How Does Content Drive Viewership?

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Abstract

Why do some webpages receive massive numbers of page views? To determine how content drives viewership, we construct a unique dataset of all articles published by the New York Times (NYT) in August 2013. Our dataset is built from 2 major components, the NYT's internal web traffic data and article content data parsed from the NYT website. We use the internal web traffic data to accurately track the number of page views of each article as well as construct a set of robust control variables such as the desk and section of each article. To build content features, we use various machine learning and statistical natural language processing techniques on our parsed article content data and construct features such as article perplexity, sentiment, reading difficulty, and indicators that denote the presence of pictures, videos, etc. Additionally, we have access to the NYT's internal website traffic data. We feed all of our constructed features to into a predictive regression model. We find [MAJOR RESULTS HERE].

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Contents

1 Introduction 1
2 Data 2
2.1 NYT Internal Web Traffic Data 2
2.2 Parsed NYT Article Content Data 2
3 Constructed Features 3
3.1 Article Sentiment 4
3.2 Article Perplexity 5
4 Predictive Regression Model 5
Acknowledgments 6
References 6

1. Introduction

In today's digital economy, many companies are very interested in attracting users to visit their websites in order to earn ad revenue. While many factors might motivate a user to visit a particular page, certainly one important factor is the content in that webpage. This paper explores the relationship between the content of a webpage and the number of page views it ultimately ends up receiving by constructing a unique dataset of all articles published by the New York Times (NYT) during August 2013. This dataset is built from two major components: the NYT's internal web traffic data and parsed NYT article content data.

Typically, a study such as ours tends to be very difficult to conduct as either accurate measures of viewership are unavailable[1] or the feature extraction of the content is too challenging (for example Youtube), or or both. Fortunately, our access to the the NYT's internal web traffic data allows us to exactly measure the number of page views an article receives. The web traffic data is rather rich and also includes internal meta-data that we use to build various control features. Moreover, since we are working with mostly textual data, we are able to take advantage of recent advancements in machine learning and statistical NLP to do feature extraction on article text.

[1] While oftentimes precise viewership data tends to be not available openly, oftentimes researchers use related observables, such as Facebook likes

A similar study by Berger and Milkman (2012) [1] examines the relationship between content and word-of-mouth virality. They find that the emotional content of a NYT article is predictive of its virality. Using simple measures of an article's sentiment and emotionality, Berger and Milkman show that positive articles are more likely to show up on the New York Times "Most-Emailed" list. They also show that articles that evoke high physiological positive or negative arousal (such as awe or anger) tend to be more viral than articles that evoke deactivating emotions (sadness). We build on this study in two ways: first, we relate an article's content back to the number of page views it receives rather than its virality[2]. Second, we employ more sophisticated machine learning feature extraction techniques to see if they work any better over their simple measures.

2. Data

2.1 NYT Internal Web Traffic Data

Our NYT internal web traffic dataset is a record of all individual user activity on the NYT website covering the period of April 3rd, 2013 to October 31st, 2013. This activity data is stored as individual lines of json and includes who (if available) accessed what page at what time. Overall, it is over 20 terabytes in size and contains over 3 billion page views[3] Since the scope of this dataset is so large, we initially restrict this project to a single month, August 2013.

We limit our dataset to consist of pages that only contain articles or blogposts published during the month of August. We parse the data to obtain a list of urls, which need to be stripped of potential garbage. After cleaning up the url data, we are left with 6682 unique pieces of content. We then parse our dataset and aggregate the number of counts each url receives. In order to make the comparison between articles fairer since an article that's been out longer will have more page views on average, we only count the number of page views received up to 7 days after publication[4]. In total, our data consists of over 250 million page views. As seen in Figure 1 below, the distribution of page views is highly skewed with very heavy tails. After applying a log transformation (as seen in Figure 2), our distribution looks considerably more normal.

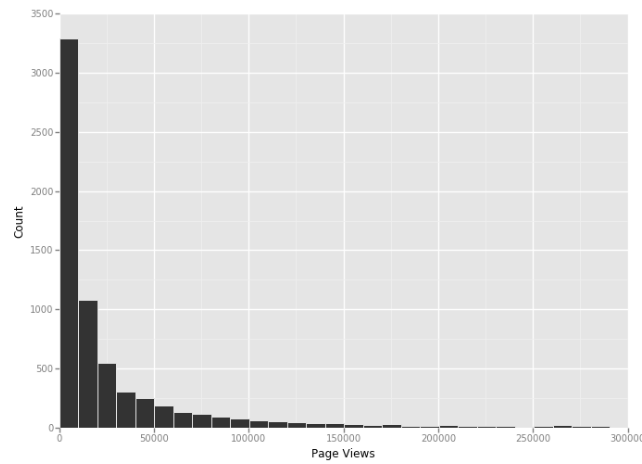

Figure 1. Histogram of Articles by Number of Page Views

Table 1. Page Views Distribution Summary Statistics

Total Page Views	248161455
Min	1
Max	2545288
Mean	37138.8
Median	10298.5
Std. Dev.	88972.9
Skewness	9.52191
Kurtosis	173.061
Observations	6682

In addition to aggregating the counts, when

2.2 Parsed NYT Article Content Data

[2] Which companies arguably care more about since word-of-mouth virality is usually a means to increase page views

[3] Not all page views are content views, for example, some events that are also tracked are searches, or user account settings.

[4] Given that page views tend to sharply drop off soon after publication since recency is quite important to the News, the number of page views obtained during the 7 days after an article is published represents the vast majority (usually well over 90%) of total page views an article receives.

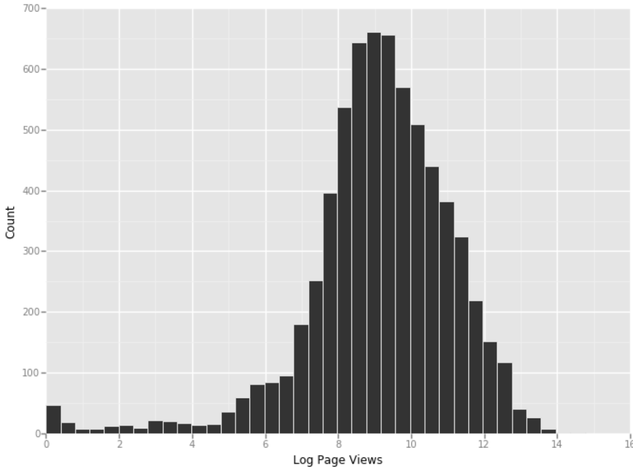

Figure 2. Histogram of Articles by Log of Page Views

Table 2. Log Page Views Distribution Summary Statistics

Min	0
Max	14.74975
Mean	9.122868
Median	9.239754
Std. Dev.	2.028668
Skewness	-1.270368
Kurtosis	3.800911
Observations	6682

3. Constructed Features

In preparing to perform our regression, we construct a number of features, using both the parsed NYT article data and secondary sources. These features include the Flesch reading ease, the (guessed) gender of the author(s), the popularity of the author(s), the sentiment of the article text, the perplexity of the article text, and variables indicating the section the article appeared in and the article's content type. Found below is a full list of these features, as well as the methodology used to construct them and validation of the features, where appropriate.

Flesch Reading Ease The Flesch reading ease is a metric developed by Flesch in 1948 [2]. The score indicates how difficult a piece of English text is to understand. Lower scores correspond to more difficult passages, and

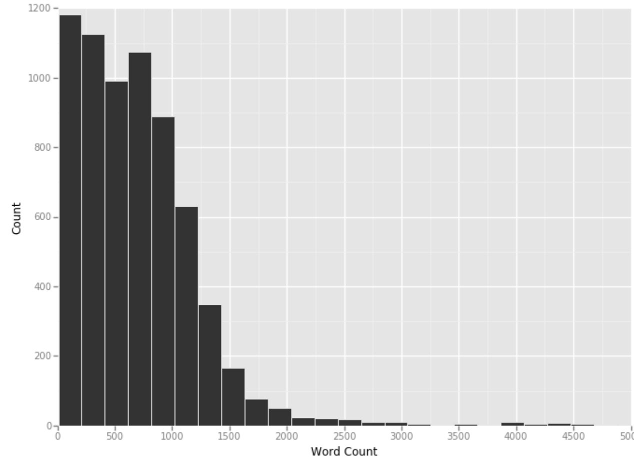

Figure 3. Histogram of Articles by Word Count

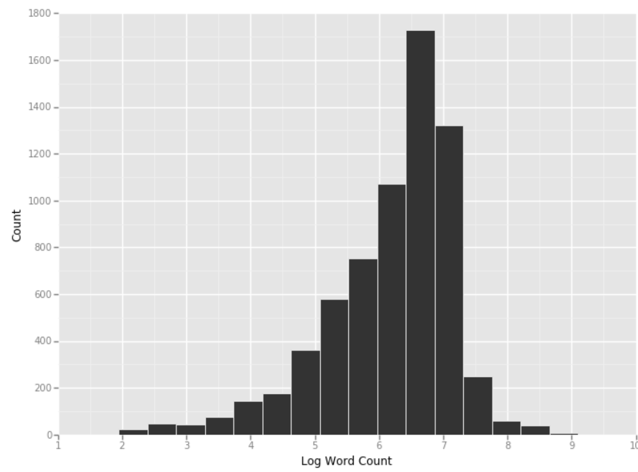

Figure 4. Histogram of Articles by Log Word Count

the highest score attainable is 120.0. The formula for calculating a passage's Flesch reading ease is

$$206.835 - 1.015\left(\frac{\#\text{ words}}{\#\text{ sentences}}\right) - 84.6\left(\frac{\#\text{ syllables}}{\#\text{ words}}\right) \quad (1)$$

To calculate the Flesch reading ease, we use the python library "textstat." Despite the fact that the above formula is relatively straightforward, the task of counting the number of syllables in a block of text is non-trivial, so we rely on "textstat" to do so accurately. In cases where the Flesch reading ease was for some reason null (e.g., a blog post containing only a picture), we assign the Flesch reading ease its median value.

Author Popularity We attempt to include some measure of a particular author's popularity. It stands to reason that a new article by Paul Krugman or A.O. Scott should garner more readership than a new article by an unknown graduate student enrolled in 6.867 at MIT!

In order to measure something that will serve as a decent proxy for popularity, we programmatically searched for every distinct author in our dataset using Bing, and recorded the number of search results that were returned by the query. In cases where a particular article has more than one distinct author, we calculate an "effective" popularity by simply calculating the average number of search results over all article authors.

Author Gender We also attempt to construct a feature that indicates the most likely gender of the article author(s). In cases where the gender of the author is unclear (e.g., Robin) or there are likely multiple authors with different genders (e.g., The New York Times Staff), we record a third gender value, "ambiguous / unknown."

We construct our gender data by cross-referencing the first names of all of the authors in our dataset against U.S. Social Security Administration baby name data from 1935 to 1997. If over 90% of the babies with a given name have been male, we assume a given author is male. If over 90% of the babies with a given name have been female, we assume a given author is female. Otherwise, we record "ambiguous / unknown."

Material Type, Section, Desk, and Article Type We also include dummy variables including the material type (e.g., 'News' or 'Obituary'), desk (e.g., 'Weekend' or 'Real Estate'), article type ('Blog post' or 'Article'), and section (e.g., 'Movies' or 'World').

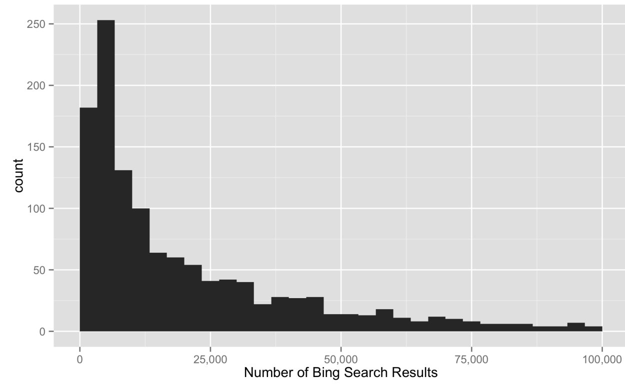

Figure 5. Histogram of Bing Search Results

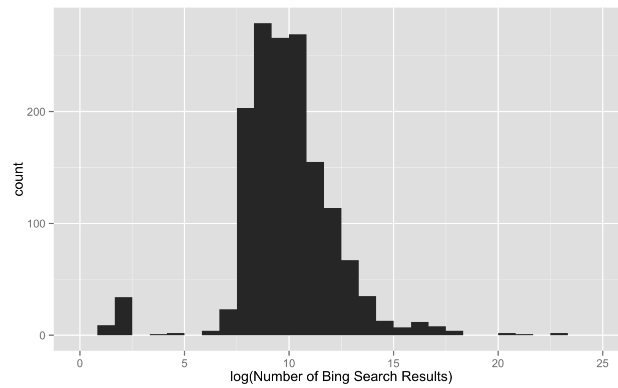

Figure 6. Histogram of log(Bing Search Results)

We also include features that attempt to capture the article sentiment and the article text perplexity. Since the construction of these features was more involved and involved validation of our algorithms, we discuss these two features in separate subsections.

3.1 Article Sentiment

In order to measure article sentiment, we use a Naives Bayes text classification algorithm, as described in Rennie et al (2003) [3]. We assume that each article in our corpus can belong to one of three classes - 'negative' sentiment, 'neutral' sentiment, and 'positive' sentiment, which we will denote as C_k. The Naive Bayes model assumes that the likelihood of observing a given article $\mathbf{x} = (x_1, ..., 1_n)$, where x_i is the number of times that word i appears, is

$$p(\mathbf{x}|C_k) = \frac{(\sum_i x_i)!}{\prod_i x_i!} \prod_i p_{ki}^{x_i}, \tag{2}$$

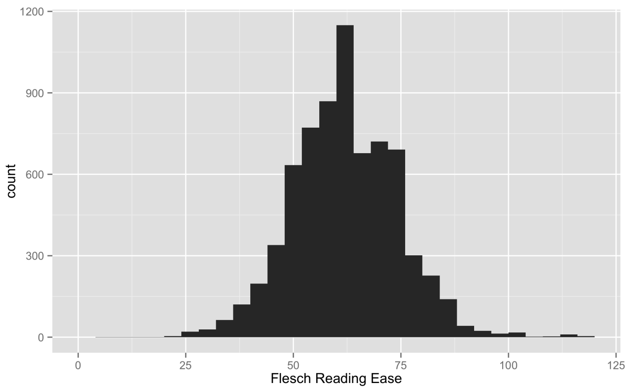

Figure 7. Histogram of Flesch Reading Ease

where p_{ki} is the probability of a document of class K including word i. Given that we transform this problem into log space, we can compute $\log(p(\mathbf{x}|C_k))$ as

$$\log(p(\mathbf{x}|C_k)) = \log(p(C_k)) + \sum_{i=1}^{n} x_i \cdot \log(p_{ki}). \quad (3)$$

We coded up a basic implementation of the Naive Bayes algorithm, drawing heavy inspiration from Greg Lamp's 2014 python tutorial on Naive Bayes [4]. In order to get the probabilities $p(C_k)$ and p_{ki}, we developed a training set of NY times data by providing 200 articles to workers on Amazon Mechanical Turk. Each turker was asked to score the sentiment toward the subject of the article in question on a scale from -2 to +2, with -2 being extremely negative and +2 being extremely positive. We recorded 5 scores for every article, and calculated the average sentiment reported by the Turkers. We classified any article having an average score greater than 0.5 as 'positive'. Any article with an average sentiment less than -0.5 was 'negative.' Any other articles were classified as 'neutral.' Ultimately, our labels were 66% neutral, 14.5% negative, and 19.5% positive. This is unsurprising, as a newspaper such as the New York Times likely strives for neutrality when reporting on most topics.

We wanted to determine how our Naive Bayes implementation did compared to an off-the-shelf implementation of the same algorithm. In order to do so, we trained NLTK's multinomial Naive Bayes classifier on the same training data, and then evaluated the sentiment of 1,000 articles. A comparison of the two implementations is found below, where the columns indicate the prediction by the NLTK Naive Bayes implementation and the rows indicate the prediction by our implementation:

	negative	neutral	positive
negative	0	54	0
neutral	2	894	0
positive	0	50	0

Overall, we find 89.4% agreement between the two algorithms. However, alarmingly, the NLTK implementation seems to predict neutral an overwhelming percentage of the time (99.8% of the time). This warrants further investigation, and may be due to small differences in implementation, or peculiarities in the sample of 1,000 articles we chose to compare the two algorithms across. In any case, our algorithm seems to be performing in the same neighborhood as the NLTK implementation (if not better), so we feel relatively comfortable moving forward using our sentiment labels.

3.2 Article Perplexity

4. Predictive Regression Model

Once we have constructed our full set of features, we aim to predict log(article pageviews), $\mathbf{y}$, using our full set of variables, which we include in our design matrix, $\mathbf{X}$. We estimate the feature weights using the closed form solution for both OLS and ridge regression,

$$\beta = (\mathbf{X}^T\mathbf{X} + \lambda\mathbf{I})^{-1}\mathbf{X}^T\mathbf{y} \quad (4)$$

where $\mathbf{I}$ is the $k \times k$ identity matrix, and λ is our regularization parameter. Setting $\lambda = 0$ corresponds to OLS, whereas non-zero values of λ correspond to ridge regression. The motivation for performing ridge regression as opposed to OLS is to not overfit on our data.

In order to choose an appropriate value of λ, we split our data into a training and validation set. 90% of the data is allocated to the training set, and 10% of the data is allocated to the test set. We cross-validate the estimated β values on our validation set for each λ, and choose the value of λ that produces the lowest MSE on the validation data.

The table below displays the 20 feature weights with the largest magnitudes given our model. A bar chart showing the magnitude of all of the weights (excluding the intercept weight) can be found in Figure 8.

Figure 9 shows the training and holdout MSE for various values of Lambda. There are a few things in this plot worth discussing. First, note that the holdout MSE is consistently lower than the training data MSE. Given the (relatively) small size of our dataset (6,687 observations), this is likely due to the sampling we used to separate our data into training and validation data. However, this shouldn't effect the validity of our cross validation.

Another thing worth noting is that even on the training dataset, the MSE goes down once we choose a non-zero value of λ. At first, this was surprising to our group, as conceptually OLS is often thought of as the linear regression method that minimizes MSE. However, it is important to note that OLS only holds this distinction amongst unbiased estimators. Hoerl and Kennard (1970) [5] prove the existence theorem for ridge regression, which proves that there exists a value of λ for which β_{ridge} produces a lower MSE than β_{OLS}.

Another way of framing this finding is through bias-variance tradeoff. Recall that the MSE can be written as a function of the bias and variance:

$$MSE = (\text{Bias})^2 + \text{Var}. \tag{5}$$

For some values of λ, ridge regression is able to lower the MSE by decreasing variance, but adding a non-zero bias term. We believe this is what is happening in our data when cycling through different λ values.

Feature	Weight
intercept	9.114
log(Word Count)	0.736
Desk: Foreign	0.561
Desk: Travel	-0.478
Section: World	-0.410
Type: BlogPost	-0.394
Type of Material: Schedule	-0.330
Type of Material: Review	-0.324
Type of Material: Letter	-0.311
Section: Fashion & Style	0.275
Section: Movies	-0.267
Desk: National	0.245
Section: Opinion	0.245
Time of Day: 12-17	0.239
Section: Books	0.219
Section: Health	0.200
Section: Sports	-0.191
Desk: Society	-0.178
Section: Corrections	-0.167
Desk: BookReview	-0.167

Acknowledgments

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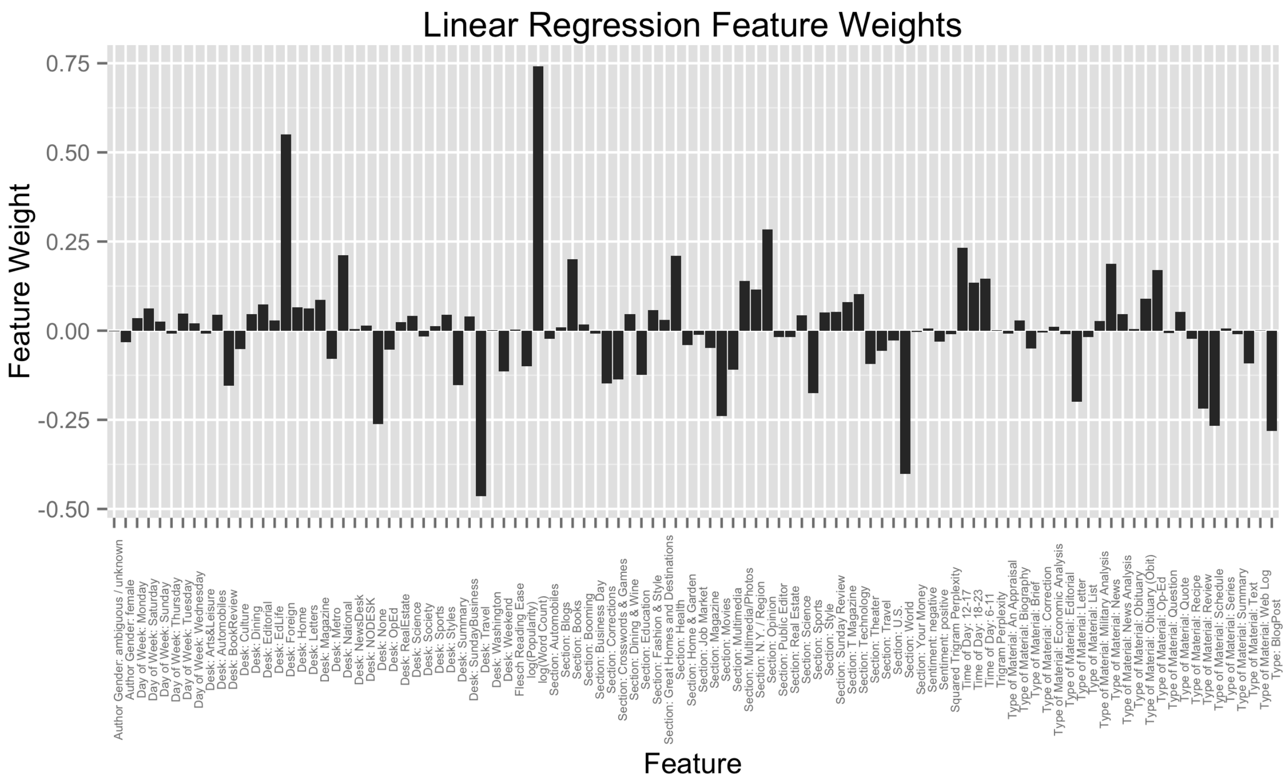

Figure 8. Linear Regression Feature Weights (excluding intercept term)

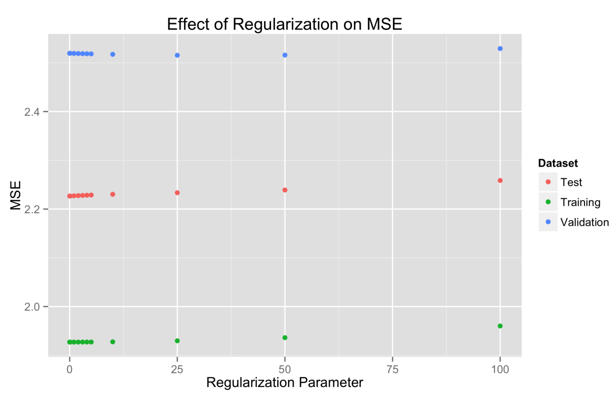

Figure 9. The effect of regularization on MSE