# Predicting the Popularity of Mashable.com News Articles

Josh Wilder, Chi-Hua Wu, Vicky Pang, Akshay Pokharkar, Anant Khandelwal

University of Connecticut

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Professor Jennifer Eigo

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## Executive Summary

For online news companies like Mashable to succeed, they need to determine patterns and trends that contribute to the popularity of their models. Our goal was to create and develop a model predicting which Mashable articles were widely shared on social networks based on several features of online news. Based on the results, we determined which variables would contribute toward future content creations having a broader reach on social media through organic sharing.

Our business insights and recommendations for Mashable are based on our logistic regression model, which was implemented on a dataset built using stratified undersampling. This model provides many insights and recommendations that will help Mashable improve their business. These insights include the impact of image insertions, article categorization, keyword strength, and article release day. We then conclude with direction and specific actions Mashable could take to improve their articles' virality.

## Problem Statement

Mashable is a global, multi-platform media and entertainment company, and they post articles of multiple genres online from which they earn revenue from advertisers. For companies like Mashable to succeed, they must be aware of the trends within their successful articles. Without learning these trends, a company like Mashable may fail against competitors who also use data-driven strategy. Therefore, it is imperative to understand and predict what article characteristics are most appealing to readers.

Our solution to this problem involves predicting which articles are widely shared on social media. Shares on social media is a key metric for article virality, and the specific business insight we are looking for is which factors lead to higher article virality. This is very significant for business because it results in more article views without requiring paid marketing.

## Dataset Introduction

The dataset is called "Online News Popularity Data Set" and it can be accessed from UCI Machine Learning Repository (https://archive.ics.uci.edu). Each row represents a news article and was collected from January 7, 2013 to January 7, 2015. There are 39,797 rows and 61 columns as shown in the Appendix Table 1. The original dataset contained 37 attributes of articles, and several natural language processing features were extracted by previous researchers (Fernandes, Vinagre & Cortez, 2015). In this study, 17 selected predictors are used to build models.

## Methodology

The methodology of this study is followed by SEMMA. SEMMA stands for Sample, Explore, Modify, Models, and Assess (Shmueli, Bruce, Stephens & Patel, 2017, p. 18). During this process, our data visualizations were created by both Tableau and JMP software, and the models were built via JMP software.

### Sample

In the Sample section, the dataset was partitioned into 50% training, 30% validation, and 20% testing set split. The partition was created by JMP (with the fixed random seed of 1234). The training set was used for building models, the validation set was used for accessing the model to avoid overfitting problems, and the test set was used for selecting the best model. However, the results of data visualization showed that this dataset is imbalanced, and we later used undersampling to resolve this problem.

### Explore

During data exploration, we discovered anticipated and unanticipated relationships between variables. We began our data exploration focusing on our target variable, "shares." We then continued to use visualizations on all of our data to detect outliers, missing values, abnormal features, and highly correlated predictors.

**1. The Distribution of Shares**

The distribution of shares resembles a Johnson Su distribution, as shown in Appendix **Figure 1**. This distribution was very skewed. Although the majority of the articles have between 1,000 and 3,000 shares, there are thousands of articles with over 10,000 shares, and the highest shared articles had hundreds of thousands of shares. The mean number of shares were over double the median, which is a sign that the distribution was very skewed to the right. Please see Appendix **Figure 2**. We determined that this distribution was a problem because we would expect models like linear regression to be very sensitive, but wildly inaccurate with very highly shared articles. On the other hand, very highly shared articles were the most important in terms of business results, so keeping them in the data is desirable.

**2. The Correlations Between Variables.**

As the color maps of correlation shows in Appendix **Figure 3**, several variables had high correlations. This meant that they provided similar or overlapping information that could be overly repetitive during the prediction of a target variable. These variables often were similar in meaning, for example, “self_reference_max_shares”, “self_reference_min_shares”, and “self_reference_avg_shares,” whose correlations were near 1.

**3. Missing Values and Outliers.**

As shown in Appendix **Figure 4** (the portion of the scatterplot Matrix), there was a row with abnormally high values for multiple attributes. This included values above 1 for variables that are meant to rate from 0 to 1. In the next section, we detected and excluded them to prevent these extreme values from impairing our modeling.

There are 1181 rows which contained a large portion of zero values in “n_token_content” to “average_token_length”, “self_reference” related variables, and “global_subjectivity” to “max_negative_polarity.” These zeroes suggest, for example, that these articles have no words. Viewing a handful of these articles allowed us to confirm our suspicion that these articles did have words, and there was a flaw in data collection. Therefore, we viewed these rows as ones containing missing values.

## Modify

Using exploratory analysis and visualizations, we found high values that were considered potential outliers. This section would include statistical methods used to detect outliers. This section would also include data preprocessing, undersampling, and variable selection.

### 1. Excluding Missing Data.

Although no data was “missing” as represented by a dot in JMP, this dataset did contain missing data. As shown in Appendix **Figure 5**, we found rows that had zeros in multiple columns. Our challenge was differentiating between zeroes that genuinely represented zeros and zeroes that were missing data. After checking a couple of articles to make sure that there weren't wordless video articles, we went ahead and deleted all rows, which had zero in the column. We continued to do this analysis for multiple columns, and some of which included missing data as -1’s instead of zeros (over 2,000 rows were excluded). One downfall of our strategy was that we deleted rows based on missing data in columns that we later deleted. However, we did our best to un-exclude rows that could be used after excluding the problem columns, but this procedure became tedious to do each time. The minor impact on our results would not have been worthwhile.

### 2. Excluding Outliers.

Since the popularity of news varies, we applied JMP's interquartile range outlier detection technique to examine our data, setting tail quantile equal to 0.1 and Q equal to 10. The results are shown in Appendix **Figure 6**. It showed that there were three variables that contained wrong data, "N_tokens_content", "non_stop_words", and "n_non_stop_unique_tokens." These are variables that should be rates between 0 and 1, and values outside of this range are invalid data. Our analysis determined that these invalid values are outliers and we excluded them.

### 3. Principal Component Analysis.

As is shown in the correlations color map, the keyword-related variables had both positive and negative relationships with each other. We then applied principal component analysis to reduce the number of variables. We decided to use three components to represent six similar variables because the three components cumulatively capture 84.5% of the six variables' information. Detailed technical results are shown in Appendix Figure 7.

### 4. Combined Dummy Variables into One Categorical Variable.

JMP software handles united categorical variables as a unit. Our dataset initially had several separate dummy variables that JMP inaccurately handled as unrelated categories during modeling. As seen in Appendix **Figure 8**, we used the formula in JMP to create the integrated categorical variable.

### 5. Creating an Alternate Decision Variable.

After observing the skewness of the distribution for shares, we considered altering our response column. We also considered a slight reframing of our business goal, would it make more sense to predict the number of shares that each article gets or should we predict a group of articles that would account for a disproportionality high number of shares? Attempting to determine the feasibility of the second idea, we created a column with a binary response where a 1 is an article which had at least 2900 shares. This came out to be the top 24% most shared articles, and they accounted for 71.68% of the total shares of all Mashable articles on social media. Based on this data exploration, we decided it would make sense (in terms of our business problem) to focus on this group of valuable articles. We created "IsAtLeast2900Shares" and used it as our target variable. The formula is as shown in Appendix **Figure 9**.

**6. Variable Selection.**

The results of Natural Language Processing usually depend on the researcher's interpretation and programming methods. Since a large portion of our dataset consisted of natural language processing based variables, we decided to limit the amount we used in our modeling. These variables were hard to interpret as documentation regarding their exact meaning was unavailable. Based on the results in data exploration and our best business judgement, we chose variables that were unique and descriptive. **Table 2** in the Appendix contains the variables we selected for building models.

**7. Undersampling.**

The unbalanced proportion in shares over 2900 and less caused the model to predict the class with a large proportion. We undersampled to create a 50/50 balanced proportion of 1's and 0's in the response column (in the training and validation data). We used this dataset to build and tune most of our models. The proportion of the data can be found in Appendix **Figure 10**.

## Models

Moving forward, we created our models, which were used to predict which articles had at least 2900 shares. We used Logistic Regression, Decision Tree, Bootstrap Forest, Boosted Tree, K-Nearest Neighbors, Neural Network, and Discriminant Analysis models. We tuned each of these models based on accuracy or error statistics regarding the validation set that were readily available in JMP.

### 1. Logistic Regression.

After our original variable selection, we reduced the numbers of predicting variables by implementing stepwise selection. Regardless of whether we used forward, backward, or mixed selection, the same 17 of the 22 considered variables were always chosen, counting each category of the categorical variable "data channel" as separate variables. We conducted stepwise selection using Max Validation R-Square as the stopping rule when possible but based on p-values otherwise. The results can be seen in Appendix **Figure 11**.

Since we were dealing with a “rare event” problem, we decided to use a stratified undersampling dataset to see if it would improve our logistic regression model. We built this second model using the same stepwise selection process. As shown in Appendix **Figure 12**, the model outperformed our original logistic regression (model comparison is explained in ASSESS section).

Although we acknowledged that this was insufficient evidence to prove that stratified undersampling would improve all of our models, we decided to build the rest of our models on the dataset we built using stratified undersampling, because of the improvement we saw here. A second reason for this choice was that it would eliminate the need for using alternate cutoffs for each model.

### 2. Decision Tree.

We tried a decision tree on the original dataset, but it found less than ten true positives. This section would detail the decision tree implemented on the stratified dataset, and both models used “IsAtLeast2900Shares” as the target variable. During splitting and pruning, we found that the optimal number of splits were 12, achieving the best possible validation R-square, of 0.1037. Screenshots of these models can be found in the Appendix **Figure 13**.

**3. Bootstrap Forest.**

As single trees may not have great predictive ability, we combined results from multiple trees to improve the performance. The multi-tree approach that we used was the Bootstrap Forest technique. This method had a lesser chance of overfitting and was not sensitive to outliers. We proceeded with 50 to 100 to 1000 of trees, and later found that 50 trees showed that the accuracy was lower. For 100 trees, the accuracy was higher and any trees larger than 100 almost yielded the same results. As shown in Appendix **Figure 14**, the results we obtained from 100 trees were as follows: RMSE = 0.4612 and Accuracy = 65.47%.

**4. Boosted Tree.**

The advantage of using the boosted tree technique was that it supported loss function. Each subsequent tree was designed to correct errors of ones that came prior. In this case, it helped boost the performance where it made mistakes. By keeping the number of trees as 100, the RMSE came out to 0.4694, and the Accuracy came out to 66.46%. The results are shown in Appendix **Figure 15**.

**5. K-Nearest Neighbor (KNN).**

The most challenging aspect of KNN models were software crashes. When we used all of the dataset (39,644 total row numbers) to build a model with data partition rule 50-30-20, the JMP software crashed for two group members who have attempted to build a KNN model on two different computers. A third group member tried KNN on the undersampled dataset with 23,617 total row numbers and succeeded. We believed that the reduced number of rows made computation easier. We used the same variables that we used in the regression model after the stepwise selection. Tuning to minimize validation set misclassification rate, we decided to use K equals 81, considering all Ks are up to 100. The accuracy of this model was 69.307%, as shown in Appendix **Figure 16**. Unfortunately, the KNN models had limited interpretation. Aside, suggesting "make articles similar to ones that have succeeded in the past," there was little to recommend for business without actually using the model.

**6. Neural Network.**

During this procedure, we used the same variables that we used in the regression model after the stepwise selection. We tested a multitude of different neural network structures in terms of the number and types of nodes in each hidden layer. Sparing the details, we ultimately found that a two hidden layer model with 3 TanH nodes, 3 linear nodes, and 4 gaussian nodes in both layers worked best. We implemented this model using 12 tours, improving accuracy by avoiding starting values that lead to poor performance. The difficulty of model interpretation limits the number of business insights that can be drawn from this model. The results can be found in Appendix **Figure 17**.

**7. Linear Discriminant Analysis.**

We used stepwise selection in order to achieve the lowest validation misclassification rate. The resulting model only used four predictors: the first two Keyword Strength principal components, self_reference_avg_shares, and num_hrefs. As shown in Appendix **Figure 18**, the validation misclassification rate was 31.95%. This model was limited because it could only be built using continuous predictors.

## Assess

The first two models that we compared were both logistic regressions that also used the stepwise selection to select predictor variables. The first model was built on the original dataset (with excluded data), and the second model was built on the undersampled dataset. At first, we thought to compare the models using RMSE, Accuracy, or Accuracy of 1's, but realized that these were all problematic. The first model used a cutoff of .50, which excelled in terms of these test metrics, but only actually found 159 true positives, while the second model found over a thousand. We then realized that we could compare the models using test AUC (area underneath the test ROC curve) in order to quickly compare these models considering all possible cutoffs. We knew that selecting a specific alternate cut off wasn't necessary for business recommendations.

The second model, which was the logistic regression model was built on the undersampled dataset, had high test AUC. Therefore, we selected this as the best model and decided to continue testing models built on the undersampled data. Due to the structure of the undersampled data, models built upon it did not have an issue with finding too few true positives. We compared all of these models using RMSE and Accuracy, both of which ranked our models the same way. We found that our KNN model was the best model statistically, but knew it would not help us make any useful business insights. Due to interpretive ability, we chose the logistic regression model as our best model for making business insights and recommendations. Please see model comparisons in Appendix **Table 3**.

## Results

We will make business recommendations for Mashable based on our logistic regression model built on the stratified undersampling dataset which used stepwise selection. During stepwise selection, one variable that was eliminated was the number of images. For this reason, we recommend Mashable to not worry about including many images in their articles.

Based on variable significance and the formula of our model, we recommend making less world, business, and entertainment articles (**Appendix Figure 19**). We recommend making more articles categorized as social media, tech, lifestyle, and others. We make this recommendation noting that we are doing so assuming the goal of maximizing shares on social media, but recognize that although making more social media articles contribute to this goal, it may not translate to more total views or profit.

Our next recommendation is to focus on keyword strength. Based on the significance of multiple keyword strength predictor variables in our model, we believe that having popular keyword is crucial to having a popular article. In terms of business practice, I would recommend having at least one employee whose sole job is to improve keyword strength. We believe that an expert in this specific task would do much better than writers or editors, and would have a significant impact on article virality on social media.

Our last recommendation is to publish more articles on the weekend. Although it is essential to engage audiences as news occurs in real-time and before competitors, for less time-sensitive articles, they should be published on the weekend to reach a broader audience through social media sharing.

## Conclusion

In conclusion, to improve social media virality, we suggest Mashable focus most on publishing the right types of articles, with the right keywords, at the right time. Specifically, efforts like publishing articles on the weekend would cost Mashable little to nothing and would significantly increase social media visibility, while efforts like including many images in articles cost Mashable time and money and achieve very little. With our insights and recommendations, we believe that the average popularity of Mashable articles on social media would increase considerably.

**References**

Taylor, C. (2016, October 26). How Internet Affects the Newspaper Business. Retrieved from: https://smallbusiness.chron.com/

Bryant, M. (2016, 3 Mar).*"20 Years Ago Today, the World Wide Web Was Born",* TNW Insider. Retrieved from: https://thenextweb.com/insider/

Laird, S., & Laird, S. (2012, April 18). *How Social Media Is Taking Over the News Industry* [INFOGRAPHIC]. Retrieved from: https://mashable.com/

Shmueli, G., Bruce, P. C., Stephens, M. L., & Patel, N. R. (2017). *Data Mining for Business Analytics: Concepts, Techniques, and Applications with JMP Pro.*John Wiley & Sons.

Fernandes, K., Vinagre, P., & Cortez, P. (2015, September). *A proactive intelligent decision support system for predicting the popularity of online news*. In Portuguese Conference on Artificial Intelligence (pp. 535-546). Springer, Cham.

# Appendix - Tables

**Table 1**. List of attributes by category.

| Variable Names | Features |
|---|---|
| **Words** | |
| n_tokens_title | Number of words in the title |
| n_tokens_content | Number of words in the content |
| n_unique_tokens | Rate of unique words in the content |
| n_non_stop_words | Rate of non-stop words in the content |
| n_non_stop_unique_tokens | Rate of unique non-stop words in the content |
| average_token_length | Average length of the words in the content |
| **Links** | |
| num_hrefs | Number of links |
| num_self_hrefs | Number of links to other articles published by Mashable |
| self_reference_min_shares | Min. shares of referenced articles in Mashable |
| self_reference_max_shares | Max. shares of referenced articles in Mashable |
| self_reference_avg_sharess | Avg. shares of referenced articles in Mashable |
| **Digital Media** | |
| num_imgs | Number of images |
| num_videos | Number of videos |
| data_channel_is_lifestyle | Is data channel 'Lifestyle'? |
| data_channel_is_entertainme | Is data channel 'Entertainment'? |
| data_channel_is_bus | Is data channel 'Business'? |
| data_channel_is_socmed | Is data channel 'Social Media'? |
| data_channel_is_tech | Is data channel 'Tech'? |
| data_channel_is_world | Is data channel 'World'? |
| **Time** | |
| is_weekend | Was the article published on the weekend? |
| weekday_is_monday | Was the article published on a Monday? |
| weekday_is_tuesday | Was the article published on a Tuesday? |
| weekday_is_wednesday | Was the article published on a Wednesday? |
| weekday_is_thursday | Was the article published on a Thursday? |
| weekday_is_friday | Was the article published on a Friday? |
| weekday_is_saturday | Was the article published on a Saturday? |
| weekday_is_sunday | Was the article published on a Sunday? |

| Variable Names | Features |
|---|---|
| **Keywords** | |
| num_keywords | Number of keywords in the metadata |
| kw_min_min | Worst keyword (min. shares) |
| kw_max_min | Worst keyword (max. shares) |
| kw_avg_min | Worst keyword (avg. shares) |
| kw_min_max | Best keyword (min. shares) |
| kw_max_max | Best keyword (max. shares) |
| kw_avg_max | Best keyword (avg. shares) |
| kw_min_avg | Avg. keyword (min. shares) |
| kw_max_avg | Avg. keyword (max. shares) |
| kw_avg_avg | Avg. keyword (avg. shares) |
| **Natural Language Processing** | |
| LDA_00 | Closeness to LDA topic 0 |
| LDA_01 | Closeness to LDA topic 1 |
| LDA_02 | Closeness to LDA topic 2 |
| LDA_03 | Closeness to LDA topic 3 |
| LDA_04 | Closeness to LDA topic 4 |
| global_subjectivity | Text subjectivity |
| global_sentiment_polarity | Text sentiment polarity |
| global_rate_positive_words | Rate of positive words in the content |
| global_rate_negative_words | Rate of negative words in the content |
| rate_positive_words | Rate of positive words among non-neutral tokens |
| rate_negative_words | Rate of negative words among non-neutral tokens |
| avg_positive_polarity | Avg. polarity of positive words |
| min_positive_polarity | Min. polarity of positive words |
| max_positive_polarity | Max. polarity of positive words |
| avg_negative_polarity | Avg. polarity of negative words |
| min_negative_polarity | Min. polarity of negative words |
| max_negative_polarity | Max. polarity of negative words |
| title_subjectivity | Title subjectivity |
| title_sentiment_polarity | Title polarity |
| abs_title_subjectivity | Absolute subjectivity level |
| abs_title_sentiment_polarity | Absolute polarity level |
| **Target** | |
| shares | Number of shares (target) |

**Table 2**. Variable Selection List

| **Variable Names** | |
|---|---|
| **Words** | **Time** |
| n_tokens_title | is_weekend |
| n_tokens_content | **Keywords** |
| n_unique_tokens | num_keywords |
| n_non_stop_words | Keyword Strength Principal Components (3) |
| average_token_length | **Natural Language Processing** |
| **Links** | global_sentiment_polarity |
| num_hrefs | title_sentiment_polarity |
| self_reference_avg_shares | **Target** |
| **Digital Media** | shares |
| num_imgs | |
| num_videos | |
| data_channel (combined) | |

**Table 3**. The Comparison of models

| Models | Parameters | Values (Test data) |
| --- | --- | --- |
| Forward/Mixed/Backward (Max validation R-Square) on Stratified dataset | Accuracy (in %) | 67.67 |
| | True positives | 1048 |
| | AUC | 69.21 |
| On unstratified dataset | Accuracy (in %) | 75.63 |
| | RMSE | 0.4151 |
| | True positives | 159 |
| | AUC | 67.59 |
| Decision tree with 12 splits | Accuracy (in %) | 60 |
| | RMSE | 0.4745 |
| Boot strap (with 100 no. of trees) | Accuracy (in %) | 65.47 |
| | RMSE | 0.4612 |
| Boosted (with 100 no. of trees) | Accuracy (in %) | 66.46 |
| | RMSE | 0.4694 |
| KNN (K=81) | Accuracy (in %) | 69.307 |
| Neural network | Accuracy (in %) | 66.1226 |
| | RMSE | 0.4604 |

## Appendix - Figures

**Figure 1**. The Result for the Distribution for the number of shares

**Compare Distributions**

| Show | Distribution | Number of Parameters | -2*LogLikelihood | AICc |
|---|---|---|---|---|
| ☑ | Johnson Su | 4 | 689984.419 | 689992.42 |
| ☐ | SHASH | 4 | 692930.958 | 692938.959 |
| ☐ | Johnson Sl | 3 | 699454.576 | 699460.576 |
| ☐ | LogNormal | 2 | 699457.542 | 699461.542 |
| ☐ | GLog | 3 | 699457.542 | 699463.542 |
| ☐ | Normal 3 Mixture | 8 | 701686.599 | 701702.602 |
| ☐ | Weibull | 2 | 719743.219 | 719747.22 |
| ☐ | Extreme Value | 2 | 719743.219 | 719747.22 |
| ☐ | Gamma | 2 | 723568.005 | 723572.005 |
| ☐ | Exponential | 1 | 723913 | 723915 |
| ☐ | Normal 2 Mixture | 5 | 723905.534 | 723915.536 |
| ☐ | Normal | 2 | 854725.191 | 854729.191 |

**Fitted Johnson Su**

**Parameter Estimates**

| Type | Parameter | Estimate |
|---|---|---|
| Shape | γ | -1.398659 |
| Shape | δ | 0.6673207 |
| Location | θ | 673.72591 |
| Scale | σ | 197.2462 |

| Measure | |
|---|---|
| -2*LogLikelihood | 689984.42 |
| AICc | 689992.42 |
| BIC | 690026.77 |

**Figure 2**. The distribution of the count of shares when shares under 20K.

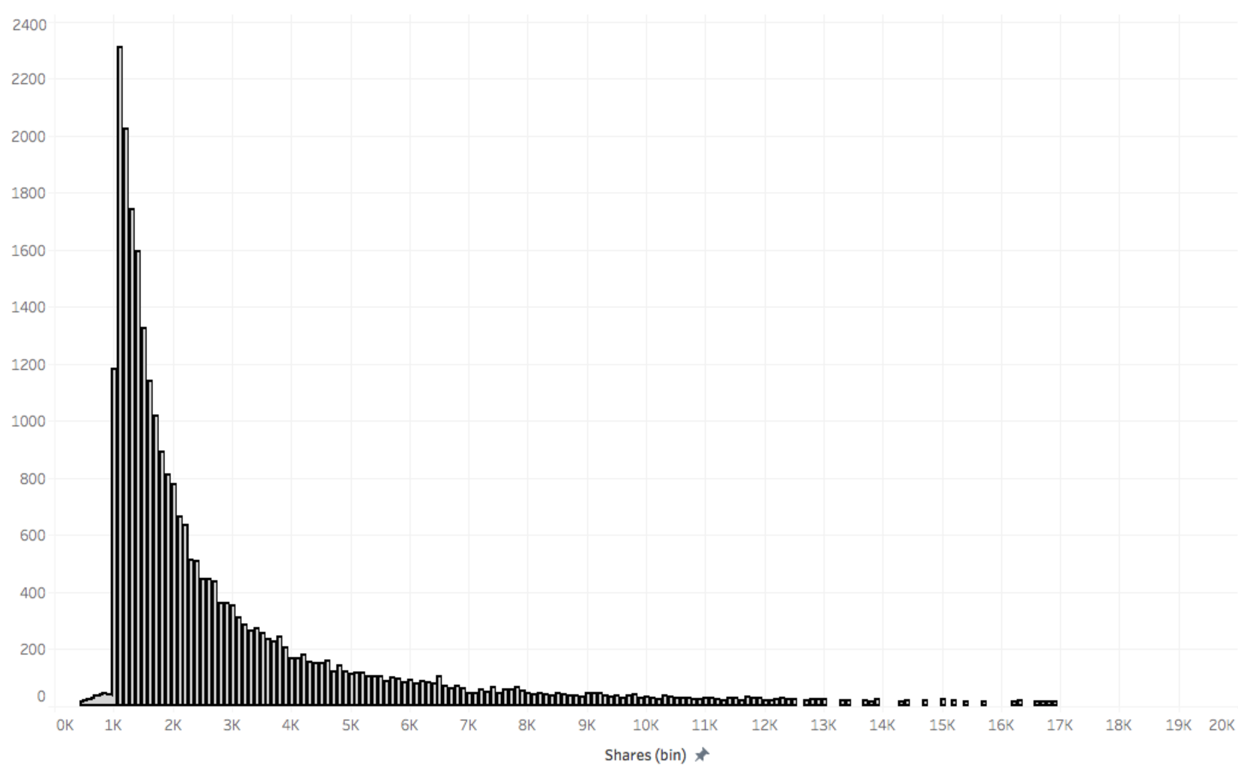


**Figure 3**. The color Map on Correlations

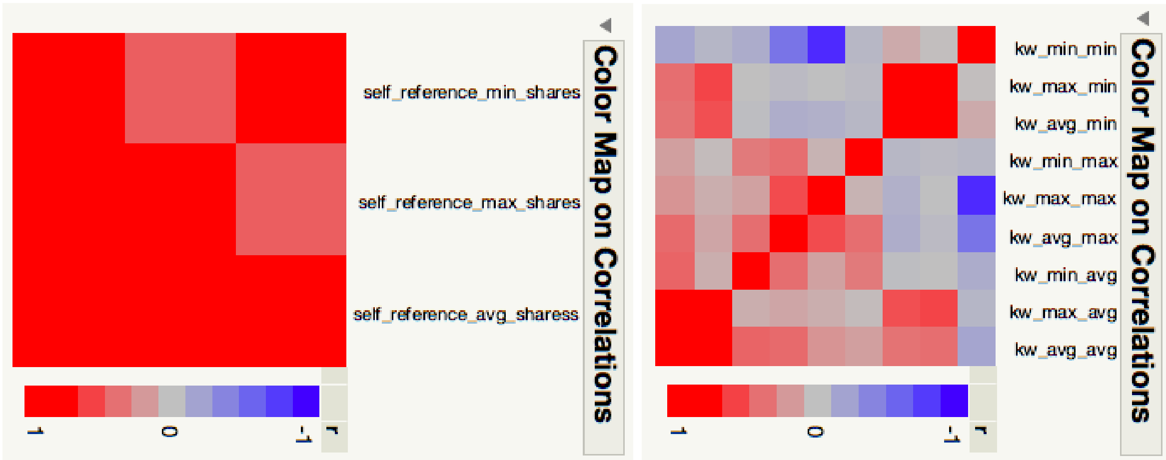



**Figure 4.** Scatterplot Matrix (a portion of the variables)

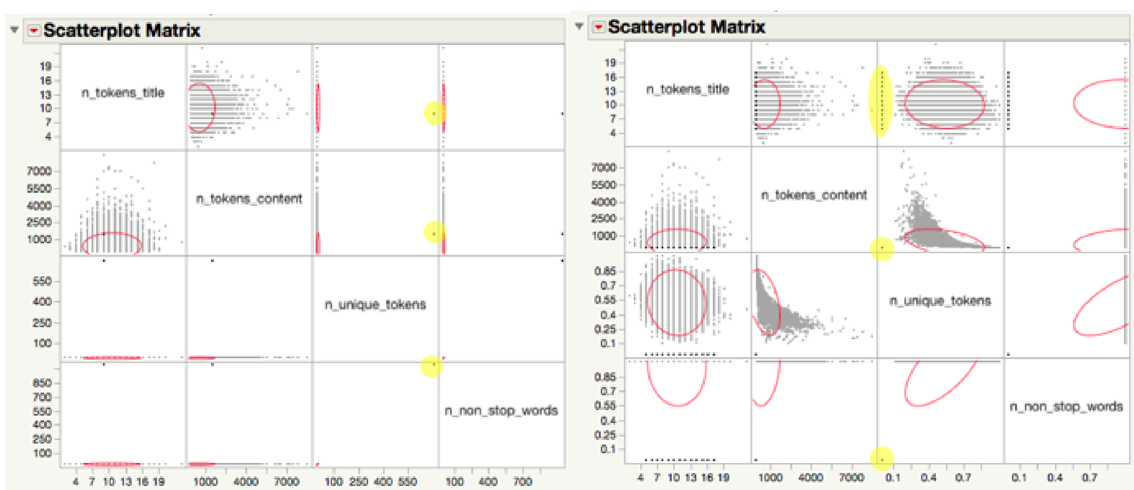
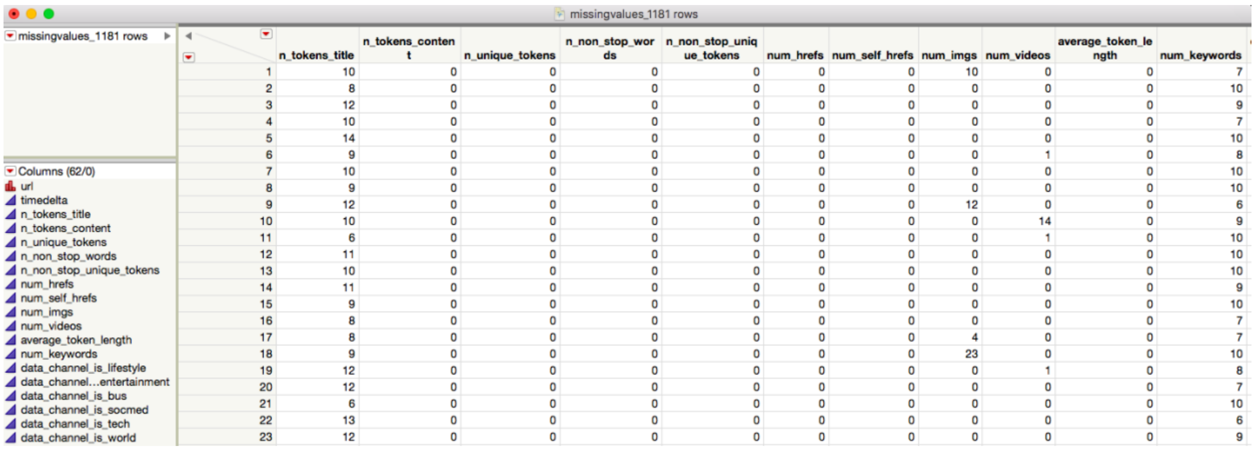


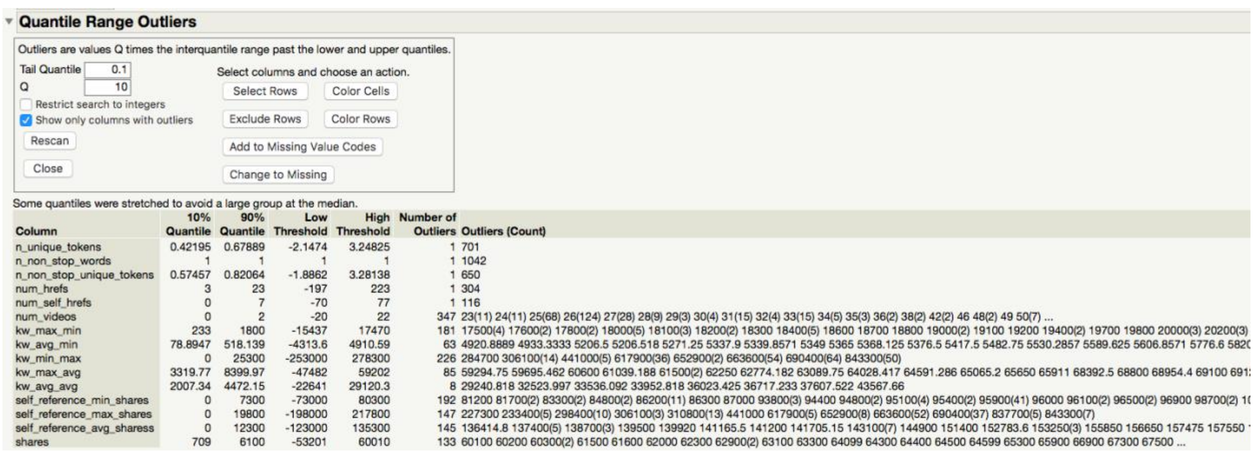
**Figure 5**. An Example of Rows with Missing Data Shown as Zeroes.



| | 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 | num_videos | average_token_length | num_keywords |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 0 | 0 | 7 |
| 2 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 |
| 3 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9 |
| 4 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 |
| 5 | 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 |
| 6 | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 8 |
| 7 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 |
| 8 | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 |
| 9 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 12 | 0 | 0 | 6 |
| 10 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 0 | 9 |
| 11 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 10 |
| 12 | 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 |
| 13 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 |
| 14 | 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9 |
| 15 | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 |
| 16 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 |
| 17 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 7 |
| 18 | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 0 | 0 | 10 |
| 19 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 8 |
| 20 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 |
| 21 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 |
| 22 | 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 |
| 23 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9 |



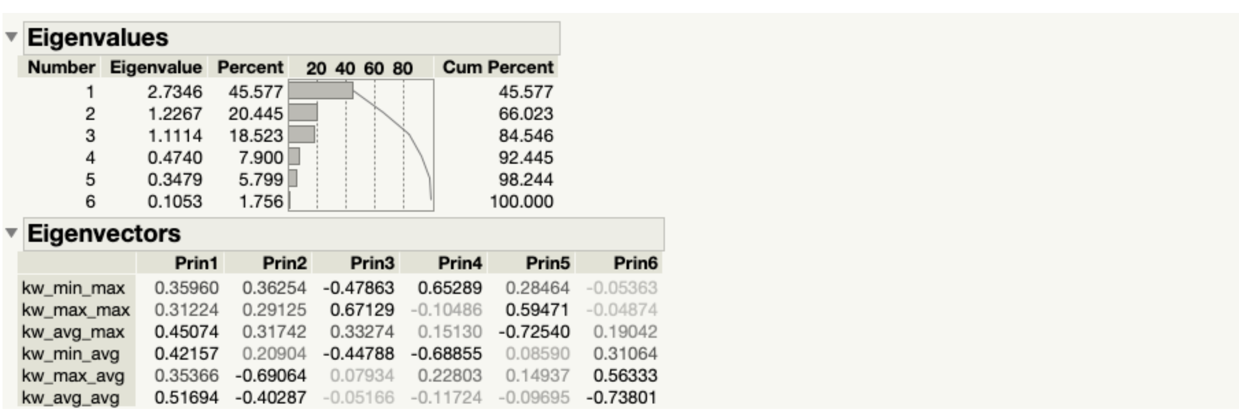
**Figure 6.** The results of using Quantile Range Outliers.





| Column | 10% Quantile | 90% Quantile | Low Threshold | High Threshold | Number of Outliers | Outliers (Count) |
|---|---|---|---|---|---|---|
| n_unique_tokens | 0.42195 | 0.67889 | -2.1474 | 3.24825 | 1 | 701 |
| n_non_stop_words | 1 | 1 | 1 | 1 | 1 | 1042 |
| n_non_stop_unique_tokens | 0.57457 | 0.82064 | -1.8862 | 3.28138 | 1 | 650 |
| num_hrefs | 3 | 23 | -197 | 223 | 1 | 304 |
| num_self_hrefs | 0 | 7 | -70 | 77 | 1 | 116 |
| num_videos | 0 | 2 | -20 | 22 | 347 | 23(11) 24(11) 25(68) 26(124) 27(28) 28(9) 29(3) 30(4) 31(15) 32(4) 33(15) 34(5) 35(3) 36(2) 38(2) 42(2) 46 48(2) 49 50(7) ... |
| kw_max_min | 233 | 1800 | -15437 | 17470 | 181 | 17500(4) 17600(2) 17800(2) 18000(5) 18100(3) 18200(2) 18300 18400(5) 18600 18700 18800 19000(2) 19100 19200 19400(2) 19700 19800 20000(3) 20200(3) |
| kw_avg_min | 78.8947 | 518.139 | -4313.6 | 4910.59 | 63 | 4920.8889 4933.3333 5206.5 5206.518 5271.25 5337.9 5339.8571 5349 5365 5368.125 5376.5 5417.5 5482.75 5530.2857 5589.625 5606.8571 5776.6 |
| kw_min_max | 0 | 25300 | -253000 | 278300 | 226 | 284700 306100(14) 441000(5) 617900(36) 652900(2) 663600(54) 690400(64) 843300(50) |
| kw_max_avg | 3319.77 | 8399.97 | -47482 | 59202 | 85 | 59294.75 59695.462 60600 61039.188 61500(2) 62250 62774.182 63089.75 64028.417 64591.286 65065.2 65650 65911 68392.5 68800 68954.4 69100 |
| kw_avg_avg | 2007.34 | 4472.15 | -22641 | 29120.3 | 8 | 29240.818 32523.997 33536.092 33952.818 36023.425 36717.233 37607.522 43567.66 |
| self_reference_min_shares | 0 | 7300 | -73000 | 80300 | 192 | 81200 81700(2) 83300(2) 84800(2) 86200(11) 86300 87000 93800(3) 94400 94800(2) 95100(4) 95400(2) 95900(41) 96000 96100(2) 96500(2) 96900 98700(2) |
| self_reference_max_shares | 0 | 19800 | -198000 | 217800 | 147 | 227300 233400(5) 298400(10) 306100(3) 310800(13) 441000 617900(5) 652900(8) 663600(52) 690400(37) 837700(5) 843300(7) |
| self_reference_avg_sharess | 0 | 12300 | -123000 | 135300 | 145 | 136414.8 137400(5) 138700(3) 139500 139920 141165.5 141200 141705.15 143100(7) 144900 151400 152783.6 153250(3) 155850 156650 157475 157550 |
| shares | 709 | 6100 | -53201 | 60010 | 133 | 60100 60200 60300(2) 61500 61600 62000 62300 62900(2) 63100 63300 64099 64300 64400 64500 64599 65300 65900 66900 67300 67500 ... |

**Figure 7**. The Result of Principal Components Analysis





| Number | Eigenvalue | Percent | Cum Percent |
|---|---|---|---|
| 1 | 2.7346 | 45.577 | 45.577 |
| 2 | 1.2267 | 20.445 | 66.023 |
| 3 | 1.1114 | 18.523 | 84.546 |
| 4 | 0.4740 | 7.900 | 92.445 |
| 5 | 0.3479 | 5.799 | 98.244 |
| 6 | 0.1053 | 1.756 | 100.000 |



| | Prin1 | Prin2 | Prin3 | Prin4 | Prin5 | Prin6 |
|---|---|---|---|---|---|---|
| kw_min_max | 0.35960 | 0.36254 | -0.47863 | 0.65289 | 0.28464 | -0.05363 |
| kw_max_max | 0.31224 | 0.29125 | 0.67129 | -0.10486 | 0.59471 | -0.04874 |
| kw_avg_max | 0.45074 | 0.31742 | 0.33274 | 0.15130 | -0.72540 | 0.19042 |
| kw_min_avg | 0.42157 | 0.20904 | -0.44788 | -0.68855 | 0.08590 | 0.31064 |
| kw_max_avg | 0.35366 | -0.69064 | 0.07934 | 0.22803 | 0.14937 | 0.56333 |
| kw_avg_avg | 0.51694 | -0.40287 | -0.05166 | -0.11724 | -0.09695 | -0.73801 |

**Figure 8**. The Formula to Combine Dummy Variables into One Categorical Variable

$$
\text{If}\begin{pmatrix}
\mathit{data\_channel\_is\_lifestyle} == 1 & \Rightarrow \text{"lifestyle"} \\
\mathit{data\_channel\_is\_entertainment} == 1 & \Rightarrow \text{"entertainment"} \\
\mathit{data\_channel\_is\_bus} == 1 & \Rightarrow \text{"bus"} \\
\mathit{data\_channel\_is\_socmed} == 1 & \Rightarrow \text{"socmed"} \\
\mathit{data\_channel\_is\_tech} == 1 & \Rightarrow \text{"tech"} \\
\mathit{data\_channel\_is\_world} == 1 & \Rightarrow \text{"world"} \\
\text{else} & \Rightarrow \text{"other"}
\end{pmatrix}
$$

**Figure 9**. The Formula to Create an Alternative Decision Variable

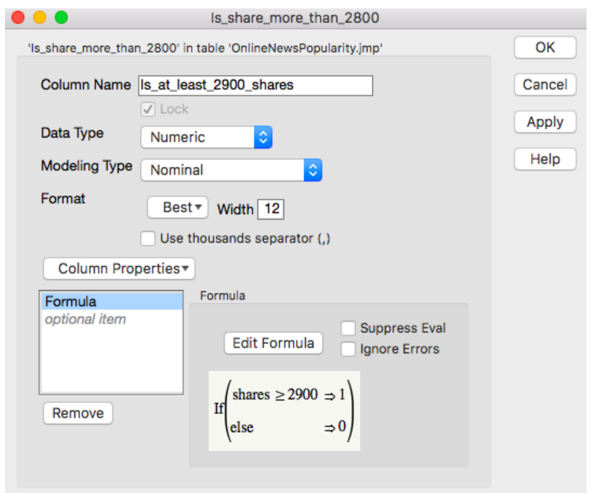
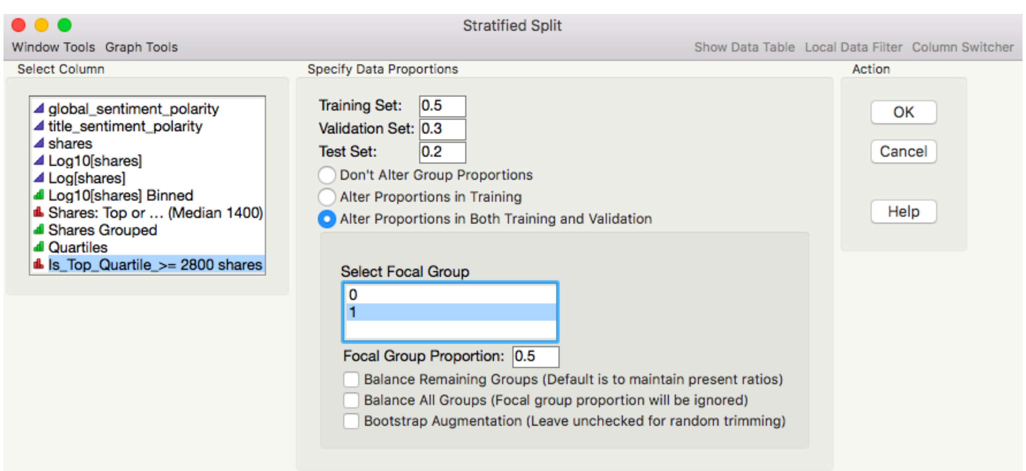
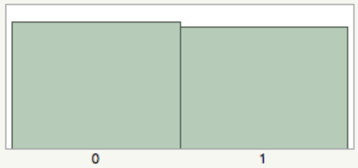



**Figure 10.** The Results of Undersampling



### Distributions Validation Stratified by IsAtLeast2900Shares=Training

#### IsAtLeast2900Shares



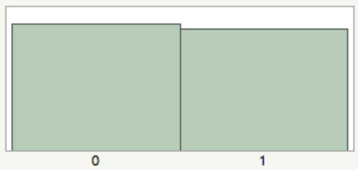

**Frequencies**

| Level | Count | Prob |
|---|---|---|
| 0 | 4700 | 0.51120 |
| 1 | 4494 | 0.48880 |
| Total | 9194 | 1.00000 |

N Missing 0
2 Levels

### Distributions Validation Stratified by IsAtLeast2900Shares=Validation

#### IsAtLeast2900Shares



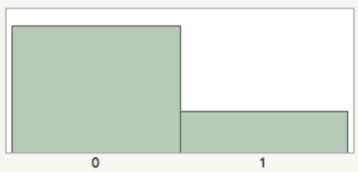

**Frequencies**

| Level | Count | Prob |
|---|---|---|
| 0 | 2826 | 0.51038 |
| 1 | 2711 | 0.48962 |
| Total | 5537 | 1.00000 |

N Missing 0
2 Levels

### Distributions Validation Stratified by IsAtLeast2900Shares=Test

#### IsAtLeast2900Shares




**Frequencies**

| Level | Count | Prob |
|---|---|---|
| 0 | 5668 | 0.75836 |
| 1 | 1806 | 0.24164 |
| Total | 7474 | 1.00000 |

N Missing 0
2 Levels

**Figure 11**.The Results of Stepwise

## Stepwise Fit for IsAtLeast2900Shares

### Stepwise Regression Control

Stopping Rule: Max Validation RSquare

Direction: Mixed

Rules: Combine

Enter All | Make Model | Remove All | Run Model

Go | Stop | Step

| -LogLikelihood | p | RSquare | AICc | BIC | RSquare Validation | Avg Log Error Validation | RSquare Test | Avg Log Error Test |
|---|---|---|---|---|---|---|---|---|
| 5833.1443 | 18 | 0.0843 | 11702.4 | 11830.6 | 0.0722 | 0.64291 | -0.141 | 0.630736 |

### Current Estimates

| Lock | Entered | Parameter | Estimate | nDF | Wald/Score ChiSq | "Sig Prob" |
|---|---|---|---|---|---|---|
| ✓ | ✓ | Intercept[0] | -0.8405525 | 1 | 0 | 1 |
| | | n_tokens_title | 0 | 1 | 1.574858 | 0.2095 |
| | ✓ | n_tokens_content | -0.0001138 | 1 | 10.56714 | 0.00115 |
| | | n_unique_tokens | 0 | 1 | 6.116267 | 0.01339 |
| | | n_non_stop_words | 0 | 0 | 0 | . |
| | ✓ | num_hrefs | -0.0083665 | 1 | 24.53737 | 7.29e-7 |
| | | num_imgs | 0 | 1 | 0.139764 | 0.70852 |
| | ✓ | num_videos | -0.0142974 | 1 | 4.417768 | 0.03557 |
| | ✓ | average_token_length | 0.28280011 | 1 | 13.04491 | 0.0003 |
| | ✓ | num_keywords | -0.0403248 | 1 | 2.511881 | 0.11299 |
| | ✓ | Data Channel{world&entertainment&bus-tech&lifestyle&socmed&other} | 0.30605394 | 2 | 211.9387 | 9.5e-47 |
| | ✓ | Data Channel{world-entertainment&bus} | 0.14891394 | 1 | 28.53257 | 9.21e-8 |
| | ✓ | Data Channel{entertainment-bus} | 0.17333484 | 1 | 12.80408 | 0.00035 |
| | ✓ | Data Channel{tech&lifestyle-socmed&other} | 0.14122148 | 1 | 5.820752 | 0.01584 |
| | ✓ | Data Channel{tech-lifestyle} | -0.0847385 | 1 | 1.928921 | 0.38119 |
| | ✓ | Data Channel{socmed-other} | -0.1252752 | 1 | 6.570546 | 0.03743 |
| | ✓ | Prin1 Keyword Strength | -0.1621603 | 1 | 125.4578 | 4e-29 |
| | ✓ | Prin2  Keyword Strength | 0.20910218 | 1 | 89.94699 | 2.4e-21 |
| | ✓ | Prin3 Keyword Strength | 0.09518453 | 1 | 15.08266 | 0.0001 |
| | ✓ | self_reference_avg_sharess | -2.3554e-5 | 1 | 73.44018 | 1e-17 |
| | ✓ | is_weekend{0-1} | 0.30571061 | 1 | 95.57213 | 1.4e-22 |
| | | global_sentiment_polarity | 0 | 1 | 0.092783 | 0.76067 |
| | ✓ | title_sentiment_polarity | -0.0968225 | 1 | 2.851602 | 0.09128 |

**Figure 12**. The Results of Logistic Regression

## Nominal Logistic Fit for IsAtLeast2900Shares

### Effect Summary

| Source | LogWorth | PValue |
|---|---|---|
| Data Channel | 40.658 | 0.00000 |
| Prin1 Keyword Strength | 26.536 | 0.00000 |
| is_weekend | 21.520 | 0.00000 |
| self_reference_avg_sharess | 21.383 | 0.00000 |
| Prin2 Keyword Strength | 17.985 | 0.00000 |
| Prin3 Keyword Strength | 5.114 | 0.00001 |
| num_hrefs | 3.491 | 0.00032 |
| average_token_length | 3.086 | 0.00082 |
| num_keywords | 2.560 | 0.00275 |
| n_tokens_content | 1.532 | 0.02940 |
| num_videos | 1.220 | 0.06031 |
| title_sentiment_polarity | 0.610 | 0.24543 |

Remove Add Edit FDR

Converged in Gradient, 5 iterations

### Iterations

### Whole Model Test

### Fit Details

| Measure | Training | Validation | Test | Definition |
|---|---|---|---|---|
| Entropy RSquare | 0.0843 | 0.0722 | -0.141 | 1-Loglike(model)/Loglike(0) |
| Generalized RSquare | 0.1471 | 0.1270 | -0.252 | (1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n)) |
| Mean -Log p | 0.6345 | 0.6429 | 0.6307 | ∑ -Log(ρ[j])/n |
| RMSE | 0.4705 | 0.4743 | 0.4668 | √ ∑(y[j]-ρ[j])²/n |
| Mean Abs Dev | 0.4437 | 0.4480 | 0.4410 | ∑ \|y[j]-ρ[j]\|/n |
| Misclassification Rate | 0.3507 | 0.3619 | 0.3233 | ∑ (ρ[j]≠ρMax)/n |
| N | 9194 | 5537 | 7474 | n |

### Confusion Matrix

Training

| Actual IsAtLeast2900Shares | Predicted Count 1 | Predicted Count 0 |
|---|---|---|
| 1 | 2640 | 1854 |
| 0 | 1370 | 3330 |

Validation

| Actual IsAtLeast2900Shares | Predicted Count 1 | Predicted Count 0 |
|---|---|---|
| 1 | 1526 | 1185 |
| 0 | 819 | 2007 |

Test

| Actual IsAtLeast2900Shares | Predicted Count 1 | Predicted Count 0 |
|---|---|---|
| 1 | 1048 | 758 |
| 0 | 1658 | 4010 |

**Figure 13**. The Results of Decision Tree

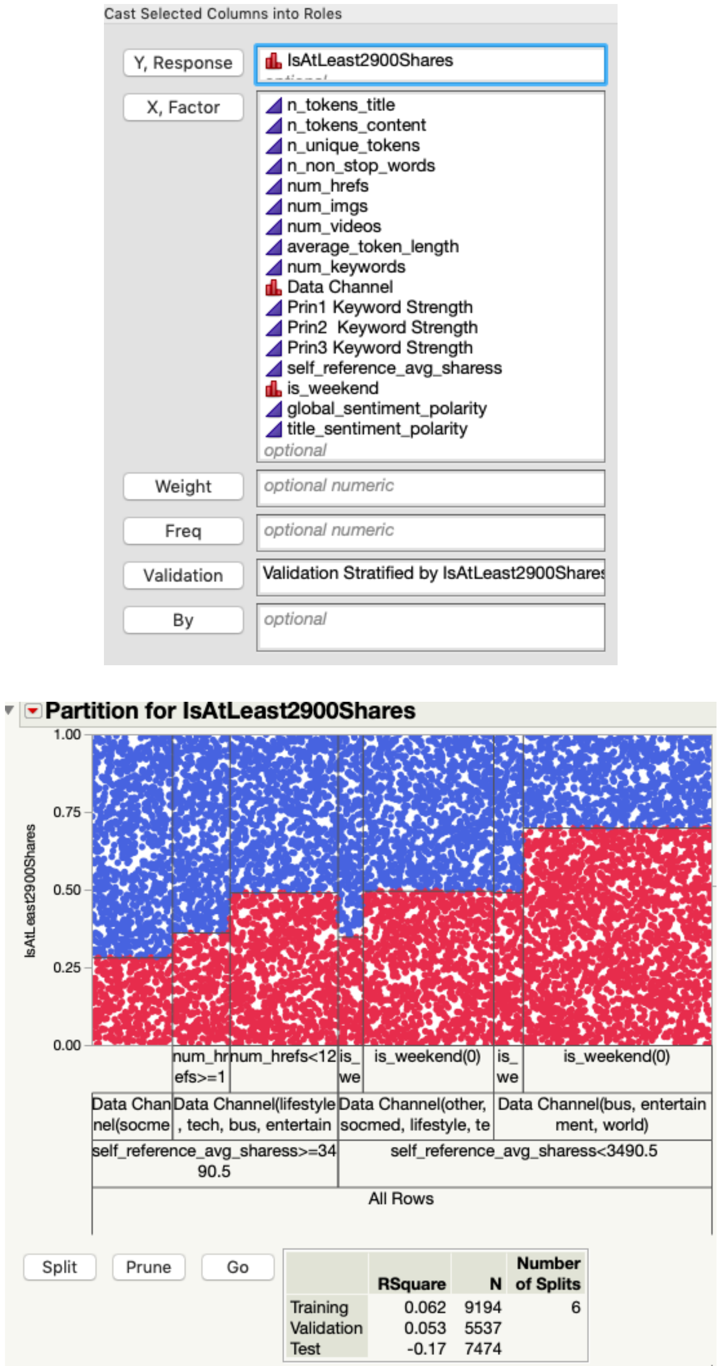
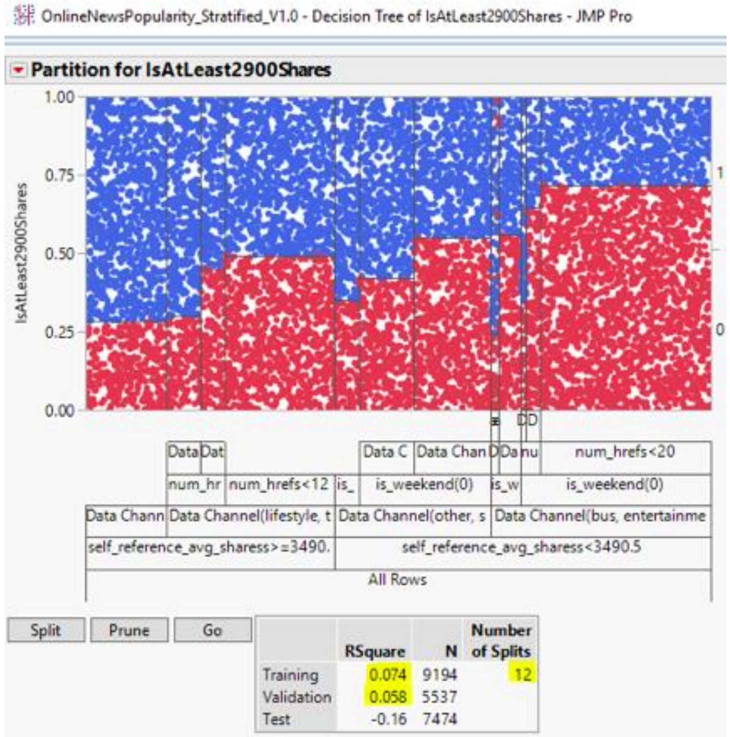


**Figure 13**. The Results of Decision Tree (continued)



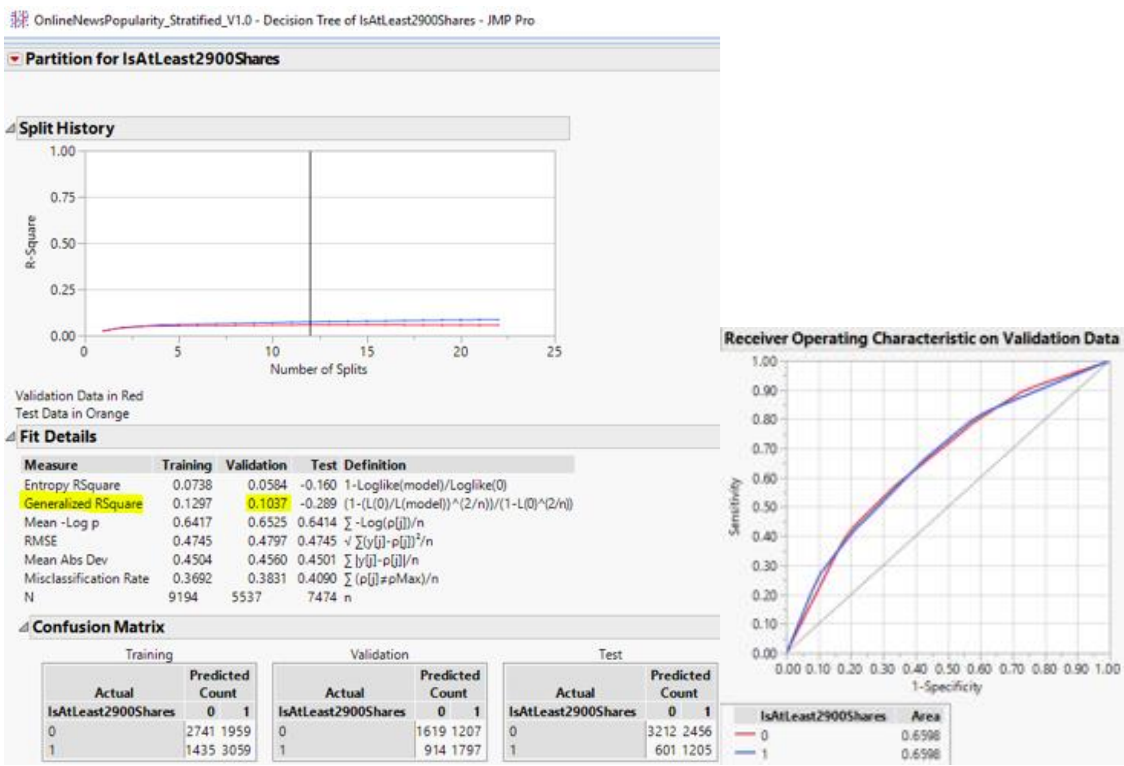
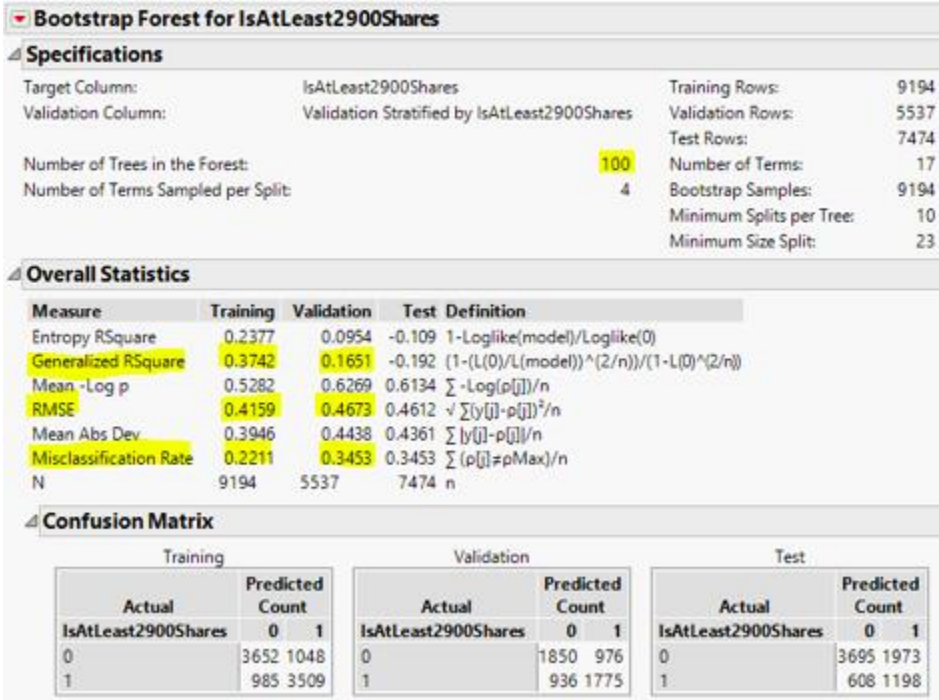



**Figure 14.** The Results of Bootstrap Forest



**Bootstrap Forest for IsAtLeast2900Shares**

**Specifications**

| | | | |
|---|---|---|---|
| Target Column: | IsAtLeast2900Shares | Training Rows: | 9194 |
| Validation Column: | Validation Stratified by IsAtLeast2900Shares | Validation Rows: | 5537 |
| | | Test Rows: | 7474 |
| Number of Trees in the Forest: | 100 | Number of Terms: | 17 |
| Number of Terms Sampled per Split: | 4 | Bootstrap Samples: | 9194 |
| | | Minimum Splits per Tree: | 10 |
| | | Minimum Size Split: | 23 |

**Overall Statistics**

| Measure | Training | Validation | Test | Definition |
|---|---|---|---|---|
| Entropy RSquare | 0.2377 | 0.0954 | -0.109 | 1-Loglike(model)/Loglike(0) |
| Generalized RSquare | 0.3742 | 0.1651 | -0.192 | (1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n)) |
| Mean -Log p | 0.5282 | 0.6269 | 0.6134 | ∑ -Log(ρ[j])/n |
| RMSE | 0.4159 | 0.4673 | 0.4612 | √ ∑(y[j]-ρ[j])²/n |
| Mean Abs Dev | 0.3946 | 0.4438 | 0.4361 | ∑ \|y[j]-ρ[j]\|/n |
| Misclassification Rate | 0.2211 | 0.3453 | 0.3453 | ∑ (ρ[j]≠ρMax)/n |
| N | 9194 | 5537 | 7474 | n |

**Confusion Matrix**

Training

| Actual IsAtLeast2900Shares | Predicted Count 0 | 1 |
|---|---|---|
| 0 | 3652 | 1048 |
| 1 | 985 | 3509 |

Validation

| Actual IsAtLeast2900Shares | Predicted Count 0 | 1 |
|---|---|---|
| 0 | 1850 | 976 |
| 1 | 936 | 1775 |

Test

| Actual IsAtLeast2900Shares | Predicted Count 0 | 1 |
|---|---|---|
| 0 | 3695 | 1973 |
| 1 | 608 | 1198 |

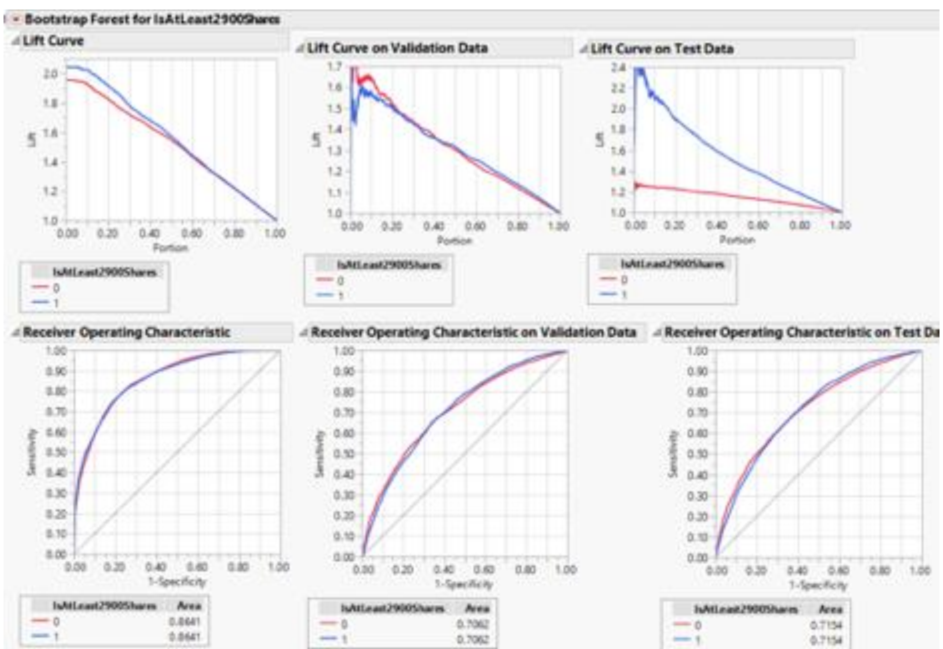


**Figure 15.** The Results of Boosted Tree

**Boosted Tree for IsAtLeast2900Shares**

**Specifications**

**Overall Statistics**

| Measure | Training | Validation | Test | Definition |
|---|---|---|---|---|
| Entropy RSquare | 0.1031 | 0.0719 | -0.143 | 1-Loglike(model)/Loglike(0) |
| Generalized RSquare | 0.1775 | 0.1264 | -0.256 | (1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n)) |
| Mean -Log p | 0.6215 | 0.6431 | 0.6320 | ∑ -Log(ρ[j])/n |
| RMSE | 0.4644 | 0.4751 | 0.4694 | $\sqrt{\sum(y[j]-\rho[j])^2/n}$ |
| Mean Abs Dev | 0.4452 | 0.4560 | 0.4499 | ∑ \|y[j]-ρ[j]\|/n |
| Misclassification Rate | 0.3376 | 0.3655 | 0.3354 | ∑ (ρ[j]≠ρMax)/n |
| N | 9194 | 5537 | 7474 | n |

**Confusion Matrix**

| | Training | | Validation | | Test | |
|---|---|---|---|---|---|---|
| Actual IsAtLeast2900Shares | Predicted Count 0 | Predicted Count 1 | Predicted Count 0 | Predicted Count 1 | Predicted Count 0 | Predicted Count 1 |
| 0 | 3383 | 1317 | 1984 | 842 | 3935 | 1733 |
| 1 | 1787 | 2707 | 1182 | 1529 | 774 | 1032 |

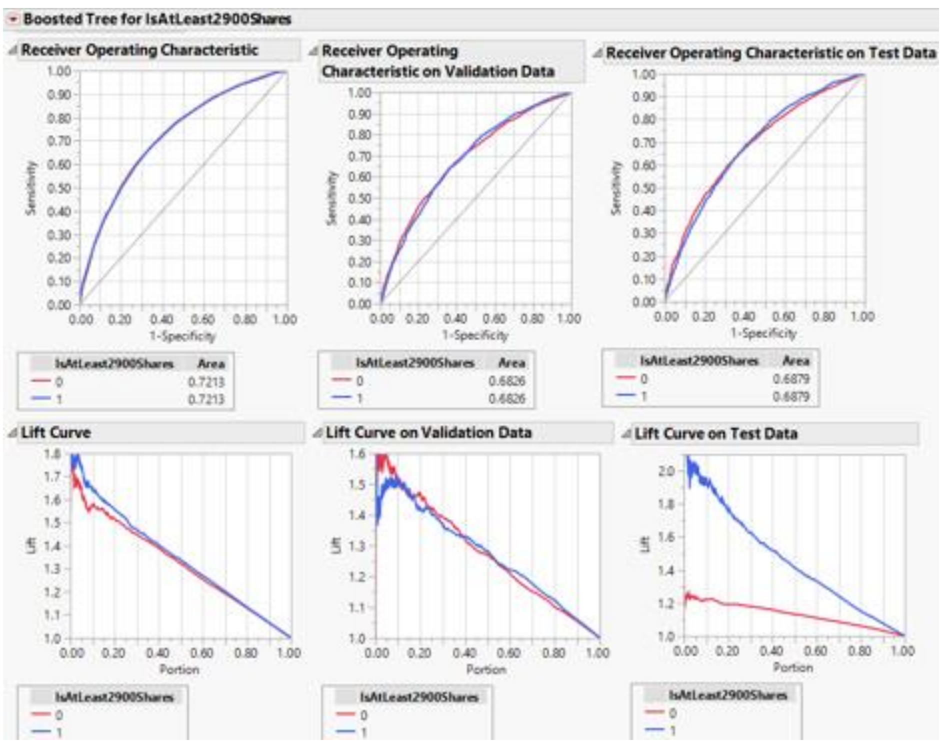
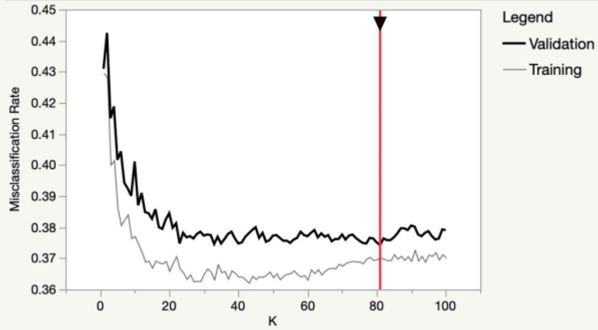


**Figure 16.** The Results of K-Nearest Neighbor

### K Nearest Neighbors

### IsAtLeast2900Shares

#### Model Selection




#### Training

| K | Count | Misclassification Rate | Misclassifications |
|---|---|---|---|
| 42 | 9194 | 0.36317 | 3339 |
| 43 | 9194 | 0.36219 | 3330 * |
| 44 | 9194 | 0.36437 | 3350 |
| 45 | 9194 | 0.36339 | 3341 |
| 46 | 9194 | 0.36426 | 3349 |
| 47 | 9194 | 0.36404 | 3347 |
| 48 | 9194 | 0.36469 | 3353 |
| 49 | 9194 | 0.36578 | 3363 |
| 50 | 9194 | 0.36393 | 3346 |
| 51 | 9194 | 0.36513 | 3357 |

#### Validation

| K | Count | Misclassification Rate | Misclassifications |
|---|---|---|---|
| 80 | 5537 | 0.37511 | 2077 |
| 81 | 5537 | 0.37421 | 2072 * |
| 82 | 5537 | 0.37638 | 2084 |
| 83 | 5537 | 0.37584 | 2081 |
| 84 | 5537 | 0.37584 | 2081 |
| 85 | 5537 | 0.37674 | 2086 |
| 86 | 5537 | 0.37800 | 2093 |
| 87 | 5537 | 0.37963 | 2102 |
| 88 | 5537 | 0.37963 | 2102 |
| 89 | 5537 | 0.37909 | 2099 |

#### Test

| K | Count | Misclassification Rate | Misclassifications |
|---|---|---|---|
| 80 | 7474 | 0.30666 | 2292 |
| 81 | 7474 | 0.30693 | 2294 |
| 82 | 7474 | 0.30693 | 2294 |
| 83 | 7474 | 0.30653 | 2291 |
| 84 | 7474 | 0.30693 | 2294 |
| 85 | 7474 | 0.30613 | 2288 * |
| 86 | 7474 | 0.30854 | 2306 |
| 87 | 7474 | 0.30773 | 2300 |
| 88 | 7474 | 0.30720 | 2296 |
| 89 | 7474 | 0.30827 | 2304 |

#### Confusion Matrix for Best K=81

##### Training

| Actual IsAtLeast2900Shares | Predicted Count 0 | 1 |
|---|---|---|
| 0 | 3479 | 1221 |
| 1 | 2184 | 2310 |

##### Validation

| Actual IsAtLeast2900Shares | Predicted Count 0 | 1 |
|---|---|---|
| 0 | 2105 | 721 |
| 1 | 1351 | 1360 |

##### Test

| Actual IsAtLeast2900Shares | Predicted Count 0 | 1 |
|---|---|---|
| 0 | 4216 | 1452 |
| 1 | 842 | 964 |

#### Mosaic Plot

Mosaic Plot for K=81

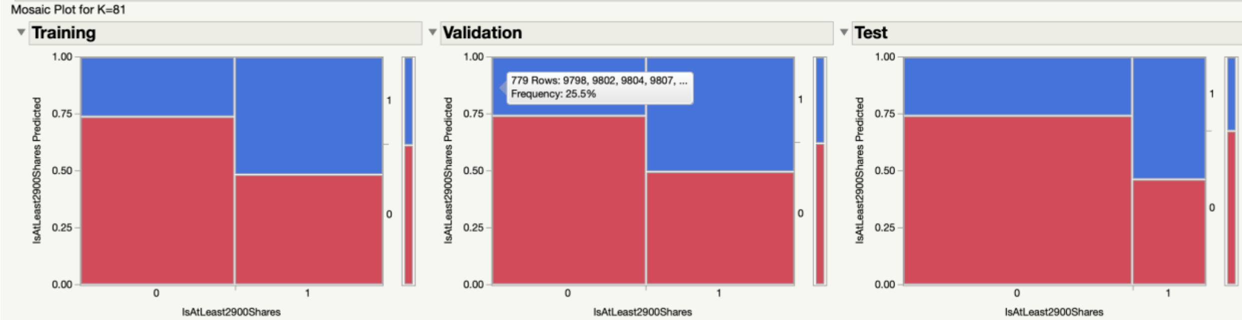


**Figure 17**. The Results of Neural Network

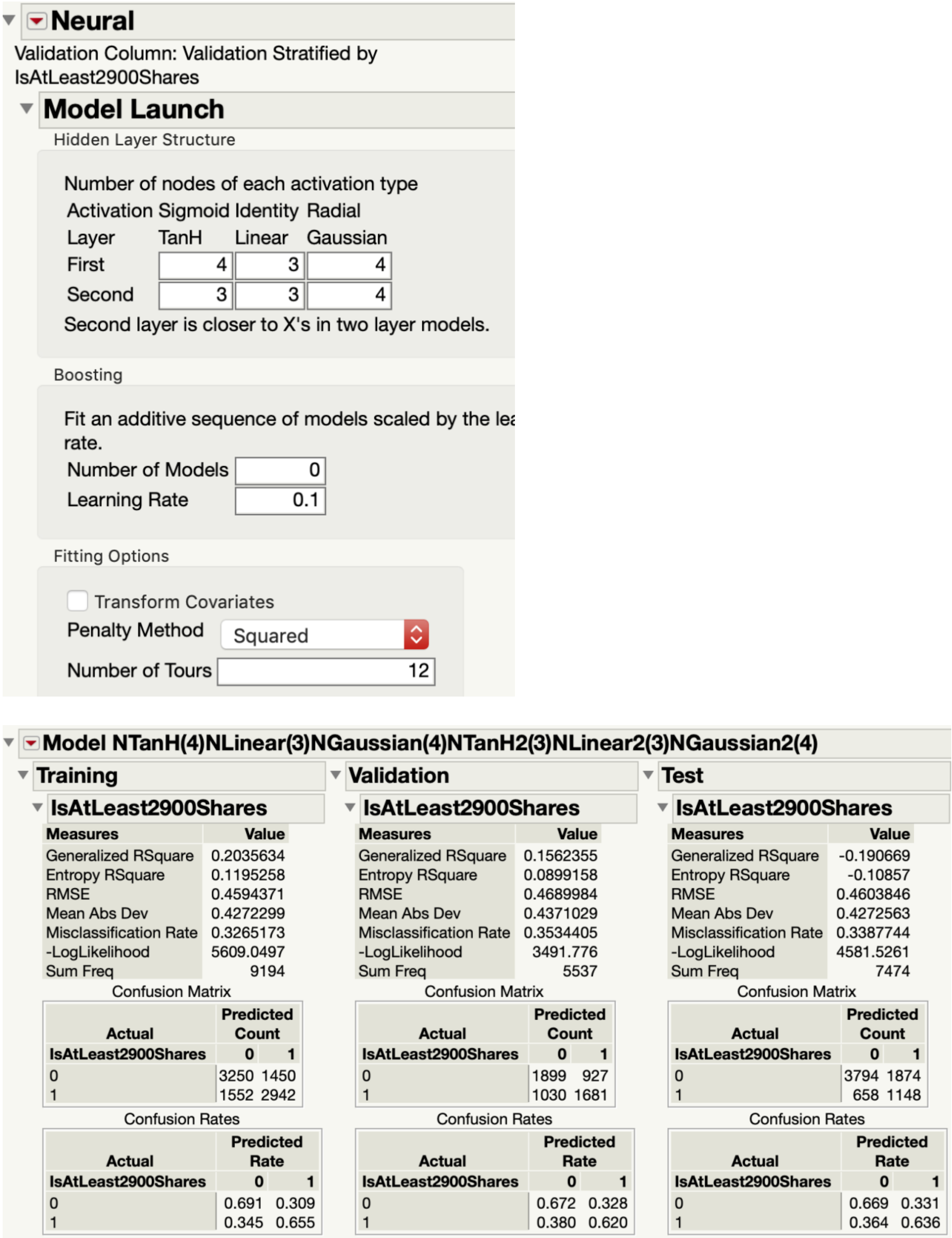


**Figure 18.** The Results of Linear Discriminant Analysis

# Discriminant Analysis

## Column Selection

| | | | | | |
|---|---|---|---|---|---|
| Columns In | 13 | Smallest P to Enter | 0.3918129 | Validation Entropy RSquare | 0.04968 |
| Columns Out | 2 | Largest P to Remove | 0.0502593 | Validation Misclassification Rate | 0.38577 |

Step Forward | Enter All | Go

Step Backward | Remove All | Apply This Model

| Lock | Entered | Column | F Ratio | Prob>F |
|---|---|---|---|---|
| ☐ | ☑ | n_tokens_title | 9.767 | 0.0017827 |
| ☐ | ☐ | n_tokens_content | 0.127 | 0.7220542 |
| ☐ | ☐ | n_unique_tokens | 0.733 | 0.3918129 |
| ☐ | ☑ | n_non_stop_words | 4.682 | 0.0305088 |
| ☐ | ☑ | num_hrefs | 35.827 | 0.0000000 |
| ☐ | ☑ | num_imgs | 7.648 | 0.0056959 |
| ☐ | ☑ | num_videos | 8.908 | 0.0028471 |
| ☐ | ☑ | average_token_length | 39.077 | 0.0000000 |
| ☐ | ☑ | num_keywords | 43.862 | 0.0000000 |
| ☐ | ☑ | Prin1 Keyword Strength | 154.546 | 0.0000000 |
| ☐ | ☑ | Prin2 Keyword Strength | 30.335 | 0.0000000 |
| ☐ | ☑ | Prin3 Keyword Strength | 36.936 | 0.0000000 |
| ☐ | ☑ | self_reference_avg_sharess | 67.410 | 0.0000000 |
| ☐ | ☑ | global_sentiment_polarity | 3.834 | 0.0502593 |
| ☐ | ☑ | title_sentiment_polarity | 4.383 | 0.0363369 |

# Discriminant Analysis

## Group Means

| Count | IsAtLeast2900Shares | n_tokens_title | n_tokens_content | n_unique_tokens | n_non_stop_words | num_hrefs | num_imgs | num_videos | average_token_length | num_keywords |
|---|---|---|---|---|---|---|---|---|---|---|
| 4700 | 0 | 10.41574 | 559.70809 | 0.546061 | 1.000000 | 10.591064 | 4.2734043 | 0.8972340 | 4.698605 | 7.152766 |
| 4494 | 1 | 10.24655 | 588.73275 | 0.543639 | 1.000000 | 12.958611 | 5.7394304 | 1.2483311 | 4.672386 | 7.415665 |
| 9194 | All | 10.33304 | 573.89526 | 0.544877 | 1.000000 | 11.748314 | 4.9899935 | 1.0688492 | 4.685789 | 7.281270 |

| Prin1 Keyword Strength | Prin2 Keyword Strength | Prin3 Keyword Strength | self_reference_avg_sharess | global_sentiment_polarity | title_sentiment_polarity |
|---|---|---|---|---|---|
| -0.1437157 | 0.1028 | 0.0229 | 4285.0979 | 0.121457 | 0.06547 |
| 0.4979853 | -0.2856 | -0.0978 | 7791.1088 | 0.130723 | 0.08522 |
| 0.1699459 | -0.0870 | -0.0361 | 5998.8257 | 0.125986 | 0.07512 |

Standardized Scoring Coefficients

| | n_tokens_title | n_non_stop_words | num_hrefs | num_imgs | num_videos | average_token_length | num_keywords | Prin1 Keyword Strength |
|---|---|---|---|---|---|---|---|---|
| Canon1 | -0.128623 | 0 | 0.2799056 | 0.1233586 | 0.1223414 | -0.25936 | 0.2920224 | 0.5424221 |

| Prin2 Keyword Strength | Prin3 Keyword Strength | self_reference_avg_sharess | global_sentiment_polarity | title_sentiment_polarity |
|---|---|---|---|---|
| -0.240342 | -0.252434 | 0.3326569 | 0.0821341 | 0.0866562 |

**Figure 18.** The Results of Linear Discriminant Analysis (continued)

| Source | Count | Number Misclassified | Percent Misclassified | Entropy RSquare | -2LogLikelihood |
|---|---|---|---|---|---|
| Training | 9194 | 3491 | 37.9704 | 0.05556 | 12033.1 |
| Validation | 5537 | 2136 | 38.5768 | 0.04968 | |
| Test | 7474 | 2593 | 34.6936 | -0.1810 | |

Training

| Actual IsAtLeast2900Shares | Predicted Count 0 | 1 |
|---|---|---|
| 0 | 3239 | 1461 |
| 1 | 2030 | 2464 |

Validation

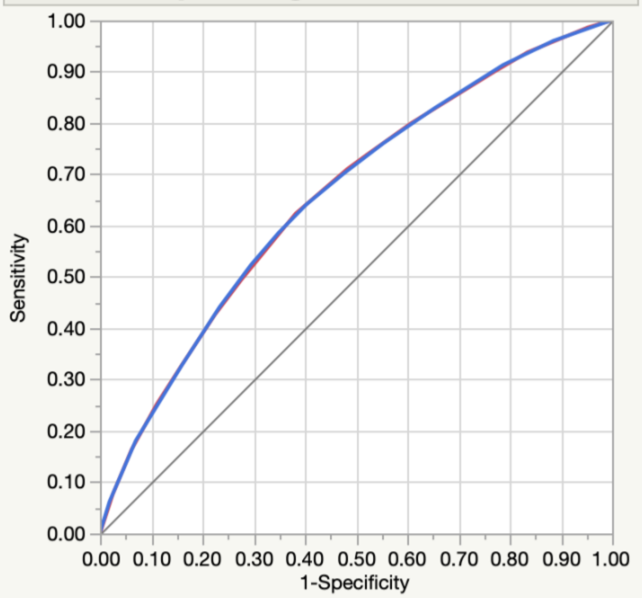
| Actual IsAtLeast2900Shares | Predicted Count 0 | 1 |
|---|---|---|
| 0 | 1924 | 902 |
| 1 | 1234 | 1477 |

Test

| Actual IsAtLeast2900Shares | Predicted Count 0 | 1 |
|---|---|---|
| 0 | 3892 | 1776 |
| 1 | 817 | 989 |

Groups

Receiver Operating Characteristic




| IsAtLeast2900Shares | Area |
|---|---|
| 0 | 0.6579 |
| 1 | 0.6579 |

**Figure 19**. Best Model Interpretation

## Nominal Logistic Fit for IsAtLeast2900Shares

### Effect Summary

| Source | LogWorth | PValue |
|---|---|---|
| Data Channel | 40.658 | 0.00000 |
| Prin1 Keyword Strength | 26.536 | 0.00000 |
| is_weekend | 21.520 | 0.00000 |
| self_reference_avg_sharess | 21.383 | 0.00000 |
| Prin2  Keyword Strength | 17.985 | 0.00000 |
| Prin3 Keyword Strength | 5.114 | 0.00001 |
| num_hrefs | 3.491 | 0.00032 |
| average_token_length | 3.086 | 0.00082 |
| num_keywords | 2.560 | 0.00275 |
| n_tokens_content | 1.532 | 0.02940 |
| num_videos | 1.220 | 0.06031 |
| title_sentiment_polarity | 0.610 | 0.24543 |

Statistical Significance

$$+\ \mathrm{Match}\left(\mathit{Data\ Channel}\right)\begin{pmatrix} \text{"bus"} & \Rightarrow & -0.046518973 \\ \text{"entertainment"} & \Rightarrow & -0.38996469 \\ \text{"lifestyle"} & \Rightarrow & 0.0127791243 \\ \text{"other"} & \Rightarrow & 0.2597765574 \\ \text{"socmed"} & \Rightarrow & 0.5022854897 \\ \text{"tech"} & \Rightarrow & 0.1843706904 \\ \text{"world"} & \Rightarrow & \boxed{-0.522728199} \\ \text{else} & \Rightarrow & . \end{pmatrix}$$

Coefficients for specific Data Channels