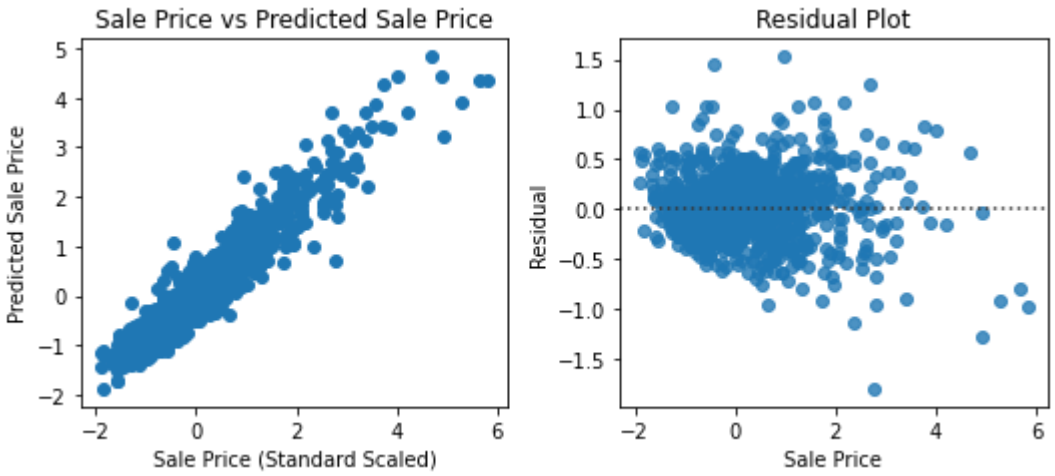
Out[83]:
```
<AxesSubplot:>
```

Out[83]:
```
Text(0.5, 0, 'Sale Price')
```

Out[83]:
```
Text(0, 0.5, 'Residual')
```

Out[83]:
```
Text(0.5, 1.0, 'Residual Plot')
```

```
x_shape_transformed (1455, 45)
x_shape_original (1455, 8)
MSE: 0.08760165238841165
R_sq: 0.9123983476115883
R_sq_adjusted: 0.9096005659526256
```



In [58]:
```
#define cross-validation method to use

cv = KFold(n_splits=10, random_state=1, shuffle=True)

#build multiple linear regression model
model = LinearRegression()

#use k-fold CV to evaluate model
scores_mse = cross_val_score(model, poly_x_values, y_scale, scoring='neg_mean_absolute
                             cv=cv, n_jobs=-1)
```

```
print("Over 10 folds: %0.2f MSE with a standard deviation of %0.2f" % (scores_mse.mean


#use k-fold CV to evaluate model R2
scores_r2 = cross_val_score(model, poly_x_values, y_scale, scoring='r2',
                            cv=cv, n_jobs=-1)
print("Over 10 folds: %0.2f r2 with a standard deviation of %0.2f" % (scores_r2.mean()
```

```
Over 10 folds: -0.21 MSE with a standard deviation of 0.03
Over 10 folds: 0.90 r2 with a standard deviation of 0.01
```

We will need to verify that better fit is not just from including more variables. We do this using cross validation to assess out of sample accuracy.

The residuals are a bit more scattered, but there are still some more large negative residuals for higher sales prices.

In [59]:

```
# Lastly, try a regularization technique

from sklearn.linear_model import ElasticNet

scaler = StandardScaler()

# As an experiment, use on an original set of x variables...

x_raw = housing_training_data[numerical_vars].drop(columns = 'SalePrice')
x_scale = scale(x_raw)

#x_raw_new = housing_training_data.select_dtypes(exclude=['object']).drop(columns = [
#x_scale = scaler.fit_transform(x_raw_new)

regr = ElasticNet()
regr.fit(x_scale, y_log_scale)

ElasticNet(random_state=0)
print(regr.coef_)
print(regr.intercept_)

y_pred = regr.predict(x_scale)

plt.subplot(1, 2, 1)
plt.scatter(y_log_scale, y_pred)
plt.xlabel('Sale Price (Standard Scaled)')
plt.ylabel('Predicted Sale Price')
plt.title('ElasticNet: Sale Price vs Predicted Sale Price')

# Residuals

plt.subplot(1, 2, 2)
sns.residplot(x=y_log_scale, y=y_pred)
plt.xlabel('Sale Price')
plt.ylabel('Residual')
plt.title('Residual Plot')


MSE = np.square(np.subtract(y_scale,y_pred)).mean()
print("MSE:",MSE)
```

```
r2 = r2_score(y_scale, y_pred)
print("R_sq:",r2)
```

Out[59]:
```
ElasticNet(alpha=1.0, copy_X=True, fit_intercept=True, l1_ratio=0.5,
           max_iter=1000, normalize=False, positive=False, precompute=False,
           random_state=None, selection='cyclic', tol=0.0001, warm_start=False)
```

Out[59]:
```
ElasticNet(alpha=1.0, copy_X=True, fit_intercept=True, l1_ratio=0.5,
           max_iter=1000, normalize=False, positive=False, precompute=False,
           random_state=0, selection='cyclic', tol=0.0001, warm_start=False)
[ 0.          0.          0.17296878 -0.          0.          0.
  0.          0.          0.          0.          0.00587394  0.
  0.         -0.          0.06700516  0.         -0.          0.
  0.          0.         -0.          0.          0.          0.
  0.02809537  0.00115474  0.          0.         -0.          0.
  0.          0.         -0.        ]
[-2.46470368e-15]
```

Out[59]:
```
<AxesSubplot:>
```

Out[59]:
```
<matplotlib.collections.PathCollection at 0x7fc18b1c6350>
```

Out[59]:
```
Text(0.5, 0, 'Sale Price (Standard Scaled)')
```

Out[59]:
```
Text(0, 0.5, 'Predicted Sale Price')
```

Out[59]:
```
Text(0.5, 1.0, 'ElasticNet: Sale Price vs Predicted Sale Price')
```

Out[59]:
```
<AxesSubplot:>
```

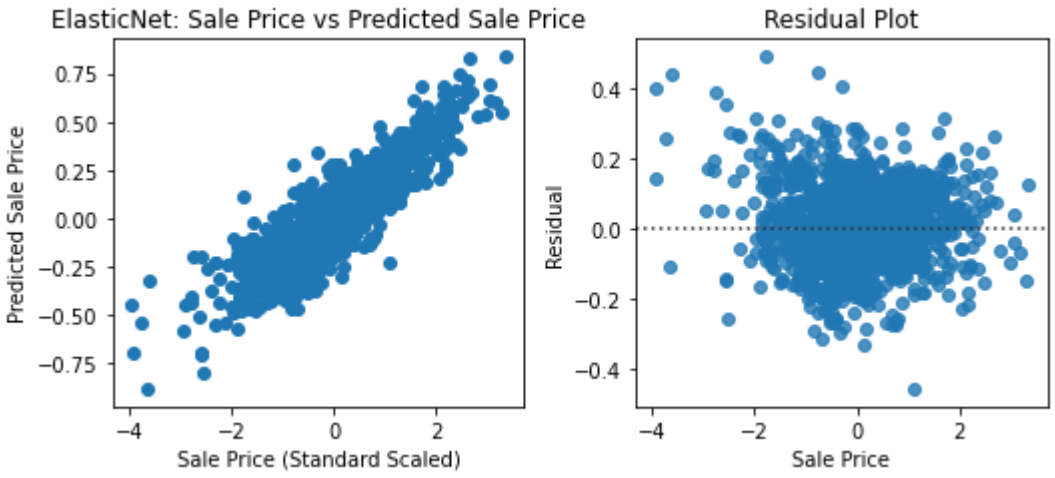
Out[59]:
```
<AxesSubplot:>
```

Out[59]:
```
Text(0.5, 0, 'Sale Price')
```

Out[59]:
```
Text(0, 0.5, 'Residual')
```

Out[59]:
```
Text(0.5, 1.0, 'Residual Plot')
```

```
MSE: 1.058250120091334
R_sq: 0.36078782270420806
```



In [60]:
```
x = housing_training_data[['OverallQual','TotalBsmtSF','GrLivArea','GarageCars','Garag
y_log = np.log(housing_training_data['SalePrice'])

#polynomial_features= PolynomialFeatures(degree=2)
#xp = polynomial_features.fit_transform(x)
#xp.shape

#add constant to predictor variables
```

```
#x = sm.add_constant(xp)
x = sm.add_constant(x)

#fit polynomial regression model
model = sm.OLS(y_log, x).fit()

#view model summary
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.825
Model:                            OLS   Adj. R-squared:                  0.825
Method:                 Least Squares   F-statistic:                     1370.
Date:                Sun, 09 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:59:59   Log-Likelihood:                555.36
No. Observations:                1455   AIC:                            -1099.
Df Residuals:                    1449   BIC:                            -1067.
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         10.5342      0.020    524.743      0.000      10.495      10.574
OverallQual    0.1194      0.005     25.963      0.000       0.110       0.128
TotalBsmtSF    0.0002    1.3e-05     15.556      0.000       0.000       0.000
GrLivArea      0.0002   1.11e-05     21.632      0.000       0.000       0.000
GarageCars     0.0689      0.013      5.246      0.000       0.043       0.095
GarageArea     0.0001   4.51e-05      3.118      0.002    5.22e-05       0.000
==============================================================================
Omnibus:                      321.730   Durbin-Watson:                   1.974
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1037.251
Skew:                          -1.085   Prob(JB):                    5.80e-226
Kurtosis:                       6.522   Cond. No.                     9.24e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 9.24e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Polynomial regression using predictors from PCA for Kaggle

In [61]:

```
from sklearn.preprocessing import PolynomialFeatures
ypolyscaler = StandardScaler()
poly_y_scale = ypolyscaler.fit_transform(np.array(housing_training_data['SalePrice']).
#define our polynomial model, with whatever degree we want
degree=2

# PolynomialFeatures will create a new matrix consisting of all polynomial combinatior
# of the features with a degree less than or equal to the degree we just gave the mode
poly_model = PolynomialFeatures(degree=degree)

# transform out polynomial features
poly_x_values = poly_model.fit_transform(x_pca_scale)

poly_regression_model = LinearRegression()
poly_regression_model.fit(poly_x_values, poly_y_scale)
```

```
y_pred = poly_regression_model.predict(poly_x_values)

plt.subplot(1,2,1)

plt.scatter(poly_y_scale, y_pred)
plt.xlabel('Sale Price (Standard Scaled)')
plt.ylabel('Predicted Sale Price')
plt.title('Sale Price vs Predicted Sale Price')

# Residuals
plt.subplot(1,2,2)
plt.title('Residuals')
sns.residplot(x=poly_y_scale, y=y_pred)

# Mean Squared Error

MSE = np.square(np.subtract(poly_y_scale,y_pred)).mean()
print("MSE:",MSE)

r2 = r2_score(y_scale, y_pred)
print("R_sq:",r2)
```

Out[61]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

Out[61]: <AxesSubplot:>

Out[61]: <matplotlib.collections.PathCollection at 0x7fc18d57fe10>

Out[61]: Text(0.5, 0, 'Sale Price (Standard Scaled)')

Out[61]: Text(0, 0.5, 'Predicted Sale Price')

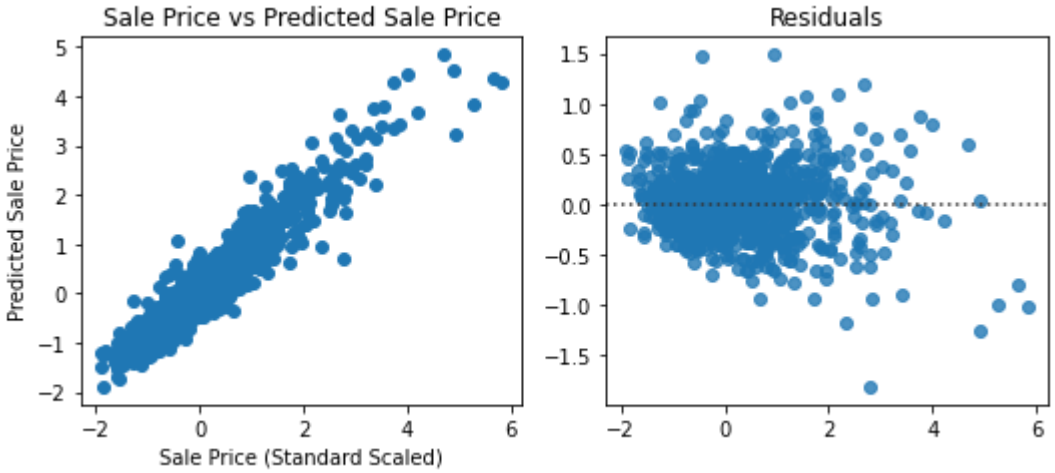
Out[61]: Text(0.5, 1.0, 'Sale Price vs Predicted Sale Price')

Out[61]: <AxesSubplot:>

Out[61]: Text(0.5, 1.0, 'Residuals')

Out[61]: <AxesSubplot:title={'center':'Residuals'}>

```
MSE: 0.08710552160586477
R_sq: 0.9128944783941353
```



Ridge regression using predictors from PCA with Cross Validation to find the best alpha

Principal components have no collinearity by definition. However, we were interested in applying a Ridge regularization model to our PCA and seeing how it would perform, including what value of alpha it would select. There are many methods aimed at making our PCA more robust/reduce overfitting inherent in their calculation. See below for comments about the loading within our components.

In [62]:
```
from sklearn.model_selection import GridSearchCV
yscaler = StandardScaler()
y_log_scale = yscaler.fit_transform(np.array(np.log(housing_training_data['SalePrice']

pca = PCA(n_components=8)

## independent variables ###
xscaler = StandardScaler()
x_raw = housing_training_data.select_dtypes(exclude=['object']).drop(columns = ['SaleP
x_scale = xscaler.fit_transform(x_raw)

x_pca_raw = pca.fit_transform(x_raw)

x_pca_scale = pca.fit_transform(x_scale) # PCA is affected by scale. We use the scaled


# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(x_pca_scale, y_log_scale, test_siz

# Set the alpha values to test
alpha_values = np.logspace(-4, 4, num=50)

# Create the Ridge Regression model
ridge = Ridge()

# Set up the grid search with cross-validation
param_grid = {'alpha': alpha_values}
grid_search = GridSearchCV(ridge, param_grid, cv=5, scoring='neg_mean_squared_error',

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best alpha value
best_alpha = grid_search.best_params_['alpha']
print("Best alpha value:", best_alpha)

# Create and fit the Ridge Regression model with the best alpha value
ridge_best = Ridge(alpha=best_alpha)

ridgemodel = ridge_best.fit(X_train, y_train)
# View the coefficients of the ridge model
coefficients = ridgemodel.coef_
print("Coefficients:", coefficients)

# Predict
y_pred = ridgemodel.predict(X_test)

# plot predictors against log scaled
plt.scatter(y_test, y_pred)
plt.xlabel('Sale Price (Standard Scaled)')
plt.ylabel('Predicted Sale Price')
```

```
plt.title('Sale Price vs Predicted Sale Price')
# Calculate the mean squared error (MSE) of the predictions
MSE = np.square(np.subtract(y_test,y_pred)).mean()
print("MSE:",MSE)

# Calculate the R^2 of the predictions
r2 = r2_score(y_test, y_pred)
print("R_sq:",r2)
```

Out[62]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=Ridge(alpha=1.0, copy_X=True, fit_intercept=True,
                             max_iter=None, normalize=False, random_state=None,
                             solver='auto', tol=0.001),
             iid='deprecated', n_jobs=-1,
             param_grid={'alpha': array([1.00000000e-04, 1.45634848e-04, 2.12095089e-
04, 3.08884360e-04,
       4.49843267e-04, 6.55128557e-04, 9.54095476e-04, 1.38949549e-03,
       2.02358965e-...
       1.67683294e+01, 2.44205309e+01, 3.55648031e+01, 5.17947468e+01,
       7.54312006e+01, 1.09854114e+02, 1.59985872e+02, 2.32995181e+02,
       3.39322177e+02, 4.94171336e+02, 7.19685673e+02, 1.04811313e+03,
       1.52641797e+03, 2.22299648e+03, 3.23745754e+03, 4.71486636e+03,
       6.86648845e+03, 1.00000000e+04])},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='neg_mean_squared_error', verbose=0)
Best alpha value: 16.768329368110066
Coefficients: [[ 0.29564598  0.01399251  0.05131192 -0.09043666 -0.04930898  0.078021
45
   0.00204428  0.00818516]]
```

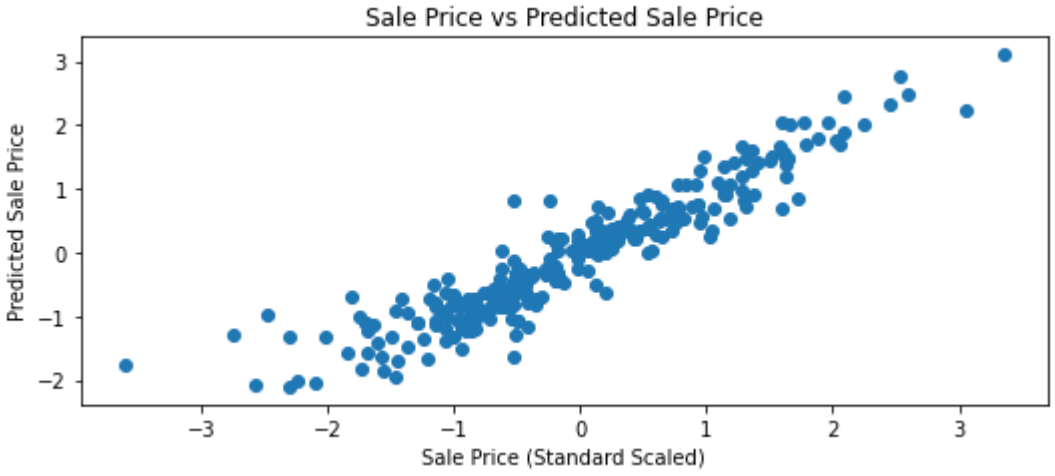
Out[62]:
```
<matplotlib.collections.PathCollection at 0x7fc18d5da210>
```

Out[62]:
```
Text(0.5, 0, 'Sale Price (Standard Scaled)')
```

Out[62]:
```
Text(0, 0.5, 'Predicted Sale Price')
```

Out[62]:
```
Text(0.5, 1.0, 'Sale Price vs Predicted Sale Price')
```

```
MSE: 0.1357921550273285
R_sq: 0.8806208257731393
```



In [63]:
```
x_raw.columns
```

Out[63]:
```
Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
       'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'ExterQual',
       'BsmtQual', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF',
       'CentralAir', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea',
       'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath', 'BedroomAbvGr',
       'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd', 'Fireplaces',
       'FireplaceQu', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF',
       'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea',
       'MiscVal', 'MoSold', 'YrSold', 'Excellent_Exterior_Quality',
       'YrSinceRemod', 'TotalSF'],
      dtype='object')
```

Interpret the coefficients

Coef0: (0.29916159) has a positive impact on Sale Price. Given thatAs this feature increases, the predicted house price also increases. This coefficient has the largest positive effect among all features. In the PCA loadings for PC1, TotalSF and OverQual accounting for over 0.50 of the component, indicating both these features have a larger postive impact on Sale Price.

Coef1: (0.01065569) has a small positive impact on Sale Price. As this feature increases, the predicted house price marginally increases.

Coef2: (0.05379505) has a positive impact on Sale Price. As this feature increases, the predicted house price increases.

Coef3: (0.08326186) has a positive impact on Sale Price. As this feature increases, the predicted house price increases.

Coef4: (-0.09188438) has a negative impact on Sale Price. As this feature increases, the predicted house price decreases. This coefficient has the largest negative effect among all features.

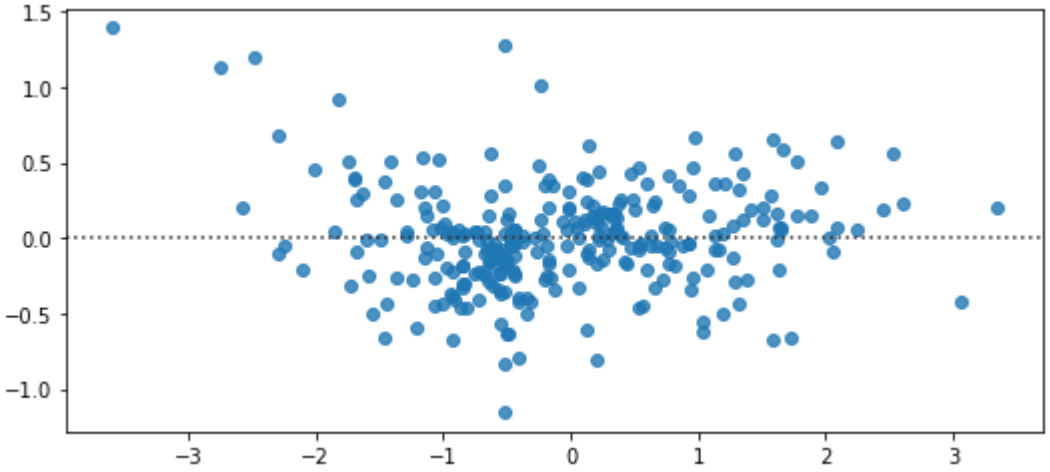
Coef5: (0.03202796) has a positive impact on Sale Price. As this feature increases, the predicted house price increases.

Coef6: (0.01423303) has a small positive impact on Sale Price. As this feature increases, the predicted house price marginally increases.

Coef7: (-0.01638527) has a small negative impact on Sale Price. As this feature increases, the predicted house price marginally decreases.

In [64]:
```
# Residuals

sns.residplot(x=y_test, y=y_pred)
```

Out[64]:
```
<AxesSubplot:>
```



Prepare Test Data

In [65]:
```
# load test data
housing_testing_data = pd.read_csv('test.csv')
```

In [66]:
```
# process columns, apply LabelEncoder to categorical features
for i in important_categorical:
    lbl = LabelEncoder()
    lbl.fit(list(housing_testing_data[i].values))
    housing_testing_data[i] = lbl.transform(list(housing_testing_data[i].values))
```

Out[66]: LabelEncoder()

Out[66]: LabelEncoder()

Out[66]: LabelEncoder()

Out[66]: LabelEncoder()

Out[66]: LabelEncoder()

Handle Null values, matches how we dealt with Nulls in the training dataset

In [67]:
```
# find null counts, percentage of null values, and column type
null_count = housing_testing_data.isnull().sum()
null_percentage = housing_testing_data.isnull().sum() * 100 / len(housing_testing_data
column_type = housing_testing_data.dtypes

# show null counts, percentage of null values, and column type for columns with more t
null_summary = pd.concat([null_count, null_percentage, column_type], axis=1, keys=['Mi
null_summary_only_missing = null_summary[null_count != 0].sort_values('Percentage Miss
null_summary_only_missing
```

Out[67]:

	Missing Count	Percentage Missing	Column Type
PoolQC	1456	99.794380	object
MiscFeature	1408	96.504455	object
Alley	1352	92.666210	object
Fence	1169	80.123372	object
LotFrontage	227	15.558602	float64
GarageCond	78	5.346127	object
GarageYrBlt	78	5.346127	float64
GarageQual	78	5.346127	object
GarageFinish	78	5.346127	object
GarageType	76	5.209047	object
BsmtCond	45	3.084304	object
BsmtExposure	44	3.015764	object
BsmtFinType1	42	2.878684	object
BsmtFinType2	42	2.878684	object
MasVnrType	16	1.096642	object
MasVnrArea	15	1.028101	float64
MSZoning	4	0.274160	object
BsmtFullBath	2	0.137080	float64
BsmtHalfBath	2	0.137080	float64
Functional	2	0.137080	object
Utilities	2	0.137080	object
GarageArea	1	0.068540	float64
TotalBsmtSF	1	0.068540	float64
GarageCars	1	0.068540	float64
BsmtUnfSF	1	0.068540	float64
BsmtFinSF2	1	0.068540	float64
BsmtFinSF1	1	0.068540	float64
Exterior2nd	1	0.068540	object
Exterior1st	1	0.068540	object
SaleType	1	0.068540	object

In [68]:

```
# PoolQC, MiscFeature, Alley, Fence all have over 50% of missing values, we will remov
housing_testing_data.drop(['Alley','PoolQC','Fence','MiscFeature'],axis=1,inplace=True

columns_None = ['SaleType','BsmtCond','BsmtExposure','BsmtFinType1','BsmtFinType2','Ga
```

```
# set Nulls in non-numeric columns to 'None'
housing_testing_data[columns_None] = housing_testing_data[columns_None].fillna('None')
```

In [69]:
```
# change Null values to 0 for the following variables
columns_zero = ['MasVnrArea','GarageArea','GarageCars','TotalBsmtSF','BsmtUnfSF','Bsmt
housing_testing_data[columns_zero] = housing_testing_data[columns_zero].fillna(0)


# fill Nulls for Lot Frontage with median value
housing_testing_data['LotFrontage'].fillna(housing_testing_data['LotFrontage'].median(


# fill Nulls with year garage was built with median value
housing_testing_data['GarageYrBlt'].fillna(housing_testing_data['GarageYrBlt'].median(
```

In [70]:
```
# create new variable TotalSF
housing_testing_data['TotalSF'] = housing_testing_data['TotalBsmtSF'] + housing_testir

# create new variable, years since the house has been remodeled from selling date (use
housing_testing_data['YrSinceRemod'] = housing_testing_data['YrSold'] - housing_testir

# create excellent exterior quality variable
housing_testing_data['Excellent_Exterior_Quality'] = np.where(housing_testing_data['Ex
```

Scale x-values and transform using PCA, then use those values in the ridge model we created above to predict values of Sales Price

In [71]:
```
# select numeric variables in the test data for x
x_test_raw = housing_testing_data.select_dtypes(exclude=['object'])
# scale x-values
x_test_scale = xscaler.fit_transform(x_test_raw)
# transform x-values using PCA
x_test_pca_scale = pca.transform(x_test_scale)
# use x-values to predict y values
scaled_y_predtest = ridgemodel.predict(x_test_pca_scale)

# Apply inverse scaling transformation to predicted y-values
y_predtest = yscaler.inverse_transform(scaled_y_predtest)
# Exponential transform the predictions (since the model output log transformed y-valu
y_pred_final = np.exp(y_predtest)
```

Create dataframe with Id and Sales Price predictions

In [72]:
```
# Create a dataframe with the y predictions
predictiondf=pd.DataFrame(y_pred_final, columns=['SalePrice'])
# Add the Id column to the front of the dataframe
predictiondf.insert(0, 'Id', housing_testing_data['Id'])

predictiondf.head()
```

Out[72]:

	Id	SalePrice
0	1461	124923.795956
1	1462	161182.690072
2	1463	184946.275551
3	1464	196901.378439
4	1465	162679.619736

In [73]:
```
#output predictions to csv
predictiondf.to_csv('test_salespriceridge_v6_ridge.csv', index=False)
```

Kaggle Results - Ridge Regression

Upon submission of our home price predictions from the ridge regression model into Kaggle using Claire Markey's username, the team achieved a RMSE (as calculated using the log of the predicted and actual home prices) of 0.16954 for the testing dataset as displayed in the screenshot from the Kaggle leaderboard below.

In [74]:
```
plt.figure(figsize = (15, 15))
kaggle_results = plt.imread('Kaggle_RMSE_ridge.jpg')
plt.imshow(kaggle_results)
plt.axis("off")
plt.show()
```

Out[74]:
```
<Figure size 1080x1080 with 0 Axes>
```

Out[74]:
```
<matplotlib.image.AxesImage at 0x7fc18d72ef90>
```

Out[74]:
```
(-0.5, 1246.5, 126.5, -0.5)
```

Predicting Home Sale Prices In the Testing Dataset using the Polynomial Model

Let's predict Sales Price using our polynomial model

In [75]:
```
poly_model = PolynomialFeatures(degree=degree)

# transform out polynomial features
poly_x_test_values = poly_model.fit_transform(x_test_pca_scale)

y_poly_pred = poly_regression_model.predict(poly_x_test_values)

# Apply inverse scaling transformation to predicted y-values
y_poly_predtest = ypolyscaler.inverse_transform(y_poly_pred)
```

In [76]:
```
# Create a dataframe with the y predictions
predictionpolydf=pd.DataFrame(y_poly_predtest, columns=['SalePrice'])
# Add the Id column to the front of the dataframe
predictionpolydf.insert(0, 'Id', housing_testing_data['Id'])
predictionpolydf.head()
```

Out[76]:

	Id	SalePrice
0	1461	132548.140244
1	1462	163901.344392
2	1463	185518.483857
3	1464	195882.852061
4	1465	153642.714468

In [77]:
```
#output predictions to csv

predictionpolydf.to_csv('test_salespricepoly_v5.csv', index=False)
```

Kaggle Results - Polynomial Regression

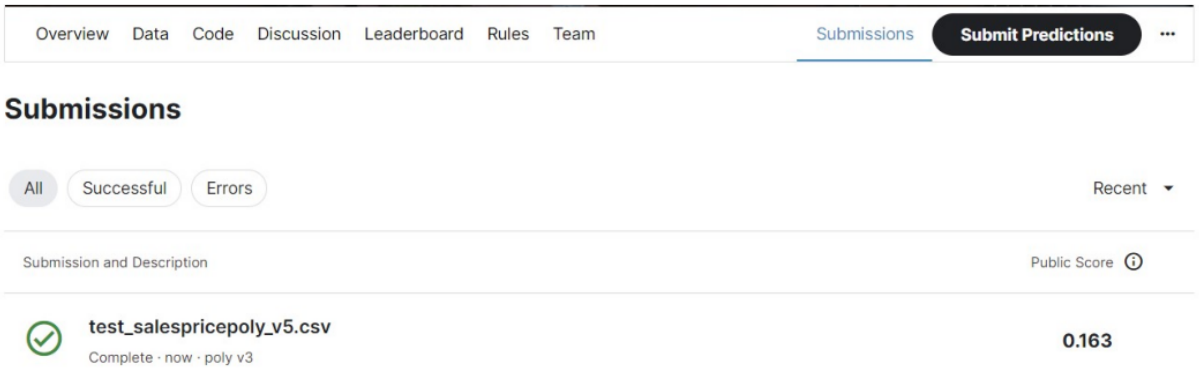
Upon submission of our home price predictions from the polynomial model into Kaggle using Claire Markey's username, the team achieved a RMSE (as calculated using the log of the predicted and actual home prices) of 0.163 for the testing dataset as displayed in the screenshot from the Kaggle leaderboard below.

In [78]:
```
plt.figure(figsize = (15, 15))
kaggle_results = plt.imread('Kaggle_RMSE_poly.jpg')
plt.imshow(kaggle_results)
plt.axis("off")
plt.show()
```

Out[78]:
```
<Figure size 1080x1080 with 0 Axes>
```

Out[78]:
```
<matplotlib.image.AxesImage at 0x7fc18c070e10>
```

Out[78]:
```
(-0.5, 1300.5, 420.5, -0.5)
```



In [ ]: