The Spread of True and False Information Online

Firstly, they use k-s test (a nonparametric test based on CDF, and is used in comparing whether two empirical distributions have significant variance, or it can be used in testing if an empirical distribution fits a theoretical distribution) to verify whether there are differences between true information cascades and false information cascades in depth, size, breadth, and structural virality.

Besides, the k-s test is also used in verifying the falsity of the hypothesis that users who spread false information follow more users, have more followers, and are more active on Twitter, etc. They also used the likelihood ratio test (Wald Chi-Square Test) to conclude that falsehoods are more likely (70%) to be retweeted than truth. However, the hypothesis was rejected and neither user features nor network structure can explain the different diffusion between falsehood and truth.

Moreover, to test if falsehood has more novel contents than truth and user are more attracted by novelty, they design an LDA model to measure the information distance between rumor topics, and they found that false news is more novel than truth by three metrics: IU, K-L, and Bhattacharyya distance. Then they measured the user's emotions in order to verify whether users were aware false information is more novel than true information. They basically use k-s test again to compare true and false cascades distribution for each emotion so there's no need to discuss it again.

I have get the array of the number of tweets in the unit of days, and tried to do the hypothesis testing to verify if the distribution fits half-normal distribution and Chi-Squared Test distribution with n = 2 and 4.

Rumor Cascade

Authors pointed out false information is more likely to elicit Snopes links by presenting a graph (Fig 4) of the fraction of comments linking to Snopes depends on the veracity of the rumor. They also documented the distribution of the number of shares of uploads before and after their estimation, and we can do the similar work that analyzing the characteristics (like the max-breadth and number of retweets) of true and false cascade before and after Snopes posted the fact-checking information.

Based on figure 8 in their paper, we have recorded the number of rumor topics for each category, and the number of users, the number of retweets, and the number of cascades can be calculated. We can also do some structural analysis of our dataset, including the cascade characteristics of cascades (number of cascades for each category).

For the rest of the paper, since they focused more on the reshare deletion and a certain rumor's propagation, there's one thing I think it's worth to mention: we are looking at rumors were created after April 2017 only, which all composed some small size cascades. If we go to collect more data for some certain rumors, we can study the evolution of rumor and figure out why a rumor was still be discussed after one or two years.

User Behaviors in Newsworthy Rumors: A Case Study of Twitter

Authors in the paper mentioned several ways of utilizing user's information to analyze fake news. They draw a graph of user belief distribution and evolution over time. We can also draw a graph that the user's emotion change before and after the rumor topic was checked. In terms of user, we can check the user's features and emotions before and after the fact was checked. Described by the paper, we can use whether the user is verified, whether it's a News Org., whether it's highly visible, and whether it has low credibility.

DEMO: Using TwitterTrails.com to Investigate Rumor Propagation

This article gave a good reference website - TwitterTrails.com, which allows users to investigate the origin and propagation characteristics of a rumor and its refutation. With some keywords, as long as the rumor topic is documented by them, we can get a topic's originator, basic characteristics, propagators, etc. And the question raised from last paper of keeping track of the origin of 2016 rumors in our dataset can be addressed. I have tested and there are only some really popular rumor topics can be tracked.

Political Rumoring on Twitter During the 2012 US Presidential Election: Rumor Diffusion and Correction

In this article, the author firstly mentioned there may exist overlap membership between same category rumors, and we may check if this exists in our dataset. Besides, they are working on splitting the dataset with before and after the rumor was fact-checked, and they monitored there's a small increase of rejection of misinformation after the debunking information. I am thinking we can also run some k-s test or chi-square test to verify the difference of supporting and rejecting tweet distribution. If the propagation of rejecting tweets significantly increased after Snopes posted the debunking information, we can also claim that the debunking information can mitigate the spread of rumor cascades. Besides, all other features with distribution in the unit of a day can be used to do the hypothesis testing.

On Analyzing Hashtags in Twitter

In this article, authors used Hashtag-Entity Graph, which is graph made up of hashtags and entities drawn from a set of tweets, properly connected via weighted edges which take into account hashtag-entity and entity-entity relations. Author mentioned relation between cascades of a topic can be established by hashtags. I think Hashtags and textual information can be well-utilized in our task. Perhaps we can compare whether there's a difference between true information and false information before and after Snopes messages. We can run some hypothesis testing to verify it.

Nasty, Brutish, and Short: What Makes Election News Popular on Twitter?

This article studies some Hypotheses like whether story length, emotionality, and positivity have negative or positive correlations with Twitter shares, and I think we can also use this strategy to find if there're correlations between before and after Snopes message of the above three features. Besides, they studied the distribution difference between four presidential candidates, which inspires me that we can pick three major rumor topics in three veracity (True, False, Mixed) categories with relatively comprehensive dataset, and compare the statistics of them. We can also prove the difference before and after the posting of debunking information. Lastly, this article gave some useful models like OLS, Possion distribution testing and naive bayes, which is worth to consider as the new way of hypothesis testing.