Social Media Island: Interactive User Profiling and Information Diffusion Exploration with 3D Visual Metaphors

Jinjing Jiang*
School of Data Science, Fudan University

Yuheng Zhao†
School of Data Science, Fudan University

Jun-Hsiang Yao
School of Data Science, Fudan University

Huiting Wang
School of Data Science, Fudan University

Xuexi Wang
School of Data Science, Fudan University

Lana Blue
Northwest University, Xi'an

Chen Guo
James Madison University

Xudong Li
School of Data Science, Fudan University

Siming Chen‡
School of Data Science, Fudan University

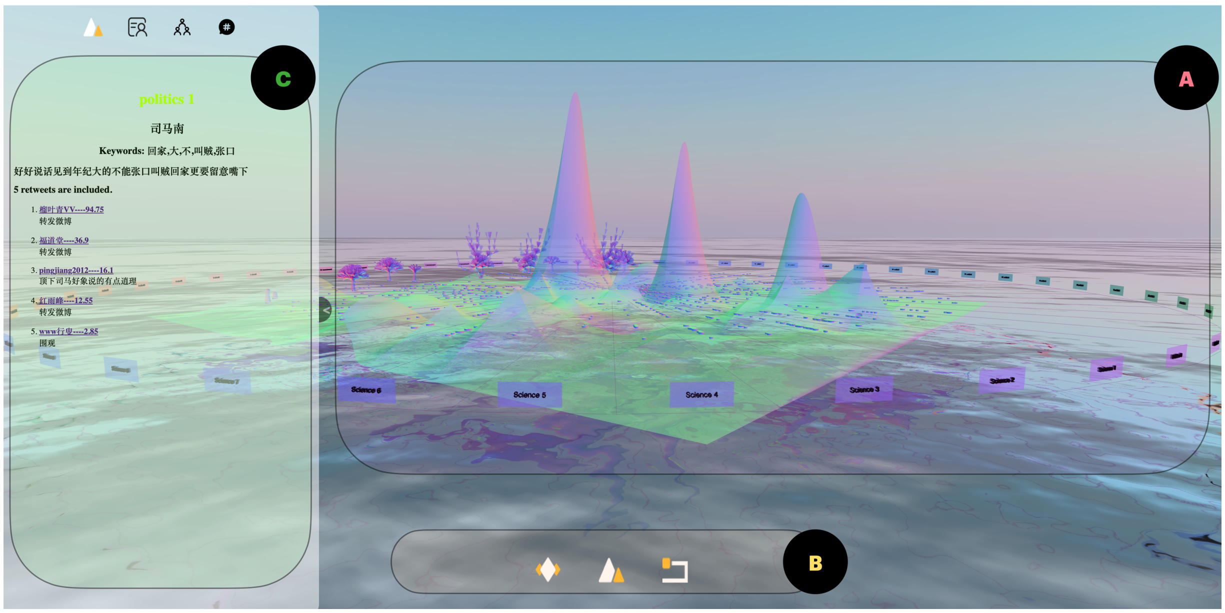

Figure 1: Social Media Island visualization system. (A) The main 3D interface, featuring mountain and tree metaphors, supports the exploration of topics, information diffusion, and user influence. (B) The control bar offers three primary interaction options: radial cut, height cut, and circular cut. Each enables targeted exploration and segmentation of the mountain and tree metaphors for detailed analysis. (C) The Information Panel complements the 3D interface by displaying details about tweets and retweets.

Abstract

Understanding user profiling on social media poses significant challenges due to the intertwined complexities of network structures, user interactions, and the multi-dimensional nature of the data. To reduce visual clutter and offer complementary perspectives for engagingly exploring user profiling within these networks, we propose Social Media Island, an interactive 3D metaphoric visualization system. Our system uses 3D mountain metaphors to visualize user profiling, capturing user influence and activity, while tree metaphors visualize the information forwarding process. To support a flexible scope for users to explore in a more intriguing way, we design various interactions such as cutting the mountain to split out a subset with similarity to some extent for further exploration. By using these 3D visualizations with user interactions, Social Media Island facilitates immersion in the data, the fluid exploration of user influence, topic evolution, and the spread of information. The effectiveness of metaphors is evaluated by user studies, and that of the system is evaluated through two case studies.

Keywords: Data Visualization, Social Media, 3D Metaphor

1 Introduction

Social media platforms generate vast amounts of multi-modal data, including time, geography, and hierarchy, which are crucial for analyzing information diffusion and user relationships [9, 15, 66]. User profiling, focusing on interests, social impact, and semantic evolution, can uncover valuable insights, especially in identifying opinion leaders, tracking semantic changes, and comparing public attitudes over time. Various visualization methods have been proposed [9, 15, 66] to help analyze information diffusion and user relationships. However, traditional visualizations struggle to represent complex data structures for user profiling. Challenges exist mainly in the following two perspectives. First, how to solve the conflicting relationship between semantic information and forwarding relationships in visualization is a tough task, as existing methods focus on one or the other [9, 66, 68, 75]. The second challenge is the lack of a highly generalized and conclusive visualization for user profiling. Using 2D map metaphor [14, 15, 46] is effective if we need to display both semantic evolution and reposting behavior but it is not an effective way to directly form an overview and support

*e-mail: 21210980039@m.fudan.edu.cn.
†e-mail: yuhengzhao@fudan.edu.cn, Jinjing and Yuheng contributed equally.
‡e-mail: simingchen@fudan.edu.cn, corresponding Author

comparison of multi-users.

The above challenges on this core issue are ultimately owing to the fact that social media data has a variety of data types and structures. The complexity of the data puts forward higher requirements for the dimension of visualization. Naturally, we came up with an idea to visualize the data simultaneously by adding dimensions to the space, that is, by constructing 3D visual metaphors. The benefits are apparent: 3D metaphors can capture more information, resolve conflicting relationships in 2D, and better utilize space. The added dimensionality not only makes the data more engaging and intuitive but also improves users' ability to perceive intricate relationships within the data. Indeed, there are some inherent limitations in 3D visualization, such as perspective deformation, object occlusion, and illegibility of text [50]. Interaction technique is a way to alleviate this defect to a certain extent and bring exploration experience. Moreover, with the development of VR technologies, strong interactions and immersive experiences can bring more immersive experience [17]. This combination of interactivity and realism enhances the effectiveness of 3D metaphors, making them a powerful tool for visualizing complex, multi-dimensional data [72].

We propose Social Media Island, a 3D visualization system (Fig. 1), to boost the understanding and exploration of user profiling and the process of user-centered information diffusion. A combination of 3D metaphors and other auxiliary views make up the entire system, to achieve the initial purpose of displaying a general picture of the user profiling and simultaneous visualization of the forwarding process and semantic change. Two key 3D metaphors are designed and realized: "TweetMount" and "RetweetTree". TweetMount is innovatively designed to display a conclusive structure illustrating user profiling. Specifically, the shape of **TweetMount** is generated by points, each of which represents one piece of the original tweets posted by the target user. **RetweetTree** is a figurative tree-like visualization to show a general and conclusive forwarding process of one tweet from the target user. In a RetweetTree, each branch stands for a tweet retweeted by other participants. In order to support a flexible scope for users to explore in a more intriguing way, we design various interactions such as cutting the mountain to split out a subset with similarity to some extent for further exploration.

To the best of our knowledge, this is the first effort to use the 3D visualization method for user profiling analysis based on semantics and reposting relationships. We hope to provide an effective solution to visualize forwarding and semantic information in a user-centric way. The main contributions are summarized as follows:

- **Novel 3D visual metaphors** visualize the ego-centric information diffusion and user profiling. We use the shape of mountains, trees, etc., to design "TweetMount", "RetweetTree" and "Ripple" metaphors to meet the requirements of specific visualization tasks.
- **An immersive analytics system** to support users interactively building a comprehensive impression of user profiles and boosting the understanding of the process of information diffusion from two perspectives: forwarding relations and semantic change on a user-centric basis in social media.

We take Social Media Island a step further by leveraging VR technology to place the system into an immersive environment. Access to virtual reality not only justifies the effectiveness of 3D metaphors but also provides a possible solution to generate digital scenes driven by abstract data from the perspective of 3D visualization. The design of metaphors is evaluated by the user study. The efficiency of Social Media Island is validated by case studies.

2 Related Work

We introduce previous work from three perspectives: research related to specific tasks in the domain of social media analytics and research on visual metaphor and 3D visualization methods.

2.1 Social Media Analytics

User profiling in social media refers to extracting user features and characteristics when communicating online. It needs to deal with text and user-related retweet structure to describe user activities on a specific social media topic.

Different approaches have been used to quantify information diffusion, with some studies modeling it as a graph problem focusing on user relationships and pathways [19], while others incorporate dimensions like time, influence, and user behavior [33, 76]. To visualize this dynamic process, novel metaphors are often employed. R-Map [15] uses map metaphors, with rivers representing forwarding behaviors and routes for following relations. Google+Ripples [66] uses a "Balloon Treemap" that combines circular and traditional tree structures for user diffusion. Whisper [9] applies the sunflower metaphor to integrate user, time, and place, addressing the challenge of tracking real-time diffusion.

For visualizing semantic evolution, many studies [65, 68, 75] focus on tracking topic changes over time, typically using stacked graphs [21, 23, 68, 73, 77], where each layer represents a topic and its temporal changes are visualized as flows. Other approaches, like ThemeCrowds [1], filter and track keywords across multiple time windows for comparative analysis, while topic network structures [32] enable exploration of topic transfers among users at specific moments. Additionally, 3D environments have been shown to alleviate common issues in 2D visualizations, such as edge crossings and node overlaps [39], which could improve clarity in complex semantic evolution analysis.

Building on these works, we extend 2D approaches by integrating semantic evolution, user profiling, and retweet structures in a 3D space, allowing for a more immersive and detailed analysis of these interconnected elements.

2.2 3D Visualization Methods

The application scenarios of 3D visualization mainly focus on the visualization of 3D object structure aiming to improve understanding of real physical structure data in digital world [6, 47, 62], 3D GIS [30, 38, 41] and digital twins [4, 17, 27, 42, 60]. In addition, 3D visualization methods are also considered potential methods for complex data by integrating more dimensional information into the limited visual space. Many scholars use 3D visualization methods to visualize hierarchical data, such as constructing a 3D tree [55], or using cube nested wrapping structure [53, 54], or even through a multi-layer sunburst diagram [59]. Furthermore, some works use 3D visual metaphors such as city to visualize code structures [7, 36, 70, 71]. Some visual metaphors were first designed in 2D form but developed into 3D form, such as SeeSoft [2, 24, 48] and its 3D version sv3D [48]. Hadlak [31] proposed a visualization scheme to deal with spatial-temporal hierarchical data structure, which "flattens" the hierarchical data of each region at the same time, supporting immersive exploration in 3D space with a time-sliced interaction. These cases show that the 3D visualizations and metaphors are benefit for reveal the internal structure of complex data, enhancing the understanding of the hierarchical structure. Built on these works, we propose 3D visualizations to demonstrate hierarchical retweet trees with multi-attributes, providing an immersive experience when exploring social media data.

2.3 Design of Visual Metaphors

In the field of visualization, different visual metaphors were designed for specific problems. We first summarize the previous work related to visual metaphors and summarize their design space. The visual metaphors can be summarized into two types: one is nature-inspired, and the other is social-inspired.

Naturally inspired metaphors previous work can be classified into three types: geographical visual metaphors such as landscapes [25, 26, 63] and rivers [8, 21, 23, 45, 67, 68, 73, 77], animal-based visual metaphors plant-based visual metaphors. The animal-based visual metaphors are mainly divided into two types. One is to use biological structure [10] to construct visual metaphors, and the other is to use animal behavior [5, 49] to construct metaphorical mapping of data to support simulation visualization. plant-based visual metaphors mainly include trees [55, 58, 61], flowers [9, 12, 74, 79] and weed [56].

Social-inspired visual metaphors are mainly divided into two categories according to whether they have entities: one is visual metaphors with entities, mainly cities and buildingss [3, 7, 11, 36, 52, 69–71]. The other category is visual metaphors of abstract concepts without entities, such as map metaphors [13–15, 22, 28, 29, 46] and abstract visual structural metaphors [59, 64]. These works demonstrate that designing metaphorical visualizations for specific data can enhance understanding.

We try to focus on four major questions based on these studies: the basic logic and methods of constructing metaphors, the common problems that need to be paid attention to when constructing, and the balance between the advantages and disadvantages of 3D visual metaphors compared with 2D forms. Through the investigation and comparison of the above research, we propose a 3D visual metaphor, which will be explained in detail in Sec. 4.

3 OVERVIEW

In this section, we briefly introduce the background of our study, the description of data, and summarize the analytical tasks and the derived design requirements of our analysis system.

3.1 Background

This paper explores the solution by constructing proper 3D metaphors to support the interactive analysis of information diffusion and semantic evolution process simultaneously, which is to observe how the posts from a single user gets retweeted and how the topics or keywords change during the diffusion process specifically. Based on Sec. 2, we identified three main challenges:

C1: The contradiction between the visualization of semantic information and the structure of the forwarding relationship. Forwarding relationship is the basic structure of tweet data, and semantic information is obtained by processing forwarded text. Many research works only focus on one or both, but in fact, these two relationships are information of the same data from different angles. The simultaneous analysis will enhance the process. However, due to the limitations of the 2D interface, these two structures are usually displayed in two views separately. There is still room for improvement with the higher-dimensional support.

C2: Lack of highly conclusive visualization form of user profiling. Current research on visualizing user profiling lacks a general picture of a user. In the process of analyzing a user, extracting key information from a large amount of high-dimensional data and reducing complexity are very important to accelerate the analysis process. Complex visual coding in 2D visualization will lead to a longer learning curve. A concise visual metaphor can not only perceive complex user information as a whole, form a perceptual cognition of user profiling, but also support the overall comparison between multiple users, which can not be supported by the 2D map visualization metaphor mentioned above.

C3: Inability to effectively support the scaling of the research scope and control the depth of mining information on a root user. In terms of information diffusion, most studies focus on grasping the change in the overall information diffusion degree over time and cannot control the scope of research to explore. For example, it is hard to control whether the user's analysis on information diffusion is applied to all microblogs, small-scale microblog groups with similar topics or similar times, or even a single microblog. However, in 3D space, new control methods can be realized through gamified transformation methods.

3.2 Data Description

In this paper, we use data from Sina Weibo, a social media platform. A dataset in our system contains all original microblogs sent by a user within a certain period of time and all subsequently forwarded microblogs. For each microblog (including original microblogs and forwarded microblogs), collect microblog properties such as *id*, user name, and text content of the microblog, and all subsequent forwarding microblogs of this microblog reserved as children nodes. In order to better explain the data analysis and processing process, in this case, we define and distinguish the following terms:

- **Root user:** is the creator of all original microblogs in a dataset.
- **Participants:** refers to other users who appear in the data set except the root user.
- **Key user:** refers to the participants whose reposted microblog forms a popular discussion.
- **Forwarding microblog:** refers to a microblog that forwards the microblog posted by the root user or participant. Thus, the forwarding process is a tree.
- **Microblog Influence:** is the number of re-posts and the value of followers.
- **Hot microblog:** refers to the original microblog with a high influence on the root user.
- **Hot discussion:** refers to highly influential retweets forwarded by participants.

3.3 Design Requirements

According to the studies and challenges we discussed, we will explore an effective solution through immersive 3D visualization methods, which can assist users in understanding both the information dissemination process and semantic changes, while helping them form a comprehensive impression of user profiling. Therefore, we formulate the following design requirements:

R1: Visualize relationships and semantic information simultaneously in a user-centric way. A clear and effective visual analytic method should be provided to illustrate the reposting structure and semantic information simultaneously. This will help reduce the cost of data exploration to understand two parts respectively and combine them together. And because of the inevitable occurrence of new semantics in the process of tweet propagation, we hope our system can provide visual aids for semantic evolution analysis and narrow down the scope of concern from the information propagation chain.

R2: The design of visual metaphors and the encoding of data should be of rationality and abstraction. When designing visual metaphors with social media data, we expect to use visual elements that are both rational and innovative. We expect the mapping between the visual encoding and data attributes in a way that is both understandable and aesthetically smooth. Especially when dealing with a 3D metaphor, a logical visual encoding can help users understand data faster, perceiving data immersively, thus amplifying the advantages of 3D visualization.

R3: Support intuitive interactions for users to explore in detail. Another requirement that cannot be ignored is the design requirement of the interaction in 3D space. For the system users, the interaction process should be natural and the exploration process should be smooth. This requires that the mechanism of the interaction implemented by our system highly match the visual metaphor of the design, and the visual encoding of data attributes, thus allowing the user to spontaneously operate and drive the data exploration deeper wherever in a computer interface ou a virtual reality environment. This will promise us to design a data exploration system that is both practical and interesting, interpretable and intuitive.

4 KEY VISUAL METAPHORS

We will summarize the design space of 3D metaphors, and introduce the design and implementation of RetweetTree and TweetMount that we propose in this section.

4.1 The Design of 3D Metaphors

Based on the studies on 3D visualization in Sec. 2, we summarize visual metaphor refers to a known concept that has a certain similarity to an abstract concept. The metaphor derived from three-dimensional spatial constructs, which facilitates enhanced data visualization, is termed a three-dimensional visualization metaphor. Under three specific application scenarios, using a 3D visualization metaphor would be a better strategy:

Complex Visualization with Spacial Layout or Hierarchy Structure. 3D visualization can intuitively display the spatial layout and hierarchical relationship of data, especially in applications such as tree structures, geographic data [43], and network diagrams [51]. 3D can effectively convey the interconnections between complex data through physical spatial relationships, such as depth, position, and relative direction [34].

Mapping with multi-dimensional data. When the data dimensions increase, 2D encoding can provide certain information expression, but due to dimensional limitations, it often leads to information overlap or visual confusion, especially when multiple data points interact with multiple dimensions. 3D introduces the depth dimension to make each data point more abundant in 3D space, which can effectively alleviate this information overlap problem [35].

Intuitive Interaction Included. 3D visualization allows users to flexibly adjust the perspective and view different parts of the data through gesture interactions such as rotation, zooming, and panning. This interactivity can greatly improve users' ability to understand complex data sets. However, 2D glyphs or channel encodings often lack this flexible interactivity. Users can only gradually obtain information by selecting, zooming in, etc., and cannot freely explore data in the entire space like 3D visualization.

4.1.1 Design Space

As shown in Fig. 2, for a visualization metaphor, its metaphor attributes are mainly divided into three aspects: position, appearance and interaction.

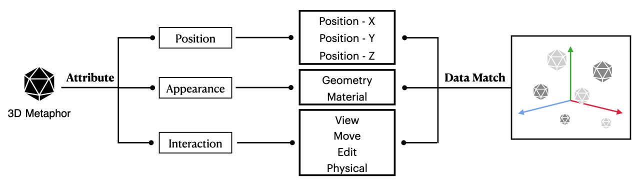

Figure 2: The design space of 3D metaphors.

Position corresponds to the 3D coordinates of the visualization metaphor in the 3D space. **Appearance** attribute can be further divided into geometric encoding and material encoding. The geometric encoding mainly refers to the geometric shape of the visualization metaphor, including the shape, size, and other parts directly related to mesh structure. The material encoding refers to the color, texture, transparency, and other attributes of the visualization metaphor. **Interaction** of a 3D metaphor includes: view, move, edit, and physical interaction. View interaction supports users to observe a 3D visualization metaphor from all directions or select it for viewing. Move interaction includes two ways: users define the moving path of the metaphor and move it by dragging. Edit interaction mainly modifies the geometric structure and material of the metaphor. Physical interaction mainly supports the interaction between users and 3D visualization metaphors in 3D space by defining physical fields.

4.1.2 Principles

In order to better design and implement 3D visualization and differentiate it from 2D visualization, we conclude four constructive principles of 3D visual metaphors further to promise the design requirements that we put forward in Sec. 3. P1: Compared with 2D structures, the density of information is increased. P2: Compared with 2D visualization, the user interaction methods are increased. P3: Avoid designing counter-intuitive and overly complex 3D interactions that increase time costs of learning. P4: When using 3D visualization metaphors for data display, the problems of element stacking and perspective occlusion ar e minimized.

4.1.3 Characteristics

Based on the important characteristics of a 3D visualization metaphor, basic ideas and methods can be provided for the construction of a 3D visualization metaphor. We conclude three important characteristics a 3D visualization metaphor must have:

(1) Detachability. A single visual metaphor must have at least one element attribute that can be disassembled. This topic proposes that a basic visual metaphor can be split into several visual elements or multiple attributes of a single element.

(2) Difference. Driven by different data, using the same visual metaphor for data visualization needs to present different visual effects so as to enhance the observer's ability to discover and capture the data features that have changed significantly.

(3) Interactive. If the 3D visualization metaphor does not define the interaction method, then the 3D visualization metaphor will be displayed as 2D, which will not only waste the advantages of strong interaction and high dimensionality of 3D space but also will be affected by the deformation of the perspective and the object occlusion problem.

4.2 Design of Mountain Metaphor: Tweet Mount

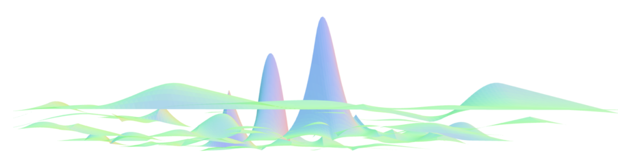

Figure 3: Shaded effect of a mountain-shaped surface created using Bezier curves, highlighting the contour lines and peaks.

In order to generate a highly conclusive visualization for one target user, we introduce the mountain metaphor and construct it by referring to the shape and characteristics of the mountain itself, such as the peaks, valleys, cross-sections in a mountain, and the contour lines commonly used in displaying the shape, so as to grasp the distribution characteristics of the data.

4.2.1 Design of Mountain Metaphor

The mountain-shaped metaphor can be used to visually present the overall information of a collection subject, so as to quickly grasp the trend characteristics and distribution of it. This method helps address C1, allowing us to simultaneously depict both the semantic clusters (e.g., similar topics) and the forwarding relationships between tweets (represented by the terrain's shape), thereby reconciling the need to show both semantic information and structural relationships (P1).

Each mountain metaphor is drawn based on multiple data points, each data point represents one original tweet post by our target user. The coordinates are expressed as $p_j = (\rho_j, \theta_j, z_i)$. Fig. 4 shows the layout logic of data points. Those microblogs in the same radius represent similar topics and consistent clusters. To be specific, we use BERT [20] to build sentence embedding and train a neural network with THUCNews [1], a Chinese news classification dataset. Further, we use DBSCAN for clustering within each topic. Grid search is used in the optimization of hyperparameters, such as determining the number of clusters. The whole process can be seen on the left side of Fig. 10.In the same radius, each microblog point is sorted by global time, that is, two points with the same distance from the center of the circle have the same posting time.

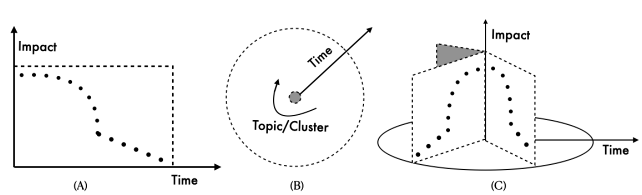

Figure 4: The layout logic of TweetMount. (A) The radial section layout where $\theta = \theta_i$ represents different topic clusters arranged in a circular layout. (B) The top view where $z = z_i$ indicates the global time ordering of posts within the same topic cluster. (C) The 3D layout logic of the entire data point cloud, showing how topics, time, and user activities are spatially distributed to provide an intuitive representation.

[1]https://github.com/ShannonAI/ChineseBert/tree/main/tasks/THUCNew

4.2.2 Implementation of Mountain Metaphor

As shown in Fig. 5, the shape of the mountain is constructed by combining multiple Bezier surfaces. It generates multiple surfaces by dividing data blocks and it connects those surfaces to simulate a mountain shape. We use a cubic Bezier curve in our work, which is defined in 3D space by four points: the starting point P_0, the ending point P_3 and two control points P_1 and P_2. The construction formula of the cubic Bezier curve is given below:

$$\mathbf{B}(t) = \mathbf{P}_0(1-t)^3 + 3\mathbf{P}_1 t(1-t)^2 + 3\mathbf{P}_2 t^2(1-t) + \mathbf{P}_3 t^3 \text{ , } t \in [0,1] \quad (1)$$

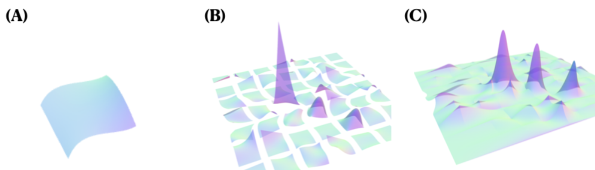

Figure 5: Visualization of the mountain shape generated using Bezier surfaces. The construction method combines multiple Bezier surfaces (A) to simulate a mountain-like structure, with each surface representing a segment of the data distribution (B), allowing for smooth transitions and accurate data representation (C).

In the process of constructing the entire mountain-shaped Bezier surface, the data needs to be processed based on the size and layout of the data set, and then a single Bezier surface is constructed by looping multiple calls to achieve a large-area Bezier surface. The data processing flow contains four main steps:

- **Data partitioning**: The dataset is divided parallel to any axis except the height. Taking the Y-axis as an example, we traverse the set of data points, retain the Z-coordinate value in all 3D coordinates, and then divide the range of X-coordinate values into N intervals. Each point's X-coordinate is assigned to the middle value of the corresponding interval.
- **Data cleansing and alignment**: We traverse each sub-array and remove neighboring points that show the same trend in the Z-coordinate to generate a smoother curve. We take out three consecutive points at a time. Let $p_0 = (x_0, y_0, z_0)$, $p_1 = (x_1, y_1, z_1)$, and $p_2 = (x_2, y_2, z_2)$ be the selected points. If $sign(z_0 - z_1)$ is the same as $sign(z_2 - z_1)$, we keep the point p_1.
- **Data completion**: We then fill in the gaps in the $N \times N$ grid using Z-value interpolation.
- **Data division**: The data is divided into $M \times M$ ($N = 4M$) blocks, with each block used as input to construct a Bezier surface. The overall Bezier surface is obtained by translating all 4×4 data blocks and merging them together. The effect of the colored block is shown in Fig. 3.

4.2.3 Interactions

To address C3, we implemented two interaction methods—Orbit controls and Pointer Lock controls—to reduce element stacking and perspective occlusion. Under Orbit controls, the user can perform cutting operations on the entire mountain. The cutting facet can assist users in further exploring subsets with similarity. Users can perform three cutting methods: radial cutting, height cutting, and circular cutting to filter data and form cut surfaces (P2). As shown in Fig. 6, we can see cutting planes are displayed to give hints of interaction. In fact, not everywhere of the formed Bezier surface is backed by true data since the data is sparse. We stipulate that the cutting must occur where there are actual data points. Therefore, we overlay the data points that constitute the surface (Fig. 6).

In order to enhance the user's sense of immersion and experience when exploring the terrain, we utilize Pointer Lock Controls and

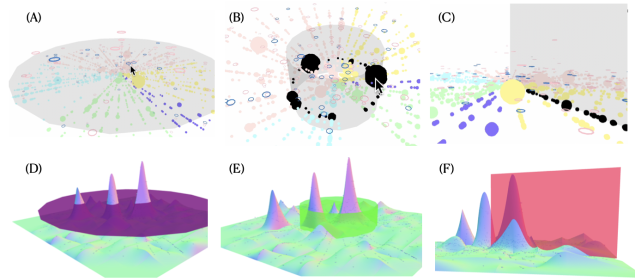

Figure 6: The effect of cutting the TweetMount using Orbit Controls to reveal data points and patterns. The cuts are performed using three methods from left to right: height cut, circular cut, and radial cut, allowing users to explore different aspects interactively.

established an interactive method from the first perspective. As shown in Fig. 7, the user can walk, jump (P3), etc. on the mountain-shaped plane constructed by the data drive, which is similar to the operation of the first-person game user. Overall, Orbit controls allow flexible rotation to avoid occlusion, while Pointer Lock controls "lock" the view, minimizing visual clutter (P4).

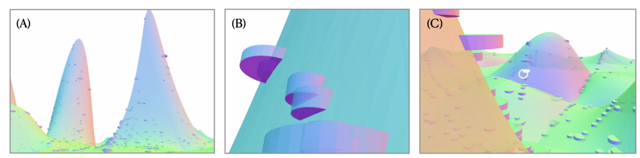

Figure 7: Exploring the mountain terrain using Pointer Lock Controls, which enables a first-person perspective for immersive navigation. (A) The user walks on the data-driven terrain. (B) The user interacts with the environment by jumping and climbing the mountain. (C) The user gains an overhead view of the island from a cliff.

4.3 Design of Tree Metaphor: Retweet Tree

We introduce the tree metaphor, and construct a more concrete hierarchical data visualization by referring to the shape of the tree itself, so as to grasp the overall characteristics of the data structure.

4.3.1 Design of Tree Metaphor

The tree metaphor addresses C2, visualizing the forwarding situation of one original tweet post by our target user, so as to quickly grasp the pattern and distribution of the hierarchical structure in a vivid and concrete way. We bind the data of each child node in the tree data structure to the branches in the tree metaphor, so that the entire tree can be generated by traversing the entire data structure.

4.3.2 Implementation of Tree Metaphor

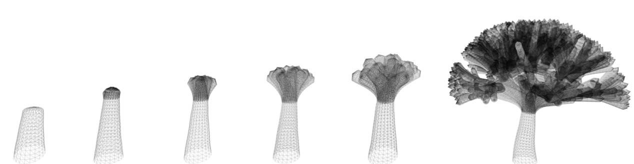

Figure 8: The tree metaphor's morphological variations based on different data. This metaphor visualizes the forwarding structure of a tweet, where each branch represents a repost, and the branches grow according to the number of reposts.

The rendering of the tree is mainly divided into two parts: defining classes and element construction. In the class definition step, give the definition of the *Tree* class, including the construction and corresponding methods. On this basis, given the construction algorithm of each branch and the layout path between branches, the constructed branch elements can be spliced to construct a tree. Driven by different data, the tree structure will take on different forms. As shown in Fig. 8, as the number of leaf nodes increases, the number of its branches also increases, and the angle and width of branches will be adjusted according to the number of leaf nodes.

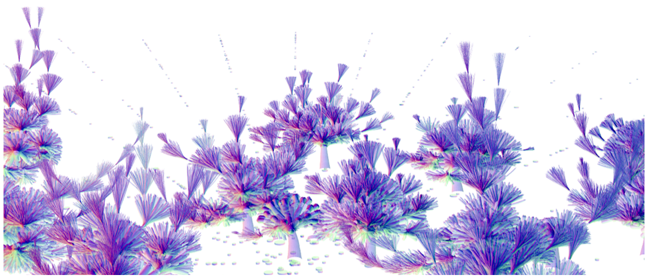

Figure 9: A digitally generated forest composed of multiple tree metaphors, where each tree represents the forwarding structure of a different tweet. The colors of the branches signify the engagement level of the reposts, with brighter colors indicating higher influence.

Multiple trees can be preserved simultaneously in a forest as shown in Fig. 9. The tree metaphor is very concrete but weakly abstract, thus there are certain merits when comparing branches and shapes, but there are deficiencies as well when comparing the details of multiples. From the effect of digital scene generation, the forest scene is both realistic and beautiful, which will highly engage users to further explore the abstract data structure in an immersive way.

5 Social Media Island

The workflow chart of Social Media Island is shown in Fig. 10. The left half shows the process of feature engineering, the other part shows the workflow of users and the corresponding information they can get from each interface or operation.

Our system is mainly composed of three 3D interfaces: the initial interface, the selection interface, and the cutting surface interface, as shown in Fig. 1 (A). Interfaces are switched through user gestures or control bar, as shown in Fig. 1 (B). Through the switching of multiple scenes, the user can obtain information on different granularities and dimensions. To supplement the text information deficiency of 3D, we provide an auxiliary information panel Fig. 1 (C). The auxiliary information panel will refresh based on user operations.

5.1 Initial Interface

The initial interface of the system is mainly formed by the superposition of four visual metaphors: pebble (flat cylinder), tree, and mountain as shown in Fig. 1 (A), and torus as shown in Fig. 17 (C). In this interface, each **pebble** represents an original microblog of our target user. The arrangement of pebbles is the same as the layout of data points when constructing a mountain in Sec. 4, except that the size of a pebble represents the influence of the original microblog, and the larger the pebble corresponds to the original microblog with greater influence.

By clicking on each pebble, the corresponding **RetweetTree** will be expanded to display an overview of the forwarding structure (C2). **TweetMount** displays the influence fluctuations of all microblogs over different topics of our target user (C1). The **torus** floating above a pebble indicates that there is a hot discussion in the follow-up forwarding of this tweet. The ground projection coordinates of the torus are consistent with that of the corresponding pebble, and the height of the torus is bound to the time when the hot discussion appeared. The longer the appearance time is from the original tweet, the higher the position of the torus. The color of the torus indicates the overall sentiment of the trending discussion. Pink represents positive attitudes, blue represents negative attitudes, and yellow represents neutrality.

In order to enable users to better grasp the spatial layout, an information vertical board is added at each angle and the theme and cluster number to which the radial direction belongs are indicated. Besides, for the sake of aesthetics, the sky, and water are added to the space. As shown in Fig. 1 (C), the white translucent part on the left is the auxiliary information panel, and the part that cannot be efficiently assembled in the 3D space will be displayed in the information panel, especially texts and words.

5.2 Selection Interface

The user can enter the selection interface by interacting with the control bar shown in Fig. 1 (B). After clicking the right button in the bar, we will switch to the selection interface with three options as illustrated in Fig. 12 (A).

The user can choose one of three cutting gestures to cut the mount (C3): **radial cut** will retain all microblog groups belonging to the same cluster with closer text similarity than others; **height cut** will retain the microblogs with influence close to ($n \pm 10\%n$) that of the selected one (suppose the influence of the clicked one is n); **circular cut** will keep all tweets with similar time (within 7 days before and after the time, 14 days in total) with the clicked microblog. Taking radial cut as an example, after users choose the radial cutting mode, they can select similar topic microblog groups that need further research in the next step. Before the formal cutting (by clicking), the user can preview (by hovering) the related information about the group as shown in Fig. 12 (B).

5.3 Cutting Surface Interface

After the official cutting, users will enter the cutting surface interface, in which users can observe the influence fluctuation line of the microblog group, as the red line floating in the sky demonstrated in Fig. 12 (C), and expand each a single point to explore the forwarding structure of one tweet. As explained before, the tree metaphor lacks confidence when it comes to precise comparison. Therefore we design a new prototype of the expanded structure called **ripple**, as shown in Fig. 11, to make up for the deficiency of RetweetTree. Similar to the tree metaphor, the ripple is used to visualize the overall forwarding situation of a single tweet. The original tweet post by our target user is omitted in the ripple, and the innermost layer is composed of several equal-sized spheres, each of which represents one direct retweet of the original one. These children nodes will be sorted clockwise by time.

We introduce the concept of the **possible semantic evolution point** to illustrate the semantic change in the **ripple** (C3). The semantic evolution point indicates that semantic changes are likely to occur on this retweet. The nodes in the microblog chain will be judged as possible semantic evolution points under the following circumstances: (1) Node with a high-ranking keyword proposed for the first time; (2) Node with high influence in the forwarding layer where it is located; (3) The first occurred node of a recurring user. The **possibility** of semantic changes refers to the likelihood of a node triggering a semantic shift, based on these factors. After calculation, we connect all marked points in the second layer in the forwarding structure to form a polygon (the red line in Fig. 11). Then we use translucent colored disks (the colored circles in Fig. 11) to mark points in other layers. The size of the disks indicates the possibility of their semantic changes.

Compared with the RetweetTree in the initial interface, ripple visualizes the data more abstractly, thus it is clearer when comparing multiple microblogs. Fig. 12 (C) shows the subsequent forwarding of some microblogs.

6 Evaluation

The evaluation of both visual metaphors and the system will be discussed in this section.

6.1 User Study on Visual Metaphors

To evaluate the effectiveness of the visual metaphors used in the system, we conducted a user study. The user study includes three parts, video introduction, case exploration and the comparative evaluation of key metaphors used in the system.

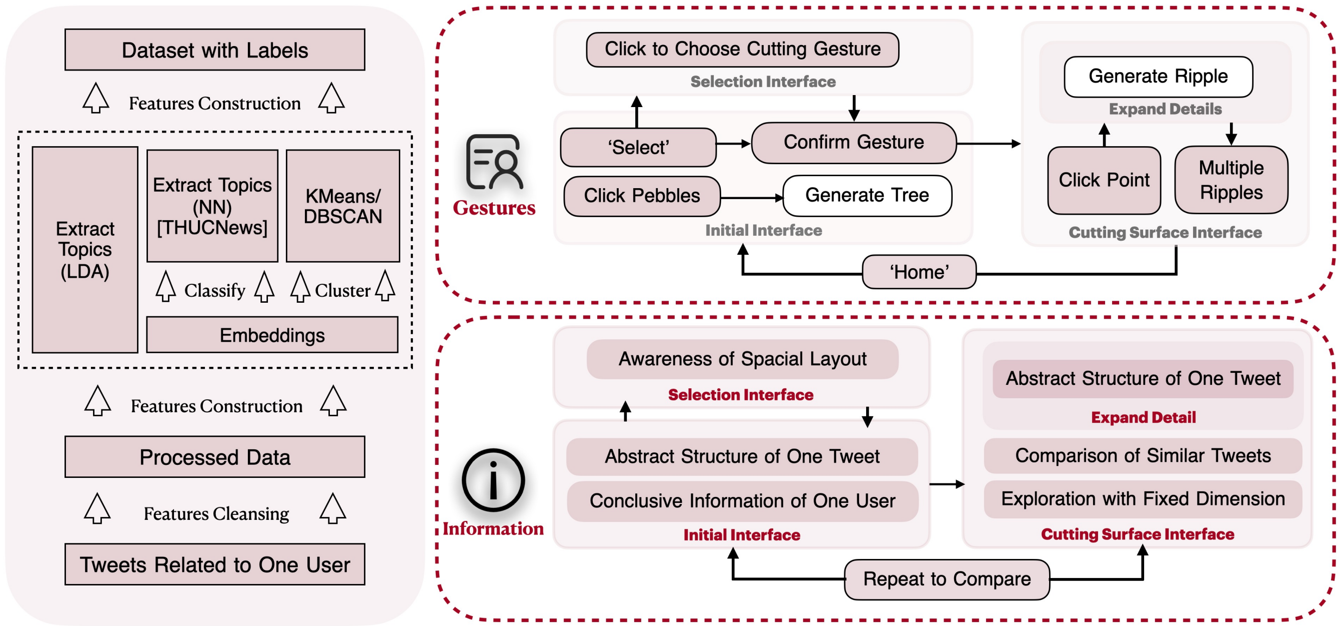

Figure 10: The workflow of Social Media Island. The left side illustrates the feature engineering process, including data processing steps such as topic extraction, event detection, and possible semantic changes. The right side outlines the user workflow, detailing how users interact with different 3D interfaces (initial, selection, and cutting) to explore and analyze data at various granularities.

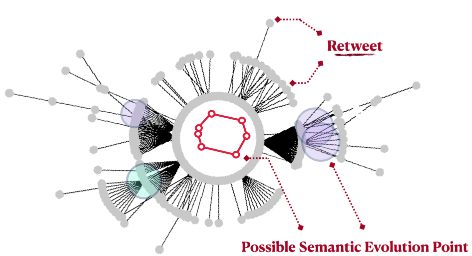

Figure 11: The layout of the ripple visualization, designed to overcome limitations of the RetweetTree metaphor. Each sphere in the innermost layer represents a direct retweet of the original tweet. The red polygon and colored disks highlight the possible semantic evolution points.

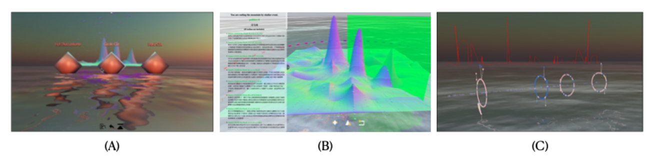

Figure 12: The process of applying a radial cut on the TweetMount. (A) The user can select a cutting method through the control bar. (B) Previewing the radial cut, which retains microblog groups with closer text similarity for further exploration, allows users to inspect details before finalizing the cut.(C) After cutting, users can see the forwarding status and detailed information of the relevant microblogs.

Study setup We recruited 23 graduate students to evaluate our visual metaphors. All participants had experience in visualization or data science. The study began with a tutorial in which the usage and cases of our system were introduced to the participants. After that, they interacted with this system using a computer interface to use the 2D and 3D visualizations. Finally, participants were invited to complete a questionnaire including six questions to compare pairs of 2D and 3D visualizations. Each question was rated on a scale from 0 to 10 across five criteria:

- *Aesthetic*: How visually appealing and artistic the visualization is.
- *Figurative*: How closely the visualization resembles the real-world metaphor it represents (e.g., a tree or mountain).
- *Understandable*: How easy it is to comprehend the data conveyed by the visualization.
- *Conclusive*: Whether the visualization effectively summarizes the whole data set or process (e.g., the entire forwarding structure of a tweet).
- *Comparable*: How easily the visualization allows users to compare different data elements or patterns.

Results The result of the usability questionnaire is summarized in Fig. 13. Overall, the results indicated that the 3D metaphors (TweetMount and RetweetTree) consistently scored higher than their 2D counterparts (heatmap and node-link diagram), especially in terms of aesthetic appeal and inclusiveness. Participants found the 3D metaphors to be more immersive and visually engaging, though some found it slightly more challenging to understand the 3D representations compared to the simpler 2D versions. The 3D metaphors provided better comparability for understanding complex patterns in interactive mode, especially in understanding how retweets spread across networks and how topics evolved over time.

6.2 Cases

System findings will be elaborated then by exploring Social Media Island to answer the exploration tasks mentioned earlier.

6.2.1 Mining the Pattern of Visual Metaphors

The following takes the ripple and tree structure as examples to verify the vividness, feasibility, and reliability of our visual metaphors for pattern mining. By comparing a sufficient number of samples, we found that there are two typical ripple diagrams as shown in Fig. 14.

The ripple of **Type I** is generally circular, and the distribution of points in each layer is relatively uniform. We select three examples of ripple structures that basically conform to the description of Type

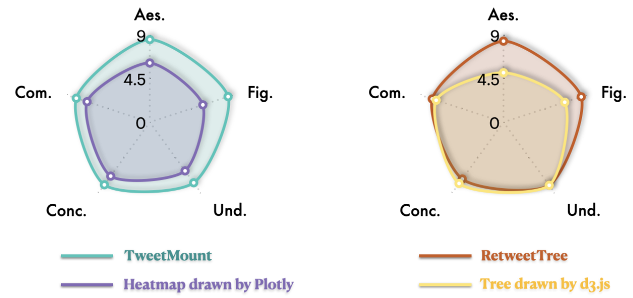

Figure 13: Results of the user study on the evaluation of visual metaphors compared to other common visualization methods.

I. We can explain the pattern by further exploring the information details: most such microblogs usually do not have strong barriers to information dissemination caused by different communities or different topics, so retweeting will not be interrupted by such barriers during the information dissemination process, but will be interrupted because of time validity issue.

In contrast, **Type II** is similar to a bouquet of flowers. Compared with Type I, the overall structure is more slender. It has longer derivations at two or fewer points. The secondary forwarding breadth of this type of forwarding tree itself may not be large, and only one or a few branches have a certain depth of expansion. The reason for the high impact is usually related to the deep involvement of another opinion leader or debates generated by certain participants. Similar tree patterns for both types can be found as shown in Fig. 14.

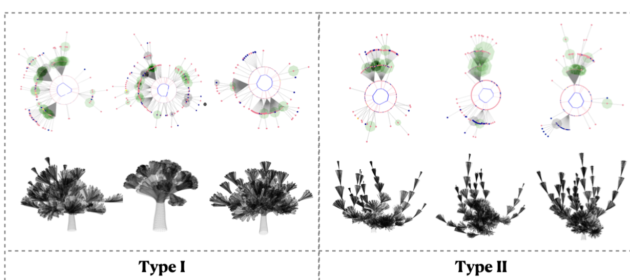

Figure 14: Type I: The circular-shaped ripple structure of hot tweets; Type II: The bouquet-shaped ripple structure of hot tweets and corresponding tree structures.

The difference between 2D and 3D. Both Ripple structure and RetweetTree can help users perceive different patterns of information diffusion process. However there are certain scenarios suitable for these two metaphors respectively, especially in the multiples juxtaposed situation. **3D multiples** are convenient for perceiving spatial relationships and topological structures, such as the height of different trees, the size of trees, the degree of lushness, etc. **2D multiples** are more suitable for comparing details, comparing attribute values, specific structural differences, and statistical features.

We noticed that there are also some patterns in the semantic evolution process, visualized as polygons. We notice that the polygons in the middle of the two types have many sides, which means that large number of nodes qualify the criteria. We observe and collect other microblogs with less influence for comparison. As shown in Fig. 15, semantic evolution seldom occurs in the second-layer forwarding in these cases, the corresponding polygons are with fewer sides.

6.2.2 User Profile

The Pointer Locker Control is used in this case, which allowing users freely explore the space in virtual reality environment, to figure out certain user profile based on three aspects: user interests, impact, and public feedback.

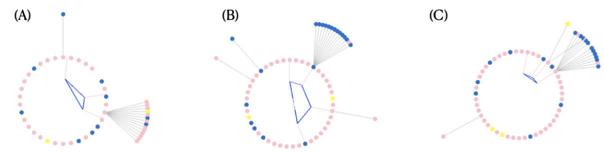

Figure 15: Other forms of semantically evolved polygons.

User Interests After entering the system, we can observe the shape of the terrain generated by our target user. As shown in Fig. 17 (A), the size of the coverage area indicates the number of related microblogs has posted. Simultaneously observing the information panel, we conclude that the root user is very interested in five topics: politics, entertainment, stocks, education, and science. After cutting the mountain shape, we can further explore the group of similar microblogs according to different cutting gestures, so as to deeply dig out the details of the microblog information to form the bigger picture, especially the semantic change of topics and keywords that the root user paid attention to. By simply exploring the microblog points in the same radial direction, we can grasp the semantic evolution of microblogs on similar topics.

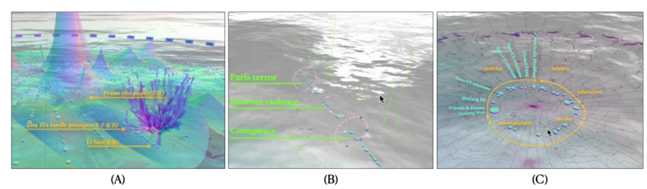

Figure 16: Exploring microblog groups: (A) Mining the semantic change (annotation) of tweets in the radial direction in the Initial Interface (B) Exploring microblogs with similar topics radially in the Cutting Surface Interface (C) Exploring microblogs with similar time circularly in the Cutting Surface Interface.

For example, as shown in Fig. 16 (A), the microblog that has expanded the forwarding tree structure is talking about topics related to the traditional Chinese calligraphy work "Li Sao". Along this direction, we found that in the earlier time, the user had talked about topics also related to traditional Chinese calligraphy such as "Xuan" paper and "Zhu Zi's Family Instructions". These microblogs show the interest of the root user in traditional Chinese calligraphy and are sorted by time. Through the exploration of microblog groups in this direction, we can obtain the fluctuation in the influence of microblogs over one particular topic. The semantic evolution over the cluster of similar microblogs can be visualized as well.

By reading more details in the information panel, we also captured the specific content to help build a concrete user profile with regard to one topic. For instance, through the comparison of points standing in this radii, we now obtain a comprehensive understanding of the content and frequency of the root user's calligraphy morning class over different time periods. The same result can be achieved by entering the Cut Surface Interface with a radial cut gesture. We can extract couples of similar social events that the root user followed in different time periods by further exploring those points in the selected radial cut section. Fig. 16 (B) shows a case on one political-related topic with keywords on "terror", "violence", etc. We can see events such as "Paris terror", "internet violence" and events related to "Cops" have been lined up for further exploration. In additions, users can also use circular cuts to retain microblog groups over a similar time period. Apart from the acquisition of topic distributions, users can also obtain and compare keywords that appear repeatedly in that time period, so as to capture the events the root user cares about at a certain time period. In Fig. 16 (C), we can see that keywords such as "Sino-US relations", "genetic modification", etc., repeatedly appear, indicating the key events our target user was discussing with other participants at that time.

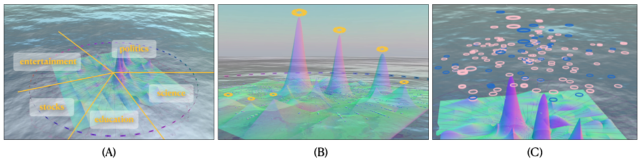

Figure 17: Building user profile by exploring Social Media Island.

User Impact It can be seen from the shape of TweetMount in Fig. 17 (B) that political microblogs have higher influence and dissemination, while science and entertainment microblogs have a relatively low influence. Educational microblogs are usually associated with topics on the plain daily lives of our target user, which are not intriguing to his fans and other possible participants who have a tendency to be intrigued by political topics and events. The emergence of two consecutive peaks in the political slice shows that topics related to politics tend to generate higher retweets and discussions. In addition, we found that the higher peaks appeared near the center of the circle, indicating that the early retweets caused more debate, while over time, different topics formed many other scattered but less intense discussions.

Public Response By exploring the distribution of the torus, we found that most of the torus are close to the ground in the 3D space, and there are fewer torus in the middle and upper parts of the sky, as shown in Fig. 17 (C). This shows that, overall, trending discussions always appear close to the time when the corresponding original microblog was posted, and the probability of a trending discussion is greatly reduced over time. The slightly larger percentage of blue in the larger torus indicates that participants who use negative terms when discussing are more likely to trigger trends. In addition, the blue torus always appear closer to the time of the original Weibo. We randomly observe samples and find that this nuance is caused probably because participants who rejoin the discussion after the main attention time of the tweet has passed are usually those who have a closer social relationship with the target user on the social media platform, such as their fans, which makes them more likely to rejoin the discussion using positive terms. The same information can be shown by mapping aggregated public attitudes into the color attribute of the surface material of TweetMount.

7 Discussion and Future Work

Although the usefulness of our system has been evaluated in Sec. 6, it still has limitations and room for improvement. In this section, we will focus on the limitations and possible future work of Social Media Island.

Implications While the evaluations have reflected that our system can address the initial research questions, we also highlight broader insights gained from this study.

- **Applicable Scenarios of 3D Visualization:** Compared with 2D visualization, 3D visualization has its own set of applicable scenarios. The inherent spatiality and depth offered by 3D visualizations make them particularly effective for tasks that benefit from exploration and immersion, such as understanding complex patterns and the evolution of data over time. Additionally, we found combined with cutting interactions and metaphors in immersive VR environments, 3D visualizations can provide a more intuitive and engaging experience. These interactions allow user freely explore patterns from different views that might be difficult to grasp using 2D representations alone.
- **Context-Specific Utility of 2D vs 3D Layouts**: Our evaluation highlights the unique advantages of 3D metaphoric visualizations in perceiving the conclusive shape of data, spatial relationships and topological structures. In contrast, 2D visualizations excel at providing clear and detailed comparisons, especially when analyzing specific attributes, structural differences, and statistical features. We found that combining 3D with 2D layouts with different context in VR environments, facilitate "overview + detail" exploration. Future research could explore further optimization of this hybrid approach to enhance the experience in immersive exploration [34].
- **Challenges of Perspective and Interaction in 3D Visualizations**: The 3D visualizations may not always be suitable for high-efficiency data analysis, especially in non-interactive systems. For example, in a 3D environment, the automatic adjustment of text orientation based on the user's perspective can create readability issues. As users move or rotate within the space, text may shift or become difficult to read, adding extra cognitive load and slowing down the analysis process. Future work should focus on improving 3D fluidity through techniques like dynamic text orientation methods [57], or consider using 2D for tasks where efficiency and accuracy are critical.

Generalization Ability This visualization system can be applied to any hierarchical textual data with a similar forwarding structure, such as email chains, forum discussions, or academic citation networks. With the development and diversification of social platforms, social media data is not limited to text and social relations but also includes images, voice, video, etc. To accommodate this diversity, future work could focus on integrated analysis of multimodal data [16] and optimizing layouts for presenting information from multiple sources [44], ensuring both clarity and efficiency in visual representation.

Limitation on User Study The user study conducted in this research has several limitations. First, the scale and volume of data used in the study may lead to interaction lag when comparing multiple users or large data points simultaneously, which can affect the overall user experience. Additionally, the user study was initially conducted in a computer-based environment to maintain consistency and fairness in comparison of 2D and 3D visualizations. We also conducted a case study to investigate the immersion, engagement and data findings brought about by 3D metaphor in the VR environment. However, the number of participants is limited. To gain a more comprehensive understanding of the system's effectiveness in the VR environment, a large-scale evaluation is needed to have more diverse groups and get more feedback. This would help further refine the 3D metaphor design space, improving its usability and immersion in a wider range of VR contexts.

Limitation on Data Processing The current system faces two main limitations related to data processing. (1) Clustering Algorithm Limitations: While DBSCAN is effective in detecting arbitrary-shaped clusters and handling noise, it struggles with spatial sparsity, especially when a user focuses heavily on one topic, resulting in empty regions in the spatial representation. Combining partition-based methods like K-means could help mitigate this issue [40]. Additionally, DBSCAN's performance may degrade with high-dimensional datasets due to its increased time complexity, and future work could apply dimensionality reduction techniques [18] to improve scalability. (2) Real-time Data Processing: The system's reliance on preprocessed data limits its ability to handle real-time or rapidly changing datasets, restricting its use for live social media monitoring. Future work should explore real-time clustering [37] and topic analysis [78] for streaming data to enable dynamic updates.

8 Conclusion

In this paper, we present Social Media Island, a 3D interactive visualization system designed to simplify user profiling and facilitate the combined analysis of information diffusion and semantic evolution. The system addresses the inherent challenges of visualizing complex network structures and multidimensional social media data by employing two distinct 3D visual metaphors: the mountain metaphor for profiling user influence and activity and the tree metaphor for representing the information forwarding process. The integration of extended reality technologies further enhances the clarity of visualizing intricate relationships between reposting structures and semantic changes, while providing flexibility in controlling the level of detail in data exploration. The effectiveness of the system's metaphors and interaction capabilities was demonstrated through user studies, and its practical value was showcased in two case studies.

Acknowledgments

This work is supported by Natural Science Foundation of China (NSFC No. 62202105 and No.62472099).

References

[1] D. Archambault, D. Greene, P. Cunningham, and N. Hurley. ThemeCrowds: Multiresolution Summaries of Twitter Usage. In *Proceedings of the 3rd international workshop on Search and mining user-generated contents*, pp. 77–84, 2011. 2

[2] T. Ball and S. G. Eick. Software Visualization in the Large. *Computer*, 29(4):33–43, 1996. 2

[3] M. Balzer, A. Noack, O. Deussen, and C. Lewerentz. Software Landscapes: Visualizing the Structure of Large Software Systems. IEEE TCVG, 2004. 2

[4] S. Beckett et al. Smart City Digital Twins, 3D Modeling and Visualization Tools, and Spatial Cognition Algorithms in Artificial Intelligence-based Urban Design and Planning. *Geopolitics, History, and International Relations*, 14(1):123–138, 2022. 2

[5] A. Braun, S. R. Musse, L. P. L. de Oliveira, and B. E. Bodmann. Modeling Individual Behaviors in Crowd Simulation. In *Proceedings 11th IEEE International Workshop on Program Comprehension*, pp. 143–148. IEEE, 2003. 2

[6] D. Brazina, R. Fojtik, and Z. Rombova. 3D Visualization in Teaching Anatomy. *Procedia-Social and Behavioral Sciences*, 143:367–371, 2014. 2

[7] R. Brito, A. Brito, G. Brito, and M. T. Valente. GoCity: Code City for Go. In *2019 IEEE 26th International Conference on Software Analysis, Evolution and Reengineering (SANER)*, pp. 649–653. IEEE, 2019. 2

[8] L. Byron and M. Wattenberg. Stacked Graphs-Geometry & Aesthetics. *IEEE transactions on visualization and computer graphics*, 14(6):1245–1252, 2008. 2

[9] N. Cao, Y.-R. Lin, X. Sun, D. Lazer, S. Liu, and H. Qu. Whisper: Tracing the Spatiotemporal Process of Information Diffusion in Real Time. *IEEE transactions on visualization and computer graphics*, 18(12):2649–2658, 2012. 1, 2

[10] N. Cao, L. Lu, Y.-R. Lin, F. Wang, and Z. Wen. Socialhelix: Visual Analysis of Sentiment Divergence in Social Media. *Journal of visualization*, 18(2):221–235, 2015. 2

[11] S. M. Charters, C. Knight, N. Thomas, and M. Munro. Visualisation for Informed Decision Making; from Code to Components. In *Proceedings of the 14th international conference on Software engineering and knowledge engineering*, pp. 765–772, 2002. 2

[12] M. Chau. Visualizing Web Search Results using Glyphs: Design and Evaluation of a Flower Metaphor. *Acm transactions on management information systems (tmis)*, 2(1):1–27, 2011. 2

[13] S. Chen, S. Chen, L. Lin, X. Yuan, J. Liang, and X. Zhang. E-map: A Visual Analytics Approach for Exploring Significant Event Evolutions in Social Media. In *2017 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pp. 36–47. IEEE, 2017. 3

[14] S. Chen, S. Chen, Z. Wang, J. Liang, X. Yuan, N. Cao, and Y. Wu. D-map: Visual Analysis of Ego-centric Information Diffusion Patterns in Social Media. In *2016 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pp. 41–50. IEEE, 2016. 1, 3

[15] S. Chen, S. Li, S. Chen, and X. Yuan. R-map: A Map Metaphor for Visualizing Information Reposting Process in Social Media. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):1204–1214, 2019. 1, 2, 3

[16] Z. Cheng, J. Zhang, X. Xu, G. Trajcevski, T. Zhong, and F. Zhou. Retrieval-augmented hypergraph for multimodal social media popularity prediction. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 445–455, 2024. 9

[17] J. Cug, P. Suler, and E. Taylor. Digital Twin-based Cyber-physical Production Systems in Immersive 3D Environments: Virtual Modeling and Simulation Tools, Spatial Data Visualization Techniques, and Remote Sensing Technologies. *Economics, Management and Financial Markets*, 17(2):82–96, 2022. 2

[18] A. Datta, S. Ghosh, and A. Ghosh. Pca, kernel pca and dimensionality reduction in hyperspectral images. *Advances in Principal Component Analysis: Research and Development*, pp. 19–46, 2018. 9

[19] M. De Choudhury, Y.-R. Lin, H. Sundaram, K. S. Candan, L. Xie, and A. Kelliher. How does the Data Sampling Strategy Impact the Discovery of Information Diffusion in Social Media? In *Fourth international AAAI conference on weblogs and social media*, 2010. 2

[20] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. Bert: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv preprint arXiv:1810.04805*, 2018. 4

[21] M. Dörk, D. Gruen, C. Williamson, and S. Carpendale. A Visual Backchannel for Large-scale Events. *IEEE transactions on visualization and computer graphics*, 16(6):1129–1138, 2010. 2

[22] D. Dorling, A. Barford, and M. Newman. WORLDMAPPER: the World as You've Never Seen it Before. *IEEE transactions on visualization and computer graphics*, 12(5):757–764, 2006. 3

[23] W. Dou, X. Wang, D. Skau, W. Ribarsky, and M. X. Zhou. Leadline: Interactive Visual Analysis of Text Data Through Event Identification and Exploration. In *2012 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pp. 93–102. IEEE, 2012. 2

[24] S. G. Eick, J. L. Steffen, E. E. Sumner, et al. Seesoft-A Tool for Visualizing Line Oriented Software Statistics. *IEEE Transactions on Software Engineering*, 18(11):957–968, 1992. 2

[25] S. I. Fabrikant. Visualizing Region and Scale in Information Spaces. In *Proceedings of the 20th International Cartographic Conference*, pp. 2522–9. Beijing China, 2001. 2

[26] S. I. Fabrikant, D. R. Montello, and D. M. Mark. The Natural Landscape Metaphor in Information Visualization: the Role of Commonsense Geomorphology. *Journal of the American Society for Information Science and Technology*, 61(2):253–270, 2010. 2

[27] Y. Fan, J. Yang, J. Chen, P. Hu, X. Wang, J. Xu, and B. Zhou. A Digital-twin Visualized Architecture for Flexible Manufacturing System. *Journal of Manufacturing Systems*, 60:176–201, 2021. 2

[28] E. R. Gansner, Y. Hu, and S. Kobourov. GMap: Visualizing Graphs and Clusters as Maps. In *2010 IEEE Pacific Visualization Symposium (PacificVis)*, pp. 201–208. IEEE, 2010. 3

[29] E. R. Gansner, Y. Hu, and S. North. Visualizing Streaming Text Data with Dynamic Graphs and Maps. In *International Symposium on Graph Drawing*, pp. 439–450. Springer, 2012. 3

[30] C. Gold, M. Chau, M. Dzieszko, and R. Goralski. 3D Geographic Visualization: the Marine GIS. *Developments in Spatial Data Handling*, pp. 17–28, 2005. 2

[31] S. Hadlak, C. Tominski, H.-J. Schulz, and H. Schumann. Visualization of Attributed Hierarchical Structures in a Spatiotemporal Context. *International Journal of Geographical Information Science*, 24(10):1497–1513, 2010. 2

[32] X. Han and J. Wang. Modelling and Analyzing the Semantic Evolution of Social Media User Behaviors during Disaster Events: A Case Study of COVID-19. *ISPRS International Journal of Geo-Information*, 11(7):373, 2022. 2

[33] C.-T. Ho, C.-T. Li, and S.-D. Lin. Modeling and Visualizing Information Propagation in a Micro-blogging Platform. In *2011 International Conference on Advances in Social Networks Analysis and Mining*, pp. 328–335. IEEE, 2011. 2

[34] J. Hong, R. Hnatyshyn, E. A. Santos, R. Maciejewski, and T. Isenberg. A survey of designs for combined 2d+ 3d visual representations. *IEEE Transactions on Visualization and Computer Graphics*, 2024. 3, 9

[35] K. Kim, J. V. Carlis, and D. F. Keefe. Comparison techniques utilized in spatial 3d and 4d data visualizations: A survey and future directions. *Computers & Graphics*, 67:138–147, 2017. 4

[36] C. Knight and M. Munro. Virtual but Visible Software. In *2000 IEEE Conference on Information Visualization. An International Conference on Computer Visualization and Graphics*, pp. 198–205. IEEE, 2000. 2

[37] J. Knittel, S. Koch, T. Tang, W. Chen, Y. Wu, S. Liu, and T. Ertl. Real-time visual analysis of high-volume social media posts. *arXiv:2108.03052 [cs]*, Aug. 2021. 9

[38] D. Koller, P. Lindstrom, W. Ribarsky, L. F. Hodges, N. Faust, and G. Turner. Virtual GIS: A Real-time 3D Geographic Information System. In *Proceedings Visualization'95*, pp. 94–100. IEEE, 1995. 2

[39] J. Kotlarek, O.-H. Kwon, K.-L. Ma, P. Eades, A. Kerren, K. Klein, and F. Schreiber. A study of mental maps in immersive network visualization. In *2020 IEEE pacific visualization symposium (PacificVis)*, pp. 1–10. IEEE, 2020. 2

[40] B. J. Kremers, J. Citrin, A. Ho, and K. L. van de Plassche. Two-step clustering for data reduction combining dbscan and k-means clustering. *Contributions to Plasma Physics*, 63(5-6):e202200177, 2023. 9

[41] M.-P. Kwan and J. Lee. Geovisualization of Human Activity Patterns using 3D GIS: A Time-geographic Approach. *Spatially integrated social science*, 27:721–744, 2004. 2

[42] A. Lee, J. Kim, and I. Jang. Movable Dynamic Data Detection and Visualization for Digital Twin City. In *2020 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia)*, pp. 1–2. IEEE, 2020. 2

[43] W. Li, Z. Wang, Y. Wang, D. Weng, L. Xie, S. Chen, H. Zhang, and H. Qu. Geocamera: Telling stories in geographic visualizations with camera movements. In *Proceedings of the 2023 CHI conference on human factors in computing systems*, pp. 1–15, 2023. 3

[44] Z. Li, C. Gebhardt, Y. Inglin, N. Steck, P. Streli, and C. Holz. Situationadapt: Contextual ui optimization in mixed reality with situation awareness via llm reasoning, Sept. 2024. 9

[45] S. Liu, M. X. Zhou, S. Pan, W. Qian, W. Cai, and X. Lian. Interactive, Topic-based Visual Text Summarization and Analysis. In *Proceedings of the 18th ACM conference on Information and knowledge management*, pp. 543–552, 2009. 2

[46] X. Liu, Y. Hu, S. North, and H.-W. Shen. Compactmap: A Mental Map Preserving Visual Interface for Streaming Text Data. In *2013 IEEE International Conference on Big Data*, pp. 48–55. IEEE, 2013. 1, 3

[47] A. Lovett, K. Appleton, B. Warren-Kretzschmar, and C. Von Haaren. Using 3D Visualization Methods in Landscape Planning: An Evaluation of Options and Practical Issues. *Landscape and Urban Planning*, 142:85–94, 2015. Special Issue: Critical Approaches to Landscape Visualization. 2

[48] A. Marcus, L. Feng, and J. I. Maletic. 3D Representations for Software Visualization. In *Proceedings of the 2003 ACM symposium on Software visualization*, pp. 27–ff, 2003. 2

[49] A. V. Moere. Time-varying Data Visualization using Information Flocking Boids. In *IEEE Symposium on Information Visualization*, pp. 97–104. IEEE, 2004. 2

[50] T. Munzner. *Visualization Analysis and Design*. CRC press, 2014. 2

[51] R. Pan, H. C. Purchase, T. Dwyer, and W. Chen. Extending adjacency matrices to 3d with triangles. In *2024 IEEE 17th Pacific Visualization Conference (PacificVis)*, pp. 232–241. IEEE, 2024. 3

[52] T. Panas, R. Berrigan, and J. Grundy. A 3D Metaphor for Software Production Visualization. In *Proceedings on Seventh International Conference on Information Visualization, 2003. IV 2003.*, pp. 314–319. IEEE, 2003. 2

[53] S. P. Reiss. An Engine for the 3D Visualization of Program Information. *Journal of Visual Languages & Computing*, 6(3):299–323, 1995. 2

[54] J. Rekimoto and M. Green. The Information Cube: Using Transparency in 3D Information Visualization. In *Proceedings of the Third Annual Workshop on Information Technologies & Systems (WITS'93)*, pp. 125–132, 1993. 2

[55] G. G. Robertson, J. D. Mackinlay, and S. K. Card. Cone Trees: Animated 3D Visualizations of Hierarchical Information. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 189–194, 1991. 2

[56] S. J. Rose and P. C. Wong. DriftWeed: A Visual Metaphor for Interactive Analysis of Multivariate Data. In *Visual Data Exploration and Analysis VII*, vol. 3960, pp. 114–121. SPIE, 2000. 2

[57] R. Rzayev, P. Ugnivenko, S. Graf, V. Schwind, and N. Henze. Reading in VR: The effect of text presentation type and location. In *Proceedings of the 2021 CHI conference on human factors in computing systems*, pp. 1–10, 2021. 9

[58] A. Sallaberry, Y.-C. Fu, H.-C. Ho, and K.-L. Ma. ContactTrees: A Technique for Studying Personal Network Data. *arXiv preprint arXiv:1411.0052*, 2014. 2

[59] M. Schedl, P. Knees, G. Widmer, K. Seyerlehner, and T. Pohle. Browsing the Web using Stacked Three-dimensional Sunbursts to Visualize Term Co-occurrences and Multimedia Content. In *Proceedings of the 18th IEEE Visualization Conference*, 2007. 2, 3

[60] G. Schrotter and C. Hürzeler. The Digital Twin of the City of Zurich for Urban Planning. *PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, 88(1):99–112, 2020. 2

[61] X. Shen and P. Eades. Using Moneytree to Represent Financial Data. In *Proceedings. Eighth International Conference on Information Visualisation, 2004. IV 2004.*, pp. 285–289. IEEE Computer Society, 2004. 2

[62] C. Silén, S. Wirell, J. Kvist, E. Nylander, and Ö. Smedby. Advanced 3D Visualization in Student-centred Medical Education. *Medical teacher*, 30(5):115–124, 2008. 2

[63] A. Skupin and S. I. Fabrikant. Spatialization Methods: a Cartographic Research Agenda for Non-geographic Information Visualization. *Cartography and Geographic Information Science*, 30(2):99–119, 2003. 2

[64] J. Stasko and E. Zhang. Focus+ Context Display and Navigation Techniques for Enhancing Radial, Space-filling Hierarchy Visualizations. In *IEEE Symposium on Information Visualization 2000. INFOVIS 2000. Proceedings*, pp. 57–65. IEEE, 2000. 3

[65] G. Sun, Y. Wu, S. Liu, T.-Q. Peng, J. J. H. Zhu, and R. Liang. EvoRiver: Visual Analysis of Topic Coopetition on Social Media. *IEEE Transactions on Visualization and Computer Graphics*, 2014. 2

[66] F. Viégas, M. Wattenberg, J. Hebert, G. Borggaard, A. Cichowlas, J. Feinberg, J. Orwant, and C. Wren. Google+ Ripples: A Native Visualization of Information Flow. In *Proceedings of the 22nd international conference on World Wide Web*, pp. 1389–1398, 2013. 1, 2

[67] M. Wattenberg. Baby Names, Visualization, and Social Data Analysis. In *IEEE Symposium on Information Visualization, 2005. INFOVIS 2005.*, pp. 1–7. IEEE, 2005. 2

[68] 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*, pp. 153–162, 2010. 1, 2

[69] R. Wettel and M. Lanza. Program Comprehension through Software Habitability. In *15th IEEE International Conference on Program Comprehension (ICPC'07)*, pp. 231–240. IEEE, 2007. 2

[70] R. Wettel and M. Lanza. Visualizing Software Systems as Cities. In *2007 4th IEEE International Workshop on Visualizing Software for Understanding and Analysis*, pp. 92–99. IEEE, 2007. 2

[71] R. Wettel and M. Lanza. Codecity: 3D Visualization of Large-scale Software. In *Companion of the 30th international conference on Software engineering*, pp. 921–922, 2008. 2

[72] A. Wijayawardena, R. Abeysekera, and P. Maduranga. A systematic review of 3d metaphoric information visualization. *International Journal of Modern Education and Computer Science*, 15:73–93, 02 2023. doi: 10.5815/ijmecs.2023.01.06 2

[73] Y. Wu, S. Liu, K. Yan, M. Liu, and F. Wu. Opinionflow: Visual Analysis of Opinion Diffusion on Social Media. *IEEE transactions on visualization and computer graphics*, 20(12):1763–1772, 2014. 2

[74] R. Xiong and J. Donath. PeopleGarden: Creating Data Portraits for Users. In *Proceedings of the 12th annual ACM symposium on User interface software and technology*, pp. 37–44, 1999. 2

[75] P. Xu, Y. Wu, E. Wei, T.-Q. Peng, S. Liu, J. J. Zhu, and H. Qu. Visual Analysis of Topic Competition on Social Media. *IEEE transactions on visualization and computer graphics*, 19(12):2012–2021, 2013. 1, 2

[76] J. Yang and S. Counts. Predicting the Speed, Scale, and Range of Information Diffusion in Twitter. In *fourth international AAAI conference on weblogs and social media*, 2010. 2

[77] J. Zhao, N. Cao, Z. Wen, Y. Song, Y.-R. Lin, and C. Collins. # FluxFlow: Visual Analysis of Anomalous Information Spreading on Social Media. *IEEE transactions on visualization and computer graphics*, 20(12):1773–1782, 2014. 2

[78] Y. Zhao, X. Wang, C. Guo, M. Lu, and S. Chen. Contextwing: Pair-wise visual comparison for evolving sequential patterns of contexts in social media data streams. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW1):1–31, 2023. 9

[79] B. Zhu and H. Chen. Communication-Garden System: Visualizing a Computer-mediated Communication Process. *Decision Support Systems*, 45(4):778–794, 2008. 2