A survey on Information Visualization in light of Vision and Cognitive sciences

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Abstract

Information visualization techniques are built on a context with too many factors, making it difficult to systematically deal with their underlying bases. In the intent of promoting a better comprehension, here, we survey concepts on vision, cognition, and Information Visualization organized in a theorization named Visual Expression Model. With a reduced level of complexity, our model organizes the bases of visualization techniques; nevertheless, it is complete enough to discuss guidelines related to design and analytical tasks. Organized in a coherent account, our work introduces the following contributions: (1) Theoretical compilation of vision, cognition, and Information Visualization; (2) Meticulous discussions supported by vast literature; and (3) Recommendations to have visualizations satisfy visual-cognitive aspects. We expect our contributions will improve the practice of InfoVis by promoting comprehension and by proposing the use of simple recommendations.

Keywords: Information Visualization, Vision Science, Cognitive Science, visualization model

1. Introduction

Understanding why and how visual representations operate is an important issue addressed in many works on Information Visualization [19][61]. This comprehension passes through the sciences of vision and cognition: vision is the gate through which computer graphics reach the human brain; cognition refers to the processing represented by such graphics. Vision and cognition are closely intertwined, a fact to be considered in the design of visualizations. Accordingly, understanding Information Visualization in light of these sciences may improve design principles that, usually, are performed intuitively. To do so, we review the steps that take place during vision-cognition phenomena when the goal is data analysis. In survey fashion, we compile the literature introducing the following contributions:

- Theoretical compendium: we draw a coherent relationship between vision, cognition, and Information Visualization;
- Meticulous discussions: we comprehensively debate our rationalizations over extensive literature;
- Recommendations: we compile extensive knowledge into applied directives for design.

We organize visualization concepts aiming at the needs pointed out by Johnson et al. [34], who recommend the characterization of how and why visualizations work, and by Scaife and Rogers [57], who stress the importance of the cognitive aspects underlying visualization. Furthermore, we review principles for visual representations that, according to Card et al. [8], are an initial step towards more effective visualization techniques, a demand defended by Wong et al. [73].

We note that, while we build a coherent association between Information Visualization, vision and cognitive sciences, we do not reach a definitive settlement; that is because neither vision nor cognition are yet fully understood. Rather, we introduce an organizational model that discusses use and design, along with a set of practical recommendations.

2. Related work

The literature presents several models that lay the bases to Information Visualization. Bertin [3] introduced the
concept of deriving visual structures from a set of fundamental components. Cleveland and McGill [14], and Mackinlay [48], conducted empirical studies on the usefulness of visual patterns. Card et al. [8] follow Bertin by discussing the importance of the spatial substrate. Keim [38] suggests a taxonomical space for quick referencing. Schneiderman [58] reasons about the possibilities of visualization and interaction, and Chi [12] focuses on data transformations. In the realm of design, Bugajska [6] deals with spatial and abstract visualizations considering the design guidelines of Tweedie [67]. In the line of works that reflect about the visualization field, van Wijk [68] systematically discusses visualizations based on a cost-oriented analysis; and Green et al. [25] research many cognitive and perceptual aspects [55] to build a model and a set of guidelines for design.

In order to organize our Information Visualization compilation on vision and cognitive sciences, we depart from the Visualization Pipeline of Card et al. [8] to propose the Visual Expression Model, a sequence of events delineated by the possibilities of the visual-cognitive interplay. According to our organization, (1) vision phenomena (pre-attentive stimuli) determines a map of potential interesting objects. Then, attentive selection concentrates on one single element, part of a set of (2) visual analytical perceptions; such perceptions go through a pattern-matching process that translates them into (3) abstract analytical patterns that, in working memory, support cognition in combination with domain knowledge originated from long-term memory, finally leading to (4) cognitive decision support. Nevertheless, our model does not explain the intercourse between vision, cognition, and Information Visualization; this is not feasible considering the current knowledge, and neither it would fit in an article. Rather, we introduce a model that drives considerations on design whose bases come from consolidated theories.

The rest of the paper is organized as follows. Section 3 draws a detailed panorama of vision and cognition in the realm of Information Visualization. Section 4 introduces the Visual Expression Model, our organizational model; and the last section presents conclusive remarks.

3. Concepts on Cognition, Vision, and Visualization

According to Vision Science, the visual process has two stages, namely, the parallel extraction of low-level properties, called pre-attentive processing, followed by a slower detailed scan. The first stage promotes the major benefit of visualizations, that is, improved data comprehension [63]; meanwhile, the second stage addresses conventional reading practices that do not contribute towards faster cognition, but that are necessary for further analysis. In fact, Ware [69] states that understanding what is processed pre-attentively is probably the most important contribution that Vision Science can bring to visualization.

This two-stage process is the motivation for the broadly referenced “visualization mantra”: overview first, zoom and filter, then details on demand [58], as discussed in the following sections and reinterpreted by our model in section 4.

3.1. Maps of Saliences

In the early stages of vision, the brain deals with the problem of casting potential elements of interest, that is, regions of the scene that should be considered for cognition. To cope with that, a complex process takes place so that certain characteristics pop out to the eyes. These characteristics appear as saliences over the scene. They define the so-called maps of saliences, exemplified in Figure 1, the first step of our reference framework, mentioned throughout the rest of the text.

The principle of salience is to reinforce the perception of the areas in the scene whose visual-properties contrast with those of their surroundings [33]. It is a process that considers different visual aspects, such as position and color, and that ends as it combines them onto a single scene [52].

The occurrence of salient features stems from their interaction with other stimuli, depending on a context that favors conspicuousness. The brain is highly trained to detect such configurations, being able to track salient features in parallel, in real-time, and covering the entire visual field.

3.2. Attention and Attentive Selection

Although the brain perceives visual targets simultaneously in a map of saliences, it cannot process all of them in parallel. This is considered a prohibitively computational task even to the most sophisticated brains [65]. Primates and other animals handle this by restricting the consideration of the objects presented to their eyes: their vision concentrates on small regions considering objects one after the other; a serialization process ruled by what is called attention.

Thus, once a map of candidates for attention is ready, it is necessary to “filter out” one of them. This filtering has been modeled as a pyramidal neuronal structure [17] [22], which predicts a broad layer of neurons in its first level, narrowing down as it advances to upper layers.
Figure 1: (a) Example of a salience map over the Gapminder tool (open material from www.gapminder.org). Saliences corresponding to the bubbles that represent countries of interest. (b) The result is a map of potential targets that pop out due to their color, or their shape.

The layers intercommunicate through feed-forward and feedback connections and, according to Cutzu and Tsotsos [17, 64], a pyramid of neurons successively performs three stages of processing, illustrated in Figure 2: (a) bottom-up feed-forward, (b) top-down winner-take-all feedback [42], and (c) bottom-up straight path. This process explains what is broadly referenced as filtering.

3.3. Cognition, Memory and Vision

After a target is selected, it is potentially useful for “details on demand”, or cognition. In general terms, cognition refers to the acquisition or use of knowledge [4], a process mediated by the memory system. The relationship between memory and cognition is studied by works on Cognitive Architectures, such as ACT-R [7] and Soar [75].

In Soar and other theories, the structural configuration of memory roughly reflects the model of Baddeley and Hitch [1]: working memory includes three components: the central executive module, the phonological loop, and the sketchpad. The central executive module determines the attention focus, guiding the visual system, for example, by biasing the pyramidal selection mechanism. The phonological loop stores information related to sound. The sketchpad (also known as Visual Short-Term Memory – VSTM [1]) is associated with the maps of saliences discussed in Section 3.1, storing information related to space and to visual features.

Following these lines, VSTM comes to be the main element in supporting cognition and, consequently, visualization systems. Miller’s Law [50] states that VSTM is limited to 7+/−2 elements; this is a severe limitation because the greater the capacity of an individual’s memory, the more information she/he has available for solving problems [35].

VSTM supports cognition in two ways: by retaining a list of elements for quick referencing, and by assisting in the construction of mental models. According to Johnson-Laird [35], mental models preserve the relationship between entities by defining analogies that save on logical reasoning, the principle behind complex visualization techniques. Following the study of Logie [46], mental models are created in the visuo-spatial sketchpad, a specialization of VSTM.

3.4. Comments

The concepts presented in this section rely on ideas posed by widely accepted theories, among several others, for the visual-cognitive process. The choice for this specific line of thought has been motivated by its intuitive coherence and scope of influence in the literature. Notwithstanding, other theories are widely referenced, such as the Spotlight [21] and the Gradient [10] models.

4. The Visual Expression Model

In this section, we review the practice of visualizing data by considering the concepts presented so far. We organize the relationship among visualization, vision, and cognition according to a framework named Visual Expression Model – Figure 3. Our model has four components: (1) pre-attentive stimuli, (2) analytical perceptions, (3) analytical patterns, and (4) decision support.

According to our model, (1) pre-attentive stimuli come from the neuronal reaction to light, determining a map of potential interesting objects, or saliences. Then, attention concentrates on one single element, part of a limited taxonomic vocabulary of (2) analytical perceptions; such perceptions go through a pattern-matching...
process that translates them into (3) analytical patterns. Finally, analytical patterns in working memory support cognition in combination with domain knowledge originated from long-term memory, leading to (4) decision support; detailed as follows:

4.1. Pre-attentive Stimuli - channels for data encoding

Pre-attentive stimuli impel maps of saliences, as highlighted on the leftmost side of Figure 3. In a complementary work [56], we verified that such stimuli manifest through position, shape, color, and time; here, we refer to these factors as channels for data encoding. In this work, we provide further discussions comprising the realms of vision and cognition.

Although the consideration of four channels is a reductionist classification, it is supported by the literature. About color and texture, Watt [70] affirms that, just like texture, color is the psychological response to the spectral characteristics of a surface; and that, different surfaces are perceived as having different colors. Furthermore, Motter [51] observes that, early in visual processing, the incoming information is sorted and grouped according to the similarity of simple shape features, such as orientation or size, and of surface features, such as color, luminance, or texture.

The features of each channel span to a large set, but Card et al. [8] observe that just a limited number of the many existing graphical properties are used for Information Visualization. Table [1] presents a non-exhaustive list of such features.

A well-designed visual representation, thus, must present a high overlap between its map of saliences and its (implicit) map of semantic relevance. That is, the design of visual representations is supposed to maximize pre-attentive effects. However, such maximization may not be possible without flexible human intervention over the channels of data encoding. In other words, from the perspective of channels, interaction refers to the active redefinition of the visual stimuli, what is a need for any kind of visualization, as proposed in the following recommendation:

**Recommendation 1:** visualizations must present features that are potentially pre-attentive in a way that users can interactively redefine each visual stimuli.

Recommendation 1 is intuitive, still, Liu et al. [44] point out that many visualization systems are not sufficiently flexible to support user customization and appropriation. In fact, it is not difficult to find visualization tools that are limited in allowing the user to determine how to encode data. In such circumstances a user may ask “may I change the positioning order of the elements?”, “can I have each year represented with a different shape?”, “can I color the left group in red?”, or “can I see that animated?”. Each of these examples refers to a particular pre-attentive feature or, as we propose, to a data encoding channel.

For instance, consider the seminal system GGobi [16], which introduced a large set of features if compared to its former version, system XGobi. Many of the new features address the claims of our recommendation; still, a brief analysis reveals that many things are yet to be satisfied: positioning of views is limited, except for Parallel Coordinates; shape is not an option for coding in the same way that color is; and animation is restricted to scatter plots through touring...
techniques. Those design issues contrast to what is observed in commercial systems like TIBCO’s Spotfire (http://spotfire.tibco.com/) and Google’s Gapminder (http://www.gapminder.org/), which present higher levels of freedom for each encoding channel.

4.2. Visual Analytical Perceptions

Data encoding channels provide maps of potential targets for attention; now, following vision theory, the next mechanism is attentive selection – see Figure 3. Biased by user intention, a subset of the prominent entities in a visualization will reach the working memory. Once selected, the chosen visual stimuli will be the basis of the analogies that lead to mental models, see Section 3.3. Here, one question comes up – which notions are produced by the targets of attention in an information visualization design?

To answer this question, we have extensively inspected the literature tracking the ways in which visual manifestation occurs when the goal is data analysis. We have found a limited set of possibilities, defining a visual taxonomic vocabulary whose elements appear currently. We call these elements analytical perceptions, depicted in the second part of Figure 3.

Analytical perceptions are the traits that any user attentively seeks for in a visual representation. Our investigation indicates that such elements include correspondence, differentiation, recognition, connectivity, arrangement, and variation in time. The most verified of these phenomena, correspondence and differentiation, are noted by Bertin [3] and by Card et al. [8]. The third analytical perception is presented by Mackinlay [48] who states that the notion of relationship among graphical entities comes from the perception of connectivity. Meanwhile, arrangement arises from group positional configurations, largely studied by the Gestalt psychology [40] as what occurs, for example, in graph layouts [20][62]. Recognition, in turn, takes place as a resemblance to previous knowledge and/or expertise, a concept studied in psychological models and Information Visualization models; as Liu and Stasko [45] point out, internalization involves the encoding of information abstracted from perception into long-term memory. Lastly, variation, manifests only along time – not necessarily for temporal data – and in combination to the other five perceptions.
The notion of analytical perceptions becomes evident when they are not found and the pipeline outlined in Figure 3 is broken, preventing Visual Expression – if none of the aforementioned perceptions occur, the user is unable to make sense. As depicted in our model, analytical perceptions occur after pre-attention (Section 4.1) and before analytical patterns (Section 4.3), independently of the data domain; they bridge vision and data interpretation. Specifically, we discuss the visual perceptions and how they relate to the data encoding channels in the following:

- **correspondence:** each position/shape/color has a direct correspondence to a referential map – discrete or continuous – that is part of the scene (explicit) or that is mental (implicit). Explicit maps include axes, geographical maps, shape/color dictionaries, and position/shape/color ranges. Implicit maps include known orderings and shape metaphors;

- **differentiation:** each position/shape/color discriminates graphical items. Differentiation is a correspondence achieved by the user, who creates a referential map in memory. Such map is limited in the number of elements (or differentiations) according to Miller’s Law;

- **recognition:** positions/shapes/colors whose decoding comes from the expertise of the user or from previous knowledge – recognition is a correspondence established from visual entities to concepts retained/learned in long-term memory;

- **connectivity:** shapes, mainly edges, that convey information about relationships among entities in VSTM memory;

- **arrangement:** Gestalt principles of organization – positional placements (closure, proximity, and symmetry) that convey perception about group properties, for example, clusters and structural cues;

- **variation in time:** obtained when the parameters of position/shape/color are altered along time, inducing new perceptions for each of these channels.

Our set of analytical perceptions is not an exhaustive listing, but a first reference. Over this notion, we make a second recommendation:

**Recommendation 2:** visual perceptions, which are recurrently observed in visualization techniques, must be the bases for design, and evaluation.

Recommendation 2 translates the fact that visualization designs tend to resort to the same basic set. For instance, the design of Google’s Gapminder tool, although contemporaneous, reproduces the same dispersion plots of statistical books a hundred years old. Nevertheless, as observed by Liu et al. [43], works on new designs and on the evaluation of existing ones have not considered that there is a limited set of elements to instantiate in data representations. This fact could fruitfully support the definition of design languages and frameworks, which would benefit from recurrent constructs that lead to a limited set of visual perceptions; differently current languages and frameworks rely on graphical patterns and it is up to the user to build the desired visual perception; see Table 2 for a representative set.

By considering our recommendations so far, it is possible to conceive a design language whose approach is based on cognition, and whose elements are interactive coding channels, and visual perceptions – refer to Table 2 for comparison. For example, in this design language, one would be able to state a visualization by choosing channel color and visual perception differentiation; this same visualization would demand a few more elements, as channel position and visual perception correspondence, and so on. As in any language, these elements would receive parameters according to an extensible library of data-to-marks mapping. As a design language, this approach would bring the benefit of discriminating the recurrent elements of visualization techniques and having them in libraries for composition; that, in contrast to the usual practice of combining them in ensembles assumed as new techniques. Note that we propose a different way of thinking about visualization techniques, a way that differs from existing lines of thoughts – Table 2 and that arises from visual-cognitive aspects.

4.3. Abstract Analytical Patterns

According to Hutchins [32], tools – or externalizations [29] – transform difficult tasks into in-mind manipulations of physical systems, or into pattern-matching problems [24]. Pattern matching is the basis of data visualization and the second step of the Visual Expression Model – see Figure 3.

According to our organization, once a user focuses on an analytical perception, she/he proceeds to match that perception with an analytical pattern, or inner abstraction. Based on the theory of vision – seen in section 3.3 the generation of analytical patterns is supported
Table 2: Previous works on languages and frameworks for visualization design.

| Work            | Approach                  | Elements                                      |
|-----------------|---------------------------|-----------------------------------------------|
| Protovis [4][27]| Graphical                 | Marks, color, and position                    |
| D³ [5]          | Visualization pipeline    | Selection, operation, join, layout, and transformation |
| Improvise [71]  | Link and coordinate       | Variable, function, and view                  |
| Prefuse [28]    | High-level API            | Layout, and interaction                       |
| ggplot2 [72]    | Domain specific           | Layer, scale, coordinate system, and facet    |
| Flexible Linked Axes [13] | Linked axes | Axes mapping, interaction, line, and point |

by VSTM memory, which is filled with data from long-term memory or from the sensorial system. This visual-sensorial system provides spatial information at rates higher than that of long-term memory [69], in a time ranging from 100 to 250 ms [39]. Hence, analytical perceptions in the visual-sensorial system work similarly to the images stored in long-term memory, providing efficient pattern-matching.

A suggestive set of the abstract analytical patterns – third part of Figure 3 – that arise from the perception-to-pattern matching in memory includes: correlation, tendency, classification, relationship, order, summarization, outlier, cluster, structure, and reading. Tufte [66] provides a more exhaustive listing that follows a different rationalization. At this point, we make a third proposition:

**Recommendation 3:** the design of systems shall consider a perceptual perspective, offering users pattern and domain-oriented choices rather than design-oriented choices.

Recommendation 3 refers to current practices, according to which, instead of a set of analytical patterns, the user has to choose among a set of visualization designs that, quite often, they have little experience with [11]. We suspect that, because design-oriented interfaces neglect the more natural notion of analytical patterns, this is possibly one of the reasons why visualization techniques have struggled to achieve a wider commercial dissemination.

Thomas and Cook [61] provide bases for recommendation 3 stating that analytical patterns correspond to the second factor of their four-steps analytical-reasoning process. Following their process – a pattern-to-construct sequence, users have constraints in relation to what they can search for in face of a given analytical pattern. For example, suspiciousness tends to appear by means of tracking for outliers; while evidences of illegal lobbying practices emerge from clusters; and community detection in graphs is a task for relationship. Still, users are often offered a menu whose options are, for instance, dimensional stacking [41], star coordinates [37], and table lens [54]; alternatives far from the pattern-to-construct task they have in their minds.

Take, for instance, the visualization technique Treemap [60], introduced for visualizing hierarchical data in general. In two decades, Treemap gained popularity at the academy, but, as a general hierarchical tool, it has failed in reaching a wider use. This is, possibly, because it has been criticized since its introduction [2, 9, 23], being accused of lacking cognitive plausibility, having poorly perceived aesthetic qualities, and presenting poor task-driven performance [74]. Despite all, however, an especial design of the Treemap has remarkably succeeded. The SequoiaView system (www.win.tue.nl/sequoiaview) has achieved wide dissemination (check [68] for some impressive numbers), far beyond the academic walls. But, how can we have two flavors of the same technique evolve in different ways? Certainly, not one single aspect explains everything, but an outstanding factor comes up: the SequoiaView is domain and pattern-oriented, it is distributed to visualize the structure and the sizes of the files in your hard-drive, specifically. In accordance with our recommendation, users do not have to discover that the tool is good at doing this; instead, when they have this specific problem at hand, they are guided to SequoiaView, a more natural process.

In designing systems, an alternative course of action would be to initially present the user with a set of analytical patterns to choose from; after what, she/he would be offered a set of visualization techniques that better suit the pattern they are seeking. Users may know what to look for by means of previous knowledge of the data domain, by means of known problems to be solved, by
means of suspicious clues perceived along the data usage, and also by means of previous visual exploration of the data.

Note at this point that, while Recommendation 2 is concerned about design languages for InfoVis techniques; Recommendation 3 refers to the design of InfoVis systems that put together multiple techniques.

4.4. Cognitive Decision Support

After producing analytical patterns, vision is no longer an active agent, neither pre-attentively nor attentively; now the analysis follows the widely accepted pattern-then-cognition process [49] [47] to achieve decision support. Indeed, according to the analytical reasoning of Thomas and Cook [61], Information Visualization cannot ultimately provide decision support, which can only be achieved after interpreting the analytical patterns in light of the data domain – rightmost side of Figure 3. That is, even though users can come up with analytical patterns without considering the underlying data, these patterns are not of great use if the domain is not deeply understood.

The next recommendation is to avoid unsatisfied expectations in relation to InfoVis, preventing situations in which a user is presented to a supposedly insightful visualization but, then, everything one hears is “so what”? A disappointment that happens due to the enthusiasm according to which one can solve a wide range of problems just by looking at the data. However, visualization tools can do little if the analyst is not well-prepared to assess what the data ultimately describes and potentially carries within.

**Recommendation 4:** InfoVis systems must define systematic means to aid the user in recording and accessing the domain knowledge related to the problems at hand.

An interesting approach to overcome the gap of domain knowledge, satisfying to Recommendation 4, is to use annotations, either automatic or manual. As pointed out by Hullman et al. [30], annotations help direct a users attention and foreground particular insights, supporting the most efficient inferences. The work of Hullman et al. [31] exemplifies this issue; their work focuses on stock-price time series, which are hard to understand if one is not aware of the facts that influenced the behavior of the market. Their system solves this problem by identifying news that happened contemporaneously to outstanding patterns found in the plots, presenting them on demand. Similar approaches [15] [15] have been proposed for genomic data, an extreme case of domain in which domain knowledge is necessary, otherwise no reading of the data (either visual or textual) will make sense.

An alternative is to use technique storytelling, as surveyed by authors Segel and Heer [59]. Indeed, Plaisant [53] defends that advanced interfaces need to address the longer term process of analysis that may require annotation, history keeping, collaboration with peers, and the dissemination of results and procedures used. Storytelling not only attacks the problem of lacking domain knowledge, it also provides knowledge about new findings in the form of further “story chapters” interactively created. The visual analysis, potentially, becomes an incremental set of insights from multiple experts in the form of bookmarks, keyword tags, text comments, and audio annotations.

4.5. Discussion

Putting all together, we conclude that (1) InfoVis systems must be pre-attentively interactive – according to pre-attentive channels of position, shape, color, and time; (2) they must be designed according to visual perceptions of correspondence, differentiation, recognition, connectivity, arrangement, and variation; (3) their interfaces shall consider analytical patterns of correlation, tendency, classification, relationship, order, summarization, outlier, cluster, structure, and reading; and (4) they must rely on systematic methods to assist the analyst during visual analysis.

We have drawn such conclusions by surveying accepted concepts of vision and cognition; notwithstanding, we state these conclusions as conjectures with theoretical evidence only. This is because the validation of these hypotheses would encompass vast experimentation; reaching a material enough to spam a few papers or a book, to be conservative. Therefore, we leave our recommendations both as contributions – to guide new systematizations; and, as future work – to drive further refinements and discoveries.

Our conclusions also point to a challenging systematization; rendering all the recommended aspects, together with multiple techniques and data domains, might involve a development effort similar to that of huge software pieces, as office suites for instance – this is academically non-attractive, and economically risky. Possibly, the solution is to set a well-defined development framework for collaborative work, with ample acceptance, and standard interfacing; in the realm of machine learning, software Weka [26] has achieved great success in a similar endeavor. However, the graphical nature of InfoVis, together with elaborated data preprocessing techniques, imposes big challenges.
5. Conclusions
We reviewed concepts on vision, cognition, and Information Visualization by introducing the organizational framework Visual Expression Model, which proposes a course of action to explain how visual data analysis works. Over an extensive literature survey, the framework provides comprehension and science for data graphical presentation; a new perspective to make design and usage less dependent on intuition and experience. Our contributions are as follows:

- Theoretical compendium: we plotted the Visual Expression Model to interrelate vision, cognition, and Information Visualization;
- Meticulous discussions: we provided an extensive survey from different fields of science to serve as basis for further studies;
- Recommendations: we constructed recommendations to cope with the aspects of the visual-cognitive process.

Overall, we have put together key concepts to draw a different perspective of how to compose visualizations, reaching a theoretical framework. The reductionist perspective of our model leads to a simplified comprehension – yet practical – of the factors that define techniques and systems.

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