Collection Space Navigator: An Interactive Visualization Interface for Multidimensional Datasets

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ABSTRACT

We introduce the Collection Space Navigator (CSN), a browser-based visualization tool to explore, research, and curate large collections of visual digital artifacts that are associated with multidimensional data, such as vector embeddings or tables of metadata. Media objects such as images are often encoded as numerical vectors, based on metadata or using machine learning embeddings. Yet it remains a challenge to explore, analyze, and understand the resulting multidimensional spaces. Dimensionality reduction techniques such as t-SNE or UMAP often serve to project high-dimensional data into low dimensional visualizations, but require interpretation themselves given their typically abstract dimensions. The Collection Space Navigator provides a customizable interface that combines two-dimensional projections with an array of configurable multi-functional filters and navigation controls. The user is able to view and investigate collections by zooming and scaling, transforming between projections, and filtering dimensions via range sliders and text filters. Insights gained through these interactions can be used to augment original data via easy to use export capabilities. This paper comes with a functional online demo showcasing a large digitized collection of classical Western art. Users can reconfigure the interface to fit their own data and research needs, including projections and filter controls. This open source tool is intended to be applicable in a broad range of use cases, types of collections and across diverse disciplines.

CCS CONCEPTS

• **Human-centered computing** → **Visual analytics**; **Information visualization**; **Visualization toolkits**.

KEYWORDS

visualization, vector embeddings, metadata, interface, cultural data, datasets, text-to-image, information visualization

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1 INTRODUCTION

Large collections of digital artifacts and associated metadata can be effectively studied using browsable interactive visualizations that reflect and resonate with the intrinsic shape of their data [20]. Mapping the topology of a collection into a multidimensional space can help to better understand the overall structure of a dataset and can uncover patterns hinting at underlying trends and dynamics. For example, a researcher or curator may visually explore the space, as constituted by some measure of artifact similarity, looking at different groups of similar objects to identify regions of interest for further quantitative and qualitative investigation.

Multidimensional feature vectors can be used to further describe artifact properties. This can include both categorical and numerical information. Numerical properties can be derived directly from metadata, such as in the case of artifact creation dates, or constructed through various feature extraction techniques. Neural network methods, for example, can encode measures of complex text semantics [8], of visual image properties [12, 15, 16, 33], of joint image-text pair embeddings [27, 29, 35], or of spectral audio features [28]. Hand-crafted feature engineering approaches [41] and algorithmic approaches such as compression ensembles [14] offer interpretable vector representations. Visualizing and exploring patterns in metadata such as artwork creation or acquisition dates can also be informative on its own [36].

Dimensionality reduction techniques can be used to reduce high-dimensional data to a more manageable number of dimensions by remapping or projecting the multidimensional topology into a lower-dimensional coordinate space [2, 22, 24, 37, 38]. For visual interpretation of multidimensional embedding spaces, such projection methods are used to present the data in two or three dimensions, which essentially can function as a reference topography of the original high-dimensional topology. The challenge for dimensionality reduction techniques is to preserve complex relationships, while necessarily compressing information: objects close to each other in the original space should ideally also be close in the low-dimensional topographic projection space.

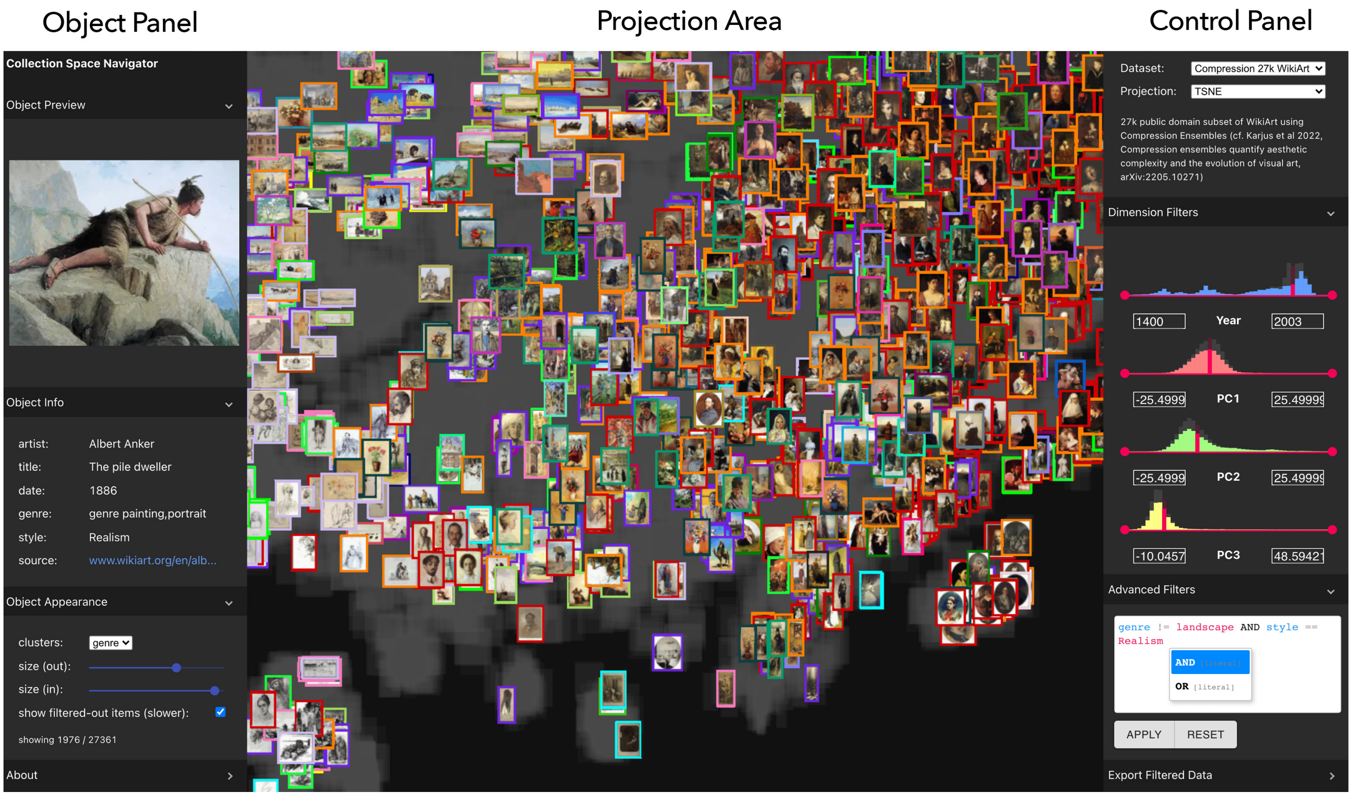

Figure 1: The Collection Space Navigator (CSN). The central *Projection Area* displays a x-y scatter plot of images based on the selected projection (e.g. UMAP, t-SNE), with filtered images greyed out, and mouse-over highlight. The *Object Panel* (left) shows a larger *Object Preview* of the highlighted image, together with *Object Info* based on selected metadata; *Object Appearance* visualizes clusters (optional), sets the projection thumbnail size (zoomed-out and zoomed-in). The *Control Panel* (right) allows for selection of *Data and Projections*; custom interactive *Dimension Filters* and *Advanced Filters* facilitate dataset exploration, analysis, and understanding (see text); the filtered object metadata and current projection view can be downloaded via *Export Filtered Data*.

Multiple projection views can help to better understand multidimensional data [2]. Two-dimensional static projections are visually comprehensible, but can only provide a limited view into multidimensional data. To gain intuition over a high-dimensional vector space, it can be helpful to interpret and compare many different projections. Interactive components in graphical user interfaces (GUI) can further help to gain intuition over the complex interactions between many dimensions. GUI elements such as range sliders are particularly useful to navigate through multiple features and dimensions, and to query and filter the data [1, 40].

2 RELATED WORK

Several interactive visualization experiments and prototypes have emerged in recent years which mediate high-dimensional embeddings through low-dimensional projections. Their focus vary: some aim to provide an intuitive understanding of multidimensionality and embedding methods by visualizing datasets commonly used for Machine Learning tasks [7, 13, 17, 34], or offer explorative interfaces to similarity spaces of cultural collections [9–11, 42]. These interactive visualization projects aim to provide overview and deeper insight into their collections, tailored to specific datasets. The VIKUS Viewer [25, 26] offers a more general framework for exploring cultural collections. It allows not only to view a collection as a similarity map of its image embeddings, but also to dynamically filter metadata such as time and categories. The Selfiexploratory of the Selfiecity project [21] similarly uses a number of range sliders to filter a multidimensional image dataset.

The CSN user interface aligns with classic conventions of cultural cartography and scholarly figure design, using a cartesian projection with an auxiliary index and call-out details [23]. It combines this with the modern paradigm of interactive figure design [5, 39], allowing for a deeper functional user experience (UX) and understanding of multidimensional data. The navigation paradigm of the CSN range sliders, which function as Dimension Filters, further resonates with the recent state-of-the-art of understanding mathematical multidimensionality via interactive animation [30]. The CSN combines these foundations with the paradigm of a scatter plot of images [19]. The CSN is also functionally similar to network visualization applications, such as Cytoscape [31], Helios Web [32] or Gephi [3], which focus on depicting another (yet related) form of multidimensionality in node-link diagrams of complex networks [6].

Relatedly, the authors of the TensorFlow Embedding Projector [34] suggest to include multipanel projections, i.e. more than one simultaneous projection panel. This would also make sense as a possible extension of the CSN and would be in line with the prevalence of "multi-chart" figure panels in multidisciplinary science journals [4, 18].

3 THE COLLECTION SPACE NAVIGATOR

3.1 Motivation

We developed the CSN as a flexible browser-based research tool applicable across various use cases and research domains:

(1) Researching large collections of digital objects (e.g. images, videos, audio, text, 3D models) with the ability to identify patterns and similar groups based on metadata and vector embeddings;
(2) Understanding multidimensionality and projection methods by comparing different embedding spaces and dimensionality reduction techniques through intuitive navigation;
(3) Presenting entire media collections online and communicating research findings with diverse audiences.

While prototypes and use cases exist for each of these aspects as discussed above, we are not aware of a tool that meets all of these requirements. Our contribution therefore lies in the combination and extension of existing interfaces to work towards a more universal, cross-platform, open modular research and curation system. It is highly optimized and capable of displaying large collections of hundreds of thousands of artifacts even on consumer hardware.

3.2 Design principles

To make complex interactions in multifaceted datasets comprehensible while meeting the diverse needs of users such as researchers and curators, we formulated three design principles for the tool:

(1) Providing an open modular system that adapts to different research needs, domains and datasets while preventing information overload;
(2) Providing a complete overview of the collection while encouraging immersive exploration of the objects;
(3) Providing a multitude of interaction mechanisms and modalities to foster intuition, such as zooming, panning, hovering, and sliding through feature dimensions.

3.3 Components

3.3.1 Projection Area. The central part of the interface is the *Projection Area* (Figure 1 center). It maps the given input collection in its entirety as miniature images in an interactive 2D scatter plot, with coordinates defined by the chosen projection method (Figure 2). Basic navigation operations such as zooming or "drag and move" allow free exploration of the projection space. While the user sees only 2 dimensions in the central projection area, the CSN technically includes a third axis for depth. Moving along the depth axis (by zooming) effectively reveals overlapping objects. The appearance of the thumbnails can be adjusted in the *Object Panel*.

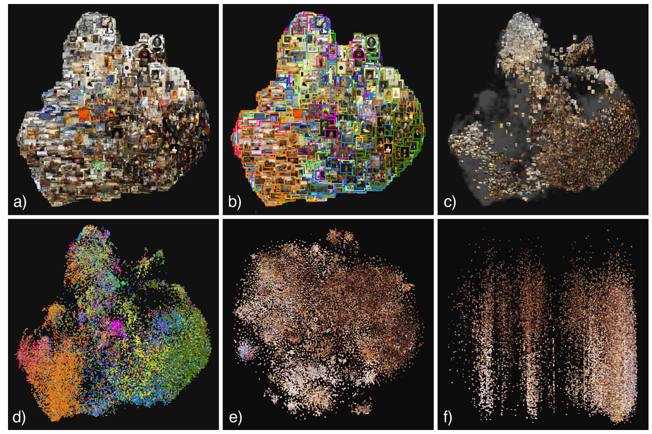

Figure 2: Examples of various 2D projections and visualization features in the CSN tool. a) UMAP projection with large thumbnails, providing a comprehensive view of the image content; b) UMAP projection with medium size thumbnails and cluster colors of categorical data selected in *Object Appearance*; c) UMAP projection with medium size thumbnails and filtered-out objects in grey; d) UMAP projection with small thumbnails and cluster colors, providing a more compact representation; e) t-SNE projection, showing an alternative dimensionality reduction technique; f) Simple x/y plot, here showing a principal component over time for temporal analysis. This flexible tool enables effective explorations and comparison of data across different visualization methods via multiple different 2D projections. These are flexible and based on data import configuration, selectable in *Data & Projections*. Thumbnail size and cluster highlights can be simultaneously adjusted via the *Object View Settings*.

3.3.2 Object Panel. The *Object Panel* (Figure 1 left) has three collapsible sub-menus: *Object Preview*, *Object Info* and *Object Appearance*. The *Object Preview* section displays a larger version of the miniature thumbnail currently hovered on in the *Projection Area*. By default it simply shows a larger version of the same thumbnail, but it can be set to display a higher resolution version of the hovered image, stored either locally or remotely.

The *Object Info* section provides detailed information on the currently selected object. This aspect of the CSN is highly flexible, as the metadata fields that provide this information can be easily defined in the separate configuration file. Minimally it can display just the file name, but it can equally well include extensive metadata — for example in the case of art collections, the author, production year, location, genre, style, and other details.

The *Object Appearance* section contains options to control the visual appearance of the objects in the *Projection Area*. A predefined group (from categorical metadata) can be selected from a drop-down list to show clusters. Objects of the same category are depicted with the same color border around their thumbnails. The size and scale of the thumbnail images are adjustable with convenient sliders. Size

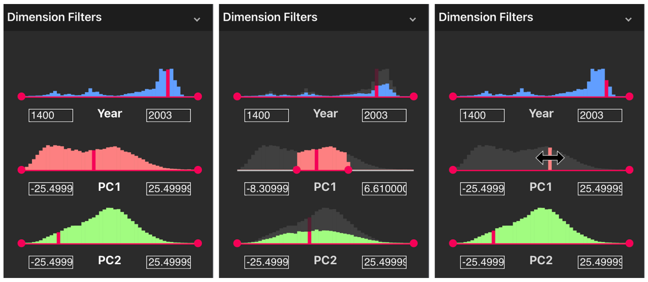

Figure 3: Interactive Dimension Filters. Left: Unfiltered Dimension Filters, consisting of range sliders with interactive histograms above them, showing the distribution of all objects along the slider's dimension with the bin of the currently selected object highlighted in red. Center: reducing the range of one slider affects the distribution of all dimensions, reflected by the histograms. Right: *Bin Mode* functionality is activated by clicking on a histogram, allowing the user to activate one bin at a time, with the Projection Area displaying the corresponding objects within the active bin. These interactive Dimension Filter features allow in-depth exploration and visualization of multi-dimensional data distributions to gain a deeper understanding of the relationships between data points.

determines how large the thumbnails should be when fully zoomed out, while Scale affects the size when zoomed in.

3.3.3 Control Panel. The *Control Panel* (Figure 1 right) has four collapsible sub-menus: *Data & Projections*, *Dimension Filters*, *Advanced Filters*, and *Export Filtered Data*. The *Data & Projections* section contains a *Dataset* drop-down list of selectable datasets. For very large collections, we recommend providing a smaller subset by default and offering the entire set on demand (such subsets can be conveniently produced using the CSN configuration Python notebook). The section also contains a *Projection* drop-down list of selectable projections and mappings. Switching between different projections, e.g. different embedding or reduction methods, smoothly rearranges the positions of the objects in the *Projection Area*. These intuitive animations can provide new insights into the intermediate state between two projections and expose their differences.

The *Dimension Filters* are optional interactive elements that function to filter the objects in the *Projection Panel* (Figure 3). They control the range of the assigned variables, which could be dimensions of the embedding, metadata such as date or year of creation of an artwork, or inferred properties of the image such as colorfulness or contrast. Histograms above the range sliders provide additional statistical information and feedback on how changes affect the distribution of the mapping. They are constantly updated to reflect the distribution of the entire dataset as well as the distribution of filtered and unfiltered objects. Clicking on a histogram activates the *Bin Mode*: moving the cursor over the bars of the histogram temporarily displays only objects within the narrow range of the bar. A second click terminates this function and sets the filters back to the previous state. Additionally, hovering over the thumbnails in the *Projection Area* highlights the corresponding vertical bar in each histogram.

The *Advanced Filters* section is a text field to construct and apply search and filter queries. By default, it handles basic query operators such as AND, OR, equals (==), does not equal (!=), as well as custom operators. Nested and complex search queries are also supported using round brackets. When setting up the CSN for a new collection, using the configuration file (in Jupyter notebook format), each metadata field can be defined as a Free Text Entry (enabling queries) or as a Categorical Selection (generating drop-down lists, i.e. GUI elements that allow simple search and selection). The *Export Filtered Data* section in the *Control Panel* allows downloading the metadata of the currently filtered objects as a CSV file, and the current projection view as PNG file.

4 CONCLUSION

The CSN is a flexible and powerful tool for visualizing large multidimensional datasets, including embedding vectors and metadata. Available publicly on Github, the CSN includes a demo and a usage guide via an interactive Jupyter notebook. It's adaptable to a range of research and data needs, supporting various vector types, metadata, projection methods, and representations, in a user-friendly interface. Though we demonstrate CSN using visual data, it's not limited to image-derived vectors. It can equally visualize embeddings or metadata from audio or text, represented by appropriate thumbnails or labels, to explore non-visual meaning spaces. The CSN is open-source, and we encourage development and extensions. In conclusion, the CSN is a research tool for exploring, studying and curating large digital artefact collections that supports multidisciplinary research and understanding of multidimensional meaning spaces.

CODE AVAILABILITY AND DEMO

The CSN is released as MIT license with code and documentation available at https://github.com/Collection-Space-Navigator/CSN
A live demo, using the same example data as in the paper figures, is available at https://collection-space-navigator.github.io/CSN

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