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Perspective:

Perspectives on cross-domain visual analysis of cyber-physical-social big data*

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The domain of cyber-physical-social (CPS) big data is generally defined as the set consisting of all the elements in its defined domain, including domains of data, objects, tasks, application scenarios, and subjects. Visual analytics is an emerging human-in-the-loop big data analytics paradigm that can exploit human perception to enhance human cognitive efficiency. In this paper, we explore the perspectives on cross-domain visual analysis of CPS big data. We also highlight new challenges brought by the cross-domain nature of CPS big data—data, subject, and task domains—and propose a novel visual analytics model and a suite of approaches to address these challenges.

1 Introduction

The CPS space is a product of the information age, and is represented by the Internet of Things, cloud computing, and mobile Internet. It is co-occurring, highly integrated, deeply related, and has high system complexity and uncertainty (Wang FY, 2010). Analysis and application of CPS big data can provide a powerful tool for situational awareness (Cao et al., 2020), status monitoring, anomaly warning, and scenario simulation, which can improve the efficiency of social governance.

The CPS space is a typical complex system, and requires an appropriate analysis method (Manyika et al., 2011). Existing methods, such as those for complex networks (Pan et al., 2020), data mining, machine learning, and data intelligence, are used to analyze CPS big data from different perspectives and levels. However, there is still no general and easy-to-use big data analysis system. The reasons are threefold. First, CPS big data includes multi-domain and multi-modal system phenomena. The research community does not yet have an efficient big data analysis theory or method that can be adapted to such complex giant systems. Second, artificial intelligence algorithms usually require precise prior knowledge (Xu, 2020). When there is a lack of prior knowledge, it is difficult to ensure the accuracy of the results (Zhou, 2016). Third, CPS big data is based on complex and large-scale spatial structures, rapid physical evolution, and social activities. The analysis of CPS big data should be flexible and cannot be simply customized.

By visualization, data is converted into easily understandable and interpretable representations that assist humans in gaining knowledge from data (Munzner, 2014; Wang XM et al., 2020a; Zhang

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et al., 2021). Because visualization provides an overview of data and allows users to explore data subsets of interest, it is an important means of conducting big data analysis in the CPS space. It integrates human intelligence and machine intelligence in the analysis process, which can significantly improve the efficiency, accuracy, and application of automatic analysis (Chegin et al., 2020; He et al., 2020). However, visual analysis of CPS big data faces two critical challenges:

1. Challenge 1 (C1 for short): Existing visual analytics methods still lack intelligence. Intelligent visual analysis of CPS big data should overcome the stereotype of data intelligence, the inefficiency of automatic visualization, and the unavailability of human–machine collaboration (Ma KL and Shen, 2020; Ma RX et al., 2021).

2. Challenge 2 (C2 for short): CPS big data is cross-domain in nature. There are multiple domains in the CPS space, such as space, data, task, application scenario, and analysis subject. In this paper, we focus on three domains: data domain, subject domain, and task domain.

In this paper, we uncover the perspectives on cross-domain visual analysis of CPS big data. We propose an innovation in the visual analytics mode to address the aforementioned challenges posed by exploiting the cross-domain nature of CPS big data (Schirner et al., 2013) (C1). We focus on critical challenges of CPS big data in the cross-data domain, cross-subject domain, and cross-task domain (C2). Cross-data representation constructs a unified data representation model for cross-subject collaborative visual analysis and cross-task guided visual analysis; cross-subject collaborative visual analysis realizes efficient integration of different subjects' intelligence; cross-task guided visual analysis realizes cross-domain migration of analysis tasks. We attempt to build a new cross-domain visual analytics theory and methods to overcome the shortcomings of existing visual analytics methods, which are applicable only to a single domain. Fig. 1 illustrates the proposed pipeline of cross-domain visual analysis of CPS big data.

2 Federated data representation

CPS big data is hyper-dimensional, heterogeneous, and cross-domain. A federated framework integrates techniques of differential privacy and homomorphic encryption, and can effectively avoid privacy leakage. Seeking privacy-preserving analysis for CPS big data, we design a new mechanism of federated data representation that supports visual analysis. Specifically, in this new mechanism different data application scenarios, modalities, and sources should be considered. Fig. 2 illustrates

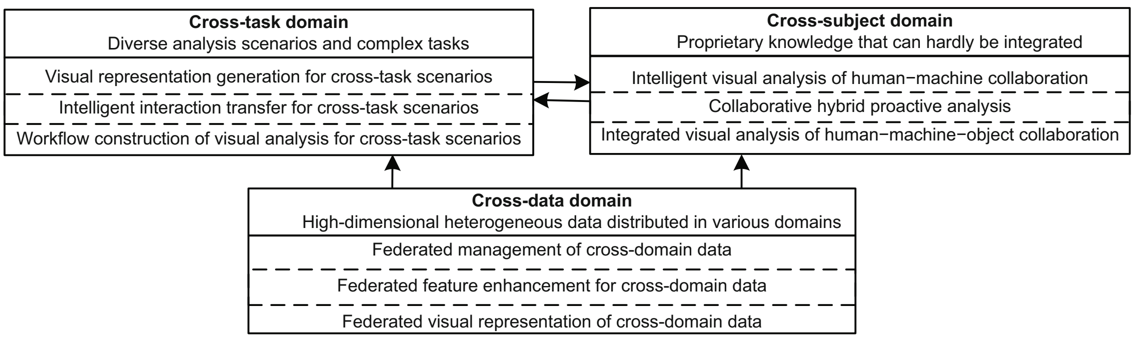

Fig. 1 The pipeline of cross-domain visual analysis of CPS big data

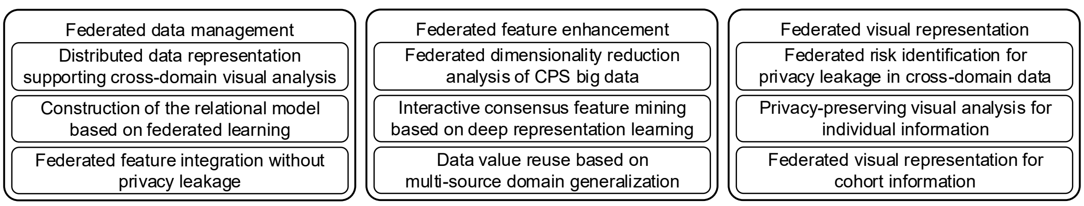

Fig. 2 The pipeline of federated representation of cross-domain data

the pipeline of federated representation of cross-domain data, including federated management, feature enhancement, and visual representation of cross-domain data.

2.1 Federated management of cross-domain data

CPS big data faces challenges of data quality and privacy protection (Aledhari et al., 2020). To support cross-domain visual analytics, it is necessary to design and implement cross-domain data integration and management in a privacy-preserving way.

We propose three ways to realize federated data management: (1) novel distributed data representation paradigms to extend single-domain data representation methods (e.g., hash functions, R-trees, and data cubes) to cross-domain representations in the CPS space; (2) cross-domain data association models based on the federated framework to help construct association models, such as data similarity association and semantic association ones; (3) a new paradigm for federated information integration to ensure privacy protection of data from multiple parties involved in the visualization and analysis process.

2.2 Federated feature enhancement for cross-domain data

CPS big data is always collected from multiple sources that are heterogeneous in nature. Moreover, its features can be offset, unevenly distributed, and heterogeneous. Therefore, it is necessary to efficiently carve out the important features and patterns to improve user experience and analysis efficiency while protecting user privacy.

One possible solution is to improve dimensionality reduction methods, e.g., t-distributed stochastic neighbor embedding (t-SNE), multidimensional scaling (MDS), and principal component analysis (PCA), which are applicable only to single-domain high-dimensional data and support dimensionality reduction of high-dimensional data in the CPS space. Another possible solution is to build consensus feature-mining methods for cross-domain data. The generalization of cross-domain mining models based on feature transfer can transfer models trained in high-quality data domains to low-quality "bad data domains" after fine-tuning. This can effectively reduce the complexity of user search, interaction, and analysis during visual analysis.

2.3 Federated visual representation of cross-domain data

A critical challenge in cross-domain visual analytics is to protect the security and privacy of the data (Wang XM et al., 2018, 2019, 2020b). In a conventional federated learning process, the algorithm varies while the data does not (Meng et al., 2021). Therefore, the federated learning framework cannot support visual representation of full-domain data, making it difficult to gain insight from the data.

To achieve the federated visual representation of cross-domain data, we propose the following three key points. First, it is important to identify privacy exposure risks. We emphasize that the coordinating complex background knowledge in the CPS space should be used to decipher sensitive information. Second, it is important to use privacy-preserving models to build visual representations of features that can adequately characterize data under the premise of resisting diverse privacy threats. Third, it is important to build a federated visual representation of cross-domain data. A possible method is to extend the federated mechanisms designed for training general data mining models to the construction of visual representation.

3 Cross-task visual analysis

For big data analysis in the CPS space, we need to cope with the challenges of multi-task and cross-task analysis. To flexibly adapt to different kinds of complex tasks, it is necessary to study the automatic generation of visual expressions and intelligent transfer of visual interactions across tasks. This benefits knowledge generation, reasoning, and method reuse, so that visual analytics methods for CPS big data can be standardized and generalized. Fig. 3 illustrates the pipeline of cross-task visual analysis.

3.1 Automatic generation of visual representations

For a given data set and an analysis task, automatic generation of visual representations that match human visual perception is the basis for cross-task visual analysis. Here, we discuss automatic visualization recommendations that serve multiple tasks. To realize the mapping from the data space to the visual space, the studies should be twofold. First, a new metric for visualization quality is needed to reflect the distributional characteristics of the input

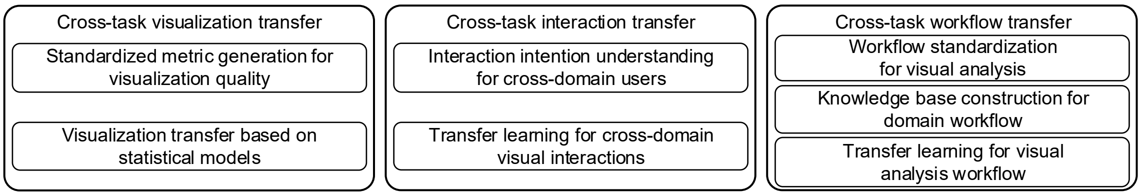

Fig. 3 The pipeline of cross-task visual analysis

data and the impact of different analysis tasks on visualization quality. This new metric should be built on multiple perspectives, such as visual psychology and machine vision. Second, it is important to investigate new methods for automatic visualization generation, optimization, and style transfer for a given visualization quality metric to migrate existing visual representations to new data and analysis task scenarios.

3.2 Automatic transfer of visual interactions

Existing multi-level task abstraction frameworks decompose complex tasks into multiple simple tasks. This requires many iterations of exploratory visual analytics. In cross-task analysis, automatic transfer of intent-driven interactions can significantly shorten the tedious interaction process.

We emphasize three key points. First, it is necessary to build a visual interaction space based on user intent. We propose to mine user intent through existing interaction methods in visual analytics systems, study the shared representation of cross-task visual interactions, and construct an intent-based visual interaction specification. Second, it is necessary to study the user-intent construction model using different analysis tasks. This realizes interaction reuse, transfer, and automatic generation.

3.3 Automatic construction of the visual analytics workflow

The visual analytics workflow usually cannot be reused for different tasks, resulting in the need to repeat the entire analysis process for new tasks and data, which is extremely inefficient. This issue can be addressed by constructing workflows that support cross-task analysis, which enables reuse of the workflows and improves the efficiency of interactive analysis (Giovannangeli et al., 2020).

We emphasize two key points here. First, the standardization of the visual analytics workflow should be studied. This requires examination of the cross-task analytics workflow mapping and construction of a visual analysis oriented workflow. After that, the visualization results can be interpreted, and interactions can be intelligently recommended (Zhu et al., 2020). Second, it is important to study associations within the cross-task workflow. The mechanism of reusing knowledge reasoning can realize the automatic generation of knowledge across task domains, and can construct the criterion of cross-task visual analysis. Specifically, we suggest building a modular cross-task workflow, which can be applied to both related and unrelated tasks.

4 Collaborative visual analytics

In exploratory visual analytics approaches, humans dominate the interactive analytics process. Establishing a new workflow across human and machine intelligence can reduce human cognitive costs and intervention. Moreover, exploring the new cross-subject (human, machine, and object) visual interaction theory can help form a human–machine–object collaborative agent. Fig. 4 illustrates the pipeline of collaborative visual analysis across subject domains. Among them, intelligence-driven visual analysis is the foundation of collaborative visual analysis and human–machine–object intelligent fusion. In turn, progress on the last two sub-tasks will provide guidance to the first sub-task.

4.1 Human–machine integration

Conventional exploratory visual analytics is expensive and requires human intervention. It is necessary to integrate machine intelligence into the visual analytics process to compensate for human deficiencies in long-term memory, computing power, and deep search.

First, visual interactions that support multichannel interactions, such as integrating voice, gesture, touch, and other forms of interaction, can form an immersive interaction environment and improve user perception of massive data visualization

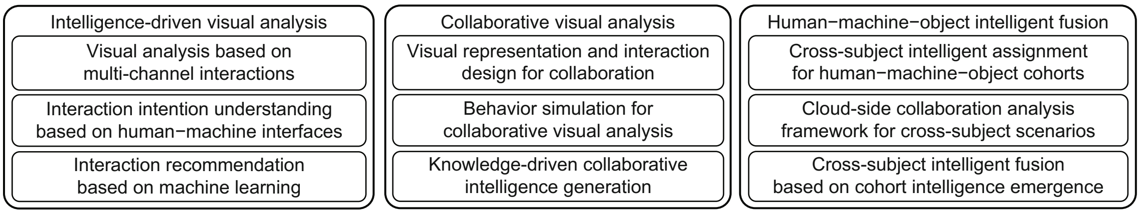

Fig. 4 The pipeline of collaborative visual analysis across subject domains

elements. Second, techniques for perceiving visual interaction intention can analyze and understand human intention, and therefore automatically recommend visualization and interaction solutions accordingly. Third, new guidelines for visualization understanding and visual interaction reuse should be proposed. These guidelines should be able to support automatic recommendation of visual patterns in visualization results and user guidance during the interaction process (Deng et al., 2021). This significantly reduces the perceptual and cognitive burden of users during visualization exploration.

4.2 Mixed-initiative visual analytics

Collaborative visual analysis of multiple persons can bring together individual analyses to obtain holistic insights that are not available to individuals (Tang et al., 2019, 2021). However, this can lead to different perspectives of human–computer interaction, interpersonal interaction, and multi-computer interaction information, which need to be analyzed in a comprehensive manner.

First, we propose the design of visual representation and interaction paradigms to support multi-person collaboration by exploring the same or different visual views from multiple perspectives. Second, we emphasize the invention of new paradigms of mixed-initiative analysis for multi-person collaboration. The key points are to mine the history of interactions and results of different individuals and to realize multi-person knowledge integration. Analysis of multi-person knowledge and interpersonal communication information can help discover shared knowledge, which can resolve disagreements, integrate knowledge, and generate new insights.

4.3 Fused visual analytics

During the visual analysis of CPS data, different subject domains play different roles. For example, people generate knowledge through cognition and reasoning (Umbleja et al., 2020), machines are good at memory, perception, and high-speed computing, and things (sensors) sense the external environment and generate a large amount of real-time dynamic data. People, machines, and things process a large amount of data, which will eventually converge in the visual analysis interface to realize collaborative analysis and allow emergence of group intelligence.

This new paradigm should be studied from three perspectives. First, the assignment mechanism of tasks and goals should be studied when interacting among human, machines, and objects (Liu et al., 2017; Weng et al., 2018). Second, to support efficient intelligent cross-subject distribution and realize cross-subject collaboration, a cross-subject collaborative analytics framework based on cloud-side collaboration needs to be adopted. Third, new theories and methods should be proposed to support the emergence of group intelligence for human–machine–object collaboration. We expect machines to evolve by learning from human decisions and their consequences, which requires human intervention in the process of data preparation, model training, model evaluation, and model interpretation.

5 Conclusions

We propose a new model for cross-domain visual analysis of CPS big data. Specifically, we propose the integration of machine intelligence in the three key processes of data processing, visualization presentation, and human–machine interaction. This will enable efficient integration and presentation of cross-domain data, distillation of knowledge, and human–machine collaboration, which will lead to the development of the fundamental theory of visual analytics. We believe that our theory and methods can be applied in multiple application scenarios (e.g., medical insurance analysis), and that our theory can effectively support cross-domain visual analytics by reducing human intervention and improving analysis accuracy.

Contributors

Wei CHEN conceptualized the main idea and led the research. Wei CHEN and Yunhai WANG surveyed the relevant materials. All the authors had in-depth discussions; they drafted, revised, and finalized the paper.

Compliance with ethics guidelines

Wei CHEN, Tianye ZHANG, Haiyang ZHU, Xumeng WANG, and Yunhai WANG declare that they have no conflict of interest.

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