Modeling and Predicting Fake News Spreading on Twitter

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Fake news becomes a palpable potential risk to society because of the growing use of mobile devices and the immense increase in Internet access across the world. It is essential to develop a simple mathematical model to understand the mechanism of the online dissemination of fake news. In this paper, we propose a point process model for predicting the spreading of the fake news on Twitter. This model describes the cascade as a two-stage process: initially, a cascade spreads as an ordinary news story; a second cascade then emerges through attempts to disclose and rectify the falsity of the news story. We validate this model through the collection of two datasets of fake news cascades from Twitter. We show that the proposed model is superior to the current state-of-the-art methods in accurately predicting the evolution of the fake news cascades. Moreover, the proposed model can appropriately infer the correction time when some users realize the falsity of the news. The proposed model contributes to understand the dynamics of fake news spread in social media and is potentially advantageous in extracting a compact representation of the temporal information of the cascades.

Keywords: Fake news, Point process, Time series prediction, Twitter

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I. INTRODUCTION

As smartphones become more widespread, people are increasingly seeking and consuming news from social media, rather than traditional media (e.g., newspapers and TV). Social media has enabled us to share various types of information and to discuss such information with other readers. However, social media seems to have become a hotbed of fake news, with a potentially negative influence on society. For example, Carvalho et al.\(^1\) found that a false report of bankruptcy of the parent company of United Airlines in 2008 caused the company’s stock price to drop by as much as 76% in just a few minutes, which closed 11% below the previous day’s close, with the negative effect persisting for more than 6 days. In the area of politics, Bovet and Makse\(^2\) found that 25% of news outlets linked from tweets before the 2016 U.S. presidential election were either fake or extremely biased, and their causal analysis suggests that the activities of Trump supporters influence the activities of the top fake news spreaders. In addition to the stock market and elections, fake news has emerged for other events as well, including natural disasters, such as the East Japan Great Earthquake in 2011\(^3,4\), often causing widespread panic or even criminal activity\(^5\).

There have been numerous attempts at an automatic detection of fake news and rumors\(^6-9\). Typically, fake news is detected based on the textual content of the news. This problem is formulated as a classification task where multiple categories of features from the sentences\(^10\) or the word vectors\(^11\) are applied to classification methods. Interestingly, it has been shown that the temporal aspect of the information cascade, i.e., the posts and re-shares related to the original news, improves the performance of rumor detection\(^12,13\), fake news detection\(^14\), rumor stance classification\(^15\), and the detection of the fake retweeting account\(^16\). These works have suggested that an accurate temporal model of such cascades is essential to improve the performance of the fake news detection. Although several works have developed a temporal model for cascades on meme data\(^17\) and Twitter\(^18,19\), little attention has been paid to the modeling of the fake news cascades.

In this study, we propose a point process model of the information cascade of fake news posts by extending the Time-Dependent Hawkes process (TiDeH)\(^18\), which is a state-of-the-art model for predicting the popularity dynamics of a cascade. The proposed model describes the fake news cascade as a two-stage process (Fig. 1). Initially, a cascade spreads as an ordinary news item. After a correction time, the second cascade emerges to disclose
FIG. 1. Schematics of the proposed model (for details, see Section 3). We propose a model that describes the information cascades of a fake news (i.e., posts or re-shares related to the fake news). The model assumes that such a cascade consists of two cascades. Initially, a cascade due to the original news occurs (1st cascade). After a correction time $t_c$, another cascade emerges to disclose the falsity of the original news and correct it (2nd cascade). The posting activity of the cascade $\lambda(t)$ (Right: black) is given by the summation of the two cascades activity (Left: magenta and green).

and rectify the falsity of the original news. To validate the proposed method, we collected two datasets of cascade of fake news from Twitter. We demonstrate that the proposed model outperforms existing methods for accurately predicting the fake news spreading in future. Furthermore, the experimental results suggest that our methodology is useful in inferring the correction time of a fake news based on the time series (i.e., posted or re-shared times).

II. RELATED WORK

Predicting the future popularity of an online content has been studied extensively. A standard approach for predicting popularity is to apply a machine learning framework, that is, the prediction problem can be formulated as a classification or regression task. Another approach to the prediction problem is to develop a temporal model and fit the model parameters using a training dataset. This approach consists of two types of models: time series and point process. A time series model describes the number of posts in a fixed window. For example, Matsubara et al. proposed SpikeM for reproducing the temporal activity on Google Trends, meme data, and Twitter. In addition, Proskurnia et al. proposed a time series model that considers the promotion effect by the social media and the front page of
the web page for predicting the popularity dynamics on an online petition site. A point process model describes the posted times in a probabilistic way, which can incorporate the self-exciting nature of a cascade. Various point process models have been proposed for predicting the final number of re-shares on Twitter\textsuperscript{19} and Sina Weibo\textsuperscript{26}, predicting the temporal patterns of retweet activity on Twitter\textsuperscript{18}, and interpreting the endogeneous and exogeneous shocks to Youtube view activity\textsuperscript{27}, and Twitter hashtag activity\textsuperscript{28}. Our model is also a Point process model, which is an extension of TiDeH\textsuperscript{18}. To the best of our knowledge, the proposed model is the first quantitative model incorporating an essential property of the information cascade of fake news. A few studies\textsuperscript{29} proposed a model of fake news. However, they focused on the qualitative aspects and did not evaluate the prediction performance using a real dataset.

Our contribution is related to the study of fake news detection. There have been a number of attempts to detect fake news or rumors based on the content of the news. For instance, Hassan et al.\textsuperscript{10} extracted multiple categories of features from the sentences and applied a support vector machine classifier to detect fake news. Rashkin et al.\textsuperscript{11} developed a Long Short-Term Memory (LSTM) neural network model for fact-checking of the news. Other types of information can be combined with textual information to further improve the detection performance. Kwon et al.\textsuperscript{12} showed that the structural (e.g., graph structure) and temporal information of the cascade improve the rumor classification performance. Ruchansky et al.\textsuperscript{14} developed a deep neural network model that utilizes the textual, temporal, and user information, and showed that temporal information improve the performance of the fake news detection. Limitations of the deep model is that they utilize only a part of temporal information (the time interval between the posts) and cannot handle the cascades with many user responses. Conversely, the proposed model is potentially useful for obtaining a compact representation of the temporal information in a cascade.
III. MODELING INFORMATION CASCADE OF FAKE NEWS POST

Here we develop a Point Process model for describing and predicting the dynamics of the information cascade of fake news posts. A schematic of the proposed model is shown in Fig. 1. In our model, the cascades are described as a two-stage process: Initially, the cascade is spread as ordinary news after the first post (Fig. 1: 1st cascade). At the correction time $t_c$, the users realize that the news is fake or false information and the second cascade of the correcting information emerges (Fig. 1: 2nd cascade). To describe each cascade, we use Time-Dependent Hawkes process model (TiDeH), which properly considers the circadian nature of the users and the aging of the information.

A. Time-Dependent Hawkes process (TiDeH): Model of cascades of post sharing

In point process models, the probability of getting a post or reshare in a small time interval $[t, t + \Delta t]$ is written as $\lambda(t)\Delta t$, where $\lambda(t)$ is the instantaneous rate of the cascade, i.e., intensity function. The intensity function of the TiDeH model depends on the previous posts in the following manner:

$$\lambda(t) = p(t)h(t),$$

with

$$h(t) = \sum_{i:t_i<t} d_i \phi(t - t_i),$$

where $p(t)$ is the infectious rate, $t_i$ is the time of the $i$-th post, and $d_i$ is the number of the followers of $i$-th post. The infectious rate $p(t)$ incorporates two main properties in the cascade: the circadian rhythm and decay owing to the aging of information

$$p(t) = a \left\{ 1 - r \sin\left(\frac{2\pi}{T_m}(t + \theta_0)\right) \right\} e^{-t/\tau},$$

where the time of original post is assumed to be $t_0 = 0$ and $T_m = 24$ hours is the period of oscillation. The parameters, $a, r, \theta_0$, and $\tau$, correspond to the intensity, the relative amplitude, and the phrase of the oscillation, and the time constant of decay, respectively. The memory kernel $\phi(t)$ represents the probability distribution for the reaction time of a
follower. A heavy tailed distribution was adopted for the memory kernel\textsuperscript{18,19}

$$
\phi(s) = \begin{cases} 
c_0 & (0 \leq s \leq s_0) 
c_0(s/s_0)^{-(1+\gamma)} & \text{(Otherwise)}
\end{cases}
$$

The parameters were set to $c_0 = 6.94 \times 10^{-4}$ (/s), $s_0 = 300$ s, and $\gamma = 0.242$.

**B. Proposed model: Incorporating the effect of fake news correction**

We propose a model of the fake news cascade. Our model assumes that a cascade consists of two cascading processes, namely, the one owing to the original news and the other owing to the correction of the news. The activity of the fake news cascade can be written as the sum of two cascades using TiDeH

$$
\lambda(t) = p_1(t)h_1(t) + p_2(t)h_2(t).
$$

The first term $p_1(t)h_1(t)$ represents the cascade by the original news.

$$
p_1(t) = a_1 \left\{ 1 + r \sin \left( \frac{2\pi}{T_m}(t + \theta_0) \right) \right\} e^{-t/\tau_1}, \quad h_1(t) = \sum_{i: t_i < \min(t, t_c)} d_i \phi(t - t_i),
$$

where $\min(a, b)$ represents the smaller of the two values ($a$ or $b$) and $t_c$ is the correction time of the fake news. The second term $p_2(t)h_2(t)$ represents the cascade by the correction.

$$
p_2(t) = a_2 \left\{ 1 + r \sin \left( \frac{2\pi}{T_m}(t + \theta_0) \right) \right\} e^{-(t-t_c)/\tau_2}, \quad h_2(t) = \sum_{i: t_c < t_i < t} d_i \phi(t - t_i),
$$

where $t_c$ is the correction time and the circadian rhythm of $p_2(t)$ is assumed to be the same as $p_1(t)$.

**IV. PARAMETER FITTING**

Here we describe the procedure for fitting the parameters from the time series (i.e., the tweeted times). Seven parameters $\{a_1, \tau_1; a_2, \tau_2; r, \theta_0; t_c\}$ were determined by maximizing the log-likelihood function

$$
l = \sum_i \log \lambda(t_i) - \int_0^{T_{\text{obs}}} \lambda(s)ds,
$$

where $t_i$ is the $i$-th tweeted time, $\lambda(t)$ is the intensity given by Eq. (3), and $T_{\text{obs}}$ is the observation time. We first fix the correction time $t_c$ and the other parameters are optimized.
using the Newton method\textsuperscript{30}, provided by Scipy\textsuperscript{31}, within a range of $12 < \tau_1, \tau_2 < 2T$ h. The correction time is separately optimized using Brent’s method\textsuperscript{32} within a range of $0.1T_{\text{obs}} < t_c < 0.9T_{\text{obs}}$.

We validate the fitting procedure by applying synthetic data generated by the proposed model (Eq. 3). Figure 2 shows the dependency of the observation time $T_{\text{obs}}$ on the estimation accuracy. To evaluate the accuracy, we calculate the median and interquartile ranges of the estimates from 100 trials. The estimation error decreases as the observation time increases. The result suggests that this fitting procedure can reliably estimate the parameters for sufficiently long observations ($\geq 36$ hours). The medians of the absolute relative errors obtained from 36 h of synthetic data are 18%, 11%, 38%, 38%, and 10% for $a_1$, $\tau_1$, $a_2$, $\tau_2$, and $t_c$, resp.

![Figure 2](image)

FIG. 2. Dependency of the estimation accuracy of parameters $\{a_1, \tau_1; a_2, \tau_2; t_c\}$ on the observation time. Red points and black bars represent the median and interquartile ranges of the estimates obtained from 100 synthetic data. The blue lines indicate the true value.

V. DATASET

We evaluate the proposed model and examine the correction time of fake news based on two datasets of the fake news cascades. Datasets of fake news cascades\textsuperscript{33,34} have been publicly available, which are based on the retweets of the original news post. However, rather than a simple retweet or hashtag, the information sharing of fake news is complex. To cover the information cascade in detail, we manually collected two datasets of fake news cascades from Twitter. In our dataset, 61 % and 20 % of the tweets are the retweets of
the original posts in Recent Fake News and 2011 Tohoku earthquake and tsunami dataset, respectively.

1. **Recent Fake News (RFN):**

   We collected 10 fake news from two fact-checking sites, Politifact.com\textsuperscript{35} and Snopes.com\textsuperscript{36}, between March and May in 2019. PolitiFact is an independent, non-partisan site for online fact-checking, mainly for the U.S. political news and the statements by politicians. Snopes.com, one of the first online fact-checking websites, handles political and other social and topical issues. Using the Twitter API, tweets highly relevant to the fake news stories were crawled based on the keywords and the URL. We selected seven fake news stories based on two conditions: 1) the number of tweets must be greater than 300 and 2) the observation period must be longer than 36 h based on the experiments conducted on synthetic data (Section IV). A summary of the collected fake news stories is presented in Appendix A.

2. **Fake news in 2011 Tohoku earthquake and tsunami (Tohoku):**

   Numerous fake news stories emerged after the 2011 earthquake off the Pacific coast of Tohoku\textsuperscript{4,37}. We collected tweets posted in Japanese from March 12 to March 24, 2011, by using sample streams from the Twitter API. There were a total of 17,079,963 tweets. We then identified the fake news based on a fake news verification article\textsuperscript{38}. Again, we collected the tweets highly relevant to the fake news. Then, we selected 19 fake news stories on the same conditions as used in the RFN dataset. A summary of the collected fake news is presented in Appendix A.

VI. **EXPERIMENTAL EVALUATION**

   To evaluate the proposed model, we consider a following prediction task: for a cascade of interest, we observe a tweet cascade \( \{t_i, d_i\} \) up to time \( T_{\text{obs}} \) from the original post, where \( t_i \) is the \( i \)-th tweeted time (\( t_0 = 0 \) is the time of the original post), \( d_i \) is the number of followers of the \( i \)-th tweeting person, and \( T_{\text{obs}} \) represents the duration of the observation. Then, we seek to predict the time series of the cumulative number of tweets related to the fake news during the test period \([T_{\text{obs}}, T_{\text{max}}]\), where \( T_{\text{max}} \) is the end of the period. In this section, we
describe the experimental setup and the proposed procedure for prediction, and compare
the performance of the proposed method to state-of-the-art approaches.

A. Setup

Here we describe the setup of experiments. The total time interval $[0, T_{\text{max}}]$ was divided
into the training and test periods. The training period was set to the first half of the total
period $[0, 0.5T_{\text{max}}]$ and the test period was the remaining one $[0.5T_{\text{max}}, T_{\text{max}}]$. The prediction
performance was evaluated by the mean and median absolute error between the actual time
series and its predictions:

$$\text{Mean Error} = \frac{1}{n_b} \sum_k |\hat{N}_k - N_k|,$$

$$\text{Median Error} = \text{Median}(|\hat{N}_k - N_k|) \quad (k = 1, 2, \cdots n_b),$$

where $\hat{N}_k$ and $N_k$ are the predicted and actual cumulative numbers of tweets in a $k$-th bin
$[(k-1)\Delta + T_{\text{obs}}, k\Delta + T_{\text{obs}}]$, respectively, $n_b$ is the number of bins, and $\Delta = 1$ h is the bin
width.

B. Prediction procedure based on the proposed model

We describe the procedure for the prediction method. First, we fit the model parameters
using the maximum likelihood method from the observation data (see Section 4). Second,
we calculate the intensity function $\hat{\lambda}(t)$ during the prediction period $t \in [T_{\text{obs}}, T_{\text{max}}]$

$$\hat{\lambda}(t) = \hat{\lambda}_1(t) + \hat{\lambda}_2(t)$$

with

$$\hat{\lambda}_1(t) = p_1(t) \sum_{i: t_i < t_c} d_i \phi(t - t_i),$$

where $\hat{\lambda}_1(t)$ and $\hat{\lambda}_2(t)$ are the intensity of the first and second cascades, respectively. The
intensity due to the original news $\hat{\lambda}_1(t)$ is calculated using the fitted parameters $\{a_1, \tau_1; r, \theta_0\}$
and the observations $\{t_i, d_i\}$ before the correction time $t_c$. The intensity due to the correction
$\hat{\lambda}_2(t)$ is given by the solution of the integral equation:

$$\hat{\lambda}_2(t) = f(t) + d_p p_2(t) \int_{T_{\text{obs}}}^t \hat{\lambda}_2(s) \phi(t - s) ds,$$
where
\[ f(t) = p_2(t) \sum_{i: t_c < t_i < t_{\text{obs}}} d_i \phi(t - t_i). \]
and \( d_p \) is the average number of followers during the observation period.

C. Prediction results

We evaluate the prediction performance of the proposed model and compare it with three baseline methods: linear regression (LR)\(^{24}\), reinforced Poisson process (RPP)\(^{26}\) and TiDeH\(^{18}\). We used the python code in Github\(^{39}\) to implement TiDeH. Details of LR and RPP methods are summarized in Appendix B. Figure 3 shows three examples of the time series of the cumulative number of tweets in cascades and their prediction results. The proposed method (Fig. 3: purple) follows more closely the actual time series data than the baselines. In particular, the proposed method reproduces the slowing down effect in the posted activity of the cascade and the amplitude of the second cascade \( a_2 \) is smaller than the that of the first cascade \( a_1 \): the ratio was \( a_2/a_1 = 0.13, 0.0055, \) and 0.57 for RFN: Sonictrans, Tohoku: Visit, and Tohoku: Remark2, respectively.

We evaluate the prediction performance using the two fake news cascade datasets (Table I). Table I demonstrates that the proposed method clearly outperforms the baseline methods in both datasets and metrics. In terms of the error, the error of the proposed model is 32 % (Mean) and 28 % (Median), and 42 % (Mean) and 10 % (Median) smaller than the error of the runner-up (TiDeH) in RFN and Tohoku dataset, respectively. Consistent with previous studies\(^{18,19}\), the methods based on point-process (the proposed method, TiDeH, and RPP) clearly perform better than the linear regression (LR) method. These results suggest the proposed method is effective for predicting the spread of fake news posts on Twitter.

VII. INFERRING THE CORRECTION TIME

We have demonstrated that the proposed method outperforms the existing method for predicting the evolution of the fake news cascade (Section 6). The proposed model can also infer the correction time when the users realize the falsity of the news. In this section, we examine the validity of the correction time using text mining.
FIG. 3. Time series predicting of the cumulative number of tweets in a fake news cascade. Three examples of the prediction result are shown. Green, orange, and blue lines represent the prediction results of the baselines (LR, RPP, and TiDeH, respectively). Black and magenta lines represent the observations and their prediction result of the proposed model.

TABLE I. Prediction performance on two datasets: mean and median errors per hour. Best results are shown in bold for each case.

| Datasets | RFN | Tohoku |
|----------|-----|--------|
| Metric   | Mean| Median | Mean | Median |
| LR       | 88.3| 5.08   | 13.9 | 4.51   |
| RPP      | 61.8| 3.12   | 8.23 | 2.30   |
| TiDeH    | 54.2| 1.89   | 4.12 | 1.99   |
| Proposed | 36.9| 1.37   | 2.40 | 1.80   |

We calculated the frequency of the fake words (e.g., false rumors, fake, not true, and not real) in the fake news cascade and compared the time series of the frequency with the correction time $t_c$ inferred from the cascade. Figure 4 shows the comparison for the fake news cascades with frequent fake words posts. The fake news cascades in RFN dataset contains less fake words than in those in Tohoku dataset: 277 and 43 fake words in Sonictrans and
FIG. 4. Time series of the frequency of fake words for six fake news cascades. In each panel, the black line represents time series of the fake words count in an hour and the blue vertical line represents the correction time $t_c$.

RBsinger in RFN dataset, and 1,616, 1,930, 1,752, and 1,723 fake words in Tohoku dataset during the observation period (150 hours), respectively. It is because most of the cascades are retweets to the original post in RFN dataset. We observed that the fake words started to be posted around the correction time. For Cartoonist and Taiwan news in Tohoku dataset, the peak time of the fake words frequency is close to the correction time (Fig. 4).

Finally, we compared the word cloud before and after the inferred correction time $t_c$. Fig. 5 demonstrates an example of a fake news cascade: “Turkey” in Tohoku dataset. The fake news story is about the huge financial support (10 billion yen) from Turkey to Japan. The word cloud before the correction time implies that the fake news story spread due to the fact that Turkey is considered as a pro-Japanese country. The word “False rumor” starts to appear after the correction time. The word “Taiwan” also appears after the correction time, which is related to another fake news story about “Taiwan”. These results suggest that some users realize the falsity of the news story around the inferred correction time, which supports the key assumption of the proposed model.
FIG. 5. Example of word cloud before (left) and after (right) the correction time $t_c$. Each cloud shows the top 10 most frequent words in a fake news cascade (Turkey in Tohoku dataset).

VIII. CONCLUSION

We have proposed a point process model for predicting the future spread of the fake news cascade (i.e., social media posts and re-shares related to a fake news story). The proposed model describes the cascade as a two-stage process: first, the cascade spreads as an ordinary news, and the second cascade emerges to rectify the falsity of the news story. We have validated this model by collecting two datasets of the fake news cascade from Twitter. We have shown that the proposed model outperforms the state-of-the-art methods for accurately predicting the spread of the fake news cascade. Moreover, the proposed model was aptly able to infer the correction time of the news story. Our result based on text mining indicates that some users realize the falsity of the news story around the inferred correction time. We believe that the proposed model provides an important contribution for the modeling of fake news spreading and it is also beneficial for the extraction of a compact representation of the temporal information of a cascade.
## APPENDIX

### A. LIST OF FAKE NEWS IN DATASET

| News No. | Title                                                                 | Date      | No. Posts |
|----------|----------------------------------------------------------------------|-----------|-----------|
| a. Abolish | America came along as the first country to end (slavery) within 150 years. | 2019-03-21 | 1159      |
| b. Notredame | A video clip from the Notre Dame cathedral fire shows a man walking alone in a tower of the church “dressed in Muslim garb.” | 2019-04-16 | 1641      |
| c. Islamic | Did Ilhan Omar Hold ‘Secret Fundraisers with ‘Islamic Groups Tied to Terror? | 2019-03-27 | 10811     |
| d. Lionhunter | Was a Trophy Hunter Eaten Alive by Lions after He Killed 3 Baboon Families? | 2019-03-25 | 25071     |
| e. Newzealand | Did New Zealand Take Fox News or Sky News Off the Air in Response to Mosque Shooting Coverage? | 2019-03-25 | 11711     |
| f. Sonictrans | Will the Animated Character of Sonic the Hedgehog Be Transgender in a New Film? | 2019-05-06 | 2319      |
| News No. | Title                                                                 | Date       | No. Posts |
|---------|-----------------------------------------------------------------------|------------|-----------|
| a.      | Saveenergy Large scale power saving required in the Kansai region.     | 2011-03-12 | 2846      |
| b.      | EscapeTokyo The bureaucracy in Ministry of Defense says “You should escape from Tokyo” | 2011-03-18 | 1056      |
| c.      | Isodin Isodin is effective for radiation.                             | 2011-03-12 | 1787      |
| d.      | Seaweed Seaweed is effective for radiation.                           | 2011-03-12 | 1798      |
| e.      | Blog The blog “I want you to know what a nuclear plant is”.           | 2011-03-13 | 501       |
| f.      | Hutaba Officials in Hutaba hospital left patients behind and fled.    | 2011-03-17 | 1525      |
| g.      | Remark1 Chief Cabinet Secretary’s remark was inappropriate in Tokushima. | 2011-03-13 | 638       |
| h.      | Remark2 Former prime ministers remark was inappropriate in Tokushima. | 2011-03-16 | 955       |
| i.      | Visit Chief Cabinet Secretary visits Korea a few days after the earthquake. | 2011-03-15 | 1973      |
| j.      | Regulation Ms. Renho proposes to regulate convenience stores for saving energy. | 2011-03-12 | 7561      |
| k.      | Rescue Ms. Tsujimoto protests the rescue activities of U.S. military | 2011-03-16 | 1887      |
| l.      | Taiwan Taiwan’s aid is rejected by the Japanese government.           | 2011-03-12 | 2736      |
| m.      | Schoolsesmic Budget for school seismic retrofitting cut in project screening. | 2011-03-12 | 1044      |
| n.      | Debt South Korea offers to borrow money to Japan.                     | 2011-03-16 | 399       |
| o.      | Sanjyo Sanjo Junior High School stopped functioning due to international students. | 2011-03-17 | 379       |
| p.      | Fujitv Japanese TV company Fuji donations to UNICEF Japan.            | 2011-03-16 | 885       |
| q.      | Cartoonist Japanese cartoonist Mr. Oda donated 1.5 billion yen.       | 2011-03-12 | 2546      |
| r.      | Starvation An infant dies of starvation in Ibaraki.                  | 2011-03-16 | 2025      |
| s.      | Turkey Turkey donates 10 billion yen for Japan.                       | 2011-03-12 | 2380      |
B. BASELINE METHODS

We summarize the baseline methods for predicting the evolution of the fake news cascade: Linear regression (LR) and Reinforced Poisson process (RPP).

Linear regression (LR)

Linear regression is applied to the logarithm of the cumulative number of posts up to time \( t \):

\[
\log R(t) = \alpha_t + \log R(T_{\text{obs}}) + \sigma_t \xi_t,
\]

where \( R(t) \) is the cumulative number of posts at the prediction time \( t \), \( T_{\text{obs}} \) is the observation time, and \( \xi_t \) represents Gaussian random variable with zero mean and unit variance. The parameters \( \{\alpha_t, \sigma_t^2\} \) are estimated by the maximum likelihood method from the training dataset of the cascades \( \{R(t), R(T_{\text{obs}})\} \). The cumulative number of tweets is predicted by the unbiased estimator

\[
\hat{R}(t) = R(T) \exp(\hat{\alpha}_t + \hat{\sigma}_t^2/2),
\]

where, \( \hat{R}(t) \) is the prediction of the cumulative number, and \( \hat{\alpha}_t \) and \( \hat{\sigma}_t^2/2 \) are the fitted parameters.

Reinforced Poisson process (RPP)

RPP is a Point process model, same as TiDeH, where the instantaneous function is written as

\[
\lambda(t) = cf_\gamma(t)r_\alpha(R(t)),
\]

where \( f_\gamma(t) = t^{-\gamma} \) describes the aging effect, \( r_\alpha(R) = \epsilon + \frac{1-e^{-\alpha(R+1)}}{1-e^{-\alpha}} \) is a reinforcement mechanism associated to the multiplicative nature of the spreading. The model parameters \( \{c, \gamma, \alpha\} \) are determined by the maximum likelihood method. The cumulative number of post is evaluated by the expectation of the RPP model, described as below

\[
\frac{dR}{dt} = \lambda(t)
\]

which can be solved analytically

\[
R(t) = (\log(1 + e^x) - x - \log \bar{\epsilon} - \alpha)/\alpha,
\]
with
\[ x(t) = \frac{\tilde{\epsilon}\alpha(T_{\text{obs}}^{1-\gamma} - t^{1-\gamma})}{(1 - \gamma)(1 - e^{-\alpha})} - (R(T_{\text{obs}}) + 1)\alpha - \log(\tilde{\epsilon} - e^{-\alpha(R(T_{\text{obs}})+1)}) \]
and \( \tilde{\epsilon} = 1 + \epsilon(1 - e^{-\alpha}) \). This expression is used to predict the cumulative number of tweets.

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