

## **Poster/Work-In-Progress (WIP) Paper Abstract Template**

### **Title:**

**News Diffusion on Twitter: Comparing the Dissemination Careers for Mainstream and Marginal News**

Select one:

Poster

**Work-in-Progress Paper**

### **ABSTRACT**

#### **Background:**

Current scholarly as well as mainstream media discussion expresses substantial concerns about the influence of ‘problematic information’ (Jack 2017) from hyperpartisan and downright fraudulent news sources on public debate and public opinion formation (e.g., Humprecht 2018). Often encapsulated by the imprecise term ‘fake news’, the publishers of such content seek to exploit network effects, that is, the absence of echo chambers and filter bubbles in social media spaces (Bruns 2019) to maximise the visibility and dissemination of their content. They do so for a combination of political and commercial reasons (Wardle & Derakhshan 2017).

Some recent studies – most prominently an article by Vosoughi *et al.* (2018) in *Science*, examining story dissemination on *Twitter* – present evidence that such marginal, hyperpartisan and propagandist sites are outpacing their more mainstream counterparts in the dissemination of content: put simply, ‘fake news’ content seems to spread more quickly across social networks than ‘real news’. The generalisability of such findings is limited, however, by the source data: for instance, to establish a comparison between ‘real’ and ‘fake’ news, Vosoughi *et al.* (2018) consider only news stories that were evaluated by a fact-checking organisation. But this introduces a systematic bias: news stories that were dubious or controversial enough to warrant fact-checking may well disseminate in entirely different ways from stories that are more obviously truthful or incorrect. Uncontroversially truthful stories from mainstream news outlets could well disseminate across *Twitter* with greater speed than the ‘fake news’ content observed by Vosoughi *et al.*, but such stories would not have been included in their analysis unless they had been fact-checked. Thus, we cannot conclude from this study that lies always travel faster than the truth.

#### **Objective:**

To further investigate this question and extend our evidence base, this work-in-progress paper examines the sharing patterns for all major stories on selected mainstream and marginal news sites, independent of whether they have received external fact-checking. We do so to determine whether there are typical and divergent ‘dissemination careers’ on *Twitter* for the news stories published by each site, and subsequently to examine whether any differences in these typical dissemination patterns result from differences in the promotional

strategies employed by the sites themselves, from differences in the audiences they address, or from the artificial boosting of content dissemination through legitimate or nefarious means.

## Methods:

For this study we draw on two unique and long-term datasets: the Australian Twitter News Index (ATNIX) has tracked the dissemination of URLs linking to the 35 most prominent Australian news sites since 2012 (Bruns 2017), and captures any tweets that contain a link to one or more of these sites (even if such links were shortened using *Twitter's t.co* or other URL shorteners). A similar project, FakeNIX, has tracked the dissemination of URLs to several hundred marginal and suspect news sites since 2017. Its selection of sites is continuously updated, and combines several public lists of such sites from recent publications, including Allcott *et al.* (2018), Grinberg *et al.* (2019), Guess *et al.* (2018; 2019), and Starbird *et al.* (2017).

In the case of each index, we select those sites whose content has been shared most widely on *Twitter* during 2019. For ATNIX, this includes the public service media organisation *ABC News*, the mass-market *news.com.au*, the broadsheet newspaper *Sydney Morning Herald*, and the scholarly news and commentary platform *The Conversation*. For FakeNIX, we include *Breitbart*, *Daily Beast*, *Daily Caller*, *Gateway Pundit*, *Judicial Watch*, *Raw Story*, and *Russia Today (RT)*. From each set of sites, for the purposes of this work-in-progress paper we select only those news stories that were first shared on *Twitter* during 1-7 July 2019. We also select only those stories that were shared widely on *Twitter* during July and August 2019: for ATNIX stories we set a threshold of at least 200 tweets sharing a news story; for FakeNIX stories our threshold is at least 1,000 shares. This leaves 85 stories from the four Australian news sites, and 201 stories from the seven FakeNIX sites. We make these selections so that little-shared stories cannot distort our overall analysis.

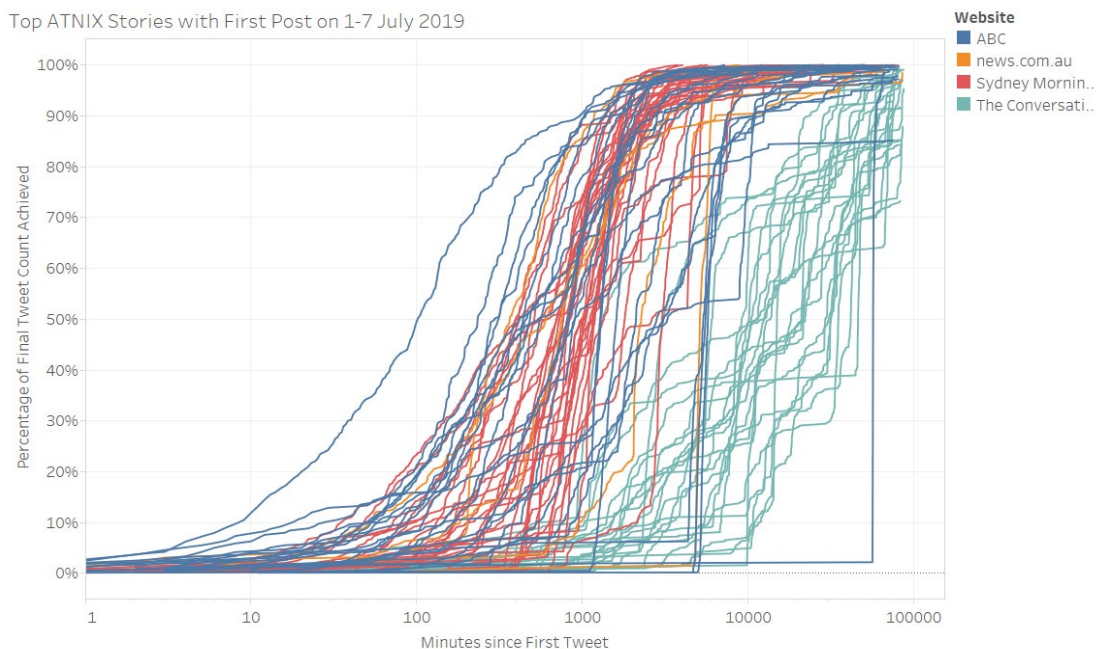


Fig. 1: ATNIX Story Dissemination Careers, July/Aug. 2019 (note: x-axis is logarithmic)

Setting the time of the first tweet for each story  $i$  as  $t_i = 0$ , we now calculate what percentage of the total number of shares for story  $i$  at the end August 2019 it had received by each subsequent minute  $t_i > 0$  of the story's dissemination career. This produces a set of dissemination curves per story, as illustrated for the four ATNIX sites in fig. 1. From these, we calculate the average and median *Twitter* dissemination careers for the stories published by each site, which show how quickly prominent stories from these sites *typically* disseminate across the Twittersphere. This method has several key advantages over the approaches favoured by other studies in this field, including Vosoughi *et al.* (2018): first, by showing the growth curve towards the 100% mark reached after two months, we normalise the dissemination careers and account for the differing audience sizes enjoyed by these sites due to their domestic or international orientation. Further, by selecting the most prominent stories from a range of sites we avoid a categorical judgment on whether individual news stories are 'real' or 'fake'. Indeed, it is important to note in this context that our intent in this research is not to establish definitively whether a given site should or should not be considered as 'fake news', whatever the definition of that term. Rather, we are interested in determining whether there are any significant and systemic differences in the *Twitter* dissemination careers for content published by sites generally accepted as mainstream on the one hand, and by sites often accused of taking hyperpartisan political positions and/or of promoting mis- and disinformation. Subsequently, we also intend to explore whether such differences can be explained by the specific news sharing behaviours of their audiences, and/or whether there is evidence of deliberate attempts to boost the dissemination of stories through automated and coordinated activity.

## Results:

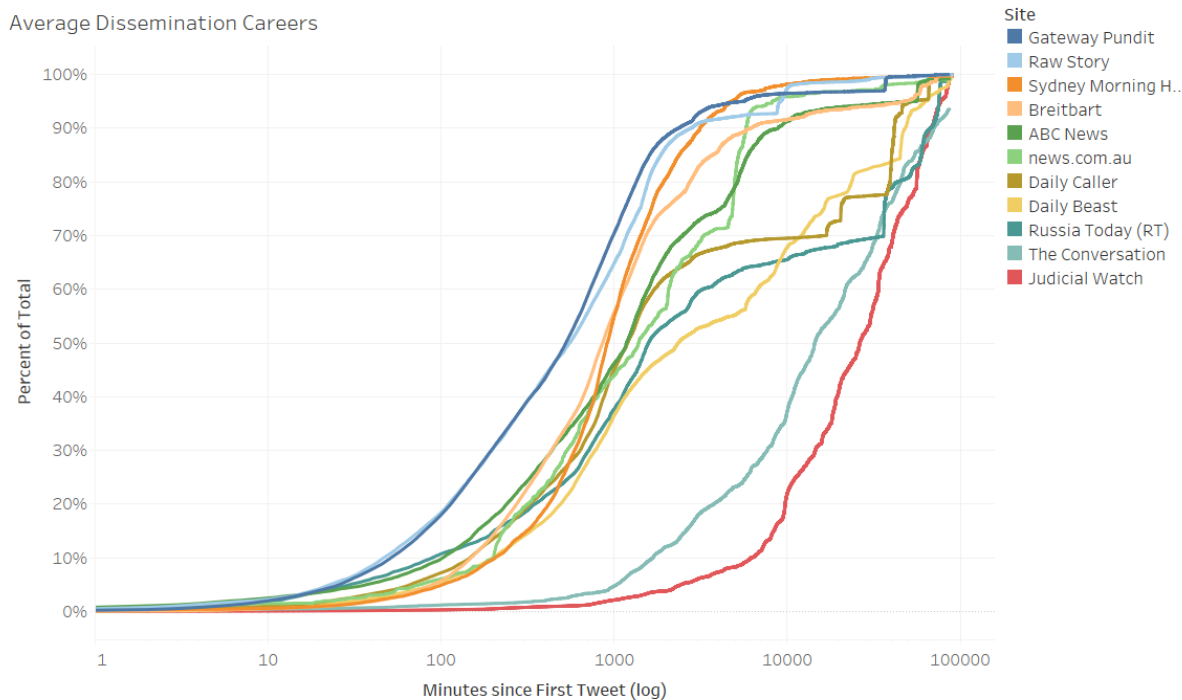


Fig. 2: Average Dissemination Careers, July/Aug. 2019 (note: x-axis is logarithmic for improved readability)

Our preliminary results show a number of noteworthy patterns (fig. 2): first, and most crucially, we see no evidence that content from hyperpartisan sites consistently disseminates more quickly – *pace Vosoughi et al. (2018: 1146)*, such content did not “diffuse significantly farther, faster, deeper, and more broadly” during our period of analysis. Rather, there appear to be systemic differences within both groups of sites themselves. Content from *Gateway Pundit* and *Raw Story* diffuses substantially more quickly than material from any other sites, on average reaching 50% of its eventual dissemination well within the first ten hours; most other sites – including both mainstream news sites like *ABC News* and *Sydney Morning Herald*, and hyperpartisan outlets like *Breitbart* and *Daily Caller* – reach 50% within the first twenty hours. Both the scholarly site *The Conversation* and the right-wing legal activist outlet *Judicial Watch*, by contrast, disseminate considerably more slowly: perhaps due to their more specialised content, they each take ten days or more to reach 50% of their eventual shares (table 1). This also means that their content continues to circulate in more tweets for a longer period of time, however.

Site	Minutes to 10%	Minutes to 30%	Minutes to 50%	Minutes to 70%	Minutes to 90%
<i>Raw Story</i>	47	196	549	1173	2754
<i>Gateway Pundit</i>	51	194	523	980	2337
<i>Russia Today (RT)</i>	89	709	1568	35838	66351
<i>ABC News</i>	102	435	1171	2477	8803
<i>Daily Caller</i>	146	631	1187	16755	41278
<i>Breitbart</i>	149	432	854	1518	6105
<i>Daily Beast</i>	197	773	2329	12016	47633
<i>news.com.au</i>	200	531	1375	3248	5752
<i>Sydney Morning Herald</i>	205	587	907	1415	3115
<i>The Conversation</i>	1661	7610	14323	32848	69541
<i>Judicial Watch</i>	6133	14432	26097	40581	67282

Table 1: Average Time to Percentage of Full Dissemination, July/Aug. 2019

### Future Work:

In further work ahead of the presentation of this paper at Social Media & Society 2020, we intend to expand this analysis to further mainstream and hyperpartisan sites, and to extend the timeframes considered here. We will also conduct a detailed investigation and interpretation of these preliminary results, identifying and testing hypotheses about the various possible factors influencing the dissemination of these sites’ news stories across the Twittersphere. This will both take into account what is known about the content and the audiences of these sites, and examine the possible roles that human influencers and retweeters as well as automated social bots may play in the dissemination of their stories. For now, however, it is already possible to conclude from our analysis that the simplistic assumption that biased propaganda and outright disinformation from hyperpartisan sites will generally disseminate more quickly than professionally produced stories from mainstream news outlets can no longer hold.

## References:

- Allcott, H., Gentzkow, M., & Yu, C. (2018). Trends in the Diffusion of Misinformation on Social Media. Retrieved from <https://arxiv.org/abs/1809.05901v1>
- Bruns, A. (2017). Making Audience Engagement Visible: Publics for Journalism on Social Media Platforms. In B. Franklin & S. A. Eldridge II (Eds.), *The Routledge Companion to Digital Journalism Studies* (pp. 325–334). London: Routledge.
- Bruns, A. (2019). *Are Filter Bubbles Real?* Cambridge: Polity.
- Grinberg, N., Joseph, K., Friedland, L., Swire-Thompson, B., & Lazer, D. (2019). Fake News on Twitter during the 2016 U.S. Presidential Election. *Science*, 363(6425), 374–378. <https://doi.org/10.1126/science.aau2706>
- Guess, A., Nyhan, B., & Reifler, J. (2018). Selective Exposure to Misinformation: Evidence from the Consumption of Fake News during the 2016 US Presidential Campaign. Retrieved from Dartmouth College website: <http://www.dartmouth.edu/~nyhan/fake-news-2016.pdf>
- Guess, A., Nagler, J., & Tucker, J. (2019). Less than You Think: Prevalence and Predictors of Fake News Dissemination on Facebook. *Science Advances*, 5(1), eaau4586. <https://doi.org/10.1126/sciadv.aau4586>
- Humphreht, E. (2019). Where 'Fake News' Flourishes: A Comparison across Four Western Democracies. *Information, Communication & Society*, 22(13), 1973–1988. <https://doi.org/10.1080/1369118X.2018.1474241>
- Jack, C. (2017). *Lexicon of Lies: Terms for Problematic Information*. Retrieved from Data & Society Research Institute website: [https://datasociety.net/pubs/oh/DataAndSociety\\_LexiconofLies.pdf](https://datasociety.net/pubs/oh/DataAndSociety_LexiconofLies.pdf)
- Starbird, K. (2017, March 15). Information Wars: A Window into the Alternative Media Ecosystem. *Medium*, 3 April 2017. <https://medium.com/hci-design-at-uw/information-wars-a-window-into-the-alternative-media-ecosystem-a1347f32fd8f>
- Vosoughi, S., Roy, D., & Aral, S. (2018). The Spread of True and False News Online. *Science*, 359, 1146–1151. <https://doi.org/10.1126/science.aap9559>
- Wardle, C., & Derakhshan, H. (2017). *Information Disorder: Toward an Interdisciplinary Framework for Research and Policy Making*. Report No. DGI(2017)09. Retrieved from Council of Europe website: <https://shorensteincenter.org/wp-content/uploads/2017/10/Information-Disorder-Toward-an-interdisciplinary-framework.pdf>