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Data Visualization Analysis Based on Explainable Artificial Intelligence: A Survey

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Abstract. With the rapid development of computer hardware and big data processing technology, the bottleneck of intelligent analysis of massive data has changed from "how to deal with massive data quickly" to "how to mine valuable information quickly and effectively from massive data". Visualization and visualization analysis based on human visual perception characteristics, combined with data analysis and human-computer interaction and other technologies, use visual charts to deconstruct the knowledge and rules contained in complex data. This technology runs through the whole life cycle of data science, known as the last kilometer in the field of big data intelligence, and has achieved remarkable results in many big data application analysis scenarios. Traditional visualization analysis is extremely dependent on the user's frequent active participation in the whole life cycle of visualization analysis, including data preparation, data conversion, visualization mapping, visual rendering, user interaction, visual analysis and other stages, which require high professional skills of users and low intelligence of the system. Therefore, the traditional visualization analysis mode and systems have the challenges of high threshold of visualization analysis, high cost of data preparation, high latency of interaction response, and low efficiency of interaction mode. Therefore, this paper introduces the application, challenges in visualization based on explainable AI.

Keywords: Big data, Human-computer interaction, Visualization analysis, Explainable AI.

1. Introduction

Recently, large-scale language models led by Chat Generative Pre-trained Transformer (ChatGPT) [1] have shocked the world with their ability to simulate human language behavior. It has triggered a great discussion on the application of artificial intelligence (AI) in human society. The development of artificial intelligence can not only process a large number of random high-dimensional dynamic data in a timely manner, but also promote physical information coupling with mechanism knowledge to further improve energy utilization efficiency.

In order to improve the overall efficiency of the visual analysis system, researchers [2-5] from the perspective of artificial intelligence and data management, artificial intelligence and data management technology to enable visualization and visual analysis system, improve the intelligence of the system. And then it helps users to efficiently participate in the whole life cycle of visual analysis data preparation, visualization, visual analysis interaction and other links, optimizes the man-machine collaboration mode of visual analysis, improves the quality and efficiency of visual analysis. Based on this, the concept of intelligent data visualization analysis was born, with the core idea of "algorithm empowerment" and "simplification ", enabling the workflow of visual analysis through data management and artificial intelligence techniques. The user's active exploration and analysis in the traditional visual analysis workflow is changed into the intelligent assisted exploration and analysis of machine algorithms, reducing the production and consumption costs of visual analysis and visual analysis, and cooperating to optimize the man-machine collaboration mode of data management and visualization and visual analysis in the whole life cycle of visual analysis, and is committed to assisting users to efficiently perform visual analysis [6-8]. Intelligent data visual analysis is supported by data management and artificial intelligence technology, interactive data analysis through human-computer interaction means, data information deconstruction and visual presentation of analysis results through visual means, to help users quickly dig out valuable information from massive data. Intelligent data visual analysis technology can optimize the man-machine cooperation mode of traditional visual analysis workflow and improve the efficiency of visual analysis. Specifically, intelligent data visual analysis technology can optimize the traditional visual analysis workflow of data preparation, visual generation, big data efficient visual analysis and visual analysis human-computer interaction interface four modules.

1. Data preparation for visual analytics. The data preparation in traditional visualization and visual analysis workflow is not optimized according to the characteristics of visualization and visual analysis, and there are

challenges such as high cost of data preparation, sensitive data quality and incomplete analysis dimension. First of all, in the data discovery stage, traditional methods fail to discover relevant data sets/data tuples according to users' analysis tasks, resulting in the fusion of a large number of data sets that are irrelevant to visual analysis or do not contain enough insight in the data preparation stage, which increases the burden of subsequent visual analysis. Second, in the data cleaning phase, traditional methods strive to find all errors in the data set and clean it to provide a high-quality data set for subsequent visual analysis. However, this method of data cleaning is often costly, and if the intention of visual analysis is considered in advance in the data preparation stage, that is, cleaning the subset of data related to visual analysis queries, the cost of data cleaning can be reduced while improving the quality of visual analysis. In addition, if the dataset attributes obtained are too single, the dimensions of the analysis are often too limited. Therefore, data can be enhanced by associating related data sources to enrich the dimensions of visual analysis. Data preparation technology for visual analysis aims to use data management and artificial intelligence technology, combined with the characteristics of visualization and visual analysis, to optimize the man-machine collaboration mode in the data preparation stage of visual analysis workflow. Prepare high-quality and semantically rich data for users in a low-cost manner to support high-quality visualization and visual analysis [9,10].

2. Intelligent data visualization. Data visualization deconstructs the knowledge and rules contained in complex data by visualizing diagrams. The traditional visualization method requires the user to select and filter out the data subset used to generate the visualization result on the basis of the understanding of the data set, select the appropriate data dimension and carry out a series of data conversion operations (such as aggregation operations). Finally, visualization tools are used to map the data table into the visualization space and render the visual results. If the generated visual results do not meet the task requirements of users in visual analysis, several steps above need to be repeated until the visual results are found to the satisfaction of users. It is not difficult to see that the traditional visualization process is usually circular and iterative, requiring users to participate in data selection, transformation and visualization mapping, and there are challenges such as high threshold of visual analysis [11,12], low efficiency of interaction mode, inaccurate analysis results and incomplete analysis dimension. In order to solve the above challenges, intelligent data visualization technology needs to combine the user's analysis intention, data characteristics, domain knowledge, etc., to automatically generate and recommend valuable visual results in a given data set, and help users to efficiently perform visualization and visual analysis.
3. Efficient visual analysis. In the case of the rapid growth of data volume, constrained by the scalability of computing power and the limitations of display devices, the interactive response latency of visual analysis is high. On the one hand, this is due to the longer data processing and analysis time of the visual analysis system; On the other hand, large-scale data points are difficult to render efficiently and render and interact in real time on a limited number of display devices [13,14]. In order to solve the above challenges, researchers from the hardware and computing framework, data management, artificial intelligence and visualization technology to study efficient visual analysis technology, collaborative optimization of visual analysis of data management and visual interaction efficiency, for example, based on visual perception of data indexing technology and approximate query processing technology, efficient data organization and processing; Using artificial intelligence technology to predict user interaction behavior, efficient rewriting of user analysis queries and data prefetching; Based on visual perception sampling, progressive visualization and real-time rendering technology, efficient rendering and real-time interaction of large-scale data.
4. Intelligent visual analysis interface. Visual analysis interface is the medium for users to interact with the system. On the one hand, the system needs to obtain the user's visual analysis intention and operation instructions through the interactive interface. Traditional interaction methods require users to learn the interaction mode of a specific system (such as programming instructions or graphical interface operation mode, etc.) according to the interaction design rules of the visual analysis system, which requires high professional skills for users, and the learning cost of interactive interfaces is also large, resulting in challenges such as high threshold of visual analysis and low efficiency of interaction mode. On the other hand, the results of visual analysis need to be presented to the user through an interactive interface [15,16]. The traditional method only presents the fragmented findings of visual analysis directly to users, requiring users to further excavate the internal logical relationship and causality of these fragmented visual analysis conclusions, and further organize them into visual analysis reports that can be disseminated within the organization. There is a challenge that visual analysis results are difficult to consume. Based on the above discussion, on the one hand, intelligent visual analysis interface needs to provide users with a simple interactive interface (such as the interface based on natural language query), and use intelligent algorithms to understand the user's analysis intention and generate and recommend visual analysis results, so as to reduce the use threshold of visual analysis system and optimize the man-machine collaboration mode of the system. On the other hand, the intelligent visual analysis interface also needs to automatically mine the internal connections between the visual analysis results based on artifi-

cial intelligence technology. Through relationship mining, information completion, text generation and other technologies, based on the fragmented results obtained from user visual analysis, the analytical dashboard and visual analysis story narrative are intelligently generated, improving the efficiency of user sorting and sharing visual analysis results, thus alleviating the challenge of difficult consumption of visual analysis results.

To sum up, intelligent data visual analysis is supported by artificial intelligence and data management technology, combined with visualization and visual analysis, human-computer interaction and other technologies, and collaboratively optimized four modules of visual analysis workflow: data preparation, visual generation, efficient visual analysis of big data and human-computer interaction interface of visual analysis. Optimize the human-machine collaboration model in the data preparation phase of visual analytics to support users in preparing high-quality analytical data in a cost-effective manner; Intelligent visualization means to automatically generate and recommend meaningful visualization and visual analysis results in data sets to users. Optimize visual production models; Improve the processing efficiency of analytical data based on data management and visualization technology to support real-time analysis and interaction of massive data; Based on data mining, natural language processing and visualization technology, it provides users with a question-and-answer visual analysis interface, and intelligently generates analytical dashboards and visual analysis stories according to the results of visual analysis, reducing the cost of users using visual analysis results.

2. Classical Explainable AI (XAI) Methods

Classical XAI can be divided into two categories according to the interpretation methods, namely, artificial intelligence models with self-interpretation capabilities and artificial intelligence model interpretation methods [17-19]. The former refers to the models with certain explanatory power, including linear models, decision trees, random forests, attention mechanisms, etc. The latter refers to a class of methods used to explain AI models that often have little to do with the model, common methods such as Shapley additive explanations (SHAP) [20], localinterpretable model-agnostic explanations (LIME [21]), gradient-weighted class activation mapping (Grad-CAM) [22] and so on.

2.1. Self-explanatory AI Models

A. Linear Model

Linear models are the simplest and self-explanatory AI models in machine learning, which make predictions by establishing a linear relationship between input features and output features [23]. The predictions of a linear model can typically be modeled as:

$$y = w_1 x_1 + \cdots + w_n x_n + \varepsilon. \tag{1}$$

Where y is the prediction result. x_i is the input feature. w_i is the feature weight that the model needs to learn. ε is the difference between the predicted result and the true value. The main goal of a linear model is to find an optimal set of parameters w_i, which minimizes the error between the predicted output and the actual output, and the common methods include least square method and gradient descent method.

The explainability of linear models is reflected in the importance of intuitively explaining the influence of each input feature on the output result. Since only addition and multiplication are involved, linear models have high computational efficiency and are suitable for practical problems with high data dimensions. However, linear models assume that there is a linear relationship between input and output, so their fitting ability is limited when dealing with nonlinear problems, and there are problems that are more sensitive to outliers.

B. Decision trees and random forests

Decision tree [24] is an interpretable learning method that splits on each node by calculating the entropy of leaf nodes to find the optimal segmentation feature. The interpretability of decision tree is reflected in its ability to transform data into an interpretable form. Each node refers to a decision that can be judged, and a conclusion can be reached through a series of decisions along the branches of the tree. Random forests based on decision trees also have a certain degree of interpretability. As an ensemble learning algorithm, this method aggregates the prediction results of all trees by constructing multiple decision trees to determine a common output result.

However, decision tree and random forest have common defects, that is, when the decision tree has a large number of layers or a complex reasoning process with multiple decision trees, it will become very difficult to explain the reasoning process according to prior knowledge, and the interpretability will be limited to a certain extent. However, decision trees and random forests with large number of layers can also be interpreted and analyzed.

2.2. Artificial Intelligence Model Interpretation Methods

The artificial intelligence model interpretation method mainly refers to the method that can explain the existing artificial intelligence black box model. In general, common AI black box models in power systems include DNN, deep reinforcement learning (DRL) [25], and Gaussian processes.

1. The unexplainability of DNN is mainly reflected in the interaction between its complex network structure and multi-level network parameters, which makes it difficult to interpret the final prediction results intuitively. In addition, there may be multiple combinations of activation modes of different neurons for the same input, which also increases the difficulty of understanding the internal principles of the model.
2. The unexplainability of DRL is mainly reflected in its learning process, which optimizes strategies through interaction with the environment. The state transitions and reward changes in this interaction are often difficult to explain intuitively. At the same time, the parameter updating process of DRL policy network and value network is complex and interdependent, which makes the decision-making process of the model difficult to explain.
3. The unexplainability of Gaussian process is mainly reflected in its inference process based on probability distribution. The Gaussian process calculates the covariance matrix of the input data to obtain a predicted distribution. However, this probability-based reasoning process is often difficult to explain intuitively when dealing with high-dimensional data and complex relationships.

3. Intelligent Data Visualization

Data visualization is the most important part of visual analysis workflow. It maps the original data into visual charts and helps users to quickly capture the data information conveyed by visual charts. However, creating visualizations from data tables that help users understand the data or present the knowledge contained in the data is a challenging task. First of all, visualization is a tedious task that requires relevant professional skills, requiring users to master a specific programming language or data visualization system, which has a high threshold. Secondly, ordinary users and even many analysts need to spend a lot of time to understand the semantics of data sets, select data attributes for visualization, perform appropriate data conversion operations, and finally select appropriate visual charts for rendering. The whole process is cyclic iteration, which is characterized by low efficiency of interaction mode. In addition, because data visualization is highly dependent on the user's professional skills, for complex data or complex data analysis tasks, there may be inaccurate analysis results and incomplete analysis dimensions. Generally speaking, data visualization has challenges such as high threshold of visual analysis, low efficiency of interaction mode, inaccurate analysis results, and incomplete analysis dimensions [26-28].

(1) Knowledge guidance. The knowledge-guided intelligent data visualization recommendation method is mainly to construct the knowledge graph of the visualization domain or to encode the visualization domain knowledge and integrate the relevant domain knowledge to make the visualization result recommendation. The knowledge-guided approach first limits the search space of candidate visualizations, and then provides a basis for the classification, ranking and recommendation of candidate visualizations.

(2) Data-driven. Data-driven intelligent data visualization recommendation methods mainly refer to the means such as machine learning and deep learning. Based on a large number of visual corpora learning visualization results recommendations.

(3) Hybrid mode. A hybrid model is a system that combines a knowledge-guided and data-driven approach to make recommendations for visual results. For example, a series of constraints on visual domain knowledge are obtained through knowledge-guided approach to limit the visual recommendation space, and a data-driven approach is combined with a machine learning ranking model to recommend visual results.

Data2Vis [29] regards the data visualization recommendation task as a sequence-to-sequence translation task, that is, from the data sequence to the visual query language sequence. Based on this assumption, Data2Vis built a sequence-to-sequence automatic data visualization model based on bidirectional recurrent neural networks (BiRNN). The input to Data2Vis is a pre-processed data sequence and the output is a visual sequence represented in the Vega-Lite query language. Data2Vis learns based on 4300 training samples (data sequence, visualization sequence) generated from 11 different data sets, although Data2Vis can recommend visualization results based on data features through a model from the training data sequence to the visualization sequence. However, Data2Vis has some disadvantages such as poor interpretability, few data conversion operations, poor generalization, and only support for Vega-Lite visual syntax.

Compared to Data2Vis's small-scale training data, VizML9 considers more than 100 data features relevant to visualization design and trains neural network models from millions of real-world visualization data to learn automatic recommendations of visualization Spaces in automatic data visualization. Compared with the aforementioned data visualization recommendation work, which also considers the operation of data space and visualization space in the process of automatic recommendation visualization, VizML only considers two types of automatic design recommendation tasks with a total of 5 kinds of visualization Spaces, and does not consider the recommendation task of data space. For example, given data columns for visualization,VizML only considers what visualization types those data columns should map to and how they map to the X/Y axis of the visualization type [30,31].

Similar to Data2Vis, Table2Charts [32] also views data visualization recommendations as a task of learning from data sequences to visual sequences. As mentioned earlier, Data2Vis' visual sequences are represented in the Vega-Lite language, while Table2Charts uses a common serialized visual chart template. The chart template contains only the necessary visualization elements (such as visualization types, data columns, and so on). As a result, Table2Charts can support rendering of the final result in a variety of visual languages. Compared to Data2Vis, which uses data sequences as direct input, Table2Charts learns from the presentation of data columns and statistics in the data table. Table2Charts generates data sequences to visual template sequences through deep Q-learning with replication mechanisms and heuristic search.

In recent years, with the wide application of deep learning technology in the field of natural language processing, a number of advanced natural language processing models based on deep learning have emerged, which show that they are comparable to humans in tasks such as machine translation. Based on the above discussion, the researchers began to explore how to use deep learning techniques to complete the NL2VIS task.

In order to train and evaluate NL2VIS models based on deep learning, SEQ2VIS proposes nvBench, the first NL2VIS data visualization benchmark dataset. The dataset contains 153 databases, 780 tables and 25750 natural language query and visual result sample Pairs ((NL, VIS)Pairs) and covers 105 domains (such as healthcare and sports). Based on the proposed NL2VIS benchmark dataset nvBench, SEQ2VIS proposes an NL2VIS model based on sequence-based model. The input of the model is a natural language query sequence and the output of the model is a data visualization query language. Through this model, SEQ2VIS provides users with an end-to-end deep learning-based visual recommendation system that integrates user analysis intent [33,34].

In the continuous visual recommendation scenario, the existing visual recommendation system does not consider the characteristics of the previous recommended visual results (anchor visual results) when recommending new visual results. Therefore, it may occur that the visual mapping and data conversion mode of the current recommendation results are different from the historical recommendation results, which increases the difficulty of users' understanding of the current recommendation results. To address the above challenges, Dziban considered the properties of anchor visualization results when recommending current visualization results. In summary, Dziban recommends other visualizations that are perceptually similar to the results of anchor visualizations within the constraints of user-given data sets and partial data visualization queries. Dziban uses the Draco visual knowledge base to automate the auto-completion of part of the visual query, and recommends results that are similar to the provided anchor visualization through the similarity algorithm. VISER [35] proposed the idea of visualization by example for visualization results. VISER automatically synthesized visual query language based on the data table provided by the user and part of the visualization as sample input. Recommend candidate visualization results with the same visualization form on the data table [36-39].

4. Conclusion and Future Work

Intelligent data visualization and visual analysis based on data management, visualization, human-computer interaction, artificial intelligence and other technologies, collaboratively optimize the man-machine collaboration mode of visualization and visual analysis, improve the intelligence degree of visual analysis system and reduce the threshold of visual analysis, can promote the popularization of visual analysis. Based on the above vision, this chapter will look into the development trend and research opportunities of intelligent data visual analysis from the aspects of data preparation for visual analysis, intelligent data visualization, efficient visual analysis and intelligent visual analysis interface.

Supporting for privacy protection of multi-party collaborative visual analysis. In real-world scenarios, data is often held by different data providers, and although industry and academia are concerned about how to efficiently analyze these data held by multiple data providers, the following challenges remain. First of all, the existing visual analysis system usually assumes that the data source is stored in the analysis side, if the multi-party data is directly collected for visual analysis, on the one hand, there may be problems such as data security, data copyright and legal compliance. On the other hand, there is additional overhead in the transmission and storage of multi-party data in visual analysis interaction, and secondly, multi-party collaborative visual analysis will also face the challenges of data version control, analysis interaction and collaboration. Therefore, how to explore a new interactive mode of multi-party collaborative visual analysis based on key technologies such as secure multi-party computing, confidential computing, federated learning and differential privacy, and realize the multi-party collaborative visual analysis for privacy protection is worthy of research. The realization of multi-party collaborative visual analysis for privacy protection is conducive to alleviating the problem of data silos in many analysis scenarios. It is conducive to promoting cross-domain multi-dimensional data enhancement and enriching the dimensions of visual analysis. It is beneficial to play the data advantages of different data providers and improve the quality and efficiency of visual analysis.

Interpretable intelligent visual analysis. Existing visualization and visualization analysis systems mainly focus on how to help users generate meaningful data visualization results, so that users can analyze and reason through visual results. However, these visualizations often do not have a good ”explanatory ”, which is mainly reflected in the fact that the user may only draw a conclusion from the current visual results, but cannot know the root cause of the conclusion. Therefore, visualization and visual analysis systems need to provide some interpretation of the results to help users better make accurate reasoning judgments and avoid drawing wrong inferences. In a nutshell, the goal of interpretable visual analysis is to make users ”realize the lineage and why”. The research of interpretable visual analysis can be carried out in combination with technologies such as data lineage and root cause analysis.

In the era of big data, the efficient visual analysis of massive data faces the challenge of high latency in interactive response. Most of the existing research focuses on the constraints of computing power scalability, and optimizes it from four perspectives: hardware and computing framework, data management, artificial intelligence and visualization. However, existing research has not well considered the characteristics of visualization and visual analysis tasks to synergistically optimize the challenges posed by the two constraints of computing power scalability and display device limitations. Future research can start from the perspective of artificial intelligence, and collaboratively optimize data management, user interaction behavior modeling, user analysis intention prediction [40,41], and visual representation in visual analysis workflow based on artificial intelligence technology to support real-time interaction of visual analysis of massive data. For example, you can analyze and learn from historical user interactions to predict future visual analysis queries. Intelligent data management techniques can also be used for visual analysis query rewriting and accurate data prefetching for analysis scenarios. For the huge storage overhead brought by massive data, deep learning technology can also be used to compress the expression of data and visual results, reducing the cost of data communication and display rendering.

At present, most visual analysis systems are built by researchers using different technical routes and frameworks according to different visual analysis tasks. Therefore, it is not difficult to find that there are two major problems in the application ecology of intelligent data visual analysis: (1) Lack of public reusable intelligent visual analysis modules; (2) Collaboration and compatibility between different visual analysis systems are difficult, and it is difficult to seamlessly interface with other data science systems. One of the factors that can make a significant impact on deep learning/machine learning in various industries is the establishment of a good application ecosystem, such as the development and maintenance of common basic computing models (such as scikit-learn) and the construction of multi-party shared and co-built machine learning development frameworks (such as PyTorch). Therefore, academia and industry need to work together to condense the standard calculation and development framework of intelligent visual analysis, jointly build the basic calculation and analysis model of intelligent visual analysis, and promote the construction and development of intelligent visual analysis application ecology.

5. Conflict of Interest

All authors disclosed no relevant relationships.

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