NYCDSA Machine Learning Project:

House Prices: Advanced Regression Techniques

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The Project

"Predict sales prices and practice feature engineering, RFs, and gradient boosting"

1,460	80	Sale Price	4,357
OBSERVATIONS	FEATURES	DEPENDENT VARIABLE	TEAMS
Medium-sized dataset	Detailed descriptions and circumstances of sales	Regression	Highly popular competition on Kaggle

Workflow

In conducting our research, we emphasized on a clearly defined workflow to increase the degree of comprehensibility of our findings

EDA

Numerical and visual exploratory data analysis

DATA PREPARATION

Analyzing features, dropping statistically irrelevant / highly correlated features, as well as filling in NA's

FEATURE ENGINEERING

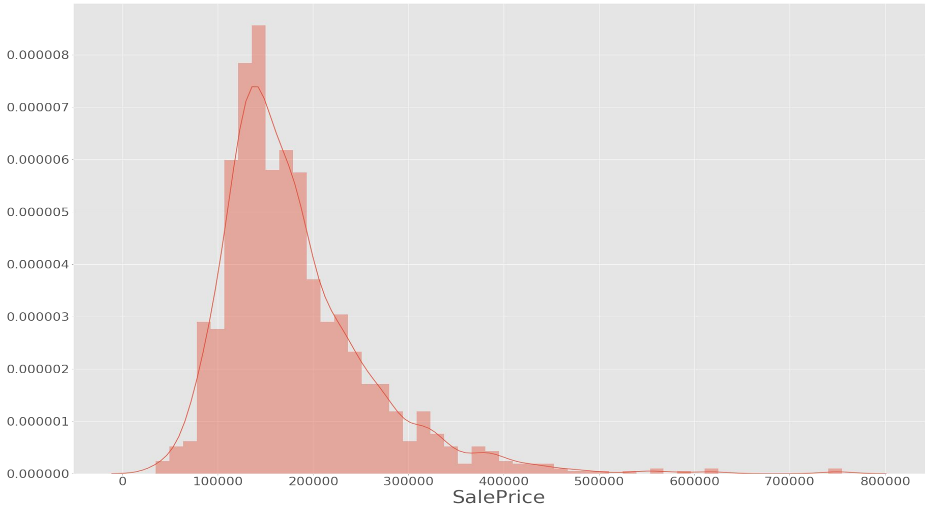
Creating two new features

TRAINING & TUNING MODELS

Training and tuning several ML algorithms in sklearn

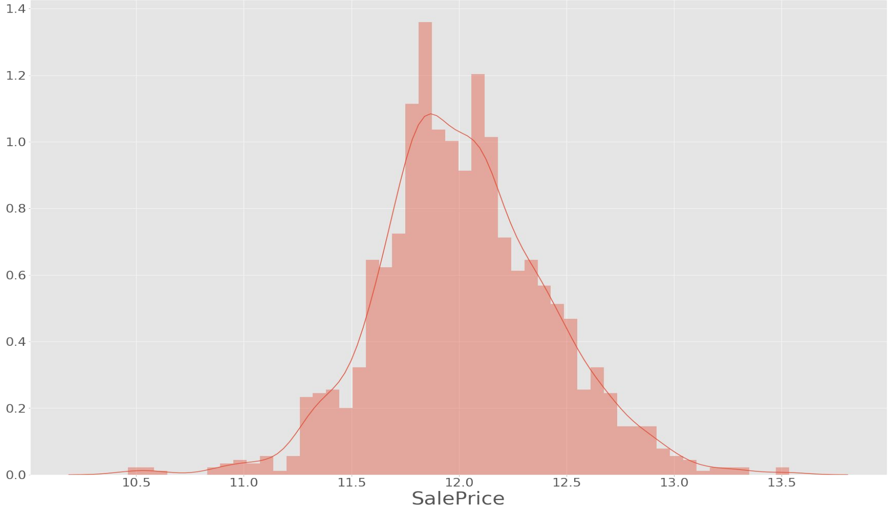
Sale Price Original

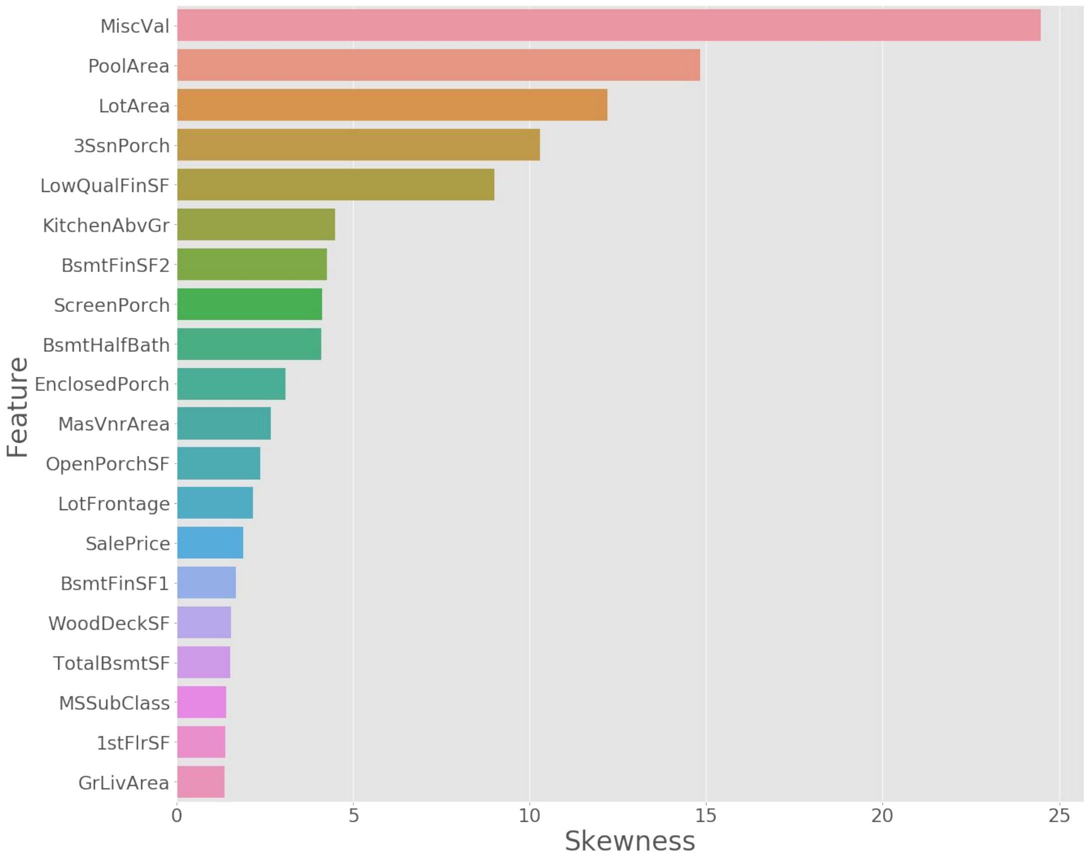
Heavily right-skewed distribution



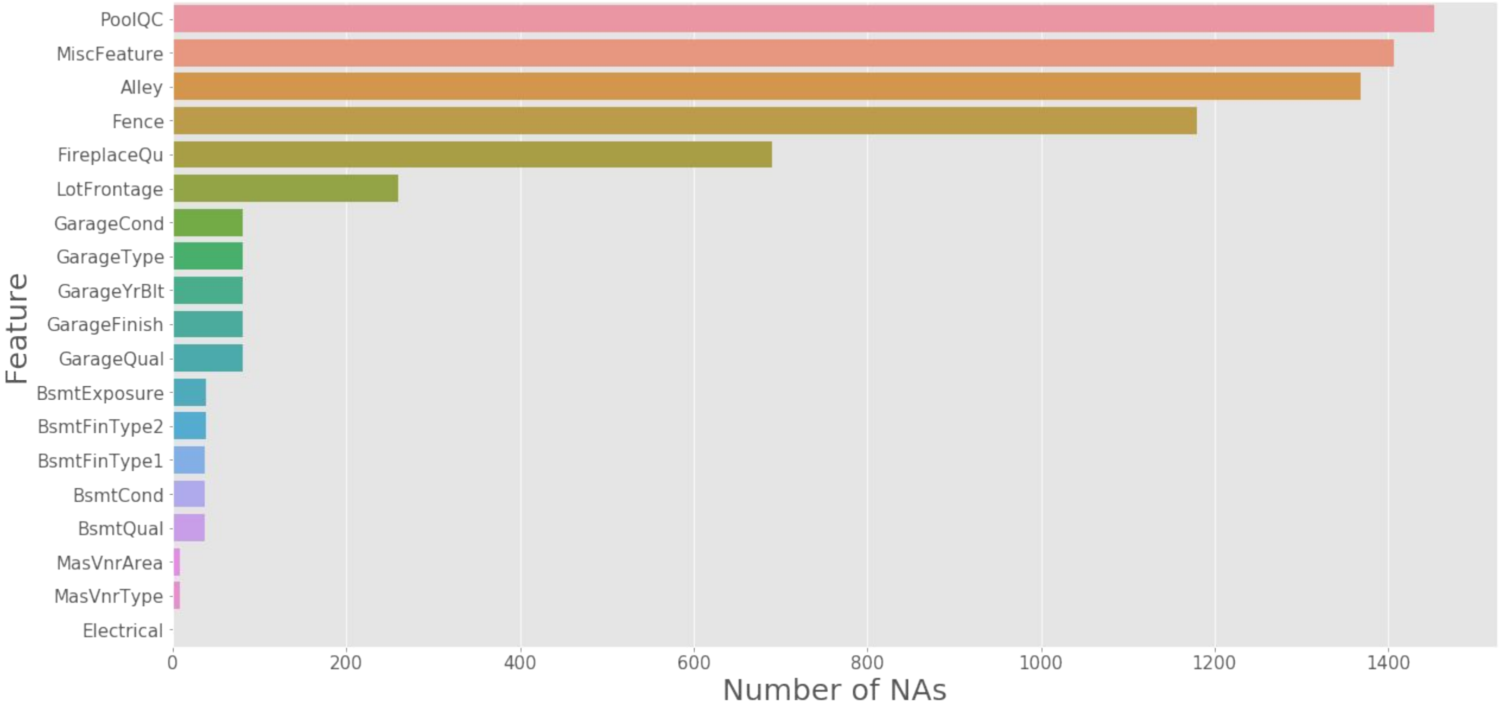
Sale Price After Log+1

Log transformation of the sale price distribution to achieve approx. normal distribution





FEATURES WITH SKEWNESS > 1



Lots of NAs

Some features almost exclusively filled with NAs

NAs with meaning

Some NAs have explicit meanings and do not represent missing observations

Different types of NAs

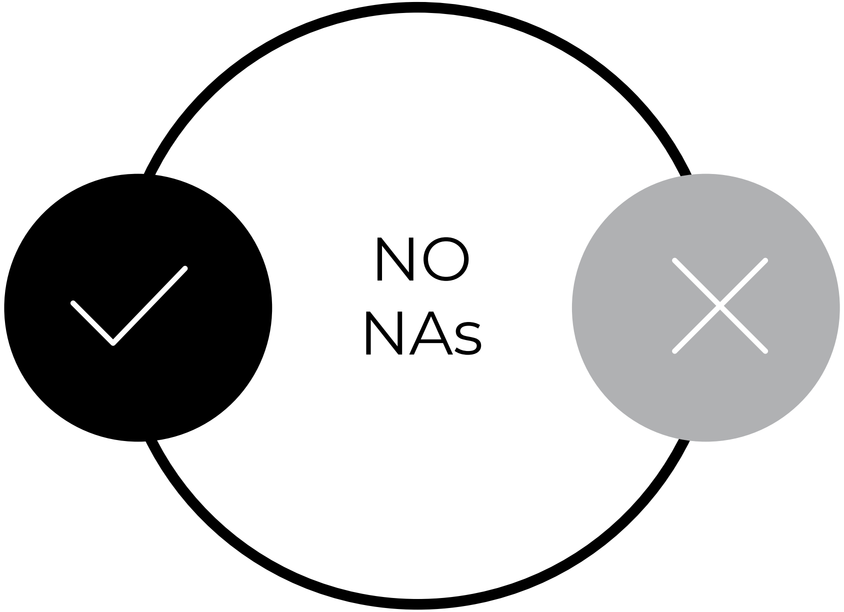
Not all NAs have meaning

DEALING WITH NAs

The different types of NAs within the data set require different forms of treatment in order to avoid suffering a loss of information.

NAs with Meaning

We replaced these NAs with their actual meanings from the data description



NAs without Meaning

Depending on the type of missingness, we imputed the missing values

FEATURE ENGINEERING

We individually analyzed features and discussed their relevance to this project

1

DROPPING FEATURES

We decided to drop features irrelevant to the Sales Price and features with high multicollinearity

2

ORDINAL ENCODING

Replacing ordinal categorical features with corresponding integers

3

YearSinceRemod

YrSold - YearRemodAdd

4

Bathrooms

BsmtFullBath + FullBath + .5*(BsmtHalfBath + HalfBath)

Regression Algorithms

We decided to apply both linear and non-linear algorithms in order to determine the best fit for our data

LINEAR

Starting Point

Multiple Linear Regression and Penalized Regressions (Ridge, Lasso, Elastic Net)

NON-LINEAR

Basic Algorithms

KNN

ENSEMBLES

Exploring Powerful Algorithms

Random Forests, XGBoost

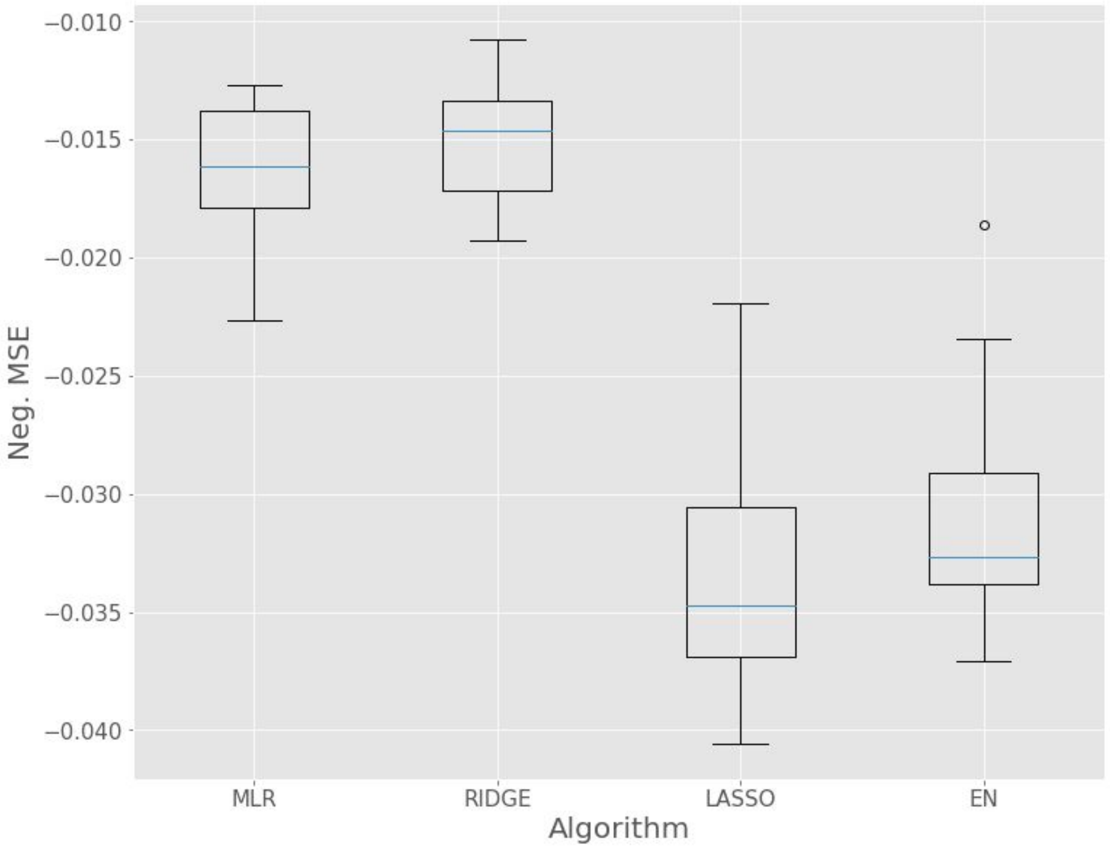
STACKING

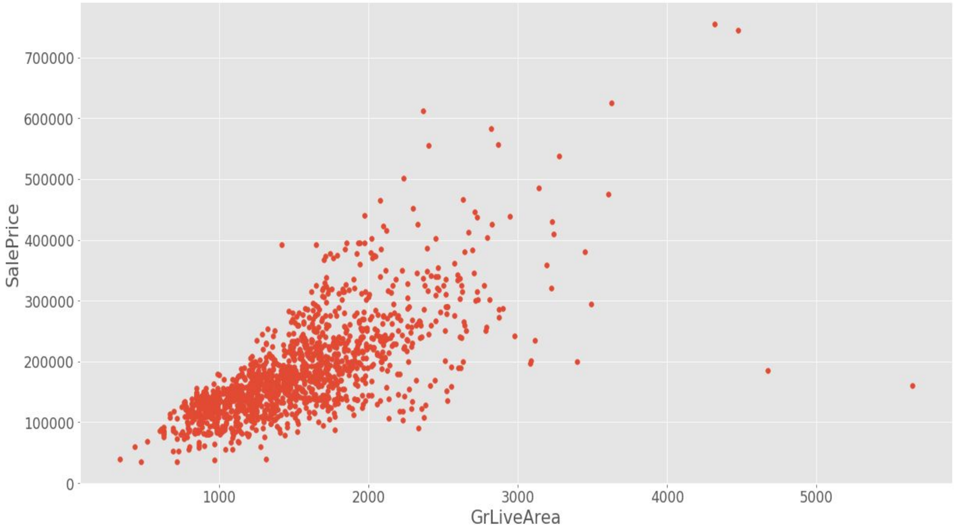
Combining Algorithms

Stacking XGBoost and Random Forests

Baseline Linear Models

To get a first impression, we ran the linear regression algorithms on our data without making any adjustments





No Outlier Removal

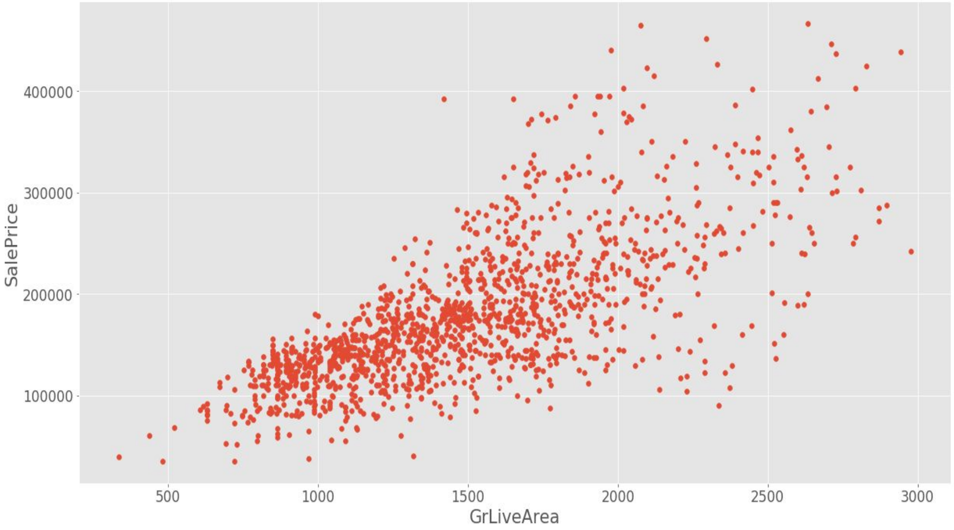
Original Data

Some outliers that might skew our results

After Outlier Removal

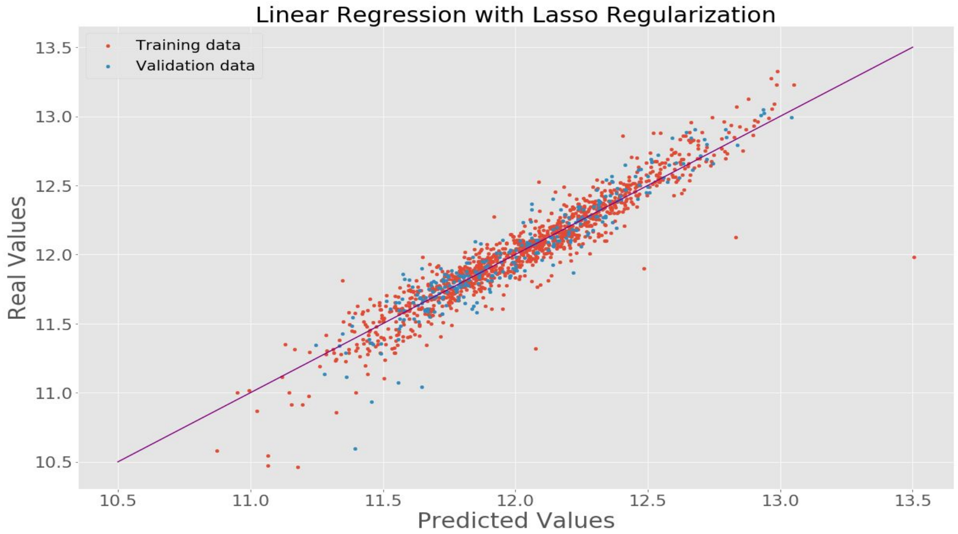
Data After Outlier Removal

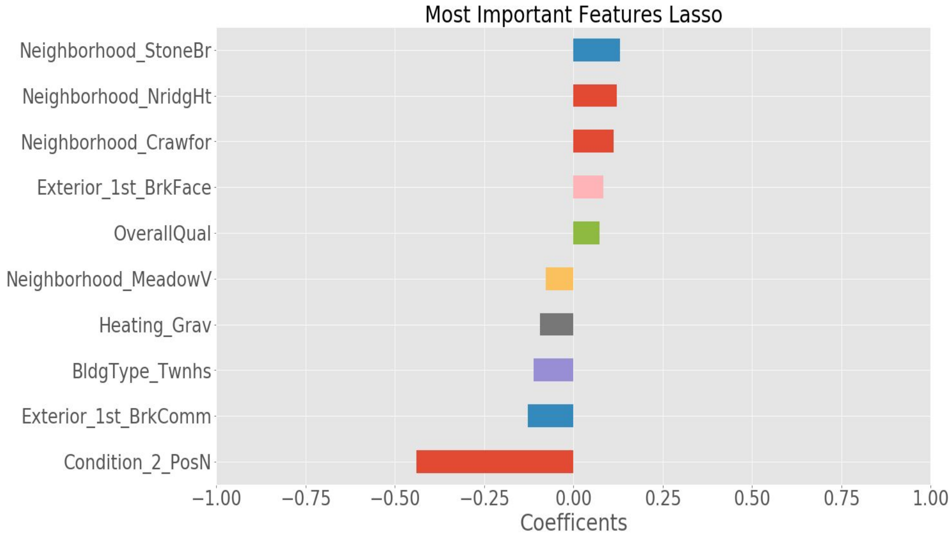
Removing all observations with GrLiveArea > 3k and SalePrice > 500k



TRAIN VS. TEST PREDICTIONS LASSO

Except for a few outliers very accurate



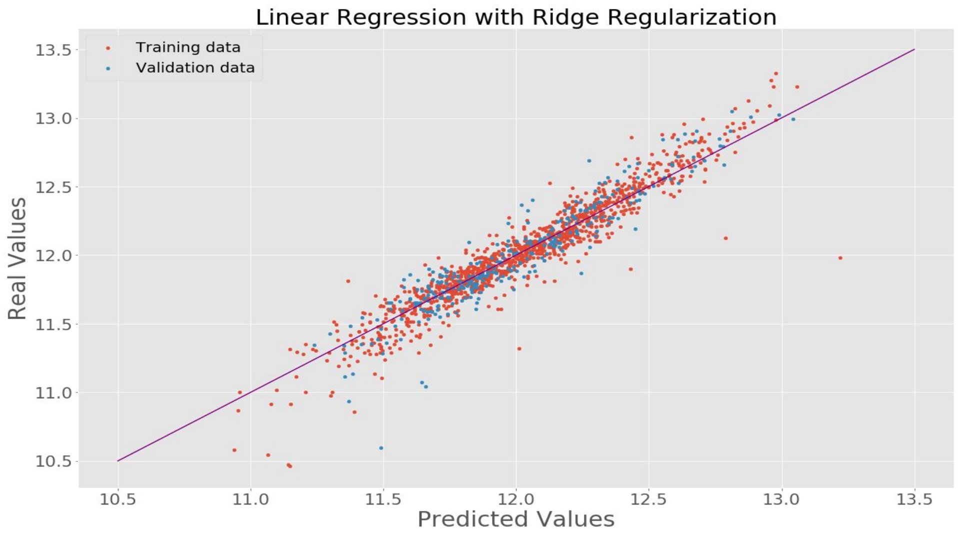


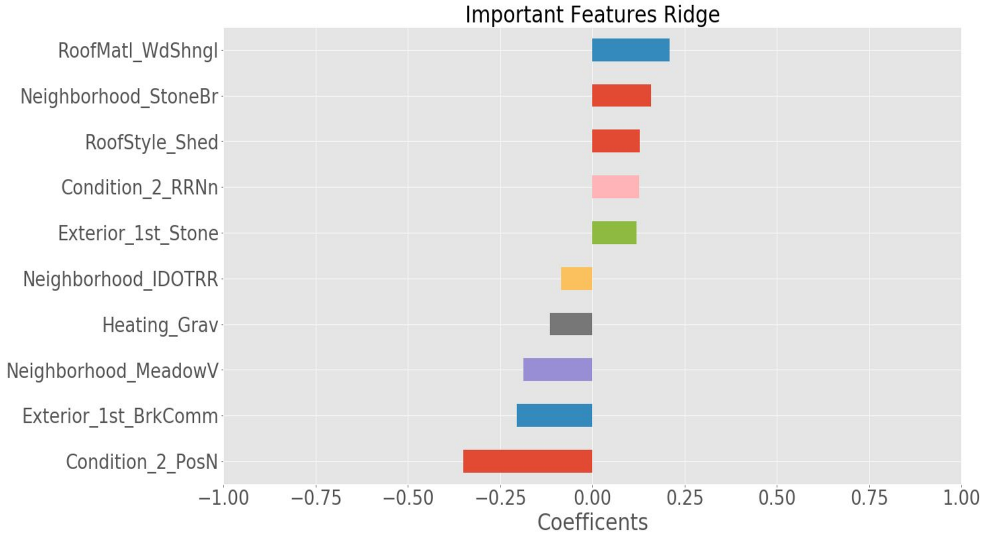
FEATURE IMPORTANCES

Neighborhood very important

TRAIN VS. TEST PREDICTIONS RIDGE

Also very accurate except for a few predictions





FEATURE IMPORTANCES

Neighborhoods still important, but not as important as in Lasso

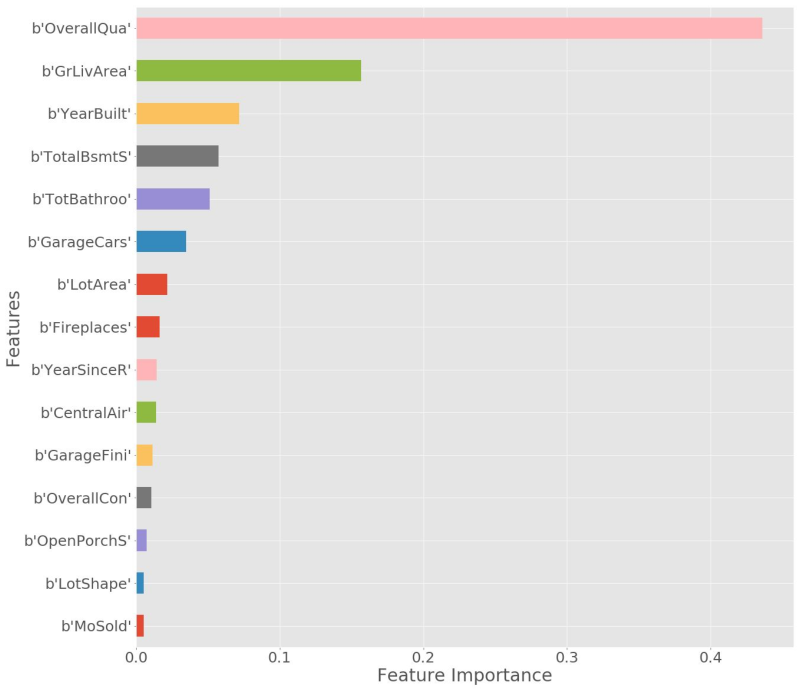
Results Linear Models

All of the results represent the RMSE (Root Mean Squared Error) on the test data set

MLR	LASSO	RIDGE	ELASTIC NET
0.180875	**0.128068**	**0.138817**	**0.131943**

RANDOM FOREST

One of the most powerful non-linear algorithms



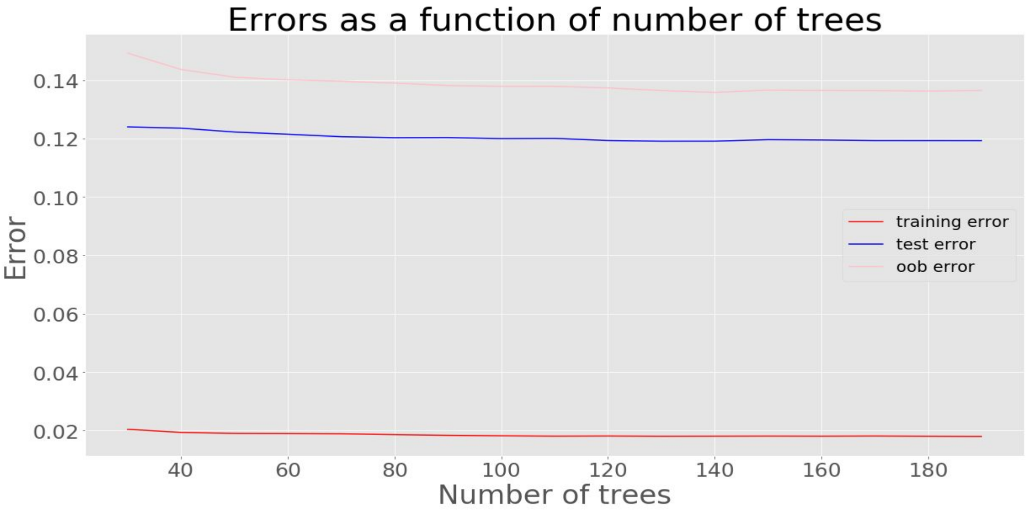
TOP 3:

- OverallQuality
- GrLiveArea
- YearBuilt

Random Forest

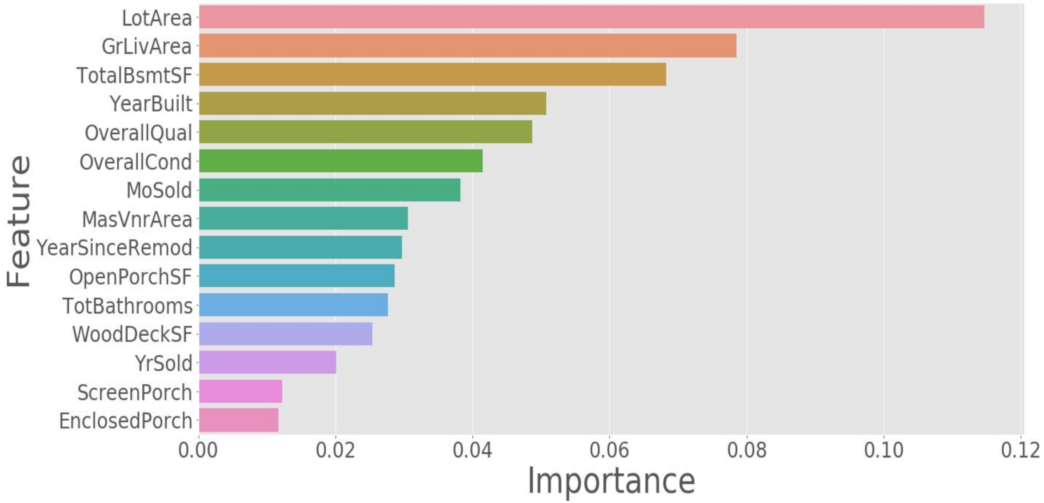
Comparing the errors as we increased the number of trees

- **Errors do not improve significantly**
- **Worse performance than linear models**
- **RMSE: 0.137845**



XGBoost

Extreme Gradient Boosting



- **Different results from RF**
- **LotArea way more important**
- **GrLiveArea very important as well**

STACKED MODEL

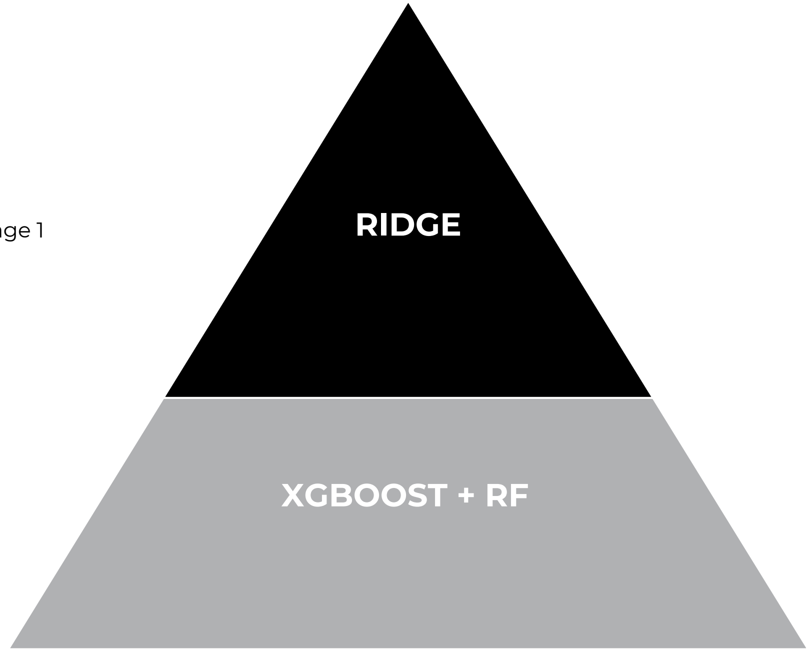
Attempt to stack several models to increase the combined performance

STAGE TWO

Fitting a model on the results of stage 1

STAGE ONE

Predicting SalePrice for each XGBoost and RF



BEST RESULTS & KAGGLE SCORES

After tuning our models we submitted the predictions to Kaggle

	LASSO	RIDGE	RF	XGBOOST	STACKED
Our RMSE	**0.128068**	**0.138817**	**0.137845**	**0.125280**	**0.125301**
Kaggle Score	**0.12406**	**0.13061**	**0.14962**	**0.13256**	**0.13318**

THANK YOU!

QUESTIONS?