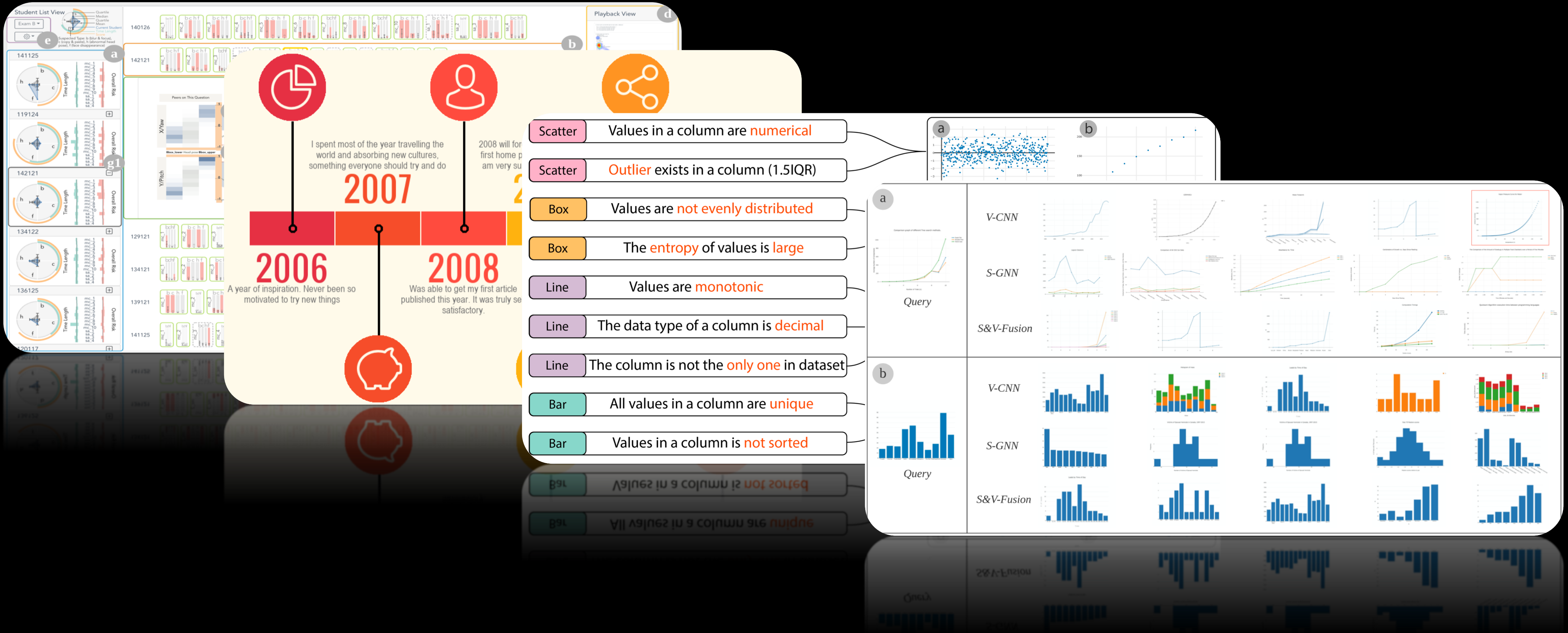

可视化科研论文的那些事儿

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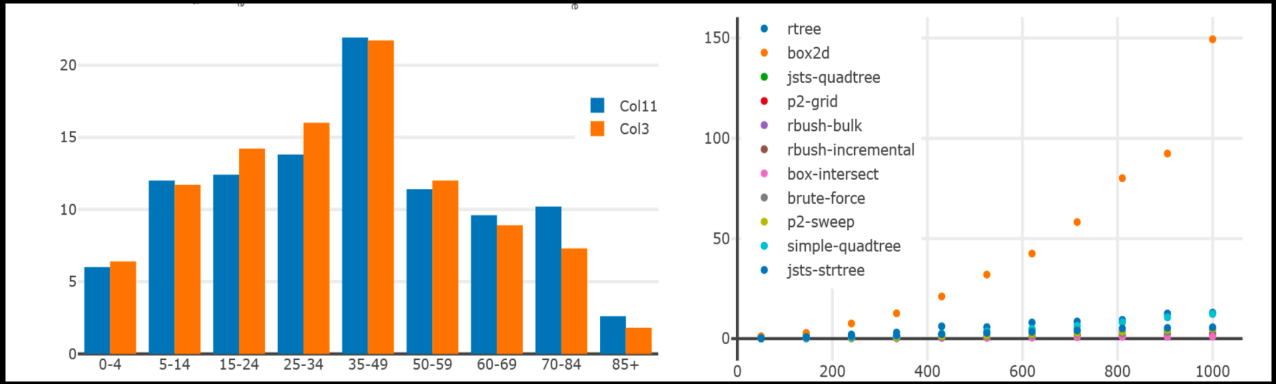
AI for VIS: Automated Visualization Design and Evaluation

Visualization Design



(KG4Vis, *IEEE VIS 21*,
Best Paper Honorable Mention Award)

Visualization Evaluation

(Structure-aware Visualization Similarity, *CHI 22*,
Best Paper Honorable Mention Award)

Standard Charts

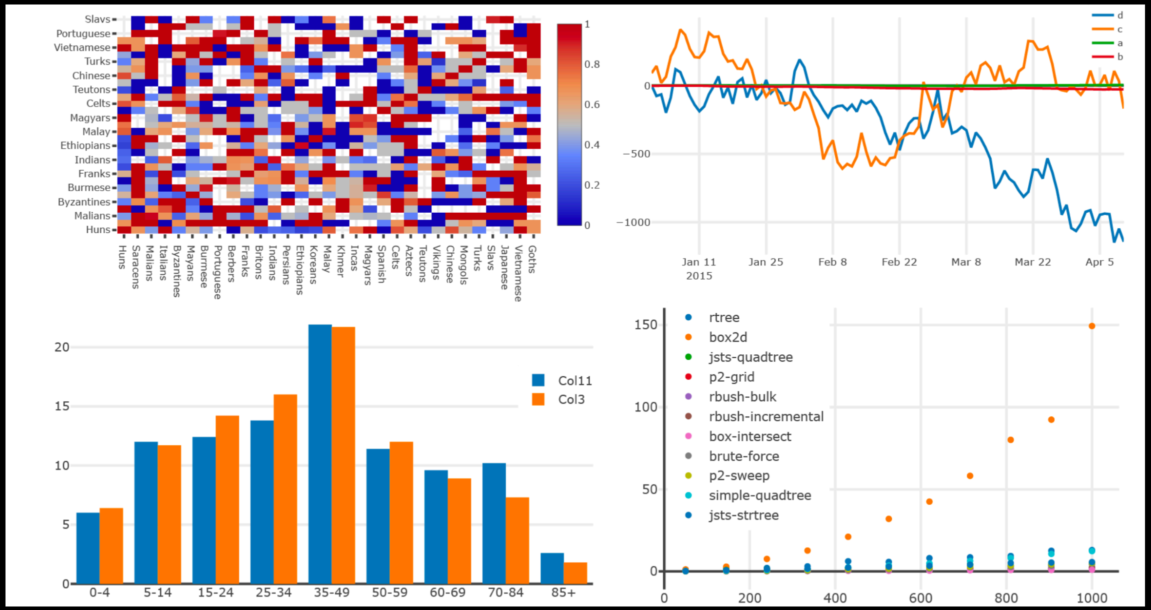
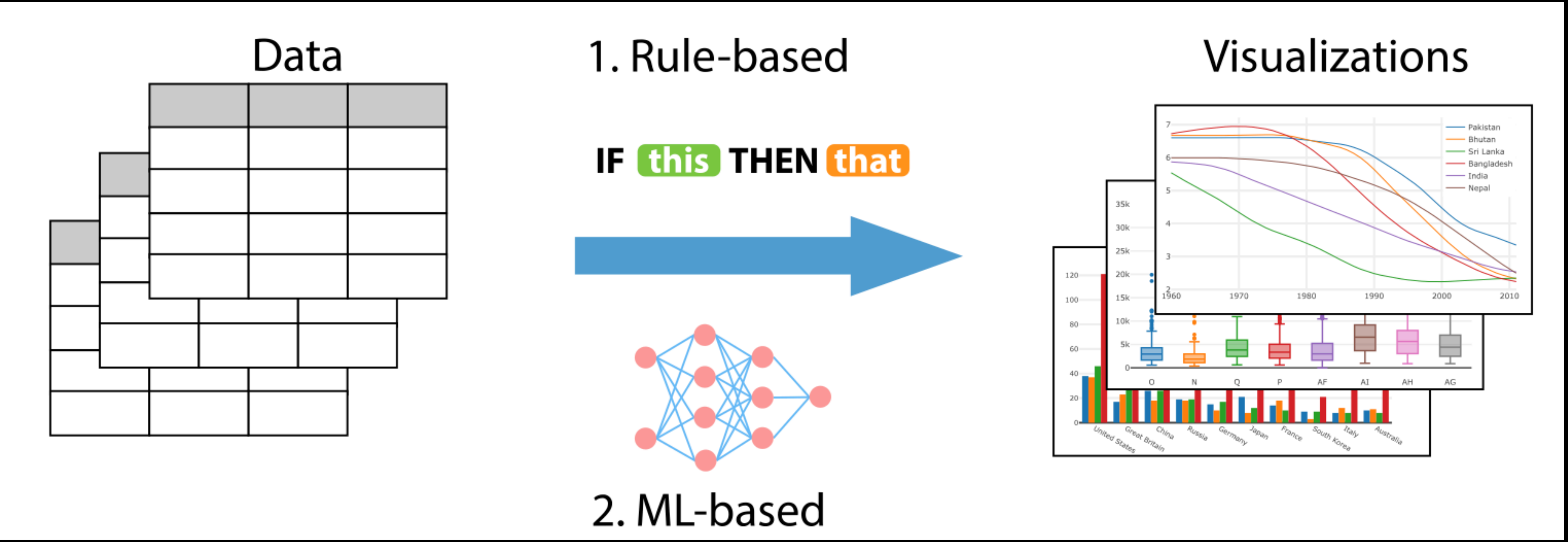


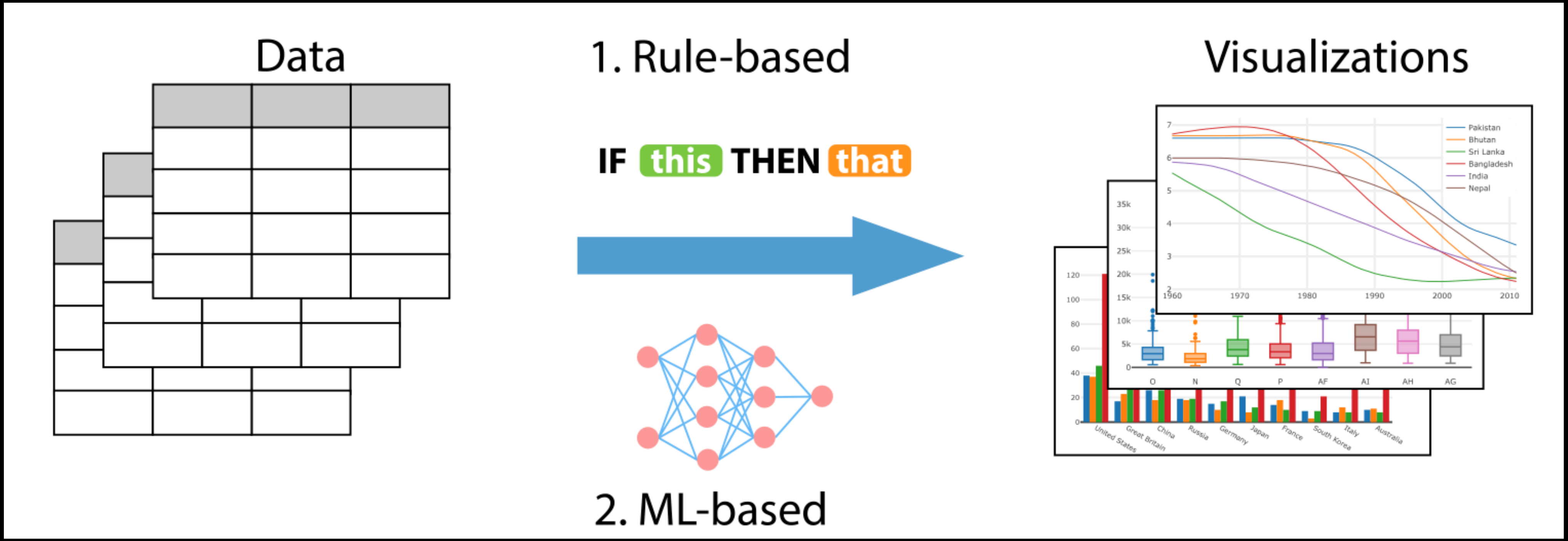
Chart Recommendation



K. Z. Hu, M. A. Bakker, S. Li, T. Kraska, and C. A. Hidalgo. Vizml: A machine learning approach to visualization recommendation. CHI, 2019.

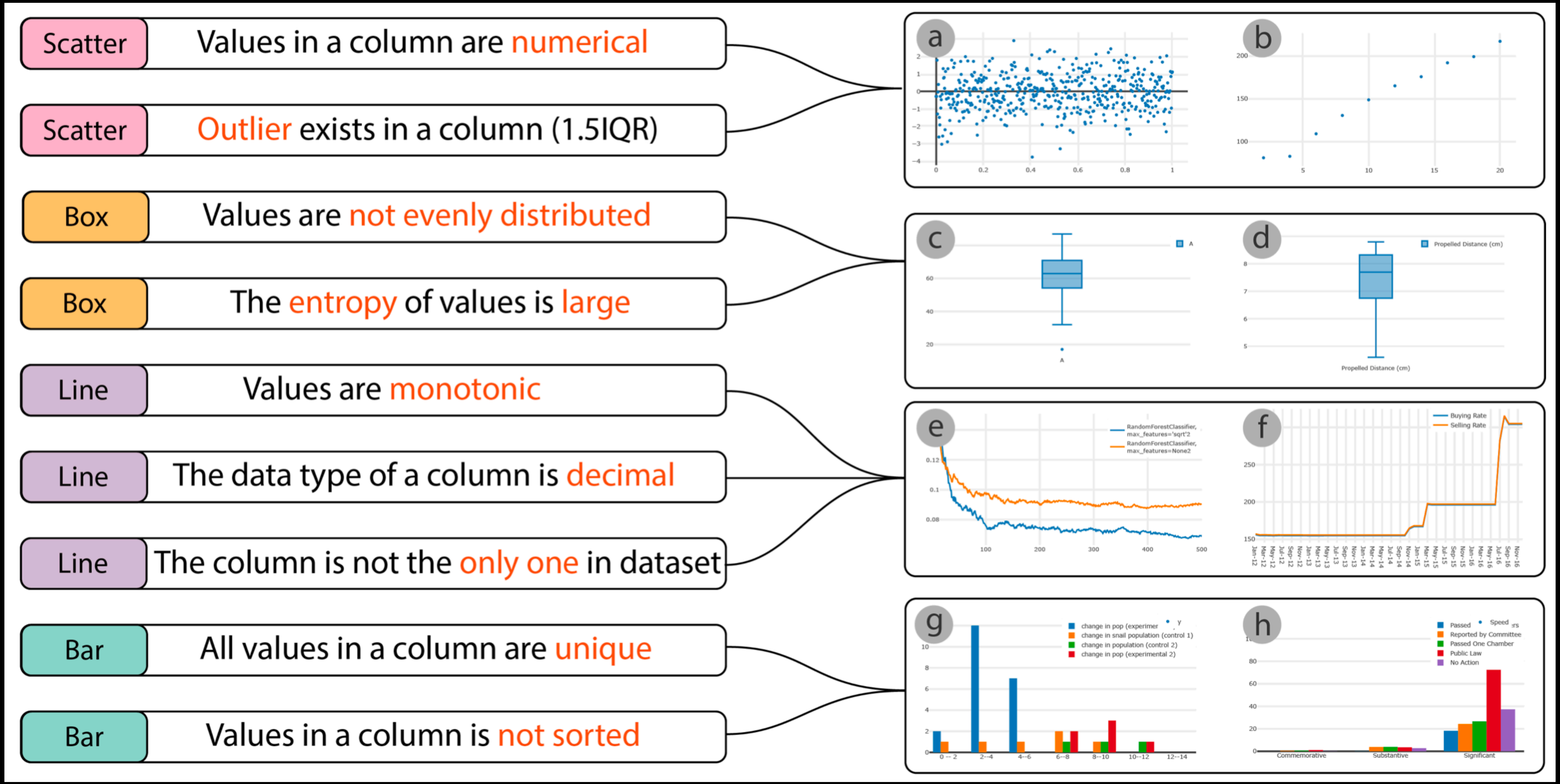
Research Question

Can we achieve visualization recommendation that **requires no manual specifications of rules** and **guarantees good explainability**?



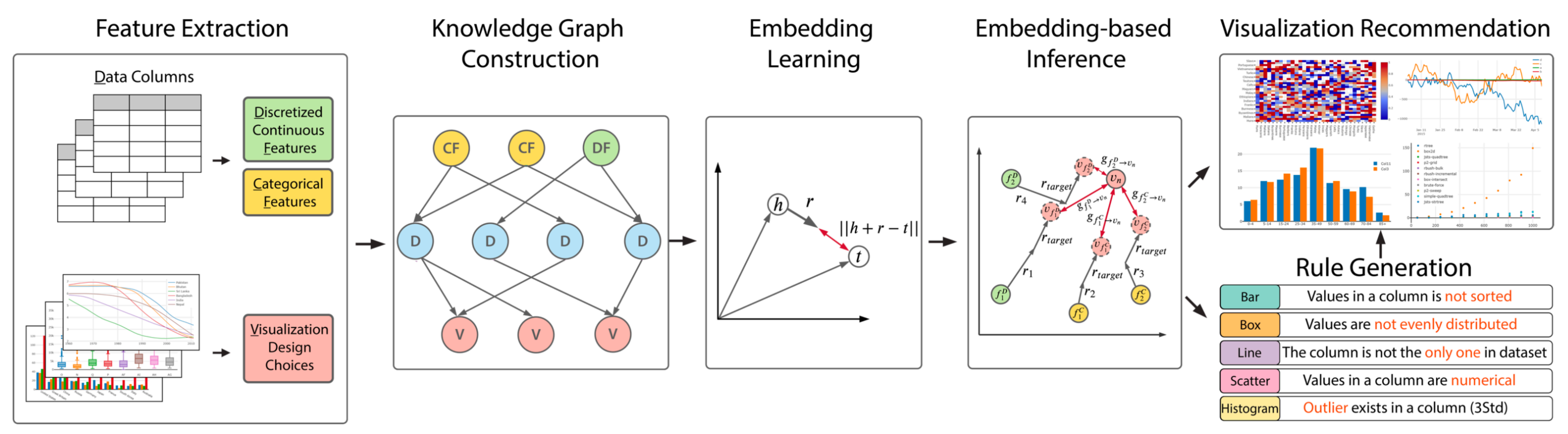
K. Z. Hu, M. A. Bakker, S. Li, T. Kraska, and C. A. Hidalgo. Vizml: A machine learning approach to visualization recommendation. CHI, 2019.

KG4Vis: A Knowledge Graph Based Approach for Visualization Recommendation



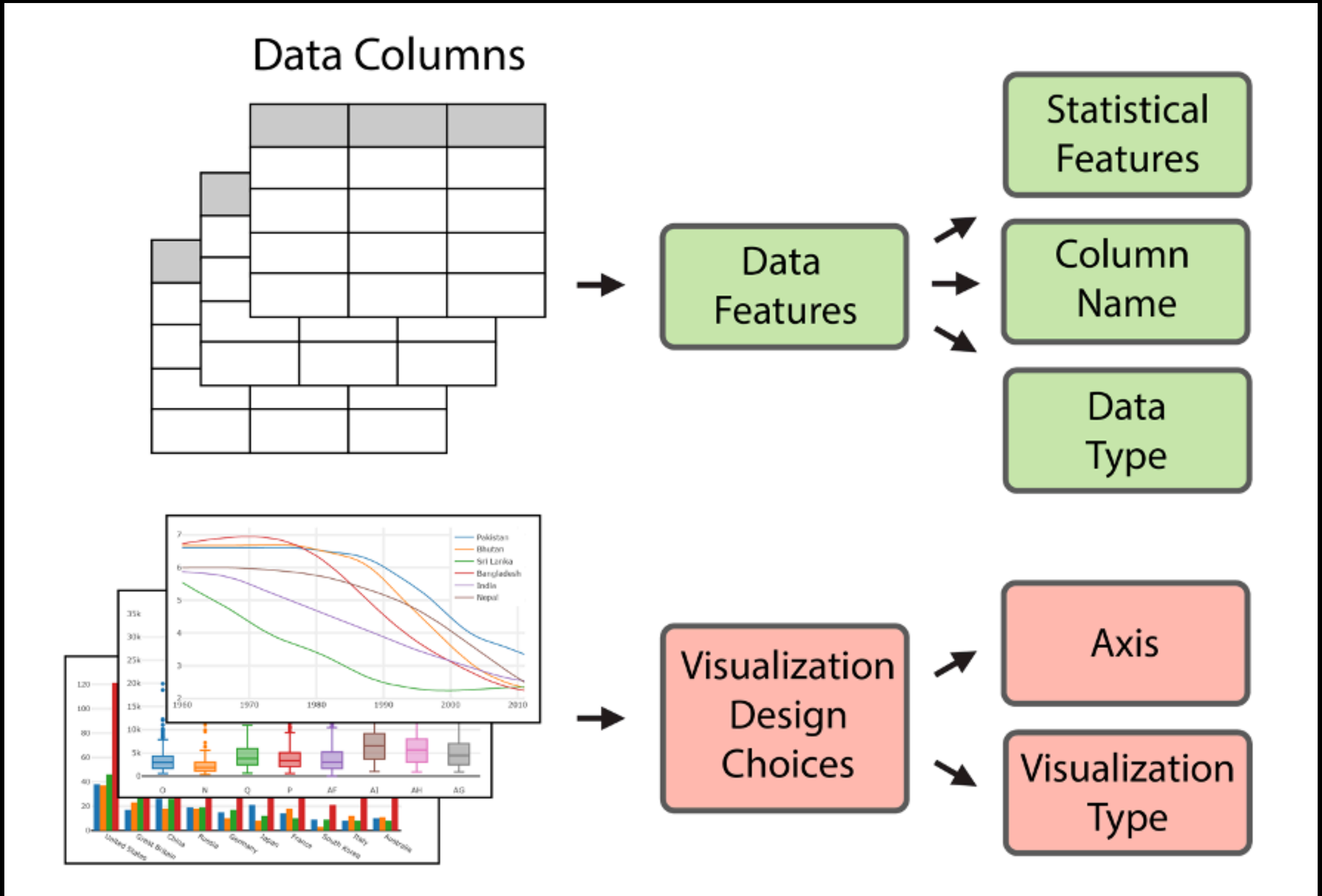
(KG4Vis, *IEEE VIS 2021*, *Best Paper Honorable Mention Award*)

KG4Vis



Our knowledge graph (KG)-based visualization recommendation approach is **data-driven** and **explainable**.

Feature Extraction



K. Z. Hu, M. A. Bakker, S. Li, T. Kraska, and C. A. Hidalgo. Vizml: A machine learning approach to visualization recommendation. CHI, 2019.

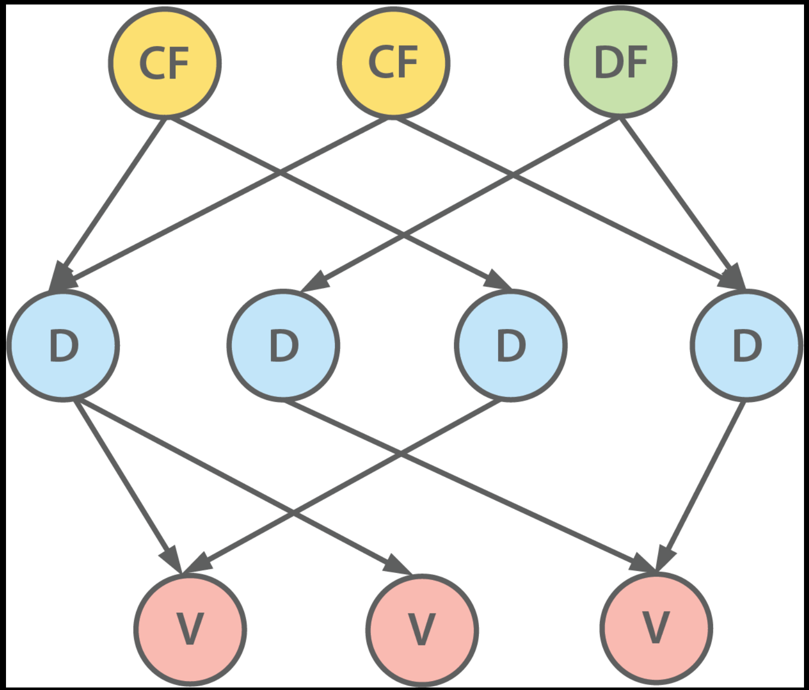
KG Construction

Entities:

- Discretized continuous features
  - Use each interval after discretization as an entity
- Categorical features
- Data columns
- Visual designs

Relations:

- Defined based on entity types



Embedding Learning

Triplet (denotes an edge in KG):

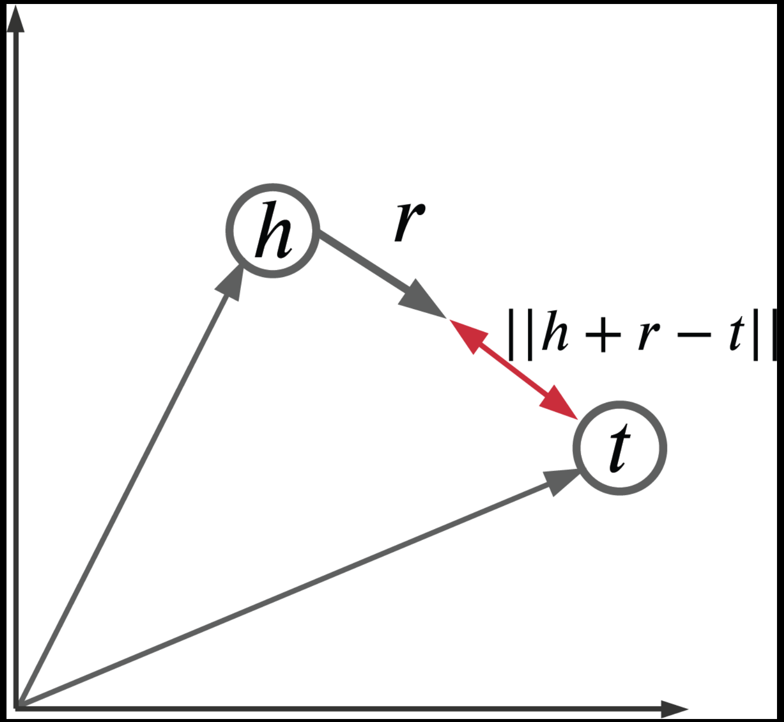
$$(head\ entity, relation, tail\ entity) \text{ or } (h, r, t)$$

TransE assumption:

$$\mathbf{h} + \mathbf{r} \approx \mathbf{t}$$

TransE scoring function (measures the possibility of a triplet):

$$g(h, r, t) = -||\mathbf{h} + \mathbf{r} - \mathbf{t}||_{1/2}$$



A. Bordes, N. Usunier, A. Garcia-Duran, J. Weston, and O. Yakhnenko. Translating embeddings for modeling multi-relational data. NeurIPS, 2013.
Z. Sun, Z. Deng, J. Nie, and J. Tang. Rotate: Knowledge graph embedding by relational rotation in complex space. ICLR, 2019.

Inference

Rule structure:

$$\textit{a data feature} \rightarrow \textit{a visual design choice} \text{ or } f_i \rightarrow v_n$$

Inference steps:

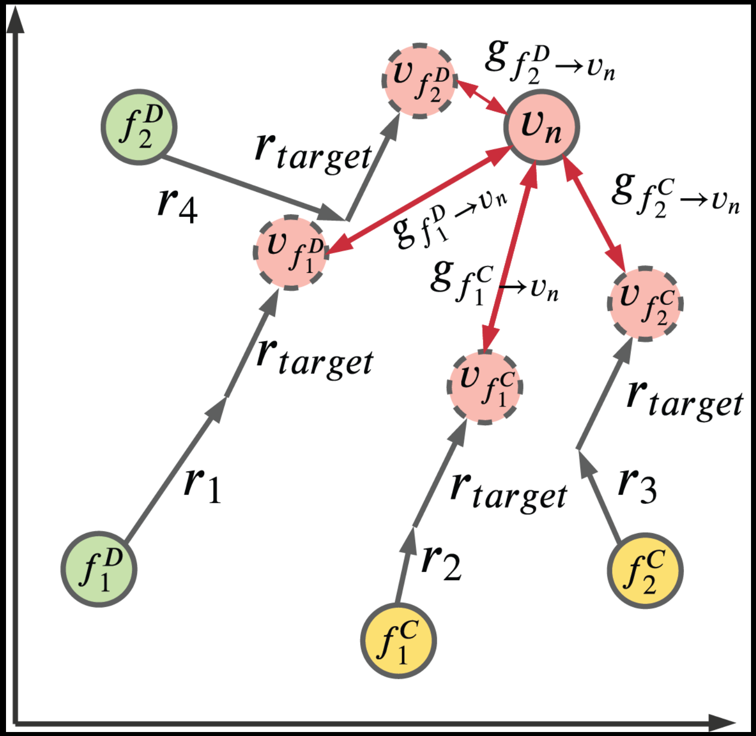
1. Compute rule score (possibility of the rule):

$$g_{f_i \rightarrow v_n} = -||\mathbf{f}_i + \mathbf{r}_j + \mathbf{r}_{target} - \mathbf{v}_n||$$

2. Aggregate all suitable rules' scores of a data column:

$$g(d_{new}, r_{target}, v_n) = \frac{1}{|F_{new}|} \sum_{f_i \in F_{new}} g_{f_i \rightarrow v_n}$$

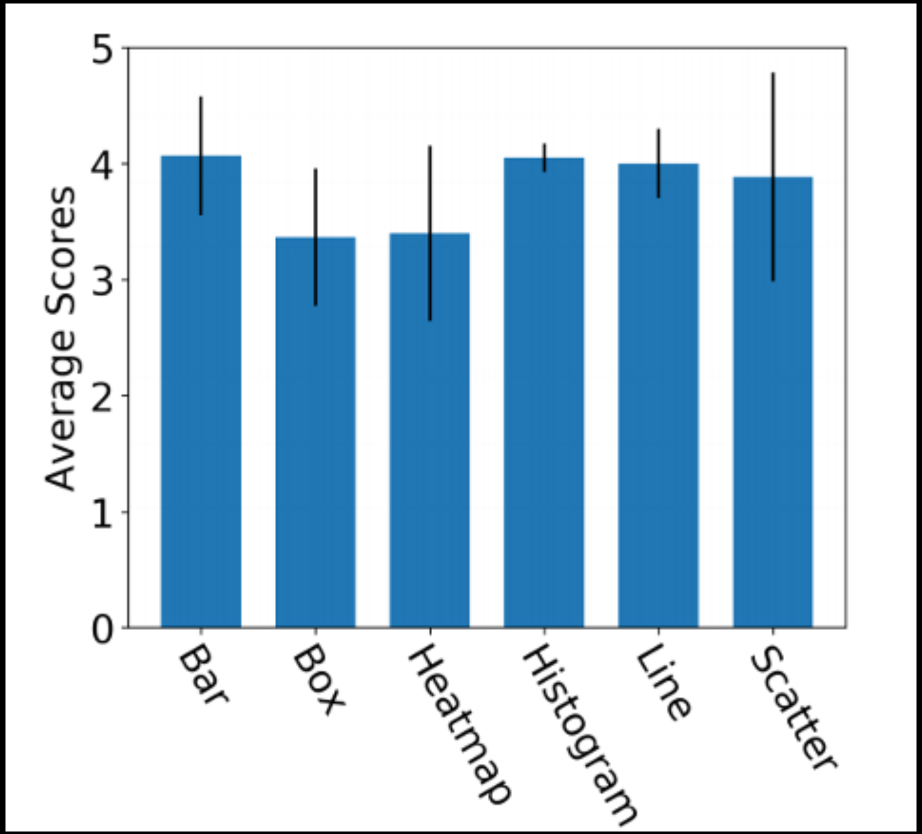
3. Recommend the design with the highest score



Results – Expert Interviews

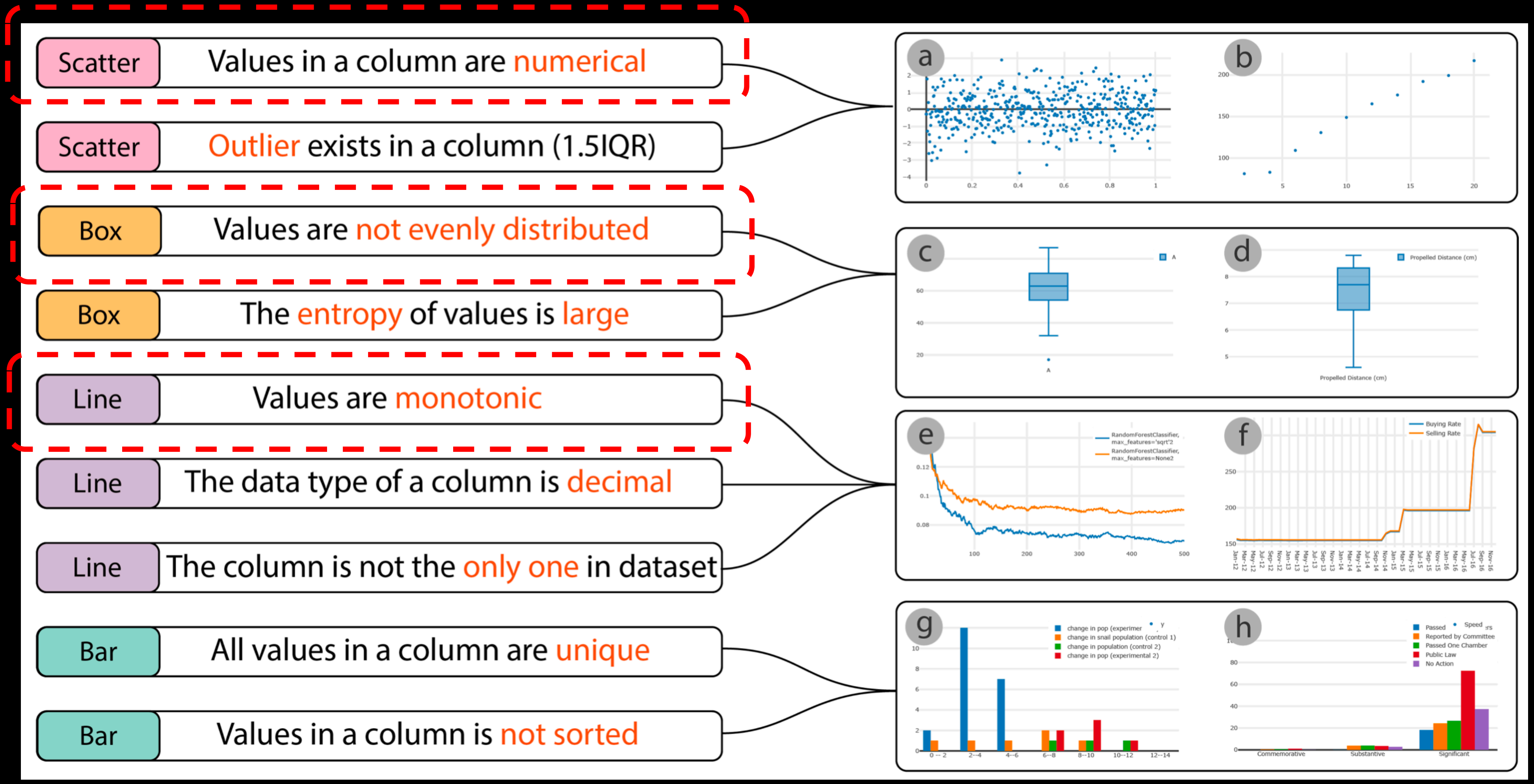
- Most of the rules are of high quality, but some features need to be further improved

- The recommended visualizations are correct



Average scores of recommended visualizations

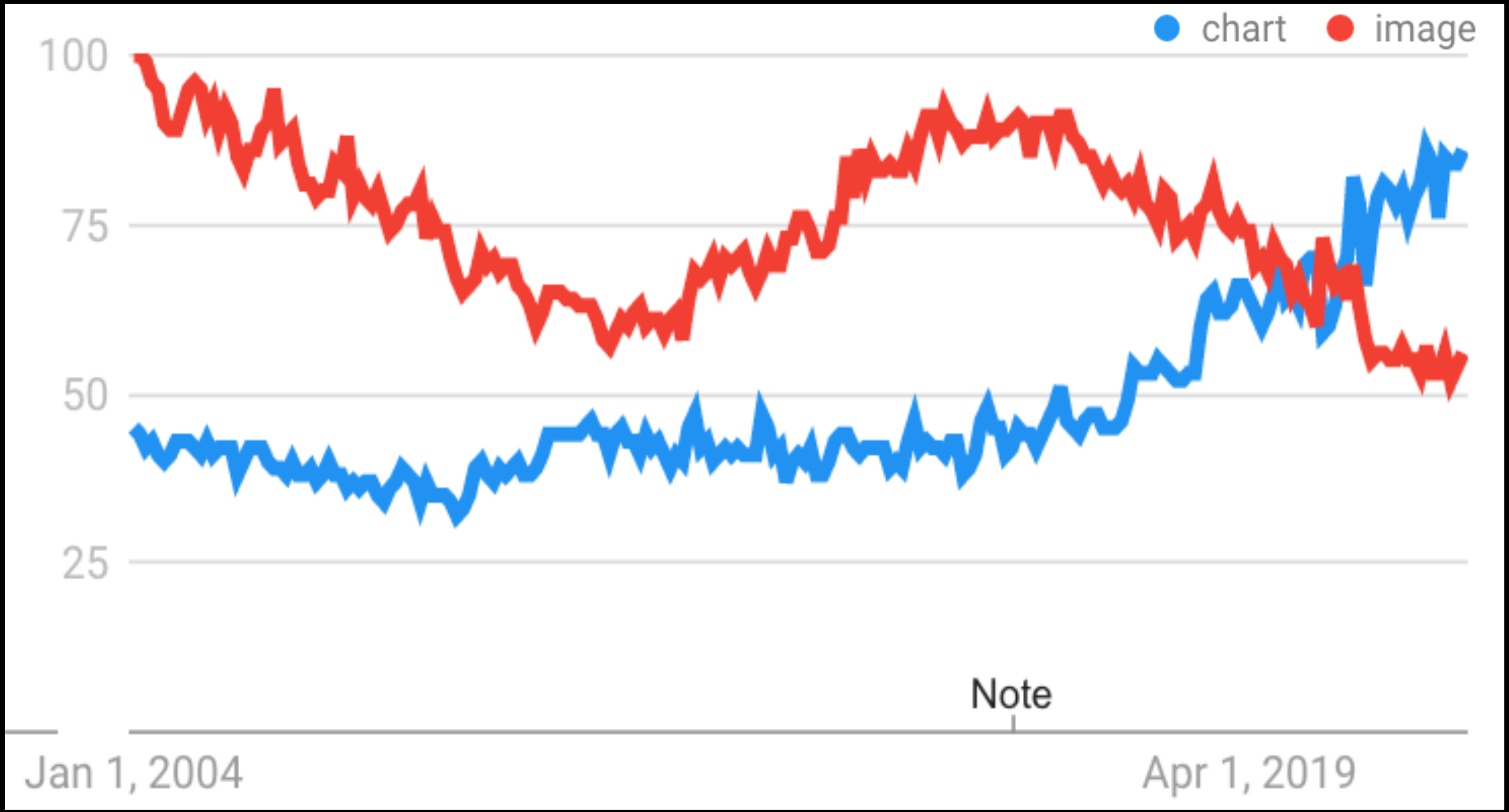
Results – Case Study



Explainable Visualization Recommendation

Evaluation of Visualization Similarity

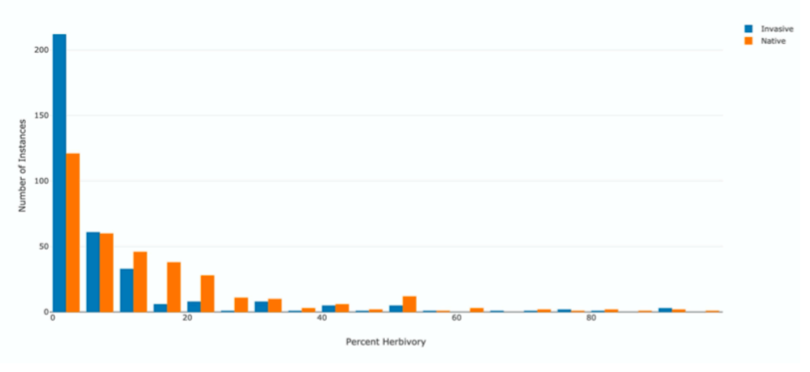
It is the key task of chart retrieval!



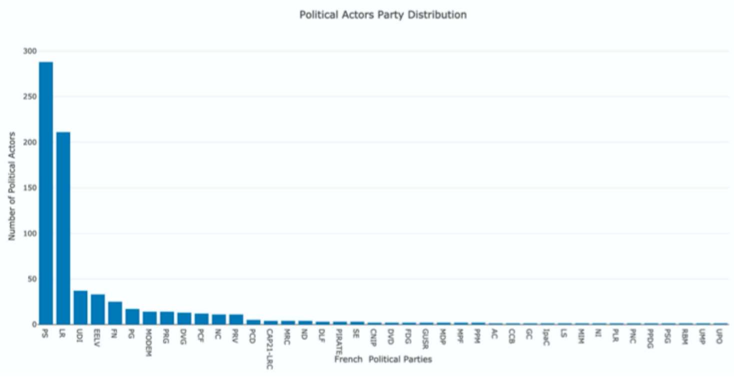
Google Search Trend: Chart has surpassed Image around 2020

Evaluation of Visualization Similarity

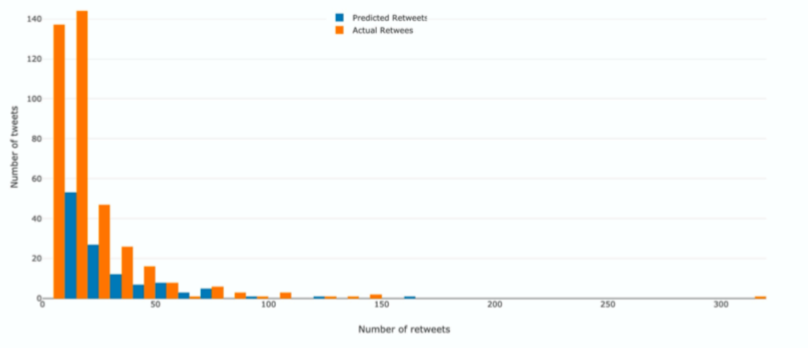
Visualization similarity == image similarity?



(a) Query



(b) Visual Information (CNN)



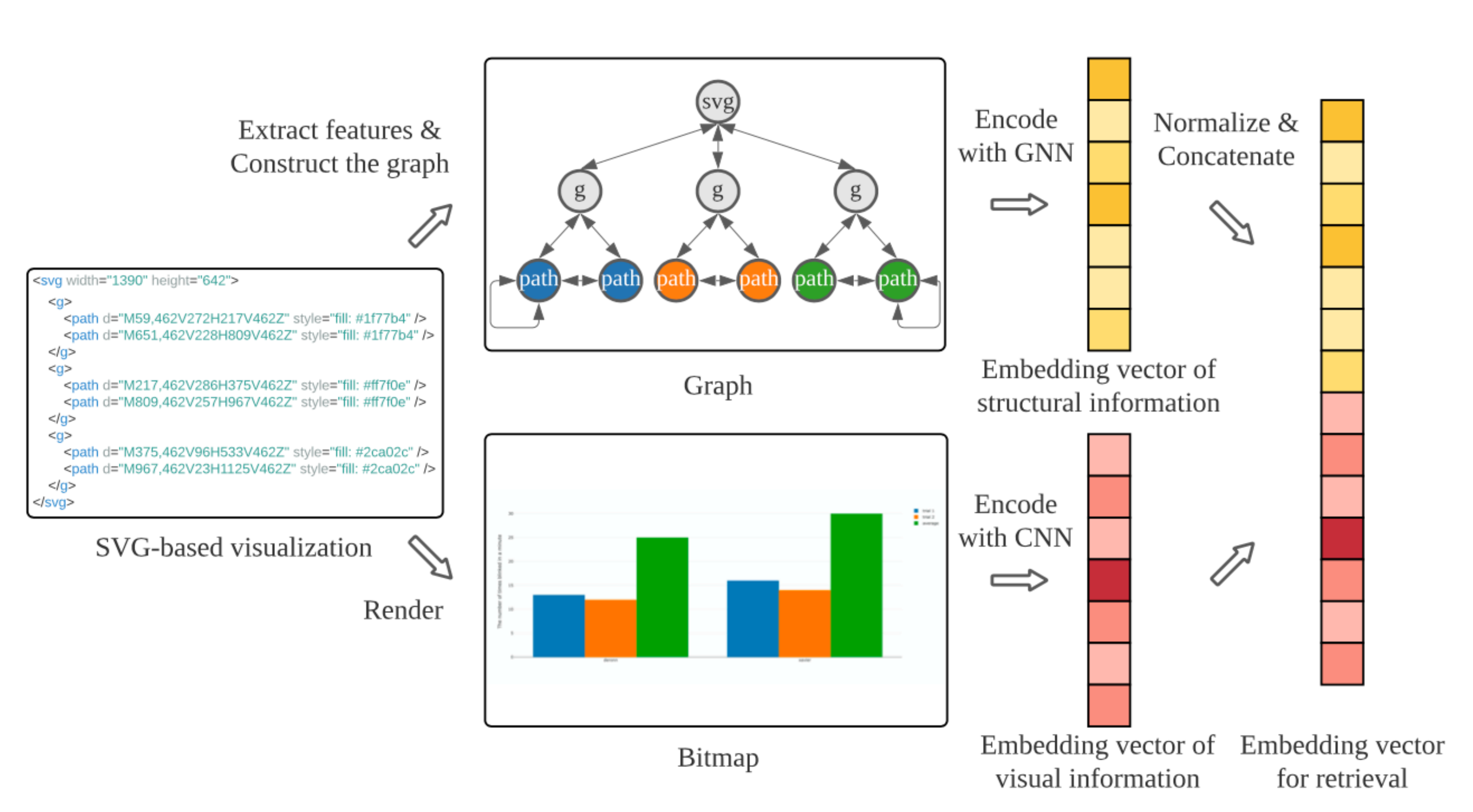
(c) Structural and Visual Information

Structure-aware Visualization Retrieval

H. Li, **Y. Wang**, A. Wu, H. Wei and H. Qu

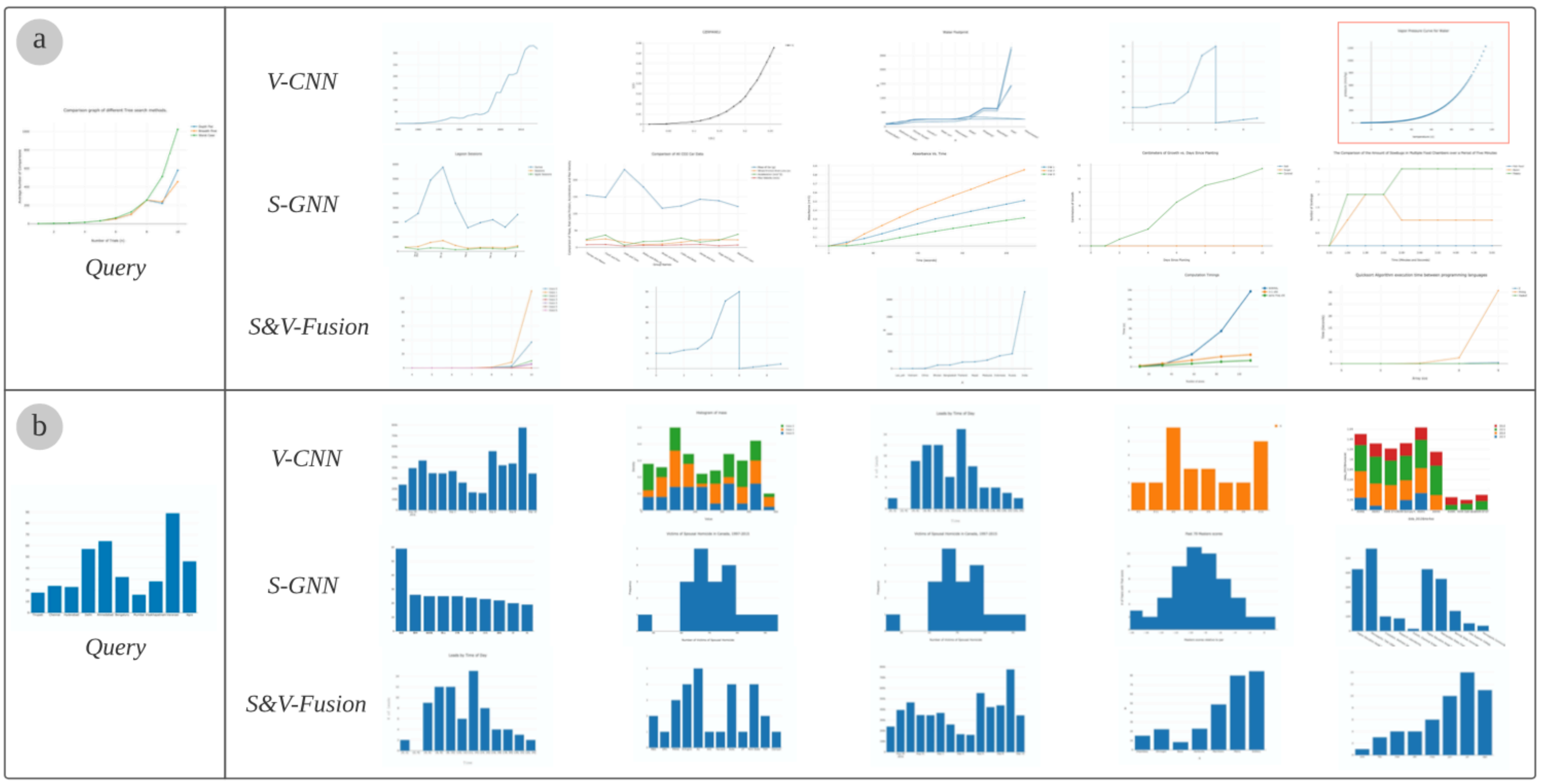
CHI 2022 (Best Paper Honorable Mention Award)

Structure-aware Visualization Similarity



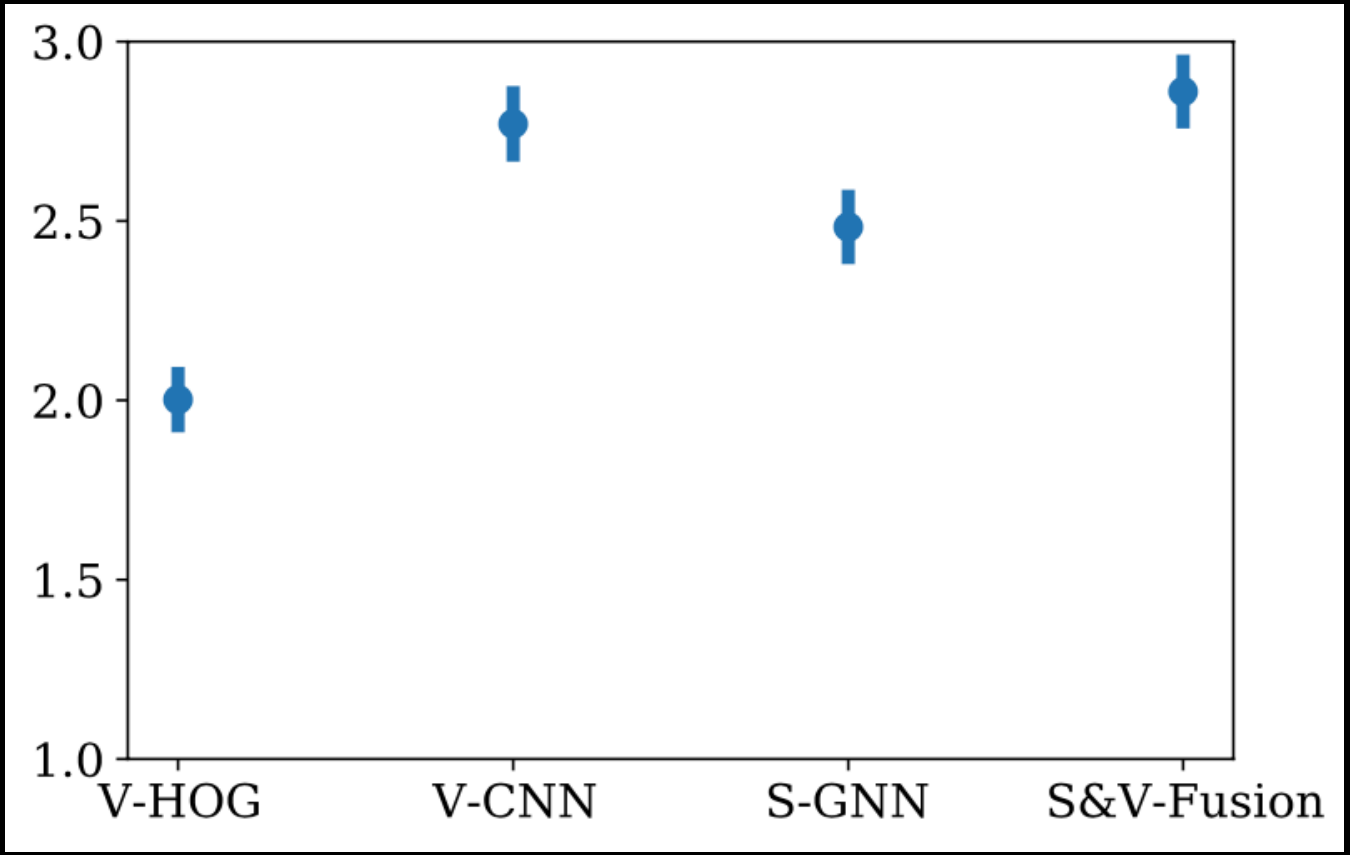
Our approach extracts both **structural** and **visual information** from visualizations

Results – Case Study



Top-5 retrieved similar visualizations

Results – User Study



Our approach (***S&V-Fusion***) outperforms others with statistical significance ($p < 0.001$).

Experience and Tip Sharing

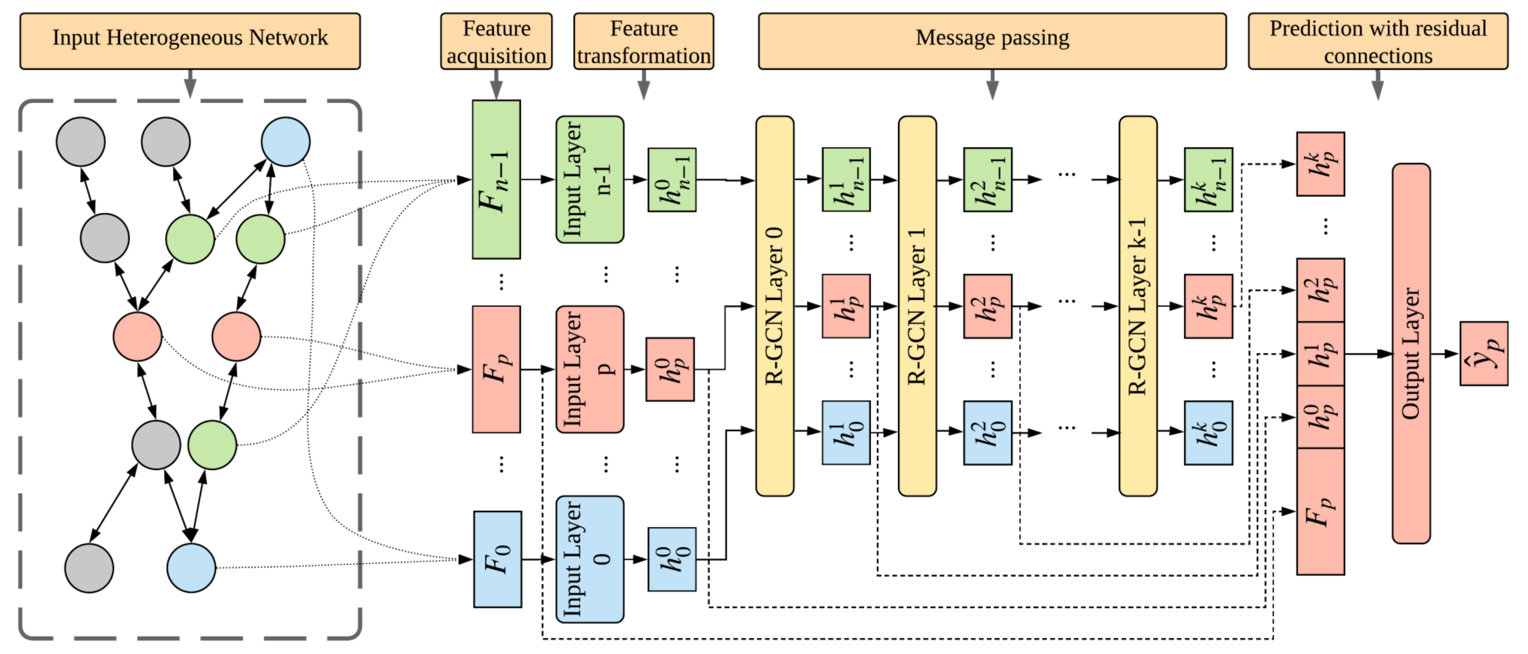
1. Massive Reading, Writing and Thinking

- Regular and massive reading

- Curiosity

1. Massive Reading, Writing and Thinking

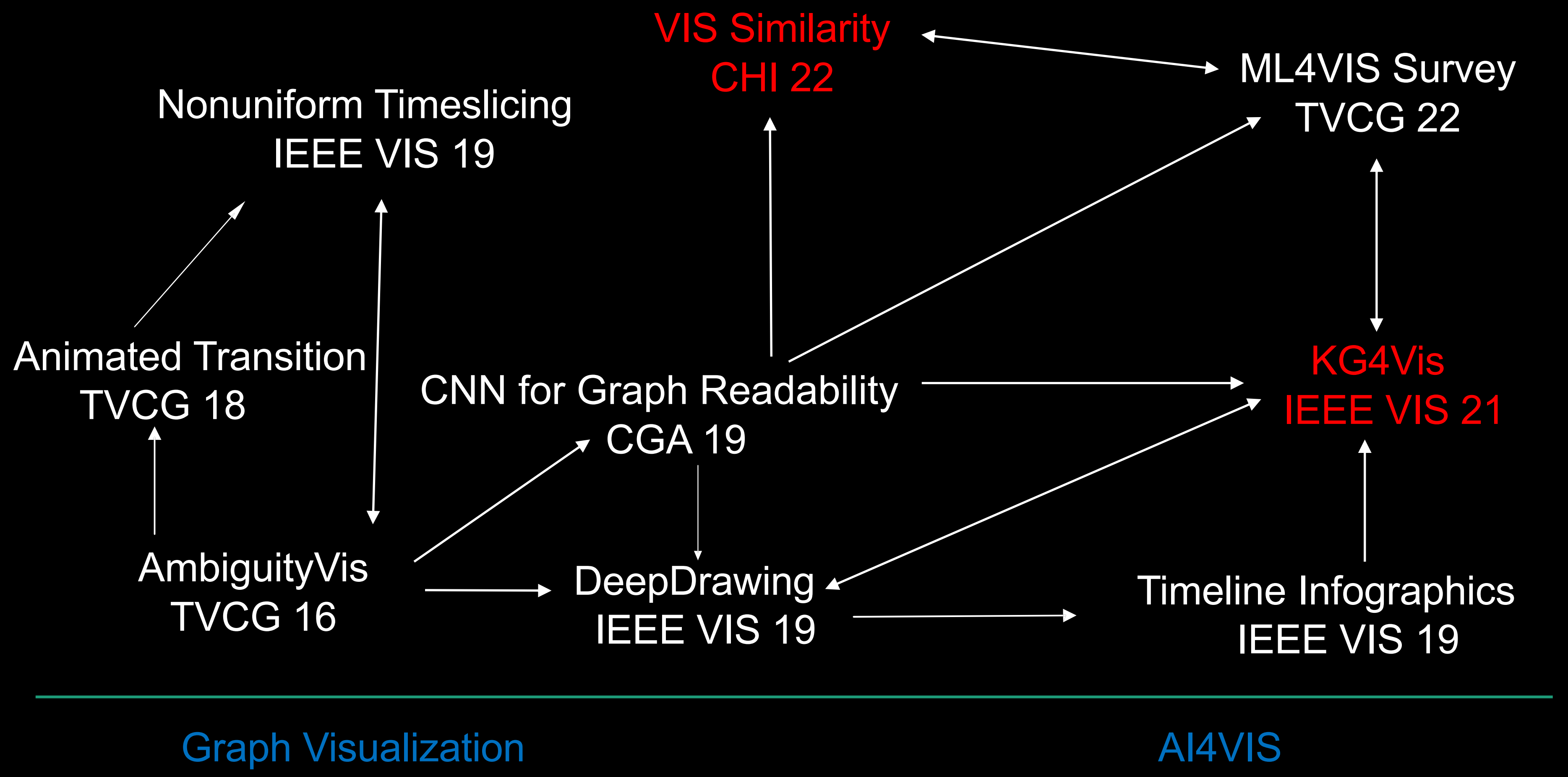
Example 1: KG4Vis



Li, Haotian, Huan Wei, Yong Wang, **Yangqiu Song**, and Huamin Qu. "Peer-inspired student performance prediction in interactive online question pools with graph neural network." CIKM 2020.

1. Massive Reading, Writing and Thinking

My research path towards AI4Vis



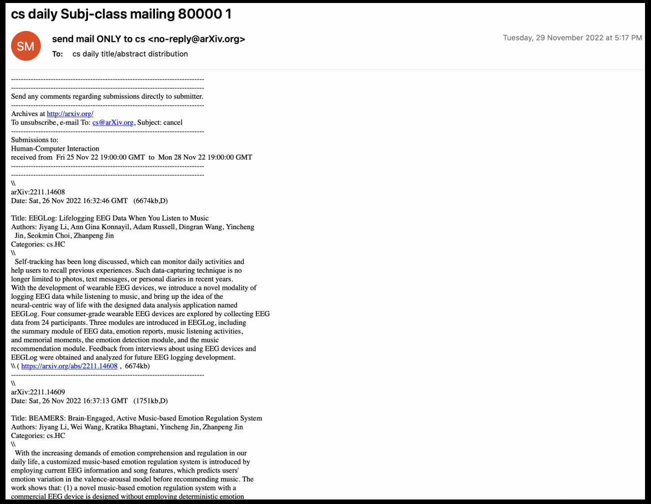
1. Massive Reading, Writing and Thinking

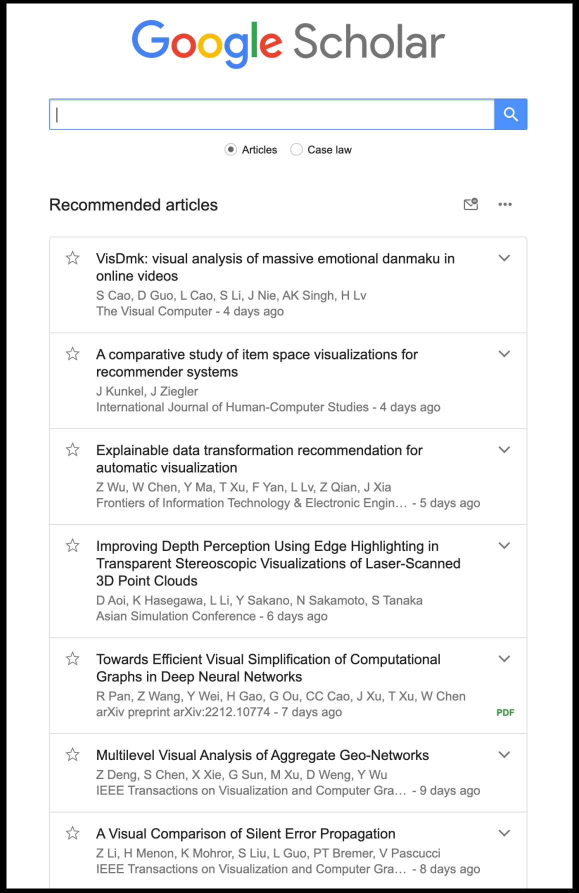
Some useful tools to keep yourself updated on the latest VIS research:

- Google scholar recommendation

- Subscribe the mail list of Arxiv, TVCG, CGA, etc.

- Go through the latest conference proceedings





1. Massive Reading, Writing and Thinking

"The best way to have a good idea is to have a lot of ideas and throw away the bad ones."

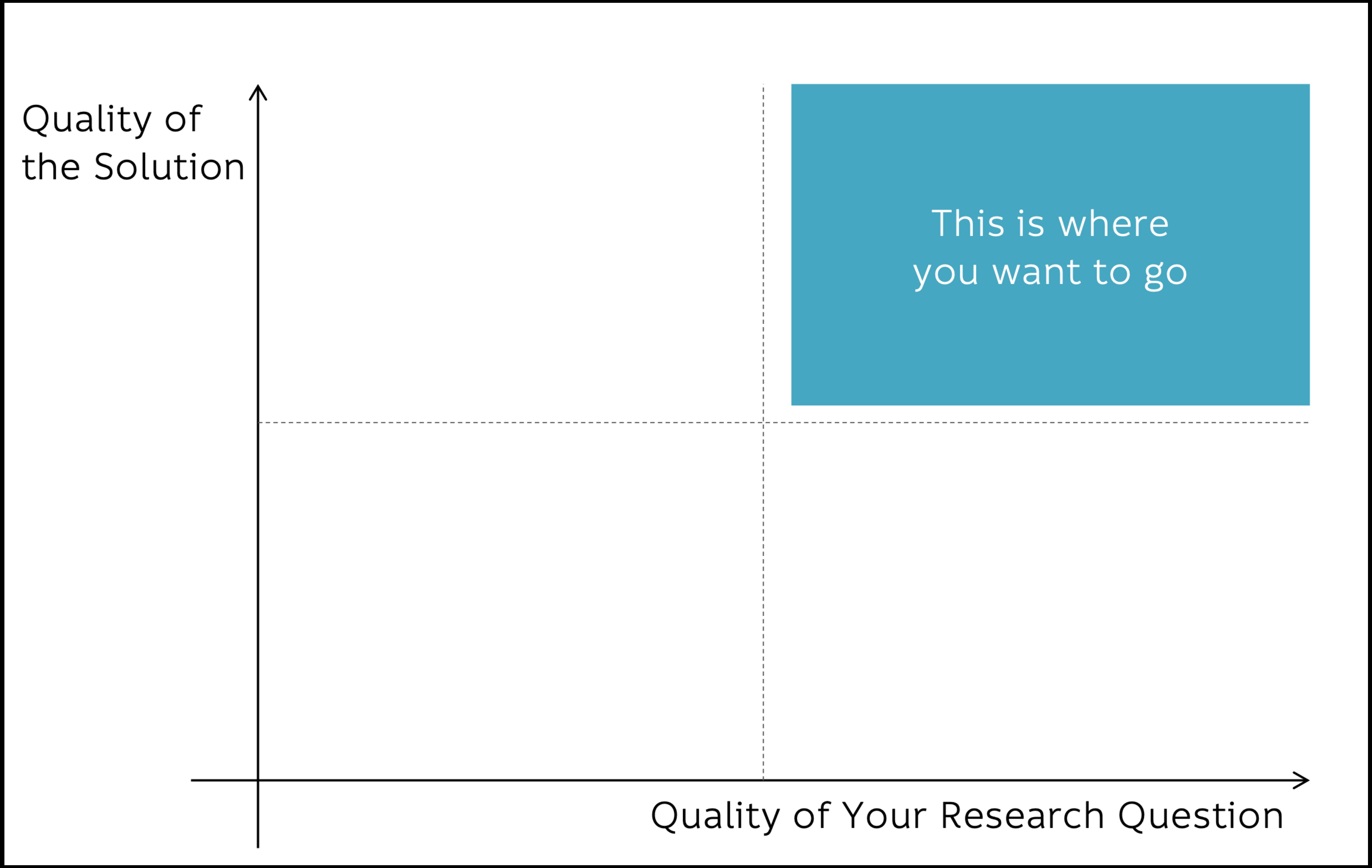
- Linus Pauling

2. Do Research of High Impact

Research Contribution = Intellectual value of your research x Number of people you reach out

https://speakerdeck.com/kotarohara/identifying-research-questions

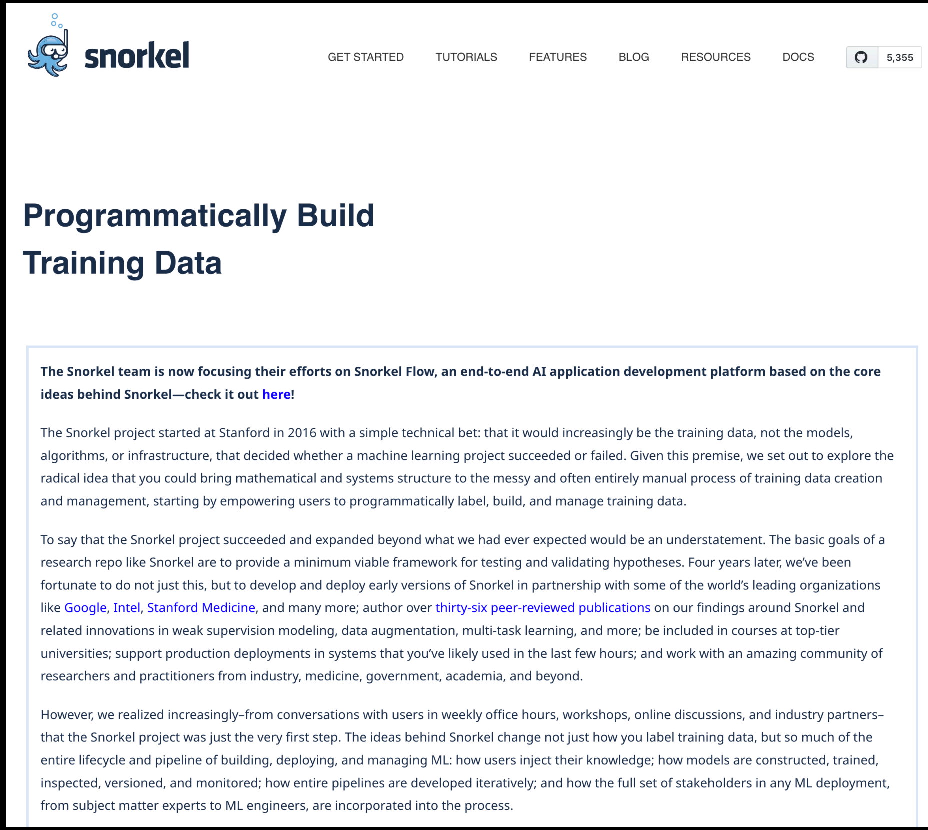
2. Do Research of High Impact



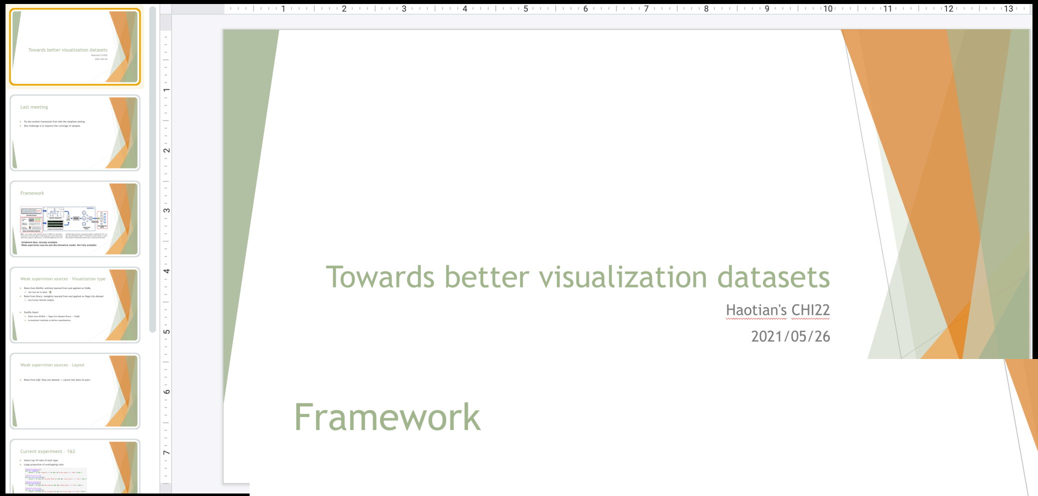
https://speakerdeck.com/kotarohara/identifying-research-questions

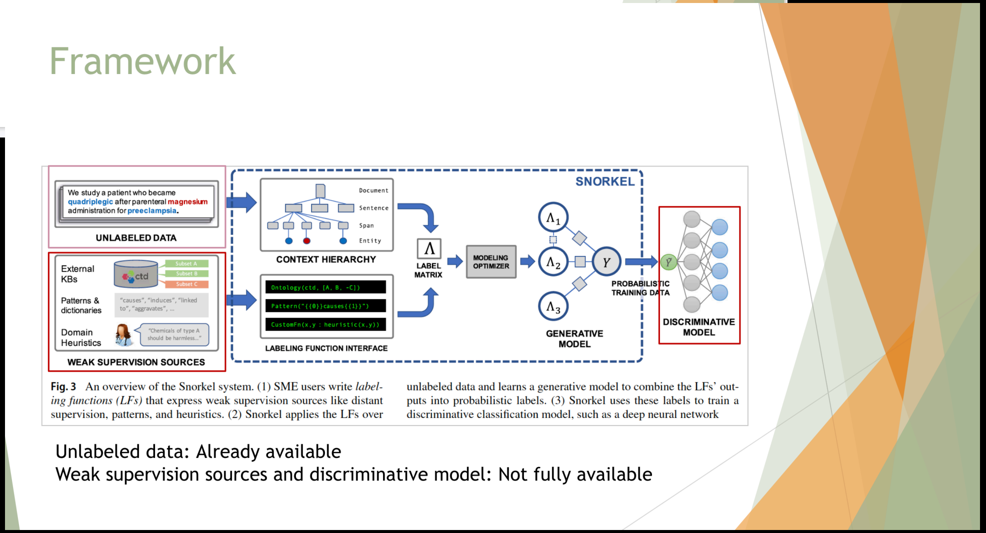
3. Get Used to the Uncertainty of Research

Example 1: Structure-aware Visualization Retrieval



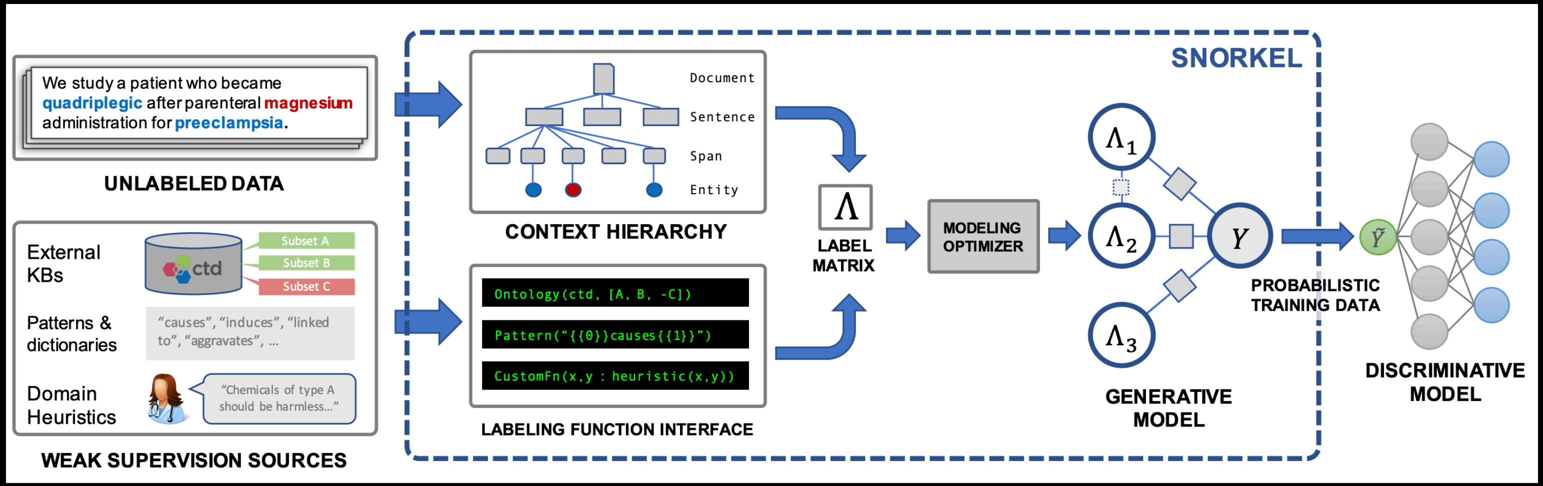
https://www.snorkel.org/





3. Get Used to the Uncertainty of Research

Example 1: Structure-aware Visualization Retrieval



How can we achieve efficient visualization labeling?

How can we evaluate the similarity between visualizations?

3. Get Used to the Uncertainty of Research

唐本忠院士：几乎没有任何研究课题会完全按照预期发展；如果有，这种研究不会有任何突破、不会给人带来任何惊喜。

请点击关注： Paper绘图 2021-09-30 11:30

作者 | Philip Ball（《国家科学评论》特约作者）

今年是中科院院士唐本忠及其同事提出聚集诱导发光（AIE）概念20周年。2001年，唐本忠团队偶然观察到了这一有悖常理的光物理现象，从而在发光材料研究领域取得了重大原创突破。2016年，Nature将AIE点（聚集诱导发光纳米粒子）列为支撑和驱动“未来纳米光革命”的四大纳米材料之一。这也是唯一一种由中国科学家原创的新材料。

谈及发现AIE现象的体会，唐本忠表示，“几乎没有任何研究课题会完全按照预期发展；如果有，这种研究不会有任何突破、不会给人带来任何惊喜。”

对从事科学研究的学者来说，什么最重要？唐本忠认为，选准一个正确的研究方向对一个科学家，尤其是年轻人，至关重要。要成就一番科学事业，必须要有燃烧的热情、顽强的斗志、高雅的鉴赏力、勇敢的批评精神、深入的融会贯通思索……

《国家科学评论》（以下简称NSR）最近就聚集体学研究的历史起源及其发展前景与唐本忠（以下简称唐）进行了对话和访谈。

https://mp.weixin.qq.com/s/3yyX0biQ9VIyB4kM2TfuPA

4. The Secret of Paper Awards

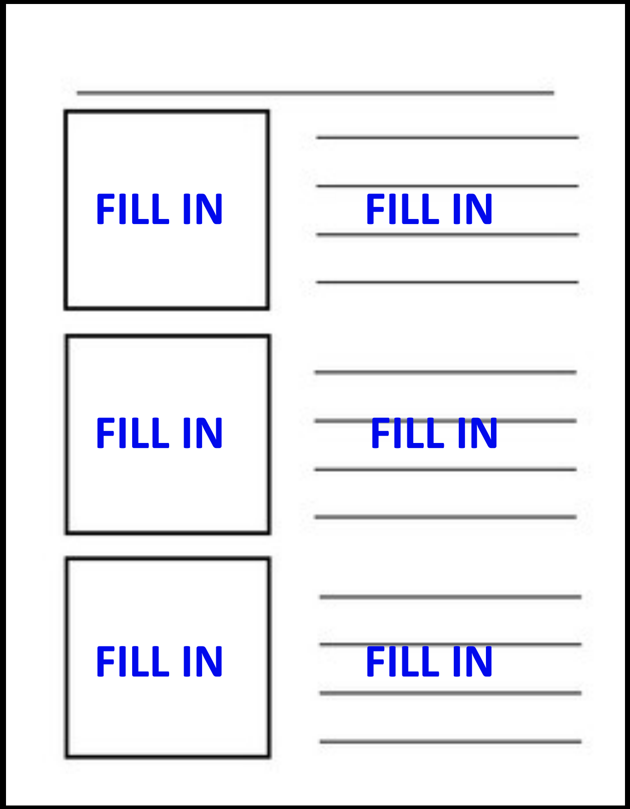
(Research Quality) x (Luck)

5. Visualization Paper Writing

Writing VIS Research Paper is Easy

- **Template Structure**
  - Introduction
  - Background/Literature Review
  - Proposed Method
  - Experimental Results and Analysis
  - Conclusions

- **Template Paragraphs/Sentences…**
  - No need to have rich vocabulary!



Note: Part of the visualization paper writing slides are adapted from the sharing by Dr. Yi Mei (Victoria University of Wellington) at SSCI 2022.

5. Visualization Paper Writing

Writing VIS Research Paper is Hard

- Make readers **understand** your work
- Make readers **like** your work
- Make readers **benefit from** your work

5. Visualization Paper Writing

Lessons I learned

D A S H

- Clearly **Distinguish** existing work and your new work
- Consider your **Audience**
- Tell a good **Story** (which can be different from the fact)
- Be **Honest** (NO over-claim / under-claim)

5. Visualization Paper Writing

Introduction

- **Key**: Motivations and Goals/Contributions
- Focus on the “**Why**” questions
  - Why do you study this problem?
  - Why do you use this visualization or technique?
  - Why do you propose this contribution (e.g., a new visualization design)?
- Follow a clear logic flow

Structure-aware Visualization Retrieval

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ABSTRACT

With the wide usage of data visualizations, a huge number of Scalable Vector Graphic (SVG)-based visualizations have been created and shared online. Accordingly, there has been an increasing interest in exploring how to retrieve perceptually similar visualizations from a large corpus, since it can benefit various downstream applications such as visualization recommendation. Existing methods mainly focus on the visual appearance of visualizations by regarding them as bitmap images. However, the structural information intrinsically existing in SVG-based visualizations is ignored. Such structural information can delineate the spatial and hierarchical relationship among visual elements, and characterize visualizations thoroughly from a new perspective. This paper presents a structure-aware method to advance the performance of visualization retrieval by collectively considering both the visual and structural information. We extensively evaluated our approach through quantitative comparisons, a user study and case studies. The results demonstrate the effectiveness of our approach and its advantages over existing methods.

CCS CONCEPTS

• **Human-centered computing** → **Visualization**; • **Information systems** → *Information retrieval*; • **Computing methodologies** → *Machine learning*.

KEYWORDS

Data Visualization, Visualization Retrieval, Visualization Similarity, Representation Learning, Visualization Embedding

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ACM Reference Format:
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1 INTRODUCTION

Data visualization provides users with a powerful approach to analyze enormous data, communicate insights and achieve efficient decision-making. Along with the popularity of visualizations, a huge number of visualizations based on Scalable Vector Graphics (SVGs) have been created and shared online. Compared with bitmap-based visualizations, SVG-based visualizations have many advantages such as the support of interactions [1] and quality-preserving resizing. Thus, SVGs have been adopted by various online platforms to store and present visualizations, for example, Plotly[1] and Observable[2]. With such a large volume of visualizations online, how to retrieve similar visualizations has attracted growing research interest from both academia and industry [31, 32, 36] due to its significant importance for many downstream tasks. Specifically, the retrieval of similar visualizations is fundamental to downstream tasks such as creating visualization collections [32] and recommending visualizations [31].

To achieve effective retrieval of similar visualizations, the core problem is to characterize the similarity between two visualizations. Existing studies mainly focus on estimating the similarity between visualizations according to the data or perceptual similarity. The existing methods based on data similarity [31, 42, 43, 48] focus on the characteristics of data such as data distribution or metadata, ignoring the visual appearance of visualizations. Since the original data is not always available with the visualizations, the application of visualization retrieval methods based on data similarity is quite limited. Perceptual similarity mainly refers to the similarity of visualizations perceived by users, which can also reflect the data similarity. Compared to the direct computation of data similarity, the computation of perceptual similarity does not rely on the original data. To compute the perceptual similarity, existing approaches [29, 36, 61] first extract the visual feature vectors from

[1] https://plotly.com/
[2] https://observablehq.com/

Why do you focus on visualization retrieval?

What are the limitations of existing studies?

visualizations and further calculate the distance between feature vectors to measure their similarity. These methods mainly extract the visual features of visualizations at the level of pixels. For example, Saleh et al. [36] measured the visualization similarity by using the color distribution of different pixels (i.e., color histograms). Recently, deep learning-based methods [29, 61] have been proposed to extract visual features automatically by treating visualizations as bitmap images (e.g., the images in ImageNet [10]). However, few prior studies have considered the *structural information of visualizations* that exists in SVGs by nature, when characterizing the perceptual similarity of visualizations.

Structural information of visualizations mainly describes the spatial and hierarchical relationship between elements, such as the position, grouping and hierarchy of the basic visual elements (e.g., *<rect>* and *<path>*). Compared with the commonly-used *visual information* (i.e., the visual features to describe the appearance of visualizations) of visualizations, structural information enables a unique perspective to characterize the appearance of visualizations at the level of visual elements instead of pixels. It provides an accurate description of how different visual elements are organized in visualizations. For example, as shown in Figure 1, a grouped bar chart with two groups of bars (Figure 1(a)) and a bar chart with only one group of bars (Figure 1(b)) seem to show the same trend and are regarded as similar charts, if only the visual information is considered by using a computer-vision-based method (e.g., convolutional neural network (CNN) models). However, the grouped bar chart actually shows how two sets of data are compared and it should not be treated as a similar visualization as the bar chart with a single group of bars. Instead, another grouped bar chart (Figure 1(c)) with both similar *structure* and appearance should be regarded similar to the query bar chart (Figure 1(a)). From the example above, it is obvious that structural information plays an important role in characterizing the perceptual similarity between visualizations. However, it still remains unclear what kind of structure-based features can be extracted and how these structure-based features can be leveraged to facilitate similar visualization retrieval.

In this paper, we aim to fill the research gap by leveraging both structural and visual information to accurately evaluate the *perceptual similarity* between visualizations. We first conducted a preliminary study to better understand users' criteria on assessing the perceptual similarity of visualizations and identified the three most important criteria, i.e., *the type of a visualization*, *the number of visual elements* and *the overall trend of visualized data*. Building upon these results, we propose to transform SVG-based visualizations to *graphs* and *bitmap images* that reflect the structure and the appearance of visualizations, respectively. Then we utilize contrastive representation learning to comprehensively delineate structural and visual information in a visualization with embedding vectors. Contrastive representation learning is a type of self-supervised learning method and can minimize the distance between similar samples and maximize the distances between diverse samples [21]. With contrastive learning, we avoid manually labeling the similarity between different visualizations, enabling us to easily generalize our approach to various visualizations. Finally, we gain an embedding vector for each visualization that characterizes its structural and visual information and is used for retrieving similar visualizations. Using the VizML corpus [19], we extensively evaluate our approach through a crowdsourced user study, multiple case studies and quantitative comparisons. The results demonstrate the effectiveness of our approach.

The major contributions of this paper are summarized as follows:

- We present a novel structure-aware approach to characterize the perceptual similarity between visualizations through embedding vectors, which enables effective similar visualization retrieval.
- We conduct extensive evaluations including a crowdsourced user study with 50 participants, multiple case studies and quantitative comparisons with existing visualization retrieval methods. The results verify the effectiveness of our structure-aware visualization retrieval approach.
- We summarize the lessons we learned during exploring the usage of structural information in visualization retrieval.

2 RELATED WORK

The related work of this study can be categorized into three parts: retrieval of visualizations, visualization similarity estimation and visualization storage formats.

2.1 Visualization Retrieval

Visualization retrieval has attracted researchers' interests in recent years along with the increasing number of visualizations. According to the type of queries, there are two major classes of methods for retrieving visualizations [45], retrieval by definition and retrieval by example.

Retrieval by definition means that users can explicitly specify the criteria of retrieving visualizations using either programming language or natural language. For example, Hoque and Agrawala [18] enable users to create a JSON-like specification to indicate their target characteristics of visualizations such as encoding types. Some other prior studies [7, 27, 44, 45] also provide users with tools to search for visualization using explicit queries. Compared to retrieval by definition, retrieval by example provides an intuitive way for users to define the criteria of retrieving visualizations. Users can use existing visualizations or sketches to search for other visualizations. Several recent studies [29, 34, 36] take example visualizations as inputs and return similar ones for data exploration or visualization re-use. Zenvisage [42] and ShapeSearch [43] allow users to sketch their desired data pattern in visualizations. Then they retrieve the data which matches the pattern from the database and visualize them to users. In this line of research, one of the core problems is how to define the similarity between visualizations, which will be further discussed in Section 2.2.

Our structure-aware approach falls in the category of retrieval by example. Our approach takes SVG-based visualizations as the input and then represents the visual and structural information of them as embedding vectors for similar visualization retrieval.

2.2 Visualization Similarity

Computing the similarity of visualizations benefits various downstream tasks such as assisting in exploratory data analysis [62], querying visualizations [29] and generating visualization collections [32]. Inspired by a previous study [29], prior methods on

Why is the structural information so important?

What is the major idea/contribution of the proposed approach?

5. Visualization Paper Writing

Related Work

- **Key**: Taxonomy and Major Difference
- What is the taxonomy of existing research?
- What is the major difference between your work and existing studies?
- NO important literature is missing

visualizations and further calculate the distance between feature vectors to measure their similarity. These methods mainly extract the visual features of visualizations at the level of pixels. For example, Saleh et al. [36] measured the visualization similarity by using the color distribution of different pixels (i.e., color histograms). Recently, deep learning-based methods [29, 61] have been proposed to extract visual features automatically by treating visualizations as bitmap images (e.g., the images in ImageNet [10]). However, few prior studies have considered the *structural information of visualizations* that exists in SVGs by nature, when characterizing the perceptual similarity of visualizations.

Structural information of visualizations mainly describes the spatial and hierarchical relationship between elements, such as the position, grouping and hierarchy of the basic visual elements (e.g., *<rect>* and *<path>*). Compared with the commonly-used *visual information* (i.e., the visual features to describe the appearance of visualizations) of visualizations, structural information enables a unique perspective to characterize the appearance of visualizations at the level of visual elements instead of pixels. It provides an accurate description of how different visual elements are organized in visualizations. For example, as shown in Figure 1, a grouped bar chart with two groups of bars (Figure 1(a)) and a bar chart with only one group of bars (Figure 1(b)) seem to show the same trend and are regarded as similar charts, if only the visual information is considered by using a computer-vision-based method (e.g., convolutional neural network (CNN) models). However, the grouped bar chart actually shows how two sets of data are compared and it should not be treated as a similar visualization as the bar chart with a single group of bars. Instead, another grouped bar chart (Figure 1(c)) with both similar *structure* and appearance should be regarded similar to the query bar chart (Figure 1(a)). From the example above, it is obvious that structural information plays an important role in characterizing the perceptual similarity between visualizations. However, it still remains unclear what kind of structure-based features can be extracted and how these structure-based features can be leveraged to facilitate similar visualization retrieval.

In this paper, we aim to fill the research gap by leveraging both structural and visual information to accurately evaluate the *perceptual similarity* between visualizations. We first conducted a preliminary study to better understand users' criteria on assessing the perceptual similarity of visualizations and identified the three most important criteria, i.e., *the type of a visualization*, *the number of visual elements* and *the overall trend of visualized data*. Building upon these results, we propose to transform SVG-based visualizations to *graphs* and *bitmap images* that reflect the structure and the appearance of visualizations, respectively. Then we utilize contrastive representation learning to comprehensively delineate structural and visual information in a visualization with embedding vectors. Contrastive representation learning is a type of self-supervised learning method and can minimize the distance between similar samples and maximize the distances between diverse samples [21]. With contrastive learning, we avoid manually labeling the similarity between different visualizations, enabling us to easily generalize our approach to various visualizations. Finally, we gain an embedding vector for each visualization that characterizes its structural and visual information and is used for retrieving similar visualizations. Using the VizML corpus [19], we extensively evaluate our approach through a crowdsourced user study, multiple case studies and quantitative comparisons. The results demonstrate the effectiveness of our approach.

The major contributions of this paper are summarized as follows:

- We present a novel structure-aware approach to characterize the perceptual similarity between visualizations through embedding vectors, which enables effective similar visualization retrieval.
- We conduct extensive evaluations including a crowdsourced user study with 50 participants, multiple case studies and quantitative comparisons with existing visualization retrieval methods. The results verify the effectiveness of our structure-aware visualization retrieval approach.
- We summarize the lessons we learned during exploring the usage of structural information in visualization retrieval.

2 RELATED WORK

The related work of this study can be categorized into three parts: retrieval of visualizations, visualization similarity estimation and visualization storage formats.

2.1 Visualization Retrieval

Visualization retrieval has attracted researchers' interests in recent years along with the increasing number of visualizations. According to the type of queries, there are two major classes of methods for retrieving visualizations [45], retrieval by definition and retrieval by example.

Retrieval by definition means that users can explicitly specify the criteria of retrieving visualizations using either programming language or natural language. For example, Hoque and Agrawala [18] enable users to create a JSON-like specification to indicate their target characteristics of visualizations such as encoding types. Some other prior studies [7, 27, 44, 45] also provide users with tools to search for visualization using explicit queries. Compared to retrieval by definition, retrieval by example provides an intuitive way for users to define the criteria of retrieving visualizations. Users can use existing visualizations or sketches to search for other visualizations. Several recent studies [29, 34, 36] take example visualizations as inputs and return similar ones for data exploration or visualization re-use. Zenvisage [42] and ShapeSearch [43] allow users to sketch their desired data pattern in visualizations. Then they retrieve the data which matches the pattern from the database and visualize them to users. In this line of research, one of the core problems is how to define the similarity between visualizations, which will be further discussed in Section 2.2.

Our structure-aware approach falls in the category of retrieval by example. Our approach takes SVG-based visualizations as the input and then represents the visual and structural information of them as embedding vectors for similar visualization retrieval.

2.2 Visualization Similarity

Computing the similarity of visualizations benefits various downstream tasks such as assisting in exploratory data analysis [62], querying visualizations [29] and generating visualization collections [32]. Inspired by a previous study [29], prior methods on

What is the taxonomy of existing work?

What is the main difference?

5. Visualization Paper Writing

Proposed Visualization or Method

- **Key**: Be Clear
- NO mixture with existing work! **Highlight the new/different parts**
- Overview first, details in the subsections
- Provide necessary justifications for your visualization designs or techniques

5. Visualization Paper Writing

to verify that the participant has basic knowledge of visualizations, each participant was required to answer three simple visualization-related questions, for example, *"what is the chart type of the given visualization?"*. Only participants who correctly answered the three verification questions were allowed to join the study. No other criteria were used in the participant recruitment. In the second part of the study, to encourage the participants to reflect on how they judge the similarity of visualizations, each participant was presented with five query visualizations and their retrieved top-5 similar visualizations by using visual information only. The participants were asked to give each retrieved visualization a score ranging from 1 (the least similar) to 5 (the most similar). After finishing the scoring, in the last part of the study, we asked participants to write down their criteria of scoring the retrieved visualizations in a text box.

After the study, we summarized the responses from participants. Since there may be ambiguity in understanding the criteria mentioned by participants, we first classified the major criteria into six major categories and two co-authors of this paper labeled all responses individually. If the annotations were inconsistent on any response, we examined and discussed together to reach an agreement on these cases.

4.2 Results

The six major criteria and their frequency are shown in decreasing order in Figure 3. In the results, we can notice that there are three important criteria (i.e., visualization type, the trend of data and the number of visual elements) with much higher frequency than other criteria. The results of our preliminary study also align with a previous study [23] well. Specifically, the number of visual elements and the trend of data are also considered when measuring the difference between two visualizations in the previous research [23]. Thus, the type of visualization, the trend of data and the number of visual elements are necessary to be considered explicitly in our approach when characterizing similarity of visualizations.

[5] The protocol of the preliminary study and the user study has been approved by the Institutional Review Board of our institution.
[6] https://www.prolific.co/

5 METHOD

In this section, the method of our structure-aware visualization retrieval is introduced. An overview is shown in Figure 4. To extract and represent the structural information in a visualization, we first construct a graph of visual elements with features and then apply a GNN encoder to generate the embedding vector of it (Section 5.1). Then we also render the visualization to a bitmap and use a CNN model to encode the visual information as an embedding vector as well (Section 5.2). Here we applied contrastive representation learning to train both CNN and GNN encoders since it can eliminate human efforts on data annotation. Finally, we normalize and concatenate the embedding vectors of structural and visual information for similar visualization retrieval (Section 5.3).

Figure 4: Our approach extracts both structural and visual information from visualizations first. Then the two types of information are encoded to embedding vectors separately. Finally, two embedding vectors are normalized and concatenated as the final representation of the visualization.

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(a) Rendered visualization and SVG (b) Initial graph of visual elements (c) Final graph of visual elements

Figure 5: This figure illustrates how we transform an SVG to a graph of visual elements. In the SVG, each bar can be either represented by a *<path>* or *<rect>*. Due to the limited space, we only show partial SVG and the corresponding subgraph. Each node represents an element in the SVG. The colors of nodes in the graph indicate the corresponding bars in the visualization. In (c), all leaf nodes are with self-loop edges, which are not all shown in this figure.

5.1 Representation Learning of Structural Information

As introduced before, structural information in SVGs can reflect the hierarchical and spatial relationship between visual elements explicitly. To utilize the structural information, we first extract visual element-level features and construct a graph of visual elements. Then, we apply a GNN-based graph contrastive learning method to generate the embedding vector of the structural information.

Feature Extraction. In the first step, we aim to extract features to describe the characteristics of elements in SVGs. These features are designed to reflect the types, styles and shapes and positions of elements. To make our approach simple and generalizable, we only

features to describe the trend. Thus, we use the predicted values of LOESS on five evenly sampled vertices as features of the trend. Since *<text>* can hardly be described by the features above, we further add the length of the text as a feature. Furthermore, the relationship between positions of elements within the same group is also necessary to reflect the overall trend in the visualizations. Thus, we sort the visual elements according to their positions on the horizontal and vertical axes and introduce the differences in positions as features of each element as well. Finally, for elements without certain features (e.g., *<g>* does not have specified width and height), we fill zeros as the placeholders. All features are also scaled according to their ranges. For example, positions are scaled using the height and width of the entire SVG.

Method Overview

Details in the subsections

5. Visualization Paper Writing

Evaluation

- Case study vs. usage scenario
- Who conducted the study?
- Are the authors involved?

5. Visualization Paper Writing

Abstract

- **Key**: Why, what, how

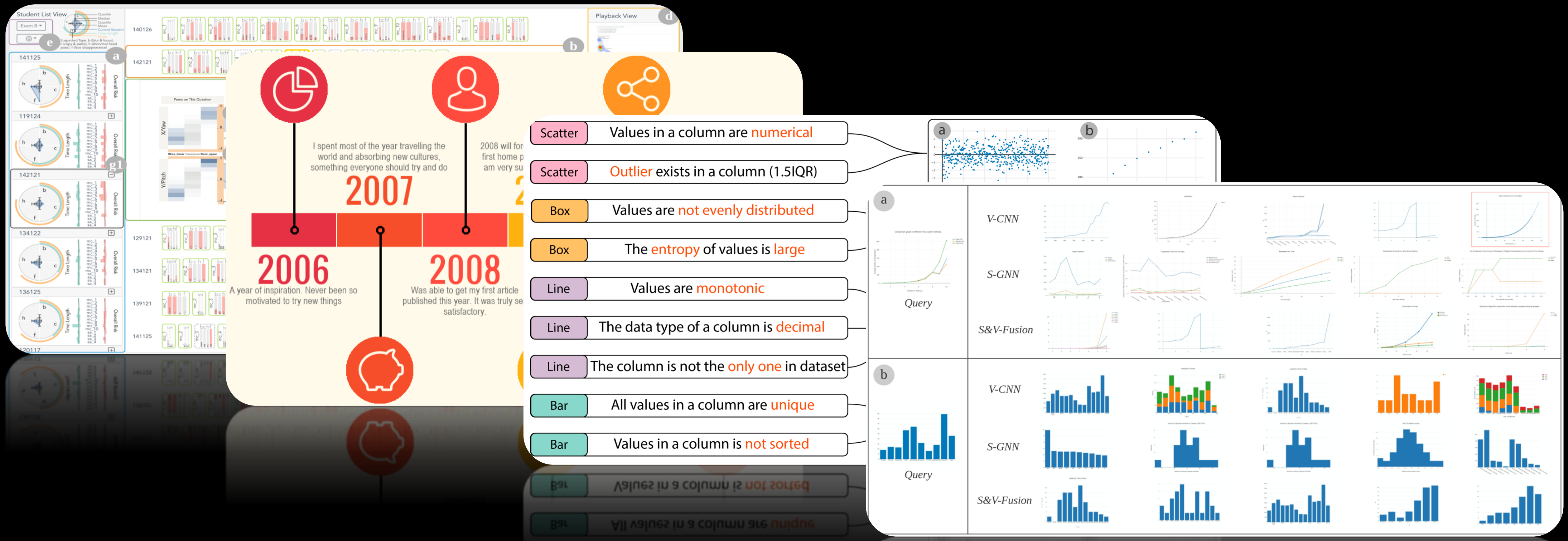
- The hardest part to write
- Although at the beginning, usually the last to write
- Notice the word limit: write everything first, and then cut

5. Visualization Paper Writing

Tips

- **Keep writing**, don't worry about writing quality in the first place
- Use **topic sentences**: One topic sentence per paragraph, then expand
- Maintain a database of **template sentences/words**

Of course, good **PAPER** comes from good **WORK**



可视化科研论文的那些事儿

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