

# Exploratory Data Analysis Written Report

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Introduction:

## Exploratory Data Analysis:

### Data Set Description:

Our project utilizes the University of California Irvine Machine Learning Repository's "Online News Popularity" data set. It includes share counts and descriptive characteristics for articles published by Mashable over two years (from 2013 to 2015). Mashable Inc. is a digital media website founded in 2005 and as of November 2015, it has over 6,000,000 Twitter followers and over 3,200,000 fans on Facebook. The data set in total, has 39644 observations, each representing an individual article. Observations include characteristics such as: Number of Words in Title/Content, Rate of Unique Words, Number of Images, Data Channel, Day Published, Rate of Positive/Negative Words, Polarity, etc. Our intention is to use the data set to predict the number of shares/virality of an article based on different variables.

### Key Variables:

rate\_positive\_words - rate of positive words among non-neutral tokens, which captures how emotionally charged the language is.

Rate\_negative\_words - rate of negative words among non-neutral tokens, which captures how emotionally charged the language is.

title\_sentiment\_polarity - A measure of how polarizing the title is

N\_tokens\_content - A measure of how long the article's content is

N\_tokens\_title - A measure of how long the article title is

data\_channel - a categorical variable denoting article topic merged from: Data\_channel\_is\_entertainment, data\_channel\_is\_bus, data\_channel\_is\_socmed, data\_channel\_is\_tech, and data\_channel\_is\_world.

day\_published- a categorical variable indicating publication day merged from indicators: Weekday\_is\_monday, weekday\_is\_tuesday, weekday\_is\_wednesday, weekday\_is\_thursday, weekday\_is\_friday, weekday\_is\_saturday, weekday\_is\_sunday

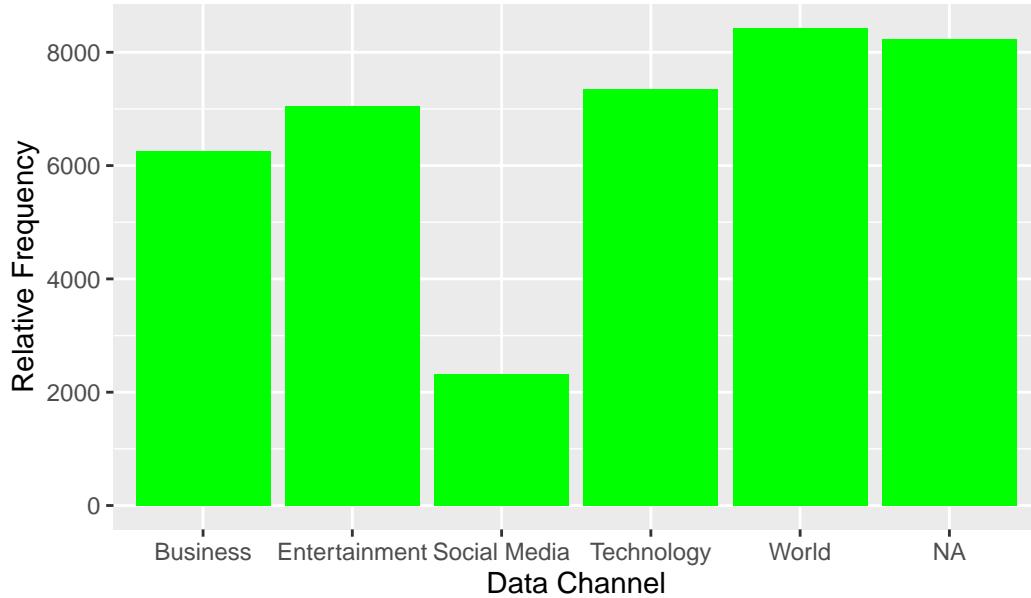
## Data Cleaning

First we have to combine the existing weekday and data\_channel indicator variables into their respective categorical variables.

Table 1: Transformed Data

url	day_published	data_channel
http://mashable.com/2013/01/07/amazon-instant-video-browser/	Monday	Entertainment
http://mashable.com/2013/01/07/ap-samsung-sponsored-tweets/	Monday	Business
http://mashable.com/2013/01/07/apple-40-billion-app-downloads/	Monday	Business
http://mashable.com/2013/01/07/astronaut-notre-dame-bcs/	Monday	Entertainment
http://mashable.com/2013/01/07/att-u-verse-apps/	Monday	Technology

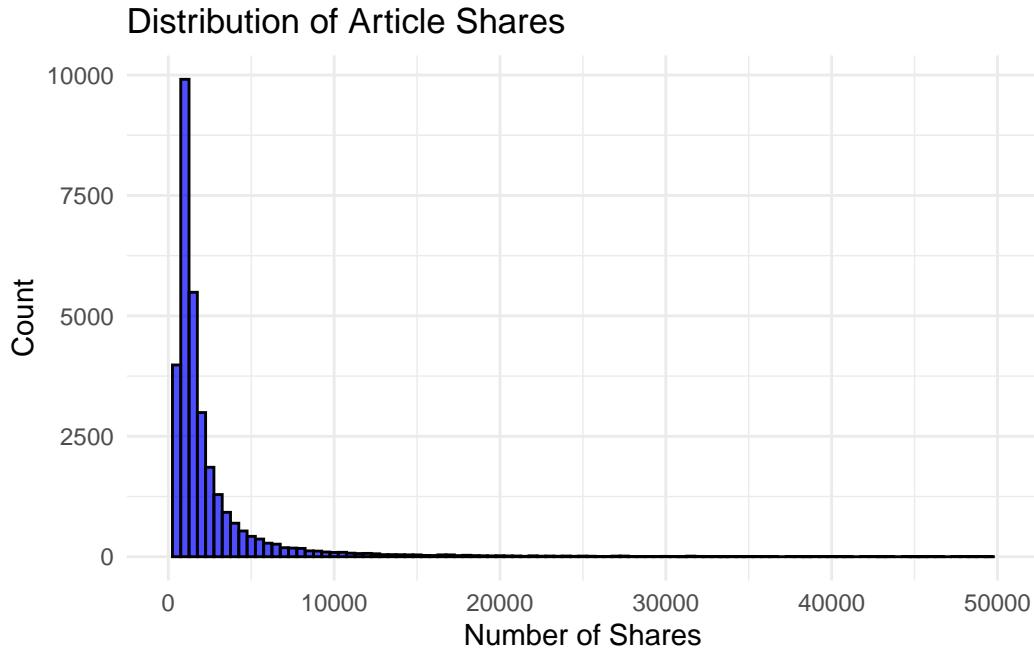
Distribution of article categories



Next, we discovered that approx 8,233 articles are not tagged for a specific data channel. Due to the nature of the dataset, it's unclear if this was because the article was simply missing a tag, it was mis-tagged while being collected, or if it simply doesn't belong in any of these categories. With the relatively large size of our dataset, we decided to exclude entries lacking a

data tag NA's from our data channel analysis altogether. These articles lacking a data channel were filtered out.

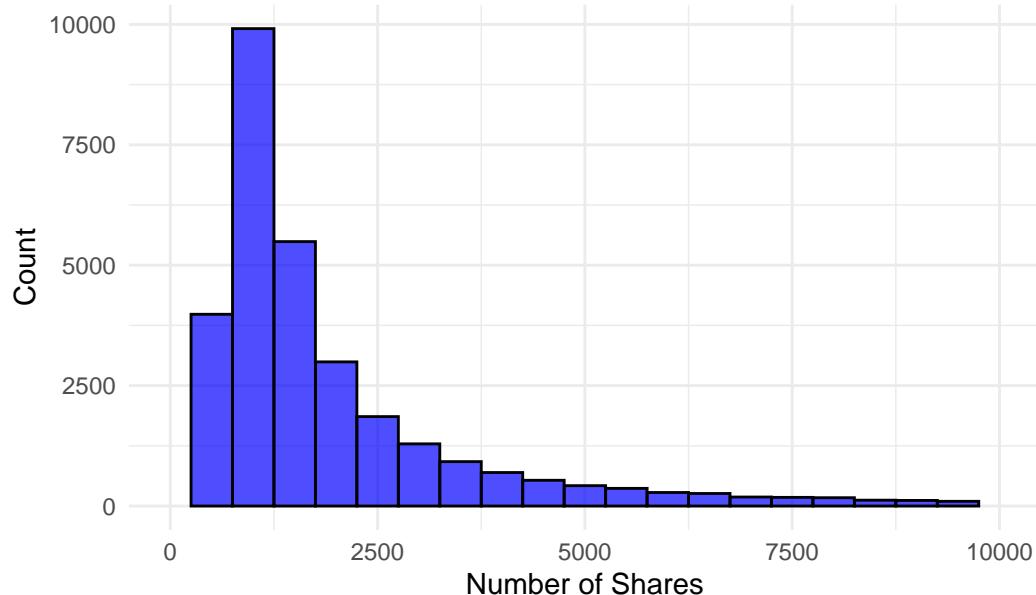
#### Response Variable/Univariate EDA



```
# A tibble: 1 x 7
  mean_shares median_shares sd_shares min_shares max_shares     q1     q3
    <dbl>        <dbl>      <dbl>      <dbl>      <dbl> <dbl> <dbl>
1     2878.       1400      9506.       1     690400     923   2500
```

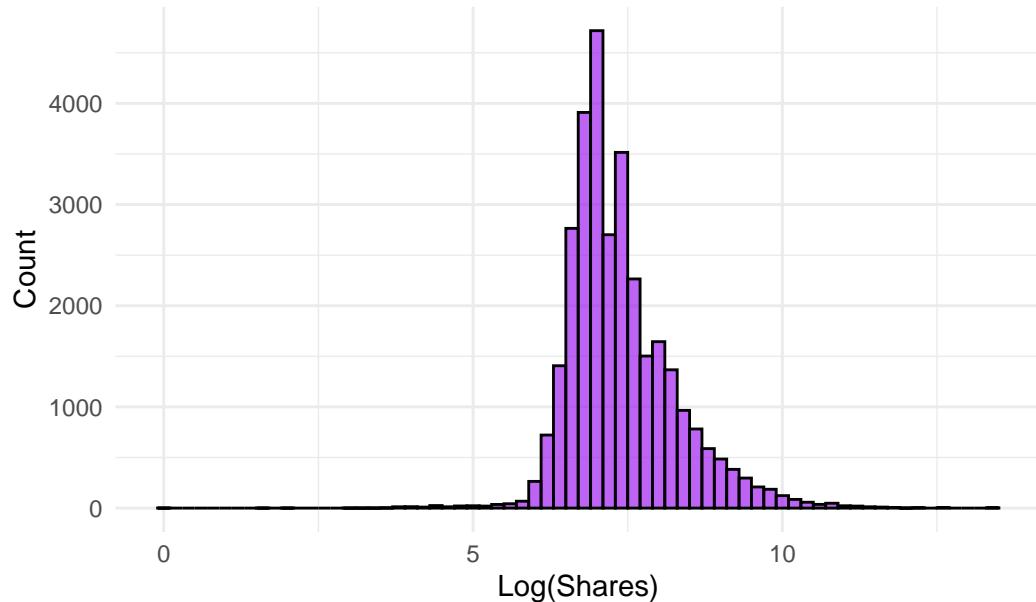
The distribution of # of shares is highly right skewed, a median of 1400 shares and a few highly shared articles. Notably, the mean of 2878 shares is far larger

## Distribution of Article Shares (Zoomed In)

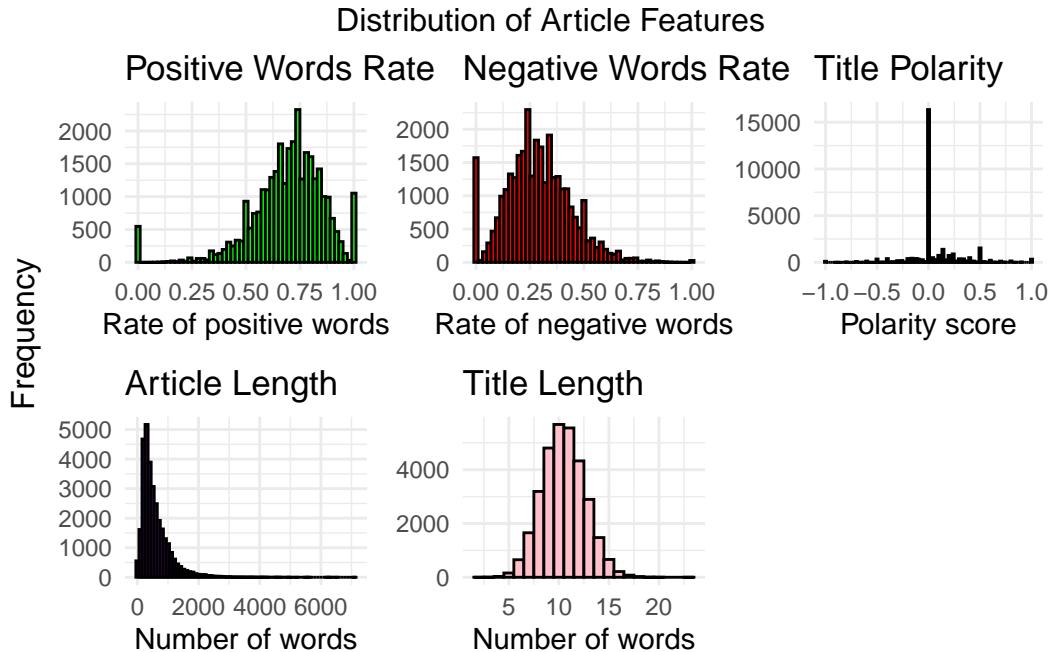


To make deal with this strong right skew, we applied a log transformation to the share variable, yielding a less skewed distribution.

## Log–Transformed Distribution of Shares

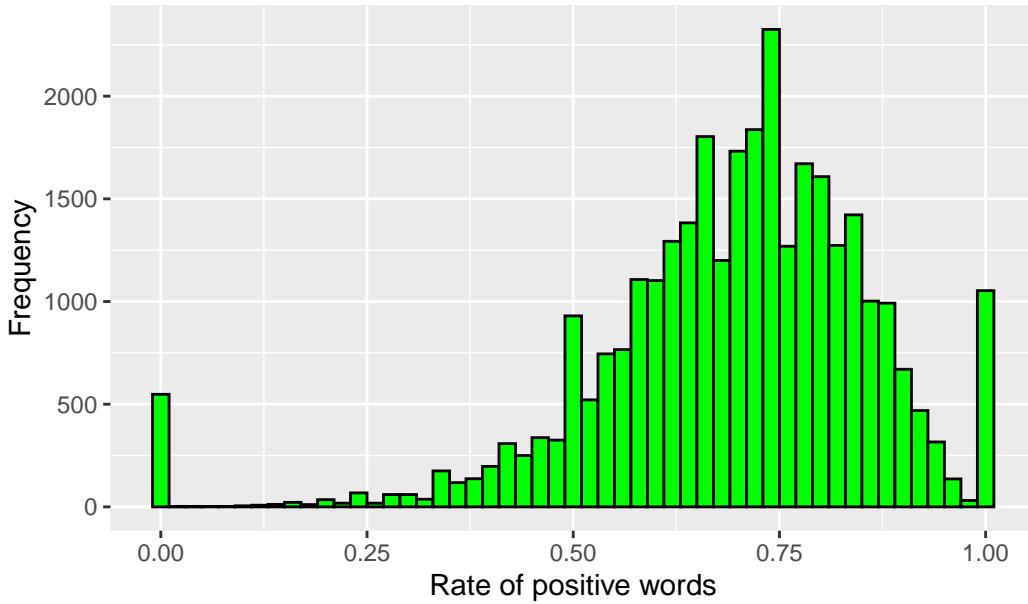


## Predictor Variable/Univariate EDA



Examining the rate of positive words in an article, we see a left skewed distribution, with modes at  $\sim 0$ ,  $\sim 0.75$  and  $\sim 1$ . The median positivity is approx 0.71 positivity rate, and the range is from 0 to 1.

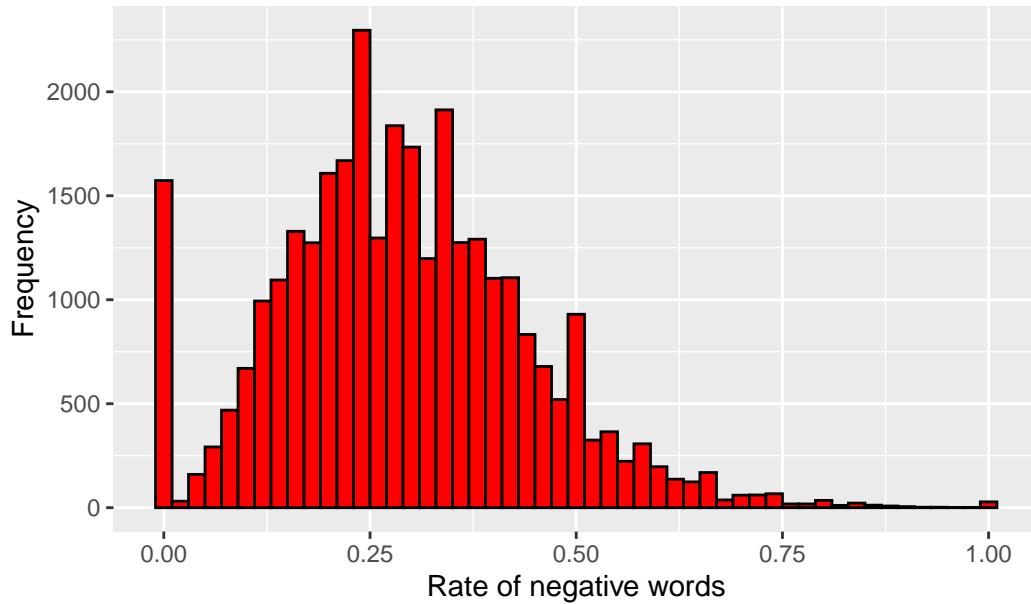
**Rel. Freq of Positive Words Rate**



```
# A tibble: 1 x 5
  mean median std.dev   min   max
  <dbl>  <dbl>   <dbl> <dbl> <dbl>
1 0.694  0.714   0.172    0     1
```

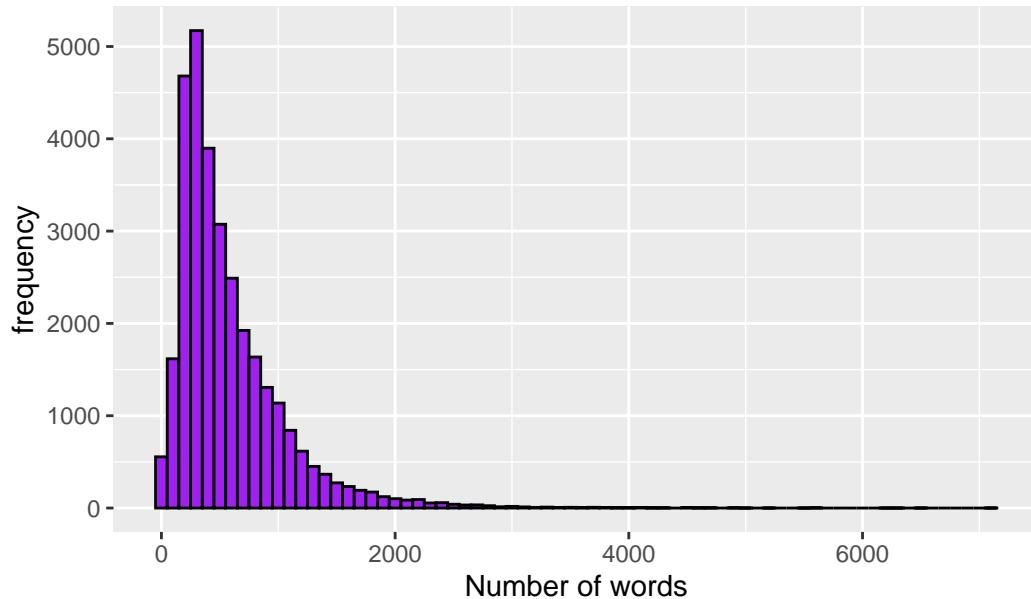
The rate of negative words shows the opposite trend, with a slight right skew. Similarly, there seems to be a second mode at 0 negativity. The median is approx 0.28 negativity rate, with an approximately equal mean.

**Rel Freq of Negative Words Rate**



```
# A tibble: 1 x 5
  mean median std.dev   min   max
  <dbl>  <dbl>   <dbl> <dbl> <dbl>
1 0.290  0.280   0.152    0     1
```

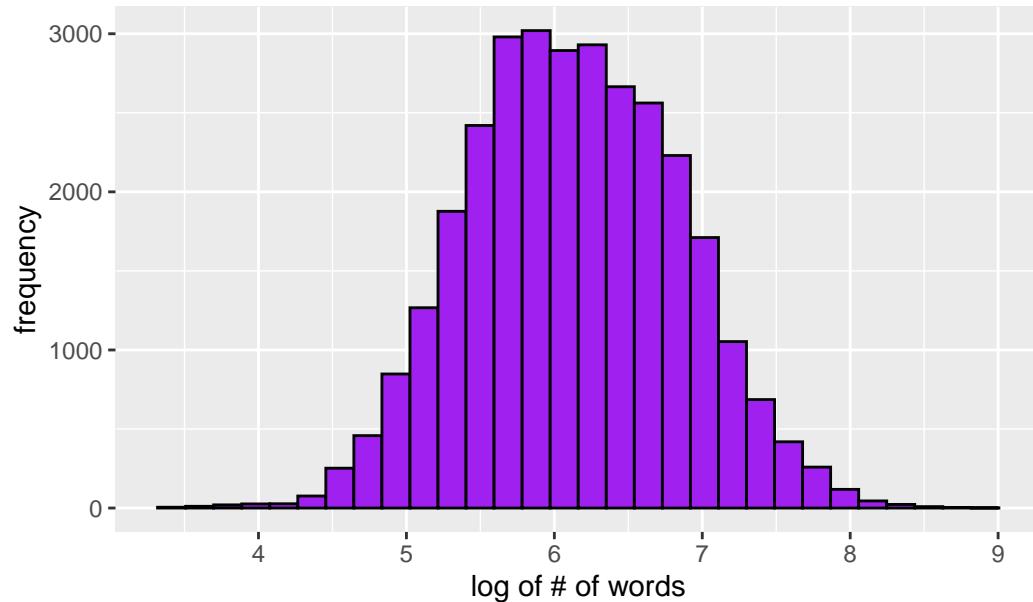
Rel. Freq. of Article Length



```
# A tibble: 1 x 5
  mean median std.dev   min   max
  <dbl>  <dbl>   <dbl> <dbl> <dbl>
1  583.    444    478.     0  7081
```

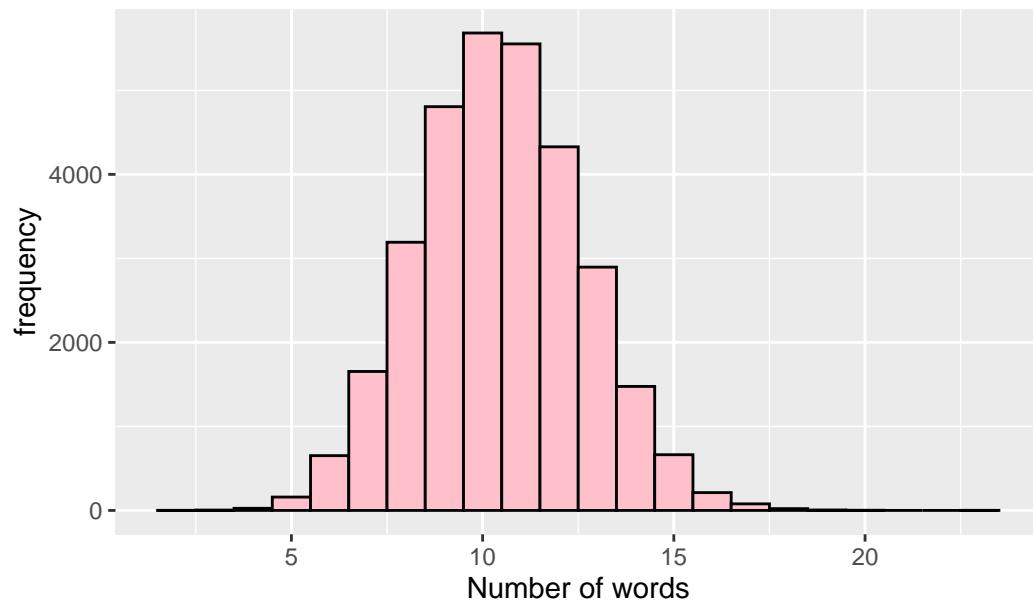
For article length, the graph shows a strongly right-skewed distribution, with a median length of 444 and a high standard deviation of 477 words. To remedy this, we might consider a log transformation which yields a more even distribution.

### Rel. Freq of Log transformed Article Length



For the number of tokens in the title, we can see a highly symmetric distribution centered at 10, with a standard deviation of 2.14.

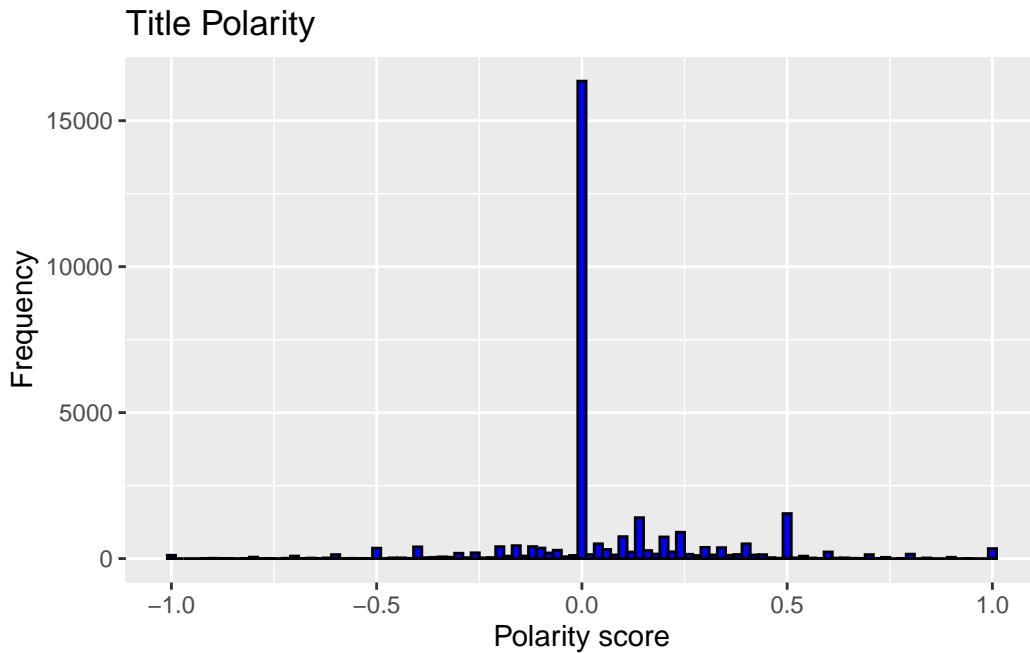
### Rel. Freq. of Title Length



```
# A tibble: 1 x 5
```

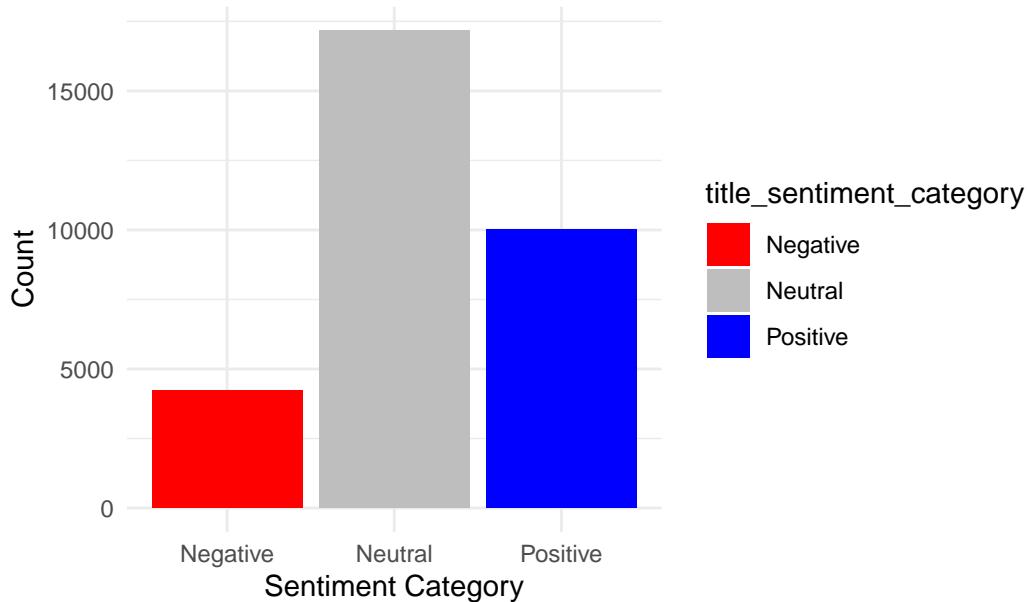
	mean	median	std.dev	min	max
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	10.5	10	2.14	2	23

Finally, our initial EDA of title polarity found a massive frequency spike at 0 frequency, which might correspond to failed measurements or the vast majority of our articles not presenting significant title polarity.

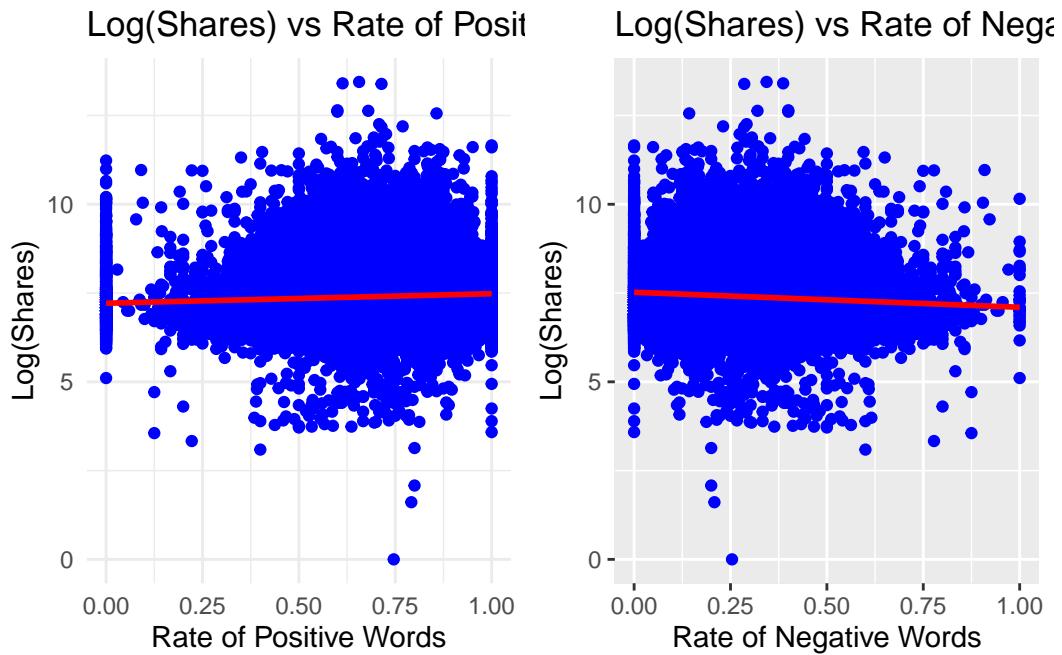


To fix this issue and for ease of use, we categorized articles into negative, neutral and positive polarity, with a threshold of  $0 \pm 0.05$  for neutral. Most titles remain neutral, and there are more positive than negative headlines.

## Distribution of Title Sentiment Polarity

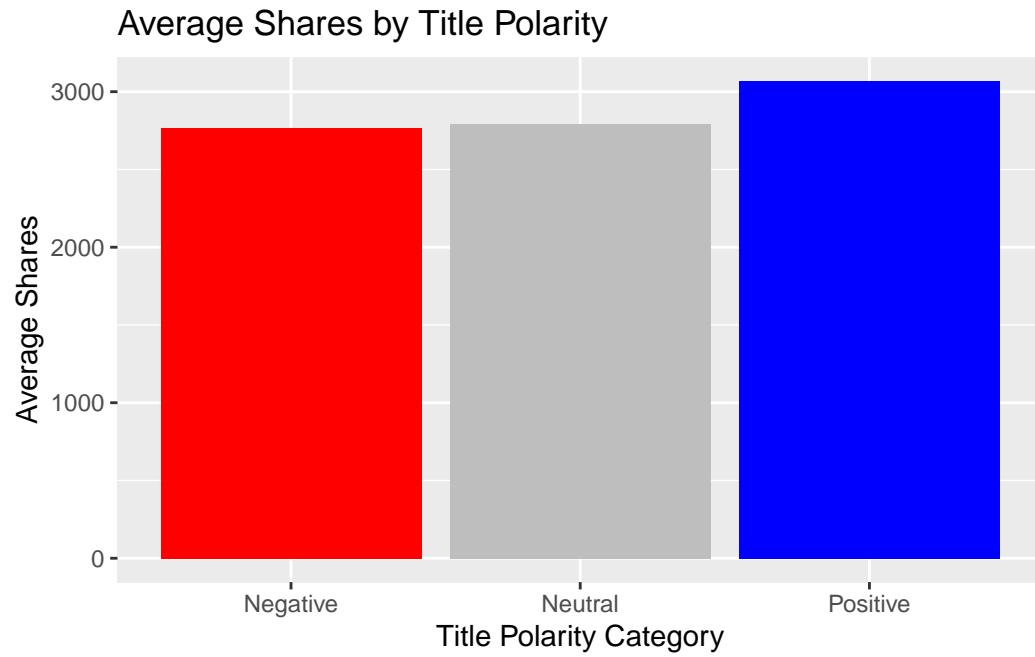


### Bi-variate EDA



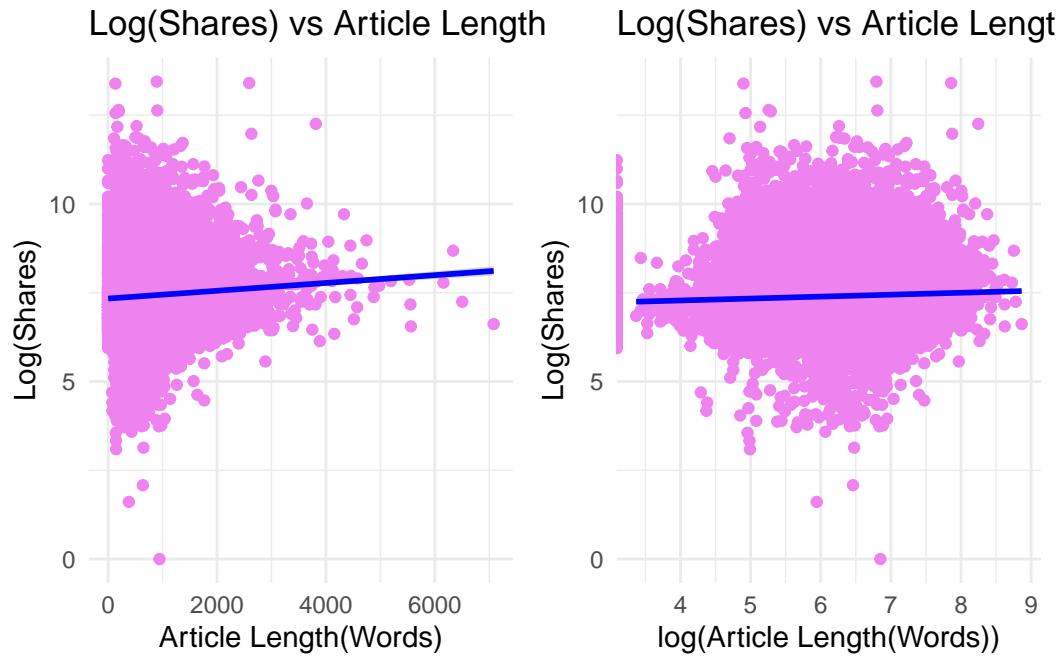
By plotting the rate of positive words and the rate of negative words against the log transformed share, we can see that neither have a particularly strong relationship with how often the article

is shared. The rate of positive words seems to have a weak positive relationship with shares, and the rate of negative words seems to have a weak negative relationship, but both have significant outliers are 1 and 0.



In contrast, there seems to be some relationship between title polarity and the number of shares, with positive polarity associated with greater share counts.

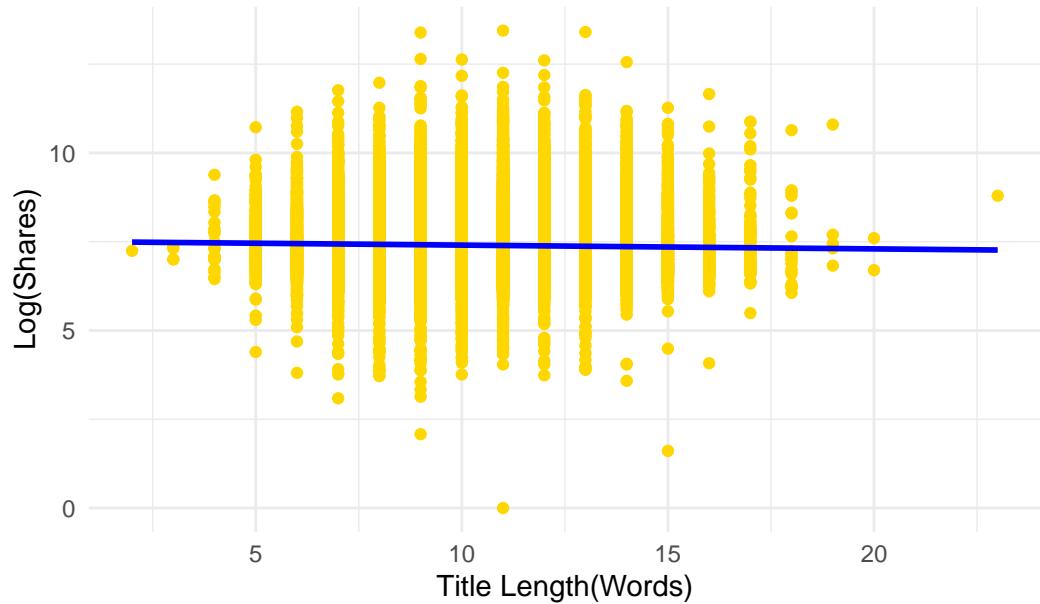
Next,



These graphs show a weak, positive relationship between article length and the log transformed number of shares. Due to the skew, we can apply the log transform to the article length. This shows a more even distribution, with no clear relationship.

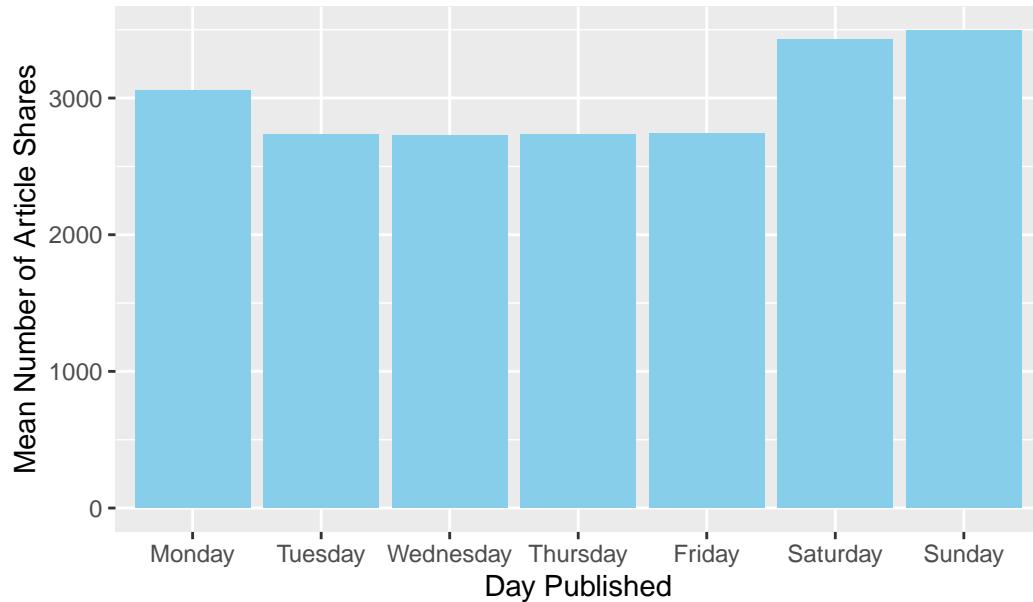
Similarly, there doesn't seem to be any clear relationship between title length and the number of shares in the graph below.

Log(Shares) vs Title Length



```
# A tibble: 6 x 2
  day_published mean_shares
  <fct>           <dbl>
1 Monday            3057.
2 Tuesday           2731.
3 Wednesday         2727.
4 Thursday          2737.
5 Friday            2741.
6 Saturday          3431.
```

## Mean Number of Article Shares vs. Day Published



term	estimate	std.error	statistic	p.value
(Intercept)	7.505	0.038	197.123	0.000
rate_negative_words	-0.408	0.045	-9.071	0.000
rate_positive_words	0.017	0.040	0.437	0.662

```
[1] "Variance Inflation Factors:"
```

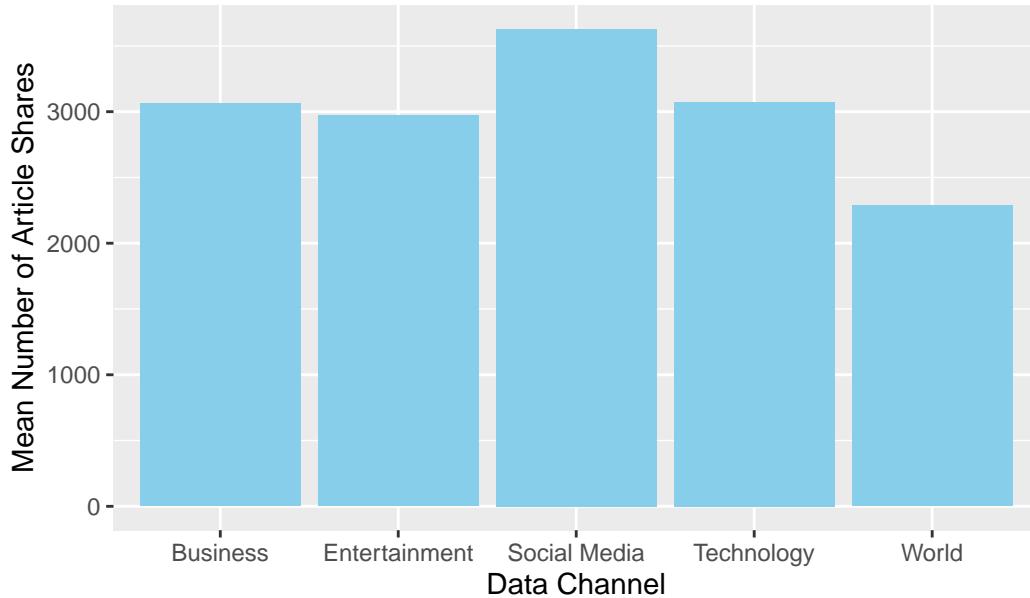
```
rate_negative_words rate_positive_words
1.946291           1.946291
```

This visualization and summarization suggests that the day an article is published does not have a significant impact on the virality of an article, as the mean number of article shares do not differ much between days. Therefore, this predictor may not be as important as others when it comes to predicting the virality of an article.

```
# A tibble: 5 x 2
  data_channel  mean_shares
  <fct>          <dbl>
1 Business       3063.
2 Entertainment   2970.
3 Social Media   3629.
```

4 Technology	3072.
5 World	2288.

### Mean Number of Article Shares vs. Data Channel



From our visualizations, it appears that articles that are in the social media data channel perform the best in terms of average number of shares (~3600), while articles that are in the World data channel perform the worst (~2250). Business, Entertainment, and Technology articles all seem to receive a mean of about 3000 shares. However, from our earlier univariate analysis, we saw that the Social Media Data Channel has the lowest number of articles, and thus there is a possibility that any outliers for this data channel category would have a larger impact in skewing the mean.

#### Interaction Effects Exploration

Table 3: Regression Coefficients for Both Models

Term	Estimate	Std. Error	t value	p-value	Model
(Intercept)	7.451	0.025	297.679	0.000	Model 1
n_tokens_content	0.000	0.000	10.822	0.000	Model 1
n_tokens_title	-0.011	0.002	-4.886	0.000	Model 1
(Intercept)	7.248	0.038	192.902	0.000	Model 2
n_tokens_content	0.000	0.000	9.410	0.000	Model 2
n_tokens_title	0.008	0.004	2.308	0.021	Model 2
n_tokens_content:n_tokens_title	0.000	0.000	-7.265	0.000	Model 2

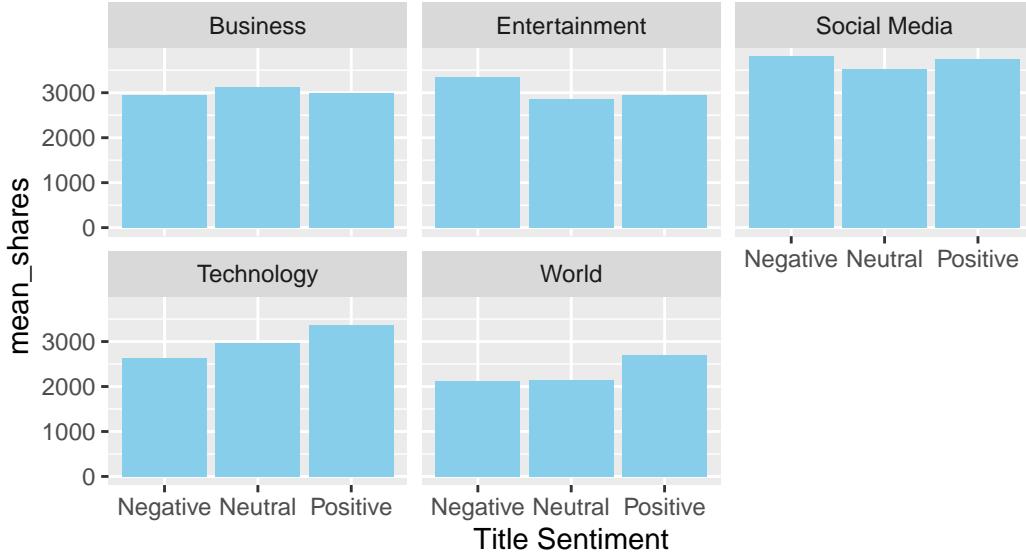
Table 4: ANOVA Comparison of Models

term	df.residual	rss	df	sumsq	statistic	p.value
log(shares) ~ n_tokens_content + n_tokens_title	31408	23701.16	NA	NA	NA	NA
log(shares) ~ n_tokens_content + n_tokens_title +	31407	23661.401	39.762	52.779	0	
n_tokens_content:n_tokens_title						

When comparing linear models with the title and article length as predictors, we explored to see if an interaction effect would have a meaningful difference. Our results show that the effect of title length depends on article length. IE, for very short articles, we'd expect longer titles to be beneficial and for longer articles, vice versa.

### Mean Shares for Title Sentiment Categories

Faceted by Data Channel Type



From this visualization, it's suggested that the title sentiment may have different impacts on the mean number of shares depending on the type of data channel, thus suggesting that there may be a statistically significant interaction effect between the title sentiment and the data channel type. For instance, while for Social Media and Entertainment, it appears that articles with a Negative sentiment have the greatest number of mean shares, for World and Technology articles, Positive sentiment articles had the greatest mean shares, and for Business, Neutral sentiment articles had the greatest number.

term	estimate	std.error	statistic	p.value
(Intercept)	7.341	0.033	220.412	0.000
data_channelEntertainment	-0.032	0.042	-0.768	0.443
data_channelSocial Media	0.418	0.066	6.322	0.000
data_channelTechnology	0.144	0.046	3.111	0.002
data_channelWorld	-0.177	0.040	-4.406	0.000
title_sentiment_categoryNeutral	0.071	0.036	1.969	0.049
title_sentiment_categoryPositive	0.083	0.038	2.169	0.030
data_channelEntertainment:title_sentiment_categoryNeutral	0.046	0.046	-1.863	0.062
data_channelSocial	-0.043	0.072	-0.595	0.552
Media:title_sentiment_categoryNeutral				
data_channelTechnology:title_sentiment_categoryNeutral	0.050	0.405	0.685	
data_channelWorld:title_sentiment_categoryNeutral	-0.059	0.044	-1.326	0.185
data_channelEntertainment:title_sentiment_categoryPositive	0.049	0.049	-1.252	0.211
data_channelSocial	-0.077	0.075	-1.024	0.306
Media:title_sentiment_categoryPositive				
data_channelTechnology:title_sentiment_categoryPositive	0.053	0.929	0.353	
data_channelWorld:title_sentiment_categoryPositive	0.039	0.048	0.810	0.418

However, when looking at the actual fitted model, all the interaction terms between the data channel and the sentiment category have large p-values (greater than 0.05) suggesting that none of the interaction terms are actually statistically significant between data channel and title sentiment category. In the future we could consider looking at the mean of the shares rather than the log, as it appears as though there may be interaction effects for the mean but not the log of the shares.

term	estimate	std.error	statistic	p.value
(Intercept)	7.430	0.052	141.723	0.000
n_tokens_title	-0.002	0.005	-0.417	0.677
data_channelEntertainment	-0.150	0.076	-1.978	0.048
data_channelSocial Media	0.419	0.098	4.270	0.000
data_channelTechnology	0.292	0.072	4.064	0.000
data_channelWorld	-0.415	0.071	-5.827	0.000
n_tokens_title:data_channelEntertainment	0.005	0.007	0.676	0.499
n_tokens_title:data_channelSocial Media	-0.005	0.010	-0.554	0.579
n_tokens_title:data_channelTechnology	-0.012	0.007	-1.712	0.087
n_tokens_title:data_channelWorld	0.020	0.007	2.956	0.003

From this model, we found that while the data channel type at times has a statistically significant linear relationship to log(shares), specifically for Social Media, Technology, and World,

the number of words in the title does not have a linear relationship to  $\log(\text{shares})$ , based on their respective p-values. For instance, the p-value for `n_tokens_title` is 0.677, thus suggesting that there is not a statistically significant linear relationship between `n_tokens_title` and  $\log(\text{shares})$ . However, while the number of words in the title does not have a significant linear relationship with  $\log(\text{shares})$  directly, its interaction term specifically with when the data channel is World, is significant (as shown by the p-value of 0.003).