A Comparative Study of Visualizations for Multiple Time Series

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Abstract: Different visualization techniques are suited for visualizing data of multiple time series. Choosing an appropriate visualization technique depends on data characteristics and tasks. Previous work has explored such combinations of data and visualization techniques in lab-based studies to find the most suited technique for a task. Using these previous findings, we performed an online study with 51 participants, during which we compare line charts, stream graphs, and aligned area charts based on completion time and accuracy regarding three common discrimination tasks. Our online study includes a novel combination of visualization techniques for time-dependent data and indicates that there are certain differences and trends regarding the suitability of the visualizations for different tasks. At the same time, we can confirm results presented in previous work.

1 INTRODUCTION

Visualizations can make use of many different techniques for displaying time-dependent data (Aigner et al., 2011; Brehmer et al., 2017). Analysts must take space limitations and over-plotting into account when choosing a technique for visualizing multiple time series at once. Analysts also need to consider the specific tasks the visualization should support to select an appropriate visualization solution. Another trade-off to bear in mind is that between speed and accuracy when performing a task: A quick, but approximate retrieval of values or trends is more favorable in certain situations, whereas others require precise retrieval.

We present the results of an online study in which we compare line charts, stream graphs, and aligned area charts (multiple area charts with separate vertical axes, but a shared horizontal axis, see Figure 1c) for the visualization of four and seven time series. These are common visualization techniques for time-dependent data; with each having particular strengths and weaknesses when visualizing multiple time series: Line charts can suffer from overdrawing, stream graphs cannot show a zero baseline for each time series, and aligned area charts' height decreases with increasing number of time series. These drawbacks are more or less severe depending on the task, and it is important to understand under which circumstances each visualization technique is suitable. To test these circumstances, we consider three discrimination tasks: Identifying the time series with the largest value at a specific point in time, identifying which of two points in time has the highest sum of values over all time series, and identifying the time series with the highest integrated area between two points in time. These tasks are partly a reproduction of previous work (Heer et al., 2009; Javed et al., 2010; Thudt et al., 2016). We then quantitatively evaluate the results. We discuss the results in relation to previous work, which found similar results. We found weak evidence for stream graphs and aligned area charts being more suitable for estimating area under a time series than line charts. We further identified a trend indicating the superiority of line charts for identifying the highest-valued time series at a specific point in time. Finally, we found a trend towards the suitability of stream graphs to compare aggregated values over all time series across two points in time. Because the differences between the techniques are small, or not detectable in many cases, we conclude that analysts have some flexibility in choosing which visualization technique to use when addressing similar visual tasks on time series data. However, they should avoid line charts when integration of values over time is part of the analysis, and should consider stream graphs if totals over all time series are of interest.

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2 RELATED WORK

Our work is closely related to previous work by Heer et al. (2009), Javed et al. (2010), and Thudt et al. (2016). Those publications focus on the comparison of superimposed and juxtaposed techniques (Gleicher et al., 2011) for visualizing time series data. A significant difference between their work and ours is that the studies were all performed in person, while we conducted an online study.

Heer et al. (2009) compared line charts with different variants of *horizon graphs*. A horizon graph is a variant of an area chart where the area is layered into vertical bands, which are then superimposed with increasing color intensity. The authors explored the influence of the number of bands in a graph for their variants on two basic tasks: *Discrimination,* where participants were asked which of two graphs had the larger value at a given point; and *estimation,* where participants had to gauge the difference between the two values at that point. The authors found that the accuracy for the *discrimination* task was at least 99 %, and therefore focused their analysis on the *estimation* task. Here, error rates were higher for four bands than for two or three, and answer times increased with number of bands. In the second experiment, the authors explored readability of different chart heights and scaling. They found that error rate increased with decreasing chart height, and that horizon graphs with one band had lower error rates than line charts of the same height. Heer et al. concluded that horizon charts can improve readability for small diagram heights. Our work differs from theirs insofar as we explore differences between one superimposed and two juxtaposed techniques with three tasks; that we look at more time series at once; and that we do not consider the horizon graph, but instead the aligned area chart.

Javed et al. (2010) examined both superimposed and juxtaposed techniques, with the main focus being whether complex representations have advantages over simple line charts in certain situations; in particular restricted vertical space and large number of time series. Their study compared four visualization techniques: line charts, braided graphs, small multiples, and horizon graphs. For each, participants had to solve three tasks: finding the time series with the largest value at a certain point in time *(maximum),* finding the time series with the largest *slope* within a certain interval, and deciding which of two time series A, B has the higher value at two different points in time t_A, t_B *(discrimination).* The study further considered three numbers of time series (2, 4, 8) and three diagram heights (48, 96, and 192 px). The study revealed that the time needed to solve a task did not change with the available vertical space, but the accuracy of the answer decreased with decreasing vertical space, which Javed et al. describe as *"classic time/accuracy trade-off"* (p. 934). Increasing the number of time series shown resulted in increasing answer times and decreasing accuracy. For the superimposed techniques, increasing the number of time series increased overlap and disarray, while the juxtaposed techniques proved more robust. In total, answer times for line charts and small multiples were often faster than for horizon graphs and braided graphs. While our work examines one task also examined by Javed et al., the other tasks we examine differ. We further keep diagram sizes constant and examine a visualization with a non-zero baseline, the stream graph.

Thudt et al. (2016) examined the readability of layered charts. Their focus was on the influence of static and interactively selectable baselines, symmetry, and wiggle factor on the extraction and comparison of values or aggregations of values, and on the readability of trends. Their study consisted of three tasks on four visualization types: stacked area charts, the *ThemeRiver* (Havre et al., 2002), stream graphs (Byron and Wattenberg, 2008), and their own variant of the ThemeRiver with interactive baseline correction. These tasks were a direct comparison of two values from two timelines, where participants had to decide which value was larger; the identification of one time series, visualized as an area chart, in a layered chart; and the comparison of aggregated values at two points. The authors found that performance varied greatly, depending on the task at hand, but that the stream graph performed better for individual and aggregated comparison than the other static visualizations. The authors' own interactive version of the ThemeRiver performed best when comparing streams. In contrast to their work, we compare both superimposed and juxtaposed techniques. However, we do not include the interactive component, and use a considerably smaller number of time series at the same time (4 and 7) than Thudt et al., who used 10, 30, and 300.

SineStream (Bu et al., 2021) enhances stream graphs by optimizing stream order and the baseline to reduce sine illusion effects (Day and Stecher, 1991). The authors evaluated the generated variants by asking participants to gauge stream trend, individual value retrieval and comparison, and total value comparison; the latter two tasks being comparable to the tasks we chose. Walker et al. (2016) ropose TimeNotes for the exploration and representation of high-volume, high-frequency time series data. Their approach utilizes a hierarchical layout to represent and compare the time series at different levels of granularity. Other works explore the visualization of one or multiple time series in constrained spaces: considering color and texture (Jabbari et al., 2018), compacted horizon graphs (Dahnert et al., 2019), and density-estimating *CloudLines* (Krstajic et al., 2011).

3 METHOD

The goal of this work is to compare the readability of three visualization techniques for temporal data. These are the line chart (Figure 1a); the stream graph (Byron and Wattenberg, 2008) (Figure 1b); and the aligned area chart, a juxtaposed visualization technique (Figure 1c). We design three discrimination tasks and perform an online study, during which we measure completion time and accuracy of the participants' answers.

3.1 Tasks

We design the online study in a way that allows us to investigate the relative readability of the three different visualization techniques. The concept of readability has been introduced by others already: Javed et al. (2010) and Thudt et al. (2016) use similar tasks to the ones we present to explore the readability and efficacy of different visualization techniques.

Our first task, **MAXIMUM**, asks participants to decide which time series has the highest value at a specified point along the timeline. The second task, **SUM**, asks participants to decide for two points in time at which of these the sum of all time series values is larger. The third task, **AREA**, asks participants to decide which time series has the largest area between two points in time. Figure 1 shows example stimuli for all three visualization techniques for the three tasks. The stimuli for the **MAXIMUM** task contain one marked point in time, whereas the more complex **SUM** and **AREA** tasks mark two points. We introduce the tasks in ascending order of complexity here, but randomized their order for each participant to rule out effects of fatigue.

The **MAXIMUM** task could be classified as an *elementary* task in the definition by Andrienko and Andrienko (2006). The **SUM** and **AREA** tasks show increasing complexity, as more context and a more holistic view on the data is required to solve them, and could therefore be classified as a *synoptic* tasks. The task typology by Brehmer and Munzner (2013) deconstructs tasks into *why, how,* and *what;* thereby allowing to classify and compare complex tasks and break them down into smaller sub-tasks. Our tasks would fit into the *query* category of their typology ("identify, compare, summarize"), and would be useful components of many larger, more abstract data analysis tasks. Such analyses could concern, for example, results of topic modeling or clustering, where the frequency of different topics over time is of interest for analysis questions such as: *"What topics were most discussed at time X?"* (**MAXIMUM**), *"When were discussions most diverse?"* (**SUM**), or *"What topics were most dominant during an interval?"* (**AREA**). Often, combinations and frequent repetition of these tasks and questions are required to gain insight on a higher level, which precludes computational solutions. The choice of visualization to best support exploratory analysis therefore depends on the relevant low-level tasks for the data.

3.2 Study Design

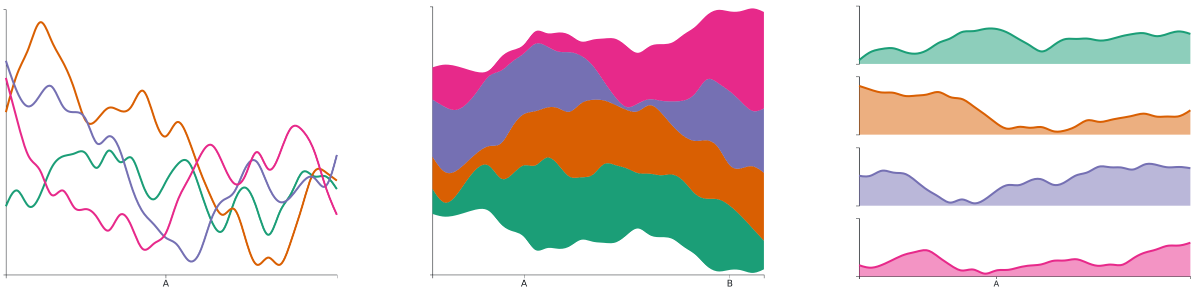
We conducted the study in English on the Prolific platform (Prolific, 2021) with 51 participants, mainly from English-speaking countries (Prolific, 2014). The study was designed as within-subjects, such that each participant solved all three tasks in random order for all three types of visualization techniques. The participants would perform the task and indicate their answer by selecting a time series using radio buttons (see Figure 2). As soon as one of these radio buttons was selected, the answer was transmitted and the response time was measured. The time for moving the mouse cursor was taken into account.

3.2.1 Apparatus

The uniformity of the devices used could not be ensured due to the online nature of the study. Participants were asked to conduct the study on a device with a mouse; and to refrain from using mobile devices, such as smartphones or tablets. Because we did an online study and participants used their own devices, we could not control the size of the stimuli directly. Thus, participants had to first complete a short scaling task. This was done by asking participants to take a credit card (86 mm $\times$ 54 mm) and drag a displayed rectangle to the size of the card with the mouse. Then, the experimental setup scaled the visualization techniques such that they had the same size of 17 cm $\times$ 10.5 cm, or 20 cm diagonally, on different screens. Participants were also required to maintain a distance from the monitor and were prohibited from zooming in. Zooming events were recorded and the corresponding measurement data was discarded.

3.2.2 Data

We created random time series using a modified random walk algorithm (see Algorithm 1). To make the



(a) Line chart. (b) Stream graph. (c) Aligned area chart.

Figure 1: Examples for randomly generated stimuli with the three visualization techniques: (a) Line chart, (b) stream graph, and (c) aligned area chart. The point at which values should be compared is indicated on the time axis for the **MAXIMUM** task (see (a) and (c)). For the **SUM** and **AREA** tasks, two points (see (b)) are indicated for comparison.

series more realistic, we ensure non-negative values and add a random offset to all values. All figures containing stimuli in this work show examples of this random walk. For our study, each time series consists of 30 time steps, which is similar to previous works (Thudt et al., 2016). We generated 60 samples containing four time series and 60 samples containing seven time series. We settled on a maximum of seven time series as that seemed a good upper bound for the number of topics to analyze at one time (Miller, 1956). We also found it challenging to find an appropriate colorblind-friendly scheme with more colors (see Section 3.2.3). For the **AREA** and **SUM** tasks, the two points in time were placed randomly, but at least 5 time steps apart. Samples were chosen completely at random out of the random walk-generated time series. There was no guaranteed minimum difference between the correct answer for a stimulus and the other shown time series. In cases where two answers would have been correct, both were accepted. However, the statistical probability of such situations occurring during the study were negligible.

Algorithm 1: Time series generation using random walk. The series' lowest point is between 0 and 5.

function TIMESERIESRANDOMWALK(n)
    $s := \{-5, -4, \dots, 0, \dots, 4, 5\}$ ▷ Step set
    $r := [1, \dots, n]$ ▷ Time series
    $l :=$ DRAWUNIFORMRANDOM(s) ▷ Walker
    for $i \in \{1, \dots, n\}$ **do**
        $l := l +$ DRAWUNIFORMRANDOM(s)
        $r[i] := l$
    minimum $:= \min(s)$ ▷ Lowest point
    offset $:=$ DRAWUNIFORMRANDOM($\{0, \dots, 5\}$)
    for $i \in \{1, \dots, n\}$ **do**
        $r[i] := r[i] -$ minimum $+$ offset
    return r

3.2.3 Conditions

We designed the within-subject study with the following factors: *Visualization technique (V):* line chart, stream graph, aligned area chart; *tasks (T):* **MAXIMUM**, **AREA**, **SUM**; and *number of time series (N):* four or seven. This created a design with $|V \times T \times N| = 18$ different conditions for all participants. Each condition was repeated five times to obtain a more precise and robust result. This resulted in 90 trials per participant during the main runs. Including the test runs, in which each condition was repeated once, the total number of trials is at least 108, depending on whether participants decided to repeat test runs. The order of the tasks was randomized using simple randomization, as was the order of visualization types within a task and the number of time series.

Choosing a color palette was a challenge in this study. We started with *Dark2* from ColorBrewer2 (Harrower and Brewer, 2013). Javed et al. (2010) also used this color palette in their study because of a guarantee of graphical perception of each time series. During the pre-studies, we realized that this palette is problematic because of two green-heavy colors. We adapted our color palette to accommodate this effect (Figure 2).

3.2.4 Procedure

We asked participants to read the displayed information and instructions carefully. To create a consistent initial state, we asked them not to use external aides such as pens or their hands, to sit in an upright position, and to not move their head closer to the screen.

After reading the instructions, participants filled out a questionnaire regarding their demographic background and performed a calibration task for their screen scaling (see Section 3.2.1). To test for participants with color blindness, they then had to enter the number shown on an Ishihara test stimulus.

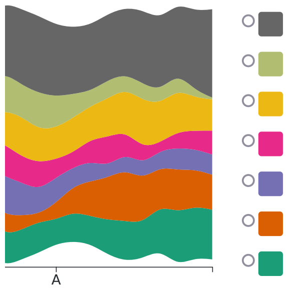


Figure 2: Example of a stimulus with radio buttons.

Participants then saw the first of three tasks, with the order of tasks being random for each participant. For each task, an exemplary scenario was described to help them understand the task and its motivation. Participants were asked to do one test run for each task to reduce training effects. During the test run, each visualization type was shown once for each number of time series, resulting in six stimuli. The first stimulus was shown after the participant pressed the start button, and the stimulus was faded out when the participant chose their answer using the radio buttons. After a two second pause, the next stimulus was shown. During the test run, participants received feedback on whether their answers were correct. After the test run, participants could decide whether they wanted to proceed with the study or repeat the test run.

The main study was performed analogous to the test run, but with a larger number of stimuli, and without feedback on the correctness of the answers. Participants were shown a progress bar indicating the total progress through the study. After each task, the description and exemplary scenario for the next task was shown. At that point, participants were encouraged to take a small break, should they require it. No breaks were intended during the tasks.

After completing all three tasks, participants were asked which visualization technique they liked the most and which the least, with the possibility of indicating no preference. After participants submitted their answers, we thanked them and provided them the Prolific completion code. They were paid 5.25 GBP each via the Prolific platform.

3.2.5 Pre-studies

To both identify ambiguities and potential problems and to test the feasibility of the study, we conducted two pre-studies. Issues found in a pre-study were resolved before conducting the next one. In both pre-studies, a small number of participants completed the three different tasks of the study, including a short survey afterwards. Because the purpose of the pre-studies was to identify problems at an early stage, the results of the response times and correctness were of secondary importance. The procedure of both pre-studies was almost identical to the procedure mentioned in Section 3.2.4, but with fewer repetitions. We estimated an average study duration of 32 min from the pre-studies, which we used to determine compensation for participants.

The majority of participants in the first pre-study mentioned the predominant green tone of the colors in the time series, as well as confusion between an ocher and orange color. This caused participants to lose time in selecting the radio button, which skewed the results. We subsequently updated the color palette.

In the second pre-study, participants again remarked on problems with the color palette, which we subsequently adapted to the final version shown in Figure 2. Although the newly inserted colors were colorblind-friendly colors, a distorted perception of the colors due to color vision impairment could not be ruled out. Besides the difficulties with the colors, some participants complained about thin line widths in the aligned area charts and the line charts, which we increased as a consequence.

One of the participants stated that they had problems with the stream graph visualization technique. Because the time series are arranged around a central axis, an empty or white area appears between the lowest time series and the horizontal axis. The participant interpreted this area as a time series during the exercise, which caused confusion on the part of the participant. Because this is part of the visualization technique and was not criticized by anyone else, we did not apply any changes here.

A small number of participants stated that they looked at the progress bar more often towards the end. One of the participants felt that the number of stimuli was too high. We discussed and rejected the option of reducing the number of repetitions of each condition, as a lower number of repetitions could lead to a less robust result. By randomizing the order of tasks, we counteracted effects of fatigue in the main study.

4 RESULTS

We had 51 participants in our study; 40 were between 18 and 30, 7 were between 31 and 40, and 4 were between 41 and 50 years old. Twenty-six (26) held the equivalent of a high school diploma, 16 had a Bachelor's degree, 7 a Master's degree, and 2 had a lower education level. Five (5) of the 51 participants declared that they use reading aids. We did not inquire about the participants' gender because we deemed it irrelevant for the study, and wanted to reduce the

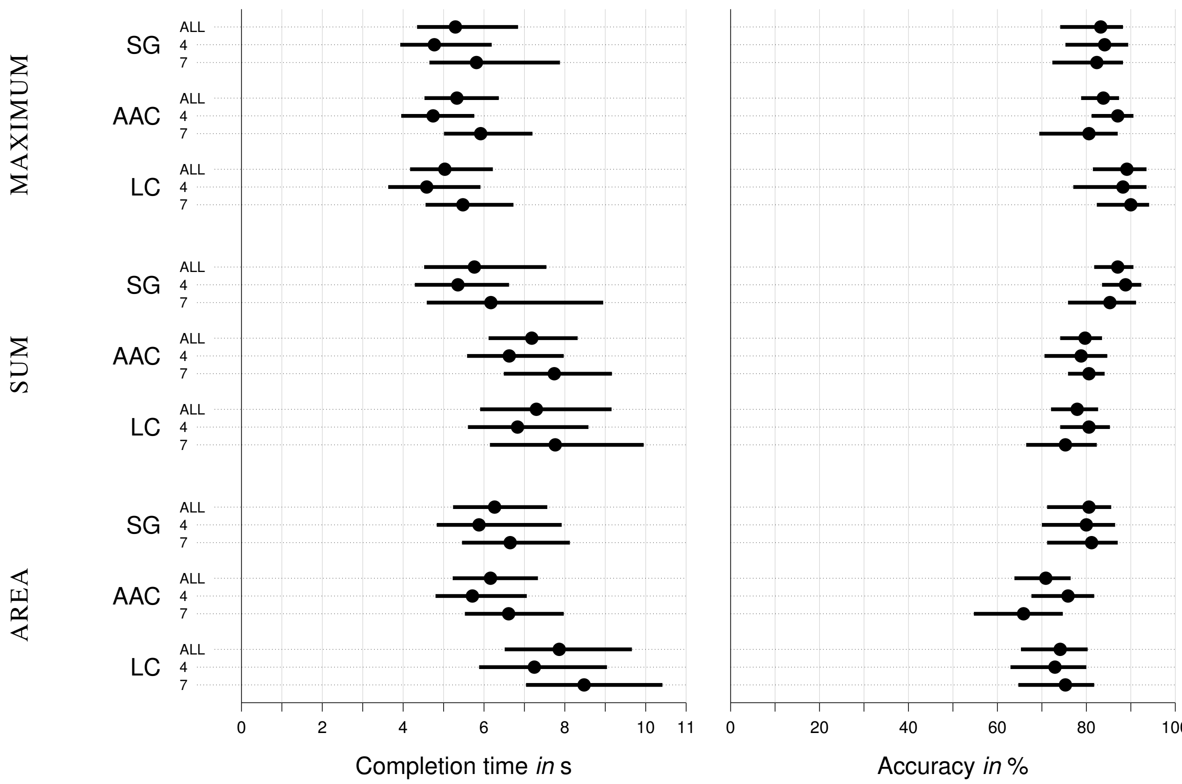


Figure 3: Completion time (left) and accuracy (right) analysis of the study data obtained from 34 participants. We visualize mean values and confidence intervals (CIs) for all three visualization techniques for all three tasks. We show the comparisons for all data, the data for four time series, and for seven time series. The error bars represent the 95 % bootstrapped CIs. Completion times are given in seconds, accuracy in percentage values.

amount of personal data collected.

A disproportionate number (14 out of 51, about 27.5 %) of the participants did not pass the Ishihara color blindness test done before the start of the study. Even assuming an all-male participant pool, this number is over 1.5 times higher than what we expected from the base rate for this type of color blindness. Combined with higher error rates and larger spread in task completion time in that group, we suspect that some participants either did not understand the task, or did not invest the required effort to solve it. We cannot separate such candidates out post-hoc because of the online nature of the study, so we decided to omit the data from participants failing the Ishihara test from the analysis. Three more participants were excluded because they solved the initial scaling task in under one second. These participants might also not have solved the tasks thoroughly, and the stimuli were not displayed in the appropriate scaling on their monitors. This left us with the data of 34 participants.

The results of the study are task completion time and accuracy. With those, we carried out a time and error analysis with the sample mean per participant and condition. We calculate these sample means using interval estimation with 95 % confidence intervals, which we adjust for multiple comparisons using Bonferroni corrections (Higgins, 2004). By using BCa bootstrapping with 10,000 iterations to construct the confidence intervals, we can be 95 % certain that the population mean is within that interval. In addition to the confidence intervals on the measured data, we also calculate the pairwise differences between the three visualization techniques' results using estimation techniques. We interpret the strength of the evidence as recommended in the literature (Cumming, 2013; Dragicevic, 2016; Besançon and Dragicevic, 2017, 2019; Cockburn et al., 2020): Confidence intervals of mean differences show evidence if they do not overlap with 0, and the strength of the evidence increases for tighter intervals and intervals farther away from 0. Equivalent p-values can be calculated using the method by Krzywinski and Altman (2013).

We have published the study data and analysis scripts in a data repository (Franke et al., 2021). We show the calculated results in Figure 3, and the calculated confidence intervals of mean differences in Figure 4. Results are grouped by task, then by visualization technique. We further calculate the results on

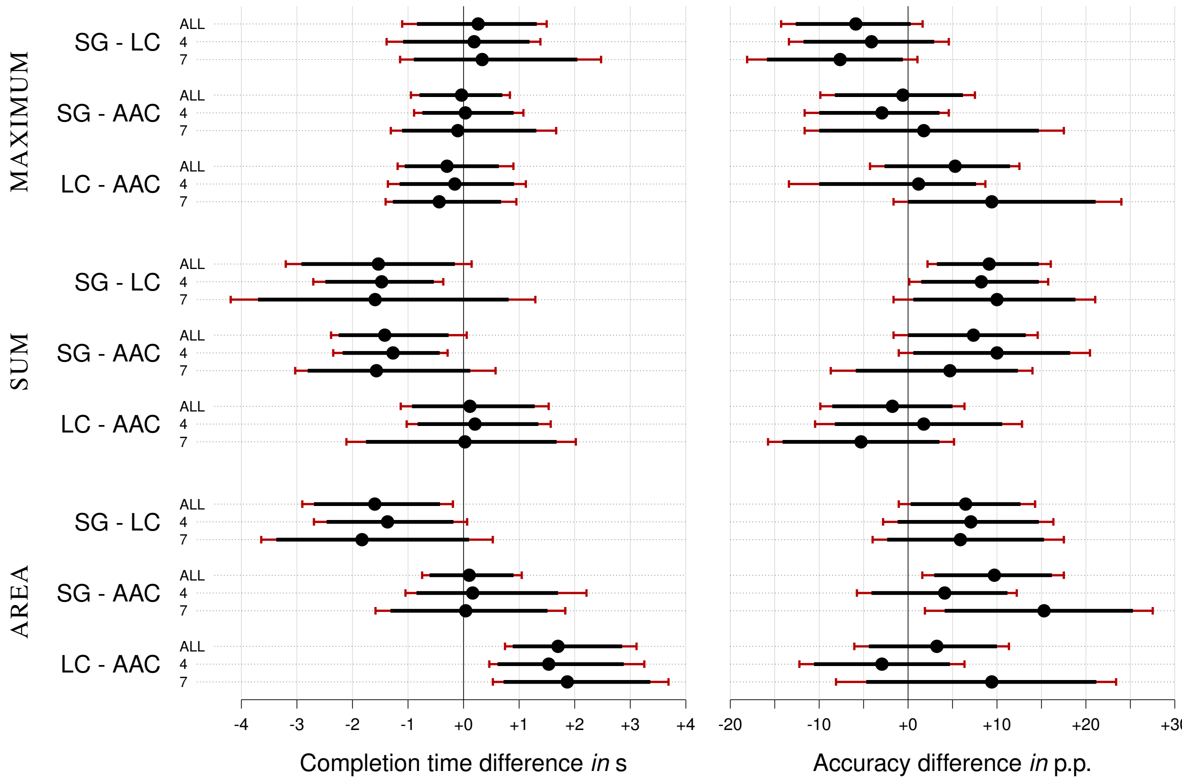


Figure 4: Completion time (left) and accuracy (right) analysis of the study data obtained from 34 participants. We visualize pairwise comparisons between the three visualization techniques for all three tasks. We show the comparisons for all data, the data for four time series, and for seven time series. The error bars represent the 95 % bootstrapped CIs, adjusted using Bonferroni correction (red). Time differences are given in seconds, accuracy differences in percentage points (p.p.s).

two levels: once for all data of a condition, regardless of the number of time series shown, and once for the stimuli with four and seven time series, respectively.

4.1 Maximum Task

For the MAXIMUM task, participants took an average of 5.22 s, with the line chart being slightly faster with 5.03 s. On the second level, the average times for line charts and aligned area charts were slightly higher for seven time series than for four. Regarding accuracy, there were no larger differences, but the line chart was the most precise with 89.12 %, followed by the stacked area chart (83.82 %) and the stream graph (83.24 %). The average accuracy dropped by 2 p.p.s for seven time series for the stream graph, improved by 2 p.p.s for the line chart, and dropped by over 6 p.p.s for the aligned area chart.

We found no evidence for better completion times of any visualization technique, but there is a slight trend for the line chart being faster (Figure 4 left). The trend towards the superiority of the line chart for accuracy is stronger, but we find no concrete evidence.

4.2 Sum Task

For the SUM task, participants took an average of 6.75 s; the stream graph took on average 5.76 s, while the other two took about 7.1 s. On the second level, times increased by about 1 s from four to seven time series for all visualizations. Accuracy values ranged between 77.94 % for the line chart and 87.06 % for the stream graph. Going from four to seven time series, accuracy dropped by 3.5 p.p.s for the stream graph, increased by 1.8 p.p.s for the aligned area chart, and dropped by 5.3 p.p.s for the line chart.

We found no evidence that any visualization technique is faster, although Figure 4 reveals a trend towards the stream graph being faster. We found weak evidence that the stream graph is more accurate than the line chart for this task, and found a trend that indicates that the stream graph is also more accurate than the aligned area chart.

4.3 Area Task

For the AREA task, participants took on average 6.76 s; however, the line chart took on average 7.86 s, while the other two took around 6.2 s. Going from four to seven time series, times increased by about 0.5 s for the stream graph and aligned area chart. Times for the line chart increased most, from 7.25 s to 8.48 s. Accuracy values ranged between 70.88 % for the aligned area chart and 80.59 % for the stream graph. Going from four to seven time series, accuracy improved slightly for the stream graph and the line chart, but dropped by 10 p.p.s for the aligned area chart.

We found weak evidence that both the stream graph and the aligned area chart were faster than the line chart for this task, as shown in Figure 4. We found weak evidence that the stream graph is more accurate than the aligned area chart. We further identified a trend for the stream graph to be more accurate than the line chart, but no concrete evidence.

4.4 Other Results

For all tasks and visualization techniques, we found that completion times increased consistently going from four to seven time series (see Figure 3). On average, completion times increased by 0.99 s, or 17.15 %. Accuracy dropped noticeably for some combinations of task and visualization technique, but not as consistently.

For the participants who failed the Ishihara test and were therefore not included in the study, accuracy values were considerably lower; as low as 56.43 % for the AREA task with the aligned area chart, and never over 77.14 % (SUM task, stream graph). Average completion times did not change much, but were more varied, and their CIs were considerably wider.

Of the 34 participants considered in the evaluation, 18 found the line chart to be their favorite visualization, followed by 13 for the stream graph, 2 for the aligned area chart, and 1 with no preference. Eighteen (18) participants answered that the aligned area chart was their least favorite visualization, followed by the stream graph with 8, the line chart with 7, and 1 participant with no preference.

5 DISCUSSION

In the statistical evaluation of our study data, we did not find strong evidence for the superiority of any of the three visualization techniques for the tasks we examined. However, we obtained some weak evidence, most prominently in the AREA task. Here, it is clear that the completion times are slower for the line chart than for the other two visualization techniques. One explanation for this could be that the visual overlap of lines makes it harder to gauge area, even with a clear baseline. The stream graph, which does not have the advantage of a zero baseline, still exhibited weak evidence of being more accurate than the aligned area chart, and a trend towards being more accurate than the line chart. In contrast, the aligned area chart, while being faster than the line chart, showed no evidence for being more accurate. In fact, accuracy is ever so slightly better for the line chart with seven time series. The straightforward explanation here is that the reduced height of the juxtaposed charts makes exact retrieval of values harder. This effect was also noted by Javed et al. (2010, p. 934) as the *"classic time/accuracy trade-off."*

We also found a trend indicating the superiority of the stream graph for the SUM task, both regarding speed and accuracy. Compared to the line chart, we even found weak evidence that the stream graph is more accurate. We ascribe this to the fact that, for the stream graph, the sum of all values at one point in time can be found by estimating the thickness of the graph at that point. This should be faster and more accurate than estimating multiple values and then summing them up. This result should be kept in mind, especially when designing visualizations where the relationship of one time series to the whole is of interest.

Finally, we found a trend that for identifying the time series with the MAXIMUM value at one point, line charts are most accurate. We found no evidence for them being faster. Our explanation is that, for line charts, this task can be solved by comparing *positions* at one point, whereas for the aligned area chart, *length* needs to be compared across different places. The stream graph has the additional hurdle of potentially introducing sine illusions (Day and Stecher, 1991), which might hinder precise retrieval.

Our study considered visualizations showing four or seven time series. Real-world data sets often include larger numbers of time series, but we would argue that for the tasks we studied, these numbers were appropriate. Especially for the aligned area chart, scalability was already becoming a problem. Arguably, the line chart cannot be used for many more time series at a time before readability is a problem (Munzner, 2014). The stream graph, which is already a visualization technique focused more on overview, has the potential to scale further. At that point, however, color scales become problematic, which inhibits the use of the tasks we studied. In their study, Thudt et al. (2016) show 30 time series at a time, but skirt the coloring challenge by only coloring one or two time series of interest in their stimuli. For larger numbers of time series, other tasks and strategies emerge, and filtering, aggregation, and interaction become necessary.

Participants in the preliminary study drew our attention to the risk of confusing the greens as well as the orange and ocher tones in the used *Dark2* color palette (Harrower and Brewer, 2003). Javed et al. (2010), who used the same color palette, do not mention any such issues. However, their participant pool was smaller (16), and might not have included any colorblind participants. We describe the colors we finally used in the study material (Franke et al., 2021).

Another point of discussion is how representative our study is towards the general public, and how robust the online study results are. By using the Prolific platform, the study was performed with a participant pool consisting mainly of US and UK citizens. The participants did also, on average, have an above-average education level, which might affect how familiar they were with the presented visualization techniques. We would argue that our study results are representative at least for the demographics that would come into contact with these visualizations regularly. Although we made arrangements to get study conditions as uniform as possible, the online nature of the study reduced our control. For example, even though we asked them not to, it is possible that some participants moved their heads closer to the screen or used their hands to support them in the tasks. However, we were able to eliminate obvious outliers from the data, and other work (e.g., Heer and Bostock, 2010) indicates that online studies generate results of similar quality, but with greater reach and cost-effectiveness.

A confounding factor of our study relates to the within-subject design. We had to limit the number of stimuli shown per condition to avoid exhausting participants. We tested 18 different conditions (see Section 3.2.3), and with only five stimuli per condition, the study already took about 30 min to complete. With the 34 participants, this means we only collected 170 data points per condition, which limits the robustness of our results and may be responsible for the moderate expressiveness of our results. To further reduce load on the participants, we only let them solve each task once for four and once for seven time series in the test runs for each visualization technique. While participants could choose to repeat the test runs, we did not force them to do so if their answers were incorrect. It is therefore possible that some participants might not have completely understood how some of the visualization techniques are supposed to be read, especially the less commonly known stream graph and aligned area chart. We take away that for future studies of this kind, a between-subject study with more time per condition would be more reasonable, with the trade-off of needing more participants.

One final challenge worth discussing is the large number of colorblind participants we encountered. We believe that this was a mixture of actual colorblind people and participants who, willfully or not, did not answer the questions thoroughly. The fact that, while the accuracy of the answers of this group decreased, the completion times as a total did not, implies to us that the issue was not with colorblindness itself. We see this as a larger issue with online studies and take away from this experience that our future online studies need to include regular attention and sanity checks. This would make it possible to identify test subjects answering conscientiously more effectively, and reduce the loss of valuable study data.

6 CONCLUSION

We have compared three visualization techniques for depicting multiple time series; line charts, stream graphs, and aligned area charts; regarding three discrimination tasks with increasing complexity. With our online study, we found weak evidence for the inapplicability of line charts for deciding on the timeline with the highest integrated value between two points in time. We also found trends indicating the suitability of line charts for identifying time series with high values at one point, and the suitability of stream graphs for gauging the higher of two total values between two points in time. In other words, we found that, with some exceptions, there are no larger differences in the efficacy of the visualization techniques for these tasks. However, we suggest that analysts should not use line charts if integrating values over time is part of the analysis task, and that they use stream graphs if comparison of overall values of all time series is important. Future work could extend our study to additional visualization techniques and other data characteristics, such as multivariate or categorical time-dependent data, as well as to other tasks, or including interaction.

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REFERENCES

Aigner, W., Miksch, S., Schumann, H., and Tominski, C. (2011). *Visualization of Time-oriented Data*. Springer, London, UK.

Andrienko, N. and Andrienko, G. (2006). *Exploratory analysis of spatial and temporal data: A systematic approach*. Springer, Berlin, Germany.

Besançon, L. and Dragicevic, P. (2017). The significant difference between p-values and confidence intervals. In *Proc. IHM*, pages 53–62. ACM.

Besançon, L. and Dragicevic, P. (2019). The continued prevalence of dichotomous inferences at CHI. In *Proc. CHI Extended Abstracts*. ACM.

Brehmer, M., Lee, B., Bach, B., Riche, N. H., and Munzner, T. (2017). Timelines revisited: A design space and considerations for expressive storytelling. *IEEE TVCG*, 23(9):2151–2164.

Brehmer, M. and Munzner, T. (2013). A multi-level typology of abstract visualization tasks. *IEEE TVCG*, 19(12):2376–2385.

Bu, C., Zhang, Q., Wang, Q., Zhang, J., Sedlmair, M., Deussen, O., and Wang, Y. (2021). SineStream: Improving the readability of streamgraphs by minimizing sine illusion effects. *IEEE TVCG*, 27(2):1634–1643.

Byron, L. and Wattenberg, M. (2008). Stacked graphs–geometry & aesthetics. *IEEE TVCG*, 14(6):1245–1252.

Cockburn, A., Dragicevic, P., Besançon, L., and Gutwin, C. (2020). Threats of a replication crisis in empirical computer science. *Comm. ACM*, 63(8):70–79.

Cumming, G. (2013). *Understanding the new statistics: Effect sizes, confidence intervals, and meta-analysis*. Routledge, New York City, NY, USA.

Dahnert, M., Rind, A., Aigner, W., and Kehrer, J. (2019). Looking beyond the horizon: Evaluation of four compact visualization techniques for time series in a spatial context. arXiv: 1906.07377v1 [cs.HC].

Day, R. H. and Stecher, E. J. (1991). Sine of an illusion. *Perception*, 20(1):49–55.

Dragicevic, P. (2016). Fair statistical communication in HCI. In *Modern statistical methods for HCI*, pages 291–330. Springer International Publishing.

Franke, M., Knabben, M., Lang, J., Koch, S., and Blascheck, T. (2021). A comparative study of visualizations for multiple time series: Data repository of the University of Stuttgart. https://doi.org/10.18419/darus-2134, `DOI: 10.18419/darus-2134`. [Online; accessed 2021-11-26].

Gleicher, M., Albers, D., Walker, R., Jusufi, I., Hansen, C. D., and Roberts, J. C. (2011). Visual comparison for information visualization. *Information Visualization*, 10(4):289–309.

Harrower, M. and Brewer, C. A. (2003). Colorbrewer.org: An online tool for selecting colour schemes for maps. *The Cartographic Journal*, 40(1):27–37.

Harrower, M. and Brewer, C. A. (2013). Colorbrewer 2.0. https://colorbrewer2.org/. [Online; accessed 2021-06-07].

Havre, S., Hetzler, E., Whitney, P., and Nowell, L. (2002). ThemeRiver: Visualizing thematic changes in large document collections. *IEEE TVCG*, 8(1):9–20.

Heer, J. and Bostock, M. (2010). Crowdsourcing graphical perception: Using Mechanical Turk to assess visualization design. In *Proc. CHI*, pages 203–212. ACM Press.

Heer, J., Kong, N., and Agrawala, M. (2009). Sizing the horizon: The effects of chart size and layering on the graphical perception of time series visualizations. In *Proc. CHI*, pages 1303–1312. ACM.

Higgins, J. (2004). *Introduction to Modern Nonparametric Statistics*. Brooks/Cole, Pacific Grove, CA, USA.

Jabbari, A., Blanch, R., and Dupuy-Chessa, S. (2018). Beyond horizon graphs. In *Proc. IHM*, pages 73–82. ACM.

Javed, W., McDonnel, B., and Elmqvist, N. (2010). Graphical perception of multiple time series. *IEEE TVCG*, 16(6):927–934.

Krstajic, M., Bertini, E., and Keim, D. A. (2011). CloudLines: Compact display of event episodes in multiple time-series. *IEEE TVCG*, 17(12):2432–2439.

Krzywinski, M. and Altman, N. (2013). Points of significance: Error bars. *Nature Methods*, 10:921–922.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, 63(2):81–97.

Munzner, T. (2014). *Visualization analysis and design*. CRC Press, New York City, NY, USA.

Prolific (2014). Prolific: Demographics. https://app.prolific.co/demographics. [Online; accessed 2021-05-21].

Prolific (2021). Prolific. https://prolific.co/. [Online; accessed 2021-06-07].

Thudt, A., Walny, J., Perin, C., Rajabiyazdi, F., MacDonald, L., Vardeleon, R., Greenberg, S., and Carpendale, S. (2016). Assessing the readability of stacked graphs. In *Proc. GI*, pages 167–174. CHCCS/SCDHM.

Walker, J. S., Borgo, R., and Jones, M. W. (2016). TimeNotes: A study on effective chart visualization and interaction techniques for time-series data. *IEEE TVCG*, 22(1):549–558.