Towards a Model of Information Aesthetics in Information Visualization

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Abstract

This paper proposes a model of information aesthetics in the context of information visualization. It addresses the need to acknowledge a recently emerging number of visualization projects that combine information visualization techniques with principles of creative design. The proposed model contributes to a better understanding of information aesthetics as a potentially independent research field within visualization that specifically focuses on the experience of aesthetics, dataset interpretation and interaction. The proposed model is based on analysing existing visualization techniques by their interpretative intent and data mapping inspiration. It reveals information aesthetics as the conceptual link between information visualization and visualization art, and includes the fields of social and ambient visualization. This model is unique in its focus on aesthetics as the artistic influence on the technical implementation and intended purpose of a visualization technique, rather than subjective aesthetic judgments of the visualization outcome. This research provides a framework for understanding aesthetics in visualization, and allows for new design guidelines and reviewing criteria.

Keywords -- **information aesthetics, information visualization, aesthetics, visualization art.**

1. Introduction

Information visualization has recently emerged as an independent research field which aims to amplify cognition by developing effective visual metaphors for mapping abstract data [1]. The design of such effective data representations are generally supported by insights from visual cognition and perception research [2], as well as taxonomies which match data types to the most effective mapping technique [3, 4]. Some researchers have suggested that information visualization may be further augmented by engaging in an interdisciplinary discourse with design and art communities, or vice versa, and have proposed that artistic expression can be effectively supported by better understanding existing information visualization techniques [5-7]. Driven by a parallel stream of independent designers and artists, an increasing number of such *visualization art* (or *data art*) works have emerged that aim to express the subjective experience of our information society by artistically motivated but data-driven visual forms [8].

However, such works have not yet been readily acknowledged in either the art or visualization community. While information visualization predominantly focuses on effectiveness and functional considerations, it may be neglecting the potentially positive influence of aesthetics on task-oriented measures. Conversely, the reflection of artistic intent in visualization art often disregards functionality, making some works unintentionally incomprehensible. We propose that information aesthetics bridges this apparent gap between functional and artistic intent by focusing on aesthetics as an independent medium that augments information value and task functionality.

Aesthetics has been identified as one of the key problems yet to be solved in current information visualization research [9]. Accordingly, this paper proposes a conceptual model of information aesthetics in an aim to better understand its core characteristics, as well as its commonalities and differences with the fields of information visualization and visualization art. By better appreciating its intentions and employed techniques, this research aims to describe how data can be represented in insightful and appealing ways.

2. Background

2.1. Aesthetics & Information Aesthetics

Aesthetics has already been discussed as a key factor in several subfields of information visualization. This is reflected in *ambient visualization* – informative displays communicating information in the periphery of attention – which explicitly recommends aesthetics as a method to ensure displays remain unobtrusive in the physical settings in which they are placed [10]. Metrics for aesthetics have also been defined in the field of *graph drawing*, in terms of readability, such as minimising the number of edge crossings or maximising symmetry [11]. In the context of industrial design, the scientific discipline of *engineering aesthetics* proposes more rigorous empirical methods for evaluating aesthetics. It aims to systematically identify how people's multiple senses work together to form aesthetic judgements to assess the potential success of products in the marketplace [12]. Research in aesthetics is also a focus in the fields of *affective computing* [13] and *user experience* research [14, 15], which aim to develop computational interfaces that react to or provoke human emotions.

In this research, 'aesthetics' is used to refer to the degree of artistic influence on the visualization technique and the amount of interpretative engagement which it facilitates. This is in contrast with 'aesthetics' as the visual appeal and quality of visual artefacts, which largely depends on human subjective judgment. To the best of our knowledge, the term 'information aesthetics' was first used by Bense (cited [16]) to refer to a quantitative measure of aesthetics according to the information content of an image's constituent parts. More recently, Manovich [8] used the term 'info-aesthetics' to refer to an emerging theoretical concept which reflects digital society through digital interfaces. This paper uses 'information aesthetics' in the context of visualization only, while 'information aesthetic visualization' refers to visualization techniques demonstrating both artistic and informative value.

2.2. Towards Information Aesthetics

The following factors have facilitated the recent growth and importance of information visualization, & in particular, information aesthetics, in popular culture.

Software Availability. A number of applications have recently emerged that specialise in the production of complex visual artefacts. Designed for creative individuals, the intuitive visual programming interfaces employed[1] have resulted in a process of programming which resembles sketching. This allows designers to realise their ideas in a direct and iterative way, using high-level technical sophistication without requiring a full understanding of complex configuration issues. Some applications are supported by a growing online community who encourage creativity and sharing.

Dataset Availability. The Internet has made the individual creation, collection and sharing of data easier. Next to personal content creation, the *Freedom of Information* legislation has allowed the public to gain access to previously unattainable government and corporation data. Non-government-organisations have started to collect and expose data as a means of provoking and persuading opinions in relevant cultural issues. Several involuntary leaks have led to the exposure of proprietary, sensitive data.

Internet Speed & Distribution. The capabilities related to increasing Internet bandwidth have allowed data to become more accessible. This availability is not limited to raw datasets as new interfaces have been created that allow interactive access to large sets of information. Online software 'mash-ups' are becoming more common, bringing together distributed data sources into common, highly interactive interfaces.

Interdisciplinary Skills. Design students, from digital media to architecture, are increasingly exposed to cross-disciplinary knowledge such as programming and interface techniques, supplementing creative design experience with state-of-the-art computer science skills. An emerging group of visualization designers wish to cross boundaries between fields, by inventing, designing and prototyping novel techniques.

Evolving Aesthetics. Evolving forms of aesthetics are emerging, especially driven and appreciated by online media, exploiting visual appeal to entice users. New visual forms are created as a result of designers attempting to out-do each other, in a never-ending quest for the most impressive design portfolios.

2.3. Models of Visualization

Figure 1 illustrates a simple conceptual model of the collaboration between visualization researchers and artists [6]. The linear spectrum shows how techniques which are highly data-accurate often limit an artist's creative input, whilst those created with full artistic freedom are often less representative. It is suggested that rather than collaborating at either extreme, artists and researchers should work closely together to develop novel techniques. Similarly, examples of museum technology demonstrate the ability for interfaces to act as 'art' to be appreciated and as 'tool' with which to perform tasks [17]. These issues are related to information aesthetics in its aim to convey both informative and aesthetic value.

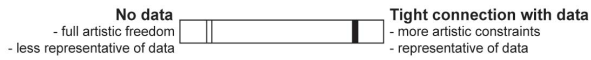

Figure 1. Data versus artistic freedom [6].

Several theoretical visualization models exist. The Periodic Table of Visualization Methods [18] organises one hundred visualization techniques based on context, purpose, and type of representation, allowing creators to combine appropriate techniques based on their requirements. Other models classify visualization techniques according to underlying interdisciplinary factors, such as the relationship between a user's expectations and a visualization designer's mapping assumptions [19]. The user expectations may match the designer's assumptions, so that the data mapping is clear. In other cases, the mapping technique may be more arbitrary and determined by context and data. Data is thus an inefficient determining factor for classifying techniques. Another visualization model classifies representations through an empirical assessment of perceived similarity in features, such as attractiveness and understandability [20]. The groups of representations inform creators by examining the limitations and strengths of each factor. Other task- and problem-oriented models classify techniques in terms of user goals and intended functionality [21, 22].

These models are extended in this research. It considers visualization as an artefact which is to be interpreted, rather than a means to facilitate tasks or represent a certain dataset. The model aims to facilitate an understanding of information aesthetics from the perspective of information visualization and visualization art, in its intentions and used techniques.

[1] For example: *Max/MSP* (cycling74.com), *Virtools* (virtools.com), *VVVV* (vvvv.org), Processing (processing.org).

3. Model of Information Aesthetics

3.1. Domain Model

The unique characteristics of information aesthetics and its relationships with related fields are mapped in Figure 2. Each field is defined according to three factors: *data*, *aesthetics*, and *interaction*. Information visualization, for instance, is located on the bottom edge, as it focuses on representing data using interactive methods with little concern for aesthetics.

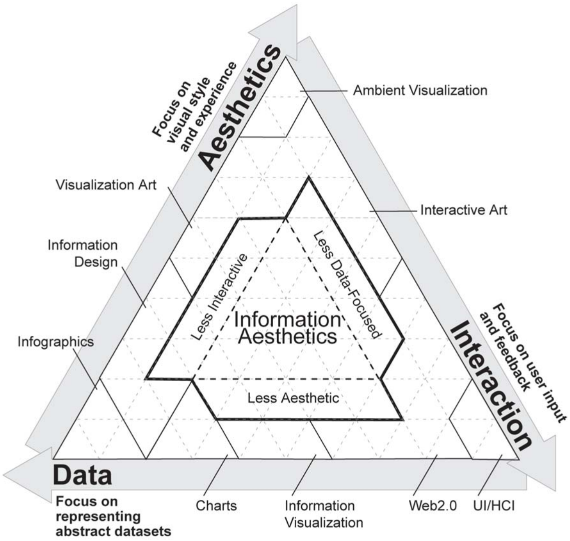

Figure 2. Domain model for information aesthetics.

The model shows information aesthetics' focus on the three issues of: representing abstract data, providing an interactive interface, and using visual appeal to engage the user. Extending the two visualization-related sides of the model, information aesthetics adopts more interactive methods than visualization art and places more emphasis on visual style and experience than information visualization. In this way, it is proposed that information aesthetic visualization employs techniques from, and is directly related to, both information visualization and visualization art. In its aim to realise the collective purpose of these two fields, an expanded model is required to describe its influencing factors.

3.2. Information Aesthetics Model

The proposed model of information aesthetics is defined by two characteristics which highlight the relationship between what a visualization facilitates and the means by which it achieves this. In other words, information aesthetics is analysed from an information visualization perspective, in terms of functionality and effectiveness, and from visualization art, in terms of artistic influence and meaningfulness. Two factors define the model: *data focus* and *mapping technique* (Figure 3). Mapping technique is determined through observations made in terms of what methods of representation have been used to map the data into visual form. Data focus is determined by observing how the visualisation facilitates knowledge acquisition. This model is based on objective observations rather than an examination of creators' intentions, as we have found that textual descriptions of a visualization's intentions do not always match the final outcomes, as its purpose is not always fully realised.

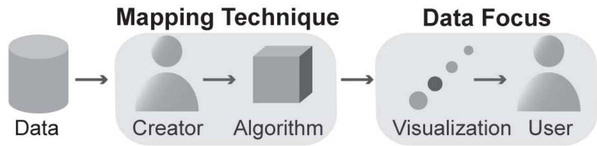

Figure 3. Mapping technique and data focus.

Forty-seven existing applications which visually represent abstract data have been analysed and were placed on a model (see Figure 4), after which the resulting configuration was considered. One should note that the respective data focus and mapping technique of these techniques are mapped to the model proportionally. That is, the extremes represent a complete focus on the factor, whilst techniques possessing characteristics of both ends of the extreme are located in the centre.

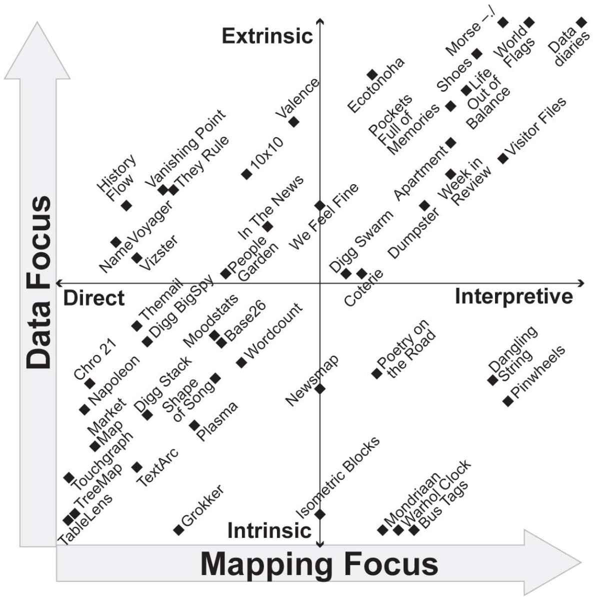

Figure 4. Model of information aesthetics.

3.2.1. Mapping Technique: Direct vs Interpretive. Mapping technique is a concept which describes the methods employed by a visualization creator to represent an abstract dataset. It is the process of translating data values to a visual representation. The focus on *direct* mapping is generally driven by standards learnt from visual cognition research, including Gestalt rules and perception psychology [2], and guidelines which determine which representations are most ideal depending on data type [4]. The use of more systematic mapping techniques is prevalent in visualization which focuses on direct representations. However, this model does not define direct mapping as a one-to-one correlation between data and representation as created by a computational algorithm. Rather, visualization techniques which employ direct mapping are inversible. That is, a user is able to infer underlying data values from the visual representation.

On the other hand, mappings which involve subjective decisions and stylistic influences are highly *interpretive*. The visualization design may be stylised, adopted from cross-disciplinary inspirations. Such more subjective mapping techniques can be characterised in their inability to be inversed. That is, users perceiving the visualization have more difficulty in comprehending underlying data values or patterns.

3.2.3. Data Focus: Intrinsic vs Extrinsic. Data focus is a concept which defines a visualization's ability to facilitate the communication of information, and the type of information disseminated. Here, data focus is considered as a reflection of what the visualization allows users to accomplish rather than what the creator intended for the visualization to achieve. Visualization techniques with *intrinsic* data focus aim to facilitate insight into data by employing cognitively effective visual mapping. This intrinsic focus can be seen as synonymous with functional 'tools' [17] which aim to support user tasks and disseminate information. These techniques allow users to discover useful patterns in data, such as outliers, trends, and clusters.

In contrast, those with *extrinsic* data focus facilitate the communication of meaning that is related to or underlies the dataset. These extrinsically-focused techniques are aimed towards visualization which are able to be appreciated and interpreted, and to invoke personal reflection. The creation of 'art' [17] is often synonymous with a focus on extrinsic data meaning. Such visualization techniques allow high-level goals to be fulfilled, such as understanding underlying meaning in the context of social and cultural issues.

3.2.3. Other Factors. The following factors have not been explicitly mapped to the proposed model, but are relevant in their analysis of existing techniques.

Interaction allows the user to explore the dataset by dynamically manipulating the mapping metaphor, through actions such as filtering or zooming. The ability to aggregate, summarise, and cluster the data allows users to gain a better understanding of the patterns hidden inside dataset. The predefined choice of what to represent and how to represent thus determines how users build up different perspectives to test their assumptions. In general, information visualization techniques with an intrinsic focus thus contain interactive features. Those techniques which aim for extrinsic meaning often explicitly limit interactivity, ensuring the communication of the creator's predefined perspective rather than fundamentally unpredictable user interpretations of the data.

Platforms utilised in the creation of visualization often reflect the data and mapping focus. In general, those which emphasise data patterns and direct mapping are task-oriented, and therefore utilise familiar, generic user interface elements and interaction metaphors. In contrast, information aesthetic techniques tend to be developed using designer-targeted software, such as Processing and Macromedia Flash, affording greater creative and stylistic flexibility in mapping and interaction. Visualization art is often created using alternative media, providing creators with the creative freedom to explore highly interpretive mappings and communicate multiple, potentially ambiguous meanings.

Dataset Attributes such as size, data type and time-dependency vary widely, and have not been included in the proposed model. Similarly, the degree of data aggregation in the resulting visualization has not been correlated. However, the model demonstrates how the nature of the dataset often determines an information aesthetic approach. For instance, techniques with an extrinsic focus often represent datasets that can be understood by non-experts, such as social data, and datasets which are reflective of the state of society, such as news headlines or speeches. Such techniques often provide insights into underlying meanings that are related to the dataset, proposing new perspectives on culture and society as a whole instead of highlighting or explaining data patterns or tendencies.

4. Model Analysis

The proposed model demonstrates that mapping technique and data focus are qualitatively correlated, i.e. the choice of mapping technique generally determines the resulting data focus (and vice versa). That is, visualization techniques that are based on direct mapping often focus on intrinsic patterns, whilst interpretive mapping highlights extrinsic data meaning. Closer analysis shows these two extremes can be identified as the fields of information visualization and visualization art, respectively, although a wide spectrum of other visualization techniques fall between them (see Figure 5). We propose that it is this field that can be identified as 'information aesthetics', which includes the subfields of social visualization, ambient visualization and informative art.

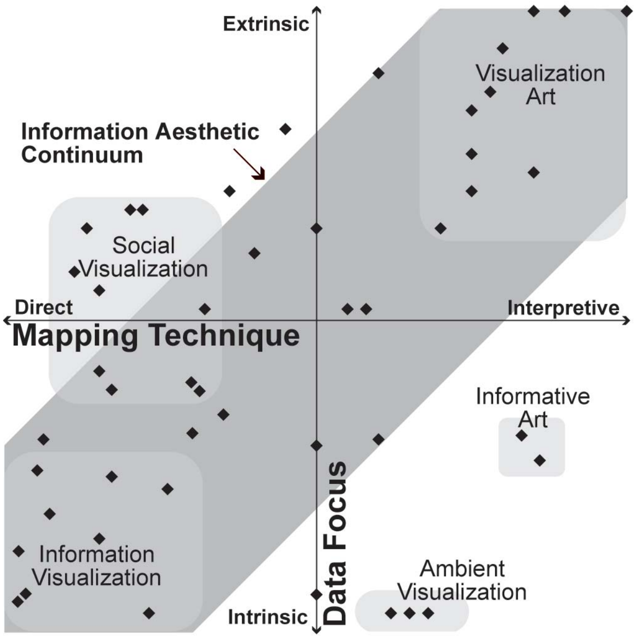

Figure 5. Categories within the model of information aesthetics.

4.1. Information Visualization

Information visualization mapping techniques draw from visual cognition research in order to maximise the effectiveness and efficiency of the user's ability to detect data patterns [2, 4]. However, techniques which target non-expert or general users tend to employ more interpretive mapping. Visual appeal is treated as a means of attracting and maintaining user engagement so that the visualization – often a commercial tool – increases in popularity. On the other hand, there are some techniques which place a slightly greater focus extrinsic meaning. These techniques are often specific to a dataset and while remaining highly effective, provide the interactivity and flexibility which enables higher-level interpretation.

4.2. Visualization Art

Visualization art techniques often tend to employ ambiguous and interpretive mapping methods in order to facilitate the expression of some underlying message extrinsic to the data, by engaging the user and provoking personal reflection [23]. Their data mappings are also often highly arbitrary or subjective, and not linked to effective visual perception guidelines as in information visualization. Instead, visualization art focuses on novel techniques for mapping data, or appropriating existing methods, but mostly with the aim to provoke open interpretation, facilitating the expression of meaning underlying the data rather than the presentation of patterns. Some visualization art techniques employ novel data metaphors in order to elicit curiosity and personal engagement. Other techniques re-contextualise existing data mapping methods taken from information visualization to question its 'scientific' credibility and power to sway human opinions and attitudes.

4.3. Information Aesthetic Visualization

Information aesthetic visualization techniques facilitate both intrinsic insight into patterns and extrinsic meaning underlying the data. Its mapping techniques are generally direct and accurate, similar to those in information visualization, but stylistic and artistic, as in visualization art. This means that information aesthetic works can exploit typical visualization techniques for alternative purposes than they were intended for. While such approaches might map data directly, it is not the primary intent of the works to augment understanding of the dataset. Its outcome might closely resemble typical information visualization techniques, in an effort to increase the credibility of the resulting visual artefact, or to allow users to investigate message-enforcing data patterns. However, by including aesthetic aspects, it reaches beyond simple data pattern detection, often conveying a more subjective, deeper meaning about what the data, and therefore the visualization itself, represents.

Ambient Visualization & Informative Art aim to inform viewers of data patterns through visually engaging displays. Although such approaches are often inspired by art [10], they are limited to conveying only meaning embedded within the dataset itself. By obscuring data mappings behind aesthetic means they intend to entice interest over longer periods of time, but do not focus on the conceptual perspective to reach beyond communicate patterns within data.

Social Visualization employs direct mapping techniques augmented by artistic styles, to engage, and promote exploration and interpretation. Users interacting with social visualizations tend to interpret intrinsic data patterns as a reflection of their personality and history. While their technique might be inspired by information visualization, their intent towards extrinsic concepts resembles that of art.

4.4. Implications

Information visualization, information aesthetics, and visualization art form a continuum between direct mapping with intrinsic focus, and interpretive mapping with extrinsic focus. Although the model reveals a relationship between mapping technique and data focus, one should note that the two factors do not always correlate exclusively with each other. For instance, fields which do not fall directly in the continuum include social visualization, informative art, and ambient visualization. These are distinct fields that are nevertheless part of and most probably formed the foundation for the information aesthetic movement.

This model shows that information aesthetics reaches beyond the combination of information visualization and visualization art. It is based on both intrinsic and extrinsic data meaning, and the use of artistically-enhanced but effective mapping techniques. Thus, aesthetics, considers the context in which the data should be interpreted, rather than the subjective judgment. Often, information aesthetic works use visualization techniques to convey patterns, but leaving their interpretation open to the user. Aesthetics is then used as a means of appealing to users that may have never considered visualization before, in order to attract attention, encourage personal involvement, and allow for more profound, long-term impressions.

The proposed model can be used by visualization designers from different fields to ascertain which technique is best for a particular visualization purpose. For instance, a visualization aimed at communicating the effects of global climate change (i.e. extrinsic focus) may adopt highly interpretive mapping techniques with little concern for the effective representation of the complex data involved, thereby demonstrating the power of visualization for mostly propaganda purposes. However, the misuse of such approaches may endanger the trustworthiness of the visualization field as a whole, but at the same time demonstrates new potential avenues in visualization research. By considering cross-disciplinary influences, information visualization can allow for high-level interpretations of ever-more complex datasets.

5. Discussion & Conclusion

This paper has identified *information aesthetics* as a visualization field which closely merges aspects of aesthetics, data and interaction. Accordingly, the proposed model investigated the influence of data focus and mapping technique on a large collection of existing abstract visualization techniques. Information aesthetics forms a cross-disciplinary link between information visualization and visualization art. It adopts more interpretive mapping techniques to augment information visualization with extrinsic meaning, or considers functional aspects in visualization art to more effectively convey meanings underlying datasets.

The model is unique in its focus on aesthetics as the degree of artistic influence on the mapping technique of a specific visualization, and the aesthetic engagement it affords, as opposed to aesthetics as a measure of subjective appeal. More specifically, our model analyses the intent (i.e. meaning) of a specific technique, and the mechanics (i.e. data mapping) that it uses to accomplish this. More detailed user studies to assess the influence of these two subjective qualities form future work.

This paper demonstrates how information aesthetics can be interpreted beyond the simple notion of subjective appeal, and that different degrees of information aesthetic quality exist. The proposed model creates an opportunity for a cross-disciplinary community of researchers and artists to develop design guidelines and more accurate reviewing criteria for information aesthetics, and provides an initial framework for understanding aesthetics in information visualization.

Acknowledgements

Due to space constraints, the visualization techniques of the model as depicted in Figure 4 are referenced at http://lisa.arch.usyd.edu.au/~andrew/iv07/.

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