Tracking Reads to Understand the "Fake News" Dynamics on Twitter

Abstract

Fake news and other misinformation distributed through social media blurs truth and fiction, and threatens our modern society. However, measuring and modeling how fake news and biased content is shared is non-trivial. Today, many studies trying to capture the information spread, rely on Twitter's open API to measure the number of times news articles are shared/retweeted. In this paper, we go one step further and develop a methodology (using also the Bitly API) to collect and study the number of reads (or clicks) generated by links posted in the Twitter feed. By classifying the articles into "fake/biased" articles and "regular" articles and by comparing the dynamics associated with news websites with different reputations about their degree of fact checking and political view/objectivity, we provide a first glance into the insights that such framework can provide. Interestingly, articles (and websites) that we deem are more likely to be fake/biased typically have a slower news cycles (as measured by the cumulative fraction reads over time), suggesting that these articles can impact opinions, belief, and opinion longer after they were published than perhaps suggested by studies considering the "traditional" news cycle.

Introduction

Information in social media can have large impact on thoughts, beliefs, and opinions. Social media have therefore become an important channel for many organizations to distribute information to sway opinions, often for organizations' own benefit, but also to undermine other organizations or even to weaken entire countries. We have seen an increase in false information, often loosely referred to as "fake news", being disseminated over social media and increased polarization in the opinions held in our societies.[1] These trends can have devastating effects on our society, and false news have already been suggested to have impacted in the results of major elections such as the Brexit vote in the U.K. and the 2016 U.S. election.

The above examples just scratch the surface of an escalating problem that blurs truth and fiction, and threatens our entire modern society. As spreading of misinformation is becoming an increasing concern, it is therefore important to understand how fake news and biased content is shared.

While recent political developments have resulted in companies developing their own policies for how to combat fake news, considered one of the 21st century grand challanges[2], limited research has been done to analyze and model the spreading of fake news and biased information.

A popular metric when studying information spreading on social media such as Twitter is the number of retweets. However, with many bots and other orchestrated efforts contributing to the information spreading, using only such first-order metrics can result in the wrong conclusions and estimates of the relative impact different articles have. For example, in a recent 2016 study, Gabielkov et al. (2016) shows that articles generally are read over a longer time compared to the time period than the links to the articles are shared on Twitter. This shows that the 24-hour news cycle (Leskovec, Backstrom, and Kleinberg 2009) may actually have longer term impact than suggested if only look at the retweets.

To help improve the understanding of the popularity dynamics of news articles, we (i) develop a novel measurement methodology that allows us to track news article reads generated through social networks promotion, and (ii) present a longitudinal characterization of the articles promoted on Twitter on May 3, 2017, in which we classify articles as more/less biased, associate them with the news websites that publish them, and track their reads (clicks) over time. Interestingly, substantial differences in the ongevity of the relative popularity are observed. In particular, we find that articles that are more likely to be fake/biased and content posted by Breitbart News generate reads over a relatively longer time period than articles classified as non-biased or by BBC News, for example. This may suggest that the traditional news industry still (mostly) operates on the 24-hour cycle, whereas fake/biased news can gain reads for a somewhat longer time periods.

[1] C. Cillizza, CNN (Oct. 2017). "Why we are to blame for our broken politics, in 1 chart". http://edition.cnn.com/2017/10/05/politics/pew-poll-ideology/

[2] R. Gray, BBC (March 2017), "Lies, propaganda and fake news: A challenge for our age", http://www.bbc.com/future/story/20170301-lies-propaganda-and-fake-news-a-grand-challenge-of-our-age

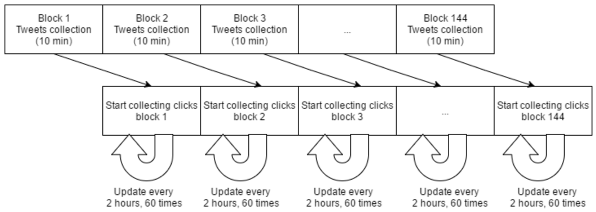


Figure 1: Methodology overview: six-day campaign.

Methodology

Similar to the work by Gabielkov et al. (2016), we combine the use of the Twitter and Bitly APIs to collect statistics about how many clicks that a Bitly links embedded in a series of (re)tweets generate. While their research focus on the difference between the number of retweets and the clicks that a tweeted link generates, we focus on the (longitudinal) number of reads/clicks generated over time. For that reason, we develop a novel collection framework that carefully tracks the number of clinks over time, allowing us to capture the dynamics of the news cycle.[3]

Figure 1 illustrates the steps taken during a six day example measurement campaign using our framework, in which we followed all Bitly links tweeted during a 24-hour news cycle for five days. To allow timely processing, we break time into ten-minute blocks and track the clicks associated with the tweets in each such block over time.

Collection of Bitly links to know news websites: First, during each ten-minute block we use Twitter's streaming API to extract all tweets with Bitly links posted during that block, and save the corresponding tweets to text files in a JSON format. Second, using the Bitly API, from the set of Bitly links observed in the 10 minute block that have not yet been observed, we extract the full URLs associated with 1000 randomly selected Bitly links and use these to identify links to seven known news domains. The selected news websites are: BBC, The Times, The Guardian, Huffington Post, CNN, Fox News, and Breitbart. These sites cover a wide spectrum of political biases and have been suggested to publish fake or incorrect news at vastly different rates. To stay below Bitly's rate limit, we keep track of unique Bitly links, and only makes new calls for previously unseen links. In this step, we also collect our first "0-hour" measurement for the number of clicks associated with the links.

Longitudinal collection of read statistics: Third, for each ten-minute block, we periodically (every 120 minutes), use the Bitly API to collect the number of clicks associated with each link. For each block, this process is repeated for a total of five days. By breaking the sequence of tweets into ten-minute blocks and monitoring the time that it takes to work with the Bitly API we can ensure that each snapshot is evenly spaced by two hours, plus/minus a few minutes.

Per-website and per-article analysis: For our analysis, we compare the dynamics observed for links based on (i) the news websites that publish the corresponding article, and (ii) a machine learning based classification of the article. For article classification, we use the Multinomial Naive Bayes (MNB) (Manning, Raghavan, and Schtze 2009; Rennie et al. 2003) on the text of each news articles (after having removed all `html` tags, metadata, and comments, for example). For training data, we used 40 texts that had been manually classified as "fake news" and 40 texts that had been classified as "regular" articles. The accuracy of the classifier was evaluated using another set of 40 articles (20 fake and 20 regular). All the articles used for training and classifier evaluation were written about the American election of 2016 and have been classified manually.[4]

We used scikit-learn's gridsearchcv function and the training dataset to train the classifier and tune parameters. The settings that were chosen were that unigrams and up to 4-grams were used for features and 800 features were selected. All characters were turned into lowercase and no stop words were used. To smooth the probabilities of the features a smoothing of $\alpha = 0.25$ was selected. When testing the classifier against the evaluation data it received a score of 89.7% correct classifications.

Limitations: In practice, there is no black-and-white and reliable way to classify entire articles into two categories. There also exists more advanced and accurate classification methods. Furthermore, since we did not perform the measurement campaign during the same time period as the manually classified training and evaluation datasets, the per-article "accuracy" of the classifier is unclear and the classification should hence not be interpreted as an accurate per-article classifier. Instead, we use it as a tool to identify sets of articles that as an aggregate are expected to more closely resembles the "fake news" articles. In the following we refer to the two categories as "fake/biased" and "regular". Our classifier only works reasonably for English text, further motivating our choice to select known news websites and also studying differences both between and within the set of articles published by each separate website.

Our methodology is limited to short-links using the Bitly API and only covers a subset of all news articles advertised through Twitter. We do not try to distinguish between links/clicks generated by bots vs humans, but note that bots trying to influence opinion are more likely to (re)tweet than follow links, whereas crawlers are more likely spread their bias evenly across links. Finally, we note that the Twitter API limits the total tweet volume to 1% and the Bitly API limits the request rate and number of concurrent connections (to five). The Twitter constraints did not impact our results since we seldom reached the 1% threshold. The Bitly API constraints, on the other hand, forced us to use a 2-hour spacing between calls for each link of interest, and use ten-minute blocks to spreads the potential missing data points (similar to the 1% threshold used by the Twitter API) in the case not all links can be resolved in a particular ten-minute block.

[3]Code and datasets will be published with the paper.

[4]Craig Silverman, BuzzFeed News (Nov. 2016), "This Analysis Shows How Viral Fake Election News Stories Outperformed Real News On Facebook", `https://www.buzzfeed.com/craigsilverman/viral-fake-election-news-outperformed-real-news-on-facebook`.

Table 1: Summary of dataset and our *simple* classifier.

	All articles			Less than 50% at start		
News site	Total	Fake/biased		Total	Fake/biased	
Guardian	127	6	(4.7%)	73	4	(5.5%)
BBC	202	25	(12.4%)	111	19	(17.1%)
Huffington	121	15	(12.4%)	69	12	(17.4%)
The Times	11	2	(18.2%)	7	1	(14.3%)
Fox News	120	31	(25.8%)	63	19	(30.2%)
CNN	169	59	(34.9%)	82	29	(35.4%)
Brietbart	84	69	(82.1%)	39	29	(74.4%)
Totals	834	207	(24.8%)	444	113	(25.5%)

Preliminary results

The results presented here were collected during a six-day measurement campaign started on May 3, 2017. During the one-day Twitter phase (where the tracking of ten-minute Bitly blocks are initiated), we collected 11 million tweets that contained at least one Bitly link. With at least unique 1000 samples per ten-minute block, we ended up with 144,000 full URLs. Of these, only 834 contained links to the seven selected websites and 207 (24.8%) were classified as "fake/biased". Table 1 a per-website breakdown. Substantial differences are observed in the percent of articles associated with each news website classified as fake/biased. Regardless of opinions of what "fake news" are, this suggests that there are substantial differences in the way these articles are written. For example, less than 1/8 (12.5%) of the articles observed for the Guardian, BBC, and the Huffington Post are classified in this dubious category. In contrast, Fox News (25.8%) CNN (34.9%), and Breitbart (82.1%) have substantially larger fraction classified into this category.

The large difference between sites such as BBC and Breitbart are expected, as BBC is well known for publishing legitimate news[5], whereas Breitbart often are criticized for publishing fake news with a strong political agenda. Breitbart was also prominent in the manually classified training data.

For the analysis presented here, we focus on new tweets. For that reason, we remove all links for which at least 50% (or 25%) of the clicks happened before our first Bitly measurement for that link. The right-most columns in Table 1 summarizes the statistics for these links. In total, there are 444 links satisfying this criteria, 113 of which are classified as fake/biased, and all seven news websites see similar filtering. We have found that using a different threshold (e.g., 50% vs 25%) does not impact the results significantly, except that we get slightly smaller/larger datasets to work with. For example, when requiring that at most 25% of the clicks, 87 of 345 articles (25.2%) are classified as fake/biased compared to 25.5% when using the 50% threshold.

We have observed similar skew in how the clicks are distributed among the links, regardless whether the article associated with a link is classified as "fake/biased" or "regular". This is illustrated by the mostly matching curves in Figure 2. In general, we observe very high concentration of clicks (Figure 2(a)) and a heavy tail (Figure 2(b)) of a few links that are responsible for most of the clicks. For example, as shown in Figure 2(a), more than 90% of the clicks are associated with less than 10% of the links (in both categories). From the Complementary Cumulative Distribution Function (CCDF) shown in Figure 2(b), we note that the distribution does not appear power-law and that most views have been obtained already after 24 hours.

While the popularity distribution looks relatively similar, there appear to be significant differences in the evolution of clicks observed for links associated with "fake/biased" articles and "regular" articles. Figure 3 shows the cumulative percent of clicks obtained over time for these categories (using both the 25% and 50% thresholds). Interestingly, and perhaps most importantly, for both cases we observe that the clicks of links associated with "regular" articles peak noticeably sooner than to "fake/biased" articles. This suggests that "fake/biased" articles may have somewhat longer-term impact than "regular" articles and their expected 24-hour news cycle (Leskovec, Backstrom, and Kleinberg 2009). The sharp spike in clicks at at the 56 hour mark is due to one Foxnews article from Associated Press (about an army photographer capturing her own death in mortar explosion) going from 113 cumulative clicks to 47,208 clicks during that two-hour window and appears to be due to an influential retweeter help attracting clicks to the article.

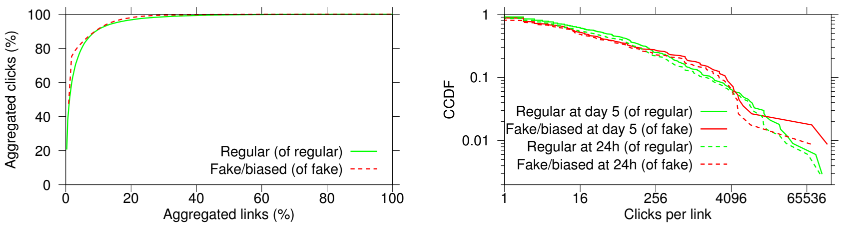
Figure 4 provides a head-to-head comparison of the four news websites with at least 5000 cumulative clicks. These results provide some initial validation of our conjecture that fake/biased news may have somewhat longer life cycle than regular articles. For example, the CDF of BBC articles (which we argue are the least biased among the four) always dominates the other three sites, whereas Beitbart (which we argue is the most biased among the four) sees a much later peak. Again, Fox News stick out significantly because of the previously discussed link.

Finally, we evaluate if our conjecture holds on a per-website basis. Figure 5 shows the cumulative fraction of clicks over time, broken down per-category (fake/biased vs regular) normalized either across all clicks or across only the clicks associated with that category. Looking at the dotted lines (normalized on a per category basis), we note that "regular" links peak significantly sooner for both BBC and Fox News than "fake/biased". For CNN and Breitbart the differences are very small. In fact, for Breitbart the two curves are closely overlapping. Given that these categories have a much larger fraction "fake/biased" links, it may be that also the articles classified as "regular" have similar characteristics and therefore sees similar viewer behavior, as indicated by the shifted click progression compared to the "regular" BBC curves, for example.

Related work

Recent related research include a study by Allcott and Gentzkov (2017) that looks at how many people that remember fake news headlines during the 2016 U.S. election, and a study by Garrett et al. (2016) about misperceptions due

[5] Jasper Jackson, The Guardian (Dec. 2015), "BBC rated most accurate and reliable TV news, says Ofcom poll", `https://www.theguardian.com/media/2015/dec/16/bbc-rated-most-accurate-and-reliable-tv-news-says-ofcom-poll`



(a) Concentration after 5 days (b) CCDF

Figure 2: Skew in clicks across links: “fake/biased” vs “regular” with 50% criteria.

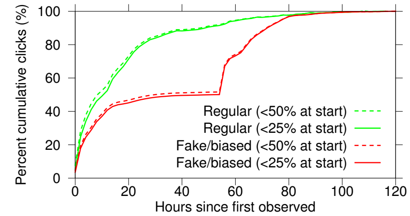


Figure 3: Cumulative clicks obtained over time: “fake/biased” vs “regular” .

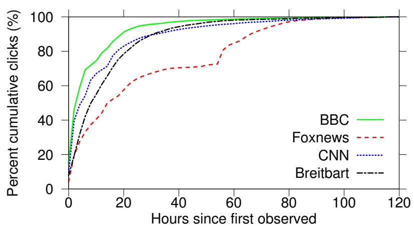
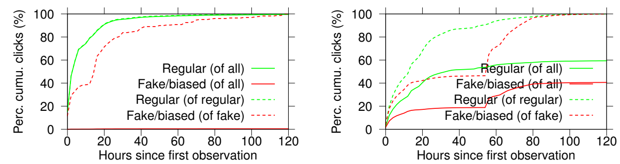
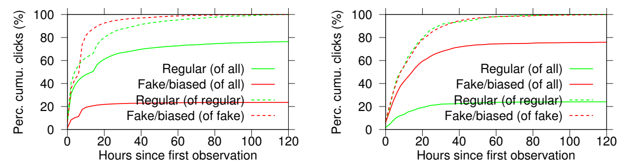


Figure 4: Cumulative clicks over time: news sites with at least 5000 cumulate clicks after 50% criteria.



(a) BBC (b) Fox news



(c) CNN (d) Breitbart

Figure 5: Cumulative clicks over time: all sites with at least 5000 cumulate clicks after 50% criteria.

to ideologically biased news media online in the 2012 election. For their works, Allcott and Gentzkov (2017) use surveys while Garrett et al. (2016) classify entire news outlets by their idiological bias based on contrast analysis of semantic similarity (Holtzman et al. 2011). Others have identified problems and presented methods to tune MNB classifiers (Rennie et al. 2003), achieving good scores on the Industry Sector (93.4%) and 20-Newsgroups (86.7%) datasets.

Perhaps most closely to our work is the work by Gabielkov et al. (2016). Combining the use of the Twitter and Bitly API (similar to us), they show that the number of times that news articles are shared/retweeted do not map well to the number of times users click (and read) the articles. In contrast, we focus entirely on the reads, and use periodic Bitly calls to gain insights into differences in how the reads (estimated by click) differ over time for links associated with the articles of different news websites and articles that reminds our classifier more or less of articles that in the past have been judged to be “fake news”. Finally, we note that research have been done to study various aspects of the 24-hour news cycle (Leskovec, Backstrom, and Kleinberg 2009). We believe that the methodology and tools presented here will greatly help towards better understanding how this cycle differ for different article types.

Conclusions

In this paper we have presented a longitudinal methodology to collect and study the number of reads (or clicks) generated by links posted in the Twitter feed and presented a preliminary analysis based on the text of the published articles (classified as either “fake/biased” or “regular”) and the seven new websites that published them. Our results show that articles that are more likely to be fake/biased and content posted by Breitbart News generate reads over a relatively longer time period than articles classified as regular or published by BBC News, for example. Also, the articles classified as “fake/biased” published by websites with less “fake/biased” articles appear to have this characteristic, showing that this class of links indeed appears to have different dynamics than links to “regular” articles.

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