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Fake News and its Credibility Evaluation by Dynamic Relational Networks: A Bottom up Approach

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Abstract

The world has become *flat* through the Web and the recent proliferation of social network services, allowing anyone to be a news writer without requiring much effort, thus creating an epidemic of fake news (microblogs in particular). This note proposes a bottom up approach with relative, mutual, and dynamic credibility evaluation using a dynamic relational network (or mutual evaluation model), where each node can evaluate and in turn be evaluated by other nodes for credibility based on the consistency of the content of the node. Our stance is that 1) it would be difficult to evaluate credibility of news solely on the content of the news (except obvious ones using fake photos and images); 2) hence, allow related news articles to mutually evaluate each other based on the facts' (5W1H— who, what, where, when, why, and how) consistency; 3) however, this poses the problem of fake evaluation, thus allowing any users to build their own evaluation network for fairness.

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Keywords: fake news; credibility evaluation; web mining; dynamic relational networks; sensor networks; self-recognition model

1. Introduction

With the proliferation of social network services (SNS) on the Web and the *world is flat* phenomena driven by the ability to broadcast messages globally, anyone can broadcast their own news on their blog sites. Many news posts with unknown credibility are flooding the Web. This highlights the trade-off of between f*reedom of expression* and *welfare of the public*. Our approach here is that evaluation of news postings be free and promoted; hence, a bottom up approach is proposed.

The scope of the news we consider is the ones that include some facts, where the facts can be evaluated. The news that include photos and sounds that are artificially modified or tempered to exaggerate or twist the message delivered are considered as fake news. Some news, such as completely fake news, and even some related news may be evaluated objectively as fake (if it includes evidence such as falsified photos, sounds, or personal identity). Our stance to evaluate the news is similar to a mathematical proof: it would be difficult to prove news is not fake, but some incorrect evidences are sufficient to prove that the news is fake. However, unlike a mathematical proof, falsification is difficult to prove because of

Nomenclature

$R_i(t)$	a credibility (normalized to a continuous value from 0 to 1) of a (virtual) node i at time t.
T_{ij}	an evaluation from node i to j: 1 when node i evaluates node j as credible; -1 otherwise.

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its relativeness. Thus, our approach is again a bottom up one: anyone can build a dynamic relational network that evaluates the news' relative credibility from the viewpoint of each person. Collecting and synthesizing the averaged credibility can produce an aggregated credibility snapshot from the Web at a given time.

Section 2 briefly explains the recent ecology of fake news initiated by the wide-spread use of SNS and recent studies related to fake news. Section 3 reviews the dynamic relational network with several algorithms for evaluation of credibly. Section 4 extends the dynamic relational network to evaluate the credibility of news dynamically, relatively, and mutually. Section 5 presents several examples of credibility evaluation on several types of news. The merits and demerits of the proposed framework are also discussed by comparing it with other proposed frameworks.

2. Fake News and their Ecology on the SNS Ecosystem

2.1. Ecology of fake news

The situation causing the fake news pandemic is the wide-spread use of SNS (or microblogs) and *flat world* caused by the SNS (messages can reach anyone globally). Further, even though there is a strong incentive to post and spread news on SNS, there appears to be little incentive to incur the costs necessary to prevent and check the credibility of news posts. Although the lack of effort to check the credibility of news is an important and difficult issue, and it should be solved at a system level in the long term, we focus on a short-term solution to deal with fake news in microblogs by using the spatiotemporal distribution of credibility calculated by a dynamic relational network [15].

When Japan suffered from a recent natural disaster, the Japanese public endured rumors that spread just after the disaster. The spreading of the rumor obeys certain rules. In emergency or scary situations, any information requires broad transmission, so transferring or broadcasting will generally be performed without reconfirmation and checking of the facts originating from the news source. As a general rule, when the information is transferred from a person to another without confirmation, the information will be easily modified by each person's (as a medium) own concern, interest, and subjective perspective. Motivations for fake news thus span from:

- Just for fun (Pranksters)
- For earning money
- Political motivations

Further, news itself has a propelling potential if it involves a rare and unusual event, simply because it is *new*s. As in the proverb: "Bad money drives out good," we suppose bad news drives out good news. In this case, rare news (even involving fake information) would drive out honest but less-appealing news.

From observations on fake news creation and its spread, we assume the following:

- To evaluate the credibility of the news on the web, SNS in particular, the number of the same or similar news items does not count, as the propagative power of the news does not depend on whether the news is true or not.
- Whether the news is valuable or not does not depend on it being true or not, but on the perspective or the interest of the readers.
- The value of the news has a certain life time; thus, fading out dynamics are involved.
- The value of the news is relative to the perspective or interest of the reader.

2.2. Related work to detect and prevent fake news

Fake news has been noted not only in news media ([1, 4] to mention only a few in Japanese news media) and internet media [2, 3] and has been studied extensively by academics [5-11, 16-27].

Extensive types of studies have considered fake news: detecting fake news [7, 8, 9, 11, 16, 19, 20, 21, 22], filtering fake news [6, 18], and classifying fake news [19, 23]

Information spread and propagation among communities is an important issue in information science. Many studies on rumor spreading have been conducted, such as modeling the spreading process with a probabilistic approach [5] to a network model, among others. We need to consider how fake news is spread through microblog space. Many studies have considered rumor spreading through blogs (e.g., [12] and references therein) using epidemic models of disease. The spreading process can be related to the pattern of credibility distribution of the related news (Sec. 5).

For the recent spread of fake news through microblogs, a fake image or photo is used where the photo is a composite, modified from one used in other news [25]. For assessing the credibility of web pages (which could involve news), a page ranking algorithm such as PageRank [18] has been studied. This algorithm is based on the number linked to a page (index ranking the page). Google recently modified their page ranking system considering the recent increase of fake news [3]. Detecting fake sites [6] is also an important element to detect fake news.

Detecting some fake news, which may be determined independent from users' viewpoints and political stances, was raised as a computational and machine learning challenge. Several benchmarks and datasets have been proposed [22]. Studies have been conducted using various natural language processing (NLP) and classification techniques (e.g., by computing the F-score [11]).

Viewpoints and political stances may determine whether the news is true or false [17, 24]. Roughly two types of fake news may be identified:

- Subjective news, whose truth or falseness depend upon viewpoints or political stances
- Objective news, whose credibility is based on the objective facts included in the contents

We focus on the latter objective news but do not completely exclude the former case, for the former case may also include objective facts and is thus suited to relative and mutual analysis in some cases.

Credibility assessment studies (e.g., [6]) for a site can also be used for fake news detection and evaluation. Our approach also uses credibility; however, the marked difference is that our approach is bottom up, allowing anyone to perform their own evaluation in a dynamic-relative-mutual manner [13-15]. The very person who posted the news can perform the evaluation on his/her own news, but if the evaluation includes their own subjective perspective, the credibility of the evaluation will be lowered by other evaluations or by the other evaluation network(s).

3. Credibility Evaluation based on Dynamic Relational Networks

This section reviews the dynamic relational networks (or self-recognition model) [15] on which credibility evaluation network is constructed. The essence of the dynamic relational network is as follows:

- **Dynamic**: credibility of every node depends upon the credibility of the connected node, and hence it changes as the credibility of other nodes changed and even when new node is added or some existing nodes are deleted.
- **Relative**: credibility of every nodes is interacting with credibility of other nodes and the evaluation of (or consistency with) other nodes, thus the credibility cannot be determined solely by the content of the target node.
- **Mutual**: credibility evaluation is done mutually with credibility evaluation of the connected nodes, thus more than two nodes are required and more importantly, fake evaluation of other nodes will be reflected to lowering the credibility of the evaluating node.

In sum, the dynamic relational network is a convolutional weighting vote by evaluating nodes and being evaluated by nodes where overall inconsistency among involved nodes' credibility and their evaluation will be minimized. As easily imagined, simple voting does not work for the fake news, for overwhelming number of the fake news will be posted simultaneously or the *population* of the news will become huge during the spreading process.

The dynamic relational network consists of nodes capable of recognizing the states of other nodes: normal or abnormal, and being recognized by the other nodes, hence mutual. The results of recognition are indicated by the arcs from recognizing nodes to being-recognized nodes, and by the sign associated with the arcs: + when recognized as normal and – when abnormal. Recognition by abnormal nodes is unreliable.

The dynamic relational network can be mapped to a dynamic system as a dynamic voting where the weighted vote changes through feedback of the changing vote. Weighting the votes and propagating them identifies the abnormal nodes correctly under certain conditions. A continuous dynamic system is constructed by associating the time derivative of the state variable (expressing the vote) with the state variables of other nodes connected by the evaluation chain. The vote is normalized to a continuous value (called credibility) ranging from 0 to 1 to show the inferred results as a binary value: 1 as true and 0 as false. Further, considering not only the effect from evaluating nodes but also that from evaluated nodes leads to the following dynamic system for the gray model used in this note [13, 14]:

$$\frac{dr_i(t)}{dt} = \sum_j T_{ji}^{+} R_j(t) - r_i(t),$$

$$R_i(t) = \frac{1}{1+\exp(-r_i(t))}$$

where

R_i: credibility, which is the normalized value of r_i,

r_i: credibility before normalization,

T^{+}_{ij}: T_{ij}: + T_{ij} −1 (0) if at least one arc between node i and j (for no arc).

T_{ij}: +1 (−1) for the arc from node i to node j with + (−) sign; 0 otherwise (for no arc).

The difference from the black and white model is that it has the viscosity term:- $r_i(t)$ that slows down the convergence on the extreme values 1 or 0; permitting the equilibrium R_i^* such that:

$$\sum_j T_{ji}^{+} R_j^* = r_i^* \text{ where}$$

$$R_i^* = \frac{1}{1+\exp(-r_i^*)}$$

Example 1. (Who is the Liar Puzzle with Gray model)

Suppose there are five persons A, B, C, D and E; and they have mutual evaluations as shown in Fig. 1 where positive sign means they mutually believe as honest with each other, while negative sign means they mutually suspect as liar with each other. This puzzle can be solved logically assuming up to two liars can exist among five persons. For example, assuming D honest would lead to A, B and C are liars thus contradicting to the up-to-two-liars assumption. Therefore, D must be a liar. Further, assuming E honest would lead to B and C as liars thus again contradicting to the up-to-two-liars assumption, thus E must be a liar. Altogether, D and E are liars and the rest are honest under the up-to-two-liar assumption. In fact, the hard threshold permitting the identification of the liars is the number of liars must not exceed the half of the total number. Second threshold for the identification of the liars is that the number of liars must not exceed the minimum in-degree of all the node (3 in this example). The liars can be identified by the black and white model [15] as shown in Fig. 1 *left*. Gray model allows the network to keep the intermediate credible value (gray color) between fully credible 1 (white) and incredible 0 (black). In Fig. 2, the network *left* is the initial network where credibility of every nodes is set to be 1 (honest), while after weighted propagation the credibility of nodes becomes: A: 0.794, B: 0.677, C: 0.677, D: 0.002 and E: 0.017 as indicated by the gray color in the network *right*.

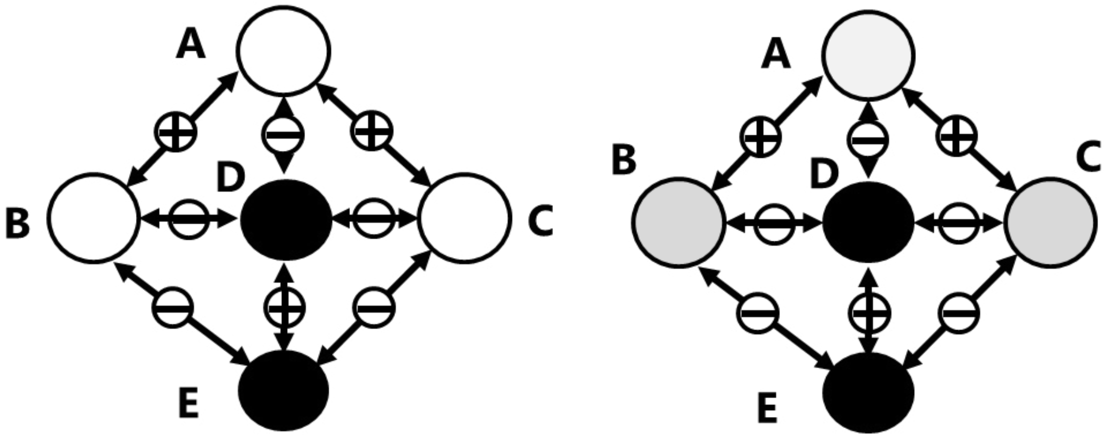

Fig. 1. Black & White model forces every credible values either fully credible 1 (white) and incredible 0 (black) (the network *left*). Gray model allows the network to keep intermediate credible values (gray colour) between 1 and 0 (black): A: 0.794, B: 0.677, C: 0.677, D: 0.002 and E: 0.017 as indicated by the gray level in the network *right*.

This example illustrates that not only the node contents but also the relation (positive sign or negative sign) can involve noise, and the noise can be filtered out by the credibility if the noise does not exceed a certain level. In the credibility evaluation of news studied in this note, the relation is mutual evaluation which is done by the consistency between the content (text) held by the node. Even by using natural language processing technology such as similarity check, it is still difficult to automate the consistency check between two contents. In the case studies of Sect. 5, we compare two contents and manually determine the sign.

The dynamic relational network can be used for credibility reasoning not only for the credibility evaluation of each node but also for the events that the nodes are monitoring (anomaly detection) as in the sensor network [13, 14]. These two modes of detection will be used for two types of fake news: news containing false information and news where the event reported by the news does not exist. This credibility reasoning method can be compared with evidential reasoning based on the Dampster-Shafer theory and probabilistic reasoning based on Bayesian networks. The fundamental difference from these reasoning methods is that the nodes are evaluators themselves and at the same time being evaluated (distributed and mutual perspective in contrast to one evaluator outside from the network evaluates with the network).

Although it is possible to force the credibility of nodes to be binary by devising the energy (Hamiltonian) or Lyapunov function as explained above, there are cases where we need the intermediate value in cases where binary evaluation would be difficult. We suppose that credibility evaluation of news in the situation that news may contain several types of fakeness require the intermediate values. We will use the gray model that allows the network to keep the intermediate value in this note.

Nevertheless, we admit that binary evaluation could make the situation simple and plain even for some cases of fake news evaluation such as the case of the final and absolute evaluation phase. In that case, we can always switch to the binary evaluation with switching to the black and white model on the same network.

Although the initial credibility is set to be 1 in the Example 1, it can be set to value reflecting the credibility of the site where the news is posted or the credibility of the person or the party who posted the news if such credibility is available.

4. Credibility Evaluation of News by Dynamic Relational Networks

As a primitive for building a dynamic relational network, we introduce an article unit. An article unit consists of one article node and several fact nodes, where fact nodes are of several types such as who, what, where, when, why, and how (5W1H) (Fig. 2). Because most news includes media such as photos or movies (“Seeing is believing”), we can add an image node. Often, image data contains time stamps, the location and the face of the person; hence, the fact nodes of image types can be related with fact nodes of text data of 5W1H.

Example 2. (Evaluation network built with the article units)
Suppose we have the news: “Mob of 1000 people sets fire to the oldest church in Dortmund on New Year’s Eve.” Fig. 2 in the box *left* shows the article node and the fact nodes: when (“New Year’s Eve”), who (“mob of 1000 people”), where (“Dortmund”), and what (“set fire to the oldest church”). Suppose also as related news “Festival participants made a bonfire in the church at Dortmund on 31st Dec.,” where the fact nodes are: when (“31st Dec”), who (“Festival participants”), where (“Dortmund”), and what (“bonfire in the church”). These two news articles are related by the consistency among the fact nodes of the corresponding article units (Fig. 2).

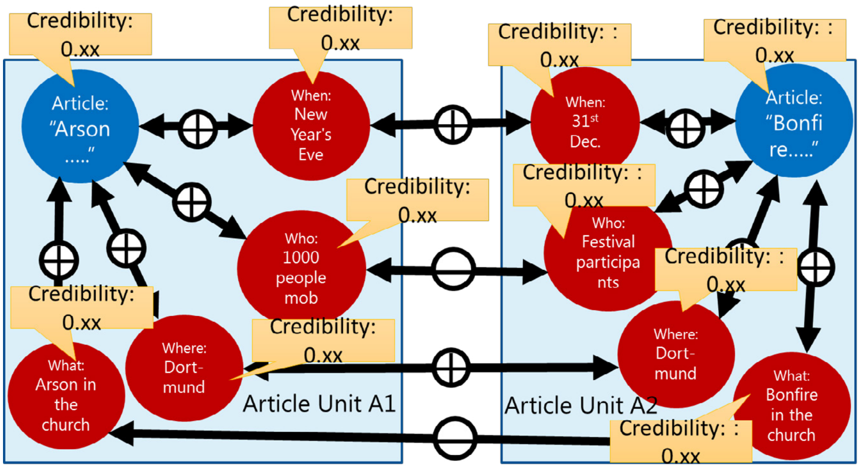

Fig. 2. The box left shows the article unit corresponding to the article: “Arson in the oldest church 1000 people mob on New Year's Eve”. Article unit consists of an article node (blue) and fact nodes (red) Several types of fact nodes can be used corresponding to 5W1H. Types of the fact nodes should be same for the related news articles for the evaluation consistency. For this example, only 4W: when, where, who and what. Article units of the related articles can be relatively connected if the fact nodes are the same types. Article unit A1 is related to the article unit A2. Some of the fact nodes are evaluated their consistency with other each other. The credibility of the fact nodes will be calculated by the consistency, while the credibility of the article nodes will be propagated from the fact nodes.

The credibility evaluation network for news will be built through mutual evaluation among related news. Thus, the credibility evaluation network is a mutual evaluation network among the article units, where article units mutually evaluate by consistency among their fact nodes.

5. Case Studies for Possible Fake News Evaluation

5.1. Examples

To evaluate the credibility evaluation by the dynamic relational network, we conducted simulations on several test cases: one with regular news (not fake) (Example 3) and others with fake news (Examples 4, 5, and 6). The experiments by computer simulation are carried out in the following manner:

1. Choose the target news
2. Collect the news related to the target news from the Web (Google in Japan (https://www.google.co.jp/) is used with the title or headline input for October 2017)
3. Build the dynamic relational network for the related news

Example 3. (Credibility evaluation for nonfake regular news)

As the nonfake regular news, we chose the news story: 「給食の牛乳に“異臭”新宿区で児童ら 1300 人訴える」“1300 children complained of off-flavor milk served for school lunch at Shinjukuku-Ku.” Fig. 3 shows the evaluation network where the news in question A1 is placed at the top left and the article unit A1 is related through consistency of the fact nodes of nine other article units A2, …, A10. Fig. 4 shows the credibility obtained through the simulation on the network. The article unit in question, A1, attains a high credibility score of 0.88 by observing the credibility R1 of the article node. Most of other article units of the related news have a similar credibility of more than 0.8 except for article units A3 (R1=0.5) and A4 (R1=0.5). Compared with *Who* and *What* nodes, *When* and *Where* nodes are usually specific; hence, their consistency with other Article's *When* and *Where* nodes is strong. Thus, the credibility of *When* and *Where* nodes tend to result in specific score values of 1 or 0, while the credibility of the *Who* and *What* nodes resulted in the intermediate values for A3 and A4 in this case.

As demonstrated in Example 3, nonfake news generally can attain reasonably high credibility with other non-fake news. However, even non-fake news cannot attain a credibility of 1 (fully credible) because the nodes of *Who* and *What*, for their text expression, involve orthographical variants or their specificity can vary in many ways, even if their facts are not fake. In other words, the network can identify facts or even news whose content cannot be specific and hence is difficult to check objectively through mutual consistency. Furthermore, if such nodes do contain fake facts or news, it would be difficult to identify the fake facts or the fake news.

Example 4. (Credibility evaluation of fake news: satire and jokes)
As an example of the fake news with satire or jokes, we chose the news:「琵琶湖で 1 メートル超の人魚釣れる　人魚拓も展示」“A fisherman caught a mermaid who was longer than one meter in the Lake Biwa. The mermaid fish print was exhibited.” Fig. 5 shows the evaluation network where the news in question A1 is placed at the top left and the article unit A1 is related through consistency of the fact nodes of nine other articles, units A2, …, A10. Fig. 6 shows the credibility obtained through the simulation on the network. It is observed that the credibility of all the article nodes, including the unit in question A1, achieve intermediate credibility of 0.5. Most fact nodes tend to a similar credibility (close to 0.7) except the article units A9 and A10 (R4, R5=0.69), and A7 (R2, R3, R4, R5=0.495) where A9 and A10 miss the facts of *When* and *Where*.

As observed in Example 4, fake news with jokes/pranks may be detected as fake by the intermediate credibility value, as it spread from one source and created many similar related news articles whose contents are not fully contradictory and not fully consistent. In many cases, it is obvious that they are jokes solely based on content or even by the occasion (such as being posted on April Fool's Day), and hence harmless or even amusing readers. However, stories of this type could raise local and group ire depending on the mass psychology present, such as after a natural or economic disaster.

Example 5. (Credibility evaluation for fake news: News with false information)
As an example of fake news with false information, we chose the news article:「その企業は非公開フォルダの中の著作権侵害ファイルを削除できる」“The company can remove the copyright infringement files in the private folder.” Fig. 7 (*left*) shows the evaluation network where the news in question A1 is related to A2, A3, and A4. Fig. 7 (*right*) shows the credibility obtained through the simulation on the network. It can be observed that even though the article unit A1 contains false information in the fact node *How*, its credibility as well as the credibility of the other fact nodes and the article node remain relatively high: R1 (article node) = 0.941, R2 (fact node of *Who*) = 0.98, R3 (fact node of *What*) = 0.944 and R4 (fact node of *How*) = 0.847. Although it contains false information involving *How* and the credibility of R4 is relatively low compared with other fact nodes, the credibility of R4 is relatively high compared with R4 of other article units. In fact, it is higher (0.847) than R4 of A2 (0.013) with true content, and then R4 of A4 (0.012) with false content.

As demonstrated in Example 5, the mutual evaluation method could not identify the news unit that contains false information. It could possibly detect which fact nodes contain false information through the related news articles (the fact nodes of *How* in the Example 5). It is analogous to using the dynamic relational network for sensor based diagnosis [14]. If one or few sensors fail, it can identify which sensor(s) is faulty. However, it is impossible to identify the faulty sensor when multiple sensors fail simultaneously. The network can detect some sensors are faulty, but cannot identify specific ones.

Example 6. (Credibility evaluation for fake news: Large-scale hoax)
As an example of fake news involving a large-scale hoax, we chose the news:「クーポンを使うと料理の量が減る」“If you use the coupon, the amount of food will be reduced.” The evaluation network consists of only three article units A1, A2, and A3 which are mutually inconsistent. Thus, the credibility of all the nodes becomes 0 even with a gray model starting from the initial credibility 1. This amounts to a global anomaly as a sensor reading if we consider the network as a coordinated monitor of the Web [14, 15].

First, we encountered great difficulty in finding *related* news, for most of the related news articles appeared to be almost exact copies of the original one. It is obvious that using these same news articles, even with weighted voting with initial credibility of 1, would not make sense. We manually managed to select two news articles that are related (but not the same) to the news in question. However, we must admit that this very selection phase involved some subjective component. All we can conclude from this case is that the fake news involving large-scale hoaxes is difficult to identify locally, but there is the possibility that it can be detected if most of the news stories have the same content and that any related (but not identical) news stories are mutually inconsistent, leading to low credibility for all news items evaluated.

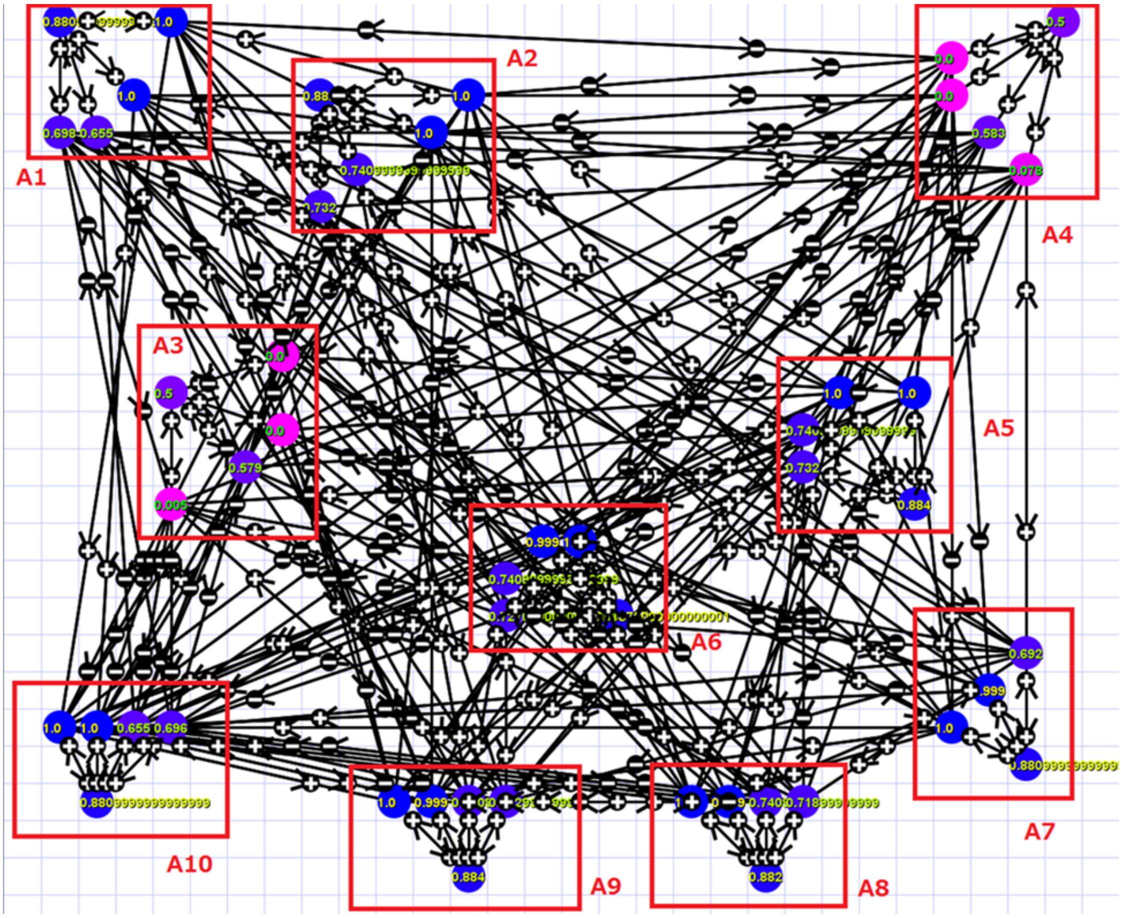

Fig. 3. A dynamic relational network of Example 3 for the regular nonfake news “1300 children complained of off-flavor milk served for school lunch at Shinjukuku-Ku.” Credibility distribution by the simulation is also shown in Fig. 4.

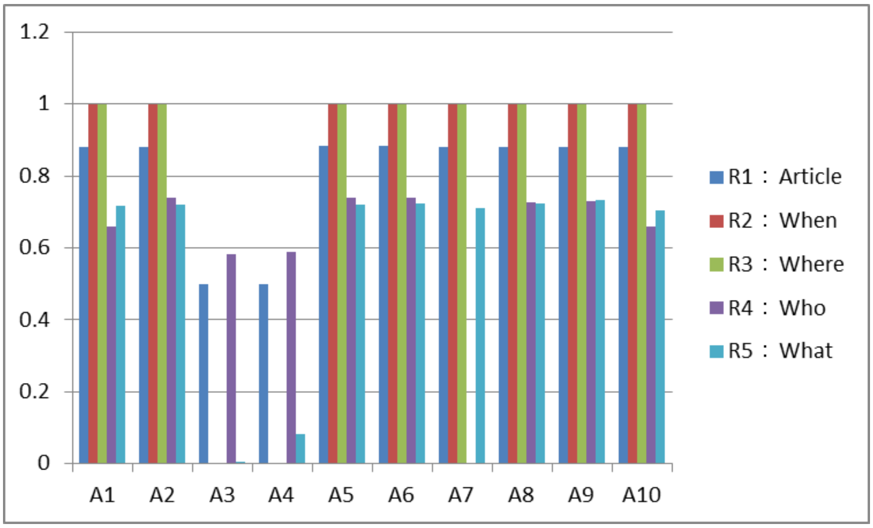

Fig. 4. A simulation for the dynamic relational network (Fig. 3) for the regular nonfake news. Each bar shows the credibility of the nodes of article units A1, A2, ….,A10.

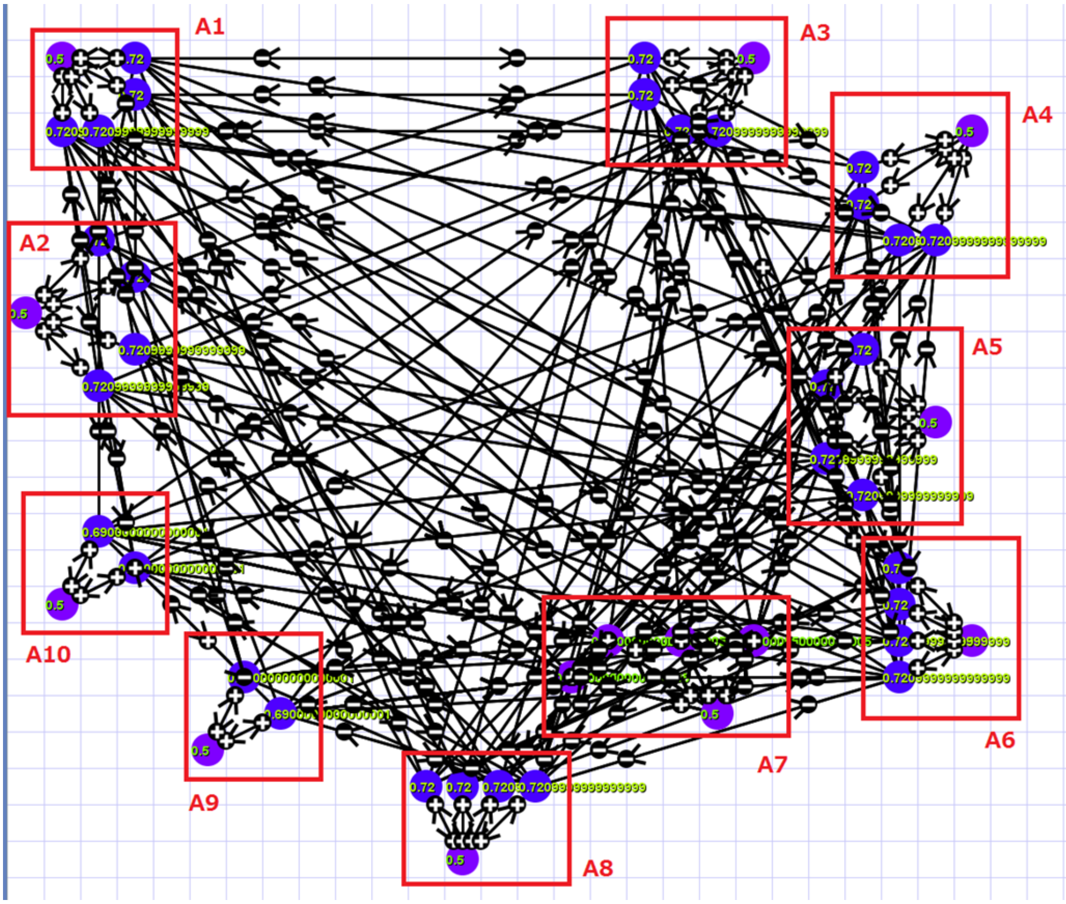

Fig. 5. A dynamic relational network of Example 4 for the joke "A fisherman caught a mermaid who was longer than one meter in the Lake Biwa. The mermaid fish print was exhibited.". Credibility distribution by the simulation is also shown in Fig. 6.

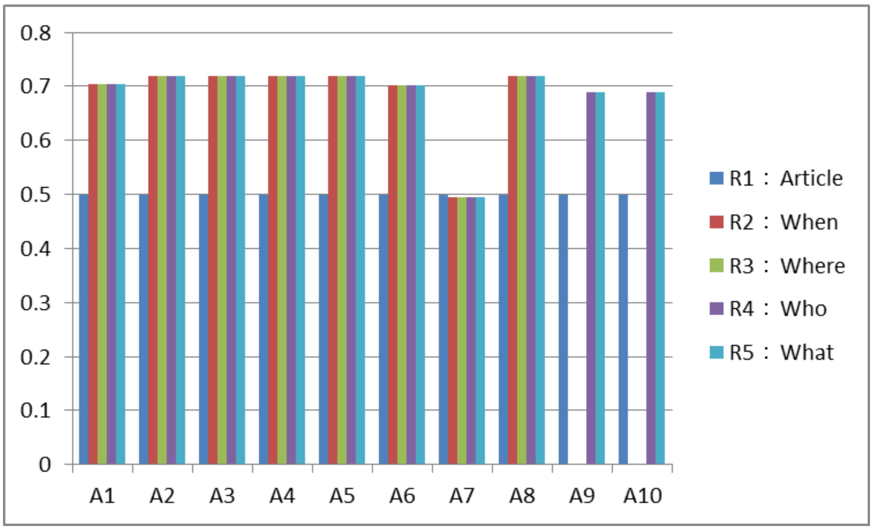

Fig. 6. A simulation for the dynamic relational network (Fig. 5) for the joke of the Example 4. Each bar shows the credibility of the nodes of article units A1, A2, ….,A10.

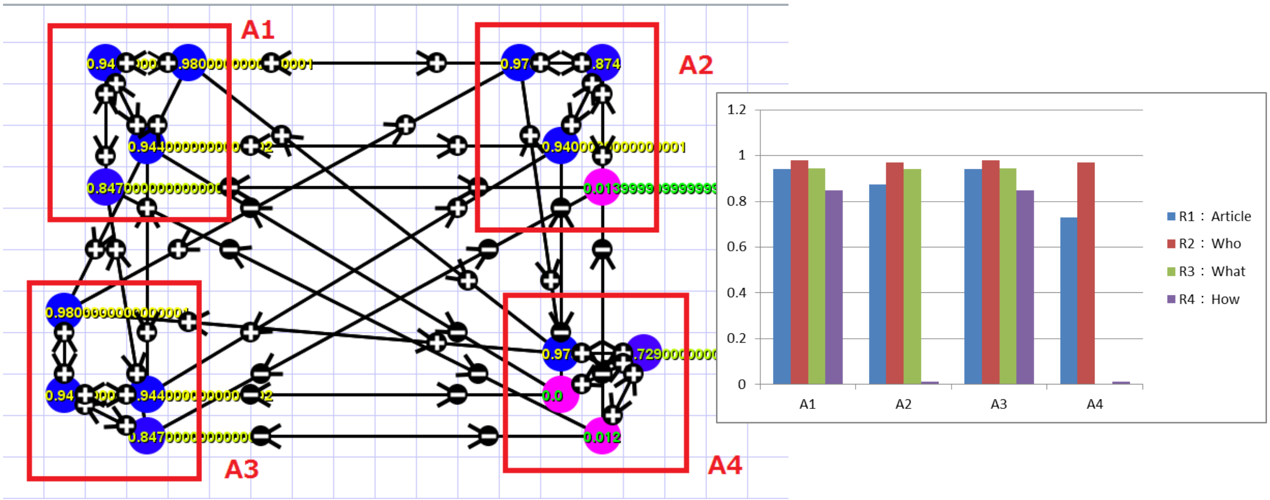

Fig. 7. The figure *left* shows the dynamic relational network of Example 5.for the news with false information "The company can remove the copyright infringement files in the private folder." Credibility distribution by the simulation is also shown in the figure *right* where bar indicated the credibility of the nodes of article units A1, A2, A3 and A4.

5.2. Discussion

From the simulations on the different types of news, it can be observed that:

- (Low credibility spread) Large-scale false rumor and jokes: credibility of fact nodes is low (low credibility is spread over the nodes of the news units)
- (Localized low credibility) News with false facts: credibility of only the corresponding fact nodes is low (low credibility is localized)

For the former case, it may be speculated that the contents (including false and true parts) undergoes an extensive falsifying process through spreading; hence, the content of the news becomes diversified, resulting in many news articles with slightly different content. This situation leads the large scale false rumors with slightly distinct content to achieve low credibility overall. However, when the large scale false rumor is organized and on purpose, the same content will be posted to the different news sites simultaneously and hence, their credibility (based on mutual consistency) is high. In case of Example 6, we had to manually remove the copied fake news from the related news candidates.

In contrast, for the latter case of localized low credibility, the technical false content is restricted on one or few fact nodes, so the credibility of the node will be low, and the credibility of the other nodes remains high, thus creating a localized low credibility node. In Example 5, the fact nodes of *How* with low credibility are identified in two news units. However, it should be noted that the news units containing true information of the fact node *How* are lowered. Thus, we cannot identify the news containing false information; however, we can identify which fact nodes (*How* in case of Example 5) contain false information among other fact nodes.

We can use the spatial and temporal distribution pattern of credibility to classify the types of fake news: whether the news is large scale and organized fake news or fake news containing false information. Because we used the dynamic relational network for the sensor network for fault diagnosis, the former case corresponds to a *process fault* where the target process monitored by the sensor set has a fault, while the latter case corresponds to the *sensor fault* where the sensor itself has a fault. When the credibility distribution data is viewed as time series data, the former case is a global anomaly, while the latter case is a localized anomaly.

Another advantage of the dynamic-relative-mutual approach is that it allows evaluations for evaluation in a further meta-hierarchy, thus allowing a more global evaluation in space (more evaluators) and time (higher evaluators for evaluation of evaluations). However, this involves more cost and effort, and most importantly, there is no incentive for both the one posting fake news and the one reading the fake news to evaluate the veracity of the news. This asymmetry between the one posting the fake news and the one preventing the fake news from being posted is similar to the spam mail sender and the general reader of the mails (whose solution is to ignore spam).

6. Conclusions

Although there are incentives for posting and spreading fake news, there seems almost no incentive to overcome the cost for preventing and checking fake news. Society needs time to reach equilibrium in the trade-off between freedom to post and public wealth lost by fake news. Although some security technology exists to assure the news is posted by a real person, again there are situations where social consensus is necessary to reconcile the protection of private information and public wealth.

As a second best solution, we proposed a method with which anyone can evaluate the credibility of target news by building his/her own evaluation on the news by relatively and mutually evaluating the credibility of the related news. Because any person can have a different perspective and stance, their evaluation of the same news will be different. Further meta-level evaluation would be possible by mutually and relatively comparing their evaluations, thus making the evaluation network a hierarchical one. The simulations also suggest that the evaluated credibility distribution over the related news will provide sufficient information to classify the target news in many cases.

Disclaimer

We masked some proper nouns in the examples, because this paper merely aims to illustrate how and why the dynamic relational network may be used on the Web, rather than highlighting the originators of fake news. All keywords used for searching in the examples were Japanese, and were translated into English for illustrative purposes only.

References

[1] ASAHI DIGITAL, http://www.asahi.com/topics/word/%E3%83%95%E3%82%A1%E3%82%AF%E3%83%88%E3%83%81%E3%82%A7%E3%83%83%E3%82%AF.html (in Japanese) (accessed on 2018/1/15)

[2] Facebook newsroom, "News Feed FYI: Addressing Hoaxes and Fake News" https://newsroom.fb.com/news/2016/12/news-feed-fyi-addressing-hoaxes-and-fake-news/ (in Japanese) (accessed on 2018/01/15)

[3] Google https://webmaster-ja.googleblog.com/2017/04/our-latest-quality-improvements-search.html (in Japanese) (accessed on 2018/01/15)

[4] NIKKEI, https://www.nikkei.com/article/DGXMZO10119170Q6A131C1X13000/ (in Japanese) (accessed on 2018/01/15)

[5] Hunt Allcott and Matthew Gentzkow (2017) "Social Media and Fake News in the 2016" *Journal of Economic Perspectives* (**31**)**2**: 211–236.

[6] Abbasi et al. (2010) "Detecting Fake Websites: the Contribution of Statistical Learning Theory" *MIS Quarterly* (**34**) **3**: 435-461.

[7] Cheng Chen et. al (2013) "Battling the Internet Water Army: Detection of Hidden Paid Posters" IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining.

[8] Yimin Chen, Niall J. Conroy, and Victoria L. Rubin (2015) "News in an Online World The Need for an "Automatic Crap Detector"" *Proceedings of the Association for Information Science and Technology* (ASIST 2015), November 6-10.

[9] Niall J. Conroy, Victoria L. Rubin, and Yimin Chen (2015) "Automatic Deception Detection: Methods for Finding Fake News" *Proceedings of the Association for Information Science and Technology* (ASIST 2015), November 6-10.

[10] Emilio Ferrara et. al (2016) "The Rise of Social Bots" Communications of The ACM (**59**) **7.**

[11] Manisha Gahirwal et.al. (2018) "Fake News Detection" *International Journal of Advance Research, Ideas and Innovations in Technology*, (**4**) **1.**

[12] D. Gruhl, R Guha, D Liben-Nowell, A Tomkins (2004) "Information diffusion through blogspace" WWW2004, May 17–22, New York, USA. ACM 1-58113-844-X/04/0005

[13] Yoshiteru Ishida and Ryunosuke Chiba (2015) "Fermi Estimate on the Web: Placing Sensor Networks on the Web with Noise" *Procedia Computer Science* **60**: 1753–1762t.

[14] Yoshiteru Ishida (2006) "Designing an Immunity-Based Sensor Network for Sensor-Based Diagnosis of Automobile Engines" *Lecture Notes in Computer Science* **4252:** 146-153.

[15] Yoshiteru Ishida (2004) *Immunity-Based Systems: A Design Perspective*. Springer.

[16] Benjamin Markines, Ciro Cattuto, Filippo Menczer (2009) "Social Spam Detection, p41-markines" AIRWeb '09, April 21 Madrid, Spain.

[17] Regina Marchi (2012) "With Facebook, Blogs, and Fake News, Teens Reject Journalistic "Objectivity"" *Journal of Communication Inquiry* 36(3): 246–262.

[18] Lawrence Page, Sergey Brin, Rajeev Motwani and Terry Winograd. (1999) "The PageRank citation ranking: Bringing order to the web" *Technical report*, Stanford University, 1999.

[19] Victoria L. Rubin, Yimin Chen and Niall J. Conroy (2015) "Deception Detection for News: Three Types of Fakes" *Proceedings of the Association for Information Science and Technology* (ASIST 2015), November 6-10.

[20] Kai Shu et. al (2017) "Fake News Detection on Social Media: A Data Mining Perspective" arXiv:1708.01967v3 [cs.SI] 3 Sep 2017.

[21] James Thorne (2017) "Fake News Detection using Stacked Ensemble of Classifiers" *Proceedings of the 2017 EMNLP Workshop on Natural Language Processing meets Journalism*, pages 80–83 Copenhagen, Denmark, September 7, 2017.

[22] William Yang Wang (2017) " "Liar, Liar Pants on Fire": A New Benchmark Dataset for Fake News Detection" arXiv:1705.00648v1 [cs.CL] 1 May 2017.

[23] Claire Wardle (2016) "6 types of misinformation circulated this election season" *Columbia Journalism Review*, https://www.cjr.org/tow_center/6_types_election_fake_news.php (accessed on 2018/01/15)

[24] Meital Balmas (2014) "When Fake News Becomes Real: Combined Exposure to Multiple News Sources and Political Attitudes of Inefficacy, Alienation, and Cynicism" *Communication Research* **41**(**3**): 430–454.

[25] Aditi Gupta et. al (2013) "Faking Sandy Characterizing and Identifying Fake Images" WWW 2013 Companion, May 13–17, Rio de Janeiro, Brazil. ACM 978-1-4503-2038-2/13/05

[26] Jin, Z et. al. (2016) "News Verification by Exploiting Conflicting Social Viewpoints in Microblogs" *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence* (AAAI-16) 12128-56242-1-PB.

[27] Jin, Z et. al. (2014) "News Credibility Evaluation on Microblog with a Hierarchical Propagation Model" *IEEE International Conference on Data Mining* (ICDM), 2014.