HousePricesPart2

October 14, 2021

1 House Prices: Advanced Regression Techniques (Part 2)

We now move to the actual model building part. As usual, we first import some of the libraries we will be needing.

```
[ ]: import pandas as pd
     import numpy as np
     import seaborn as sns
     import matplotlib

     import matplotlib.pyplot as plt
     from scipy import stats
     from scipy.stats import skew
     from scipy.stats import norm
     from scipy.stats.stats import pearsonr

     %config InlineBackend.figure_format = 'retina' #set 'png' here when working on␣
      ↪notebook
     %matplotlib inline
```

1.1 Read the Cleaned Data

First we load the data we cleaned in the previous part.

```
[ ]: X_train_complete = pd.read_csv("HousePricesTrainClean.csv")
     X_test = pd.read_csv("HousePricesTestClean.csv")
     X_train_complete.head()
```

```
[ ]:    Unnamed: 0  MSSubClass  LotFrontage   LotArea  OverallQual  OverallCond  \
     0           0    4.110874     4.189655  9.042040            7            5
     1           1    3.044522     4.394449  9.169623            6            8
     2           2    4.110874     4.234107  9.328212            7            5
     3           3    4.262680     4.110874  9.164401            7            5
     4           4    4.110874     4.442651  9.565284            8            5

        YearBuilt  YearRemodAdd  MasVnrArea  BsmtFinSF1  …     SaleType_New  \
     0       2003          2003    5.283204    6.561031  …                0
     1       1976          1976    0.000000    6.886532  …                0
```

```
2        2001        2002    5.093750    6.188264    …                0
3        1915        1970    0.000000    5.379897    …                0
4        2000        2000    5.860786    6.486161    …                0

   SaleType_Oth  SaleType_WD  SaleCondition_Abnorml  SaleCondition_AdjLand  \
0             0            1                      0                      0
1             0            1                      0                      0
2             0            1                      0                      0
3             0            1                      1                      0
4             0            1                      0                      0

   SaleCondition_Alloca  SaleCondition_Family  SaleCondition_Normal  \
0                     0                     0                     1
1                     0                     0                     1
2                     0                     0                     1
3                     0                     0                     0
4                     0                     0                     1

   SaleCondition_Partial  SalePrice
0                      0  12.247699
1                      0  12.109016
2                      0  12.317171
3                      0  11.849405
4                      0  12.429220

[5 rows x 302 columns]
```

[ ]:
```
X_train = X_train_complete.loc[:,'MSSubClass':'SaleCondition_Partial']
y = X_train_complete['SalePrice']
```

1.2 Linear Regression Models

Now we are going to use plain linear regressio and regularized models (both L_1 Lasso and L_2 Ridge) from the scikit learn module. I'll also define a function that returns the cross-validation rmse error so we can evaluate our models and pick the best tuning par

[ ]:
```
from sklearn.linear_model import LinearRegression, Ridge, RidgeCV, ElasticNet,␣
↪Lasso, LassoCV
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error


def r2_cv(model, X_train, y, random_state=12345678):
    r2= cross_val_score(model, X_train, y, scoring="r2", cv =KFold(10,␣
↪shuffle=True, random_state=random_state))
```

```
    return(r2)

def rmse_cv(model, X_train, y, random_state=12345678):
    rmse= np.sqrt(-cross_val_score(model, X_train, y,␣
 ↪scoring="neg_mean_squared_error", cv =KFold(10, shuffle=True,␣
 ↪random_state=random_state)))
    return(rmse)
```

[ ]:
```
model_simple = LinearRegression()
model_simple.fit(X_train, y)
yp = model_simple.predict(X_train)

# compute R2 for train and using crossvalidation
r2_simple_train = r2_score(y,yp)
r2_xval_simple =  r2_cv(model_simple, X_train, y)

# compute RMSE for train and using crossvalidation
rmse_simple_train = mean_squared_error(y,yp,multioutput='raw_values')
rmse_xval_simple =  rmse_cv(model_simple, X_train, y)

print("Linear Regression")
print("==================================================")
print("\t                  Train R2=%.3f"%(r2_simple_train))
print("\t10-fold Crossvalidation R2=%.3f"%(r2_xval_simple.mean()))
print("\t                  Train RMSE=%.3f"%(rmse_simple_train))
print("\t10-fold Crossvalidation RMSE=%.3f"%(rmse_xval_simple.mean()))
```

```
Linear Regression
==================================================
                          Train R2=0.947
        10-fold Crossvalidation R2=0.720
                          Train RMSE=0.008
        10-fold Crossvalidation RMSE=0.171
```

1.3 Ridge Regression

We now try ridge regression (L_2) and for this purpose we need to select a value of α. The higher the α, the higher the penalization of weights with a large absolute value. We select a possible range of values of α and apply ridge for each value.

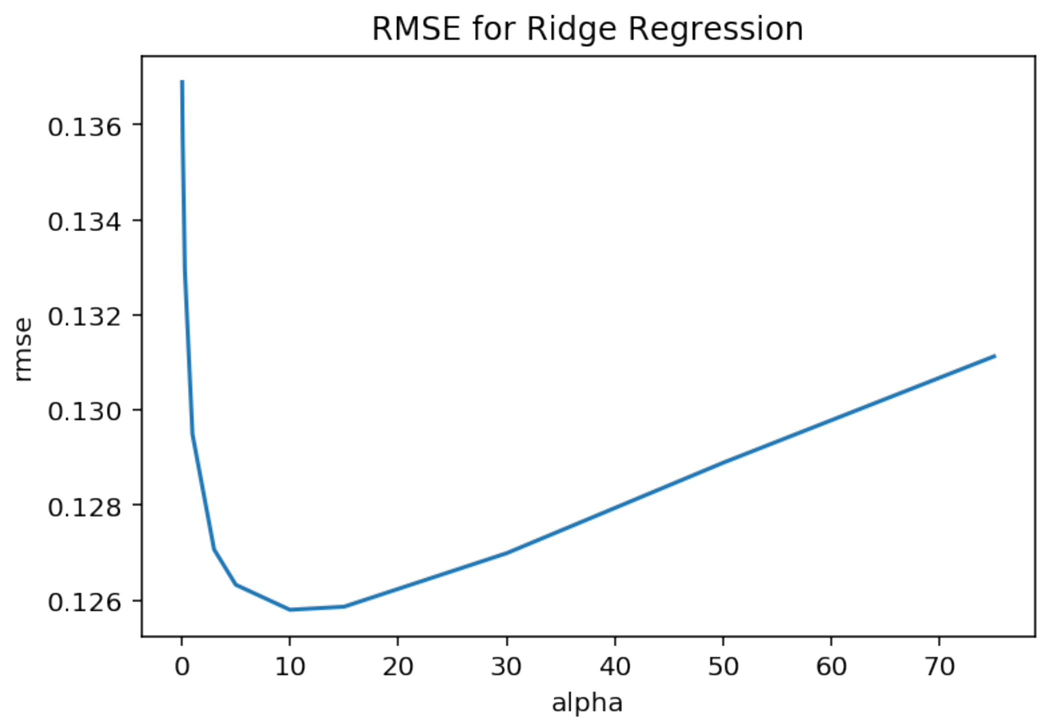
[ ]:
```
alphas = [0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 50, 75]
cv_ridge = [rmse_cv(Ridge(alpha = alpha), X_train, y).mean() for alpha in␣
 ↪alphas]
cv_r2_ridge = [r2_cv(Ridge(alpha = alpha), X_train, y).mean() for alpha in␣
 ↪alphas]
```

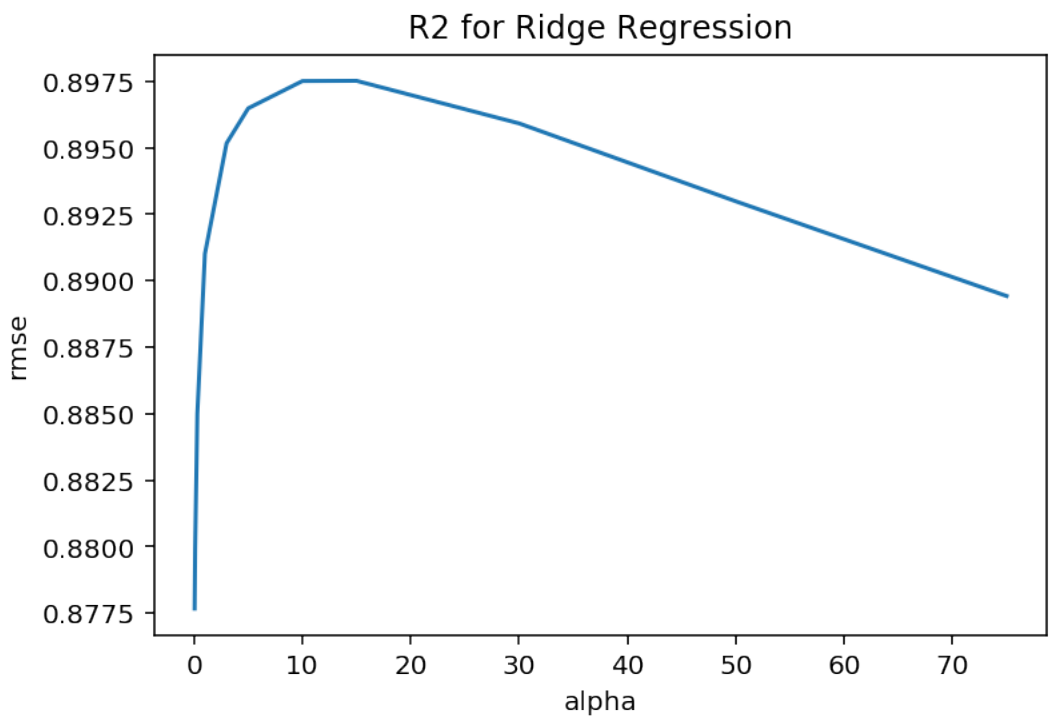
Put the values into a table and plot them

[ ]:
```
cv_ridge = pd.Series(cv_ridge, index = alphas)
cv_r2_ridge = pd.Series(cv_r2_ridge, index = alphas)

cv_ridge.plot(title = "RMSE for Ridge Regression")
plt.xlabel("alpha")
plt.ylabel("rmse")
plt.show()

cv_r2_ridge.plot(title = "R2 for Ridge Regression")
plt.xlabel("alpha")
plt.ylabel("rmse")
plt.show()
```





Note the U-ish shaped curve above. When alpha is too large the regularization is too strong and the model cannot capture all the complexities in the data. If however we let the model be too flexible (alpha small) the model begins to overfit. A value of alpha = 10 is about right based on the plot above.

[ ]:
```
print("Best RMSE %.3f for alpha %.3f"%(cv_ridge.min(),cv_ridge.idxmin()))
print("Best R2 %.3f for alpha %.3f"%(cv_r2_ridge.max(),cv_r2_ridge.idxmax()))
print("Why the difference? R2[10]=%.6f R2[15]=%.6f"%(cv_r2_ridge[cv_ridge.
 ↪idxmin()],cv_r2_ridge[cv_r2_ridge.idxmax()]))
```

```
Best RMSE 0.126 for alpha 10.000
Best R2 0.898 for alpha 15.000
Why the difference? R2[10]=0.897505 R2[15]=0.897513
```

So for the Ridge regression we get a rmse of about 0.126

1.4 Lasso Regression (L_1)

We now test Lasso regression. As before we need to test different values of α. Let's try out the Lasso model. For some reason the alphas in Lasso CV are really the inverse or the alphas in Ridge.

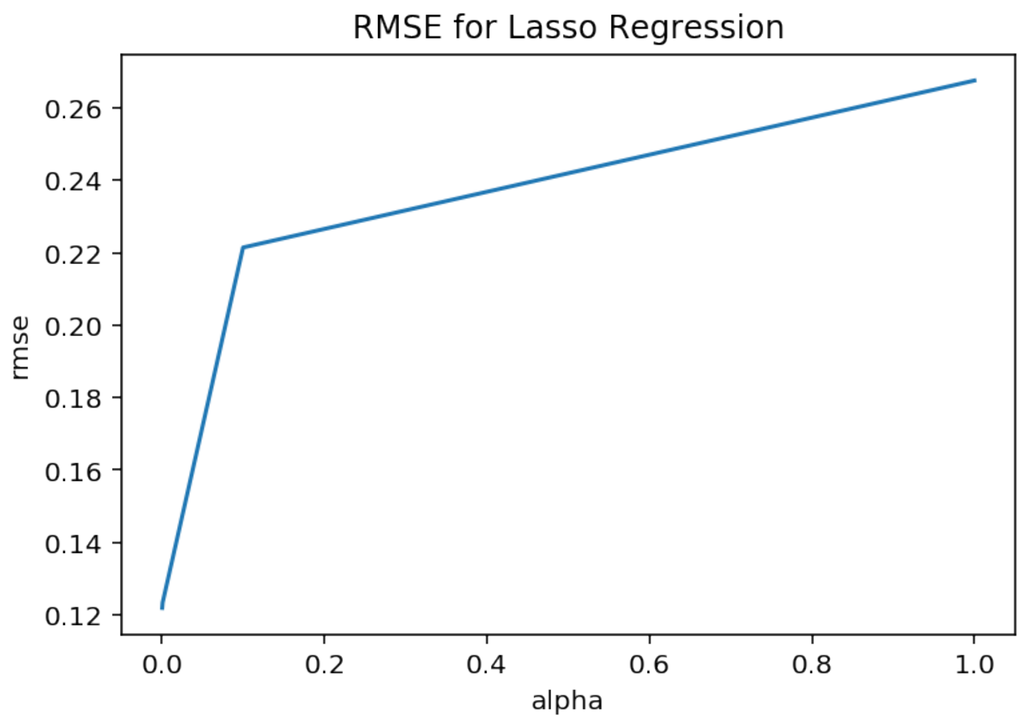
[ ]:
```
alphas = [1, 0.1, 0.001, 0.0005]
cv_lasso = [rmse_cv(Lasso(alpha = alpha), X_train, y).mean() for alpha in␣
 ↪alphas]
```

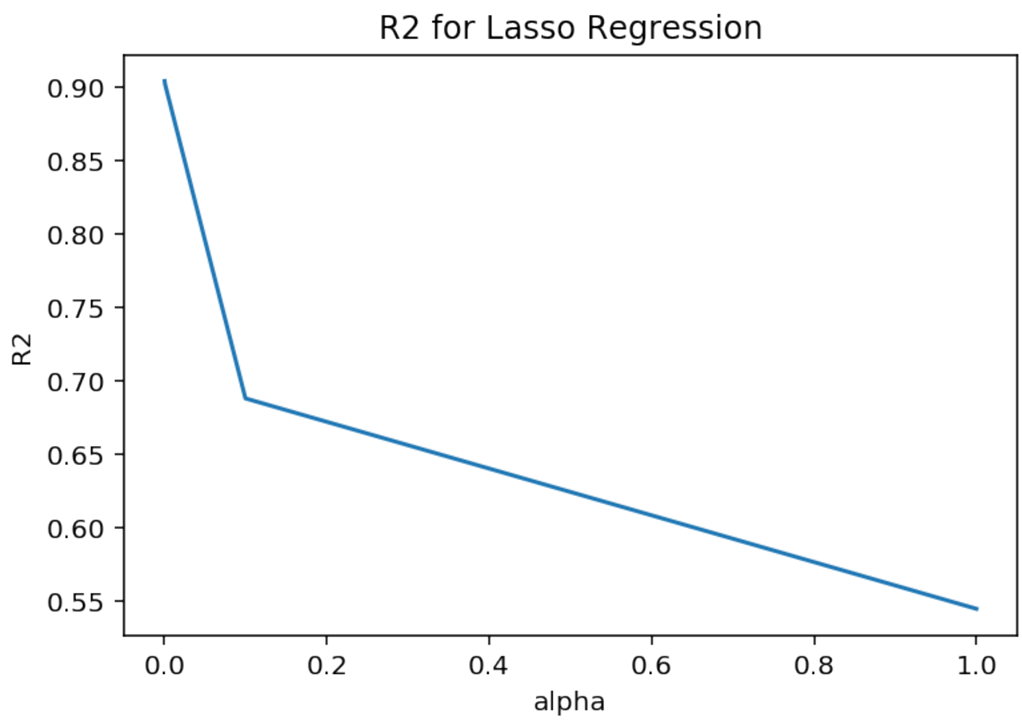
```
cv_r2_lasso = [r2_cv(Lasso(alpha = alpha), X_train, y).mean() for alpha in␣
↪alphas]

cv_lasso = pd.Series(cv_lasso, index = alphas)
cv_r2_lasso = pd.Series(cv_r2_lasso, index = alphas)

plt.figure(figsize=(6,4))
cv_lasso.plot(title = "RMSE for Lasso Regression")
plt.xlabel("alpha")
plt.ylabel("rmse")
plt.show()

plt.figure(figsize=(6,4))
cv_r2_lasso.plot(title = "R2 for Lasso Regression")
plt.xlabel("alpha")
plt.ylabel("R2")
plt.show()
```





[ ]:
```
print("Best RMSE %.3f for alpha %.3f"%(cv_lasso.min(),cv_lasso.idxmin()))
print("Best R2 %.3f for alpha %.3f"%(cv_r2_lasso.max(),cv_r2_lasso.idxmax()))
```

```
Best RMSE 0.122 for alpha 0.001
Best R2 0.904 for alpha 0.001
```

1.5 Lasso & Ridge with Built-in Crossvalidation

We performed the cross validation explicitly, but sklearn also provides two functions that include crossvalidation as part of the process, namely, LassoCV and RidgeCV.

[ ]:
```
model_ridge = RidgeCV(alphas = [0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 50, 75],␣
 ↪cv=KFold(10, shuffle=True, random_state=12345678)).fit(X_train, y)
model_lasso = LassoCV(alphas = [1, 0.1, 0.001, 0.0005],cv=KFold(10,␣
 ↪shuffle=True, random_state=12345678)).fit(X_train, y)
```

We evaluate the resulting model using the same procedure we applied before.

[ ]:
```
rmse_lasso2 = rmse_cv(model_lasso, X_train, y)
rmse_ridge2 = rmse_cv(model_ridge, X_train, y)

r2_lasso2 = r2_cv(model_lasso, X_train, y)
r2_ridge2 = r2_cv(model_ridge, X_train, y)
```

Finally, we compare the results achieved with this procedure with the ones compared with the explicit cross validation.

```
[ ]: print("Ridge Regression (10-fold crossvalidation)")
     print("\tRMSE=%.3f R2=%.3f for Alpha=%.3f"%(rmse_ridge2.mean(), r2_ridge2.
      ↪mean(), model_ridge.alpha_))
     print("\n")
     print("Lasso Regression (10-fold crossvalidation)")
     print("\tRMSE=%.3f R2=%.3f for Alpha=%.3f"%(rmse_lasso2.mean(), r2_lasso2.
      ↪mean(), model_lasso.alpha_))
```

```
Ridge Regression (10-fold crossvalidation)
        RMSE=0.126 R2=0.896 for Alpha=15.000


Lasso Regression (10-fold crossvalidation)
        RMSE=0.122 R2=0.904 for Alpha=0.001
```

The results are similar to the ones we obtained with the explicit search for α.

1.6 Feature Selection

One nice feature of Lasso regression is that by zeroing out the coefficients of variables that it deems unimportant, it actually performs feature selection. In practise, it simplifies the data while building the model.

```
[ ]: coef = pd.Series(model_lasso.coef_, index = X_train.columns)
```

```
[ ]: print("Lasso picked " + str(sum(coef != 0)) + " variables and eliminated the␣
      ↪other " +  str(sum(coef == 0)) + " variables")
```

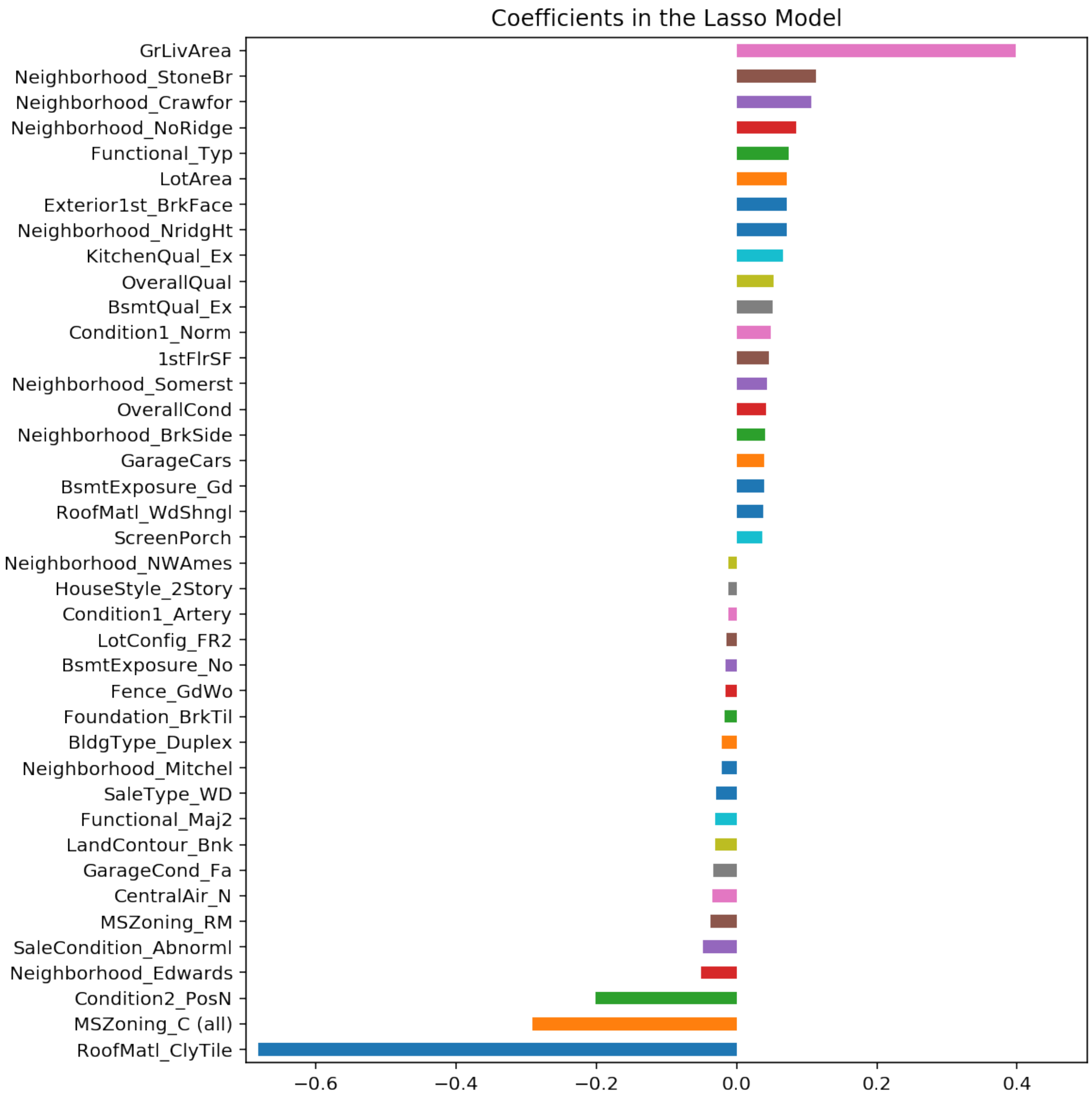
```
Lasso picked 105 variables and eliminated the other 195 variables
```

Note that, the process is stochastic and thus we cannot be sure that the selected variables are exactly the good ones so one approach is to run the procedure several times (using bootstrap which we will discuss later in the course) to check how robust the feature selection is. For instance, we check if there are variables whose weight is always zeroed out. As an example, let's plot the largest and the smallest coefficients.

```
[ ]: imp_coef = pd.concat([coef.sort_values().head(20),
                          coef.sort_values().tail(20)])
```

```
[ ]: matplotlib.rcParams['figure.figsize'] = (8.0, 10.0)
     imp_coef.plot(kind = "barh")
     plt.title("Coefficients in the Lasso Model")
     plt.xlim(-0.7,0.5)
```

```
[ ]: (-0.7, 0.5)
```



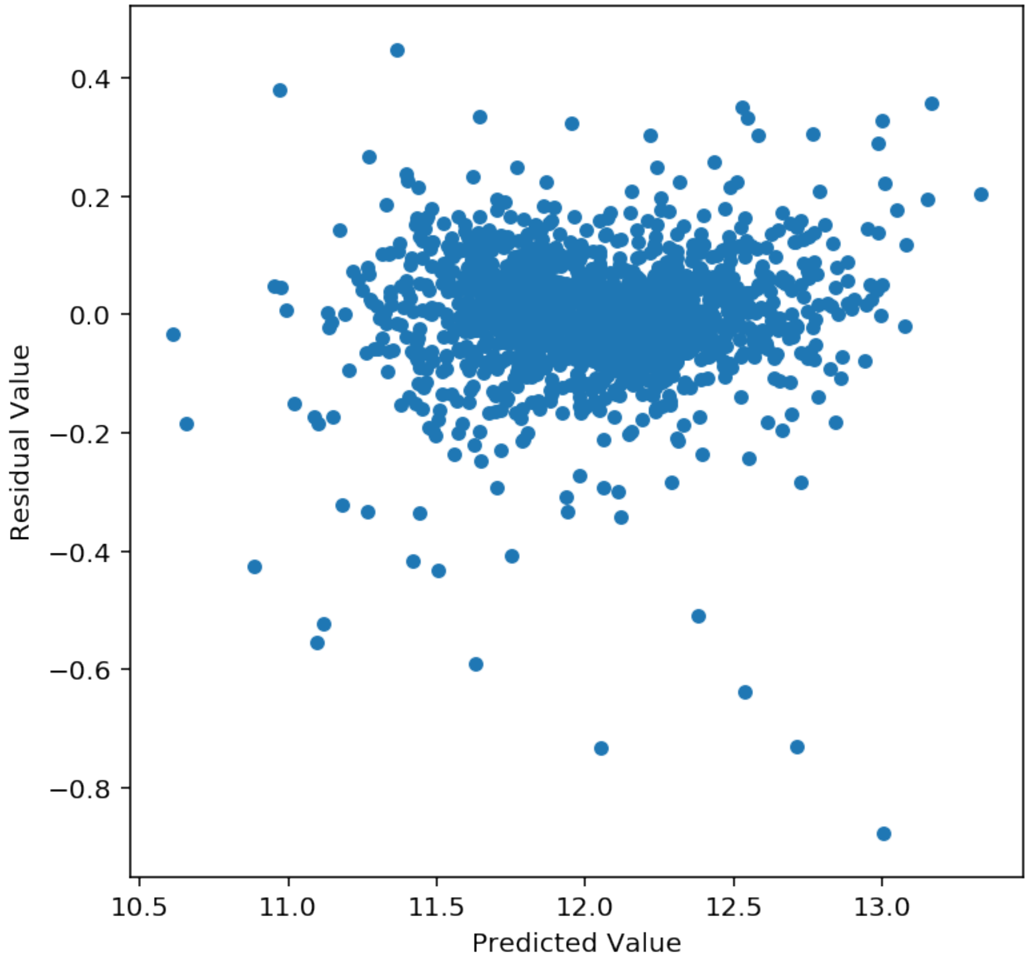
GrLivArea appears to be the most important positive feature (it identifies the above ground area by area square feet so it makes sense). Then a few other location and quality features contributed positively. Some of the negative features make less sense and would be worth looking into more.

Let's also check the residuals, that is the difference between the predicted and the actual value plotted against the predicted value.

[ ]:
```
matplotlib.rcParams['figure.figsize'] = (6.0, 6.0)

preds = pd.DataFrame({"preds":model_lasso.predict(X_train), "true":y})
preds["residuals"] = preds["true"] - preds["preds"]
preds.plot(x = "preds", y = "residuals",kind = "scatter")
plt.xlabel("Predicted Value")
plt.ylabel("Residual Value")
```

[ ]: Text(0,0.5,'Residual Value')

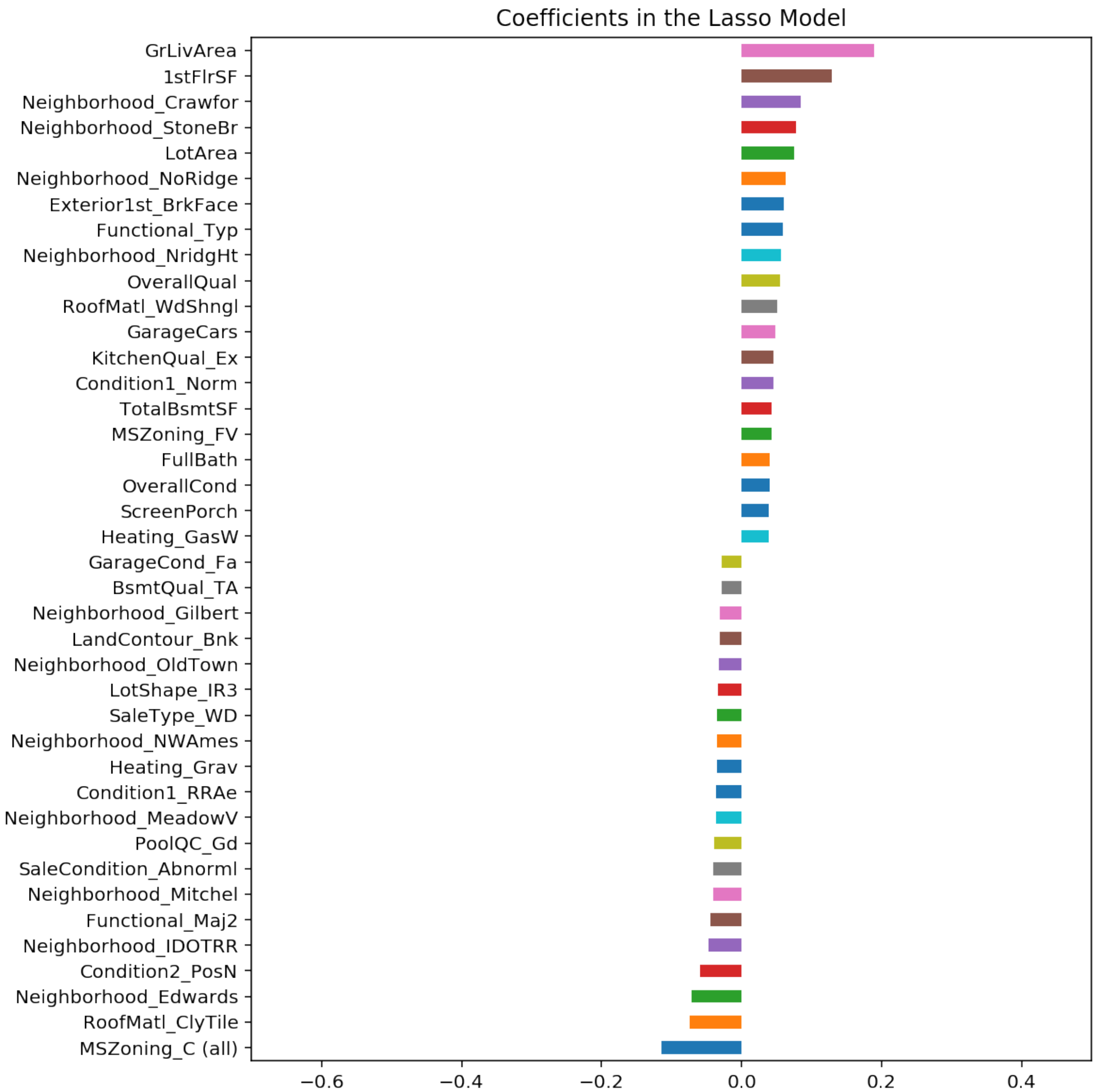



```
[ ]: ridge_coef = pd.Series(model_ridge.coef_, index = X_train.columns)
print("Ridge picked " + str(sum(ridge_coef != 0)) + " variables and eliminated␣
 ↪the other " +  str(sum(ridge_coef == 0)) + " variables")
```

Ridge picked 300 variables and eliminated the other 0 variables

```
[ ]: ridge_imp_coef = pd.concat([ridge_coef.sort_values().head(20),
                         ridge_coef.sort_values().tail(20)])
matplotlib.rcParams['figure.figsize'] = (8.0, 10.0)
ridge_imp_coef.plot(kind = "barh")
plt.title("Coefficients in the Ridge Model")
plt.xlim(-0.7,0.5)
```

[ ]: (-0.7, 0.5)


Coefficients in the Lasso Model
GrLivArea
1stFlrSF
Neighborhood_Crawfor
Neighborhood_StoneBr
LotArea
Neighborhood_NoRidge
Exterior1st_BrkFace
Functional_Typ
Neighborhood_NridgHt
OverallQual
RoofMatl_WdShngl
GarageCars
KitchenQual_Ex
Condition1_Norm
TotalBsmtSF
MSZoning_FV
FullBath
OverallCond
ScreenPorch
Heating_GasW
GarageCond_Fa
BsmtQual_TA
Neighborhood_Gilbert
LandContour_Bnk
Neighborhood_OldTown
LotShape_IR3
SaleType_WD
Neighborhood_NWAmes
Heating_Grav
Condition1_RRAe
Neighborhood_MeadowV
PoolQC_Gd
SaleCondition_Abnorml
Neighborhood_Mitchel
Functional_Maj2
Neighborhood_IDOTRR
Condition2_PosN
Neighborhood_Edwards
RoofMatl_ClyTile
MSZoning_C (all)
−0.6
−0.4
−0.2
0.0
0.2
0.4