

Cody Dunne Northeastern University

VALIDATION & EVALUATION



READING QUIZ

<u>Q4—Validation & Evaluation</u>



Friday: Marvin Zelen Symposium

~5 min



THE NESTED MODEL FOR VISUALIZATION VALIDATION







"Nested Model"

Domain situation L

Data/task abstraction

Algorithm WW

Analyze results qualitatively

Measure adoption

- Observe target users using existing tools

 - Visual encoding/interaction idiom Justify design with respect to alternatives
 - Measure system time/memory Analyze computational complexity
- Measure human time with lab experiment (*lab study*)
- Observe target users after deployment (*field study*)





✓ *Final Project validation* Threats to Validity





EMPIRICAL STUDIES IN INFORMATION VISUALIZATION: SEVEN SCENARIOS



Empirical Studies in Information Visualization: Seven Scenarios

Heidi Lam, Enrico Bertini, Petra Isenberg, Catherine Plaisant, and Sheelagh Carpendale

Abstract—We take a new, scenario-based look at evaluation in information visualization. Our seven scenarios, evaluating visual data analysis and reasoning, evaluating user performance, evaluating user experience, evaluating environments and work practices, evaluating communication through visualization, evaluating visualization algorithms, and evaluating collaborative data analysis were derived through an extensive literature review of over 800 visualization publications. These scenarios distinguish different study goals and types of research questions and are illustrated through example studies. Through this broad survey and the distillation of these scenarios, we make two contributions. One, we encapsulate the current practices in the information visualization research community and, two, we provide a different approach to reaching decisions about what might be the most effective evaluation of a given information visualization. Scenarios can be used to choose appropriate research questions and goals and the provided examples can be consulted for guidance on how to design one's own study.

Index Terms—Information visualization, evaluation.

1 INTRODUCTION

T VALUATION in information visualization is complex discussion of evaluation scenarios, categorized into those L since, for a thorough understanding of a tool, it not for understanding data analysis processes and those which only involves assessing the visualizations themselves, but evaluate visualizations themselves. also the complex processes that a tool is meant to The scenarios for understanding data analysis are support. Examples of such processes are exploratory data analysis and reasoning, communication through visualiza- Understanding environments and work practices tion, or collaborative data analysis. Researchers and (UWP), practitioners in the field have long identified many of • evaluating visual data analysis and reasoning the challenges faced when planning, conducting, and (VDAR), executing an evaluation of a visualization tool or system evaluating communication through visualization [10], [41], [54], [63]. It can be daunting for evaluators to (CTV), and identify the right evaluation questions to ask, to choose evaluating collaborative data analysis (CDA). the right variables to evaluate, to pick the right tasks, The scenarios for understanding visualizations are users, or data sets to test, and to pick appropriate evaluation methods. Literature guidelines exists that can • Evaluating user performance (UP), help with these problems but they are almost exclusively • evaluating user experience (UE), and focused on methods-"structured as an enumeration of evaluating visualization algorithms (VA). methods with focus on how to carry them out, without Our goal is to provide an overview of different types of evaluation scenarios and to help practitioners in setting the

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published online 30 Nov. 2011.

prescriptive advice for when to choose between them." ([54, p.1], author's own emphasis). right evaluation goals, picking the right questions to ask, This paper takes a different approach: instead of and to consider a variety of methodological alternatives to focusing on evaluation methods, we provide an in-depth evaluation for the chosen goals and questions. Our scenarios were derived from a systematic analysis of 850 • H. Lam is with Google, Inc, Mountain View, CA. papers (361 with evaluation) from the information visuali-E-mail: heidi.lam@gmail.com. zation research literature (Section 5). For each evaluation • E. Bertini is with the Department of Computer and Information Science, scenario, we list the most common evaluation goals and outputs, evaluation questions, and common approaches in • P. Isenberg is with INRIA, Université Paris-Sud, Team Aviz, Bat 650, Section 6. We illustrate each scenario with representative Saclay, Orsay Cedex 91405, France. E-mail: petra.isenberg@inria.fr. published evaluation examples from the information • C. Plaisant is with the University of Maryland, 2117C Hornbake South Wing, College Park, MD 20742. E-mail: plaisant@cs.umd.edu. visualization community. In cases where there are gaps in • S. Carpendale is with the Department of Computer Science, University of our community's evaluation approaches, we suggest ex-Calgary, 2500 University Dr. NW, Calgary, AB T2N 1N4, Canada. amples from other fields. We strive to provide a wide coverage of the methodology space in our scenarios to offer Manuscript received 8 Sept. 2010; revised 6 Nov. 2011; accepted 9 Nov. 2011; a diverse set of evaluation options. Yet, the "Methods and Recommended for acceptance by C. North. Examples" lists in this paper are not meant to be For information on obtaining reprints of this article, please send e-mail to: comprehensive as our focus is on choosing among evaluatvcg@computer.org, and reference IEEECS Log Number TVCG-2010-09-0224. tion scenarios. Instead, we direct the interested reader Digital Object Identifier no. 10.1109/TVCG.2011.279.







Empirical Studies in Information Visualization: Seven Scenarios



Visualization

- ----UE User Experience
- ----UP User Performance
- ----VA Vis. Algorithms

Process

- Collab. Data Analysis —CDA
- Env. & Work Practices UWP
- CTV Communication

Lam et al., 2012 9







7 Evaluation Scenarios

How to understand your data:

- Understanding Environments and Work Practices
- Evaluating Visual Data Analysis and Reasoning
- Evaluating Communication Through Visualization
- Evaluating Collaborative Data Analysis
- How to understand your visualization:
 - Evaluating User Performance
 - Evaluating User Experience
 - Evaluating Visualization Algorithms

Vork Practices Reasoning Visualization









Understanding environments and work practices

- Goals & outputs

 - Understand work, analysis, or information processing practices of people • Without software in use: inform design
 - With software in use: assess factors for adoption, how appropriated for future design
- Evaluation Questions
 - Context of use?
 - Integrate into which daily activities?
 - Supported analyses?
 - Characteristics of user group and environment?
 - What data & tasks?
 - What visualizations/tools used?
 - How current tools solve tasks?
 - Challenges and usage barrier?

Domain situation



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Understanding environments and work practices

- Methods
 - Field Observation
 - Real world, free use of tool
 - Derive requirements
 - Interviews
 - Contextual inquiry: interview then observe in routines, with little interference
 - Pick the right person
 - Laboratory context w/domain expert
 - Laboratory Observation
 - How people interact with each other, tools
 - More control of situation

Domain situation







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Understanding environments and work practices: Example



Pandey, Dunne, et al., 2019 13





Evaluating visual data analysis and reasoning

- Goals & outputs
 - Assess visualization tool's ability to support visual analysis and reasoning
 - As a whole! Not just a technique
 - Quantifiable metrics or subjective feedback
- Evaluation Questions: Does it support...
 - Data exploration?
 - Knowledge discovery?
 - Hypothesis generation?
 - Decision making?

Data/task abstraction



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Evaluating visual data analysis and reasoning

- Methods
 - Case studies
 - Motivated experts with own data in own environment
 - Can be longitudinal
 - Insight-Based (Saraiya et al., 2004)
 - Unguided, diary, debriefing meetings
 - MILCS: Multidimensional In-depth Long-term Case studies (Shneiderman & Plaisant, 2006)
 - Guided, observations, interviews, surveys, automated logging
 - Assess interface efficacy, user performance, interface utility
 - Improve system during
 - Lab observations and interviews
 - Code results
 - Think aloud
 - Controlled Experiment
 - Isolate important factors

Data/task abstraction









Evaluating visual data analysis and reasoning



Perer et al., 2006 16





Evaluating communication through visualization

- Goals & outputs
 - How effectively is a message delivered and acquired
- Evaluation Questions
 - Quantitative: learning rate, information retention and accuracy
 - Qualitative: interaction patterns
- Methods
 - Controlled experiments
 - Field observation & interviews



Visual encoding/interaction idiom





Evaluating communication through visualization: Example



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<u>Sedig et al., 2003</u> 18





Evaluating Collaborative Data Analysis

- Goals & outputs
 - Evaluate support for taskwork and teamwork
 - Holistic understanding of group work processes or tool use
 - Derive design implications
- Evaluation Questions
 - Effective and efficient?
 - Satisfactorily support or stimulate group sensemaking?
 - Support group insight?
 - Is social exchange and communication facilitated?
 - How is the tool used? Features, patterns...
 - What is the process? User requirements?

Data/task abstraction



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Evaluating Collaborative Data Analysis

- Methods
 - Context critical, but early formative studies less dependant
 - Heuristic evaluation
 - Heuristics: actions, mechanics, interactions, locales needed
 - Log analysis
 - Distributed or web-based tools
 - Combine with questionnaire or interview
 - Hard to evaluate unlogged & qualitative aspects
 - Field or laboratory observation
 - Involve group interactions and harmony/disharmony
 - Combine with insight-based?

Data/task abstraction



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Evaluating Collaborative Data Analysis: Examples

Planarity Party

Can you untangle the graph? See if you can position the vertices so that no two lines cross.

Level 1. Number of line crossings detected: 2.

0 moves. Next Level



<u>Schwab, ... Dunne, ... et al., 2020</u>



<u>Zhang, ... Dunne, ... et al., 2018</u> 21







Evaluating Collaborative Data Analysis









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Evaluating User Performance

- Goals & outputs
 - Measure specific features

 - Descriptive statistics results
- Evaluation Questions
 - What are the limits of human perception and cognition?
 - How do techniques compare?
- Methods
 - Controlled experiment \rightarrow design guideline, model, head-to-head
 - Few variables
 - Simple tasks
 - Individual differences matter
 - Field logs
 - Suggest improvements, recommendation systems



• Time, accuracy, and error; work quality (if quantifiable); memorability



Evaluating User Performance: Examples

Question 6 / 12

Time remaining: 48:39 minutes



• Find playlists that have at least 3 different tracks that are in the same album and they are all made by the same composer.

Find playlists that have at least 3 different tracks so that at least 2 of them are in the same album but all 3 tracks are made by the same composer.

) Find playlists that have at least 3 different tracks so that at least 2 of them are in the same album and made by the same composer.

) Find playlists that have at least 3 different tracks that are in the same album and at least 2 of them are made by the same composer.

Submit



Tutorial (PDF)

Leventidis, Dunne, et al., 2020



Di Bartolomeo, Dunne, et al., 2020 25



In-Class Study—Graphical

Perception



You are done with section 5 of 5! Thank you for completing the study! We will email you soon with your rewards card.

More Accurate



~16 min

All Done!







Done

Panavas et al., 2022 26





Paper results



The absolute error |Actual – Guessed| value for each task. Error bars represent 95% bias-corrected and accelerated (BCa) bootstrapped confidence intervals.

Fig. 5. Summative results for Hypothesis 1 and 2 and an exploratory analysis of individual differences in rankings. In (A, B), and (G, B)the error bars show 95% bias-corrected and accelerated (BCa) bootstrapped confidence intervals [23]. (A rough rule of thumb for reading 95% CIs is that if two intervals overlap by less than 1/4 of their average length, then the comparison will have p < .05 [22].) The mean absolute error for each encoding is shown in O for children and B for adults. In O, the previous two charts are rearranged to compare children with adults. Children are clearly less accurate when using each of the encodings. The exploratory analysis included, , shows the variation in encoding rankings among individual children (left) and adults (right). Each line represents an encoding, ranked left-to-right in increasing mean absolute error for each task. The grey rows are sized to represent the count of individuals with a shared ranking. E.g., the top row shows that 5 children ranked 🕒 Position Along a Common Axis as most accurate, followed by 📭 Length, E Position Along an Unaligned Axis, <>> Angle, and lastly •• Area. The line-row intersections show the encoding ranking for that row. Children displayed a larger variety of individual differences in encoding rankings than adults. Finally, 🕒 shows more simply the *overall* rankings we found for adults and children.



Panavas et al., 2022 27







For Next Time

neu-ds-4200-s22.github.io/schedule

Look at the upcoming assignments and deadlines

- Textbook, Readings, & Reading Quizzes—Variable days
- In-Class Activities—If due, they are due 11:59pm the same day as class

Everyday Required Supplies:

- 5+ colors of pen/pencil
- White paper
- Laptop and charger

Use Canvas Discussions for general questions, email <u>codydunne-and-tas@ccs.neu.edu</u> for questions specific to you.

Week	Topics	Assignments
1: Jan 17–21	What is visualization Design rules of thumb	A1—Setting up
2: Jan 24–28	JS development, projects Marks & channels	A2—Encodings & xenographics
3: Jan 31–Feb 04	Data types and tasks, Tableau D3 tutorial 1/2	P1—Pitches★
4: Feb 07–11	In-class group formation D3 tutorial 2/2	A3—Tableau analysis P2—Proposal★
5: Feb 14–18	Altair and JupyterLab Practice Design Study	A4—D3 basic charts
5: Feb 21–25	Arrange Tables Color, pop-out, illusions	A5—Altair basic charts P3—Interview & tasks
7: Feb 28–Mar 04	Interaction & animation In-class project meetings 1/2	A6—D3 event handling P4—Data and sketches
8: Mar 07–11	In-class project meetings 2/2 Trees & networks	P5—Final sketches & plan★
ar 14–18	Spring Break	
): Mar 21–25	Spatial, 3D, and scientific vis. Office hours	A7—D3 brushing ≭ P6—Implementation 1 ≭
10: Mar 28–Apr 01	Validation & evaluation Marvin Zelen Symposium	
1: Apr 04–08	How to give a talk, storytelling Project usability testing	A8—Brushing & linking ≭
2: Apr 11–15	Project presentations 1/2 Project presentations 2/2	P7—Presentations★ ≭
3: Apr 18–22	Flex day	P8—Presentation peer review
14: Apr 25–29	Reflecting & project work	
av 02–06		P9—Video & Final Deliverables★▼