Our exploratory data analysis examined the housing market in Ames, Iowa, using the house price [SalePrice] as the dependent variable of interest. The initial dataset includes 1460 data records and 81 fields. The test data has a mean sale price of $180,921.20 and a standard deviation of $79442.50. We cleaned the data by removing fields with null values and trimmed the dataset using an isolation forest algorithm to detect and remove 5% of the anomalies in [SalePrice]. We also removed all non-numeric features. The cleaned test data has 1,387 data records, 37 fields, a median sale price of $173,354.52, and a standard deviation of $59,601.46. (Previously, we removed outliers more than two standard deviations away and ended with 1,459 data records, a median sale price of $165,228.32, and a standard deviation of $58,943.80.) The isolation forest algorithm improved our models' accuracy but decreased the correlation coefficient for all predictor variables.

We engineered four new features to use as predictor variables. A [baths] feature took [FullBath] plus half of [HalfBath]; and a [newnes_value] feature took the [YearBuilt] plus [YearRemodAdd] divided by [YearBuilt], giving older, remodeled homes a modernity adjustment. We also continued to use a total square foot variable [tot_sq] that measures the houses' total square footage (including basements) and a quality space [qual_space] variable that multiplies [total_sq] by overall quality [OverallQual]. See Figure 1 in the index for correlation coefficients of some variables used in our models.

Following our exploratory data analysis, we did feature selection. Our linear regression models generally used int64 features from the original dataset and features that we engineered. Our Lasso, Ridge, and ElasticNet regression used the 12 most important numeric features as determined by recursive feature elimination. We prepared all of our models with a cross-validation design. We divided our training data set into two groups: a training data set of 932 (80%) and a testing data set of 23 (20%). We tested all of our models and chose the linear regression model that best predicted the “test” training data and all three machine learning models to use with the “real” test data.

Using the k-fold cross-validation method, we built four regression models using the training data to predict the [SalePrice] for each house: Linear (OLS), Lasso, Ridge, and ElasticNet regression models. Linear regression Model One has the best fit out of the four linear regression models since it has the highest mean r-squared score of 0.70 and the lowest standard deviation of 0.10 (slightly better than the Ridge Regression). Our other regression models all had increased r-squared scores and larger standard deviations. Our Ridge Regression is our best model did best with the test data and had a mean r-squared score of 0.78 and a standard deviation of 0.12. The Lasso Regression had a mean r-squared score of 0.76 and a standard deviation of 0.18. Finally, the initial ElaticNet Regression model has a mean r-squared score of 0.47 and a standard deviation of 0.11. We tuned our hyperparameter for this model using an alpha = 0.10 and l1_ratio = 0.75. This resulted in increasing the mean r-squared score to 0.76 and the standard deviation to 0.18.

Our ElasticNet Regression model was determined to be the best predictor based on its Kaggle score of 0.18135. Our three machine learning regression models received similar r-squares scores and standard deviations, so it's not too much of a surprise that the ElasticNet Regression model did better with the actual test data, while the Ridge Regression model did best with the training “test” data. Our other regression models ranked in the following order: Ridge, 0.18569; Lasso, 0.18589; Linear, 0.20912. Our previous linear model received a slightly better Kaggle score of 0.20317, but all of our machine learning models beat our previous Kaggle score.

MSDS 422-57 | Module 3 Assignment 1 | Group 5
Jul 9, 2022 | House Prices: Advanced Regression Techniques EDA | Scott Jue
Dr. Anil Chaturvedi | | Zach Watson

Index:

Kaggle user name for upload: ZachWat

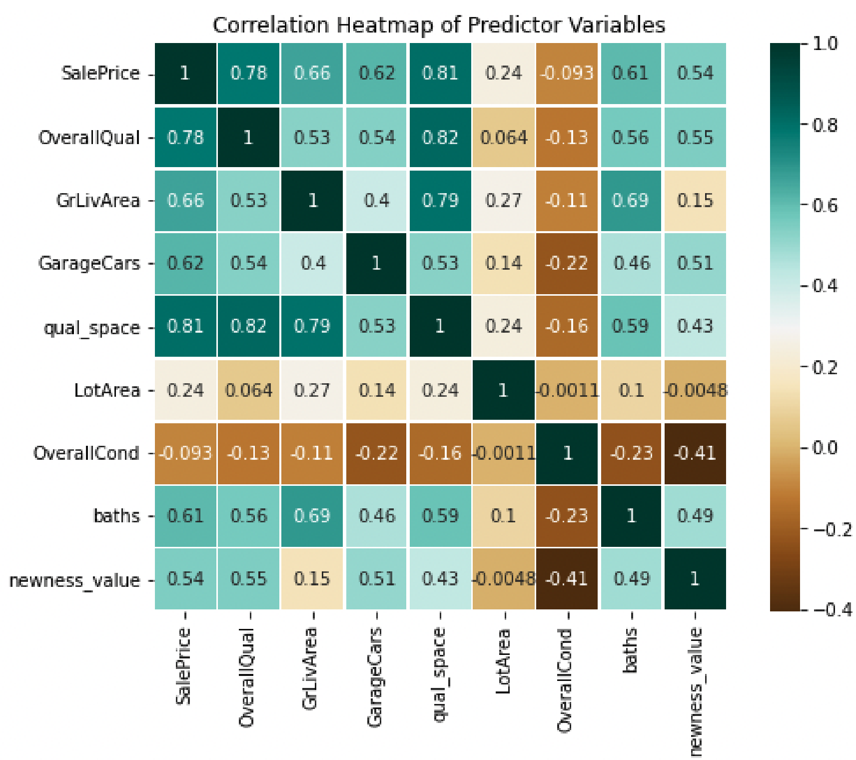
group_5_elasticnet_m3 (1).csv — **Score: 0.18135**
Submitted by ZachWat · Submitted just now

group_5_lasso_m3 (1).csv — **Score: 0.18589**
Submitted by ZachWat · Submitted just now

group_5_ridge_m3 (1).csv — **Score: 0.18569**
Submitted by ZachWat · Submitted just now

group_5_linear_m3 (1).csv — **Score: 0.20912**
Submitted by ZachWat · Submitted 2 minutes ago

Figure 1:



Intro

Links

https://canvas.northwestern.edu/courses/167719/assignments/1078600

https://www.kaggle.com/c/house-prices-advanced-regression-techniques

Modules

In [1]:

```
#For data manipulation and visualization
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

#For Isolation Forest from sklearn
from sklearn.ensemble import IsolationForest
from enum import auto

#Models from sklearn (Linear, Lasso, and Ridge)
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge

#ElasticNet from sklearn
from sklearn.linear_model import ElasticNet
from sklearn.linear_model import ElasticNetCV
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RepeatedKFold
from numpy import arange

#Other from sklearn
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error

#Other
from math import sqrt
import warnings
```

Import Files

In [2]:

```
#Import train.csv and test.csv from the Kaggle page linked above
#from google.colab import files
#uploaded = files.upload()
```

In [3]:

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

EDA

Intro Stats

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1460 non-null   int64  
 1   MSSubClass     1460 non-null   int64  
 2   MSZoning       1460 non-null   object 
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64  
 5   Street         1460 non-null   object 
 6   Alley          91 non-null     object 
 7   LotShape       1460 non-null   object 
 8   LandContour    1460 non-null   object 
 9   Utilities      1460 non-null   object 
 10  LotConfig      1460 non-null   object 
 11  LandSlope      1460 non-null   object 
 12  Neighborhood   1460 non-null   object 
 13  Condition1     1460 non-null   object 
 14  Condition2     1460 non-null   object 
 15  BldgType       1460 non-null   object 
 16  HouseStyle     1460 non-null   object 
 17  OverallQual    1460 non-null   int64  
 18  OverallCond    1460 non-null   int64  
 19  YearBuilt      1460 non-null   int64  
 20  YearRemodAdd   1460 non-null   int64  
 21  RoofStyle      1460 non-null   object 
 22  RoofMatl       1460 non-null   object 
 23  Exterior1st    1460 non-null   object 
 24  Exterior2nd    1460 non-null   object 
 25  MasVnrType     1452 non-null   object 
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object 
 28  ExterCond      1460 non-null   object 
 29  Foundation     1460 non-null   object 
 30  BsmtQual       1423 non-null   object 
 31  BsmtCond       1423 non-null   object 
 32  BsmtExposure   1422 non-null   object 
 33  BsmtFinType1   1423 non-null   object 
 34  BsmtFinSF1     1460 non-null   int64  
 35  BsmtFinType2   1422 non-null   object 
 36  BsmtFinSF2     1460 non-null   int64  
 37  BsmtUnfSF      1460 non-null   int64  
 38  TotalBsmtSF    1460 non-null   int64  
 39  Heating        1460 non-null   object 
 40  HeatingQC      1460 non-null   object 
 41  CentralAir     1460 non-null   object 
 42  Electrical     1459 non-null   object 
 43  1stFlrSF       1460 non-null   int64  
 44  2ndFlrSF       1460 non-null   int64  
 45  LowQualFinSF   1460 non-null   int64  
 46  GrLivArea      1460 non-null   int64  
 47  BsmtFullBath   1460 non-null   int64  
 48  BsmtHalfBath   1460 non-null   int64  
 49  FullBath       1460 non-null   int64  
 50  HalfBath       1460 non-null   int64  
```

```
 51  BedroomAbvGr   1460 non-null   int64  
 52  KitchenAbvGr   1460 non-null   int64  
 53  KitchenQual    1460 non-null   object 
 54  TotRmsAbvGrd   1460 non-null   int64  
 55  Functional     1460 non-null   object 
 56  Fireplaces     1460 non-null   int64  
 57  FireplaceQu    770 non-null    object 
 58  GarageType     1379 non-null   object 
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object 
 61  GarageCars     1460 non-null   int64  
 62  GarageArea     1460 non-null   int64  
 63  GarageQual     1379 non-null   object 
 64  GarageCond     1379 non-null   object 
 65  PavedDrive     1460 non-null   object 
 66  WoodDeckSF     1460 non-null   int64  
 67  OpenPorchSF    1460 non-null   int64  
 68  EnclosedPorch  1460 non-null   int64  
 69  3SsnPorch      1460 non-null   int64  
 70  ScreenPorch    1460 non-null   int64  
 71  PoolArea       1460 non-null   int64  
 72  PoolQC         7 non-null      object 
 73  Fence          281 non-null    object 
 74  MiscFeature    54 non-null     object 
 75  MiscVal        1460 non-null   int64  
 76  MoSold         1460 non-null   int64  
 77  YrSold         1460 non-null   int64  
 78  SaleType       1460 non-null   object 
 79  SaleCondition  1460 non-null   object 
 80  SalePrice      1460 non-null   int64  
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

In [5]:

```
df.head()
```

Out[5]:

	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

Descriptive statistics and visualizations to help understand the marginal distribution of the dependent variable.

In [6]:

```
df["SalePrice"].describe()
```

Out[6]:

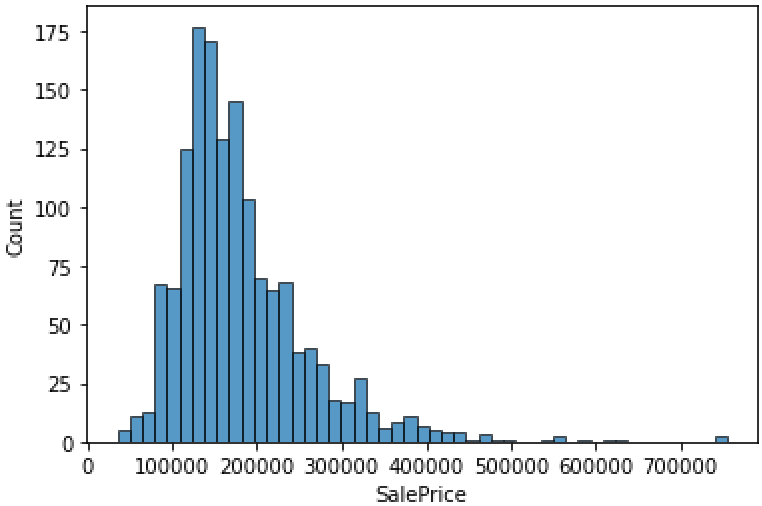
```
count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
50%      163000.000000
```

```
75%       214000.000000
max       755000.000000
Name: SalePrice, dtype: float64
```

EDA SalePrice Graphs

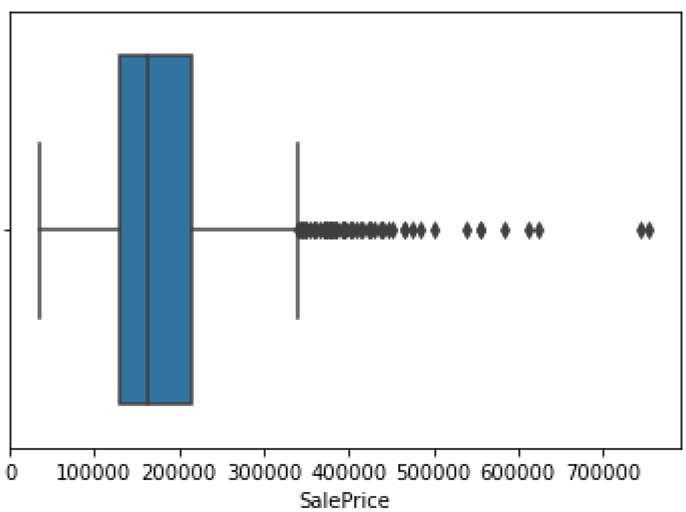
In [7]:
```
sns.histplot(x="SalePrice", data=df)
```

Out[7]: <AxesSubplot:xlabel='SalePrice', ylabel='Count'>



In [8]:
```
sns.boxplot(x="SalePrice", data=df)
```

Out[8]: <AxesSubplot:xlabel='SalePrice'>



Investigate Missing Data and Outliers

Missing Data:

In [9]:
```
#Toggle this to see results below
pd.set_option('max_rows', 20)
```

In [10]:
```
df.isnull().sum()
```

Out[10]:
```
Id                 0
MSSubClass         0
MSZoning           0
LotFrontage      259
LotArea            0
                ... 
MoSold             0
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
Length: 81, dtype: int64
```

The following categories have null values:

- LotFrontage
- Alley
- MasVnrType
- MasVnrArea
- BsmtQual
- BsmtCond
- BsmtExposure
- BsmtFinType1
- BsmtFinType2
- Electrical
- FireplaceQu
- GarageType
- GarageYrBlt
- GarageFinish
- GarageQual
- GarageCond
- PoolQC
- Fence
- MiscFeature

We're not concerned about most of these columns having null values. It makes sense that some of the data would be missing for each (if a house doesn't have a pool, for example). We're going to drop all of the columns that have null values with the exception of "Electrical." For 'Electrical,' we'll remove the row with the null value.

In [11]:
```
col_to_drop = ['LotFrontage','Alley','MasVnrType','MasVnrArea',
               'BsmtQual', 'BsmtCond', 'BsmtExposure','BsmtFinType1', 'BsmtFinType2', '
               'GarageFinish', 'GarageQual', 'GarageCond', 'PoolQC', 'Fence', 'MiscFeat

df2a = df.drop(columns=col_to_drop, inplace=False)

col_to_drop_2 = ['MSZoning', 'Street','LotShape','LandContour', 'Utilities', 'LotConfig
                 'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle','R
                 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'ExterQual', 'ExterCond', 'Fo
                 'Heating', 'HeatingQC','CentralAir', 'Electrical', 'KitchenQual', 'Func
                 'PavedDrive', 'SaleType', 'SaleCondition']
df2b = df2a.drop(columns= col_to_drop_2, inplace=False)
```

```
df3 = df2b.dropna()
df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 0 to 1459
Data columns (total 35 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   LotArea        1460 non-null   int64
 3   OverallQual    1460 non-null   int64
 4   OverallCond    1460 non-null   int64
 5   YearBuilt      1460 non-null   int64
 6   YearRemodAdd   1460 non-null   int64
 7   BsmtFinSF1     1460 non-null   int64
 8   BsmtFinSF2     1460 non-null   int64
 9   BsmtUnfSF      1460 non-null   int64
 10  TotalBsmtSF    1460 non-null   int64
 11  1stFlrSF       1460 non-null   int64
 12  2ndFlrSF       1460 non-null   int64
 13  LowQualFinSF   1460 non-null   int64
 14  GrLivArea      1460 non-null   int64
 15  BsmtFullBath   1460 non-null   int64
 16  BsmtHalfBath   1460 non-null   int64
 17  FullBath       1460 non-null   int64
 18  HalfBath       1460 non-null   int64
 19  BedroomAbvGr   1460 non-null   int64
 20  KitchenAbvGr   1460 non-null   int64
 21  TotRmsAbvGrd   1460 non-null   int64
 22  Fireplaces     1460 non-null   int64
 23  GarageCars     1460 non-null   int64
 24  GarageArea     1460 non-null   int64
 25  WoodDeckSF     1460 non-null   int64
 26  OpenPorchSF    1460 non-null   int64
 27  EnclosedPorch  1460 non-null   int64
 28  3SsnPorch      1460 non-null   int64
 29  ScreenPorch    1460 non-null   int64
 30  PoolArea       1460 non-null   int64
 31  MiscVal        1460 non-null   int64
 32  MoSold         1460 non-null   int64
 33  YrSold         1460 non-null   int64
 34  SalePrice      1460 non-null   int64
dtypes: int64(35)
memory usage: 410.6 KB
```

Removing Anomolies

In [12]:

```
#Isolation Forest Removes anomalies
model=IsolationForest(n_estimators=100, contamination=float(.05), random_state=42)

model.fit(df3[['SalePrice']])

print(model.get_params())
```

```
{'bootstrap': False, 'contamination': 0.05, 'max_features': 1.0, 'max_samples': 'auto',
'n_estimators': 100, 'n_jobs': None, 'random_state': 42, 'verbose': 0, 'warm_start': Fal
se}
```

In [13]:

```
df3['scores'] = model.decision_function(df3[['SalePrice']])
```

```python
df3['anomaly_score'] = model.predict(df3[['SalePrice']])

df4 = df3[df3['anomaly_score']!=-1]

df4.shape
```

Out[13]: (1387, 37)

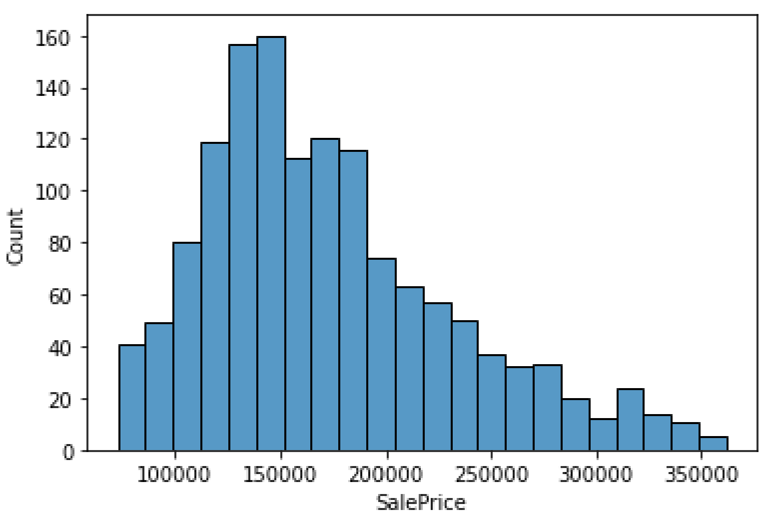
EDA SalePrice Stats/Graphs (Cleaned Data)

In [14]:
```python
df4["SalePrice"].describe()
```

Out[14]:
```
count      1387.000000
mean     173354.517664
std       59601.459217
min       72500.000000
25%      130000.000000
50%      160200.000000
75%      206600.000000
max      361919.000000
Name: SalePrice, dtype: float64
```

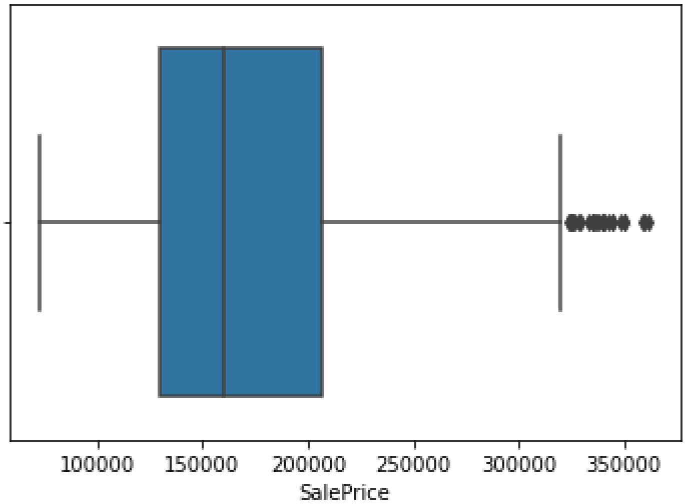
In [15]:
```python
sns.histplot(x="SalePrice", data=df4)
```

Out[15]: <AxesSubplot:xlabel='SalePrice', ylabel='Count'>



In [16]:
```python
sns.boxplot(x="SalePrice", data=df4)
```

Out[16]: <AxesSubplot:xlabel='SalePrice'>



Feature Engineering

In [17]:

```
# sum 1st floor, 2nd floor, and basement square footage to get total square footage
sum_column = df4['1stFlrSF'] + df4['2ndFlrSF'] + df4['TotalBsmtSF']

# multiply total square footage by overall quality to generate new predictor variable q
mult_column = sum_column*df4['OverallQual']

#Sum the baths and the halfbaths
bath_column = df4['FullBath'] + 0.5*df4['HalfBath']

#Create a newness score (YearBuilt + (YearRemodAdd/YearBuilt))
newness_column = df4['YearBuilt'] + (df4['YearRemodAdd'] / df4['YearBuilt'])



# add new predictor variables to dataframe
df4['tot_sq'] = sum_column
df4['qual_space'] = mult_column
df4['baths'] = bath_column
df4['newness_value'] = newness_column
df4.head()
```

```
<ipython-input-17-d7942eafcf14>:16: 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/user_
guide/indexing.html#returning-a-view-versus-a-copy
  df4['tot_sq'] = sum_column
<ipython-input-17-d7942eafcf14>: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/user_
guide/indexing.html#returning-a-view-versus-a-copy
  df4['qual_space'] = mult_column
<ipython-input-17-d7942eafcf14>: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/user_
guide/indexing.html#returning-a-view-versus-a-copy
```

```
  df4['baths'] = bath_column
<ipython-input-17-d7942eafcf14>: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/user_
guide/indexing.html#returning-a-view-versus-a-copy
  df4['newness_value'] = newness_column
```

Out[17]:

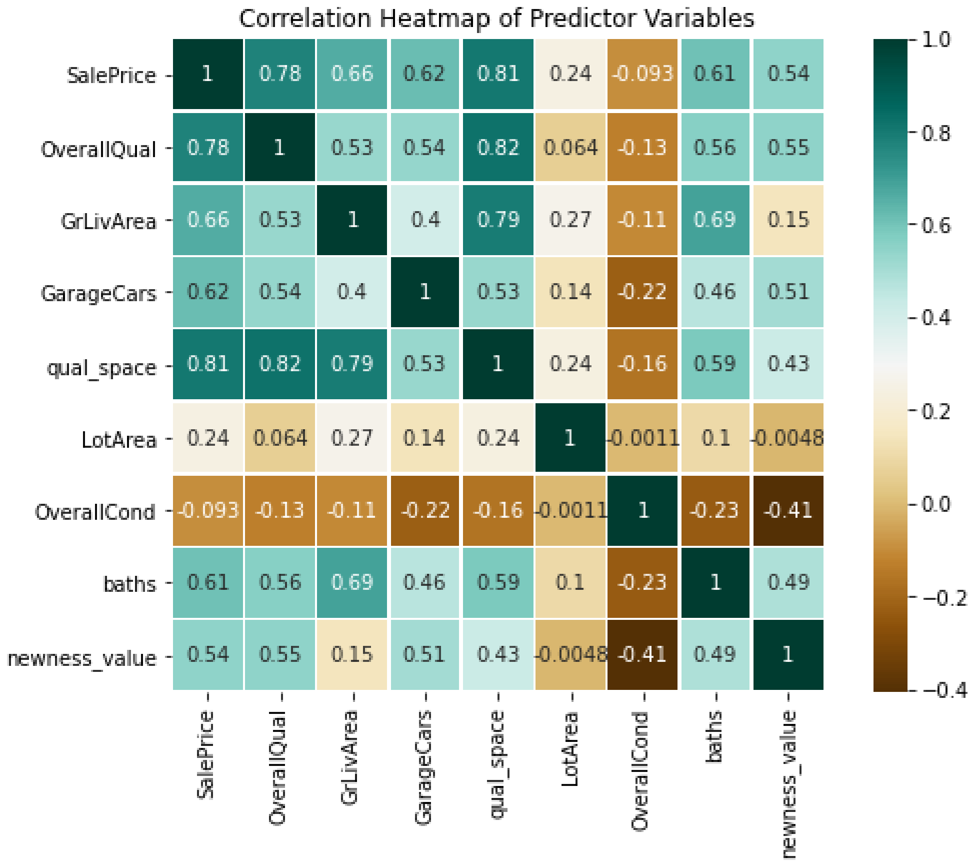
	Id	MSSubClass	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	BsmtFinSF1	BsmtFin
0	1	60	8450	7	5	2003	2003	706	
1	2	20	9600	6	8	1976	1976	978	
2	3	60	11250	7	5	2001	2002	486	
3	4	70	9550	7	5	1915	1970	216	
4	5	60	14260	8	5	2000	2000	655	

5 rows × 41 columns

Correlations

In [18]:

```
# setting the columns to correlate

columns = ['SalePrice', 'OverallQual', 'GrLivArea', 'GarageCars', 'qual_space', 'LotAre
df_corr = df4[columns]
# running the correlation
df_corr.corr()

# setting up the heatmap
corrmat = df_corr.corr()

# set the figure size
f, ax = plt.subplots(figsize=(9, 6))

# pass the data and set the parameters
sns.heatmap(corrmat, vmax=1, square=True, annot=True, cmap='BrBG', linewidths=.5 )
plt.title('Correlation Heatmap of Predictor Variables')

# images can be saved - default is .png
# https://matplotlib.org/3.1.1/api/_as_gen/matplotlib.pyplot.savefig.html
plt.savefig('Correlation Heatmap of New Predictor Variables')
```



	SalePrice	OverallQual	GrLivArea	GarageCars	qual_space	LotArea	OverallCond	baths	newness_value
SalePrice	1	0.78	0.66	0.62	0.81	0.24	-0.093	0.61	0.54
OverallQual	0.78	1	0.53	0.54	0.82	0.064	-0.13	0.56	0.55
GrLivArea	0.66	0.53	1	0.4	0.79	0.27	-0.11	0.69	0.15
GarageCars	0.62	0.54	0.4	1	0.53	0.14	-0.22	0.46	0.51
qual_space	0.81	0.82	0.79	0.53	1	0.24	-0.16	0.59	0.43
LotArea	0.24	0.064	0.27	0.14	0.24	1	-0.0011	0.1	-0.0048
OverallCond	-0.093	-0.13	-0.11	-0.22	-0.16	-0.0011	1	-0.23	-0.41
baths	0.61	0.56	0.69	0.46	0.59	0.1	-0.23	1	0.49
newness_value	0.54	0.55	0.15	0.51	0.43	-0.0048	-0.41	0.49	1

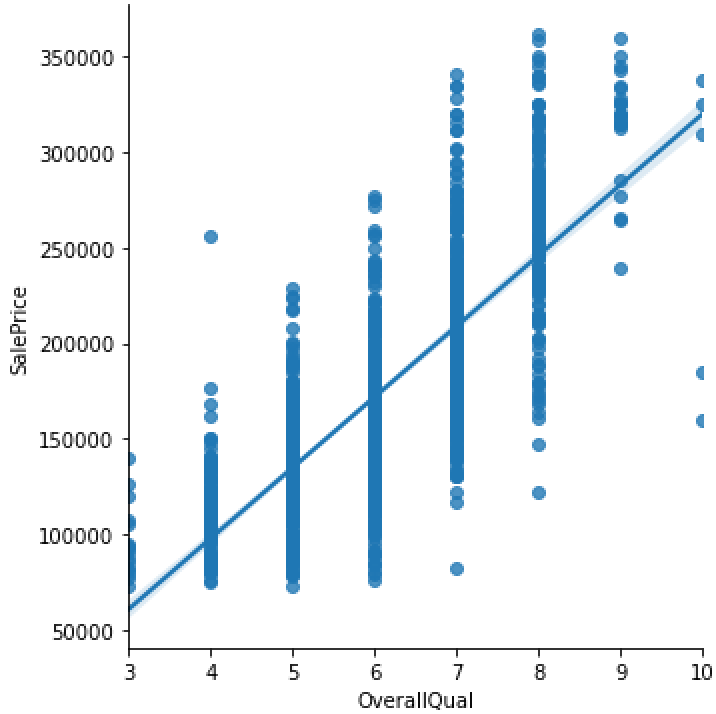
Graphs

Scatterplots

In [19]:

```
#sns.scatterplot(x='OverallQual', y='SalePrice', data=df4)
sns.lmplot(x='OverallQual', y='SalePrice', data=df4)
```

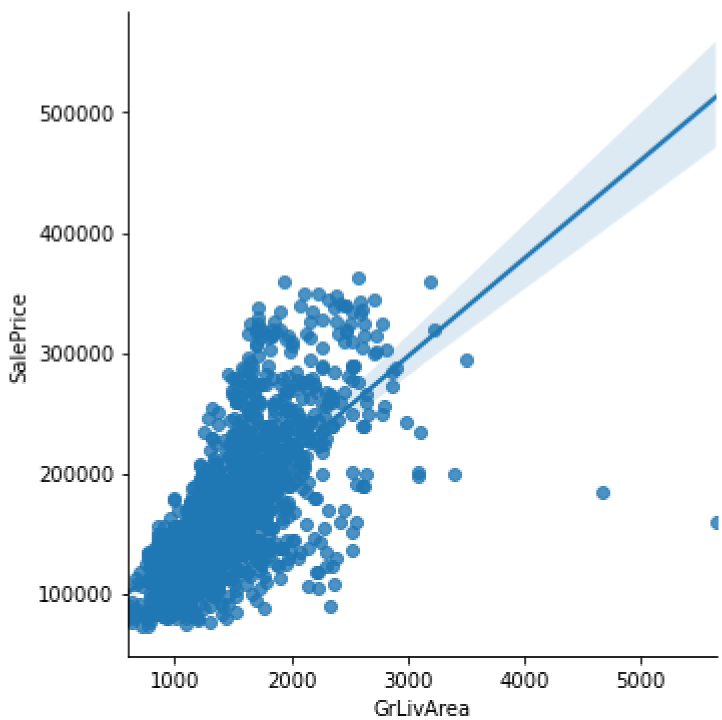
Out[19]: <seaborn.axisgrid.FacetGrid at 0x1990479ab80>



In [20]:

```
#sns.scatterplot(x="GrLivArea", y="SalePrice", data=df4)
sns.lmplot(x="GrLivArea", y="SalePrice", data=df4)
```

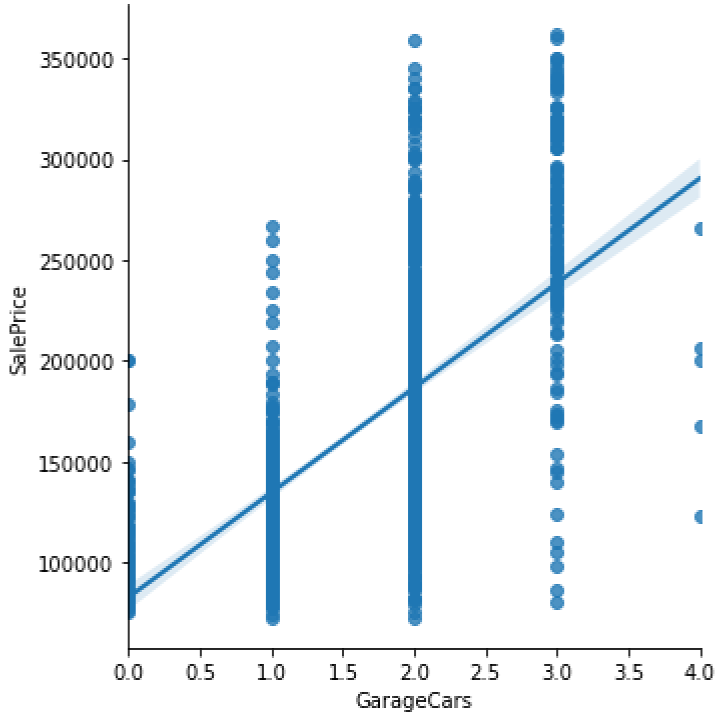
Out[20]: <seaborn.axisgrid.FacetGrid at 0x19904600e20>



In [21]:

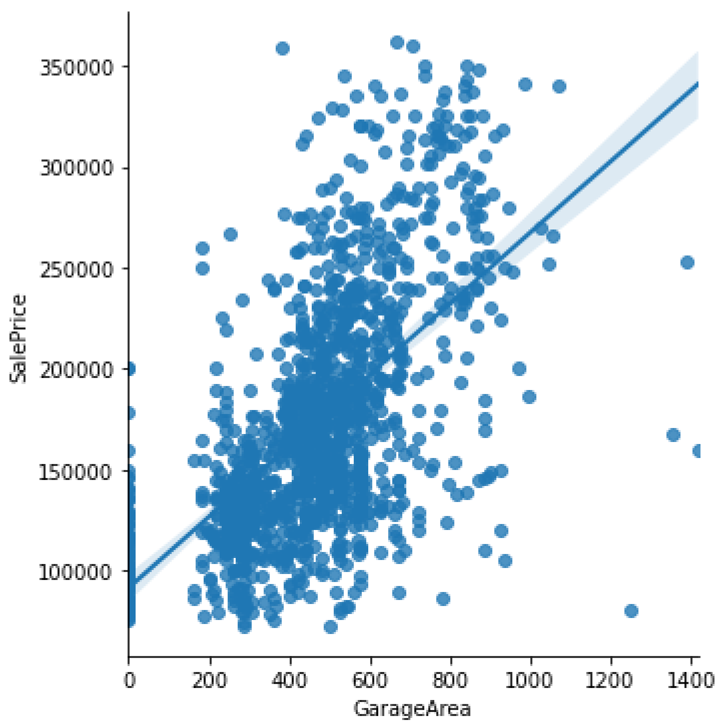
```
#sns.scatterplot(x="GarageCars", y="SalePrice", data=df4)
sns.lmplot(x="GarageCars", y="SalePrice", data=df4)
```

Out[21]: <seaborn.axisgrid.FacetGrid at 0x19904600e50>



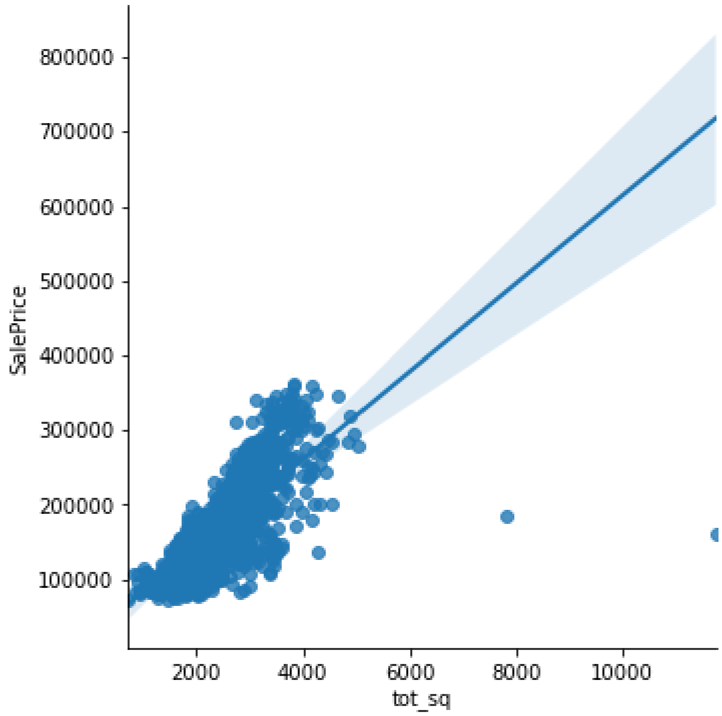
In [22]:
```python
#sns.scatterplot(x="GarageArea", y="SalePrice", data=df4)
sns.lmplot(x="GarageArea", y="SalePrice", data=df4)
```

Out[22]: <seaborn.axisgrid.FacetGrid at 0x199057b1ac0>



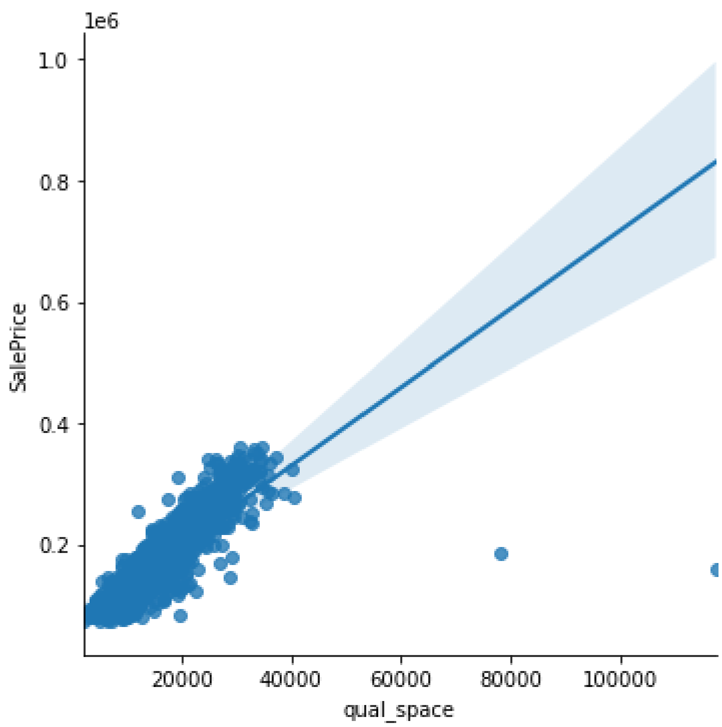
In [23]:
```python
#scatterplot total square ft vs. SalePrice
sns.lmplot(x="tot_sq", y="SalePrice", data=df4)
```

Out[23]: <seaborn.axisgrid.FacetGrid at 0x19903a61c10>



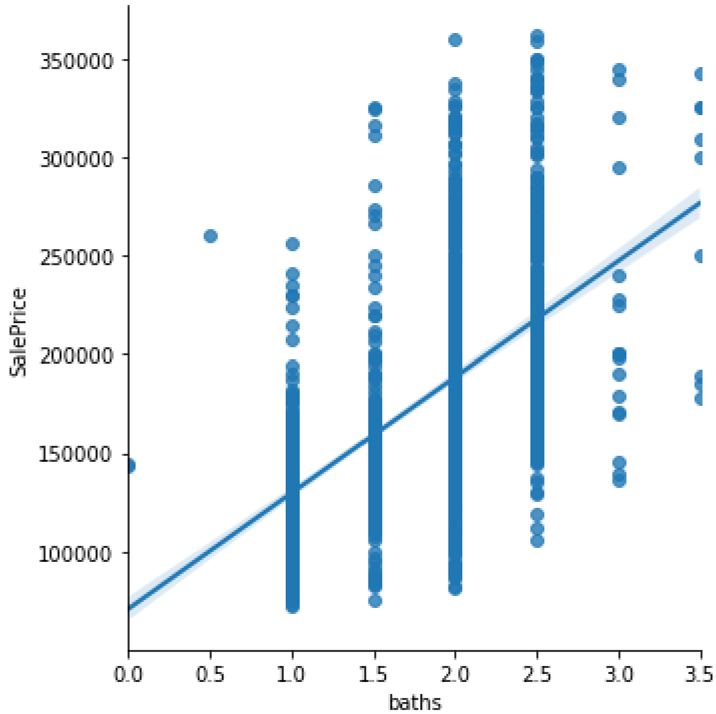
In [24]:
```
#scatterplot qual_space vs. SalePrice
sns.lmplot(x="qual_space", y="SalePrice", data=df4)
```

Out[24]: <seaborn.axisgrid.FacetGrid at 0x1990587bb50>



In [25]:
```
#scatterplot baths vs. SalePrice
sns.lmplot(x="baths", y="SalePrice", data=df4)
```

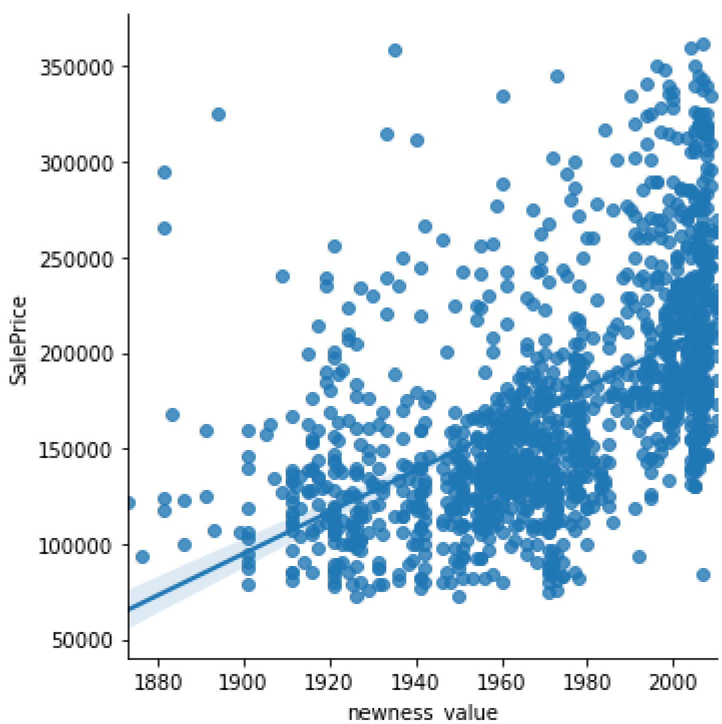
Out[25]: <seaborn.axisgrid.FacetGrid at 0x199058b64f0>



In [26]:

```
# scatterplot of newness value vs SalePrice
sns.lmplot(x="newness_value", y="SalePrice", data=df4)
```

Out[26]: <seaborn.axisgrid.FacetGrid at 0x199058cf850>

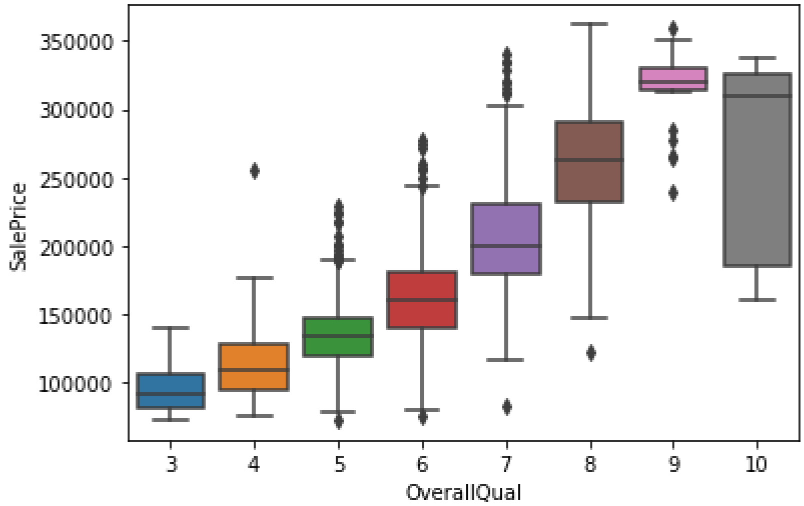


Boxplots

In [27]:

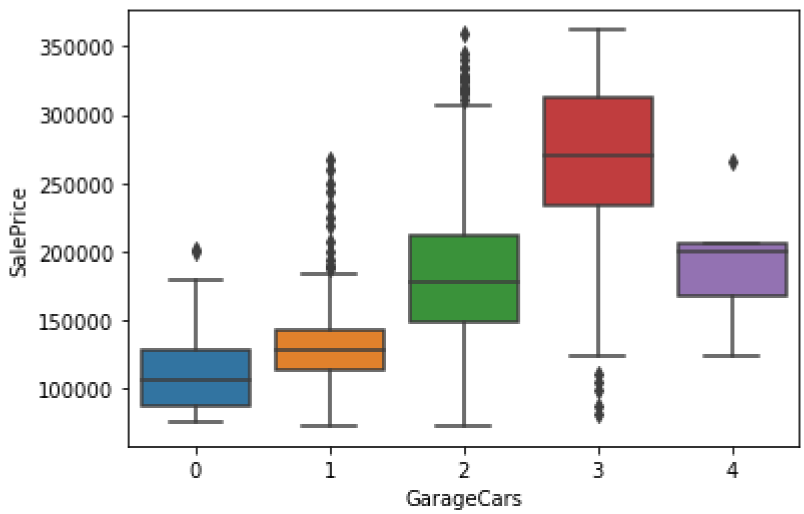
```
var = 'OverallQual'
data = pd.concat([df4['SalePrice'], df4[var]], axis=1)
sns.boxplot(x=var, y='SalePrice', data=data)
```

Out[27]: <AxesSubplot:xlabel='OverallQual', ylabel='SalePrice'>



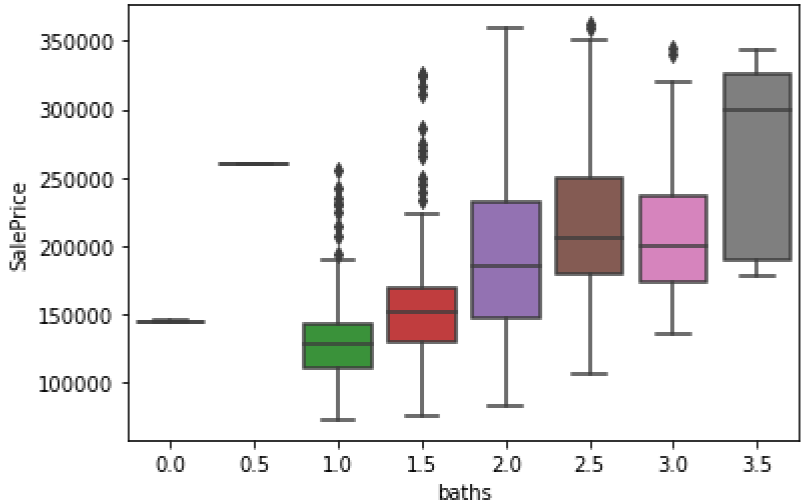
In [28]:
```
var = 'GarageCars'
data = pd.concat([df4['SalePrice'], df4[var]], axis=1)
sns.boxplot(x=var, y='SalePrice', data=data)
```

Out[28]: <AxesSubplot:xlabel='GarageCars', ylabel='SalePrice'>



In [29]:
```
# side by side boxplot of baths vs. SalePrice
var = 'baths'
data = pd.concat([df4['SalePrice'], df4[var]], axis=1)
sns.boxplot(x=var, y='SalePrice', data=data)
```

Out[29]: <AxesSubplot:xlabel='baths', ylabel='SalePrice'>



Regression Models

Lasso, Ridge, and ElasticNet

Variable Selection

In [30]:

```
z = df4.drop(columns = ['SalePrice', 'Id', 'scores', 'anomaly_score'])
y = df4['SalePrice']
```

In [31]:

```
from sklearn.feature_selection import RFE
from sklearn.svm import SVR
estimator = SVR(kernel="linear")
selector = RFE(estimator, n_features_to_select=12, step=1)
selector = selector.fit(z, y)

df_ranks = selector.ranking_
df_ranks
```

Out[31]:

```
array([ 1, 24,  1,  1,  1,  1, 13, 18, 19,  6, 23, 16,  3,  1,  1, 21, 11,
       14,  1,  4, 25,  1,  9,  2,  8,  5, 10, 17,  1, 15, 26,  1,  7, 22,
       20, 12,  1])
```

In [32]:

```
for i in range(z.shape[1]):
    print('Column: %d, Selected %s, Rank: %.3f' % (i, selector.support_[i], selector.ra
```

```
Column: 0, Selected True, Rank: 1.000
Column: 1, Selected False, Rank: 24.000
Column: 2, Selected True, Rank: 1.000
Column: 3, Selected True, Rank: 1.000
Column: 4, Selected True, Rank: 1.000
Column: 5, Selected True, Rank: 1.000
Column: 6, Selected False, Rank: 13.000
Column: 7, Selected False, Rank: 18.000
Column: 8, Selected False, Rank: 19.000
Column: 9, Selected False, Rank: 6.000
Column: 10, Selected False, Rank: 23.000
Column: 11, Selected False, Rank: 16.000
Column: 12, Selected False, Rank: 3.000
```

```
Column: 13, Selected True, Rank: 1.000
Column: 14, Selected True, Rank: 1.000
Column: 15, Selected False, Rank: 21.000
Column: 16, Selected False, Rank: 11.000
Column: 17, Selected False, Rank: 14.000
Column: 18, Selected True, Rank: 1.000
Column: 19, Selected False, Rank: 4.000
Column: 20, Selected False, Rank: 25.000
Column: 21, Selected True, Rank: 1.000
Column: 22, Selected False, Rank: 9.000
Column: 23, Selected False, Rank: 2.000
Column: 24, Selected False, Rank: 8.000
Column: 25, Selected False, Rank: 5.000
Column: 26, Selected False, Rank: 10.000
Column: 27, Selected False, Rank: 17.000
Column: 28, Selected True, Rank: 1.000
Column: 29, Selected False, Rank: 15.000
Column: 30, Selected False, Rank: 26.000
Column: 31, Selected True, Rank: 1.000
Column: 32, Selected False, Rank: 7.000
Column: 33, Selected False, Rank: 22.000
Column: 34, Selected False, Rank: 20.000
Column: 35, Selected False, Rank: 12.000
Column: 36, Selected True, Rank: 1.000
```

In [33]:

```
cols_to_keep = selector.support_

columns_to_remove = z.columns.values[np.logical_not(cols_to_keep)]
columns_to_remove
```

Out[33]:

```
array(['LotArea', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF',
       '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'KitchenAbvGr', 'TotRmsAbvGrd', 'GarageCars',
       'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch',
       '3SsnPorch', 'PoolArea', 'MiscVal', 'YrSold', 'tot_sq',
       'qual_space', 'baths'], dtype=object)
```

In [34]:

```
X = z.drop(columns=columns_to_remove)
```

In [35]:

```
name_list = list(X.columns.values)
```

In [36]:

```
# split data in to training and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4
```

Lasso

In [37]:

```
lasso_model = Lasso().fit(X_train, y_train)
```

```
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 252181185368.77197, tolerance: 391652989.5874466
  model = cd_fast.enet_coordinate_descent(
```

In [38]:

```
# display model coefficients and r-sqaured scores
print('Coefficient:', lasso_model.coef_)
print('Scores:', lasso_model.score(X_train, y_train), lasso_model.score(X_test, y_test)
```

```
Coefficient: [ -184.8503518  16919.65968894  4601.01154766   773.00000906
   242.8726669     47.86135961 12663.89886906  -146.81819531
  9517.1057251     38.50881059   441.93502156  -261.3806402 ]
Scores: 0.7850997031385983 0.8452896114591302
```

In [39]:

```python
y_prediction = lasso_model.predict(X_test)
```

In [40]:

```python
RMSE = sqrt(mean_squared_error(y_true = y_test, y_pred = y_prediction))
print(RMSE)
```

```
23671.36807136452
```

In [41]:

```python
# K-fold CV
score_lasso = cross_val_score(lasso_model, X_train, y_train, cv=10)
score_lasso
```

```
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 159442389699.83508, tolerance: 349942370.4286453
  model = cd_fast.enet_coordinate_descent(
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 240491473312.28214, tolerance: 358098534.9982602
  model = cd_fast.enet_coordinate_descent(
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 257471428599.45276, tolerance: 352103963.30287695
  model = cd_fast.enet_coordinate_descent(
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 234137496056.25336, tolerance: 350488682.0942842
  model = cd_fast.enet_coordinate_descent(
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 224939046827.40213, tolerance: 354871608.4190128
  model = cd_fast.enet_coordinate_descent(
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 235702317972.3842, tolerance: 353892070.0463491
  model = cd_fast.enet_coordinate_descent(
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 228559442578.34668, tolerance: 358505522.52503693
  model = cd_fast.enet_coordinate_descent(
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 234993704730.1338, tolerance: 354596261.958572
  model = cd_fast.enet_coordinate_descent(
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 204457064914.1339, tolerance: 342271461.336998
  model = cd_fast.enet_coordinate_descent(
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:53
0: ConvergenceWarning: Objective did not converge. You might want to increase the number
of iterations. Duality gap: 228607664943.06372, tolerance: 349753857.90445185
  model = cd_fast.enet_coordinate_descent(
```

Out[41]:

```
array([0.21617453, 0.81793705, 0.814242  , 0.80530174, 0.84199673,
       0.77720259, 0.83293262, 0.86101777, 0.84267756, 0.83439144])
```

In [42]:
```
print("CV mean score:", score_lasso.mean())
print("CV mean std dev score:", score_lasso.std())
```

```
CV mean score: 0.7643874019363353
CV mean std dev score: 0.1840699886195586
```

Ridge

In [43]:
```
ridge_model = Ridge().fit(X_train, y_train)
```

In [44]:
```
# display model coefficients and r-sqaured scores
print('Coefficient:', ridge_model.coef_)
print('Scores:', ridge_model.score(X_train, y_train), ridge_model.score(X_test, y_test)
```

```
Coefficient: [ -184.89174119 16898.96824051  4600.54796505   110.86242785
   242.67866877    47.90472505 12623.20965672  -159.96286104
  9500.41241026    38.55707027   441.83585603   401.52193551]
Scores: 0.7850995219712469 0.8452618243769616
```

In [45]:
```
y_prediction = ridge_model.predict(X_test)
```

In [46]:
```
RMSE = sqrt(mean_squared_error(y_true = y_test, y_pred = y_prediction))
print(RMSE)
```

```
23673.493748650915
```

In [47]:
```
# K-fold CV
score_ridge = cross_val_score(ridge_model, X, y, cv=10)
score_ridge
```

Out[47]:
```
array([0.85424213, 0.82381643, 0.84794958, 0.69904866, 0.80175182,
       0.84572206, 0.86013341, 0.84208571, 0.45201179, 0.80802269])
```

In [48]:
```
print("CV mean score:", score_ridge.mean())
print("CV mean std dev score:", score_ridge.std())
```

```
CV mean score: 0.783478428785822
CV mean std dev score: 0.11912645070598336
```

ElasticNet

In [49]:
```
# assigning the 3 predictor variables with the highest correlation coefficient
y = df4['SalePrice']
# split data in to training and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4
```

In [50]:
```
elasticnet_model = ElasticNetCV().fit(X_train, y_train)
print('alpha: %f' % elasticnet_model.alpha_)
print('l1_ratio_: %f' % elasticnet_model.l1_ratio_)
```

```
alpha: 38192.218001
l1_ratio_: 0.500000
```

In [51]:
```
# display model coefficients and r-sqaured scores
print('Coefficient:', elasticnet_model.coef_)
print('Scores:', elasticnet_model.score(X_train, y_train), elasticnet_model.score(X_tes
```

```
Coefficient: [-17.22392455   0.60378846  -0.          37.30089983  20.67096224
  74.35217833   0.          -0.           0.           6.05083074
   0.          37.29217547]
Scores: 0.4777999630212376 0.47266375696458496
```

In [52]:
```
y_prediction = elasticnet_model.predict(X_test)
```

In [53]:
```
RMSE = sqrt(mean_squared_error(y_true = y_test, y_pred = y_prediction))
print(RMSE)
```

```
43702.615614180504
```

In [54]:
```
# K-fold CV
score_en = cross_val_score(elasticnet_model, X_train, y_train, cv=10)
score_en
```

Out[54]:
```
array([0.19161431, 0.44163616, 0.4326376 , 0.44292176, 0.59162816,
       0.56427655, 0.56562971, 0.48415912, 0.50829106, 0.4319808 ])
```

In [55]:
```
print("CV mean score:", score_en.mean())
print("CV mean std dev score:", score_en.std())
```

```
CV mean score: 0.4654775219223496
CV mean std dev score: 0.10778052509578841
```

Tuning hyperparameters for ElasticNetCV():

In [56]:
```
def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn
```

In [57]:
```
# define model evaluation method
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)

# define model
ratios = arange(0, 1, 0.01)

alphas = [1e-5, 1e-4, 1e-3, 1e-2, 1e-1, 0.0, 1.0, 10.0, 100.0]

model = ElasticNetCV(l1_ratio=ratios, alphas=alphas, cv=cv, n_jobs=-1);

# fit model
model.fit(X_train, y_train)
elasticnet_tuned_model = model.fit(X_train, y_train)

warnings.filterwarnings("ignore")
```

In [58]:
```
# summarize chosen configuration
print('alpha: %f' % elasticnet_tuned_model.alpha_)
```

```
print('l1_ratio_: %f' % elasticnet_tuned_model.l1_ratio_)
```

```
alpha: 0.100000
l1_ratio_: 0.750000
```

In [59]:
```
score_en_2 = cross_val_score(elasticnet_tuned_model, X_train, y_train, scoring='r2', cv
warnings.filterwarnings("ignore")
```

In [60]:
```
print("CV mean score:", score_en_2.mean())
print("CV mean std dev score:", score_en_2.std())
```

```
CV mean score: 0.7648433160971997
CV mean std dev score: 0.18398241474890692
```

Linear Regression Models

Liner Regression Model One ([OverallQual] [GRliveArea] [GarageCars])

In [61]:
```
# assigning the 3 predictor variables with the highest correlation coefficient
features = ['OverallQual', 'GrLivArea', 'GarageCars']
```

In [62]:
```
X = df4[features]
```

In [63]:
```
y = df4['SalePrice']
```

In [64]:
```
# split data in to training and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4
```

In [65]:
```
# creating linear regression model
model_1 = LinearRegression().fit(X_train, y_train)
```

In [66]:
```
# display model coefficients and r-sqaured scores
print('Coefficient:', model_1.coef_)
print('Scores:', model_1.score(X_train, y_train), model_1.score(X_test, y_test))
```

```
Coefficient: [22538.88119918    38.51336476 20167.98961928]
Scores: 0.7206411884255531 0.7741153103217534
```

In [67]:
```
# predicted housing prices
y_prediction = model_1.predict(X_test)
```

In [68]:
```
# model RMSE
RMSE = sqrt(mean_squared_error(y_true = y_test, y_pred = y_prediction))
print(RMSE)
```

```
28602.699133713417
```

In [69]:

```
# k-fold CV
scores_1 = cross_val_score(model_1, X_train, y_train, scoring='r2', cv=5)
scores_1
```

Out[69]: array([0.49854734, 0.7155773 , 0.7375631 , 0.77589921, 0.78229407])

In [70]:

```
print("mean cv score:", scores_1.mean())
print("std dev cv score:", scores_1.std())
```

```
mean cv score: 0.7019762044171018
std dev cv score: 0.10464252297556577
```

Liner Regression Model Two ([OverallQual])

In [71]:

```
x = df4['OverallQual'].values.reshape((-1, 1))
y = df4['SalePrice']

# split data in to training and test data
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=4

# creating linear regression model
model_2 = LinearRegression().fit(X_train, y_train)

# display model coefficients and r-sqaured scores
print('Coefficient:', model_2.coef_)
print('Scores:', model_2.score(X_train, y_train), model_2.score(X_test, y_test))

# predicted housing prices
y_prediction = model_2.predict(X_test)

# model RMSE
RMSE = sqrt(mean_squared_error(y_true = y_test, y_pred = y_prediction))
print('RMSE:', RMSE)
```

```
Coefficient: [37061.76313825]
Scores: 0.5904688256569957 0.6768312441106439
RMSE: 34211.9873818558
```

In [72]:

```
# k-fold CV
scores_2 = cross_val_score(model_2, X_train, y_train, scoring='r2', cv=5)
scores_2
```

Out[72]: array([0.45569586, 0.58430409, 0.58196803, 0.63339208, 0.65503852])

In [73]:

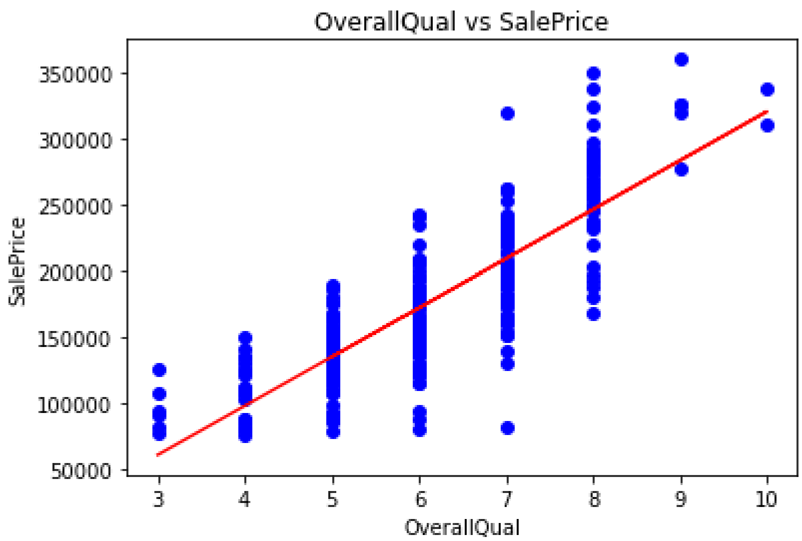
```
print("mean cv score:", scores_2.mean())
print("std dev cv score:", scores_2.std())
```

```
mean cv score: 0.5820797157345505
std dev cv score: 0.06918639380526288
```

In [74]:

```
plt.scatter(X_test, y_test, color = "blue")
plt.plot(X_train, model_2.predict(X_train), color = "red")
plt.title("OverallQual vs SalePrice")
plt.xlabel("OverallQual")
```

```
plt.ylabel("SalePrice")
plt.show()
```



Liner Regression Model Three ([qual_space])

In [75]:
```
x = df4['qual_space'].values.reshape((-1, 1))
y = df4['SalePrice']

# split data in to training and test data
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=4

# creating linear regression model
model_3 = LinearRegression().fit(X_train, y_train)

# display model coefficients and r-sqaured scores
print('Coefficient:', model_3.coef_)
print('Scores:', model_3.score(X_train, y_train), model_3.score(X_test, y_test))

# predicted housing prices
y_prediction = model_3.predict(X_test)

# model RMSE
RMSE = sqrt(mean_squared_error(y_true = y_test, y_pred = y_prediction))
print(RMSE)
```

```
Coefficient: [6.18124111]
Scores: 0.6121381394496235 0.7881827084140843
27697.739433000243
```

In [76]:
```
# k-fold CV
scores_3 = cross_val_score(model_3, X_train, y_train, scoring='r2', cv=5)
scores_3
```

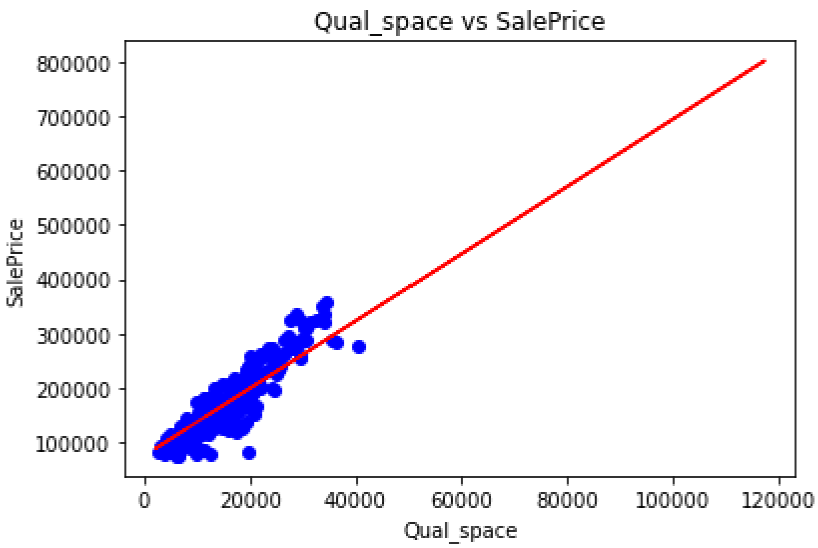
Out[76]:
```
array([-0.48826011,  0.72447673,  0.72755186,  0.76212847,  0.73907445])
```

In [77]:
```
print("mean cv score:", scores_3.mean())
print("std dev cv score:", scores_3.std())
```

```
mean cv score: 0.49299427905186183
```

```
std dev cv score: 0.490805507437618
```

In [78]:
```
plt.scatter(X_test, y_test, color = "blue")
plt.plot(X_train, model_3.predict(X_train), color = "red")
plt.title("Qual_space vs SalePrice")
plt.xlabel("Qual_space")
plt.ylabel("SalePrice")
plt.show()
```



Liner Regression Model Four ([qual_space] and [GarageCars])

In [79]:
```
features_2 = ['qual_space', 'GarageCars']
```

In [80]:
```
x = df4[features_2]
```

In [81]:
```
# split data in to training and test data
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=4
```

In [82]:
```
# creating linear regression model
model_4 = LinearRegression().fit(X_train, y_train)

# display model coefficients and r-sqaured scores
print('Coefficient:', model_4.coef_)
print('Scores:', model_4.score(X_train, y_train), model_4.score(X_test, y_test))
```

```
Coefficient: [4.98130032e+00 2.37770262e+04]
Scores: 0.6740395847353984 0.7992757120508557
```

In [83]:
```
# predicted housing prices
y_prediction = model_4.predict(X_test)

# model RMSE
RMSE = sqrt(mean_squared_error(y_true = y_test, y_pred = y_prediction))
print(RMSE)
```

```
26962.7126297012
```

In [84]:
```
# k-fold CV
scores_4 = cross_val_score(model_4, X_train, y_train, scoring='r2', cv=5)
scores_4
```

Out[84]:
```
array([-0.24877286,  0.76434323,  0.73928354,  0.77900656,  0.77871593])
```

In [85]:
```
print("mean cv score:", scores_4.mean())
print("std dev cv score:", scores_4.std())
```

```
mean cv score: 0.5625152805883451
std dev cv score: 0.405901757942075
```

When comparing the linear regression models above, the final model using [OverallQual] and [GarageCars] produced the lowest Root Mean Square Error (RMSE). However, the results appear to have slight instability. Using k-fold cross validation, Model 1 has the highest mean score and lowest standard deviation.

Testing

In [86]:
```
# create dataframe using test data from kaggle
df_test = pd.read_csv("test.csv")
```

In [87]:
```
# replace NaN values with zero for the test data
df_test = df_test.fillna(0)
```

In [88]:
```
# sum 1st floor, 2nd floor, and basement square footage to get total square footage
sum_column = df_test['1stFlrSF'] + df_test['2ndFlrSF'] + df_test['TotalBsmtSF']

# multiply total square footage by overall quality to generate new predictor variable q
mult_column = sum_column*df_test['OverallQual']

#Sum the baths and the halfbaths
bath_column = df_test['FullBath'] + 0.5*df_test['HalfBath']

#Create a newness score (YearBuilt + (YearRemodAdd/YearBuilt))
newness_column = df_test['YearBuilt'] + (df_test['YearRemodAdd'] / df_test['YearBuilt']

# add new predictor variables to dataframe
df_test['tot_sq'] = sum_column
df_test['qual_space'] = mult_column
df_test['baths'] = bath_column
df_test['newness_value'] = newness_column
```

Linear Regression Model One

In [89]:
```
features_test = ['OverallQual', 'GrLivArea', 'GarageCars']
```

In [90]:
```
X = df_test[features_test]
```

In [91]:

```
test_prediction_linear = model_1.predict(X)
```

Lasso, Ridge, and ElasticNet

In [92]:

```
X = df_test[name_list]
```

In [93]:

```
test_prediction_lasso = lasso_model.predict(X)
test_prediction_ridge = ridge_model.predict(X)
test_prediction_elasticnet = elasticnet_tuned_model.predict(X)
```

In [95]:

```
#from google.colab import files

df_linear = pd.DataFrame({'id':df_test['Id'], 'SalePrice':test_prediction_linear})
df_lasso = pd.DataFrame({'id':df_test['Id'], 'SalePrice':test_prediction_lasso})
df_ridge = pd.DataFrame({'id':df_test['Id'], 'SalePrice':test_prediction_ridge})
df_elasticnet = pd.DataFrame({'id':df_test['Id'], 'SalePrice':test_prediction_elasticne

df_linear.to_csv('group_5_linear_m3.csv', index=False)
df_lasso.to_csv('group_5_lasso_m3.csv', index=False)
df_ridge.to_csv('group_5_ridge_m3.csv', index=False)
df_elasticnet.to_csv('group_5_elasticnet_m3.csv', index=False)

# files.download('group_5_linear_m3.csv')
# files.download('group_5_lasso_m3.csv')
# files.download('group_5_ridge_m3.csv')
# files.download('group_5_elasticnet_m3.csv')
```