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Data visualization pitfalls: a systematic review

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Abstract

Data visualization visual or pictorial representations of facts that are easy to comprehend. It aids in the explanation of facts and the selection of appropriate actions. It may be used in any sector that needs new methods to convey enormous amounts of data. Modern visualisation has been shaped by the introduction of computer graphics. Data visualisation is the subject of this study, which provides a quick overview.

Charts, plots, infographics, and even animations may be used to convey data in a visually appealing way. Data-driven insights may be communicated in a clear and concise manner using these graphic representations of information.

There are many uses for data visualisation, and it's vital to remember that it's not only for data teams. Data analysts and data scientists, on the other hand, utilise it to find and explain patterns and trends in the organization's structure and hierarchy.

Keywords: Data visualization, Information Visualization, Scientific Visualization, big data.

Introduction

Since an a while, there have been a pressing need to make large amounts of data easily accessible and understood. All the time, organizations are producing data. As a result, the amount of information that can be found on the Internet has skyrocketed. For the average user it's tough to comprehend the sheer volume and complexity. Scientific research heavily relies on the capacity to visualise data. Computers today are capable of handling massive volumes of data.

Graphical representations of data created by computers are the primary focus of data visualisation. In this way, data from many sources may be represented clearly and effectively.

A visual representation of the data makes it easier for decision-makers to comprehend it. As a result, they learn to see patterns, make sense of data, and create opinions. This type of visualisation can also be referred to as information or scientific visualisation. Visualizations have traditionally been used by humans to ensure that information or messages are remembered for a long period of time. Visual representations of things that can't be felt, smelled, or tasted are possible.

- **VISUALIZATION TECHNIQUES**

Data can be represented in a visually appealing manner by means of computer-assisted visualisation. Interactive data visualisation, as opposed to static data visualisation, allows users to determine the format of the shown data.

- *Line graph:* To see how everything are linked, look at this picture. Monitoring changes over time is possible with this tool.
- *Bar chart:* Comparing the amounts of various categories is done using this.
- *Scatter plot:* This is a two-dimensional chart showing the changes in two different variables.

- *Pie chart:* Compares different components of the same whole.

As a result, graphs and charts could be presented in a variety of ways, including bar charts, pie charts, line graphs, and so on. Understanding which chart or graph to employ for your data is essential. Computer graphics are used to demonstrate patterns, trends, and relationships between data items.

A simple pull-down menu and a few mouse clicks may produce pie charts, bar charts, scatter plots, and other sorts of data visualisations. For some forms of visualisation, colour schemes are meticulously honed before being used.

We must pick colours that effectively distinguish data pieces when they are utilised to portray data through colour. Data is abstracted and summarised in data visualisation. Key aspects in the data are represented by spatial variables, such as position, size, and form.

Visualization systems are designed to convert and display the original dataset on a computer screen. Charts and graphs should be used to convey data in an easy-to-understand manner.

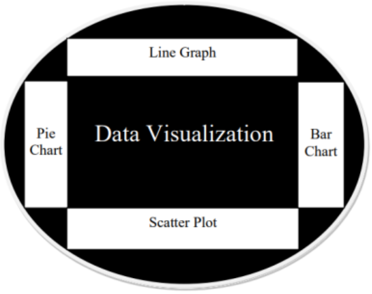

Figure 1. Commonly used data visualization techniques.

- **APPLICATIONS**

The primary purpose of most visualisations is to help decision-making and enhance cognition. When creating a data visualisation prototype, it's important to keep the end user's intended use in mind. It's not enough to just display numerical data; effective data visualisation also includes carefully selecting and rethinking the numerical data on which it is built.

An essential subject of computer science, data visualisation has a wide range of applications. It is now possible to analyse individual datasets in many different medical and scientific domains using a variety of application-specific technologies.

- **Public Health:** Data analysing are essential for public health surveillance to be successful. Helpful and sophisticated tools for health researchers are essential. In cloud-based medical data visualisations, security is essential. The medical and health magazines of today have a wide range of visual representations of medical and health information.
- **Renewal Energy:** An ideal solution necessitates a comparison of energy use and production.
- **Environmental Science:** Environmental managers need visualisation to help them make decisions based on extremely complicated data. The use of visualisation in environmental research is beginning to develop. A variety of applications for visualising outcomes is ideal to have on hand.
- **Fraud Detection:** In the early phases of a fraud investigation, data visualisation is critical. Data visualisation may be used by fraud investigators as a proactive strategy to detecting fraudulent activities.
- **Library-Decision Making:** Allows librarians to better organise and present information from a variety of sources using data visualisation tools. Their ability to communicate in a creative and captivating manner is enhanced by this training.

When library data is represented visually, it is easier to see library purchases and long-term plans. Students, educators, and researchers can benefit from the expertise of librarians in data visualisation.

- **CHALLENGES**

Data visualisation of large, time-varying datasets seems to be a major difficulty because of the massive volume of data. Using real-time data visualisation, users may respond to concerns before they become problems. Interactive data exploration is made possible by using animation creation techniques. It depicts the passage of time by imitating the structure of a story. Different users have different levels of proficiency with data visualisation and the capacity to make quick judgments under pressure.

It's difficult to put a monetary value on the effectiveness of a data visualisation approach. It's because of this reason that there's so many different visualisation methods and programmes. These applications have not taken advantage of the new devices' multi-touch interactions & direct manipulation capabilities.

DATA: WHAT IS VISUALIZATION DATA

Data visualisation is defined in this section. We discuss and classify visualisation data specifically in terms of the raw data format and representations that it takes. Data visualisation formats are divided into visuals, programmes, and hybrids that combine the best features of each.

Visualizations are sometimes provided as carefully defined internal representation formats, in addition to raw data, in the systems we've evaluated. Usually internal representations are suggested in order to simplify computing by reducing unneeded information, for example the VQL format only maintains data transformation and encoding information without style details..

This means that most internal representations are not made public (outputted and shared). Finally, we look into feature presentations, including feature engineering and feature learning. Machine learning tasks rely on feature presentations because they organise visuals into features that are easy to analyse mathematically and computationally. When it comes to applying machine learning to visualisations, they discuss them.

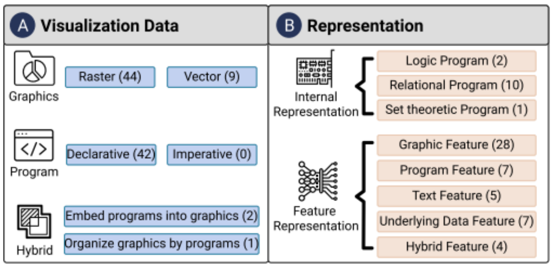

Fig. 2. Summary of categorization of A visualization data and B its representation. Numbers in the parentheses indicate the count.

Data

In addition to visuals and programming, visualisation data may be saved in a variety of content types. Because various types use their own benefits and limitations, the downstream operation on visualisation data may be directly influenced by the choice of content formats. Graphics, programmes, and hybrids are all discussed in this section. Three recent studies offer hybrid formats for the combined power of visuals and programmes (see Figure 2), which are both frequent in the corpus.

- ***Graphics***

Graphics visualisations are described as a graphical representation of data, they are a natural and expressive content structure for visualisations. Thus, they make up a large portion of our corpus. Raster graphics (bitmaps) are commonly used to create and store visualisations for ease of use and distribution.

Retaining its visual meaning, however, is a disadvantage of using raster graphics (e.g., chart type, visual encoding, underlying data). Reverse engineering, i.e., utilising computer vision and machine learning methodologies to rebuild lost information, is sometimes a prerequisite for doing automated analysis.

- ***Vector***

Vector graphics provides a less damaging alternative to the current situation. Because they can be scaled up without aliasing, vector graphics offer an advantage over raster graphics. Scalable Vector Graphics (SVG) is the most common format used to store visualisations, allowing for the description of visual components like shapes (e.g., rectangles and text) with a variety of different styles (e.g., positions and fill-color). It is no longer essential to use computer vision techniques to recognise items like texts because of these low-level descriptions.

In addition, this format supports animation and interaction. However, high-level visualisation semantics, such as visual encoding and underlying data, remain lost and need great work to be extracted.

- **Big Data Visualization Problems**

Researchers may notice the following issues if they pay attention to the Big Data features described above, making visualisation not a simple operations.

Visual Noise: It's possible to get bogged down in a confusion of points if we had just display the entire variety of data being evaluated on a computer screen. In the dataset, most of the items are also too close to one other for the screen-watcher to distinguish them as distinct entities. Because of this, an analyst may be unable to get any actionable insights from a data visualisation without first performing some preliminary processing.

Large Image Perception**:** An strategy that results in data dissemination atop a wider screen is proposed as a solution to the aforementioned issue. However, it can occasionally lead to another issue, namely the impression of huge images. Various data visualisations have various types of human comprehension.

No matter how much better than table data display this technique is, there are still drawbacks. And the human being loses all potential to obtain any helpful information from the data overloaded vision after reaching this degree of awareness.

Information Loss: Several ways can also be used to reduce the amount of data that can be seen. However, despite the fact that the aforementioned issues are resolved, these methods lead to a new issue: information loss. Based on the relatedness of objects in specific datasets by one or more criteria, these systems work by aggregating and limiting data.

A sophisticated aggregation method may cost a significant amount of time or performance resources in order to obtain the information that the analyst is looking for, and these approaches might be misleading when the analyst does not detect certain relevant hidden items.

High Performance Requirements: Static image representation is simply one part of a graphical study; dynamic visualisation magnifies these issues. In addition, because static visualisation has lower speed requirements than dynamic visualisation, another issue—high performance—can be overlooked.

Even if there is no need for a frequent refresh rate, the analyst will often want to view the whole data array, and this procedure might take a long time.

As a result, processing resources are continually increased or data is continually filtered. When it comes to actual usage, it's common to combine these two methods due to their low initial setup costs and great organisation, support, and efficiency.

High Rate of Image Change: Furthermore, there's a difficulty with the rapid evolution of the visual representation. When ever a person watching the data simply can react to the quantity of data changes or the severity of those changes displayed, this problem becomes critical. The human reaction speed directly depends on the rate of change, hence a decrease in the rate of change is not enough to achieve the intended goal.

Because of this, it could be claimed that Big Data visualisation lowers the overall of analysis, underscoring the relevance of this research even further.

- **Data Visualisation Pitfalls**

As a result, you'll be able to notice patterns, trends and correlations that weren't obvious in the rows and columns of days gone by, thanks to all these simple platforms. Since we all know, a picture is worth a thousand words, thus today it is much easier to grasp your facts.

Data Visualisation Pitfalls #1 – Colour Abuse

Color seems to have a role in data visualisations, but it's crucial not to overuse it. Confusion or worse, misunderstanding might result from the use of the incorrect colour.

Priority is always given to in-depth investigation. As a result, brand colours aren't always the greatest choice for visualisations, despite what your branding department would tell you. Consider persons who are color-blind while designing your website. Don't rely just on colour to communicate your message.

Data Visualisation Pitfalls #2 – Misuse of Pie Charts

Researchers all like a good pie, however a mere sliver isn't doing it justice. Trying to include too much information into a pie chart obscures what the overall image is. Your viewers will be left feeling unsatisfied and bewildered if you go into too much detail.

Pie charts work best with data that has a small number of dimensions, so that each slice of the pie can be readily differentiated. In general, don't use pie charts to compare multiple sets of data. To make comparisons simpler, organize your slices in descending size order.

Data Visualisation Pitfalls #3 – Visual Clutter

Finding new data in an overcrowded visualisation is like discovering a needle in an overgrown flower bed. An overabundance of information thwarts the goal of clarity and obscures meaning, leading to incorrect judgments.

A dashboard should include no more than eight things. Remember to keep your visualisations basic by avoiding the use of too many things. Getting the gist of anything is made simpler when there isn't as much to interpret. Change the format if your visual appears crowded. Generally speaking, the simplest format is the best.

Data Visualisation Pitfalls #4 – Poor Design

To claim that a representation is efficient doesn't really imply that it has been visually appealing. Visualisations that are effective employ design best practises in order to communicate facts more effectively. Design the visualisations and dashboards, not simply produce them. Make sure the visualisation is as effective as feasible by working with designers.

Data Visualisation Pitfalls #5 – Bad Data

Amazing data seems to be the foundation for great visualisations. It's possible that you've been the victim of faulty data if the visualisation yields surprising findings. The culprit for faulty data should not be your visualisation.

Before presenting any statistics, look for problems in your data using the charts. Avoid blaming your visualisation for incorrect data. Which counts as an unexpected finding and what counts as a data issue?

Data visualisation techniques are used by statisticians throughout the world to make their findings easier to understand and communicate. As a result, organisations reap a slew of practical advantages, including reduced costs and increased productivity:

- The ability to understand relations between actions and consequences.
- The potential to communicate analytical findings in a meaningful manner.

- The chance to act faster and make data-driven decisions.
- The power to identify emerging trends.

Even though benefits of data visualisation are obvious, the process itself has several drawbacks, as you may have seen. Seven main mistakes in data visualisation would be discussed in this post, along with tips on how to prevent them.

The following are amongst the most popular kinds of data visualisation:

- Frequency distributions
- Time series
- Nominal comparisons
- Ranking charts
- Correlation maps
- Geospatial maps
- Deviations
- Part-to-whole

Common Data Visualization Traps and Misunderstandings

1. **Not knowing how to visualize information:** There's a simple solution to the most typical issue. When it comes to data visualisation and presentation, many business professionals are inadequately. Because data visualisation tools make it simple to generate graphs or visuals, many users adopt a well-known template without assessing if it is the best answer for their particular needs.
2. **Not providing formal training to employees:** This is indeed a logical result of the pervious issue. Assuming that their personnel are capable of handling data visualisation without any formal training or education, many firms take it for granted.
   Data visualisation training for employees may be tailored to meet the specific needs of a company's workforce and ensure that they have the best possible knowledge and understanding of data visualisation.
3. **The human limitations of algorithms:** A major drawback of data science is the reliance on human input, which can cause delays and misinterpretations for specific projects. Human teachers are prone to prejudice and are often unable to discern the most pertinent ideas and viewpoints. It's best if you have numerous analysts working on the project and a thorough brainstorming session before creating the program.
4. **Not created with the audience in mind:** Even if individuals have by far the most thorough and visually stunning data visualisation project, it probably doesn't mean anything if it doesn't meet the needs of the intended audience. Be conscious of their data interpretation abilities and construct the presentation to meet their degree of expertise and understanding of data. For your clients, it is the only way to make an impact.
5. **Oversimplification:** Oversimplification seems to be a risk if the audience is unfamiliar with data visualisation methods. You'll miss the objective of the study if you do this, as you won't be able to offer the correct data. Those who make things easy to understand by simplifying graphs and charts because they are generally speaking to students who are younger. By displaying the proper information at the right time, you may help avoid this from happening.
6. **Paying too much attention to form:** Since data visualisation relies heavily on visual elements, it's only logical that the final document strives to be quite as visually appealing as possible. However, you should not allow it all to impact the reasoning or decision-making process. To the contrary, if

you still want the data visualisation to have more impact on your audience, you must strike a balance between professional understanding and aesthetics.

7. **Over-relying on visuals:** Although data visualisation is the most effective means of conveying information, it isn't always sufficient to rely just on visual elements. Your presentation should include a limited amount of written information to support statistical findings. Don't think of it as a weakness. If you depend too much on visuals, you risk making the presentation unclear or even meaningless.

Literature review

While using information and knowledge visualisations online, in social media, in education, and in management, it really is critical to recognise the limitations of graphic representations and the mistakes that can be made when building or viewing them. To help students better grasp a crucial part of visual literacy, it's a good idea to look at typical pitfalls and blunders while interpreting and creating visualisations.

The term "visualisation" is used in this article to describe the presentation of information and knowledge in a visual form. In practical terms, a list of visual problems may be utilised as an educational tool, providing a comprehensive list, a vocabulary, and definitions of essential terminology connected to the risks of visualisation.

practitioners may use the classification to evaluate photographs and enhance the design of documents, infographics or digital images as a checklist.

Ware, (2000): Research presentations and communications rely heavily on visualisation since it can condense enormous volumes of data into easily understandable visuals. Adopting excellent visuals in academic writing is essential since images are easier for the brain to absorb than words or numbers (Cukier, 2010).

Szalay and Gray, (2006): Datasets are becoming more and more commonly accessible, which necessitates the development of efficient methods for analysing and disseminating the information they contain in plain, basic formats (Cukier, 2010).

Xu et al., (2010): In both data analysis and data presentation (Jeong et al, 2006; Kollat and Reed 2007, Wagener and Kollat 2007, respectively), visualisation is an essential tool. If the analysis is complete, the latter will be the emphasis of this work. A data visualisation is a type of graphic that analyses or conveys data in any subject, whereas scientific visualisation is a word that addresses visualisation of physical and scientific data.

Card et al., (1999): Research in visualizing data focuses on how different forms of visuals may be used to communicate facts. Despite recent breakthroughs in transdisciplinary research, typical faults in scientific visualisations persist and frequently restrict the effectiveness of visuals in conveying information.

There are varying interpretations of the word "effective visualisation," which has been widely used in visualisation literature. Some academics believe that the success of a visualisation is primarily dependent on the accuracy of the data it depicts.

Dastani [4] According to, "a visualisation successfully conveys the input data if the intended structure of the data and perceived structure of the representation coincides." Additionally [5] Wattenberg and Fisher state that a visualization's structure should reflect the data's. Similarly, Tufte [6] also voiced the same sentiment.

Visualization designers should have a precise goal in mind while creating a visualisation, according to Bertin [9]. In an empirical research, Nowell et al. [10] found that tasks rather than data should be the primary emphasis of evaluating good visualisation.

Amar and Stasko [11] have also challenged the "representational dominance" in contemporary visualisation research and urged a knowledge task-based paradigm for visualisation design and assessment. Research has challenged the task-centric paradigm of visualising effectiveness.

Objectives

- To study of the characteristics of evaluations performed in the literature of software visualization.
- To make it easier to identify patterns, trends and outliers in large data sets.
- To increased understanding of the next steps that must be taken to improve the organization.

Scope of the study

There seem to be no limitations to the kind of discussions that can be addressed by systematic reviews. s the effect of interventions on a certain human population. In spite of these limitations, systematic studies investigating the effects of intervention(s) might differ greatly in their objectives. There is a wide number of approaches that may be used to analyse the effectiveness of an intervention, and some are more focused on comparing it to a specific alternative.

Significance of the study

Visualizing data in a clear and effective manner is the act of presenting data in a visual form. A strong and frequently used tool for analysing and deciphering massive and complicated data has emerged from its incubation.

It has become a fast and straightforward way to communicate global thoughts. It must be able to convey complicated ideas in a straightforward, accurate, and time-saving manner. These advantages have made data visualisation useful in a wide range of academic subjects.

Limitation

Data visualization has the ability to help anyone & the team work more quickly, better, and more efficiently. Even while it may appear straightforward at first glance, data visualisation isn't without share of potential pitfalls and flaws.

Discussion

The main goal of this work is to provide a quick overview of some of the multi-dimensional visualisation approaches used in big data, while keeping in mind that the techniques presented here are just a small subset of the total available.

While the field of data visualisation is rapidly expanding in our economy's business sector, little progress has been made in this area, and it is unfortunate that businesses are still unable to get the exact results they desire when attempting to visualise their data using any of the available data visualisation methods..

In part, this issue remains because many of our business people are still unfamiliar with the appropriate visualisation approaches to utilise for a given task, and as a result, they wind up using the wrong technique for the correct data and receiving the wrong results.

Data visualisation techniques can be both interesting and challenging, depending on how well they are used. However, in order to select the best underlying visualisation technique to display data effectively, you must first understand the data being visualised with its size and cardinality (the uniqueness of data value contained in a column), as well as determine what you want to see in the visualisation.

Expected outcomes

It would be the main goal of this research to define the structural correspondence requirement, which really is essential for effective data visualisation. When it comes to visualising data, researchers believe that the structure of the data and its depiction should match up in terms of perceptually driven correspondence.

Perceptually motivated structures that could be employed in data structure visualisations have already been investigated to this goal.

In terms of perceivable relations that are imposed on visual elements by means of visual qualities, these perceptual structures were formalised. Using formal definitions of data and perceptual structures, researchers defined the structural correspondence requirement as a structure-preserving mapping between data and perceptual structures. While data visualisation literature frequently uses the phrase "visual languages," they have avoided it in our study.

Each visualisation is viewed as a statement or a phrase in a visual language in these researches.. In the suggested framework, a visual language may be defined as having two relational systems, a visual system and a mapping between them.

The denotation link between visuals and data was represented by the mapping between these relational systems. The visual languages specified by various relational systems change depending on the pair in question. It's also feasible to relate multiple relational systems to one other utilizing different visual languages.

Utilizing different number of visual system pieces or different values for their visual qualities, a visual language can produce various visuals. There seems to be a single visual language, the bar-chart language, shared by two separate bar charts that differ in their bar counts or visual attribute values. There are many various forms of maps, diagrams, graphs, and £ow-charts that might be termed visual languages. In our approach, they leave the specifics of establishing distinct visual languages for future study.

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