

OmniArt: Sentiments through Colours

Arumoy Shome
arumoy.shome@gmail.com
University of Amsterdam
Amsterdam

Riccardo Bianci
rcdwhites@gmail.com
University of Amsterdam
Amsterdam

Shruti Rao
shrutirao94@gmail.com
University of Amsterdam
Amsterdam

ABSTRACT

Art has been the cornerstone of human expression and social progress through time. It is no wonder that art historians and daily enthusiasts alike have spent countless hours trying to understand more than what meets the eye. What an individual can draw from a painting is very subjective, but we now know that human mind has a high sensibility for well-defined subset of traits - one of them being colour. This paper describes the process of bringing a new light on how colours and emotional tone (sentiment) can be interlaced with one another. This is achieved with the use of widespread artificial intelligence techniques, a vast dataset of art meta-data (OmniArt) and state-of-the-art visual interaction tools.

KEYWORDS

omniart, d3, visualisation, sentiment analysis

ACM Reference Format:

Arumoy Shome, Riccardo Bianci, and Shruti Rao. 2020. OmniArt: Sentiments through Colours. In *Proceedings of* . ACM, New York, NY, USA, 8 pages. <https://doi.org/10.1145/nnnnnnn.nnnnnnn>

1 INTRODUCTION

The team members shared an interest in examining and understanding art and so the OmniArt dataset was chosen for the visualization. The dataset presented a unique opportunity to engage with art from a different perspective. Moreover, due to it being a popular choice for past visualisations, the dataset presented a design challenge that required coming up with unique ways to present the dataset. As the description associated with the art pieces were not very well examined, it was decided that sentiment analysis should be used to add additional information to the dataset. It was believed that the sentiment analysis might bring to light some key "sentiments" that were associated with each painting, based on its description. These descriptions could have been influenced by the painter, the colours in the painting or anything else that the writer was experiencing while writing the descriptions. The team wanted to know if such an influence did exist. And if it did, did the colours in the paintings specifically play any role in influencing the description.

OmniArt dataset itself was the result of gathering rich metadata along with artistic images from various sources. This dataset was the result of improvement to the quality of categorical analysis by

Strezoski and Worring [11]. They proposed a method that efficiently and accurately performs multi-task learning on the features in the OmniArt dataset.

Further, in order to encourage researchers and professionals towards deep learning models, Strezoski and Worring used the models trained from artistic paintings in the OmniArt dataset to demonstrate a plug and play deep learning model for the web [12]. This web application can in turn allow users to add their own models and examine them.

Outside of the OmniArt dataset, Gajarla and Gupta conducted an emotion based analysis by using deep learning for predicting emotions based on images [7]. Using the features extracted from images, they predicted an emotion value based on five distinct categories.

With this visualisation, the team attempted to provide a sentiment score based on description and see if any connections could be made between the sentiment values and the colours in the artworks. So far, most sentiment analysis research focuses on improving techniques to gather sentiments of people across the globe from social media [3, 5, 8]. On the other hand, in the art community, research is focused mainly on advancing human study of paintings and their interpretations [4, 10]. This project however, tries to combine these two very different worlds by introducing an algorithmic means of doing the same. The art community has mostly relied on human expertise to analyse artwork. There is no denying that human expertise in art analysis cannot be replaced. However, with this project, the team hoped to provide additional aid to these human efforts. Further, by providing an interactive visualisation, the team hoped that art analysis can be made more approachable to enthusiasts from varied backgrounds.

2 THE DATA

The OmniArt dataset provides a complete collection of paintings and relevant meta-data for exploration and research from BC till the present [11]. After exploring and evaluating the dataset attributes, it was agreed that attributes related to colour, time and description of the painting would be chosen. These values were used for analysing the relationship and evolution between colour and sentiment. The sentiments themselves were extracted using sentiment analysis. Sentiment analysis is a method that identifies and extracts subjective information from text and assesses the sentiment polarity of the content using techniques of contextual mining and natural language processing [13]. The data was further mapped to various visualisations so that findings could be shared with users. This section focuses on how the dataset was processed and how various attributes were mapped to each graph in the visualisation.

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ACM ISBN 978-x-xxxx-xxxx-x/YY/MM...\$15.00
<https://doi.org/10.1145/nnnnnnn.nnnnnnn>

2.1 Data Selection and Data Processing

In the OmniArt dataset, there were about 30 attributes that described the paintings and their relevant properties. Eight attributes were extracted from the OmniArt dataset and sentiment values were added as an additional attribute of the dataset.

- (1) *omni_id*: The collection number
- (2) *date*: The creation year of the painting
- (3) *century*: The century in which painting was created
- (4) *dominant_colour*: The hex colour code representing the painting's dominant colour
- (5) *dominant_colour_family*: The colour family of the painting's dominant colour
- (6) *palette*: A list of twelve hex colour codes representing all the colours in the painting
- (7) *description*: Textual description of the painting
- (8) *image_url*: The link to digital painting collection
- (9) *sentiment*: The sentiment rating of the painting

Python along with its data analysis packages - *Pandas*, *Numpy* and *Matplotlib* were used to examine the dataset. Upon examination, it was found that several paintings had several missing attribute values, as in the case of *date* and *century* and so they were removed. Before any sentiment analysis could be performed, the *description* column had to be cleaned up using *Regular Expression* (*Regex*). The description contained HTML tags such as ``, `<h>`, `<p>`, newline characters and special symbols that were removed. *description* that contained urls or irrelevant text (that were not descriptions) were then removed using a combination of *Python* scripts. The hex codes of colours in *palette* were stored as unicode values, so they were converted to *String* and stored as lists. Finally, dates in the BC period were identified and marked as negative values so that they could be correctly interpreted by *JavaScript*.

For the sentiment analysis itself, the recommended library *SentiStrength* was used. This library was appropriate for the task at hand because it specialises in short, informal text, which was the case with the *description* data [13]. *SentiStrength* further exploits a handmade dictionary of sentiment words with associated strength measures that prevented results from being generic [13]. *SentiStrength* also provides rating scales with values between -4 to +4, which return a more comprehensive sentiment result. Compared to some other sentiment analysis tools that return a sentiment polarity of positive, negative and neutral, nine levels of sentiment rating had a better impact in terms of visualisation and understanding [13].

2.2 Data Mapping

The *date* attribute records the year in which a painting was created and is used for the first form of grouping and categorization of the data. The dataset is grouped into the major art periods recorded through time which are listed in Table 1.

The *dominant_colour* and *sentiment* attributes are visible on the Radial Graph. Each concentric circle of the graph represents a sentiment value with positive sentiment values placed on the outer rings and negative sentiments placed on the inner rings, in an ordered manner. Each art piece is represented by its dominant colour in the form of a colour block, placed in the corresponding sentiment ring.

Period	Duration
Roman	-500 to 476
Middle Ages	476 to 1400
Renaissance	1400 to 1580
Baroque	1580 to 1750
Neoclassical	1750 to 1850
Realism	1850 to 1900
Impressionism	1865 to 1885
Post-Impressionism	1885 to 1910
Fauvism and Expressionism	1900 to 1935
Dada and Surrealism	1917 to 1950
Abstract Expressionism and Pop Art	1940 to 1970
Postmodernism and Deconstructivism	1970 to 2019

Table 1: Division of time

The Stream Graph can be thought of as an alternative visualization to the Radial Graph if it were "unrolled" and placed onto a linear timeline. Each stream belongs to a *sentiment* value whose thickness is determined by the magnitude of paintings associated with that sentiment value.

The Colour Palette displays all the colours of the paintings in the selection made using the brush of the Stream Graph. The colours are grouped by hue and sorted by frequency thus, most frequently occurring colours appear on the top left and least frequently occurring colours appear on bottom right. The Colour Palette utilises a Treemap algorithm to display the colours in an efficient manner.

Finally, using the *image_url* attribute, the Gallery Viewer is populated with at most 10 random sample of paintings from the selection made using the Stream Graph brush.

3 INTERACTION DESIGN

The visualisation is overall a multiview design with three graph components - a Radial Graph, a Stream Graph and a Colour Palette Graph and a fourth Gallery Viewer. Ensuring appropriate interactions were crucial in order to guide the user through the visualisation in appropriate manner. To aid with this, insight was drawn from the interaction techniques in the InfoVis community [15]. Key interaction features were added to the visualisation, namely *Select*, *Explore*, *Reconfigure*, *Encode*, *Abstract/Elaborate*, *Filter* and *Connect*.

Select. The brush was used as selection tool to allow users to mark and select data. On the Radial Graph, users can select areas of interest based on the dominant colours in a given time period and examine the Stream Graph. Time on the Stream Graph can be further narrowed down to specific years for a micro-level examination. With the selection brush, users can be enabled to view different data or subsets of the same data at a given time.

Explore. Users are able to explore the evolution of colours and number of art pieces through the major art periods by interacting with the Radial Graph. Furthermore, by scrolling the Stream Graph brush, users are also able to see the evolution of the colour palette through time.

Reconfigure. Reconfiguration is favoured over Encoding in the system to reduce cognitive load from context switching. Changing the art period updates the Radial Graph showing only the relevant art pieces. The concentric circles of the Graph are also updated such that only the sentiments for which data is available are shown. Selections made using the circular brush on the Radial Graph instantly updates the Stream Graph. Similar philosophy is used in the Stream Graph to keep the visual representation uniform (users will only see 2 streams if there are only 2 circles) and interactions with the brush of the Stream Graph updates the Colour Palette and Gallery Viewer. By allowing the users to view the same data through different representations, it is hoped that there can be better cognitive perception of the ideas being expressed.

Abstract/Elaborate. Users are able to look at a subset of the data using the brushes provided with the Radial and Stream Graph. Users are able to select a subset of paintings using the circular brush of the Radial Graph. This updates the Stream Graph which now represents the data of the paintings selected by the circular brush. Hovering over a stream on the Stream Graph distinguishes it from the others thus allowing users to carefully observe the flow of a particular stream. Users are further able to make a sub selection using the brush on the Stream Graph. This allows them to (a) look at the colours used in the paintings that were selected and (b) look at how the palette evolves over time.

Filter. Filters are applied at all levels, across all the graphs. The Radial Graph presents dominant painting colours based on the sub-period of art history. Moving across these art periods, the Radial Graph selectively displays dominant colour data, relevant to that specific period. The brush on the Radial Graph further allows for a sub-selection of dominant colours already present on the Radial Graph. The Colour Palette Graph also shows colour palette based on the time period that can be highlighted on the Stream Graph by the user. Finally, based on the Stream Graph selection, the Gallery Viewer also displays just 10 randomly sampled images. These filters were considered necessary due to the size of the data and the complexity of the information being conveyed. With the filters in place, users can selectively expose themselves to different amounts of data being displayed at their own pace.

Connect. All the three graphs and the Gallery Viewer together play a role in connecting the idea that sentiment may be related to colours. After examining the spread of dominant colours for each sentiment value, the Stream Graph provides additional information regarding the distribution of paintings for each sentiment. Thus, once the user gets an idea of the overall distribution of dominant colours, they can visually examine the number of pieces that were found for each sentiment. Moreover, having viewed the dominant colours for a time period, users can next use the Colour Palette Graph to view all the colours supporting those dominant colours. Once on the Palette Graph, they can see evidence of the colours in the Gallery Viewer.

The state diagram for the system is shown in Figure 1. The 4 individual components of the system, namely the Radial Graph, Stream Graph, Colour Palette and Gallery Viewer were chosen as the states. This is because each component represents the state

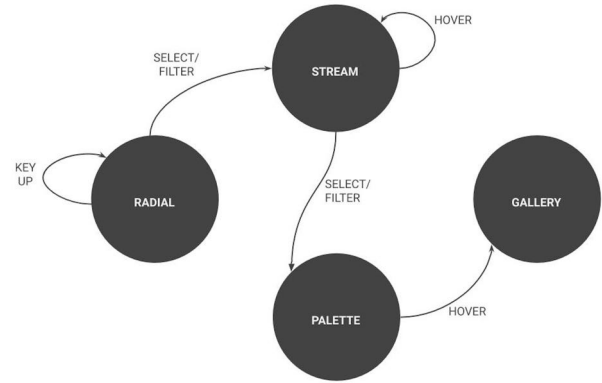


Figure 1: State Diagram of visualisation system

that the user should be exploring after interacting with the prior component.

4 EVALUATION DESIGN

The system was presented to our colleagues and several other UvA students over a duration of an hour. During this session, the users were given a short demo highlighting the functionality of the entire system. Following this demo, users were able to use the system themselves and express their feedback, questions and comments. Most users were extremely pleased with the overall aesthetics of the system. Many users felt that the system looked nice and thought that it was fast and responsive, lacking any significant lag or delay. There were a few concerns regarding the navigation of the system. Due to the absence of an interactive walkthrough or tutorial which explained the functionality and interactions available to each components of the system, some users felt that navigating the system was challenging. Many users felt that they were able to gain some valuable insight into the data with the visualisations. One major concern that a few users had was regarding the method used to conduct the sentiment analysis. Users felt that the sentiment analysis should have been conducted directly on the colours of a painting (instead of the description text) since our main idea was to look at sentiments through colour. The team is well aware of this limitation and given the focus of the project was towards visualisation of data (not accuracy of the visualisation) chose to move forward with sentiment analysis using the description text.

5 VISUAL ANALYTICS DESIGN

The data is transformed and mapped to the visualisation as described in section 2. The aim of the project was to be able to do some story telling but primarily focus on information visualisation. As such, the system is not geared towards visual analytics and falls short on several design criteria for visual analytics as laid out in the *Knowledge Generation Model for Visual Analytics* by Sacha et al. [9]. There is no notion of a model in the system, thus users are not able to visualise the model in an iterative manner and make changes to it. The system provides users with a rich exploration loop, primarily through interactions with the visualisation. Users are able to see the

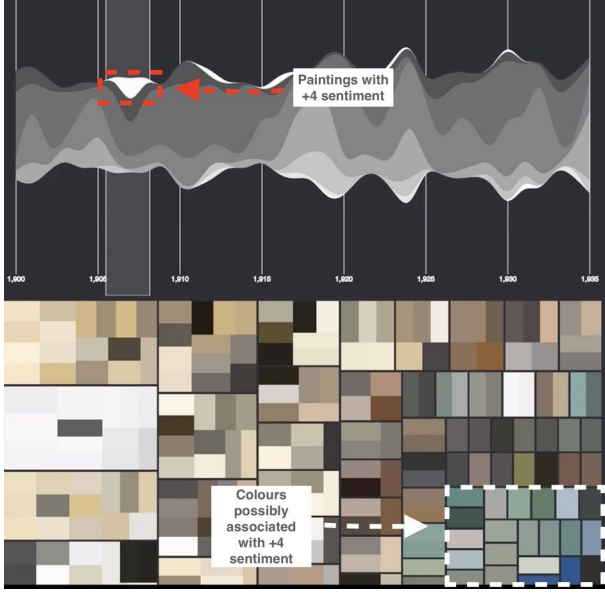


Figure 2: Example scenario of insight gained from Stream Graph and Colour Palette

dominant colours of paintings and how they change through various art periods such as Stone Age, Rome, Classical, Neo-Classical, Pop Art and many more from the Radial Chart (see Figure 4). The Stream Graph allows users to look at the distribution of art pieces through time for each sentiment group (see Figure 5). This allows users to gain insights such as which art period had the most amount of paintings, how the number of paintings change through time, and which sentiment groups contain the most paintings in a given art period.

Users are further able to make a time based selection on the Stream Graph, which presents the colour palette of all paintings (for given selection) grouped by hue and count (see Figure 6). This allows users to see the most and least frequently used colours (most frequent colours appear on top left and least frequent colours appear bottom right).

Figure 2 presents an example of an insight that was gained by users whilst using the system. In the *Fauvism and Expressionism* art period, it was noticed that a small speck of paintings between X and Y were associated with a highly positive (+3) sentiment. Using the brush on the Stream Graph, the colour palette associated with that time range was viewed. From the Colour Palette Graph, it could be speculated that the bright colours towards the bottom right, likely belonged to those paintings.

The system provides users with a partial verification loop. Once a selection is made on the Radial Graph, the Stream Graph gets updated based on the selection of the Radial Graph. However, the user is unable to map the colours on the Radial Graph to a position on the Stream Graph, thus causing an incomplete verification loop.

As shown in Figure 3, the system is however, able to provide a complete verification loop for a sub-system of the visualisation using the Stream Graph, Colour Palette and Gallery Viewer. When the user makes a selection on the Stream Graph, the Colour Palette

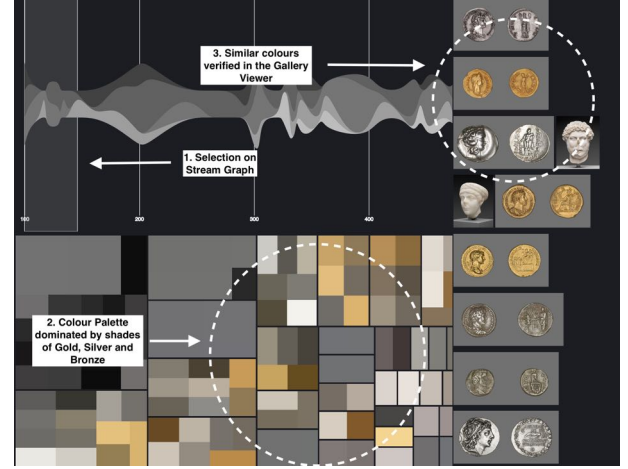


Figure 3: Example scenario of verification loop provided by Stream Graph, Colour Palette and Gallery Viewer

is updated allowing users to see all the colours in the selected painting. The users are then able to verify that these colours have actually been used in the painting, by hovering over the Colour Palette. This brings out the Gallery Viewer on the right side of the screen containing a random sample of at most 10 paintings from the selection.

The system can be extended into a full visual analytic system by introducing a model. This model should ideally be changed in an iterative manner using the visualisation as a guide and incorporate user feedback into the system.

6 STORY TELLING DESIGN

The visualisation is geared towards a general audience possessing a wide range of backgrounds. The team wanted to share the hypothesis that colours could be compared against sentiments and that this relationship could be observed over time. The data for this purpose mainly comprised of colour values in the form of dominant colours and colour palettes. The data also contained numerical sentiment values and images of paintings.

The general approach was to have vertical logic in terms to storytelling [15]. Each graph is related to the other and information from one graph complements or supplements the others. Keeping these factors in mind, the overall design had to be a journey to visually see the dominant colours across sentiments in some time period. Starting with the very first visual element - the Radial Graph, users should be able to understand that the visualisation is about relating sentiments with dominant colours in paintings. After manipulating the Radial Graph, users should be motivated to learn more about sentiments and the complete colour palettes from all paintings associated with the time period. At any point, users should be able to go back and forth between visual elements in order to re-examine certain aspects of the graphs. They should finally be able to validate these colours by looking at the paintings that they were extracted from and have formed some conclusions.

The very first feature that users examine is the relationship between dominant colours and sentiments across various time periods.

Here, users should be able to move back and forth between the various time periods and view the dominant colours for sentiments. For this, it was decided to use a radially designed graph (Figure 4). Each concentric circle in the graph indicates a level of sentiment, starting from the most positive sentiment in the outer most circle to the most negative sentiment in the inner most circle. The dominant colours for each painting are placed within each circle, and denoted the sentiment associated with it. The time periods are changeable and a brush overlaid on top of the chart enables users to select a specific set of colours. A radial shape was chosen for this key visualisation because of its symmetric nature. The human brain subconsciously prefers symmetry and a circle is the most symmetric shape of all. Further, art pieces from the very beginning of art history up until the very latest are in the dataset [6]. The team wanted to convey a natural sense of completeness in time - beginning at the very earliest time period, cycling through following periods and eventually coming back to the very first period again. Again, a circle was the perfect shape for conveying this continuity and completeness [2, 6]. An overlaying data selection brush was added in the shape of a pie to indicate it as a subset of the Radial Graph. The brush was further made semi-opaque to avoid confusion with the already present colours in the chart. By subtly undermining it's presence with the absence of colour, the brush's role was clearly maintained as that of a selection tool. A simple text indicator of the current time period was aligned in an arc over the top of the Radial Graph to maintain the overall circular shape. Using a combination of numbers and text, the pieces selected by the brush are shown in the centre of the chart to avoid being missed by the viewer. During the transitioning of periods, there was a lot of motion in the graph - from the colours and concentric circles being added or removed. Thus, only the numeric values in the text in the middle were allowed to change. This was done to minimise unnecessary motion in the graph.

To show the distribution of various sentiments for the selected time period, a stream graph was used [1]. A stacked chart such as the stream graph was seen as the simplest way to show categorical information changing with time [1]. In order to combat the sometimes hard to follow nature of the Stream Graph, a tool-tip style highlight was added. Based on the user's mouse position, the stream directly under it gets highlighted to bring it to the users attention and provide visual cues. Further, the sentiment associated with that stream is displayed. This was done to avoid having a separate legend and further cluttering the graph space.

Given the highly colour dependent nature of the visualisation, various shades of grey were chosen as colours for the Stream Graph. This is because the team clearly wanted to express that the colours for the individual streams had no meaning. The Stream Graph also has an overlaying brush that was designed with the exact principles as the Radial Graph's brush. It is meant to be noticed by the user only while interacting with the graph and not otherwise (Figure 5).

The Colour Palette Graph is a very colour heavy visualisation and it's sole purpose is to give users a visual idea of all the colours used in paintings over the chosen time period in one glance. The graph is meant to invoke the idea of an artist paint box inlaid with various paints. Colours in the palette graph are divided into the hue groups. To avoid any further clutter and keep the focus on colours, **Gestalts Law** were applied to design [15]. By this Law,

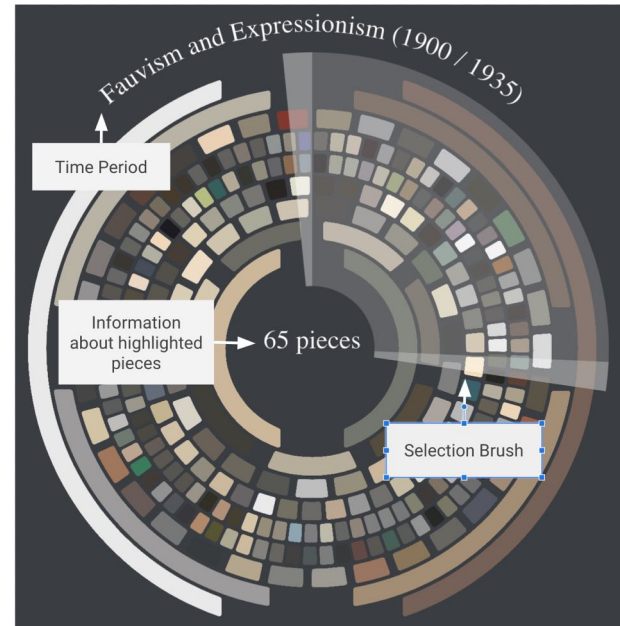


Figure 4: Radial Chart

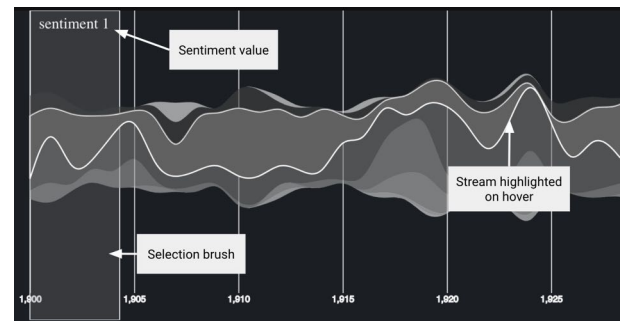


Figure 5: Stream Graph

humans naturally perceive objects as organised patterns and objects [15]. Thus, additional information about hue groups and colour frequencies are conveyed via design rather than text.

The background colour of the visualisation was made visible via the padding and this automatically added gaps to give users visual cues regarding the separate hue groups. Within each hue group, the colours were tiled seamlessly to give the impression of a palette. Further, the most frequently occurring colours got represented by the largest hue boxes. Thus the size of the hue rectangle indicates the frequency of the colour appearing in the paintings in a given period (Figure 6).

Overall, the focus was kept on visualising the various colours. User attention was steered through the visualisation via the help of non-intrusive selection brushes. Inspired by Gestalts Law, additional chart information was displayed in a minimal fashion, choosing to rely on visual cues rather than textual information. For the Stream Graph that showed no colour data, grey was used to



Figure 6: Colour Palette Graph

prevent confusion with colours from the other graphs. Visual cues were instead used via tool-tips to add information.

7 VISUAL THINKING DESIGN

As described in [14], the absence of a model of the world in our head, asks for the development of different techniques to exploit the human rapid eye movements and sampling of the environment in gaining insights of the art pieces. Starting from this evidence, the visualisation was built around a cohesive exploration flow where each component exhibits sensible patterns in response to a subset of possible user queries that were thought to be common in this case study. Before diving into the details of the various adopted patterns, a list containing some of the critical visual queries to solve is presented below:

- What time period is currently being displayed?
- How many art pieces is the user able to view?
- How is the sentiment distributed among the art pieces?
- What does the Stream Graph express regarding the sentiment?
- What connections does the Stream Graph have with the Colour Palette and the Radial Graph?
- How is the brush selection dynamically linked to the Colour Palette?
- What does the colour arrangement in the Colour Palette or the Radial Graph show?
- How does the paintings displayed in the Gallery Viewer relate to the overall visual process?

Researches have suggested that a pattern is easy-to-see if it relies upon a division in regions through a combination of shapes, colours, motion and texture. Following this principle, the visualisation is rooted in three main panels with custom scaling and visibility controls triggered by mouse interaction and key events.

This initial structure enables to fit the information acquired with eye movements in the same screen and increases its availability while reducing the user query cost. Two panels containing the Radial Graph, Stream Graph and Colour Palette are displayed that inhibit the user's initial scan of the environment aided by the power of human parallel perceptual processing 7. The user abstracts a regionally distributed hierarchical/flow structure and registers the 3-weighted components into their visual working memory. This

visual impact also intuitively targets the user attention to the main Radial Graph region while distinguishing colour as an exploration feature of the visualisation.

The Radial Graph uses an aesthetically pleasing symmetrical structure with word symbols that instantly focuses the user's attention to label the concept of the displayed time period and the corresponding number of art pieces to be loaded into their verbal working memory. Here, the embedded organisational structure of the chart and the layout of the coloured tiles/blocks (art-pieces) within each of the concentric circles also activates the user's visual working memory to search and identify nested patterns. A key-event interaction is used to switch between time periods to explore as a whole. Within a period, the user can now explore the interaction feature of the Radial Graph. As brushing is a rapid interactive technique that binds the user and the computer into a coupled system, this chosen feature enables the user to filter and select a subset of the art pieces from the Radial Graph for further examination. As the user plays with the brushing arc/window, the resulting change in the other components (Stream Graph and Colour Palette Graph), steer the user's attention to the overall flow structure and dependent updates in the visualisation.

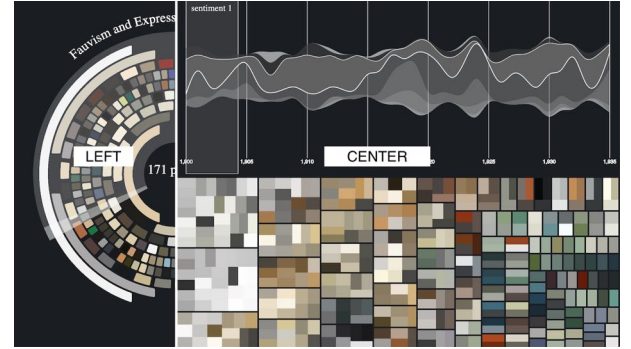


Figure 7: Enriched information context triggered by the user interaction with panels

Once a range of art pieces has been selected from the Radial Graph, a simple mouse hover over the second panel brings its components to the main focus of the user. This shadows the previously focal Radial Graph while keeping it partially visible for feedback/reference and easy of navigation. 7 The panel displays two dynamically linked components that are arranged to ease a parallel perceptual view as this stage of the visualisation process can be interactive-feedback intensive. The Stream Graph shows a temporal distribution of each sentiment (concentric circles of the Radial Graph) for pieces enclosed in the radial graph brush selection. It uses the full potential of an interactive display for visual cues as a mouse-hover over each stream highlights its unique pattern, illuminates its semantic meaning and displays a pop-out label as a cognitive marker to a transitional object in the visual working memory. Fixating at different streams and deeper processing of relationships and links, corresponding to knowledge structures in the verbal working memory, reveal some insight into the sentiment analysis over a period. Another interactive feature of the Stream Graph is the dynamic brush slider that can be used to further filter

a sub-time range for the Colour Palette. As the user triggers the brush filter on the Stream Graph, an instant change of the Colour Palette being updated captures user attention for a targeted visual analysis. This linked dynamic change of the Colour Palette enables the possibility of an enhanced rate of several queries per second. Visual scanning of the Colour Palette induces the concept of an organised, ratio and size-based mapping of colour boxes. Here, an adaptive colour-density visual pattern is loaded into the user's visual working memory for slider several queries. As the visual information available here is manipulated by the dynamic brush selection over the Stream Graph, an exploratory visual feedback navigation between the Stream Graph and the Colour Palette can reveal insightful relations between sentiment and colour of the art pieces. Another mouse-hover over the Colour Palette results in a gallery of pictures, corresponding to the actual encoded art pieces for the Steam Graph slider selection, that pops-out as the of the visualisation 8. The user can also navigate colour presence similarities between the paintings in the Gallery and a egocentric map of the Colour Palette. They are now given a chance to reflect on their personal-built visual perception of the art pieces with respect to time, colour and sentiment.

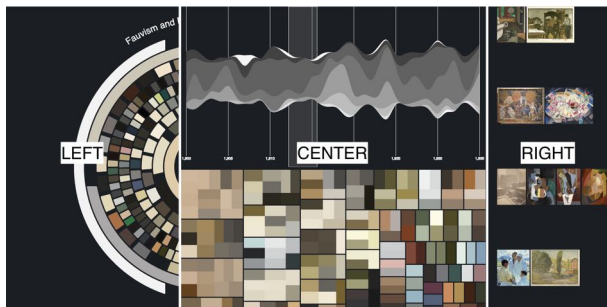


Figure 8: All three visualisation panels in parallel

Finally, the user can navigate back and forth to any stage of the visualisation process by a simple hover over the components to reinforce different filters and selections for comparisons or detailed analysis.

8 SCIENTIFIC EXCELLENCE

Since the beginning, the aim of the visualisation was to take the user into a journey across art movements with a special focus on the linkage between colours and sentiment. The study matter (art pieces) is always on screen, but it takes different forms and by doing so allows the user to explore potential connections from different angles.

The most immediate insight is obtained from the Radial Graph as soon as the visualisation system loads. The difference in density and colours of art pieces, along with the sentiments on concentric circles, direct the user towards specific areas that stand out. The circular brush visually defines a chosen area for which in-depth aspects get projected on to the other panels. After the first interaction with

the Radial Graph, the focus is now on the central panel, where sentiment and colours are presented through patterns that leverage

grouping by properties and magnitudes. Here the user can observe and hypothesise on how fluctuation in thickness in the sentiment stream are induced by certain subsets of the Colour Palette. The way these two row correlate and evolve together at each interaction, sparks immediate matching with consequent insights on the user side.

With a newly added time reference and after two-thirds of the journey through the visualisation, the user is now fully aware about the different factors that shaped the patterns into their current appearance. The final step is to provide a possible materialisation of the insights assembled so far. This objective is achieved with the right-most panel that showcases a sample of related art pieces. The presence of the raw data at the end provides a logical conclusion and connects the end of the visualisation with its beginning.

Two good examples of significant insights are given by the exploration of Abstract Expressionism/Pop Art and Roman periods.

Abstract Expressionism and Pop Art

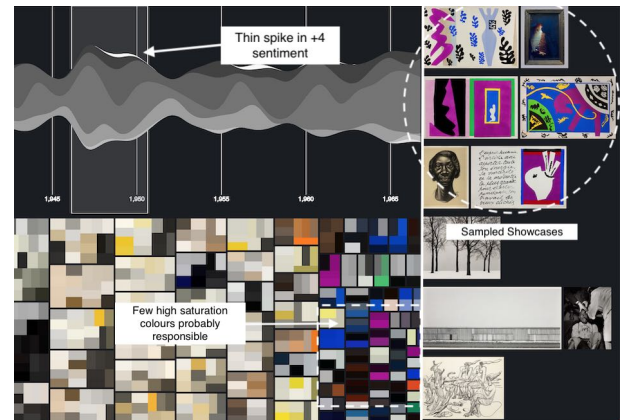


Figure 9: Examples of insights from the Pop Art movement.

In the five years spanning from 1945 to 1950, the presence of a thin white stripe with high sentiment value catches the attention of the user. When scaled and positioned, the brush triggers the update of the colour palette which in return shows an interesting area in the bottom right corner. Here the less frequent colours show very strong tints. After hovering said section, the Gallery Viewer is quick to reveal a small number of very peculiar paintings which are with all probabilities related to strong emotional states.

Roman

In the Roman case study, the attention is captured by a very thick stream section among a neutral sentiment value. With the same navigation process, it is possible to see that the most frequent colours for that time range are very mild with low saturation values. The sampling shows mostly picture of artefacts, known to carry a smaller emotional value compared to paintings. This might justify the shape of the Stream Graph in the area surroundings of sentiment 0.

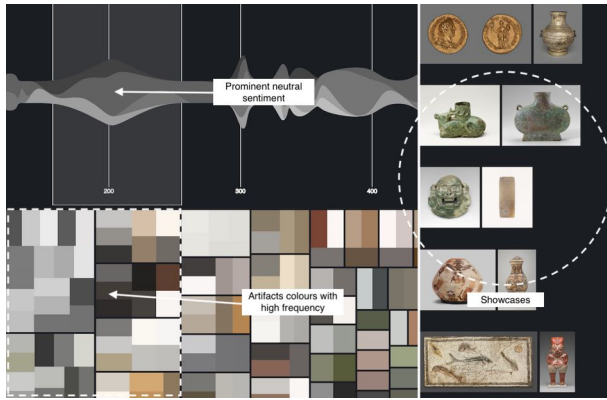


Figure 10: Examples of insights from the Roman art movement.

9 CONCLUSION

While the visualisation is a positive step towards enriching the art community with A.I. generated insights, there are several aspects of the visualisation that can be improved. First, the sentiment analysis itself is flawed. It depends entirely on the description provided by a single user. Thus the sentiments obtained are possibly highly biased. An improvement could be to gather real user impressions of various paintings or combine text from multiple sources to generate painting descriptions. Next, the sentiment analysis tool itself has a corpus that can be updated with context relevant words.

In terms of the visualisation itself, an interactive walk through should be provided so that users can better understand the system. A sentiment scale placed directly on the Radial Graph can provide further context to the user in terms of which concentric circle represents what sentiment. The Gallery Viewer can be updated to show image data on hover. The Stream Graph could also show the counts of the paintings on hover and not rely on the user to visually examine the stream thickness. Finally, the Colour Palette has no interaction at this moment. The Gallery Viewer could instead show images based on hover over the various hue groups. This would allow users to verify and compare paintings for each hue group.

ACKNOWLEDGMENTS

The work of this paper was supported by Gjorgji Strezoski, he was of great help in all the critical phases and provided us with his valuable time and point of view. The appreciation goes also towards Prof. Marcel Worring and his staff for having introduced us with engaging lectures and materials to the ever-evolving and fascinating field of Information Visualization.

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