Data Relation and Similarity Analysis and Visual Presentation via PaintRelVis: A Functional Art Gallery

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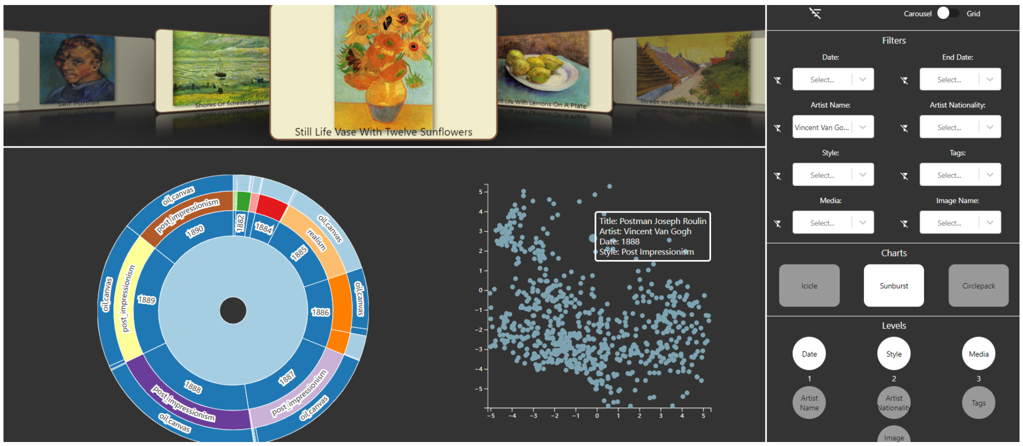

Fig. 1. User Interface of the Visualization Project, a Web-based visualization system to search for paintings filtered by painters or styles within specific time period; the system visualizes the distribution of every searched results through Sunburst or Scatter plot; clicking on a painting in the scrolling view will show the three paintings that are most similar to it.

Abstract—If a user wants to browse paintings, there are different criteria that can be considered. For example, paintings can be considered similar based on the date of creation, similar painting styles, the media used, nations that are close geographically, or artists of compatible doctrines. According to our research, there are not many applications that are capable of providing users with a robust filter function based on painting metadata. Moreover, there are no simple and free applications to intuitively display the similarities between paintings and the various correlations in the data. In this paper, we design and implement an interactive page, which showcases 23,245 paintings and related information, aiming to provide users with a unified platform to browse paintings. The main contributions of our design can be categorized as two aspects: the utilization of a pre-trained VGG16 network to obtain image embeddings and calculate the cosine similarity between paintings, and an interactive and user-friendly visualization page based on the D3 library and the React framework for users to operate and browse the wide assortment of paintings.

Index Terms—Visualization, Image Embedding, Similar Paintings, User Interaction, Hierarchical Analysis

1 Introduction

Currently, there are no obvious options for browsing extensive selections of paintings. For the sake of building a knowledge base and for scientific reasons, most websites just contain basic information about the paintings and links to separate pages with images of said paintings.

In this project, we attempt to alleviate this issue by creating an interactive application that allows for intuitive visualisation and filtering of a large collection of images.

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We apply our solution to the Artistic Visual Storytelling dataset, consisting of roughly 23 000 paintings and additional information about each painting.

In order to enrich the dataset, we sought external data like information about the paintings, using websites like Wikipedia. We found that many paintings do not have information that is ready to be retrieved and there are translation problems in the dataset, probably because the artists are from different nationalities. Also, many paintings do not have information in the original records and users need to create corresponding pages and add information manually. At the same time, we also investigated other large websites that focus on art information, such as Arthive[1], WikiArt[2], Internationl Foundation for Art Research (IFAR)[3], etc. Unfortunately, they all suffer from incomplete or missing information.

Our aim with PaintRelVis is to create an application as a web-based system to implement interaction and visualization exploring paintings from various styles, created by numerous famous painters in different dates.

Consequently, our aspirations for an effective visualization tool were the following:

I. Retrieve information about paintings with high similarity according to the presentation in the gallery.

II. Obtain historical context by comparing the original region, painting style and artist information of paintings that are deemed similar.

III. Obtain the popularity and evolution of painting styles over a historical period.

IV. Examine the representative styles of a specific artist at relative era and percentage of the respective.

V. Understand the influence of the mediums of painting on the style of artworks and their geographical distribution at the national level.

PaintRelVis gets inspiration from an article that proposes a framework for analyzing multitask learning in works of art [2],which is a system as well as an application which is published to the open-source library Github[4].

The structure of this paper will be as follows. In section *Related Work*, we will examine a selection of academic work related to our research question. In section *Application Background and Motivation*, we will introduce the required knowledge and motivation of our project. Then in section *Requirement Analysis*, user scenarios and functional requirements will be analysed in detail. In section *Design of System Architecture*, we will go through the individual part of our user interface. Next, in section *Implementation Methods and Details*, we will outline the methods we used to perform this research, including data processing, front-end and back-end. In section *Results*, we will present the results of our research. Finally, in section *Reflection*, effectiveness and limitation of our research will be discussed and in section *Conclusion and Future work*, we will summarize our work and provide future directions for improvement.

2 Related Work

Research scholars have long worked on developing art visualization systems, starting with projects such as Painting-91 [10]. The original visual arts field did not have the algorithms present in today's artificial intelligence field at their disposal, but only proposed a "novel" large-scale digital painting dataset. Therefore, in order to get good performance from their work, the artist and the artistic style of the image are classified by combining local or global features.

Subsequent research areas gradually transitioned from huge datasets to exploratory interfaces. ArtSight [11] is a comprehensive query-by-color interactive interface built on the large art dataset OmniArt.This project allows users to browse some 3 million artworks in the OmniArt collection by color, and filter each result set hierarchically by multiple properties present in the collection itself. This is the first time a researcher has tried to apply a search engine to the visual arts, and the filtering function of the paintings in our project is based on the achievements of this project.

Due to the wide application of neural networks, branching methods allow us to exploit both the coarse layout and fine-grained structure of paintings. A typical example is multi-task painting classification based on deep multi-branch neural networks [12]. The project relies on a trained transformer network to identify the most recognizable sub-regions in a painting. Similar to the multi-task learning method used in our project to identify painters and artistic styles

In recent visual arts research, more and more works of art are digitized. Models are commonly used in art classification as a necessary method. Studies have shown that the art classification performance when using transfer learning has been greatly improved compared to previous work [13]. Therefore, we also compared the classification capabilities of multiple models in the project, and finally used the optimized model structure to effectively improve the model performance, so that higher-speed similarity calculation can be achieved.

3 Application Background and Motivation

3.1 Background concepts of our project

VGG16 network The VGG16 network is characterized by its simplicity, as both the convolutional and pooling layers

[1] Arthive https://arthive.com/

[2] WikiArt:Visual Art Encyclopedia https://www.wikiart.org/

[3] IFAR https://ifar.org/cat_rais.php

[4] PaintRelVis https://github.com/mark-alence/multimedia-analytics

use the same parameters. Therefore, the VGG16 network was chosen to obtain the image embeddings. In addition, it can achieve faster and more robust learning than ResNet, and can better adapt to users' high concurrent requests, thereby achieving faster responses.

D3 D3.js is a JavaScript library based on data manipulation documents. D3 implements binding arbitrary data to the Document Object Model (DOM) and then applies data-driven transformations to the document. As a result, D3 is capable of supporting large datasets and dynamic behaviors for interaction and animation with minimal overhead, and is extremely fast.

React framework React is an open-source JavaScript framework used for building or rendering a hierarchy of UI components and providing support for the front-end and server-side. Tthe React framework has independent logic and helps to build reusable components. Moreover, the React framework uses a virtual structure to update data, which means it doesn't take extra load when loading web pages, resulting in faster response times and a smooth client-side experience. This is exactly what the visualization page needed, as the interface needed to host a larger dataset.

3.2 Limitations of existing visualization interfaces and the motivation for our work

Art appreciation has always been easily overlooked due to its niche nature. However, based on information on social networks, there is no highly integrated page with filtering functions for users to appreciate paintings. Users had to look up different pages in search engines to browse the paintings they wanted to see. This complicated and tedious process often frustrates those who are interested in art. Therefore, this project is motivated by the goal to design and implement an interactive page containing 23,245 paintings and related information, aiming to provide users with a unified painting browsing platform. In this way, users will not be bothered by the complicated search process, and simple clicks in our interactive interface can complete the functions that the search engine cannot.

In addition, the VGG16 architecture is used, which is a neural network that has proven to dominate in art analysis. Apart from neural networks, the visual art domain is characterized by the complexity and richness of its data, such as the semantic relationship between artists and their paintings. Our project explores the connections that are present in the data and present them in a visual way.

4 Requirement Analysis

The goal of this section is to develop requirements for a system to analyze and propagate painting similarity for this visualization. For this purpose, we analyze the usage scenarios and the reasoning processes that should be able to be predicted for the study. This analysis allowed us to derive the functional requirements for the system.

4.1 Usage Scenarios

PaintRelVis was designed with the idea to satisfy not only the basic analysis of the painting data in the original dataset such as the presentation of the data association hierarchy and the display of the status of the data divisions, but also the dissemination of the results of the paintings with a high degree of similarity resulting from the algorithmic calculation for research value.

Through this system, it is possible to achieve the visual collection and organization of various information about paintings [6], and also to provide means according to having different directions of research, making it reproducible and scalable [8] for users and researchers. According to the above, our system has two main types of users. On the one hand, there are those who use it to collect, organize and analyze pictorial artworks, who can customize the way important information is combined according to different selectors, and who visualize the correlation and divisional status of data through multiple views, which we call this type of user *Researcher*. On the other hand, paintings can be viewed by regular users. We envision a way to show basic information about a painting on mouse hover, as well as to select a grid gallery and to view a clear larger image of a single painting by clicking on it. We call this type of user an *Appreciator*.

4.2 Functional Requirements

The user's intention for using the system may vary to a great extent, for example, more complex for research and relatively simple for education and for the presentation of drawings. The painting dataset has 5 to 7 important categories of metadata, so researchers want to investigate the impact of historical events on paintings through their correlation with paintings, but also want to be able to carry out their research on paintings through different permutations, based on national history and style, among others.

Demonstration Users want interactive carousel (which would make each painting appear larger visually) and an at-a-glance gallery, so we set up a switch to split the basic gallery display into a grid (for displaying multiple paintings side-by-side) and a carousel (for rotating and interacting with eligible paintings) according to some analysis in [7].

Selection&Filtering The researcher wanted to present the connections between paintings in multiple arrangements and to create a hierarchical relationship or a subordinate or divisional relationship that could be visualized. The system therefore needed to have multiple selection capabilities, i.e., multiple filters that would allow the user to make custom selections. The filters also need to have a certain logic, for example, the selection of the year cannot start with 1858 and end with 1496, the selection of a painter cannot be presented in the style filter without options corresponding to his style, and so on. In order to provide the convenience for users, system should be equipped with the function of corresponding content compensation, that is, for example, when user already input the first two digits of a year like *15*, the filter will automatically display all the options avaliable like *15xx* for subsequent selection.

Multiple Analysis Diagrams Among the user community, on the one hand, appreciators want to see a fantastic interactive graphical presentation, on the other hand, researchers want to investigate in depth the influence of different metadata in single or combined ways on historical paintings, including custom hierarchical and wrapping relationships. For example, the investigator wants to see all the painting styles that emerged between 1580 and 1629, and correlate with different countries, and therefore wants to study the influence of geographical and historical event factors on painting styles, or wants to understand the paintings created and the media used by specific painters in some individual years. Therefore, our system has the function to provide a variety of suitable analytical and interactive visualizations [9] to show the divisions, inclusion and correlations of the data.

5 Design of System Architecture

We developed PaintRelVis as a Web-based system to fulfill the above requirements through the user interface, visualizations and interaction concept of the system. PaintRelVis interface consists of three main views. The first one is a selector interface on the right of the page including filters, charts and levels selector. In this way, users are able to decide displayed painting subset in a carousel or grid, specify filters like date, painter and style, choose a kind of charts to display and specify the hierarchy of the chart. The second one is a display zone to exhibit currently specified painting subset in a carousel or grid, which is on the upper half of the page. The last view at the bottom is for some optional charts including Sunburst[5], Icicle[6] and Circular Packing[7] chart, and a scatter plot[8]. We will give detailed descriptions in the following subsections.

5.1 Painting Data Sets

Before describing visualization parts, we first introduce the painting dataset of our system. The overall style of the dataset is similar to that of WikiArt[9]. The dataset contains the original images of the 23K paintings in JPG format. The following table1 shows the statistical totals for each category. In the field of painting, [5] points out that different artists tend to have one or several relatively fixed stylistic schools, which in turn are often determined by historical factors of the era, such as the political situation, cultural environment, religious faith, and fairy tales as well as the means and media (tools, materials) available on the painting level. For instance, during the Renaissance, paintings often had a strong religious and mythological theme, as in the case of Leonardo da Vinci, whose painting style was influenced by this and was stored as *early_renaissance* in the dataset. Accordingly, although the metadata are presented independently, the field of art is heavily influenced by the reality of the situation, and researchers are able to create a lot of knowledge for KBS[10] of different associated content and relational features through this association for subsequent deeper and broader artistic research.

Data Type	Count
Id(painting)	23245
Date(year)	561
Artist	432
Nationality	83
Style	20
Media	160

Table 1. Metadata Statistics

5.2 Selector Interface

The selector interface on the right of the web page is the essential part of interaction. Users make their choices there to get the corresponding visualization results. This interface includes three main parts.

Filter: The filter allows users to obtain painting subset under specific categories. A wide spectrum of filter types that can be combined to versatile queries are provided. We mainly classify filters in seven categories, which are time period(start and end date), artist name, artist nationality, painting style(e.g. "cubism"), painting tag(e.g. "female-nude"), painting media(the material(s) that each painting was made from) and painting name. Users are able to choose one single label or combination of labels they are interested in. What's more, we provide a small

[5]SunburstChart https://www.anychart.com/zh/chartopedia/chart-type/sunburst-chart/

[6]IcicleChart https://www.jetbrains.com/help/dotmemory/Icicles.html

[7]CircularPacking https://www.data-to-viz.com/graph/circularpacking.html

[8]ScatterPlot https://en.wikipedia.org/wiki/Scatter_plot

[9]WikiArt Data https://github.com/cs-chan/ArtGAN/tree/master/WikiArt%20Dataset

[10]Knowledge-based systems generate specific *"knowledge"* from widely sourced data utilize artificial intelligence concepts to solve complex problems.

button for each category to clear a certain option and a button on the top of the filter interface to erase all filters.
Charts selector: Three types of charts are available: Sunburst, Icicle and Circular Packing chart. This selection determines the type of chart displayed in the bottom left corner of the page.
Level selector: The visualization of the chart we select is based on the filtered painting subset and it would display different categories and their level structure. Since the hierarchy in those charts is significant, we give users ability to decide it by choosing one or more labels that will be kept as well as their order. These levels is the same categories as the filter. For instance, if we choose the name of the artist as the first level and the painting style as the second level, the chart will convey information about different styles of a particular painter among filtered paintings. Sometimes too much directories makes the chart a little overwhelming. Therefore, this feature allows users to decide what information will be presented on the chart, enabling them to focus on what they consider to be more important and of greater interest. This process is real-time and interactive. Users are able to make a variety of choices.

5.3 Displayed Paintings

The upper part of web page provides a visual subset of the paintings, which is a central element of the user interface. After the user makes filters, those in the currently specified subset will be listed. There are two ways to display: carousel or grid, determined by the choice button on the top of selector interface. The information of a painting will be displayed when the mouse points to it. Another way to interact with users is that these images are all scrollable and clickable. There would be a pop-up notification after the user clicks on a painting. If the user makes confirmation, the paintings exhibited in this display zone will become the clicked painting and 50 most similar paintings to it in the entire dataset. This operation could be repeated as many times as the user wants. The selected painting will be in the first position and the distance represents the degree of similarity, which means the second painting next to it is the most similar one. Displaying similar paintings is the main function of this system. The method to calculate similarities will be discussed in next section. Moreover, we provide a rollback button on the top of the selector interface that enables the user to go back to the state where the previously filtered paintings was displayed.

5.4 Data Visualization

This view on the bottom of the page includes two parts: chart and scatter plot.
Chart: Optional analysis charts and their hierarchy depend on the choice of users in charts selector and level selector. The chart is based on the filtered painting subset and if user clicks one painting to exhibit similar sets, the chart will also change accordingly to show information about those similar paintings. In addition, these charts are all highly interactive. Each area in the charts are clickable, and then the painting(s) in the selected category will be navigated in the display space.
Scatter Plot: We reduced dimensions of painting embeddings using UMAP in order to present the similarities and distributions of the painting subset with 2D diagram. In the scatter plot, each dot represents an painting in the currently specified subset. The shorter the distance between dots means that their corresponding images are more similar. When the mouse points to one of the dots, the information of the corresponding painting will be displayed. Furthermore, if the user clicks a dot, the corresponding painting will become focal in the display area. In this way, users will know the position of each painting in the scatter plot. At last, same situation as charts that the scatter plot will change once user enters similar paintings display. Theoretically in this case, the points in the scatter plot would be highly concentrated.

6 Implementation Methods and Details

6.1 Global implementation of front-end and back-end

The application consists of a front-end developed in Javascript, using a library called React. The front-end is responsible for receiving data, displaying it to the user, and allowing the user to interact with the data. Our front-end enables the user to interact with the data by editing filters, clicking on sections of interest in our charts, and clicking over images to collect similar data. The data the user requests are sent via an HTTP request to our Python server on the back-end.

The back-end of our application was developed using a micro web framework called Flask. It contains a Pandas dataframe that holds information about each painting. When a user performs a filtering operation on the front-end, the dataframe on the back-end is filtered, and the data is returned to the front-end for the user to visualize.
The advantage of our approach is that we can leverage React's extensive user interface components in the front-end and the data processing packages in Python packages like Pandas and NumPy to handle user requests in the back-end.

The paintings themselves were downloaded with the dataset and were processed offline. This way, the user does not have to wait for additional computations to be completed.

6.2 Embeddings

First, the paintings were fed into a pre-trained VGG16, which outputs 1000-dimensional embedding vectors. These vectors are then used while the user is using the application to calculate the most similar paintings to the one the user has currently selected.

6.3 Dimensionality Reduction

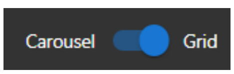
The 1000-dimensional embeddings are representations of paintings in 1000-dimensional space. However, this is impossible to intuitively visualize for humans. Using the dimensionality reduction method UMAP, the 1000-dimensional vectors were compressed to (x,y)-pairs. These values were then used to plot the paintings in the scatterplot.

6.4 Scatterplot

The scatterplot is located on the bottom half of the page and displays the paintings by coordinates obtained by the dimensionality reduction techniques. It only displays those paintings that have been selected by the user, and are clickable to view similar paintings and paintings that are less similar in the current subset.

7 Results

Demonstration Navigator For expanding visual diversity and switching between the Carousel and Grid views.



Carousel and Grid View The system provides two kinds of views2: a Carousel view with mouse wheeling where users can click to update and view the top 50 similar paintings, and a display Grid with global browsing feature where users can click to view the paintings in their full size.

Fig. 2. Different demonstration way of paintings

Functional Filters There are eight filters3 which correspond to the most important metadata in the dataset. The drop-down lists can also be treated as input boxes which support user input and provide logical association(for example, the end date only contains the years which are after the start date, and only existing specific years exist in the dataset) and adaptive prompt completion(if user input letter "van" in to the Artist Name box, it will give Vincent van Gogh and other name stuff associatively).

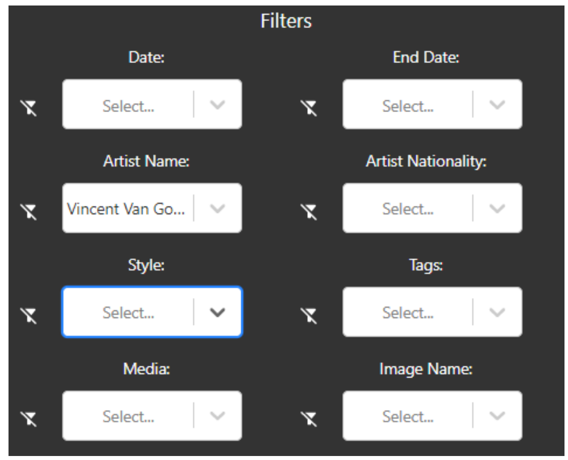


Fig. 3. Categorized filters for data screening

Interactive Analytical Charts PaintRelVis offers an intuitive demonstration of the distribution and relevance of the various types of data (features). The application makes the user capable of selecting a maximum of seven hierarchical levels viewed in an icicle chart or sunburst(multi-level ring chart) based on the content they need and the relation that researchers want to create, and it has multiple options covering almost all basic metadata which means it can paint a full picture of the multiple layers of data among the interactive hierarchical groups. Simultaneously, it also provides an interactive circle packing chart for visualizing proportions in hierarchical data, where nodes of a tree are represented as nested circles. Figure4 is a combination of those three powerful interactive analytical charts.
Analytical Charts Selection and Hierarchy Options Select up to three different analysis images for research purposes and interactive viewing5. Gives users a free and customizable way to create sequential data hierarchies/levels, and when an option is clicked, the corresponding chart will add new encompassing and hierarchical data that has already been filtered by the previous layer and will be automatically filled with color blocks to differentiate.

UMAP Scatter Plot A presentation6 is mainly designed to jump interactively with the carousel of the 50

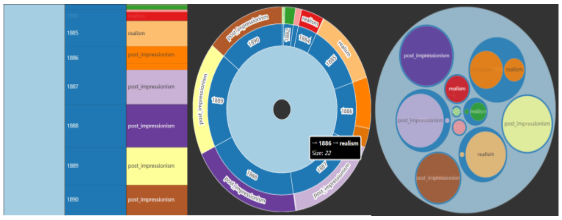


Fig. 4. Interactive analytical charts including function of creating hierarchical relation: Icicle, Sunburst, Circlepack(from left to right)

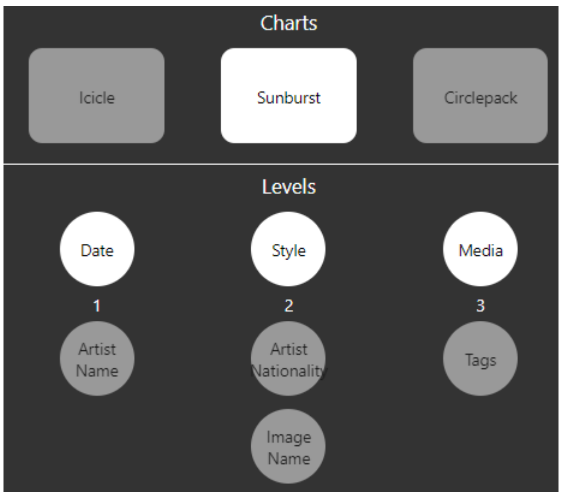


Fig. 5. Charts Selection and Hierarchy Options

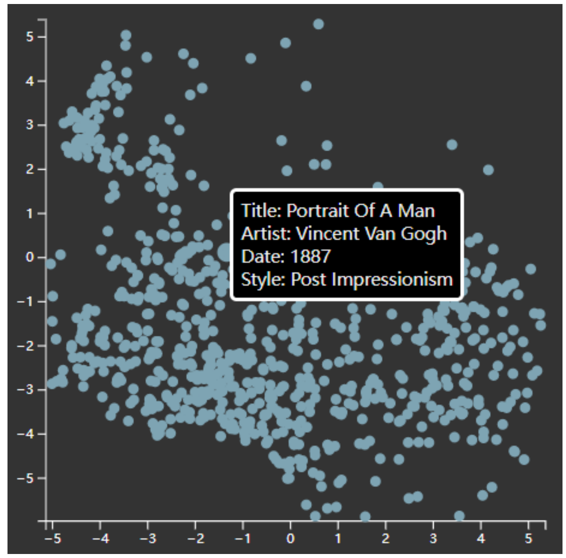


Fig. 6. Dimensionality Reduction with UMAP (each dot in the figure represents an individual painting)

most similar pictures. When the user clicks on a specific dot in the scatter plot coordinate system, the carousel will automatically refer to the transition effect for positioning and jumping. On this figure, the distance between two points also represents the degree of similarity between the two pictures, and the two closest points indicate that the similarity between these two pictures is at its peak value.

8 Reflection

8.1 Effectiveness

PaintRelVis is highly interactive and practical. Rather than presenting overwhelming information to users, we offer great flexibility to ensure that users are able to specify the information they truly require.

The pre-trained *VGG-16* network model saves a lot of time and resources and brings good accuracy for following research on similarity. When get into the gallery, top 50 similar images can be viewed in depth and can be interactively clicked an infinite number of times to see through the whole dataset within a short response time.

Available analytical charts provide researchers with the freedom to create a hierarchy of associations in order to observe and study the impact of historical events on the art of painting. The *icicle* and *sunburst* diagrams show the correlation of the data, and the *circlepack* better represents the wrapping of the data, e.g. to observe which painters worked in 1926.

8.2 Limitation

When we use UMAP for dimensionality reduction to turn multidimensional painting embeddings into two dimensions, a lot of information will be lost. This may lead to inconsistency between the similarities shown in the scatter plot and what we have actually computed.

There are some missing pieces in the dataset that need to be filled in. For the feature - media, there may be some overlap in the hierarchical relationship that may cause some ambiguity in understanding such as oil and oil,canvas, and oil includes the latter but cannot be distinguished completely. Moreover, the information about the paintings is not very comprehensive, only some basic data, based on some research and educational significance of PaintRelVis, it is better to have more detailed background information.

9 Conclusion and Future Work

In this paper, we designed and implemented an interactive visual interface with filtering functions and similarity calculation based on a painting dataset. Using the VGG16 network, we obtained the embeddings of the images and calculated the similarity. In addition to this, the use of D3 and React framework enabled the creation of an intuitive visual interface.

Preliminary demonstrations show that the current application is valuable, PaintRelVis has innovations based on the filtering function of painting data attributes. At the same time, according to the user's evaluation, its operation is simple and user-friendly; the interface is beautiful and decent.

For the future, we can expand and complete the dataset, add more background story descriptions of the paintings, work to better present the artworks for appreciation purposes, and also create some Feature Crosses for some machine learning tasks on art research.

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