Data Prep, Exploration and Visualization

The most difficult part of this assignment was choosing the variables I wanted to input into my model and how to deal with variables that had NA values. In lines 212-218, I counted the number of variables with NA values and distinguished between categorical variables and numerical values. From there I filtered out NA values in line 289 to "none" and began replacing the numerical variables that I wanted to use in my model with "0" so that the regression would be able to read the variable (as an int and not a string). In lines 343 through 457 I logged the saleprice variable to understand the skewness, then correlated the variables 1stflr, 2ndflr, LowQualFinSF, GRLivArea to see if they would be good variables to use for regression. From there I checked if there were outliers in this data set, removed the outliers, put them in a range and correlated the variables to the response variable Saleprice. After creating multiple scatter plots for each one of the variables and confirming their normality in lines 457-464, I decided to use these variables for my regression.

Design and Modeling Methods

After prepping the data and deciding which categories to utilize, the three machine learning techniques I explored were a traditional linear regression, a lasso regression and elastic net and an elastic net regression. I wanted to test the accuracy of all three types of regressions to see the impact it had on the dataset. In lines 455 I finalized the variables I was going to use from my EDA into a list called data. The way I approached modeling these regressions is by splitting my data set into a test set and train set in lines 468-469.

Results Review and Model Evaluation

In lines 468, 420-424, I evaluated the linear regression accuracy and RSME as well as plotted a chart of the correlation of the predicted vs real models and checked the accuracy score as well. For the linear regression, the accuracy score was 62.94% and the RSME was 184.68. The reason the RSME is so high is because I didn't used the scaled variables for this model, but the residuals fall in on accurate scale for this dataset. For the Lasso regression, the RSME was 184.69 and the accuracy score was around 62%, and lastly for the Elastic Net regression, the RSME was also 184.68 with an accuracy score of around 62.9%. In line 453, I outputted the results from the linear regression for the Kaggle submission and the output results are in the appendix.

Kaggle Implementation

For https://www.kaggle.com/c/house-prices-advanced-regression-techniques/leaderboard#score. My Kaggle ran was 4299 with a score of 0.24249.

Insights, Exposition, Problem Description and Management Recommendations

The management question for this assignment was how can we most accurately predict the price of a house utilizing variables we chose from a dataset. The problem is that the data set given has many null values and categorical variables that skew the models. From testing out regression models, I recommend initially using a linear regression through analyzing the variables 1stflr, 2ndflr, LowQualFinSF, GRLivArea. This is because these variables are numerical and have the most amount of non-null values in the dataset. Using this model caused 63% accurate results compared to the lasso and elastic net which was around 62% accuracy. Based on this linear regression accuracy, my recommendation is to look at houses based on area of rooms and size. The larger the squarefootage the area is, the more expensive a home tends to be based on this linear regression output. While linear regression is a great way to initially look at this problem, I truly believe there are more machine learning techniques that would help provide a more accurate predictive sales price model. However the linear regression does prove the intuitive concept that the greater the area of a house is (in this case in the Ames, Iowa area), the more expensive a house will be. I am excited to revisit this Kaggle competition in assignment 4 to see if I can produce a more accurate sales price model for this dataset!

In [209]:

```
import pandas as pd
import math
from math import sqrt
import numpy as np

import random
np.random.seed(42)
import matplotlib.pyplot as plt
import seaborn as sns
import IPython
from IPython.display import display
from scipy.stats import skew
%matplotlib inline
import sklearn
from sklearn import linear_model
from sklearn.model_selection import cross_val_score, train_test_split, cross_val_pr
edict
from sklearn.linear_model import LinearRegression, RidgeCV, LassoCV, ElasticNetCV
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, r2_score, make_scorer
pd.set_option('display.float_format', lambda x: '%3f' %x)
from sklearn.utils import resample
from sklearn.decomposition import PCA
from scipy import misc
from scipy import stats as st
from sklearn.model_selection import KFold, GridSearchCV
```

In [210]:

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

In [211]:

```
#counting the number of null values in the data set
```

In [212]:

```
nan_data = pd.DataFrame(train.isnull().sum().sort_values(ascending=False)[:20])
nan_data.columns = ['NaN Count']
nan_data
```

Out[212]:

	NaN Count
PoolQC	1453
MiscFeature	1406
Alley	1369
Fence	1179
FireplaceQu	690
LotFrontage	259
GarageCond	81
GarageType	81
GarageYrBlt	81
GarageFinish	81
GarageQual	81
BsmtExposure	38
BsmtFinType2	38
BsmtFinType1	37
BsmtCond	37
BsmtQual	37
MasVnrArea	8
MasVnrType	8
Electrical	1
Utilities	0

In [213]:

```
#counting the number of categorical values and numerical values
```

In [287]:

```
cat_features = train.select_dtypes(include = ["object"]).columns
num_features = train.select_dtypes(exclude = ["object"]).columns
num_features = num_features.drop("SalePrice")
print("Numerical features : " + str(len(num_features)))
print("Categorical features : " + str(len(cat_features)))
```

```
Numerical features : 38
Categorical features : 42
```

In [288]:

```
#filtering out the most frequent null values that are not in the test set
```

In [289]:

```
nan_is_none_cols = ["PoolQC", "MiscFeature", "Alley", "Fence", "GarageQual", \
        "GarageCond", "GarageType","BsmtCond","BsmtExposure","BsmtQual",\
        "BsmtFinType2","BsmtFinType1","MasVnrType","FireplaceQu","GarageFinish"]

for c in nan_is_none_cols:
    train[c] = train[c].fillna("None")
```

In [290]:

```
train.head()
```

Out[290]:

	Id	MSSubClass	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotCo
0	1	60	65.000000	8450	Pave	None	Reg	Lvl	AllPub	In
1	2	20	80.000000	9600	Pave	None	Reg	Lvl	AllPub	
2	3	60	68.000000	11250	Pave	None	IR1	Lvl	AllPub	In
3	4	70	60.000000	9550	Pave	None	IR1	Lvl	AllPub	Co
4	5	60	84.000000	14260	Pave	None	IR1	Lvl	AllPub	

5 rows × 81 columns

In [291]:

```
#The variables still left with null values
```

In [292]:

```
print(train.columns[train.isnull().any()])
```

```
Index(['GarageYrBlt', 'GarageYrBuilt'], dtype='object')
```

In [293]:

```
#filling lotFrontage with values
```

In [294]:

```
train["LotFrontage"] = train.groupby("Neighborhood")["LotFrontage"].transform(
    lambda x: x.fillna(x.median()))
```

In [295]:

```
#filling MasVnArea with values
```

In [296]:

```
train.loc[train["MasVnrArea"].isnull(),"MasVnrArea"] = 0
```

In [297]:

```
#1 missing value for electrical, fill it with year value
```

In [298]:

```
train["Electrical"] = train["Electrical"].fillna(0)
```

In [ ]:

```

```

In [299]:

```
#missiing valuef for garage built, replacing with 0
```

In [300]:

```
train.loc[train["GarageYrBlt"].isnull(),"GarageYrBuilt"] = 0
```

In [301]:

```
train.loc[train["GarageYrBlt"].isnull(),"GarageYrBuilt"] = 0
```

In [ ]:

```

```

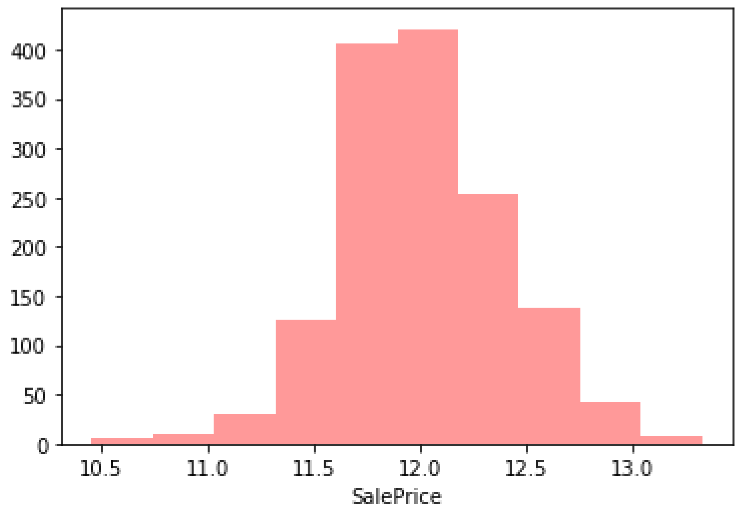
In [302]:

```
# Transforming the training data to have a more normal distribution
```

In [303]:

```
log_SalePrice = np.log(train.SalePrice)
print("Skewness:", log_SalePrice.skew())
sns.distplot(log_SalePrice, bins = 10, kde = False, color='red')
plt.show()
```

Skewness: 0.016117885353183668



In [304]:

```
#correlating variables with targret variable sales price to see if viable for model
```

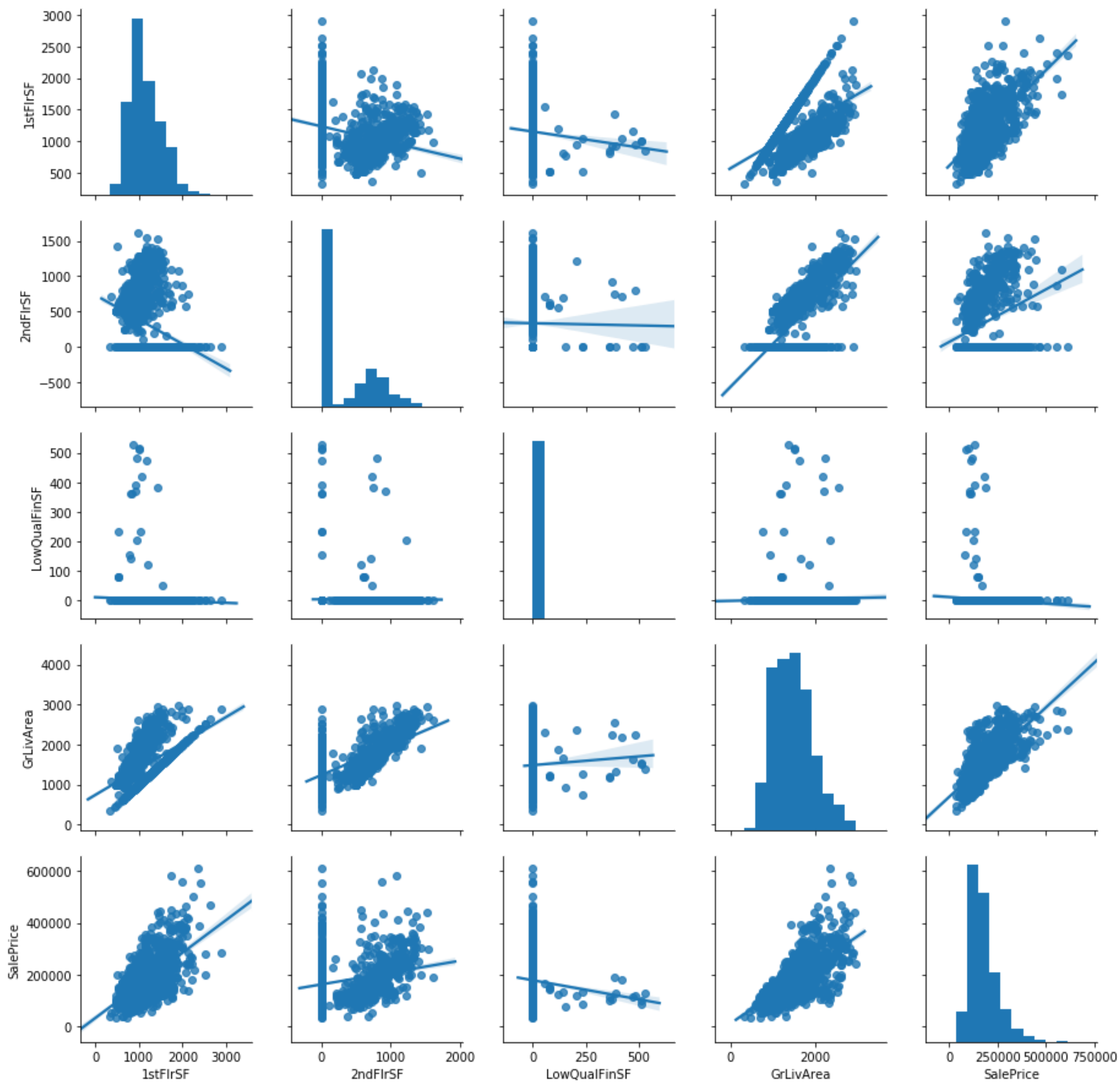
In [455]:

```
data = train.loc[:,["1stFlrSF", "2ndFlrSF", "LowQualFinSF", "GrLivArea", "SalePric
e" ]]
print(data.corr())
sns.pairplot(data, kind="reg")
```

	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	SalePrice
1stFlrSF	1.000000	-0.297247	-0.055769	0.502802	0.616656
2ndFlrSF	-0.297247	1.000000	-0.006082	0.671745	0.260519
LowQualFinSF	-0.055769	-0.006082	1.000000	0.037756	-0.080308
GrLivArea	0.502802	0.671745	0.037756	1.000000	0.706825
SalePrice	0.616656	0.260519	-0.080308	0.706825	1.000000

Out[455]:

```
<seaborn.axisgrid.PairGrid at 0x1c414266a0>
```

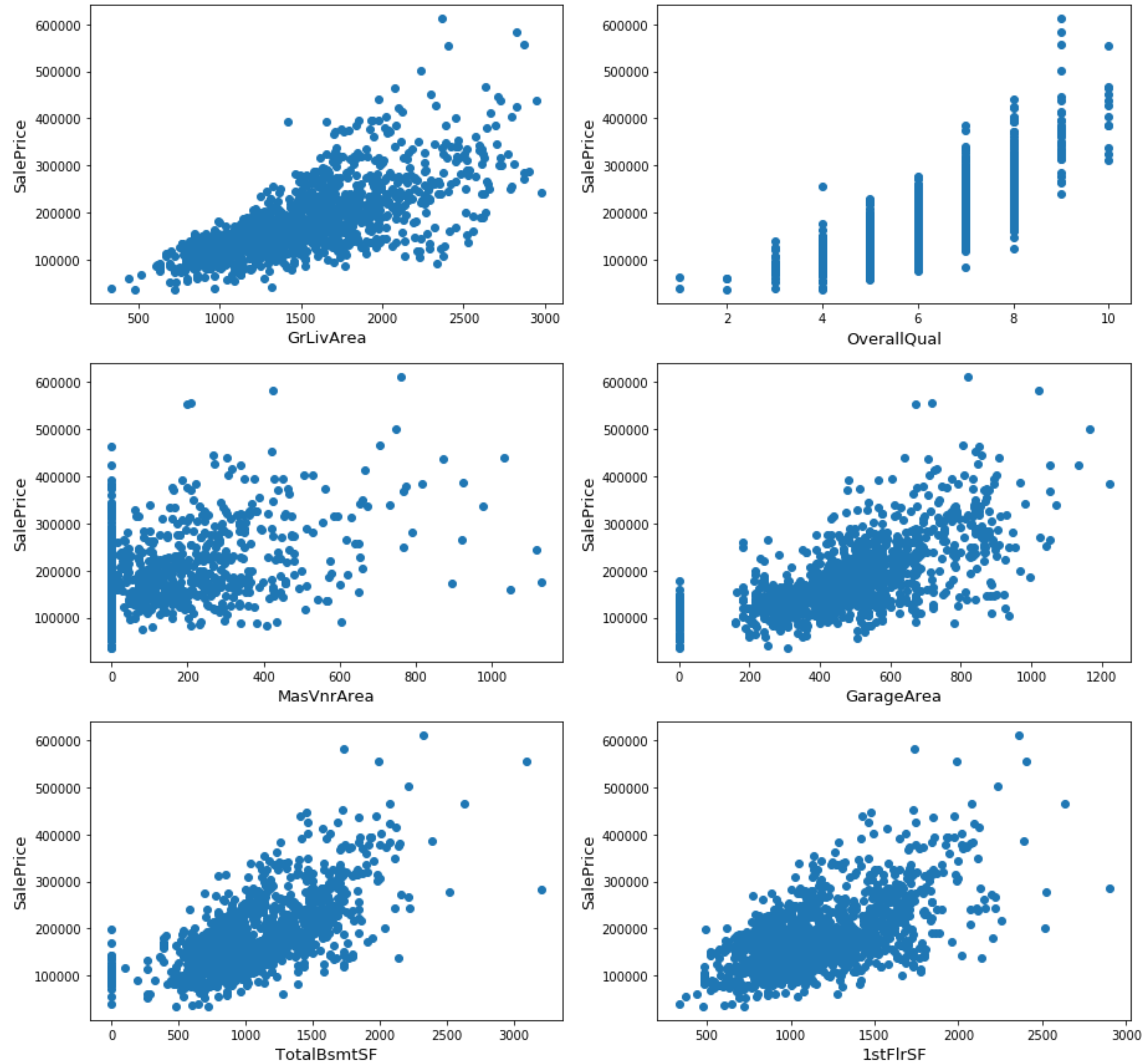


In [456]:

```
#removing the outliers and retraining them
```

In [457]:

```
train = train.drop(train[(train['GrLivArea'] > 4000)&(train['SalePrice'] < 250000)]
.index)
train = train.drop(train[(train['OverallQual'] == 10)&(train['SalePrice'] < 210000
)].index)
train = train.drop(train[(train['MasVnrArea'] > 1400)&(train['SalePrice'] < 300000
)].index)
train = train.drop(train[(train['GarageArea'] > 1200)&(train['SalePrice'] < 300000
)].index)
train = train.drop(train[(train['TotalBsmtSF'] > 5000)&(train['SalePrice'] < 250000
)].index)
train = train.drop(train[(train['1stFlrSF'] > 4000)&(train['SalePrice'] < 250000)].
index)

fig = plt.figure(figsize=(15,15))
ax1 = plt.subplot2grid((3,2),(0,0))
plt.scatter(x = train['GrLivArea'], y = train['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GrLivArea', fontsize=13)



ax1 = plt.subplot2grid((3,2),(0,1))
plt.scatter(x = train['OverallQual'], y = train['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('OverallQual', fontsize=13)



ax1 = plt.subplot2grid((3,2),(1,0))
plt.scatter(x = train['MasVnrArea'], y = train['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('MasVnrArea', fontsize=13)



ax1 = plt.subplot2grid((3,2),(1,1))
plt.scatter(x = train['GarageArea'], y = train['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GarageArea', fontsize=13)




ax1 = plt.subplot2grid((3,2),(2,0))
plt.scatter(x = train['TotalBsmtSF'], y = train['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('TotalBsmtSF', fontsize=13)



ax1 = plt.subplot2grid((3,2),(2,1))
plt.scatter(x = train['1stFlrSF'], y = train['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('1stFlrSF', fontsize=13)
plt.show()
```



In [458]:

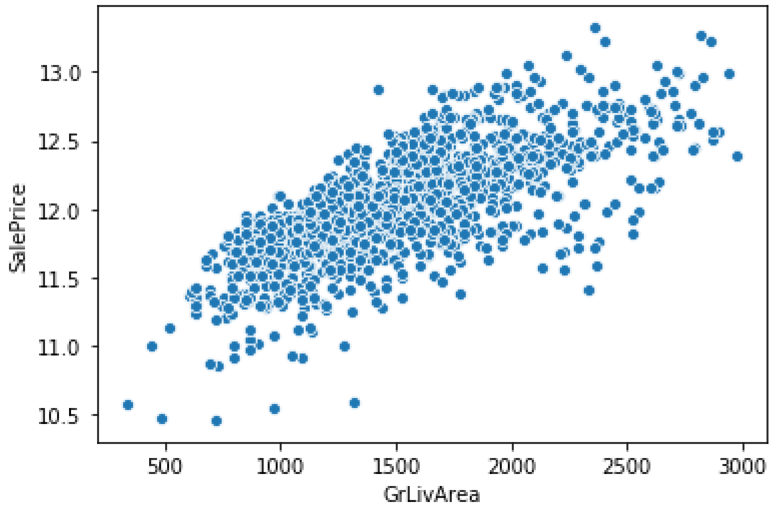
```
#further exploration of variables that correlate
```

In [459]:

```
#Relationship between GrLivArea and SalePrice
```

In [460]:

```
sns.scatterplot(x=train['GrLivArea'], y=log_SalePrice)
plt.xlabel('GrLivArea')
plt.ylabel('SalePrice')
plt.show()
```



In [461]:

```
#remove outliers
```

In [462]:

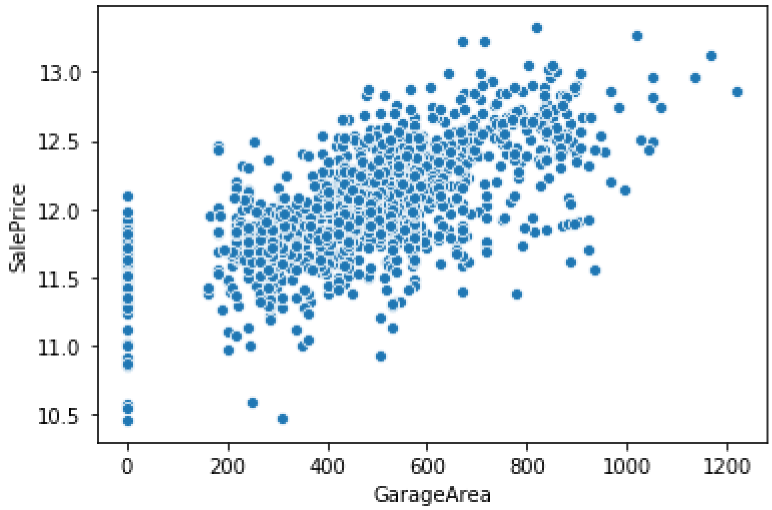
```
train = train[train['GrLivArea'] < 3000]
```

In [463]:

```
#relationship between GarageArea and SalePrice
```

In [464]:

```
sns.scatterplot(x=train['GarageArea'], y=log_SalePrice)
plt.xlabel('GarageArea')
plt.ylabel('SalePrice')
plt.show()
```



In [ ]:

In [465]:

```
#no outliers to remove
```

In [ ]:

In [ ]:

In [466]:

```
##Setting up final data set for regression testing
```

In [467]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [468]:

```
X = data.iloc[:,1:-1] #independant variables
y = data.iloc[:,-1] #response variable mv
```

In [469]:

```
#Split data to test and train data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3)
```

In [470]:

```
# Create regressor object
reg = LinearRegression()

# Fitting data
reg.fit(X_train, y_train)
```

Out[470]:

```
LinearRegression()
```

In [420]:

```
y_pred = reg.predict(X_test)
```

In [421]:

```
from sklearn.metrics import mean_absolute_error

rmse = sqrt(mean_absolute_error(y_pred, y_test))
print('RMSE = ', rmse)
```

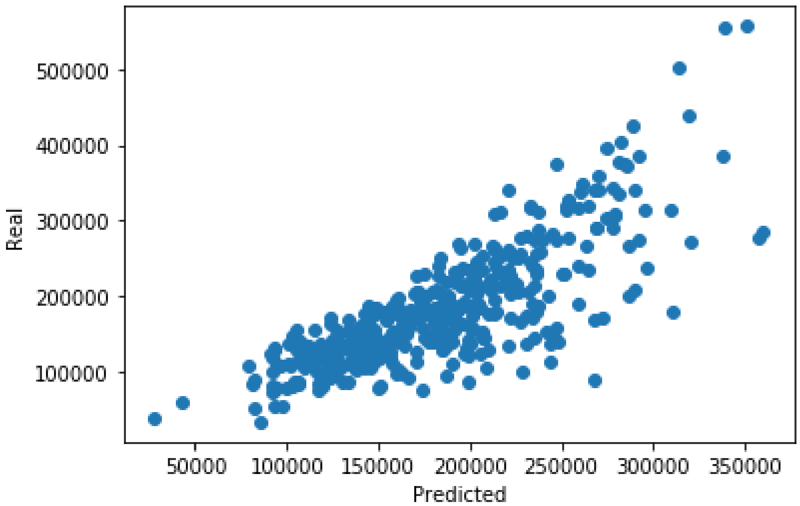
```
RMSE =  184.68242777372694
```

In [422]:

```
plt.scatter(y_pred, y_test)
plt.xlabel('Predicted')
plt.ylabel('Real')
```

Out[422]:

```
Text(0, 0.5, 'Real')
```



In [453]:

```
linear_reg_df = pd.DataFrame(y_test)
linear_reg_df['predicted_value'] = y_pred
linear_reg_df
linear_reg_df.to_excel("output.xlsx", sheet_name='Sheet_name_1')
```

In [424]:

```
print("Score ", reg.score(X_test, y_test))
```

```
Score  0.6294954433684751
```

In [ ]:

In [425]:

```
#Lasso Regression
```

In [433]:

```
lasso_reg = Lasso(alpha=0.1)
lasso_reg.fit(X_train, y_train)
lasso_pred = lasso_reg.predict(X_test)
```

In [434]:

```
rmse3 = sqrt(mean_absolute_error(lasso_pred, y_test))
print('RMSE = ', rmse)
```

```
RMSE =  184.68242777372694
```

In [ ]:

```

```

In [435]:

```
print("Score ", lasso_reg.score(X_test, y_test))
```

```
Score  0.6294954412185361
```

In [ ]:

```

```

In [ ]:

```
#elastic net
```

In [442]:

```
b_elastic_net = ElasticNet(alpha=0.1, l1_ratio=0.5)
b_elastic_net.fit(X_train, y_train)
e_pred = b_elastic_net.predict(X_test)
```

In [443]:

```
rmse2 = sqrt(mean_absolute_error(e_pred, y_test))
print('RMSE = ', rmse)
```

```
RMSE =  184.68242777372694
```

In [444]:

```
#Accuracy Score
print("Score ", b_elastic_net.score(X_test, y_test))
```

```
Score  0.6294952511737565
```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

Output csv from my model

ID	SalePrice
1461	125500
1462	157000
1463	181000
1464	181000
1465	179200
1466	178000
1467	173000
1468	193000
1469	167000
1470	123000
1471	162000
1472	83000
1473	88000
1474	148500
1475	120000

1476	320000
1477	255000
1478	232000
1479	232000
1480	385000
1481	255000
1482	208900
1483	176432
1484	179000
1485	189000
1486	195000
1487	232000
1488	232000
1489	147000
1490	153500
1491	186500
1492	125000
1493	157000
1494	250000
1495	271000
1496	208900
1497	186500
1498	151000
1499	151000
1500	162000
1501	177500
1502	177500
1503	189000
1504	189000
1505	208900
1506	185000
1507	220000
1508	143000
1509	193000
1510	143000
1511	142000
1512	143000
1513	112000
1514	157000
1515	139000
1516	160000
1517	147000

1518	145000
1519	220000
1520	142000
1521	142000
1522	143000
1523	115000
1524	145000
1525	139000
1526	80000
1527	145000
1528	105000
1529	155000
1530	167000
1531	138000
1532	105000
1533	125000
1534	112000
1535	133000
1536	119000
1537	100000
1538	136000
1539	193000
1540	136000
1541	117000
1542	117000
1543	177000
1544	125500
1545	132500
1546	132500
1547	131000
1548	131000
1549	134900
1550	149000
1551	157000
1552	153900
1553	130500
1554	112000
1555	163500
1556	67000
1557	139000
1558	125500
1559	122000

1560	95000
1561	136000
1562	130000
1563	125000
1564	171000
1565	154000
1566	196000
1567	105000
1568	190000
1569	168000
1570	140000
1571	140000
1572	157000
1573	335000
1574	180500
1575	153500
1576	145000
1577	185000
1578	112000
1579	152000
1580	186500
1581	193000
1582	125500
1583	350000
1584	178000
1585	136500
1586	86000
1587	112000
1588	142000
1589	110000
1590	155000
1591	139000
1592	120000
1593	110000
1594	112000
1595	169000
1596	163000
1597	160000
1598	112000
1599	189000
1600	170000
1601	100000

1602	147000
1603	124000
1604	275000
1605	193000
1606	171000
1607	171000
1608	179000
1609	147000
1610	167500
1611	135000
1612	145000
1613	181000
1614	133000
1615	88000
1616	88000
1617	88000
1618	130000
1619	147000
1620	200000
1621	167500
1622	119500
1623	210000
1624	164000
1625	123000
1626	167900
1627	164000
1628	164000
1629	193000
1630	187500
1631	189000
1632	138000
1633	189000
1634	193000
1635	185000
1636	176000
1637	171000
1638	195000
1639	181000
1640	197500
1641	157000
1642	193000
1643	186500

1644	190000
1645	157000
1646	155000
1647	134000
1648	140000
1649	135000
1650	120500
1651	120500
1652	83000
1653	125000
1654	155000
1655	147000
1656	146000
1657	146000
1658	124000
1659	148500
1660	145000
1661	315000
1662	325000
1663	335000
1664	320000
1665	147000
1666	385000
1667	335000
1668	284000
1669	325000
1670	320000
1671	290000
1672	385000
1673	325000
1674	232000
1675	175900
1676	196000
1677	214000
1678	385000
1679	285000
1680	193000
1681	208900
1682	315000
1683	202500
1684	174000
1685	174000

1686	179000
1687	189000
1688	193000
1689	178000
1690	193000
1691	162000
1692	164000
1693	112000
1694	193000
1695	176000
1696	214000
1697	176500
1698	310000
1699	275000
1700	230000
1701	222000
1702	239000
1703	232000
1704	193000
1705	201000
1706	345000
1707	201000
1708	201000
1709	325000
1710	147000
1711	225000
1712	232000
1713	320000
1714	189000
1715	193000
1716	147000
1717	189000
1718	179000
1719	195000
1720	190000
1721	155000
1722	179000
1723	155000
1724	232000
1725	193000
1726	227000
1727	179200

1728	189000
1729	177500
1730	112000
1731	125000
1732	129000
1733	144000
1734	112000
1735	112000
1736	112500
1737	385000
1738	145000
1739	193000
1740	222000
1741	162000
1742	144000
1743	144000
1744	272000
1745	190000
1746	160000
1747	185000
1748	200000
1749	175000
1750	157000
1751	190000
1752	130000
1753	167000
1754	185000
1755	175000
1756	138000
1757	130000
1758	153000
1759	235000
1760	163000
1761	167000
1762	185000
1763	171000
1764	122000
1765	167000
1766	176500
1767	153500
1768	136000
1769	143000

1770	134500
1771	124000
1772	145000
1773	139000
1774	180500
1775	132500
1776	110000
1777	136000
1778	138000
1779	158000
1780	154000
1781	135000
1782	109900
1783	145000
1784	112000
1785	130000
1786	135000
1787	140000
1788	55000
1789	125000
1790	105000
1791	200000
1792	167000
1793	142000
1794	147000
1795	110000
1796	140000
1797	127500
1798	127000
1799	138000
1800	140000
1801	135000
1802	140000
1803	140000
1804	147000
1805	139000
1806	117000
1807	98000
1808	125500
1809	112000
1810	125500
1811	112000

1812	112000
1813	125500
1814	115000
1815	60000
1816	125000
1817	167500
1818	136000
1819	120000
1820	67000
1821	125000
1822	125000
1823	67000
1824	144000
1825	117000
1826	83000
1827	119000
1828	128000
1829	124000
1830	145000
1831	161000
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