INTERSECTING HORIZONS: EXPLORING THE DUAL PATHWAYS OF ART AND SCIENCE IN IMAGE CREATION AND CONSUMPTION THROUGH DATA VISUALIZATION

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Abstract

Data analysis has long relied on visual representation as a means of understanding and conveying explanations. With the continuous advancement of computing technology, storage and processing capacities have significantly improved. Simultaneously, the democratization of technology has allowed for an increase in artistic contributions to data visualization, resulting in novel creative forms and alternative approaches compared to those found in the realm of science. This article examines the reciprocal influences between art and science within the field of data visualization. By analyzing literature from primary bibliographic databases and exploring the thriving community of practitioners that encompasses scientists, designers, artists, and other professionals, we provide a comprehensive overview of data visualization. Drawing upon historical examples from prehistory to the present, we explore various instances where art and science have jointly contributed to advancing the communication of phenomena and the formulation of data-driven inquiries. Additionally, we reflect on the challenges faced by data visualization and the opportunities that arise from them.

Keywords: Data visualization, big data, technology, science, visual arts, communication.

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Introduction

Data Visualization (DV) is a research area that has been strongly consolidated in the last decade. Even though, as we will see, its origins are as old as humankind, it can be affirmed that the contributions of DV have a global impact at the beginning of the second decade of the 21st century, in all branches of knowledge and in the daily activities of most people.

Traditionally, data visualization techniques have been developed in areas of science (biology, medicine, astronomy, statistics) and were primarily oriented to allow expert users to explore and analyze data (Azzam et al., 2013; Friendly, 2008; Friendly and Wainer, 2021; Meyer, 2013) quickly and accurately. The definitive impetus for DV has been the amount and complexity of scientific data that has continued to grow because of technological advances in computational performance and storage capacity (Chittaro, 2001). Simultaneously, the availability of open data sets and software for data visualization has encouraged artists and designers to create data visualizations for purposes other than the scientific field, targeting different groups of lay users (Quispel et al., 2018).

Beyond the use of DV as a tool for producing images that are useful or necessary for various domains, DV itself has recently become an object of study from the perspective of different disciplines, such as communication sciences (Cavaller, 2021) or graphic design (Marchese, 2021).

This article offers an overview of the place that DV currently occupies, understood both as a discipline and as a tool for creating images from data, within the broad spectrum that delimits the art-science relationship. The historical development of DV is addressed through a selection of examples of how data visualizations are used in art and science, identifying mutual influences, and reflecting on the main challenges it faces as a discipline and community of practice. This is an ambitious task that will start with a characterization of data visualization.

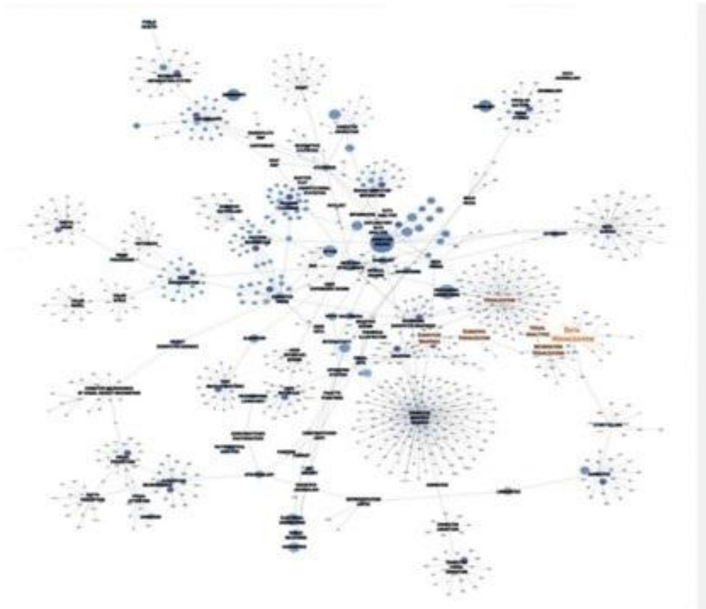
What is data visualization?

If one looks up the definitions in dictionaries, the term "visualization" originally meant forming a visual image in the mind (REAL ACADEMIA ESPAÑOLA, sf). However, in current usage, it refers to the graphic representation of data or concepts (Ware, 2019). Instead of selecting a specific definition of data visualization from the various options found in the literature (C. Chen et al., 2007; Friendly and Wainer, 2021; Meyer, 2013; Munzner, 2002; Valero Sancho, 2014; Ward et al., 2010; Wright, 2008), the focus is placed on the creation of images from data.

We encounter our first obstacle in the variety of terms used in different traditions and disciplines to describe the transformation of data into visual representations. In the fields of computer science and statistics, terms such as data visualization, information visualization, scientific visualization, or simply visualization are used - more recently, these terms are also associated with data science. From the field of design and visual arts, terms such as infographics, information design, or information architecture are used. This is not an exhaustive list of terms, but it illustrates the challenge in characterizing the production of images from data, which allows us to delve into the implications arising from the dual nature of art and science.

The Microsoft Academic search engine, utilizing artificial intelligence and semantic understanding of content, classifies publications into a hierarchy of topics or fields of study.

Figure 1. Network of research topics around «Data visualization» in Microsoft Academic
Source: Own elaboration from Microsoft Academic topic explorer



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Source: Own elaboration from Microsoft Academic topic explorer

Figure 1 depicts the intricate network of relationships between research topics in the field of data visualization (highlighted in orange). The closest fields, characterized by shared interests, methods, and techniques (visualization, information visualization, scientific visualization, computer graphics), are highlighted in brown. Notably, Figure 1 demonstrates the strong relationship that data visualization has with computer science (represented by the largest circle in the centre of the figure) and, to a lesser extent (following the diagonal towards the upper left corner), with statistics and cartography. Near are also fields related to data analysis (data analysis, data mining, and data science), human-computer interaction, artificial intelligence, and machine learning. On the left side of the figure, the significance of digital images, image processing, color spaces, and models is evident, all of which are related to computer vision, pattern recognition, and cognitive psychology. Furthermore, cognitive psychology connects with perception and attention, as shown in the lower left part of the figure. Finally, in the lower central part of the figure, the research fields of visual arts are displayed, including graphic computing and computer graphics. Within visual arts, the connections extend to graphics, graphic design, user interfaces, news media, data journalism, and animation. The visual arts field also demonstrates links to pigments, painting, art history, epistemology, figurative art, narrative, and storytelling, with the latter directly connected to data visualization through narrative visualization.

It should be noted that this graph depicting the relationships between fields of study is not exhaustive, and the represented topics often correspond to higher levels in the hierarchy. If all the subfields and their interrelationships were included, the resulting network would be much more detailed but less comprehensible. Therefore, this incomplete perspective has been chosen to provide a bird's eye view of data visualization.

Irrespective of the nomenclature, a common objective is identified: the transformation of information/data into visual representations intended to be perceived by an audience. The types of representations and processes used to derive them from the original data are diverse and numerous, especially when considering their applications in scientific and artistic disciplines, as well as their mutual influences. The complexity of this task is reflected in the absence of a clear or universally accepted definition for visualization as a discipline (Kosara, 2007) or any of its sub-disciplines.

Thus, it is common to find in the bibliography the characterization of data visualization as a contrast between different visualization variants that have evolved and coexisted throughout history. For instance, the distinction between scientific visualization, where the spatial arrangement in the generated image is implicitly derived from the data, and information visualization, where this spatial translation is not inherent in the data, has been commonly used (Munzner, 2002). However, an increasing number of authors avoid such a distinction, considering that both cases involve visual representations of data (Ward et al., 2010).

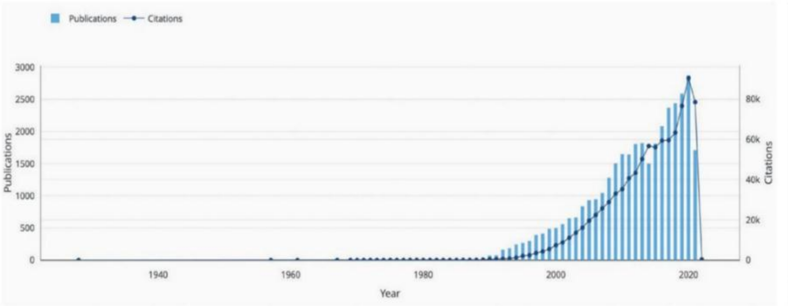
Two important aspects regarding data visualization and computing should be highlighted. Firstly, it is currently understood as the translation of digital data into a visual image (Wright, 2008). Secondly, with the integration of computers and various electronic devices, data visualization goes beyond static representation and becomes a true interface between people and data, facilitating dialogue through interactive elements (Dimara and Perín, 2019).

A fundamental characteristic of the data visualization field is its interdisciplinary (Kosara, 2007; Parsons et al., 2011; Viégas and Wattenberg, 2007) or multidisciplinary (Brodlie et al., 2012; Masud et al., 2010) nature (Olshannikova et al., 2015; Kirk, 2012; Ware, 2019). Disciplines such as computer science, statistics, mathematics, physics, biology, cartography, graphic design, cognitive psychology, linguistics, communication, art, and human-computer interaction all contribute their knowledge and methods, in varying combinations based on the nature of the data and the visualization goals, to the creation of data visualizations. Understanding how each of these disciplines contributes to shaping data visualization as it stands today is worth exploring.

An approach to answering this question can be made through an examination of the scientific literature produced around data visualization. It is important to note that this approach has limitations. It does not entail a systematic review of the literature and may not capture the extensive practices and contributions to data visualization that exist outside academic settings or those not recorded in the form of journal articles or conference proceedings. However, an examination of the literature can provide insights into the attention given to data visualization in different disciplines and help establish its coordinates within the broader landscape.

For the topic of "data visualization," Microsoft Academic has indexed 35,933 documents with an estimated 919,561 citations. Figure 2 illustrates the sustained growth of publications in this field since the beginning of the 21st century, with a significant increase in production in the last decade. In 2010, there were 1,647 publications and 35,248 citations, which rose to 2,875 publications and 90,387 citations in 2020.

Figure 2. Publications and citations for the topic "data visualization" indexed in Microsoft Academic

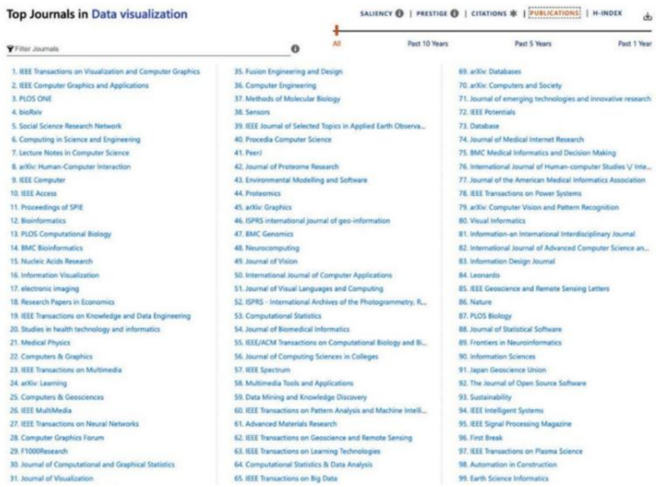


Source: Microsoft Academic

Beyond confirming the growing interest in this emerging field of study, it is crucial to identify the areas of knowledge where data visualization research is taking place. One way to address this question is by examining the academic journals in which data visualization work is being published. The choice of a bibliographic data source should consider factors such as coverage, metadata quality, search functionality, and access options. If comprehensive lists of citation sources are required, Microsoft Academic is the preferred alternative (Martín-Martín et al., 2021).

Figure 3 presents a list of the one hundred academic journals with the highest number of articles published on the topic of "data visualization" among the publications indexed in Microsoft Academic. It is evident that these journals belong to various disciplines within the realm of science, and all of them are related to computing. Leading positions include journals on computer graphics, bioinformatics, medicine, geology, statistics, artificial intelligence, and more. Primarily, these journals focus on the application of data visualization as tools for analysis and decision-making purposes. In terms of visual arts, it is necessary to reach positions 83 (Information Design Journal) and 84 (Leonardo) to find journals dedicated to the intersection of science, technology, and the visual arts, serving as bridges between research and practice in these disciplines.

Figure 3. Ranking of academic journals with the highest number of articles in the "data visualization" field indexed in Microsoft Academic



Source: Microsoft Academic

A similar analysis is not provided for articles published in conferences, but the findings are expected to be similar, encompassing the major conferences in the respective research areas highlighted in the journal analysis. To exemplify, the top 10 conferences are as follows: CVPR (Computer Vision and Pattern Recognition), IEEE VIS (IEEE Visualization), INFOVIS (IEEE Symposium on Information Visualization), VAST (Visual Analytics Science and Technology), ICCV (International Conference on Computer Vision), PacificVis (IEEE Pacific Visualization Symposium), CSE (Computational Science and Engineering), CHI (Human Factors in Computing Systems), SMC (Systems, Man and Cybernetics), and HICSS (Hawaii International Conference on System Sciences).

Gain a more comprehensive understanding of data visualization, a similar inquiry can be conducted using the Web of Science database. By employing the query "TS= ("data vis*")," one can access all publications on the topic of "data visualization" or "data visualisation" to encompass both American and British spellings. Figure 4 and Figure 5 present the respective treemaps, illustrating the primary research domains and research areas identified from the 47,076 indexed documents related to the topic of "data visualization."

Figure 4. Distribution by research domains of «data visualization» documents indexed in the Web of Science

Source: Web of Science

On the Web of Science, it is possible for the same document to belong to multiple research domains. In Figure 4, the domains of Science and Technology stand out with 97.60% (45,946 documents) and Technology with 92.34% (43,467 documents). Following closely behind in terms of importance are Physical Sciences with 39.57% (18,630 documents), Social Sciences with 34.82% (16,392 documents), and Life Sciences Biomedicine with 29.64% (13,952 documents). Notably, Arts and Humanities represents only 3.66% with 1,722 documents.

Considering that the same document is typically indexed in multiple research areas, a more detailed analysis can be conducted by examining the primary research areas in which data visualization is the subject of research. Figure 5 displays the top twenty-five research areas out of a total of 155, providing a more focused perspective. It should be noted that while numerical data from other minor research areas are not explicitly shown, they will be discussed later in the analysis.

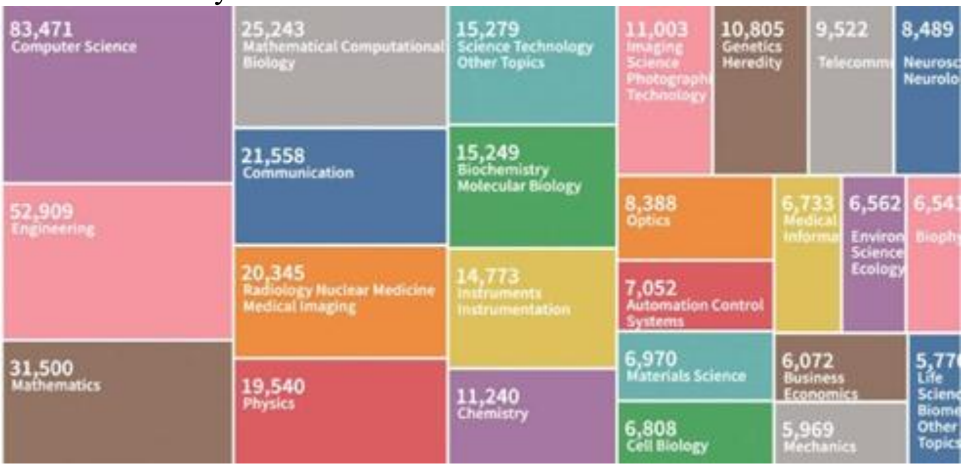
In the treemap, there are specific research areas that are of great interest for the argument presented in this article, despite not being prominently displayed. Precisely, 87.30% (41,097) of the documents belong to the field of Computer Science, indicating its significant contribution. Engineering follows with 37.24% (17,529) of the documents. Mathematics (22.63%, 12,183) and Mathematical Computational Biology (17.96%, 8,455) are represented to a lesser extent but still hold importance.

It is noteworthy that Communication, despite ranking fifth, only accounts for 15.02% (7,069) of the documents. In the case of Art and Humanities, it holds the 29th position and represents only 2.6% (1,225) of the indexed documents. Art itself, positioned at 76, reaches a mere 0.47% (220 documents).

Figure 5. Distribution of documents by research area for the topic «data visualization» indexed in the Web of Science

Source: Web of Science

Figure 6. Distribution by research areas of «data visualization» documents in files on the



Source: Web of Science

Lastly, within the Arts and Humanities domain, there has been a notable increase in interest in data visualization, with half of the documents (788, which is 45.77% of the 1,722 documents indexed in the Web of Science for this domain) published in the last five years.

Figure 7 presents a treemap featuring the twenty-five main publication sources, highlighting the significant fragmentation in terms of sources. The source with the highest number of documents, Lecture Notes in Computer Science, encompasses articles from various conferences and represents only 7.96% of the total articles in the domain with 137 documents. Leonardo, a prominent example of a magazine specialized in the art-science relationship that is the subject of investigation, accounts for 5.11% of the total with eighty-eight documents. Notably, these 1,722 documents have been published across 1,516 different sources, with 1,356 sources having only one published document. Only fifteen sources have published more than 1% (17 articles or more). Among these, the International Journal of Architectural Computing, Digital Scholarship in the Humanities, and Digital Creativity stand out, as they fall within the field of arts, which sets them apart from most examples discussed thus far.

Figure 7. Main sources of documents in the Arts Humanities domain on the subject of "data visualization"

Source: Web of Science

Does this bibliometric analysis provide a realistic reflection of the impact of data visualization on the visual arts and vice versa? The answer is clearly no.

Firstly, most bibliometric databases have limited coverage in the field of Humanities, Literature, and Arts, with only 25% coverage in Web of Science and 39% coverage in Microsoft Academic compared to the higher coverage in Engineering and Computer Science, which ranges from 48% to 63% (Martín-Martín et al., 2021).

Secondly, as previously mentioned, many of the significant contributions and innovative approaches in data visualization emerge from fields outside academia and are nurtured by various communities of practice that can be associated with the visual arts. One notable example of such communities is the realm of data journalism (Bounegru et al., 2012), which has experienced substantial growth to the point where online media outlets now offer daily news accompanied by interactive data visualizations. Designers are also increasingly involved in creating "popular" data visualizations (Quispel et al., 2018).

Considering these factors, it is evident that the impact of data visualization on the visual arts and vice versa cannot be adequately captured through bibliometric analysis alone. The influence extends far beyond academic circles and encompasses diverse communities of practice, emphasizing the need to consider alternative approaches to comprehensively understand the relationship between data visualization and the visual arts.

It is increasingly common to encounter data visualizations in art museums, exemplified by the Museum of Modern Art in New York (MoMA), which features notable works like "Mapping the Internet" by Barret Lyon, "Distellamap (Pac-Man)" by Ben Fry, and "Wind Map" by Fernanda Viégas and Martin Wattenberg. Numerous events focused on the intersection of technology and art, such as the EYEO Festival, VISUALIZED, and the Malofiej Awards, also emphasize the significance of data visualization.

Furthermore, the influence of these communities of practice surrounding data visualization is evident in the growing number of books tailored for non-expert readers. These publications, including works by authors such as Kirk, McCandless, Yau, Knaflic, Cairo, Schwabish, Bremer and Wu, Levin, and Brain, provide manuals for creating and interpreting data visualizations, while showcasing leading examples. These resources cater to the diverse needs of different communities.

By the end of the second decade of the 21st century, this vibrant ecosystem reached a level of maturity, resulting in the formation of a large community of practice centred around the technologies that shape data visualization. In 2019, the Data Visualization Society (DVS) was established with the aim of serving as a professional home for practitioners in the field, while also promoting the visibility and value of data visualization for the public (Data Visualization Society, 2020). This new community embraces a holistic vision of data visualization, acknowledging the validity of approaches employed in business intelligence, art, data journalism, science communication, analytics, and other realms. Within one year of its inception, the DVS boasted over 11,600 members worldwide and actively engages with its community through various social media channels, the publication Nightingale (the society's magazine dedicated to disseminating articles and best practices), and the organization of events such as the Outlier conference.

The Data Visualization Society (DVS) conducts an annual survey known as the "State of the Industry Survey" among its members. The most recent survey was conducted in 2020 and received responses from over 1,700 participants. Most respondents (39%) had previous training in science, mathematics, or technology. However, 15% of participants came from

arts and humanities backgrounds, and 13% had backgrounds in social sciences.
A significant finding from the survey is that a vast majority of participants (69%) reported learning data visualization skills through self-teaching. Only 6% obtained formal education specifically in data visualization, and 21% indicated a combination of formal education and self-learning.
In 2007, Kosara proposed the existence of two cultures within the field of visualization: one focused on technical aspects and analysis, and the other comprised of artistic works. Kosara advocated for the creation of a third culture that would foster integration and encourage a strong exchange of ideas between specialists from both fields (Kosara, 2007).
Until the emergence of a fully established third culture in data visualization in the third decade of the 21st century, the channels of exchange and influence between the two existing cultures of data visualization remain an area that has received limited research attention.

The two cultures of data visualization in history
The boundaries between art and science in the production of images are often blurred (Gómez-Isla, 2013) and are frequently framed within the tension between objectivity and subjectivity (Daston and Galison, 1992). In the case of data visualization (DV), a desire for neutrality is attributed to support analytical reasoning through visualization as an objective tool, contrasting with visual artists who, utilizing techniques similar to scientific visualization, create artistic works based on data with new and distinct motivations, strongly influenced by the artist's perspective (Viégas and Wattenberg, 2007; Li, 2018).
We are faced with the daily challenge of interpreting the world through visual data presented to us by the media. Graphics amplify the communication power of complex physical phenomena or abstract concepts. Consequently, the ability to persuade or unintentionally confuse also increases.
Like the difficulty of comprehending a text when unfamiliar words are used, our ability to misinterpret a graphic depends on our familiarity with the codes used to generate it.
Throughout history, various representation techniques have been employed to enhance our cognitive capacity, aid in understanding reality, and facilitate decision-making. However, as we will explore, graphs can lead to new knowledge that is not immune to problems of interpretation.
This inherent complexity in reception is characteristic of DV as a technical image, influenced by the wills, intentions, and interests of the agents involved in the communication process (Gómez-Isla, 2013). Cavaller recently analyzed the construction of data visualizations, aligning the components of the communication framework with those of DV: message/content, form/graphic representation, encoder/encoding configuration, context/graphic design and approach, channel/media, and decoder/user (Cavaller, 2021).

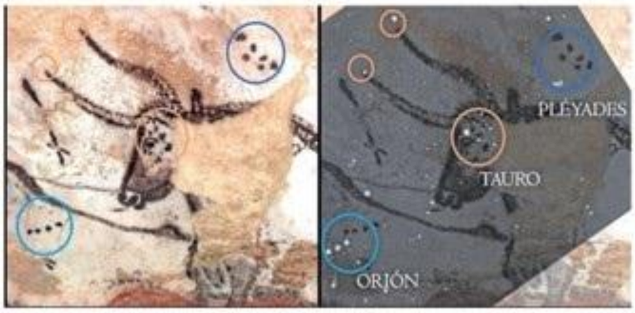
Cavaller's approach aligns with that of Ware (Ware, 2019), who, from a cognitive and perceptual perspective, breaks down the DV process into four fundamental stages, intertwined through a series of feedback loops: 1) collection and data storage, 2) pre-processing to transform the data into a manipulable format, 3) translation of the data into a visual representation using computer algorithms, and 4) the human cognitive and perceptual system (the perceiver). Interestingly, despite Ware's scientific approach, he explains in the preface of his book that, after obtaining a degree as a specialist in the psychology of vision, he decided to pursue art, spending three years exploring perception from a different perspective outside academia.

However, he returned to academia, earning a doctorate in the psychology of perception, and later becoming a computer scientist. The book, in the author's words, "is about art in the sense that 'form must follow function,' and about science because the science of perception can tell us what kinds of patterns are most easily perceived."

Over 30 years ago, Sorensen reflected on the contribution of artists to scientific visualization (Sorensen, 1989), arguing that creative and scientific thinking are closely intertwined. Throughout history, artists have also functioned, to some extent, as scientists or technologists.

Among the numerous treasures preserved on the walls of the French caves of Lascaux for over 17,000 years, a depiction of a bull's head with long horns and decorative dots was discovered. Initially, these manifestations were interpreted as a form of magical ritual, where hunters painted the animals, they sought to hunt. However, in the 1970s, Alexander Marshack (Marshack, 1972) proposed an alternative perspective, suggesting that these prehistoric artistic expressions were an early form of scientific understanding. In her doctoral thesis defended in 1991, Luz Antequera Congregado (Antequera Congregado, 2001) further argued that these dots mimicked the position of the Pleiades cluster within the constellation of Taurus. Therefore, we are confronted with the earliest known map in history, albeit a stellar one (see Figure 8).

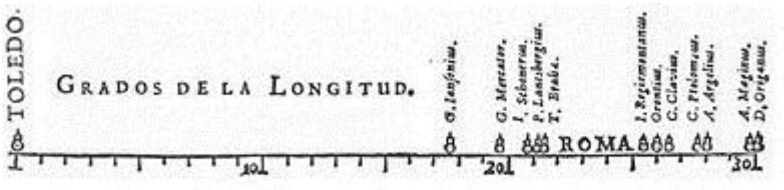
Figure 8. Interpretation as a star map in prehistoric art (left) and superimposition of a modern star map (right)



Source: self-made

We now jump to the 17th century to find in 1644 the Flemish astronomer of the Spanish court, Michael Florent Van Langren, who holds the honor of having created the first representation of statistical data (Tufte, 1997; Friendly, 2005): the 12 known estimates of the difference in longitude between Toledo and Rome, together with the name of the astronomers (Mercator, Tycho Brahe, Ptolemy, etc.) who provided them. Van Langren's merit lies in the fact that the wide variation in the estimates can only be understood graphically – ROMA wrote in the central gap, thus communicating the uncertainty and the most probable place for the correct value. A later interpretation indicates with an arrow the correct measurement (16º 30') (Friendly, 2005), which allows us to understand the upward bias introduced by the 12 astronomers (see Figure 9).

Figure 9. First graph of statistical data, Michael Florent Van Langren (1644)



Source: Degrees of Longitude

Van Langren, in addition to being an astronomer, was also a cartographer. Driven by his belief that geographical longitude could be more accurately measured from the sea by observing the visibility of different lunar features, he published the oldest surviving lunar map in 1645 in his book Plenilunii lumina Austriaca Philippica (see Figure 10) (Whitaker, 2003).

Following Van Langren's work, Johannes Hevelius published a new lunar map in 1647, and Jesuit Giambattista Riccioli published one in 1651. These pioneers of selenography not only transferred their observations through telescopes into drawings and engravings but also grappled with questions about the role of representation and the types of knowledge that could be generated visually (Vertesi, 2007). Galileo Galilei himself described the surface of the moon that he observed using his self-designed telescope in 1610.

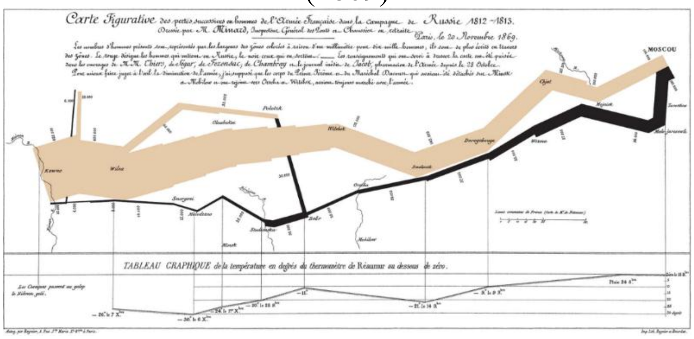
Edgerton frames this moment as an exemplary instance of the influence of art on science (Edgerton Jr., 1984), where the development of modern experimental science is a consequence of artistic practices during the Italian Renaissance. The principles of perspective postulated by Leonardo da Vinci and Galileo's relationship with Florentine disegno (design) are seen as foundational elements. Galileo's 35 drawings of sunspots made between June 2 and July 8, 1612, were highly regarded by his contemporary Federico Cesi, who praised them for their wonder and precision, serving as an example of what Tufte calls "beautiful evidence" (Tufte, 2006). Edgerton also highlights the reverse influence of science on Baroque painting in the context of lunar representation. In 1642, Grand Duke Ferdinand de' Medici proposed a contest to Florentine painters to depict the marvelous lunar spots observed through Galileo's telescope.

Another widely recognized example in the field of data visualization comes from cartography. Charles Joseph Minard's "figurative map" illustrating Napoleon's Grande Armée during the Russian campaign (1812-1813) is highly regarded (see Figure 11). This map is frequently featured in books on visualization, design, cartography, and statistics for its ability to evoke the tragedy of human lives lost in relation to the army's movements and the extreme weather conditions during the campaign. The effectiveness of a simple design choice, the thickness of the line representing the army's size at each moment, is emphasized (Tufte, 1983; C. Chen et al., 2007; Meirelles, 2013; Lauer and Pentak, 2011; Thrower, 2008; Johnson and Bhattacharyya, 2019; Rendgen, 2018).

Figure 10. First lunar map, Michael Florent Van Langren (1645)

Source: https://en.wikipedia.org/wiki/Charles_Joseph_Minard#/media/File:Minard.png

Figure 11. Map of Napoleon's Russian campaign of 1812-1813, Charles Joseph Minard (1869)



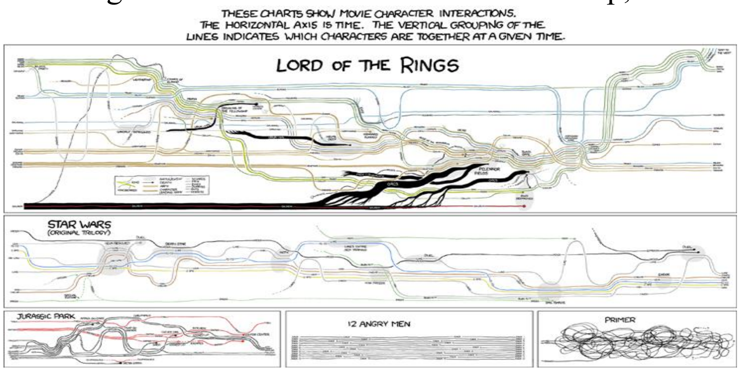
Source: https://en.wikipedia.org/wiki/Charles_Joseph_Minard#/media/File:Minard.png

We are interested in exploring the influences and derivations in visual art that the Minard map promotes. Taws recently offers an art-historical approach to the map that goes beyond its merit as a data visualization (Taws, 2021). Taws highlights the shared characteristics between the map and contemporary visual genres, particularly military art, drawing connections to painters like Alphonse Marie de Neuville. Both authors respond to the same question of how to represent the story, albeit using different visual languages.

In terms of visualization technique, the Minard map is a flow map, a variant of a thematic map that combines a map with a flow diagram to represent movement. The earliest documented example of this technique was published by engineer Henry Drury Harness in 1838. It is uncertain whether Minard was aware of Harness's work (Robinson, 1955; Robinson, 1967; Friendly, 2002; Rendgen, 2018). The visual capturing of movement in Minard's map clearly influenced the French scientist and chrono photographer Étienne-Jules Marey and his graphic method (Taws, 2021), where he reproduced the Minard map.

Friendly argued in a 2002 article that despite its influence on statisticians and geographers over generations, the Minard map was unknown, representing a missed opportunity in terms of the lessons it could teach in data visualization. Friendly also reviewed recreations of the map in computer systems for data analysis and discussed its influence on Leland Wilkinson's Grammar of Graphics, which inspired the popular data visualization package ggplot2 in the R programming language (Friendly, 2002; Wilkinson, 2005; Wickham, 2010).

Figure 12. Narrative diagrams of films in the XKCD comic strip, Randall Munroe (2009)



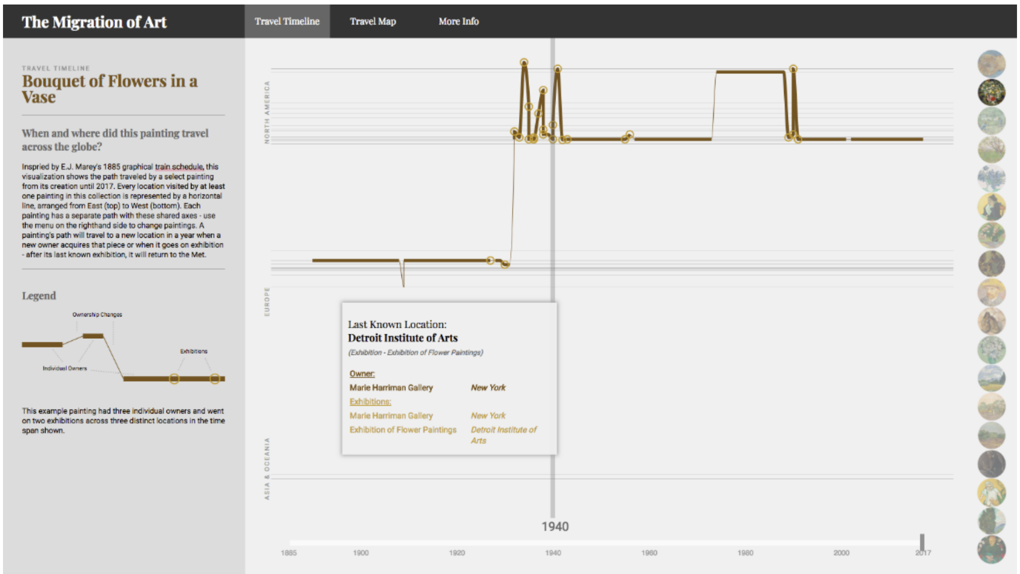
Source: https://imgs.xkcd.com/comics/movie_narrative_charts.png

On November 2, 2009, the webcomic strip titled "Movie Narrative Charts" (Munroe, 2009) was published on XKCD. The influence of Minard is evident in the comic strip, but the artist's motivation was different. The aim was to capture the interactions between characters in a film as a function of time and space, while also incorporating a comic effect through the choice of films depicted. These diagrams represent an idealized structure of the films, subject to various design choices made by the author, such as the characters, locations, and moments included or omitted. Despite the intentional elimination of information, the comic strip has had an enormous impact on popular culture and has been regarded as an accurate representation of the depicted works. This deliberate reduction of information is also recognized as one of the main attributes of the Minard map (Rosenberg, 2005).

Interestingly, it is the comic strip, not the Minard map, which has inspired the development of a data visualization technique called storyline (Ogawa and Ma, 2010). The authors adapted Munroe's representation for analyzing the interactions between developers in a software project. Since then, several proposals have emerged to automate the creation of these types of diagrams (T. Chen et al., 2012; Tanahashi and Ma, 2012; van Dijk et al., 2017; Tang et al., 2018; Padia et al., 2018; Tang et al., 2020; Araya et al., 2021).

In a similar vein, Ryan Best's visualization titled "The Migration of Art" (Best, 2018) explores the interactive visualization of the geographical movements of Van Gogh's artworks in the collection of the Metropolitan Museum of Art (MET) based on changes in ownership. Best describes the design process leading to the result and shares it on his website the source code of the developed tool. It is striking that Best declares that his greatest influence is Marey's diagrams for train schedules, from 1885, included in his Graphic Method – Marey himself attributes the invention of these graphs to Charles Ibry. These charts were used since before 1845 by the Northern Railway Company in France (Rendgen, 2019).

Figure 13. Migration of Art. Evolution of the location of works of art in history Ryan Best (2018)



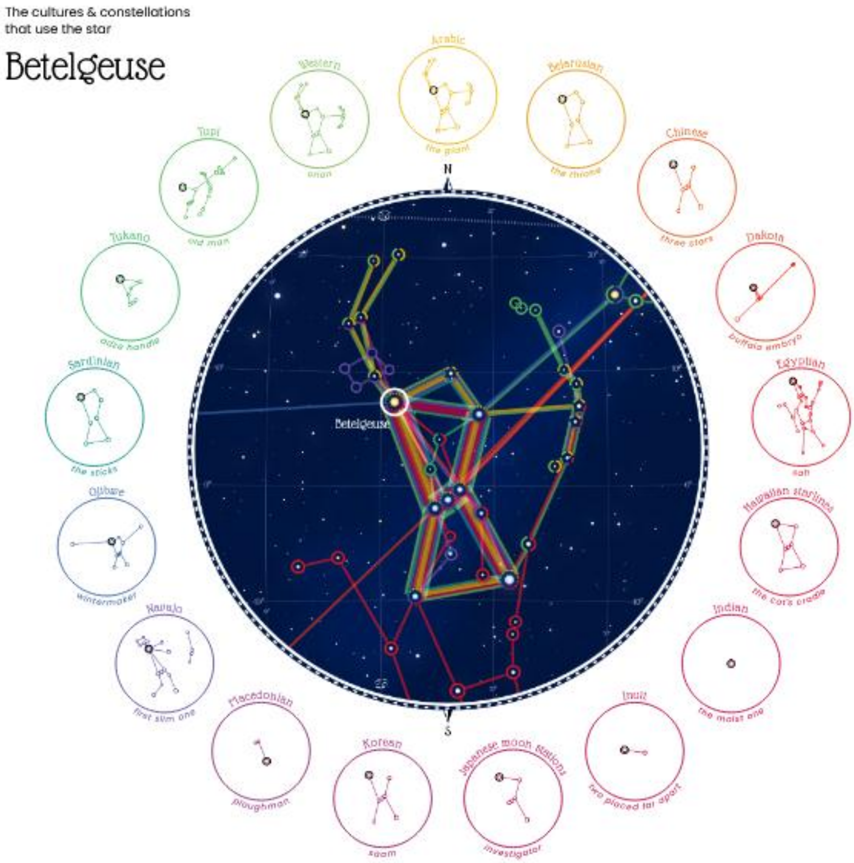
Source: https://ryanabest.com/work/MigrationOfArt/

Nadieh Bremer and Shirley Wu first met at the OpenVis conference in 2016. Soon after, they embarked on a collaborative project called Data Sketches, where they committed to creating one interactive visualization project each month for a year. The project involved everything from data collection and design to coding the visualizations and documenting the entire process. Initially published on the web, the project has recently been released as a book (Bremer and Wu, 2021).

Bremer, an astronomer by training, and Wu, a computer scientist, both share a focus on creating visualizations and art from data. One of Bremer's projects in Data Sketches is Figures in the Sky (Figure 14), which serves as a fitting conclusion to this section of the article as it directly relates to the first example discussed, the first star chart (see Figure 8).

In Figures in the Sky, Bremer explores how different cultures perceive and interpret the stars. She delves into the shapes and figures they recognize in the night sky, as well as the myths and legends associated with the stars. The documentation process for this project captures the various phases and challenges that an artist faces when creating data visualizations. It encompasses the difficulties of finding suitable data, the pre-processing and exploration of openly available datasets, the search for alternative data sources to complete missing information, the design process to convey the desired representation, the mathematical complexities involved, the programming of the visualization, and the consideration of user interaction and necessary annotations to aid interpretation.

Figure 14. Visualization allows us to see similarities and differences in the forms that different cultures identify in the sky. Figures in the sky, Nadieh Bremer (2017)



Source: https://figuresinthesky.visualcinnamon.com/

In Figures in the Sky, visitors can explore and compare 28 different cultures' interpretations of the starry sky using various representation techniques. This interactive experience allows users to discover the diverse forms that humans have recognized in the night sky across different regions and throughout thousands of years. Figure 14 depicts a particular moment of interaction, where the visitor has selected the constellation of Taurus in Western culture. The focus is on the star Atlas, which is part of the Pleiades cluster and holds significance in other cultures with different figures, myths, or legends associated with it.

Conclusions

Data Visualization, encompassing both its artistic and scientific aspects, integrates knowledge from diverse disciplines that can be challenging for a single individual to encompass. The advancements achieved in this field are the result of a complex network of interconnected pathways between art and science throughout human history.

While there have been previous calls for greater collaboration between artists and scientists, the field of Data Visualization has reached a level of maturity that holistically incorporates the contributions of both domains. However, several challenges still need to be addressed:

a) Availability of data: Although there is an increasing availability of public datasets, such as the recent example of COVID data, there are still areas where data is not accessible for scrutiny by scientists and artists. For instance, data related to climate

change and global energy consumption remains limited.
b) Mastery of tools: While the use of tools for creating data visualizations has been made more accessible, it has also led to the creation of poorly designed visualizations due to a lack of understanding of the underlying functionality of the tools. Like how painters possess profound knowledge of pigments, artists need to master these tools as new artistic materials. Furthermore, certain design decisions, such as choosing appropriate color schemes, continue to pose challenges in both scientific and artistic contexts.
c) Visual and data literacy: Despite the current popularity of Data Visualization, there is still a need to promote visual literacy and data literacy among users. Building an understanding of how to interpret and critically engage with visualizations is crucial.
d) Reception of visualizations: Beyond cognitive studies focused on visualization techniques, such as the visualization of uncertainty, there is still a lack of exploration into the reception of data visualizations from various perspectives. Understanding how individuals perceive and interpret visualizations remains an understudied area.
e) Communication and recognition: While the community of practice surrounding Data Visualization is moving towards equal participation from visual artists, scientists, and engineers, the academic field continues to operate within compartmentalized spaces with limited channels for communication and recognition.
Addressing these challenges will require ongoing efforts to enhance data accessibility, promote tool mastery, foster visual and data literacy, explore the reception of visualizations, and foster collaboration and communication across disciplines within the academic field.

Data Availability

The data used is available from the corresponding author upon request.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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