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Bibliometric Analysis On Techniques for Data Visualization

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ABSTRACT

The objective of this paper is to conduct an in-depth bibliometric analysis of various techniques used in data visualization. The methodology involves collecting and analyzing bibliographies and relevant scientific publications related to data visualization techniques, specifically Multidimensional Scaling (MDS), Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), T-Distributed Stochastic Neighbor Embedding (T-SNE), Tree Map (TMAP), Uniform Manifold Approximation (UMAP). The findings from this analysis are expected to provide a comprehensive overview of trends, patterns, and developments in data visualization techniques within the scholarly literature. However, this research has limitations, such as the availability of data and bibliometric methodology constraints. The social implications of an in-depth understanding of these data visualization techniques may contribute to enhancing broader understanding and application across various fields, spanning from sciences to industries. The novelty of this research lies in its comprehensive approach to bibliometric analysis, particularly focusing on data visualization techniques, and the value of this research resides in its contribution to knowledge that can serve as a foundation for further developments in the domain.

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INTRODUCTION

Visualization refers to the process of creating visual representations of data or information. The goal of data visualization is to communicate information through visual media, enabling users to access insights within the data. The properties of a given dataset typically determine the type of visual encoding that is most effective[1] [2].Data visualization plays a crucial role in revealing relationships and trends that might not be apparent when examining raw multidimensional datasets.[3]. Complex datasets often consist of numerous interrelated variables. In such cases, data visualization employs mathematical techniques to reduce the dimensionality of data, allowing for a more intuitive and effective way to observe and understand the relationships between variables.[4]. Data visualization relies on the premise that a picture is worth a thousand words, stating that visualization has the ability to communicate information with high intensity and effectiveness, which can replace or surpass lengthy textual explanations[5]. Progressively, visualization has been positioned at the forefront of research in this century and has rapidly developed in the last decade[6]. Data visualization is beneficial because it transforms the complexity of information into a visually understandable form, revealing hidden insights, facilitating communication, and supporting better decision-making in big data[5]. High-dimensional data visualization is challenging due to various factors such as the number of dimensions, samples, dataset size, density, sparsity, cluster density, and data structure. All these parameters pose challenges in visualizing complex data[7].

The challenges in visualizing high-dimensional data with a low sample size often involve difficulties and issues such as overfitting, the curse of dimensionality, computational infeasibility, and strong model assumptions.[8]. Visualization depends on the number of dimensions and the number of samples in the dataset. The higher the number of dimensions, the more complex the data, while a large number of samples can affect the complexity and total size of high-dimensional data.[9]. High-dimensional data poses challenges such as data management issues. This situation arises from an increase in the number of features or dimensions, making data modeling and analysis more difficult and complex[10]. Furthermore, this data continues to grow and undergo changes over time.[11].

The literature is repeated with statements emphasizing the importance of visualization. Data visualization transforms complex information into easily understandable visual forms, revealing hidden insights, facilitating effective communication, supporting accurate decision-making, and enabling team collaboration in data analysis[11]. Data visualization plays a crucial role in relationships revealing and trends that may not be apparent when looking at multidimensional datasets. The right visualization approach allows users from various backgrounds, both in industry and academia, to gain valuable insights without having to perform complex calculations[12]. Visualization holds a central role in the development of the Metaverse, not only influencing its visual construction processes but also determining how users interact with and understand the created world[13]. With the significant increase in data from rapidly advancing bioinformatics analysis technology, the importance of genomic data visualization becomes increasingly crucial in facilitating the understanding and efficient analysis of structural variations[14]. Visualization is critical in explaining information complexity. Graphs depicting usage changes, maps of marine distribution, sensor infographics, and layouts provide an overview of technology evolution and surveillance areas[15]. Visualization offers significant benefits in aiding the understanding of structures and distributions of solutions generated by algorithms, enabling holistic performance evaluation, facilitating interaction, allowing users to select appropriate solutions, efficiently exploring solution spaces, and reducing problem complexity[16]. The development of high-dimensional data visualization has become a significant source of innovation and identification of promising future research directions. The article emphasizes dimensionality reduction as a key technique in analyzing and visualizing high-dimensional data[17].

In the process of improving visualization quality, researchers have developed techniques focused on handling high-dimensional data to make visualizations easier and more efficient. Borg and Groenen in 1997 developed Multidimensional Scaling (MDS), focusing on transforming high-dimensional data into lower dimensions[18], the t-SNE algorithm[10], the development of t-SNE algorithm based on gradient descent

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approaches[19], Tree Map Technique (TMAP)[9], Linear Discriminant Analysis (LDA)[20], Principal Component Analysis (PCA)[13], Uniform manifold approximation (UMAP)[21].

This article presents a comprehensive examination of research on data visualization, particularly studies addressing data visualization techniques. The basis of this article is a literature review of visualization research and visualization techniques published in academic journals between 1997 and 2023. This study employs network analysis and text mining to identify how research defines data visualization and the techniques used in data visualization.

METHOD

The method of writing this scientific article uses qualitative methods and literature reviews. Through a literature review, this article examines theories and the relationship or influence between variables from trusted sources originating from leading journals that are consistent with the type of qualitative research, namely exploratory research. .

Data Source

Activities in this research include systematic steps, starting with selecting relevant databases such as Web of Science and Scopus. Searches are carried out using predetermined keywords, such as data visualization and data visualization techniques. Bibliographic data from related publications are identified and stored, including information about title, author, journal, year of publication, and number of citations.

Data analysis

To Perform Analysis Involves filtering data to select the most relevant documents based on certain criteria such as year of publication and type of document. Bibliometric analysis was carried out using the special tool VOSviewer to explore patterns, trends and interrelationships among related publications. The results of the analysis are then presented in the form of informative visualizations, such as graphs, cluster maps and networks, to facilitate understanding of the development of data visualization techniques. Careful interpretation of the analysis results is carried out to reveal important trends, Research Focus, And Evolution in the Data Visualization domain. Critical conclusions are explored, and the final report is prepared by considering accuracy, reliability, and limitations of the methodology applied in this research.

Research Instruments

Elements that will be discussed include the number of publications per year, the number of citations or citations received, the name of the model used, the differences or features of the research, the variables that are the focus of the research, and the limitations that influence the scope and results of the research. the research. An in-depth analysis of the research instruments will provide a better understanding of the methods and scope of the study conducted

RESULT AND DISCUSSION

Bibliometric analysis is an approach used to measure and analyze scientific literature in a specific field by utilizing bibliographic data and bibliometric metrics such as the number of citations and journals in which these works are published. The aim is to evaluate the trends, impact and development of a topic in scientific research. In the context of data visualization techniques research, bibliometric analysis provides deep insight into the development, popularity, and contribution of scientific work in the domain by analyzing citations, journal publications, and related literature patterns. Such research leads to a deeper understanding of the evolution of data visualization techniques, including the identification of key contributors, the spread of new ideas, and emerging trends. The results of this analysis provide important information for researchers, practitioners, and policymakers to understand recent developments and future directions in visualizing data effectively, demonstrating the crucial role of bibliometric analysis in providing essential information to stakeholders.

Influence of Data Visualization

Visualization plays an important role in data modeling and knowledge extraction processes, enabling a better understanding of data representations and patterns[22],In the context of healthcare, visualization systems can be used to facilitate the ability of doctors to explain disease details to patients by providing a clear view of internal 3D organs without the need for virtual reality glasses[23]. Visualization plays an important role in facilitating the understanding and interpretation of complex genomic data, and helps present research results in a clearer and more interesting way[7]. Visualization is used to observe the interactions of water droplets and air vortices as well as other microphysical processes in cloud life. This helps researchers understand the phenomena that occur and makes it easier to communicate research results to others[24].

Data visualization has the role of representing and understanding complex data sets in a visual format[25]. Visualization helps in the exploration and analysis of large-scale data sets, enabling the discovery of semantically significant patterns, associations, changes, anomalies and structures in the data[10]. Collaborative data analysis often requires visualization to facilitate coordination and understanding of data among team members[26]. Visualization-assisted data analysis can help in comparing feature distributions, identifying root causes of false classifications, and understanding the performance of machine learning-based models[2]. exploration of sensory substitution for accessible visualization for blind and visually impaired individuals[27]. Visualizations are developed for Education related Course Information with Creation of game based projects[28].

Influence of Data Visualization Techniques

In an era where data is becoming increasingly complex and diverse, the use of visualization methods such as Multidimensional Scaling (MDS) is crucial for understanding complex data structures. In this study, an in-depth analysis will be carried out on the use of MDS techniques and developing techniques for visualizing data. This study aims to evaluate the development of the MDS model by focusing on aspects of differences, relevant research variables, as well as research objectives and limitations. Through an in-depth analysis of these factors, this research will illustrate the importance of applying MDS in this specific context as well as its benefits in uncovering valuable insights from multidimensional data.

MDS techniques have been widely developed over the last few decades by researchers to improve the quality of visualization with the main aim being the creation of low-dimensional space representations from high-dimensional spaces. MDS has developed into two categories, namely Classic MDS by maintaining distance differences in lower multidimensional space, Modren's MDS includes a variety of techniques that do not follow the classical approach, including the use of non-Euclidean distances and additional information such as subjective preferences[29].

Erez Developed the MDS model into MDS+ which significantly improves performance by representing data better and converting data into lower dimensions compared to classic MDS, so that it becomes a more effective tool in dealing with complexity, but the research conclusion states that even though it has better performance than Classic MDS, MDS+ is less reliable or less accurate when working in situations where there is a lot of variability or noise in the data being processed[30].

António M. Lopes a, et.al conducted research aimed at identifying phases and phase transitions in the dynamics of complex systems using an unsupervised machine learning approach with a focus on the use of multidimensional scaling (MDS) as a relevant modeling tool. The results show that the clustering method in multidimensional time-series analysis is able to reveal emergent patterns in data and has the potential to process complex data with more features. Limitations of this study include a dataset that may have bias, a limited data period, and variable selection limited to the number of victims and incidents, which makes the results difficult to generalize into the future.[31].

The MSSPD model was developed to find population structure in 2D maps and is more effective in maintaining global structure compared to other techniques with the limitation that it is difficult to project if there is additional new data in the data set so further development is needed[32]. Geometric MDS with the SMACOF version of MDS was developed to map data from high-dimensional space to lower-dimensional space. Research focuses more on comparing the performance of Geometric MDS and SMACOF rather than the advantages and disadvantages of both. There is a lack of details about how data size and projection dimensions affect the results, and a more in-depth explanation and empirical evidence is needed regarding the generalization of the Guttman transformation in Geometric MDS[33].

The UAMDS model was developed as an extension of MDS to handle uncertain data, with a generic and robust mathematical formulation that supports various types of distributions and specific types of stress, including special formulations for normally distributed data and quadratic stress. Additionally, various visualization techniques focused on uncertainty are available, helping in evaluating the reliability and sensitivity of dimensionality reduction in the context of uncertainty. Limitations in this research include the limitation of distribution models to normal distributions, the assumption of independence in real world situations, the suppression of pairs of distributions that are far apart by using quadratic distances, as well as the relevance of the assumption of local linear continuity in cases of overlapping distributions in high-dimensional spaces. It is necessary to pay attention to these limitations in uncertainty analysis and dimensionality reduction[34].

Daniel Probst conducted research with the object of studying chemistry that the distribution of data obtained produced high-dimensional data by developing a new approach called TMAP (Tree Map) and concluded that the resulting visualization was more efficient than T-SNE (T-distributed stochastic neighbor embedding), by maintaining visualization based on global and local features, the advantages resulting from TMAP are low storage space and shorter time required compared to available methods such as T-SNE, UMAP (Uniform manifold approximation), and PCA.[35]Cai T, ma R conducts a fundamental search by conducting a basic study of the use of the T-SNE method by offering a new theoretical framework for t-SNE analysis based on the gradient descent approach, by providing theoretical guidance for implementing t-SNE and selecting tuning parameters in various application[35].

Haiyang Zhu said that the developed approach achieves a five-fold speedup for KNN graph visualization compared to LargeVis and produces aesthetically attractive visualization results. In this paper, we carry out two comparisons of LargeVis with the weakness that when applied to very large data it will produce better visualizations. less interesting due to the non-convexity of the cost function and visualization of the KNN graph still takes a long time. The results in the research make it possible to optimize the speed of visualization by developing a new approach[35].

Han D developed WebGL which can be accessed openly to support the speed of graph data visualization on a large scale up to 50,000 – 1,000,000 nodes and concluded that the web GL developed is faster in terms of performance compared to toolkits that have been developed such as Sigma.js, D3.js, Cytoscape.js, and Stardust.js. the results of the study did not involve heterogeneous graphs[35]. Toward conducted a study on exploring the correlation between humans and deep learning-based computer vision techniques to evaluate graph visualization techniques, in this section the research does not discuss interactive visualization in the evaluation process[27].

Ding said that Many-objective optimization problems (MOPs) are one of the most challenging problems in multi-objective optimization problems (MOPs). Researchers propose an objective reduction algorithm based on adaptive distribution tree clusters for MOPs. This algorithm is suitable for solving MOPs by the shape of the sample set is irregular, and can improve the usefulness of the human-computer interaction visualization of the Pareto Front. The research does not specifically explain the comparison of the performance of this algorithm with other algorithms, the algorithm developed also does not define a matrix as a reference in measuring the algorithm developed.[16]. Ishii developed a graphical user interface-based Python application called BOXVIA. BOXVIA allows the use of BO without having programming skills, the content of the application being developed is still limited to certain algorithms so that more innovative development is needed to be able to solve and manage multi-objective optimization problems.[36].

CONCLUSION

Based on bibliometric analysis carried out on various data visualization techniques, data visualization plays an important role in transforming complex information into a visual form that is easy to understand. Techniques such as Multidimensional Scaling (MDS), Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), T-Distributed Stochastic Neighbor Embedding (T-SNE), Tree Map (TMAP), and Uniform manifold approximation (UMAP) have been developed as a solution to overcome challenges in high-dimensional data visualization. The importance of data visualization in supporting understanding, communication, decision making, and development of technologies such as Metaverse and its applications in the bioinformatics domain is very significant. This means that the use of these data visualization techniques not only helps in data analysis, but also provides valuable insights in various industries and scientific fields. However, this study has limitations, such as limited data available and limitations of bibliometric methodology. In exploring trends, patterns, and developments in data visualization techniques, bibliometric analysis has provided a comprehensive picture, but there is still room for further development in this domain.

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