Best Model for Predicting House Prices in Ames, Iowa

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Introduction

Our data is a collection of variables about houses in Ames, Iowa (80 independent variables and house sale price) (www.kaggle.com).

Goal: To find the best model to predict the Selling Price from the given housing features

Possible predictors: neighborhood, square footage of the lot, number of bedrooms, year built, etc.

Possible concerns: missing values, highly skewed variables (high number of zero's), categorical variable handling, and computational speed

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Data Cleaning

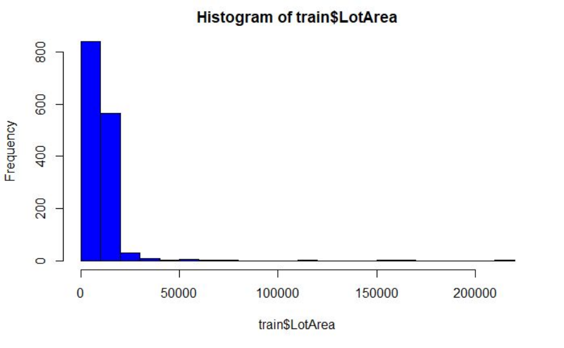
- Missing categorical entries
  - Add a new level called "Missing" to store all of the NA's
- Missing numerical variables
  - Replace with median values

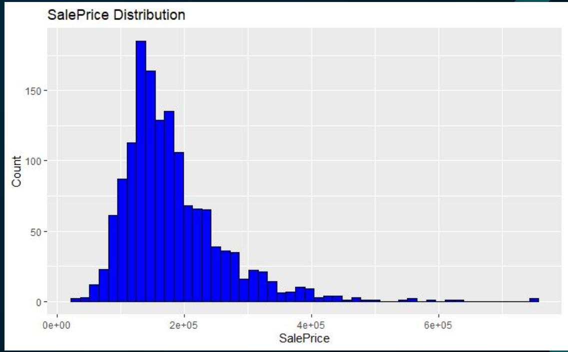
```
summary(train$Alley)

Grvl Pave NA's
  50   41 1369
```

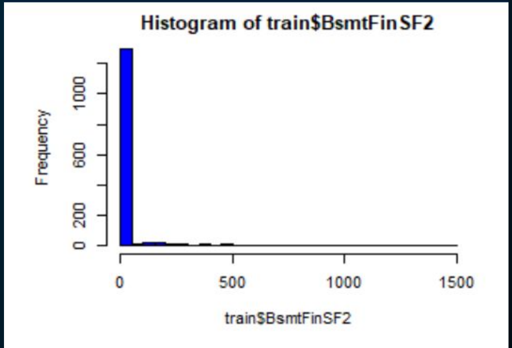
```
summary(train$Alley)

   Grvl    Pave Missing
     50      41    1369
```

Data Cleaning

- Variable Distribution Assessment - Skewness
  - Log transformation on “LotArea” and “Sale Price” (response variable)
  - Categorization of several numerical variables into “0” or “More than 0” (or “1” or “More than 1”)







Data Cleaning

- Dummy variables transformation
  - For each categorical variable, we turned it into multiple dummy variables (each dummy represents one sub-category)
  - Number of independent variables increases from 80 to 314

```r
library(dummies)
train_off <- dummy.data.frame(train_off, sep = ".")
```

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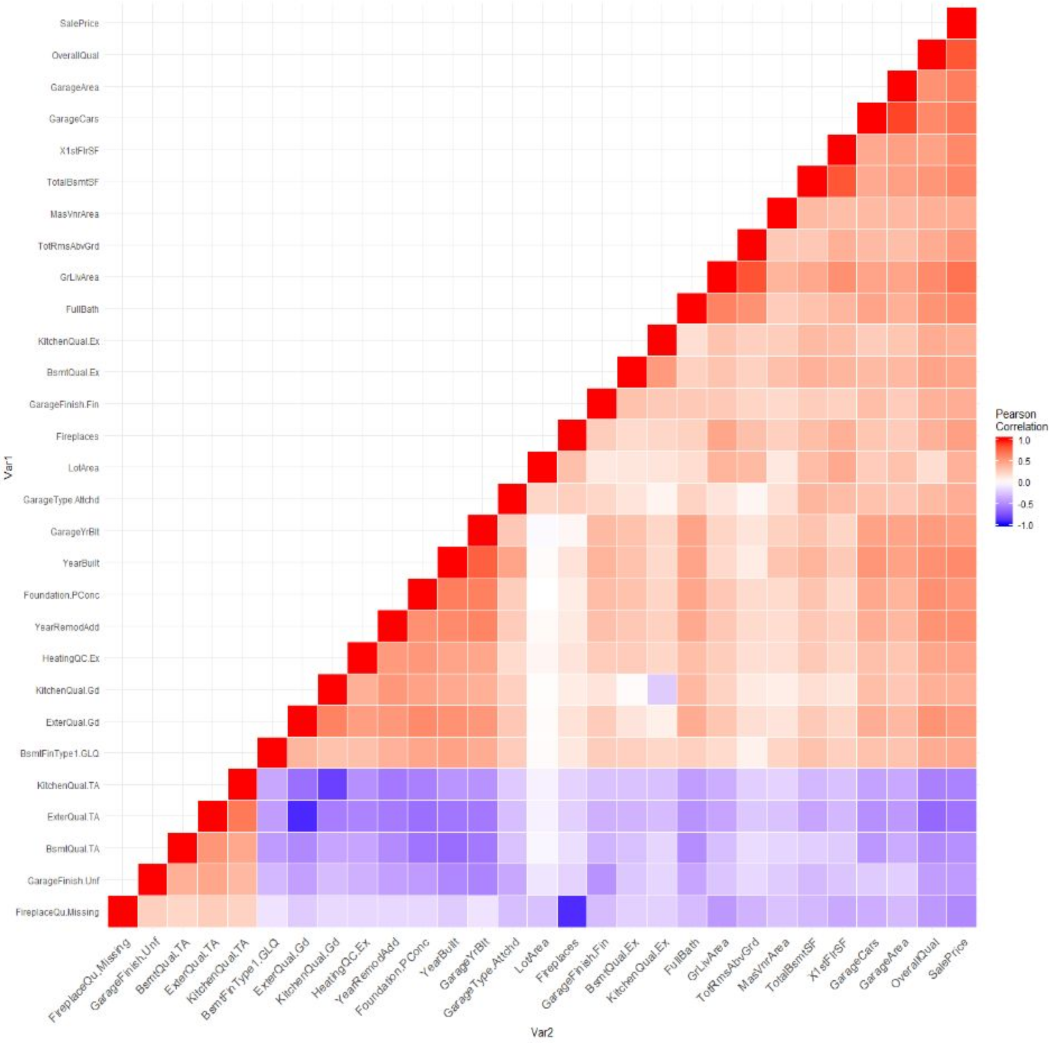
Variable Filtering

- Only select predictors with moderately high correlation with response y = SalePrice
  - Corr(X,Y) > 0.4
  - From 314 predictors down to 28 predictors



Linear Regression Techniques

Subset Selection: Best Subset Selection

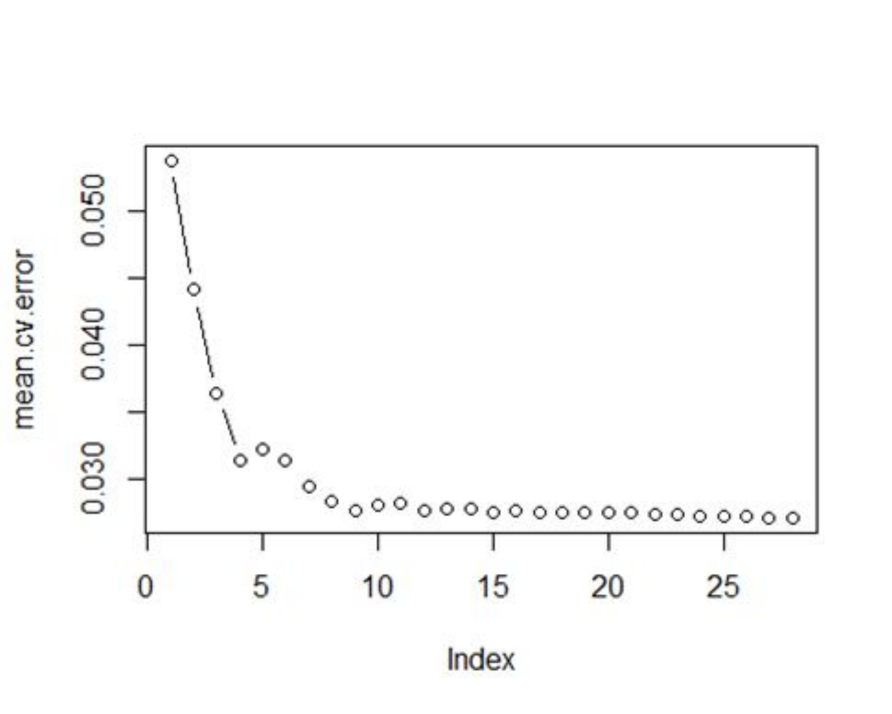
Regularization: Lasso & Ridge

Dimension Reduction: PCR and PLS

Best Subset Selection

Test MSE: 0.0188, 9 predictors

- **Pros:**
  - Has simple fitting procedure
  - Gives sparse model (feature selection)
  - Assesses all possible subset of variables
  - Presents the best candidate for a least-squared model with q variables
- **Cons:**
  - Takes a long time to process large models; computationally expensive

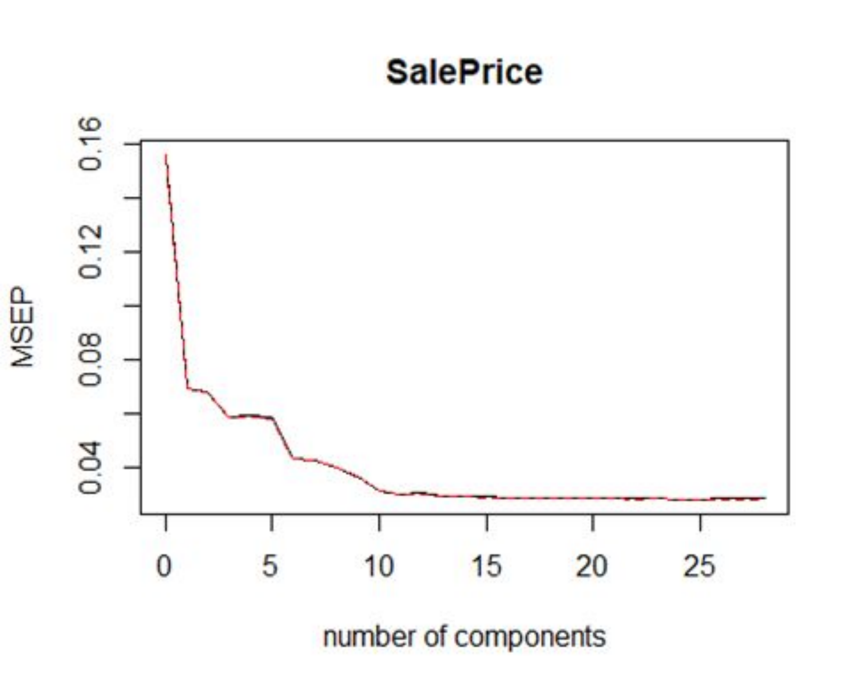


Principal Component Regression

Creates new components from linear combinations of original variables such that they capture as much variability in the predictors as possible

- Pros:
  - Reduces data dimension
  - When the number of components is small, overfitting can be avoided
- Cons:
  - Does not yield feature selection
  - The first M principal components, though may best explain the predictors, are not necessarily predictive of the response

Test MSE: 0.0216
28 Variables (10 PCs)



Partial Least Squares

A *supervised* alternative to PCR - PLS approach attempts to find directions that help explain both the predictors AND the response.

Pros:

- All the pros of PCR
- The supervised dimension reduction can reduce bias

Cons:

- Does not yield feature selection
- The supervised dimension reduction can increase variance => will not perform that much better than PCR

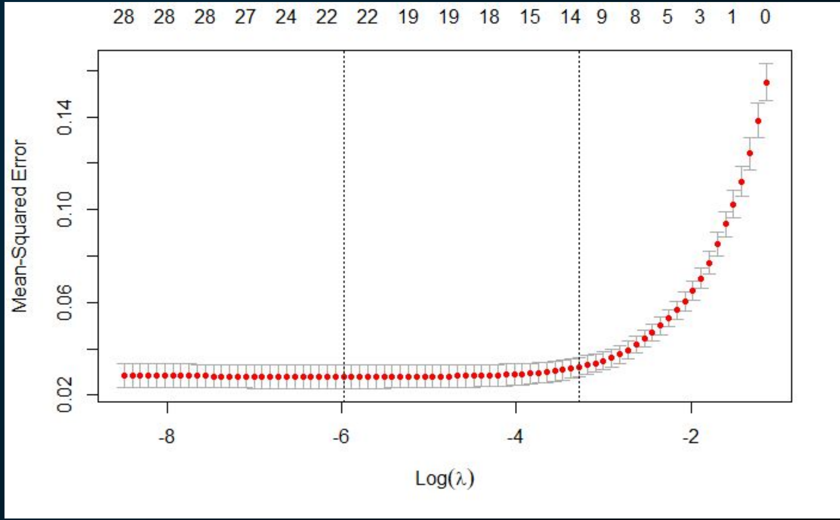
Test MSE: 0.0201
28 Variables (9 components)

Lasso

Test MSE: 0.0184, 23 predictors

Pros

- Eliminates many variables in its model (sparse)
- Can create flexible models that do not rely on hierarchies, unlike forward and backward subset
- Gives better predictions than Variable filtering and fwd/bwd stepwise



Cons

- Interpretability - why does it select certain variables and not others?
- Complicated model-fitting procedure (hard to do without statistical software)

The best Log(Lambda) = -5.978623
23 predictors in best model

Ridge

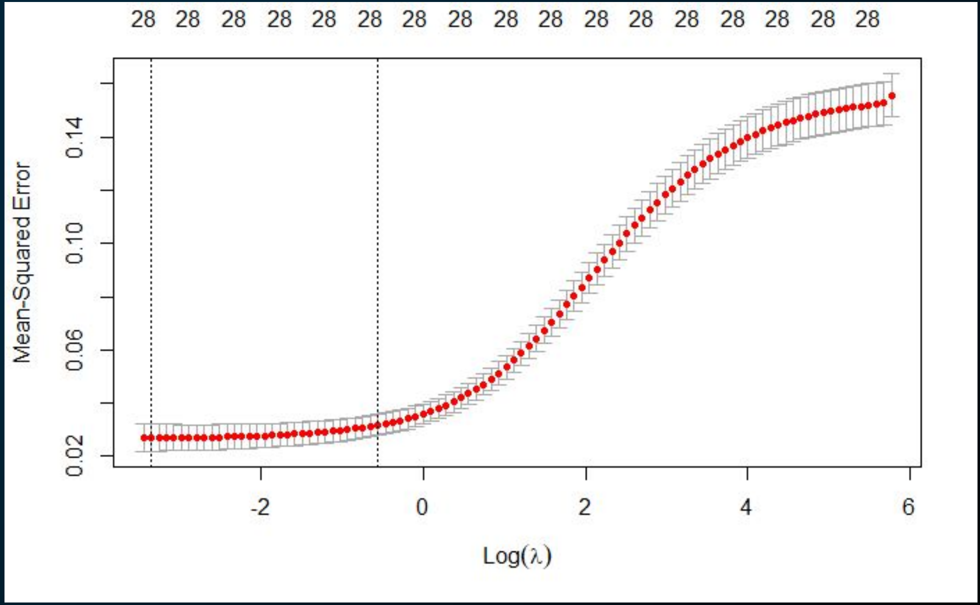
Test MSE: 0.0191, 28 predictors

Pros

- Can create flexible models that do not rely on hierarchies, as opposed to forward and backward subset selection
- Gives better performance than Lasso if all variables are significant

Cons

- Does not eliminate any variables (as opposed to Lasso)
- Can also lead to high variance due to no variable reduction (high flexibility)



Best log(lambda) = -3.35042

Non-linear Regression Techniques

K Nearest Neighbors

Regression Tree

Bagging & Random Forest

Boosting

K-nearest neighbors

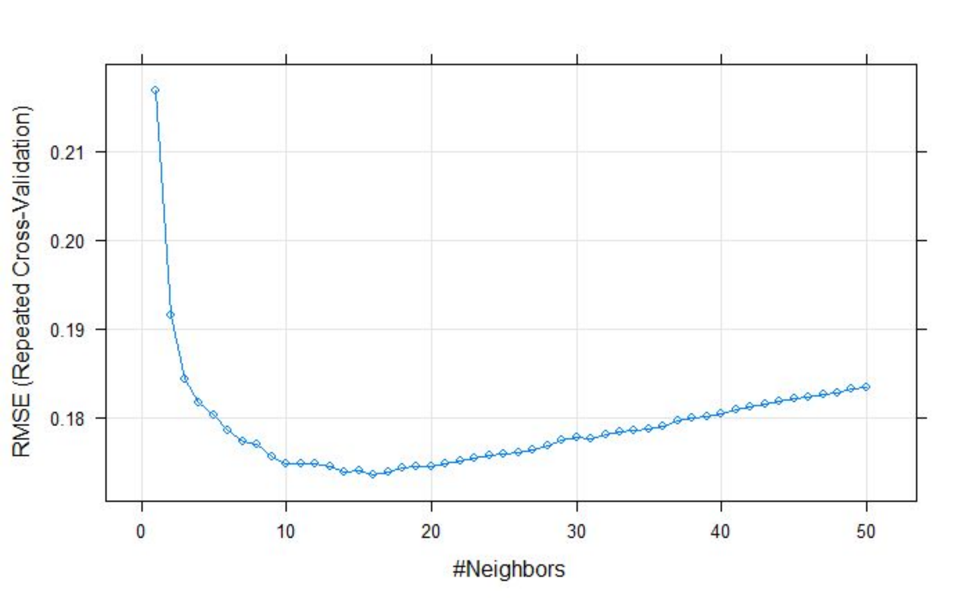
Test MSE: 0.0264, k=16

Pros

- Non-parametric, more flexible
- Offers a more accurate model if the true shape is non-linear
- Simple fitting process

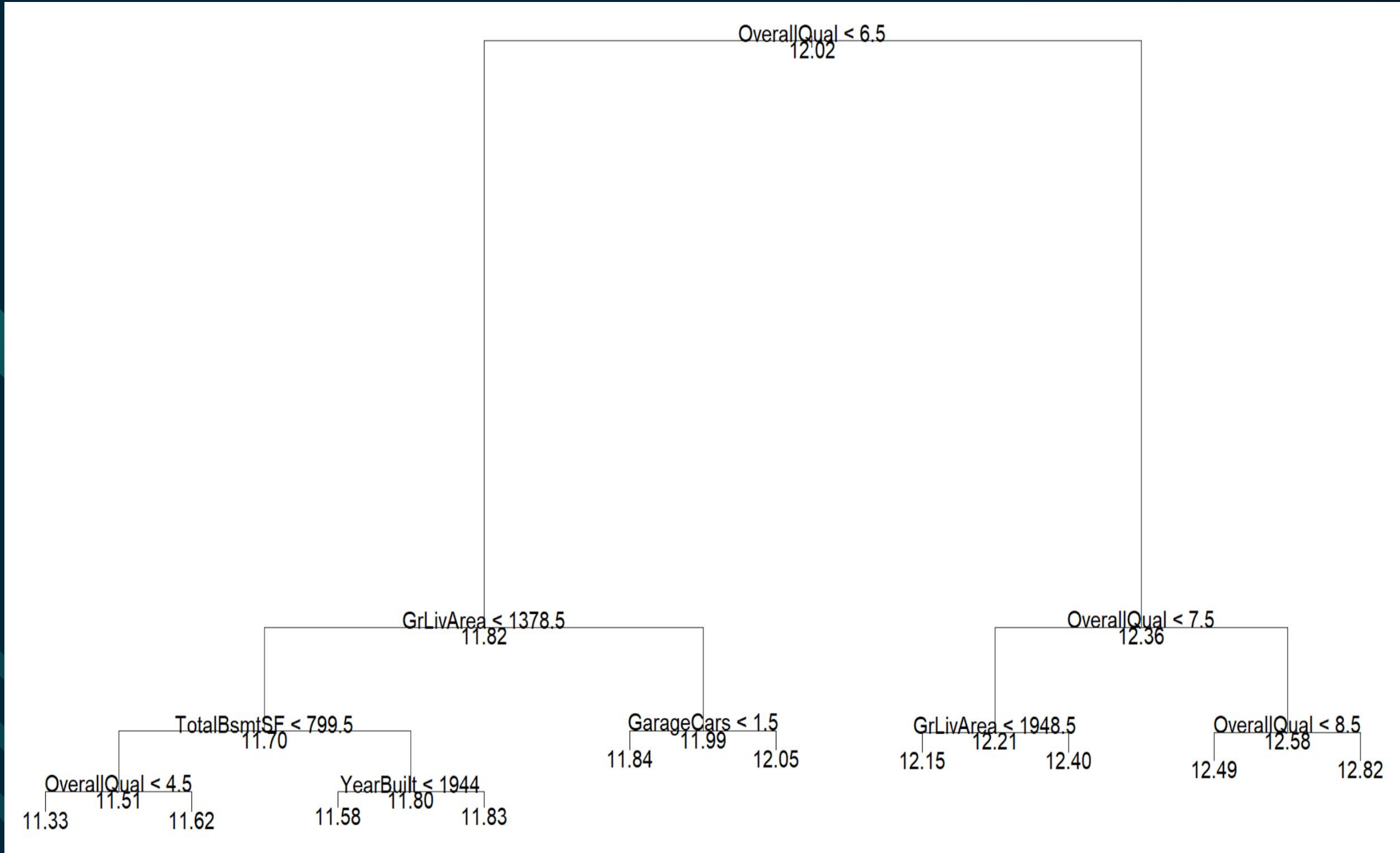
Cons

- Rarely outclass parametric approaches
- Does not work well with high dimensions
- Difficult to identify importance of variables
- Sensitive to noisy data, missing values and outliers



Regression Tree

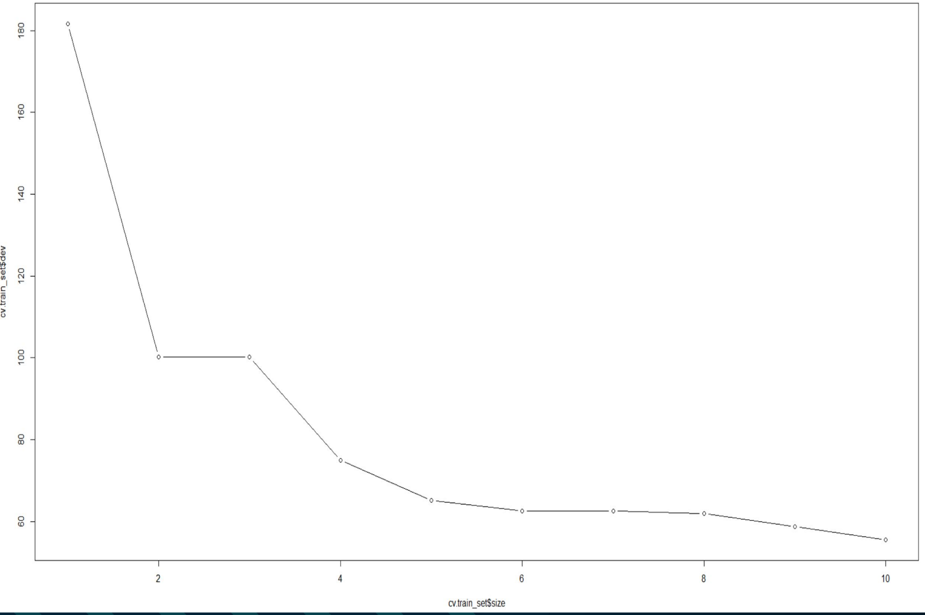
Test MSE: 0.0443

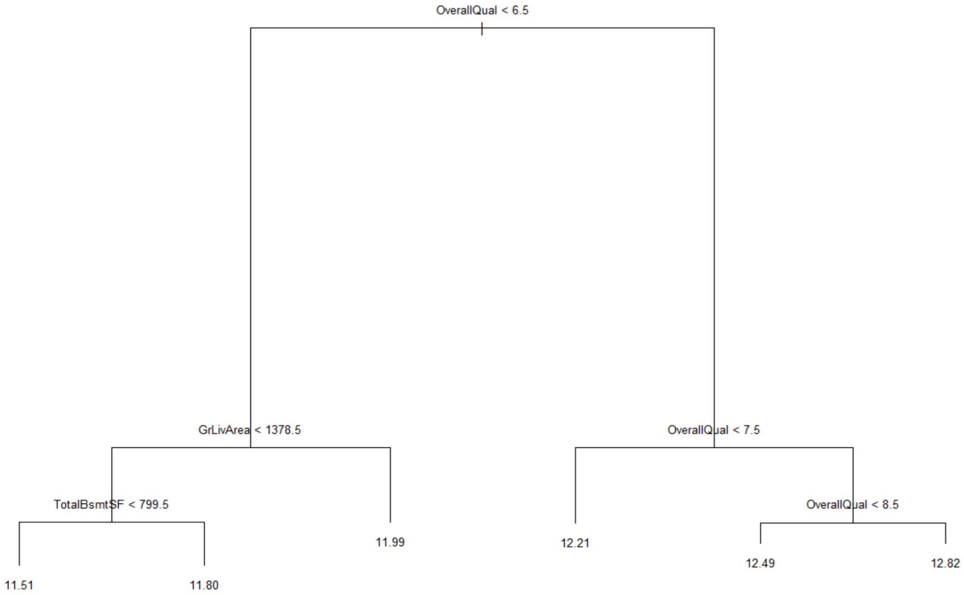


Regression Tree

```
# for more interpretability and overfiting concerns do some pruning within 6-9 terminal nodes
prune.train_set = prune.tree(tree.train_set, best = 6)
```

After pruning (Test MSE): 0.0553





Regression Tree

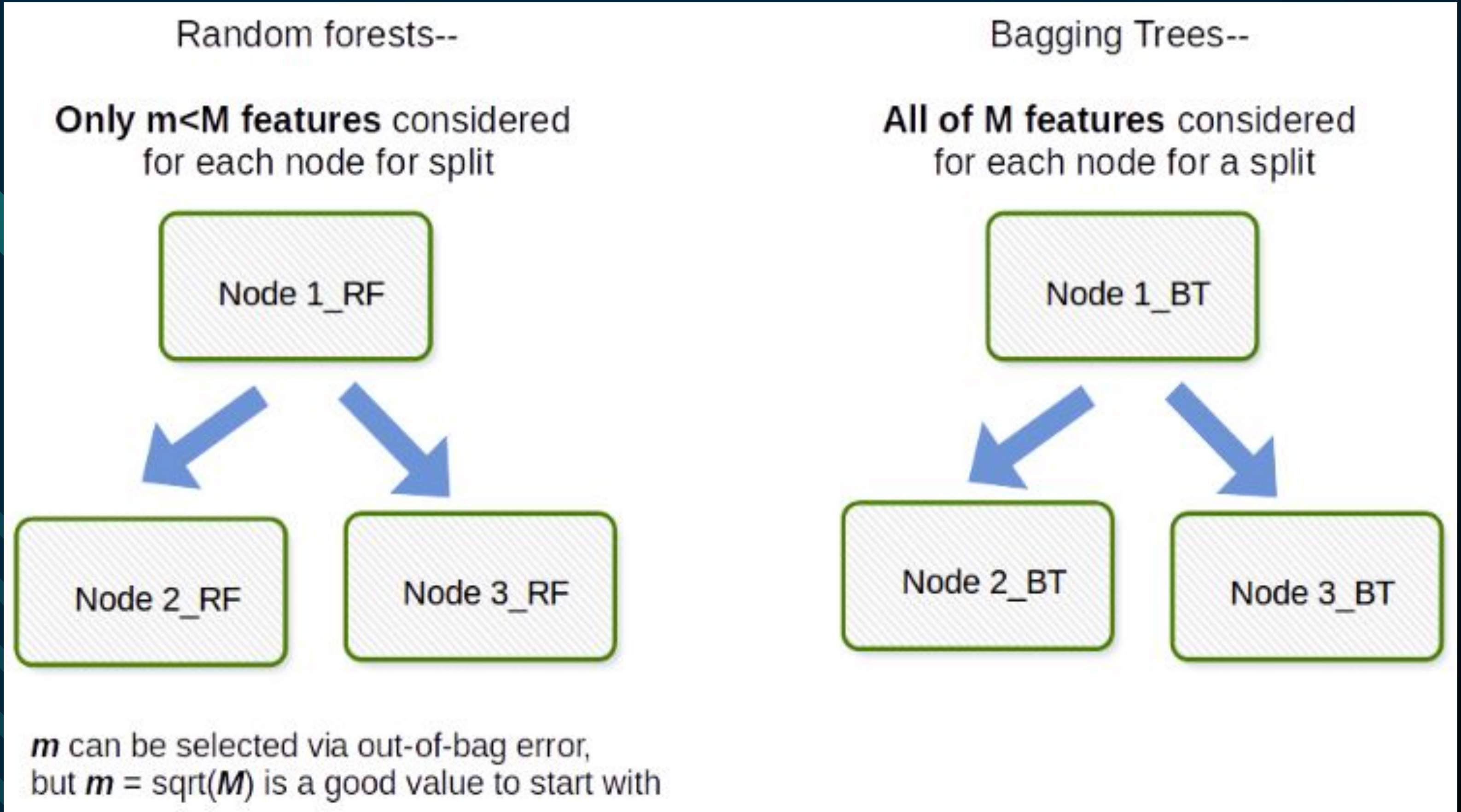
Pros

- Interpretability & visual representation
- Numerical and categorical features accommodation
- Little data preprocessing
- Feature selection happens automatically

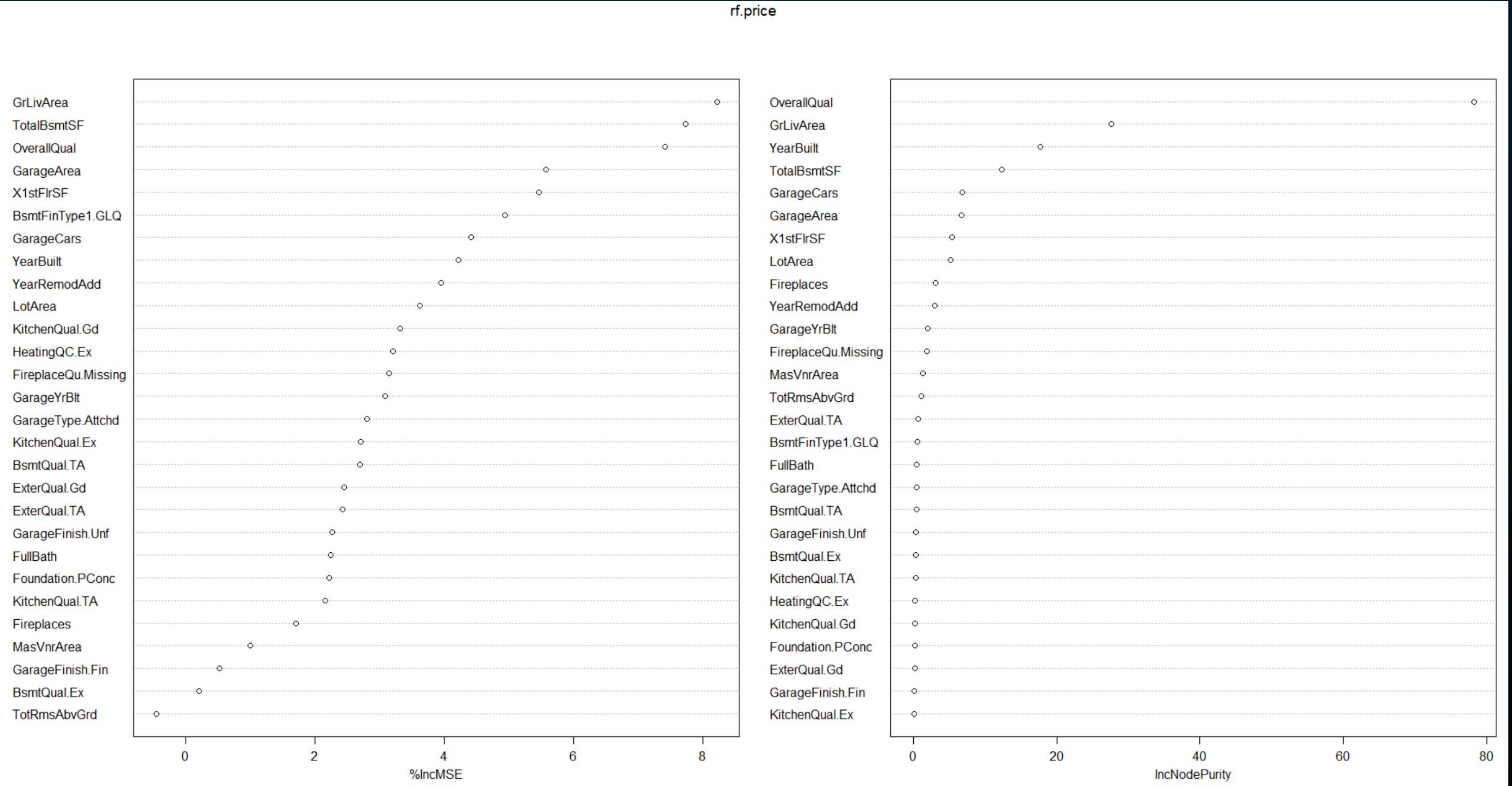
Cons

- Inflexible: dynamic model adjustment
- Unstable
- Overfitting, which can be mitigated by:
  - Limiting tree depth
  - Minimal # of objects in leaves
  - Tree pruning

Bagging and Random Forest



Random Forest



Bagging and Random Forest

Test MSE: 0.0194 -- ntree=500, mtry=28
Test MSE: 0.0207 -- ntree=25, mtry=28
Test MSE: 0.0200 -- ntree=25, mtry=20 (RF)

Pros

- Impressive in versatility
- Parallelizable
- Robust to outliers and nonlinear data
- Low bias, moderate variance

Cons

- Complexity
- High computational resources requirement
- Overfit --- solved by tuning hyperparameters

Boosting

Gradient Boosting

- Fits a new predictor in the residuals committed by the preceding predictor
- By combining one weak learner to the next learner, the error is reduced significantly over time

Tuning Parameters

- N.minobsinnode = c(10,15)
- Interaction.depth = c(1,3)
- N.tree = c(1000, 1500)
- Shrinkage = c(0.05,0,1)

Boosting

```
```{r, include = FALSE}
# hyper-parameter tuning of gradient boosting
set.seed(7)
grid <- expand.grid(n.trees = 900, interaction.depth=2, shrinkage=c(0.05,0.1),n.minobsinnode=c(10,15))
ctrl <- trainControl(method  = "cv",number  = 10)
```

Tuning Parameters

- N.minobsinnode = c(10,15)
- Interaction.depth = c(1,3)
- N.tree = c(1000, 1500)
- Shrinkage = c(0.05,0,1)

Test MSE: 0.0173, all predictors

- N.minobsinnode = 10
- Interaction.depth = 2
- N.tree = 900
- Shrinkage = 0.05
```

Boosting

Pros

- Easy to read and interpret
- Resilient method that curbs over-fitting easily

Cons

- Sensitive to outliers
- Almost impossible to scale up

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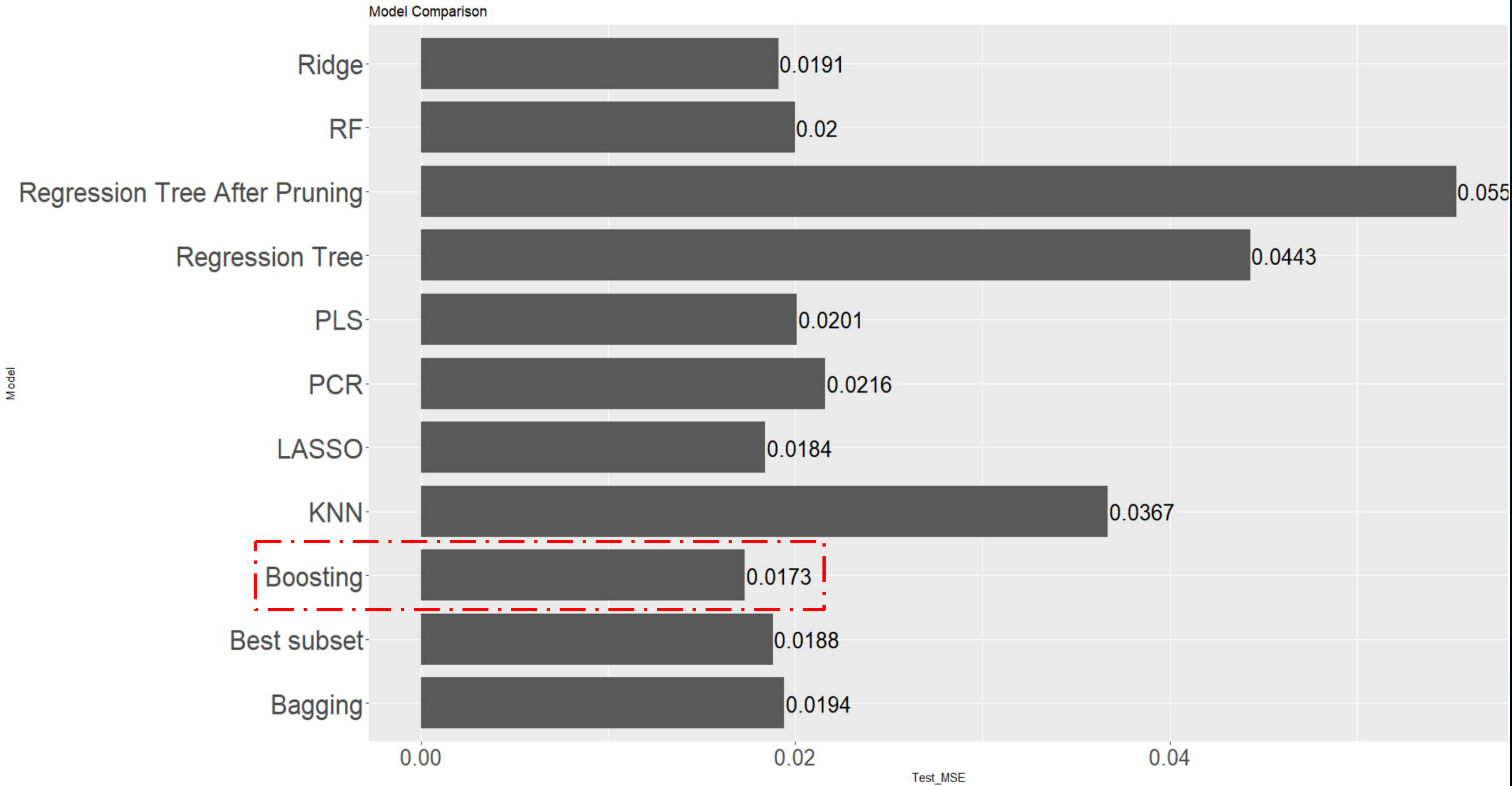
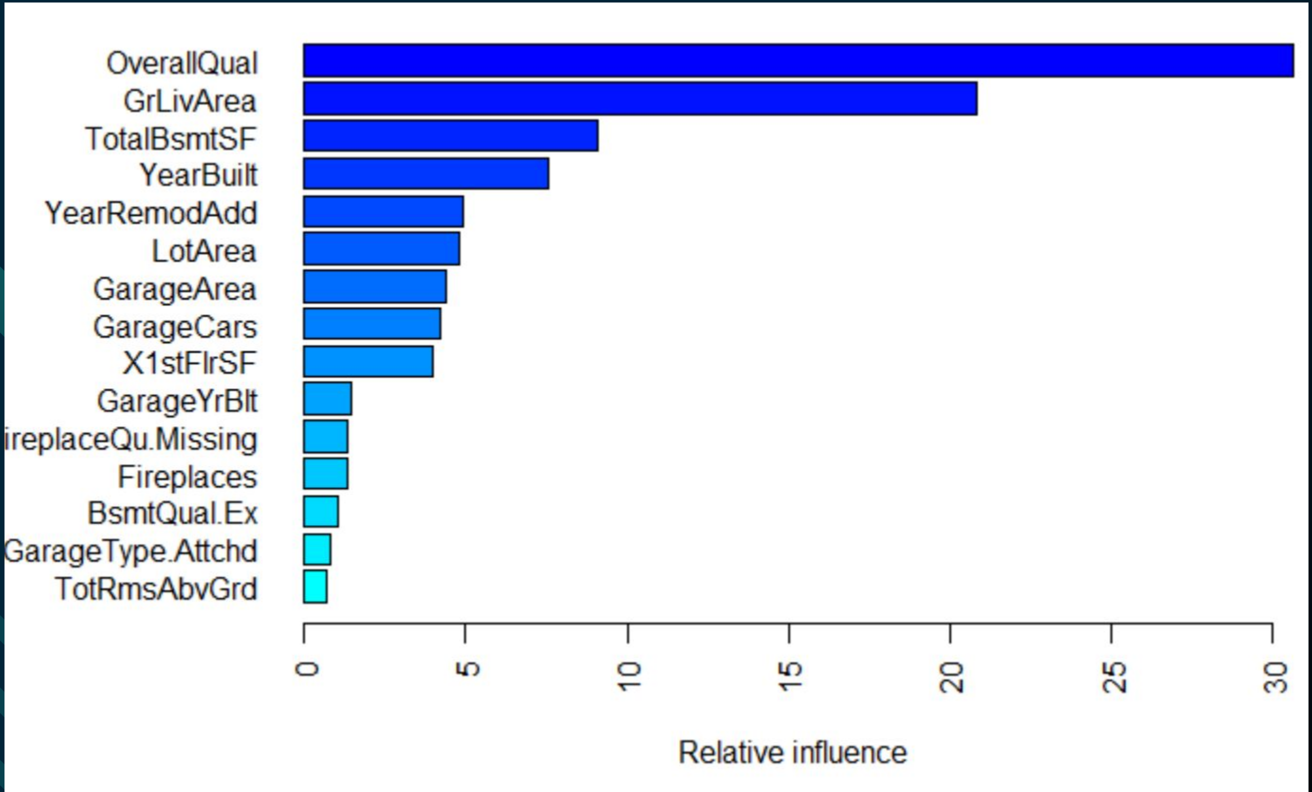
Model Comparison - Test MSE



Most important variables from Boosting model



Conclusions

- Best method: Gradient Boosting
- Performance Accuracy: 86% on average
- Most important variables
    - OverallQual - Overall material and finish quality
    - GrLivArea: Above grade (ground) living area square feet
    - TotalBsmtSF: Total square feet of basement area
    - YearBuilt: Original construction date
- Surprises: No location indicator; Garage-related features importance
- Improvement: Better handling of high dimension next time without variable filtering

Thanks!

Do you have any questions?