Research on Evaluation Methods for Information Credibility in Online Communities Based on Online Reviews: Postprint

Authors: Guo Jia, Guo Yong, Shen Wang, Pan Mengya

Date: 2023-07-26T00:00:00+00:00

Abstract

[Purpose/Significance] This paper proposes an evaluation method for information credibility in online communities based on online reviews, providing an effective basis for information governance. [Method/Process] An evaluation index system for information credibility in online communities is constructed based on online reviews, employing improved Analytic Hierarchy Process (AHP) theory to determine index weights; utilizing an LSTM model for sentiment classification of reviews, and adopting an improved D-S evidence theory model to fuse sentiment classification data as the index quantification calculation method. Taking the Zhihu online community as an example, the credibility of online information content is calculated from three perspectives: screened online reviews with credible opinion evaluations, all online reviews, and questionnaires. [Results/Conclusion] Experimental results demonstrate that the credibility ranking based on credible opinion comments is substantially consistent with that based on questionnaires, demonstrating the feasibility of utilizing online reviews for network information credibility evaluation.

Full Text

Research on Evaluation Methods for Information Credibility in Online Communities Based on Online Reviews

Guo Jia, Guo Yong, Shen Wang, Pan Mengya

School of Management, Jilin University, Changchun 130025

Abstract:

[**Purpose/Significance**] This paper proposes an evaluation method for information credibility in online communities based on online reviews, providing an effective basis for information governance. [**Method/Process**] The study constructs an evaluation index system for network community information credibility based on online reviews, using improved AHP theory to determine indicator weights. An LSTM model is employed to classify review sentiment, and an improved D-S evidence theory model is used to fuse sentiment classification data as the indicator quantification calculation method. Taking the Zhihu online community as an example, the credibility of network information content is calculated from three perspectives: screened online reviews with credible opinion evaluations, all online reviews, and questionnaires. [**Result/Conclusion**] Experimental results show that the credibility ranking based on credible opinion reviews is basically consistent with that based on questionnaires, demonstrating the feasibility of using online reviews to evaluate network information credibility.

Keywords: online reviews; information credibility; improved D-S evidence theory model; online community

Introduction

With the explosive growth of network information, online information has become the primary source for people. Under conditions of unrestricted network data access, large amounts of unverified information spread through platforms such as WeChat, Weibo, and Q&A communities, exerting significant influence on various aspects of people' s lives. The dissemination of false and unreliable information has become rampant, causing substantial damage to the online information ecosystem. In unfamiliar domains, people find it difficult to distinguish between true and false information. Researchers have proposed using "information governance" to address this challenge, with the prerequisite for effective information governance being the identification of false information to control its spread at the source. Early research primarily constructed evaluation index systems based on three dimensions—information source, information content, and media platform—to assess information credibility. Among these, credibility evaluation of information content mainly relied on rhetorical and text classification methods, whose accuracy, professionalism, and other aspects required expert judgment and could not handle massive network information resources. Therefore, this paper aims to obtain group user opinions from online reviews to compensate for existing method limitations and construct a more reasonable and effective evaluation method for network community information credibility.

1 Related Theoretical Research

1.1 Research on Evaluation Indicators for Network Information Credibility Through literature review, network information credibility evaluation mainly includes three perspectives: information source credibility, information content credibility, and media credibility.

Information source credibility primarily examines the influence of different communicator characteristics on the information processing process within media contexts, where communicators can be individuals, groups, or organizations [1]. Therefore, research on information source credibility is typically divided into institutional and individual aspects. Institutional type, authority, and other factors influence institutional information source credibility [2], while author identity, status, and reputation are key factors in evaluating personal information source credibility [3]. Gao Mingxia et al. evaluated Sina Weibo user information source credibility using total information volume, verification status, and total follower count [4]. M. Alrubaiian et al. assessed Twitter social network user credibility from the perspectives of professionalism and reputation [5].

Information content credibility explores users' perception of credibility regarding the information object itself [6]. C. N. Wathen et al. argued that information content credibility evaluation should include professionalism, timeliness, accuracy, and relevance [7]. R. Li et al. believed that argument strength and information quality affect information credibility [8]. T. Lucassen et al. divided information content credibility into semantic features and surface features: semantic features include accuracy, completeness, comprehensiveness, and neutrality, while surface features include length, references, images, and writing style [2]. Gao Mingxia et al. evaluated information content credibility using surface features such as text length, spelling errors, charts, repeated punctuation, emotional words, repost counts, and comment counts [4]. G. Sarna et al. evaluated user credibility by detecting cyberbullying in network information content [9]. Li Baozhen et al. used user evaluation information as prior experiential information for information content evaluation to assess information content credibility [10].

Media credibility focuses on the communication channels of information content rather than the sender [1]. C. N. Wathen and J. Burkell believe that website interface design, loading speed, interface attractiveness, usability, accessibility, interactivity, and flexibility and other technical factors affect users' credibility perception [7]. R. Li et al. verified the impact of media dependence, interactivity, and media transparency on information credibility [8]. B. J. Fogg et al. used questionnaire surveys to study factors affecting website credibility, finding that website interface design, information design/structure, information focus, advertising, information usefulness and accuracy, website creators, and customer service all influence credibility [11].

Through the above literature review, we constructed an evaluation index system containing 3 dimensions and 26 indicators [12]. However, during the analysis of Zhihu answer online comments (coding 50,000+ online comments according to the constructed evaluation index system), we found some indicators were rarely used. Therefore, we deleted indicators with statistical frequency less than 0.1% [12], ultimately forming an evaluation index system containing 3 dimensions and 21 indicators, as shown in Table 1 .

Table 1 Framework for Network Community Information Credibility Evaluation Indicators Based on Reviews

Dimension	Indicator	Description
Source Credibility	Institutional Reputation & Status	Institution' s visibility and position in the industry
	Institutional URL	Institution' s website URL, whether the URL has detailed institution information (name, etc.), number of authoritative authors, sponsors, etc.
	Author Identity	Typically refers to author' s name, title, professional background, and qualifications
	Author Reputation & Status	Author' s visibility and industry status, including author' s creation volume, comment repost volume, etc.
	Author Affiliation	Author' s organization; the nature and status of the unit often affect user trust
	Author Purpose	Author' s purpose for publishing information, either to tell the truth about a topic or to serve self-interest with biased information
	Author Expertise	Relatively stable, systematic knowledge formed by the author in a professional field
Information Structure & Content Credibility	Format Universality	Whether text format and media format in information are universal; text formats include .doc, .txt, etc.; media formats include video, audio, etc.
	Expression Clarity	Whether text expression is clear and logical
	Writing Style	Whether writing style is easy to accept

Dimension	Indicator	Description
	Information Accuracy	Whether information content is true and verifiable
	Information Neutrality	Degree of impartiality in describing facts
	Information Timeliness	Whether information publication or update time meets user requirements
	Information Sufficiency	Degree to which system can provide required information or degree of adequate updating for the task at hand
	Information Completeness	Degree of information completeness, whether there is information omission or component incompleteness
	Information Relevance	Degree of match between information content and user' s target value, i.e., whether information content is relevant to user needs
	Information Coverage	Scope of subject areas and related areas involved in information content
	Information Understandability	Whether information content is easy to understand
	Information Rationality	From a natural perspective, whether information description conforms to natural common sense and objective laws; from a social perspective, whether it conforms to social norms and public opinion
Media Credibility	Contact Method	Ways and processes for information publishers to connect with information users

Dimension	Indicator	Description
	Publication Channel Authority	Whether information publication and dissemination channels are authoritative and convincing

1.2 Research on Network Information Credibility Evaluation Methods In network information credibility evaluation methods, credibility indicator features are primarily extracted and different evaluation models such as SVM models, hidden Markov models, and Bayesian inference theory are employed. Gao Mingxia et al. proposed a Chinese microblog credibility assessment framework based on information fusion (CCM-IF) [4]. G. Sarna et al. first extracted cyberbullying features—links, badmouthing, negative/positive emotions, proper nouns, pronouns, etc.—then used SVM models to assess user credibility [9]. M. Park et al. used topic models and hidden Markov models to evaluate the credibility of online medical data [13]. M. Kakol et al. constructed a network information credibility evaluation prediction model based on user evaluations, with model construction based on empirical data [14]. Y. Namihira et al. proposed an automatic credibility evaluation method based on topic and opinion classification [15]. Li Baozhen et al. proposed a network information content credibility measurement model based on Bayesian inference theory [10]. Meng Meiren et al. selected four types of features—content completeness, emotional balance, comment timeliness, and publisher identity clarity—based on empirical results, using CRFs models for 4-level comment credibility classification and conducting feature combination experiments to obtain optimal feature combinations [16].

Existing information credibility evaluation methods such as Bayesian inference theory models, hidden Markov models, and SVM require empirical data to construct evaluation models. However, network information credibility evaluation has strong subjectivity, and currently no dataset is available for network information credibility evaluation. Therefore, this paper uses weighted D-S evidence theory to fuse user evaluation opinion data, obtains scores for each indicator, uses improved AHP to determine indicator weights, and finally calculates information credibility evaluation results.

2 Network Community Information Credibility Based on Online Reviews

2.1 Credibility Evaluation Sentiment Classification of Online Reviews Based on the constructed credibility evaluation index system, this paper manually annotates comments for credibility evaluation. Comment sentiment classification is used to obtain credibility evaluation opinion data from comments. For example, the comment "Please understand homologous recombination; imagination is unreliable" evaluates information accuracy; the comment "Makes sense" evaluates information rationality; comments such as "The most rational answer I' ve seen so far~" and "I also spotted a flaw in his argument here" both evaluate information rationality—the former is classified as positive, indicating the commenting user believes the information is rational, while the latter is classified as negative, indicating the commenting user believes the information is irrational.

Comment sentiment classification methods mainly include dictionary-based methods, support vector machine methods, LDA models, and machine learning methods [17-19]. In recent years, deep learning has achieved good results in text sentiment classification research. This paper adopts the LSTM deep learning model to identify sentiment polarity. The processing mainly includes comment text data preprocessing, word vector training, and LSTM sentiment classification model construction. This paper uses a two-level classification model for sentiment classification, i.e., sentiment classification results are either positive or negative. The specific analysis process is shown in Figure 1 [Figure 1: see original paper].

(1) word2vec word vector training. Before constructing the LSTM sentiment analysis model, words need to be converted into word vectors. The word2vec model is a word vector modeling tool developed by Mikolov et al. [20], which can be used to solve natural language problems and has achieved good results in Chinese comment sentiment classification applications [21]. Since large-scale, high-quality Chinese corpora are relatively scarce, and Wikipedia corpora represent daily life and general knowledge well, and Zhihu as a knowledge-based Q&A community contains not only daily life comments but also general knowledge, using Wikipedia corpora is feasible. On August 13, 2018, this paper downloaded the Chinese Wikipedia corpus package from the network (https://dumps.wikimedia.org/zhwiki/20190101/), processed it (including traditional-simplified conversion), performed word segmentation, and used word2vec for word vector training to obtain word vectors.

(2) LSTM sentiment classification model training. In natural language processing, recurrent neural networks (RNN) are typically used. In deep learning language processing models, sentences are input as sequences—adjacent characters form words, adjacent words form phrases, and adjacent phrases form sentences. RNN can effectively integrate neighboring positional relationships, better complete language tasks, make good use of contextual feature information, retain text sequence information, automatically select features, and perform classification. Therefore, this paper adopts the LSTM model as the learning model for sentiment polarity identification. The specific processing is shown in Figure 1: obtained sentiment-annotated corpora are processed, then segmented, sentence vectors are constructed based on word2vec-trained word vector models, and sentence vectors are input into the LSTM model for training to obtain the LSTM sentiment classification model.

Finally, the constructed LSTM sentiment classification model is used to perform sentiment classification on comment text content.

2.1.1 Comment Text Data Preprocessing This includes: (1) processing collected comment data, including redundant data cleaning, incomplete data deletion, symbol conversion, and other data cleaning work; (2) coding comments according to the constructed credibility evaluation index system, then selecting comments with credibility indicator evaluations—for example, the comment "Data speaks, I' m convinced" evaluates rationality and is a comment with credibility indicator evaluation, while the comment "I have thalassemia genes, can I not donate blood?" does not evaluate information credibility indicators; (3) segmenting comment text into sentences, then cleaning the segmented text again by deleting meaningless numbers, symbols, etc.; (4) word segmentation.

2.1.2 Construction of LSTM-Based Sentiment Analysis Model See section 2.1 for details.

2.2 Network Community Information Credibility Evaluation Method

2.2.1 Comment Fusion Method—Improved D-S Evidence Theory Model User comment data has strong subjectivity, creating uncertainty in information credibility evaluation. Therefore, how to utilize user comment data and establish a reasonable evaluation model is crucial. Evidence theory modeling tools have excellent evidence aggregation effects and have been widely applied in information fusion for expert systems, decision analysis, fault diagnosis, target recognition, etc. [22]. In the comment fusion process, the Zadeh paradox problem emerges. To address this issue, an improved D-S evidence theory model is adopted to process user comment data. In terms of user identification, this paper calculates both comment authors and users who liked the comments—i.e., users who liked a comment are considered to hold the same view as the comment author and are treated as independent evidence. The following is the mathematical model for comment fusion based on improved D-S evidence theory.

Let Θ be a recognition framework. The basic probability assignment on the recognition framework is a function m: $2^\Theta \rightarrow [0,1]$, called the mass function, satisfying m( ) = 0 and Σm(A) = 1. Then m is the basic credibility assignment on framework Θ, and the function Bel: $2^\Theta \rightarrow [0,1]$ defined by Bel(A) = Σm(B) (B Θ) is the belief function on Θ. Let pl: $2^\Theta \rightarrow [0,1]$, pl(A) = 1 - Bel(A), then pl is called the plausibility function of Bel. This function indicates the degree to which we do not doubt A or find A reliable or plausible. According to the above formula, we have Pl(A) = Σm(B) for all B A $\neq$. For a finite number of mass functions m_1, m_2, ⋯, m on Θ, the Dempster combination rule is:

$(m_1 \quad m_2 \quad \cdots \quad m\ )(A) = (\Sigma\_\{A_1\ A_2 \cdots A\ = A\}\ m_1(A_1) \times m_2(A_2) \times \cdots \times m\ (A\ ))$ / $(1 - \Sigma\_\{A_1 \cdots A\ =\ \}\ m_1(A_1) \times m_2(A_2) \times \cdots \times m\ (A\ ))$

where K is the normalization constant.

Based on the above theory, the evaluation framework is defined as:

(1) Let Θ be a recognition framework containing two incompatible hypothesis propositions, with power set 2^Θ = $\{A_1, A_2\}$. The focal elements are A_1 and A_2, where A_1 represents positive opinions and A_2 represents negative opinions.

(2) Each user's comment serves as a piece of evidence. For n pieces of evidence E_1, E_2, ···, E with basic trust assignment functions m_1, m_2, ···, m , the probability of positive comment opinions is p_1, p_2, ···, p . When p = 1, the comment is completely positive; when p = 0, the comment is completely negative.

(3) According to the Dempster combination rule, the ith feature value corresponds to the ith mass function m , and the n-dimensional feature vector F corresponds to n mass functions. When set A = $\{A_1\}$, i.e., the opinion is positive, the corresponding n mass functions are (m_1, m_2, ···, m) = (p_1, p_2, ···, p). Similarly, when set A = $\{A_2\}$, the corresponding n mass functions are (m_1, m_2, ···, m) = (1-p_1, 1-p_2, ···, 1-p).

(4) Let the number of positive opinion sentences be Pos and the number of negative opinion sentences be Neg, then:

p = Pos / (Pos + Neg)

(5) Comment information fusion. Due to significant contradictions in comment sentiment polarity, leading to evidence theory synthesis paradoxes, this paper adopts the weighted average method to solve this problem [23]. The specific method is as follows:

Step 1: Calculate the similarity coefficient between evidences and list the similarity matrix. The similarity coefficient between evidences E_1 and E_2 can be expressed as:

d_{12} = Σ_{A B = A ≠ } $m_1(A_1)m_2(A_2)$ / (Σ_{A B = A ≠ } $m_1(A_1)m_2(A_2)$ + Σ_{A B = } $m_1(A_1)m_2(A_2)$)

d_{12} [0,1]

Based on formula (4), calculate the similarity coefficients between evidences and represent them in matrix form:

[1 d_{12} ···d_1 d_{21} 1 ···d_2 ············d $_1$ d $_2$ ···1]

Step 2: Calculate the support degree of each evidence. Sum each row of the matrix to obtain the support degree for each evidence pair E :

sup(m) = Σd (i,j = 1,2,···,n)

Step 3: Calculate the credibility of each evidence. Normalize to obtain the credibility of evidence E :

Crd(m) = sup(m) / Σsup(m) (i,j = 1,2,···,n)

Step 4: Use credibility as weights to perform weighted average of the basic trust assignments of evidences.

Step 5: Use the D-S combination rule (formulas (1) and (2)) to synthesize the weighted average evidence, and take the weighted average evidence result as the credibility evaluation result for each indicator.

2.2.2 Indicator Weight Determination Method This paper uses the improved AHP method to determine indicator weights. The traditional AHP method requires consistency test results to judge result validity and needs multiple adjustments to pass consistency tests. This paper draws on Liang Xian et al. [24] to determine indicator weights. This method uses the optimal transfer matrix to determine weights in one step without requiring consistency tests. The calculation process is as follows:

Step 1: Use the Delphi method to construct the judgment matrix A, perform pairwise comparisons of indicators at all levels in the system to determine relative importance of each indicator. The scale for indicators at all levels is shown in Table 2 .

Table 2 Scale for Indicator Matrix Comparison

Attribute	Description	f(x,y)
x is equally important as y	x and y contribute equally to the overall goal	1
x is slightly more important than y	x’ s contribution is slightly greater than y’ s	3
x is obviously more important than y	x’ s contribution is obviously greater than y’ s	5
x is strongly more important than y	x’ s contribution is strongly greater than y’ s	7
x is extremely more important than y	x’ s contribution is overwhelmingly greater than y’ s	9
x is between levels compared to y	Compromise between adjacent judgments	2,4,6,8

Step 2: Calculate the optimal transfer matrix of judgment matrix A:

$b = \lg(a)\ (i,j = 1,2,\cdots,n)$

$c = (1/n)\Sigma(b - b)\ (i,j = 1,2,\cdots,n)$

Step 3: Calculate the quasi-optimal consistent matrix:

$a^* = 10\hat{}c\ \ (i,j = 1,2,\cdots,n)$

Step 4: Find the eigenvector of A* (using the root method):

$\bar{w} = (\Pi a^*)^\wedge(1/n)$ (i = 1,2,···,n)

Step 5: Normalize to obtain indicator weights:

$w = \bar{w} / \Sigma\bar{w}$ (i = 1,2,···,n)

3 Application Research

3.1 Data Collection and Preprocessing Empirical data comes from the Zhihu Q&A community. After analyzing Zhihu topics, we selected blood donation and genetically modified topics, which attracted significant user attention and debate, as collection themes. Using web crawlers, we crawled 54,021 comments and related information (including questions, answers, like counts, etc.) from November 15-23, 2017. We used grounded theory to code the 54,021 comments for information credibility evaluation, with 29,096 comments evaluating credibility. Due to the large number of answers, we selected 10 answers with more credible opinion comments as samples. Basic information for each answer is shown in Table 3 .

Table 3 Basic Information Table of Zhihu Answers

No.	Topic	Viewpoint	Author Background	Likes	Comments
1	Blood donation	Support	Clinical medicine PhD	998	1,280
2	Blood donation	Oppose	Civil engineering student	1,280	2,560
...	...	...	...	...	...
9	GMO	Neutral	GMO industry personnel	1,500	890
10	GMO	Support	Well-known online novelist	890	450

After segmenting comments, this paper deleted character strings and numbers without emotional meaning, obtaining 15,562 sentences, then used the Jieba segmentation tool to segment comment sentences.

3.2 Online Review Credibility Evaluation Sentiment Classification First, download the latest Chinese data from Wikipedia as word vector training corpus, removing help pages, redirects, and other useless pages. Second, filter special non-text markers. Finally, convert traditional Chinese to simplified Chinese in text information. Clean the corpus by removing punctuation, numbers, non-Chinese characters, etc. After word segmentation, perform word vector training with a dimension of 300 and a sliding window size of 5 to obtain the word vector model library.

This paper constructed a network community comment sentiment classification corpus containing 5,000 manually annotated sentiment polarity instances by analyzing collected comments. Use Jieba software for corpus segmentation and construct sentence vectors based on word vectors. The LSTM model input nodes are set to 256, hidden nodes to 128. After training, the LSTM sentiment classification model is obtained with a classification accuracy of 90.01%.

Transform cleaned and processed online comments into sentence vectors, input them into the LSTM sentiment classification model to obtain sentiment classification based on the LSTM model.

3.3 Network Community Information Credibility Evaluation Results Based on Online Reviews According to the comment fusion method in section 2.2.1, perform fusion calculation on sentiment classification data. In the calculation process, not only comment users' viewpoints are calculated but also users who liked the comments—i.e., when a user likes a comment, they are considered to hold the same viewpoint and are calculated as independent evidence. Fuse sentiment evidence from various users to obtain credibility indicator values for each answer, as shown in Table 4 .

Based on the weight calculation method in section 2.2.2, use expert judgment matrices to calculate indicator weights, as shown in Table 5 . Finally, calculate the information credibility evaluation results for each question, as shown in Table 6 .

3.4 Evaluation Result Analysis Information credibility is the degree of belief that users judge something to be true based on experience, representing subjective perception. In the Zhihu community, answer agreement counts and comment counts cannot reflect answer credibility (for example, an answer containing only a funny sentence may receive higher agreement not because users believe the answer but because they find it interesting). Therefore, to verify evaluation result validity, this paper selected 50 survey participants to conduct questionnaires on each question' s credibility, removing 6 invalid questionnaires and finally collecting 44 questionnaires—hoping to obtain users' subjective judgments of answer credibility. Survey participants ranged in age from 18-35, involved 19 industries or professions, with education levels of high school, undergraduate, and master' s. Participants needed to review each answer in detail and complete the questionnaire. Survey question one asked whether question credibility was credible, uncertain, or not credible, corresponding to values of 0, 0.5, and 1; question two asked about familiarity with the question, corresponding to values of 1, 3, and 5. Use question familiarity as weights to calculate each answer' s credibility, as shown in formula (13). Calculation results are shown in Table 6. To verify whether using all comment data can evaluate information content credibility, this paper performed sentiment analysis on all comments and used evidence fusion methods to calculate network information content credibility values based on all comments, also shown in Table 6.

$$C = c \times \Sigma(f_1 + f_2 + \cdots + f\ ) \ (i = 1,2,\cdots,n)$$

Where C is the final credibility evaluation result of the answer, n users evaluated answer credibility, f is the ith user' s familiarity with the question, and c is the ith user' s credibility evaluation value for the question.

This paper reordered evaluation results obtained by three methods according to numerical value for result analysis, as shown in Table 7 . Through credibility value ranking, we found that after removing answer 2, the ranking based on questionnaire credibility values is basically consistent with that based on credible opinion comment sentiment analysis, demonstrating the effectiveness of credibility evaluation methods based on credible opinion sentiment analysis. The ranking based on all comment sentiment analysis is inconsistent with questionnaire-based credibility evaluation results, indicating that using all comment sentiment analysis to evaluate information content credibility is inaccurate. Questionnaire-based credibility values are slightly higher than those based on credible opinion comment sentiment analysis, as shown in Figure 2 [Figure 2: see original paper]. This occurs because when users question information content, they are more likely to lead to credibility opinion comments. From Figure 2, we also observe an interesting phenomenon: when credibility evaluation values are in the 0.4-0.7 range, questionnaire-based credibility values are basically consistent with credible opinion comment sentiment analysis-based credibility values, indicating that when credibility evaluation is uncertain, credible opinion comment sentiment analysis-based credibility evaluation is closer to actual evaluation. When credibility evaluation results tend toward credible or not credible, credible opinion comment sentiment analysis-based credibility evaluation values are lower than actual values.

This paper analyzed outliers. Survey participants rated answer 2 highly (ranked 4th), while comment sentiment analysis-based credibility value ranked 10th, showing a large difference. Answer 2' s viewpoint was "Do not encourage blood donation; the school blood donation truck experience felt bad." Comment content mostly described personal blood donation facts, such as "I fainted during my first blood donation because I hadn' t eaten," "My health hasn' t been as good since then," and "I fainted for five minutes right after donating." According to sentiment analysis results, these comments were all negative evaluations, representing that answer content was not credible. However, their viewpoints actually aligned with the answer' s viewpoint, indicating the answer was credible, thus causing evaluation result differences. This issue points to a direction for further research: when comments contain factual descriptions, sentiment classification cannot represent comment credibility evaluation. It is necessary to verify the consistency between factual description viewpoints and answer content viewpoints to evaluate information credibility.

Conclusion

This paper proposes an evaluation method for calculating network information credibility based on online reviews. First, it constructs a network information credibility evaluation index system based on online reviews, uses an improved AHP model to determine weights; employs an LSTM model to calculate comment sentiment polarity, fuses user comment data through an improved evidence theory model, and finally calculates network information credibility values combined with weights. By processing comment information from 10 samples under two Zhihu themes, the proposed method is experimentally verified. Results show that after removing one outlier, the ranking of network information credibility values based on questionnaires is basically consistent with that based on credible opinion comments, effectively ranking network information credibility. Using all comments to evaluate network information has low accuracy; credible opinion comment screening must be performed before evaluating network information credibility based on comments. This study also has limitations: sample types only selected comments from two Zhihu themes, comment quantity scale is limited, and outliers appear, indicating that network information credibility evaluation is a complex process. When comments contain factual descriptions, further research is needed on the consistency between comment viewpoints and information content viewpoints. Future research hopes to expand sample size and scope and comprehensively use multiple methods to solve these problems.

References

[1] KIOUSIS S. Public trust or mistrust? perceptions of media credibility in the information age[J]. Mass communication & society, 2001, 4(4): 381-403.

[2] LUCASSEN T, SCHRAAGEN J M. Factual accuracy and trust in information: the role of expertise[J]. Journal of the American Society for Information Science and Technology, 2011, 62(7): 1232-1242.

[3] WESTERMAN D, SPENCE P R, HEIDEB V D. Social media as information source: recency of updates and credibility of information[J]. Journal of computer-mediated communication, 2014, 19(2): 171-183.

[4] GAO Mingxia, CHEN Furong. Chinese microblog credibility assessment method based on information fusion[J]. Computer applications, 2016, 36(8): 2071-2075.

[5] ALRUBAIAN M, AL-QURISHI M, AL-RAKHAMI M, et al. Reputation-based credibility analysis of twitter social network users[J]. Concurrency & computation practice & experience, 2017, 29(7): 1-12.

[6] RIEH S Y, DANIELSON D R. Credibility: a multidisciplinary framework[J]. Annual review of information science & technology, 2010, 41(1): 307-364.

[7] WATHEN C N, BURKELL J. Believe it or not: factors influencing credibility on the Web[J]. Journal of the Association for Information Science and

Technology, 2002, 53(2): 134-144.

[8] LI R, SU A. Factors influencing information credibility on social media platforms: evidence from facebook pages[J]. Procedia computer science, 2015, 72: 314-328.

[9] SARNA G, BHATIA M P S. Content based approach to find the credibility of users in social networks: an application of cyberbullying[J]. International journal of machine learning & cybernetics, 2015, 8(2): 1-13.

[10] LI Baozhen, WANG Ya, ZHOU Ke. Social media network information content credibility measurement based on Bayesian theory[J]. Data analysis and knowledge discovery, 2017, 1(6): 83-92.

[11] FOGG B J, SOOHOOC, DANIELSON D R, et al. How do users evaluate the credibility of Websites? a study with over 2,500 participants[M]. New York: Association for Computing Machinery, 2003.

[12] SHEN Wang, KANG Xiaopu, WANG Jiaxin, et al. Social Q&A community information credibility evaluation from user perspective[J]. Library and information service, 2018, 62(17): 104-111.

[13] PARK M, SAMPA THKUMAR H, LUO B, et al. Content-based assessment of the credibility of online healthcare information[C]//IEEE international conference on big data. USA: IEEE, 2013: 51-58.

[14] KAKOL M, NIELEK R, WIERZBICKI A. Understanding and predicting Web content credibility using the content credibility corpus[J]. Information processing & management, 2017, 53(5): 1043-1061.

[15] NAMIHIRA Y, SEGAWA N, IKEGAMI Y, et al. High precision credibility analysis of information on Twitter[C]//International conference on signal-image technology & internet-based systems. Kyoto: IEEE, 2013: 909-915.

[16] MENG Meiren, DING Shengchun. Research on credibility of online Chinese product reviews[J]. Modern library and information technology, 2013, 29(9): 60-66.

[17] TANG Xiaobo, LAN Yuting. Microblog product review sentiment analysis based on feature ontology[J]. Library and information service, 2016, 60(16): 121-127, 136.

[18] CAO Yu, WANG Mingyang, HE Huixin. Multi-sentiment classification of microblog text based on emotional dictionary expansion[J]. Intelligence journal, 2016, 35(10): 185-189.

[19] HE Yue, ZHAO Shupeng, HE Li. Combined micro-text sentiment orientation classification research based on sentiment knowledge and machine learning algorithms[J]. Intelligence journal, 2018, 37(5): 189-194.

[20] WANG Qinqin, ZHANG Yuhong, LI Peipei, et al. Cross-domain sentiment classification method based on word2vec[J]. Computer application research,

2018, 35(10): 50-53.

[21] ZHANG Dongwen, YANG Pengfei, XU Yunfeng. Chinese comment credibility research based on word2vec and SVMperf[J]. Library and information service, 2018, 62(17): 104-111.

[22] HE Jingjing, CAI Desheng, JIE Fei, et al. Feature fusion using D-S evidence theory for synonymous entity recognition[J]. Computer application research, 2018, 35(5): 1429-1433.

[23] YANG Fengbao, WANG Xiaoxia. Conflict evidence synthesis method for D-S evidence theory[M]. Beijing: National Defense Industry Press, 2010.

[24] LIANG Xian, SHENG Zhaohan, XU Nanrong. An improved analytic hierarchy process[J]. Systems engineering, 1989(3): 5-7.

Author Contributions

Guo Jia: Paper writing, data analysis, and final manuscript revision; Guo Yong: Data analysis and processing; Shen Wang: Research design; Pan Mengya: Data analysis.

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