WordleNet: A Visualization Approach for Relationship Exploration in Document Collection

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Abstract: Document collections do not only contain rich semantic content but also a diverse range of relationships. We propose WordleNet, an approach to supporting effective relationship exploration in document collections. Existing approaches mainly focus on semantic similarity or a single category of relationships. By constructing a general definition of document relationships, our approach enables the flexible and real-time generation of document relationships that may not otherwise occur to human researchers and may give rise to interesting patterns among documents. Multiple novel visual components are integrated in our approach, the effectiveness of which has been verified through a case study, a comparative study, and an eye-tracking experiment.

Key words: document relationship; interaction techniques; text visualization; relationship visualization; visual analytics

1 Introduction

To quickly pass through a variety of documents and grasp their key points is a common task in many domains, such as academia, journalism, politics, and business. It is not an easy job, however, since a document collection not only contains rich semantic information, but also a variety of implicit or explicit relationships that intertwine with each other to form a complex knowledge network[1], the understanding of which is necessary for making sense of what the document collection really expresses.

Document analysis has recently been a hot research topic in the visualization field. Representing documents as individual objects and analyzing their content and relationships are helpful for many scenarios[2]. Using literature retrieval as an example, when looking for relevant papers for citation, a researcher will generally search for papers using keywords, and then filter out unrelated papers by viewing the abstract or other metadata. When a researcher uncovers a relevant paper, he will inspect the documents that it references, as well as seeking further related papers by looking for articles that make reference to it. Multiple factors, such as keywords, topic, authors, and publisher, should be considered during the retrieval, making it a time consuming process. A tool that can provide intuitive visualizations of important aspects of the document collection is definitely helpful, especially for large collections.

Existing works mainly focus on visualizing and analyzing specific kinds of relationships[3–5]. Zhao et al.[1] proposed a tool to visualize the citation relationship and metadata of a document collection, in which the documents are divided into several groups, but no overview is provided showing the general similarity among the documents. We believe such contextual information to be an important reference for document exploration, providing a cue for finding documents with potential similarity. Nonetheless, the concept of a textual relationship is comprehensive and may involve a variety of factors, such as semantics, content, and metadata. Different tasks may need to
define different relationships through which to drill down to arrive at interesting patterns. An analytic framework that enables relationships to be flexibly defined is thus necessary.

In this paper, we propose an approach to exploring relationships among document collections. We define the document relationship as a linear combination of multiple factors, such as content, keywords, metadata, and citations. The synthetic relationships are visualized through an improved multi-dimensional scaling algorithm to show the general similarity of the documents. The user can interactively adjust the weights of different factors involved in the relationship definition to explore interesting patterns. Semantic content and detailed referential relationships can also be displayed to provide more complete information while exploring the document collection. In summary, the contributions of this paper include:

- A definition of the document relationship that considers multiple factors to enable customized relationship exploration and potential pattern discovery within document collections;
- An interface that provides a compact and comprehensive representation of multiple categories of document relationships; and
- An evaluation that integrates a case study and an eye-tracking-based user study, thus providing a comprehensive verification of our approach.

The remaining parts of this paper are organized as follows. Section 2 reviews the related work. The problem statement is described in Section 3, while the visual design is presented in Section 4. Section 5 gives details of the evaluative case study and two user studies, the results of which are discussed in Section 6. Finally, we conclude the paper in Section 7.

## 2 Related Work

### 2.1 Text visualization

Text visualization is a popular focus of visualization research. A classic example in the field is Wordle\(^6\), which shows semantic content by displaying a number of word-tags with sizes proportional to the frequency with which they occur in the document. In recent years, many novel Wordle-based techniques have been developed. ManiWordle\(^7\) and Rolled-out Wordle\(^8\) use a spiral growth placement strategy in word cloud arrangement to provide for the flexible interactive manipulation of word cloud layouts. Paulovich et al.\(^9\) computed a neighborhood relationship to place similar words close to each other. These works focus on adjusting the layout to attain a better representation of unstructured texts. Wu et al.\(^10\) proposed a technique named semantic-preserving word clouds, in which semantically related words are positioned together. Different from the above works that mainly focus on semantic content, the main purpose of our approach is to reveal potential relationships in document collections, in which semantic similarity is viewed as just one aspect of document relationships, thus providing a more comprehensive framework for exploring large document collections.

It is common to use a graph-based method to show document information. From the visual metaphor perspective, the river\(^11, 12\) and map metaphors\(^13–15\) are two typical document visualization methods. The use of different metaphors reveals different aspects of the document and its text: the river metaphor focuses on the temporal evolution of the textual information, while the map metaphor visually and intuitively maps semantic information from set space to Euclidean space. Phrase nets\(^16\) organize extracted words as a network based on user-defined relationships. Chuang et al.\(^17\) proposed a method based on key phrases, which extends the technique to n-grams to show the words in context. Cui et al.\(^18\) visualized the relationships of word clouds using the force-directed algorithm. Cao et al.\(^19\) presented FacetAtlas, a multifaceted visualization system which addresses multiple dimensions of documents in complex document collections. PivotPaths\(^20\) is another classic interactive visualization for the exploration of faceted information, exposing faceted relationships as visual paths that allow users to stroll through an information space. Barth et al.\(^21\) proposed a proper, consistency-preserving editing approach to make sure semantically-ordered word clouds. Dubinko et al.\(^22\) designed a semantically consistent layout with a multi-dimensional projection. Strobel et al.\(^23\) designed a novel visualization that represents a document as a mixture of images and several key terms. These works have attended to the intrinsic relationships within document collections, but most of them only work on one category of relationships; our purpose is to provide a general conceptual framework to enable systematic exploration of various potential relationship patterns within document collections.

There are also many tools dedicated to corpus
visualizations. These works, however, view a collection of documents as integral, and only offer an overview of the document collection without providing any detail on individual documents. Different from these works, we encode each document as a separate word cloud, based on which a graph is constructed. This enables an in-depth exploration of document collection at both the individual and group levels.

### 2.2 Relationship exploration

There has been extensive research on relationship visualization. A classic visualization method is the plotting of parallel coordinates [26]. Over the last decade, a number of more advanced techniques have been proposed to analyze various kinds of relationships. Shadoan and Weaver [27] proposed a method to explore many-to-many relationships among different dimensions. Alsallakh et al. [28] designed a radial representation to visualize collection relationships. Wood et al. [29] designed an origin-destination relationship visualization technique. Collins and Carpendale [30] used links to connect the visual elements in different views that have specific semantic relationships. Entity-relationship research is mainly based on certain shallow and direct relationships, while our approach can not only express the direct relationship between documents, such as referential relationships, but also delve deeper into textual relationships.

Many existing studies focus on identifying the attribute-level relationships based on analysis models or computation frameworks. Basole et al. [31] analyzed the differences in business ecosystems between international corporations. Janicke et al. [32] constructed a similarity model and used it to analyze the life and artistic experiences of musicians. Zhang et al. [33] devised a correlation analysis method which was able to handle both categorical and numerical variables within a unified framework. Xia et al. [34] proposed a multi-dimensional visualization method based on dimension relationship detection to reduce the workloads of further detailed investigations. As the exploration of semantic relationships became popular, an application named Jigsaw [35] was developed for analyzing relationships between entities in document collections. Yang et al. [36] derived a hybrid semantic similarity model from analyzing the semantic distance of concepts and the relationship between attributes and concepts. Our approach takes much inspiration from these works to seek out additional textual relationships worth exploring in document collections. Considering that existing research on textual relationships is biased either towards attributes or towards semantic similarity, our approach aims to fuse these different types of relationships to provide a more general and comprehensive relationship definition to present documents and their relationships in an intuitive manner.

In general, the current state of research into relationship analysis within document collections is to focus on either semantic similarity or a single category of relationship. Our approach provides a more comprehensive relationship definition that simultaneously considers multiple relating factors, such as semantics, text, and attributes, thus enabling users to gain insights into various potential relationship patterns within a document collection.

### 3 Problem Statement

#### 3.1 Definition of document relationship

In order to better analyze and explore a collection of documents, we first provide a definition of a document relationship. Considering the common properties of textual data, we propose that if two documents have some specific relationship, they should have similar semantics, common document attributes (metadata), or common keywords. We define these three factors as follows:

- **Semantic similarity**: The semantic similarity describes the general relationship between documents. There are many algorithms that can be used to quantitatively measure the semantic similarity, such as topic models, term-frequency based methods, and distance-based methods. The higher the semantic similarity of two documents, the closer their relationship.

- **Common words**: Each document of a collection will have some words that occur with a high frequency or carry a heavy weight. If two papers have more of these words in common, it is likely that their research direction may overlap to some extent. It can be seen that the common words reflect another textual relationship different from mere semantic similarity, and therefore at a more refined level of exploration of key information.

- **Attribute coincidence**: The relatedness of text corpora depends on specific attributes. The current practice when considering text attributes is performing...
a simple filter selecting documents with the same attributes. This selection method is too coarse and does not take into account the degree to which a set of documents shares attributes, thus it is not sufficient to fully explore the relationship between texts. Therefore, we decided to quantify the text-specific attributes that strengthen the connection between documents. The more specific attributes shared between the documents, the closer their connection is deemed to be. Considering the fit of text attributes is one of the highlights of our definition of textual relationships.

3.2 Modelling textual relationships

In this section, we provide a model for quantitatively measuring document relationships based on the proposed three factors.

**Semantic similarity:** Given a collection of documents, we first need to build a corpus to form a word space. We then use the one-hot method to represent each document encoded as a word vector of the same length; this is one of the most common word embedding techniques in the bag-of-words model. With these word vectors, we are able to calculate the cosine similarity between two documents. Suppose there are two word vectors, \( A \) and \( B \); the cosine similarity between them, \( Sim(A, B) \), can be expressed as

\[
Sim = \frac{\sum_{m=1}^{M} (A_m \cdot B_m)}{\sqrt{\sum_{m=1}^{M} A_m^2} \cdot \sqrt{\sum_{m=1}^{M} B_m^2}}
\]  

(1)

where \( m \) is the dimension of the document word vector.

**Common words:** Suppose that the two papers \( A \) and \( B \) have the collection of words \( K(A) \) and \( K(B) \), respectively, and that \( k^{Ai} \) is the \( i \)-th pivotal word of Paper \( A \) and \( k^{Bi} \) is the \( j \)-th pivotal word of Paper \( B \) (here, pivotal words are those with higher occurrence frequencies rather than author-defined keywords). The common words, i.e., \( Rat(A, B) \), can then be calculated as

\[
Rat = \frac{|k^{Ai} \cap k^{Bi}|}{|k^{Ai} \cap k^{Bi}| + |k^{Ai} - k^{Bi}| + |k^{Bi} - k^{Ai}|}
\]

(2)

where \( |k^{Ai} \cap k^{Bi}| \) indicates the number of words common to both Papers \( A \) and \( B \), \( |k^{Ai} - k^{Bi}| \) is the number of words in Paper \( A \) but not in Paper \( B \), and \( |k^{Bi} - k^{Ai}| \) is the number of pivotal words that are in Paper \( B \) but not in Paper \( A \).

**Attribute coincidence:** Suppose that each document in a collection contains \( N \) attributes, and \( p^{An} \) is the \( n \)-th attribute. The attribute coincidence for the \( n \)-th attribute between two documents \( A \) and \( B \) is denoted as \( Deg(p^{An}, p^{Bn}) \), which can then be formulated as

\[
Deg(p^{An}, p^{Bn}) = \begin{cases} 
\frac{1}{N}, & p^{An} = p^{Bn}; \\
0, & p^{An} \neq p^{Bn}
\end{cases}
\]

(3)

The general coincidence of all the \( N \) attributes between documents \( A \) and \( B \) is

\[
Deg = \sum_{n=1}^{N} Deg(p^{An}, p^{Bn})
\]

(4)

The final synthetic relationship can be viewed as the linear combination of all the three factors,

\[
R = \alpha Sim + \beta Rat + \gamma Deg
\]

(5)

where \( \alpha, \beta, \gamma \in [0, 1] \) are the weights of the three factors. Our approach supports the adjustment of the factor weights, thus providing flexibility in the exploration of relationships and enabling the discovery of a variety of potential patterns.

3.3 Goal and task

The main goal of our approach is to design and implement a system supporting the exploration of document relationships with respect to all three of the factors identified above. We conducted several discussions to identify the different analysis tasks of our approach. Among all the candidate tasks, analyzing the synthetic relationship is the most important. For example, we want to be able to answer the questions: “Which documents are most closely related to a specific document?” and “Can we identify any document clusters in which the inner documents have similar relationships?”. Furthermore, users are also interested in concrete statuses of the individual factors of the relationship. For example, users may want answers to questions like: “What is the semantic content of a document?”, “Do any papers have the same co-author?”, and “Does a specific document cite other documents in the collection?”. Therefore, it is also important to understand the concrete statuses of the factors of relationships. To help produce a design that meets our goals, we classify the most important tasks into two major categories:

- **T1:** Interactively generate, visualize, and analyze the synthetic relationship.
- **T2:** Seamlessly visualize the three factors within the synthetic relationship to show an information-rich analytic context.

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4 Approach

4.1 Design rationale

To provide the best support for a user-customized exploration of relationships in a document collection, we first identify three important requirements on which to base our design: interactive relationship generation, integrated relationship visualization, and context-preserving relationship analysis.

R1: Interactive relationship generation. The relationships should be generated in an interactive way. The reason for striving for interactivity is to instill flexibility in the exploration process. Since only the user knows the relationship that he is seeking, and this may frequently change as he continues to explore, the possibility of performing these tasks in interactive way can improve the usability and generalizability of the approach.

R2: Integrated relationship visualization. The synthetic relationship and its factors should be visualized in an integrated view. The main consideration behind this requirement is the need to reduce visual clutter and improve the cognition effects. Since the relationship and its factors have different visual features, an integrated view may effectively increase compactness and decrease the undesired gaze transitions among different parts of the interface.

R3: Context-preserving relationship analysis. The relationships between any pair of documents should be maintained during the exploration. Interesting relationship patterns may exist within any part of the collection, and we wish to avoid imposing divisions that may present an obstacle to the discovery of potential patterns. Therefore, a context-preserving relationship overview is important in providing users with an overview of the entire document collection and guiding them where to drill down for further exploration.

4.2 Visual design

Figure 1 shows the interface of our visual relationship exploration framework for document collections, consisting of four components: a main relationship overview together with three auxiliary components.

4.2.1 Relationship overview

The relationship overview (as shown in Fig. 1a) is the most important component, used to visualize the synthetic relationship and its factors. Essentially, the relationship overview is a scatter plot, with each node encoding a document. The distance between two nodes is proportional to their synthetic relationship, with a close projecting distance indicating a close relationship. We use an improved MultiDimensional Scaling (MDS) algorithm to generate the layout, which
is a classic technique for Dimensionality Reduction (DR). Compared with other DR algorithms, MDS is able to preserve the distances among objects in high-dimensional space when projecting them to a low-dimensional space\(^{(23)}\). The position of the nodes obtained by MDS may suffer from a high degree of overlap because of the relatively large radius of the nodes; we use the helical spring algorithm to resolve this problem. As shown in Fig. 2, when projecting a node, the algorithm first detects whether it will intersect with any other nodes. If there is an overlap, a position adjustment is conducted by altering the angle and radius relative to the original projected position. The change in radius is relatively small and the angle is spiraled with each adjustment in order to avoid any serious distortion that may lead to misleading output. In effect, the helical spring algorithm conducts a spiral position search until it finds a position without overlap.

To better visualize the concrete content of a document, we encode each node as a word cloud rather than depicting it as a basic geometric shape. The contents of each word cloud are the keywords occurring with the highest frequency in the document. To ensure readability of the output, the number of words in each word cloud is limited to the range of 12–20. We follow a convention that uses the font size to encode the word frequency, thus promoting words with higher frequencies, which may better reflect the semantics of the document\(^{(38, 39)}\). We utilize a radial layout, in which words with the highest frequency of occurrence are placed at the center and words with lower frequency to the outside; the benefits of this layout for cognition have been shown in Ref. \(^{(40)}\).

Color is another important visual feature of a word cloud. It is desirable for the colors assigned to words to be meaningful, as this can effectively reduce the cognition burden on users. For this purpose, we generate a corpus based on all the documents in the collection, and generate vectors using Word2Vec. We then use MDS to project these vectors on a two-dimensional plane with a colorful background, as shown in Fig. 3. By setting the color of each word equal to the color of its projected position, we can have the color reflect the semantic similarity, i.e., words with similar colors have similar semantic meanings. Using Fig. 4 as an example, the word clouds in Figs. 4a and 4b are similar with each other in both general content and color, but Fig. 4a has the word “stable” marked in blue, indicating that Fig. 4a has greater focus on the stability of the tree layout than Fig. 4b.

### 4.2.2 Auxiliary components

In this section we introduce the three auxiliary components: the keyword filter, the relationship adjuster, and the reference widget.

The **keyword filter** is used to select interesting documents having specific keywords, as shown in Fig. 1b. The user can select one or more keywords by checking the boxes in front of them. In order to help users to explore and discover information, we allow them to select multiple words, and fulfill the search with an “or” operation, i.e., documents containing any of the
selected keywords will be collected. This component is always used to choose a starting point for relationship exploration.

The **relationship adjuster** consists of three sliders that can be used to adjust the weights of the three factors to synthesize the relationship, as shown in Fig. 1b. The range of values for each slider is 0–1. For the attribute factor, we integrate three candidates: author, author affiliation, and the journal or conference proceedings in which the document is published. Additional or alternative attributes could be integrated to meet different application scenarios. An attribute can be selected by checking the corresponding box. We recommend a progressive step-by-step adjustment to see the gradual changes in node position and better understand the effects of different parameters on the synthetic relationship.

The **reference widget** is used to reveal the referential relationship among papers, which is very significant but has a different form and thus cannot be integrated with the other three numeric factors. When the cursor hovers on a particular node, the nodes of all the documents cited by the document of that node will be highlighted, and several lines will be drawn, each connecting a cited node to the selected node. When the selected node is clicked, a bar chart will appear that displays the extent of the relationship of each of the cited documents to the selected document, as shown in Fig. 1d.

### 4.3 Interaction

Here we use a complete analytic flow to illustrate the usage supported by our approach. Since there are many document nodes of word clouds in Fig. 1a, users may not be able to quickly find which node to use as a starting point. To begin, they can select the keywords that they want to study using the keyword filter, as shown in Fig. 1b. In order to respond to the user’s developing ideas, they are permitted to select multiple keywords. In this way, the corresponding word cloud nodes can be filtered out, and the user can select the node from which to start exploring according to the semantic information provided in the word cloud.

Figure 5 shows the nodes filtered after the user selected the words “topic”, “evolution”, and “time” in the keywords filter.

Having chosen an initial node, users can hover over that word cloud, at which point two types of contents displayed: the name of the selected document and the nodes with specific referential relationships to the selected document. An example can be found in Fig. 6, in which the nodes that have referential relationships with the selected Node 2 named **TextFlow: Towards better understanding of evolving topics in text** are shown. While users have a cluster of documents to explore through a simple hover, the distance between nodes is not sufficient to accurately provide details on which node’s textual relationship is most similar to the selected, or what the range of similarity is, etc. The user can therefore click on the word cloud of the selected node to populate the reference widget under the overview. Furthermore, users can hover over the bar so that the specific values of the current textual relationships can be viewed in the bar chart; this can help with tasks such as finding the most similar document or learning the range of relationships.

The synthetic relationship can be adjusted with the

![Fig. 5 Node filter. The keywords “topic”, “evolution”, and “time” are selected to collect documents with one of them.](image-url)
relationship adjuster, as shown in Fig. 1c. A user is given the ability to freely adjust the relative weight of each textual relationship, or to select the type of attributes they want to research based on their own interests. Figure 7 shows the distribution of nodes when considering only the attribute factors related to authors’ affiliations and publication titles.

4.4 Hierarchical exploration

This subsection presents a proposed solution to the problems that a very large document collection would be created, which could be developed as an extension of the currently completed tool. At present, our tool has an upper limit to the number of documents it can display, reflecting the common number of references in academic papers (40–100). If the number of documents reaches tens or even hundreds of thousands, an alternative approach is necessary; therefore, we provide an outline of a display solution to be pursued in future work.

The proposed system would work as follows. As shown in Fig. 8a, when the number of documents is too large, the documents will be preprocessed and aggregated to represent each class of papers as an elementary geometric shape. The user will then be able to browse several keywords of the current class of documents interactively, and each keyword will be equipped with a corresponding color of sparklines, as shown in Fig. 8b. Different from SparkClouds[41], which visualizes trends among multiple word clouds by integrating sparklines into a word cloud, we intend to use sparklines to show that the current class of documents also contains several subclasses, and to reveal the importance of the current keywords for each subclass. In the next level of exploration, shown in Fig. 8c, through interaction the user will be able to reveal all documents in the current class, with each document represented by a separate elementary geometric shape, and divided into different subclasses according to the main keywords, with the same color corresponding to the same keywords. The lowest level would be the document word cloud display as shown in the final interaction in Fig. 8d.

5 Evaluation

5.1 Case study on literature collection

Imagine that a postgraduate analyst, Harry, is writing
Fig. 8 An illustration of the solution to display of large document content. (a) An elementary geometric shape is an aggregated class of document. (b) Specific visualization of the red node, sparklines represent the importance of the keyword in the subclasses of documents. (c) The subclasses of documents. Each document is represented as a node. (d) The word cloud of a document will be shown by interaction.

a paper on visual analysis. Finding references is a key step, but the typical method of searching for papers on the Internet is time-consuming. Harry therefore wants to use WordleNet to identify some excellent related papers. Harry is interested in data visualization and text analysis, and wants to explore papers by Huamin Qu and Shixia Liu who he knows to be professionals in this field and co-authors of some important papers, so he generates a word net with the help of WordleNet. Because the theme of Harry’s paper is topic evolution, he firstly selects the keywords “topic” and “evolution”. After running his eyes over all the word clouds that are collected by the filter, he notices Node 2 with the selected keywords marked, as shown in Fig. 5. Restoring the original data interface and hovering the cursor over the node, Harry learns that the name of this paper is *TextFlow: Towards better understanding of evolving topics in text*, and also notices that all the word clouds of papers that have a citation relationship with this paper are now highlighted. The sliders in the initial state are all in the middle position, so the three textual relationships contribute half of the force. Harry clicks on the selected node, and the bar chart widget below the overview shows the names and approximate relationship values of all the cited papers. It can be clearly seen that three particular papers are most closely related to the selected paper, and the bar chart shows that the current textual relationship values for these four papers are much higher than others. Based on this, Harry wants to explore in more detail.

Above all, Harry adjusts the content slider to the maximum and the words and attributes to zero to explore the impact of text similarity (see Fig. 6). Clicking on the selected node, he sees that Node 28, named *How hierarchical topics evolve in large text corpora* is the most closely related, so he zooms in on this node to clearly reveal the word cloud. He guesses that the main topic of this paper is the evolution of hierarchical topics and finds the words “stable”, “tree”, and “cut” with colors biased toward blue, so he comes to the conclusion that the paper named *How hierarchical topics evolve in large text corpora* on the subject of topic evolution puts forward the idea of making more stable the layout of hierarchical topics. Harry also notices that there are three nodes relatively closer to the selected one. One paper at Node 17 named *Visual analysis of topic competition on social media* has the words “topics” and “timeline” among others in its word cloud, indicating that it may discuss the timeline of topic competition on social media. Another paper at Node 25 is called *Understanding text corpora with multiple facets*, with words in its cloud indicating that it may analyze text by trend and several other facets. The last Node 11, named *StoryFlow: Tracking the evolution of stories* is likely to focus on the evolution of stories and the hierarchical relationships therein. Harry senses that these papers can inspire him from different perspectives, and should provide interesting input to his research. Knowing that these four papers are relevant, Harry plans to read and explore further.

In order to discover more potential patterns, Harry then turns up the words slider to the maximum. He is pleasantly surprised to find that there are three nodes (75, 19, and 14) surrounding the selected node but with no referential relationship to it. He firstly views Node 75 named *Online visual analytics of text streams* and clicks on it, producing the visualization shown in Fig. 9. The bar chart widget shows that Node 75 has a high current textual relationship with Node 28, and its word cloud proves this point. Node 75 also has referential relationship with Node 19. When Harry also clicks on 19, he learns that it has the highest
current textual relationship value with Node 17, and that their word clouds are relatively similar. This shows that users can easily find related papers with the help of WordleNet, even where there are no direct referential relationships. Nodes 19 and 17 are both highly similar to 14, whose word cloud shows that the textual focus of their research is on public opinion diffusion and social media. Scanning the whole word net, Harry realizes that social media visualization and information propagation are topics worth integrating into his research, thus broadening his research ideas.

Finally, Harry makes use of some of the novel aspects of the textual relationship to find papers with high levels of similarity and available in the same publication. He selects the third attribute (publication title) and increases its weight using the attribute slider. Because Nodes 2, 17, 19, 28, and 75 gather together (as shown in Fig. 10), Harry can conclude that these papers have been published in the same journal or conference proceedings. As long as he knows the publication details of one of them, he can learn the level of relatedness of these articles and then decide which related papers to read first. Using WordleNet for reference exploration, Harry discovers many papers related to understanding textual data are potentially valuable for his future research. He is inspired by the combination of the textual relationships, word clouds, and interaction design in the visual analysis.

5.2 User Study I: Comparative study

The first part of the evaluation of WordleNet was a small comparative experiment to verify that the design of WordleNet does speed up the search for relevant documents. Because word cloud can be viewed as an abstraction of the original semantic content of documents, we regarded the collection of all the word clouds in our dataset as the control group. In order to test the effectiveness of our tool for searching related papers, we used a literature collection as the experimental dataset. We recruited 10 participants with a variety of research interests but all majoring in computer science at Tianjin University. All of the participants had strong English reading abilities.

Experiment design. The purpose of our experiment was to compare our approach with the control group with respect to the speed and efficiency of document search. We began with a brief explanation of the study goals and overall procedure, following which the participants were given an introduction to the word cloud set and a tutorial on the use of WordleNet. They
were then asked to complete the following task twice: Find five documents (word clouds) whose content may involve “topic”. The completion times were recorded separately and a questionnaire was administered after the study.

**Results.** The results of the comparative study are shown in Fig. 11. The measurements of completion time showed the design of WordleNet to be more time-efficient and direct than a naked-eye search of word clouds. The average task time for all participants was 18.59 seconds for WordleNet (marked blue in Fig. 11) and 83.97 seconds for the word clouds set (marked orange). Participants were significantly faster and more accurate when using WordleNet.

**Feedback.** At the end of the study, we asked participants to rate their satisfaction with WordleNet on four criteria. All ratings were made on a 1–7 Likert scale ranging from “strongly disagree” to “strongly agree”. WordleNet was highly rated. On average, the participants deemed it easy to learn (6.8) and use (6.7), and they were highly satisfied with the definition and adjustment of textual relationships (6.6). Finally, they indicated a desire to use WordleNet to perform literature searches in the future (6.4), and expected the tool to help facilitate their thinking. Participants elaborated on the usefulness of WordleNet as follows: “Through the comparison, I think this is really a good idea. 42 word clouds have made me be dazzled, if there are more documents, the effect will be more remarkable.” (P5, who wasted the most time searching for word clouds); “The definition of the text relationships is meaningful, it’s much more convenient than searching for relevant literature on search engines.” (P2); “Well, the relationship adjuster is cool, the text relationship between documents can be adjusted so skillfully. This is very useful for us to read the relevant literature in the future.” (P4); and “It’s so ingenious and time-saving to see the reference relationship through some interaction.” (P10).

5.3 User Study II: Usability experiment

For the second part of the evaluation, we conducted a usability experiment to evaluate the effectiveness and interactivity. This experiment analyzed the impact of each visual element on the overall cognitive performance, and the effectiveness of the analysis tools that make up the multiple views. The experimental results can also guide users to better use the tool to meet their specific needs.

In addition to the usual experimental parameters, such as completion time and accuracy, eye tracking has also been used by researchers as an important means of evaluating visualization. Eye tracking devices continuously record eye movements throughout a visualization task and gain insight into how users use a visual environment\([42]\). Therefore, spatiotemporal eye movement data may be more useful for diagnostics than some experimental parameters, telling us whether users can operate and use our tools correctly. In our experiment, to analyze the effects of the cooperation of the three views (the overview, the text relationship adjuster, and the reference relationship widget), we set four Areas Of Interest (AOIs) closely related to our tasks, as labelled in Figs. 12 and 13. Multiple availability patterns can be identified by observing the direct transitions of the eye movement trajectory of subjects between the AOIs.

5.3.1 Tasks

To perform the experiment, we proposed three interrelated tasks regarding the exploration of a collection of papers, all of which are closely related to our visual design elements. The specific tasks were as follows:

- Find the word cloud of the paper whose theme is...
most likely to be “topic evolution” in Fig. 12.
- Determine which textual relationship has been adjusted to generate the current distribution in Fig. 12.
- Find the name of the paper that has the closest relationship with the marked node in Fig. 13.

5.3.2 Preparation

Stimuli. As shown in Figs. 12 and 13, the tool used in the experiment contains three views, of which the relationship overview can be used to view the distribution, referential relationships, and general content of document nodes (AOIs 1 and 3), while the other two views specialize in adjusting and displaying the textual relationships (AOI 2) and showing the names of cited papers and the concrete values of the current textual relationships (AOI 4). To support interactions, an executable program with the predefined operations was used, and shown to each subject after a calibration procedure. We used the dataset from the above case
study on paper collection, with the content slider adjusted to the maximum, the words and attributes set to zero for the first two tasks, and the node of the paper named *TextFlow: Towards better understanding of evolving topics in text* selected in the third task.

**Subjects.** For this experiment we chose 10 subjects, all of whom are graduate students with the College of Intelligence and Computing of Tianjin University, with different levels of experiences in visualization. Six of the participants are male and four were female, with an average age of 24.2 (between 21 and 31). None of the subjects have used our tool before, but all of them are confident with mouse and keyboard interaction and capable of reading papers.

**Environment.** All the trials were conducted in a laboratory environment during a vacation to minimize outside distractions. We used a Tobii T60 XL eye tracking system with a Thin Film Transis (TFT) screen resolution of 1920×1200 pixels. On the eye-tracking software, the fixation duration was set to 60 ms and the fixation size to 10 pixels.

**Trials.** Each subject underwent trials on all three tasks, resulting in a total of 30 trials.

### 5.3.3 Procedure

We firstly gave each of the subjects a brief introduction to our tool, and then spent 10–15 minutes training them in the use of the tool across the three views. As part of this, we answered any questions raised by the subjects to ensure that they would be capable of completing the tasks. The eye-tracking software created an account for each subject with their name, age, gender, and prior knowledge of visualization. Before the experiment began, any technical problems arising during the training procedure were solved.

At the beginning of the experiment, the eye tracker calibrated the subjects’ eyes using the 5-point calibration technique. Once this was done, the test program was shown to each subject. To keep the subjects facing the screen as much as possible, the administrator recorded the solutions and answers orally described by subjects, and also clicked a button on the keyboard when necessary to jump to the next screen. Accuracy was manually recorded, while the completion time and the eye-tracking duration were automatically recorded by the eye-tracking system. This experiment sets no time limit for any task, simply instructing the subjects to complete the tasks as accurately and quickly as possible. Emphasizing a need for a rapid solution or imposing a strict time limitation may have led to high error rates and possibly chaotic gaze trajectories, as subjects would be placed under pressure to guess the answers, this was not the intention of our user study[43].

### 5.3.4 Results

The overall accuracy of task completion was 95.67%, and each session of 3 trials took between 24.489 and 47.359 seconds to complete. The high level of accuracy was in accordance with our expectations, since the preset was carefully selected to ensure that the patterns would be obvious.

We mainly focus on the exploration behavior of the participants, and the gaze plots for the experiment are shown in Figs. 12 and 13. To quantitatively analyze the gaze plots, we also provide the results for three important metrics in Table 1, with the results summarized as follows:

- The importance of our design approach for this tool is obvious from the experiment. Subjects relied heavily on the relationship overview to complete related tasks, as shown by AOIs 1 and 3—both located in the overview component—having more fixations than the other two views.
- The frequent fixation transitions between the relationship overview and the other two views prove the coherence and tight coupling as the two views are used to adjust the layout of the nodes in the overview and to explain the textual relationship underlying the referential relationship. In contrast, the other auxiliary views are relatively loosely connected due to their respective functions and the order of interaction, such that they are not evaluated on the same screen, although their role cannot be ignored. Since the relationship adjuster (AOI 2) is preset, very little gazing time is required to make a simple resolution. On the other hand, the reference widget (AOI 3) provides relevant information about cited papers and the values of the current relationships, so it receives the additional attention needed by users to read valid information from it.
- AOI 1 receives more attention than AOI 3, because

| AOI | Mean fixation duration (s) | Mean total fixation duration (s) | Mean fixation count |
|-----|-----------------------------|----------------------------------|--------------------|
| AOI 1 | 0.52                        | 11.70                            | 22.60              |
| AOI 2 | 0.45                        | 6.89                             | 15.20              |
| AOI 3 | 0.47                        | 9.15                             | 19.40              |
| AOI 4 | 0.39                        | 10.46                            | 26.90              |
it is relatively time-consuming to find the node of a topic in the absence of keyword filtering. Therefore, it can be concluded that even though we did not evaluate the keyword filter, its importance was indirectly reflected in the results.

5.3.5 User feedback

An open-ended discussion with all of the subjects was held after the experiment. We encouraged the subjects to talk about their experiences and noted their feedback. The feedback from the subjects is mostly positive. They expressed that the tool was useful and easy to learn. Furthermore, they agreed that every view has its own role. The relationship adjuster can explore textual relationships based on the researcher’s specific interests, and an effective keyword search for papers was very helpful while developing ideas. The subjects felt that the overview was the most important component, showing not only the main content of papers, but also the textual and referential relationships. The usefulness of the reference widget in providing the names and the concrete relationship values of cited papers was confirmed. Several subjects highlighted the particular importance of interactions, especially the operation of hovering to show the document and referential relationships. They also mentioned that through interactive operations, selecting nodes and adjusting the relationships can permit more in-depth analyses, such as anomaly detection.

The subjects also made constructive suggestions for improvements. Six subjects mentioned that if the dataset was larger, the word clouds would become too dense and overlap. We noted the suggestion to use an ordinary node and then interactively display the word cloud, and would like to implement this in future work. Three subjects also advised us that adding a history box to prompt users with the basic information of previously explored nodes may prevent any confusion caused by large number of nodes. One subject proposed that our approach could be usefully adopted to find patterns in other kinds of document collections.

6 Discussion

In this paper, we have presented WordleNet, an approach to explore systematic relationships in a document collection. A specific feature of our approach is the systematic definition and modelling of textual relationships being combined with the design of an interactive visual interface. In what follows, we discuss some different aspects of our approach.

Scalability. The document collection we have used in this paper is relatively small, so as to demonstrate the visual design more clearly. Although the limited size of the relationship overview means that it cannot simultaneously show a large number of word clouds, we can improve its scalability with a simple change, which is to replace the word clouds encoding the documents with an elementary geometric shape, and to show word clouds only of documents that are interactively selected. With this modification, we believe our approach can be used to analyze collections containing thousands of documents. If the number of documents is larger than the number of pixels, an aggregated class of documents will need to be represented by another elementary geometric shape. A more detailed exploration would then be achieved through interaction, thus enabling scalability.

Information loss. Since the layout of the relationship overview component is generated by an improved MDS, it inevitably entails information loss. As the amount of data increases, this loss may become serious. Considering that this dimensionality reduction approach makes the distance of all data node pairs in low-dimensional space approximately equal to their distance in high-dimensional space, it is not possible to completely eliminate the information loss. Our approach supports interactive relationship adjustment and visualization. For a specific goal, the user is able to make slight changes to the relationship parameters and repeatedly execute similar operations for confirmation, thus effectively decreasing the effects of information loss by the dimensionality reduction algorithm.

Visualization effectiveness. We have designed a visual interactive interface that supports all previously defined task types, as was proved in the case study. The main content of each document is shown in its word cloud node, and the textual relationships are also clearly displayed in the close cooperation between the relationship overview and the auxiliary views. Some visual problems were raised in the user study; for example, users may forget the nodes they have previously explored. We were advised to add a viable historical browsing history view to help users explore more easily.

Practical usefulness. In terms of the practical application value of this approach, we believe that it can be used for a variety of document collections, as long as the collection contains a relatively high level
of textual information and the textual relationships are clearly defined. While we present our approach using the example of a literature collection, it could be fruitfully applied to document collections of a similar structure in other domains.

7 Conclusion and Future Work

We have developed a visualization approach to systematically revealing relationships among a document collection. The design integrates a novel relationship overview, which utilizes an improved multidimensional scaling technique to encode document relationships through the projection of multiple word clouds, each of which encodes a document. Three auxiliary components are integrated in our tool to support interactive node retrieval, relationship adjustment, and reference observation, thus enabling a systematic and customized relationship exploration. We demonstrate the usefulness and usability of our tool through a case study and two usability experiments.

In the future, we plan to improve the WordleNet in two respects. First, we plan to test WordleNet using additional larger-scale datasets. Second, we plan to provide a document trajectory for a specific exploration requirement, showing the semantic evolution within the collection and helping users to grasp the key points of the collection more efficiently.

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References

[1] J. Zhao, C. Collins, F. Chevalier, and R. Balakrishnan, Interactive exploration of implicit and explicit relations in faceted datasets, IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 12, pp. 2080–2089, 2013.
[2] W. Dou, L. Yu, X. Wang, Z. Ma, and W. Ribarsky, Hierarchical topics: Visually exploring large text collections using topic hierarchies, IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 12, pp. 2002–2011, 2013.
[3] C. Collins, F. Viegas, and M. Wattenberg, Parallel tag clouds to explore and analyze faceted text corpora, in IEEE Symposium on Visual Analytics Science and Technology (VAST), Atlantic City, NJ, USA, 2009, pp. 91–98.
[4] J. Zhang, M. L. Huang, W. B. Wang, L. F. Lu, and Z.-P. Meng, Big data density analytics using parallel coordinate visualization, in Proc. of the 17th International Conference on Computational Science and Engineering, Chengdu, China, 2014, pp. 1115–1120.
[5] Y. Wang, X. Chu, C. Bao, L. Zhu, O. Deussen, B. Chen, and M. Sedlmair, EdWordle: Consistency-preserving word cloud editing, IEEE Transactions on Visualization and Computer Graphics, vol. 24, no. 1, pp. 647–656, 2018.
[6] J. Feinberg, Wordle-beautiful word clouds, http://www.wordle.net, 2009.
[7] K. Koh, B. Lee, B. Kim, and J. Seo, Maniwordle: Providing flexible control over wordle, IEEE Transactions on Visualization and Computer Graphics, vol. 16, no. 6, pp. 1190–1197, 2010.
[8] H. Strobel, M. Spicker, A. Stoffel, D. Keim, and O. Deussen, Rolled-out wordles: A heuristic method for overlap removal of 2D data representatives, Computer Graphics Forum, vol. 31, no. 3, pp. 1135–1144, 2012.
[9] F. V. Paulovich, F. Toledo, G. P. Telles, R. Minghim, and L. G. Nonato, Semantic wordification of document collections, Computer Graphics Forum, vol. 31, no. 3, pp. 1145–1153, 2012.
[10] Y. Wu, T. Provans, F. Wei, S. Liu, and K.-L. Ma, Semantic preserving word clouds by seam carving, Computer Graphics Forum, vol. 30, no. 3, pp. 741–750, 2011.
[11] W. Cui, S. Liu, L. Tan, C. Shi, Y. Song, Z. J. Gao, H. Qu, and X. Tong, Textflow: Towards better understanding of evolving topics in text, IEEE Transactions on Visualization and Computer Graphics, vol. 17, no. 12, pp. 2412–2421, 2011.
[12] F. Wei, S. Liu, Y. Song, S. Pan, M. X. Zhou, W. Qian, L. Shi, L. Tan, and Q. Zhang, Tiara: A visual exploratory text analytic system, in Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD ’10), New York, NY, USA, 2010, pp. 153–162.
[13] M. Liu, S. Liu, X. Zhu, Q. Liao, F. Wei, and S. Pan, An uncertainty-aware approach for exploratory microblog retrieval, IEEE Transactions on Visualization and Computer Graphics, vol. 22, no. 1, pp. 250–259, 2016.
[14] S. Chen, S. Chen, Z. Wang, J. Liang, Y. Wu, X. Yuan, D-Map+: Interactive visual analysis and exploration of ego-centric and event-centric information diffusion patterns in social media, ACM Transactions on Intelligent Systems and Technology (TIST), vol. 10, no. 1, pp. 1–26, 2018.
[15] S. Liu, X. Wang, J. Chen, J. Zhu, and B. Guo, Topic panorama: A full picture of relevant topics, in IEEE Conference on Visual Analytics Science and Technology (VAST), Paris, France, 2014, pp. 183–192.
[16] F. van Ham, M. Wattenberg, and F. B. Viégas, Mapping text with phrase nets, IEEE transactions on Visualization and Computer Graphics, vol. 15, no. 6, pp. 1169–1176, 2009.
[17] J. Chuang, C. D. Manning, and J. Heer, Without the clutter of unimportant words: Descriptive key phrases for text visualization, ACM Transactions on Computer—Human Interaction (TOCHI), vol. 19, no. 3, pp. 1–29, 2012.
[18] W. Cui, Y. Wu, S. Liu, F. Wei, M. Zhou, and H. Qu, Context-preserving, dynamic word cloud visualization,
IEEE Computer Graphics and Applications, vol. 30, no. 6, pp. 42–53, 2010.

[19] N. Cao, J. Sun, Y.-R. Lin, D. Gotz, S. Liu, and H. Qu, FacetAtlas: Multifaceted visualization for rich text corpora, IEEE Transactions on Visualization and Computer Graphics, vol. 16, no. 6, pp. 1172–1181, 2010.

[20] M. Dork, N. H. Riche, G. Ramos, and S. T. Dumais, PivotPaths: Strolling through faceted information spaces, IEEE Transactions on Visualization and Computer Graphics, vol. 18, no. 12, pp. 2709–2718, 2012.

[21] L. Barth, S. I. Fabrikant, S. G. Kobourov, A. Lubiw, M. Nöllenburg, Y. Okamoto, S. Pupyrev, C. Squarcella, T. Ueckerdt, and A. Wolff, Semantic word cloud representations: Hardness and approximation algorithms, in LATIN 2014: Theoretical Informatics, P. Alberto and V. Alfredo, eds. Springer, 2014, pp. 514–525.

[22] M. Dubinko, R. Kumar, J. Magnani, J. Novak, P. Raghavan, and A. Tomkins, Visualizing tags over time, in Proceedings of the 15th International Conference on World Wide Web, Edinburgh, UK, 2006, pp. 193–202.

[23] H. Strobelt, D. Oelke, C. Rohrdantz, A. Stöffel, D. A. Keim, and O. Deussen, Document cards: A top trumps visualization for documents, IEEE Transactions on Visualization and Computer Graphics, vol. 15, no. 6, pp. 1145–1152, 2009.

[24] Y. Chen, L. Wang, M. Dong, and J. Hua, Exemplar-based visualization of large document corpus, IEEE Transactions on Visualization and Computer Graphics, vol. 15, no. 6, pp. 1161–1168, 2009.

[25] V. Thai, S. Handschuh, and S. Decker, IVEA: An information visualization tool for personalized exploratory document collection analysis, in Proceedings of the 5th European Semantic Web Conference (ESWC ’08), Tenerife, Spain, 2008, pp. 139–153.

[26] C. Tominski, J. Abello, and H. Schumann, Axes-based visualizations with radial layouts, in Proceedings of ACM Symposium on Applied Computing (SAC’04), Nicosia, Cyprus, 2004, pp. 1242–1247.

[27] R. Shadoan and C. Weaver, Visual analysis of higher-order conjunctive relationships in multidimensional data using a hypergraph query system, IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 12, pp. 2070–2079, 2013.

[28] B. Alsallakh, W. Aigner, S. Miksch, and H. Hauser, Radial sets: Interactive visual analysis of large overlapping sets, IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 12, pp. 2496–2505, 2013.

[29] J. Wood, J. Dykes, and A. Slingsby, Visualization of origins, destinations and flows with OD maps, The Cartographic Journal, vol. 47, no. 2, pp. 117–129, 2010.

[30] C. Collins and S. Carpendale, VisLink: Revealing relationships amongst visualizations, IEEE Transactions on Visualization and Computer Graphics, vol. 13, no. 6, pp. 1192–1199, 2007.

[31] C. Weaver, Multidimensional data dissection using attribute relationship graphs, in Proceedings of the IEEE Symposium on Visual Analytics Science and Technology (VAST), Salt Lake City, UT, USA, 2010, pp. 75–82.

[32] R. C. Basole, T. Clear, M. Hu, H. Mehrrota, and J. Stasko, Understanding interfirm relationships in business ecosystems with interactive visualization, IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 12, pp. 2526–2535, 2013.

[33] S. Janicke, J. Focht, and G. Scheuermann, Interactive visual profiling of musicians, IEEE Transactions on Visualization and Computer Graphics, vol. 22, no. 1, pp. 200–209, 2016.

[34] Z. Zhang, K. T. McDonnell, E. Zadok, and K. Mueller, Visual correlation analysis of numerical and categorical data on the correlation map, IEEE Transactions on Visualization and Computer Graphics, vol. 21, no. 2, pp. 289–303, 2015.

[35] J. Xia, W. Chen, Y. Hou, W. Hu, X. Huang, and D. S. Ebert, DimScanner: A relation-based visual exploration approach towards data dimension inspection, in IEEE Conference on Visual Analytics Science and Technology (VAST), Baltimore, MD, USA, 2016, pp. 81–90.

[36] J. Stasko, C. Gorg, and Z. Liu, Jigsaw: Supporting investigative analysis through interactive visualization, Information Visualization, vol. 7, no. 2, pp. 118–132, 2008.

[37] N. N. Yang, Q. N. Zhang, and J. Q. Niu, Computational model of geospatial semantic similarity based on ontology structure, Science of Surveying and Mapping, vol. 40, no. 3, pp. 107–111, 2015.

[38] S. Bateman, C. Gutwin, and M. Nacenta, Seeing things in the clouds: The effect of visual features on tag cloud selections, in Proceedings of the 19th ACM Conference on Hypertext and Hypermedia (HT ’08), Pittsburgh, PA, USA, 2008, pp. 193–202.

[39] M. A. Hearst and D. Rosner, Tag clouds: Data analysis tool or social signaller? in Proceedings of the 41st Annual Hawaii International Conference on System Sciences (HICSS ’08), Waikoloa, HI, USA, 2008, p. 160.

[40] C. Felix, S. Franconeri, and E. Bertini, Taking word clouds apart: An empirical investigation of the design space for keyword summaries, IEEE Transactions on Visualization and Computer Graphics, vol. 24, no. 1, pp. 657–666, 2018.

[41] B. Lee, N. H. Riche, A. K. Karlson, and S. Carpendale, SparkClouds: Visualizing trends in tag clouds, IEEE Transactions on Visualization and Computer Graphics, vol. 16, no. 6, pp. 1182–1189, 2010.

[42] K. Kurzhals, B. D. Fisher, M. Burch, and D. Weiskopf, Evaluating visual analytics with eye tracking, in Proceedings of the Fifth Workshop on Beyond Time and Errors: Novel Evaluation Methods for Visualization (BELIV’14), Paris, France, 2014, pp. 61–69.

[43] J. Li, Z. P. Meng, M. L. Huang, K. Zhang, An interactive radial visualization of geoscience observation data, in Proceedings of the 8th International Symposium on Visual Information Communication and Interaction (VINCI’15), Tokyo, Japan, 2015, pp. 93–102.
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