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Citation: Chen, S., Andrienko, N., Andrienko, G., Li, J. & Yuan, X. (2020). Co-Bridges: Pair-wise Visual Connection and Comparison for Multi-item Data Streams. IEEE Transactions on Visualization and Computer Graphics, 27(2), pp. 1612-1622. doi: 10.1109/tvcg.2020.3030411

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Co-Bridges: Pair-wise Visual Connection and Comparison for Multi-item Data Streams

Siming Chen, Natalia Andrienko, Gennady Andrienko, Jie Li, and Xiaoru Yuan

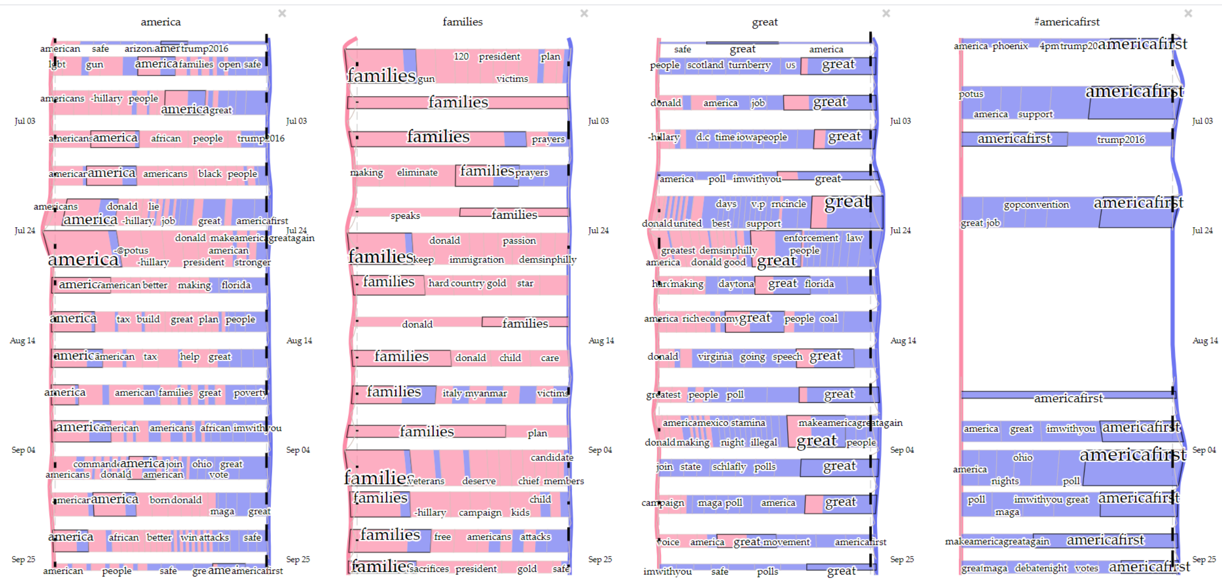

Fig. 1. Examples of comparing the tweets of Hilary Clinton (pink) and Donald Trump (blue) during the presidential election of 2016 with the use of Co-Bridges. Representations of the discussions concerning issues “America”, “families”, “great”, and “AmericaFirst” are juxtaposed for comparison.

Abstract—In various domains, there are abundant streams or sequences of multi-item data of various kinds, e.g. streams of news and social media texts, sequences of genes and sports events, etc. Comparison is an important and general task in data analysis. For comparing data streams involving multiple items (e.g., words in texts, actors or action types in action sequences, visited places in itineraries, etc.), we propose Co-Bridges, a visual design involving connection and comparison techniques that reveal similarities and differences between two streams. Co-Bridges use river and bridge metaphors, where two sides of a river represent data streams, and bridges connect temporally or sequentially aligned segments of streams. Commonalities and differences between these segments in terms of involvement of various items are shown on the bridges. Interactive query tools support the selection of particular stream subsets for focused exploration. The visualization supports both qualitative (common and distinct items) and quantitative (stream volume, amount of item involvement) comparisons. We further propose Comparison-of-Comparisons, in which two or more Co-Bridges corresponding to different selections are juxtaposed. We test the applicability of the Co-Bridges in different domains, including social media text streams and sports event sequences. We perform an evaluation of the users’ capability to understand and use Co-Bridges. The results confirm that Co-Bridges is effective for supporting pair-wise visual comparisons in a wide range of applications.

Index Terms—Visual Comparison, Pair-wise Analysis, Multi-item Data Stream, Social Media

1 Introduction

Nowadays there are more and more data streams in our lives: messages are posted on social media; series of news stories are presented on the Internet; events and actions occurring in sports competitions and games are tracked; people record and share their travel diaries; and many others. These data streams usually involve multiple *items*, e.g. keywords, types of actions or events, participants of activities, or visited places. In exploring these data, one may be interested not only to see patterns of item involvement (what items, when, and how much) within individual streams but also to compare the patterns between data streams. For example, during a presidential election campaign, people may wish to see the differences between the candidates’ agendas and ideas concerning multiple issues and explore how these evolved over time, as reflected in the streams of the candidates’ social media messages. Thus, techniques are required for supporting comparison of such multi-item data streams.

Comparison is a general and important task for many analysis scenarios [28]. Our research goal is to provide a general solution supporting pair-wise comparison of multi-item data streams in terms of the involvement of different items along time. The research challenge is two-fold. First, each data stream by itself is a complex dynamic phenomenon involving diverse items, and it is thus not easy to compare two such streams. Second, it is not obvious how to generate an informative visual summary for the comparison that conveys the similarities and

- *S. Chen, G. Andrienko and N. Andrienko are with Fraunhofer Institute IAIS, Germany. N. Andrienko and G. Andrienko are also with City, University of London, UK. S. Chen is also with University of Bonn, Germany.*
- *J. Li is with Tianjin University, and X.Yuan is with Peking University, China.*

Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of Publication xx xxx. 201x; date of current version xx xxx. 201x. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org. Digital Object Identifier: xx.xxxx/TVCG.201x.xxxxxxx

differences of the dynamic patterns.

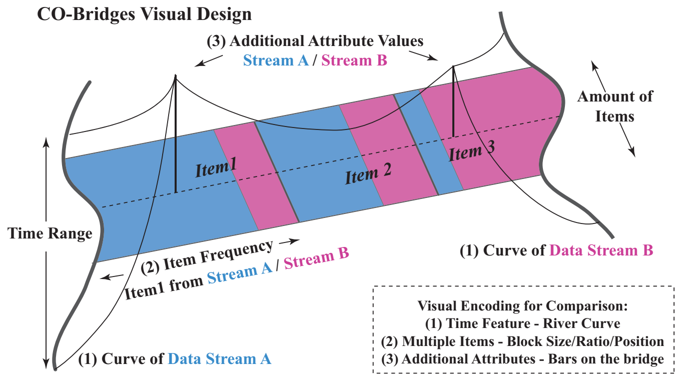

Fig. 2. The visual metaphor for comparison. A bridge connects corresponding segments of two data streams. Multiple items appearing in these parts of the streams are shown on the bridge.

To address the above challenges, we propose Co-Bridges, a visualisation technique for pair-wise visual connection and comparison of multi-item data streams (Figure 2). We base on a river-and-bridge metaphor in the visualisation design. The river metaphor is quite often adopted for representing data streams [21, 53]. We take this popular metaphor but adapt it to the need of supporting stream comparison. In Co-Bridges, each of the two river sides represents one data stream. We choose to show the river flow along the vertical display dimension; hence, the time or sequence is encoded by the vertical axis. The vertical layout allows several river instances to be juxtaposed in a display. The items occurring in the streams under comparison are shown on the bridges connecting corresponding parts of the river sides, i.e., parts of the streams having the same positions along the time or in the sequence. The design is aimed to provide a quick visual summary of the frequently occurring items, their relative frequencies, and the qualitative and quantitative changes over time.

To further support the exploration process, we provide interactive techniques for attribute-based selection of sub-streams for focused comparisons and enable the exploratory operation "Comparison of Comparisons" by juxtaposing several instances of Co-Bridges connecting and comparing different sub-streams. These techniques allow performing sophisticated analytical workflows.

Our paper has the following research contributions:

- **A new visualisation metaphor for pair-wise visual comparison**. Co-Bridges supports both qualitative and quantitative comparisons of general multi-item data streams.
- **Interaction techniques for sub-stream selection and exploratory operation Comparison-of-Comparisons**. The user can select sub-streams according to different criteria and compare dynamic similarity-difference patterns between different sub-stream pairs.
- **Generalizability to different applications**. We tested the design in case studies and conducted a formal user study with two applications: social media text streams and events of a football game. Our studies showed that the design of Co-Bridges is general and easy to use for comparison tasks.

The paper is structured as follows. Section 2 reviews the related work. We define the comparison elements, challenges, and strategy overview in Section 3. We present the design of Co-Bridges in Section 4 and the suggested visual comparison workflow in Section 5. We present two data analysis cases in Section 6 and a user study in Section 7. Finally, we discuss the limitations and the generalizability of the proposed approach and conclude in Section 8.

2 Related Work

We review the related work on data stream visual analytics, the use of visual metaphors for visual analytics, and visual comparison techniques.

2.1 Data Stream Visual Analytics

Various domains are generating multi-item data streams [1]. Social media visual analytics is one of the spotlight field analyzing data streams [17, 49]. Analysis of dynamic text streams may focus on topics and sentiments [24, 44, 55] or event evolution [13, 15, 23, 50]. Diakopoulos et al. [23] used multiple word clouds along the time to visualize how events were reflected in social media. Textflow visualized evolving topics in social media with a visual metaphor of a river [21]. Leadline summarized the event definition as "Topic, Time, People, Location" and visualized the events with multiple timeline streams [24]. Researchers further focused on the dynamic relationship between topics, including topic competition [53] and topic cooperation [44]; the river metaphor was also used in these works. These approaches didn't explicitly focus on stream comparison tasks. OpinionFlow [51] addressed comparison tasks, but the primary focus was on revealing opinion propagation among groups of social media users rather than considering similarities and differences between streams.

Besides social media, much research has been devoted to analyzing various data streams including event sequences, such as gene sequences [54], web clickstream sequences [38], medical record sequences [30], etc. Chen et al. [18] and Guo et al. [31] focused on generating visual summaries of event sequences. Gotz et al. [29, 30] deal with high-dimensional event sequences using aggregation.

Comparison is a general task being explicitly or explicitly involved in many data stream analyses. However, to the best of our knowledge, no prior works address the task of pair-wise visual comparison of data streams. Supporting such comparison can be useful for various applications,

2.2 Visual Metaphors in Visual Analytics

A good visual metaphor can help analysts to explore and interpret information. General design guidelines and tools are described by Borgo et al. [5]. PeopleGarden uses the metaphors of a flower and a garden to encode people's profiles [52]. In Whisper, the sunflower metaphor is used to visualize information spreading among different regions of the world [8]. SentenTree provides a new perspective to understand the relationship among keywords and their context in the sentence and visualize the structure with the tree metaphor [32]. In the following, we discuss the metaphors that related the most to our design, including the river and map metaphors.

Due to the association between the flow of a river and the flow of time, the river metaphor is widely used for different analysis scenarios involving dynamic phenomena [21, 36, 46, 48]. Tiara visualized the text cloud in multiple layers of a theme river-like visualization [48]. RankExplorer developed glyphs indicating the change of ranking in the river metaphor [42]. Other river-like visualizations can indicate branching patterns of topic evolution [21] or lead-lag patterns of topics [46]. Some other designs extend the river metaphor. Episogram visualized the social interactions as curved glyphs along the time [9]. SocialHelix visualized the divergences and how they evolved among different social groups with a DNA-like design [10]. Semantic Space Time Cube visualized the spatial-temporal and topic variation with river and card designs [36].

Another representative series of visual metaphors is map-like visual designs. GMap visualizes clusters and graphs in the form of a cartographic map [25]. Chen et al. proposed a series of map-like visualization, including D-Map [14], E-Map [13], and R-Map [16] for exploring contents of social media. The idea of the map-like visualization is using a familiar concept as a metaphor helping users to explore complex data, e.g. texts or other multi-item data.

Inspired by both river-like metaphors showing dynamic features and map-like metaphors focusing on the spatial arrangement, we design the Co-Bridges metaphor for visual comparison.

2.3 Visual Comparison

One of the important analysis tasks to be supported by visualization is comparison. Gleicher et al. summarized three main approaches to enabling visual comparison: juxtaposition, superposition, and explicit encoding of relationships [28]. For example, genomics sequences were visualized side by side using juxtaposition [2]. Hexagon maps were superposed as information layers in a common display space [39]. Mauve used explicit encoding by linking to correlate the conservative parts of the genomics sequences [22]. There were many works in visualization on supporting visual comparison of different kinds of information, including tree structures [7, 35], spatio-temporal data [4, 37], sequences and time-series [20, 37], images [41], models [3, 33], etc. Von Landesberger summarized the research challenges for visual comparison [45]. Researchers from the perception and psychology domain also conducted studies of perceptual aspects of visual comparison [40, 43]. A tool called Duet was developed to enable data analysis novices easily conduct pair-wise comparisons [34]. By investigating many comparison examples, Gleicher summarized the design considerations for visual comparison [27], which guided us in our work.

Visual comparison of texts is one of the application scenarios related to our research. Text comparison is mostly supported by means of juxtaposition. It was applied, for example, to the results of word embedding [12] and multiple word clouds [11]. Parallel tag clouds combine the techniques of the word cloud and parallel coordinates to support the comparison of keyword usage in multiple documents [19]. Wang et al. proposed several glyph designs supporting the comparison of online reviews for companies [47]. Alexander and Gleicher proposed a visual comparison method for topic models [3]. They allowed analysts to interactively align details of topic models. OCTVis used explicit linking encoding to compare the ontology of different models [26].

Different from previous works, we propose a design for visual comparison based on a new metaphor that can be used for comparing multi-item data streams.

3 Overview

We follow the design consideration proposed by Gleicher [27] to frame our research. We discuss the comparison elements, comparison challenges, comparison strategies, and comparison designs.

3.1 Comparison Elements

Comparison is an analysis with more than one target [6, 27]. Our target data type is general data streams containing multiple different items. A **data stream** is an ordered collection of data records in which each record refers to a time moment or a position (step) in a sequence. In our research, we consider data streams in which data records include or refer to multiple different **items** (entities of any nature), denoted by their labels. Apart from the temporal or sequential references and labeled items, data in the streams may include other components. We shall refer to them as *attributes*.

The goal of analysis in our research is to compare two data streams in terms of the items appearing in the data over time or along the sequence. The comparison concerns the qualitative and quantitative aspects of the item appearance, that is, the item identities and the frequencies of their appearance or degrees of their involvement. As the amounts of information in the full streams may be too large, users should be able to select sub-streams for detailed comparison. A sub-stream is an ordered subset of records from a stream. Sub-streams can be selected based on different attributes available in the stream data.

We give two examples to illustrate the concepts and show the possible stream comparison tasks. In social media, the comparison target can be text streams, such as a series of tweets, produced by different users. The items in these streams are meaningful keywords used in the texts. One can select different sub-streams of these streams for comparison based on attributes of the data, such as text topic, or location from which the messages were posted, or the time of the day when the texts were produced. For example, one may select tweets discussing the issue “healthcare”, see what significant keywords were used in the discussion, and compare the usage of these keywords by different people. Another data example is a sequence of events happening in a ball game conducted by two teams of players. The comparison target is the sequences of the actions and events that happened under the ball possession by the two teams. The items are the players, the actions performed by them, and events like goal or foul.

The comparison tasks can be summarized as follows:

- **Comparison of data stream dynamics**: Compare the temporal or sequential patterns of data streams, focusing on the (**T1**) numerical trends at (**T2**) different levels of granularity.
- **Comparison of items**: Provide (**T3**) qualitative comparison (common or distinct) and (**T4**) quantitative comparison (relative frequencies, absolute amounts, etc.) of the items in the streams.
- **Comparison of comparisons**: Compare overall similarity-difference patterns and numeric trends of different pairs of sub-streams (**T5**).

3.2 Comparison Challenges

The streams may be large (include many data records) and complex (include many data items). Currently, there is a lack of an intuitive approach to the comparison of such data and a suitable method of creating a visual summary for general multi-item data streams. The challenges can be summarized as:

- ***C1****: High cardinality of the item set*, such that a comprehensive view of complete streams is hardly possible.
- ***C2****: Dynamic character of the data* regarding the stream volumes, the presence of different items, and their frequencies or amounts.
- ***C3****: Comparison of sub-stream pairs*, which requires a compact representation of the similarities and differences and their dynamics in each pair.

3.3 Comparison Strategy

A comparison strategy summarizes how we intend to support users in comparing data streams. For creating an appropriate design, we need to envisage how users would possibly conduct the comparison. We assume that users will apply the following strategies for dealing with the comparison challenges [27]:

- ***S1****: Scan sequentially and drill down.* According to the dynamic and sequential nature of the data streams, users will compare items while scanning the streams sequentially. Users can drill down to a time range of interest for a more detailed comparison.
- ***S2****: Iteratively select subsets based on attributes.* Users select data subsets for comparison based on various attributes. The data in the subsets are ordered in the same manner as in the whole streams and can thus be seen as sub-streams and visualised in the same way as the original streams.
- ***S3****: Gain an overview of comparison.* Users obtain an abstracted visual summary of dynamic similarity-difference patterns of a pair of data streams. Summaries for different sub-stream pairs can be compared.

Our design should enable the foreseen comparison tasks and support the users' strategies in addressing the challenges. We describe our visualisation design in the following section.

4 Co-Bridges: Visualisation Design

Figure 2 presents the main idea of our design. An implementation of this design for supporting comparison of social media text streams is used for illustration (Figure 3b).

4.1 Design Rationale: Why Bridge?

Combining the river and bridge visual metaphors, Co-Bridges is a design including multiple connecting bridges for visual comparison of two multi-item data streams associated with two sides of a river.

River metaphor. Our design builds on the Theme River metaphor [21, 48], which presents a single multi-item stream. This metaphor gained high popularity and is considered successful. However, it has not been designed for explicit pair-wise comparison. We extend this idea to supporting comparison of two streams. We maintain the basic concept and appearance of a river but use the river sides to refer to two streams. The shapes of the river sides encode the evolution of numeric features of the data streams, e.g., stream volumes.

Bridge metaphor. We need to make connections between corresponding parts of the two streams for presenting their similarities and differences regarding the items involved. For this purpose, we introduce the metaphor of bridges, which fits naturally to the river metaphor.

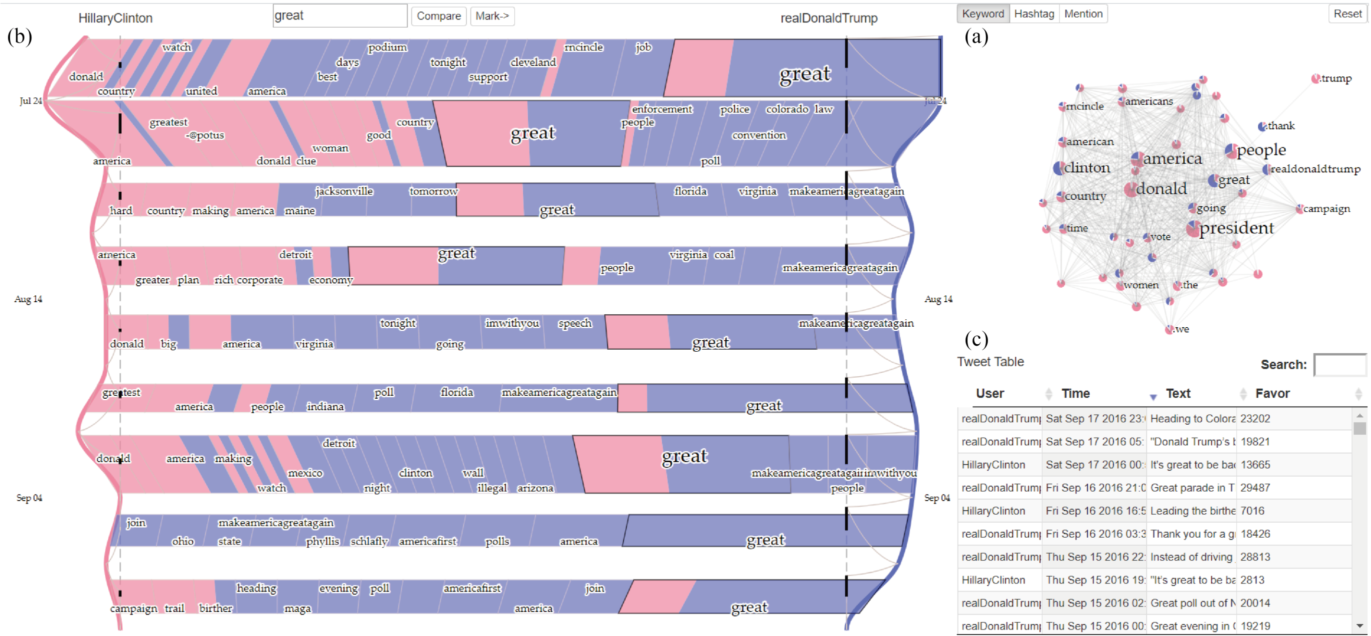

Fig. 3. A visual exploration interface for pair-wise comparison using Co-Bridges is illustrated using social media data (b). The issue selection view (a) provides a graph of significant keywords. When a user selects some keyword in a specific time, the corresponding texts (tweets) containing the keyword are shown in the detail view (c).

4.2 Comparison Design

The design includes two main components: a river and bridges. Two distinct colors are assigned to indicate the two data streams and their items. The two sides of the river are line charts showing the evolution of a numeric characteristic, such as the volume, of the two data streams. Between the river sides, there are multiple bridges connecting the corresponding parts, according to the time or sequential steps, of the two data streams. The bridge interior is used to visualize items from two data streams aggregated over the respective time or sub-sequence of steps. The bridge interior is divided into blocks representing different items. The size of an item block encodes the frequency of the appearance of this item, the degree of item involvement in each stream, or other numeric information concerning the item. To simplify the description, we shall mainly refer to item frequencies. Each item block has two color regions, encoding the item frequencies in the corresponding stream. The order in which the items are put on a bridge is calculated based on $T_{i_{sa}} - T_{i_{sb}}$, where T_{i_s} is the frequency of the item i in the data stream *sa* or *sb* in the selected period. Such ordering puts items that are more prominent in one of the data streams nearer to the corresponding side of the river. The order, color, and size mapping of the item appearances are core design features of Co-Bridges, which reveal patterns of similarity and difference and support both quantitative and qualitative comparison.

The width of a bridge encodes the accumulated frequency of the items. On a bridge, depending on its width, there can be one or multiple lanes of items. Items can be separated into different lanes based on selected attributes, or the lanes can be used for showing more items without occlusions. There is a bar in the corner of each side of the bridge, which can be customized for showing value statistics of some numeric attributes for the period the bridge corresponds to. The time or sequence length is equally distributed among the bridges, but each bridge has a different width proportional to the combined stream volumes. To mark the exact time range, there are two gray curved lines linking the bridge sides to the accurate temporal or sequential positions on the river banks, The appearance of these visual elements fits the bridge metaphor. We summarize how our Co-Bridges design supports the comparison tasks.

- **River sides**: Visualizing and comparing numeric dynamic features of two streams. The line plots making the river sides represent the evolution of a quantitative aspect of the data streams. (T1). Multiple-level zooming along the banks enables comparisons at multiple levels of granularity. (T2)
- **Bridges**: Visualizing and comparing multi-item features.
  - Qualitative comparison of the presence of items in the two streams is supported by showing the item labels (T3).
  - Quantitative comparison is supported by employing the sizes and positions of the item blocks, the heights of the curves, and the height of the bars on the bridges (T4).
- **Visual summary**: To support the comparison of comparisons, several Co-Bridges are laid out side by side as small multiple displays (T5) (Figure 1).

In the social media example, (Figure 3b), we processed 3,416 tweets from Hillary Clinton (indicated by pink) and Donald Trump (blue) in the 2016 presidential election in the USA. Each bridge corresponds to one week. We have selected the sub-streams containing tweets including the keyword "great". The visualization shows the contextual keywords (items) used in the texts. The line plots (river sides) show the amounts of the tweets mentioning "great". On most bridges, the keyword "great" is laid out at the Trump's side, which indicates that Trump used this word more often than Clinton. The width of the bridge near Jul.24 indicates that more tweets concerning "great" were posted in that week. We set the heights of the black bars on the bridges to show the counts of the followers who liked the tweets in the corresponding periods. We can see that Trump's tweets got more "likes".

4.3 Parameter Setting

In our Co-Bridges design, four main parameters affect the visual appearance and possibilities for comparison.

Granularity of time. Users can customize the granularity based on the defined tasks (e.g. Figure 7 – daily). We propose an automatic granularity setting method based on an empirical parameter of how many bridges are shown at the same time. This parameter affects the overall visual appearance and the expressiveness of each bridge. We found $5-25$ bridges to be a good default setting. In our evaluation study, we tested two examples with the number of bridges 9 and 20, and both worked well. Were there too many bridges, the details on each bridge could not be clearly shown. With too few bridges, too many items would be aggregated. Thus, we choose the granularity of time that gives a moderate number of bridges.

Number of extracted items. Due to space restriction, it is not possible to show hundreds or thousands of items at the same time. We let Co-Bridges show the items with top frequencies, assuming that such items are more important than others. The frequency threshold needs to be adapted to the specific properties of available data. Thus, in the social media example, we show the top 10% of the items according to their frequencies.

The number of visible labels. Each item has a descriptive label: keyword, action name, entity name, event category, etc. Showing too many labels will result in visual clutter and occlusions, which will hinder the user's perception. We, therefore, determine the space available for the label in each item block on a bridge and show the label when the space in this block, possibly, combined with unused spaces in the neighbouring blocks, is sufficient. The labels that would overlap with others are hidden. More labels are displayed when a bridge is wider and thus provides more space. In this case, the labels are put in different vertical positions.

Selection of colors. We select colors with a strong contrast to ensure that data items are visually distinguishable.

4.4 Design Alternatives

We consider design alternatives in two levels: the overall layout and the item-wise comparison.

Fig. 4. An alternative for the overall layout. The positions along the X-axis correspond to items, and the y-axis represents time.

Overall layout. In our alternative design, the line plots are put on the sides, so that the space in the middle can be utilized for item comparison (Figure 4). The vertical axis represents time, and the items are laid out along the horizontal dimension in the same way as in Co-Bridges, based on the accumulated differences between the item frequencies in the two streams. The items are represented by segmented vertical bars, such that the heights of the segments are proportional to the frequencies of the item appearance in the respective streams.

There are the following differences of the alternative design from the Co-Bridges: 1) The items are laid out globally while Co-Bridges layout the items locally, i.e., on each bridge independently. 2) In the design alternative, the items can be easier compared among different time periods, but the efficiency of the space usage is low. The visual marks (i.e., the bars) representing the items become too small to discern and to compare the item frequencies in the streams.

We performed a user evaluation for comparing the effectiveness of this design to that of Co-Bridges. The study is described in Section 7. Our evaluation results indicate that, generally, Co-Bridges is more effective than the alternative for comparison tasks.

Item-wise comparison. In an item block, the two color sections corresponding to the two data streams can be put together in different ways. The users are supposed to compare the sizes of these sections. According to [28], there are generally three approaches to supporting comparison: juxtaposition, superposition, and explicit encoding of differences or relationships. In application to the color blocks, these approaches can be described as follows.

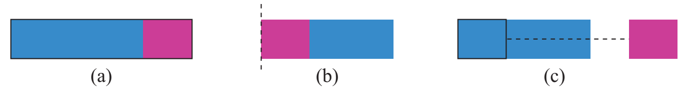

Fig. 5. Illustration of item-wise comparison alternatives: (a)Juxtaposition; (b)Superposition; and (c) Explicit encoding.

- *Juxtaposition* puts two color sections side by side, which is the design we choose. The advantage of the juxtaposition is that both the individual frequencies of the item in the two data streams and the total frequency of the item can be clearly seen (Figure 5a).
- *Superposition* better shows the difference between the frequencies but lacks the capability to show the overall frequency of an item (Figure 5b). When the smaller section is shown in a semi-transparent mode, the color fusion can lead to visual clutter.
- *Explicit encoding* can facilitate assessing the difference; (Figure 5c) however, the use of additional marks complicates the appearance. These marks would be hardly discernible in the "small multiples" mode used for the "comparison of comparisons" operation. Therefore, we avoid additional encoding of the differences, which would complicate the design.

By considering the two-level design alternatives as baselines, we conclude that the design of Co-Bridges is more suitable for our purposes.

5 Interactive Visual Comparison

In this section, we propose a workflow for the interactive visual comparison by means of Co-Bridges (Figure 6). To illustrate the supporting functions, we have implemented a visual analytics system (Figure 3) customized to Twitter Data. Users' comparison strategy (Section 3.3) is supported through the visual exploration workflow.

5.1 Comparison Entry: Sub-stream Selection

At the beginning of a session, Co-Bridges show an overview of all data. The bridges accommodate the items with the highest frequencies in the whole dataset. For a more detailed exploration, users need to select subsets of the data, further referred to as sub-streams. We provide three ways to enable users to select sub-streams for comparison: textual query, item graph node selection, and iterative attribute-based filtering applied to the currently explored (sub)set. These three ways complement each other and provide exploration flexibility for the users.

The first way is the textual query tool, which provides an input box for users to type in the expected item labels. Suggestions and auto-completion based on processed items will pop up to help users better search for appropriate items. The textual query is a classical way of item selection. The advantage is that the textual query provides a comprehensive entrance that any words in the data can be queried. Another advantage is that such tools are quite familiar to users. The drawback is that users may not know what items to search for.

The second way is aimed to compensate for the latter drawback of the use of a textual query, We create a graph display of the items and their co-occurrence relationships (Figure 3a). Each node represents an item. The size and/or color of a node can encode item-related information. In particular, the node size can encode the overall frequency, and colored segments can represent the frequencies in the two streams. A link between two nodes indicates the co-occurrence relationship between two items. If two items occur together more often, their positions will be closer in the force-directed layout. The rationale for showing co-occurrences is that they are likely to reflect important relationships among items, which may inform and guide users' selections. To avoid clutter, we apply a collision detection and resolving technique for both labels and nodes. Users can select nodes by clicking or brushing to

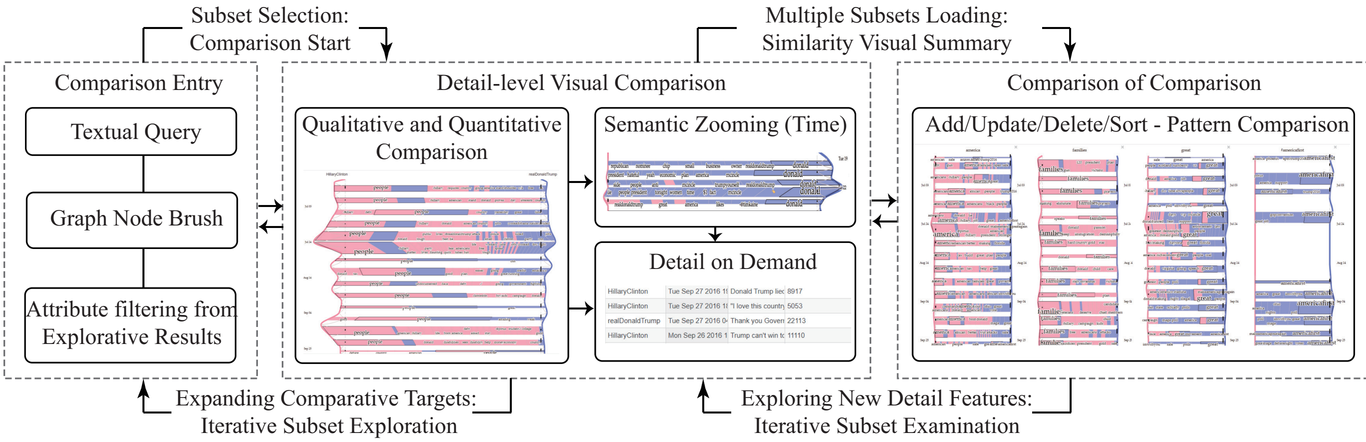

Fig. 6. Visual comparison workflow. Iterative visual exploration is supported and Comparison-of-Comparisons provide further insight. .

select the sub-streams containing the corresponding items for comparison. The graph view can be customized for different applications. In the social media example, we construct a graph of keywords appearing in the texts (Figure 3a) and, additionally, a graph of hashtags (words starting with #) and a graph of usernames mentioned in the texts (words starting with @).

Third, users can employ an attribute-based filter, in which any attributes available in the data can be used. Generally, the design of the attribute-based filtering tool is application-dependent (it depends on the attributes present in the data). However, there is a common operation: selection of items shown on the bridges for iterative comparison (**S2**). In response, the sub-streams involving the selected items are shown, and the other items related to the selected items can be seen. This feature encourages users to explore relationships between items.

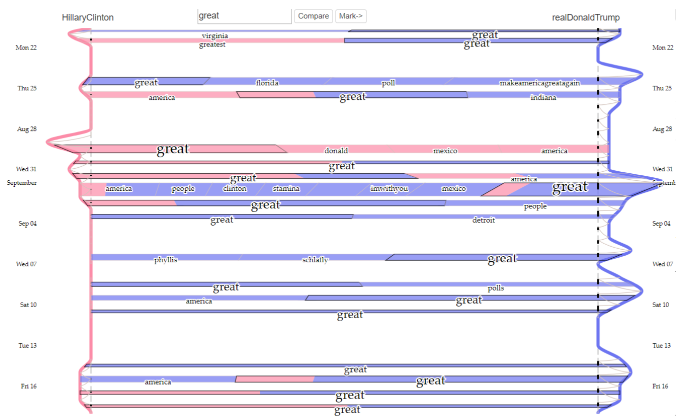

Fig. 7. By brushing a time period, users can conduct semantic zooming to examine finer patterns with smaller temporal granularity.

5.2 Detail-level Visual Comparison

At this level, the user performs detailed comparison of two selected sub-streams. Both the visual design and interaction facilities work together to achieve the comparison tasks.

In Co-Bridges, users can observe the overall temporal pattern by scanning sequentially along the river direction (**S1**). Peaks and general trends are reflected in the shapes of the river sides, i.e., the line plots. For example, in Figure 3b), users can compare the trends of the sub-streams containing the item “great”. There are two large peaks on the left (Hillary Clinton), whereas Trump (on the right) consistently posts more tweets containing “great”.

To investigate more details, users can brush a time period along the river side. We provide semantic zooming that exposes more details in a finer granularity of time. In the same example, users brush the time period from Aug.22 to Sep.18. The zoomed Co-Bridges view shows the temporal patterns with the data aggregated by days (Figure 7). More details are revealed: in some days (e.g. Aug.29, 31), Clinton also mentioned “great” several times.

To further support interactive qualitative and quantitative comparison, we provide, additionally to the visual encoding, highlighting and selection functions. When a user hovers an item, the same item appearing in other time periods will be highlighted with a red stroke, which helps users see the variation of the item’s frequencies and relative positions over different bridges. Quantitative information about the item also pops up. Items shown in Co-Bridges are also selectable. As described previously, selection of an item results in selecting sub-streams of data containing this item. For the selected sub-streams, an additional instance of Co-Bridges is created. Multiple instance of Co-Bridges shown simultaneously serve as visual summaries of pair-wise similarities and differences, supporting the exploratory operation “comparison of comparisons”.

5.3 Visual Summary Level: Comparison of Comparison

When users select different sub-streams for detailed comparison, they can put interesting instances of Co-Bridges into the Comparison of Comparison view (Figure 1). This view contains the small multiples of the visual comparison summaries for different pairs of sub-streams (**S3**). In this way, the users can compare the similarity-difference patterns shown by the visual summaries. A text above each Co-Bridges instance indicates the criterion by which the sub-streams were selected.

The possible patterns that can be compared include: (1) Dominating items for one side; (2) Items with significant quantitative difference; (3) Items co-occurring with distinct contextual items; (4) Items with different temporal patterns of appearance. For example, in Figure 1, we can see the following differences: (1) Only Trump mentioned “#AmericaFirst”, and he mentioned it as a slogan. (2) Clinton mentioned “families” more often, and Trump liked to say “great”. These words are mostly put on one or another side, which highlights the difference. (3) Concerning the item “America”, both politicians mentioned it quite frequently. Clinton mentioned it slightly more frequently and often in connection to words like “gun”, “people”, etc, while Trump preferred to use keywords “great” and “MakeAmericaGreatAgain”. (4) The time pattern of Trump’s “#AmericFirst” is different from others, with a gap at Jul.24 and late August.

The “Comparison of comparisons” view is linked to the detailed comparison view. Users can brush the time in the detailed view, and the small multiples will be updated to show the selected time interval in more detail. When users highlight items in one Co-Bridges instance, the occurrences of the same items in other instances will also be highlighted to help users see similarities and differences in the times, frequencies, and co-occurrences with other items. This helps users con-

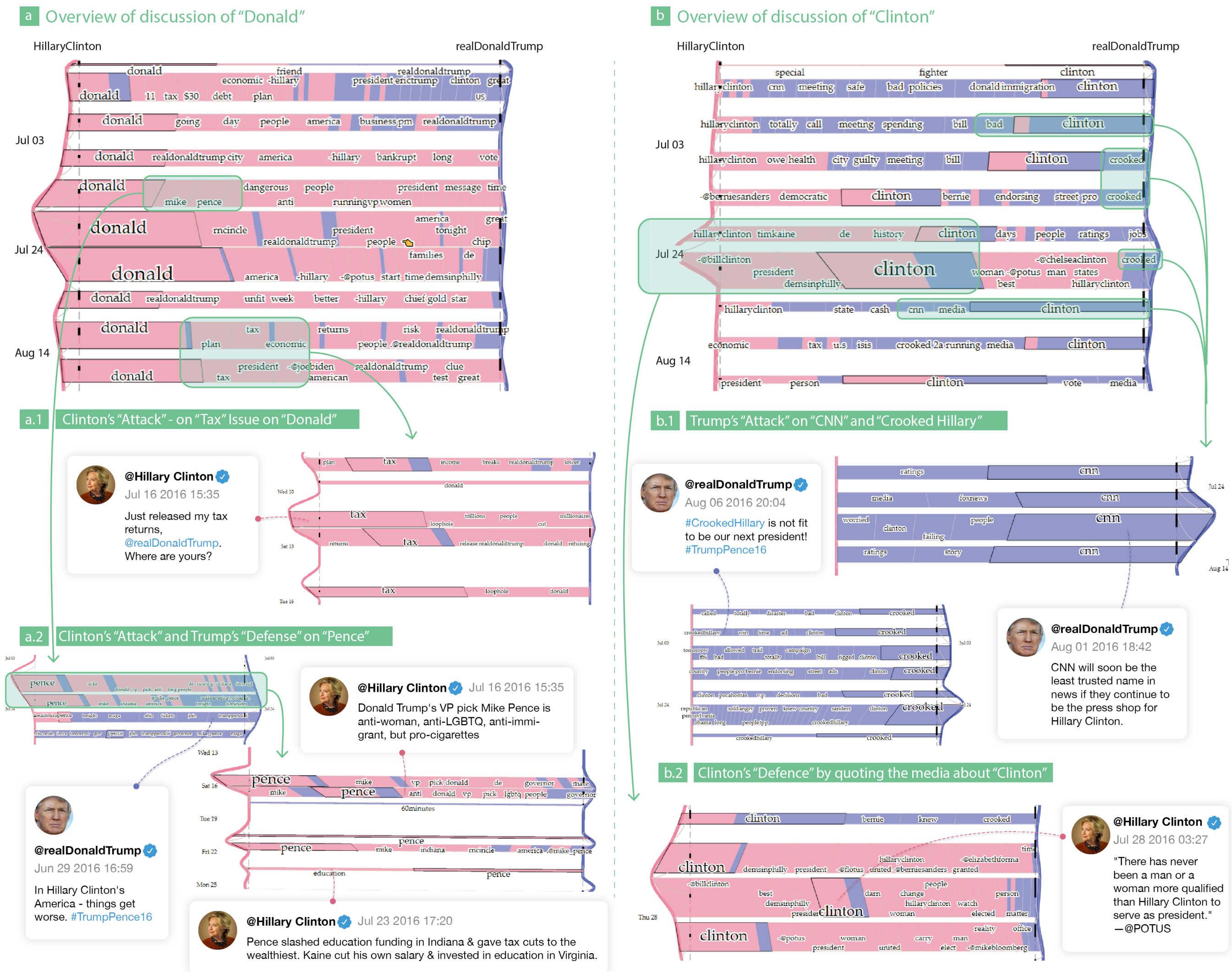

Fig. 8. Comparative exploration of the tweets of Hillary Clinton and Donald Trump in the U.S Presidential Election Campaign of 2016. We investigate the virtual battle between them looking at the sub-streams containing the items (a) "Donald" and (b)"Clinton". From the discussion overview of "Donald" , we iteratively explore how Clinton "attacked" Donald on (a1) "tax" and (a2) "Pence" issues as well as Trump's "defence". From the discussion overview of "Clinton", we identified (b1) Trump's "attack" with words like "Crooked" and "CNN" as well as (b2) Clinton's defence. Interesting patterns can thus be derived from Comparison of Comparisons.

nect information pieces from multiple views. Users can interactively add or delete an instance of Co-Bridges. A function of sorting the small multiples based on different criteria, e.g. accumulated difference of the items, is provided.

5.4 Iterative Exploration

The combination of the visual displays and interaction facilities enables high flexibility in comparing the data streams. We support multiple ways of selecting sub-streams to be compared. Users can refine the exploration through further selections within already selected sub-streams and/or by focusing on smaller time intervals. In the "Comparison of comparisons" view (Figure 1), visual summaries can be added, deleted, and updated according to the user's current interests. In the iterative process, various insights can be derived by exploring different aspects of the data streams (Figure 8).

6 Generalization Study

To test the generality of the Co-Bridges design and approach to comparative exploration, we apply it to two example datasets: texts from social media and events that happened in a football game. We test whether Co-Bridges can enable us to obtain interesting findings from these datasets.

6.1 Social Media Comparison

With Co-Bridges, we have found several interesting patterns by comparing the tweets of Hillary Clinton and Donald Trump in their presidential election campaign of 2016.

From the overview, we find that "Donald" and "Clinton" were mentioned frequently by Clinton and Trump, respectively. It indicates that they commented and criticized each other. We are curious about what they usually said when they mentioned their opponent's name. Co-Bridges provides two comparative overviews for the items "Donald" (Figure 8a) and "Clinton" (Figure 8b). In the texts related to "Donald", words from the Clinton's texts dominated. The words "Tax", "People", and "Pence" were frequently mentioned. We select "Tax" and find that Clinton continuously criticized Trump's "tax plan", which is good for the wealthy people. Besides, Clinton challenged Trump's tax declaration (Figure 8-a1). By exploring "Pence", we found that Clinton criticized Pence for being anti-women, anti-LGBTQ, anti-immigrant, etc. (Figure 8-a2). Trump somehow tried to "fight back" by using "TrumpPence16", signifying the close collaboration between Pence and him. By semantically zooming in to the daily level, we find that on Jul.23 Clinton criticized Pence for slashing education funding.

In the texts related to "Clinton" (Figure 8b), not only Trump mentioned Clinton many times, but also Clinton herself mentioned this item frequently in the weeks around Jul.24. Different from the "soft" words Clinton used, Trump used the words like "crooked" and "bad" in relation to Clinton and CNN. He even created a hashtag "#Crooked-Hillary" (Figure 8b1). For the Clinton's side, we are curious how she defended herself when mentioning her name. We drill down to the week around Jul.24. We find that Clinton was re-posting the messages praising herself from other social media users or media accounts, e.g. Potus, with most of the words being good (Figure 8b2).

In this case, we compared the text streams of Clinton and Trump regarding multiple discussing issues and different levels of time granularity. The iterative exploration and "Comparison of comparisons" enabled us to compare multiple aspects of the two data streams.

6.2 Football Event Sequence Comparison

In this example, we apply Co-Bridges to compare the sequences of events that happened during a football match under the ball possession by two opponent teams. Our example dataset describes the game of Brazil vs. Belgium in the World Cup 2018. The event records include two kinds of items: action types (shooting, passing, etc.) and the names of players who performed the actions. We select the sub-streams consisting of the recorded shooting events (not necessarily successful) by an attribute-based filter. Figure 9-left illustrates the comparison of the event sequences between the teams. Brazil is encoded in pink and Belgium in blue. The final result of the game was Brazil 1:2 Belgium. Among the scores, there was an own-goal of Brazil. Our session of comparative exploration includes the following activities and respective findings:

- **Exploration of different stages of the game**: In general, there were more shooting attempts from the Brazil side, but in some time periods, e.g. around 2:45, Belgium shot more times.
- **Qualitative and quantitative item comparison**: We see most of the actions co-occurring with the shots are passing actions. Douglas Costa and Neymar were among the major players related to shooting (i.e., they shot or assisted) in Brazil. On the Belgium side, De Bruyne was related to most of the shooting actions.
- **Item comparison in different times**: We can compare the dynamics of shooting-related players and actions at different times. Neymar was more active in the first quarter and the last quarter of the game. Douglas was especially active and involved in multiple shots during 3:00-3:15. We can also identify time periods with specific features. For example, at 2:05-2:15, there was a high number of distinct Belgian players involved in shots.

The possibility of applying the approach to different kinds of data signifies its generality. Moreover, the two applications of Co-Bridges were also tested in the user study, and the results confirmed that users can successfully use our tool and obtain most of the above-mentioned findings (Section 7).

7 User Evaluation

To evaluate the effectiveness of Co-Bridges, we conducted a between-subject user study. In this controlled study, we compare Co-Bridges to the baseline shown in Fig. 4 using both the Twitter data and the football events data.

7.1 User Study Method

The main independent variable explored in the study is the use of Co-Bridges or the baseline visualization. Given that the Twitter and football datasets have different types of data and different complexity, we analyze and report the result of each dataset separately, and thus, do not include the dataset as an independent variable for analysis.

Participants: We recruited 38 participants (17 females), including visualization researchers (8), college students who majored in visualization (17), and participants without visualization experience (15).

Datasets: We chose the Twitter data and the football data described in Section 6. The twitter data has a larger number of items, and they are more diverse (words), while the football data has fewer items and a smaller number of item types (events and players). In the Twitter data, we select all Hillary Clinton's and Donald Trump's Tweet data sub-streams involving "great" (Figure 3b). In the football data, we select the sub-streams containing the "shots" events (Figure 9). To ensure a fair comparison, we controlled the aggregation level, showing the labels at the same aggregation level for Co-Bridges and the baseline visualization.

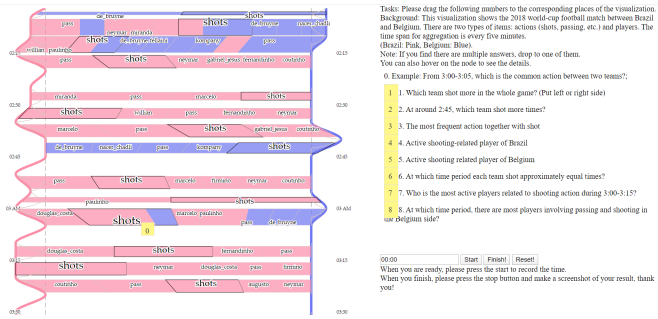

Fig. 9. User study interface with the drag-and-drop tool for task answering. It is one of the four analysis environments, in which Co-Bridges is used with the football event sequence data.

Procedure and Tasks: The participants were divided into two groups with 18 participants in each. All participants were presented a video tutorial explaining the Co-Bridges and the baseline visualization. To mitigate the possible learning effect, group 1 first worked on Co-Bridges design with twitter data (Figure 3b) and then the baseline visualization with football data (The figure is in the supplementary material). Group 2 first worked on the baseline visualization with Twitter data (Figure 4) and then the Co-Bridges design with football data (Figure 9). For each dataset, we conducted a between-subject study for evaluating the accuracy and completion time of their corresponding tasks.

We developed an interactive drag-and-drop environment for the user study (Figure 9). In this environment, each participant gets an image of the visualization to evaluate with only the hovering function and a list of tasks. Each task has a label $1,2,3\ldots8$. To answer the tasks, the participants needed to drag these labels to the corresponding parts of the visualization in the provided image, according to their understanding of the tasks. We record the accuracy and completion time of this process, which reflect participants' understanding and usage of the visualization. Dropping the corresponding task labels to the correct parts of the images indicates a correct answer. We also provide an example for the participants (e.g. Figure 9 – task0). For this study, we presented four settings across two groups of users (two visualizations $\times$ two datasets).

There are eight concrete tasks for each dataset, based on the general tasks T1 - T4 in Section 3.1. An example task list for the football data is in Figure 9. The ground-truth answers are correspondingly in Section 6.2. Information with task details can be found in the supplemental materials. After completing the tasks, participants were asked to fill out a questionnaire focusing on their subjective evaluation of the following three criteria: (1) Ease/difficulty in understanding Co-Bridges and the baseline visualization; (2) Ease/difficulty in using the two approaches for comparison; (3) the aesthetic appearance of the two approaches. Besides, we also asked for their general feedback.

7.2 User Study Results

Each user submitted two screenshots of their task completion. The completion time was recorded. The accuracy was verified based on the ground truth. For the tasks with multiple possible answers, the selection of any of these answers was treated as a correct answer. For both datasets, we performed unpaired t-tests for comparing the significance in the difference of the accuracy and the completion time between the two visualizations. Finally, we performed the paired t-tests for all the participants about their subjective feedback on the aforementioned three criteria.

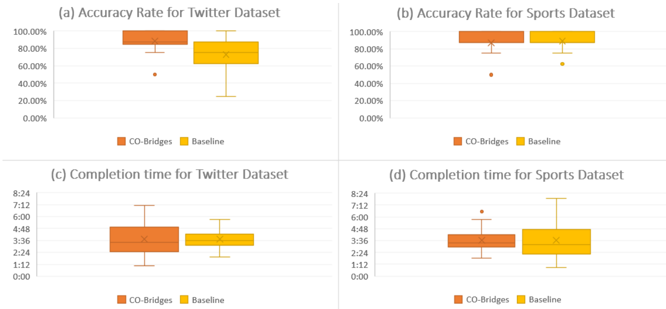

Fig. 10. Accuracy rate and completion time for the Twitter and football datasets with the Co-Bridges and baseline visualization. Each group has 18 participants, and the time unit is one minute.

7.2.1 Twitter Dataset

Significant difference was found in the accuracy rate ($t_{(36)} = 2.92$, $p < 0.01$, $\eta^2 = 0.95$) (Figure 10a). The analysis result indicated that Co-Bridges (M=0.88, SD = 0.13) enabled significantly higher accuracy than the baseline visualization (M=0.73, SD = 0.18). By examining the detailed task accuracy, we found that the accuracy of tasks 1 - 5 with both designs was relatively high (> 80%). Tasks 6, 7, 8 are 94.4%/77.8%, 72.2%/44.4%, and 61.1%/11.1% (Co-Bridges/baseline visualization). It turned out that Co-Bridges is easier to use for local comparisons in particular time ranges. The completion time difference was not statistically significant. The times for Co-Bridges (M=3.73 min, SD = 1.65) and baseline visualization (M =3.72 min, SD=0.91) were quite similar (Figure 10c). The variance of the completion times with the use of Co-Bridges was much larger for this dataset.

7.2.2 Football Dataset

The complexity of the football data is lower. Both groups achieved relatively high accuracy rates ,and there was no statistically significant difference: Co-Bridges (M=0.88, SD = 0.12) and baseline visualization (M=0.87, SD = 0.15) (Figure 10b). For tasks 1 - 6, the accuracy rates for both designs were high. The accuracy rates of Tasks 7 and 8 were 77.8%/66.7% and 50%/66.7% (Co-Bridges/baseline visualization). We found that the accuracy of Task 8 in Co-Bridges was relatively low due to the limitations of Co-Bridges, which will be discussed in the next section. The completion time of the two designs was also not significantly different: Co-Bridges (M=3.63 min, SD=1.89) and baseline visualization (M=3.64 min, SD = 1.19). In short, with this study, it was confirmed that our approach can be applied to different applications, and participants could understand and conduct a comparison with Co-Bridges (average accuracy rate:86.8%).

7.2.3 General Subjective Feedback

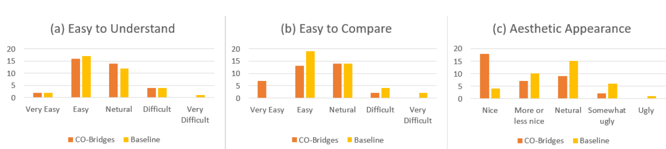

Fig. 11. Subjective feedback from 36 participants, including the ease for understanding, comparison and the aesthetic appearance.

The questionnaire uses a 5-point Likert scale. We map the five points from best to worst to 1, 0.75, 0.5, 0.25, and 0. Because both groups of participants used Co-Bridges and the baseline visualization, we conducted paired t-tests for the three quantified subjective feedback (Figure 11). For the ease of understanding, there was no significant difference for the participants: Co-Bridges (M=0.61, SD=0.19, between neutral and easy to understand) and baseline visualization (M=60, SD=0.22, between neutral and easy to understand) (Figure 11a). For the ease of comparison, the opinions from the participants towards the two designs are significantly different ($t_{(36)} = 2.17$, $p < 0.05$, $\eta^2 = 0.95$) (Figure 11b). Co-Bridges (M=0.67, SD = 0.21, between neutral and easy to use) were regarded better for the comparison tasks than the baseline visualization (M=0.58, SD=0.22, between neutral and easy to use). For the aesthetic appearance, the users preferred Co-Bridges more. The difference was significant ($t_{(36)} = 4.31$, $p < 0.001$, $\eta^2 = 0.95$) (Figure 11c): Co-Bridges (M=0.78, SD = 0.25, between more or less nice to nice) and the baseline visualization (M=0.57, SD = 0.24, between neutral to more or less nice). Some participants mentioned that the baseline visualization wastes more space and the items are smaller.

7.3 User Study Summary and Discussion

Our study confirmed that Co-Bridges designs are generally understandable and can be used to conduct comparison tasks. For a simpler dataset (football), Co-Bridges achieved the same high accuracy as the baseline visualization. For a more complex dataset (social media), Co-Bridges had higher accuracy for conducting comparison tasks, while taking a similar completion time as the baseline visualization. Subjective feedback also reflected participants' preference for Co-Bridges.

The evaluation results are generally positive and provide evidence of the good potential of our approach. We investigate the task for which the accuracy was low in the football application. The task is to identify the time period with the most involvement of players from the Belgium side (Figure 9-task8), which requires quantitative comparison. The correct answer is 2:10-2:15, with four players involved. We examined the wrong answers and found that many wrong answers referred to 2:40-2:45 with three players. One possible reason for the failure might be that the people might be misled by the dominating visual effect of Belgium in the bridge for the interval 2:40-2:45, even though this bridge is thinner and the players are less than at 2:10-2:15. This indicates that the Co-Bridges design might not be suitable for global comparisons with small differences between time intervals. The interaction functions in the visual analytics system can be helpful to compensate for this weakness. At the same time, Co-Bridges are especially well suited for local comparisons, which can be confirmed by a positive example. The answer to task 8 in the social media dataset (Figure 3b) should be the word "MakeAmericaGreatAgain". In Co-Bridges, the word is laid out on the rightmost and stands out. However, in the baseline visualization, it is not easy to spot this answer. This explains why the accuracy rate of task 8 for Co-Bridges was much higher than for the baseline visualization.

We also interviewed several users, and most of them expressed positive feedback regarding our method. We were especially interested to test the understanding and usage among the audience without visualization background. These participants expressed that the bridge metaphor triggered their curiosity to explore the visualization.

8 Overall Discussion and Conclusion

We have conceived and developed Co-Bridges as a general, widely applicable visual comparison approach. We presented the approach in general, domain-independent terms, and we tested it in two quite different domains. We have several take-away messages for applying Co-Bridges to a new dataset. First, choosing different types of elements for comparison makes the application range even wider. For example, in the Twitter dataset, we can compare data related to different users, different keywords from the texts, different hashtags, different topics extracted by topic modeling, or streams of the same user produced in different time periods, or event streams of different users from different periods (e.g., texts from Obama and Trump produced during their respective election campaigns). It is also the motivation for us to define Co-Bridges as general as possible. Second, the river design is, in principle, applicable for the comparison of dynamic streams with new data appearing over time. Third, Co-Bridges can be applied to outcomes of various data processing and analysis methods, such as entity recognition, topic modeling, event extraction, and others.

A general limitation of the Co-Bridges is the scalability regarding the number of distinct items. The current solution is to show the most prominent items and to enable flexible selections for seeing more details. In the future, we shall also consider providing further semantic zooming in the horizontal dimension.

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