VIS30K: A Collection of Figures and Tables from IEEE Visualization Conference Publications

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Abstract—We present the VIS30K dataset, a collection of 29,689 images that represents 30 years of figures and tables from each track of the IEEE Visualization conference series (Vis, SciVis, InfoVis, VAST). VIS30K's comprehensive coverage of the scientific literature in visualization not only reflects the progress of the field but also enables researchers to study the evolution of the state-of-the-art and to find relevant work based on graphical content. We describe the dataset and our semi-automatic collection process, which couples convolutional neural networks (CNN) with curation. Extracting figures and tables semi-automatically allows us to verify that no images are overlooked or extracted erroneously. To improve quality further, we engaged in a peer-search process for high-quality figures from early IEEE Visualization papers. With the resulting data, we also contribute VISImageNavigator (VIN, `visimagenavigator.github.io`), a web-based tool that facilitates searching and exploring VIS30K by author names, paper keywords, title and abstract, and years.

Index Terms—Visualization, IEEE VIS, InfoVis, SciVis, VAST, dataset, bibliometrics, images, figures, tables.

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1 INTRODUCTION

VISUALIZATION is a discipline that inherently relies on images and videos to explain and showcase its research. Images are thus an essential component of scientific publications in our field. They facilitate comprehension of complex scientific concepts [11], [41] and enable authors to refer to their proposed visualization solutions, alternatives, and competing approaches or to graphically explain algorithms, techniques, workflows, and study results.

Browsing a domain's images can reveal temporal trends and common practices. It facilitates the comparison of sub-disciplines [24]. Although figures are ubiquitous in visualization publications, they are embedded in PDFs and remain largely inaccessible via scholarly search tools such as digital libraries, Google Scholar, CiteSeerX, or MS Academic Search. The primary goal of our work—similar to that of past work on IEEE VIS papers [15], keywords [16], or EuroVis papers [39]—is to extend the corpora of data we can use for studies of the visualization field.

Our primary contribution is a dataset we call VIS30K (Fig. 1). It contains images and tables from 30 years (1990–2019) of the IEEE VIS conference, spanning all tracks: Vis, InfoVis, SciVis, and VAST. IEEE VIS is the longest-running and largest conference focusing on visualization and its images reflect the evolution of the field. Our primary data sources include IEEE Xplore, conference CDs, and hard copies of the conference proceedings from which we obtain the images in their best possible quality. In addition to images, we include tables as special form of data organization that can be informative to the community. Our dataset can serve

many purposes. It enables researchers to study the visual evolution of the field from an objective, image-centric point of view. It assists teaching about visualization by providing fast visual access to refereed research images and contributions. It also can serve as a data source for researchers in other fields such as computer vision or machine learning. And, finally, it supports visualization researchers when browsing and discovering new work.

Collecting these figures and tables was challenging. We optimized data quality with a hybrid solution. We first extracted figures via convolutional neural networks (CNNs), followed by expert curation. This way we ensure reliable data (i. e., completeness and image locations/dimensions), while at the same time requiring a manageable amount of manual cleaning and verification.

Our secondary contribution is a web-based tool, VISImage-Navigator (VIN, `visimagenavigator.github.io`), that allows people to search and explore our dataset. We cross-link VIN to the metadata of KeyVis [16] and VisPubData [15] and their detailed bibliometric metadata. This metadata associated to papers, and thus all images, allows us to support searching using text-based queries.

2 RELATED WORK

Previous work from three areas inspired our own. The first surveys past work and offers visual access to past publications. A second group collects and analyzes metadata derived from visualization research papers. The third group relates to the CNN-based extraction algorithms we employed for our data extraction.

Visual Collections of Visualization Research. We are not the first to attempt a visual overview of the visualization field. Yet past work generally focuses on specific subareas of the research, each of which provides an overview of work on the subtopic rather than a comprehensive and browsable image database. For instance, some work has focused on providing references and representative images of specific data or layout techniques: Schulz's 300 tree-layout methods [35], Kucher and Kerren's more than 470 text visualizations [21], Aigner et al.'s over 100 temporal data visualizations [1], and Kehrer and Hauser's multivariate and

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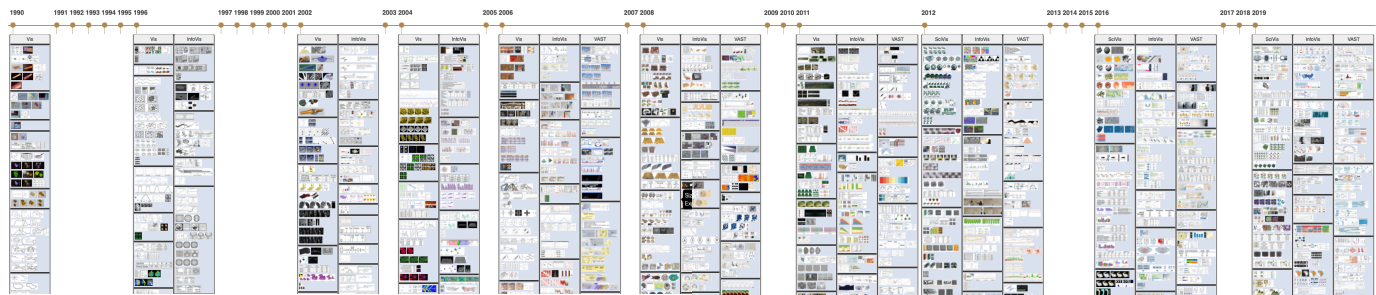
Fig. 1. A timeline of selected images from all 30 years (1990—2019) of IEEE Visualization conference showing diverse and trending research work. Best viewed electronically, zoomed in.

multifaced data of more than 160 images [18]. Others examine specific visualization applications, e. g., Kerren et al.'s biological data [19], Kucher et al.'s sentiment analysis [22], Chatzimparmpas and Jusufi's trustworthy machine learning [4], and Diehl et al.'s VisGuides [9] on advice and recommendations on visual design. In contrast to these focused perspectives, VIS30K provides a broader coverage of all 30 years of IEEE VIS. Our downloadable dataset comprises all the images contained in each paper, rather than just a few samples per publication or approach.

The work most closely related to ours is Deng et al.'s VisImages collection of IEEE InfoVis and IEEE VAST images [8] and Zeng et al.'s VISstory [44]. Both sets of authors plan to release their datasets but only provide a subset of our data. VISstory only covers data from 2009–2018, while VisImages does not include IEEE Vis and SciVis paper images. Our work also differs in its approach to quality control. We rely on expert input to check the capture of all images, while VisImages uses crowd-sourcing. VISstory only tests a subset of images for quality. Similar to these tools, we provide a web-based tool to explore the image data although focus on different aspects. VisImages categorizes image content in addition to metadata and VISstory focuses on a paper rather than image-centered views where each paper is encoded as a ring with sectors standing for individual images.

Meta-Analysis of Visualization Publications. Another direction of research centers on meta-analyses of the visualization field, without focusing on visual content. Lam et al. [23], e. g., established seven empirical evaluation scenarios by analyzing 850 papers appearing in the 'information visualization' subcommunity of IEEE VIS. Isenberg et al. [17] later extended this historical analysis of evaluation practices to all tracks of IEEE VIS in a systematic review of 581 papers. Isenberg et al. [16] further collected IEEE VIS paper keywords to derive visualization topics from a metadata collection of IEEE VIS publications [15]. We make use of metadata from this collection in our work to gather paper PDFs prior to automatic extraction. Conceptually, our new VIS30K extends this line of work by leveraging new image-based extraction methods [27] and search tools to make the figure and table data accessible.

CNN-based Extraction Algorithms. Using data-driven CNN algorithms to train classifiers to extract figures and tables is becoming increasingly popular [6], [31], [37]. Current approaches to fine-grained recognition involve the important step of preparing the annotated training data with ground-truth labeling prior to training a model for prediction. Problems in this area have inspired research in three major directions. The first is crowdsourcing to annotate the document manually [37]. We did not use this solution for two reasons. First, cleaning noisy crowdsourced annotations is time-consuming in itself and also needs effective quality control [38]. Second, crowdsourcing lacks flexibility: often we must know in advance if we are to extract figures, equations, texts, tables or all of these. It may not be realistic to determine complete categories in advance. Another solution is to mine information from an XML schema [6], [29] or from LaTeX [38] or PDF [25] syntax. We could not use this approach since early IEEE VIS PDF papers are lack corresponding LaTeX or XML source files. The most popular figure-extraction algorithms rely on manually defined rules and assumptions. These techniques are typically successful for the particular type of figure for which these rules are followed, but suffer from the classical problem with rule-based approaches: when rules are broken, the algorithm fails. For example, an intuitively reasonable rule is to assume captions always exist. An algorithm can locate a figure by searching for caption terms such as *Fig.* and *Table* [6], [25]. However, about 2% of our VIS30K images do not satisfy this assumption and thus can cause the extraction algorithm to fail. Choudhury et al.'s algorithm [5] focuses on specific figure types, such as line charts and scatter plots, while our goal is to extract a comprehensive collection of figures and tables. For these reasons, annotated ground-truth data are not publicly available for automatic figure and table extraction.

3 DATASET DESCRIPTION

We now describe the data format and information stored for each figure and table in our database and the decisions we made concerning the figure extraction task. But we start by defining the terms we use throughout the remainder of the paper.

3.1 Terms

IEEE VIS. Over its history, IEEE VIS has undergone a number of name changes (Fig. 2). It started out in 1990 as IEEE Visualization (Vis), then added IEEE InfoVis in 1995 followed by IEEE VAST in 2006. In 2008–2012, all three venues were jointly called IEEE VisWeek, and since 2013 the blanket name IEEE VIS has been used. From 2013 onward, the IEEE Vis ceased to exist, replaced by the IEEE Scientific Visualization (SciVis) conference. Here we use VIS to refer to all four venues: Vis, InfoVis, VAST, and SciVis, for the entire time period covered by our dataset.

Figures and Tables. We refer to a *figure* as a container for graphical representations. These representations can be images, screenshots of visualization techniques, user interfaces, photos, diagrams, and others. We classify algorithms, pseudocode, and equations as textual content and thus do not include them in VIN. Including these additions is left as future work. A *table* is a row-column representation of relations among related data concepts or categories [13], usually composed of cells [20], [28].
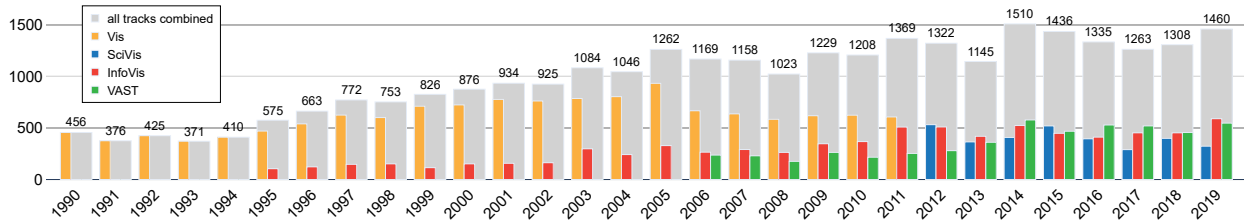
(a) Total # of images (figures and tables), by year.
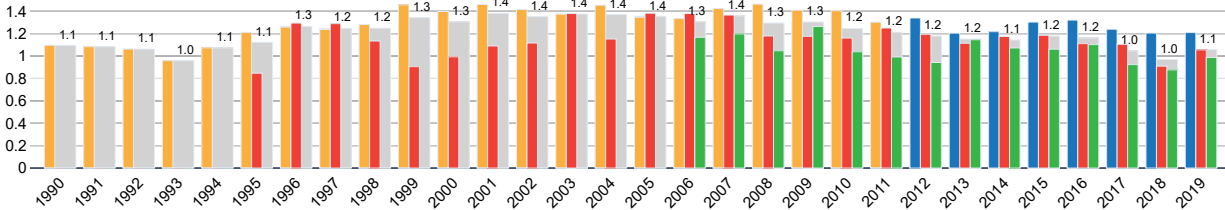
(b) Average # of images (figures and tables) per page, by year. We included potential color plate pages from early years (1990–2001) in the page count for this analysis, and only counted an image once if that same image appeared in both the paper and its color plate.

Fig. 2. We extracted 29,689 images (26,776 figures, 2,913 tables) from the 2,916 IEEE Visualization conference papers, spanning 30 years (Vis: 13,509; SciVis: 3,232; InfoVis: 7,834; VAST: 5,114). Numbers for the joint conference are depicted as wide pale gray bars. The individual tracks are overlaid on top. On average, Vis/SciVis has more images per paper page than InfoVis and VAST.

3.2 Image Data Collection

We collected 29,689 images (26,776 figures and 2,913 tables from 2,916 conference and journal publications of the IEEE VIS conference from 1990 to 2019 (Fig. 2). Our collection also includes case studies and late-breaking results from earlier years as they are included in the digital library. We do not include the more recent short papers as only 3 years of data are available. We also exclude posters as they do not appear consistently in the IEEE Xplore digital library, our primary data source for the paper PDFs.

We include tables as a separate category alongside figures as we consider them, unlike unstructured text, as a form of structured and visual data representation that might be useful to analyze. Not only the visual layout of tables may be interesting, but also, more importantly, the relative frequency of tables in published research results and the amount of space tables occupy in papers. Data stored in tables can be further extracted and cross-linked into a knowledge base. Tables can be filtered out for other use cases such as searching for related work or searching for images for teaching.

3.3 Choosing Figures and Tables

Scholarly articles are often structured based on a template and are properly referenced, yet authors use varying approaches to generate figures and tables and to embed them in their papers (Fig. 3). These varying practices required us to make decisions about which types of visual representations to include and exclude in our database:

High Variation in Composition of Figures and Tables. Authors often treat *algorithms*, *pseudocode*, and *tables* as figures with figure numbers. In our data collection, we separated *algorithms* and *pseudocode* from *figures* and tagged *tables* and *figures* separately. While both pseudocode and algorithms are important scientific content in papers, they generally consist of text and are not the forms of visual data representations we target with VIS30K.

Occasionally, authors placed figures and tables wrapped within the text flow without captions or figure/table numbers. We collected such figures and tables nonetheless but excluded small, often repetitive word-scale visualizations and word-scale graphics such as those in Blascheck et al.'s work [2]. In our dataset, we list tables that contain primarily text but sometimes also small inline

images (e. g., Fig. 3(f)) as tables. We include other column-row representations such as heatmap matrices and table lenses (e. g., Fig. 3(g)) that use a primarily graphical encoding as figures.

Handling of Subfigures and Subcaptions. A figure can be composed of multiple images or be a combination of images and text. Such *composite figures* are common in visualization papers (e. g., Fig. 3). We initially hope to dissemble these composite figures into subfigures, but ultimately choose not to due to their variable degree of separability. Composite figures, e. g., are used to report related sets of design results (Fig. 3(a)). They sometimes do not have subcaptions (Fig. 3(b)). In other cases, the subfigure indices just label different views of the same data (e. g., (b) is a magnified view of (a)) and are monolithic (e. g., Fig. 3(c)). Composite figures also sometimes place subfigures side-by-side to compare techniques or parameters (Fig. 3(d)). Separating these subfigures would defeat the functional value of these figure compositions.

Composite figures can contain subcaptions that are explicitly associated with subfigures through spatial proximity (e. g., Fig. 3(a)). Subfigures and subcaptions in the same composite figure often have similar content. Subcaptions can contain a few lines (like our own Fig. 3), a brief term, or merely an index (e. g., (a)–(g) as in Fig. 3(a)). Because we maintain composite figures and do not split them into subfigures, we have no choice but to include subcaptions in our collection—even though we did remove the main caption of the figures, except when the caption was inside the figure's bounding box (Fig. 3(e)). We also retained the markers of index-only subcaptions to help viewers to identify the subdivision of composite figures.

Low Quality and Noisy Figures. Images in IEEE Xplore papers from 2001 onward generally have excellent visual quality. However, we found errors and many unclear figures in earlier papers. We sought to correct these in our data to provide a more reliable source for IEEE VIS publication figures. In particular, images from papers from 2000 and earlier often are of low quality. We replaced images from these early years with better versions when the paper copy in the ACM DL had better quality, when we could find it on the conference CD or proceedings, or when we found a better (author) copy online. Papers published in 1995
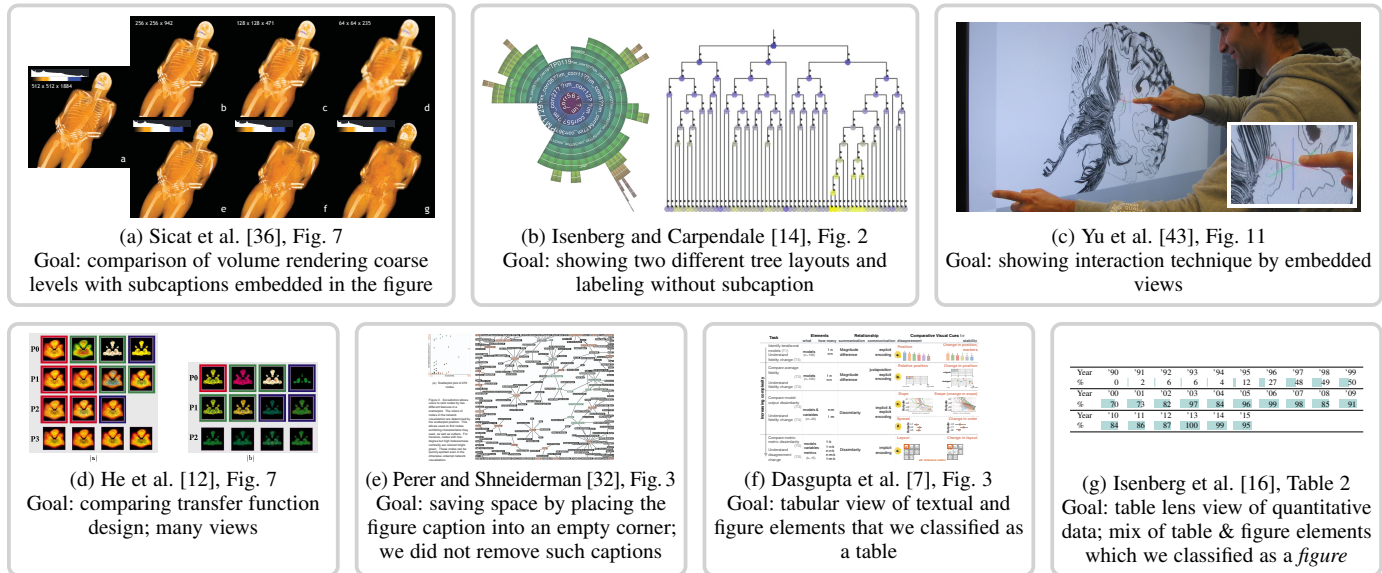
(a) Sicat et al. [36], Fig. 7
Goal: comparison of volume rendering coarse levels with subcaptions embedded in the figure

(b) Isenberg and Carpendale [14], Fig. 2
Goal: showing two different tree layouts and labeling without subcaption

(c) Yu et al. [43], Fig. 11
Goal: showing interaction technique by embedded views

(d) He et al. [12], Fig. 7
Goal: comparing transfer function design; many views

(e) Perer and Shneiderman [32], Fig. 3
Goal: saving space by placing the figure caption into an empty corner; we did not remove such captions

(f) Dasgupta et al. [7], Fig. 3
Goal: tabular view of textual and figure elements that we classified as a table

(g) Isenberg et al. [16], Table 2
Goal: table lens view of quantitative data; mix of table & figure elements which we classified as a *figure*

Fig. 3. The use of figures and tables shows great variation. Here, we place subfigures side-by-side for comparison to present different techniques, as in (a). Subfigures may not have subcaptions (b). They can be embedded (c) or contain tabular views of different parameter choices (d). Figure captions sometimes appear inside the figure's rectangular bounding box (e). Tables often contain visual separators, but the content can be hierarchical and can contain figures (f) or use table lenses (g). These variations lead us to retain composite figures and tables in our data cohort to preserve the functional values of these paper elements. All images © IEEE, used with permission.

or earlier often have color-plate pages, causing IEEE and ACM to list different page numbers for some papers. Also, figures in these color-plate pages may or may not be the same as the figures on the main paper pages. When they were the same, we used the color version. Otherwise we collected both. We corrected errors such as missing pages in the printed or digital library version (e. g., Dovey [10]) and added additional pages found in conference proceedings. We also found entries on IEEE Xplore that linked to a paper under a different title or in which the last page was the first page of the next paper. Some papers contained white pages or duplication which we excluded from the total paper pages count.

4 FIGURE AND TABLE COLLECTION PROCEDURE

We designed and implemented a new CNN-based data-driven solution to harvest figures and tables embedded in IEEE VIS research papers to avoid manual labeling. The input to our CNNs is the paper pages and the output is a structured representation of all the figures and tables within the input files and the associated bounding box locations.

4.1 Overview

The main idea behind our approach is to train a CNN with automatically synthesized papers. Our approach works by 'pasting' different paper component parts including figures, tables, and text onto a white image to create a "pseudo-paper" collection. These pseudo-papers are sufficient to guide CNNs to detect and localize the figures and tables from real documents. While the simulation approach has been used in other realistic environments [42], ours is to our knowledge the first use for scholarly document analysis.

Our approach leverages the simple assumption that the *form* and *structural* content of a page are more important for detecting images than the factual content. The advantage is that, in theory, it allows a CNN algorithm to act on any document layout and labels, even new and unknown ones. Rule-based or XML-based methods would require us to keep stipulating new rules or define suitable XML tags

to cope with complex documents. Our method, in contrast, always generates its own synthetic appearance to minimize the differences between the training data and the real papers, to improve prediction accuracy as it produces accurate "ground-truth" data (Fig. 4).

4.2 Training Data Preparation: Pseudo-Papers

The essential part of our approach is to treat training data as a composition of individual document elements, where the goals are (1) to record bounding boxes for each of the labels and components in a PDF image to produce high-quality labels for the training data; and (2) to synthesize appearance to reduce the differences between the training data and the real papers to some extent.

Image and Text Corpora. To reduce the number of training images needed and to increase training data diversity, we used image collections from Borkin et al.'s MASSVIS dataset [3] and from the SciVis memorability data by Li and Chen [26]. Early papers are often black and white and may contain salt-and-pepper image noise. This variation in image appearance (brightness, contrast) can reduce our CNN's image detection accuracy. To match such visual variations, we doubled the figure/table samples by converting these images to black and white, with a range of gray-scale variations. We assembled the text corpus using Stribling et al.'s SCIgen [40] so the textural content remains coherent, although not necessarily being relevant to IEEE VIS (Fig. 4(a)).

Pseudo-paper Corpora. We used this image and text corpus to automatically synthesize a large set of papers to depict *paper titles*, *abstracts*, (*body text*, *document headers*, *figures*, *tables*, and *captions*) (Fig. 4). Our document-production algorithm inserted the text, figures, and tables into white pages of particular size and coordinates with particular fonts and styles, to match the IEEE VIS paper structure. We also inserted *bullets and equations* because pilot tests revealed that, without them, bullets and equations from the real papers were often misclassified as *point-based visualizations* [3], a figure type containing dot or scatter plots or similar elements.

In total, we generated 13,000 pages (10,000 for training, 3,000 for validation), each with 1075×1400 pixel resolution and labeled
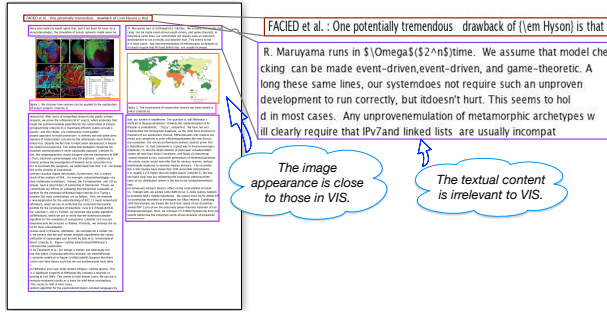
(a) An inner page with two figures each occupying a single column.
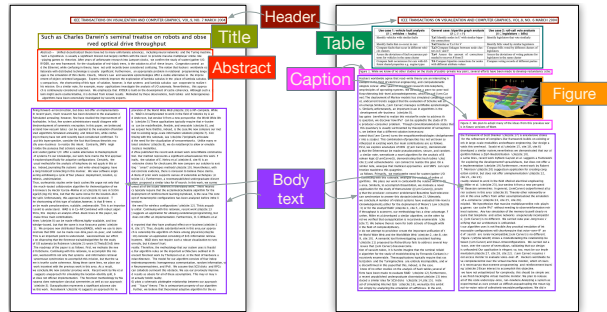
(b) A first page without figure, and an inner page with a table crossing two columns and a single-column figure.

Fig. 4. Automatically rendered pseudo-paper pages in our training data generation with ground-truth labels. The text content in (a) is grammatically correct but not semantically meaningful in the visualization domain. Page samples of (b), header, title, abstract, body text, figure, table, captions, and other document components are shown. We diversified the page layout structures to render pages both with and without images. When images are shown, they appear in single or double columns.

4.3 Integrating CNN Models for Figure Extraction

We trained two complementary CNNs, YOLOv3 [33] and Faster R-CNN [34], independently for subsequent figure extraction from the actual papers. One may think of this combination as a means to boost performance of our learning algorithm as we only used a very small set of labeled examples, compared to millions of training samples in other solutions [38]. YOLOv3 is a single-stage detector network—fast and accurate for object detection. Faster R-CNN [34] is a multi-stage proposal and sampling-based approach where a certain number of candidates were sampled from a large pool of generated ROIs. Both YOLOv3 and Faster R-CNN returned the four coordinates of each bounding box, along with class labels. We trained both models under TensorFlow and executed it on a single nVIDIA GeForce RTX 2080 Ti GPU, with 11 GB memory.

In the prediction stage, we downloaded the paper PDFs by following the links in the VisPubData database [15]. We excluded short papers, posters, panels, and keynote files, so our collection comprised 2,916 full papers for the years 1990–2019. We first converted these PDFs to PNG pixel images using the *convert* command with dpi = 300 and pixel resolution up to 2353×3213. This conversion was necessary to capture all images in their camera-ready rendered visual form in the paper PDF, including scanned pages from early years, vector images, pixel graphics, simple text versions, and any combinations thereof. We then fed these images into the CNNs to extract figures, tables, captions, etc. For each
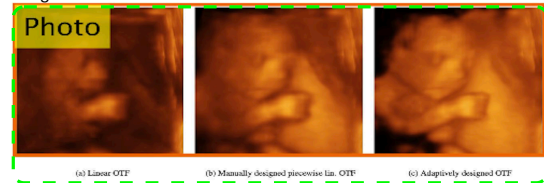
Fig. 5. Fine-grained human recognition to correct CNN errors. The orange boxes show the machine prediction and the green boxes the human results to curate bounding box regions.

paper page, we thus produced the bounding boxes of the 17 classes (6 textual content, 11 figures/tables).

After model prediction, we used heuristics in [27] to combine both models' results by merging the bounding boxes from Faster R-CNN (better localization) with any additional images/bounding boxes detected by YOLOv3 (better detection) into an initial set of labeled bounding boxes. We further tightened or expanded these bounding boxes to acquire accurate regions for each figure and table. Since the visualization type is not of current interest and since CNN models make mistakes, we combined the 10 figure classes into a single *figure* label type in our post-processing.

4.4 Fine-Grained Recognition and Data Validation

Fine-grained recognition refers to the task of distinguishing very similar categories or correcting the results to obtain the ground truth. CNN results can lead to errors or imprecision in image detection and localization [31]. We obtained the final cohort by manually cleaning the CNNs' predictions using a collaborative annotation tool with two interfaces: one enables us to edit the content of the dataset and the other provides an overview of the data collection by year (see supplementary materials Sec. B for these two interfaces). We used the first interface to examine all pages in our dataset and check the labeling to remove, add, move, and resize the machine-generated bounding boxes as needed. After this individual pass, the first two authors of this paper used the second interface to verify the results for the entire dataset. Through this process we cleaned 26,776 figures and 2,913 tables from all 30 years of the IEEE Visualization conference, as described in Sec. 3.

Using the manually cleaned data as the ground truth, we evaluated our CNN-based labeling following the evaluation metrics of PDFFigure2.0 [6], using intersection over union ($IoU = area\ of\ overlap / area\ of\ union$) as 0.8. We found the overall *recall* of our CNN-based extraction approach on the VIS30K images to be 0.84, with *precision* 0.94 and F1 score 0.89. For this analysis we only used the "image" label in our dataset because our training phase images came from two limited datasets—they did not capture the full range of images in visualization papers. Nonetheless, we analyzed the entire dataset, including the early years with their low-quality images for which other algorithms would fail. We considered predicted figures and tables that did

not exist in the final human-curated labels as false positives. As a figure could contain multiples, we also considered it as detected if we detected such multiples in the form of several bounding boxes.

The present measurement results mean that our CNN model requires at least 22% manual effort (to add 16% false negatives and remove 6% false positives). Removing false positives requires us to detect duplicate "detection frames," while false negatives are images that go undetected. In addition to the cost of cleaning (22%), there are aspects of the manual labor that are difficult to measure, i. e., fine-tuning results that are considered correct using a machine's standard ($IoU \geq 80\%$), but not based on human-centered heuristics. Fig. 5 shows three example cases when a user needs to locate and resize the bounding boxes (*region error*) or update the class labels manually (*class error*). These are instances of *region error* where subcaptions are excluded or included in the prediction of multi-composite views. *Class errors* are also corrected when a table is inferred to be a figure. We estimate that about 20% of the images required a final adjustment to fine-tune the CNNs' output.

5 VISIMAGENAVIGATOR (VIN): EXPLORING FIGURES AND TABLES IN THE LITERATURE

We posit that our ability to extract data must be accompanied by the community's ability to use, further classify, manage, and reason about the content of the figures and tables. Our second contribution is thus the design and implementation of VISImageNavigator (VIN; see Fig. 6 and `visimagenavigator.github.io`), a lightweight online browser to view and query the dataset and its metadata. VIN can be used to explore VIS figures and tables, VIS publication venues, keywords, and authors over time.

### 5.1 Browsing the Image Collection

The VIN interface has three styles: The *default browser layout* (Fig. 6(a)) was inspired by the VizioMetrix search engine [24]. Figures are arranged next to each other following the "brick wall" metaphor. The second *timeline-centric paper piles* facilitates viewing temporal trends (Fig. 6(b)), while the last one presents a *paper-centric view* (Fig. 6(c)). Figure and table captions are available on demand. The images are ordered by conference year and by the order of appearance in the proceedings. VIN is not designed to support dedicated statistical analyses of the data itself. We implemented backend by indexing the authors, captions, and author keywords, crossed-linked to the paper keywords in `keyvis.org` [16]. We also implemented term-based search in titles and abstracts. The *by-title-and-abstract mode* enables users to directly search by title and abstract explore and often returns more complete results than searching images *by author keywords*, likely because not all papers comprise author keywords or these do not cover all aspects.

Naturally, the results can be sorted several ways: by author to study people's presentation styles or by year to retrieve the most recent images for a given search term. Using VIN, the user can answer questions such as *'Which figures are used in evaluation papers?'* by searching for "evaluation" and reading the results. One can also just examine the figures but not tables or ask *'What are the result figures in John T. Stasko's evaluation papers?'* by filtering both the *authors* and *terms* fields (Fig. 6(b)).

Since VIS is the premier conference of our field, decisions about what topics appear and what methods are published can profoundly influence applications. Consider questions like *what illustrative*
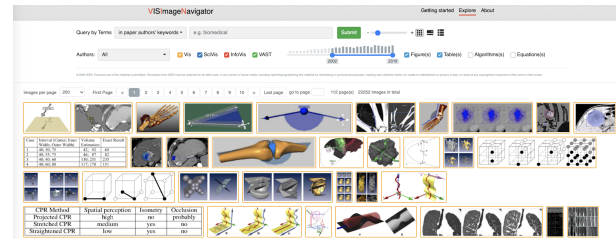
(a) Image-centric view using a "brick wall" layout.
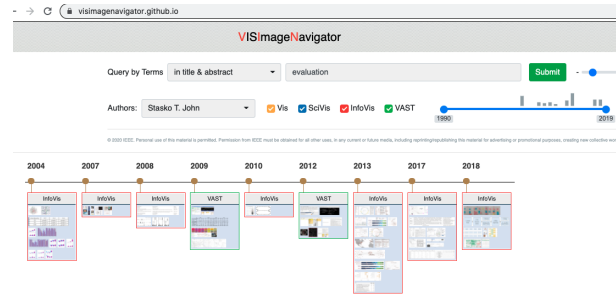
(b) Timeline-centric view of paper image cards. Here results show all images where the paper title and abstract contain the term "evaluation" of authors field "Stasko T. John".
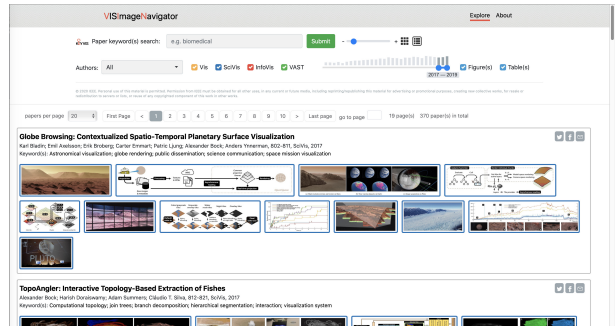
(c) Paper-centric view using a paper layout for a query of papers appeared between 2017 and 2019.

Fig. 6. Our VISImageNavigator (VIN) interface and search engine. We arranged figures and tables using (a) a "brick wall" layout, (b) a timeline view, or (c) a paper list layout We color-coded the images with frames based on the conference types. Users can query the database, by *terms* (using authors' keywords or terms in titles and abstracts), by image type (figure, table, or both), by conference category (Vis, SciVis, InfoVis, VAST), or by year. A click on an image displays article details including authors and a hyperlink to the full PDF in IEEE's digital library.

visualization techniques have been developed? and *what are the techniques in domains such as "brain imaging" and "quantum physics"*? (cf. see Fig. 10 of the supplemental material Sect. D). To answer this question using VIN, the user can query the term 'brain' to reveal diverse advances in showing tomography in the nineties, tensor lines, as well as metaphorical maps. In contrast, searching "quantum" returns fewer results with a major focus on depicting symmetrical structures. Switching to the paper-centric view reveals the paper titles that confirm that most 'quantum' papers use volume rendering to show particle interactions.

5.2 Use-Cases for VIS30K

We envision the following use-cases for VIN and VIS30K:

1. Identifying Related Work. Typically, when researchers search for related work, they either rely on text search in digital libraries or they manually follow trails of citations from one paper to the next. In addition to offering a text-based search in paper metadata, VIN offers a focused, visual way to quickly browse

related work that is impossible with other research databases or generic online image search tools. This visual search can complement the traditional related work search and enable researchers to stumble upon papers with similar layouts, data representations, or interfaces that may not show up in text searches. Image overviews also help them to see and describe differences in data visualization styles spanning multiple years that may be more difficult to grasp from images confined to individual papers.

2. Teaching and Communication. Our image database and VIN can also be used to quickly find images for teaching and communication. By filtering out later years of the conference, for example, historic examples from the community can be retrieved and compared to the current state-of-the-art. Browsing the most recent years reveals new contributions and the latest advances. Our images are stored in a lossless format at a resolution that supports their use for teaching and communication. In addition, extracting paper references is made simple through the VIN interface (Fig. 6(c)). Further, there may be users outside the community who are interested in the types of representations published by the community but lack easy access to papers or are not accustomed to reading scientific content. For these groups of users, VIN can serve as an entry point to research in the visualization community and spark interest in exploring its work further. Thus, VIN also serves as a bridge to other communities.

3. Understanding VIS. Both the Visualization community itself and external researchers interested in the history of visual data analysis may be curious about the evolution of the field. Past efforts on understanding practices in the community were listed in Sec. 2. Complementing this past work, our data and tool now offers overviews of our community's visual output both in the form of both figures and tables. Researchers can either engage assess and analyze the data qualitatively using VIN or download it to build additional tools that use their own metrics to support quantitative study of the image content.

4. Tool Building and Testing. Our database can be used by others to extend VIN or build novel tools for other types of image analysis tasks. For example, future projects could build a dedicated image similarity search tool on top of VIN, use the database as training data for machine learning algorithms, or look into visualizing image content (e.g.visual question answering and visualization re-targeting). The database can also be used for computer vision projects. Our results demonstrate that the state-of-the-art CNN solutions and figure and table extractions do not achieve human-level accuracy. This finding suggests that our VIS30K dataset could present a grand challenge for future benchmarking of machine learning research.

6 DISCUSSION AND CONCLUSION

We introduce VIS30K, a curated and complete dataset of all figures and tables used in IEEE VIS conference publications over its 30-year history. We also provide a data exploration tool, VIN, that facilitates interactive exploration of this scholarly resource as well as a collection of the relevant metadata. For the first time, our VIN tool enables researchers and practitioners to search for approaches related to their own or solutions for their data analysis problems in a visual way—after all, most of us remember images we have seen in the past much better than the specific names of the relevant papers. Our search also enables researchers to quickly find related work they may not even be aware of, without requiring them to read and download several possibly related papers from digital libraries.

In addition to these immediate benefits of our interactive search, our dataset will allow us to explore a number of interesting research questions in the future. For example, *how has visual encoding been used in the past, and has this changed over time? Do the three conference tracks use specific forms of encoding in a similar way or are there differences? How can we create a visualization with a similar style?*

Our work also has implications that arise from our specific extraction approach. We used CNNs to extract the image and table locations via generated pseudo papers, followed by a manual cleaning step to ensure quality. Without CNNs, a huge amount of manual work would have been needed. Without our manual cleaning, similarly, we could not have ensured our high data quality. While we worked on published papers, our hybrid CNN-manual approach is not limited to such documents: it could well be applied more broadly, e.g., to XML-based solutions such as GROBID [29]. We also anticipate that DeepPaperComposer [27], a newer model for non-textual content extraction can provide a scalable solution for information extraction from future VIS publications. Our constructive experience could inspire future work on pipelines that seek to extract images and tables from documents.

Naturally, our work is not without limitations. Our dataset does not represent all of visualization scholarship. We examined papers in only a single venue and did not collect scholarly figures presented at other venues, e.g., EuroVis, PacificVis, CHI, and other related conferences. We also did not collect visualization-related journal articles in the *IEEE Transactions on Visualization and Computer Graphics* and in *IEEE Computer Graphics and Applications*. As the visualization field in itself is cross-disciplinary, we also did not examine domain-specific journals that provide applications and real-world impact (see an excellent review of visualization uses in studying the human connectome by Margulies et al. [30]).

Reproducibility. We have released three data collections and our CNN models. The main contribution in this work is the VIS30K image collection and ground-truth bounding box types and locations of all images released through the IEEE dataport at DOI `10.21227/4hy6-vh52`. Metadata for our VIS30K dataset is accessible via a public Google spreadsheet (`go.osu.edu/vis30k`). The 13K training and validation data of the synthetic pages and their ground-truth and the text and image corpora are accessible via `go.osu.edu/vis30ktrainingdata`. The tensorflow models we used are accessible online through the VIN website. We have also released the pre-trained CNN models at `go.osu.edu/vis30kpretrainedmodels`.

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REFERENCES

[1] W. Aigner, S. Miksch, H. Schumann, and C. Tominski, "Survey of visualization techniques," in *Visualization of Time-Oriented Data*. London: Springer, 2011, ch. 7, pp. 147–254. doi: 10.1007/978-0-85729-079-3_7

[2] T. Blascheck, L. Besançon, A. Bezerianos, B. Lee, and P. Isenberg, "Glanceable visualization: Studies of data comparison performance on smartwatches," *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 1, pp. 616–629, Jan. 2019. doi: 10.1109/TVCG. 2018.2865142

[3] M. A. Borkin, A. A. Vo, Z. Bylinskii, P. Isola, S. Sunkavalli, A. Oliva, and H. Pfister, "What makes a visualization memorable?" *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 12, pp. 2306–2315, Dec. 2013. doi: 10.1109/TVCG.2013.234

[4] A. Chatzimparmpas and I. Jusufi, "The state of the art in enhancing trust in machine learning models with the use of visualizations," *Computer Graphics Forum*, vol. 39, no. 3, pp. 713–756, Jun. 2020. doi: 10.1111/cgf.14034

[5] S. R. Choudhury, P. Mitra, and C. L. Giles, "Automatic extraction of figures from scholarly documents," in *Proc. DocEng*, 2015, pp. 47–50. doi: 10.1145/2682571.2797085

[6] C. Clark and S. Divvala, "PDFFigures 2.0: Mining figures from research papers," in *Proc. ACM/IEEE-CS Joint Conference on Digital Libraries*. New York: ACM, 2016, pp. 143–152. doi: 10.1145/2910896.2910904

[7] A. Dasgupta, H. Wang, N. O'Brien, and S. Burrows, "Separating the wheat from the chaff: Comparative visual cues for transparent diagnostics of competing models," *IEEE Transactions on Visualization and Computer Graphics*, vol. 26, no. 1, pp. 1043–1053, Jan. 2020. doi: 10.1109/TVCG.2019.2934540

[8] D. Deng, Y. Wu, X. Shu, M. Xu, J. Wu, S. Fu, and Y. Wu, "VisImages: A large-scale, high-quality image corpus in visualization publications," arXiv preprint 2007.04584, Jul. 2020.

[9] A. Diehl, A. Abdul-Rahman, M. El-Assady, B. Bach, D. A. Keim, and M. Chen, "VisGuides: A forum for discussing visualization guidelines," in *EuroVis Short Papers*. Goslar, Germany: Eurographics Association, 2018, pp. 61–65. doi: 10.2312/eurovisshort.20181079

[10] D. Dovey, "Vector plots for irregular grids," in *Proc. Visualization*, 1995, pp. 248–253. doi: 10.1109/VISUAL.1995.480819

[11] E. E. Fırat and R. S. Laramee, "Towards a survey of interactive visualization for education," in *Proc. Computer Graphics and Visual Computing*, 2018, pp. 91–101. doi: 10.2312/cgvc.20181211

[12] T. He, L. Hong, A. Kaufman, and H. Pfister, "Generation of transfer functions with stochastic search techniques," in *Proc. Visualization*, 1996, pp. 227–234. doi: 10.1109/VISUAL.1996.568113

[13] M. Hurst, "Towards a theory of tables," *International Journal of Document Analysis and Recognition*, vol. 8, no. 2–3, pp. 123–131, Mar. 2006. doi: 10.1007/s10032-006-0016-y

[14] P. Isenberg and S. Carpendale, "Interactive tree comparison for co-located collaborative information visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 13, no. 6, pp. 1232–1239, Nov./Dec. 2007. doi: 10.1109/TVCG.2007.70568

[15] P. Isenberg, F. Heimerl, S. Koch, T. Isenberg, P. Xu, C. D. Stolper, M. Sedlmair, J. Chen, T. Möller, and J. Stasko, "Vispubdata.org: A metadata collection about IEEE visualization (VIS) publications," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 9, pp. 2199–2206, Sep. 2016. doi: 10.1109/TVCG.2016.2615308

[16] P. Isenberg, T. Isenberg, M. Sedlmair, J. Chen, and T. Möller, "Visualization as seen through its research paper keywords," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 1, pp. 771–780, Jan. 2016. doi: 10.1109/TVCG.2016.2598827

[17] T. Isenberg, P. Isenberg, J. Chen, M. Sedlmair, and T. Möller, "A systematic review on the practice of evaluating visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 12, pp. 2818–2827, Dec. 2013. doi: 10.1109/TVCG.2013.126

[18] J. Kehrer and H. Hauser, "Visualization and visual analysis of multifaceted scientific data: A survey," *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 3, pp. 495–513, Mar. 2013. doi: 10.1109/TVCG.2012.110

[19] A. Kerren, K. Kucher, Y.-F. Li, and F. Schreiber, "BioVis Explorer: A visual guide for biological data visualization techniques," *PLoS One*, vol. 12, no. 11, pp. e0187341:1–e0187341:14, Nov. 2017. doi: 10.1371/journal.pone.0187341

[20] S. Khusro, A. Latif, and I. Ullah, "On methods and tools of table detection, extraction and annotation in PDF documents," *Journal of Information Science*, vol. 41, no. 1, pp. 41–57, Feb. 2015. doi: 10.1177/0165551514551903

[21] K. Kucher and A. Kerren, "Text visualization techniques: Taxonomy, visual survey, and community insights," in *Proc. IEEE Pacific Visualization Symposium*, 2015, pp. 117–121. doi: 10.1109/PACIFICVIS.2015.7156366

[22] K. Kucher, C. Paradis, and A. Kerren, "The state of the art in sentiment visualization," *Computer Graphics Forum*, vol. 37, no. 1, pp. 71–96, Feb. 2018. doi: 10.1111/cgf.13217

[23] H. Lam, E. Bertini, P. Isenberg, C. Plaisant, and S. Carpendale, "Empirical studies in information visualization: Seven scenarios," *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 9, pp. 1520–1536, Sep. 2012. doi: 10.1109/TVCG.2011.279

[24] P. Lee, J. D. West, and B. Howe, "Viziometrics: Analyzing visual information in the scientific literature," *IEEE Transactions on Big Data*, vol. 4, no. 1, pp. 117–129, Mar. 2017. doi: 10.1109/TBDATA.2017.2689038

[25] P. Li, X. Jiang, and H. Shatkay, "Figure and caption extraction from biomedical documents," *Bioinformatics*, vol. 35, no. 21, pp. 4381–4388, 2019. doi: 10.1093/bioinformatics/btz228

[26] R. Li and J. Chen, "Toward a deep understanding of what makes a scientific visualization memorable," in *Short Papers of IEEE Visualization/SciVis*, 2018, pp. 26–31. doi: 10.1109/SciVis.2018.8823764

[27] M. Ling and J. Chen, "DeepPaperComposer: A simple solution for training data preparation for parsing research papers," in *Proc. EMNLP/Scholarly Document Processing*. Stroudsburg, PA, USA: ACL, 2020, pp. 91–96. doi: 10.18653/v1/2020.sdp-1.10

[28] V. Long, R. Dale, and S. Cassidy, "A model for detecting and merging vertically spanned table cells in plain text documents," in *Proc. International Conference on Document Analysis and Recognition*, 2005, pp. 1242–1246. doi: 10.1109/ICDAR.2005.21

[29] P. Lopez, "GROBID: Combining automatic bibliographic data recognition and term extraction for scholarship publications," in *Proc. International Conference on Theory and Practice of Digital Libraries*. Berlin: Springer, 2009, pp. 473–474. doi: 10.1007/978-3-642-04346-8_62

[30] D. S. Margulies, J. Böttger, A. Watanabe, and K. J. Gorgolewski, "Visualizing the human connectome," *NeuroImage*, vol. 80, no. 15, pp. 445–461, Oct. 2013. doi: 10.1016/j.neuroimage.2013.04.111

[31] S. S. Paliwal, D. Vishwanath, R. Rahul, M. Sharma, and L. Vig, "TableNet: Deep learning model for end-to-end table detection and tabular data extraction from scanned document images," in *Proc. International Conference on Document Analysis and Recognition*, 2019, pp. 128–133. doi: 10.1109/ICDAR.2019.00029

[32] A. Perer and B. Shneiderman, "Balancing systematic and flexible exploration of social networks," *IEEE Transactions on Visualization and Computer Graphics*, vol. 12, no. 5, pp. 693–700, Sep./Oct. 2006. doi: 10.1109/TVCG.2006.122

[33] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, 2016, pp. 779–788. doi: 10.1109/CVPR.2016.91

[34] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, Jun. 2017. doi: 10.1109/TPAMI.2016.2577031

[35] H.-J. Schulz, "Treevis.net: A tree visualization reference," *IEEE Computer Graphics and Applications*, vol. 31, no. 6, pp. 11–15, Nov./Dec. 2011. doi: 10.1109/MCG.2011.103

[36] R. Sicat, J. Krüger, T. Möller, and M. Hadwiger, "Sparse PDF volumes for consistent multi-resolution volume rendering," *IEEE Transactions on Visualization and Computer Graphics*, vol. 20, no. 12, pp. 2417–2426, Dec. 2014. doi: 10.1109/TVCG.2014.2346324

[37] N. Siegel, Z. Horvitz, R. Levin, S. Divvala, and A. Farhadi, "FigureSeer: Parsing result-figures in research papers," in *Proc. European Conference on Computer Vision*. Berlin: Springer, 2016, pp. 664–680. doi: 10.1007/978-3-319-46478-7_41

[38] N. Siegel, N. Lourie, R. Power, and W. Ammar, "Extracting scientific figures with distantly supervised neural networks," in *Proc. ACM/IEEE-CS Joint Conference on Digital Libraries*. New York: ACM, 2018, pp. 223–232. doi: 10.1145/3197026.3197040

[39] L. F. Smith and S. Jänicke, "The impact of EuroVis publications," in *EuroVis Posters*, 2020, pp. 25–27. doi: 10.2312/eurp.20201120

[40] J. Stribling, M. Krohn, and D. Aguayo, "SCIgen – An automatic CS paper generator," Online tool: https://pdos.csail.mit.edu/archive/scigen/, 2005.

[41] H. Strobelt, D. Oelke, C. Rohrdantz, A. Stoffel, D. A. Keim, and O. Deussen, "Document cards: A top trumps visualization for documents," *IEEE Transactions on Visualization and Computer Graphics*, vol. 15, no. 6, pp. 1145–1152, Nov./Dec. 2009. doi: 10.1109/TVCG.2009.139

[42] A. Tsirikoglou, G. Eilertsen, and J. Unger, "A survey of image synthesis methods for visual machine learning," in *Computer Graphics Forum*, vol. 39, no. 6, 2020, pp. 426–451. doi: 10.1111/cgf.14047

[43] L. Yu, P. Svetachov, P. Isenberg, M. H. Everts, and T. Isenberg, "FI3D: Direct-touch interaction for the exploration of 3D scientific visualization spaces," *IEEE Transactions on Visualization and Computer Graphics*, vol. 16, no. 6, pp. 1613–1622, Nov./Dec. 2010. doi: 10.1109/TVCG.2010.157

[44] W. Zeng, A. Dong, X. Chen, and Z. Cheng, "VIStory: Interactive storyboard for exploring visual information in scientific publications," *Journal of Visualization*, 2021, to appear. doi: 10.1007/s12650-020-00688-1

VIS30K: A Collection of Figures and Tables from IEEE Visualization Conference Publications

Additional material

A. DATABASES

Our dataset collection includes figures and tables in the 2,916 conference and journal publications of the IEEE VIS conference from 1990 to 2019. We store the IEEE VIS paper images in PNG format in our VIS30K data. Metadata of the dataset is accessible via a public Google spreadsheet (`go.osu.edu/vis30k`) whose columns **A–D** are:

- **A** The **paper DOI** as a unique identifier to cross-link to other databases such as VisPubData [15], KeyVis [16], and the Practice of Evaluating Visualization [17], [23].
- **B** A **thumbnail of each image**, which is a low-resolution version of each image extracted from the paper. This provides a gateway to data analyses, e. g., through Google CoLab.
- **C** The **image type**: either figure (F) or table (T).
- **D** An **image link** that points to its web storage address where a full-resolution version is accessible through IEEE DataPort. Please note that all image files are copyrighted, and for most the copyright is owned by IEEE. Some have creative commons licenses or are in the public domain. Yet other images are subject to different, specific copyrights as indicated in the figure caption in the paper.

B. INTERACTIVE LABEL CLEANING TOOLS

Fig. 7 shows screenshots of two tools we used during our interactive cleaning process.

C. IMAGE DISTRIBUTION IN THE TRAINING DATA CORPUS

The diversity of image data in the training data is critical for developing useful image data extraction algorithms. We employed two databases collected by Borkin et al. [3] and Li and Chen [26]. We removed images if they contained abundant text. We construct an image dataset with 12 categories shown in Table 1.

D. ADDITIONAL USE-CASES

In the paper we present three interfaces in an interactive web-based tool, VIN, that allows the general public to perform their own analyses on the entire 30 years of IEEE visualization image datasets. We show in this part example questions the VIN tool can help answer.

What are the illustrative visualization techniques in literature? Looking at images allows scholars to "see" the techniques invented over the years and obtain a gist of the development of techniques over time. Fig. 8 shows an exploratory process for someone, here Jerry, who has taken a visualization class in graduate school to explore techniques related to "illustrative visualization". Jerry puts "illustrative visualization" in the query by *author keywords* and ses that the tool returned 243 figures and 13 table images ranging from see-through views to distorted rendering to depth-based techniques. Jerry first observes that most of the early techniques were about transfer functions and then newer techniques address interactive exploration and augmented depth perception (Fig. 8(a)–(b)). The most recent work in 2019 is different enough to catch Jerry's attention in that only one paper at InfoVis was about non-spatial data (Fig. 8(a)). Wondering what that paper is about, Jerry switches to the paper-centric view to learn that it was about setting parameters in a high-dimensional space. Apparently this paper has a novel use of terminology compared to other papers, which largely focused on spatial data representation. Curious about why he did not see Ebert and Rheingans' work on shading-based illustrative visualization, Jerry tries a similar term 'non-photorealistic rendering' and added 'Penny Rheingans' to the author's name field; now it returned several of Rheingans' and her students' work (Fig. 8(b)). Trying the same keywords and author's field and filtering by 'title and abstract' instead returns fewer results (Fig. 8(c)). Jerry learns that next time he should try both search options. Further exploration by updating the keywords to "illustration" reveals that this term was largely used in hand-drawn techniques (Fig. 8(d)).

What work has been published by Sheelagh Carpendale? Assume that André is a new PhD student working with Prof. Carpendale at Simon Fraser University who would like a quick understanding of Prof. Carpendale's work in interactive visualization before reading her other HCI (human-computer interaction) journal and conference papers. André selects the author's name from the author category and then clicks the timeline view to obtain an overview of the work (Fig. 9). He sees diverse contributions in visual representations and novel interaction techniques on tabletop and large displays. Since André likes interactive techniques, André quickly begins to explore the early papers related to focus+context. Curious what concepts these focus plus context describe, André switches to the paper view. Here he learns that Dr. Carpendale published several focus+context applications in the area of biology. Interested, André decides that he should read these papers to learn about the details.

What visualization applications center around quantum physics? For Emma, a scholar whose goals are related to examine complex structures in quantum physics data, our VIN tool is a resource for research techniques she could adapt or reuse rather than reinventing the wheel. Emma knows that she could query "quantum" from the authors' keywords or more specific terms in abstract and title that target specific design choices (e. g., showing the data with line or volume rendering) or stylistic decisions (e. g., color space and line styles) (Fig. 10). She is interested in the most frequent visual encodings (e.g., what data attributes are mapped to which marks and channels) and best practices (e.g.

TABLE 1

The image class distribution of our training data corpus. Our pseudo-paper page composer randomly pastes 10 classes of *figures* and one *table*, and one *bullets and equations* classes onto white paper pages. These images are subset of figures and tables from the MASSVIS and scientific visualization images collected by Borkin et al. [3] and Li and Chen [26].

Table	Area and circles	Bars	Bullets and equations	Line chart	Maps
232	148	362	380	330	268
Matrix and parallel coordinates	Multiple types	Photos	Point-based	Scientific data visualization	Tree and Networks
62	460	120	120	262	134
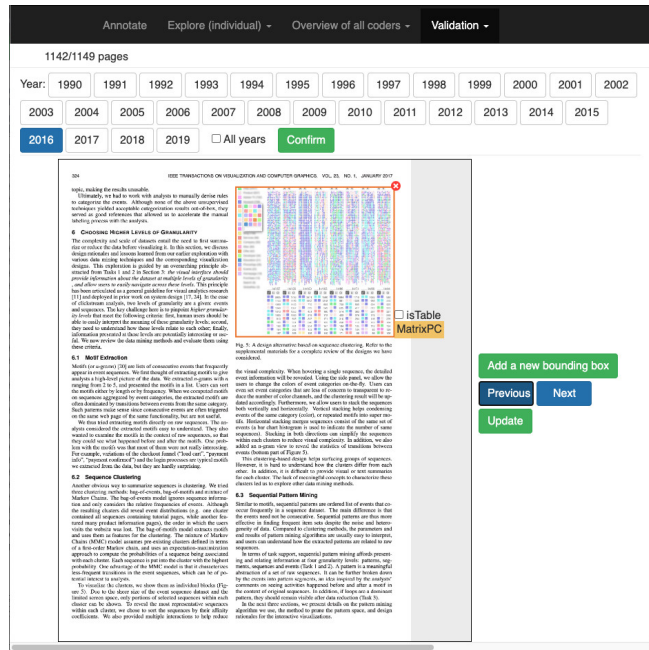
(a) Interface to verify results for individual coders.

(b) Interface to examine all coders' results.

Fig. 7. Screenshots of the tools used to clean the results of CNN-based labels. Although large labeled databases in natural scenes are becoming standard, they are comparatively rare in scholarly document databases. This tool is used for easily correcting, adding, and annotating figures and tables using the orange bounding boxes and tags.
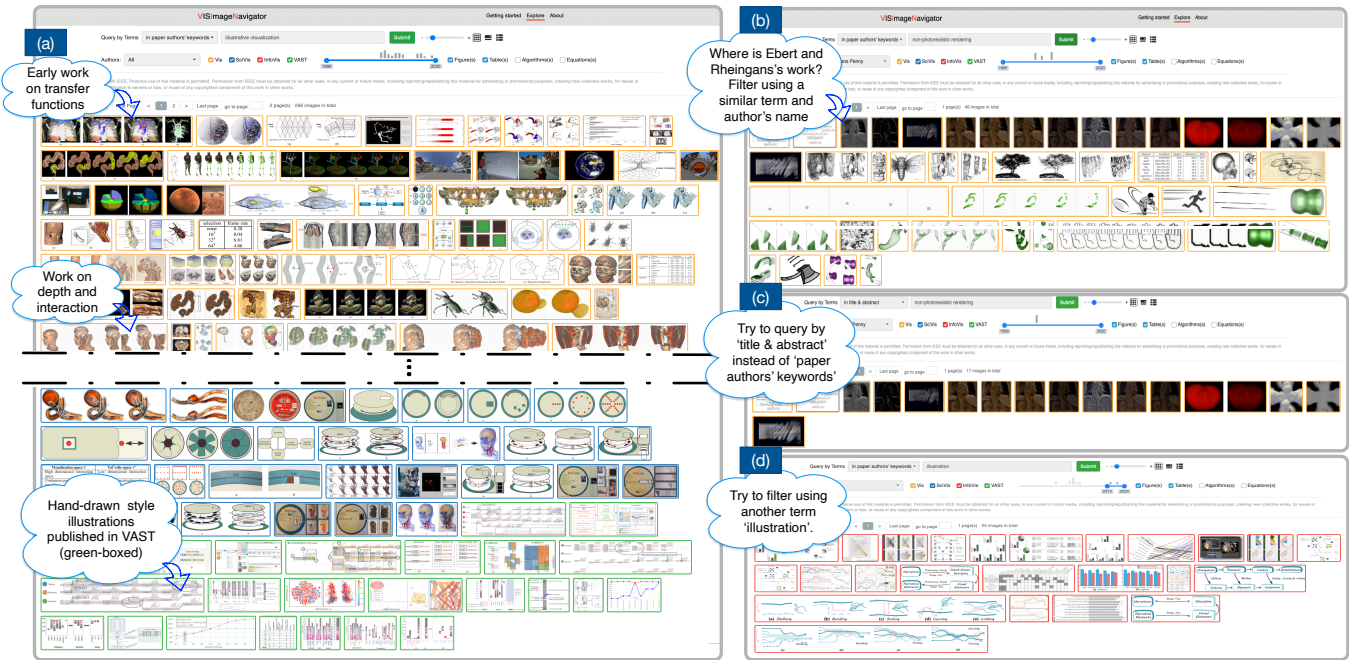
Fig. 8. VIN use-case scenario: Identify work related to "illustrative visualization." This scenario illustrates a use case when the user identifies the related work. VIN offers a focused, visual way to quickly browser related work progressively. It can complement the traditional text-based related work search.
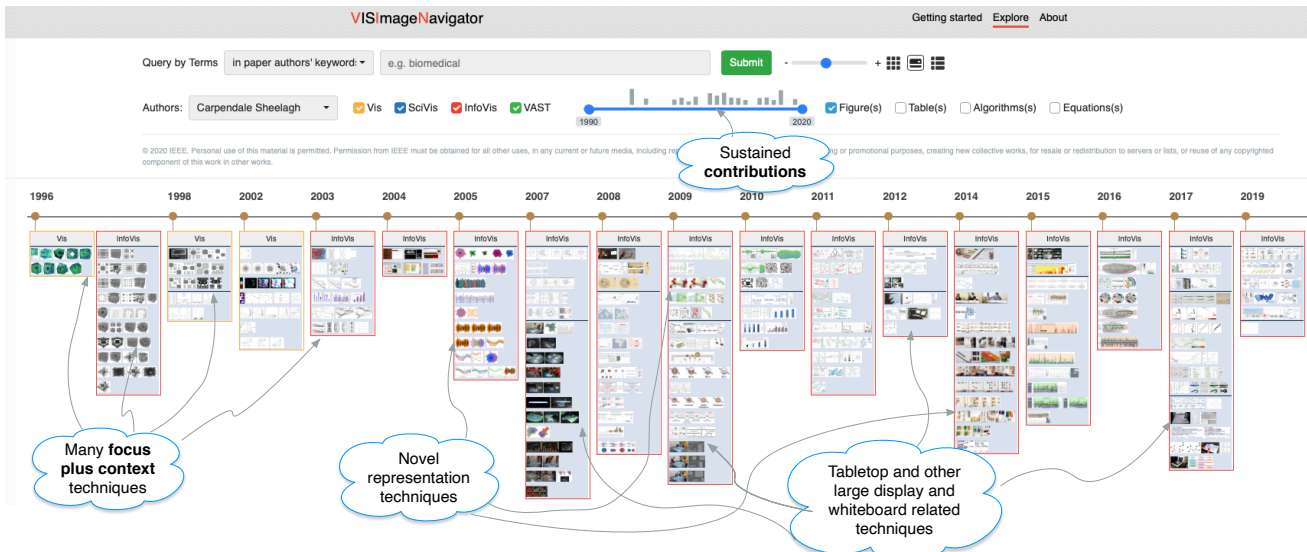

Fig. 9. VIN use-case scenario: Students searching for scholarly work by Prof. Sheelagh Carpendale at IEEE Vis and InfoVis. This scenario describes how VIN can facilitate learning and communication. It shows the types of representations published by a specific scholar in VIS.

the use of transfer functions in volume graphics). She finds that the brick wall interface provides a better understanding of the design patterns, and shows which techniques are most frequently used to show topological structures. She understands that she could create new methods to meet the data exploration goals of the quantum physicists' new design goals.
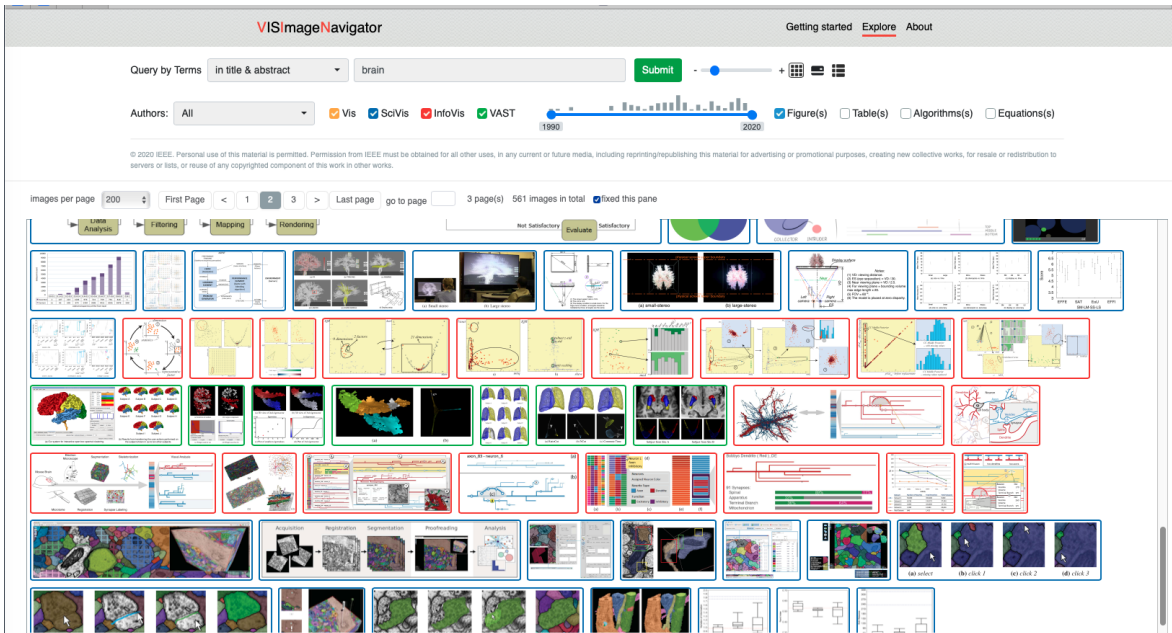
(a)
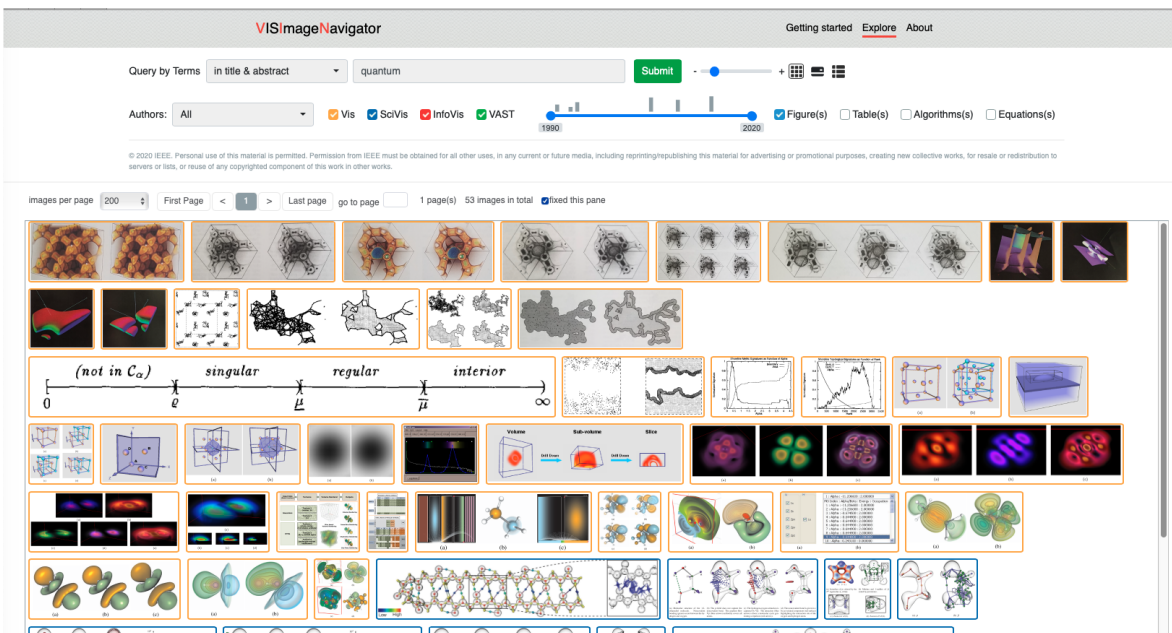
(b)

Fig. 10. VIN use-case scenario: Paper images containing "brain" or "quantum" in the paper title or abstract. We see significant advances in brain visualization compared to those for exploring quantum data.