Information Visualization in a Business Decision Support System

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Helsinki May 2008

Master's thesis

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HELSINGIN YLIOPISTO — HELSINGFORS UNIVERSITET — UNIVERSITY OF HELSINKI

Tiedekunta/Osasto — Fakultet/Sektion — Faculty	Laitos — Institution — Department
Faculty of Science	Department of Computer Science

Tekijä — Författare — Author
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Työn nimi — Arbetets titel — Title

Information Visualization in a Business Decision Support System

Oppiaine — Läroämne — Subject
Computer Science

Työn laji — Arbetets art — Level	Aika — Datum — Month and year	Sivumäärä — Sidoantal — Number of pages
Master's thesis	May 2008	71

Tiivistelmä — Referat — Abstract

Information visualization is a process of constructing a visual presentation of abstract quantitative data. The characteristics of visual perception enable humans to recognize patterns, trends and anomalies inherent in the data with little effort in a visual display. Such properties of the data are likely to be missed in a purely text-based presentation. Visualizations are therefore widely used in contemporary business decision support systems. Visual user interfaces called *dashboards* are tools for reporting the status of a company and its business environment to facilitate *business intelligence* (BI) and *performance management* activities. In this study, we examine the research on the principles of human visual perception and information visualization as well as the application of visualization in a business decision support system. A review of current BI software products reveals that the visualizations included in them are often quite ineffective in communicating important information. Based on the principles of visual perception and information visualization, we summarize a set of design guidelines for creating effective visual reporting interfaces.

ACM Computing Classification System (CCS):
H.1.2 [Models and Principles]: User/Machine Systems — Software psychology
H.4.2 [Information Systems Applications]: Types of systems — Decision support
H.5.2 [Information Interfaces and Presentation]: User Interfaces — Screen design
J.1 [Administrative Data Processing]: Business

Avainsanat — Nyckelord — Keywords
information visualization, decision support system, business intelligence, dashboard

Säilytyspaikka — Förvaringsställe — Where deposited
Kumpula Science library, technical reports, C-

Muita tietoja — övriga uppgifter — Additional information

Contents

1 Introduction

Recent advances in information technology have enabled the automatic collection of massive amounts of data from a wide variety of sources, including the World Wide Web. The rapid increase in the size of modern data stores also imposes new challenges for the efficient presentation of information. The data contained within a large data store can reveal significant, valuable and even previously unknown facts to people, if they are summarized and presented in an appropriate and illustrative manner. A visual format is often the best choice for this purpose.

Information visualization is an old concept. Map-making is one of its oldest forms, but also statistical data has been visualized for over two centuries already [Tuf01]. The goal of visualization is to create a graphical representation of abstract quantitative data that is concise and easy to interpret even when the amount of presented data is very large. Its foundation lies in the study of human visual perception. Understanding the properties of the visual system may explain why one image is considered clear and simple by most people and another one very difficult to perceive, even if those two images are merely different presentations of the same information. The presentation format is especially important in complex situations, when a lot of information needs to be displayed in a small space, such as a single computer screen. An efficient visualization at its best is an extremely powerful cognitive tool that integrates the ingenious pattern-finding mechanisms of the human visual system with the computational power and information resources of modern computer systems [War04].

Visualizing information involves not only collecting and processing the data that are to be displayed, but also defining the graphical elements that will display them on the screen as well as the relationships between these elements. Displaying quantitative data outside its logical context, without any context or even in the wrong context might lead to incorrect interpretation of the information it is supposed to convey. However, when the appropriate data are presented together in the right context, they can help the reader to understand the situation they are depicting or even discover new relationships that have been previously hidden in the data. In addition to the context, the type of graphical element chosen to display certain data is of great importance. There are numerous different types of graphical elements available for displaying quantitative data, such as line graphs, bar graphs, sparklines and bullet graphs [Tuf01, Few06].

Not all elements are suitable for different kinds of data, however. This only emphasizes the importance of choosing the display element. On the other hand, numerical values do not always require a graphical representation – sometimes the information is best conveyed by showing the actual numbers instead of an image.

A *decision support system* is a general term for an information system used for acquiring information for decision-making purposes. Decision support systems have been used for several decades in many different fields, such as medicine, agriculture or environmental crisis management, but they have had an important role especially in assisting business decision-making. For historical reasons, business decision support systems are known by many names, such as *management information systems* or *executive information systems*. Recently, decision support systems in business have been focused to support *business intelligence* (BI) activities and *performance management*. These concepts are related to the strategic and operational management of a company and involve collecting data both inside the company and from its business environment. The large quantities of data create a need for effective presentation of summarized information in order to avoid an "information overload". Information visualization techniques provide a solution to this problem, and therefore most tools for reporting (called *dashboards*) and analysis are based on visualization.

This study has two main objectives: first, to review literature on the principles of information visualization and the underlying principles of visual perception in order to understand which factors influence the effectiveness of visual presentations of abstract quantitative data. Our second objective is to learn how these principles can be utilized in designing visual reporting and analysis interfaces in business intelligence and performance management systems. For the latter objective, an introduction to business intelligence and performance management is also included.

The sources referred to in this study include Edward Tufte [Tuf01, Tuf97, Tuf06], Colin Ware [War04] and Stephen Few [Few06]. Tufte is perhaps the best known person in the field of visualization; references to his ideas are found in numerous books and research articles throughout the field, as well as in many articles of cognitive science and psychology. Ware has a less general point of view, related more to computer science than Tufte's, and he also considers the technical aspects of visualization. His work, too, is very often cited. Few is not very well known in the academic community, since his playground is the business world.

His ideas rely on Tufte and Ware to a great extent, but he has made some significant contributions of his own as well, especially related to dashboards. In addition, he tries to bridge the gap between academic visualization research and the business world, which, he argues, unfortunately are too far apart[1]. We think this is an idea definitely worth supporting.

On the psychological aspects our main sources are Goldstein [Gol07], Palmer [Pal99] and Bruce *et al.* [BGG03], who provide a deeper understanding on the inner workings of the human visual system than the visualization experts. The performance management issues are based mainly on Kaplan and Norton's concepts [KN96], but we will also refer to several research articles due to the fast pace of advancement in this field. Pirttimäki's [Pir07] dissertation is one of the few and probably the most comprehensive academic study on business intelligence available, so it is an important source on this topic.

The rest of this study is organized as follows. Section 2 briefly discusses the principles of visual perception that may be regarded as most important for understanding information visualization. Section 3 presents the principles of information visualization. Section 4 includes an introduction to decision support systems, with an emphasis on business intelligence and performance management. Since many of the terms discussed in this section, such as "business intelligence", "decision support system" and "dashboard", appear to be rather vague to many people and their definitions vary greatly in different contexts, we shall try to resolve the historical backgrounds of these terms. Knowing the origin of an unclear term often helps to understand its meaning and why such a term is used in the first place. Section 5 discusses how the principles of information visualization can be used to design effective visual interfaces in business intelligence and performance management systems. We will also briefly analyze a few examples of visual interfaces in commercial software products. Section 6 presents a summary of our findings.

[1]For example, Few addressed this issue in the IEEE InfoVis 2007 conference; http://vis.computer.org/vis2007/session/tutorials.html#t11.

2 Understanding visual perception

The graphical displays of statistical data consist of quite simple geometrical shapes, such as straight or curved lines, circles, dots and rectangles. One might easily assume that it is not important how these shapes are organized on the screen – after all, a group of dots, for example, is always seen in the same way by all people, isn't it? The answer, however, is both "yes" and "no": it is true that due to the fundamental characteristics of the human visual system, people usually do perceive figures arranged in a certain way. Yet when there are a lot of shapes on the screen, the relations between these shapes may change their perceived organization.

In this section, we will briefly discuss the fundamental principles of visual perception. Our goal is to provide some psychological insight into the way the human mind processes and interprets visual information and how it affects what we see. The topic of the psychology and physiology of visual perception is very wide and complex, so we will not discuss them in great detail. For a comprehensive reference, see e.g. Palmer [Pal99].

2.1 Perceptual organization and the perception of shapes

When one looks at a picture on the computer screen, whether it was a photograph or a simple line drawing, one does not see just a collection of disconnected elementary geometrical shapes or lines, but a set of well-organized objects that form groups and more complex entities. Naturally this grouping occurs for real-world perception as well. So somehow the human mind seems to automatically perform the grouping, because it happens very quickly and without any conscious effort or thinking.

In the 1920's a group of psychologists proposed a set of principles that describe the way in which different objects are grouped together by the visual system. These principles are called the Gestalt[2] laws [Kof35]. Although originally called "laws", they are not really absolute laws in the same sense as, for example, in physics; they are in fact merely rules that the human brain seems to follow in most real-life situations [Gol07]. The physiological processes in the brain that cause these effects are still being researched and not very well known [Pal99, BGG03]. The principles thus only explain *why*, not *how* the grouping occurs.

[2]The German word *gestalt* means *figure* or *pattern*.

Nevertheless, these principles seem to be very powerful – in most situations all people will immediately perceive figures in only one way. Even though other perceptual groupings are also possible, they are not easily seen until one concentrates on the figure for a longer time. The Gestalt psychologists concluded this in their principle of "good figure" or *Prägnanz*:

> Of several geometrically possible organizations, that one will actually occur which possesses the best, simplest and most stable shape [Kof35].

The Gestaltists emphasized that *the whole is greater than the sum of its parts* [Gol07]. This means that a figure consisting of several subelements, such as a curved line of small dots, may contain perceptual properties (in this case, the curvature, orientation and length of the "line") that can not be inferred from the properties of the individual elements (the dots in this example) [Pal99].

Let us now briefly describe the Gestalt laws by their definitions and examples that illustrate how they affect perceptual grouping. However, the number of presented principles varies in different sources [Gol07, Pal99, War04, BGG03, Few06]. We will follow Palmer's definitions, because he has made significant contributions to this research by introducing additional grouping principles [Pal99]. Examples illustrating the grouping effects are shown in Figure 1.

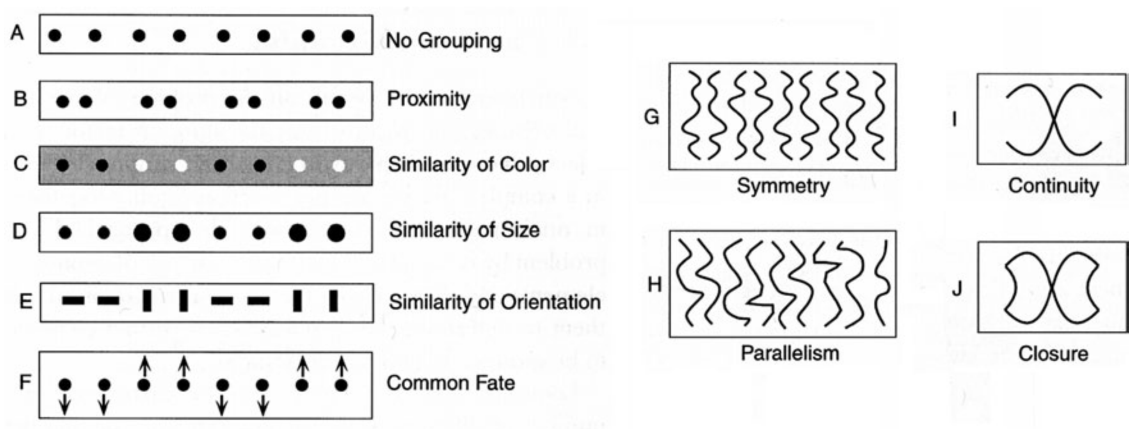

Figure 1: Demonstrations of the Gestalt principles [Pal99].

Proximity. Objects that are close to each other appear to be grouped together. In Figure 1b, the dots clearly seem to form four pairs, because distances between the paired dots are smaller than the distances of the pairs.

Similarity. Objects that have similar properties appear to be grouped together. Figures 1c–1e illustrate how shapes with the same color, size and orientation seem to form pairs.

Common fate. Objects moving in the same direction appear to be grouped together. In Figure 1f, the arrows indicate the direction of movement. Although difficult to illustrate in a static image, it is easy to agree that in a computer animation one would really see two pairs of dots moving upwards and two pairs moving downwards.

Symmetry. Symmetrical lines appear to belong together. In Figure 1g, four symmetrical shapes are seen, and the rightmost line seems to be on its own without a pair.

Parallelism. Parallel lines appear to belong together. Once again, the lines in Figure 1h form four shapes, even though the lines are not identical. The rightmost line seems to be without a pair.

Continuity. Elements that can be seen as smooth continuations of each other tend to be grouped together. Figure 1i is seen as two continuous intersecting lines rather than two angles whose vertices meet at one point.

Closure. Elements forming a closed countour appear to be grouped together. Figure 1j shows the same two lines as Figure 1i, but connecting the ends of the lines changes the perception to two angular shapes that meet at one point.

Common region. Palmer [Pal99] has proposed a principle that was not presented by the Gestaltists: Elements that are within the same region of space appear to be grouped together. Although some circles in Figure 2 are close to each other, they are not grouped together because of the ovals that surround them. Common region thus overrides proximity in this figure.

Figure 2: Principle of common region [Pal99].

Element connectedness. Another principle proposed by Palmer [Pal99] states that elements that are connected together by other elements are grouped together. Figure 3 illustrates this principle, and in this case it overrides proximity (a) as well as similarity of color, size and shape (b-d).

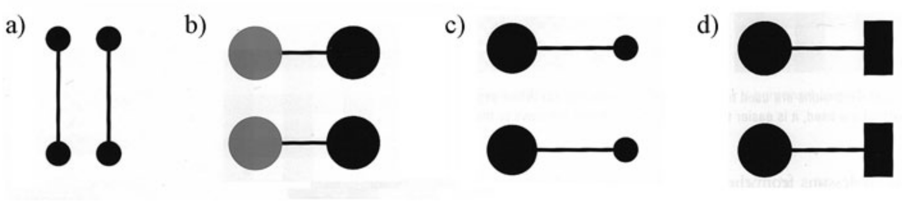

Figure 3: Principle of element connectedness [Pal99].

The examples above show that the principles of perceptual organization are hierarchical, i.e. some principles are stronger than others. Moreover, the "strength" of each principle depends on the situation, so it is ambiguous. A figure often contains many elements which have several possible groupings, but as the principle of Prägnanz states, the one with the simplest shape and "best" figure is perceived [Kof35]. Although it is not always easy to predict the perceived grouping of a complex figure in advance, these principles should be taken into account when designing graphical displays of statistical information [War04].

2.2 Perceiving color

Being able to discriminate different colors is an essential part of the visual system and sometimes even crucial for survival. Color helps us to facilitate perceptual organization, to discriminate objects from one another or to recognize and identify them [Gol07]. Light and color are not the same, however, for light in itself has no specific color, and objects in our environment appear to have different colors only because they reflect light in different ways. The experience of color is formed only in the visual nervous system of the observer [Pal99].

The human eyes contain four types of receptor cells sensitive to light: three types of *cones* constitute the basis of color vision, and the fourth type, *rods*, dominates vision in the dark[3] [Gol07]. The experienced color depends on the wavelength of light; a *monochromatic* light contains only one wavelength, but usually the light coming to the eye is a mixture of many different wavelengths. Although all three types of cone cells respond to all wavelengths of light, each of them is most sensitive to a different wavelength: one to short wavelengths (blue), one to middle- (green) and one to long-wavelength (green-yellow) light [Gol07]. The differences in the intensity of stimulation in each cone type is then processed in the visual system, resulting in the experience of certain color.

All people do not perceive colors the same way. Approximately 8% of males and 1% of females have some form of *color deficiency* [Pal99, BGG03], and these people cannot see all colors. Whereas people with "normal" vision (called *trichromats*) are able to distinguish all wavelengths of visible light, people with a color deficiency are insensitive to certain wavelengths, because their eyes lack one of the three types of receptor cells related to color vision [Gol07]; this is called *dichromatism*. The most common form of dichromatism is "red-green blindness" or *protanopia*, which means that a person cannot discriminate between red and green. Such persons will perceive colors in shades of blue, yellow and grey [Gol07]. In a very rare case of *monochromatism*, a person will perceive all colors as mere shades of black, grey and white [Gol07]. There are also people with *color anomalies*, who can see all colors, but they might be less sensitive to certain colors and thus find it difficult to separate different hues [Gol07].

The physiological structure of the visual system has led to the introduction of the *trichromatic theory of color vision*, which states that every shade of color can be produced by mixing three lights of different wavelengths in certain proportions [Gol07]. This is also the reason why color televisions and computer screens produce color by mixing red, green and blue in varying proportions [War04]. However, color theories do not speak of colors in terms of the wavelengths of light; instead, color is defined by three properties: *hue*, *saturation* and *lightness*.

[3] Rods are much more sensitive to light than cones. Therefore they are the primary type of receptors that control vision in the dark, and for this reason humans cannot distinguish colors in low light conditions [Gol07].

Hue or *chromatic color* is determined by the dominant (or mean) wavelength of the light. Hue is what people associate with a named color, such as "yellow" or "green" [Gol07]. When there is no dominant wavelength present in the light, i.e. there are equal amounts of all wavelengths across the spectrum, it is perceived as white, black or some shade of gray, depending on the levels of saturation and lightness.

Saturation indicates the intensity of the light. Highly saturated colors are intense and vivid, while decreasing saturation by adding white makes the perceived color paler; for example intense red turns to pink when white is added [Gol07]. Light with very low saturation is perceived as gray.

Lightness specifies the "overall amount" of light compared to the available maximum. High lightness makes the color appear bright, and decreasing lightness makes the color darker [Pal99]. Zero lightness yields, of course, black.

The difference between two colors[4] – *contrast* – also plays a significant part in how colors are perceived. Figure 4 illustrates how changes in contrast may affect perception, and in this case the readability of text [War04]. The blue gradient in the background has varying lightness, and in the upper part, where the difference in lightness is greater, the text is easy to read. However, in the lower part, where the lightness of the background is close to that of the text, it becomes almost impossible to read the text. On the other hand, the hues of the background and the text are very different, as displayed on the right.

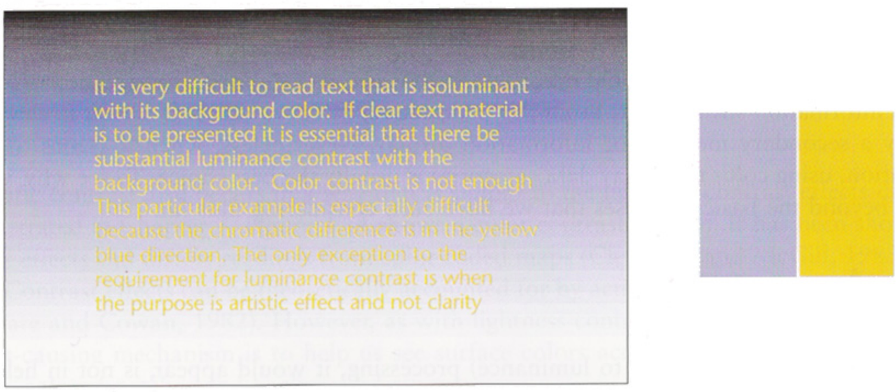

Figure 4: Color contrast [War04].

[4] We use the word "color" here to refer to the combination of hue, saturation and lightness.

2.3 Visual attention and memory

The visual system receives enormous amounts of information every moment when the eyes are open. In fact, the visual load is so heavy that all of the information can not even be cognitively processed: perhaps only 1% or less receives further processing [War05]. Some points in the visual field receive the attention – perhaps because the viewer is conducting a *visual search* in order to find some information, or simply something that "pops out" and draws his or her interest. Whatever the reason, attention is usually focused on one point of the visual field at a time. The rest is ignored, at least until the next point of focus is selected, i.e. *fixated* [Gol07]. Attention has thus two roles: first, to filter out irrelevant information and protect the visual system from being overloaded, and secondly, to control eye movements in order to execute the cognitive task at hand [War04]. In this way, attention provides the interface between the physiological visual system and the cognitive processes in the human mind.

The memory plays a significant part when the visual field is being cognitively processed. There are many individual memory subsystems, but the ones related to visual perception are *iconic memory*, *visual working memory* and *visual long-term memory*. Similar memory systems exist also for verbal and auditory information as well as other sensory experiences [Pal99].

The iconic memory is a very short-term (less than 1 second) buffer that stores information about the position, shape, color and texture of objects in the visual field from one fixation to the next [War04]. This information can then be accessed and transferred to visual working memory for further processing and recognition. Information is retained in the working memory for less than 30 seconds. The number of objects stored in the visual working memory is usually between three and five [War04]. Long-term memory is where the identified objects are stored more or less permanently[5]. Information is also retrieved from the long-term memory to the working memory in order to assist in the identification of objects [War04].

An important mechanism involved in perception, which is also significant for information visualization, is *preattentive processing*. It is the first step in processing the visual information before attention and cognition are involved.

[5]Some visual images can be remembered throughout a person's life, such as childhood landscapes; some memories, on the other hand, might be forgotten after some time despite being stored in the long-term memory [Pal99].

Ware [War04] presents an excellent demonstration of how preattentive processing can improve the cognitive task (Figure 5). The cognitive task at hand is to "count all number 3s in a table of digits". In Figure 5a, completing this task requires scanning all the numbers sequentially and fixating on each digit, which involves cognition and is relatively slow. On the other hand, in Figure 5b the number 3s stand out very clearly because of their different color. Recognizing the red numbers happens almost instantly, contrary to the slow attentive scanning. The reason for this is that color is preattentively processed, as are also shape, size, orientation, curvature, number, position and motion [War04]. This phenomenon is also called *visual pop-out* [Pal99].

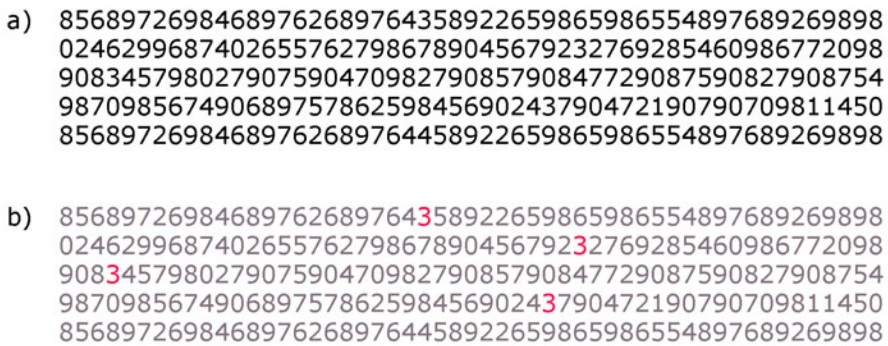

Figure 5: Preattentive processing [War04].

Preattentive processing is powerful, because it induces *parallel* visual processing [War04]: the *bottom-up* process in the above example brings the red numbers in the table to the working memory and gives the immediate sensation that the colored numbers have a special significance. On the other hand, the *top-down* process is based on the current cognitive task; the mind guides the eye movements from one colored number to another and counts the instances of number 3s. In Figure 5a the lack of preattentively processed information leaves top-down processing as the only option, and it is performed *serially* by guiding fixations to one digit at a time. Compared to the parallel bottom-up and top-down processing, this results in considerably slower problem solving due to an increased cognitive load. This is one of the most important reasons why large tables of numbers are in general much harder to comprehend than graphical representations of the same numbers.

3 Principles of information visualization

Information visualization is defined as the "use of interactive visual representations of abstract, nonphysically based data to amplify cognition" [CMS99]. This definition captures several key aspects of the field and explains its importance. First of all, constructing visual representations of data takes full advantage of the capabilities of human visual perception and enable rapid finding of interesting and unknown patterns and relationships in the data. Secondly, the nature of the data is abstract – such as stock market information or the distribution of votes in a parliamentary election – and does not directly correspond to any physical object or process in the real world. In fact, the term *scientific visualization* is used for visualization of data based on physical measurements, for example the ozone concentration in the atmosphere or electrical activity in the human brain [CMS99]. Moreover, the overall purpose of visualization is to assist the user in understanding the meaning of the data; to provide *insight* and increase the user's knowledge. It aims to help the user to complete cognitive tasks with little effort compared to e.g. textual representations.

Although the result is meant to be as simple to the user as possible, designing visualizations is anything but simple. Figure 6 illustrates different phases of the visualization process [Wün04]. It shows that visualization includes not only encoding the original data in a visual format by using different visual attributes, such as shape, size, position, orientation and color. It also includes a decoding step: transforming the visual attributes into a mental representation in the brain of the viewer, and the patterns perceived in this representation are combined with knowledge stored in the long-term memory to finally construct the interpretation of the image.

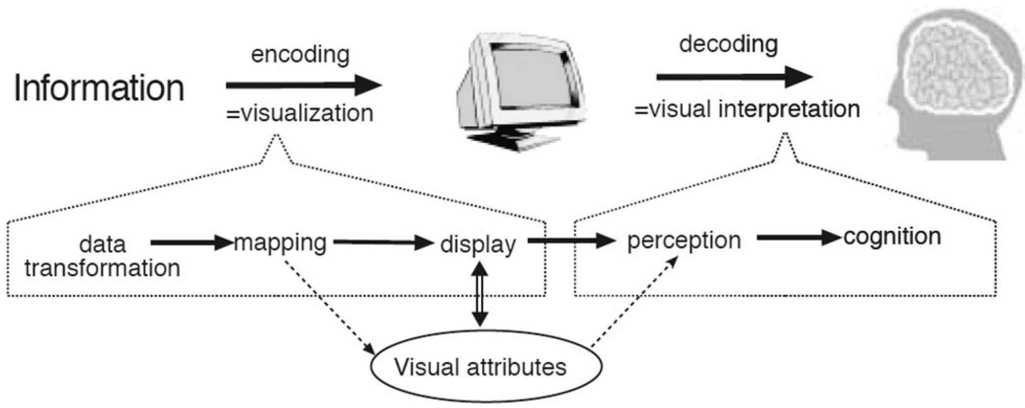

Figure 6: Information visualization process [Wün04].

This fact emphasizes the inter-disclipinary nature of the information visualization field: mastering it requires expertise in several fields, such as cognitive psychology, computer science, mathematics and statistics, and even art and architecture [Erb07]. Also knowledge of the specific domain for which the visualization is created is crucial in order to make it effective [Erb07].

In this section we will describe some key aspects of information visualization and useful techniques for creating visualizations. The issues presented do not cover all topics in the field, since the field is wide and today visualizations are used in very different kinds of applications, many of which (such as virtual reality-based visualizations) have their own specialized techniques [War04, CMS99, Spe01]. We will therefore limit our discussion to topics that are relevant with regard to displaying quantitative information visually in order to support business decision-making.

3.1 Maximizing the information content

Examples from existing statistical graphics indicate that many graphical displays of data are filled with irrelevant or redundant visual information, which only complicates understanding the actual content of the display and creates undesired "visual clutter". Tufte [Tuf01] has therefore presented the concept of *data-ink ratio* to measure the proportion of the graphic's ink (the *data-ink*[6]) that is used to present the actual information in the graphic:

$$\text{Data}-\text{ink ratio} = \frac{\text{data}-\text{ink}}{\text{total ink used to print the graphic}}$$

One of the main principles in statistical graphics should be to maximize the proportion of data-ink, which can be done e.g. using a method called *erasing* [Tuf01]: editing the graphical content by removing all unnecessary components that represent the non-data-ink. Figure 7a shows a *box plot*, in which each data point is presented by a box and dashed lines [Cle93]. A single data point thus describes five numbers: median, high and low quartiles and minimum and maximum values. These elements are quite commonly used to present e.g. data from physical measurements or stock markets. Nevertheless, after erasing all non-data-ink the graphic in Figure 7b is what results. Both graphs now display the same five values for each data point, but the erased version looks much "lighter" and clearer.

[6]Naturally the concept can be applied in the computer world just by replacing "ink" with "pixels".

The median dots are now perceived as a continued line due to the Gestalt principle of continuity (see Section 2.1), allowing one to assess the trend of change in the data. Such a trend line is not easily seen in the original graph, because the large boxes distract the display.

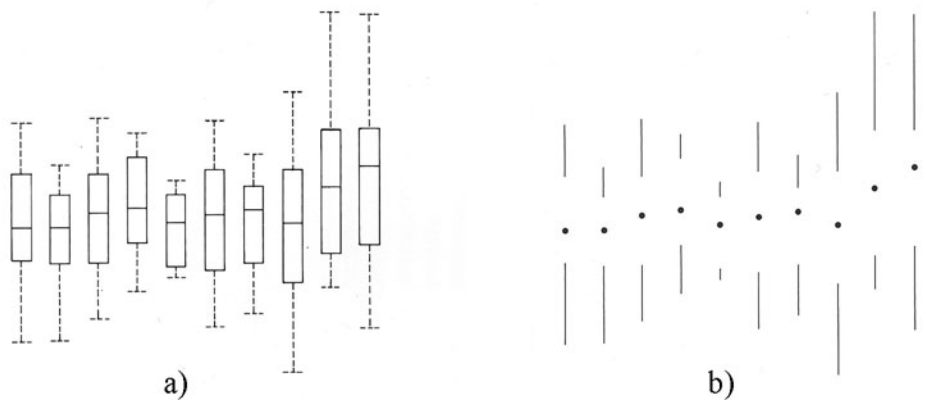

Figure 7: Maximizing the data-ink ratio [Tuf01].

It has been claimed [Tuf01] that the numerous graphical tools and effects available in commercial spreadsheet software have dramatically increased the amount of irrelevant information in statistical graphs. These tools and effects are provided to assist in creating different kinds of decorations, but while looking impressive and attractive, they severely obfuscate the information content. This is why Tufte [Tuf01] has introduced the term *chartjunk*, which is divided in three categories:

Unintentional optical art. Using texture fill effects, such as thin parallel lines of different orientations, to fill up certain areas of the graph (for example the bars in a bar graph) often cause *moiré effects*[7] that bring a sense of "vibration" or movement to the display. This is an effective way to cause irritation and to draw the viewer's attention away from the main target of interest – the data. Research [Tuf01] indicates that this is a surprisingly common phenomenon found in scientific journals, user manuals for computer graphics programs and even handbooks of statistical graphics.

[7] A *moiré effect* is an optical illusion that occurs when thin lines are close to each other [Spi93, Wad78].

The Grid. Very often dark gridlines are present in statistical graphics, causing distraction and competing with the data [Tuf01]. In many cases, however, the grid is very useful and helps to read and interpolate the data. Nevertheless, if a grid is present, it should not be too dense and preferably light in color.

Self-promoting graphics: The Duck. An analogy to architecture describes this phenomenon: in United States, there is a store called the "Big Duck", and the building itself has the form of a duck [Tuf01]. This means that the graphic is taken over by decoration and the data measures and structures become merely design elements. Such a graph is only meaningful as an exhibit of graphical style. For example, the graph in Figure 8 vividly resembles a mountain landscape (there are even "snowcaps" on the "blue mountain" in the center), and the overall impression efficiently draws attention away from the main issue: the actual revenues.

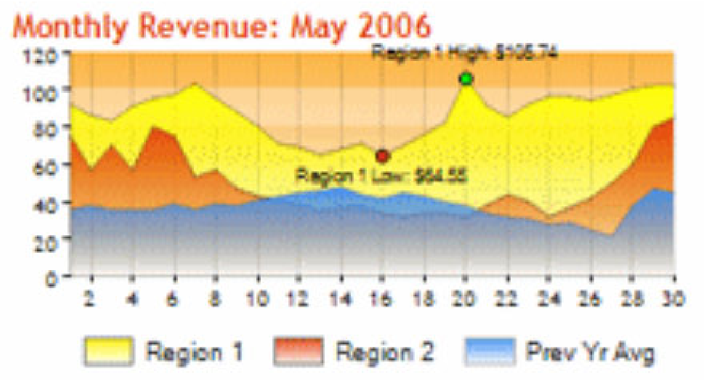

Figure 8: Exhibiting graphical style rather than data[8].

Tufte's principles and opinions about effective statistical graphics [Tuf01, Tuf06, Tuf97] may seem strange and perhaps provocative at first, but his observations are very sharp and his arguments well-founded. Many, although not all, of his opinions about effective graphical designs are also supported by psychological theories, as we saw in Figure 7. We will return to the issue of designing effective statistical graphics in Section 5.

[8]This graph is part of a visual user interface that is analyzed in Section 5.3.

3.2 Color coding

Humans can generally distinguish only about 200 different hues [War04, Gol07]. The millions of colors in modern computer screens are therefore meaningful only for situations which do not require exact discrimination between each hue, e.g. scientific visualizations or viewing digital photographs of the real world. For purposes of color coding in graphical displays of statistical data where the accurate discrimination of hues is important, one must be careful when selecting the color palette. Colors that are too similar in terms of hue, lightness or contrast might be easily confused. One way to avoid confusion is to choose all colors used for coding should from different categories of hues, meaning that for example multiple shades of green should not be used as color codes [War04]. Figure 9 displays a set of 12 colors that are distinct enough so that they can "safely" be used for color coding without causing judgmental errors [War04].

Figure 9: The "safe" categories for color coding [War04].

The primary colors red, green, blue and yellow are naturally the most distinctive colors, so they should be the first four categories. After them, black and white are also easy to distinguish – although the use of black and white is somewhat questionable, since white is very often the color of the background and black the color of text.

One benefit of using color to label information is that it may ease the classification of data into separate categories that are in no particular order [War04]. In some cases the meaningful use of color will also invoke preattentive processing, as seen in Figure 5 in Section 2.3. However, it easy to misuse color; the most common mistake is to use too much of it. A useful guideline is that if color is to be used for highlighting, the display should be quite homogeneous with respect to other colors, and the highlighting color should have a great contrast to other colors [War04, Tuf01]. However, extensive highlighting adds noise to the display, thus decreasing the *signal-to-noise ratio* [Tuf06]: if every item is highlighted, in fact none are. It has even been proposed that in statistical graphics the data should always be presented in varying shades of gray [Tuf01], thus reserving other colors only for highlighting purposes and perhaps categorizing data values.

A serious problem with color is that some people have color deficiencies as discussed in Section 2.2. Red-green blind persons, for example, will not be able to distinguish red and green but perceive those colors as gray or a greatly desaturated hue [Gol07]. Although color-deficient people are a minority, it must be kept in mind that these people will likely miss most of the information encoded with color unless a special color palette is used that takes the color deficiencies into account [Rig02]. One option is to introduce *redundancy* in the graphic, i.e. to present color-encoded information in some other formats as well, such as shapes or labels. This takes color deficiencies into account, but on the other hand makes color encoding little more than decoration for people with perfect color vision.

The issue of using color in displays of quantitative data is quite complicated and its usefulness seems to be somewhat questionable. So and Smith [SS02] point out that the effect of color in visual representations has not been studied very much, and most of the existing studies focus on educational or search and identification tasks. Thus very little is actually known about how color affects the perception of statistical graphics in decision-making tasks; it is often considered self-evident that color naturally eases the comprehension of graphical displays. However, this was not confirmed in So and Smith's experiment [SS02]. They concluded that color coding results in performance benefit only when the task at hand is complex and that even in complex tasks the benefit applies only to females and has only a small effect. For males the performance was independent of task complexity or the use of color [SS02]. Moreover, quite small performance gains have been indicated by studies in educational as well as search and identification contexts, and other experiments have also indicated a similar gender-dependency on those gains [SS02]. Hence, the research seems to confirm that the benefits of using color for encoding information in statistical graphics are very limited, which justifies the claim for grayscale palettes [Tuf01]. We therefore conclude that *in general, the use of color is not recommended in statistical graphics*, with the exception of special highlighting and categorization purposes as mentioned above. However, it has been pointed out that gray shades are not the only possible option [Few06]: any palette containing a single hue with varying saturation and lightness levels is perceptually equivalent with the grayscale palette even for a color-deficient viewer, but may add to the visual aesthetics of the display.

3.3 Scaling

Scale is a very important factor in presenting data. A good example of the importance of scale is a geographical map. If we look at a map of Europe, for instance, it is impossible to see any details of a certain city. On the other hand, if we look at a map of a single city, we miss the information about the surrounding regions outside the city. Just like the scale of a map, the scale of a graphical representation of quantitative data may reveal important details (or hide them, if chosen poorly). The correct scale naturally depends on the characteristics of the data and the information that should be conveyed.

An example of a positive effect achieved by rescaling a graph is shown in Figure 10. It contains two graphs that display historical changes in the number of sunspots[9] during 175 years [Tuf97]. Both graphs clearly show that solar activity has peaks once in every eleven years. However, the graph in Figure 10b reveals another interesting fact: the higher peaks rise very fast and decline slowly, while the lower peaks are less dramatic. This cannot be easily seen in the graph of Figure 10a, which has a larger scale on the value axis. The relative heights of the peaks are still visible despite the change of scale, so the small graph presents the same information as the large one – and a little more.

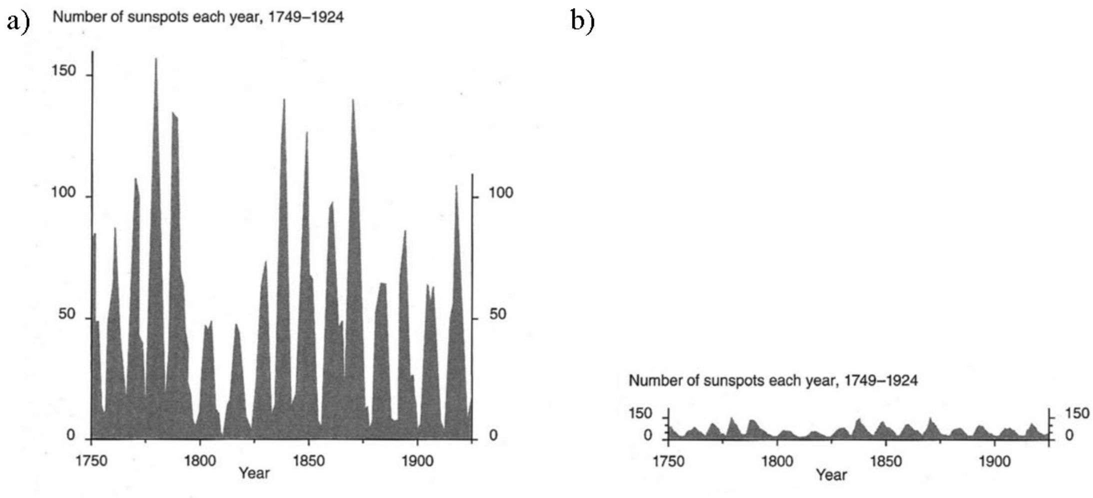

Figure 10: Two scales for historical solar activity data [Tuf97].

[9] Sunspots indicate disturbances on the surface of the Sun, and thus the intensity of solar activity.

The method used to change the scale is called *banking to 45°* [Cle93]. It maximizes the discriminability of the orientations of line segments in the graph by finding an aspect ratio (width/height) such that the slopes are as close to 45° as possible. This method works especially well with cyclic data sets when the inclinations and declinations of the slopes are relatively similar, such as the sunspot data in Figure 10. If the data contains many different kinds of slopes, some of which are steep and some gentle, a choice must be made about whether to emphasize the gentle slopes (and make the high peaks very sharp) or clarify the steep slopes (which makes the most gentle slopes almost flat). Naturally this choice depends on the data set and also the information that is considered most valuable for that data.

3.4 Ordering the data set

Sometimes simply changing the ordering of data points may reveal previously undiscovered patterns in the data. If the data includes a time dimension – which is very common – it is an easy solution to use time as the ordering criteria. But the data usually includes many other dimensions as well, and ordering the data by some of those dimensions might be more useful than just ordering by time.

Perhaps the most tragic example of the significance of ordering data is related to the space shuttle *Challenger* accident in 1986 [Tuf97]. Only 73 seconds after its launch the shuttle exploded and caused the death of seven astronauts. The reason for the explosion was a leak in one of the so called *O-rings* that were supposed to seal the adjoining segments of the solid-fuel tanks of the booster rockets. However, the weather was very cold on the day of the launch (-2 ℃), and the O-rings had lost their resiliency because of the low temperature.

What is most dramatic about the accident is that the engineers at the rocket manufacturer company were well aware of the resiliency problem of the O-rings in low temperatures. In fact they opposed the launch on the scheduled day and insisted on postponing it to a warmer day, but they failed to communicate their concern efficiently enough to convince the NASA officials. Tufte [Tuf97] performs a detailed analysis about this communication. There was clear evidence that the O-rings had been damaged already during previous cool-weather launches, and the laws of physics and experimental data confirmed that a disastrous failure was more than likely to occur in very cold conditions predicted by the weather forecast for the launch day. The engineers presented 13 charts which attempted to convey the message that the shuttle must not be launched – but the message was not understood.

First of all, there had been 24 successful launches before Challenger; only six of them were mentioned in the charts, and most of the discussion focused on just two launches: the other one occurred on a “cold” day (+12 ℃) and the other one on a warm day (+24 ℃). Both of these launches caused a little damage to the booster rockets, but only the colder one caused erosion, which is what ultimately led to the leak in the Challenger’s O-ring. Tufte [Tuf97] points out that a sample of two launches is ridiculous when there is much more data available and that the launches which caused no damage also provide significant information about the launch conditions. Nevertheless, the apparent difference between these two examples concealed the link between the temperature and the damage.

In addition to this, all the charts that included numerical data about temperatures were in tabular format and ordered by *flight number*, which is equivalent to launch date. As we have discussed earlier (see Section 2.3), the amount of cognitive processing required by reading single numbers is much greater than that provided by visual information. The ordering of data and the presentation format together effectively guided the reader’s attention away from the temperature. However, calculating a “damage index” for each of the previous launches and showing the information in a scatterplot arranged by temperature (Figure 11) reveals the risk [Tuf97].

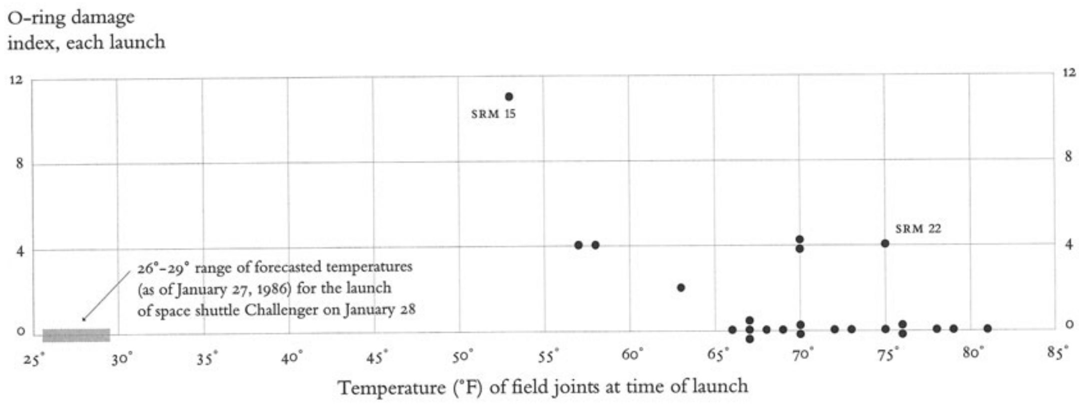

Figure 11: Relationship between the launch temperature and O-ring damage of space shuttle launches before the Challenger accident [Tuf97].

The graph in Figure 11 conveys a much clearer message than any of the 13 charts: all launches that occurred in a temperature lower than +19 °C (66 °F) had experienced damage to the booster rockets, and the most severe damage occurred in the coldest lauch to date. The graph also illustrates the great difference in the temperatures of the previous launches and the one forecasted for Challenger, which only further emphasizes the degree of risk.

If the manufacturer's engineers had succeeded in communicating the great risks of launching the shuttle on a cold day, the decision-makers might have been conviced and the lauch postponed. It is always crucial that the data presented displays *all* the data available and that it is arranged in a way that best narrates the message of the data [Tuf97]. As this example dramatically demonstrates, the common temporal ordering of data is not always the best choice.

Friendly and Kwan [FK03] have studied the methods for ordering different kinds of multivariate data in visual displays. Their idea is that the data could be sorted *by the effects to be observed*. In the Challenger case, the main effect to be observed would be the temperature. However, the main effect is not always known in advance, and often the data is categorical, such as the names of business units in a company or geographical regions. In these cases, simply sorting the categories in alphabetical order is "almost always a bad choice" [FK03]. Several statistical methods for effect-ordering both numerical and categorical data. They may be generalized as optimization problems whose solutions may be expressed in terms of eigenvectors or singular vectors, and the angles between these vectors provide the ordering for the data [FK03].

The ordering of categorical data for visualization has also been studied by Beygelzimer *et al.* [BPM02], who have developed an algorithm for efficiently finding the optimal ordering of the values of two categorical variables in large data sets. Friendly and Kwan [FK03] note that the ordering of data has great significance especially when the user's taks is to perform comparison or to detect patterns, trends or anomalies in the graph. Information may be *available* in the display, but it might not be *accessible* if the ordering of the data is ineffective. Similar arguments can be found in other sources as well [Spe01, Kos89, BPM02].

3.5 Small multiples

Large data sets usually contain a lot of attributes, and it is necessary to compare their values with each other in order to find out their relationships. However, it is only possible to display the relations of three variables geometrically, since our world is limited to three geometrical dimensions. Comparison of more than three variables therefore requires different display methods. One simple, but effective way to facilitate comparisons in data sets that include categorical variables is to use matrices of small graphs to display the relationships between variables. Cleveland [Cle93] often uses so called *multiway dot plots* for this, as illustrated in Figure 12.

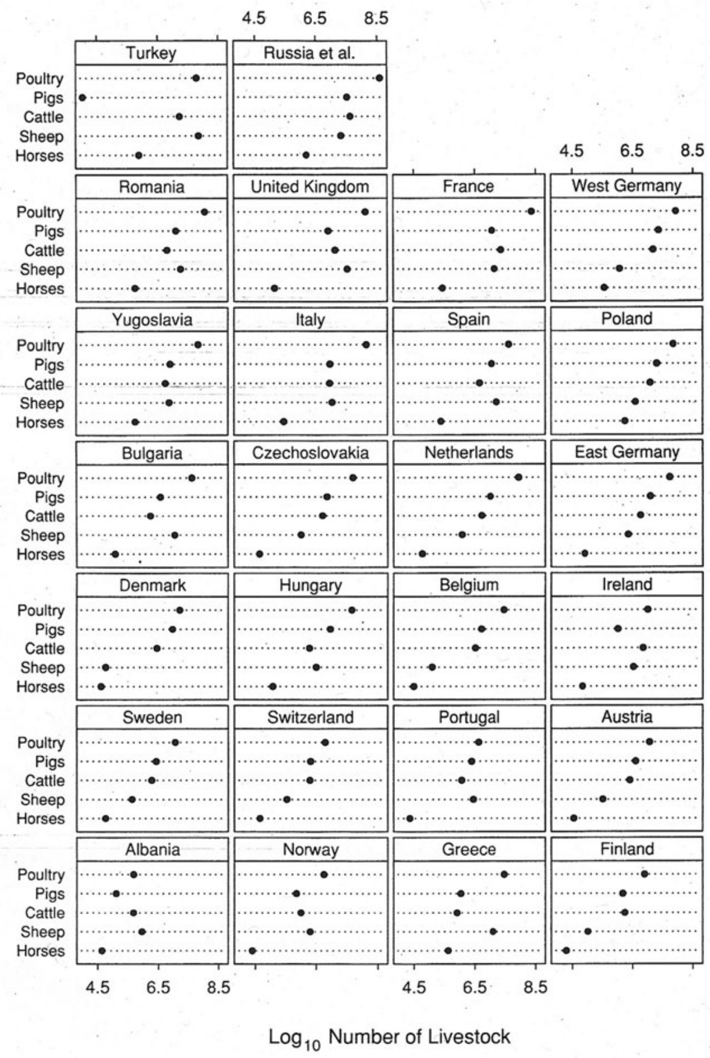

Figure 12: A multiway dot plot contains many small displays showing the relations of several variables [Cle93].

The display in Figure 12 contains data about the number of livestock in 26 countries. The data for each country is plotted in a separate panel (in this case country is the *index variable*), and the panels are organized in from left to right, bottom to top by increasing median of total number of livestock. This display enables quick comparisons between different types within each country as well as seeing the differences in distributions between the countries. For example, it is easy to say that in most countries the number of horses is the lowest and the number of poultry is the highest. Anomalies, such as the very low number of pigs in Turkey and peculiar overall distribution in the United Kingdom, are clearly visible.

Tufte [Tuf01] has introduced the term *small multiples* for displays of multivariate data. The idea is equivalent to that of Cleveland's: a series of small graphics that show multiple combinations of several variables is very effective for comparisons and clearly display the relationships between variabels [Tuf01]. It is consistent with the requirement for high information density (see Section 3.1), because a lot of data values are presented in a small space (see Figure 12). The psychological properties of the human visual system explain the usefulness of small multiples. Because each of the graphs in the display are quite small, it is easy to perceive the overview of a single graph without moving the point of focus; eye movement is only required when shifting the attention from one graph to another, which reduces the cognitive effort required in interpretation. The small size also eases perceptual grouping (see Section 2.1).

In Figure 12 many countries have a "rising" line pattern from horses to poultry, and the countries that do not follow this trend are perceived as "exceptional" (e.g. Albania, Greece, Turkey). If small bar graphs were used for each country, they would form shapes, and differences between small shapes are also very easy to distinguish.

Small multiples can be used in a variety of ways. Another example is to display time series in small multiples with time as the index variable so that each graphic shows the data set at a specific moment [Tuf01]. This an alternative to using animation for illustrating changes in a time series, and when everything else is equal, the viewer's attention is inevitably drawn to the changes in the data between different graphs in the display. Once again the comparison between instances requires little effort and the changes are easy to determine, since all the data is visible at once.

One must remember that the nature of the display often changes significantly if the arrangement of the data is changed, as discussed in Section 3.4. For example, if the multiway dot plot of Figure 12 was changed to contain five graphs (poultry, pigs, cattle, sheep, horses) with all countries plotted in each graph, it could reveal new interesting facts about the distributions and relationships in the data that can not be seen in the current display. Different arrangements should therefore always be explored when analyzing the data before making any final conclusions about it [Cle93]. Fortunately the interaction capabilities provided by computers enable the dynamic rearrangement of the graphic with little effort.

3.6 Interactive visual displays

One of the most important features of computer-based visual displays is that they allow the reader to interact with the information and perform *dynamic queries* on the data. Especially in business intelligence systems[10] there are vast amounts of summarized information available. This requires that users must be able to focus on the details on some part of the data that seems important and to dynamically explore the properties of individual pieces of that information. This operation is usually referred to as *drill-down* [War04].

The famous *visual information seeking mantra* condenses the idea in a few simple words [Shn96]:

> Overview first, zoom and filter, then details-on-demand.

Another similar suggestion is that a statistical graphic should contain at least three viewing depths [Tuf01]:

1. What is seen from a distance – overview of the data
2. What is seen up close and in detail – the fine structure of the data
3. What is seen implicitly, underlying the graphic – the “story” being told by the data

[10] We will discuss business intelligence systems and tools in more detail in Section 4.

The visual information seeking mantra is a result of empirical research, whereas the proposition of the three viewing depths is purely intuitive, but they have a lot in common. In most visual problem-solving tasks the users indeed want to take these steps when they are exploring and analyzing the data set; this is called *exploratory data analysis* [Cle93, War04]. The large-scale overview facilitates comparisons between data points and the detailed views provide the lookup functionality that is often necessary for analyzing the data set [War04]. These two together help to reveal the "story" of the data to the viewer.

There are a lot of methods to choose from when designing and implementing the interaction in visual displays. The traditional approach for moving from the overview to the detailed level is changing the magnification of the display, i.e. *zooming*, which can be done by either selecting an area to focus on or sometimes simply clicking the mouse on the desired focus point in the graph [Spe01].

In addition to these, Cleveland [Cle93] has introduced a technique called *brushing*, which means that the details of a data point are displayed when the mouse pointer is moved on top of that point. The details displayed may be just a single value of the data point, but sometimes the popup may include several attributes of the data point or even information about other data points related to the current point. Such extended popups are referred to as *hover queries*, since they actually present additional information about the data set [War04]. Brushing and hover queries enable very fast exploration of the data set as the user can retrieve information by simply moving the mouse pointer over the display.

Another popular method of interaction in visualizations is the use of different *distortion* tehcniques. Distorting the graphic means that the scale of the data is intentionally varied in different parts of the display [Spe01]. A subset of the data is in *focus* and it has a smaller scale to enable displaying more details of the focused data, while other parts outside the focused subset have a larger scale thus showing the *context* of the focused data.

The *Table Lens* introduced by Rao and Card [RC99] is one of the many applications using distortion in visualization, and it is well suited for displaying multivariate relational information. It combines the traditional spreadsheet with graphical representations by showing a small graph in each cell. Figure 13 displays statistics for baseball players in a Table Lens. It has one row for each player and 17 variables for each player in the columns. In columns containing numerical values, each cell contains a horizontal bar, whereas in categorical columns (there are six of them in this example) the cell's graphical element is a colored and positioned small rectangle.

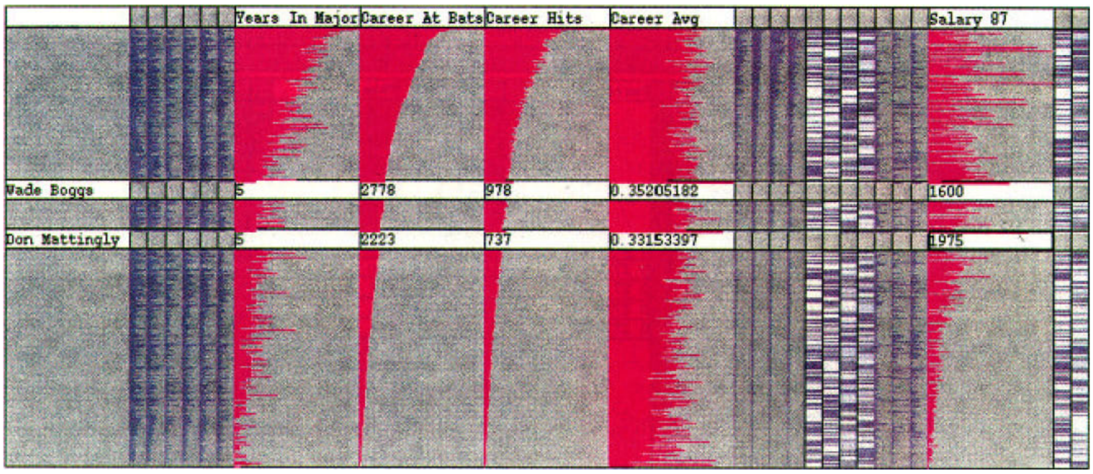

Figure 13: The Table Lens visualization [RC99].

Multiple rows and/or columns may be focused at the same time independently, and focused cells also display the value of the cell. Columns can be sorted by clicking the column title, which reveals correlations between variables: in this example, the correlation between the "Years in Major League" and "Career hits" variables is clearly visible. The Table Lens thus provides the overview of the entire data set and details about selected individual objects in a single display.

3.7 Evaluating the visual efficiency of statistical graphics

What makes a statistical graphic "effective"? This question is important, but very difficult to answer, because the comprehension of a graphic involves visual perception and cognitive processing in the brain, which are not very well understood. No generally accepted theory about the cognitive processes involved in graph comprehension seems to exist [CM84, SR96], so therefore the estimations about the effectiveness of graphical presentations rely mostly on the results of empirical experiments.

The data variables, also called *dimensions*, presented in a graph have different *scales of measurement*, i.e. different properties that affect the way they can be measured – and encoded graphically. Stevens [Ste46] classified the scales into four types:

Nominal scales are categorical. They only support equality comparisons (whether two items are the same or not), have no magnitude and cannot be ordered. For example, a "Department" variable (with values like Sales, Marketing, Finance etc.) has a nominal scale.

Ordinal scales have no magnitude, but they do have an intrinsic order that enables ranking between different items. For example, a variable with the domain {small, medium, large} has an ordinal scale, since the semantics imply that small < medium < large.

Interval scales can be ordered, have equal intervals and a magnitude that allows the comparison of difference. For example, a time variable has an interval scale. Moreover, an interval scale has no absolute zero point.

Ratio scales can be ordered, have an absolute zero point and a magnitude that allows comparisons of ratios. For example, a "Revenue" variable has a ratio scale, since we can say that a revenue of 200 000 € is twice as much as 100 000 €.

Extracting information from a graph involves one or more of *elementary perceptual tasks* of judgments that are performed to detect the visual attributes in the graph, which are then mentally processed to decode the values (cf. Section 3, p. 12). The key to estimating the efficiency of a graph is that the accuracy of judging different visual attributes varies, and the accuracy is also influenced by the scale of the encoded variable. Cleveland and McGill [CM84] empirically verified the relative accuracy of several elementary perceptual tasks considering ratio-scaled data, and the experiment was later extended with new task types and applied to all scales by Mackinlay [Mac99]. The order of accuracy for the tasks[11] is shown in Figure 14.

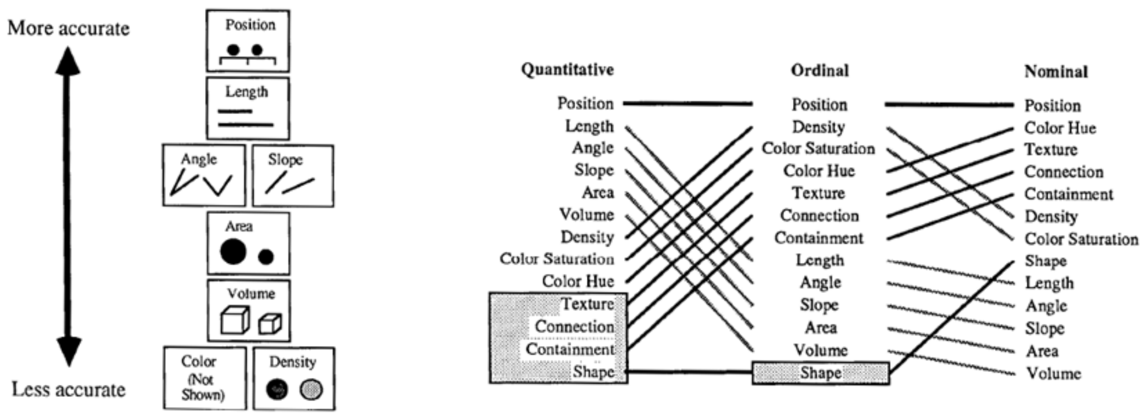

Figure 14: Ordering of elementary perceptual tasks according to Cleveland and McGill [CM84] (left) and Mackinlay [Mac99] (right).

Using a graphical encoding that suits the scale of the variables in the data often leads to an effective visual presentation. For example, color hue is a good way to encode nominal variables, because the only type of comparison is equality and color hues are very easy to discriminate if the difference between hues is large enough; however, encoding ratio-scaled data with color would be very inefficient due to the inaccuracy of color discrimination. Nevertheless, the cognitive tasks at hand also affect the choice – for example, a line graph is ideal for displaying trends in a time series, but if the primary task is to perform comparisons between individual data points, a bar graph might be a better choice for the same data due to the greater accuracy of length estimation. We will return to this topic in Section 5.1.

[11] In Figure 14, the term "quantitative" refers to both ratio and interval scales; nominal and ordinal scales are regarded as non-quantitative [Ste46]. The gray-shaded tasks are not applicable for quantitative and ordinal variables.

4 Decision support systems and business decision-making

Business has changed tremendously during the last decade. Companies are facing great challenges: fierce competition toughened by globalization and the growth of the Internet and electronic commerce, forcing them to change business processes, to improve the quality and speed of service and therefore to continuously develop new products and services. At the same time operating profits, shareholder value and productivity are expected to increase and production costs to decrease to ensure steady growth. It is clear that these facts also impose great challenges on the managers of virtually every company. Strategic and operational business decisions must be made on time and they must rely on as much relevant information as possible in order to be accurate and successful [Pir07, WW07].

The rapid development of information technology is in part responsible for the increased challenges, but on the other hand it can also bring along new means and tools to assist managerial decision-making. In fact, *decision support systems* are not a brand new invention – the first ones were described as early as the 1950s even before the first computer system had been introduced in practice [BO06]. As soon as the first mainframe computers arrived in the business world, computer-based *management information systems (MIS)* were adopted during the 1960s [FA06]. At that time they were quite simple systems used merely to collect and store for example accounting information in an electronical form, and the data was then manually processed further to produce managerial reports on numerous sheets of paper.

As computer systems evolved and became more commonplace, more sophisticated methods and tools to assist corporate management began to emerge. Systematic research on computerized decision support systems started in the 1970s, and they extended the MIS concept with user interaction and querying capabilities. Implementations of decision support systems in business increased significantly during the 1980s [BO06]. Advances in database technologies during the 1990s, such as data warehousing, online analytical processing (OLAP) and data mining, dramatically improved the availability of information for the decision makers, and *executive information systems (EIS)* were introduced as the latest innovation for analyzing enterprise-wide aggregated data through a single, consistent view of integrated data that originates from multiple sources [FA06].

As the Internet became available everywhere, the concept of *business intelligence* emerged, and at the same time the introduction of the *Balanced Scorecard* quickly gained popularity and inspired new developments in *performance management* [FA06]. In the beginning of the new millenium, the emphasis has been shifting to web-based decision support and mobile technologies to further enhance the quick availability of information anytime, anywhere [TAL05].

Because computer-based tools for decision support have been studied, developed and used already for several decades (which is a long time in the history of information technology), the variety of concepts and systems related to them is wide and even confusing, as discussed above. Turban *et al.* [TAL05] point out that *there is no universally accepted definition of a decision support system.*

Different approaches have been taken, and classifications have been made based on conceptual models, system functionalities, technologies and characteristics of the decision task [TAL05]. The list of systems and tools found under the concept of decision support systems is therefore long, which is perhaps also influenced by the fact that these systems are used in many different fields of modern societies, such as medicine, manufacturing, engineering, politics, environmental decision-making, crisis management, retail and finance to name just a few.

In this section we will describe how contemporary decision support systems can be utilized in the strategic management of a company. The emphasis is on business intelligence, performance management and the Balanced Scorecard as an example of a formal approach for performance management[12]. We will especially provide a review of how these systems are used in Finland and other Nordic countries. Finally, the *dashboard* is introduced as a visual tool for managerial decision-making.

[12] We acknowledge that there are several other frameworks as well, and new ones are constantly being developed. However, a detailed review of existing frameworks is outside the scope of this study. We will therefore limit our discussion to one example to provide a general understanding of the issues related to performance management.

4.1 Performance management and the Balanced Scorecard

If you can't measure it, you can't manage it. [KN96]

Every company must have a clear strategy in order to survive the ever-toughening competition in today's business. Simply defining a strategy is not enough, though; throughout the entire organization, managers on all levels should align their actions with it when planning the everyday operations of the organizational units. Implementing a strategy defined on the top level of the organization, however, is a very challenging task if the lower-level managers have no means to connect their everyday operations and decisions to the strategy. A simple slogan or mission statement provides little guidance to a business unit manager on which actions should be taken today in order to achieve the strategic goal in the future. Moreover, the performance of the organization as well as its subunits is often measured only in financial terms.

In response to the overemphasis of measuring only the financial results of a company, Kaplan and Norton [KN96] developed the *Balanced Scorecard* framework during the first half of the 1990s. They point out that focusing on the past financial results, such as operating profit and return-of-capital-employed, and maximizing them may be beneficial on short term, but the company's success and growth on the long term requires that non-financial measures must also be taken into account, since they are often the drivers of future performance. Companies have many intangible and intellectual assets, for which a direct financial value is very difficult or impossible to determine, yet which are critical factors for success on the long term. Such assets are for example high-quality products and services, motivated and skilled employees, responsive and predictable internal processes as well as satisfied and loyal customers [KN96].

The scorecard is balanced between the objective *outcome measures* (called *lagging indicators*), which indicate past performance and are easy to quantify, and the subjective *performance drivers* of the outcome measures (or *leading indicators*), which in turn affect future performance and are therefore harder to quantify. The measures are organized in four perspectives, each of which has its own set of objectives linked to the strategy and measures that quantify them in appropriate ways [KN96].

Financial perspective. Despite the critique against measuring financial results, those results are still valuable in summarizing the economic consequences of actions that have already been taken [KN96]. Financial performance measures indicate whether the strategy and its implementation are successful. Measures in the financial perspective, e.g. the aforementioned operating profit and return-of-capital-employed, are always lagging indicators since they only measure past performance.

Customer perspective. The customer and market segments in which the company competes should be identified and measures developed to indicate performance in these targeted segments. The customer perspective usually contains lagging indicators for measuring the outcomes, such as customer satisfaction (quantified by e.g. surveys), customer retention, new customer aqcuisition and market share [KN96]. On the other hand, leading indicators measure factors that are critical for the customers to switch to or remain loyal to their suppliers. Fast and on-time delivery, continuous development of new products and services or the capability to anticipate customers' emerging needs and satisfy them quickly are a few examples of such factors, but of course they vary according to the company's business.

Internal business process perspective. Each company has different internal processes for delivering products and services to customers, but in general they can be divided to innovation (development of new products), operations (sales and delivery) and postsale service (e.g. warranty, maintenance and customer support) processes [KN96]. Naturally the measures for these processes vary accordingly, but typically this perspective includes both leading and lagging indicators which measure the time, quality or cost of processes. A few examples are revenue from new products and service request fulfillment time as lagging indicators and product development cycle time and hours spent with customers as leading indicators.

Learning and growth perspective. In order to continuously improve its capabilities for delivering value to customers and shareholders, a company should invest in enhancing the employees' skills and improving information systems as well as aligning organizational procedures. These are the long-term drivers of performance in the other three perspectives [KN96]. Especially the weight of employee skills and motivation have increased significantly as the nature of work has changed from physical to intellectual.

> Measures in the Learning and growth perspective might include for example employee satisfaction, retention and productivity (lagging indicators) as well as staff competencies, strategic information coverage[13] or percentage of employees whose personal goals are aligned with the scorecard (leading indicators).

In addition to the identification of strategic objectives and selection of meaningful measures, the cause-and-effect relationships between the leading and lagging indicators must also be defined [KN96]. The scorecard should not include any measures that are not linked to at least one other measure. Together the measures and their relationships communicate the company's strategy and provide guidance to employees on all organizational levels on what actions should be taken today to achieve the strategic goals in the future. Kaplan and Norton [KN96] note that a well-designed scorecard consists of at most 15 to 20 strategic measures. Figure 15 on page 34 illustrates an example of a Balanced Scorecard implemented in an insurance company.

Some critical remarks on the Balanced Scorecard have been made, although in general it has been widely accepted in the business world. Bessire and Baker [BB05] question the entire value of the framework as a new innovation, because in France a very similar framework, the *Tableau de bord*, has been developed as early as the 1930s and is still used in the majority of French companies and non-profit organizations. The Tableau de bord also contains non-financial measures, although it has been noted that in practise they often tend to focus too much on the financial ones [EM98]. Bessire and Baker [BB05] argue that the fundamental limitation of both frameworks is that they view the organization as a "machine" and its executives as "pilots" steering the machine to certain direction. The use of such metaphors hides the human aspects of organizations, they claim, "prompting forgetfulness about the fact that directing and controlling an organization is far more complex than operating a machine" [BB05].

[13] The *strategic information coverage* assesses the availability of information relative to anticipated needs, e.g. percentage of customer-facing employees having online access to information about customers [KN96].

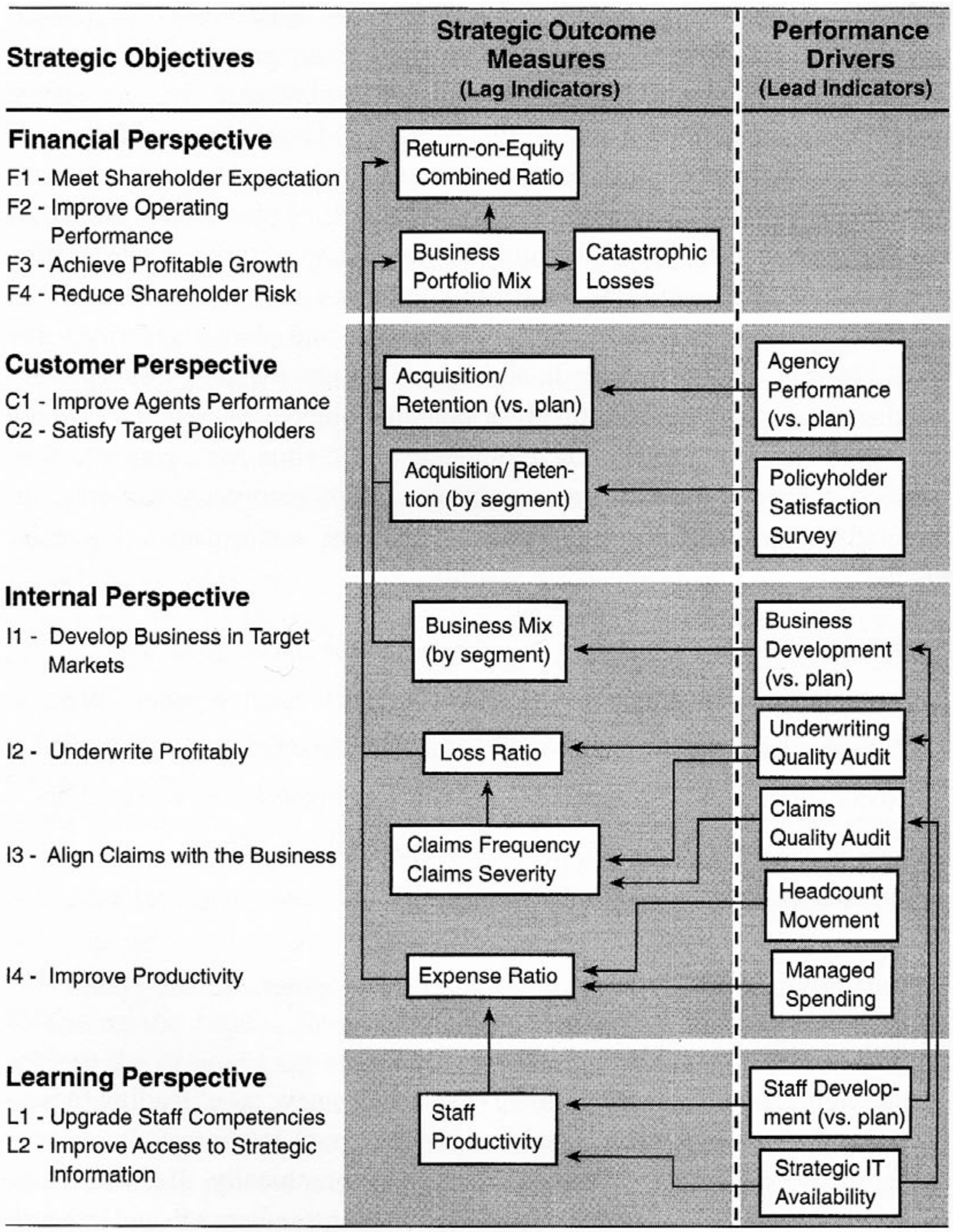

Figure 15: A balanced scorecard for an insurance company [KN96].

Paranjape *et al.* [PRP06] present a review of the debate and academic research about the Balanced Scorecard. They note that not all implementations of the framework are successful – some studies have actually reported negative effects on performance, which has led the companies to discard the framework [PRP06]. Of course the Balanced Scorecard itself cannot be blamed alone for the failure; selection of inappropriate or excessive measures, inefficient implementation by the management, delay in feedback and over-emphasis on financial measures are listed as the most common reasons for failure [PRP06], which contradicts with the original propositions for e.g. selecting only a small number of the most important measures and giving all perspectives equal emphasis [KN96]. In addition to complete failures, some researchers have questioned the performance improvements achieved by using the scorecard, while others have criticized it for the inability to adopt to changes in the organization and the lack of social and environmental aspects [PRP06].

The most severe problem in performance measurement seems to be the design and implementation of the measures. Even the Balanced Scorecard framework does not offer any concrete guidelines on *how* to measure; it only gives directions on *what* to measure [PRP06]. Many companies probably end up selecting too many measures because of this, and measuring too many things usually generates more problems than it solves [KN96]. For example, employees may start to focus on maximizing performance on one measure (e.g. reliability of electrical equipment), but at the same time generate unnecessary costs that have a negative impact on some other measure (e.g. replacing parts before they break) [PRP06]. On the other hand, too much data will decrease the overall effectiveness of the performance measurement system by causing "information overload" for the managers.

The critique presented does not seem to have influenced the popularity of the Balanced Scorecard. Although other methods for measuring business performance have been proposed, the details of which are outside the scope of this study, the Balanced Scorecard has dominated the discussion on performance measurement ever since its introduction. Kaplan and Norton have been among the most frequently cited authors for many years [MS03], and the results of a worldwide survey by Bain & Company [Rig07] in 2006, which covered over 1200 companies, showed that the Balanced Scorecard was implemented in around 66 % of the companies, and the percentage is expected to increase in the future. We can thus say that this framework is currently by far the most popular tool for performance measurement.

Those companies that do not use Balanced Scorecard or some other formal framework (of which there are several) have simply developed a collection of *key performance indicators (KPI)*. This means measures that are not directly linked to the organization's strategy, but to the day-to-day activities taking place in the organization. Kaplan and Norton [KN96] mention the use of "diagnostic" measures in addition to the strategic measures, because in some cases they might prevent over-focusing on certain individual strategic measures. A recent survey in large British companies [BLS07] confirms that most companies – even those that are using the Balanced Scorecard – use a wide variety of both financial and non-financial measures that are not linked to strategy, but are useful for lower-level managers in tracking the status of their own subunits. The emphasis in implementation seems to be on the financial measures [BLS07]; this might be due to the difficulty of implementing quantitative non-financial measures, as discussed earlier.

4.2 Business intelligence (BI)

One of the most commonly heard terms in the business world today is *business intelligence*, or BI. Like "decision support system", this term is also ambiguous and has no single widely accepted definition. The introduction of the BI concept dates back to around the middle of the 1980s, when Gilad and Gilad [GG86] defined a process, the input of which is raw data and the end result is "knowledge in a form that decision makers can use to make important strategic decisions". According to Pirttimäki [Pir07], business intelligence is a process that involves identifying information needs, gathering data and information both inside the organization and from outside sources and processing it into valuable managerial knowledge. In this sense, the term is to some extent related to "military intelligence": it refers to activities that aim at acquiring knowledge that helps the company to outperform its competitors.

Business intelligence has many dimensions: it can be seen as a process, a management tool, a technology or a philosophy [Pir07]. BI has a much broader meaning in Europe than in North America [Pir07], where it often refers merely to a technological solution to consolidate vast amounts of data [FA06]. In North America, *competitive intelligence* is a more similar concept to the European meaning of BI [Pir07], but it refers only to gathering external information, i.e. information about competitors, markets, business environment etc. In Europe, BI is generally understood as gathering and processing both internal and external information [Pir07].

Performance management and business intelligence are related to each other, but not synonyms. For example, the Balanced Scorecard includes measures for both external information (customer satisfaction, market share etc.) and internal information, and collecting data for these measures may be regarded as an intelligence activity. On the other hand, the BI process itself can be subject to performance measurement, as suggested by Lönnqvist and Pirttimäki [LP06]. One differentiating character between these two is that performance measures serve as a *reporting* function: the values of the measures are based on static predefined rules and formulas, whereas BI is an *analytical* process that dynamically refines the raw information (by automatic data mining and modeling processes or through user interaction, such as *ad hoc* querying) to produce a deeper insight for decision-making [Pir07]. BI can thus also be seen as the operation that provides the data for performance management. However, both functions are important and useful for managing a business. We therefore consider both performance management and business intelligence systems as the latest step in the continuum of decision support systems' evolution [AP08].

A business intelligence system is usually based on *data warehouse* technology [WW07, FA06, Pir07, TAL05]. Collecting all data in a single repository offers an integrated view on all information regardless of its original source, and it also facilitates improving and controlling the quality of data, especially when some data are transferred from legacy systems that may have different encodings for the same information [WW07]. In large companies, the data may be further replicated to subunits as *data marts*, which are similar to the main warehouse, but each data mart contains only a subset of the warehouse data (based on e.g. geographic location or business function) that is relevant to that subunit [TAL05]; smaller companies might resort to independent data marts that are essentially "small warehouses".

Data in the warehouse or data marts can be utilized for business intelligence activities in many ways (see Figure 16). These include data mining, ad hoc querying, reporting and predictive analysis [WW07]. Especially in reporting, visual displays of summarized data, i.e. dashboards, seem to be the most common format for user interfaces; some software products also include information visualization techniques for analysis functions. This may indicate either that the advantages of visual displays over text and tables have been implicitly recognized by software vendors and business users, or that they have become popular just because they make the interfaces more appealing. Whatever the reason, the trend is that "business intelligence methods and tools are highly visual in nature" [TAL05]. We will discuss dashboards further in Section 4.5 and developing user interfaces for BI in Section 5.

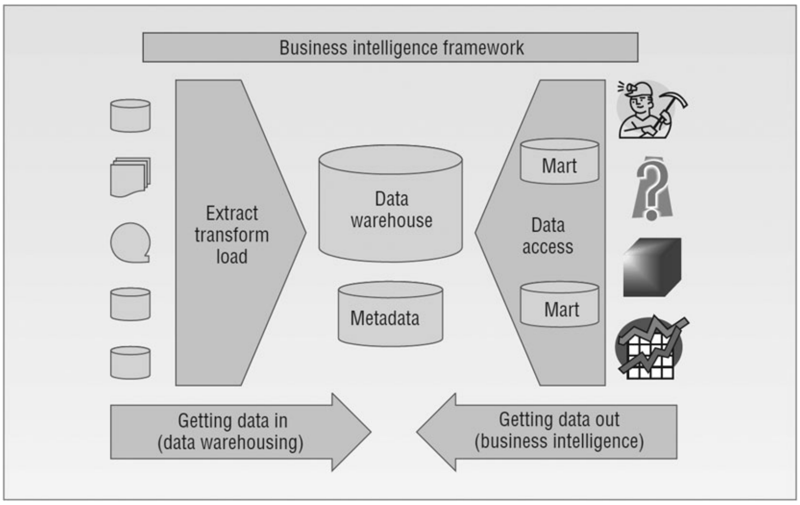

Figure 16: Business intelligence framework [WW07].

4.3 BI and performance management in the Nordic countries

Finland and the other Nordic countries are among the most advanced countries in the world, when it comes to information technology[14]. Therefore one may assume that decision makers in Nordic companies would utilize the latest information technology to a great extent. Some empirical studies on decision support systems in Finland and the Nordic countries have been conducted, although the small number of both worldwide and country-specific studies on this topic is addressed in many articles [KN02, UTR07, Pir07].

The results of a survey of over 200 companies in Finland, Sweden, Denmark and Norway by Kald and Nilsson [KN02] indicate that performance management systems are used for decision support on both the top management and the operating levels, and that they are used for strategic planning as well as monitoring and reporting purposes. Financial measures still seem to have the greatest importance, although in Finnish companies the role of non-financial measures seems to be somewhat greater than in other Nordic countries [KN02]. Measures focused on development – such as employee satisfaction, competence and level of technology – are generally not considered very important, which raises some concern since they affect long-term strategy and competitiveness [KN02].

[14] In the latest report by World Economic Forum, Finland was ranked 6th in information technology [Wor08]. All Nordic countries are in the top 10.

Consistent with Kald and Nilssons's findings [KN02], Ukko *et al.* [UTR07] have studied the impacts of performance management in eight Finnish companies that are using the Balanced Scorecard framework and the measurements are applied both on top management level and operational level. They interviewed both executives and employees in the companies and found out that the implementation of a measurement system has had a positive effect on organizational performance both in terms of financial results and improved quality of products and services due to better allocation of resources [UTR07]. At the same time they emphasize that the operating-level employees should be involved at an early stage of the implementation by means of information sharing, training and communication between the management and the employees. The eight companies studied had succeeded quite well in aligning the measures on the operational level with the strategic objectives on the organization level, which is critical for the successful implementation of a performance management system [UTR07].

Business intelligence systems seem to play an important role at least in the largest Finnish companies: according to Pirttimäki's two surveys [Pir07], 95 percent of the top 50 companies (by turnover) in Finland reported that they are using business intelligence systems in 2005, whereas in 2002 the percentage was 80. The most important information needs covered by BI regarded competitors, one's own industry and customers. In addition to strategic management on corporate level, BI tools are used to an increasing extent on the operational level, e.g. by middle management and experts [Pir07]. The survey results indicate that in 2005, 73% of the companies used their own in-house resources for BI activities, and 82% have a dedicated information system for business intelligence. These systems are used for continuous monitoring and regular reviews as well as *ad hoc* reporting [Pir07].

Despite the fact that advanced information systems ideally have a positive impact on decision-making and also organizational performance [Hyv07], there are some problems that often hinder their use. Some survey respondents pointed out that the present tools and systems do not always match real demands [Pir07]. In another survey [STS+07], the executives of nearly 200 large Finnish companies often mentioned issues such as "tools are complicated and heavy to master", "interpretation of the results is difficult" and "form goes over substance" as the greatest disadvantages of desicion support tools. Perhaps due to these facts, only a few executives confirmed that they use BI systems for making major strategic decisions [STS+07]. This might signify that BI is indeed used more on the operating level [Pir07].

In conclusion, the above studies indicate that there is a great deal of interest towards both performance management and BI systems in Finnish companies. It must be noted, however, that these studies are not very extensive and cover only a small sample of companies. Nevertheless, we believe that they do reflect the overall trends of development in the country.

4.4 Implementing a performance management system

While selecting appropriate measures is the key to successful performance management, it has also been identified as the greatest challenge in performance management [KN96, FA06, PRP06]. A common mistake is to have too much measures. When almost everything is being measured, the massive amount of data will make it practically impossible to identify what is important to determining organizational progress [FA06]. Implementing the data collection and reporting for a large number of measures is also expensive and often results in over-quantification and a large number of inappropriate measures [PRP06]. On the other hand, focusing on past performance alone – whether financial or non-financial (for example, market share and customer satisfaction are non-financial measures, but they are still lagging indicators) – will not lead to success on the long term [KN96]. However, the past performance indicators are simple to implement and easily accessible [FA06], which makes them an attractive choice.

What is then a good way for finding the relevant measures? There is no simple and universally applicable answer to this question, since each organization has a unique set of customers, internal business processes and resources [KN96]. Therefore a set of measures that are appropriate for one company will probably not suit any other company, even if they operated in the same industry. Some guidelines have been provided in the literature, however. It is widely agreed that the measures should be initially developed at the top management level of the organization in order to ensure that the measurements are aligned with the organization's strategic objectives [KN96, BMW+00], although the bottom-up approach may also sometimes be successful when executed carefully [FA06].

Kennerley and Neely [KN03] summarize a set of common qualities of relevant measures, suggesting that they should at least:

- be derived from strategy
- be simple to understand and exact about what is being measured
- provide timely and accurate feedback
- relate to specific goals (targets)
- focus on improvement
- be consistent (maintain its significance as time goes by)

Performance measurement is a dynamic process. As the business environment changes, an organization must adapt to the change, which is likely to change also the needs for measurement [PRP06, BMW+00]. It therefore suggested that the measures should be reviewed on a regular basis to ensure that the current measures are relevant and to discuss whether new measures should be developed or some current measures discarded [PRP06]. Auditing the measurement process may sometimes also lead to discussion about the validity of the strategic objectives themselves [BMW+00].

As an empirical example, we will describe how strategic measures have been developed in a Finnish IT company. The development process may not qualify as an ideal example, but at least in the company in case it has been considered successful, and it follows many of the principles discussed earlier in this section. The company's strategy was recently revised, and the new strategy is strongly focused on sales, based on the reasoning that an excellently performing sales "machinery" ensures the continuous growth of the entire company. The top management therefore developed strategic measures for sales performance and established an internal process to monitor it. In this company, strategy formulation was considered a much more challenging process than selecting the measures. When the new strategy had been clarified, a consensus on the measurements could be found with relatively little effort. This approach is somewhat contradictory to the argument that defining the measures should help the company to clarify its mission and strategy [KN96]. Could it be that the problems in defining the measures are caused by a lack of clarity in strategy?

The design process started by defining the financial measure which indicates past performance; sales revenue was an obvious choice as the indicator for a sales-driven company. Revenue is the end result produced by the "sales pipeline": it starts from customer meetings, some of which lead to sales projects; some of the sales projects lead to making an offer, and some of the offers lead to signing contracts. The volume of the sales pipeline is thus a measure of the current performance. It is a leading indicator, because if the pipeline appears to be too "narrow" at the moment, corrective action can be taken immediately to achieve a positive outcome. Since the sales pipeline starts from customer meetings, they ultimately determine the amount of contracts that will be signed and thus affect the sales revenues in the future. Therefore the amount of customer meetings was selected as a leading indicator.

The company management initiated a routine of weekly meetings, in which the status of these measures and the achievement of target values is evaluated and decisions upon corrective actions are made, if necessary. In order to facilitate the collection of performance data, the customer relationship management (CRM) system was extended, and all sales personnel are required to keep the system up to date at all times. This procedure shows that the measurement process is tightly controlled by the management. On the other hand, a strong commitment by the management is considered very important for the success of the implementation [FA06, BMW+00], so it probably had a positive impact on the adoption of the system.

The length of the measurement development and implementation process was around one year. This is not unusual, since similar time spans have been reported in other companies as well [BMW+00]. The measurements have been used for less than a year now, and the system is constantly evolving with new measures being discussed and the accuracy of data collection being improved.

4.5 Dashboard – a visual information interface

The advantages of displaying numerical data in a graphical format have been recognized centuries ago[15], and even the first management information systems produced results in a graphical format. Today, as the amount of information is vast compared to past decades, the need for visual tools in decision-making is therefore emphasized. Most vendors of BI and performance management tools now offer *dashboards* as the graphical user interface for reporting, but none of them really explain what a dashboard is [Few06].

The origin of the term is probably in the French performance measurement framework Tableau de Bord, which literally means "dashboard". The thinking behind the dashboard metaphor is probably that performance management is often regarded similar to driving a car, flying an aeroplane or steering a ship, as discussed earlier in Section 4.1. Nonetheless, the term has rooted itself firmly in marketing slogans (such as "What's happening? – Check the dashboard" or "Your business dashboard: knowing when to change the oil") and it has also been adopted by the end users to the extent that this tool is not likely to be known by any other name, even if its current name is quite misleading and non-descriptive. After a thorough search for a definition of a dashboard with no results, Few [Few06] decided to create a definition applicable to all dashboards:

> A dashboard is a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance [Few06].

This definition is very general in nature and carefully avoids any specific association with performance measurement or business intelligence; in fact, considering that after all *a dashboard is a graphical user interface*, it could be used to display any information that is necessary, meaningful and possible to represent in a concise visual format. However, the applications of dashboards are at the moment limited to BI and performance management, since dashboards were originally introduced in this context; therefore the terms "performance dashboard" and "executive dashboard" are often used.

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[15] English economist William Playfair was presumably the first person to use statistical graphics in 1786 [Tuf01].

The dashboard is only a "tip of the iceberg": behind it there is a massive infrastructure in which the data are collected in their operational sources – be it a database, spreadsheet, text file or the Internet –, moved into a data warehouse or mart through an *extract-transform-load* (ETL) process, and then processed in OLAP cubes that provide an integrated, multi-dimensional view on the data. Although the underlying structures of course play a significant role, we may say that the dashboard is the most important part of the information processing chain in the sense that it is the interface through which the human interacts with the computer system and the data. The user only sees the consolidated results on the dashboard, not the intermediate components of the data processing chain. The dashboard is thus a tool for *reporting*, not a full-scale *analysis* tool (unless the user is allowed to build the dashboard from scratch, which is quite laborious), although some means of simple interaction with the data are usually featured.

In order to achieve its goal, to provide *information* about the data that is turned into *knowledge* in the human mind, the dashboard must communicate the information as efficiently as possible and preferably in a manner that requires little cognitive effort. A visual presentation format makes it possible to fulfil these requirements, but not any given visual format. As we have discussed earlier in Sections 2 and 3, there are certain principles that the human brain follows when the visual image is interpreted; therefore some formats are more suitable than others, depending on the context. We will discuss how these principles can be taken into account in the design of a dashboard in Section 5, which also contains illustrated examples of dashboards (Section 5.3).

5 Visualization in decision support systems

In the previous sections we have discussed the principles of visual perception, information visualization and decision support systems. The theoretical approach is now changed into a practical one, focusing on issues regarding the effective design of visual reporting interfaces such as dashboards. We will first introduce some of the most common and useful display formats in Section 5.1 and discuss their characteristics in order to guide the choice of correct display format for different display tasks. Section 5.2 discusses some additional theoretical and practical topics essential for statistical graphics that have not been discussed previously. Section 5.3 presents a brief review of the visual interfaces implemented in some current business intelligence software products. The review reveals that the design of these interfaces is unfortunately often – but certainly not always – quite poor in terms of effectiveness, i.e. ease of comprehension.

5.1 Graphical elements for visualizing statistical data

The most frequently used types of graphical displays are without a doubt the *line graph*, *bar graph* and *pie chart*. The vast majority of all graphs drawn every day consists of these types, which can be easily confirmed by choosing any newspaper, magazine or a business document at any company. However, the characteristics of the data vary from case to case, and also the goals of visualization are different. Many other types of graphs exist, and they might be more effective in telling the story on the data than the basic line graph, bar graph or pie chart. Still, any other graph types are quite rarely used outside the scientific community, which may be due to lack of experience in statistics and unawareness of the available graphical methods. In this section, we will present some graphical elements that are most commonly seen on dashboards and visual analysis tools and discuss their strengths and weaknesses.

5.1.1 Line and bar graphs

Both line and bar graphs are in general the most effective display media for many reporting applications. They serve different purposes: a line graph provides an *overall* view of the entire data set, showing the variation in the values, while a bar graph focuses on the *local* details, facilitating comparisons between individual values [Few06, CR97]. Both graphs make use of accurate perceptual tasks: length (bar graph) and position (line graph) judgment. Line graphs also enable slope jugments, which are not very accurate absolutely, but indicate the direction and rate of change in the data from one point the another; this is often of particular interest for the viewer.

Scaling is sometimes misused in bar graphs. If the value scale does not begin from zero, the lengths of the bars will be distorted and may lead to incorrect conclusions [Few06] unless the viewer notices the distortion, which cannot be assumed. For example, in Figure 17 the January revenues appear to be more than four times the costs, judging by bar length. Only looking at the scale reveals that this is not true; actually the ratio is around 10:6, i.e. the length of the cost bar should be 60% of the revenue bar. In line graphs, however, the scale need not begin at zero, since the perceptual task is position judgment, i.e. distance, not length. Sometimes adjusting the scale to fit the minimum and maximum values of the data set may in fact improve the readability of a line graph, because it might result in a better aspect ratio (see Section 3.3) than a zero-based scale.

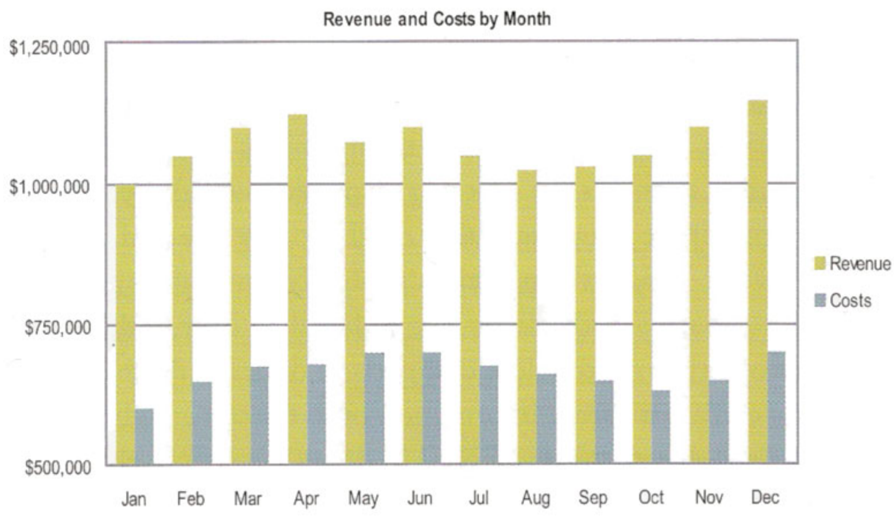

Figure 17: Inaccurate scale on a bar graph [Few06].

5.1.2 Pie charts

> *The only worse design than a pie chart is several of them. — Given their low data-density and failure to order numbers along a visual dimension, pie charts should never be used.* [Tuf01]

The blunt argument against the use of pie charts mentioned above is supported by empirical experiments [CM84, Few06]. The elementary perceptual task in a pie chart is angle judgment [CM84], which is not very accurate (see Section 3.7). The fundamental purpose of a pie is to facilitate *part-to-whole* comparisons, i.e. judging the proportion of each slice compared to the total, which is represented by the full circle. However, the problem is that part-to-whole comparison is the *only* type of judgment that can be carried out reliably in all situations – neither absolute value estimates nor relative size comparisons between slices are easy to perform accurately in a pie chart [Few06]. For example, consider the slices of "Competitor B" and "Us" in the pie chart in Figure 18. The sizes of the slices are so close to each other that it is practically impossible to say which one is greater; one must inspect the numbers below the category labels (which is difficult because the labels are far apart from each other) to determine the actual values in order to perform comparisons.

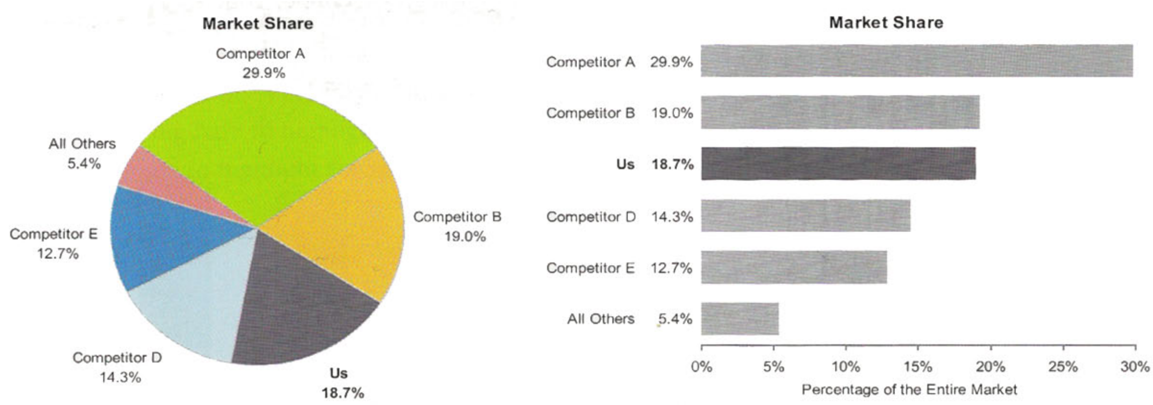

Figure 18: Comparison of a pie chart and a bar graph [Few06].

There is very little psychological evidence that would favor the use of pie charts over bar graphs. Hollands and Spence [HS98, HS01] have reported some such evidence, but the benefits of their results are somewhat questionable. For example, in one experiment [HS98] they note that even though people made more accurate part-to-whole judgments with pies than with bar graphs, adding a percentage scale to the bar graph instead of an absolute scale would make the two charts equally efficient in terms of part-to-whole estimation. In another experiment [HS01], Hollands and Spence conclude their discussion by pointing out that difference estimates are more accurate between two pies of unequal sizes than two unequally sized divided bar graphs[16], but that the estimates are equally accurate when the two pies or divided bar graphs are of the same size. In other words, these experiments do not demonstrate very much benefits for using pie charts apart from certain rather rare special situations.

In Figure 18, the same market share information is presented by a pie chart and a bar graph. The bar graph has a percentage scale, which facilitates part-to-whole comparisons as efficiently as the pie chart [HS98]. In addition, the bar graph enables effortless comparison of the shares between companies and a reasonably accurate estimation of the absolute market shares of each company based on bar length; when needed, the exact numbers are available in a single vertical column that is easier to scan than the scattered labels in the pie chart. Moreover, the darker shade of the “Us” bar highlights the most interesting fact for the intended audience: how is *our* company situated? The overwhelming colourfulness present in the pie chart, like virtually all pie charts created these days, hinders preattentive processing and makes highlighting difficult.

For the reasons explained above, we agree with the following recommendation:

> Even when you wish to display values that represent parts of a whole, you should use a bar graph rather than the ever popular pie chart [Few06].

[16] In a *divided bar graph* each bar is divided into several, usually color-encoded, parts that show the disribution of a third variable in proportion to the variable encoded by bar length. For example, bars representing total sales could be divided to show the amount of sales in different continents. Cleveland and McGill [CM84] have shown that a grouped bar graph with individual bars for the third variable is actually more effective than a divided bar graph.

5.1.3 Sparklines

The superior pattern recognition capabilities of the human visual system have already been discussed earlier (see Section 2). Recognizing overall trends and reoccurring patterns in time-dependent data is also very useful in business, when the state of a company is being analyzed. Tufte [Tuf06] has introduced a new way of facilitating pattern recognition: an element that he calls *sparklines*. He defines sparklines as data-intense, design-simple, word-sized graphics that are usually embedded in a context of words, numbers and images. An example of sparklines is illustrated in Figure 19.

Figure 19: Sparklines displaying the history of currency exchange rates [Tuf06].

The idea behind sparklines is very simple: when the graph is compressed in a very small space, it can be used "like a word" and placed immediately next to numbers that provide more details about the data. Sparklines usually have no quantitative scales printed in the graph, because of their small size and also because their fundamental purpose is not to provide exact quantitative information. On the contrary, sparklines display the overall patterns in the data set and enable the reader to quickly evaluate those patterns at a glance. The quantitative imprecision can be overcome by accompanying sparklines with numbers that provide the necessary details about the most important features of the data, such as minimum, maximum, average, first or last value.

Sparklines are also useful in reducing *recency bias*, "the persistent and widespread over-weighting of recent events in making decisions" [Tuf06]. Data tables consisting of numbers often display only current levels or recent changes; one obvious reason for this is that showing a large amount of numeric details would require a lot of screen space (or paper), and often conciseness is preferred over detail. Since sparklines are word-like by definition, they can be included in a data table together with the numeric details without consuming much more space, and the resulting small multiples display (see Section 3.5) also facilitates comparisons between different rows of the table, as can be seen in Figure 19.

5.1.4 Displaying key performance indicators: Gauges vs. Bullet graphs

The most common use for dashboards is reporting for performance management; therefore the display of key performance indicators is an important topic. In addition to its actual value, the target value specified for the measure is important. Often a qualitative range, which defines the good, satisfactory and poor levels of performance, is associated with the measure. In principle, the idea of a generic graphical element for displaying these properties of the indicator is good. However, there are many ways to design the layout for such an element.

By far the most popular type of graphical element for key performance indicators is a *gauge* (Figure 20). Very often the gauge is designed to look like a speedometer in a car (due to the vehicle metaphor, see Section 4.5) and usually the colors of the qualitative levels are encoded with "traffic lights", i.e. red, yellow and green. Surprisingly, many gauges lack the labels that indicate scale and sometimes they do not even display the actual numerical value, which makes them purely qualitative elements.

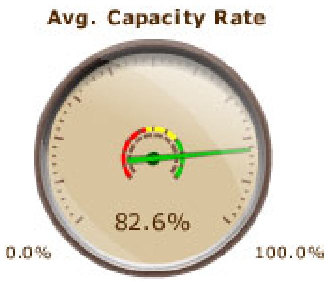

Figure 20: A typical gauge used on dashboards[17].

A gauge is a very inefficient way of presenting a key performance indicator. First of all, the circular gauges reserve a lot of space on the screen unnecessarily – they are usually quite large, since it would be difficult to distinguish the details in a small gauge. Secondly, the "speedometer" design, with all its fine details, is nothing but decoration; its purpose is to attract the viewer, but it adds no information value to the display. Calculating the data-ink ratio [Tuf01] (see Section 3.1) would result in a value close to zero. Third, since color encoding in general is unnecessary, as discussed in Section 3.2, the traffic light encoding is also merely decoration. Moreover, when there are many of such indicators on screen, they introduce noise that may distract the viewer from paying attention to the important issues.

[17] http://www.businessobjects.com/product/catalog/xcelsius/demos.asp

An alternative for a gauge that performs the same function is a *bullet graph* introduced by Few [Few06]. It displays the actual and target values of a performance measure and a qualitative range in a smaller space than a gauge and without any unnecessary decoration. Figure 21 illustrates the structure of a bullet graph.

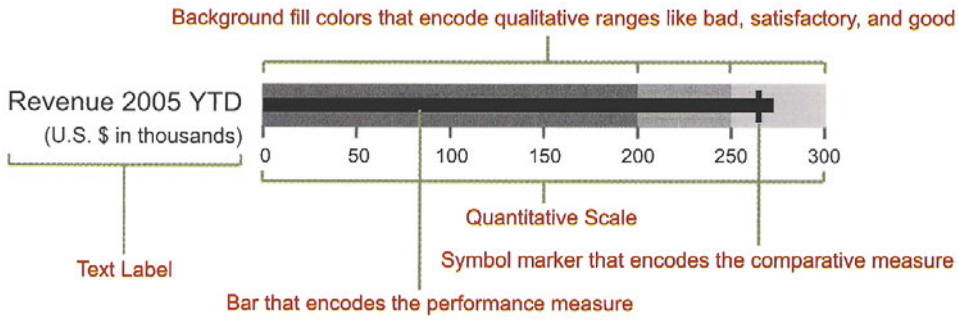

Figure 21: Structure of a bullet graph [Few06].

A bullet graph consumes considerably less screen space than a gauge. This enables many of them to be placed next to each other to facilitate comparison in a bar graph-like manner, and scanning through an array of bullet graphs facilitates preattentive processing (see Section 2.3): the vertical lines indicating target levels stand out especially when the actual value is below the target [Few06]. Even if the values of performance measures have different scales and units, the comparison of target attainment for each measure is still a good reason to create an array of bullet graphs. An example of using bullet graphs on a dashboard is presented in Section 5.3.

5.2 Some additional guidelines for designing dashboards

A dashboard, as a single-screen user interface, sets certain special requirements for its visual design. Some issues are rarely encountered in other types of user interfaces (such as the requirement for using as concise display elements as possible); on the other hand, some issues that are very common to other interfaces (such as navigation) are not applicable to dashboards. In this section, we will discuss some design principles that not been addressed earlier in this study. In addition to the other issues presented in Sections 3 and 5.1, these principles complete our discussion on the visual design of graphical displays of quantitative information.

5.2.1 Context

The organization of information on a dashboard should be done with great care. It is very easy to present information that looks very credible but actually leads the reader astray – either accidentally or on purpose. Throughout history, people have exploited this in their own interests. An illustrative example of the misuse of context is shown in Figure 22, which presents the changes in stock prices in the New York and London stock exchanges as well as the intensity of solar radiation in 1929 [Tuf01]. All three lines are astonishingly similar. Should we then come to the conclusion that stock prices indeed are in some mysterious way affected by changes in solar activity? Of course not. By choosing appropriate scales and data sets, almost any things can be made to look as if they had some kind of correlation.

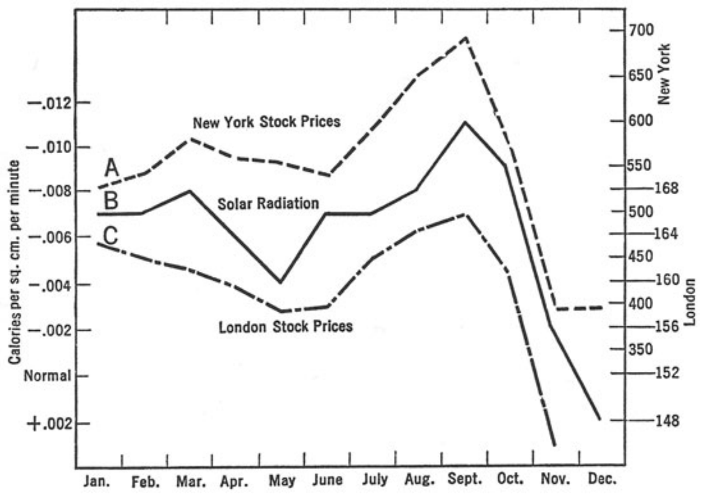

Figure 22: Solar radiation and stock prices in 1929 [Tuf01].

The above example is of course exaggerated, but it clearly demonstrates how data presented in the wrong context may lead the reader to false conclusions. This can be avoided by carefully choosing the data series that are to be plotted together on the same graph or displayed side by side in separate graphs or tables. Moreover, the questions *why* and *how* are often much more interesting than *what* [Tuf01]. Displaying only the effects of past actions will not give any clues to decision makers on which decisions should be made in order to solve problems, if and when any emerge. Whether a strategic framework such as the Balanced Scorecard is implemented in a company or not, it is probably a good idea to consider the cause-effect relationships between the internal processes. Finding out those relationships and displaying the causes and effects in the same context will likely provide more useful information for the decision makers than displaying the causes or effects alone.

Sparklines are especially useful for providing context to the data due to their small size and amount of encoded information. For the same reasons, bullet graphs are useful for presenting data in context with other relevant information.

5.2.2 Perspective and other visual effects

Many statistical graphics today include a three-dimensional (3D) effect even though the data set is plotted along only two geometrical dimensions; this effect is most often used in bar graphs and pie charts[18]. The perspective is thus purely decoration and provides no additional information compared to a two-dimensional (2D) graph; it is only meant to make the graph more attractive. It is not surprising that Tufte [Tuf01] regards this perspective effect as "chartjunk" (see Section 3.1) and recommends always avoiding it. However, all opinions have not been unanimous about whether the irrelevant perspective really does affect the comprehension of the graph [Sie96, ZLTS98, CM84, Tuf01]. Fischer [Fis00] reviews the debate and points out that the experiments have mostly focused on perceptual efficiency, whereas the comprehension of a graph involves also cognition. His experiment showed that cognitive processing was significantly slower with 3D bar graphs than 2D bar graphs, indicating that perspective does make a bar graph more difficult to comprehend [Fis00].

[18] We will not discuss 3D effects in pie charts here, since using them is not recommended (see Section 5.1.2)

Moreover, empirical results indicate that it is not the perspective on the bars, but the perspective of the frame that causes the extra processing [Fis00]. Complexity generally slows down graph comprehension, which in itself is a sufficient reason to recommend avoiding 3D effects in graphs [Fis00], as well as other decorative visual effects that contribute to nothing else but complexity – such as shadows, gradient fills and background images. Figure 23 illustrates an example of a purely decorative perspective effect. This example is not the worst possible, since the depth effect is quite mild; the deeper the perspective, the slower the cognitive processing required for comprehension [Fis00].

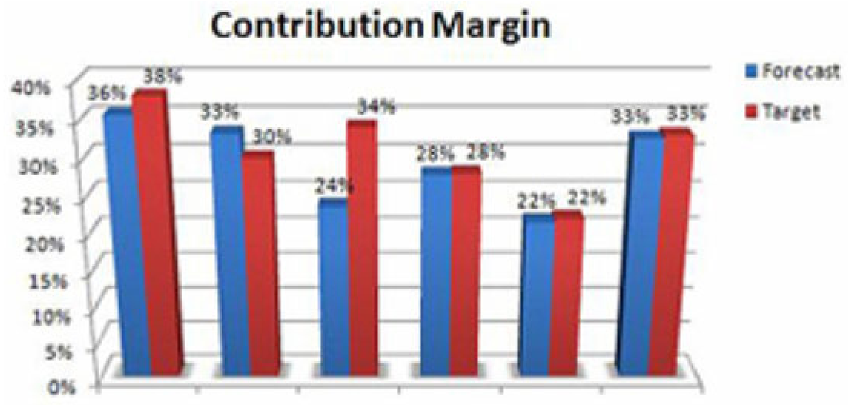

Figure 23: A typical example of an unnecessary 3D effect[19].

5.2.3 User interaction

Navigation in general is one of the most important topics in user interface design, but it should not be a relevant issue in dashboards, since they are single-screen displays by nature (see Section 4.5). Therefore neither scrolling down or changing the contents of the display by clicking a button or selecting a value from a dropdown menu are necessary. Dividing information into several screens breaks the context and forces the viewer to memorize the data on one screen before moving to another screen in order to compare data [Few06]. The graphical display media and visualization methods that have been discussed earlier in this study provide means for incorporating all relevant data on a single screen. If data needs to be displayed that is out of context, it is better to create another dashboard for that context than to complicate the current one with irrelevant information [Few06].

[19] This graph is part of a visual user interface that is analyzed in Section 5.3.

Although the purpose of a dashboard is to present summarized information and it is thus not a tool for analysis, some simple forms of interacting with the data might be useful and increase the user's understanding of the data. Such interaction includes hover queries, filtering (e.g. hiding some variables from a multi-dimensional bar or line graph by clicking their labels on the legend to simplify comparisons of the visible variables) or perhaps switching between bar and line graphs in order to support both pattern identification and local comparisons in a data set. Reordering the data set is also important for exploring different views of the data. This may bring new valuable information to the viewer (see Section 3.4).

5.2.4 Graphics vs. tables

The question about whether data should be displayed in a tabular or graphical format has been discussed for several decades. While it is agreed that visual presentations are the superior display format for very large data sets, the issue is much more complex for small data sets [CR97]. What complicates the issue is that the limit of "small" data sets is rather difficult to determine.

Tufte [Tuf01] recommends using a tabular format for all data sets with less than 20 values, but clearly this is not a reasonable requirement for business data which often deals with time series, especially monthly summaries over one year that contain 12 items. A line graph will still be more effective in displaying overall trends in this data set. Carswell and Ramzy [CR97] concluded that line and bar graphs are easier to comprehend than tables as the size and complexity of the data set increases. The data sets in their experiment consisted of 4, 7 and 13 data points, and only with the smallest data sets there was no effect between tables and graphs in terms of time taken to study the data set and the comprehension of its local details and overall content. Furthermore, the role of individual differences in cognition is emphasized when the data set is small, regardless of the display format [CR97].

It seems rather impossible to determine any number of data points, above which it would be unfeasible to display data in a tabular format. Moreover, the choice between tables and graphs is also afftected by the cognitive task: tables, even large, serve a *lookup* task well, i.e. finding the value of a variable based on some (ordered) index variable [Tuf01]. A phonebook is a good example of this. In some situations, a table of numbers may therefore be a more appropriate choice than a graph containing only a few data points.

5.3 Evaluation of visualizations in commercial BI software products

To conclude our discussion on creating visual reporting and analysis interfaces, we will briefly review and analyze five examples of how these interfaces are implemented in existing commercial software products. Our focus is slightly on the products offered by the largest vendors (currently SAP, Oracle, IBM and Microsoft), since these products account for most of the BI software market and are commonly used in millions of offices around the world every day. In addition, the BI software market has been characterized by mergers and acquisitions lately, as the large vendors have aqcuired small companies specialized in BI products to extend their product range; some large vendors have also merged (Oracle and Hyperion, SAP and Business Objects, IBM and Cognos), which has centralized the market even further. We note that several smaller vendors' products have also been reviewed, but in most cases the quality of visual displays exhibited flaws similar to – or worse than – the ones described here. These examples, apart from the last one, were selected for analysis, since they exhibit different kinds of problems. However, the misuse of color seems to be a common problem in most displays.

The examples provided are based on the marketing material available on each vendor's web site, and, as such, they of course represent only a small portion of the capabilities of the products. However, there is a good reason to present these examples: in practice, all vendors have implemented tools that enable the end users to customize the reporting interfaces to suit their own reporting needs by using "Dashboard Designer Studios" and the like. While the "create your own dashboard" approach is currently very popular and a great demand for such features seems to exist, it must be noted that *most end users of BI interfaces are not experts in designing effective visual displays.* As they create their own reporting interfaces, the end users therefore probably often resort to the examples provided by the vendors believing that the vendors are aware of the most effective ways to present data in a graphical format, and that the demonstrations and the default settings in these products show the best practices for designing visual displays. An example is a powerful teacher, and even if the examples demonstrated poor design, the users will nevertheless absorb them, often without questioning their effectiveness. Unfortunately, too often the examples provided seem to focus on nearly everything else but effectiveness in visual display, despite the fact that visualization is a strong sales argument for BI products today.

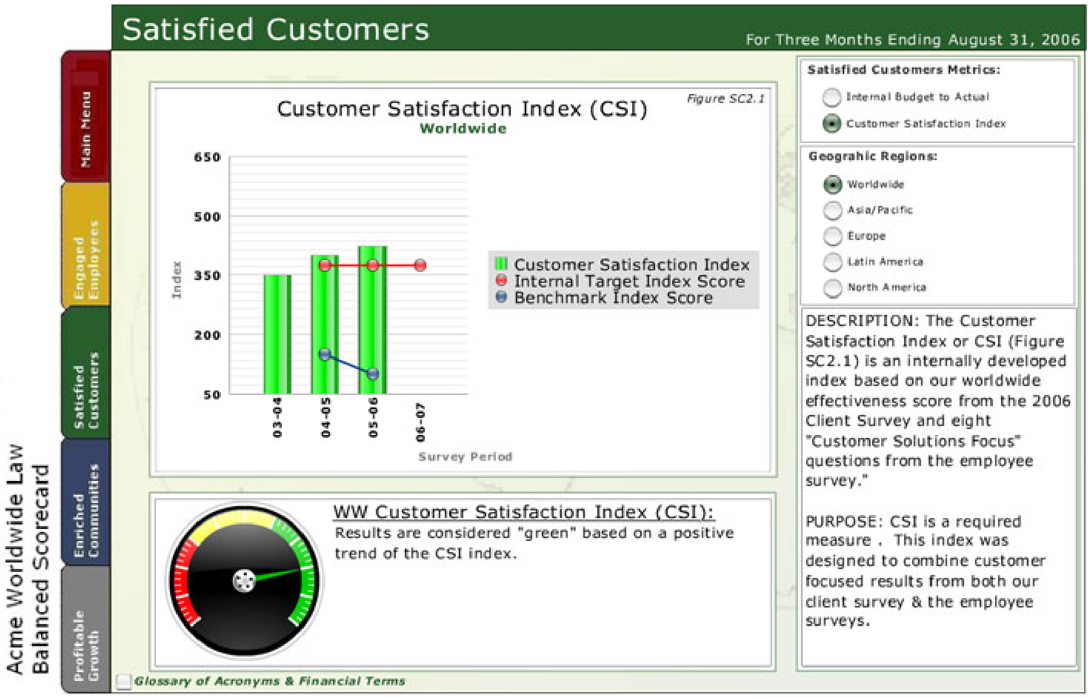

Figure 24: Example of a Balanced Scorecard reporting interface[20].

Figure 24 presents a Balanced Scorecard reporting interface by BusinessObjects. The most serious problem of this display is unnecessary waste of screen space. The graphical elements displayed (the combined bar/line graph and the gauge) are relatively large considering their information content and the legend of the graph consumes half of the space reserved for the Customer Satisfaction Index. This results in a very low data density, with only 9 values on the entire screen, and forces the viewer to use the radio buttons on the right to navigate to other similar screens to view the values for different continents. Comparisons between continents are possible only after memorizing the values on each screen. The gauge at the bottom has no quantitative scale, and in fact the variable displayed by the gauge has an ordinal scale with only three possible values. The text next to the gauge presents the same information. Moreover, including verbal descriptions for the measures on the right is a good idea, but the descriptions consume a lot of space unnecessarily, and experienced users will remember them without having to read them every time.

[20] http://www.businessobjects.com/product/catalog/xcelsius/demos.asp

The display in Figure 24 could be made more effective by using more concise elements, such as a small multiples (Section 3.5) display of five concise graphs. This would allow placing the worldwide index and the indexes of each continent on the same screen, thus reducing the need for navigation and facilitating comparisons between continents. The legend could be placed e.g. under the graphs to make the use of space more efficient, and converting the vertical bars to horizontal bars would also save some space. The scales of the bar graphs should begin at zero to avoid distortion in bar length estimations (see Section 5.1.1). The gauge could be replaced by a single small symbol that indicates the trend of the customer satisfaction index in a smaller screen space. The descriptions of the measures could be placed behind a help button to save space for the data. These changes would probably leave enough space at the bottom for another small multiples display that shows the "Internal budget to actual" graphs for each continent and worldwide, which would completely eliminate the need for navigation.

Figure 25: Example of a sales forecast analysis tool[21].

[21]http://www.microsoft.com/business/performancepoint/resources/demo/index.htm

Figure 25 (see previous page) displays a sales forecast analysis tool by Microsoft. In general, Microsoft's BI tools by are not as highly visual as the tools of many competitors, but their examples of visualization often display excessive use of color. In this display, the blue row and column headings draw attention and undermine the highlighting in cells. The overall visual impression is a "colorful mess". Dark and highly saturated colors should be used only to highlight data, not for decoration [Few06]. Moreover, color is used inconsistently. Yellow is used as a "traffic light" to indicate a satisfactory level in Contribution Summary and Production Assumptions, but it is also a cell background color (Production Plan, Demand and Contribution Summaries), apparently with no information value: the hue is different than the yellow of the traffic light and the Build column has different symbols indicating good and poor levels regardless of the background. Red, on the other hand, is used as a traffic light to indicate a poor level in several columns, but it is also used in the bars in Corporate Contribution Target with no apparent meaning – why would any company aim at poor performance? Also the pie chart includes green and red slices and the bar graph includes red bars; these may be associated with performance levels, although the colors clearly serve as mere category labels in these graphs. In Production Assumptions, the cells contain varying shades of green, yellow and red, which gives an impression of more than three performance levels. The numeric values reveal that this is not true; for example, there are three cells with the value 33%, but one of them has a different hue than the other two. Such inconsistencies at least create confusion and may lead to false conclusions in the worst case. The bottom of the display contains a pie chart and a bar graph with unnecessary 3D effects (see Section 5.2.2).

The display of Figure 25 could be improved simply by reducing the amount of color. The blue background of the row and column headings could replaced by a lighter shade to make the highlighted items stand out (see Section 3.2). For the same reason, the yellow background of the cells in Production Plan, Demand and Contribution Summary sections could be replaced by the same light gray shade that is the background of other cells. The green hue could be completely omitted from the display, since it indicates a good or expected level of performance and this is probably not the primary concern for the viewer [Few06]. Attention should be drawn to items that require corrective actions, not the ones that are performing well. The cell colors in the Production Assumptions section could be harmonized to include only two hues, yellow and red.

Moreover, the pie chart in Figure 25 could be replaced by a bar graph with a percentage scale as discussed in Section 5.1.2, and the 3D effect could be removed from the Contribution Margin graph. The red bars in this graph could also be changed to some other color, for example light blue. Finally, the small bars inside the cells in the Contribution Summary section are a clever innovation, but the gradient fill of these bars prevents accurate bar length comparisons. The red bars in the Corporate Contribution Target column could be changed to another hue, for example the same blue that is used in the Contribution Forecast column.

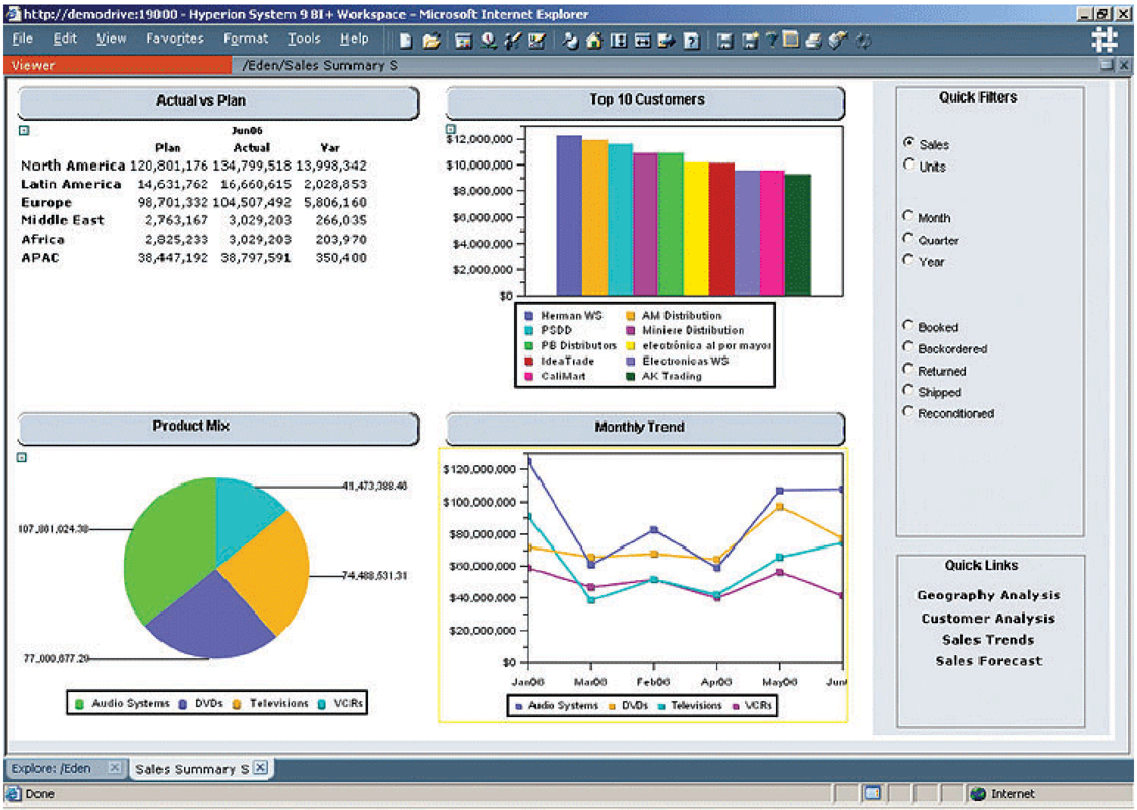

Figure 26: Example of a sales dashboard[22].

Figure 26 presents a sales dashboard by Oracle. The graphical elements in this display are not very effective; for example, displaying the Top 10 Customers list as a bar graph makes finding the sales amount of a certain customer difficult, because the viewer has to search the name and color of the customer in the legend in order to find out the sales amount. The colors used to encode customers are also problematic, since there are three different green hues and three different red hues.

[22]http://www.oracle.com/appserver/business-intelligence/essbase.html

Color-deficient users might have problems with discriminating between these hues (see Section 2.2), which may lead to incorrect conclusions about the sales amounts. This applies to the Monthly Trend graph as well: all lines have the same symbols for data points, which leaves color as the only discriminating factor between the four lines. Color-deficient users might not be able to recognize the colors correctly – or at least it will be difficult for them. Moreover, the Product Mix values are displayed as a pie chart, which is not an effective display element (see Section 5.1.2).

The dashboard in Figure 26 could be improved by changing display elements and reducing the dependency on color encoding. First of all, the Top 10 Customers graph could be replaced by a horizontal bar graph that would eliminate the need for a legend and color encoding in the bars (see Figure 18 in Section 5.1.2 for an example). A similar horizontal bar graph with a percentage scale could replace the pie chart in Product Mix. Second, the Monthly Trend line graph could use varying line types or different symbols for each data series, which would make the graph easier to comprehend for color-deficient viewers. Finally, the Actual vs Plan table has 18 data points. A bar graph would perhaps make the comparisons of target attainment easier.

Figure 27 (see next page) presents a sales dashboard by Dundas, one of the small vendors. The aggressive use of bright yellow and orange hues draws the viewer's attention away from the actual data and brings problems for color-deficient users, who might confuse the red and orange hues in the display. The color palette used is also unconventional: on the map, for example, red encodes the highest sales. Usually red is associated with poor performance, but in this case it indicates good performance. On the other hand, using color to encode revenue intervals on the map is very ineffective (see Section 3.7), since color judgments are very inaccurate when the hues are close to each other. Moreover, the two graphs on the right are filled to the brim with "chartjunk" [Tuf01] that severely weakens the readability of the data values (see Section 3.1). The gauges at the bottom consume screen space unnecessarily, which has led the designers to add a Region filter with a Refresh button next to them. This complicates comparisons of regional performance.

The first step in improving the dashboard in Figure 27 would be to reduce color. The bright orange background could be replaced by a light and neutral color, preferably other than orange, because orange is also used to encode data variables on the map.

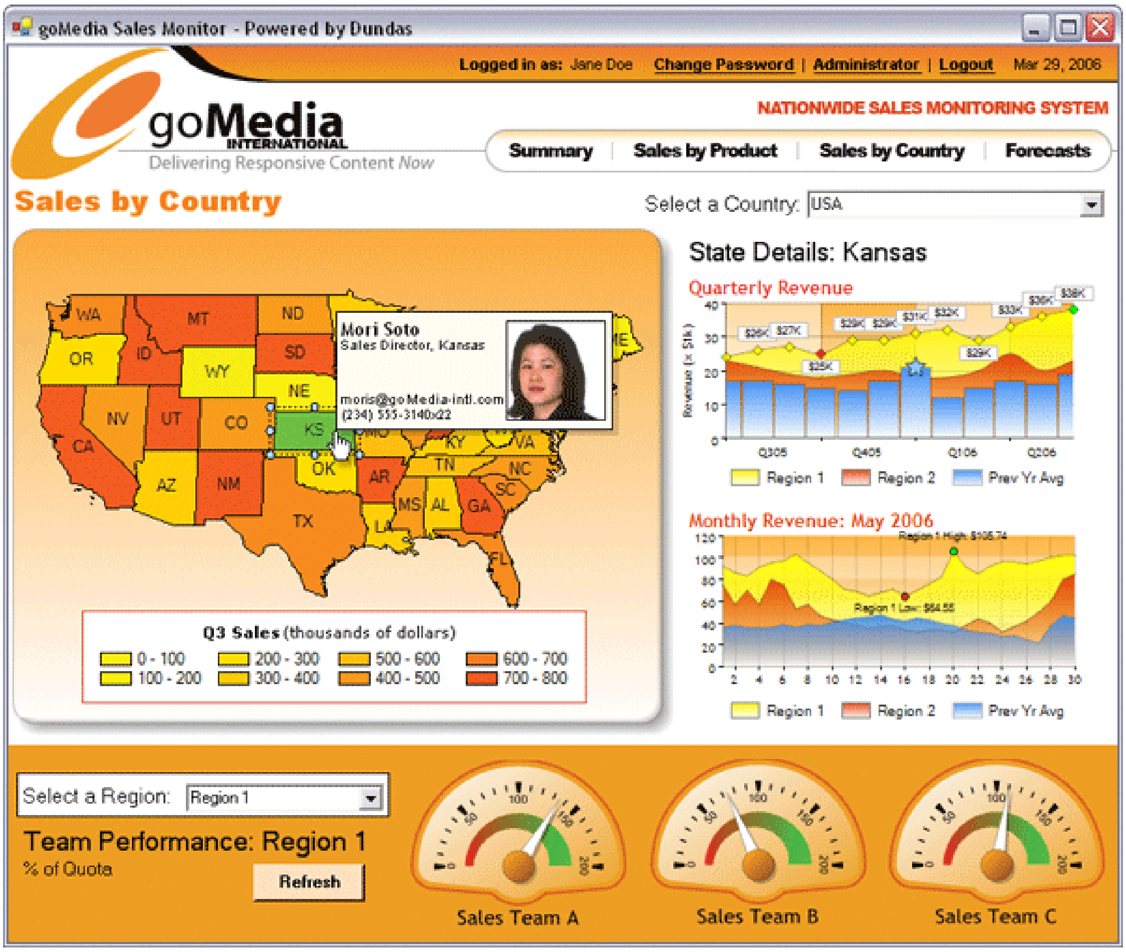

Figure 27: Example of a sales dashboard[23].

On the other hand, the interval-scaled revenues on the map could be encoded by a more effective visual attribute than color. An alternative might be to use a small vertical bar for each state [CM84] – this would even eliminate the need for intervals and allow the exact values to be encoded in the length of the bars. The two graphs on the right could be simplified by removing the "chartjunk" in order to make the data stand out. This includes at least removing the gradient fills from the bars in the upper graph, changing the orange backgrounds to a paler shade and converting the area graphs that occlude each other to simple lines. The gauges at the bottom could be replaced by bullet graphs (see Section 5.1.4). This would perhaps allow the values of all regions to be displayed at once in small multiples (see Section 3.5) and eliminate the need for the region filter and free even more space. If there are many regions, small bar graphs might be a better choice than bullet graphs.

[23] http://www.dundas.com/dashboards/bestpractices2.aspx

Figure 28: Example of a customer support dashboard[24].

In Figure 28, the customer support dashboard by MicroStrategy presents an example of effective visual design. In this display, color is used sparingly, which makes the most important data stand out and draw the viewer's attention. The Top 5 lists on the top are displayed as bar graphs to facilitate meaningful comparisons between the workloads in two months or the proportion of critical cases to all open cases. Case Summary, on the other hand, is a table, because the numbers displayed are not comparable with each other (see Section 5.2.4). The Case Trends section in the middle displays both exact values and overall trends for the last 12 months, thus providing historical context for the current values (see Sections 5.1.3 and 5.2.1). Key performance indicators (Closed Cases) are also displayed in context directly next to other relevant information. The bullet graphs provoke preattentive processing and enable the viewer to quickly estimate the achievement of targets. Finally, the concise design leaves space at the bottom for displaying additional useful information related to open support cases.

[24] http://www.microstrategy8.com/dynamicdashboards.asp

6 Conclusion

> *What is to be sought in designs for the display of information is the clear portrayal of complexity. Not the complication of the simple.* [Tuf01]

In this study, we have investigated the principles of information visualization and how these principles can be taken into account when creating visual reporting interfaces to support business decision-making. The topics discussed are extremely complex, even controversial in some parts, and cover a very wide range of academic research, including e.g. psychology, cognitive science, computer science, statistics and management accounting.

Graphical design is a highly subjective matter. Some people might welcome a novel design principle with enthusiasm while others might perhaps question its usability or aesthetic beauty. It is thus obvious that not all people share Tufte's opinions on the most effective designs of statistical graphics, and some argue that his opinions rely too much on intuition rather than theoretical results. However, many theories of psychology and cognitive science are based on a similar reasoning: they answer the question *why* but not *how*. For example, the Gestalt principles of perceptual organization have been studied for nearly a hundred years, yet there still is no widely accepted theory that would explain exactly what processes in the visual system produce these perceptions. Nevertheless, empirical experiments have confirmed that the principles seem to apply in most situations, and they are commonly used in visual design.

Information technology is altogether in high season. New technologies and tools keep on emerging at a breathtaking pace and marketing departments are creating impressive demonstrations filled with clever terminology and complex acronyms to boost the sales of their software and keep the "hype" alive. Business intelligence systems are nowadays among the best-selling solutions in software industry, and the term "visual analytics" is often encountered in BI marketing materials. One of our main goals in this study was to dive beneath the surface of the sales slogans to find out whether any academic research would explain the deeper meanings and justify the use of these concepts.

The first of our findings is that “business intelligence” means much more than merely a technological solution, contrary to the common belief reflected in the explanations of many software vendors. It is a method of gathering information inside a company and from its business environment, and then transforming that information into valuable knowledge to be utilized in strategic and operational decision-making. BI activities have been carried out long before computer systems were able to support the collection and processing of massive amounts of business data. This may explain the popularity of computerized BI systems today: the infrastructure in many companies may have now developed to a level that enables automatic data collection from various sources, including the World Wide Web, thus reducing the amount of manual work required for BI activities.

Our second finding is that the rather quick emergence of visual reporting and analysis software tools seems to be the result of the aforementioned improvement in data collection and processing capabilities, which have dramatically increased the amount of data available in recent years. Visual perception is the most powerful channel for absorbing large amounts of information with little effort, and more importantly, visual displays offer new possibilities for understanding the inherent characteristics of data that would be almost impossible to detect by any other means. Furthermore, computerized reporting interfaces are far more versatile than the traditional paper reports. The need for visual tools is therefore genuine and well justified.

The principles reviewed in this study provide a set of guidelines that may be used in creating and evaluating the design of visual reporting and analysis tools. Our brief informal review of these tools embedded in the BI products currently available reveals that often their user interfaces are quite inefficient in communicating the properties of the data. This may indicate that software vendors consider the other parts of BI systems (involving data collection, integration and processing) more important than the user interfaces. However, user interfaces are an extremely important part of the systems, since they constitute the channel through which humans interact with the data in the first place. We therefore suggest that effective information visualization in business decision support systems should be paid more attention to. After all, the primary purpose of visual information displays is to assist people in *using their vision to think* [CMS99].

References

AP08 Arnott, D. and Pervan, G., Eight key issues for the decision support systems discipline. *Decision Support Systems*, 44,3(2008), pages 657–672.

BB05 Bessire, D. and Baker, C. R., The French *Tableau de bord* and the American Balanced Scorecard: a critical analysis. *Critical Perspectives on Accounting*, 16,6(2005), pages 645–664.

BGG03 Bruce, V., Green, P. R. and Georgeson, M. A., editors, *Visual perception: physiology, psychology and ecology.* Psychology Press, fourth edition, 2003.

BLS07 Bhimani, A. and Langfield-Smith, K., Structure, formality and the importance of financial and non-financial information in strategy development and implementation. *Management Accounting Research*, 18,1(2007), pages 3–31.

BMW+00 Bourne, M., Mills, J., Wilcox, M., Neely, A. and Platts, K., Designing, implementing and updating performance measurement systems. *International Journal of Operations & Production Management*, 20,7(2000), pages 754–771.

BO06 Buchanan, L. and O'Connell, A., A brief history of decision making. *Harvard Business Review*, 84,1(January 2006), pages 32–41.

BPM02 Beygelzimer, A., Perng, C.-S. and Ma, S., Fast ordering of large categorical datasets for visualization. *Intelligent Data Analysis*, 6,4(2002), pages 379–395.

Cle93 Cleveland, W. S., *Visualizing data.* Hobart Press, 1993.

CM84 Cleveland, W. S. and McGill, R., Graphical perception: Theory, experimentation, and application to the development of graphical methods. *Journal of the American Statistical Association*, 79,387(1984), pages 531–554.

CMS99 Card, S. K., Mackinlay, J. D. and Shneiderman, B., Information visualization. In *Readings in information visualization: using vision to think*, Card, S. K., Mackinlay, J. D. and Shneiderman, B., editors, Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1999, pages 1–34.

CR97 Carswell, C. M. and Ramzy, C., Graphing small data sets: should we bother? *Behaviour & Information Technology*, 16,2(1997), pages 61–71.

EM98 Epstein, M. and Manzoni, J.-F., Implementing corporate strategy: from Tableaux de Bord to Balanced Scorecards. *European Management Journal*, 16,2(1998), pages 190–203.

Erb07 Erbacher, R. F., Exemplifying the inter-disciplinary nature of visualization research. *IV '07: Proceedings of the 11th International Conference on Information Visualization*, Washington, DC, USA, 2007, IEEE Computer Society, pages 623–630.

FA06 Frolick, M. N. and Ariyachandra, T. R., Business performance management: One truth. *Information Systems Management*, 23,1(Winter 2006), pages 41–48.

Few06 Few, S., *Information Dashboard Design: The Effective Visual Communication of Data*. O'Reilly, 2006.

Fis00 Fischer, M. H., Do irrelevant depth cues affect the comprehension of bar graphs? *Applied Cognitive Psychology*, 14,2(2000), pages 151–162.

FK03 Friendly, M. and Kwan, E., Effect ordering for data displays. *Computational Statistics & Data Analysis*, 43,4(2003), pages 509–539.

GG86 Gilad, T. and Gilad, B., Business intelligence: The quiet revolution. *Sloan Management Review*, 27,4(1986), pages 53–61.

Gol07 Goldstein, E. B., *Sensation and perception*. Thomson Wadsworth, 7th edition, 2007.

HS98 Hollands, J. G. and Spence, I., Judging proportion with graphs: The summation model. *Applied Cognitive Psychology*, 12,2(1998), pages 173–190.

HS01 Hollands, J. G. and Spence, I., The discrimination of graphical elements. *Applied Cognitive Psychology*, 15,4(2001), pages 413–431.

Hyv07 Hyvönen, J., Strategy, performance measurement techniques and information technology of the firm and their links to organizational performance. *Management Accounting Research*, 18,3(2007), pages 343–366.

KN96 Kaplan, R. S. and Norton, D. P., *Balanced scorecard: Translating strategy into action.* Harvard Business School Press, 1996.

KN02 Kald, M. and Nilsson, F., Recent advances in performance management: The Nordic case. *European Management Journal*, 20,3(2002), pages 235–245.

KN03 Kennerley, M. and Neely, A., Measuring performance in a changing business environment. *International Journal of Operations & Production Management*, 23,2(2003), pages 213–229.

Kof35 Koffka, K., *Principles of Gestalt psychology.* Harcout-Brace, New York, 1935.

Kos89 Kosslyn, S. M., Understanding charts and graphs. *Applied Cognitive Psychology*, 3,3(1989), pages 185–226.

LP06 Lönnqvist, A. and Pirttimäki, V., The measurement of business intelligence. *Information Systems Management*, 26,1(2006), pages 32–40.

Mac99 Mackinlay, J., Automating the design of graphical presentations of relational information. In *Readings in information visualization: using vision to think*, Card, S. K., Mackinlay, J. D. and Shneiderman, B., editors, Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1999, pages 66–82.

MS03 Marr, B. and Schiuma, G., Business performance management: past, present and future. *Management Decision*, 41,8(2003), pages 680–687.

Pal99 Palmer, S. E., *Vision science: Photons to phenomenology.* MIT Press, 1999.

Pir07 Pirttimäki, V., *Business Intelligence as a Managerial Tool in Large Finnish Companies.* Ph.D. thesis, Tampere University of Technology, Publication 646, 2007.

PRP06 Paranjape, B., Rossiter, M. and Pantano, V., Performance measurement systems: successes, failures and the future – a review. *Measuring Business Excellence*, 10,3(2006), pages 4–14.

RC99 Rao, R. and Card, S. K., The table lens: merging graphical and symbolic representations in an interactive focus + context visualization for tabular information. In *Readings in information visualization: using vision to think*, Card, S. K., Mackinlay, J. D. and Shneiderman, B., editors, Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1999, pages 343–349.

Rig02 Rigden, C., Now you see it, now you don't [graphical user interface design]. *Computer*, 35,7(July 2002), pages 104–105.

Rig07 Rigby, D., *Bain & Company: Management Tools and Trends 2007 study*. `http://www.bain.com/management_tools`. [05.04.2008]

Shn96 Shneiderman, B., The eyes have it: a task by data type taxonomy for information visualizations. *Proceedings of the 1996 IEEE Symposium on Visual Languages*. IEEE Computer Society, 1996, pages 336–343.

Sie96 Siegrist, M., The use or misuse of three-dimensional graphs to represent lower-dimensional data. *Behaviour & Information Technology*, 15,2(1996), pages 96–100.

Spe01 Spence, R., *Information Visualization*. Addison-Wesley, 2001.

Spi93 Spillmann, L., The perception of movement and depth in moiré patterns. *Perception*, 22,3(1993), pages 287–308.

SR96 Scaife, M. and Rogers, Y., External cognition: how do graphical representations work? *International Journal of Human–Computer Studies*, 45,2(1996), pages 185–213.

SS02 So, S. and Smith, M., Colour graphics and task complexity in multivariate decision-making. *Accounting, Auditing & Accountability Journal*, 15,4(2002), pages 565–593.

Ste46 Stevens, S. S., On the theory of scales of measurement. *Science*, 103,2684(1946), pages 677–680.

STS$^+$07 Stenfors, S., Tanner, L., Syrjänen, M., Seppälä, T. and Haapalinna, I., Executive views concerning decision support tools. *European Journal of Operational Research*, 181,2(2007), pages 929–938.

TAL05 Turban, E., Aronson, J. E. and Liang, T.-P., *Decision Support Systems and Intelligent Systems.* Pearson Education, 7th edition, 2005.

Tuf97 Tufte, E., *Visual Explanations: Images and Quantities, Evidence and Narrative.* Graphics Press, second edition, 1997.

Tuf01 Tufte, E., *The Visual Display of Quantitative Information.* Graphics Press, second edition, 2001.

Tuf06 Tufte, E., *Beautiful Evidence.* Graphics Press, 2006.

UTR07 Ukko, J., Tenhunen, J. and Rantanen, H., Performance measurement impacts on management and leadership: Perspectives of management and employees. *International Journal of Production Economics*, 110,1–2(2007), pages 39–51.

Wad78 Wade, N. J., Op art and visual perception. *Perception*, 7,1(1978), pages 21–46.

War04 Ware, C., *Information visualization: Perception for design.* Morgan Kaufmann, second edition, 2004.

War05 Ware, C. *Knowledge and Information Visualization: Searching for Synergies*, volume 3426 of *Lecture Notes In Computer Science*, chapter Visual Queries: The Foundation of Visual Thinking, pages 27–35. Springer Berlin / Heidelberg, 2005.

Wor08 World Economic Forum, *The Global Information Technology Report 2007-2008.* `http://www.weforum.org/gitr`. [09.04.2008]

Wün04 Wünsche, B., A survey, classification and analysis of perceptual concepts and their application for the effective visualisation of complex information. *APVis '04: Proceedings of the 2004 Australasian symposium on Information Visualisation*, Darlinghurst, Australia, 2004, Australian Computer Society, Inc., pages 17–24.

WW07 Watson, H. J. and Wixon, B. H., The current state of business intelligence. *Computer*, 40,9(2007), pages 96–99.

ZLTS98 Zacks, J., Levy, E., Tversky, B. and Schiano, D. J., Reading bar graphs: Effects of extraneous depth cues and graphical context. *Journal of Experimental Psychology: Applied*, 4,2(1998), pages 119–138.