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The Impact of Crowds on News Engagement: A Reddit Case Study

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Abstract

Today, users are reading the news through social platforms. These platforms are built to facilitate crowd engagement, but not necessarily disseminate useful news to inform the masses. Hence, the news that is highly engaged with may not be the news that best informs. While predicting news popularity has been well studied, it has not been studied in the context of crowd manipulations. In this paper, we provide some preliminary results to a longer term project on crowd and platform manipulations of news and news popularity. In particular, we choose to study known features for predicting news popularity and how those features may change on reddit.com, a social platform used commonly for news aggregation. Along with this, we explore ways in which users can alter the perception of news through changing the title of an article. We find that news on reddit is predictable using previously studied sentiment and content features and that posts with titles changed by reddit users tend to be more popular than posts with the original article title.

Introduction

It is well-known that an operational and useful democracy relies on an educated and well-informed population (Lewandowsky et al. 2012). The primary way this population is informed is through the news. While traditionally, news is received through print, television, or online articles, increasingly more people consume news through social platforms. On these platforms, both crowds and the system work together to makes decisions on what information is important. These decisions may be informed by many factors such as homophily, estimated interests, self-selection of sharing, or the crowd voting on the information. Recently, many researchers have begin studying the system side impact of social platforms on information engagement (Bakshy, Messing, and Adamic 2015) (Horne, Adalı, and Chan 2016), but very few studies have looked at the crowds' effect on these information decisions, especially in the context of news. If we understand both the impact of the platform and the impact of the platform user on news engagement and popularity, we can better build social platforms that not only engage users, but better inform users.

One such social platform is reddit.com. In the context of news, reddit is a platform where users post links to news articles and vote on their importance or relevance. The number of votes will roughly determine the order in which news is sorted on the page. When users post links, they have the option to use the title of the article they are linking to, or to create their own. In addition, users can comment on the news article posts to start a discussion with the community. Hence, on reddit, crowds can influence news consumption through crowd selection, voting, title changing, and direct discussion.

In this paper, we will report preliminary findings on three of these crowd effects: voting, commenting, and title changing. In particular, we will ask two questions: (1) Can known features from the news popularity literature predict the number of votes and the number of comments on reddit news posts? (2) Does the crowd affect the number of votes and number of comments through changing the news headlines? To answer these questions, we will compute features and predict popularity on scraped news articles posted to the reddit community: `r/worldnews`. After assessing our prediction models, we will introspect on our features to gain further insight into how each important feature predicts news popularity on reddit. Lastly, we will perform pairwise hypothesis testing on news media made titles and reddit user made titles to gain insight into one specific way the crowd can manipulate news.

We find that both the number of votes and the number of comments on reddit news posts is predictable using previously known, non-temporal news popularity features. We find that votes (also known as the score) are predicted well by a mixture of content, sentiment, and subjectivity features, whereas the number of comments is predicted well by using only sentiment and subjectivity features. Hence, the motivation to vote on an article and the motivation to engaged with an article are different. Specifically, voting is based on content quality, while commenting is based solely on emotion. In addition, we find that post titles that are changed from the original news article title tend to receive slightly higher scores and slightly more comments than posts using the original news article title. When titles are changed, they are changed to be significantly more positive, less negative, more informal, more difficult to read, and longer overall. These findings illustrate the reddit community's ability to make news headlines that engage their audience by adding their own positive analysis to the headline.

Related Work

News Popularity

News and information popularity is well-studied. We know that, in general, shared news tends to be more negative, and that people tend to share information that will get an emotional response (Harcup and O'neill 2001) (Lewandowsky et al. 2012). One recent study demonstrated that headline negativity and overall sentiment is important in news popularity. (Reis et al. 2015). The authors extract sentiment features from the headlines of four major news sources and use the bit.ly API to infer popularity. The study shows that the majority of news produced negative headlines and this negativity is fairly constant over time. Along with this, extreme sentiment on both the positive and negative side tends to attract more popularity. To test these finding in our study, we will use the same sentiment tool, SentiStrength (Thelwall et al. 2010), to evaluate the intensity of sentiment in highly engaged news. In a similar study, Keneshloo et al.'s work, on predicting the popularity of news articles in the Washington Post (Keneshloo et al. 2016), shows that only the neutrality of content is an important sentiment predictor of popularity. However, the authors do not give us any insight as to if high neutrality means high popularity or if low neutrality means high popularity. To test this finding in our study, we will also use the sentiment tool used in Keneshloo et al.'s work, Vader-Sentiment (Hutto and Gilbert 2014), to compute the positive, negative, neutral, and composite (overall) sentiment. Keneshloo et al. also show that readability using the SMOG index and the title length are important content features in popularity prediction. Hence, we will also implement these features in our study.

From a traditional journalism perspective, there exists what are called news values. (Harcup and O'neill 2001) While these values differ slightly between authors, we will implement features on some commonly held news values, including simplicity, sentiment, surprise, and unambiguous arguments.

Also, related to this study, is the large body of work on general information popularity prediction. These studies include predicting retweets on Twitter (Zaman et al. 2014) and the number of comments on a news article (Tsagkias, Weerkamp, and De Rijke 2009). Some of our features will overlap with these general popularity studies.

News Headlines

There has also been significant work on the influence of news headlines. While on the surface changing a title seems trivial, it can have an substantial impact on how people perceive and consume news. In a 2014 study, Ecker et al. found that misleading news titles can emphasize secondary content rather than the primary content of the article, and that misleading titles affect the readers memory, reasoning, and intentions, as they struggle to update their memory to more exact information (Ecker et al. 2014). Furthermore, in a 2007 study by Surber and Schroeder, titles were found to improve recall of important information (Surber and Schroeder 2007). If title information is false or even slightly misleading, this information recall will be flawed. To make matters worse, it is well known that humans take shortcuts in information trust decisions when there is a low need for cognition, low energy, or high cognitive strain (Petty and Cacioppo 1986). Hence, users are prone to formulate opinions about the news simply from the title. This effect may be multiplied on platforms such as reddit, as users may be prone to voting on information without fully exploring the news article. Therefore, we will explore the impact of many different features on the both the titles of the articles and the titles of the reddit posts.

Reddit

Reddit, as a platform, has also been very well studied. In particular, we know that the posts' timing and the posts' titles are important factors in popularity on reddit (Lakkaraju, McAuley, and Leskovec 2013) (Tran and Ostendorf 2016), but this popularity can be different across communities (Jaech et al. 2015). In addition, we know that reddit user reputation has little influence on popularity, unlike on Twitter where users are not anonymous.

There has also been numerous studies that explore the higher-level behavior of reddit, and the many confounding factors in popularity on reddit. Hessel, Tan, and Lee study the nature of spin-off or highly-related communities on reddit using a large comprehensive data set that spans over 8 years (Hessel, Tan, and Lee 2016). They show that users who explored new "spin-off" communities become more active in the original community rather than the spin-off community they explored. In Hessel, Lee, and Mimno's 2017 work, they find that visual and text features together predict popularity better than author-based features across several image-based communities (Hessel, Lee, and Mimno 2017). They again show that popularity is influenced by timing factors including the time of day. Gilbert shows that reddit overlooks about 52% of the most popular links at first submission (Gilbert 2013). This early finding is likely due to the recently found popularity factors such as the timing of posts and the noisy sorted order on the page, which is only roughly reflected by the community votes. Further, these factors can cause "rich-get-richer" senerios, where already popular posts continue to gain popularity, while not so popular posts continue to get overlooked (Hessel, Lee, and Mimno 2017). All of these studies provide insight into the confounding factors in reddit popularity that may impact our predictions: timing, user activity, sorting displayed, noise in scores, community differences, and author popularity.

Since timing is both a confounding factor in reddit popularity and in general news popularity, one might expect that non-temporal features will have very little predictive power. We will investigate this further in this paper to check if the content of news still matters in determining its popularity above and beyond its timing. Performing this same analysis with time controlled data is left for our future work.

subreddit	year	# posts	# news articles scraped
r/worldnews	2012	60734	31938
r/worldnews	2013	93254	40809
total		**154K**	**72.7K**

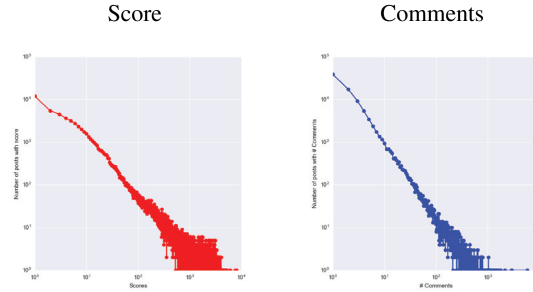
Table 1: The number of posts and scraped articles per data set in this study.

Methods

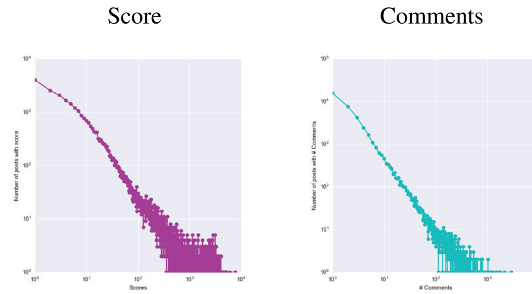
Data Sets

We extract posts from 2012 and 2013 for one popular news community on reddit: `r/worldnews`. Once we extract all posts, we extract the voting score, number of comments, post title, and news story urls from each post. These news story urls are used to scrape a sample of news articles, including the body text and title text, using a mix of our own code and the Python Goose library. We will filter out any article that is under 100 characters or blocked by a paywall. This reddit data comes from Tan and Lee's reddit post data set (Tan and Lee 2015) and Hessel et al.'s full comment tree extension to that reddit dataset (Hessel, Tan, and Lee 2016). Both of these data sets are based on a reddit API collection originally done by Jason Baumgartner of pushshift.io. Our newly collected data set of news articles with corresponding reddit engagement statistics can be found at https://github.com/rpitrust/reddit-scraped-worldnews-dataset.

The number of posts extracted and number of articles scraped in each year can be seen in Table 1. In Figure 1, we show the distribution of scores and distribution of number of comments for the full reddit data set and for the articles scraped. As expected, both distributions are power-law (or more precisely Zipfian) distributions (Jaech et al. 2015), and our scraped data set provides an adequate random sample of the distributions for both the score and the number of comments.



(a) All Data



(b) Scraped Data

Figure 1: The **Score** and **# of Comment** distributions on teh full reddit data set and on the article scraped data set for `r/worldnews` 2013. The distributions are similar for `r/worldnews` 2012.

Features

We engineer features with two questions in mind: (1) What do we already know about popular news? (2) In what ways may reddit crowds change what news is popular? From this perspective, we implement many features from the popularity literature and some features of our own. These features can be divided into three main classes: sentiment, subjectivity, and content structure. We will provide detailed descriptions of the more complex features here. The complete feature set can be found in Table 2.

To compute sentiment features, we will use 3 different approaches from literature: SentiStrength, Vader-Sentiment, and LIWC. SentiStrength is a machine learning based method that provides the polarity of sentiment, with -5 being very negative and +5 being very positive (Thelwall et al. 2010). In previous work, it has been shown to work well with news data (Reis et al. 2015). Vader-Sentiment is a lexicon and rule-based sentiment tool that is built for sentiment expressed on social media (Hutto and Gilbert 2014). It provides measures of positive, negative, and neutral sentiment, along with a composite measure to provide a single overall measure of sentiment. Vader-Sentiment was found to work well on news data in previous work (Keneshloo et al. 2016). Lastly, Linguistic Inquiry and Word Count (LIWC) is a well known bag of words (or dictionary) based method for measuring many different psychological and language dimensions (Tausczik and Pennebaker 2010). We will specifically use the positive emotion, negative emotion, tone, and affect word counts to measure sentiment and emotion. Along with sentiment, we will compute several features that capture the general subjectivity of a news article or title. Primarily, we will use a Naive Bayes classifier which we have trained on a data set of 10K labeled subjective and objective sentences from Pang and Lee's 2004 work (Pang and Lee 2004). The classifier achieves 92% 5-fold cross-validation accuracy. We will use the classifier to create three features: the probability the text is objective, the probability the text is subjective, and a hard binary classification of objective or subjective. While this data set has been used in many different scenarios, to our knowledge it has not been used on news data. In addition to these features, we provide several LIWC features that capture something about the objectivity of the articles, including analytic, insight, authentic, tentative, certain, affiliation, focus-present, and focus-future word counts.

Additionally, we will provide simple content features to capture some other findings in the news popularity literature and general information trust literature. These include readability using three different well-known readability metrics (SMOG, Gunning-Fog, Flesh-Kincaid), a measure of lexical diversity (Type-Token Ratio), and a set of LIWC language

Abbr.	Description
str_neg	negative emotion using SentiStrength
str_pos	positive emotion using SentiStrength
vad_neg	negative sentiment score Vader-Sentiment
vad_pos	positive sentiment score Vader-Sentiment
vad_neu	neutral sentiment score Vader-Sentiment
vad_comp	composite sentiment score Vader-Sentiment
NB_psubj	probability of subjectivity using a learned Naive Bayes classifier
NB_pobj	probability of objectivity using a learned Naive Bayes classifier
NB_subjcat	binary category of objective or subjective
posemo	number of positive emotion words LIWC
negemo	number of negative emotion words LIWC
tone	number of emotional tone words
affect	number of emotion words (anger, sad, etc.)
analytic	number of analytic words
insight	number of insightful words
authent	number of authentic words
tentat	number of tentative words
certain	number of certainty words
affil	number of affiliation words
focuspresent	number of present tense words
focusfuture	number of future tense words

(a) Sentiment and Subjectivity Features

Abbr.	Description
WC	word count
WPS	words per sentence
GI	Gunning Fog Grade Readability Index
SMOG	SMOG Readability Index
FK	Flesh-Kincaid Grade Readability Index
flu_coca_c	avg. frequency of least common 3 words using all of the coca corpus
flu_coca_d	avg. frequency of words in each document using all of the coca corpus
TTR	Type-Token Ratio (lexical diversity)
avg_wlen	avg. length of each word
quote	number of quotation marks
ppron	number of personal pronouns
i	number of I pronouns
we	number of we pronouns
you	number of you pronouns
shehe	number of she or he pronouns
quant	number of quantifying words
swear	number of swear words
netspeak	number of online slang terms (lol, brb)
interrog	number of interrogatives (how, what, why)
per_stop	percent of stop words (the, is, on)
allPunc	number of punctuation
function	number of function words

(b) Content Features

Table 2: Different features used in our study

dimension features. In addition, we will compute a feature called fluency from Horne et al. (Horne et al. 2016). Fluency is a measure of word commonality and technicality. It is computed by counting the frequency of each word appearing in a large English corpus. If a piece of text has a high fluency score, we would expect the words being used are more common words. On the other hand, if the fluency score is low, we would expect many of the words to be highly technical or rare. We choose compute the feature using the Corpus of Contemporary American English (COCA) (Davies 2008). While fluency has not been explicitly tested in news popularity scenarios, it is meant to capture the well known information processing concept of perceived familiarity and coherence of information. It is known that people may determine the believability of information by how coherent that information is cognitively. Information that is familiar or has been seen before tends to be more coherent, even if that information is false (Lewandowsky et al. 2012).

Testing News Popularity Findings

To test our feature sets and what we already know about popular news, we will use the following methodology:

1. Learn models to predict the score of a news article in terms of various combinations of feature sets.
2. Learn models to predict the number of comments under a news article in terms of various combinations of feature sets.
3. Assess all models on the task of ranking.

Since, each reddit community is set up as a ranking of posts based on voting (and some unknown noise to keep the system from being manipulated), it is natural for us to evaluate our models on the task of ranking.

Learning to Rank To perform learning to rank, we will use the Lasso regression algorithm from the Python scikit-learn library (Pedregosa et al. 2011), with the fitting and regularization parameters being chosen by cross-validation. Lasso is a linear model that performs L1 regularization and provides sparse solutions. It is known for its ability to handle a large number of correlated features well.

Preprocessing We will perform one preprocessing step on each data set, in which all scores or number of comments that fall below 30th percentile will be removed. Since the distributions are fat-tailed, these removed posts roughly have scores of 1 or below and number of comments of 0. We perform this step to ensure we are learning the difference between the engagement of actual news and not spam submitted to the community. While our news scraping methodology removes much of the spam, we want to ensure our learning algorithm is not skewed towards spam, creating a different problem of separating spam from news. Choosing the 30th percentile is simply a heuristic to remove posts with scores and number of comments of 1 or 0.

Learning to Rank Metrics To evaluate the performance of our models, we will first divide the data into a train and test set with 80% of the data being for training and 20% of the data being for testing. Once the models are learned, we evaluate the performance on the test set by the following metrics from the learning to rank literature:

1. Precision @ k: Percentage of top k posts we were able to retrieve correctly.
2. Kendall-tau distance (KT-distance) @ k: Kendall-tau distance between the relative ranking of the top k posts according to the real score versus the relative ranking of the same k posts by their predicted scores.

We will report $k = 3, 10, 100, 500$. We use both precision and Kendall-tau distance to gain a complete picture of our prediction quality. If we achieve high precision on large test sets and the Kendall-tau distance is low, it means that the top k posts were correctly retrieved and the relative ranking of the top posts are close to the real ranking. This allows us to conclude that the predicted ranking is close to the real ranking overall. A rule of thumb for assessing these results is to have a high precision at low values of k and a low Kendall-tau distance at high values of k.

Feature Introspection To better understand how our features predict news determined popular by the crowd, we will perform a two step post-hoc analysis methodology. First, we will perform stability selection (implemented in the Randomized Lasso class of Python Scikit-learn) to select the most important features used in the prediction of each model. Second, we will perform traditional hypothesis testing using Wilcox Rank-Sum tests on a two-class divide of those selected important features. This step will describe the shift in each independent feature distribution, thus, helping describe exactly what ways highly popular news and not highly popular news differ. The data will be divided into a high class (any story with a score or number of comments above the 90th percentile) and a low class (any story with a score or number of comments below the 50th percentile). These divides are simply heuristics for capturing the top and bottom of our heavily skewed distributions. Once again, our goal in creating this divide is to provide a better understanding of how our features are predicting, not just which features are important. We will report the direction each features shifts between the two-classes and if the shift is statistically significant.

Exploring Title Change

Additionally, we find that users on reddit tend to significantly edit the titles that they post. In 85% of the posts in 2012 and 72% of posts in 2013, titles have been edited by at least one word. We would like to study both how the titles are changed and what effect these changes have on popularity of the posts. To do this, we will first compute the cosine similarities between each reddit user title and the original title from the news source. This will determine the distribution of title changes. Second, we will determine if changing the title has any influence on the score and number of comments a news article receives by using traditional hypothesis testing on a 2 class divide as described previously. We will also report several signficance test measures on this divide, including the Wilcox Rank-Sum p-values, the Cohen's d effect size, and the Grissom-Kim probability. The Grissom-Kim probability is simply the probability that a randomly selected number in group A is greater than a randomly selected number in group B. Grissom and Kim propose this method to check the effect size on nonparametric tests, as Cohen's d may not always be accurate on heavily skewed distributions (Grissom and Kim 2012). Reporting both metrics will provide a complete picture of the titles in this data set. Finally, we will use Wilcox Rank-Sum tests on extracted title pairs that have a similarity less than 0.1. This step will describe how the users change titles. We will report both the direction of change for statistically significant features and the Cohen's d effect size of that change. Since our features are roughly normally distributed, unlike the scores and number of comments, the Cohen's d effect size should be accurate.

Results and Discussion

Ranking News Popularity

First, we will present our findings on general news popularity on reddit. In Table 3 and Table 4, we report our results for each data set and several models. Table 3 is reporting the results for ranking by score and Table 4 is reporting the results for ranking by the number of comments.

When ranking by score, we find that the use of all of features (sentiment, subjectivity, and content) works best, achieving very high precision for all values of k. However, when separating the models, we find that content features predict slightly better than sentiment and subjectivity features.

When ranking by the number of comments, we find that the use of only sentiment and subjectivity features is best, achieving a much higher precision in values of small k than content features. In fact, when adding content features to the model, we find a harsh decrease in performance, likely due to over-fitting or skewing the learning to less useful content features rather than more useful sentiment features.

This difference in ranking performance suggests that the motivation of of the crowd in voting and commenting may be different. While these metrics of popularity are highly correlated, we do find distinct differences in the types of features that perform well in prediction. Predicting the score is based on both content and sentiment, while predicting the number of comments is based on sentiment only. This finding needs to be explored more fully, but is worth mentioning here. More importantly, we find that despite the salience of timing on reddit and in general news popularity, we are

Dataset	Model	Precision @ k					KT-distance @ k				
		$k=3$	$k=10$	$k=50$	$k=100$	$k=500$	$k=3$	$k=10$	$k=50$	$k=100$	$k=500$
r/worldnews 2012	Senti+Subj	1.0	0.9	0.78	0.78	0.76	3	26	572	2300	62262
r/worldnews 2013	Senti+Subj	0.677	0.667	00.80	0.78	0.78	3	27	703	2362	64177
r/worldnews 2012	Content	1.0	1.0	0.84	0.77	0.84	2	20	526	2063	59334
r/worldnews 2013	Content	1.0	0.90	0.78	0.82	0.78	1	26	546	2776	62657
r/worldnews 2012	All	1.0	1.0	0.88	0.87	0.86	3	30	560	2553	60182
r/worldnews 2013	All	1.0	0.70	0.80	0.78	0.71	4	18	559	2516	55869

Table 3: Evaluation of Lasso Regression models **Ranked by Score**. The test sets that are being ranked on range from 3000 to 8000 data points.

Dataset	Model	Precision @ k					KT-distance @ k				
		$k=3$	$k=10$	$k=50$	$k=100$	$k=500$	$k=3$	$k=10$	$k=50$	$k=100$	$k=500$
r/worldnews 2012	Senti+Subj	1.0	1.0	0.88	0.87	0.86	3	30	560	2553	60182
r/worldnews 2013	Senti+Subj	1.0	0.80	0.80	0.78	0.734	6	16	643	2689	58089
r/worldnews 2012	Content	0.334	0.60	0.62	0.31	0.062	0	9	656	656	656
r/worldnews 2013	Content	0.66	0.20	0.66	0.60	0.25	1	1	482	1406	8476
r/worldnews 2012	All	1.0	0.90	0.76	0.79	0.78	4	29	596	2519	45293
r/worldnews 2013	All	0.0	0.0	0.78	0.79	0.75	0	0	68	1745	57661

Table 4: Evaluation of Lasso Regression models **Ranked by # of comments**, The test sets that are being ranked on range from 3000 to 8000 data points.

able to predict the crowds voting and engagement well without temporal features. This result both strengthens previous news popularity findings and illustrates the robustness of this feature set.

To better understand these models, we will discuss our post-hoc analysis findings for three of our models: sentiment and subjectivity features for each ranking and all features combined for score ranking. Due to space constraints, we will only discuss these results, rather than display them in a table.

We find that many of the results in previous news popularity literature still hold with crowds on reddit. Specifically, we find that higher score news is more negative, more emotional overall, more certain, and focuses on the present. These findings align with (Reis et al. 2015), (Harcup and O'neill 2001), and (Lewandowsky et al. 2012). Further, we find that higher score news is less subjective, displays more affiliation and more clout. These findings make intuitive sense with what we know about traditional news organizations. Similarly, when ranking by comments, we find that news with a higher number of comments is more negative, but less emotional overall, more insightful, more certain, less subjective, and focuses on the present.

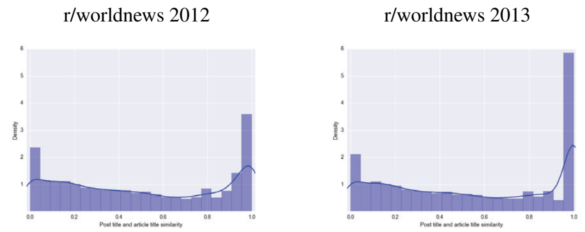
When adding in content features, we find that higher score news is longer, uses more quotes, more personal pronoun references, and uses more simple, more readable words. These findings also align with previous literature, in particular with results in (Keneshloo et al. 2016). Interestingly, and somewhat counter-intuitively, we also see that articles With swear words in the original title from the news source tend to get higher scores. While this feature does not get very strong statistical significance on the two-class divide, it is used to predict in the models over both data sets. This may be due to the specific reddit community or a few high score outliers that contain swear words. Further investigation of this we leave to future work.

Feature	r/worldnews 2012	r/worldnews 2013	Avg. Effect
posemo	changed > original	changed > original	0.0507
negemo	changed < original	changed < original	0.1497
ttr	changed > original		0.1448
affect	changed < original		0.0922
clout	changed > original		0.0123
swear	changed > original	changed > original	0.0154
informal	changed > original		0.0705
per_stop	changed > original		0.4634
WC	changed > original	changed > original	0.4457
FKE	changed > original	changed > original	0.3416
word_len	changed > original	changed > original	0.1595
tone		changed < original	0.1001
vad_pos		changed > original	0.0678
netspeak		changed > original	0.0616
pos_str		changed > original	0.2147
sixltr		changed > original	0.0116

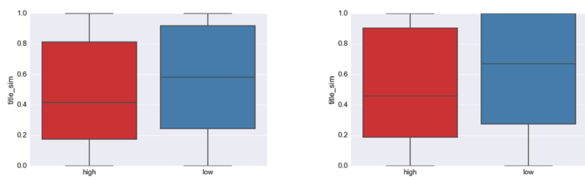
Table 5: Features that significantly differ between post titles and articles titles when title pair has less than 0.1 cosine similarity. If a feature is significant in both data sets, we report the average effect size between the two, otherwise we report the effect size in the single data set. All results have Wilcox Rank-Sum P-values of at least less than 0.05.

Title Changing

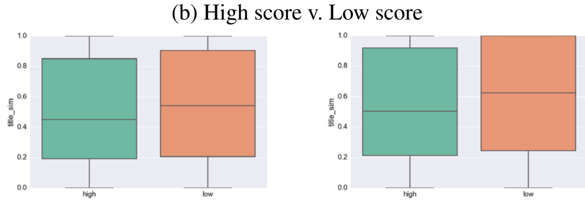
Next, we will present some findings on title changing behavior. First, we find that most titles are changed with 85% of titles being changed in 2012 and 71% of titles being changed in 2013. In Figure 2a, we can see that the distribution of title similarities shows many titles being changed significantly. Saliently, we also find that changed titles tend to get a higher score than those that are not changed. In Table 6, we show that both the Wilcox Rank-Sum p-value and the Cohen's d effect size demonstrate a significant shift in the title similarity distributions of the top 90th percentile of scores and



(a) Title Similarity Distributions



(b) High score v. Low score



(c) High # comments v. Low # comments

Figure 2: (a) Distribution of cosine similarities between post title and article title. (b) Box plots of title similarity between top 90th percentile of scores and bottom 50th percentile of scores. (c) Box plots of title similarity between top 90th percentile of # comments and bottom 50th percentile of # comments. See Table 6 for significance statistics.

the bottom 50th percentile of scores. The corresponding box plots can be found in Figure 2. We find the same trend with the number of comments under a news post, but with less significance. It is critical to note that these significance values may be slightly inflated due to the skew in our score and number of comment distributions. To show this, we also compute the probability that random post in the high score category has a lower title similarity than a random post in the low score category. This method is meant to estimate effect size for nonparametric test (Grissom and Kim 2012), but can be influenced by imbalanced sets as we have in our two-class divide. As expected, we get less significant effect sizes using this method, but still better than random chance. We can conclude that there is a significant difference in the distributions, but it may be less significant than our Cohen's d effect sizes show. As a whole, this is a surprising finding. It suggests that the crowd on reddit has a noticeable impact on news popularity and new engagement, which in turn, may change how people interpret the news and form public opinion.

To dive deeper into the behavior of title changing, we perform hypothesis testing on pairs of titles with cosine similarity less than 0.1. We find that users change titles to

data	Sig Metric	Score	# Cmts
2012	Wilcox P-Value	7.736e-05	8.403e-05
	Cohen's d Effect Size	0.1557	0.1439
	Grissom-Kim Probability	0.55	0.53
2013	Wilcox P-Value	8.194e-11	1.107e-13
	Cohen's d Effect Size	0.1368	0.1256
	Grissom-Kim Probability	0.54	0.51

Table 6: Significance and effect size tests for the title similarities on a high vs low popularity split. Grissom-Kim probability is the probability that a random highly popular article has a lower title similarity than a random lowly popular article. See Figure 2 for boxplots and distributions.

be more informal, contain more swear words, more clout words, more difficult to read, and longer overall. Saliently, we find that original titles are significantly more negative than changed titles. These findings suggest that users are both adding their own analysis in the post title and providing a positive spin. This added positive analysis is in turn gaining slightly more popularity and engagement than the story may have with its original title. These results should be further inspected, but provide some insight into how crowds can change not just the popularity of news, but other users' perceptions when reading the news. These results and their corresponding effect sizes are shown in Table 5.

Conclusions and Future Work

In this paper, we present a preliminary data exploration of popular and highly engaged news on reddit. We found that many previous findings about news popularity still hold true on reddit, including stories with negative titles are more popular and stories that are more emotional overall are more popular. We also found that despite the confounding impact of time on reddit and news popularity in general, we are able to predict popularity reasonably well without temporal features. We find that content features can do reasonably well in predicting the votes of the community, but do not do well at predicting the length of discussion under the news article. On the other hand, sentiment features seem to be an excellent predictor of both the score and the length of discussion. In addition, we find that the crowd does have a noticable impact on news popularity and discussion through changing the article headline. When members of the crowds do change the headline, they add their own analysis and make the headline more positive than the news producers headlines.

In the future, we want to extend this work in two ways. First, we want to explore more in depth popularity analysis and crowd effects across multiple platforms. For example, is a news article that is highly popular on reddit also popular on Facebook or Twitter? If this popularity differs, in what ways does it differ? Second, we would like to further investigate the impact changed news headlines. Specifically, we would like to expand this data set to include more reddit news communities and more social platforms over a longer period of time.

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