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Computational Aesthetics of the Collective Affective Dynamics of IMDB Movie Reviews

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This paper proposes an approach to visualising affective metadata from movie reviews on IMDB. First, a natural language processing (NLP) method is applied for automatic topic modelling and sentiment analysis using contextual valence and subjectivity as measures of emotional expression intensity. A t-Distributed Stochastic Neighbour Embedding (t-SNE) was used to project these metadata into a compact 2D representation. A cluster analysis was used to extract the spatial dynamics of this representation, which were mapped into a generative visualization. Each generated visual 'signature' represented the emotional dynamics of a single movie extracted from 150 reviews, for a total of 20 movies. Based on the visualised metadata, a qualitative evaluation of 79 participants demonstrated the capacity to communicate affective metaphors, as well as a robust sense of perceptual consistency. Furthermore, we assert that the generative visualisation of data shows a nuanced expression of an aesthetic approach instead of an abstract articulation of an idea.

Keywords affective computing, NLP, data art, data visualization, generative art, information aesthetics, dimensionality reduction

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1. Introduction

Since the very first days of computer science, data visualization has been evolved as an academic domain associated with empirical research techniques to interpret patterns and extract insights. While serving specialized needs in the research community, visualization techniques also focus on the effective communication of the meaning of data to generalist audiences. Information visualization has been used to explore the creative potential of data and the aesthetics of information, instead of focusing entirely on the data (Li 2018). These novel visualization techniques can be a powerful communication tool as they can enhance the aesthetic experience and thus facilitate understanding of large and complex data.

Nowadays, vast amounts of emotionally coloured text are being produced by humans expressing thoughts and opinions in a continuous way. Rosalind Piccard was among the first to highlight the importance of emotions in human computer interaction (Picard 1997). Communication of emotional states are ubiquitous features of the human world crossing the boundaries of many psychological subsystems, including the physiological, cognitive, motivational, and experiential systems (Salovey 1990).

The analysis of textual content, for emotion characterisation, adds an important dimension that enhances the understanding of the data. A data-driven design approach serves as a creative method to display data while revealing their underlying relationships, in order to facilitate understanding (Tufte 2001), (Moere 2007), and to bring focus on the aesthetic potential of the data (Li 2018). Emphasizing engagement and interest within the data, such as in the case of data art, could form data-driven visualizations that communicate not only information but also affective states (Viegas 2007).

The current research explores interdisciplinary concepts, such as machine learning, visual communication, aesthetics and art. It unfolds as follows. First, we describe a scheme for sentiment feature extraction from IMDB reviews. Second, we utilize a generative design approach for data visualization to communicate the subsequent features of topic modelling, sentiment and subjectivity for a target audience. Finally, we consider an assessment method for the communication capacity of the chosen visualization approach, from a cognitive - perceptive perspective.

2 Related Work

2.1 Information Aesthetics and Data Art

'Form follows function' is a principle in design and architecture which means that the purpose of an object or building should be the starting point for its design. This principle was the manifestation of the cultural movements of modernism, such as the Bauhaus (Droste 2002), which emphasized utility and eschewed ornamentation in favour of function. In a similar mentality, researchers and engineers prioritize the informativeness over attractiveness of their data visualizations. The most common visualizations are used to reveal the underlying structures of data, spatial and temporal relationships, with all of them paying a rather little or no attention to design aesthetics or visual communication principles.

On the other hand, 'Information Aesthetics' a term used in conjunction with concepts such as generative aesthetics, generative art or computational architecture (Nake 2012) focuses on the aesthetic experience of the data visualization. A number of research methodologies into aesthetics of data visualization pose fundamental questions such as what constitutes good data visualization and whether data visualization needs to be beautiful (Li 2018). It is certainly difficult to define what constitutes aesthetics; (Card 1999) suggests that applying aesthetics to data visualization could invoke a sensation on two levels. First, on an objective level, it can promote the focus on accuracy, efficiency, which are important attributes in scientific visualization. At the same time, it can be used to evoke a subjective experience of understanding in the form of an emotional response. Data art is a different form of 'information aesthetics' in that it consists of data representations that deliberately hinder and obscure the understanding of a dataset by integrating elements of subjectivity in the data mapping process (Lau 2007), (Billeskov 2018). The objective of data art is then to create aesthetic forms and artistic works by overstating and dramatizing some underlying qualities of the dataset instead of revealing trends or patterns (Moere 2007). Such visualizations are generally commissioned by non-governmental organizations and museums, which typically aspire to popularize a predefined message, or communicate a subjective interpretation of the data to a wide, lay public. From a broad perspective, encoding the information visually varies across research domains, depending on its purpose, from being purely functional with focus towards the visualization's maximum informativeness (Lunterova 2019) to more artistic and exploratory approaches with more attention towards its aesthetics and creative expression (Moere 2007).

2.2 The Aesthetic Experience

A highly criticized challenge of the aesthetic approach, is that the assessment of artistic value of the visual is considered as highly subjective and in lack of an adequate way to provide quantitative measurements (Brown 2011), (Li 2018). David Hume thought that aesthetic value was objective to some extent, and that we are predisposed to find certain objects and patterns to be aesthetically pleasing (Graham 2005). The recently established field of neuro-aesthetics brought an empirical approach with an attempt to explain and understand the aesthetic experiences at the neurological level. The early pioneers of neuro-aesthetics were seeking to understand how the brain creates and experiences art. They were primarily interested in the ways in which different parts of the brain are activated when we experience or create art (Chatterjee 2014). A growing body of neuro-aesthetic research examines the ways in which art can support cognitive function, emotional well-being, and social interaction (Nielsen 2017). Kandel suggests that abstraction and generalization are important for aesthetic appreciation. Our brain is constantly trying to find patterns and to make sense of the world. In order to appreciate the beauty of a work of art, we need to be able to see the big picture and to abstract the essential features of the work (Kandel 2016).

The cognitive-affective processing model (Mischel 1995) suggests that, while the functional approach involves the cognitive processes that interpret the content, aesthetics of the stimuli engage the affective processes. The functionality of affect can be directly observed in the way people react to certain stimuli in the environment, and indirectly in the way people cognitively process information about the environment (Schnall 2010). Although aesthetics are considered highly subjective, having a 'good taste' is not innate and can be taught which suggests the existence of underlying principles, that from a Kantian perspective, can be universal.

It is an open question as to how art drives human emotion, but the need for establishing aesthetic rules remains important. Art, by definition, is an expression of human creativity. It can be abstract or realistic, representational or non-representational. Art cannot be defined in one way. However, it is generally accepted that it is meant to evoke an emotional response in the viewer. Different people will react differently to the same work of art. Some might find a painting highly emotional, while others might find it merely decorative. Despite this, there are certain universals in art across cultures and over time that suggest there might be some features in art that are appreciated by all. One of these features is symmetry. There is strong evidence that people from all cultures prefer symmetrical shapes and patterns, perhaps because symmetry is associated with stability and order. Perspective is also widely appreciated. When an artist uses perspective in a painting, it gives the impression of depth and realism. This is because our brains are hardwired to detect depth.

Design concepts such as contrast, symmetry, and rhythm are being experienced in a similar way (Coren 1980) because of common pathways, neural activations and aesthetic preferences across individuals (Chatterjee 2014). Brown suggests that the aesthetic processing, as the appraisal of the valence of perceived artworks or everyday objects (Brown 2011) is the cooperative function of different brain areas of different sensory modalities. This further supports the hypothesis of the applied pre-attentive visual properties, producing specific affected states across groups of people based on specific art attributes such as path curvatures, shapes, colors, directions, trajectories, smoothness, acceleration, linear vs radial shapes etc (Feng 2017).

2.3 Assessing Art

The experience of art and aesthetics is a complex one, emerging from the interaction of multiple cognitive and affective processes. Understanding how this synergistic process produces an aesthetic experience remains a monumental challenge. Motivated by this need, Chatterjee et.al suggested the use of a questionnaire to quantitatively assess attributes of visual artwork (Chatterjee 2010) which they call “The Assessment of Art Attributes” (AAA). Based on this tool, attributes are divided into two classes. a) The formal perceptual attributes: balance, color saturation, color temperature, depth, complexity, and stroke style. b) The content representational attributes: abstractness, animacy, emotionality, realism, representational accuracy, and symbolism.

3. Augmenting text with affect metadata

Measuring the emotional dimension of textual data is important when quantifying individual opinions and personal attitudes from unstructured text, and natural language processing (NLP) can fulfil this requirement. NLP offers a range of computational techniques that can perform linguistic analysis for the purpose of achieving a better understanding of human language. We chose three categories of meaning to shape the identity of the visualizations; topic modelling, sentiment analysis, and subjectivity analysis.

3.1 Topic Modelling

This is primarily a methodology to detect relationships and semantic structures, referred to as topics, from a large collection of otherwise unorganized documents (Jelodar 2019). Topic modelling can be based on word embeddings which is a method to represent words in a text as vectors based on their relative meaning derived from co-occurrences in this text. Representing words in a vector space is commonly used for locating similar words that share common contexts.

A popular method to calculate word embeddings is the word2vec (Mikolov 2013), which can map words from a document into a high dimensional space, with each word being assigned to a corresponding vector. High-quality distributed vector representations of words can grasp quite precisely the syntactic and semantic word relationships of an input text. GloVe (Pennington 2014) is another popular word embedding project that uses a large corpus of crawled web pages to train a model on global word relationships. Because of the large pre-trained map of word-vectors, GloVe eliminates the need to train a model from scratch or estimate its parameters. GloVe was recently open-sourced by Stanford University which made it available to the public. Methods for topic analysis often include deep learning algorithms (Mikolov

2013), and regression models for unsupervised learning of word representations (Pennington 2014).

3.2 Sentiment Analysis

Detecting emotion from text can be summed into three categories, Knowledge based approaches, Learning based and Hybrid (Shaheen 2014).

3.2.1 Knowledge based approach

The key advantage of this approach is that it is easy to implement and does not require any special training or data. It is based on a pre-defined set of emotions, and the text is analysed to determine which of these emotions are expressed. However, the disadvantage is that the pre-defined set of emotions may not always be accurate in capturing the true emotion being expressed in the text. WordNet-Affect (Strapparava 2004) and NRC-VAD (Mohammad 2018) are examples of lexicons used in knowledge-based approaches. Word embeddings, such as word2vec, can be used for sentiment analysis and to estimate emotional polarity, but they cannot predict the emotional component, resulting in an imprecise distribution of emotionally colored words (Seyeditabari 2017).

3.2.2 Learning based approach

The goal of this approach is to learn how to detect emotions in text without a lexicon by either using a trained classifier or by using unsupervised learning techniques to discover the hidden structure of unlabelled data (Ahmad 2017). A supervised learning algorithm requires a large number of samples and thus the need to label them, whereas an unsupervised learning algorithm uses statistics to measure semantic relations between words within sentences and their relevance to targeted emotions.

3.2.3 Hybrid approach

It combines the strengths of knowledge-based and learning-based approaches. A pre-defined list of emotions is used to train a machine learning algorithm to recognize emotions from text. It’s more accurate than a knowledge-based method and more efficient than a learning-based approach (Cambria 2017).

3.3 Text Subjectivity

Subjectivity is a measure of whether comments are more factually stated, or more opinionated, usually ranging from (0, 1) where the author is expressing either own feelings and opinions or describing facts. It has been used in many applications such as to predict consumer's attitude towards brands (Mostafa 2013). Sentiment analysis and subjectivity detection are both methods of understanding the attitude of a text, be it positive, negative or neutral. Sentiment analysis is the process of identifying the attitude of a text, while subjectivity detection is the process of identifying how opinionated the text is. There are two main approaches to subjectivity detection:

1. *Rule-based approach:* This approach uses a set of rules to detect how opinionated a text is. The advantage of this approach is that it is easy to implement and does not require any special training data. However, the disadvantage is that the rules may not always reflect the true subjectivity of a text.
2. *Machine learning approach:* As a result of this approach, it is possible to identify non-rule-based subjectivity. However, it requires special training data and is more difficult to implement.

4. Generative Design & Aestheticization of Data

> As creation is related to the creator, so is the work of art related to the law inherent in it. The work grows in its own way, on the basis of common, universal rules, but it is not the rule, not universal a priori. The work is not law, it is above the law (Klee 1961).

Galanter describes generative art (Galanter 2003) as a creative practice where "the artist uses a system, such as a set of natural language rules, a computer program, a machine, or other procedural invention, which is set into motion with some degree of autonomy contributing to or resulting in a completed work of art". A particular advantage of generative design is that it can use metaphors to conceptualize abstract ideas, and convey meanings, thoughts and feelings in a more implicit and subconscious way (Feng 2017).

Generative art and information aesthetics could be seen as a vernacular response to the increasingly digital and automated world in which we live. The traditional art world has been critiqued for its focus on the elite and the inaccessible, while generative art can be seen as a democratizing force, providing a way for anyone with access to a computer to create and share art. Moreover, as the world becomes increasingly more data-driven, generative art can be seen as a way to make sense of the overwhelming amount of information that is now available to us. Generative art can be seen as having an important role in helping us to navigate and make sense of the complex world in which we live. In this context, information aesthetics and data art could be seen as important sub-disciplines of generative art where the focus is on the visual representation of data.

There are a few key features that make generative art well-suited for data visualization. First, generative art is often based on rules or algorithms that can be used to create a wide variety of visual results. This allows for a high degree of flexibility and variation, which is important for data visualization as it allows for the exploration of a large amount of data in a visually engaging way. Second, generative art often employs abstraction, which can be used to simplify complex data sets and make them more comprehensible. Third, generative art often has a modular structure, which allows for the easy reuse of individual elements and the construction of complex visual compositions. This is also important for data visualization as it allows for the easy creation of complex and varied visualizations. Finally, generative art often has a performative aspect, which can be used to create dynamic and interactive visualizations.

5. Methods

Two phases are outlined in the proposed methodology: First, we perform a topic modelling, sentiment and subjectivity analysis on a set of IMDB reviews, and then we generate a series of data visualizations that are evaluated for their communication reliability and validity. Based on generative art principles, the data visualization uses linguistic rules to generate various abstract designs.

5.1 Emotional Metadata from IMDB reviews

A set of 20 movies were selected, each representing a different genre, rating, and country of origin. For each movie, 150 reviews were randomly chosen. We used two versions of the same dataset, a pre-processed version for topic modelling and the original unprocessed data for sentiment analysis. The first version used various filters such as special character removal and lowercase reformatting to clean the text. The second version included the original reviews, since raw text has more affective connotations. Pre-processed data were tokenized and frequencies calculated for each token.

5.2 Visualizing Topic Similarity

A Glove model was used to convert the most frequent words found in the reviews into vectors. Each vector was weighted based on its frequency of occurrence in the review. Finally, a topic vector emerged based on the average of those cumulative values. Essentially, a review topic is a vector that represents the most frequent words within a review. On the unprocessed dataset, we used the Vader library as an interpreter of sentiment or polarity. Vader considers lexicons, syntax rules, emoticons, and slang, so the unclean dataset can give a more accurate interpretation of sentiment. Sentiment polarity lies between -1 and 1, with -1 indicating a negative sentiment and 1 indicating a positive sentiment (Hutto 2014).

Finally, the TextBlob library was used to calculate the subjectivity of the unprocessed version of reviews. TextBlob, which was chosen for its popularity and simplicity, comes with its own pre-trained model. The sentiment analysis was performed on the unprocessed reviews. The subjectivity of a text indicates how much personal opinion is contained in it, and how much information is factual. A higher subjectivity signifies that there is more personal opinion than information. As with sentiment, subjectivity lies between [-1,1]

Based on the t-distributed stochastic neighbor embedding (t-SNE) algorithm (Van der Maaten 2008) and affinity propagation clustering (APC) algorithm (Wang 2008), a visual inspection of the topic distribution was performed across a selection of 20 movies from the dataset (figure 1). The t-SNE is a nonlinear dimensionality reduction technique that preserves the neighbourhood properties of high-dimensional data in a low-dimensional space, usually 2D or 3D. Using the APC algorithm, the data can be clustered without a predefined number of clusters, providing a quick overview of the distribution of review topics. A visualization of the landscape can be formed by combining these two techniques, in which 'similar' points are kept together and 'dissimilar' points are moved apart, with color indicating similarity between topics. Since the GloVe analysis returned a large number of vector dimensions (n = 300), the final 2D coordinates were used as topic modelling components.

It is evident from this visualization (Figure 1) that despite the fact that review topics vary across movies, there is also considerable overlap. For example, a number of the movies are about relationships (e.g., *Eternal Sunshine of the Spotless Mind (2004), The Notebook (2004), The Fault in our Stars (2014)*), while others are about war (e.g., *Saving Private Ryan (1998), The Thin Red Line (1998)*) or mental health (e.g., *A Beautiful Mind (2001), Shutter Island (2010)*).

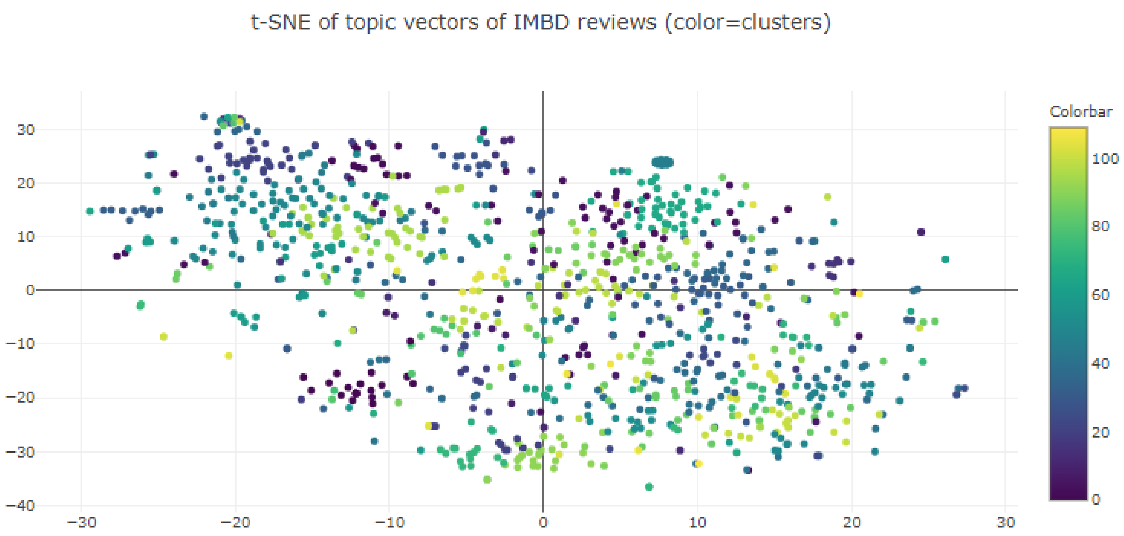
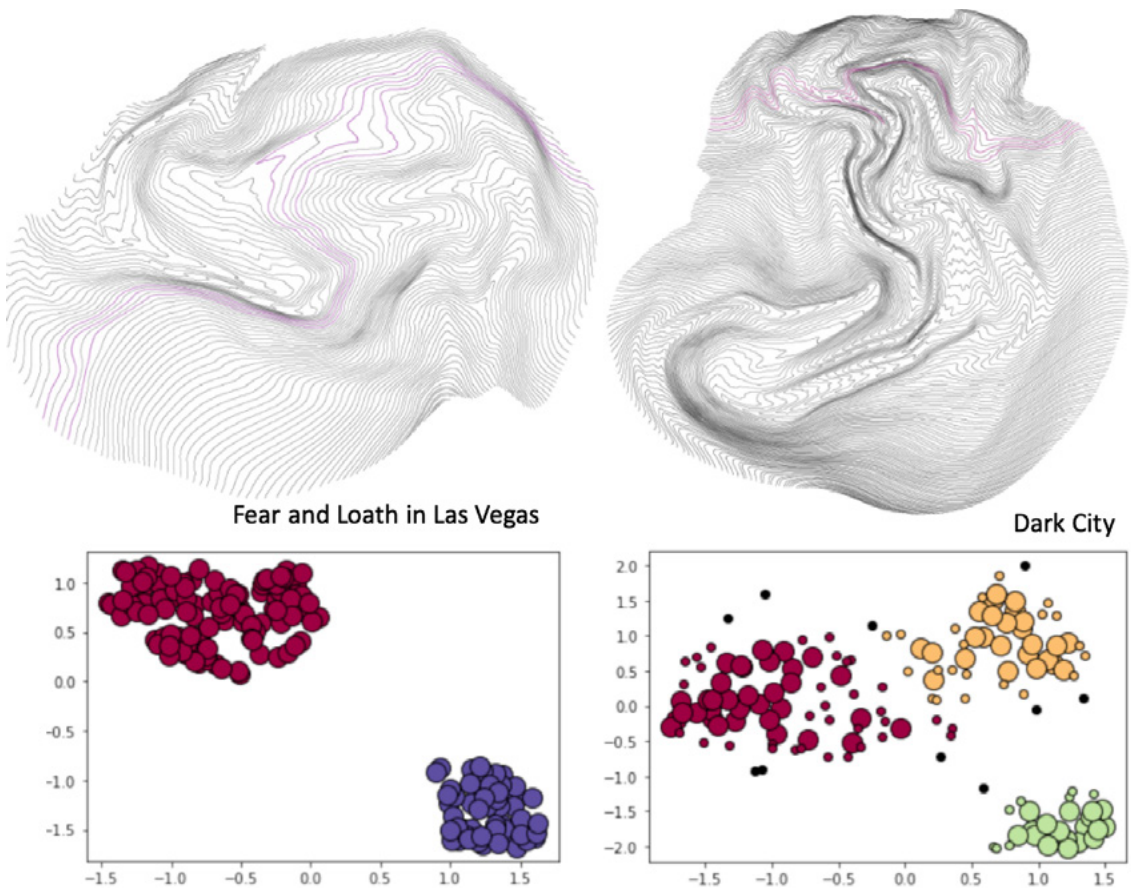


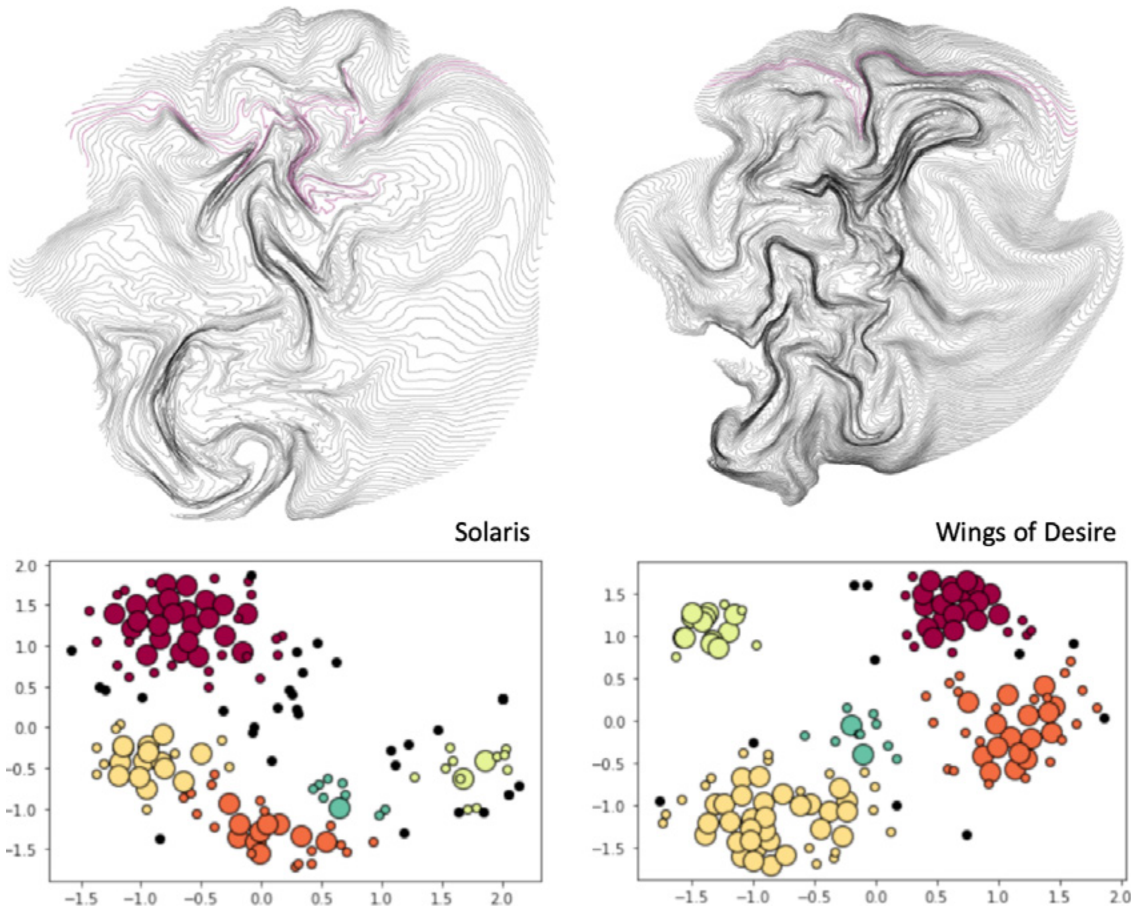
Fig. 1. t-SNE visualization of topic vectors on a 2D plane and subsequent cluster analysis based on APC. The visualization illustrates the distribution of movie topics for 20 movies with 150 reviews each.

5.3 Collective Emotional Signatures
5.3.1 Metadata

The t-SNE was applied to 150 random reviews for each movie. Each review is represented by a feature vector with a size of 4: Two for topic modelling coordinates, one for subjectivity, and one for valence. On each t-SNE map, we applied DBSCAN (Schubert 2017), an algorithm based on spatial density clustering, to detect agglomerations of reviews. In addition, DBSCAN returns the diversity of clusters, which measures the diversity of reviews as measured by the number of clusters, the size of the clusters, the mean values of the clusters, and finally noise, which measures the number of unallocated free points among the clusters. Among the essential metadata to communicate through the generative visualization were the mean value of valence, the number of clusters, the number of noise points, the size of the clusters, and their means. (Figure 2) shows the visual representation of 4 different movies accompanied by corresponding outcomes from DBSCAN analysis.

Fig. 2. DBSCAN clustering and corresponding visualizations based on the t-SNE maps of NLP metadata extracted for 4 different movies (150 reviews each).





The mean value of valence was positive for most movies, even for those with low ratings, however the range of values was much higher and therefore considered as representative attribute of the collective sentiment.

5.3.2 Visual form

Visual design style was inspired by the circular TV test patterns and TV scan-lines of cathode ray tubes (CRT) displayed on analogue television sets that form a raster scanning pattern (figure 3). Despite considering other shapes, the minimalistic disc with horizontal lines was chosen for its simplicity and because of its perceived mildness and neutrality. The test pattern and the TV scan-lines are highly identifiable patterns that refer back to the projection screen, which is the medium that shows movies. The visualization needs to be aesthetic and non-narrative, so the audience should interpret the work themselves and create their own interpretations. In that sense, the medium is the message since it communicates how audiences interact with projection screens and how they are integral to the movie-going experience (Mcluhan 1994).

Fig. 3. The popular test pattern and the analogue TV scan-lines inspired the visual form. (c) The generative form before deformations were applied.}

5.4 Visualizing Emotional Dynamics

Visualization was based on a simplified simulation of a magnetic-like field with local deformations caused by exerted torques induced by magnetic moments (Bohnacker 2012). This design style was preferred because of the capacity to render the dynamics of the multiplicity of opinions and emotions as beams of fine lines interacting with each other. From a metaphorical standpoint, magnetic moments resemble fabric deformations such as stretching and shearing (figure 3). Magnetic moments or “Attractors” are characterized by their strength, ramp, radius, and direction, with the main deformations being stretching, repulsing, holes, and twirling. The strength of the moment is determined by the magnitude of the magnetic field. The ramp is determined by the rate of change in the magnitude of the field. Radius is determined by the distance from the centre of the moment to the edge of the deformation. The direction of the moment is perpendicular to the ramp or field. Twirling was chosen as the main visual component due to its expressive appearance.

5.4.1 Mapping Metadata

The encoding of sentiment metadata as metaphors was determined by the hierarchy of elementary perceptual tasks (Cairo 2016). Thus, the visual elements defining the generative function were selected according to their importance in being perceived. The visual elements that define the generative form and their hierarchy are shown below (figure 4).

Fig. 4. Hierarchy of elementary perceptual tasks.

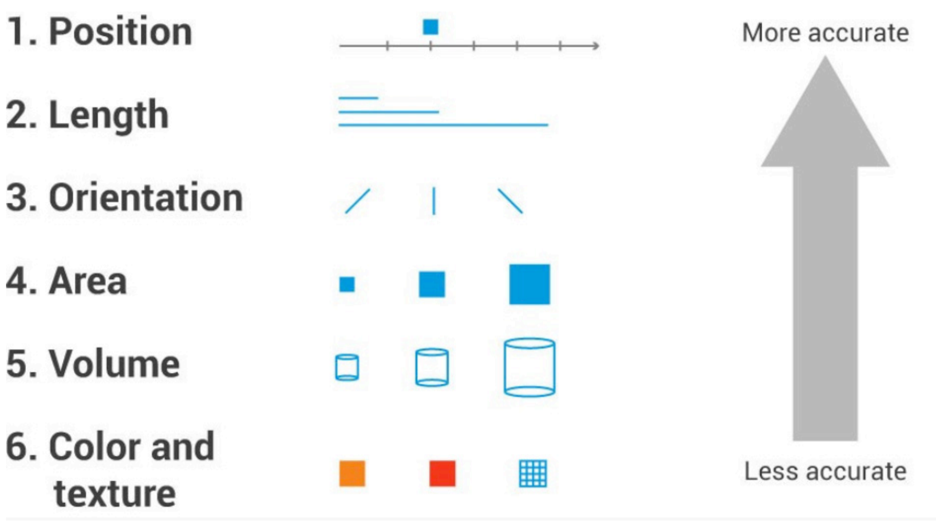
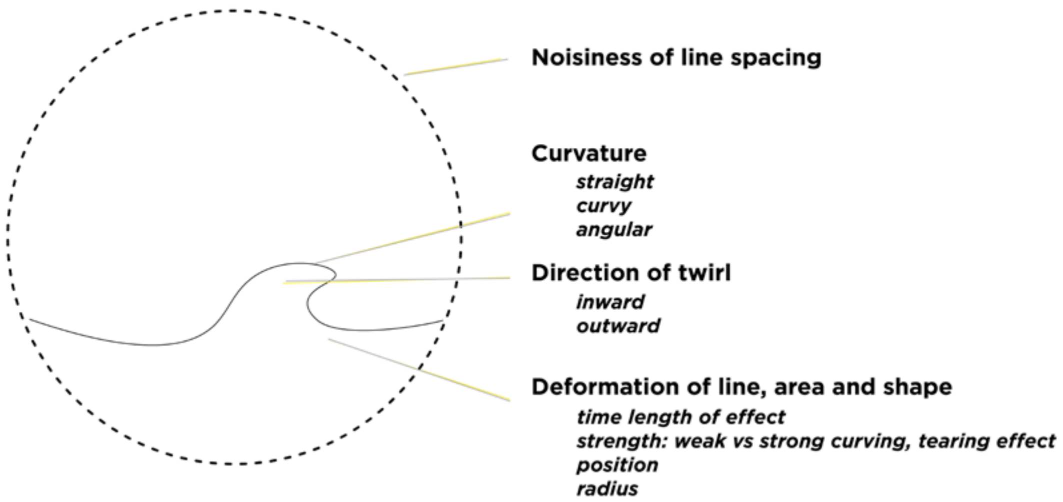


Fig. 5. The main design features used to essentially communicate the sentiment metadata of each movie.



The numbers of force attractors corresponded to the number of clusters generated by DBSCAN. The attractors' positions were the actual cluster centroids, and the radius of influence of the applied forces was proportional to their cluster size. A higher number of outliers (metaphor of noise) translates to higher distortion (uniformity of scan-line placement) as shown in (figure 5). A rounded object is generally perceived as calming and positive, whereas angular or pointy objects will be perceived as more intense and dominating. The direction of the twirl is controlled by the number of returned clusters. The effect of more or fuzzy clusters is one of subtle transformation, which indicates a lack of aligned opinions. Well-defined clusters, on the other hand, would add to the sensation of 'disturbance' with deeper distortions. To improve the communication of valence, a coloured line was added to the scan-line disk and its position determined by the actual valence value. Those of a positive valence will be on the upper part of the circle, and those of a negative valence will be on the lower part, with the color ranging from lighter pink to dark purple.

From this mapping, a set of 20 unique visuals was generated that can be described as signatures of the collective sentiment dynamics of each movie. These dynamics can be traced as deformations that express movement, energy, tensions, and entropy. As can be seen in (figure 2) well defined clusters, such as in the case of the movie ‘fear and loathing in Las Vegas’, indicates clearly separated and opposite clusters of opinions. Almost no outliers were found. The ‘wings of desire’ movie exhibits a multiplicity of dynamics as a result of the higher complexity of the data returned by DBSCAN. In that case, five clusters and sixteen outliers were found. Though it may be assumed that the form can be predicted from the corresponding cluster analysis, it represents a complex system that is quite sensitive to its initial conditions. (Figure 6) shows the expressive power of the generative scheme. With the ‘night of the living dead’ movie, there are only three well defined clusters, but their proximity and shape produce overlapping magnetic torques that produce local vorticities in the magnetic field. The purple lines are located in the lower part of the disc, which means the mean valence is negative, with the outliers contributing to a more-noisy form. This might be due to a low valence received even by the fans of the movie. This is quite normal given that this is a popular horror film and that even positive reviews contain many words with a negative connotation. In contrast, the movie “Plan Nine from Outer Space” appears more peaceful. Two clusters appear to be in an attraction dynamic, with only one outlier. A symmetrical, balanced, and low-noise visual results from the balanced and symmetrical collective opinion.

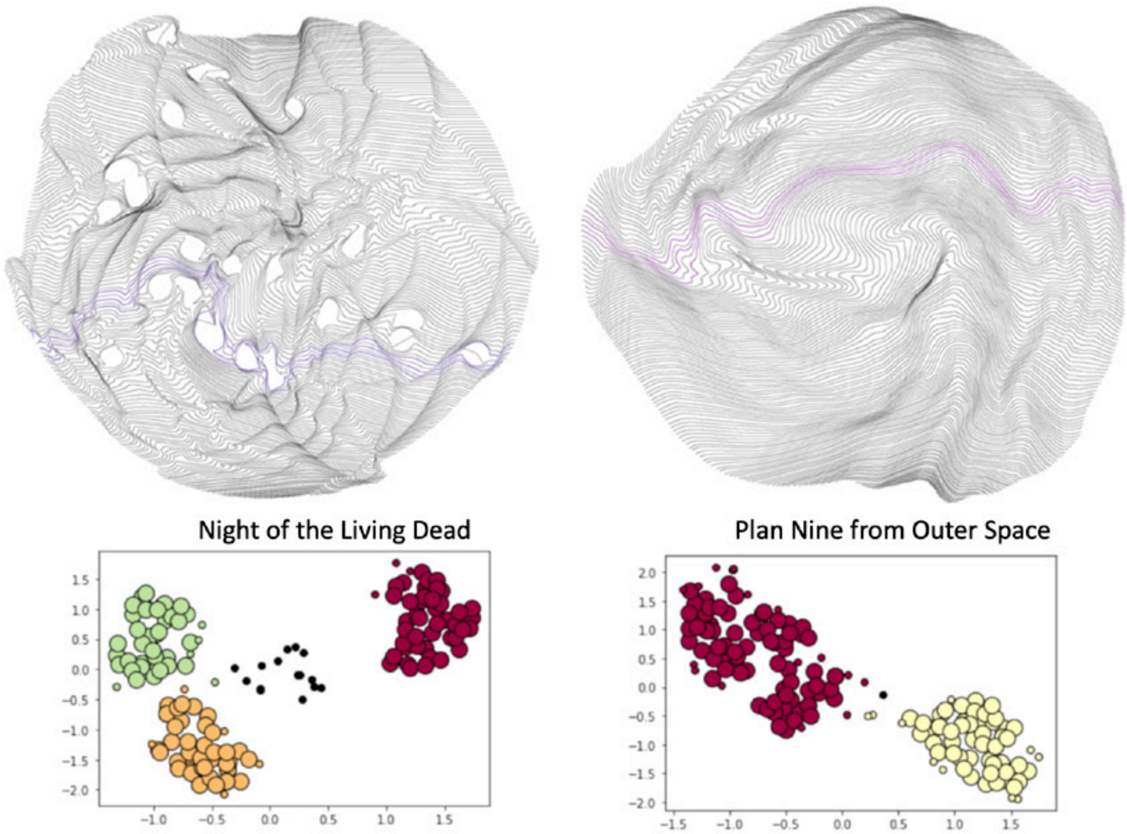


Fig. 6. Two visualizations based on emotion metadata. In the first visualization, the shapes are deeper and more chaotic, representing an intense and active emotional state. In the second visualization, the shapes are more orderly, representing a calmer emotional state. *Plan nine from outer space* and *Night of the Living Dead* belong to the same genre, fiction-horror movies, however their affective content differs. *Night of the living dead* creates a feeling of intense fear in the viewer, whereas *Plan Nine from Outer Space* creates a sense of humor and amusement :)

6. Evaluation and Results

A semi-structured interview with 79 participants evaluated the visuals based on their perceived valence as well as their metaphors, using a Likert scale ranging from 1-9, and the values were compared with the valence calculated from the NLP models. A set of synonyms describing appearance qualities was provided for each visual metaphor. Four of these metaphors were used to describe intrinsic data quality (randomness, diversity, separation, noise). Eight metaphors (harmony, calm, simplicity, loose, cold, strength, movement) were used to evaluate aesthetic perception of the generative artwork. The metaphors were derived from the art attributes assessment (AAS) questionnaire. A Krippendorff's alpha coefficient was used to measure the overall reliability of the metaphors and the percentage of agreement between individuals. The study found that there was a high level of agreement between individuals when it came to the metaphors and valence used to describe the intrinsic data quality of the visuals. From a total of 135 visuals with positive valence, 75 were correctly assigned as positive, with an accuracy of 57%. From the 22 negative visuals, 22 were correctly assigned, yielding an accuracy of 100%. The average accuracy error was 19% between participants and the pre-calculated valence values. That is, 97 out of 157 correct guesses corresponded to 62.3% of respondents who perceived correct values. Interesting to note is that although there were 135 positive visuals, only 76 were viewed positively, while 81 were perceived negatively. There was no surprise in this as many people are not in agreement with what is considered a positive valence in an abstract data visualization because it is often culturally bound or subjective. The coefficient of success for assigning data qualities was 0.63, while the coefficient of success for agreement rate was 0.75. For visual qualities, the coefficient of success was 0.58, while the average agreement rate was 0.74.

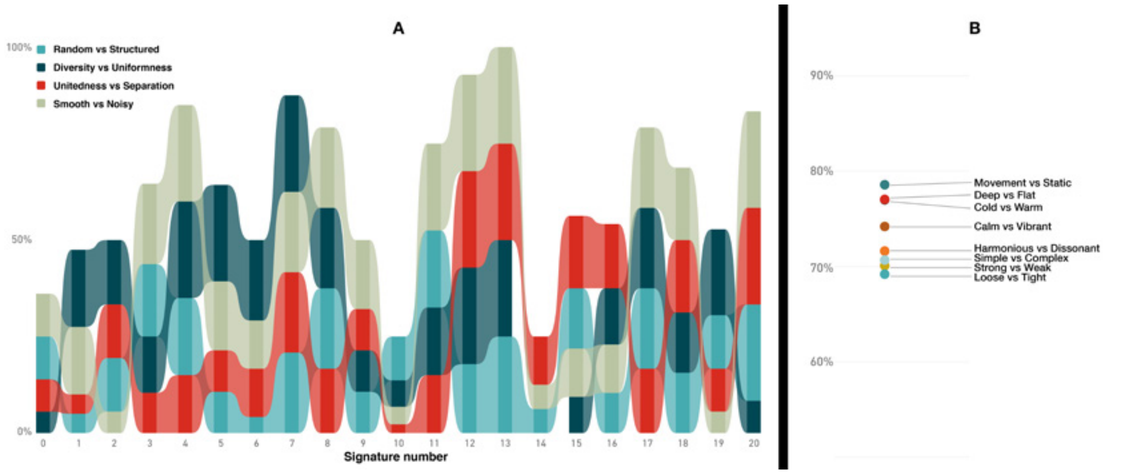


Fig. 7. A: Percentage of correctly assigned data qualities between movie signatures. B: Percentage of visual quality agreement between movie signatures.

In addition, some visual qualities resulted in a high agreement rate but low success rate, suggesting that some qualities were mapped in a way that produced the opposite perceptual effect. During the evaluation, participants were asked to assign their own expressive keywords to 3 different visuals in order to assess the consistency in perception when translated freely into words. Figure 8 shows the density distribution of the most commonly used words from a total of 373 words. A further interesting finding was that reviews with a negative level of subjectivity were often rated highly subjective.

Fig. 8. The keyword density visualization between movie signatures.

7. Discussion and Conclusions

This study shifted the focus from the 'form follows function' principle, to the aesthetic experience of the data visualization. A set of metadata extracted from textual data and a set of metaphors were used to express the intrinsic data qualities of a generative artwork. Engaging user's attention to the visual stimulus by emphasizing aesthetics within the data, such as in the case of data art, could form data-driven visualizations that communicate not only information but also subjective states of affection. Moreover, desired attributes of the data could be mapped as features of an artistic style in order to communicate an appearance based 'aura' of meaning. The results suggest that reducing a vast amount of data, and their inherent complexity, to a thinner set of metadata and using them as metaphors might bring clarity and increase communication capacity. The aesthetics criteria utilized for this study were based on empirical evidence and have not been evaluated from the general public's point of view. Adding further quantitative data, such as measuring pupil dilation, or monitoring brain activity through EEG or MRI could facilitate better understanding of the cognitive processes involved in the aesthetic experience. The use of quantitative data could complement the qualitative data in all the aforementioned domains. This suggests further research using a range of assessment methods for different communication strategies, with different approaches to aesthetics and their intersection.

We believe there is a big potential in merging the functional and aesthetic approach in data visualizations. Augmenting data with sentiment metadata as a visualization of collective affect can enhance the communication capacity and foster deeper understanding and empathy to the lay public. Communicating aesthetics based on the structural nature of the data rather than accurate depiction of the complexity of the data, can be a powerful technique to enhance the aesthetic experience of the public and everyday lives, ultimately facilitating social change.

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