A User-Centric Taxonomy for Multidimensional Data Projection Tasks

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Abstract: When investigating multidimensional data sets with very large numbers of objects and/or a very large number of dimensions, a variety of visualization methods can be employed in order to represent the data effectively and to enable the user to explore the data at different levels of detail. A common strategy for encoding multidimensional data for visual analysis is to use dimensionality reduction techniques that project data from higher dimensions onto a lower-dimensional space. In this paper, we focus on projection techniques that output 2D or 3D scatterplots which can then be used for a range of data analysis tasks. Existing taxonomies for multidimensional data projections focus primarily on tasks in order to evaluate the human perception of class or cluster separation and/or preservation. However, real-world data analysis of complex data sets often includes other tasks besides cluster separation, such as: cluster identification, similarity seeking, cluster ranking, comparisons, counting objects, etc. A contribution of this paper is the identification of subtasks grouped into four main categories of data analysis tasks. We believe that this user-centric task categorization can be used to guide the organization of multidimensional data projection layouts. Moreover, this taxonomy can be used as a guideline for visualization designers when faced with complex data sets requiring dimensionality reduction. Our taxonomy aims to help designers evaluate the effectiveness of a visualization system by providing an expanded range of relevant tasks. These tasks are gathered from an extensive study of visual analytics projects across real-world application domains, all of which involve multidimensional projection. In addition to our survey of tasks and the creation of the task taxonomy, we also explore in more detail specific examples of how to represent data sets effectively for particular tasks. These case studies, while not exhaustive, provide a framework for how specifically to reason about tasks and to decide on visualization methods. That is, we believe that this taxonomy will help visualization designers to determine which visualization methods are appropriate for specific multidimensional data projection tasks.

1 INTRODUCTION

Visualization is a crucial step in the process of data analysis. Often, when analyzing multidimensional data, dimensionality reduction (DR) techniques are displayed in form of 2D or 3D scatterplots that project the multidimensional points onto a lower-dimensional visual space. Methods using different algorithms to generate scatterplots with particular point placements are the most common visual encoding (VE) techniques for the resulting lower-dimensional data. DR techniques, coupled with appropriate VEs, enable an understanding of the relations that exist within the higher-dimensional data by displaying them in such a way that makes it easier for users to discover meaningful patterns (Samet, 2005).

Data analysis tasks are primarily concerned with the detection of structures such as patterns, groups, and outliers. Within a multidimensional data set, data points can be grouped manually into classes or automatically into clusters. For example, classes may be defined through manually labeling a collection of documents so that each document belongs to one topic within a set of topics, or by splitting an image collection into ten classes by assigning each image a particular theme from a set of ten themes. Clusters, on the other hand, are generated automatically using a clustering algorithm that may, for instance, identify groupings of similar points, or partition the data into dissimilar groups where each cluster contains similar items (Müller et al., 2009). However, it may be difficult to see these clusters or classes when projected onto a lower-dimensional space. To make sense of this multidimensional data, it can be useful to know how the clusters or classes are defined and structured in the original multidimensional attribute space. However, multidimensional projection mappings are especially prone to distortion because projection methods may not necessarily preserve the spatial relations of the data. Thus, it is important to know how effective the scatterplots are at preserving segregation of the data (Sips et al., 2009).

Several studies evaluate the quality of projections with respect to preserving certain properties, thus guiding a user to select the most appropriate projection method for their task. Various numerical and visual methods have been introduced to quantify the accuracy of projection methods with respect to such properties (Sips et al., 2009; Tatu et al., 2009). Recent studies (Sedlmair et al., 2012b) have shown that the quality of cluster separation by these measures was highly discrepant with user assessment of the cluster separation within the same data sets. Lewis et al. (Lewis and Ackerman, 2012) believe that accurate evaluation of clustering quality is essential for data analysts, and they showed that such clustering evaluation skills are present in the general population.

On the other hand, other studies have attempted to find a perception-based quality measure for scatterplots. They either evaluated users' performance on layouts generated by different projection techniques (Etemadpour et al., 2014c) or allowed users to assess a series of scatterplots (Albuquerque et al., 2011). Etemadpour et al. (Etemadpour et al., 2014c) used eye-tracking in a user study, asking users to perform typical analysis tasks for projected multidimensional data. Other studies have investigated the perception of correlation in scatterplots from a psychological perspective; however these studies did not consider real-world data sets (Rensink and Baldridge, 2010), (Etemadpour et al., 2014a).

Because of the absence of a standard approach for evaluating multidimensional data projection, the results of these studies, and others like them, are difficult to compare. We present a taxonomy of visual analysis tasks for multidimensional data projection that we believe could be a useful means for evaluation. The idea of creating a task taxonomy has been recently explored by Brehmer and Munzner (Brehmer and Munzner, 2013). They contribute a multi-level typology of visualization tasks that augments existing taxonomies by filling a gap between low-level and high-level tasks. Specifically, they distinguish what the task inputs and outputs are, as well as why and how a visualization task is performed. In doing so, they more thoroughly organize the motivations for and methods of specific tasks for particular data analysis situations. Their task taxonomy is more general, and does not address multidimensional data projection in any detail. In this paper, we provide a taxonomy of visual analysis tasks related to multidimensional data projection. Our task taxonomy enables evaluation designers to investigate visualization performance effectively on both synthetic and real-world data sets. The main contributions of the paper is:

- We provide a systematic user-centric taxonomy of visual tasks related to projected multidimensional data.
- We divide the projection-related tasks into different categories based on their impact on the analysis of multidimensional data. The categories we identify are relation-seeking, behavior comparison, membership disambiguation, and pattern identification tasks.
- We enable, via our task taxonomy, visualization designers to improve visualization tasks related to the analysis of multidimensional data.
- We present our taxonomy as a guideline for researchers in choosing visualization techniques for these tasks, and provide explicit examples.
- We adapt Brehmer and Munzner's multilevel typology of abstract visualizations to multidimensional data projection tasks (Brehmer and Munzner, 2013).

In the next section, we provide a brief review of existing task taxonomies for DR and VE techniques. In Section 3, we introduce our task taxonomy for multidimensional data projection by describing new sets of tasks related to typical analysis tasks, including *pattern identification*, such as detecting clusters, *behavior comparison*, such as comparing characteristics of subsets, *membership disambiguation*, such as counting the number of objects in a cluster, and *relation seeking*, such as correlating subsets to each other. We discuss the effects of our proposed tasks on the evaluation of scatterplots by providing some examples of how different tasks support decision making respective to human perception over multidimensional data projections. We also characterize our proposed tasks using the multi-level typology of abstract visualization tasks (Brehmer and Munzner, 2013). We applied Brehmer and Munzner's multilevel topology concept for describing two tasks as guidelines, while the three questions (WHY, WHAT, HOW) can be used to structure the description of all tasks.

2 Related Work

Many projection methods exist to generate 2D similarity-based layouts from a higher-dimensional space. The design goals include maintaining pairwise distances between points as implemented in multidimensional scaling (MDS) (Borg and Groenen, 2010), maintaining distances within a cluster, or maintaining distances between clusters (Tenembaum et al., 2000). Principal component analysis (PCA) generates similarity layouts by reducing data to lower dimensional visual spaces (Jolliffe, 1986). Some projection methods, such as isometric feature mapping (Isomap), favor maintaining distances between clusters instead. Isomap is an MDS approach that has been introduced as an alternative to classical scaling capable of handling non-linear data sets. It replaces the original distances by geodesic distances computed on a graph to obtain a globally optimal solution to the distance preservation problem (Tenembaum et al., 2000). Least-Square Projection (LSP) computes an approximation of the coordinates of a set of projected points based on the coordinates of some samples as control points. This subset of points is representative of the data distribution in the input space. LSP projects them to the target space with a precise MDS force-placement technique. It then builds a linear system from information given by the projected points and their neighborhoods (Paulovich et al., 2008).

The correlations of data points or clusters are not always known after they have been mapped from a higher-dimensional data space to 2D or 3D display space. Thus, several approaches evaluate the best views of multidimensional data sets. Sips et al. (Sips et al., 2009) provide measures for ranking scatterplots with classified and unclassified data. They propose two additional quantitative measures on class consistency: one based on the distance to the cluster centroids, and another based on the entropies of the spatial distributions of classes. They propose class consistency as a measure for choosing good views of a class structure in high-dimensional space. Tan et al. (Tan et al., 2005), Paulovich et al. (Paulovich et al., 2008), and Geng et al. (Geng et al., 2005) also evaluate the quality of layouts numerically. By ranking the perceptual complexity of the scatterplots, other studies investigate user perception by conducting user studies on scatterplots, finding that certain arrangements were more pleasing to most users (Tatu et al., 2010), (Albuquerque et al., 2011). However, these operational measures were not necessarily equivalent to the measures of user preference based on their qualitative perceptions.

Sedlmair et al. (Sedlmair et al., 2012a) have discussed the influence of factors such as scale, point distance, shape, and position within and between clusters in qualitative evaluation of DR techniques. They examined over 800 plots in order to create a detailed taxonomy of factors to guide the design and the evaluation of cluster separation measures. They focused only on using scatterplot visualizations for cluster finding and verification. DimStiller (Ingram et al., 2010) is a system to provide global guidance for navigating a data-table space through the process of choosing DR and VE techniques. This analysis tool captures useful analysis patterns for analysts who must deal with messy data sets.

Rensink and Baldridge (Rensink and Baldridge, 2010) explore the use of simple properties such as brightness to generate a set of scatterplots in order to test whether observers could discriminate pairs using these properties. They found that perception of correlations in a scatterplot is rapid, and that in order to limit visual attention to specific information it is more effective to group features together. Etemadpour et al. (Etemadpour et al., 2014c) postulate that cluster properties such as density, shape, orientation, and size influence perception when interpreting distances in scatterplots, and specifically, observe that the density of clusters is more influential than their size.

In general, little attention has been paid to providing details about low-level tasks that guide users to choose DR and VE techniques. However, both high-level goals and much more specific low-level tasks are important aspects of analytic activities. Amar et al. (Amar et al., 2005) presented a set of ten low-level analysis tasks that they found to be representative of questions that are needed to effectively facilitate analytic activity. Andrienko and Andrienko distinguish elementary tasks that address specific elements of a set and synoptic tasks that address entire sets or subsets, according to the level of analysis (Andrienko et al., 2011).

Brehmer and Munzer (Brehmer and Munzner, 2013) emphasize three main questions, *why* the tasks are performed, *how* they are performed, and *what* are their inputs and outputs. These questions encompass their concept of multi-level typology. They believe that "low-level characterization does not describe the user's context or motivation; nor does it take into account prior experience and background knowledge." Their typology relies on a more abstract categorization based on concepts, rather than a taxonomy of pre-existing objects or tasks. In contrast, we attempt to specify tasks at the lowest level that can provide details about multidimensional data projection. However, the general approach of Brehmer and Munzner can be easily adopted as a tool to put these low-level tasks in context, facilitating the evaluation of user experiences by evaluation designers. This approach provides essential information, such as motivation and user expertise, for field studies that examine visualization usage. Therefore, we show how our defined tasks can be described according to a typology of abstract tasks relating intents and techniques (how) to modes of goals and tasks (why).

We 1) categorize possible tasks performed when analyzing a specific multidimensional data visualization, and 2) formulate guidelines for analysts to assist in selecting appropriate projection techniques for performing specific visualization tasks on data sets.

3 Task Taxonomy for Multidimensional Data Projection

We define a list of tasks from studies of different projection techniques and their 2D layouts such as PCA (Jolliffe, 1986), Isomap (Tenembaum et al., 2000), LSP (Paulovich et al., 2008), Glimmer (Ingram et al., 2009), and NJ tree (Paiva et al., 2011), as well as the applications behind the data (e.g. document and image data). We explain some of these tasks in detail and provide examples of effective data representations for relevant visual analysis tasks. As explained in Section 2, how well groups of points can be distinguished by users in scatterplots defines visual class separability. Our cluster-level tasks also focus on how easily a grouping of related points in multidimensional space (e.g., clusters) can be detected by users when projected into lower-dimensional space. However, rather than only looking at visual class separability, we consider how effective users are performing meaningful tasks related to the perceived clusters.

Although other researchers have explored some of these tasks, we systematically list the full range of analytic tasks for multidimensional projection techniques appropriate for large data sets. Additionally, our organization of these tasks takes into consideration user perception.

We divided the tasks into four categories according to the typical visualizations required to support them:

Pattern identification tasks: We examine trends, which are more obvious for lower-dimensional data than for projected higher-dimensional ones. Relevant issues include cluster/class preservation and separation.

Relation-seeking tasks: Relationships and similarities between different reference sets are considered.

Behavior comparison tasks: To compare characteristics of subsets (or clusters), we consider capturing different data behaviors (like asking the subjects to compare the point densities within clusters, where density is defined as the number of points per area).

Membership disambiguation tasks: Positional and distributional relationships within classes/clusters are particularly considered where objects occlude each other. Clutter and noise obscure the structure present in the data and make it hard for users to find patterns and relationships. Peng et al. (Peng et al., 2004) state that clutter reduction is a visualization-dependent task. Therefore, the DR and VE need to minimize the amount of confusing clutter. We believe that clutter can be measured by users using a wide variety of visualization techniques.

We now clarify these taxonomic categories by looking at common tasks found in the literature.

3.1 Pattern identification task

Multidimensional data sets may include hundreds or thousands of objects described by dozens or hundreds of attributes. Data characteristics regarding the distribution within multidimensional feature spaces vary for different application domains. For example, consider document data versus image data: text usually produces sparse spaces while imagery produces dense spaces. As Song et al. (Song et al., 2006) state, traditional document representation like bag-of-words leads to sparse feature spaces with high dimensionality. This makes it difficult to achieve high classification accuracies. Figure 1 shows histograms of the distribution of the pairwise distances between four data objects after normalization to the interval [0; 1]. The document data sets are referred to as CBR and KDViz [1]. The image data sets are referred to as Corel [2]

[1] CBR comprises 680 documents, which include title, authors, abstract, and references from scientific papers in the four different subjects, leading to a data set with 680 objects and 1,423 dimensions. KDViz data has been generated from an Internet repository on the topics bibliographic coupling, co-citation analysis, milgrams, and information visualization, leading to 1,624 objects, 520 dimensions, and four highly unbalanced labels (http://vicg.icmc.usp.br/infovis2/data sets).

[2] 1,000 photographs on ten different themes. Each image is represented by a 150-dimensional vector of SIFT descriptors (3UCI KDD Archive, http://kdd.ics.uci.edu).

and Medical [3]. The revealed histograms illustrate different characteristics for document data sets and image data sets. Both image data sets exhibit lower mean distance values and much wider variance (representative of a denser feature space) than the document data sets.

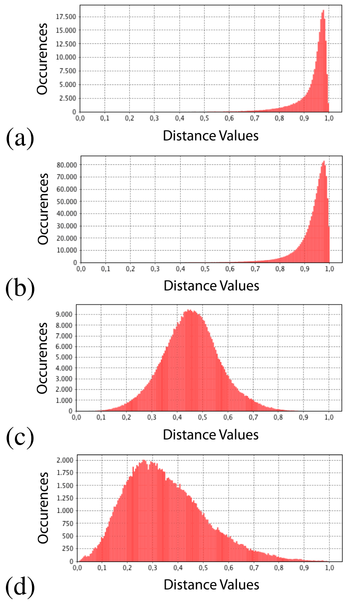


Figure 1: Histograms of document data (top) and image data (bottom) exhibit characteristic distance distributions: (a) CBR. (b) KDViz. (c) Corel. (d) Medical.

Identifying patterns in high-dimensional spaces and representing them using dimensionality reduction techniques, in order to reveal trends, is a challenge in many scientific and commercial applications. To identify outliers, trends and interesting patterns in data, one of the many objectives of data exploration is to find correlations in the data, thus uncovering hidden relationships in the data distribution and providing additional insights about the high-dimensional data (Zhang et al., 2008). Therefore, a list of questions are suggested that can reveal user's perspective about local and global correlations with respect to features – for instance, those subsets of data which form relevant patterns (e.g. subsets of data within dense feature groups):

- Estimate the number of outliers in the given layout.
- Estimate the number of observed clusters.
- Find the number of clusters in a selected region.
- Find the number of subclusters in a given cluster.
- Find a cluster with a specific characteristic (e.g., longish).
- Find the specific characteristics (e.g., sparsity) of a cluster.
- Determine the number of outliers in a given cluster.

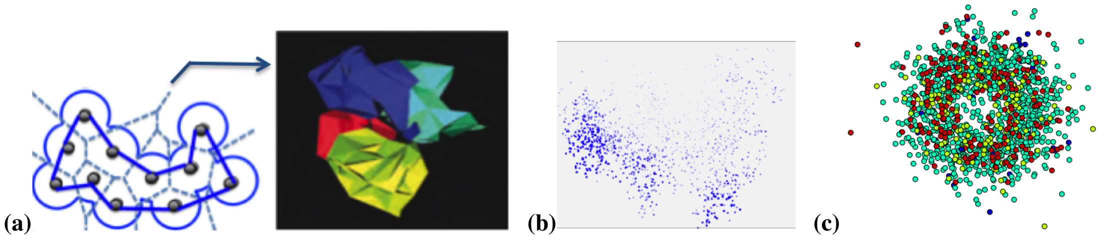
If researchers aim to find the user's performance on class segregation, it is important to draw the user's attention to global project views. Thus, we suggest asking *Estimate the number of clusters in the given layout* to identify the informative aspects of the data.

Pattern identification tasks often favor clear segregation by class, which means that techniques which incorporate cluster enclosing surfaces can be helpful. In some situations, the labeled classes in each data set can be considered as ground truth. For such cases, Poco et al. (Poco et al., 2011) developed a 3D projection method by generalizing the LSP technique from a 2D to a 3D scheme. A non-convex hull (of each cluster) that is computed from a 3D Voronoi diagram of the cluster points is illustrated in Figure 2(a). This representation, when it is possible to construct, is both accurate and satisfying to users, compared to other techniques.

While this projection works well when the data's pre-assigned class structure accurately models the data's inherent organization, this is often not feasible. In many situations, analysts want to leverage human perception to identify "visual groupings" of points, and in this case a point cloud representation produces favorable results. For example, when grouping information is not available, a point-based visualization as shown in Figure 2(b) is still applicable. Also, Glimmer (Ingram et al., 2009), as a technique representative of force-directed placement MDS, does not favor class segregation when employed on the KDViz data set[4]. Thus, color coding to separate nodes of different classes can be useful as shown in Figure 2(c). Therefore, if we have accurate class labels and good class separation, we suggest enclosing surfaces like nonconvex hulls. According to the eye-tracking study on Glimmer projection, the visual attention pattern is scattered and it is hard to identify any meaningful area of interest (AOIs) for Glimmer (Etemadpour et al., 2014c). Hence, it is useful to differentiate classes when the projection doesn't reflect the class distribution at all.

[3]Each image is represented by 28 features, including Fourier descriptors and energies derived from histograms, as well as mean intensity and standard deviation computed from the images themselves. Hence, the data set contains 540 objects and 28 dimensions

[4]KDViz contains documents collected from an Internet repository related to four different topics with 1,624 unique documents, 520 different dimensions, and 4 highly unbalanced labels, http://vicg.icmc.usp.br/infovis2/data sets



(a) (b) (c)

Figure 2: Estimate the number of observed clusters: (a) Non-convex hulls computed from enclosing surfaces isodistant to cluster using LSP projection; (b) Point-based visualization using PCA projection taken from (Schreck et al., 2010); (c) The layout obtained with Glimmer projection on the KDViz data set. Circle color indicates instance class label.

3.2 Relation-seeking tasks

Relation-seeking tasks investigate the similarities and differences between subgroups which represent clusters or individual objects. Similarity layouts employ projection techniques to reducing data to lower-dimensional visual spaces, but in a different manner from that used in pattern identification. In this application, an analyst is interested in investigating whether a point (or object) is more similar to one cluster or to another, or whether a whole cluster is more similar to a second cluster or a third. We believe that relationship-seeking is a search task, Andrienko's visual task taxonomy model notwithstanding (in which search tasks are limited to lookup and comparison) (Andrienko et al., 2000). In contrast, Zhang et al. (Zhang et al., 2009) consider comparison and relationship-seeking to be compound tasks, containing at least two relationships, one being the data function and the other being relationships between values (or value sets) of a variable. Under this definition, we believe that finding similarities in projected high-dimensional data can be considered as a relation-seeking tasks. Users perform comparison tasks with respect to a given reference set, which can be a cluster or an individual object, and can undertake a similarity search by identifying a given cluster's neighbors. In such a search, the specified relationship is defined by a distance search within a high-dimensional data projection.

A list of potential tasks within the relation-seeking task category can be considered for multidimensional data visualization:

- Identify the closest cluster to a given cluster.
- Identify the most similar cluster to a given cluster.
- Identify the closest cluster to a reference point.
- Identify the most similar cluster to a given object.
- Find *k* closest (most similar) clusters to the given cluster.
- Find *k* closest (most similar) objects to the given cluster.
- Find *k* closest (most similar) objects to the reference object.
- Find the closest (most similar) cluster to a cluster with a specific characteristic (e.g., Find the closest cluster to the longish cluster).
- Identify the cluster to which the reference set/sets belong.
- Find the closest (most similar) cluster to the set of points with specific characteristics (e.g., points that have identical movement).
- Find *k* closest (most similar) points to the set of points with specific characteristics.
- Find the clusters that have hierarchical relations.
- Find *k* similar objects within a cluster.
- Find a cluster that is the parent of two reference sets.

Etemadpour et al. (Etemadpour et al., 2014b) investigated how domain-specific issues affect the outcome of the projection techniques. They used a number of similarity interpretation tasks to assess the layouts generated by projection techniques as perceived by their users. To show that projection performance is task-dependent, they generated layouts of high-dimensional data with five techniques representative of different projection approaches. To find a perception-based quality measure, they asked individuals to identify the closest cluster to a given cluster and object. Users also ranked the *k* nearest objects to a given object. As shown in Figure 3, the target cluster/object was shown in one color (red) and two other clusters in other colors (green and blue), from which the one closer to the target cluster/object should be identified.

Node-link diagrams have been studied in detail in many graph drawing topics or graph visualization approaches, where a node is representing an entity that is connected to other nodes through lines (i.e., links). Although the node-link diagram is an intuitive way to visually represent relationships between entities for relatively small data sets (Henry and Fekete, 2006),

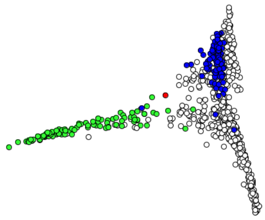


Figure 3: Task: determine whether green or blue cluster is closer to red object in order to investigate PCA projection performance.

there may be too many lines crossing with each other that obscure relationships among entities when dealing with larger data sets. In order to represent spatial distance visually in cases like these, a technique like the Force-Directed Placement approach (Eades, 1984) can be used to reveal connections and similarity magnitude between entities. This technique relies on iterative algorithms that model the data points as a system of particles attached to each other by springs. The length of the spring connecting two particles is given by the distance between their corresponding data points as shown in Figure 4. A spatial embedding is obtained with an iterative simulation of the spring forces acting on this hypothetical physical system, until it reaches an equilibrium state.

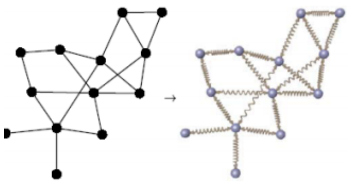


Figure 4: The spring embedder model (Eades et al., 2010).

To *Find k closest objects to the reference object*, if the performance of a projection in terms of maintaining distances within a cluster is under investigation and the cluster structure is known, a combination of hull-based and point-based visualizations can be used. Schreck et al. (Schreck et al., 2010) implemented an interactive system that combined these two visual presentations letting users choose the best visual representation of the projected data. They believed that such combined representations introduce visual redundancy; however, it can improve user's perception of the projection precision information depending on the application. Poco et al. (Poco et al., 2011) improved the performance of their 3D point representation when they combined standard point clouds with this user-guided process. Figure 5 demonstrates finding 3 closest objects to the red object within a cluster when the convex hull of the points is used.

Brehmer and Munzner's typology is intended to facilitate understanding of users' individual analytical strategies. We employ their multi-level code, used to label user behaviour, to enhance the evaluation of high-dimensional data projection. By utilizing the Brehmer and Munzner multi-level typology, we provide a systematic way of justifying the choice of a particular task through asking three main questions: Why, What and How. This multi-level typology of abstract visualization tasks fills the gap between low-level and high-level classification to describe user tasks in a useful way. This approach to analyzing visualization usage supports making precise comparisons of tasks between different visualization tools and across application domains (Brehmer and Munzner, 2013). For an effective design and evaluation of multidimensional data visualization tools, one should consider why and how our defined tasks should be conducted, and what are their potential inputs and outputs. Meanwhile, sequences of tasks can be linked, so that the output of one task may serve as input to a subsequent task. We focused on *Find k closest clusters to the given cluster* in the relation-seeking category. We did not consider any specific projection technique because it can be changed based on the evaluator's motivation.

Find k closest cluster to the given cluster: **WHY:** The goal is to *Discover k* groups that are closest to a given cluster. A known target (given cluster) and the whole projection visualization are provided. If the location of a given cluster was known (or given by the examiner), then participants perform a *Lookup*. If the characteristic of the given cluster was given, the user can *Locate* the given cluster with specific characteristics (e.g., searching for a given cluster in which the elements are colored red). Then individuals search for *k* clusters that are in the neighborhood of the given cluster and list these groups. **WHAT:** The input for this task is a given cluster; this can be shown by the examiner or can be indicated by a particular characteristic like the color red. All other clusters in the entire visualization are also visible to the participants. The output is a list of *k* groups that are closest to the given cluster. **HOW:** Participants identify the *k* closest clusters to the given cluster. For example, they determine whether the green or blue cluster is closer to the red cluster. They provide a list of clusters that follow an ascending order, so that the distance of the first cluster in this list to the given cluster is shortest compared to the other clusters. *Select* refers to differentiating selected elements from the unselected remainder.

Trees are a natural form for depicting hierarchical relations and can be used to *Find the clusters that*

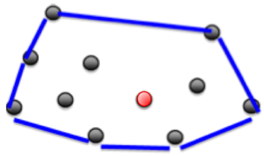


Figure 5: Find 3 closest objects to the red object: Convex-hull of the point clusters.

have hierarchical relations. A distinct category of 2D mapping employs tree layouts to convey similarity levels contained in a distance matrix. The algorithms to generate similarity layouts (Cuadros et al., 2007; Paiva et al., 2011) are inspired by the well-known Neighbor-Joining (NJ) heuristic originally proposed to reconstruct phylogenetic trees. Similar points among members of the same subsets are placed at the ends of branches. The points nearer the root of the tree are less similar when compared with the points at the ends of branches.

Similarity trees generate a hierarchy, creating a tree structure where interpretation is subject to organization of the branches; for example, mapping data setswith the NJ and LSP projections are compared in Figure 6. In this example, the INFOVIS04 data set is composed of documents published in a conference on information visualization, and its content is homogeneous. Using NJ, documents with a high degree of similarity are placed along the same branch. The branches circled in the figure are examples of long branches without too many ramifications, and probably represent specific sub-topics inside the collection. LSP, on the other hand, has a tendency to create clusters in round clumps. This representation performs well for certain tasks, but is less useful for finding the closest clusters to selected objects (Etemadpour et al., 2014b).

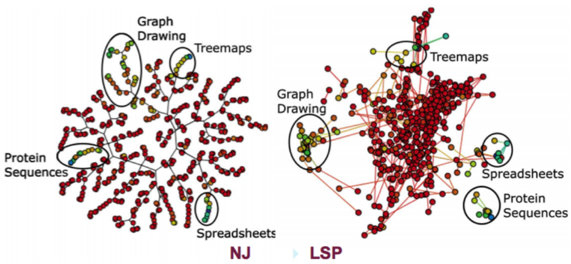


Figure 6: Comparison of INFOVIS04 document data set map using Neighbor Joining and LSP projections: Four different topics of information visualization are identified by coloring points. Figure is taken from (Cuadros et al., 2007).

Collins et al. (Collins et al., 2009) introduced BubbleSets as a visualization technique for data that makes explicit use of grouping and clustering information. Members of the same set are in continuous and concave isocontour, while a primary semantic data relation is maintained with spatial organization. These delineated contours do not disrupt the primary layout, so they avoid layout adjustment techniques. This visualization technique is designed in order to facilitate depicting more than one data relationship in data sets that contain multiple relationships. Using this concept, we suggest contours around nodes belonging to the same set to *Find k similar objects within a cluster* in a projection technique. Figure 7 shows an example that uses the BubbleSets concept for an NJ heuristic projection. The points that are sharing the same contour are members of the same set. These boundaries are used to indicate the grouping clearly.

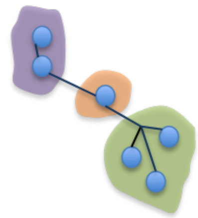


Figure 7: NJ projection: geometric relationships, hierarchy and cluster perimeter are all clearly defined using BubbleSets concept.

3.3 Behavior comparison tasks

A third way in which high-dimensional data projections can display data items in lower-dimensional subspaces can provide insight into important data dimensions and details. Our taxonomy distinguishes the subsets of tasks used for behavior comparison:

- Find the cluster with the largest (smallest) occupied visual area.
- Find the cluster with the most (least) number of points or size.
- Find densest (sparsest) cluster.
- Given specific number of clusters (e.g. 5 clusters is given).
- Rank the clusters by density.
- Rank the clusters by their occupied visual area.
- Rank the clusters by their size.
- Compare density of two given clusters with different or similar characteristics (e.g., density of a longish cluster vs. a roundish cluster).
- Compare the size of two given clusters with different or similar characteristics.
- Compare the visual area of two given clusters with different or similar characteristics.

Density is an important metric because it indicates stronger relationships between points within a cluster. Moreover, many studies have indicated that representations of density can play an important role in visualization (Ahuja and Tuceryan, 1989; Sears, 1995; Tullis, 1988). Further, studies in psychophysics have shown that visual search can be affected by the variance in the number of objects within groups (Duncan and Humphreys, 1989; Rosenholtz et al., 2009; Treisman, 1982). Sedlmair et al. (Sedlmair et al., 2012b) named density as one of the Within-Cluster factors, namely, the ratio between count and size. This can range from sparse, with few data points and a large spread, to dense, with many points and a small spread. If the task is to *Compare density of two given clusters with different or similar characteristics*(i.e. different shapes), we suggest a point-based visualization. This allows users to easily see the point distribution within a cluster and the occupied visual space. Moreover, as investigated in (Etemadpour et al., 2014c), according to the Gestalt principle (Koffka, 1935), the shape and orientation of a cluster should also influence decisions during visual analysis. For example, when two stretched clusters are aligned, they may be perceived as a continuation of one cluster or in other words, characteristics of the clusters influence the visual analysis from a perceptual view. Following these ideas, continuity and closure create the perception of a whole cluster. Figure 8 illustrates the density of a longish cluster versus a cluster that looks more roundish. In this example, cluster shape (e.g., whether a cluster appears to be round or elongated) has been examined, while density and size of the clusters were the same. In addition, 2D scatter plots are manually generated using synthetic clusters (Etemadpour et al., 2014c). Cluster shape (in projected space) influences users' performance on various inference tasks.

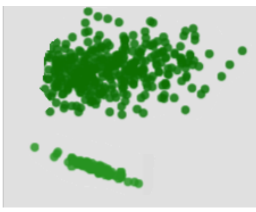


Figure 8: Task: Compare the density of the longish cluster versus the roundish cluster. Scatter plots were generated with varying shapes, while holding density and size constant, in order to investigate the effect of cluster shape (in projected space) on a user's inferences and perceptions of the data.

Again by utilizing the Brehmer and Munzner multi-level typology, we provide an example that shows how our defined tasks can be fitted to this multi-level typology of abstract visualization tasks, in order to concisely describe our pre-defined tasks. *Find the cluster with the highest number of sub-clusters* in the behavior comparison category has been considered. Additionally, we did not consider any specific projection technique because it can be changed based on the evaluator's motivation.

Find the cluster with the highest number of sub-clusters: **WHY:** The purpose is to *Discover* a cluster with the highest number of sub-clusters. The cluster characteristic is not provided; therefore, the search target is unknown and *Explore* entails searching for the cluster with the highest number of sub groups. Once the search process is done, *Identify* returns the desired reference. **WHAT:** The input for this task is the entire visualization, including all clusters and their sub-groups. The output is the identity of a cluster with the largest number of sub-clusters. **HOW:** Individuals need to estimate the number of sub-clusters of each cluster. This involves counting sub-groups within successive clusters until the largest number is found. Therefore, they must *Derive* new data elements, then *Select* the desired cluster.

3.4 Membership disambiguation

It is desirable for the visual representation to avoid clutter, resolve ambiguity and handle noise. At times, "identifying overlaps" may indicate that the classes are not clearly separable, which suggests that the overriding task is one of pattern identification. However, too much data on too small an area of the display, such as a dense region of entangled clusters, diminishes the potential usefulness of the projections even if the projection consists of some clearly separated clusters. This is especially true when the user is exploring the data to:

- Estimate the number of objects in a selection.
- Find an object with specific characteristic (e.g. labeled point) within a cluster.
- Count the number of objects in a given cluster.
- Identify the objects that overlap in a selected area.

When *Finding an object with a specific characteristic within a cluster*, a visualization can favor good performance in preserving distances and relationships, but only at the expense of producing visual clutter. As an example, the PCA scatterplot of KD-Viz is too cluttered and distinguishing a specific object within a cluster is not an easy task (Figure 9).

To *Estimate the number of objects in a selection*, a target cluster/selection can be highlighted with a different color as shown in Figure 10.

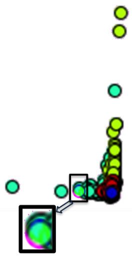


Figure 9: Find a purple object within the green cluster. Using a PCA projection employed on the KDViz data set, it is hard to distinguish the purple point.

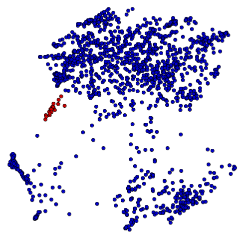


Figure 10: Estimate the number of objects in a selection in LSP projection.

3.5 Meta-projection

The tasks that are explained above can be used as given, or can be combined into multi-step macrotasks. We note that the tasks that we have provided may not cover all possible tasks of a given type, but they can be used as exemplars when defining new tasks. Sub-clusters of a given cluster or group of points can be considered as a meta-object. Meta-objects can create a meta-projection, and new tasks can be executed on this projection based on this process. In Figure 11(a), the task is: "*Find the closest cluster to the given cluster*". For instance, as apparent "Linear Square" is the closest sub-cluster to the "Information Visualization" sub-cluster and "Tree" is the closest sub-cluster to "Graph Drawing". Therefore, as shown in Figure 11(b) we can analyze the meta-projection to see that "Time Varying Filtering" is the closest cluster to the "Visualization" cluster and similarly "Visualization" is the closest cluster to "Data Mining". Using this meta-projection, we can get more insight into our data.

Thus, in section 3, we saw examples of how appropriate visualization methods could be determined for specific tasks.

4 Conclusion

Our taxonomy supports precise comparisons across different multidimensional data projection

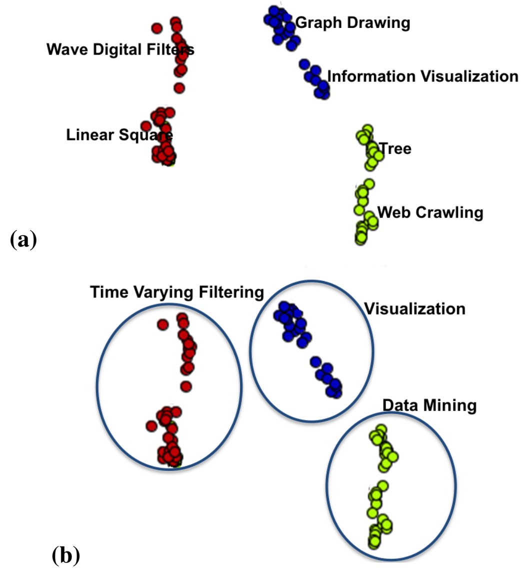


Figure 11: A meta-projection: (a) sub-clusters; (b) clusters (meta-objects).

techniques. However, it can be extended by considering more application domains like volumetric data sets, which may introduce new VEs like continuous scatterplots. We argue that projection methods are distinct in their characteristics in terms of sparseness and distance distribution, and that the nature of the task (in taxonomic terms) should guide the visualization design. We believe that our taxonomy can be used for examining projection layouts and scatterplots to see how users perceive multidimensional data. We also incorporate findings about perception rules (e.g., Gestalt laws) and cognitive processes like visual attention as a valuable source of information for such analyses. Our taxonomy can help in categorizing possible tasks when analyzing a multidimensional data visualization. These tasks can be used as guidelines for assessing other visualization techniques as well, such as Star Coordinates (Van Long and Linsen, 2011).

Our tasks are not projection-specific or data-set-specific. We list a number of example tasks within each taxonomic task classification; these are not intended to be exhaustive. Other tasks can be placed within our taxonomic categories, and our visualization recommendations applied appropriately. We may extend our study to look into whether certain tasks are specific for certain applications.

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