VTT TIEDOTTEITA
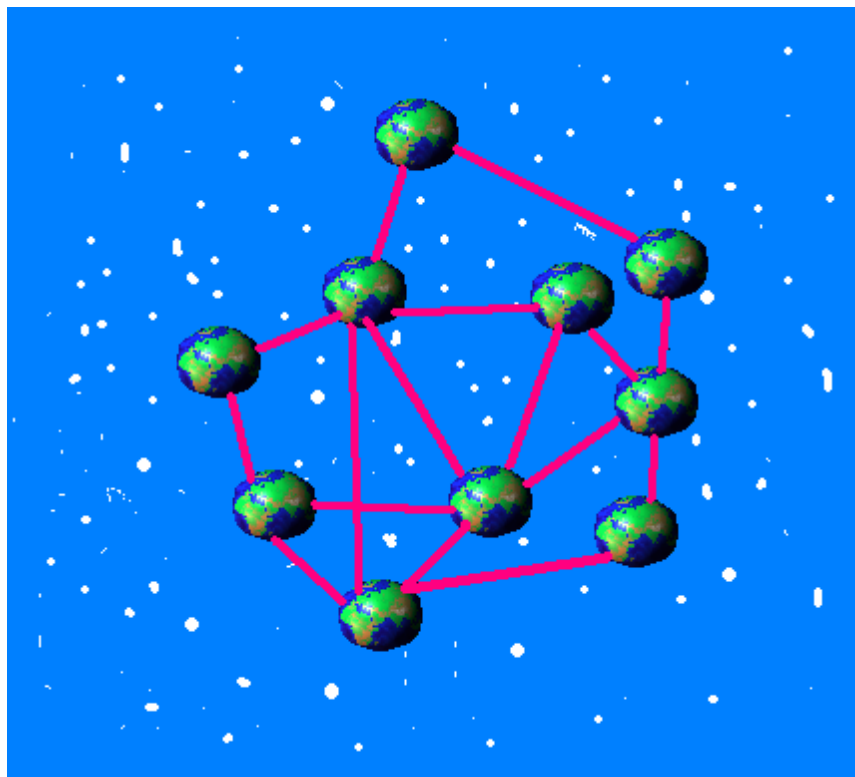
Anna Sachinopoulou

Multidimensional Visualization

Multidimensional Visualization

Anna Sachinopoulou

VTT Electronics

Cover: Multidimensional World, by Anna Sachinopoulou

Abstract

Visualization is a powerful tool for data mining. During the last 30 years, multi-dimensional visualization methods and techniques have been developed in order to conduct data mining (Visual Data Mining) or to efficiently present and evaluate the results of a data mining query. The purpose of this review is to list and shortly describe such methods and give some examples of multidimensional visualization so that the tool designers and data mining analysts can get an overview of the existent possibilities. The methods described are divided into six groups: Geometric techniques where the methods described are based on the Cartesian coordinates; Icon techniques where the main tool and basic unit of the visualization technique is an icon; Pixel Oriented techniques where the pixels are used as the basic visualization unit; Hierarchical techniques where the data items and the query results are presented in hierarchical displays; Distortion techniques where the three-dimensional space is distorted to allow more information to be visualized; and Graph Based techniques where the information is presented using nodes and edges. Examples of visualization tools give a more complete image of the application of these methods.

Preface

This report is the start off report of the VTT Electronics Knowledge engineering team's strategic project MOSE (Multidimensional Sequences). The project is about the creation of a multidimensional sequences data mining tool where multidimensional visualization is needed.

Anna Sachinopoulou

Contents

1. Introduction

1.1 Importance and Definitions

Visualization in a general dictionary is defined as:

1. The act to form a mental image of;

2. The act of making visible [1].

The latter definition of the word applies to the scientific representation of information in order to make it understandable for the observer. The visualization of information is an old faculty. During the last decades, along with the rapid development of the computer science, it has become a necessity for many disciplines.

Multidimensional data implies that the data is described by more than one attributes from which some might be dependent and some independent. Wong et al. [2] use the following conformance:

– multidimensional implies dimensionality of independent variables

– multivariate implies dimensionality of dependent variables.

The terms hyperdimensional and highdimensional are also used in the literature referring to the multiattribute aspect. We will use the general term multidimensional, referring to both multidimensional and multivariate terms.

A few hundred years ago, it was possible to have a general knowledge of every scientific, or another kind, discipline. Today, the information stored in databases and data warehouses around the world needs specific data mining tools and methods to lead to knowledge. A powerful way of discovering knowledge is by means of visualization. Multidimensional Visualization plays a very important part in data mining [3, 4, 5, 6, 7, 8].

Association rule, as the result of data mining, is the relationship between a certain profile and an action. When the data signify discrete events which have a temporal or spatial ordering and the time information is included in the data mining, this consequently results in sequential associations or sequential patterns of the form: when A occurs, B occurs within certain time. When the events are described by many attributes, then the sequential patterns are multidimensional and require multi-dimensional visualization.

1.2 Limitations

While visualization is a powerful tool, there are two basic things connected to it that limits the possibilities: the human ability to distinguish image details and memorize them, and the available computer power.

There have been so called preattentive studies made already from the first steps of the visualization research addressing the ability of the humans to distinguish patterns, colours and other image details and to derive knowledge and permanent memory from those [9]. For the former limitation, there is not much more one can do other than understand how the human beings interact with information, how they perceive it visually or non-visually, how the mind works when searching for known or unknown information and how it solves the problems and use this knowledge to improve the visualization systems and techniques.

As for the latter limitation, the computer technology continues to develop rapidly so that every day, more means are available for the visualization designers and data analysts.

1.3 Aims

Three distinctive visualization goals can be mentioned:

* Explorative Analysis: where the visualization of data or data objects provides hypotheses about the data

* Confirmative Analysis: where the visualization of data provides confirmation for already existing hypotheses

* Presentation: where a priori fixed facts are being visualized [10].

In a data mining environment, all three goals can be important but the major part belongs to Explorative Analysis. The analyst starts exploring the database or the data warehouse to discover relationships that would lead to conclusions. However, the conclusions might have to be tested and the predictions visualized against the initial theories. In the end, when the data analysis is completed, the analyst will present his work to other interested parties such as councils, consumers and clients, who will act upon the results.

The aim of this report is to review briefly the existing Multidimensional Visualization techniques and some tools, and provide the background for the development of a multidimensional sequences visualization method.

2. Overview of Multidimensional Visualization Techniques

During the last three decades, different techniques have been developed which can be categorised into the following subgroups: Geometric techniques, Icon techniques, Pixel Oriented techniques, Hierarchical displays, and Distortion techniques.

In his tutorial in KDD'97, Daniel Keim presented the graph of Figure 1 as a classification scheme of the visualization methods. Following this, a method could be positioned at any point on this graph according to which techniques are used and what additional attributes are present such as brushing, zooming and linking.
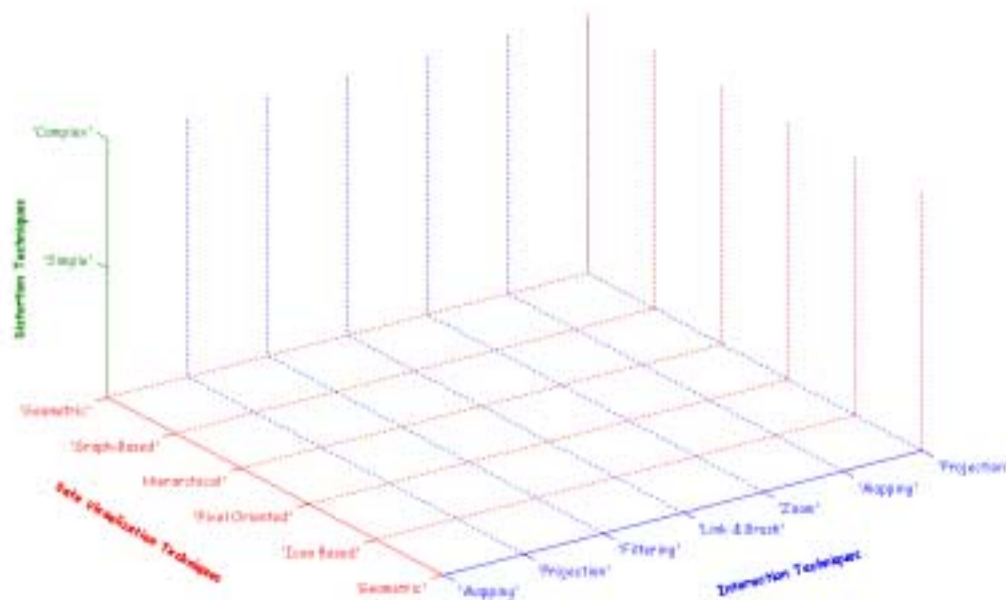
Figure 1. Classification of Visualization Techniques [10].

2.1 Geometric Techniques

The basic idea of these techniques is to visualize the transformations and projections of the data in Cartesian and Non-Cartesian Geometrical Spaces [10].

2.1.1 Plots and Matrices

The Scatterplot Matrix is a visual combination of scatterplots where more than one attributes are represented. The attributes are assigned to the diagonal cells of the matrix

and the rest of the cells represent the relationship of the attributes. For example, in Figure 2, there is a 5x5 matrix. Along the diagonal there are the 5 attributes, and the cell (2,3) represents the relationship att.2=f(att.3) while the cell (3,2) represents the relationship att.3=f(att.2).
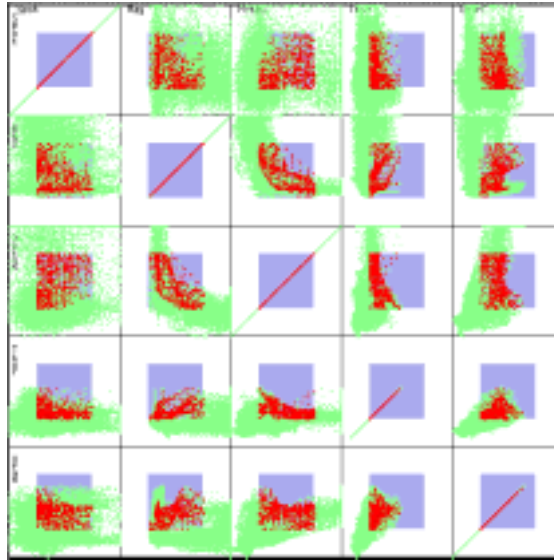
Figure 2. Scatterplot matrix [12].

In the interactive version, brushing and linking is used so that when the user brushes or clicks on a certain point on one of the relationship-representing cells or if he encircles and selects a few points, the equivalent points in the rest of the matrix cells are highlighted [2].

2.1.2   Hyperslice

Hyperslice [2] could be considered as an evolution of the scatterplot matrix. The basic concept is the same. In the diagonal of the matrix, there are scalar functions of single variables represented and the other cells show the scalar relationships of many variables. The user can define a focus point $c=(c_1, c_2, ...c_n)$ and a set of scalar widths, setting a range slice such as in the cell (2,3) in Figure 3. Only the data within the range are viewed. By steering the focus point, the user can fast explore other data near the set range and visualize the trends in the cells where the linked data can be found.

Figure 3. Hyperslice [2].

2.1.3   Prosection Views

In this method [11], the basic idea of the Hyperslice is extended to discrete data sets. The projection of a graph section of two variables where a range has been imposed on a third variable so as to cut a section of the distribution is presented in a space fillings plot (Figure 4). A matrix is formed by all the projection plots and every variable is represented in the matrix. A colour filling technique is then applied to smoothen out the granularity of the graphs. The method has been developed to externalize mathematical models and the authors claim to have transformed a very difficult cognitive problem into a much easier perceptual task.

Figure 4. Prosection Views [11].

2.1.4   Surface plots, Volume plots, Contours

In early phases, a large amount of continuous data can be viewed as a volume. Volume rendering techniques enable the user to view inside the volume. Colours, hue and opacity are used to depict different distributions and attribute values. Moving surfaces are used to visualize different volume slices.

Surface plots (Figure 5) are the 3D representation of a surface where relationships of data could be discovered.
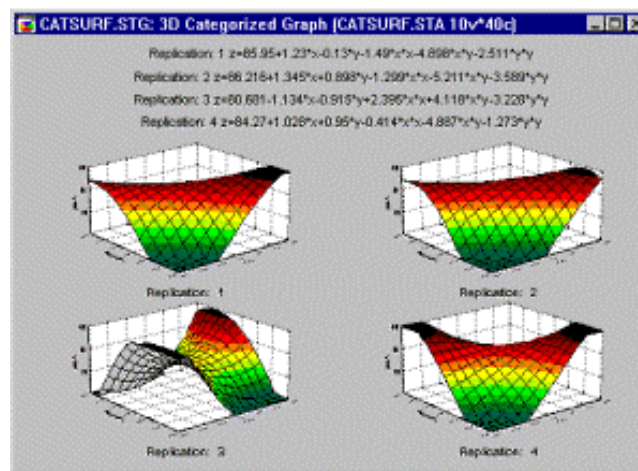
Figure 5. Example of Surface Plots [12].

Contours are used to connect data or data objects with one or more data points of the same attribute value [12–16].

However, the representation of large amounts of data using the above techniques can be difficult due to obscuring, and furthermore, the possible dimensionality is not very high.

2.1.5   Parallel Coordinates

Parallel Coordinates [17–19] signify a Non-Cartesian method where the variables are represented with vertical lines (Figure 6). A point of a scatterplot is represented by a polyline. The polyline cuts the dimensional parallel lines at the respective value of the attribute. Although this is a very simple way to represent high dimensional sets of data, for large data sets, overloading of the space is nevertheless a fact and information can be easily obscured. By imposing a hierarchical distribution on the data, sets of up to 10^9 data objects can be visualized [17].
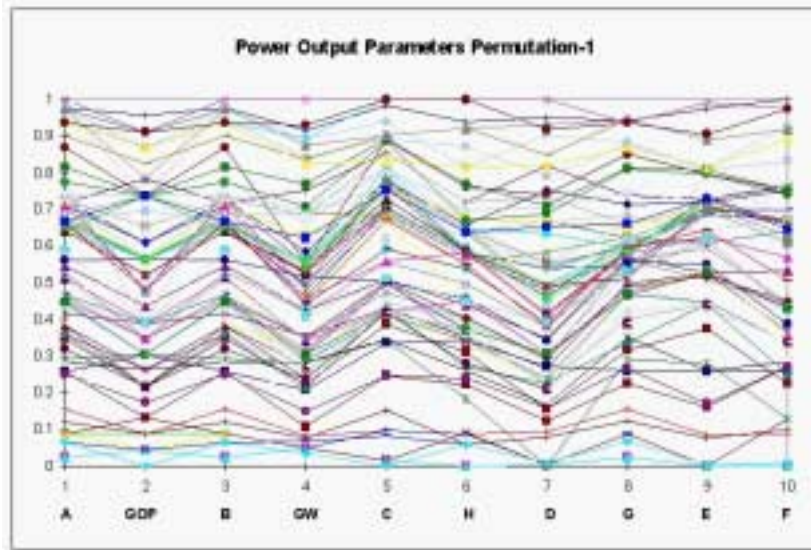
Figure 6. Parallel Coordinates [12].

2.1.6   Textures and Rasters

As stated before, preattentive studies have displayed the ability of the human eye to recognize textures and patterns before the visual attention. These techniques are aiming to increase the number of attribute values that can be displayed by using textures and other visual features such as hue and intensity [20].

In Figure 7, textures representing vector plots and contour plots are applied to a surface.

Figure 7. Texture and Raster Impression [12].

2.2   Icon Techniques

In these techniques, each data item is represented by an icon and the values of attributes are assigned to the colour, shape and orientation of the icon. Then, the icons are plotted in graphs or matrices and the analyst can extract information by viewing data objects as a whole [2].

2.2.1   Stick Figure

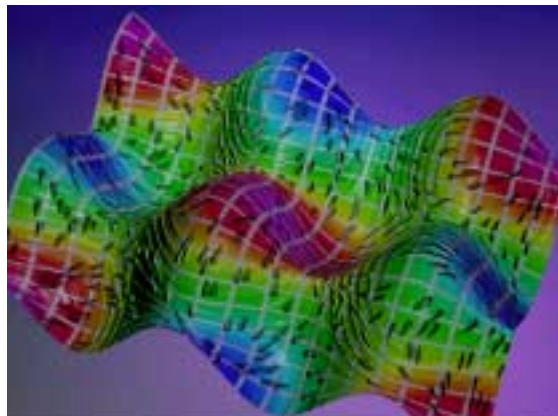The stick figure is an icon with a number of sticks, for example four limps and the body (Figure 8) [2, 21]. An attribute can be assigned to each limp whose length represents the value, while a fifth attribute can be assigned to the body and represent its value by the inclination. Colour has been added to assign more attributes and the stick figures are put into an image where colour groups and texture impressions reveal the hidden knowledge (Figure 9). The stick figures have been used to represent up to 20 attributes at a time.
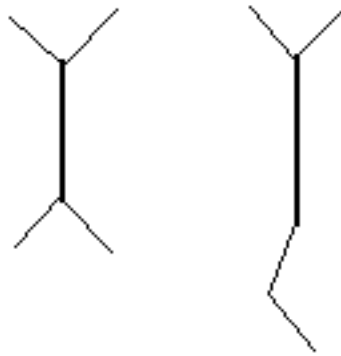
Figure 8. Example of a Stick Figure representing five variables.

Figure 9. Example of a Stick Figure Visualization representing 7 variates: the merged image of the Great Lakes [2].

2.2.2 Chernoff Faces

Another well-known and picturesque method consists of the Chernoff faces (Figure 10) where the ability of humans to distinguish different expressions and family characteristics on human faces is being exploited [2, 12]. Each attribute is assigned to different face characteristics and its length or shape or distance represents the value. "Neighbour" and "family" algorithms have been used for the analysis of the graphs where "strangers" can be discovered.
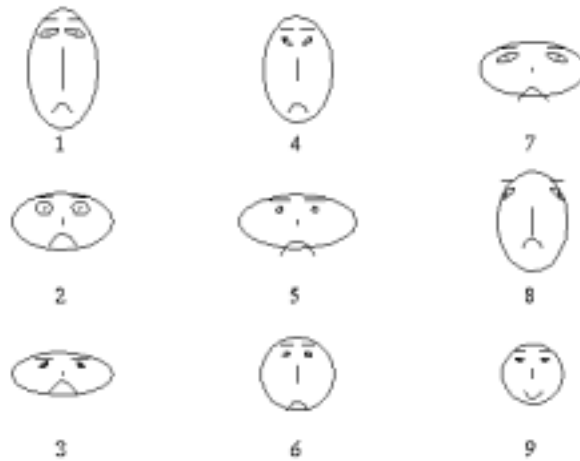
Figure 10. Examples of Chernoff faces [12].

2.2.3 Colour Icon

A colour icon is an area in a display to which colour, shape, size, orientation, boundaries and area subdividers can be mapped by multivariate data [2].

There are two ways to paint a colour icon. One is to assign the colour to the lines that represent the variables (for example, subdividers in a square area) and interpolate between the lines, and the other to assign a colour to each slice of the icon, that represents the variables (Figure 11).
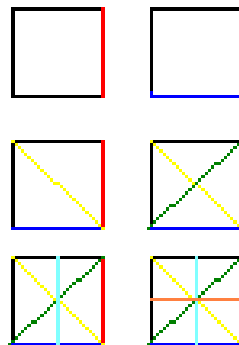
Figure 11. The Colour Icon mapped with 6 variables.

2.2.4   Autoglyph

An Autoglyph [2, 12] is a rectangle representing each variant. The variant is normalized and divided into three groups, based on the standard deviation or threshold defined values and missing values. Then, a shade of grey is assigned to each of the two standard deviation groups and white is used for the missing data. The rectangle is then coloured accordingly. Other applications use the primary colours instead of grey shades.

An Autoglyph was initially developed to study the correlation between large numbers of variables.
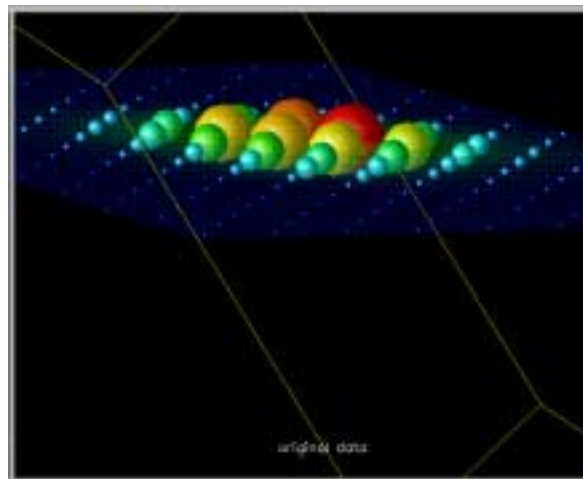
2.2.5   Glyphs

Glyphs are pixels with more than one dimension. They are placed on a 2D-floor matrix and their positions depict two attributes while other attributes and variables are assigned to their shape and colour. Some examples include the sunflower glyphs, the star glyphs, the stereo ray glyphs etc. In Figure 12, there is an example of scalar glyphs.

Figure 12. Scalar Glyphs [12].

2.3   Pixel Oriented Techniques

These techniques manipulate pixels in order to present the data.

2.3.1   Space Fillings

In Space fillings techniques, each attribute is assigned a pixel and the pixel is coloured according to a colour scale depicting the values range [22]. Then the sets of pixels for each item are being arranged into different patterns such as spiral patterns, line by line loops, back and forth loops, etc.

2.3.2 Recursive Patterns, Spiral and Axes Technique

This technique is the combination of the space filling pixels in multiple display [10, 23, 24]. In recursive patterns, the pixels are positioned in loops and in spiral order, starting from the center and heading outward (Figure 13). In the Axes display, an additional direction sign (– or +) is assigned to the data object, according to its relevance to the query.

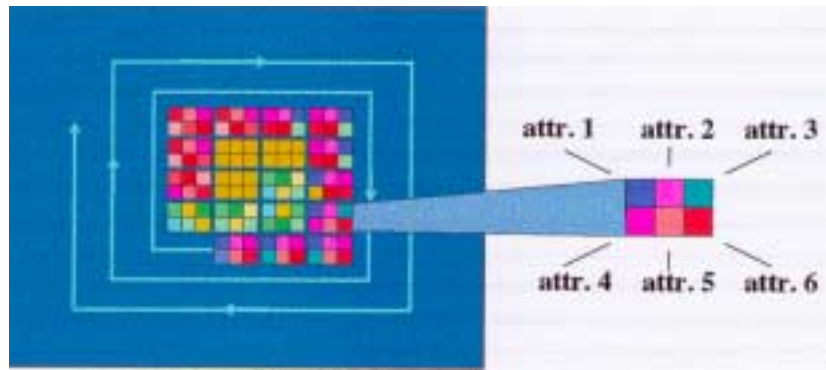*Figure 13. Space Fillings Technique [10].*

2.3.3 Mosaic Plots

Hartigan and Kleiner (1981) induced Mosaic plots (Figure 14) as a graphical analogue of multivariate contingency tables and they are the natural extensions of the one dimensional spineplot [25]. Spine plots of one attribute are grouped together and the spineplot groups are grouped into the display.
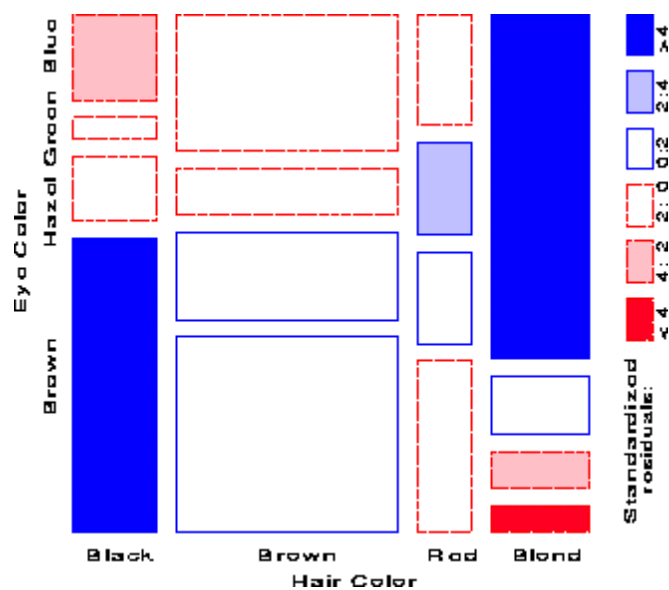

Figure 14. Mosaic Plot [26].

2.4   Hierarchical Displays

These displays include trees and hierarchies and have been very popular in the visualization of archives and relationships

2.4.1   Hierarchical Axes

Axes representing each attribute are laid horizontally with the fastest changing value having the first place in the hierarchy. Once the axes are laid, histograms within histograms can be used to display the data. The tool can display as many as 20 variables in one screen. For larger amounts of data, a technique called subspace zooming is used which resembles the tree structures.

One simple example is the histogram plot of Figure 15. The height of the black rectangle shows the value of the dependent variable z. The independent variables x and y are described by the horizontal hierarchical axes located at the bottom. In the middle plot, the height of the light grey rectangle is defined as the sum of all z variables, that is, the black rectangles, enclosed inside. In this example the sum equals 2. The third plot includes additional data. The histogram in the middle becomes embedded inside another histogram, which shows the sum of the values of each inner histogram. Other possible functions in addition to the sum function are the min/max and mean/standard functions.
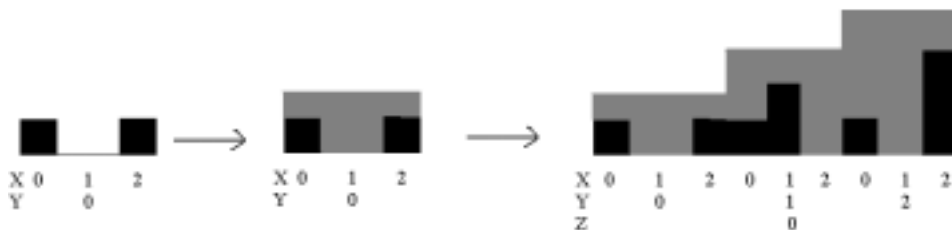
Figure 15. Hierarchical Axes [2].

2.4.2   Dimension Stacking

This is a variant of the hierarchical axis [2, 12]. While in the hierarchical axis each element on the fastest axis is a one-dimensional histogram, in this technique, the element is a 2D xy histogram (Figure 16).
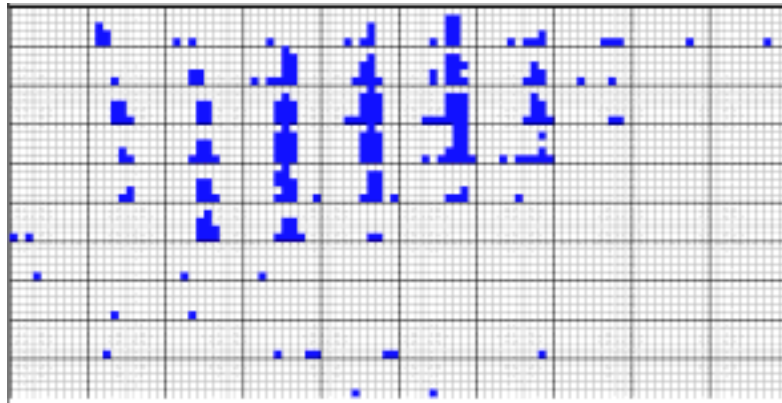
Figure 16. Dimension Stacking Example [12].

2.4.3   Trees

A Tree Display represents nodes or vertices in hierarchies [10, 27–31]. Branches or edges, directed by conditions or constraints, are proliferating from a top hierarchy set of objects (Figure 17. Apart from the typical tree structure, there are also treemaps, Cone trees and Hyperbolic trees that are later described as part of the Distortion methods.

Figure 17. Tree Display [12].

2.4.3.1 Tree Maps

A Treemap (Figure 18) is a hierarchical partitioning of a screen using screen filling techniques [31, 43]. It uses enclosure to visualize trees. The following properties are always held:

1. If Node 1 is an ancestor of Node 2, then the bounding box of Node 1 completely encloses, or is equal to, the bounding box of Node 2.

2. The bounding boxes of two nodes intersect if one node is an ancestor of the other.

3. Nodes occupy a display area strictly proportional to their weight.

4. The weight of a node is greater than or equal to the sum of the weights of its children.

Colour is principally used to depict the type of contents of a node and hues, textures and brightness have secondary parts.

Treemaps ensure a fixed size presentation, but are complex and many users require a lot of training to explore multi-hierarchical data sets.

Figure 18. Tree Map [12]

2.4.3.2   Cone Tree

A Cone Tree (Figure 19) is a tree figure that can interactively rotate and reveal new branches with data [12].
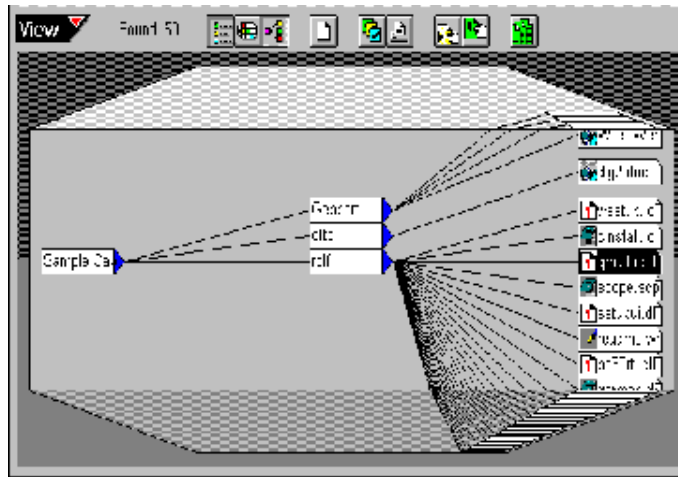

Figure 19. Cone Tree [12].

2.4.4   Worlds within Worlds

This is the nesting of dimensions within dimensions so as to generate an interactive hierarchy of displays [32]. A data glove is used to manipulate the displays (Figure 20).
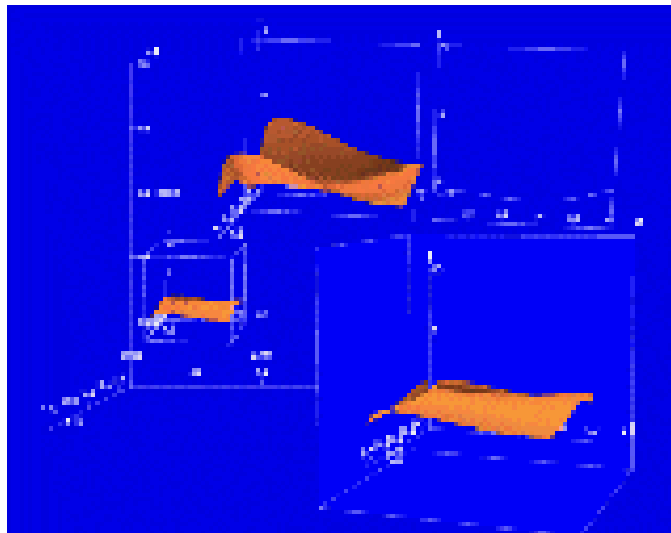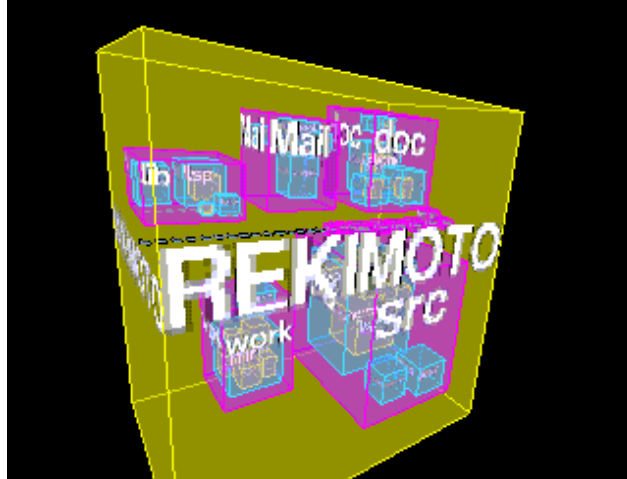

Figure 20. Worlds within worlds.

2.4.5　Info Cube

In this display (Figure 21), the information is presented within nested cubes, having the highest hierarchical level as the outer cube [33]. The environment is virtual and the user can manipulate, rotate and select the cube of interest using a Data Glove, similarly to the previous technique.

Figure 21. The Information Cube [33].

2.5　Distortion Techniques

This category includes the visualization techniques that distort the image to allow a visualization of larger amounts of data.

2.5.1　Perspective Wall

A Perspective Wall is the display of a wall in 3D [10]. On each face of the wall the data is presented (Figure 22). The user can interactively rotate the wall and reveal more faces where other data are displayed.
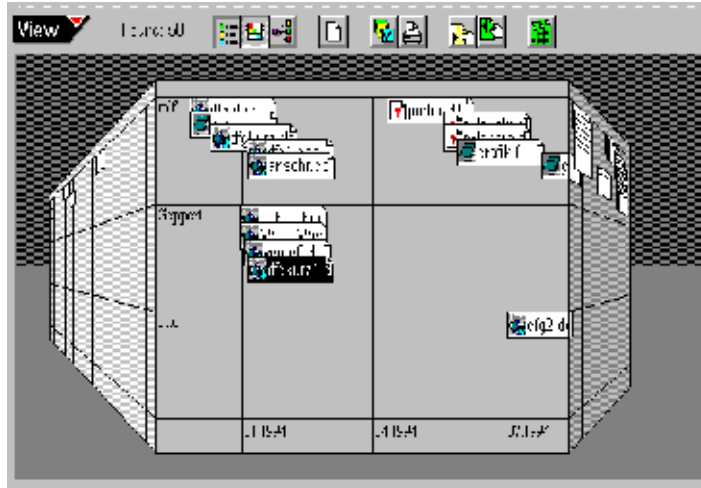
Figure 22. Perspective Wall [12].

2.5.2   Pivot Table and Table Lens

A Pivot table is a table where there is a possibility to pop up an extra table where the details or more data can be shown [34]. In the Pivot table, the user can rotate the attributes and explore relationships and aggregation from different sides.

The Table Lens has evolved from the Pivot Table. In the table lens technique, parts of a table can be enlarged through an interactive action similar to that one of using a magnifying lens in order to visualize parts of the table where the information is hidden (Figure 23).

Figure 23. Table Lens [12].

2.5.3   The Fish Eye View

A Fish Eye View Graph (Figure 24) is the display of a graph where some parts are enlarged to show the detail while displaying the context containing the details [10, 12].
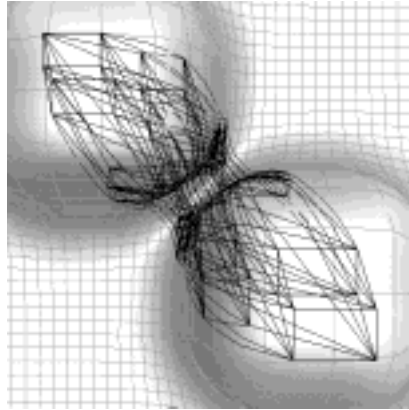

Figure 24. The FishEye View [12].

2.5.4   Hyperbolic Trees

A Hyperbolic Tree is the viewing of a tree in a hyperbolic space where there are different foci [10]. By manipulating the foci more details can be viewed at the branches (Figure 25).
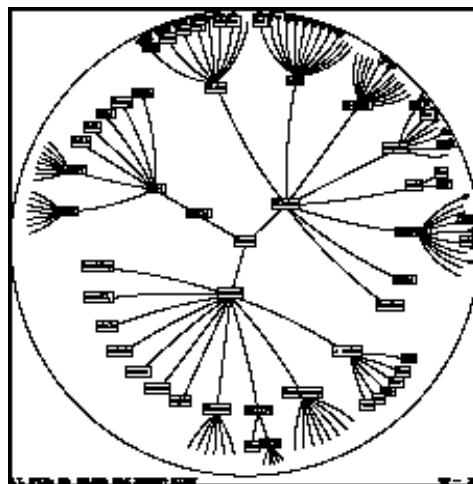

Figure 25. The Hyperbolic tree [12].

2.5.5   Hyperbox

This is a display (Figure 26) of an n-dimensional box that has n(n-1) faces [2, 10]. Lines with the same orientation form a direction set. Each attribute is displayed in one direction. Each face of the box displays the relationship of the attributes along the directions of the face. By selecting variables, the user can cut the box along each direction set. However, when the amount of attributes is too large, the human perception makes it difficult for the user to view the information correctly.
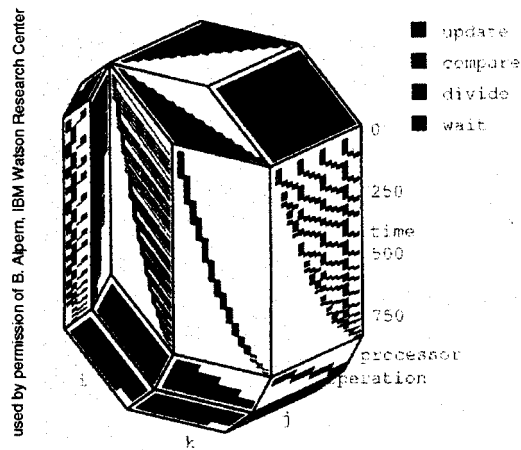
Figure 26. The Hyperbox [10].

2.6   Graph Based Techniques

The visualization of large graphs using these techniques conveys the meaning of the graph clearly and quickly [10].

2.6.1   Basic Graphs

Simple representations of polylines, straight lines and curved lines linking the objects. The objects can be data objects, relationships, rules e.t.c.

2.6.2   2D Graphs

To optimize the graphs of a large amount of objects, the graph should display the possible clusters among the objects and the symmetries existing between the objects, and there should be minimal bending of curves and a uniformity in the distribution of the vertices or nodes and the edge length.

2.6.3   3D Graphs and Hygraphs

A more sophisticated representation of the graphs, in 3D (Figures 27 and 28) or hyperbolic spaces (Figure 28).

Figure 27. Cluster Relations over large datasets [35].

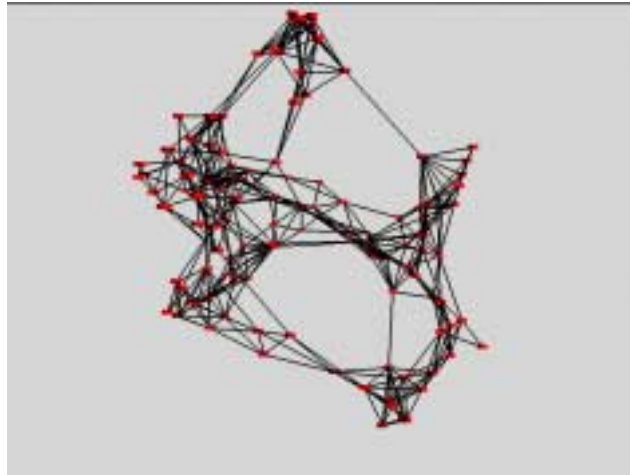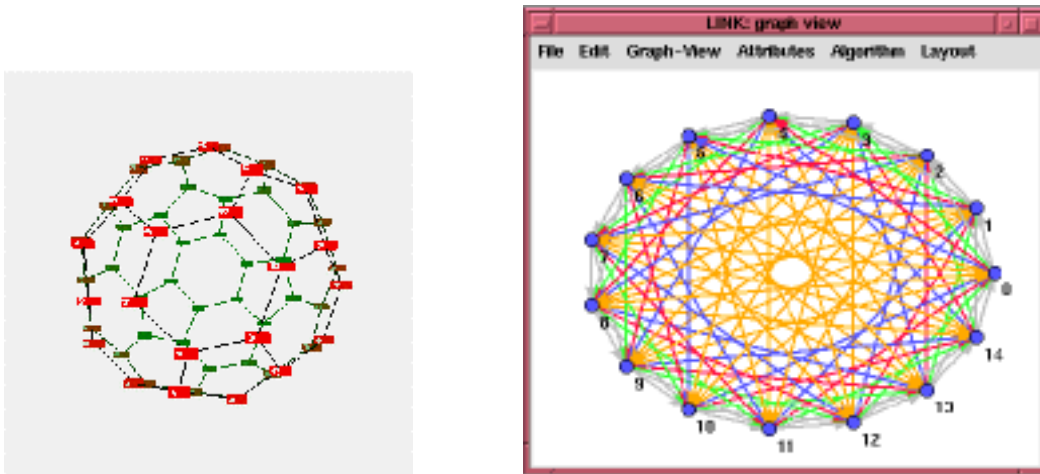*Figure 28. A ball 3D graph [35] and an example of a hyperbolic graph generated using the LINK program [36].*

Table 1. Comparison of Information Visualization Techniques.

		Clustering	Multi-variate Hot spot	No of variates	No of data items	Categori-cal data	Visual overlap	Learning curve
Geometric techniques	Scatterplot matrices	++	++	+	+	−	0	++
	Prosection views	++	++	+	+	−	0	+
	Hyperslice	+	+	+	+	−	0	0
	Parallel Coordinates	0	++	++	−	0	--	0
Icon techniques	Stick figure	0	0	+	−	−	−	0
	Shape coding	0	−	++	+	−	+	−
	Colour Icon	0	−	++	+	−	+	−
Pixel Oriented techniques	Query independent	+	+	++	++	−	++	+
	Query dependent	+	+	++	++	−	++	−
Hierarchical techniques	Dimensional Stacking	+	+	0	0	++	0	0
	Worlds-within-worlds	0	0	0	+	0	0	0
	Treemap	+	0	+	0	++	+	0
	Conetrees	+	+	0	+	0	+	+
	Infocube	0	0	−	-	0	0	+
Graph techniques	Basic Graphs	0	0	−	+	0	0	+
	Specific Graphs	++	+	−	+	0	+	+

Daniel Keim in his tutorial presentation about the information visualization has compiled a table (Table 1) where different methods are being compared by considering the possibilities to view clusters, multivariate hot spots, the amount of variates, the amount of data items, categorical data, and furthermore: how much visual overlap occurs and how good the learning curve is [10]. We can see that with the exception of icon methods, clustering can be viewed well. All the methods mentioned have a potential for displaying multivariate data except the graphs, unless one includes brushing in them. Categorical data can be viewed better using hierarchical techniques as expected. Parallel Coordinates is probably the technique with the worst visual overlap.

In general terms, the use of a certain method should be decided upon the following criteria:

–   data kind (scalar, categorical etc.)

–   data amount

–   data dimensionality.

One should also consider the kind of queries and answers the analyst would want to extract from the data in order to finalize an interactive exploring visualization tool.

3. Additional Methods for "Multidimensionality"

3.1   Zooming

By zooming (Figure 29) onto smaller portions of the display, the user can view hidden details or even similar displays of lesser attributes.


Figure 29. Zooming.

3.2   Brushing

An interactive brush such as a mouse pointer can be used to cause the popping up of hidden windows, tables spread sheets, etc., and consquently the display of hidden information in detail (Figure 30).

Together with the brushing function one could consider the linking. Such is the example of the Scatterplot matrices where the user can "brush" points on one Scatterplot and the same points are highlighted in the linked graphs of the matrix.
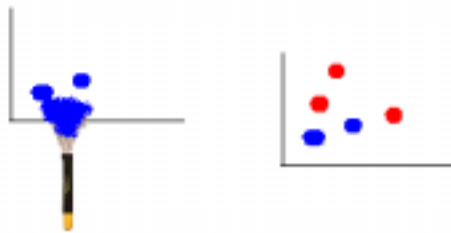
Figure 30. Brushing.

3.3   Animation

In time and serial data, animation (Figure 31) can be used to view information at different parts of space and of time.
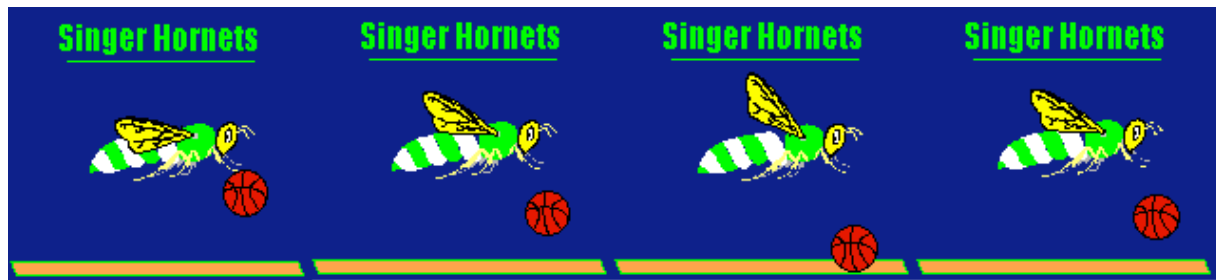
Figure 31. Animation Frames.

3.4   Virtuality

Virtual models have been built in combination with some of the above mentioned displays. Displays of natural scene paradigms or similar to the world in Figure 32 are common virtual visualizations.

Figure 32. Virtual Worlds.

4. Examples of Visualization Tools

Several visualization tools for representing multidimensional data have been developed, commercial as well as experimental. In the following, there are some examples from literature.

VisDB [23, 24]

Using this tool, the user can visualize the relevance of multidimensional data answering to a query. The relevance is appointed to colours and pixels are accordingly coloured. Then, the highest relevance objects are positioned in the middle and the less relevant are evolving to a spiral pattern outwards. By relating corresponding regions in different windows, presented all together in one screen, the user can perceive data characteristics such as multidimensional clusters or correlations (Figure 33).
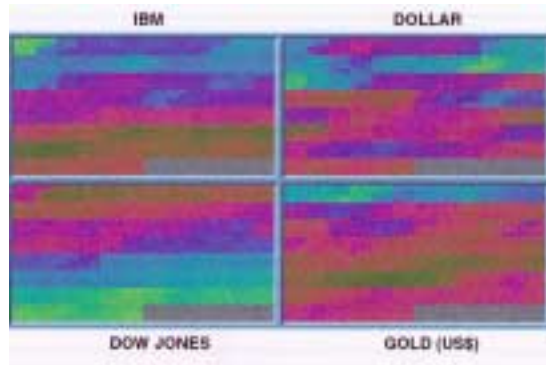

Figure 33. VisDB: Recursive Pattern Example; Stock Market Data.

The user can give a direction to the relevance of the query result and visualize the overall results in two axes techniques, adding information in this way.

AutoVisual [32]: This tool designs interactive visual worlds for visualizing and exploring multivariate relationships using the worlds within worlds technique (see also Fig. 20). The user designs n-Vision worlds and explores them using a Data Glove. An n-Vision virtual world is a hierarchy of interactors. Each interactor consists of four basic components: a set of encoding space (where the graph is rendered), a set of encoding objects (the body of the graph), a set of selections (a subset of the parent interactor's encoding space), and a user interface (bindings between the user's actions and the interactor's properties).

Auto Visual uses two criteria to establish a successful visualization, potential expressiveness and potential effectiveness. Expressiveness refers to the potential to display all assigned information over time, and effectiveness is referring to the potential of presenting the information sufficiently clearly.

SGI Data explorer's Glyphmaker [38]: The tool allows the user to build customized representations (glyphs) of multivariate data. The glyphs properties (shape, colour, size etc.) are bound to data attributes. Important parts of the tool are the Data Reader (to read data), the Glyph editor (to draw and design the glyphs), and the Glyph binder (allows interactive bindings between glyph elements and data variables). The glyphs are put in a 3D Box, the Conditional Box.

Xdmv Tool [2]: The tool uses four tools to visualize multivariate data: scatterplot matrix, dimension stacking, star glyphs, and parallel coordinates

Polaris [34]: In this tool, the Pivot Table interface is extended. Relational databases are organized into tables where rows are the events and columns are the attributes or parameters of each event. Then, by choosing among representations, the user drags and drops areas selected from the table and constructs a matrix of graphics (Figure 34).
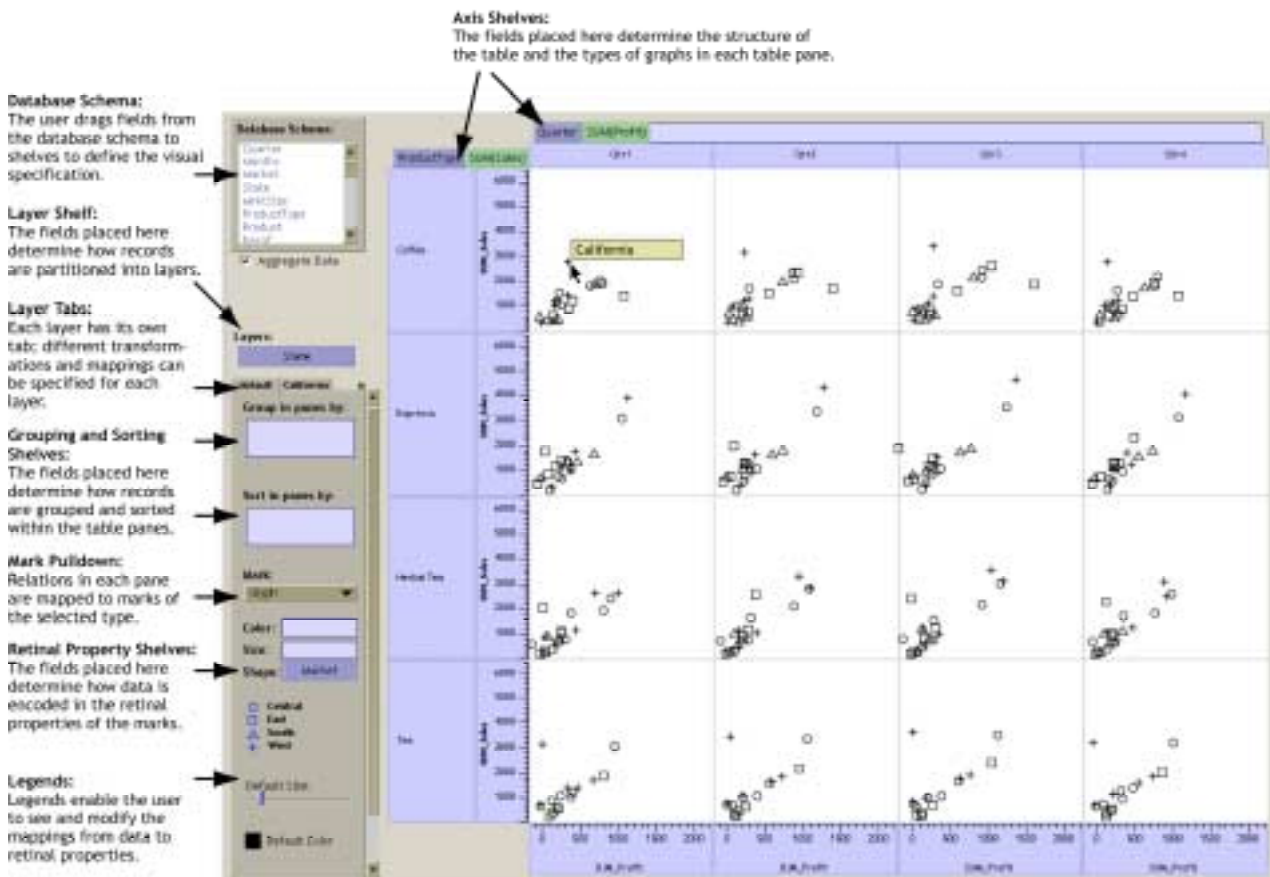

Figure 34: The Polaris Tool User Interface.

There are Ordinal-Ordinal graphs such as tables, Ordinal Quantitative graphs such as barcharts and Quantitative-Quantitative graphs such as scatterplots.

NETMAP [39]: This is a link analysis tool using different displays to show links between sets of data. Among others, there is the "Cartesian display" where the user is allowed to position nodes on any point on the screen.

MineSet [40]: This is a tool using tree display, 3D scatterplots, a map visualizer and a rules visualizer similar to the Polaris tool (Figure 35).

Figure 35. MineSet: Tree Display

Note: None of these has been tested by the author.

References

1. http//:www.dictionary.com, 2001 Lexico LLC.

2. Wong, P. C. & Bergeron, R. D. 30 Years of Multidimensional Multivariate Visualization. In: Nielson, G. M. Scientific visualization: overviews, methodologies, and techniques. IEEE Computer Society, Washington, 1997. ISBN 0-8186-7777-5

3. Inselberg, A., Grinstein, G., Mihalisin, T. & Hinterberger, H. Visualizing Multi-dimensional (Multivariate) Data and Relations. Proc. of IEEE Conf. VISUALIZATION, 94. Pp. 404–409.

4. Beckamn, P. E. On The Problem of Visualizing Point Distributions in High Dimensional Spaces. Computers & Graphics, 1995, 19(4), pp. 617–629.

5. Han, J. Data mining techniques; SIGMOD Record (ACM Special Interest Group on Management of Data). Proceedings of the 1996 ACM SIGMOD International Conference on Management of Data, Montreal, Can, June 4–6, 1996. P. 545.

6. Fayyad, U., Piatetsky-Shapiro, G. & Smyth, P. The KDD Process for extracting Useful Knowledge from Volumes of Data. Communications of the ACM, 1996, 39(11), pp. 27–34.

7. Gershon, N., Eick, S. G. & Card, S. Information Visualization. Interactions, 1998, 2, pp. 9–15.

8. Mackinlay, J. Automating the Design of Graphical Presentations of Relational Information. ACM Transactions on Graphics, 1986, 5(2), pp. 110–141.

9. Healy, C. G., Booth, K. S. & Enns, J. T. Visualizing Real Time Multivariate Data Using Preattentive Processing. ACM transactions on Modelling and Computer Systems, 1995, 5(3), pp. 190–221.

10. Keim, D. A. Visual Techniques for Exploring Databases. Invited Tutorial, Int. Conference on Knowledge Discovery in Databases (KDD'97), Newport Beach, CA, 1997.

11. Tweedie, L., Spence, R., Dawkes, H. & Su, H. Externalising Abstract mathematical Models. Proceedings of the Conference on Human Factors in Computing Systems (SIGCHI '96), 1996. Pp. 406–412.

12. Yli-Nikkola, H. Information Visualization Techniques Report. VTT Electronics internal report, 1999.

13. Zuffo, M. K., de Deus Lopes, R., Santos, E. T., Zuffo, J. A. & Grant, A. J. A programming environment for high performance volume visualization applications. Computers & Graphics, 1996, 20(3), pp. 358–394.

14. Greiner, G., Kolb, A., Pfeifle, R., Seidel, H. P., Slusallek, P., Encarna, M. & Klein, R. A Platform for Visualizing Curves and Surfaces. Computer Aided Design, 1995, 27(7), pp. 559–566.

15. Hamman, B. Curvature approximation of 3D manifolds in 4D space. Computer Aided Geometric Design, 1994, 11(6), pp. 621–632.

16. Dong, F. & Shi, J. Multiresolution data modelling for irregular data fields based on wavelets. Proceedings of the 1997 International Conference on Information Visualization, IV, Aug. 27–29 1997, London, England. Pp. 64–70.

17. Fua, Y. H. & Ward, M. O. Hierarchical Parallel Coordinates for Exploration of Large Datasets. Rundensteiner, E. A. Proc. of Visualization '99, Oct. 1999.

18. Goel, A., Baker, C., Shaffer, C. A., Grossman, B., Haftka, R. F., Mason, W. H. & Watson, L. T. VizCraft: A Multidimensional Visualization Tool for Aircraft Configuration Design. Proceedings of IEEE, Visualization '99, San Francisco, CA, October 1999.

19. Hoffman, P., Grinstein, G., Marx, K., Gorse, I. & Stanley, E. DNA Visual And Analytic Data Mining. IEEE Visualization 1997, October 1997, Phoenix, Arizona, USA.

20. Healy, C. G. & Enns, J. T. Building Perceptual Textures to visualize multi-dimensional Databases. IEEE Visualization 1998, October 1998, USA.

21. Erbacher, R. F., Grinstein, G., Lee, J. P., Levkowitz, H., Masterman, L., Pickett, R. & Smith, S. Exploratory visualization research at the University of Massachusetts at Lowell. Computers & Graphics, 1995, 19(1), pp. 131–139.

22. Fukuda, T., Morimoto, Y., Tokuyama, T. & Morishita, S. Data mining using two-dimensional optimized association rules: Scheme, algorithms, and visualization. SIGMOD Record (ACM Special Interest Group on Management of Data), Proceedings of the 1996 ACM SIGMOD International Conference on Management of Data, June 4–6, 1996, Montreal, Can. Pp. 13–22.

23. Keim, D. & Kriegel, H.-P. VisDB: Database Exploration using Multidimensional Visualization. IEEE Computer Graphics and Applications, 1994, 14(5), pp. 40–49.

24. Keim, D. & Kriegel, H.-P. Visualization Techniques for Mining Large Databases: A comparison. IEEE Transactions on Knowledge and Data Engineering, 1996, 8(6), pp. 923–938.

25. Hofmann, H. Exploring Categorical Data: Interactive Mosaic Plots. Metrika 2000, 51. Pp. 11–26.

26. Theus, M. Plots in Manet. Found in
http://www1.math.uni-augsburg.de/Manet/plots.html#plots

27. Greenhill, S. & Venkatesh, S. Semantic Data Modelling and Visualization using Noetica. Data and Knowledge Engineering 2000, 33, pp. 241–276.

28. Koonce, D. A., Fang, C.-H. & Tsai, S.-C. A Data Mining Tool for Learning from Manufacturing Systems. Computers ind. Engng 1997, 33(1–2), pp. 27–30.

29. Ankerst, M., Elsen, C., Ester, M. & Hriegel, H.-P. Visual Classification. An Interactive Approach to Decision Tree Construction. Proc. 5th Int. Conf. on Knowledge Discovery and Data Mining (KDD'99), San Diego, CA, 1999. Pp. 392–396.

30. Mehta, D. P. & Sahni, S. Models and techniques for the visualization of labelled discrete objects. Proceedings of the 1992 ACM/SIGAPP Symposium on Applied Computing SAC '92, March 1–3, 1992, Kansas City, KS, USA. Pp. 1224–1233.

31. Baker, M. J. & Eick, S. G. Visualising Software systems. Proceedings of the 16th International Conference on Software Engineering, 1994. Pp. 59–67.

32. Beshers, C. & Feiner, S. AutoVisual: Rule-based Design of Interactive Multivariate Visualizations'. Computer Graphics & Applications, 1993, 13(4), pp. 41–49.

33. Rekimoto, J. & Green, M. The Information Cube: Using Transparency in 3D Information Visualization. Proceedings of the Third Annual Workshop on Information Technologies & Systems (WITS'93), 1993. Pp. 125–132.

34. Stolte, C. & Hanrahan, P. Polaris: A system for Query, Analysis and Visualization of Multidimensional relational Databases. Proceedings of the Sixth IEEE Symposium on Information Visualization, October 2000.

35. Frick, A. Graph Drawing. Last modified: Fri Jul 12 11:11:58 MST, http://i44s11.info.uni-karlsruhe.de/~frick/gd/index.html

36. DIMACS projects, LINK, 2000, http://zhivago.elon.edu/~berryj/LINK.html

37. Ellershaw, S. K. & Oudshoorn, M. J. Visualization techniques for various programming paradigms. Proceedings of the 1993 IEEE Region 10 Conference on Computer, Communication, Control and Power Engineering (TENCON 93). Part 1 (of 5), Oct 19–21, 1993, Beijing, China. Pp. 360–363.

38. Ribarsky, M. W., Tumblin, J. & Vetter, J. Glyphmaker: An Interactive, programmless Approach for Custom Visualization and Analysis of Data, 1994. http://www.gvu.gatech.edu/gvu/reports/1993/abstracts/93-26.html

39. Pickover, C. A. & Tewksbury, S. K. Frontiers of scientific visualization. John Wiley & Sons, New York. 1994. ISBN 0-471-30972-9.

40. MineSet, Sgi 2001, http://www.sgi.com/software/mineset/mineset_data.html

41. Wong, P. K., Whitney, P. & Thomas, J. Visualizing Association Rules for Text Mining. Proceedings of IEEE Information Visualization '99, Los Alamitos, CA, 1999.

42. Lux, M. Visualization of Financial information. ACM NPIV '97, Las Vegas Nevada. Pp. 58–61.

43. Johnson, B. & Shneiderman, B. Treemaps: A Space-Filling Approach to the Visualization of Hierarchical Information Structures. ftp://ftp.cs.umd.edu/pub/hcil/Reports-Abstracts-Bibliography/91-06html/91-06.html

Author(s)
Sachinopoulou, Anna

Title

Multidimensional Visualization

Abstract

Visualization is a powerful tool for data mining. During the last 30 years, multi-dimensional visualization methods and techniques have been developed in order to conduct data mining (Visual Data Mining) or to efficiently present and evaluate the results of a data mining query. The purpose of this review is to list and shortly describe such methods and give some examples of multidimensional visualization so that the tool designers and data mining analysts can get an overview of the existent possibilities. The methods described are divided into six groups: Geometric techniques where the methods described are based on the Cartesian coordinates; Icon techniques where the main tool and basic unit of the visualization technique is an icon; Pixel Oriented techniques where the pixels are used as the basic visualization unit; Hierarchical techniques where the data items and the query results are presented in hierarchical displays; Distortion techniques where the three-dimensional space is distorted to allow more information to be visualized; and Graph Based techniques where the information is presented using nodes and edges. Examples of visualization tools give a more complete image of the application of these methods.