Imports and reading in the csv

In [370…

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import scipy.stats as stats
import math
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn import ensemble
from sklearn.utils import shuffle
from sklearn.model_selection import cross_val_score
```

In [371…

```
df_train = pd.read_csv('train_house_price.csv')
df_test = pd.read_csv('test.csv')
dependentVariable = df_train['SalePrice']

df_train
```

Out[371…

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

1460 rows × 81 columns

Create at least one feature from the data set.

In [372…

```
df_train['LivingLotAreaRatio'] = df_train.GrLivArea / df_train.LotArea
```

Conduct EDA and provide appropriate visualizations in the process.

In [373…

```
df_train.head()
```

Out[373…

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

5 rows × 82 columns

There are a lot of missing values in certain features - we must filter or clean the data so then we can begin modeling

In [374…

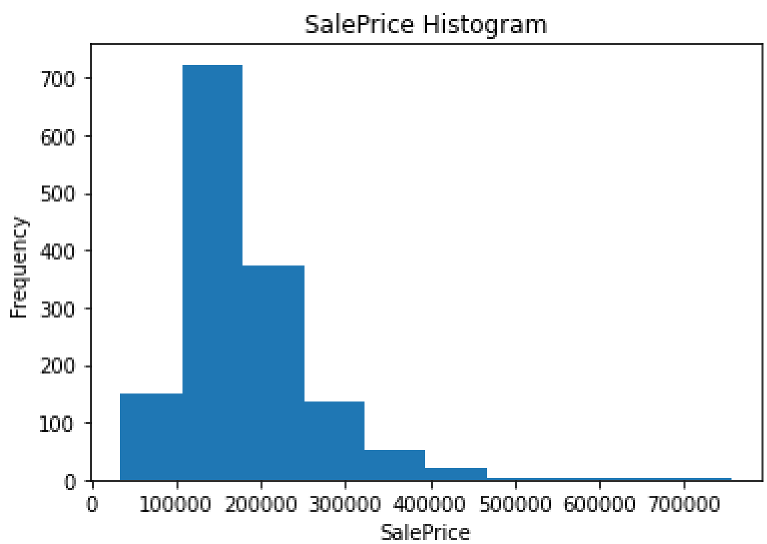
```
print(df_train.describe())
```

```
                Id   MSSubClass  LotFrontage        LotArea  OverallQual  \
count  1460.000000  1460.000000  1201.000000    1460.000000  1460.000000   
mean    730.500000    56.897260    70.049958   10516.828082     6.099315   
std     421.610009    42.300571    24.284752    9981.264932     1.382997   
min       1.000000    20.000000    21.000000    1300.000000     1.000000   
25%     365.750000    20.000000    59.000000    7553.500000     5.000000   
50%     730.500000    50.000000    69.000000    9478.500000     6.000000   
75%    1095.250000    70.000000    80.000000   11601.500000     7.000000   
max    1460.000000   190.000000   313.000000  215245.000000    10.000000   

       OverallCond    YearBuilt  YearRemodAdd   MasVnrArea   BsmtFinSF1  ...  \
count  1460.000000  1460.000000   1460.000000  1452.000000  1460.000000  ...   
mean      5.575342  1971.267808   1984.865753   103.685262   443.639726  ...   
std       1.112799    30.202904     20.645407   181.066207   456.098091  ...   
min       1.000000  1872.000000   1950.000000     0.000000     0.000000  ...   
25%       5.000000  1954.000000   1967.000000     0.000000     0.000000  ...   
50%       5.000000  1973.000000   1994.000000     0.000000   383.500000  ...   
75%       6.000000  2000.000000   2004.000000   166.000000   712.250000  ...   
max       9.000000  2010.000000   2010.000000  1600.000000  5644.000000  ...   

       OpenPorchSF  EnclosedPorch    3SsnPorch  ScreenPorch     PoolArea  \
count  1460.000000    1460.000000  1460.000000  1460.000000  1460.000000   
mean     46.660274      21.954110     3.409589    15.060959     2.758904   
std      66.256028      61.119149    29.317331    55.757415    40.177307   
min       0.000000       0.000000     0.000000     0.000000     0.000000   
25%       0.000000       0.000000     0.000000     0.000000     0.000000   
50%      25.000000       0.000000     0.000000     0.000000     0.000000   
75%      68.000000       0.000000     0.000000     0.000000     0.000000   
max     547.000000     552.000000   508.000000   480.000000   738.000000   

            MiscVal       MoSold       YrSold      SalePrice  \
count   1460.000000  1460.000000  1460.000000    1460.000000  
mean      43.489041     6.321918  2007.815753  180921.195890  
std      496.123024     2.703626     1.328095   79442.502883  
min        0.000000     1.000000  2006.000000   34900.000000  
25%        0.000000     5.000000  2007.000000  129975.000000  
```

```
50%         0.000000     6.000000  2008.000000  163000.000000
75%         0.000000     8.000000  2009.000000  214000.000000
max     15500.000000    12.000000  2010.000000  755000.000000

       LivingLotAreaRatio
count         1460.000000
mean             0.180590
std              0.111914
min              0.009459
25%              0.119041
50%              0.155687
75%              0.195149
max              0.945385

[8 rows x 39 columns]
```

In [375…

```
# testing normality - fairly normal
plt.hist(dependentVariable)
plt.xlabel('SalePrice')
plt.ylabel('Frequency')
plt.title('SalePrice Histogram')
plt.show()
```



In [376…

```
# Some possible features we can use to help train on, we explored further last w
# Using spearman correlation to leverage the ranking system
correlations = df_train.corr(method='spearman')['SalePrice'].sort_values(ascendi
correlations_abs = correlations.abs()
# showing low correlated features with SalePrice so we know to remove them
print('\nLow correlations (absolute):\n', correlations_abs.head(35))
```

```
Low correlations (absolute):
 EnclosedPorch         0.218394
KitchenAbvGr          0.164826
OverallCond           0.129325
LowQualFinSF          0.067719
MiscVal               0.062727
BsmtFinSF2            0.038806
YrSold                0.029899
Id                    0.018546
BsmtHalfBath          0.012189
MSSubClass            0.007192
```

```
PoolArea              0.058453
3SsnPorch             0.065440
MoSold                0.069432
ScreenPorch           0.100070
BsmtUnfSF             0.185197
LivingLotAreaRatio    0.197813
BsmtFullBath          0.225125
BedroomAbvGr          0.234907
2ndFlrSF              0.293598
BsmtFinSF1            0.301871
HalfBath              0.343008
WoodDeckSF            0.353802
LotFrontage           0.409076
MasVnrArea            0.421309
LotArea               0.456461
OpenPorchSF           0.477561
Fireplaces            0.519247
TotRmsAbvGrd          0.532586
YearRemodAdd          0.571159
1stFlrSF              0.575408
GarageYrBlt           0.593788
TotalBsmtSF           0.602725
FullBath              0.635957
GarageArea            0.649379
YearBuilt             0.652682
Name: SalePrice, dtype: float64
```

In [377…

```
# in order to clean our data, we drop the uneccesary features that were determin
# as well as duplicated features or unneccessary ones for training such as 'Id'
# Sadly the feature we created was deemed not as relevent as the others, thus we


train_data = df_train[['LotFrontage', 'OverallQual', 'YearBuilt', 'YearRemodAdd'
        'MasVnrArea', 'BsmtFinSF1', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'GrLi
       'FullBath', 'TotRmsAbvGrd', 'Fireplaces', 'GarageYrBlt', 'GarageCars',
       'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'SalePrice']]

test_data = df_test[['LotFrontage', 'OverallQual', 'YearBuilt', 'YearRemodAdd',
        'MasVnrArea','BsmtFinSF1', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'GrLiv
       'FullBath', 'TotRmsAbvGrd', 'Fireplaces', 'GarageYrBlt', 'GarageCars',
       'GarageArea', 'WoodDeckSF', 'OpenPorchSF']]
```

Data Cleaning & Pre-processing

In [378…

```
# the amount of missing data
nullTotals = train_data.isnull().sum().sort_values(ascending = False)
percentageOfNull = (train_data.isnull().sum() / df_train.isnull().count()).sort_
emptyVals = pd.concat([nullTotals, percentageOfNull], axis=1, keys=['Total Missi
emptyVals.head(20)
```

Out[378…

	Total Missing Values	Percentage of Feature Specific Data that is Null
LotFrontage	259.0	0.177397
GarageYrBlt	81.0	0.055479
MasVnrArea	8.0	0.005479

	Total Missing Values	Percentage of Feature Specific Data that is Null
FullBath	0.0	0.000000
OpenPorchSF	0.0	0.000000
WoodDeckSF	0.0	0.000000
GarageArea	0.0	0.000000
GarageCars	0.0	0.000000
Fireplaces	0.0	0.000000
TotRmsAbvGrd	0.0	0.000000
GrLivArea	0.0	0.000000
OverallQual	0.0	0.000000
2ndFlrSF	0.0	0.000000
1stFlrSF	0.0	0.000000
TotalBsmtSF	0.0	0.000000
BsmtFinSF1	0.0	0.000000
YearRemodAdd	0.0	0.000000
YearBuilt	0.0	0.000000
SalePrice	0.0	0.000000
3SsnPorch	NaN	NaN

In [379…

```
# deleting missing data that has more than 80% missing
train_data = train_data.drop((emptyVals[emptyVals['Total Missing Values'] > 81])
```

```
/var/folders/sz/wyddnfrs2pzfs3g11779b4g00000gn/T/ipykernel_47671/1755087760.py:
2: FutureWarning: In a future version of pandas all arguments of DataFrame.drop
except for the argument 'labels' will be keyword-only
  train_data = train_data.drop((emptyVals[emptyVals['Total Missing Values'] > 8
1]).index,1)
```

In [380…

```
# test data
nullTotals = test_data.isnull().sum().sort_values(ascending = False)
percentageOfNull = (test_data.isnull().sum() / df_train.isnull().count()).sort_v
emptyVals = pd.concat([nullTotals, percentageOfNull], axis=1, keys=['Total_Missi
emptyVals.head(20)
```

Out[380…

	Total_Missing_Values	Percentage of Feature Specific Data that is Null
LotFrontage	227.0	0.155479
GarageYrBlt	78.0	0.053425
MasVnrArea	15.0	0.010274
GarageArea	1.0	0.000685
BsmtFinSF1	1.0	0.000685
TotalBsmtSF	1.0	0.000685

	Total_Missing_Values	Percentage of Feature Specific Data that is Null
GarageCars	1.0	0.000685
TotRmsAbvGrd	0.0	0.000000
WoodDeckSF	0.0	0.000000
Fireplaces	0.0	0.000000
GrLivArea	0.0	0.000000
FullBath	0.0	0.000000
OverallQual	0.0	0.000000
2ndFlrSF	0.0	0.000000
1stFlrSF	0.0	0.000000
YearRemodAdd	0.0	0.000000
YearBuilt	0.0	0.000000
OpenPorchSF	0.0	0.000000
3SsnPorch	NaN	NaN
Alley	NaN	NaN

In [381…

```
# again dropping the features that contain A LOT of missing values
test_data = test_data.drop((emptyVals[emptyVals['Total_Missing_Values'] > 78]).i
```

```
/var/folders/sz/wyddnfrs2pzfs3g11779b4g00000gn/T/ipykernel_47671/138826562.py:2:
FutureWarning: In a future version of pandas all arguments of DataFrame.drop exc
ept for the argument 'labels' will be keyword-only
  test_data = test_data.drop((emptyVals[emptyVals['Total_Missing_Values'] > 7
8]).index,1)
```

In [382…

```
# showing which features still need cleaning in both test and training data

print(train_data.isnull().sum().sort_values(ascending=False).head(20))
print('____________________\n')
print(test_data.isnull().sum().sort_values(ascending=False).head(20))
```

```
GarageYrBlt     81
MasVnrArea       8
OverallQual      0
TotRmsAbvGrd     0
OpenPorchSF      0
WoodDeckSF       0
GarageArea       0
GarageCars       0
Fireplaces       0
FullBath         0
YearBuilt        0
GrLivArea        0
2ndFlrSF         0
1stFlrSF         0
TotalBsmtSF      0
BsmtFinSF1       0
YearRemodAdd     0
```

```
SalePrice        0
dtype: int64
```

```
GarageYrBlt     78
MasVnrArea      15
BsmtFinSF1       1
TotalBsmtSF      1
GarageArea       1
GarageCars       1
OverallQual      0
TotRmsAbvGrd     0
WoodDeckSF       0
Fireplaces       0
GrLivArea        0
FullBath         0
YearBuilt        0
2ndFlrSF         0
1stFlrSF         0
YearRemodAdd     0
OpenPorchSF      0
dtype: int64
```

In [383…

```
# replacing the possibly relevent features that have missing valus
# with the mean of their respective columns
train_data['GarageYrBlt'] = train_data['GarageYrBlt'].fillna(train_data['GarageY
train_data['MasVnrArea'] = train_data['MasVnrArea'].fillna(train_data['MasVnrAre
```

In [384…

```
test_data.isnull().sum().sort_values(ascending=False).head(20)
```

Out[384…

```
GarageYrBlt     78
MasVnrArea      15
BsmtFinSF1       1
TotalBsmtSF      1
GarageArea       1
GarageCars       1
OverallQual      0
TotRmsAbvGrd     0
WoodDeckSF       0
Fireplaces       0
GrLivArea        0
FullBath         0
YearBuilt        0
2ndFlrSF         0
1stFlrSF         0
YearRemodAdd     0
OpenPorchSF      0
dtype: int64
```

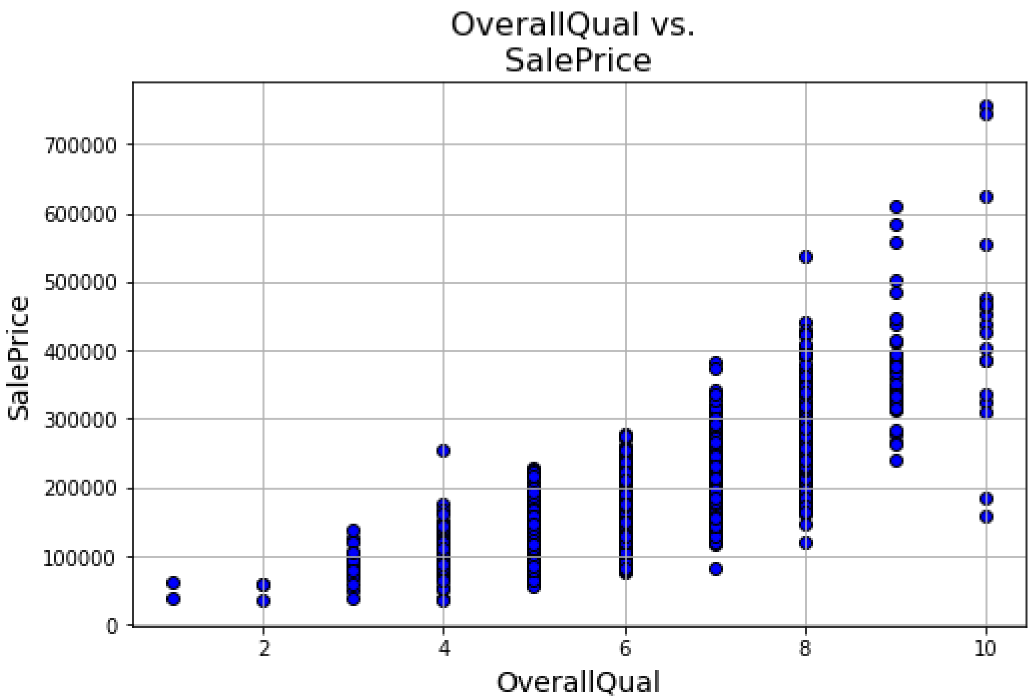
In [385…

```
# replacing areas in the test data that are missing with their means
test_data['MasVnrArea'] = test_data['MasVnrArea'].fillna(test_data['MasVnrArea']
test_data['TotalBsmtSF'] = test_data['TotalBsmtSF'].fillna(test_data['TotalBsmtS
test_data['GarageArea'] = test_data['GarageArea'].fillna(test_data['GarageArea']
test_data['BsmtFinSF1'] = test_data['BsmtFinSF1'].fillna(test_data['BsmtFinSF1']
test_data['GarageYrBlt'] = test_data['GarageYrBlt'].fillna(test_data['GarageYrBl
test_data['GarageCars'] = test_data['GarageCars'].fillna(test_data['GarageCars']
```

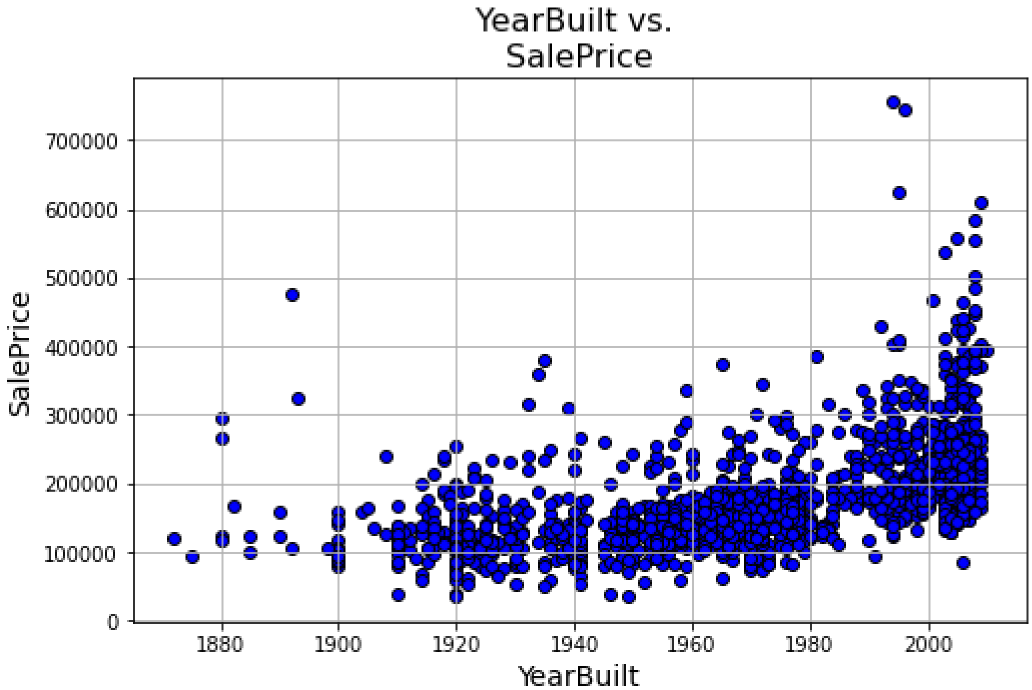
In [386…

```
for c in train_data.columns[:-1]:

        plt.figure(figsize=(8,5))
        plt.title("{} vs. \nSalePrice".format(c),fontsize=16)
        print(c)
        print(type(c))
        print(df_train[c].dtype.type)
        #if df_train[c]. !=
        plt.scatter(x=df_train[c],y=df_train['SalePrice'],color='blue',edgecolor
        plt.grid(True)
        plt.xlabel(c,fontsize=14)
        plt.ylabel('SalePrice',fontsize=14)
        plt.show()
```

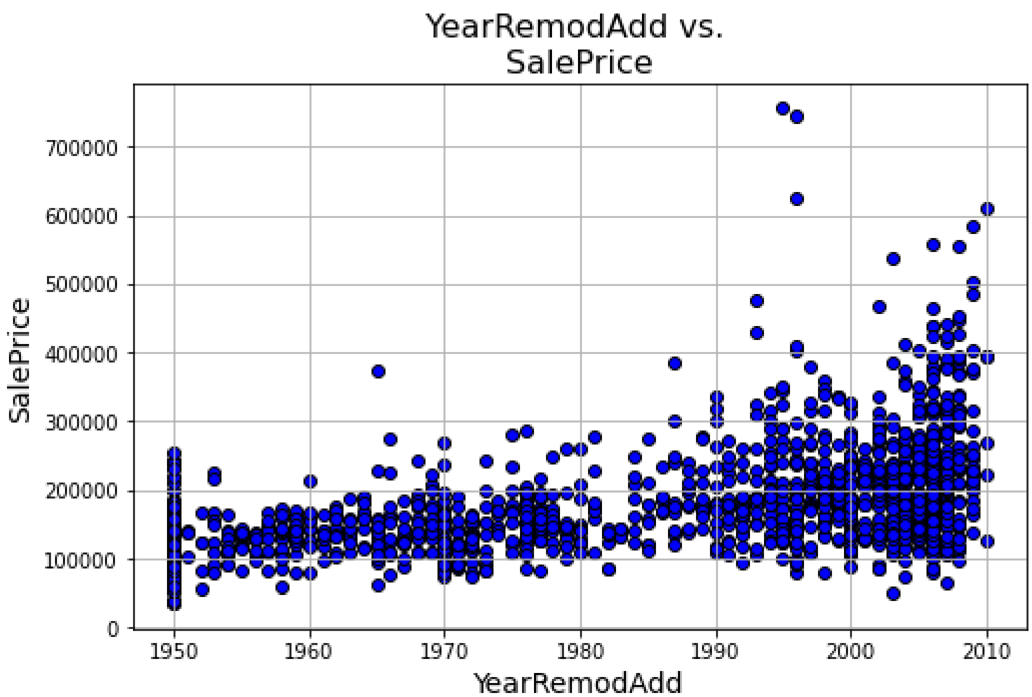
```
OverallQual
<class 'str'>
<class 'numpy.int64'>
```



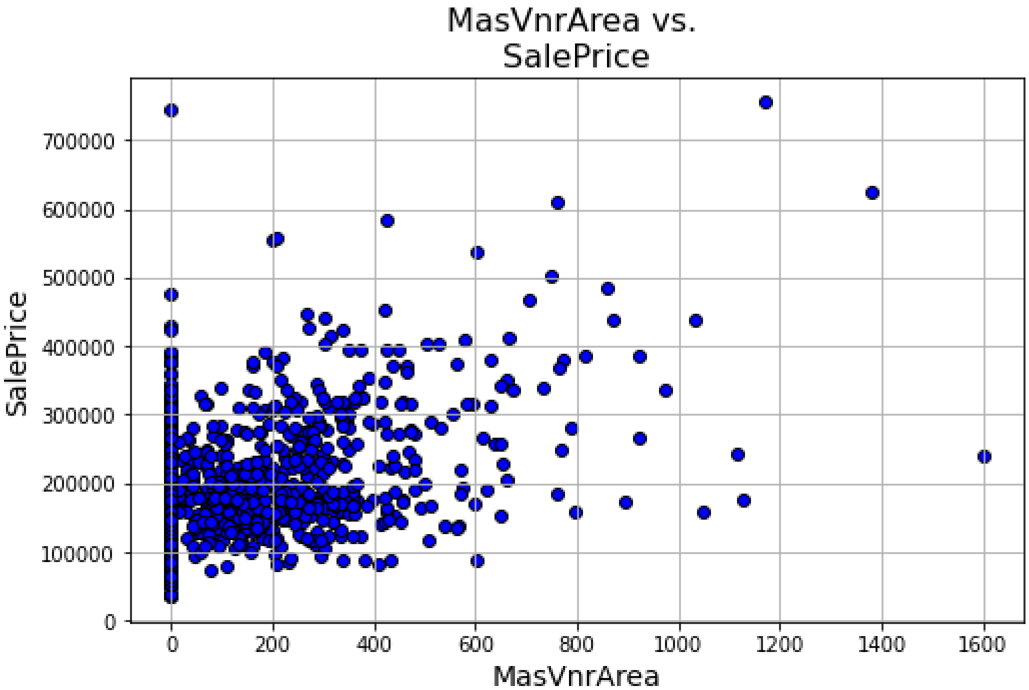

```
YearBuilt
<class 'str'>
<class 'numpy.int64'>
```



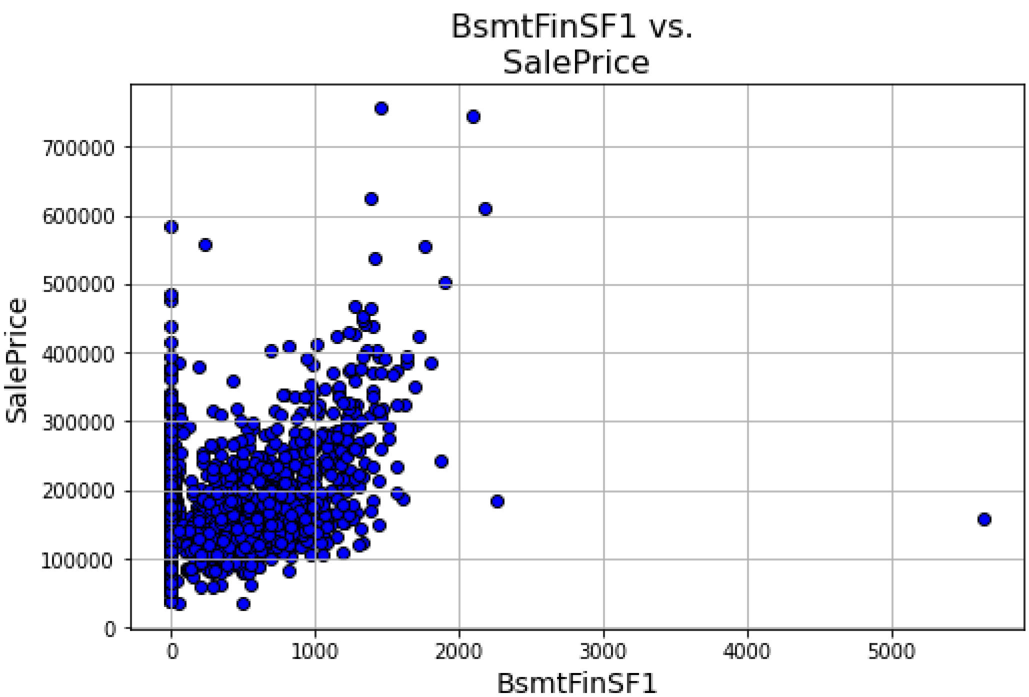

```
YearRemodAdd
<class 'str'>
<class 'numpy.int64'>
```



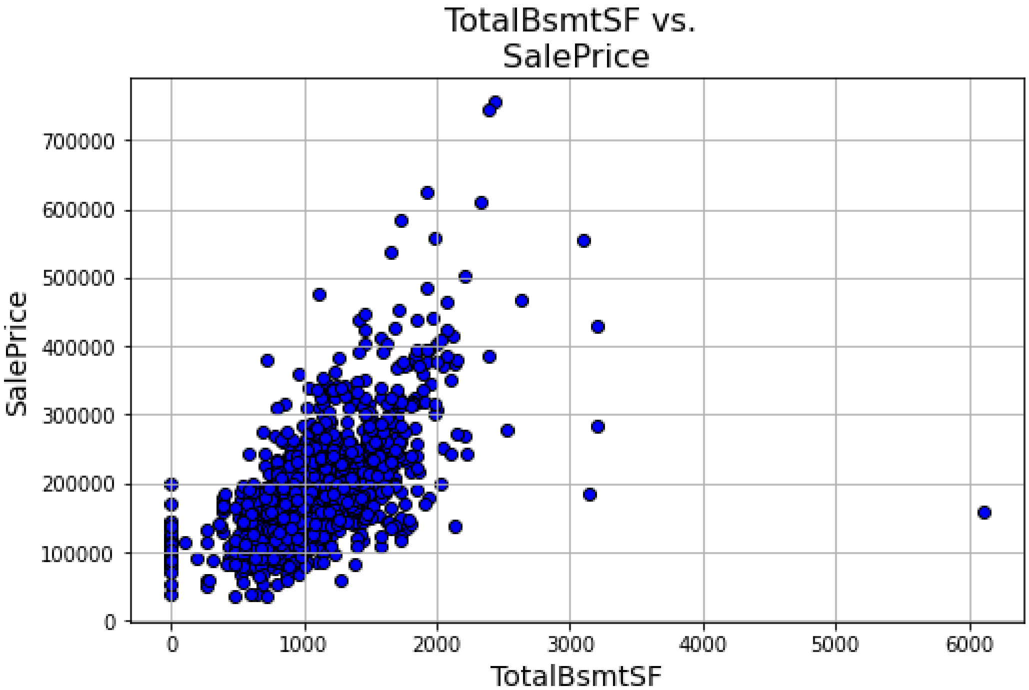

```
MasVnrArea
<class 'str'>
<class 'numpy.float64'>
```



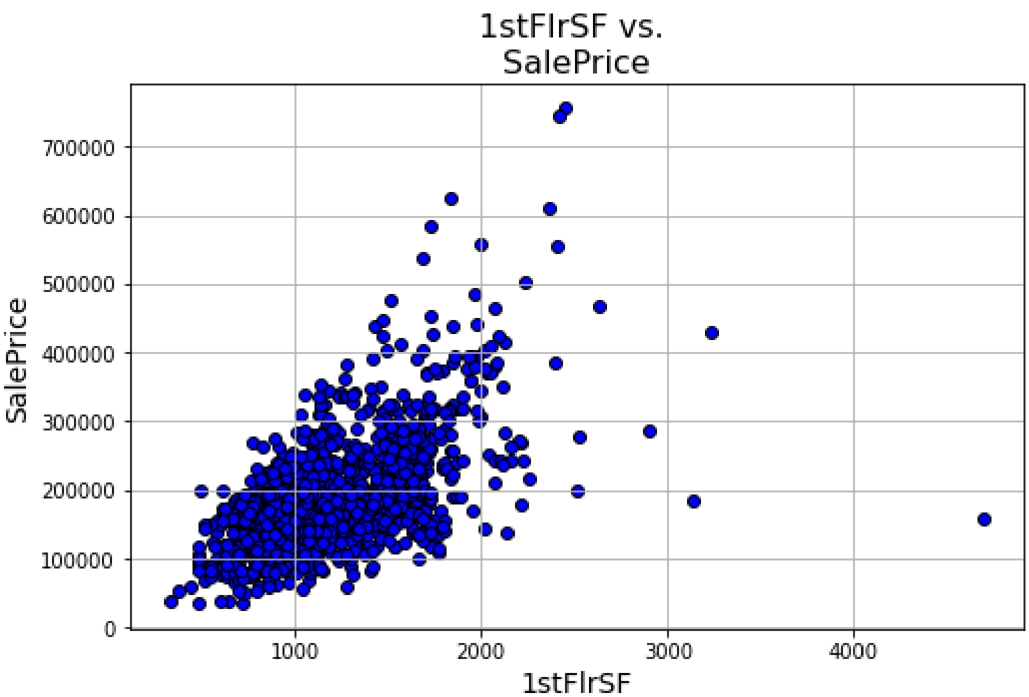

```
BsmtFinSF1
<class 'str'>
<class 'numpy.int64'>
```



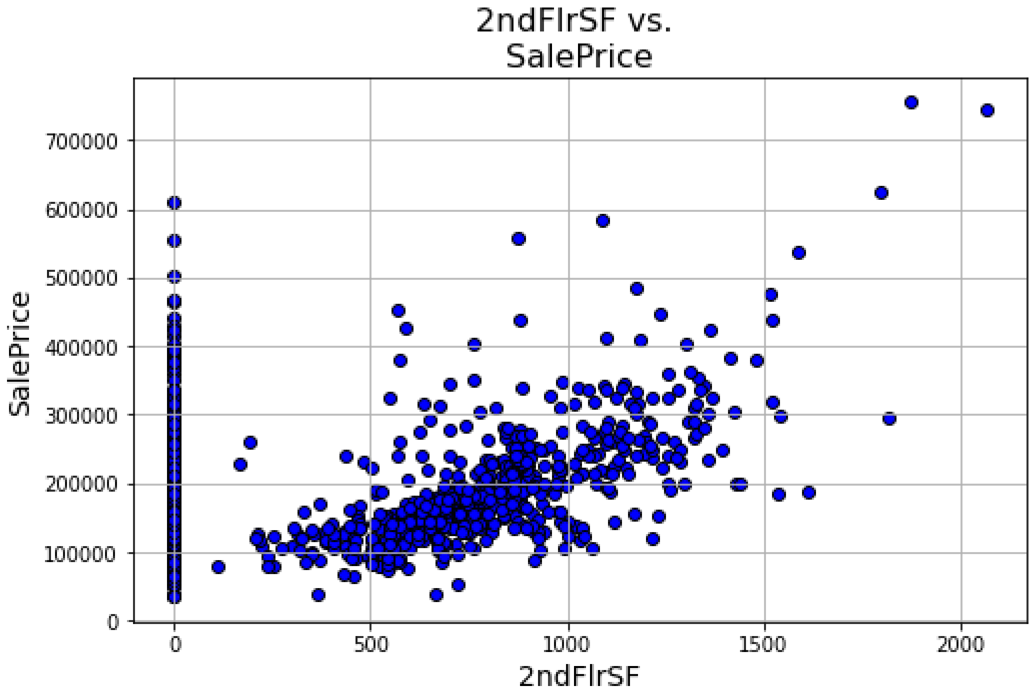

```
TotalBsmtSF
<class 'str'>
<class 'numpy.int64'>
```



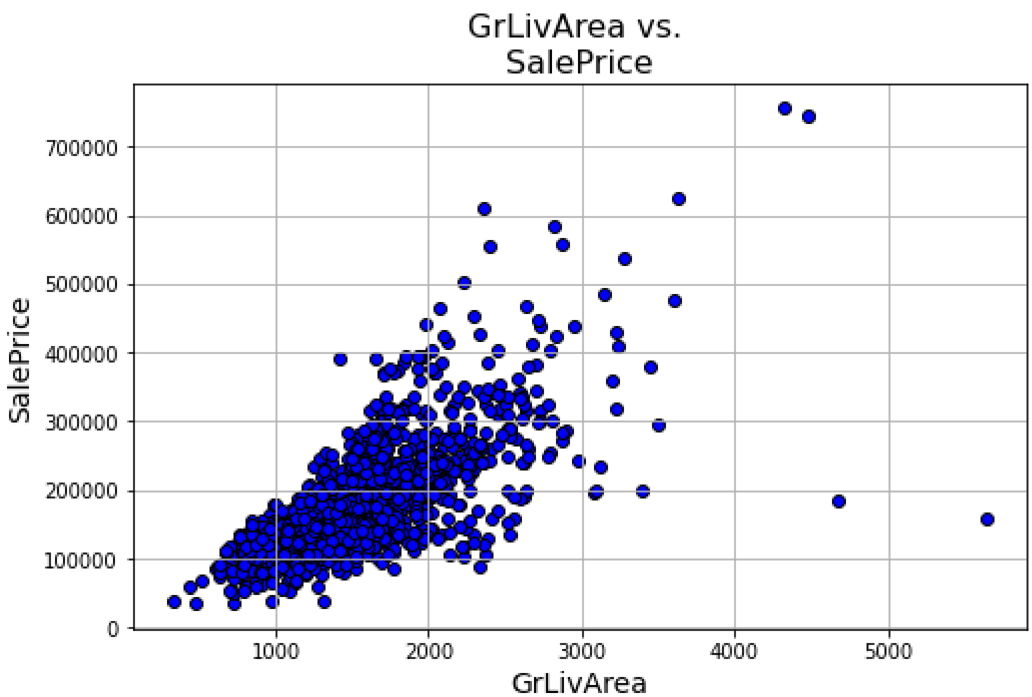

```
1stFlrSF
<class 'str'>
<class 'numpy.int64'>
```



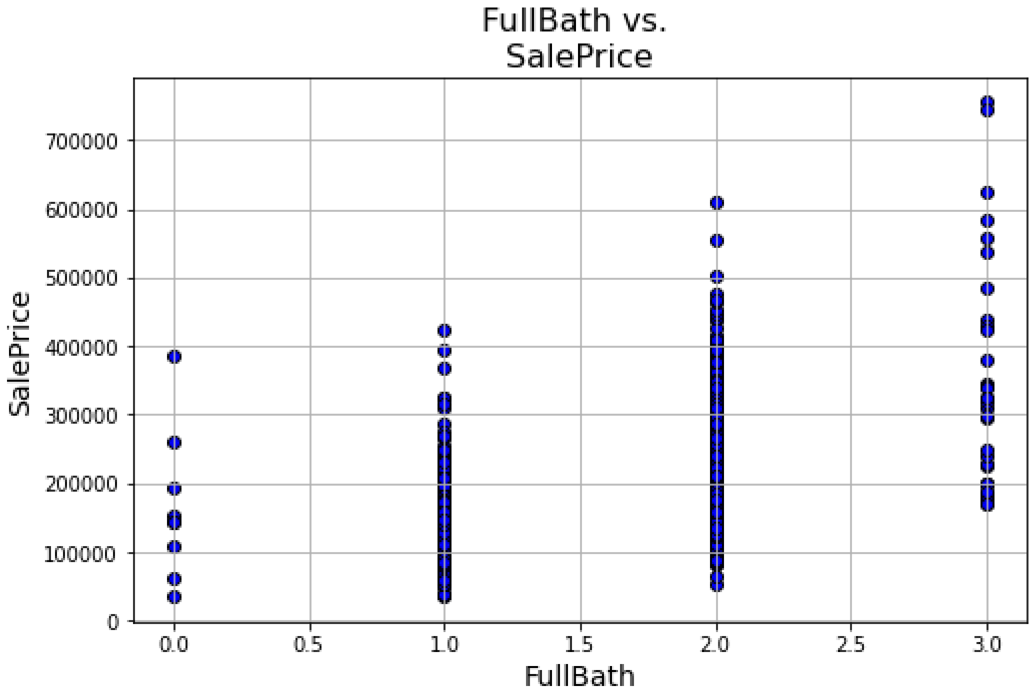

```
2ndFlrSF
<class 'str'>
<class 'numpy.int64'>
```



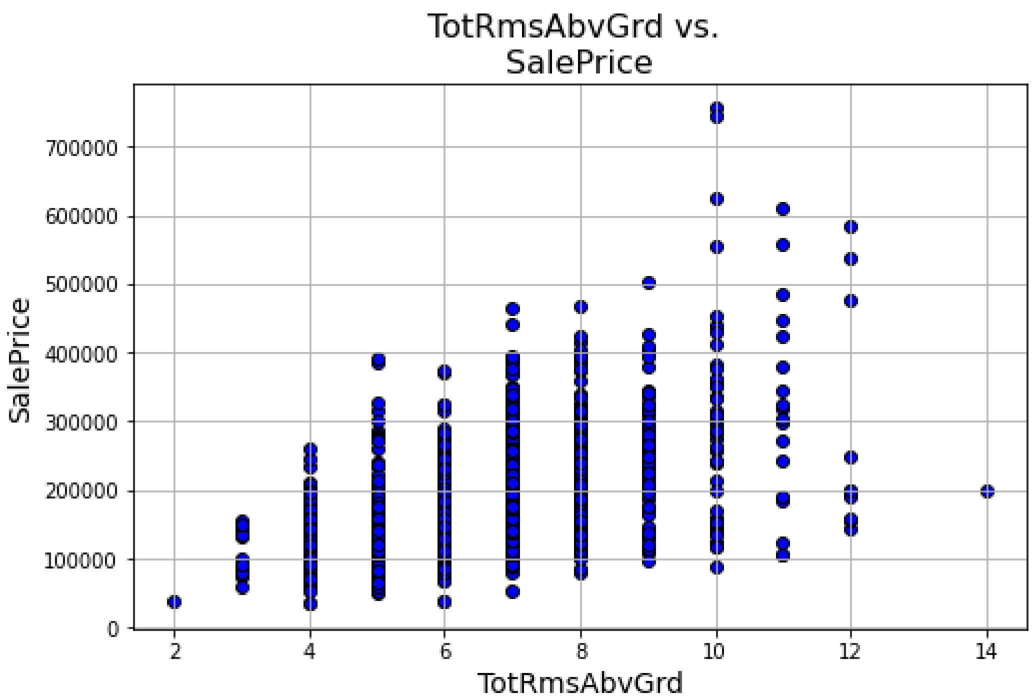

```
GrLivArea
<class 'str'>
<class 'numpy.int64'>
```



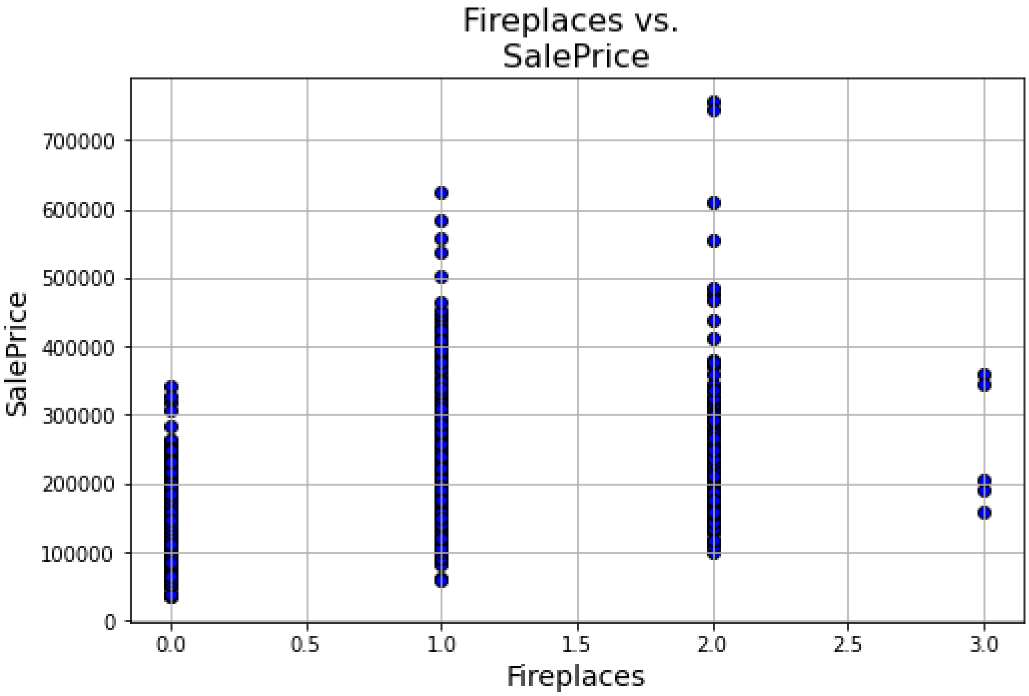

```
FullBath
<class 'str'>
<class 'numpy.int64'>
```



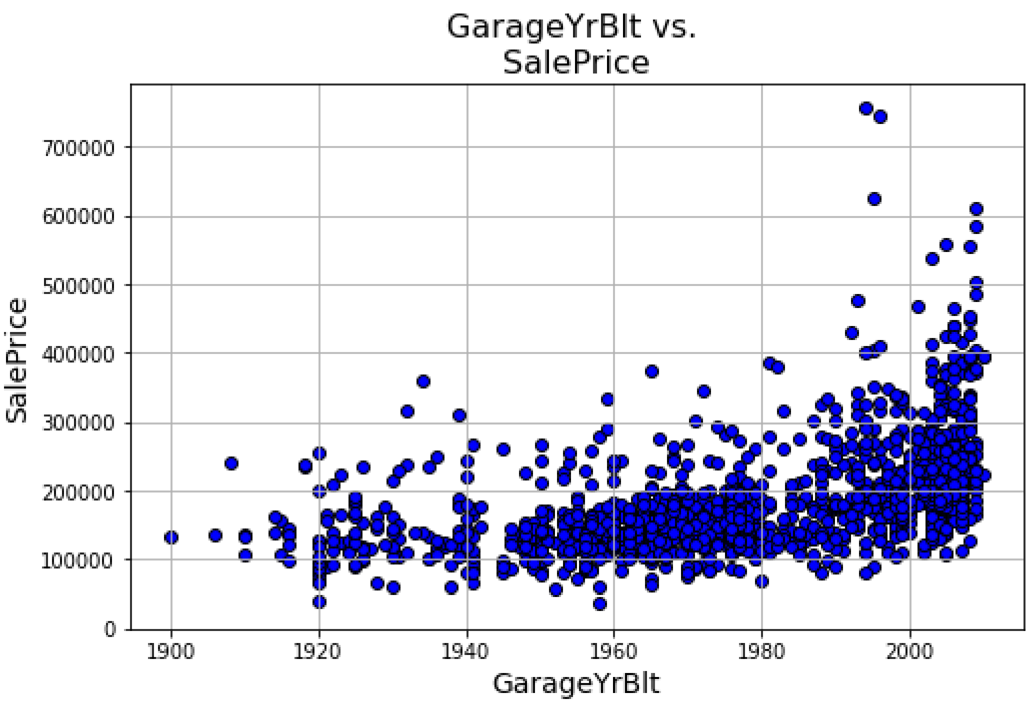

```
TotRmsAbvGrd
<class 'str'>
<class 'numpy.int64'>
```



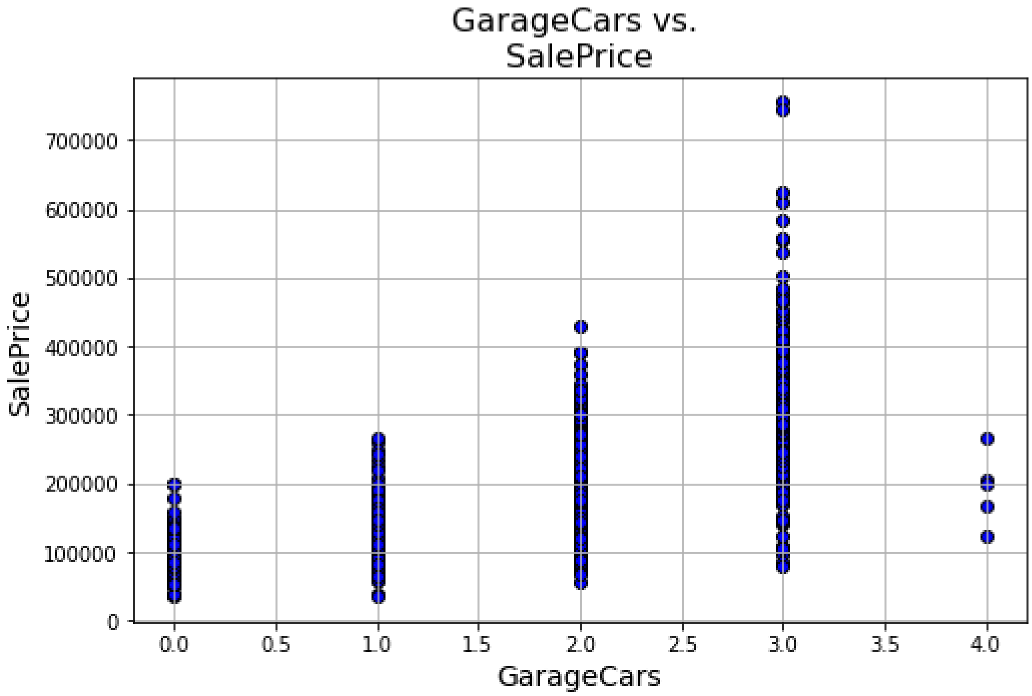

```
Fireplaces
<class 'str'>
<class 'numpy.int64'>
```



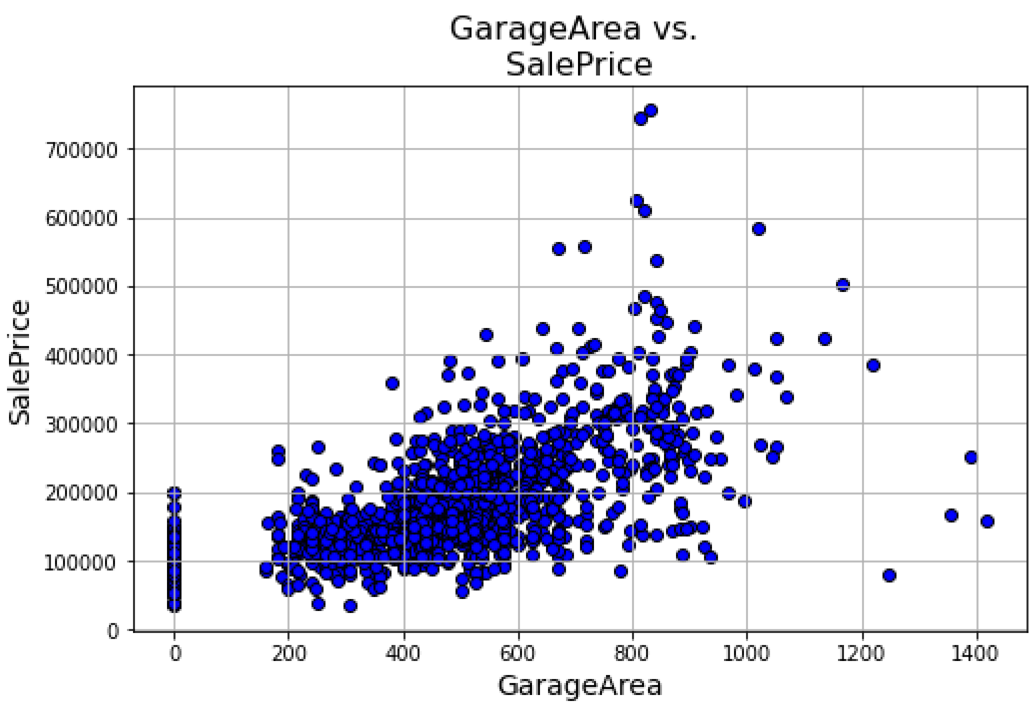

```
GarageYrBlt
<class 'str'>
<class 'numpy.float64'>
```



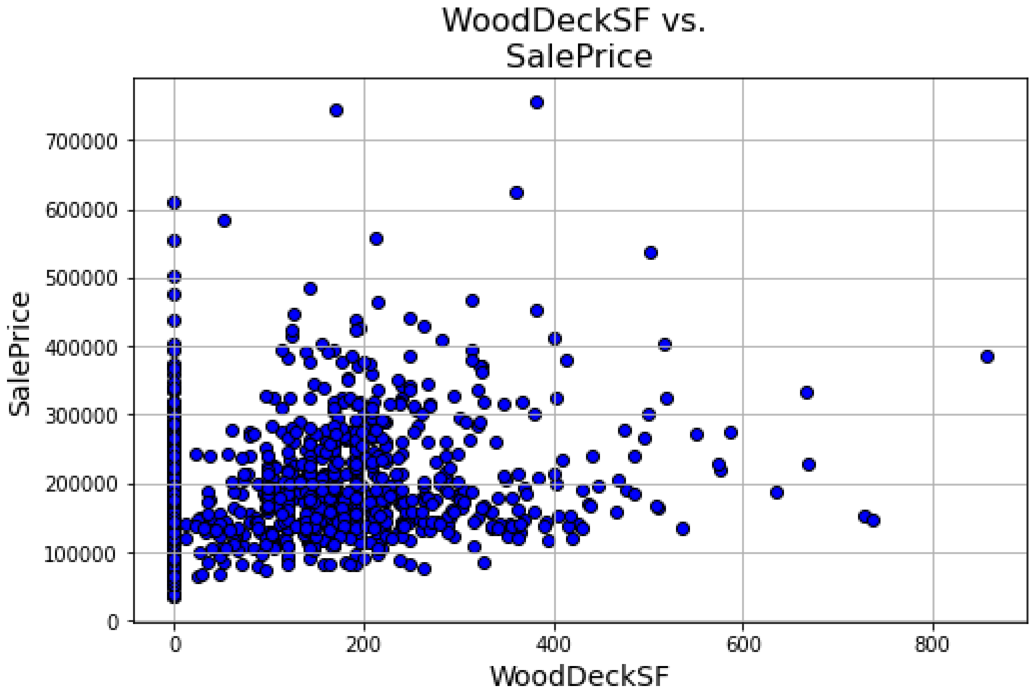

```
GarageCars
<class 'str'>
<class 'numpy.int64'>
```



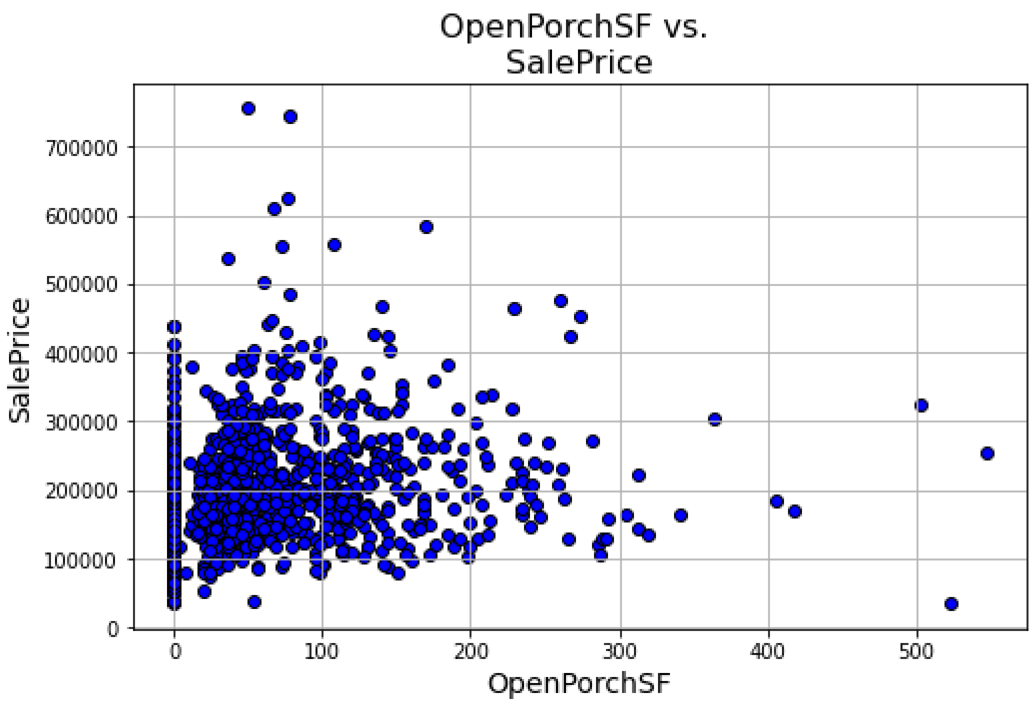

```
GarageArea
<class 'str'>
<class 'numpy.int64'>
```




```
WoodDeckSF
<class 'str'>
<class 'numpy.int64'>
```




```
OpenPorchSF
<class 'str'>
<class 'numpy.int64'>
```



Some of the features do not really offer a great idea or visualization between SalePrice and itself such as OpenPorchSf - we need to explore further to help understand the relevent features

Build a minimum of two separate regression models using the training set.

Conduct your analysis using a cross-validation design.

In [387…

```
# Creating the top 15 correlated features
cols = train_data.corr().nlargest(15, 'SalePrice')['SalePrice'].index
train_data_top_15 = train_data[cols]
```

In [388…

```
# splitting the training data by the top 15 correlated features
x_train, x_test, y_train, y_test = train_test_split(
    train_data_top_15.drop('SalePrice', axis=1), train_data_top_15['SalePrice'],
    test_size=0.3, random_state=101)
```

In [389…

```
x_test.columns
```

Out[389…

```
Index(['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'TotalBsmtSF',
       '1stFlrSF', 'FullBath', 'TotRmsAbvGrd', 'YearBuilt', 'YearRemodAdd',
       'MasVnrArea', 'GarageYrBlt', 'Fireplaces', 'BsmtFinSF1'],
      dtype='object')
```

In [390…

```
# in order for the data points to be of the same unit, we must scale the data

scalerX = StandardScaler()
scalerY = StandardScaler()

y_train= y_train.values.reshape(-1,1)
y_test= y_test.values.reshape(-1,1)


x_train = scalerX.fit_transform(x_train)
x_test = scalerX.fit_transform(x_test)
y_train = scalerX.fit_transform(y_train)
y_test = scalerY.fit_transform(y_test)
```

```
/Library/Frameworks/Python.framework/Versions/3.9/lib/python3.9/site-packages/sk
learn/base.py:441: UserWarning: X does not have valid feature names, but Standar
dScaler was fitted with feature names
  warnings.warn(
```

In [391…

```
# creating the LinearRegression model
lm = LinearRegression()
lm.fit(x_train,y_train)
print(lm.intercept_)
print(lm.coef_)
```

```
[6.60022817e-17]
[[ 0.29434388  0.31107005  0.05109985  0.06398884  0.11932473  0.02209143
  -0.044909    0.0334707   0.07675313  0.09456834  0.05714788  0.01910605
   0.04584189  0.1392006 ]]
```

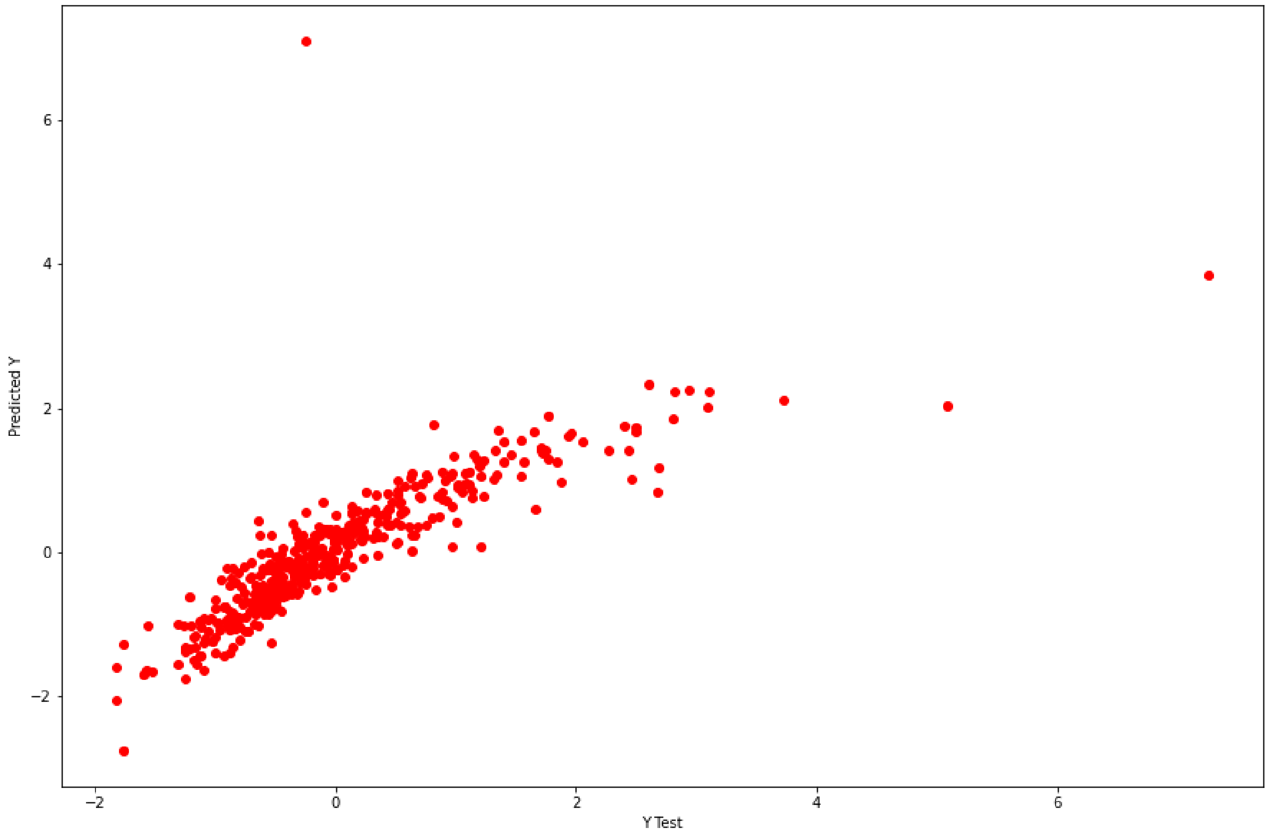
In [392…

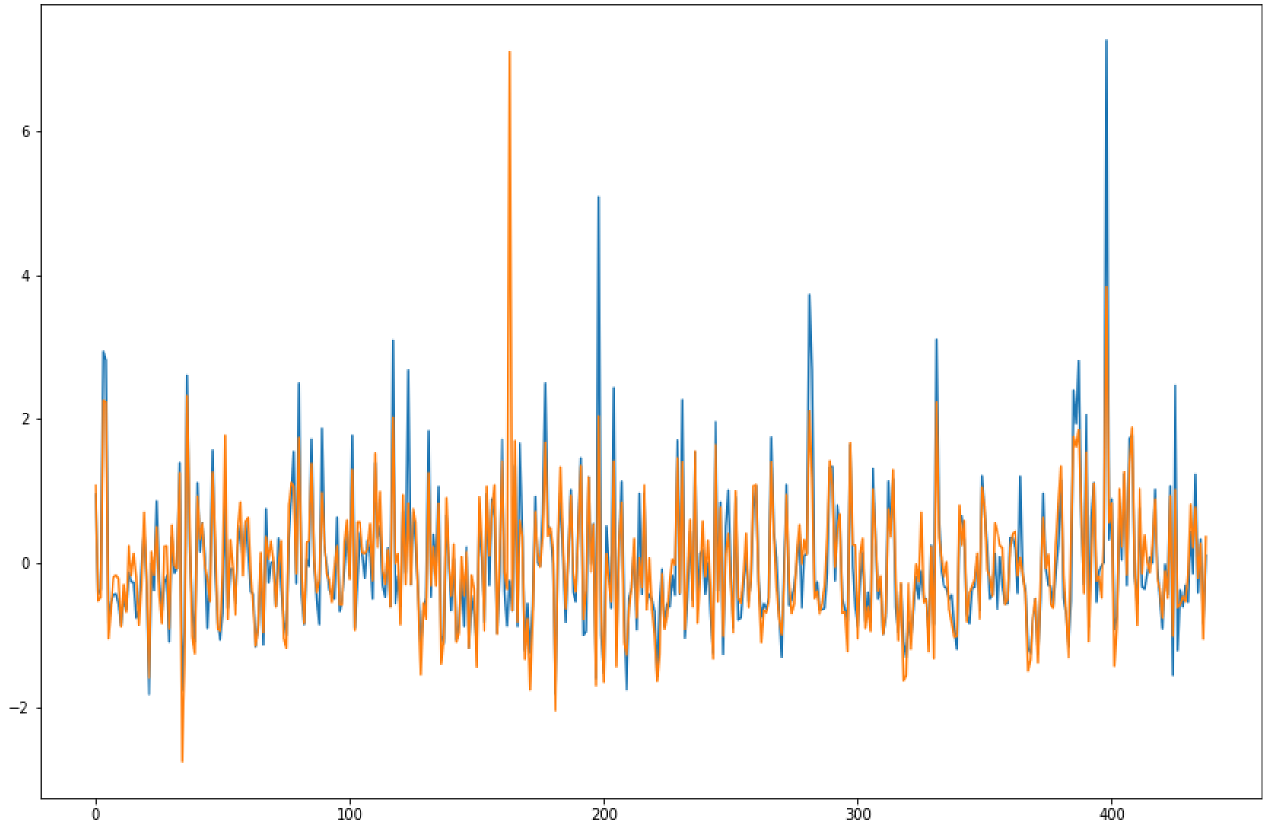
```
# creating predictions
predictions = lm.predict(x_test)
predictions = predictions.reshape(-1,1)
```

In [393…

```
# plotting our linear model based on the predictions
plt.figure(figsize=(15, 10))
plt.scatter(y_test,predictions, color = 'red')
plt.xlabel('Y Test')
```

```
plt.ylabel('Predicted Y')
plt.show()

# some of the outlying data can be seen that it does not fully predict it as we
plt.figure(figsize=(15, 10))
plt.plot(y_test,label = 'Test Data')
plt.plot(predictions, label = 'Predictions')
plt.show()
```

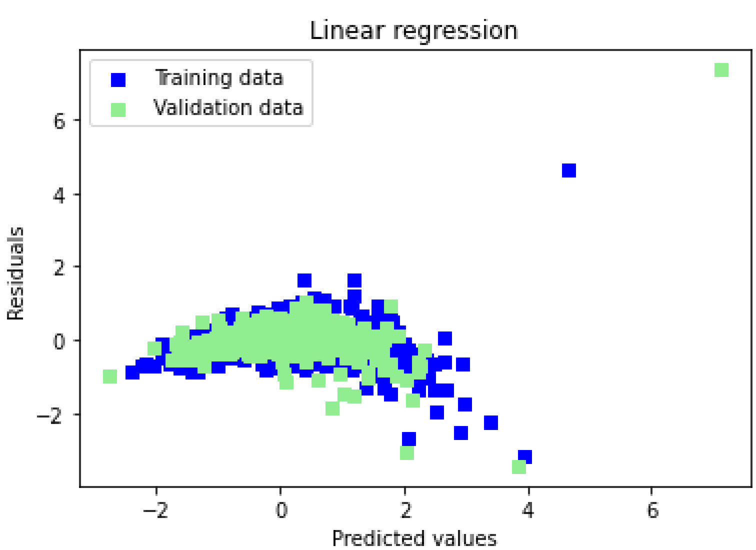




The data is fairly linear, where it rises

In [394…

```
# Testing assumptions further - plotting residuals in a different way
y_train_pred = lm.predict(x_train)

plt.scatter(y_train_pred, y_train_pred - y_train, c = "blue", marker = "s", labe
plt.scatter(predictions, predictions - y_test, c = "lightgreen", marker = "s", l
plt.title("Linear regression")
plt.xlabel("Predicted values")
plt.ylabel("Residuals")
plt.legend(loc = "upper left")
plt.show()
```



https://towardsdatascience.com/what-are-the-best-metrics-to-evaluate-your-regression-model-418ca481755b A way I used to evaluate the metrics of our predicted values derived from this article

In [395…

```
print('Mean squared error: ', metrics.mean_squared_error(y_test, predictions))
print('Square root mean squared error: ', np.sqrt(metrics.mean_squared_error(y_t
print('Mean absolute error: ', metrics.mean_absolute_error(y_test, predictions))
```

```
Mean squared error:  0.29995756024517584
Square root mean squared error:  0.5476838141164807
Mean absolute error:  0.29105407971784336
```

In [396…

```
scores = cross_val_score(lm, x_train, y_train,
                         scoring="neg_mean_squared_error", cv=10)
rmse_scores = np.sqrt(-scores)
print("Scores:", rmse_scores)
print("Mean:", rmse_scores.mean())
print("Standard deviation:", rmse_scores.std())
```

```
Scores: [0.37919289 0.50562717 0.31491863 0.62473208 0.35770218 0.48368237
 0.49510348 0.35126944 0.32836494 0.38027292]
Mean: 0.42208661126251634
Standard deviation: 0.09496690132189657
```

The mean squared is good for now, we can do better though

https://scikit-learn.org/stable/modules/ensemble.html

https://datascience.stackexchange.com/questions/61501/what-is-the-difference-between-gradient-descent-and-gradient-boosting-are-they

https://stackoverflow.com/questions/67275792/optimizing-learning-rate-and-number-of-estimators-for-multioutput-gradient-boost

Some links I used to help use "ensemble"

In [397…

```
# the parameters I used from the scikit-learn docs example
parameters = {'n_estimators': 100, 'max_depth': 4, 'min_samples_split': 2,
          'learning_rate': 0.05, 'loss': 'squared_error'}
boost = ensemble.GradientBoostingRegressor(**parameters)

boost.fit(x_train, y_train.ravel())
```

Out[397…

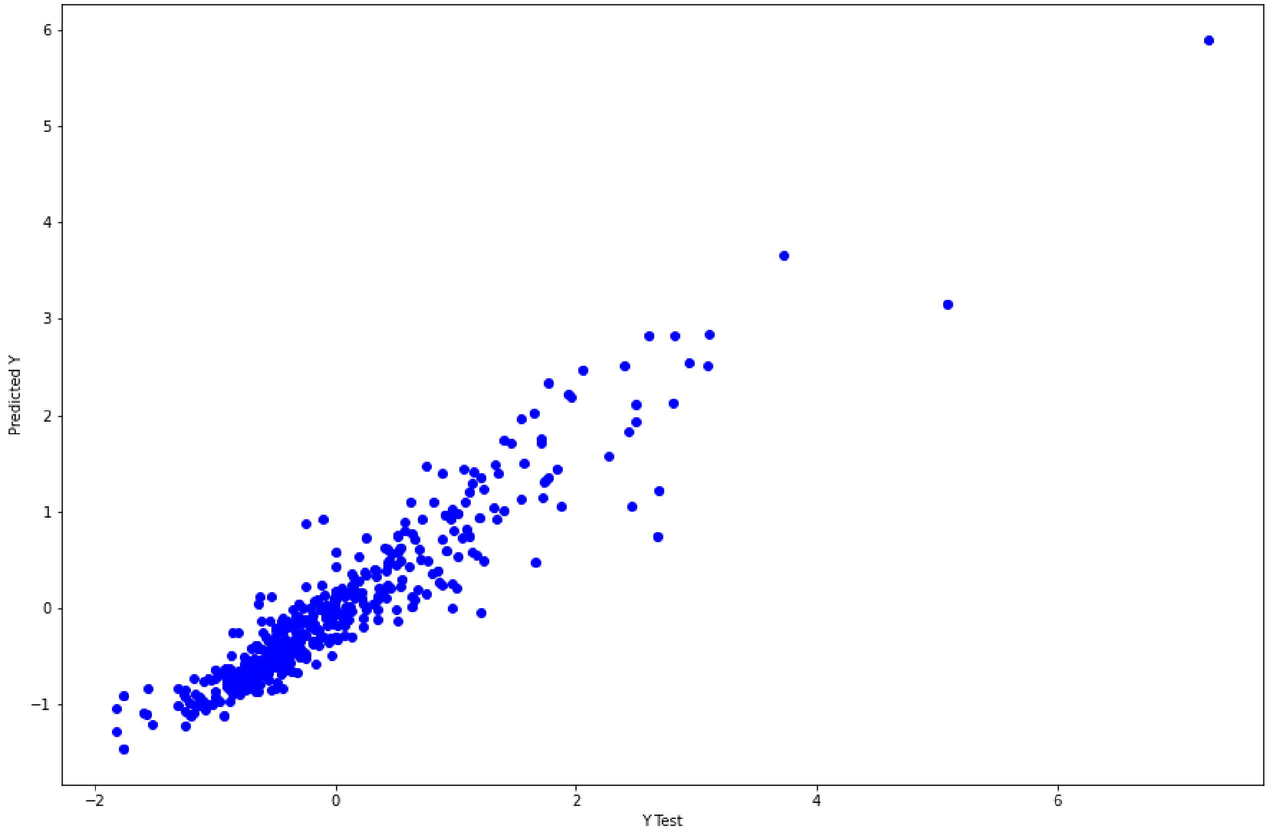
```
GradientBoostingRegressor(learning_rate=0.05, max_depth=4)
```

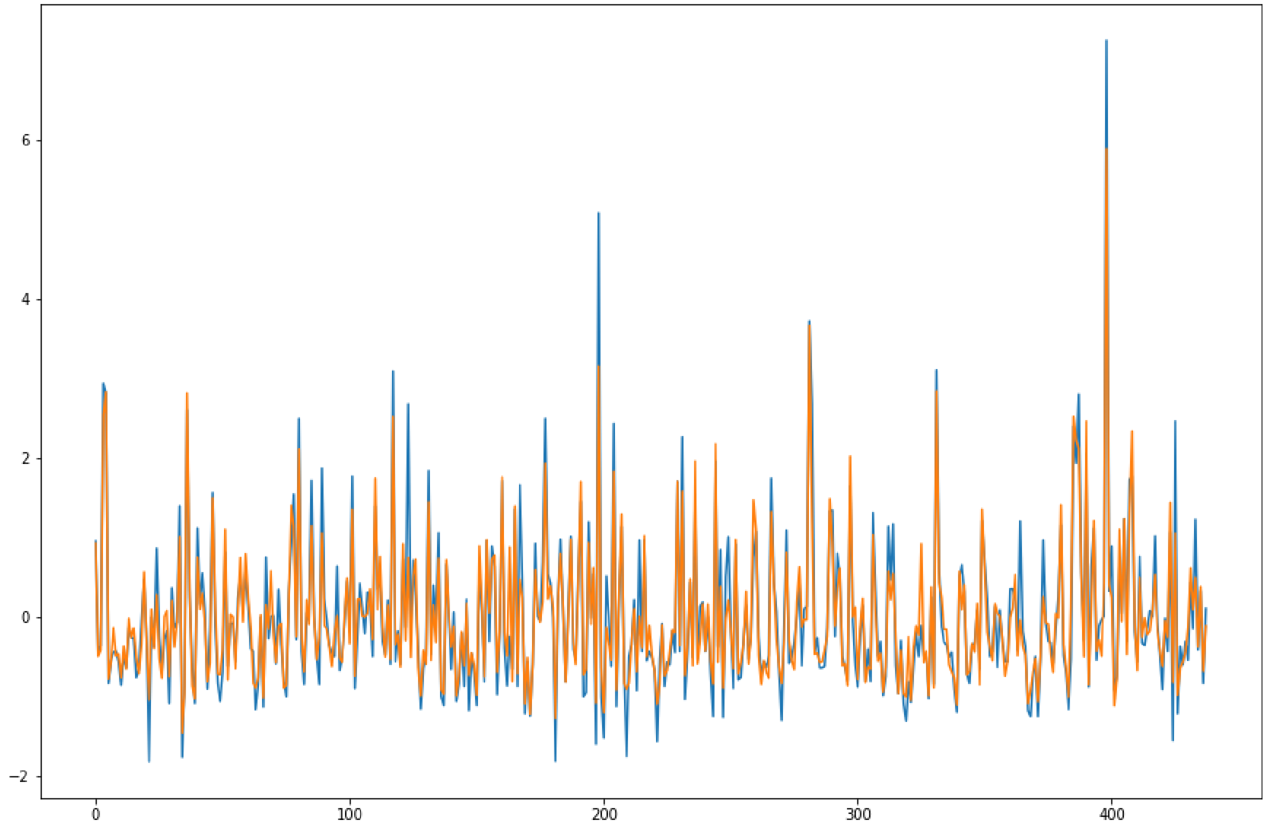
In [398…

```
predictions = boost.predict(x_test)
predictions = predictions.reshape(-1,1)

print('Mean absolute error: ', metrics.mean_absolute_error(y_test, predictions))
print('Mean squared error: ', metrics.mean_squared_error(y_test, predictions))
print('Square root mean squared error: ', np.sqrt(metrics.mean_squared_error(y_t

plt.figure(figsize=(15,10))
plt.scatter(y_test, predictions, color = 'blue')
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

```
plt.show()

plt.figure(figsize=(15,10))
plt.plot(y_test,label = 'Test Data')
plt.plot(predictions, label = 'Predictions')
plt.show()
```

```
Mean absolute error:  0.2301315578108763
Mean squared error:  0.11602098713788545
Square root mean squared error:  0.3406185361043721
```





Much better due to better scores offered by mean absolute error, additionally the top graph does not have weird outliers that could sway our results

In [399…

```
scores = cross_val_score(boost, x_train, y_train.ravel(),
                         scoring="neg_mean_squared_error", cv=10)
rmse_scores = np.sqrt(-scores)
print("Scores:", rmse_scores)
print("Mean:", rmse_scores.mean())
print("Standard deviation:", rmse_scores.std())
```

```
Scores: [0.30263508 0.42646428 0.3099625  0.6863058  0.32655988 0.39903377
 0.49507083 0.36159565 0.28494782 0.36405501]
Mean: 0.3956630633675787
Standard deviation: 0.11423954881948836
```

In [400…

```
test_data_dropped = test_data.copy()
test_data_dropped
```

Out[400…

	OverallQual	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	TotalBsmtSF	1stFlrSF	2r
0	5	1961	1961	0.0	468.0	882.0	896	
1	6	1958	1958	108.0	923.0	1329.0	1329	
2	5	1997	1998	0.0	791.0	928.0	928	
3	6	1998	1998	20.0	602.0	926.0	926	
4	8	1992	1992	0.0	263.0	1280.0	1280	
...	...	...	...	...	...	...	...	
1454	4	1970	1970	0.0	0.0	546.0	546	

	OverallQual	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	TotalBsmtSF	1stFlrSF	2r
1455	4	1970	1970	0.0	252.0	546.0	546	
1456	5	1960	1996	0.0	1224.0	1224.0	1224	
1457	5	1992	1992	0.0	337.0	912.0	970	
1458	7	1993	1994	94.0	758.0	996.0	996	

1459 rows × 17 columns

OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'TotalBsmtSF', '1stFlrSF', 'FullBath', 'TotRmsAbvGrd', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'GarageYrBlt', 'Fireplaces', 'BsmtFinSF1'

These are the columns used in the linear regression model, so dropping the unused columns in the test set

In [401…

```
test_data_dropped.drop(['2ndFlrSF', 'WoodDeckSF',
                        'OpenPorchSF'], axis=1, inplace=True)
```

In [402…

```
test_data_dropped = scalerX.fit_transform(test_data_dropped)
test_data_dropped
```

Out[402…

```
array([[-0.75110125, -0.34094461, -1.07288463, ..., -0.65048832,
        -0.98801273,  1.18594459],
       [-0.05487716, -0.43969491, -1.21490841, ..., -0.76719424,
        -0.98801273, -0.7412126 ],
       [-0.75110125,  0.844059  ,  0.6787419 , ...,  0.74998273,
         0.30162251,  0.04255946],
       ...,
       [-0.75110125, -0.37386137,  0.58405938, ..., -0.6893903 ,
         0.30162251,  0.47593931],
       [-0.75110125,  0.67947517,  0.39469435, ...,  0.        ,
        -2.27764797, -2.17966486],
       [ 0.64134693,  0.71239193,  0.48937687, ...,  0.59437483,
         1.59125775,  0.81711068]])
```

In [403…

```
test_prediction_lm = lm.predict(test_data_dropped)
test_prediction_lm = test_prediction_lm.reshape(-1,1)
test_prediction_lm = scalerY.inverse_transform(test_prediction_lm)
test_prediction_lm = pd.DataFrame(test_prediction_lm, columns=['SalePrice'])
test_prediction_lm.head()
```

Out[403…

	SalePrice
0	136469.718438
1	146062.762588
2	200572.494637
3	218578.408209
4	218426.912146

In [404…

```
test_id = df_test['Id']
ids = pd.DataFrame(test_id, columns=['Id'])
result = pd.concat([ids,test_prediction_lm], axis=1)
result.head()
```

Out[404…

	Id	SalePrice
0	1461	136469.718438
1	1462	146062.762588
2	1463	200572.494637
3	1464	218578.408209
4	1465	218426.912146

In [405…

```
#result.to_csv('submission.csv', index=False)
```

Gradient descent submission over linear regression - due to a better means squared error

In [406…

```
test_prediction_boost = boost.predict(test_data_dropped)
test_prediction_boost = test_prediction_boost.reshape(-1,1)
test_prediction_boost = scalerY.inverse_transform(test_prediction_boost)
test_prediction_boost = pd.DataFrame(test_prediction_boost, columns=['SalePrice'
test_prediction_boost.head()
```

Out[406…

	SalePrice
0	132789.166328
1	152239.583470
2	179563.833531
3	199244.841393
4	210698.431266

In [407…

```
test_id = df_test['Id']
ids = pd.DataFrame(test_id, columns=['Id'])
result = pd.concat([ids, test_prediction_boost], axis=1)
result.head()
```

Out[407…

	Id	SalePrice
0	1461	132789.166328
1	1462	152239.583470
2	1463	179563.833531
3	1464	199244.841393
4	1465	210698.431266

In [408…

```
result.to_csv('submission.csv', index=False)
```

In [ ]: