VIStory: Interactive Storyboard for Exploring Visual Information in Scientific Publications

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ABSTRACT

Many visual analytics have been developed for examining scientific publications comprising wealthy data such as authors and citations. The studies provide unprecedented insights on a variety of applications, e.g., literature review and collaboration analysis. However, visual information (i.e., figures) that are widely employed for storytelling and methods description are often neglected. We present *VIStory*, an interactive storyboard for exploring visual information in scientific publications. We harvest the data using an automatic figure extraction method, resulting in a large corpora of figures. Each figure contains various attributes such as dominant color and width/height ratio, together with faceted metadata of the publication including venues, authors, and keywords. To depict these information, we develop an intuitive interface consisting of three components: 1) Faceted View enables efficient query by publication metadata, benefiting from a nested table structure, 2) Storyboard View arranges paper rings – a well-designed glyph for depicting figure attributes, in a themeriver layout to reveal temporal trends, and 3) Endgame View presents a highlighted figure together with the publication metadata. The system is especially useful for scientific publications containing substantial visual information, such as the visualization publications. We demonstrate the effectiveness of our approach using two case studies conducted on past ten-year IEEE VIS publications in 2009 - 2018.

CCS CONCEPTS

• **Human-centered computing → Visualization systems and tools**.

KEYWORDS

visualization survey, document visualization, image browser, faceted metadata

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1 INTRODUCTION

Publications are one of the most important outcomes of scientific research. Together with the development of science itself, substantial amounts of scientific publications have been generated. Though digital libraries like *Google Scholar* and *Microsoft Academic* provide powerful searching and browsing functionalities, they are often found ineffective for high-level tasks such as collaboration analysis. Visual analytics has gained intense interest in exploring scientific publications, as it can enable human cognition and reasoning with machine's powerful computing capacity [16]. Vast amounts of visual analytics have been developed that facilitate applications including literature review and citation analysis [4, 11, 18, 30].

Prior visual analytics, however, typically focus on metadata of scientific publications such as authors and citations [7], while neglect visual information (i.e., figures) that are employed for describing facts, methods, or telling stories [27]. In fields such as visualization, research processes generate imagery data [3] that can substantially reflect content and quality of the research. Taking visualization publications for an example, studying the visual information can benefit the field from multiple perspectives: to generate compact visual representations [27], to guide design processes to make memorable, recognizable, and recallable visualizations [1, 2], and to provide quality metrics for evaluating visualizations [14, 21].

1.1 Users and Tasks

In this work, we aim for exploring visual information in scientific publications, which can benefit different users in addressing various tasks, e.g.,

- *Students* would like to compare profiles of different authors/topics when choosing supervisors/research topics.
- *Researchers* wish to understand what the others have developed when expanding their research areas.
- *Reviewers* may need to confirm if a visual design has been published when reviewing papers.

1.2 Requirements

Inspired by *Treevis.net* [24], we opt to develop an interactive storyboard to facilitate exploration. We consider that the storyboard should meet the following requirements:

- *R1. Automation*: The system should enable automatic collection of visual information from scientific publications. In this way minimum maintenance efforts are required, rather than heavy manual work by professional experts.
- *R2. Multi-faceted analysis*: The system should support multi-faceted analysis to meet different tasks, e.g., to help students find active researchers in the field, or to assist researchers in revealing trend of research topics in recent years.
- *R3. Intuitive visual design*: The system should incorporate intuitive visual design to effectively depict hidden information from figures in scientific publications. More details are presented in Sec. 4.1.

1.3 Contributions

We develop *VIStory* – an interactive storyboard that fulfills the above requirements. Our contributions are presented in the remaining parts of this paper.

- First, we develop an automatic method to extract figures and multi-faceted metadata from scientific publications. A total of 1171 figures are collected from past ten-year IEEE VIS publications in 2009 - 2018. A nested table structure is constructed to support efficient query of these figures. (Section 3)
- Second, we design a compact glyph design of paper ring that represents multi-dimensional attributes of figures in a publication. The paper rings are arranged in a themeriver layout in the Storyboard View for depicting temporal trends. The interface further includes Faceted View and Endgame View to support details-on-demand exploration. (Section 4)
- Lastly, we present two case studies conducted on the collected figures, to support real-world usage scenarios: author profile probe and VIS trend analysis. (Section 5)

2 RELATED WORK

2.1 Visual Document Analysis

The plethora of scientific publications poses challenges for literature review. Though digital libraries such as *Google Scholar* and *Microsoft Academic* enable search by concepts or keywords, researchers can easily lose focus as little abstraction of tremendous raw publications are made by the digital libraries [4]. Many visual analytics have been developed to fill the gap. The systems can be categorized by data types of multi-faceted metadata including authors, references, title, and publication date [7]. Exemplary work include PaperVis [4] and CiteRivers [11] for citation, and egoSlider [30] and Vis Author Profile [18] for authorship analysis. Coupled with advanced analysis techniques and intuitive visual designs, these systems have been proven effective in facilitating the understanding and assessment of scientific publications [7].

However, only a few visualizations are developed for depicting visual information in scientific publications. Strobelt et al. [27] organized key figures and important terms in a compact manner to generate an abstraction for documents. Schulz [24] collected all tree visualization techniques, and developed a reference system that supports interactive exploration. A similar reference website was later developed for text visualization [17]. Unfortunately, the visualizations are either suitable for only a small amount of documents [27], or relying heavily on developer expertises for maintenance [17, 24]. Instead, this work aims for interactive storyboard for vast amounts of figures automatically extracted from scientific publications.

2.2 Image Browser

To visualize massive amounts of figures calls for effective image browser. A common approach is to organize images in a layout based on pairwise image similarities [22]. The layout has many variations, such as Neighbor-Joining tree [6], multidimensional scaling [15], Voronoi treemap [28], or picture collage [19]. Some image browsers make use of images' semantic information that can be generated from conventional image annotation [32] or emerging deep learning [31]. Besides similarities and semantics, images can also comprise multi-dimensional metadata such as place and categories, which can be used to facilitate searching and browsing [5]. PICTuReVis [29] showed that relations among people can be revealed based on their image collections. StreetVizor [25] compared attributes extracted from spatial-dependent street views in cities.

This work adopts a conventional approach of browsing images using multi-faceted metadta [33], which is naturally compatible with conventioanl visualization mantra 'overview first, zoom and filter, then details on demand' [26]. Moreover, publication figures exhibit multi-dimensional and temporal properties, requiring new visual design for depicting high-level patterns such as temporal variations. We employ glyph-based designs to intuitively depict multi-dimensional attributes, and arrange them in a themeriver layout to reveal temporal variations.

3 MODELING PUBLICATION FIGURE

We experiment with representative visualizations from proceedings of renowned IEEE VIS conference (including VAST, InfoVis, and SciVis). To better understand trend of the field, we choose past 10-year papers published in 2009 - 2018. Thanks to a well-organized IEEE VIS dataset [12], we can crawl all papers using provided digital object identifier (DOI). In total, we collect 1171 papers, of which 383 are VAST, 403 are InfoVis, and 385 are SciVis.

3.1 Automatic Figure Extraction

Though we have crawled all the paper, it remains challenging to extract figures in an automatic way (*R1*). We develop an automatic figure extraction method with the following steps.

(1) We first convert a PDF paper to JPG images using ghostscript[1], and to an XML file using pdftohtml[2]. The XML file records ordered text boxes $\{B_i\}$ and their corresponding attributes of position (x, y), width (w), and height (h).
(2) We search for keywords of *Fig.* and *Figure* appearing as the first word of a text box, which indicate either figure captions or descriptions. Here, we make a reasonable heuristic that figure captions are placed below figures. Thus if attribute y_i

[1] www.ghostscript.com
[2] pdftohtml.sourceforge.net

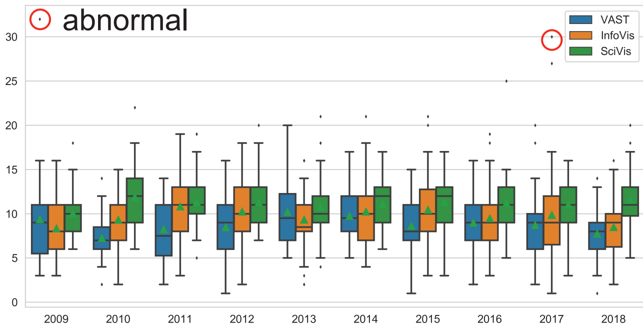

Figure 1: Number of figures included in VAST, InfoVis, and SciVis proceedings in 2009 - 2018.

of a text box B_i to $(y_{i-1} + h_{i-1})$ of the previous box B_{i-1} is small, we regard the text box as text description.

(3) After identifying a text box B_i as figure caption, we can determine a figure's position in y-dimension as $(y_{i-1}+h_{i-1}, y_i)$. Position in x-dimension are determined by x_i and w_i. A two-column figure is identified if x_i is less than while $(x_i + w_i)$ is larger than half page width.

(4) We use the identified positions to extract a figure in the corresponding JPG image. Lastly, we crop out background by identifying the minimum bounding box of pixels in different colors with the background color.

Figure 1 presents average number of figures in the collected VAST, InfoVis, and SciVis publications. We can identify that most publications include 5 - 15 figures, whilst SciVis publications tend to have a slightly higher mean. Nevertheless, there are also several abnormalities. A VAST and InfoVis paper (highlighted by red circles) include over 30 figures, which is about three times than other papers. A detailed examination of the paper may reveal interesting findings.

3.2 Data Characteristics

The IEEE VIS dataset [12] also records multi-faceted metadata for each publication, including *venue* (i.e., VAST, InfoVis, SciVis), *publication year*, *authors*, and *keywords*. The metadata can reveal many interesting knowledge. For instance, we can figure out researchers who are active in the field by *author*, or find out what topics are becoming popular by *keyword*. Thus, we decide to support interactive exploration of the dataset using the metadata. We regard *publication year* as a key factor for depicting trends over time, thus it is fixed as a factor during interactive exploration.

Besides publication metadata, we would like to further explore figure attributes of *image size*, *width/height (w/h) ratio*, and *color*. These attributes reveal intrinsic properties of visualizations as color and shape are pre-attentive visual stimuli [23]. In addition, it can also benefit paper writing, as researchers would like to know how much space and what w/h ratio is suitable. Specifically, we identify median color in a figure defined as centroid of a cube representing all the colors enclosed by the cube [10]. The median color can be efficiently quantified using median-cut algorithm. Notice that image size and w/h ratio are scalar values, while color is represented as a vector of red, green, blue values.

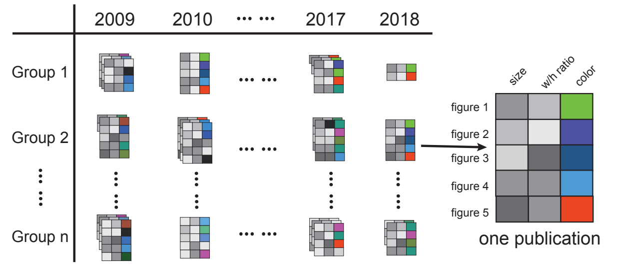

Figure 2: A nested table structure that organizes all figures according to publication metadata and figure attributes.

3.3 Nested Table Structure

The processed data exhibit properties of *multi-faceted* (publication metadata) and *multi-dimensional* (figure attributes). Such complex data nature brings in challenges for accomplishing the requirement of *R2. multi-faceted exploration*. Based on the universal relational model – 'one can place all data attributes into a table, which may then be decomposed into smaller tables as needed' [9], we organize the data in a nested table structure as illustrated in Fig. 2.

- We first group all publications by publication year in rows, and another attribute (venue, author, keyword, number of figures) in columns. By this, each cell consists of different number of publications.
- Each publication is further represented as a table recording figures as rows and figure attributes as columns. The number of rows is dynamical depending on number of figures, while column number is fixed to three for attributes of image size, w/h ratio, and color.

4 VISTORY INTERFACE

Designing an intuitive visual interface is a key requirement of this work (*R3*). This section first summarizes carefully-considered design rationales to fulfill the requirements, followed by detailed descriptions of components of VIStory.

4.1 Design Rationales

We consider an intuitive visual design should meet the following rationales to fulfill the requirements:

- *Complete*: The interface should support exploration of both publication metadata and figure attributes. The twofold perspective information complement each other in supporting high-level analytical tasks. For instance, to figure out what colors (*figure attributes*) are frequently used by a visualization expert (*publication metadata*).
- *Overview + Details*: No surprisingly, tremendous amount of figures will be collected from the publications. The system should provide overviews of the figures from different perspectives. Meanwhile, interactive techniques should be integrated to support details-on-demand exploration.
- *Faceted Browsing*: As described above, the publication metadata are faceted, i.e., composed of orthogonal sets of categories. To support *R2. Multi-faceted analysis*, the interface should allow users to manipulate the figures for analysis

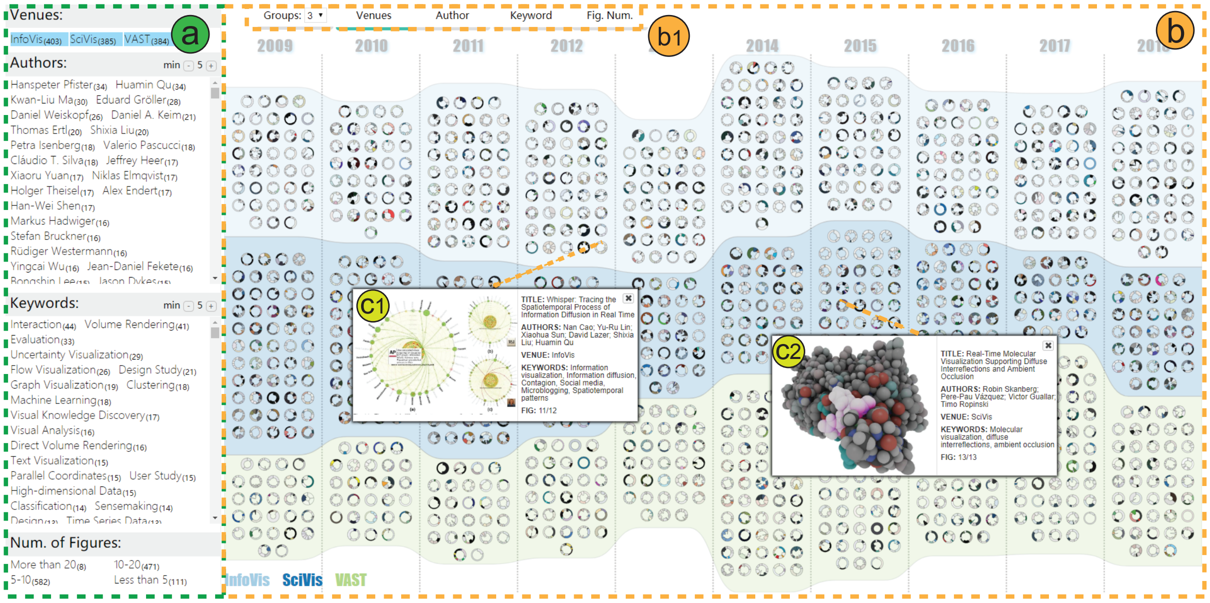

Figure 3: VIStory interface for exploring a collection of scientific publications. (a) The Faceted View enables efficient query of publications through multi-faceted metadata of venues, authors, and keywords. (b) The queried publications are encoded as glyphs arranged in a themeriver layout to depict temporal trends in the Storyboard View. (c) The Endgame View presents a highlighted figure along with information of the publication.

using faceted metadata, rather than projecting all figures into low-dimensions using MDS or t-SNE.

Based on these rationales, we finally come up with VIStory interface as shown in Fig. 3. The interface mainly consists of three view components: Faceted View (Fig. 3(a)), Storyboard View (Fig. 3(b)), and Endgame View (Fig. 3(c)).

4.2 Faceted View

Inspired by [33], we design Faceted View as shown in Fig. 3(a) to fulfill the rationale of *Faceted Browsing*. The view consists of four faceted panels of *Venues*, *Authors*, *Keywords*, and *Num. of Figures*, corresponding to first level of metadata terms. Each panel is comprised of attributes of second level of metadata terms, e.g., *InfoVis*, *SciVis*, and *VAST* in the *Venues* panel. Specifically, we divide the numerical *Number of Figures* into four ranges of *more than 20*, *10 - 20*, *5 - 10*, and *less than 5*. In this way, all faceted attributes are categorical. The attributes are sorted in descending order by the number of publications with the attribute. An exception is attributes in the fourth panel, which are sorted by number of figures. Notice that there can be too many attributes in *Authors* and *Keywords* panels. We further add a minimum threshold controller to filter out attributes with fewer publications than the threshold.

To support *Overview + Details* rationale, the Faceted View enables visual query of publications for exploration by clicking on the user-interested attributes. Let denote the multi-faceted dataset of n publications as $\mathcal{P} = \{p_i\}_{i=1}^{n}$. We note the categorical facets as V (venues), A (authors), K (keywords), and N (num. of figures). For simplicity, we refer all of the facets as X unless stated explicitly. Let x_j as the jth attribute of facet X, $X(p_i)$ be the attribute value of facet X for publication p_i. Note that $V(p_i)$ and $N(p_i)$ are single values, while $A(p_i)$ and $K(p_i)$ can be a vector of values as a publication may have multiple coauthors and keywords.

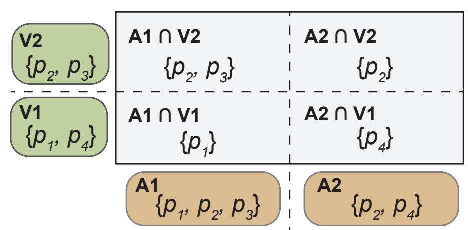

Figure 4: An example of query operations in VIStory.

Let denote the list of publications with attribute x_j as $\mathcal{P}_{x_j}$. Thus, we have $\mathcal{P}_{x_j} = \{p \in \mathcal{P}, X(p) \in \{x_j\}\}$. In VIStory, users can select multiple attributes from the same or different facets. Figure 4 shows an example of visual query results made by two attributes V_1 and V_2 from facet V, and two attributes A_1 and A_2 from facet A.

- *Union.* In case multiple attributes from the same facet are selected, query result is union of publications with the attributes, i.e., $\mathcal{P}_{x_{j1},x_{j2}} = \{p \in \mathcal{P}, X(p) \in \{x_{j1}, x_{j2}\}\}$. For instance, when users select both A_1 and A_2 as illustrated in Fig. 4, the query result is $\{p_1, p_2, p_3, p_4\}$.
- *Intersection.* In case multiple attributes from different facets are selected, query result is intersection of publications with the attributes, i.e., $\mathcal{P}_{x_j,x'_l} = \{p \in \mathcal{P}, X(p) \in \{x_j\}$ *and* $X'(p) \in \{x'_l\}\}$. For instance, when users select both A_1 and V_1, only publication p_1 will be queried.

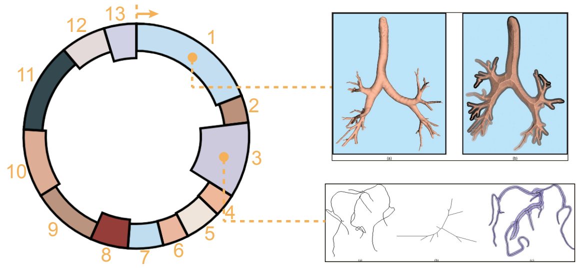

Figure 5: Paper ring glyph for [20]: Arcs in clockwise layout depict figures in a paper, with arc length for figure size, arc height as w/h ratio, and color as domain color.

By default, *InfoVis*, *SciVis*, and *VAST* attributes in *Venues* facet are selected (see Fig. 3(a)), i.e., all publications in the dataset are chosen for exploration.

4.3 Storyboard View

After a user selects certain attributes, a subset of publications $\mathcal{P}_s \subseteq \mathcal{P}$ is filtered for exploration. $\mathcal{P}_s$ can be further grouped based on user-defined attribute of *Venues*, *Authors*, *Keyword*, or *Fig. Num.*, using the buttons in Fig. 3(b1). Users can also control the number of groups to be visualized using the drop down selection list. After selecting the grouping attribute and number of groups, the relative information are presented in Storyboard View as shown in Fig. 3(b). As a main view component in VIStory, the view employs the following intuitive visual designs.

4.3.1 Paper Ring. To support *Complete* rationale, we need to depict multi-dimensional figure attributes, including *size*, *w/h ratio*, and *domain color*. We come up with a glyph of paper ring as shown in Fig. 5. Here, all figures in one publications are represented as arcs, which are arranged in a clockwise order corresponding to the figure order in the publication. For each figure, its *size* is encoded as arc length, *w/h ratio* encoded as arc height, and *domain color* as the arc color. Notice that arc lengths indicate only relative sizes of figures in the same publication, but not absolute sizes across multiple publications. This work treats every publication equally, hence all paper rings share the same radius.

Figure 5 shows a paper ring glyph for a SciVis publication [20]. As the glyph depicts, there are in total 13 figures in the publication, and most figures exhibit brownish domain color. Obviously, the first figure occupies the largest size, while the third figure has biggest w/h ratio. These two figures may reveal the main contributions of the publication. By examining the original figures, we can notice that the first figure includes two subfigures, while the third figure has three. These subfigures are arranged side-by-side, probably for comparative analysis.

4.3.2 Themeriver. There can be numerous number of papers in $\mathcal{P}_s$, where a worst case can be 1171 when $\mathcal{P}_s = \mathcal{P}$. Remember that we treat year as a fixed analytical factor (Sec. 3.2). Thus, we employ themeriver [8] – a classical visual representation for depicting temporal trends design, to arrange the paper rings. Here, the rendering canvas is first divided into 10 equal parts horizontally, corresponding to 10-years publication year. The river height corresponds to the number of publications. From Fig. 3, we can notice that the height of SciVis river (middle) is decreasing, while that of VAST river (bottom) is increasing.

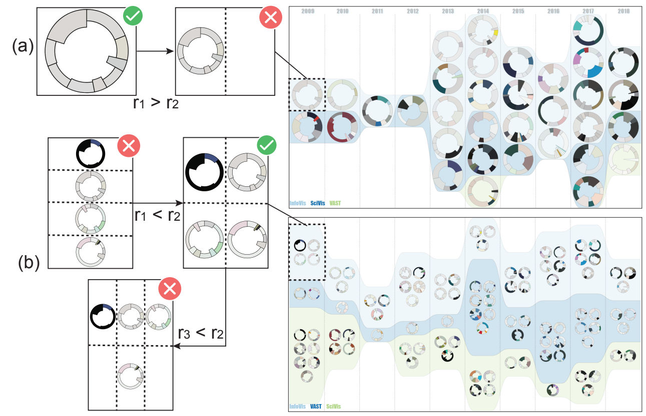

Figure 6: A greedy algorithm for deciding radius of paper ring. r_1 is chosen in (a) while r_2 is chosen in (b). See Sec. 4.3

4.3.3 Layout. Next, we need to position the paper rings in the themeriver in a meaningful way. Let denote a group of publications in one year as $\mathcal{P}_g := \{p_i\}_{i=1}^m$, where m indicates the number of publications in the group. We can extract a bounding box ($\mathbf{B}_g := (cx_g, cy_g, w_g, h_g) \in \mathbb{R}^2$) in the themeriver, where cx_g & cy_g indicate center position of $\mathbf{B}_g$, and w_g & h_g indicate its width and height respectively. Our problem is to find $p_i := (cx_i, cy_i, r), \forall p_i \in \mathcal{P}_g$.

We develop a simple yet effective greedy algorithm to address this problem. The algorithm work as follows:

(1) $\mathbf{B}_g$ is first divided into 1 column and m rows, yielding $1 \times m$ grids and each grid can store one paper ring. We denote paper ring radius r as r_{g1}, and $r_{g1} = min(w_g, \frac{h_g}{m})$.
(2) We next divide $\mathbf{B}_g$ into 2 columns and $\lceil m/2 \rceil$ rows, where $\lceil m/2 \rceil$ indicates the ceiling of $m/2$. In this way, we can derive $r_{g2} = min(\frac{w_g}{2}, \frac{h_g}{\lceil m/2 \rceil})$.
(3) We check condition $r_{g2} > r_{g1}$: if the condition is not met, we stop the process and return r_{g1}; otherwise, we continue step 2 by increasing the column number until $r_{gn} < r_{g(n-1)}$ and return $r_{g(n-1)}$.
(4) In the same way, we derive radii for all groups, and choose the minimum value as the final radius r.
(5) After deciding r, we start from (cx_g, cy_g) and find a minimum bounding box that can pack all paper rings. In this way, paper rings in the same group are positioned close to each other and far from rings in other groups.

To better illustrate our solution, we give two examples shown in Fig. 6. The first example is storyboard for publications by *Hanspeter Pfister*, who got the most number of 34 IEEE VIS publications in 2009 - 2018 (together with Huamin Qu). The second example is storyboard for publications by top-3 authors of {*Hanspeter Pfister, Huamin Qu, Kwan-Liu Ma*}. Both views are grouped by *Venue* attribute. We select the first groups from both views, which contain one publication in (a) and four publications in (b). In (a), r_1 is chosen since $r_1 > r_2$; by contrast in (b), r_2 is chosen since $r_2 > r_1$ & $r_2 > r_3$.

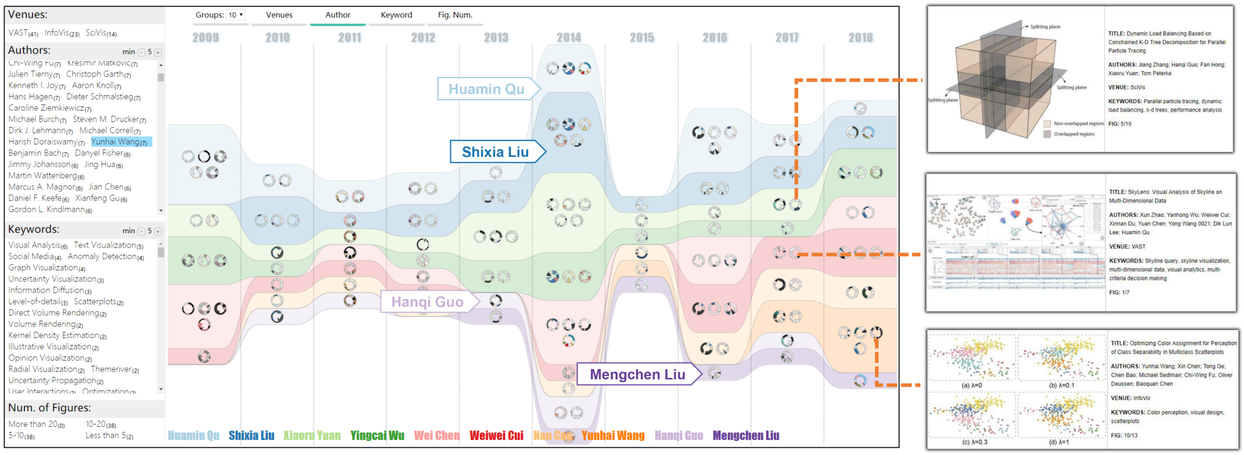

Figure 7: Author profiles of top visualization researchers in mainland China who contributed most publications to IEEE VIS publications in 2009 - 2018, i.e., *{Shixia Liu, Xiaoru Yuan, Yingcai Wu, Wei Chen, Weiwei Cui, Nan Cao, Yunhai Wang}*. Notice that Huamin Qu, Hanqi Guo, and Mengchen Liu are not in the selection list, but still appear in the view.

4.4 Endgame View

To further support *Overview + Details* rationale, we further design Endgame View as shown in Fig. 3(c1)&(c2). The view consists of two perspectives of information: First, the raw figure is presented on the left side; Second, the publication metadata, including *title*, *authors*, *venues*, *keywords*, and *order of the figure*, are presented on the right side. The view is connected to the center of its corresponding arc by a dashed line. It can be dragged around to avoid occlusion of important visuals. Multiple endgame views can be enabled at the same time, such that to enable comparison. Taking Fig. 3(c1) and (c2) for an example, it is obvious that (c1) presents a 2D abstract visualization with nodes and links, while (c2) is a scientific visualization with 3D visual cues.

5 CASE STUDY

We conduct two case studies to demonstrate efficacy of VIStory on exploring the collected figures. Real-world usage scenarios are presented: *author profile probe* and *VIS trend analysis*.

5.1 Study 1: Author Profile Probe

VIStory can be applied to probe author profile, including number of publications and topics over years. To demonstrate this, we first filter publications made by active visualization researchers in mainland China. This is accomplished by selecting seven researchers of *{Shixia Liu, Xiaoru Yuan, Yingcai Wu, Wei Chen, Weiwei Cui, Nan Cao, Yunhai Wang}* (ordered by number of publications in past 10-year IEEE VIS conference) from *Author* panel in *Faceted View*. We then select author as grouping factor and set group number to 10, yielding a Storyboard View as in Fig. 7.

From the view, we can obtain several interesting discoveries.

- First, the view presents 10 author groups, meaning that there are three additional authors. We can identify they are *Huamin Qu*, *Hanqi Guo*, and *Mengchen Liu*, and they exhibit different patterns. (1) *Huamin Qu*: Surprisingly *Huamin Qu* obtains the most number of publications in the query result, indicating he had close collaborations with the selected seven researchers. (2) *Hanqi Guo*: We can notice that the river of *Hanqi Guo* starts from 2010, and many paper rings are the same with those of *Xiaoru Yuan*. A quick examination reveals that they collaborated on seven publications in past 10 years. (3) *Mengchen Liu*: We can observe that *Mengchen Liu* stably contributed at least one publication every year starting from 2013, and all of them are in collaboration with *Shixia Liu*. The observations infer that *Hanqi Guo-Xiaoru Yuan* and *Mengchen Liu-Shixia Liu* were probably in supervisee-supervisor relationship.
- We can also obverse peak and bottom publications years from the changes over time. In 2014, both *Shixia Liu* and *Xiaoru Yuan* contributed five publications, followed by four from *Wei Chen* and three from *Yingcai Wu*. In contrast, much fewer publications are made in 2011 and 2015.
- Lastly, we would like to retrieve what topics the authors worked on, by clicking on figure arcs and examining the Endgame View. Here, we select three representative works as the insets by *Xiaoru Yuan* (top), *Weiwei Cui* (middle), and *Yunhai Wang* (bottom), which are published in SciVis, VAST, and InfoVis respectively. The figures reflect different visualization techniques employed by the three publications. Scientific visualization (top inset) employs 3D visual representation to represent spatial attributes, visual analytics (middle inset) integrates coordinated multiple views to depict data from multiple perspectives, and information visualization (bottom inset) focuses on improving human's visual perception on abstract 2D data.

5.2 Study 2: VIS Trend Analysis

VIStory can also be utilized to analyze trend of visualization topics, by exploring keyword attribute. Here, we filter publications by selecting three top keywords of *{Interaction, Volume Rendering, and*

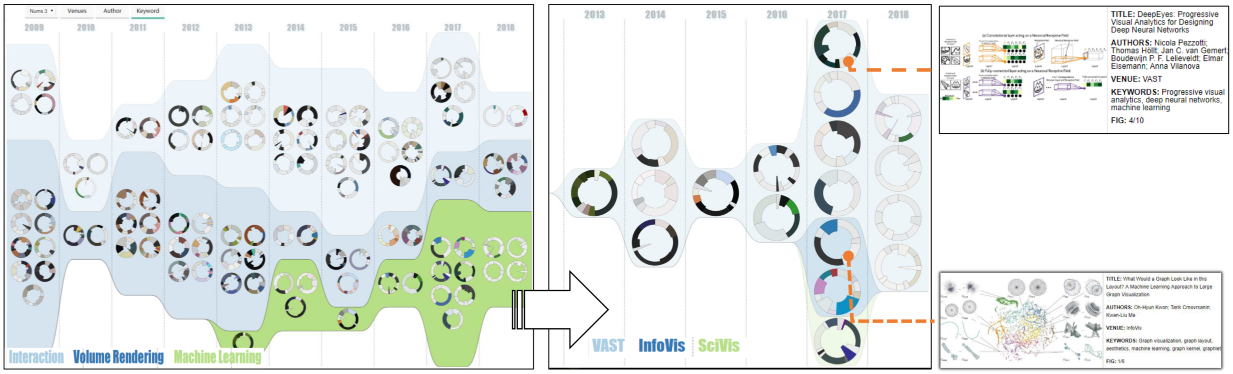

Figure 8: Exploring trends of visualization topics of *Interaction*, *Volume Rendering*, and *Machine Learning* in 2009 - 2018. Left: Number of publications on interaction remains stable, on volume rendering is decreasing, while on machine learning gets popular. Middle: Closer examination of publications on machine learning shows that most publications are in VAST conference. Right: Top Endgame View shows that the VAST paper is to explain CNN, while the bottom view shows a InfoVis paper utilizing machine learning to facilitate graph layout.

Machine Learning} from the *Keyword* panel in *Faceted View*. There are in total 44 publications with keyword of *interaction*, 41 for *volume rendering*, and 18 for *machine learning*. Keyword is also selected as grouping factor and group number is set to 3, yielding a Storyboard View presented in Fig. 8(left).

Through the storyboard, we can observe different trend pattens of the topics in past 10-year IEEE VIS conference. First, number of publications on *interaction* remains relatively stable, with several publications accepted each year. Interaction is a fundamental component for interactive visualization, so many researches were conducted to improve interaction efficiency. Second, *volume rendering* becomes less popular, as the number of publications are decreasing. This is probably because volume rendering has been exhaustively studied since the beginning of scientific visualization. In contrast, we can observe that more publications on *machine learning* were accepted in last two years. A heuristic is that many visual analytics systems have been developed to open the black box of deep learning techniques.

To verify the heuristic, we dis-select *interaction* and *volume rendering*, and change grouping factor to venue. This results in a Storyboard View as presented in Fig. 8(middle). A first glimpse shows that most machine learning publications are in VAST conference, while only two in InfoVis and one in SciVis. Deeper examination by viewing a Endgame View (top inset) reveals that the work is to visualize training process of a convolutional neural network (CNN). In contrast, another Endgame View (bottom inset) shows that the work utilized machine learning to facilitate graph layout. The findings indicate that the heuristic is reasonable.

6 DISCUSSION

The case studies demonstrate the efficacy of VIStory in probing author profiles and understanding visualization trends. These information can benefit real-world applications, e.g., to help students find suitable supervisors, and to help researchers find hot topics. Nevertheless, there are still some limitations of our system.

First, this analysis are conducted on past 10-year IEEE VIS publications. The information only covers a small amount of visualization work. For instance, volume rendering as a pioneering visualization topic has now been widely used for visualizing medical images and flow simulations. Many studies on volume rendering have been published on other venues such as *IEEE Transactions on Medical Imaging (IEEE TMI)*. Similarly, IEEE VIS publications only count a small portion of outcomes of an author. Many publications, such as those in *IEEE Transactions on Visualization and Computer Graphics (IEEE TVCG)*, are not counted here. In this sense, we can only claim that study 1 reveals author profiles, and study 2 indicates trends of visualization topics in IEEE VIS conference. Nevertheless, we regard this as a common limitation for similar studies using only IEEE VIS publications [12, 13].

A feasible solution to address the limitation is to incorporate more data for analysis, e.g., other publications in IEEE TVCG, EuroVis, PacificVis, and VINCI. In this way, a more complete overview of the visualization field can be achieved. However, this can cause another limitation regarding scalability of the system. Experiments reveal that paper rings in Storyboard View becomes too small to be observable when the total number of publications reaches 1000 (see Fig. 3 for an example). Though the scalability issue can be mitigated through filtering interactions, we would like to examine more visual design alternatives. A feasible solution here is to employ advanced semantic image projection methods, which has been shown effective for handling millions of images [31]. To integrate semantic image projection with faceted visual interaction [33] would be an interesting direction.

7 CONCLUSION AND FUTURE WORK

This paper presents VIStory, a new storyboard that supports interactive exploration of visual information collected from scientific publications. The work is motivated by practical needs of various users including students, researchers, and reviewers. VIStory incorporates advanced data processing techniques and noveal visual designs to fulfill the domain requirements: For *R1. Automation*, we develop automatic figure extraction method to extract figures from publications (Sec. 3.1); For *R2. Multi-faceted analysis*, we organize collected figures in a nested table structure (Sec. 3.3) and employ overview+details interaction strategy. For *R3. Intuitive visual design*, we design paper ring – a new glyph design that encodes multi-dimensional attributes of figures in a publication, and organize the glyphs in a themeriver layout to depict temporal variations (Sec. 4). Applicability and effectiveness of the system are demonstrated through two case studies of author profile probe (Sec. 5.1) and VIS trend analysis (Sec. 5.2).

There are several promising directions for our future work. First, we spent much time on extracting figures from visualization publications. We would like to make it open for future researches, e.g., to extract visualization related image metrics using deep learning techniques. We also call for collaborations on enriching the dataset, such as to manually label all the figures. We will soon make VIStory system open to the public. Second, with the automatic figure extraction method, we can easily harvest more figures from scientific publications. We plan to do so on publications in past 10-year IEEE TVCG, EuroVis, and PacificVis. Lastly, we would like to continue working on the visual interface to incorporate more analytical features and improve the system scalability.

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