标题：测量有效的数据可视化
文件：2007_Measuring_Effective_Data_Visualization_annotated.pdf

注解
这些项目符号上的数字与添加到研究论文上的数字相对应。

1. 在本文中，我们研究了可视化的两个基本问题—如何定义可视化的有效性以及如何对其进行衡量
2. 尽管“有效可视化”一词已在许多出版物中广泛使用，但该词还没有一个一致且被普遍接受的定义。关于“有效可视化”的真正含义和现有定义不完整，存在不同的观点。我们研究了现有的有效性衡量标准并讨论了它们的局限性。
3. 如果数据的预期结构和可视化的感知结构相吻合，则可视化将有效地显示输入数据。
4. 可视化应该针对特定任务而设计，有效的可视化可以提高任务效率。 Bertin [9]建议，可视化设计师在设计可视化时应铭记特定的任务。
5. 到目前为止，心理学和计算机与人之间互动的实证研究似乎支持以任务为中心的观点。
6. 可视化的结构和内容应与所需心理表示的结构和内容相对应。根据“理解原则”，可视化的结构和内容应易于准确地感知和理解。
7. 数据，任务和内部表示不是影响可视化效果的唯一因素。许多心理学家还认为，可视化的有效性取决于读者的工作记忆能力，领域知识，可视化技术经验以及他们的解释和推理能力。
8. 现有研究已经确定了影响可视化效果的一系列因素，但是这些因素尚未在一个全面，一致的框架中进行组织。
9. 通常有两种评估可视化效果的方法：启发式评估和用户研究。
10. 需要对启发式规则和原则进行分类或分类。规则和原则通常是在没有上下文的情况下提出的。
11. 改善信息可视化有效性措施的主要任务:
    1.制定有效可视化的全面定义。
    2.研究影响可视化效果的因素。确定每个因素的措施并将其组织在一个一致的框架中。
    3.开发和完善系统的启发式评估方法，以产生更多量化的有效性度量。可视化规则和原理需要分类，有条理，并经过实证验证。
    4.为信息可视化的主要应用程序域创建带注释的基准数据库，基准任务和基准度量。标准化用户研究程序，并使用基准数据库进行用户研究，以使结果在不同研究中具有可比性。
    5.将系统的启发式评估与用户研究紧密相关。使用启发式评估的结果来指导用户研究，并设计用户研究以测试启发式评估的假设。

12. 为了使可视化有效，可视元素的属性应与数据项的属性匹配，并且可视化的结构应与数据集的结构匹配。
13. 可视化设计者应确定视觉属性和数据属性之间可能的映射以及视觉结构和数据结构之间的映射。
14. 有效的可视化应有助于用户实现特定任务的目标
15. 可视化可以设计用于多个任务，但是应该明确指定任务，以便可以测量可视化的效用和效率。
16. 有效的可视化应该比非可视表示减轻特定任务的认知负担。
    效率原则定义了可视化与用户之间的关系。这意味着可视化应该易于学习并提高任务效率。效率的常用衡量标准是完成任务的时间
17. 表1总结了准确性，实用性和效率的定量和定性指标。
18. (可能具有有用信息的研究论文)

Measuring Effective Data Visualization

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Abstract. In this paper, we systematically examine two fundamental questions in information visualization – how to define effective visualization and how to measure it. Through a literature review, we point out that the existing definitions of effectiveness are incomplete and often inconsistent – a problem that has deeply affected the design and evaluation of visualization. There is also a lack of standards for measuring the effectiveness of visualization as well as a lack of standardized procedures. We have identified a set of basic research issues that must be addressed. Finally, we provide a more comprehensive definition of effective visualization and discuss a set of quantitative and qualitative measures. The work presented in this paper contributes to the foundational research of information visualization.

1 Introduction

Information visualization research can be divided into three categories – basic or foundational work, transitional approaches to create and refine techniques, and application-driven efforts [1]. In the 2006 NIH-NSF Visualization Research Challenges Report [1], Johnson, et al. pointed out that "a disproportionate amount of attention is currently devoted to incremental refinement of a narrow set of techniques." In view of this problem, a number of prominent researchers have called for more emphasis on engaging foundational problems in visualization [1-3]. For example, Jarke van Wijk [3] wrote, "If we look at the field now, many algorithms and techniques have been developed, but there are few generic concepts and theories. … methodological issues have to be studied further. This concerns questions like how to design visualizations and how to measure and evaluate the effectiveness of various solutions."

In this paper, we examine two foundational problems of visualization – how to define the effectiveness of visualization, and how to measure it? First, we survey the current literatures and find that, although the term "effective visualization" has been used extensively in many publications, there has not been a consistent and universally accepted definition for this term. There are different views on what "effective visualization" really means and the existing definitions are incomplete. We examine the existing measures of effectiveness and discuss their limitations. Through this analysis, we have identified a list of basic research issues that must be addressed in order to improve the measures of effectiveness.

G. Bebis et al. (Eds.): ISVC 2007, Part II, LNCS 4842, pp. 652–661, 2007.

To address some of the issues we have identified, we propose a more comprehensive definition of effective visualization. We point out that the effectiveness of visualization depends on the interaction between visualization, data, task, and user. We examine a set of interdependent factors that influence the effectiveness of visualization and discuss approaches to measure these factors.

2 A Review of the Current Definitions of Effective Visualization

Although the term "effective visualization" has been used extensively in visualization literatures, there are different views on what this term means. Some researchers take a more data-centric view and suggest that effectiveness largely depends on the correspondence between the visualization and the data it displays. Dastani [4] states that "a visualization presents the input data effectively if the intended structure of the
3 data and the perceptual structure of the visualization coincide." Similarly, Wattenberg and Fisher [5] point out that the structure of a visualization should match the structure of the data. Tufte [6] has also expressed a similar view.

Tufte [6] suggests that a effective visualization is the one that maximizes the data/ink ratio. As a result, Tufte essentially recommends that a visualization should be packed with as much data as possible [6, 7]. This view is very influential in the current practice of visualization design. However, Kosslyn [7] has challenged the use of data/ink ratio as a primary guidance for visualization design. In addition, there is no empirical evidence that links maximizing data/ink ratio with more accurate interpretation or better task efficiency.

Some researchers take a task-centric view and believe that the effectiveness of visualization is task specific. For example, Casner [8] strongly argues that a visualization should be designed for a specific task, and the effective visualizations
4 are the ones that improve task efficiency. Bertin [9] suggests that visualization designers should have a specific task in mind when they design the visualization. In an empirical study, Nowell, et al. [10] conclude that the evaluation of effective visualization should focus more on tasks than data. Amar and Stasko [11] have also criticized the "representational primacy" in the current visualization research, and advocated a knowledge task-based framework for visualization design and evaluation. However, the task-centric view of visualization effectiveness has been disputed by some researchers. Tufte, for example, doesn't seem to believe that the designer should be specific about the tasks that a visualization is designed for [6, 7]. Tweedie [12] dismisses the task-specific argument as irrelevant because user interactions can make a visualization suitable for different tasks.

So far the empirical studies in psychology and computer-human interaction seem
5 to support the task-centric view. Many psychological studies have shown that the effectiveness of visualizations is task specific [10, 13-16]. In particular, a number of psychological studies have shown that visualizations have little impact on task performance when task complexity is low [17-19], suggesting that the effectiveness of visualization needs to be evaluated in the context of task complexity [19].

From a psychological point of view, Scaife and Rogers [15] point out that the effectiveness of visualization depends on the interaction between the external and internal representation of information. Cleveland and McGill [20], as well as

Mckinlay [21], think that effectiveness of visualization is about how accurate a data visualization can be interpreted. Along the same line, Tversky, et al. [22] give two principles for effective visualization – the Principle of Congruence and Principle of Apprehension. According to the Principle of Congruence, the structure and content of
6 a visualization should correspond to the structure and content of the desired mental representation. According to the Principle of Apprehension, the structure and content of a visualization should be readily and accurately perceived and comprehended. Tversky's principles seem to be an attempt to unify different views on the effectiveness of visualization. This definition covers the mapping between visual structure and data structure as well as the efficiency and accuracy of visualization. However, the influence of task is not mentioned in this definition.

Data, task, and internal representation are not the only factors that influence the
7 effectiveness of visualization. Many psychologists also believe that the effectiveness of visualization depends on the reader's working memory capacity, domain knowledge, experience with visualization techniques, as well as their explanatory and reasoning skills [13, 14, 16, 23]. Particularly, studies by Petre and Green [24] show that visualization readership skill must be learned, and there is a clear difference between the way novice users and experienced users explore visualizations. However, the influence of domain knowledge, working and long-term memory, and visualization readership skill on the effectiveness of visualization is not well understood.

In summary, there has not been a universally accepted definition of effective visualization. Most of the existing definitions are incomplete and only focus on one aspect of the effectiveness. The existing research has identified a set of factors that
8 influence the effectiveness of visualization, but these factors have not been organized in a comprehensive and coherent framework.

The lack of such a theoretical framework has deeply affected the design and evaluation of visualization. First, there is no clear consensus as to what criteria should be used to guide the visualization design. In many case, it is not clear what the visualization techniques are optimized for. Is it optimized for accurate interpretation, task efficiency, data/ink ratio, or all of them? These questions are rarely addressed explicitly. Second, even when these questions are addressed by designers, they tend to focus narrowly on one or two factors. For example, Casner [8] emphasizes task efficiency, Mackinlay [21] focuses on accurate interpretation, and many other designers (consciously or unconsciously) focus on data/ink ratio. What's needed is a systematic design and evaluation approach that considers a comprehensive set of factors.

3 A Review of the Current Measures of Effectiveness

There are generally two methods to evaluate the effectiveness of visualization –
9 heuristic evaluation [25, 26] and user studies. Heuristic evaluation is a type of discount evaluation in which visualization experts evaluate the visualization designs based on certain rules and principles. For example, Bertin [9], as well as a number of other visualization designers [6, 27-30], provide many rules and examples of good visualization design. Schneiderman's "visual information-seeking mantra" and his

taxonomy for information visualization are often used as guidelines for design and heuristic evaluations [25, 31]. Amar and Stasko's knowledge task framework [11] and Tversky's two principles on visualization effectiveness [22] are the more recent additions to the rules and principles.

Most of the heuristic evaluations generate qualitative measures of effectiveness, but there are also a number of quantitative measures. Tufte [6] uses data/ink ratio as a measure for visualization effectiveness, which is challenged by Kosslyn [7]. Wattenberg and Fisher [5] use a machine vision technique to extract the perceptual structure from a visualization and use it to match the structure of the data presented. Kosslyn [23] has developed a method for analyzing visualizations to reveal design flaws. This method requires isolating four types of constituents in a visualization, and specifying their structure and interrelations at a syntactic, semantic, and pragmatic level of analysis. This method has the potential to generate some quantitative measures.

There are several limitations with the current heuristic evaluations. First, most of the rules and principles are not empirically validated – a long standing problem in the visualization field. Second, many rules and principles are abstract and vaguely defined, leading to ambiguous interpretations. There needs to be a classification or taxonomy of the heuristic rules and principles. Third, the rules and principles are often presented without a context. Under what circumstances should a rule or principle apply? This type of question is rarely investigated and discussed. Fourth, there have not been standard procedures for conducting heuristic evaluations. For example, what is the optimal data/ink ratio for a particular type of visualization? What is considered an optimal mapping between the visual structure and the perceived data structure? What are the procedures for evaluating a visualization based on the Principle of Congruence and Principle of Apprehension? Kosslyn's method [23] is perhaps the closest to a systematic heuristic evaluation methodology, but we have not found an example of its application in visualization design and evaluation.

The second evaluation approach is user study, and the most common measures of effectiveness are task completion time, error rate, and user satisfaction. A number of researchers in psychology and information visualization have measured task efficiency of visualization [8, 10, 17, 32, 33]. However, the results are mixed – visualizations do not always lead to shorter task completion time. Cleveland and McGill [20] record the subjects' judgments of the quantitative information on graphs. Cox, et al. [13, 34] measure the number of errors made in interpreting the visualizations. Saraiya, et al. [35] propose an interesting method that evaluate bioinformatics visualization by measuring the amount and types of insight they provide and the time it takes to acquire them. Beyond error rate and task completion time, Schneiderman and Plaisant [36] recently propose a method called Multi-dimensional In-depth Long-term Case studies that involve documenting usage (observations, interviews, surveys, logging etc.) and expert users' success in achieving their professional goals.

While user studies are extremely useful for evaluating visualizations, measuring task completion time and error rates also have their limitations. First, these are largely black-box approaches that do not help explain specifically what causes the performance problem or improvement.

One way to address this issue is to establish a correlation between heuristic evaluation and user studies. Specifically, what's needed is a methodology that systematically analyzes the various factors that influence the efficiency and accuracy of visualization comprehension. Through this analysis, the evaluators attempt to predict the benefits of different visual features over non-visual representations. User studies should be designed accordingly to test these hypotheses. To address this issue, we have developed a complexity analysis methodology that systematically analyzes and quantify a set of parameters to predict the cognitive load involved in visual information read-off and integration [37]. We have applied this approach to a number of computer security visualization programs and are currently expanding to other areas.

Another major problem facing user studies today is the lack of standard benchmark databases, benchmark tasks, and benchmark measures. The user study procedures have not been standardized. As a result, the user study data are not generally comparable with each other. There has been some progress in this area. For example, the Information Visualization Benchmarks Repository [38] has been established. More importantly, fully annotated benchmark databases for major application areas of information visualization, such as computer security and bioinformatics, are needed. In addition, benchmark task specifications, standardized user study procedures, as well as baseline measures need to be developed.

In summary, much foundational research needs to be done to improve the measures of effectiveness in information visualization. The major tasks include the following:

1. Develop a comprehensive definition of effective visualization.
2. Study the factors that influence the effectiveness of visualization. Identify the measures for each factor and organize them in a coherent framework.
3. Develop and refine systematic heuristic evaluation methods that generate more quantitative measures of effectiveness. (Kosslyn's method [23] is a good start. The complexity analysis method [37] that we propose is also an attempt to address this issue.) The visualization rules and principles need to be classified, organized, and empirically verified.
4. Create annotated benchmark databases, benchmark tasks, and benchmark measures for major application domains of information visualization. Standardize user study procedures and use benchmark databases for user studies so that the results are comparable across different studies.
5. Closely correlate systematic heuristic evaluation with user studies. Use the outcome of heuristic evaluations to guide user studies, and design user studies to test the hypotheses from heuristic evaluations.

In the next section, we will address the first two issues by providing a definition of effective visualization and discuss a framework for the measures of effectiveness.

4 Define and Measure the Effectiveness of Visualization

We define the effectiveness of data visualization in terms of three principles: accuracy, utility, and efficiency. Under each principle, we also discuss the steps to measure the effectiveness.

12 Principle of Accuracy: For a visualization to be effective, the attributes of visual elements shall match the attributes of data items, and the structure of the visualization shall match the structure of the data set.

The accuracy principle defines the relationship between visualization and data. Measuring the accuracy involves several steps. First, a taxonomy of visualization techniques should be developed to classify the various attributes and structures of visualization. So far there has not been a generally accepted taxonomy of visualization techniques, although many attempts have been made [9, 31, 39-43]. Further research is needed to develop a unified classification of visualization techniques. To address this issue, we have proposed a hierarchical classification of visual elements [37].

Second, a domain specific data analysis should be conducted to develop a data taxonomy that classifies data properties and data structures. There has been a number of domain independent taxonomies of data [31, 42], but domain specific data classifications are needed for better accuracy assessment.

Third, once the classifications of visualization and data are developed, the
visualization designers shall identify the possible mapping between visual attributes
13 and data attributes as well as the mapping between visual structures and data
structures. An accuracy score shall be assigned to each visualization-data mapping as
a measure of accuracy. The accuracy score shall be determined by consulting the
relevant psychological studies or visualization rules [4, 5, 9, 20, 30, 44]. The initial
values of the accuracy scores may be based on intuition, but shall be continuously
refined by domain specific empirical studies or newer psychological theories.

14 Principle of utility: An effective visualization should help users achieve the goal of specific tasks.

The utility principle defines the relationship between visualizations and tasks. A
visualization may be designed for multiple tasks, but the tasks should be explicitly
15 specified so that the utility and efficiency of the visualization can be measured.
Measuring the utility also involves multiple steps. First, a domain task analysis should
be conducted to develop a task classification. Second, an annotated benchmark
database should be established, and clearly specified benchmark tasks and measurable
goals should be developed. Third, the utility of the visualizations is evaluated by
measuring how well they help achieve the goal of the benchmark tasks, using the
benchmark data set. A utility score for each task can be calculated for the
visualization based on the number of benchmark goals achieved. A baseline utility
score can be calculated using non-visual display.

16 Principle of efficiency: An effective visualization should reduce the cognitive load for a specific task over non-visual representations.

The efficiency principle defines the relationship between visualizations and users. It means the visualization should be easy to learn and improve task efficiency. The common measure of efficiency is the time to complete a task [8, 10, 33]. Benchmark databases and benchmark tasks should be used in the user studies so that the results are comparable across different studies. Baseline task completion times should be recorded for non-visual displays and used as references. To address the limitation of task completion time, we have proposed a method to analyze the complexity of visualization, which serves as an indicator of the perceptual and cognitive load involved in exploring the visualization [37]. Therefore the outcome of complexity analysis is another measure of efficiency.

Eye movement tracking is often used to study a reader's attention. But it can also be used as a measure of efficiency – frequent eye movement is a major factor that influences task performance in visual comprehension. In addition, both task completion time and eye movements can be recorded over a period of time to measure the learning curve of a visualization design.

Finally, users' subjective opinions on the accuracy, utility, and efficiency of the visualization should be collected through interviews and observations. It is also important to point out that the accuracy, utility, and efficiency of visualization are greatly influenced by users' domain knowledge, experience with visualization, and visual-spatial capability. It remains a major challenge to measure the impact of these factors. A possible approach is to observe or record the use of visualization by experts and novices and conduct expert-novice comparisons – a method that has been used successfully in the field of psychology.

17 Table 1 summarizes both the quantitative and qualitative measures for accuracy, utility, and efficiency.

Table 1. Quantitative and qualitative measures of effectiveness

	Quantitative measurements	*Qualitative measurements*
Accuracy	• Measure the number of interpretation errors	• Interview • Observation • Expert-novice comparison
Utility	• Measure the number of achieved benchmark goals • Record the number of times a visualization design is selected by users to conduct a task	• Interview • Observation • Expert-novice comparison
Efficiency	• Record task completion time • Record eye movements • Measure the learning curve	• Visualization complexity analysis • Interview • Observation • Expert-novice comparison

5 Summary

The research presented in this paper is an attempt to systematically analyze two foundational problems in information visualization – how to define effective visualization and how to measure it? A review of the literatures shows that the current definition of effective visualization is incomplete and often inconsistent. We have pointed out a number of basic research issues that need to be addressed. Finally, we provide a comprehensive definition of effective visualization and present a set of quantitative and qualitative measures of effectiveness.

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