

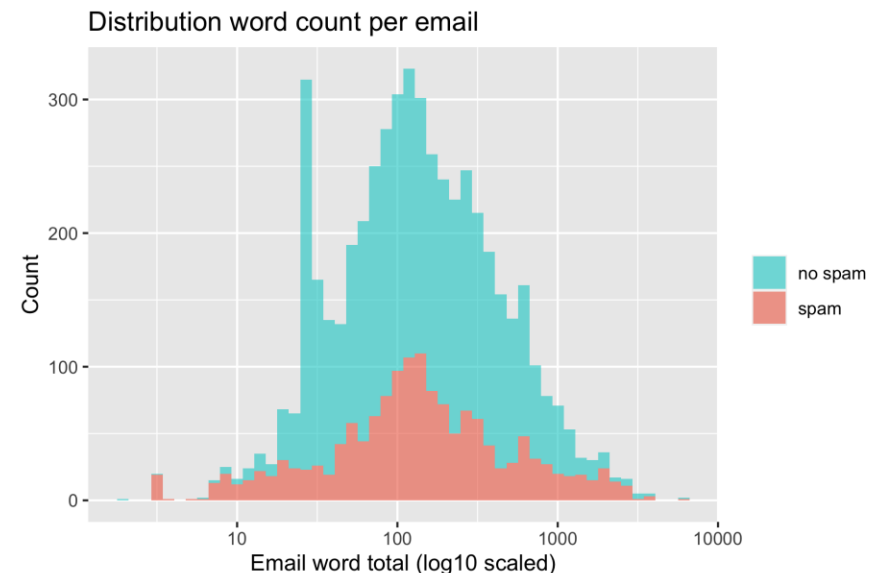
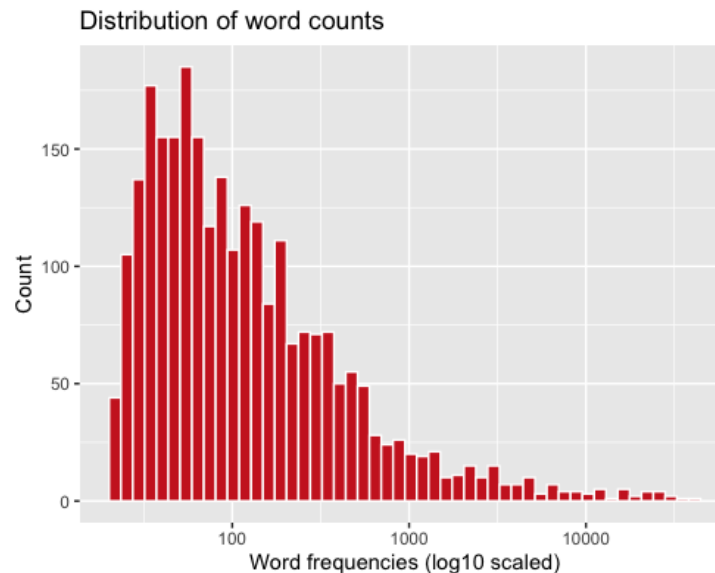
# Email Spam Classification

Group 7: David Genfan, Brian Louie, Davin Yu



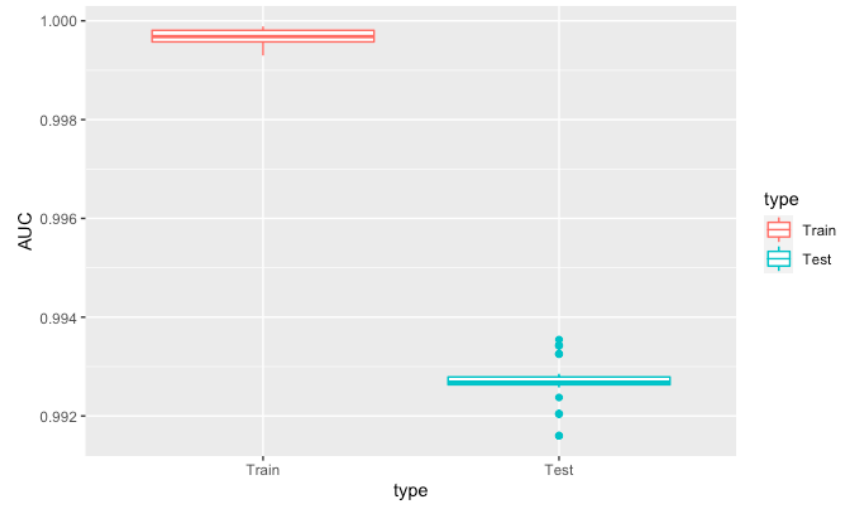
# Overview

- Data contains 5172 emails with the 3000 most commonly used words from all emails and a label if the email is spam (1) or not spam (0)
  - Removed stop words from the features (“and”, “most”, “very”, etc.)
- Emails (n) = 5172, Words (P) = 2619
- Imbalance ratio:  $n+/n- = 1500 / 3672$
- With this data set, we sought to determine if we could classify spam based on the composition of the email

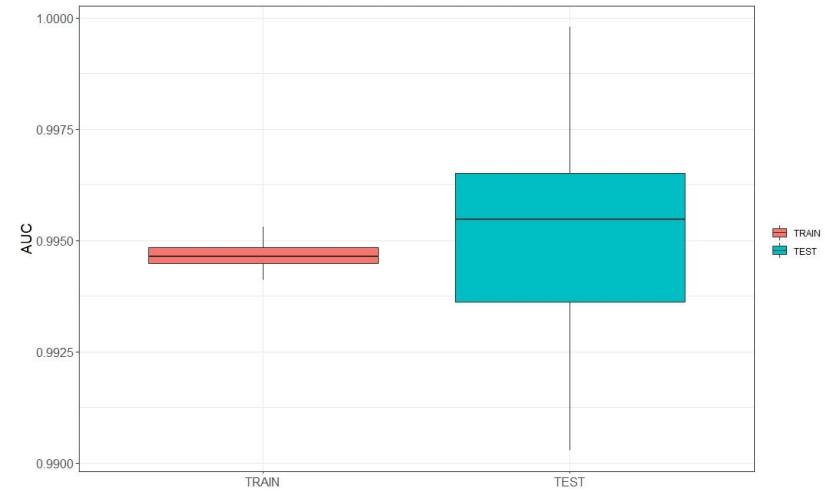


# AUC's for $D_{\text{train}}$ and $D_{\text{validation}}$

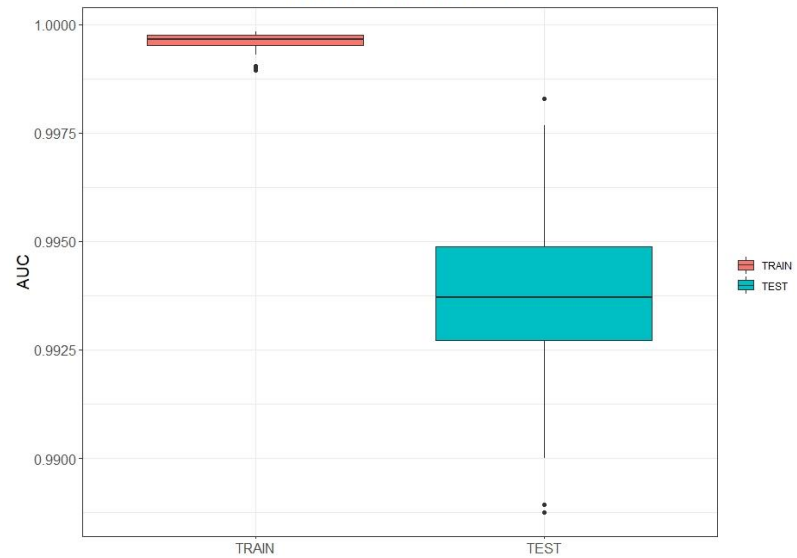
Comparison AUC scores for Train and Test (RIDGE model)



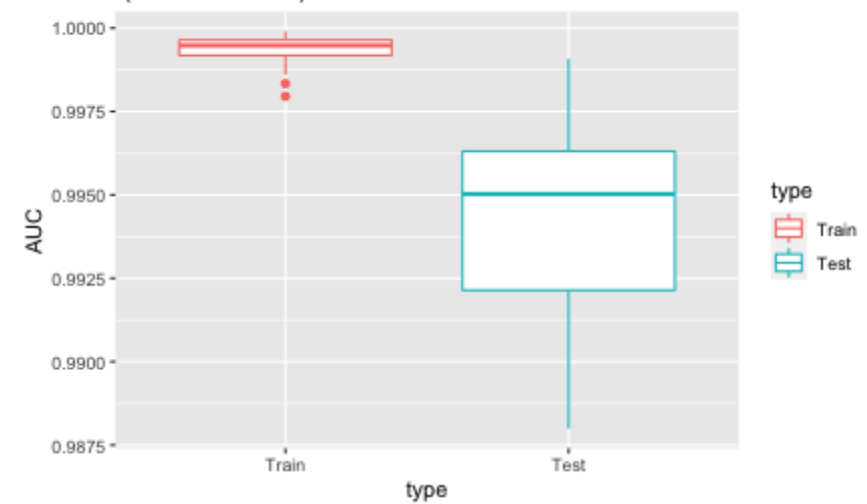
Random Forest Train & Test AUCs

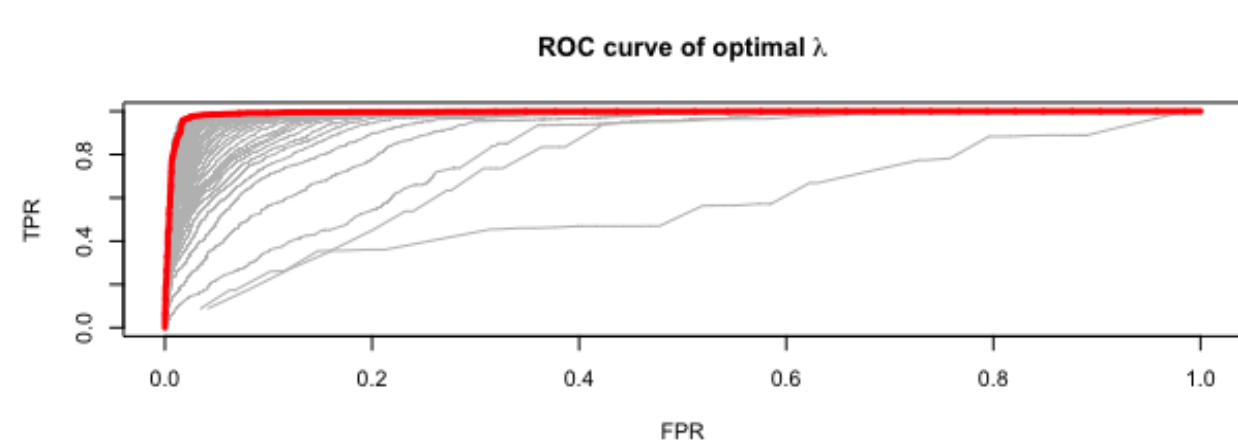
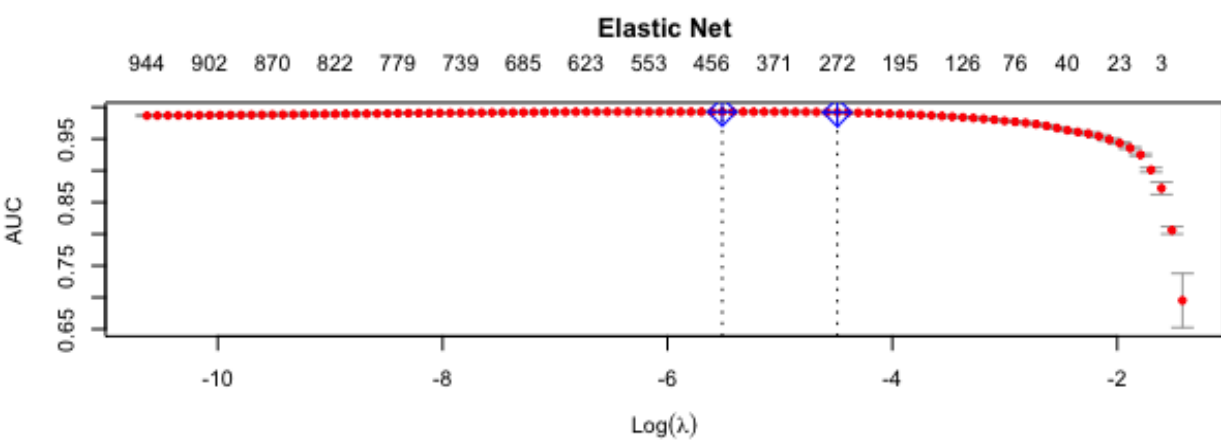
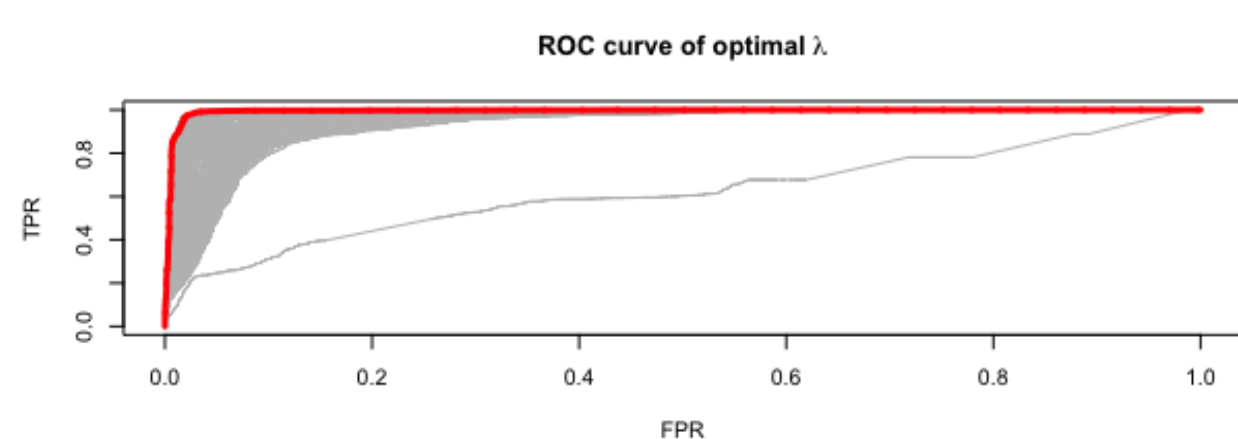
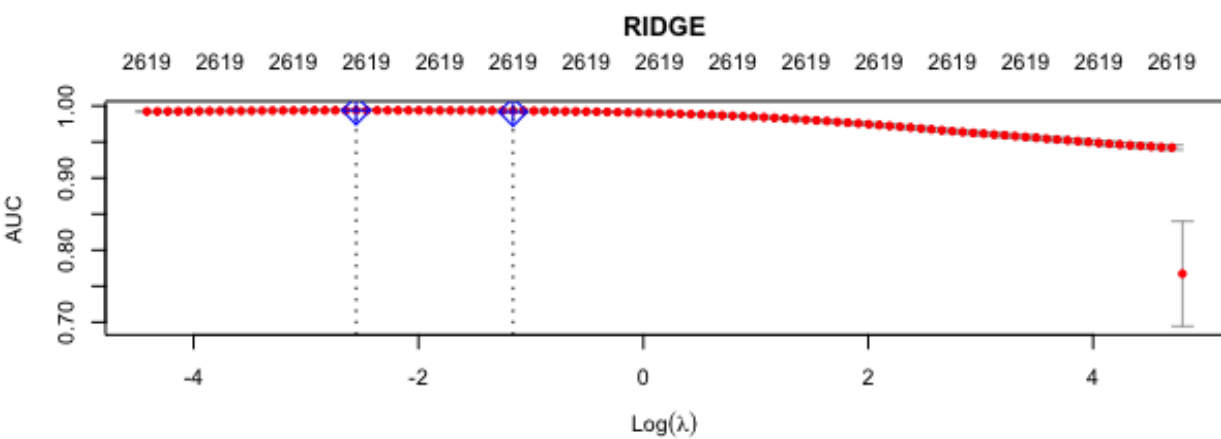
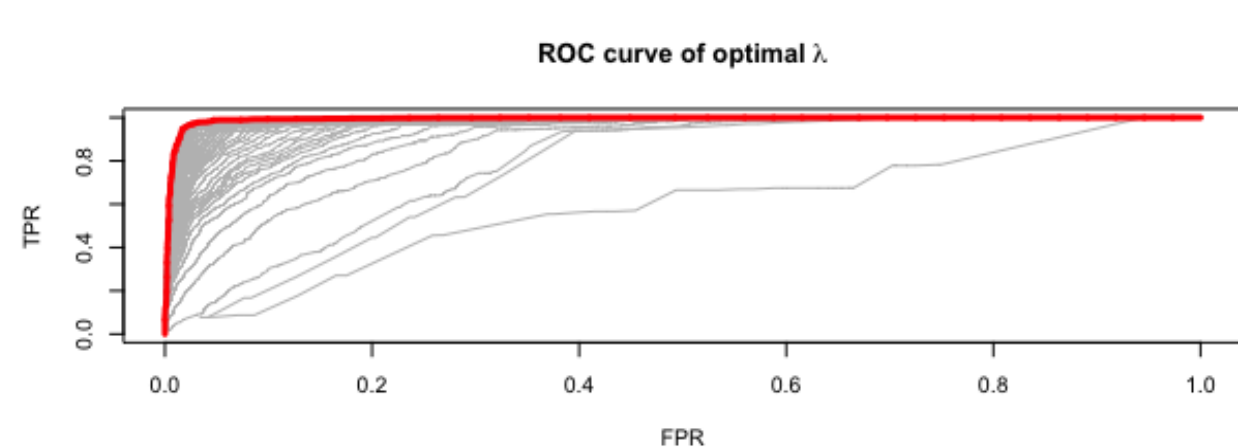
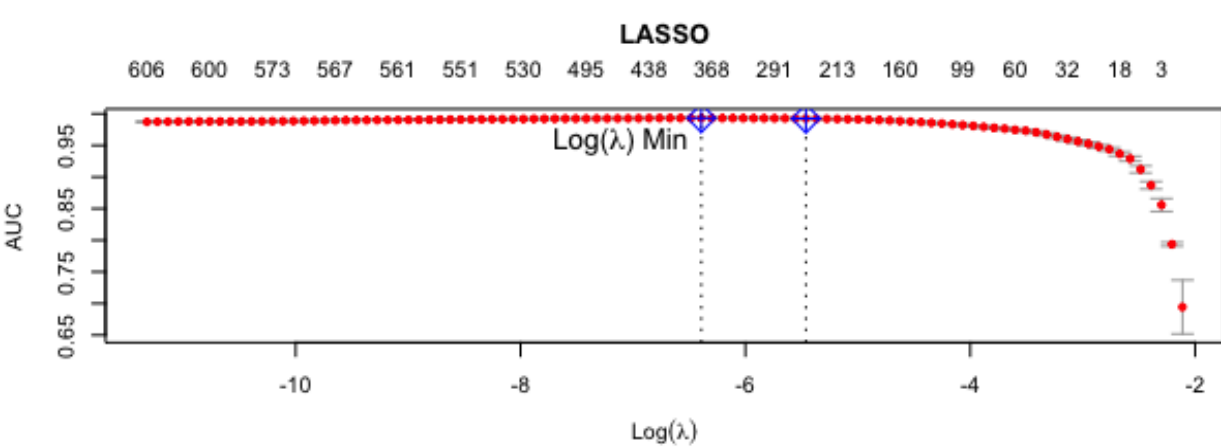


Elastic-Net Train & Test AUCs



Comparison AUC scores for Train and Test (LASSO model)



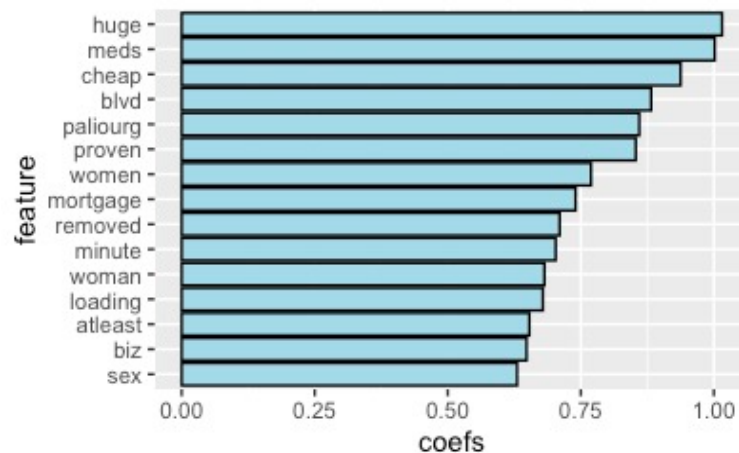


<b>Method</b>	<b>Median test AUC</b>	<b>Time of single cross-validation</b>	<b>Time of full model fitting including cross-validating parameter tuning</b>
Logistic Lasso	0.99	2 min 4 sec	4 min 45 sec
Logistic Ridge	0.99	6 min 9 sec	7 min 56 sec
Elastic Net	0.99	2 min 46 sec	3 min 4 sec
Random Forest	0.99	N/A	16 min 28 sec

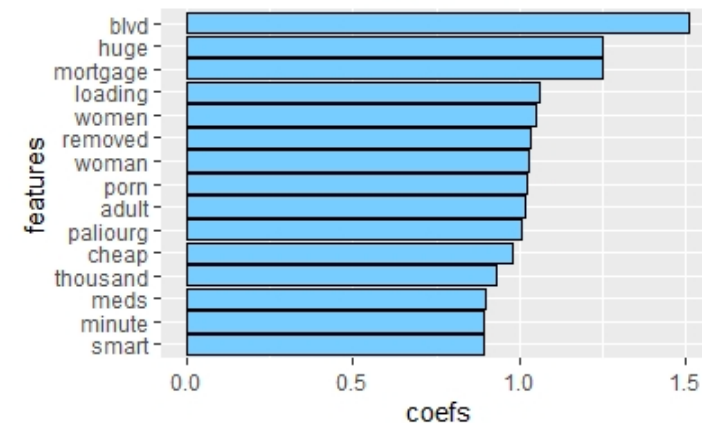
## Top 15 Spam Features

Across all models, the most common features for spam emails were words such as "huge", "adult", "meds", typically associated with pornography

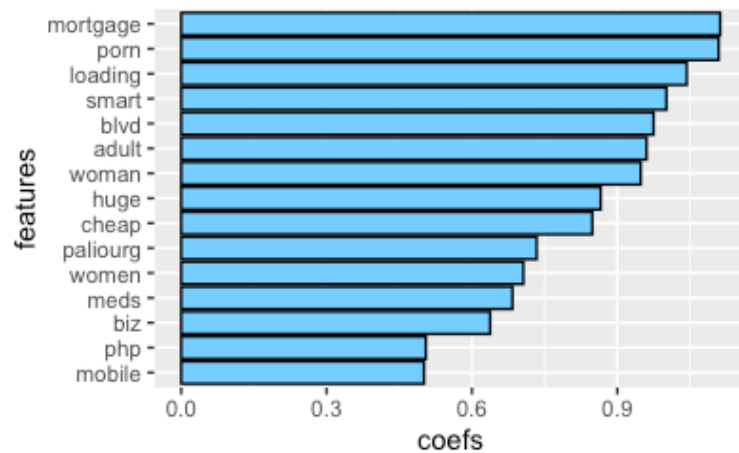
LASSO



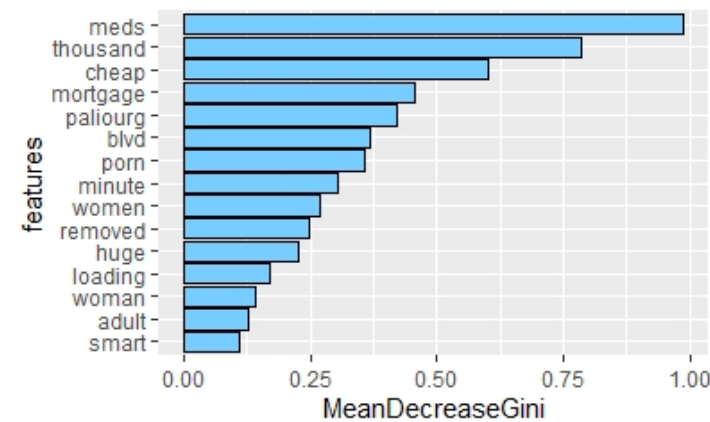
Elastic-Net



Ridge

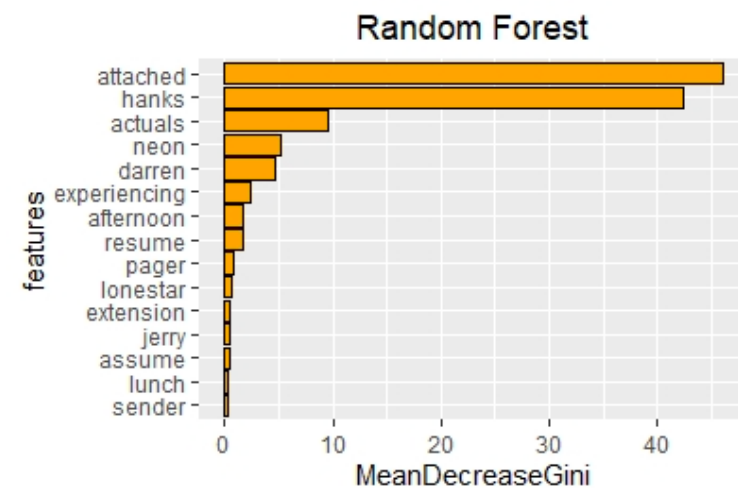
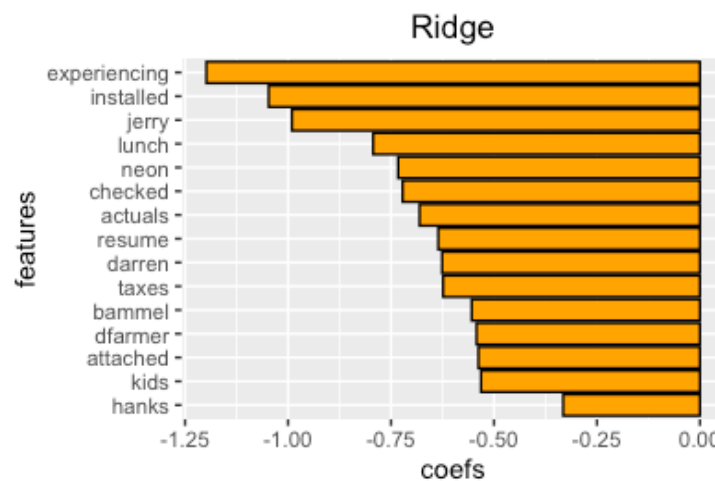
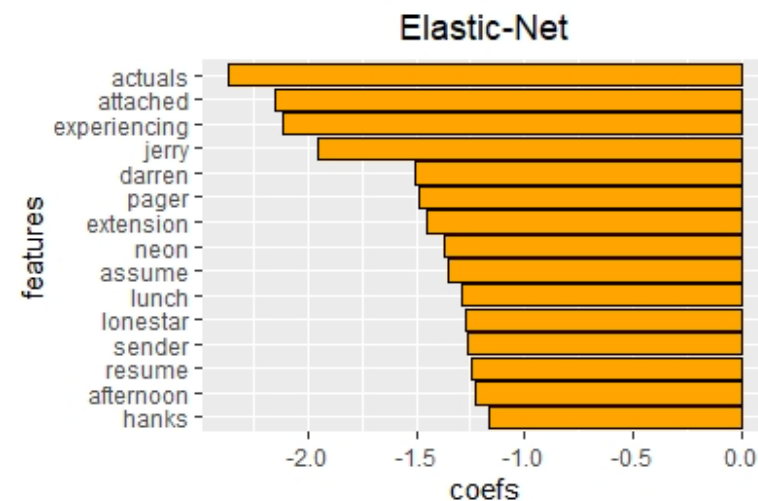
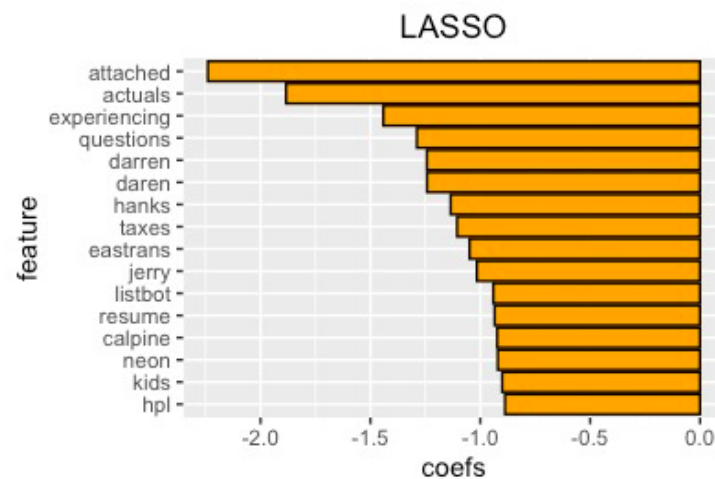


Random Forest

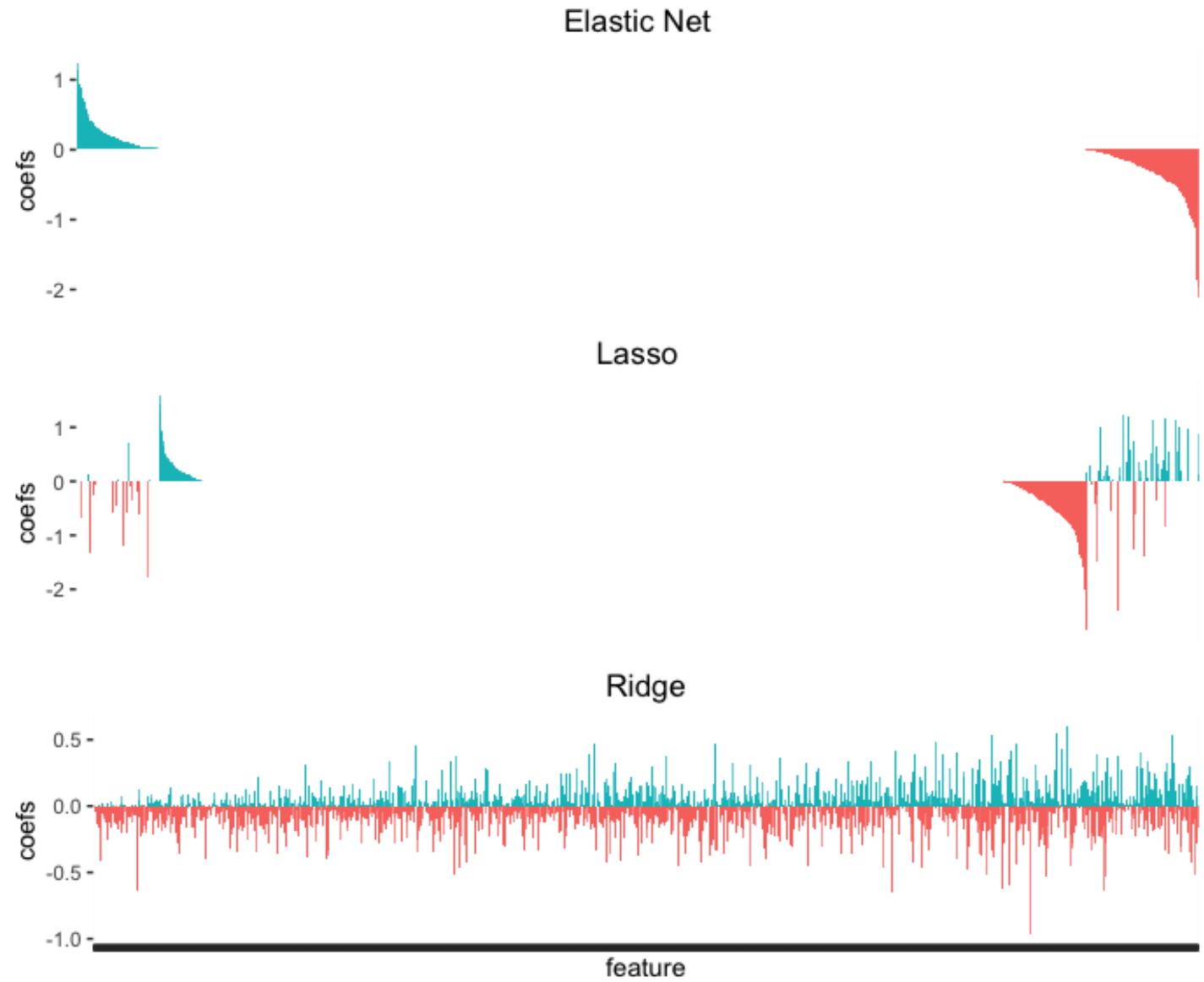


## Top 15 Non-Spam Features

The top 15 non-spam features have more professional words such as "resume", "attached", "actuals".



# Updated Feature Importance





## Conclusion

- Performance is similar across all methods, with train AUCs being clustered closer to 1 and test AUCs hovering around 0.99
- Longer training time does not always mean more accuracy in results. Sometimes, overfitting may be occurring which would require more analysis.
- The top 15 Spam features were consistent across models, with words such as "adult", "mortgage", and "woman" included as spam triggers.