Lasso_Regression_Housing_Price

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```
In [52]: # Name:Rohit Yadav (6219913)
         # House Price prediction
         import numpy as np
         import pandas as pd
         import seaborn as sns
         import matplotlib
         import matplotlib.pyplot as plt
         from sklearn.preprocessing import scale
         from scipy.stats import skew, skewtest
         import warnings
         warnings.filterwarnings('ignore')
```

```
In [5]: path = '../input/'
        #path = 'dataset/'
        train = pd.read_csv('Desktop/HousePricesDataset/train.csv')
        test = pd.read_csv('Desktop/HousePricesDataset/test.csv')
        print('Number of rows and columns in train dataset:', train.shape)
        print('Number of rows and columns in test dataset:', test.shape)
```

```
('Number of rows and columns in train dataset:', (1460, 81))
('Number of rows and columns in test dataset:', (1459, 80))
```

```
In [6]: datasetHasNan = False
        if train.count().min() == train.shape[0] and test.count().min() == test.shape[0] :
            print('We do not need to worry about missing values.')
        else:
            datasetHasNan = True
            print('yes, we have missing values')

        # now list items
        print('--'*40)
        if datasetHasNan == True:
            nas = pd.concat([train.isnull().sum(), test.isnull().sum()], axis=1, keys=['Train I
            print('Nan in the data sets')
            print(nas[nas.sum(axis=1) > 0])
```

```
yes, we have missing values
--------------------------------------------------------------------------------
```

```
Nan in the data sets
              Train Dataset  Test Dataset
Alley                  1369        1352.0
BsmtCond                 37          45.0
BsmtExposure             38          44.0
BsmtFinSF1                0           1.0
BsmtFinSF2                0           1.0
BsmtFinType1             37          42.0
BsmtFinType2             38          42.0
BsmtFullBath              0           2.0
BsmtHalfBath              0           2.0
BsmtQual                 37          44.0
BsmtUnfSF                 0           1.0
Electrical                1           0.0
Exterior1st               0           1.0
Exterior2nd               0           1.0
Fence                  1179        1169.0
FireplaceQu             690         730.0
Functional                0           2.0
GarageArea                0           1.0
GarageCars                0           1.0
GarageCond               81          78.0
GarageFinish             81          78.0
GarageQual               81          78.0
GarageType               81          76.0
GarageYrBlt              81          78.0
KitchenQual               0           1.0
LotFrontage             259         227.0
MSZoning                  0           4.0
MasVnrArea                8          15.0
MasVnrType                8          16.0
MiscFeature            1406        1408.0
PoolQC                 1453        1456.0
SaleType                  0           1.0
TotalBsmtSF               0           1.0
Utilities                 0           2.0
```

```
In [8]: # Explore features
        def feat_explore(column):
            return train[column].value_counts()

        # Function to impute missing values
        def feat_impute(column, value):
            train.loc[train[column].isnull(),column] = value
            test.loc[test[column].isnull(),column] = value
```

```
In [9]: #PoolQC, MiscFeature, Alley, Fence will all be removed as they are missing over half o
```

```python
features_drop = ['PoolQC','MiscFeature','Alley','Fence']
train = train.drop(features_drop, axis=1)
test = test.drop(features_drop, axis=1)
```

In [11]:
```python
print('TRAIN: FireplaceQu Missing Before:', train['FireplaceQu'].isnull().sum(),'\n',
      'TEST: FireplaceQu Missing Before:', test['FireplaceQu'].isnull().sum())
```

```
('TRAIN: FireplaceQu Missing Before:', 690, '\n', 'TEST: FireplaceQu Missing Before:', 730)
```

In [9]:
```python
#TRAIN: missing 690 observations.
#TEST: missing 730 observations.
#However, these nulls may be attributed to homes that do not have fireplaces at all.
#If this assumption proves to be true, we can impute these nulls with '0' as they do n

# checking this assumption
assumption1 = pd.concat([(train[train['FireplaceQu'].isnull()][['Fireplaces','Fireplac
                (test[test['FireplaceQu'].isnull()][['Fireplaces','FireplaceQu']])],
                axis=1, keys=['Train Dataset',' Test Dataset'])
print(assumption1)
```

```
     Train Dataset             Test Dataset
        Fireplaces FireplaceQu   Fireplaces FireplaceQu
0              0.0         NaN          0.0         NaN
1              NaN         NaN          0.0         NaN
4              NaN         NaN          0.0         NaN
5              0.0         NaN          NaN         NaN
6              NaN         NaN          0.0         NaN
9              NaN         NaN          0.0         NaN
10             0.0         NaN          NaN         NaN
11             NaN         NaN          0.0         NaN
12             0.0         NaN          0.0         NaN
14             NaN         NaN          0.0         NaN
15             0.0         NaN          NaN         NaN
16             NaN         NaN          0.0         NaN
17             0.0         NaN          NaN         NaN
18             0.0         NaN          NaN         NaN
19             0.0         NaN          NaN         NaN
22             NaN         NaN          0.0         NaN
23             NaN         NaN          0.0         NaN
26             0.0         NaN          NaN         NaN
28             NaN         NaN          0.0         NaN
29             0.0         NaN          NaN         NaN
30             0.0         NaN          0.0         NaN
31             0.0         NaN          0.0         NaN
32             0.0         NaN          NaN         NaN
36             0.0         NaN          0.0         NaN
37             NaN         NaN          0.0         NaN
38             0.0         NaN          0.0         NaN
```

```
39            0.0        NaN         0.0        NaN
40            NaN        NaN         0.0        NaN
41            NaN        NaN         0.0        NaN
42            0.0        NaN         NaN        NaN
...           ...        ...         ...        ...
1419          NaN        NaN         0.0        NaN
1422          0.0        NaN         NaN        NaN
1425          0.0        NaN         NaN        NaN
1426          NaN        NaN         0.0        NaN
1427          NaN        NaN         0.0        NaN
1428          NaN        NaN         0.0        NaN
1429          NaN        NaN         0.0        NaN
1430          NaN        NaN         0.0        NaN
1431          0.0        NaN         0.0        NaN
1432          0.0        NaN         0.0        NaN
1433          NaN        NaN         0.0        NaN
1436          0.0        NaN         NaN        NaN
1437          NaN        NaN         0.0        NaN
1438          0.0        NaN         0.0        NaN
1439          NaN        NaN         0.0        NaN
1441          NaN        NaN         0.0        NaN
1444          0.0        NaN         0.0        NaN
1445          0.0        NaN         0.0        NaN
1446          0.0        NaN         NaN        NaN
1447          NaN        NaN         0.0        NaN
1448          0.0        NaN         0.0        NaN
1449          0.0        NaN         0.0        NaN
1450          0.0        NaN         0.0        NaN
1452          0.0        NaN         0.0        NaN
1453          0.0        NaN         0.0        NaN
1454          0.0        NaN         0.0        NaN
1455          NaN        NaN         0.0        NaN
1457          NaN        NaN         0.0        NaN
1458          0.0        NaN         NaN        NaN
1459          0.0        NaN         NaN        NaN

[1057 rows x 4 columns]
```

In [12]:
```python
print('TRAIN: shape :', (train[train['FireplaceQu'].isnull()][['Fireplaces','Fireplac
      '\n','TEST: shape :',  (train[train['FireplaceQu'].isnull()][['Fireplaces','Fi
```

```
('TRAIN: shape :', (690, 2), '\n', 'TEST: shape :', (690, 2))
```

In [13]:
```python
# Impute the nulls with None
train['FireplaceQu'] = train['FireplaceQu'].fillna('None')
test['FireplaceQu'] = test['FireplaceQu'].fillna('None')
```

```
# Cross check columns
print('Confirm Imputation for train')
print(pd.crosstab(train.FireplaceQu,train.Fireplaces,))
print('--'*40)
print('Confirm Imputation for test')
print(pd.crosstab(test.FireplaceQu,test.Fireplaces,))
```

```
Confirm Imputation for train
Fireplaces     0    1   2  3
FireplaceQu
Ex             0   19   4  1
Fa             0   28   4  1
Gd             0  324  54  2
None         690    0   0  0
Po             0   20   0  0
TA             0  259  53  1
--------------------------------------------------------------------------------
Confirm Imputation for test
Fireplaces     0    1   2  3  4
FireplaceQu
Ex             0   18   1  0  0
Fa             0   35   6  0  0
Gd             0  303  58  3  0
None         730    0   0  0  0
Po             0   26   0  0  0
TA             0  236  39  3  1
```

```
In [12]: print('TRAIN: LotFrontage Missing Before:', train['LotFrontage'].isnull().sum(),'\n',
```

```
('TRAIN: LotFrontage Missing Before:', 259, '\n', 'TEST: LotFrontage Missing Before:', 227)
```

```
In [14]: #TRAIN: missing 259 observations.
         #TEST: missing 227 observations.
         #First check if there are other variables that are strongly correlated with LotFronta
         #Otherwise impute with the median LotFrontage value.

         # Check above mentioned assumption
         corr_lf = train.select_dtypes(include = ['float64', 'int64']).iloc[:, 1:].corr()
         cor_dict_lf = corr_lf['LotFrontage'].to_dict()
         del cor_dict_lf['LotFrontage']
         print("Numeric features by Correlation with LotFrontage:\n")
         for ele in sorted(cor_dict_lf.items(), key = lambda x: -abs(x[1])):
             print("{0}: \t{1}".format(*ele))
```

```
Numeric features by Correlation with LotFrontage:
```

```
1stFlrSF:         0.457181001995
LotArea:         0.426095018772
GrLivArea:         0.402797414085
TotalBsmtSF:         0.392074576379
MSSubClass:         -0.386346885345
TotRmsAbvGrd:         0.35209594766
SalePrice:         0.351799096571
GarageArea:         0.344996724106
GarageCars:         0.285690924685
Fireplaces:         0.26663948256
BedroomAbvGr:         0.263169915881
OverallQual:         0.251645775481
BsmtFinSF1:         0.23363316702
PoolArea:         0.206166775276
FullBath:         0.198768677897
MasVnrArea:         0.193458060558
OpenPorchSF:         0.151972227681
BsmtUnfSF:         0.132643741625
YearBuilt:         0.123349467033
BsmtFullBath:         0.100948566949
YearRemodAdd:         0.0888655724921
WoodDeckSF:         0.0885209332894
2ndFlrSF:         0.0801772706242
GarageYrBlt:         0.0702497819166
3SsnPorch:         0.0700292277309
OverallCond:         -0.0592134500052
HalfBath:         0.0535318549796
BsmtFinSF2:         0.049899676691
ScreenPorch:         0.041382790675
LowQualFinSF:         0.038468534329
MoSold:         0.0111999547591
EnclosedPorch:         0.0107003366389
YrSold:         0.00744958920978
BsmtHalfBath:         -0.00723430452492
KitchenAbvGr:         -0.00606883016131
MiscVal:         0.00336755659619
```

In [15]:
```
train['LotFrontage'] = train['LotFrontage'].fillna(train['LotFrontage'].median())
test['LotFrontage'] = test['LotFrontage'].fillna(test['LotFrontage'].median())
```

In [14]:
```
#TRAIN: missing 259 observations.
#TEST: missing 227 observations.
#First check if there are other variables that are strongly correlated with LotFronta
#Otherwise impute with the median LotFrontage value.

# Check above mentioned assumption
corr_lf = train.select_dtypes(include = ['float64', 'int64']).iloc[:, 1:].corr()
```

```
cor_dict_lf = corr_lf['LotFrontage'].to_dict()
del cor_dict_lf['LotFrontage']
print("Numeric features by Correlation with LotFrontage:\n")
for ele in sorted(cor_dict_lf.items(), key = lambda x: -abs(x[1])):
    print("{0}: \t{1}".format(*ele))
```

```
Numeric features by Correlation with LotFrontage:

1stFlrSF:         0.457181001995
LotArea:         0.426095018772
GrLivArea:         0.402797414085
TotalBsmtSF:         0.392074576379
MSSubClass:         -0.386346885345
TotRmsAbvGrd:         0.35209594766
SalePrice:         0.351799096571
GarageArea:         0.344996724106
GarageCars:         0.285690924685
Fireplaces:         0.26663948256
BedroomAbvGr:         0.263169915881
OverallQual:         0.251645775481
BsmtFinSF1:         0.23363316702
PoolArea:         0.206166775276
FullBath:         0.198768677897
MasVnrArea:         0.193458060558
OpenPorchSF:         0.151972227681
BsmtUnfSF:         0.132643741625
YearBuilt:         0.123349467033
BsmtFullBath:         0.100948566949
YearRemodAdd:         0.0888655724921
WoodDeckSF:         0.0885209332894
2ndFlrSF:         0.0801772706242
GarageYrBlt:         0.0702497819166
3SsnPorch:         0.0700292277309
OverallCond:         -0.0592134500052
HalfBath:         0.0535318549796
BsmtFinSF2:         0.049899676691
ScreenPorch:         0.041382790675
LowQualFinSF:         0.038468534329
MoSold:         0.0111999547591
EnclosedPorch:         0.0107003366389
YrSold:         0.00744958920978
BsmtHalfBath:         -0.00723430452492
KitchenAbvGr:         -0.00606883016131
MiscVal:         0.00336755659619
```

In [15]:
```
# Nothing highly correlated to LotFrontage so we will impute with the mean
```

```
        train['LotFrontage'] = train['LotFrontage'].fillna(train['LotFrontage'].median())
        test['LotFrontage'] = test['LotFrontage'].fillna(test['LotFrontage'].median())
```

```
In [16]: print('Garage Features Missing Before')
         print('--'*40)
         print(pd.concat([(train[['GarageYrBlt', 'GarageType', 'GarageFinish','GarageQual','Ga
                         (train[['GarageYrBlt', 'GarageType', 'GarageFinish','GarageQual','Gara
                         axis=1, keys=['Train Dataset',' Test Dataset']) )
```

```
Garage Features Missing Before
--------------------------------------------------------------------------------
              Train Dataset   Test Dataset
GarageYrBlt              81             81
GarageType               81             81
GarageFinish             81             81
GarageQual               81             81
GarageCond               81             81
```

```
In [17]: #TRAIN: missing 259 observations.
         #TEST: missing 227 observations.
         #These null values are assumed to be in the same rows for each column and associated
         #that do not have garages at all.
         #If these assumptions are correct, the nulls can be inputed with zero as these are pr

         # Assumptions check
         print('--'*40)
         print('Assumption Check TRAIN DATASET')
         null_garage = ['GarageYrBlt','GarageType','GarageQual','GarageCond','GarageFinish']
         print(train[(train['GarageYrBlt'].isnull())|
                          (train['GarageType'].isnull())|
                          (train['GarageQual'].isnull())|
                          (train['GarageCond'].isnull())|
                          (train['GarageFinish'].isnull())]
                          [['GarageCars','GarageYrBlt','GarageType','GarageQual','GarageCond',
         print('--'*40)
         print('Assumption Check TEST DATASET')
         print(test[(test['GarageYrBlt'].isnull())|
                          (test['GarageCond'].isnull())|
                          (test['GarageQual'].isnull())|
                         (test['GarageFinish'].isnull())|
                         (test['GarageType'].isnull())|
                         (test['GarageCars'].isnull())|
                         (test['GarageArea'].isnull())]
                          [['GarageYrBlt','GarageCond','GarageQual', 'GarageFinish','GarageTyp
```

```
--------------------------------------------------------------------------------
Assumption Check TRAIN DATASET
      GarageCars  GarageYrBlt GarageType GarageQual GarageCond GarageFinish
```

39	0	NaN	NaN	NaN	NaN	NaN
48	0	NaN	NaN	NaN	NaN	NaN
78	0	NaN	NaN	NaN	NaN	NaN
88	0	NaN	NaN	NaN	NaN	NaN
89	0	NaN	NaN	NaN	NaN	NaN
99	0	NaN	NaN	NaN	NaN	NaN
108	0	NaN	NaN	NaN	NaN	NaN
125	0	NaN	NaN	NaN	NaN	NaN
127	0	NaN	NaN	NaN	NaN	NaN
140	0	NaN	NaN	NaN	NaN	NaN
148	0	NaN	NaN	NaN	NaN	NaN
155	0	NaN	NaN	NaN	NaN	NaN
163	0	NaN	NaN	NaN	NaN	NaN
165	0	NaN	NaN	NaN	NaN	NaN
198	0	NaN	NaN	NaN	NaN	NaN
210	0	NaN	NaN	NaN	NaN	NaN
241	0	NaN	NaN	NaN	NaN	NaN
250	0	NaN	NaN	NaN	NaN	NaN
287	0	NaN	NaN	NaN	NaN	NaN
291	0	NaN	NaN	NaN	NaN	NaN
307	0	NaN	NaN	NaN	NaN	NaN
375	0	NaN	NaN	NaN	NaN	NaN
386	0	NaN	NaN	NaN	NaN	NaN
393	0	NaN	NaN	NaN	NaN	NaN
431	0	NaN	NaN	NaN	NaN	NaN
434	0	NaN	NaN	NaN	NaN	NaN
441	0	NaN	NaN	NaN	NaN	NaN
464	0	NaN	NaN	NaN	NaN	NaN
495	0	NaN	NaN	NaN	NaN	NaN
520	0	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...
954	0	NaN	NaN	NaN	NaN	NaN
960	0	NaN	NaN	NaN	NaN	NaN
968	0	NaN	NaN	NaN	NaN	NaN
970	0	NaN	NaN	NaN	NaN	NaN
976	0	NaN	NaN	NaN	NaN	NaN
1009	0	NaN	NaN	NaN	NaN	NaN
1011	0	NaN	NaN	NaN	NaN	NaN
1030	0	NaN	NaN	NaN	NaN	NaN
1038	0	NaN	NaN	NaN	NaN	NaN
1096	0	NaN	NaN	NaN	NaN	NaN
1123	0	NaN	NaN	NaN	NaN	NaN
1131	0	NaN	NaN	NaN	NaN	NaN
1137	0	NaN	NaN	NaN	NaN	NaN
1143	0	NaN	NaN	NaN	NaN	NaN
1173	0	NaN	NaN	NaN	NaN	NaN
1179	0	NaN	NaN	NaN	NaN	NaN
1218	0	NaN	NaN	NaN	NaN	NaN

```
1219            0          NaN        NaN        NaN        NaN          NaN
1234            0          NaN        NaN        NaN        NaN          NaN
1257            0          NaN        NaN        NaN        NaN          NaN
1283            0          NaN        NaN        NaN        NaN          NaN
1323            0          NaN        NaN        NaN        NaN          NaN
1325            0          NaN        NaN        NaN        NaN          NaN
1326            0          NaN        NaN        NaN        NaN          NaN
1337            0          NaN        NaN        NaN        NaN          NaN
1349            0          NaN        NaN        NaN        NaN          NaN
1407            0          NaN        NaN        NaN        NaN          NaN
1449            0          NaN        NaN        NaN        NaN          NaN
1450            0          NaN        NaN        NaN        NaN          NaN
1453            0          NaN        NaN        NaN        NaN          NaN

[81 rows x 6 columns]
--------------------------------------------------------------------------------
Assumption Check TEST DATASET
      GarageYrBlt GarageCond GarageQual GarageFinish GarageType  GarageCars  \
53            NaN        NaN        NaN          NaN        NaN         0.0
71            NaN        NaN        NaN          NaN        NaN         0.0
79            NaN        NaN        NaN          NaN        NaN         0.0
92            NaN        NaN        NaN          NaN        NaN         0.0
96            NaN        NaN        NaN          NaN        NaN         0.0
98            NaN        NaN        NaN          NaN        NaN         0.0
100           NaN        NaN        NaN          NaN        NaN         0.0
130           NaN        NaN        NaN          NaN        NaN         0.0
133           NaN        NaN        NaN          NaN        NaN         0.0
134           NaN        NaN        NaN          NaN        NaN         0.0
154           NaN        NaN        NaN          NaN        NaN         0.0
155           NaN        NaN        NaN          NaN        NaN         0.0
257           NaN        NaN        NaN          NaN        NaN         0.0
261           NaN        NaN        NaN          NaN        NaN         0.0
327           NaN        NaN        NaN          NaN        NaN         0.0
348           NaN        NaN        NaN          NaN        NaN         0.0
350           NaN        NaN        NaN          NaN        NaN         0.0
351           NaN        NaN        NaN          NaN        NaN         0.0
359           NaN        NaN        NaN          NaN        NaN         0.0
362           NaN        NaN        NaN          NaN        NaN         0.0
371           NaN        NaN        NaN          NaN        NaN         0.0
374           NaN        NaN        NaN          NaN        NaN         0.0
376           NaN        NaN        NaN          NaN        NaN         0.0
379           NaN        NaN        NaN          NaN        NaN         0.0
387           NaN        NaN        NaN          NaN        NaN         0.0
433           NaN        NaN        NaN          NaN        NaN         0.0
550           NaN        NaN        NaN          NaN        NaN         0.0
621           NaN        NaN        NaN          NaN        NaN         0.0
630           NaN        NaN        NaN          NaN        NaN         0.0
633           NaN        NaN        NaN          NaN        NaN         0.0
```

...	...	...	...	...	...	...
939	NaN	NaN	NaN	NaN	NaN	0.0
962	NaN	NaN	NaN	NaN	NaN	0.0
966	NaN	NaN	NaN	NaN	NaN	0.0
1092	NaN	NaN	NaN	NaN	NaN	0.0
1093	NaN	NaN	NaN	NaN	NaN	0.0
1097	NaN	NaN	NaN	NaN	NaN	0.0
1115	NaN	NaN	NaN	NaN	NaN	0.0
1116	NaN	NaN	NaN	NaN	Detchd	NaN
1119	NaN	NaN	NaN	NaN	NaN	0.0
1143	NaN	NaN	NaN	NaN	NaN	0.0
1149	NaN	NaN	NaN	NaN	NaN	0.0
1231	NaN	NaN	NaN	NaN	NaN	0.0
1233	NaN	NaN	NaN	NaN	NaN	0.0
1248	NaN	NaN	NaN	NaN	NaN	0.0
1307	NaN	NaN	NaN	NaN	NaN	0.0
1311	NaN	NaN	NaN	NaN	NaN	0.0
1329	NaN	NaN	NaN	NaN	NaN	0.0
1331	NaN	NaN	NaN	NaN	NaN	0.0
1339	NaN	NaN	NaN	NaN	NaN	0.0
1399	NaN	NaN	NaN	NaN	NaN	0.0
1402	NaN	NaN	NaN	NaN	NaN	0.0
1410	NaN	NaN	NaN	NaN	NaN	0.0
1428	NaN	NaN	NaN	NaN	NaN	0.0
1431	NaN	NaN	NaN	NaN	NaN	0.0
1432	NaN	NaN	NaN	NaN	NaN	0.0
1433	NaN	NaN	NaN	NaN	NaN	0.0
1449	NaN	NaN	NaN	NaN	NaN	0.0
1453	NaN	NaN	NaN	NaN	NaN	0.0
1454	NaN	NaN	NaN	NaN	NaN	0.0
1457	NaN	NaN	NaN	NaN	NaN	0.0

	GarageArea
53	0.0
71	0.0
79	0.0
92	0.0
96	0.0
98	0.0
100	0.0
130	0.0
133	0.0
134	0.0
154	0.0
155	0.0
257	0.0
261	0.0
327	0.0

```
348          0.0
350          0.0
351          0.0
359          0.0
362          0.0
371          0.0
374          0.0
376          0.0
379          0.0
387          0.0
433          0.0
550          0.0
621          0.0
630          0.0
633          0.0
...          ...
939          0.0
962          0.0
966          0.0
1092         0.0
1093         0.0
1097         0.0
1115         0.0
1116         NaN
1119         0.0
1143         0.0
1149         0.0
1231         0.0
1233         0.0
1248         0.0
1307         0.0
1311         0.0
1329         0.0
1331         0.0
1339         0.0
1399         0.0
1402         0.0
1410         0.0
1428         0.0
1431         0.0
1432         0.0
1433         0.0
1449         0.0
1453         0.0
1454         0.0
1457         0.0

[78 rows x 7 columns]
```

In [18]:
```
# Impute nulls at index 666 that have a garage with most common value in each column
test.iloc[666, test.columns.get_loc('GarageYrBlt')] = test['GarageYrBlt'].mode()[0]
test.iloc[666, test.columns.get_loc('GarageCond')] = test['GarageCond'].mode()[0]
test.iloc[666, test.columns.get_loc('GarageFinish')] = test['GarageFinish'].mode()[0]
test.iloc[666, test.columns.get_loc('GarageQual')] = test['GarageQual'].mode()[0]
test.iloc[666, test.columns.get_loc('GarageType')] = test['GarageType'].mode()[0]

# Impute nulls at index 1116 that have a garage with most common value in each column
test.iloc[1116, test.columns.get_loc('GarageYrBlt')] = test['GarageYrBlt'].mode()[0]
test.iloc[1116, test.columns.get_loc('GarageCond')] = test['GarageCond'].mode()[0]
test.iloc[1116, test.columns.get_loc('GarageFinish')] = test['GarageFinish'].mode()[0
test.iloc[1116, test.columns.get_loc('GarageQual')] = test['GarageQual'].mode()[0]
test.iloc[1116, test.columns.get_loc('GarageType')] = test['GarageType'].mode()[0]

# Impute nulls at index 1116 that have a garage with median value in each column for
test.iloc[1116, test.columns.get_loc('GarageCars')] = test['GarageCars'].median()
test.iloc[1116, test.columns.get_loc('GarageArea')] = test['GarageArea'].median()
```

In [19]:
```
# Impute the remaining nulls as None
null_garage2 = ['GarageYrBlt','GarageCond','GarageFinish','GarageQual', 'GarageType',

for cols in null_garage2:
    if(train[cols].dtype ==np.object)&(test[cols].dtype ==np.object) :
         feat_impute(cols, 'None')
    else:
         feat_impute(cols, 0)
```

In [20]:
```
# Cross check columns

print('Confirm Imputation')
for cols in null_garage:
    print(pd.crosstab(train[cols],train.GarageCars))
    print(pd.crosstab(test[cols],test.GarageCars))
```

```
Confirm Imputation
GarageCars    0   1   2   3  4
GarageYrBlt
0.0          81   0   0   0  0
1900.0        0   0   1   0  0
1906.0        0   1   0   0  0
1908.0        0   0   1   0  0
1910.0        0   1   2   0  0
1914.0        0   1   1   0  0
1915.0        0   2   0   0  0
1916.0        0   4   0   1  0
1918.0        0   0   1   1  0
1920.0        0  10   3   1  0
```

1921.0	0	2	1	0	0
1922.0	0	4	1	0	0
1923.0	0	2	1	0	0
1924.0	0	3	0	0	0
1925.0	0	7	3	0	0
1926.0	0	6	0	0	0
1927.0	0	0	1	0	0
1928.0	0	3	1	0	0
1929.0	0	1	1	0	0
1930.0	0	5	3	0	0
1931.0	0	2	2	0	0
1932.0	0	1	2	0	0
1933.0	0	1	0	0	0
1934.0	0	1	1	0	0
1935.0	0	2	2	0	0
1936.0	0	5	0	0	0
1937.0	0	2	0	0	0
1938.0	0	3	0	0	0
1939.0	0	7	2	0	0
1940.0	0	13	1	0	0
...	..	..	..	..	..
1981.0	0	3	6	1	0
1982.0	0	3	0	1	0
1983.0	0	0	7	0	0
1984.0	0	2	6	0	0
1985.0	0	1	9	0	0
1986.0	0	0	6	0	0
1987.0	0	2	9	0	0
1988.0	0	1	12	1	0
1989.0	0	2	7	1	0
1990.0	0	2	11	3	0
1991.0	0	1	7	1	0
1992.0	0	0	13	0	0
1993.0	0	0	17	5	0
1994.0	0	1	12	5	0
1995.0	0	0	13	5	0
1996.0	0	1	15	4	0
1997.0	0	2	15	1	1
1998.0	0	1	25	5	0
1999.0	0	1	25	4	0
2000.0	0	0	23	4	0
2001.0	0	0	17	3	0
2002.0	0	2	19	5	0
2003.0	0	1	39	10	0
2004.0	0	0	43	10	0
2005.0	0	0	49	16	0
2006.0	0	0	28	31	0
2007.0	0	0	24	25	0

```
2008.0        0   1   9  19  0
2009.0        0   0  11  10  0
2010.0        0   0   1   2  0

[98 rows x 5 columns]
GarageCars   0.0  1.0  2.0  3.0  4.0  5.0
GarageYrBlt
0.0           76    0    0    0    0    0
1895.0         0    1    0    0    0    0
1896.0         0    1    0    0    0    0
1900.0         0    3    2    0    0    0
1910.0         0    5    2    0    0    0
1915.0         0    4    1    0    0    0
1916.0         0    0    1    0    0    0
1917.0         0    2    0    0    0    0
1918.0         0    1    0    0    0    0
1919.0         0    1    0    0    0    0
1920.0         0   14    5    0    0    0
1921.0         0    2    0    0    0    0
1922.0         0    3    0    0    0    0
1923.0         0    3    0    0    0    0
1924.0         0    3    2    0    0    0
1925.0         0    5    0    0    0    0
1926.0         0    8    1    0    0    0
1927.0         0    3    1    0    0    0
1928.0         0    1    1    1    0    0
1930.0         0   13    6    0    0    0
1932.0         0    1    0    0    0    0
1934.0         0    2    0    0    0    0
1935.0         0    1    3    0    0    0
1936.0         0    2    0    0    0    0
1937.0         0    3    1    0    0    0
1938.0         0    7    1    0    0    0
1939.0         0    8    4    0    0    0
1940.0         0    8    3    0    0    0
1941.0         0    3    0    1    0    0
1942.0         0    4    0    0    0    0
...          ...  ...  ...  ...  ...  ...
1982.0         0    1    2    1    0    1
1983.0         0    2    2    0    0    0
1984.0         0    4    7    0    0    0
1985.0         0    1    7    0    0    0
1986.0         0    0    6    0    0    0
1987.0         0    2    5    0    0    0
1988.0         0    0    6    0    0    0
1989.0         0    0    8    1    0    0
1990.0         0    1    9    0    0    0
1991.0         0    0    8    0    0    0
```

```
1992.0          0    2   10    2    0    0
1993.0          0    1   20    5    1    0
1994.0          0    1   18    2    0    0
1995.0          0    3   11    3    0    0
1996.0          0    1   15    4    0    0
1997.0          0    3   20    0    2    0
1998.0          0    1   16   10    0    0
1999.0          0    0   22    2    0    0
2000.0          0    0   19    5    4    0
2001.0          0    2   17    2    0    0
2002.0          0    1   19    7    0    0
2003.0          0    0   30   12    0    0
2004.0          0    3   30   13    0    0
2005.0          0    1   52   25    1    0
2006.0          0    0   30   26    0    0
2007.0          0    0   35   31    0    0
2008.0          0    1   11   20    0    0
2009.0          0    0    4    4    0    0
2010.0          0    0    1    1    0    0
2207.0          0    0    1    0    0    0

[98 rows x 6 columns]
GarageCars   0    1    2    3  4
GarageType
2Types       0    0    1    4  1
Attchd       0  171  560  138  1
Basment      0    8   11    0  0
BuiltIn      0    8   50   30  0
CarPort      0    3    6    0  0
Detchd       0  179  196    9  3
None        81    0    0    0  0
GarageCars  0.0  1.0  2.0  3.0  4.0  5.0
GarageType
2Types        0    1    6    8    2    0
Attchd        0  189  522  140    4    0
Basment       0    8    9    0    0    0
BuiltIn       0    9   45   40    4    0
CarPort       0    4    1    1    0    0
Detchd        0  196  188    4    1    1
None         76    0    0    0    0    0
GarageCars   0    1    2    3  4
GarageQual
Ex           0    2    0    1  0
Fa           0   33   13    2  0
Gd           0    2   12    0  0
None        81    0    0    0  0
Po           0    3    0    0  0
TA           0  329  799  178  5
```

```
GarageCars  0.0  1.0  2.0  3.0  4.0  5.0
GarageQual
Fa            0   55   18    1    1    1
Gd            0    1    7    2    0    0
None         76    0    0    0    0    0
Po            0    2    0    0    0    0
TA            0  349  746  190   10    0
GarageCars   0    1    2    3  4
GarageCond
Ex           0    2    0    0  0
Fa           0   21   12    2  0
Gd           0    2    7    0  0
None        81    0    0    0  0
Po           0    6    1    0  0
TA           0  338  804  179  5
GarageCars  0.0  1.0  2.0  3.0  4.0  5.0
GarageCond
Ex            0    0    1    0    0    0
Fa            0   26   13    0    0    0
Gd            0    1    3    1    1    0
None         76    0    0    0    0    0
Po            0    4    3    0    0    0
TA            0  376  751  192   10    1
GarageCars     0    1    2   3  4
GarageFinish
Fin            0   23  231  96  2
None          81    0    0   0  0
RFn            0   60  297  65  0
Unf            0  286  296  20  3
GarageCars    0.0  1.0  2.0  3.0  4.0  5.0
GarageFinish
Fin             0   28  226  106    7    0
None           76    0    0    0    0    0
RFn             0   67  254   66    2    0
Unf             0  312  291   21    2    1
```

```
In [21]: null_bsmt = ['BsmtFullBath','BsmtHalfBath','BsmtFinSF1','BsmtFinSF2','BsmtUnfSF',
                      'TotalBsmtSF','BsmtCond','BsmtExposure','BsmtQual','BsmtFinType1','BsmtF
         print('Missing Data Before','\n')
         for cols in null_bsmt:
             print('TRAIN:',cols,train[cols].isnull().sum())
             print('TEST:',cols,test[cols].isnull().sum())
             print('--'*40)
```

```
('Missing Data Before', '\n')
('TRAIN:', 'BsmtFullBath', 0)
('TEST:', 'BsmtFullBath', 2)
```

```
--------------------------------------------------------------------------------
('TRAIN:', 'BsmtHalfBath', 0)
('TEST:', 'BsmtHalfBath', 2)
--------------------------------------------------------------------------------
('TRAIN:', 'BsmtFinSF1', 0)
('TEST:', 'BsmtFinSF1', 1)
--------------------------------------------------------------------------------
('TRAIN:', 'BsmtFinSF2', 0)
('TEST:', 'BsmtFinSF2', 1)
--------------------------------------------------------------------------------
('TRAIN:', 'BsmtUnfSF', 0)
('TEST:', 'BsmtUnfSF', 1)
--------------------------------------------------------------------------------
('TRAIN:', 'TotalBsmtSF', 0)
('TEST:', 'TotalBsmtSF', 1)
--------------------------------------------------------------------------------
('TRAIN:', 'BsmtCond', 37)
('TEST:', 'BsmtCond', 45)
--------------------------------------------------------------------------------
('TRAIN:', 'BsmtExposure', 38)
('TEST:', 'BsmtExposure', 44)
--------------------------------------------------------------------------------
('TRAIN:', 'BsmtQual', 37)
('TEST:', 'BsmtQual', 44)
--------------------------------------------------------------------------------
('TRAIN:', 'BsmtFinType1', 37)
('TEST:', 'BsmtFinType1', 42)
--------------------------------------------------------------------------------
('TRAIN:', 'BsmtFinType2', 38)
('TEST:', 'BsmtFinType2', 42)
--------------------------------------------------------------------------------
```

In [22]:
```
train['BsmtQual'].fillna('NA', inplace = True)
test['BsmtQual'].fillna('NA', inplace = True)

train['BsmtCond'].fillna('NA', inplace = True)
test['BsmtCond'].fillna('NA', inplace = True)

train['BsmtExposure'].fillna('NA', inplace = True)
test['BsmtExposure'].fillna('NA', inplace = True)

train['BsmtFinType1'].fillna('NA', inplace = True)
test['BsmtFinType1'].fillna('NA', inplace = True)

train['BsmtFinType2'].fillna('NA', inplace = True)
test['BsmtFinType2'].fillna('NA', inplace = True)
```

```
test['BsmtFullBath'].fillna('NA', inplace = True)
test['BsmtHalfBath'].fillna('NA', inplace = True)
test['BsmtFinSF1'].fillna('NA', inplace = True)
test['BsmtFinSF2'].fillna('NA', inplace = True)
```

In [27]:
```
print('Masonry Features Missing Before')
print(pd.concat([(train[['MasVnrArea', 'MasVnrType']].isnull().sum()),
                (test[['MasVnrArea', 'MasVnrType']].isnull().sum())],
                axis=1, keys=['Train Dataset',' Test Dataset']) )
```

```
Masonry Features Missing Before
            Train Dataset   Test Dataset
MasVnrArea              8             15
MasVnrType              8             16
```

In [28]:
```
# MasVnrArea and MasVnrType are each missing 8 observations
# Confirm that the missing values in these columns are the same rows
print('Check Assumptions FOR TRAIN SET')
print(train[(train['MasVnrArea'].isnull())|(train['MasVnrType'].isnull())]
                 [['MasVnrArea','MasVnrType']])

print(train[(train['MasVnrArea'].isnull())|(train['MasVnrType'].isnull())]
                 [['MasVnrArea','MasVnrType']].shape)

# View nulls in masonry features in Test set now
print('--'*40,'\nAssumption Check FOR TEST SET')
print(test[(test['MasVnrType'].isnull())|(test['MasVnrType'].isnull())|
                (test['MasVnrArea'].isnull())|(test['MasVnrArea'].isnull())]
                 [['MasVnrType','MasVnrArea']])
```

```
Check Assumptions FOR TRAIN SET
      MasVnrArea MasVnrType
234          NaN        NaN
529          NaN        NaN
650          NaN        NaN
936          NaN        NaN
973          NaN        NaN
977          NaN        NaN
1243         NaN        NaN
1278         NaN        NaN
(8, 2)
('--------------------------------------------------------------------------------', '\nAssump
     MasVnrType  MasVnrArea
231         NaN         NaN
246         NaN         NaN
422         NaN         NaN
532         NaN         NaN
544         NaN         NaN
```

```
581          NaN          NaN
851          NaN          NaN
865          NaN          NaN
880          NaN          NaN
889          NaN          NaN
908          NaN          NaN
1132         NaN          NaN
1150         NaN        198.0
1197         NaN          NaN
1226         NaN          NaN
1402         NaN          NaN
```

In [29]:
```
# Impute `MasVnrArea` with the most frequent values
# feat_explore('MasVnrArea')
# feat_impute('MasVnrArea','None')
train['MasVnrArea'] = train['MasVnrArea'].fillna(train['MasVnrArea'].mode()[0])

# Impute `MasVnrType` with the most frequent values
# feat_explore('MasVnrType')
# feat_impute('MasVnrType',0.0)

# Impute exceptions to assumption that nulls correspond to homes with no exposure
test.iloc[1150, test.columns.get_loc('MasVnrType')] = test['MasVnrType'].mode()[0]

train['MasVnrType'] = train['MasVnrType'].fillna(train['MasVnrType'].mode()[0])
```

In [30]:
```
# create list
null_masonry = ['MasVnrType','MasVnrArea']

for cols in null_masonry:
    if((train[cols].dtype ==np.object)&(test[cols].dtype ==np.object)):
        feat_impute(cols, 'None')
    else:
        feat_impute(cols, 0)
```

In [31]:
```
# Electrical is only missing one value

print('Electrical Feature Missing Before')
print(train[['Electrical']].isnull().sum())
```

```
Electrical Feature Missing Before
Electrical    1
dtype: int64
```

In [32]:
```
# Impute Electrical with the most frequent value, 'SBrkr'
train['Electrical'] = train['Electrical'].fillna(train['Electrical'].mode()[0])
```

```
#check now
print('Electrical Feature Missing After')
print(train[['Electrical']].isnull().sum())
print('--'*40)
```

```
Electrical Feature Missing After
Electrical    0
dtype: int64
--------------------------------------------------------------------------------
```

```
In [33]: null_others = ['MSZoning', 'Utilities','Functional','Exterior2nd','Exterior1st','Sale

         print('REMAINING Missing Data TEST SET')

         for cols in null_others:
             print(cols,test[cols].isnull().sum())

         print('--'*30,'\n','REMAINING Missing Data TRAIN SET')

         for cols in null_others:
             print(cols,train[cols].isnull().sum())
```

```
REMAINING Missing Data TEST SET
('MSZoning', 4)
('Utilities', 2)
('Functional', 2)
('Exterior2nd', 1)
('Exterior1st', 1)
('SaleType', 1)
('KitchenQual', 1)
('------------------------------------------------------------', '\n', 'REMAINING Missing Data
('MSZoning', 0)
('Utilities', 0)
('Functional', 0)
('Exterior2nd', 0)
('Exterior1st', 0)
('SaleType', 0)
('KitchenQual', 0)
```

```
In [34]: for cols in null_others:
             test[cols] = test[cols].mode()[0]

         print('--'*40)
         print('TEST SET : Missing Data After Imputation')
         for cols in null_others:
             print(cols,test[cols].isnull().sum())
```

```
--------------------------------------------------------------------------------
TEST SET : Missing Data After Imputation
('MSZoning', 0)
('Utilities', 0)
('Functional', 0)
('Exterior2nd', 0)
('Exterior1st', 0)
('SaleType', 0)
('KitchenQual', 0)
```

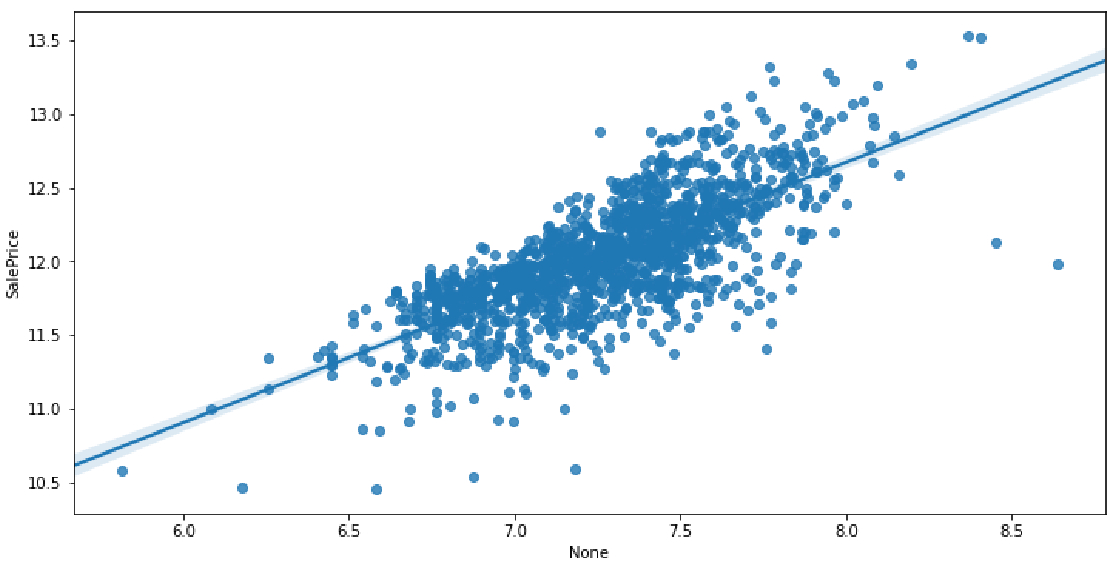
In [36]:
```
#Proposed feature: '1stFlrSF' + '2ndFlrSF' to give us combined Floor Square Footage

try_feature = (train['1stFlrSF'] + train['2ndFlrSF']).copy()
print("Skewness of the original intended feature:",skew(try_feature))
print("Skewness of transformed feature", skew(np.log1p(try_feature)))
```

```
('Skewness of the original intended feature:', 1.3291026531678385)
('Skewness of transformed feature', -0.03365667635294192)
```

In [37]:
```
# we'll use the transformed feature:)
try_feature = np.log1p(try_feature)
matplotlib.rcParams['figure.figsize'] = (12.0, 6.0)

# seaborn's regression plot
sns.regplot(x=(try_feature), y=np.log1p(train['SalePrice']), data=train, order=1);
```



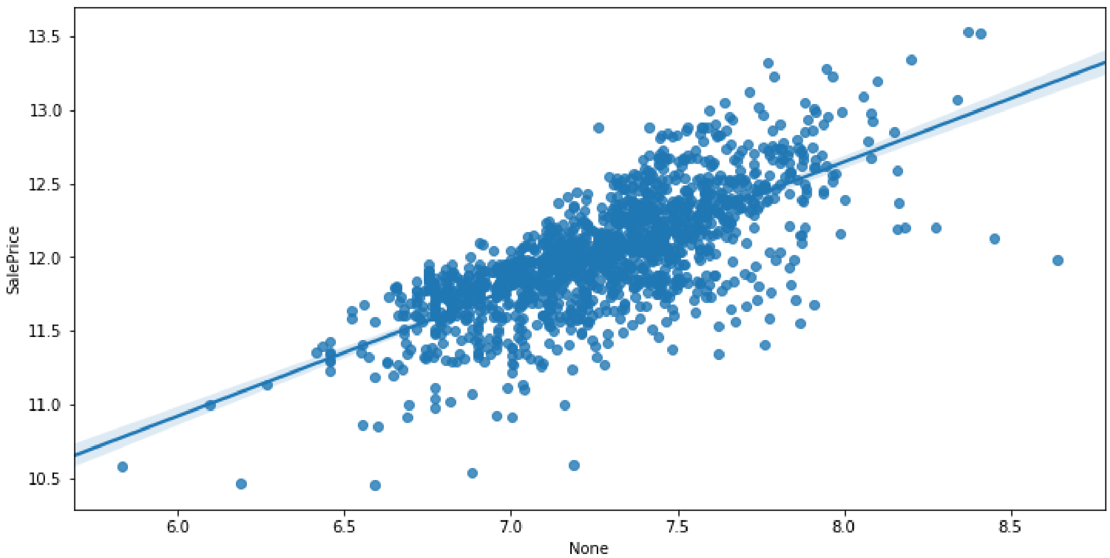
In [38]:
```
# lets create the feature then
train['1stFlr_2ndFlr_Sf'] = np.log1p(train['1stFlrSF'] + train['2ndFlrSF'])
test['1stFlr_2ndFlr_Sf'] = np.log1p(test['1stFlrSF'] + test['2ndFlrSF'])
```

In [39]:
```
#Feature number 2 -> 1stflr+2ndflr+lowqualsf+GrLivArea = All_Liv_Area
try_feature = (train['1stFlr_2ndFlr_Sf'] + train['LowQualFinSF'] + train['GrLivArea']
print("Skewness of the original intended feature:",skew(try_feature))
print("Skewness of transformed feature", skew(np.log1p(try_feature)))
```

```
('Skewness of the original intended feature:', 1.427345461344283)
('Skewness of transformed feature', 0.022891569554582644)
```

In [40]:
```
# hence, we'll use the transformed feature
try_feature = np.log1p(try_feature)
matplotlib.rcParams['figure.figsize'] = (12.0, 6.0)

# seaborn's regression plot
sns.regplot(x=(try_feature), y=np.log1p(train['SalePrice']), data=train, order=1);
```



In [41]:
```
train['All_Liv_SF'] = np.log1p(train['1stFlr_2ndFlr_Sf'] + train['LowQualFinSF'] + tra
test['All_Liv_SF'] = np.log1p(test['1stFlr_2ndFlr_Sf'] + test['LowQualFinSF'] + test[
```

In [42]:
```
# get all features except Id and SalePrice
feats = train.columns.difference(['Id','SalePrice'])

# the most hassle free way of working with data is to concatenate them
data_combo = pd.concat((train.loc[:,feats],
                        test.loc[:,feats]))
```

```
# But first, we log transform the target:
train["SalePrice"] = np.log1p(train["SalePrice"])
```

In [43]:
```
numeric_feats = data_combo.dtypes[data_combo.dtypes != "object"].index
skewed_feats = train[numeric_feats].apply(lambda x: skew(x.dropna())) #compute skewne
skewed_feats = skewed_feats[skewed_feats > 0.75]
skewed_feats = skewed_feats.index

data_combo[skewed_feats] = np.log1p(data_combo[skewed_feats])
```

In [44]:
```
# getting dummies for all features.

data_combo = pd.get_dummies(data_combo)
```

In [45]:
```
print(data_combo.shape)
```

```
(2919, 1557)
```

In [46]:
```
# creating matrices for sklearn:

X_train = data_combo[:train.shape[0]]
X_test = data_combo[train.shape[0]:]
y = train.SalePrice
```

In [53]:
```
#But first, Let's devise a cross-validation methodology once and for all

from sklearn.model_selection  import cross_val_score

def rmse_cv(model):
    rmse= np.sqrt(-cross_val_score(model, X_train, y, scoring="neg_mean_squared_error
    return(rmse)
```

In [54]:
```
# first import library
from sklearn.linear_model import LassoCV

#now create our object
model_lasso = LassoCV(alphas = [1, 0.1, 0.001, 0.0005], selection='random', max_iter=
res = rmse_cv(model_lasso)
print("Mean:",res.mean())
print("Min: ",res.min())
```

```
('Mean:', 0.12248799239421615)
('Min: ', 0.10273186844817653)
```

In [55]:
```
coef = pd.Series(model_lasso.coef_, index = X_train.columns)
print("Lasso picked " + str(sum(coef != 0)) + " variables and eliminated the other " +
```

```
Lasso picked 117 variables and eliminated the other 1440 variables
```

```
In [57]:  #plotting feature importances!
          imp_coef = pd.concat([coef.sort_values().head(10),
                               coef.sort_values().tail(10)])
          matplotlib.rcParams['figure.figsize'] = (8.0, 10.0)
          imp_coef.plot(kind = "barh")
          plt.title("Coefficients in the Lasso Model")
```

```
Out[57]: Text(0.5,1,'Coefficients in the Lasso Model')
```