Are You Spreading Misinformation? Analyzing How Influential Twitter Users Contribute to the Spread of COVID-19 Information

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Abstract

When COVID-19 was declared a pandemic in early 2020, a virtual pandemic of misinformation had gone undeclared. While some of these misinformed claims may be tame, others could lead to the loss of life (e.g. Hydroxychloroquine curing COVID-19) and behavioral changes with larger ramifications (e.g. Bulk buying hand sanitizer). Therefore, detecting and removing instances of misinformation could reduce the consequences that arise from a misled public. In particular, misinformation tends to pervade social media platforms. Its convenience allows users to easily consume and spread information to others through posting. As a result of this accessibility, many have turned to these outlets as their primary source of news [1]. In 2020, the three most used social media platforms were Facebook, YouTube, and Twitter. While Facebook dominates as the go-to platform for general use, over half of Twitter's user base (59%) is reliant on the platform for news [2]. Furthermore, Twitter is known as the platform that houses the personal thoughts of many well-known figures. As opposed to Facebook or YouTube, where these interactions are scarce, users can directly engage with these influencers and easily pass on the content produced by these figures for the user's own network to see. Thus, Twitter's social structure allows information to easily propagate between influencer and user, and amongst users themselves. Accordingly, this paper examines the correlation between influential Twitter accounts – right and left-leaning news sources, health organizations, celebrities, and right and left-wing politicians – and the spread of misinformed claims on Twitter. Being higher-level nodes in their social networks, these Twitter accounts are selected as their large follower counts allow for information to easily disseminate to a wider audience [3]. Visualizing these interactions can provide insight into the patterns and trends allowing for the identification and cessation of misinformation spread. This paper concentrates on misinformation, predominantly in the USA, during the early stages of COVID-19 by comparing tweets from well-known Twitter accounts to datasets consisting of "fake" and "true" claim tweets. Additionally, engagement metrics are used to gauge how much traction tweets from different influential Twitter accounts garner. With this, timelines of tweet frequency and engagement are used to determine the correlations, via application of the Kendall Rank Correlation Coefficient and Mann-Kendall significance test, between influential Twitter accounts and general fake and true tweets. The results show that the most statistically significant relationship found is between the distribution of real tweets and average likes and retweets from health organizations. Other social network nodes do not have concrete relationships with fake and real tweets.

Keywords
COVID-19, Pandemic, Fake News, Misinformation, Tweets, Social Media, Twitter

1 Introduction

Since the introduction of social media, people have been able to connect with one another in an instant. While this leads to information quickly spreading amongst individuals and groups, it also leads to swift spread of misinformation.

Furthermore, social media has overtaken mainstream news networks as the predominant news source, with 86% of Americans using social media over other news outlets [1]. Since social media content is heavily dependent on user engagement (e.g. retweets, sharing, and posting), false claims can be easily proliferated by extensive engagement, leading to misinformed claims reaching a wider audience. Additionally, as a result of the current over-reliance on social media for news, people could easily be misled when encountering misinformation. Recently, under the influence of the COVID-19 pandemic, dozens of false claims and headlines surfaced, with some of the notable claims connecting COVID-19 to 5G/radio-waves [4], proposing disinfectant as a preventative measure, and that the use of hydroxychloroquine can cure COVID-19 [5]. This surge of misinformation impacts the livelihoods and health of those led to believe them, as well as the general public that lives alongside them. In response to this, the World Health Organization had resurfaced a previously coined term, “infodemic,” to describe the overabundance of misinformation emerging online and offline in their efforts to bring awareness to this misinformation pandemic [6].

In 2020, the three most used social media platforms were Facebook, YouTube, and Twitter. While Facebook dominates as the go-to platform for general use, over half of Twitter’s user base (59%) is reliant on the platform for news [2]. Furthermore, Twitter is known as the platform that houses the personal thoughts of many well-known figures. As opposed to Facebook or YouTube, where these interactions are scarce, users can directly engage with these influencers and easily pass on the content produced by these figures for the user’s own network to see.

Similar to social network analysis (SNA) [7], this paper views influential figures as social network nodes. The social structure of Twitter allows for users to connect and engage over common ideologies. With larger network nodes amassing large follower counts, the information they release easily disseminates along its many edges. Therefore, according to Dynamic Social Impact Theory (DSIT), higher-level nodes in central positions of a network are perceived as more influential and powerful [8]. In the context of COVID-19, these high nodes can contribute to the spread of true and fake news. To better understand how misinformation spreads on social media, the correlations between influential social network nodes and the spread of fake and real news are studied. Using data sets consisting of tweets between March and May 2020, correlations were calculated between the spread of misinformation and social network nodes based on their tweet frequency, average number of likes, and average number of retweets.

2 Materials & Methods

Table 1 provides examples of the Twitter accounts considered as influential social network nodes in different groups. The three main groups considered were "Health Organizations", "News Outlets", and "Individuals". The latter two groups were further subdivided based on their political views into "Left" and "Right". Accounts for the “Health Organizations” category were restricted to governmental and educational establishments related to the medical field. The “Left” and “Right" news outlets were determined based on a study classifying the political-leaning of each news network [9]. “Political Left” and “Political Right” individuals were chosen strictly based on their political affiliations (e.g. Republican/Democrat). Finally, sixty-three “Celebrities” were taken out of the top hundred most followed Twitter accounts, excluding politicians and groups (e.g. Barack Obama, Manchester United, One Direction). Tweets made after January 1, 2020, from accounts in each group were scrapped using Twint [10], where relevant tweets were extracted by filtering for case-insensitive COVID-specific substrings:

- covid
- coronavirus
- rona
- wearamask
- socialdistancing
- stayathome
- ncov
- symptomatic
- covax

Data containing tweets that contribute to the spread of COVID-19 misinformation are collected from various open-source datasets. The specific sources of datasets are shown in Table 2. These datasets are already labelled as "real" or "fake" news. The two categories were separated for independent comparison with each Twitter group. To ensure consistency of the distribution of all datasets, only tweets from March to May of 2020 are used.

Examples of Influential Twitter Accounts	
	Examples
Health Organizations	CDCgov, WHO, HarvardChanSPH, JohnsHopkinsSPH
Right-Leaning News Outlets	FoxNews, Real Daily Wire, The Blaze
Left-Leaning News Outlets	ABC News, CNN, Guardian, VICE, TheDailyShow
Political Right	Boris Johnson, Dave Rubin, Donald Trump
Political Left	Andrew Yang, Hillary Clinton, Justin Trudeau
Celebrities	Adele, Bill Gates, Elon Musk, Jimmy Kimmel

Table 1: Examples of Influential Twitter Accounts

A timeline of tweet frequency as well as two types of engagement timelines were created to assess the spread of misinformation. The two categories of engagement include the average number of likes and retweets per tweet over time (i.e. $\frac{Likes}{Tweets}$ and $\frac{Retweets}{Tweets}$). While replies are another significant form of platform engagement, this metric is neglected as not all data sets provided reply counts. These timelines are created using the Python libraries Pandas [11], Matplotlib [12], and NumPy [13].

Finally, tests to measure the correlation between timelines are performed using the Kendall Rank Correlation Coefficient (KRCC). This coefficient is a non-parametric hypothesis test that provides insight into the strength of dependence between two variables [14] - in this case, the tweet frequencies and engagement metrics between two groups. To test for their significance, their p-values are calculated based on the Mann-Kendall significance test, with the null-hypothesis being a KRCC of 0 (no dependence). After binning the data in intervals of three-days, the KRCC value, τ_b, is calculated by plotting the binned y-axis values of the timelines of each influential Twitter groups against the datasets of real and fake tweets and performing the following operation with the set of (x,y) pairs: [14]

$$\tau_b = \frac{n_c - n_d}{(n * (n-1)/2)}$$

Where n_c is the number of concordant pairs where for $i < j$, $x_i < x_j$ or $y_i < y_j$, n_d is the number of discordant pairs if the pair is not concordant, and n is the total number of pairs.

The p-values are calculated using the kendalltau function in Python's Scipy [15] library with the following theory behind it [16]:

$$z_b = \frac{3(n_c - n_d)}{\sqrt{n(n-1)(2n+5)/2}}$$

where for a two-tailed hypothesis test, the p-value is twice the z_b statistic.

Open-source Data Sets Used for Analysis
TathyaCov: Detecting Fake Tweets in the times of COVID 19 [17]
Cross-SEAN: A Cross-Stitch Semi-Supervised Neural Attention Model for COVID-19 Fake News Detection [18]
COVID-19-FAKES: A Twitter Dataset for Detecting Misleading Information on COVID-19 [19]
Dataset for COVID-19 Misinformation on Twitter [20]
CMU-MisCov19: A Novel Twitter Dataset for Characterizing COVID-19 Misinformation [21]

Table 2: Open-source Data Sets Used for Analysis

3 Results

Figure 1 shows the various frequency timelines from March 1^{st} to May 25^{th} 2020 separated into each category of influential Twitter accounts. The two last plots represent the spread of fake and real tweets collected from open-source datasets. The blue line represents the daily tweet frequency fluctuations, while the histogram is binned every three days.

Figure 2 and Figure 3 represent the engagement timeline plots over the same period as Figure 1. Figure 2 shows the average daily likes timelines and Figure 3 shows the average retweets timelines. Similar to Figure 1, a histogram binned every three days is used. Note that since the quantity of data across all categories varies and no normalization was applied, the magnitudes of the vertical axes differ.

From these timelines, the Kendall Rank Correlation Coefficient (KRCC) and the Mann-Kendall significance test p-value are determined to evaluate the correlation between pairs of influential social network nodes and false and true tweets. Tables 3 through 8 show the calculated pairs of KRCC and p-values for tweet frequency and the two engagement metrics (average likes and average retweets).

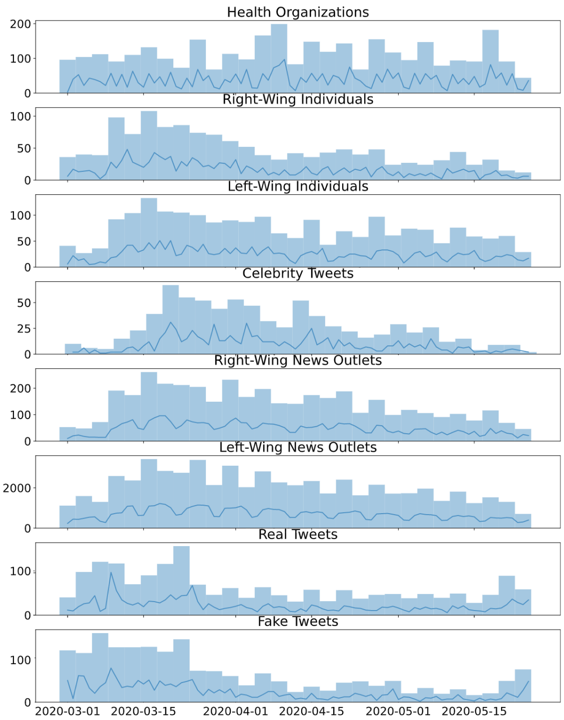

Figure 1: Timelines for Tweet Frequency

KRCC for Tweet Frequency		
	Real	Fake
Health Organization	0.1513	-0.0145
Right News	0.3048	0.2156
Left News	0.2283	0.2624
Political Right	0.3208	0.3430
Political Left	0.3339	0.2184
Celebrities	0.1082	0.1021

Table 3: KRCC Values for Tweet Frequency Timeline Correlation

P-Values Tweet Frequency		
	Real	Fake
Health Organization	0.1572	0.8917
Right News	0.0209	0.1024
Left News	0.0840	0.1024
Political Right	0.0027	0.0013
Political Left	0.0018	0.0410
Celebrities	0.3141	0.3402

Table 4: Mann-Kendall P-value Significance Testing for Tweet Frequency

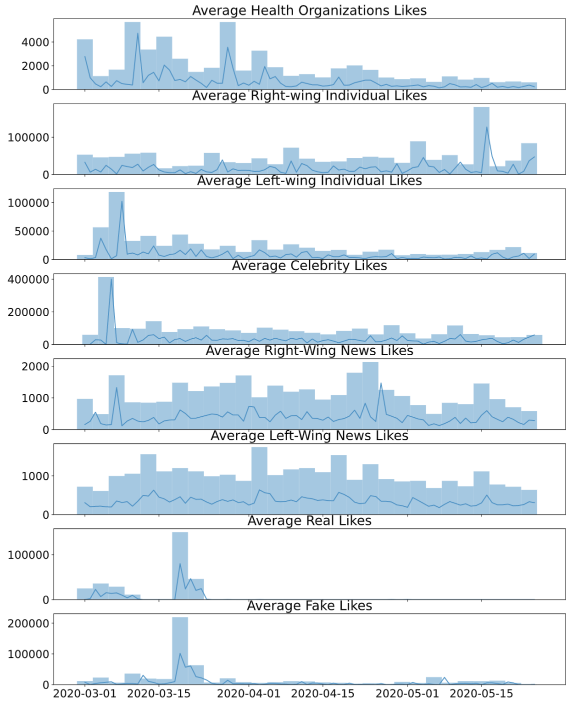

Figure 2: Timelines for Average Likes

KRCC for Average Likes		
	Real	Fake
Health Organization	0.2808	-0.0690
Right Leaning News	0.2070	-0.2217
Left Leaning News	0.0197	-0.0640
Political Right	-0.1429	-0.1281
Political Left	0.2020	≈ 0
Celebrities	0.0099	-0.1823

Table 5: KRCC Values for Average Likes Timeline Correlation

P-Value for Average Likes		
	Real	Fake
Health Organization	0.0332	0.6156
Right Leaning News	0.1201	0.0952
Left Leaning News	0.8965	0.6420
Political Right	0.2878	0.3419
Political Left	0.1295	≈ 1.0
Celebrities	0.9555	0.1724

Table 6: P-value for Average Likes Timeline Significance

Figure 3: Timelines for Average Retweets (placeholder)

KRCC for Average Retweets		
	Real	Fake
Health Organization	0.3153	-0.0739
Right Leaning News	-0.1576	-0.0837
Left Leaning News	0.0394	-0.0049
Political Right	-0.2315	-0.0197
Political Left	0.3448	-0.0345
Celebrities	0.1133	-0.1872

Table 7: KRCC Values for Average Retweets Timeline Correlation

P-Value for Average Retweets		
	Real	Fake
Health Organization	0.0162	0.5896
Right Leaning News	0.2400	0.5392
Left Leaning News	0.7804	0.9852
Political Right	0.0083	0.8965
Political Left	0.0810	0.8091
Celebrities	0.4020	0.1608

Table 8: P-value for Average Retweets Timeline Significance

4 Discussion

After producing the timelines, KRCC values are used to evaluate the correlation as they are a distribution-free test that can measure the strength of dependence between two variables [22]. As the distribution of the timelines produced are unknown, KRCC is a preferable way to assess their correlations. Its limitation of assessing between only two variables also fits into the problem definition of this project as we do not test for correlations between different influential social nodes as they are linked poorly. [23].

The KRCC between tweet frequency and real vs fake news is interpreted as the correlation between the user's posts and the spread of either form of information. The KRCC between engagement metrics of likes and retweets, and real and fake tweets is interpreted as a measure of similarity between the two audience groups. It is used as an additional metric for how each group contributes to the spread of misinformation, as different audience demographics interact differently with social media [24].

Likes and retweets were measured separately as they measure different forms of engagement. Retweets represent a higher level of engagement compared to likes, as users must consciously decide to share the information [25]. Furthermore, likes are a passive activity, and this form of engagement contributes less to the spread of content.

To go about defining different levels of significance interpreted from the KRCC, this paper follows the proposed scale: [26]

- $|\tau_b| = 0.07$ indicates a weak association
- $|\tau_b| = 0.21$ indicates a medium association
- $|\tau_b| = 0.35$ indicates a strong association

Overall, health organizations and left-wing political figures show a constantly moderate correlation across all three metrics. Looking at frequency alone, news groups and political figures generally have a moderate correlation with all types of news, while health organizations and celebrities have a low correlation. However, for most groups, these results are not corroborated by either the average likes or average retweets.

From the KRCC and p-values, one can see that for health organizations, the tweet frequency KRCC is a negative value of -0.0145 for its correlation to fake news, while it has a higher tweet frequency KRCC of 0.1513 for true news in comparison as shown in Table 3. The p-values for fake tweet frequency of 0.6156 in Table 4 is high which indicates that health organizations have a high probability of achieving the null-hypothesis: not correlated to fake tweets. These trends are further reflected in the engagement correlations from Tables 5 and 7, where average likes and retweets both have a much higher correlation to true news compared to fake news. This could suggest that groups following real news are more likely to also follow health organizations.

From Table 3, the tweet frequency of politically right-leaning news sources has a moderately strong and moderate correlation with real and fake tweets, respectively. Furthermore, the relationship between average likes and real/fake tweet frequency is shown to have a low correlation and negative correlation for real and fake tweets, respectively. Finally, average retweets appear to show no discernible correlation. However, in analyzing the p-values from Tables 4, 6, and 8, the only statistically significant value is the relationship between right-wing news sources and true tweet frequency with a KRCC of 0.3048 and a p-value of 0.0209 as shown in Table 3 and 4 (all other relationships would then require further evidence to support any relationship). Therefore, relative to fake tweets, real tweets may have a more correlated distribution to right-wing news sources. No other engagement metric shows that right-wing news sources have any significant trends. Consequently, no further inference on whether or not information propagates between right-wing news and real tweets can be clearly stated.

The correlations for politically right-wing individuals have varying results across all three metrics of comparison for KRCC values as shown in Tables 3 to 8. Focusing on tweet frequency, real and fake tweets both have moderately strong correlations of 0.3208 and 0.3430 with the frequency of right-wing individuals' tweets, shown to be statistically significant through p-values of 0.0027 and 0.0013, respectively. However, when analyzing average retweets, real tweets have a moderately uncorrelated statistically significant relationship, a KRCC of 0.0083, with right-wingers. In context with the high tweet frequency relationship, this could imply that real tweets may spike at similar times as right-wing tweets, but do not propagate the same information from the influencers' tweets. On the other hand, average likes show mostly low negative correlations with both real and fake tweets but are not statistically significant.

When examining Table 3, tweet frequency from politically left-wing individuals appear to have moderately strong correlations with real tweets of 0.3339, as opposed to a moderate correlation with fake tweets of 0.2184. From Table 4, these correlations are shown to be statistically significant with a p-value of 0.0018 and 0.0013 for true and fake tweets, respectively. From Tables 5 through table:8, the average likes and average retweets show a moderate-to-strong correlation with real tweets with a KRCC of 0.2020 and 0.3448, but are statistically insignificant with p-values of 0.1295 and 0.0810, respectively. Considering the lack of statistical significance, further evidence must be provided to support a correlation. While tweet frequency might be correlated, suggesting the possibility that politically-left individuals may impact the spread of real news more than fake news, the lack of statistical significance for the engagement metrics reduces any further inferences that could be made on this matter.

Across Tables 3 through 8, there seems to be an overwhelmingly low to moderate correlation with KRCC values below 0.21 between celebrity tweets and real and fake tweets across all metrics. Furthermore, the large p-values indicate that the null hypotheses were failed to be rejected, suggesting that celebrity tweets and engagement have little influence on the spread of real and fake tweets. Similarly, politically left-leaning news sources are shown to be moderately correlated with both real and fake news tweets. However, neither of these relationships are statistically significant, thereby requiring further investigation.

A number of future works may be completed to further this study. Currently, the engagement correlations for likes and retweets are not weighted and are treated to have a similar significance as tweet frequency correlations. However, retweets often contribute more to the spread of information compared to likes. Therefore, for future improvements, retweets can be weighted exponentially to mimic the distribution of info through networks while likes can be weighted as a constant. Furthermore, the engagement data used is biased towards individuals who are active on social media and does not account for those who have been affected by the information but do not like or retweet. However, as the focus on the study is the spread of misinformation on social media, it makes sense to not account for the silent users.

There are other limitations to this study, a key source of error being the periods of time each open-source dataset used, affecting the frequency of real and fake tweets. The datasets each focused on a different time frame from which tweets were collected. To counter this, the analysis interval was cut off to between March 1^{st} and May 25^{th}, which had a large number of tweets for each dataset. To ensure each dataset contained the same number of points and to reduce noise, the data was binned every three days. Additionally, there is an uneven number of tweets in each dataset. This is not thought to impact the correlations between each timeline greatly, as the relative fluctuations in frequency should still be correlated.

Furthermore, the classification method of the real and fake tweets differ as they were obtained from different open-source datasets. Some authors used machine learning models, while others relied on fact-checking websites. Additionally, different authors may have had different interpretations of what was considered "fake" and "real". In particular, tweets that fell into a grey-area of "partially" true or false may not be equally classified across different datasets.

What's more, the tweets of influential nodes used were not originally filtered when scrapped by Twint. During data pre-processing, related tweets were filtered on the basis of whether they contained particular keywords. However, it is possible that unrelated tweets may have been included as this filtration method relied on substring searching (e.g. rona is a substring of other common, non-COVID related words). Similarly, related tweets may have been missed as some COVID-related terms were too vague to effectively filter out non-relevant tweets (e.g. while 'vaccine' retrieves tweets related to COVID-19, it may also retrieve tweets related to other illnesses such as the common flu).

We also recognize that a low correlation with a high p-value cannot be used to reject the alternate hypothesis that the datasets are correlated; rather, it suggests that it is likely that there is no correlation between the datasets. Further comparisons using a null hypothesis where the KRCC is 1 must be done to reject the correlation.

Conclusion

Living in the Information Age, the wonders of quick info and knowledge access can easily be misused for harmful intents. In difficult times like the COVID-19 pandemic, it is nevertheless more important to be able to learn and identify ways that can reduce the spread of misinformation.

This study examines how specific categories of influential social nodes correlate to the spread of misinformation to find potential ways to limit the propagation of fake news and its harm. The current research and analysis shows that as expected, health organizations strongly correlate to the spread of real news and poorly correlates to the spread of misinformation. Therefore, by encouraging users to follow official medical accounts, this would reduce the exposure and spread of misinformation. Furthermore, the current methods find that politically left individuals help spread more true news than misinformation.

Surprisingly, other categories of influencers have conflicting results or moderate to low correlation to both the spread of true and fake news. This could mean that they do not play a significant role in the spread of misinformation. On the other hand, these results can also be due to the sources of error discussed previously and the use of KRCC instead of other correlation coefficients. Therefore, future work with larger sets of consistent data as well as different correlation measurements should be explored to confirm the validity of the produced results.

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