

The Feasibility of Optimization for Online News Popularity Prediction

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Abstract

The internet has expanded into an immense data ocean and has become the main resource of how people absorb information on a daily basis. ABC evening news viewership grew 16% to 7.6 million viewers in 2020, following an 11% increase in 2019. CBS evening news viewership grew 7% to about 5 million viewers in 2020, while NBC viewership rose 8% to 6.5 million (Pew Research Center, 2021). In this paper, we analyze 39,644 online articles using a broad set of extracted features (e.g., number of words in the title, contents, keywords, polarity) to find the optimal machine learning model for predicting number of article shares. The optimal performance was provided by stochastic gradient boosting with 100 regression trees, maximum interaction depth of 5, shrinkage of 0.1, and minimum node observations of 10.

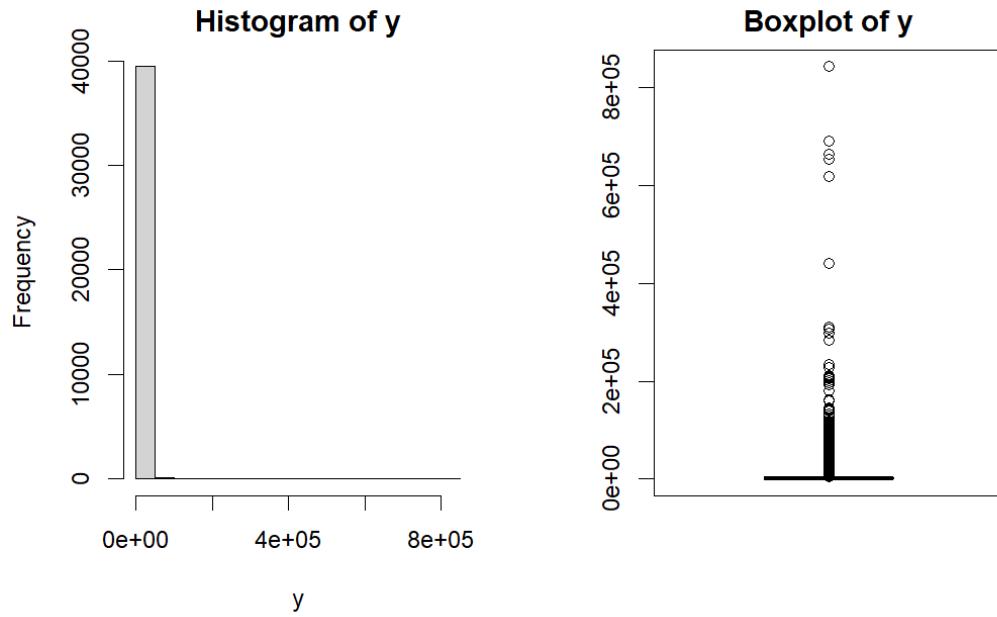
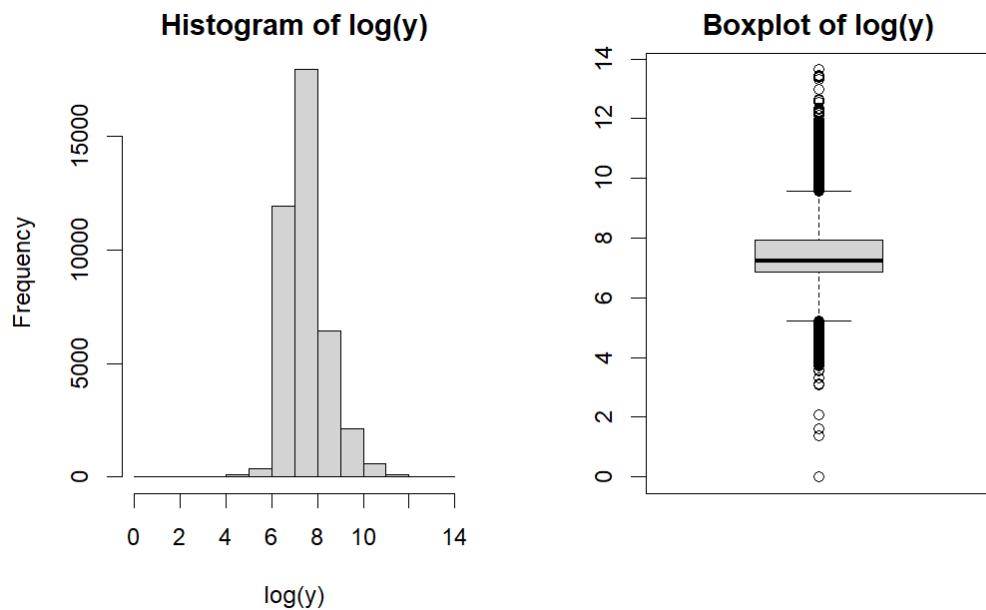
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Introduction

As the trends for Machine Learning (ML) and Artificial Intelligence (AI) have gradually become more and more popular in the last decade or two, Intelligent Decision Support Systems (IDSS) has drawn attention of all industries to help with decision making especially at the online platforms. While the resources for online information can be overwhelming, we could help with increasing the exposure and provide solutions to upscale the popularity of online news. Given a large set of data with different features and our target variable “shares”, we would like to train a machine learning model to provide an optimization for “shares” of the online news before they are published to maximize the exposure. While Fernandes et al. (2015) frame the prediction objective as a classification problem (popular vs. not popular), we instead approach it as a regression problem (number of shares). The final model would aim for the lowest Root Mean Squared Error (RMSE) with the highest R-squared value to ensure we can achieve the highest accuracy on the predictions while considering the Bias-Variance Tradeoff. RMSE is interpreted as how far, on average, the residuals are from zero (Kuhn, 2008).

Exploratory Data Analysis

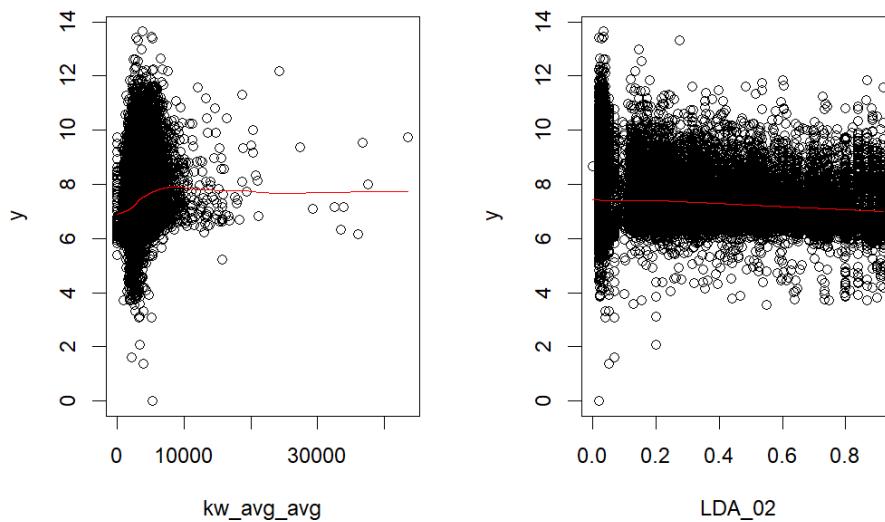
The dataset contains 39,644 samples and 61 variables. One of the variables, “url,” was discarded because it is a sample identifier, not a predictor. The target variable, “shares,” ranges from 1 to 843,300, has a median of 1400, and a mean of 3,395. It is heavily right-skewed, as shown in Figure 1. The natural logarithm transformation was applied to “shares” to correct its skew and facilitate modeling (Feng et al., 2014). While the log version still has outliers, its distribution is much more symmetrical and was used as the modeling target (See Figure 2).

Figure 1*Shares Distribution***Figure 2***Log of Shares Distribution*

The Pearson correlation coefficient was calculated between each predictor and the target. “kw_avg_avg” and “LDA_02” are the predictors most positively and negatively correlated with the target, with coefficients of 0.22 and -0.17, respectively (see Figure 4). This suggests a lack of strong linear relationships between the target and predictors.

Figure 4

Strongest Linear Target-Predictor Relationships



Note. The red line in this figure represents the LOWESS smoothing with a span of 0.66, a delta of 0.01, and 3 robustifying iterations.

Data Wrangling and Pre-Processing

There are no missing values in the dataset, so imputation was not needed. All outliers were retained because they are not the result of incorrect data and therefore provide useful information about the prediction target: news article virality. Each predictor was checked for near-zero variance, as defined by having 10% or fewer unique values out of the total number of samples or having the ratio of the most common value to the second most common value by

greater than or equal to 95:5. “kw_min_max” was the only predictor that met these criteria and was removed to avoid model failure (Kuhn, 2008).

The predictors were also checked for multicollinearity, which can result in unstable regression coefficient estimations (Daoud, 2017). The predictors were split into binary and non-binary sets and their pairwise correlations were calculated (See Figure 5 and Figure 6). Predictors that contributed to correlations greater than or equal to 0.7 were removed. For binary predictors that included the “is_weekend” indicator, which intuitively has a large correlation with the “weekday_is_saturday” and “weekday_is_sunday” flags. “weekday_is_sunday” was also removed to avoid the dummy variable trap where each dummy can be perfectly predicted by the others (Fernandes, Solimun, & Nurjannah, 2022). The data channel flags, in contrast, do not always sum to one and therefore do not fall into that trap. 12 of the non-binary predictors were also removed using the same 0.7 threshold. 44 predictors remained after this filtering process.

Figure 5

Binary Predictor Correlations

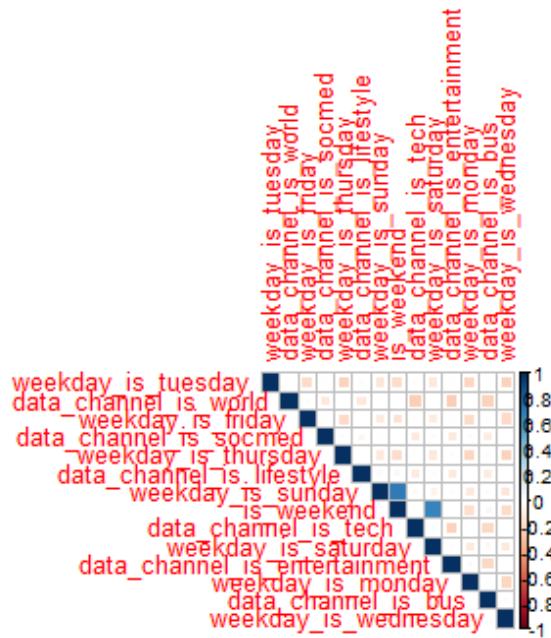
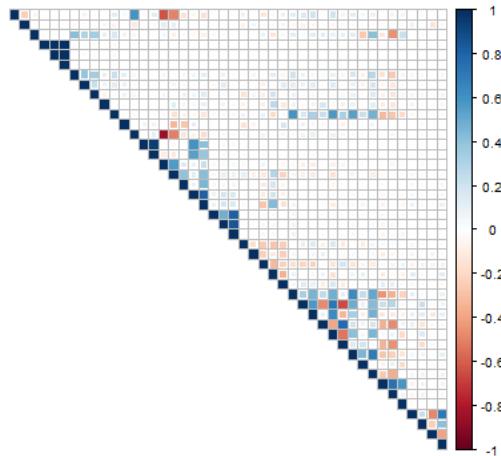


Figure 6*Non-Binary Predictor Correlations***Data Splitting**

We used stratified sampling to assign 80% of the data for training, and the remaining 20% for testing. We chose stratified sampling to ensure the target distribution was consistent across training and testing (Menon, 2020). We then split the training set into 10 folds for cross-validated model tuning (Sanjay, 2020).

Methods**Model Strategy**

The logarithm of the number of news article shares is a numeric variable, so predicting it is a regression problem. We wanted to try a variety of regression models, both in terms of type and complexity, because we did not know how much information was present in the dataset. The candidates represented linear, non-linear, and tree-based models. The linear models included elastic net regression (enet), principal component regression (PCR), and partial least squares regression (PLS). K-nearest neighbors (k-NN) was the only non-linear model because support vector machines (SVM) and neural networks were too computationally expensive for our limited

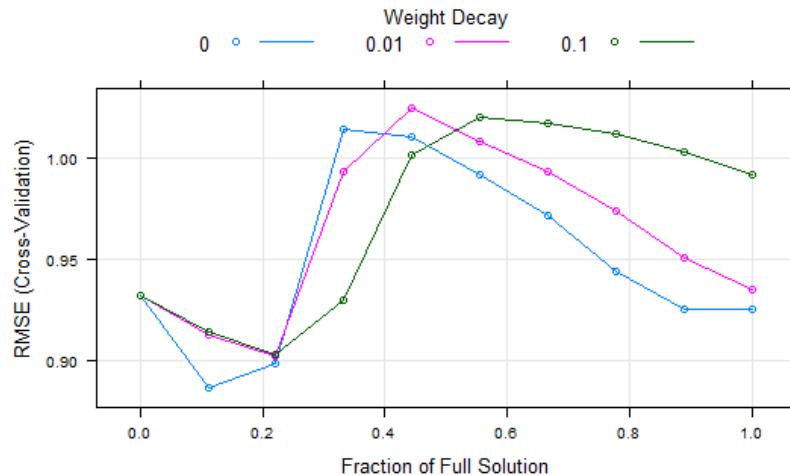
resources. Classification and regression tree (CART) and stochastic gradient boosting machines (GBM) were the tree-based candidates.

Model Tuning and Validation

Each model was hyperparameter tuned using 10-fold cross validation on the training set. All training, validation, and test sets were independently centered and scaled to facilitate modeling. Elastic net was chosen as the first linear model because it combines the ridge and lasso penalties, which each tend to outperform non-penalized ordinary least squares (Zou & Hastie, 2005). Elastic net was tuned on hyperparameters alpha (fraction of full solution) and lambda (shrinkage or weight decay). The advantage of using Elastic net is that regularization is very effective as the ridge-type penalty has the feature selection of a lasso penalty method. We had 10 values of alpha between 0 and 1, and values 0, 0.01, and 0.1 of lambda were evaluated (See Figure 7). Alpha of 0.111 and lambda of 0 yielded the best performance, with a cross-validated RMSE and R-squared of 0.886 and 0.097, respectively.

Figure 7

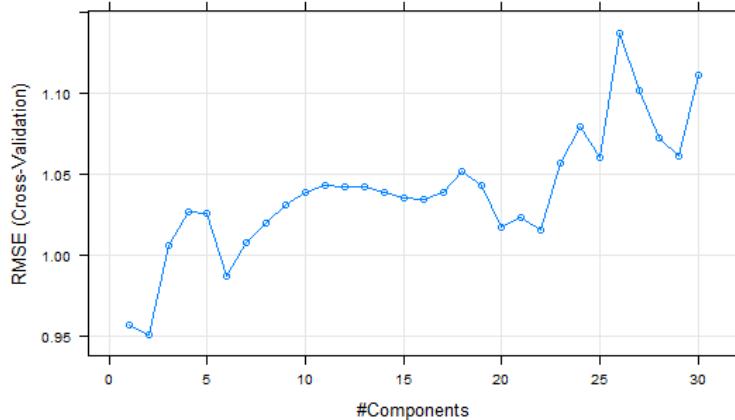
Elastic Net Hyperparameter Tuning



Pre-processing predictors via PCA prior to performing regression is known as principal component regression (PCR) (Massy 1965); this technique has been widely applied in the context of problems with inherently highly correlated predictors or problems with more predictors than observations (Kuhn, 2008). We chose the PCR model as it would give us a good understanding whether a predictive relationship is present by determining whether the variability in the predictor space is not related to the variability of the response. PCR was tuned on the number of principal components, ranging from 1 to 30 (See Figure 8). The best tune used two principal components and yielded a cross-validated RMSE and R-squared of 0.951 and 0.014, respectively.

Figure 8

Principal Component Regression Hyperparameter Tuning

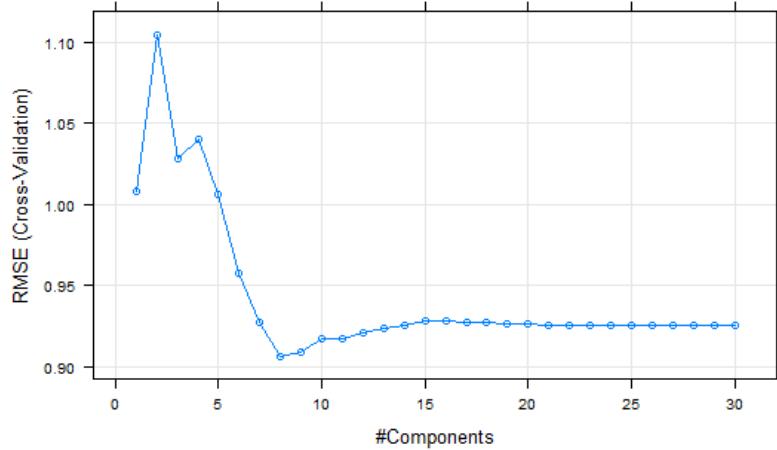


The Partial Least Squares (PLS) model is very similar to the PCR model but instead tries to find a linear regression model by having the predicted and observable variables projected into a new space. We chose the PLS model so that we can compare it to the PCR model results. The main difference between the two is that PCR focuses on variance while reducing the dimensionality while PLS focuses on covariance. PLS helps reduce dimensionality of the

correlated variables and model the underlying information of those variables. PLS was also tuned on 1 to 30 components (See Figure 9). 8 components was the best tune with an RMSE and R-squared of 0.906 and 0.092, respectively.

Figure 9

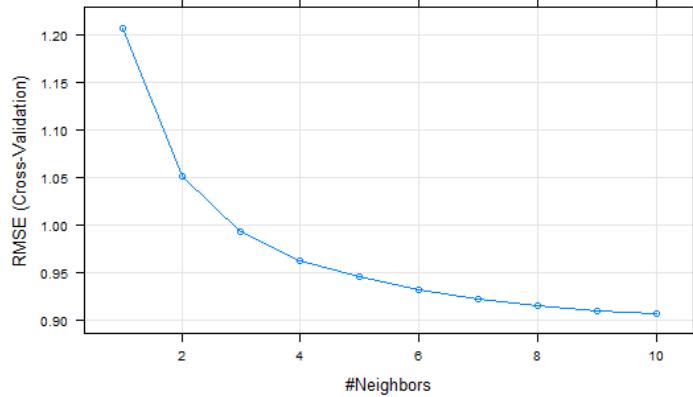
Principal Least Squares Hyperparameter Tuning



Similar to the regression context, k-NN for classification predicts a new sample using the K-closest samples from the training set. “Closeness” is determined by a distance metric. We chose this model because of the fact that the training portion of this model is done relatively quickly and due to the fact it is very simple to explain and implement. For K-NN, 1 to 10 neighbors were assessed, and 10 performed the best (See Figure 10). 10-NN resulted in an RMSE and R-squared of 0.906 and 0.082, respectively.

Figure 10

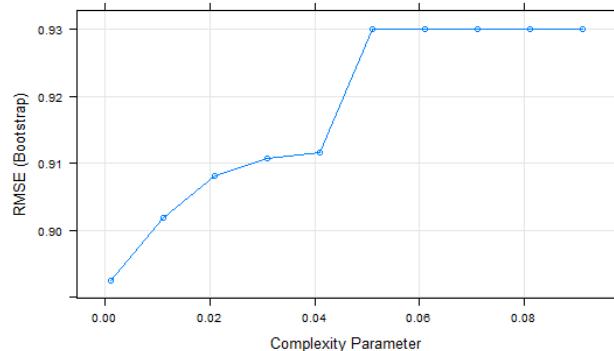
K-Nearest Neighbors Hyperparameter Tuning



CART was tuned along 10 complexity parameter values between 0.001 and 0.091 (See Figure 11). The complexity parameter of 0.001 returned the best RMSE and R-squared values of 0.892 and 0.090, respectively. The complexity parameter is a penalty proportional to the size of the tree (Camdeviren et al., 2005). The cross-validated RMSE only increased as the complexity parameter increased, meaning more complex trees performed consistently better than less complex ones. This suggests the predictive patterns in the dataset may be too complex for simple models to learn.

Figure 11

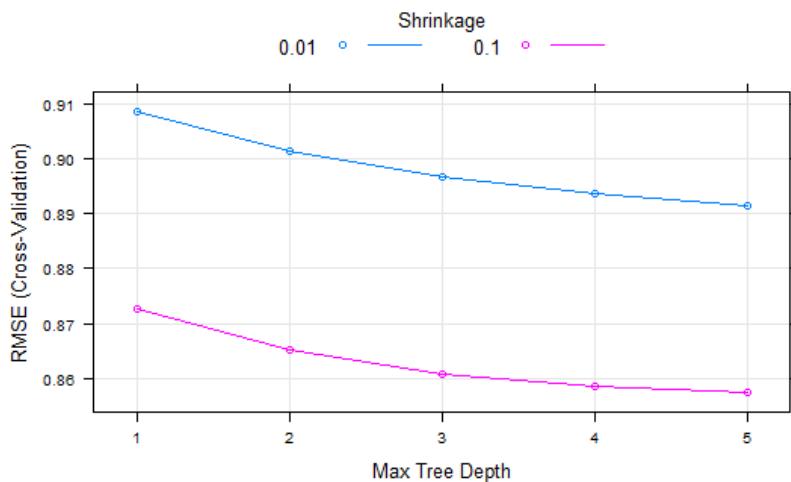
CART Hyperparameter Tuning



GBM was tuned across values of shrinkage 0.01 and 0.1 and interaction depth, or max tree depth, 1 to 5 (See Figure 12). Number of trees and minimum number of observations in node were held constant at 100 and 10, respectively. Shrinkage of 0.1 and interaction depth of 5 resulted in the best tune, yielding RMSE and R-squared values of 0.857 and 0.155, respectively. These tuning results corroborate those of CART, showing that more complex trees consistently outperform simpler ones.

Figure 12

GBM Hyperparameter Tuning



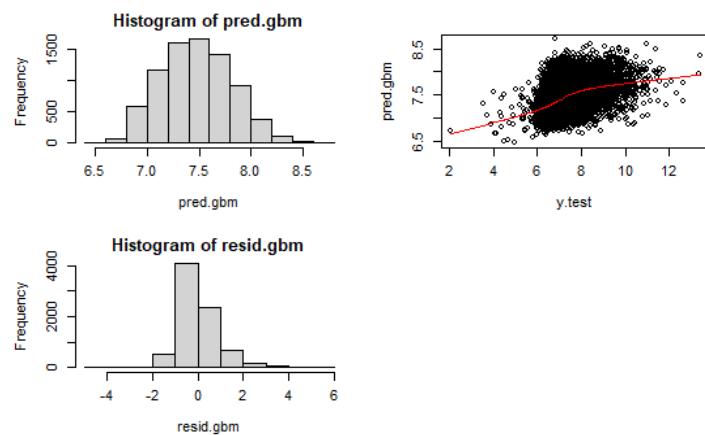
Results

This is a regression problem so the objective is to predict as closely as possible the target values of new data. Test RMSE was used as the primary performance metric because it penalizes predictions that are far from the actual unseen target values. R-squared was also considered, as it represents the proportion of target variance captured by the model. The baseline model simply always predicts the mean of the training target, 7.47, which results in a test RMSE of 0.923. All of the tuned candidate models beat this benchmark (See Table 1). GBM, however, achieved the lowest test RMSE of 0.848 and was therefore chosen as the final model. Its predictions are quite

symmetrical, but its residuals are slightly right-skewed (See Figure 13). The residual distribution shows that the model tends to slightly overestimate the target, but when it does underestimate it does so more dramatically.

Table 1*Performance of Tuned Models*

Model	RMSE CV		RMSE Test	R-squared	R-squared	R-squared
	CV	SD		CV	CV SD	Test
enet	0.886	0.022	0.874	0.097	0.017	0.104
PCR	0.951	0.084	0.915	0.014	0.006	0.017
PLS	0.906	0.075	0.874	0.092	0.029	0.104
k-NN	0.906	0.019	0.902	0.082	0.01	0.046
CART	0.892	0.007	0.877	0.09	0.007	0.097
GBM	0.857	0.018	0.848	0.155	0.01	0.156

Figure 13*GBM Test Predictions and Residuals*

Discussion

According to the final model, the variables most predictive of article shares are “kw_max_avg,” “self_reference_avg_sharess,” “timedelta,” and “kw_min_avg.” “kw_max_avg” and “kw_min_avg” represent the popularity of the article’s keywords on Mashable, “self_reference_avg_sharess” represents the popularity of the other Mashable articles it links to, and “timedelta” is the number of days since the article was published (Fernandes et al., 2015). The model is therefore saying that the popularity of an article’s keywords and related articles, and how long ago it was published, are the most important factors for predicting how many times it will be shared. This is intuitive because one would expect articles related to trending topics to be more popular.

While the final model outperforms the baseline test RMSE, the tuning process suggests further improvement is possible. Greater tree depth consistently improved the cross-validated RMSE, but tuning was halted at 5. Furthermore, only two shrinkage values were tested, so there could be opportunity for improvement in that dimension as well. Finally, the number of trees was not tuned and simply set constant at 100. These decisions were due to computing constraints. Future research should leverage greater computing resources to explore a larger GBM hyperparameter space. More computing power and memory would also provide the opportunity to test more complex nonlinear models like SVM and neural networks, which may outperform GBM.

References

- Camdeviren, H., Mendes, M., Ozkan, M. M., Toros, F., Sasmaz, T., & Oner, S. (2005). Determination of depression risk factors in children and adolescents by regression tree methodology. *Acta Medica Okayama*, 59(1), 19-26. <https://doi.org/10.18926/AMO/31985>
- Daoud, J. I. (2017, August 8-9). Multicollinearity and regression analysis. *Journal of Physics: Conference Series*, 949. <https://doi.org/10.1088/1742-6596/949/1/012009>
- Feng, C., Wang, H., Lu, N., Chen, T., He, H., Lu, Y., & Tu, X. M. (2014). Log-transformation and its implications for data analysis. *Shanghai Archives of Psychiatry*, 26(2), 105-109. <https://doi.org/10.3969/j.issn.1002-0829.2014.02.009>
- Fernandes, A. A. R., Solimun, & Nurjannah. (2022). Computational statistics with dummy variables. In Lopez-Ruiz, R. (Ed.), *Computational Statistics and Applications*. IntechOpen. <https://doi.org/10.5772/intechopen.95652>
- Fernandes, K., Vinagre, P., & Cortez, P. (2015). A proactive intelligent decision support system for predicting the popularity of online news. *Lecture Notes in Computer Science*, 9273, 525-546. https://doi.org/10.1007/978-3-319-23485-4_53
- Fernandes, K., Vinagre, P., & Cortez, P. (2015). *Online news popularity data set* [Data set]. UCI Machine Learning Repository. <https://archive.ics.uci.edu/ml/datasets/online+news+popularity>
- Kuhn, M. (2008). Building predictive models in R using the caret package. *Journal of Statistical Software*, 28(5), 1-26. <https://doi.org/10.18637/jss.v028.i05>
- Pew Research Center. (2021, December 15). *Network News Fact sheet*. Pew Research Center's Journalism Project. <https://www.pewresearch.org/journalism/fact-sheet/network-news/>

Menon, S. (2020, December 8). *Stratified sampling in machine learning*. Medium.

<https://medium.com/analytics-vidhya/stratified-sampling-in-machine-learning-f5112b5b9cfe#:~:text=Why%20stratified%20sampling%3F,the%20entire%20population%20being%20studied.>

Sanjay.M. (2020, August 19). *Why and how to cross validate a Model?* Medium.

<https://towardsdatascience.com/why-and-how-to-cross-validate-a-model-d6424b45261f>

Zou, H. & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, 67(2), 301-320.

<https://www.jstor.org/stable/3647580>

Appendix

ADS 503 Team 4: Predicting Article Shares

Code ▾

Load Data

Hide

```
df <- read.csv("Datasets/OnlineNewsPopularity.csv")
dim(df)
```

```
[1] 39644    61
```

Hide

```
summary(df)
```

url_tokens	timedelta	n_tokens_title	n_tokens_content	n_unique_tokens	n_non_stop_words	n_non_stop_unique
Length:39644	Min. : 8.0	Min. : 2.0	Min. : 0.0	Min. : 0.0000	Min. : 0.0000	Min. : 0.0000
Min. : 0.00	Min. : 0.000	Min. : 0.000				
Class :character	1st Qu.:164.0	1st Qu.: 9.0	1st Qu.: 246.0	1st Qu.: 0.4709	1st Qu.: 1.0000	1st Qu.: 0.6257
1st Qu.: 4.00	1st Qu.: 1.000	1st Qu.: 1.000				
Mode :character	Median :339.0	Median :10.0	Median : 409.0	Median : 0.5392	Median : 1.0000	Median : 0.6905
Median : 8.00	Median : 3.000	Median : 1.000				
	Mean :354.5	Mean :10.4	Mean : 546.5	Mean : 0.5482	Mean : 0.9965	Mean : 0.6892
Mean : 10.88	Mean : 3.294	Mean : 4.544				
	3rd Qu.:542.0	3rd Qu.:12.0	3rd Qu.: 716.0	3rd Qu.: 0.6087	3rd Qu.: 1.0000	3rd Qu.: 0.7546
3rd Qu.: 14.00	3rd Qu.: 4.000	3rd Qu.: 4.000				
	Max. :731.0	Max. :23.0	Max. :8474.0	Max. :701.0000	Max. :1042.0000	Max. :650.0000
Max. :304.00	Max. :116.000	Max. :128.000				
num_videos	average_token_length	num_keywords	data_channel_is_lifestyle	data_channel_is_entertainment	data_channel_is_bus	data_channel_is_socmed
						data_channel_is_world
Min. : 0.00	Min. :0.000	Min. : 1.000	Min. :0.00000		Min. :0.000	
0	Min. :0.0000	Min. :0.0000	Min. :0.0000			Min. :0.000
1st Qu.: 0.00	1st Qu.:4.478	1st Qu.: 6.000	1st Qu.:0.00000		1st Qu.:0.000	
0	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000			1st Qu.:0.000
Median : 0.00	Median :4.664	Median : 7.000	Median :0.00000		Median :0.000	
0	Median :0.0000	Median :0.0000	Median :0.0000			Median :0.000
Mean : 1.25	Mean :4.548	Mean : 7.224	Mean : 0.05295		Mean :0.178	
9	Mean :0.0586	Mean :0.1853	Mean :0.2126			Mean :0.157
3rd Qu.: 1.00	3rd Qu.:4.855	3rd Qu.: 9.000	3rd Qu.:0.00000		3rd Qu.:0.000	
0	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000			3rd Qu.:0.000
Max. :91.00	Max. :8.042	Max. :10.000	Max. :1.00000		Max. :1.000	
0	Max. :1.0000	Max. :1.0000	Max. :1.0000			Max. :1.000
kw_min_min	kw_max_min	kw_avg_min	kw_min_max	kw_max_max	kw_avg_max	kw_min_avg
						kw_max_avg
Min. : -1.00	Min. : 0	Min. : -1.0	Min. : 0	Min. : 0	Min. : 0	Min. : -1
:	0	Min. : 0	Min. : 0	Min. : 0	Min. : 0	Min. : 0
1st Qu.: -1.00	1st Qu.: 445	1st Qu.: 141.8	1st Qu.: 0	1st Qu.:843300	1st Qu.:172847	1st Qu.: 0
u.: 3562	1st Qu.: 2382	1st Qu.: 639				1st Q
Median : -1.00	Median : 660	Median : 235.5	Median : 1400	Median :843300	Median :244572	Median :1024
n : 4356	Median : 2870	Median : 1200				Media
Mean : 26.11	Mean : 1154	Mean : 312.4	Mean : 13612	Mean :752324	Mean :259282	Mean :1117
:	5657	Mean : 3136	Mean : 3999			Mean
3rd Qu.: 4.00	3rd Qu.: 1000	3rd Qu.: 357.0	3rd Qu.: 7900	3rd Qu.:843300	3rd Qu.:330980	3rd Qu.:2057
u.: 6020	3rd Qu.: 3600	3rd Qu.: 2600				3rd Q
Max. :377.00	Max. :298400	Max. :42827.9	Max. :843300	Max. :843300	Max. :843300	Max. :3613
:	298400	Max. :43568	Max. :843300			Max.
self_reference_max_shares	self_reference_avg_shares	weekday_is_monday	weekday_is_tuesday	weekday_is_wednesday	weekday_is_thursday	weekday_is_friday
						weekday_is_saturday
Min. : 0	Min. : 0.0	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000
00	Min. :0.0000	Min. :0.00000	Min. :0.00000			
1st Qu.: 1100	1st Qu.: 981.2	1st Qu.:0.000	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.00
00	1st Qu.:0.0000	1st Qu.:0.00000	1st Qu.:0.00000			
Median : 2800	Median : 2200.0	Median :0.000	Median :0.0000	Median :0.0000	Median :0.0000	Median :0.00
00	Median :0.0000	Median :0.00000	Median :0.00000			
Mean : 10329	Mean : 6401.7	Mean :0.168	Mean :0.1864	Mean :0.1875	Mean :0.18	
33	Mean :0.1438	Mean :0.06188	Mean :0.06904			
3rd Qu.: 8000	3rd Qu.: 5200.0	3rd Qu.:0.000	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.00
00	3rd Qu.:0.0000	3rd Qu.:0.00000	3rd Qu.:0.00000			
Max. :843300	Max. :843300.0	Max. :1.000	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.00
00	Max. :1.0000	Max. :1.00000	Max. :1.00000			
is_weekend	LDA_00	LDA_01	LDA_02	LDA_03	LDA_04	global_subjectivity
global_sentiment_polarity	global_rate_positive_words					
Min. :0.0000	Min. :0.00000	Min. :0.00000	Min. :0.00000	Min. :0.00000	Min. :0.00000	Min. :0.0000
Min. :-0.39375	Min. :0.00000					
1st Qu.:0.00000	1st Qu.:0.02505	1st Qu.:0.02501	1st Qu.:0.02857	1st Qu.:0.02857	1st Qu.:0.02857	1st Qu.:0.3962
1st Qu.: 0.05776	1st Qu.:0.02838					
Median :0.0000	Median :0.03339	Median :0.03334	Median :0.04000	Median :0.04000	Median :0.04073	Median :0.4535
Median : 0.11912	Median :0.03902					
Mean :0.1309	Mean :0.18460	Mean :0.14126	Mean :0.21632	Mean :0.22377	Mean :0.23403	Mean :0.4434
Mean : 0.11931	Mean :0.03962					
3rd Qu.:0.0000	3rd Qu.:0.24096	3rd Qu.:0.15083	3rd Qu.:0.33422	3rd Qu.:0.37576	3rd Qu.:0.39999	3rd Qu.:0.5083
3rd Qu.: 0.17783	3rd Qu.:0.05028					
Max. :1.0000	Max. :0.92699	Max. :0.92595	Max. :0.92000	Max. :0.92653	Max. :0.92719	Max. :1.0000
Max. : 0.72784	Max. :0.15549					
global_rate_negative_words	rate_positive_words	rate_negative_words	avg_positive_polarity	min_positive_polarity	max_positive_polarity	avg_negative_polarity
Min. :0.000000	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.000000	Min. :0.00
00	Min. : -1.0000	Min. : -1.0000				
1st Qu.:0.009615	1st Qu.:0.6000	1st Qu.:0.1852	1st Qu.:0.3062	1st Qu.:0.05000	1st Qu.:0.60	
00	1st Qu.: -0.3284	1st Qu.: -0.7000				
Median :0.015337	Median :0.7105	Median :0.2800	Median :0.3588	Median :0.10000	Median :0.80	
00	Median : -0.2533	Median : -0.5000				
Mean :0.016612	Mean :0.6822	Mean :0.2879	Mean :0.3538	Mean :0.09545	Mean :0.75	
67	Mean : -0.2595	Mean : -0.5219				
3rd Qu.:0.021739	3rd Qu.:0.8000	3rd Qu.:0.3846	3rd Qu.:0.4114	3rd Qu.:0.10000	3rd Qu.:1.00	
00	3rd Qu.: -0.1869	3rd Qu.: -0.3000				
Max. :0.184932	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.00000	Max. :1.00	

```

00      Max. : 0.0000      Max. : 0.0000
max_negative_polarity title_subjectivity title_sentiment_polarity abs_title_subjectivity abs_title_sentiment_polarity      s
hares
Min. :-1.0000      Min. :0.0000      Min. :-1.00000      Min. :0.0000      Min. :0.0000      Min.
: 1
1st Qu.:-0.1250    1st Qu.:0.0000    1st Qu.: 0.00000    1st Qu.:0.1667    1st Qu.:0.0000    1st Q
u.: 946
Median :-0.1000    Median :0.1500    Median : 0.00000    Median :0.5000    Median :0.0000    Media
n : 1400
Mean :-0.1075    Mean :0.2824    Mean : 0.07143    Mean :0.3418    Mean :0.1561    Mean
: 3395
3rd Qu.:-0.0500    3rd Qu.:0.5000    3rd Qu.: 0.15000    3rd Qu.:0.5000    3rd Qu.:0.2500    3rd Q
u.: 2800
Max. : 0.0000    Max. :1.0000    Max. : 1.00000    Max. :0.5000    Max. :1.0000    Max.
:843300

```

The dataset has 39,644 samples and 61 variables.

Missing Data

[Hide](#)

```
sum(is.na(df))
```

```
[1] 0
```

None of the variables is missing any data so there is no need for imputation.

Define Target and Predictors

[Hide](#)

```

df <- df[, names(df) != "url"] # drop the url column, which functions as a sample ID
y <- df$shares # shares is the target variable
X <- df[, names(df) != "shares"]

```

Target Distribution

[Hide](#)

```
summary(y)
```

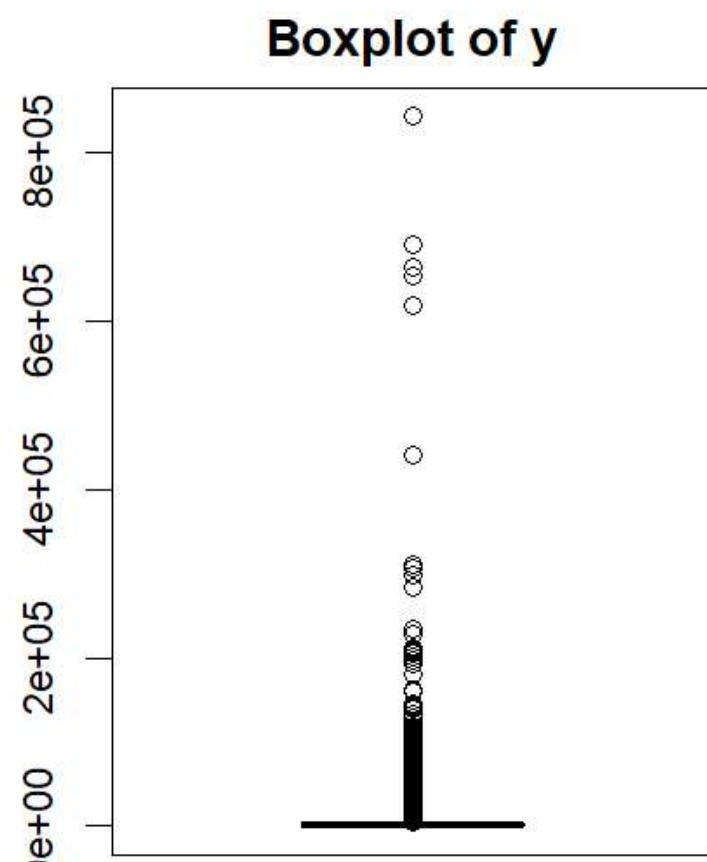
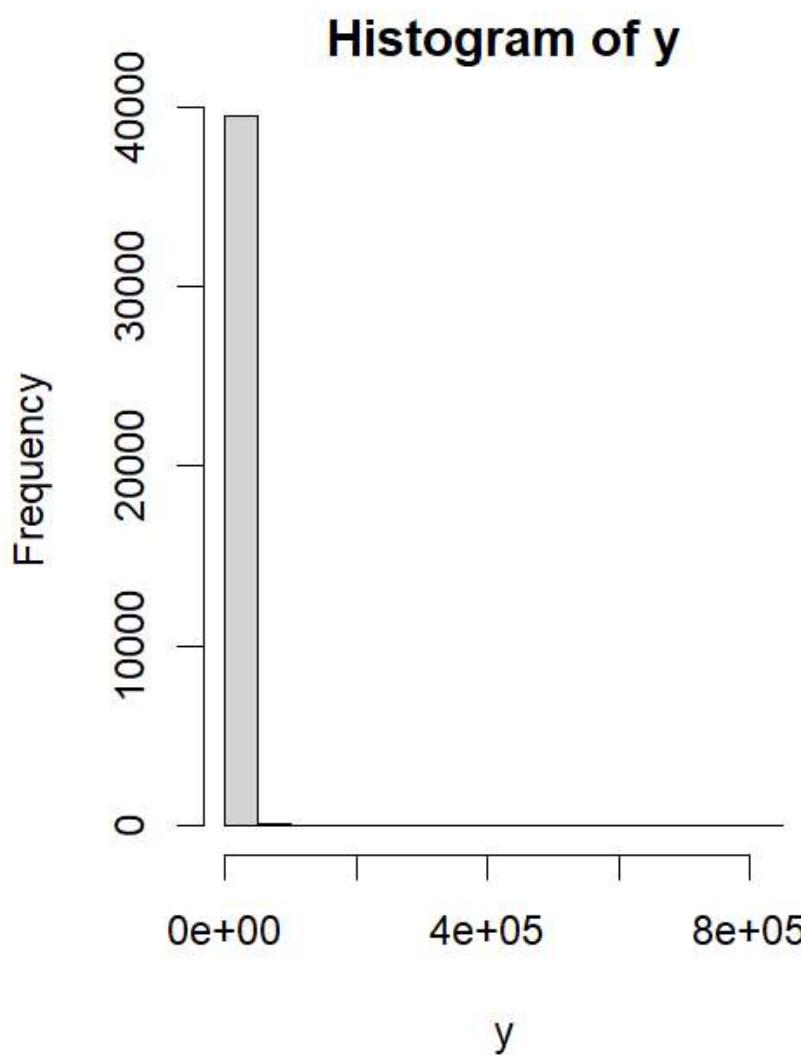
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	946	1400	3395	2800	843300

[Hide](#)

```

par(mfrow = c(1, 2))
hist(y)
boxplot(y, main = "Boxplot of y")

```



The target distribution is highly right-skewed. Let's try log transforming it.

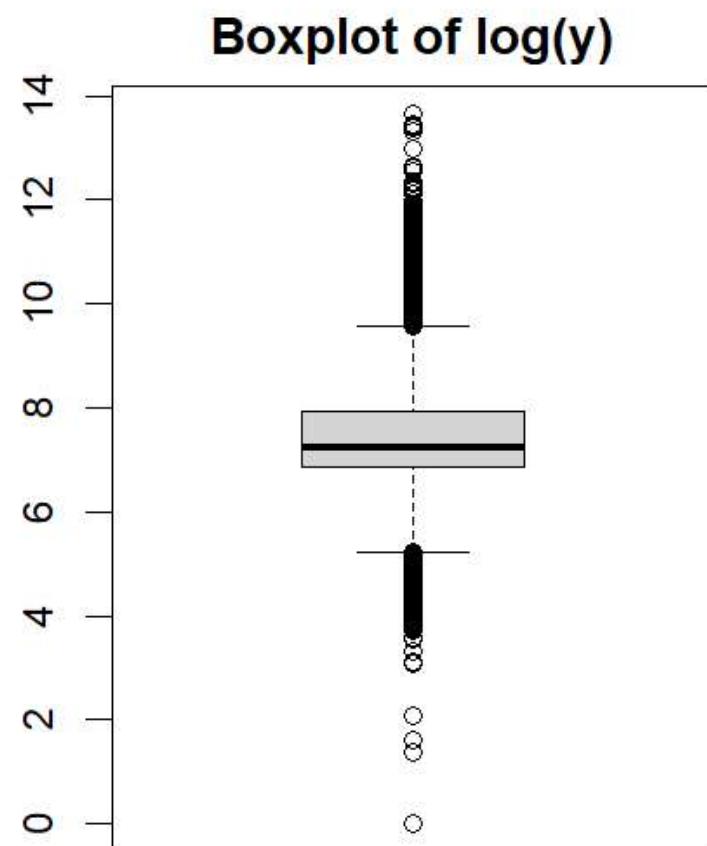
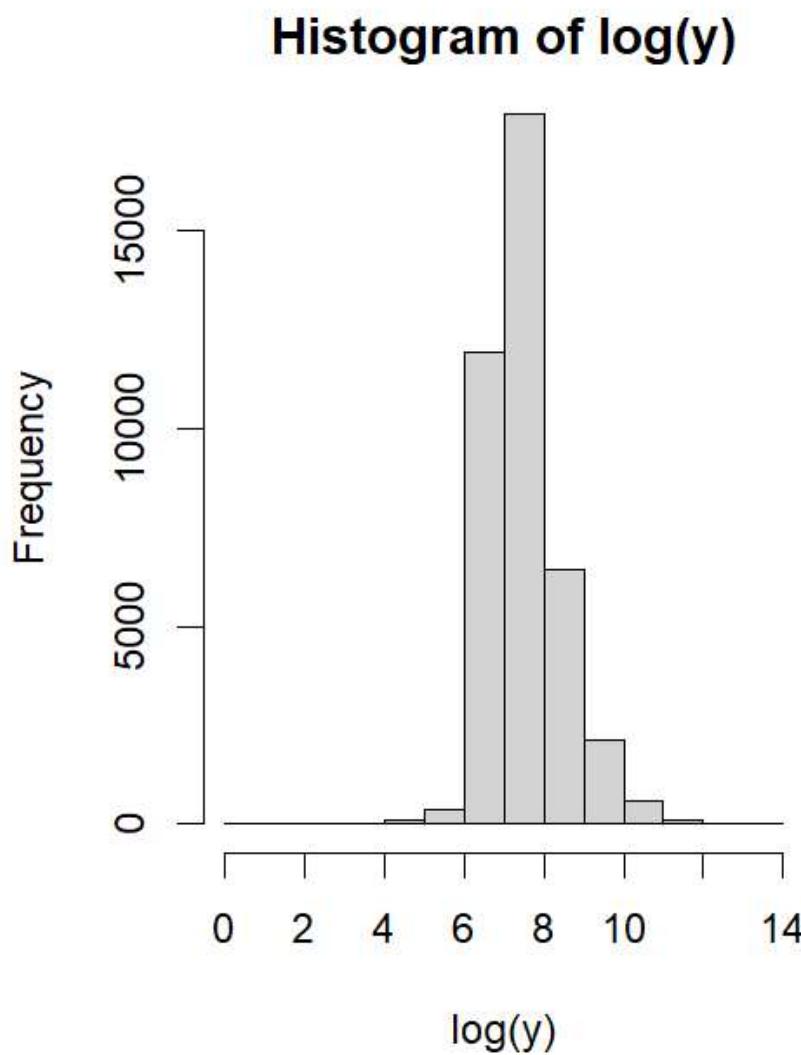
[Hide](#)

```
summary(log(y))
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.000	6.852	7.244	7.475	7.937	13.645

[Hide](#)

```
par(mfrow = c(1, 2))
hist(log(y))
boxplot(log(y), main = "Boxplot of log(y)")
```



The log of the target is much less skewed. Let's use the log-transformed version.

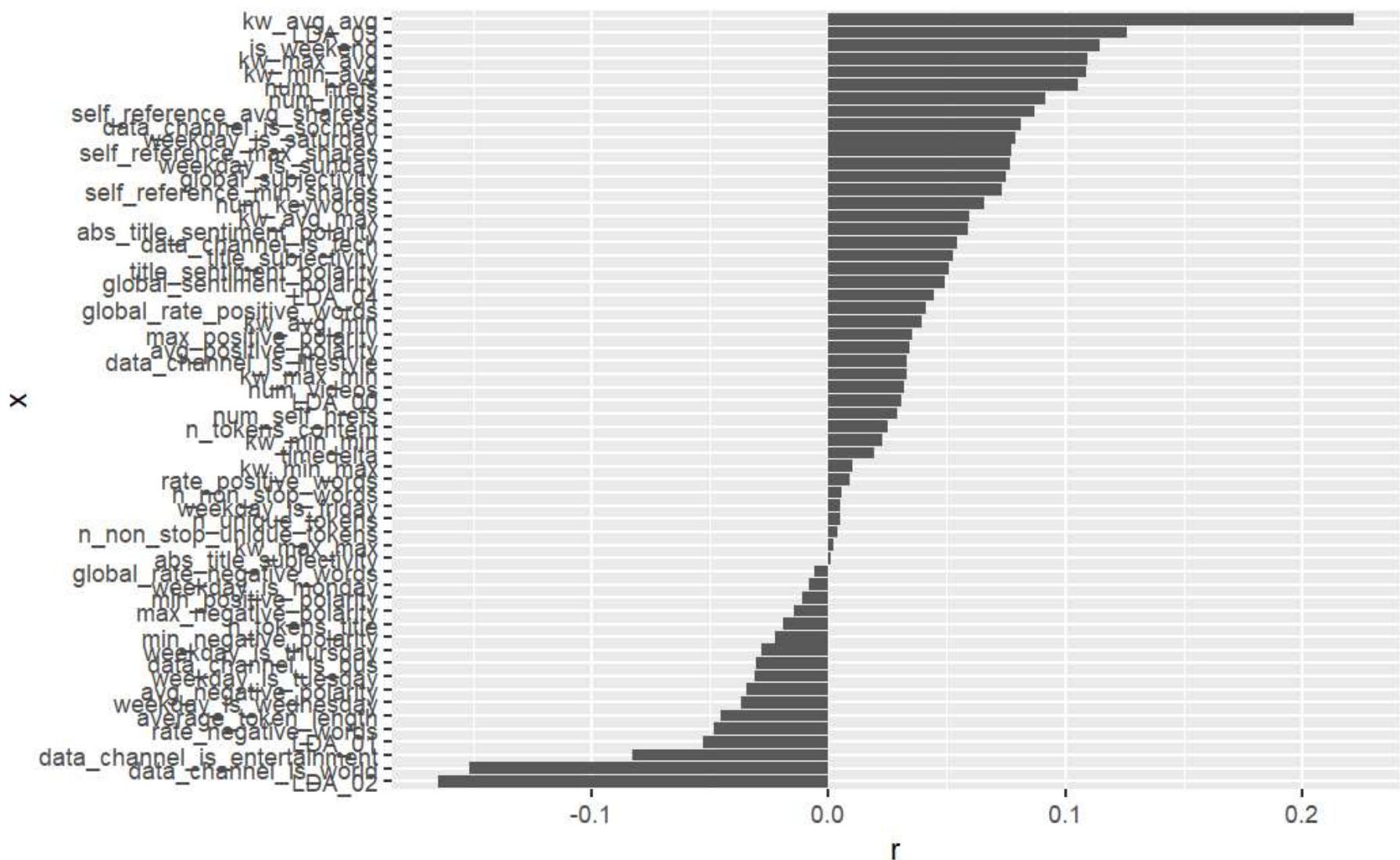
[Hide](#)

```
y <- log(y)
```

Target-Predictor Correlations

[Hide](#)

```
library(tidyr)
library(dplyr)
library(ggplot2)
x <- names(X)
correlations <- data.frame(x)
correlations$r <- apply(correlations, 1, function(row) cor(X[, row["x"]], y)) # correlation between each predictor and the target
correlations <- correlations %>%
  dplyr::arrange(r) %>%
  dplyr::mutate(x = forcats::fct_inorder(x))
ggplot(correlations) +
  geom_col(aes(x = x, y = r)) +
  coord_flip()
```

[Hide](#)

```
correlations
```

x	r
	<dbl>
LDA_02	-0.1650336120
data_channel_is_world	-0.1516506202
data_channel_is_entertainment	-0.0825036542
LDA_01	-0.0529932702
rate_negative_words	-0.0481707553
average_token_length	-0.0452834316
weekday_is_wednesday	-0.0365902248
avg_negative_polarity	-0.0343099860
weekday_is_tuesday	-0.0310734298
data_channel_is_bus	-0.0305990105

1-10 of 59 rows

Previous 1 2 3 4 5 6 Next

None of the target-predictor correlations is very strong. The strongest positive correlation is with kw_avg_avg, while the strongest negative correlation is with LDA_02.

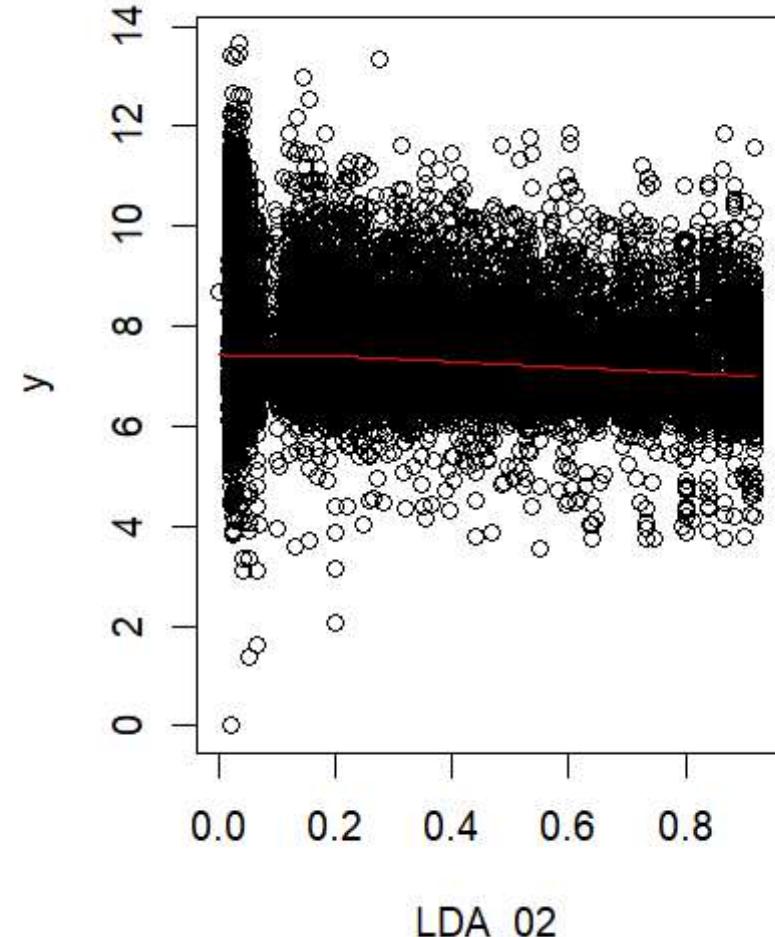
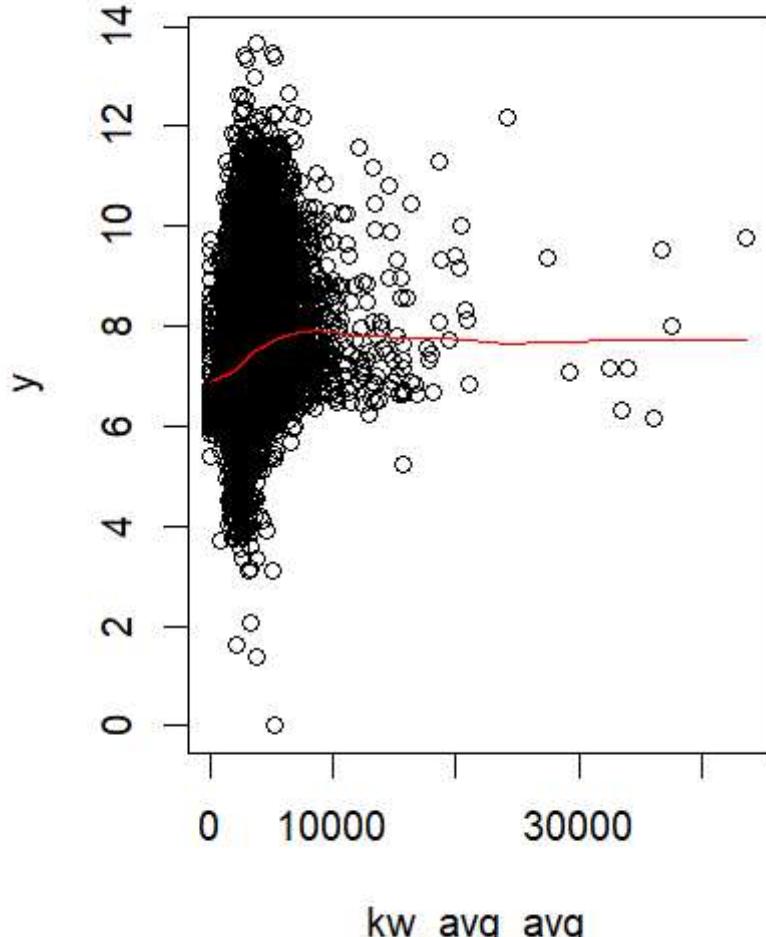
[Hide](#)

```
par(mfrow = c(1, 2))

plot(X[, "kw_avg_avg"], y, xlab = "kw_avg_avg")
lines(lowess(X[, "kw_avg_avg"], y), col = "red")
```

Hide

```
plot(X[, "LDA_02"], y, xlab = "LDA_02")
lines(lowess(X[, "LDA_02"], y), col = "red")
```



Predictor Distributions

Near-Zero Variance

Hide

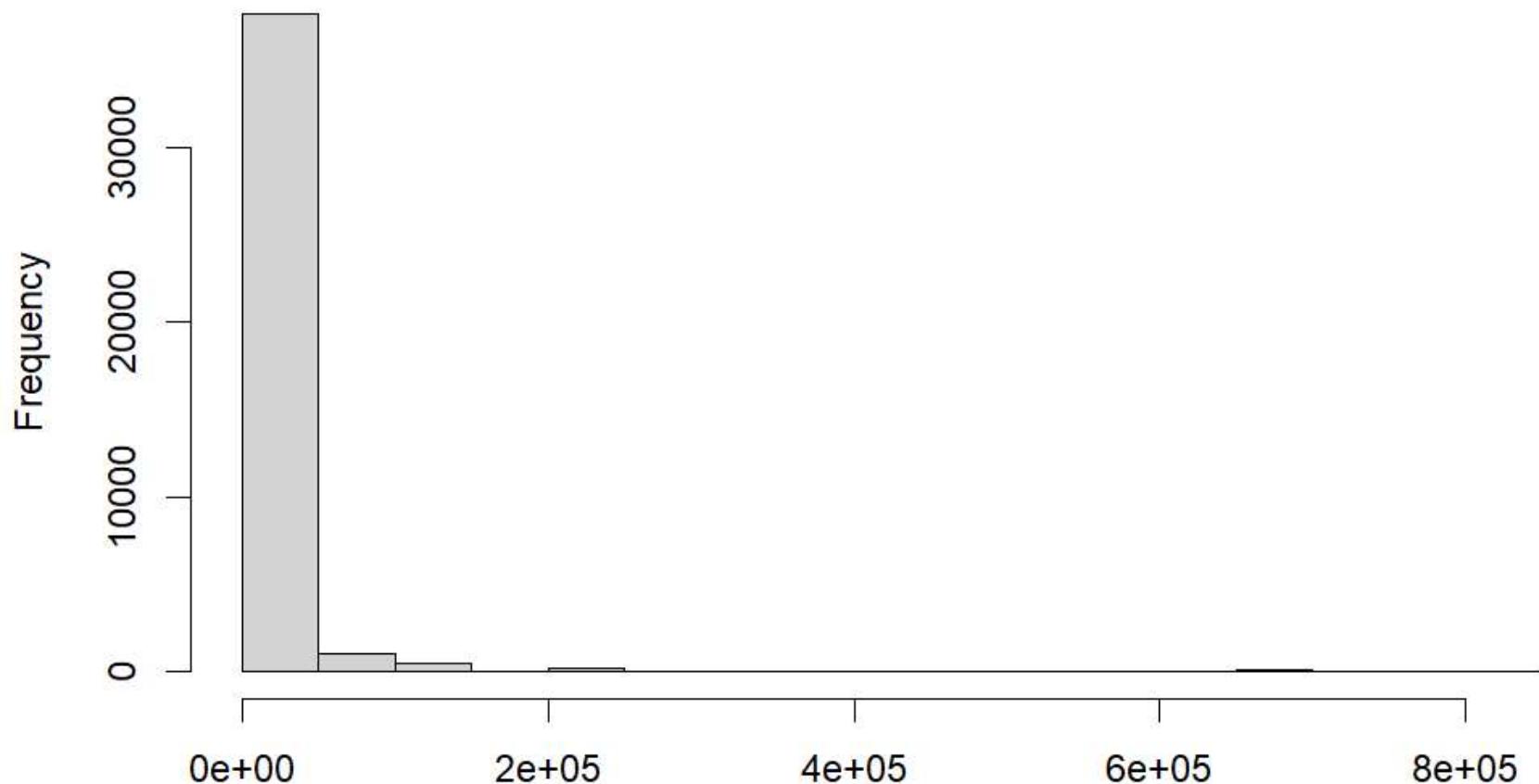
```
library(caret)
```

```
Loading required package: ggplot2
Loading required package: lattice
```

Hide

```
degen.cols <- nearZeroVar(X)
for (i in degen.cols) {
  col.name <- names(X)[i]
  hist(X[, col.name], main = col.name, xlab = col.name)
}
```

kw_min_max



kw_min_max

kw_min_max has near-zero variance so let's remove it.

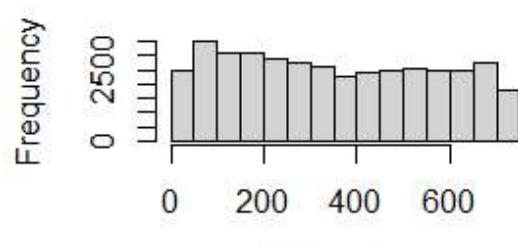
[Hide](#)

```
X <- X[, -degen.cols]
```

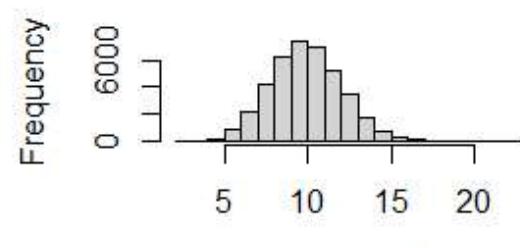
Skew

[Hide](#)

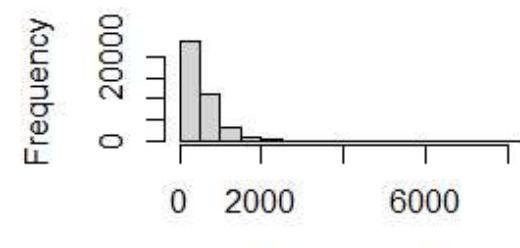
```
par(mfrow = c(3, 3))
for (i in 1:ncol(X)) {
  hist(
    X[, i],
    main = NULL,
    xlab = colnames(X)[i]
  )
}
```



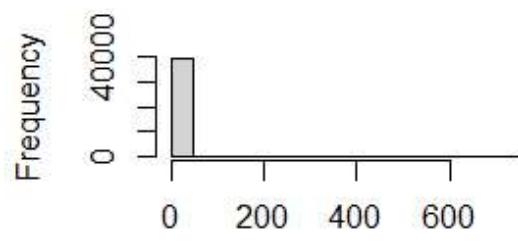
timedelta



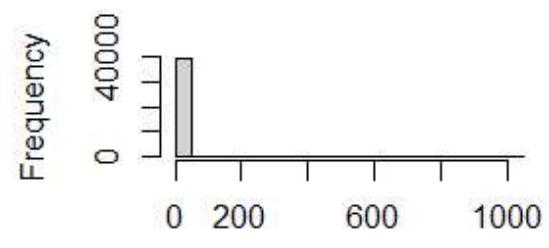
n_tokens_title



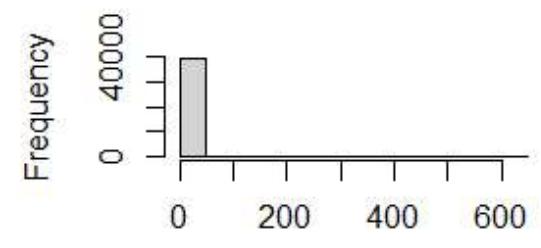
n_tokens_content



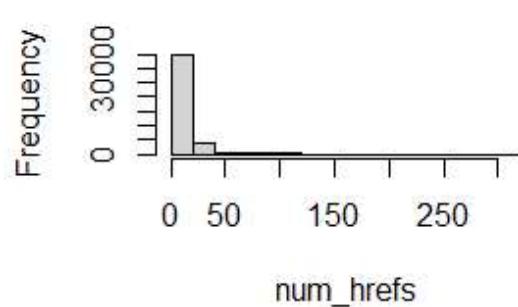
n_unique_tokens



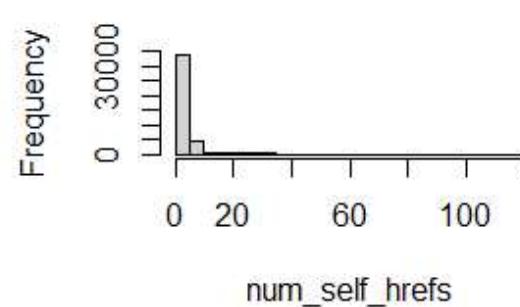
n_non_stop_words



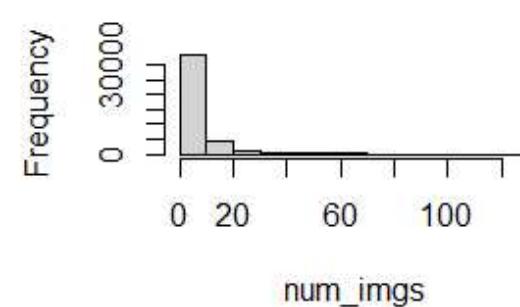
n_non_stop_unique_tokens



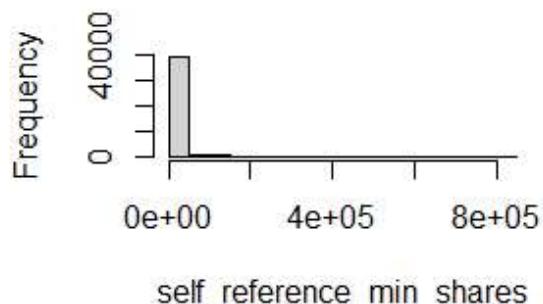
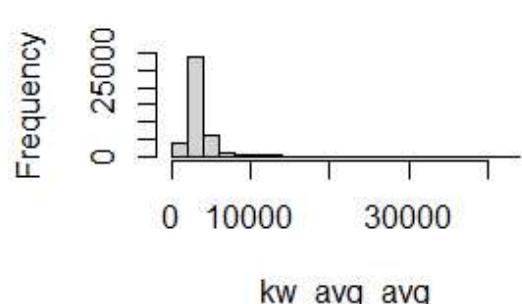
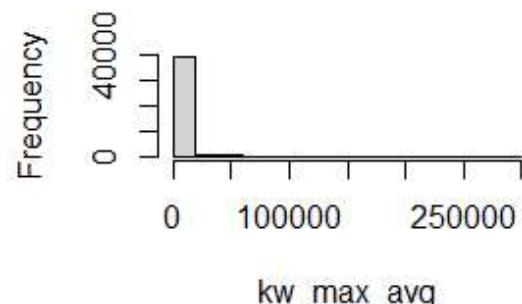
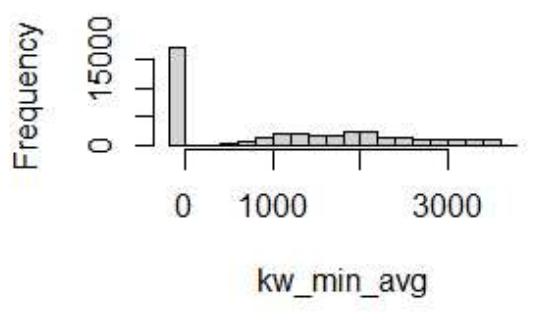
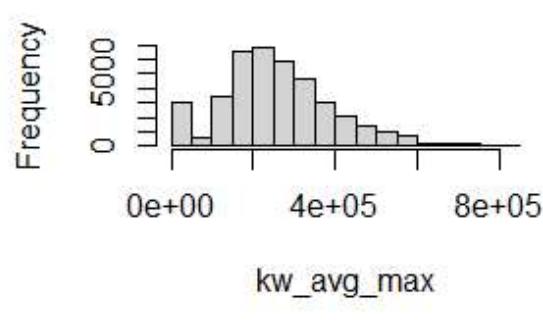
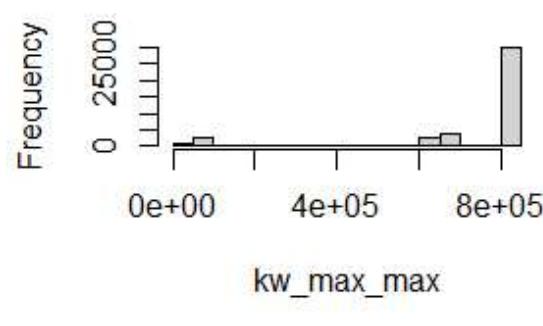
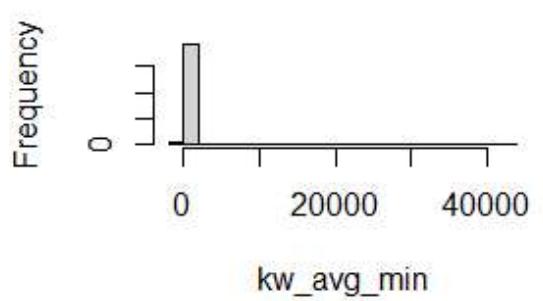
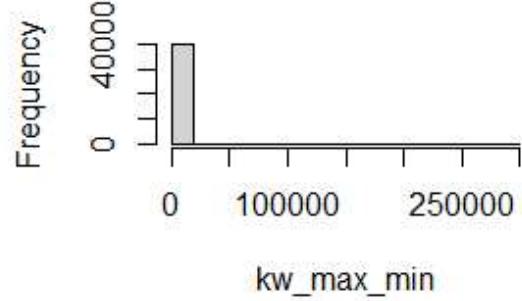
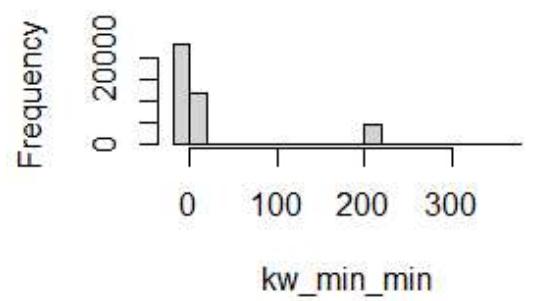
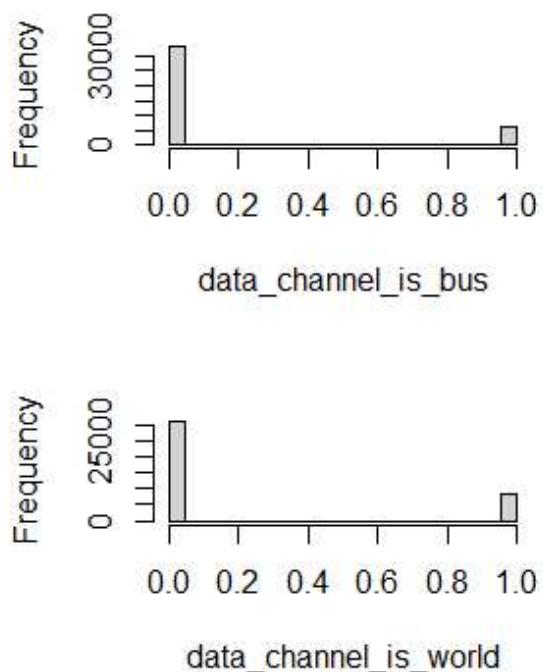
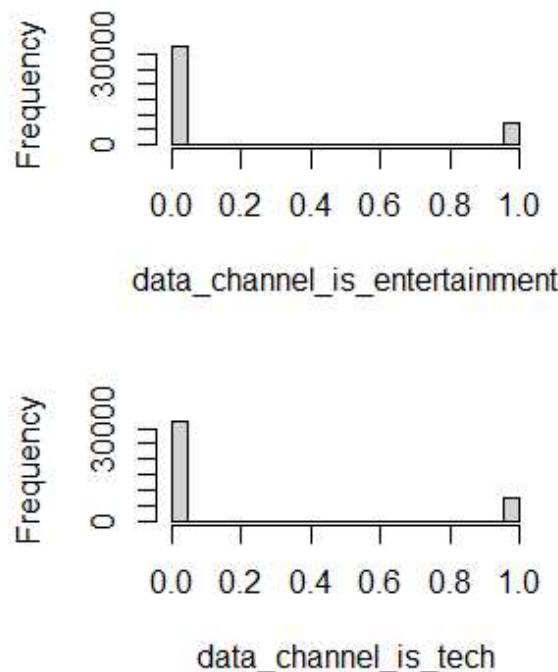
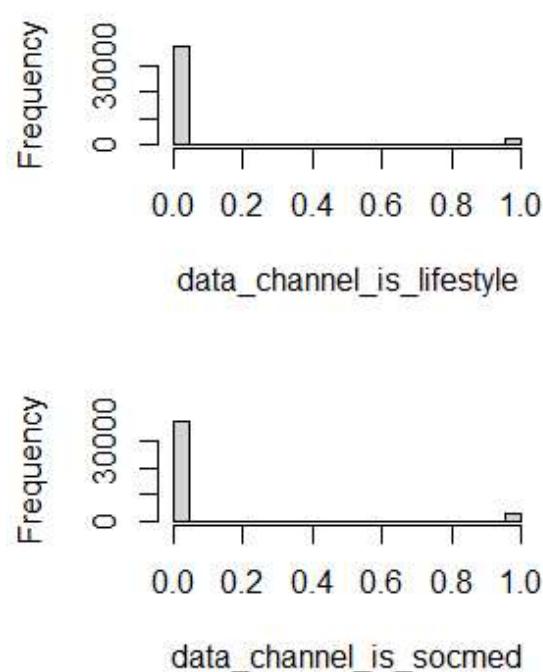
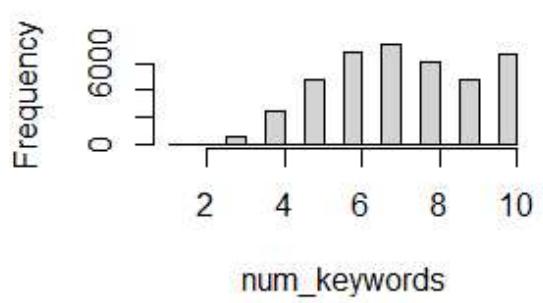
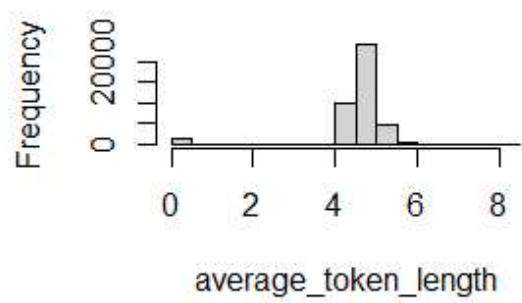
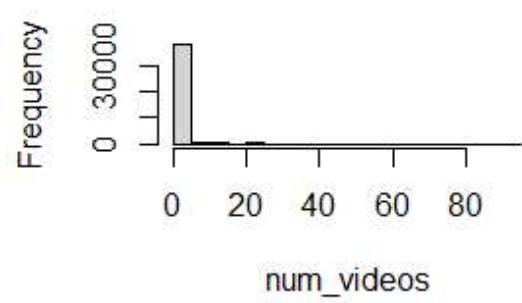
num_hrefs

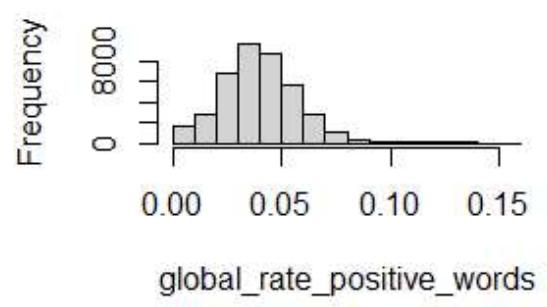
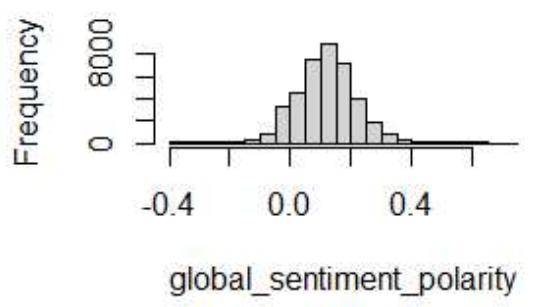
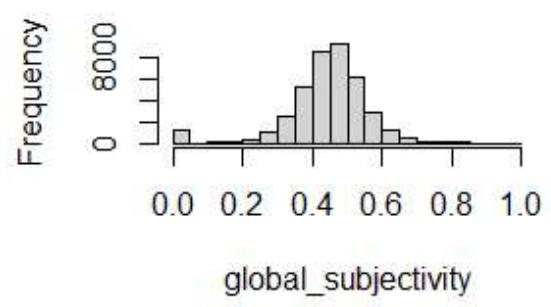
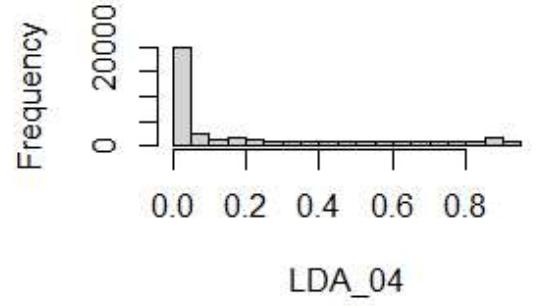
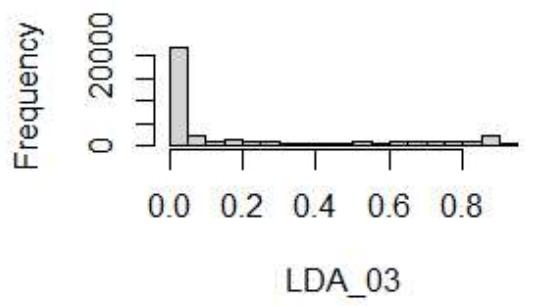
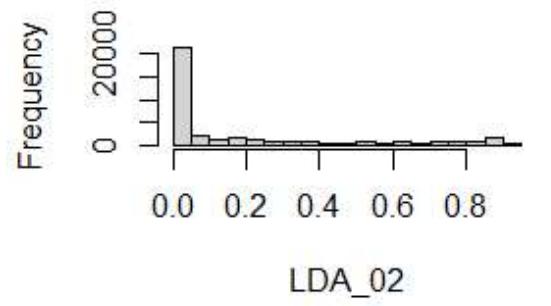
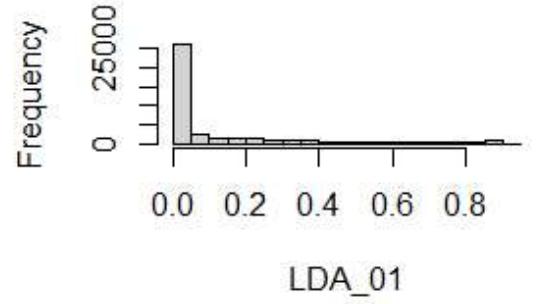
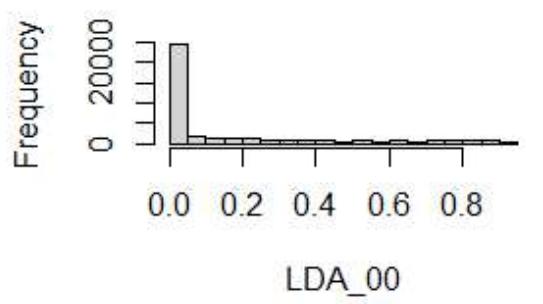
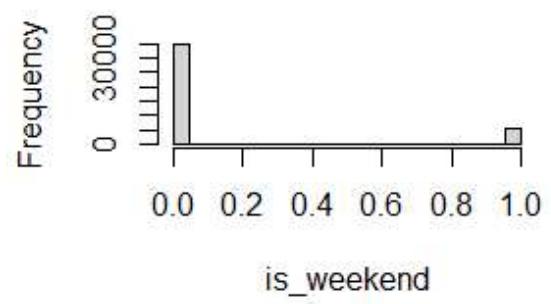
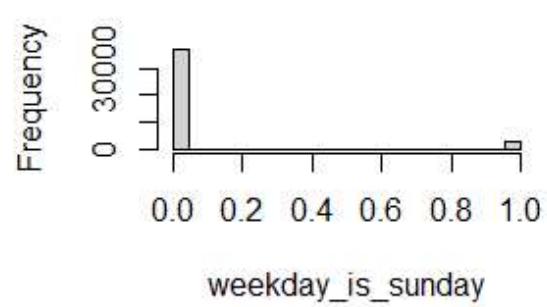
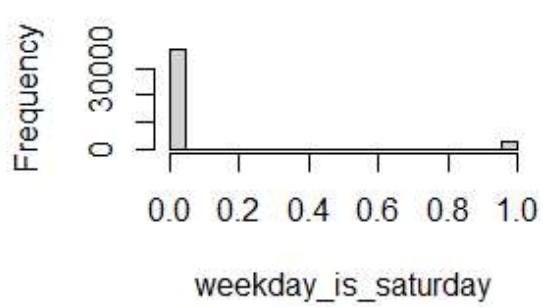
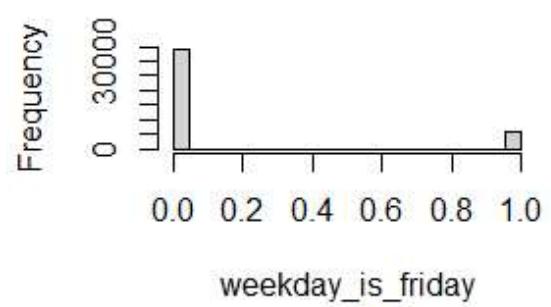
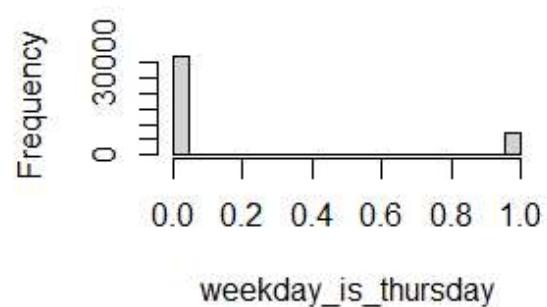
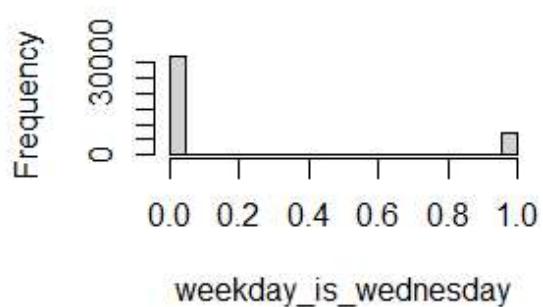
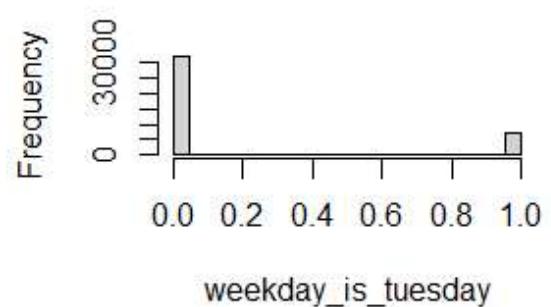
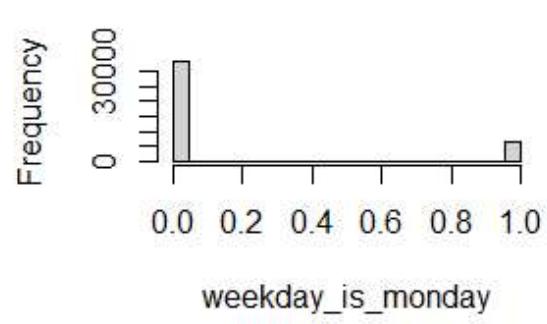
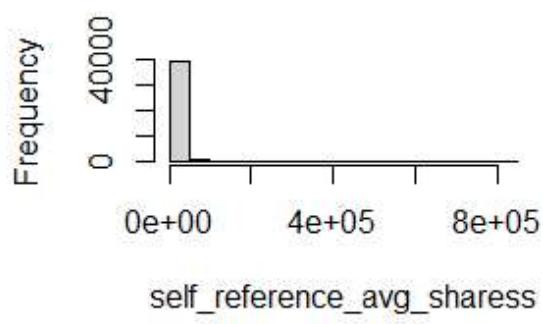
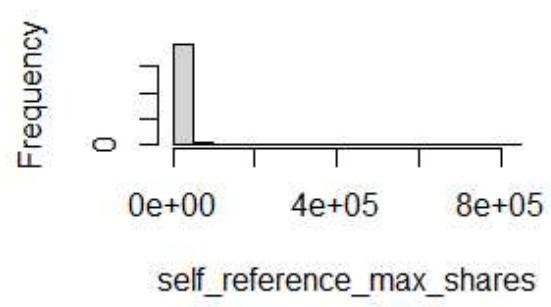


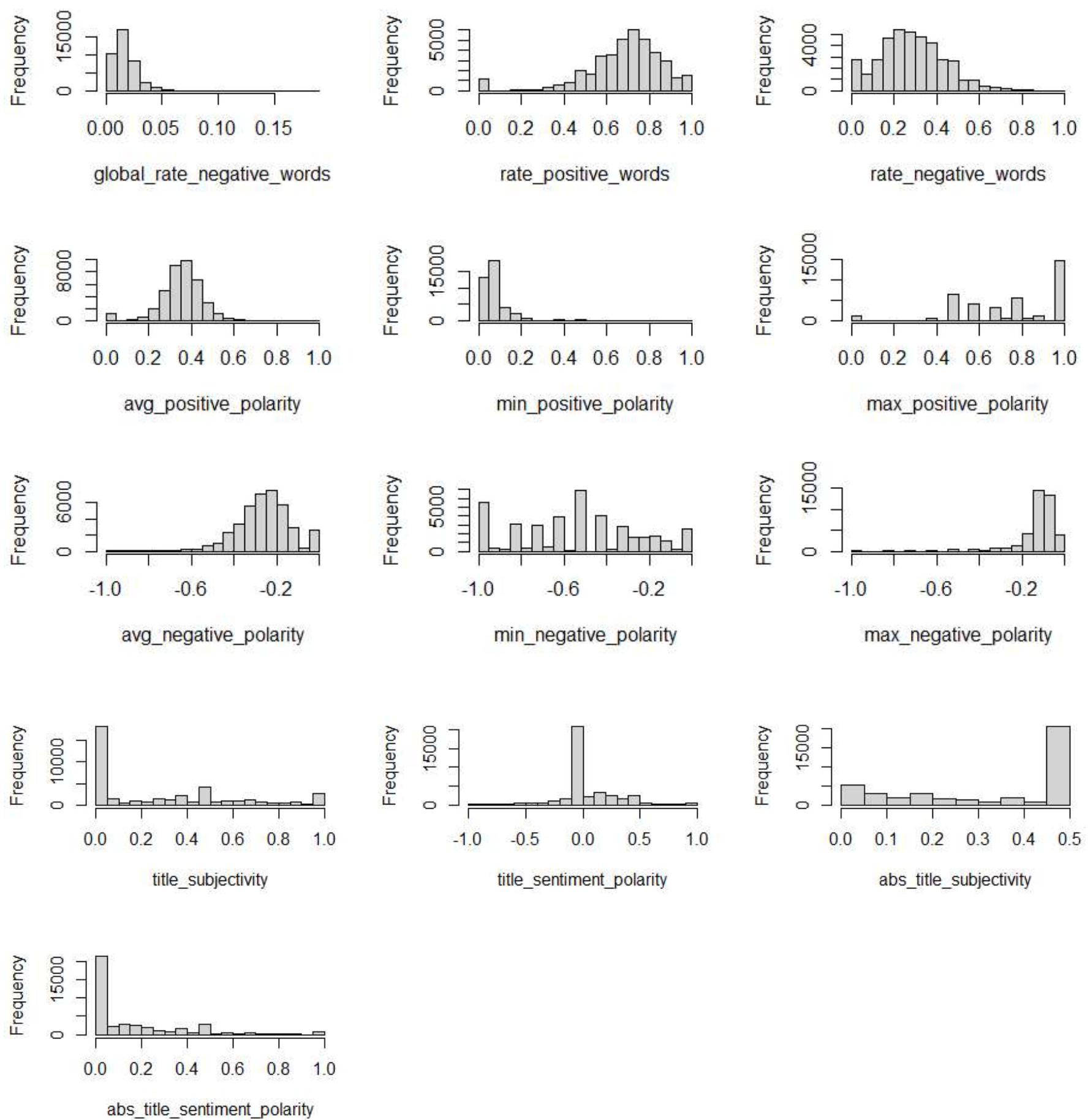
num_self_hrefs



num_imgs







The predictors have widely varying ranges and many are quite skewed. We'll need to center and scale them before modeling.

Correlations

Binary Predictor Correlations

[Hide](#)

```
library(corrplot)
```

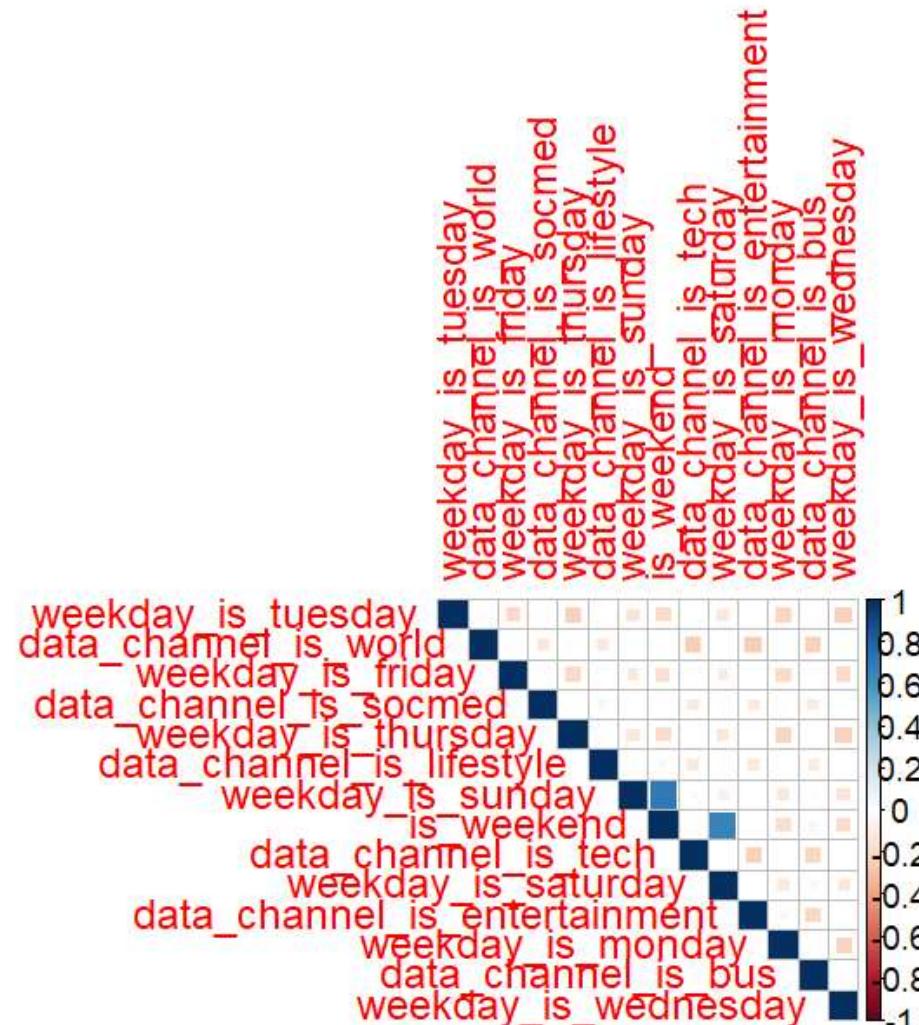
```
corrplot 0.92 loaded
```

[Hide](#)

```

X.bi <- Filter(function(x) all(x %in% c(0, 1)), X)
X.non.bi <- X[, !names(X) %in% names(X.bi)]
cor.bi <- cor(X.bi)
corrplot(
  cor.bi,
  method = "square",
  type = "upper",
  order = "hclust"
)

```



The only strong correlations among the binary predictors are between weekday_is_sunday and is_weekend and between weekday_is_saturday and is_weekend, which makes sense.

```

high.cor.bi <- findCorrelation(cor.bi, cutoff = .7)
names(X.bi)[high.cor.bi]

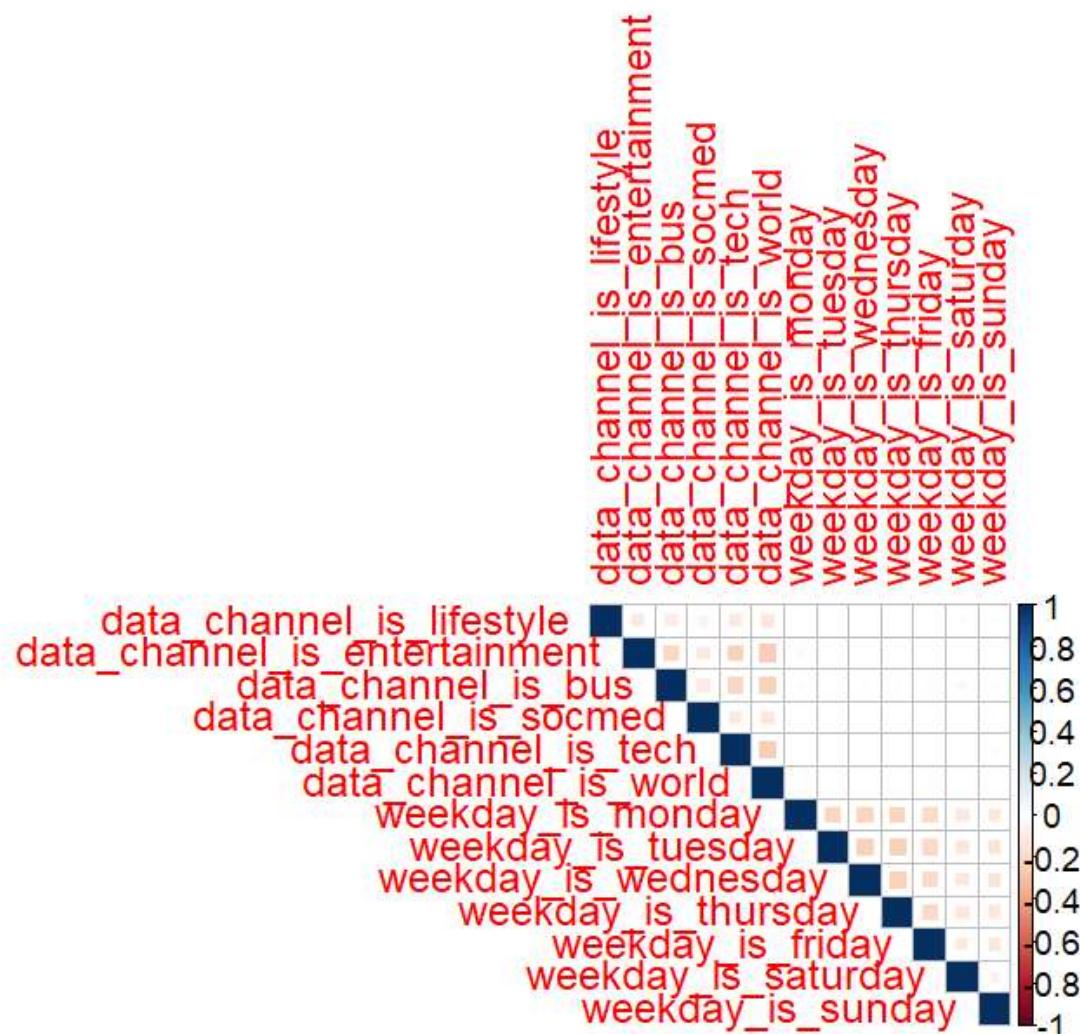
```

```
[1] "is_weekend"
```

```

X.bi <- X.bi[, -high.cor.bi] # remove is_weekend
cor.bi.filtered <- cor(X.bi)
corrplot(
  cor.bi.filtered,
  method = "square",
  type = "upper"
)

```



Remove weekday_is_sunday to avoid the dummy variable trap. Let's also check the data channel binary predictors for the dummy variable trap.

[Hide](#)

```
X.bi <- X.bi[, names(X.bi) != "weekday_is_sunday"]
channels <- c(
  "data_channel_is_world",
  "data_channel_is_socmed",
  "data_channel_is_tech",
  "data_channel_is_bus",
  "data_channel_is_entertainment",
  "data_channel_is_lifestyle"
)
summary(apply(X[, channels], 1, sum)) # check if they always sum to 1 for every sample
```

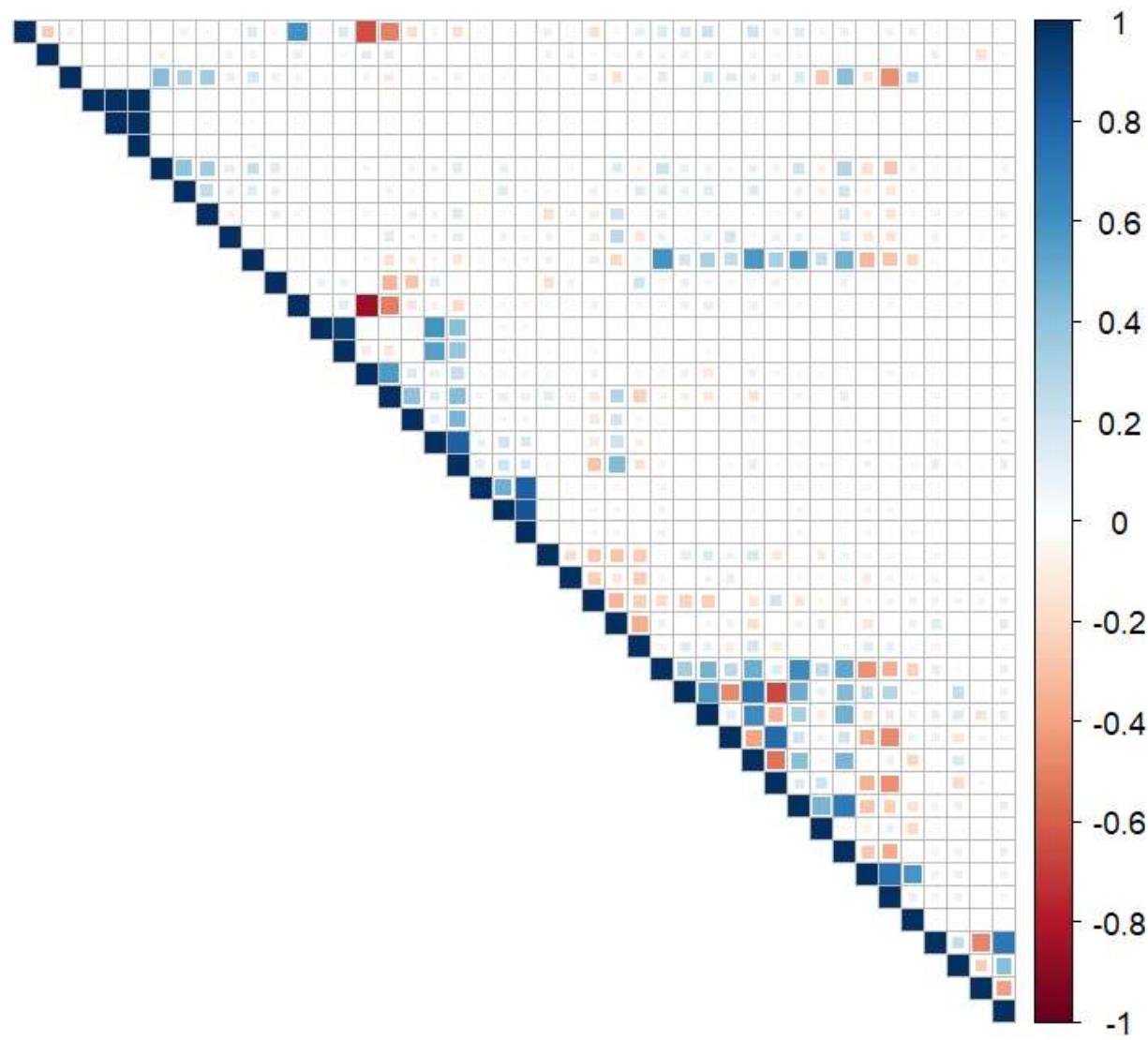
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.0000	1.0000	1.0000	0.8453	1.0000	1.0000

The channel predictors do not always sum to 1, so they do not fall into the dummy variable trap.

Non-Binary Predictor Correlations

[Hide](#)

```
cor.non.bi <- cor(X.non.bi)
corrplot(
  cor.non.bi,
  method = "square",
  type = "upper",
  tl.pos = "n"
)
```



We can see some strong positive and negative correlations between the non-binary predictors.

[Hide](#)

```
high.cor.non.bi <- findCorrelation(cor.non.bi, cutoff = .7)
length(high.cor.non.bi)
```

[1] 12

[Hide](#)

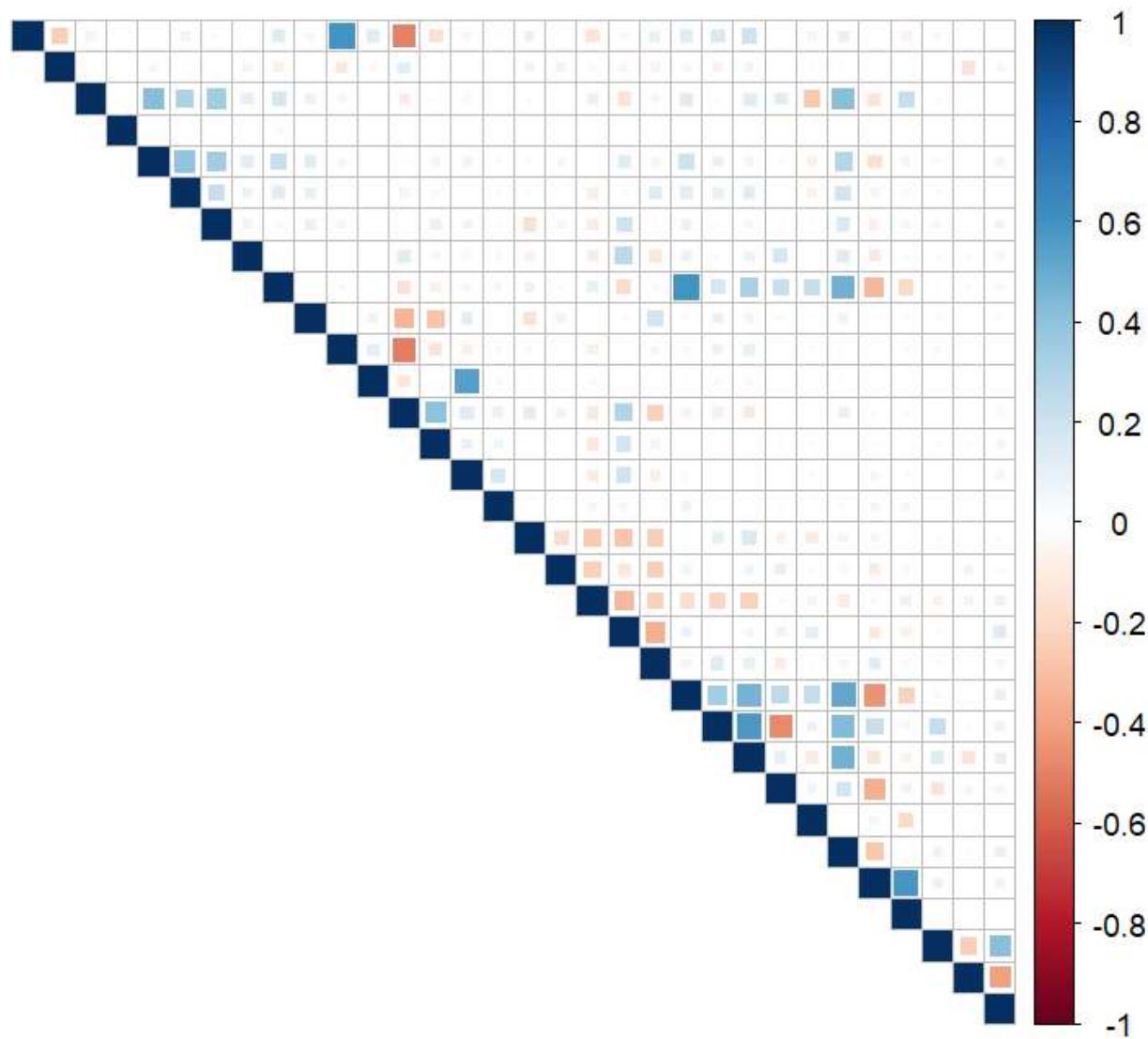
```
names(X.non.bi)[high.cor.non.bi]
```

```
[1] "rate_positive_words"      "avg_positive_polarity"
[3] "kw_avg_avg"              "min_negative_polarity"
[5] "rate_negative_words"     "kw_max_max"
[7] "title_subjectivity"      "self_reference_max_shares"
[9] "kw_max_min"              "n_non_stop_words"
[11] "self_reference_min_shares" "n_unique_tokens"
```

12 variables contribute to high pairwise correlation between the non-binary predictors. Let's remove them

[Hide](#)

```
X.non.bi <- X.non.bi[, -high.cor.non.bi]
cor.non.bi.filtered <- cor(X.non.bi)
corrplot(
  cor.non.bi.filtered,
  method = "square",
  type = "upper",
  tl.pos = "n"
)
```



Let's update our master predictor matrix to only retain the non-problematic predictors.

[Hide](#)

```
cols.to.keep <- c(names(X.bi), names(X.non.bi))
X <- X[, names(X) %in% cols.to.keep]
```

Split the Data

[Hide](#)

```
set.seed(100)
train.rows <- createDataPartition(y, p = .8, list = FALSE)
y.train <- y[train.rows]
y.test <- y[-train.rows]
X.train <- X[train.rows, ]
X.test <- X[-train.rows, ]
idx <- createFolds(y.train, returnTrain = TRUE)
ctrl <- trainControl(method = "cv", index = idx)
```

Modeling

Linear Models

Elastic Net

[Hide](#)

```
enetGrid <- expand.grid(lambda = c(0, 0.01, .1),
                         fraction = seq(0, 1, length = 10))
set.seed(100)
enet <- train(x = X.train, y = y.train,
              method = "enet",
              tuneGrid = enetGrid,
              trControl = ctrl,
              preProc = c("center", "scale"))
```

Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo, :
There were missing values in resampled performance measures.

[Hide](#)

```
enet
```

Elasticnet

31716 samples
44 predictor

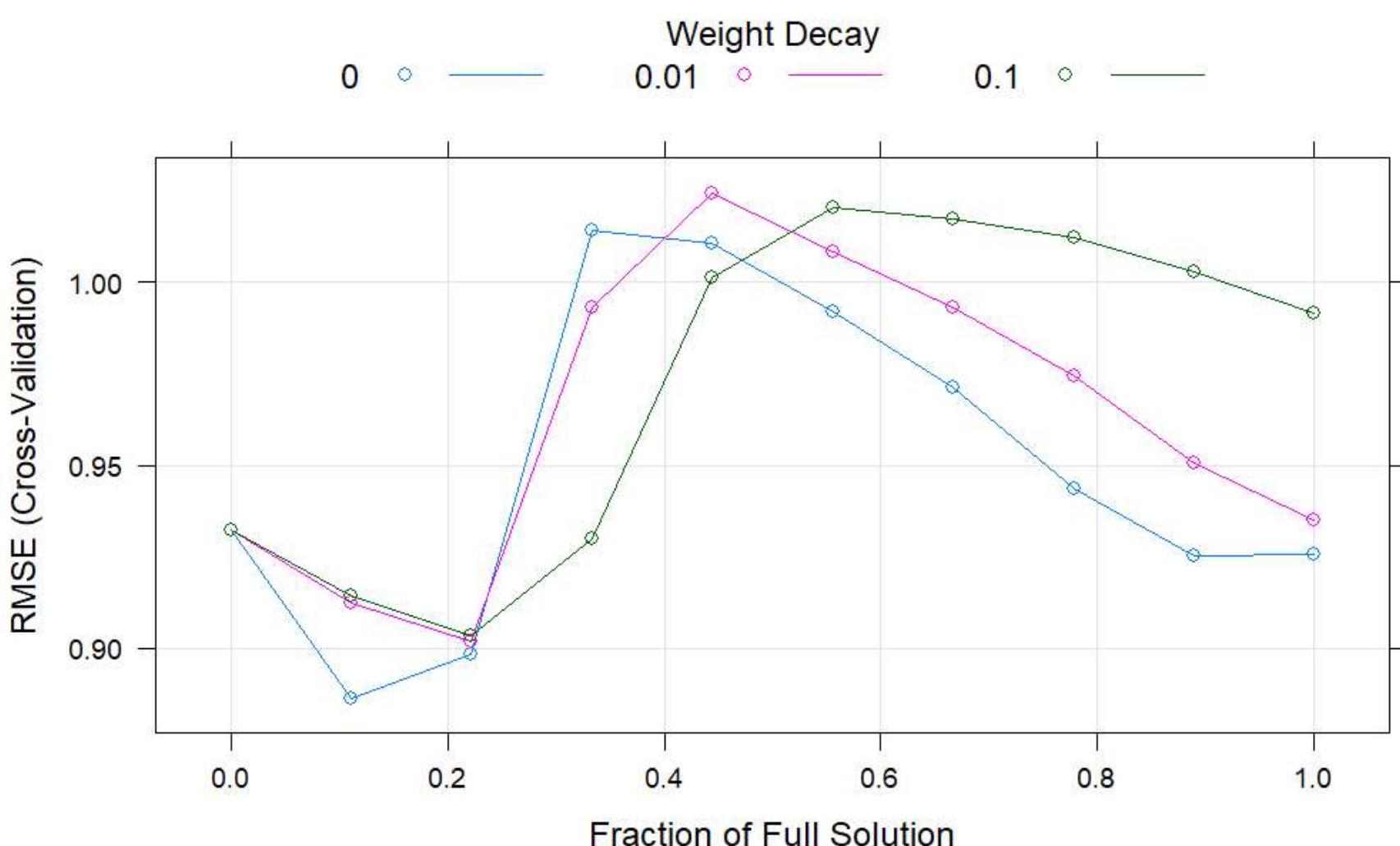
Pre-processing: centered (44), scaled (44)
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 28545, 28543, 28544, 28545, 28545, 28543, ...
Resampling results across tuning parameters:

lambda	fraction	RMSE	Rsquared	MAE
0.00	0.0000000	0.9321901	NaN	0.7055694
0.00	0.1111111	0.8864478	0.09719415	0.6583323
0.00	0.2222222	0.8984610	0.09224848	0.6581408
0.00	0.3333333	1.0141256	0.09176563	0.6601719
0.00	0.4444444	1.0105262	0.09178231	0.6597225
0.00	0.5555556	0.9917711	0.09181401	0.6591108
0.00	0.6666667	0.9714230	0.09187086	0.6585251
0.00	0.7777778	0.9437185	0.09203142	0.6578012
0.00	0.8888889	0.9253482	0.09228926	0.6573308
0.00	1.0000000	0.9255977	0.09228056	0.6573320
0.01	0.0000000	0.9321901	NaN	0.7055694
0.01	0.1111111	0.9124461	0.06195643	0.6876086
0.01	0.2222222	0.9020839	0.07603802	0.6761242
0.01	0.3333333	0.9930125	0.07909097	0.6712378
0.01	0.4444444	1.0242694	0.08325657	0.6672900
0.01	0.5555556	1.0084331	0.08667635	0.6639962
0.01	0.6666667	0.9932545	0.08918634	0.6617399
0.01	0.7777778	0.9742261	0.09087545	0.6599432
0.01	0.8888889	0.9506518	0.09180482	0.6584963
0.01	1.0000000	0.9352032	0.09208036	0.6576853
0.10	0.0000000	0.9321901	NaN	0.7055694
0.10	0.1111111	0.9144814	0.05737692	0.6895019
0.10	0.2222222	0.9034129	0.07577590	0.6787493
0.10	0.3333333	0.9301465	0.07640761	0.6725192
0.10	0.4444444	1.0012548	0.08049357	0.6692252
0.10	0.5555556	1.0204530	0.08394508	0.6662717
0.10	0.6666667	1.0174417	0.08655568	0.6638276
0.10	0.7777778	1.0120269	0.08835610	0.6620833
0.10	0.8888889	1.0030191	0.08960134	0.6607376
0.10	1.0000000	0.9915162	0.09028498	0.6597427

RMSE was used to select the optimal model using the smallest value.
The final values used for the model were fraction = 0.1111111 and lambda = 0.

Hide

```
plot(enet)
```



Hide

```
library(Metrics)
pred.enet <- predict(enet, X.test)
resid.enet <- y.test - pred.enet
rmse(y.test, pred.enet)
```

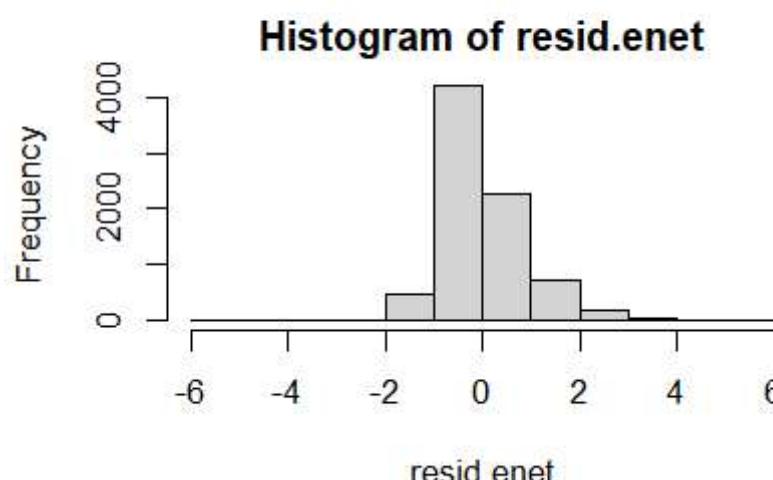
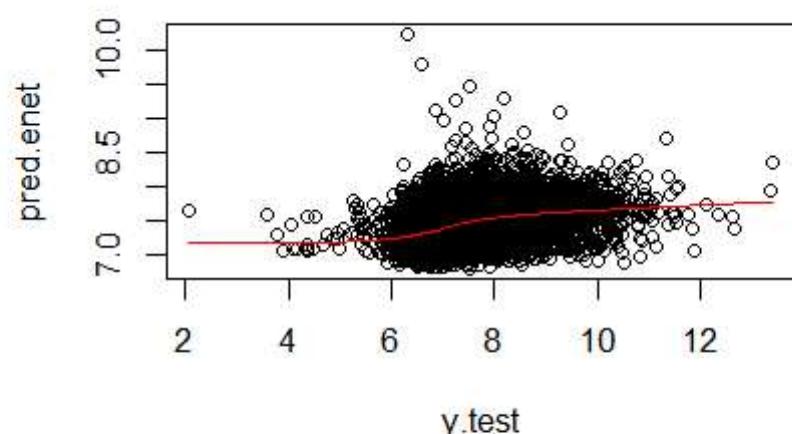
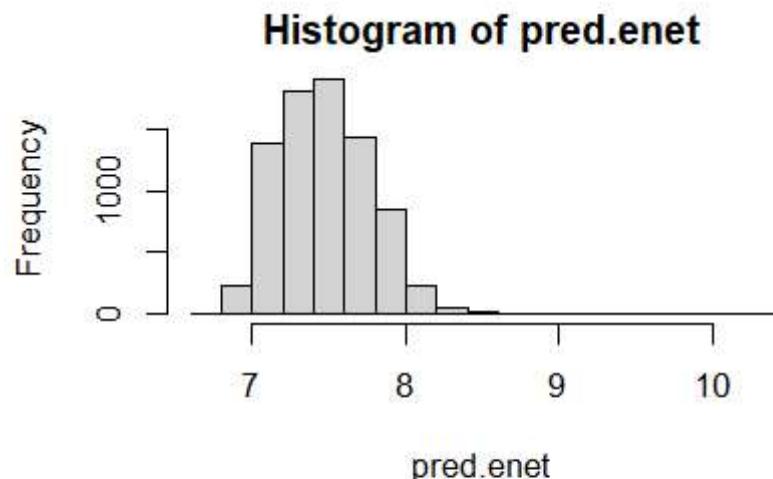
```
[1] 0.8736786
```

Hide

```
par(mfrow = c(2, 2))
hist(pred.enet)
plot(y.test, pred.enet)
```

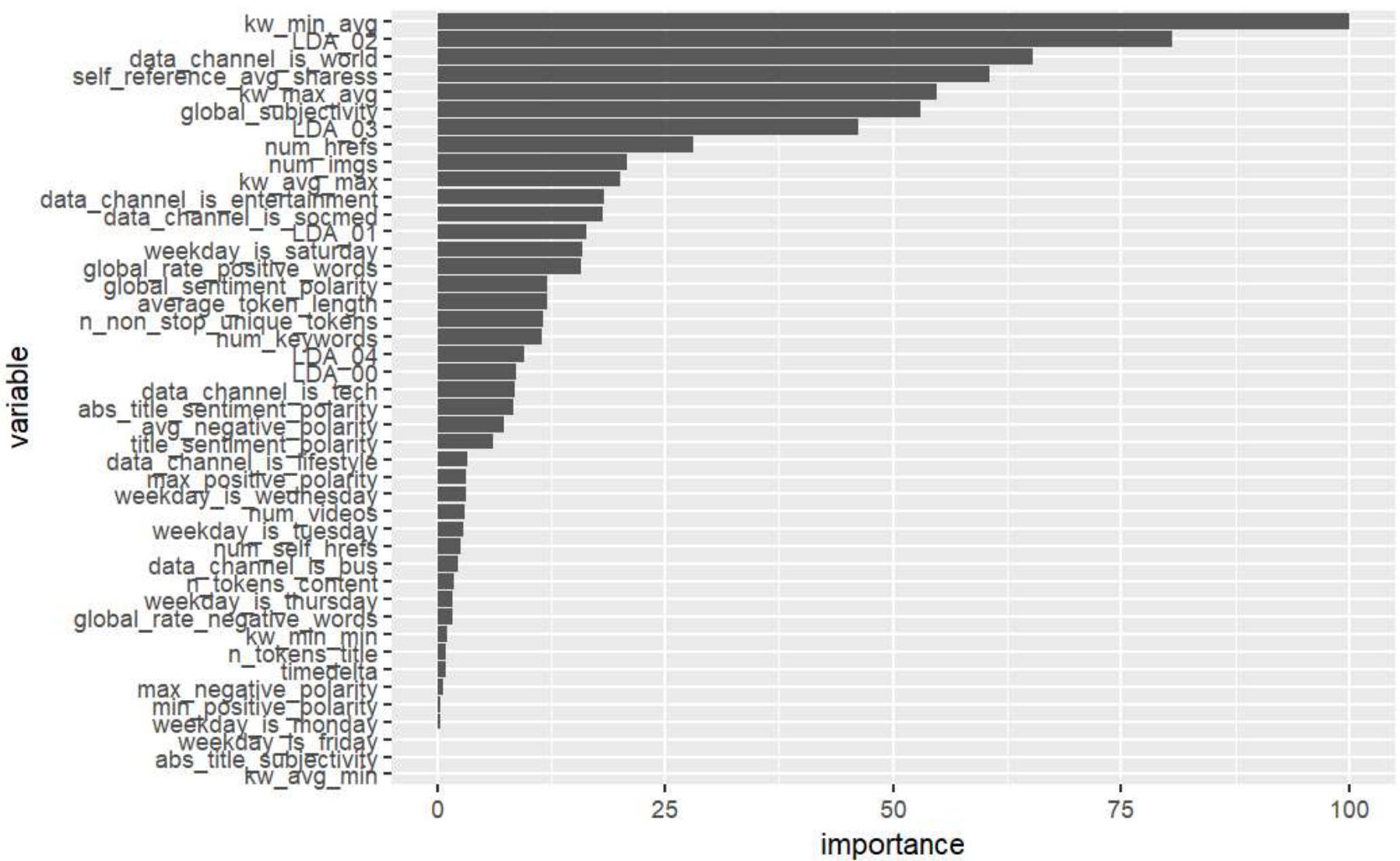
Hide

```
lines(lowess(y.test, pred.enet), col = "red")
hist(resid.enet)
```



```
library(tidyr)
library(dplyr)
plot.var.imp <- function(model) {
  imp <- varImp(model)$importance
  names(imp) <- "importance"
  df <- imp %>%
    tibble::rownames_to_column() %>%
    dplyr::rename("variable" = rowname) %>%
    dplyr::arrange(importance) %>%
    dplyr::mutate(variable =forcats::fct_inorder(variable))
  ggplot(df) +
    geom_col(aes(x = variable, y = importance)) +
    coord_flip()
}
plot.var.imp(enet)
```

Hide



Principal Component Regression (PCR)

[Hide](#)

```
set.seed(100)
pcr <- train(
  x = X.train,
  y = y.train,
  preProc = c("center", "scale"),
  method = "pcr",
  tuneGrid = expand.grid(ncomp = 1:30),
  trControl = ctrl
)
pcr
```

Principal Component Analysis

31716 samples
44 predictor

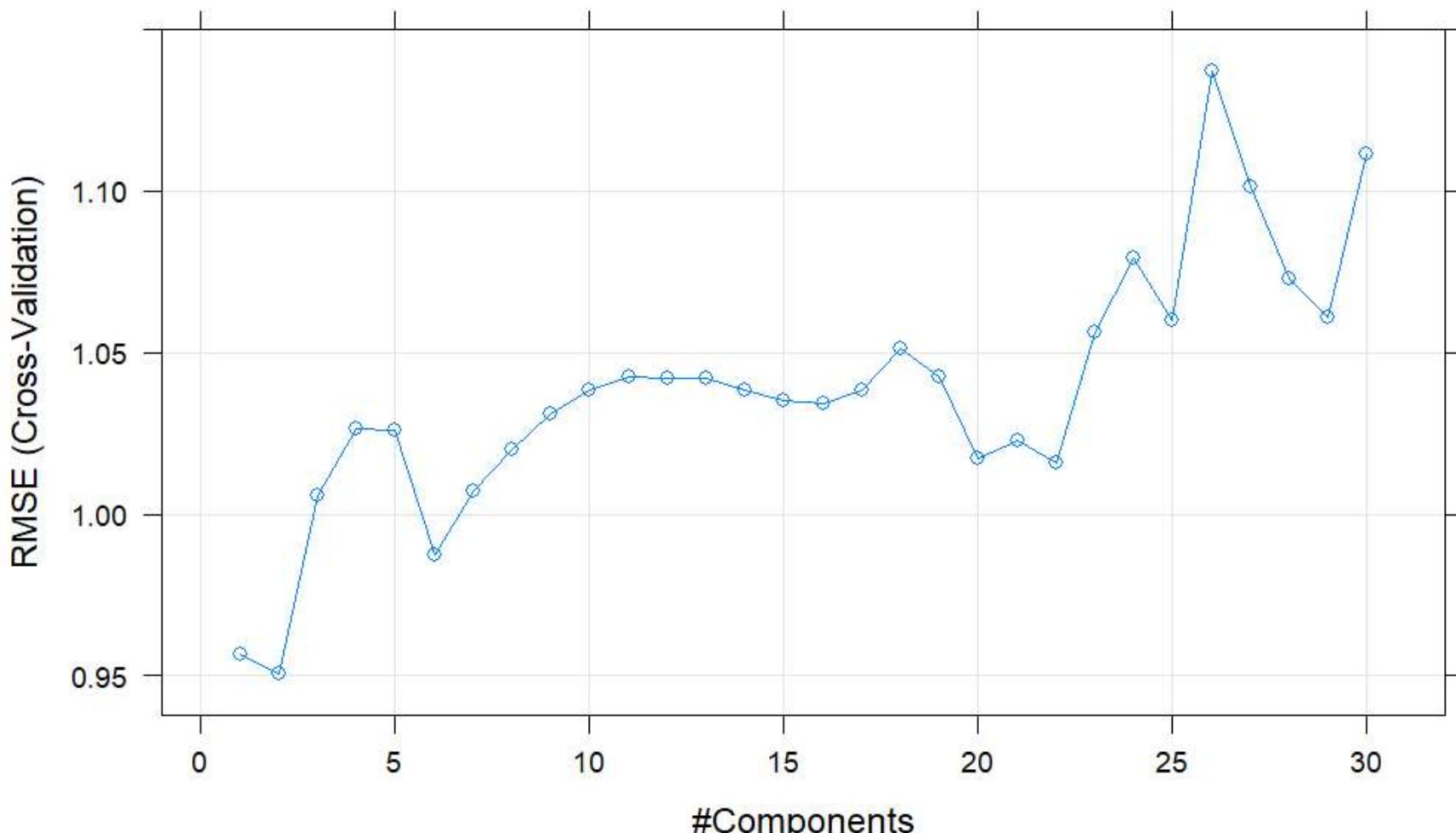
Pre-processing: centered (44), scaled (44)
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 28545, 28543, 28544, 28545, 28545, 28543, ...
Resampling results across tuning parameters:

ncomp	RMSE	Rsquared	MAE
1	0.9564855	0.01178708	0.6999365
2	0.9506298	0.01371925	0.7006422
3	1.0055397	0.02027480	0.6970122
4	1.0264125	0.03108140	0.6935467
5	1.0258371	0.03710015	0.6902230
6	0.9872631	0.03973736	0.6891277
7	1.0072425	0.05075586	0.6836527
8	1.0197577	0.06103294	0.6775825
9	1.0310467	0.06189408	0.6769297
10	1.0383555	0.06427197	0.6760569
11	1.0425336	0.06435240	0.6760535
12	1.0421863	0.06436422	0.6760670
13	1.0419949	0.06435685	0.6760890
14	1.0385274	0.06455183	0.6759535
15	1.0353205	0.06469239	0.6757173
16	1.0343919	0.06572786	0.6746489
17	1.0384508	0.06716957	0.6735439
18	1.0513084	0.06916830	0.6725950
19	1.0424204	0.06925672	0.6722834
20	1.0171999	0.06929440	0.6717861
21	1.0226609	0.07085403	0.6712181
22	1.0156971	0.07082380	0.6711018
23	1.0563385	0.07131937	0.6715888
24	1.0791325	0.07329755	0.6707452
25	1.0598179	0.07402953	0.6700027
26	1.1370649	0.07432287	0.6709589
27	1.1013242	0.07903175	0.66679192
28	1.0725556	0.08054003	0.66667135
29	1.0606241	0.08064363	0.6663973
30	1.1111882	0.08255071	0.6665347

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was ncomp = 2.

Hide

```
plot(pcr)
```



Hide

```
pred.pcr <- predict(pcr, X.test)
resid.pcr <- y.test - pred.pcr
rmse(y.test, pred.pcr)
```

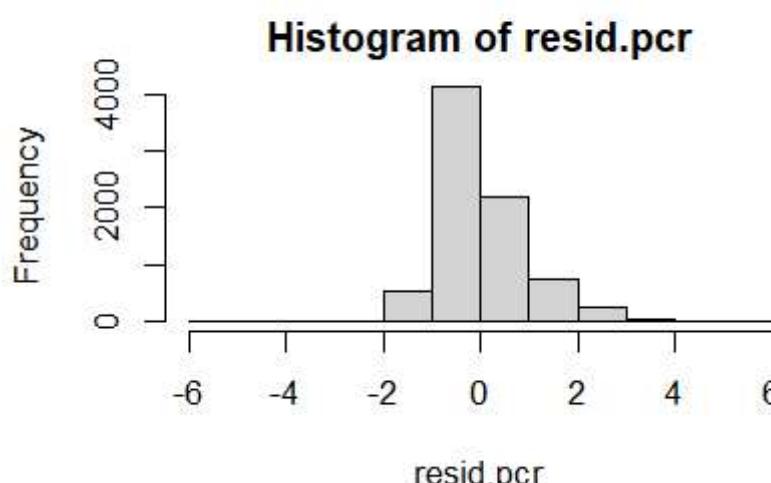
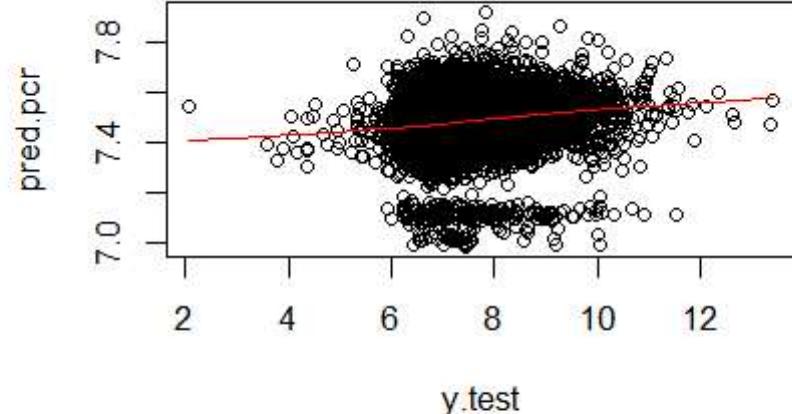
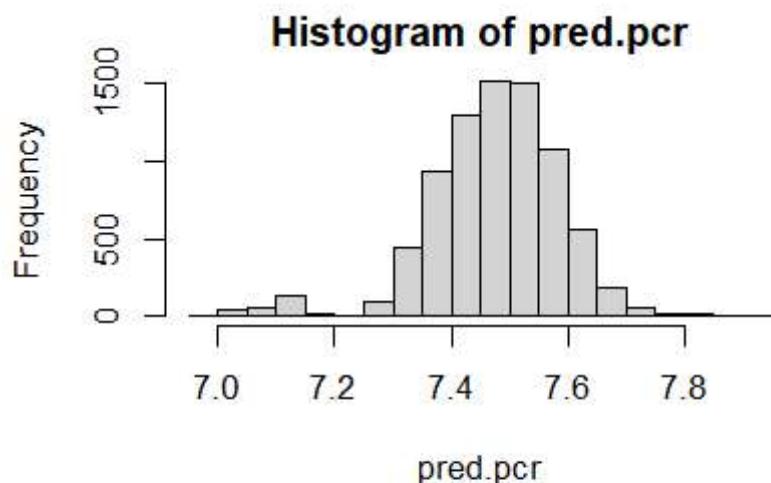
```
[1] 0.9152851
```

Hide

```
par(mfrow = c(2, 2))
hist(pred.pcr)
plot(y.test, pred.pcr)
```

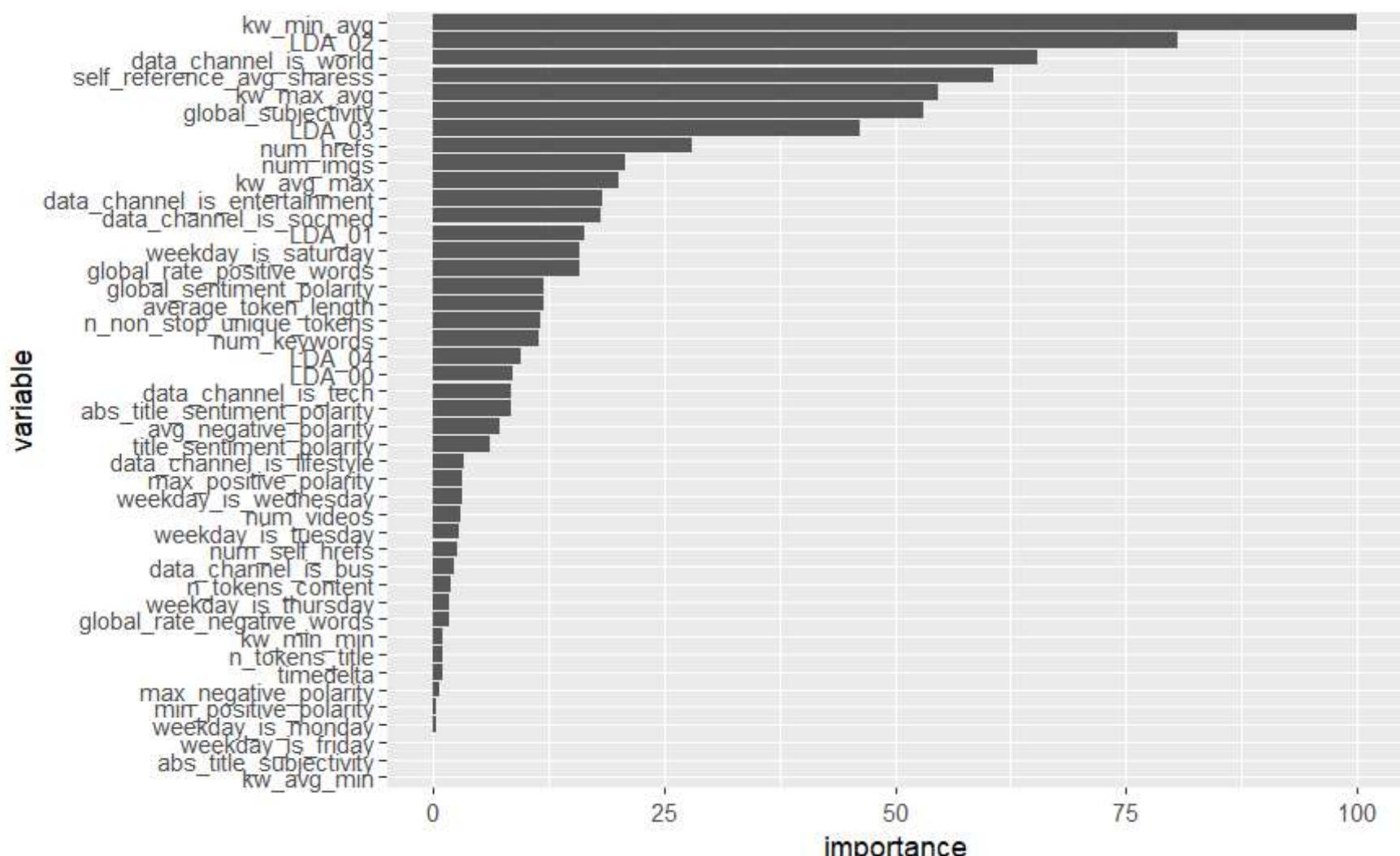
Hide

```
lines(lowess(y.test, pred.pcr), col = "red")
hist(resid.pcr)
```



```
plot.var.imp(pcr)
```

Hide



[Hide](#)

```
set.seed(100)
pls <- train(
  x = X.train,
  y = y.train,
  preProc = c("center", "scale"),
  method = "pls",
  tuneGrid = expand.grid(ncomp = 1:30),
  trControl = ctrl
)
pls
```

Partial Least Squares

31716 samples
44 predictor

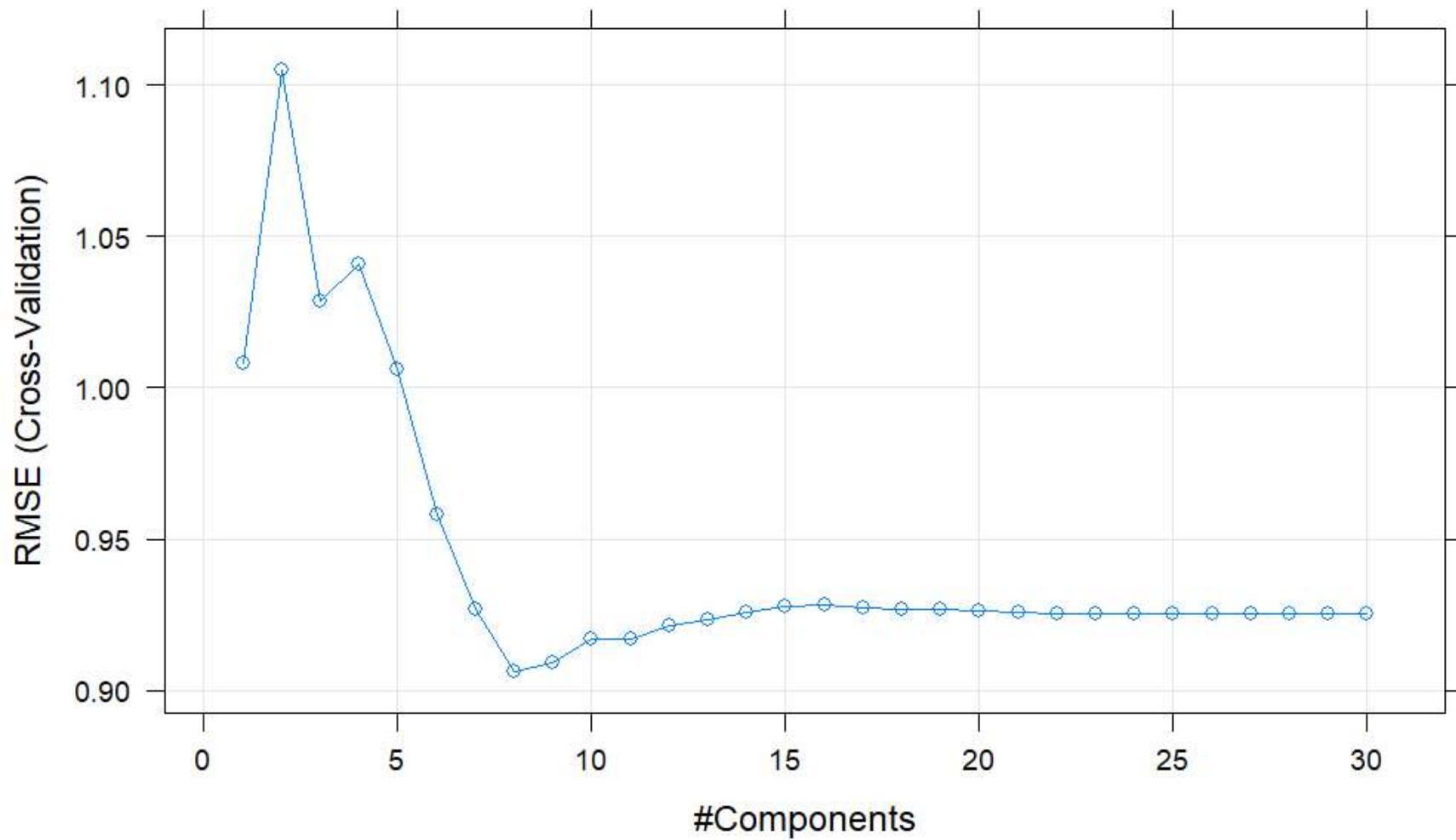
Pre-processing: centered (44), scaled (44)
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 28545, 28543, 28544, 28545, 28545, 28543, ...
Resampling results across tuning parameters:

ncomp	RMSE	Rsquared	MAE
1	1.0081791	0.07008790	0.6725356
2	1.1050275	0.08177957	0.6672321
3	1.0287718	0.08596654	0.6621882
4	1.0406781	0.08813904	0.6619958
5	1.0062603	0.08918816	0.6604577
6	0.9580051	0.08998082	0.6593843
7	0.9269833	0.09102492	0.6577060
8	0.9061434	0.09218942	0.6572565
9	0.9091684	0.09232601	0.6571385
10	0.9168351	0.09231033	0.6572566
11	0.9169095	0.09238749	0.6571904
12	0.9212655	0.09232177	0.6573581
13	0.9233782	0.09230921	0.6573563
14	0.9255953	0.09226908	0.6574269
15	0.9278961	0.09220801	0.6574667
16	0.9280959	0.09221487	0.6574630
17	0.9274290	0.09223820	0.6574367
18	0.9269394	0.09225409	0.6574205
19	0.9268117	0.09225790	0.6574163
20	0.9262709	0.09226743	0.6574045
21	0.9257207	0.09227697	0.6573907
22	0.9254667	0.09228171	0.6573851
23	0.9252826	0.09228470	0.6573812
24	0.9251623	0.09228687	0.6573780
25	0.9251541	0.09228683	0.6573780
26	0.9251689	0.09228654	0.6573783
27	0.9251916	0.09228610	0.6573788
28	0.9252020	0.09228594	0.6573791
29	0.9252086	0.09228577	0.6573793
30	0.9252110	0.09228584	0.6573792

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was ncomp = 8.

[Hide](#)

```
plot(pls)
```

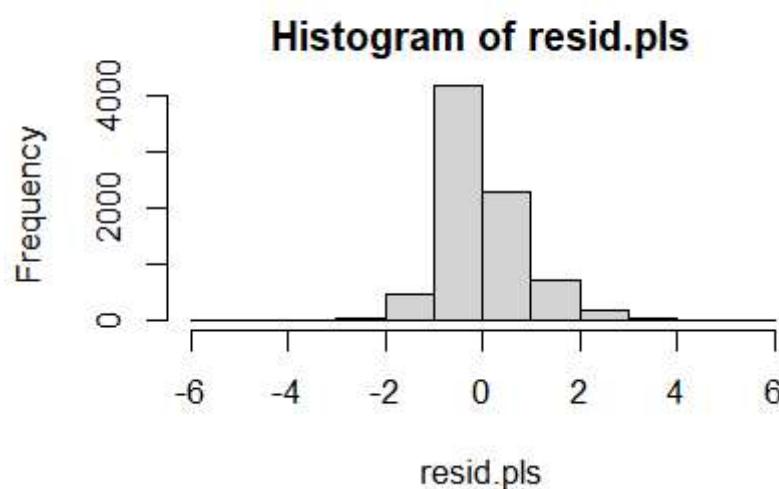
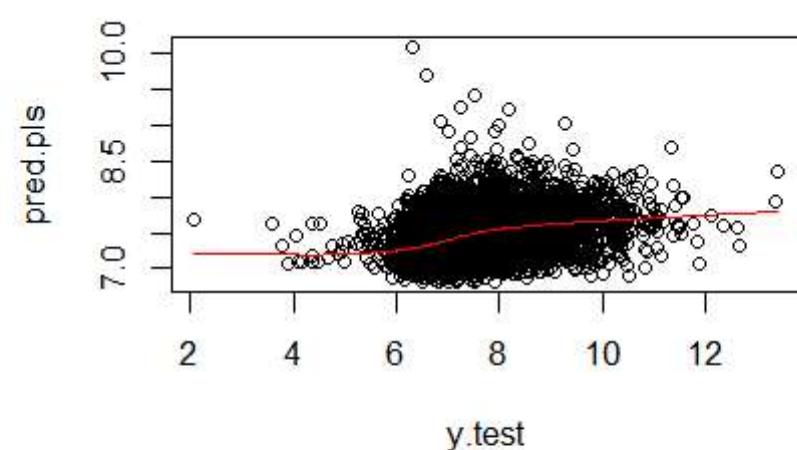
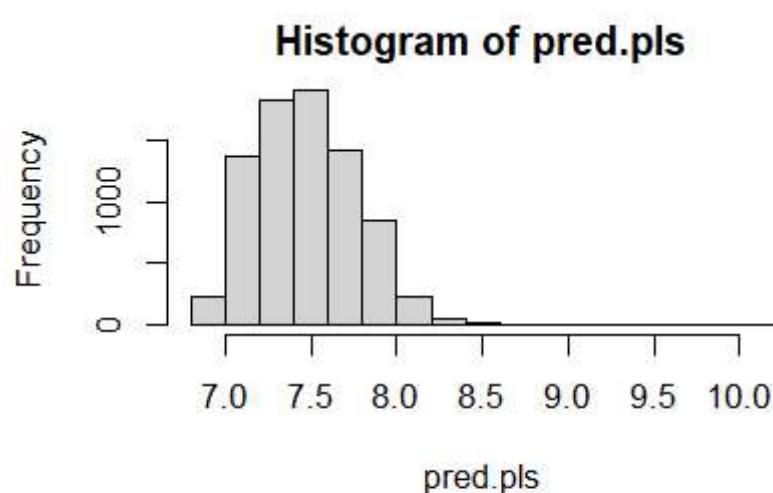


```
pred.pls <- predict(pls, X.test)
resid.pls <- y.test - pred.pls
rmse(y.test, pred.pls)
```

[1] 0.8735161

```
par(mfrow = c(2, 2))
hist(pred.pls)
plot(y.test, pred.pls)
```

```
lines(lowess(y.test, pred.pls), col = "red")
hist(resid.pls)
```



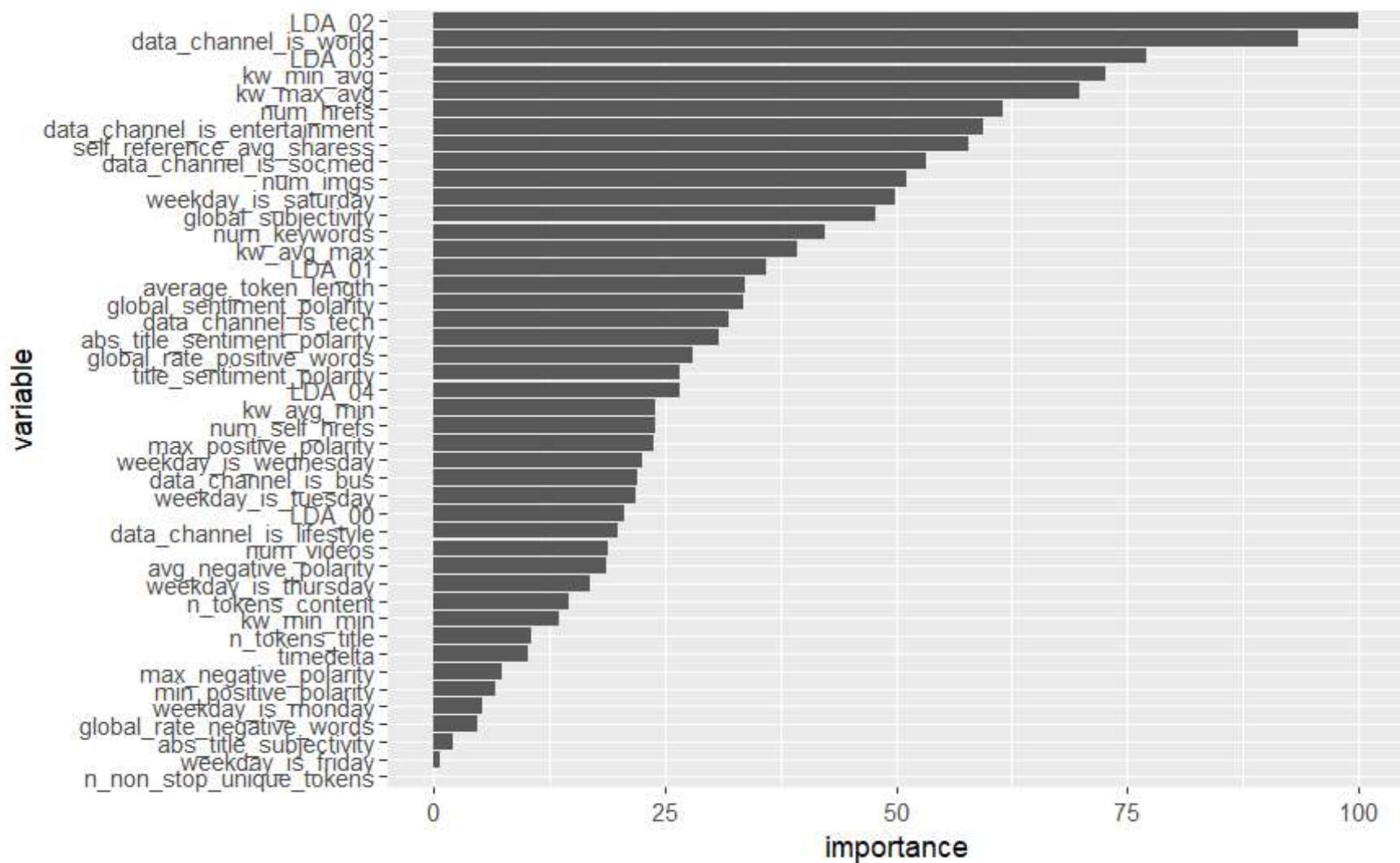
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```
plot.var.imp(pls)
```



Non-Linear Models

K-Nearest Neighbors (k-NN)

Hide

```
set.seed(100)
knn <- train(
  x = X.train,
  y = y.train,
  preProc = c("center", "scale"),
  method = "knn",
  tuneGrid = expand.grid(k = 1:10),
  trControl = ctrl
)
knn
```

k-Nearest Neighbors

```
31716 samples
44 predictor

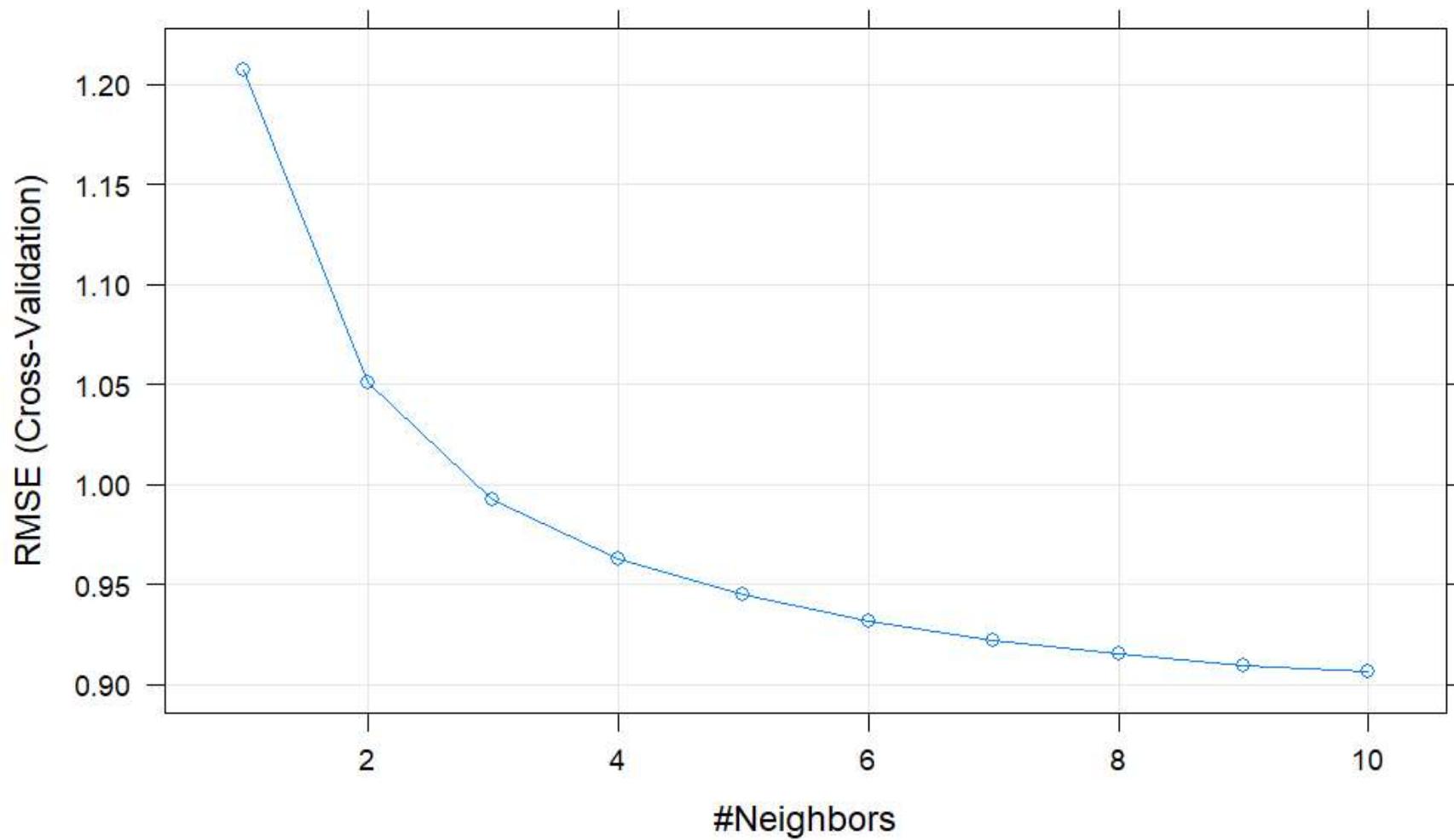
Pre-processing: centered (44), scaled (44)
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 28545, 28543, 28544, 28545, 28543, ...
Resampling results across tuning parameters:
```

k	RMSE	Rsquared	MAE
1	1.2072226	0.02173822	0.8848739
2	1.0509486	0.03416209	0.7788457
3	0.9922019	0.04473664	0.7359284
4	0.9623583	0.05301447	0.7129060
5	0.9447195	0.05963674	0.6985403
6	0.9311917	0.06663565	0.6866949
7	0.9219106	0.07177303	0.6787405
8	0.9153567	0.07573898	0.6731041
9	0.9095756	0.08010333	0.6678407
10	0.9062993	0.08204549	0.6646600

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was k = 10.

Hide

```
plot(knn)
```

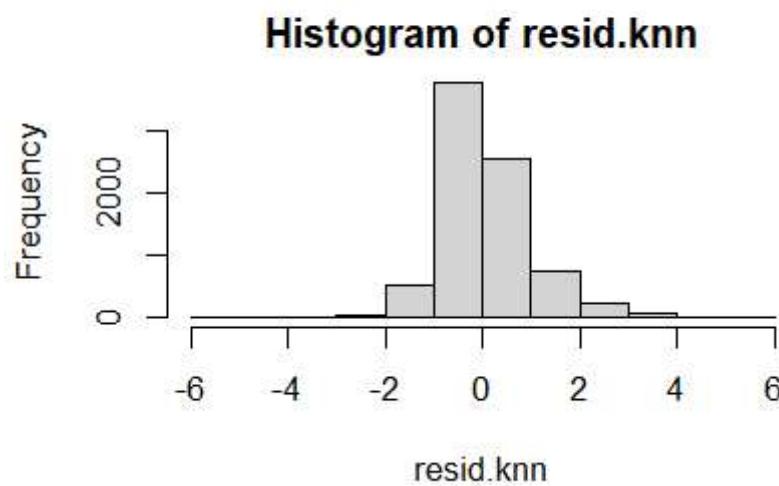
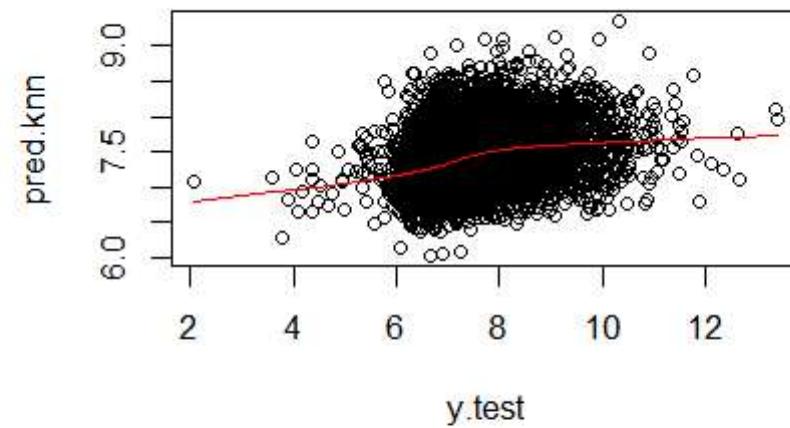
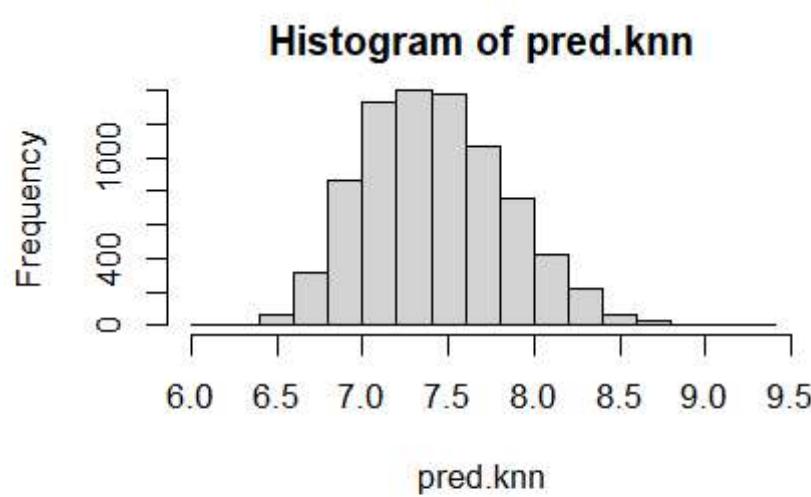


```
pred.knn <- predict(knn, X.test)
resid.knn <- y.test - pred.knn
rmse(y.test, pred.knn)
```

[1] 0.9015301

```
par(mfrow = c(2, 2))
hist(pred.knn)
plot(y.test, pred.knn)
```

```
lines(lowess(y.test, pred.knn), col = "red")
hist(resid.knn)
```



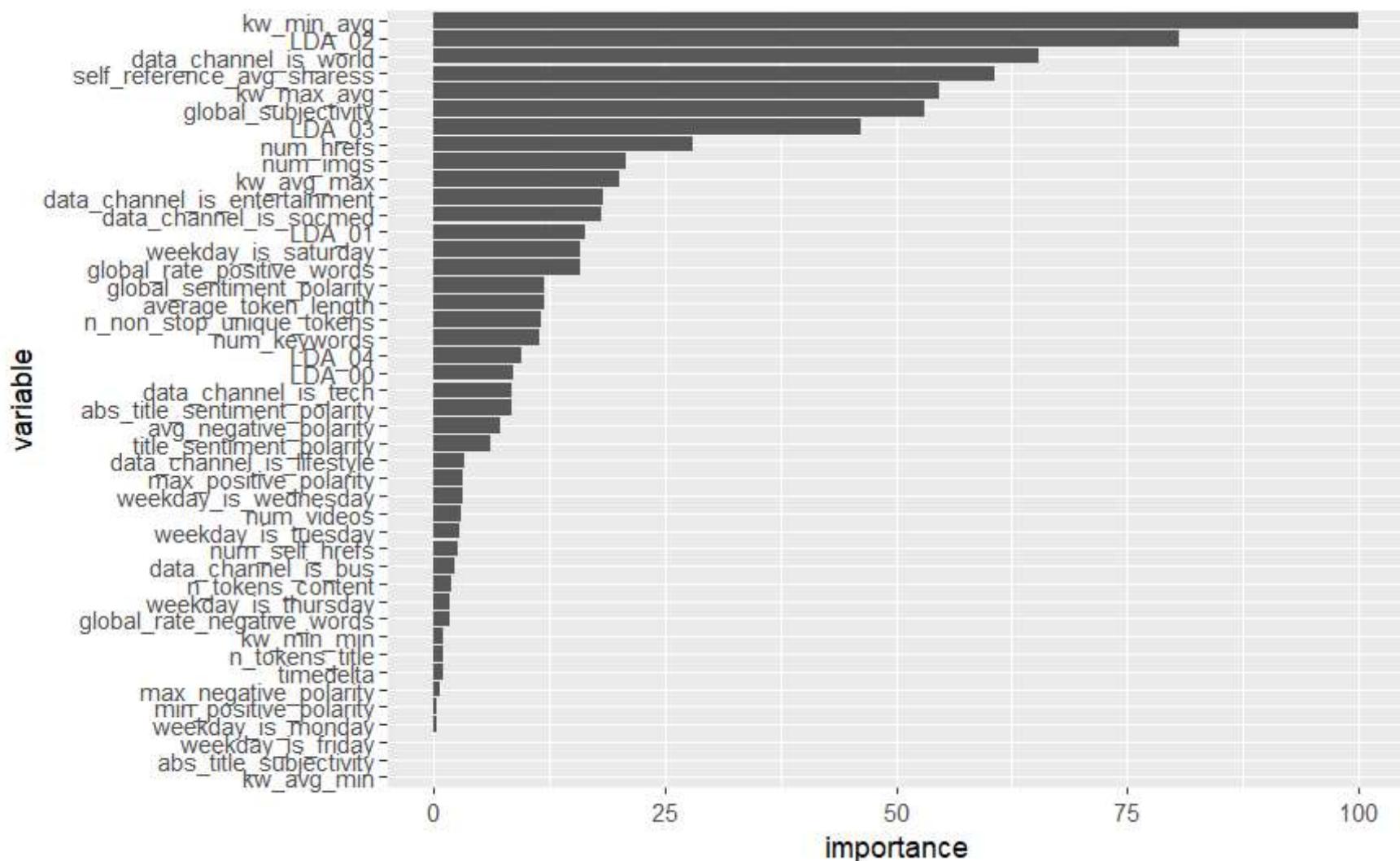
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```
plot.var.imp(knn)
```



Classification and Regression Tree (CART)

[Hide](#)

```
set.seed(100)
cart <- train(
  x = X.train,
  y = y.train,
  preProc = c("center", "scale"),
  method = "rpart",
  tuneGrid = expand.grid(cp = seq(0.001, 0.1, 0.01))
)
```

Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo, :
There were missing values in resampled performance measures.

[Hide](#)

```
cart
```

```
CART
```

```
31716 samples
44 predictor

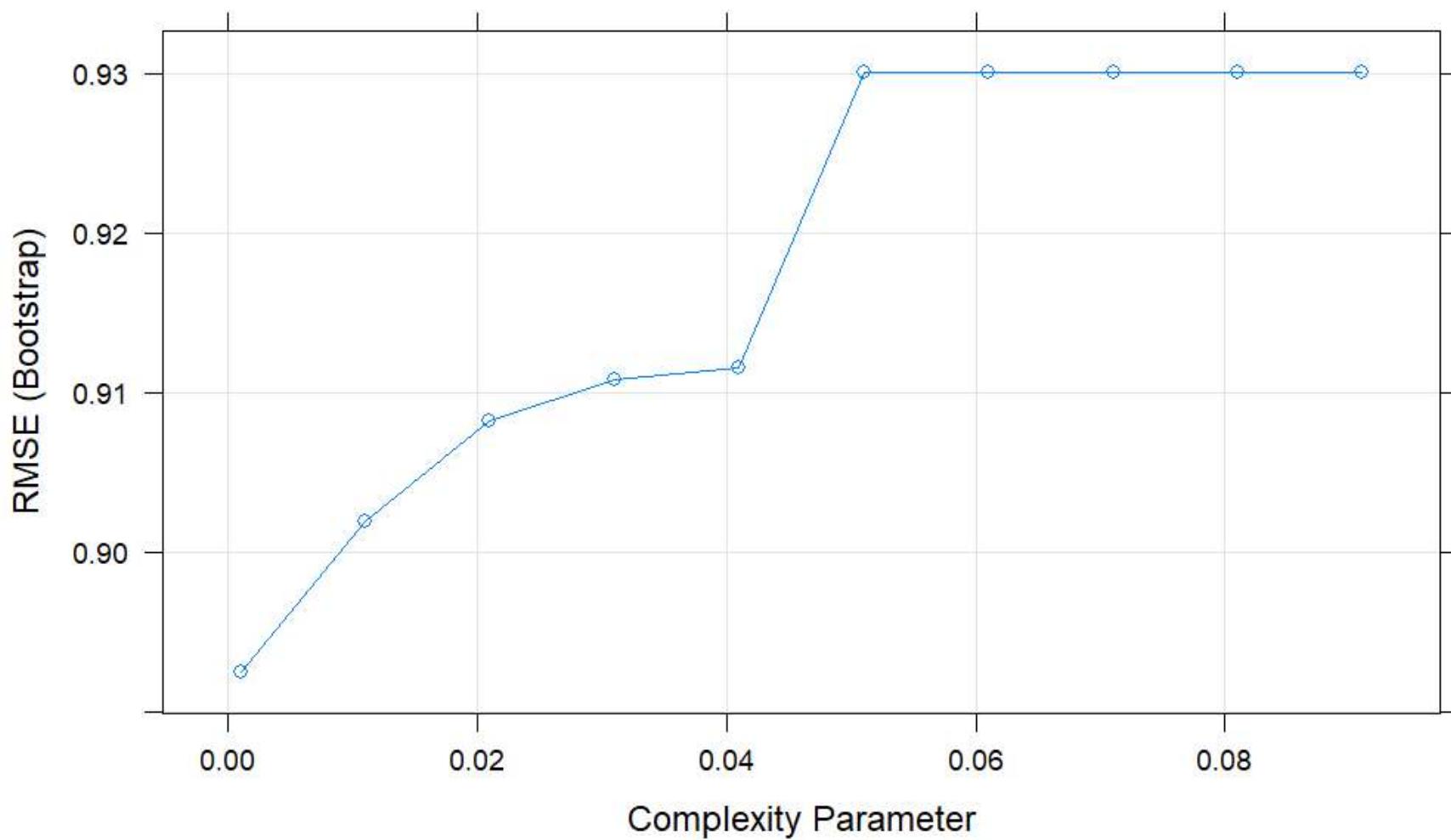
Pre-processing: centered (44), scaled (44)
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 31716, 31716, 31716, 31716, 31716, 31716, ...
Resampling results across tuning parameters:
```

cp	RMSE	Rsquared	MAE
0.001	0.8924639	0.08998393	0.6621639
0.011	0.9019196	0.05988036	0.6800254
0.021	0.9081914	0.04668786	0.6855366
0.031	0.9107644	0.04119749	0.6878669
0.041	0.9115580	0.04114349	0.6885583
0.051	0.9300558	NaN	0.7044480
0.061	0.9300558	NaN	0.7044480
0.071	0.9300558	NaN	0.7044480
0.081	0.9300558	NaN	0.7044480
0.091	0.9300558	NaN	0.7044480

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was cp = 0.001.

[Hide](#)

```
plot(cart)
```

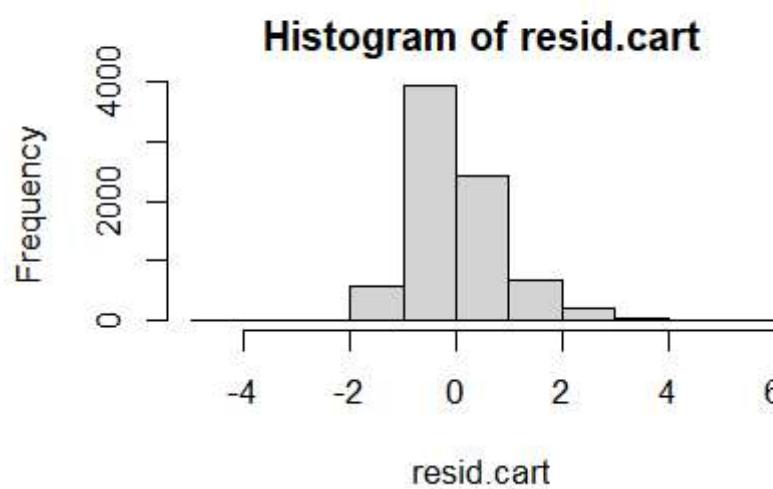
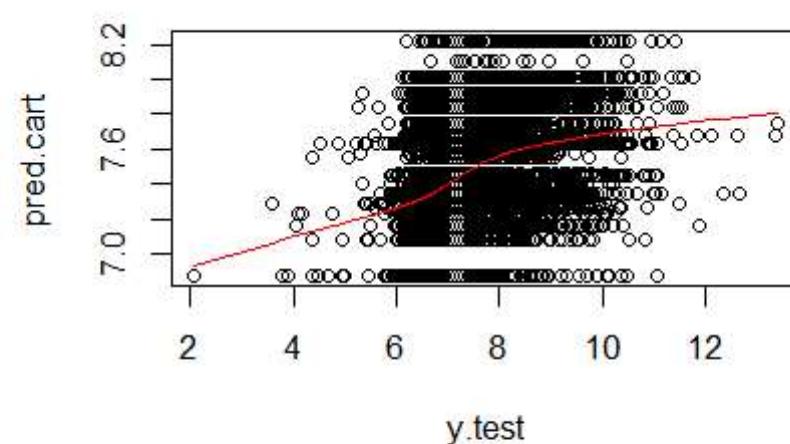
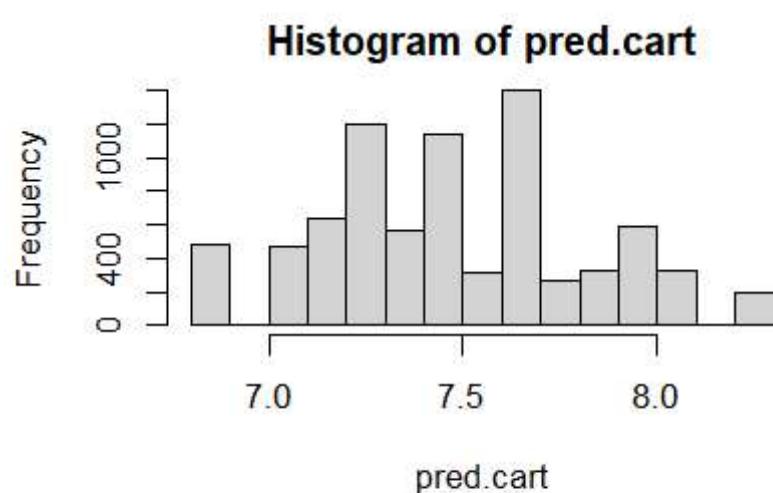


```
pred.cart <- predict(cart, X.test)
resid.cart <- y.test - pred.cart
rmse(y.test, pred.cart)
```

[1] 0.8773104

```
par(mfrow = c(2, 2))
hist(pred.cart)
plot(y.test, pred.cart)
```

```
lines(lowess(y.test, pred.cart), col = "red")
hist(resid.cart)
```



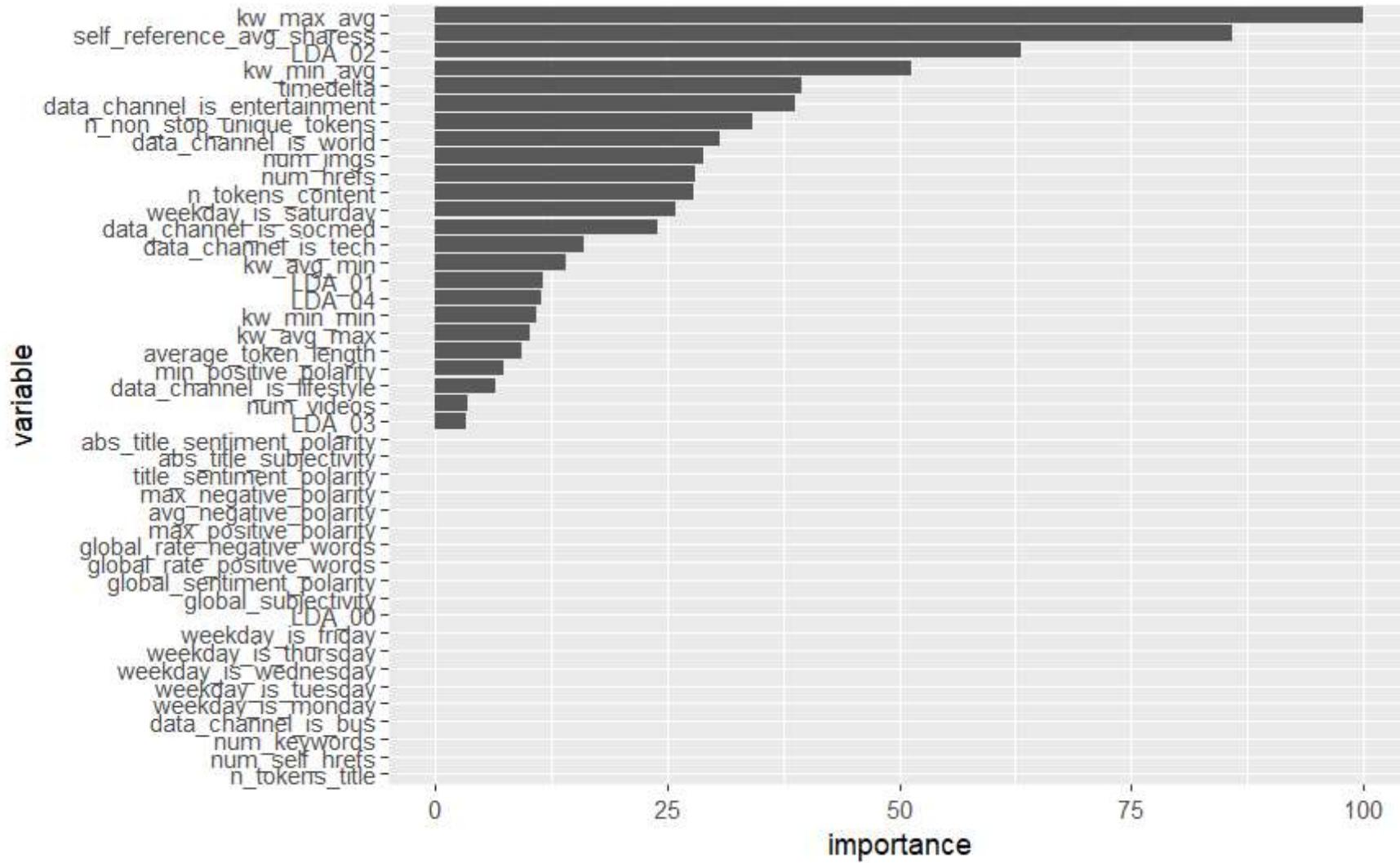
Hide

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```
plot.var.imp(cart)
```



Stochastic Gradient Boosting

[Hide](#)

```
set.seed(100)
gbm.grid <- expand.grid(n.trees = 100, interaction.depth = 1:5, shrinkage = c(0.01, 0.1), n.minobsinnode = 10)
gbm <- train(
  x = X.train,
  y = y.train,
  trControl = ctrl,
  preProc = c("center", "scale"),
  method = "gbm",
  tuneGrid = gbm.grid
)
```

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8679	nan	0.0100	0.0008
2	0.8671	nan	0.0100	0.0007
3	0.8664	nan	0.0100	0.0007
4	0.8657	nan	0.0100	0.0007
5	0.8650	nan	0.0100	0.0007
6	0.8643	nan	0.0100	0.0007
7	0.8637	nan	0.0100	0.0007
8	0.8630	nan	0.0100	0.0006
9	0.8623	nan	0.0100	0.0006
10	0.8617	nan	0.0100	0.0006
20	0.8558	nan	0.0100	0.0006
40	0.8457	nan	0.0100	0.0004
60	0.8373	nan	0.0100	0.0004
80	0.8303	nan	0.0100	0.0003
100	0.8242	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8675	nan	0.0100	0.0011
2	0.8665	nan	0.0100	0.0011
3	0.8654	nan	0.0100	0.0011
4	0.8643	nan	0.0100	0.0010
5	0.8633	nan	0.0100	0.0010
6	0.8624	nan	0.0100	0.0009
7	0.8615	nan	0.0100	0.0009
8	0.8606	nan	0.0100	0.0009
9	0.8596	nan	0.0100	0.0009
10	0.8588	nan	0.0100	0.0008
20	0.8505	nan	0.0100	0.0007
40	0.8371	nan	0.0100	0.0005
60	0.8267	nan	0.0100	0.0005
80	0.8180	nan	0.0100	0.0004
100	0.8108	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8674	nan	0.0100	0.0012
2	0.8662	nan	0.0100	0.0012
3	0.8650	nan	0.0100	0.0011
4	0.8639	nan	0.0100	0.0011
5	0.8627	nan	0.0100	0.0011
6	0.8616	nan	0.0100	0.0011
7	0.8605	nan	0.0100	0.0011
8	0.8594	nan	0.0100	0.0011
9	0.8583	nan	0.0100	0.0011
10	0.8573	nan	0.0100	0.0010
20	0.8478	nan	0.0100	0.0009
40	0.8324	nan	0.0100	0.0007
60	0.8203	nan	0.0100	0.0005
80	0.8106	nan	0.0100	0.0004
100	0.8023	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8673	nan	0.0100	0.0013
2	0.8659	nan	0.0100	0.0013
3	0.8646	nan	0.0100	0.0012
4	0.8634	nan	0.0100	0.0013
5	0.8622	nan	0.0100	0.0012
6	0.8610	nan	0.0100	0.0012
7	0.8597	nan	0.0100	0.0012
8	0.8586	nan	0.0100	0.0011
9	0.8575	nan	0.0100	0.0011
10	0.8563	nan	0.0100	0.0011
20	0.8459	nan	0.0100	0.0009
40	0.8290	nan	0.0100	0.0007
60	0.8160	nan	0.0100	0.0005
80	0.8053	nan	0.0100	0.0005
100	0.7966	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8672	nan	0.0100	0.0014
2	0.8658	nan	0.0100	0.0014
3	0.8645	nan	0.0100	0.0013
4	0.8632	nan	0.0100	0.0013
5	0.8619	nan	0.0100	0.0013
6	0.8606	nan	0.0100	0.0013
7	0.8593	nan	0.0100	0.0012
8	0.8580	nan	0.0100	0.0012
9	0.8568	nan	0.0100	0.0012
10	0.8555	nan	0.0100	0.0012
20	0.8445	nan	0.0100	0.0010
40	0.8265	nan	0.0100	0.0008
60	0.8125	nan	0.0100	0.0006
80	0.8015	nan	0.0100	0.0004

100	0.7924	nan	0.0100	0.0004
-----	--------	-----	--------	--------

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8612	nan	0.1000	0.0072
2	0.8554	nan	0.1000	0.0056
3	0.8495	nan	0.1000	0.0055
4	0.8447	nan	0.1000	0.0048
5	0.8402	nan	0.1000	0.0042
6	0.8363	nan	0.1000	0.0036
7	0.8328	nan	0.1000	0.0033
8	0.8291	nan	0.1000	0.0035
9	0.8258	nan	0.1000	0.0034
10	0.8231	nan	0.1000	0.0026
20	0.8027	nan	0.1000	0.0011
40	0.7821	nan	0.1000	0.0008
60	0.7708	nan	0.1000	0.0005
80	0.7629	nan	0.1000	0.0003
100	0.7574	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8583	nan	0.1000	0.0104
2	0.8497	nan	0.1000	0.0084
3	0.8430	nan	0.1000	0.0065
4	0.8371	nan	0.1000	0.0056
5	0.8315	nan	0.1000	0.0054
6	0.8265	nan	0.1000	0.0051
7	0.8217	nan	0.1000	0.0045
8	0.8175	nan	0.1000	0.0040
9	0.8137	nan	0.1000	0.0037
10	0.8104	nan	0.1000	0.0031
20	0.7866	nan	0.1000	0.0017
40	0.7631	nan	0.1000	0.0005
60	0.7512	nan	0.1000	0.0004
80	0.7446	nan	0.1000	-0.0000
100	0.7397	nan	0.1000	-0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8573	nan	0.1000	0.0114
2	0.8481	nan	0.1000	0.0090
3	0.8397	nan	0.1000	0.0083
4	0.8325	nan	0.1000	0.0072
5	0.8259	nan	0.1000	0.0066
6	0.8205	nan	0.1000	0.0054
7	0.8152	nan	0.1000	0.0046
8	0.8097	nan	0.1000	0.0052
9	0.8054	nan	0.1000	0.0041
10	0.8020	nan	0.1000	0.0030
20	0.7750	nan	0.1000	0.0020
40	0.7523	nan	0.1000	0.0002
60	0.7415	nan	0.1000	0.0002
80	0.7332	nan	0.1000	0.0002
100	0.7263	nan	0.1000	-0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8558	nan	0.1000	0.0125
2	0.8455	nan	0.1000	0.0104
3	0.8364	nan	0.1000	0.0089
4	0.8281	nan	0.1000	0.0078
5	0.8207	nan	0.1000	0.0069
6	0.8149	nan	0.1000	0.0056
7	0.8099	nan	0.1000	0.0049
8	0.8044	nan	0.1000	0.0051
9	0.7996	nan	0.1000	0.0049
10	0.7961	nan	0.1000	0.0033
20	0.7686	nan	0.1000	0.0019
40	0.7443	nan	0.1000	0.0002
60	0.7332	nan	0.1000	0.0001
80	0.7240	nan	0.1000	0.0000
100	0.7173	nan	0.1000	-0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8551	nan	0.1000	0.0131
2	0.8443	nan	0.1000	0.0110
3	0.8347	nan	0.1000	0.0093
4	0.8263	nan	0.1000	0.0085
5	0.8186	nan	0.1000	0.0069
6	0.8120	nan	0.1000	0.0062
7	0.8060	nan	0.1000	0.0057
8	0.8011	nan	0.1000	0.0045
9	0.7955	nan	0.1000	0.0052
10	0.7908	nan	0.1000	0.0042
20	0.7624	nan	0.1000	0.0017
40	0.7396	nan	0.1000	0.0000

60	0.7263	nan	0.1000	0.0000
80	0.7162	nan	0.1000	-0.0001
100	0.7077	nan	0.1000	-0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8694	nan	0.0100	0.0007
2	0.8687	nan	0.0100	0.0007
3	0.8680	nan	0.0100	0.0007
4	0.8673	nan	0.0100	0.0007
5	0.8666	nan	0.0100	0.0007
6	0.8659	nan	0.0100	0.0006
7	0.8652	nan	0.0100	0.0007
8	0.8646	nan	0.0100	0.0006
9	0.8639	nan	0.0100	0.0006
10	0.8633	nan	0.0100	0.0006
20	0.8574	nan	0.0100	0.0005
40	0.8473	nan	0.0100	0.0005
60	0.8389	nan	0.0100	0.0004
80	0.8316	nan	0.0100	0.0003
100	0.8255	nan	0.0100	0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8690	nan	0.0100	0.0011
2	0.8680	nan	0.0100	0.0011
3	0.8669	nan	0.0100	0.0011
4	0.8659	nan	0.0100	0.0010
5	0.8648	nan	0.0100	0.0010
6	0.8638	nan	0.0100	0.0010
7	0.8628	nan	0.0100	0.0010
8	0.8619	nan	0.0100	0.0009
9	0.8610	nan	0.0100	0.0009
10	0.8601	nan	0.0100	0.0009
20	0.8518	nan	0.0100	0.0008
40	0.8385	nan	0.0100	0.0006
60	0.8279	nan	0.0100	0.0004
80	0.8190	nan	0.0100	0.0004
100	0.8118	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8688	nan	0.0100	0.0012
2	0.8677	nan	0.0100	0.0012
3	0.8665	nan	0.0100	0.0011
4	0.8654	nan	0.0100	0.0011
5	0.8642	nan	0.0100	0.0011
6	0.8631	nan	0.0100	0.0011
7	0.8620	nan	0.0100	0.0010
8	0.8609	nan	0.0100	0.0011
9	0.8599	nan	0.0100	0.0010
10	0.8588	nan	0.0100	0.0010
20	0.8493	nan	0.0100	0.0009
40	0.8336	nan	0.0100	0.0006
60	0.8214	nan	0.0100	0.0005
80	0.8113	nan	0.0100	0.0005
100	0.8032	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8688	nan	0.0100	0.0013
2	0.8674	nan	0.0100	0.0013
3	0.8661	nan	0.0100	0.0013
4	0.8649	nan	0.0100	0.0012
5	0.8636	nan	0.0100	0.0013
6	0.8624	nan	0.0100	0.0012
7	0.8612	nan	0.0100	0.0012
8	0.8599	nan	0.0100	0.0012
9	0.8588	nan	0.0100	0.0011
10	0.8577	nan	0.0100	0.0011
20	0.8472	nan	0.0100	0.0010
40	0.8299	nan	0.0100	0.0007
60	0.8167	nan	0.0100	0.0005
80	0.8059	nan	0.0100	0.0004
100	0.7972	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8686	nan	0.0100	0.0014
2	0.8672	nan	0.0100	0.0014
3	0.8658	nan	0.0100	0.0013
4	0.8645	nan	0.0100	0.0013
5	0.8631	nan	0.0100	0.0013
6	0.8617	nan	0.0100	0.0013
7	0.8605	nan	0.0100	0.0012
8	0.8593	nan	0.0100	0.0013
9	0.8580	nan	0.0100	0.0012
10	0.8568	nan	0.0100	0.0012

20	0.8457	nan	0.0100	0.0010
40	0.8276	nan	0.0100	0.0008
60	0.8134	nan	0.0100	0.0007
80	0.8020	nan	0.0100	0.0005
100	0.7929	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8630	nan	0.1000	0.0069
2	0.8571	nan	0.1000	0.0056
3	0.8513	nan	0.1000	0.0055
4	0.8465	nan	0.1000	0.0045
5	0.8421	nan	0.1000	0.0045
6	0.8385	nan	0.1000	0.0035
7	0.8346	nan	0.1000	0.0039
8	0.8313	nan	0.1000	0.0032
9	0.8278	nan	0.1000	0.0034
10	0.8248	nan	0.1000	0.0029
20	0.8037	nan	0.1000	0.0013
40	0.7829	nan	0.1000	0.0007
60	0.7712	nan	0.1000	0.0004
80	0.7636	nan	0.1000	0.0003
100	0.7584	nan	0.1000	0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8601	nan	0.1000	0.0100
2	0.8522	nan	0.1000	0.0072
3	0.8444	nan	0.1000	0.0077
4	0.8377	nan	0.1000	0.0064
5	0.8319	nan	0.1000	0.0059
6	0.8269	nan	0.1000	0.0049
7	0.8226	nan	0.1000	0.0041
8	0.8185	nan	0.1000	0.0040
9	0.8147	nan	0.1000	0.0037
10	0.8115	nan	0.1000	0.0033
20	0.7864	nan	0.1000	0.0022
40	0.7632	nan	0.1000	0.0006
60	0.7525	nan	0.1000	0.0003
80	0.7456	nan	0.1000	-0.0001
100	0.7401	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8586	nan	0.1000	0.0114
2	0.8488	nan	0.1000	0.0094
3	0.8403	nan	0.1000	0.0081
4	0.8332	nan	0.1000	0.0072
5	0.8273	nan	0.1000	0.0056
6	0.8211	nan	0.1000	0.0061
7	0.8160	nan	0.1000	0.0049
8	0.8112	nan	0.1000	0.0041
9	0.8063	nan	0.1000	0.0046
10	0.8019	nan	0.1000	0.0043
20	0.7760	nan	0.1000	0.0016
40	0.7531	nan	0.1000	0.0005
60	0.7419	nan	0.1000	0.0002
80	0.7338	nan	0.1000	-0.0001
100	0.7277	nan	0.1000	0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8572	nan	0.1000	0.0127
2	0.8462	nan	0.1000	0.0107
3	0.8366	nan	0.1000	0.0089
4	0.8286	nan	0.1000	0.0077
5	0.8218	nan	0.1000	0.0064
6	0.8161	nan	0.1000	0.0054
7	0.8101	nan	0.1000	0.0059
8	0.8049	nan	0.1000	0.0050
9	0.8004	nan	0.1000	0.0041
10	0.7962	nan	0.1000	0.0038
20	0.7689	nan	0.1000	0.0021
40	0.7449	nan	0.1000	0.0004
60	0.7338	nan	0.1000	0.0003
80	0.7248	nan	0.1000	0.0000
100	0.7175	nan	0.1000	-0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8560	nan	0.1000	0.0133
2	0.8444	nan	0.1000	0.0108
3	0.8350	nan	0.1000	0.0094
4	0.8266	nan	0.1000	0.0083
5	0.8195	nan	0.1000	0.0068
6	0.8120	nan	0.1000	0.0072
7	0.8056	nan	0.1000	0.0059
8	0.8006	nan	0.1000	0.0046

9	0.7959	nan	0.1000	0.0047
10	0.7918	nan	0.1000	0.0039
20	0.7646	nan	0.1000	0.0018
40	0.7402	nan	0.1000	0.0002
60	0.7280	nan	0.1000	0.0003
80	0.7183	nan	0.1000	-0.0001
100	0.7113	nan	0.1000	-0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8652	nan	0.0100	0.0007
2	0.8644	nan	0.0100	0.0007
3	0.8637	nan	0.0100	0.0007
4	0.8630	nan	0.0100	0.0007
5	0.8623	nan	0.0100	0.0007
6	0.8616	nan	0.0100	0.0007
7	0.8610	nan	0.0100	0.0006
8	0.8603	nan	0.0100	0.0006
9	0.8597	nan	0.0100	0.0006
10	0.8591	nan	0.0100	0.0006
20	0.8532	nan	0.0100	0.0005
40	0.8432	nan	0.0100	0.0004
60	0.8350	nan	0.0100	0.0004
80	0.8281	nan	0.0100	0.0003
100	0.8221	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8649	nan	0.0100	0.0011
2	0.8638	nan	0.0100	0.0011
3	0.8628	nan	0.0100	0.0010
4	0.8618	nan	0.0100	0.0010
5	0.8607	nan	0.0100	0.0010
6	0.8597	nan	0.0100	0.0010
7	0.8588	nan	0.0100	0.0009
8	0.8578	nan	0.0100	0.0009
9	0.8569	nan	0.0100	0.0009
10	0.8560	nan	0.0100	0.0009
20	0.8479	nan	0.0100	0.0008
40	0.8346	nan	0.0100	0.0005
60	0.8241	nan	0.0100	0.0004
80	0.8154	nan	0.0100	0.0004
100	0.8083	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8647	nan	0.0100	0.0012
2	0.8635	nan	0.0100	0.0011
3	0.8624	nan	0.0100	0.0012
4	0.8612	nan	0.0100	0.0011
5	0.8601	nan	0.0100	0.0011
6	0.8590	nan	0.0100	0.0011
7	0.8579	nan	0.0100	0.0010
8	0.8568	nan	0.0100	0.0011
9	0.8558	nan	0.0100	0.0010
10	0.8548	nan	0.0100	0.0010
20	0.8454	nan	0.0100	0.0008
40	0.8303	nan	0.0100	0.0006
60	0.8181	nan	0.0100	0.0005
80	0.8084	nan	0.0100	0.0004
100	0.8002	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8646	nan	0.0100	0.0013
2	0.8633	nan	0.0100	0.0013
3	0.8621	nan	0.0100	0.0012
4	0.8608	nan	0.0100	0.0012
5	0.8596	nan	0.0100	0.0012
6	0.8584	nan	0.0100	0.0012
7	0.8573	nan	0.0100	0.0011
8	0.8561	nan	0.0100	0.0012
9	0.8549	nan	0.0100	0.0011
10	0.8538	nan	0.0100	0.0011
20	0.8435	nan	0.0100	0.0009
40	0.8268	nan	0.0100	0.0007
60	0.8139	nan	0.0100	0.0006
80	0.8035	nan	0.0100	0.0004
100	0.7946	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8645	nan	0.0100	0.0014
2	0.8631	nan	0.0100	0.0013
3	0.8618	nan	0.0100	0.0013
4	0.8604	nan	0.0100	0.0013
5	0.8592	nan	0.0100	0.0012
6	0.8579	nan	0.0100	0.0012

7	0.8566	nan	0.0100	0.0012
8	0.8554	nan	0.0100	0.0012
9	0.8541	nan	0.0100	0.0012
10	0.8530	nan	0.0100	0.0012
20	0.8418	nan	0.0100	0.0010
40	0.8241	nan	0.0100	0.0008
60	0.8104	nan	0.0100	0.0006
80	0.7993	nan	0.0100	0.0005
100	0.7903	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8589	nan	0.1000	0.0071
2	0.8532	nan	0.1000	0.0058
3	0.8480	nan	0.1000	0.0053
4	0.8435	nan	0.1000	0.0042
5	0.8385	nan	0.1000	0.0047
6	0.8345	nan	0.1000	0.0038
7	0.8307	nan	0.1000	0.0034
8	0.8275	nan	0.1000	0.0032
9	0.8243	nan	0.1000	0.0031
10	0.8214	nan	0.1000	0.0027
20	0.8011	nan	0.1000	0.0015
40	0.7810	nan	0.1000	0.0006
60	0.7695	nan	0.1000	0.0004
80	0.7620	nan	0.1000	0.0002
100	0.7566	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8556	nan	0.1000	0.0104
2	0.8474	nan	0.1000	0.0083
3	0.8403	nan	0.1000	0.0071
4	0.8344	nan	0.1000	0.0056
5	0.8295	nan	0.1000	0.0045
6	0.8238	nan	0.1000	0.0051
7	0.8191	nan	0.1000	0.0044
8	0.8150	nan	0.1000	0.0038
9	0.8111	nan	0.1000	0.0037
10	0.8077	nan	0.1000	0.0027
20	0.7832	nan	0.1000	0.0018
40	0.7611	nan	0.1000	0.0003
60	0.7498	nan	0.1000	0.0003
80	0.7432	nan	0.1000	0.0000
100	0.7381	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8543	nan	0.1000	0.0117
2	0.8449	nan	0.1000	0.0091
3	0.8367	nan	0.1000	0.0082
4	0.8293	nan	0.1000	0.0068
5	0.8226	nan	0.1000	0.0062
6	0.8172	nan	0.1000	0.0053
7	0.8124	nan	0.1000	0.0046
8	0.8073	nan	0.1000	0.0048
9	0.8033	nan	0.1000	0.0038
10	0.7993	nan	0.1000	0.0036
20	0.7738	nan	0.1000	0.0014
40	0.7505	nan	0.1000	0.0006
60	0.7406	nan	0.1000	0.0001
80	0.7325	nan	0.1000	0.0001
100	0.7274	nan	0.1000	-0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8532	nan	0.1000	0.0125
2	0.8427	nan	0.1000	0.0103
3	0.8339	nan	0.1000	0.0091
4	0.8261	nan	0.1000	0.0077
5	0.8196	nan	0.1000	0.0061
6	0.8131	nan	0.1000	0.0063
7	0.8078	nan	0.1000	0.0051
8	0.8029	nan	0.1000	0.0041
9	0.7976	nan	0.1000	0.0050
10	0.7937	nan	0.1000	0.0038
20	0.7675	nan	0.1000	0.0013
40	0.7441	nan	0.1000	0.0002
60	0.7319	nan	0.1000	0.0003
80	0.7232	nan	0.1000	0.0001
100	0.7162	nan	0.1000	-0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8528	nan	0.1000	0.0124
2	0.8422	nan	0.1000	0.0105
3	0.8314	nan	0.1000	0.0097
4	0.8233	nan	0.1000	0.0081

5	0.8155	nan	0.1000	0.0073
6	0.8086	nan	0.1000	0.0061
7	0.8029	nan	0.1000	0.0049
8	0.7974	nan	0.1000	0.0050
9	0.7931	nan	0.1000	0.0040
10	0.7894	nan	0.1000	0.0033
20	0.7616	nan	0.1000	0.0016
40	0.7378	nan	0.1000	0.0003
60	0.7253	nan	0.1000	-0.0000
80	0.7158	nan	0.1000	-0.0000
100	0.7074	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8655	nan	0.0100	0.0007
2	0.8648	nan	0.0100	0.0007
3	0.8641	nan	0.0100	0.0007
4	0.8634	nan	0.0100	0.0007
5	0.8627	nan	0.0100	0.0007
6	0.8619	nan	0.0100	0.0007
7	0.8613	nan	0.0100	0.0007
8	0.8606	nan	0.0100	0.0006
9	0.8600	nan	0.0100	0.0006
10	0.8593	nan	0.0100	0.0006
20	0.8533	nan	0.0100	0.0006
40	0.8430	nan	0.0100	0.0005
60	0.8346	nan	0.0100	0.0004
80	0.8275	nan	0.0100	0.0003
100	0.8215	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8652	nan	0.0100	0.0011
2	0.8641	nan	0.0100	0.0011
3	0.8630	nan	0.0100	0.0011
4	0.8620	nan	0.0100	0.0010
5	0.8610	nan	0.0100	0.0010
6	0.8600	nan	0.0100	0.0010
7	0.8590	nan	0.0100	0.0010
8	0.8580	nan	0.0100	0.0010
9	0.8570	nan	0.0100	0.0009
10	0.8561	nan	0.0100	0.0009
20	0.8479	nan	0.0100	0.0008
40	0.8347	nan	0.0100	0.0005
60	0.8241	nan	0.0100	0.0005
80	0.8152	nan	0.0100	0.0004
100	0.8081	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8651	nan	0.0100	0.0012
2	0.8638	nan	0.0100	0.0012
3	0.8626	nan	0.0100	0.0012
4	0.8614	nan	0.0100	0.0012
5	0.8603	nan	0.0100	0.0011
6	0.8592	nan	0.0100	0.0011
7	0.8581	nan	0.0100	0.0011
8	0.8570	nan	0.0100	0.0011
9	0.8560	nan	0.0100	0.0010
10	0.8549	nan	0.0100	0.0011
20	0.8454	nan	0.0100	0.0009
40	0.8298	nan	0.0100	0.0006
60	0.8177	nan	0.0100	0.0005
80	0.8077	nan	0.0100	0.0004
100	0.7994	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8649	nan	0.0100	0.0013
2	0.8637	nan	0.0100	0.0013
3	0.8624	nan	0.0100	0.0013
4	0.8611	nan	0.0100	0.0012
5	0.8598	nan	0.0100	0.0013
6	0.8586	nan	0.0100	0.0012
7	0.8574	nan	0.0100	0.0012
8	0.8562	nan	0.0100	0.0012
9	0.8550	nan	0.0100	0.0011
10	0.8539	nan	0.0100	0.0011
20	0.8434	nan	0.0100	0.0009
40	0.8263	nan	0.0100	0.0007
60	0.8131	nan	0.0100	0.0005
80	0.8025	nan	0.0100	0.0004
100	0.7938	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8648	nan	0.0100	0.0015
2	0.8634	nan	0.0100	0.0013

3	0.8621	nan	0.0100	0.0014
4	0.8607	nan	0.0100	0.0013
5	0.8594	nan	0.0100	0.0013
6	0.8581	nan	0.0100	0.0013
7	0.8569	nan	0.0100	0.0013
8	0.8556	nan	0.0100	0.0012
9	0.8544	nan	0.0100	0.0012
10	0.8531	nan	0.0100	0.0012
20	0.8418	nan	0.0100	0.0010
40	0.8237	nan	0.0100	0.0008
60	0.8098	nan	0.0100	0.0006
80	0.7985	nan	0.0100	0.0005
100	0.7896	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8590	nan	0.1000	0.0072
2	0.8530	nan	0.1000	0.0057
3	0.8474	nan	0.1000	0.0053
4	0.8426	nan	0.1000	0.0048
5	0.8384	nan	0.1000	0.0039
6	0.8346	nan	0.1000	0.0037
7	0.8305	nan	0.1000	0.0040
8	0.8268	nan	0.1000	0.0033
9	0.8234	nan	0.1000	0.0031
10	0.8206	nan	0.1000	0.0025
20	0.8001	nan	0.1000	0.0015
40	0.7792	nan	0.1000	0.0005
60	0.7679	nan	0.1000	0.0004
80	0.7605	nan	0.1000	0.0002
100	0.7555	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8558	nan	0.1000	0.0107
2	0.8473	nan	0.1000	0.0085
3	0.8400	nan	0.1000	0.0070
4	0.8341	nan	0.1000	0.0058
5	0.8284	nan	0.1000	0.0056
6	0.8237	nan	0.1000	0.0043
7	0.8190	nan	0.1000	0.0049
8	0.8150	nan	0.1000	0.0037
9	0.8113	nan	0.1000	0.0036
10	0.8072	nan	0.1000	0.0038
20	0.7832	nan	0.1000	0.0015
40	0.7612	nan	0.1000	0.0006
60	0.7499	nan	0.1000	0.0003
80	0.7435	nan	0.1000	0.0001
100	0.7382	nan	0.1000	0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8544	nan	0.1000	0.0115
2	0.8446	nan	0.1000	0.0091
3	0.8356	nan	0.1000	0.0088
4	0.8283	nan	0.1000	0.0071
5	0.8222	nan	0.1000	0.0060
6	0.8168	nan	0.1000	0.0052
7	0.8117	nan	0.1000	0.0049
8	0.8068	nan	0.1000	0.0041
9	0.8028	nan	0.1000	0.0038
10	0.7986	nan	0.1000	0.0039
20	0.7739	nan	0.1000	0.0014
40	0.7517	nan	0.1000	0.0004
60	0.7402	nan	0.1000	0.0003
80	0.7319	nan	0.1000	-0.0001
100	0.7253	nan	0.1000	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8535	nan	0.1000	0.0127
2	0.8423	nan	0.1000	0.0108
3	0.8333	nan	0.1000	0.0085
4	0.8252	nan	0.1000	0.0075
5	0.8184	nan	0.1000	0.0067
6	0.8118	nan	0.1000	0.0062
7	0.8066	nan	0.1000	0.0049
8	0.8009	nan	0.1000	0.0054
9	0.7964	nan	0.1000	0.0041
10	0.7923	nan	0.1000	0.0039
20	0.7647	nan	0.1000	0.0017
40	0.7415	nan	0.1000	0.0007
60	0.7308	nan	0.1000	0.0003
80	0.7224	nan	0.1000	-0.0000
100	0.7158	nan	0.1000	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve

1	0.8521	nan	0.1000	0.0138
2	0.8407	nan	0.1000	0.0113
3	0.8311	nan	0.1000	0.0097
4	0.8225	nan	0.1000	0.0085
5	0.8148	nan	0.1000	0.0070
6	0.8087	nan	0.1000	0.0063
7	0.8033	nan	0.1000	0.0049
8	0.7980	nan	0.1000	0.0050
9	0.7936	nan	0.1000	0.0040
10	0.7889	nan	0.1000	0.0040
20	0.7602	nan	0.1000	0.0013
40	0.7370	nan	0.1000	0.0003
60	0.7247	nan	0.1000	0.0004
80	0.7156	nan	0.1000	-0.0001
100	0.7073	nan	0.1000	-0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8672	nan	0.0100	0.0008
2	0.8665	nan	0.0100	0.0007
3	0.8657	nan	0.0100	0.0007
4	0.8650	nan	0.0100	0.0007
5	0.8643	nan	0.0100	0.0007
6	0.8637	nan	0.0100	0.0006
7	0.8630	nan	0.0100	0.0007
8	0.8623	nan	0.0100	0.0007
9	0.8616	nan	0.0100	0.0007
10	0.8610	nan	0.0100	0.0006
20	0.8549	nan	0.0100	0.0006
40	0.8445	nan	0.0100	0.0005
60	0.8360	nan	0.0100	0.0004
80	0.8288	nan	0.0100	0.0003
100	0.8226	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8670	nan	0.0100	0.0010
2	0.8659	nan	0.0100	0.0011
3	0.8648	nan	0.0100	0.0011
4	0.8637	nan	0.0100	0.0010
5	0.8627	nan	0.0100	0.0010
6	0.8617	nan	0.0100	0.0010
7	0.8607	nan	0.0100	0.0010
8	0.8597	nan	0.0100	0.0010
9	0.8588	nan	0.0100	0.0008
10	0.8579	nan	0.0100	0.0009
20	0.8494	nan	0.0100	0.0008
40	0.8359	nan	0.0100	0.0005
60	0.8253	nan	0.0100	0.0004
80	0.8164	nan	0.0100	0.0004
100	0.8090	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8667	nan	0.0100	0.0012
2	0.8655	nan	0.0100	0.0012
3	0.8642	nan	0.0100	0.0012
4	0.8631	nan	0.0100	0.0012
5	0.8619	nan	0.0100	0.0011
6	0.8608	nan	0.0100	0.0011
7	0.8596	nan	0.0100	0.0011
8	0.8585	nan	0.0100	0.0011
9	0.8574	nan	0.0100	0.0011
10	0.8564	nan	0.0100	0.0010
20	0.8467	nan	0.0100	0.0009
40	0.8311	nan	0.0100	0.0007
60	0.8187	nan	0.0100	0.0006
80	0.8087	nan	0.0100	0.0005
100	0.8003	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8667	nan	0.0100	0.0013
2	0.8654	nan	0.0100	0.0013
3	0.8641	nan	0.0100	0.0012
4	0.8628	nan	0.0100	0.0013
5	0.8615	nan	0.0100	0.0013
6	0.8603	nan	0.0100	0.0012
7	0.8590	nan	0.0100	0.0012
8	0.8578	nan	0.0100	0.0012
9	0.8567	nan	0.0100	0.0011
10	0.8555	nan	0.0100	0.0011
20	0.8448	nan	0.0100	0.0009
40	0.8278	nan	0.0100	0.0007
60	0.8144	nan	0.0100	0.0006
80	0.8038	nan	0.0100	0.0004
100	0.7946	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8665	nan	0.0100	0.0015
2	0.8650	nan	0.0100	0.0014
3	0.8637	nan	0.0100	0.0013
4	0.8623	nan	0.0100	0.0013
5	0.8609	nan	0.0100	0.0013
6	0.8595	nan	0.0100	0.0013
7	0.8582	nan	0.0100	0.0012
8	0.8569	nan	0.0100	0.0012
9	0.8557	nan	0.0100	0.0012
10	0.8545	nan	0.0100	0.0012
20	0.8431	nan	0.0100	0.0010
40	0.8250	nan	0.0100	0.0008
60	0.8109	nan	0.0100	0.0006
80	0.7996	nan	0.0100	0.0004
100	0.7903	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8607	nan	0.1000	0.0073
2	0.8549	nan	0.1000	0.0058
3	0.8487	nan	0.1000	0.0056
4	0.8437	nan	0.1000	0.0047
5	0.8393	nan	0.1000	0.0040
6	0.8354	nan	0.1000	0.0035
7	0.8312	nan	0.1000	0.0041
8	0.8277	nan	0.1000	0.0033
9	0.8243	nan	0.1000	0.0032
10	0.8214	nan	0.1000	0.0027
20	0.8003	nan	0.1000	0.0013
40	0.7800	nan	0.1000	0.0006
60	0.7684	nan	0.1000	0.0003
80	0.7612	nan	0.1000	0.0001
100	0.7559	nan	0.1000	0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8587	nan	0.1000	0.0094
2	0.8495	nan	0.1000	0.0092
3	0.8424	nan	0.1000	0.0070
4	0.8359	nan	0.1000	0.0064
5	0.8302	nan	0.1000	0.0058
6	0.8254	nan	0.1000	0.0045
7	0.8213	nan	0.1000	0.0039
8	0.8173	nan	0.1000	0.0038
9	0.8125	nan	0.1000	0.0045
10	0.8084	nan	0.1000	0.0037
20	0.7840	nan	0.1000	0.0015
40	0.7610	nan	0.1000	0.0006
60	0.7498	nan	0.1000	0.0004
80	0.7436	nan	0.1000	0.0000
100	0.7377	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8563	nan	0.1000	0.0113
2	0.8453	nan	0.1000	0.0100
3	0.8371	nan	0.1000	0.0077
4	0.8295	nan	0.1000	0.0073
5	0.8234	nan	0.1000	0.0058
6	0.8179	nan	0.1000	0.0053
7	0.8121	nan	0.1000	0.0055
8	0.8074	nan	0.1000	0.0048
9	0.8034	nan	0.1000	0.0038
10	0.7992	nan	0.1000	0.0038
20	0.7735	nan	0.1000	0.0017
40	0.7508	nan	0.1000	0.0008
60	0.7403	nan	0.1000	0.0002
80	0.7332	nan	0.1000	0.0002
100	0.7272	nan	0.1000	-0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8550	nan	0.1000	0.0125
2	0.8442	nan	0.1000	0.0108
3	0.8347	nan	0.1000	0.0089
4	0.8262	nan	0.1000	0.0082
5	0.8195	nan	0.1000	0.0063
6	0.8133	nan	0.1000	0.0057
7	0.8073	nan	0.1000	0.0058
8	0.8023	nan	0.1000	0.0049
9	0.7981	nan	0.1000	0.0039
10	0.7936	nan	0.1000	0.0043
20	0.7672	nan	0.1000	0.0016
40	0.7436	nan	0.1000	0.0004
60	0.7327	nan	0.1000	0.0002

80	0.7244	nan	0.1000	0.0001
100	0.7180	nan	0.1000	-0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8542	nan	0.1000	0.0135
2	0.8423	nan	0.1000	0.0113
3	0.8326	nan	0.1000	0.0092
4	0.8246	nan	0.1000	0.0074
5	0.8169	nan	0.1000	0.0074
6	0.8104	nan	0.1000	0.0059
7	0.8044	nan	0.1000	0.0059
8	0.7993	nan	0.1000	0.0049
9	0.7947	nan	0.1000	0.0038
10	0.7904	nan	0.1000	0.0041
20	0.7616	nan	0.1000	0.0018
40	0.7371	nan	0.1000	0.0009
60	0.7254	nan	0.1000	0.0002
80	0.7156	nan	0.1000	0.0001
100	0.7071	nan	0.1000	-0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8739	nan	0.0100	0.0008
2	0.8732	nan	0.0100	0.0007
3	0.8724	nan	0.0100	0.0007
4	0.8717	nan	0.0100	0.0007
5	0.8710	nan	0.0100	0.0007
6	0.8703	nan	0.0100	0.0007
7	0.8696	nan	0.0100	0.0006
8	0.8689	nan	0.0100	0.0007
9	0.8683	nan	0.0100	0.0006
10	0.8676	nan	0.0100	0.0006
20	0.8616	nan	0.0100	0.0006
40	0.8514	nan	0.0100	0.0005
60	0.8428	nan	0.0100	0.0004
80	0.8357	nan	0.0100	0.0003
100	0.8296	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8736	nan	0.0100	0.0011
2	0.8725	nan	0.0100	0.0011
3	0.8715	nan	0.0100	0.0010
4	0.8706	nan	0.0100	0.0008
5	0.8696	nan	0.0100	0.0010
6	0.8686	nan	0.0100	0.0010
7	0.8676	nan	0.0100	0.0010
8	0.8666	nan	0.0100	0.0010
9	0.8657	nan	0.0100	0.0010
10	0.8647	nan	0.0100	0.0009
20	0.8563	nan	0.0100	0.0007
40	0.8427	nan	0.0100	0.0006
60	0.8321	nan	0.0100	0.0004
80	0.8235	nan	0.0100	0.0004
100	0.8163	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8734	nan	0.0100	0.0012
2	0.8722	nan	0.0100	0.0012
3	0.8710	nan	0.0100	0.0012
4	0.8698	nan	0.0100	0.0012
5	0.8686	nan	0.0100	0.0012
6	0.8675	nan	0.0100	0.0011
7	0.8664	nan	0.0100	0.0011
8	0.8654	nan	0.0100	0.0010
9	0.8643	nan	0.0100	0.0011
10	0.8633	nan	0.0100	0.0010
20	0.8538	nan	0.0100	0.0009
40	0.8384	nan	0.0100	0.0006
60	0.8262	nan	0.0100	0.0005
80	0.8160	nan	0.0100	0.0005
100	0.8078	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8733	nan	0.0100	0.0013
2	0.8720	nan	0.0100	0.0013
3	0.8707	nan	0.0100	0.0013
4	0.8694	nan	0.0100	0.0013
5	0.8682	nan	0.0100	0.0012
6	0.8668	nan	0.0100	0.0012
7	0.8657	nan	0.0100	0.0011
8	0.8645	nan	0.0100	0.0012
9	0.8633	nan	0.0100	0.0012
10	0.8621	nan	0.0100	0.0012
20	0.8516	nan	0.0100	0.0010

40	0.8344	nan	0.0100	0.0007
60	0.8207	nan	0.0100	0.0005
80	0.8101	nan	0.0100	0.0004
100	0.8013	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8732	nan	0.0100	0.0014
2	0.8718	nan	0.0100	0.0014
3	0.8704	nan	0.0100	0.0013
4	0.8691	nan	0.0100	0.0013
5	0.8678	nan	0.0100	0.0013
6	0.8665	nan	0.0100	0.0012
7	0.8651	nan	0.0100	0.0013
8	0.8639	nan	0.0100	0.0012
9	0.8626	nan	0.0100	0.0012
10	0.8614	nan	0.0100	0.0012
20	0.8500	nan	0.0100	0.0010
40	0.8318	nan	0.0100	0.0007
60	0.8177	nan	0.0100	0.0006
80	0.8068	nan	0.0100	0.0005
100	0.7976	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8677	nan	0.1000	0.0065
2	0.8614	nan	0.1000	0.0062
3	0.8556	nan	0.1000	0.0055
4	0.8506	nan	0.1000	0.0048
5	0.8463	nan	0.1000	0.0044
6	0.8423	nan	0.1000	0.0037
7	0.8387	nan	0.1000	0.0035
8	0.8350	nan	0.1000	0.0035
9	0.8317	nan	0.1000	0.0033
10	0.8290	nan	0.1000	0.0028
20	0.8087	nan	0.1000	0.0016
40	0.7882	nan	0.1000	0.0005
60	0.7764	nan	0.1000	0.0002
80	0.7690	nan	0.1000	0.0003
100	0.7636	nan	0.1000	0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8640	nan	0.1000	0.0105
2	0.8557	nan	0.1000	0.0080
3	0.8483	nan	0.1000	0.0070
4	0.8425	nan	0.1000	0.0056
5	0.8368	nan	0.1000	0.0055
6	0.8316	nan	0.1000	0.0052
7	0.8270	nan	0.1000	0.0045
8	0.8232	nan	0.1000	0.0034
9	0.8194	nan	0.1000	0.0034
10	0.8163	nan	0.1000	0.0030
20	0.7928	nan	0.1000	0.0016
40	0.7691	nan	0.1000	0.0005
60	0.7577	nan	0.1000	0.0003
80	0.7508	nan	0.1000	-0.0000
100	0.7454	nan	0.1000	0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8629	nan	0.1000	0.0117
2	0.8526	nan	0.1000	0.0097
3	0.8444	nan	0.1000	0.0079
4	0.8376	nan	0.1000	0.0069
5	0.8313	nan	0.1000	0.0059
6	0.8261	nan	0.1000	0.0047
7	0.8203	nan	0.1000	0.0051
8	0.8157	nan	0.1000	0.0045
9	0.8118	nan	0.1000	0.0035
10	0.8083	nan	0.1000	0.0033
20	0.7821	nan	0.1000	0.0014
40	0.7584	nan	0.1000	0.0004
60	0.7478	nan	0.1000	0.0003
80	0.7406	nan	0.1000	0.0002
100	0.7347	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8615	nan	0.1000	0.0128
2	0.8505	nan	0.1000	0.0104
3	0.8414	nan	0.1000	0.0088
4	0.8331	nan	0.1000	0.0080
5	0.8258	nan	0.1000	0.0067
6	0.8200	nan	0.1000	0.0057
7	0.8139	nan	0.1000	0.0059
8	0.8089	nan	0.1000	0.0046
9	0.8046	nan	0.1000	0.0041

10	0.8009	nan	0.1000	0.0033
20	0.7738	nan	0.1000	0.0017
40	0.7518	nan	0.1000	0.0003
60	0.7398	nan	0.1000	0.0005
80	0.7311	nan	0.1000	0.0001
100	0.7245	nan	0.1000	-0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8611	nan	0.1000	0.0134
2	0.8501	nan	0.1000	0.0108
3	0.8401	nan	0.1000	0.0097
4	0.8318	nan	0.1000	0.0079
5	0.8235	nan	0.1000	0.0081
6	0.8169	nan	0.1000	0.0061
7	0.8103	nan	0.1000	0.0062
8	0.8053	nan	0.1000	0.0049
9	0.8006	nan	0.1000	0.0043
10	0.7962	nan	0.1000	0.0038
20	0.7690	nan	0.1000	0.0013
40	0.7461	nan	0.1000	0.0003
60	0.7341	nan	0.1000	0.0001
80	0.7249	nan	0.1000	-0.0000
100	0.7170	nan	0.1000	-0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8740	nan	0.0100	0.0008
2	0.8733	nan	0.0100	0.0008
3	0.8725	nan	0.0100	0.0007
4	0.8718	nan	0.0100	0.0007
5	0.8711	nan	0.0100	0.0007
6	0.8704	nan	0.0100	0.0007
7	0.8697	nan	0.0100	0.0007
8	0.8690	nan	0.0100	0.0007
9	0.8684	nan	0.0100	0.0007
10	0.8677	nan	0.0100	0.0007
20	0.8617	nan	0.0100	0.0006
40	0.8512	nan	0.0100	0.0005
60	0.8427	nan	0.0100	0.0004
80	0.8355	nan	0.0100	0.0003
100	0.8294	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8737	nan	0.0100	0.0011
2	0.8726	nan	0.0100	0.0011
3	0.8715	nan	0.0100	0.0011
4	0.8704	nan	0.0100	0.0010
5	0.8693	nan	0.0100	0.0010
6	0.8684	nan	0.0100	0.0008
7	0.8676	nan	0.0100	0.0009
8	0.8666	nan	0.0100	0.0010
9	0.8656	nan	0.0100	0.0010
10	0.8647	nan	0.0100	0.0008
20	0.8561	nan	0.0100	0.0008
40	0.8426	nan	0.0100	0.0005
60	0.8321	nan	0.0100	0.0004
80	0.8235	nan	0.0100	0.0003
100	0.8163	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8736	nan	0.0100	0.0013
2	0.8723	nan	0.0100	0.0012
3	0.8711	nan	0.0100	0.0012
4	0.8699	nan	0.0100	0.0012
5	0.8688	nan	0.0100	0.0011
6	0.8677	nan	0.0100	0.0010
7	0.8666	nan	0.0100	0.0011
8	0.8654	nan	0.0100	0.0011
9	0.8644	nan	0.0100	0.0011
10	0.8633	nan	0.0100	0.0010
20	0.8537	nan	0.0100	0.0009
40	0.8381	nan	0.0100	0.0007
60	0.8260	nan	0.0100	0.0005
80	0.8158	nan	0.0100	0.0005
100	0.8074	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8734	nan	0.0100	0.0013
2	0.8720	nan	0.0100	0.0013
3	0.8708	nan	0.0100	0.0013
4	0.8695	nan	0.0100	0.0013
5	0.8682	nan	0.0100	0.0013
6	0.8670	nan	0.0100	0.0012
7	0.8658	nan	0.0100	0.0012

8	0.8646	nan	0.0100	0.0012
9	0.8633	nan	0.0100	0.0012
10	0.8622	nan	0.0100	0.0011
20	0.8516	nan	0.0100	0.0009
40	0.8344	nan	0.0100	0.0007
60	0.8211	nan	0.0100	0.0006
80	0.8104	nan	0.0100	0.0005
100	0.8017	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8734	nan	0.0100	0.0014
2	0.8720	nan	0.0100	0.0013
3	0.8706	nan	0.0100	0.0014
4	0.8692	nan	0.0100	0.0014
5	0.8679	nan	0.0100	0.0013
6	0.8666	nan	0.0100	0.0013
7	0.8653	nan	0.0100	0.0012
8	0.8640	nan	0.0100	0.0013
9	0.8627	nan	0.0100	0.0013
10	0.8615	nan	0.0100	0.0012
20	0.8500	nan	0.0100	0.0010
40	0.8316	nan	0.0100	0.0008
60	0.8177	nan	0.0100	0.0006
80	0.8063	nan	0.0100	0.0004
100	0.7973	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8674	nan	0.1000	0.0073
2	0.8614	nan	0.1000	0.0059
3	0.8557	nan	0.1000	0.0056
4	0.8508	nan	0.1000	0.0051
5	0.8465	nan	0.1000	0.0041
6	0.8423	nan	0.1000	0.0042
7	0.8386	nan	0.1000	0.0037
8	0.8351	nan	0.1000	0.0033
9	0.8318	nan	0.1000	0.0032
10	0.8289	nan	0.1000	0.0026
20	0.8085	nan	0.1000	0.0013
40	0.7879	nan	0.1000	0.0006
60	0.7763	nan	0.1000	0.0004
80	0.7689	nan	0.1000	0.0003
100	0.7635	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8643	nan	0.1000	0.0106
2	0.8555	nan	0.1000	0.0088
3	0.8481	nan	0.1000	0.0069
4	0.8419	nan	0.1000	0.0063
5	0.8362	nan	0.1000	0.0054
6	0.8309	nan	0.1000	0.0052
7	0.8265	nan	0.1000	0.0043
8	0.8226	nan	0.1000	0.0035
9	0.8187	nan	0.1000	0.0037
10	0.8153	nan	0.1000	0.0033
20	0.7912	nan	0.1000	0.0016
40	0.7683	nan	0.1000	0.0006
60	0.7573	nan	0.1000	0.0001
80	0.7502	nan	0.1000	0.0002
100	0.7450	nan	0.1000	-0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8632	nan	0.1000	0.0115
2	0.8530	nan	0.1000	0.0101
3	0.8449	nan	0.1000	0.0076
4	0.8371	nan	0.1000	0.0072
5	0.8307	nan	0.1000	0.0064
6	0.8248	nan	0.1000	0.0056
7	0.8186	nan	0.1000	0.0057
8	0.8137	nan	0.1000	0.0043
9	0.8090	nan	0.1000	0.0045
10	0.8053	nan	0.1000	0.0034
20	0.7797	nan	0.1000	0.0020
40	0.7572	nan	0.1000	0.0002
60	0.7460	nan	0.1000	0.0001
80	0.7392	nan	0.1000	-0.0000
100	0.7328	nan	0.1000	-0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8618	nan	0.1000	0.0125
2	0.8506	nan	0.1000	0.0109
3	0.8417	nan	0.1000	0.0089
4	0.8341	nan	0.1000	0.0073
5	0.8266	nan	0.1000	0.0073

6	0.8205	nan	0.1000	0.0060
7	0.8146	nan	0.1000	0.0055
8	0.8091	nan	0.1000	0.0057
9	0.8044	nan	0.1000	0.0045
10	0.8004	nan	0.1000	0.0036
20	0.7738	nan	0.1000	0.0013
40	0.7513	nan	0.1000	0.0002
60	0.7393	nan	0.1000	0.0005
80	0.7313	nan	0.1000	0.0001
100	0.7239	nan	0.1000	0.0005

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8609	nan	0.1000	0.0136
2	0.8492	nan	0.1000	0.0110
3	0.8390	nan	0.1000	0.0092
4	0.8309	nan	0.1000	0.0077
5	0.8238	nan	0.1000	0.0070
6	0.8173	nan	0.1000	0.0057
7	0.8107	nan	0.1000	0.0061
8	0.8057	nan	0.1000	0.0048
9	0.8012	nan	0.1000	0.0040
10	0.7971	nan	0.1000	0.0035
20	0.7679	nan	0.1000	0.0015
40	0.7441	nan	0.1000	0.0002
60	0.7319	nan	0.1000	0.0003
80	0.7216	nan	0.1000	-0.0001
100	0.7134	nan	0.1000	-0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8715	nan	0.0100	0.0007
2	0.8708	nan	0.0100	0.0007
3	0.8701	nan	0.0100	0.0007
4	0.8694	nan	0.0100	0.0007
5	0.8687	nan	0.0100	0.0006
6	0.8681	nan	0.0100	0.0007
7	0.8674	nan	0.0100	0.0007
8	0.8668	nan	0.0100	0.0006
9	0.8661	nan	0.0100	0.0006
10	0.8655	nan	0.0100	0.0006
20	0.8597	nan	0.0100	0.0005
40	0.8496	nan	0.0100	0.0004
60	0.8412	nan	0.0100	0.0004
80	0.8342	nan	0.0100	0.0003
100	0.8282	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8711	nan	0.0100	0.0011
2	0.8701	nan	0.0100	0.0010
3	0.8691	nan	0.0100	0.0010
4	0.8680	nan	0.0100	0.0010
5	0.8671	nan	0.0100	0.0010
6	0.8662	nan	0.0100	0.0009
7	0.8652	nan	0.0100	0.0010
8	0.8643	nan	0.0100	0.0009
9	0.8635	nan	0.0100	0.0008
10	0.8625	nan	0.0100	0.0009
20	0.8542	nan	0.0100	0.0007
40	0.8410	nan	0.0100	0.0006
60	0.8308	nan	0.0100	0.0004
80	0.8222	nan	0.0100	0.0004
100	0.8151	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8710	nan	0.0100	0.0012
2	0.8698	nan	0.0100	0.0012
3	0.8687	nan	0.0100	0.0012
4	0.8675	nan	0.0100	0.0011
5	0.8664	nan	0.0100	0.0011
6	0.8653	nan	0.0100	0.0010
7	0.8642	nan	0.0100	0.0011
8	0.8631	nan	0.0100	0.0011
9	0.8620	nan	0.0100	0.0010
10	0.8610	nan	0.0100	0.0010
20	0.8516	nan	0.0100	0.0008
40	0.8364	nan	0.0100	0.0006
60	0.8242	nan	0.0100	0.0005
80	0.8143	nan	0.0100	0.0004
100	0.8064	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8709	nan	0.0100	0.0013
2	0.8696	nan	0.0100	0.0013
3	0.8683	nan	0.0100	0.0013

4	0.8671	nan	0.0100	0.0012
5	0.8658	nan	0.0100	0.0011
6	0.8646	nan	0.0100	0.0012
7	0.8634	nan	0.0100	0.0012
8	0.8623	nan	0.0100	0.0012
9	0.8612	nan	0.0100	0.0011
10	0.8600	nan	0.0100	0.0011
20	0.8496	nan	0.0100	0.0009
40	0.8330	nan	0.0100	0.0007
60	0.8199	nan	0.0100	0.0006
80	0.8093	nan	0.0100	0.0004
100	0.8006	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8708	nan	0.0100	0.0014
2	0.8694	nan	0.0100	0.0013
3	0.8681	nan	0.0100	0.0013
4	0.8668	nan	0.0100	0.0013
5	0.8654	nan	0.0100	0.0013
6	0.8641	nan	0.0100	0.0013
7	0.8627	nan	0.0100	0.0013
8	0.8615	nan	0.0100	0.0012
9	0.8602	nan	0.0100	0.0012
10	0.8590	nan	0.0100	0.0011
20	0.8479	nan	0.0100	0.0011
40	0.8299	nan	0.0100	0.0007
60	0.8162	nan	0.0100	0.0005
80	0.8051	nan	0.0100	0.0005
100	0.7962	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8653	nan	0.1000	0.0069
2	0.8595	nan	0.1000	0.0059
3	0.8539	nan	0.1000	0.0053
4	0.8489	nan	0.1000	0.0049
5	0.8448	nan	0.1000	0.0039
6	0.8409	nan	0.1000	0.0040
7	0.8371	nan	0.1000	0.0037
8	0.8337	nan	0.1000	0.0031
9	0.8306	nan	0.1000	0.0030
10	0.8279	nan	0.1000	0.0024
20	0.8074	nan	0.1000	0.0012
40	0.7866	nan	0.1000	0.0006
60	0.7750	nan	0.1000	0.0003
80	0.7673	nan	0.1000	0.0003
100	0.7621	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8621	nan	0.1000	0.0102
2	0.8541	nan	0.1000	0.0078
3	0.8465	nan	0.1000	0.0075
4	0.8403	nan	0.1000	0.0061
5	0.8348	nan	0.1000	0.0051
6	0.8297	nan	0.1000	0.0049
7	0.8250	nan	0.1000	0.0045
8	0.8209	nan	0.1000	0.0036
9	0.8172	nan	0.1000	0.0036
10	0.8139	nan	0.1000	0.0030
20	0.7894	nan	0.1000	0.0018
40	0.7675	nan	0.1000	0.0006
60	0.7558	nan	0.1000	0.0006
80	0.7494	nan	0.1000	0.0002
100	0.7443	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8603	nan	0.1000	0.0114
2	0.8506	nan	0.1000	0.0095
3	0.8427	nan	0.1000	0.0078
4	0.8358	nan	0.1000	0.0067
5	0.8291	nan	0.1000	0.0061
6	0.8237	nan	0.1000	0.0049
7	0.8186	nan	0.1000	0.0049
8	0.8133	nan	0.1000	0.0051
9	0.8096	nan	0.1000	0.0035
10	0.8055	nan	0.1000	0.0037
20	0.7785	nan	0.1000	0.0019
40	0.7571	nan	0.1000	0.0006
60	0.7458	nan	0.1000	0.0003
80	0.7382	nan	0.1000	0.0001
100	0.7322	nan	0.1000	-0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8596	nan	0.1000	0.0124

2	0.8495	nan	0.1000	0.0102
3	0.8400	nan	0.1000	0.0091
4	0.8319	nan	0.1000	0.0075
5	0.8250	nan	0.1000	0.0063
6	0.8187	nan	0.1000	0.0059
7	0.8128	nan	0.1000	0.0058
8	0.8080	nan	0.1000	0.0045
9	0.8035	nan	0.1000	0.0042
10	0.7990	nan	0.1000	0.0040
20	0.7722	nan	0.1000	0.0021
40	0.7496	nan	0.1000	0.0005
60	0.7369	nan	0.1000	0.0002
80	0.7289	nan	0.1000	0.0001
100	0.7217	nan	0.1000	0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8585	nan	0.1000	0.0131
2	0.8470	nan	0.1000	0.0111
3	0.8368	nan	0.1000	0.0094
4	0.8289	nan	0.1000	0.0076
5	0.8214	nan	0.1000	0.0072
6	0.8153	nan	0.1000	0.0057
7	0.8102	nan	0.1000	0.0046
8	0.8047	nan	0.1000	0.0051
9	0.8006	nan	0.1000	0.0042
10	0.7965	nan	0.1000	0.0039
20	0.7677	nan	0.1000	0.0019
40	0.7433	nan	0.1000	0.0006
60	0.7315	nan	0.1000	0.0002
80	0.7218	nan	0.1000	0.0001
100	0.7139	nan	0.1000	-0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8674	nan	0.0100	0.0007
2	0.8666	nan	0.0100	0.0007
3	0.8659	nan	0.0100	0.0007
4	0.8652	nan	0.0100	0.0007
5	0.8645	nan	0.0100	0.0007
6	0.8638	nan	0.0100	0.0007
7	0.8632	nan	0.0100	0.0007
8	0.8625	nan	0.0100	0.0007
9	0.8619	nan	0.0100	0.0006
10	0.8612	nan	0.0100	0.0006
20	0.8554	nan	0.0100	0.0005
40	0.8455	nan	0.0100	0.0004
60	0.8373	nan	0.0100	0.0004
80	0.8304	nan	0.0100	0.0003
100	0.8245	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8670	nan	0.0100	0.0011
2	0.8659	nan	0.0100	0.0011
3	0.8648	nan	0.0100	0.0010
4	0.8638	nan	0.0100	0.0010
5	0.8628	nan	0.0100	0.0010
6	0.8619	nan	0.0100	0.0009
7	0.8609	nan	0.0100	0.0009
8	0.8599	nan	0.0100	0.0010
9	0.8590	nan	0.0100	0.0009
10	0.8581	nan	0.0100	0.0009
20	0.8499	nan	0.0100	0.0008
40	0.8368	nan	0.0100	0.0006
60	0.8265	nan	0.0100	0.0005
80	0.8180	nan	0.0100	0.0004
100	0.8109	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8669	nan	0.0100	0.0012
2	0.8658	nan	0.0100	0.0012
3	0.8646	nan	0.0100	0.0011
4	0.8635	nan	0.0100	0.0011
5	0.8624	nan	0.0100	0.0011
6	0.8613	nan	0.0100	0.0011
7	0.8602	nan	0.0100	0.0011
8	0.8590	nan	0.0100	0.0011
9	0.8580	nan	0.0100	0.0010
10	0.8570	nan	0.0100	0.0010
20	0.8476	nan	0.0100	0.0009
40	0.8324	nan	0.0100	0.0006
60	0.8207	nan	0.0100	0.0005
80	0.8108	nan	0.0100	0.0004
100	0.8027	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8669	nan	0.0100	0.0012
2	0.8656	nan	0.0100	0.0012
3	0.8644	nan	0.0100	0.0012
4	0.8632	nan	0.0100	0.0012
5	0.8620	nan	0.0100	0.0012
6	0.8607	nan	0.0100	0.0012
7	0.8595	nan	0.0100	0.0012
8	0.8583	nan	0.0100	0.0011
9	0.8571	nan	0.0100	0.0011
10	0.8560	nan	0.0100	0.0011
20	0.8457	nan	0.0100	0.0009
40	0.8291	nan	0.0100	0.0007
60	0.8160	nan	0.0100	0.0006
80	0.8057	nan	0.0100	0.0004
100	0.7971	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8667	nan	0.0100	0.0014
2	0.8654	nan	0.0100	0.0013
3	0.8640	nan	0.0100	0.0014
4	0.8626	nan	0.0100	0.0013
5	0.8613	nan	0.0100	0.0013
6	0.8601	nan	0.0100	0.0012
7	0.8588	nan	0.0100	0.0012
8	0.8575	nan	0.0100	0.0012
9	0.8564	nan	0.0100	0.0012
10	0.8551	nan	0.0100	0.0012
20	0.8442	nan	0.0100	0.0010
40	0.8264	nan	0.0100	0.0007
60	0.8127	nan	0.0100	0.0006
80	0.8017	nan	0.0100	0.0004
100	0.7927	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8612	nan	0.1000	0.0072
2	0.8554	nan	0.1000	0.0057
3	0.8498	nan	0.1000	0.0053
4	0.8450	nan	0.1000	0.0047
5	0.8407	nan	0.1000	0.0042
6	0.8366	nan	0.1000	0.0039
7	0.8332	nan	0.1000	0.0031
8	0.8297	nan	0.1000	0.0032
9	0.8267	nan	0.1000	0.0031
10	0.8237	nan	0.1000	0.0029
20	0.8036	nan	0.1000	0.0014
40	0.7831	nan	0.1000	0.0007
60	0.7717	nan	0.1000	0.0003
80	0.7641	nan	0.1000	0.0002
100	0.7590	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8576	nan	0.1000	0.0101
2	0.8491	nan	0.1000	0.0084
3	0.8422	nan	0.1000	0.0068
4	0.8364	nan	0.1000	0.0058
5	0.8314	nan	0.1000	0.0047
6	0.8268	nan	0.1000	0.0043
7	0.8225	nan	0.1000	0.0039
8	0.8179	nan	0.1000	0.0043
9	0.8144	nan	0.1000	0.0034
10	0.8109	nan	0.1000	0.0033
20	0.7874	nan	0.1000	0.0015
40	0.7643	nan	0.1000	0.0007
60	0.7540	nan	0.1000	0.0002
80	0.7470	nan	0.1000	0.0000
100	0.7413	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8565	nan	0.1000	0.0112
2	0.8470	nan	0.1000	0.0094
3	0.8391	nan	0.1000	0.0076
4	0.8323	nan	0.1000	0.0064
5	0.8258	nan	0.1000	0.0061
6	0.8207	nan	0.1000	0.0049
7	0.8155	nan	0.1000	0.0049
8	0.8106	nan	0.1000	0.0046
9	0.8061	nan	0.1000	0.0040
10	0.8020	nan	0.1000	0.0039
20	0.7763	nan	0.1000	0.0018
40	0.7540	nan	0.1000	0.0005
60	0.7429	nan	0.1000	-0.0000
80	0.7357	nan	0.1000	-0.0000

100	0.7297	nan	0.1000	-0.0000
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Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8556	nan	0.1000	0.0124
2	0.8450	nan	0.1000	0.0101
3	0.8361	nan	0.1000	0.0083
4	0.8280	nan	0.1000	0.0079
5	0.8215	nan	0.1000	0.0062
6	0.8149	nan	0.1000	0.0066
7	0.8089	nan	0.1000	0.0052
8	0.8041	nan	0.1000	0.0044
9	0.7997	nan	0.1000	0.0040
10	0.7955	nan	0.1000	0.0040
20	0.7698	nan	0.1000	0.0015
40	0.7451	nan	0.1000	0.0008
60	0.7334	nan	0.1000	0.0001
80	0.7257	nan	0.1000	0.0000
100	0.7190	nan	0.1000	-0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8549	nan	0.1000	0.0130
2	0.8433	nan	0.1000	0.0108
3	0.8337	nan	0.1000	0.0095
4	0.8254	nan	0.1000	0.0077
5	0.8182	nan	0.1000	0.0067
6	0.8123	nan	0.1000	0.0060
7	0.8065	nan	0.1000	0.0050
8	0.8009	nan	0.1000	0.0057
9	0.7958	nan	0.1000	0.0046
10	0.7916	nan	0.1000	0.0040
20	0.7641	nan	0.1000	0.0017
40	0.7399	nan	0.1000	0.0003
60	0.7277	nan	0.1000	0.0002
80	0.7187	nan	0.1000	-0.0000
100	0.7104	nan	0.1000	0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8630	nan	0.0100	0.0008
2	0.8622	nan	0.0100	0.0007
3	0.8615	nan	0.0100	0.0007
4	0.8608	nan	0.0100	0.0007
5	0.8601	nan	0.0100	0.0007
6	0.8594	nan	0.0100	0.0007
7	0.8588	nan	0.0100	0.0006
8	0.8581	nan	0.0100	0.0007
9	0.8574	nan	0.0100	0.0006
10	0.8568	nan	0.0100	0.0006
20	0.8509	nan	0.0100	0.0005
40	0.8407	nan	0.0100	0.0004
60	0.8324	nan	0.0100	0.0004
80	0.8254	nan	0.0100	0.0003
100	0.8193	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8626	nan	0.0100	0.0011
2	0.8615	nan	0.0100	0.0011
3	0.8605	nan	0.0100	0.0011
4	0.8595	nan	0.0100	0.0010
5	0.8585	nan	0.0100	0.0010
6	0.8576	nan	0.0100	0.0008
7	0.8566	nan	0.0100	0.0010
8	0.8556	nan	0.0100	0.0010
9	0.8547	nan	0.0100	0.0009
10	0.8538	nan	0.0100	0.0009
20	0.8455	nan	0.0100	0.0007
40	0.8321	nan	0.0100	0.0005
60	0.8216	nan	0.0100	0.0004
80	0.8133	nan	0.0100	0.0004
100	0.8061	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8625	nan	0.0100	0.0012
2	0.8613	nan	0.0100	0.0012
3	0.8601	nan	0.0100	0.0012
4	0.8589	nan	0.0100	0.0012
5	0.8577	nan	0.0100	0.0012
6	0.8566	nan	0.0100	0.0011
7	0.8555	nan	0.0100	0.0011
8	0.8544	nan	0.0100	0.0010
9	0.8534	nan	0.0100	0.0010
10	0.8523	nan	0.0100	0.0010
20	0.8427	nan	0.0100	0.0008
40	0.8276	nan	0.0100	0.0006

60	0.8155	nan	0.0100	0.0005
80	0.8057	nan	0.0100	0.0004
100	0.7974	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8624	nan	0.0100	0.0013
2	0.8610	nan	0.0100	0.0013
3	0.8597	nan	0.0100	0.0013
4	0.8584	nan	0.0100	0.0013
5	0.8571	nan	0.0100	0.0012
6	0.8559	nan	0.0100	0.0012
7	0.8547	nan	0.0100	0.0012
8	0.8535	nan	0.0100	0.0012
9	0.8524	nan	0.0100	0.0011
10	0.8513	nan	0.0100	0.0011
20	0.8409	nan	0.0100	0.0009
40	0.8241	nan	0.0100	0.0007
60	0.8110	nan	0.0100	0.0006
80	0.8006	nan	0.0100	0.0004
100	0.7919	nan	0.0100	0.0003

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8623	nan	0.0100	0.0014
2	0.8609	nan	0.0100	0.0013
3	0.8595	nan	0.0100	0.0013
4	0.8582	nan	0.0100	0.0013
5	0.8569	nan	0.0100	0.0013
6	0.8556	nan	0.0100	0.0013
7	0.8543	nan	0.0100	0.0013
8	0.8531	nan	0.0100	0.0012
9	0.8518	nan	0.0100	0.0012
10	0.8506	nan	0.0100	0.0012
20	0.8395	nan	0.0100	0.0010
40	0.8214	nan	0.0100	0.0008
60	0.8076	nan	0.0100	0.0005
80	0.7963	nan	0.0100	0.0005
100	0.7870	nan	0.0100	0.0004

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8566	nan	0.1000	0.0072
2	0.8508	nan	0.1000	0.0059
3	0.8455	nan	0.1000	0.0053
4	0.8407	nan	0.1000	0.0046
5	0.8364	nan	0.1000	0.0043
6	0.8324	nan	0.1000	0.0041
7	0.8288	nan	0.1000	0.0034
8	0.8254	nan	0.1000	0.0032
9	0.8224	nan	0.1000	0.0027
10	0.8195	nan	0.1000	0.0025
20	0.7986	nan	0.1000	0.0013
40	0.7780	nan	0.1000	0.0007
60	0.7665	nan	0.1000	0.0003
80	0.7589	nan	0.1000	0.0002
100	0.7535	nan	0.1000	0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8534	nan	0.1000	0.0106
2	0.8445	nan	0.1000	0.0086
3	0.8371	nan	0.1000	0.0068
4	0.8308	nan	0.1000	0.0060
5	0.8256	nan	0.1000	0.0052
6	0.8202	nan	0.1000	0.0051
7	0.8161	nan	0.1000	0.0040
8	0.8117	nan	0.1000	0.0039
9	0.8082	nan	0.1000	0.0033
10	0.8046	nan	0.1000	0.0033
20	0.7806	nan	0.1000	0.0017
40	0.7581	nan	0.1000	0.0007
60	0.7473	nan	0.1000	0.0003
80	0.7403	nan	0.1000	0.0006
100	0.7348	nan	0.1000	0.0000

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8524	nan	0.1000	0.0117
2	0.8426	nan	0.1000	0.0092
3	0.8342	nan	0.1000	0.0078
4	0.8268	nan	0.1000	0.0070
5	0.8207	nan	0.1000	0.0060
6	0.8147	nan	0.1000	0.0059
7	0.8092	nan	0.1000	0.0051
8	0.8049	nan	0.1000	0.0041
9	0.8007	nan	0.1000	0.0039
10	0.7963	nan	0.1000	0.0042

20	0.7703	nan	0.1000	0.0015
40	0.7476	nan	0.1000	0.0004
60	0.7364	nan	0.1000	0.0001
80	0.7282	nan	0.1000	0.0004
100	0.7221	nan	0.1000	-0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8506	nan	0.1000	0.0129
2	0.8396	nan	0.1000	0.0105
3	0.8306	nan	0.1000	0.0085
4	0.8225	nan	0.1000	0.0079
5	0.8159	nan	0.1000	0.0064
6	0.8092	nan	0.1000	0.0063
7	0.8045	nan	0.1000	0.0047
8	0.7997	nan	0.1000	0.0048
9	0.7949	nan	0.1000	0.0043
10	0.7906	nan	0.1000	0.0041
20	0.7636	nan	0.1000	0.0015
40	0.7400	nan	0.1000	0.0007
60	0.7289	nan	0.1000	-0.0000
80	0.7204	nan	0.1000	-0.0002
100	0.7137	nan	0.1000	0.0002

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8496	nan	0.1000	0.0135
2	0.8375	nan	0.1000	0.0112
3	0.8280	nan	0.1000	0.0095
4	0.8198	nan	0.1000	0.0078
5	0.8124	nan	0.1000	0.0071
6	0.8062	nan	0.1000	0.0057
7	0.8010	nan	0.1000	0.0049
8	0.7961	nan	0.1000	0.0046
9	0.7912	nan	0.1000	0.0043
10	0.7862	nan	0.1000	0.0046
20	0.7574	nan	0.1000	0.0013
40	0.7350	nan	0.1000	0.0004
60	0.7225	nan	0.1000	0.0001
80	0.7129	nan	0.1000	-0.0001
100	0.7048	nan	0.1000	-0.0001

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	0.8555	nan	0.1000	0.0133
2	0.8444	nan	0.1000	0.0107
3	0.8349	nan	0.1000	0.0095
4	0.8261	nan	0.1000	0.0087
5	0.8189	nan	0.1000	0.0073
6	0.8125	nan	0.1000	0.0059
7	0.8061	nan	0.1000	0.0063
8	0.8013	nan	0.1000	0.0044
9	0.7963	nan	0.1000	0.0045
10	0.7919	nan	0.1000	0.0044
20	0.7639	nan	0.1000	0.0018
40	0.7398	nan	0.1000	0.0002
60	0.7268	nan	0.1000	0.0004
80	0.7186	nan	0.1000	0.0000
100	0.7113	nan	0.1000	0.0001

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gbm

Stochastic Gradient Boosting

31716 samples
44 predictor

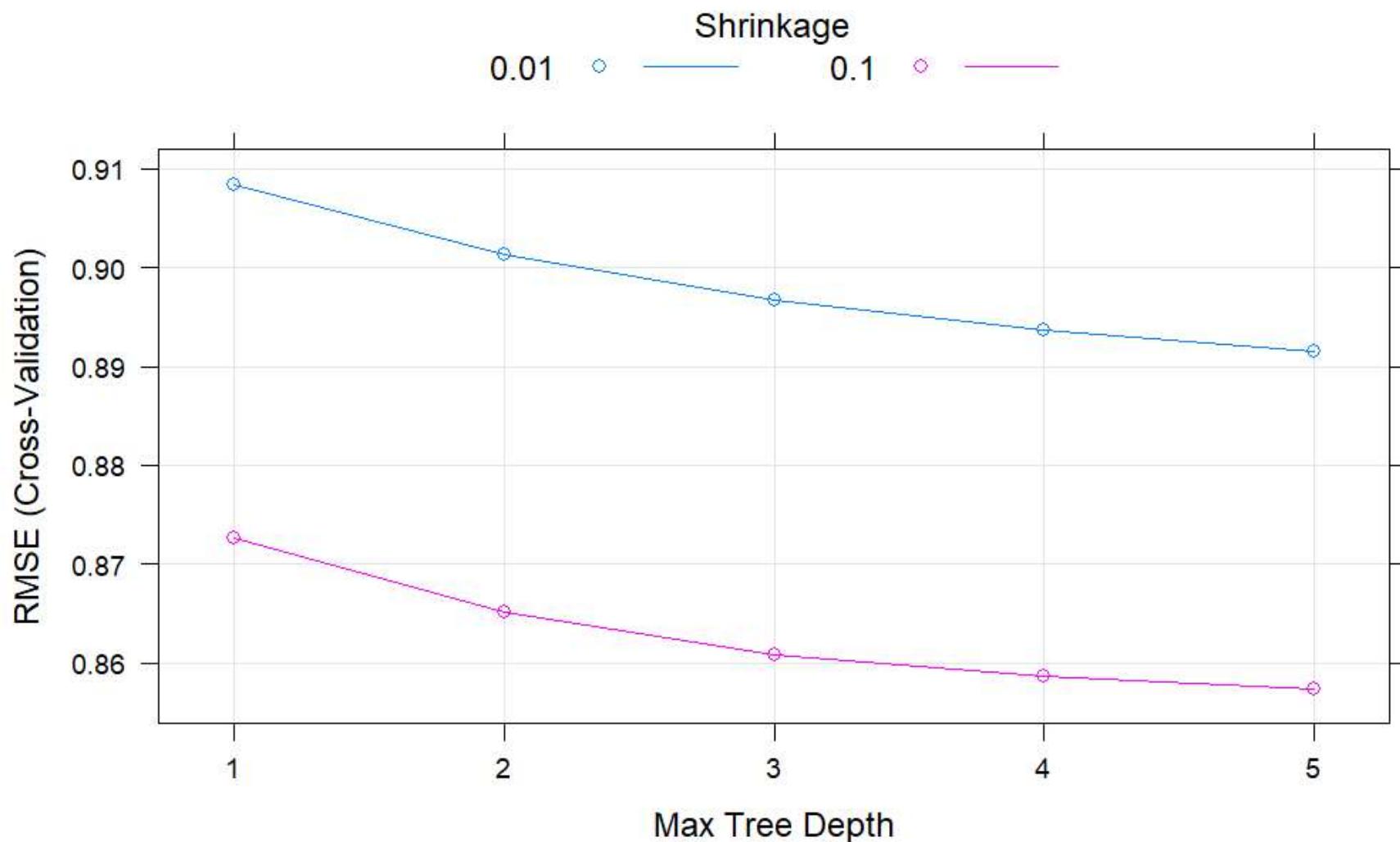
Pre-processing: centered (44), scaled (44)
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 28545, 28543, 28544, 28545, 28545, 28543, ...
Resampling results across tuning parameters:

shrinkage	interaction.depth	RMSE	Rquared	MAE
0.01	1	0.9083963	0.08445183	0.6855248
0.01	2	0.9012932	0.09478318	0.6790713
0.01	3	0.8966554	0.10567896	0.6742977
0.01	4	0.8936561	0.11116160	0.6713627
0.01	5	0.8914927	0.11522411	0.6690840
0.10	1	0.8726627	0.12823473	0.6497059
0.10	2	0.8651327	0.14071612	0.6416147
0.10	3	0.8608702	0.14864414	0.6381675
0.10	4	0.8586408	0.15283182	0.6358339
0.10	5	0.8573851	0.15501048	0.6346975

Tuning parameter 'n.trees' was held constant at a value of 100
Tuning parameter 'n.minobsinnode' was held constant at a value of 10
RMSE was used to select the optimal model using the smallest value.
The final values used for the model were n.trees = 100, interaction.depth = 5, shrinkage = 0.1 and n.minobsinnode = 10.

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```
plot(gbm)
```



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```
pred.gbm <- predict(gbm, X.test)
resid.gbm <- y.test - pred.gbm
rmse(y.test, pred.gbm)
```

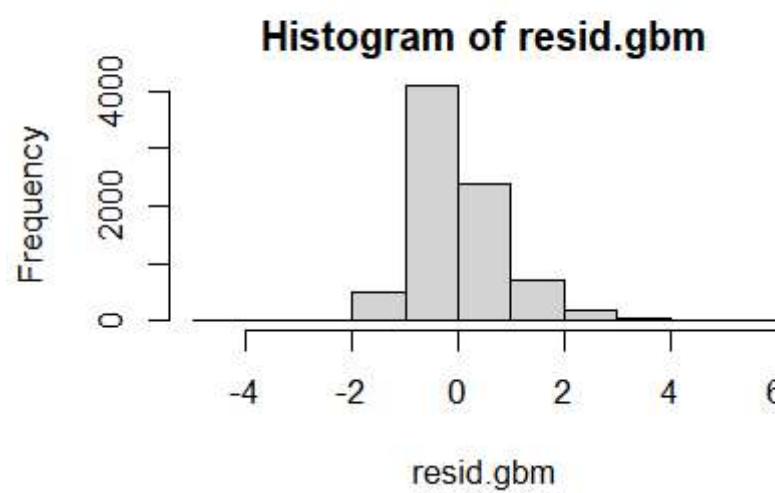
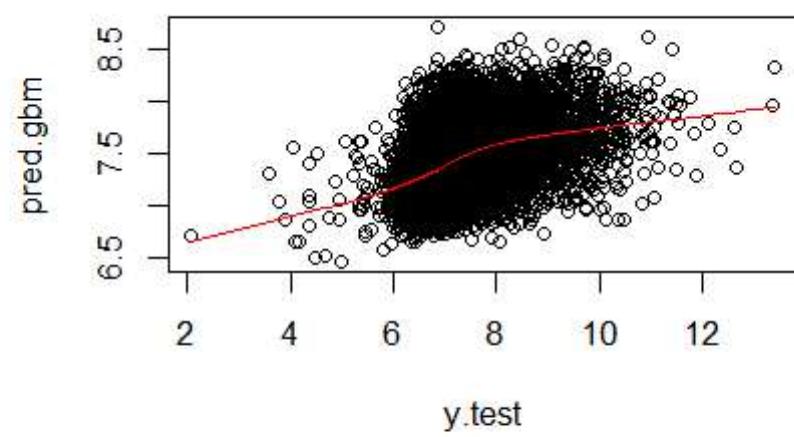
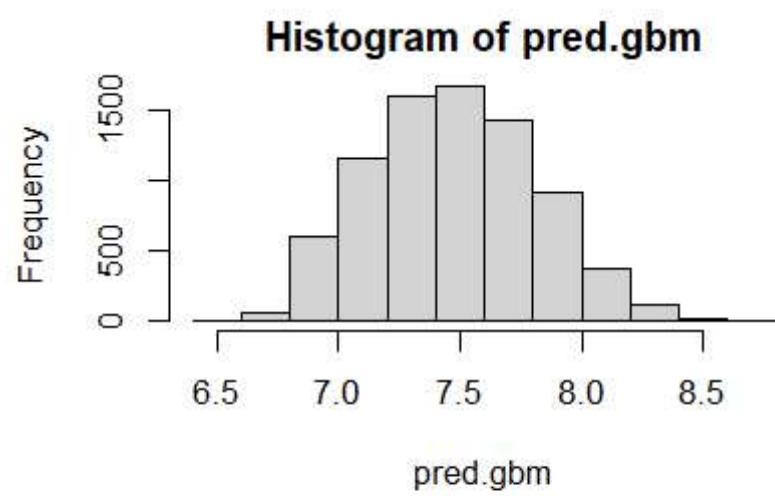
```
[1] 0.8479553
```

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```
par(mfrow = c(2, 2))
hist(pred.gbm)
plot(y.test, pred.gbm)
```

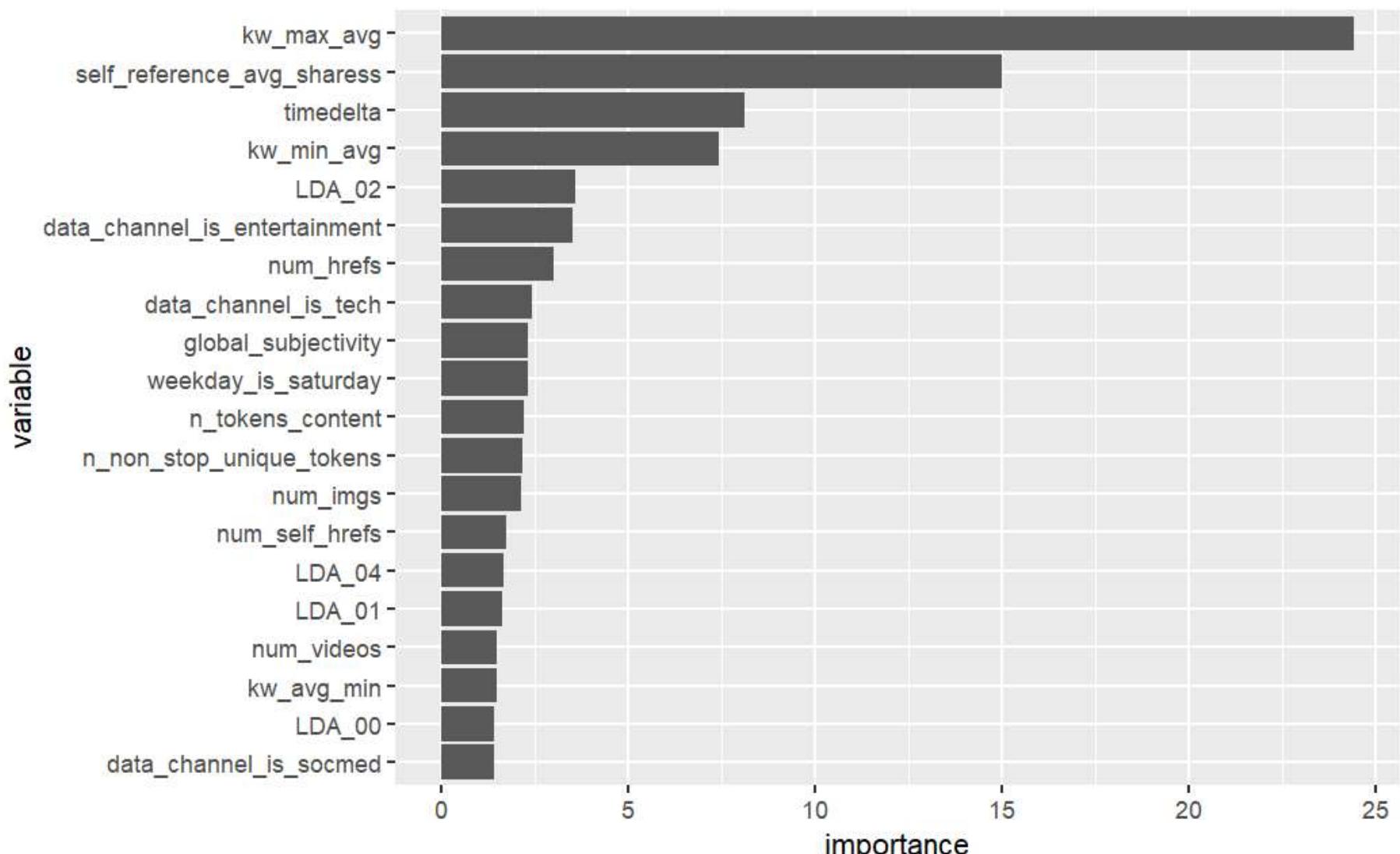
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```
lines(lowess(y.test, pred.gbm), col = "red")
hist(resid.gbm)
```



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```
library(gbm)
gbm.imp <- summary.gbm(gbm$finalModel, plotit = FALSE)[1:20, ]
names(gbm.imp) <- c("variable", "importance")
gbm.imp.df <- gbm.imp %>%
  dplyr::arrange(importance) %>%
  dplyr::mutate(variable = forcats::fct_inorder(variable))
ggplot(gbm.imp.df) +
  geom_col(aes(x = variable, y = importance)) +
  coord_flip()
```



Compare Model Performance

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```
# function to calculate R-squared
r.squared <- function(actual, predicted) {
  actual.mean <- mean(actual)
  RSS <- sum((actual - predicted)^2)
  TSS <- sum((actual - actual.mean)^2)
  R2 <- 1 - (RSS/TSS)
  return(R2)
}
```

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```

# create dataframe to contain all model results
models <- c("enet", "pcr", "pls", "knn", "cart", "gbm")
results <- data.frame(row.names = models)
results$RMSE.cv <- NA
results$RMSE.cv.sd <- NA
results$RMSE.test <- NA
results$Rsquared.cv <- NA
results$Rsquared.cv.sd <- NA
results$Rsquared.test <- NA

# add enet results
results.enet <- enet$results %>%
  filter(lambda == enet$bestTune$lambda & fraction == enet$bestTune$fraction) %>%
  select(RMSE, RMSESD, Rsquared, RsquaredSD)

results["enet", "RMSE.cv"] <- results.enet$RMSE
results["enet", "RMSE.cv.sd"] <- results.enet$RMSESD
results["enet", "RMSE.test"] <- rmse(y.test, pred.enet)
results["enet", "Rsquared.cv"] <- results.enet$Rsquared
results["enet", "Rsquared.cv.sd"] <- results.enet$RsquaredSD
results["enet", "Rsquared.test"] <- r.squared(y.test, pred.enet)

# add PCR results
results.pcr <- pcr$results %>%
  filter(ncomp == pcr$bestTune$ncomp) %>%
  select(RMSE, RMSESD, Rsquared, RsquaredSD)

results["pcr", "RMSE.cv"] <- results.pcr$RMSE
results["pcr", "RMSE.cv.sd"] <- results.pcr$RMSESD
results["pcr", "RMSE.test"] <- rmse(y.test, pred.pcr)
results["pcr", "Rsquared.cv"] <- results.pcr$Rsquared
results["pcr", "Rsquared.cv.sd"] <- results.pcr$RsquaredSD
results["pcr", "Rsquared.test"] <- r.squared(y.test, pred.pcr)

# add PLS results
results.pls <- pls$results %>%
  filter(ncomp == pls$bestTune$ncomp) %>%
  select(RMSE, RMSESD, Rsquared, RsquaredSD)

results["pls", "RMSE.cv"] <- results.pls$RMSE
results["pls", "RMSE.cv.sd"] <- results.pls$RMSESD
results["pls", "RMSE.test"] <- rmse(y.test, pred.pls)
results["pls", "Rsquared.cv"] <- results.pls$Rsquared
results["pls", "Rsquared.cv.sd"] <- results.pls$RsquaredSD
results["pls", "Rsquared.test"] <- r.squared(y.test, pred.pls)

# add KNN results
results.knn <- knn$results %>%
  filter(k == knn$bestTune$k) %>%
  select(RMSE, RMSESD, Rsquared, RsquaredSD)

results["knn", "RMSE.cv"] <- results.knn$RMSE
results["knn", "RMSE.cv.sd"] <- results.knn$RMSESD
results["knn", "RMSE.test"] <- rmse(y.test, pred.knn)
results["knn", "Rsquared.cv"] <- results.knn$Rsquared
results["knn", "Rsquared.cv.sd"] <- results.knn$RsquaredSD
results["knn", "Rsquared.test"] <- r.squared(y.test, pred.knn)

# add CART results
results.cart <- cart$results %>%
  filter(cp == cart$bestTune$cp) %>%
  select(RMSE, RMSESD, Rsquared, RsquaredSD)

results["cart", "RMSE.cv"] <- results.cart$RMSE
results["cart", "RMSE.cv.sd"] <- results.cart$RMSESD
results["cart", "RMSE.test"] <- rmse(y.test, pred.cart)
results["cart", "Rsquared.cv"] <- results.cart$Rsquared
results["cart", "Rsquared.cv.sd"] <- results.cart$RsquaredSD
results["cart", "Rsquared.test"] <- r.squared(y.test, pred.cart)

# add GBM results
results.gbm <- gbm$results %>%
  filter(shrinkage == gbm$bestTune$shrinkage & interaction.depth == gbm$bestTune$interaction.depth) %>%
  select(RMSE, RMSESD, Rsquared, RsquaredSD)

results["gbm", "RMSE.cv"] <- results.gbm$RMSE
results["gbm", "RMSE.cv.sd"] <- results.gbm$RMSESD
results["gbm", "RMSE.test"] <- rmse(y.test, pred.gbm)
results["gbm", "Rsquared.cv"] <- results.gbm$Rsquared
results["gbm", "Rsquared.cv.sd"] <- results.gbm$RsquaredSD
results["gbm", "Rsquared.test"] <- r.squared(y.test, pred.gbm)

results

```

	RMSE.cv <dbl>	RMSE.cv.sd <dbl>	RMSE.test <dbl>	Rsquared.cv <dbl>	Rsquared.cv.sd <dbl>	Rsquared.test <dbl>
enet	0.8864478	0.021979139	0.8736786	0.09719415	0.016801650	0.10398836
pcr	0.9506298	0.084007318	0.9152851	0.01371925	0.006115983	0.01661621
pls	0.9061434	0.074589273	0.8735161	0.09218942	0.028958196	0.10432158
knn	0.9062993	0.019273590	0.9015301	0.08204549	0.009945894	0.04595076
cart	0.8924639	0.007097887	0.8773104	0.08998393	0.006609173	0.09652342
gbm	0.8573851	0.017649409	0.8479553	0.15501048	0.010350722	0.15597315

6 rows