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Misinformation and the Factors that Lead to Greater Belief and Spread

ABSTRACT

This paper will discuss the ideas surrounding misinformation and the factors that lead to an increased belief or expand the spread of sources of misinformation. This was first done through a literature review of previous works that discussed misinformation and the methodology used to get results. It was found that machine learning models, specifically NLPs are very common techniques in trying to find misinformation factors. After this, analysis was done on a dataset containing conspiracy theory posts. Many techniques were used in this process such as histograms, regression plots, correlation heatmaps, Mann Whitney U tests, Point Biserial Correlation tests, and a poisson regression model. The results of these tests showed that many factors lead to the greater belief and spread of misinformation, such as closeness to account owner, perceived authority status of account owner, and group size. In the end it was found that misinformation belief and spread usually grows in smaller close knit communities, where the main community leader has some small semblance to authority.

INTRODUCTION

In recent years the ideas of misinformation and disinformation have been very prevalent throughout most recent current events and are mentioned a lot in both the news and in online circles. The prevalence of both concepts has been mentioned in many recent elections regarding candidates stating mistakenly and purposefully false information. During the Covid 19 pandemic, multiple people were spreading misinformation regarding ineffective treatments for the virus, which led to a few people actually getting put in harm's way due to the false health information they were given. Since these instances have been so prevalent recently, many social scientists have begun to study misinformation and disinformation. This idea has led to many studies to be conducted on the subject, especially using computational and quantitative means. There are many questions researchers ask when trying to conduct research into misinformation and disinformation, but a very big question many try to answer is how communities are affected by the spread of both misinformation and disinformation. In this paper I hope to analyze the factors that lead to greater belief and spread of misinformation. I will first try to accomplish this goal by performing a literature analysis on previous academic papers that tried to explain the subject, especially the methodology used to analyze misinformation. Then I will perform an analysis of a misinformation dataset and interpret the results from the analysis. Lastly, I will discuss the limitations of my analysis and how future research into the factors of misinformation belief and spread can be further expanded on the analysis of the topic of misinformation.

LITERATURE REVIEW

There are plenty of previous works that look into the factors that lead to the spread and the increased belief of sources of misinformation. One of these sources is an article titled "Conspritial Narratives at Scale: False Alarms and Enormous Connections", which follows what types of factors in Reddit posts might lead to the spread of conspiratorial narratives. This source uses multiple Techniques to analyze the data found in the dataset. One of these methods researchers used was Natural Language Processing models or NLPs, which include BERT, ALBERT, ROBETA, DistillBERT, DEBERTa, and T5, to analyze speech patterns in reddit posts to try and see if the author of the post genuinely had belief in the ideas he was spreading or if he was spreading it for different purposes (Diab et al, 2024). The authors also used GPT models to test its aptitude for classifying misinformation and if the model could tell if a certain source was a conspiracy or not (Diab et al, 2024). Lastly the authors also used classical machine learning models, which include Linear Regression, K Nearest Neighbor, Decision Tree, Random Forest, XGBoost, and SVM, to aid in the analysis of the conspiratorial posts and determine what data points are important in predicting conspiratorial posts (Diab et al, 2024).

Another paper that previously looked into the factors leading to the spread of or greater belief in misinformation was a paper titled “You are a Bot!- Studying the Development of Bot Accusations on Twitter”. This paper was looking at how bot accusations have evolved overtime to become more pieces of misinformation being used to spread misinformation about users, and they did this by analyzing Twitter API post data. This paper used multiple tools for analyzing the data. First the authors of this study used BERT, an NLP, to detect when Posts about bots were talking about a bot accusation (Assenmacher et al, 2024). The authors then used unsupervised learning models to cluster them to help better group bot reactions together (Assenmacher et al, 2024). The researchers then began their analysis of the data by using a sentiment analysis model called the Detoxify classifier, which could be used to measure toxicity levels in accusation messages and possibly show a factor in greater spread of misinformation (Assenmacher et al, 2024). The researchers also used a supervised ML model called the botometer, which determines how bot-like an account is really acting and can possibly aid in the belief in certain bot accusation misinformation being more easily believed for certain accounts (Assenmacher et al, 2024). Lastly, the authors used Barbera’s method for ideal point estimation, which gives an account posing an accusation a ideology score and can possibly show how certain ideologies might lead to the spread of false bot accusations (Assenmacher et al, 2024).

One last paper that previously investigated factors of misinformation spread and belief was titled "Socio-Linguistic Characteristics of Coordinated Inauthentic Accounts". The authors for this paper used Twitter API data from the 2017 French election to determine factors in speech that led to the greater spread of misinformation during the election. For this task the authors used a lot of NLP models for analysis of the Twitter text. The authors used WSBERT and XLM'T to extract wording and gain understanding of what a misinformation sentiment was around a candidate and what exact wording they used to get that sentiment across (Burgharrdt et al, 2024). Then they used MFTC and XKM-T to see whether a post was wording a candidate as immoral or moral (Burgharrdt et al, 2024). Then the researchers used BERTweetFr as a way of viewing the political concerns that were being mentioned in the tweets and Demux to show the emotions that were being used in the tweet (Burgharrdt et al, 2024). Lastly, researchers used these factors to create a model that groups certain accounts as being used to spread political misinformation which can then be analyzed to see which factors are most popular in helping spread misinformation and getting more people to believe in it (Burgharrdt et al, 2024).

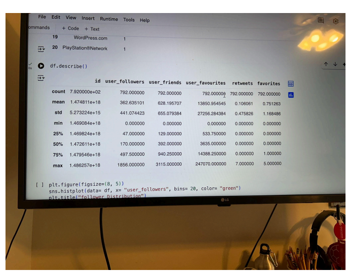
In total, these posts help show that throughout current literature a wide variety of analyses are being used to help spread misinformation. Some of the most well used forms of analysis are machine learning models, which can sort of be created to help automate analysis of misinformation data. The most popular of these methods are NLP models, which are very useful in analyzing certain aspects of misinformation speech to help find factors that help lead in the greater spread and belief of misinformation.

Methodology

For my personal analysis of misinformation sources, I acquired a dataset from Kaggle which had data collected from the Twitter API. This dataset had information related to posts and accounts that spread misinformation about a conspiracy that birds were not real. The data contained information such as account information of the users posting the conspiracy tweets, the tweets themselves, and public metric information for retweets, likes, shares, and etc.
For Preprocessing of the data I first checked the columns that were to be used for the analysis and searched for missing values in the data. This was done by seeing if there were any NA values reported on Kaggle for the columns. The result was that there were no missing values reported in the data. Next the data was searched for outliers. There were multiple outliers found when a boxplot was performed on the columns being used for analysis. This was fixed by performing IQR transformations on the columns to be used for analysis, which ridded the data of more extreme outliers. Lastly, the data was checked for inconsistencies in how the data was written by searching for unique values in each column to be used for analysis. There were no inconsistencies found in the data.

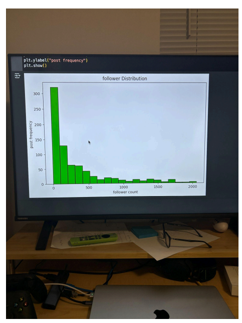
For the analysis of the data multiple visualizations and tests were performed on the data. The first test was the checking for basic descriptive statistics for all the numeric data that would be used for analysis. Next, a histogram looking at the distribution of followers was performed to help me get an understanding if certain ideas around having high followers is important in spread or belief. Then, a regression plot was performed to look at the relationship between followers and favorites in the twitter data to gain an understanding of if people were actually following the beliefs of people they follow. Then, a correlation heatmap was created to look at the correlational relationships between different numeric values correlated with each other and to see if any might be important factors in the spread and belief of misinformation. For testing, a Mann Whitney U test was created to look to see if there is a difference between verified and non verified accounts. My hypothesis for this test is that there will be a difference between verified and unverified accounts. Next, a point biserial correlation test was performed to see the correlational direction this factor had with the number of followers. My hypothesis for the test is that users may go more towards unverified accounts that may have less authority since many of the accounts looked small and did not seem to have that much authority. Lastly, a poisson regression to analyze the relationship between favorites and verified users. This is to help try and explain some assumptions created by the hypothesis tests done before and gain more evidence around it.

Results and Discussion



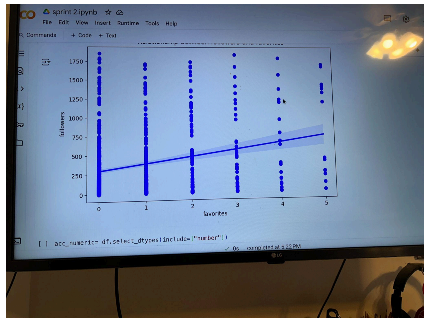
(Figure 1)

When it comes to results, there was a mix in the significance when it came to the results of the data. From the results of the descriptive statistics, which are in Figure 1, certain data points seemed to show a pattern. Many of the min and max values for the numeric values in the data were kind of low, this could possibly show that many of these accounts are not that popular and coil possibly show that the users that follow this account may not follow these accounts for their popularity or even authority. This is also shown to be a truth in Figure 2, which deptics the distribution of followers for these accounts. Many accounts, like the ones discussed above, do not have very many followers, with many not even having over 500 followers. This could possibly show that these accounts aren't as popular as originally shown in previous literature about the spread of misinformation from conspiracy theory sources as originally thought. This might also show that, like before, many people who do get information from these accounts may not follow or try to spread these accounts' opinions due to popularity or proof of authority since many of these accounts don't have much of a following.



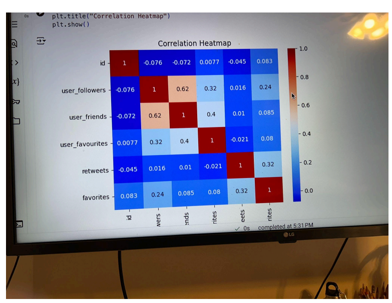
(Figure 2)

Figure 3, which shows the relationship between followers and favorites of tweets, seems to show that there is a slight increase in favorites when follower accounts go up. This shows that there is a slight correlation between favorites and followers. This might show that at least for some of the people, they might genuinely believe some of the ideas that they see from these accounts posting this misinformation due to them favoriting and following the account. This could also mean certain factors in the post might actually influence their beliefs as I hope to find, which fits with previous literature.



(Figure 3)

Figure 4, which shows the correlations between different factors in the data shows correlations already shown in the data and some new ones. When it comes to new ones, friends and followers seem to be common. This might show that most of the people that follow these accounts are close to the poster of the accounts, which may explain both greater belief and spread. This could possibly mean people who are closer with each other might more easily believe things people told them and spread it with friends that might have similar ways of thinking. There also seems to be a correlation between retweets and favorites. This might suggest that people who more likely believe in these posts might be more likely to spread it, which is not that uncommon a thought from previous literature. So the higher the belief might mean the more likely someone will try and spread that belief.



(Figure 4)

When it comes to the hypothesis tests, The Mann Whitney U test showed there was a difference between verified and unverified users, This shows that more people might have a belief or be more likely to spread the ideas of one of these posts rather than the other. The Point Biserial Correlation test shows this as true as well. This test showed there was a significant enough positive correlation with verified users and followers. This means verified users had more followers, which went against my hypothesis and some ideas discussed earlier. Since there were more followers for verified accounts, the idea that I discussed earlier of these people who follow these accounts might be wrong. People might see some sort of authority in these posts since people might see the verified sign and be more likely to trust users that have it, which could make people believe misinformation coming from this type of account since they might deem it to be an authority figure. For the Poisson regression model the results showed no significance between favorites and verified user status. This could possibly mean that authority status may cause some belief and spread of the ideas, but strong belief in the ideas may be linked to certain other factors in the data that may not be as present as originally shown.

Limitations and Implications

When it comes to the limitations of the study, there was one main thing that could limit the accuracy of the results. When looking for outliers in the data, there were a l;large amount of outliers in the data. While the IQR method did remove a large portion of these more extreme outliers, there were still outliers in the data present. This might have been caused due to the prevalence of lower values in the data, which then caused higher values to be considered outliers. Though many of the extreme outliers were removed from the data, the results discussed in this paper should be taken with a grain of salt. Also, not every column was used for analysis in this paper, so not all columns were pre processed due to time constraints, which means only columns that contained information for the analysis were preprocessed and that there might still be factors unseen in this analysis of the data.

As for the implications of the result of this paper, there are many implications that could be derived from the results. One such implication that can be made is that many of the accounts that post this type of misinformation online are not that popular and usually foster smaller communities around these misinformation concepts. Some of the members of these communities may actually believe in the misinformation being sprouted by these accounts spreading misinformation. Another implication that was shown through this analysis was that many of the people who follow these accounts may be considered closer relationships with the people behind these accounts, which could possibly lead to greater belief and spreading of these ideas. These accounts may also be more believed if the account posting them is verified. This may be because many people may believe in these ideas due to a perceived sense of authority given from an account being verified, which could lead others that believe this sense of authority to try and pass these pieces of misinformation on to others. So in summary these ideas may spread in more smaller tight knit communities, where a perceived sense of authority is present in the original relayer of information, which leads to greater belief and spread of misinformed ideas to other groups.

Conclusion and Future Work

As shown throughout this paper, there are many factors that may lead to a wider belief in and spread of misinformation. Previous works have shown how in different situations, whether in be conspiracy theories, politics, or false accusations, many different factors lead to a wider belief in and spread of misinformation for different scenarios. My analysis, even with certain flaws of the data, also showed how misinformations spread through social media also has different factors that lead to a greater belief in and spread of misinformation. Whether due to the smaller size of the communities, the aspect of verified or unverified accounts, or the close knitness of the communities.

For future work in the field, the focus should possibly look into other factors in different scenarios that also lead to the spread of misinformation sources. This could possibly help with figuring out the sources of spread for these pieces of information and more widely figure out why people fall for these types of false information. Another avenue that could be researched into is looking at the factors already presently known about that spread misinformation and finding out how to prevent these methods from causing future spread. This could possibly aid future generations in figuring out tactics to use so that people can spot misinformation and safely know what the real facts are behind certain scenarios. This could possibly be done by gaining more insights in increasing media or digital literacy, which are a common tool for helping in detecting misinformation.

Misinformation is becoming more and more prevalent across the world. As it keeps growing more and more prevalent across the world, It is also becoming more and more unrecognizable from the truth. So if we are hoping to find a way to prevent this greater spread, we need to keep looking at the factors that cause this spread to happen in the first place so that we can hope to end this spread quickly and efficiently.

Annotated Bibliography

Assenmacher, D., Fröhling, L., & Wagner, C. (2024). You are a bot! – studying the development of bot accusations on Twitter. *Proceedings of the International AAAI Conference on Web and Social Media*, *18*, 113–125. https://doi.org/10.1609/icwsm.v18i1.31301

This article discusses how the definition of a bot on Twitter has changed over the years. They discuss what the original meaning of bot was to the term now being used to spread misinformation about users so they can be targeted and banned from the site. The article also goes into how certain ideologies might have a role to play in the spread of these bot accusations on the Twitter space. From what I can tell about this article, it seems to be from a trustworthy source since it comes from a journal article, which is usually trustworthy. This article is also relevant due to the fact that these types of allegations are a form of spreading misinformation, which is what I am trying to study.

Burghardt, K., Rao, A., Chochlakis, G., Sabyasachee, B., Guo, S., He, Z., Rojecki, A., Narayanan, S., & Lerman, K. (2024). Socio-linguistic characteristics of coordinated inauthentic accounts. *Proceedings of the International AAAI Conference on Web and Social Media*, *18*, 164–176. https://doi.org/10.1609/icwsm.v18i1.31305

This article discusses the characteristics in the language used in coordinated inauthentic accounts, which are used to spread misinformation, especially for political purposes. This source is a very trustworthy source since the information was posted in an academic journal, which are usually trustworthy sources. This article is also very relevant since it helps show how language certain sources of misinformation use can help people more easily believe and spread misinformation about certain topics, especially in politics.

Diab, A., Nefriana, Rr., & Lin, Y.-R. (2024). Classifying conspiratorial narratives at scale: False alarms and erroneous connections. *Proceedings of the International AAAI Conference on Web and Social Media*, *18*, 340–353. https://doi.org/10.1609/icwsm.v18i1.31318

This article discusses the factors that may lead to the spread of conspiratorial narratives online and how it is hard to detect conspiratorial narratives. This source is overall trustworthy since it comes from an academic journal and most of the time those are very trustworthy sources. When it comes to relevance this source is relevant to what I am researching because it discusses the spread of conspiracy theories online and what factors make them so prevalent which fits with what I am trying to study with what factors cause misinformation to spread more easily online.