

Postprint of Information Propagation Based on the IBU Model

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Date: 2019-04-01T00:00:00+00:00

Abstract

The assessment of information veracity by Internet users constitutes a critical phase in the information dissemination process. The general public's personal evaluation of acquired information and their judgment of information content authenticity directly impact the breadth and effectiveness of information propagation. Considering that differential credibility among information publishers exerts certain effects on the information dissemination process, this study proposes a novel IBU model to investigate the influence of information content authenticity and publisher credibility on information dissemination dynamics. Through MATLAB simulation experiments on the model's propagation effectiveness, the results indicate that regardless of the magnitude of publisher credibility, this factor is independent of information credibility per se, being solely contingent upon the intrinsic veracity of the information content; higher publisher credibility correlates with prolonged information dissemination duration; conversely, lower credibility leads to shorter propagation times, yet does not alter the fundamental nature of information content veracity. These research findings provide a theoretical foundation for relevant functional departments in information control and management.

Full Text

Preamble

Vol. 37 No. 5

Application Research of Computers

Information Dissemination Based on the IBU Model

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Abstract: The judgment of information falsity by network users represents a critical stage in the information dissemination process. The personal evaluation of obtained information and the determination of its authenticity by the general public directly influence both the breadth and effectiveness of information spread. Considering that credibility differences among information publishers exert certain influences on the dissemination process, this paper proposes a novel IBU model to investigate the breadth and impact of true and false information propagation. The model examines how information content authenticity and publisher credibility affect the dynamics of information dissemination. MATLAB simulations were conducted to test the model's propagation effects. Experimental results demonstrate that regardless of the publisher's credibility, the outcome is independent of the information's perceived credibility and depends solely on whether the information content itself is trustworthy. Higher publisher credibility leads to longer dissemination times, while lower credibility shortens propagation duration, though this does not alter the fundamental true/false nature of the information content. These findings provide a theoretical foundation for relevant functional departments in information management and control.

Keywords: user credibility; information dissemination; communication effect; network rumors

Classification: TP309

doi: 10.19734/j.issn.1001-3695.2018.10.0832

0 Introduction

Online social networks contain substantial extreme and false content, with microblogging platforms severely polluted by spam and rumor information. Contemporary online news media is similarly saturated with unverified "news" [1], directly impacting mainstream media. As Liu et al. [2-4] demonstrated in their research on malware propagation, malicious information spreading across networks can generate significant adverse effects on people's lives. Consequently, research into information credibility holds profound historical significance, capable of reducing rumor propagation and mitigating the societal impact of untrustworthy information.

Jiang Shengyi et al. [5] provided a brief description of information credibility analysis on microblogs, defining relevant concepts for microblog information credibility research. Current research on microblog information credibility primarily focuses on content detection [6], rumor detection [7], and credibility analysis of topical news [8]. Meanwhile, Liu et al. [9, 17] examined the influence of network characteristics on malware propagation, prompting consideration of how network structural features affect spreading across arbitrarily connected real-world networks.

Internationally, Howell et al. [10] identified massive digital false content as a

major threat to modern societal development. Gupta et al. [11] found that approximately 52% of Twitter content is definitively credible, 35% is generally credible, and 13% is definitively non-credible. However, Zhang Mingxin [12] discovered in credibility theory that significant differences exist in credibility across different media and information types, with online and broadcast credibility substantially lower than television and newspapers. Online news and reference information rank as most credible, followed by entertainment information, with commercial information being least credible.

Liu et al. [13] proposed a novel network rumor compartmental isolation model incorporating rumor behavior into network propagation dynamics, addressing equilibrium stability in model systems. Fogg [14] introduced a “Prominence-Interpretation” model for evaluating internet information credibility, positing that people first attend to information elements and then interpret them when assessing online information credibility. In practical business marketing applications, structural equation modeling has been employed to study how brand microblog information content and comment content influence brand microblog credibility [15].

Although existing research has achieved certain results, numerous deficiencies remain in theoretical analysis and methodological approaches for information credibility, particularly given diverse languages and stylistic variations. This presents significant challenges for future researchers investigating information propagation directions. This paper examines information credibility from the perspective that when propagation begins, regardless of whether the original information from ignorant users is trustworthy, people judge information based solely on human credibility. As understanding deepens and knowledge accumulates, users gradually transition into believed or unbelieving information users. Ultimately, when the conversion probability from unbelieving to believed users exceeds the reverse conversion probability, the final equilibrium state shows more users considering the information credible than not. Conversely, when conversion from believed to unbelieving users dominates, more users ultimately consider the information non-credible.

1 Theoretical Model

The “Boy Who Cried Wolf” fable illustrates a Bayesian probability problem for assessing a child’s credibility. This paper assumes two mutually exclusive events, H and $\neg H$, with occurrence probabilities $P(H)$ and $P(\neg H)$, sharing a common characteristic D that occurs with probabilities $P(D|H)$ and $P(D|\neg H)$ respectively. Bayesian inference yields:

Let D represent the event “the child lies” and H represent “the child is credible.” Initially, villagers assign the child a credibility of $P(H) = 0.8$, thus $P(\neg H) = 0.2$. A credible child lies with probability $P(D|H) = 0.1$, while a non-credible child lies with probability $P(D|\neg H) = 0.5$. Table 1 shows villagers’ updated credibility assessment after each lie, with Figure 1 [Figure 1: see original paper]

comparing credibility trends after lying versus truth-telling.

Table 1 Comparison of Child Credibility

Initial	$P(H)=0.8$	Non-credible	$P(\neg H)=0.2$			
Credible child lies	$P(D H)=0.2$		$P(D \neg H)=0.5$	First lie	$P(D H)=0.444$	
	$P(D \neg H)=0.556$	Second lie	$P(D H)=0.138$		$P(D \neg H)=0.872$	Third lie
	$P(D H)=0.031$		$P(D \neg H)=0.969$			

This story demonstrates that credibility declines with repeated lies, eventually leaving the child's warnings disbelieved. In contemporary social network information propagation, considering information credibility itself, we establish a compartment model based on credibility. Network users capable of receiving information constitute a whole population N . Initially, all users are considered ignorant (I). As information spreads, users divide into two categories: those who believe the information is credible (B) and those who consider it non-credible (U). Based on this, we define a credibility benchmark to determine the probability of information authenticity when published, proposing a novel IBU model to study information propagation dynamics.

Network user states can thus be categorized into three types:

- a) **Ignorant (I):** Users who have not yet seen the information in their social circle when a message remains unpropagated, or who encounter the information but cannot determine its authenticity and have not yet made a judgment.
- b) **Believed-User (B):** WeChat users who, upon seeing information, judge it credible and forward it.
- c) **Unbelieved-User (U):** WeChat users who, upon seeing information, judge it non-credible and do not forward it.

Figure 2 [Figure 2: see original paper] illustrates the state transition diagram for network nodes during information propagation.

Figure 2 Schematic diagram of network node state transition

The established interaction rules for the information propagation process are as follows:

When a user publicly publishes information in their social circle at a given moment, friends who have not yet seen the information are considered ignorant (I). Assuming all friends in the social circle can view the information, as proposed in the generalized connectivity network model in literature [18], then within a unit time starting at time t , the probability that a friend considers the information credible is α and forwards it, while the probability of considering it non-credible is β , resulting in no forwarding.

As time progresses and users accumulate knowledge, both credible and non-credible user states may change. Therefore, within a unit time starting at t , the probability that a believed-user considers the information non-credible is γ ,

converting to an unbelieved-user who may delete or block the posted information. Conversely, the probability that an unbelieved-user considers the information credible is δ , converting to a believed-user who may forward or comment on the previously unforwarded information.

Based on these interaction rules for the authenticity-based model, the following system of kinetic differential equations is established:

$$\begin{cases} \frac{dI(t)}{dt} = -(\alpha + \beta)I(t) \\ \frac{dB(t)}{dt} = \alpha I(t) - \gamma B(t) + \delta U(t) \\ \frac{dU(t)}{dt} = \beta I(t) + \gamma B(t) - \delta U(t) \end{cases}$$

where $I(t)$, $B(t)$, and $U(t)$ represent the proportions of ignorant users, believed-users, and unbelieved-users respectively at time t , with I_0 , B_0 , U_0 denoting initial state values, all non-negative.

Regarding credibility assessment of information publishers among social circle friends, we define: when friend j sees the information, they can directly judge its credibility based on their impression of the publisher (trust degree T_{ij}). The average credibility probability of the publisher among friends is T_i , while the non-credibility probability is $1 - T_i$.

Thus, incorporating publisher credibility, Equation (2) can be modified into the following system:

$$\begin{cases} \frac{dI(t)}{dt} = -(T_i\alpha + (1 - T_i)\beta)I(t) \\ \frac{dB(t)}{dt} = T_i\alpha I(t) - \gamma B(t) + \delta U(t) \\ \frac{dU(t)}{dt} = (1 - T_i)\beta I(t) + \gamma B(t) - \delta U(t) \end{cases}$$

In this model, the probability that social circle friends consider the publisher's information credible is $T_i\alpha$, while the probability of considering it non-credible is $(1 - T_i)\beta$. The IBU information propagation model has three equilibrium points. After reaching equilibrium, network information propagation achieves dynamic balance.

Applying the "threshold theorem" from epidemic propagation yields the propagation threshold R_0 in information spreading. Based on the method for calculating general compartment model thresholds proposed by Driessche and Watmough [16], the propagation threshold for model (3) is:

$$R_0 = \frac{\alpha\delta + \beta\gamma}{\gamma\delta}$$

In the conversion processes among ignorant, believed, and unbelieved users, people acquire relevant information over time. Considering individual differences

in learning ability and information acquisition, we temporarily define the self-learning rate as a constant value of 1, enabling self-judgment of information credibility based on existing discrimination capabilities. While conversions between believed and unbelieved users occur with certain probabilities, in real networks this conversion is a dynamic process. The system accounts for psychological changes, allowing all individuals to hold personal viewpoints and choose whether to consider information credible. Without verification, this choice has only two options: believed (considering the information credible) or unbelieved (considering it non-credible).

2 Experimental Numerical Simulation Results Analysis

Based on the established model and rules, MATLAB software was used for numerical simulation experiments to verify consistency with the model's interaction rules.

2.1 Parameter Analysis

Considering the impact of social circle publisher credibility on information content, Equation (2) can be improved under ideal special initial conditions where $\alpha + \beta = 1$. The initial values are set as $I_0 = 0.95$, $B_0 = 0.05$, $U_0 = 0$. This analysis examines how changes in α (while β decreases correspondingly) affect the model's propagation dynamics.

In network information propagation, after some time the system reaches equilibrium, where the three state proportions (I, B, U) remain stable. Assuming the system initially satisfies $I(t) + B(t) + U(t) = 1$, the system can be divided into two compartments based on the state transitions shown in Figure 2. The equilibrium solution for the network model is obtained by solving:

$$\begin{cases} \frac{dI(t)}{dt} = 0 \\ \frac{dB(t)}{dt} = 0 \\ \frac{dU(t)}{dt} = 0 \end{cases}$$

yielding equilibrium points $E_0 = (1, 0, 0)$, $E_1 = (0, \frac{\delta}{\gamma+\delta}, \frac{\gamma}{\gamma+\delta})$, and $E_2 = (\frac{\gamma\delta - \alpha\delta - \beta\gamma}{\alpha\beta}, \frac{\alpha\delta}{\alpha\beta}, \frac{\alpha\gamma}{\alpha\beta})$.

2.2 Simulation Results

Scenario 1: With $\alpha + \beta = 1$, $\gamma = 0.3$, $\delta = 0.01$, and initial conditions $I_0 = 0.95$, $B_0 = 0.05$, $U_0 = 0$, we observe IBU state evolution under different α values (0, 0.5, 1).

Figure 3 Figure 3: see original paper-(c) shows that when the system reaches equilibrium, the three states occupy identical proportions across different α values. The I state proportion consistently decreases, while the B state proportion

increases until stabilizing. The U state proportion in Figure 3(a) first increases then decreases, contrasting with the gradual growth curves in (b) and (c). This occurs because initial conditions convert all I state to U state, causing U to peak before declining due to conversion probability δ from U to B, despite the reverse probability γ . This pattern aligns with model assumptions. At equilibrium, the system reaches proportions I=0, B=0.97, U=0.03.

Figure 4 [Figure 4: see original paper] compares system stabilization times across different α values. The time to reach equilibrium shows a multiplicative relationship: $T_{\alpha=0} = 30s$, $T_{\alpha=0.5} = 15s$, $T_{\alpha=1} = 7.5s$. This demonstrates that increasing α accelerates system stabilization proportionally, though it does not alter the final state proportions.

Scenario 2: With other parameters constant, when α and β do not satisfy $\alpha + \beta = 1$, Figure 5 [Figure 5: see original paper] and Figure 6 [Figure 6: see original paper] show that as α increases, both I and B states reach equilibrium more rapidly. System balance time decreases with increasing α , accelerating convergence.

Scenario 3: Figure 7 [Figure 7: see original paper] examines I state evolution under different parameter combinations. In Figure 7(a), with $\alpha\beta = 0.4$ fixed, varying α produces minimal change in I state evolution. In Figure 7(b), with $\alpha\beta = 0.4$ fixed, varying β significantly impacts I state evolution. This indicates that β substantially influences believed-users, affecting propagation duration, while α has minimal impact. Single-factor analysis corresponds to Scenario 1, while multi-factor analysis corresponds to Scenario 2.

Publisher credibility affects information propagation in social circles, with system balance time decreasing as credibility increases. However, this only influences convergence speed, not the fundamental nature of information authenticity.

3 Conclusion

This paper introduces information and human credibility through an Aesop's fable, proposing an IBU model based on information propagation characteristics. Real-world conversions between believed and unbelieving users effectively categorize information into two opposing types. The division of uncertain ignorant users into believed and unbelieving categories stems from insufficient knowledge and information discrimination capabilities.

Simulation results demonstrate that the model captures social network propagation characteristics, successfully dividing information into opposing categories. Through fixed conversion rates within unit time, dynamic changes between believed and unbelieving users during propagation ultimately stabilize. This aligns with real-world information network propagation. Regardless of how original information credibility probability varies (0~1), the final equilibrium remains consistent, proving that information credibility depends on content authenticity

rather than publisher credibility. User subjective attitudes affect propagation duration but not final outcomes.

Model limitations include: (1) only dividing ignorant users into two categories, without considering neutral users who remain skeptical, and (2) treating learning rates as constant when in reality individual learning absorption varies temporally. These factors present significant challenges for future information credibility research while providing deeper research directions and theoretical foundations for information management and control personnel.

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Note: Figure translations are in progress. See original paper for figures.

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