Introduction

This kernel is an attempt to use every trick in the books to unleash the full power of Linear Regression, including a lot of preprocessing and a look at several Regularization algorithms.

At the time of writing, it achieves a score of about 0.121 on the public LB, just using regression, no RF, no xgboost, no ensembling etc. All comments/corrections are more than welcome.

In [1]:
```
# Imports
import pandas as pd
import numpy as np
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, RidgeCV, LassoCV, Elastic
NetCV
from sklearn.metrics import mean_squared_error, make_scorer
from scipy.stats import skew
from IPython.display import display
import matplotlib.pyplot as plt
import seaborn as sns

# Definitions
pd.set_option('display.float_format', lambda x: '%.3f' % x)
%matplotlib inline
#njobs = 4
```

In [2]:
```
# Get data
train = pd.read_csv("../input/train.csv")
print("train : " + str(train.shape))
```

```
train : (1460, 81)
```

In [3]:
```
# Check for duplicates
idsUnique = len(set(train.Id))
idsTotal = train.shape[0]
idsDupli = idsTotal - idsUnique
print("There are " + str(idsDupli) + " duplicate IDs for " + str(idsTotal) +
" total entries")

# Drop Id column
train.drop("Id", axis = 1, inplace = True)
```

```
There are 0 duplicate IDs for 1460 total entries
```

Preprocessing

In [4]:
```
# Looking for outliers, as indicated in https://ww2.amstat.org/publications/
jse/v19n3/decock.pdf
plt.scatter(train.GrLivArea, train.SalePrice, c = "blue", marker = "s")
plt.title("Looking for outliers")
plt.xlabel("GrLivArea")
plt.ylabel("SalePrice")
plt.show()

train = train[train.GrLivArea < 4000]
```

There seems to be 2 extreme outliers on the bottom right, really large houses that sold for really cheap. More generally, the author of the dataset recommends removing 'any houses with more than 4000 square feet' from the dataset.
Reference : [https://ww2.amstat.org/publications/jse/v19n3/decock.pdf (https://ww2.amstat.org/publications/jse/v19n3/decock.pdf)](https://ww2.amstat.org/publications/jse/v19n3/decock.pdf)

In [5]:
```
# Log transform the target for official scoring
train.SalePrice = np.log1p(train.SalePrice)
y = train.SalePrice
```

Taking logs means that errors in predicting expensive houses and cheap houses will affect the result equally.

In [6]:
```
# Handle missing values for features where median/mean or most common value
doesn't make sense

# Alley : data description says NA means "no alley access"
train.loc[:, "Alley"] = train.loc[:, "Alley"].fillna("None")
# BedroomAbvGr : NA most likely means 0
train.loc[:, "BedroomAbvGr"] = train.loc[:, "BedroomAbvGr"].fillna(0)
# BsmtQual etc : data description says NA for basement features is "no basem
ent"
train.loc[:, "BsmtQual"] = train.loc[:, "BsmtQual"].fillna("No")
train.loc[:, "BsmtCond"] = train.loc[:, "BsmtCond"].fillna("No")
train.loc[:, "BsmtExposure"] = train.loc[:, "BsmtExposure"].fillna("No")
train.loc[:, "BsmtFinType1"] = train.loc[:, "BsmtFinType1"].fillna("No")
train.loc[:, "BsmtFinType2"] = train.loc[:, "BsmtFinType2"].fillna("No")
train.loc[:, "BsmtFullBath"] = train.loc[:, "BsmtFullBath"].fillna(0)
train.loc[:, "BsmtHalfBath"] = train.loc[:, "BsmtHalfBath"].fillna(0)
train.loc[:, "BsmtUnfSF"] = train.loc[:, "BsmtUnfSF"].fillna(0)
# CentralAir : NA most likely means No
train.loc[:, "CentralAir"] = train.loc[:, "CentralAir"].fillna("N")
# Condition : NA most likely means Normal
train.loc[:, "Condition1"] = train.loc[:, "Condition1"].fillna("Norm")
train.loc[:, "Condition2"] = train.loc[:, "Condition2"].fillna("Norm")
# EnclosedPorch : NA most likely means no enclosed porch
train.loc[:, "EnclosedPorch"] = train.loc[:, "EnclosedPorch"].fillna(0)
# External stuff : NA most likely means average
train.loc[:, "ExterCond"] = train.loc[:, "ExterCond"].fillna("TA")
train.loc[:, "ExterQual"] = train.loc[:, "ExterQual"].fillna("TA")
# Fence : data description says NA means "no fence"
train.loc[:, "Fence"] = train.loc[:, "Fence"].fillna("No")
# FireplaceQu : data description says NA means "no fireplace"
train.loc[:, "FireplaceQu"] = train.loc[:, "FireplaceQu"].fillna("No")
train.loc[:, "Fireplaces"] = train.loc[:, "Fireplaces"].fillna(0)
# Functional : data description says NA means typical
train.loc[:, "Functional"] = train.loc[:, "Functional"].fillna("Typ")
# GarageType etc : data description says NA for garage features is "no garag
e"
train.loc[:, "GarageType"] = train.loc[:, "GarageType"].fillna("No")
train.loc[:, "GarageFinish"] = train.loc[:, "GarageFinish"].fillna("No")
train.loc[:, "GarageQual"] = train.loc[:, "GarageQual"].fillna("No")
train.loc[:, "GarageCond"] = train.loc[:, "GarageCond"].fillna("No")
train.loc[:, "GarageArea"] = train.loc[:, "GarageArea"].fillna(0)
train.loc[:, "GarageCars"] = train.loc[:, "GarageCars"].fillna(0)
# HalfBath : NA most likely means no half baths above grade
train.loc[:, "HalfBath"] = train.loc[:, "HalfBath"].fillna(0)
# HeatingQC : NA most likely means typical
train.loc[:, "HeatingQC"] = train.loc[:, "HeatingQC"].fillna("TA")
# KitchenAbvGr : NA most likely means 0
train.loc[:, "KitchenAbvGr"] = train.loc[:, "KitchenAbvGr"].fillna(0)
# KitchenQual : NA most likely means typical
train.loc[:, "KitchenQual"] = train.loc[:, "KitchenQual"].fillna("TA")
# LotFrontage : NA most likely means no lot frontage
train.loc[:, "LotFrontage"] = train.loc[:, "LotFrontage"].fillna(0)
# LotShape : NA most likely means regular
train.loc[:, "LotShape"] = train.loc[:, "LotShape"].fillna("Reg")
# MasVnrType : NA most likely means no veneer
train.loc[:, "MasVnrType"] = train.loc[:, "MasVnrType"].fillna("None")
train.loc[:, "MasVnrArea"] = train.loc[:, "MasVnrArea"].fillna(0)
# MiscFeature : data description says NA means "no misc feature"
train.loc[:, "MiscFeature"] = train.loc[:, "MiscFeature"].fillna("No")
train.loc[:, "MiscVal"] = train.loc[:, "MiscVal"].fillna(0)
# OpenPorchSF : NA most likely means no open porch
train.loc[:, "OpenPorchSF"] = train.loc[:, "OpenPorchSF"].fillna(0)
# PavedDrive : NA most likely means not paved
train.loc[:, "PavedDrive"] = train.loc[:, "PavedDrive"].fillna("N")
# PoolQC : data description says NA means "no pool"
train.loc[:, "PoolQC"] = train.loc[:, "PoolQC"].fillna("No")
train.loc[:, "PoolArea"] = train.loc[:, "PoolArea"].fillna(0)
# SaleCondition : NA most likely means normal sale
```

In [7]:
```
# Some numerical features are actually really categories
train = train.replace({"MSSubClass" : {20 : "SC20", 30 : "SC30", 40 : "SC4
0", 45 : "SC45",
                                       50 : "SC50", 60 : "SC60", 70 : "SC7
0", 75 : "SC75",
                                       80 : "SC80", 85 : "SC85", 90 : "SC9
0", 120 : "SC120",
                                       150 : "SC150", 160 : "SC160", 180 : "
SC180", 190 : "SC190"},
                       "MoSold" : {1 : "Jan", 2 : "Feb", 3 : "Mar", 4 : "Ap
r", 5 : "May", 6 : "Jun",
                                   7 : "Jul", 8 : "Aug", 9 : "Sep", 10 : "Oc
t", 11 : "Nov", 12 : "Dec"}
                      })
```

In [8]:
```
# Encode some categorical features as ordered numbers when there is informat
ion in the order
train = train.replace({"Alley" : {"Grvl" : 1, "Pave" : 2},
                       "BsmtCond" : {"No" : 0, "Po" : 1, "Fa" : 2, "TA" : 3,
"Gd" : 4, "Ex" : 5},
                       "BsmtExposure" : {"No" : 0, "Mn" : 1, "Av": 2, "Gd" :
3},
                       "BsmtFinType1" : {"No" : 0, "Unf" : 1, "LwQ": 2, "Re
c" : 3, "BLQ" : 4,
                                         "ALQ" : 5, "GLQ" : 6},
                       "BsmtFinType2" : {"No" : 0, "Unf" : 1, "LwQ": 2, "Re
c" : 3, "BLQ" : 4,
                                         "ALQ" : 5, "GLQ" : 6},
                       "BsmtQual" : {"No" : 0, "Po" : 1, "Fa" : 2, "TA": 3,
"Gd" : 4, "Ex" : 5},
                       "ExterCond" : {"Po" : 1, "Fa" : 2, "TA": 3, "Gd": 4,
"Ex" : 5},
                       "ExterQual" : {"Po" : 1, "Fa" : 2, "TA": 3, "Gd": 4,
"Ex" : 5},
                       "FireplaceQu" : {"No" : 0, "Po" : 1, "Fa" : 2, "TA" :
3, "Gd" : 4, "Ex" : 5},
                       "Functional" : {"Sal" : 1, "Sev" : 2, "Maj2" : 3, "Ma
j1" : 4, "Mod": 5,
                                       "Min2" : 6, "Min1" : 7, "Typ" : 8},
                       "GarageCond" : {"No" : 0, "Po" : 1, "Fa" : 2, "TA" :
3, "Gd" : 4, "Ex" : 5},
                       "GarageQual" : {"No" : 0, "Po" : 1, "Fa" : 2, "TA" :
3, "Gd" : 4, "Ex" : 5},
                       "HeatingQC" : {"Po" : 1, "Fa" : 2, "TA" : 3, "Gd" :
4, "Ex" : 5},
                       "KitchenQual" : {"Po" : 1, "Fa" : 2, "TA" : 3, "Gd" :
4, "Ex" : 5},
                       "LandSlope" : {"Sev" : 1, "Mod" : 2, "Gtl" : 3},
                       "LotShape" : {"IR3" : 1, "IR2" : 2, "IR1" : 3, "Reg"
: 4},
                       "PavedDrive" : {"N" : 0, "P" : 1, "Y" : 2},
                       "PoolQC" : {"No" : 0, "Fa" : 1, "TA" : 2, "Gd" : 3, "
Ex" : 4},
                       "Street" : {"Grvl" : 1, "Pave" : 2},
                       "Utilities" : {"ELO" : 1, "NoSeWa" : 2, "NoSewr" : 3,
"AllPub" : 4}}
                     )
```

Then we will create new features, in 3 ways :

1. Simplifications of existing features
2. Combinations of existing features
3. Polynomials on the top 10 existing features

In [9]:

```
# Create new features
# 1* Simplifications of existing features
train["SimplOverallQual"] = train.OverallQual.replace({1 : 1, 2 : 1, 3 : 1,
# bad
                                                       4 : 2, 5 : 2, 6 : 2,
# average
                                                       7 : 3, 8 : 3, 9 : 3,
10 : 3 # good
                                                      })
train["SimplOverallCond"] = train.OverallCond.replace({1 : 1, 2 : 1, 3 : 1,
# bad
                                                       4 : 2, 5 : 2, 6 : 2,
# average
                                                       7 : 3, 8 : 3, 9 : 3,
10 : 3 # good
                                                      })
train["SimplPoolQC"] = train.PoolQC.replace({1 : 1, 2 : 1, # average
                                             3 : 2, 4 : 2 # good
                                            })
train["SimplGarageCond"] = train.GarageCond.replace({1 : 1, # bad
                                                     2 : 1, 3 : 1, # average
                                                     4 : 2, 5 : 2 # good
                                                    })
train["SimplGarageQual"] = train.GarageQual.replace({1 : 1, # bad
                                                     2 : 1, 3 : 1, # average
                                                     4 : 2, 5 : 2 # good
                                                    })
train["SimplFireplaceQu"] = train.FireplaceQu.replace({1 : 1, # bad
                                                       2 : 1, 3 : 1, # avera
ge
                                                       4 : 2, 5 : 2 # good
                                                      })
train["SimplFireplaceQu"] = train.FireplaceQu.replace({1 : 1, # bad
                                                       2 : 1, 3 : 1, # avera
ge
                                                       4 : 2, 5 : 2 # good
                                                      })
train["SimplFunctional"] = train.Functional.replace({1 : 1, 2 : 1, # bad
                                                     3 : 2, 4 : 2, # major
                                                     5 : 3, 6 : 3, 7 : 3, #
minor
                                                     8 : 4 # typical
                                                    })
train["SimplKitchenQual"] = train.KitchenQual.replace({1 : 1, # bad
                                                       2 : 1, 3 : 1, # avera
ge
                                                       4 : 2, 5 : 2 # good
                                                      })
train["SimplHeatingQC"] = train.HeatingQC.replace({1 : 1, # bad
                                                   2 : 1, 3 : 1, # average
                                                   4 : 2, 5 : 2 # good
                                                  })
train["SimplBsmtFinType1"] = train.BsmtFinType1.replace({1 : 1, # unfinished
                                                         2 : 1, 3 : 1, # rec
room
                                                         4 : 2, 5 : 2, 6 : 2
# living quarters
                                                        })
train["SimplBsmtFinType2"] = train.BsmtFinType2.replace({1 : 1, # unfinished
                                                         2 : 1, 3 : 1, # rec
room
                                                         4 : 2, 5 : 2, 6 : 2
# living quarters
                                                        })
train["SimplBsmtCond"] = train.BsmtCond.replace({1 : 1, # bad
                                                 2 : 1, 3 : 1, # average
                                                 4 : 2, 5 : 2 # good
                                                })
```

In [10]:
```
# Find most important features relative to target
print("Find most important features relative to target")
corr = train.corr()
corr.sort_values(["SalePrice"], ascending = False, inplace = True)
print(corr.SalePrice)
```

```
Find most important features relative to target
SalePrice           1.000
OverallQual         0.819
AllSF               0.817
AllFlrsSF           0.729
GrLivArea           0.719
SimplOverallQual    0.708
ExterQual           0.681
GarageCars          0.680
TotalBath           0.673
KitchenQual         0.667
GarageScore         0.657
GarageArea          0.655
TotalBsmtSF         0.642
SimplExterQual      0.636
SimplGarageScore    0.631
BsmtQual            0.615
1stFlrSF            0.614
SimplKitchenQual    0.610
OverallGrade        0.604
SimplBsmtQual       0.594
FullBath            0.591
YearBuilt           0.589
ExterGrade          0.587
YearRemodAdd        0.569
FireplaceQu         0.547
GarageYrBlt         0.544
TotRmsAbvGrd        0.533
SimplOverallGrade   0.527
SimplKitchenScore   0.523
FireplaceScore      0.518
                     ...
SimplBsmtCond       0.204
BedroomAbvGr        0.204
AllPorchSF          0.199
LotFrontage         0.174
SimplFunctional     0.137
Functional          0.136
ScreenPorch         0.124
SimplBsmtFinType2   0.105
Street              0.058
3SsnPorch           0.056
ExterCond           0.051
PoolArea            0.041
SimplPoolScore      0.040
SimplPoolQC         0.040
PoolScore           0.040
PoolQC              0.038
BsmtFinType2        0.016
Utilities           0.013
BsmtFinSF2          0.006
BsmtHalfBath       -0.015
MiscVal            -0.020
SimplOverallCond   -0.028
YrSold             -0.034
OverallCond        -0.037
LowQualFinSF       -0.038
LandSlope          -0.040
SimplExterCond     -0.042
KitchenAbvGr       -0.148
EnclosedPorch      -0.149
LotShape           -0.286
Name: SalePrice, dtype: float64
```

In [11]:
```
# Create new features
# 3* Polynomials on the top 10 existing features
train["OverallQual-s2"] = train["OverallQual"] ** 2
train["OverallQual-s3"] = train["OverallQual"] ** 3
train["OverallQual-Sq"] = np.sqrt(train["OverallQual"])
train["AllSF-2"] = train["AllSF"] ** 2
train["AllSF-3"] = train["AllSF"] ** 3
train["AllSF-Sq"] = np.sqrt(train["AllSF"])
train["AllFlrsSF-2"] = train["AllFlrsSF"] ** 2
train["AllFlrsSF-3"] = train["AllFlrsSF"] ** 3
train["AllFlrsSF-Sq"] = np.sqrt(train["AllFlrsSF"])
train["GrLivArea-2"] = train["GrLivArea"] ** 2
train["GrLivArea-3"] = train["GrLivArea"] ** 3
train["GrLivArea-Sq"] = np.sqrt(train["GrLivArea"])
train["SimplOverallQual-s2"] = train["SimplOverallQual"] ** 2
train["SimplOverallQual-s3"] = train["SimplOverallQual"] ** 3
train["SimplOverallQual-Sq"] = np.sqrt(train["SimplOverallQual"])
train["ExterQual-2"] = train["ExterQual"] ** 2
train["ExterQual-3"] = train["ExterQual"] ** 3
train["ExterQual-Sq"] = np.sqrt(train["ExterQual"])
train["GarageCars-2"] = train["GarageCars"] ** 2
train["GarageCars-3"] = train["GarageCars"] ** 3
train["GarageCars-Sq"] = np.sqrt(train["GarageCars"])
train["TotalBath-2"] = train["TotalBath"] ** 2
train["TotalBath-3"] = train["TotalBath"] ** 3
train["TotalBath-Sq"] = np.sqrt(train["TotalBath"])
train["KitchenQual-2"] = train["KitchenQual"] ** 2
train["KitchenQual-3"] = train["KitchenQual"] ** 3
train["KitchenQual-Sq"] = np.sqrt(train["KitchenQual"])
train["GarageScore-2"] = train["GarageScore"] ** 2
train["GarageScore-3"] = train["GarageScore"] ** 3
train["GarageScore-Sq"] = np.sqrt(train["GarageScore"])
```

In [12]:
```
# Differentiate numerical features (minus the target) and categorical featur
es
categorical_features = train.select_dtypes(include = ["object"]).columns
numerical_features = train.select_dtypes(exclude = ["object"]).columns
numerical_features = numerical_features.drop("SalePrice")
print("Numerical features : " + str(len(numerical_features)))
print("Categorical features : " + str(len(categorical_features)))
train_num = train[numerical_features]
train_cat = train[categorical_features]
```

```
Numerical features : 117
Categorical features : 26
```

In [13]:
```
# Handle remaining missing values for numerical features by using median as
replacement
print("NAs for numerical features in train : " + str(train_num.isnull().valu
es.sum()))
train_num = train_num.fillna(train_num.median())
print("Remaining NAs for numerical features in train : " + str(train_num.isn
ull().values.sum()))
```

```
NAs for numerical features in train : 81
Remaining NAs for numerical features in train : 0
```

In [14]:
```
# Log transform of the skewed numerical features to lessen impact of outlier
s
# Inspired by Alexandru Papiu's script : https://www.kaggle.com/apapiu/house
-prices-advanced-regression-techniques/regularized-linear-models
# As a general rule of thumb, a skewness with an absolute value > 0.5 is con
sidered at least moderately skewed
skewness = train_num.apply(lambda x: skew(x))
skewness = skewness[abs(skewness) > 0.5]
print(str(skewness.shape[0]) + " skewed numerical features to log transfor
m")
skewed_features = skewness.index
train_num[skewed_features] = np.log1p(train_num[skewed_features])
```

```
86 skewed numerical features to log transform
```

In [15]:
```
# Create dummy features for categorical values via one-hot encoding
print("NAs for categorical features in train : " + str(train_cat.isnull().va
lues.sum()))
train_cat = pd.get_dummies(train_cat)
print("Remaining NAs for categorical features in train : " + str(train_cat.i
snull().values.sum()))
```

```
NAs for categorical features in train : 1
Remaining NAs for categorical features in train : 0
```

Modeling

In [16]:
```
# Join categorical and numerical features
train = pd.concat([train_num, train_cat], axis = 1)
print("New number of features : " + str(train.shape[1]))

# Partition the dataset in train + validation sets
X_train, X_test, y_train, y_test = train_test_split(train, y, test_size = 0.
3, random_state = 0)
print("X_train : " + str(X_train.shape))
print("X_test : " + str(X_test.shape))
print("y_train : " + str(y_train.shape))
print("y_test : " + str(y_test.shape))
```

```
New number of features : 319
X_train : (1019, 319)
X_test : (437, 319)
y_train : (1019,)
y_test : (437,)
```

In [17]:
```
# Standardize numerical features
stdSc = StandardScaler()
X_train.loc[:, numerical_features] = stdSc.fit_transform(X_train.loc[:, nume
rical_features])
X_test.loc[:, numerical_features] = stdSc.transform(X_test.loc[:, numerical_
features])
```

```
/opt/conda/lib/python3.5/site-packages/pandas/core/indexing.py:465: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  self.obj[item] = s
```

Standardization cannot be done before the partitioning, as we don't want to fit the StandardScaler on some observations that will later be used in the test set.

In [18]:
```
# Define error measure for official scoring : RMSE
scorer = make_scorer(mean_squared_error, greater_is_better = False)

def rmse_cv_train(model):
    rmse= np.sqrt(-cross_val_score(model, X_train, y_train, scoring = score
r, cv = 10))
    return(rmse)

def rmse_cv_test(model):
    rmse= np.sqrt(-cross_val_score(model, X_test, y_test, scoring = scorer,
cv = 10))
    return(rmse)
```

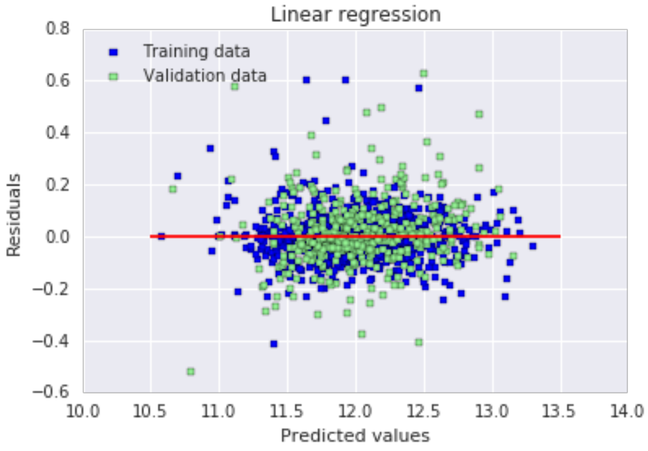
Note : I'm not getting nearly the same numbers in local CV compared to public LB, so I'm a tad worried that my CV process may have an issue somewhere. If you spot something, please let me know.

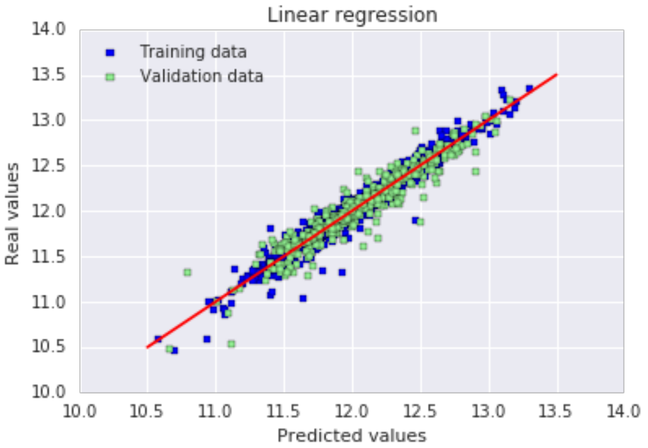
1* Linear Regression without regularization

In [19]:

```
# Linear Regression
lr = LinearRegression()
lr.fit(X_train, y_train)

# Look at predictions on training and validation set
print("RMSE on Training set :", rmse_cv_train(lr).mean())
print("RMSE on Test set :", rmse_cv_test(lr).mean())
y_train_pred = lr.predict(X_train)
y_test_pred = lr.predict(X_test)

# Plot residuals
plt.scatter(y_train_pred, y_train_pred - y_train, c = "blue", marker = "s",
label = "Training data")
plt.scatter(y_test_pred, y_test_pred - y_test, c = "lightgreen", marker = "
s", label = "Validation data")
plt.title("Linear regression")
plt.xlabel("Predicted values")
plt.ylabel("Residuals")
plt.legend(loc = "upper left")
plt.hlines(y = 0, xmin = 10.5, xmax = 13.5, color = "red")
plt.show()

# Plot predictions
plt.scatter(y_train_pred, y_train, c = "blue", marker = "s", label = "Traini
ng data")
plt.scatter(y_test_pred, y_test, c = "lightgreen", marker = "s", label = "Va
lidation data")
plt.title("Linear regression")
plt.xlabel("Predicted values")
plt.ylabel("Real values")
plt.legend(loc = "upper left")
plt.plot([10.5, 13.5], [10.5, 13.5], c = "red")
plt.show()
```

```
RMSE on Training set : 15758371373.7
RMSE on Test set : 0.395779797728
```





RMSE on Training set shows up weird here (not when I run it on my computer) for some reason.
Errors seem randomly distributed and randomly scattered around the centerline, so there is that at least. It means our model was able to capture most of the explanatory information.

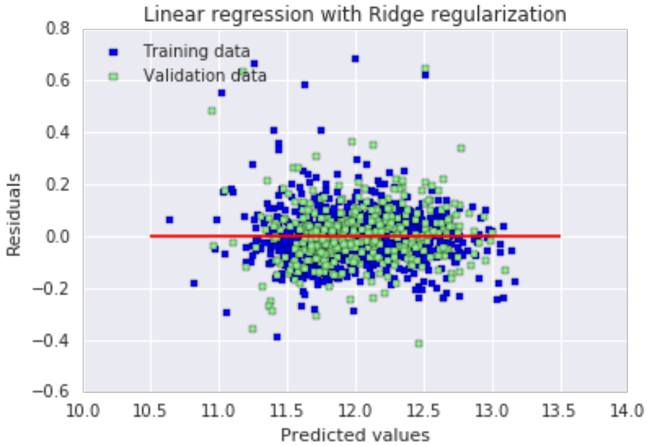
2* Linear Regression with Ridge regularization (L2 penalty)

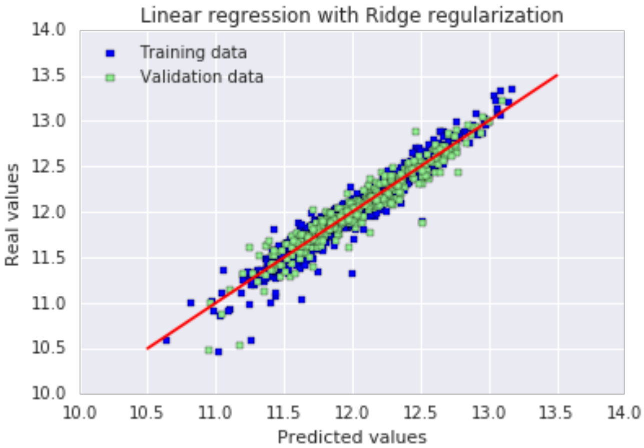
From the *Python Machine Learning* book by Sebastian Raschka : Regularization is a very useful method to handle collinearity, filter out noise from data, and eventually prevent overfitting. The concept behind regularization is to introduce additional information (bias) to penalize extreme parameter weights.

Ridge regression is an L2 penalized model where we simply add the squared sum of the weights to our cost function.

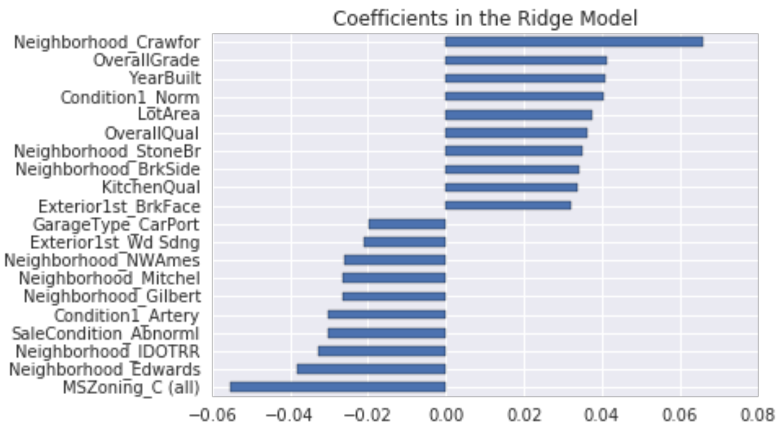
In [20]:
```
# 2* Ridge
ridge = RidgeCV(alphas = [0.01, 0.03, 0.06, 0.1, 0.3, 0.6, 1, 3, 6, 10, 30,
60])
ridge.fit(X_train, y_train)
alpha = ridge.alpha_
print("Best alpha :", alpha)

print("Try again for more precision with alphas centered around " + str(alph
a))
ridge = RidgeCV(alphas = [alpha * .6, alpha * .65, alpha * .7, alpha * .75,
alpha * .8, alpha * .85,
                          alpha * .9, alpha * .95, alpha, alpha * 1.05, alph
a * 1.1, alpha * 1.15,
                          alpha * 1.25, alpha * 1.3, alpha * 1.35, alpha *
1.4],
                cv = 10)
ridge.fit(X_train, y_train)
alpha = ridge.alpha_
print("Best alpha :", alpha)

print("Ridge RMSE on Training set :", rmse_cv_train(ridge).mean())
print("Ridge RMSE on Test set :", rmse_cv_test(ridge).mean())
y_train_rdg = ridge.predict(X_train)
y_test_rdg = ridge.predict(X_test)

# Plot residuals
plt.scatter(y_train_rdg, y_train_rdg - y_train, c = "blue", marker = "s", la
bel = "Training data")
plt.scatter(y_test_rdg, y_test_rdg - y_test, c = "lightgreen", marker = "s",
label = "Validation data")
plt.title("Linear regression with Ridge regularization")
plt.xlabel("Predicted values")
plt.ylabel("Residuals")
plt.legend(loc = "upper left")
plt.hlines(y = 0, xmin = 10.5, xmax = 13.5, color = "red")
plt.show()

# Plot predictions
plt.scatter(y_train_rdg, y_train, c = "blue", marker = "s", label = "Trainin
g data")
plt.scatter(y_test_rdg, y_test, c = "lightgreen", marker = "s", label = "Val
idation data")
plt.title("Linear regression with Ridge regularization")
plt.xlabel("Predicted values")
plt.ylabel("Real values")
plt.legend(loc = "upper left")
plt.plot([10.5, 13.5], [10.5, 13.5], c = "red")
plt.show()

# Plot important coefficients
coefs = pd.Series(ridge.coef_, index = X_train.columns)
print("Ridge picked " + str(sum(coefs != 0)) + " features and eliminated the
other " +  \
      str(sum(coefs == 0)) + " features")
imp_coefs = pd.concat([coefs.sort_values().head(10),
                     coefs.sort_values().tail(10)])
imp_coefs.plot(kind = "barh")
plt.title("Coefficients in the Ridge Model")
plt.show()
```

```
Best alpha : 30.0
Try again for more precision with alphas centered around 30.0
Best alpha : 24.0
Ridge RMSE on Training set : 0.115405723285
Ridge RMSE on Test set : 0.116427213778
```






```
Ridge picked 316 features and eliminated the other 3 features
```



We're getting a much better RMSE result now that we've added regularization. The very small difference between training and test results indicate that we eliminated most of the overfitting. Visually, the graphs seem to confirm that idea.

Ridge used almost all of the existing features.

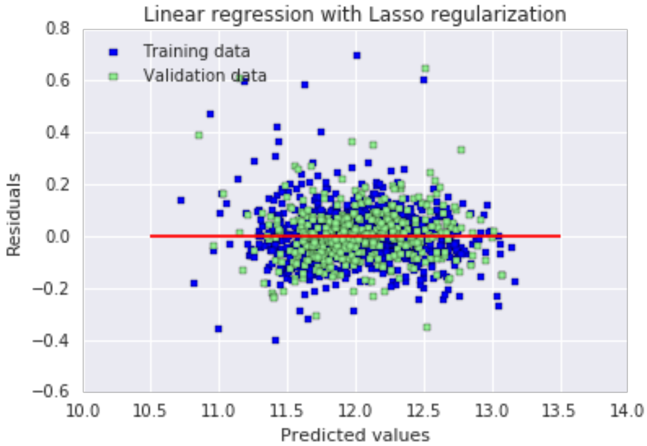
3* Linear Regression with Lasso regularization (L1 penalty)

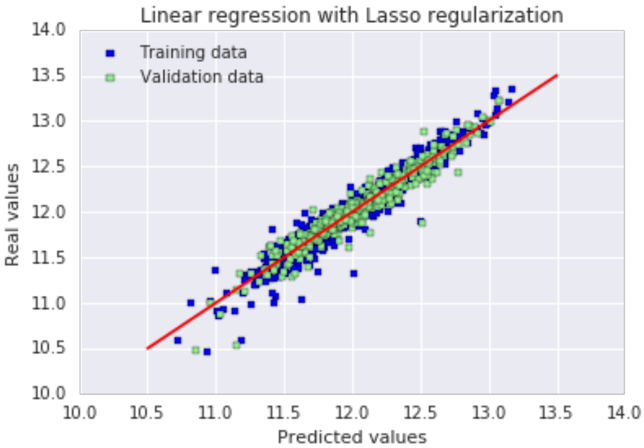
LASSO stands for *Least Absolute Shrinkage and Selection Operator*. It is an alternative regularization method, where we simply replace the square of the weights by the sum of the absolute value of the weights. In contrast to L2 regularization, L1 regularization yields sparse feature vectors : most feature weights will be zero. Sparsity can be useful in practice if we have a high dimensional dataset with many features that are irrelevant.

We can suspect that it should be more efficient than Ridge here.

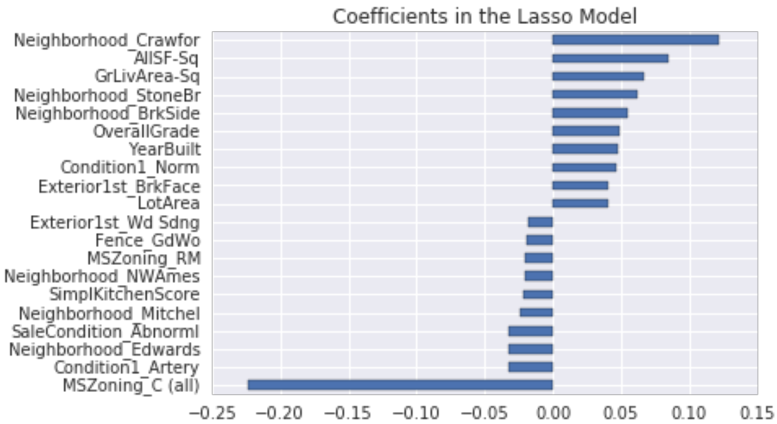
In [21]:
```
# 3* Lasso
lasso = LassoCV(alphas = [0.0001, 0.0003, 0.0006, 0.001, 0.003, 0.006, 0.01,
0.03, 0.06, 0.1,
                          0.3, 0.6, 1],
                max_iter = 50000, cv = 10)
lasso.fit(X_train, y_train)
alpha = lasso.alpha_
print("Best alpha :", alpha)

print("Try again for more precision with alphas centered around " + str(alph
a))
lasso = LassoCV(alphas = [alpha * .6, alpha * .65, alpha * .7, alpha * .75,
alpha * .8,
                          alpha * .85, alpha * .9, alpha * .95, alpha, alpha
* 1.05,
                          alpha * 1.1, alpha * 1.15, alpha * 1.25, alpha *
1.3, alpha * 1.35,
                          alpha * 1.4],
                max_iter = 50000, cv = 10)
lasso.fit(X_train, y_train)
alpha = lasso.alpha_
print("Best alpha :", alpha)

print("Lasso RMSE on Training set :", rmse_cv_train(lasso).mean())
print("Lasso RMSE on Test set :", rmse_cv_test(lasso).mean())
y_train_las = lasso.predict(X_train)
y_test_las = lasso.predict(X_test)

# Plot residuals
plt.scatter(y_train_las, y_train_las - y_train, c = "blue", marker = "s", la
bel = "Training data")
plt.scatter(y_test_las, y_test_las - y_test, c = "lightgreen", marker = "s",
label = "Validation data")
plt.title("Linear regression with Lasso regularization")
plt.xlabel("Predicted values")
plt.ylabel("Residuals")
plt.legend(loc = "upper left")
plt.hlines(y = 0, xmin = 10.5, xmax = 13.5, color = "red")
plt.show()

# Plot predictions
plt.scatter(y_train_las, y_train, c = "blue", marker = "s", label = "Trainin
g data")
plt.scatter(y_test_las, y_test, c = "lightgreen", marker = "s", label = "Val
idation data")
plt.title("Linear regression with Lasso regularization")
plt.xlabel("Predicted values")
plt.ylabel("Real values")
plt.legend(loc = "upper left")
plt.plot([10.5, 13.5], [10.5, 13.5], c = "red")
plt.show()

# Plot important coefficients
coefs = pd.Series(lasso.coef_, index = X_train.columns)
print("Lasso picked " + str(sum(coefs != 0)) + " features and eliminated the
other " +  \
      str(sum(coefs == 0)) + " features")
imp_coefs = pd.concat([coefs.sort_values().head(10),
                     coefs.sort_values().tail(10)])
imp_coefs.plot(kind = "barh")
plt.title("Coefficients in the Lasso Model")
plt.show()
```

```
Best alpha : 0.0006
Try again for more precision with alphas centered around 0.0006
Best alpha : 0.0006
Lasso RMSE on Training set : 0.114111508375
Lasso RMSE on Test set : 0.115832132218
```






```
Lasso picked 110 features and eliminated the other 209 features
```



RMSE results are better both on training and test sets. The most interesting thing is that Lasso used only one third of the available features. Another interesting tidbit : it seems to give big weights to Neighborhood categories, both in positive and negative ways. Intuitively it makes sense, house prices change a whole lot from one neighborhood to another in the same city.

The "MSZoning_C (all)" feature seems to have a disproportionate impact compared to the others. It is defined as *general zoning classification : commercial*. It seems a bit weird to me that having your house in a mostly commercial zone would be such a terrible thing.

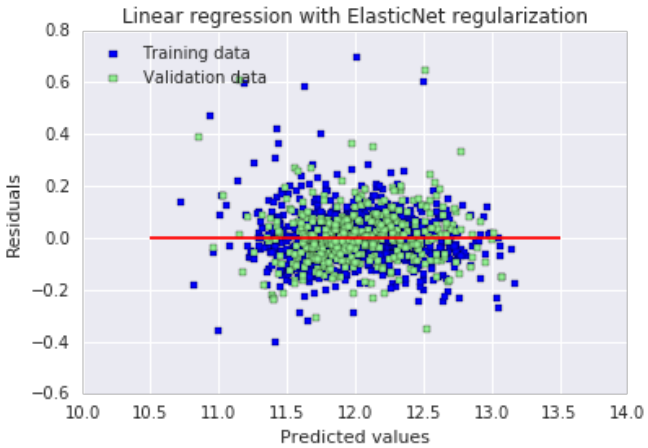
4* Linear Regression with ElasticNet regularization (L1 and L2 penalty)

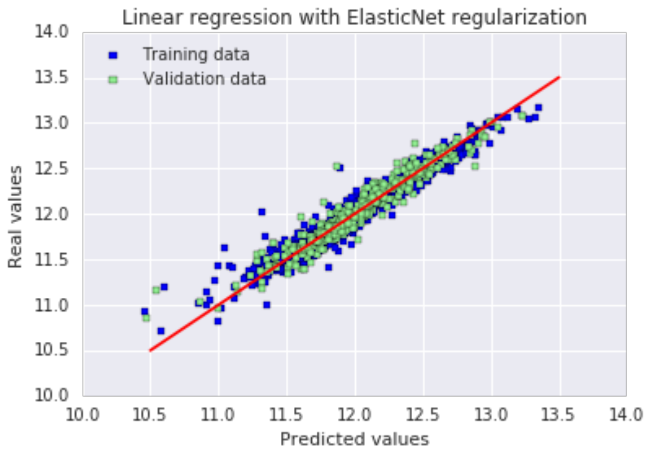
ElasticNet is a compromise between Ridge and Lasso regression. It has a L1 penalty to generate sparsity and a L2 penalty to overcome some of the limitations of Lasso, such as the number of variables (Lasso can't select more features than it has observations, but it's not the case here anyway).

In [22]:
```
# 4* ElasticNet
elasticNet = ElasticNetCV(l1_ratio = [0.1, 0.3, 0.5, 0.6, 0.7, 0.8, 0.85, 0.
9, 0.95, 1],
                          alphas = [0.0001, 0.0003, 0.0006, 0.001, 0.003, 0.
006,
                                    0.01, 0.03, 0.06, 0.1, 0.3, 0.6, 1, 3,
6],
                          max_iter = 50000, cv = 10)
elasticNet.fit(X_train, y_train)
alpha = elasticNet.alpha_
ratio = elasticNet.l1_ratio_
print("Best l1_ratio :", ratio)
print("Best alpha :", alpha )

print("Try again for more precision with l1_ratio centered around " + str(ra
tio))
elasticNet = ElasticNetCV(l1_ratio = [ratio * .85, ratio * .9, ratio * .95,
ratio, ratio * 1.05, ratio * 1.1, ratio * 1.15],
                          alphas = [0.0001, 0.0003, 0.0006, 0.001, 0.003, 0.
006, 0.01, 0.03, 0.06, 0.1, 0.3, 0.6, 1, 3, 6],
                          max_iter = 50000, cv = 10)
elasticNet.fit(X_train, y_train)
if (elasticNet.l1_ratio_ > 1):
    elasticNet.l1_ratio_ = 1
alpha = elasticNet.alpha_
ratio = elasticNet.l1_ratio_
print("Best l1_ratio :", ratio)
print("Best alpha :", alpha )

print("Now try again for more precision on alpha, with l1_ratio fixed at " +
str(ratio) +
      " and alpha centered around " + str(alpha))
elasticNet = ElasticNetCV(l1_ratio = ratio,
                          alphas = [alpha * .6, alpha * .65, alpha * .7, alp
ha * .75, alpha * .8, alpha * .85, alpha * .9,
                                    alpha * .95, alpha, alpha * 1.05, alpha
* 1.1, alpha * 1.15, alpha * 1.25, alpha * 1.3,
                                    alpha * 1.35, alpha * 1.4],
                          max_iter = 50000, cv = 10)
elasticNet.fit(X_train, y_train)
if (elasticNet.l1_ratio_ > 1):
    elasticNet.l1_ratio_ = 1
alpha = elasticNet.alpha_
ratio = elasticNet.l1_ratio_
print("Best l1_ratio :", ratio)
print("Best alpha :", alpha )

print("ElasticNet RMSE on Training set :", rmse_cv_train(elasticNet).mean())
print("ElasticNet RMSE on Test set :", rmse_cv_test(elasticNet).mean())
y_train_ela = elasticNet.predict(X_train)
y_test_ela = elasticNet.predict(X_test)

# Plot residuals
plt.scatter(y_train_ela, y_train_ela - y_train, c = "blue", marker = "s", la
bel = "Training data")
plt.scatter(y_test_ela, y_test_ela - y_test, c = "lightgreen", marker = "s",
label = "Validation data")
plt.title("Linear regression with ElasticNet regularization")
plt.xlabel("Predicted values")
plt.ylabel("Residuals")
plt.legend(loc = "upper left")
plt.hlines(y = 0, xmin = 10.5, xmax = 13.5, color = "red")
plt.show()

# Plot predictions
plt.scatter(y_train, y_train_ela, c = "blue", marker = "s", label = "Trainin
g data")
plt.scatter(y_test, y_test_ela, c = "lightgreen", marker = "s", label = "Val
```

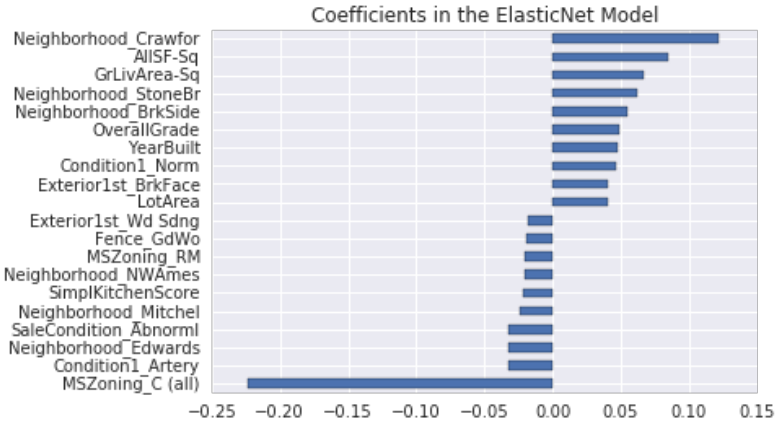
```
/opt/conda/lib/python3.5/site-packages/sklearn/linear_model/coordinate_descen
t.py:479: ConvergenceWarning: Objective did not converge. You might want to i
ncrease the number of iterations. Fitting data with very small alpha may caus
e precision problems.
  ConvergenceWarning)
```

```
Best l1_ratio : 1.0
Best alpha : 0.0006
Try again for more precision with l1_ratio centered around 1.0
Best l1_ratio : 1.0
Best alpha : 0.0006
Now try again for more precision on alpha, with l1_ratio fixed at 1.0 and alp
ha centered around 0.0006
Best l1_ratio : 1.0
Best alpha : 0.0006
ElasticNet RMSE on Training set : 0.114111508375
ElasticNet RMSE on Test set : 0.115832132218
```






```
ElasticNet picked 110 features and eliminated the other 209 features
```



The optimal L1 ratio used by ElasticNet here is equal to 1, which means it is exactly equal to the Lasso regressor we used earlier (and had it been equal to 0, it would have been exactly equal to our Ridge regressor). The model didn't need any L2 regularization to overcome any potential L1 shortcoming.

Note : I tried to remove the "MSZoning_C (all)" feature, it resulted in a slightly worse CV score, but slightly better public LB score.

Conclusion

Putting time and effort into preparing the dataset and optimizing the regularization resulted in a decent score, better than some public scripts which use algorithms that historically perform better in Kaggle contests, like Random Forests. Being fairly new to the world of machine learning contests, I will appreciate any constructive pointer to improve, and I thank you for your time.