A Comparative Evaluation on Online Learning Approaches using Parallel Coordinate Visualization

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ABSTRACT
As visualizations are increasingly used as a storytelling medium for the general public, it becomes important to help people learn how to understand visualizations. Prior studies indicate that interactive multimedia learning environments can increase the effectiveness of learning [11]. To investigate the efficacy of the multimedia learning environments for data visualization education, we compared four online learning approaches–1) baseline (i.e., no tutorial), 2) static tutorial, 3) video tutorial, and 4) interactive tutorial–through a crowd-sourced user study. We measured participants' learning outcomes in using parallel coordinates with 18 tasks. Results show that participants with the interactive condition achieved higher scores than those with the static and baseline conditions, and reported that they had a more engaging experience than those with the static condition.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords
Interactive tutorial; learning by doing; visualization literacy

INTRODUCTION
We frequently encounter the use of visualizations as a storytelling medium in news media, blog posts, and social media. In addition, people increasingly use visualizations not only for their professions but also for personal matters [5]. In response to this trend, the visualization research community has started to pay attention to non-expert users' cognitive behaviors to understand visualizations [9] and the visualization education for them [16]. For example, the community had workshops on "visualization literacy" [21, 22] and "personal visualization" [20] in recent visualization conferences. These workshops highlighted the need to find effective means for improving the visualization literacy within the larger population that produces and consumes visual data.

CHI'16, May 7–May 12, 2016, San Jose, CA, USA.

ACM 978-1-4503-3362-7/16/05$15.00
DOI: http://dx.doi.org/10.1145/2858036.2858101

Prior education research indicates that multimedia learning environments with the learning-by-doing approaches can increase the effectiveness of learning [11]. For example, a promising approach is multimedia learning in which people learn through verbal and pictorial information. Due to the limited capacity of cognitive processing, learners can only process a limited amount of information over a short period. Researchers stress the importance of learner's "active learning," which refers to learner's cognitive process to construct knowledge by reorganizing inputs from stimuli (e.g., text, image, video) instead of passively viewing materials [17].

Research results are not consistent on which multimedia methods are most effective in encouraging the active processing. While static illustrations can help learners control their learning pace, animated ones can reduce their cognitive efforts in creating mental representation [10]. The "learning-by-doing" approach (a.k.a. experiential learning) allows learners to actively engage in hands-on experience using learning materials [14]. Web-based environments for e-learning allow us to implement interactive activities that follow such approaches, and the effectiveness of multimedia forms may also depend on the education topic. Education of visualization covers from abstract concepts (e.g., how visual elements are mapped from data [18]) to problem-solving skills (e.g., how to read and manipulate visualizations for given tasks [3]). It is yet unclear which media formats yield the best learning outcome for education of data visualization.

To investigate the potential of multimedia learning for teaching novices unfamiliar data visualization, we chose Parallel Coordinates (PC) as a target visualization. PC is an effective way to visualize multidimensional data being used in a wide range of domains including finance and biology. In PC, multiple axes are drawn parallel to one another with data items represented as lines crossing axes (see Figure 1). Due to its unusual representation, it is difficult for novices to learn the meaning of patterns without explicit instruction [12], making it a good candidate to test the effectiveness of the learning-by-doing approach.

The main contribution of this work is to adapt and test the active learning theory (i.e., learning-by-doing) for educating PC. In doing so, we synthesized core concepts and tasks of PC, and translated them into learning-by-doing activities. In addition, through an empirical study using a crowdsourcing platform, we showed that the participants with interactive conditions scored higher in the assessment and felt more confident and engaged than those with the static tutorial.

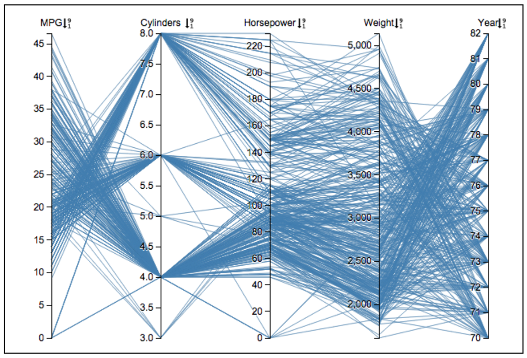


Figure 1. An example parallel coordinates for data items with five attributes (dimensions) used in the study.

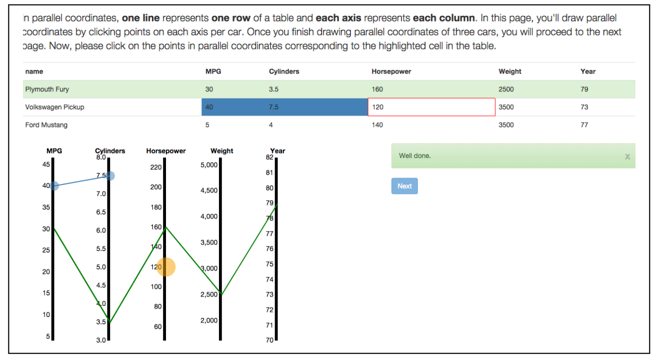


Figure 2. The Build tutorial page: as people click on points in parallel coordinates, lines are drawn connecting them.

DESIGNING INTERACTIVE TUTORIAL

In this section, we describe the design of interactive tutorial. We created three other variations based on the same content, which will be briefly explained in the Evaluation section.

Experiential Learning Model

Experiential learning model defines learning as the process in which knowledge is constructed via concrete experience and reflection on the experience [6]. This principle has been successfully used to design tutorials for education of mathematics (linear equation) [15], design [4], and music [23]. We chose to adopt this model because education of visualization requires conceptual learning as well as practice for problem-solving skills. To achieve learner's concrete experience, we follow the four-stage experiential learning model [7] to build a sequence of interactive tutorial pages each of which is designed to cover one activity type. *Concrete Experience*–in each page, people are asked to complete a mission related to the activity type. *Reflective Observation*–the system interprets learner's mistakes and provides hints at failed attempts. *Abstract Conceptualization*–the system shows the conceptual goal of the activity at a successful completion. *Active Experimentation*–after each activity, the instruction suggests to try repeating the activity to strengthen their learning. As the complexity of tasks increases, the system allows people to proceed to the next page only after they finish the current one.

Developing Tasks

The goal of the tutorial is to help people learn parallel coordinates by leveraging a "learning-by-doing" approach. We compiled a set of tasks for parallel coordinates by reviewing the visualization literature [1, 2, 13, 19]. Adapting the examples for our tutorial purpose, we created and organized 18 visualization tasks into four task categories–"Mapping" between data points and visual elements, "Distribution, Comparison, and Similarities," "Correlation and Cluster," and "Filtering and Multicriteria Evaluation" (see Table 1). We used a simple dataset about cars, having three items and five attributes. In each page, we provided both the table of data items and corresponding parallel coordinates (Figures 2).

Designing Activities

We designed the following two activities to provide concrete experience of parallel coordinates for the four task types.

Mapping Activities

The goal of **Mapping** Activities is to train people in understanding how data items are mapped to visual elements in parallel coordinates. We thus created the following four pages, asking people to read data out of visualizations as well as create visual objects based on data. 1) *Build*: We ask people to draw lines based on a data table by clicking on corresponding points in each axis; as they click on points, lines are drawn connecting them (Figure 2). 2) *Table to Vis*: We ask people to update data values in a table and then watch how the corresponding line changes; they need to change a value at least once for each axis. 3) *Fill in Table*: We ask people to enter correct data values in a table based on given parallel coordinates; they need to fill the five blanks in the table. 4) *Vis to Table*: We ask people to observe how data values in a table change as they manipulate parallel coordinates; as they move the circles for data points on an axis, the data table updates the corresponding values; they need to move lines at least five times. The series of activities strengthen people's understanding of the relation between data and visual elements by engaging in the mapping process in four different ways.

Table 1. Classification of tasks for parallel coordinate visualization.

Task Category	Visualization Tasks
Mapping between data points and visual elements	Choose a row/column in a table that corresponds to a line/axis in parallel coordinates, and vice versa; Count the number of attributes; Find the maximum/minimum value of an attribute.
Distribution, comparison and similarities	Estimate similarities between multiple lines on one/multiple attribute(s); Estimate/compare distributions of one/multiple attributes; Describe the distribution of two lines
Correlation and cluster	Find/describe the correlation between multiple attributes; Find/describe groups of lines with respect to distributions.
Filter and multicriteria evaluation	Describe values of an attribute of lines that satisfy criteria; Choose the best line that satisfies given conditions

Analytics Activities

The goal of **Analytics** Activities is to train people in accomplishing analytics tasks with parallel coordinates. We first taught how to do four different tasks–1) comparison, 2) correlation, 3) distribution, and 4) cluster–with static pages. For each task, we created a page that provides pictures and descriptions on what to look for and how to solve questions. For example, we explain how to estimate correlations between two attributes by looking at line crossings between them.

In following pages, we ask people to interact with parallel coordinates so that they could learn a set of interactions that are useful to achieve analytics tasks. 1) *Sort*: we ask people to sort attributes by clicking on the axis header; they need to arrange all attributes in an ascending order. 2) *Reorder*: we ask people to arrange the axes by dragging them to match the attribute order in a given table of data. 3) *Filter*: we ask people to apply filters by performing a marquee selection on the axis for certain criteria; they need to create filters on at least three different axes. These interaction activities improve people's skills to use visualizations for given analytics tasks.

EVALUATION

Experimental Conditions

Based on the tutorial design described above, we created four experimental conditions: 1) Baseline (i.e., no tutorial), 2) Static, 3) Video, and 4) Interactive. Supplementary materials include tutorial pages used in the study. The Baseline condition provided only a single page description about how data are mapped to visual elements in parallel coordinates. The three other conditions contained, in addition to the description, equivalent tutorial contents using different media types. The Interactive condition provided the interactive tutorial, where participants can draw parallel coordinates, enter values, and perform interactions. It also provided corrective feedback when participants failed to perform actions required to proceed to the next page. The Static condition showed instruction with screenshots taken from the Interactive condition without feedback; the Video condition provided recorded screen activities of a walk-through on the activities in the Interactive mode, so it included the same feedback. Participants could pause or replay the video as many times as they want.

For the Analytic Activities, we provided the description on what patterns to look for and which interactions can be used to solve questions in a static page in all conditions. Then, we provided instructions on how to perform each interactive feature using different media.

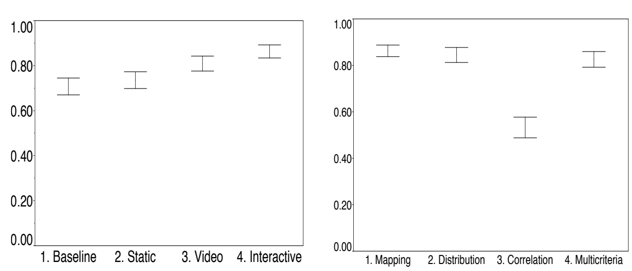
Participants and Methods

We conducted our experiment on Amazon Mechanical Turk with the following recruiting specification, i.e., Compensation: \$1.50; Turker requirement: 10,000 # HITs approved, 99 HIT Approval Rate (%). We excluded people who have prior knowledge about parallel coordinates (n = 49). To remove random clickers, we filtered out participants who completed a question under three seconds for more than three times (n = 19). Among the remaining 120 participants (30 participants per condition), 75 were male (62.5%); 78 had some college degrees, 21 had some high school diplomas, and 21 had postgraduate degrees. Each participant was randomly assigned to one of the four experimental conditions. There was no significant differences on self-reported measures between conditions: age, gender, education, and understanding of graph and math. The participants' age ranged from 20 to 61 with an average age of 33.6 years old.

After the tutorial session, we asked participants to answer 18 questions that are related to analytics tasks for parallel coordinates, e.g., "What is the minimum value of Horsepower approximately?" (mapping), "Which attribute has values that are the most proportionally and widely spread?" (distribution), "Which attribute has the highest correlation with MPG?" (correlation), "Which car would you buy if you consider a car with the highest MPG and Horsepower?" (multicriteria). For each question, we provided interactive parallel coordinates (same as tutorial) with a chosen subset of car datasets (100 to 500 data points with the five attributes). We collected task time and accuracy per trial. We also surveyed six questions regarding tutorials (except for the Baseline condition) on the 5-point Likert scale: 1) Engagement, 2) Fun, 3) Interestingness, 4) Easiness of the tutorial; their 5) Confidence and 6) Understanding of parallel coordinates. Lastly, participants provided comments on tutorials.

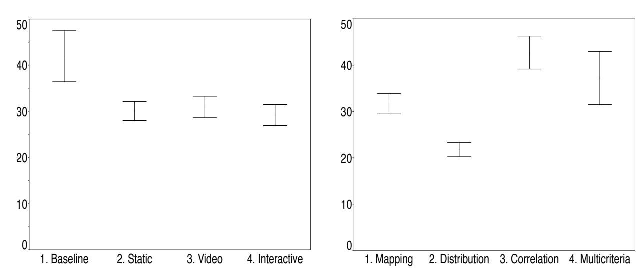
Results

We analyzed score (i.e., accuracy) and duration (i.e., time in seconds) using an analysis of variance (ANOVA). For score, we found a significant main effect of Condition, $F(3, 2264)$ = 17.18, $p < .001$. The Tukey HSD test shows that the mean score was higher in the Interactive condition (M = .86, SD = .11) than both the Static (M = .73, SD = .19) and Baseline (M = .71, SD = .19) conditions, and that the Video condition (M = .80, SD = .16) was higher than the Baseline condition (Figure 3(a)). We also found a significant main effect of Question $F(3, 2264)$ = 82.39, $p < .001$. Post hoc analysis shows that the score was lower in Correlation & Cluster than the scores



(a) Score by Condition (b) Score by Task Category

Figure 3. The 95% Confidence Interval Plots of Score per Question.



(a) Duration by Condition (b) Duration by Task Category

Figure 4. The 95% Confidence Interval Plots of Duration per Question.

in other task categories (Figure 3(b)). We did not find interaction effects between Condition and Question.

For duration, we found a significant main effect of Condition, $F(3, 2264) = 11.09$, $p < .001$. Post hoc analysis shows that the mean duration of the Baseline condition was significantly higher than the rest (Figure 4(a)). We also found a significant main effect of Question $F(3, 2264) = 24.08$, $p < .001$. Post hoc analysis shows that the mean duration of the Distribution & Comparison category ($M = 21.78$, $SD = 1.83$) was lower than those of Correlation & Cluster ($M = 42.70$, $SD = 1.83$) and Filter and Multicriteria evaluation ($M = 36.70$, $SD = 1.82$), respectively (Figure 4(b)). The mean duration of the Mapping category ($M = 31.65$, $SD = 1.48$) was lower than that of the Correlation & Cluster category.

We analyzed survey responses using a Kruskal-Wallis test, and found a significant association between condition and all survey responses: engagement level of the tutorial ($\chi^2(2, 90) = 12.81$, $p = .002$), the fun level of the tutorial ($\chi^2(2, 90) = 10.93$, $p = .004$), interestingness of the tutorial ($\chi^2(2, 90) = 16.04$, $p < .001$), easiness of the tutorial ($\chi^2(2, 90) = 24.68$, $p < .001$), participants' confidence of parallel coordinates ($\chi^2(2, 90) = 12.92$, $p = .002$), and their perceived understanding of parallel coordinates ($\chi^2(2, 90) = 10.07$, $p = .007$). Pair-wise Wilcoxon test shows that participants with the Video and Interactive tutorials felt more engaged and interested, had more fun, found it easier to follow the tutorial, understood better, and felt more confident with parallel coordinates than those with the Static tutorial.

DISCUSSION AND CONCLUSION

Reflecting upon our results, we discuss implications and future direction from our study.

Potential of Online Learning for Visualizations

Our study showed that crowdsourced non-experts could learn parallel coordinates and perform analytic tasks through 10-minute guided tutorials for learning. As the parallel coordinate is believed to be difficult for the general public to learn and understand, we are pleasantly surprised by the overall accuracy (mean score across all conditions = .77). In particular, participants with Video and Interaction conditions achieved higher scores than those with the Baseline condition, which indicate that this short tutorial can improve students' understanding of parallel coordinates.

In addition, participants generally liked the idea of the online learning tutorials for parallel coordinates regardless of their conditions. They acknowledged that learning parallel coordinates seemed difficult at first, but it turned out to be very easy and fun to follow structured guidance: "*This is how it should be taught in high school and grade school.*" (P54, Interactive); "*I took one look at the beginning and almost backed out but decided to give it a try. I am so glad I did.*" (P16, Video). However, participants of the Static condition reported difficulty in absorbing concepts. Some participants of the Static condition could not grasp the parallel coordinate visualization in the end: "*It was a bit confusing, I had trouble knowing I understood the principles*" (P36, Static).

Interactive Tutorial vs. Video Tutorial

Though we did not find statistical differences between the Interactive and Video conditions in terms of accuracy, participants with the Interactive condition performed better than the Static and Baseline conditions while those with the Video condition performed better than the Baseline condition only. Furthermore, participants feedback generally favored the Interactive condition. Some participants of the Video condition commented that they had to watch multiple times to understand the concept. : "*Some videos I had to watch a few times to grasp the idea*" (P52, Video).

Note that participants of the Interactive condition acknowledged that the tutorials were easy to follow without reporting any difficulty: "*Loved the way it was presented. Coming into this I had no experience in the subject. I found it to be very interesting and easy to follow*" (P17, Interactive). Furthermore, they enjoyed following the tutorial activities: "*I thought the tutorial was fun and interactive. I liked that I got to apply what I learned right away to ensure that I got what it was talking about*" (P77, Interactive).

Learning Core Concepts of Parallel Coordinates

Contrary to our expectation, participants achieved high overall accuracy even with Baseline. This might be because we used a simple and small dataset, which would not overwhelm lay people but would still be useful to teach the core concepts for the PC comprehension. On the other hand, they did poorly on correlation tasks. These results suggest that it is not very difficult to learn how data items are mapped to visual elements in PC, but it is not easy to understand the patterns for correlation and to interact with PC to find the appropriate view to identify those patterns. The real-world datasets would be much larger than the simple datasets we used in our study, and performing an exploratory analysis with real-world data to identify hidden insights would require more advanced skills than understanding the basic concepts of parallel coordinates. Further research is needed to design better activities potentially with more complex datasets, and to study interactive tutorials for advanced tasks such as complex decision-making tasks with large datasets.

Toward Generalizing Guided, Interactive Tutorials

Our results can be generalized to other multidimensional visualizations with unfamiliar layouts such as star coordinates. We also believe that the interactive tutorial approach can be applied to other visualization types (e.g., pixel bar chart, matrix visualization) where one data item can be mapped to graphic elements such as size or color. For example, we could create a guided, interactive tutorial for a matrix-based graph visualization based on existing graph visualization task taxonomies (e.g., [8]). Rows and columns can be coupled with a list of nodes, and each cell can be connected with a list of links. Our study results also encourage the further investigation into a systematic approach to teach visualizations by leveraging the learning-by-doing approach.

ACKNOWLEDGEMENT

We thank Sukwon Lee, Sung-Hee Kim, and Paul Johns for their valuable feedback on the draft.

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