Final Presentation - The Gould-en Rule

Stats 101C Lecture 3

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Section 1

Introduction

Introduction

- With the rise in popularity of YouTube, many people are now making a living off creating YouTube videos
- The more views gained by the video, the more likely it is for that channel to profit
- We are interested in predicting the growth rate in video views between the **second** and **sixth** hour that a YouTube video is published

Section 2

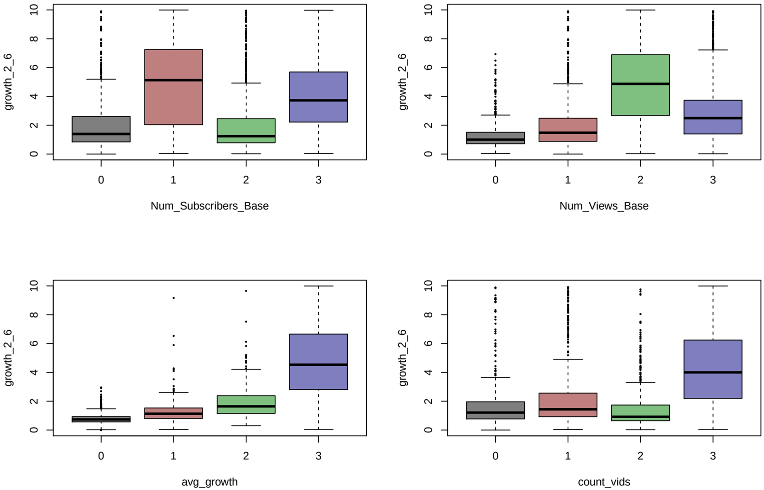
Methodology

Subsection 1

Preprocessing

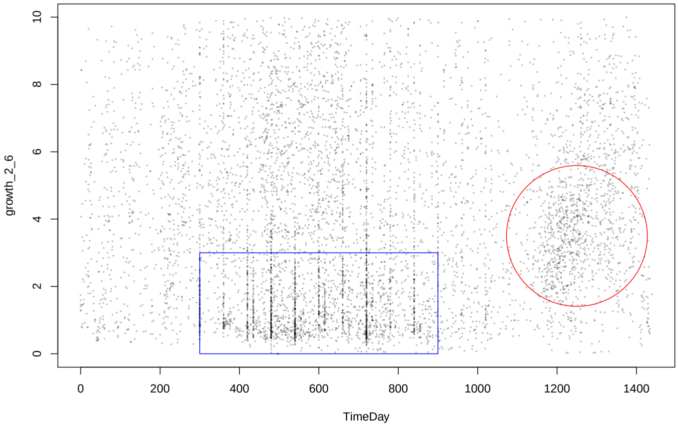
Feature Transformation

- Combined binary variables into a single factor with four levels



Feature Expansion

- `TimeDay`: What time in the day was a video published? (made continuous)



- Small upward cluster toward 1200 (lower clusters earlier in the day)

Outliers

- Examined a univariate plot to look for stray points and removed them systematically
  - Based off personal judgment and inference on the effect of the stray points
- We also remove highly correlated variables as indicated by a heat map
  - To avoid overfitting based on having too many predictors

Predictor Selection

- We use LASSO to select significant predictors
  - LASSO pushes the coefficients of non-significant predictors to zero
  - Keeps the most significant ones
- Fit a LASSO model and select our optimal value of λ as the one that resulted in the **lowest cross-validation MSE** (10^{-2})
- Extract the predictors with nonzero coefficients in the LASSO model as our predictors for the candidate model

Subsection 2

Statistical Model

Overview

- Most of our models were fit using bagging or random forest
  - Only adjusted certain parameters at a time (number of trees and m)
- Preliminary least-squares model
  - Kaggle score of $\sim$1.65

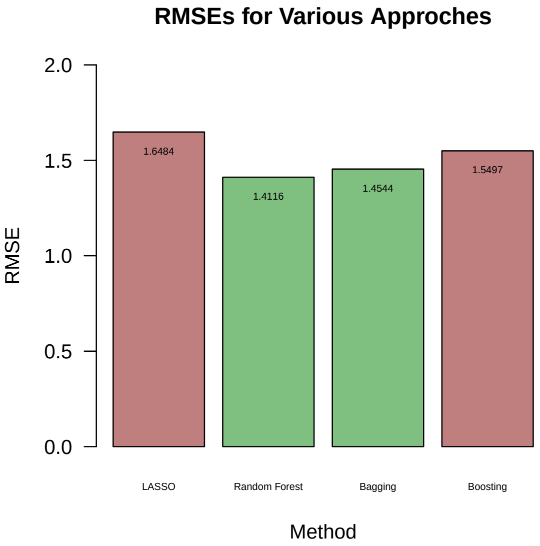
Candidate Model: Random Forest

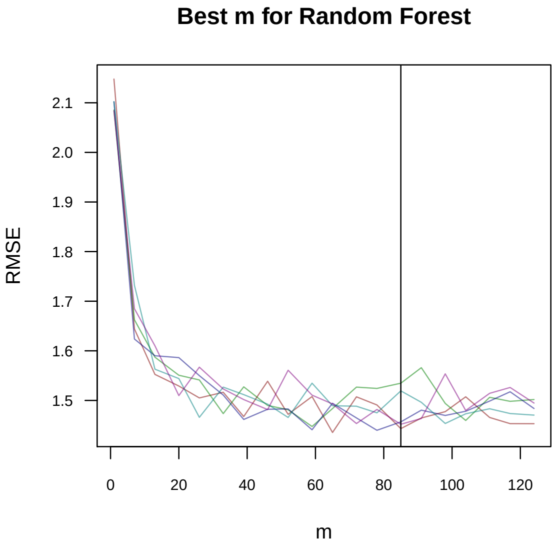
- Use subset to choose m for random forest
  - Find optimal m with 5-fold cross-validation: select m corresponding to the lowest *median* RMSE of the 5 folds
    - Median is more preferable than mean due to the mean's sensitivity to extreme points
- Once optimal m is selected, fit random forest model to 80% of the preprocessed training data
  - Extra model and validation RMSE ensures consistent performance

Candidate Model: Bagging

- Considered a bagging approach ($m = p$) as a secondary model to random forest

RMSEs


RMSEs for Various Approches
RMSE
Method
2.0
1.5
1.0
0.5
0.0
1.6484
1.4116
1.4544
1.5497
LASSO
Random Forest
Bagging
Boosting


Best m for Random Forest
RMSE
m
2.1
2.0
1.9
1.8
1.7
1.6
1.5
0
20
40
60
80
100
120

Section 3

Results

Results

Kaggle scores:

A. 1.39753 (1.41019)
B. 1.40285 (1.41321)

Model (B) (`Model 15e`) only differs from (A) (`Model 15d`) in that $m = p$ as opposed to m equaling the value with the lowest median RMSE. Here p is the number of predictors.

Section 4

Conclusion

Conclusion

- We believed our model performed well due to the fact that it works as an ensemble method
  - Combines multiple individual models to get more accurate responses
- By using cross-validation for our selection of m, we limit the potential effect of a random seed showing us an inaccurately good or bad RMSE
- `TimeDay` custom variable is important (11th out of 120+) - creating our own variables helped
- All 4 factor variables in the top 12

Variable Importance