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Measuring Data Abstraction Quality in Multiresolution Visualizations

Qingguang Cui
Worcester Polytechnic Institute

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Measuring Data Abstraction Quality in Multiresolution Visualizations

by

Qingguang Cui

A Thesis

Submitted to the Faculty

of the

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In partial fulfillment of the requirements for the

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in

Computer Science

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APPROVED:

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Professor Matthew O. Ward, Thesis Advisor

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Professor Elke A. Rundensteiner, Thesis Reader

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Professor Michael Gennert, Head of Department

Abstract

Data abstraction techniques are widely used in multiresolution visualization systems to reduce visual clutter and facilitate analysis from overview to detail. However, analysts are usually unaware of how well the abstracted data represent the original dataset, which can impact the reliability of results gleaned from the abstractions. In this thesis, we define three types of data abstraction quality measures for computing the degree to which the abstraction conveys the original dataset: the Histogram Difference Measure, the Nearest Neighbor Measure and Statistical Measure.

They have been integrated within XmdvTool, a public-domain multiresolution visualization system for multivariate data analysis that supports sampling as well as clustering to simplify data. Several interactive operations are provided, including adjusting the data abstraction level, changing selected regions, and setting the acceptable data abstraction quality level. Conducting these operations, analysts can select an optimal data abstraction level.

We did an evaluation to check how well the data abstraction measures conform to the data abstraction quality perceived by users. We adjusted the data abstraction measures based on the results of the evaluation. We also experimented on the measures with different distance methods and different computing mechanisms, in order to find the optimal variation from many variations of each type of measure. Finally, we developed two case studies to demonstrate how analysts can compare different abstraction methods using the measures to see how well relative data density and outliers are maintained, and then select an abstraction method that meets the requirement of their analytic tasks.

Acknowledgements

I would like to express my gratitude to my advisor, Prof. Matthew Ward, for his patient guidance and invaluable contributions to this work. I would like to thank Prof. Elke Rundensteiner for making various suggestions for improving the displays, and for being the reader of this thesis.

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Chapter 1

Introduction

Very large multivariate datasets are increasingly common in many applications, including bioinformatics, social science, and data analysis for homeland security. To be effective, visualization tools must be increasingly capable of handling such huge datasets. As the number of data elements increases, two problems arise: displays become cluttered and response time deteriorates. Clutter saturates visualizations, obscures the structure of the visual display, and hinders visual data analysis. Increase in response time makes effective and efficient interactive exploration difficult.

Many techniques have been proposed to address this scalability problem. They can be classified into two groups: data abstraction techniques in the data space and clutter reduction techniques in the visual space. We define data abstraction as the process of hiding details of data while maintaining the essential characteristics of data. Techniques for data abstraction found within information visualization include filtering [2], clustering [13] and sampling [11]. Clutter reduction assigns more screen space to interesting data elements than to less interesting ones; common techniques include zooming [5] and distortion [20].

We are faced with a new challenge when working with the abstracted data in place of the original data. Namely, analysts should know how well the selected abstraction represents the whole dataset and how reliable the patterns discovered based on this abstraction are. Analysts should be able to compare different abstraction methods in order to select one abstraction method that best fits their task. Further analysts should be able to choose an abstraction level for a specific abstraction method. The measurement of data abstraction quality is one possible solution to resolve the above problems and should be an essential component of multiresolution visual analysis. Bertini and Santucci [8] present a quality measure for sampling and apply it to finding the optimal sampling level. This measure, however, is limited to sampling. The authors do not consider other types or usages of abstraction measures. Boutin and Hascoet [9] review and compare various measures for graph clustering, and propose modified ones. These measures are designed specifically for clustering and their extensibility into other types of visualization is not clear.

In this thesis, we present three general abstraction quality measures, namely HDM (Histogram Difference Measure), NNM (Nearest Neighbor Measure) and SM (Statistical Measure). We also show how they can be utilized in visualization. The HDM is derived based on the average relative error [4] of aggregation used in approximate query processing of databases as well as image similarity measures [22, 31] used in image retrieval. The NNM is derived based on the nearest neighbor algorithm [12] used in pattern recognition and image quality measurement [26] used in image compression. SM utilizes the statistical properties of a dataset, and we use mean values as an example, though others are equally possible.

We integrated these measures into several multivariate visualizations, including parallel coordinates, scatterplot matrices and glyphs, employing two dynamic bar charts to display the measures for the selected and the unselected regions of data. Several interactive operations were designed for operating in this quality space, including adjusting the data abstraction level, changing the selected regions, regenerating the abstraction, and setting a desired quality level. Quality measures are recomputed whenever the above operations are performed. The measures and interactions together form an environment in which analysts can explore multiresolution visualizations with abstraction quality information available.

We conducted an evaluation to check how well the data abstraction measures conform to the data abstraction quality perceived by users. We designed 13 questions for this evaluation. For each question, users chose the quality according to their perception. Then we compared the perceived qualities with our quality measures. We adjusted the data abstraction measures based on the results of the evaluation. We also experimented on the measures with different distance methods and different computing mechanisms in order to find the best variation for each type of measure.

Visual analysts can benefit from data abstraction quality measures in several ways. First, these measures give analysts a confidence level in the given abstraction they work with and thus also for any observation made based on the abstracted dataset. This enables them to make more informed decisions. Second, these measures make analysts aware of the abstraction quality of the dataset. Better yet, interactive mechanisms are available for the analysts to control the abstraction quality. Thus they can find an appropriate abstraction level by trading off the accuracy of representing the data subset and the degree of visual clutter. Third, these measures can be used to compare the effectiveness of different abstraction methods. Analysts can thus select the abstraction method via a compromise between response time and the features of the abstraction, such as the relative data density and the degree to which outliers are preserved. For some applications, it may be acceptable to use the abstracted datasets with moderate quality as long as the decisions can be rapidly made, while other applications may require a higher level of confidence in the data being utilized.

The rest of the thesis is organized as follows. We review related work in Chapter 2 and introduce XmdvTool, the implementation foundation of this research, in Chapter 3. We define three types of abstraction quality measures in Chapter 4. Chapter 5 describes the integration of these measures with multiresolution visualization using sampling and clustering. Chapter 6 describes the evaluation of these measures. Chapter 7 details the experiments on these measures. Chapter 8 presents two case studies of the measures in use. Chapter 9 concludes this thesis and discusses future work.

Chapter 2

Related Work

Several researchers have proposed measures for visual quality, visual clutter and data abstraction. They have employed the measures to control interactive analysis on the visualization. Tufte [33] describes general measures for visual quality, such as the lie factor (the ratio between size of the effect shown in the graphic and size of the effect in data) and the data density (the ratio between the drawn data entries and the graph area). Bertini et. al. [7] give a model for measuring visual density and clutter in 2D scatterplots. They develop a clutter measure represented by the percentage of colliding pixels in all possible permutations. Peng et al. [23] propose visual clutter measures for parallel coordinates, scatterplots matrices, star glyphs and dimensional stacking. They use these measures to compute dimension orders with reduced visual clutter. Rosenholtz et al. [27] present a feature congestion measure for displaying clutter based on image retrieval techniques, evaluating similarity and correlation among different features in the visualization. This measure can be used in an automated user interface critiquing tool. The work of Bertini et al. [8] is closest to ours in that they have designed a quality measure for data abstraction. They partition 2D scatterplots into a grid of blocks, compare data densities of the original dataset and the data densities of samples in each block, and then calculate the percentage of matching blocks to achieve this measure. They use this quality measure to find an optimal sampling level. This measure is similar to the Histogram Difference Measure in our work, but the matching method of blocks is much coarser than our calculation of the histogram difference.

Sampling refers to the process of selecting and using subsets of observations to estimate some parameters about a population [32]; techniques include simple random sampling, stratified sampling and quota sampling. Sampling techniques have been well studied in statistics and widely applied in social science. In Computer Science, sampling is used for many tasks, including optimizing queries in databases with approximate information from samples [4, 1]. In recent years, faced with increasingly dense visualizations, researchers have begun to explore combining sampling with visualization. Dix and Ellis [11] demonstrate that random sampling can make the visualization of large datasets more perceptually effective. Their Astral Telescope Visualiser employs a 2D zooming interface to show data with different sampling levels. Bertini and Santucci [7, 8] employ a non-uniform sampling algorithm to select less data in dense areas to reduce clutter, and more data in sparse areas to maintain data characteristics. Rafiei and Curial [24] apply simple random sampling into network visualization and show that this sampling preserves the common characteristics of the network.

Clustering refers to the process of partitioning a dataset into groups of objects based on similarity between objects or proximity according to some distance measure [6]. Each group, called a cluster, consists of objects that are similar among themselves and dissimilar to objects in other groups. Clustering is an aggregation method, since a cluster is regarded as a higher level object that represents all objects it contains. It is widely used because of two reasons: 1) By visualizing cluster attributes rather than the original data, the number of visual elements displayed can be greatly reduced; 2) Clustering itself is a pattern discovering process. Thus visualizing clusters can explicitly reveal hidden patterns to viewers. Many visualization systems have adopted clustering methods to reduce clutter and analyze datasets. Fua et al. [13] cluster multivariate datasets, and navigate the hierarchy from clustering with a structure-based tool that supports drill-down, roll-up and brushing operations. They present a hierarchical version of parallel coordinates and later extend the work to other multivariate visualizations [37]. The InfoSky visual explorer [14] supports interactively exploring large, hierarchically structured document collections based on clustering. Kreuseler et al. [18] present a scalable framework for information visualization that can compute the clustering and hierarchy dynamically and support different methods to visualize clusters.

Chapter 3

Background on XmdvTool

XmdvTool is a public-domain software package for interactive visual exploration of multivariate data sets [34]. XmdvTool version 7.0 is based on OpenGL and Tck/Tk and is available for Windows95/98/NT/2000/XP and Linux platforms. It supports five classes of techniques for displaying both (non-hierarchical) flat form data and hierarchically clustered data, namely scatterplots, star glyphs, parallel coordinates, dimensional stacking and pixel-oriented techniques. XmdvTool also supports a variety of interaction modes and tools, including brushing in screen, data, and structure spaces, zooming, panning, and distortion techniques, and the masking and reordering of dimensions. Univariate displays and graphical summarizations, via tree-maps and modified Tukey box plots, are also supported. Finally, color themes and user customizable color assignments permit tailoring of the aesthetics to the users. XmdvTool has been applied to a wide range of application areas, such as remote sensing, financial, geochemical, census, and simulation data.

In the following sections, we will briefly introduce the five visualization techniques in Xmdvtool. We will also introduce the data abstraction technique used in XmdvTool, hierarchical visualization based on clustering.

3.1 Flat Visualization Techniques

In parallel coordinates [16, 35], each dimension corresponds to an axis, and the N axes are organized as uniformly spaced vertical lines. A data item in this multidimensional space is mapped to a polyline that traverses across all the axes. Figure 3.1 shows the Iris data set (4 dimensions, 150 data items) using parallel coordinates.

A scatterplot is a visual representation of data that illustrates the relation or association between two or three variables. The positions of data points represent the corresponding dimension values. Two or three dimensions are shown directly, and additional dimensions can be mapped to the color, size or shape of the plotting symbol. For visualizing multivariate data, the scatterplot matrix is an efficient and common tool. Given a dataset with N dimensions, the matrix consists of N^2 scatterplots arranged in N rows and N columns. The plot in row i and column j uses dimensions i and j to create a scatterplot. Each scatterplot reveals relationships between the two dimensions. Figure 3.2 shows the Iris data set using a scatterplot matrix.

In star glyphs, each glyph [3, 25] is a representation of a data element that maps data values to various geometric and color attributes of graphical primitives or symbols. In this technique, each data element occupies one portion of the display window. Data values control the length of rays emanating from a central point. The rays are then joined by a polyline drawn around the outside of the rays to form a closed polygon. Figure 3.3 shows the Iris data set using star glyphs.

The dimensional stacking technique is a recursive projection method developed by LeBlanc et al. [19]. It displays an N dimensional dataset by recursively embedding pairs of dimensions within each other. Each dimension of the dataset is first discretized into a user-specified number of bins, which is termed the dimension cardinality. Then two dimensions are defined as the horizontal and vertical axes, creating a grid on the display. Within each box of this grid this process is applied again with the next two dimensions. This process continues until all dimensions are assigned. Each data point maps to a unique bin based on its values in each dimension, which in turn maps to a unique location in the resulting image (See Figure 3.4). In XmdvTool, the dimensions are mapped to horizontal and vertical axes alternatively, from outer-most (slowest) to inner-most (fastest), based on their order in the input file. Figure 3.4 shows the Iris data set using dimensional stacking.

Pixel oriented techniques map each attribute value of the data to a single colored pixel, theoretically yielding the display of the maximum possible information at a time. A large number of pixel layout methods have been proposed, each of which enables users to perform their visual exploration tasks to varying degrees. Pixel oriented techniques typically maintain the global view of large amounts of data while still preserving the perception of small regions of interest. This makes them particularly interesting for visualizing large multidimensional data sets. Pixel based methods also provide feedback on the given query by presenting not only the data items fulfilling the query but also the data that approximately fulfill the query. Figure 3.5 shows a remote sensing data set using pixel oriented techniques.

3.2 Data Abstraction Technique in XmdvTool: Hierarchical Visualization

The flat visualizations become very crowded when they are applied to large-scale data sets. To overcome this clutter problem, Yang et al [38] developed an Interactive Hierarchical Display framework for XmdvTool. The key strategy is to put fewer items on the screen. Thus they compress the data sets while preserving their

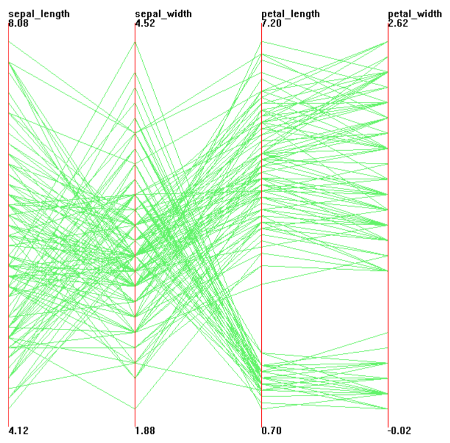


Figure 3.1: Flat Parallel Coordinates, Iris Dataset

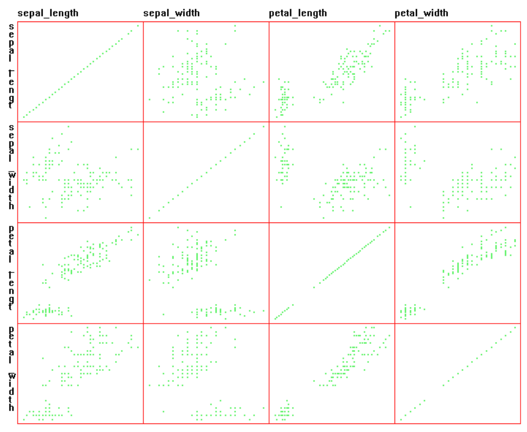


Figure 3.2: Flat Scatterplot Matrices, Iris Dataset

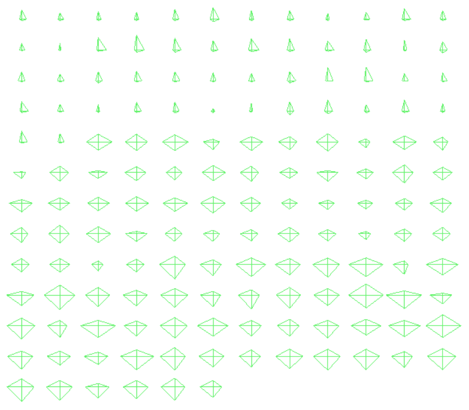


Figure 3.3: Flat Star Glyphs, Iris Dataset

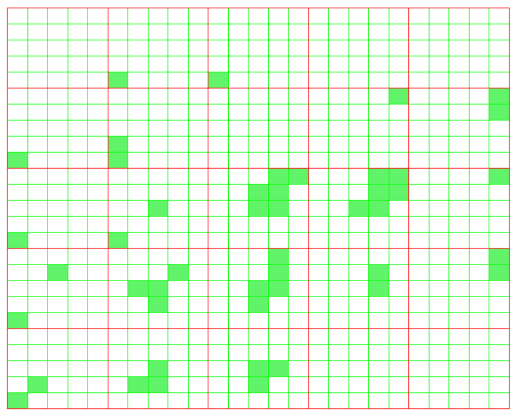


Figure 3.4: Flat Dimensional Stacking, Iris Dataset

significant features. Moreover, they support multiresolution displays so that users can interactively select their preferred level of detail. Given the above considerations, they have explored the concept of constructing a hierarchical cluster tree for a data set and designing hierarchical displays capable of conveying the contents of this tree.

Each node T_i of a hierarchical cluster tree represents a cluster. A non-leaf cluster is composed of all its children clusters, while a leaf cluster contains only a single data

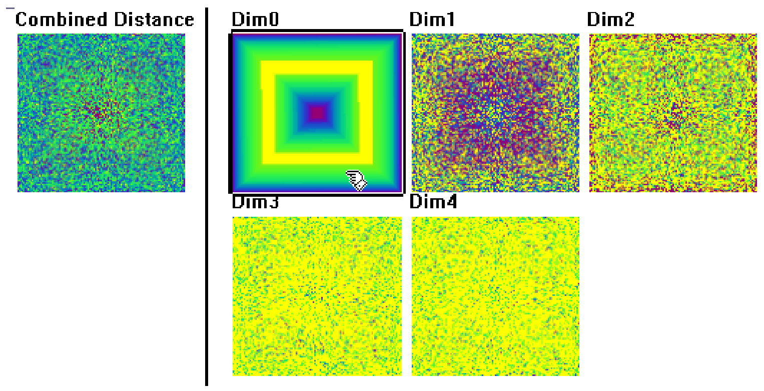


Figure 3.5: Pixel-oriented Visualization, Remote Sensing Dataset

item from the data set. A hierarchical cluster tree structures and presents a large data set at different levels of abstraction. On extreme points, the leaf clusters each present exactly one data item of the data set, while the root is a cluster representing the data set as a whole.

A hierarchical cluster tree is typically formed by grouping data items based on some measure of proximity between pairs of objects [17]. A number of clustering algorithms have been proposed for building hierarchical cluster trees of large data sets [15, 39]. Those visualization techniques are independent of the particular choice of the clustering algorithms and in fact could equally be applied to hierarchical data sets constructed based on any explicit hierarchical clustering. Yang et al [38] use a bottom-up agglomerative clustering algorithm based on Euclidean distance as an example.

Hierarchical techniques can be applied to parallel coordinates, scatterplots, star glyphs, dimensional stacking and Pixel-oriented techniques. Here I only show an example of parallel coordinates. Hierarchical parallel coordinates are an extension of traditional (flat) parallel coordinates. In hierarchical parallel coordinates, the centers of the clusters replace the data items. The mean of a cluster is mapped to a polyline traversing across all the axes, with a band around it depicting the extents of the cluster in each dimension. The lower edge of the band intersects each axis at the minimum value of its respective cluster in that dimension. The upper edge of the band intersects each axis at the maximum value of its respective cluster in that dimension. To give the user a sense of the location of data points in a cluster and to convey the overlap among clusters, each band is translucent. There is a linear drop-off in the density of cluster data from its center to the edge, and the maximum opacity is proportional to the population. Figure 3.6 show an example of parallel coordinates with the Iris dataset.

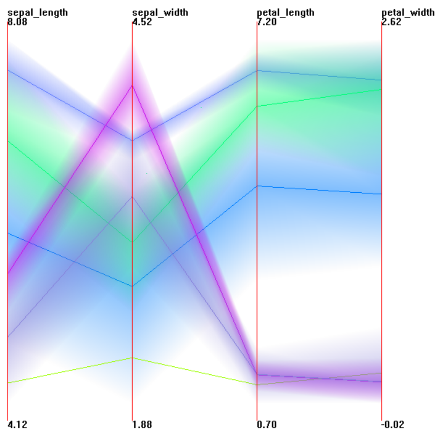


Figure 3.6: Hierarchical Parallel Coordinates, Iris Dataset

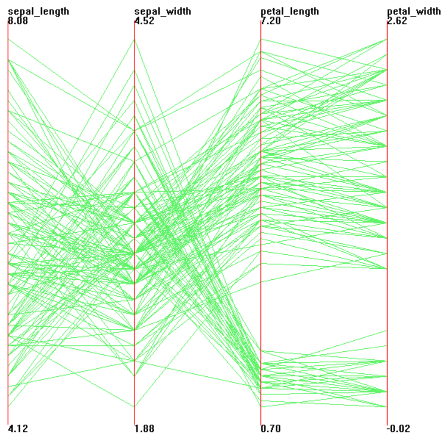


Figure 3.7: Flat Parallel Coordinates, Iris Dataset

Chapter 4

Data Abstraction Quality Measures

Data abstraction is the process of simplifying a large dataset into one of moderate size, reducing the detail of data while maintaining the dominant characteristics of the original dataset. Some data abstraction methods select a subset of the original dataset as the abstraction, such as sampling [11] and filtering [2], while other data abstraction methods construct a new, more abstract representation, such as clustering and summarizing. Measurement generally refers to the process of estimating the magnitude of a quantitative property [10]. Measurement is essential for scientific research; with measurement, researchers can compare different objects and evaluate the effectiveness of programs or processes.

In this section, we will describe three types of abstraction quality measures that we have proposed. To facilitate explanation of these measures, we define two terms. **D**ata **A**bstraction **L**evel (DAL) refers to the ratio between the size of the abstracted dataset and the original dataset. **D**ata **A**bstraction **Q**uality (DAQ) denotes the degree to which the abstracted dataset represents the original dataset.

At a given DAL, the DAQ will vary based on the different abstraction methods used or even on different invocations of a given abstraction operation. A good abstraction method should maximize the data abstraction quality and minimize the variance of data abstraction quality in different invocations of data asbtraction with the same parameters. The DAL can be considered as a very coarse data abstraction quality measure. Other data abstraction quality measures will, in general, be better descriptors than the DAL.

4.1 Histogram Difference Measure

A histogram is an aggregation method that conveys data distribution. To construct a histogram, the data space is partitioned into many small ranges, with each range corresponding to a histogram bin. The height of a histogram bin is determined by the percentage of data points that fall in the corresponding range. It reveals the data density within each subrange.

Because a histogram is a common data descriptor and is fast to compute, we propose to use the difference between the normalized histograms of the original dataset and the abstracted dataset as a measure to gauge the DAQ. First we compute two histograms with the same number of bins from the original dataset and the abstracted dataset. If the distributions are skewed, we can use non-uniform bin widths. Bin sizes correspond to the percentage of the total number of data points that fall in the bins. Bin difference is defined as the absolute difference between two bins. Then the histogram difference corresponds to the summation of bin differences between the corresponding bins in the two histograms. **HDM** (Histogram Difference Measure) is defined as the normalized histogram difference. Its range is from 0 to 1. 0 s in every pair of corresponding bins, at least one is empty, and 1 indicates a perfect match. We express these with the following equations:

$$Pb_i = |Po_i - Pa_i| \tag{4.1}$$

where Po_i is the percentage of data that fall into the i-th bin of the original histogram, Pa_i is the percentage of data that fall into the i-th bin of the abstracted histogram, and Pb_i corresponds to their bin difference.

$$Ph = \sum_{i=1}^{N} Pb_i = \sum_{i=1}^{N} |Po_i - Pa_i| \tag{4.2}$$

where Ph is the histogram difference, and N is the number of bins.

$$HDM = 1.0 - \frac{Ph}{MAX(Ph)} \tag{4.3}$$

where HDM is the Histogram Difference Measure, and $MAX(Ph)$ is the maximum histogram difference. These equations generate the HDM for one data dimension. The HDM for an N-dimensional dataset is defined as the average of the N HDMs for the N dimensions. Recall that the histogram represents a data distribution. Thus the proposed HDM represents the difference between the data distributions in the two datasets. If this difference is very small, the HDM will be near 1. In this case, the abstracted dataset represents the original dataset very well, implying the data abstraction method has a very high quality.

Thus far, we use the absolute difference between bins to calculate the histogram difference. If we consider a histogram as a vector, then we can treat the histogram difference as the distance between two vectors. Thus many general methods of calculating vector distances can be used to calculate the histogram difference. For example, the equation for Minkowski distance is:

$$Ph = \sum_{i=1}^{N} Pb_i = (\sum_{i=1}^{N} |Po_i - Pa_i|^p)^{\frac{1}{p}} \tag{4.4}$$

where p is the distance type, $p > 0$. For p=1, it is the Manhattan distance, which coincides with our definition of histogram difference above. For p=2, it is the Euclidean distance. We first use the Manhattan distance as the histogram difference, because it represents the absolute density difference between two datasets. Different distance methods will be evaluated in our future work. The number of bins in a histogram influences its effectiveness in conveying information. We can compute the bin size by setting a bin width. The default bin width in our work is calculated using the equation: $W = 3.49S \times N^{-\frac{1}{3}}$, where S is the standard deviation in a given dimension and N is the number of data points. It has been illustrated by Scott [29] that this generally results in an effective bin size.

4.2 Validating Histogram Difference Measures

Aggregate queries refer to queries involving aggregation, such as summary, average and maximum. For very large databases, it may be prohibitively expensive to get exact results for aggregate queries. We note that the result of an aggregate query lists aggregate values in each sub-category. This in fact parallels a histogram, and each sub-category corresponds a range in histogram. Error metrics are needed to measure the accuracy of the estimated query result compared to the actual query result. Babcock et al. [4] define the average relative error with the following equation:

$$RelErr = \frac{1}{n}(k + \sum_{j=1}^{m} \frac{|x_j - x'_j|}{x_j}) \tag{4.5}$$

where n is the number of bins, k is the number of empty bins in the estimated histogram, m is equal to $n - k$, x_j is the actual value of the j-th bin, and x'_j is the estimated value of the j-th bin. This metric is similar to our histogram-based measure except that it uses the percentage of each bin, while our measure uses the percentage of the whole dataset. With this error measure, they demonstrated that dynamic sampling can provide more accurate approximate results than non-adaptive uniform or non-uniform sampling.

In the image retrieval field, features are extracted from images in order to facilitate searching over images. Image features are an abstraction of the image and often are described as a histogram on image parameters such as color. Similarity measures are needed to compare histograms of image features. Swain and Ballard [31] first proposed the color indexing method, which compares the color histograms of two images, defined in Equation 4.6. Niblack et al. [22] proposed measuring the image similarity with a quadratic distance metric of a histogram using Equation 4.7.

$$Similarity(H_1, H_2) = \sum_{i=1}^{N} |H_{1i} - H_{2i}| \tag{4.6}$$

$$Similarity(H_1, H_2) = (H_1 - H_2)^T A (H_1 - H_2) \tag{4.7}$$

where H_1 and H_2 are two histograms, H_{1i} is the i-th bin of the first histogram, H_{2i} is the i-th bin of the second histogram, $(H_1 - H_2)^T$ is the transpose of $(H_1 - H_2)$, and A is matrix, where a_{ij} is the element of A in row i and column j, and indicates the corelationship between H_{1i} and H_{1j}. $a_{ii} = 1$, because the corelationship between one random variable and itself is 1. If all $a_{ij}(i \neq j) = 0$, then it becomes the Euclidean distance between the two histograms (Equation 4.8).

$$Similarity(H_1, H_2) = (\sum_{i=1}^{N} |H_{1i} - H_{2i}|^2)^{\frac{1}{2}} \tag{4.8}$$

Siggelkow [30] provided a comprehensive list of image similarity measures used in image retrieval systems. Our proposed histogram-based measure is similar to the first image similarity measure listed by Siggelkow, and is based on the same model as all similarity measures.

4.3 Nearest Neighbor Measure

As the name implies, nearest neighbor algorithms [12] search for the object nearest to a given object. They are widely used to classify data into groups in data clustering and pattern recognition. Every object corresponds to a record. We assume that each record in the original dataset has a nearest neighbor in the abstracted dataset, called its representative. The records in the original dataset that are represented by the same record in the abstracted dataset form a cluster. Currently only numeric values are considered. We define the **NNM** (Nearest Neighbor Measure) as the normalized average of distances between every record in the original dataset to its representative.

The following steps show the algorithm to calculate the NNM.

1. Choose a distance method to calculate the distance between two records. We use the normalized Euclidean distance because it is the most commonly used method. Our future work will compare the NNMs with different parameters, including different ways to compute the distance. The equation is:

$$D(x, y) = \frac{\sqrt{\sum_{k=1}^{N}(x_k - y_k)^2}}{\sqrt{N}} \tag{4.9}$$

where x and y are two arbitrary records, $D(x, y)$ is the normalized distance between x and y, x_k and y_k are the k-th normalized dimension values of records

x and y, respectively, ranging from 0 to 1, N is number of dimensions, and $\sqrt{N}$ is the maximum distance in the N dimensional space. The maximum value is met when all dimension values in one record are 0 and all dimension values in the other record are 1. We normalize the distance by dividing by the maximum distance $\sqrt{N}$.

2. Find a representative for each record in the original dataset. For the i-th record in the original dataset, we calculate the distances to all the records in the abstracted dataset, select the one with the smallest distance as the representative, and store this distance. The process is described with the following equation:

$$D_i = \min_{j=1}^{K} D(x_i, y_j) \tag{4.10}$$

where x_i (i=1, 2, ..., N) is the i-th record in the original dataset, y_j is the j-th record in the abstracted dataset, K denotes the number of records in the abstracted dataset, and D_i is the distance of the i-th record to its representative.

3. Normalize the average of the minimum distances into the NNM. We use the following equation to do this:

$$NNM = 1.0 - \frac{\sum_{i=1}^{M} D_i}{M} \tag{4.11}$$

where D_i is the normalized distance of the i-th record to its representative, NNM is the Nearest Neighbor Measure, and M denotes the number of records in the original dataset.

4.4 Reconsidering Normalization of NNM

As will be described in Chapter 6, the original version of NNM produces values much higher than the quality perceived by users. In this section, we propose a new approach to normalize NNM. The idea of this approach is shown in figure 4.1. A data record in the abstracted dataset and the records represented by it in the original dataset form a cluster. The whole original dataset also forms a cluster. We assume each cluster has a radius. We define the centroid of a cluster as the data record that can represent the whole cluster. We define the radius of a cluster as the average distance from each record in the cluster to the centroid of cluster. The cluster formed by the whole dataset also corresponds to a radius, whose value is fixed.

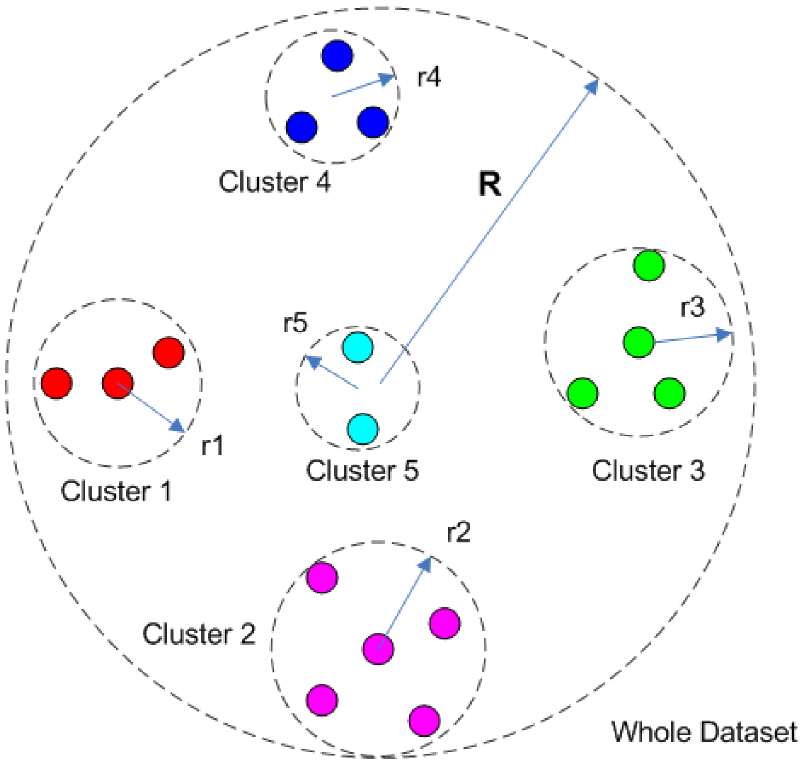


Figure 4.1: Radiuses of Clusters and Whole Dataset

An abstracted dataset forms a data abstraction. We define the radius of an abstraction as the average radius of clusters, formed by the data records in the abstracted dataset and the data records represented by them, respectively. The quality measure is related to the ratio between the radius of abstraction and the radius of the original dataset. As the DAL increases, the radius of abstraction will decrease, while the quality will increase. Thus the quality measure should be negatively related to this ratio.

The detail of this approach is described in the following steps.

1. The radius of a cluster is defined with the following equation:

   $$r_k = \frac{\sum_{i=1}^{J_k} D_i}{J_k} \tag{4.12}$$

   where r_k denotes the radius of this kth cluster, J_k denotes the number of data records in the kth cluster, and D_i denotes the normalized distance of the i-th record to its representative.

   The radius of an abstraction is defined with the following equation:

   $$r = \frac{\sum_{k=1}^{L} r_k}{L} \tag{4.13}$$

   where r denotes the radius of this abstraction, r_k denotes the radius of the kth cluster, and L denotes the number of clusters (the number of records in the abstracted dataset).

   As one variation of the radius, we might consider the importance or weight of each cluster radius. If we use the percentage of data records of each cluster as its importance, then the radius of the abstraction can described with the following equation:

   $$p_k = \frac{J_k}{M} \tag{4.14}$$

$$r = \sum_{k=1}^{L} r_k p_k \tag{4.15}$$

Where r denotes the radius of this abstraction, r_k denotes the radius of the kth cluster, J_k denotes the number of data records in the kth cluster, p_k denotes the importance of the kth radius, and M denotes the number of records.

When we replace r_k and p_k, it will become the average distance from each data record in the original dataset to its representative, as used in Equation 4.11.

$$r = \sum_{k=1}^{L} r_k p_k = \frac{\sum_{i=1}^{M} D_i}{M} \tag{4.16}$$

Where r denotes the radius of this abstraction, r_k denote the radius of the kth cluster, J_k denotes the number of data records in the kth cluster, p_k denotes the importance of the kth radius, D_i is the normalized distance of the i-th record to its representative, and M denotes the number of records.

2. To get the radius of the original dataset, we need to find the data record that represents the whole dataset. We name this data record the centroid of this dataset. In our algorithm, we use the data record nearest to all the data records as the centroid, meaning, it has the smallest average distance to all other records. The average distance from the centroid to all other records will become the radius of the whole dataset.

$$AvgD_k = \frac{\sum_{i=1}^{M} D(k,i)}{M} \tag{4.17}$$

$$R = AvgD_c = \min_{i=1}^{M} AvgD_i \tag{4.18}$$

Where $AvgD_k$ denotes the average distance from k to all other records, c

denotes the centroid, $AvgD_c$ denotes the average distance from c to all other records, R denotes the radius of original dataset, and M denotes the number of data records in the original dataset.

3. The data abstraction quality can be described with the following equation.

$$NNM = 1.0 - \frac{r}{R} = 1.0 - \frac{\sum_{i=1}^{M} D_i}{MR} \tag{4.19}$$

where D_i is the normalized distance of the i-th record to its representative, NNM is the Nearest Neighbor Measure, R denotes the radius of the original dataset, and M denotes the number of records.

Other aproaches are possible for defining data abstraction quality. The one that we considered employs the average distance bewteen any two data records to represent the cohesion of a cluster, instead of using the above radius. We will compare this method to our current method in our future work.

4.5 Validating Nearest Neighbor Measures

The Nearest Neighbor Measure employs an algorithm to find a representative for each record, averages the normalized distances between data records and their representatives, and normalizes this value. To support the use of the Nearest Neighbor Measure, we first show that the nearest neighbor algorithm has been successfully used in pattern recognition. We also show that some image quality measures in image compression are derived from the average distance between pairs of image pixels in a method similar to our measure.

In pattern recognition, the nearest neighbor algorithm is used to classify phenomena based on observed features [12]. Phenomena and features are described in a vector. In the training stage, feature vectors are extracted from a set of observed objects. In the testing stage, a vector is extracted from a new phenomena, and the distances from this vector to all feature vectors are computed. The feature vector with the smallest distance is the nearest neighbor. This phenomena is assigned to the class that its nearest neighbor belongs to. We use the same algorithm to find the representative for each data record.

Image quality measure is essential for image compression. It is not only used to evaluate compression techniques, but also to control the compression process and decide how many bits are allocated to each subband [26]. Many image quality measures can be derived from the total or average distance between pairs of image pixels. The PSNR (peak signal-to-noise ratio) is the most common image quality measure, derived from MSE (mean squared error) and used in the JPEG 2000 Standard [28]. It is defined by the following equations:

$$MSE = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M}(F(i,j) - \hat{F}(i,j))^2}{NM} \tag{4.20}$$

where MSE is the mean squared error, $F(i,j)$ is the pixel value at (i,j) in the original image, $\hat{F}(i,j)$ is the pixel value at (i,j) in the compressed image, and M and N are the length and height of the image.

$$PSBR = 10\log_{10}(\frac{MAX_I^2}{MSE}) \tag{4.21}$$

where $PSBR$ is the peak signal-to-noise ratio and MAX_I is the maximum pixel value. As we can see, NNM employs the same method to compute the average distance between two datasets. The only difference is that they employ different methods to process the average distance to get the measures.

4.6 Statistical Measures

Statistics is a mathematical science involving the study of data collection, data analysis, data interpretation and presentation. It is used in nearly all academic disciplines, from the natural sciences to social sciences. When a statistical algorithm is applied to a dataset, we get one or more statistic. The most common statistics are mean value and variance. In this section, we use mean value as an example to measure data abstraction quality. The **SM** (Statistical Measure) is defined as the distance between two sets of statistics.

The following steps show the process to calculate the SM based on mean values.

1. Compute the mean value of each dimension for the original dataset and abstracted dataset, respectively.

$$Mean_i = \frac{\sum_{j=1}^{M} x(i,j)}{M} \tag{4.22}$$

   Where $Mean_i$ is the mean value of the i-th dimension, $x(i,j)$ is the normalized value of the j-th element in the i-th dimension, and M is the number of records in the dataset.

2. Compute the distance between mean values of the original dataset and the abstracted dataset.

$$D = \sqrt{\frac{\sum_{i=1}^{N}(MeanO_i - MeanA_i)^2}{N}} \tag{4.23}$$

   Where $MeanO_i$ is the mean value of the i-th dimension in the original dataset, $MeanA_i$ is the mean value of the i-th dimension in the abstracted dataset, N is the number of dimensions, and D is the distance between two sets of statistics.

3. Transform the distance into SM. The range of distance and SM are both from 0.0 t0 1.0. The transformation makes SM positively related to data abstraction quality.

$$SM = 1.0 - D \tag{4.24}$$

Chapter 5

Integrating Quality Measures with Multiresolution Visualization

In this section, we describe our work on integrating quality measures into XmdvTool to develop effective and quality-aware multiresolution visualization. First we describe the widget that we use to display quality measures. Then we present the interactive operations we support for quality measures. Next, we discuss the view continuity problem of sampling, and finally we give an overview of the Structure-Based Brush (SBB) that we use to control abstraction parameters in clustering data. Analysts can adjust the DAL of clustering through both the general widget for all abstraction methods and the SBB, while they can only brush the structure formed by clustering through the SBB.

5.1 Displaying Measures

XmdvTool supports interactive selection via brushing [13, 21] using a rich assortment of tools. The data selected through brushing is called the selected data, while the remaining data are called the unselected data. Analysts can adjust the DAL for the selected data as well as the unselected data. Each DAL of selected data or unselected data corresponds to several abstraction qualty measures. We use bar charts to display them. Figure 5.1 shows two such bar charts, the left one conveys the quality measures for the selected data, and the right one conveys the quality measures for the unselected data.

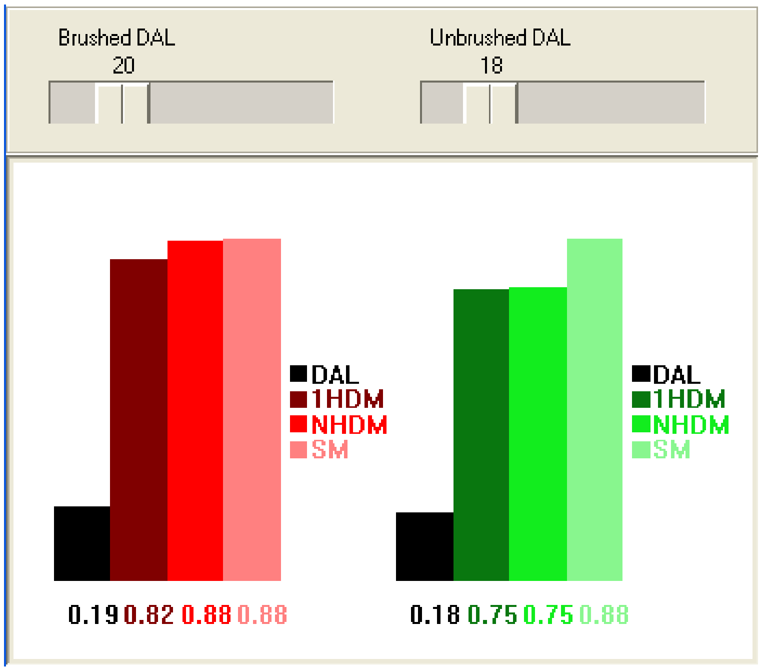


Figure 5.1: Plot to display measures and sliding bars to adjust the DAL

These charts only illustrate the quality measures at a single DAL. We use 1D plots to illustrate quality measures and their relationship to the DAL. In Figure 5.2, the left and right plot show the quality measures for the selected and unselected regions, respectively. In each plot, the x-axis represents the DAL and the y-axis represents the quality measures. In Figure 5.2, we use HDM and NNM as examples. The red and blue line represent the changes of abstraction quality measures against the abstraction level. A vertical line called the DAL handle is drawn to indicate the current abstraction level. The cross points of this vertical line and the plot lines denote the corresponding measures of this abstraction level. The DAL and measures are displayed to the right of the DAL handle. With these plots, analysts can know the quality of the current DAL in the context of the entire quality space.

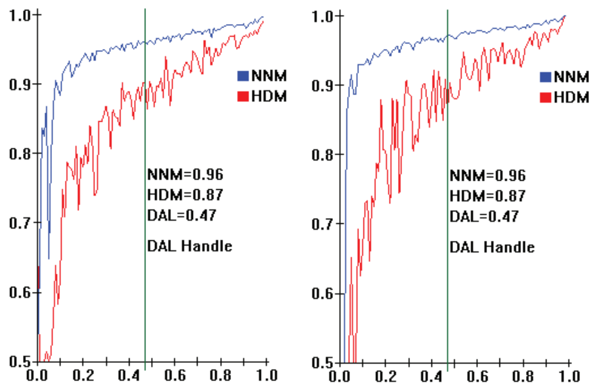


Figure 5.2: 1D plots of quality measures. (a) 1D plot for selected data; (b) 1D plot for unselected data.

5.2 Interactive Operations

Several interactive operations are supported. Users can move the slider bar in Figure 5.1 or the DAL handle in Figure 5.2 to adjust the data abstraction level. After the DAL has been changed, the system will generate an abstracted dataset and display it in the data visualization. The DALs for selected and unselected data can be adjusted independently. Users can also modify the location of one of the boundaries of the selected region by clicking the left mouse button on or near the boundary and dragging it in the desired direction. In addition, the selected region can be moved by choosing a region on the data display, and then adjusting the DAL for the region. This usually means that the user knows the data subset that she wants to explore and wants to take advantage of the scalability of multiresolution visualization. Alternatively a user can first choose a DAL in the current selected region, and then adjust the selected/brushing boundary to enlarge or diminish the size of the region. This often indicates that an acceptable data abstraction level had been found, but the area of interest needs to be increased or decreased.

For some abstraction methods, each abstraction generates the same results, such as clustering; for other abstraction methods, each abstraction may generate different results, such as sampling. Analysts can also instruct the system to run the abstraction algorithm again to generate a new abstraction. For example, resampling can help analysts verify patterns that had been discovered in the previous samples. If a pattern still exists after resampling several times, this pattern is most likely a robust one. Furthermore, analysts can compare the abstraction measures from multiple resamplings, and select an abstraction with the best quality. Finally, a user can indicate a desired quality level based on one of the measures and let the system decide the appropriate DAL.

5.3 View Continuity for Sampling

When analysts change the DAL, the patterns in the previous sample can be more easily remembered and compared with those in the current sample if view continuity is maintained. This can be accomplished following the three guidelines below:

1. When changing from a low DAL to a higher DAL, all the records in the previous sample should be kept.

2. When changing from a high DAL to lower DAL, all the records in the new sample should come from the previous sample.

3. When broadening or narrowing the brushing boundary, the system should keep

the records from the previous view, and then employ the same rules as above. We follow the above guidelines to maintain view continuity. Analysts still have the option to resample at any time or whenever they change the DAL or the selected region.

5.4 Widget to Control Cluster-Based Abstraction

Hierarchical clustering generates a tree of clusters ranging from a single cluster containing the entire dataset to terminal clusters containing one record each. To represent a cluster in multiresolution visualization, one member of the cluster can be selected as a representative or a new record can be constructed to summarize the records in this cluster. This new record becomes the parent of all the records or clusters it contains. By recursively clustering data into related groups, a tree of clusters is formed.

The abstracted dataset in clustering is defined as all the items with a specific node depth. This node depth represents the DAL. If the tree is visited using an in-order traversal algorithm, then all the nodes of this tree will be sorted and each node corresponds to a unique position in this order. Brushing is thus achieved via selecting a range of nodes in this order. We employ two handles to control this range. All the nodes in this range form a subtree. Analysts can adjust the abstraction level and visualize selected nodes in more or less detail.

Figure 5.3 shows the widget to control both the level of abstraction and brushing, referred to as the Structure-Based Brush (SBB) [13], designed by Ying-Huey Fua. The triangular frame depicts the tree (see (a)). The leaf contour (see (c)) depicts the silhouette of the tree. It delineates the approximate shape formed by chaining the leaf nodes. The colored bold contour (see (b)) across the tree delineates the tree cut that represents the abstracted dataset in a specific data abstraction level. Analysts can adjust the DAL by moving this contour. The two movable handles (see (e)) on the base of the triangle are called range handles. The range handles, together with the apex of the triangle, form the selected region in the structure space (see (d)). Analysts can adjust the selected region by moving the left handle, the right handle or both. This interface, while specific to hierarchically clustered data, can support all of the interactions on the abstraction.

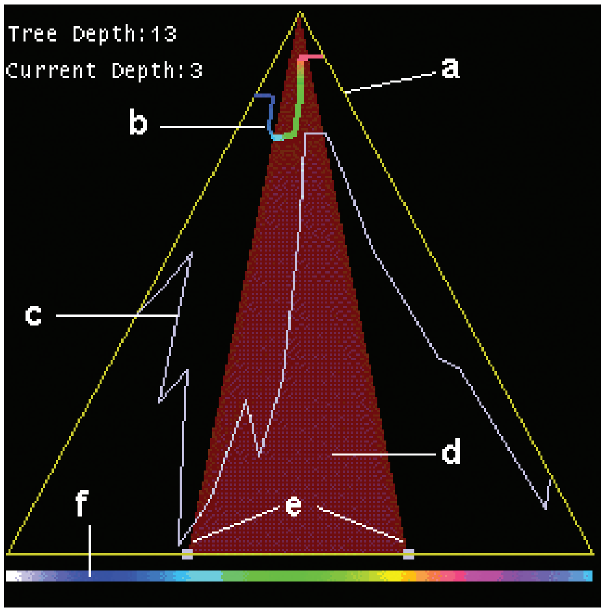


Figure 5.3: Structure-based brushing tool. (a) The tree frame; (b) Contour corresponding to current level-of-detail; (c) Leaf contour approximates shape of the tree; (d) Structure-based brush; (e) Interactive brush handles; (f) Colormap legend for level-of-detail contour.

Chapter 6

Evaluation of Abstarction Quality Measures

In this chapter, we will present the evaluation we performed on the abstraction quality measures. Our goal is to validate the accuracy of the proposed data abstraction measures. Ideally, abstraction quality measures should conform to the data abstraction quality perceived by analysts. Abstraction quality measures estimates how well the abstracted dataset represents the original dataset.

6.1 Description of Evaluation

We have designed two groups of questions for this evaluation: one group contains 9 questions based on the Iris dataset and employs parallel coordinates to display data, while the other group contains 4 questions using the Out5d dataset and employs Scatterplots to display data. For each question, the left figure displays the original dataset, and the right figure shows the abstracted dataset. Users are asked to input the answer by selected one quality level ranging from 0 to 10. All evaluation questions are listed in Appendix A.

15 people evaluated this system, most of them students in the Department of Computer Science at WPI. Four of them are visualization experts, five of them have intermediate knowledge of visualization, and four of them had little prior knowledge of visualization. On average, it took a person 30 seconds to answer each question.

6.2 Results of Evaluation

15 people responded to each question. Each question corresponds to a DAL. We average the qualities perceived by the subjects to get the perception quality for a DAL. The perceived quality is named PQ. The standard deviation of the perceived qualities is also computed to show the variance of the perceived qualities, labelled Stdev. We first employ a 2D chart to illustrate the relation between DAL and HDM, NNM, SM, PQ and Stdev. Figure 6.1 shows the result for the first group, while figure 6.2 shows the results for the second group.

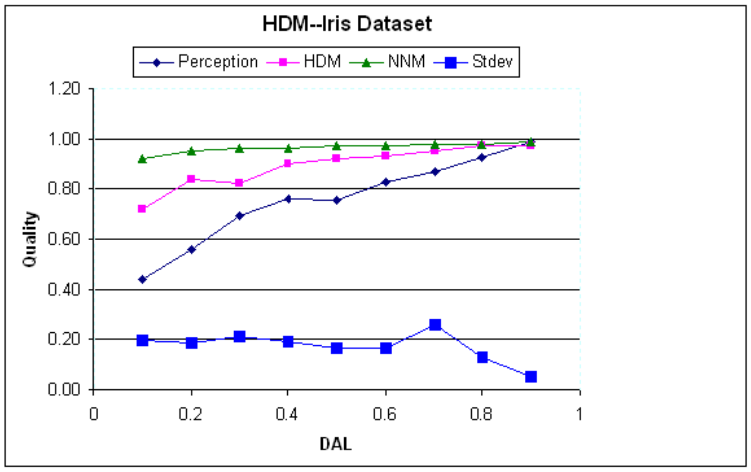


Figure 6.1: Evaluation Results 1

Next, we employ parallel coordinates to show the results. The result dataset contains five dimensions, vis_type (Parallel coordinates or Scatterplots matrices),

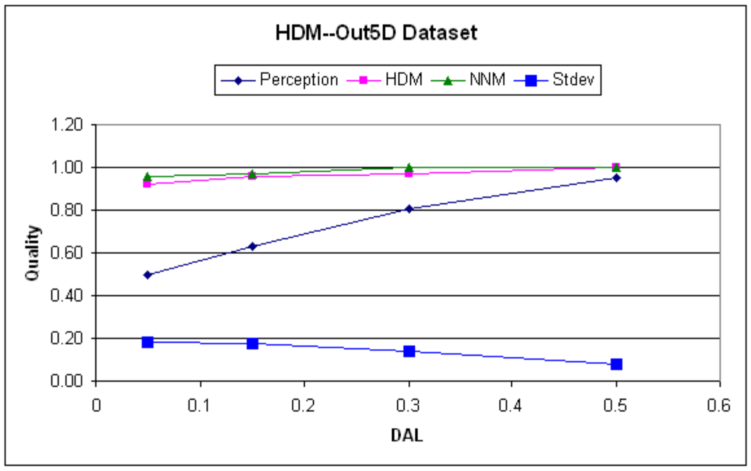


Figure 6.2: Evaluation Results 2

Stdev (Stanard Deviation), PQ (Perceived Quality), DAL, HDM and NNM. Figure 6.3 shows the 13 data records with parallel coordinates. The results from the first 9 experiments are brushed.

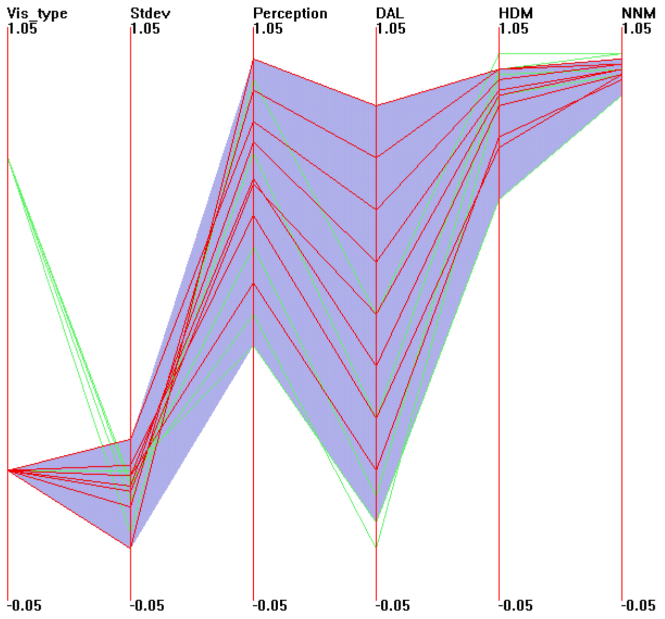


Figure 6.3: Evaluation results shown by parallel coordinates

6.3 Analysis of Evaluation

From Figure 6.1, 6.2, and 6.3, we summarize several observations regarding our measures and evaluation.

1. As the abstraction level increases, the perceived quality increases, and our quality measures (HDM and NNM) increase as well, although they fluctuate. This shows that our measures can be used to differentiate data abstraction qualities, and our measures can indicate data abstraction quality. This also informs us that we are going in the right direction in our search for quality measures.

2. Our measures, including HDM, NNM and SM, are higher than the qualities perceived by users. Thus we need to adjust methods or parameters used in the process of computing measures to make them closer to the perceived qualities. We will discuss this problem in the next chapter.

3. As the abstraction level increases, the standard deviation of quality perceived by users decreases, although it fluctuates. This shows that users agree with each other on data abstraction quality as the abstraction level increases.

Chapter 7

Experiments on Data Abstraction Measures

In this chapter, we will present experiments we did on data abstraction measures. For one kind of measure, many variations exist because there are different distance metrics and/or different mechanisms to choose during the computation of measures. For HDM, we may use 1-D histograms or N-D histograms. After selecting the type of histogram, we can use one of many distance measures to compute HDM. For NNM, we can select one of many possible distance metrics. We may also use different mechanisms to normalize the NNM. The objective of these experiments is to find the best measure of each type of measure from variations of each type through comparing them.

Table 7.1 lists the measures, metrics and mechanisms that they use.

We choose 100 abstraction levels from 0.01 to 1.00. For each abstraction level, we compute the corresponding quality measures. The result is a measure dataset. It contain 100 records, and each record contain 11 attributes: DAL, HDM1, HDM2, NHDM1, NHDM2, NNM1-1, NNM2-1, NNM2-2, SM1 and SM2. Figure 7.1 shows

Name	Mechanism and Metric
1-HDM	1-D Histogram
N-HDM	N-D Histogram
1-HDM-1	1-D Histogram, Manhattan distance
1-HDM-2	1-D Histogram, Euclidean distance
N-HDM-1	N-D Histogram, Manhattan distance
N-HDM-2	N-D Histogram, Euclidean distance
NNM-1	Manhattan distance
NNM-2	Euclidean distance
NNM-a	Regular Normalization
NNM-b	New Normalization
NNM-a-1	Regular Normalization, Manhattan distance
NNM-a-2	Regular Normalization, Euclidean distance
NNM-b-1	New Normalization, Manhattan distance
NNM-b-2	New Normalization, Euclidean distance
SM-1	Manhattan distance
SM-2	Euclidean distance

Table 7.1: List of Quality Measures

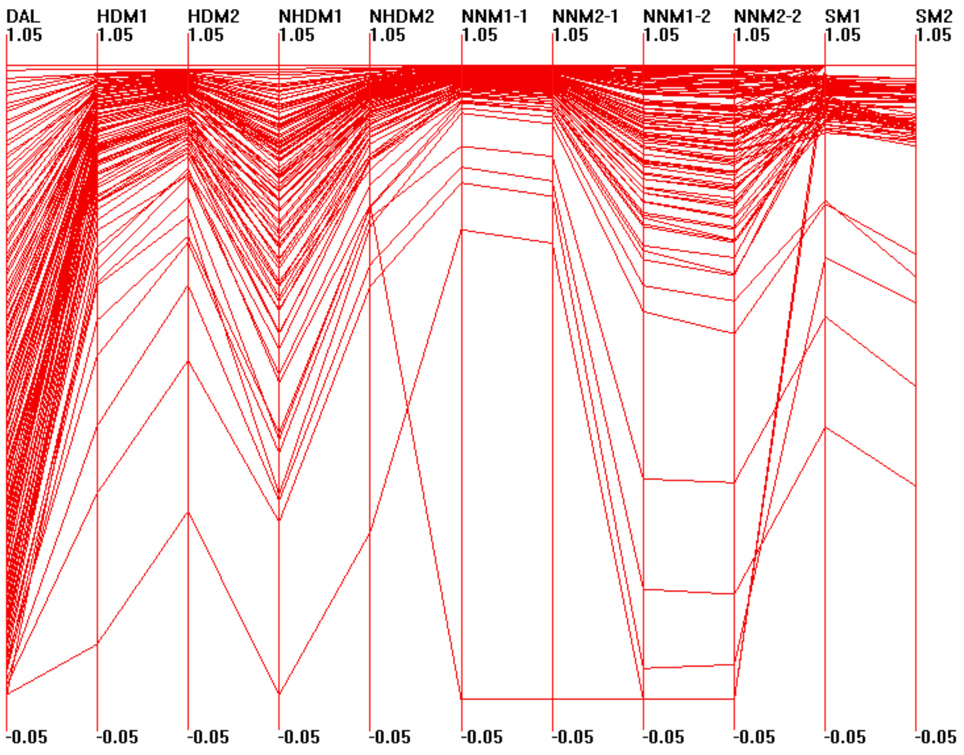


Figure 7.1: Quality Measures with Metrics and Mechanisms of them

this dataset with parallel coordinates. We will analyze this dataset together with the quality perceived by users in the following sections.

7.1 Comparing HDM with Different Histograms

HDM may employ different histogram methods, such as 1-D histograms and N-D histograms, or different distance metrics. For distance metrics, we prefer the Manhattan distance metric because it represents the difference between two histograms. Thus the HDM can represent the difference between data distributions of these two datasets. In this section, we will compare 1-HDM-1 and N-HDM-1. 1-HDM-1 represents the HDM based on 1-D histograms, N-HDM-1 represents the HDM based on an N-D histogram, and both of them use Manhattan distance.

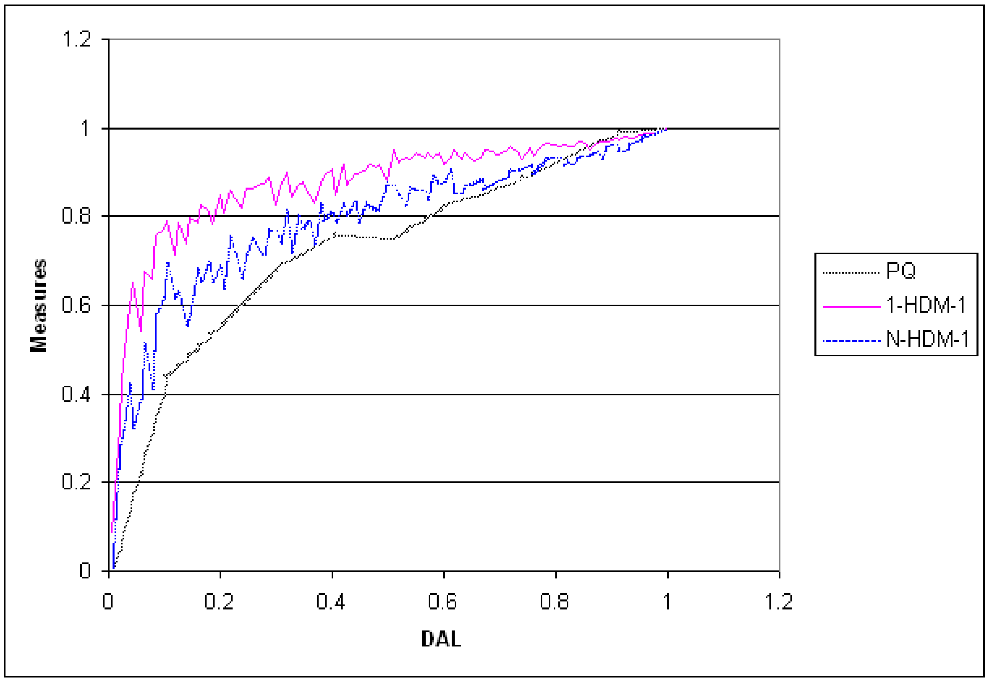


Figure 7.2: 1-HDM-1 and N-HDM-1

Figure 7.2 shows the changes of 1-HDM-1 and N-HDM-1 with the increase of data abstraction level. As we can see, 1-HDM-1 is higher than N-HDM-1 in nearly all data abstraction levels. In the previous chapter, our evaluation indicates that the HDM measure is higher than the quality perceived by users. So N-HDM-1 is closer to the quality perceived by users than 1-HDM-1.

Why is N-HDM-1 closer to the quality perceived by users than 1-HDM-1? We first review the steps to compute 1-HDM-1 and N-HDM-1.

Steps to compute 1-HDM-1:

1. Compute 1 dimensional histogram for each dimension in the abstracted dataset and the original dataset;
2. Compute 1 dimensional histogram distances for each dimension;
3. Compute average for distances of all dimensions;
4. Normalize this average value into 1-HDM.

Steps to compute N-HDM-1:

1. Compute N dimensional histogram for the abstracted dataset and the original dataset;
2. Compute N dimensional histogram distance;
3. Normalize this distance into 1-HDM-1.

1-HDM-1 indicates the average difference of data distribution of each dimension independently, while N-HDM-1 indicates the difference of data distribution of all dimensions together. N 1-D histograms may lose some information about data distribution compared to an N dimensional histogram. Hence N-HDM-1 is closer to the quality perceived by users than 1-HDM-1 in most of cases.

7.2 Comparing NNM with Different Normalization Methods

In Chapter 4, we presented two methods to normalize the NNM. One method uses the average distance from each data record to its representative. The other method considers the radius (R) of the original dataset, whose value is the average distance from the centroid to all records in the original dataset. The centroid is the data record with the minimum distance to all records in a dataset. The average distance from each data record to its representative is considered as the radius (r) of the data abstraction.

We use the following formulas to compute NNM, respectively:

NNM-a $= 1.0 - AvgD = 1.0 - r$

NNM-b $= 1.0 - \frac{r}{R}$

Figure 7.3 shows the changes of NNM-a-1 and NNM-b-1 with the increase of data abstraction level. Figure 7.4 shows the changes of NNM-a-2 and NNM-b-2 with the increase of data abstraction level. As we can see, NNM-b is closer to the quality perceived by users than NNM-a. Since NNM is higher than the quality perceived by users, we prefer NNM-b to NNM-a to measure data abstraction quality. From the definition of NNM-a and NNM-b, NNM-b is less than NNM-a because the radius R, the normalized distance, is less than 1.

7.3 Comparing HDM and NNM with Different Distance Methods

In this section, we compare 1-HDM, N-HDM, NNM-a, NNM-b and SM (Statistical Measure) using the Manhattan distance and the Euclidean distance.

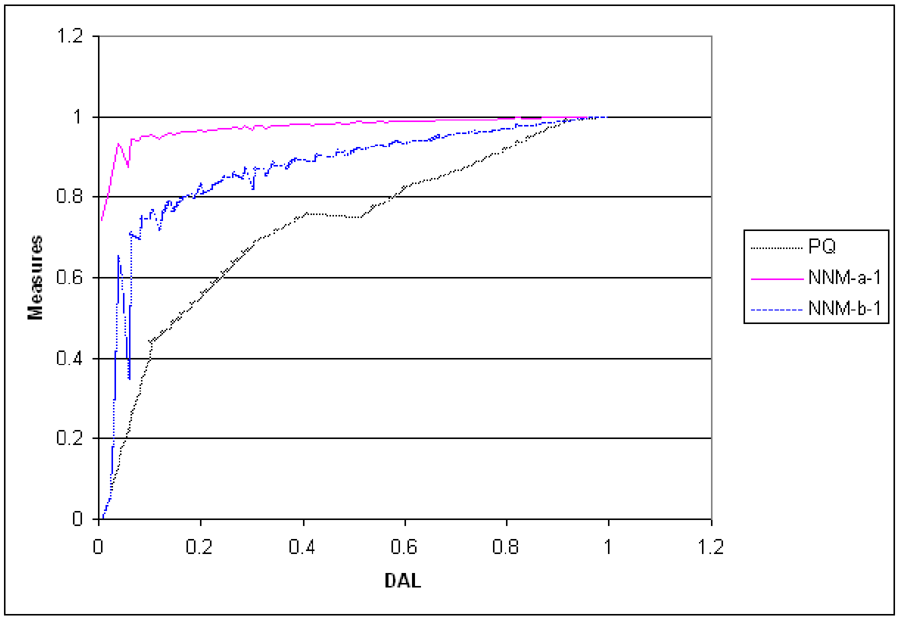


Figure 7.3: NNM-a-1 and NNM-b-1

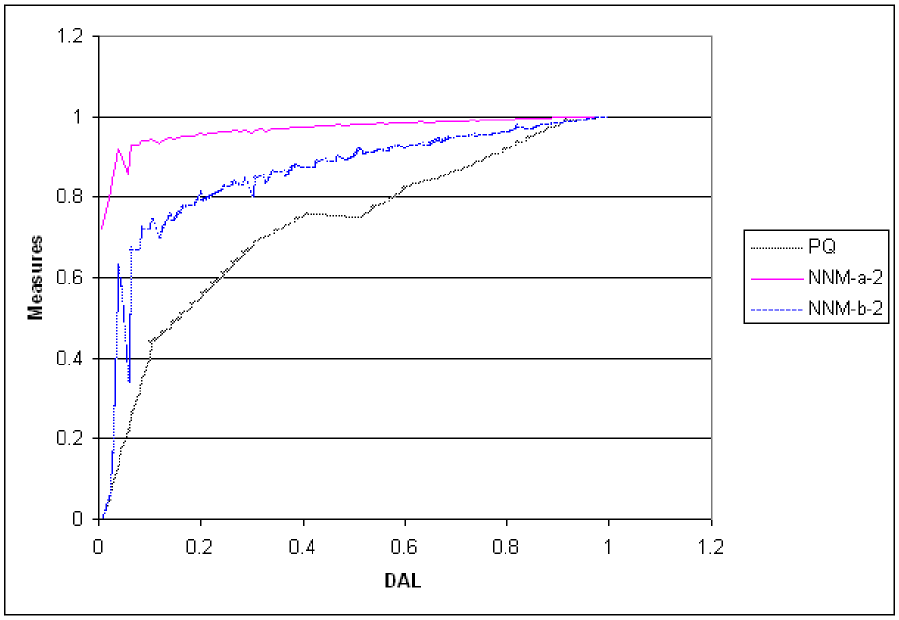


Figure 7.4: NNM-a-2 and NNM-b-2

Figures 7.5 and 7.6 show 1-HDM and N-HDM using Manhattan distance and Euclidean distance respectively. We can see that HDM using Manhattan distance is closer to the quality perceived by users than HDM using Euclidean distance. Thus

HDM (N-HDM as well as 1-HDM) using Manhattan distance is more accurate on measuring data abstraction quality than HDM using Euclidean distance. We will analyze this in our future work.

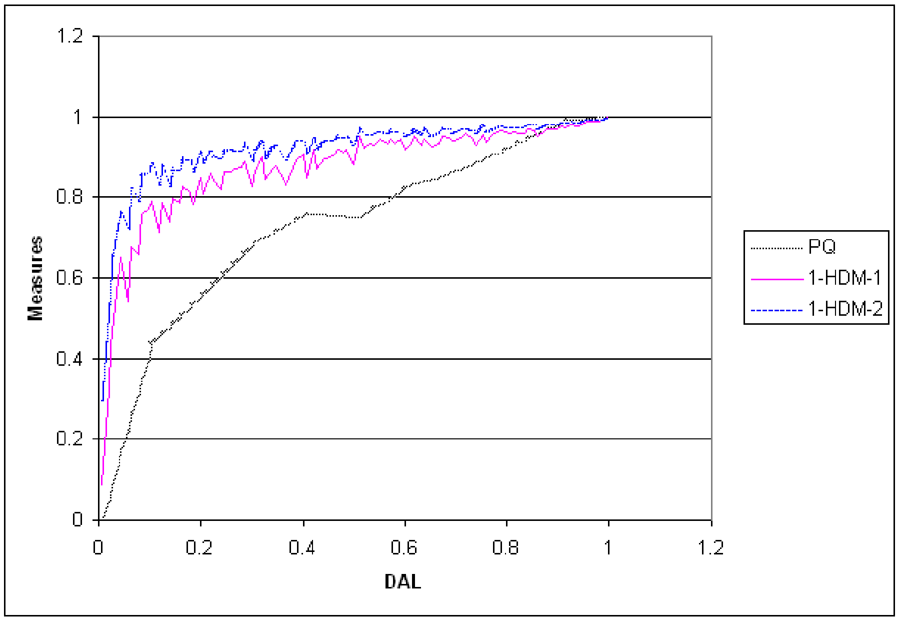


Figure 7.5: 1-HDM-1 and 1-HDM-2

Figures 7.7, 7.8 and 7.9 show NNM-a, NNM-b and SM using Manhattan distance and Euclidean distance respectively. We can see that NNM and SM using Euclidean distance are slightly closer to the quality perceived by users than NNM and SM using Manhattan distance. Thus NNM and SM using Euclidean distance are slightly more accurate on measuring data abstraction quality than NNM and SM using Manhattan distance. We will analyze this in our future work.

7.4 Conclusion of Experiments

In this chapter, we compared HDM with different histograms, NNM with different normalization methods, and HDM/NNM with different distance methods. We

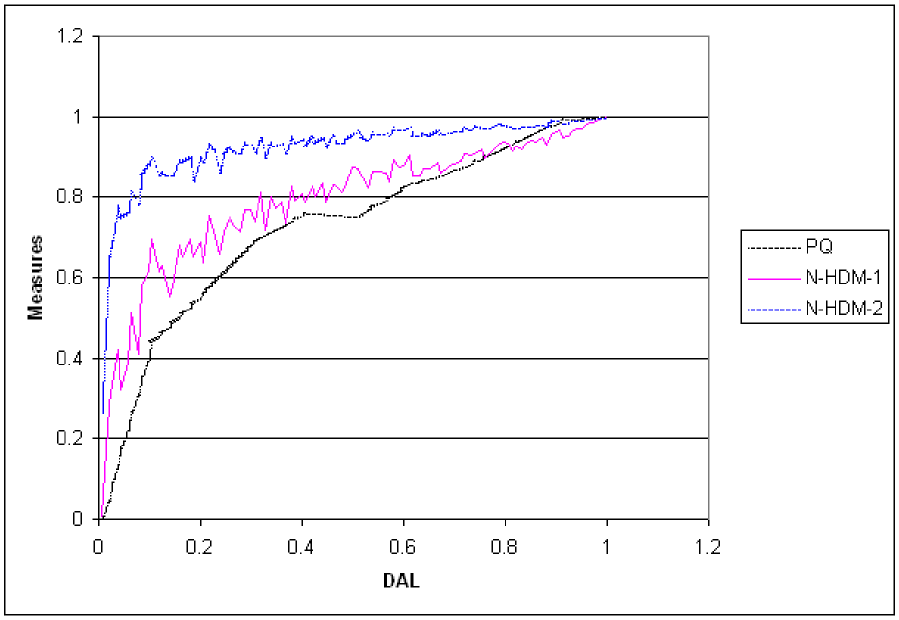


Figure 7.6: N-HDM-1 and N-HDM-2

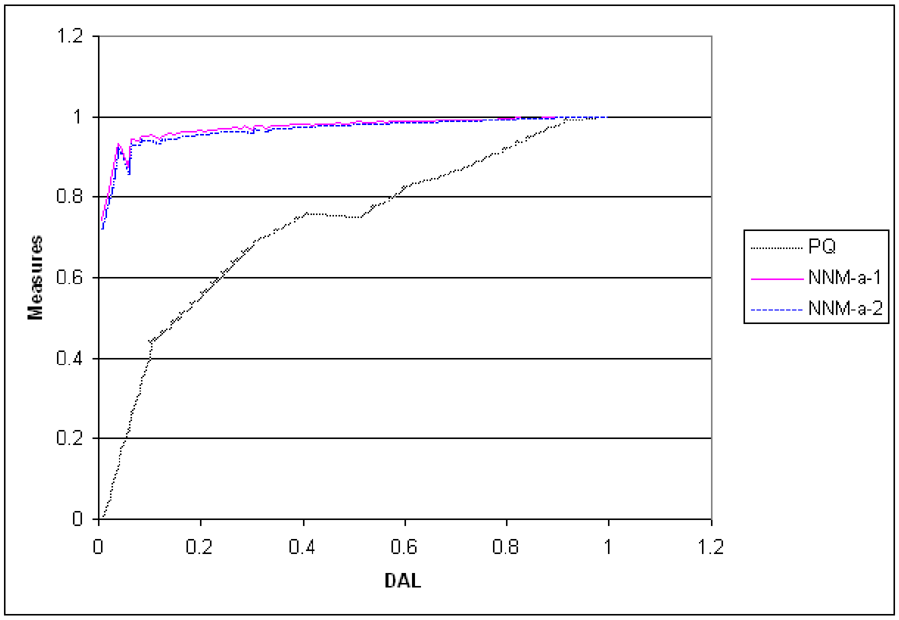


Figure 7.7: NNM-a-1 and NNM-a-2

noticed that SM-2 is closer to user's perceived quality than SM-1, thus we recommend SM-2, the SM using Euclidean distance. We found that N-HDM is closer to the perceived quality than 1-HDM, and HDM-1 is closer to the perceived quality

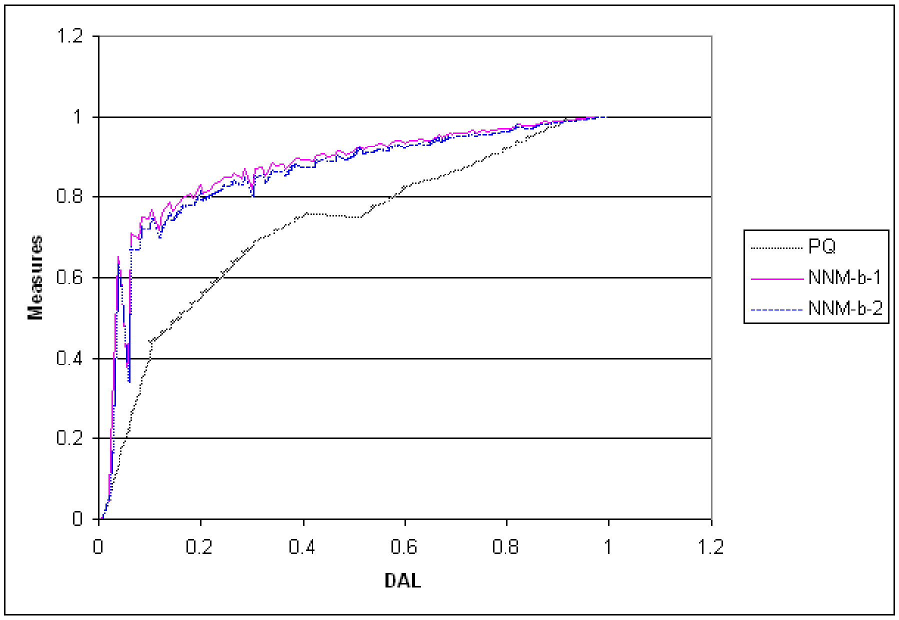


Figure 7.8: NNM-b-1 and NNM-b-2

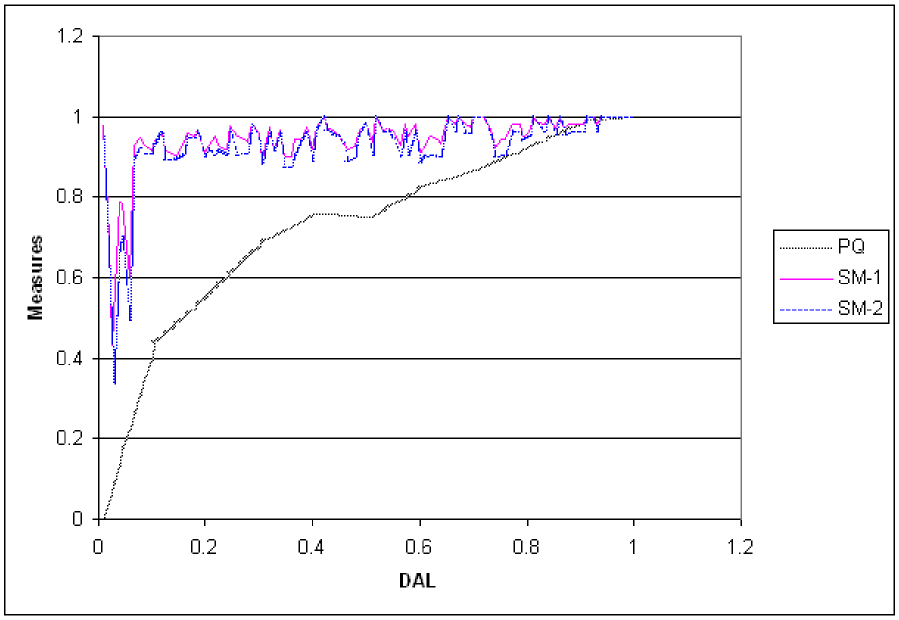


Figure 7.9: SM-1 and SM-2

than HDM-2, thus we recommend N-HDM-1, the HDM using N-D histogram and Manhattan distance. We also found that NNM-2 is closer to perceived quality than NNM-1, NNM-b is closer to perceived quality than NNM-a, thus we recommend

NNM-b-2, the NNM using the new normalization method and Euclidean distance.

Chapter 8

Case Studies

8.1 Case Study 1: Choosing a Data Abstraction Level (DAL)

In this section, we show how to choose an appropriate DAL. At this level, the abstracted dataset should have a high data abstraction quality (equal or more than 0.90) and the visualization should have the best visual quality under the constraints of the data abstraction quality. The analytic task is to search for clusters in the OUT5D dataset. This dataset consists of five remote sensing channels: SPOT, Magnetics, Potassium, Thorium and Uranium, with 16384 records. We employ scatterplots to visualize this dataset. Figure 8.1 shows the original dataset. Data points have significant overlaps with each other. We cannot distinguish relative data density in different regions and have difficulty observing any trends within this dataset.

First we make an abstraction with the DAL equal to 0.02. The corresponding HDM is 0.92 and the NNM is 0.93; this abstraction quality meets our requirements. The abstraction quality is positively related to the data abstraction level in general,

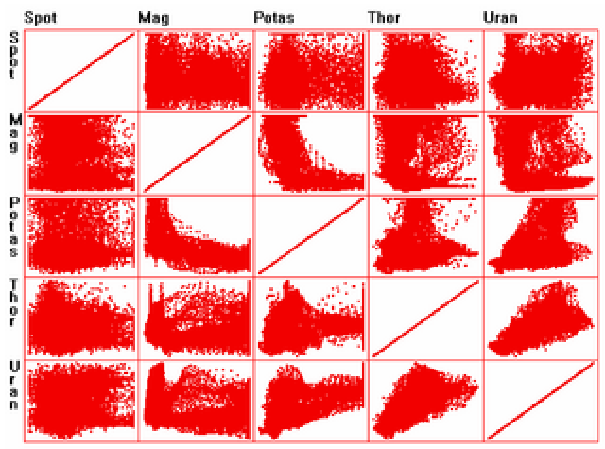


Figure 8.1: Scatterplots of original dataset (DAL=1.00)

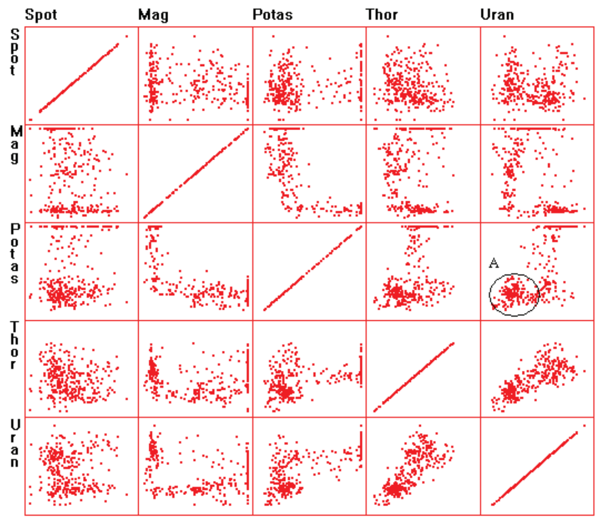


Figure 8.2: Scatterplots of abstracted dataset (DAL=0.02)

although small fluctuations may exist. The scatterplot matrix with DAL equal to 0.02 is shown in Figure 8.2. We can see that a cluster (named Cluster A) exists in the marked scatterplot, but data points in other places are too sparse to be able to observe definitive clustering behavior. Next we will focus on searching for a visualization with the best visual quality.

We change the DAL to 0.08. As shown in Figure 8.3, the sparse region in the marked scatterplot illustrates very good visual quality. However, data points in

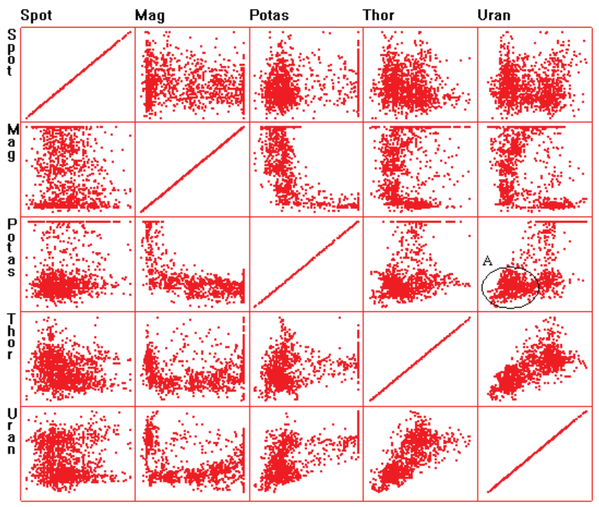


Figure 8.3: Scatterplots of abstracted dataset (DAL=0.08)

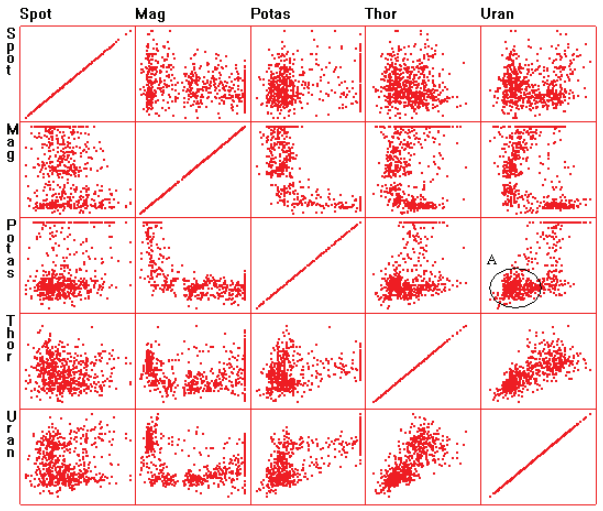


Figure 8.4: Scatterplots of abstracted dataset (DAL=0.04)

Cluster A are overplotted, thus the relative data density in Cluster A is higher than the relative data density we observe. Next we adjust the DAL to 0.04. As shown in Figure 8.4, the visual quality in the marked scatterplot is very good while the relative data density is maintained, although a small number of data points in Cluster A still overlap with each other. The quality measures of this abstraction are shown in Figure 8.5. This quality meets our requirement and we terminate our

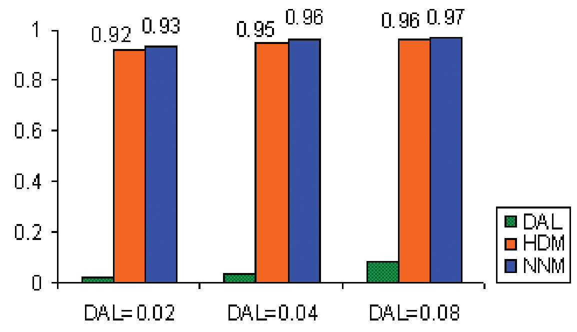


Figure 8.5: Data abstraction measures

exploration.

Abstraction quality measures give us confidence in the pattern we discovered. If we only know that the DAL, the ratio between the number of abstracted records and the number of original records, is 0.04, we cannot have much confidence in our discoveries because we know that 96 percent of the data are not shown. However, with the HDM more than 0.95 and the NNM more than 0.96 for both clustering and sampling, we are fairly certain that the abstracted dataset represents the original dataset very well and that the pattern (Cluster A in this case) is very likely valid. In general, we can assign the abstraction quality measures to the discovered pattern to indicate the confidence level of the pattern, which enables analysts to make more accurate decisions.

8.2 Case Study 2: Comparing Data Abstraction Methods

In this application, two data abstraction methods, clustering and sampling, are compared using the proposed data abstraction measures embedded within our multiresolution visualization system. We employ the AAUP dataset, which surveys the number, salary and compensation of professors at 1161 institutions. We use parallel coordinates to visualize this dataset. Through this case study, we find that sampling has the advantage of maintaining the relative density of datasets while clustering has the advantage of maintaining the outliers of the dataset.

First we briefly review some characteristics of the HDM and NNM. The HDM is based on the histogram and minimizes the difference between the distributions of two datasets, so it excels in detecting changes in the relative density of data. The NNM minimizes the distance between the original dataset and the abstracted dataset. Outliers cannot be eliminated during abstraction without a noticeable increase of the average distance, because they tend to be far from most of the data records. Thus the NNM method gives high priority to outliers and is good at monitoring the change of outliers.

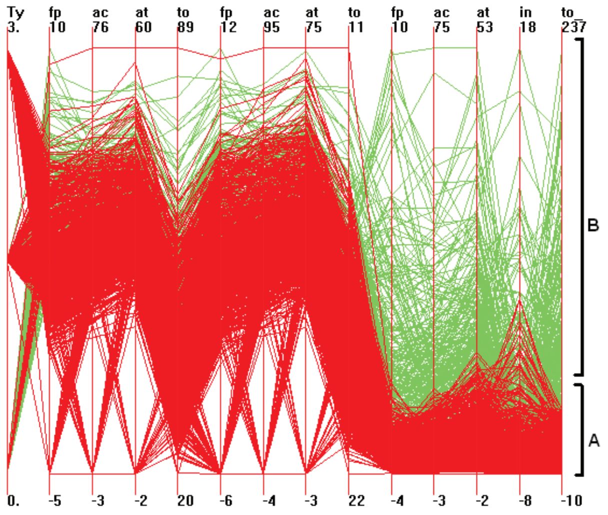


Figure 8.6: Parallel Coordinates of AAUP dataset

The original dataset is shown in Figure 8.6. On the last dimension, the dense range with low values is marked as A and highlighted in red; the sparse range is marked as B and drawn in green. We can see that most of the data records are gathered in range A. We sample the original dataset and tentatively set the DAL

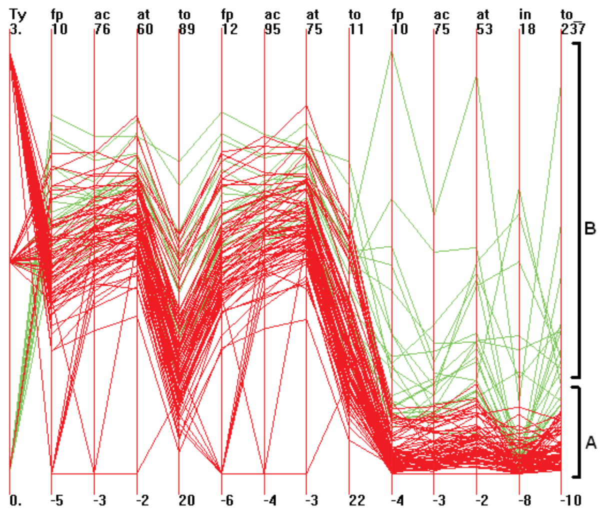


Figure 8.7: Parallel Coordinates of sampled AAUP dataset (DAL=0.08)

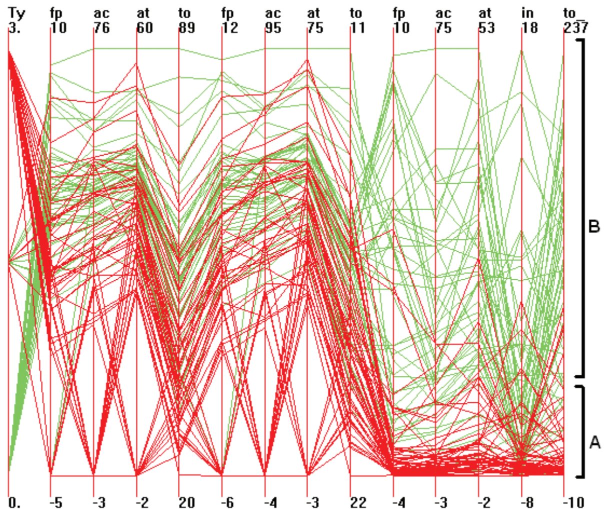


Figure 8.8: Parallel Coordinates of clustered AAUP dataset (DAL=0.08)

to 0.08. Figure 8.7 shows the visualization of this abstraction. Figure 8.9a shows the data abstraction quality of the whole dataset: HDM is 0.90 and NNM is 0.95. We then cluster this dataset, and also set the DAL to 0.08 to facilitate comparison. As displayed in Figure 8.8, the visual clutter is significantly reduced. Figure 8.9b shows the data abstraction quality of the whole dataset: HDM is 0.66 and NNM is 0.96.

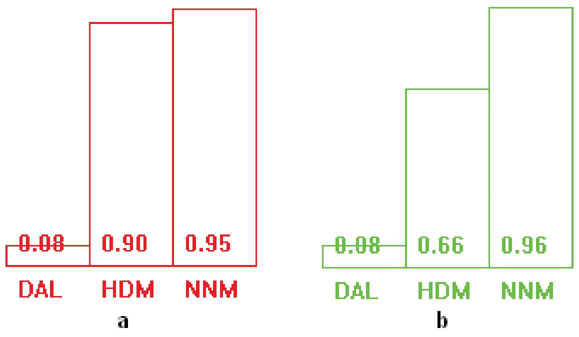


Figure 8.9: a. Quality measures for the abstraction of sampling; b. Quality measures for the abstraction of clustering

We can see that the HDM of sampling is much better than the HDM of clustering. Thus we conclude that sampling maintains the relative density of the dataset much better than clustering. This can be explained by the fact that clustering finds one representative for each cluster, no matter how many members the cluster represents. Thus it loses the relative density. This can be verified by the visualizations. We can clearly see that sample-based visualization maintains the relative density, while cluster-based visualization reduces the relative density in range A and enlarges it in range B. On the other hand, the NNM is slightly better than that for sampling. We tested sampling and clustering at other abstraction levels and got similar results. So we verified that clustering maintains the outliers better than sampling. Analysts can consider the importance of maintaining relative density versus outliers for their analytic tasks, observe the HDM or NNM measures, and then select an abstraction method that balances relative density and outliers to meet their goals.

Chapter 9

Conclusions and Future Work

9.1 Conclusions

In this thesis, we have identified data abstraction as a common mechanism for dealing with large-scale data visualization. We have designed three data abstraction quality measures to gauge how well the abstracted dataset represents the original dataset: the Histogram Difference Measure (HDM) , the Nearest Neighbor Measure (NNM) and the Statistical Measure (SM). We implemented these measures within XmdvTool, which supports both sampling and clustering as abstraction methods. Several interactive operations were developed, including adjusting the data abstraction level, changing selected regions, regenerating the abstraction, and setting the desired abstraction quality. The quality measures indicate the quality of the abstraction and thus also indirectly the quality of any patterns discovered through the abstraction.

Data abstraction quality measures should conform to the data abstraction quality as perceived by analysts. We did an evaluation to check this in Chapter 6. We found that our measures are larger than the quality perceived by analysts. Thus we designed several experiments to compare each type of measure with different distance methods and different computing mechanisms, such as different histograms or normalization approaches. We conclude that HDM using N-D histogram and Manhattan distance is better than other HDMs, NNM using our new normalization method and Euclidean distance is better than others NNMs, and SM using Euclidean distance is better than other SMs.

Aided by these measures, analysts can find the most appropriate data abstraction level for a given task, that is, one with a reasonable abstraction quality and acceptable data density. These measures can also be used to compare different data abstraction methods in terms of how well they maintain relative data density and outliers. Thus our framework enables analysts to select abstraction methods that best fit their analytic tasks. We provide two case studies to illustrate the usefulness of these measures and the effectiveness of our proposed interactive tools related to the measures. Different abstraction measures may be sensitive to the changes in different dataset features, such as the relative data density and characteristics of outliers. We plan to evaluate the advantages and limitations of abstraction measures in the presence of different dataset features.

9.2 Future Work

In chapter 4, we introduced the radius based approach to normalizing NNM. Instead of using the radius of a cluster, we may consider employing the average distance between any two data records to represent the cohesion of a cluster. We will compare this approach with the approach based on radius in our future work.

In Chapter 6, we assessed the accuracy of data abstraction measures through user evaluation. We compared the perceived quality with data abstraction measures, and then adjusted the computing approaches of measures. However, the user evaluation method used has limitations: users cannot exactly decide how well an abstraction represents the original dataset. In our future work, we will use synthetic datasets or datasets on which the quality for each abstraction is already known to assess the accuracy of data abstraction measures.

In Chapter 7, the experiments show that HDM (N-HDM as well as 1-HDM) using Manhattan distance is more accurate at measuring data abstraction quality than HDM using Euclidean distance, and that NNM and SM using Euclidean distance are slightly more accurate on measuring data abstraction quality than NNM and SM using Manhattan distance. We will investigate the reasons for this in our future work.

Peng et al. [23] designed and implemented several quality measures based on visual clutter into XmdvTool. Xie et al. [36] also integrated data quality attributes into our visualizations. In our future work, we plan to integrate these three efforts at quality measurement, representation and optimization and provide a quality-aware visualization framework to support the visual analysis process. Through this framework, analysts will be able to interactively explore very large datasets with quality information and refinement techniques available at each stage of the visualization process.

Appendix A

Evaluation Questions

We have two groups of experiments. The first group has 9 questions and the second has 4 questions. Please estimate the data abstraction quality regarding to preserving dominant characteristics of the original dataset. The left figure shows the original dataset, while the right figure shows the abstracted dataset. Please input your answer by selected one quality level ranging from 0 to 10.

A.1 Group 1: 9 Questions

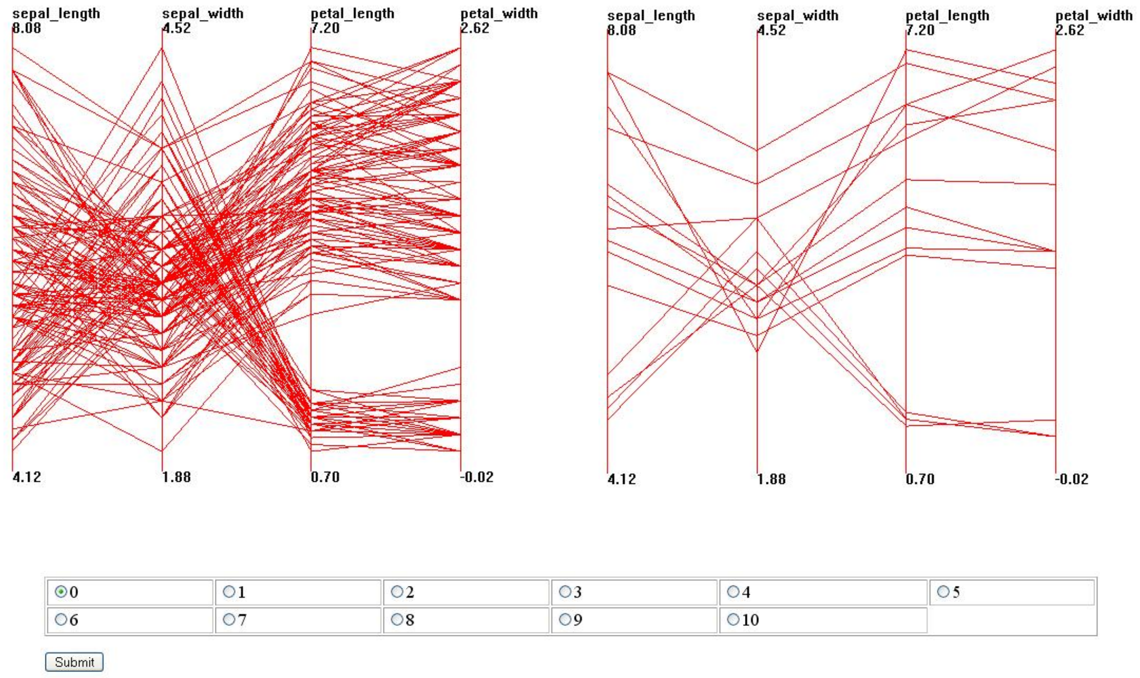
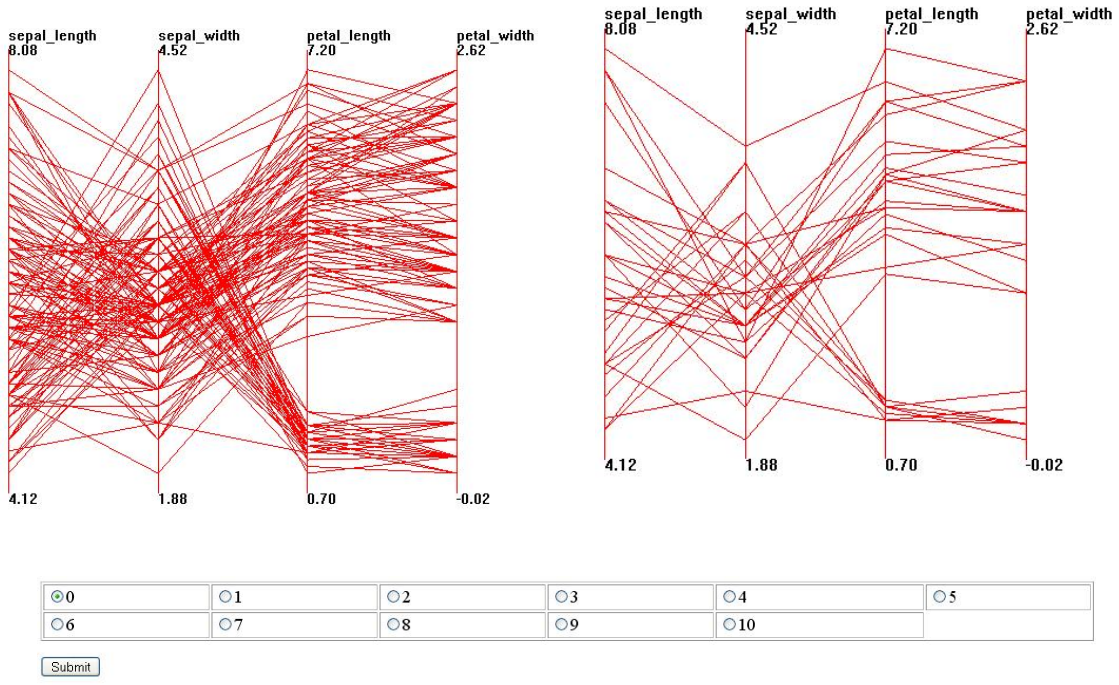
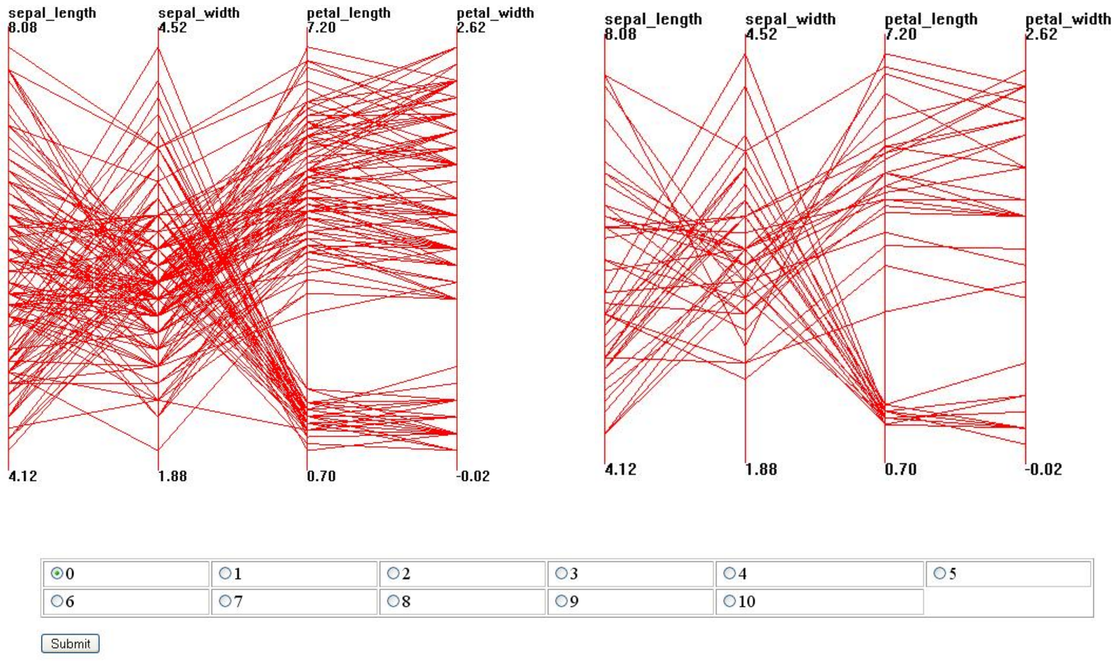


Figure A.1: Q1, how well does the abstracted dataset represents the original dataset? (Range: 0-10)



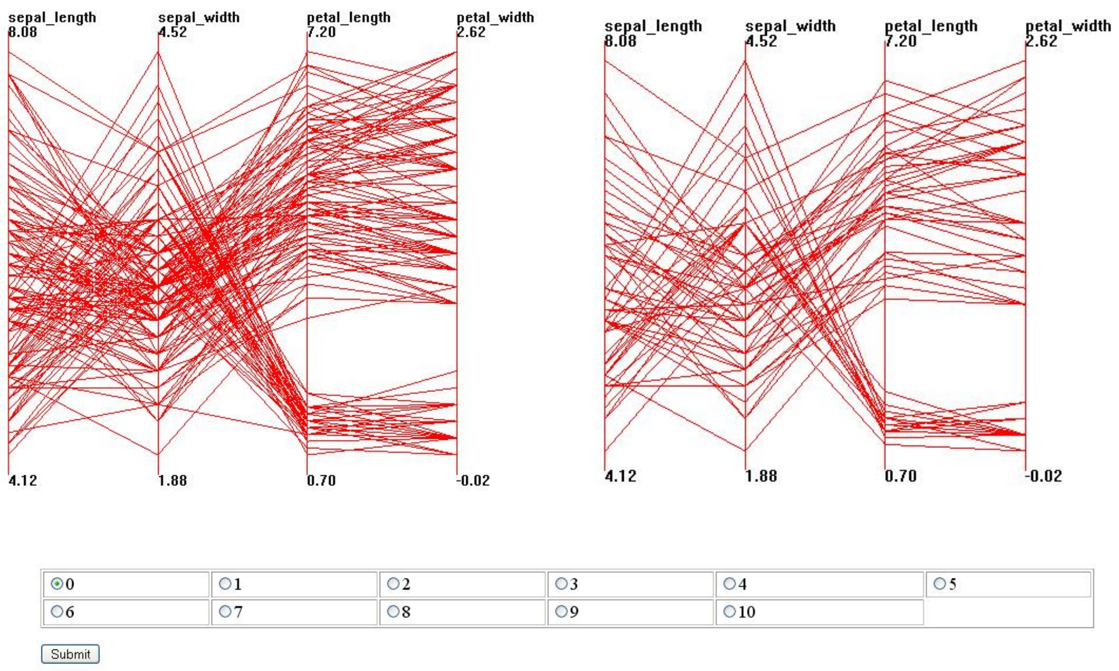
[✓ 0]	1	2	3	4	5
6	7	8	9	10	

Figure A.2: Q2, how well does the abstracted dataset represents the original dataset? (Range: 0-10)



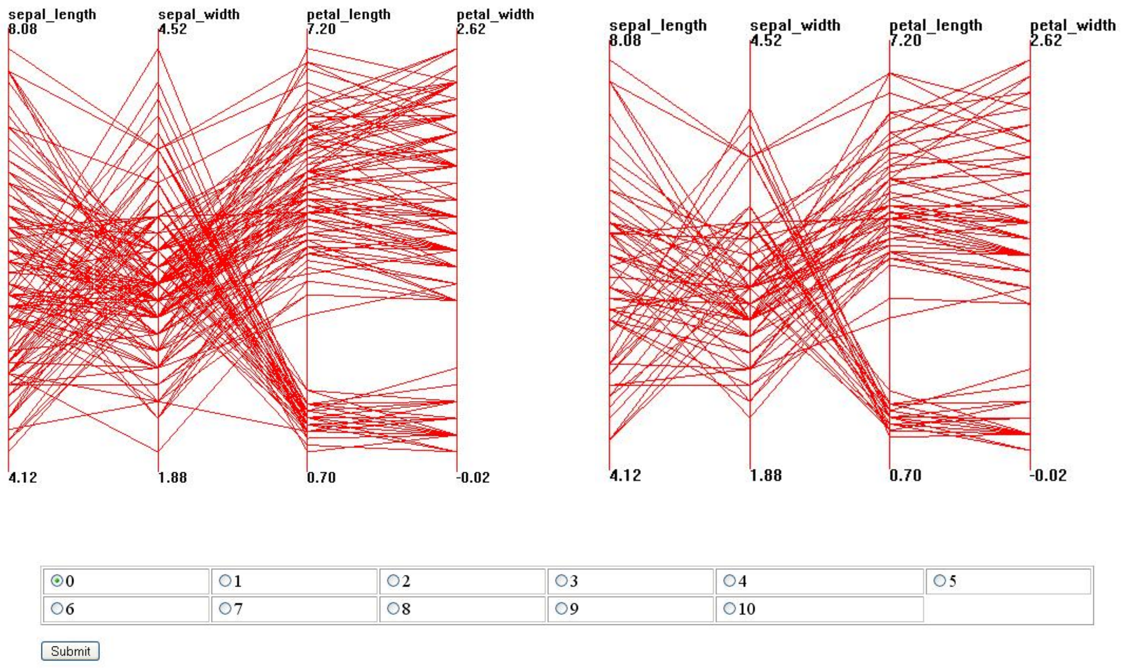
[✓ 0]	1	2	3	4	5
6	7	8	9	10	

Figure A.3: Q3, how well does the abstracted dataset represents the original dataset? (Range: 0-10)



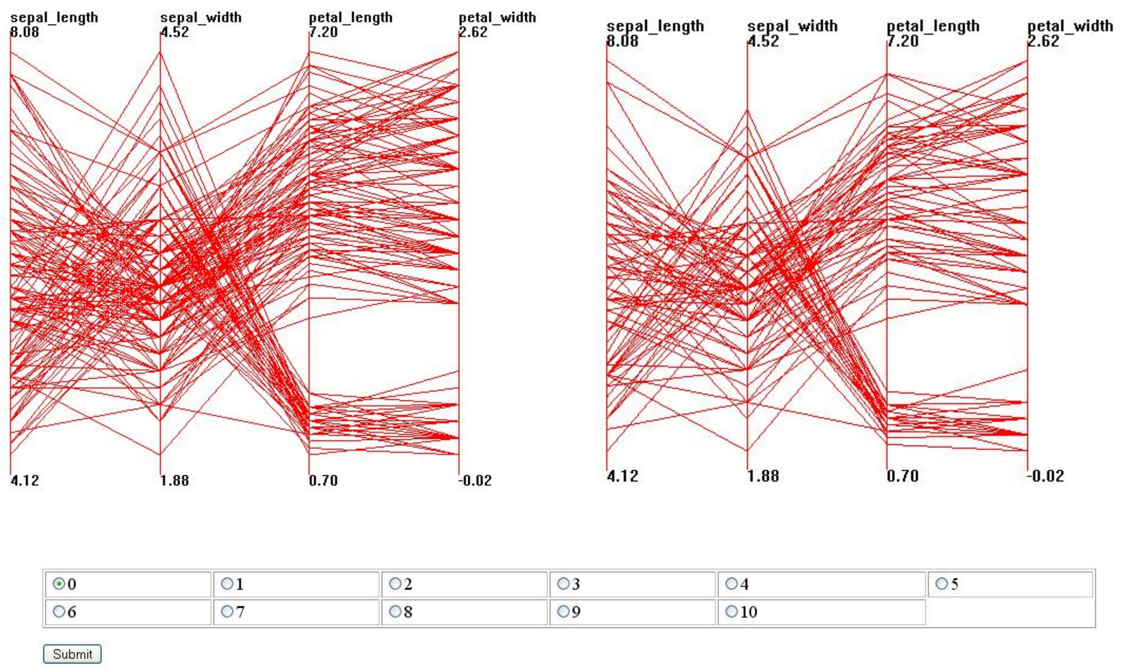
[✓ 0] 1 2 3 4 5 6 7 8 9 10

Figure A.4: Q4, how well does the abstracted dataset represents the original dataset? (Range: 0-10)



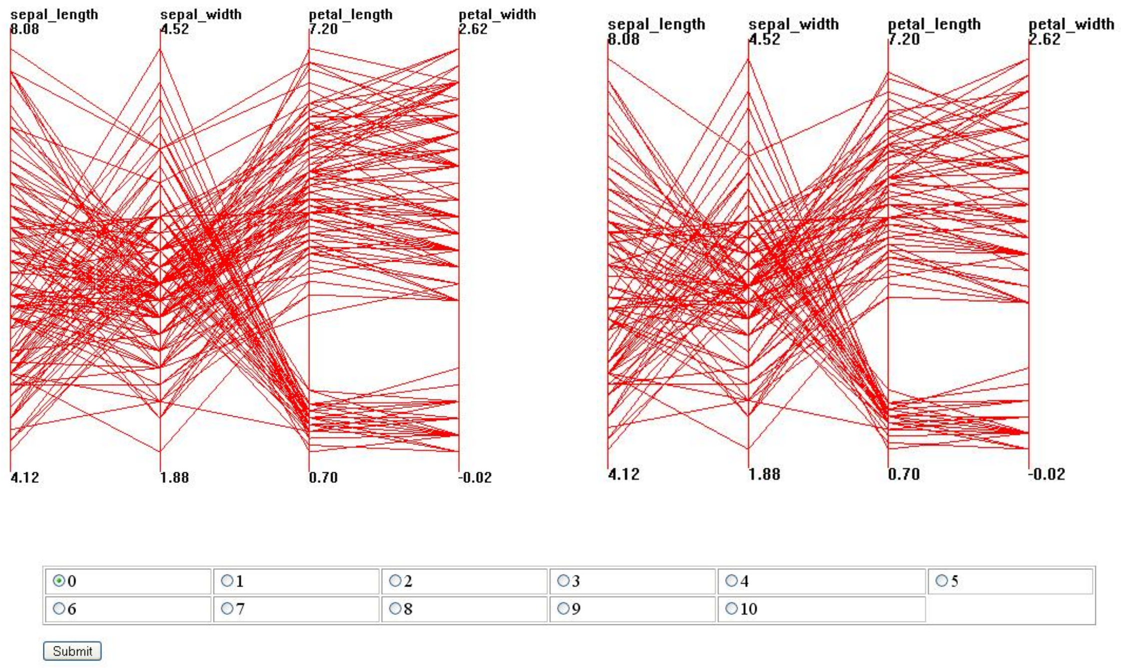
[✓ 0] 1 2 3 4 5 6 7 8 9 10

Figure A.5: Q5, how well does the abstracted dataset represents the original dataset? (Range: 0-10)



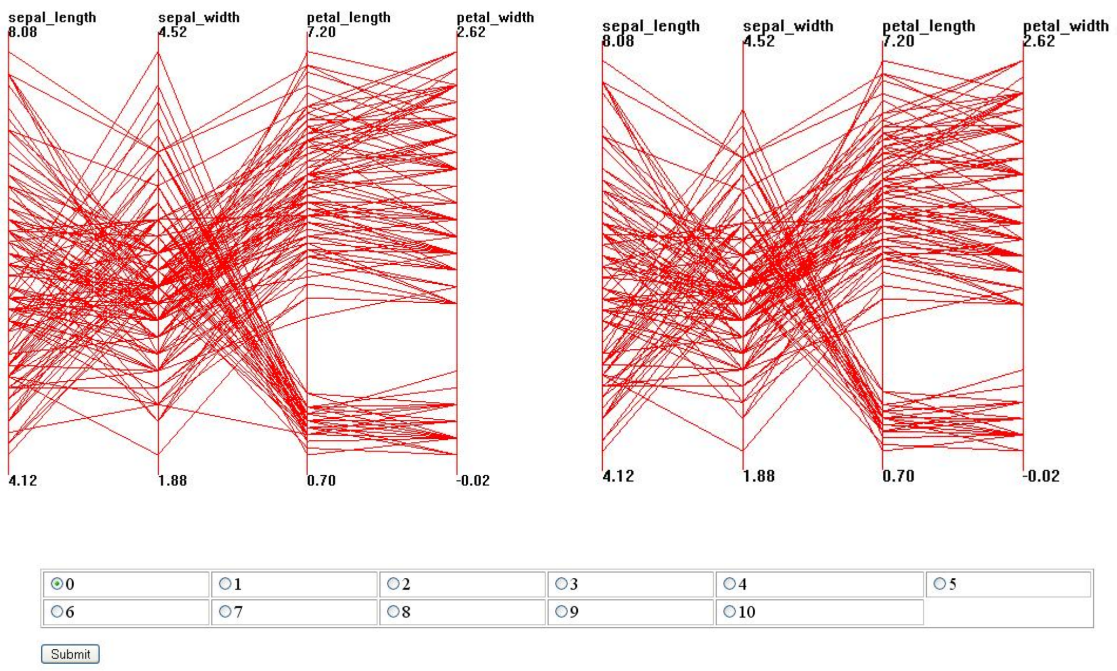
[✓ 0]	1	2	3	4	5
6	7	8	9	10	

Figure A.6: Q6, how well does the abstracted dataset represents the original dataset? (Range: 0-10)



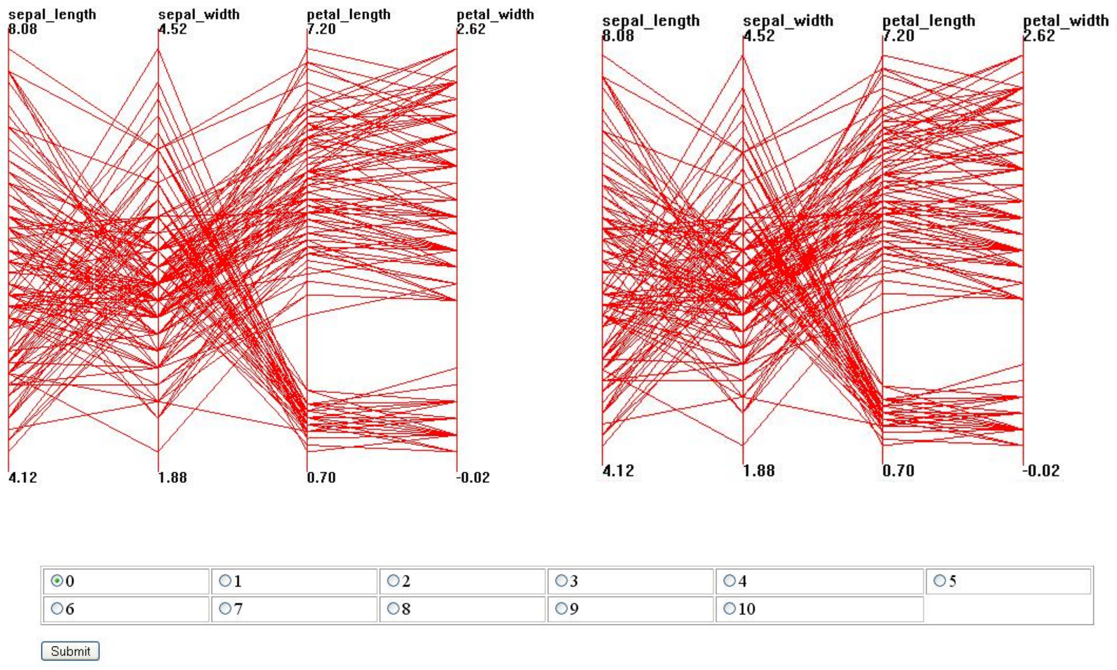
[✓ 0]	1	2	3	4	5
6	7	8	9	10	

Figure A.7: Q7, how well does the abstracted dataset represents the original dataset? (Range: 0-10)



[✓ 0]	1	2	3	4	5
6	7	8	9	10	

Figure A.8: Q8, how well does the abstracted dataset represents the original dataset? (Range: 0-10)



[✓ 0]	1	2	3	4	5
6	7	8	9	10	

Figure A.9: Q9, how well does the abstracted dataset represents the original dataset? (Range: 0-10)

A.2 Group 2: 4 Questions

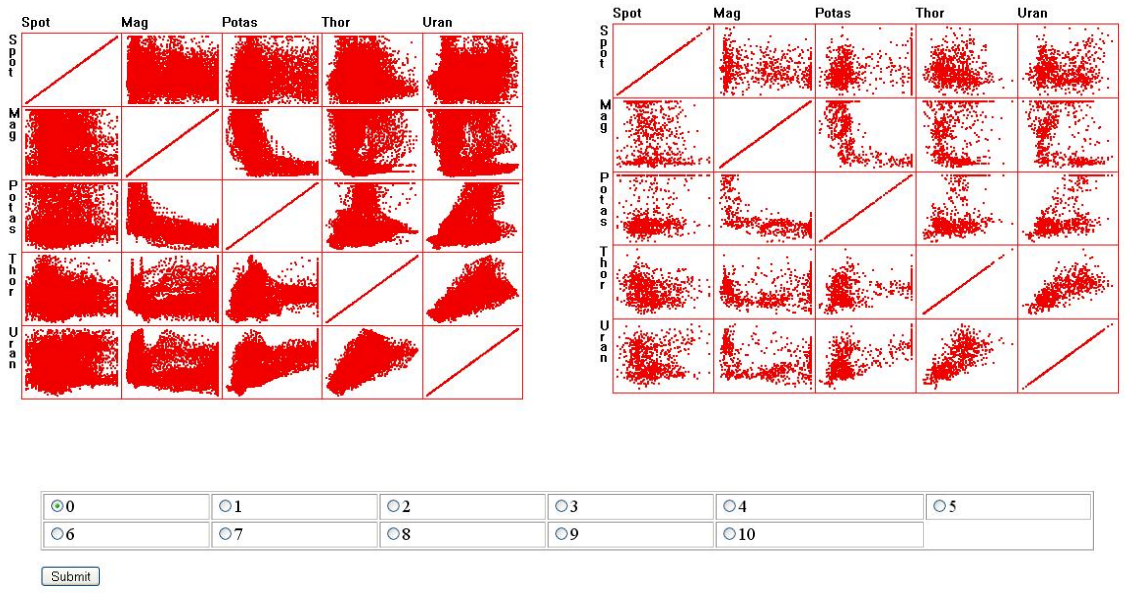


Figure A.10: Q1, how well does the abstracted dataset represents the original dataset? (Range: 0-10)

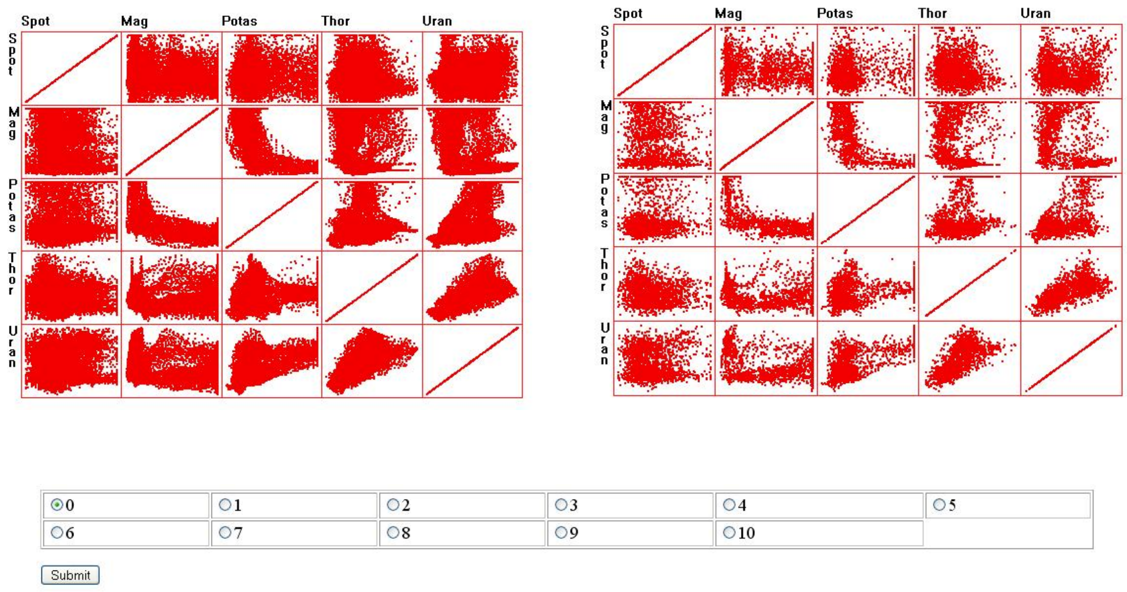


Figure A.11: Q2, how well does the abstracted dataset represents the original dataset? (Range: 0-10)

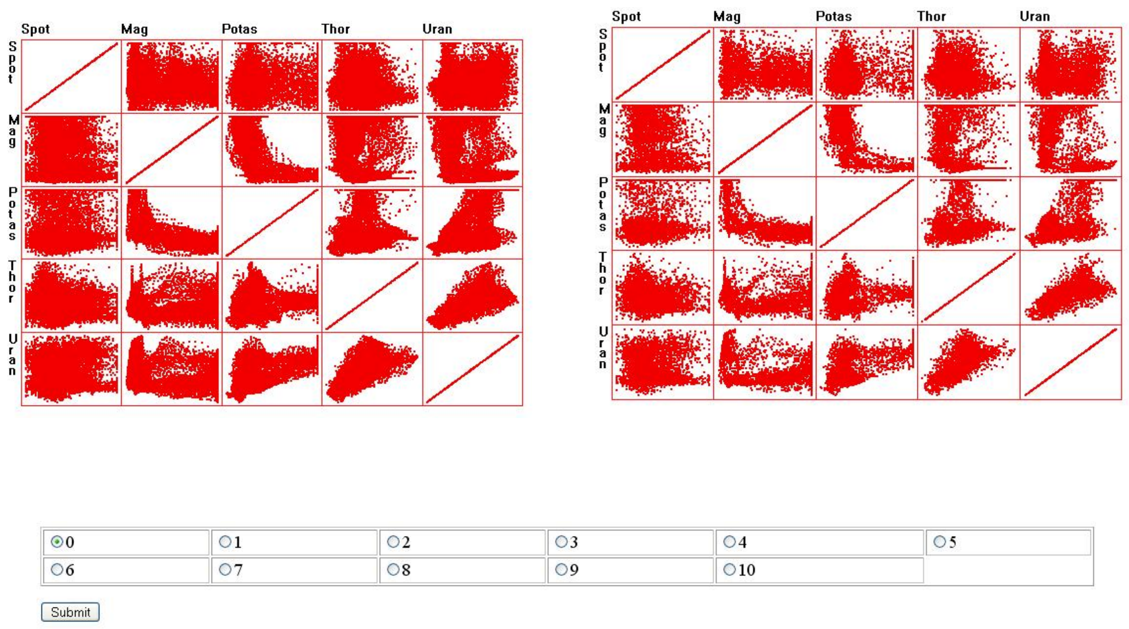


Figure A.12: Q3, how well does the abstracted dataset represents the original dataset? (Range: 0-10)

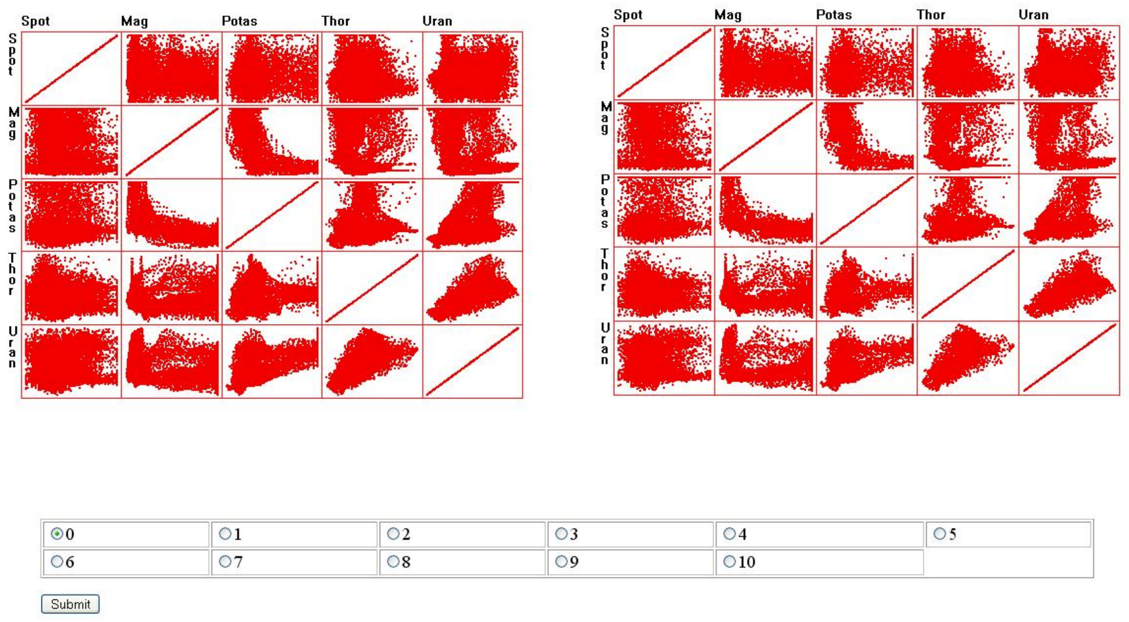


Figure A.13: Q4, how well does the abstracted dataset represents the original dataset? (Range: 0-10)

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