

# Hypervariate Information Visualization

Florian Müller

**Abstract**— In the last 20 years improvements in the computer sciences made it possible to store large data sets containing a plethora of different data attributes and data values, which could be applied in different application domains, for example, in the natural sciences, in law enforcements or in social studies. Due to this increasing data complexity in modern times, it is crucial to support the exploration of the hypervariate data with different visualization techniques. These facts are the fundament for this paper, which reveals how the information visualization can support the understanding of data with high dimensionality. Furthermore, it gives an overview and a comparison of the different categories of hypervariate information visualization, in order to analyse the advantages and the disadvantages of each category. We also addressed in the different interaction methods which help to create an understandable visualization and thus facilitate the user's visual exploration. Interactive techniques are useful to create an understandable visualization of the relationships in a large data set. At the end, we also discussed the possibility of merging different interactions and visualization techniques.

**Index Terms**—informaton visualization, hypervariate data, visualization of hypervariate(multivariate) data, visualization of large data set, interactive visualization methods

## 1 INTRODUCTION

Visualizing data means translating different measurements of a scientific, business, or social topic in a view which facilitates the understanding of the relationship between different data items[28]. Furthermore, the data which needs to be visualized always has high dimension, which means more than three attributes. How to visualize data with high dimension, it is the essence of Hypervariate Information Visualization. Comparing with the uni-, bi- or trivariate data[17] which have less than three attributes, it is difficult to map hypervariate data in a normal cartesian plot or scatterplot without any loss of information or overview. Therefore an understandable and intuitive visualization is very important for the user exploring the hypervariate data[28]. The visualization should support the user to discover the relationship between different data or different attributes of the same data. Different extensive techniques, which will be discussed in later sections, were developed to support visualization of hypervariate information. For example, the parallel coordinate plots[17, 23], star plots[17, 4] and pixel-oriented techniques[9] etc. Due to the data complexity it is not enough and might be problematic in some cases to generate only a static visualization. The user should have options to explore the data set in an intuitive and interactive way. Discussing all these problems and facts, the structure of this paper is organized as follows: Section 2 gives an overview over the different application domains of hypervariate information visualization(HyperInfoVis), and points out how Information Visualization can support the understanding of data with high dimensionality. Section 3 explores and compares the different traditional technical categories concerning hypervariate InfoVis. Section 4 explores the extensive techniques in which system-driven dimension reduction are applied, before visualizing the reduced dimensions with the traditional techniques. Section 5 discussed the problems of the traditional techniques and techniques with system controlled dimension reduction, which leads to interactive methods to create intuitive visualizations, for example the user-driven dimension reduction, brushing, different navigation tools and sharing extracted Informations. Section 6 discusses for further developments.

## 2 APPLICABLE DESIRE FOR HYPERINFOVIS

Most of the collected data in the scientific research, such as natural science and social studies, have more than three attributes. To ex-

- Florian Müller is studying Media Informatics at the University of Munich, Germany, E-mail: Florian.Josef.Mueller@campus.lmu.de
- This research paper was written for the Media Informatics Advanced Seminar on Information Visualization, 2008/2009

tract useful information statistical techniques could be applied which work directly with the measured data. One prominent problem of this approach is the compression of the extracted information makes it difficult to comprehend the relationship between all involved data items. That means it is hard to find clusters or outliers. So it is important to translate the data in visual patterns which make it easier to analyze the data and to understand their relations[28]. Figure 1 shows an visualization example for a parallel coordinate plot, which shows the data of different cars, produced between 1968 and 1983. Each axis represents a dimension and each line represents the relation between the dimensions. Based on the information shown in the figure, it is possible to detect at least two valuable information at the first glance. Firstly, it is obvious that the most cars which was produced during these 15 years have more than two cylinders, on the other hand, all cars was produced in Europe, in Japan or in the USA. Using ,for example, a table only showing the pure measured data, it will cost much time to extract the same information. Different application domains, which have to work

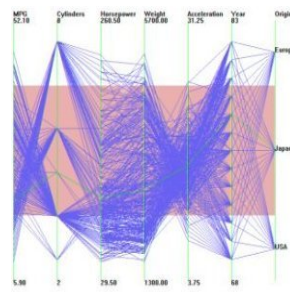


Fig. 1. Parallel Plot created with the XmdvTool[22].

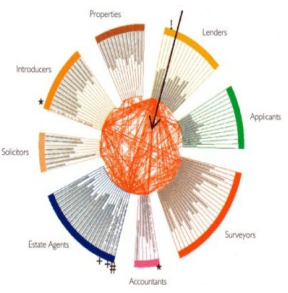


Fig. 2. Unusual mortgage transactions[17].

with and explore increasing large multivariate data sets, have arisen the last years. Not only in the natural sciences' research, such as the bioinformatics or earth sciences, but also in law enforcements, social studies or in the engineering which require for methods mapping hypervariate data into an understandable visual pattern[28]. In the field of law enforcement visualization techniques are applied to detect cheating delicts or reconstructing crimes with the aid of so called association or timeline style charts[17]. Figure 2, for example, displayed data with unusual activities on the mortgages market. Through the lines it is possible chasing suspicious transactions between different lenders, applicants and institutions. In the field of social studies, most of the census and the surveys produce high dimensional data sets[27], which have to be visualized accurately and intuitively (as figure 3 shows). In

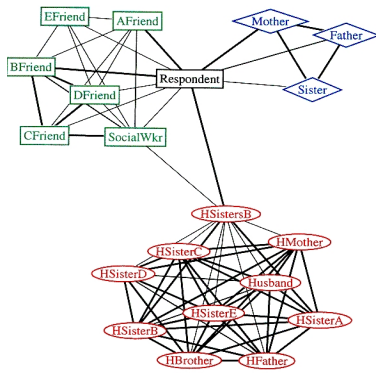


Fig. 3. Social choices and connections of a single mother with her family, her earlier husband's family and her circle of friends[6].

the bioinformatic's research visualizing genome informations is important for understanding the basic structure of the human genotype. On base of these different application domains and advantages of understandability of visual patterns, a multiplicity of more or less extensive multivariate visualization techniques were developed, which will be discussed in detail in sector three and four.

### 3 TRADITIONAL HYPERVARIATE VISUALIZATION TECHNIQUES

The techniques, which are described in this section were developed in the earlier years in the field of hypervariate visualization. Because of their today's wide dispersion in visualizing high dimensional data, the more extensive techniques use them to display the dimension reduced data set. Due to these facts, these methods are called "Traditional hypervariate visualization techniques". Before discussing the different technical categories of these methods, it is important to explore the existing possibilities of encoding relations among the explorative data items. Several options are given to represent a connection between two or more dimensions or data items. Hence, choosing the appropriate one, is fundamental for creating an intuitive visual pattern. The usage of lines and colour, for example, is often adequate to show a relation between different attributes. The lines associate two related attributes while the colour marks similar data items or attributes. Due to this, it is possible to distinguish very difficult relations with the aid of this simple technique. As shown in figure two and three, this method is applied to visualize social networks and to show complex scenarios for the law enforcements or reveal different business procedures. Other techniques represent relations by an intersection of different plains. Venn-diagrams, for example, display the dimensions as circles that adhere belonging data items. Items which are a member of two or more dimensions get mapped into the intersection of these circles. On the base of the given encoding methods were developed special techniques which are fitted to the hypervariate visualization information problems. They can be subdivided in two different types[17]:

- Techniques supporting attribute visibility
- Techniques supporting object visibility

#### 3.1 Techniques supporting attribute visibility

Methods with attribute visibility point out the apportionment of given object's attribute values in each dimension. So, it is easier for the user, finding clusters or outliers of visualized hypervariate data during the visual exploration process. The most important techniques that fall in this category will be discussed in the following.

##### 3.1.1 Parallel Plot

A widespread attribute visible method is the parallel coordinate plot(see figure 1). Parallel plots are emanated from the cartesian plots, which are not able to visualize data with more than 3 dimensions. For example, a point P in the 5th dimension with the coordinate

$\vec{v} = \{5,2,9,7,6\}$ , can not be displayed in a cartesian plot. Due to this, the points used as coordinates in the cartesian plots are translated into lines, whereas the axes were conveyed into a parallel constellation. The number of axes depends on the dimension. Regarding the example, there would be five parallel axes in the generated parallel plot. And the point with the given coordinate would be translated into a line which is drawn by points from each axis. A parallel plot is able to contain more than one high-dimensional coordinate. It is obvious that this method can be used for hypervariate information visualization. If P represents the data, for example, of a car, it is possible to map these high-dimensional attributes with the data of many other different cars in the same parallel plot [23].

##### 3.1.2 Scatterplot Matrix

The Scatterplot Matrix is also a established attribute visible technique. A single scatterplot have the same problem as the traditional cartesian plot: It is impossible to visualize data with more than three dimensions. But arranging a number of scatterplots to a scatterplot matrix can solve the problem. The size of the Matrix is conditional to the level of the displayed dimensions. Visualizing data from a n-Dimensional data set needs a  $n \times n$ -Scatterplot Matrix. Each Scatterplot in the Scatterplot Matrix visualizes the relation of two different dimensions. So, the Scatterplot Matrix is able to show the coherence between all values which are displayed in the different scatterplots[28]. Take the car example with seven dimensions as example, there is generated a  $7 \times 7$ -Matrix(see figure 4).

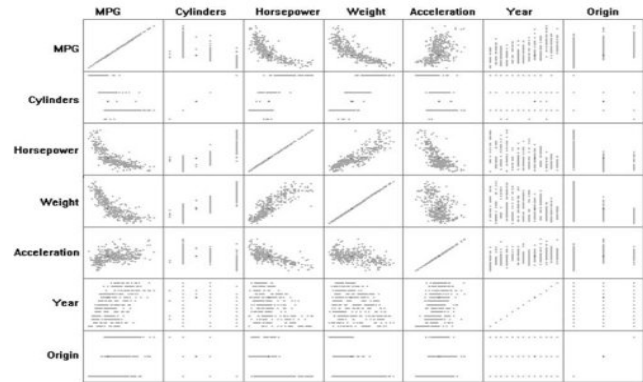


Fig. 4. A scatterplot displaying the relations of seven dimensions[28].

##### 3.1.3 Linked Histograms

Another current technique which falls in the attribute visible archetype is the linked histogram. This method is developed from the normal histogram which is used to visualize two dimensional data. In order to visualize the dimensions and data items as well as the relation between them, a linked Histogram is consisted of multiple single histograms and shows the attribute values of a corresponding dimension. It is also linked with all other histograms. Now, if a user select his/her desired data in one of the histograms, all the others brushes exactly this values, in their own view, which have the same characteristics, like the user's desired data[16]. Apparently, the user needs different

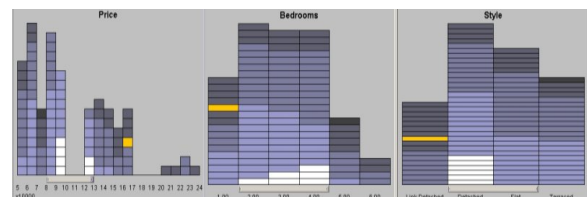


Fig. 5. This linked histogram visualize three attributes of different houses[21].

interaction methods enabling the exploration of the hypervariate data with the aid of linked histograms. These methods, like navigation and brushing will be discussed in section 5. To improve the comprehension of the functionality of linked histograms, an other example should be considered(see figure 5).

### 3.1.4 Mosaic Plot

The techniques which were presented so far, are all advancements of existing uni-/bi-/ or trivariate visualization methods, whereas the attribute visible mosaic plot has no precursor. Starting with a huge rectangle the mosaic plot is splitted up for every dimension, which he has to visualize additionally. The extent of a splitted part depends on the commonness of the represented attribute values[19]. Visualizing a n-dimensional data set, generated a mosaic plot with n splitted parts of different extents(see figure 6).

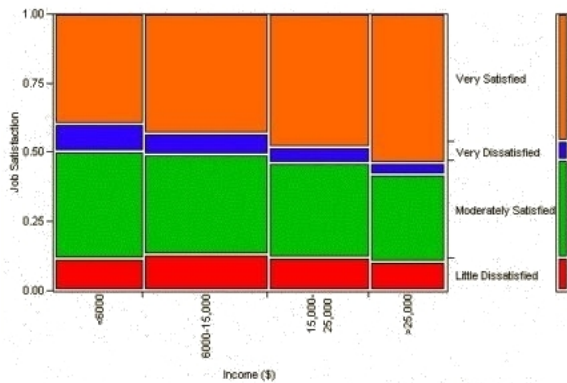


Fig. 6. A exemplarily mosaic plot[20] visualizing employees' Job satisfaction, depending on the income.

## 3.2 Techniques supporting object visibility

Object visibility techniques display the objects as single glyphs on the screen. Each glyph represents the attributes values of the corresponding object. With the aid of this type of technique, the user is able to compare the relation between different objects in different dimensions[17].

### 3.2.1 Star Plots

Two representative examples of object visible techniques are the star plots, and the metaphorical icons. The Star plot technique(see figure 7) is similar to the Parallel Plots. The attribute values of a object are

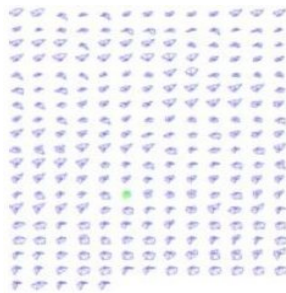


Fig. 7. Exemplary star plot[22] based on the same data like figure 1.

visualized as points on a coordinate axes and they are linked by lines. Every axis represents, like the axes in a parallel plot, a dimension. However, the main difference is, that the axes are arranged radiately from a common root[2], which belongs to one specific object.

### 3.2.2 Icons

Other object visible methods are the metaphorical icons, which can be divided in two different groups[17]:

- icons with a direct relation between icon and object
- icons with no direct relation between icon and object

The idea behind items out of the first group is simple. A direct related metaphorical icon attempts to display a given object by drawing his attribute values in a direct way. Using the car example again, the created icon would have the shape of a car with attached symbols representing the values of different dimensions. No-direct related icons are, above all, represented through the so called Chernoff faces[17, 1, 3](see figure 8). Generating a chernoff face, attribute values were encoded into human facial characteristics. The emerging facial expression supports the user to identify interesting objects out of the analyzed data set.



Fig. 8. Five example Chernoff faces[13].

### 3.2.3 Infocrystals

The Infocrystal(see figure 9) is an improved pattern which merges all relations between the attributes within a Venn-diagram to regions inside a specific crystal[18].



Fig. 9. The development process from a Venn-diagram to an Infocrystal[17].

### 3.2.4 Tree Views

Further possibilities for object visible views are tree representations. Although all of these trees are used to display data out of hierarchical structured data sets, they can be subdivided in different illustrations: In trees, which mirror relations between the data in a noticeable hierarchical form, for example, the cone tree or the Hyperbolic Browser; The other reflecting method is in a plain way, like it is seen in treemaps. One problem which occurs using tree descriptions is the possible huge horizontal display of an ordinary tree. This problem leads to the development of the Cone trees which reconfigure the subordinate nodes to a circle structure in order to create a cone in cooperation with their superordinate node[17]. A Hyperbolic Browser[12] is also a effective to limit the depending space. Every node of an ordinary tree is translated into a corresponding location inside, for example, a circle(see figure 10). The tree's root is in the middle of the generated structure, whereas its child nodes are arranged around it. The distance between an subordinate node to the corresponding superordinate node in the middle is represented through the size of the particular child node. To assure the visualization of all involved data, the user is able to move an interesting node in the center of the hyperbolic browser followed by their subordinate nodes. An alternative technique concerning the trees is the treemap[15]. The root node is depicted as huge rectangle. The direct subordinate nodes are drawn as smaller rectangles within this first one. This process is continued till all nodes are translated into smaller rectangles within their direct superordinate nodes' rectangles.

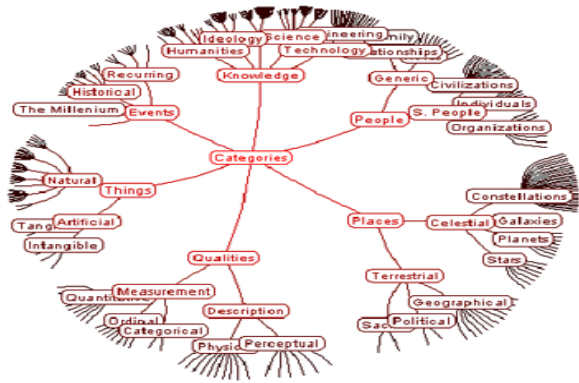


Fig. 10. An ordinary tree was mapped into an Hyperbolic Browser[8].

Because of this method's plain structure, there is no sign relative to the depth of the tree. So the leaves have to be highlighted with the aid of colour encoding.

### 3.3 Discussion

After the overview of the established traditional techniques it is important to discuss the advantages and disadvantages of the particular types and techniques. So for example, the difference between the attribute visible parallel plot and the object visible Star plot is illustrative. Figure one and seven visualize the same car attributes out of a 7-dimensional data set. In figure one, every car is encoded through one line, in figure seven every car has its own corresponding glyph. The advantage of the attribute visible techniques can be seen in the concept of attribute visibility. The user is able to find clusters or outliers inside the visualized data. The fast identification of those coherences supports the user's exploration of hypervariate data by visualizing an understandable pattern. On the other hand, the attribute visible techniques make it difficult to compare different objects in different dimensions. This can be seen, for example, in the parallel Plot, which encodes every object in different points linked with a line. The disadvantages of the attribute visible methodes could be compensated by the object visible techniques, which supports comparison of different objects. However, these techniques lose the advantage of attribute visible techniques, identifying clusters or outliers. One big problem concerning both maybe the overcoming clutter[28, 24, 27, 25] on the screen by increasing numbers of dimension and data items. From an specific number of visualized dimension or data items, the today's screens are overloaded with informations which makes it impossible analyzing the displayed data or create intuitive visual patterns. Therefore, extensive techniques were further developed to deal with the problem of clutter and to enhance the interactivity.

## 4 EXTENSIVE HYPERVARIATE VISUALIZATION TECHNIQUES

There are three categories for the techniques which target solving the problem of dimension reduction.[25]:

- System-Driven Dimension Reduction
- User-Driven Dimension Reduction
- Combination of both Approaches

The first category applied automatic process which map a high dimensional data collection on a regular, 2-dimensional pattern[10]. The second category integrates the user in the dimension reduction process. The third category use the system-driven reduction to map the data into a specific view, where the user is able to select the desired dimensions for mapping them in a traditional hypervariate information visualization techniques. On base of the given groups there are different types of developed extensive techniques: The pure

system-driven techniques[10, 11], techniques using visual hierarchical methodes[27, 26], techniques using glyphs filled with pixel patterns showing the dimensions relation[25, 9, 14], techniques allowing the user to define his/her own information nuggets[24] and pure user-driven reduction techniques using metaphors[28]. In this section, above all the techniques which use system-driven dimension reduction, will be discussed and the user driven methods will be explored in section 5.

### 4.1 Techniques using System-Driven methods

The pure system driven techniques, such as the Self-Organizing Maps[10] or the Multidimensional Scaling[11] accrue from the statistic area. These methods use a distance matrix to capture the relation between the given dimensions as similarity or dissimilarity. The equations, which are used to calculate the similarity of different dimensions will be presented at the end of this section. Then, the system is able to map the high-dimensional data into a two-dimensional view, whereas the dimensions are represented by glyphs and the dimensions' relation is shown by the distance between the visualized glyphs. It is possible to avoid the clutter problem, but due to the reduction from a n-dimensional data set into a two-dimensional view, the output of a pure system-driven technique delivers a rather unintuitive visual pattern[28]. In order to avoid this problem and to assure intuitive visual patterns to facilitate the user's exploration of high-dimensional data sets, there were developed techniques which integrated user in the loop.

#### 4.1.1 Visual Hierarchical methods

One member of these types is the visual hierarchical technique(see figure 11)[27, 26]. Using the dimensions belonging to a multidimen-

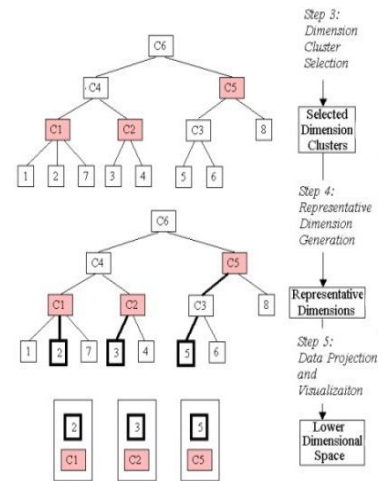


Fig. 11. Overview of the last three steps which shows the user driven part.[27].

sional data set, this method generates a so called hierarchical dimension cluster tree. Thereby, all original dimensions get translated into the leaf nodes. The dimensions which are similar to each other get mapped together and form a cluster and similar clusters analogous form cluster on a higher level. Although this approach is completely system-driven, the user is also able to build up the tree manually[27]. After the tree has been generated, the user is able to use several interaction methods to navigate through the cluster tree and therefor has the chance to attain a better understanding and has options to modify the tree. In the third step the user can select the desired dimension cluster, which should be mapped in a lower dimensional subspace. Now, the system generates the so called representative dimension generation(RD), out of the selected clusters, which mirror the attributes of their corresponding dimension. In the end, the system use the RDs to map the high-dimensional data set into the low dimensional subspace, which can be visualized in any existing traditional technique[27]. It is

obvious, that the visual hierarchical technique combine both existing conceptual reduction approaches, because it alter between system-driven and user-driven dimension reduction during the reduction process.

#### 4.1.2 Glyph representations

The techniques, which apply glyphs for visualizing the dimensions and their relationships, belongs also to the combined group. Examples for applications using this sort of technique are the Glyphmaker[14] or the Value and Relation Display (VRD) [25]. The system-driven part of these methods use Multidimensional Scaling in order to map given dimensions in a two-dimensional view on the screen. So, one glyph encode one dimension of a given data set. The dimension's relation is represented by the distance between the shown glyphs. In order to assure the creation of a understandable visual pattern, there exists different methods which can be user-driven or system driven. Whereas the Glyphmaker-application allows the user to rearrange the glyphs in different structures, like in a Sphere or on a 2D-Grid, the Value and Relation Display use pixel-oriented techniques[9] to map the attribute values of a dimension in the corresponding glyph[14, 25]. Therefore, the glyphs are created as so called subwindows, which contains the relation of the attribute values in form of a specific pixel pattern[9]. Based on these patterns the user is able to compare the relation between the different dimensions by measuring their distance and the specific pixel arrangements in each glyph(see figure 12). Just as the

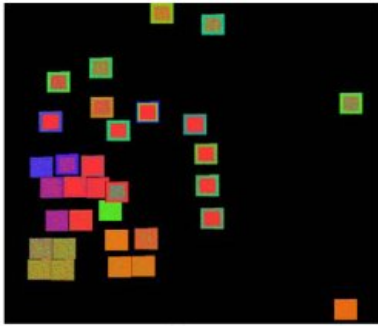


Fig. 12. Visualization of value and relation[25].

system has built up the view, the user is able to navigate through the Value and Relation Display selecting interesting glyphs. Apart from the possibility of selecting a glyph, there are other interactive methods which supports the creation of an understandable visual patterns. The different methods will be discussed in section 5. The chosen dimensions can be mapped in any traditional hypervariate information visualization technique[25]. The Glyphmaker application, however, offers a so called Conditional Box, which the user can move over a interesting subregion of the displayed dimensions[14]. The enclosed dimensions are visualized on a high detail level at a special part inside the application.

#### 4.1.3 Information nuggets

The techniques which allow the user to define his/her own information nuggets, for example the Nugget Management System[24], also applying system and user-driven methods. At first, the user is able to mark interesting values and dimensions intra a traditional technique, in order to create an information nugget which contains the user's valuable information. The marked values are highlighted and possible occurring clusters can be detected easier. If the user don't mark all values belonging to a cluster, the system is able to detect this by calculating the similarity of the data items which are in the area of the defined information nugget. After a detection, the system adds the missing data to the user defined information nugget[24].

### 4.2 Discussion

In each of the extensive techniques with the participation of the system driven dimension reduction, there was needed a method which

calculate the similarity of the corresponding dimensions. In order to work with the attribute values, they have to be normalized in each dimension. Then they could be compared for each pair of dimension. Is the difference of the compared values lower than a given threshold, the dimensions are similar to each other[27, 25]. The extensive techniques are able to solve the clutter problem of the traditional techniques, but,as mentioned above, a new problem appeared caused by the system-driven dimension reduction. The view which is created through this sort of reduction is rather unintuitive and only skilled users are able to extract useful informations out of the visualized data.

## 5 INTEGRATING THE USER IN THE LOOP

In the area of HyperInfoVis emerges several issues which have to be solved in order to generate an intuitive and understandable visual pattern. Apart from the problems mentioned in the previous sections, like the overcoming clutter problem by an increasing number of dimensions[28, 24, 27, 25](see figure 13) or the unintuitive views which are generated through a system-driven dimension reduction[28], there are also other problems. A directly consecution out of these difficulties, is that the discoveries which were made only on the basis of visual explorations are not accurate. Additionally, there appear further problems which were not touched upon so far. So, the user needs a specific discovery management mechanism to organize the extracted and valuable informations and to make them available for other users[24]. It is obvious, that static visualizations can not solve these problems. The common interactions supporting the navigations are zooming and panning, showing the name of the corresponding dimension, the extent scaling, comparing the different data items and above all the selection of several interesting visualized dimensions[25]. These interaction methods were applied to avoid the mentioned issues and they also afford a basis for more complex interaction approaches.

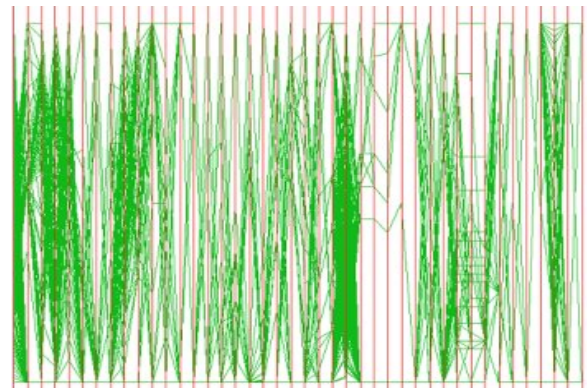


Fig. 13. clutter with increasing number of dimensions[27].

### 5.1 Brushing

Using the "Pop out" -phenomen[17],brushing is a easy but effective method to encounter the clutter problem and to support the visual exploration process. The user can chose the desired data items and the system highlights the relationship between the different dimensions. Therefore, he/she is able to select the values directly in the view, or enter them into special menus[7]. All presented hypervariate information visualization techniques profit from this technique, above all the linked histograms and the Nugget Management System works with this interaction method. Besides the normal brushing, different ways of brushing can be mentioned[7]:

- Smooth Brushing
- Composite Brushing
- Multiple Brushing

The Smooth Brushing allows the user to define a center-of-interest(COI) inside the used visualization. After selecting the desired point the system denotes the surrounding data. But in contrast to the normal brushing the smooth version highlights the relevant data according to the distance from the COI. The farther the distance of a data item the weaker is the used colour. With the Composite Brush, the user is able to combine different single brushes by using logical operators. The desired data only will get highlighted, if they comply the predefined conditions. At last, Multiple Brushing sets up a entry in a detached brush list, for every normal brush which is initiated by a user. To improve the clarity of the brushing list, every entry can be named. Exploring a visualized data set, the user is now able to browse through this list[7]. All these brushing methods can be combined, in order to increase the understandability of a given hypervariate visualization

### 5.2 User-driven dimension reduction

The unintuitive visual patterns caused by the pure system driven dimension reduction was attenuated, by introducing the combined methods. Although these techniques already use many interactive elements to support the visual exploration, the system still translated the dimensions into the particular view. Only experienced users are able to extract useful information out of a special data representation. The dimension reduction should be completely user driven, in order to increase the understandability of visual patterns. Additionally, novice users should become acquainted faster with the visualized views. Extensive techniques which base on metaphors apply this sort of reduction method. The developers try to project the functionality of a real-world object into the problem of visualizing hypervariate data sets. So, the dimension reduction approach and the visual pattern itself should be intuitive and understandable. Based on the appropriated metaphor, the user should be able to accomplish the dimension reduction with the given interaction methods[28]. For example, the object visible Dust& Magnet - Application (DM)[28] and "Worlds within Worlds"[5] applies user driven techniques. In DM data items are represented as "dust" in the middle of the display, whereas the user is able to arrange "magnets" around these values. The virtual magnets operate like the real ones and attract those data items which are closely related(see figure 14). Each magnet represents one dimension and can be itemized by the user. So, every step of dimension reduction is comprehensible and leads to an understandable visual pattern.

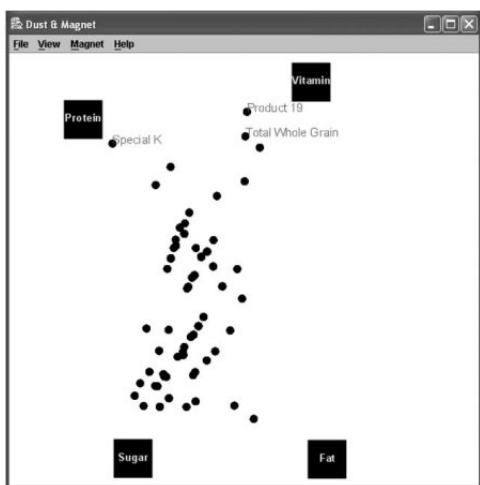


Fig. 14. Here, the dust represents cereals with different attribute values. The magnets represent different attributes.[28].

### 5.3 Sharing extracted informations with other users

Managing the extracted information is an important point, which has to be discussed. Such a discovery management mechanism has to offer a method, which makes it possible to organize these information and to compare them with other similar data. One possible mechanism

could allow the user to store discovered cluster and outlier in a special data-pool. There, the user can work with the stored information and order them according to the importance or commonness of each entry. This approach supports also other users to find valuable information. A good example for such a mechanism is the Nugget-pool, which is applied in the Nugget-Management-System[24]. Another possibility is storing the bindings between the visual patterns and the dimension names. So everyone who loads the stored bindings can explore the same displayed dataset. How the Glyphmaker-Application[14] shows it.

## 6 CONCLUSION AND OUTLOOK

Many application domains which work with high-dimensional data sets need intuitive and understandable visual representations of the hypervariate data. This search for possibilities to extract informations out of such a data set, leads to a multiplicity of hypervariate visualization techniques. Due to the specific problems of the traditional and extensive methods, there were developed different interaction methods supporting the user's visual exploration. But all techniques, which was presented so far, use a two dimensional display. So, one potential advancement could be found in 3D-visualizations. Possible disadvantages of the flat views, for example the overcoming clutter or the specific problems of attribute and object visible techniques, would be avoided. Additionally, a 3D view offers alternative interaction methods. Altogether, a 3D-Display supports the user's visual exploration by generating an understandable visual pattern. Such a technique is represented in a paper, written by Fanea et al[4]: "An Interactive 3D Integration of Parallel Coordinates and Star Glyphs". Fanea presents a new visualization technique by merging the attribute visible Parallel Coordinates and the object visible Star Glyphs into the so called Parallel Glyphs(see figure 15). Translated into a three dimensional view, this combination uses the advantages of both techniques and evades their disadvantages. Due to the gained dimension, the user has different new interaction methods. So, for example, he/she is able to rotate a Parallel Glyph, in order to detect covered relations in a highly cluttered display. Giving different examples for methods concerning the

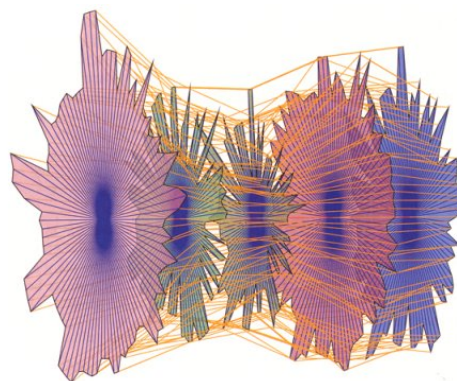


Fig. 15. Each Star Plot in the Parallelglyph replaces an axis of the Parallel Coordinate Plot. So, every dimension is visualized by a Star Plot, and the relations are represented by the Parallel Plot's polylines. [4].

HyperInfoVis, this work should support everybody who looks for hypervariate visualization techniques and to give hints, which technique is appropriate to extract valueable information out of a specific hypervariate data set.

## REFERENCES

- [1] L. BRUCKNER. Chernoff faces. In *Proceedings of the Symposium on Graphic Representation of Multivariate Data*, 1978.
- [2] J. Chambers, W. Cleveland, B. Kleiner, and P. Tukey. *Graphical Methods for Data Analysis*. Belmont, 1983.
- [3] H. Chernoff. The Use of Faces to Represent Points in n-Dimensional Space Graphically. 1971.

- [4] E. Fanea, S. Carpendale, and T. Isenberg. An Interactive 3D Integration of Parallel Coordinates and Star Glyphs. In *Information Visualization, 2005. INFO VIS 05. Proceedings of the 2005 IEEE Symposium on*, pages 20–20, 2005.
- [5] S. Feiner and C. Beshers. Worlds within worlds: metaphors for exploring n-dimensional virtual worlds. In *Proceedings of the 3rd annual ACM SIGGRAPH symposium on User interface software and technology*, pages 76–83. ACM New York, NY, USA, 1990.
- [6] L. C. Freeman. Social choice - network display. <http://www.cmu.edu/joss/content/articles/volume1/Freeman.html>, 2008. visited 20.11.2008.
- [7] H. Hauser, F. Ledermann, and H. Doleisch. Angular Brushing of Extended Parallel Coordinates. In *Proceedings of the IEEE Symposium on Information Visualization*, pages 127–130, 2002.
- [8] J. Heer. Position paper. <http://vw.indiana.edu/ivsi2004/jherr/index.html>, 2004. visited 25.11.2008.
- [9] D. Keim. Designing Pixel-Oriented Visualization Techniques: Theory and Applications. *IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS*, pages 59–78, 2000.
- [10] T. Kohonen. The self-organizing map. *Neurocomputing*, 21(1-3):1–6, 1998.
- [11] J. Kruskal and M. Wish. *Multidimensional Scaling*. Sage Publications, 1978.
- [12] J. Lamping and R. Rao. The Hyperbolic Browser: A Focus+ Context Technique for Visualizing Large Hierarchies. *Journal of Visual Languages and Computing*, 7(1):33–55, 1996.
- [13] M. Lee, R. Reilly, and M. Butavicius. An empirical evaluation of Chernoff faces, star glyphs, and spatial visualizations for binary data. In *Proceedings of the Asia-Pacific symposium on Information visualization-Volume 24*, pages 1–10. Australian Computer Society, Inc. Darlinghurst, Australia, Australia, 2003.
- [14] W. Ribarsky, E. Ayers, and S. Mukherjea. Using Glyphmaker to Create Customized Visualizations of Complex Data.
- [15] B. Shneiderman. Tree visualization with tree-maps: 2-d space-filling approach. *ACM Transactions on Graphics (TOG)*, 11(1):92–99, 1992.
- [16] B. Shneiderman. The eyes have it: a task by data type taxonomy for information visualizations. In *Visual Languages, 1996. Proceedings., IEEE Symposium on*, pages 336–343, 1996.
- [17] R. Spence. *Information Visualization: Design for Interaction*. Prentice-Hall, Inc. Upper Saddle River, NJ, USA, 2007.
- [18] A. Spoerri. InfoCrystal: A visual tool for information retrieval. In *Visualization, 1993. Visualization '93, Proceedings., IEEE Conference on*, pages 150–157, 1993.
- [19] M. Theus and S. Lauer. Visualizing Loglinear Models. *JOURNAL OF COMPUTATIONAL AND GRAPHICAL STATISTICS*, 8:396–412, 1999.
- [20] unknown. Summarizing bivariate categorical data. <http://web.utk.edu/~leon/stat571/jmp/Categorical2way/default.html>, 2008. visited 27.11.2008.
- [21] G. Waloszek. Summarizing bivariate categorical data. [http://www.sapdesignguild.org/community/design/print\\_attributes\\_2.asp](http://www.sapdesignguild.org/community/design/print_attributes_2.asp), 2008. visited 4.12.2008.
- [22] M. Ward. XmdvTool: integrating multiple methods for visualizing multivariate data. In *Proceedings of the conference on Visualization '94*, pages 326–333. IEEE Computer Society Press Los Alamitos, CA, USA, 1994.
- [23] E. Wegman. Hyperdimensional data analysis using parallel coordinates. *Journal of the American Statistical Association*, 85(411):664–675, 1990.
- [24] D. Yang, E. Rundensteiner, and M. Ward. Analysis guided visual exploration of multivariate data. In *Proceedings of the IEEE Symposium on Visual Analytics Science and Technology*, pages 83–90.
- [25] J. Yang, A. Patro, S. Huang, N. Mehta, M. Ward, and E. Rundensteiner. Value and Relation Display for Interactive Exploration of High Dimensional Datasets. In *Information Visualization, 2004. INFOVIS 2004. IEEE Symposium on*, pages 73–80.
- [26] J. Yang, M. Ward, and E. Rundensteiner. Interactive hierarchical displays: a general framework for visualization and exploration of large multivariate data sets. *Computers & Graphics*, 27(2):265–283, 2003.
- [27] J. Yang, M. Ward, E. Rundensteiner, and S. Huang. Visual hierarchical dimension reduction for exploration of high dimensional datasets. In *Proceedings of the symposium on Data visualisation 2003*, pages 19–28. Eurographics Association Aire-la-Ville, Switzerland, Switzerland, 2003.
- [28] J. Yi, R. Melton, J. Stasko, and J. Jacko. Dust & Magnet: multivariate information visualization using a magnet metaphor. *Information Visualization*, 4(4):239–256, 2005.