NOVA IMS Information Management School

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Data Science and Advanced Analytics

Decreasing subjectivity in the assessment of visualizations using the Wheel of Visualization: A case study in the education sector

Pedro Martins Costa Mendes

Master Thesis
presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

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Instituto Superior de Estatística e Gestão de Informação
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by

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Business Analytics

Supervised by: Mijail Naranjo, PhD, Invited Assistant Professor at Nova IMS

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Pedro Mendes
Lisboa, October 2023

Abstract

The evaluation of visuals becomes a crucial task as data visualization develops popularity across a variety of fields. However, this assessment process often faces the challenge of subjectivity, as the interpretation and evaluation of visualizations can vary among individuals. To address this problem and find possible alternatives, Alberto Cairo's "Wheel of Visualization" method will be used in this master's thesis, with a specific focus on the educational field.

The main goal of this research is to examine how the Wheel of Visualization, a systematic framework incorporating several components of visualization design, might be used to reduce subjectivity in the assessment of visualizations. Through a comprehensive case study conducted within the education sector, this thesis examines the effectiveness of the Wheel of Visualization in promoting consistent and objective evaluation criteria.

The case study involves university students enrolled in a data visualization course who are tasked with creating a poster and interactive visualization and then, via blind peer-review, evaluate their peers' work and give feedback based on The Wheel of Visualization's principles.

The findings of this study contribute to a deeper understanding of how the Wheel of Visualization can mitigate subjectivity and enhance the assessment of visualizations. At the same time, insights are gained and discussed into the practical challenges and benefits of implementing such a structured framework in an educational context where subjectivity may be involved to a certain degree.

- **Keywords:** Data visualization, Evaluation framework, cognitive factors, perception, Uncertainty visualization, infographics, wheel of visualization, education

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1. Introduction

The amount of data generated globally is exponentially increasing driven by several factors, including the growth of the Internet of Things (IoT), the widespread use of social media and mobile devices, and the rise of digital transformation in various industries. Data-driven insights can lead to better business performance, including higher productivity, faster innovation, and improved customer satisfaction; also, data analytics can help companies to identify new revenue streams, optimize pricing and promotions, and improve supply chain management, among other benefits. (Henke et al., 2016)

It is then of the utmost importance to find ways to analyze and effectively visualize such huge amounts of information while preventing cognitive overload (Sweller, 2010): a condition where the human brain becomes overwhelmed with too much information, making it difficult to understand and process the data.

This is what data visualization proposes to do: presenting data in a graphical or pictorial format that helps people understand the significance of the data while preventing information overload. However, creating these data visualizations is not a simple task. When designing a visualization, it is important to carefully examine several variables, including the audience, the purpose, and the sort of data being visualized. Additionally, the design process frequently involves subjectivity, which can result in poor visualizations and a lack of comprehension among the audience.

Given the growing importance of data analysis and visualization in the world and its peculiarities, we tried to understand how this subject is being taught and evaluated in higher education institutions and offer a possible assessment alternative.

The main objective of this thesis is to explore the use of The Wheel of Visualization method, developed by Alberto Cairo, in decreasing the subjectivity in the assessment of data visualization design at an academic level. The Wheel of Visualization is a tool that offers a systematic method for creating powerful data visualizations, by which designers can ensure that their visualizations are optimized for their intended purpose and audience and are based on sound principles (Cairo, 2013)

Through a case study in a Higher Education institution, we will demonstrate that the Wheel of Visualization can be a valid alternative for assessing large classes of students where we want to take into consideration both technical design heuristics and subjective visualization interpretation principles while keeping the much-needed assessor’s feedback and opinion included in the evaluation.

1.1. Research Question

This thesis uses data collected from two classes of Universidade Nova de Lisboa (hereby known has Master’s course 1 and Master’s course 2) to apply the method proposed by Alberto Cairo (Cairo, 2013).

The research questions we are trying to answer are:

- How can The Wheel of Visualization method provide a less subjective evaluation of data visualizations?
- What impact do different visualization features have on the effectiveness and efficiency of visualization design?
- Can The Wheel of Visualization be an assessment method in a higher education data visualization course?

In summary, this motivation chapter highlights the importance of data visualization in today's data-driven world and challenges involved in designing effective visualizations. It introduces *The Wheel of Visualization* method as a possible tool for reducing subjectivity in visualization design and evaluation and improving the effectiveness of visualizations. Finally, it presents three complementary and significant research questions object of the study, emphasizing the potential of them to contribute to the field of data visualization design and improve decision-making based on accurate and relevant information.

2. Literature Review

2.1. What is data visualization and why is it important?

"Where is the Life we have lost in living?
Where is the wisdom we have lost in knowledge?
Where is the knowledge we have lost in the information?"

"The Rock" by T.S. Eliot

The classic "seeing is believing" succinctly expresses the significance of data visualization. One of the most effective tools at our disposal for studying large datasets, expressing data in meaningful ways, or captivating the audience with the story behind the data is justly data visualization. What exactly is data visualization, then? It is "the representation and presentation of data that exploits our visual perception abilities in order to amplify cognition" (Kirk, 2012). Let's breakdown this:

- **Representation:** From raw, unedited data, there isn't much we can infer. However, we can begin to gain understanding if we can represent facts in ways that are better recognizable to us (for example, using geometric objects). Data is represented through data visualization in a way that is easy for our brains to understand.

- **Presentation:** To ensure that the narrative underlying the data is revealed, careful presentation of the data is required. When presenting your visualization, there are an unlimited number of options and decisions to be taken.

- **Visual perception:** The mechanism for pattern identification and processing in our brains is incredibly sophisticated and potent. We can use our ability to digest visual information to understand data rapidly and effectively. A good data visualization makes use of our visual systems and steers clear of their faults.

- **Amplify cognition:** Data visualization should always inform and increase knowledge.

Information can be defined as the value we extract from data. But the real value on information, is the knowledge we get from it. As T.S. Elliot says in his poem above, "where is the knowledge we have lost in the information?”. Data visualization plays a crucial role in building knowledge from the information collected.

Visualizing data can help to uncover patterns, relationships, and insights that might be difficult to discern from raw data alone, even using proper tools. Data visualization can be used in a variety of contexts, from business intelligence and market research to scientific discovery and public policy. By presenting data in a clear, engaging, and accessible way, data visualization can help to inform decision-making and drive action.

Data visualization can also be used to tell stories and communicate complex ideas in a more engaging way. By combining data itself with visual elements such as charts, graphs, and infographics, data visualization can help to capture the audience's attention and make data objects more memorable. These graphical methods generate and show datasets, allowing us to summarize the general behavior and to insight and explore details. But when did we start using visualizations to interpret data?

2.2. Historical context of data visualization design

Data visualization made major strides between the 17th and 19th centuries (Donska, n.d.). René Descartes (1596-1650) developed a two-dimensional coordinate system in the 18th century to represent values for mathematical operations, which gave rise to the idea of presenting quantitative data graphically (the famous x-y-z cartesian graphs). When William Playfair (1759-1823) invented the first modern graphical forms, cartesian techniques were enhanced using line and bar graphs, then pie charts and circle graphs (Figure 1).

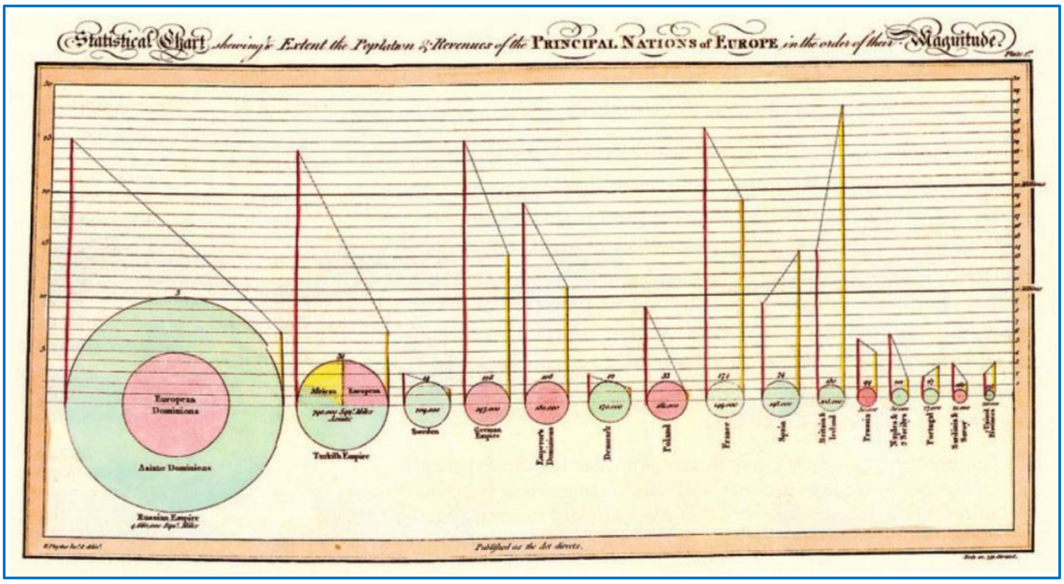


Figure 1: *Statistical chart by William Playfair*

Quantitative graphs have increasingly been used as the amount of data available has grown throughout time. The publication, originally published in French in 1967, of Jacques Bertin's book *The Semiology of Graphics* (Bertin et al., 2011), in which he examined the efficacy of many forms of charts, considerably improved their approach and effectiveness in the latter half of the 20th century. Let’s look at the following example from his book: the pie charts in the graphic below depict the production of various types of meat in different nations. They were deemed "useless" by Bertin. In the middle, high-level patterns are made more readily apparent by using matrix graphics. And on the right, rearranging of categories greatly enhanced the presentation of data thus providing greater clarity (Figure 2).

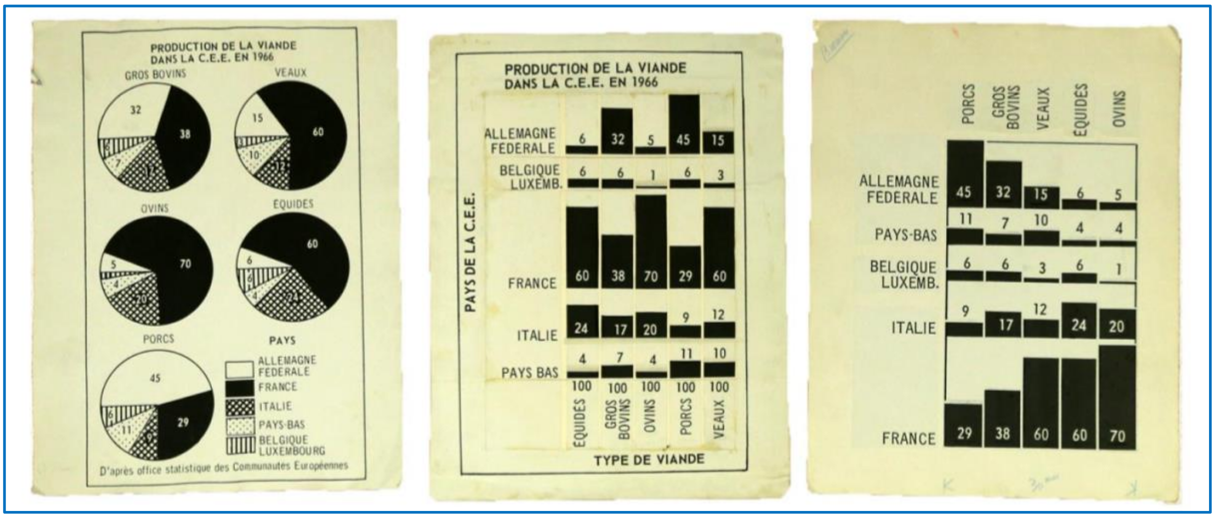


Figure 2: *Jacques Bertin example on the efficacy of many forms of charts*

2.3. How to design effective data visualizations?

Data visualization can be quite powerful since it makes use of the brain's inherent capabilities: it is quick and effective. John Tukey (1915-2000), an influential American mathematician and theoretical statistician, said: *“The greatest value of a picture is when it forces us to notice what we never expected to see.”*.

Processing information through cognition, which is controlled by the cerebral cortex, takes longer and more work. Visual data presentation speeds up our perception and lowers cognitive stress.(Kazakova, 2021)

According to a Harvard Business Review article the three most important elements of an effective data visualization are (Stikeleather, 2013):

1) *Audience*: The audience's needs and expectations should be considered when designing the visualization. This includes factors such as their level of expertise in the subject matter, their preferred visual style, and their goals in viewing the visualization.
2) *Purpose*: The visualization should have a clear purpose, such as highlighting trends, identifying outliers, or comparing data sets. Without a clear purpose, the visualization may confuse rather than inform the audience.
3) *Context*: The context in which the visualization will be viewed should be considered. This includes factors such as the medium (e.g., print, web, mobile), the time available for viewing and the surrounding environment (e.g., distractions, lighting).

By considering these three elements when designing a data visualization, designers can create visualizations that effectively communicate their insights to the intended audience in a clear, engaging, and informative way.

As mentioned, the first important step when designing a visualization is to analyze and identify our audience. Some important information to ask and collect can be:

- How broad or diverse is the audience? Are they varied (like the people of Australia generally) or rather homogeneous (like a group of engineers)? What differences do they have in terms of background, education, and age?
- What size audience do you have? Personalization can be possible with smaller audiences.
- How technical is the audience? Can we presume that they are familiar with data visualization? Do they have competence in the topic matter? Are they familiar with statistics?
- Are there any unique criteria for the audience? Color blindness, poor vision, cognitive limitations, and English as a second language are all criteria that should be considered.
- How much time do you have with your audience?
- What motivates your target audience? You can engage them more effectively if you know what drives them.

Let us look at an example of how the purpose and audience of a visualization can affect the way an infographic is designed: consider the figure below (Figure 3) showing the Artic Sea Ice, published in The New York Times in 2015 (Watkins, 2015).

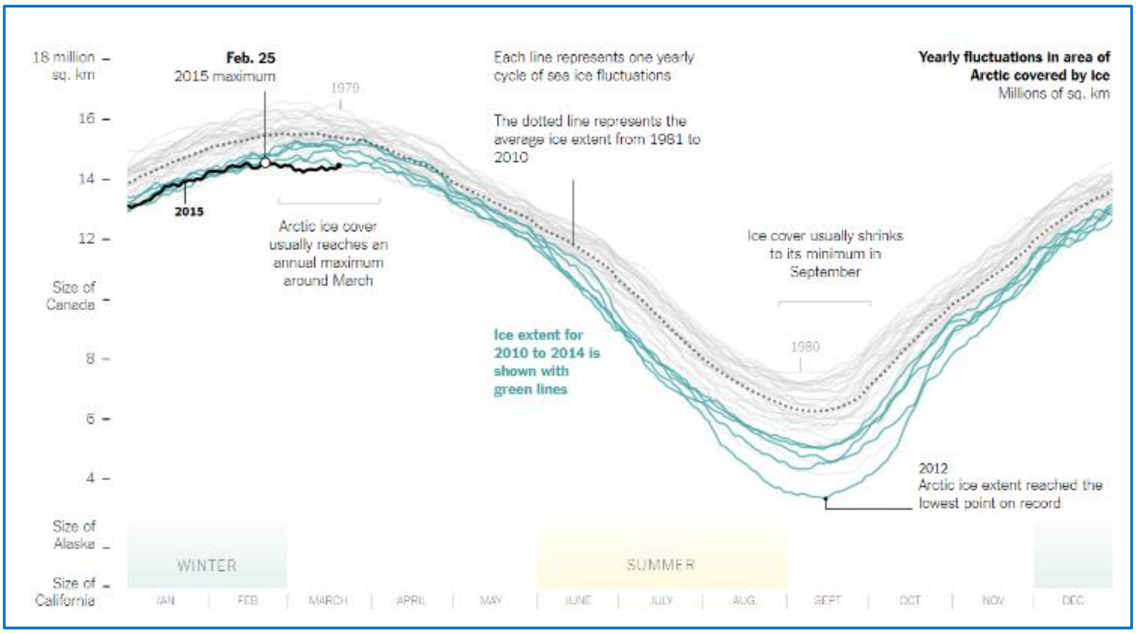


Figure 3*: Artic ice reaches a low winter maximum. (Watkins (2015), NY Times)*

The fact that it appeared in an esteemed news source, The New York Times (NYT), gives us a solid indication of the target audience of this visualization, but the plot's more obvious elements also reveal further information. Take note of the usage of annotations to clarify crucial aspects of the visualization, support interpretation, and convey a narrative. A contextualized *x* and *y* axis is used. The spectator can better understand arctic seasons by seeing how the months of the year are connected to the seasons. Reference lines on the *y-axis* compare the area of the ice to that of well-known states and nations in North America. To aid the observer in focusing on important details, color is used. You can infer that this plot was created for a wide readership in North America, primarily in the U.S., based on the contextualization, comments and highlighting. There is no surprise there, but this does show how a visualization's target audience can influence the design.

After the audience is defined, it is time to look at the purpose of our visualization and what we want to communicate to the audience. Without completing this stage, one can risk wasting time and designing a visualization that lacks a clear purpose and misses its mark.

Every data visualization project must have a specific goal in mind. This was referred to as the "so what?" query (Evergreen et al., n.d.). Why is there a visualization? What outcome may we expect? If you can't come up with a solid response to this query, you should rethink your design. Your design's goal is distinct from the query or real-world issue it addresses. Considering how perplexing that sounds, let's explain this in the context of the Arctic Sea Ice visualization (Figure 3, above).

"How is the volume of arctic sea ice changing over time?" is the subject or issue that the visualization addresses. The visualization provides a simple solution to the query. The observer can see that data from 2010 to 2014 has a lower trend than data from earlier years. Question answered, but so what?

One will comprehend the goal or aim of the visualization if you can respond to the "so what?" inquiry. We can understand the goal because it was used in a New York Times piece about climate change. Thanks to the user-friendly design and illuminating annotations, you can understand the concept even without reading the article. The goal of Watkins' essay was to make their readers *aware of and sympathetic to* the problem of climate change.

There can be many different purposes and a visualization can, and frequently does, serve multiple. The purpose of a visualization can be divided into two basic roles (Kirk, 2012):

- **Function**
  - **Explanatory:** When the purpose is to explain, the graphic is frequently built around a story. Every element of the visualization has been thoughtfully designed to make it easier to convey a gripping tale.
  - **Exploratory:** When the purpose is to explore, one story does not predominate, and the visualization's emphasis encourages self-discovery of hidden stories in the data. Interactive elements are frequently used in exploratory visualizations to help the viewer become fully immersed in the material.
- **Tone:** The elements of a visualization that are employed to provoke an emotional reaction are referred to as the visualization's tone. Visualizations that are pragmatic, analytical, or employed for technical reasons, frequently have a straightforward design that prioritizes accuracy and detail over form. On the other hand, visualizations may use abstraction and manipulate aesthetic qualities (e.g., color) to convey different emotive tones.

After understanding who our audience is and the purpose of our visualization, it is time to consider the context where our visualization will be viewed. But how to choose the right visualization for the right context?

Although this paper does not intend to deeply analyze the technicalities of data visualization design, an overall view of the topic may be useful to the reader. Different types of visualizations are better suited to different types of data and research questions and can help to highlight different aspects of the data. For example:

- Bar charts are often used to compare different categories of data, while line graphs are better suited to tracking changes in data over time.
- Scatter plots can be useful for identifying patterns or relationships between different variables, while heat maps are often used to visualize data that is distributed across a geographic area.
- Histograms are effective at showing the distribution of data, like a random draw of values from a Poisson distribution.

To choose the right type of visualization, it's important to consider factors such as the type of data being presented (e.g., categorical, numerical, spatial), the research question being asked (e.g., what patterns or trends are present in the data), and the intended audience (e.g., what level of detail or complexity is appropriate for the audience).

Finally, we will design the visualization considering factors such as the color scheme, typography, layout, and labels.

Having a design process ensures you approach a visualization task in a systematic way that is efficient and effective depending on the context. Andrew Kirk has four overarching principles that he considers governing the entire design process (Kirk, 2012):

1) **Strive for form and function:** The perceived tension between making a data visualization seem attractive and accurately expressing the story behind the data is related to the phrase "form versus function" (or "style versus substance"). Data visualization is situated at the nexus of art and science (see chapter "The subjectivity of visualizations"). If you focus too much on form, statistical accuracy could be compromised. If you focus on function too much, you may lose a visual's captivating impact (we will discuss later the views of Tufte and Holmes on exactly this issue). The key is to strike a balance between the two ends, occasionally veering slightly to one side or the other depending on your target audience. Despite the seeming conflict between these two objectives, it may be said that proper form can improve function. Aesthetic appeal for your data visualization is always an objective of the design process.

2) **Justify your decision-making in whatever you do**: Complex designs like Sankey flow or network type diagrams are not always necessary, especially when a straightforward bar chart might accomplish the same task. Data visualization and statistical data analysis are identical in process. Every step and choice you make along the route needs to be documented, justified, explained and repeatable. Stop and ponder if you are doing something and can't explain why you are doing it that way. You can avoid making many false beginnings by taking more time to consider what you are going to do.

3) **Creating accessibility through intuitive design**: Designing intuitively and simply to understand visuals should always be a goal while creating accessibility. If you can, keep it straightforward and capitalize on people's preexisting perceptions and expertise. When the intricacy of the data or story prevents you from keeping the visualization simple, you must nevertheless try your hardest to make the visualization as accessible as possible.

4) **Never deceive the receiver:** Data visualization has the potential to mislead the audience or alter the meaning of the data, whether purposefully or unintentionally. You should be aware of the typical traps of poor visualization and resolve to never purposefully adopt these subpar design approaches.

2.4. The subjectivity of visualizations

As mentioned before, data visualization is situated at the nexus of art and science. "Art and Visual Perception" book (Arnheim, 2004) is considered a classic in the field of art and psychology. It explores the relationship between art and perception, arguing that the visual arts are not just a matter of aesthetics, but are deeply connected to our perceptual processes. Arnheim explores how visual components like line, color, and form (highly used in any type of data visualization technique) are used by artists to convey meaning and stir feelings in viewers. He also looks at how viewers perceive and interpret art as well as how cultural, social, and psychological aspects affect our perceptions. One of the main conclusions of the book is that there is no "correct" or objective way to perceive art, but rather that our individual experiences, backgrounds, and cultural contexts shape our interpretations. Discussion takes place about how artists use visual elements to create meaning and how viewers bring their own experiences and perspectives to the art, leading to a subjective and varied interpretation.

But being data visualization such a subjective field, how can we distinguish a good visualization from a bad one? Even if we take into consideration the goal of the visualization, identify the audience correctly, collect the data, choose the chart type that we believe make the best fit and consider factors like color, layouts and labels, are we sure the visualization created will be successful in transforming information into correct knowledge?

2.5. Assessment of subjectivity

Assessing how a visualization is perceived and interpreted by an audience should always be a top-of-mind concern to the designer. Tijmen van Willigen in his graduation project emphasized the value of quantifying user experience in the conception and assessment of data visualizations (Willigen, 2019). He contends that the demands and experiences (that will ultimately lead to the subjectiveness in interpretation) of the people who will be interacting with data visualizations are frequently neglected in favor of technical considerations. In this paper, Tijmen focuses on the value of user-centered design in producing powerful data visualizations and offers a framework for gauging how well these visualizations are received by their intended audience.

Willingen's work covers a wide range of topics related to data visualization and user experience, including the psychology of perception, the role of interaction design in data visualization, and the use of metrics and user testing to measure the effectiveness of visualizations. Some of the most relevant metrics mentioned are the following:

- **Task completion time**: Measures how long it takes users to complete a task using a visualization. For example, if a user needs to find a specific data point in a chart, task completion time measures how long it takes him to locate that data point.
- **Error rate**: Measures the number of errors users make when interacting with a visualization. For example, if a user misinterprets a data point in a chart, that will count as an error.
- **User satisfaction**: Evaluates how satisfied users are with a visualization. User satisfaction can be measured using surveys or interviews and can provide valuable feedback on the effectiveness of a visualization.
- **Engagement**: Quantifies or qualifies how engaged users are with a visualization. For example, if users spend more time interacting with a visualization or explore different aspects of the visualization, this indicates higher engagement.

Friedman and Rosen (Friedman & Rosen, 2021) developed a heuristic-based framework to evaluate their students; one of the heuristics considered, "narrative consideration," is to be defined as "critical in projects where the story surrounding the visualization is as important as the visualization itself" (Friedman & Rosen, 2021), giving another example of how subjectivity is currently being evaluated and taken into consideration when building visualizations.

This discussion brings two questions to mind that we'll try to address in the following chapters: How can we objectively evaluate how well a data visualization is received by users and identify areas for improvement? What impact do different visualization tools and platforms have on the effectiveness and efficiency of visualization design?

2.6. Edward Tufte and Nigel Holmes philosophies

In information graphics and visualization, there has always been a basic conflict between those who take a logical, scientific approach to the field, emphasizing usefulness, and those who consider themselves "artists," emphasizing emotion and aesthetics.

The line separating the two concepts is hazy, and there is a middle ground between the two parties. However, according to Cairo in his book *The Functional Art*, people in the first category typically have technical backgrounds (statistics, cartography, computer science and engineering), whereas those in the second group are alums of graphic design, art, and journalism programs (Cairo, 2013).

These discussions were initiated by Edward R. Tufte (arguably the most influential theoretician in information design and visualization) in 1990. In *Envisioning Information (Tufte, 2013a)*, he was very critical of illustrated charts and pictorial maps that were becoming increasingly popular at the time in the United States. Tufte even coined a term to define pictograms and illustrations within charts and maps: 'chartjunk'.

"Lurking behind chartjunk is contempt both for information and for the audience. Chartjunk promoters imagine that numbers and details are boring, dull, and tedious, requiring ornament to enliven. Cosmetic decoration, which frequently distorts the data, will never salvage an underlying lack of content. If the numbers are boring, then you've got the wrong numbers (…) Worse is contempt for our audience, designing as if readers were obtuse and uncaring. In fact, consumers of graphics are often more intelligent about the information at hand than those who fabricate the data decoration (...) The operating moral premise of information design should be that our readers are alert and caring; they may be busy, eager to get on with it, but they are not stupid." (Tufte, p.34-35)

Tufte defends bot minimalist and efficient visualizations: a visual design project is good if it communicates a lot with little. According to his principles, graphical excellence consists of complex ideas communicated with clarity, precision, and efficiency. It is that which gives to the viewer the greatest number of ideas in the shortest time with the least ink in the smallest space (Tufte, 2013b).

More precisely, Tufte defines this efficiency principle as the *data-ink ratio*, which is a measurement of how much ink is utilized to display data in a chart. Data-ink components, according to him, are those that can't be removed without compromising the presentations' integrity. The rest of the content, which is essentially decoration, can be removed because it is either unnecessary or detracts from the main points. The closer the data-ink ratio is to 1.0, the better the graphic is:

Data-ink ratio = Ink that encodes data / Total amount of ink used to print the graphic

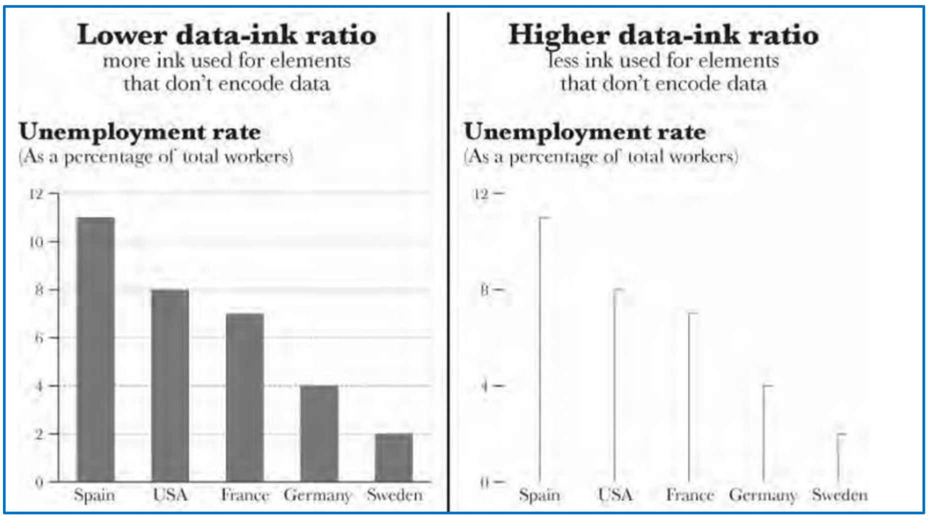


Figure 4*: A traditional bar chart (left) and its minimalist version (right)*

The critics of Tufte's approach, most notably Nigel Holmes, advocate for the humanization of information graphics and using humor to instill affection in readers for numbers and charts.

> *"If you belong to the school of people who believe that charts should only present statistics in the most straightforward, plain way, with no other visual help to the reader, for example, than the bar of the bar chart, the line of the fever graph, the circle of the pie chart, or the rules of the table, then move on to another part of the book. As long as the artist understands that the primary function is to convey statistics and respects that duty, then you can have fun (or be serious) with the image; that is, the form in which those statistics appear"* (Holmes, 1984)

Holmes also referenced this passage from 'A Primer of Visual Literacy' a classic book by Donis A. Dondis (Dondis, 2007):

> *"Boredom is as much a threat in visual design as it is elsewhere in art and communication. The mind and eye demand stimulation and surprise."* (Dondis, cited in Holmes, 1984, pp 72-76)

He praised the power of humor as well as a strong and strengthening tool:

> *"Humor is a great weapon in your visual arsenal. As long as it is not malicious, making people laugh with you will usually help them remember your image and therefore the point of the chart. Even a smile will encourage a reader to look into the statistics if he or she might not have thought of reading in a less-embellished chart."* (Holmes, pp 72-76)

In the end, who is right? Tufte's defense of dense graphics, highly functional and multidimensional? Or Nigel Holmes approach, where he favors lighter charts, where decoration is figuration are most prevalent? The answer obviously depends on the context, audience, and context of the visualization.

2.7. Data visualization evaluation in Education

So far, we've discussed the increasing importance of data in the world, starting by giving an historical context and then by identifying literature that highlighted the importance of correct data representation and analysis in today's world. It is, however, an ongoing job as the amounts of data needed to be analyzed grow exponentially with time and there is always a degree of subjectivity inherent to data visualization interpretation. Even two of the biggest names in the field (Edward Tufte and Nigel Holmes, mentioned is previous section) have profound differences in the way they think data should be represented visually. After previous remarks concerning the main principles of effective data visualization design that are broadly accepted and taught, let's pivot the focus of this paper attention to another important topic: being data visualization a subjective field, how are universities effectively evaluating their students' performance in these courses?

As data becomes more relevant for companies but also more complex to analyze and interpret, universities made visualization courses an integral part of their curriculum (Leidig & Salmela, 2022) (Nestorov et al., 2019). Easily accessible software packages like *Tableau*, *Power BI* or *R* made it easier for students and professionals alike to create attractive visualizations and combine different data sources in a single visualization; however, these sophisticated technologies do not necessarily ensure better visual designs and interpretations (Kostelnick, 2008). It can take a lot of effort to teach students how to successfully gather, collect, analyze, visualize, and convey data (Camm et al., 2017). The teaching focus may shift to tools, approaches, and procedures for a more limited range of graphical conventions due to time restrictions, which can greatly impact students' understanding and study of the subjectiveness of data visualization (Burch & Melby, 2020). Even though there are many outstanding studies that conceive and evaluate the best practices for visuals, there isn't much advice on how to apply these ideas to the evaluation of visualizations in actual classroom settings (Friedman, 2019). Recent descriptions of courses with sizable visualization components usually omit discussion of evaluation (Jeyaraj, 2019) (Nestorov et al., 2019) (Stephens & Young, 2020) (Limin Zhang et al., 2020)

After some research on the subject, basically we find out that two evaluation methods are widely used in data visualization pedagogy nowadays:

1) *Heuristic approach*: This approach focuses on the correct construction of visualizations using the principles described before. It can be defined as "using the right algorithms and visualization principles in creating visualizations" (Beasley et al., 2020). This evaluation approach mainly uses heuristics (meaning a set of guidelines against which one should judge a visualization). An illustrative example of this can be found in (Friedman & Rosen, 2021) that use technical elements to evaluate a visualization. This evaluation method has the drawback of being incredible time consuming for the educators as, for each visualization, they would need to evaluate all the different heuristics covering all students (see Figure 5). In this example, Friedman and Rosen evaluate on a scale how their students did in each one of the items; it is interesting to notice that most of the items evaluate the technical aspects of visualization construction but the "narrative consideration" category is "critical in projects where the story surrounding the visualization is as important as the visualization itself" (Friedman & Rosen, 2021), giving subjectiveness an important role in this framework.

Area	Item	Scale		
Algorithmic Design	Selection of Algorithm	Below Average	Average	Above Average
	Correct implementation	No	Minor Errors	Appears Correct
	Efficient implementation	Much Slower	As Expected	Much Faster
	Featureful implementation	Major Features Missing	As Expected	Major Features Added
	Datasets Used	Not Useful	As Expected	Better than Expected
Visual Design	Visual Channels: (check which present) Position, Length, Area, Shape, Color Hue, Animation, Angle			
	Intended Encodings	Many Unintended	Few Unintended	All Intended
	Encoding Expressiveness	Many Errors	Few Errors	Correctly Assigned
	Encoding Effectiveness	Many Ineffective	Few Ineffective	Most Effective
	Effective Use of Color	Mostly Ineffective	None Used	Highly Effective
Interaction	Interaction Selection: (check which present) Selection, Highlighting, Linked Views, Pan/Translate			
	Interaction Effectiveness	Missing	As Expected	Better than Expected
Design Consideration	Clear/Thorough Labeling	No labels	Some Missing labels	Completely labeled
	Data/Ink Ratio	Way Too Little/Much Ink	Slightly Too Little/Much Ink	Perfect Amount of Ink
	Missing Scales	No Scales	Some Missing Scales	All Scales Present
	Missing Legend	No Legend	Incomplete Legend	Complete Legend
	Scale Distortion	Severe Distortion	Minor Distortion	No Distortion
	Lie Factor	Major Lie	Minor Lie	No Lie
	Chart Junk & Embellishments	Way Too Little/Much	A Bit Too Little/Much	Perfect Amount
	Data Density	Too Sparse	Expected	Too Dense
	Gestalt Principals	No Gestalt Principals	Some Gestalt Principals	Many Gestalt Principals
Narrative Consideration	Accurate & Informative	No Description	Incomplete/Self-Explanatory	Complete Description
	Support of Narrative	No Description	Incomplete/Self-Explanatory	Complete Description
	Datasets Used provide enough information and detail to support narrative	Not At All	Partially	Completely

Figure 5: *Rubric of Friedman and Rosen (2021)*

2) *<u>Subjective evaluation</u>*: This approach is supported on a subjective evaluation of quality and accuracy which are very difficult to map to a checklist. The instructor considers the student's work holistically—whether it adequately satisfies the user's stated purpose—rather than just as a successful application of features like color or shape. Subjective evaluation is not only important for the instructor's assessment of students but for students to develop the ability to evaluate others' visualizations critically (Beasley et al., 2020).

Professors often play the role of both heuristic evaluators and end users (in the case of subjective evaluations) providing feedback, comments, and grading to the students. However, as the number of graduate students increases educators can find themselves struggling to provide detailed, consistent, and timely feedback. This is extremely worrying as effective feedback should help students see where to go next, close the knowledge gap between present understanding and goals, and match the time of the ongoing task cycle (Wisniewski et al., 2020).

A possible way to solve this assessment and feedback issue is peer-review. Peer-review has come to be recognized as a crucial part of many professional procedures, including the process of scholarly publication. The essential tenet of peer review is that professionals in any given field evaluate the skill, originality, or caliber of scientific work done by others in their area of expertise. Peer review is frequently described as the assessment of work by one or more individuals with comparable skill to the work's creators (Spier, 2002). The primary element of student peer review is the evaluation of students by other students including feedback. In a data visualization course, peer-reviewing can allow students to have the chance to reinforce previously learned course ideas by critically analyzing the work of others during the evaluation process itself. Finally, it is a scalable strategy for instructors: adding students to a course only slightly increases administrative work because students give feedback to one another.

In the next chapter, we will introduce an evaluation framework that uses both heuristics and subjective evaluation approaches and can give an alternative method of evaluation for data visualization courses: The Wheel of Visualization (Cairo, 2013). It has less heuristics than the example given before, which can save time to the evaluators, but still focuses the student attention on what is important, how, and why the students went astray, the rationale for evaluation and how to make improvements. Peer-reviewing techniques were also used in the empirical study that we will discuss in the empirical study chapter.

2.8. The Wheel of Visualization

In his book, '*The functional art: An introduction to information graphics and visualization'*, Cairo writes about a chart that he created for a Brazilian magazine that turned out to be unexpectedly contentious. The feedback he received from the editors was unfavorable; they thought the graphics were ugly, too complex, too abstract, and too dense, even though he adhered to all the best practices rules discussed above on the guidelines for effective data visualizations and explained to them how he gathered the data, the structure, the narrative, and the depth (Cairo, 2013).

After listening to the feedback from his colleagues and summarizing it schematically, Cairo used a conceptual device that he developed while writing his first book '*Infografía 2.0: Visualizacion Interactiva De Informacion En Prensa*' (Cairo, 2008). He called it '**The Visualization Wheel'** (see Figure below).

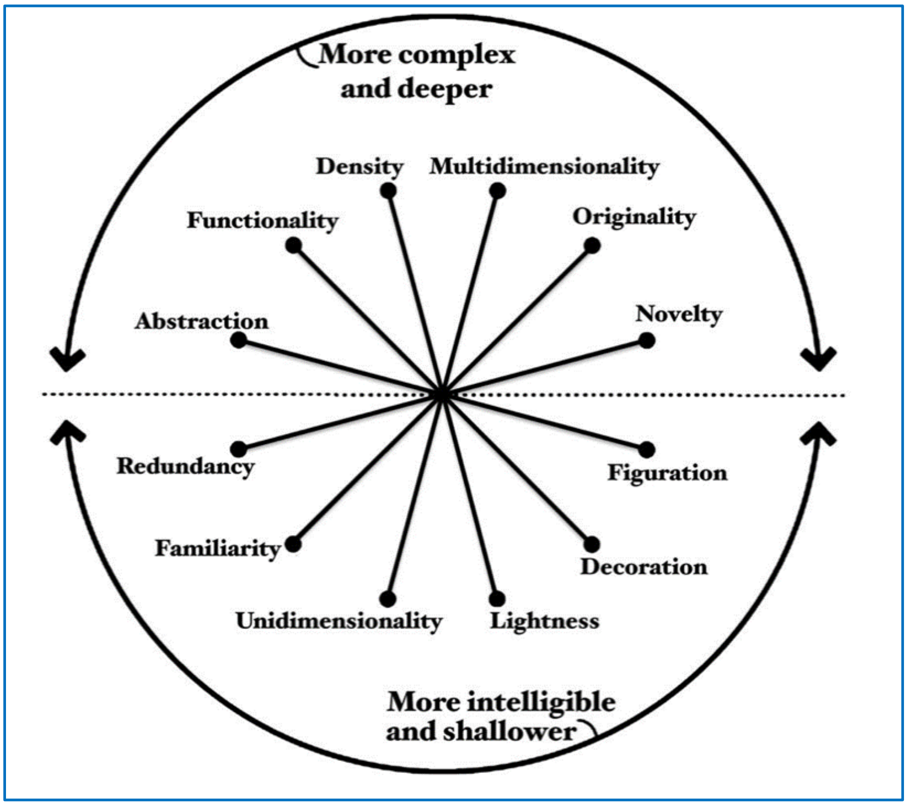


Figure 6*: The Wheel of Visualization, conceived by Alberto Cairo (Cairo, A., 2013)*

The "Visualization Wheel Model" is based on 12 factors in contraposition representing six different axes of the key elements that need to be balanced when designing a visualization. Each of the two hemispheres has six features: the upper hemisphere characterizes more complex and deeper visualizations while the bottom one is for more intelligible and shallower ones. Cairo defines *complexity* as the amount of work readers must put in to understand a specific visual; *depth* is the number of layers a graphic has. A graphic could be simple and deep if it uses standard visual forms to convey a large amount of data, or complicated and shallow if it uses a quirky graphic form to encode unnecessary information.

Let’s look at the axes with a bit more in detail:

- **Abstraction vs Figuration**

When the referent and its representation have an exact mimetic relationship, an information graphic (or a portion of it) is fully figurative. The infographic will be more abstract the farther away the depiction and its referent are from one other: For instance, a realistic illustration of a person is more figurative than a pictorial symbol of that same person.

- **Functionality vs Decoration**

Naturally, a graphic can be functional and visually appealing, but in this case the author is considering stylistic components that enhance reading, including the appropriate use of elegant fonts and properly chosen color schemes. This axis concerns the usage of visual components that do not immediately improve reader understanding of the text. These non-functional visual elements are purely ornamental and, if used improperly, can obstruct a chart's information.

- **Density vs Lightness**

The position a visualization holds on Density/Lightness axis is determined by how much information it presents in comparison to the quantity of space it takes up.

- **Multidimensionality vs Unidimensionality**

This axis measures two related variables: how many levels of depth a visual allows users to traverse through, and the various ways it uses to encode data. A good example of multidimensionality is an illustration published by the New York Times shortly after the 2004 U.S. presidential elections (see Figure 8). County and population density both reflect the popular vote. In both a cartogram (a map that distorts the relative size of regions proportionately to a variable—in this case, the number of electoral votes each state has) and a standard

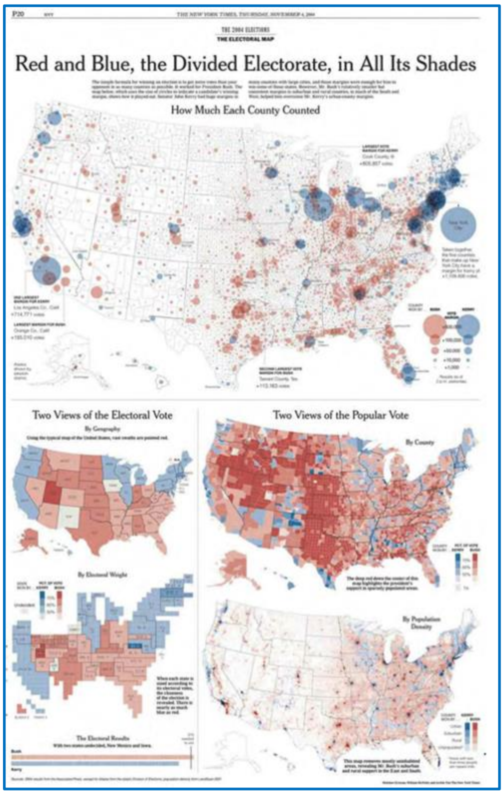


Figure 7 *Multidimensional infographic published after the 2004 U.S. presidential elections.*

choropleth map (a map that uses various colors and shades), the electoral vote is displayed state by state.

- **Originality vs Familiarity**

Some visual formats have spread so widely that some people can read them almost as easily as text: consider pie charts, bar charts, and line graphs. However, the widespread adoption of information graphics and visualization across a variety of industries — from academic computer science departments to marketing firms, among others — has stoked interest in developing fresh graphical formats. Visualizations that show the most used keywords or expressions in a recorded conversation are an example of a form that some people today might find original.

- **Novelty vs Redundancy**

A single information graphic can cover a wide range of topics (novelty), or it might repeat the same information in multiple ways (redundancy). It's desirable to strike a balance between novelty and redundancy. While it's crucial to keep things fresh to prevent boring your readers, understanding a topic requires a certain amount of repetition: for example, some of the information encoded in an illustration can be repeated in the text that goes with each step of the explanation.

3. Methodology

3.1. Course content and evaluation

To understand if the wheel of visualization can be used as an assessment method in a higher education data visualization course, we tested this evaluation method in two classes of Universidade Nova de Lisboa: hereby known as master's course 1 and master's course 2. The course objective was to teach students how to create visualizations that effectively communicated the meaning behind data through visual perception; ideas related to how people interpret graphic information as well as several approaches of mapping various types of quantitative and qualitative data were also one of the main topics in discussion.

Students had this course twice a week (totaling 2h 30m a week) for a total of 7 weeks between February and April 2022. In the theoretical classes, students were introduced to data visualization to understand its main concepts (how to choose the best chart types; how to visualize distributions and relationships; how to map data and visualize uncertainty; the selection of color to transmit information) and to the wheel of visualization as an assessment method of a visualization or infographic. Then, in the practical classes, students learned how to use *Python* and *Plotly* to create a poster and an interactive visualization.

The evaluation method used by the professor was quite innovative:

- Forty percent of the grade would be a group project where each group had to design a poster. The assessment would be via blind-peer review assessment, which means that both the reviewer and author identities are concealed from each other to prevent any type of bias or corrupted evaluation. The final grade of the group was the average of all the blind-peer reviews received (usually 3 or 4).

- Also, as a group project worth 40% of the final grade, students had to design an interactive dashboard which would also be assessed via blind-peer review. The final grade of the project was the average of all the blind-peer reviews received (usually 3 or 4).

- Finally, the remainder twenty percent consisted of two individual peer reviews (one for each project) that each student had to do using the visualization wheel. This was done to make sure every student would evaluate two projects and give honest feedback to each project, so the groups would understand the reasoning behind their grade.

3.2. Data collection

The data was collected from the individual evaluation of each student. To be a valid evaluation that was taken into consideration for this study, students had to deliver a *Word* document with the number of the group they were evaluating, written feedback on the visualizations, a visualization wheel with all 12 features evaluated and a final grade of the project from 0 to 20.

From the class of the master's course 1 we had 143 individual valid evaluations for the poster and 142 for the interactive dashboard. From the class of master's course 2, 45 individual evaluations were taken into consideration for the poster and 48 for the interactive visualization. This gives us a total of 188 observations of the poster and 190 of the interactive dashboards.

Table 1 *Summary of the dataset*

Number of students	Master's course 1	Master's course 2	Total (valid observations)
Poster	143	45	188
Interactive dashboard	142	48	190

As mentioned before, to be considered a valid evaluation for this study there were several criteria that had to be met, but this paper focused in only two of them: the final peer grade evaluation of the group work and the evaluation on the wheel of visualization. There were several ways the students decided to do this:

- Some of them decided to draw a wheel of visualization with the different features and grade them graphically (Figure 9)

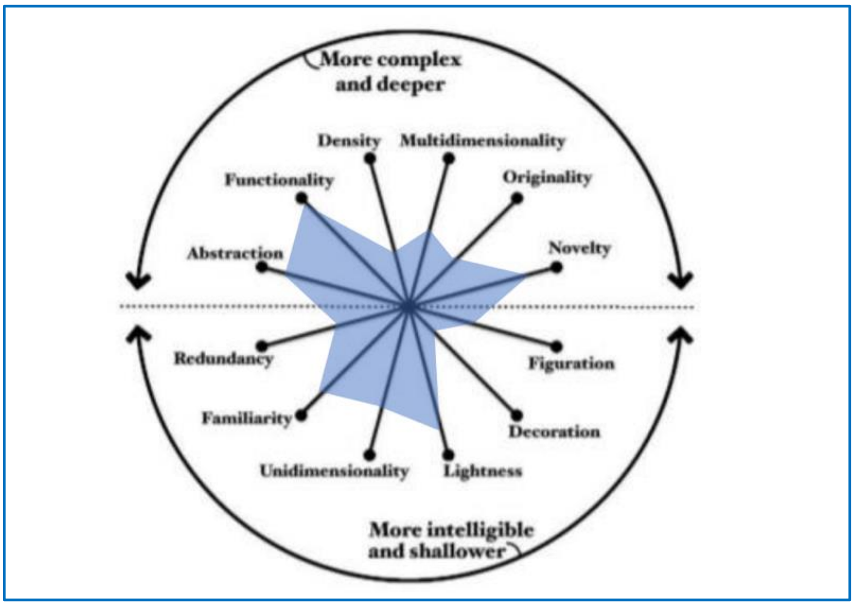


Figure 8: *Example of wheel of visualization with the different features graded graphically.*

- Others decided to draw scales in the wheel of visualization where we could clearly see the grades that were given to each feature (Figure 10).

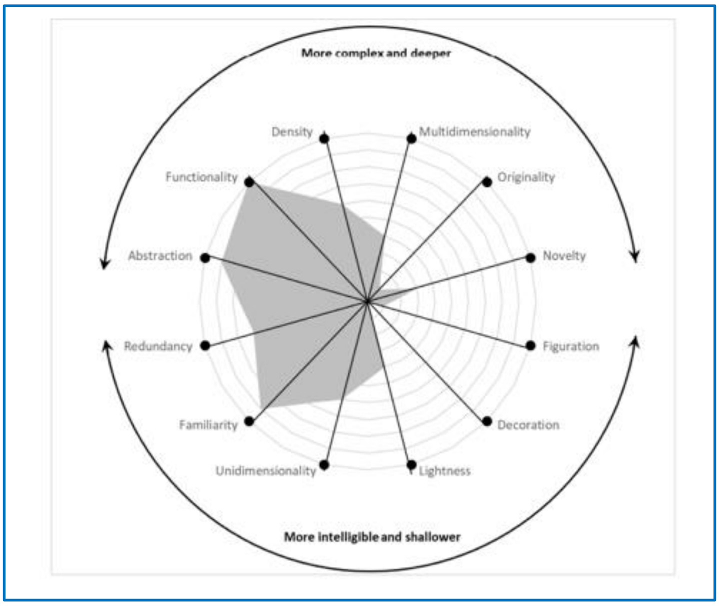


Figure 9*: Example of scales used as an evaluation method.*

- Some of the other students evaluated decided to give numerical evaluations on the wheel of visualization:

Originality 20% - Familiarity 80%

All the plots are familiar plots(scatter plots, bar charts) except the one in tab 4, a bubble plot, that is a clever plot to show the differences between each country and the average of the continent or the world.

Novelty 30% - Redundancy 70%

The same information are displayed many times (f.e. in both tab 1 and tab 2 there is the representation of the evolution of the cases in the country), even if the different analysis conducted in each tab are different every time.

Functionality 100% - Decoration 0%

As explained in the report, the dashboard is fully functional and very minimalistic, without any embellishment, even though overall is still vey nice to look at.

Figure 10*: Example of numerical evaluations of the wheel of visualization*

With all these different ways to demonstrate the wheel of visualization results, we've compiled each individual evaluation in a scale of zero to ten to be able to access the results in a uniform way. Let's give an example: for the last evaluation discussed, the student gave Originality 20% - Familiarity 80% which was translated to Originality 2 – Familiarity 8 in a scale of 0 to 10; on the second evaluation discussed, we can visually observe that the student gave a 7/10 to redundancy and 3/10 in novelty. This information is visually observable, but it was converted to a numerical form for all the observations in both the poster and interactive visualization results.

3.3. Key concepts

When analyzing the results, we used both Pearson and Spearman correlation to understand which were the features that were more valued (or undervalued) towards the final grade given:

- *Pearson correlation*: The Pearson correlation coefficient is widely used to measure the linear relationship between two variables. It assesses the extent to which the variables move together or apart in a linear fashion, ranging from -1 to +1. A coefficient close to +1 indicates a strong positive linear relationship, while a coefficient close to -1 indicates a strong negative linear relationship. A coefficient of 0 suggests no linear correlation between the variables.
- *Spearman correlation*: According to (Schober et al., 2018), "*The Spearman correlation coefficient is a robust measure for assessing the monotonic relationship between variables. It is based on the ranks of the data rather than the original values, making it suitable for non-linear relationships. A coefficient close to +1 indicates a strong positive monotonic relationship, while a coefficient close to -1 indicates a strong negative monotonic relationship. A coefficient of 0 suggests no monotonic correlation between the variables.*"

4. Results and discussion

The study tries to measure the effectiveness and subjectivity of the visualizations through objective criteria, such as FAMILIARITY, ORIGINALITY, MULTIDIMENSIONALITY, etc, and through subjective feedback from the audience (final grade). As it was briefly discussed before, the fact that double blind peer-review was used also diminishes the possibility of bias of any kind.

From the analysis done in our dataset regarding the poster grades, we concluded that *Decoration* has a big positive impact in the final grade that each project got: with a 0,174 Pearson correlation and 0,185 Spearman correlation we can see weak but positive impact of higher levels of *Decoration* in the final grade of a project. This means that the students of these courses valued visualizations with more artistic embroilments, which might increase the memorability of the visualization for the user: this makes sense, as the students when evaluating different projects, would give a higher grade to the ones that would “stick” with them longer and create a greater impact. *Novelty* also has a positive impact on the final grades of students from both a Pearson and Spearman correlation point of view (0,189 and 0,17, respectively) while *Redundant* visuals negatively impact the final grade of a poster (-0,17 and -0,157, respectively), which means that students from these courses prefer visuals that represent a certain subject using only one element to show a single phenomenon. The most interesting and relevant features, however, are *Originality* and *Familiarity*: *Originality* showed a 0,344 Pearson correlation and 0,331 Spearman correlation while *Familiarity* showed -0,329 Pearson and -0,321 Spearman. First, we should say that the almost inverse relationship between *Originality* and *Familiarity* correlations are understandable, as usually familiar visualizations use common graphical representations for data that are widespread like bar graphs, pie charts and line charts, whereas original graphics generally are seen as fresh graphical formats. As an opposite example, visualizations that show the most used keywords or expressions in a recorded conversation are often perceived as an option that some people today might find original. From the results discussed, we can infer that a poster that would value more the features of *Decoration*, *Novelty* and *Originality* would have, on average, a higher final grade on the project. From these results we can infer that this audience, when analyzing the posters, highly values visualizations that focus on:

- Differentiation: When many students are working on similar projects, those who prioritize decoration, novelty and originality will stand out. This differentiation will make their work more memorable, potentially leading to higher grades.

- Mastery: Incorporating all these features in a single visualization indicates that the students not only understand the data but can also creatively represent it in an engaging manner, which a very valuable skill in this course.
- Engagement and Interest: Visual appealing and novelty capture the attention of the evaluators, making them more invested in the content of the posters and thus, increasing the final grades given.

In the interactive dashboard visualization, the conclusion was somewhat similar: *Originality* comes as the feature with the biggest positive impact on the grade with a Pearson correlation of 0,344 and a Spearman of 0,336. *Familiarity* also has a somewhat big impact, although negative in the final grade with a Pearson of -0,337 and a Spearman of -0,390. The fact that this phenomenon happens on both visualizations might indicate that students see original visualizations as more valuable than familiar ones; maybe an original visualization is perceived as being harder to design and execute when compared to a bar or line chart and thus, deserving of a better grade. The Pearson correlation also shows interesting results when analyzing the *Novelty* feature (+0,211) and the *Redundancy* (-0,231). Unlike in the poster, *Multidimensionality* and *One-dimensionality* also have a significant impact on the final grade of the interactive visualization: *Multidimensionality* shows a 0,207 positive Pearson correlation and 0,188 Spearman correlative whereas One-dimensionality presents a negative impact on the final grade according to both correlations: -0,204 in Pearson and -0,184 in Spearman. In the interactive dashboard, Multidimensionality has a higher weight in the final grade as students can 'play around' with the interactive aspect of the dashboard to explore the different levels of depth a visual allows users to traverse through. One-dimensionality visualizations can be perceived as somewhat bland and not taking advantage of the full potential of the dashboard.

From the results discussed, we can infer that an interactive visualization that would value more the features of Originality, Novelty and Multidimensionality would have, on average, a higher final grade on the project. From these results we can infer that this audience, when analyzing the interactive visualizations, highly values visualizations that focus on (besides the abovementioned aspects related with originality and novelty):

- Comprehensive understanding of the subject: multidimensionality in a visualization implies that the designer tried to give the audience several layers of knowledge and provide a comprehensive understanding of the data, which is highly valued in academic projects.

- Real-world relevance: Multidimensionality shows the intricacies and connections of data in the real world. For example, if looking at a map of Portugal, one can deep dive at the state and city level this will bring much added value to the audience to use this data for their better understanding of the topic in discussion.

Table 2 *Pearson Correlation results*

Feature	Decoration	Originality	Familiarity	Novelty	Redundancy	Multidimensionality	One-dimensionality
Poster	0,174	0,344	-0,329	0,189	-0,172	No correlation	No correlation
Interactive	No correlation	0,308	-0,337	0,211	-0,231	0,207	-0,204

Table 3 *Spearman Correlation results*

Feature	Decoration	Originality	Familiarity	Novelty	Redundancy	Multidimensionality	One-dimensionality
Poster	0,185	0,331	-0,321	0,170	-0,157	No correlation	No correlation
Interactive	No correlation	0,338	-0,390	No correlation	No correlation	0,187	-0,184

4.1. Implications for Higher Education

An aspect that is important to be mentioned and one of the main takeaways we would like the reader to take from this work, is that the Wheel of Visualization can also be used as an assessment method to decrease subjectivity in the evaluation of other courses where subjectivity plays an important role (courses like design or fine arts, for instance).

The Wheel of Visualization encourages more objective evaluation criteria by providing explicit points of reference for each dimension such as “functionality” and “abstraction”. The framework offers clear and concise definitions for each feature which can help assessors objectively evaluate these criteria, rather than solely rely on their personal opinions.

The Wheel of Visualization can also include scoring rubrics that assign specific numerical values to different achievements for each criterion (somewhat like what we did in data collection). These rubrics can even have different pre-defined weights (for instance, if the evaluator wants to give more importance to original works, it can give a higher weight to that specific feature) thus giving a structured way to quantify the assessment, reducing, once again, subjectivity in grading.

While using this framework, the evaluation process becomes more transparent and consistent for both students and instructors: for the assessors, by evaluating the different submissions based on the same set of criteria, helps making objective comparisons between different projects and explain the grades based on well-defined parameters; students can now precisely understand how their work is assessed which reduces uncertainty and a sense of injustice.

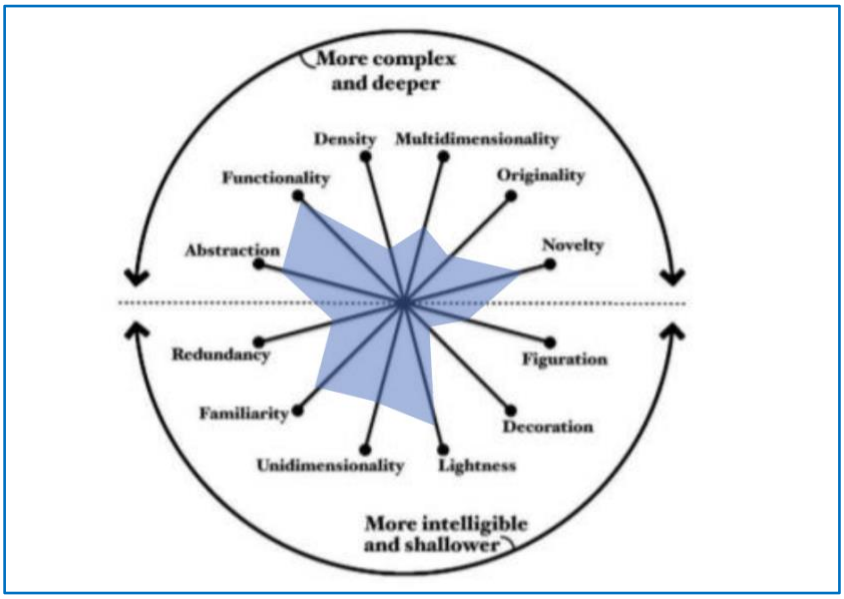
It is also worth mentioning that this framework and the way we used double peer blind review, allows students to have consistent and actionable feedback standards on their work. This framework promotes a structured and objective approach to feedback, where each student can exactly know in which areas they performed better and what are the areas where improvement is needed.

4.2. Limitations and future work

Regarding the limitations of this work, there are a few aspects that need to be mentioned that could potentially be explored in future research and theses.

First, it is important to mention that my interpretation of each wheel of visualization evaluation can be biased, thus affecting the data collected: for students that gave numerical evaluations a straightforward conclusion can be drawn; however, for those that chose to draw

Figure 11: *Evaluation that can be biased depending on the interpretation of each feature*



their wheel, my interpretation of a 4/10 in Originality, for example, could really be slightly different for the student that has decided to evaluate it graphically. This does not have an overall expressive impact on the study as my interpretation can be sometimes above the intended evaluation but other times it will be lower than what the student initially intended.

As a possible way around this issue, it would be interesting to have a study where students would clearly state, numerically, what is the intended evaluation of each of the features.

This thesis relies on the comparison of different assessment methods, the decreasing impact of subjectivity on the final grade of a visualization course when using the wheel of visualization and the much-needed feedback a student needs to learn and correct his/her mistakes, but no survey was done to the students at the end of the Data Visualization course to compare this evaluation method to a more "traditional" one. The absence of student feedback on this evaluation method limits our ability to gauge their perspectives on the fairness, effectiveness, and overall impact of these methods on their learning experience. The wheel of visualization tackled some of the limitations in data visualization previously mentioned: the limited time teachers now have to evaluate multiple projects and visualizations with the growing numbers of students attending these courses, the subjectivity in evaluation, etc, but we are not sure if the students felt they learned more or were evaluated more fairly when compared to other courses and evaluation methods. It would be interesting to understand if the wheel of visualization framework helped them evaluate their peers more objectively, if the feedback received from their peers was valuable and more extensive than in other courses. If they found the evaluation method fair and unbiased or even if the wheel of visualization framework helped them or influenced their designing of each evaluation. All these points are valid questions in my opinion and could provide valuable feedback to understand how the students perceived the wheel of visualization and blind peer-reviewing as an effective and useful evaluation and learning method.

It would also be an interesting study to understand how the results of this analysis could be confirmed or influence students in the following semester when designing their posters and interactive visualizations: would they give more importance to Originality and Novelty and avoid familiar visualizations? What would be the impact on the average final grade of the posters and interactive visualizations in a new semester if these findings were considered?

In future works more students could give feedback on each project (maybe each student could evaluate 5 or 6 projects) so we could have a more diverse evaluation of each project with increased feedback given, further wheels of visualization and more final grades that could decrease the subjectivity inherent to data visualization. A drawback of this approach however could be that, as the number of projects asked to be evaluated per student increases, their attention and detail on each grade and feedback given would diminish, resulting in less trustworthy results and valuable feedback provided.

Finally, topics like sample size, diversity and time frame should also be taken into consideration for future research: to enhance generalizability, a new study could include multiple institutions or a more diverse student population (different courses, different levels of education, etc.).

5. Conclusions

In conclusion, this master's thesis addresses three pivotal research questions, each shedding light on the efficacy and applicability of the Wheel of Visualization method in decreasing subjectivity in the assessment of data visualizations. The first question examines how the framework can provide a less subjective evaluation of visualizations. Acknowledging the inherent subjectivity in data visualization, the paper emphasizes the framework's role in structuring assessments, allowing both educators and students to characterize visualizations with a set of predefined features. By doing so, subjectivity is transparently explained by the preferences of the audience for specific features, enhancing the clarity of the evaluation process.

The second research question explores the impact of different visualization features on the effectiveness and efficiency of visualization design. Drawing on empirical studies involving two distinct classes, the thesis identifies features that significantly influence final grades on data visualization projects. It emphasizes the context-dependent nature of these impacts, highlighting the importance of understanding the audience. While not claiming universal applicability, the research provides a replicable method for identifying features that are impactful within specific contexts.

The third and central question explores whether the Wheel of Visualization can serve as an assessment method in higher education data visualization courses. Recognizing the scarcity of literature on this crucial topic, the paper underscores the importance of a scalable and feedback-centric evaluation method. The Wheel of Visualization, coupled with blind peer review, emerges as a promising approach, addressing both technical and subjective aspects of visualizations. By providing a framework for students to design visualizations and gain insights into audience perceptions, the method contributes to the teaching of critical visualization concepts despite challenges such as large class sizes and online formats.

In essence, this research not only validates the effectiveness of the Wheel of Visualization in mitigating subjectivity in assessment but also contributes to filling a gap in the literature by proposing a unique method for educators to apply and evaluate critical visualization knowledge. The framework, blending heuristic and user-centered techniques, serves as a valuable starting point for discussions on data visualization assessment methods in higher education. While not claiming to present the ultimate data visualization assessment method, the paper is positioned as a meaningful starting point for an important and ongoing discussion in the field.

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