A Review on Visualization Recommendation Strategies

Pawandeep Kaur and Michael Owonibi
Heinz-Nixdorf Chair for Distributed Information Systems, Friedrich-Schiller-University, Jena, Germany

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Abstract: Choosing the best visualization of a given dataset becomes more and more complex as not only the amount of data, but also the number of visualization types and the number of potential uses of visualizations grow tremendously. This challenge has spurred on the research into visualization recommendation systems. The ultimate aim of such a system is the suggestion of visualizations which provide interesting insights into the data. It should ideally consider data characteristics, domain knowledge and individual preferences to produce aesthetically appealing and easy to understand charts. Based on the mentioned factors, we have reviewed in this paper the state-of-the-art in visualization recommendation systems starting from the earliest attempt made on this subject. We identify challenges to visualization and visualization recommendation to guide future research directions.

1 INTRODUCTION

In this big data era, there has been an increase in the use of data visualization tools and techniques as a means to gain insight in the data. It is a lot easier to understand images than words or numbers because of the ability of human cognition to detect, analyze and interpret patterns, anomalies, texture, distance etc. in graphics. This makes data visualization an important tool in exploring, analyzing, and presenting both the obvious and less obvious features of data. Visualization summarizes data and presents the most relevant information in a simple and easy-to-understand way. The increasing awareness of the importance of visualization and the vast diversity in types of data visualized have led to the generation of a plethora of visualization classes. For instance, as of the time of this writing, more than 300 different visualizations are listed on the D3.js site. Given this plethora of visualization classes, and the various ways each class can be used to show a certain aspect of the data, and ever increasing visualization (analytics) requirements (e.g. presentation, data quality management, trend analysis etc.), individuals are increasingly faced with the difficulty of deciding which visualization is most appropriate for their task. This has led to the development of visualization recommendation systems.

According to Vartak et al., (2015), a system providing visualization recommendation should consider factors such as data characteristics, intended goal of the representation, semantics and domain knowledge represented in the data, ease of understanding and aesthetics, and user preference. In this paper, we use these factors to review the state-of-the-art in visualization recommendation. The structure of this paper is as follows: In Section 2, we introduce and define some visualization terms and concepts. In Section 3 we present and categorize visualization recommendation studies based on the area of their contribution. We identify remaining challenges in Section 4 before concluding our paper (Section 5).

2 IMPORTANT CONCEPTS

We would like to introduce some concepts related to the data visualization creation process, which are used several times in this paper.

Data attributes are associated with variables and describe their measurement scales, e.g., quantitative, categorical, ordinal, nominal etc.

Each data attribute is mapped via a process called **visual mapping** to some **visual mark**. The visual marks of scatterplot, e.g., include points, X and Y axis etc.

Each visualization consists of different visual marks with different properties. Points in a scatterplot, e.g., have some size, shape or color. Bertin (1983) names them **visual variables**.

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Visualizations can be classified by their **representational goals or tasks**. Scatterplots, e.g., are relevant for representing 'correlation' and 'distribution'.

These goals can be achieved by **low-level tasks**. Consider, e.g., a bar chart. To achieve the goal "Comparison, one needs to identify the sizes of at least two bars. Here, "identify" is a low-level task and "size" is a visual variable.

3 VISUALIZATION RECOMMENDATION STRATEGIES

Based on the most distinguishing of the factors identified by Vartak et al. (2015), we classify approaches to visualization recommendation into four distinct categories. These categories are defined according to the main contribution of their research in providing techniques, guidelines or directions that assist in recommending visualization.

1. Data Characteristics Oriented: Studies which fall in this category recommend visualizations based on data characteristics.
2. Task Oriented: Studies that fall under this category use the representational goals along with the data characteristics to recommend visualizations.
3. Domain Knowledge Oriented: Studies which fall under this category improve the visualization recommendation process with domain knowledge.
4. User Preferences Oriented: Studies which fall under this category gather the information about the user presentation goals and preferences explicitly through user interaction with the visualization system.

3.1 Data Characteristics Oriented

Visualization recommendation research studies in this category have tried to improve the understanding of the data, of different relationships that exist within the data and of procedures to represent them. The choice of variables to represent different aspects of the same information can greatly influence the perception and understanding of the presented information. Therefore, the research under this category focuses on: the definition of new data dimensions or attributes, the formalization of the process of visual mapping from data attributes to visual marks, and the introduction of new techniques for visual mapping.

The earliest known study that proposes an automation of graphical designs was that of Gnanamgari's Bharat in 1981. As cited by Bouali et al. (2015), Bharat proposed some rules for determining which type of visualization is appropriate for certain data attributes. However, their work is based on the limited set of visualizations available in 1981.

Mackinlay's APT system (Mackinlay, 1986) proposes to formalize and codify the graphical design specification to automate the graphics generation process. This is based on composition algebra, which consists of basis set and composition operators. Before applying this algebra, data attributes need to be encoded with the respective visual mark which should be consistent with the rules presented in Table 1.

Table 1: Data attributes to visual marks mapping (Mackinlay, 1986).

	Nominal	Ordinal	Quantitative
Size	–	●	●
Saturation	–	●	●
Texture	●	●	●
Color	●	●	
Orientation	●		
Shape	●		

In Composition Algebra, the basis set encodes data attributes to visual variables (as in Table 1). Compositional operators generate different presentations by composing different basis sets from different data attributes. They compose visualizations by merging parts which encode the same information. For example, two single axis plots with the dot visual mark can be composed to a 2D scatterplot.

Later, the specifications based on Mackinlay's heuristics were used to develop a research system called Polaris (Stolte et al., 2002). These specifications were then revised into a formal declarative visual language known as VizQL (Hanrahan, 2006). The visualization software Tableau's (https://public.tableau.com/s/) "Show Me" module (Mackinlay et al., 2007) uses VizQL specifications to automatically recommend visualizations. When the user selects the data attributes of his interest, Show Me uses Tableau's Visual Mapping rules (Table 2) to define the visualization types.

In order to enhance the understandability of the data and the process of visual encoding, Roth and Mattis (1990) argued that more structural and semantic information about the data which is relevant to the presentation design should be provided. Therefore, they proposed a richer set of data characterizations, divided into different data domains, to be used by humans or machines for designing visualizations. It includes original data measurement scales as by (Mackinlay, 1986), along with new data descriptors: Spatial (coordinates, name of the city, etc.), Amount (count and discrete data), Range (duration). They have identified and grouped the data domains into *coverage*, *cardinality* and *uniqueness*. Coverage conveys whether every element of a set can be mapped to at least one element of another set. Cardinality expresses the dependency and 'within' relationship between two or more attributes of the same dataset: one to one, one to many, many to many. Uniqueness refers to the uniqueness of values within a set or data column. Their proposed characteristics are used in SAGE, which is a System for Automatic and Graphical Explanation.

Table 2: Tableau Visual Mapping Rule (Mackinlay et al. 2007).

Pane Type Field 1	Pane Type Field 2	Mark Type	View Type
C	C	Text	Cross-tab
Qd	C	Bar	Bar view
Qd	Cdate	Line	Line view
Qd	Qd	Shape	Scatterplot
Qi	C	Gantt	Gantt view
Qi	Qd	Line	Line view
Qi	Qi	Shape	Scatter plot

Unlike previous work where researchers seek knowledge from within the relationship between the variables of the dataset. Shneiderman's theory (Shneiderman, 1996) has emphasized considering the dataset as a whole collection and understanding the overall relationship between a single collection (like hierarchical data) or within different data collections. He has categorized the data into seven dimensions: 1-dimensional, 2-dimensional, 3-dimensional, multi-dimensional, temporal, tree and network data. This proposal serves as the basis of the implementation of the TIBCO Spotfire (Shneiderman, 1999).

In the previously mentioned studies and tools, visualizations were generated offline by specialists. 'Many Eyes' changes this trend and provides a first known public web site where users may upload data and create interactive visualizations collaboratively (Viegas et al., 2007). In Many Eyes, a visualization is created by matching a dataset with a visualization component (or visualization techniques). The list of visualization components is provided in Figure 1.

Technique	**Data schema**
Bubblechart Histogram Pie Chart Maps Tag Cloud	{Labels / item names : T, Values : N}
Bar chart Line graph Stack graph	{Axis labels : T, Values : N+}
Network diagram	{From : T, To : T}
Scatterplot	{Xaxis : N, Yaxis : N, Label: T, [Dotsize : N] }
Stack graph/ categories	{Hierarchy : T+, Values : N+}
Treemaps	{Hierarchy : T+, Size : N , Color : N}
Tag Cloud	{U}

Figure 1: Many Eyes Visual Mapping Scheme (Viegas et al., 2007).

Visualization components are separated by horizontal lines. Each component consists of some visualizations which share a common data schema. When the user selects some data columns, they are mapped with the data schema which is associated to some data visualization. A data schema is a set of named, typed slots. For example: 'T' in the above table is single column textual data and 'T+' means that the dataset has more than one textual data column. Thus, a treemap (as in Figure 1) can be expressed as an ordered set of textual columns, where each row in the set describes the path from the top of the hierarchy to the leaf item. The dataset and produced visualization then can be shared with other users for comments, feedback and future improvement, thus providing a collaborative workbench for visualization creation.

The popularity of Many Eyes has proved the usability and ease of access of deploying visualization software as a web application. Along with that, the dashboard environment provided by Tableau also became a standard for visualization creation interfaces. Voyager (Wongsuphasawat et al., 2016) is a recent visualization recommendation web application based on the dashboard type environment. Voyager uses the Compass Recommendation Engine, which suggests visualizations based on the statistical properties of the data. The suggestions are produced in the form of Vega-lite specifications (Satyanarayan et al., 2017). A Vega-lite specification is a JSON object (see Figure 2) that describes a single data source, a mark type, visual encodings of data variables, key-value, and data transformations including filters and aggregate functions. The Compass Recommendation Engine first suggests a list of visualizations based on the univariate summary of each variable in the dataset. Then the user can exclude or include variables from the list to focus on a particular variable set of interest.

Similar to the study by (Wongsuphasawat et al., 2016), recent studies have tried to exploit the statistcal

```
{
  "data": {"url": "data/cars.json"},
  "marktype": "point",
  "encoding": {
    "x": {
      "name": "Miles_per_Gallon",
      "type": "Q",
      "summarize": "mean"
    },
    "y": {
      "name": "Horsepower",
      "type": "Q",
      "summarize": "mean"
    },
    "row": {
      "name": "Origin",
      "type": "N",
      "sort": [{"name": "Horsepower",
          "summarize": "mean", "reverse": true}]
    },
    "color": {"name": "Cylinders","type": "N"}
  }
}
```

Figure 2: Vega-lite JSON Object (Wongsuphasawat et al., 2016).

characteristics of data as an assistance to visualization recommendation. VizDeck (Key et al., 2012) is another such initiative. It automatically recommends ranked and coordinated visualizations (vizlets) based on the statistical properties of the data. They adopts a card game metaphor to organ-ize multiple visualizations into interactive visual dashboard applications. When user selects the data the system initially presents the small multiple views of the XY Charts (scatterplot or line chart based on the data attributes). Users interacts with these vizlets while keeping the good one and discarding the unwanted vizlets. User interaction makes a system to learn that which vizlets are more likely to be effective for a dataset with particular features. The learned information enhances the system's ability to recommend more suitable visualizations when provided with similar data in the future.

Vartak et al., (2015) uses statistical methods of probability distribution, distance matrices and deviations to suggest different views of bar chart and line chart. Their prototype SEEDB computes a deviation of the subset of the data in comparison to the whole dataset. It then recommends those visualizations for which the underlying data (subset of data) has a high deviation from the current and normal trends reflected in the whole dataset. They argue that users find visualizations with high deviations more interesting and expressive.

As summarized in Table 3, the contributions provided by the studies in this section can be classified into four broad areas on the basis of their contribution towards better visualization recommendation:

- Data properties definition: by providing richer sets of data dimensions and characterization
- Rule definition: by providing rules, specifications and schemas to manipulate the data and perform visual mapping
- Language formalization: by defining the specification in system understandable language to automate the process of visual mapping
- Statistics based: by using statistical and exploratory data analytics procedures to recommend visualization

Table 3: Classification Table.

Categories	Studies
Data Properties	SAGE (Roth and Mattis, 1990), TIBCO Spotfire (Shneiderman, 1996)
Rule Definition	APT (Mackinlay, 1986), Many Eyes (Viegas et al., 2007)
Language Formalization	VizQL (Hanrahan, 2006) Vega-Lite (Satyanarayan et al., 2017)
Statistics	Voyager (Wongsuphasawat et al., 2016), VizDeck (Key et al., 2012), SeeDB (Vartak et al., 2015)

3.2 Task Oriented

Visualization recommendation research studies in this category have designed different techniques to infer the representational goal or user's intentions behind visualizing the data. Differences in goals can greatly alter the effectiveness of graphical designs.

Roth and Mattis (1990) were the first to contribute to the idea of instigating the user's information seeking goal in the visualization design. In their study they identified different domain-independent information seeking goals, e.g. comparison, distribution, correlation etc.

Based on some sets of representational goals, a classification scheme for visualization recommendation was proposed by Wehrend and Lewis (1990) in the form of a 2D matrix of "objects" vs "operations". In this matrix, "objects" are data attributes, "operations" are representation goal and cells contain visualization techniques.

According to Kerpedjiev et. al. (1997), visualization recommendation can be further enhanced by the use of domain level tasks. Hence, they proposed a model (Figure 3) to hierarchically decompose domain-specific user's goals (for the "transportation scheduling" domain) into common domain independent goals or representation goals which are further associated with some graphical actions or operations. For example, in Figure 3, domain-specific goals like "know-shortfalls" (which means to know the daily shortfalls in the goods transported) was decomposed to tasks which include "know-difference". In turn, "know-difference" is associated with "differentiate" which is a high level domain independent task or goal which acts on data. Actions associated with "differentiate" include "enable-lookup" on value of individual days and "enable-comparison" on those values. This approach was applied in the development of AutoBrief (Kerpedjiev et. al. 1997) which is a multimedia presentation system that assists in data analysis.

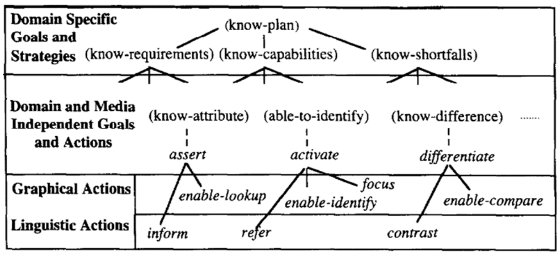

Figure 3: Goals and Actions (Kerpedjiev et al., 1997).

In all the previous studies, the user task list was manually created. By introducing advanced linguistic techniques in the visualization creation process, researchers seek an opportunity to automate the derivation of the user task from a natural language query. One such study (Zhou and Feiner, 1998) introduced visual task taxonomy to automate the process of gaining a high level of presentation intents from the text. This taxonomy interfaces between high level tasks (presentation intent) that can be accomplished by low level visualization techniques (visual action). For example, the visual task *Focus<?x>* implies that visual techniques such as *Enlarge<?x>* or Highlight*<?x>* could be used to focus attention on *?x*. Their taxonomy and techniques are implemented in IMPROVISE (Illustrative Metaphor Production in Reactive Object-oriented Visual Environments)

3.3 Domain Knowledge Oriented

In the visualization development process, it is important to first characterize the task and data in the vocabulary of the problem domain, so that a visualization can fulfill the requirements of users in any particular target domain (Munzner, 2009). The objectives of domain knowledge oriented approaches include sharing such knowledge among different designers and end users, and reducing the burden upon users to acquire knowledge about complex visualization techniques. Such approaches are not core techniques to produce visualization, but they provide assistance to other techniques for improving the performance while recommending visualizations. The studies falling into this category deal with gaining the domain knowledge from existing knowledge sources or creating a new one which further assists in the visualization recommendation process.

The earliest known domain knowledge oriented visualization recommendation study is RAVE (Klumpar et al., 1994). RAVE has been used for the visualization of in-situ measurement data captured by the NASA spacecraft. The user needs to select either a visualization type or a representational goal from a provided list. On user selection, RAVE triggers the visualization technique associated with the entries in a list and provides the resultant graphics. RAVE's knowledge-base contains: (1) a set of visualization objects that corresponds the technique that can create a specific visualization, (2) a set of rules that corresponds to the selection of one particular visualization technique, (3) the high level task that visualization can perform like correlation for scatterplot, (4) the refinements that a visualization can accept and (5) the domain(s) in which it can be used. For example, the visualization object that corresponds to the 2D scatterplot can satisfy the rule "attribute x is related to attribute y", can accept zooming and color as refinements, and can be applied in any domain where numeric-valued attributes are compared.

To include semantic abilities in the process of recommendations, Gilson et al., (2008) propose a pragmatic approach for automatic generation of visualizations from domain-specific data available on the web in the form of ontologies. They have described a pipeline that combines ontology mapping from three different ontologies. In this approach, a web page is first mapped to a "domain ontology", which stores the semantics of the specific subject domain. The "domain ontology" is then mapped to one or more "visual representation ontologies", each of which captures the semantics of a visualization style (e.g., treemaps). A "Semantic bridging ontology" bridges the information from the two ontologies and holds key knowledge about the relationships between data entities of the source, the subject domain and the visual artifacts of the target visualizations. They have implemented the visualization pipeline in a prototype, SemViz which functions end-to-end from source web page to target visualization.

Building upon somewhat similar grounds, Voigt et al., (2012) propose a novel approach for knowledge-assisted, context-aware visualization recommendation for semantic web data. VISO is a modular visualization ontology composed of seven different modules that provides a vocabulary to annotate both data sources and visualization components. GRAPHIC module formalizes knowledge in the domain of visualization. DATA module characterizes the data variables and structure. ACTIVITY module is concerned with the human aspects of visualization i.e. tasks, actions and operations. SYSTEM, USER and DOMAIN module describes the data and visualization context and the domain information. Based on the shared knowledge from the different modules, a recommendation algorithm covers both discovery and context-aware ranking of suitable graphic representations.

3.4 User Preferences Oriented

Here, those visualization recommendation strategies are grouped which gather users' intentions explicitly from their behavior and interactional records while they communicate with the visualization system. They are also known as behavior driven studies. Some studies also use probabilistic and machine learning techniques to predict the patterns of user choice from these interactional records.

The first known behavior driven study is from Gotz and Wen (2009). BDVR (Behaviour Driven Visualization Recommendation) consists of two distinct phases: Pattern Detection and Visualization Recommendation. In the first phase, user behavior while interacting with the visualization system is analyzed to find meaningful interaction patterns. These patterns are, e.g., scan, flip, swap and drill-down. In the second phase, a recommendation engine infers a user's intent from these detected patterns. In case of "scan pattern", e.g., the user interactively 'inspects' values over a series of data. Then he 'compares' those series within themselves or over time. From these intents, visual tasks are inferred which later suggest an alternative visualization to the user which suits more accurately than their current visualization selection.

A similar study conducted by Steichen et al., (2013), has provided results on accumulating information from user eye gaze patterns. They recorded the interaction of the user with a given visualization to predict the users' visual tasks, as well as user cognitive abilities, including perceptual speed (a measure of speed when performing simple tasks), verbal working memory (a measure of storage and manipulation capacity of verbal information), and visual working memory (a measure of storage and manipulation capacity of visual and spatial information). They have shown that such characteristics have a significant effect on task efficiency, user preference and ease of use with visualization systems. These findings are presented in view of designing visualization systems that can adapt to each individual user in real-time.

Growing towards the recommendation of more user-centric and user adaptive visualization, many systems have applied machine and probabilistic learning approaches from the user interactions while browsing through the recommended visualization as in the case of VizDeck (Key et al., 2012) as discussed in section 3.1. A study from Mutlu et al. (2016) used techniques like collaborative and content based filtering to suggest charts by deriving similarity matrix according to the information needs of the user and chart characteristics. First they have designed a crowdsource study to obtain personalized scores and tags on each visualization. Then a multi-dimensional scale is used to estimate aspects of quality of charts for collaborative filtering and a tag vector is used to recommend potentially interesting chart based on content.

4 CHALLENGES AND RESEARCH DIRECTION

The ultimate aim of all visualization recommendation systems is the suggestion of visualizations which automatically provide interesting insights in data. Over the years, researchers have continually expanded the set of requirements addressed by their systems to develop more aesthetically appealing and user adaptive visualizations. One such requirement is to apply an appropriate technique to score and rank the suggested visualization according to the data domain and the user preference. Along with this requirement Vartak et al. (2015) opined to include factors such as relevance, surprise, non-obviousness, diversity, etc. in the visualization recommendation process.

The challenges of other visualization domains such as information visualization, scientific visualization etc. also affect the visualization recommendation process. As investigated by Chen (2005) some of these include usability of a recommendation, scalability, visual thinking and analytics, etc.

Looking at the trends in the visualization studies, we can see that researchers have acknowledged the need of more user and domain centric visualization by providing domain specific knowledge based approaches. However, at the same time the research in generic recommender systems (e.g. data charactersticss and statistics oriented) is rapidly developing. As a result, there is also a challenge of keeping pace with this in the visualization recommender systems community. Overall, there is the question of which concepts in these generic recommender systems can be re-used and how can they be effectively implemented in visualization recommendation.

Moreover, there is an ongoing investigation into use of formal languages, standards or ontologies to describe the structure, and specifications of classes of visualization, and the different tasks that can be associated with the classes.

Another challenge is the efficiency of visualization recommendation given the growing space of combinational possibilities of ever increasing data sizes (rows and column), classes of visualization, and intended tasks. In addition, there is also the challenge of effectively incorporating human computer interactions into visualization systems.

Furthermore, some other research studies are investigating the use of visualization recommendation in data-driven science, and visual analytics. The list of research directions/challenges are not exhaustive, but they are interesting examples of the current and future research activities.

5 CONCLUSIONS

Visualization is becoming an increasingly more important tool for getting insights into the ever bigger and more complex data being generated in this era. As a result, different kinds of visualizations with different characteristics are constantly being developed. Consequently, deciding which visualization best suits a user's data and intention becomes more and more complex. Visualization recommendation systems attempt to support the user in the decision making. In this paper, we have discussed research on this topic has gone through several phases beginning from only considering the data and chart characteristics to now where several other factors such as individual preferences, insight tasks, and domain knowledge are considered in varying degrees. Still, there is strong need for additional research in particular to keep the visualization, visualization recommendation and recommender system communities synchronized.

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