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Empowering Data-Driven Decision Making: A Review on Visual Analytics

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Abstract: The power of analyzing large, complex, diverse, or dynamic data is associated with how effectively we can find the patterns or associations the data holds, and gain insights from it within time constraints. Visual analytics, termed as a blend of analytical reasoning and visualization, helps in increasing this effectiveness. In the modern era of technological revolution, the importance of finding rapid solutions to any problem is immense. With the complete reliance on data rather than intuitions, data-driven decision making improves efficiency, accuracy, scalability and reduces potential risks related to deriving effective solutions. One among the approaches of empowering data-driven decision making is Visual Analytics. This paper presents a detailed review on visual analytics. A proper definition of visual analytics is put forward, followed by reviewing the works done in the area for various fields. The state of the art and challenges are investigated and future scope of visual analytics is addressed. Furthermore, the paper explores basic visual analytics approach by conducting a case study on implementing a model to diagnose common cold and influenza in patients with suspected symptoms.

Keywords: *Analytical Reasoning, Data Visualization, Data-Driven Decision Making, Human Perception, Interactive Visualization, Visual Analytics*

1. Introduction

As the data volume and complexity increase day by day, the relevance of updating tools and techniques for big data management and handling also raises. Effective decision making can only be done by getting better insights from this large and complex data. How is that possible? Visual analytics is the absolute answer.

No matter how large and diverse the data is, it becomes futile if no conclusions can be drawn from it. Visual analytics facilitate the analytics of large, complex, ambiguous, dynamic and diverse data by drawing insights from the visually represented results using human perception and cognition. Visual analytics deals efficiently with information overload, turning the massive information into patterns and support finding correlations that exist within the information. Being multidisciplinary, visual analytics aids in many different fields like medicine, business, education, and environment [3]. In the present scenario where data is highly voluminous, visual analytics opens the door for better decision making and problem solving.

The purpose of this article is to bring forward what exactly is visual analytics, how visual analytics differs from and how it is connected to data visualization, interactive visualization and data analytics, and, how can we do visual analytics for a specific problem so as to get better insights for decision-making. The state of art of visual analytics is discussed, challenges are analyzed and based on the study conducted, the future changes that can strengthen visual analytics are brought up. The paper also demonstrates a case study on simple visual analytics approach for detection of intensity of common cold and influenza in patients with suspected symptoms.

1.1. The Evolution of Visual Analytics

The need for visual analytics was largely identified in homeland security of United States, back in 2001 September 11, when there was terrorist attack and the security needs were indispensable. The grand challenge back then was to identify emergence of attacks, threats, protection of homeland borders expeditiously and take optimal actions based on cognition. Since the environment was dynamical and the data changed in real-time, a strong methodology was needed to enforce the security systems. Analyzing the data containing geographic location information of terrorists, immigration records, patterns of travel, affiliations and names of terrorists, and phone call logs together within very short time to get effective responses to make proper decisions were very difficult only with data analytics techniques [1]. This led to the emergence of visual analytics, a combined approach of analytical reasoning and visualization, which made data-driven decision making rapid and effective.

1.2. Motivation

As an evolving area, visual analytics reviews are low in count. Some of the reviews explains categories of visual analytics based on observed factors like dimensions or type

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of data, whereas other reviews classify visual analytics based on different fields on which the techniques are implemented. Table 1 illustrates the published works on study of visual analytics done so far to the best of our knowledge, and their area of focus.

Table 1. Articles on study of visual analytics

Paper	Year	Focus on
[2]	2008	- Visual analytics process - Scope and Challenges - Use of visual analytics in some application areas
[3]	2008	- Areas related to visual analytics - Visual analytics process - Challenges - Examples of visual analytics applications
[4]	2009	- Scope of visual analytics - Challenges and Advantages of Automated analysis and visualization
[5]	2010	- Visual analytics process - Human involvement in visualization - Reviewing application areas and tools for visual analytics
[6]	2013	- Visual analytics process - Categories of visual analytics applications - Challenges and future scope
[7]	2019	- Definition and evolution of visual analytics - Studies on visual analytics - Visual analytics process - Visual analytics techniques and applications - Challenges and future directions

Reviews on visual analytics has also been done based on specific areas like visual analytics for machine learning, software maintenance, image and video dataset, pipeline-based models and so on [8-17]. From the table, it is evident that most of the works does not cover all aspects of visual analytics, [7] being an exception. However, the misconceptions might exist like visual analytics being addressed as data analytics aided with interactive visualization. In spite of this being mostly true, it has to be convinced that the simplest form of visual analytics can be a little different. Furthermore, a detailed review on visual analytics has not been put forward in the last 4 years, which implies recent developments in the area are hardly emphasized. Since there are many related terms like data visualization, information visualization, analytical reasoning, data analytics, interactive visualization and so forth, the concept of visual analytics has to be clearly understood to proceed with the same. Through this paper, we would like to clarify any misconception, thus giving a definite idea of what visual analytics is and how the process of visual analytics can be carried out.

2. From Data Visualization to Visual Analytics

The definition of data visualization is explained by the term itself. Data visualization is the act of visualizing complex and large data in different forms using visual metaphors, with the aim of getting insights from it, which further aids in decision making related to the problem. If no insights can be drawn from the visual representation, data visualization is said to be ineffective. The need for data visualization arises when the data is very complex or the data volume is constantly increasing to an extent where it becomes difficult to perceive knowledge from it. Visual representation of data gives a quick understanding of what has to be convinced and interpreted, as the human brain is wired to process visual data more efficiently. By data visualization, we can visualize the complex data using charts or graphs like line chart, pie chart, scatter plot, bubble plot, word cloud, histogram, or heatmaps [18]. From the representations, the correlation between data attributes or patterns the data holds can be perceived and used for further analysis or decision-making processes.

The difference of data visualization from information visualization is solely the gap between data and information; data visualization provides graphical representation of raw data, whereas information visualization holds more meaning to it by depicting meaningful data [19,20]. Scientific visualization, a connective term, is responsible for the representation of scientific data [21].

Interactive visualization, which can be identified as an advanced version of data visualization, enhance human cognition by improving level of exploration in visual representations. Interactive visualization systems combine visualization with interactivity by providing the overview of the data through visualization while embedding the detailed visual representations within it [23], which can be attained through interactions such as selection, zooming, or mouse movements, facilitating the perceiver in deeper understanding and analysis of the data.

Analytical reasoning is the process of analyzing organized data of any size and complexity by applying human intelligence and grasping insights which support certain kinds of planning or decision making [1]. When data subject to analysis is large or complex, the process is termed as data analytics. Data analytics deduce patterns, correlations, and trends from data using statistical methods to make data-driven decisions.

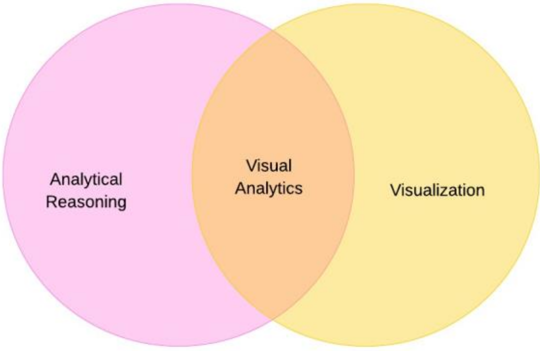

Fig 1. Relationship of visual analytics with analytical reasoning and visualization

Visual analytics is an umbrella term encompassing analytical reasoning and visualization. In visual analytics, analytical reasoning and visualization are equally important. A beautifully visualized data with poor analysis technique is same as the best analytics algorithm working over a poorly visualized data. In the first case where visualization is at its best, the result might be eye-pleasing while being easy to interpret, but lack of better analytics demotes the process of finding patterns and correlations. Whereas in the second case, poor representation of the result makes it difficult for human cognition to conclude what interpretation actually the data gives.

2.1. Definition of Visual Analytics

The growth of data volumes and complexity in the structure of data streams inhibit human ability to perceive insights from it. The concept of visual analytics has evolved due to the difficulty in making rapid data-driven decisions from massive and dynamic datasets.

A proper definition of visual analytics was given in the book, "Illuminating the Path: The Research and Development Agenda for Visual Analytics", which is apparently identified as the first book on visual analytics by James J Thomas and Kristin A Cook. They define visual analytics as "the science of analytical reasoning facilitated by interactive visual interfaces" [1].

In the paper, "Visual analytics: definition, process, and challenges", Daniel A Keim et. al gives a more specific definition as "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" [23].

When the visual analytics mantra by Shneiderman, "Overview first, Filter and zoom, Details on demand" [24] gave a strong definition for visual analytics process, Wenquiang Cui in his paper [7] created a mantra using the so-called visual analytics mantra as "Analyze/Overview first, interaction and visualization repeatedly, insights into data".

In this review, we define visual analytics as the combined process of analytical reasoning and visualization of large, complex, dynamic and/or diverse data, from which insights can be drawn, contributing to efficient decision making.

The data subjected to visual analytics need not be voluminous always. If the data is complex enough to hinder extracting information required for proper decision-making, we can call for visual analytics. As mentioned in section 1.2, the simplest form of visual analytics is the one which facilitates decision-making through:

1. Insights from the visualized result of data underwent any type of analytical reasoning, including basic inductive reasoning.

2. Findings drawn from the analytical reasoning of information gathered from visualization of data.

On the contrary, visual analytics can also be as complicated as it can, based on the type of data, analysis and visualization methods, and nature of decision to be made.

2.2. Visual Analytics Pipeline

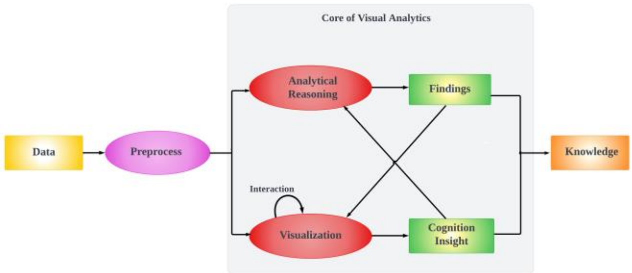

Fig 2. The Visual Analytics Pipeline

As Figure 2 depicts, the whole visual analytics process is carried out through a number of steps, briefed here as a generalized procedure:

Step 1: Collect the raw data

Step 2: Preprocess the data to facilitate further processing

Step 3: Use analytical reasoning to gain information from the data

Step 4: Visualize the gained information with appropriate representations

Step 5: Use perceiver's cognition to draw insights. If knowledge required for decision making is drawn, to step 8

Step 6: Integrate the analytical reasoning by the drawn insights

Step 7: Repeat steps 3 to 6 till the knowledge for effective decision -making is derived

Step 8: Use the knowledge to make decisions

The process of visual analytics begins with the fundamental step of collecting data. In the context of visual analytics, the data can be large, complex, dynamic, diverse, or ambiguous. Various methods can be used for data collection. Once the data is collected, preprocessing is done for the purpose of refinement of the data. The collected data might contain noise, missing values or it might not be in the form for proper analysis. This is solved with preprocessing, which involves techniques like data cleansing, handling missing values, removing outliers, and clustering [1]. The preprocessing of data is done to reduce the chance of error occurrence in further processing. Preprocessed data is then subject to the actual visual analytics system, where analytical reasoning and visualization plays equal important roles. The data can be analyzed first to gather findings and then visualize these findings to get insights from the data. Alternatively, the processed data can be visualized first, then the insights drawn from the visual representation can be passed to analytical reasoning, to collect the findings. The result of the visual analytics process is knowledge, whether it is the findings discovered from analytical reasoning or the insights drawn from visualized data, which can be used for better decision-making purposes for the existing problem. Analytical reasoning can use statistical methods, mathematical formulations or human experience and ability, whereas visualization can incorporate interactivity for deeper exploration [1]. The method used for both analytical reasoning and visualization process varies according to the depth of response expected, level of understanding and range of exploration. The combined process of analytical reasoning and visualization, that is, visual analytics cycle is expected to continue till the knowledge for supporting data-driven decision for the problem is derived.

2.3. Case Study: A Visual Analytics Approach to Detect Common cold Vs Influenza

In this section, we build a visual analytics approach for diagnosing the intensity of common cold and influenza in patients suffering from symptoms of fever, sneeze, cough and headache. We used fuzzy inference system for analytical reasoning to precise the uncertainty in the symptoms and heatmap is used for interactive visualization of the findings collected from the fuzzy system. This approach is very basic, and the purpose of presenting this is to elucidate the construction of a simple visual analytics system.

Input to the system is the patient dataset containing patient ID and the value of recorded symptoms. The output shows an interactive heatmap, by which the diagnosis, which is the insight here, can be drawn. The step-by-step procedure of the visual analytics approach is as follows:

Procedure for Visual Analytics approach to diagnose the intensity of common cold and influenza

Step 1: Input the patient dataset

Step 2: Create the fuzzy inference system

a. Define antecedent variables for the four symptoms, fever, sneeze, cough, and headache

b. Define consequent variables for the outputs, common cold and influenza

c. Fuzzify antecedent and consequent variables by assigning membership values to address uncertainty

d. Define fuzzy rules with fuzzy variables

e. Create fuzzy control system for consequent variables and simulate the system

Step 3: Interpret membership values of fuzzy consequent variables, which addresses the intensity

Step 4: Generate heatmap visualization with proper interactivity to display intensity of common cold and influenza

Step 5: Analyze the heatmap and draw insights

The dataset is created using sample values and the rules are constructed depending on [84]. Membership values for the symptoms and intensity of diseases are assigned with the method of intuition. The visual analytics result of the system is shown through Figure 3 and Figure 4.

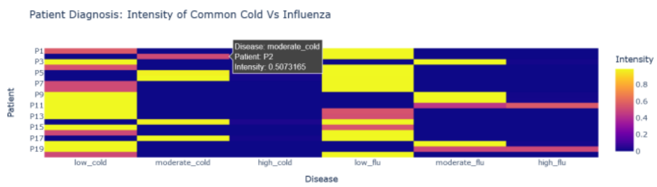

Fig 3. Interactive heatmap visualization of intensity of common cold and influenza in patients P1 to P20.

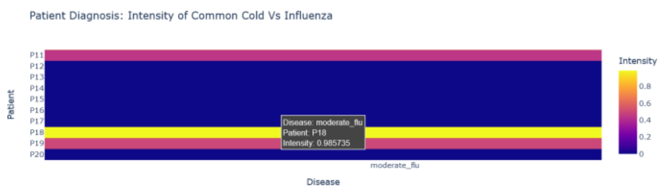

Fig 4. Interactive heatmap visualization of intensity of moderate flu in patients P11 to P20.

Figure 3 shows the intensity values of common cold and influenza in 20 patients, where yellow indicates highest chance of detection of the particular disease and blue shows the least chance, according to the heatmap. From the visualization, it is easy to conclude the condition of the patient; for instance, we can say that none of the patients are diagnosed with a high rate of common cold. The intensity values are displayed by incorporating interactivity with mouse hovering over the colored cell of heatmap. Zooming is used to extract the diagnosis of moderate common cold for 10 patients, which is depicted by Figure 4.

More relevant and more complex visual analytics tools, techniques, or applications can be implemented with adequate analytical reasoning and visualization methods and by integrating related technologies to the visual analytics process.

3. Visual Analytics Tools, Techniques, and Applications

Even though Visual analytics contributes towards many different fields, they are mostly used in business intelligence, finance, marketing, advertising, logistics and the like. When it comes to business intelligence where decisions are made based on the analytics results, tools like Tableau, Power BI, SaS Visual Analytics, and Spotfire are widely used. Figure 5 is a dashboard created using Tableau to analyze superstore data, which is one of the sample data provided by Tableau [25]. The use of tools saves time and gives better insights, also allowing to interact with the visual elements.

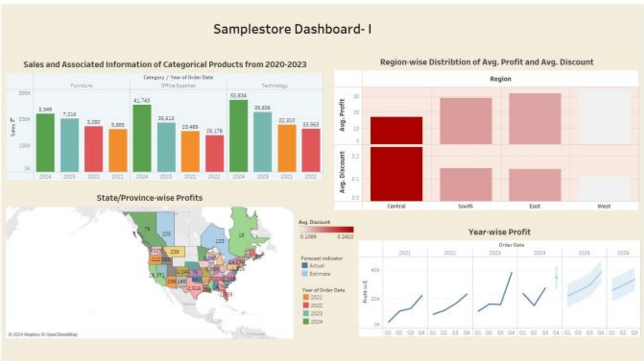

Fig 5. Dashboard of sample Superstore data [25].

Tools are set of programs act together to build visual analytics, whereas the visual analytics techniques incorporate various methods and algorithms used to derive insights from given data. Human perception is an inevitable element of visual analytics technique. On the other hand, visual analytics applications are context-based. Since application is problem oriented, it can make use of visual analytics tools and/or techniques according to the requirement.

Haotian Li et. al. [26] proposed a visual analytics approach combining human efforts with machine learning techniques to facilitate in effective proctoring of online exams. To detect and visualize suspected cheating behaviors, this approach analyzes exam videos and mouse movement data. From head movements from the exam videos and spatio-temporal information about mouse positions, the visual analytics system represents the details and allows proctors to quickly identify cheating behaviors of the students. David Gotz and Harry Stavropoulos introduced DecisionFlow [27], an easy-to-use visual analysis tool for high-dimensional temporal event sequence data. The system was tested in a 12-person user study from which it is found that DecisionFlow enables users to issue queries, aggregate data, visualize, interact, and analyze event sequences. Siming Chen et. al. proposed E-Map [28], a visual analytics approach to explore the evolution of important events in social media. The visual analytics system is a map constructed from unstructured social media messages which includes cities, towns surrounding the cities, regions, islands and continents where rivers represent highlighted social media users' behaviors of reposting. Users' trajectories and connections are encoded to find user behaviors, thus identifying the significant events. Fan Du et. al. came up with a prescriptive visual analytics interface, EventAction [29], which aids in identification of similar records, explore potential outcomes and review recommended sequences based on which personalized action plans can be implemented further. Taking into account the challenging process of financial planning, Stephen Rudolph et. al. developed FinViz [30], a visual analytics tool for personal finance planning. The tool helps users interpret financial data related to return, risk and correlation and allows them to make personal finance decisions by exploring different financial portfolio options and viewing potential outcomes. With a user friendly and interactive visual interface, FinViz aids in overcoming cognitive limitations and improved decision-making. Developed by Guilherme X. Ferreira et. al., Fleet Profile [31] paves way for better decision making in the field of logistics through visual analytics. Fleet Profile supports quick decision making in industrial vehicle fleet planning by using visual representations that helps to evaluate fleet utilization and identify gaps for fleet optimization. To explore complex economic networks, Roger A. Leite et. al. developed a guidance-enriched visual analytics system named Hermes [32]. Hermes facilitates in informed decision making and evaluation of the economic network by use of interactive visualization tolls and analyzing investment flows, supply chains, and sector-to-sector relationships within economic networks.

Visual analytics serves in various application areas including business, finance, health, education, agriculture and so forth. Table 2 gives a few of the published works on visual analytics based on application domains.

Table 2. Published works on visual analytics

Application Domain	Paper
Business	[33] [34] [35] [36] [37]
Education	[26] [38] [39] [40] [41] [42] [43]

Healthcare	[44] [45] [46] [47] [48] [49] [50] [51] [52] [53] [54]
Agriculture	[55] [56] [57]
Network	[28] [32] [40] [58] [59] [60] [61] [62]
Finance	[30] [33] [63] [64] [65] [66] [67] [68] [69]
Social media	[28] [70] [71] [72]
Security	[73] [74] [75] [76] [77] [78] [79] [80] [81]

3.1. Visual Analytics in Healthcare

The emergence of visual analytics made significant change in analysis of biological data in genomics, proteomics and metabolomics in the early days itself [82]. With the certainty of medical data being complex, diverse and voluminous, and quick decisions have to be made considering the time limits, visual analytics can provide great help. From disease detection to treatment and aftercare, visual analytics aids in the process by contributing in disease surveillance, patient monitoring, treatment progression, personalized treatment and so forth. Many works have been done in the field of medicine and healthcare using visual analytics since 2011.

Andreas Gerasch et al. proposed BiNA [44], a visual analytics technique for exploring biological network data. BiNA uses advanced graph drawing techniques for visualization in high quality graphics. It also provides integration with databases and incorporates customization for analysis algorithms and visual representations. A visual analytics tool for breast cancer treatment stratification was put forward by Lara Schneider et. al., named ClinOmicsTrail bc [45]. The tool is a decision support system that offers an integrated analysis of key characteristics of tumor which assists oncologists in discovering the best treatment methods for breast tumor patients. Developed by Bum Chul Kwon et. al., DPviz [46] is a visual analytics system for observing disease progression patterns. The system integrates Hidden Markov Models with interactive visual interfaces and visually summarizes disease states, builds, analyzes and compares clinically relevant patient subgroups. VERONICA [47] is a visual analytic system developed by Neda Rostamzadeh et al. for the identification of feature groups with strong predictive power in electronic health records for disease classification. VERONICA uses supervised machine learning techniques and provides interactive visualizations for supporting users to develop predictive models. The scalability is addressed to an extent where the design adapts to different datasets and analysis requirements. Quang Vinh Nguyen et. al. [48] proposed visual analytics framework for supporting the analysis of complex genomic data by utilizing various technologies like Unity3D platform, Game technology and 3D game engine techniques. The framework captures the complexity of the genome, thus facilitating in personalized treatment strategies. RetainVis [49], a visual analytics tool proposed by Bum Chul Kwon et. al. analyzes Electronic Medical Records by utilizing interpretable and interactive Recurrent Neural Networks. The tool covers various areas including patient overview, patient summaries, lists of patients, patient details and a patient editor. RetainVis contains a user-friendly interface with effective interactive visualization and provides enhanced decision-making by combining interactive visualizations with interpretable Recurrent Neural Networks.

4. Visual Analytics: State of the Art

Visual analytics can take advantage of many areas to improve the understanding of data it deals with. Combining the techniques from fields of artificial intelligence, machine learning and such integrates visual analytics process. The current trends in visual analytics employs this idea, thus, the state of art of visual analytics follows from it. This section describes the state of art, elaborating the utilization of various disciplines for integrating visual analytics approaches to a wide variety of problems.

4.1. Augmented Reality

Introduced to bridge the gap between real world and virtual world both spatially and cognitively [85] [86], augmented reality contributes to efficiency of decision making with visual analytics once integrated with it. The important aspect of visual analytics being human perception by which the analyst makes decisions, laying out the digital visual representations in real environment in three dimension opens opportunities for better decision making for the problems containing complex structured data, for instance, geospatial data. One of the areas that created a revolution in this regard is medicine [85]. Overlaying the medical images directly over patients' body gives better visualization of the condition, substantially reduces chances of error and misdiagnosis, and promote better insights and conclusions based on interactive visual interfaces used. Furthermore, use of augmented reality in visual analytics also helps in medical training by providing interactive learning experiences and practice [87]. Tools like SPARVIS [88] and MARVIS [89] were developed by combining augmented reality with mobile devices for visual analytics.

4.2. Machine Learning

Machine learning algorithms have been successfully implemented in diverse fields ranging from information retrieval, data mining, and speech recognition, to computer graphics, visualization, and human–computer interaction

[90]. Integration of machine learning algorithms into visual analytics, specifically in analytical reasoning part enables faster data exploration and consequently, faster insights. Techniques like dimensionality reduction, clustering, classification and regression analysis exist for integrating machine learning algorithms into user experience design for visual analysis of data [91]. Usage of machine learning techniques are incorporated in most of the analysis tasks of visual analytics, neural networks being one of the prominent models among them [92-94].

4.3. Interactive Data Storytelling

At times, visualization of the raw data or findings drawn from analytical reasoning can itself be complex and turns out to be tough to obtain conclusions. This is where storytelling helps. Storytelling enhances the interpretability of visual representation by providing extra information through narration about the visualization [95]. Interactive data storytelling combines visualization, interaction and narration to facilitate the perceiver to get a clear picture of what the data tells. Narration helps the users to actively explore the visualized data, with or without interaction, in the form of text, images or videos. Works have been done on story synthesis to bridge the gap between storytelling and visual analytics [96], to integrate the potential of decision making through visual analytics.

4.4. Natural Language Processing (NLP)

The motive behind integrating Natural Language Processing and visual analytics is basically to facilitate human cognition. The user can interact more liberally with the visual interfaces with the help of NLP, for instance, if the user can generate queries in natural language, then, based on the query, the response can be shown through visual representation. This saves a lot of time with respect to the analyst for figuring out the information they need. One of such tools was developed by Siwei Fu et. Al. [97], which provides a visual natural language interface which allows user to interact with data. IBM's Watson analytics platform and Tableau also provides natural language query facility and generates corresponding visual outputs. Strengthening visual analytics with the power of NLP is substantial and effective considering the time bound decision-making based on massive data streams, with limited ability of human perception.

4.5. Artificial Intelligence (AI) and Explainable Artificial Intelligence (XAI)

Artificial Intelligence is capable of integrating both analytical reasoning and visualization process, thus strengthening visual analytics to a higher level. AI can be integrated to visual analytics by incorporating different branches of it such as machine learning, computer vision, Natural Language Processing, robotics, expert systems, and more into visualization or analytics in compliance with suitability. As an example, expert systems which mimic the ability of human experts in specific fields to solve problems, can be used to improve the analysis and insight generation in visual analytics systems [98]. Explainable AI approach provides explanation for black box models; hence fusion of XAI with visual analytics support interactive exploration and explanatory visualization of data. Visual-based XAI, an emerging area in the field of visual analytics, uses special methods for model usage and visual approaches for data representation [99]. Regarded as an extensive domain, Artificial Intelligence definitely enhances the power of visual analytics.

4.6. Automated Insight Generation

Chang et. al. [100,101] defined insight in two ways; as spontaneous insight, which is as "Aha!" moment that represent an enlightenment, and as an advance knowledge or information obtained from data. Insight generation is an important step in the visual analytics process. Depending upon the insight generated, decisions are made for the specific problem. Automated insight generation speeds up the insight generation process and helps the perceiver to reach to conclusions faster in this modern world of rapidly growing data [102]. Artificial intelligence techniques such as machine learning can be applied to generate more comprehensible visualizations, so as to support human perception to bring out supportive insights for decision making.

4.7. Collaborative Visual Analytics

When most of the visual analytics systems considers a single-user cognition for drawing insights from the visual representation, collaborative visual analytics thinks different. Collaborative visual analytics is a highly demanding concept that leverage data-driven decisions based on collective analysis of people from different backgrounds, expertise and diverse views. Since every person has their own perspective, collaboration in visual analysis of large, complex, and diverse data derives better decision from work parallelization, communication and social organization between the perceivers. The collaboration can be synchronous, asynchronous, or remote based on the requirement [103]. There are many visual analytics tools that allows collaboration like Tableau, Power BI, and Datawrapper in the market. Two of the most important criteria to be considered while addressing collaborative visual analytics is the selection of perceivers and division of work. Some of the other factors affecting collaborative visual analytics are addressed and resolved in [104] and [105].

Visual analytics is addressed as a multidisciplinary area [3] that embodies data analytics, human-computer interaction, cognitive science, statistics, knowledge-discovery and more. Accordingly, as many areas can be integrated with visual analytics that enhances the multidisciplinary elements.

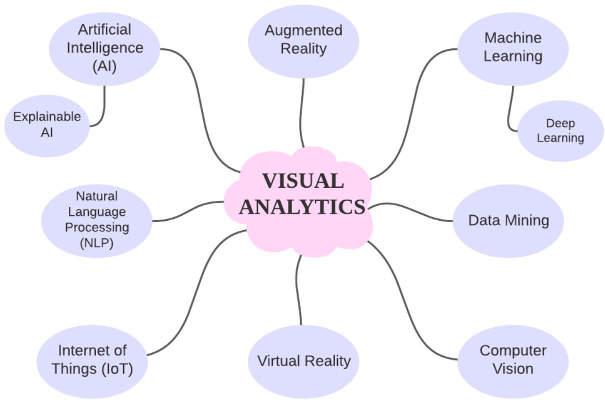

Fig 6. Areas that integrate visual analytics

Visual analytics is also problem-oriented and the approaches to decision-making encapsulates diverse technologies depending upon the type of data and nature of decision. Figure 6 illustrates different areas of interest of visual analytics to aid problem-specific, data-driven decisions. The key to a better visual analytics solution lies in the selection of appropriate technologies to be integrated to both analytical reasoning and visualization processes.

5. Visual Analytics Challenges

With the enormously growing data, the techniques to visually analyze them should also be upgraded. Visual analytics has been making progress over the past 20 years with new tools, technologies and applications; still, the information overload challenges visual analytics in many ways.

Primarily, scalability is a great challenge for visual analytics. Highly efficient visual analytics systems should be able to provide all aspects of information. There is always a limit to human skills of perception, for instance, our eyes do not have the capacity to adjust zoom levels, nor we can remember and process large volumes of data in a less duration of time. Basic human skills do not accelerate with rapid growth of data. This is the major cause of scalability challenge. To make it easy for human analysis, the visual analytics should be able to deal with scalability issues. Scalability challenge comes in five ways. To start with, Information scalability implies the flexibility of extracting information from massive data streams, adhering to the dynamic change of data. Information scalability should also address the type of receivers to whom the information is delivered, by scaling the volume of information to be presented to different kinds of audience. Visual scalability addresses the ability to effectively represent the visual elements without the constraints relating to data volume, complexity and diversity. Visual scalability is affected by factors like visual metaphors and interaction techniques. New techniques are needed to bridge the gap between current methods of visual representations and enormously growing data streams. Another type of scalability challenge comes in association with visual display units is display scalability, which aims to represent very large and complex information in any kind of display units, varying from wall-sized displays in large rooms to phone-sized displays in a hand. The problem faced here is to represent information from massive datasets, which is also complex in structure and which incorporates interactivity, compatible to all types of display devices. Software scalability allows a software system to perform visual analytics on large-scale data. To increase software scalability, new algorithms should be developed to visually analyze the diverse and dynamic, large data streams. An inevitable part of visual analytics systems is human perception. Human scalability comes from the same. No matter how large and rapidly growing the data streams are, there is always limits to human perception and cognition skills. Since these skills are not constantly growing unlike the data volumes, visual analytics systems must scale according to human's ability to perceive information, representing the data in a way that can easily and quickly be perceived and subjected to judgement [1].

Another major problem that exists with visual analytics is that it does not have a proper algorithm or generalized framework. Visual analytics techniques and applications are highly dependent on the problem, so it differs from context to context. In this article, we observed the visual analytics process and outlined it as a generalized procedure to facilitate in implementing visual analytics for various decision-making problems.

Evaluation of visual analytics systems are also lacking efficient methods. Expert opinions are used largely as evaluation technique since the results rely on what human perceives, which cannot be calculated based on any accounts other than the perceivers' opinion. So, experts are chosen from the field, who are mostly the users of the system to assess the performance of the visual analytics tool, technique, or application. Although techniques are being developed for evaluating the performance of visual analytics systems [83], it is far more distant from a generic and effective method.

6. Future Scope of Visual Analytics

Future scope of visual analytics primarily emerges from its challenges. Overcoming various scalability challenges opens the door to innovations in visual analytics. Making a generalized framework for visual analytics will help to solve any problem that requires effective analysis which cannot be done with analytical reasoning or visualization solely. Using advanced algorithms or hybrid extraction methods in selecting needed information from massive data volumes helps in enhancing information scalability. Introducing new visual metaphors to effectively represent the information, bringing new visual interaction mechanisms with respect to data dimensions, and proposing new visualization algorithms to ease complexity of graphical representations will bring great reduction in scalability issues. Also, research can be done with regard to optimizing the display sizes so that the information to be visualized stays versatile irrespective of display specifications.

Since limitation of human cognition skills hinders the growth of visual analytics, integrating artificial intelligence and artificial neural networks to the visual analysis process can boost the understanding of what data says. The same can be applied to evaluation techniques. Since many visual analytics systems use expert assessment as evaluation method, incorporating artificial intelligence and generative preprogrammed systems will certainly improve the efficiency of evaluation.

According to the analysis of over many years, it is indisputable that data streams will keep volumizing to greater extents. That being the case, bringing quantum computing in analysis techniques and interactive visualizations will speed up the process despite the data being complex, massive and dynamic, thus pave the way for visual analytics solutions to a wide variety of problems that needs data-driven decisions.

7. Conclusion

In accordance with the advancements in technology, state of art of visual analytics is constantly evolving. Integration of artificial intelligence and machine learning techniques facilitate human perception and improves the efficiency of visual analytics systems. Also, the development in the field of analytical reasoning as well as interactive visualization leads to positive changes in visual analytics. Even though there is constant progression, challenges exist in efficient representation of data as well as systematic evaluation and understanding of the result, and overcoming these challenges using existing technologies enhances data-driven decision making through visual analytics.

This review laid out a clear picture of visual analytics definitions, process, state of art, challenges in the field, and future directions for visual analytics. The published works on visual analytics and reviews are also taken into account, driving to the significance of this article. In addition, a simple visual analytics approach to detect the intensity of common cold and influenza is also explained through a case study, with the motive of understanding how a visual analytics system can be implemented.

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Author contributions

Megha Narayanan: Conceptualization, Methodology, Literature review, Visualization, Writing-Original draft preparation **Sanil Shanker K P:** Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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