Interactive Information Visualization Models: A Systematic Literature Review

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Abstract. Interactive information visualization models aim to make dimensionality reduction (DR) accessible to non-expert users through interactive visualization frameworks. This systematic literature review explores the role of DR and information visualization (IV) techniques in interactive models (IM). We search relevant bibliographic databases, including IEEE Xplore, Springer Link, and Web of Science, for publications from the last five years. We identify 1448 scientific articles, which we then narrow down to 52 after screening and selection. This study addresses three research questions, revealing that the number of articles focused on interactive DR-oriented models has been in the minority in the last five years. However, related topics such as IV techniques or RD methods have increased. Trends are identified in the development of interactive models, as well as in IV techniques and RD methods. For example, researchers are increasingly proposing new DR methods or modifying existing ones rather than relying solely on established techniques. Furthermore, scatter plots have emerged as the predominant option for IV in interactive models, with limited options for customizing the display of raw data and details in application windows. Overall, this review provides insights into the current state of interactive IV models for DR and highlights areas for further research.

Keywords: information visualization · dimensionality reduction · interactive models

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1 Introduction

Developing tools that enable users to explore data and discover underlying patterns becomes increasingly important, with stored data exponential growth, where dimensionality reduction (DR) and information visualization (IV) techniques play a critical role. Moreover, interactive models (IM) have been developed to make dimensionality reduction more accessible to non-expert users by providing a generalized interactive visualization framework [1, 2]. The inception of interactive dimensionality reduction using a linear mixture of DR methods is attributed to study presented in [3]. These models can be classified into various types: geometric approximation or homotopy, color-based, Geo-Desic approximation and similarity-based [2]. Modern DR approaches use improved versions of stochastic neighbor embedding [4]. Similarly, IV techniques are classified into two groups: a) navigation strategies (Zoom and Pan, Overview + Detail, Focus + Context) and b) visual interaction strategies (Selecting, Linking, Filtering, and Rearranging and Remapping) [5]. Additionally, DR methods can be classified into linear and nonlinear techniques [6].

This work conducts a systematic literature review (SLR) to obtain the latest information on technologies used for IV with a focus on DR, by addressing three research questions. We perform a search in three relevant bibliographic databases (IEEE Xplore, Springer Link, Web of Science) covering the period between 2016 and 2022. We adapt the search strings to each database based on the supported format. Our search yields 1448 scientific articles, which we then narrow down to 52 publications through a selection process. We concluded that there was a remarkable increase in articles treating either IV techniques or DR methods, while the number of articles focusing on interactive models for DR is relatively low. Among various trends in IM, IV and DR, authors tend to propose new or modified DR formulations instead of using established ones. Additionally, the degree of customization in how data and details are displayed in application windows is another trend in this area.

The rest of the article is organized as follows. Section 2 presents the methodology used to conduct the systematic literature review. In Sect. 3, we present our key results. Section 4 provides a discussion of the findings and highlights the contributions and limitations of the present work. Finally, in Sect. 5, we draw conclusions and suggest future research directions, emphasizing the potential of interactive models for dimensionality reduction.

2 Methodology

We select the methodology proposed by [7–9] to conduct this SLR. The review protocol is illustrated in Fig. 1 and comprises four stages: (i) defining research questions, (ii) conducting a literature search, (iii) selecting relevant articles, and (iv) extracting and synthesizing data.

2.1 Research Questions

Our review process on interactive IV for DR uses three established research questions (RQ) as its guidelines, as summarized in Table 1. In addition, we consider three scientific

databases that are accessible at our institution (Technical University of the North, Ibarra), namely IEEE Xplore Digital Library [10], Springer Link [11], and Web of Science [12].

Table 1. Research Questions (RQ).

Number	Research Question	Objectives
RQ1	Which interactive IV models have been developed specifically for DR purposes?	Identify IMs that allow for parameter or method selection in controlling DR
RQ2	Which information visualization techniques are commonly used to represent DR?	Identify IV techniques that display DR and offer interactivity beyond basic rotation and zooming
RQ3	What are the most widely adopted methods of DR in IV?	Identify DR methods used in IV that are aligned with the IMs identified in RQ1

2.2 Literature Search

We use ("data visualization" AND "dimensionality reduction") as our baseline search string. Although, for each database search string, we consider each platform's distinct criteria and search functionalities. As a result, we found 1448 documents, with 464 from Web of Science, 639 from Springer Link, and 345 from IEEE Xplore.

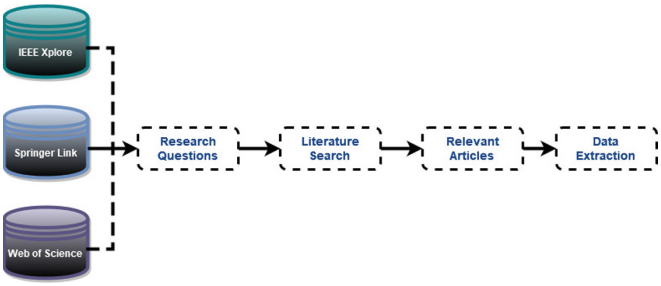

Fig. 1. SLR protocol diagram.

2.3 Selection of Articles

Three phases are set for the selection of articles. In the first phase, we apply inclusion and exclusion criteria. The inclusion criteria are Computer Science related scientific articles and reviews, published between 2016 and 2022 in English. The exclusion criteria are (i) duplicate works, (ii) technical reports, (iii) book chapters, (iv) theses, and (v) studies published in other fields.

In the second phase, we apply criteria related to search strings to highlight the most pertinent literature and respond to the proposed RQs. Then, we order the documents according to the publication, and we initially review the title, abstract, and keywords. Finally, in the third phase, we examine the Introduction and Conclusion sections to confirm their relevance and connection to the three established RQs. Table 2 presents the total number of documents retrieved after the three-phase review process.

Table 2. Selection of Articles for the SLR

Database	Phase I	Phase II	Phase III
IEEE Xplore	345	46	17
Springer Link	639	28	15
Web of Science	464	34	20
Total	*1.448*	108	52

Table 3 presents key details of the 52 scientific articles ultimately selected through our review process. These details include titles, databases, publication years, and countries of publication.

Table 3. Selected Articles for the SLR

Code	Title	Database	Year	Country
A1	A novel color-based data visualization approach using a circular interaction model and dimensionality reduction	Springer	2018	Colombia
A2	Angle-based model for interactive dimensionality reduction and data visualization	Springer	2018	Colombia
A3	Comparative analysis between embedded-spaces-based and Kernel-based approaches for interactive data representation	Springer	2018	Colombia
A4	Dimensionality reduction for interactive data visualization via a Geo-Desic approach	IEEE	2016	Colombia
A5	Generalized Low-Computational Cost Laplacian Eigenmaps	Springer	2018	Colombia
A6	Generalized Spectral Dimensionality Reduction Based on Kernel Representations and Principal Component Analysis	Springer	2021	Ecuador
A7	Interactive data visualization using dimensionality reduction and dissimilarity-based representations	Springer	2017	Colombia

(*continued*)

Table 3. (*continued*)

Code	Title	Database	Year	Country
A8	Interactive Data Visualization Using Dimensionality Reduction and Similarity-Based Representations	Springer	2017	Ecuador
A9	Interactive Visualization Interfaces for Big Data Analysis Using Combination of Dimensionality Reduction Methods: A Brief Review	Springer	2020	Ecuador
A10	Interactive visualization methodology of high-dimensional data with a color-based model for dimensionality reduction	IEEE	2016	Colombia
A11	Introducing the Concept of Interaction Model for Interactive Dimensionality Reduction and Data Visualization	Springer	2020	Ecuador
A12	Inverse Data Visualization Framework (IDVF): Towards a prior-knowledge-driven data visualization	Springer	2020	Ecuador
A13	Data visualization using interactive dimensionality reduction and improved color-based interaction model	Springer	2017	Ecuador
A14	Semantic-aware visual abstraction of large-scale social media data with geo-tags	IEEE	2019	China
A15	Visual Interaction with Dimensionality Reduction: A Structured Literature Analysis	IEEE	2016	Germany
A16	Improved interactive color visualization approach for hyperspectral images	Web of Science	2021	China
A17	Explaining dimensionality reduction results using Shapley values	Web of Science	2021	Brazil
A18	ExplorerTree: A Focus + Context Exploration Approach for 2D Embeddings	Web of Science	2021	Brazil
A19	What you see is what you can change: Human-centered machine learning by interactive visualization	Web of Science	2017	Germany
A20	Supporting Analysis of Dimensionality Reduction Results with Contrastive Learning	IEEE	2020	EE. UU
A21	Scaled radial axes for interactive visual feature selection: A case study for analyzing chronic conditions	Web of Science	2018	Spain
A22	Feature selection based on star coordinates plots associated with eigenvalue problems	Web of Science	2021	Spain

(*continued*)

Table 3. (*continued*)

Code	Title	Database	Year	Country
A23	Designing Progressive and Interactive Analytics Processes for High-Dimensional Data Analysis	IEEE	2017	UK
A24	Hinted Star Coordinates for Mixed Data	Web of Science	2019	Germany
A25	Adaptable Radial Axes Plots for Improved Multivariate Data Visualization	Web of Science	2017	Spain
A26	Cluster aware Star Coordinates	Web of Science	2018	China
A27	SADIRE: a context-preserving sampling technique for dimensionality reduction visualizations	Web of Science	2020	Brazil
A28	DimLift: Interactive Hierarchical Data Exploration through Dimensional Bundling	IEEE	2021	EE. UU
A29	Dimensionality reduction for data visualization and linear classification, and the trade-off between robustness and classification accuracy	IEEE	2020	Germany
A30	Immersive Visualization of Abstract Information: An Evaluation on Dimensionally-Reduced Data Scatterplots	IEEE	2018	Brazil
A31	ChemVA: Interactive Visual Analysis of Chemical Compound Similarity in Virtual Screening	IEEE	2020	Argentina
A32	Focus + context exploration of hierarchical embeddings	Web of Science	2019	Netherlands
A33	PolarViz: a discriminating visualization and visual analytics tool for high-dimensional data	Web of Science	2019	Singapore
A34	SeekAView: An Intelligent Dimensionality Reduction Strategy for Navigating High-Dimensional Data Spaces	IEEE	2016	EE. UU
A35	Glyphboard: Visual Exploration of High-Dimensional Data Combining Glyphs with Dimensionality Reduction	IEEE	2020	Germany
A36	A Graphical User Interface for Fast Evaluation and Testing of Machine Learning Models Performance	IEEE	2019	Mexico
A37	Temporal MDS Plots for Analysis of Multivariate Data	IEEE	2016	Germany
A38	SolarView: Low Distortion Radial Embedding with a Focus	IEEE	2019	Netherlands

(*continued*)

Table 3. (*continued*)

Code	Title	Database	Year	Country
A39	NetScatter: Visual analytics of multivariate time series with a hybrid of dynamic and static variable relationships	IEEE	2021	EE. UU
A40	Gaussian Cubes: Real-Time Modeling for Visual Exploration of Large Multidimensional Datasets	IEEE	2017	EE. UU
A41	Random forest similarity maps: A scalable visual representation for global and local interpretation	Web of Science	2021	Canada
A42	CoeViz: A web-based integrative platform for interactive visualization of large similarity and distance matrices	Web of Science	2018	EE. UU
A43	Scalable Visual Exploration of 3D Shape Databases via Feature Synthesis and Selection	Springer	2022	China
A44	Focused multidimensional scaling: Interactive visualization for exploration of high-dimensional data	Web of Science	2019	Finlandia
A45	Multi-level Massive Data Visualization: Methodology and Use Cases	Web of Science	2018	Lithuania
A46	A general framework for visualization of sound collections in musical interfaces	Web of Science	2021	UK
A47	Interactive browsing of large image repositories	Springer	2019	UK
A48	Interactive Dimensionality Reduction for Comparative Analysis	Web of Science	2022	EE. UU
A49	Attribute-based Explanations of Non-Linear Embeddings of High-Dimensional Data	Web of Science	2021	Germany
A50	SemanticAxis: exploring multi-attribute data by semantic construction and ranking analysis	Web of Science	2021	China
A51	Projective Latent Interventions for Understanding and Fine-tuning Classifiers	Springer	2020	UK
A52	Recommendations Based on Collective Intelligence – Case of Customer Segmentation	Springer	2019	Polonia

2.4 Data Extraction

After a thorough screening process, we extracted data from the articles according to the objectives of the RQs, where several studies addressed more than one research question. We review interactive IV models developed for DR methods in the last five years to identify the most frequently used DR methods in those models and information visualization techniques.

3 Results

In this section, we present the 52 articles (refer to Table 3) that offer insights into the research questions in Table 1. The first question, RQ1, serves as the main inquiry, with RQ2 and RQ3 as sub-questions. Thus, we follow a hierarchical order in presenting the articles, starting with those that answer the main question, followed by those that address the sub-questions.

Interactive Models

An interactive model is defined as a mixture of DR techniques with a generalized interactive IV framework [2, 3] and is intended to bring DR closer to non-expert users [4]. This definition allows for various IMs approaches to be considered. For example, in the work of [4], a literature review shows several types of IM by geometric approximation or homotopy, color-based, Geo-Desic approximation, and similarity-based. The paper published by [13] proposes a geometric IM based on a chromatic circle that distributes three DR methods at 120°. To interact with this model, users can drag a small circle from the edge toward the center using the cursor. The work published by [14] proposes a geometric IM based on the angles of a triangle, where each vertex represents a DR method. These models differ from the IM in [15], which uses the latitude and longitude coordinates of the map of the Earth to mix four DR methods. On the other hand, [16] and [17] propose color-based IM methods where a chromatic triangle represents three DR methods for each corner: CMD, LE, and LLE. Selecting a point within the triangle area initiates DR mixing. Within the same field, [17] develops an interface that interacts with the weights of the DR mixture through horizontal bars, each with one of the RGB colors. In a similar fashion, the model in [18] uses a vertical bar equalizer corresponding to five available DR methods (CMDS, LE, LLE, SNE and t-SNE). Choosing a value in any of the bars initiates a DR mixture. Finally, the result is processed with a similarity-based approximation and displayed in a scatter plot.

The interactive model (IDVF) proposed by [19] allows users to move the points that result from the DR directly on the scatter plot. After that, the reverse process obtains the DR mixture that best fits the new location of the points. However, other types of IM approaches exist, as proposed in [20], which creates a Visual Interaction SLA with DR. This study identifies four types of IM processes for DR: iPCA, Cluster Separation, StarSPI-RE, and Persistent Homology. On the other hand, the work of [21] proposes a framework for expert users like visualization technicians or data operators. This model integrates Machine Learning and Visual Analytics. Moreover, [22] addresses high-dimensional data analysts, and [23] introduces a graphical tool to evaluate machine learning algorithms' performance in classification tasks quickly. Users can access customization options for the data set's characteristics, DR method size, and training batch size. The tool then generates a plot displaying the model's results and accuracy. In [24], an interactive system allows for dataset selection, projection, and clustering. Also, the system updates the scatter plots and generates heat maps of each cluster as the view

changes. Finally, [25] proposes a methodology for IV of multilevel data at scale which improves visual data analysis especially for complex data sets.

Information Visualization Techniques and Dimensionality Reduction Methods Used in Interactive Models

This section outlines the most recurrent IV techniques and DR methods in the selected papers. Works by [1, 2, 13–18, 26–29] utilize the Zoom and Pan strategy through an unmodified scatter plot in either 3D or 2D formats. These works share some similarities in their use of DR methods, which include LE, CMDS, and LLE, with minor variations such as t-SNE [13], RBF [15], SNE [4], or KPCA [19]. Additionally, the selected articles offer clear instances of various IV strategies. For example, [30] presents a Focus + Context interactive exploration tool (SolarView), where the user can click on any entity to focus on it or use the search bar. Meanwhile, [19] proposes a Linking and Selecting interactive model (IDVF) that performs the reverse process of DR mixing (CMDS and KPCA) by allowing the user to move the resulting DR points directly on the 2D scatter plot.

The Filtering strategy reduces the amount of visualized data and focuses on relevant features [5]. For example, [23] introduces a graphical tool to evaluate ML algorithms' performance in classification tasks quickly. The tool offers customization options for the data set's characteristics, DR method size (Linear, Polynomial, RBF, Sigmoid, Cosine), and training batch size. By combining multiple navigation strategies, researchers have developed novel techniques to visualize high-dimensional data. For example, [31] and [32] combine Zoom and Pan and Focus + Context by adding a new context to the data displayed on the scatter plot. In addition, [33] allows the user to explore the scatter plot in a VR environment. PCA is used as the DR method in [33] and [34].

Several works have employed the combination of Overview + Detail for displaying geotagged social media data in multiple windows, including [22, 34], and [35]. In terms of DR, [34] uses t-SNE, while both [22] and [35] use PCA. Rearranging and Remapping is the ability to customize the application [5], as shown in [36], the display changes by reducing the pixels on the screen using DR at varying reduction levels. In addition, [37] maps the data into glyphs that are encoded using DR (PCA, t-SNE and MDS). Several papers adopt more than one navigation and visual interaction strategy. For example, [38] and [39] combine Zoom and Pan, Focus + Context, Selecting, and Filtering. Similarly, [40–42] use Focus + Context, Selecting, and Linking. Moreover, [43] and [44] use Focus + Context, Selecting, and Filtering strategies. In [45], an IV technique based on astronomical coordinates combines Zoom and Pan, Focus + Context, Linking, and Filtering strategies. The user can interact with a bar chart to compare data or remove some features from the plot based on PCA. In addition, The IV technique in [31] is based on radial axes which modify axials by including weights and constraints in the optimization problem, enabling the ordering of attributes using PCA and LDA. The work in [25] proposes a methodology for the interactive visualization of multilevel data at scale. This methodology uses DR techniques such as LLE, PCA, Isomap, and MDS. Meanwhile, [46] proposes a general framework for a modular combination of segmentation, analysis, and projection to two-dimensional spaces using UMAP.

The IV techniques of Zoom and Pan, Overview + Detail, Selecting, Linking, and Filtering are employed in [47] and [48], while [49] and [50] also use Filtering. Similarly,

[51] uses Focus + Context, Selecting and Linking, as well as [52] and [53], which also employ Filtering. Also, the work of [54] presents the Hue Sphere ImageBrowser, an interface for interactively browsing large image repositories, which employs the Zoom and Pan, Selecting, and Filtering strategies. In contrast, [55] proposes SemanticAxis, which creates semantic vectors in a two-dimensional space through interactive means. This technique uses Overview + Detail, Linking, and Filtering strategies. The work in [56] proposes Gaussian Cubes to aid the exploration of large datasets in real-time. In addition, [57] improves Hyperspectral Imaging (HSI) analysis and visualization tools. The work [58] proposes a new IV interface for clusters using celestial coordinate axes. The user can manipulate the points' values and move the axes with an assistance system. Likewise, [59] develops an IV application for long molecule assemblies. Using a Hexagon view, the features are represented by colors and opacity. A difference view compares multiple DR projections and evaluates their reliability. This approach uses t-SNE for DR. Finally, [60] proposes an IV technique that computes one-dimensional temporal MDS plots for time-evolving multivariate data through a sliding window. In [20], a Visual Interaction SLA with DR is developed, including four interactive model processes: iPCA, Cluster Separation, StarSPIRE, and Persistent Homology. These processes utilize various IV techniques, such as scatter plots and Word Maps, and DR methods like PCA, t-SNE, HLLE, or Isomap. Meanwhile, [21] proposes a framework that integrates Machine Learning and Visual Analytics (VA), with a visual interface acting as a mediator between the analyst and the Machine Learning algorithm. Furthermore, the interface allows changes in the observed visualization, restarting the cycle. This framework provides four IV examples: iPCA, Regression, ForceSPIRE, and Baobab-View, which employ IV techniques such as scatter plots and Word Maps, and DR methods like PCA and t-SNE.

4 Discussion

Most articles do not explicitly refer to interactive IV models for DR [1, 2], however, several articles combine the DR and IV domains (see Fig. 2). Also, PCA is the most used DR method, accounting for 16% of the articles reviewed, t-SNE comes in a close second with 14%. However, the "Others" category in Fig. 3, represents methods mentioned or used only once in the SLR, accounting for 20%. These methods are often modifications of existing techniques, but once analyzed together, there is a trend in proposing new DR methods instead of relying solely on existing techniques.

Multiple IV strategies are employed in the selected articles, including navigation and/or visual interaction (see Fig. 4). Zoom and Pan is the most used navigation technique, due to the widespread use of scatter plots in various rendering libraries. On the other hand, Overview + Detail is the least used strategy suggesting a trend toward concealing raw data in the displayed views. Furthermore, Filtering is the most used visual interaction strategy whereas Rearranging and Remapping are the least used. Hence, there is an upward trend in providing filtering tools to the users in the interactive view context, rather than offering customization options to create new types of views.

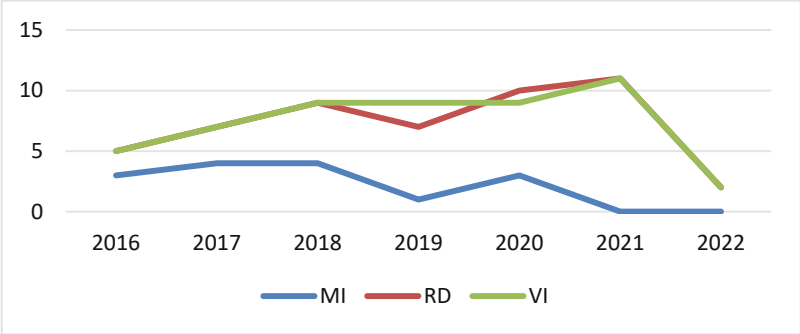

Fig. 2. Number of articles found between 2016 and 2022 in the SLR.

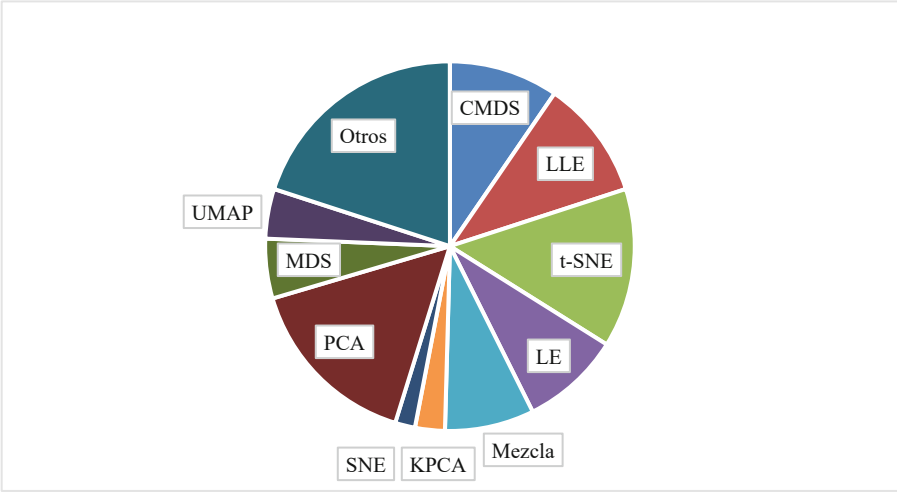

Fig. 3. DR Methods found in the SLR.

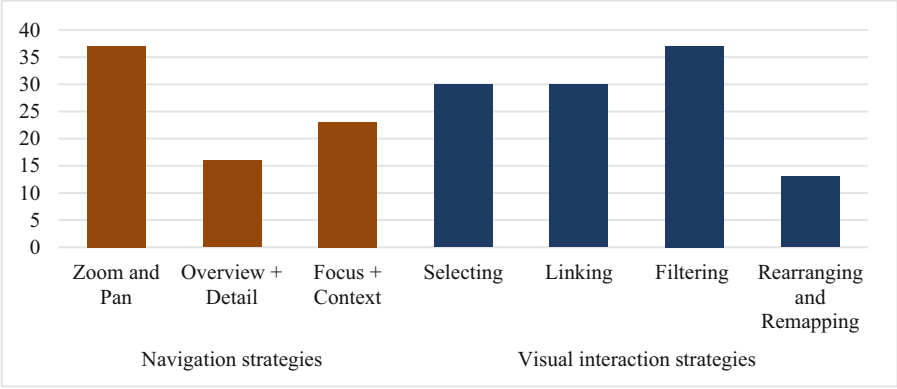

Fig. 4. IV Techniques found in the SLR.

5 Conclusions

A significant number of articles and reviews concentrate on information visualization techniques for dimensionality reduction, while fewer articles address interactive models for dimensionality reduction. This disparity does not imply that research in interactive models is nonexistent. In fact, there has been an increase in the number of articles focusing on interactive information visualization techniques and dimensionality reduction methods since 2020. Our systematic literature review highlights relevant trends and patterns in the use of interactive models for dimensionality reduction. Some studies went for proposing new dimensionality reduction methods instead of using existing ones, with the widespread use of the scatter plot as the primary visualization technique. Furthermore, there is a growing trend toward concealing raw data in the views presented to end-users. Overall, this study provides valuable insights into current research on interactive models for dimensionality reduction and suggests potential avenues for future research.

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