ANIMATED PROPORTIONAL VENN DIAGRAMS: A STUDY INTO THEIR DESCRIPTION, CONSTRUCTION AND BUSINESS APPLICATION

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CERTIFICATION

I certify that except where due acknowledgement has been made, the work is that of the author alone. I certify that the work has not been submitted previously, in whole or in part, to qualify for any other academic award and I certify that the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; and, any editorial work, paid carried out by a third party is acknowledged.

Phillip Anthony Hingston

Date:

ACKNOWLEDGMENTS

I would like to acknowledge the consistent support of my supervisors, Professor Tim Fry and Dr John Byrne. They have been able to steer the thesis through an overwhelmingly large interdisciplinary field and keep the work focussed. Special acknowledgment is made of the effort that Professor Rob Brooks and Professor Ross Day made to encourage the development of my initial ideas. The extra exertion made by Dr Jenny Diggle to help me through the early stages of thesis development was particularly valued. At a time when I was confronted by many competing time pressures, both at work and at home I am indebted to Professor Sinclair Davidson for particularly useful advice on how to move forward.

I would also like to take this opportunity to reflect on the role that the University has played in providing a terrain, both physical and virtual, that has facilitated my journey of discovery. This reflection may seem obvious and even trivial, however in an economy that is characterised by rapid change and global consequence, the support given by scholars who enthusiastically give of their time to encourage those of us who undertake the realisation of fledgling ideas is nothing short of marvellous. In the era of increasing workloads and competing time pressures, the freely offered goodwill and advice, not just here but also from abroad, must now rank as unique in the world of business. Such selflessness has been an inspiration and I will strive to uphold the collegiate spirit that characterises scholarly research. By so doing I hope to contribute to the preservation of the institution in its current form, as it takes little imagination to envision an alternative research environment dominated solely by proprietary considerations.

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ABSTRACT

Anecdotal observation of the way in which data visualisation techniques are utilised to present relationships in data to audiences informed the author's view that data visualisation had not evolved to utilise the capabilities of ubiquitous business computer equipment. In an information rich but attention poor business environment, a search for a new tool was undertaken to supplement those techniques available to help audiences understand statistical relationships in presentation data.

This search resulted in the development of a practical software tool based on animated Venn diagrams (Dvenn) that attempted to exploit the inherent human ability to perceive quantities visually, a faculty described herein as visual numeracy. The exploitation of this faculty is considered here to be a valuable aid for group understanding of business presentation data. The development of the tool was an essential part of the research that was undertaken and the resulting software forms a significant portion of this practise based research. The aim of the software development was to develop a readily accessible tool that could be utilised in a non-specialist business environment to better facilitate an honest shared meaning of numerical data between a presenter and their audience.

The development of the tool progressed through a number of iterations and the software that accompanies this work is an important component that needs to be viewed in conjunction with the text. The test of the final version was undertaken with undergraduate University students in an attempt to validate the efficacy of the data visualisation technique. The test of the Dvenn software was made against the mature yardstick of scatter-plots. Interestingly, the correlations presented by scatter-plot were not as readily identified as would have been assumed, however, the results for the Dvenn tests were not supportive of the technique for widespread adoption. Nevertheless, further research into the best method of harnessing visual numeracy would seem to be justified.

Chapter 1

INTRODUCTION

1.1 Study Overview

Broad educational theory as described by Markova and Powell (1992) suggests that learning is acquired through the visual, auditory and kinaesthetic (VAK) sensory channels. In brief, this theory takes the view that learning transpires through a combination of visual (V), auditory (A) or kinaesthetic (K) stimuli and that, for most, learning comes about through a preference for one of these channels. An example often cited is the experience of learning multiplication tables. A visual learner is likely to utilise a book and writing approach, whereas an auditory learner is likely to say or sing the tables aloud and a kinaesthetic learner is likely to tap or mime a corresponding rhythm to the multiplication sequence. What this thesis will argue is that the principal of these learning channels is the visual pathway and, in particular, this work will focus on the primacy of the visual pathway for learning and, in turn, emphasise the way that visual aspects of learning theory apply to the presentation of business data to an audience as an aid to comprehension of a collective shared understanding.

This thesis will argue that visual learning is the dominant form of learning, and, that the presentation of information to an audience is greatly facilitated by crafting a presentation to maximise the visual learning pathway. Further, where voluminous business data are available for presentation to an audience, visualisation of those data is the most effective means of promoting a shared understanding of key points with that audience. Suitable, targeted and coherent data visualisations are an extremely powerful means of conveying business information to a generalist audience. Based on a summary of the topic by Card, Mackinlay, and Shneiderman (1999), data visualisation may be defined as the use of visual representations of data to amplify cognition. Further, the technology available in the business environment is now sufficiently powerful and ubiquitous to enable new automated methods of projection such as data animation to be more narrowly investigated. In a practical sense, data animation is simply defined as projecting suitable static graphical elements at such a speed as to render the appearance of movement to an audience. Such a technique renders large amounts of data visible to viewers in a manner that would be onerous in the case of projecting those same data as small multiples in individual frames. Both Tufte (1983) and Nielsen (2000) provide suitable design criteria for computer projected presentations and they postulate design rules for the visual display of data at a time when personal computer hardware continues to reduce in price and increase in functionality. Such cheap capacity should be expected to be a boon to any business and an expectation, by now, would be for widespread adoption of dynamic, visualisation techniques. However, not only are automated data visualisation techniques not generally apparent in presentations, even conventional graphical presentations show little progress from those types that were being utilised decades ago. In fact, it may be argued that personal computer use has lowered the standard of presentation graphics because they promote ill-considered utilisation of tools that are selected primarily for ease of use rather than purpose.

The tools that are now utilised by generalist presenters certainly promote colour and movement, but does the audience gain business insight and meaning from flashing smiley faces, exploding talk balloons and a visually carnival atmosphere? Even without the superfluity of visual effects, graphical presentations do not appear to have evolved in commensurate steps with available computer power. Critical analysis of data visualisations by Tufte (1990, 1997) indicates that graphical representations of data, particularly in the field of business, suffer from ambiguity, distortion and inconsistency. His timely work should have served to focus the attention of creators of software for spreadsheets and databases on quality outcomes. From anecdotal experience garnered from years of bearing witness to academic presentations in the field of business, the author concludes that the ubiquitous pie chart is adorning more business presentations than ever before!

Admonishing the “complication of the simple” that has burgeoned forth on the wave of the information revolution, Tufte (1983, p191) states that the task of the designer is the “revelation of the complex”. Above all, the key to presentation graphics is the unambiguous display of meaning to a target audience. The term applied to such meaning by Chi (2000) is ‘visual sense-making’. Consider further the business environment in which this ‘sense-making’ occurs, where a wealth of information creates a poverty of attention (Simon, 1979). Due to advances in business information technology, the creation of a presentation no longer demands a premium in terms of the presenter’s time, rather it is now the time taken by an audience to digest and assimilate information from that presentation that represents a vast collective poverty of attention. We can be trained individually to craft a presentation but, as an audience, we are not trained collectively to receive information. It is largely consumed as it comes. The disparity in quality outcomes is due to an anxiety about the increasing volumes of information that we are required to assimilate. No wonder the pie chart is popular because of its one-dimensional nature. Shneiderman cites Wurman (1989) to succinctly illustrate the exciting promise of technology tempered with trepidation:

> *“Information exploration should be a joyous experience, but many commentators talk of information overload and anxiety”*
>
> *(Shneiderman, 1996 p2)*

It may not always be the case that information exploration and presentation need be joyous, however it should not be a burden for an audience to assimilate a message. Indeed, pattern recognition is a fundamental human cognitive faculty and little training is required to interpret pie charts as they do not mandate ordinality. The viewer is able to look at a pie chart, assess relative segments regardless of their order, and form an opinion about the performance of competing segments. Therefore scale or annotation is not necessary in order for segments in a pie to be rendered meaningful to the average viewer. Is it the case that pie charts are a success because presenters choose a format to project data that is simple to use, or do presenters utilise pie charts because audiences prefer them? In order to answer these questions, a serious consideration of our perceptual apparatus is required.

Drawing on the general field of cognition that is defined by Day (2004) as ‘knowing’ through ‘perception’, which will be explored in more detail in Chapter 2, the concept of visual learning is straightforward enough. However, in order to understand the power of visual presentation, consider an alternative path to understanding.

Hearing is one faculty that is acutely tuned in humans to enable meaningful sounds to be distinguished from random sounds. These patterns are analysed with minimal conscious effort on the part of the listener and, in preference for a simpler definition than that offered by Perceptual Theory and Gestalt Psychology, the views of a musician (Marsalis, 1995) are suggested. He characterises music as sound organised in time. To comprehend an audible stimulation so set in time requires no special learning. Our tastes in music develop through exposure to various manifestations of sound and pattern arrangements, but the fundamental ability to recognise music, as opposed to noise, requires no revealed secrets, no special reasoning. We are simply equipped to do so. Further, to comprehend and disseminate music non-acoustically, a notation has been developed and refined over centuries to *visualise* music and aid its communication and accurate replication. Such a notation consists of a staff and dots designating pitch and duration of tones. Musical notation is widely accepted throughout the world as it accommodates all manner of tone creation. As a remnant of a previous age, it has nevertheless become a de-facto standard, the basics of which have evolved very little since the Middle Ages. Music notation survives because it is so effective. Those little dots and lines accomplish the astonishing feat of rendering the invisible tangible.

The revelation of the message encoded in a sheet of music is as powerful today as when it was first written. What can be demonstrated is that an aural tradition can be supplanted by a visually oriented tradition. The actual appreciation of music does not require a listener to understand music notation, but music can now be comprehended visually. It might be argued, therefore, that music can be appreciated intrinsically as well as being able to be understood symbolically. The key feature of Marsalis’ definition is that what differentiates ‘music’ from ‘noise’ is that it is organised and that such organisation is definitive of pattern recognition. In the field of mathematics, such pattern recognition is the foundation of simple set theory. From set theory a whole mathematical edifice has arisen, but the root of this edifice consists of the simple faculty we all share, and that is the ability to differentiate and categorise. Such ability is no less than our ability to count.

Research is now reporting that sound, too, is a powerful cognitive stimulus for categorising quantitative data, so much so that exploratory data analysis is being undertaken in the auditory domain (Hermann & Ritter, 2000). What is even more exciting for the potential exploitation of intrinsic pattern recognition for business presentations is the discovery that confirms that counting is both primitive, in that it is shared with animals such as pigeons and rats, and also that counting in the auditory and visual domain occurs in parallel (Dehaene, 1997). Such a discovery would infer that there is no single counting faculty, but at least two pathways upon which patterns can be isolated and recognised. It might be suggested that we are pre-wired to count. We can't help but count. Acknowledging a primitive ability opens up the possibility of exploiting an easier way to understand a quantitative message. As Dehaene writes:

> *An organ specialized in the perception and representation of numerical quantities lies anchored in our brains. Its characteristics unequivocally connect it to the protonumerical abilities found in animals and in infants. It can accurately code only sets whose numerosity does not exceed 3, and it tends to confuse numbers as they get larger and closer. It also tends to associate the range of numerical quantities with a spatial map, thus legitimizing the metaphor of a mental number line oriented in space.*
>
> *Obviously compared to babies and animals, human adults have the advantage of being able to convey numbers using words and digits. … language eases the computation and communication of precise numerical quantities. However, the availability of precise number notations does not obliterate the continuous and approximate representation of quantities with which we are endowed. Much to the contrary, experiments show that the adult human brain, whenever it is presented with a numeral, rushes to convert it in into an internal analogical magnitude that preserves the proximity relations between quantities. This conversion is automatic and unconscious. It allows us to retrieve immediately the meaning of a symbol such as 8, a quantity between 7 and 9, closer to 10 than to 2, and so on.*
>
> *A quantitative representation, inherited from our evolutionary past, underlies our intuitive understanding of numbers. If we*

> *did not already possess some internal, non-verbal representation of the quantity "eight," we would probably be unable to attribute a meaning to the digit 8. We would then be reduced to purely formal manipulations of digital symbols, in exactly the same way that a computer follows an algorithm without ever understanding its meaning.*
>
> *Dehaene (1997 p.87)*

Dehaene classifies this innate counting preference as “numerosity”, however Dehaene’s definition does not reveal the innate nature of this preference and the author suggests that a case may be made in Australia for the adoption of the term ‘visual numeracy’ to define the particular faculty that humans have for quantitative visual pattern recognition. Such a suggestion is explored in more detail in Chapter 2. It may seem odd to suggest that simple counting is unconscious and can occur without individual words to represent values. However, only an ability to distinguish *more* from *less* is really required. In terms of a number line, symbols of quantity are dispersed along the imaginary line in order of magnitude. Any two numbers can be differentiated in space, and their relationship to each other is simply determined by their distance from the line’s starting point. It is perfectly feasible to contemplate a numerical system based solely on the primary rainbow colours (the visual spectrum of 400 – 700 nanometres). In such a case, say that red represents the start of the colour line and purple the other end, and the order of the intermediate colours is understood to be consistently arranged as in a rainbow. Adding colours together is quite feasible. The colour resulting from operations of addition and subtraction can be compared to the colour line to establish ordinality. Red is less than green is less than blue etc. Not a precise calculator, but nevertheless a calculator! As will be shown in Chapter 2, there are many uses made of colour coding in data visualisation, but no international standards exist for ascribing a particular quantitative value to colours[1]. Certainly in the representation of hot and cold, red and blue are commonly used respectively to indicate magnitude, but there is no universal agreement for the colour representation of quantity with respect to velocity, mass, depth, pressure or sales etc. There is no substantive agreement that a red value is always more and blue value less, as even

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[1] The commercial standard for RGB monitors does allow for incremental changes for hue from 0-255, however, these hues are not an international standard and a wide variation between computer monitors does exist in the expression of colour for the same binary value.

meteorological charts and maritime charts are ambiguous on this point. Further, Abramov (1994) indicates that what we see as colours in the spectral band is not equally weighted for attention. Even the names given to colours underpin their relative importance. Of the one-hundred and ten world languages studied for colour names, only sixteen had a word for purple (Hardin and Maffi, 1997) for further discussion on the relevance of colour, see Appendix I.

So how does one exploit the primacy of visual sense and our predisposition to count to make better presentations of business data? Is there a simple perceptual characteristic waiting to be uncovered through an investigation into how best to make business presentations more useful? Certainly there seems to be a demand for any lightening of our information load. The wealth of information of our age need not necessarily create the poverty of attention that Simon (1979) suggests is the case. The appeal of leveraging visual numeracy in presentations of business data is that it may decrease the cognitive workload of an audience. The inference here is that primitive abilities require little or no training to be fully functional. As music appeals to us without effort, any primitive faculty that is a parallel conduit that can assist in facilitating understanding of meaningful patterns should be rigorously explored. An example of pattern recognition through music has been outlined, but concentrating now on numerical representation by visualisation rather than numerical representation by sonification, the question remains; does there exist a visual method of rendering statistical significance to an audience without the impost of a high cognitive load? Can presentation techniques be developed that function for an audience of business data in the same way that an audience can hear a new piece of music without the requirement for training in the appreciation of music? What forms would 'visually numerate' presentations take? Is an appeal to 'visually numerate' business presentations an attempt to appeal to the lowest common denominator in an audience and 'dumb down' a presentation?

This thesis will attempt to shed some insight into the problems of data presentation, as briefly outlined above, but first a delineation of the major problem that is being faced by business audiences must be made. This problem is the increased volume of data that is captured by businesses on a daily basis. The data volumes are such that, even with simple data sources like cash register outputs, they are becoming difficult to comprehend easily or utilise without recourse to highly trained analysts. To bestow the increased volume of data to an audience to leverage the realisation of collective goals requires new forms of data presentation. Therefore, exploration of potential new explanatory tools, that may serve the lay user of quantitative data, seems to be warranted.

> *Designers are just discovering how to use the rapid and high resolution colour displays to present large amounts of information in orderly and user-controlled ways. Perceptual psychologists, statisticians, and graphic designers…offer valuable guidance about presenting static information, but the opportunity for dynamic displays takes user interface designers well beyond current wisdom*
>
> *(Shneiderman, 1996, p.4)*

Shneiderman's observation, that the technology available in 1996 was then creating opportunities for dynamic displays of data, appears to have stimulated little change in the way business presentations are conducted. Shneiderman's 'dynamic displays' may be considered to include 'data animation'. Data must be made to move in relationship to its increasing or decreasing quantitative value in order to aid contrast and inference. So, is it simply a matter that the 'user interface' designers have not found new *wisdom* as Shneiderman suggests, or is it the case that visual complexity is as difficult to manage for the average viewer as data complexity? Why is it apparent that advances in computing technology have not led to a commensurate advance in the quality of presentation data to non-technical audiences?

Unquestionably, there are better resources available to an audience through the utilisation of what was once termed 'office automation' but is now represented by those enabling technologies that extend beyond the office into all facets of life. For instance, the Internet is an enabling tool of enormous potential to an individual for the acquisition of information and the capacity to analyse such information. It is possible to increase one's knowledge of a topic through iterative, practical examples. By way of illustration, take two self-help sites selected from the Internet, the first is the visual demonstrations developed by Bogacki (1996) for an introductory numerical methods course that includes some limited animation. Originally developed as computer based training in 1991 and now freely available to anyone with a web connection, this course would be expected to empower those who seek better numerical understanding. The second example is a site devoted to the teaching of statistical concepts to any person who might be interested (Stirling, 2000). This site is a comprehensive introduction to statistical concepts with many examples of business and economic relevance. The software is named CAST for Computer-Assisted Statistics Teaching and represents the true potential of the web to deliver content of a very high standard for the enlightenment of anybody regardless of their economic or educational circumstances. So not only does the Internet provide data, it also provides the tools to increase understanding of those data.

However, how far can self-education go? Regardless of in-house standards and conventions for presentations, themselves subject to fashion rather than solid principles of design, staff turnover alone ensures that the problem of disparate methods of presenting business information is perpetual. Nevertheless, with web based self help resources such as the examples mentioned, the expectation would be that, over time, the sophistication of the business audience would increase as a reflection of the capacity of that audience to understand the form and content of quantitatively based presentations. This is truly learning by doing. If the underlying concepts are the same, then any course that truthfully presents the underlying principles of the topic will suffice as long as it can hold the learner's attention. Therefore, rather than the presenter being the problem behind the poor quality of business data visualisations, it is the audience that drives the effectiveness of a presentation. Rather like a convoy of ships being defined by its slowest member, the audience itself is the limiting factor for the development of better business presentation tools.

There is a major problem with focussing on the audience for a solution to more effective presentations given the current poor standing of business data visualisations. Better education at all levels is desirable for a flexible and intelligent workforce, but are we all destined, through the availability of education and technology alone, to become more articulate with statistics? Certainly the presenter should become so, but do we, as an audience, *want* to be so? Knowing what to learn is part of the anxiety of the modern workplace. There is a focus on life-long learning that appears to be laudable, but is this focus one more pressure to acquire and use information that ultimately is increasing our poverty of attention? Is it likely that members of an audience who feel statistically challenged are going to spontaneously acknowledge their deficiency and attempt to institute a self paced remedy?

There is an alternative strategy for making business presentation data more meaningful for the audience. That strategy is to make the presentation of business information more engaging by making it simpler, by appealing to the level of understanding with which we are already equipped. So the two solutions are possible, one, to better educate an audience to understand presentations of business data or, alternatively, make business presentations easier to understand using the experience and education present in a typical business audience today. The main thrust of this thesis is, therefore, to facilitate better utilisation of what we have as a result of our common experience and educational endowment. Hence, the challenge remains to discover a tool that has the ease of use of a pie chart, but the power to visualise multidimensional data.

Chapter 2 presents one possible taxonomy of data visualisation and discusses the characteristics of several forms of visualisation that have relevance for business. The pie chart is examined for clues regarding its success, in the face of strident academic criticism, as a de facto presentation standard for business audiences. Examination of the characteristics of the pie chart suggest that modification of the simple Venn diagram could be selected as the most promising visualisation method for exploiting visual numeracy in an audience. Data animation is incorporated into the examination of possible improvements to increase the capability of the tool to visualise multidimensional data.

1.2 Research Objective

The principal objective of this research is to investigate and narrow the possible options for the delivery of animated data presentations that conform to the requirement of good visualisation design. Such presentations must be useful as an aid to enable a presenter to bring an audience to a shared understanding. That is, the audience must be *influenced* to hold an opinion based upon the presentation of animated data. Such presentations must be available to a broad audience and must be widely applicable to non-scientific problems. Above all they must make sense to an audience. A yardstick for usability would be that any presentation delivered in this manner should require no more effort on the part of an audience to garner sense of, than that required of an audience to listen to a new piece of music. Whilst fine details may be overlooked, the big picture should be apparent, just as identification of fast and slow movements and change of key would be expected to stand out from a new musical piece. Above all, the audience must be influenced by an overall perception of what was presented. The conclusion of the presentation should result in a shared understanding, based on intuitive good judgement, as a result of perceiving visual consistency from what has been presented. Any confusion for the audience should result from the effort of the presenter, bad presentations will always be bad, but the presentation tools themselves should reflect robust perceptual characteristics that are tuned to the capability of the audience to understand collectively significant patterns in quantitative data.

1.3 Research Question

To concisely define the driving motivation behind this thesis the following question has been posed:

> *Is the presentation of data to an audience via an animated proportional Venn diagram a useful tool for promoting shared recognition of relationships in high volume quantitative data?*

To expand upon the terms used, and by way of explanation, ‘presentation’ encompasses the usual screen projection of information to an audience by means of a computer. Animated proportional Venn diagrams constitute the actual novel contribution of this thesis, of which more detail follows in the body of the work. ‘Shared understanding’ is a nebulous phrase that attempts to represent the purpose of a presentation. One might assume that the audience does recognise something of meaning to themselves individually, however, at what stage of the presentation this occurs or whether such recognition is similar to their neighbours’ is speculative. The difference between ‘shared understanding’ and ‘shared recognition’ is the context of the presentation. An audience is likely to agree that they all recognised a circle on the screen. If the aim of the presentation was simply to demonstrate a circle, then shared recognition and shared understanding are the same. However, is it possible to measure a shared understanding of the quantitative representation of that circle? If a value is ascribed to the size of the circle, how does one know that the audience collectively understands the quantitative component? The author does not naively suggest that this thesis expounds a generic method of measuring ‘understanding’, but what it does attempt to do, in a very basic way, is establish to what degree the audience agrees on the values represented by the quantitative component of the presentation.

1.4 Methodology

Based on an examination of current data visualisation techniques for business presentations with a view to identifying gaps in recent lines of investigation of the topic, and, drawing on practise based research for the design and construction of a software package, a practical tool is constructed, which the author has named a Dvenn. The Dvenn utilises animated proportional Venn Diagrams to simplify the projection of relationships in data to a business audience. To establish the efficacy of such a tool, a series of empirical tests were devised and administered to undergraduate University students.

The benchmark for comparison of the performance of the Dvenn tool is a statistical analysis of the rates of successful identification of reported correlations in a test dataset. A control group is used to identify correlations in scatter-plots of those same data. Scatter-plots are suggested as an ideal evaluation standard because they are a mature form of data presentation. The single hypothesis tested is that the Dvenn is no worse than scatter-plots for visually conveying correlations of data to a business audience.

The software itself is offered as an important component of the research and the code is printed in full in Appendix XI. In the case of this practise based research paradigm, the tangible manifestation of the software is tended by the author as only one of many possible forms of the concept that could be realised by undertaking similar research. It must be viewed as illustrative in nature rather than definitive and represents the start of a journey of discovery rather than its conclusion.

1.5 Scope of the Study

The field of this research is broad and encompasses learning theory, perceptual psychology, economics, statistics and computer science. Above all, the emphasis of this research is of a practical nature. Not only is a theory of use discussed, but also a tangible, working example of the concept is created. If, through use of visualisation software, an audience improves their shared understanding of what the presenter is trying to persuade them of, then the software may be said to be useful. It is not the intention of the author to warrant that the functionality displayed in this embodiment of the Dvenn software tool is the only application possible. What is covered in this thesis is an attempt to justify, demonstrate and evaluate the efficacy and potential of animated Venn diagrams through a sole, but no means exclusive, realisation of the concept.

For the purpose of *presentation*, where the audience is likely to be a collection of generalists rather than trained specialists, the explanatory opportunity that graphs offer must be paramount. The scope of the research presented in this thesis excludes specialist data presentation that is the domain of particular fields of scientific endeavour such as medical imaging, weather prediction and visualisation evident in a host of sophisticated specialist software tools. No claim is made by this researcher to have found a panacea for business data presentations.

Some discussion in this thesis will briefly cover issues surrounding what might constitute pre-wired versus learned ability (the nature /nurture debate), but only to the degree that consideration of such issues informs the design and creation of the Dvenn software tool. No attempt is made to endorse a particular theory; rather, the multidisciplinary nature of the research demands a catholic approach to the assessment of competing theories and simply acknowledges the size and complexity of these issues. In the case of the ethics of persuasion, that is, the potential use of the Dvenn software tool for deliberate misrepresentation of information to an audience, no comment will be made, as all current tools suffer from the same potential abuse. In the case of the actual definition of data, information and knowledge, and how these terms are used, the author expends no effort in claiming particular meaning for them due to the lack of a consistent definition that spans several disciplines. These terms are simply defined in the context in which they are used.

The aim of this thesis is to plainly present research into the development of a tool that might boost “attention” without degrading “information”. After all, information is the life-blood of business and, taking the lead from Stigler's (1961) seminal work on the economics of information, this research draws heavily on psychological research in an attempt to amend some long standing assumptions business presenters typically make about the way people utilise information. Data presentation should not focus on audience entertainment or the promotion of the talent of the presenter, rather it should assist the audience to share a group perspective that lasts long beyond the actual presentation. The Dvenn tool is software that is meant to empower an audience rather than the presenter.

1.6 Particular Attribution of Ideas

The study of any perceptual faculty must include mention of the vast body of knowledge accumulated on the topic. Perceptual theory has many branches and Gestalt Psychology would seem to provide a relevant structure to support how an audience might collectively perceive a presentation in total (Zalta, 2002), (see Appendix II). Special focus is given to the problems of perception and how those problems hint at neurological limitations to the capacity to refine and improve the way that information is acquired.

Perceptual illusions in particular are discussed as a way of exploring neurological limitations that apply to an individual and therefore to an audience, it being no more than a collection of individuals. Gestalt ideas of how perception of objects is categorised by the laws of Simplicity, Similarity, Proximity and Closure, appear to underpin and justify research into a new data presentation tool (Kearsley, 1998). Full acknowledgment of the veracity of such an approach is here made, however, this is not the approach that the author adopts. Instead a Structuralist[1] stance is embraced that relies heavily on Triesman's (1986) identification of 'pre-attentive processing' as an essential bridge to how an individual is informed by their

[1] Acknowledging Ferdinand de Saussure but concentrating on the way the individual rather than society creates "meaning" from inter-relationships, in this case making 'sense' of simple visual structures for the communication of a shared meaning. Structuralism tries to comprehend life based on semiotic theory. Abstract signifiers play a crucial role for developing an understanding of ourselves. Indeed, are there universal abstract signifiers as suggested by Structuralist theory? If so, are these a potentially powerful shortcut for sharing mundane business related information?

visual acquisition of *meaningful* patterns[2]. Some meaning is instant, as when an icon is identified, drawing on simple unconscious pattern matching abilities that are neurologically constrained, in that we cannot learn to identify them any faster. In the case of a visual field that contains many competing targets for identification a different identification strategy is required that is, indeed, influenced by learning.

Of particular note is Triesman's notion that 'frames' that constitute an 'object' must be identified before the object itself is recognised. This idea has a strong bearing on the formulation of a justification for animated data presentation. Conceptually, pre-attentive processing represents a definitive barrier to devising strategies to accurately identify meaningful signals in a distractive field more quickly. Whether this barrier is like a sound barrier that may one day be broken by new knowledge remains to be seen, however the barrier is considered by the author to be real enough at present. A neurological limitation for enhanced recognition performance clearly defines the potential of the Dvenn tool because such a limitation is unable to be extended by training or technique. Therefore, an opportunity exists to explore new data presentation methods, but this opportunity is tightly constrained within the framework of Triesman's discoveries.

Allied with Treisman's important work is the research done by Dehaene (1997) on 'number sense', that is, the identification of our inherent computational limitations based on brain structure. The work of both these researchers has informed the author's reliance on multidiscplinary insights to underpin this thesis rather than adoption of a particular school of thought such as Gestalt Psychology. Thus, the semiotic orientation of the thesis is underpinned by Tversky (1998) and Bertin (1983) who both provide comprehensive enlightenment for the definition of signs and signifying practices and how best to design a presentation to maximise both recognition and understanding.

[2] Appendix IV contains an account of pre-attentive processing and examples of the experiments utilised to define the term.

1.7 Instructions for Viewing the Dvenn Animations

A significant component of the research presented herein is the outcome of programming effort that is attached to this thesis. This software represents a number of variations and illustrates a journey of discovery as various forms of animation were investigated, programmed and rejected. The last version of the software, included in Appendix XVI, is named a Dvenn and represents a type of animated Venn diagram. The resultant Dvenn is not a single final product but the latest in a number of iterations. The developmental software was designed to be accessible by means of a common interface of labelled buttons. In the text of this thesis there are specific references to particular versions of the software and they are indicated by the symbol ‡. This symbol is used to indicate that the particular animation should be run to elucidate the visualisations and relate them to the discussion presented in the text. Of course there is no obligation to adhere to this regime, nevertheless it is recommended that the reader familiarise themselves with the icons in Appendix XVI with a view to better understanding the aims of the aims of this research.

A note of caution must be made regarding the computer required to run the program. The software has been tested on a number of platforms and problems were found with the aspect ratio of the screen of laptop computers. Therefore access to a desktop computer would confer the greatest advantage for viewing the software in the form that the author intended. The buttons that are presented require a single click only to select the option. Double-clicking a button will run the selected version twice. The software requires the floppy disk to be left in the drive, as the data file resides on the floppy disk. For this reason it will not run from the hard disk.

1.8 Thesis Outline

1.8.1 Chapter 1

Chapter 1 gives an introduction to the topic and identifies the research as being multidisciplinary in nature. It establishes that current business presentations lag behind the technological capability to deliver better, more effective presentations and re-introduces the term ‘visual numeracy’ in the Australian context to define a semiotic orientation to presentation design and its application to business problems. In particular, it is suggested that business audiences may benefit from presentations that exploit pre-attentive recognition for the purpose of reducing the concentration required to understand the presenter’s message. That message is now routinely buried in the wealth of information made available by the widespread adoption of business enabling automation technologies. At the conclusion of this chapter, the reader should have a solid understanding of why the research was undertaken and what underpins the theoretical justification of the research. Above all, the reader should understand that the aim of this academic undertaking is to construct and evaluate a *concrete* tool that any presenter may utilise to enhance the absorption of meaning from a presentation by their audience.

1.8.2 Chapter 2

Chapter 2 reviews the background to the field of research and identifies a taxonomy based on Keim's (1997) classification of data visualisation as it applies to business, rather than scientific data visualisation. The review of this taxonomy attempts to identify gaps in the research on this topic whilst at the same time justifying a tool based on the underlying set theory of Venn diagrams.

The number of possible presentation methods is not exhaustively covered, the focus falls upon those that are most likely to be utilised for presentation to business audiences. Examples of the most applicable methods are given to help orient the reader through a visually stimulating field where words alone do not do justice to the topic. The figures are presented in the hues that are most formally associated with them, and the earliest chart (1856) reproduced here is in colour as it was hand coloured when it was first published. Colour is now readily applied to all manner of figures in publications, yet the charts presented herein are only in colour if that was required by design rather than artefact. For example, the contemporary display of Chloropleth charts[3] seems to require lurid colouration, however this is not necessary and the original type was typically produced in greyscale as would befit the publishing techniques of the time.

[3] Displaying quantitative or qualitative information by way of subdivisions of a map in terms of symbols or colours. The perception of regional correlations are greatly facilitated in such charts.

Therefore the mixture of both monochrome and colour figures in this work is deliberate, as is the lack of borders for figures as this conforms to Tufte's (1983) suggestion that graphical excellence is evidenced by, amongst other things, the minimisation of "non data ink" where possible. Indeed, the pursuit of graphical excellence underpins the desire on the part of the author to present this thesis in as "readable" a form as possible. The multidisciplinary nature of the topic suggests that a reader would not be expected to have a deep understanding of all the topics that are covered. Therefore the author has attempted to write clearly, without obfuscation, as jargon is only likely to detract from the reader being able to straddle the various disciplines that contribute to the formation of a theory that underpins the viability of animated proportional Venn diagrams. Footnotes are utilised throughout the work to add information where concepts that are discussed in the body of the text may be ambiguous or discipline specific.

Keim's taxonomy forms the core of the literature review, however some additional material is included as it relates to the discussion of Venn diagrams and why they are deemed a suitable vehicle for the representation of quantitative data. The substantive part of this additional material is an examination of the Infocrystal concept proposed by Spoerri (1995).

1.8.3 Chapter 3

Chapter 3 defines and discusses visual numeracy in detail. This chapter focusses upon those characteristics of a presentation that enable an audience to make sense of numerical material. Visual understanding is suggested as being relatively primitive, being shared with other animals, and for this reason is likely to be easy to utilise, whereas the gist of numerical material presented as tables of numbers is more difficult to retrieve without conscious effort. The presentation of business data to business audiences (rather than scientifically based audiences) may be more effective if simplified diagrams are utilised to demonstrate significant relationships in those presentation data.

Various diagrammatic forms of presentation are assessed against the requirements established for conformance to principles of good visual numeracy The Venn diagram is suggested as being the most suitable to evaluate for the purpose of constructing a working prototype that represents voluminous data in an animated form.

1.8.4 Chapter 4

Chapter 4 discusses the research objectives and the premises that form the central research question. Chiefly the null hypothesis, H_0, states that there is no difference between an animated Venn diagram and a scatter-plot of those same underlying data. The rationale behind these sentiments is the notion that Popper (1972) had of how science validates an effect. It is difficult to demonstrate that the Dvenn is better than competing presentation methods, however it is relatively straightforward to demonstrate that they are worse. That is, any test of validity for a Dvenn, when successful, only demonstrates success for that test of that data alone. No number of tests can prove a Dvenn to be the best method of data presentation, whereas tests that show that a Dvenn performs poorly would indicate that a Dvenn is clearly *not* the best method of data presentation.

Chapter 4 also introduces the research method consisting of practise-based research to develop a software tool named Dvenn and a corresponding empirical test of the efficacy of such a tool. The development of the tool, programming language selection and iterations of the project design cycle are also covered. The selection of the test cohort is justified and discussed, as is the survey instrument. Iterative testing of the prototype and variations of animation frame rate, perceptual parameters and limitation of data dimensions are also discussed.

1.8.5 Chapter 5

Chapter 5 presents the results in tabular format generated by SPSS™. The clear majority of trial results suggest acceptance of the null hypothesis, that is, there is no significant difference between data presented as a Dvenn and data presented as a scatter-plot. The implication of the acceptance of the null hypothesis is discussed with respect to the efficacy of the Dvenn as a presentation tool for utilisation with business audiences. A discussion of the significance of the results ensues with respect to the research question and premises and presents them in the context of other research findings, particularly with respect to static graphical presentation and the evident distortion that visual cues cause for audiences who are subjected to graphical representations of business data. Both the survey instrument and the survey cohort are examined in order to determine whether a guessing scenario might also explain the results. Of particular note is the poor performance of the control group with respect to their identification of correlations in scatter-plots.

1.8.6 Chapter 6

Chapter 6 Suggests future research as a result of the discussion. The lack of evident success for the Dvenn tool is tempered by the possibility of further exploration of meaningful ways to present animated data presentations to business audiences. The underlying justification of set theory as being a requisite for the creation of animated data visualisations is questioned. One suggested departure from the Dvenn is the possibility of utilising a "correlation court" animation that projects data as moving points in a field in a fashion reminiscent of computer games.

This chapter concludes the thesis with a concise overview of what was undertaken and what was found to be problematic in the research methodology. Whereas the actual software tool was constructed and performed to the expectation of the author, the results of the empirical trial of the Dvenn are highlighted as being unreliable for a number of reasons.

1.8.7 The Appendices

The Appendices form an important adjunct to the body of the thesis and present the detailed computer source code that formed a putative solution to the research objectives that were identified in the literature review. In any assessment of ideas that cover a range of disciplines there is the problem of how much an author should explain in the body of the work and how much should be assumed to be obvious to an academic who is versed in the topic. Even simple footnotes, asides in parentheses or passing acknowledgment by way of example, serve to reduce the narrative flow pertinent to the novel material that is the real subject of the thesis. The author has attempted to utilise the appendices as a means of making more detailed discussion of interdisciplinary[4] ideas available to the reader according to their interest and requirement for explanation. Therefore further examples of graphic invention, perceptual

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[4] Analytical incorporation of more than one discipline or area of professional knowledge, the use of one discipline to consider another and above all not defining problems through the exclusive perspective of one discipline'. (Bines, H. 1992, p127).

illusions and extra elaboration of key concepts, which would be altogether too voluminous to appear within the body of the text, are included in the appendices.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

The purpose of this chapter is to explore ideas that underpin the selection of the Venn diagram for representation of quantitative data as an improved presentation tool. It has been said that research is the process of climbing upon the shoulders of others. In the case of data visualisation, the shoulders are indeed broad and the view from the top is magnificent.

Of particular value to the focus of this thesis is the work done by Barbara Tversky both in terms of categorising the scope and meaning of data visualisation (Tversky, 1998), as well as undertaking experimental work to determine how audiences actually evaluate and make sense of graphical representations (Levy, Zacks, Tversky and Schiano 1996). Tversky's work provides a context for data visualisation within the cultural and historical development of the way messages are comprehended and communicated. This is an especially important contribution to researchers in this field. Of particular importance for this thesis is the emphasis placed by Tversky upon the *naturalness* of graphic invention. A description of this important work is elegantly summarised in Gattis (2001):

> *Depictions, such as maps, that portray visible things are ancient whereas graphics, such as charts and diagrams, that portray things that are inherently not visible, are relatively modern inventions. An analysis of historical and developmental graphic inventions suggests that they convey meaning by using elements and space naturally. Elements are based on likenesses, "figures of depiction" and analogs to*

> *physical devices. Spatial relations are used metaphorically to convey other relations, based on proximity, at nominal, ordinal, and interval levels. Graphics serve a variety of functions, among them, attracting attention, supporting memory, providing models, and facilitating inference and discovery. (p3)*

Further, Tversky (1998) states:

> *Graphics externalize internal knowledge. This has at least two benefits. The benefit to the individual mind is reducing the burden on memory and processing by off-loading. The benefit to groups of minds is joint consideration of the same set of ideas as well as collective revision of them (p248)*

As will be discussed in detail in Chapter Three in support of why Venn diagrams were selected as a supposed vehicle for more meaningful data visualisation, the *naturalness* of graphical devices as described by Tversky points to Venn diagrams being highly suitable for business presentations that have a voluminous or contrasting quantitative component. Tversky, Bauer-Morrison & Bétrancourt (2002) define *naturalness* as

> *… a convergence of inventions across cultures and ages for using space to represent space and to represent abstract concepts that suggest cognitive correspondences between mental spaces and real ones…the pictorial languages found all over the world are one example…these early written communications resemble contemporary attempts at inventing writing by preliterate children. (p249)*

Tversky et al (2002) believe that effective visualisations conform to two principles: firstly a data visualisation must have *congruity*: that is, the structure and content of a data visualisation should match the structure and content of desired representation, and, secondly a data visualisation must have *apprehension*: that is, the structure and content of a data visualisation should be readily perceived and comprehended.

An audience evaluates a presenter and absorbs messages by several means, Visual, Auditory and Kinaesthetic, as discussed at the start of Chapter One. They watch and listen to a presenter and they observe the body language of the presenter. They seek to evaluate a consistent and reliable total picture. These practices are very normal and are no different to the way many aspects of daily life are comprehended. However, the display of numerical tables, statistical formulae or graphical devices like box and whisker plots quickly force the audience to adopt very unnatural means of comprehending the presenter's message. The author contends, by making a generalisation on this point, that the sole means open to an audience for comprehension of such data visualisations is purely intellectual. Gone is any ability for an audience to utilise the multitude of sensory data available in other circumstances. Recall the discussion of music in the Introduction; this sensory channel is well stimulated in a modern business environment, from tunes heard in the lifts and telephones on 'hold' to orchestrations accompanying presentations to shareholders. In a natural manner, meaning it is not a rational process demanding prior specialised comprehension, music can set a tone or ambience conducive to decision making. Therefore, the *naturalness* that Tversky et al. (2002) refers to appeals to the inherent ability that an audience has to enhance their understanding of a presentation by utilising their daily experiences of evaluating messages presented by persons for the purpose of sharing points of view and maintaining rapport. Graphical presentations should be tuned to exploit these natural and familiar pathways that are utilised by an audience to garner understanding.

The review of graphical devices presented in this chapter attempts to comment on the suitability of them for business presentation with respect to the burden of recognition placed upon the audience. To find a better way of presenting data requires an identification of the shortcomings of currently utilised forms with respect to the naturalness of the graphical device.

The taxonomy of data visualisation created by Keim (1997) is adopted to enable a methodical introduction and evaluation of data visualisation types pertinent to a business audience. Utilising Keim's taxonomy enables the discussion of material about data visualisation to be constrained and, in contrast alternative classifications of data visualisation (Harris, 1999), Keim's taxonomy is more pertinent to computer assisted presentation types.

2.2 Data Visualisation

2.2.1 Introduction

The starting point for the evaluation of the potential for a new data visualisation tool is to acknowledge the range of current tools and suggest what shortcomings identified in current forms might be addressed, in any proposed alternative form, for it to be useful. Of crucial importance is the definition of the domain in which the proposed tool would be appropriately utilised. The focus of research is primarily that of a data presentation tool for the projection of statistical concepts, particularly correlation, in a visual format to a non-scientific audience. Special attention is given to exploiting more natural graphical representations that employ primitive and familiar visual forms and circles are initially suggested as a suitable type for conveying meaning from quantitative data.

Classification of data visualisation begins with two forms as suggested by Card et al (1999, p8)

> *Scientific visualisation is visualisation applied to scientific data, and information visualisation is visualisation applied to abstract data. The reasons why these two diverge are that scientific data are often physically based, whereas business information and other abstract data are often not.*

Scientific visualisations include many forms, such as MRI scans in the medical arena, GIS for land management systems, Monte Carlo modelling in engineering risk assessment, Gaussian plume analysis in process control and dispersion modelling, forensic profiling tools in law enforcement work and Air Traffic Control support. These and many other tools in the scientific, academic and industrial arenas, that illuminate and visually manipulate data, are utilised to aid decision making for a host of critically important problems. However, these excellent tools are not commonly applied to business problems or presented to business audiences and therefore they will not be considered further in this thesis.

Recent research suggests that scientific versus non-scientific categorisations of data visualisation serve no useful distinction and they are now of historical importance only (Tory, 2004). Supporting this contention is the observation that, in the case of TV weather maps, the particular audience of the presentation is very generalist indeed, yet the visualisation format would be classified as scientific. Further, the grouping of data visualisation into two streams, scientific and non-scientific, does not help identify the type of data utilised for the visualisation, the presentation method nor the type of audience. Nevertheless, the focus of attention on the business domain means that the exclusion of what could be loosely termed 'obvious' scientific visualisation is appropriate, even if specific boundaries that delineate "scientific visualisation" from "information visualisation" are elusive. A simple test of what 'obvious' might mean is to consider whether an audience consisting of business people would be expected to understand the data visualisation without a detailed explanation of what those data being visualised may actually mean.

The following section presents a discussion of data visualisation appropriate to the business sphere. The order of discussion does not assume any particular historical precedence, as spontaneous discoveries occur in different cultural environments. Indeed, one reason that the author chose Keim's taxonomy of data visualisation is that it serves as a standard for ordering the various types of data visualisation that is independent of historical or developmental precedence. Though of historical merit only, it is worth mentioning that the Bedolina map[5], at some 3000 years of age, is a rare surviving example of a graphical navigation aid that may be argued to be one of the earliest forms of reliable data visualisation (Thrower, 1972) . These visualisations are accurately reproducible, reflect a physical state or place and are not for decorative purposes. Historically, therefore, the evolution of data visualisation may be viewed as a distinct stream of human intellectual development rather than a series of discrete inventions. As will be discussed in the ensuing sections, data visualisation is an inevitable consequence of our reliance on visually acquired information. The traditional forms of data presentation in print media have been constrained by typesetting limitations and, even as late as 1983, Tufte considered the greatest challenge to printing the *Visual Display of Quantitative Information* was finding a publisher to faithfully reproduce his graphics. The following quotation that was taken from a press interview indicates the passion and permanence that Tufte ascribed to his work:

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[5] A map carved in rock located in the Italian Alps.

> *I also wanted to control the design to make the book self-exemplifying, i.e. the book itself would reflect the intellectual principles advanced in the book. Publishers seemed appalled at the prospect that an author might govern design. On the design side, … we spent the summer in the studio laying out the book, page by page. We were able to integrate graphics right into the text, sometimes into the middle of a sentence, eliminating the usual separation of text and image, one of the ideas Visual Display of Quantitative Information advanced.*
>
> *(Doernberg, 1997, p11)*

Now, however, personal computer technology allows enormous flexibility for the presentation of data, and, once presenters have overcome their initial experimentation with the plethora of poorly executed Powerpoint™ slides, the time is right for contributions to the field that raise the standard of computer assisted presentations of data to an audience. In particular, such a contribution should be solidly based on the perceptual capacity of the average business audience.

2.2.2 Semiotics

Description of a topic is the first step in claiming a specialist field of study. The description will include attributed special meaning to particular words, if not specifically invented for the purpose, to promote meaningful discussion tailored to the explanatory purpose of the topic. Broadly speaking, and, as discussed in further detail in the chapter on methodology, the author adopts a view of data visualisation, which, in moving from the general to the specific, suggests a deductive approach to the research paradigm (Collis, Hussey, Hussey & Staples, 2003). In the case of data visualisation, the ideas that are drawn together by Bertin (1981) serve to institute a sound basis for establishing a field of study that has important consequences for an information dependant society. His forthright inference of useful design principles, which exploit visual properties, and their concomitant application to data visualisation, pre-date popular works on the topic by Edward Tufte. Bertin's development of a nomenclature for data visualisation is profound and builds on earlier works on semiology[6]. The comments of Allot, cited by Nèoth (1990) show the expectation of the contribution of semiotics to be tempered by the lack of evident progress in the field:

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[6] The study of signs and signifying practices.

> *The ambitions of semiotics have been large; the achievements remarkably small. Why should this be? One answer may be that there was ambiguity at the very beginning in the concept of the sign, the atomic element in a hypothetical system. However, some scholars have foreshadowed a different and perhaps more promising line of attack for semiotics. Thom has expressed the view that semiotics would profit from closer contact with biology or ethology. Pinxten[7] suggested that the borders of semiotics are the neurobiological sciences where "absolutely amazing advances are being made today .. in neurophilosophy and the general model of connectionism" p257*

Certainly, those early failures in the application of semiotics stem from a lack of capacity to create valid operational definitions to problems. The challenge is to appreciate that rapid advances in neurophysiology suggest that there are more accurate tools available now for assessing semiotic capabilities. Therefore, it is important to acknowledge those early theories of semiotics and evaluate them in a modern context. Particularly noteworthy in relation to the thrust of this thesis are the semiotic concepts of "image" and "figuration" (Bertin, 1983, p8). 'Image' is important because Bertin suggests that an image is immediate and it precludes intellectual enhancement of what is seen. This concept relates to pre-attentive processing and is elaborated in section 3.1.3. Bertin limits an image to accommodating no more than three attributes. This limitation shares a recondite legacy with Dehaene (1997) and his identification of 'number sense' whereby three is the highest number to be immediately recognised as a pattern without recourse to counting individual items. Bertin also suggests the concept of "efficiency" (Bertin, 1983, p9) as part of his rules of the total graphic system. In this case, 'efficiency' consists of methodically reducing superfluous elements during the construction of graphical figures. Others have acknowledged the importance of Bertin's work (Cleveland, 1993), and, Mackinlay (1986) attempts to extend Bertin's work by adding the concept of graphical "expressiveness" that echoes Tversky's 'naturalness'.

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[7] This quotation references Pinxten, R in: Koch, Walter A. (ed.) 1989 *Culture and Semiotics.* Bochum: Brockmeyer. pp34-35. The cited article is unsighted as it was not available to the author

Bertin considers that circles are acceptable for data visualisation and he includes several examples covering unusual forms, such as the chart that resembles a nautilus shell; consisting of radiating data points, sorted by increasing value, around a mid-point. He determines that circles are suitable for data visualisation as long as "the retinal legibility[8] is less than 10% of the total area of the graph" (Bertin, 1983, p180). He suggests that retinal legibility, or those attributes of a graph that are recognised on the retina, constrains the visual complexity that may be presented to a viewer, but equally, large filled objects on the retinal surface convey no useful meaning and waste an opportunity to maximise the viewers' attention. A definition of 'retinal legibility' points to the difficulty those early researchers had in dealing with the multidisciplinary nature of the topic. Neurological science was not integrated into Bertin's attempt to define a study of data visualisation. Therefore, he considered that immediate recognition of simple patterns must occur on the retina, whereas the recognition of complex patterns must require processing in the brain rather than in the eye. Bertin grappled with the problem but his terminology is clumsy and illustrates an attempt to devise an explanation that appears to the author to be less satisfactory than a neurological approach, had it been available. Triesman's work confirms the variance in recognition time for certain shapes and sizes, but Triesman does not ascribe the term 'retinal image' to this finding, instead the term 'pre-attentive recognition' is used. Triesman does not associate pre-attentive recognition with any particular locale in the brain.

Whatever may be the merit of particular attempts to explain how signals are processed, indeed the field of neuropsychology is very large, there is nevertheless material agreement that certain visual forms are easier to recognise than others (Bertin, 1983; Dehaene, 1997; Hoffman, 1998; Piaget, Inhelder & Pomerans, 1974; Triesman, 1986; Tufte, 1983, 1990; Tversky, 1998). When utilising circular shapes, Bertin rates pie charts third in the ten ways suggested "for displaying limited quantitative series" (Bertin, 1983, p199). He does not discuss Venn

[8] Retinal legibility is that part of a pattern that is formed directly on the retina. It is subject to optical constraints such as lens clarity, condition of the macular and other physical structures. It is not subject to interpretation, but rather to definition and resolution. As with any physical device that utilises a lens, the size of the image projected on the surface of the retina determines how well it is resolved to a coherent picture. The implication of this for Bertin is that graphs can be designed to maximise retinal legibility.

Diagrams because they convey no quantitative information, and it is difficult to impute his sentiments to the defining characteristic of Venn diagrams; that being that they are commonly projected as circles. If a quantitative Venn diagram is treated as a single pie chart then Bertin would have treated it similarly to a pie chart and held them in high regard. However, if a quantitative Venn diagram was considered by Bertin to be no more than multiple pie charts sharing the same space on a page then he would consider them to be "completely useless" (Bertin, 1981, p111). Strong words indeed.

2.2.3 Exploratory Data Analysis

Exploratory Data Analysis represents an application of data visualisation for a specific purpose. In the case of exploratory data analysis, graphs are considered useful for both the exploration *and* display of data. From the perspective of a researcher, data may be considered to have numerous 'views', as no individual plot can be expected to show all aspects of those data. However from the perspective of the audience at a presentation, all data visualisation is an exploratory data analysis. The novelty of what is presented is a substantial barrier to their collective understanding of what is being presented. Anecdotally, the author regards many data visualisations to have poor impact because the presenter has explored those data, chosen the graphical form to best represent a message and then failed to understand that the audience has not had an opportunity to share that exploratory experience. Tukey (1977) was a pioneer in the use of projection techniques for data visualisation. Conceptually this is an iterative process to aid awareness of subtleties in the range of data being studied to gain meaning not necessarily apparent from statistical tests. Computer access increases the ease of use of graphing methods to facilitate such iterations, but the audience is being left further and further from the process that furnished awareness and meaning for the presenter. The author has formed the opinion based on observation, that, from the perspective of the audience, too much of the signification of data visualisation is obscure. A presenter is taken on trust that projected data represent cause and effect relationships.

Even with particularly apposite uses of data visualisation, it is not immediately obvious, due to orientation of scale, legends and so forth that there is a clear message. Many are the times that the author has looked at a data visualisation to find that, in a publishing context, it does not support the contentions of the text! It is a very common experience of the author to witness tertiary student presentations that involve data visualisations where actual signification of those data *negates* the contention of the presenter. Anecdotal observations of course, but these presentations are made by mature part-time postgraduate students employed in responsible business positions in the fields of accountancy, economics and marketing. Therefore these subjective experiences of the author hint at what data visualisation in the business arena is actually being utilised for. On that basis, what hope of collective understanding does an average business audience have?

2.2.4 Graphical Elements for an Audience

Combining the influence of Tukey with the emphasis of fitness for purpose that was defined in Bertin's work, Cleveland (1994) suggests that the usefulness of data visualisation is based upon their effect upon an audience and the persuasive purpose of graphs. Here the question "Why use graphs?" is considered. What, indeed, are the principals of graphical construction? Cleveland's ontological framework attempts to combine Bertin's semiotic view and the three thinking languages, verbal, mathematical and visual, proposed by Adams (1972) in the tradition of Ferdinand de Saussure, into a philosophical basis for appreciating the importance of data visualisation (Holdcroft, 1991).

Cleveland's principles of graphical construction highlight clarity of vision and understanding. He maintains that data visualisation is so important that the conclusions of a report should be in graphical form, it should be treated as the main event rather than an adjunct feature. Interestingly, in *Visualising Data* (Cleveland, 1993) the emphasis on classical statistics and probabilistic inference overrides the philosophical foundations established later in *The Elements of Graphing Data* (Cleveland, 1994). It is as if the study of data visualisation appears undemanding at first, simply a descriptive account of the format of graphical devices, but upon deeper investigation, it is impossible not to be affected by the fundamental nature of how we make sense of what we see. In the later work, Cleveland considers that the visualisation of data should now be presented as an opportunity to reveal effects missed in other analyses, not simply a matter of *how* to visualise data. The end product of a data visualisation is now considered by Cleveland to be a document that is readily and indefinitely accessible to a community. There is an emphasis on longevity and the persistence of meaning beyond the time of the author who created it. Data visualisation should allow for transparent access to the author's intellectual processes.

Further supporting the argument that graphical elements are a special form of the representation of ideas, Shneiderman (1996), a co-originator of the Nassi-Shneiderman chart[9], argues the case for a compressed form of data visualisation for representation of intellectual processes. Importantly, Shneiderman's work emphasises the interactive nature of computer generated data visualisation. The concept of "visual thinking"[10] is a cornerstone of Shneiderman's representation of data visualisation as a special field and underpins his longstanding focus on the interactive computer driven application of data visualisation. He emphasises the discovery of relationships in data to enhance thought and decision making (Card et al., 1999). Shneiderman discusses the value of Venn diagrams under 'tree maps', discussed further in section 2.3.6.4. Likewise, the software tool Infocrystal, discussed in detail in section 2.3.8, deconstructs Venn diagrams into intersecting segments that iconically represent all possible Boolean operations upon a data source. These examples illustrate that data visualisation is still evolving, there are no particular limits to suggest that the current forms of data visualisation are the best to be expected.

2.2.5 Data Visualisation Principles

As has been suggested in section 2.2.2, Bertin's semiotics utilise a semi-scientific[11] basis for establishing the value of graphical analysis. In contrast to Bertin, Tufte (1983) ignores any attempt to establish a neurological explanation for the value of data visualisation, instead

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[9] A chart type that provides a visual, compact overview of the relationships in computer program code,

[10] The author has sought to minimise the nomenclature that is applied to the field of data visualisation and believes that the term "visual thinking" should be omitted, as it is too broad and adds little to the debate but confusion. However, Shneiderman is such a strong contributor of practical ideas to the field of study, that such an omission of acknowledgement would be an oversight. Indeed his work has provided the foundation for commercial software such as MindManager™ that may be used to facilitate easy development of "maps" that can be utilised to capture, store, organise and present ideas and information. Therefore, in the context of constructing a new data visualisation software tool, Shneiderman's terminology is presented as originally stated, rather than being simply presented as further evidence of Tversky's concept of 'visual depiction'.

simply justifying the efficacy of data visualisation through design principles. The *Visual Display of Quantitative Information* (Tufte, 1983) is an important landmark as the work attempts to establish universal principles that relate only to the display of data. Tufte makes no attempt to attribute his contention, that data visualisation is a superior form of information communication, to psychological or scientifically based theories. Somewhat casually, he simply states in the following interview that :

> *… in data-rich sciences like meteorology or nuclear physics, which generate tremendous amounts of information, the only way you can think about it is to see it. That's the most efficient channel, the high resolution channel. The only way to see it is to see it.*
>
> *The main elements in Information Design are (1) you have to be able to see and (2) you have to be able to count. (Doernberg, 1997, p5)*

Though not based upon psychological theory (though he indirectly recognises the potential importance of cognitive psychology through elucidation of the moiré effect[12]), the work nevertheless stands on simple design principles. Chief of these is his exhortation, exactly the same as Bertin's 'efficiency principle', to apply Ockham's razor[13] and minimise the amount of ink required to display a given quantum of data (the so called 'data/ink ratio' (Tufte, 1983, p93)).

Contrasting the ease and freedom to display data, acknowledged by Tukey to have resulted from the computer revolution, Tufte compares the ease of graphing with the quality of the output. Ease of use has led to the gratuitous adornment of reports with so-called "chart junk" or embellishments of no comparative value. Tufte, like Cleveland, expects the judicious use of data visualisation to be the focal point of the discussion and presentation of ideas supported by quantitative data. To that end, data visualisations must be carefully planned and crafted to

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[11]What is meant by 'semi-scientific is that he postulates a theory, but cites no real evidence that recognition of patterns in graphical presentations is based upon universally shared perceptual faculties.

[12] The visual illusion of movement from the presentation of contrasting fine parallel lines that appears to oscillate or vibrate.

[13] Sir William of Ockham, a medieval English monk who deduced that of any two competing explanations, the simpler is inherently superior.

maximise a viewer's understanding of the concepts presented. Brevity, both in space and ink are considered virtues. He states that "the only worse design than a pie chart is several of them" (Tufte, 1983, p178). Therefore Tufte, unlike Bertin, derides the pie chart as a space-wasting, uni-dimensional, inflexible and inferior method of data visualisation. So as Tufte explains, the creation of graphs is now an easy process, however the creation of *good* graphs by design is not.

Tufte (1983) suggests that, excluding deceit or frivolous utilisation of presentation graphics for adornment, the purpose of a data visualisation should be explanatory. The exegetic perfection available to a good designer of data visualisations is worth the effort. Tufte conceives of an artistic appreciation of data visualisation akin to that used for fine art. Tufte, like Tukey, suggests that data visualisations have the ability to communicate thousands of values effectively and display multivariate relationships impossible to do in any other way. Tufte shares Cleveland's view of longevity of graphic revelation but he goes further and suggests that well designed graphics have a timeless quality befitting poetry and beauty. Good data visualisation "makes complexity accessible" to the viewer (Tufte, 1983 p180).

Tufte does not mention Venn diagrams, but a reasonable assumption would be that he would consider them unsuitable for quantitative revelation. The reason for this is consistent with Tufte's reasoning for *all* pie charts with respect to their poor data-ink ratio. Multiple pie charts only exacerbate the shortcomings of single pie charts. Whereas repetition of a single form of graph type is acceptable to Tufte to enable the projection of a further dimension to allow contrast and comparison, his so-called 'small-multiples', the repetition of imperfect forms, such as pie charts is not. This assessment of Tufte's would seem to weigh against the selection of Venn diagrams. However, as discussed later in section 3.3, Tufte's work applies to a publishing flatland where paper is the sole output for data visualisation. When animation is made possible by computers, the design criteria that Tufte espouses for "small multiples" is available for entirely new data visualisation methods. As for "data/ink" ratio, whilst not ideal for a proportional Venn diagram, it is still better than for a non-proportional Venn diagram where ink does not represent quantity at all.

2.3 Data Visualisation Taxonomy

2.3.1 Introduction

As can be deduced from the discussion of section 2.2, the terminology of data visualisation in the literature is not definitive due to its "multidisciplinary heritage" (Card et al., 1999, p17), as it borrows ideas from several fields of study. Bertin tried to isolate and define those characteristics of business data visualisation to suggest that it is a discrete field of research. Notwithstanding the valuable contribution by those authors featured in section 2.2, who to varying degrees examined the nature and aspects of data visualisation, the purpose of this thesis is an overall understanding of data visualisation that is best served by examples. Indeed, for a claim to be made that a data visualisation technique is novel, it is incumbent on the author to not only demonstrate what business data visualisation is, in a theoretical sense, but also demonstrate practical embodiments of data visualisation techniques. Only from that point can a new tool be evaluated and slotted into an identified gap in the assortment of current tools.

To facilitate the definition and categorisation of data visualisation, and, extending upon the work of the researchers outlined in section 2.2, Keim's (Keim, 1997; Keim, Bustos, Panse, Sips, Schneidewind, Schreck & Wawryniuk, 2003) data visualisation taxonomy is adopted because it is concise, logical and current, in as much that it considers computer derived graphical forms. Keim's contribution of a Data Visualisation taxonomy is based on three categories, namely *explorative data analysis*, *confirmative data analysis* and, of most importance to the development of this thesis, *data presentation*. The most striking observation about *data presentation* is that any significant relationships in those data are known *before* the data are shown to an audience. The purpose of the visualisation is to demonstrate an effect or correlation in the data to third persons. This is not to insist that there is a proscriptive requirement to use only certain data visualisation forms for particular purposes. Hypothetically, one could envisage an audience viewing data in an explorative data analysis where the presenter is not yet aware of sensible meaning in those data and being just as surprised as the audience upon any subsequent revelations. Anecdotally, however, for the day-to-day business application of data visualisation, it is *data presentations* that constitute the vast majority of what audiences view.

2.3.2 Data Dimensions

Before further examination of Keim's taxonomy can proceed, a clarification of dimensionality is worth making. In the case of data visualisation, dimensionality may refer to either data arrays or the human neurological system. Three dimensional space is the largest that can be perceived by the perceptual system, but data arrays may present the opportunity to render many more dimensions, in fact n-dimensions (Card et al., 1999). Bertin describes a graph as existing upon a plane and in the case of a simple pie chart the data dimension is uni-dimensional but perceptually it is two-dimensional. To quote Stewart (2002)

> *A dimension is a geometric way of referring to a variable. Time is a non-spatial variable, so it provides a fourth dimension, but the same goes for temperature or wind-speed. To position a point in three dimensions, space depends on three variables - Its distances East, North, and Upwards relative to some reference point. In fact, ANY complex system is multidimensional (Stewart, 2002 p47).*

Only in the case of a data visualisation having three data dimensions x, y and z does it correspond exactly with the capabilities of our visual system to perceive three dimensions. To visualise more than this (n-dimensions), computer assisted techniques have been developed to render the extra dimensions perceptible. Such forms utilise colour, texture or nested positions in the visualisation. Common usage infers that dimensions of information constitute sales, time, products, age and the like and to visualise each dimension they can be attributed colour, size, quantity, location on the display etc. It is apparent that attributes themselves may be dimensions, as the attributes represent the data. Only at the time of constructing a visualisation are the actual data dimensions selected from a data source.

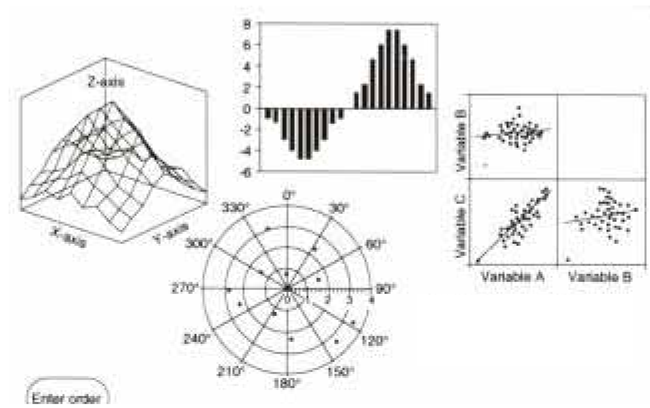
When hierarchies of data are considered, particularly in a multi-disciplinary context, it is very difficult to isolate exact meaning for the term dimension. So, even though the disciplines of statistics, computer science and cognitive science have specific definitions for 'dimension', data visualisation is not so fortunate as, referring to the discussion in section 2.2, it has been established that it is a hybrid concept. For clarity, the use of the term 'dimension' will be defined in each specific context as required and is used synonymously with ‘attribute’. The term variable is not used as this can have inference for dependencies, in the field of statistics for example, where variables and variates correspond to independent and dependent variables respectively.

2.3.3 Why Keim’s Taxonomy?

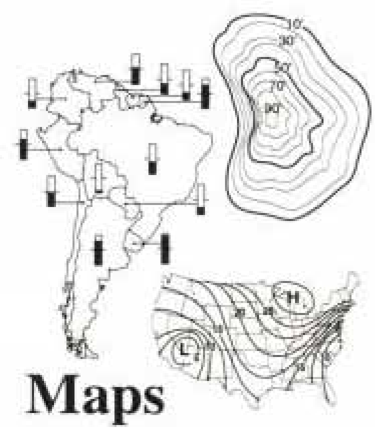
Keim developed this taxonomy for database exploration as a categorisation of tools that project a visual manifestation of patterns in underlying data. His taxonomy serves well for the grouping of data visualisation tools in order to examine the characteristics of each of these tools. However, with respect to their application, Keim’s work does not expressly attempt to warrant a fitness of purpose for each element in his taxonomy. His interest is to descriptively document possibilities for access to large repositories of data. He does not define a typical end user of these tools, nor distinguish individuals, groups or an audience. Therefore, for presentation purposes to an audience, it has not been possible to establish the comparative efficacy of each tool that Keim identifies. There is no current standard for the measurement of data visualisation effectiveness and there is a paucity of research done on the actual retention of information by a viewer for each of the numerous forms of data visualisation. As was discussed in section 2.2, Tufte attempts to define graphical excellence by examples of design but not by research. Bertin surmises that there are immutable perceptual limitations to data visualisation, but he cites no research that might measure the veracity of these claims. Nevertheless, in the absence of a matrix of suitable application of data visualisation based on respondent evaluation, the categories suggested by Keim are useful and serve the purpose of identification of data visualisation methods beyond simple data exploration as was originally envisaged by Keim.

To place Keim’s taxonomy in context it may be contrasted with categories of data visualisation that have been identified by other reference works. One such work describes, by example, each of the various forms of data visualisation utilised in traditional publishing and print media. Such a work does not cover the opportunity for computer-generated displays such as animation and three-dimensional rotation. Harris (1999) suggests a straightforward categorisation of data visualisation, but one that is not clearly delineated. For example, the following familiar types extracted from Harris (1999) may be judged to belong to more than one category. Are graphs not also charts? This is an issue for any classification of data visualisation techniques. Nevertheless, Harris does attempt to create a classification that is appealing because it is familiar. The following examples from Harris represent a brief visual summary of his classification.

- Graphs

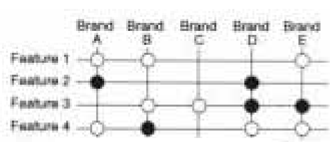


Consisting of common types like bars, lines etc.



Consisting of the representations of spatial relationships, usually to a scale.

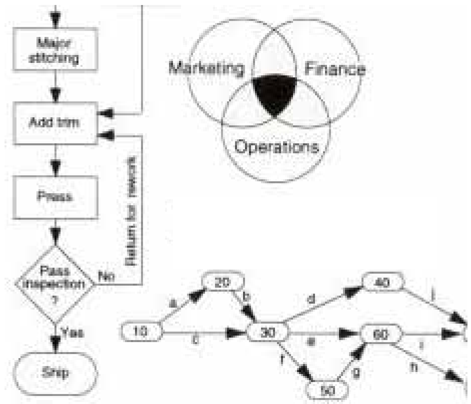
- Tables



	1993	1994	1995	1996	1997	Total
Product A	23.1	23.7	24.2	24.9	25.6	121.5
Product B	2.7	3.1	2.5	1.8	0.9	11.0
Product C	10.7	11.2	11.5	11.9	12.5	57.8
Product D	5.9	7.2	9.8	12.4	15.7	51.0
otal	42.4	45.2	48.0	51.0	54.7	241.3

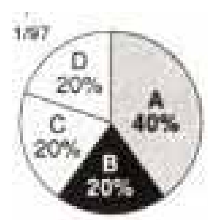
Consisting of data laid out in columns and rows.

- Diagrams



Consisting of the arrangement of relationships and dependencies in presentation data based on proximity and direction.

- Charts.



Consisting of several forms but principally defined by Harris to be the proportional representation of presentation data.

Harris (1999, p6) comprehends data visualisation as simply referring to "visual tools for analysing, managing and communicating" data. As Harris' work is principally a reference format, he does not attempt to define a theory of use that considers the perceptual constraints to successful data visualisation. Neither does he show the derivation of the various forms of data visualisation, nor does he attempt any form of rating for applicability of data visualisation in particular circumstances, such as data exploration and statistical analysis or audience persuasion.

Expanding upon the traditional forms of data visualisation considered by Harris to define the field, and, taking into account consideration of how perceptual limitations influence the acquisition and understanding of information presented visually, Spoerri (1995) extends Bertin's (1983) work by incorporating computer enhancement as a central component of data visualisation. He proposes that data visualisation be categorised not by convention but by the characteristics of the data components of a visualisation according to the following:

- Shape
  Data attributes are expressed by the shape of the figures.
- Colour
  Data attributes are expressed by the colour of the figures.
- Proximity
  Data attributes are expressed by the distance between figures.

- Rank
  Data attributes are expressed by the order of presentation of the figures.
- Orientation
  Data attributes are expressed by the orientation of the figure according to a fixed frame of reference.

Such a dissection of data visualisation is more scientifically than historically based and serves to understand better what perceptual elements data visualisations are constructed from. There is an appeal to Gestalt ideas of visual recognition[14]. They are entirely distinct from the written word or written numbers, a distinction not made by Tufte or Harris. What remains to be proved is that the elements of data visualisation are perceived differently in a neurological sense. Hoffman (1998) outlines a convincing scientific case for a grammar of vision that consists of 35 rules that govern our perception of line, colour, form, depth, and motion. In doing so he challenges the readers' apparently consistent view of the world by illustrating that much of what we see may not even exist!

To attempt to contain a discussion on this point is a nightmare invoked by the author's attempt to take a multidisciplinary tack. It is simply not feasible to enter the realm of Philosophical discourse about what constitutes meaning or reality. What the author simply states, in this case, as supported by Day (2004) and discussed in more detail in section 3.4.2, is that there *is* no higher level, or hierarchical arrangement, of perception, but only knowing through seeing. What Chi and Card (1999) simply term visual sense-making.

Keim does not contribute to the discussion about perceptual characteristics in terms of visual sense-making, acquisition of meaning or tools for persuasion. He formulates a taxonomy based on database access and visually driven exploratory data analysis. Keim pursues a narrow, practical goal and illustrates, by example, a classification that serves as a compact and useful taxonomy. Recently updated (Keim et al., 2003), his taxonomy serves the business informational aspects of data visualisation, and, for this reason, is selected from alternative classifications from which to evaluate the efficacy of a new tool. Keim does not firmly follow the footsteps of Linnaeus, the father of taxonomy, and Keim's system for naming, ranking, and classifying data visualisation is neither strictly original (Shneiderman, 1996) nor cited widely (Chi, 2000; Hoffman and Grinstein, 2000). Nor does he suggest a classification based on scientific versus non-scientific data visualisation (Tory, 2004). However, in the absence of an alternative definitive taxonomy, and, to serve the narrow purpose of this thesis, the taxonomy he proposes is adopted. Such adoption is tempered with the exclusion from his taxonomy of those visualisation techniques that are judged by the author to be used solely for analysis by a scientific cohort. Greatest emphasis will be placed upon his classifications of those visualisation techniques that best serve the purpose of *data presentation*.

Keim's view of data visualisation is that it principally entails the display of some measure of structure that might take the form of trends, clusters or anomalies, which may be interesting to an analyst. Keim does not discuss the way that the viewer assimilates the meaning of a visual

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[14] The Gestaltist recognition of patterns being categorised by Simplicity, Similarity, Proximity and Closure. It can be seen that Similarity closely describes shape and colour coding for differentiation and Proximity aligns exactly with Bertin's definition of the same.

presentation and he does not discuss the characteristics of an audience or any particular challenges that presenting to an audience may pose. Ultimately the audience must be enticed to share the presenter's point of view, therefore, for a presentation to be effective it is essential that the data visualisation method be easy to understand from the perspective of that audience. The author does not intend to define an audience, but when considering the problem of what, from the presentation perspective of a data visualisation, makes meaning or sense to an audience, Coombs, Dawes and Tversky (1970, p47) suggest that an audience should be considered "*simpleminded*" and that almost nothing should be assumed of the capability of the audience to comprehend a presentation.

What remains to be convincingly argued is that recognition of an "image", as discussed in detail in Chapter 3 as being "instant", means that training an audience in the particularities of data visualisation is not required. As any effect in presentation data should be apparent to an audience, without the necessity for the presenter to explain what the audience sees, the presenter's energy may be freed from the specific clarification of the visualisation. This leaves the presenter the opportunity to concentrate solely on the overall story of the presentation and therefore maximise the opportunity to persuade the audience of an effect in those data that are presented.

The review of graphic representation begins by presenting a summarised account of those features that are generally applied to data visualisations that are constructed for presentation to an audience as opposed to a readership of individuals in their own space and time. Whilst there are many graphic forms that are utilised in specialist fields of study, for example in statistics and combinatorial optimisation, the aim of the following section is to identify why the various types considered by Keim's taxonomy are of limited access to a generalist audience. Any element in a presentation that is novel to an audience imposes a large attention load. Therefore the impetus for presenters is to select data visualisation methods that are familiar to a generalist audience. However, as will be illustrated by example in the following sections, familiarity with existing tools alone does not explain why there are relatively few data visualisation formats used. It is not the author's intention to imply that an immutable definitive quality may be attributed to specific data visualisation types. That is, no attempt is made to indicate that certain graph types are intrinsically better or worse than one another that may suggest a particular fitness of purpose. Instead, it is simply a matter of supporting the contention that any data visualisation that appeals to inherent perceptual capabilities is going to perform better at enabling a presenter to carry an audience towards a shared point of view.

In contrasting Keim's taxonomy, which largely defines data visualisation types that are heavily dependent on technological assistance for their creation, it may be useful to consider the other end of the spectrum of classification of data visualisation. As previously discussed, Tufte has suggested design criteria for presentation styles that utilise a limited range of graph types, but he does not cover the multitude of forms and variants now readily available to presenters through the utilisation of computer software. Tufte appears to be dismissive of the capability of computer assisted data visualisation techniques to reduce the load placed upon an audience to make meaning of data presented visually[15]. To quote Tufte's preference for print media and his scepticism of Internet technology and computer based tools generally:

> *The problem with the Web is that it is low resolution in both space and time. In so far as space, the computer screen is an inherently low-resolution device, that's just a limitation of the hardware. And that resolution is made lower by the design of the images. … Information transfer is very low. The payoff, measured in bits per dollar, is very low relative to the investment in hardware, time, etc. It's another situation where we've replaced one nuisance with another. (Doernberg, 1997, p12)*

There is no International Standards Organisation rating for data visualisation and it would be imprudent to think that simple measurements are available that rate a particular presentation. As is the case with any human preference measurement, marketing feedback for example, what an audience *really* thinks about a presentation is open to conjecture. Whether a presentation is actually persuasive is even more problematic to assess. Nevertheless, samples of undergraduate university students have been used as subjects for audience preference assessment of data visualisation techniques and these experiments indicate that a limited

[15] Tufte is not alone in his scepticism of office automation, as the following quotation from a relatively recent (1999) volume relating to utilising pie charts in presentations illustrates: "This simple calculation will allow you to draw in the segments using a protractor and a compass" (Bell 1999).

hierarchy of performance can be inferred (Kahneman, & Tversky, 2000; Levy et al., 1996; Zacks & Tversky, 1998).

The discussion of the available types of data visualisation for presentation to an audience is focussed on assessing the potential for, and justification of, the proposed Dvenn tool. To this end the author has adopted two criteria to assess each of the presentation types. First, assessment is made on the basis of whether Bertin's "instant recognition" of the information content of a data visualisation is foremost. Once a data visualisation is classified as "figurative", where Bertin suggests that higher level processing is involved to understand it, the discussion focuses on what discrete figurative elements are themselves "instantly recognised". According to Bertin (1981), the more numerous the figurative elements in a single data visualisation, the more difficult it is to process for the viewer. Second, the suitability of the data visualisation for animation is assessed in support of the contention of Shneiderman (1996), cited in full in section 1.1, that the opportunity for dynamic displays, facilitated by ubiquitous computer availability must be harnessed more effectively.

It will be appreciated immediately that the evaluation of the effectiveness of data visualisations from the standpoint of presentation to an audience is purely the author's interpretation. As has been demonstrated, a number of classifications based on data visualisation *design* do exist (Bertin, 1981; Tufte, 1983; Tukey, 1977), but a suitable metric for their efficacy is just not available. Therefore, it is not the intention of the author to score each type of data visualisation classified by Keim, rather the objective is to discuss the potential improvements, based on both design and neurological research, applicable to visually numerate presentations. Of foremost consideration of each of Keim's categories is the question: how is *less* or *more* conveyed? Of the data visualisation characteristics suggested by Spoerri indicated by Shape, Colour, Proximity, Rank and Orientation, how effectively is quantitative information conveyed to an audience? Are these forms instantly recognised by an audience? How *natural* are these forms of data presentation, that is, does an increase in size, intensity or proximal velocity correspond to an increase in value? Further, does an audience intuitively distinguish patterns that are random from those patterns that are ordered?

In order to examine these questions in detail, sections 2.3.4 to 2.3.8 illustrate the main categories of data visualisation according to Keim. Each section describes the generic characteristics of the data visualisation category and utilises specific examples to highlight the variety and format of specific types. This is not an exhaustive critique of Keim's taxonomy, as it, in itself, is not complete for the field of data visualisation. Rather the purpose of choosing particular examples is to highlight the opportunity for presentations that are attuned to known perceptual shortcuts based on an emerging understanding of applied neurological research.

2.3.4 Geometric Types

Of Keim's (1997) taxonomy, *geometric* data visualisations cover a broad range of forms, encompassing both the most useful types, some of which are familiar and widely adopted such as scatter-plots and those forms introduced in section 2.3 by way of discussions of Harris' (1999) work, and some that are probably the least useful for presentation purposes such as prosections and hyper-slices. The common feature of these types is that data attributes are rendered geometrically to convey meaning. These presentation forms, in the main, are 'figurative' according to Bertin's nomenclature; they are also primarily aimed at exploratory data analysis. There is no hard and fast rule that stipulates that all geometric data visualisations cannot be used for presentation without an audience needing specific training in what they were looking at. Nevertheless, to recap Bertin's (1981) idea of instant recognition, an idea also previously discussed, as "visual sense-making" (Chi, 2000), "rapid recognition" (Shneiderman, 1996), or "pre-attentive processing" (Triesman, 1986), for those presentations defined as geometric data visualisation types, it is evident that they impose a high load for visual processing upon the audience and therefore would be difficult for that audience to collectively comprehend the presentation.

2.3.4.1 Scatter-plots

The exception to the assertion made in the preceding section that geometric types are not suitable for broadly based presentation purposes might be the scatter-plot. In its most simple form, a scatter-plot is a two-dimensional display that indicates data characteristics over two selected dimensions at a time. Examples are presented in appendix XIII. For n-dimensional space, analyses can be made on all pairs, but this method only allows structure across the two plotted dimensions to be discovered. To address this problem, more sophisticated geometric methods have been devised which are discussed in 2.3.4.3 and 2.3.4.4. Large datasets are problematic when rendered by a scatter-plot. The presenter must skilfully apply statistical techniques to reduce the total number of data points in a large dataset to as sufficient a number as to allow comparison. A solid black mass of points describes nothing. Applying Bertin's definition of an image, most forms of scatter-plot would be figurative. However one would expect that a "classic" correlation of 1 or –1 would be immediately recognised.

2.3.4.2 Landscapes

If Tversky's naturalness of imagery is considered important, then this technique may be useful. A landscape is a rendered contour plot where data is projected across a plane. A two dimensional example, in every day life, is the weather map and its associated patterns of isobars. If the isobars were to be considered a framework over which a texture was laid then the appearance of valleys and peaks would be evident in correspondence with the high and low pressure areas. Such landscapes do not have to correspond to geospatial co-ordinates, as any suitable data can be projected as a landscape. What is important is that the audience sees a landscape made of hills and valleys, highlighted and shaded, that infers some meaning about the relationship of the projected dimensions. Landscapes would be classified as figurative except for the most primitive of landscapes, such as those made of hemispheres, cones or other commonly experienced geometric shapes arranged on a plane. Figure 2.7 shows a landscape that is rendered in multiple layers to create a compound visualisation.

Even with primitive landscapes, the shared experience of the audience will not assign recognisable attributes to, say, a hemisphere. It is neutral and must have special meaning assigned to it by the presenter. However, it is possible to make a correspondence between the apparent height or mass of a dimension and the increasing value of that dimension. In such a case a natural association may be made by the audience that equates more of what they see with more of the quantity of the projected dimension. Inversely, a dimple in the plane would convey less of that attribute.

2.3.4.3 Prosection Views

Views of high dimensional objects are constructed using projection and section. Projections can display low dimensional data (x, y) and z with rotation, while sections can display subsets of multivariate data. 'Prosections' is the name suggested by Furnas (1993) for a combination of the two. Primarily an exploratory data analytic method to find interesting low dimensional views of multivariate data, the benefit of using such a tool for presentation depends on the audience being able to assimilate the association functions which drive the sections and the projections. This method will be classified as figurative.

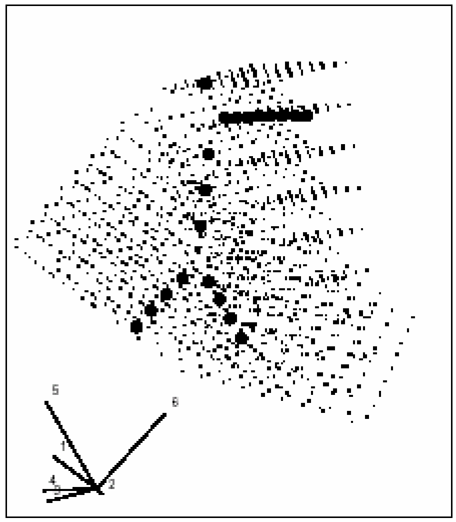


Figure 2.1 A prosection, points in four sections are highlighted.

(Furnas, 1993, p31)

The figure shows that the actual visualisation of a geometric form (in this case a Prosection) may be figuratively simple but devoid of obvious meaning to an audience unless they share common experience with this form. Even if the visualisation was readily identified as an image, the need for a dimension legend, as indicated in the bottom left hand corner of Figure 2.1, necessitates that Prosections be classified as purely figurative.

2.3.4.4 Hyperslice

The Hyperslice was first proposed by van Wijk and van Liere (1993) and consists of a computer dependant technique that is largely an interactive navigation through all possible pair-wise projections of data in multiple scatter-plots. This is a complex method of visualisation, not simply because of the steep learning curve for potential users of the visualisation method, but also because the demands made upon a viewer's visual system for recognition of meaningful patterns is very high. The method must be classified as figurative even though individual plots within the projected matrix may be instantly recognised, such as a 1 or –1 correlation, because it must be identified from all others, as, unlike a single scatter-plot taking all the viewer's attention, it must be sought out in the midst of many competing patterns. It is not readily apparent that the Hyperslice technique is actively utilised, and it seems to be the case that it has not been subsequently adopted for data visualisation. However, Keim includes it as a current method in his taxonomy.

Due to Hyperslice being an interactive computer based data visualisation method, it is difficult to provide a readily comprehensible single image that illustrates the features of the method. However, Figure 2.2, taken from the original paper, illustrates the matrix that is utilised to select the pair-wise projections. The example presented is illustrative only and the small insert at left is sliced to reveal an orthogonal matrix of two dimensional slices. van Wijk and van Liere (1993, p125) suggest that the representation is simple and easy to understand, and symmetric for all variables. Further, they suggest that the main strength of Hyperslice representation is that it lends itself very well to interaction via direct manipulation (p122). It is the contention of this author that Hyperslice is now largely only of historical interest.

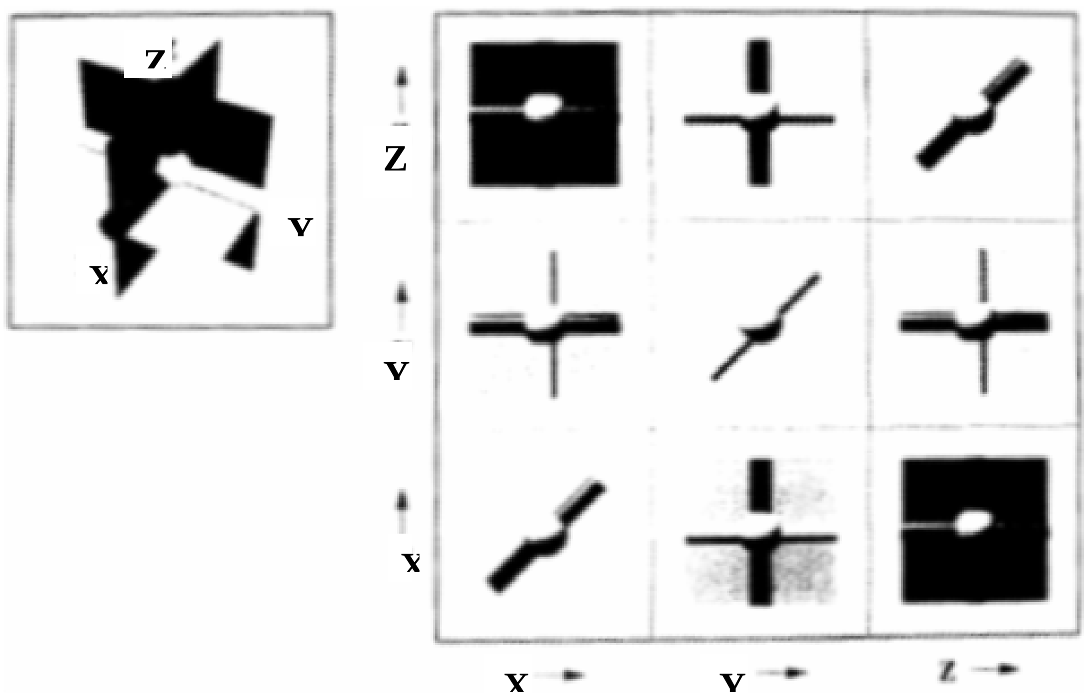


Figure 2.2 Hyperslice, a data navigation tool

(van Wijk and van Liere, 1993, p126)

2.3.4.5 Parallel Coordinates

Keim (1997) cites InselBerg (1985) as being the originator of parallel coordinates, a projection technique that consists of each dimension in the data corresponding to an axis, N axes being organised as uniformly spaced vertical lines. A data element in N-dimensional space shows as a connected set of points, one on each axis. Points lying on a common line or plane create readily perceived structures in the visualisation and clustering may be evident among some of the lines, indicating a degree of correlation. Like most of these geometric methods, the problem of a solid mass, caused by too many points producing clutter that obscures the underlying visual clusters, means that some form of averaging, or dimension reduction needs to be applied.

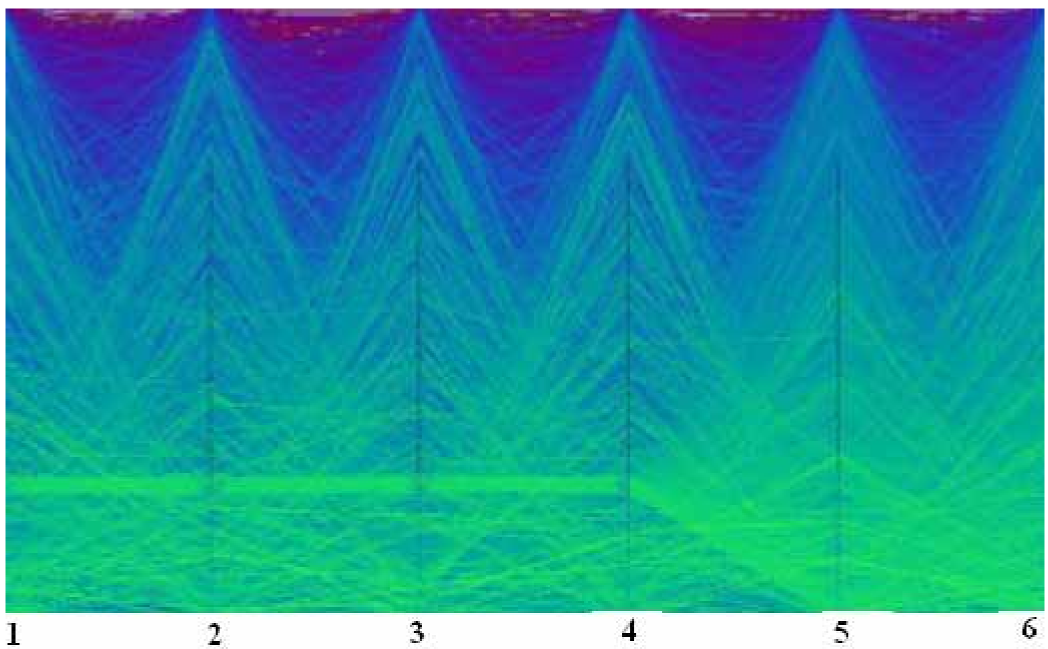


Figure 2.3 Parallel Coordinates of 15,000 Data Items Over 6 Attributes
(Keim, 1997, p9)

From the perspective of the audience, this method would be figurative. Of particular note in the example presented in Figure 2.3 is the manner in which data points are spread out along each of the attribute axes (the horizontal lines fanning out from each of the vertical lines that represent the attribute). An audience would need to be informed about what structures or clusters of lines infer particular meaning. It is not an intuitive visualisation. To make sense of this visualisation an untrained viewer would most likely focus on attributes 1, 2, 3 & 4 as being the most striking feature of the presentation. However, these attributes are the most incoherent in terms of data correlation.

2.3.4.6 Summary of Geometric Types

The utilisation of geometric graph types for data presentation to a general audience appears to be very limited. Apart from the very basic form of coordinate projection evidenced by scatter-plots, the demands made upon the attention of an audience by utilisation of these types means that it would be unlikely for them to easily assimilate the presenter's perspective. The opportunity to contrast data is there but there is no natural projection of quantity or proportion in those data so projected.

2.3.5 Graph Based

These types of visualisation are historic and require no form of computer assistance to be effective. They have a tradition of use and the simpler forms of pie, bar and line chart qualify for immediate recognition (Bertin, 1981; Cleveland, 1994; Shneiderman, 1996; Tufte, 1983; Tukey, 1977). Little progress with these types has been made since Playford in the late 18^{th} century and Minard in the mid 19^{th} century (Tufte, 1983). Tufte suggests that Figure 2.4(a) by Minard, a Frenchman, is the greatest graph of all time because it is multivariate and contrasts related aspects of Napoleon's campaign retreat from Moscow.

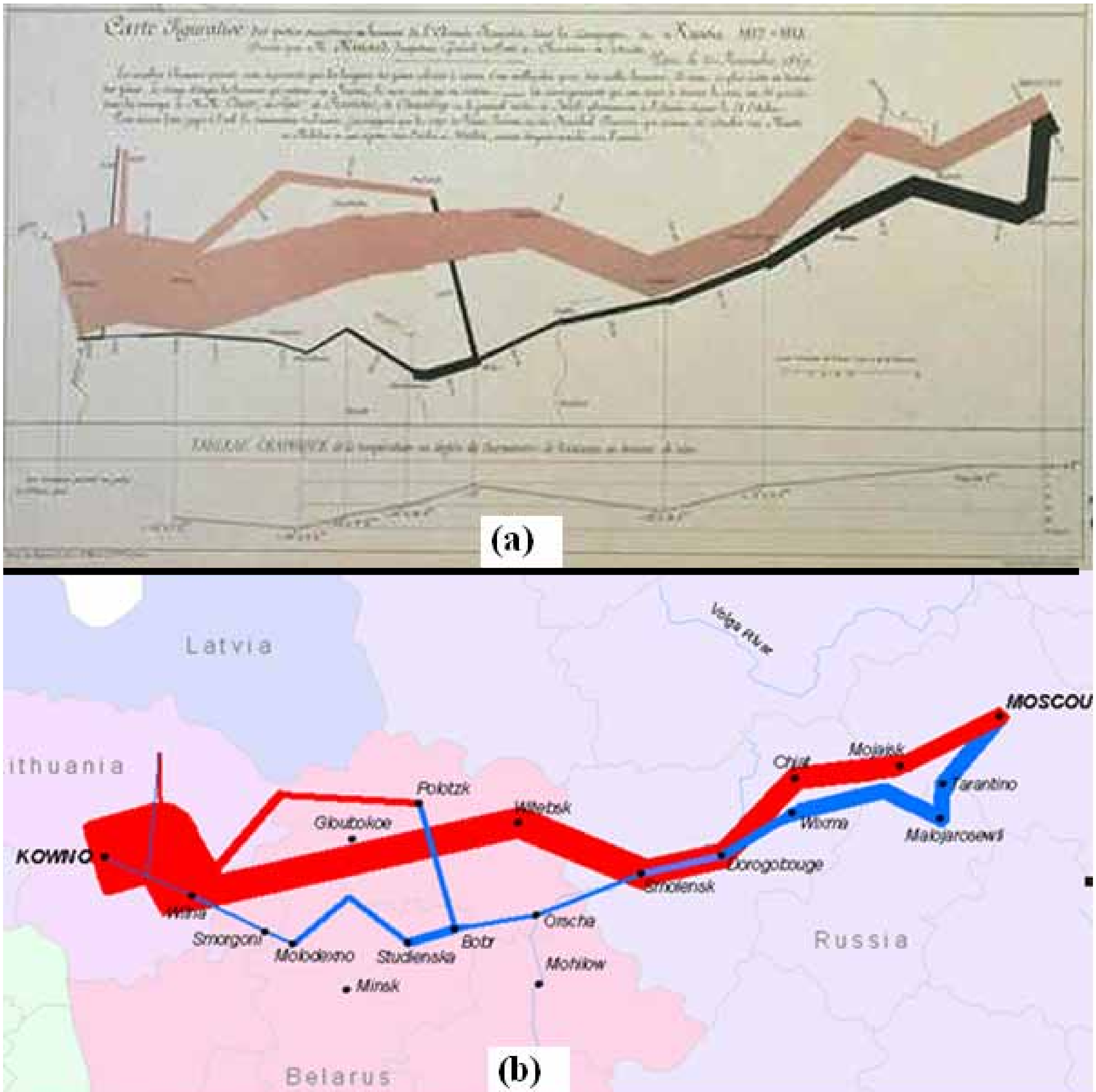


Figure 2.4(a,b) Napoleon's March to Moscow by Minard (1856)[16]

There is no doubt that Minard’s work is a great achievement, but it is also an indictment of the progress of data visualisation that such a form has not been improved upon for one hundred

[16] Figure 2.4(b) is derived from Goodchild (2005) and is a computer generated rendition of Minard’s classical work that has been superimposed on a modern map of the region. This version lacks Minard’s annotation of temperature and date and is, therefore a retrograde rendition as it contains less informational content

and fifty years! Notice that the thickness of the line in Minard's chart represents a quantitative value (the number of soldiers). The lighter colouration of the line represents the outward journey and the black line represents the return. The kinks in the line represent the actual deviation of route taken to Moscow and faithfully replicates the distances travelled, temperature at different point on the route and calendar information. These latter data are not included in the computer rendition presented in Figure 2.4(b).

Keim does consider that graphically based forms of data visualisation may be computer enhanced to meet the requirement of higher data densities. However, attempts to render Minard's work by computer have not added any qualities to the presentation standard that were not already present in Minard's original work. Indeed, it could be argued that such attempt to automate Minard's work have thus far resulted in a loss of information as Figure 2.4(b) illustrates. Neverthess, Keim includes a range of sophisticated graphical representation types that attempt to manifest the following:

- Minimal number of line crossings
- Optimal display of symmetries
- Optimal display of clusters
- Minimal number of bends in polyline graphs
- Uniform distribution of vertices
- Uniform edge lengths.

(Summarised from Keim, 1997, p 31)

It is immediately apparent that Keim is pursuing the same reductionist method suggested by Bertin's 'efficiency principle' and Tufte's 'data/ink ratio' to condense and standardise the forms of data presentation. There is a rationale in Keim's approach, it makes for neater more consistent data visualisations, but from a presentation perspective, the evident sophistication that is suggested decreases the ability of a general audience to use the recognition inherently available with familiar graph types. However, as noted above, standard graphs lack the dimensionality required to illuminate complex datasets.

The common graph based forms of data visualisation are still used with or without digital enhancement, some being quite sophisticated as choropleth maps (Figure 2.5) illustrate.

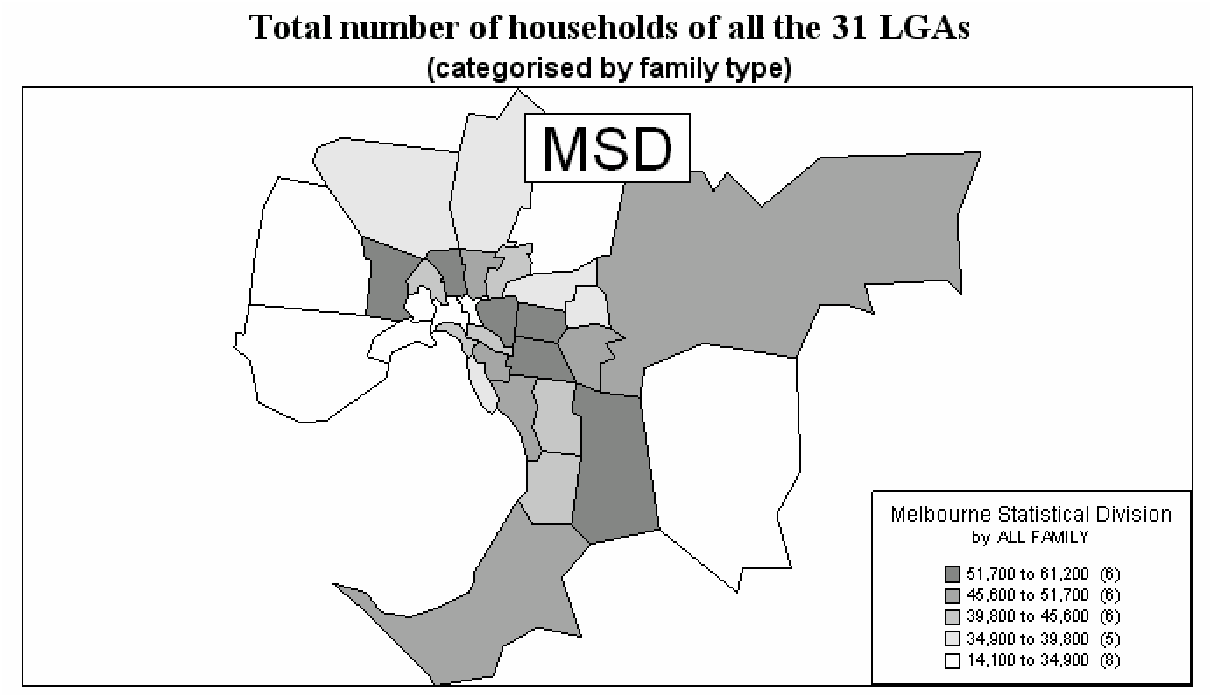


Figure 2.5 Choropleth Map (1996 ABS census data for Melbourne)

Choropleth maps suit an audience that is familiar with the territory of the map, in which case the image is recognised instantly, however the requirement to equate the colours and tones in the chart with the values in the legend *before* meaning is conveyed requires that these maps be classified as figurative. Even though the initial impression of such a data visualisation is that a realistic expression of quantity is made through colour, the category boundaries are quite artificial and the numeric distance would not be realistic according to Dehaene (1997). Utilisation of actual points decreases the data/ink ratio and at the same time increases the validity of the numeric distance by proximal representation but reduces comparative interpretation. This trade-off is common for representing quantitative information in a choropleth map.

2.3.5.1 Summary for Graph Based Types

The thrust to discover better data visualisation methods is largely borne upon the inadequacies of basic graph types to accommodate the increased data density that is characterised by modern business. Now, as was the case with scientific data visualisation being driven by the data boom of the early nineteen-nineties, non-scientific data visualisation is being impelled to find ways of illuminating the vast new quantities of business information. The scope to improve these mature traditional forms appears to be limited. Application of animation techniques does not adequately enhance such fundamentally static images. Bar charts would appear as pumping pistons, line charts as whipping snakes and pie charts as rotating wheels. So, whereas print media utilise the current forms available to good affect, the computer cannot be brought to bear to enhance the basic graph types to aid audience recognition. Instead, computer enhancement seems to be oriented towards fanciful renditions of shading and lighting effects to induce a three dimensional appearance. From a business perspective, what computer access has meant is an increase in the number of informationally impotent but colourfully rendered data presentations. This observation may explain the evident frustration that Tufte reveals in section 2.2.5 with respect to the drop in graphical excellence that he believes to accompany the widespread adoption of computer assisted data presentation.

2.3.6 Hierarchical

Hierarchical visualisation of data requires subspaces that are ordered in a logical way that imitate the real world of hierarchically structured information available in manuals, outlines, family trees, organisation charts, library cataloguing and other like sources. These structures offer a promising presentation method to a general audience if training overheads are minimal. Keim considers the major types to consist of the following:

- Dimension Stacking
- World within Worlds
- Treemaps
- Cone Trees
- Info Cube

They are largely figurative on Bertin's classification, but according to Shneiderman (1996 p152), they exploit the facility viewers have for recognising the spatial configuration of elements in a picture, enabling a rapid recognition of the relationships between elements. Further, in the absence of Keim proposing a critique, Shneiderman believes that rapid information extraction with low cognitive loads, efficient space utilisation and an *aesthetically pleasing* format are requirements for useful hierarchical data visualisation.

2.3.6.1 Dimension Stacking

This technique, an example of which appears in Figure 2.6, consists of partitioning the n-dimensional attribute space into two dimensional sub-spaces that are stacked into each other. The important attributes are utilised on the outer levels (reported by Keim to be generally known as the fastest axes). The representation method suits data with ordinal attributes of low cardinality. The ultimate appearance of such a data visualisation will vary markedly according to the selection of attributes for each of the axes. This selection process is at the discretion of the presenter and unlikely to be standardised. There is no suggestion by Keim that a rule should be applied to facilitate a standard or common way of constructing a dimension stack based on quantitative priorities.

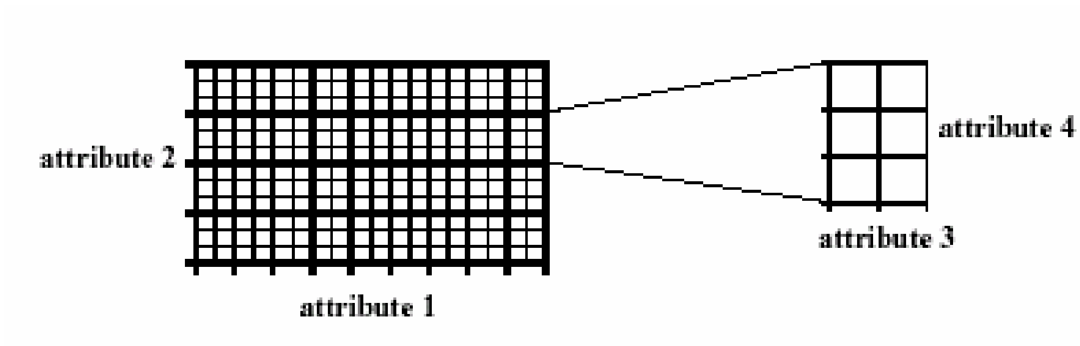


Figure 2.6 Dimension Stack

From Bertin's perspective, a dimension stack would be too complex to process as an image because the number of dimensions exceeds three. There is no doubt that an audience would be initially at a loss to make any sense of what was presented. However, over time, they would begin to recognise certain features from experience. The obvious barrier to widespread adoption of such a tool is the lack of transference from one situation to another. The naturalness that is sought through immediately recognisable patterns is not evident. There is no appeal to simple quantitative concepts like *more* or *less*.

2.3.6.2 Worlds within worlds

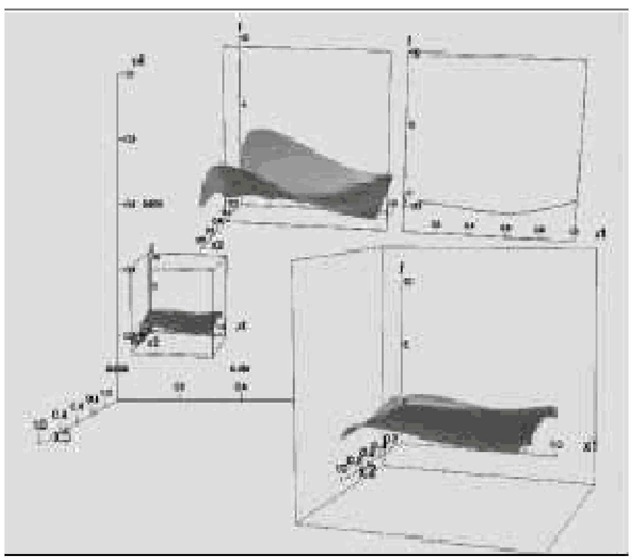
This is suggested as a particularly useful comparative tool that enables multiple views of the same data. n-dimensional space is partitioned into 3-dimensional subspaces, so a 6-

dimensional database object is visualised as having orthogonal axes for the last three dimensions sit inside the axes of the first three. From the perspective of the user they simply have to select a point in the first space to be offered a new space in which to further select a point. The recursive nesting continues until all the variations are exhausted. The final selection will reside in the innermost space or 'world'.

The ability to create copies of these worlds and compare variations visually between worlds makes this technique potentially very appealing for assisting an audience to make sense of data presentations. This method of data visualisation is usually confined to exploratory data analysis, however, it may be useful for *presentation* because relationships, once discovered, are able to be dynamically demonstrated to an audience, an imperfect example is indicated in Figure 2.7 and its reproduction suffers from the low resolution of a screen capture.

Figure 2.7 Worlds Within Worlds

Nevertheless it serves to illustrate the multi-view nature of this data visualisation technique.



Regardless of the comparative value of this technique, the attention load is such as to require some familiarisation with the technique before an audience can share the axioms of the presenter. However the technique shares some of the naturalness of landscapes and their attendant consistent projection of quantity with area or volume with the data density of dimension stacks. Nevertheless, the necessary scale and annotations require the author to consider this method to be purely figurative.

2.3.6.3 Treemaps

It is not surprising that Shneiderman promotes this technique as it has a direct lineage to the Nassi-Shniederman chart. A clever screen filling technique that maps the screen into partitions whose area is determined by attribute values and is illustrated by example in Figure 2.8. The colour of the regions formed may be selected to create proper sets from subsets to represent summaries. For example, sales of hats, coats and gloves coloured yellow to represents total sales for ‘accessories’.

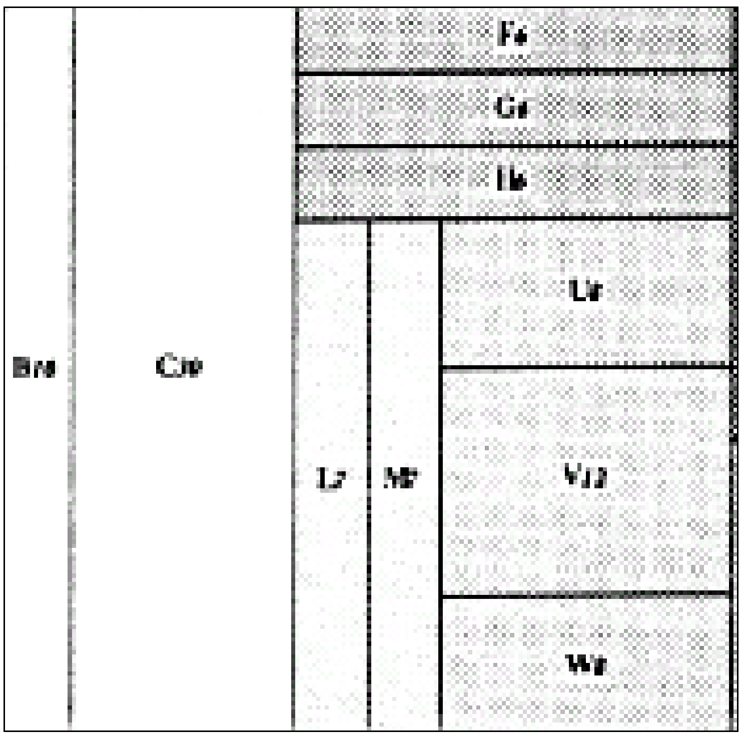


Figure 2.8 Tree Map

Figure 2.8 illustrates the basic diagram that constitutes a Treemap. It has only disjoint subsets, with each subset being proportionately accurate. Shneiderman suggest that a Treemap is superior to a Venn diagram for the purpose of displaying comparative data because the Venn diagram is a visually unusual structure, boxes and rectangles are more familiar. Also the Venn diagram wastes space, it is not efficient because it does not convey quantitative information and it becomes extremely complex for showing nested structures (Card et al., 1999; Shneiderman, 1996). A more detailed critique of Venn diagrams is given in section 3.2. A Treemap is suggested as being a viable solution to the problem of visual complexity increasing with data complexity. A Treemap is constructed by making the relational elements of the diagram box shaped, rather than circular as is the common representation of Venn diagrams, and applying a weighting algorithm. The important feature is the weight proportionate distribution of the display. The weights would be selected by the presenter to apportion the most important dimensions first.

From a presentation perspective the technique suggested by Schneiderman deserves serious consideration. Effectively this is a shape and proximity coding technique. The set relations, as normally represented by simpler Venn circles, would suggest that an audience familiar with Venn sets would quickly assimilate any dependencies in those data. However, the technique is suitable for disjoint sets only. Also the actual visualisation is not spatially balanced, there is no assurance that subset dependencies will even be visible. How is the absence of a set represented? Would this set be a blank rectangle? If so, what size would it be and would a legend be required to differentiate boundaries?

The author seriously considered Treemaps to be a fruitful technique for further research into better visual presentation of data to an audience, but problems with orientation of set dependencies and the application of animation techniques, suggested that the simple Venn diagram might be a more suitable candidate. For 'instant recognition', it is important to delete all symbolic references such as legends and scales and project only the data. Treemaps cannot achieve this in their present form.

2.3.6.4 Cone Trees

Conceptually very similar to node-link diagrams, this technique utilises computer animation to rotate a cone of hierarchically arranged linkages that visually relates the relative position of each element in the tree. Figure 2.9 shows a static example of such a layout.

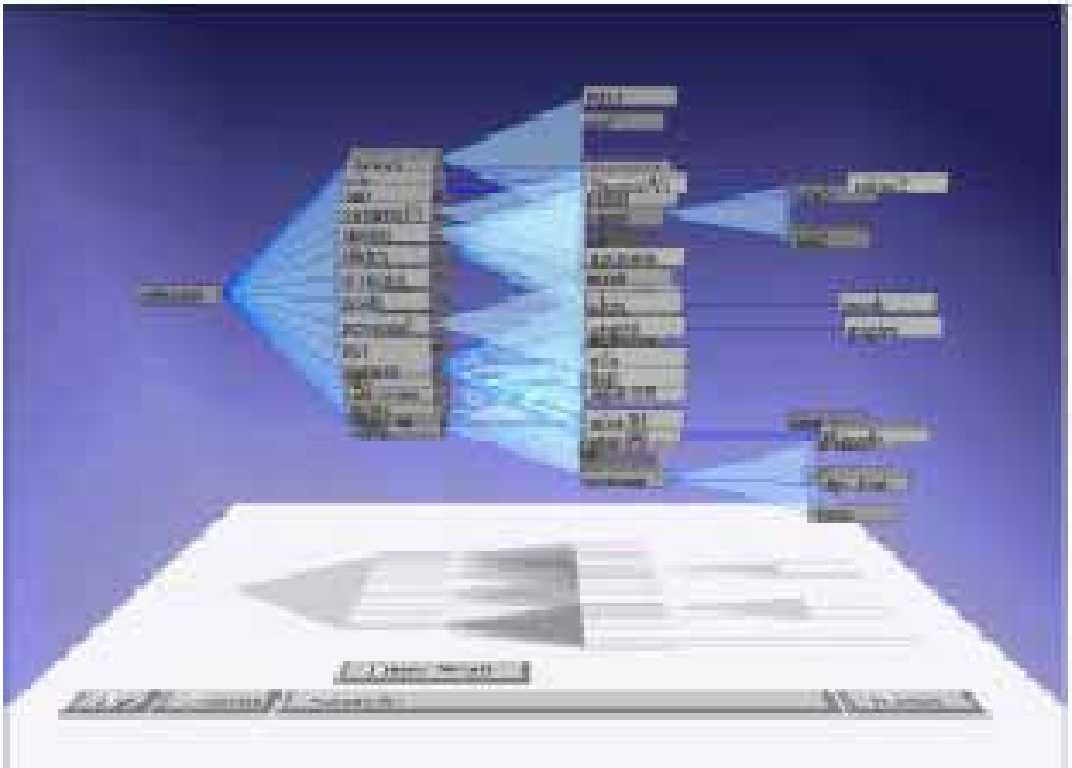


Figure 2.9 Cone Tree

Trees are commonly utilised to represent problems in the business arena for risk analyses, and marketing statistics, however they suffer a number of shortcomings. For moderately sized problems, the tree becomes unwieldy, and whilst a tree is suitable for visually representing qualitative relationships, it does not allow visual representation of quantitative information. Bordley (2002) suggests that colourisation may remedy this shortcoming. Nevertheless, a further disadvantage of the cone tree is the lack of screen filling symmetry that is assured with tree maps. Like tree maps, the entire collection of data is evident, but if a *presentation* is to be elegant and appeal to our sense of 'naturalness' as suggested by Tversky (cited in Gattis, 2001), it may be important to utilise the screen area effectively. Up to 50% of the viewing area of a cone tree may be vacant depending on the type of distribution of the 'nodes'. The area of the screen occupied by a cone tree increases with a reduction in the number of attributes being projected. For a natural presentation, the opposite would be expected. More space should not be devoted to an attribute just because there are comparatively few attributes to be projected in that particular presentation. The appearance of an attribute's value should be the same from one scene to the next. To emphasis Tufte's view on this matter, any variation in size should be the result only of a variation in the underlying value of the data, not the number of items to fit on the display. In terms of instant recognition, repeating patterns may be apparent by these overviews, but they would require a substantial amount of time for an audience to become familiar with their meaning and they are unlikely to be taken in at a glance.

2.3.6.5 Info Cube

An Info Cube is a similar concept to that of a Cone Tree except that the information to be accessed is arranged in transparent boxes. The density of similar associated structures determines the view through each box. Parts of the Info Cube may be entirely vacant indicating absence of data. So, whereas the screen might be fully deployed in presenting the data, the effect of blanks represents the same wasted space as evident with cone trees or other scale-less data visualisations.

The proximity of each internal box structure and its relative size to the collection is obvious but the orthogonal layout may be confusing to an audience that regards perspective as a primary queue to gauging relationships in space. Is depth and distance a relevant cue or is the impression of depth in the presentation structure simply an artefact that conveys no meaning to the audience? Would an audience need to be warned that apparently distant structures in the Cone Tree are not smaller or less relevant in terms of their attribute values? It is simply an arrangement that conveys no quantitative information.

2.3.6.6 Summary of Hierarchically Based Visualisation Forms

These forms are very useful tools for database exploration. They are particularly effective for demonstrating dependencies in data. Only Treemaps and Worlds-within-worlds facilitate quantitative presentations that help an audience contrast proportions that relate to discrete attributes. Less of a value does correspond to less visual information. Therefore ‘instant recognition’ should be facilitated in such presentations. However, the lack of facility to project zero values to an audience seriously hampers the usefulness of Schneiderman’s Treemap technique.

2.3.7 Icon Based

Icon based data visualisation is a potentially powerful technique for exploratory data analysis. Commonly called ‘Glyphs’, icons may have particular applicability for *presentation* due to the facility for texture to be recognised. The overall appearance of the icon changes according to the weights assigned to each attribute of the icon. Thus, the objects are given visual ‘identities’ unique for configurations of values that can be identified by the observer. Examining such icons may help to discover specific clusters of both simple relationships and interactions between data attributes.

Keim categorises the following as Icon based presentation methods:

- Chernoff Faces
- Colour Icons
- Shape Coding
- Stick Figures
- Tile Bars

Also, because of its significance to the Dvenn and Venn diagrams in general, Keim’s classification is augmented by the author with the addition of:

- InfoCrystal

A true icon should be just that, immediately and easily identified, a representation in short form of what carries meaning. Consider the universal appeal of the Olympic sport symbols. For Bertin’s immediacy of recognition, or what psychologists call pre-attentive processing (Triesman, 1986), icons represent the most likely visualisation method to explore for presentation.

2.3.7.1 Chernoff Faces

An interesting idea that attempts to exploit the ability that we have to recognise facial features by mapping attributes to characteristics of the human face (Figure 2.10) such as eyes, nose, mouth and shape of head.

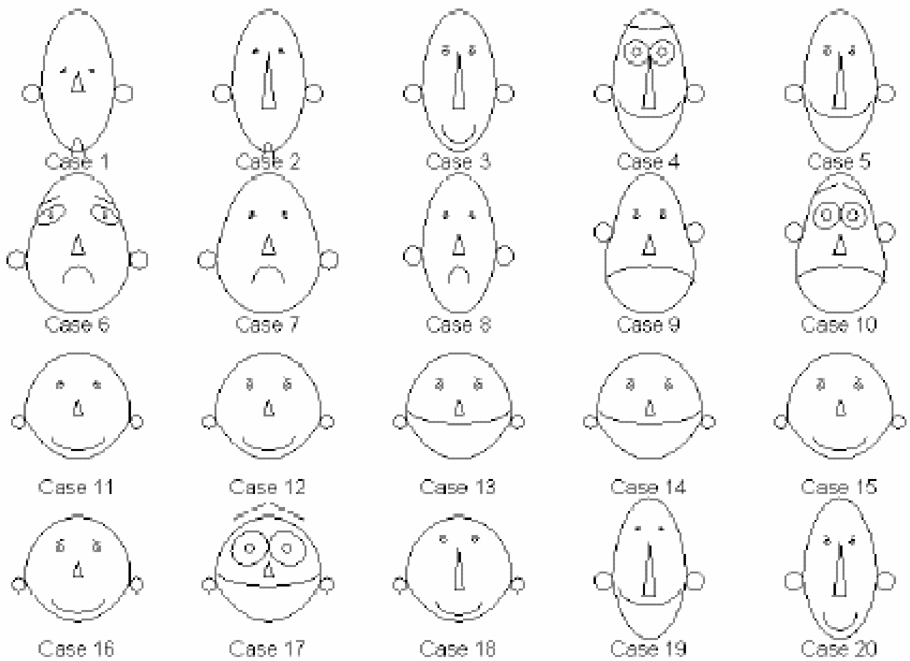


Figure 2.10 Chernoff Faces

Potentially this method breaks Bertin's rule that no more than 3 attributes may be recognised instantly. This is because the facility to comprehend the *expression* on a face conveys meaning, with immediacy, which represents more than 3 attributes. For example, if data were to be sorted to match the facial attributes (a frown when a composite of various sales indices are bad) then the ability of an audience to readily assimilate this message is very high. However this is not how Chernoff Faces are actually utilised. In the limited cases brought to light by the author where such faces have been used, it is apparent that the dimensions are not assigned purposefully to exploit facially transmitted emotions as, according to Marchette (1994), Chernoff had never intended them to be used in that manner. Rather, the face was to be used to show variance, one face from another, or clusters of similarity, a group of faces being similar compared to a different group of faces.

Not only are Chernoff Faces not mapped to represent data emotively, but they suffer from the fact that data assigned to facial features are not equally weighted by observers (Marchette, 1994). The size of the eyes is given more importance than the size of the nose. Therefore, in the absence of a reason to assign data to particular facial features, an audience may be inadvertently influenced by what they see. A particular pattern may be subliminally ‘distasteful’ when seen as a face, but the underlying data may be perfectly innocuous, it is simply a pattern.

Research now casts doubt on whether Chernoff faces are even pre-attentively recognised (Morris, Ebert & Rheingans, 1998). There must be a reason why such an apparently useful technique is used so infrequently. The limited research indicated above suggests no advantage in utilising Chernoff Faces for presentation, indeed, on balance it would appear to be a very unreliable visualisation technique for reaching as wide an audience as possible with the purpose of enabling them to collectively share the axioms of the presenter.

2.3.7.2 Colour Icons

This method consists of a technique similar to shape coding but the arrangement of the array is built in a pattern (spirals, axes or circle segments) from the screen centre cell. Instead of shapes, colours are utilised to represent the data attributes. Each data element is assigned to a pixel, the colour indicating the attribute.

In terms of revelation and data/ink ratio (Tufte, 1983), the pixel oriented techniques are perhaps the densest forms of non-scientific data visualisation. This may seem, paradoxically, the least likely selection for ‘instant’ recognition, however, the picture revealed by this method is not based on preconceived notions of spatial understanding such as that which appeals to landscape techniques. The pixel-oriented patterns are similar to the abstract Mandlebrot fractal patterns (Mandelbrot, 2003). They fascinate because, like good music, the form *is* the icon. A recent extension of Mandelbrot’s work has resulted in “Fractal foam”. This is a visualisation technique showing a view of groups of data with related attributes. A focus attribute is plotted as a large bubble with correlated attributes mapped around its perimeter. Colour, shape and orientation of each bubble depict statistical relationships.

Keim presents some examples of extraordinary data density, such as Figure 2.11 in which the segmented circle projects four trading years worth of data for the top one hundred listed companies on the Frankfurt stock exchange. This visually startling but uncommonly presented method illustrates that data visualisation techniques are evolving and may hold great promise for assisting an audience to make sense of large volumes of data. Indeed, an audience may become very good at distinguishing one pattern from another. No standard attribution of colour has yet been suggested, and an audience would need to be trained for each particular presenter's selection of colour to gauge which particular patterns are noteworthy.

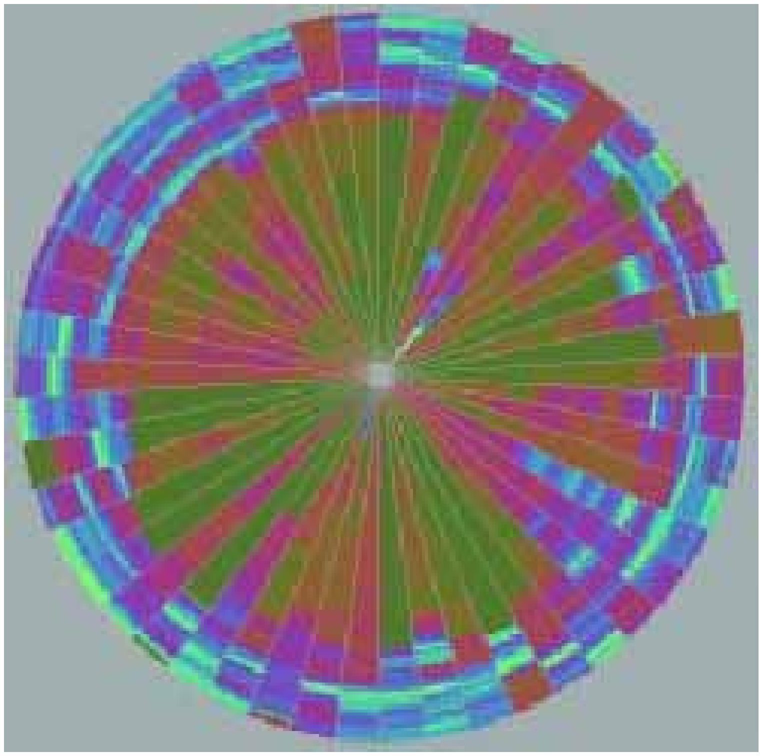


Figure 2.11 VizDB™ Representation of Stock Exchange Trading

Ultimately, the success of colour icons for *presentation* depends on the ability of the audience to accept that the otherwise aesthetically pleasing picture contains a relevant meaning. Identification of clusters may be self evident, but the overall comparative picture of two side-by-side visualisations may be confusing to an untrained observer. The product is commercially available as VisDB™. It remains to be seen whether analysts adopt the technique widely. Only after a body of experts refines the product further is there likelihood that it might be used for *presentation*.

2.3.7.3 Shape Coding

The method of shapes coding consists of generating patterns from shapes according to the attributes of the data. The shapes may consist of all manner of sizes and perimeters and are assigned to a particular cell unlike stick figures which are discussed next in section 2.3.7.5. The method Keim illustrates is generated by pairs of geometric histograms. The key feature of any technique to generate the shapes is that a starting point is selected from which a polygon is derived. The data attributes determine the size and complexity of the polygon.

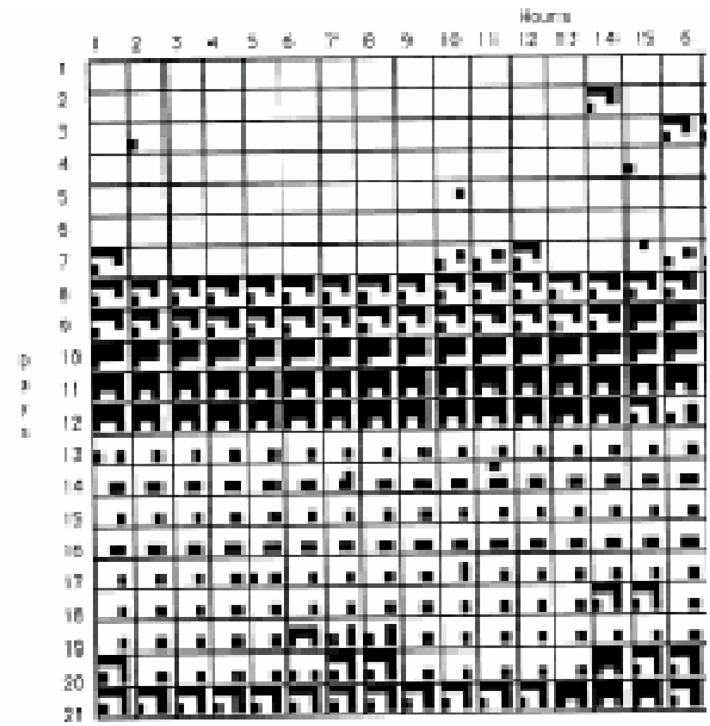


Figure 2.12 Shape Coding of Day by Hour for 13 attributes

(Beddow, 1990, p.98)

The two most important dimensions of the data are mapped to the x, y coordinates and the remaining dimensions are built row-wise from top left to bottom right forming a rectangle composed of N cells. The resultant chequered pattern, in Figure 2.12 for example, remains as a visual representation of the relationships in the data. The overall appearance is similar to stick figures which are discussed in section 2.3.7.5, but the texture is not as marked. The method is figurative, not just because it is visually complex but also because of the requirement for a legend to assign quantitative values to the attributes.

2.3.7.4 *Stick Figures*

Following the discussion of shape coding, stick figures represent a similarly arresting visual display of data. Rather than defining actual physical boundaries to contain the shape, stick figures radiate lines in representation of each data dimension. Two attributes of the data are mapped to x, y coordinates about which is built a figure from the remaining attributes. These ‘limbs’ are both angled and lengthened according to the values of each attribute. Up to thirty attributes can be accommodated in this fashion. Figure 2.13 presents a single stick figure element and Figure 2.14 a sequence of elements as a “family”.

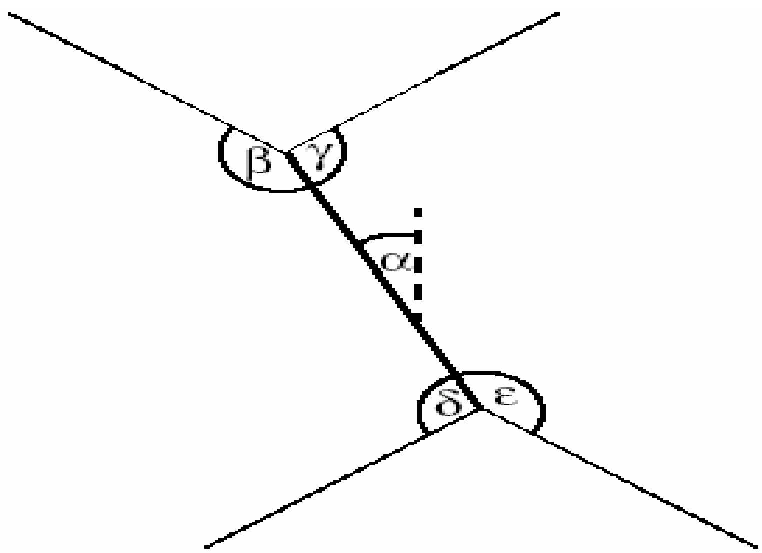


Figure 2.13 Close-up of a Single Stick Figure

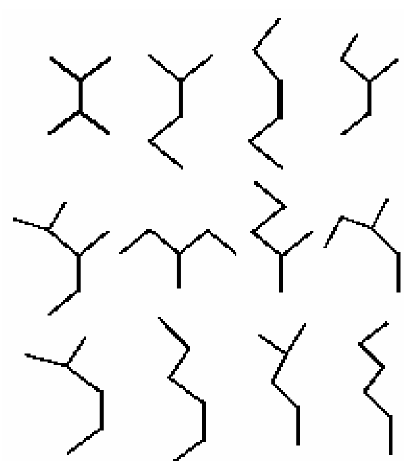


Figure 2.14 Family of Stick Figures

When a myriad of these figures is projected (Figure 2.15), the ability to discern texture is instant, however the interpretation of what the texture might mean requires careful selection of how each attribute is mapped and requires that the audience be instructed about the significant regions in the plot.

As the appearance of each stick figure changes according to how the selection of dimensions is performed, an audience can only recognise one stick figure family from another, in a comparative way, when there is a consistency of application. If the purpose of the presenter is to engage the audience and make a convincing presentation, there is no doubt that manipulating data attributes to show the most striking texture is a powerful technique to do so.

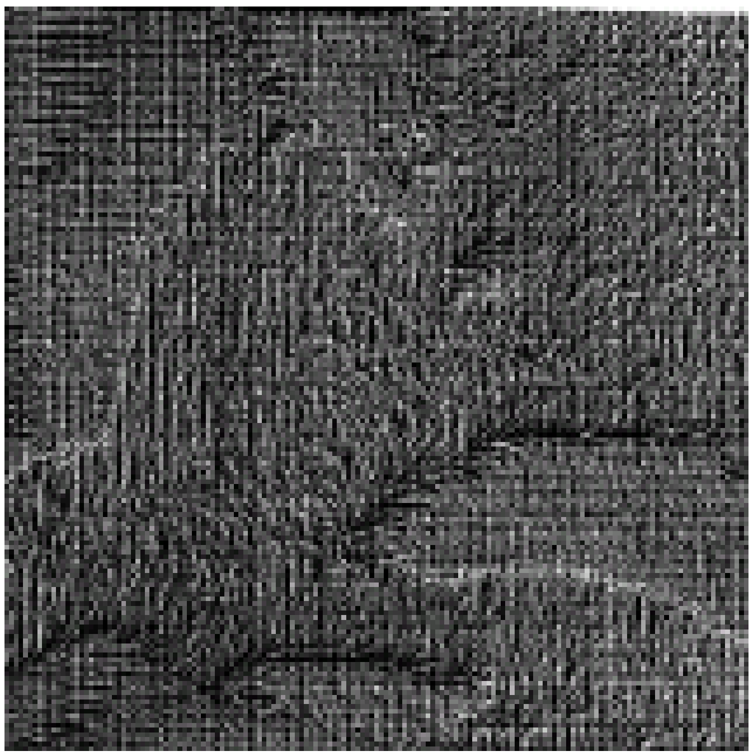


Figure 2.15 Stick Figure Visualisation of 5 Dimensions showing Texture

In terms of naturalness of the presentation, a first glance indicates that masses of stick figures mimic maps with striking physical features like dips, holes and peaks. Are these features a reflection of actual values? Is a pit or hole a representation of less? In the case of stick figures, there is no association between actual value and visual representation of that value. Depending on the collection of attributes chosen, a hole could mean a sensational sales season for a particular garment of a certain combination of size, style, fabric, manufacturer, colour and ``sales campaign. Therefore, the lack of consistent standards for recognisable features would suggest that an audience must completely trust the presenter to interpret those data that constitute a presentation.

2.3.7.5 Tile bars

Tile bars, whilst superficially similar to shape coding techniques, are very relevant to the justification of software proposed in this thesis. Hearst (1995) suggests the use of tile bars as a means of visualising document retrieval from a collection of items when utilising search terms. For representing the number of 'hits' garnered by an Internet search of a topic it would seem to be ideal. The concept consists of finding text matches and displaying them according to relevance and document length.

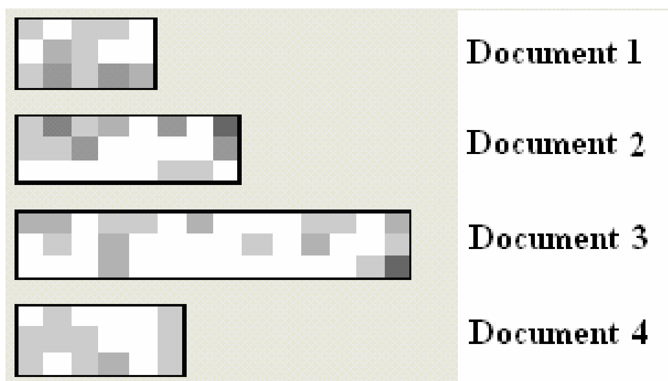


Figure 2.16 Tile Bars

The example of a Tile Bar query in Figure 2.16 illustrates that the document pool was searched yielding four relevant documents. The length of the bar represents the relative length of the document. The number of search terms, in this case three, is represented row-wise within each of the four horizontal bars. The frequency of matches of the search terms is illustrated column-wise by the greyscale. Black represents eight or more 'hits', white zero. Thus a visual comparison can be made of the relevance of the documents to the search criteria and *where* in the document the hit will be found (beginning, middle or end).

This method of visualisation is certainly iconic as an all black bar would be immediately and compellingly relevant, the example illustrating the concept rather than the sole application of the technique. However for the purpose of data presentation to an audience, the technique is unlikely to gain widespread acceptance due to the limitation of the number of dimensions that could usefully be projected.

2.3.8 InfoCrystal

Keim does not include InfoCrystal in his taxonomy as a visual data exploration technique but as a “dynamic filtering” technique (Keim, 1997, p84). Spoerri, the author of the technique, describes it as a visual tool for information retrieval (Spoerri, 1995). However, for the purpose of this thesis, the technique is an important consideration and therefore is included as a visualisation method in its own right. The rationale for the tool is to utilise Boolean operations to visually describe relevance in data rather than the actual data items themselves. However, as Keim includes Tile Bars as an iconic form of data visualisation, it seems reasonable to include InfoCrystal also. The problem, if there is one, consists of clarification of the term information and data. Spoerri claims that InfoCrystal visualises *information* and what Keim categorises are *data* visualisation tools. As discussed in 2.2.1, the term information visualisation and data visualisation are borne out of the differentiation of scientific versus non-scientific visualisation tools. In reality the use of such tools depends on the user of the tool.

What Spoerri defines as information retrieval is really a form of summarisation of data or summaries of relationships in those data. Indeed, such summarisation is typical of most forms of *presentation* based data visualisation. The essential point is that *data* are the basis for all methods of data visualisation as opposed to creative drawings or conceptual maps. The necessary prerequisite is that data enables data visualisations to be replicated consistently.

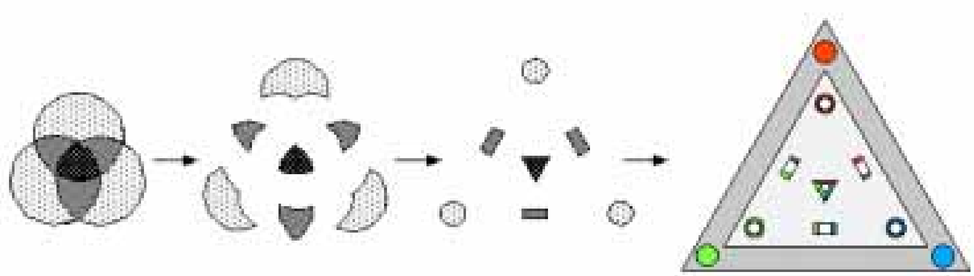


Figure 2.17 A Venn Diagram begets InfoCrystal

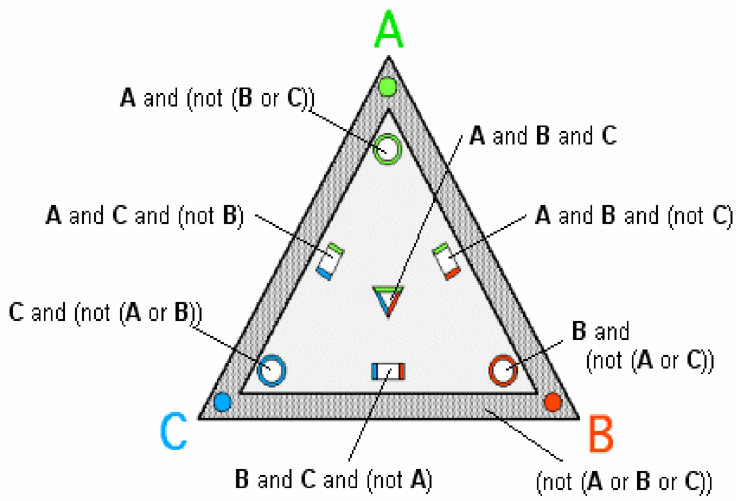


Figure 2.18 InfoCrystal and the Visualisation of Boolean Queries

(Spoerri, 1995)

The Venn diagram is an important cornerstone for understanding how the InfoCrystal functions and Figure 2.17 shows that the initial Venn diagram, borne of data, is manifested as a set of subordinate icons that focus the attention of the viewer upon the internal subsets of the Venn diagram. The visual representations of Boolean operations are illustrated in Figure 2.18. Spoerri states that Figure 2.18 represents all the potential queries of three inputs and Figure 2.19 represents four inputs. Venn diagrams are superimposed to highlight the spatial layout of the Boolean operators.

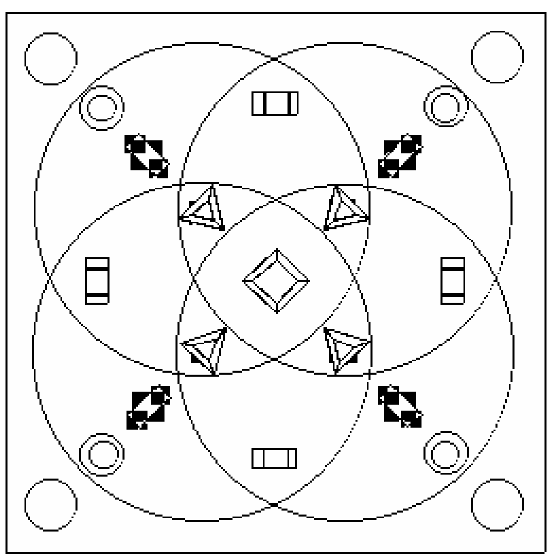


Figure 2.19 InfoCrystal with 4 Inputs

Once the patterns are established, higher density presentation may be made as shown in Figure 2.20. Here they illustrate the actual values for each of the Boolean operators (in this case, like the example for Tile Bars, the number of documents that match a certain search criteria).

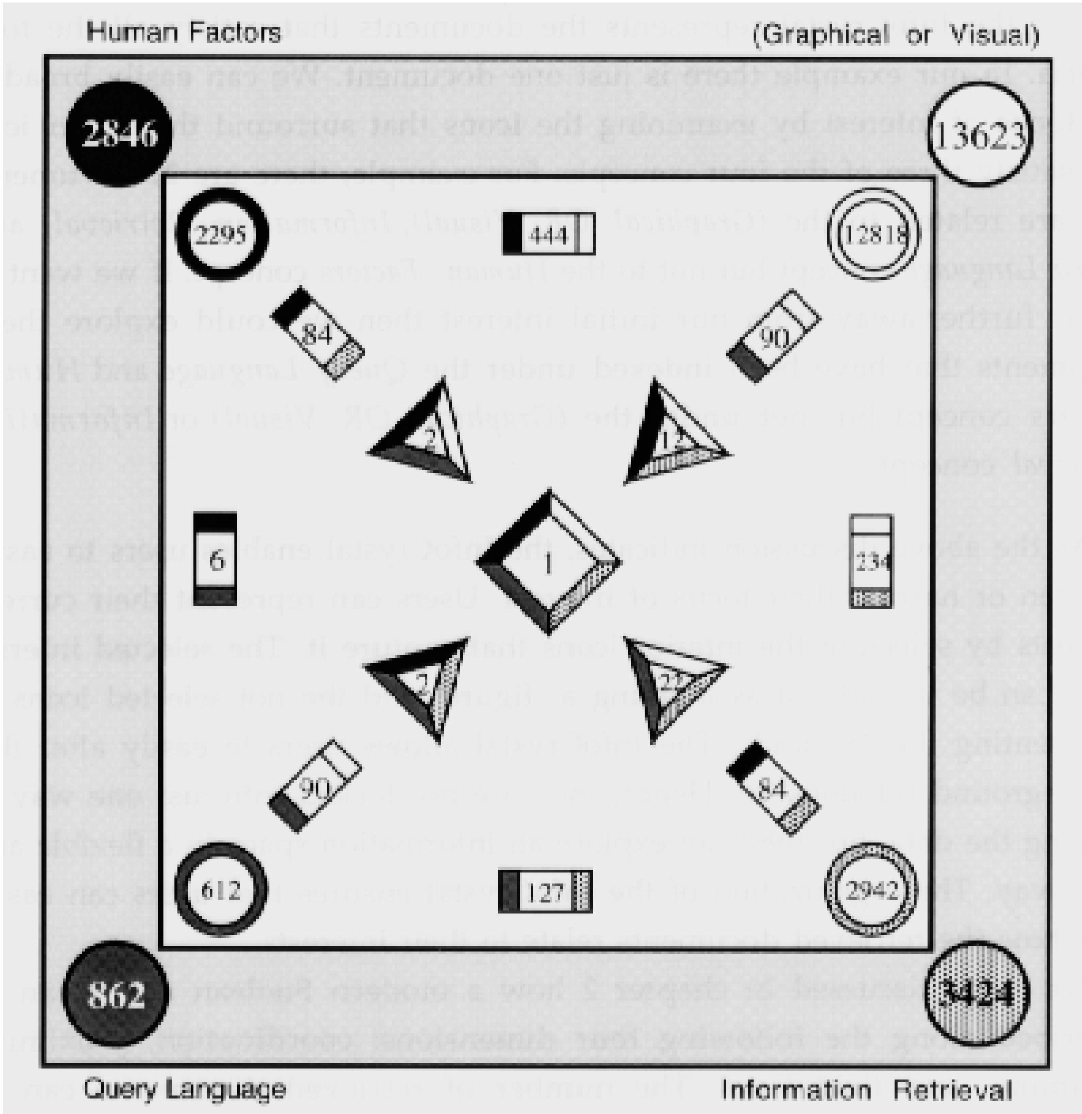


Figure 2.20 Inset of a Four Input InfoCrystal Showing Values

Extending the concept further, with even more inputs, iconic representations result, as in Figure 2.21, that resemble the pixel based iconic form in Figure 2.11.

An audience might assimilate a consistent message from the InfoCrystal only if particular distributions of information retrieved favour a symmetry that would enhance recognition of meaningful or recognisable patterns. It is not enough to know that two distributions are different, but that two distributions vary from each other in a meaningful way. Typically, an audience wants to compare and contrast data (Tufte, 1983).

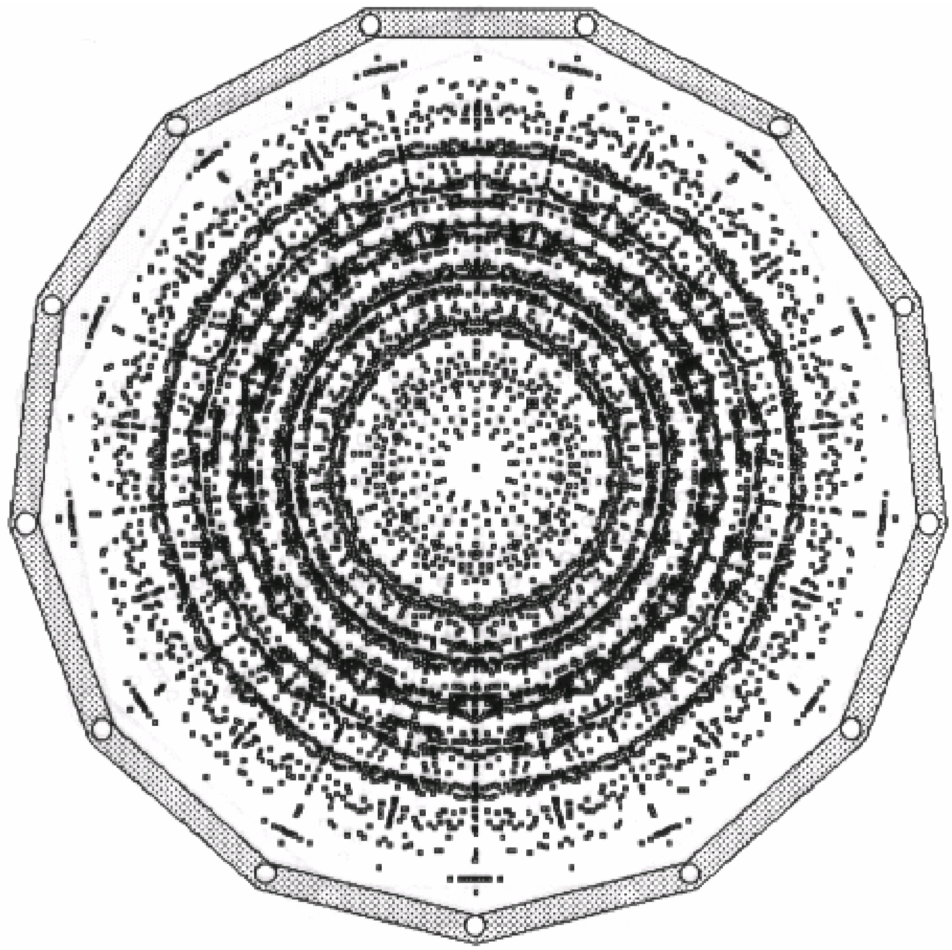


Figure 2.21 InfoCrystal with 13 Inputs

2.3.8.1 Summary of Icon Based Visualisation Forms

As is the case with Chernoff faces (section 2.3.7.2), the iconic forms of the InfoCrystal and Tilebars are not immediately relevant to the experience of the audience. Data relationships must be learned by an audience for them to gain revelation. Just as Chernoff faces do not exploit emotive values for the countenance of each face (good and bad data are not represented by a frown or smile respectively) the tools Tilebars and InfoCrystal contain no appeal to common forms of recognition from which an audience may draw any sense of significance without coaching. Nevertheless, they point the way to more natural representations of data.

2.4 Chapter Summary

The demonstration of the characteristics of current data visualisation types according to Keim's taxonomy indicates that the common utilisation of particular graphical types does not necessarily ensure their effectiveness. That is, data may be visualised in various ways, but who benefits from so many forms being available? Given the choice of so many potential visualisation types, particularly with the ubiquitous aid of personal computers, why are so few data visualisation forms presented to audiences? It appears to be the case that habits of design and graphical convention form the preference that presenters have for the selection of particular graphical tools they might choose to utilise. The author contends that there are fundamental reasons why the range of data visualisations selected for presentation purposes is so narrow, the foremost of these being the manner in which audiences process presentation data.

Before *understanding* occurs, data must be seen and processed by an audience. Bertin (1981) divided data visualisation into two forms, those that are an image and those that are figurative. By this assessment, figurative presentations require an audience to reason the value of data presented to them, they must work mentally to derive understanding. Those data presented as an image are understood implicitly. Values are conveyed instantly as a reflex. Therefore, those data visualisation forms defined by Keim as iconic suggest fertile ground for investigation. However, there are no existing standards for what the iconic forms represent. What shape or colour consistently means the same thing to an audience? It is the presenter who decides the value of an icon. This is as unsatisfactory as a presenter needing to define to an audience all the words to be used in a presentation.

So what characteristics of data visualisation are universally acceptable? Surely any presentation that utilises data visualisations that can be unambiguously understood without training constitutes a valuable contribution to Information Science. By concentrating on the characteristics of human perception, the selection of improved data visualisation tools might be possible. So, learning from the features of data visualisation as classified by Keim in this chapter, and, considering the contribution of Bertin (1981) to how data visualisation might be made more effective, the primary emphasis of the research presented in this thesis is to find a way to exploit the most effective method of harnessing visual numeracy.

Chapter 3

VISUAL NUMERACY

3.1 Visual Numeracy

3.1.1 Introduction

The previous section demonstrated that there are many ways to present data visually. What remains to be confirmed is that there is a compelling reason to utilise a visually numerate pathway to enhance understanding or sense-making. What follows is a discussion of how visualisation of data is likely to be more than simply *reading* a graph off a page. Appealing to an analogy of literacy, reading is a comprehensive process, learned over a long period of time. Each letter and each word must be understood in context to impart the meaning of a sentence. Do we learn to read graphs as if they were sentences, each element being analogous to a word?

Diagrams or pictures probably rank among the oldest forms of permanent human communication. They are not only used for representation but can also be used to carry out certain types of reasoning (Shin, 2003). Starting from a primitive or nascent level, the review of research presented herein attempts to explore briefly the preference that humans have for pattern recognition as a graphical explanation of quantitative data. In particular it attempts to establish a neurological explanation for visual numeracy as a capability that is not learned, but present during every person's development. The following quotation illustrates the universal nature of this faculty.

> *An examination of graphics produced by children and adults from many cultures reveals common underlying cognitive*

> *principles in the use of space and the elements in it to convey meaning. (Tversky, 1998, p12*

Consider the strong emphasis placed on mathematical ability during primary and secondary education. Numeracy skills are considered mandatory to prepare students for the workforce. However, rather than business presentations reflecting an increasingly numerate audience, there is anecdotal evidence to suggest that business presentations avoid numeric reasoning. Instead, simple charts are used to convey much of what could be summarised in tabular form. Such charts are often uni-dimensional and convey little information. From this observation one can only conclude that either educational numeracy is failing or audiences prefer to comprehend numeric data visually.

As the use of data visualisation for *presentation* is the focus of this thesis, particular emphasis is placed upon the reasons behind the preference of presenters for simple charts, and particularly pie charts, in an ‘information rich’ but ‘attention poor’ business environment. Is this a neurological consideration? What makes the visual processing of pie charts relatively easy for an audience?

3.1.2 What is Visual Numeracy?

The term “visual numeracy” is herein used to define the faculty that people have for visually recognising proportion. The term is specifically used in the Vocational Education and Training sector to benchmark the ability to map read and interpret graphs and is distinct from areas of mathematical, geometric and measurement competency. In primary education (NSW Department of Education) it is a term used to define a level of emerging mathematical competence. Venn diagrams feature specifically in this part of the educational program.

So why consider visual numeracy, is this not just numeracy? Is it possible to reason mathematically with our eyes alone? Dehaene (1997) certainly thinks that there is a primitive number sense in both humans and animals. To accept that visual numeracy is a faculty, and that it is different from other cognitive processes, a brief review of cognitive processes and how these differ from perceptual processes is required. However, for the purpose of this thesis, it is not possible to provide a definitive account of what constitute cognitive and perceptual processes as they have specific meaning according to particular disciplines. In the case of

Psychology, Day (2004) cites a literal translation of “cognos” to know and perception to “see”, whereas Benjafield (1997) devotes a third of a book titled “Cognition” to the coverage of perception and Hoffman (1998) eruditely undermines even the simplest distinction of perception and cognition. Whatever the case, these terms are commonly used in discussions of data visualisation, as evidenced by Chow & Ruskey, who considers that:

> *Area-proportional Venn and Euler diagrams have an advantage over traditional diagrams because they leverage both an individual's perceptual and cognitive abilities.*
>
> *(Chow & Ruskey, 2003, p10)*

Chow and Ruskey offer no further differentiation or explanation of what these perceptual and cognitive abilities are or how they might differ from each other. Suffice to say, Chow and Ruskey use the terms authoritatively for an audience versed in combinatorial optimisation.

Taking the simple definition of Day (2004), cognitive processes involve knowing (cognos) or sense-making and perceptual processes involve signal acquisition. However, the evidence of perceptual illusions is not easily explained as simply errors of perception, rather they also involve errors of cognition. Though no specific mention is made by Day of “cognitive illusions”, problems involving syllogistic reasoning might be good candidates, whereby we may determine an illusion to exist, based on a deductive process, rather than simply rely on what we see. Section 3.4.2 is devoted to the problem in detail, as, in definitional terms, it is the exception that makes the rule.

For the purpose of this thesis it may be sufficient to argue that there are no hard and fast rules about perception and cognition, rather definitions serve to fulfil the requirements of particular disciplines. However, perception is used herein to loosely encompass recognition of patterns or meaning from a presentation of data in less than 250 milliseconds. This definition freely agrees with Bertin who talked of ‘instant’ recognition as that being defined as a ‘retinal image’. The 250 millisecond timing is also highly relevant to the discussion of pre-attentive recognition that appears in section 3.3 in support of the discussion of animation. Also, the use of a metric, in this case time, even if arbitrary, helps distinguish *recognition* from *understanding* in a way that a distinction between perception and cognition cannot be made because of the problem of their definition being specific to particular fields of study (see Appendix II). Perception is not widely agreed to be defined just by time. Therefore the term recognition is used herein to be defined by elapsed time and this is consistent with usage of the term by Triesman (1986). Consider that an image may be recognised instantly, but it may not be understood; as for instance, a foreign word containing characters that are known and even pronounceable conveys no meaning[17].

3.1.2.1 A Quick Mental Note

To try and define visual numeracy with respect to why it is suggested as an under-utilised pathway to improved sense-making necessitates a brief discussion of models or representations of mental function. How is information actually understood? To make any progress with a question of such enormous scope requires a very narrow path to be navigated through the topic. The journey starts with human behaviour generally, thence to the notions of learning and *understanding* or sense-making. In historical terms, from the perspective of western philosophy, there is a fundamental dichotomy that informs any attempt to understand human behaviour. Initially a person was characterised by their brain being the centre of reasoning, with emotion being centred in their heart. This satisfied inquiring minds who sought to understand how higher level learned behaviours and lower level unlearned emotional behaviour co-existed in an individual. With advances in medicine, the physiology of the brain has become better understood, the importance of the heart being relegated to it being no more than a pump. However, obvious physical structures in the brain like the separation of the brain into two hemispheres required explanation. It is interesting to note that the shift from the heart to the brain as the centre for emotion required a part of the brain to be nominated for emotion to reside within and the dichotomy continued. Contemporary models of human learning now move away from the stark but popular representation of *left hemisphere versus right hemisphere* of the brain that started in the early 20th century. Not surprisingly, this theory suggested that each hemisphere was the repository of intellect and emotion respectively (Sperry and Trevarthen, 1990).

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[17] A demonstration of this can be made by presenting the word *piw*. The word can be recognised as a word, yet not only does it not convey any meaning but it also cannot be pronounced. Yet we instantly recognise it as a word, or, perhaps more correctly, as a *possible* word rather than a random sequence of letters.

Herrmann (1989) suggests a model that is an extension of the ‘right brain, left brain’ concept, one which proposed that an individual’s way of looking at the world was strongly influenced by the dominant side of her/his brain. ‘Right brain’ people take a holistic, broad-brush view in which the ‘whole’ dominates individual components. ‘Left brain’ people focus on specific elements and are less likely to see the total picture. A common analogy for this model is that of the forest – left brain people see the trees, and right brain people see the forest. So there is no longer a dichotomy of emotion and intellect, sense-making is now based on characteristics that are either specific of general. Not surprisingly, a definition of sense-making that is more loosely defined than that which described emotion and intellect opens up the possibility of models with more components. McLean’s triune model that accounts for a primitive, intermediate and rational brain is further enhanced by Herrmann (1989), who divides the brain further into notional quadrants, not based on physical brain structures; that are referred to as Upper and Lower Left and Upper and Lower Right. Herrmann's model indicates that the dominance of a particular quadrant of an individual’s brain impacts significantly upon the way in which the individual prefers to learn. The assumption being made is that, independent of knowledge of the physical structures of the brain, how the brain actually works has a direct and significant influence upon the way people process information. According to Herrmann, most people demonstrate clear preferences in learning style, depending on their dominant quadrant. That is not to say that Herrmann suggests that each individual has a sole quadrant, as most people learn by a combination of quadrants, but Herrmann contends that one quadrant is usually clearly dominant.

Problem Solver Mathematical Technical	Concentualiser Artistic
Planner Conservative	Talker Emotional

Figure 3.1 Hermann Brain Dominance Quadrant (abridged)

Figure 3.1 indicates the factors from each quadrant that influence the preferred learning style of an individual. Herrmann's (1989) research suggested that 60% of the population would demonstrate elements from two quadrants, described as 'double dominant'. A further 30% are likely to be triple dominant, with 7% single dominant and 3% showing characteristics from all four quadrants. Herrman has been cited here to indicate the sophistication that has been applied to models of how the brain acquires information, and how categories of learning have been deduced that are independent of brain structure.

Whereas the attempt to categorise and enumerate the various ways that people learn is to be lauded, the question remains; what does all this mean to a non specialist? How many possible models are there of how the brain functions to acquire and represent information? Is there a correspondence between physical brain structures and learning processes? It would seem that the definition of behaviour, learning and brain function is very fluid and that there exists no current multi-disciplinary consensus about which models are most accurate.[18] Indeed, one model proposes that each hemisphere is defined as being functionally interdependent (Kringelbach and Rolls, 2004; Ornstein, 1986), so that a physical separation exists between hemispheres of the brain but the physical differentiation does not translate into functional differences. No evidence of a dichotomy here. However, there are compelling reasons to believe that structure does dictate function. Less complex animals have smaller brains and they omit certain structures that are present in more complex animals. There are no brain structures that less complex animals have that are not also possessed by complex animals. So, more complex animals have extra structures. Such an observation has led some researchers to suggest an "archaic/rational" model based on the dichotomy occurring between brain stem (primitive) and cortex (advanced) as suggested by Gardner (1999). Such a model acknowledges that the brain evolved from primitive structures that are still with us rather than those older structures being *replaced* by newer more evolved structures. So the dichotomy is

[18] Such a discussion begs the question of what constitute thoughts and where and on what structures these may be actually located in the brain. Presently no amount of MRI scans can answer this question or pinpoint a particular thought. Compared to other advances in the understanding of human physiology, the brain seems to be very poorly understood.

back, emotional behaviour is seated structurally in the primitive brain stem and rational behaviour is seated in the cortex.

Whatever the actual validity of any particular model might be, the author adopts the “archaic/rational” model and contends that the *structure* of the brain affects the way information is acquired and that this has a direct bearing on the definition of visual numeracy. If visual numeracy is a primitive attribute of our cognitive development, residing in the archaic brainstem, then it is likely to be reflexive and a faculty less subject to the influences of learning style. If visual numeracy is an advanced faculty then it is likely to be part of the advanced structures of the brain that facilitate speech and rational thinking. In such a case, for the study of data visualisation, visual numeracy does not necessarily warrant special attention above that for any other symbolic representation of information. However, Dehaene cites compelling evidence of a primitive ‘number sense’ and, whilst not stating categorically that it resides in the archaic structures of the brain (see Appendix III), Dehaene suggests that it is evident in small brained animals such as birds and even fish. Therefore visual numeracy may be understood to confer a survival advantage to animals. For these animals the instant recognition of proportions and significant patterns in the environment relate to food supply and safety. We share these fundamental and primitive neurological attributes.

There are other clues that visual numeracy describes a primitive faculty that requires no specific training for it to be utilised. Of particular note is the observation that appreciation of proportions and area emerge early in childhood development (Piaget, 1952). Such an emergence pre-dates symbolic or linguistic understanding, indicating that it is, indeed, a primitive faculty. From Piaget’s work it is also interesting to note that children prefer to draw circles rather than boxes. This may be a maturational problem with motor skill development, whereby circles require less hand control than boxes, or it may indicate a reflection of the order of establishment of competent shape recognition. In the latter case, primacy of circle recognition is indicated. The early recognition of proportions in circles (Piaget, 1952), may be speculatively attributed to the reliance of primitive cultures upon the waxing and waning of the moon for timekeeping, rather than the sun. The only putative explanation offered by the author for such speculation is that shapes are easier to remember or communicate to others than complete number systems. In the case of organising a rendezvous, to say “meet back here when the moon is full” is easier to remember, and monitor progress of, than “meet back here in twenty-three days time”. The latter case requires not only a number system, but that at least one member of each party can in fact count! Further, several existing primitive languages count “one”, “two” and “many” rather than even the most obvious ten integers[19]. For them, a meeting in twenty-three days time would not be able to be conveyed numerically. Therefore, in the absence of adequate numerals, reliance must be placed on shape and pattern recognition to communicate the passing of time. A short duration may rely on the length of shadows; communication of a longer duration would appeal to the shape and position of heavenly bodies. The definition of the proportions quarter, half and three quarters is all that is required to gauge the passing of time to determine accurately the passage of a lunar month.

However, making ‘sense’ of information requires more than good visual acuity that depends on the speed of replenishment of chemical transmitters in the eye and the synaptic speed of the neurones linking the eye to the brain. Certainly learning and the acquisition of new information are constrained by the way such information is physically signalled (recognised), but what of the filtering, processing and subtle biases that are applied to the physical acquisition of a signal to render it meaningful (understanding)? How is ‘attention’ actually focussed amongst the plethora of signals? One model offered to comprehend this interaction suggests that ‘understanding’ or ‘sense-making’ is derived from the interaction of what Gardner (1997) established and subsequently revised (Gardner, 1999) as “multiple intelligences”.

3.1.2.2 Gardner’s ‘Multiple Intelligence’ Model

Gardner's model of ‘multiple intelligences’ has been widely cited, including within the field of number theory in education (Becker, 2003, Smith, 2002) but the particular significance of the model for defining visual numeracy lies in its catering for the broad spectrum of giftedness in

[19] Page 93 of Dehaene (1997) mentions the number system of the Walpiri aborigines of Australia who use the number words “one”, “two”, “some” and “many” to represent all possibilities for communication that involves transmission of quantities. This is just one example of “one”, “two” and “many” number systems. These counting systems are relatively common.

students. Giftedness is discussed here as this infers something more than just the quality of education bearing upon the maturation of a student, it suggests that there are latent predispositions to acquire and evaluate information. In Gardner's view, each individual's potential can be seen in terms of a combination of these intelligences[20]:

- verbal-linguistic
- logical-mathematical
- musical-rhythmical
- bodily-kinaesthetic
- interpersonal
- intrapersonal
- visual-spatial
- naturalist
- spiritual

The last two mentioned have been added as a result of Gardner's later work, and have not been researched as thoroughly as the original seven. What is significant is that these intelligences are suggested to vary both amongst individuals and within the individual. The interaction of the relative strengths and weaknesses for each intelligence represents a statement of the individuals' capabilities. In the Tasmanian State Education system, Gardner's work has been used to develop a concrete statement about student capabilities as outlined in brief below:

> *The personal capability comprises elements of the verbal-linguistic, intra-personal and interpersonal intelligences. A student who is gifted in the personal capability will demonstrate advanced skills in his/her understanding of self and others.*
>
> *The linguistic capability has elements of the naturalist, visual-spatial and verbal-linguistic intelligences, and supports the acquisition and conveyance of meaning across a wide range of human endeavours. A student strong in this capability will read widely and have highly developed skills in presenting information.*

[20] See the section relating to Multiple Intelligences in Appendix II for further definition.

The rational capability contains aspects of the naturalist, visual-spatial and logical-mathematical intelligences, and is evidenced in the skills to understand and relate to abstraction, physical reality and the natural world. Students with strengths in this capability will demonstrate powers of critical reasoning and will apply logical processes to explore ideas, feelings and actions. They are likely to have well-developed mathematical skills and be competent problem-solvers.

To complete the definition of visual numeracy and suggest its importance in relation to how meaning is inferred from what is seen, the author concludes that reliance upon, and utilisation of, the visual-spatial intelligence suggested by Gardner meet both the linguistic and rational capabilities that define ways of making sense from information. Therefore visual numeracy may be suggested to have a direct impact on sense-making by informing higher level processes that constitute the capabilities that are characterised by strong utilisation of visual-spatial intelligence.

The author suggests that Gardner's contribution is important, because it tries to place the way intelligence is described in a context that suggests that we are all capable of utilising talent, or giftedness, to evaluate and infer meaning from the world around us. As Gardner states:

In the heyday of the psychometric and behaviorist eras, it was generally believed that intelligence was a single entity that was inherited; and that human beings - initially a blank slate - could be trained to learn anything, provided that it was presented in an appropriate way. Nowadays an increasing number of researchers believe precisely the opposite; that there exists a multitude of intelligences, quite independent of each other; that each intelligence has its own strengths and constraints; that the mind is far from unencumbered at birth; and that it is unexpectedly difficult to teach things that go against early 'naive' theories that challenge the natural lines of force within an intelligence and its matching domains. (Gardner 1999, pp xxiii)

Therefore, visual numeracy may be seen to exist within Gardner's visual-spatial intelligence and it is not viewed as a sole pathway to understanding, but one of many pathways. It may be sharper for some than others, but we all have the propensity to visual data.

In summary, data visualisation presentations for business audiences may benefit from being tailored to stimulate an alternative, primitive, non-symbolic faculty to understanding; herein defined as "visual numeracy". Such a faculty may be inferred to reside in the primitive structures of the brain and therefore be shared by everyone and available for utilisation without formal training. However, according to Gardner's model of multiple intelligences, visual numeracy may also underpin the linguistic and rational capabilities of an individual who favours the visual-spatial intelligence. Therefore, a middle ground between a behaviourist view and a constructivist view of development might be that visual numeracy exists for all of us, but that how selectively it is utilises depends on the mix of intelligent behaviour that develops over time. What makes the application of visual numeracy such a powerful faculty for those who choose to tune in to it is the speed with which proportions are identified. The speed of recognition of visual proportions is faster than the time taken to calculate a result based on mathematical representations of the same proportions. Simple examples include questions such as "which is larger?" relating to two shapes compared to two numbers. Ordinal shapes are identified faster than ordinal numerals, even though shapes vary in representation and may be novel, whereas numerals are very familiar.

3.1.3 Pre-Attentive and Post-Attentive Recognition

In the field of psychology, the term 'pre-attentive', originally defined by Triesman (1986) in a seminal work, is still used to describe fast and accurate detection of a target pattern in a distractive field. Such detection occurs before time has elapsed for focussed attention to form. Typically, recognition of patterns in multi-element displays in less than 250 milliseconds is considered pre-attentive because eye movements take at least 200 milliseconds to initiate (Healey, 2003). Pre-attention describes the same visual acuity that is required by Bertin's definition of how an "image" is recognised (Bertin, 1983).

A simple example of a pre-attentive task is the detection of a red circle in a group of blue circles (Appendix IV). A viewer can tell at a glance whether the target is present or absent (Healey, 2003) However, only a serial scan can detect a red circle in a group of red squares and blue circles. In this case, finding the target is not pre-attentive. Further, Healey suggests, on the balance of the literature he surveyed, that recognition of patterns does not benefit from prior exposure to the target. That is to say, we distinguish patterns from what we see rather than what we have seen. There is reason to believe that we may be influenced by first impressions, and the evidence he presents is compelling, but these first impressions do not appear to aid *accurate* future identification of the same target.

The author suggests that visual numeracy is a pre-attentive faculty and that this contention is further supported by consideration of the time taken to recognise an "image" as defined by Bertin. Whereas an "image" is defined by Bertin only by its immediacy, Dehaene (1997) meticulously quantifies the nature of the "distance effect" based on neuro-physical experimentation:

> *At around 50 milliseconds, then, a mosaic of specialized visual areas recognizes the shape of numerical symbols. At that point, however, the brain has not yet recovered their meaning. It is only around 190 milliseconds that one sees a first indication that numerical quantity is being encoded. The distance effect suddenly emerges…(Dehaene, 1997: p226)*

And further that this

> *… distance effect, a fundamental characteristic of number processing in the human brain, is not a property that holds of most digital computers. Are there any other types of machines for which a distance effect comes about spontaneously. The answer is yes. Almost any analog machine can model the distance effect. Consider the simplest of them: a pair of scales. Place a one-pound weight on the left and place and a nine-pound weight on the right… the scales immediately tip to the right, indicating that 9 is larger than 1. Now replace the nine pounds with two pounds… The scales move to the right side after a greater length of time. Hence scales, just like brains, find it more difficult to compare 2 and 1 than 9 and 1. Indeed, the time that it takes for the scales to tip over is inversely proportional to the square root of the difference in weight. (Dehaene, 1997: p227)*

So, incorporating Dehaene's "distance effect" occurring as it does under 250 milliseconds, further describes visual numeracy as being based on primitive neurological structures that predate the evolution of structures in the brain used for linguistic or rational thinking. Therefore it is suggested to be pre-attentive, intuitive and non symbolic. These features of visual numeracy have an important impact upon the way that information is acquired and the ease by which ‘sense-making’ occurs. Such an understanding is imperative for the improved design of data presentation formats.

3.1.4 Data Visualisation and Pre-Attentive Recognition

In the scheme of human communication, presentation graphics are relatively recent inventions, the first western forms being attributed to Thomas Playford in 1776 by Tufte (1983). The evolution of the humble business graph from that point on has tended toward invention and complexity, as they have become increasingly more common since the late 18th century. However, for business presentations, the trend has been towards very simple bar charts, line charts and pie charts that are now very popular for reporting information to shareholders. It may be argued that the benchmark for graphical presentations lags far behind the potential of hardware and software to deliver new standards of visual excellence. The preference for simplification seems to be particularly evident in *presentation* graphics. Does the capacity of an audience to *understand* drive this simplification, or is it intuitively recognised by the presenters of messages that more effective dissemination of their message results from presentations that stimulate the intrinsically visually numerate pathway?

What has been demonstrated is that humans are adept at visually differentiating proportions by contrasting colours and/or shapes without recourse to higher intellectual processes. To discern that one enclosed shape is significantly larger than another is an easy task. Some of the methods to assist data visualisation presentations that were reviewed from Keim’s taxonomy may exploit this faculty, but such exploitation is not deliberate. The underlying design principle, if there is one, of the data visualisation methods presented by Keim, is not concerned with the enhancement of understanding from the perspective of an audience. Rather, the perspective of the presenter is the main focus, and indeed, from the viewpoint of exploratory data analysis, this is entirely logical.

Based upon an analysis of the iconic forms of data visualisation presented in Keim’s taxonomy, it can be established that they failed to demonstrate wide applicability for data visualisation presentation. In each case, the utilisation of shape and colour did not have the required universal quantitative attributes of *more* or *less*, they reveal poor congruence. An audience would need to be coached towards understanding the rules of interpretation that would be required to establish significant relationships in those data displayed by the presenter. Certainly, there are many instances where de facto standards exist for colour coding, as is evidenced by the utilisation of red for high temperatures and blue for cold temperatures in many meteorological data visualisations. However, red and blue carry many cultural intonations; these attributes for temperature may not be universally intuitive. Also, what should green or yellow represent quantitatively, and which green or yellow? Good reference material now exists for a standardised presentation of colour, for example the ISCC-NBS method of designating colours (see Appendix I) means that the accurate reproduction of colour in different presentation media, particularly computer display screens, should no longer a problem.

To find a universal presentation tool requires that it bestow data to an audience in a “self evident” form. Dehaene (1997, p180) suggests we have a “pure intuition” of numerical quantities. By stating this, he supports Gardner’s (1999) view that we are inherently gifted with respect to certain intelligences. We have a powerful unlearned ability to compare and contrast proportions and quantities. Therefore, that tool must be simple, intuitive, scalable and capable of consistent rendering; that is, the output must always reflect significant relationships in data in the same way. For icons, only their *size* is a universally accepted attribute for conveying comparative quantitative values in a data visualisation presentation.

Reflecting on Keim’s taxonomy, the InfoCrystal is particularly interesting for the purpose of this research because it does display the ability to consistently render data. However, no ability to convey quantity is present other than through numerals, and, as has been discussed, understanding derived from numerals is based on a learned, rational post-attentive comprehension. Therefore there is a need for new forms of data visualisation for *presentation* to be investigated.

3.2 Why a Venn Diagram?

3.2.1 Introduction

Having established, through adoption of Keim’s taxonomy, that many excellent forms of data visualisation exist for a variety of applications, the proposal of yet another form must be satisfactorily justified. In particular, what does a Venn diagram really offer for *presentation*? Indeed, in light of some sensible design guidelines cited in section 2.3.4-2.3.8, and the consensual abhorrence of pie charts (Cleveland, 1994; Tufte, 1983), Venn diagrams may be considered a distinctly inferior selection. If a simple Venn diagram were considered structurally similar to a pie chart, it too would be characterised by a poor data-ink ratio. Therefore, it might seem imprudent to suggest that a Venn diagram could be seen as a serious contender for a place in the toolkit of those who need to display data visualisations to a business audience, particularly if it is considered to be a form of pie chart. One critic takes specific issue with pie charts:

> *We are flooded with them every day in the newspapers, annual reports and even advertisements. The area of the circle is a poor way of comparing simple quantities because it is impossible for the eye to understand the relationship of the diameter of the circle to the area of the circle*
>
> *(Wurman, 1989, p54)*

Indeed, such was the published weight of opinion against pie charts that the author made a simple test of the competency of audiences to distinguish the visual relationship between the diameter of a circle and the area of a circle. The results of these simple tests are presented in chapter 4 and they indicate that it is certainly not *impossible* for the eye to understand the relationship. Also, Venn diagrams appeal to a broad range of potential uses, and, as demonstrated by the InfoCrystal and US patent number 5,136,530, the conceptual possibilities of a Venn Diagram still excite interest. As one Venn researcher and enthusiast notes:

> *One of the joys of working with Venn diagrams is that there have been simple delights still to be uncovered that can be appreciated by the … wider audience*
>
> *(Edwards, 2004, p.xv).*

3.2.2 Definition of a Venn Diagram

The term Venn Diagram is used to encompass a particular form of the generic Set diagram that includes the earlier Euler diagrams, which do not include shaded non sets, and Ballantyne diagrams, which include annotations of the number of items in each set (Harris, 1999). In the words of the John Venn the originator:

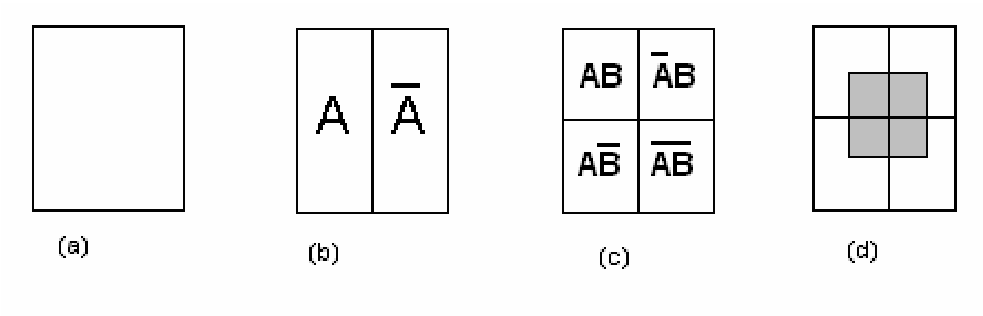
All that we have to do is to draw our figures, say circles, so that each successive one which we introduce shall intersect once, and once only, all the subdivisions already existing, and we then have what may be called a general framework indicating every possible combination producible by the given class terms.

Venn 1880, cited in (Edwards, 2004) p5)

There is no imperative that a Venn diagram be constructed of curved lines, only that the figure "shall intersect once…all the subdivisions already existing". Harris (1999) suggests that a Conceptual diagram (quadrant) and Venn diagram are two of the same. Lewis Carroll suggested such a diagram in 1896.

Figure 3.2 Rectangular Venn Diagram or Carroll Diagram

Carroll's system supersedes Venn's in that the complements of sets are explicitly represented



as regions of the diagram, rather than being left as the background region against which the circles appear (Shin, 2003). Therefore a rectangular Venn diagram is perfectly legitimate. Enhancements to Carroll's version of the Venn diagram that specifically allow for proportional representation of data values are suggested by Edwards (2004, p20) who names them metrical Venn diagrams. In electrical engineering these figures are familiar as Karnaugh maps (otherwise known as K-maps). These maps[21] are considered an important digital design tool for simplifying logic expressions or converting a truth table to its corresponding logic circuit. The process, utilising gray-codes, simplifies the logical expression for the required truth table output by eliminating pairs that appear in both complemented and uncomplemented form. Referring to Figure 3.2, (a) is the Universe, (b) is Set A and inverse (not A) or $\bar{A}$, (c)

[21] The author has been unable to find any acknowledged pedigree for this type of visualisation that connects Karnaugh maps to Lewis Carroll's (Charles Dodgson) rectangular version of a Venn diagram. It is possible that when Karnaugh developed the K-maps in the 1930's they were developed independently of Carroll's work.

has B and $\overline{B}$ added and finally in (d) the third set C is added in the centre, illustrating the unions CA, CB, CAB and their respective inverse relations. Disjoint sets are unable to be displayed; however this is not an impediment for the type of presentation envisaged for business data to a general audience.

The common use of a Venn diagram relates, as John Venn himself had envisaged, to logical associations known as syllogisms and the Dvenn is suggested by the author as being utilised in this role. Interestingly, Benjafield (1997)[22] suggests that reason can overwhelm the evidence of our senses in what would usefully be described as a cognitive illusion. He cites the Sander Parallelogram (Appendix V) to demonstrate the dominance of reason over what we see.

> *If we follow this reasoning process, then we reach a conclusion that is empirically correct…, whereas if we rely on the evidence of our senses, then we reach a conclusion that is empirically incorrect. If subjects are given the choice of reaching a conclusion logically or reaching a conclusion on the basis of making observations, they can often choose to base their conclusion on reason even if it conflicts with their observations. However, the use of reason appears to decline as the number of inferences required increases (Benjafield, 1997: p267)*

It may be deduced from Benjafield's account that as "reasoning" declines with the number of inferences then more reliance must be made upon perceptual or 'sensory cues' to make a conclusion. What an audience perceives is shaped by the ability of a presenter to make a case that appeals to reason. Where data presented visually complement a reasoned argument, the persuasive power of such a presentation is likely to be extremely effective in shaping the collective understanding of an audience.

The Venn diagram is also now a source of much interest in combinatorial optimisation (Bultena, 1998). In this application, the Venn diagram has been reduced to a visualisation of the vertices of each set alone (see Appendix VI). Whilst of no interest for quantitative display, it is a fascinating example of increasing awareness of the potential of Venn diagrams to be

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[22] Benjafield basically distinguishes perception from cognition on the basis of "senses" pertaining to perceptual processes.

applied to novel applications, including computer science where recent work visualising gray codes is yielding interesting insight into data network optimisation and telecommunications theory (Edwards, 2004).

3.2.3 Comparison of a Venn Diagram and Pie Chart

One presentation feature of data visualisation is whether such a visualisation is to "scale" or "scale-less". From a statistical perspective Coombs et al. (1970) suggest that scale is a primary consideration for making conclusions:

> *The knowledge of the scale type is important for an adequate interpretation of the scale. Inferences based on scale values should be invariant with respect to admissible transformations of the scale. Similarly, the interpretation and the meaning of various descriptive statistics depend on the scale. We cannot make justifiable inferences based on comparative statements about means, for instance, unless the relevant properties are measured on, at least, an interval scale. Otherwise, our conclusions would not be invariant.*
>
> *(Coombs et al., 1970, p47)*

However, products such as Mineset™ include navigational capabilities through tree diagrams that show direction but not distance, a feature typical of Cone Trees. In this sense they are scale-less. The separation of clusters is not based on any attribute that equates to distance between clusters. The proximity of each cluster to another is for presentation clarity and avoidance of clutter. Clusters may be rotated or brought to the front of the screen, but the distance between clusters is not based on scale in a topographical sense. The relative colours and sizes of each cluster are more important to the viewer than an exact representation of distance between clusters.

Venn diagrams are also scale-less. The important attribute of a Venn diagram is its indication of the union of sets. There is no scale attached to the degree of union. As discussed in 3.2.2, all that is required is that each set boundary overlaps each other set boundary once and once only.

For a Venn diagram to be suggested as a useful data visualisation method, it must be able to convey proportion. The pie chart does this effectively, and in its simpler forms, immediately. The scale is implicit in the total image with respect to each element and its proportion of the total and its comparative size to each other element. Therefore, by way of contrasting the suitability of the Venn diagram for data visualisation, it is fruitful to consider the attributes of a pie chart. The lack of a standard for the display of pie charts means that a pie cannot convey ordinality of the constituent elements without annotation. Sort sequences for the pie segments are at the command of the presenter, without justification. However this fact does not prevent the widespread use of such charts in presentations. Indeed, Microsoft™ includes a 2-segment pie chart in the Explorer operating system interface to indicate the amount of disk space utilised on a personal computer. This visualisation can be accessed by millions of people worldwide. Why is it not sufficient to simply state that 14% of the disk remains unused? Simply because the area of a pie is immediately recognised without "reading" the values from the numbers. A comparison would be the ease of reading an analogue clock versus a digital one. Even without the expedient of recognition time, a pie is useful because it shows the exact percentage that each slice represents of the whole. Even without labels indicating each amount explicitly, the ability of humans to quantify the values visually makes the chart type very effective.

Consider the questions that may be asked of the pie. Is it possible to say anything of the relationships between the displayed categories? Think about the simple exercise of presenting a pie chart depicting payment types available for consumers to settle transactions by credit card, cash and cheque for the purchase of goods in a store. A purchaser may choose to make a payment that consists of cash and cheque. Such a display cannot be conveyed via a pie chart. A Venn diagram, however, immediately establishes that some sets of payment transactions consist of multiple methods of payment for a single transaction. Therefore, a shortcoming of the pie chart, apart form the inability to show a mixture of positive and negative data or multidimensional data, is that it cannot show relationships without the artificial creation of new sets drawn from the existing slices. For example, payment by credit card *and* cash requires the creation of a new subset drawn from these two proper sets. Even if new sets were created, it is invalid to plot them on the same chart because a pie chart cannot add up to more than 100% of its constituent elements. A set of pies is the minimum now required to convey this information. Apart from the extra pies being required, the essential problem is that the user needs to know *in advance* that the new subsets need to be created. This drawback is also present in the bar chart, where subsets of transactions may be plotted, but the total of all transactions is unavailable without compromising the scale.

The Venn diagram automatically shows the relationship through set unions. It is the revelation of relationships within the data that makes the Venn so powerful. The importance of such revelation in a presentation cannot be overemphasised. Hofstadter (1980) urges that revelations are important to enable viewers to share the axioms of the presenter.

3.2.4 The Quantitative Venn Diagram

The ideal synthesis of the explanatory elements of the Venn diagram and the proportional exactitude of the pie chart would enable the creation of quantitative Venn diagrams; that is, Venn diagrams that not only show the relationship of entities to each other but also their relative quantities. Such diagrams could be generated automatically by computer from any sets of comparative data available to the user. Visual numeracy, being a primitive faculty, should help an audience to understand data that are presented in such a way. The immediate advantage of the quantitative Venn diagram over the simple pie chart is the richness of explanation that the user can draw from the same presentation space. The presenter and the audience need know nothing about possible relationships within the data before drawing the presentation. All that is required is that:

> *A person viewing an area-proportional Venn or Euler diagram needs to be able to determine which curves enclose a region (i.e., what the region represents) and how the size of a region compares to other regions (Chow & Ruskey, 2003, p4)*

Complex revelation is unlikely, but, within the bounds of visual numeracy, such a display tool may be an important method of overcoming the hurdle that data density usually represents to a lay audience. To be able to trust and accept the existence of meaningful patterns in data requires that the method of presentation be transparent, and, as there are many graphical presentation tools at the disposal of the presenter; the problem is that the *amount* of data now available makes these types of graphical representations useful only for very basic attempts at explanation.

3.3 The Case for Animation

3.3.1 Introduction

Revelation and explanation are greatly enhanced through being able to gauge rates of change. The use of animation techniques could reasonably be expected to permit the quantitative Venn diagram to display time-series data. By utilising controls via simple mouse button actions, the presentation may be run as a loop, sweep or even run backwards.

The lack of widely available data animation software for business presentations does not mean that the concept is new. SPSS™ software included an animation capable statistical module named the Parametric Snake in 1996. Mineset™, an industry benchmark for animated data visualisation software, was sold by SGI™ in 2003 after failing to realise its perceived potential to generate revenue amid a deficiency of enthusiasm for such products in the marketplace. Such a state of affairs appears to be counter-intuitive when compared to one of the central ideas of this thesis; that data animation holds great promise for facilitating efficient quantitative presentations to an audience. The reasons for this apparent paradox are cause for speculation and discussed further in the next section.

3.3.2 The Value of Animation

In terms of indications of widespread acceptance of data animation in the general community, scientific visualisations that utilises motion to represent flow direction, speed and volume are suggested, along with television network broadcasts of weather maps. These are obvious examples of animated data visualisation that are seen by millions of viewers worldwide on a daily basis. They indicate that correlations can be presented to audiences without a large investment in time and effort for training programs. It may be speculated that many of the public do not actually understand the significance of the relationship between barometric pressure, precipitation, wind speed and temperature that is conveyed by these animations, a speculation supported by the results of the following experiment;

> *Because the learners participating in these studies lacked expertise in the depicted domain (meteorological charts), they were apparently unable to select appropriate subsets of the information provided by the animation. This was attributed to*

> *their lack of background knowledge about the meteorological domain and a resulting dependence on perceptual characteristics rather than thematic relevance. Being unaware of the relative importance of different aspects of the presented information, they often looked in the wrong spatial or temporal locations within the animation and failed to detect key attributes of the display. (Lowe, 2004, p157)*

Nevertheless the audience is most probably able to discern whether a front is heading toward them or not. Also, requirements of the subjects in Lowe's experiment were more demanding and complex than those asked of a TV viewer.

In order to establish that animation aids recognition, it must be established that animation provides a more efficient means of pattern recognition than simply viewing many static plots of small variations in the presentation data. Tufte defines repetitive presentation of charts that convey only small variations as "small multiples" (Tufte, 1983, p170). Further, Tversky et al. (2002) suggest that:

> *even when actual motion is smooth and continuous, people may conceive of it as composed of discrete steps. p256*

Therefore, based on the idea that continuous data may be treated discretely allows the opportunity for animation techniques to freeze, rewind, slow down or speed up data without any loss of understanding that would be the case should continuous data be only understood as a flow. Animation must add value to a presentation that would otherwise be just a series of "small multiples".

There are other clues that animation is a useful technique for enhancing understanding. Bartram, Ware, and Calvert (2002) explored the relationship of the use of variations in colour, shape, and motion and showed that applying motion to a target icon made it significantly easier to recognise in a field, compared to changing the colour or shape of the icon. This was found to be true when the target was near the centre of focus as well as when it was located on the periphery of the field of view. Bartram et al (2002) also studied the distracting effects of a secondary motion in the field of view. Flicker was the least distracting, followed by oscillating motion, then divergence, and finally movement over long distances. So movement was confirmed as the most effective way to present a changing target to an audience (or distract an audience away from a target).

Without resorting to a comprehensive definition of animation, it will suffice to suggest that animation occurs when a target prepared of multiple static pictures appears to move smoothly when presented in series. A useful gauge for the presentation rate is in the order of 40 milliseconds exposure per static picture. Each exposure is well below the 250 milliseconds required for pre-attentive processing. Therefore, according to the definition of recognition offered in section 3.1.3, animation is easily accepted and does not utilise complex forms of understanding. Nonsense can be animated, it is simply understood to be nonsense. To make sense of animations requires the same access to mental processes that underpin any form of understanding. Compared to static graphical presentation, animation does not impose special barriers to acquiring information. However, research done on such comparisons (Zacks & Tversky (1998), Dehaene, (1997:p226) reveals that there are circumstances where animations of data add nothing to more to a presentation than static graphical representations of the same data. To construct an efficacious experiment that makes exact comparisons of the same data by static or animated method is not a simple matter, as discussed further in the methodology chapter. The following excerpt indicates that the very nature of an animation adds more detail to a presentation than its static counterpart, arguably a positive attribute of animation:

> *for other studies evaluating static and animated graphics, the graphics appear comparable. But on close examination, the animated graphics present information not available in the static versions, in particular the details of the microsteps between larger steps; that is, the minute spatial-temporal actions of components. Events such as those portrayed in animations can be reliably segmented into coarser and finer units by observers…. For the most part, the coarse units are segmented by objects or object parts and the fine units by different fine-grained actions on the same object or part. Many of the static graphics portray only the coarse segments whereas the animations portray both the coarse and fine segments. Thus, there is greater information in the animations than in the static displays. Any benefits, then, may be due to the added information alone rather than the format of the graphics, information that could easily have been conveyed in the static graphics. (Tversky et al., 2002 p252)*

Tversky et al suggest that conveying fine segments in static graphics is as simple as annotating arrows to indicate movement. However, Tversky et al continue with a more ascetic assessment of the value of animation for data visualisation:

> *…the literature is filled with outright failures to find benefits of animation, even when animation is in principle ideal: for conveying change over time… Morrison and Tversky (2001)[23] compared text with text coupled with either static or animated graphics in a task teaching permissible social paths among people or navigation paths among objects. Graphics yielded better performance than text alone but only for low spatial ability participants. Across all participants, diagrams that animated the path provided no benefit beyond that of the individual static diagrams. (Tversky et al, 2002, p254)*

From such a bleak outlook for animated data visualisation, and for the purposes of this thesis, the following observations may temper some of the assessments made by Tversky et al. First, Tversky et al state that animation provided no benefit *beyond* that of the individual static diagrams. It is no worse. Second, many animations are simply artefacts, unsupported by data values, to elaborate a simple static graphic. Powerpoint™ balloons, bursting stars and snipping scissors are embellishments that are easily substituted with words or arrows in a static presentation. Third, the purpose of the animations studied by Tversky et al was not to indicate proximal relationships based on quantitative attributes, the animations were not built to exploit inherent characteristics applicable to intuitive recognition of both temporal *and* spatial relationships. As was indicated in section 3.3.2, animations of conventional graph types would achieve no positive outcomes. Exploding pie slices, pumping bar charts and snake-like lines will not exploit any visually numerate recognition of relationships in presentation data. Therefore, the *type* of animation is important, not simply animation per se.

Yet there are other warnings about the value of data animation, particularly in literature that relates to learning theory (Lowe, 2004). Therefore what are the essential problems? Tversky et al (2002) maintain that, of the principles of congruence and apprehension discussed briefly in section 3.1.3, apprehension is the most problematic for animated data visualisation. Indeed,

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[23] Morrison, J.B. & Tversky, B. (2001) The (In)effectiveness of animation in instruction. In J. Jacko & A. Sears, Eds, Extended Abstracts of the ACM Conference on Human Factors in Computing Systems, pp 377-378 Seattle

Tversky et al suggest that the comparative power of animation is “a natural for conveying concepts of change” p250, and therefore fulfils the requirements of the congruence principle. It is the apprehension principle that is most likely to be violated by animation. Tversky et al cite the example of early paintings of galloping horses showing unrealistic interactions of the horses’ legs. With the advent of photography it was clear that horses’ legs did not move in this way at full gallop. Therefore animation of the type represented by photographic realism that simply reproduces an event on film, is a difficult medium to control for what the audience (rather than the presenter) actually sees and understands. However, with straightforward design in accordance with the apprehension principle, animated data visualisations are entirely feasible. As Tversky et al (2002) state:

> *animations must be slow and clear enough for observers to perceive movements, changes, and their timing, and to understand the change in relations between the parts and the sequence of events. This means that animations should lean toward the schematic and away from the realistic, an inclination that does not come naturally to many programmers, who delight in graphic richness and realism…also schematizing is simpler than it sounds; clear understanding is a prerequisite to including only the information essential to the processes to be conveyed and eliminating extraneous but sometimes appealing information. (p258)*

Therefore, for the best chance of success, any data presentation tool that utilises animation should be schematically based, able to run at varying speed and thematically narrow in scope. Such a requirement contrasts starkly with the lavish attention to realism that computer game programmers expend on their products.

3.4 Data Visualisation and Perceptual Pitfalls

3.4.1 Introduction

As discussed in section 3.1.3 the definitions for perception and cognition must be used advisedly, but any proposal that suggests an improved method of data display to an audience must ensure that distortion of the presentation by the perceptual system is minimised. Experimental evidence based upon the initial work by Tversky (1998), suggests that subjects are particularly sensitive to errors in judgements of line distance in presentation graphics and especially the effect of the length of neighbouring elements (Peebles, 2003, p1). Therefore, having established in section 3.3 that a data animation should be schematically based, the design emphasis must now focus on those schematic attributes that may be more subject to ambiguous recognition. The general conception of a Venn diagram is that it is constituted of overlapping circles. So, given the relatively few number of simple schematics available, are circles or rectangles easier to recognise?

3.4.2 The Illusions.

For pre-attentive tasks, there is evidence to suggest that consistent errors of judgment occur for circles. The DelBoeuf illusion (Appendix VII) demonstrates that gauging the relative size of two adjacent circles is prone to dramatic mistakes in proportion being made in the visual system. Longer viewing of the target does not easily compensate for such mistakes. Therefore adoption of rectangular quantitative Venn diagrams for the Dvenn application alleviates the problem of the DelBeouf illusion that mitigates against circles. Squares may not be so affected by perceptual illusions, but problems with vertical and horizontal perception remain. Problems of recognition of oblique angles require that they be avoided (Johnson-Laird, Eysenck, Hunt & Ellis, 1991). Verticals are accentuated in lines of equal length placed perpendicular to each other. The base of an upside down T (⊥) is seen consistently as a shorter length than the vertical component of the same length (Day, 2004).

The area of a circle is increased four fold with each doubling in its radius and the area of a square is also increased four fold for each doubling of its length, suggesting that perceptual errors of area should be the same for squares and circles. However, anecdotal evidence backed by a simple experiment suggests that circles are more prone to errors of judgment of relative size by a general audience. Broad confirmation of this suggestion was obtained by way of a simple test of recognition of area that was administered to 21 undergraduate students (see section 4.11.1 and Appendix VIII). The results indicated that 62% correctly identified the proportion of a smaller circle to a larger one, but 71% correctly identified the proportion of a smaller square to a larger one. Whilst the result would suggest that circle areas are not as “impossible” to evaluate as Wurman (1989) suggests, the result would indicate that circles are more problematic for an audience when they attempt to evaluate comparative areas than is the case for squares.

3.5 Prediction and Persuasion

3.5.1 Introduction

The efficacy of a presentation ultimately rests upon the ability of an audience to understand the presenter's message. There are manifold cues that an audience uses to assess a presenter, but the discussion of attributes that constitute a successful presentation must focus upon the presentation content of a Dvenn. Spectacular displays will boost attention, but having an audience understand and retain a message is the reason for a business presentation. Montgomery (2001) suggests that statistical inference is about helping an audience gauge which factors cause *differences* (or uniformity) in data and the *magnitude* of these differences. It is the very aim of constructing a Dvenn to support explanatory components of a presentation to an audience that drives this research.

3.5.2 Making Sense

Specialist decision-making is a valuable skill and actuarial tables become valuable in the hands of a specialist rather than generalist. The boundary of chance is the crucial test for whether a decision maker can evaluate information to make a successful prediction. Competent weather prediction is a good example of an everyday application of statistical science. Whether a prediction of rainfall is persuasive depends on the discrete population in a particular area, the audience. State-wide forecasts are often too coarse to enable action to be taken by regional inhabitants. In this case, intuition or cumulative experience is a more persuasive factor in changing behaviour[24] The term intuition is used here advisedly as there is no easy way to define how we make decisions, let alone isolate *all* the characteristics of decision making. Indeed, the exact scientific field that sense-making encompasses is open to lengthy discussion beyond the scope of this work. Certainly, the literature on Educational theory rages across a very large field of study, the only boundaries being Behaviourism at one end and Constructivism at the other (Latham, 2004). However the term "behaviour decision theory" is used to claim a specialist field of study and a useful taxonomy has been suggested

[24] By way of illustration, in the case of the example for being appropriately prepared for the weather, a person will decide to take an umbrella or cancel an outing based on their own assessment weather conditions. The reasons for doing so may be obscure and contradict a weather forecast that they have heard.

to define the topic (Arnott, 1998). Of the twenty-nine definitions suggested by Arnott (Appendix IX)., the author believes that the following six classifications of decision making presented in Table 3.1 are of most interest for the discussion and elucidation of visual numeracy.

• Attentuation	A best guess strategy applied to circumstances of uncertainty that results from information overload. Characterised by a strong belief in the resulting decision even though there is strong filtering of relevant information.
• Chance	Misconceptions of chance that affect unwarranted persisting beliefs
• Correlation	Overestimation of information based on associations of events that have been remembered to be relevant in the past.[25]
• Imaginability	An event can be judged more likely if it can be *easily* imagined.
• Redundancy	Repetitive presentation of large amounts of information causes an overestimation to be made of its veracity.
• Selectivity	Information is excluded when it is not consistent with experience.

Table 3.1 Selection of Decision Biases Relevant to Visual Numeracy

Intuition is not mentioned in Arnott's taxonomy and, with due respect to decision support theory and its important application to Computer Science, intuition is not merely a general term that is otherwise covered in the detailed classifications. Intuition appears to be an

[25] Surprisingly, an understanding of correlation is considered by Piaget to form very late (around 14-15 years of age) This would suggest that visual numeracy, as a primitive or inherent skill, does not provide children with the ability to recognise correlated data patterns. If visual numeracy is of benefit for visual statistical inference, it may only be so for adults (Piaget, J, Burrell Leake, P., Fishbein, H.D., 1976)

anathema to cognitive classification. The author contends that gleaning understanding and meaning from what we see is greatly influenced by factors distantly removed from purposeful comprehension or what cognitive theory suggests is metacognitive insight. Indeed, the topic is vast and the available terminology is still evolving. As Hacker (1998) notes:

> *Metacognitive thoughts are deliberate, planful, intentional, goal-directed, and future-oriented mental behaviours … Descriptions are difficult because metacognition by its very nature is a "fuzzy concept"…, which has been made even fuzzier by a ballooning corpus of research that has come from researchers of widely varying disciplines and for widely varying purposes. (p1)*

As for the importance of this form of comprehension for decision making, Byrnes (1998) concludes an extensive literature review by stating that :

> *there seems to be no correlation between metacognitive insight and decision-making skill. (p176)*

Intuition however represents a sub conscious mechanism that underwrites those aspects of our decision making that are not rational or based on declarative knowledge born of our senses. Indeed, the very idea of intuition is intriguing. Why should we not be able to account rationally for all our decisions? The origins of some of the greatest ideas in human history are inexplicable in terms of declarative knowledge. Popper (1972), suggests that the purpose of theorising should be not to prove a theory but to disprove it. So, the theory can be tested but not those processes that led to the crystallisation of that theory. Intuition is not inductively transparent, in that the decision-maker cannot readily identify the reasons for making a decision. Heuristic decision-making is self-evident as the quality of the rules determines the quality of the decision. Intuition appears to be entirely hidden from an evaluation of factors from which to draw a conclusion or make a prediction.

Some decisions are habitual as in diet selection or route selection for a given journey. Investment decisions are less likely to be habitual, and they are unlikely to be made purely by chance[26]. However, at an anecdotal level, asking a small investor why they selected a

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[26] One definition is that chance is a sequence of random events that can be mistaken for the essential characteristics of a process (Arnott,1998,p 6)

particular investment will reveal how much intuition is utilised in making predictions about likely performance outcomes. Serendipitous[27] decisions reinforce whatever behaviour may have been in train at the time. Such ill-informed decisions may accentuate rumours as valid. Confronted with information synchronicity[28], people are poor selectors of valid[29] predictors of possible outcomes.

Nevertheless, experience tells us what normality might be. Unaccounted variations from this normality can be thought of as coincidence. Take the case of separate encounters over two hours with four Icelanders who in turn had never met each other before. This would be very unlikely in normal experience but entirely feasible at an airport Arnott's taxonomy suggests circumstance to inform our comprehension of *chance* as there are no elements of a process in the interpretation of the situation. This is not a decision but a simple observation at the airport, no consequences pertain to this event that seem to be significant. Yet the event is symptomatic of the uncertain foundations pertaining to sense-making and illustrates the way that certain beliefs form that are essentially counter-productive to truthful assessment of a situation.. Take the ability of an audience to be persuaded of conspiracy from simple facts that are only temporally associated. This indicates that powerful shortcuts are applied to thinking that forms our opinions. Tragic world events based on the deaths of prominent individuals such as the assassination of JFK and the death of Princess Diana appear to many observers to require a balanced explanation. "Balance" meaning that the most powerful man in the world cannot possibly be killed by a lone gunman or a glamorous princess cannot just simply die in a car crash. Intuitively, we come to know which circumstances are either likely or unlikely and this is not just a process of exposure to events. Spirituality also may guide many to make sense of their experiences.

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[27] Used in this context to define a fortuitous coincidence, nevertheless a coincidence

[28] Synchronicity was defined by Karl Jung and expounded in his article, "On Synchronicity, An Acausal Connecting Principle' to indicate meaningful coincidence, a phenomenon he attributed great significance to, but, nevertheless, a coincidence

[29] Valid" is defined to mean simply those statistical tests that identify likely outcomes in a probabilistic way.

So how is coincidence to be evaluated? It is the generalist's guide as to how likely any particular event might be to occur, and research has concluded that intuition is not outside the scope of scientific evaluation. Ultimately, intuition can be shown to be fallible and it is really no more than a form of expert decision-making utilising judgments based on experience and skill (Simon, 1979). Experts, like an audience, make decisions that are the outcome of both intuition and logic. Simon's research indicates that intuition is a product of subconscious mental activity and is, therefore, a faculty to be evaluated like any other. Simon is not forthcoming in suggesting *how* this might be achieved, nevertheless the formal evaluation of co-incidental events is undertaken on a daily basis. Forensic police work often builds a case from a sequence of events that, taken individually, might be unremarkable, but taken together constitute an argument for guilt that is put to a jury. Such circumstantial evidence is an appeal to the balance of probability that is informed by everyday life rather than by shrewd statistical analysis. Cialdini (1993) discusses how marketers use various techniques to motivate consumers to form and change their points of view. The weight of evidence required to change a preference need not be substantial. Further study (Tversky, Slovic & Kahneman, 1990) bears out the relative ease by which audiences are influenced to change their preferences. The prior discussion of learning theory has been shown to admit that, of visual, auditory and kinetic learning, 70% of information is acquired visually. Therefore, any tool that can visually facilitate opinion shaping by helping an audience gauge coincidence intuitively is likely to be useful in the business sphere.

The final piece to the puzzle is the relationship between intuition, coincidence and correlation. The argument presented in this subsection has attempted to examine briefly an extremely wide multidisciplinary field to highlight and contrast those definitions of sense-making that apply primarily to the presentation of information to an audience visually To say that data are "highly correlated" or that the correlation coefficient is .74 requires that the audience trusts this to be so. There are few tools available to a presenter to symbolise coincidence to a generalist audience that are universal in appeal. Figure 3.3 illustrates the chasm that exists between presenting a correlation numerically and presenting the same correlation graphically. Both forms of arrangement represent the same coefficients, but no trust is required to process those data visually. The proportions are simpler for an audience to understand in visual format.

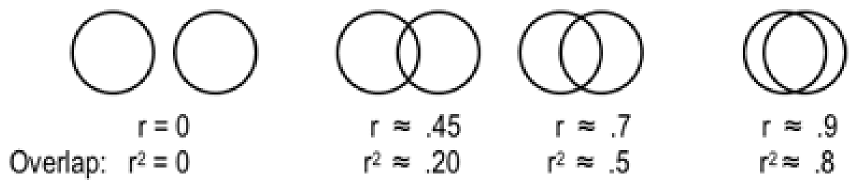

Figure 3.3 Visualisation of Various Pearson Correlation Co-efficients

3.6 Chapter Summary

Ubiquitous data may indicate wealth but the problem of a poverty of attention remains. In this chapter various means of addressing this paradox were introduced. Different methods of visualising data were reviewed, particularly with an emphasis on highlighting the underlying principles of effective data visualisation for non-scientific purposes. The field of Data Visualisation is vast and only those areas that are of particular applicability to *presentation* have been introduced in sufficient detail to underpin the theoretical justification for embarking on the construction of the Dvenn tool. What constitutes *presentation* was defined by way of Keim's Data Visualisation taxonomy. Within the boundaries of his taxonomy, particular note has been made of the perceptual primacy of pre-attentive recognition and the term visual numeracy was selected to define instant visual recognition of proportions. It is this intuitive recognition that underpins the suggested theoretical justification for the discovery of a new tool for presenting data to an audience.

The author suggests that ready recognition of significant patterns in data favours iconic forms of presentation. Shape, colour and size are used to varying degrees by each data visualisation method. However, scale-less presentations mitigate against the important universal quantitative attributes of *more* or *less* being available to an audience, that is, they manifest poor congruence (Tversky et al, 2002). The discovery of significant relationships in data should be self evident to an audience without coaching. Such discovery aids an audience to accept the credibility of a presentation and, by association, the credibility of the presenter. Persuasion of the audience, being the aim of a presentation, is thus more effective.

Particular acknowledgment of Tufte, Tversky and Bertin is made with respect to how visual understanding occurs and what may constitute sound design guidelines for prospective researchers in the field. In the case of Tufte, however, his abhorrence of pie charts would tend to mitigate against the selection of circular Venn diagrams for presentation displays. Nevertheless, the author considers Venn diagrams to be an under-utilised vehicle for the exploitation of visual numeracy for presentation of data to generalist audiences. Taking the problem of perceptual illusions into account, the Venn diagram, coupled with proportional rendering and animation techniques, is presented as a potentially powerful presentation tool herein named by the author as a Dvenn.

The purpose of utilising the Dvenn tool is to place data within a context so that an audience may be able to better evaluate and understand the information offered by the presenter. The concept of significance is shown to be difficult to define due to its encompassing intuition, metacognitive insight and multiple intelligences. However, the justification for a new presentation tool is that it may aid the shared experience of significance in a visually demonstrated way rather than in a symbolic way by spoken or written word. The intention in designing such a tool is to leverage preferred ways of making sense of data that are more intuitive rather than learned and rational. Therefore it should be easier for an audience to understand presentation material in a contemporary business environment that is characterised by its being data rich but attention poor.

Chapter 4

RESEARCH METHODOLOGY

4.1 Introduction

The purpose of the exploratory research presented in this thesis was to design and evaluate a novel tool to exploit visual numeracy in order to enhance a shared understanding of presentation data, between both the presenter and the audience as well as between the audience members themselves. This chapter presents the method chosen to accomplish that purpose and is based on an evaluation of the elements of visual presentation discussed in Chapters 2 and 3 and the important issues surrounding how an audience assimilates a message, particularly with respect to visual numeracy. The development of a software tool, herein named a Dvenn, was undertaken to test the theory that visual numeracy may be utilised to enhance the value of data visualisation as a communication method for use with business audiences. Implicit in the primary aim of this research, to attempt to discover a data presentation tool that an inexpert audience may be able to understand intuitively, is the need to evaluate the performance (Downton, 2003) of such a tool with a pilot study. This chapter outlines the propositions and resulting hypotheses to be tested as well as the manner employed to create the Dvenn tool and evaluate its performance compared to that of an industry standard data presentation format.

4.2 Propositions

From an assessment of data presentation tools discussed in Chapter 2, the following propositions are formulated:

- That the exploitation of visual numeracy for presentation of data to an audience, who are not specifically trained in pattern recognition, is a method at least as good as methods currently utilised for the graphical presentation of business information.
- That utilising a form of Venn Diagram that exhibits a capacity to quantify data will exploit viewers' inherent ability to recognise information in a visual way that promotes increased understanding and sense-making. Such facility is not being exploited in current tools.
- That animation of data via a Venn diagram (Dvenn) increases the amount of data from which an audience may absorb a shared understanding, and therefore reduce the attention load of that audience without compromising recognition of significant patterns.

4.3 The Research Question

Based on the propositions stated in section 4.2, the formulation of a central research question to be tested may be constructed as:

> *Is the presentation of data via an animated quantitative Venn diagram a useful tool for the recognition of relationships in high volume quantitative data?*

4.4 Hypothesis

In order to narrow the field of investigation and to establish the efficacy of the Dvenn tool within the bounds of a statistical test that relates specifically to the research question, a simple hypothesis is proposed:

- H_0 : That subjects' perception of a correlation in a Dvenn equals the perception of a correlation in a Scatter-plot.

This states that there is no difference in subjects' perception of correlations in data represented by the Dvenn tool and those same data represented by scatter-plot. Support for the null hypothesis would suggest that the Dvenn tool is equally reliable when compared to scatter-plots. Therefore:

- H_A : Subjects' perceptions of a correlation in a Dvenn is significantly different to those same data presented as a scatter-plot.

This states that there is a difference between the perception of correlations represented by the Dvenn and those same correlations represented by scatter-plots. That is, performance of the Dvenn is not similar to performance of scatter plots.

If, indeed, the Dvenn is perceived differently to scatter-plots, the question is then raised as to how differently they are perceived. If the Dvenn tool is better, how much better is it? This is a far more challenging proposition than H_0 which simply seeks to discover whether the supposition that the two methods are equal is false. The inference then, is that performance of the two groups of subjects on the two types is essentially the same. This statement is tempered with the advice that *a hypothesis test can never conclude that the null hypothesis is correct* (Stirling,2000). It is not within the ambit of this thesis to tackle the challenge of which is the *best* presentation method. The author seeks only to satisfy the test that the Dvenn tool is functionally no different to scatter-plots. Any suggestion that the Dvenn tool is superior to scatter-plots would necessarily become the subject of future research aimed at investigating the degree to which this may be the case. The body of the current research presented herein consists of the following:

Identification of a problem (the perception that business audiences struggle to collectively understand current data presentation forms)
Construction of a new tool, based on evaluation of current types, as a possible solution to this problem (the Dvenn software)
Evaluation of the new Dvenn tool against a common standard (Scatter-plots).

Choosing a scatter-plot presentation as a control enables the Dvenn tool to be compared in performance with an existing data presentation type, that is, to establish that recognition of significant patterns in data is as reliable through a Dvenn as with a scatter-plot of those same data. Reliability is defined in this context to be the ability of an audience to identify significant correlations in presentation data in a consistent manner. In terms of a significant result, acceptance of H_0 only requires that a Dvenn projection achieves the same result as a scatter-plot for audience recognition of correlations. Depending on the results, further research could be undertaken to gauge the degree to which the Dvenn tool was better (or worse) than other data presentation forms. Scatter-plots are utilised in the present research to represent a control for the accurate identification of correlations in test data presented to subjects.

The reason that scatter-plots have been selected from the range of common data visualisation tools for comparison with the Dvenn is because they are a mature presentation form that allows multidimensional visualisation. Mature means that very little enhancement of the standard scatter-plot is in evidence and the basic form has seen widespread acceptance over time. Scatter-plots are assumed to be familiar to most audiences, require little processing of data for presentation, and are relatively common chart types in business presentations. An essential premise to this hypothesis is that subjects are able to infer correctly any significant correlations from scatter-plots.

To construct a suitable experiment to test the hypothesis required the author to consider the selection of subjects and the length of time required for them to carry out the task. One option was to select a sample and compare their performance on the two presentation methods. However, the circumstances of the test are not a "test – retest" scenario. Indeed the author did not want any possibility of learning by subjects on the task, as visual numeracy is meant to represent an intuitive application of numerical ability. Therefore repeated presentations of correlations by the Dvenn tool and scatter-plots to each subject may have influenced them in subtle ways to that enabled them to presuppose answers. Also this test option would have invoked a lengthy time commitment for the subjects involved in the test. Thus, two samples were selected from what could be loosely termed the 'business population', one of these samples being shown the Dvenn tool and the other, or control, was shown the scatter-plot.

4.5 Research Exclusions

This research is not the quest for a new analysis tool for the purpose of replacing existing tools. It would be hoped that a new tool could be utilised to supplement the many excellent tools already available such as SPSS™, Mineset™, Saber™, Spotfire™, MapInfo™, PowerPlay™ and the like. This research does not attempt to corroborate Tufte (1983) and shed insight into what constitutes good or bad presentation. Nor is research undertaken into the relative merit of classifications of data visualisation or what applicability should be ascribed to particular data visualisation tools (see Bertin, 1983; Cleveland, 1994; Keim et al., 2003). The research is focused solely on creating a new tool and attempting to validate it by testing it for satisfactory audience recognition. The tool itself has been created on the basis of an examination of the many current forms of data visualisation and an attempt has been made to incorporate animation into the tool. The focus of evaluation of the Dvenn tool is aimed solely at establishing a concrete efficacy for the tool. To stray too far from this objective and attempt to create a general purpose evaluation metric for *all* forms of data visualisation in which to rank the Dvenn tool is simply beyond the scope of this thesis. Instead, satisfactory performance of the Dvenn tool is gauged by comparing its performance against that of an industry standard, the scatter-plot. No claim is herein made for any particular application of the Dvenn tool. As with any tool, should it be used inappropriately, it is likely to yield dubious outcomes. To borrow a phrase from Information Technology, "garbage in, is garbage out" (Ayto, 1999).

4.6 Selection of Research Methodology

The purpose of this section is to justify and elaborate the research method by describing the manner of selection and implementation of the research design. In terms of a research paradigm, the research undertaken may be classified as positivistic rather than phenomenological as it is objective in nature (Collis et al., 2003). The methodology is based on both empirical and practise based research, informed by the conclusion of the literature review, and seeks to explore how an audience may benefit from animated data visualisations that are produced to stimulate pre-attentive recognition of statistical significance.

To support the selection of an empirical approach to evaluate the practise based research methodological component (the Dvenn software), the following quotation by Downton (2003) is used to support the research paradigm applied by the author to the study of data visualisation:

> *Designers make propositions about the way some thing … could be: their propositions incorporate speculations about desired ways things will work and look… and devise tests to evaluate their propositions. (Downton, 2003, p 91)*

From the general observations made in Chapter 2 of the characteristics of current data visualisation forms, as defined by Keim's taxonomy, the author suggests that the overriding general observation that may be made is that there is a paucity of proportionally representational quantitatively based data presentation techniques. Therefore, from theories of use that were formed by the literature review, a data presentation tool was devised and constructed in an attempt to bridge the identified gap in data presentation tools. The construction of such a tool was exploratory in nature and was devised as an iterative working project. Such iterations are common to research designs such as Action Research and Praxis Inquiry as illustrated in Figure 4.1[30]. Certainly, the research undertaken represents a journey of discovery and reflection at many levels, but it is not presented in a narrative style, nor does

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[30] The figure is suggested by Zuber-Skerrit (1995) to represent a spiral, and certainly the positioning of the circles one above the other does invoke a sense of rising value, however, like similar graphics of this type, there is no weight assigned to the relative merit of each stage. They appear to be equally meritorious. Experience gained by researching the Dvenn clearly suggests that these steps are not equal.

the research engage existing practitioners of Data Visualisation to seek a consensual view of tool development.

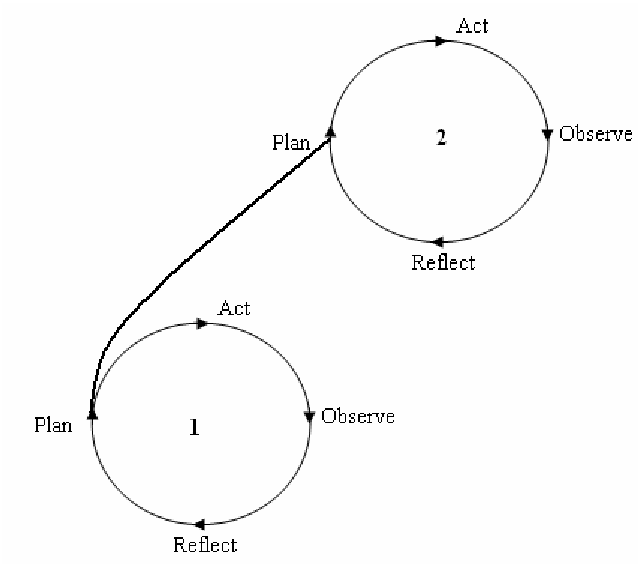


Figure 4.1 Action Research Spiral (after Zuber-Skerrit, 1995, p.13)

The object of the research was to design a tool to utilise the most direct form of visual statistical sense-making, herein described and referred to as visual numeracy. The iterative development of the software-based tool, consisting of a trial and error loop, is presented sequentially in this chapter for each major developmental revision of the tool. At the conclusion of this process, and, prior to final testing, feedback on the usefulness of the tool was sought from a focus group. The group consisted of six panel members with research and teaching expertise drawn from Information Technology, Economics and Marketing disciplines at RMIT University.

Details presented later in this Chapter that refer to a trial of the software that utilised subjects relate to the final form of the software. The detailed results of the evaluation of the Dvenn software are presented in raw form in Appendix X. The manner in which subjects were selected for the trial of the final iteration of the tool and the way the survey was administered are also covered in this chapter.

4.7 Dvenn Software Design

4.7.1 Programming Language

Microsoft Visual Basic was adopted as the programming software to facilitate prototyping of the Dvenn application. Acknowledging the inherent drawbacks[31] in using Visual Basic for animation and visualisation tasks, the flexibility and simplicity of the software for development, combined with a large support base for the product, were considered adequate to justify its selection.

The tool that was developed is simply a demonstration vehicle for the concept of animated Venn diagrams. Constructing the tool in Visual Basic was not meant to result in a definitive program and the author acknowledges that the final form of the code (Appendix XI) developed for exploitation of animation effects for this research is not as comprehensive or functional as would be expected of a mature tool.

4.7.2 Programming Considerations

The exploratory nature of the research and the adoption of an iterative approach led to the first attempted design being initiated at a stage when circles were considered to represent the closest conformance to Venn's original concept. Apart from Carroll's work, there was little evidence from the early stages of the Literature review to suggest otherwise. Therefore the first developmental attempt was borne of the idea of appropriating the visual qualities of circles as utilised in the classic rendition of Venn diagrams and pie charts. These qualities, being chiefly that they conform to the characteristics of an image as defined by Bertin (1983), are therefore pre-attentively recognisable. The ubiquity of a pie chart, if not Venn diagrams, would suggest that audiences would be expected to be familiar with circles and the relative

[31] Visual Basic is not a specialised animation package and therefore required substantial work on the part of the author to build standard animation subroutines. The construction of the Dvenn was not just an animation problem as there was a requirement to sort and calculate derived data fields prior to them being displayed. Therefore, the choice was to use either an established animation engine to receive collated data from a user written front end or write the animation routines in the same language as the front end. The author chose to control the complete development cycle and write all facets of the program in VB.

representation of comparative area made by subsets within the circle. Further, following the direction offered by Piaget (1952), that circles are the first enclosed shapes to be consistently recognised in human development, a reasonable expectation would be that an audience would be able to recognise circle segments in a conventional Venn diagram. Therefore circles were adopted for the prototype, and the pre-attentive elements of a Venn diagram are similar to segment shapes of a typical pie chart. Figure 4.2 illustrates the characteristic unions, as indicated by shape, that a three set Venn diagram would yield.

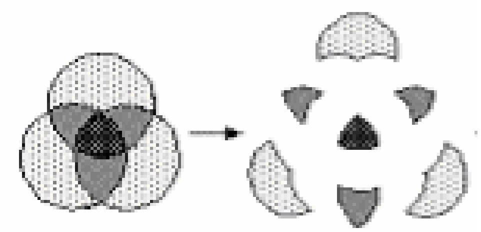


Figure 4.2 Pre-attentive Segments of a Venn Diagram

As a result of the development of the computer code for the prototyping exercise, it was apparent that the construction of Venn diagrams and their animation presented a certain degree of difficulty in algorithm design and code implementation. Whilst the difficulty is met regularly by programmers who are expert in animation and geometric rendering techniques, it was nevertheless a time consuming component of the practise based research undertaken for this study.

Subsequent research into algorithms for this method of presentation is published by Chow and Ruskey (2003) who concluded that due to *programming constraints*, the maximum number of attributes that could be displayed on a quantitative Venn diagram was three. Mention is also made by Chow and Ruskey of the specific problem of how to refine coding techniques for this purpose. It is interesting to note that the constraints on programming a fourth set suggested by Chow and Ruskey (2003) reflect Bertin's dictate that three dimensions in data is the maximum that may be recognised as constituting an image. The programming solution to this problem is not linear and suggests a firm barrier against further development of more complex forms of the Dvenn.

Indeed, John Venn himself believed (erroneously) that no more than 4 sets could be visually represented in a Venn diagram (Edwards, 2004). Ample proof of large set Venn diagrams has been presented that displays a wonderful diversity of appearance for such forms (Bultena and Ruskey, 1998). However, primarily due to the unfamiliarity of the forms for the average business audience, these forms would seem to be of doubtful practicality for the purpose of data visualisation. The abstract nature of these enhanced Venn diagram based visualisations would require a good deal of effort on the part of the presenter to match the patterns with concepts of *more* or *less*. That is, to make the presentation data quantifiable for the audience.

As illustrated in Figure 4.3, Chow and Ruskey's solution to the automatic projection of proportional Venn

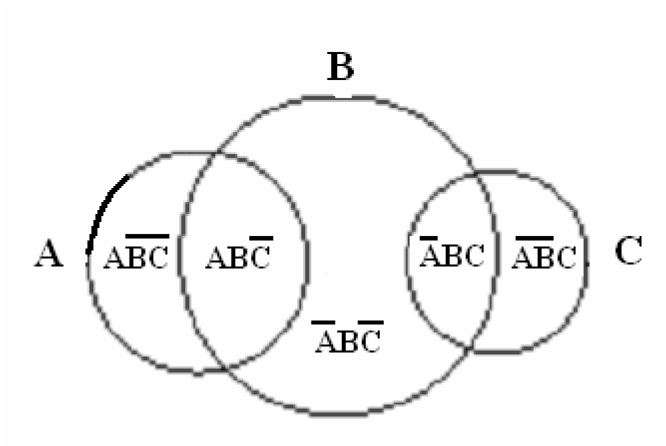


Figure 4.3 Alignment of Sets about the Horizontal Axis

diagrams schematically is achieved by the projection of each set circle area commensurate with the relative value of each set. First the largest set is established, in this case set B. Sets A and C are positioned opposite each other on the perimeter of B along an implied horizontal line that intersects the centre of each circle. At the conclusion of this step each set is positioned such that each is proportionately accurate with respect to B (the largest set).

The next step is to align sets A and C such that they remain proportionately accurate to B whilst appearing to be proportionately accurate with respect to each other. This step is indicated in Figure 4.4. The individual steps required to achieve this can be isolated and they constitute a good framework for writing the necessary computer code. First, the centre point of set A is rotated clockwise around the circumference of B until the required overlap with C is achieved. The conclusion of this process reveals a satisfactory rendition of a 3 set Venn diagram that is quantitative in nature.

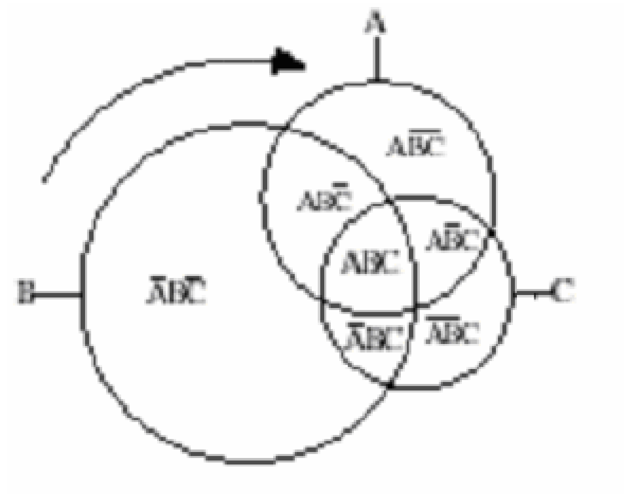


Figure 4.4 Rotation about the Circumference of the Largest Set (Chow & Ruskey, 2003)

Figure 4.5 shows a specific example of the process indicating (a) the appearance of a standard Venn diagram annotated with data values (Ballantyne format) and (b) the end result after conversion to a proportional representation. Note, complementary sets are not specifically annotated.

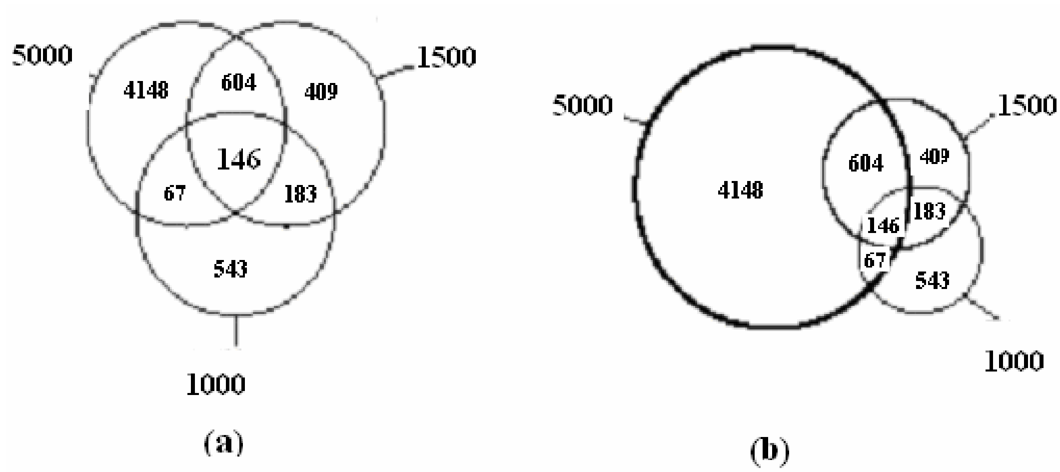


Figure 4.5 Specific Example with Values Converted to Area (Chow & Ruskey, 2003)

The argument for visual numeracy is that the actual values are unnecessary for an audience to gauge the relative contribution of each set segment and its respective unions. Certainly, the total for the largest set in Figure 4.5 (b) is required to gain insight in the upper range of data values. What *amount* does the largest area represent? Once the upper boundary is established, the allocation of values for each other set follows visually as suggested in Figure 4.5. This is not meant to be a tool of statistical precision, and the expectation would not be that the audience would know that if the largest set represented 5000 units then it follows that the smallest set must equal 1000 units. A simple table would suffice for such accuracy, but presenters use graphical representation for communicative purposes that are not just a statement of numerical values. These are visual approximations only and they are utilised by presenters to emphasise relationships. A simplified elegance is apparent from such a diagram and the areas enclosed therein may be left to speak for themselves!

As discussed in Chapter 2.3.5, the idea of a data visualisation for *presentation,* as supported by Tufte, is that the viewer is invited to compare and contrast data. Long columns of numbers do not achieve such comparison. It is not only a matter of legibility and distance from the rostrum. Numbers cannot facilitate pre-attentive recognition. Each discrete area must be scanned sequentially to read the values

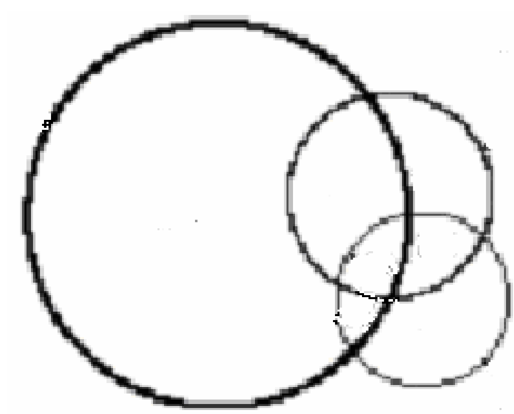


Figure 4.6 Quantitative Venn Diagram without Annotations

Notice that the appearance of Figure 4.6 is greatly simplified without the annotations and numeric values. “Reading” in this case is not a rational task; rather it is a non-symbolic comprehension of the relative values. The concept of “more” and “less” is immediately apparent. The focus of attention is now with the presenter, rather than the data visualisation, who may concentrate the audience upon the set unions according to the emphasis of the presentation. Colour and texture may be used for focussing the audience upon one particular aspect pertinent to the presentation. Even without the presenter targeting a specific set union, the audience is drawn to areas of significant interest. Those data where the variance is large (unless lack of variance is the focus of the presentation) are immediately apparent. It is not necessary to read the exact values 146 or 67 to know the relative proportion of these set unions. The author contends that it is apparent visually that one subset is less than half of the other.

4.8 Evaluation of Visual Numeracy

An underlying assumption of the research into visual numeracy was that it is a *useful* faculty for an audience to make sense of presentation data. To reiterate, visual numeracy is suggested to develop intrinsically without explicit education. Therefore it would be anticipated that visual numeracy would be readily apparent in any selection of individuals.

Whilst much popular work is devoted to perceptual illusions that show that there are many interesting anomalies still to be understood about the way humans are informed by their senses, there is little readily available data that catalogues distributions of what might be considered “normal” visual numeracy. What is the extent of this faculty? One would anticipate a wide variation in the way visual numeracy is manifest in the population as a whole. It may be the case that education departments, the armed services and professional bodies have, along with the usual metrics of physical attributes like height, weight etc, accrued large volumes of data that may be relevant to understanding visual numeracy. However those data are difficult to access and assess, and, in the absence of proscriptive design rules for the exploitation of visual numeracy, the overarching design consideration at this stage of the development cycle was to design software that both looked like a Venn diagram as well as being able to convey quantitative information.

4.9 First Dvenn Tool

The design of the first Dvenn tool began after extensive investigation of current data visualisation methods and the potential of new ones. Utilising a practise based approach to research, construction consisted of a deriving a standard two set Venn diagram from data and animating it to show the interaction of set unions whereby the size of the sets represented the actual values for the data attributes presented. This iteration of the Dvenn concept can be viewed by starting the Dvenn program that is available on the Dvenn executable media and selecting the button labelled “first” ‡. Those data represented are for test purposes only and notionally project an age profile of cigarette smokers by gender.

Building upon the observations outlined in section 3.2, a design consideration for the first prototype was to utilise animation for one data attribute in place of one set in the diagram. This was done to minimise programming complexity, as highlighted by Chow and Ruskey (2003), and enable a simple test of recognition to be undertaken with the first group of subjects. The simple test of usability consisted of requiring subjects to distinguish a pattern in time series data presented in an animated format. Therefore two sets appear to vary in size and union according to the third attribute, in this case being time. The implementation of the animation step presented few difficulties, being achieved by projecting four frames per second. Acknowledging that four frames per second falls well short of the definition of smooth image melding that was discussed in Chapter 3, it nevertheless conforms to the principle of animation, and, for the purpose of the prototype, was considered an appropriate compromise between coding constraints for a wide number of potential computer types on which to display the animation, and, for screen flicker resulting from too low an animation rate. The animation rate of four frames per second is also the minimum rate that can qualify for pre-attentive processing (Triesman, 1986).

It may be noted that a vertical line subdivided the projection space in which the Venn diagram was displayed. The purpose of this line was to provide a midpoint reference against which the animated circles could be judged to increase in size relative to each other. Movement to the right of the midpoint indicated the left set was increasing in size compared to the right set. Movement left signalled the opposite. No movement left or right indicated that both sets were static or increasing or decreasing at the same rate. The need for inclusion of this line may seem to be unnecessary given the emphasis placed by the author on as simple a diagram as possible. The rejection of scales, tick marks and other peripheral objects, those that Tufte considers “non data ink”, is an important design consideration adopted for the construction of the Dvenn. However, the author was of the view that the fixed reference point provided by the screen perimeter was not sufficient to accentuate relative movement of the two circles and therefore a strong vertical reference was included for this purpose. The subset of smokers is represented by the overlap between the two sets.

4.10 Test of the Dvenn Tool

The first iteration was considered by the author to be unsatisfactory and was not tested against an audience. Too much projection space was utilised for very little information. Therefore the program was modified to enhance the visual cues to those more suited to inference, that is, those that would be required to see a relationship in those data presented. The program can be viewed by loading the Dvenn program that is included in the accompanying software media and locating the mouse cursor over the button labelled “second” and clicking once on the left-hand mouse button ‡. As was the case for the first iteration of the software, the data utilised to generate the Dvenn was a static list embedded in the code. No database functionality was included at this stage and the selection of these data meant that scaling algorithms were not necessary, as both attributes were of the same order of magnitude and would be expected to provide useful visual comparisons. Some appropriate questions to be considered of the data over time were:

- Of various age groups, do more males than females smoke over time?
- Were there visually significant expansions and contractions in the sets?
- Did any of these visual cues correspond to significant statistical variations?

The Dvenn animation consisted of playing the 70 records of test data at the rate of four frames (records) per second. The animation was run as a continuous loop to a small focus group that was convened to provide feedback on the acceptability of this iteration of the Dvenn design before large scale testing was undertaken. The focus group was used to gather a frank assessment of the Dvenn concept and was not meant to provide feedback in the formal sense. The group consisted of five peers of the author who were selected because they held research or teaching positions either in Information Technology, Economics or Marketing at RMIT University. The focus group met together to view the animation and they were asked to provide their opinions by means of a discussion. Interaction was fostered by starting with very open ended questions to stimulate responses. The discussion was recorded in note form by the author at the time. On the whole, the feedback from the group was judged by the author to be uncommitted to either a negative or positive point of view, in that the Dvenn tool was not rejected out of hand, yet nor was it embraced enthusiastically. However, useful and practical suggestions for improvement were forthcoming and these could be incorporated as modifications to the initial design. Person B from the group suggested that the animated aspects of the design were commendable and well worth developing. Person E countered that there appeared, to him, to be little value in animation. He suggested that tried and true methods are popular because they have stood the test of time. He had reservations that any new audience for the product would emerge and that it was not an issue about technology, but rather the learning curve for such a product. Person B suggested that colour should be used more forcefully to distinguish data not movement.

In summary: the focus group members were in consensus about some perceived shortcomings with the Dvenn software and, between them, made the following valuable observations:

- Utilise the available screen area more effectively. The concept of how a scale was to be represented required more thought. Small sets were dwarfed by large sets.
- Make approximations of mid point values to prevent large and sudden fluctuations in the sets. That is, apply a smoothing algorithm to perform a rolling average, for example, based on the last four data points.
- Consider a range of different geometric shapes not just circles.

Clearly, the feedback suggested that full scale testing of the initial design would be fruitless and a third iteration of the Dvenn software was developed that resulted in the second major variant.

4.11 Subsequent Development of the Dvenn Tool

The next Dvenn tool incorporated lessons learned from construction of the previous iterations and incorporated feedback provided by the focus group who evaluated the previous version. Different shapes were considered for representation of each data attribute, but adherence to circles was a foremost consideration in order to preserve the initial theoretical structure that dictated that circles were easier to recognise and compare than alternative shapes.

Nevertheless, the utilisation of a triangle for one of the sets presented an interesting opportunity to emphasise the union of the smallest set. That is, the triangle was designated to represent the lesser of the sets that were projected. This version resulted from experimentation with circles in combination with triangles in various ways as a means to project set unions more effectively when a major disparity in size existed between sets as indicated in Figure 4.7. Note that a simplified annotation is applied to this figure and complementary sets are not explicitly indicated.

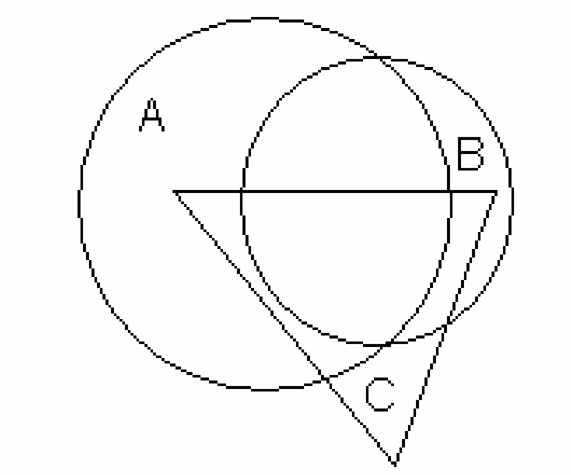


Figure 4.7 Substitution of the minor Set with a Triangle

The triangle concept was rejected on the basis that further visual complexity detracted from the original theoretical consideration of maximising the recognition of significant relationships in data by making the most of visual numeracy. Also, identification by the computer program of major and minor sets was required to establish which set was to be projected as the triangle. It is rarely the case that data are so well behaved as to have one attribute always larger in value than another. As well, it was not visually acceptable to have sets oscillate between triangles and circles according to whether they were now the numerically dominant or subordinate set.

Continuous experimentation with alternative geometric shapes (available to be viewed by selecting the buttons so labelled on the executable media[32]) for projection of Venn sets led towards rectangles ‡. This was particularly the case for effective utilisation of the aspect ratio

[32] The buttons are labelled “triangles”, “quadrant boxes”, “quadrant circles”, “circles + box”, “quad + circ + box”

of display surface area, rectangles being the standard for image projection on screens. This is true for paper as well as computer screens or projection of data onto any large surface. It is very unusual to see circular pieces of paper or curved projection spaces[33].. Therefore, in the business environment, rectangles are the normal frame of visual reference. Such a consideration is particularly important when one attribute of a dataset is a good deal larger than the other sets. Thus, after attempting various configurations of shapes to represent quantitative values, the author abandoned further development of a mixed shape tool. This was based on the belief that no satisfactory results would accrue from the second tool and therefore no formal testing of the software was undertaken.

At this point work on the tool ceased due to the need of the author to understand better the role of shape recognition in visual numeracy. For this purpose, work done by Zacks et al (1998) on subjects' interpretation of particular data presentation formats, provided inspiration to perform a simple calibration task for visual numeracy to shed light on what shapes are most suitable for exploiting visual numeracy. Therefore, in the absence of readily available metrics for visual numeracy, a basic experimental confirmation of visual numeracy in adults was undertaken. The purpose of this experiment was no more than to shed some insight into largely anecdotal claims that the comparative area of circles was difficult to measure at a glance (Wurman, 1989).

4.11.1 Change of focus from Circles to Rectangles

A simple test was designed to gauge how well a subject could differentiate the relative area in a comparison of simple imbedded squares and circles (Appendix VIII). This test consisted of a square within a square being presented to the subjects who were asked to nominate the relative area of the smaller square to that of the larger one. The second test was done with a circle within a circle. The purpose of this test was to establish what percentage of a trial group could understand the basic visual relationship of shapes that increase in size. A casual glance at the

[33] Experimentation with personal three dimensional computer displays has seen the evolution of a hemispherical display, rather like a satellite dish, in which the viewer sits with their face centred just inside the display. This technology, which promotes an immersive experience by exploiting peripheral vision, points the way to computer displays of the future being constructed in a circular format.

targets suggest that the circle appears to be half the size of the enclosing figure and the square appears to be approximately three-quarters of the larger figure. Of the targets, the circle actually represented a ratio in area of 1:4 of the larger figure and the rectangle represented a ratio of 1:2.

It would be expected that the subjects should accurately perceive the correct ratios, but the results of this very simple trial performed on 22 Tertiary Education students enrolled at RMIT University, suggests that circles are somewhat less reliably evaluated for comparative area than rectangles. One quarter of the subjects was unable to gauge accurately the comparative area of the circular target forms but the results implied that subjects were performing better than chance on the recognition tasks for both circles and squares. Table 4.1 presents the test results.

	T	Df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower Bound	Upper Bound
Rectangle test value = 50	1.71	20	0.10	4.76	-1.06	10.59
Circle test value = 25	3.21	20	0.00	11.90	4.17	19.64

Table 4.1 T Test for the Correct Perception of Area

The author formed the opinion that nothing in these results precluded moving forward with a software design that emphasised the elaboration of the rectangular form of Venn diagram.

4.12 The Final Dvenn Tool

The construction of the final tool symbolises the extent of work done for this Thesis and by no means suggests that further progress is not possible, rather it simply constitutes the final iteration of software programming development to-date and it is this version that was submitted to a group of subjects for experimental evaluation. The code for this program is presented in Appendix XI and is button “Final Test” on the Dvenn media ‡. The final Dvenn tool, informed in small part by the simple test outlined in 4.11.1, represented a clear departure from the circle format that constituted the first design that is synonymous with Venn diagrams.

The development of the Dvenn tool relied on the theoretical justification of rectangular Venn diagrams being derived from Lewis Carroll's quadrant diagram, a two set non proportional example being illustrated in Figure 4.8 (Edwards, 2004, p20).

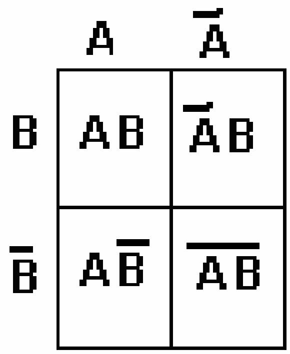


Figure 4.8 Carrol Diagram

Figure 4.9 illustrates a rectangular form of Figure 4.5(a) and 4.5(b), created from those data used by Chow and Ruskey to render an area proportional Venn diagram that utilised circles. It is worth noting here that Chow and Ruskey have contributed a good deal of work on proportional Venn diagrams, however they do not propose animation as a characteristic of a proportional Venn diagram. This fact is a substantial point of departure for the research presented in this thesis and the work done by Chow and Ruskey.

In Figure 4.9, the complementary notation has been omitted for clarity. As a developmental stage in the evolution of the final form of the Dvenn tool, this figure clearly illustrates the beneficial aspect ratio compared to circles with respect to the reference point of a rectangular page. The button "Quadrant Boxes" on the associated media illustrates the first animated realisation of this idea ‡. This rendition crystalised one of the suggestions made by the focus panel to improve the first Dvenn tool.

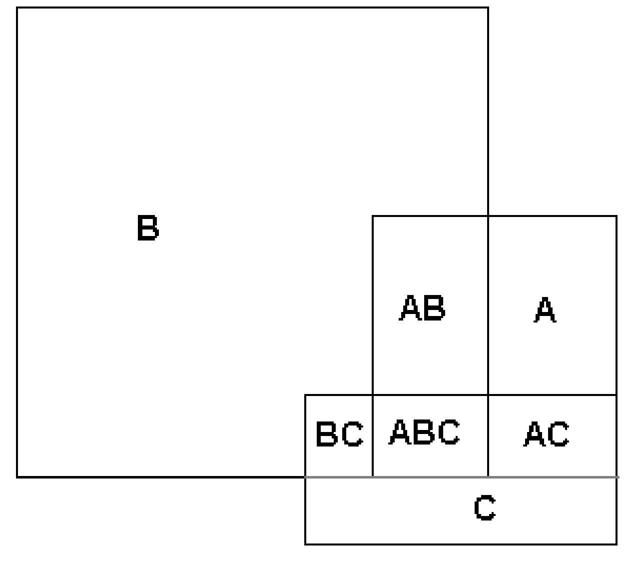


Figure 4.9 Area Proportional Rectangular Set Diagram

To maximise the projection of data onto the centre of the viewing area of the diagram, rather than have visual cues to variance occurring on the periphery of the display, animation is introduced to facilitate an understanding of variance through contrasting movements in the sets caused by the proportions of the sets changing according to the attribute chosen for animation (usually time). The principal feature of the final development of the tool was that the screen was divided into a quadrant rather than simply being vertically bisected. Each of two sets was assigned to either the left or right of the vertical midpoint. Each set was bisected horizontally, with the lower half representing the complementary sets.

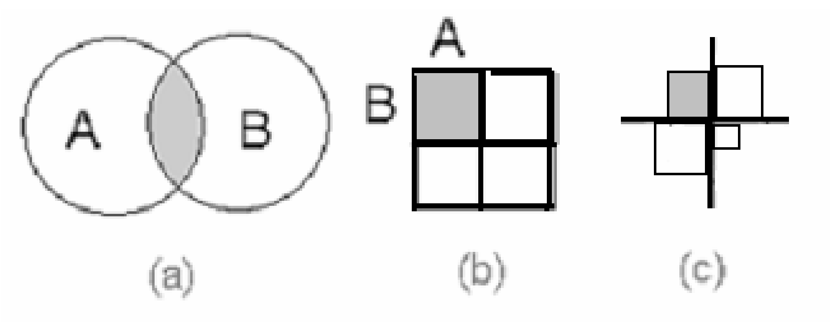


Figure 4.10 Migration from Circles to Rectangles to Dvenn

At this point of development of the tool, as indicated in Figure 4.10(a) and 4.10(b), the only difference from the first tool is figurative, with the rectangles of Figure 4.10(b) having been substituted for the circles of Figure 4.10(a). Logically, as envisioned by Venn of all Venn diagrams, the set relationships are equal in both Figure 4.10(a) and Figure 4.10(b). At first glance, the grey shaded area in Figure 4.10(b) appears to overemphasise the set union AB compared to the traditional Venn diagram. Venn never intended the proportions of his diagram to convey quantitative information, rather the purpose of the shaded area is to represent those elements that are both A and B.

To elaborate the progression of Figure 4.10 in terms of simple set theory, the inference of the subset AB, indicated in grey, is that the area represented is that which contains all elements of both A and B. All those elements that are not A exist outside of the circle labelled A. To make a straightforward transformation in diagram type, from the classical two set Venn diagram in Figure 4.10(a) to the rectangular form in Figure 4.10(b), simply requires a different geometry to be utilised that results in the same logical set associations being reflected in Figure 4.10(b). The realisation in this case is notable for its more compact form. The elements of set A indicated in Figure 4.10(b) are only those enclosed by the box labelled A, extending into the unshaded area below (column-wise). The constituents of set B exist in the shaded area and extend into the unshaded area to the right (row-wise). All those elements that are not A exist outside of the area so described for A, likewise for B. Therefore the area for those elements that are neither A nor B resides in the bottom right hand corner of Figure 4.10(b). The subset AB is shaded grey. Note that the classical Venn diagram in Figure 4.10(a) does not explicitly show the complementary set of those elements that are neither A nor B. By convention, such a set is implied to exist outside of the two circles.

Figure 4.10(c) projects the same logical association of elements as represented in Figures 4.10(a) and 4.10(b), but in a quantitative manner. It is arbitrary as to which alignment is used, that is, set A need not be the first set. All that needs to be demonstrated is that the shaded shape projected contains all those elements that are designated as combined values for A and B. The suggested value of the configuration exemplified in Figure 4.10(c) lies in the quantitative capability of the diagram, the use of ‘cross hairs’ are suggestive of a target that focusses the attention of the viewer on the centre of the diagram. This centre point becomes a reference for volatility in those data used to construct the diagram by way of the animation attribute.

The contribution of the shaded area to the total is immediately apparent in Figure 4.10(c). There is no quantifiable information available from Figure 4.10(a) and Figure 4.10(b) other than through annotation. Consistent with the discussion in 2.5.3, a ready example is that the subset highlighted in light-grey in Figure 4.10(c) represents the volume of cheque *and* credit card transactions. The area below the horizontal line and left would represent cheques presented as single payment and above right would represent the transactions for credit card as sole transaction. The area indicated at bottom right would therefore represent those transactions that were the complement of the subset indicated in light-grey, that is, those transactions that were neither cheque nor credit. Adding a third set, say gift voucher transactions, was accomplished by projecting it quantitatively around the screen midpoint according to each set union with the first two sets as illustrated in Figure 4.11. The dark grey area represents the union of sets A, B and C.

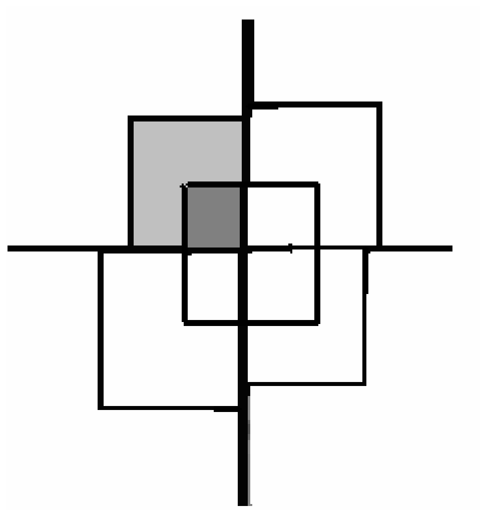


Figure 4.11 Dvenn showing Three Sets

Expanding upon the research undertaken by Chow and Ruskey (2003) into rectangular proportional Venn diagrams, the author considered a practical method of creating a Dvenn to be that which visualised a rectangle based on two data values, as utilised in the creation of an X and Y point of a scatter-plot, to form the horizontal and vertical attributes of each of the sets to be animated. However, for the purpose of prototyping, a simple square was considered to be a useful starting point both as a bridge from the previous version of a Dvenn that consisted of circles, as well as enabling a detailed exploration of the form of Venn diagram suggested by

Carrol (Edwards, 2004) that consisted of squares. More complex rectangular shapes were envisaged for a later working version that would be based on paired data values, with each data pair representing the vertical and horizontal lengths of the rectangle used for the creation of each Dvenn set. However, the complex nature of solving the problem of similes, that is, data pairs that produce the same area but different shapes, suggested that a simpler initial developmental stage be considered that allowed for an unambiguous representation of a unique value (in this case a square rendered from a single value). Should a lack of success of trials for the simpler form of Dvenn be apparent then little value would accrue to an audience who was presented with more complex shapes that introduced the added problem of similes. The foremost consideration for developing a novel way to present data to an audience was the ease and immediacy of visual recognition of meaningful quantities. Therefore, the symmetry of the square was considered by the author to be the best starting point.

Culmination of the tool was achieved by projecting a fourth set by utilising animation. Therefore, continuing the analogy of retail transactions, the attribute representing those transactions for each accounting period total, be it daily, weekly, monthly, half-yearly or yearly, are displayed in sorted sequence for that period at the rate of four frames per second. The quantity of discrete data that can be displayed via this method is apparent by a simple example of weekly retail transactions. In this case it is possible to view all the data for four attributes (covering four and a half years) in one minute of viewing. It must be emphasised that the attribute selected for animation must be able to be cross-referenced by all projected data attributes. Typical choices would consist of weights and measures, age and duration typically identified by time and date and co-ordinates for location such as latitude and longitude.

Periodic missing data for attributes other than the attribute utilised for animation do not present an insurmountable problem because the absence of data for a particular attribute is immediately apparent as a blank in that part of the Dvenn. If those missing data are formed by random omission, the value of presenting the Dvenn to the audience is only marginally diminished. In this case, data that have many breaks may cause an unpleasant flashing or blinking resonance on the display, analogous to the moire effect typically caused by crosshatching and fine lining in static graphical displays that is known to cause discomfort to some viewers. This visualisation problem is likely if missing data are flagged (null values are projected) rather than omitted altogether or substituted by deriving values from the existing distribution. Missing values that are not random do constitute a serious problem for the integrity of the presentation. In this case the use of a Dvenn would be unacceptable, as the presentation would simply present distorted information to the audience. Such distortion would be immediately obvious to an audience. For example, in the case of date being the attribute to be animated, it is expected that all records would be sorted in either ascending or descending format. Non random missing values would then be sorted to either the beginning or end of the file, depending on the collation sequence used. In this case, the consequence of sorting would be that the animated display would not reflect a realistic time sequence or natural order of the attribute that was selected for animation. Even if the display did not fluctuate wildly, the result would be a very misleading representation of those data selected for presentation to the audience. The problems specific to the animation attribute can be discussed at length, however, as mentioned in section 4.5, garbage in is garbage out, and, as Tufte has extensively catalogued, graphical excellence results from design and is not a random process. Intelligent utilisation of any tool is the best safeguard to avoid artefacts being created from data. Nevertheless, missing values in the animation attribute do create a potential trap that must be appreciated by likely new users of the Dvenn tool. It is not possible to devote programming resources to curtail all unsuitable uses of the tool.

4.13 Survey Format

Once the final Dvenn design was established it was necessary to test the tool for stability which then enabled preparation for testing on subjects. The test of stability undertaken for the Dvenn tool consisted of utilising different combinations of personal computers and Windows™ operating system software versions to establish that the aspect ratio of the display was preserved across a broad Windows™ based operational environment. The Dvenn program executable ran first time on all tested computers, but the display characteristics varied on the Laptop computers. Laptop or notebook computers proved to be problematic due to the compilation routine for Visual Basic leading to inconsistent representations of hashed lines and line thicknesses. This may be as a result of the video drivers for Laptop computers varying from those that are common for desktop units. Table 4.2 illustrates the equipment utilised for the stability test and the outcome. The result was simply recorded as satisfactory or unsatisfactory.

Computer	Type	Operating System	Satisfactory Result
Compaq Proliant 1600	Tower	NT (SP5)	Yes
HP	Desktop	Windows 2000 (SP4)	Yes
HP	Desktop	XP (SP2)	Yes
IBM Thinkpad	Notebook	Windows 2000 (SP4)	No
Compaq	Notebook	Windows 98	No
NEC	Desktop	Windows 98	Yes

Table 4.2 Equipment Test Schedule

The result of the stability test informed the author of the opinion that an online or distributed survey was not likely to be consistently viewed by the subjects, as this depended on the type of computer equipment upon which they viewed the Dvenn. Therefore a test was devised where the subjects participated in the survey in the same space and at the same time. Such a test was considered by the author to be suitable for the aim of establishing the efficacy of the tool for recognition of significant patterns in presentation data.

The survey was an attempt to elucidate some of the issues considered for discovery and outlined in section 4.2.

Is the Dvenn tool as good as other available tools?

Is sense-making via the visualisation pathway as good or better than simply reading numeric correlation coefficients?

Is visualisation of data consistently accurate?

4.13.1 Survey Task

The principal research method adopted was a simple test of the Dvenn application by using a paper based survey design (see Appendix XIII) with undergraduate university subjects being the sole respondents. The factor to be varied for the purpose of the test was the degree of correlation in the presentation data. The subjects were divided into two groups. The first group viewed those data that were created for the test as scatter-plots. The second group viewed those same data as presented by Dvenn. The degrees of correlation consisted of data that were positively correlated, negatively correlated and un-correlated.

The test task may appear simplistic, but, as discussed in section 3.4, high-density scatter-plots do present difficulties for an audience who are being expected to gauge visually degrees of correlation. Therefore, rather than attempting to provide a definitive insight into the problems faced by an audience when attempting pattern recognition of presentation data, research was undertaken solely to illuminate whether there was a general benefit in utilising the Dvenn in preference to scatter-plots. The test was not designed to define the boundaries of successful recognition of correlations in visualised data; rather, the simple idea proposed was that an audience that recognises correlations in scatter-plot data should also be able to recognise those same correlations when those data are presented as a Dvenn. Likewise, a subject who identifies a spurious correlation in a scatter-plot would just as likely be expected to identify the same spurious correlation in a Dvenn of those data.

4.13.2 Survey Instrument

The survey instrument consisted of a two page paper based one-dimensional interval response scale against which subjects recorded their impression of the correlation of multiple displays of test data. Each page had an individual interval response scale corresponding to each of the test conditions. Upon viewing the display, the subjects were required to record their estimation of whether those data that were presented as either scatter-plots or Dvenn were significantly correlated. The unnumbered range of the scale represented highly negatively correlated on the left, no correlation at midpoint and highly positively correlated on the right. The format of the response sheet is presented in Appendix XII. Numbers were not annotated upon the scale to promote a visually numerate response. If numbers had been annotated, the subjects would have had the opportunity to guess a response that implied an accuracy of identification for correlation that was not the intention of the test. It was not the expectation of the author that subjects would know an exact correlation, say .7; rather the expectation was that subjects would choose a point on the line that represented a satisfactory indication of a correlation to them. They should be able to record a response without thinking of numerical values. Rather like estimating and tracing a journey on a map as opposed to knowing how many kilometres had been covered or knowing that it will soon be mid-day rather than knowing the time to be 11:51. It is the inherent ready reckoning that people employ that was the focus of the test. Scatter-plots are not used to convey a definitive explanation, instead, for presentation, they are used to support an idea that the presenter chooses to explore with the audience.

4.13.2.1 Source Data and Correlation Generator

Unlike the attempt in the first iteration of the Dvenn software and its associated trial that utilised existing data from a large transport related dataset, the final iteration of the Dvenn was tested by means of a trial that utilised randomly created data. The reason for selecting such data was to avoid any particular bias resulting from selecting known patterns in existing data sets that could be employed to present a Dvenn in the most favourable terms. For example, transport data contain patterns that relate to the flow of commuters to and from the city centre. Generated data also enabled the subjects to be challenged by a full range of correlations from both the negatively correlated and positively correlated ends of the correlation spectrum without the intervention of the author introducing a selection bias by choosing particular segments from large data sets.

One possibility for creating data was to simply display the correlations based on target values of -.9, -.45, 0, .45, .9 to test the range of responsiveness. However the author believes that such a range would be too predictable over the repeated trials, even when presented in a random order. For example, a subject would quickly recognise that the full correlation spectrum was being covered and, having been shown .9, -.9 .45 and -.45, would probably anticipate that the last correlation in a five part sequence would be 0. Arnott(1998) suggests such a circumstance to be typical of anchoring and adjustment biases Therefore a method was required to generate random correlations that covered a wide spread of the correlation spectrum without bias towards any particular values that may have strong visual appeal. To recap, the target values for each correlation were randomly selected and these target values formed the basis for generating fifty data pairs that, when plotted, would produce a scatter-plot that conformed to a spread of points of the desired correlation (see Appendix XIII for the resulting sequences from the number generator).

Target Series 1 & 2	.1	.0
Target Series 3 & 4	.7	.1
Target Series 5 & 6	-.3	-.4
Target Series 7 & 8	.2	-.7

Table 4.3 Randomly Generated Target Correlations

To determine what number was used to target the correlation generator (that is, to start it), a list of random numbers between –1.00 and +1.00 was created. The targets for the correlation generator are presented in Table 4.3 and these values were used as input to the scatter-plot generator, the final output being paired columns of 50 values, each being randomly created but in total having a correlation of the specified target value. These pairs became the 'points' in the scatter-plots. The first column of 50 random values was nominated column A and the generator was run to provide a second column of 50 random values until such time that the correlation of the two columns equalled the target value specified. For example, to find a correlation target value of .1 involved the generator running automatically until a satisfactory result for two columns of fifty rows having a correlation of .1 (the target value) was produced. The generator was then run to create a second column of random values such that the correlation of this second column against column A equalled a correlation of zero (the second target value). This process was repeated, and for a sufficient duration, to produce paired columns of data corresponding to each of the specified target values. The correlation for .7 took a substantial amount of time and many tens of thousands of iterations to complete. The result produced by the generator was a list of pair-wise points that were used to plot series one of the first scatter-plot (scatter-plot 1). The second run produced two columns, the correlation of which was 0. These data were used to create the second series in scatter-plot 1.

A	B	A	C
4	16	**4**	18
15	9	**15**	11
19	3	**19**	4
7	2	**7**	14
4	2	**4**	18
19	16	**19**	0
1	4	**1**	2
13	19	**13**	1

Table 4.4 Example of Data Pairs Centred on Column A

Table 4.4 shows an example of the output in more detail. The rationale for keeping column A the same in each correlation was that the Dvenn purports to simultaneously show the correlation of those data in column A with those data in columns B, C and D. Therefore column A must be kept constant for each of these comparisons to be possible. A scatter-plot would not be so affected because points are inspected by a viewer individually and yield information about the specific series rather than the correlation *between* series.

The scatter-plots were presented as two series on the same plot for two reasons. First, as there were only fifty plot points for each series, the information content of the scatter-plot can be increased without producing too much visual complexity, and second, a reduction in respondent burden can be simply affected for subjects in the trial (it is quicker to show four slides of two series each rather than eight discrete slides). The presentation of data via a Dvenn, where each frame is visible for a moment in time, creates a particular problem of coherence. That is, the viewer cannot expect to glean meaning from a wildly fluctuating display. So, whereas the presentation of scatter-plots is a straightforward proposition, the Dvenn needs to be projected according to at least one of the attributes being sorted to present a coherent perspective to the audience. Should all attributes be unsorted, the result would most likely be a wildly fluctuating display of data for the viewer.

There is no exactly similar problem for a scatter-plot but a corollary might be that a scatter-plot that clustered about one part of the display would form a dense cloud that would inhibit comprehension of the underlying data. Paired data may be sorted in any sequence for a scatter-plot and the plots will appear the same, that is, the order in which the points are drawn makes no difference to the completed plot. Any extra attribute, say time, cannot be projected without elaborate and confusing scenarios such as arrow-headed interconnected points. However, the structure of the Dvenn allows that a time attribute can be incorporated easily through animation to reveal added information to an audience. Therefore, to ensure that the Dvenn was coherently projected to the subjects, each row of those data utilised for the test were sorted by the first column (A).

4.13.3 Subject Selection

The test of usability of the Dvenn software tool required a group of subjects who were available in a single location, willing to assist without remuneration and in numbers sufficient to enable a small quantity of sessions for the collection of survey data. Sourcing primary data for a simple survey is becoming more and more difficult due to problems of respondent burden, privacy legislation and the realisation that the specialised nature of survey design is a discipline in itself. Bearing the above considerations in mind, and after due ethics approval as mandated, undergraduate RMIT University students enrolled in the faculty of Business were selected as ideal subjects. The rationale for this selection is that if RMIT University students cannot understand the software, then widespread applicability is unlikely. Secondary School students were considered as an initial choice for participation in the survey, but they were rejected on the basis that the rationale behind the Dvenn tool was for the presentation of business data in a data wealthy but attention poor adult community. Secondary School students would not have the requisite experience of Business presentations to be expected to make sense of presentation data.

Subject selection was based upon Judgment, or Purposive, sampling as described by Zikmund (2003, p382) and is a non-probability sampling technique in which an experienced individual selects the sample based on their personal judgement about some appropriate characteristic required of the sample. For the purpose of this research, the appropriate characteristic was assessed to be that business students would be familiar with business charts. This sampling technique is also allied with Convenience sampling where the availability of subjects is both assured and economical to realise. As Zikmund (2003, p380) states "The college professor who uses students has a captive sample – convenient, but unrepresentative and perhaps unwilling." Further, he suggests that the sampling technique could be viewed by some as "unscientific" or random, researchers generally use convenience samples to collect questionnaires quickly and economically and are now widespread on the Internet. Zikmund suggests that convenience samples are best used for exploratory research and are subsequently followed up by research conducted with a probability sample. One distinct advantage for a researcher in using the convenience sample is the ability to avoid the formal requirement to legitimise the sample frame of a probabilistic sampleis the ith usually followed up by

Subjects were selected from the Business Faculty of RMIT University, who represented a broad range of occupational and demographic segments. The cohort consisted of volunteers who were enrolled in compulsory (non elective) courses in the final stages of completion of their Business degrees. The author had no prior contact with the subjects who were selected.

Undergraduate students may not constitute a cohort that is much more experienced in business affairs than secondary students, but for the purposes of this test the nature of study for a degree in a business discipline was considered to be a satisfactory alternative to actual business experience. Approximately one third of the cohort consisted of mature aged students, being those who had not entered RMIT University directly from secondary school.

4.13.4 Survey Administration

The subjects who participated in the trials during normal class time consisted of two groups chosen in collaboration with teaching staff of non-elective courses. The first group (group A) consisted of a class of 19 students, 11 of whom chose to participate in the trial. The second group (group B) consisted of 24 students, 16 of whom participated. The initial part of the trial was the same for both groups. After an introduction to the topic and time to read the plain language statement of the research consent form, those students who identified themselves as willing to participate were given response sheets.

Before commencement of the tests, a basic review of the concept of correlation was performed with the subjects. This consisted of a brief instructional discussion of the topic whilst showing subjects a selection of typical correlation scatter-plots for –1, 0 and 1. The term "perfect positive correlation" and "perfect negative correlation" were ascribed to a correlation of 1 and -1 respectively. The response sheet was shown to the subjects with the full range of correlation being shown on a Interval response scale stretching between –1 and 1, subdivided by intervals approximating .2 (but not actually indicated to the subjects as numeric values) with zero being the line midpoint. Questions and clarification were permitted at this stage and subjects were able to confer openly with each other. When no further questions from the subjects were forthcoming, the trials were begun. At this point until conclusion of the test, subjects were instructed to keep their responses private and not to confer with each other.

In an attempt to treat both groups equally, the author's presence in front of the projector was controlled. Possible indications of the degree of correlation, by such cues as body language, presenter's gaze, and inflection in tone were minimised to as great a degree as the author could feasibly manage short of implementing a trial in which the presenter was blind to which treatment was being administered.

4.13.5 Scatter-plot Trial

The purpose of the scatter-plot test was to ascertain whether the points presented on the scatter-plot appeared to the subjects to be correlated. Each presentation slide consisted of two series of fifty points per series, representing one-hundred points per plot (Appendix XIII). The subjects were requested to indicate on the response sheet whether they believed the points for each series to be positively or negatively correlated and, if so, to what degree, or were the points simply scattered randomly? The subjects were not shown the underlying data table or any information of a numerical nature. Figure 4.12 indicates an example of the data used for the first scatter-plot presentation slide.

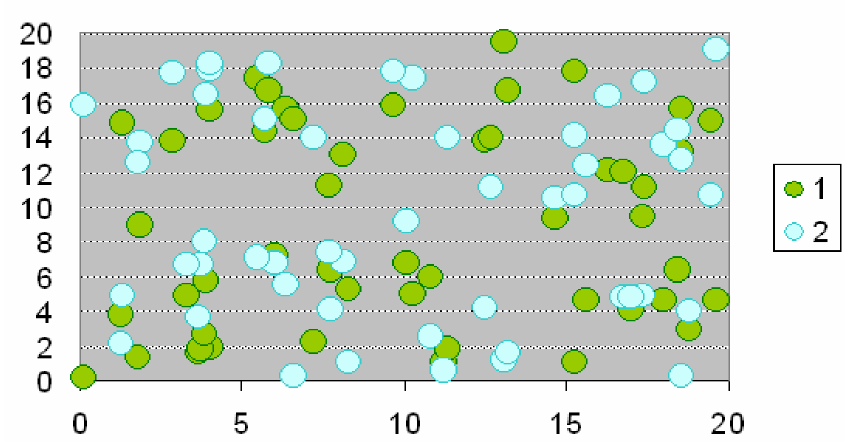
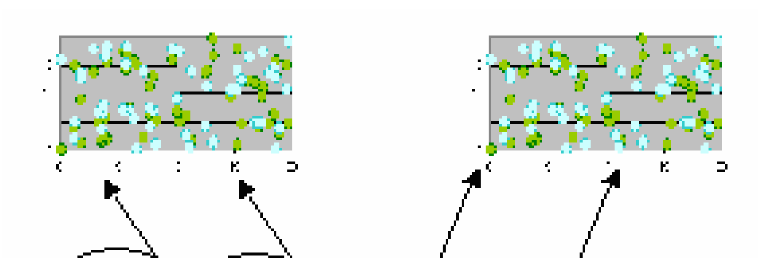


Figure 4.12 Example of Scatter-plot Slide

Reducing respondent burden was a foremost consideration in the design of this test, and, to facilitate this aim, the number of trial slides that were displayed to the subjects was reduced by overlaying two distinct scatter-plots on each presentation slide. This reduced the number of slides from eight to four and effectively halved the length of the trial. Each of the two data series per slide was distinguished by the size and colour of the points. Therefore each slide presented one hundred points in total of which fifty were from one data series and of one type of colour and size and fifty were of another. These points were intermingled, but a subject could easily distinguish that there was a representation of two separate data series on each slide.

Those data pairs that constituted the individual plot points of each series were derived from the correlation generator, the first column was utilised as the X axis and the second as the Y axis. For example, the first series of the scatter-plot presented on the first slide showed a distribution of points such that a correlation of .1 was represented by fifty points (a correlation of .1 was the correlation returned by the first run of the correlation target generator). This same slide had the series of points derived from the second run of the correlation generator (a zero correlation). Both these series were clearly differentiated by point size and hue on the single scatter-plot of the first presentation slide. Two series per scatter-plot were considered by the author to be a reasonable compromise between presenting few slides of high data density per view with concomitant visual clutter, compared to a larger number of slides of low data density per slide which would increase the length of the trial.

The actual test proceeded by utilising a projector connected to a personal computer to display each scatter-plot of two series upon a screen for thirty seconds duration. A further thirty seconds followed, during which time the scatter-plot was not visible, and this time was utilised by subjects to determine and mark their responses on an interval response scale provided to them. Valid responses consisted of circling or marking the interval most appropriate to their perceived estimation of correlation of the data sets presented to them. The order of presentation had been determined by the sequence of numbers that had originally been created for targeting the correlation generator and could be considered random. The presentation of data was labelled series A1 and series A2 for the first trial (scatter-plot one), series B1 and series B2 for scatter-plot two and C1, C2, D1, D2 for the remaining two scatter-plots, making a total of four scatter-plots that were presented to the subjects.



A	B	A	C	A	D	A	E
4	16	4	18	4	5	4	0
15	9	15	11	15	11	15	17
19	3	19	4	19	15	19	4
7	2	7	14	7	6	7	10
4	2	4	18	4	5	4	10
19	16	19	0	19	17	19	6

Figure 4.13 Pair-wise Points of a Scatter-plot[34]

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[34] Figure 4.13 is not intended to illustrate the actual scatter-plots but simply show the nexus between the data table and the plots. The points on the plots are not meant to be actual values from the table, rather they only indicate how the data table fits into the process of how the scatter-plots are created.

The plot points in series one of each scatter-plot were clearly differentiated from the points in the second series by size and hue. It was unlikely that points from each series were confused, regardless of the scatter and masking effects of the plot as a whole. Table 4.4 shows an example of the first eight rows of series one and series two in plot one. Note that the values for column A were the same in each of the trials. Another way of looking at those data is to ask; is B correlated to A? Is C correlated to A? The values for A are the same in all cases. Figure 4.13 illustrates how the derivation of these values was utilised to create the actual scatter-plots.

The question to be answered by the subjects was; were the plot points made by the data pair values of series one of scatter-plot one correlated? Likewise, were the points of series two of scatter-plot one correlated? To reiterate; the values for column A are the same in both series of the first two scatter-plots. These same data values were used for the Dvenn trials.

4.13.6 Dvenn Trial

The Dvenn group was given the same basic introduction to correlation, consisting of the same scatter-plots for –1, 0 and 1 correlations as shown to the first group. This introduction was considered suitable as a refresher for identifying correlations but there was no equivalent task available for the Dvenn group to prepare them for viewing a Dvenn. That is, the scatter-plot group had been shown plots of a type that would be used in the actual trial but the Dvenn group were prepared for the trial solely by viewing plots that were unlike those that they would observe in the actual trial. The use of animation precluded any meaningful way of presenting a snapshot of the data as an example preparatory to the actual trial.

It was ascertained, through discussion prior to the commencement of the scatter-plot trial, that most subjects were to be able to identify scatter-plots and were familiar with them on a day-to-day basis. However, the novelty of the Dvenn prevented such a presentation form being shown and discussed in detail without losing insight into their spontaneous usefulness as a tool for the exploitation of visual numeracy. To coach an audience on the meaning of Dvenn diagrams would have detracted from the very value that was claimed for them. That is, the claim for their immediacy of recognition unaided by prior training.

4.13.6.1 Trial Differences

The data used to create the presentations for both trials were the same. However, an important distinction between the scatter-plot and Dvenn trials becomes apparent when considering how the data values were presented to the Dvenn subject group. Unlike a simple scatter-plot, where an individual point represents a pair of data values, the discrete Dvenn areas were determined by a single data value. To make the trial as simple as possible, the single data value was used for the length of an imaginary diagonal that connected the opposite ends of a square. The area so formed created a visual representation of that single value.

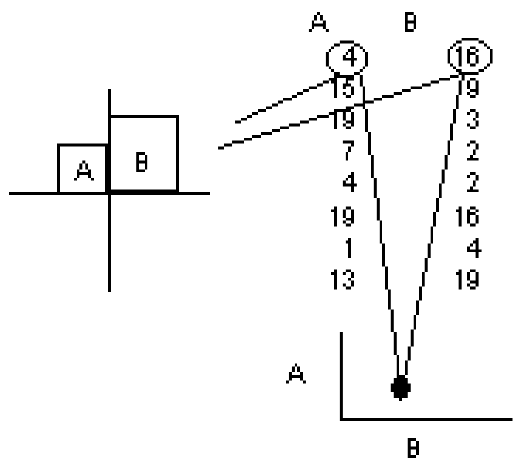

Figure 4.14 Comparison of Pair-wise Points of a Scatter-plot and a Dvenn

Thus each frame of the animation represents a new group of data values; Figure 4.14 illustrates how the pair of values that would constitute a single plot point on a scatter-plot is used to create an individual square for each component of the data pair. Therefore, as illustrated, the Dvenn quadrant A represented the first value of the first data pair of scatter-plot trial A. The second data value of the first pair of scatter-plot trial A was assigned the quadrant area B. The visual equivalent of scatter-plot trial A point one would equate to the first frame of the Dvenn A and B.

A single frame of an animated Dvenn, when compared to the scatter-plot, requires a larger area to represent the data values visually. Tufte (1983) suggests that the area thus represented would register a very poor data–ink ratio that may be considered a necessary negative attribute for a Dvenn. However, the single point on the scatter-plot represented by the data pair must be evaluated against the X and Y axes to glean meaning, particularly if the axes are inverted or the scales are not linear. The scatter-plot point must be referenced as a map. The point's location makes sense only within the confines of the Cartesian grid implied by the scale. The values of the Dvenn can be referenced simply by their size in comparison with each other. As has been argued by the author in support of the Dvenn, this is a perceptual task, not a cognitive task, and therefore should be pre-attentively recognised. A single point on a scatter-plot cannot be pre-attentively recognised due to the requirement to reference the axes for meaning. Rather than presenting pair-wise points, the Dvenn was projected with the first column (A) implicitly paired with each of the subsequent column values. Thus, A is compared to B simultaneously with the comparison of A to C and A to D. A single value is all that is required for such a comparison. As illustrated in Figure 4.13, showing series one and two in trial A and series one and two of trial B of the scatter-plot trial, column pairs necessarily duplicated the value of column A for each point pair.

The consequence of utilising single data values for the creation of each set of the Dvenn was that the second pair of values for the second trial could not be projected onto the Dvenn. As has been noted, the target values for the correlation generator created fifty pairs of data values all of which correlate with respect to column A. However, only four columns of values could be used to represent the Dvenn of sets A, B, C and D. As the scatter-plot trial utilised values for the first two trials in pairs corresponding to the correlation target values, there were two series presented per plot.

The first represented AB and AC, the second AD and AE. It is not possible to represent AE on a Dvenn as this pair would not fit on the Dvenn quadrant. The reason for this omission is apparent when viewing the Dvenn, as the correlation A to E cannot be expressed in the available space. To omit the correlation A to E from the scatter-plot group would have resulted in them being shown a single series in the final plot (just AD). The author considered this to be out of character with the previous plot having consisted of two series for the plot. Therefore, to balance the presentation of scatter-plots and not induce any unnecessary variation from one trial to the next, the final plot also had two series, the last correlation being A to E which was not used for the Dvenn.

To recap, the Dvenn quadrant consisted of the actual single values A, B, C and D. As A was used explicitly rather than as the first value in a co-ordinate pair, there was not room to present the values for AE. Figure 4.15 illustrates the problem. For the purpose of making a valid comparison between the Scatter-plot trials and the Dvenn trials, the author believed that omitting correlation AE on the basis of ‘last in first out’ was sufficient rather than selecting a correlation pair at random for exclusion.

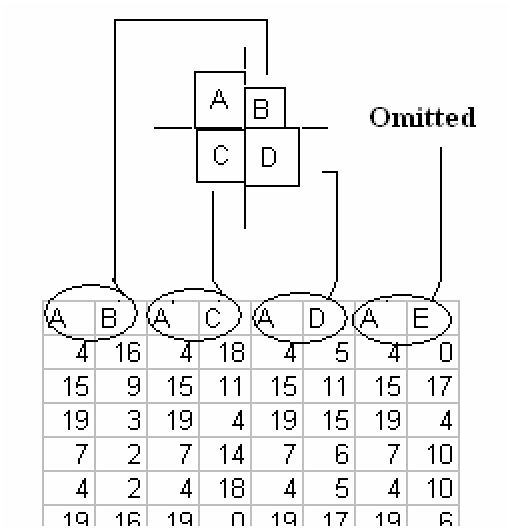

Figure 4.15 Omission of Correlation AE from the Test

4.13.6.2 Dvenn Trial as Implemented

The Dvenn trial was presented to subjects following the test of visual numeracy and the overview of correlation that consisted of viewing scatter-plots for –1, 0 and 1 correlations. The subjects were shown the Dvenn which consisted of an animation of data that proceeded at the frame rate of four frames per second for two complete passes of the data. A five second pause occurred at the end of the first presentation before the repeat presentation commenced. Two complete runs of the Dvenn were considered necessary to compensate for the fact that the subjects had not encountered a data presentation format of that nature before. Therefore the first run was problematic in that its very novelty may have constituted an actual distraction from the data being presented. By the second run of the animation, the expectation was that subjects could focus on the visual numeracy aspects of the presentation.

Upon viewing the Dvenn for the second time, subjects were expected to record their impression of the correlation of A to B, A to C and A to D. This was the same expectation as made of the scatter-plot group. The only difference between the scatter-plot group and the Dvenn group was that correlation A to E was omitted for the Dvenn group for the reasons discussed in section 4.13.6.1, The subjects of the Dvenn group were asked to record their impressions of a correlation for A to B in the same manner as the scatter-plot trial using the provided interval response scale. So, did the area of square B *appear* to increase or decrease in a significant way with the area of square A? Further, the correlation of B to b (designated by the size of the blue square b within the yellow square B) was displayed simultaneously. One of the claims of usefulness for the Dvenn tool is its ability to project increased data density. These simultaneous comparisons were the same correlations as viewed by subjects of the scatter-plot group for trials three and four. Subjects of the Dvenn trials were expected to concurrently evaluate and then record their impression for the subset Aa, Bb, Cc and Dd. All data for these trials were the same for both the Dvenn and scatter-plots groups and were obtained from the correlation generator.

4.14 Chapter Summary

The manner in which research into the efficacy of the Dvenn was undertaken was to iteratively prototype the project utilising MS Visual Basic™ software. Initial feedback was provided by focus groups and this shaped the final design towards an animated rectangular format Venn diagram based on Lewis Carroll's work on set diagrams. To test the efficacy of the design, two assessments were devised and administered to undergraduate University students enrolled in a Business course of study. The first test was a simple exploration of the ability of subjects to recognise the correct proportion of a shape contained within a larger shape. This test was undertaken to establish the degree that a cohort was visually numerate (Appendix VIII) and was utilised by the author to confirm previous results, as cited in the literature review, that audiences found circles to be more problematic than squares for the correct recognition of surface area. The second test utilised two separate groups of subjects who were shown either a scatter-plot or Dvenn of the same data and asked to rate the apparent degree of correlation visually for the scatter-plots (see Appendix XIII).

The subjects recorded their responses on an interval response scale[35] which contained no numeric information that might be used by them to guide their responses. Recording a response simply required that the respondent marked the line at the point they thought reflected the measure of correlation in the presentation. The author utilised this method to avoid any coaching of responses and the subjects were free to mark the line at any point rather than at set boundaries. Post processing of those data became necessary and this consisted of the allocation of values according to the mid-point of the interval response scale which was established as zero. Either end of the line represented -1 on the far left and 1 on the far right respectively. Each marked division between these extremes represented point two and the mid point between each division represented point one. Thus it was possible to code consistent numerical values with a resolution of point one which represented the perceived correlation values. Data collected from the participating subjects were entered into an Excel ™ spreadsheet for each group. All responses were double entered[36] to verify correct data entry and individual responses that included a null response for a particular question were included. Response sheets that were completely blank or marked in a manner unrelated to the purpose of the test were rejected. The resultant database of values was then utilised to analyse the results of both the scatter-plot trial and the Dvenn trial by employing the personal computer based statistical package for social sciences (SPSS™) for statistical analysis.

[35] Appendix XII presents a sample response sheet as utilised by subjects for the scatter-plot trials and the Dvenn trial.

[36] Data entry was performed twice on two separate spreadsheets on different occasions. The two sheets were compared for any indication of discrepancies. The result was that the author could undertake statistical testing with a high degree of confidence that the electronic copy of those data faithfully represented those data manually recorded by the respondents.

Chapter 5

RESULTS & DISCUSSION

5.1 Introduction

The purpose of this chapter is to establish the manner in which the data collected from the test were collated and analysed to shed insight on the efficacy of the Dvenn tool. The statistical analysis consisted of a straightforward t-Test of independent means, the results of which raised some interesting issues. Firstly, issues about the adequacy of the test design are raised, particularly with respect to the choice of scatter-plots for the control group. Secondly, the inherent usefulness of the Dvenn tool, being that it is suggested to utilise visual numeracy, may not have been exploited because of a lack of corroborating material made available to the subjects during the presentation trials. Put simply, insufficient allowance was made for the impact of the novelty of the Dvenn technique upon the audience. Finally, the nature of those scatter-plots and the Dvenn that were visualised correctly by the subjects are examined in detail to shed light onto the particular characteristics which led to success in these cases.

5.2 RESULTS

5.2.1 Introduction

The following statistical analyses were performed:

- The first statistical test was an independent samples comparison of means t-Test to establish acceptance or rejection of H_0. This test satisfied the essential requirement proposed in the research question that a comparison of performance *between* the two groups be undertaken. Table 5.1 presents the results of these comparisons. This test was used to answer the research question and establish whether the performance of a group of subjects viewing a Dvenn projection of a known correlation was the same as that of a group of subjects viewing the same correlation presented as a scatter-plot.

- Further statistical analyses, undertaken subsequent to the findings of the first test, were performed. These tests included an analysis of the accuracy of the Dvenn group for deciding the degree of correlation of the projected test data. That is, the Dvenn test group was assessed for the degree of accuracy that they exhibited in their selection of a particular correlation. A similar test was utilised for the control group who used scatter-plots. These statistical tests were undertaken *after* the results for the central research hypothesis were known as a means of exploring the performance characteristics of the Dvenn tool.

5.2.2 Results Fail to Reject H_0

Collation of the results and presentation in a concise format enabled some progress towards answering the central research question. To recap the research question: *Is the presentation of data via an animated quantitative Venn diagram (Dvenn) a useful tool for the recognition of relationships in high volume quantitative data*? In order to operationalise this question, the null hypothesis stated that there was no difference between projection techniques, that the average mean was no different than the mean for the control group. The alternative hypothesis would suggest that the mean of the two groups was significantly different and that the conclusion would be made that these two projection techniques were different. The test results are presented in Table 5.1.

Independent samples T Test for equality of means at the 95% Confidence Interval	t	Sig. (2-tailed)	df	Decision
Test 1 (Sets AB) Correlation target = .1	2.31	**0.030**	23	Reject H_0
Test 2 (Sets AC) Correlation target = 0	-1.17	**0.344**	23	Fail to Reject H_0
Test 3 (Sets AD) Correlation target = .7	0.66	**0.417**	23	Fail to Reject H_0
Test 4 (Sets Aa) Correlation target = -.3	-0.61	**0.830**	23	Fail to Reject H_0
Test 5 (Sets Ab) Correlation target = -.4	0.09	**0.463**	23	Fail to Reject H_0
Test 6 (Sets Ac) Correlation target = .2	-0.25	**0.347**	23	Fail to Reject H_0
Test 7 (Sets Ad) Correlation target = -.7	0.43	**0.542**	23	Fail to Reject H_0

Table 5.1 t-Test for Equality of Means

Overall, H_0 is accepted because six of the seven tests results favour the conclusion that the performance of subjects who viewed projections of correlations via the Dvenn tool is not significantly different to the performance of subjects viewing those same correlations projected via scatter-plots. However, this result is subject to ambiguity and there are a number of issues that must be discussed with respect to the actual interpretation of these data, and, in preparation for that discussion, Table 5.2 presents the individual results for each of the presentation methods.

Correlation Test value	Std. Deviation	Std. Error	t	df	Sig. (2-tailed)	Mean Difference	Lower Bound	Upper Bound	Accept/Reject H_0
Dvenn 0.1	0.41	0.11	0.88	12	0.40	0.10	-0.148	0.348	Accept
Scatter-plot	0.38	0.11	-0.49	11	0.64	-0.05	-0.299	0.190	Accept
Dvenn 0	0.39	0.11	-2.30	12	0.04	-0.25	-0.480	-0.013	Reject
Scatter-plot	0.35	0.10	0.94	11	0.37	0.10	-0.128	0.319	Accept
Dvenn 0.7	0.53	0.15	-4.54	12	0.00	-0.66	-0.979	-0.344	Reject
Scatter-plot	0.41	0.12	-4.22	11	0.00	-0.50	-0.767	-0.241	Reject
Dvenn -0.3	0.41	0.11	2.62	12	0.02	0.30	0.051	0.549	Reject
Scatter-plot	0.22	0.06	5.09	11	0.00	0.33	0.187	0.472	Reject
Dvenn -0.4	0.47	0.13	3.80	12	0.00	0.50	0.213	0.787	Reject
Scatter-plot	0.23	0.07	5.95	11	0.00	0.39	0.244	0.531	Reject
Dvenn 0.2	0.47	0.13	-0.88	12	0.40	-0.12	-0.401	0.170	Accept
Scatter-plot	0.39	0.11	-2.49	11	0.03	-0.28	-0.534	-0.033	Reject
Dvenn -0.7	0.61	0.17	4.96	12	0.00	0.85	0.475	1.218	Reject
Scatter-plot	0.44	0.13	7.75	11	0.00	0.98	0.701	1.257	Reject

Table 5.2 Individual t-Tests for Actual Correlation Values

The ρ values returned in this single sample t-Test clearly indicate that the rejection of H_0 is *highly significant* for the majority of *both* presentation test methods. Therefore, this result suggests that the findings from the first statistical test are encouraging in that those data presented in Table 5.1 suggest that, from the perspective of the subjects selected as a sample of a typical business audience, there is no significant difference in performance *between* the Dvenn projection tool and scatter-plots for the perception of correlations. However the results presented in Table 5.2 suggest that the tool is not useful in that the correlations are not reliably identified by either presentation form.

It must be noted that the two tests apply to different questions. Table 5.1 tries to address whether the two methods are different from each other. Table 5.2 addresses whether each test varies from the actual correlation value it purports to represent. All that can be garnered from the analysis presented in Table 5.1 is that the two groups vary little. Therefore, given that Table 5.2 indicates that neither method is reliable; this suggests that, somewhat surprisingly, scatter-plots do not prove to be as an effective a control as was anticipated by the author. So, it is possible to answer the research question in the affirmative but such affirmation simply suggests that that both presentation methods performed equally poorly. As will be discussed in detail in the next subsection, it is apparent that subjects failed to identify correctly the majority of correlations viewed by both projection methods.

Whereas it may be asserted that both scatter-plots and the Dvenn tool perform similarly, such an affirmation of the research question reflects directly on the theoretical justification for the study and it would be very dangerous indeed to suggest that the results infer any particular endorsement for the exploitation of visual numeracy for presentation of data to an audience. Yes, the test confirms that the Dvenn performs similarly to a control, but the choice of control is clearly the problem. Indeed, just how accurate are scatter-plots as a control? The most obvious feature of this analysis of scatter-plots presented in Table 5.2 is that in all but two of the seven tests the rejections were highly significant[37]. This result was unexpected, as no indication was forthcoming to the author that, prior to this test, there was any reason to doubt the ability of a business audience to interpret scatter-plots correctly.

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[37] A convention often utilised, but not adopted here is to designate highly significant results with a double asterisk **, significant results are designated by a single asterisk *.

The ambiguous finding for this study begs the question of whether the Dvenn exploits unlearned visual recognition as a pathway to understanding and sense-making that has been termed visual numeracy. If it had been the case that subjects had performed well on the individual Dvenn test, then the argument for visual numeracy, being an important factor in performance on the tests, may have been substantially strengthened. However, the results presented above offer no definitive answer to whether visual numeracy is a faculty that should be increasingly exploited to ease the information burden now faced by business audiences. Equally, however, these results certainly cannot be used to refute the idea that visual numeracy may have beneficial applications in other contexts.

5.3 Critical Analysis of the Research Design

The test attempted to vary the degree of correlation of the test data for the purpose of bench-marking the Dvenn based presentations against those same data presented as scatter-plots. However, as is the case when dealing with human subjects, many factors impinge on straightforward data collections that are outside the experimenters' control. Not only do environmental disturbances exist that may impair the quality of the data collected, but an individual subject's focus on the task at hand is also a factor. Though not formally ascertained by debriefing, it was apparent from the recorded survey responses that some subjects were simply not enthusiastic about participating. Examination of the experimental cohort may further elucidate this problem. There is a long tradition of utilising University students as an experimental population and the nature of the experimental task was deemed by the author to be simple enough to enlist a satisfactory group of participants. Previous experience gained by the author of collecting Business related data, both quantitatively and qualitatively, by utilising human subjects, had not posed the same degree of uncertainty with regard to the quality of responses. Such an issue is problematic for any subjective experimental design. However, given the due care afforded by University ethics procedures and the provision of a meaningful plain language statement as mandated by those procedures, each subject's participation was informed and voluntary. Therefore there would have been no expectation that subjects who had agreed to participate would do so half-heartedly. Indeed, the number of subjects who volunteered was sufficient to ensure a viable pool of respondents without consideration of possible inducements to participate and, in hindsight, the choice of University students as a test cohort is unremarkable.

Perhaps the task was unable to captivate the attention of the subjects. Respondent burden will always affect different subjects in different ways and this is difficult to control for, as equally, it is difficult for a researcher to control conditions that are peripheral to the test. However in this particular case there was evidence in the form of overheard comments, laughter and distractions to suggest that some subjects were less than committed to a frank participation in the experimental task. Of course the discussion of such unquantifiable inference may appear to be wishful thinking on the part of the author to *explain away* an unfavourable test result. Indeed, however unpalatable the test result was to the author, there were issues pertaining to the credibility of responses that should be mentioned. These issues were separate from deficiencies in the experimental design and leave a lingering suspicion that, should the test be repeated, an expectation of more completed response sheets would be not unreasonable.

5.3.1 Were Scatter-plots the right choice for a control?

In hindsight, the foremost consideration with the design was the choice of control. As the results reveal, the major problem was that subjects did not readily identify correlations in scatter-plots. Of particular concern was their inability to identify highly correlated plots (.7 & -.7) in the trials. Indeed, Table 5.2 indicates that subjects tended to underestimate these strong positive and negative correlations. This was the case for both presentation methods. What is the purpose of a scatter-plot if not to identify significant relationships between attributes and interpret correlation visually? Surely a strong correlation should be the easiest to pick. It was anticipated by the author that scatter-plots represented a familiar and useful tool for any business audience. For bi-variate data it is a reasonable choice. However, the results from the survey suggest an alternative view. Perhaps this chart type is familiar to an audience, as was envisaged at the outset of this study, but the experience of the audience of actually interpreting a scatter-plot is limited. After all, there is a great deal of difference between recognising a chart type by simply looking at it and actually trying to understand it.

A presenter, by virtue of what they are doing, is coaching an audience toward shared meaning. The chart is often a prop or focus as part of the presentation. In the scatter-plot test, as conducted, the subjects were actually asked to draw their own conclusions about significance without any coaching. In a group context, such an approach was possibly quite novel to them. In this case they had to form their own opinions without either the presenter guiding their interpretation or their having access to numerical representations of those data that formed the basis of the chart. Also there was no line superimposed on the plots that represented the mean of all the plot points. This line may be more important than the points themselves for the audience to form a ready impression of correlation.

The results in general for the scatter-plots, as for the Dvenn, were that uncorrelated data are identified as being just that. This finding is contrary to taxonomical work by Arnott (1998) who concluded on the basis of a substantial literature review that “humans are generally poor at perceiving randomness” (p 6). However, in the test presented here, randomness seems to be readily identified and such a result may have a number of possible explanations. One such explanation may be that, contrary to Arnott’s conclusion, random patterns are easier to identify than non-random patterns. That is, noise is easier to recognise than a coherent pattern. However, supporting Arnott is the classic work on this topic that suggests that random sequences presented to subjects are reported as exhibiting a consistently positive correlation when no such correlation exists (Gilovich and Tversky, 1985). The “hot hand fallacy” in basketball illustrates the fundamental difficulty individuals have in recognizing uncorrelated data and it is suggested by Gilovich and Tversky to be representative of a cognitive illusion. In this case, subjects over-report the impact of an individual who has had a succession of successes, within a short duration, on the overall outcome of a game. That is, a burst of successful activity from a player in a game overshadows the superior performance of a player who contributes consistently for the whole duration of the game. Subjects’ perception of a “hot hand” signifies that they believe the player to be most likely to add to the score even though, statistically, the player has no more likelihood of scoring than any other in a similar position.

Cummins and Nistico (2002) suggest that a bias towards positive reporting is no more than an extension of the inherent optimism that humans have for positive outcomes. The subjects’ anticipation may be that a pattern does exist. Regardless of the reasons that a subject may have for anticipating a result, all that is required for positive reporting is that there is *anticipation* of an outcome. Therefore, according to the "hot hand fallacy", subjects are optimistically primed and are likely to report positively a "hot hand" based on an anticipated result. That result being caused by an emotional investment in a "winning streak" linked to a particular player.

However, the results indicated in the scatter-plot trials would indicate the opposite of an optimistic outlook evidenced in the case of a "hot hand". This may be because subjects had a lack of connectedness to the task. There was no optimistic or pessimistic presumption based on anticipation and interest in the outcome as would be expected for a sport-based event. In the case of having no vested interest in the presentation data, as was the case with the scatter-plot trials, the subjects may have simply opted for the least controversial outcome. It may simply be the case that less visual processing is involved for a random sequence. A pattern may take more time to decipher; therefore making a *guess,* when the result of the guess has no consequential outcome, may be more likely to favour a random pattern.

To illustrate the contention that circumstances for the scatter-plot trial may be subject to a different set of decision biases than those applying to subjects of the Dvenn trial, the author proposes that a comparison of signal identification tasks be made. In the case of "spot–the-difference" tasks there is only so much time allocated by a viewer before they yield and resolve to give an answer. Where a subject is unsure of whether a signal may actually exist, a sensible strategy would be to simply stop looking and assume there is no difference. Therefore, if one treats the search for a correlation in a scatter-plot as no more than a *signal in the noise*, then it is entirely feasible that subjects simply ceased looking for a pattern. Given the time constraint of 30 seconds that was set for each of the scatter-plot trials, there was pressure created on the subjects to record a response. Under these circumstances, subjects in the scatter-plot trial would be expected to exhibit symptoms of time pressure being the primary cause of task stress leading to poor decision making typical of the Yerkes-Dodson law (Yates, 1990).[38] The intention of the author in limiting the time of exposure the subjects had to each of the scatter-plots was to facilitate a constrained, reproducible and orderly progression

[38] This law, applied to decision making by Yates (1990), states that initial stress serves to increase the quality of decisions but increasing stress past a certain point decreases the quality of decisions made.

through the test. A time limit was also important to ensure that the Dvenn was not compromised with respect to Scatter-plots because the viewing time available for each frame of a Dvenn is naturally limited because of animation, whereas scatter-plots were not. A major contention in this research is that scatter-plots are not pre-attentively recognised. Unlike pre-attentive tasks, the length of time required for the evaluation of cognitive tasks is not prescribed. Therefore substantial variation could be expected to exist for subjects to either recognise a correlation or assume the scatter-plot to be random. In the case of pre-attentive recognition, by its very nature, subjects have no control over how long they can dwell on a subliminal target. Therefore the duration of the subjects' exposure to each of the scatter-plot trials was limited to thirty seconds.

An unexpected consequence of the time limit on the efficacy of the experimental design may have been that the nature of the cognitive task required more time than the time limit allowed for the subject to be confident of their answer. Therefore an unintended outcome of limiting the response time for subjects of the scatter-plot group may have been to create a stress situation that was conducive to guessing, where the recording of a result was more important than the meaning of the result. No subjects volunteered the information that they found the time-span for completion of the task too short. Some mentioned that they thought the task was not particularly easy, but not that they would have been more 'successful' or more able to 'solve' the task given more time.

Some individual trials returned survey sheets that were completely blank, but no pattern emerges that particular correlations were associated with more indecision on the part of the subjects. This is also true for the Dvenn trials. Therefore it is only conjecture to suggest that unrecorded responses represented trials that were hard to pick and therefore were left blank, but interestingly, there were fewer unrecorded responses in total for those trials that showed random correlations. However, the result is not significant and the overall numbers are small. The timeframe of thirty seconds was simply assumed by the author to be adequate for the task at hand, but in the absence of debriefing of subjects, the doubt now remains that a constraint on the results conforming to expectation (particularly the .7 and -.7 correlations) was imposed by the exposure time for the scatter-plot trials being too short.

Shortcomings in the experimental design may account for some of the variance from expectation; however the possibility of visual artefacts may also be a factor. A careful examination of the scatter-plot of a negative correlation of .7 (Appendix XIII) does initially indicate a negative correlation, however the non-linear nature of the slope, accentuated by the clustering in the top left and bottom right might suggest only a mild negative correlation to an informed observer. One suggestion that might account for the failure of most subjects to recognise the strong correlations was that the introduction to the subjects of the scatter-plot trials consisted of a clear demonstration of perfect positive and negative correlations as well as a random scatter. As perfect correlations would be rare with real business data, it may be the case that the introduction to the task subsequently devalued any highly correlated pattern presented. Certainly the pattern presented in the negative correlation of .7 would not be consistent with the pattern displayed of an ideal correlation represented by an equal distribution of data points.

The manner and duration of the introduction may not have been the sole problem. After all, during the discussion period prior to the commencement of the trials, scatter-plots were spoken of as familiar, useful and simple by subjects. The author was unaware of any evidence that would indicate that the subjects were unsure of what a scatter-plot represented. If a contrast of the scatter-plot trial for .7 is made against the trial for -.7, it can be shown that a matched statistical correlation does have a large visual variance and can be represented by many different patterns. In the case of the scatter-plot for .7, the positive correlation is *classic* in appearance and should have presented no problem to the subjects. The pattern in the scatter-plot -.7 is harder to detect. Yet neither correlation was detected by the subjects. This suggests that the subjects were either guessing because they couldn't determine a pattern, even in a classic representation of a correlation, or guessing because they did not care. It seems unlikely to the author that so many subjects would err on this account.

Guessing a random pattern in data that are indeed random may overstate the ability of the subject to pick a pattern. The results for the scatter-plot trials show that H_0 is only supported when the patterns are random or close to random. The author suggests that true guesses would be distributed on a 50/50 basis. The results in these trials suggest that guesses seem to favour the middle of the scale. Where a subject allocates guesses without a system, one would expect such guesses to range across the scale. The clustering of results around the centre of the scale appears to indicate that guesses, if they are being made, are biased towards no correlation in the scatter-plots. The experimental design was built around the assumption that the scale used to record responses was based on a visual understanding of correlation. The author had every confidence that subjects would utilise the interval response scale to differentiate patterns that were apparent to them in those data. Instead the scale was used very bluntly with little variation for patterns that moved from correlations of .7 to minus .7. From the results presented, it appears to be the case that subjects were deciding on the *presence or absence* of a correlation, not the *degree* of correlation. For this purpose, a simple check box[39] would have been preferable for recording responses rather than the interval response scale as developed. However, even if the results are classified according to a simple scale (say -.5 to .5 to suggest no correlation and above this range to suggest a correlation), as if to impose a binary response upon the results, it is apparent that even with such a dull tool, subjects still failed to classify correctly correlations that existed in the scatter-plots. Individually, some subjects did identify the strong positive correlation for .7 but did not perceive the same degree of correlation in the negative correlation of the same amount. In hindsight, the test would have benefited from a focus group session with a selection of subjects after the trials to ascertain what it was that the subjects actually thought they were being asked to identify and what strategies they employed to form a response.

5.3.2 The Verdict on the Dvenn Tool

The experimental design was devised to create a benchmark for visual sense-making by comparing the scatter-plot results against the Dvenn results. Recognition of correlations for the Dvenn tool were to be no worse than recognition of those same correlations in scatter-plots. It was not anticipated by the author that scatter-plots would be so poorly recognised. Therefore what is the Dvenn to be compared to? If one accepts that a likely explanation for the poor identification of correlations in scatter-plots was that subjects were simply guessing or selecting the midpoint, then what were the subjects doing with the Dvenn projections? Is it a matter of one group of subjects who are simply guessing at correlations being compared to

[39] Typical of a Likert or Guttman type of response sheet.

another group who are also simply guessing? Such a scenario indicates nothing about the efficacy of one technique over another.

The following points state a simplified explanatory scenario for the results:

- The scatter-plot group is probably guessing
- The Dvenn group is probably guessing
- The Dvenn group is marginally better at guessing than the scatter-plot group

Is the conclusion then, that the Dvenn is similar to scatter-plots for facilitating pattern recognition? Ironically, for a guessing scenario, the Dvenn results would indicate that the subjects were trying harder to visualise an actual correlation than were the scatter-plot group. This is supported by the ρ values of 0.4, 0.04 and 0.4 for the Dvenn group for the .1, .0 and .2 correlations respectively. It is unlikely that the scatter-plot group developed a strategy to guess no correlation when undecided, whereas the Dvenn group independently developed an opposite strategy to guess a correlation when undecided. This observation is tempered by the result for the .0 correlation that shows that Dvenn subjects perceived a correlation in data that are actually random. Yet they could pick the correct correlation for data that was almost random (.1 & .2). Interestingly, the scatter-plot group did pick the .1, .0 & .2 correlations, but this is argued by the author to underpin an explanation of the results that suggest a guessing strategy on the part of the scatter-plot subjects. Inconsistencies are to be expected, but groups would not be expected to think erroneously in concert. Therefore the small sample size may explain some variation in the results that are otherwise hard to make sense of, but it may be the case that the Dvenn group was reacting to different visual cues than the scatter-plot group.

The experimental design and initial statistical analyses do not support the effort of further detailed examination or analysis. Beyond an explanation of a guessing strategy, which sheds no light on the contribution of visual numeracy to the visual interpretation of data, more inference is simply sophistry. Alternatives to the experimental design and suggestions for further research are offered in the subsequent chapter, but the author believes that the project, as constructed, performed as intended. It is not apparent that the Dvenn software has malfunctioned or distorted the result in any way. Indeed, any suspicion of whether software usability was a factor in the result must also be levelled at the suitability of scatter-plots for the same purpose.

This researcher may take some solace from the consideration of the problem of "small numbers" with respect to samples (Arnott, 1998, Kahneman, Slovic & Tversky, 1982). Their review of the problem of sample size indicates a propensity for researchers to over-rate the value of the mean as a yardstick. Large sample sizes help preclude the problem, but experience of experiments with human subjects suggest it is not always possible to procure a sufficient number of trials to make simple statistical assessments of the efficacy of a treatment.

Random sampling errors are problematic but the experimental design suggests that systematic errors are more likely to be the major problem. The small sample size simply exacerbates the problem. With respect to the comprehension of the Dvenn tool, comments of a casual nature by subjects suggested they understood what the animation was attempting to do and offered support spontaneously about refining the design. The general sentiment reflected similar encouragement from the focus group for the first iteration of the design who were most supportive of both the identification of an unmet need in business presentations and the proposed solution to such a need. Of speculative interest is the anticipation by the author, based on Bartram et al. (2002) that animated reversal would seem to be easily identified, particularly for an expanding or collapsing target. For example, movement of the sets in opposing directions represents negative correlations in a Dvenn. The change in relative motion of one set to another is both pre-attentive and memorable. The set (D) and its subset (d) were strongly negatively correlated. The author was of the opinion that this correlation would be easily recognised because of the dramatic effect caused by the simultaneous expansion and contraction of contrasting colours. However, the subjects in the Dvenn trial did not identify even this visually striking event.

Bertin (1981) suggests that an image can consist of only 3 elements. Any more than this requires figurative interpretation. Triesman (1986) also showed that the number of contrasting elements in total does effect the classification of a perceptual task as being pre-attentively processed by subjects as clearly shown in Appendix IV. It is probably the case that the visual processing load imposed on the audience by looking for meaning in the Dvenn was too high. Of particular note is the suggestion that pre-attentive recognition, whilst being valid descriptively, is not a boundary phenomenon (Healey, 2003). The point at which recognition of a signal occurs depends on many factors, not just whether a target can be recognised within a 250 millisecond time frame. Recognition of simultaneous multiple targets, which can be individually recognised pre-attentively, is not certain to be pre-attentively recognised as a whole. Therefore, the inference of this research, that an audience will recognise pre-attentive targets, is not predictive, either for individual members or the audience as a whole. This would suggest that an animated Dvenn may function satisfactorily, but that it would need to be very simple for a presenter to be confident that an audience could share significant insight into the presentation. Such a simplification of a Dvenn may reduce any suggested benefit for the design to the point that multivariate analysis is not possible. In this case the design would have come full circle to being little more than an animated pie chart.

5.4 Chapter Summary

A test of the Dvenn software tool was undertaken with undergraduate University students in an attempt to validate the usefulness of the data visualisation technique. The ambiguous results from the tests were not supportive of the technique for widespread adoption, but further research into the best method of harnessing visual numeracy would seem to be justified.

The design of the Dvenn software tool intended to leverage a largely untapped perceptual pathway, named visual numeracy, to facilitate greater understanding of presentation data by triggering the ability of an audience to differentiate meaningful patterns in business presentation data in a non-numerical way. The test of this tool consisted of presenting a selection of correlations by this new method and comparing the results to a control presentation of scatter-plots to a separate group. A t-Test was performed to establish the likelihood of the two results being equal; the null hypothesis suggesting there would be no difference. The result confirmed that there was no significant difference between both presentation methods. However unexpected poor performances on the control tests suggest that whilst the Dvenn tool performed equally to the control, the performance was as equally problematic as that of the control.

A suggested explanation for this result is that the subjects adopted a guessing scenario to record their responses, though there is some slight evidence that the Dvenn group was trying harder to establish a pattern. Alternatively, there may be a poor understanding of the concept of correlation within both trial groups. Anecdotal comments made by the Dvenn group suggested they were enthusiastic about the concept of the Dvenn tool but the results indicate that the tool had not actually helped them as an audience to understand the presentation.

Chapter 6

FURTHER RESEARCH & CONCLUSION

6.1 Introduction

In light of the ambiguous results of the primary research presented herein, subsequent consideration was made of the research design and also the nature of what really constitutes a visually recognisable correlation. How *is* business data best visually presented to an audience? As mentioned at the outset of this research, it would be presumptuous in the extreme to dwell on a 'breakthrough' tool that was mooted as a panacea to solve the burgeoning information explosion. The range of possible business presentations, their purpose and the interaction of human audiences mitigate against a reinvention of the pie chart. Nevertheless, there does appear to be an unmet demand to simplify the graphical presentation of business data to an audience.

What this chapter attempts to do is reflect on the nature of the research undertaken and suggest alternative ways of proceeding. As with any reflection by way of praxis enquiry, the research cannot be said to have concluded, rather the experience is one more step down the track to discovery. One indefinite experimental outcome does not terminate the search and there is much to be learned about the way an audience is actually influenced by presentation data. The result for the scatter-plot trial shakes the assumption that business audiences are familiar with the *meaning* of graphical presentations. Previous research has looked at individual preferences for visual exploitation but not whether subjects are actually able to interpret charts correctly (Levy et al., 1996). So what follows in this chapter is a series of suggestions that may serve to stimulate further debate on the topic and provide direction for those who wish to bring their talents to bear upon this interesting and relevant field of business research.

6.2 Animation to the Fore!

The research result for the Dvenn tool in no way diminishes the potential of animation to underpin a strong theoretical basis for the exploitation of visual numeracy in business presentations. The ability of humans to sequence information is greatly leveraged by utilising animation of presentation data. Tufte (1997, p170) identified the value of standardisation through "small multiples" of presentation data. Trapped as he was within a flat-space publishing dimension he was unable to utilise the power of personal computers in business to *play* the "small multiples" together. A logical progression of small multiples leads inevitably to animation that produces the required fame rate that conforms to pre-attentive recognition. Research suggests that the complexity of an image affects the pre-attentive component. (Bartram, 2002; Bétrancourt, 2005; Tversky et al ,2002). That is, individual pre-attentively recognised images may not be pre-attentively recognised when rapidly superimposed upon each other. Nevertheless, in the case of a cinema excerpt, what is being processed perceptually appears to be the *difference* between one frame and the next. These differences combine to give the *impression* to a viewer of movement and spatial orientation. A film taken of a single photograph by a very steady camera would appear to a viewer as if they were looking at a photograph not a movie.

Our visual system is acutely tuned to movement. For example, the film "Sleep" (1964) by Andy Warhol consists of 8 hours of film of a man asleep. A viewer with suitable endurance would see little perceptual difference from that registered by looking at a handful of photographs taken over the same length of time. Nevertheless, the perceptual load for a movie is equivalent to looking at 460,800 photographs[40] just to establish that nothing happens! Yet, it is not difficult to *watch* such a film. Boring perhaps, but it is not demanding. It is not a process involving a high degree of concentration, yet the pattern-matching load is substantial. So here

[40] The approximate number of frames in the movie

is an important faculty that is available to be exploited for the purposes of understanding business information.

The development of immersive three dimensional computer animated artificial reality, which can be appreciated by adults and children alike, indicates that demanding intellectual processes are not needed to make sense of novel environments. These animation techniques simply mimic a situation; they create an environment that stimulates our sensory systems in conformance with the natural acquisition of signals in our physical environment, just as a movie does. So is animated data really worth pursuing? What is the evidence to suggest that there is an unmet demand for this form of presentation? Figure 6.1 shows the growth of privately claimed real estate in a virtual world hosted by Active Worlds™[41]. This visualisation represents a remarkable collective understanding of what a virtual space may look like and illustrates how popular immersive 3D environments have become. The break on development appears to be Internet bandwidth related rather than a lessening of appetite for such environments. Their appeal is fundamentally aligned to their visual complexity.

[41] Active Worlds is a trademark to Circle of Fire and is one of the oldest and longest lived of the burgeoning 3D Internet world market.

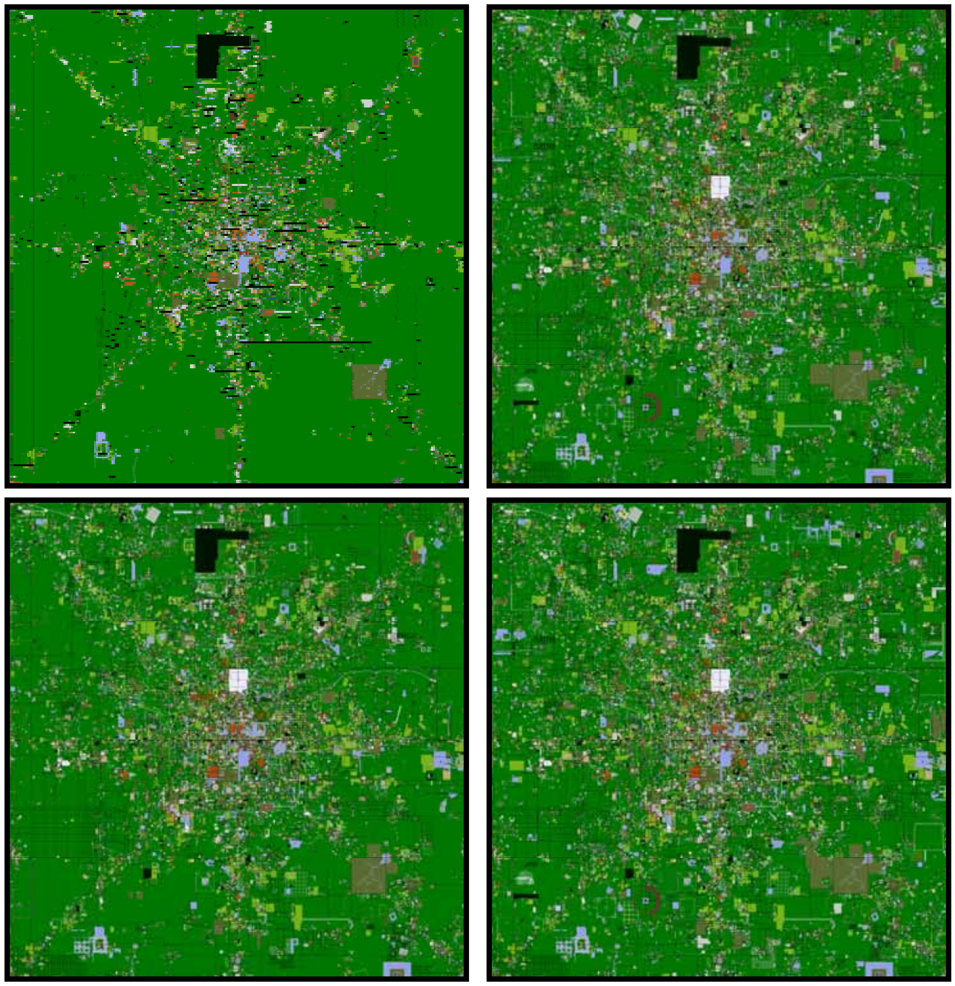

Figure 6.1 Active Worlds Real Estate from 1996 - 2001[42]

The maps represent a satellite view of the occupancy of virtual territory in the following years; 1996 (top left), 1998 (bottom left), 1999 (top right) and 2001 (bottom right). It is interesting to note that proximity to particular neighbourhoods and exclusive residential addresses is manifested by clustering along the main compass axes. This is most noticeable in the sparsely populated frame from 1996[43]. Once established, neighbourhoods are then given momentum by those who bring their own preferences in building style and bonhomie.

[42] These maps were obtained as screen shots from the Active Worlds™ website www.activeworlds.com in 1993

[43] One suggestion for this alignment is that, in the absence of street addresses, the ease of remembering where someone is located is facilitated by short addresses which are in the latitude/longitude format. An example of an easily remembered address is 10.00N, 10.00E

The ready explanation for subscribers paying real cash for virtual space is that is it easier to interact socially in an Internet chat room when it is negotiated via a three dimensional animated world, it is so compelling that individuals purchase territory in this virtual world and proceed to build houses in the virtual landscape. These buildings come to represent the individuality of the builders just as much as their clothing does in the real world. These are visually available statements about ourselves that are not simply photographic representations, but personal representations of what we wish to project to others.

It is not necessary for a text message to be delivered with personality. The keyboard has long functioned to relay information around the globe and SMS messages have taken brevity of communication to new lengths. Rather, the utilisation of visual cues in circumstances where a plethora of text based conduits exist is confirmation that people seek to exploit their visual sense as a matter of priority. The avatars that people create are not simply for play. The *appearance* of the avatar is important to facilitate online interaction in busy social environments like chat rooms. The projection of textual communication into three dimensional environments makes communicating more realistic, particularly when establishing contact for the first time or determining whether to join a group. Avatars wave, walk and change posture, they convey information in an immersive way.

By suggesting Active Worlds as a 3D Internet chat room example illustrates that tools that are utilised to convey information to an audience will increasingly be visual and animated. As computer technology becomes available to enhance visualisation it is quickly taken up and experimented with. Even tactile information is now being exploited to enhance the visual navigation of large datasets for decision support. Such technology utilises a special input device (Data Glove™) and output device (liquid crystal stereo glasses) in combination with software that projects a Worlds within Worlds compliant output (see section 2.3.6.3). The result is that navigation through data sets occurs without keyboards or mice. The pointing device is the hand itself.

Therefore, as has been extensively argued in the body of this thesis, the ease with which we undertake pattern recognition tasks suggests that more can be done to harness this ability for decreasing the burden of making sense of business information. Similarly, facial recognition is very easy to do for humans, indeed, such a ready-made cognitive ability was a driving force behind the creation of Chernov faces (see section 2.3.7.2), but it is a complex matter to program this ability into software and integrate standards for presentation of values, such as eye size, nose size etc, such that an audience would understand these features and what they convey from one presentation until the next. Herein rests the challenge to future researchers.

The Dvenn program was developed by the author after substantial background research into the problem of how best to harness visual numeracy. It may be the case, however, that concentrating on set theory detracted from the potential of other methods of conveying quantitative data to an audience being adequately canvassed. Indeed, as was evident from the scatter-plot trial, the principal requisite for development of such tools is that the audience actually *understands* them: that sense can be made of them consistently. A serious shortfall with the Dvenn tool, as with a pie chart, for contributing to sense-making is the inability of them to convey negative values. When data are positively correlated the attributes grow together, when negatively correlated, the attributes shrink. These relative movements can be quite dramatic and would be expected to help cue an audience for significant correlations in presentation data, though this has not been established in this current research. Unfortunately, the primary perceptual cues of shape, colour and orientation are all utilised for processing a Dvenn and no perceptually consistent way exists to indicate to the audience that a particular attribute has now gone through zero. At zero the attribute simply disappears, but what direction should an attribute take after the zero point? The scatter-plot communicates positive or negative value by slope, but the Dvenn tool requires serious effort to present this important parameter. To make the attribute simply reappear in a distinctive "negative" texture defeats the fundamental perceptual justification for the naturalness of the tool being that *less* is decreasing and *more* is increasing. Therefore, the Dvenn tool may not be the best candidate for attempting to exploit visual numeracy.

Such a reflection does not detract from the value of animation for presentation purposes; rather it indicates that other forms of presentation may have more merit. Perhaps the way ahead is to consider those forms of animated data presentation with which we are already familiar to some degree. One way of solving the positive/negative viewing problem of a visual presentation is to divide the viewing area into halves. That way it may be possible to project data into the positive or negative half of the screen and have the attributes presented conforming to the requirement of visually numerate presentations by conveying quantity with area. Such a technique is a radical departure from the animated Venn diagram presented in the body of this work. Nevertheless, the Dvenn results suggest that fertile ground for research resides in other directions and this form might be one of them.

One potential candidate for exploitation of visual numeracy is realised in an animated correlation "court". By way of explanation, this "court", would consist of a display screen that is simply bisected, the left half of the screen utilised to represent negative values and the right half to represent positive ones. Figure 6.2 demonstrates one such layout.

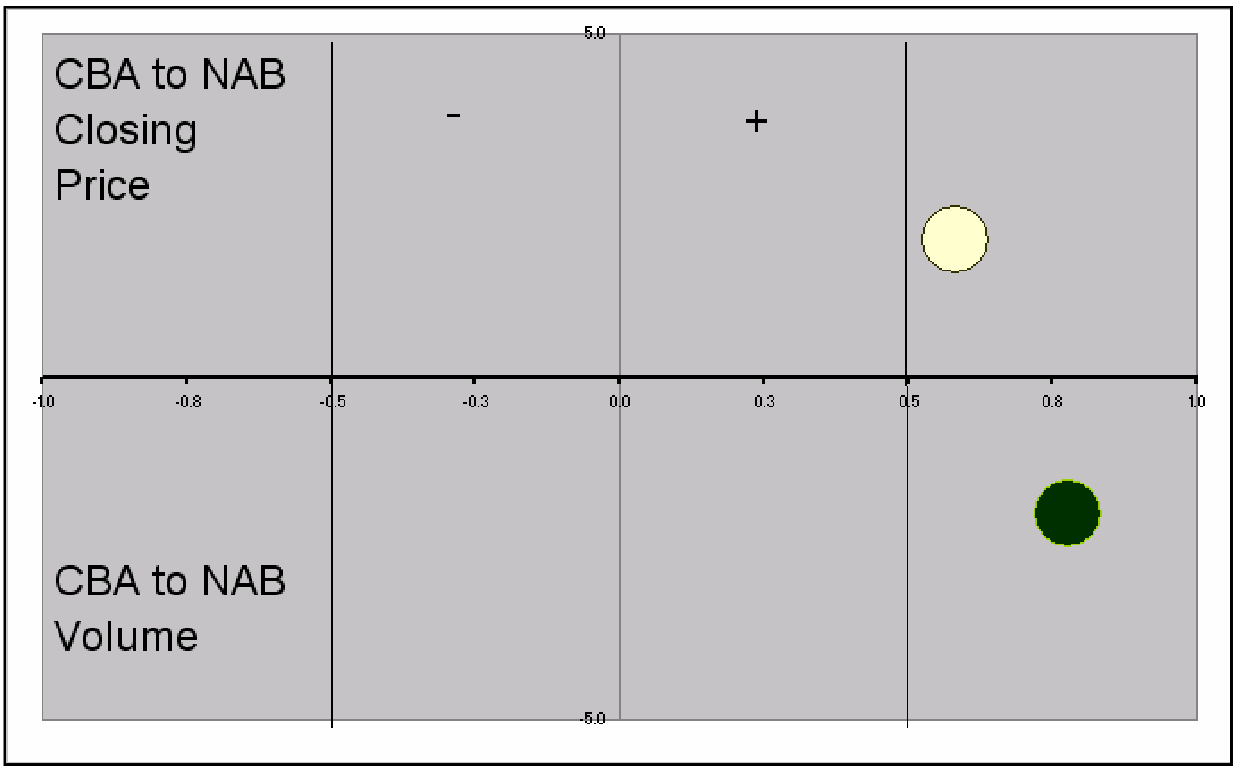

Figure 6.2 Single Frame from the Correlation Court

The animation ‡ is included as the last of the animation files in Appendix XVI. Opening this file will run the animation in a continuous loop. The reason that the animation is coarse is because this representation is only approximate. The correlations were established by using

Excel™ and animated by way of a macro script. The visual result was very poor, as the refresh rate was too slow to avoid gross flickering. The author extracted each frame from the excel animation and pasted them into a drawing package as separate frames. These frames were then animated. As they were pictorial representations that resulted from the "cut and paste" there is a small amount of movement of each frame. This appears as judder and is undesirable but this method at least avoids the gross flickering that was evident with the Excel™ animation.

6.3 Tennis Anyone?

The data animation technique proposed for exploiting visual numeracy consists of animating the movement of "balls" coloured and sized to represent the correlation of data on an area resembling a tennis court. As this a departure from a Venn diagram it is not supported by a numerical theory, nevertheless, it does hold some promise for future research. Simple demonstrations by the author of this animation technique to interested colleagues and students were positively received. The demonstration consisted of a screen layout reminiscent of the earliest computer game invented by Higinbotham and Dvorak in 1958 called "Pong" (MacIsaac, 2004). The apparent simplicity of the display belies the capability of the concept.

The problem with presenting correlation to an audience is determining the breakpoints for the display. Current display methods consist of either a correlation for an attribute being simply stated (".4") or all the points are drawn as a scatter-plot with an average slope projected through the scattered points. Indications of variance must then be conveyed to an audience. However, an alternative method is suggested by the author whereby an animation is projected by calculating a rolling correlation of ten paired numbers as a single scatter-plot dot repeatedly drawn in its own half of the screen according to whether it is positive or negative. Animation causes the dot to move closer or further away from the "net" which is the vertical line subdividing the screen. Therefore the distance from the "net" represents the degree of correlation, either positive or negative depending on which half of the "court" the dot moves in. The number of pairs utilised to create the correlation point (the breakpoint) may be varied according to the volume of data and the purpose of the presentation.

This method of animated data presentation can encompass extremely large data sets, but it only allows for a limited display of attributes. The example presented in Appendix XIV, with the corresponding data plotted as a simple line chart for comparison, projects Commonwealth Bank (CBA) and National Bank (NAB) share volume and closing prices. The points represent the degree of correlation of volume and closing price over 5 weeks for five years each for the two banks, sampled at the rate of 15 data pairs per projected dot. If the dot marker moves to the left of the screen, the correlation is negative. If the marker moves to the right, it is positive. The centre of the court represents no correlation. The marker in the top court is closing price and the marker in the bottom court is volume. Therefore the total presentation visualises the correlation of the share price of both banks and the share volume for the same period. An alternative presentation might visualise the correlation of price and volume of an individual bank.

When the example presented in Figure 6.2 and Appendix XIV is evaluated comparatively with the correlation court, it is apparent that the simple line chart is very cluttered and difficult to assess without intensive scanning of the line features, there is no appeal to visually numeracy. However, it is the author's opinion that the movement of the balls in the court and their proximity illustrate their correlation simply and effectively. The line chart is familiar and available on paper, these are its staple attributes, but with the use of the Internet and ubiquitous computer availability, the animated court could become just as familiar. What remains to be established is that an audience can actually make *sense* of these animations. There are many forms that could be suggested, including a periscope view where the quadrant is projected within a large circle to accentuate points within each quadrant and their relative movement to each other. Another method may be the use of a magnetic paradigm that utilises an orientation to a point based on north and south poles corresponding to positive and negative correlations, with point size determining less and more. Points may be projected to maximize the ability of an audience to detect closure of partially complete figures as evidenced in Johansen's light point outlines (Day, 2004). The more fragmented that the boundary of a figure may appear to an audience, the less correlated it is, whereas a figure drawn with a stark outline indicates a strong correlation.

6.4 Conclusion

The research presented herein attempted to develop and test a tool that exploited visual numeracy to make sense of business presentations. Through anecdote and observation of the way in which data visualisation techniques were utilised to present relationships in data to audiences, the author formed the view that data visualisation had not evolved to utilise the capabilities of ubiquitous business computer equipment. An ongoing search for a new tool was instigated on this perceived unmet demand for tools to supplement those techniques available to help audiences understand statistical relationships in presentation data. The theory behind visual numeracy and its attendant pre-attentive recognition suggested that animated proportional Venn diagrams would be useful for enabling audiences to garner a shared meaning from business presentations. The research differed from previous specific research on proportional Venn diagrams, namely Chow & Ruskey (2003) by introducing animation as an essential component of such data visualisations.

The research proposed that proportional animated Venn diagrams (Dvenn) could be developed for common use on standard business computer equipment. The development of the Dvenn tool proceeded in an iterative practise based research development cycle and the development of computer code for a working Dvenn constituted a significant part of the research effort. Testing on the last iteration of the tool was composed of comparison of the performance of the Dvenn tool against the scatter-plot, which had been selected from other data visualisation forms as an industry benchmark. The central hypothesis suggested that the performance of the Dvenn tool would be equal to that of the selected scatter-plots for presentations based on the same raw datasets. The results did show that the Dvenn test group performed similarly to the scatter-plot test group for the identification of correlations in presentation data. However, the scatter-plot test group were very poor at identifying correct correlations. Therefore the only available conclusion that could be made from these results was that the two groups performed equally poorly.

Nevertheless, further research into how to best leverage a visually numerate audience to make sense of business data is definitely warranted. The field of study is still a fertile area for expending more intellectual energy in the hope that concrete products may result. The inadequate result of this research is due in large part to the experimental design being insufficiently robust, as it was unable to differentiate the manner in which subjects chose to undertake resolution of the requirements of the task. The full capability of an audience to utilise visual numeracy to enhance their understanding of a presentation has not been quantified to any useful degree. Therefore, it would be prudent to undertake further evaluation into whether business audiences do make consistent sense of data visualisations with the standard suite of tools commonly utilised for this purpose.

Perhaps the most exciting discovery of this research is that the ability of an audience to understand business data visualisations is very poor, certainly in the case of scatter-plots. One explanation of the long-standing preference for presenters to utilise pie charts for business presentations is that this form of presentation may represent the very limit of simple comprehension. Any other form is possibly just too difficult to understand without an investment in the education of the audience to recognise patterns in presentation data by the presenter. Therefore one might argue, with good reason, that it is not new tools that are required, but better understanding of just how reliable existing tools are for developing shared understanding in an audience. Further, it could be argued that it is not technology that should be studied for new applications, but audiences that should be studied for how they are moved to form opinions by persuasive presentations.

The opportunity exists to study audience behaviour *and* develop new tools. These are not mutually exclusive fields of research and the use of a multidisciplinary focus is recommended to serve those who seek to explore further this endeavour, as greater understanding of the pitfalls apparent in current data visualisation tools might serve to inform future research into improved tools. Notwithstanding further research into how current data visualisation tools are comprehended, the opportunity exists to continue the development of new tools that acknowledge the potential of an understanding of the theoretical basis of visual numeracy. The author suggests that one example of a tool to be the “correlation court” for visualising correlations in data sets. It would seem that many different forms of simple data visualisation are conceivable.

Data animation in non science based disciplines shows great promise, particularly for reducing the information burden that audiences are subjected to in business presentations. The author sincerely hopes that the research presented herein will further stimulate study into this problem and that such effort might yield both more promising tools and a greater appreciation of how an audience is persuaded by the effective use of data visualisation.

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Appendix I Colour Diagram

There is no shortage of information relating to standards for colour identification and usage. According to the Universal Colour Language (UCL) described in *COLOR Universal Language and Dictionary of Names*[44], the UCL Level 3 colour descriptions consist of 267 colour blocks named by a method devised by the Inter-Society Colour Council (ISCC) and the United States Department of Commerce's National Bureau of Standards (NBS). This method is called the ISCC-NBS Method of Designating Colours and identifies 267 blocks of colour. Each block is given a colour name devised using a set of adjectives and suffixes. Each colour block defines a range of colours--not a single colour--that have the same name. This range of colour in each block is an acknowledged disadvantage, but names are analogous to calendar dates for chronological events, that is, they can be defined a number of ways; New Year or 01/01/2005, the important component is identification without ambiguity. The UCL at levels above 3 defines finer divisions of colours with no names, rising to approximately five million divisions in UCL Level 6. The colour blocks of the UCL Level 3 are defined using the scheme from the Munsell Colour Science Laboratory, Rochester Institute of Technology, which describes the hue, value, and chroma of colours. Up to 6 swatches per colour name were chosen to represent the range of colours in each block. Each block is given a unique identification, amounting to 267 UCL Level 3 colour names.

Therefore the real problem from the perspective of data visualisation is the standardisation of sematic value for, at least, each of the primary colours. What quantity is to be associated with each colour? Figure I.2 illustrates one way of presenting the colour bandwidths and their relationship to each other.

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[44]Available at http://www.december.com/html/spec/colorucl.html

Research into how different cultures define colour has been ongoing, and the World Colour Survey (WCS) has categorised 110 different languages according to how many terms are utilised for individual colours or combinations of colours. The test chart is shown below in Table I.1:

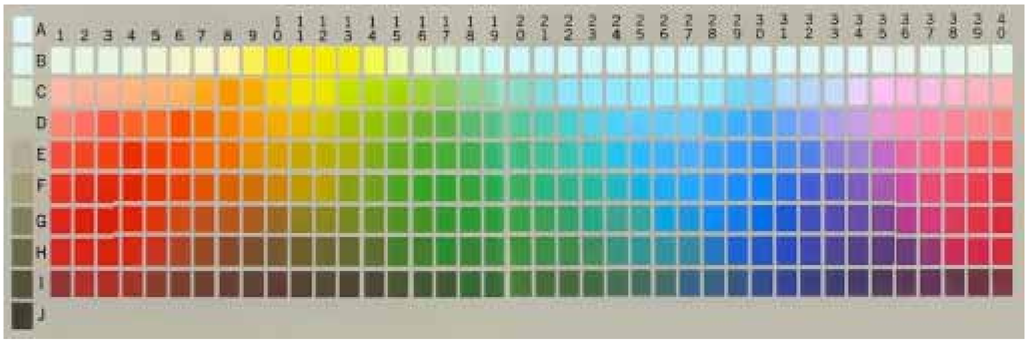


Figure I.1 Munsell Colour Chips

From the data provided, it was possible to categorise colour descriptions according to five distinct phases.

		W R/Y G/Bu Bk **III.G/Bu** w2→	W R Y G/Bu Bk **IV.G/Bu** c2↓	
W/R/Y Bk/G/Bu w1→	W R/Y Bk/G/Bu c1↑ c1→ w2↓	W R/Y G Bk/Bu **III.Bk/Bu** w2↓		W R Y G Bu Bk
		W R Y Bk/G/Bu **III.Bk/G/Bu** c1↑ c1→	W R Y G Bk/Bu **IV.Bk/Bu** c2↑	
I	II	III	IV	V

Table I.1

Table I.1, from Kay, Berlin, Maffi and Merrifield[45] shows that the identification of colour by individual words for individual colours proceeds in complexity from left to right. Phase I

[45] Book chapter 'Color Naming Across Languages', in Hardin, C. L., and L. Maffi, 1997, Color categories in thought and language: Cambridge ; New York, Cambridge University Press

languages only distinguish an individual word that represents White/Red/Yellow and a word for Black/ Green/ Blue. These are the ‘warm’ and ‘cool’ colour groups respectively. Phase II isolates White with one word, Red/Yellow with a second and Black/Green/Blue as a third. Phase III isolates, White and Green with unique words. By Phase V the individual colour names for White, Red, Yellow, Black, Green and Blue have consolidated. What these data suggest is that humans have a predisposition to name particular colour groups rather than individual wavelengths of light. Purple is the last of the rainbow primaries to be named in the evolution of colour identification by different independent cultures. Therefore any standard that is applied to ‘colour for quantity’ should take into account this apparent predisposition for colour identification, particularly with respect to ‘warm’ and ‘cool’ colours. Anecdotally, there appears to be a preference for warm colours to indicate more of something and cool colours less. This is convenient for any scheme that utilises the summing of wavelengths directly because red (warm) colours are of longer wavelengths than blue. Figure I.1 projects visible light according to the conventional tri-stimulus theory of colour perception. It clearly shows that colour perception is not a linear function of wavelength and this would predispose any ‘colour for quantity scheme to be biased towards low values as blue captures the largest part of the visible spectrum.

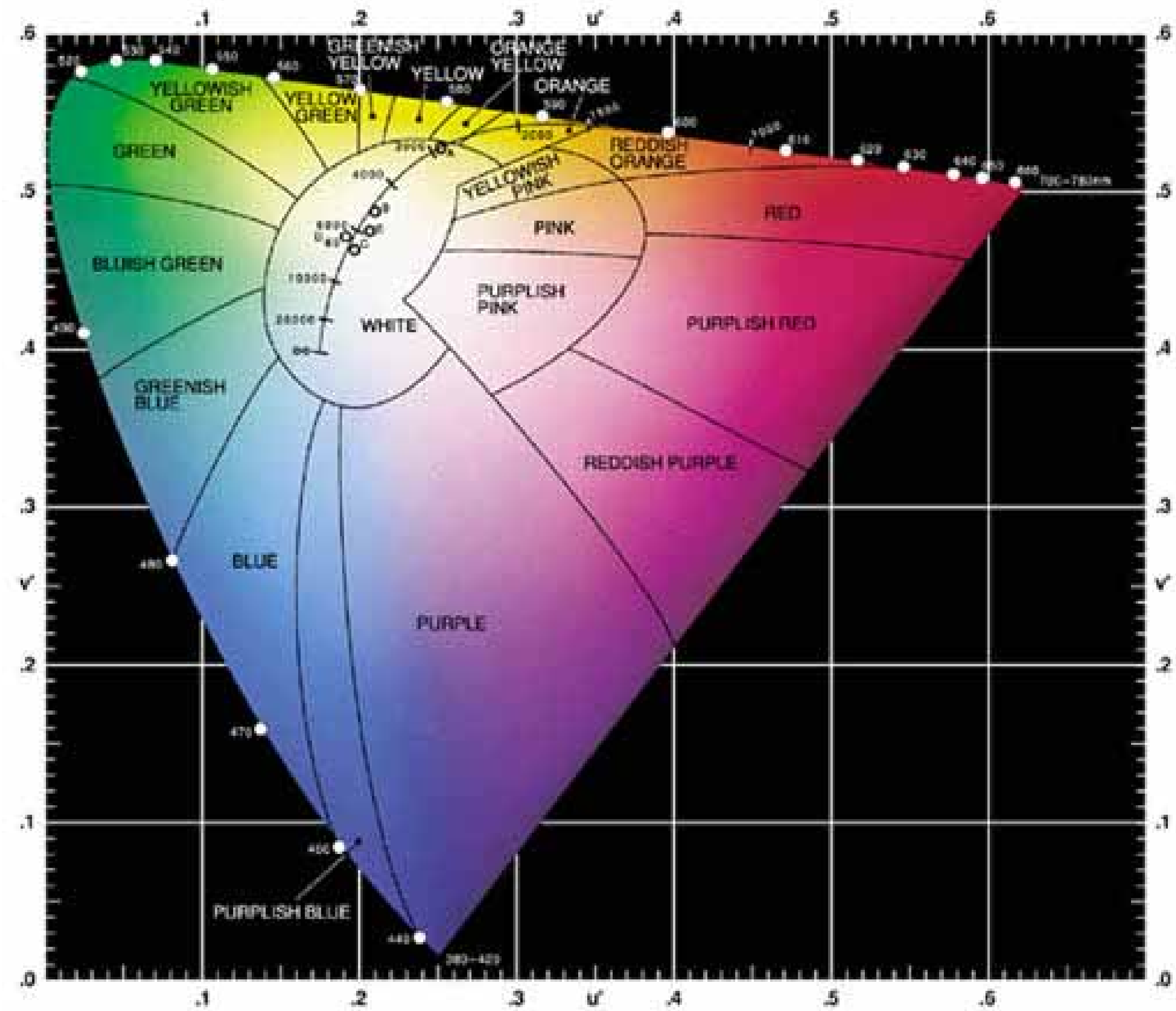


Figure I.2 CIE Colour Chart[46]

[46] Nave, R., 1997, The C.I.E. Color System, http://hyperphysics.phy-astr.gsu.edu/hbase/vision/ciecon.html#c1.

Appendix II Gestalt Concepts

A primer on Gestalt Theory based on (Kearsley, 1998) suggests that the Gestalt idea of how objects are perceived involves consideration of the whole or a frame of reference for the parts to be related to the whole. What is *experienced* consists of parts and groups. An individual's previous experience is of the utmost importance for understanding what is perceived. This seems to be a Relativist view of the world adapted for Psychology ((Zalta, 2002) Note that in this case perception is considered a dependant variable of cognition.

Dependent Variables	Independent Variables
(What is Relative)	(Relative to What)
1 Central Concepts	1 Language
2 Central Beliefs	2 Culture
3 Perception	3 Historical Period
4 Epistemic Appraisal	4 Innate Cognitive Architecture
5 Ethics	5 Choice
6 Semantics	6 Scientific Frameworks
7 Practice	7 Religion
8 Truth	8 Gender, Race, or Social Status
9 Reality	9 The Individual

What is particularly interesting for this research into the Dvenn is the similarity between Bertin and Spoerri and the Gestaltist concepts. Particularly with respect to:

Shape, Colour, Proximity, Rank, Orientation,

echoing the Gestaltist concepts of:

proximity - elements tend to be grouped together according to their nearness,

similarity - items similar in some respect tend to be grouped together,

closure - items are grouped together if they tend to complete some entity, and

simplicity -items will be organized into simple figures according to symmetry, regularity and smoothness.

How items are actually perceived also depends on predispositions we have to processing information. Gardner delineates this faculty as the application of multiple intelligences. These are:

Linguistic intelligence involves sensitivity to spoken and written language, the ability to learn languages, and the capacity to use language to accomplish certain goals. This intelligence includes the ability to effectively use language to express oneself rhetorically or poetically; and language as a means to remember information. Writers, poets, lawyers and speakers are among those that Howard Gardner sees as having high linguistic intelligence.

Logical-mathematical intelligence consists of the capacity to analyze problems logically, carry out mathematical operations, and investigate issues scientifically. In Howard Gardner's words, in entails the ability to detect patterns, reason deductively and think logically. This intelligence is most often associated with scientific and mathematical thinking.

Musical intelligence involves skill in the performance, composition, and appreciation of musical patterns. It encompasses the capacity to recognize and compose musical pitches, tones, and rhythms. According to Howard Gardner musical intelligence runs in an almost structural parallel to linguistic intelligence.

Bodily-kinesthetic intelligence entails the potential of using one's whole body or parts of the body to solve problems. It is the ability to use mental abilities to coordinate bodily movements. Howard Gardner sees mental and physical activity as related.

Spatial intelligence involves the potential to recognize and use the patterns of wide space and more confined areas.

Interpersonal intelligence is concerned with the capacity to understand the intentions, motivations and desires of other people. It allows people to work effectively with others. Educators, salespeople, religious and political leaders and counsellors all need a well-developed interpersonal intelligence.

Intrapersonal intelligence entails the capacity to understand oneself, to appreciate one's feelings, fears and motivations. In Howard Gardner's view it involves having an effective working model of ourselves, and to be able to use such information to regulate our lives.

From Howard Gardner, multiple intelligences and education web site http://www.infed.org/thinkers/gardner.htm Last viewed 19/7/2003

Appendix IIIDehaene's Quote

Dehaene does spend the last third of his book discussing the physical structures of the brain that have been inferred, by experiment with brain damaged patients (particularly split brain patients), to be involved in numeric reasoning. However, his discussion is tempered by many qualifications about the generality or principles that define brain form and function. Indeed, he suggests that

> *"…how useless it would be to seek the brain area for number meaning. p193"*

Yet he suggests that there is a specific area, shared by both hemispheres of the brain, named the parietal cortex.

> *…"Though pure quantities can reasonably be related to (sic) inferior parietal cortex, nobody knows yet which cerebral areas take on the other nonquantitative meanings of numbers. Among the many unsolved issues that the cognitive and neural sciences will have to address in the next ten or twenty years, this one certainly stands out": p195*

For the specific examples of split brain patients, where the corpus callosum has been deliberately severed to alleviate epilepsy, he makes some observations about the structures of the brain supporting a primitive structure for quantitative operations and separate structures for more advanced numerical reasoning. He specifically makes a

> *"distinction between two categories of arithmetic skills: the elementary quantitative abilities that we share with organisms devoid of a language, such as rats, apes, and human babies and the advanced arithmetic abilities that rely on symbolic notations of numbers and on the strenuous acquisition of exact calculation algorithms … those two categories rely on partially separate cerebral systems. One can be abolished while the other remains intact.*

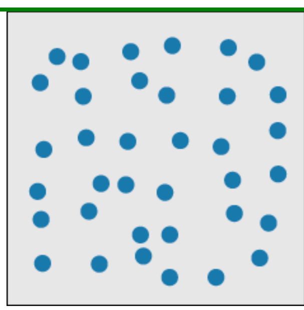
The two hemispheres do not stop at recognising digit shapes. They can also interpret them as referring to a certain quantity. To prove thus, one can present a digit together with a set of dots rather than a pair of digits. When both the digit and the dot pattern appear in the same visual field, the patient easily determines whether they match. Thus, each hemisphere knows that 3 and … represents one and the same number. Both hemispheres also appreciate the ordinal relation between numbers. Whether a digit is presented to the right or to the left, split-brain patients can quickly decide whether it is smaller or larger than some reference number." p180

See Appendix XV for a notional illustration of these functional areas.

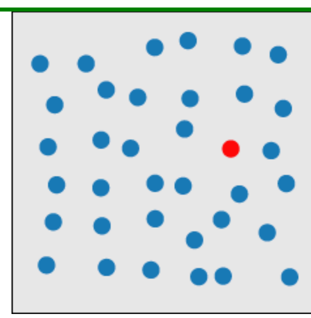
Appendix IV Pre-attentive chart

In the field of psychology, the term ‘pre-attentive’, originally defined by Triesman (1986) in a seminal work, is still used to describe fast and accurate detection of a target pattern in a distractive field. Such detection occurs before time has elapsed for focussed attention to form. Typically, recognition of patterns in multi-element displays in less than 250 milliseconds is considered pre-attentive because eye movements take at least 200 milliseconds to initiate.

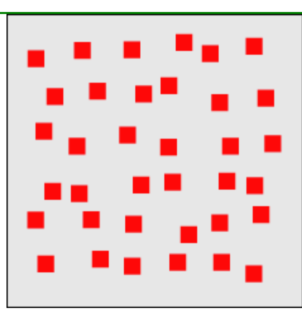
What appears below is a trial of pre-attentive processing as established by (Treisman, 1986) and presented in this form by (Healey, 2003). The target to be found in panels A – F is a red circle. At exposure times below 250 millliseconds the identification can only be pre-attentively processed.

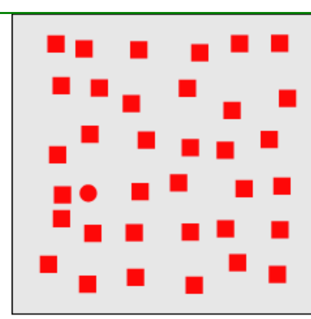


A Field of coloured distractors



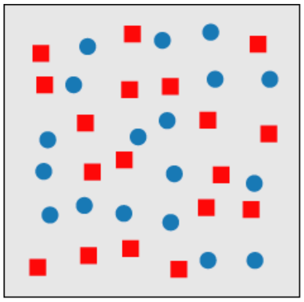
B Target (colour) in field of distractors

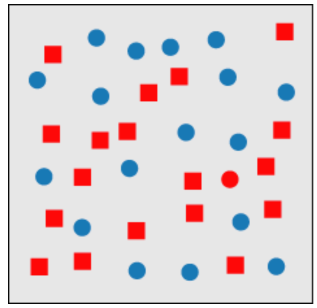




C Field of shaped distractors

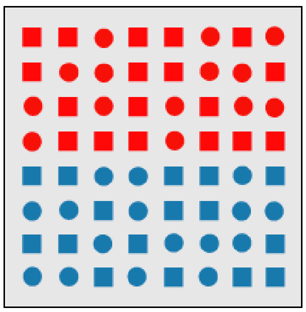
D Target (shape) in field of distractors

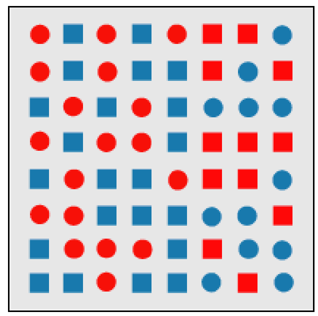




E Field of combined distractors

F Target (colour & shape) in field of distractors. This task is processed serially rather than pre-attentively.





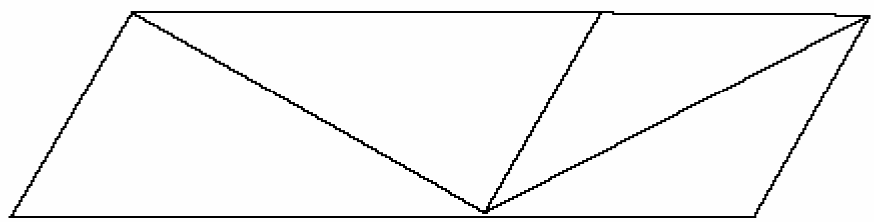
G Orientation, vertical or horizontal

H No orientation

Panels **G** and **H** represent a search for orientation rather than a red circle. **G** is true for vertical. **H** is false for both horizontal and vertical.

Appendix V Sanders Parallelogram

Sanders Parallelogram F. Sanders 1935

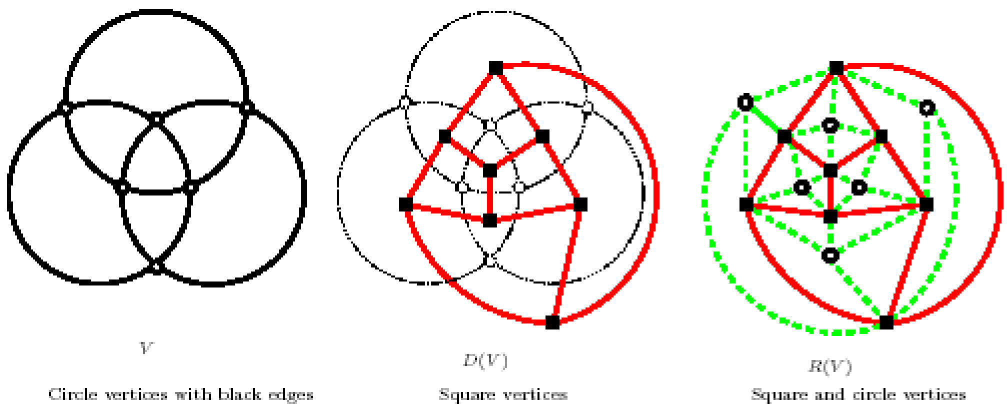


Diagonals are the same length, but strongly appear to be different.

By appealing to the geometric logic of the sum of the angles, (Benjafield, 1997) p267) subjects can be persuaded to accept a rational explanation rather than the visually apparent one.

Appendix VI Ruskey's Diagrams

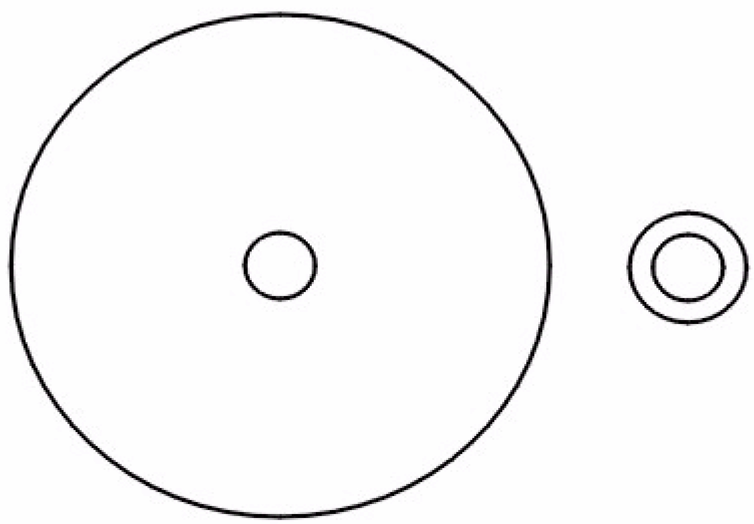
From B. Bultena and F. Ruskey, "Venn Diagrams with Few Vertices", Electronic Journal of Combinatorics, Volume 5, p 3, http://www.combinatorics.org/Volume_5/PDF/v5i1r44bw.pdf,



viewed 26/8/2001

Appendix VII delBeof Illusion

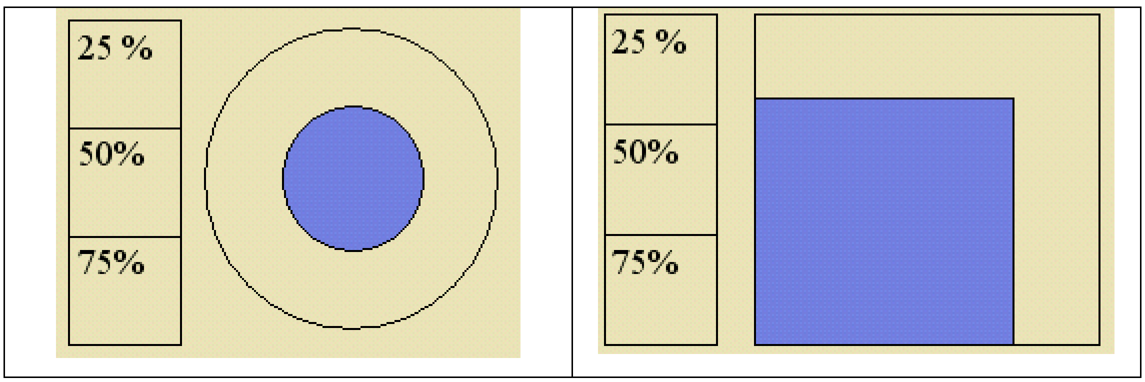
Named after F.J DelBeouf, this illusion makes a compelling perceptual case for the right-hand inner circle being larger than the left-hand inner circle. The illusion is one of thousands available to demonstrate perceptual fallibility but was chosen because of its relevance to the evaluation of comparative circles for the projection of quantity to an audience.



Appendix VIII Circle Test - Raw Results

Raw data for the test of the Circles versus Squares for area recognition.

Participation consisted of 21 undergraduate students.



Combined presentation and subject response sheet.

Raw Results

Area	Square	Circle
25	1	13
50	15	6
75	5	2
	21	21

Correct response is 25% for circle and 50% for square.

Appendix IX Arnott's Taxonomy

Bias	Cognates
Adjustment	insufficient adjustment
Attenuation	best guess strategy, ignoring uncertainty
Base Rate	insensitivity to prior probabilities of outcomes, concrete information
Chance	misconceptions of chance, gamblers fallacy
Completeness	logical data display
Complexity	decision environment
Confrmation	confirmation trap, selective perception, expectations, desire for self fulfilling prophecies, fact-value confusion
Conjunction	inertial Ψ effect
Control	illusion of control
Correlation	illusory correlation
Desire	wishful thinking
Escalation	non rational escalation of commitment, entrapment
Framing	question format
Habit	rules of thumb
Imaginability	biases of imaginability
Linear	non-linear extrapolation, inability to extrapolate growth processes
Recall	ease of recall, availability, bias due to the retrievability of instances
Redundancy	illusion of validity, repetition, implication of strength of relationship
Regression	regression to the mean
Rule	justifiability
Sample	representativeness, insensitivity to sample size, law of small numbers, inferring from small samples
Scale	powers-of-ten information bias
Search	bias due to the effectiveness of the search set, limited search strategies

Selectivity	selective perception
Similarity	representativeness
Subset	conjunction fallacy
Success	fundamental attribution error, success/failure attribution
Test	outcome irrelevant learning structures, outcome irrelevant learning systems
Testimony	logical fallacies in recall, logical reconstruction

Appendix X Raw Results

Scatter-plot Trial Results

Gender	Age	AB	AC	AD	AE	Aa	Bb	Cc	Dd
F	<30	0.00	0.00	0.00	0.00	0.00	0.00	-0.50	0.00
F	<30	-0.40	0.30	-0.30	0.10	0.20	0.30	-0.70	0.40
F	>=30	0.00	0.50	0.00	0.00	0.00	0.00	-0.50	0.50
F	>=30	0.40	-0.20	0.20	-0.10	0.10	0.25	0.50	0.50
F	>=30	0.00	0.00	0.20	0.55	0.00	-0.20	-0.45	0.55
M	<30	0.00	0.60	0.00	-0.40	0.00	0.00	-0.40	-0.40
M	<30	0.50	-0.65	-0.50	0.00	0.00	0.10	-0.25	0.50
M	<30	0.50	-0.50	1.00	-1.00	0.00	0.00	-0.10	0.50
M	<30	0.95	-0.40	0.55	-0.45	0.00	0.00	-0.50	0.50
M	<30	0.00	0.00	0.20	0.30	-0.25	0.20	-0.75	0.20
M	>=30	0.30	-0.30	0.30	-0.10	0.60	-0.40	-0.65	0.80
Actual correlation		0.10	0.00	0.70	0.10	-0.30	-0.40	0.20	-0.70

	AB	AC	AD	AE	Aa	Bb	Cc	Dd
Mode Average	0.00	0.00	0.00	0.00	0.00	0.00	-0.50	0.50
Median Average	0.00	0.00	0.20	0.00	0.00	0.00	-0.50	0.50
Average	0.20	-0.06	0.15	-0.10	0.06	0.02	-0.39	0.37
Ave Dev from Mean	0.30	0.32	0.28	0.28	0.13	0.14	0.24	0.24
Std Deviation	0.37	0.40	0.40	0.41	0.21	0.20	0.35	0.33

Dvenn Trial Results

Note: the scatter-plot trial AE was not utilised for the Dvenn trial. Nor were subjects requested to state age or gender.

Dvenn		AB	AC	AD	Aa	Bb	Cc	Dd
1		-0.9	0	-0.5	-0.5	-0.3	0.5	0.9
2		-0.6	-0.4	-0.4	0.8	0	-0.6	0.5
3		.	.	.	.	.	.	.
4		0	-0.1	-0.9	-0.9	-0.9	-0.9	-0.9
5		0	0	0.6	0.1	0.3	0.5	0.7
6		.	0.9	0.5	0	0	0	0
7		-0.4	0.4	0	0.4	0.9	0.6	0.4
8		-0.2	-0.4	0.4	0.2	-0.2	0.6	-0.4
9		0	0.5	0.5	0.5	0	0	0.5
10		0	0.2	-0.4	-0.2	0.4	0	0.8
11		0.4	-0.4	0.2	0.2	0	0.6	0
12		.	.	.	.	.	.	.
13		-0.5	0	0.7	0.7	.	.	.
14		0.5	0.7	0.7	.	.	.	0.9
15		-0.2	0.4	-0.4	-0.2	0	0.2	-0.8
16		0	0	0	0.5	-0.2	-0.2	-0.2
	Actual Correlation	0.10	0.00	0.70	0.10	-0.30	-0.40	-0.70
	Mode Average	0.00	0.00	-0.40	0.20	0.00	0.00	0.90
	Median Average	0.00	0.00	0.10	0.20	0.00	0.10	0.40
	Average	-0.15	0.13	0.07	0.12	0.00	0.11	0.18
	Ave Dev from Mean	0.30	0.33	0.44	0.38	0.27	0.39	0.52
	Std Deviation	0.39	0.41	0.52	0.49	0.43	0.49	0.62

Appendix XI Computer Code

The following computer code, as was the final version utilised for experimental purposes, code is produced solely to demonstrate the concept of the Dvenn and represents little more than functioning pseudocode. There are certain values that are static in order to produce a reliable outcome. Any production code would be fully dynamic, where all values would be derived from database inputs.

```
Option Explicit
Dim dblEndTime As Double
Dim comma As String
Dim datez, ageprev, age
Dim MaxSize, MaxSizeA, MaxSizeB, index1, i, hzntl, vrtcl, z, x, y As
Integer
Dim A, B, C, D, E, A1, B1, C1, D1, Amax, Bmax, Cmax, Dmax, Emax,
A1max, B1max, C1max, D1max As Integer
Dim fast_time, Closed_A As Boolean
Dim Array1(9, 51) As Integer
Dim Array2(9, 51) As Integer
Dim TempArray1 As Variant

Public Sub timeout(dblEndTime As Double)
Do While dblEndTime > Timer
  ' Do nothing
Loop
End Sub

Private Sub Form_Load()
```

```
Form7.WindowState = vbMaximized
Closed_A = False
fast_time = False
comma = ","
End Sub

Private Sub Quadrant_Click()
'This draws squares and squares
hzntl = (ScaleWidth + ScaleLeft) / 2 'find the x axis midpoint
vrtcl = (ScaleHeight + ScaleTop) / 2 'find the y axis midpoint
Open "A:\rawtrialdata.csv" For Input As #1
Input #1, A, B, A, C, A, D, A, E, A, A1, B, B1, C, C1, D, D1  'ignore first
record
Input #1, A, B, A, C, A, D, A, E, A, A1, B, B1, C, C1, D, D1  'first read
for loop
'Load array
For i = 1 To 50
Array1(0, i) = A
Array1(1, i) = B
Array1(2, i) = C
Array1(3, i) = D
Array1(4, i) = E
Array1(5, i) = A1
Array1(6, i) = B1
Array1(7, i) = C1
Array1(8, i) = D1
'find max value
If Array1(0, i) > Amax Then Amax = Array1(0, i)
If Array1(1, i) > Bmax Then Bmax = Array1(1, i)
If Array1(2, i) > Cmax Then Cmax = Array1(2, i)
If Array1(3, i) > Dmax Then Dmax = Array1(3, i)
If Array1(4, i) > Emax Then Emax = Array1(4, i)
If Array1(5, i) > A1max Then A1max = Array1(5, i)
If Array1(6, i) > B1max Then B1max = Array1(6, i)
```

```
If Array1(7, i) > C1max Then C1max = Array1(7, i)
If Array1(8, i) > D1max Then D1max = Array1(8, i)

Input #1, A, B, A, C, A, D, A, E, A, A1, B, B1, C, C1, D, D1  'first read
for loop
If EOF(1) Then Exit For
Next i

If Amax > Bmax Then
   If Amax > Cmax Then
      If Amax > Dmax Then
         If Amax > Emax Then
            MaxSize = Amax
         Else
            MaxSize = Emax
         End If
      Else
         MaxSize = Dmax
      End If
   Else
      MaxSize = Cmax
   End If
Else
   MaxSize = Bmax
End If
If MaxSize > 5000 Then ' natural data is larger than the screen can
show
   MaxSizeA = MaxSize * 1.5
   MaxSizeB = MaxSize * 3
   Else
   MaxSizeA = MaxSize / 3500
   MaxSizeB = MaxSize / 1500
End If
'Sort Data
```

```
TempArray1 = Array1
'Call SortData(TempArray1)
Close 1
For i = 1 To 50
Cls
DrawWidth = 1 ' 5
DrawMode = 13  ' copy pen
ForeColor = vbBlue
FillStyle = 0 ' Solid
'FillStyle = 1 ' empty - ignored if B(ox) F(ill) used
DrawStyle = 6 ' 6 unbroken line on laptop
'Yellow Boxes
'Top Left = -1 : -1
Line (hzntl, vrtcl)-Step((Array1(0, i)) / MaxSizeA * -1, (Array1(0, i)) / MaxSizeA * -1), vbYellow, BF
'Top Right 1 : -1
Line (hzntl, vrtcl)-Step((Array1(1, i)) / MaxSizeA, (Array1(1, i)) / MaxSizeA * -1), vbYellow, BF
'Bottom Left -1 : 1
Line (hzntl, vrtcl)-Step((Array1(2, i)) / MaxSizeA * -1, (Array1(2, i)) / MaxSizeA), vbYellow, BF
'Bottom Right 1 : 1
Line (hzntl, vrtcl)-Step((Array1(3, i)) / MaxSizeA, (Array1(3, i)) / MaxSizeA), vbYellow, BF
'Blue Boxes
FillStyle = 7 'crosshatch
'Top Left = -1 : -1
Line (hzntl, vrtcl)-Step((Array1(5, i)) / MaxSizeA * -1, (Array1(5, i)) / MaxSizeA * -1), vbBlue, B
'Top Right 1 : -1
Line (hzntl, vrtcl)-Step((Array1(6, i)) / MaxSizeA, (Array1(6, i)) / MaxSizeA * -1), vbBlue, B
'Bottom Left -1 : 1
```

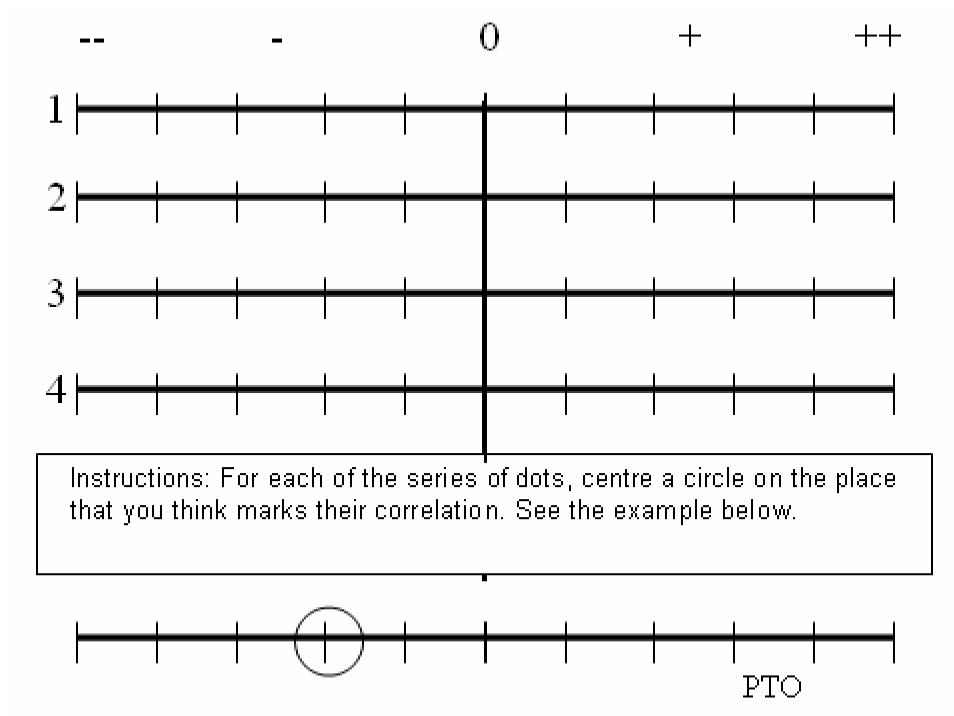
```
Line (hzntl, vrtcl)-Step((Array1(7, i)) / MaxSizeA * -1, (Array1(7, i)) / MaxSizeA), vbBlue, B
'Bottom Right 1 : 1
Line (hzntl, vrtcl)-Step((Array1(8, i)) / MaxSizeA, (Array1(8, i)) / MaxSizeA), vbBlue, B
gwange:
ForeColor = vbBlack
'Vertical Line
Line (hzntl, vrtcl + 6000)-(hzntl, vrtcl - 6000) 'Vertical Line
dblEndTime = Timer + 0.25
'Horizontal Line
Line (hzntl + 6000, vrtcl)-(hzntl - 6000, vrtcl) 'Horizontal Line
dblEndTime = Timer + 0.25
timeout (dblEndTime) 'wait predetermined amount
z = z + 0.025
Next i
Cls
End Sub
Sub SortData(Array2 As Variant)
  Dim Loop1 As Integer
  Dim Loop2 As Integer
  Dim Temp1 As Integer
  For Loop1 = 51 To 0 Step -1
    For Loop2 = LBound(Array2) + 1 To Loop1
      If Array2(0, Loop2 - 1) > Array2(0, Loop2) Then
        Temp1 = Array2(0, Loop2 - 1)
        Array2(0, Loop2 - 1) = Array2(0, Loop2)
        Array2(0, Loop2) = Temp1
        Temp1 = Array2(1, Loop2 - 1)
        Array2(1, Loop2 - 1) = Array2(1, Loop2)
        Array2(1, Loop2) = Temp1
        Temp1 = Array2(2, Loop2 - 1)
        Array2(2, Loop2 - 1) = Array2(2, Loop2)
        Array2(2, Loop2) = Temp1
```

```
        Temp1 = Array2(3, Loop2 - 1)
        Array2(3, Loop2 - 1) = Array2(3, Loop2)
        Array2(3, Loop2) = Temp1
        Temp1 = Array2(4, Loop2 - 1)
        Array2(4, Loop2 - 1) = Array2(4, Loop2)
        Array2(4, Loop2) = Temp1
        Temp1 = Array2(5, Loop2 - 1)
        Array2(5, Loop2 - 1) = Array2(5, Loop2)
        Array2(5, Loop2) = Temp1
        Temp1 = Array2(6, Loop2 - 1)
        Array2(6, Loop2 - 1) = Array2(6, Loop2)
        Array2(6, Loop2) = Temp1
        Temp1 = Array2(7, Loop2 - 1)
        Array2(7, Loop2 - 1) = Array2(7, Loop2)
        Array2(7, Loop2) = Temp1
        Temp1 = Array2(8, Loop2 - 1)
        Array2(8, Loop2 - 1) = Array2(8, Loop2)
        Array2(8, Loop2) = Temp1
      End If
    Next Loop2
  Next Loop1
For i = 1 To 50
Array1(0, i) = Array2(0, i)
Array1(1, i) = Array2(1, i)
Array1(2, i) = Array2(2, i)
Array1(3, i) = Array2(3, i)
Array1(4, i) = Array2(4, i)
Array1(5, i) = Array2(5, i)
Array1(6, i) = Array2(6, i)
Array1(7, i) = Array2(7, i)
Array1(8, i) = Array2(8, i)
Next i
End Sub
```

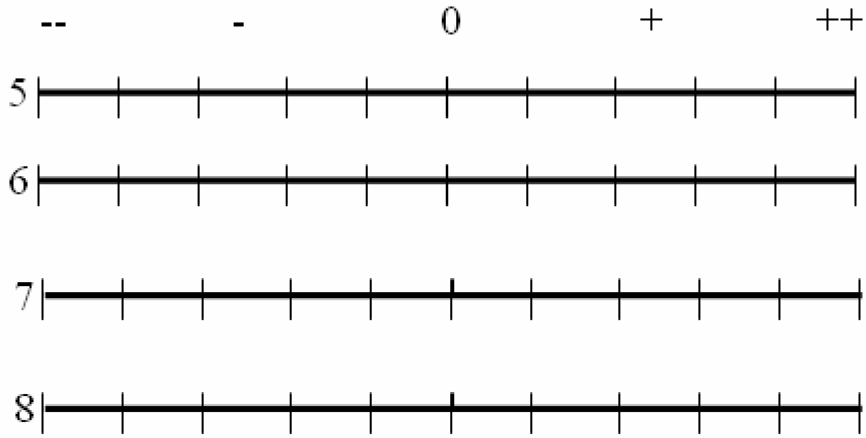
Appendix XII Interval Response Scale

Interval response scale response sheets:

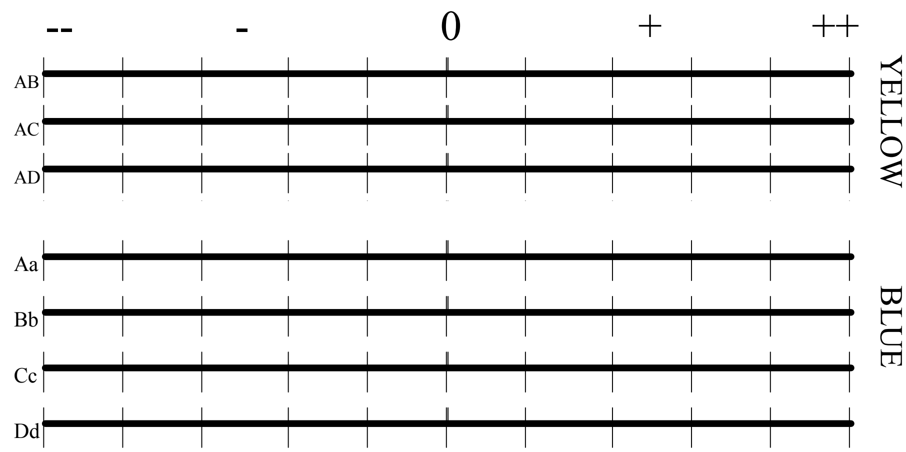
Scatter-plot trials. This was a single piece of paper printed on both sides.



Note: the responses for test 4 that represents the scatter-plot AE were discarded as there was no equivalent comparison for the Dvenn test.


-- - 0 + ++
5
6
7
8

Dvenn Trials Response sheet:



Instructions: Mark a single X per line in the place that you think marks the correlation of the yellow box pairs (AB,AC,AD). Similarly, mark an X for the correlation of the blue subset to its yellow parent (Aa,Bb,Cc,Dd). As a guide for watching the animation, think: “do any of the boxes move together? Is the movement in the same direction or opposite? Is this movement a strong or weak relationship?

Appendix XIII Values for the Tests

Statistical packages do exist that could perform the task of creating random lists within boundaries. However, after a rudimentary exploration of the options available and the learning curve required to ensure competency in such packages, the author decided to utilise existing macro tools available in Microsoft Excel™ to generate random numbers. Both the scatter-plot and Dvenn tests were based upon the same data derived from the rudimentary correlation generator built using Microsoft Excel™. Each run of the generator produced 50 rows of paired columns of data.

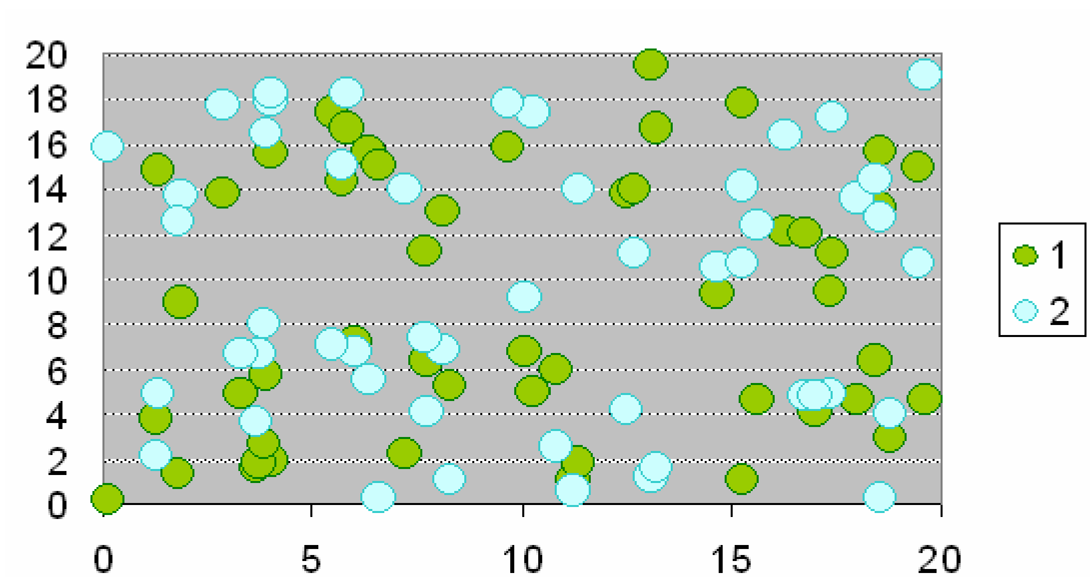
The scatter-plots are as presented to the subjects and designation A in the legend is always for the first column pair. For example, referring to trial one below, value A in the legend of the associated scatter-plot refers to column pair AB in the table of values. Value B refers to column pair AC.

The designation AB and AC refer to the labels used on the Dvenn result template that was designed for simplicity from the perspective of the subjects. Trial AE was not replicated in the Dvenn trial.

Correlation	Trial 1,2				
AB	AC				
0.1	0.0				
Sequence		A	B	A	C
1	50	4	16	4	18
2	49	15	9	15	11

3	48	19	3	19	4
4	47	7	2	7	14
5	46	4	2	4	18
6	45	19	16	19	0
7	44	1	4	1	2
8	43	13	19	13	1
9	42	6	7	6	7
10	41	1	15	1	5
11	40	8	6	8	4
12	39	16	12	16	16
13	38	5	17	5	7
14	37	15	18	15	11
15	36	4	2	4	4
16	35	6	16	6	6
17	34	4	6	4	16
18	33	11	1	11	1
19	32	10	5	10	17
20	31	10	16	10	18
21	30	13	14	13	4
22	29	7	15	7	0
23	28	17	11	17	17
24	27	20	5	20	19
25	26	18	5	18	14
26	25	8	13	8	7
27	24	8	5	8	1
28	23	13	17	13	2
29	22	4	2	4	7
30	21	10	7	10	9
31	20	3	14	3	18
32	19	18	6	18	14
33	18	11	6	11	3

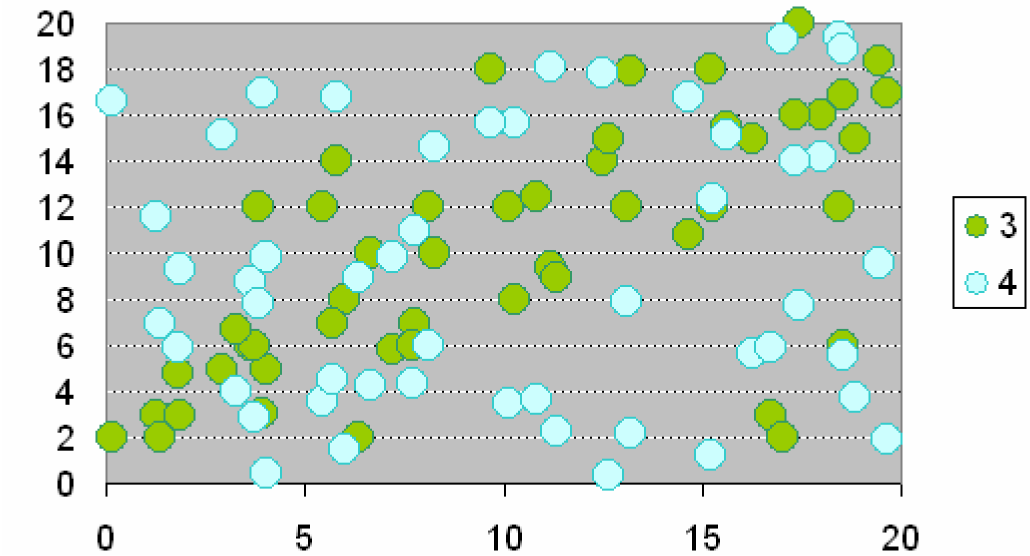
34	17	15	1	15	14
35	16	2	9	2	14
36	15	19	15	19	11
37	14	6	14	6	15
38	13	17	12	17	5
39	12	17	10	17	5
40	11	11	2	11	14
41	10	13	14	13	11
42	9	8	11	8	7
43	8	4	3	4	8
44	7	3	5	3	7
45	6	2	1	2	13
46	5	16	5	16	12
47	4	0	0	0	16
48	3	17	4	17	5
49	2	19	13	19	13
50	1	6	17	6	18



Correlation Trial 3,4

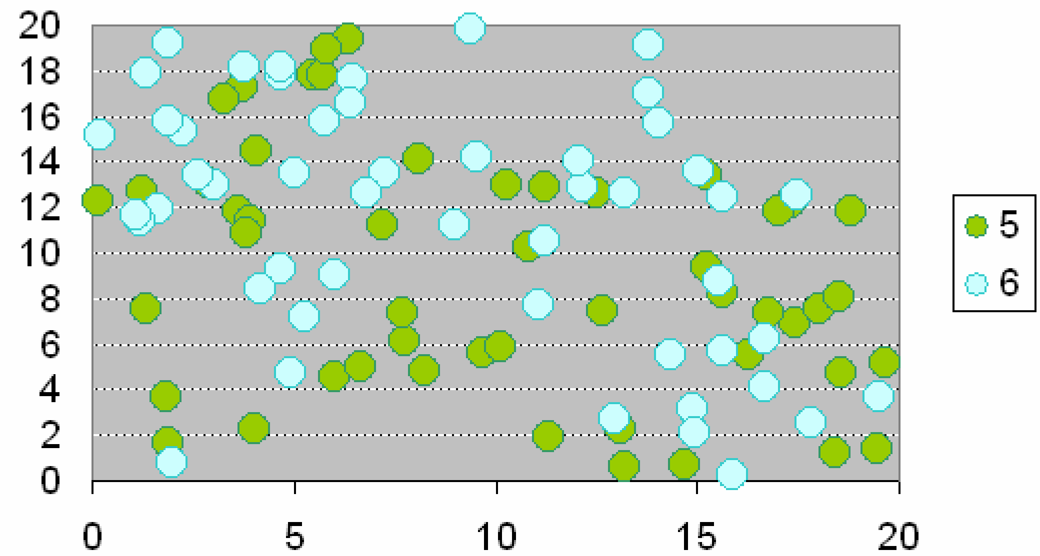
AD	AX				
0.7	0.1				
Sequence		A	D	A	X
1	50	4	5	4	0
2	49	15	11	15	17
3	48	19	15	19	4
4	47	7	6	7	10
5	46	4	5	4	10
6	45	19	17	19	6
7	44	1	3	1	12
8	43	13	12	13	8
9	42	6	8	6	1
10	41	1	2	1	7
11	40	8	7	8	11
12	39	16	15	16	6
13	38	5	12	5	4
14	37	15	12	15	12
15	36	4	6	4	9
16	35	6	2	6	9
17	34	4	3	4	17
18	33	11	9	11	18
19	32	10	8	10	16
20	31	10	18	10	16
21	30	13	14	13	18
22	29	7	10	7	4
23	28	17	20	17	8
24	27	20	17	20	2
25	26	18	16	18	14
26	25	8	12	8	6

27	24	8	10	8	15
28	23	13	18	13	2
29	22	4	6	4	3
30	21	10	12	10	3
31	20	3	5	3	15
32	19	18	12	18	19
33	18	11	12	11	4
34	17	15	18	15	1
35	16	2	3	2	9
36	15	19	18	19	10
37	14	6	7	6	4
38	13	17	3	17	6
39	12	17	16	17	14
40	11	11	9	11	2
41	10	13	15	13	0
42	9	8	6	8	4
43	8	4	12	4	8
44	7	3	7	3	4
45	6	2	5	2	6
46	5	16	15	16	15
47	4	0	2	0	17
48	3	17	2	17	19
49	2	19	6	19	19
50	1	6	14	6	17


20
18
16
14
12
10
8
6
4
2
0
0
5
10
15
20
3
4

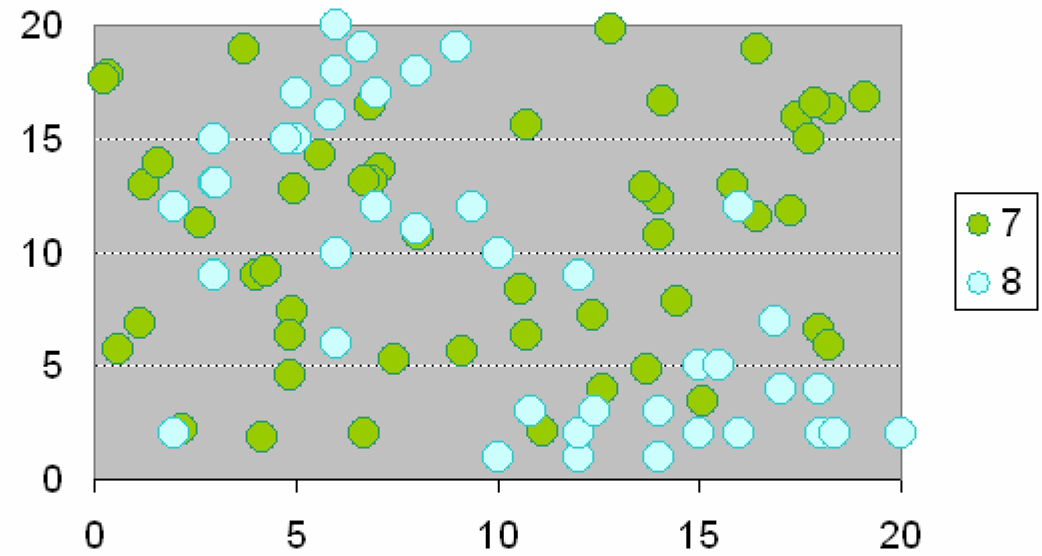
Correlation	Trial 5,6				
Aa	Bb				
-0.3	-0.4				
Sequence		A	a	B	b
1	50	4	14	16	9
2	49	15	1	9	20
3	48	19	12	3	13
4	47	7	11	2	15
5	46	4	2	2	1
6	45	19	5	16	6
7	44	1	13	4	18
8	43	13	2	19	4
9	42	6	5	7	14
10	41	1	8	15	3
11	40	8	6	6	18
12	39	16	6	12	13
13	38	5	18	17	13
14	37	15	13	18	3
15	36	4	12	2	12
16	35	6	19	16	12
17	34	4	11	6	16
18	33	11	13	1	11
19	32	10	13	5	13
20	31	10	6	16	0
21	30	13	13	14	17
22	29	7	5	15	14
23	28	17	7	11	8
24	27	20	5	5	18
25	26	18	8	5	18
26	25	8	14	13	3

27	24	8	5	5	7
28	23	13	1	17	6
29	22	4	17	2	19
30	21	10	6	7	13
31	20	3	13	14	19
32	19	18	1	6	17
33	18	11	10	6	9
34	17	15	9	1	12
35	16	2	2	9	11
36	15	19	1	15	2
37	14	6	18	14	5
38	13	17	7	12	14
39	12	17	12	10	14
40	11	11	2	2	16
41	10	13	7	14	16
42	9	8	7	11	11
43	8	4	11	3	13
44	7	3	17	5	5
45	6	2	4	1	18
46	5	16	8	5	9
47	4	0	12	0	15
48	3	17	12	4	8
49	2	19	8	13	13
50	1	6	19	17	4


20
18
16
14
12
10
8
6
4
2
0
0
5
10
15
20
5
6

Correlation	Trial 7,8				
Cc	Dd				
0.1	-0.7				
Sequence		C	c	D	d
1	50	18	7	5	15
2	49	11	8	11	3
3	48	4	9	15	2
4	47	14	12	6	16
5	46	18	16	5	15
6	45	0	18	17	7
7	44	2	2	3	13
8	43	1	13	12	2
9	42	7	16	8	18
10	41	5	13	2	12
11	40	4	2	7	17
12	39	16	19	15	5
13	38	7	14	12	1
14	37	11	6	12	2
15	36	4	19	6	10
16	35	6	14	2	12
17	34	16	12	3	13
18	33	1	6	9	12
19	32	17	16	8	11
20	31	18	17	18	2
21	30	4	9	14	3
22	29	0	18	10	1
23	28	17	12	20	2
24	27	19	17	17	4
25	26	14	13	16	12
26	25	7	13	12	2

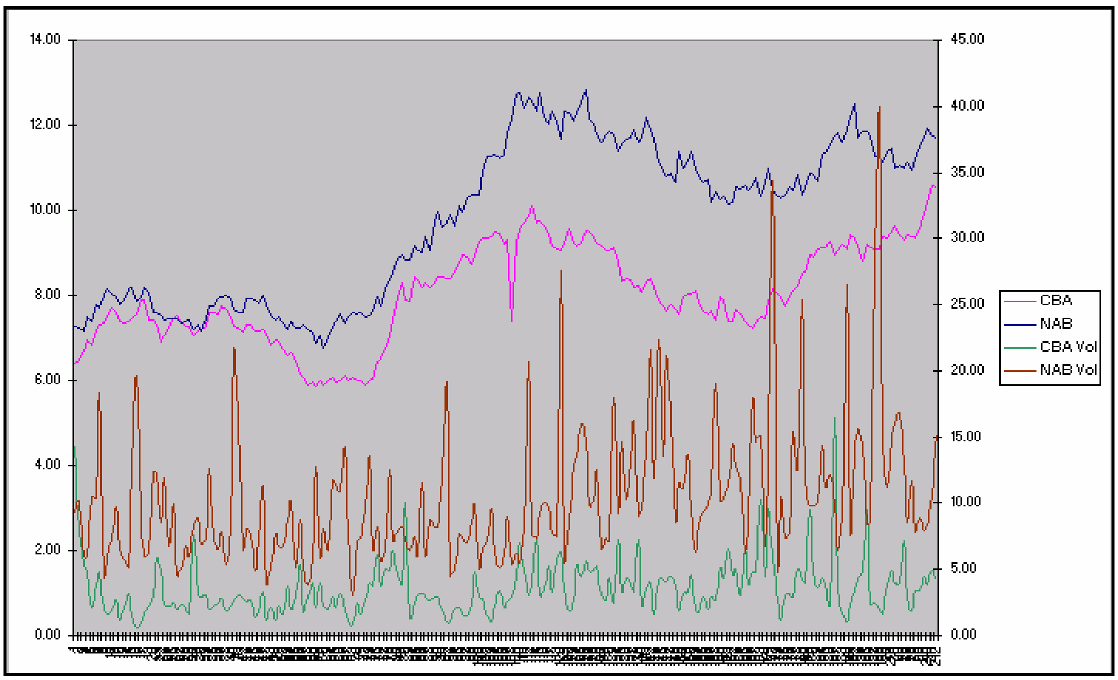
27	24	1	7	10	10
28	23	2	14	18	4
29	22	7	2	6	18
30	21	9	6	12	2
31	20	18	15	5	17
32	19	14	8	12	2
33	18	3	11	12	3
34	17	14	17	18	2
35	16	14	5	3	15
36	15	11	16	18	2
37	14	15	3	7	12
38	13	5	5	3	9
39	12	5	7	16	2
40	11	14	11	9	19
41	10	11	2	15	5
42	9	7	5	6	20
43	8	8	11	12	9
44	7	7	13	7	19
45	6	13	4	5	15
46	5	12	7	15	5
47	4	16	13	2	12
48	3	5	6	2	2
49	2	13	20	6	6
50	1	18	6	14	1



20
15
10
5
0
0
5
10
15
20
7
8

Appendix XIV   Correlation Court

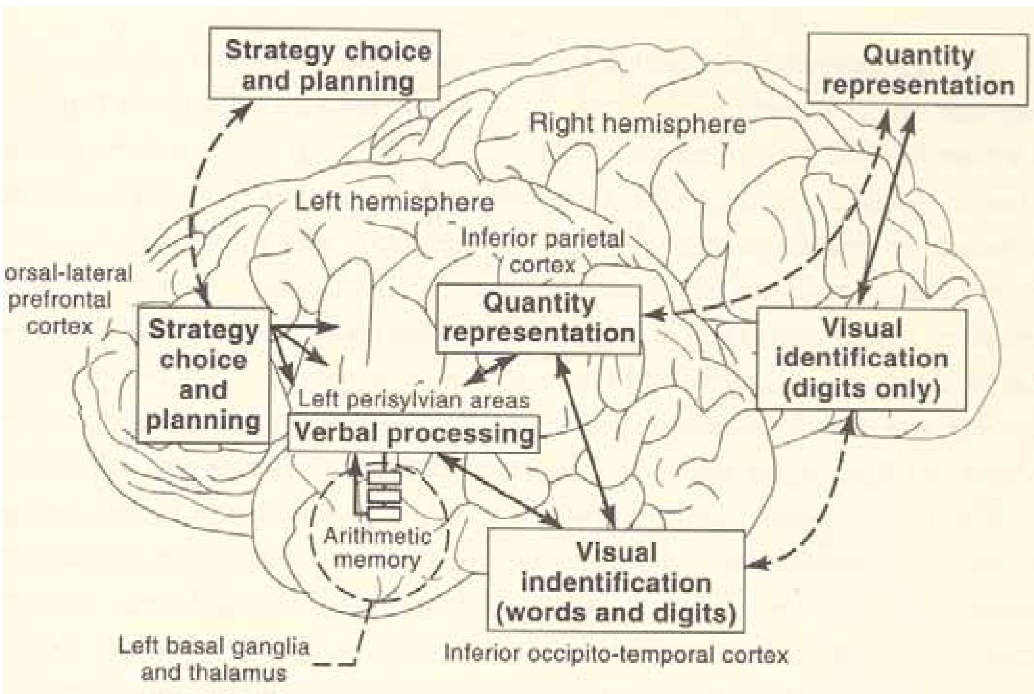
The Tennis Court data animation is based on the raw data as represented by this line chart. Whereas the correlation court has each dot representing a correlation of a data pair, with two pairs representing closing price and volume. The line chart shows each point as a raw data value. In this case the correlations must be deduced visually. This becomes difficult when the display becomes so crowded.



Line Chart of data presented in the tennis court animated visualisation.

Appendix XV Dehaene Brain Diagram

This illustration of the human brain is used by Dehaene to connect physical structures of the brain with notional functional areas (Dehaene,1997, p195)



Appendix XVI Working Animations

The following animations are included for the purposes of the single archive copy of this thesis. The individual parts of the computer program were controlled by the use of buttons and were supplied on separate media. In order to facilitate the electronic distribution of this work, all associated files have been collated into graphics images and incorporated into this archival copy. The text has been changed to reflect this amendment and all references to initiating the software now refer to this appendix.

The quality of the animations is poor and there is a great deal of noise by way of flicker, omitted frames and colourisation caused by the conversion process to accommodate integration into the body of the thesis as opposed providing the animations on separate media. A further problem is the lack of a useful interface for the viewer that would enable interaction to pause, stop, rewind or otherwise tune the presentation of data. The playback is set to full screen mode.

Note: it is obvious that a printed version of the thesis would be unable to accommodate the animations. However, if each frame of the animation was printed on a separate card and these cards arranged as a deck of playing cards and then flicked through the fingers, it would be possible to give some idea of what the Dvenn tool would look like. As the aforementioned scenario is cumbersome in the extreme, there is no available option other than to embed the animations within the document.

The icons below function as indicated in their adjacent text. Versions of MS Word earlier than edition 2003 may not have the capability to incorporate animations within the text.

The following clip is a compilation of the various stages of development of the Dvenn tool. This is not an interactive clip and all versions are queued one behind the other. To play this clip ***<u>double click on the icon</u>***. Clicking anywhere on the screen whilst it is running will stop the clip at that point. However, it is not able to be started again at any point other than the beginning.	Video Clip
The following clip is the final iteration of the Dvenn tool. To play this clip ***<u>double click on the icon</u>***.	Video Clip
This clip is the animation of the "correlation court". To play this clip ***<u>double click on the icon</u>***.	Video Clip