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ORIGINAL ARTICLE

A survey on information visualization: recent advances and challenges

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Abstract Information visualization (InfoVis), the study of transforming data, information, and knowledge into interactive visual representations, is very important to users because it provides mental models of information. The boom in big data analytics has triggered broad use of InfoVis in a variety of domains, ranging from finance to sports to politics. In this paper, we present a comprehensive survey and key insights into this fast-rising area. The research on InfoVis is organized into a taxonomy that contains four main categories, namely empirical methodologies, user interactions, visualization frameworks, and applications, which are each described in terms of their major goals, fundamental principles, recent trends, and state-of-the-art approaches. At the conclusion of this survey, we identify existing technical challenges and propose directions for future research.

Keywords Information visualization · Interactive techniques · Large datasets

1 Introduction

Information visualization (InfoVis) is a research area that aims to aid users in exploring, understanding, and analyzing data through progressive, iterative visual exploration [124].

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With the boom in big data analytics, InfoVis is being widely used in a variety of data analysis applications [22,31,97]. Examples include visual analysis of business data [22,31,80,90,92,93,123,152], scientific data [38,97], student histories [137], sports data [111], ballot data [155], images and videos [26,114,132], auction data [63], and search results [106,121]. Accordingly, from researchers to brand strategists, financial analysts and human resource managers, better understanding and analysis of data/information is becoming an increasingly powerful way for further growth, productivity, and innovation. Moreover, we see average users, including consumers, citizens, and patients, examine public data such as product specifications, blogs, and online communities to choose products to buy [39], decide issues to vote on [163], and seek health-related information [23]. Recent advances in InfoVis technologies provide an effective avenue to address the current and future "glut" of information faced by today's users.

For all these reasons, we believe InfoVis techniques are valuable and, therefore, worth studying, especially the recent research trends. Existing surveys were either conducted several years ago [47,143] or focus on a specific topic of visualization such as graph visualization [145], software visualization [24], or visualization of network security events [124]. In this paper, we have conducted a systematic analysis of recent InfoVis techniques, approaches, and applications, aiming to provide a better understanding of the major research trends and mainstream visualization work, along with their strengths and weaknesses. The objective of this survey is twofold:

– We provide researchers who work on InfoVis or related fields a comprehensive summary and analysis of the state-of-the-art approaches. As a result, this survey can

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be regarded as a brief introductory course that leads researchers to frontier research and development.
– We provide the general InfoVis audience a global picture of the area. We try to bridge the gap between the most cutting-edge research and real-world applications.

The paper is organized as follows: we first present an overview of InfoVis techniques, including the pipeline and classification schemes. We then introduce mainstream work in each of the four major categories—empirical methodologies, interactions, frameworks, and applications—in Sects. 3, 4, 5, and 6. Section 7 presents an aspiration for future research by summarizing the major challenges in this filed. Finally, in Sect. 8, we conclude our work.

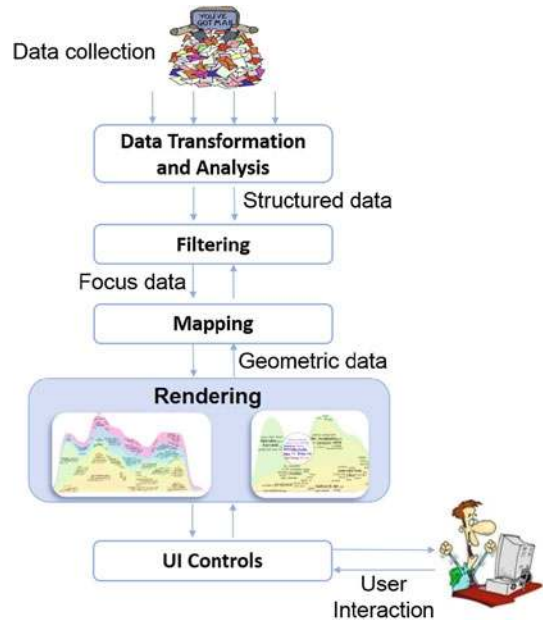


Fig. 1 Visualization pipeline

2 Overview

In this section, we briefly introduce InfoVis and its recent research trends organized by novel classification schemes.

2.1 Visualization pipeline

Figure 1 provides an overview of the InfoVis pipeline. It has five main modules: data transformation and analysis, filtering, mapping, rendering, and UI controls. The input is a collection of data that can be structured or unstructured. The data transformation and analysis module is tasked with extracting structured data from the input data. If the input data collection is too large to fit into computer memory, a data reduction technique is applied first. For unstructured data, some data mining techniques such as clustering or categorization can be adopted to extract related structure data for visualization. With the structured data, this module then removes noise by applying a smoothing filter, interpolating missing values, or correcting erroneous measurements. The output of this module is then sent to the filtering module, which automatically or semi-automatically selects data portions to be visualized (focus data). Given the results produced by the filtering module, the mapping module maps the focus data to geometric primitives (e.g., points, lines) and their attributes (e.g., color, position, size). With the rendering module, geometric data are transformed into image data. Users can then interact with the generated image data through various UI controls to explore and understand the data from multiple perspectives.

2.2 InfoVis classification schemes

Application is a strong driving force behind InfoVis research. As a result, research in this field is usually motivated by real-world data, user requirements, and tasks. In this context, a wide range of models, methodologies, and techniques have been proposed by researchers for a large number of applications. Table 1 lists representative work of recent InfoVis research, classified into four categories.

The first category, empirical methodologies, consists of dozens of visualization models and theories, as well as various evaluation studies. The major goal of the proposed visualization models and theories is to provide a theoretical foundation for large numbers of applications from different domains, while the evaluations can be used to bridge the gap between research and real-world applications. Most of the existing methods employ usability studies and controlled experiments to understand how real users carry out a task and interact with the designed visualization toolkit/technique. Visualization designers/developers can then evaluate the potential and limitations of their tools/techniques.

Techniques in the interactions category can be further categorized into two groups: WIMP (windows, icons, mouse, pointer) interactions and post-WIMP interactions. WIMP interaction techniques mainly focus on studying how users interact with visualization tools by the use of a mouse and a keyboard. Post-WIMP interaction techniques aim to explore how users leverage pen or touch interactions to interact with devices that attempt to go beyond the paradigm of windows, icons, menus and pointer devices, such as touch-enabled devices.

The research in the third category, frameworks, aims to design either a generic visualization framework for widespread deployment of visualization related techniques or applications [17,57], or a system for a certain set of applications in a specific domain such as multivariate data [28] or inhomogeneous data [89].

Table 1 A taxonomy of InfoVis techniques and representative work in recent years

InfoVis techniques	Examples
Empirical methodologies	
Model	[11,34,35,52,65,66,84,95,119,128,146,153]
Evaluation	[4,12,14,15,18,49,60,69,78,82,98,100,101,103,104,115,116,131,156]
Interactions	
WIMP interactions	[37,55,135]
Post-WIMP interactions	[13,70,147]
Frameworks	
Systems and frameworks	[2,17,28,57,89,153]
Applications	
Graph visualization	[3,8,9,13,19,20,30,36,40,42,59,62,85,91,118,120,51,133,162,167,164,170]
Text visualization	[1,5,22,32,31,83,92–94,154,159,163,169]
Map visualization	[1,44,71,102,106,117,125,136,144,148]
Multivariate data visualization	[21,48,68,72,108,112,134,139,140]

Since InfoVis research is actively driven by real-world applications, a taxonomy of the field cannot be formulated without including practical and characteristic applications. In the fourth category, applications, we aim to introduce the various applications in this field, including graph visualization, text visualization, map visualization, and multivariate data visualization.

As shown in Table 1, most of the recent InfoVis papers focus on empirical methodologies and applications (categories 1 and 4). This indicates that InfoVis is gradually becoming mature and an increasing number of researchers and practitioners have studied empirical methodologies to steadily reach users, and have actively applied the exciting research outputs to various real-world applications.

3 Empirical methodologies

To put InfoVis research into practice, researchers in this field have developed many empirical methodologies for better supporting the design and implementation of novel and useful visualizations. Empirical evaluation methods are generally based on usability studies and controlled experiments [113]. According to the generality of the empirical methodologies, we divide them into two categories: model and evaluation. If an empirical method can be applied to a wide range of applications/domains, it falls into the former category; otherwise, it belongs to the second category. In this section, we briefly review each of the categories.

3.1 Model

Models are the foundation of empirical studies. In the past years, various models have been developed to help design effective visualizations. Roughly, they can be classified into the following categories: visual representation models, data-driven models, and generic models.

Visual representation models are particularly important for putting a wide range of research outputs into practice. Researchers have introduced many models to handle different perception problems in InfoVis. For example, Steinberger et al. [128] proposed context-preserving visual links to facilitate the comparison and interpretation of related elements in different views. A visual difficulties model [65] is developed to help users understand important information in a visualization. The visual difficulties evidence emphasizes a trade-off design between efficiency and beneficial obstructions. Furthermore, the privacy-preserving model [35] and uncertainty model [34,160,161] are also studied to adaptively protect sensitive information and well illustrate the uncertainty information embedded in the data and/or caused by the visualization process.

The development of visualization is driven by real-world applications and related data. As a result, several data-driven models have been studied and applied to a variety of data, such as high-dimensional data [2,11], heterogeneous data [89,129], geographic data [95], narrative data [66], and tables of counts, proportions, and probabilities [153].

Recently, some generic theories and models have also been developed to guide the deployment of InfoVis techniques and tools [52,84,119,147]. For example, Lam et al. [84] proposed a scenario-based method to study evaluation in InfoVis. Through an extensive study of over 800 visualization publications, the authors divided the existing evaluation methods into seven scenarios: evaluating visual data analysis and reasoning, evaluating user performance, evaluating user experience, evaluating environments and work practices, evaluating communication through visualization, evaluating visualization algorithms, and evaluating collaborative data analysis. To help visualization designers/developers better conduct design study research, Sedlmair et al. [119] systematically reviewed related methods in HCI, social science, and visualization. They proposed a nine-stage framework for better conducting design studies by reflecting their own experiences and other related papers on InfoVis. The nine stages are learn, winnow, cast, discover, design, implement, deploy, reflect, and write. Practical guidance and potential disadvantages are provided for each stage.

3.2 Evaluation

User studies are the most commonly used evaluation method used in InfoVis and offer a scientifically sound method to measure visualization performance. As a result, they are an important means to translate laboratory InfoVis research into practical applications. User studies usually involve techniques ranging from informal surveys, to crowdsourcing user studies [78,103] and rigorous laboratory studies [4,15,60,69,98,116] that invite a small number of participants. Here we briefly introduce the rigorous laboratory studies and crowdsourcing user studies.

Recent work involving rigorous laboratory studies can be further classified into two categories: controlled experiments to compare design elements and controlled experiments to compare tools with similar functions. In the first category, researchers have compared and evaluated specific widgets or visual mappings ranging from artery visualization design [15] to visual semiotics and sketchiness evaluation in uncertainty visualization [18,98], aesthetics and memorability of visual features in graph drawing [101,115], and ambient and artistic visualization design related to residential energy use feedback [116], as well as rhetorical illustrations and visual features such as embellishments [14], style [104], glyph design [100], graphical overlays [82], visual variables on tiled wall-sized displays [12], strokes [49], and slope ratio [131]. In the second category, researchers and practitioners have evaluated many visualization tools such as different ways to represent dual-scale data charts [69] and an effective way to visualize set data [4].

Rigorous laboratory studies have succeeded in evaluating Infovis designs/applications. However, collecting the evaluation results from only a small number of participants may be problematic in many design situations since the results often lead to a lack of statistical reliability [79]. To solve this problem, crowdsourcing user studies [78,103,156] have attracted recent attention. For example, Micallef et al. [103] leveraged crowdsourcing to assess the effect of six visualization techniques on Bayesian reasoning. Through a crowdsourcing-based study, Kim et al. [78] systematically examined whether an eye tracker is always a useful tool to evaluate InfoVis techniques. With this empirical study, the authors found a limitation of the eye tracking method: its inability to capture peripheral vision.

4 Interactions

In InfoVis, user interactions are as important as presentation for effective information understanding and analysis. In 2007, Yi et al. [166] provided a comprehensive survey to study the role of interaction techniques in InfoVis. They classified the interaction techniques into seven categories: select, explore, reconfigure, encode, abstract/elaborate, filter, and connect. We recognize this survey by providing an update of state-of-the-art interaction techniques, which are classified into two categories: WIMP (windows, icons, mouse, pointer) interactions and post-WIMP interactions.

4.1 WIMP interactions

Recently, a set of WIMP interactions were developed to facilitate visual analysis. Typical examples include basic interactions such as selection, filtering, brushing, and highlighting [92,160], as well as advanced interactions like visual comparison [135], interest-driven navigation [55], focus-based navigation [105,138], and faceted navigation [37].

To help users better understand summarization results of a text corpus and perform deeper analysis, TIARA [93] aims to allow users to interact with the generated visual summary and examine relevant data from multiple perspectives. To this end, TIARA provides a set of interactions, for example, interactive topic ordering, topic details on demand, and strength comparison.

Inspired by real-world user comparison behaviors such as side-by-side, shine-through, and folding, Tominski et al. [135] developed a novel interaction technique coupled with several complementary visual cues. The major feature of this interaction technique is that allowing a user to freely select the visual information to be compared, which is represented by views. Then the user can arrange the views according to the analysis task. Typically, s/he can place them side-by-side or overlap them. Two interaction techniques, shine-through and folding, are provided to compare overlapping views. Figure 2 illustrates the basic idea of the folding interaction. Furthermore, supplementary visual clues, such as a hierarchy overview, an origin ghost, and difference LEDs, have also been developed to help users perform the comparison task.

4.2 Post-WIMP interactions

In addition to the classical WIMP interaction techniques that use a mouse and a keyboard, post-WIMP interaction techniques employing touch interfaces are now very common in applications ranging from visualization design [147] to co-located collaborative visual analytics [70] and science learning [13]. For example, to explore how pen and touch interactions are applied to create an InfoVis design as well as their influence on each other, Walny et al. [147] conducted a Wiz-

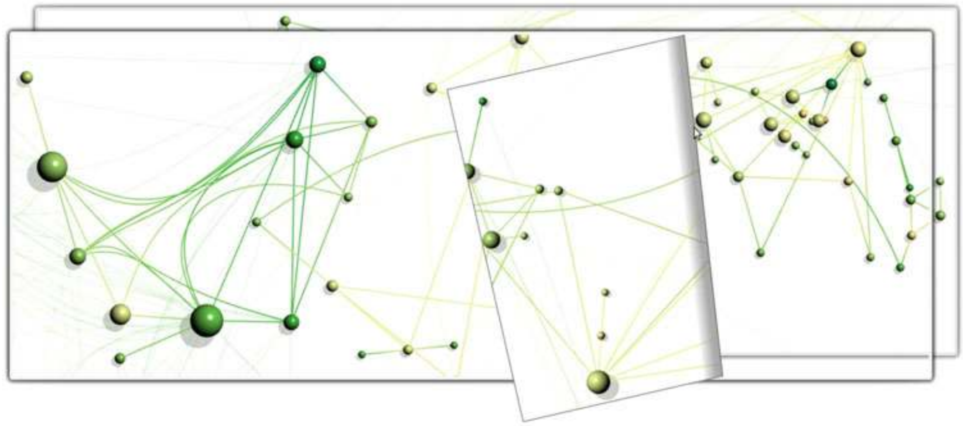


Fig. 2 Folding interaction to reveal and relate information shown in overlapping node-link diagrams [135]

ard of Oz study. In this study, an unseen human (the "wizard") partially controlled how the computer system responded to a subject's actions. The authors reported several interesting findings, including that the subjects could smoothly switch to the new interaction paradigms and were clearly aware of the use scenario of pen-and-touch interactions. Furthermore, integrated interaction helped users a great deal.

5 Systems and frameworks

The research into systems and frameworks for InfoVis has attracted a great deal of attention and developed rapidly. Researchers have introduced a number of new visualization systems [16,17,41,57,150] and frameworks [28,45,89,153,158,161] to facilitate development and deployment of InfoVis applications. In this section, systems refer to building libraries or toolkits for developing visualizations. Frameworks represent modeling different aspects of visualization techniques.

5.1 Systems

Implementing interactive visualization applications from scratch is difficult [41,57]. Towards this end, researchers have proposed a variety of visualization systems such as *Improvise* [150], the *InfoVis Toolkit* [41], and *Prefuse* [57] to support the creation and customization of visualization applications. Improvise is a visualization system that allows users to interactively create multiple, highly linked views of relational data. A sophisticated coordination mechanism based on shared objects and expressions is employed by Improvise. The InfoVis Toolkit is a Java-based InfoVis library with unified, generic data structures and visualization algorithms to simplify the development of visualization applications. Prefuse [57], based on the classic visualization pipeline (Fig. 1), is a widely used visualization toolkit that features a library of visualization-oriented data structures, layout algorithms, and interaction and animation techniques.

These traditional systems have been applied to building successful InfoVis applications. However, extending or tailoring the visualizations of the systems may be expensive and difficult [16]. Protovis [16] has emerged as a new visualization system to overcome the problem of the traditional systems using declarative, domain-specific languages. It strikes a balance among expressiveness, accessibility, and efficiency and employs JavaScript and *Scalable Vector Graphics* (SVG) to create interactive web-based visualizations [16]. Protovis has been further extended to support the Java programming language [56] to achieve better performance. More recently, a new web-based library called *Document-Driven Documents* (D^3) [17] has become a very popular toolkit to construct interactive visualizations on the web (Fig. 3). As opposed to other visualization toolkits [57,16], D^3 does not use tailored scenegraph abstractions. On the contrary, it supports direct manipulation of document elements (namely, webpage elements) by binding data to document elements.

5.2 Frameworks

In recent years, we have witnessed a growing interest in research into InfoVis frameworks. A number of frameworks [25,45,158,161] have been proposed to characterize InfoVis from different perspectives such as uncertainty [161] and information theory [25].

Chen and Jänicke [25] described a framework based on information theory to evaluate the relationship between visualization and information theory. Their findings suggested that the information-theoretic framework should be able to characterize the visualization process. Adding new visualizations with existing toolkits [57] to an application is not easy as this often requires significant changes, such as to the data structures or scene graphs. *WebCharts* [45] is a framework that provides a strategy for incorporating visualizations into existing JavaScript applications without the need for such changes.

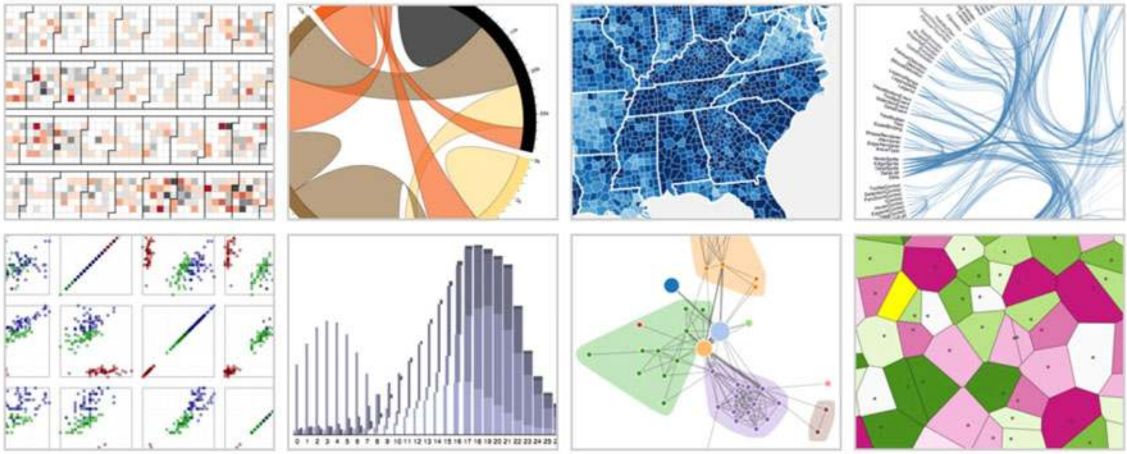


Fig. 3 Interactive visualizations created by D^3 [17]

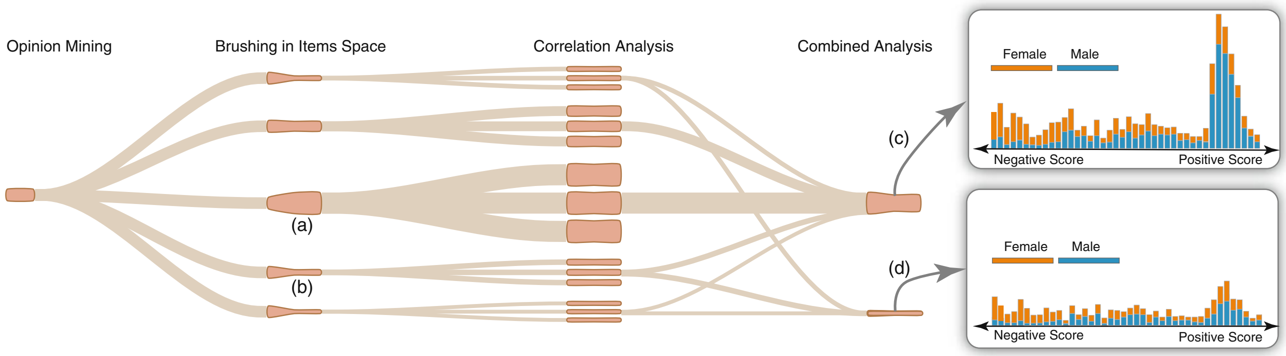


Fig. 4 Visualization of uncertainty variations in a visual analysis process using the uncertainty framework [161]

Uncertainty information can frequently show up in a visualization process [29]. When uncertainty arises, the uncertainty information may increase, decrease, split, or merge through the entire process [161]. The complexity and dynamic characteristics of uncertainty play an important role in creating trustworthy visualizations. Wu et al. [161] introduced a comprehensive framework for quantitatively charac- terizing and intuitively visualizing complex, dynamic uncertainty information through visual analysis processes. The framework uses error ellipsoids to model multidimensional uncertainty and the dynamic variation of the uncertainty. A flow-style visual metaphor is employed to visualize the evolution of uncertainty in the analysis process, as illustrated in Fig. 4.

6 Applications

Visualization design highly depends on the underlying data and the specific application. Different types of data have different characteristics and patterns of interest that require specialized tool sets to visualize.

For graph-like data, analysts are usually interested in patterns related to topological structures. For example, friend relationships among a group of people can be represented as a graph. When exploring the relations, analysts often use visualization to keep them aware of the structure context [57]. To visualize textual data, the semantic meanings in the content attract the most attention. For example, various visualization techniques [23,58,110] have been developed to help analysts understand the theme or major topics in a large collection of documents. When dealing with geographic data, understanding the spatial distribution of information is usually the key to solving many problems. For example, to reveal patterns in trajectory data, one common approach is directly visualize them on the map [120]. Multivariate data, as a general data type, exists in a variety of fields, but one common goal is to explore the inter-relationships between different dimensions. Targeting the inter-relationships, various visualization techniques [151] have emerged to help analysts identify, locate, distinguish, categorize, cluster, rank,

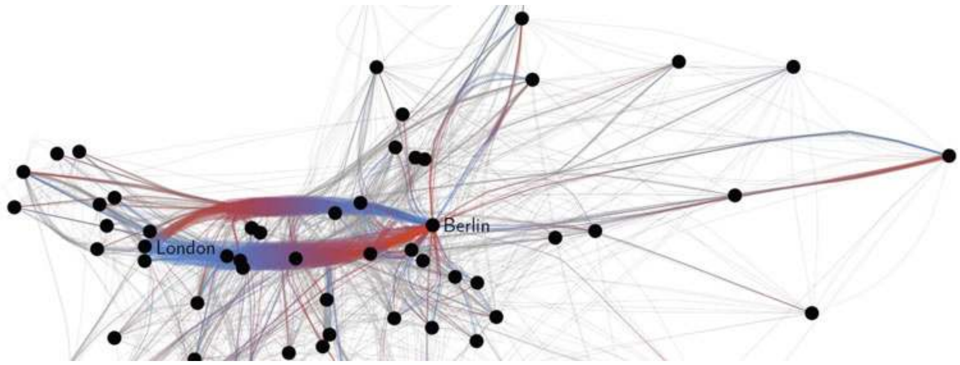


Fig. 5 Divided edge bundling [120]: the view shows the European follower graph for GitHub. *Colors* indicate edge directions (from *blue* to *red*)

compare, associate, or correlate the underlying multivariate data.

Accordingly, in this section, we categorize recent visualization work into four groups based on the characteristics of their target data. For each category, we discuss several recent examples and introduce the visualization techniques employed by each example.

6.1 Graph visualization

A graph is a powerful abstraction of data that consist of elements and connections between elements. Social contacts [57], trajectories on maps [120], and electronic communications [118] can all be modeled as graphs. According to Landesberger et al. [145], graphs can be classified into two categories: static and dynamic, based on their time dependence.

6.1.1 Static graph visualization

In this section, we briefly introduce node-link-diagram-based graph visualization techniques and other alternatives such as matrix visualization.

Node-link diagrams For centuries, node-link diagrams have been the most used visual representation for graphs. Researchers are still fascinated by their intuitiveness and power, and they have introduced various technologies taking advantage of this representation. However, recent visualization work indicates that researchers have gradually shifted their attention from finding new layout algorithms [73,77,122,130] to studying the usability in various applications.

For example, Burch et al. [20] conducted a user study to compare the readability of node-link diagram and space-filling representations. They found that space-filling results are more space-efficient but more difficult to interpret. In particular, orthogonal tree layouts significantly outperform radial tree layouts for some tasks, such as finding the least common ancestor of a set of marked leaf nodes. Yuan et al. [167] argued that a good layout cannot be achieved simply by automatic algorithms but need user inputs. Thus they proposed a framework that automatically stitches and maintains the layouts of individual subgraphs submitted by multiple users.

Another hot topic with regard to improving usability is clutter reduction. Among all the solutions to reduce visual clutter, edge bundling is still the most popular one [33,67,120]. Recently, Selassie et al. [120] proposed a bundling technique for directed graphs. In their system, edges are bundled into different groups to enhance directional patterns of connectivity and symmetry (Fig. 5), which are unfortunately obscured in previous methods. At the same time, skeleton-based edge bundling was introduced by Ersoy et al. [40]. They calculated the skeleton of edge distributions and used it to bundle the edges. Other ways to reduce clutter include density estimation, node aggregation, and level-of-detail rendering. Zinsmaier et al. [170] presented a novel approach that combines these techniques and achieves a better time performance than other state-of-art methods while generating appealing layouts (Fig. 6).

Alternative representations The traditional matrix representation is suitable for visualizing dense graphs due to its non-overlapping visual encoding of edges. However, it may be ineffective for sparse graphs. Recently, Dinkla et al. [36] designed "compressed adjacency matrices", which aim to visualize sparse graphs, such as gene regulatory networks. In their representation, each weakly connected component is treated as a separate network and placed together to generate a neat and compact visualization (Fig. 7). Similar to matrix representations, PIWI [164] uses vertex plots that show vertices as colored dots without overlap, to display the neighborhood information of communities in a large graph. Together with rich and informative interactions, PIWI enables users to conduct community-related tasks efficiently. TreeNetViz, a compound graph representation, was recently proposed by Guo and Zhang [50] to visualize hierarchical information in graphs. It combines a radial, space-filling visualization (tree structure) with a circle layout (aggregated network) to help analysts understand multiple levels of aggregated information.

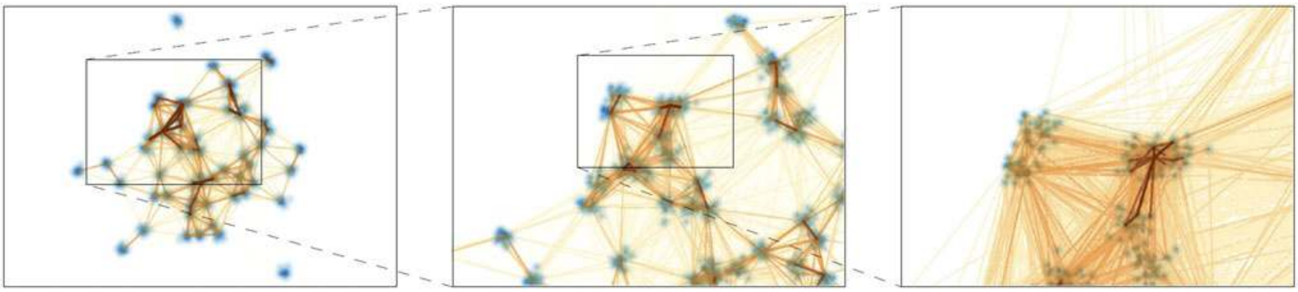


Fig. 6 Level-of-detail rendering of a large graph [170]: the visualization shows a zooming interaction: from overview (*left*) to a local region (*right*)

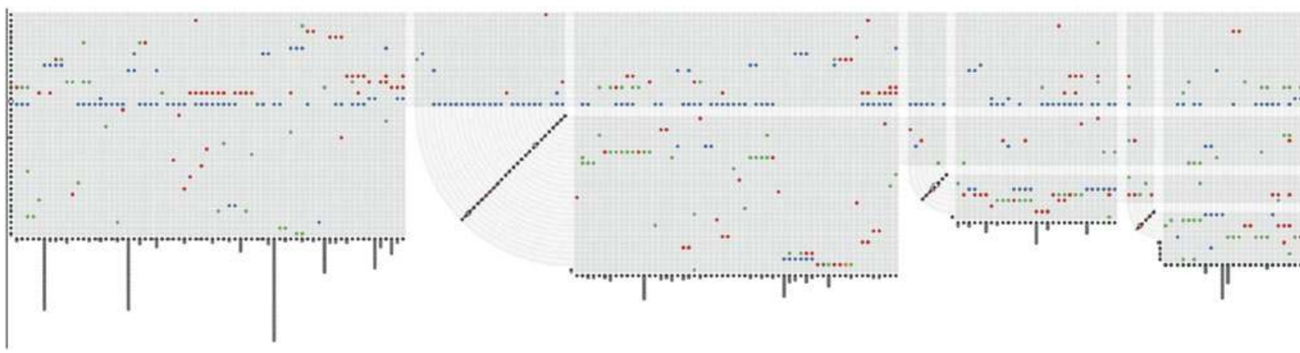
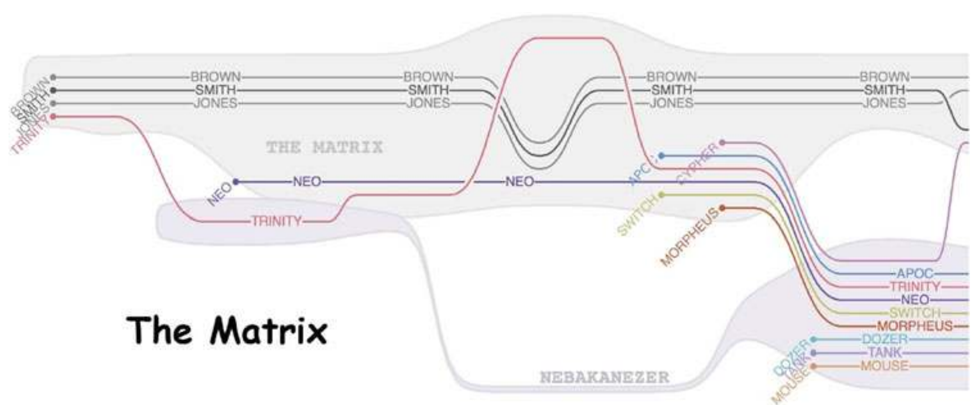


Fig. 7 Compressed adjacency matrices [36]: the visualization shows the gene regulatory network of *Bacillus subtilis* (approximately 700 genes and 1,000 regulations)

Fig. 8 Storyline visualization of the movie *The Matrix* [133]



6.1.2 Dynamic graph visualization

Animation is a natural way to illustrate changes over time since it can effectively preserve a mental map [10]. Several attempts have already been made to visualize dynamic graphs by leveraging animation techniques [10,165]. However, Archambault et al. [8] have shown that preserving a mental map does not help much in gaining insights into animated dynamic graphs. As a result, recent methods focus more on showing dynamic graphs statically [20,91,133]. To encode the time dimension in a static way, a timeline and small multiples are two popular choices.

Timeline-based approaches encode time as one axis and then draw and align the graph at each time point on the timeline. Thus, graphs that are preferably represented as 2D node-link diagrams need to be visually compressed into a 1D space, which dramatically reduces the readability and increases visual clutter. To address this issue, Burch et al. [20] developed parallel edge splatting for scalable dynamic graph visualization. In their system, temporal changes of the graph are encoded into textures that are synthesized from edge distributions.

To show entity clustering information over time, Tanahashi and Ma [133] used a generic algorithm to generate a legible and esthetic storyline visualization (Fig. 8). However, their approach is too slow to support real-time interactions. To solve this problem, StoryFlow [91] was developed to create better storyline layouts while also supporting real-time

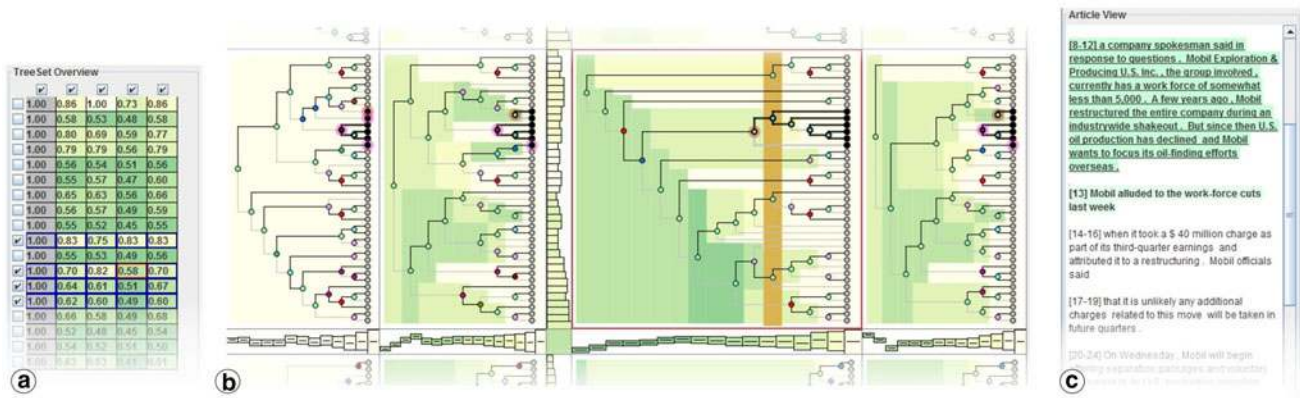


Fig. 9 DAViewer [169]: the interface shows detailed discourse trees, similarity statistics, rhetorical structures, and text content

interactions. To improve efficiency, it modeled the problem as a hybrid optimization framework that combines discrete and continuous optimizations.

Based on small multiples, Hadlak et al. [51] proposed in-situ visualization, which allows users to interactively select multiple focused regions and choose suitable layouts for the selected data. They argued that a single visualization technique may not be enough due to the complexity of large dynamic graphs. With their approach, a user can freely switch between different visualizations to adapt the analysis focus or the characteristics of regions of interest.

6.2 Text visualization

Text documents are now widely available in digital format and have received more and more attention as an emerging visualization topic. In this sub-section, we summarize and categorize recent text visualization techniques based on their target data (such as individual documents or document collections) and their target tasks (such as showing static content distributions or tracking temporal evolutions).

6.2.1 Visualization of static textual information

The visualization work on static text information can be classified into two categories: feature-based text visualization and topic-based text visualization.

In feature-based text visualization, a feature indicates a non-overlapping text chunk (e.g., keywords or phrases) or a grammatical structure (e.g., infinitives or clauses), inside a document. Word clouds, a fundamental visual metaphor, visualize a single document or a set of documents by displaying the important keywords with font sizes that indicate their frequency of occurrence. In the past few years, researchers have introduced a variety of techniques to improve esthetic appearance [32], interactivity [81], and expressiveness [32, 159]. With the aim of revealing various relationships among terms, Word Tree [149] and Phrase Nets [142] take it a step further. They build trees and graphs to visually convey occurrence relationships among terms.

Recently, many researchers have focused their attention on visualizing narrative patterns, which are more complex features that characterize text content. For example, Keim and Oelke [76,107] used a pixel-based technique, which they call "literature fingerprinting," to understand and visualize document signatures, such as vocabulary richness and sentence length. They have proven that a simple visualization can greatly help analysts characterize documents and identify authorship. The latest work on visualizing narrative patterns, including recurrence patterns [7] and discourse trees [169], has also proven helpful to analysts and linguists when analyzing the semantic and grammatical structures in text documents or human discourse. For example, DAViewer [169] integrates a dendrogram icicle into a tree-based visualization to help discourse analysis. Their system visually exposes grammatical structures inside a document, so that linguists can easily explore, compare, and evaluate the discourse parsers (Fig. 9).

To provide an overview of a document collection, static topic-based text visualization aims to detect and explore topics (or clusters) hidden inside. Topic modeling or text clustering has a long history in the data mining field [87,126,127, 168]. Traditional methods include naive Bayes, maximum entropy, and support vector machine. The basic idea behind these methods is to convert each document into a vector inside the hyperspace and then use the distance between the vectors to represent the dissimilarity value between two documents. In this way, clustering text documents can be transformed into mathematically grouping vectors in the hyperspace.

To visually represent the clustering results to users, projections are a popular metaphor. A projection is considered, in general, a technique that spatially arranges graphical elements on a 2D space to reflect the relationships among text documents.

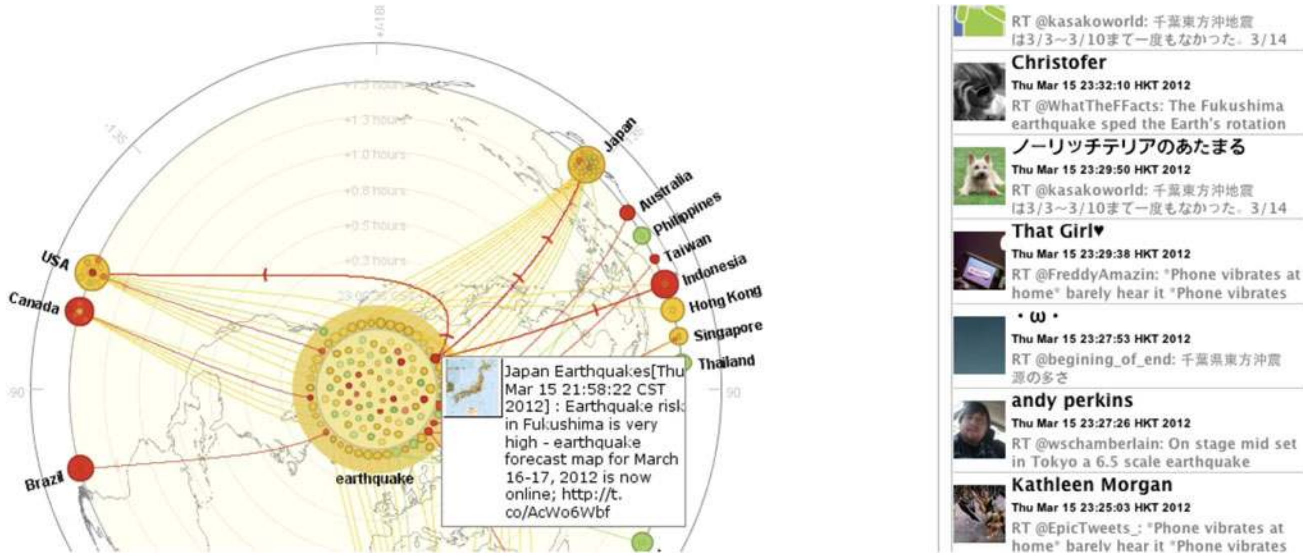


Fig. 10 Whisper [22]: information diffusion on Twitter regarding a 6.8 magnitude earthquake in Japan. Twitter activities are arranged in a radial layout, with the positions indicting their time stamps and geographic locations

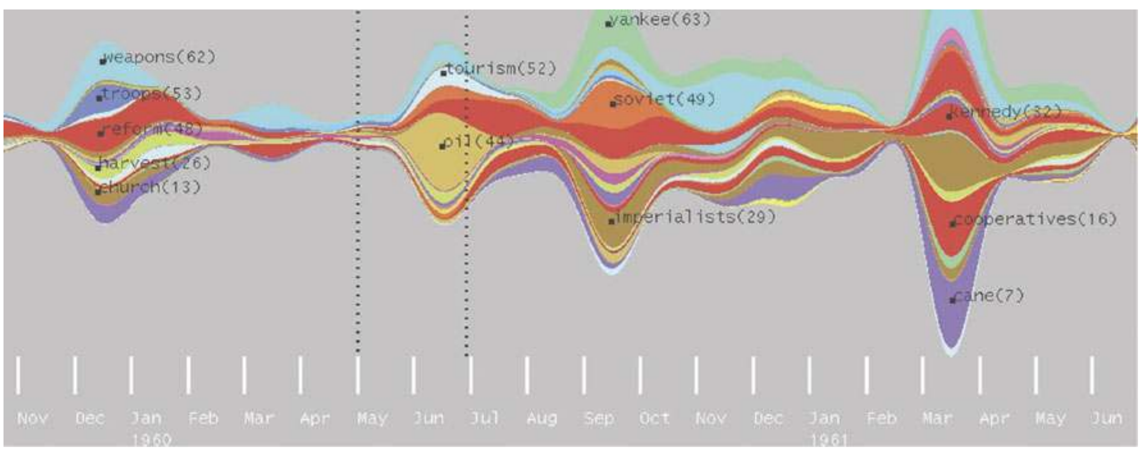


Fig. 11 ThemeRiver [54]: keywords in a document collection are shown as colored "stripes" with width indicating the occurrence frequency of keywords at different times

Based on different spatial encodings, different visualization techniques have been developed. One common projection metaphor is a "galaxy system" [110], in which the distances between graphical elements indicate the dissimilarities between documents. The major advantage is its appeal, since it mimics cartographic maps, which are intuitive to most people. For example, Heimerl et al. [58] used the Principal Components Analysis (PCA) technique to visualize supervised classification results, enabling non-experts to interactively train classifiers.

Some of the latest research into spatial encodings focuses more on document attributes. For example, FacetAtlas [23] classifies documents into clusters and draws density maps based on the facets of the document. Thus, multi-faceted relationships of documents within or across clusters can be revealed. To emphasize the spatio-temporal diffusion process in social media, Whisper [22] uses locations of graphical elements to reflect the geographic and time attributes of documents (Fig. 10).

6.2.2 *Visualization of dynamic textual information*

The time attribute poses special and exciting challenges to text visualization, since it is critical for understanding content evolution patterns in time-varying document collections. Recent research [27] has shown that temporal visualization can help analysts with additional memory aids to filter irrelevant information, view complex event sequences, and build correct storylines and solutions.

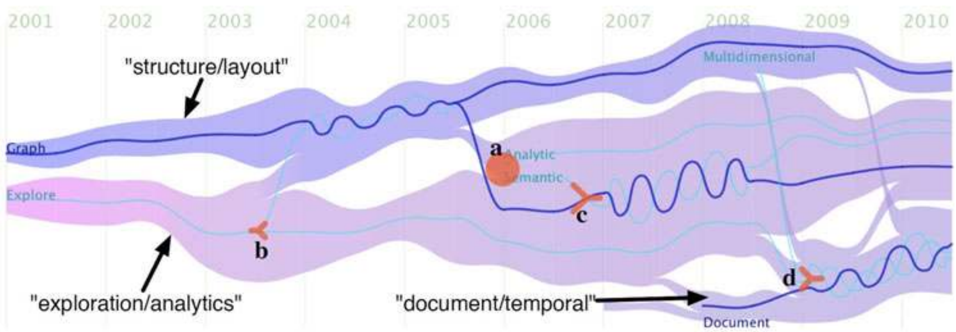


Fig. 12 TextFlow [31]: selected topic flows of VisWeek publication data with thread weaving patterns related to primary keywords GraphG and GocumentG

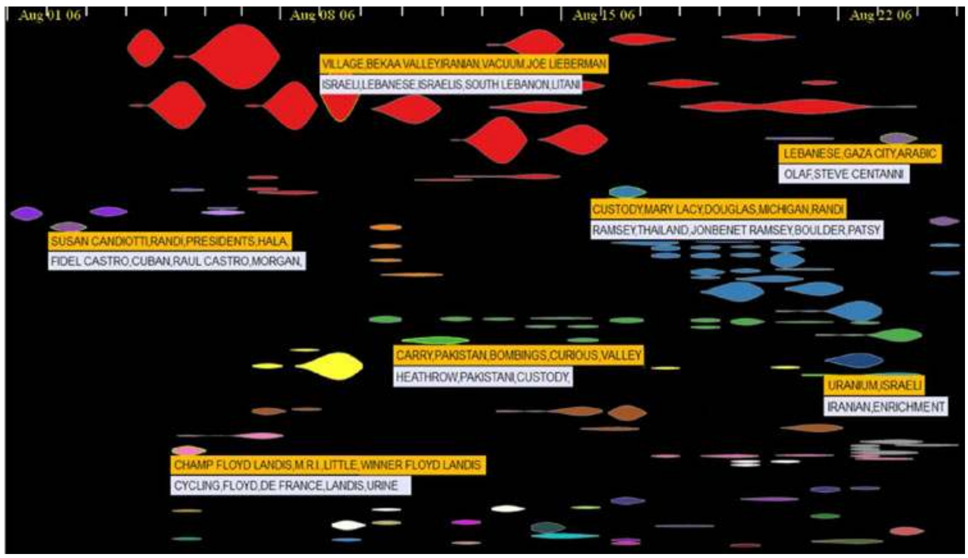


Fig. 13 EventRiver [96]: each event is represented by a bubble, whose shape encodes the number of documents and duration of that event

Fig. 14 Typographical maps [1]: the visual representation of several blocks in Chicago, IL. Text alone forms the graphical elements representing map features

Several attempts [6,32,86] have been made to extend existing visualization techniques to handle temporal document collections. For example, SparkClouds [86] combines well-accepted word clouds with sparklines to show the frequency change over time.

Another category of topic-based text visualization is based on the well-known "river" metaphor. ThemeRiver [54] was originally designed to display temporal thematic changes of selected words in a document collection (Fig. 11). In the "river" metaphor, the X-axis denotes time, while individual words are visually represented as colored "stripes" within the river. The stripe width at a specific time point indicates the occurrence frequency of the associated word.

Recent research has extended the basic "river" metaphor to depict topic evolution [31,93] (Fig. 12) and event occurrences [96]. For example, TextFlow [31,46] was developed to illustrate topic merging/splitting relationships and their evolution in a text stream. EventRiver [96] models news corpora as a consequence of relevant events occurrence. Thus, it applies a temporal-locality clustering technique to group news based on content and time-stamps, and maps them to real-life events. In the proposed visualization (Fig. 13), each

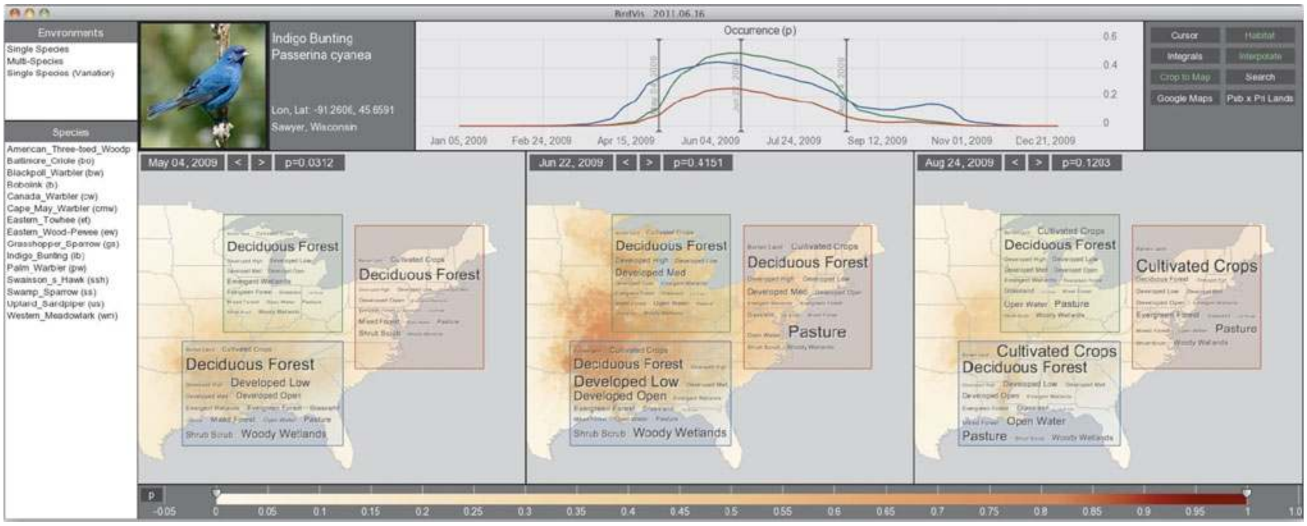


Fig. 15 BirdVis [43]: the interface shows occurrence maps for the Indigo Bunting

event is visualized as a bubble, the shape of which encodes the document number and event duration. In addition, events are connected and placed together to build a long-term story.

6.3 Map visualization

For thousands of years, paper maps and statistics were the most prominent tools for studying geo-spatial data. In the 1990s, Geographic Information Systems (GIS) changed the whole game by providing experts with the power of interactive computerized tools, such as spreadsheets, databases, and graphic tools. The ability to interact and see prompt changes in maps not only provides a quantitative difference in the number of results users can see, but also, more importantly, a qualitative change in the way they think and make decisions [157]. Maps have become a visualization interface for geographic data that supports information access and exploratory activities.

Cartography has greatly influenced and benefited the development of geographic visualization through its long history of visual language design and its knowledge of geographic information. Accordingly, many geographic visualization techniques are directly related to fundamental problems in cartography such as map projection [71], map labeling [1,44], and map generalization [53,148]. For example, Afzel et al. [1] developed typographical maps that merge text and spatial data (e.g., streets and parks) into a visual representation. The major feature of this representation is that text labels are directly used to form the graphical elements (Fig. 14).

On the other hand, the development of interactive computer tools, interface design, and related technologies has also posed a new set of challenges and introduced new opportunities to geographic visualization. Choropleth maps, a traditional tool in cartography, now take advantage of animation and interaction to provide users with richer information in support of sophisticated tasks, such as forecasting hot spots [99] and validating spatio-temporal distribution models of birds [43]. BirdVis [43] (Fig. 15) combines choropleth maps with different visual components to allow analysts to explore and correlate high-dimensional bird population data: space, time, species, probability occurrences, and predicator importance. The flexible system demonstrates the capability to confirm existing hypotheses, as well as to formulate new ones.

In addition to extending existing cartography techniques, new geographic visualization techniques are emerging. For example, Scheepens et al. [117] presented an interactive framework to composite density maps for multivariate trajectories. Through six pre-defined operations, users can flexibly create, compose, and enhance trajectories or density fields to freely explore the trajectory data from different aspects (Fig. 16). With the support of 3D rendering capabilities, researchers have also built geographic visualization into the 3D space, instead of traditional 2D maps. Tominski et al. [136] used two of the dimensions to represent the geographic map and the third to stack trajectories and detailed attribute data (Fig. 17).

6.4 Multivariate data visualization

Multivariate data, as a general type of data, are encountered in numerous situations faced by researchers, engineers, financial managers, etc. Although they have a common goal to understand the data distributions and investigate the interrelationships between different data attributes, specific tasks vary from application to application. Targeted at different tasks, various visualization techniques have emerged to help

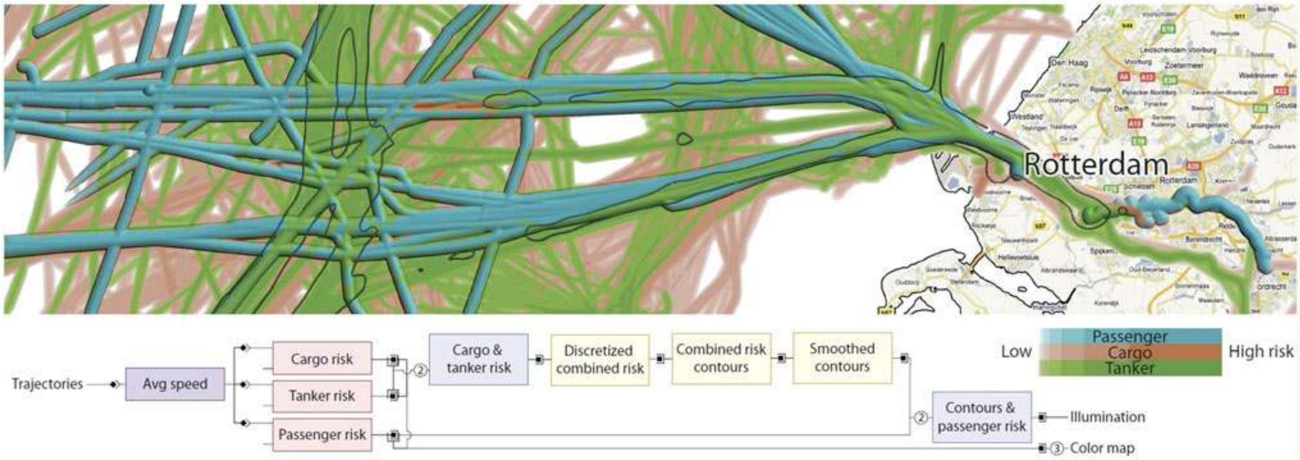


Fig. 16 Trajectory visualization [117]: the representation shows the accident risk map of passenger vessels (*turquoise*), cargo vessels (*orange*), and tanker vessels (*green*). The diagram at the bottom shows how the map was created

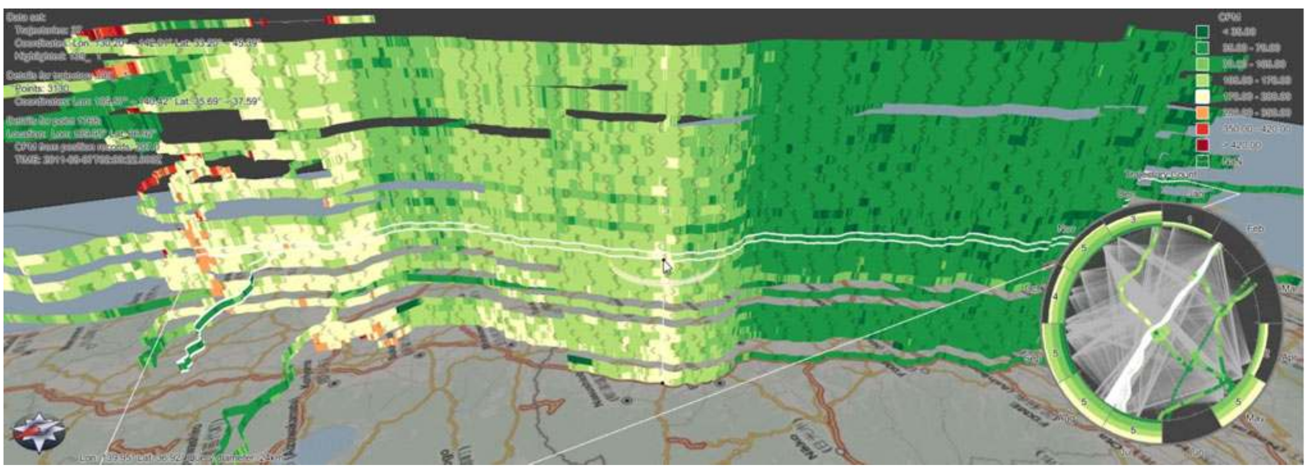


Fig. 17 Stacking-based trajectory visualization [136]: the interface shows radiation values along the Tokio-Fukushima highway

analysts identify, locate, distinguish, categorize, cluster, rank, compare, associate, or correlate the underlying data [151].

In 1996, Keim and Kriegel [74] provided an excellent categorization of visualization techniques for multivariate data: geometric, icon-based, pixel-oriented, hierarchical, graph-based, and hybrid. In this sub-section, we follow this taxonomy and review the latest developments of visual analytic techniques for multivariate data.

In the past few years, the geometric category has covered most innovations in multivariate data visualization, such as projections [72,88,112,140] and Parallel Coordinate Plots (PCPs) [28,48]. Recent research into geometry-based approaches focuses on exploring new projection techniques [72,140] to reveal unexpected data distributions or integrating multiple geometric approaches to avoid limitations of using them individually [28,88].

For example, Lee et al. [88] argued that the results of common Multidimensional Scaling (MDS) projection cannot characterize inter-cluster distances. Therefore, they integrated a structure-based distance metric into the projection pipeline to overcome the shortcomings.

Moreover, new aspects of multivariate data have been exploited to improve analysis results. Turkay et al. [139] divided the input data into two spaces: the items space and the dimensions space. By interactively and iteratively operating on both spaces, the authors argued that the joint analysis of both spaces could greatly help users understand the relationships between different data dimensions (Fig. 18).

Recently, Claessen and Van Wijk [28] visually connected various geometry-based techniques, such as PCPs, scatterplot matrices, radar charts, and Hyperboxes, together with "Flexible Linked Axes". By allowing users to draw and drag axes freely, the technique supports defining a wide range of different visualizations (Fig. 19) to aid in various analysis tasks. The authors argued that, through the highly customizable and space-efficient interface, their versatile and powerful technique can greatly benefit users in a variety of ways.

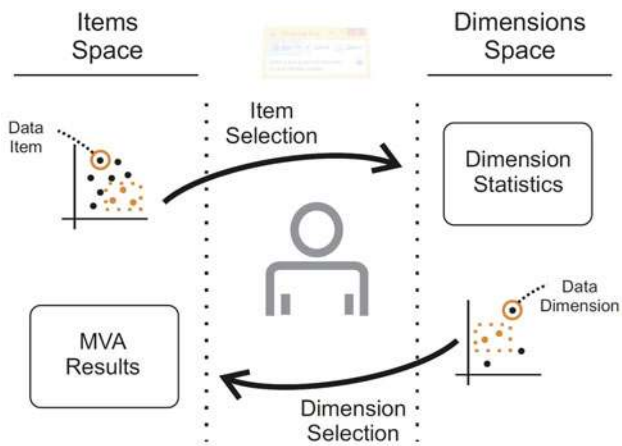


Fig. 18 The dual analysis pipeline proposed by Turkay et al. [139]

In addition to introducing new visual representations, clutter reduction still remains a hot topic in PCP visualization. In contrast to traditional transparency and bundling approaches, Geng et al. [48] proposed angular histograms and attribute curves. Their technique allows users to explore and reveal correlation patterns by investigating the density and slopes of the drawn histograms and curves (Fig. 20).

Compared with the development of the dominant geometric category, the remaining categories have received relatively less attention, yet there are several pieces of work that need to be highlighted. For example, as an icon-based approach, DICON [21], which is a treemap-style icon technique, was introduced to help compare and interpret clusters of multivariate data. Compared with previous work, DICON can additionally encode derived statistical information and be easily embedded into various existing visualization techniques.

The similarity tree technique was developed as a graph-based approach by Paiva et al. [109] for visual analysis of multivariate data. Compared with previous work, it adds hierarchy to the concept of similarity by intuitively representing the levels of similarity as different depths in the tree. In their paper, the authors applied the technique to three image datasets and demonstrated its adaptability for visual data classification tasks.

7 Technical challenges

It is not easy to design and develop a perfect visualization. There are five major technical challenges:

– *Usability* The development of InfoVis has been driven by real-world applications and user requirements. Generally, a user is heavily involved with a visualization system or toolkit to accomplish his/her analysis tasks. To help visualization designers and developers design an effective visualization system/toolkit, researchers have developed a set of advanced empirical evaluation methods and design study methods [12,49,52,60,78,84,119], as well as several design theories [11,65,66]. These methods and theories have achieved some success in designing effective and useful visualizations and moving research outputs into practice. However, most of them were designed for a specific application or a specific aspect of a visualization technique. Visualization designers and developers have a dire need to find effective usability evaluation methods that are both specific to the visualization field and generic enough for a wide range of visualization related applications or domains.

– *Visual scalability* Visual scalability is defined as the capability of visualization tools to effectively display large data sets in terms of either the number or the dimension of individual data elements [75]. Scalability is a fundamental challenge for InfoVis, especially with the boom in big data analytics. In many applications, the amount of data to be visualized is very large, often exceeding the display capability of a screen by several orders of magnitude. To solve this issue, researchers have developed many data reduction techniques such as sampling, filtering, clustering, PCA, and multidimensional scaling [75]. Although these techniques have achieved some success in handling large amounts of data, none of them are perfect and suitable for all applications. For example, with the dramatic increase of data and a relatively constant display resolution, the data reduction rate in big data visualization techniques continually needs to increase. As a result, researchers continue looking for novel data reduction techniques that can balance a high-level overview and low-level details. One interesting research topic is how to involve users in the data reduction process, allowing users to easily convey their information needs and contribute their domain knowledge to this process. Furthermore, it is worth studying the combinations of several data reduction techniques that complement each other in real-world applications.

– *Integrated analysis of heterogeneous data* Heterogeneous data are data from multiple sources and in varying formats. Integration and analysis of heterogeneous data is one of the greatest challenges for versatile applications. With the rise of big data analytics, this task is more important than ever in many functions of a business, such as customer care, human resource management, and marketing. For example, healthcare providers analyze large collections of patient records in conjunction with data on public health forums to deliver personalized patient care and manage care resources. For areas such as manufacturing, education, retail, healthcare, and the public sector, heterogeneous text data from several sources are

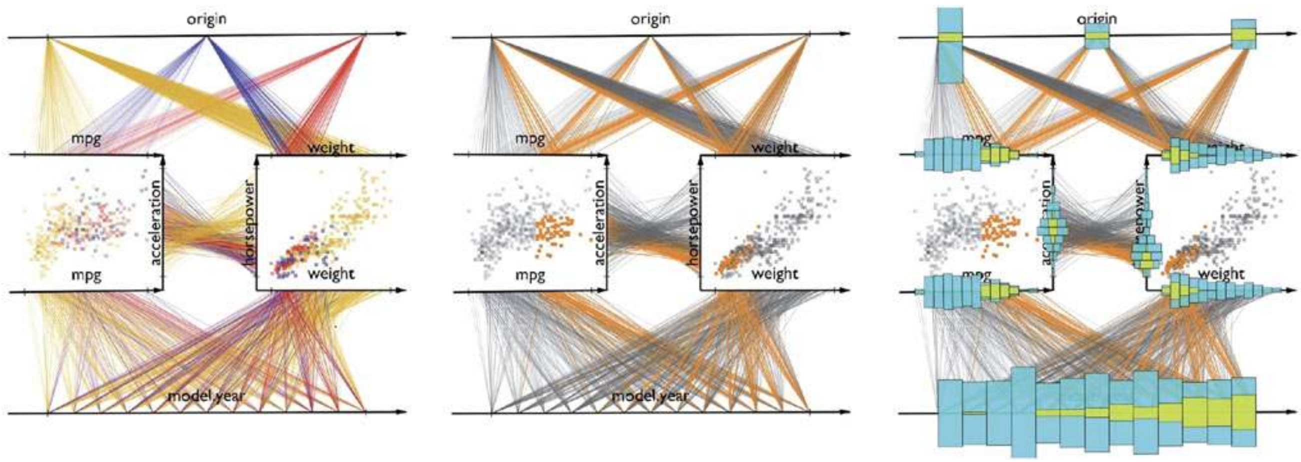


Fig. 19 FlinaPlots [28]: the representations show composited visualizations of PCPs, scatterplots, and histograms

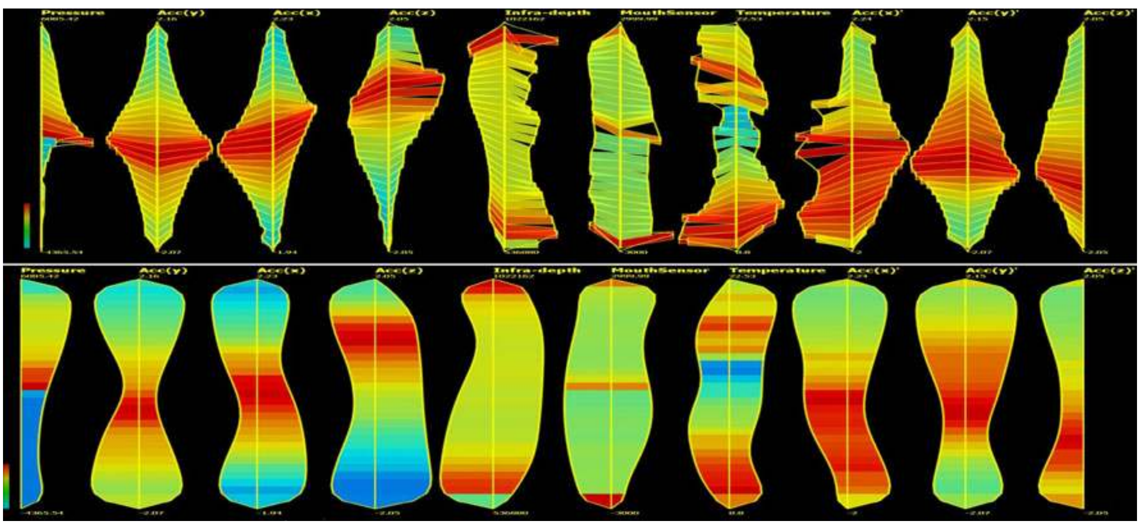


Fig. 20 Angular histograms [48]: *colors* indicate the data density (*red* indicates the largest and *light blue* indicates the smallest)

increasingly at the center of economic activity and play a crucial role in further growth, productivity, and innovation. A number of use cases have emerged, each hoping to answer a different set of questions by analyzing heterogonous textual data. How can a government improve the happiness of its citizens by analyzing their posts on various social media outlets, as well as survey data? How can a company understand issues related to a high rate of churn by examining customer feedback or call center conversations in conjunction with customer transaction data? How can a company hire their best employees by evaluating thousands of resumes submitted on the company website and correlate them with internal employee performance data? These are not simple problems and today there are not sufficient interactive visual analytic techniques and tools that can deal with heterogeneous data.

– *In-situ visualization* In-situ visualization incrementally generates visual representations when new data arrive. It is an effective way to understand and analyze streaming data. Streaming data is defined as data with a regular rate of flow through hardware. Typical examples include log data such as search logs and sensor logs, stock data, and periodically updated social media data (e.g., tweets). Due to the rapid rate of incoming data and the huge size of data sets in the stream model, analysis of such streaming data poses a great challenge in the field of InfoVis. For example, over 340 million tweets are generated daily on Twitter (according to 2013 statistics of [141]).
A variety of breaking news such as the series of protests that erupted across the Middle East, the news of bin Laden's death, and the reactions to potentially disastrous situations like earthquakes, first come from such noisy streaming tweets [61,64]. Accordingly, a natural ques-

tion is how to quickly detect breaking news events from huge amounts of streaming tweets and better understand information diffusion patterns in them.

To answer a question like this, it is necessary to study the evolving patterns of streaming data by leveraging in-situ visualizations. For example, for a breaking news event in Twitter, government officers or sociologists aim to use in-situ visualizations for better understanding how various topics compete for public attention when they are spread through social media, what roles opinion leaders play in the rise and fall of competitiveness of various topics, and who are the key people spreading news of the event [163].

However, it is not easy to design and develop in-situ visualizations. The major challenges are to effectively share the same processor and memory space, synchronize the data processing and visualization tasks, and smooth communication between the data processing module and the visualization module.

- *Errors and uncertainty* Real-world data sets often contain errors and/or uncertainties [98,161], for example, noisy and inconsistent social media data published by users every day, imprecise data from sensors, or imperfect object recognition in video streams. On the other hand, uncertainty can arise at any stage of the visualization process. For example, data sampling, data transformation, or data filtering may introduce errors and inconsistencies into the visualization, which is another major source of uncertainty [161]. In order to strengthen the truthfulness of visualization, it is important to properly convey the potential errors and uncertainty to end-users. Accordingly, it is necessary for visualization researchers and developers to understand when and why one uncertainty visualization method is more suitable for an application than another [98].

8 Conclusions

In this paper, we have presented a survey on state-of-the-art InfoVis techniques, with a focus on empirical methodologies, interactions, frameworks, and applications. A taxonomy was built based on a detailed review of the literature under the aforementioned four categories. With the taxonomy, we noticed that most recent research has focused on empirical methodologies and applications. This implies that more and more InfoVis research outputs are deployed to real-world applications with the boom of practical empirical methodologies.

As shown, many advanced InfoVis techniques have been developed in the four major categories. These techniques were applied to various applications ranging from network visualization and text visualization, to map visualization and multivariate data visualization. We also elaborated on the major advantages and limitations of the methods under each major category and shed light on future directions of research by summarizing a set of technical challenges.

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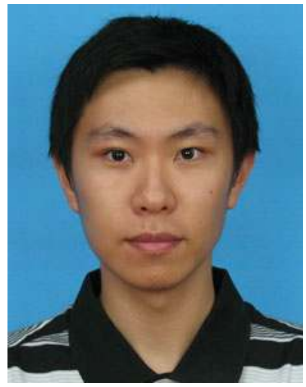

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