The role of online attention in the supply of disinformation in Wikipedia

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Abstract

Wikipedia and many User-Generated Content (UGC) communities are known for producing reliable, quality content, but also for being vulnerable to false or misleading information. Previous work has shown that many hoaxes on Wikipedia go undetected for extended periods of time. But little is known about the creation of intentionally false or misleading information online. Does collective attention toward a topic increase the likelihood it will spawn disinformation? Here, we measure the relationship between allocation of attention and the production of hoax articles on the English Wikipedia. Analysis of traffic logs reveals that, compared to legitimate articles created on the same day, hoaxes tend to be more associated with traffic spikes preceding their creation. This is consistent with the idea that the supply of false or misleading information on a topic is driven by the attention it receives. These findings improve our comprehension of the determinants of disinformation in UGC communities and could help promote the integrity of knowledge on Wikipedia.

1 Introduction

In recent years several Internet websites have become the hubs for communities where users can produce, consume, and disseminate content without central oversight. Examples of these *user-generated content* (UGC) websites include major social media platforms, like Facebook or Twitter, or global online knowledge production communities like Wikipedia, which is known as a model for the production of vast reliable, high-quality knowledge (Yasseri and Menczer, 2021).

However, a negative consequence of the popularity of UGC websites is that their low barriers to access, combined with the lack of supervision from experts or other gatekeepers, results in the proliferation of false or misleading information on the Web as a whole (Wardle and Derakhshan, 2017; Lazer et al., 2018).

False or misleading content often spreads on social networking platforms (Amoruso et al., 2020; Castillo et al., 2011; Zareie and Sakellariou, 2021; Grinberg et al., 2019; Guess et al., 2019, 2020; Allcott and Gentzkow, 2017), but there are growing concerns that other UGC communities like Wikipedia may be vulnerable to these threats too (Sáez-Trumper, 2019). This is especially worrisome since Wikipedia is one of top most visited internet websites (Similarweb LTD, 2022) and a popular source of knowledge (Okoli et al., 2014). Wikipedia contains over 50 million articles in more than 300 languages; in February 2022, the English language edition of Wikipedia alone received 781M visits (from unique devices) and was edited over 5M times (Wikipedia contributors, 2022c; Wikimedia Foundation, Inc., 2022d). Hence, preserving the integrity of Wikipedia is of paramount importance for the Web as a whole (Sáez-Trumper, 2019).

There are many potential threats to the integrity of knowledge in Wikipedia (Sáez-Trumper, 2019). One common threat comes from vandalism, which is "a deliberate attempt to compromise the integrity of the encyclopedia, often through the insertion of obscenities, insults, nonsense or crude humour, or by page blanking" (Wikipedia contributors, 2021).

Vandalism, however, is not the only threat to the integrity of Wikipedia's content. Whereas vandalism focuses on defacing existing entries, there exists evidence showing that Wikipedia is also targeted by *hoaxes*, whose aim is to create whole new entries about fake, fictitious topics. An example of a famous Wikipedia hoax is the entry *Jar'Edo Wens*, a fake Australian Aboriginal deity, which went undetected for almost 10 years before being debunked and deleted (Dewey, 2015). But hoaxes remain a threat to Wikipedia's content integrity to this day. Recently, one of the largest such incidents the platform has ever seen has been discovered on the Chinese Wikipedia: a user named *Zhemao* wrote 206 fake entries, starting from 2019 until 2022, about Russia's history in the Middle Ages (Moon, 2022).

Hoaxes are thus not to be confused with vandalism; although vandalism is a much bigger threat in scope and size compared to hoax articles, hoaxes constitute a more subtle threat, which has received less attention compared to vandalism.

A crucial question that remains unresolved is what drives the creation of hoaxes on Wikipedia. Because their original authors are aware that these articles are false, hoax articles are different from mere *misinformation*, but should rather be considered instances of *disinformation* (Wardle and Derakhshan, 2017; Lazer et al., 2018). As such, understanding the factors that determine the supply of hoaxes on Wikipedia could shed light on disinformation in general, including broader threats to the integrity of the Web, like state-sponsored propaganda (King et al., 2017; Zannettou et al., 2019; Golovchenko et al., 2020) and conspiracy theories (Starbird, 2017).

To bridge this gap, in this paper, we study the role of *online attention*, in the form of individual page views, in the supply of disinformation in Wikipedia. The idea of an economy of attention was first introduced by Simon (1971), who observed that human attention is a limited resource that needs to be allocated (Goldhaber, 1997). Here, to quantify the flow of collective attention to individual topics of knowledge, we take advantage of the unique Wikipedia traffic dataset and API. Specifically, in this work we seek to answer the following questions:

Q1. Does online attention toward a topic increase the likelihood of disinformation being created about it?

Q2. Operationally, is there a relationship between traffic to Wikipedia and the production of hoax articles?

To answer these questions, we collected a list of known hoax articles (Wikipedia contributors, 2022a) along with their creation timestamps and content. To control for potential confounding factors in the distribution of traffic to Wikipedia over time, for each hoax, we considered a cohort consisting of all the legitimate (i.e. non-hoax) Wikipedia articles that were created on the same day as the hoax. Similar to Kumar et al. (2016), we find that hoaxes differ from legitimate articles in key appearance features, but do not strongly differ in the number of hyperlinks they contain. Next, for each article (either hoax or non-hoax), we parsed its content and extracted all the outlinks, i.e. its neighbors in the Wikipedia hyperlink network. The presence of a link between two Wikipedia entries is an indication that they are semantically related. Therefore, traffic to these neighbors gives us a rough measure of the level of online attention to a topic *before* a new piece of information (in this case an entry in the encyclopedia) is created.

Finally, we measure the relative change of traffic in the 7-day period before and after the creation of a hoax and compare this change to that of the articles in its cohort. To preview our results, we find that, on average, online attention tends to precede the creation of hoaxes more than it does for legitimate articles. This observation is consistent with the idea that the supply of false and misleading information on a topic is driven by the attention it receives.

In the rest of the paper we discuss related work (Section 2), and then describe our methodology (Section 3): the details of the data collection process, the comparison between features of hoaxes and legitimate articles, and the pre-processing of the Wikipedia traffic data. Section 4 discusses the techniques used to quantify online attention and its relationship to the hoax creation, and the statistical procedures performed to asses the results. Finally, section 5 summarizes our findings and future directions.

All code and data needed to replicate the findings of this study are available on Github at github.com/CSDL-USF/wikihoaxes.

2 Related Work

Over the years Wikipedia has developed an impressive array of socio-technical solutions to ensure the quality of its content. Early work on Wikipedia has shown that most acts of vandalism are repaired manually by the crowd of contributors within a matter of minutes (Viégas et al., 2004). In addition to human interventions, automated tools like ClueBot NG play a crucial role in keeping the encyclopedic entries clear from damage (Geiger and Halfaker, 2013; Halfaker and Riedl, 2012). On top of these methods, there exist other preventive measures such as patrolling recent changes, creating watchlists, blocking frequent vandalism creators, and using editorial filters. Finally, multiple research attempts have been conducted to aid in both the manual and the automatic detection of vandalism (Potthast et al., 2008; Adler et al., 2010; Smets et al., 2008; Harpalani et al., 2011).

Despite this wealth of work, little is known about Wikipedia hoaxes. Kumar et al. (2016) collected a sample of known hoaxes from resources compiled by the Wikipedia community, and studied their longevity, along with other characteristics. They found that one in a hundred hoaxes remain undetected for more than a year, with 92% of the cases detected within the first day. They also observed that, although only 1% of all hoaxes remain undetected for more than a year, those that stay undetected have a higher chance over time of remaining so. Finally, they showed that, on average, hoaxes have a lower density of internal links and receive less traffic than legitimate (i.e., non-hoax) articles (Kumar et al., 2016).

Traffic to Wikipedia has been used before to study collective attention. García-Gavilanes et al. (2017) studied the patterns of attention to Wikipedia in the wake of airplane crashes. They found that the traffic to entries about *previous* airplane crashes was greater than that of the current crash, i.e. the one that triggered the attention surge (García-Gavilanes et al., 2017). Ciampaglia et al. (2015) studied traffic patterns during the creation of new Wikipedia entries (i.e., not just hoaxes) and observed that the creation of new information about a topic is preceded by spikes of attention toward it, as measured by traffic to neighboring entries (Ciampaglia et al., 2015). This is consistent with a model in which the demand for information on a topic drives the supply of novel information about it. Consequently, measuring traffic to Wikipedia entries can help us get a step closer to understanding why and when hoaxes are more likely to be produced.

3 Data and Methods

We first describe how the dataset of hoaxes was collected and the process of building the cohort of each hoax.

3.1 Data Collection

Prior work has relied on a broad definition of ‘hoaxes’ that leverages the ‘New Page Patrol’ (or NPP) process (Kumar et al., 2016). Unfortunately, access to these data was not public due to the nature of the NPP process. Therefore, in the present work we relied on a smaller, public list documenting known hoaxes discovered by Wikipedia editors outside of the NPP process (Wikipedia contributors, 2022a). To be included in this list, a discovered hoax must meet either of the following two characteristics: (*i*) they have gone undetected for more than a month after patrolling (Kumar et al., 2016), or (*ii*) they were discussed by reliable media sources.

To collect this list, we queried the Wikipedia API using the ‘prefix search’ endpoint (MediaWiki contributors, 2022a) to collect the titles of the hoaxes residing in the administrative list maintained by Wikimedia under the prefix ’List of Hoaxes on Wikipedia’. The total number of titles retrieved was $N_h = 190$. We then used the Toolforge (Wikitech contributors, 2021) to query the database replica of the English Wikipedia for the creation date of each hoax article, defined as the timestamp of the first revision recorded in the database. Figure 1 (left) shows a summary of the number of hoaxes created over time, with the majority of hoaxes appearing in the period 2005–2007, and a decline starting in 2008. This observed behavior can be in part explained by the fact that the Wikipedia community started patrolling new pages in November of 2007 (Kumar et al., 2016; Wikipedia contributors, 2022b) and is also consistent with the well-known peak of activity of the English Wikipedia community (Halfaker et al., 2013).

Finally, to build the cohort of each hoax, we queried the Wikipedia database replica for all legitimate articles created on the same day. Since Wikipedia entries are often accessible through different titles, in collecting the cohort, we resolved all redirects created the same day as the hoax. Treating these redirects as separate entries would inflate the cohort size and could skew traffic statistics used later for estimating the level of online attention. Figure 1 (right) shows the effect that redirects have on the size of each cohort. In some cases, failing to account for redirects can increase the size of cohorts to up to $16,000$ articles.

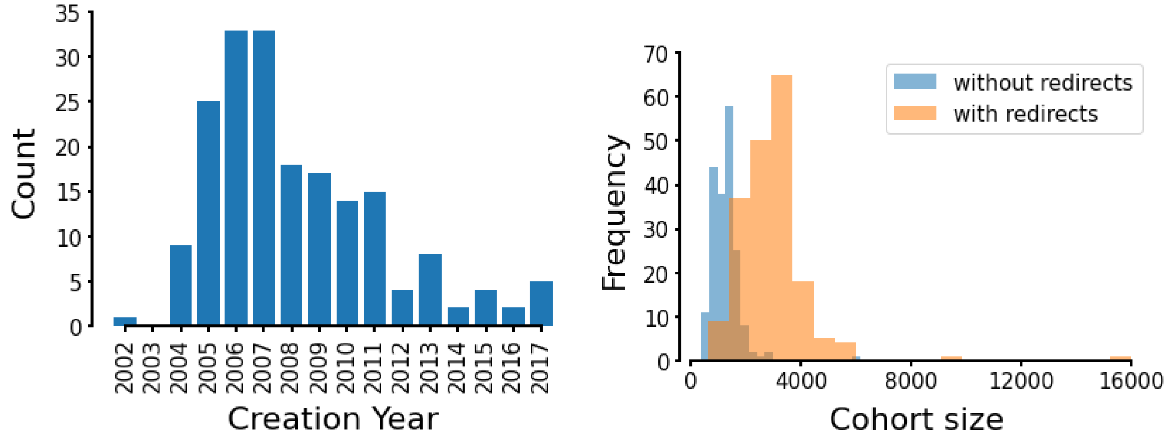


Figure 1: Left: Hoaxes detected in the English Wikipedia. Right: Cohort size distribution for hoaxes in our dataset before (solid blue) and after (solid orange) resolving redirects.

3.2 Appearance Characteristics Analysis

To understand the differences between each hoax and its cohort members, we analyzed their appearance features, inspired by the work of Kumar et al. (2016) who, in addition to appearance features, studied network, support, and editor features for both hoax and legitimate articles (Kumar et al., 2016). We considered the following four features: (*i*) the *plain text length* is the number of words in an article after removing all the wiki markup; (*ii*) the *ratio of plain to markup text* is the number of words obtained after removing all markup in the body of the article, divided by the number of words before removal; (*iii*) the *density of wiki-links* is the number of wiki-links per 100 words, counted before markup removal; and, finally, (*iv*) the *density of external links* is defined similarly as the density of wiki-links, but for links to external Web pages.

To be able to calculate these features for each hoax and its cohort, we consulted the API to extract their plain text using the *TextExtracts* extension instead (MediaWiki contributors, 2021). For the wiki markup we used the revisions API (MediaWiki contributors, 2022b). A regular expression was used to count the number of words in plain and markup text. Finally, to find the wiki and external links within each article we used *wikitextparser* (5j9, 2022).

Aside from the plain text to markup ratio, the chosen appearance features have very skewed distributions. To illustrate this point, fig. 2 shows the distribution of each score for five manually sampled cohorts in our data. For the plain text length, fig. 2 shows that the median is between 100 and $1,000$ words, yet there exist articles that reach and even exceed $10,000$ words. The same case persists in the wiki-link density — the median is under 10 links per 100 words, however some articles have up to 40 links, and similar for the other two features.

Thus, after collecting all the four features, we computed the modified z-score z' to compare different hoaxes together:

$$z' = \frac{x - \tilde{x}}{\mathrm{MAD}} \qquad (1)$$

Where x is a feature measured on a hoax, $\tilde{x}$ the median value of the feature on the non-hoaxes, and MAD the median absolute deviation of x with respect to $\tilde{x}$. We chose to use z' instead of the regular z-score since it is more resilient to outliers (Iglewicz and Hoaglin, 1993).

3.3 Analyzing Wikipedia Traffic Data

To analyze the traffic that the articles in our dataset receive, we used a dataset on traffic compiled by the Wikimedia foundation (Wikimedia Foundation, Inc., 2022b). The Wikimedia Foundation has published two main traffic datasets: the earlier *pagecounts-raw* (Dec. 2007–Aug. 2015), and the more recent *pageviews* (started Jul. 2015). Since most of the hoaxes in our dataset were created in the period between 2005 and 2011, we have decided to use the older pagecounts-raw data. This dataset contains the count of non-unique HTTP requests made for each article in an hourly time frame, collected by the proxy server of Wikipedia (Ciampaglia et al., 2015), along with request title and additional metadata. We pre-

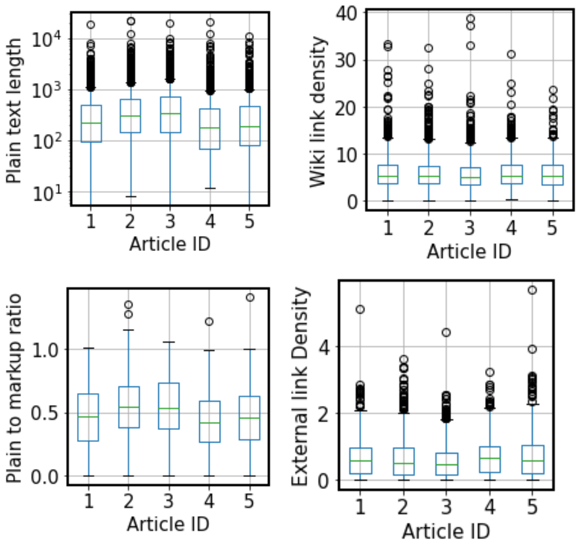


Figure 2: Distribution of appearance features for five manually sampled cohorts in our data.

processed pagecounts-raw to resolve redirects, filter unwanted entries, and clean illegal titles.

Pre-processing the data was performed over the following three steps. First, the raw data was filtered. The filtration process selected only entries related to the English Wikipedia project while removing all pages from namespaces other than the 'main' MediaWiki namespace. Second, the filtered data was cleaned from illegal titles. Illegal titles were discarded by removing characters which are not allowed in Wikipedia page titles (Wikimedia Foundation, Inc., 2022a, cf. 'Page Restrictions'). The hashtag sign '#' is considered illegal only if it is the first character in a title; otherwise it indicates a subsection within a page. Hence, a title including '#' is discarded only in the former case. In addition to removing illegal characters, we decoded common URL-encoded characters (e.g. '%20') and replaced any space with an underscore character. Third, to resolve redirects, the Toolforge was consulted to extract all the redirects within the main namespace of the English Wikipedia. The result was a cleaned and filtered hourly dataset of the view count for pages within the main namespace of the English Wikipedia.

4 Results

4.1 Appearance Features

We start by analyzing the appearance features of hoaxes relative to the non-hoaxes in their cohort. Figure 3a shows that most hoaxes have either similar or slightly smaller plain text length compared to that of their cohorts. We also observe the presence of several outliers, indicating that a subset of hoaxes in our sample tends to have unusually higher word counts. This is consistent with the results of Kumar et al. (2016), who observed that 'successful' hoaxes (i.e., that have gone undetected for at least 1 month) have a median plain text length of 134 words — almost twice as large as that of legitimate articles. However, the analysis of Kumar et al. (2016) differs from ours in multiple ways. First, as already mentioned, they used a different, larger set of hoaxes collected as part of Wikipedia's regular NPP process. Second, they used a matching procedure to compare each hoax to only one legitimate article created on the same day. They also considered other types of articles, such as wrongly flagged articles and failed hoaxes. Another potential differentiating factor is the method of extraction for the plain text, markup content, and links for each page, which might contribute to not obtaining exactly the same results.

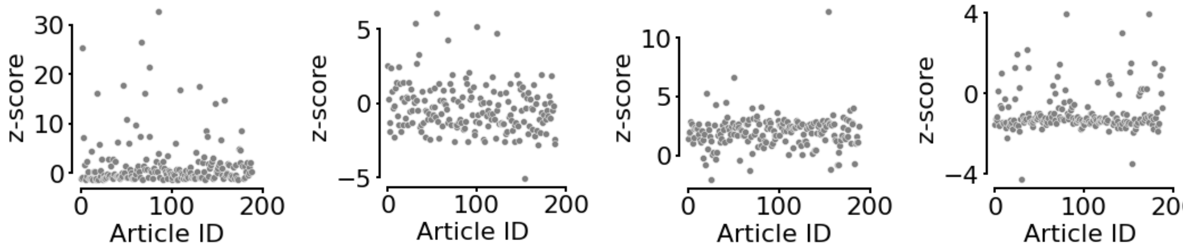
Figure 3b shows that hoaxes tend to have a similar density of wiki-links when compared to non-hoaxes. This is important, since to quantify online attention toward a topic we compute the volume of traffic to the wiki-link neighbors of an article. Thus, in the following analysis on traffic, we can safely exclude potential confounding factors due to different linking patterns between hoaxes and non-hoaxes.

Figures 3c and 3d show the distributions of the ratio of plain to markup text and of external link density, respectively. Aside from a few outliers, hoaxes almost always contain more plain text than markup text, compared with non-hoaxes. This is also consistent with the findings of (Kumar et al., 2016), who observed that, on average, 58% of a legitimate article, 71% of a successful hoax, and 92% of a failed hoax is just plain text.

In summary, hoaxes tend to have more plain text than legitimate articles and fewer links to external web pages outside of Wikipedia. This means that non-hoax articles, in general, contain more references to links residing outside Wikipedia. Such behavior is expected as a hoax's author would need to put a significant effort into crafting external resources at which the hoax can point.

4.2 Traffic Analysis

Recall that the cohort of a hoax is defined as all the non-hoax articles created on the same day it



(a) Plain text length (b) Wiki-link density (c) Plain to markup text ratio (d) External link density

Figure 3: Modified z-scores for all hoaxes in our sample relative to non-hoax articles in their cohorts for the four appearance features we considered. Hoaxes tend to have similar or slightly smaller count of plain text words (however with several higher-count outliers), lower external link density, higher plain to markup text ratio, and similar wiki-link density.

was created. To understand the nature of the relationship between the creation of hoaxes and the attention their respective topics receive, we first seek to quantify the relative volume change before and after this creation day. Here, a *topic* is defined as all of the (non-hoax) neighbors linked within the contents of an article i.e., its (non-hoax) out-links. Traffic to Wikipedia is known to fluctuate following circadian and weekly patterns, and is likely to depend on a host of additional, unknown factors, such as the relative popularity of Wikipedia over the years, the total number and geographic distribution of web users (Yasseri et al., 2012), etc. To account for these potential confounding factors, (Ciampaglia et al., 2015) proposed to quantify the volume change in a way that controls for the circadian rhythm and the fluctuating nature of traffic on the Web (Ciampaglia et al., 2015; Thompson et al., 1997). They have shown that studying traffic over a 14-day observation window, 7 days before and after the creation day, considers both short spikes in attention and weekly changes in traffic. The relative volume change is defined as:

$$\frac{\Delta V}{V} = \frac{V^{(b)} - V^{(a)}}{V^{(b)} + V^{(a)}} \tag{2}$$

where $V^{(b)}$ and $V^{(a)}$ are respectively the median traffic to neighbors in the 7 days before and after the creation of the article. According to eq. (2), $\Delta V/V > 0$ when the majority of traffic occurs before an article is created, i.e., attention toward the topic of the articles precedes its creation. When $\Delta V/V < 0$, attention tends instead to follow the creation of the hoax. Note that our traffic data covers a period spanning from December 2007 to August 2016. Since not all hoaxes in our dataset fell within that time frame, $\Delta V/V$ was calculated only for the 83 hoaxes (and their cohorts) whose creation dates fell within that period.

Figure 4 shows the distribution of the $\Delta V'/V'$ values for each cohort, the cohort mean, and the value of $\Delta V/V$ of the corresponding hoax, for a manually selected sample of hoaxes collected from our data.

Having defined a way to quantify whether traffic to a given article preceded or followed its creation, we want to determine whether hoaxes tend to have a greater $\Delta V/V$ than legitimate articles in general. Unfortunately, we know very little about the distribution of $\Delta V/V$ over multiple pages, and how it has changed over the course of the history of Wikipedia. However, if hoaxes do not differ from legitimate articles, then on average the difference the $\Delta V/V$ of a hoax and that of its cohorts should be zero. Therefore, we define:

$$D = \frac{\Delta V}{V} - \mathsf{E}\left[\frac{\Delta V'}{V'}\right] = \frac{\Delta V}{V} - \frac{1}{n}\sum_{i=1}^{n}\frac{\Delta V_i'}{V_i'} \tag{3}$$

where $\mathsf{E}\left[\frac{\Delta V'}{V'}\right]$ indicates the expected $\Delta V'/V'$ of legitimate articles. Thus, when $D > 0$ a hoax accumulates more attention preceding its creation, compared to its cohort.

To test whether $D > 0$ holds in general, we estimate the mean value of D in our sample of hoaxes, and used bootstrapping to compute the confidence interval of the mean. To perform bootstrapping, we resampled the original list of D values $10,000$ times with replacement.

In general, we observe a trend in which hoaxes tend to have greater $\Delta V/V$ than their cohort: $D > 0$ in 75 out of 83 of the hoaxes in our data. The histogram in fig. 5 (left) shows the distribution of the differences, and shows that the mean is approxi-

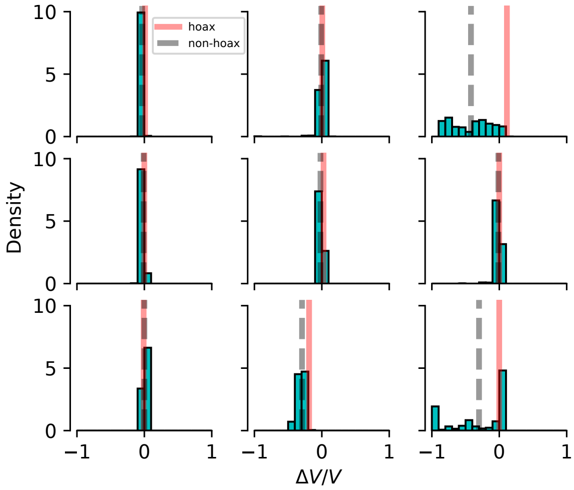


Figure 4: For a manual sample of hoaxes, the distribution of the $\Delta V'/V'$ values for each cohort (turquoise blue histograms) in comparison to the $\Delta V/V$ of the respective hoax (black dashed line). The $\Delta V/V$ of hoaxes tend to, in general, be higher than the mean of their cohorts (red solid line).

mately equal to 0.123, with a bootstrapped 95% confidence interval of $(0.1227, 0.1234)$.

According to the Central Limit Theorem (CLT), the distribution of sample means approximates the normal distribution with the increase of sample size n, regardless of the original distribution of data (Feller, 1991). Figure 5 (right) shows the distribution of the means for each of the $10,000$ resampled vectors. It is worth noting that all of the means returned were positive, implying a greater $\Delta V/V$ for the hoax.

5 Discussion and future work

Our study analyzes the role of online attention in the supply of disinformation on Wikipedia (Q1). From an operational point of view, we study the relationship between the creation of hoaxes and the traffic preceding each hoax's creation day d (Q2). To do so, we collected the view count of the out-link neighbors of the hoaxes and their cohorts for $d \pm 7$ days. Following prior work (Ciampaglia et al., 2015), to assess the allocation of attention during that period, we calculated the relative traffic volume change, which accounts for potential confounding factors due to traffic fluctuations. We observe that 90% of hoaxes have a higher $\Delta V/V$ than their respective cohort and confirmed it by means of resampling. This indicates that, on average, hoaxes tend to have more traffic accumulated before their creation than after. In summary, our observed D indicates that the generation of hoaxes in Wikipedia is associated with prior consumption of information, in the form of online attention, providing an answer to our original research question (Q1).

This study has some limitations that need to be acknowledged. First of all, our results are based on a list of only 83 hoaxes. Even though we originally collected a dataset that was twice the size of this one, we were limited by the fact that not all hoaxes were covered in our traffic dataset. Future work should extend our results to larger available samples of hoaxes (e.g., NPP-based) to ensure consistent results with prior work.

Additional limitations stem from our operational definition of the topic of a new article (hoax or non-hoax). In this work, we relied on outgoing hyperlinks (out-links) and neglected incoming hyperlinks (or in-links), owing to our lack of access to data on hyperlinks to hoaxes. This data is present but not publicly accessible in the Wikipedia database, presumably due internal regulations within the Wikipedia project. In the future, we would like to extend our analysis to include in-links as well.

Future work should also consider a more advanced definition of an article's topic that does not rely solely on hyperlinks, as they provide a very rough notion of topic. Links to very generic entries like locations or dates (e.g., 'United States of America' or '1492') typically convey little information about an article's topic .

Third, our traffic dataset is based on an older definition of pagecounts, which is affected by known limitations, including the presence of automated crawlers, which are known to generate large amounts of hits in a short period of time. To mitigate for the presence of this type of outliers, in our definitions of traffic volume we rely on the median instead of the mean, which is more robust to outliers. However, in the future we would like to include a more recent traffic dataset that is not affected by this and other biases (Wikimedia Foundation, Inc., 2022c).

In conclusion, our study sheds light on an important factor affecting the supply of disinformation on the Web. Future work should extend our results to venues other than Wikipedia, for example social media platforms like Facebook or Twitter. In addition, other types of media (like video, audio, etc.) should be considered — hoaxes do not

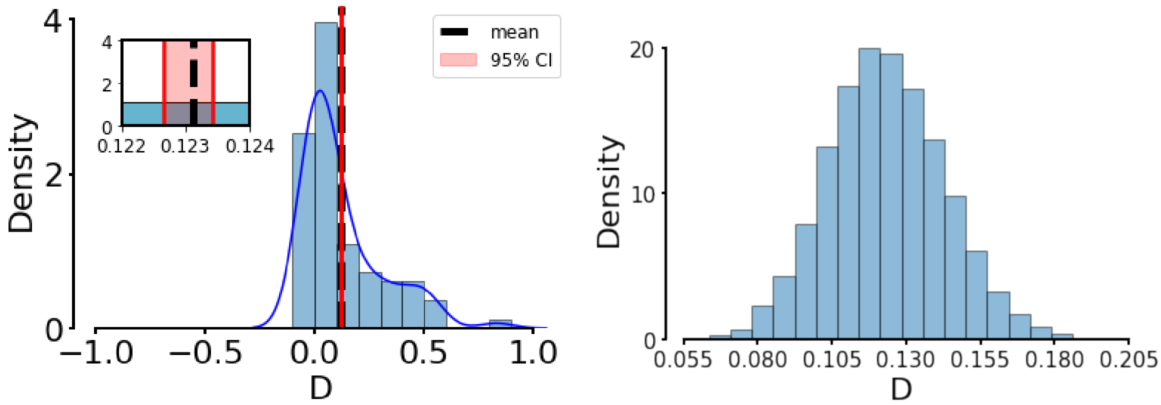


Figure 5: Left: Histogram of the relative traffic change differences D (see Equation (3)). The black dashed line is the sample mean, and the red area the 95% bootstrapped CI. The blue solid line is a kernel density estimate. The inset shows the sample mean relative to the confidence interval. Right: The sampling distribution of means obtained by bootstrapping $10,000$ samples with replacement.

only come in the form of textual articles, and attention is an effective incentive for people to keep spreading more disinformation, regardless of its medium. Future work should also consider studying the role of attention in versions of Wikipedia other than English. We expect similar trends to ones observed here to apply to non-English language editions as well. However, the signal may be weaker owing to lower traffic volume of non-English language editions. A comparative analysis of the role of attention in the supply of disinformation across cultures could shed more light about these type of threats to the Web as a whole.

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