Integrating Word2vec and WGRA for Ranking Answer Usefulness in Social Q&A Communities: A Case Study of Ctrip Q&A Postprint

Authors: Guo Shunli, Bu Hui

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Abstract

[Purpose/Significance] To address the problems of diversified user information needs and answer redundancy and overload in social Q&A communities, this paper proposes an answer usefulness ranking method oriented towards users' personalized needs, assisting users in efficiently screening and acquiring useful answer knowledge. [Method/Process] First, through literature review and expert consultation, an answer usefulness evaluation index system is constructed from three dimensions: answer characteristics, answerer characteristics, and answer timeliness. Then, users' personalized needs are integrated at the semantic level, and an answer usefulness ranking method combining weighted grey relational analysis and Word2vec is designed to achieve answer ranking oriented towards user needs. [Results/Conclusion] Through comparative analysis of experimental results, it is found that compared with traditional ranking methods based on "like counts" and "answer time," the method designed by the authors yields higher user satisfaction and better satisfies users' personalized knowledge needs.

Full Text

Research on Answer Usefulness Ranking Method in Social Q&A Communities Integrating Word2vec and WGRA: A Case Study of Ctrip Q&A

Guo Shunli, Bu Hui
School of Communication, Qufu Normal University, Rizhao 276800

Abstract

[**Purpose/Significance**] To address the diversified information needs of users and the problem of redundant and overloaded answers in social Q&A communities, this paper proposes an answer usefulness ranking method oriented toward users' personalized needs to assist users in efficiently filtering and obtaining useful answer knowledge. [**Method/Process**] First, through literature research and expert consultation, an answer usefulness evaluation index system was constructed from three dimensions: answer characteristics, answerer characteristics, and answer timeliness. Then, integrating users' personalized needs from the semantic level, an answer usefulness ranking method combining Weighted Grey Relational Analysis (WGRA) and Word2vec was designed to realize answer ranking oriented toward user needs. [**Result/Conclusion**] Through comparative analysis of experimental results, it was found that compared with traditional ranking methods based on "like counts" and "answer time," the answer usefulness ranking method designed in this study yields higher user satisfaction and better meets users' personalized knowledge demands.

Keywords: user demand; answer usefulness; WGRA; Word2vec; social Q&A community
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In recent years, with the development and popularization of social Q&A communities, these platforms have gradually become important channels for internet users to obtain high-quality information or professional knowledge, and have begun to evolve toward higher quality, specialization, and socialization. However, due to the user-generated nature of questions and answers in social Q&A communities, varying levels of user information literacy, and insufficient community moderation, user-generated content in these communities suffers from problems such as redundancy, uneven quality, and low matching degree between answers and user needs. Furthermore, personalized ranking oriented toward user needs has not been achieved. Currently, domestic and international research on answers in social Q&A communities mainly includes answer recommendation, answer quality evaluation, answer ranking, and answer fusion. Among these, answer recommendation targets questioners, automatically ranking candidate answers through algorithms to enable questioners to select the best answer more quickly. Research on answer recommendation has focused on identifying the best answer from different perspectives and using different methods. For example, Feng Wenzheng et al. used deep learning models such as bidirectional LSTM, word vectors, and 2D neural networks combined with traditional features like TF-IDF and LCS to screen best answers; Xie Zhengwen et al. shifted their approach to finding finer-grained semantic information between questions and answers to filter optimal answers; W. Ma et al. used LSTM and CNN to extract semantic features of question-answer pairs and calculate matching degree to realize answer recommendation. The answer usefulness ranking proposed in this study, however, targets most browsers, presenting answer order personalized according to the answer usefulness perceived by individual users. Thus, there is an essential difference between answer recommendation and answer usefulness ranking.

Additionally, answer usefulness and answer quality in social Q&A communities overlap but differ. Answer quality generally refers to the goodness of an answer based on certain standards, with evaluation based on answer characteristics according to artificially given criteria. Current research on answer quality mainly focuses on evaluating answer quality from answer characteristic perspectives. J. Jiwon et al. first proposed using non-textual features such as answer length, adoption rate, recommendation count, and page click-through rate, successfully identifying answer quality using a maximum entropy model; E. Agichtein et al. innovatively combined non-textual and textual features, using C4.5 decision trees to comprehensively analyze answer quality in Yahoo! Answers. The concept of answer usefulness, however, derives from the Information Acceptance Model, which suggests that when receiving external information, users use information quality and information source credibility as criteria for judging information usefulness. Therefore, answer usefulness in social Q&A communities refers to the value of an answer perceived by users according to their personal information needs when retrieving or browsing answers, and the degree to which it helps users solve problems. Consequently, answer usefulness ranking refers to personalized ranking results oriented toward user needs based on the value and usefulness of answers perceived by users.

Current domestic and international research on answer usefulness in Q&A communities mainly unfolds in two aspects: (1) Research on factors influencing answer usefulness in online Q&A communities. Many scholars have verified various factors affecting answer usefulness from different perspectives based on different theories. S. M. Mudambi et al., studying Amazon.com, found that online review usefulness is related to review depth, sentiment polarity, and product type; Xie Chenbo constructed an answer usefulness theoretical model from the perspective of information acceptance theory and proved through empirical research that out-degree centrality has no significant effect on answer usefulness while in-degree centrality has a significant positive effect; Zeng Jenni found that historical questioning experience has no significant effect on answer usefulness, while answer length, sentiment orientation, and number of images used have significant positive effects, and four factors—answerer's historical answering experience, article publishing experience, in-degree network centrality, and out-degree network centrality—all positively affect users' perceived usefulness; Wang Chen pointed out that answer text length, re-editing, and text professionalism have significant positive effects on answer usefulness, while the number of images used and sentiment orientation have negative effects, and the answerer's historical question and answer counts, Zhihu verified identity, in-degree and out-degree network centrality also positively affect answer usefulness, while column quantity has a negative effect. (2) Research on answer ranking methods in social Q&A communities. Scholars have conducted answer ranking research using different methods based on different theoretical foundations. C. Shah et al. manually scored Yahoo! Answers from dimensions such as relevance, informativeness, and completeness to explore answer usefulness; Li Chen et al. extracted textual and non-textual features of answers and used manual annotation and logistic regression for quality classification; Z. M. Zhou et al. incorporated user information into SVMRank and List-Net ranking models, achieving superior results; Lai She'an and Cai Zhongmin calculated question-answer similarity and weights from a semantic similarity perspective to select best answers; Yi Ming and Zhang Tingting believed that using K-Medoids clustering algorithm and rough set theory to modify answer quality index systems, then applying weighted grey relational analysis to calculate grey relational degree produced ranking results with higher user satisfaction; Liu Yu and Yuan Jian improved the TEM model, analyzing user behavior to form new answer ranking and automatic filtering models; L. Yang et al. modeled topic similarity and user authority in StackOverflow through the TEM model combined with text content models and link structure analysis to generate ranking results.

Through reviewing existing research, it is found that answer quality or usefulness research has attracted scholars' attention and produced a series of research results. Using different theories and multiple perspectives to analyze influencing factors of answer usefulness and their impact results, and actively improving ranking methods has laid a theoretical foundation and provided reference basis for this study. However, existing research mainly aims to identify and evaluate answer quality, with few studies combining answer usefulness and answer ranking, and even fewer considering users' personalized needs at the semantic level. Users have certain time tolerance when retrieving or browsing useful answers, expecting to quickly find answers matching their own needs, tending to obtain optimal answers at minimum cost. Based on this, this study draws on existing relevant research and proposes an answer usefulness ranking method oriented toward user needs from the semantic level. First, key indicators affecting answer usefulness in social Q&A communities are screened from three dimensions of answer characteristics, answerer characteristics, and answer timeliness and quantified respectively. Then, a new method for answer usefulness ranking in social Q&A communities is proposed by combining entropy weight method, weighted grey relational analysis, and Word2vec. Finally, the Hangzhou topic in Ctrip's Q&A community is selected as the research object to verify the effectiveness and scientificity of the proposed answer usefulness ranking method.

2 Evaluation Indicators for Answer Usefulness in Social Q&A Communities

2.1 Selection and Quantification of Key Evaluation Indicators

Based on the author's published paper "Research on Automated Evaluation of Answer Quality in Social Q&A Communities—A Case Study of Zhihu," this study believes that users are influenced by multiple factors when evaluating answer usefulness. Generally, dimensions such as answer text content quality, answerer quality, and timeliness need to be considered, and most research has confirmed that these three types of features affect answer usefulness. Yi Ming et al. compared 11 learning algorithms and found that like counts and follower counts have the greatest impact on answer quality; Shi Guoliang used content analysis and regression models to find that answerer influence, answer timeliness, and answer length positively affect answer recognition; Zhai Qian believed that product attribute feature words and emotional expression can improve users' trust and perceived usefulness of online reviews when browsing. Meanwhile, the author also consulted existing research literature and relevant experts to establish answer usefulness evaluation indicators from three perspectives: answer content characteristics, answerer characteristics, and answer timeliness. The specific indicators and their quantification methods are shown in .

shows the indicators and quantification methods for answer usefulness ranking in social Q&A communities, including: - Answer text length: Total number of valid characters, quantified by data collection and Excel functions - Number of images: Total count of valid images in answers - Number of comments: Total comments under answers - Attribute description words: Count of attribute feature words about the question subject - Sentiment analysis value: Calculated using Python's SnowNLP library - Number of likes: Total likes received by answers - Answerer authority: Follower count of answerer - Answerer likes: Total likes received by answerer across all answers - Answer timeliness: Time difference between answer publication and reading, in days

2.2 Weight Assignment Using Entropy Weight Method

The weight assignment of answer usefulness indicators is crucial for subsequent ranking. Since weights reflect the importance of each indicator in the entire answer usefulness ranking index system and relate to the contribution of indicators to ranking results, they must be scientifically and reasonably assigned according to the importance of each indicator. The entropy weight method, as a typical weight assignment approach, has wide applications. It believes that the larger the entropy value of an indicator, the greater its information content, the richer its content, the stronger its usefulness to users, and the larger its weight should be. Entropy value can represent the usefulness degree of information. When the entropy value of information reaches its maximum (i.e., entropy value is zero), the usefulness of information is also zero. The entropy weight method determines specific weights based on the information content provided by each indicator and is a relatively objective weighting method.

Scholars have widely applied the entropy weight method in various fields for indicator weight assignment. For example, Li Shuai et al. used entropy weight method and analytic hierarchy process to determine weights for Ningxia urban human settlement environment quality evaluation; Xin Guixin et al. applied entropy weight method to evaluate the post-effect of high-standard farmland construction. The entropy weight method has been widely recognized for its advantages: compared with other weighting methods, it more accurately screens useful information, and it can eliminate the negative impact of excessive subjectivity in traditional weighting methods, increasing the scientificity and credibility of weights. Therefore, this study adopts the entropy weight method to assign weights to answer usefulness indicators, determining weights based on actual data results. According to the internal principle of entropy weight method, the basic steps are as follows:

(1) Standardize indicator data. To prevent experimental errors caused by inconsistent measurement units of indicators, the original data of each indicator needs to be standardized first. Assuming there are K data items, each with X evaluation indicators, the standardized indicator is y. The specific formula is:

$$y_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})}$$

(2) Calculate the entropy value of indicators. According to the definition of information entropy in information theory, the calculation formula for the entropy of a data item is:

$$E = -\ln(n)^{-1} \sum p_{ij} \ln(p_{ij}) \quad (i = 1, 2, \dots, m; j = 1, 2, \dots, n)$$

where $p_{ij} = \frac{y_{ij}}{\sum y_{ij}}$. If $p_{ij} = 0$, then $\lim_{y_{ij}=0} p_{ij} \ln(p_{ij}) = 0$.

(3) Determine the weight of each indicator. Based on the information entropy calculation formula, calculate the information entropy of each indicator as $E_1, E_2, E_3, \dots, E_k$. Then calculate the weight W_i of each indicator through information entropy, with $0 \leq W_i \leq 1$ and $\sum_{i=1}^{k} W_i = 1$:

$$W_i = \frac{1 - E_i}{k - \sum E_i} \quad (i = 1, 2, \dots, k)$$

3 Process of Usefulness Ranking Method Integrating Weighted Grey Relational Analysis and Word2vec

3.1 Introduction to Related Technical Methods

3.1.1 Word2vec Algorithm The Word2vec word vector model was first proposed by Tomas Mikolov, with the main idea of using spatial vectors to represent words. Word2vec transforms text into K-dimensional vector operations, using vector similarity in space to represent text semantic similarity. Words are converted into points in space after training, with each point representing a word. The similarity between words is obtained by measuring the distance between word vectors in space. Therefore, this study uses Word2vec to calculate the semantic similarity of question-answer pairs.

Word2vec includes two models: CBOW and Skip-gram. CBOW predicts the probability of the current word through context, while Skip-gram predicts the probability of context words through the current word. Although the two training models are opposite in direction, they have similar principles and are both based on Huffman trees to construct a multi-layer neural network, obtaining corresponding input and output from given text, and finally obtaining word vectors through continuous training and parameter modification. Literature review shows that the Skip-gram model is superior in processing professional domain texts, so this study selects the Skip-gram model to train word vectors. The specific working principle architecture is shown in [Figure 1: see original paper].

3.1.2 Weighted Grey Relational Analysis Method Grey Relational Analysis (GRA) originates from the grey system theory proposed by Chinese scholar Deng Julong in 1982. Its basic idea is to use mathematical methods to represent data of various factors and judge the grey correlation degree according to the fitting degree of geometric shapes between experimental data curves and reference data curves. Generally, when conducting grey relational analysis, the arithmetic mean of grey relational coefficients at each time point is used as the grey relational degree, which does not consider the information entropy values of elements in the comparison sequence and reference sequence, causing certain information loss and failing to correctly reflect the relationship between experimental data and reference sequence. Therefore, this study uses the Weighted Grey Relational Analysis (WGRA) optimized by the entropy weight method to calculate the weighted grey relational degree of answers. The basic steps of WGRA are as follows:

(1) Determine analysis sequences, i.e., determine reference and comparison sequences. Quantified data of indicators of each answer constitute the analysis sequence, set as $X(i) = \{X(k)|k = 1, 2, \dots, n\}, i = 1, 2, \dots, m$, where m is the specific number of answers under each question. The reference sequence should select optimal values of each indicator as the comparison standard, set as $Y = \{Y(k)|k = 1, 2, \dots, n\}$.

(2) Perform dimensionless processing of data. Since initial measurement units and magnitude levels of indicators may differ, data need to be processed through initial value or mean value methods for accurate analysis and comparison.

(3) Calculate correlation coefficients, i.e., calculate correlation coefficients between corresponding elements of each comparison sequence and reference sequence according to formulas.

First, calculate absolute differences between corresponding elements of comparison and reference sequences:

$|x_0(k) - x_i(k)| \quad (k = 1, 2, \ldots, m; i = 1, 2, \ldots, n; n$ is the number of evaluation objects)

Second, calculate $\min_i \min_k$ and $\max_i \max_k$ as shown in formulas (5) and (6):

$$\min_i \min_k = \min_i \min_k |x_0(k) - x_i(k)|$$

$$\max_i \max_k = \max_i \max_k |x_0(k) - x_i(k)|$$

Then, calculate correlation coefficient $\xi_i(k)$ according to formula (7):

$$\xi_i(k) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \rho \cdot \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \cdot \max_i \max_k |x_0(k) - x_i(k)|}$$

where ρ is the resolution coefficient taking values in $(0, 1)$. The smaller the ρ value, the greater the difference between correlation coefficients and the stronger the distinguishing ability. Typically, ρ takes 0.5.

(4) Calculate weighted relational degree, i.e., calculate the average value of correlation coefficients at each moment to represent the specific correlation degree between comparison and reference sequences. This study uses indicator weights W_i calculated by the entropy weight method to optimize grey relational analysis, forming the weighted grey relational degree method with calculation formula (8):

$$\gamma_i = \sum_{k=1}^{n} \gamma_i(k) W_i, \quad k = 1, 2, \ldots, n$$

3.2 Steps of the Answer Usefulness Ranking Method Integrating Word2vec and Grey Relational Analysis

The answer usefulness ranking method integrating WGRA and Word2vec mainly includes three parts: first, constructing the answer usefulness indicator system; second, determining specific weights of each indicator using the entropy weight method; then calculating the weighted grey relational degree of answers and question-answer pair similarity through grey relational analysis and Word2vec algorithm respectively; finally, realizing answer ranking in social Q&A communities and conducting comparative analysis of experimental results. The specific implementation steps are shown in [Figure 2: see original paper].

The needs of users in social Q&A communities differ from those in other contexts. Driven by their personal knowledge needs, users will generate a series of knowledge acquisition behaviors, among which asking, answering, or browsing relevant questions and answers through Q&A communities is an important information acquisition approach. Therefore, question-answer pairs in social Q&A communities not only provide decision-making references for potential users but more importantly, developers can mine user needs from them. It is worth mentioning that Word2vec can not only transform text data into numerical data convenient for processing but is also good at mining users' potential needs from the semantic level. As for weighted grey relational analysis, on the one hand, it assigns weights based on information richness through combination with entropy weight method; on the other hand, it identifies the closeness degree between each answer and the standard answer according to grey relational analysis principles. Previous research often focused on innovation in ranking methods while neglecting the important factor of user needs. In summary, this study chooses to integrate WGRA and Word2vec algorithms, comprehensively considering the characteristics of answers in social Q&A communities and the diverse needs of most users.

The algorithm flow is designed based on the premise that users can fully and accurately express their information needs through proposed questions. The specific steps are as follows:

Step 1: Data preprocessing and standardization. Collected data are segmented through self-compiled Python programs, with useless information removed and standardized processing performed.

Step 2: Transform each indicator into processable numerical data according to specific quantification methods, then calculate specific indicator weights W_i through the entropy weight method, and subsequently calculate weighted grey relational degree γ_i combined with grey relational analysis.

Step 3: Input training corpus collection T, train corpus model M through Word2vec, output word vectors vec_i according to M, calculate similarity between questions and answers using cosine similarity after averaging word vectors. The specific formula is:

$$S(A,B) = \cos(\theta) = \frac{A \cdot B}{||A|| \cdot ||B||}$$

where A is the mean of question text word vectors and B is the mean of answer text word vectors. Each answer text vector is calculated sequentially with the question text vector to obtain semantic similarity $S(A,B)$ between the question and each answer.

Step 4: Calculate the weighted fused answer usefulness ranking value P. This study defines P as the weighted sum of semantic similarity and weighted grey relational degree. To avoid result deviation caused by one value being too large or too small, P is modified to weighted sum of semantic similarity and weighted grey relational degree. To obtain appropriate weight values, this study first sets both weights to 0.5 to obtain ranking results, finding unsatisfactory results due to large γ_i and small S. Based on 0.5, weight values are adjusted and optimized through multiple experiments and parameter tuning, finally discovering the weight setting with minimal numerical deviation impact on experimental results. The calculation formula is:

$$P = 0.25\gamma_i + 0.75S(A, B)$$

4 Empirical Study

4.1 Data Collection and Preprocessing

After ten years of development, Ctrip has become a professional tourism service website with comprehensive functions. The Ctrip Q&A community is characterized by user-generated answers, rich questions, high answer quality, and diverse user groups. Therefore, this study selects Ctrip's Q&A community as the research object to verify the feasibility and usefulness of the proposed answer ranking method. The particularity of Ctrip Q&A as a tourism social Q&A community lies in that user questions and generated answers are often related to specific destinations. However, due to the social attributes of Q&A communities, question-answer pairs under each destination may contain invalid data. Therefore, to maximize acquisition of coherent and valid datasets, avoid offset in answer usefulness calculation caused by isolated data, and ensure user group diversity, this study selects multiple destinations as search terms and randomly collects one question under each destination and all its answers for empirical research. First, Octopus data collection software is used to crawl question-answer pair text content, answerer follower counts, question and answer publication times, user like counts, answer reply counts, and answer order using "Hangzhou, Shanghai, Qingdao, Qinghai, Wuhan, Changsha, Sanya" as destination search terms. The initial dataset totals 924 items. Due to phenomena such as user account cancellation, duplicate answers, and irrelevant answers, problems like inaccessible data, data redundancy, and invalid data occur. After deleting invalid data, 703 valid data items remain. Relevant experimental data on question and answer quantities are shown in .

shows sample questions from the dataset, including questions about Changsha snacks, Hangzhou spring outing plans, comparison between Sanya and Qingdao, Qinghai Lake itinerary, Shanghai Disneyland hotels, and Wuhan attractions.

4.2 Application of Usefulness Ranking Method

After preprocessing experimental data with Python 3.6, indicators are quantified according to the methods described above. The weight distribution results of Q&A community usefulness indicators obtained through entropy weight method are shown in .

presents the weight matrix of answer usefulness ranking indicators, showing varying weights across different destinations for indicators such as answerer authority, answer timeliness, answerer likes, sentiment analysis value, attribute feature words, etc.

Taking the Hangzhou-themed question "Most recent plan to visit Hangzhou for spring outing, initially set for a weekend in early April…" and its answers as an example, the method integrating weighted grey relational analysis and Word2vec is applied for answer usefulness ranking. Due to space limitations, only the 4th answer text is demonstrated.

(1) Calculation of grey relational degree values for each answer. First, select reference and comparison sequences. Reference sequence indicators are quantified using the methods in Table 1. For example, the 4th answer's indicators after quantification are $\{72, 6, 5, 1084, 2, 464, 119, 1, 13\}$. The optimal values of each indicator under each question are selected as the reference sequence. The Hangzhou-themed answer reference sequence is:

$$Y = \{0.679856, 0.015108, 0.010791, 2.153957, 0.021583, 1.001439, 5.082734, 0.002158, 0.032374\}$$

Second, perform dimensionless processing using mean values. After processing:

$$X = \{0.366931, 0.030578, 0.025481, 5.524349, 0.010193, 2.364666, 0.606455\}$$

Third, calculate correlation coefficients Z between each point:

$$Z = \{0.882035, 0.999566, 0.997083, 0.626452, 0.994172, 0.961422, 0.706199\}$$

Finally, calculate the weighted grey relational degree γ_i between the 4th Hangzhou-themed answer and reference sequence Y as $\gamma_i = 0.097451$.

(2) Calculation of semantic similarity between answer and question. Since user-generated answers in Ctrip Q&A community consist of large amounts of unstructured colloquial and internet language, this study selects the most comprehensive Chinese Wikipedia corpus, processes it with Python 3.6, and after multiple experiments, finally selects word vector training dimension of 256 and window of 5 for Word2vec model training. The Skip-gram model is chosen to train the corpus and transform all data into word vectors, then cosine similarity is used to calculate similarity between questions and answers after averaging word vectors. Again using the 4th answer as demonstration: after word segmentation and stop word removal, the question is transformed into word list ['plan', 'Hangzhou', 'West Lake', 'Broken Bridge', 'Bai Causeway', 'Su Causeway', 'Quyuan Fenghe', 'Yang Gong Causeway', 'Guo Villa', 'Maojiabu', 'Longjing', 'Huagang Guanyu', 'Leifeng Pagoda', 'Jing Temple', 'planning'], and the answer into word list ['Leifeng Pagoda', 'Su Causeway', 'Huagang Guanyu', 'Beishan Road', 'Gushan Road', 'Bai Causeway', 'Broken Bridge', 'Maojiabu', 'Longjing', 'Zaofeng Nianjian', 'Longtangli', 'Hubin Commercial Street', 'popular', 'restaurant']. Using Word2vec model to transform question and answer into word vectors, question $A = [v_1, v_2, \ldots, v_{15}]$, answer $B = [v_1, v_2, \ldots, v_{14}]$, then taking averages v_a, v_b and using vector cosine angle to calculate semantic similarity. According to formula (9), the semantic similarity $S(A, B)$ between question A and answer B is 0.813627.

Finally, the weighted grey relational degree and semantic similarity are fused. According to formula (10), the final answer usefulness ranking value P for the 4th answer under the Hangzhou-themed question is 0.270854225.

Due to space limitations, the Hangzhou-themed question and its top 5 answers are selected for comparative analysis, as shown in .

presents the answer usefulness ranking results, showing the top 5 answers with their usefulness scores and content summaries, demonstrating that answers with rich content, images, high like counts, and detailed information receive higher scores.

shows Ctrip's original ranking results for comparison.

4.3 Results Analysis and Comparison

Manual ranking method can most intuitively reflect user needs and is therefore considered the optimal ranking result. To verify the significance of the answer usefulness ranking method, this study selects manual ranking for comparative analysis of experimental results. According to Baidu Index user portrait analysis from February 26 to March 28, 2021, Ctrip user age is mainly distributed between 20-39 years. Therefore, 20 users in this age group with rich Ctrip usage experience were randomly selected. After randomizing answer order, participants were asked to read each question and answer and manually rank answers based on self-perceived content richness, personal information need satisfaction, and answer usefulness. The overlap rate calculation of ranking results can not only reveal the superiority between ranking methods but also show the closeness between answer usefulness ranking results and optimal ranking results. Therefore, after comparing and integrating 20 manual ranking results, this study extracts the top 10 answers from both this study's ranking results and manual ranking results, calculates the overlap rate of top 10 answers, with specific results shown in .

shows the overlap rate comparison between manual ranking and original ranking. In question-answer pairs for destinations Changsha, Hangzhou, Qingdao, Qinghai, Shanghai, and Wuhan, the overlap rate between answer usefulness ranking results and manual ranking results is higher than Ctrip's original ranking; for Sanya destination, the overlap rate is lower. This indicates that overall, the answer usefulness ranking method proposed in this study is more similar to manual ranking and better satisfies users' personalized information needs.

5 Conclusion

Taking Ctrip Q&A community as an example and starting from the perspective of user needs and answer usefulness, this study comprehensively considers answer characteristics, answerer characteristics, and answer timeliness to construct an answer ranking indicator system based on previous research. Each indicator is quantified, and the entropy weight method is used to objectively analyze information entropy values within answers to determine indicator weights. Combined with grey relational analysis to calculate weighted grey relational degree and Word2vec to calculate text similarity between question-answer pairs, the final score of each answer is calculated with weights to obtain answer ranking results. Experimental results show that compared with Ctrip Q&A community's existing answer ranking, answers ranked higher by this method generally combine text and images, have rich content, high user like counts, high comment popularity, high sentiment analysis values, and many attribute feature words. The original ranking only considers user like counts or answer time, while this study considers more dimensions of user needs and better satisfies users' personalized information demands. However, this study also has limitations. The experimental data scale is relatively limited for various types of social Q&A communities, and is restricted to only Ctrip Q&A. Future research will expand the scope of social Q&A communities and experimental data scale.

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Author Contributions

Guo Shunli: Proposed research ideas, determined topic, revised paper.
Bu Hui: Proposed research framework, data acquisition and analysis, wrote paper.

Research on the Sorting Method of Answer Usefulness in Social Q&A Community Integrating Word2vec and WGRA—Taking Ctrip Q&A as an Example

Guo Shunli, Bu Hui
School of Communication, Qufu Normal University, Rizhao 276800

Abstract: [Purpose/significance] In order to solve the diversified information needs of users in social Q&A communities and the problem of redundant and overloaded answers, this paper proposes an answer usefulness ranking method oriented toward users' personalized needs to assist users in efficiently filtering and obtaining useful answer knowledge. [Method/process] First, through literature research and expert consultation, an answer usefulness evaluation index system was constructed from three dimensions: answer characteristics, answerer characteristics, and answer timeliness. Then, integrating users' personalized needs from the semantic level, an answer usefulness ranking method combining weighted grey relational analysis and Word2vec was designed to realize answer ranking oriented toward user needs. [Result/conclusion] Through comparative analysis of experimental results, it was found that compared with traditional ranking methods based on "like counts" and "answer time," the answer usefulness ranking method designed in this paper has higher user satisfaction and better meets users' personalized knowledge demands.

Keywords: user demand; answer usefulness; WGRA; Word2vec; social Q&A community

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