VAIR: A Novel Visualization System for Article Influence Ranking based on Citation Context

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ABSTRACT Article influence ranking is an effective way to reduce information redundancy and improve the efficiency of article retrieval. A large number of ranking models for network items have been employed for the ranking of article influence, such as PageRank and Spamming-resistant Expertise Analysis and Ranking. However, the effectiveness of article influence ranking based on the models of PageRank and SPEAR declines with the rapid growth of academic datasets, because of the increasing complexity of citation network. In order to take a rich set of contextual structures of citation context into consideration, we propose a visualization system VAIR for the citation context-based article influence ranking. Firstly, the word2vec model, a renowned technique in the field of natural language processing, is applied to transform articles into vectorized representations according to citation context. Then, a novel citation context-based article influence ranking model is designed according to the complex relationships quantified in a semantic vectorised space. Several visual designs are implemented, allowing users to perceive and compare the ranking results visually and intuitively. A set of user-friendly interactions are provided in the visualization framework, enabling users to explore the desirable article influence and obtain deep insights into the ranking model. Moreover, a series of case studies and comparison experiments are carried out based on real-world datasets, which further demonstrate the effectiveness of our algorithm for article influence ranking.

INDEX TERMS influence ranking, visualization, visual analysis, citation network, word2vec

I. INTRODUCTION

With the development of the academia and the increase in publishing scale, a large amount of academic articles has been shared, effectively promoting academic communication and innovation [1], [2]. However, the big size also causes a tough question that quickly retrieving valuable scientific articles from a large literature collection containing information of authors, citations and publication time, becomes time-consuming and laborious [3], [4]. Thus, various ranking models have been proposed to help researchers find the classical articles which are the most influential and valuable to read in a particular area [5]. In these models, the most important and widely-used factor is the citation information, such as citation counts [3]–[9], publish time [19] and the citation network [10], etc. For example, SPEAR model considers the influence of time parameters and citation counts.

In fact, a considerable number of ranking models are based on the assumption that all the citations of an article are equally important. But, important citations should be paid greater attention than trivial citations [43]. The effectiveness of these ranking results are controversial [44]. Many researches have proposed that, the citations of an article ought to be seen as having different scientific influence that can not be measured by only citation counts [45]. Therefore, citation context is employed in many ranking models to extract citation importance by exploring the use of citation, such as the frequency or location of a citation in articles [13], [46].
However, a perspective that is easily missing is the impact of structure context of citation network on the article influence ranking. For example, it frequently happens that one follows the citations of an article to find some relevant works, which means that the article may be important citations. Therefore, citation context in structure features may be an important clue for optimising the ranking of article influence, and studies are required to investigate this effect.

However, the structural role of an article in the citation network is difficult to identify, because of the big size and complex relationships among citations [11]–[13]. But in recent years, representation learning technology has been recognized as an effective way to encode context information and widely applied in a variety of research areas [43], [47]. As a popular representation learning model with good learning quality and fast computing speed, word2vec can be used to learn representations of contextual features in various data by a flexible analogy between domain interactions and NLP terms [30], [32]. It constructs a vectorized space where the geometric distribution of vectors is able to reflect contextual information of original data. Thus, it is particularly suitable for exploring the contextual structures features of large citation network, such as network roles and communities.

So, for large-scale academic data, we design a visual analysis framework to evaluate the academic influence of articles from the perspective of citation context in network structure. Firstly, a word2vec model is utilised to transform articles into high-dimensional vectors by establishing an analogy among articles in a citation network, and natural language processing (NLP) terms. Secondly, the vectors are further projected into 2D coordinates via t-SNE (t-distributed stochastic neighbor embedding), and then the vectorised difference among articles can be visually presented by means of distance in a low-dimensional space. According to the quantified difference, we further propose a novel ranking model which introduces the citation context information to optimize the SPEAR model. In demonstrating the effectiveness of our method, various visual encodings are designed, allowing users to intuitively capture the citation context of network structure and explore the academic influence of articles visually. Finally, a visualisation system for articles ranking is implemented to integrate the ranking models, visual designs and interactions, enabling users to achieve the comparative analysis of different ranking models based on a real-world dataset.

The major contributions of our work are as follows:

- An analogy between citation contexts and NLP terms is established, and a word2vec model widely used in the NLP field is further employed to represent the citation context of articles. The similarity between articles can be better achieved from the perspective of citation context.
- A novel influence ranking model is designed to combine a variety of factors, including citation context, publication time and citation count, enabling users to retrieve high-quality articles that have important contributions to the development of disciplines or other scientific research works.
- A variety of visual designs are proposed to compare the influence of articles in different ranking models, effectively demonstrating the impact of different factors.
on the ranking results.

- A set of human-computer interactions are integrated into the visualisation framework, allowing users to accomplish their expected tasks efficiently via a cooperative visual analysis of multiple views.

The rest of this paper is structured as follows. Related works are described in Section 2. Section 3 presents the analysis task and system overview. The ranking model that considers citation context is detailed in Section 4. Section 5 illustrates the visual designs and human-computer interactions of our visualisation system. Case studies are discussed in Section 6, and our conclusions are drawn in Section 7.

II. RELATED WORKS

In this section, three kinds of related studies are described including ranking techniques for article influence, visual designs for ranking and word embedding technologies.

A. RANKING TECHNOLOGY

Among big scholarly datasets, citations constitute a huge, complex network with many attributes, such as citation counts, citation objects, citation time and network structure. For different situations, many scholars synthetically consider different factors to construct a ranking model.

Citation count is a commonly used factor for measuring the academic impact of papers [14]. Usually, the more citations a paper has, the more attention it receives. However, the actual citation process suffers from objective limitations (such as discipline differences, difficulty in obtaining documents, literature language and time) and subjective problems (such as nonstandard citation behaviour and different citation motives) [2], [5]. Therefore, many scholars have paid considerable attention to the complex influence characteristics of network structure. For example, the renowned PageRank [15], [16] and HITS [17] models effectively correlate citation counts and citation network structure between papers via link analysis technology without considering the content of texts to evaluate the academic influence of papers. On this basis, additional attributes (such as time, journals and social relations of authors) have been introduced and studied by scholars to optimise the impact assessment of papers. For example, Walker et al. introduced publication time into the PageRank model by exponentially distributing random surfers and proposing a new ranking model named CiteRank [18]. Sayyadi and Getoor presented the FutureRank model to predict the future rank score of each article through a new measure defined by utilising citation and authorship networks and publication time [19]. In P-Rank, the academic prestige of papers is measured in a heterogeneous scholarly network, which is established by various entities, including publications, authors and journals [20]. Wang et al. designed a PageRank and HITS framework based on a heterogeneous network with multiple attributes. It calculates the prestige scores of articles through a graph-based propagation algorithm [12]. Michael et al. proposed the SPEAR model, which is similar to the HITS model but further considers the influence of time parameters and user attributes on ranking results [21].

B. VISUAL RANKING DESIGNS

The analysis of ranking results usually contains two aspects: vertical analysis on single attributes and horizontal comparison on multidimensional attributes. Therefore, in the field of information visualisation, many studies have been proposed for visual ranking designs based on these analysis needs [22], [23]. Seo and Shneiderman proposed a novel rank-by-feature framework that presents a ranked list together with score visualisation, enabling users to discover features of interest among different variables [24]. Aiming at the comparison of a large set of incomplete and tied rankings, Kidwell et al. defined a dissimilarity score on these rankings that corresponds to the expected or average distance between the underlying permutations [25]. The dissimilarity score is used to measure the similarity of rankings and visualise via multidimensional scaling heat maps. As the ranking results present evident dissimilarities based on different combinations of attributes, various interactive visualisation techniques have been designed for the ranking of multiattribute data. Gratzl et al. introduced LineUp to help users create and compare custom rankings by clicking and dragging columns to adjust the attribute weights interactively [26]. Some systems are also implemented to generate rankings by augmenting the visualisation of time series data [27]. Xia et al. proposed WikiTopReader, a reader of Wikipedia, through which users can explore connections among pages with similar ranking trends [28]. For large time series data, Qu et al. presented RankExplorer to visualise and explore value and ranking changes [29].

C. WORD EMBEDDING TECHNOLOGY

In the field of NLP, word embedding is a popular technology, including language model and representation learning technology [30]. Specifically, it can transform a word into a high-dimensional vector based on the corpus provided, and measure their semantic similarity by the distance between high-dimensional vector based on the corpus provided, and measure their semantic similarity by the distance between high-dimensional vector based on the corpus provided, and measure their semantic similarity by the distance between high-dimensional vector based on the corpus provided, and measure their semantic similarity by the distance between high-dimensional vector based on the corpus provided, and measure their semantic similarity by the distance between high-dimensional vector based on the corpus provided, and measure their semantic similarity by the distance between high-dimensional vectors [31], [32]. For example, the well-known Word2vec model trains vector space model through neural network [33]. It can increase the quality of learned vector representations and computational efficiency, with the help of the distributed representations of words trained with a skip-gram or CBOW model [34]– [36].

Much efforts show that the word embedding techniques can be well applied to a series of tasks in a variety of fields based on the analogies between domain interactions and NLP terms [37]– [39]. Based on the citation contexts, Cite2vec construct a joint representation of words and documents in a common high-dimensional embedding space though Word2vec model, to effectively explore and browse document collections [13]. Inspired by the word2vec model, Node2vec is designed for learning continuous feature representations for nodes in networks by a mapping between nodes and features in a low-dimensional space, to capture
the diversity of connectivity patterns observed in networks [40]. The road2vec method establishes an analogy between transportation elements and NLP terms, and the traffic similarity is measured by the cosine distance of road vectors trained by Word2Vec model. It can employed in quantifying complex traffic interactions among roads and forecasting traffic situations [41]. Zhou et al. employ Word2vec model to characterize the semantic relationship of OD flows, and define an iterative multi-objective sampling scheme to enhance the visibility of large scale geospatial OD flow map, which further enables users to quickly perceive the patterns of human mobility [42].

III. TASK ANALYSIS AND SYSTEM OVERVIEW

A. DATA DESCRIPTION

Scholarly data are provided by Web of Science (WOS), from which basic information of articles, such as journal, title, authors, keywords, citations, publication time and other details, is recorded. In our study, we select TVCG (IEEE Transactions on Visualization and Computer Graphics) as a keyword for indexing in periodicals and collect all information about articles published in TVCG from 1995 to May 2018. The size of the whole scholarly dataset is more than 2 GB, containing titles, authors, keywords, abstracts, publication time and complete bibliographic information. The number of references for an article ranges from dozens to hundreds; thus, some references are filtered from our dataset to enhance the quality of data analysis. Only cited papers published on TVCG are retained. Finally, the scholarly dataset approximately consists of 3,108 articles with 8,600 citation links.

B. TASK ANALYSIS

After a detailed discussion with domain experts through structured interviews, we compile a list of analytical tasks for the visual ranking of academic influence of articles based on semantic relationship.

T1: Representation of Citation Context: Various references contribute differently to papers. Therefore, when facing large-scale scholarly data, how can we effectively obtain implicit semantic information from a citation network to help users observe the impact of references? How can we quantify its impact to help users make a comparative analysis of the academic impact under different backgrounds or conditions?

T2: Academic Impact Ranking Model: Citations among papers have significant temporal attributes. Especially, the citation time of an article is usually after its publication time. Therefore, for big scholarly data, how can we scientifically combine the time parameters with semantic information to construct a ranking model of influence to help users quickly obtain high-quality papers?

T3: Visual Comparison of Ranking Models: Many ranking models evaluate the impact of papers based on different parameters, thereby producing varied results. Therefore, how can we analyse the performance of the same paper under different ranking models (roughly similar or completely different), and how do we help users find out their reasons for different performance?

T4: Human-Computer Interfaces for Influence Ranking: Is the semantic information hidden in a citation network effectively extracted? Does the ranking model based on time parameters and semantic information have good use effect? Moreover, what is the performance of the same articles under different ranking models? Therefore, how can we design a convenient human-computer interaction that meets the needs of users for analysis and exploration?

C. SYSTEM OVERVIEW

Analysis of the academic influence of papers based on the citation relationship in large-scale academic data is an effective way to promote and explore the context of discipline development. However, citation relationships contain rich attribute information, including citation context, citation counts and citation time. Therefore, for large-scale academic data, we design a visual framework to evaluate the academic impact of articles from the perspective of citation context. Citation context is employed to optimise the SPEAR model for obtaining the expected ranking results. The system pipeline is shown in figure 2.

First, after preprocessing, citation data are carefully analysed for the analysis tasks (T1, T2, T3, T4) to establish a new ranking model based on citation context. Then, inspired by the representation learning model, papers and their citations are transformed into words and sentences in the NLP domain. The semantic relationship of articles is represented as high-dimensional vectors using the word2vec model. This vectorisation difference is used to optimise the SPEAR model and obtain a ranking model that can consider citation context. Furthermore, various visual coding and human-computer interactions are designed to help users quickly analyse and explore the academic impact of articles. Ranking view can intuitively describe the ranking results of the academic impact of articles. Projection and network views are employed to display and analyse the semantic relationship of papers collaboratively. The comparison view vividly shows the differences in the ranking results of papers under different models via point graphs and coordinate systems. Finally, to verify the validity of our ranking method, visual designs, ranking models and human-computer interactions are effectively correlated. This correlation helps users easily pay attention to the role of semantic relationship in the impact evaluation of articles and intuitively capture the characteristics of citation context shown in a citation network.

IV. CITATION CONTEXT-BASED ARTICLE INFLUENCE RANKING

Existing ranking models for the academic impact of papers usually base on the frequency of papers appearing in references or the attribute characteristics of a citation network to provide ranking lists. For various reasons, such as large amounts of data and the weak influence of some references, these methods may not necessarily result in a useful ranking
of papers. Thus, we propose a novel method that assesses the academic impact of articles by extracting the semantic relationship from a citation network as a key influence factor.

A. CITATION CONTEXT REPRESENTATION

A citation network has semantic relationships, which may reflect actual impact patterns between papers. Accordingly, a classical NLP model is employed in our system to study the features of semantic relationships and express them quantitatively.

1) Word embeddings

The citation relationship between papers can be expressed by directed edges. In a citation network, each paper is regarded as a point, whereas a citation link is defined as a directed edge to show the citation relationship, which is generated when a paper (cited paper) is cited by another paper (origin paper). We firstly define each paper as a word. Then, each sentence consisting of a sequence of words represents a complete citation link following the order of citation. $Se = (w_1, w_2, \cdots, w_i, \cdots, w_m)$ where $m$ is the total number of papers in a complete citation link, and $w_i$ is the $i$th word in the vocabulary. For example, paper $A$ is regarded as word $A$ and a sentence consists of $(w_a, w_b, w_c)$, because paper $A$ is cited by paper $B$, which is also the reference of paper $C$, as shown in figure 3.

B. VECTORISED REPRESENTATION

The word2vec model is introduced in our study to build and train a corpus and thus provide effective reference for subsequent impact assessment [33]. This model can be used for characterising any word based on the embedding vectors learned from its corpus. The word2vec model has two common formats: the CBOW and skip-gram models. We select the skip-gram model to train the context similarity of the citation network, because it usually performs better than CBOW model in training large datasets [13], [32]. In the skip-gram model, a large sequence of words is received, and each word is assigned a high-dimensional vector in a vector space. It can
make close words in local neighbourhood contexts remain close to corresponding words in the embedding space, which is realised by maximising the average log probability [41].

\[
\frac{1}{T} \sum_{t=1}^{T} \sum_{j=-k}^{K} \log p(w_{t+i} | w_t)
\]

where \( T \) is the length of the training sequence, and \( k \) is the width of the training window. \( p(w_{t+i} | w_t) \) is regarded as the probability of predicting \( w_{t+i} \) according to a given word \( w_t \).

\[
p(w_i | w_j) = \frac{\exp(u_i^T v_{w_j})}{\sum_v \exp(u_i^T v_{w_j})}
\]

The above formula is used to express the probability of generating a background word \( w_i \) with a given central word \( w_j \), where \( u_i \) is regarded as the input vector of \( w_i \), and \( v_{w_j} \) represents the input vector. \( V \) is the number of words in the vocabulary [41]. \( T \) represents the transposition operation.

To optimise computation performance, negative sampling is used in our model as the softmax function to calculate this probability.

\[
\log p(w_i | w_j) = \sum_{c=1}^{k} E_{w_i \sim P_{a}(w)} [\log \sigma(-u_{w_i}^T v_{w_j}) + \log \sigma(u_{w_i}^T v_{w_j})]
\]

After the whole training process, vectorised representations of each article are obtained in the citation network. Euclidean distance between vectors in a high-dimensional space is used to measure the similarity between the citation links of any two papers, which is then further employed in the S-SPEAR model to obtain the expected ranking results.

**C. CITATION CONTEXT-BASED RANKING MODEL**

The SPEAR model is originally a graph-based ranking algorithm for identifying and resisting spam. Considering the time factor, the model can help users identify useful (or interested) parts with high quality. Therefore, this model is widely used in various ranking tasks. In the SPEAR model, each item contains two kinds of scores: expert and quality scores. An expert usually has a high level of knowledge in a domain and will be sensitive to high-quality items, thus finding and using them early. People who can find and use high-quality items early are likely to be experts. In other words, a relationship of mutual reinforcement exists between the expertise of an expert and the quality of an item.

Inspired by the SPEAR model, we design an optimised model called S-SPEAR, which enables users to observe the influence process of high-quality articles effectively according to citation context. We regard all authors of a paper as experts, with the assumption that excellent experts will have and tend to cite high-quality papers. The time of citation is introduced as a reliable criterion for determining expertise score. Although we never know how an author discovered these papers, the time at which an expert cited high-quality papers should be a reasonable approximation of his sensitivity to high-quality papers. In our paper, the specific steps are as follows.

1) We define \( E \) as a vector of the expertise scores of authors. \( E = (e_1, e_2, \ldots, e_M) \), where \( M \) is the number of authors. In addition, we define \( Q \) as a vector of the quality scores of papers: \( Q = (q_1, q_2, \ldots, q_N) \), where \( N \) is the number of papers. To simplify calculation, \( M = N \) in our model.

2) The citation between experts and papers is described by matrix \( A_{M \times N} \), which satisfies the following requirements:

(a) \( A_{i \alpha} > A_{j \alpha} \), if expert \( i \) quotes paper \( \alpha \) earlier than expert \( j \);

(b) \( A_{i \alpha} = 0 \), if expert \( i \) does not cite paper \( \alpha \). The more high-quality papers cited by experts and the earlier the citation time, the higher their expert score. When a paper is cited by more experts, its quality score also becomes higher.

3) We multiply the value of each cell in matrix \( A \) by the corresponding semantic similarity in the citation network, which is calculated based on word2vec. The formulae are as follows:

\[
S_{ab} = d(a, b) = \sqrt{\sum (a - b)^2}
\]

4) For assigning proper credit scores to experts, a credit scoring function \( C \) is applied to \( A \). This function can retain the order of scores in \( A \) such that discoverers still score higher than followers, but it should reduce the differences between scores, which are too high. For the context of this paper, we conduct our experiments with \( C(x) = x^{0.5} \).

5) The following formula is updated iteratively:

\[
\begin{cases}
E(t) = A \ast Q(t - 1) \\
Q(t) = E(t - 1) \ast A
\end{cases}
\]

After several iterations, the convergence of the algorithm can be obtained. After convergence, \( E \) vectors are the final expert scores, whereas \( Q \) vectors represent the final quality scores of papers. \( T \) is a timestamp.

In addition to citation count, time parameter and implicit semantic relationship based on the citation networks are considered by S-SPEAR. Especially, the semantic relationship of citation networks is employed to represent and analyse the different influences between each paper and their corresponding cited papers. Therefore, this model is supposed to perform well in the influence evaluation of papers.

**V. VISUAL RANKING SYSTEM**

In this section, a set of visual designs are illustrated, including the network view of citation data, representation view of citation context, ranking view of article influence, comparison view of ranking models and human-computer interactions. These views are designed to effectively show and compare the results of different ranking models, helping users to accomplish their expected analysis tasks efficiently.
A. NETWORK VIEW OF CITATION DATA

Citation relationships between papers constitute a complex citation network which implicitly describes the development of an article or even a discipline. Thus, analysing and exploring the citation network is necessary to evaluate the academic impact of papers effectively. However, with the increasing scale of scholarly data, exploring the citation links and structural features in citation networks has become a cognitively demanding, error-prone and tedious task. Therefore, a network view is designed to display citation information and relationships among papers by using a variety of visual coding (such as location and colour), hence allowing users to capture the features of the citation network quickly.

First, several timelines are set up to represent publication years from 1995 to 2018. Articles in our dataset are allocated to the corresponding timeline according to publication time. On each timeline, papers published in a year are sorted by their ranking results in the S-SPEAR model. The higher the position of a paper, the higher its ranking in the current year. To present a citation network structure clearly, we not only provide the direct citation links with the selected papers but also show their indirect citation links. We assign different colours to citation links with varied attributes to distinguish their relationships while enhancing display and reducing visual confusion. As shown in figure 4, the given article A (red point) is highlighted in red point. The papers (B₁, B₂, etc.) cited in paper A are connected to paper A with purple lines, whereas papers (C₁, C₂, etc.) that directly cite paper A are linked to paper A by sandybrown links. Bᵢ is linked to their references with green lines, and the connection between Cᵢ and papers citing Cᵢ is displayed using blue links. In other words, the indirect citations related to paper A are shown by sandybrown lines and purple links.

B. REPRESENTATION VIEW OF CITATION CONTEXT

In our model, each paper is trained to be vectorised in a high-dimensional semantic space using the word2vec model. We calculate the Euclidean distance between high-dimensional vectors to quantify the semantic similarity of citations in the citation network, that is, the citation similarity. However, the location and distance in a high-dimensional space are abstract, thereby rendering observation and intuitive understanding difficult. Therefore, we design a projection view to project the high-dimensional vectors onto a two-dimensional plane using t-SNE, which can help users quickly capture the semantic similarity relationship of papers in the citation network.

As a common method for data dimension reduction and visualisation, t-SNE can convert the similarity between data points into probability and evaluate the visualisation effect via the Kullback-Leibler divergence of joint probability between the original and embedded spaces (Similarity in the original space is expressed by Gauss joint probability, and similarity in the embedded space is shown by Student t distribution). This method has good performance in accurately visualising the similarity relationship between samples and can maintain the local structure of data well. Therefore, we use t-SNE to reduce the dimension of high-dimensional vectors and visually display the citation similarity characteristics of papers in a two-dimensional space. As shown in figure 5, each point represents a paper, and the distance between points maps their similarity in a high-dimensional space. The closer the two points, the more similar the citation network they present. In addition, users can click a point or define an interactive area to select a group of points, which will be highlighted in red. When users select the points of interest by zooming in the projection view, the related attributes of papers will be displayed in other views to help users further observe the implicit features of the selected articles, such as displaying network structure in the network graph and showing basic information in the information view.

C. RANKING VIEW OF ARTICLE INFLUENCE

PageRank and HITS are well-known ranking models which consider citation counts and citation network structure. SPEAR is similar to HITS but further considers the influence of time factor. The S-SPEAR model is proposed to optimise the original SPEAR model by deeply exploring the implicit semantic features of the citation network and extracting them quantitatively as an important variable to be integrated into the SPEAR model flexibly. Different algorithms are based on various combinations of attributes. Therefore, different papers often have varying performances under different models. To display the ranking results in these models vividly, we design an intuitive and simple ranking view.

Four histograms are shown in figure 6, representing the ranking results of S-SPEAR (orange), PageRank (pink), HIT-
S (blue) and SPEAR (indigo) models separately. In each histogram, each bar represents a paper, and its height indicates the impact score of a paper in the corresponding model. According to impact score, bars are arranged from left to right. The higher the score, the larger the academic influence of the paper under a given model. Thumbnails are set up in the bottom of each histogram to help users quickly obtain the global distribution of papers. To help users observe and explore the impact of a paper flexibly, some convenient interactions are designed in our system. In figure 6, when a user clicks a bar on a histogram, the corresponding bar on the three other histograms will also be quickly retrieved and highlighted with different colours. The location of a bar is also highlighted on each thumbnail to help users quickly obtain the global location of a paper of interest.

**D. COMPARISON VIEW OF RANKING MODELS**

We design a difference view, consisting of a comparison panel and counting panel, to visualise the performance of a paper under different models and help users effectively analyse the influence of various factors on evaluating the academic impact of a paper. In the counting panel, we mainly count the times that each paper has been cited and describe them with scatter plots. In figure 6(d), the horizontal axis in the scatter plot represents the publication time of a paper, and the vertical axis displays the total frequency of citations. Each paper is shown as a point. Thus, observing scatter plots can help users quickly discover the high-quality papers cited in each year and their distribution characteristics.

Furthermore, we design a comparative panel to help users efficiently explore the performance of papers of interest under various ranking models based on different assumptions. In figure 7, the upper, lower, left and right directions correspond to the S-SPEAR, HITS, PageRank and SPAR algorithms, respectively. The coordinate axis maps the ranking of articles (from high to low) from inside to outside. There are three different ways (lines, links and points) to represent the ranking changes of papers under different models. We provide a exchange function in coordinate axis to ensure that the rankings results between any two models can be compared. When a user clicks on a paper of interest, the corresponding locations on other different models will be connected to each other, helping users intuitively obtain and compare the differences of the impact evaluation of a paper under different models. At the same time, users can select multiple papers and quickly compare the balanced performance of multiple papers under different models.

**E. HUMAN-COMPUTER INTERACTIONS**

Human-computer interaction is a process of information exchange between user and computer; the interaction between system and users is taken as the research content. It helps users communicate with a system through certain interactive means to accomplish specific tasks. However, users have different ways of understanding and learning habits because of various task objectives and professional backgrounds. Therefore, how to design a user-friendly system according to their goals is an important part of realising human-computer
interaction effectively.

In our system, we not only design flexible interactive operations in various views to help users understand all aspects of the information about citation data but also establish interactive designs among different views to show the interaction among various factors. As shown in Figure 1, users can retrieve documents of interest through keywords in the information view. When the user selects a paper of interest, its spatial position in other views will be highlighted, and its related attribute information will be further displayed in different views. For example, all citation links between the paper and other papers are further described in the network view to help users observe their relationship in a citation context. The ranking differences under various models are visually displayed in the comparison view, thereby helping users perform comparative analysis between these ranking models. The ranking results of our datasets under different models are displayed in the ranking view, hence helping users effectively observe and obtain the global position of the paper of interest. Additional convenient interaction designs are elaborated in the following case analysis.

VI. EVALUATION

A web-based system implemented using Javascript supports the real-time exploration of visual analysis of citation context based on article influence ranking. Several case studies and expert interviews are conducted to validate whether our ranking method for academic influence can quickly capture the features of citation context and quantitatively measure them to optimise the ranking result.

A. CASE STUDY

For a valid evaluation of the effectiveness of our proposed system, a real-world dataset is obtained focusing on the journal of TVCG from WOS.

1) Visual Exploration of Citation Context

An analogy between citation contexts and NLP terms is used to explore the implicit semantic relationship in a citation network, which is trained by the word2vec model and projected into a two-dimensional space for intuitive display. As shown in figure 5(b), we select a group of close points in the projection view, observing the relationship between their citation network structures in the network view. As shown in figure 8(a), when a set of close points is selected (including points A, B, and C), a significant overlap exists in some citation links of these articles in the network view. As shown in the citation network displayed in figure 8(b), (c) and (d), no direct citation is found between papers B and C, but their citation networks are similar because they all cite paper A. This finding verifies that the close points in the projection view have similar network structures. Thus, the evaluation of the academic impact of papers, which is established based on citation context, can consider the impact of direct and indirect citations. Therefore, users can identify the similarity of citation links directly through the distance of points in the projection view and further analyse their characteristics by comparing the citation networks in the network view.

In addition, based on the basic information shown in the information view, the papers often share common information, such as titles, authors and keywords. For example, the topics of papers B and C are about ‘feature’, whereas the common word between papers A and C is ‘wavelets’. Moreover, the author ‘Qin, Hong’ is common in papers A, B, and C. Papers A and B share the same author, ‘Hou, Tingbo’, whereas the common author between papers B and C is ‘Wang, Shengfa’. Papers C and B share the same keyword, ‘mesh segmentation’. These commonalities confirm the effectiveness of the similarity evaluation results obtained via word2vec.

2) Effectiveness of S-SPEAR

To verify the role of citation context in the ranking model, the ranking results of the S-SPEAR model are analysed from multiple views. As shown in Figure 1, a paper titled “D-3: Data-Driven Documents” is ranked first in the S-SPEAR model. First, from the ranking results, its performance is better in PageRank and S-SPEAR and slightly worse in HITS and SPEAR. Overall, its distribution in ranking is similar to a square, showing a nearly balanced performance, indicating that its academic influence is recognised in various models. Then, citation count and publication time are observed in figure 1(d). Published in 2011, this article has a relatively new publication time, but its citation frequency is 68, which is the highest frequency of citation in our dataset. That is, this article has been quoted considerably in a short time, which shows that its influence is extensive and rapid.

The citation network displayed in figure 1(c) shows that the sandybrown links are distributed between 2012 and 2018 and are mainly concentrated in 2014 to 2018. This figure illustrates that the paper has been cited continuously between 2012 and 2018 (especially 2014 to 2018), which means that it has a sustained and relevant influence. At the same time, numerous blue links are shown, indicating that many papers that cited this paper also have many citation times. Green and purple links are mainly distributed in 2006 to 2010, and their ranking positions are high, which demonstrates that most of the references in this paper are relatively new (for its publication date, 2011) and belong to high-quality papers with considerable impact scores. In view of this phenomenon, we further explore its semantic features in citation context. In figure 1(b), purple and red dots are relatively close. This illustration shows that the papers that cite the paper directly have strong similarity with the selected paper. In other words, they are influenced by the selected paper greatly. Given that these papers belong to high-quality papers with many citations, the selected paper should also have substantial impact. Meanwhile, the brown dot is close to the red dot, indicating that these papers contribute substantially to the selected paper. The blue dot represents the high-quality papers at that time; thus, the selected paper can be inferred as belonging to a high-quality paper. Therefore, whether from the view of citing or being cited, the selected paper should
FIGURE 8. The similarity in citation network. There are citation networks of a group of closer points in picture (a), and then the similarity of paper A, B, C (several of these points) are discussed through comparing their citation networks which are displayed in picture (b), (c), (d).

TABLE 1. The top ten papers of our model

<table>
<thead>
<tr>
<th>rank</th>
<th>title</th>
<th>counts</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>D-3: Data-Driven Documents</td>
<td>68</td>
<td>2011</td>
</tr>
<tr>
<td>2</td>
<td>Hierarchical edge bundles: Visualization of adjacency relations in hierarchical data</td>
<td>57</td>
<td>2006</td>
</tr>
<tr>
<td>3</td>
<td>Graph visualization and navigation in information visualization: A survey</td>
<td>53</td>
<td>2000</td>
</tr>
<tr>
<td>4</td>
<td>Bubble Sets: Revealing Set Relations with Isocontours over Existing Visualizations</td>
<td>34</td>
<td>2009</td>
</tr>
<tr>
<td>5</td>
<td>Polaris: A system for query, analysis, and visualization of multidimensional relational databases</td>
<td>42</td>
<td>2002</td>
</tr>
<tr>
<td>6</td>
<td>A Multi-Level Typology of Abstract Visualization Tasks</td>
<td>35</td>
<td>2013</td>
</tr>
<tr>
<td>7</td>
<td>Design Study Methodology: Reflections from the Trenches and the Stacks</td>
<td>34</td>
<td>2012</td>
</tr>
<tr>
<td>8</td>
<td>Toward a deeper understanding of the role of interaction in information visualization</td>
<td>40</td>
<td>2007</td>
</tr>
<tr>
<td>9</td>
<td>ThemeRiver: Visualizing thematic changes in large document collections</td>
<td>43</td>
<td>2002</td>
</tr>
<tr>
<td>10</td>
<td>Many eyes: A site for visualization at internet scale</td>
<td>36</td>
<td>2007</td>
</tr>
</tbody>
</table>

TABLE 2. The top ten papers of PageRank model

<table>
<thead>
<tr>
<th>rank</th>
<th>title</th>
<th>counts</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Visualizing network data</td>
<td>10</td>
<td>1995</td>
</tr>
<tr>
<td>2</td>
<td>Optical-models for direct volume rendering</td>
<td>51</td>
<td>1995</td>
</tr>
<tr>
<td>3</td>
<td>Graph visualization and navigation in information visualization: A survey</td>
<td>53</td>
<td>2000</td>
</tr>
<tr>
<td>4</td>
<td>Multidimensional transfer functions for interactive volume rendering</td>
<td>63</td>
<td>2002</td>
</tr>
<tr>
<td>5</td>
<td>Designing pixel-oriented visualization techniques: Theory and applications</td>
<td>20</td>
<td>2000</td>
</tr>
<tr>
<td>6</td>
<td>Conformal surface parameterization for texture mapping</td>
<td>14</td>
<td>2000</td>
</tr>
<tr>
<td>7</td>
<td>Designing for social data analysis</td>
<td>8</td>
<td>2006</td>
</tr>
<tr>
<td>8</td>
<td>Controlled topology simplification</td>
<td>4</td>
<td>1996</td>
</tr>
<tr>
<td>9</td>
<td>Topological fisheye views for visualizing large graphs</td>
<td>21</td>
<td>2005</td>
</tr>
<tr>
<td>10</td>
<td>Tissue classification based on 3D local intensity structures for volume rendering</td>
<td>26</td>
<td>2000</td>
</tr>
</tbody>
</table>

be a high-quality paper with high influence, proving the usefulness and effectiveness of our ranking model based on citation context for the ranking of article academic impact.

3) Comparative Analysis of Different Ranking Models

To further observe the influence of different factors for ranking, we compare the ranking results of the academic impact of papers under different ranking models. All the top 10 papers in the different ranking models are counted, as shown in tables 1–4. Then, we observed the performance of different ranking results in citation counts and publication time, as shown in figure 9. First, in terms of publication time, it is obvious that the publication time of top ten papers (based on the PageRank model) are 2006 and lower, as displayed in figure 9(b). From figure 9(c), the top ten papers (based on the HITS model) were almost published after 2009. As shown in figure 9(d), seven of the top 10 papers (based on SPEAR model) were also published in 2012 and beyond, when others are published before 2003. It’s not difficult to find that the PageRank model has obvious advantages...
for papers published earlier, whereas the HITS and SPEAR models prefer papers published recently. As a result, their top ten ranking results rarely involve papers published between 2006 and 2012, but it is a significant peak period from the perspective of citation counts. Then, we make a comparison of citation counts. According to figure 11, seven papers are cited less than 28 times in the PageRank model, all of the top ten papers are cited less than 14 times in the HITS model, and six papers are cited less than 14 times in the SPEAR model. It can be found that the PageRank model is sensitive to citation counts, and in general, both the HITS and SPEAR models are not sensitive to citation counts, although the SPEAR algorithm is more sensitive to citation counts than the HITS model.

In fact, early published papers often have a higher citation counts than papers published recently, but some of them may not be able to provide cutting-edge technology and ideas because of time. Newly published papers usually record the latest research results but often lack citations which can effectively reflect the quality of papers. Therefore, influential high-quality papers should not only be in line with the current development of disciplines (publishing time will not be too long) but should also be widely recognised (with high citation). On this basis, a further observation on the ranking results of the S-SPEAR model in figure 9(a) shows that the citation of top ten papers are more than 28 times, most of which are published after 2006 (including 2006). Compared with other models, the citation times and publication time in the S-SPEAR model perform well, and its ranking results meet the basic requirements of high-impact papers.

In summary, we believe that the S-SPEAR model can effectively consider the role of citation context in the process of article impact assessment and provides a rapid access to high-quality papers as references.

### B. EXPERT INTERVIEWS

To verify the effectiveness of the system further, we invite two domain experts to use our system and collect their suggestions, which are summarised as follows.

**Visual design and human-computer interaction:** For the experts, the system interface is well designed and displays a large amount of useful information for insights of the ranking model and scholarly dataset we proposed. The visual

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**TABLE 3. The top ten papars of HITS model**

<table>
<thead>
<tr>
<th>rank</th>
<th>title</th>
<th>counts</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PIWI: Visually Exploring Graphs Based on Their Community Structure</td>
<td>1</td>
<td>2013</td>
</tr>
<tr>
<td>2</td>
<td>DimpVis: Exploring Time-varying Information Visualizations by Direct Manipulation</td>
<td>7</td>
<td>2014</td>
</tr>
<tr>
<td>3</td>
<td>VEEVIE: Visual Explorer for Empirical Visualization, VR and Interaction Experiments</td>
<td>0</td>
<td>2016</td>
</tr>
<tr>
<td>4</td>
<td>Visually Comparing Weather Features in Forecast-s</td>
<td>3</td>
<td>2016</td>
</tr>
<tr>
<td>5</td>
<td>PeakVizor: Visual Analytics of Peaks in Video Clickstreams from Massive Online Courses</td>
<td>0</td>
<td>2016</td>
</tr>
<tr>
<td>6</td>
<td>Semantic Enrichment of Movement Behavior with Foursquare-A Visual Analytics Approach</td>
<td>0</td>
<td>2015</td>
</tr>
<tr>
<td>7</td>
<td>Visualization and Exploration of Temporal Trend Relationships in Multivariate Time-Varying Data</td>
<td>6</td>
<td>2009</td>
</tr>
<tr>
<td>8</td>
<td>Visualization, Selection, and Analysis of Traffic Flows</td>
<td>1</td>
<td>2016</td>
</tr>
<tr>
<td>9</td>
<td>Effects of Stereo and Screen Size on the Legibility of Three-Dimensional Streamtube Visualization</td>
<td>4</td>
<td>2012</td>
</tr>
<tr>
<td>10</td>
<td>The DeepTree Exhibit: Visualizing the Tree of Life to Facilitate Informal Learning</td>
<td>4</td>
<td>2012</td>
</tr>
</tbody>
</table>

**TABLE 4. The top ten papars of SPEAR model**

<table>
<thead>
<tr>
<th>rank</th>
<th>title</th>
<th>counts</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ViOHIC: Designing Visual Analytics for Online Health Communities</td>
<td>2</td>
<td>2016</td>
</tr>
<tr>
<td>2</td>
<td>Screenit: Visual Analysis of Cellular Screens</td>
<td>0</td>
<td>2017</td>
</tr>
<tr>
<td>3</td>
<td>Graph visualization and navigation in information visualization: A survey</td>
<td>53</td>
<td>2000</td>
</tr>
<tr>
<td>4</td>
<td>Polaris: A system for query, analysis, and visualization of multidimensional relational databases</td>
<td>42</td>
<td>2002</td>
</tr>
<tr>
<td>5</td>
<td>GosperMap: Using a Gosper Curve for Laying Out Hierarchical Data</td>
<td>2</td>
<td>2013</td>
</tr>
<tr>
<td>6</td>
<td>A Multi-Level Typology of Abstract Visualization Tasks</td>
<td>35</td>
<td>2013</td>
</tr>
<tr>
<td>7</td>
<td>Interaction Support for Visual Comparison Inspired by Natural Behavior</td>
<td>7</td>
<td>2012</td>
</tr>
<tr>
<td>8</td>
<td>SketchStory: Telling More Engaging Stories with Data through Freeform Sketching</td>
<td>5</td>
<td>2013</td>
</tr>
<tr>
<td>9</td>
<td>PETMiner-A Visual Analysis Tool for Petrophysical Properties of Core Sample Data</td>
<td>0</td>
<td>2018</td>
</tr>
<tr>
<td>10</td>
<td>ThemeRiver: Visualizing thematic changes in large document collections</td>
<td>43</td>
<td>2002</td>
</tr>
</tbody>
</table>

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C. DISCUSSION

Despite the advantages of our visual analysis of citation context based on article influence ranking, some problems are not well resolved in our work and would be further addressed in future works. First, the influence pattern of articles is usually similar to a tree structure; thus, identifying key levels or key nodes for evaluating the impact of papers is important. In our future work, we will design a prediction task based on semantic context to help users predict the possible future performance of newly published papers while effectively detecting key references. Second, the impact of articles is not only influenced by the quality of articles but also by their authors, their journals and other factors. For example, co-authors will have obvious mutual citations, and papers published in journals with high impact factors will be recognised more quickly. These factors influence each other and form a complex heterogeneous network, which brings challenges to the ranking of paper influence based on semantic relationship. In our future work, we will consider the impact of various factors on the dissemination and evaluation of article influence, and will attempt to realise the visual exploration of semantic relations from the perspective of heterogeneous networks to help users acquire and analyse the impact patterns of articles of interest better.

VII. CONCLUSION

Semantic relationship is an implicit attribute in big scholarly data and is important to the analysis of an author’s citation behaviour. However, semantic relationships are too abstract to understand, making it difficult to analyse and apply to related research. Especially with the increase in the scale of dataset, semantic relationships inevitably become interlaced and complex. Aiming at large-scale academic data, this study provides a visual analysis system for the ranking of paper influence from the perspective of citation context.

Word2vec is used to train the citation relationship into a vector representation, which can quantify the similarity of articles on the citation link. Then, the similarity of citation effectively correlates with the SPEAR model to realise the analysis of article influence based on citation context. In addition, the ranking results under different algorithms are compared through numerous visual designs and human-computer interactions, which are used to help users efficiently analyse the role of citation context in the ranking of influential papers. Finally, case studies based on real data sets and interviews with experts in the field further prove the effectiveness of our system in the visual ranking of academic influence using the citation context.

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