Quantitative assessment of cognitive interpretability of visualization

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Abstract

The article shows results of the research of cognitive interpretability of visualization and approaches to obtaining empirical estimates of the practical effectiveness of visualization tools. Estimated results are used in the development of technology of cognitive interpretation of heterogeneous data and necessary means of visual analytics.

Keywords: visual analytics, visual model, data analysis, visual interpretation, visual perception.

1. Introduction

A specific effect of using visualization, according to [10], is the influence on the mind of an observer through the formation of a new informational reality. The explanation of this result is based on the study of the illusion influence of visualization objectivity on the result of its interpretation. For systems of scientific visualization, the usage and consideration of all the features of cognitive interpretability of visualization are primary tasks [2, 7], which solution is complicated by the lack of information in systematic approaches to visual analytics.

Researchers [3] gave a rating of unsolved problems of visualization. Nowadays, this list can be refined, taking into account current tasks, which solution can involve visualization, including scientific and cognitive ones:

1. Quantitative measurement. The problem of comparing and choosing visualization tools due to an absence of a generalized visualization

scheme and the corresponding system of evaluation criteria.

- 2. Usability. The problem of achieving by means of user characteristics visualization, providing a possibility of obtaining a reliable solution for research problem while using only visual interpretation.
- 3. Perception. The task of increasing the information content and interpretability of visual analytics tools as a result of directional usage of visual perception potential.
- 4. Pre-awareness. The problem of users over-informing, which reduces cognitive effectiveness of visualization and increases resources intensity of visualization tools.
- 5. Training. The increase of complexity of tasks of visual research and visual analytics tools creates the need of preliminary user's training.
- 6. Scalability. The task of finding ways to visualize information that preserves high cognitive interpretabil-

ity with any changes in detail or volume of studied data.

- 7. Interpreted aesthetics. An exclusion or usage of the subjective criteria of visual aesthetics to achieve the goal of the study.
- 8. Dynamics. The task of using perception of changing images to enhance cognitive interpretability of visualization.
- 9. Intra-system logic. Formalization of visualization usage as a sign language system for obtaining new knowledge using only intersystem operations.
- 10. Presentation of knowledge. The solution of a complex task of efficient storage, transmission, acquisition and use of information as a result of creating its visual presentation.

Cognitive interpretation of visual images imposes requirements to developers of visualization tools, which fulfillment might be difficult, because of the need of the directed use of perception features and thinking, many of which are not studied well [1, 4]. In this article results obtained from the study of features of visual perception and cognitive interpretation of abstract images are presented.

2. The balanced model of visualization assessment

In this article [8], there was used a meaning of a visualization structural unit, which allows to systematize tools designed to solve problems of various types and levels of complexity. Combination of structural units in current system of visual analytics, leads to the construction of a visual model, which cognitive value exceeds the effectiveness of the study of individual images. Emergence of a visual model is provided by links of its structural elements.

Based on differences in ways of the final implementation and practical use of structural elements of a visual model, the links between them are divided into two functional groups: informative and control links (Fig. 1). Informative links are processes of transferring the necessary data between structural units, which create the basis for building an image of data interpreted while solving a task. Control communications are data management processes. Management includes making a decision about the form of the visual image necessary to answer the question, as well as the correspondence between the question and the formulated hypothesis.

Based on results of solving a number of practical tasks, a balanced model of overall effectiveness of W_F visualization was introduced, which combines positive and negative factors characterizing visualization processes, including cognitive interpretability. Thus, the overall effectiveness is:

 $W_F = W^+(K_{Trg}(T_A)) + W^+(K_{Add}(T_A)) - W^C$ (T_A) - W^M(T_A),



Fig. 1. Informative and control links in the process of visualization.

where $W+(K_{TRG}(T_A))$ is the value of solving the problem of analysis, $W+(K_{ADD}(T_A))$ is the value of additional knowledge gained from formulating and testing solution hypotheses, $W_C(T_A)$ is the value of resources spent to create a visual model, $W_M(T_A)$ - is the value of resources used to control properties of the model in the process of obtaining a solution.

3. Software

To obtain empirical data, which confirm the developed visualization scheme, as well as to determine factors affecting its effectiveness, the corresponding «Visual Representation Analyzer» software has been proposed and developed (Fig. 2). The algorithm of this software is based on the assertion about the direct relationship between effectiveness of the process of visual research and time taken by a user to achieve the goal of analysis. Thus, the main task for developers of data visualization is to reduce time of a visual research. Usage of the software "Visual Representation Analyzer allows to obtain data of dependence of research time at each stage of solving the problem of analysis from any factors that have a significant impact on it.

4. Research methodology

Obtaining and the correct interpretation of empirical data creates the conditions for construction of visualization tools, which have a reasonable and guided cognitive effect [5]. To achieve this goal, a technique of studying possibilities of visual representation has been developed, it was tested on several versions of means of visual analysis of multidimensional heterogeneous data. The technique consists in implementing a series of solutions of test problems, accompanied by a number of controlled restrictions, and measuring time intervals of interaction between the researcher and the visual model. User's interaction with the model, in this case, implies any operations available to the user, with the exception of changing the function of the visual representation. Permissible operations are the adaptation of data visual representation to peculiarities of user's perception, data filtering, transition to the next task, reading attribute values of visualized data and some others.

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Fig. 2. Interface of "Visual representation Analyzer" software.

The test solution involves creating an image of studied data using a predefined method of visual representation (Fig. 3). The choice of the initial method of visualization corresponds to the type of the research task (the task of training, informing, making a decision) and does not depend on preferences of the researcher. Thus, at the initial moment, a user has a visual data model and knows the purpose (question) of the problem being solved by him [9].

While making the test solution, the researcher, who analyzes the image of data, is allowed to formulate an unlimited number of hypotheses to answer the problem's question; each hypothesis is considered as a step of analysis. The formulation of the correct hypothesis means the completion of the test solution. The cyclical nature of the solution procedure allows to automatically record the duration of each stage for subsequent analysis of the effectiveness of visualization.

The obtained results allowed to make a number of conclusions about the nature of the interaction between the user and the visual model in the process of solving the problem of analysis. First of all, the proposed method of studying cognitive interpretability of visualization made it possible to estimate the total time period and influence of a number of factors on the duration of the decision. For example, in case of a series of measurements with participation of a single user, it made it possible to assess individual characteristics of cognitive processes. A typical example of results of such measurements (Fig. 3) shows a significant change in speed of a researcher's thinking during solving research problems of any given type.

5. Results

According to results of measurements, in the process of the user and the visual model interaction, intervals are allocated, where time spent by the user on building the next hypothesis is continuously reducing. In many cases, intervals with similar signs are located at the beginning of the analysis process, however, they may occur in further steps of the solution. In accordance with the definition of a visualization structural unit and the definition of the analytical visual model, similar intervals occurred in initial steps (Fig. 4) could be defined as learning steps that correspond to a user's familiarization with the used visual representation function. Selecting this stage of familiarization allows entering a qualitative assessment of the visual representation function, which determines the consistency of perception of the particular user and properties of the selected data visualization method.



Fig. 3. Change of speed of visualization interpretation.

Based on these measurements, the effect of individual properties of the researcher on the duration of the learning interval, which is concluded with the transition to the rapid construction of new hypotheses, is shown. Individual characteristics of perception, according to results of measurements, include both possibilities of visual perception and user's prior knowledge that has an influence on results of cognitive interpretation of visualization. Targeted use of prior knowledge of a user and properties of his perception are ways to increase effectiveness of visual analysis.

A change of construction time of new hypotheses, observed throughout the analysis process, is periodic. During solving the problem of analysis, the user did not receive information from external sources, so a change in time spent at each step of the analysis can be explained by a change in ratio between direct and inverse processes [6]. A slight decrease of speed of making the decision leads to an increase in time spent on constructing and testing the next hypothesis, and can be interpreted as a doubt in correctness of actions, caused by errors made in previous steps. A significant reduction in speed of analysis that arises differently depending on a user can be interpreted as a user's need for an additional pause before building a new hypothesis. In most dimensions, a fast increase of construction time of a new hypothesis arises after series of quick erroneous assumptions. That means a user does not understand an information presented as a visual image.



Fig. 4. Periods of training and reflection.

Basing on observations of solving problems of analysis by various users, there is an assumption, which explains the arising slowdown by the need of rethinking mistakes. The completion of the reflection phase corresponds to an increase in the awareness of a researcher, and its duration also depends on individual characteristics of a researcher.

6. Interpretability assessment

Constructing the scheme of the process of visual research using the concept of a visualization structural unit made it possible to develop a number of concepts and processes for answering general visualization questions mentioned above. Some of these new results are: the algorithm for building visualization tools, which meet requirements of a specific problem to be solved, the methodology for conducting a visual study aimed to increase its effectiveness, as well as a general classification of visualization tasks. The proposed method, which use the software "Visual Representation Analyzer", allows obtaining numerical estimates of changes in the visualization performance, which arise from the involvement of these results in solving practical problems of data research.

Creation of a classification of visualization tasks gave several positive results in terms of cognitive interpretability of visualization. Firstly, there is a simplification and formalization of part of the processes necessary for creating new visualization tools. Secondly, the presence of classification of visualization tasks makes it possible to accumulate and systematize an experience of a user. Increasing a user's prior awareness provides conditions for successful cognitive interpretation of visualization while solving new problems. The developed classification [8] allows to increase effectiveness of creation or selection of visual analytics tools, which are necessary for processing heterogeneous data, because of justification of requirements for visualization tools (about 25% time reduction for choosing visual analytics tools). To assess effectiveness there was used data (Table 1) obtained during receiving test measurements. It is assumed that the use of classification allows to determine a type of visualization task and to accurately exe-

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		Table 1.
		Test results.
Building	Classification	Average
a model,	efficiency, %	classification,
sec		%
150,34		
190,12	26,46	26,46
201,23	33,85	30,15
202,16	34,47	31,59
200,43	33,32	32,02
191,45	27,34	31,09
192,51	28,05	30,58
178,10	18,46	28,85
193,16	28,48	28,80
164,07	9,13	26,62
199,21	32,51	25,21
169,52	12,76	24,17
180,28	19,91	23,84
178,99	19,06	23,50
183,43	22,01	23,40
161,30	7,29	22,40
191,01	27,05	22,67
199,43	32,65	23,22
156,32	3,98	22,21
185,53	23,41	21,43
193,25	28,54	21,71
192,21	27,85	21,95

cute an algorithm for constructing a visual research tool using data from a preliminary study. The increase in effectiveness in case of increasing volume of source data, manifested in the reduction of analysis time, is the basis for using visual analytics tools as tools for processing empirical data for weakly formalized tasks.

While determining factors, which have a significant impact on cognitive interpretation of visualization, effectiveness of an integrated approach to visualization took a special attention [11]. It is assumed that the use of an integrated approach reduces time of usage of a visualization structural unit as a result of changes in a user's subjective awareness. To obtain a numerical evaluation of the effectiveness of the integrated approach, a comparison of the total learning interval durations and reflection for the sequence of solutions of the same type problems were proposed. The obtained experimental data allowed to conclude that the proposed integrated approach to visualization and interpretation of heterogeneous data allows to increase effectiveness (more than 40% time reduction of a hypothesis formation) of visual analytics tools as a result of sharing computational and cognitive resources.

7. Conclusion

There were proposed and developed tools for obtaining experimental evaluations of effectiveness of visual analysis tools. The obtained values allowed to determine the degree of influence of factors included in the general definition of effectiveness of visual analysis on its value.

Comparative values of effectiveness of stages of creating visual analysis tools using the proposed algorithm for constructing visual data models for various formulations of analysis tasks were obtained. The possibility of increasing effectiveness of visual analysis as a result of use of visual analytics tools, which ensure the interaction of specialists from various fields of specialization and prior awareness, is shown.

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