Fake News Analysis Modeling Using Quote Retweet

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Introduction

The spread of information in social media is not systematically controlled, there is a risk that incorrect information will spread.

Twitter is one of the social media services that is commonly used for sharing information and building rapport, and a considerable part of Twitter is also used for the delivery of newsflashes or headlines.

This characteristic of Twitter creates a sufficiently favourable environment for using it as a tool for political propaganda.

Fake News

Recently, false information, also known as fake news, has been causing a lot of confusion among people and attracting a great deal of attention since the 2016 United States presidential election, as shown in the figure.

Fake news refers to untrue information that has a format like real news reports; it spreads usually through social media for political or economic Gains. Such fake news can stir confusion in people and exerted significant influence on the maximisation of political polarisation in the 2016 US presidential election.
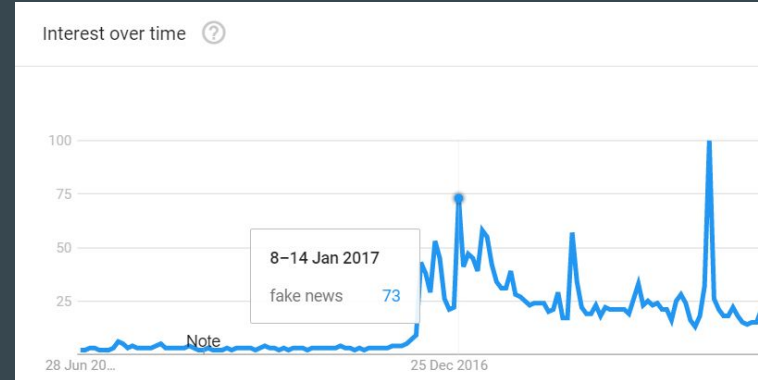
The Project

This project proposes an analysis model to identify the best features to identify fake news by using the information of Quote Retweet (Quote RT) as well as conventional Tweets.

Quote RT, was added as a feature of Twitter in 2015, facilitating retweets by allowing to add a comment to a previously written Tweet. Based on this, there is an advantage that not only more text information can be collected compared to conventional Retweets, but also the depth of propagation can be easily measured because the parent Tweets can be tracked.

Parts of a tweet
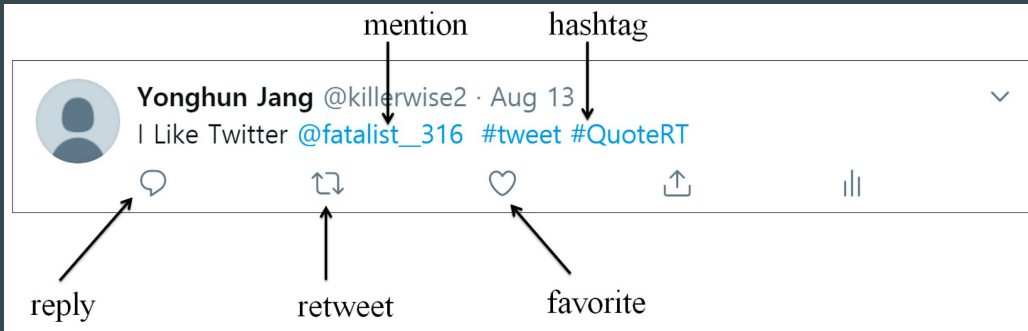
An example of a quote retweet

Data Collection and Preprocessing

The figure displays an overview of fake news analysis modelling using Twitter data. It shows a method of collecting Twitter data, including news reports, for which the veracity has been confirmed, Tweets, Quote Retweets, and user information.

In addition, the figure shows the preprocessing, visualisation, and statistical analysis for data analysis. A Tweet that mentioned a news directly was called ST (Seed Tweet) and a Quote Retweet was called QRT (Quote ReTweet). Moreover, Tweets, including both ST and QRT, were called TW (Tweets).
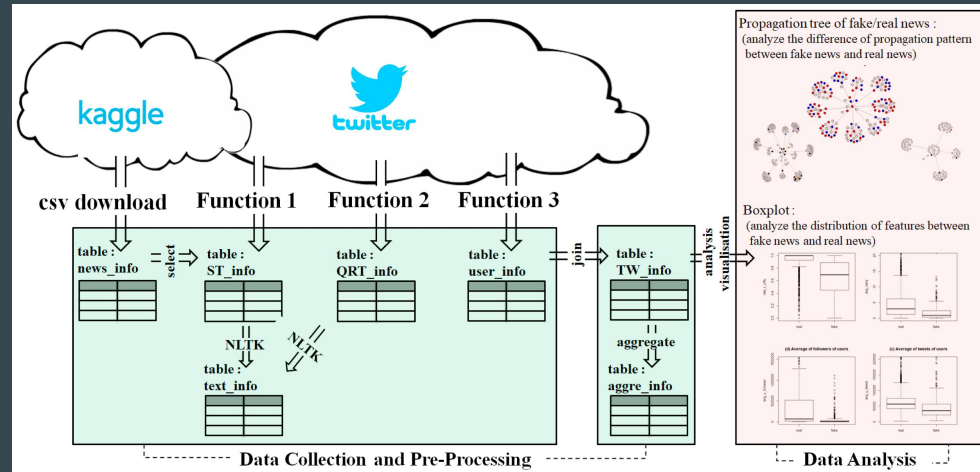
Data Collection

For the fake news and real news to be used in the analysis, data provided by Kaggle was used. Kaggle provides global open data for various areas in the csv or json format and provides data for already-confirmed fake news and real news. The collected information consisted of the news article's headline, writer, date of the Tweet, and real/fake news status, and was stored in the 'news_info' table in the database. For data analysis, the news released after 2015 were used.

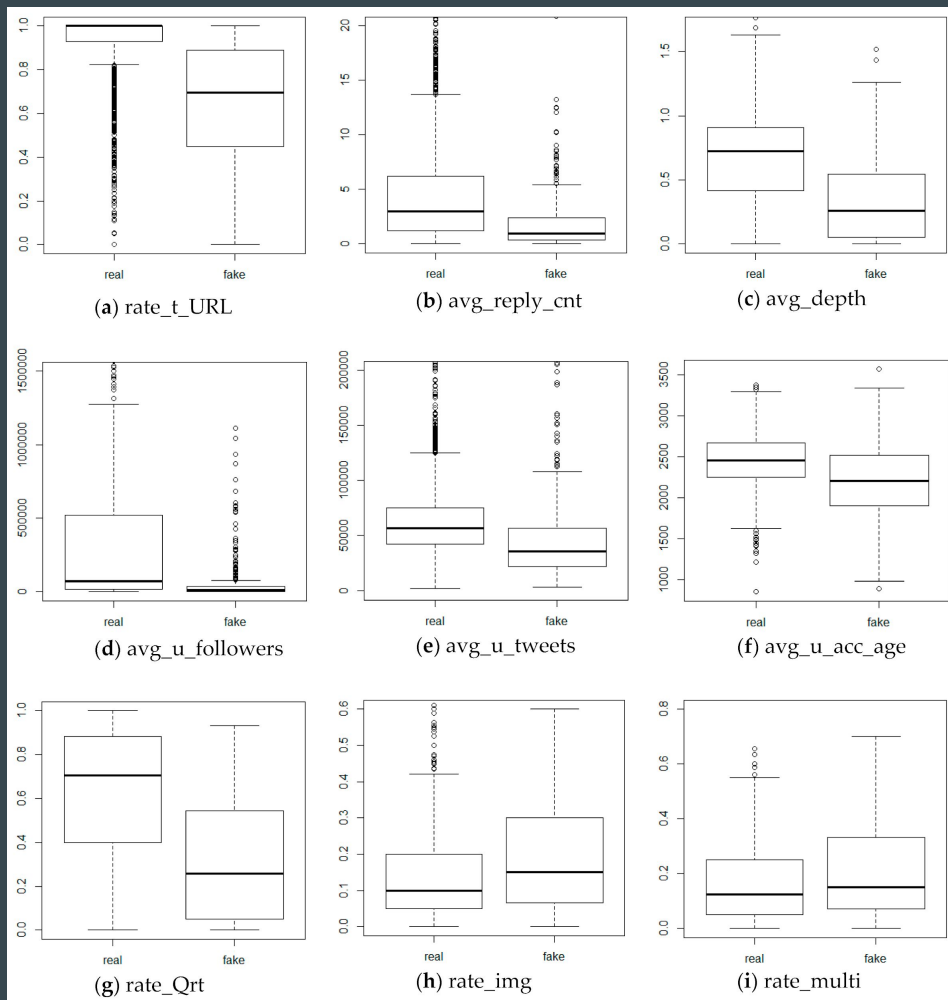| Detail	Compact	Column						10 of 20 columns ∨
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Preprocessing

This section describes the preprocessing of the collected data for data analysis. As TW's text information contained a variety of information, information extraction through text analysis was required. Therefore, URL information, special characters (hashtag, mention, question, emphasis), emphasised words, emotion information (number of positive/negative words, emotional score) were extracted from the TW text information, and the extracted information was saved in 'text_info'.

The NLTK package was used for the words and sentences expressing emotions in texts. 1 point was assigned whenever a strong positive word was present in the text information and 0.5 point in the case of weak positive word. Likewise, −1 point was assigned for a strong negative word and −0.5 point for a weak negative word.

Data Analysis

Statistical analysis was performed to find the best features of fake news, and the results were visualised in boxplots.

The attributes that showed significant differences between fake news TW and real news TW were the average number of replies, average depth of propagation tree, proportion of including URL, user's influence/activeness/active period, QRT's proportion, proportion of including multimedia, etc.

(a) rate_t_URL

(b) avg_reply_cnt

(c) avg_depth

(d) avg_u_followers

(e) avg_u_tweets

(f) avg_u_acc_age

(g) rate_Qrt

(h) rate_img

(i) rate_multi

The figure expresses the propagation patterns of real news and fake news based on the information collected. In the propagation tree, the centre Root node indicates a news report, and child nodes consist of TWs that mentioned the news report (the nodes with the tree level of 1 are ST, and the nodes with higher number than 1 are QRT). The nodes expressed in black indicate the highly influential users. Having at least 200,000 followers was assigned as the threshold for being a highly influential user.
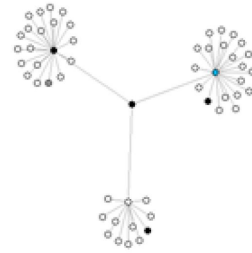

(a) TW propagation tree of fake news;   (b) TW propagation tree of real news
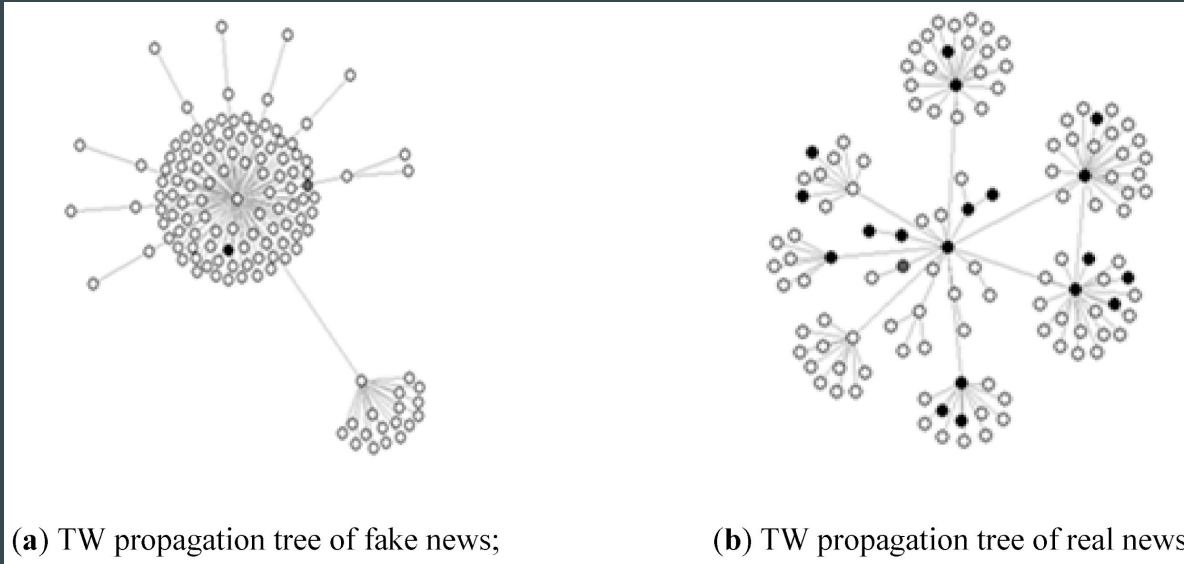
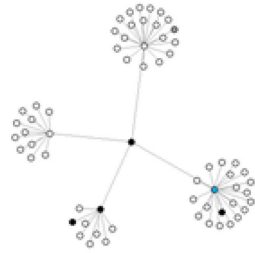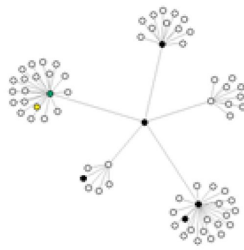# The Tweet (TW) propagation tree of real news over time
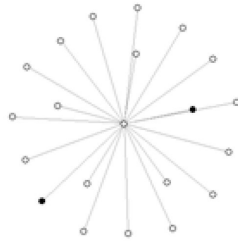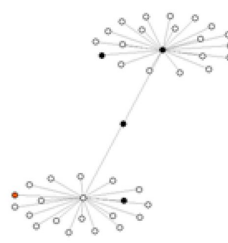
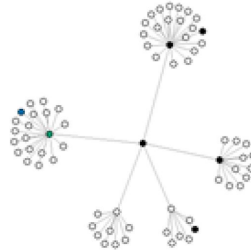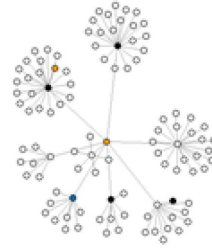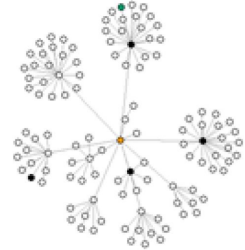Dec. 13, 2017   Mar. 07, 2018   May. 09, 2018   May. 23, 2018
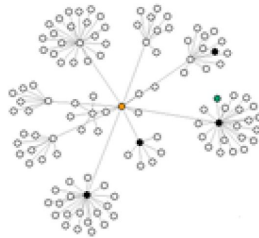
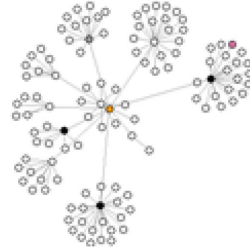Jun. 06, 2018   Jun. 13, 2018   Aug. 29, 2018   Sep. 19, 2018

Sep. 26, 2018   Oct. 10, 2018   Nov. 07, 2018   Nov. 09, 2018
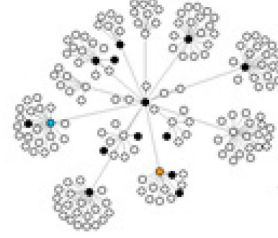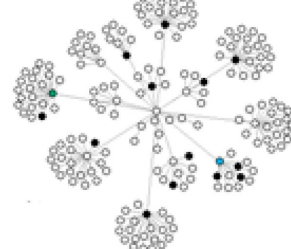
The TW propagation tree of fake news over time

Mar. 22, 2015   Mar. 29, 2015   Apr. 05, 2015   Apr. 12, 2015   May. 24, 2015

Jun. 14, 2015   Sep. 06, 2015   Sep. 13, 2015   Sep. 20, 2015   Oct. 11, 2015

Oct. 25, 2015   Nov. 01, 2015   Nov. 22, 2015   May. 08, 2016   May. 15, 2016

Jun. 26, 2016   Jul. 24, 2016   Aug, 14, 2016   Sep. 25, 2016   Oct. 02, 2016

Oct. 09, 2016   Oct. 16, 2016   Dec. 04, 2016   Dec. 11, 2016   Apr. 23, 2017

Apr. 30, 2017   May. 28, 2017   Jul. 16, 2017   Aug. 13, 2017   Nov. 05, 2017
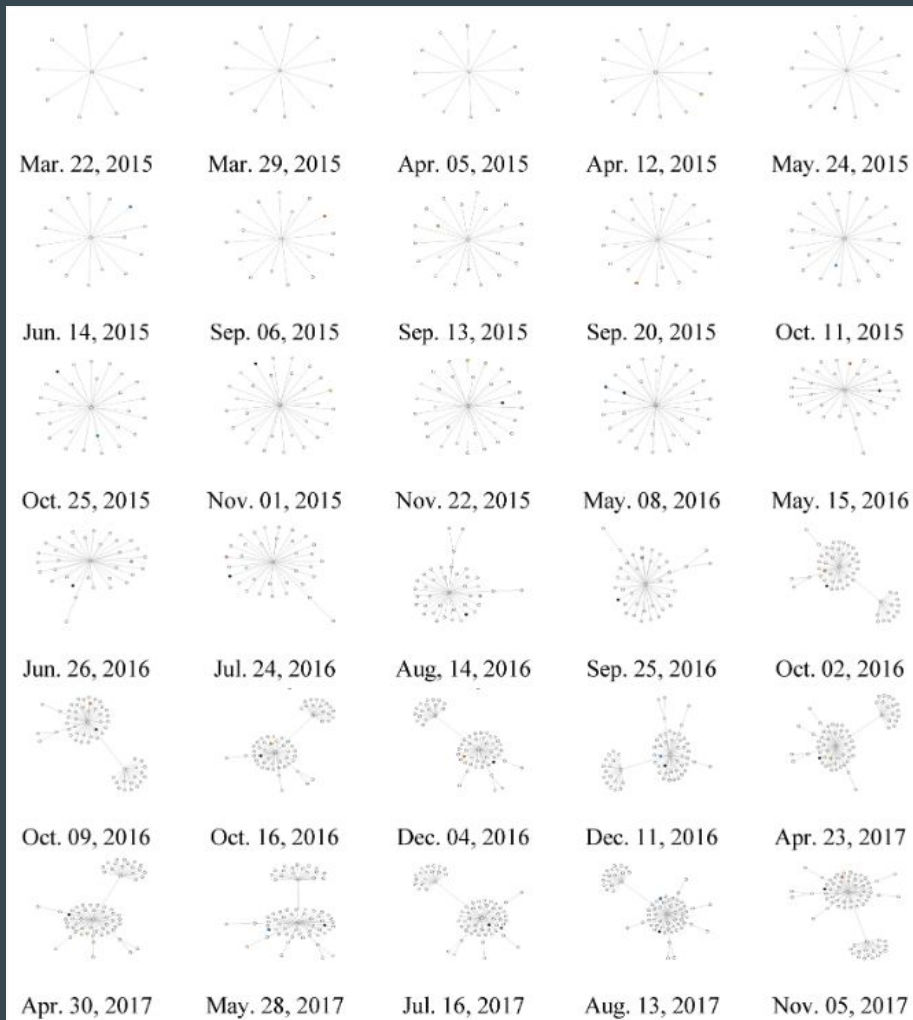
Performance evaluation

Performance evaluation was performed using the neural network-based fake news classifier to investigate whether the best features identified through the proposed method really had a positive impact on the fake news classification accuracy. In the results, the classification model that added Quote Retweet information showed 4.57%, 10.51%, and 9.79% higher classification accuracy for fake news, real news, and total, respectively, compared to the classification model using the conventional Tweet information only. Furthermore, in the performance comparison between the classification model using all features and the classification model using the best features only, the classification model that learned the best features only showed 8.48% higher classification accuracy for fake news, thereby confirming that the best features had a positive impact on fake news classification.

	Fake News	Real News
average propagation period (days)	706.61	107.72

Conclusion

The results of visualisation and statistical analysis to investigate the best features from the collected data indicated significant differences between fake news and real news in terms of existence/absence of information source, replies for Tweets, influencing power of Tweets, rate of using Quote Retweet, depth of Tweet propagation tree, and rate of quoting picture/video. Furthermore, the results of propagation period confirmed that fake news was propagated for a longer period gradually but constantly compared to real news.