ABSTRACT

We present a contemporary classification of visual knowledge representations into clusters within a two-dimensional space, as well as a visual hierarchy depicting pairwise similarity between representations. The work in this paper follows the process carried out by Lohse et al. in their paper entitled ‘Classifying Visual Knowledge Representations’ [4]. The images for the study were collected from the InfoVis conference proceedings. The results show a progressive blending of visualization types that was not so prevalent in the Lohse paper. This is indicative of the progression from distinct visualization categories to composite designs within the visualization community.

Keywords: Taxonomies, Design Studies, Visual Design

Index Terms: H.5.2 [Information Interfaces and Presentation]: Taxonomies, Design Studies, Visual Design

1 INTRODUCTION

Visual knowledge representations attempt to display data in intuitive ways that offer insight and clarity. They are used to communicate complex ideas between individuals, businesses, scientific institutions and governments, and have been doing so for many thousands of years [2].

Common examples of visual knowledge representations include, but are not limited to, bar charts, line graphs, maps, dendrograms, scatter plots, tables and networks. Visualization scientists are constantly developing new representations that add to the already vast collection of visualization types.

Classification allows researchers to label, organise, distinguish between and define objects, and helps guide the direction of further research [3]. The research presented is based upon that conducted by Lohse et al. into the classification of visual knowledge representations [4], and seeks to identify how the visualization landscape has changed over the past 23 years. In the original paper 12 subjects were asked to hierarchically sort visual knowledge representations. The data collected from these sortings was used to develop both a hierarchy and a two-dimensional representation of visualizations. A complete description of their methods can be found in Lohse et al. [4].

2 METHODOLOGY

To attain a true picture of the changes in the visualization landscape since Lohse et al. [4], several factors had to be taken into consideration. Firstly the images used in the study must be a good representation of modern visualization techniques. It was decided that the images would come from publications for the InfoVis conference at VisWeek 2012. This offered two benefits, the images would include cutting edge representations ensuring our comparison between the two time periods was representative, and that the images were crafted by visualization practitioners ensuring high quality. In total 42 images were selected, one from each paper from InfoVis.

Care was taken to select a diverse range of representations that not only included the visualizations being presented in the papers but also statistical and illustrative diagrams.

Secondly, the subjects taking part in the study must also be a representative sample of the general population. The subjects in the study were aged between 22 and 36, had education ranging from college level to doctorates in a variety of fields including Computer Science, Marine Biology, Engineering and History. The subjects were from various locations within the UK. The final consideration was that the techniques used for data collection and analysis must reflect the process previously followed [4].

2.1 The Task

The study was conducted via a custom web interface written in Php and HTML with a MySQL database to store the results. The task was divided into two distinct sections. Before each section the subjects were presented with instructions of the task. The subjects were not offered examples, such to avoid bias in the results. In the first section the subjects were presented with images one at a time in a pseudo-random order. For each image the subject was required to provide a name for the type of visual knowledge representation shown. Where the subjects did not recognise a representation they were asked to think of an appropriate name. The subjects’ previous inputs were displayed as radio buttons allowing them to easily enter a type that they had seen before. This offered a similar experience to the paper-based sorting used by Lohse et al. [4]. This process enables the subjects to create any number of groups with any number of visualizations per group.

In the second section the subjects were presented with a complete list of the types that they had defined in the first section. For each type a pseudo-random selection of up to three example images was displayed. This was done to assist the visual memories of the subjects and aid comparisons. Subjects were asked to select types that could be combined into larger parent types and provide them with a title, or if a type could not be combined with another, declare it as ‘unique’. This section was further split into stages with each stage representing a level within a hierarchy structure. For example, in the first stage the subject could only see the initial groupings that they had made. In the second stage the subject could see any groupings that they had made in the first along with any types that had been declared unique in the previous stage. This continued until either only two groups remained or the subject declared that there were no further combinations.

3 RESULTS

Since pairs of visual knowledge representations could be considered as either the same type or not, each subjects’ first section results were placed in a matrix where a ‘1’ denotes that two representations were from the same group and a ‘0’ denotes that they were not. In total there were 861 possible pairs \( n(n-1)/2 \) [4]. The results were checked for homogeneity by comparing the subjects matrices. The summation of instances where two subjects had placed a pair of images into the same group was taken. From this the hypergeometric distribution was calculated. The hypergeometric distribution:

\[
P(X = k) = \frac{\binom{K}{k} \binom{N-K}{n-k}}{\binom{N}{n}}
\]

describes the probability that one subject placed a pair of representations into the same group.
as another subject by chance. Where \( N \) is the number of possible pairs, \( K \) is the number of pairs made by the first subject, \( n \) is the number of unique pairs made between both subjects and \( k \) is the number of times two subjects placed the same pair of images into the same group.

The hypergeometric distributions show a much greater impact of chance on this data than in [4], with the highest probability being 0.2047 and only 53% of the probabilities being less than .00001. This shows that the agreement between subjects was less substantial than the work of Lohse et al. in the 1990s [4].

4 Analysis

The individual subjects’ matrices were summed together to produce a similarity matrix. Each value in the resulting matrix represents the number of subjects who placed the pair of knowledge representations into the same group. As per Lohse et al. [4] hierarchical cluster analysis and non-metric multidimensional scaling were applied to the resultant matrix.

Hierarchical cluster analysis [1] builds a tree structure that describes the similarity between objects. The objects form the leaves of the tree, nodes in the tree represent clusters of objects where the root node is the most general cluster, the cluster that all objects fall within. The tree is built by repeatedly pairing the most similar objects into clusters. After each pairing the cluster that results is considered an object that can then be further paired. A number of different algorithms are available for the clustering, single and complete-linkage were used as per [4].

The cophenetic correlation coefficient between the original similarity data and the clusterings was .7877 and .8595 for the single and complete linkage solutions respectively. The correlation between the clusterings was .8065.

A dendrogram of the complete linkage clustering is shown in Figure 1. Each of the leaf nodes was assigned a name, where possible this name was based on the original image caption. Five main clusters were labelled on the diagram using the responses of the subjects to the second section of the study.

Non-metric multidimensional scaling [5] was applied to the data to produce a two-dimensional plot showing the similarity relationship between the knowledge representations. The plot demonstrates the merging of visualization types and the relative lack of consensus between subjects when compared to Lohse et al. [4].

5 Conclusions

We have presented a hierarchical clustering of visualizations that offers a point of reference for historical comparison. By closely following an established procedure [4], direct comparisons can be made. In fact, we found similar clusters [4] (graphs, diagrams, maps and tables, see Figure 1). However our analysis also shows a reduction in agreement between subjects; this suggests that there is greater uncertainty as to the specific type of a visualization. We propose that this lack of agreement may be due to composite designs becoming more prevalent and the topic itself broadening.

This work provides practitioners insight into the landscape of visual communication design; it encourages educators and teachers to re-think how they use the known classifications; and because of the increased breadth of designs we believe there are many opportunities for further novel designs, ideation and new visualization types. A further study is planned involving a much broader gamut of both, subjects and visual representations.

References