A Kaleidoscopic View of Artist Co-Exhibition Networks

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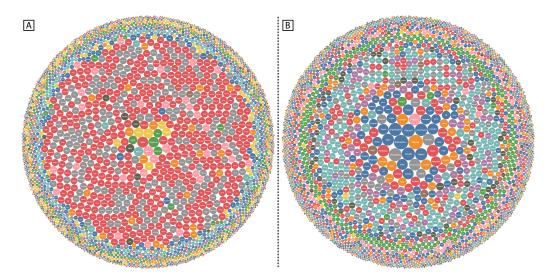


Figure 1: Node sizes show the degree centralities, node colors the nationalities of the artists. (A) degree centralities in 1908, where artists from Great Britain (red nodes) clearly dominate the view. (B) degree centralities in 1910, where the center is dominated by German artists (blue nodes) and concentric circles are dominated by different nationalities.

ABSTRACT

Centralities are network measures that reveal important nodes in a network. We visualize four different centralities in a co-exhibition network of artists in a Kaleidoscope-like visualization that makes it possible to see different patterns over the years.

Index Terms: Graph/Network and Tree Data, Centrality, Art History.

1 Introduction

Art History (AH) is a visually oriented discipline that traditionally works with qualitative data, but often lacks methods to visually analyze it. A multitude of art historical databases exist [1, 13, 6, 14], but they often come without visualizations or simple ones, like bar charts or maps, and lack a starting point for exploration, providing no overview of the data. A core topic in AH is to identify influential artists or key figures in networks [17]. However, this task cannot be achieved with the above-mentioned visualizations. Visual Analytics (VA) approaches and specifically network visualization techniques offer possibilities to analyze networks and even their changes over time in dynamic visualizations [3, 12]. The challenge with vast dynamic networks is how to visualize them without introducing too much clutter caused by the number of nodes and edges, and only focus on important attributes. Centralities are used in different domains, like social network analysis [8, 16] or art history [8, 9] and can be helpful to show, e.g., key actors [7] or influ-

TU Wien E-mail: firstname.lastname@tuwien.ac.at University of Vienna E-mail: firstname.lastname@univie.ac.at ential nodes [8, 15]. However, even though centralities are explored in AH, the temporal dimension is not considered, making it impossible to analyze evolution or changes. Also, most of the graph visualization techniques that are used in AH are static and do not allow art historians to interact with the data [17]. When designing visualizations for the Digital Humanities, aesthetics are important [11]. A Kaleidoscope is an optical instrument that shows colorful patterns in a circular arrangement with applications in the fine arts [5].

Contribution: We created a dynamic Kaleidoscope-like visualization of a co-exhibition network of modern European artists showing their centralities and nationalities. It enables art historians to (i) **observe changes** in artists' centralities and their evolution across different years; (ii) **compare the centralities and patterns** of different artists and their nationalities; and (iii) **weigh the centralities** by artist contribution.

2 DATA

The Database of Modern Exhibitions (DoME) [1] contains more than 13.000 modern European artists and their exhibitions between 1905 and 1915. We created co-exhibition networks (i.e., which artists exhibited together in the same exhibitions) for these eleven years and computed four different centralities (i.e., degree, betweenness, closeness, and Eigenvector centrality) across the co-exhibition networks. We also offer the option to weigh centralities according to the contribution of artists in a certain year (i.e., the number of paintings an artist exhibited compared to other artists), which increases the centralities of artists with higher exhibition activities in that year.

Degree Centrality is well-suited to find artists with many connections to other artists [10]. Betweenness Centrality highlights important bridge nodes in a network [10] and makes it possible to find artists who were part of many different groups. Closeness Cen-

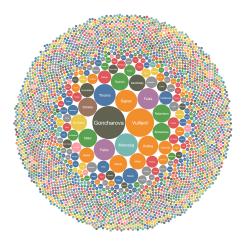


Figure 2: Weighted betweenness centralities in 1914, where Natalia Goncharova (gray node in the center) is very prominent.

trality measures the proximity of a node to all other nodes in the network [2] and, therefore, shows which artists can quickly connect to other artists and might be important for collaborations. Eigenvector Centrality highlights influential artists in the network, taking into account the connections and the importance of the connections [4].

3 DESIGN

In order to assist domain experts from AH in getting an overview of the more than 13.000 artists and identifying key actors or patterns that might be interesting for further investigations, analyzing influences, and observing changes over time, we created a dynamic visualization that shows artists as nodes, their centralities as node sizes, and nationalities as node colors (see Figure 1). For better clarity and to avoid clutter, we decided to omit the links between the artists in the visualization. This results in a Kaleidocsope-like visualization, where artists are aligned in concentric circles around the center, and centralities decrease the further the nodes are away from the center. A view like this allows art historians to analyze patterns and get different perspectives on the data, comparing changes across years, nationalities, but also different centrality measures. In Figure 1 (A), we see degree centralities in 1908, where artists from Great Britain (in red) clearly dominate the view, suggesting that they exhibited with many other artists that year. However, the most connected artists in the middle are mostly not from Great Britain. Figure 1 (B) shows the degree centralities in 1910, which look very different from the ones two years before. The center is dominated by German artists (in blue) who co-exhibited with many other artists that year. We further see concentric circles dominated by different nationalities. They show that in 1910, Italian artists (light blue circle) were better connected to other artists than Dutch artists (green circle), which were in turn better connected than artists from the United States (pink circle).

4 CASE STUDY

We conducted a case study with an expert from AH, where they freely explored our visualization approach. The expert was interested in artists acting as bridge nodes between different groups (i.e., high betweenness centrality), weighted the centralities by contributions, and selected the year 1914. A prominent node that shows up (see Figure 2) is Natalia Goncharova (grey node in the center), who is an important Russian avant-garde artist and co-founded many artist groups. This explains Goncharova's high betweenness centrality and role as a bridge node between different groups, especially when weighted by contribution, since she exhibited 340 paintings in 1914.

5 DISCUSSION AND FUTURE WORK

The case study showed the usefulness of our visualization in identifying important artists in the network of more than 13.000 artists. However, a limitation of the approach is that it is unclear which artists are connected to each other, because the edges are not shown. In the future, we want to include a detailed view integrating artist centralities in a visualization that displays the network of artists, as well as using dynamic centrality measures to calculate how much the co-exhibition networks of different artists change over time.

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