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Visual Analytics: A Comprehensive Overview

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ABSTRACT With the ever-increasing amount of data, the world has stepped into the era of "Big Data". Presently, the analysis of massive and complex data and the extraction of relevant information, have been become essential tasks in many fields of studies, such as health, biology, chemistry, social science, astronomy, and physics. However, compared with the development of data storage and management technologies, our ability to gain useful information from the collected data does not match our ability to collect the data. This gap has led to a surge of research activity in the field of visual analytics. Visual analytics employs interactive visualization to integrate human judgment into algorithmic data-analysis processes. In this paper, the aim is to draw a complete picture of visual analytics to direct future research by examining the related research in various application domains. As such, a novel categorization of visual-analytics applications from a technical perspective is proposed, which is based on the dimensionality of visualization and the type of interaction. Based on this categorization, a comprehensive survey of visual analytics is performed, which examines its evolution from visualization and algorithmic data analysis, and investigates how it is applied in various application domains. In addition, based on the observations and findings gained in this survey, the trends, major challenges, and future directions of visual analytics are discussed.

INDEX TERMS Visual analytics, information visualization, interactive visualization, data analysis, analytical reasoning, knowledge representations, visual data mining, perception, cognition, sense-making, high-dimensional data.

I. INTRODUCTION

We are living in the age of data and advanced analytics. With recent advances in computing resources and data management technologies, our ability to generate, collect and store a wide variety of large and complex data sets continues to grow. According to the International Data Corporation's (IDC's) Digital Universe forecasts, the overall created and copied data volume worldwide will rise to approximately 40 zettabytes (ZB, 44 trillion GB) by 2020 [1]. This rapidly increasing amount of data has triggered an information revolution and enormous challenges that in turn will bring incredible scientific and industrial opportunities.

Nowadays, the analysis of massive amounts of data, which are typically messy, inconsistent and complex, as well as the subsequent extraction of relevant information, is becoming an essential task in numerous field of studies, such as health, biology, chemistry, social science, astronomy, and physics [2]. However, our ability to collect and store massive amounts of data far outstrips our ability to analyze the collected data [3], [4]. This has led to the well-known problem of "information overload" [5] (or the so-called "data deluge" [6]) in the age of information.

To address this data deluge, new technologies and methods have been investigated in many disciplines, such as visualization, statistics-based data analysis, machine learning, data mining, and perceptual and cognitive sciences, to extract useful information and generate reliable knowledge from unexplored data. However, it is questionable whether these sub-specialties are adequate to simply and effectively extract information from the ever-increasing massive data. Keim *et al.* indicated that "approaches, which work either on a purely analytical or on a purely visual level, do not sufficiently help to filter substantial information from fast-growing complex data sets and to communicate it to humans in an appropriate way" [7].

To generate knowledge and discover hidden opportunities from massive and complex data, James (Jim) Joseph Thomas (March 26, 1946 – August 6, 2010) created, promoted and established the visual-analytics field [8]–[10]. Visual analytics is "the science of analytical reasoning facilitated by interactive visual interfaces", which uses visualization and interaction techniques to integrate expert human judgment in the data analysis process [2], [3]. Such an approach requires

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TABLE 1. Some key terms related to visual analytics.

Key terms	Explanation
Visualization	Refers to the theories and techniques of creating visual representations of data, which includes information visualization and scientific visualization [11].
Information visualization	Refers to the theories and techniques that use (interactive) visual computing and representations to amplify human cognition with abstract information [12], [13].
Scientific visualization	Refers to the theories and techniques that use visual display and realistic renderings to gain information from spatial data associated with scientific processes [14].
Interactive visualization	Refers to the techniques that visualize and explore data by manipulating the color, brightness, size, and shape of its visual representation.
Human-computer interaction	Refers to "the study of the way in which computer technology influences human work and activities" [15].
Data analysis	Refers to the process of analyzing data with the goal of discovering useful information by applying statistical procedures and/or logical techniques [16]. In statistics, data analysis is divided into confirmatory and exploratory data analyses.
Confirmatory data analysis	Refers to the statistical process of evaluating pre-specified hypotheses (assumptions) on existing data sets (evidence) through a statistical hypothesis test [17].
Exploratory data analysis	Refers to approaches to analyzing data sets that reveal hidden and unknown information from data beyond the formal modeling or hypothesis-testing task.
Visual data mining	Refers to "the process of interaction and analytical reasoning with visual representations of data that leads to the visual discovery of robust patterns in these data that form the information and knowledge utilized in informed decision making" [18].
Visual analytics	Refers to the science of analytical reasoning supported by interactive visual interfaces [19].

the integration of algorithmic data analysis methods, innovative interactive techniques and data visualization, which allows decision makers to optimize the analytical-reasoning process and make sound decisions by their human flexibility, creativity, and background knowledge.

As information visualization has changed our view on databases, the ways of analyzing data and filtering information is being made transparent for an analytics discourse by visual analytics [4]. This article presents a complete picture of visual analytics to direct future research by examining the related research in various application domains. It gives an in-depth understanding of "*what is visual analytics*", "*how visual analytics is applied in various application domains*", "*the state of the art of visual analytics*", and "*what are the challenges and opportunities of visual-analytics research*".

There are several key terms, such as visualization, information visualization, scientific visualization, interactive visualization, human-computer interaction, data analysis, confirmation data analysis, exploratory data analysis, visual data mining and visual analytics, which are highly connected, easily confused and are also the key terms widely used in this article. Table 1 lists and explains them.

A. RECENT SURVEY STUDIES ON VISUAL ANALYTICS

Table 2 lists and compares recent surveys on visual analytics. It shows that existing surveys mainly concentrated on one aspect of visual analytics, such as its challenges, opportunities, techniques or applications in a specific field. This leaves a gap between its theory and applications when applying visual analytics in different application domains.

According to Table 2, although a few articles and references have discussed visual analytics from a theoretical perspective, they are generally narrowed to a single or two specific aspects of visual analytics, such as its definition, scope or processes. Additionally, they lack a connection between the theory and its applications. For instance, Keim *et al.* [20] compared the differences between visual analytics and information/scientific visualization from several aspects, including data analysis, perception and cognition, and human-computer interaction. However, the authors did not discuss these differences in related applications.

On the other hand, some visual-analytics surveys mainly focused on the techniques and applications without relating it to a theoretical background. Additionally, they are commonly limited to a single type of data or a specific application domain. For instance, Andrienko and Andrienko [21] presented a survey of the state-of-the-art visual-analytics techniques that support the analysis and understanding of various aspects of movement data. Caban and Gotz [22] and West *et al.* [23] presented systematic reviews of visual-analytics approaches which have been proposed to explore complex clinical data.

B. RESEARCH OBJECTIVES

Visual analytics has been applied in many different application domains, such as economics, bioinformatics, health, and social media. The ultimate purpose of this article is to draw a complete picture of visual analytics to direct future research by examining the related research in various application domains. It aims to bridge the gap between theory and practice when applying visual analytics in different application domains.

Sun *et al.* [28] classified visual-analytics applications into a set of categories, including *space and time*, *multivariate*,

TABLE 2. Recent surveys related to visual analytics.

Survey	Area of Interest	Pros	Limitations
[20] [2]	- Definition - Scope - Process - Challenges	An overview on visual analytics that compares and distinguishes visual analytics and information visualization from a theoretical perspective.	- Lack of discussion on applications. - Limited application challenges.
[24]	- Information in time and space. - Spatio-temporal analysis.	An overview of spatio-temporal visual analytics and its open issues.	- Lack of visual analytics background and its technical challenges. - Limited overview of applications.
[25]	- Commercial systems and frameworks.	An survey of the state-of-the-art commercial visual-analytics systems and frameworks for big data.	- Lack of visual analytics background. - Limited overview of commercial systems.
[26]	- Open source toolkits. - Visualization functions. - Analysis capabilities.	An overview of open-source visual-analytics toolkits.	- Lack of visual analytics background. - Limited overview of open-source toolkits.
[21] [27]	- Movement data. - Methods, tools and procedures.	A survey of visual-analytics techniques and applications for analyzing movement data.	- Lack of visual-analytics background and its challenges. - Discusses visual analytics on a single data type.
[28]	- Visual-analytics techniques and applications.	An overview of the state-of-the-art visual-analytics techniques and applications.	- Limited visual-analytics background. - Limited classification of applications. - Lack of technical challenges.
[29]	- Social media data.	A survey of the state-of-the-art visual-analytics techniques for analyzing social media data.	- Lack of visual-analytics background and its challenges. - Discusses visual analytics on a single data type.

text, *graph and network*, and *other applications*. This classification naturally differentiates visual-analytics applications to a specific data type or application domain. However, visual-analytics applications with different data types can share a common technique. For example, Jeong *et al.* [30] and El-Assady *et al.* [31] used the same visualization technique (parallel coordinates plots, PCPs) within multivariate and textual data, separately.

To avoid limiting this survey to a specific data type or application domain, a novel categorization of visual-analytics applications from a technical perspective is proposed, which is based on the dimensionality of visualization and the type of interactions. Based on this categorization, in this article an organized overview of visual analytics is constructed, which discusses the theory and evolution of visual analytics, and investigates how visual analytics is applied in various application domains. It aims to bridge the gap between the challenges of discovering knowledge in large and complex data sets and visual-analytics solutions by investigating state-of-the-art visual-analytics applications. In addition, the major challenges and future directions of visual analytics are targeted. To the best of our knowledge, this article is the first to classify visual-analytics applications from a technical perspective. By sharing the observations and findings gained in this survey, it is expected that this article could direct future research of visual analytics in different application domains.

In this survey, to demonstrate the proposed categorization and how visual analytics is applied in various disciplines, a careful examination of papers from premier conferences and journals that are related to visual analytics, such as Computer Graphics Forum (CGF), ACM SIGKDD Explorations, ACM Transactions on Graphics (TOG), IEEE Transactions on Visualization and Computer Graphics (TVCG), IEEE Visual Analytics Science and Technology (VAST), IEEE Information Visualization (InfoVis), EG/VGTC Conference on Visualization (EuroVis), and IEEE Pacific Visualization Symposium (PacificVis), is presented. The papers are filtered and analyzed within the Web of Science and Google Scholar according to the proposed categorization.

The remainder of the survey is organized as follows. In Section II, the evolution of visual analytics from data analysis and visualization is tracked, which addresses the fundamental question: "*What is visual analytics?*". In Section III, state-of-the-art visual-analytics techniques and applications are introduced. In particular, these applications are classified into eight categories according to the dimensionality of visualization and the type of interaction. In Section IV, the challenges and future research directions of visual analytics are discussed. Finally, in Section V the conclusions of this work are summarized.

II. FROM DATA ANALYSIS, VISUALIZATION TO VISUAL ANALYTICS

In this section, the question "*What is visual analytics?*" is addressed by investigating the evolution of visual analytics from visualization and algorithmic data analysis. The definition, model and process of visual analytics are discussed as the fundamentals of the proposed categorization of visual-analytics applications.

A. THE VISUAL ANALYTICS JOURNEY

Visual analytics is an outgrowth of the fields of scientific and information visualization. It is likely that the first appearance of "visual analytics" as a term in the literature was in the

"Guest Editors' Introduction-Visual Analytics" [32] of a special issue of IEEE Computer Graphics and Applications (CG&A) in 2004. In that introduction, *visual analytics* was defined as "the formation of abstract visual metaphors in combination with a human information discourse (interaction) that enables detection of the expected and discovery of the unexpected within massive, dynamically changing information spaces." Recently, by the combination of algorithmic data analysis and visualization, visual analytics started utilizing visualization as a medium and interaction as a means to involve human judgment in the data analysis process [33].

1) VISUALIZATION

Visualization can be broadly classified into scientific and information visualization. "Scientific visualization evolved first in the late 1980s, while information visualization matured in the mid-1990s" [34]. Scientific visualization focuses on visual display and realistic renderings of spatial data associated with scientific processes, for example, three-dimensional (3D) phenomena (architectural, meteorological, medical, biological, etc.) [35]. Information visualization examines visual representations of abstract and non-inherently spatial data which includes both numerical and non-numerical data, such as textual and geographical information [36], [37]. In information visualization, during the last decade, novel visualization techniques, such as parallel coordinates and its numerous extensions [38], tree-maps [39], Glyph- [40] and Pixel- [41] based visual data representations, have been developed to map a variety of abstract data to display space. Although scientific and information visualization have different research focuses and priorities, both of these subfields of visualization have the same goal: the visual communication of valuable data with understandable meaning. Accordingly, most research efforts in visualization have concentrated on producing different views.

2) DATA ANALYSIS

Data analysis is a process of modeling and exploring data with the goal of discovering useful information and supporting decision making by applying statistical procedures and/or logical techniques [16]. In statistical applications, data analysis is divided into confirmatory data analysis (CDA) and exploratory data analysis (EDA) [42]. CDA is a statistical process that evaluates pre-specified hypotheses (assumptions) on existing data sets (evidence) through a statistical hypothesis test [43]. It uses the traditional statistical tools of inference, significance, and confidence. In contrast, EDA is a quantitative process of isolating patterns and features of data, and revealing hidden and unknown information from data when little or no statistical hypotheses exist [44]. It is an approach which employs a variety of techniques (mostly visual methods) to summarize characteristics of data sets. It was first utilized in the statistics research community by Tukey in 1977 [45].

3) JOURNEY TO VISUAL ANALYTICS

As data volumes grow dramatically in a wide variety of fields, knowledge discovery in databases (KDD) was proposed at the first "Knowledge Discovery and Data Mining" workshop in 1989 [46]. KDD is the process of discovering understandable patterns in data, which emphasizes that knowledge is the end-product of the process [47]. With the goal of extracting useful information (knowledge) from data, KDD has evolved from the intersection of many research fields including statistics, pattern recognition, machine learning, artificial intelligence, and data visualization.

Before EDA was proposed, "data analysis techniques such as statistics and data mining developed independently from visualization and interaction techniques" [48]. Unlike CDA where visualization is used to present results, EDA employs visualization to interact with data. Therefore, moving from CDA to EDA is one of the most important steps in forming the research field of visual analytics.

In the information-visualization research community, with improvements in graphical user interfaces, "they recognized the potential of integrating the user in the KDD process through effective and efficient visualization techniques, interaction capabilities and knowledge transfer leading to visual data exploration or visual data mining" [48]. This implies a certain overlap between interactive visualization and visual analytics. However, interactions in interactive visualization are mainly used to present different views by manipulating graphical elements. In interactive visualization, much less has been discussed on interactions with data itself rather than interactions with graphical elements because data analysis is not "a must". To explore the relationship between visual data representation, data analysis and the knowledge discovery process, visual data mining was proposed and defined as "a step in the KDD process that utilizes visualization as a communication channel between the computer and the user to produce novel and interpretable patterns" [49]. Visual data mining is the process of interaction and analytical reasoning based on data visualization to discover understandable patterns (knowledge) in data [18].

Visual data mining considerably widened the scope of both the information-visualization and data-mining research fields. More importantly, as an important technique for visual analytics, visual mining data supports the formation of visual analytics by combining a collection of information-visualization metaphors and techniques with algorithmic data analyses through human information discourses (interactions) [50]. In 2004, visual analytics was first proposed by Wong and Thomas [32]. A year later, visual analytics was defined, illustrated and discussed in the book "Illuminating the path: The research and development agenda for visual analytics" [19]. More recently, visual analytics has become a multidisciplinary field that combines various research fields including visualization, human-computer interaction, data analysis, statistics, perception and cognition, and analytical reasoning. Figure 1 summarizes the visual

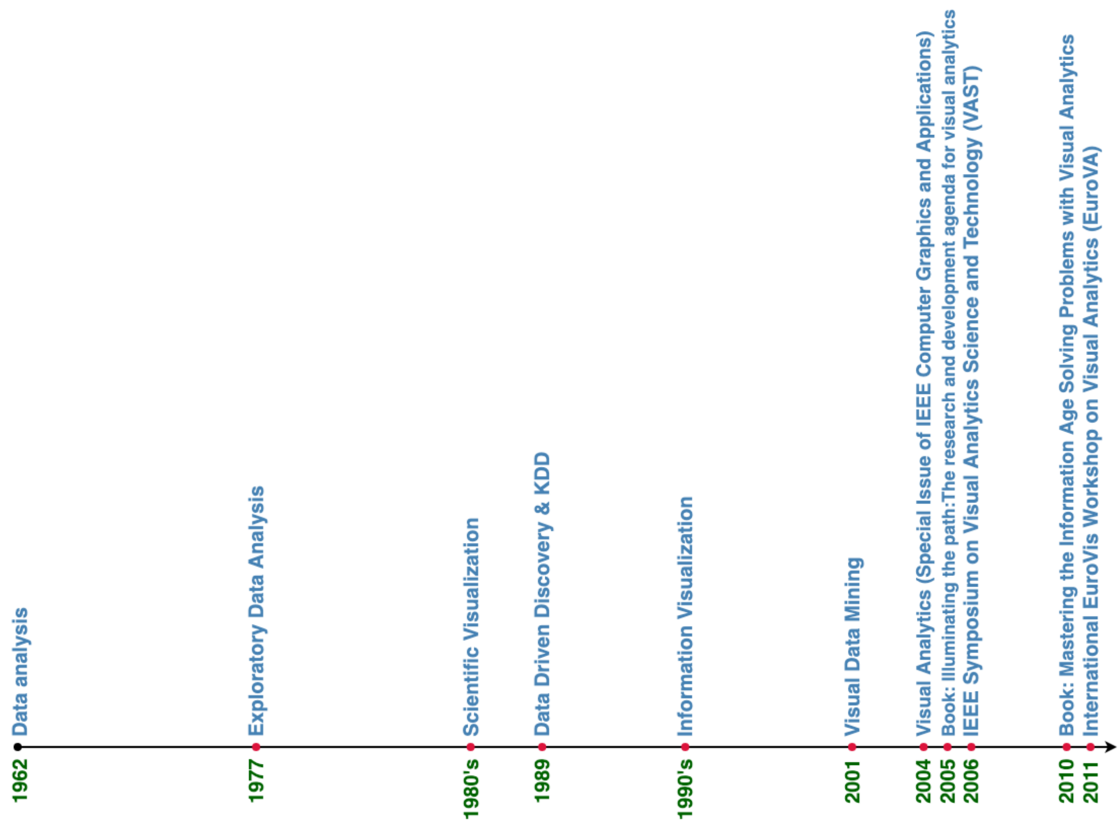

FIGURE 1. Visual analytics journey with respect to key events.

analytics journey. It presents the evolution of visual analytics in terms of representative moments, events and major aspects of its disciplinary development.

B. DEFINITION OF VISUAL ANALYTICS

Visual analytics was proposed to turn the information overload into an opportunity by creating tools and techniques to facilitate human judgment in the KDD process. In the book "*Illuminating the path: The research and development agenda for visual analytics*", visual analytics was first defined as:

Definition 1: Visual analytics is "the science of analytical reasoning facilitated by interactive visual interfaces" [19].

Nowadays, visual analytics, as an integrated approach combining visualization, algorithmic data analysis, human-computer interaction, and analytical reasoning, has attracted increasing interest from a wide range of domains and disciplines. With its development, researchers from different backgrounds have given detailed definitions of it with different focuses:

Definition 2: Visual analytics is "a method to synthesize information and derive insight from massive, dynamic, ambiguous, and often conflicting data; detect the expected and discover the unexpected; provide timely, defensible, and understandable assessments; and communicate assessment effectively for action" [3].

Definition 3: Visual analytics "combines automated analysis techniques with interactive visualizations for an effective understanding, reasoning and decision making on the basis of very large and complex data sets" [20].

Built on the evolution of visual analytics from visualization and data analysis, a more detailed and comprehensive definition of visual analytics to emphasize its research goals is presented in this review:

Definition 4: Visual analytics is a multidisciplinary research field mainly based on visualization, algorithmic data analysis and analytical reasoning, which takes advantage of visualization and interactions as suitable tools to integrate human judgment into the KDD process to visually discover explainable patterns (knowledge) and to gain insight into large and complex data sets.

According to Definition 4, visual analytics has the same ultimate research goal as EDA, which is to discover knowledge and gain insight from data sets. However, visual analytics exploits visualization as a tool to integrate human cognition, perception abilities, and human intelligence into the data-analysis process to obtain explainable results. Relative to visualization, visual analytics places higher priority on analyzing data and discovering knowledge in data, rather than just presenting and understanding the data. Meanwhile, based on visualization, visual analytics addresses the challenge in data analysis that the discovered complex patterns could be hard to interpret in an intuitive and meaningful manner.

C. HUMAN INFORMATION DISCOURSE IN VISUAL ANALYTICS

According to Definition 1, as a science of analytical reasoning, the core idea of visual analytics is to integrate human cognitive, perceptual and reasoning abilities, and their knowledge into an analysis process to gain insight from data that is difficult to explore with pure visualization or analysis techniques. Analytical reasoning encompasses different kinds of reasoning, such as deductive, inductive, and analogical, which is based on a rational, logical analysis and evaluation of data [51]. Pohl *et al.* [52] discussed several theories, including sense-making theories, gestalt theories, distributed cognition, graph comprehension theories and skill-rule-knowledge models, and their relevance to visual analytics. In visual analytics, analytical reasoning is facilitated by creating appropriate visualizations and interactions that maximize human capacity to perceive and explore data. It adapts existing analysis processes by integrating visualization and algorithmic data analysis, which was discussed by [48].

Visual analytics is built upon an understanding of the reasoning process, as well as an understanding of the underlying cognitive and perceptual principles when applying human judgment to reach conclusions from data [3]. Human judgment is an integral part of the visual-analytics process, which relies on human-in-the-loop (HITL, a model that requires human interaction [53]) based interactions. In visual analytics, the interaction is not only a means to an end of finding a good representation of data, but also a valuable exploration process to apply human judgment and reveal insight from data [54]. Since interactions affect users' understanding of visually presented data, human-factor-based designs are the basis of visual analytics [55]. To study human factors in visual analytics, Green *et al.* [56] proposed a modeling framework of human "higher cognition". Miksch and Aigner [57] proposed a design triangle for visual-analytics methods that focused on time and time-oriented data. Dasgupta *et al.* [58] proposed a trust-augmented design of the visual-analytics system that explicitly took into account domain-specific tasks, conventions, and preferences.

Furthermore, recent work has emphasized that visual-analytics theories must move beyond HITL to "human-*is*-the-loop" analytics in order to integrate human cognition and reasoning process with analytics [59]. Figure 2 illustrates how human cognition, perception, and reasoning are employed in visual analytics. It shows that human judgment (perceptive skills, cognitive reasoning and domain knowledge) and algorithmic data analyses are effectively coupled through interactive visual representations in the visual-analytics process to gain insight from data.

D. THE VISUAL-ANALYTICS PROCESS

Shneiderman's celebrated mantra "Overview first, Filter and zoom, Details on demand" clearly emphasized the role of visualization in the knowledge-discovery process [60]. As visual analytics is an outgrowth of the fields of scientific

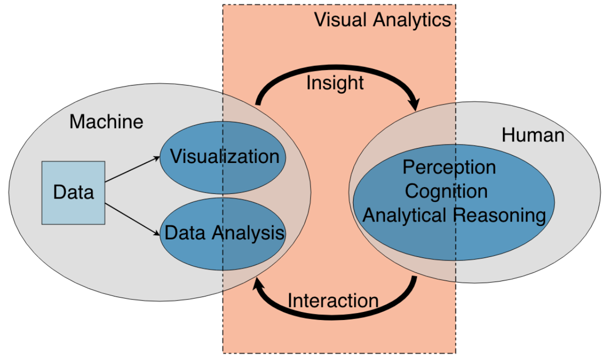

FIGURE 2. Visual analytics as the interplay between data analysis, visualization, and human analytical reasoning.

and information visualization, to give an overview of the visual-analytics process, inspired by Shneiderman's mantra, a mantra is created here that focuses toward visual analytics: "Analyze/Overview first, interaction and visualization repeatedly, insights into data".

Based on the observations gained in this survey, the typical steps in the visual-analytics process are summarized as follows:

Step 1 Preprocess (clean, transform, integrate) the data in order to prepare it for further processing.
Step 2 Apply algorithmic analysis methods to the data.
Step 3 Visualize the (processed) data with appropriate visualization techniques.
Step 4 Users generate insightful knowledge through human perception, cognition, and reasoning activities.
Step 5 Users make new hypotheses and integrate the newly generated knowledge into the analysis and visualization through interactions.
Step 6 Regenerate an updated visualization based on the interactions to reflect the user's understanding of the data.

In many visual-analytics scenarios, heterogeneous data sources need to be integrated before algorithmic analysis methods or visualization can be applied. Therefore, the first step of the visual-analytics process is to preprocess data. The typical tasks in *Step* 1 could be data cleaning, normalization, transformation, grouping, and/or integration of the heterogeneous data into a common schema. In the visual-analytics process, knowledge can be gained from each step. However, the initial algorithmic analysis (*Step* 2) and visualization (*Step* 3) of the data are often not sufficient for problem-solving and decision making. Accordingly, human perception, cognition and reasoning activities are performed in *Step* 4 to generate insightful knowledge. Meantime, the knowledge is used for making new hypotheses. In *Step* 5, new knowledge and hypotheses are integrated into the data-analysis and visualization processes through interactions made by the user. Then, the data-analysis algorithms and visualizations are updated according to the user's interactions in *Step* 6. After the first loop of the visual-analytics process, it continuously iterates from *Step* 4 to *Step* 6 until enough

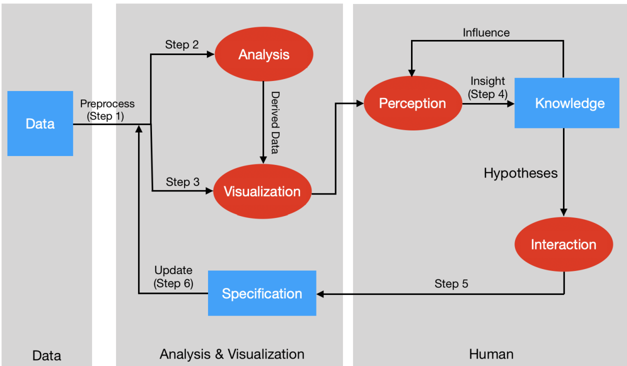

FIGURE 3. **The visual-analytics process as a sense-making loop.**

insight has been gained into the data for making decisions or solving the problems associated with the data. In some visual-analytics applications, *Step* 2 may be removed since it is not a must for all types of data and scenarios. This iterative process well illustrates the ''human-is-the-loop'' philosophy described in Section II-C. The generated knowledge is stored in the visual-analytics process through the feedback loop in *Step* 5, which enables the user to continuously draw faster and better conclusions and gain insight from the data. Figure 3 illustrates this visual-analytics process as a sense-making loop, in which each step is labeled. Figure 3 is composed and adapted from several diagrams, including analytical processes in visual analytics [61], visualization models [62], knowledge conversion processes [63] and knowledge generation models for visual analytics [64].

E. TRENDS IN THE FIELD OF VISUAL ANALYTICS

To discuss the trends in the field of visual analytics, the related academic papers in the Web of Science and Google Scholar, which are well-known academic database and search engine, are analyzed. In the Web of Science, all the papers which took visual analytics as the topic were counted and grouped by publication years from 2004 to 2018. Within Google Scholar, all the papers which discussed ''visual analytics'' as a term were searched, counted and grouped by publication years from 2004 to 2018.

Figure 4 illustrates the search results of the Web of Science and Google Scholar. Although the analysis of published papers in visual analytics does not reflect the full picture of the field, Figure 4 indicates the following: (1) Visual analytics is a relatively new research (it was created in 2004) area compared to other research fields, such as data analysis and visualization. (2) Visual analytics is a continuously and rapidly growing research field. In the field of visual analytics, the number of published papers in 2018 was six times larger than the corresponding number a decade previous.

The papers in the Web of Science were also analyzed according to the Web of Science Categories, as shown in Figure 5 as a tree-map. The figure shows that visual analytics is widely applied in different disciplines such as telecommunications, optics, cybernetics, geography, mathematical computational biology, education, medical informatics, remote sensing, etc.

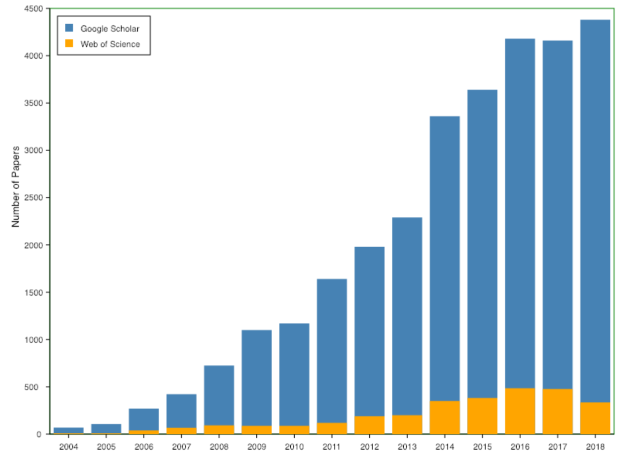

FIGURE 4. **Trends in visual-analytics research based on the statistics of related papers. *Note:* The data were collected on 26 December 2018.**

III. VISUAL-ANALYTICS TECHNIQUES AND APPLICATIONS

Visual analytics has been applied in many different application domains, such as economics, bioinformatics, health, and social media. In this section, state of the art in visual-analytics applications are examined.

Sun *et al.* [28] identified five categories of visual-analytics applications according to the type of considered data. In their research, visual-analytics applications were classified as *space and time*, *multivariate*, *text*, *graph and network*, and *other applications*. However, they did not provide a comprehensive classification. Firstly, it is difficult to categorize a visual-analytics application which deals with several different types of data at the same time. For example, Chen *et al.* [65] proposed a visual-analytics system to analyze and explore multiple types of data and correlate them for intelligence analysis. The data analyzed in their system included GPS logs, which contained spatial and temporal data, news and email headers, which are textual data, and transaction logs which contained network data. Secondly, a complex data set may have two or more characteristics so that the corresponding visual-analytics application will be classified into two or more categories simultaneously. For example, Andrienko *et al.* [66] analyzed streaming-tweets data which consisted of geographical coordinates, time of tweeting, and the tweet text itself in their visual-analytics system. According to the classifications of [28], this visual-analytics application can be classified into the category *space and time* as well as the category *text*. Furthermore, with the rapid development of visual analytics in different domains, increasing numbers of visual-analytics applications can be classified into the category *other applications*.

To address the challenges arising from the limitations of the classification scheme of [28], and direct the future research of visual analytics, in this survey, a new comprehensive

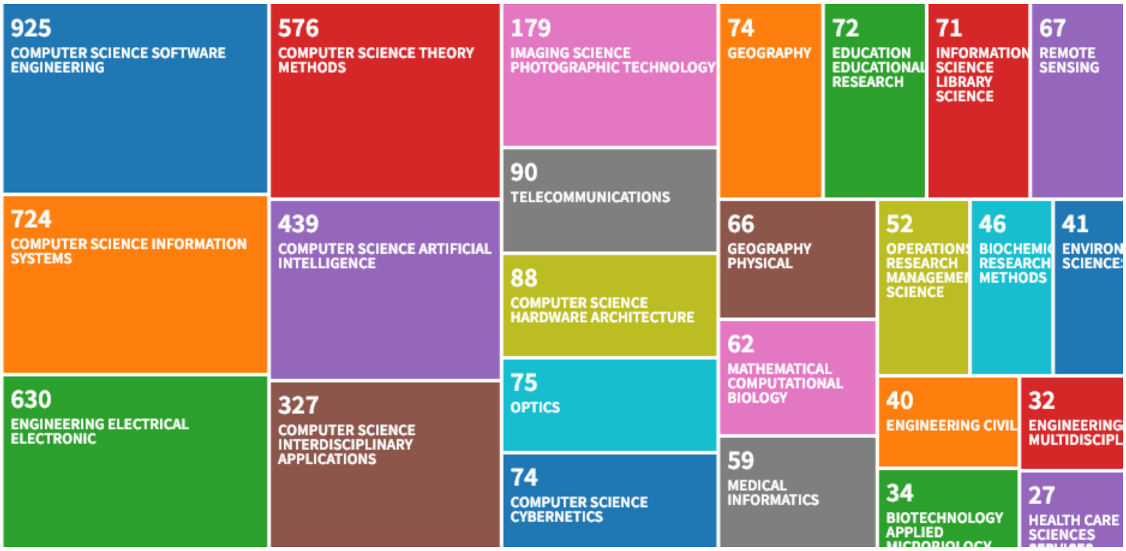

FIGURE 5. **Application domains of visual analytics based on the statistics of related papers.** ***Note:*** **The data were collected on 26 December 2018.**

categorization of visual-analytics applications from a technical perspective is proposed. According to the process of visual analytics summarized in Section II-D and the ‘‘human-is-the-loop’’ philosophy described in Section II-C, two technical components of visual analytics are identified: visualization and interactions. To integrate human judgment into the data-analysis process in visual analytics, users gain insight from data through visualization and apply their judgment to the data through interactions, such as zooming in different visualization areas, changing visualization methods, modifying the parameters of data models, and investigating different visual views on data. Therefore, visual-analytics applications can be categorized according to the dimensionality of visualization and the type of interaction.

A. VISUALIZATION-BASED CLASSIFICATION

According to the dimensionality of the data and visualization techniques, four categories of visual-analytics applications are identified: *2D-to-2D*, *multi-dimensional-reduction-2D*, *multi-dimensional-to-2D*, and *multi-dimensional-to-3D*.

1) 2D-TO-2D

Two-dimensional (2D) visualization is the most common way to visualizing data in information visualization. Within 2D visualization, binary data is naturally visualized in 2D space through the Cartesian coordinate system. A visual-analytics application will be classified as *2D-to-2D* if it fulfills the following requirements:

– The data is 2D.
– The data are visualized in 2D visualization.

For visual-analytics applications in this category, users will gain insight from data by performing analytical reasoning on 2D data through 2D visualization. For example, Bögl *et al.* [67] developed a *2D-to-2D* visual-analytics application (TiMoVA) to guide domain experts in model-selection tasks based on user stories and iterative expert feedback on users experiences. It closely combined human perception and analytical reasoning and automated computation. Figure 6 shows an overview of TiMoVA.

In addition, *2D-to-2D* visual analytics are commonly used for another type of 2D data: movement data. The research of [21], [68] used different visualization techniques, such as mapping and clustering movement data on 2D maps, to analyze and explore various aspects of movement through visual analytics.

2) MULTI-DIMENSIONAL-REDUCTION-2D

With the ever-increasing amount of data sets, multi-dimensional data show up in numerous fields of study, such as economics, biology, chemistry, political science, astronomy, and physics [69]. In this survey, multi-dimensional data are defined as:

Definition 5: A data set that has more than three dimensions/attributes.

However, the high dimensionality of a multi-dimensional data set represents a critical obstacle: humans are biologically optimized to see the world and the patterns in it in three dimensions [70]. This challenge and the wide availability of multi-dimensional data have led to new opportunities for visual analytics.

A visual-analytics application will be classified as *multi-dimensional-reduction-2D* if it fulfills the following requirements:

– The data is multi-dimensional.
– The dimensionality of the data is reduced by algorithmic approaches to two dimensions.
– The processed data are visualized in 2D visualization.

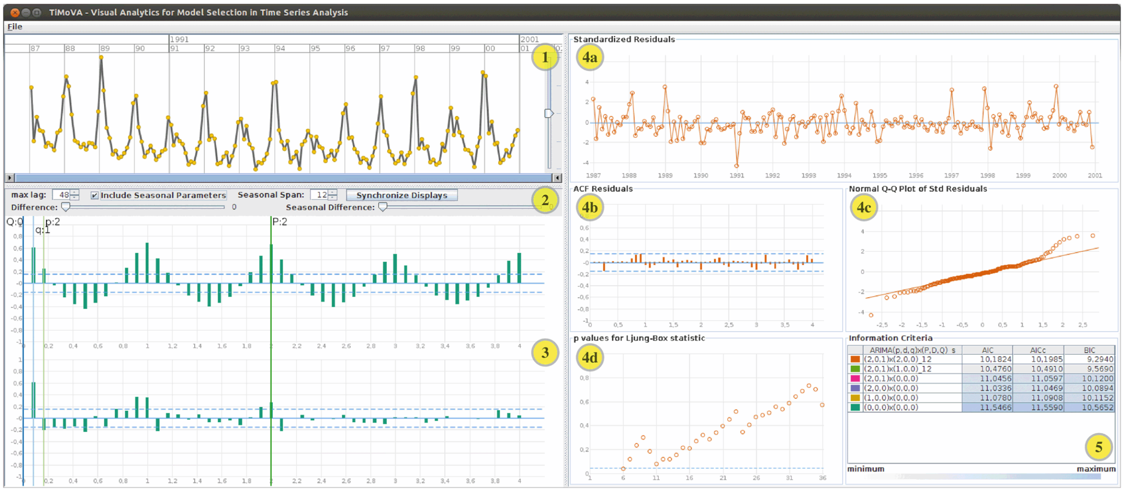

FIGURE 6. **TiMoVA Overview. A *2D-to-2D* visual-analytics application for finding an adequate model for a given time-oriented data set [67].**

To break the physical limitations of the human visual system, a variety of analysis-centric dimension-reduction methods have been investigated for reducing the dimensions of multi-dimensional data, such as principal component analysis (PCA), multi-dimensional scaling (MDS) and linear discriminant analysis. However, it is usually difficult to understand and interpret the result of these algorithmic approaches in an intuitive and meaningful manner. To address this challenge, *multi-dimensional-reduction-2D* visual-analytics applications integrate dimension-reduction approaches into the human analytical reasoning process to reduce the data items presented in the visualization. For example, Choo *et al.* [71] presented a *multi-dimensional-reduction-2D* visual-analytics system (iVisClassifier) for classifications based on a supervised dimension-reduction approach, which is shown in Figure 7.

Wu *et al.* [72] introduced a *multi-dimensional-reduction-2D* visual-analytics system (OpinionFlow) to empower analysts to detect opinion-propagation patterns and glean insights, which is shown in Figure 8. OpinionFlow uses an information diffusion model to reduce the dimension of the social-media data.

3) MULTI-DIMENSIONAL-TRANSFORMATION-2D

Another category of visual-analytics applications is *multi-dimensional-transformation-2D*, which visualizes multi-dimensional data without analysis-centric dimension-reduction approaches. A visual-analytics application will be classified as *multi-dimensional-transformation-2D visualization* if it fulfills the following requirements:

- The data is multi-dimensional.
- The multi-dimensional data is transformed and mapped in 2D visualization.
- The dimension of the data is not reduced by algorithmic approaches.

Within *multi-dimensional-transformation-2D* visual-analytics applications, multi-dimensional data is transformed and mapped in 2D space, which encodes data to different representations, such as PCPs and coordinated multiple views (CMVs). PCPs align axes parallel to each other and data points are mapped to lines intersecting the axes at the respective values. They allow the simultaneous display of a number of dimensions by embedding the corresponding number of parallel axes into a plane to reveal trends and patterns in the data. CMVs encompass a specific exploratory visualization technique that uses two or more distinct views to support the investigation of a single conceptual entity [73]. Guo *et al.* [74] presented a *multi-dimensional-transformation-2D* visual-analytics system, Triple Perspective Visual Trajectory Analytics (TripVista), for exploring and analyzing complex traffic trajectory data, which was mainly based on a parallel coordinate plot and coordinated multiple views. TripVista is shown in Figure 9.

4) MULTI-DIMENSIONAL-TO-3D

Three-dimensional (3D) visualization was developed for converting 3D objects/phenomena into 2D images through a computer-graphics process. Presently, 3D visualization is widely used in scientific visualization to graphically illustrate scientific data, which enables scientists to understand and illustrate the data. Moreover, 3D visualization is often integrated with a variety of approaches to visually analyze multi-dimensional data. For example Achtert *et al.* [75] and Johansson *et al.* [76] visualized parallel coordinates in 3D space to explore the complicated relationships between the axes, which arranged more than two neighboring axes around the central attribute.

Multi-dimensional-to-3D visual-analytics applications are based on the 3D visualization of multi-dimensional data. A visual-analytics application will be classified as *multi-dimensional-to-3D* if it fulfills the following requirements:

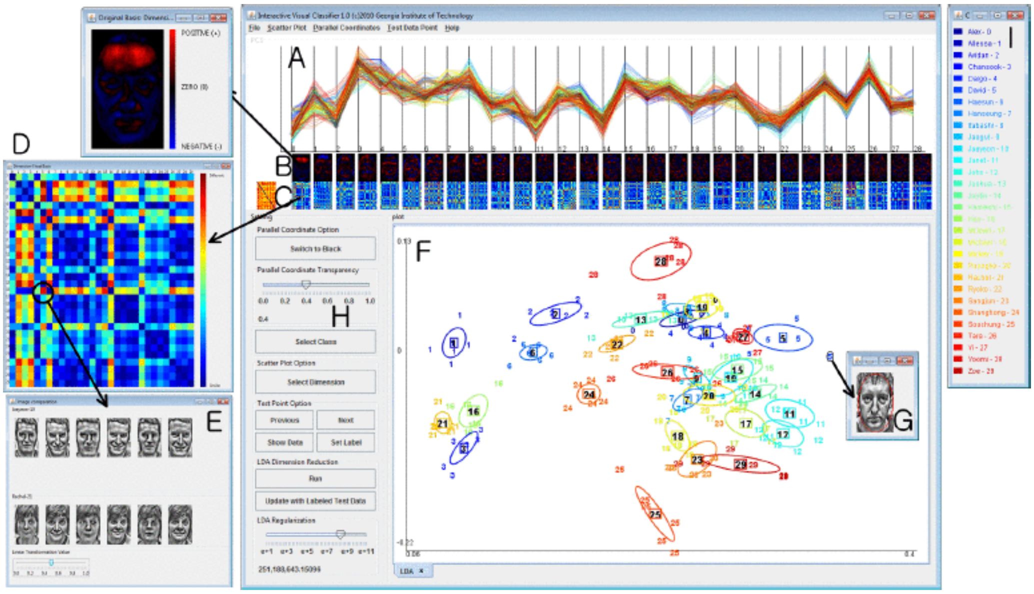

FIGURE 7. An overview of iVisClassifier [71].

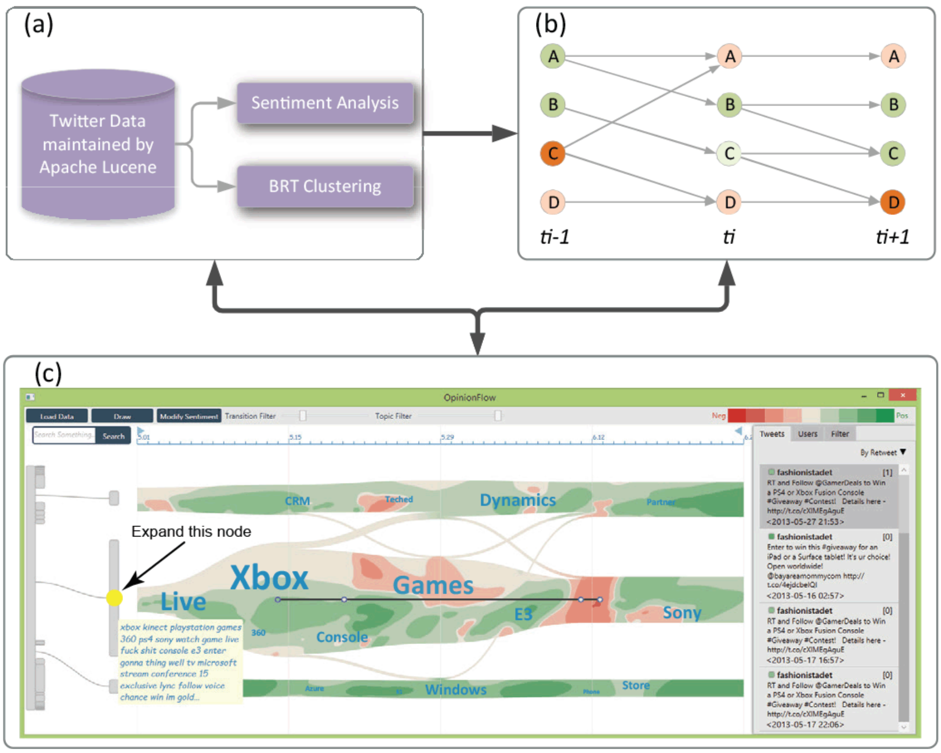

FIGURE 8. Three major parts of OpinionFlow: (a) Data preprocessing, (b) diffusion modeling, and (c) interactive visualization [72].

– The data is multi-dimensional.
– The multi-dimensional data is transformed and mapped in 3D visualization.

For example, Kurzhals and Weiskopf [77] introduced a *multi-dimensional-to-3D* visual-analytics method to analyze eye-tracking data recorded for dynamic stimuli such as video or animated graphics, which is shown in Figure 10.

B. INTERACTION-BASED CLASSIFICATION

In visual analytics, the analytical-reasoning process is facilitated by interactive visual exploration of data through various interaction techniques. According to the visual-analytics process (II-D), users can directly interact with data, algorithms, and visualization [78]. Heer and Shneiderman [79] gave a taxonomy of interactive dynamics for visual analysis,

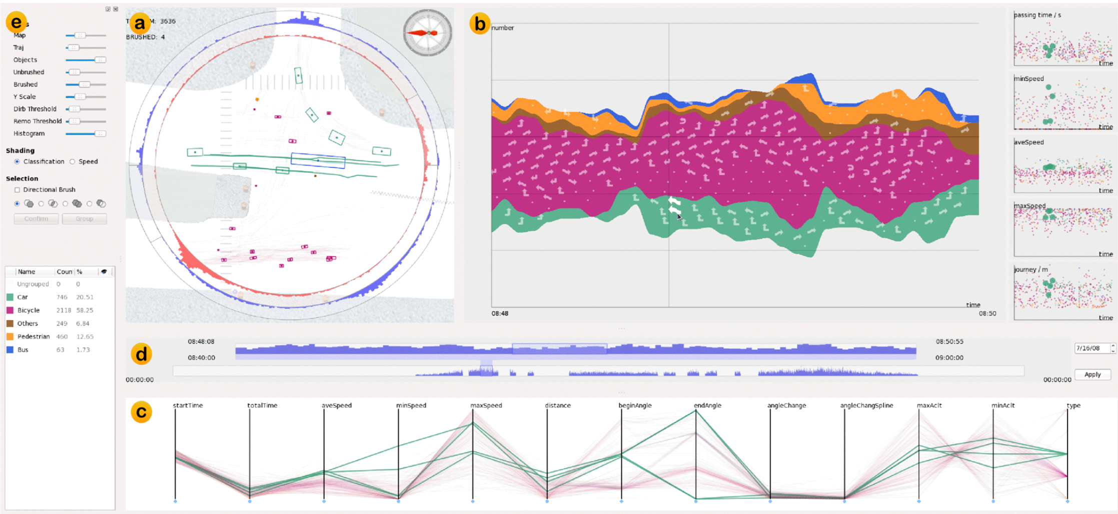

FIGURE 9. TripVista overview [74].

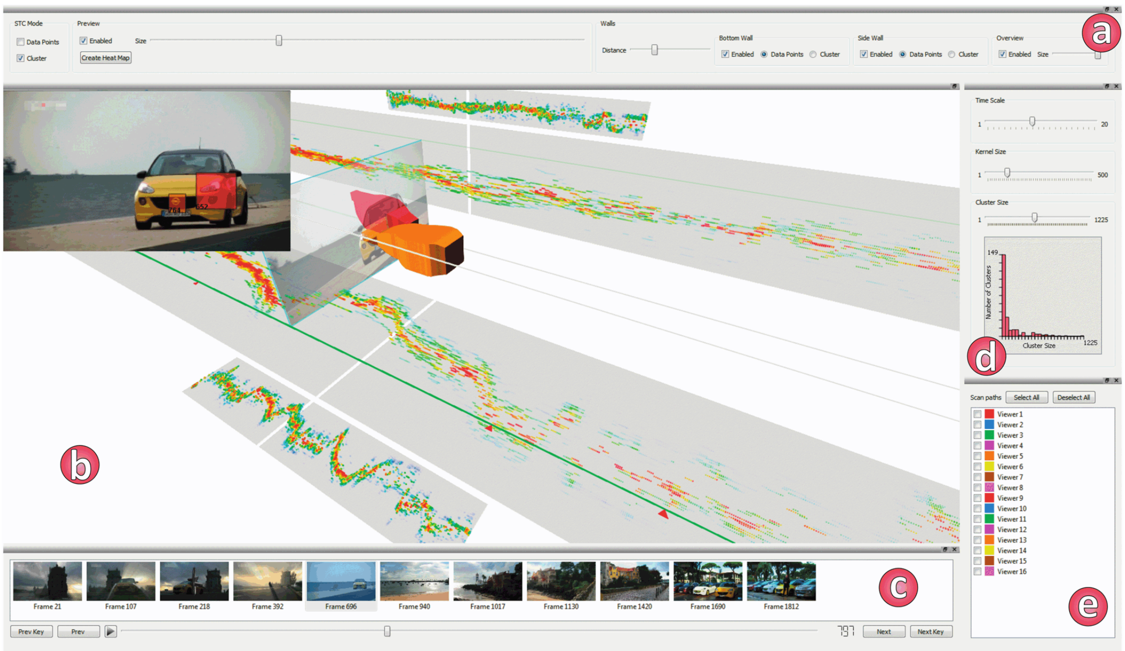

FIGURE 10. A ***multi-dimensional-to-3D*** visual-analytics application for eye-tracking data [77].

which included data and view specifications (filtering, sorting, deriving values or models from source data, etc.), view manipulations (selecting, navigation, etc.), and processes and provenances (recording, guiding or sharing, etc.). Endert *et al.* [80] divided interactions into two categories *exploratory* and *expressive* from observation-level.

In this survey, the taxonomy of [79] and the classifications of [80] are combined to classify visual-analytics applications from the interaction perspective. Visual-analytics applications are classified into two categories: *exploratory-oriented* and *expressive-oriented*, based on their interactions. An application will be classified as *exploratory-oriented* if its interactions are designed to explore data and visualization space. For example, the interactions of selecting different encoding, modifying zoom levels and of filtering data are considered as *exploratory-oriented*. Within *exploratory-oriented* visual-analytics applications, users gain insight from data by observing how data reacts during interactions in a dynamic visual representation.

An application will be classified as *expressive-oriented* if its interactions are designed to change the algorithms for rendering the visualization or the underlying models for data analysis. The interactions of modifying the parameters of the underlying mathematical models or rendering algorithms,

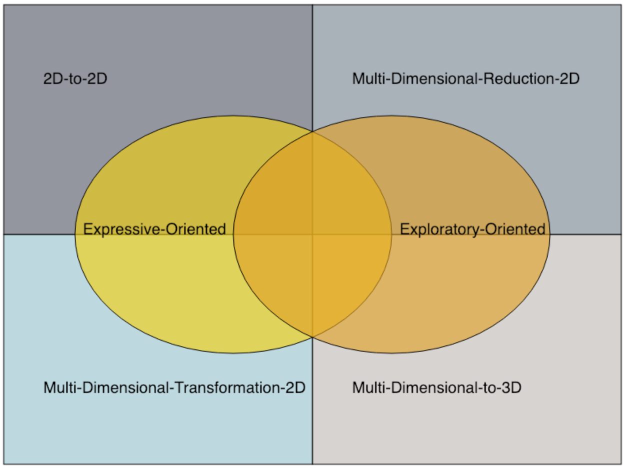

FIGURE 11. The complete classification of visual-analytics applications.

and deriving values or models from source data, are considered as *expressive-oriented*. Within *expressive-oriented* visual-analytics applications, interactions are therefore commonly coupled with the statistics-based data-analysis process. For example, Interactive Principal Component Analysis (iPCA) [30] changes the weight for each dimension in calculating the direction of projection using multiple sliders through user interactions. Also, for visual-analytics applications using MDS [81], the dissimilarities in the calculation of the stress function can be weighted through visual controls.

C. A COMPLETE CATEGORIZATION OF VISUAL-ANALYTICS APPLICATIONS

For the visualization-based classification of a visual-analytics application, 3D data are not considered for two reasons: 1) 3D data can be naturally classified as multi-dimensional data, and 2) 3D data can be easily visualized in several 2D visualizations. Therefore, it is not necessary to create a category for 3D data. Furthermore, both types of interaction can be used by an application at the same time. Accordingly, there is an overlap between the categories of *exploratory-oriented* and *expressive-oriented* in the interaction-based classification scheme.

From a technical perspective, visualization- and interaction-based classifications form a complete categorization of visual-analytics applications. Figure 11 illustrates the relationship of two classifications of visual-analytics applications. It covers all technical components of state-of-the-art visual-analytics applications, including 2D- and 3D-visualization techniques, algorithmic dimension reduction and data-analysis methods, and exploratory and expressive interactions. Therefore, this categorization can direct researchers toward selecting the appropriate techniques for applying visual analytics and building an application on complex data sets. Table 3 shows the categorizations of the visual-analytics applications examined in this survey.

IV. VISUAL ANALYTICS: CHALLENGES AND FUTURE DIRECTIONS

Visual analytics has made great progress over the past 15 years. The inevitable trend of visual analytics brought us not only opportunities but also challenges. In this section, these challenges characterized by the scalability, interaction, infrastructure, and evaluation from both technical and application perspectives are discussed. In addition, the future directions accompanying these challenges in an effort to provide a stimulus for research are presented.

A. CHALLENGES

1) SCALABILITY

The explosion of data presents a significant challenge for exploring large and complex data sets. Visual-analytics techniques need to be able to scale with both the size and dimension of the data. However, there is a growing mismatch between data size/complexity and the human ability to explore and interact with the data [144], which makes scalability a fundamental challenge of visual analytics.

The scalability of visual analytics is defined as ''its capability to effectively display large data sets in terms of either the number or the dimension of individual data elements'' [145]. Presently, most research in improving the scalability of visual analytics is primarily focused on investigating visualization devices [146]. For example, with the growing availability of large-scale high-resolution displays, large high-resolution displays [147], [148] and power wall display [149] have been investigated to display more overview and detail for large data sets in visual-analytics research. However, compared with the amount of data which is continuously growing at a rapid pace, the number of pixels on current displays has remained rather constant. In this case, the amount of data still commonly exceeds the limited amount of pixels of a display by several orders of magnitude. In addition, although it is possible to build ever-larger and higher-resolution displays, human visual acuity is limited to match the extreme large-screen approach. Meantime, algorithmic dimension-reduction techniques have been investigated to improve the scalability of visual analytics, especially for multi-dimensional data sets. For example, both linear and non-linear dimension-reduction algorithms, such as PCA [150] and MDS [151], have been applied to visualize multi-dimensional data sets. However, the use of these algorithms has been somewhat limited in visual analytics because they have been too slow for interactive use when the number of dimensions is scaled up [144]. This significantly hinders the integration of human judgment into the data-analysis process. More importantly, more dimension reduction and a higher rate of compression of data on displays mean more abstract representations and more lost details [152], which requires additional interpretation when performing analytical reasoning.

The scalability challenge of visual analytics involves both human and machine limitations. It is expected that the

TABLE 3. Complete categories of the examined papers.

Category		Paper
2D-to-2D	exploratory-oriented	[68] [82] [83] [84] [21]
	expressive-oriented	[85] [67]
multi-dimensional-reduction-2D	exploratory-oriented	[86] [87] [71] [88] [89] [90] [72] [91] [92] [93] [94] [31]
	expressive-oriented	[81] [30] [71] [95] [96] [97]
multi-dimensional-transformation-2D	exploratory-oriented	[98] [99] [100] [101] [102] [103] [104] [105] [106] [107] [108] [109] [110] [111] [112] [113] [114] [115] [116] [117] [66] [118] [119] [120] [121] [122] [123] [124] [125] [126] [127] [65] [128] [129] [130] [131] [132] [133] [134] [135] [136]
	expressive-oriented	[137] [138] [74] [139] [140] [116] [126] [141]
multi-dimensional-to-3D	exploratory-oriented	[111] [113] [77] [142] [143]
	expressive-oriented	[77] [142]

integration of algorithms and visualization techniques for large data in visual analytics can help reduce the mismatch between data size/complexity and human ability.

2) INTERACTION

Interaction is a fundamental component of visual analytics. The grand challenge of interaction is to develop a taxonomy to describe and clarify the interaction design space since there is hardly ever an explanation of what the benefits of interaction actually are as well as how and why they work [19], [153]. There are several taxonomies [154]–[156] that have been devised for describing and structuring interaction space. However, it is still a challenge to develop a comprehensive taxonomy that captures all possible interactions that may be performed, which includes an explication of the cognitive and perceptual impact of each individual interaction [157].

In this survey, interaction methods in visual analytics are classified into two categories: *exploratory-oriented* and *expressive-oriented*. Both of them are equally important to visual analytics. However, according to Table 3, compared with *exploratory-oriented* interactions, *expressive-oriented* interactions are used much less in recent visual-analytics applications. Only a few applications have tried to use these two different kinds of interactions together, such as [71], [77], [110], [142]. One of most possible reasons for this situation is that *expressive-oriented* interactions are associated with the modification of the underlying mathematical models or rendering algorithms, which may delay the response of the interactions when the size and complexity (dimension) of the input data are scaled up.

In addition, there have been rapid advances in interaction technologies; however, their advantages have not been fully investigated as most visual-analytics applications are still based on the traditional desktop, mouse, and keyboard setup of WIMP (Windows, Icons, Menus, and a Pointer) interfaces [158]. A few researchers have focused on new possibilities in interaction technologies in visual analytics; however, they have only been tested with simple data sets and scenarios. For example, PaperLens [159] uses a handheld lens and a tracked sheet of paper to navigate the 3D virtual information spaces above a tabletop. Interactive Whiteboards [160] leverages hand-drawn input for exploring data through simple charts. Ball and North [147] discussed embodied interactions, such as physical navigation, by physically interacting with large-scale visualizations for improving performance times on analytics tasks through an empirical study.

Therefore, in visual analytics, the challenge of interaction is to investigate its cognitive and perceptual impacts for integrating human judgment in the data-analysis process, as well as developing novel interactions by taking advantage of new algorithms and devices.

3) INFRASTRUCTURE

Based on the observation gained in this survey, in the field of visual analytics, there is an urgent need for a common framework to accelerate the research and development of new techniques. This has neither been fully valued nor discussed in recent research.

A few frameworks have been proposed for various purposes in visual analytics. For example, Aigner *et al.* [161] proposed a conceptual visual-analytics framework specifically for time and time-oriented data. Garg *et al.* [162] describe a visual analytic framework which uses logic programming as the underlying computing machinery to encode the relations as rules and facts and compute with them. Chen *et al.* [95], Brennan *et al.* [99] and Aragon *et al.* [163] proposed three frameworks for collaborative visual analytics with different focuses. However, these frameworks were designed for a specific domain/problem or data type. None of them can be reused as a common framework, which hinders the rapid development of visual-analytics techniques, and communications in the visual-analytics research community.

More importantly, the lack of a visual-analytics framework that works on high-performance computing platforms, such as Elasticsearch [164], Apache Kafka [165], and Apache Spark [166], is especially frustrating for visual analytics of large-scale data.

Therefore, in visual analytics, the infrastructure challenge is to develop reusable libraries and frameworks for common research questions, such as heterogeneous-data fusion, collaborative analytics, information sharing, and large-scale data processing, to accelerate the research of visual analytics, and facilitate communications in the research community. Such libraries and frameworks must support multiple levels of abstraction, including unwrapping the logic within the products, adding new reasoning and facts, and turning the results into new products.

4) EVALUATION

As cognition, perception and analytical reasoning are significant factors in the visual-analytics process, human information discourse constitutes a challenge for evaluating the utility, effectiveness, and trustworthiness of visual-analytics applications. Some methods have been investigated for evaluating visual-analytics applications, for example, insight- and task-based methodologies for evaluating spatiotemporal visual-analytics applications [167]. However, in various application domains, the complexity of a visual-analytics application still makes its evaluation a challenge.

For visual-analytics applications in different problem domains, such as biology, medical, astrophysics, and geography, three methods that adapted from the field of information visualization are used, including case studies, user studies based on controlled experiments, and expert reviews. However, each of these methods has its own strengths and weaknesses. For example, Tory and Moller [168] indicated that expert reviews can quickly assess usability, however, they may miss important issues in their evaluations due to a lack of user involvement. More importantly, these methods are mainly focused on evaluating the usability and effectiveness of the visualization components of visual-analytics applications, which lack an evaluation of the data analysis components, such as accuracy and efficiency.

In addition, during the visual-analytics process, the uncertainties in data may arise, propagate and compound, which results in impaired decision making, misleading analysis results, and misinterpretations [169]. This challenges the trustworthiness of visual-analytics applications, which is one of the most important evaluation criteria. Sacha *et al.* [170] illustrated the relationship between human's perceptual and cognitive biases and the trustworthiness of visual-analytics applications, in which the user's awareness of the uncertainties in the data is influenced by their perceptual and cognitive biases. Presently, techniques, such as uncertainty modeling and visualization, have been proposed to quantitatively characterize and intuitively display the uncertainty information in data sets [171], [172]. However, due to the complexity of the visual-analytics process, there are still no widely accepted evaluation techniques to ensure the trustworthiness of the visual-analytics process.

Therefore, we need science, support structures and data to perform encompassing evaluations of visual-analytics applications. The challenge of proposing a theoretically founded evaluation framework for visual analytics is expected to gain more interest in the field.

B. FUTURE DIRECTIONS

In spite of all the challenges, the rapid development of visual analytics will lead to numerous opportunities for making progress in many fields. Several future directions are discussed in this section to tackle many challenges and open issues with visual analytics.

To address the scalability challenge of visual analytics, investigating novel visualization algorithms and methods for large-scale data is one significant research direction. In the field of information visualization, most methods are focused on relatively small data sets. For example, various studies [173]–[175] on PCPs for visualizing high-dimensional data are limited when the size of the data is scaled up. Therefore, re-designing these methods specifically for large-scale data would be a potential solution for visual analytics of large-scale data. In addition, since there are no strict boundaries among the proposed categorization of visual-analytics applications, combining techniques from different categories is a potential research direction. For example, combining algorithmic dimension-reduction methods and parallel coordinates would be a possible way for visual analytics of high-dimensional data.

To facilitate collaboration and information sharing in visual analytics, building a web-based framework for visual analytics is a potential research direction. A web-based framework could break temporal and spatial constraints in communication and collaboration. Moreover, it could also facilitate the integration of visual-analytics applications with other big data platforms, since most recent big-data platforms provide web services for accessing and processing the data stored within them [176]. This will not only address the scalability challenge of visual analytics but also will accelerate the research and development of visual analytics. Another future research direction of visual analytics is to extend it into immersive and stereoscopic visualization (virtual reality) environments. Although several devices, such as consumer-grade 3D displays and immersive head-mounted displays enable immersive and stereoscopic visualization environments, the related visualization techniques have not been explored extensively for information visualization and visual analytics [177]. Investigating these new devices and related visualization techniques could provide potential solutions that address the scalability and interaction challenges of visual analytics. In addition, to address the evaluation challenges, developing evaluation standards for visual analytics by selecting and combining proper evaluation methods from the fields of visualization and algorithmic data analysis [178] is another possible direction.

The challenges and future directions discussed in this section were selected based on the observations made in this survey. For the entire field of visual analytics, there are many more challenges and opportunities than what have been discussed in this section. Readers are hence encouraged to use these as guides to deeper investigation and prospective thinking toward future possibilities of visual analytics.

V. SUMMARY

Visual analytics is a fast-growing field of research combining strengths from visualization, data analysis, knowledge discovery, data management, analytical reasoning, cognition, perception, and human-computer interaction. Its goal is to discover knowledge and gain insight from large and complex data sets through integrating human judgment into the data-analysis process.

This survey has drawn a complete picture of visual analytics to direct future research by examining the related research in various application domains. To avoid limiting this survey to a specific data type or applications domain, a novel categorization of visual analytics applications from a technical perspective was proposed. Based on this categorization, an organized overview of visual analytics in over 200 publications was constructed, which discussed the theory, evolution, and trends of visual analytics, and how visual analytics is applied in various application domains was investigated. To better understand visual analytics, the human-information discourse of visual analytics was discussed, a formal model of the visual analytics process was summarized, which provided a detailed definition of visual analytics, and the visual analytics mantra ''Analyze/Overview first, interaction and visualization repeatedly, insights in data'' was presented. Under the proposed categorization, state-of-the-art techniques and applications of visual analytics in different application domains that can bridge the gap between the challenges of discovering knowledge in large and complex data sets and visual analytics solutions were presented. Finally, an overview of the major challenges and future directions of visual analytics was given.

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