BEA
Educating for Tomorrow's Media

Routledge
Taylor & Francis Group

Combining Cultural Analytics and Networks Analysis: Studying a Social Network Site with User-Generated Content

Almila Akdag Salah, Lev Manovich, Albert Ali Salah, and Jay Chow

Humanities and social sciences require new research approaches to deal with and to benefit from the explosion of digital media. Thanks to large scale data storage and processing, close reading of individual items can be supplemented with analysis of broader trends from massive amounts of data. Cultural Analytics (CA) is a recently developed methodology for the exploration of content and visual form in large image and video collections. It has already been applied to a variety of media types, including TV programs, feature films, newspapers, and video games. However, until now these applications did not take into account the social context of media. In many cases, media artifacts under scrutiny are generated or used by people in a social setting, either in forms of (digital) communities, or in terms of social relations, which can be also analyzed as a valuable source of information. Social network analysis (SNA) is a set of methods for the analysis of human networks, including massive online social networks. In this article, we argue that CA and SNA can be combined synergistically, using data and images from deviantArt, the leading online network of user-created art, as a case study.

The contemporary struggle of humanities to cope with data explosion gave birth to approaches of digital humanities, where traditional methods of the humanities scholar are supplemented with computer-based methods that allow bird's eye views

---

Almila Akdag Salah *(Ph.D., UCLA) is a lecturer at the University of Amsterdam. Currently she is working on the project "Deviant Art: Mapping the Alternative Art World."*

Lev Manovich *(Ph.D., University of Rochester) is a professor of Computer Science at the City University of New York. His research interests include theory of digital culture, visualization of massive cultural data sets, and digital humanities.*

Albert Ali Salah *(Ph.D., Bogazici University) is an assistant professor of Computer Engineering at Bogazici University. His research interests include computer analysis of human behavior, pattern recognition, and multimodal interaction.*

Jay Chow *(B.A., UCSD) is a researcher at the Software Studies Initiative at Calit2, developing tools for analysis and visualization of large image and video collections for the humanities.*

Journal of Broadcasting & Electronic Media 57(3), 2013, pp. 409–426
DOI: 10.1080/08838151.2013.816710 *ISSN: 0883-8151 print/1550-6878 online*

at large data collections, thereby allowing the scholars to explore novel means of knowledge generation. Cultural analytics (CA) is one such approach that transforms regularities of well-structured data collections to regularities of visual patterns, and through information visualization and scalable interaction with the visualized material, permits the scholar to gain insight about patterns and disruptions thereof, which are converted back to propositions of the knowledge domain by the close reading of the scholar.

The CA methodology has been successfully used to analyze various types of digital media. However, these applications so far did not take into account additional superposed information structures that are not always easily depicted via traditional data organization methods. Most importantly, multitudes of semantic relations defined between data items are difficult to express using tables of data items, where each column stands for one unique property, and items in different tables are related through shared property values (which is what a standard relational database stores). On the other hand, these semantic relations, whose mathematical expression is most adequately achieved with graph structures, are not rare occurrences at all; all social relations and communications would naturally fall under this category.

The starting point of this study is the need for adequate procedures in enhancing the domain and applicability of cultural analytics to data collections born out of the interactions in a social network. These data are twofold: the content, which is produced by the actors of the social network via domain-specific activity (e.g., the photographs in Flickr), and the structure, which is the topology and connection structure of the social network itself. This structure is continuously re-created, and directly influences the dissemination of digital content, as well as the form of production and consumption thereof.[1] Consequently, the content cannot be dissociated from the structure, just as an artwork cannot be read independently from its production conditions and context. It is therefore essential to analyze both in tandem.

The data generated in larger social networking sites exist in such high volumes that it is only possible to churn them through computer programs. It is important to understand how automated mechanisms that sift through the data should be ideally deployed to suit the particular needs of a scholar precisely. Given a social network where each node harbors a certain amount of information, existing methods either look at a small subsample of the network to apply traditional social scientific approaches, or use broader models originally developed for the analysis of evolution and dynamics in complex systems, whereas the useful resolution of analysis should look at a large population without missing the answers found only in detailed, focused analysis of parts.

This article uses deviantArt, the largest online platform of user-generated artworks, as its case study for a social network with associated visual content. The sheer size of the archive (224 million artworks, generated by a densely connected community of 22 million artists), as well as its relevance for digital arts make deviantArt a particularly alluring case study, but it is essentially there to address a larger methodological question: How to combine established media and communication ways of working with media (which often involve close readings of selected artifacts) and "computational readings" of patterns across massive media datasets?

The Impact of Big Data

The last decade has seen the rise of two different research strategies: information visualization and network analysis. While these methods originated as research tools, they have become part of daily life thanks to many free software applications, via which non-researchers are able to "play" with "data," and draw conclusions. Both methods have a long history in various fields of natural sciences. However, the growth of their influence beyond their home disciplines to the academy at large, as well as their dissemination into the popular culture is predictable and it overlaps with the phenomenon of Big Data.

According to a recent editorial of the Internet Science Journal, "Big Data is a loosely defined term used to describe data sets so large and complex that they become awkward to work with using standard statistical software." (Snijders et al., 2012, p. 1). In case of visual material, special tools are needed to browse and search through such data repositories, but these are typically query-based systems that target users with specific needs, rather than data exploration and searching for cultural patterns (Plant & Schaefer, 2011).

Today's technology not only equips scholars with tools and methods to analyze Big Data, but also generates the Big Data itself by creating platforms over which ordinary people lead traceable social lives, and get transformed into behavior patterns: Their activities, connections, and products are collected, saved, and can be subjected to analysis. Papacharissi (2009, p. 200) notes that "the architecture of virtual spaces, much like the architecture of physical spaces, simultaneously suggests and enables particular modes of interaction."

Typical and widely known examples of such Big Data resources are the various social network sites (SNS) on the Internet. boyd & Ellison (2007, p. 1) formulate the definition of SNS as Web-based services for users to construct a public or private profile and to connect with other users in a bounded system. The SNS usually share a similar technology, and as social platforms, create their own sub-cultures, which can be significantly different from each other. Among these cultures, SNS with a specific thematic focus, such as Youtube (for sharing videos), Flickr (for sharing photos), or Wikipedia (for sharing knowledge), i.e., the ones with user-generated content, are not only interesting in terms of their dynamics, but also with respect to the content that is created by their users.

SNS are studied so far either by social scientists, who lacked the necessary tools and expertise to conduct research on large-scale datasets, or by physicists who lacked the research goals of social scientists in exploring the SNS for inquiries about social phenomena. While natural scientists are interested in the dynamics of SNS networks themselves (Clauset, Newman, & Moore, 2006), social scientists mostly focus on very small parts of an SNS (on the order of several thousand users at most)

(Hargittai, 2007; Liu, 2007), and rather than adopting new techniques capable of dealing with this new medium, apply existing quantitative and qualitative methods (Bertrand & Hughes, 2005).

While the SNS that forms the structure of interaction represents a large data analysis problem, the content of the SNS, which naturally scales with the size of the SNS, is no less of a problem. The methodology of cultural analytics, described in the next section, was proposed as a possible way of dealing with the content (Manovich, 2009). The present study proposes to combine the approach of natural scientists with social scientists, which in practice means getting a snapshot of the whole SNS via ''machine reading,'' and then performing focused, in-depth analyses of certain parts of it, as the ''close reading.'' On a case study, this article will illustrate how social network analysis can guide the selection of relevant sub-networks, which is followed by a detailed inspection of the sub-network, as well as the relevant user-generated content with the cultural analytics methodology.

Cultural Analytics

Cultural Analytics is a methodology for exploring massive image and video collections. It combines digital image processing with easy-to-use and intuitive visualization techniques to allow researchers discover patterns in the data (Manovich, 2009).

Today media researchers rely on the existing software for media viewing, cataloging, and editing. These applications allow users to browse through and search image and video collections, and display image sets in an automatic slide show or a PowerPoint-style presentation format. However, as research tools, their usefulness is quite limited. Desktop applications such as iPhoto, Picasa, and Adobe Bridge, and image sharing sites such as Flickr and Photobucket can only show images in a few fixed formats—typically a two-dimensional grid, a linear strip, or a slide show, and, in some cases, a map view (photos superimposed on the world map). To display photos in a new order, a user has to invest time in adding new metadata to all of them. She cannot automatically organize images by their visual properties or by semantic relationships. Nor can she create animations, compare collections that each may have hundreds of thousands of images, or use various information visualization techniques to explore patterns across image sets.

Graphing and visualization tools that are available in Google Docs, Excel, Tableau,[2] *manyeyes*,[3] and other graphing, spreadsheet, and statistical software do offer a range of visualization techniques designed to reveal patterns in data. However, these tools have their own limitations. A key principle, which underlies the creation of graphs and information visualizations, is the representation of data using points, bars, lines, and similar graphical primitives. This principle has remained unchanged from the earliest statistical graphics of the early nineteenth century to contemporary interactive visualization software that can work with large data sets. Although such representations make clear the relationships in a data set, they also hide the objects behind the data from the user. While this is perfectly acceptable for many types of data, in the case of images and video, this becomes a serious problem. For instance, a 2D scatter plot which shows a distribution of grades in a class with each student represented as a point serves its purpose, but the same type of plot representing the stylistic patterns over the course of an artist's career via points has more limited use if we cannot see the images of the artworks themselves.

Plot-making software can only display data as points, lines or other graphic primitives. To deal with these shortcomings, the method of media visualization has been developed by the Software Studies Initiative at University of California, San Diego. Their approach focuses on visual techniques that combine the strengths of media viewing applications with the strengths of graphing and visualization applications.[4] In this methodology, graphs are created to show relationships and patterns in a data set, where the actual images in the collection are shown. The images are organized in special layouts, which facilitate discovering interesting patterns. Figures 1, 3 and 4 show examples of such a visualization technique.

Typical information visualization examples involve first translating the world into numbers and then visualizing relations between these numbers. In contrast, media visualization focuses on translating a set of images into a new image that can reveal patterns in the set. In short, pictures are translated into pictures.

Media visualization can be formally defined as creating new visual representations from the visual objects in a collection. In the case of a collection containing single images, media visualization means displaying all images, or their parts, organized in a variety of configurations according to their metadata (dates, places, authors), content properties (for example, presence of faces), and/or visual properties (composition, line orientations, contrast, textures, etc.). If we want to visualize a video collection, it is usually more convenient to select key frames that capture the properties and the patterns of video. This selection can be done automatically using a variety of criteria—for example, significant changes in color, movement, camera position, staging, and other aspects of cinematography, changes in content such as shot and scene boundaries, start of music or dialog, new topics in characters conversations, and so on. A good example is the visualization of the film The Eleventh Year (1928) by the famous Russian director Dziga Vertov, via the montage of every shot in the film by its first frame (Manovich, 2013). These few hundreds frames are arranged in a grid layout. In this way, a film is represented by a single image, which allows seeing patterns in content, cinematography and editing.

The media visualization techniques of cultural analytics can be used independently, or in combination with digital image processing. Digital image processing is conceptually similar to automatic analysis of texts, a method that already is widely used in digital humanities: Text analysis involves automatically extracting various statistics about the content of each text in a collection, such as word usage frequencies, their lengths, and their positions, sentence lengths, noun and verb usage frequencies, etc. These statistics (referred in computer science as "features") are then used to study the patterns in a single text, relationships between texts, literary genres, etc. Similarly, we can use digital image processing to calculate statistics about various visual properties of images: average brightness and saturation, the number and the properties of shapes, the number of edges and their orientations, key colors, and so on. These features can be then used for similar investigations—for example, the analysis of visual differences between news photographs in different magazines or between news photographs in different countries, the changes in visual style over the career of a photographer, or the evolution of news photography in general over twentieth century. They can also be used in a more basic way—for the initial exploration of any large image collection. In parallel to the exploratory data analysis method in statistics, this approach can be called ''exploratory media analysis.''

In computer science, many researchers already used image analysis of digital images of artworks for several purposes: to determine aesthetic qualities of artworks (Datta, Joshi, Li, & Wang, 2006; Dhar, Ordonez, & Berg, 2011), to classify their emotional content (Datta et al., 2006; Yanulevskaya et al., 2008), to determine similarity between artworks and artists (Bressan, Cifarelli, & Peronnin, 2008), or to derive information about authenticity and style of an artist or a method of production (Stork, 2006; Coddington, Elton, Rockmore, & Wang, 2008).

Analysis can target low-level features like texture or color features (what we also do in this article), compositional attributes like the usage of rule of thirds, chiaroscuro lighting or opponent colors, content attributes like the presence of faces, and illumination attributes (Dhar et al., 2011). Multimedia and image retrieval communities have largely focused on photographs for determining aesthetic quality, as query-based retrieval of high-quality photographs from large image collections is a very appealing application (Marchesotti, Perronnin, Larlus, & Csurka, 2011; Murray, Marchesotti, & Perronnin, 2012).

An illustrative case study is presented here. For exploratory media analysis, first a digital image processing software was run on all images in a collection (or selected frames from a video). Next, visualizations which show all images organized in two dimensions according to their visual features and/or existing metadata were rendered. For example, in Figure 4, 90.000 images sampled from a large image collection are arranged according to their average brightness (x-axis) and average saturation (y-axis). The spatial layout of the visualization can follow other patterns. For instance, the images can be arranged horizontally, using metadata such as upload dates, and thereby making use of the ubiquitous (Western) metaphor of time as a line that stretches from left to right.

Media visualization can be contrasted with content analysis (manual coding of a media collection typically used to describe semantics) and automatic media analysis methods commonly used by commercial companies (video fingerprinting, content-based image search, cluster analysis, concept detection, image and video mining, etc.). In contrast to content analysis, media visualization techniques do not require time-consuming creation of new metadata about media collections. And, in contrast to automatic computational methods, media visualization techniques do not require specialized technical knowledge and can be used by anybody with only a basic familiarity with digital media tools (e.g., QuickTime, iPhoto, and Excel).

Media visualization method exploits the fact that image collections typically contain at least minimal metadata. These metadata define how the images should be ordered, and can be used to group them in various categories. In the case of digital video, the ordering of individual frames is built into the format itself. Depending on the genre, other higher-level sequences can be also present: shots and scenes in a narrative theme, the order of subjects presented in a news program, the weekly episodes of a TV drama.

It is possible to exploit the already existing sequence information in two complementary ways. On one hand, one can bring all images in a collection together in the order provided by metadata. For example, in the visualization of 4.535 Time magazine covers (Figure 1)[5], the images are organized by publication dates. On the other hand, to reveal patterns that such an order may hide, the images can also be placed in new sequences and layouts. In doing this, we deliberately go against the conventional understanding of cultural image sets which metadata often reify. We call such conceptual operations ''remapping.'' By changing the accepted ways of sequencing media artifacts and organizing them in categories, we create new ''maps'' of our familiar media universes and landscapes.

Social Networks Analysis

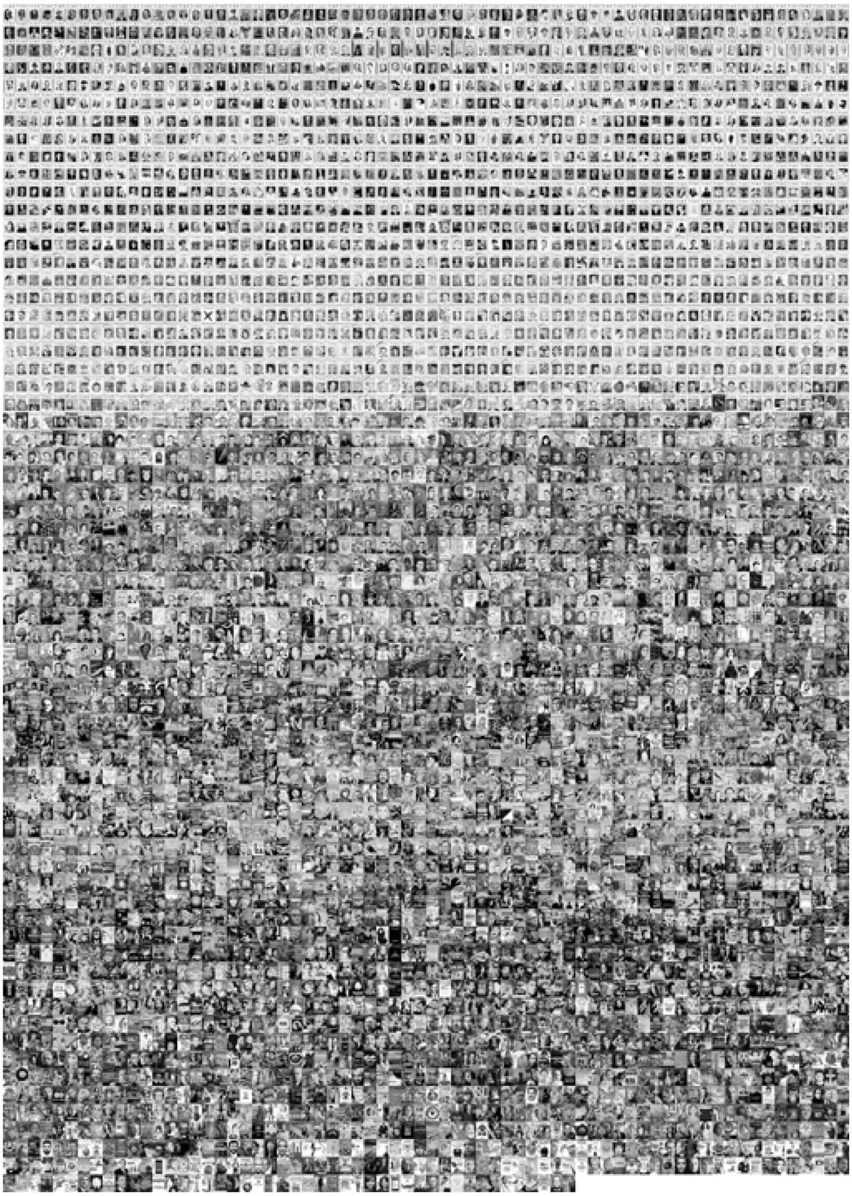
As a social construct, a network is made up of people that are related to each other through specific relations like friendship, co-publication, and such. These relations can be symmetrical, meaning that if A and B are related via relation r(A,B), it is implied that r(B,A) holds as well. The term network, as a mathematical entity, will often refer to a graph structure, which represents people or objects as nodes, and relations with undirected edges (for symmetric relations) or with directed arcs (for relations that are not necessarily symmetric).

Today there are at least three mainstream methodologies for analyzing social networks that share the same background structurally: Social Network Analysis (SNA), Actor Network Theory (ANT), and Complex Network Analysis (or Network Science). These approaches emphasize different aspects of a given network, and consequently generate weakly related perspectives about such networks.

SNA focuses on the relations between social ties, and aims to map out patterns of social/cultural relations while analyzing the results in a way to 'discern the deeper organizing principles that generate meaning structures' (Mohr, 1998, 2000). ANT, on the other hand, stresses the importance of relations of materials/concepts, and defines the network in much more fluid terms, as it tries to capture the ''transformations'' between relations. In contrast to these approaches, complex networks analysis is mostly interested in the network structure itself, and researches the topographical attributes, as well as evolution of real world networks (Albert & Barabási, 2002; Newman, 2003).

Social Network Analysis became a niche-methodology in the social sciences in the late 1960s and early 1970s. As Mohr observes, ''network scholars have

Figure 1
4.535 Covers of Time Magazine (1923–2009)



traditionally been a relatively insular community. Like Macintosh computers users in a DOS driven world, they have founded their own journals, congregated at their own conferences, and developed their own software packages'' (2000, p. 60). A beneficial outcome of this isolation was the meta-discussions about the methodology they used: in the end, network scholars in the social sciences have contributed to this technique both by developing it to fit social sciences methodologically, and by expanding it technically (Lorrain & White, 1971).

Actor-Network Theory, on the other hand, has its roots in the early science studies, and is known and criticized by/about its insistence on attributing ''agency to non-humans'' (Latour, 2005). The power of ANT derives from the way it maps relations that are both material (between things) and semiotic (between concepts), since it assumes that relations can be both, whereas its weakness lies in its terminology: the terms ''agency'' and ''network'' are catch-words, and have different connotations in closely related fields. In the words of Latour, one of the co-founders of ANT, there have been three different approaches to agency: ''The first one is to attribute to them naturality and to link them with nature. The second one is to grant them sociality and to tie them with the social fabric. The third one is to consider them as a semiotic construction and to relate agency with the building of meaning.'' (Latour, 1996, p. 379). ANT tries to take into account all these three approaches by not limiting the attribute of agencies to any social, semiotic or natural construct.

Combining Social Network Analysis with Cultural Analytics

Combining a network analysis approach with cultural analytics means that data used for visualization will be selected and structured according to the relations described by the network. The data used in the case study of this paper consists of artworks shared over an SNS. Image analysis of artworks has been previously combined with network analysis, albeit for purposes different than the present study. Bressan et al. (2008) prepared a network of painters, where each painter is represented with a node, and the edges between painters are weighted by the painters' similarity, which is computed by comparing the galleries of the painters via image retrieval techniques. This analysis produces a fully connected graph, as similarity can be defined for any two painters, but thresholding or ranking methods can be used to keep the complexity of the network low. Applying such a method to ten million artists would result in a network with a hundred trillion edges, which is at the moment beyond ordinary means of analysis. Ideally, other semantic information about the artists can be used to produce a much smaller network.

The use of a similarity-based approach is primarily shaped by the qualities of the similarity measure(s) used. State-of-the-art image retrieval techniques are largely optimized for speed and memory usage. Typically, low-dimensional feature vectors are used to represent each image. While this kind of analysis can give a broad idea of the trends in the data via information visualization, it may not be accurate enough to compare individual artworks. Slight artistic modifications of a given artwork will produce large changes in the image descriptors. The reason is that a ''slight'' artistic modification is ''slight'' in a perceptual sense, but may nonetheless involve large pixel changes.

To compare individual artists, Buter et al. (2011) proposed a system that computes a number of simple color and texture based image features, in addition to several perceptual features from artworks. Given two artists, the proposed system uses machine learning techniques to automatically select features that would maximally separate the galleries of the artists. Subsequently, the measure of ''similarity'' is adapted each time for any given pair of artists.

In the following section, we describe our case study, namely the deviantArt SNS for sharing user generated artworks. The case study illustrates a basic methodology: Network analysis is used to identify users relevant for subsequent exploration, and cultural analytics is used to visualize data pertaining to the subset of users identified as relevant. The former both reduces the data for visualization, and brings focus to it. The latter allows interpretation of cultural artifacts (e.g., images) in a visual way, which is not possible by automatic analysis tools.

Dissecting deviantArt

Analysis of deviantArt with SNA

deviantArt (dA) has a rich social structure that permits looking at its network structure from different points of view. It has 22 million members interacting around specific artistic styles or topics, many emerging communities, and an image archive of 224 million images, over which it is possible to derive further information about social relations.

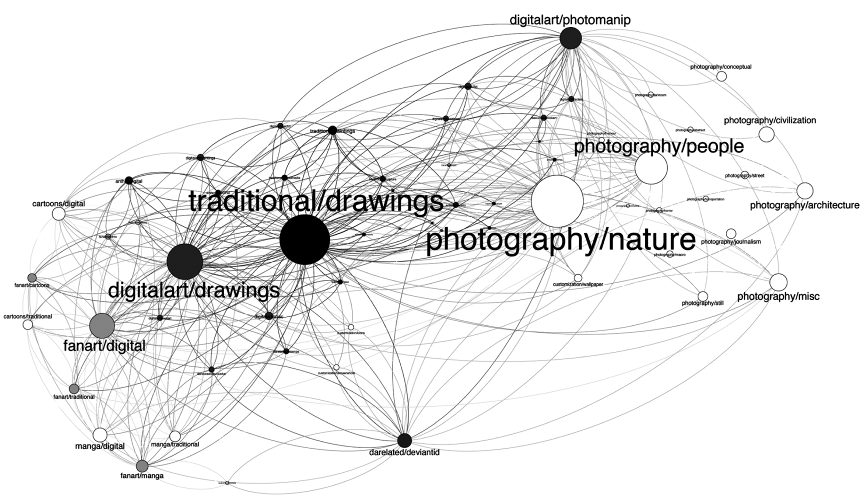
Attempting a complex network analysis of the whole site would not be very productive. This is generally true for levels of abstraction at which social scientists work; analysis of the entire network means treating it as uniform with respect to several dimensions, which may lead to over-generalizations. Instead, the feasible approach is to use certain parameters to collect representative data samples from dA, tailored for specific questions. Also, in this case study, there are multiple superposed graph structures to represent different relations, specifying for instance which members follow a certain artist, and which artworks are connected to a specific category. This multitude makes it difficult to encapsulate all relational information about the dA in a single multigraph structure; it is much more preferable to work with selected relations and single graph structures. Obviously, different choices in selecting data representations will reveal different aspects of the network.

It has been mentioned that network analysis serves to reduce the data volume for processing. For this case study, other data reduction filters were used initially, as any kind of analysis on a network with 22 million nodes requires special computing facilities. The analysis was restricted to the paying members of the site, since these members have access to additional services, and professional artists operating within dA are almost always among the paying members. The resulting network, which is called the professionals network of dA here, has 107.554 nodes and 5.252.685 edges. The 107.554 paying members of dA had a total number of 12.962.560 works in the dA archive at the time of data retrieval in May 2010 (Figure 2).

The artworks uploaded to deviantArt have some metadata associated with them. It is possible to conduct exploratory analysis by using this metadata, and network analysis methodology. The most consistent of these is the ''category'' tag, which is a mandatory field by dA policy, and indicates a single user-assigned category per work. These categories typically describe the production mode of the artwork (e.g., digital art, photography, cartoon, etc.). Thanks to the single-category policy, dA has an intricate category structure, and using this information, a network that represents the distribution of artworks into categories, as well as the ''proximity'' between categories was generated. The Category Network was produced by assigning nodes to each category, and creating edges between two given categories with weights proportional to the number of artists producing jointly in these categories (Figure 2).

This initial analysis revealed that the technique used to produce an artwork has a stronger impact than the artistic style in positioning the artwork. In other words, dA categories are developed to accommodate creation techniques rather than genres (Akdag Salah et al., 2012). Akdag Salah and Salah (2013) focus on a particular category in dA, and show that the member-to-member links (as opposed to member to artwork links) also revolve strongly around production technique.

Figure 2
Category Network [61 Nodes, 272 Edges] Where Nodes are Scaled according to the Number of Works in the Category Represented by the Node

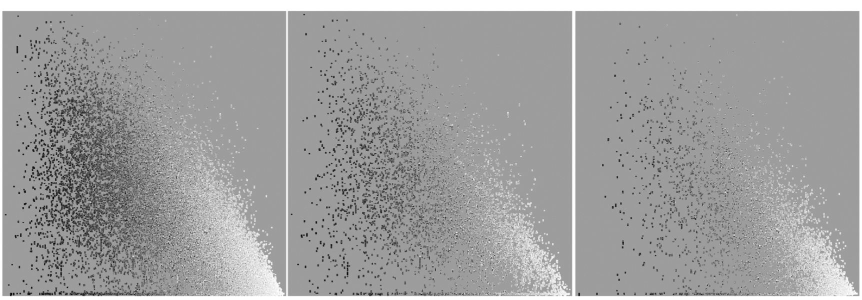


Another important result of the category network analysis was the relations between the top categories: before the network was generated, it was known that the most populated artwork category in dA was Photography. However, it was unexpected to find that Photography with all its subcategories is the only closed community in this network. Other top categories have strong connections with each other, especially if they share similar techniques. For example, Fan Art and Manga are closely linked, meaning that for people producing in one of these categories there is a high probability of producing in the other category. This rule seems to be broken in the case of the Digital Art and Traditional Art categories: even though they do not share production techniques, still they are directly and closely linked. We have decided to inspect this irregularity further, and applied Cultural Analytics tools to analyze the artworks from Digital Art and Traditional Art categories, as well as Manga and Fan Art categories.

Image Analysis for Visualization of deviantArt

To get a visual intuition about the production of artworks, entire galleries of images can be visualized according to social and categorical information. However, a more meaningful way of visualization of images would be to use image features. In cultural analytics (CA), computational image analysis is used for three main purposes. The first is to systematically compare large sets of visual artifacts—such as a large image set from different sub-categories in deviantArt, as in the Figure 3, where all artworks from Manga and Fan Art categories are analyzed. The second purpose is to understand temporal patterns of cultural and artistic evolution. For example, if one wants to find out if particular aspects of visual form of images in Digital Art category changed between 2001 (when deviantArt was started) and

Figure 3
Visualizations of Images in (a) Manga and Fan Art/Manga Categories; (b) Manga/Digital Media Category; (c) Manga/Traditional Media Category. The X-axis Denotes Average Brightness (i.e., Amount of Light), and the Y-axis Denotes Average Saturation (i.e., Amount of Color).



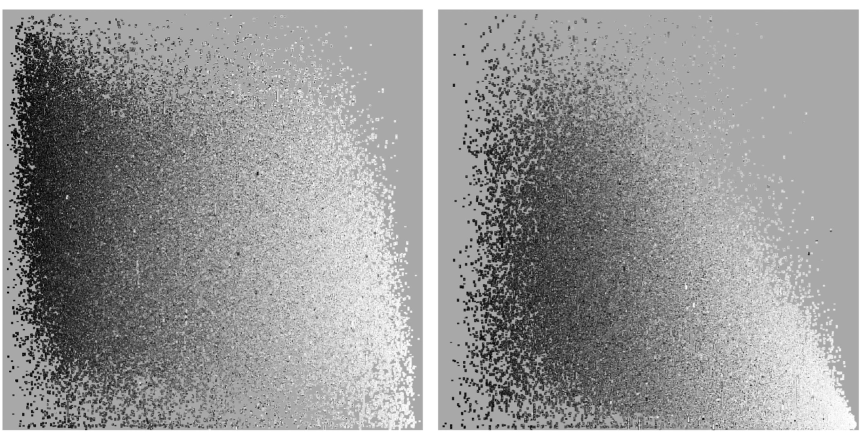
(a) (b) (c)

2011, it is possible to plot the values of corresponding visual features of these images over time and observe any trends which may be present. (Figure 1 presents such a case study with another dataset.) The third purpose is the exploration of large media collections. Given the size of image sets that can be downloaded from social media sites, just to "look" at them already presents a challenge. CA's solution to this challenge is visualizing all images from a collection together, sorted and arranged in different ways. When sorted by metadata and by extracted visual features, and with the help of different layouts, one can notice various patterns that might not have been visible otherwise. The two visualizations in Figure 4 that compare two sets of 90.000 images each are examples of such exploratory visualizations.

In this section, two subcategories of the Manga category are under focus, named Digital Media and Traditional Media (12.232 images and 6.284 images, respectively). One obvious question is the following: Are there significant differences in Manga images in these two subcategories? In other words, does the use of digital vs. traditional tools affect the kinds of Manga images being created by deviantArt artists? In order to explore this question, we visualized images in Manga/Digital Media and Manga/Traditional Media categories separately. And finally, in order to understand whether the observed differences are specific to Manga images, or can also be observed in the rest of the image set, we visualized 90.000 works that belong to the Traditional Art and Digital Art categories.

To visualize the images in such a way that both the larger patterns but also details of individual images can be seen, the images were positioned in a 2-dimensional space according to their visual characteristics (e.g., "features"), automatically ex-

Figure 4
Visualizations of (a) 90.000 Images in Top Category Digital Art, and (b) 90.000 Images in Top Category Traditional Art. X-Axis: Average Brightness. Y-axis: Average Saturation



(a) **(b)**

tracted by image analysis software. To make all visualizations comparable, the same two features were used in all of them: average (mean) image brightness (horizontal axis), and average (mean) image saturation (vertical axis), which are extracted using open source software tools written in Software Studies Lab (see Manovich, Douglass, Zepel, & Zeng et al., 2011). The images are automatically positioned vertically and horizontally according to their feature values.[6] Many other features and their combinations can be used. After initial explorations using other features with deviantArt images, it was found that the combination of average brightness and average saturation sorts the images in a way which is easy to understand, and yet allows one to see a variety of patterns related to color, style and medium.

The first visualization (Figure 3a) shows 23.327 images, which the artists have uploaded in either Manga or Fan Art/Manga category. It is possible to observe here that the most-dense part of the visualization is in the lower-right corner (large average brightness and low average saturation), with smaller numbers of images in other parts. The distinct shape of the ''cloud'' formed by these 23.327 images defines what ''Manga'' means in the deviantArt network (in brightness-saturation space)—which is quite different from the images from professionally drawn and commercially distributed Manga books.

In the deviantArt network, the Manga category is divided into two second-tier categories: Digital Media and Traditional Media. Therefore, it is logical to ask if the shape seen in Figure 3(a) might actually consist of two distinct image groups corresponding to these secondary categories. If the answer is affirmative, this means that there are significant differences in ''Manga'' images in deviantArt related to the use of digital vs. traditional tools. Figure 3(b) shows 6.284 images from the Manga/Digital Media category; Figure 3(c) shows the same number of images from the Manga/Traditional Media category.

To interpret these visualizations better, we take a look at the visualizations, which use 90.000 image samples from top Traditional Art and Digital Art categories in Figures 4(a) and 4(b). As observed in the visualization of Category Network (Figure 2), Digital Art and Traditional Art categories are closely linked, having many members producing in both of these categories. The stimulating question to ask here is whether these members use the same techniques in producing artworks of different genres. Another motivation in generating Figure 4 is that visualizing larger image sets may show patterns of difference better. This will help to notice if the same patterns may be present in visualizations of smaller image sets.

Looking at visualizations in Figures 4(a) and 4(b), it can be seen that Traditional Art also has a larger proportion of images in the lower right corner (high average brightness and low average saturation). These are drawings on paper. In contrast, Digital Art has a higher proportion of images on the left side of the visualization (low average brightness). One interpretation of this difference is that the use of digital tools allows the artists to set image backgrounds to arbitrary brightness and color, including very dark or black tones. In contrast, it is rare for artists working in traditional images to make drawings on dark or black paper. Another key difference is a higher variability of images in Digital Art than in Traditional Art, i.e., the former are more spread out both horizontally and vertically, covering a larger range of possible values. Our interpretation is that the use of digital tools leads artist to try out many visual possibilities, which results in higher visual variability of image samples created with these tools. Yet another difference is the use of color—Digital Art has a much higher proportion of colorful images (central part of the visualization). Thus, even though a high proportion of artists produce in both Digital Art and Traditional Art categories, the resulting artworks show stylistic differences that arise due to the differences in the production technique.

Having observed these patterns in Figures 4(a) and 4(b), we now come back to Figure 3(b) and 3(c). Each of the differences we saw between larger samples of images from Traditional Art and Digital Art are also present in smaller samples from Manga/Traditional Media and Manga/Digital Media. As we expected, these patterns are easier to notice when visualizations use much larger numbers of images (90.000 in Figure 4 vs. 6.284 in Figure 3). The fact that one can see the same type of differences between these two sets of visualization is an important finding. It suggests that the different types of tools used by artists who upload their images to deviantArt have significant effect on their visual form, regardless of the image categories.

Conclusions

This article aims to illustrate how two methodologies for analyzing a set of media artifacts and the activities of the creators and consumers of these artifacts (Cultural Analytics [CA] and Social Network Analysis [SNA], respectively) can be used together productively and efficiently. Given the current prominence of online networks such as Flickr, Facebook, Twitter, and YouTube, where the users upload media, and act on it (comment, link to, etc.), existing methods of media analysis would benefit from computer-based social network analysis.

The detailed case study presented in this article aims to describe how domain-level expertise is employed in directing the analysis throughout the process, to illustrate the data reduction and selection in the network analysis step, as well as the use of different visualizations that permit the scholar to spot visual patterns in the dataset in a way that is impossible to achieve with only network analysis approaches. Similarly, network analysis clearly contributes to cultural analytics visualizations by pointing out to relational patterns.

Network analysis as a method is an all-encompassing approach, open to many possibilities. It is possible to collect and analyze different types of data from a single social network. Among many data relations, some will reveal themselves as more relevant for answering the set of questions the specific research project wants to address. In the case of the deviantArt network for user-created art, these were the categories of images, and the relations between members. This kind of expert knowledge should be the basis for the construction of the representation of any real social network, such as deviantArt. Only then, complex network analysis, or social network analysis (if this methodology is used) can be a useful step before applying the cultural analytics methodology. More detailed analysis of networks may also point to important actors in the network such as hubs, authority or gatekeeper nodes, and the analysis then can focus on individual actors. This way, instead of processing tens of millions of images, a scholar can work on a small but relevant part of the data. The described methodology is not specific to platforms of sharing digital artworks, and could be transformed for the analysis of any type of data-source with relational information, and relevant visual content.

Hayles (2012, p. 12) stresses that "attention" is the scarce resource of scientific scrutiny in the age where information is abundantly available in all forms. Deploying attention intelligently becomes possible by a "machine reading," on a scale impossible to perform by an individual (e.g., our processing of 12 million artists), followed by a "close reading" (e.g., our analysis of certain sub-categories). On a related note, Jensen (2002) remarked that "media and communication studies have tended to take either an external perspective in information as a technical, neutral carrier, or an internal perspective on meaning as an always interpreted and interested construct" (p. 256). It is the interplay of machine reading and close reading that may bring together the two theoretical perspectives together, where the former deals with information, and the latter with meaning.

Notes

[1] Katherine Hayles alludes to the Baldwin effect in biology, where the environment and the individual develop or change together, to stress the importance of such mutual dependencies (Hayles, 2012).

[2] http://www.tableausoftware.com

[3] http://www-958.ibm.com/software/data/cognos/manyeyes

[4] http://www.softwarestudies.com

[5] High-resolution color versions of all images in the article can be obtained from http://www.cmpe.boun.edu.tr/~salah/.

[6] For a detailed discussion of this visualization method and other examples of its application, see Manovich, 2012.

References

Akdag Salah, A. A., Salah, A. A., Buter, B., Dijkshoorn, N., Modolo, D., Nguyen, Q., ... & van de Poel, B. (2012). DeviantArt in spotlight: A network of artists. *Leonardo*, *45*(5), 486–487.

Akdag Salah, A. A., & Salah, A. A. (2013). Flow of innovation in deviantArt: Following artists on an online social network site. *Mind & Society*, *12*(1), 137–149.

Albert, R. & Barabási, A.-L. (2002). Statistical mechanics of complex networks. *Review of Modern Physics, 74*, 47–97.

Bertrand, I., & Hughes, P. (2005). *Media research methods: Audiences, institutions, texts*. Basingstoke, UK: Palgrave Macmillan.

boyd, d. m., & Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication 13*(1), article 11. http://jcmc.indiana.edu/vol13/issue1/boyd.ellison.html

Bressan, M., Cifarelli, C., & Peronnin, F. (2008). An analysis of the relationship between painters based on their work. In *Proceedings of the ICIP*, 113–116.

Buter, B., Dijkshoorn, N., Modolo, D., Nguyen, Q., van Noort, S., van de Poel, B., ... Akdag Salah, A. A. (2011). Explorative visualization and analysis of a social network for arts: The case of deviantArt. *Journal of Convergence, 2*(2), 87–94.

Clauset, A., Newman, M. E. J., & Moore, C. (2006). Finding community structure in very large networks. *Physical Review E 74*, 036104.

Coddington, J., Elton J., Rockmore, D., & Wang Y. (2008). Multifractal analysis and authentication of Jackson Pollock paintings. *Proceedings of SPIE*, 68100F.

Datta, R., Joshi, D., Li, J., & Wang, J. Z. (2006). Studying aesthetics in photographic images using a computational approach. *Proceedings of the ECCV*, 288–301.

Dhar, S., Ordonez, V. & Berg, T. L. (2011). High level describable attributes for predicting aesthetics and interestingness. *Proceedings of the CVPR*.

Hargittai, E. (2007). Whose space? Differences among users and non-users of social network sites. *Journal of Computer-Mediated Communication 13*(1), article 14. http://jcmc.indiana.edu/vol13/issue1/hargittai.html

Hayles, N. K. (2012). *How we think: Digital media and contemporary technogenesis*. Chicago, IL: University of Chicago Press.

Jensen, K. B. (2002). The complementarity of qualitative and quantitative methodologies in media and communication research. In K. B. Jensen (Ed.), *A handbook of media and communication research* (pp. 254–273). New York, NY: Routledge.

Latour, B. (1996). On actor-network theory: A few clarifications. *Soziale Welt, 47*(4), 369–381.

Latour, B. (2005). *Reassembling the social: An introduction to actor-network-theory*. Oxford, UK: Oxford University Press.

Liu, H. (2007). Social network profiles as taste performances. *Journal of Computer-Mediated Communication 13*(1), article 13. http://jcmc.indiana.edu/vol13/issue1/liu.html

Lorrain, F. & White, H. C. (1971). Structural equivalence of individuals in social networks. *Journal of Mathematical Sociology, 1*(1), 49–80.

Manovich, L. (2009). Cultural analytics: Visualizing cultural patterns in the era of ''more media.'' *Domus*. Retrieved from http://softwarestudies.com/cultural_analytics/Manovich_Domus.doc

Manovich, L. (2012). How to compare one million images? In D. Berry (ed.), *Understanding Digital Humanities* (pp. 249–278). London, UK: Palgrave.

Manovich, L. (2013). Media visualization: Visual techniques for exploring large media collections. In K. Gates (ed.), *Media Studies Futures*. West Sussex: Blackwell.

Manovich, L., Douglass, J., Zepel, T. & Zeng, X. (2011). ImagePlot v 0.9. http://lab.softwarestudies.com/p/imageplot.html.

Marchesotti, L., Perronnin, F., Larlus, D. & Csurka, G. (2011). Assessing the aesthetic quality of photographs using generic image descriptors. *Proceedings of the ICCV*, 1784–1791.

Mayer, A. & Puller, S. L. (2008). The old boy and girl network: Social network formation on university campuses. *Journal of Public Economics, 92*, 329–347.

Mohr, J. W. (1998). Measuring meaning structures. *Annual Review of Sociology, 24*, 345–370.

Mohr, J. W. (2000). Introduction: Structures, institutions, and cultural analysis. *Poetics, 27*, 57–68.

Murray, N., Marchesotti, L., & Perronnin, F. (2012). AVA: A large-scale database for aesthetic visual analysis. *Proceedings of the CVPR*, 2408–2415.

Newman, M. E. J. (2003). The structure and function of complex networks. *SIAM Review, 45*(2), 167–256.

Papacharissi, Z. (2009). The virtual geographies of social networks: A comparative analysis of Facebook, LinkedIn and ASmallWorld. *New Media Society, 11*, 199–220.

Plant, W., & Schaefer, G. (2011). Visualisation and browsing of image databases. In W. Lin, D. Tao, J. Kacprzyk, E. Izquierdo, & H. Wang (Eds.), *Multimedia Analysis, Processing and Communications* (pp. 3–57). Berlin, Heidelberg: Springer.

Snijders, C., Matzat, U., & Reips, U. (2012). ''Big Data'': Big gaps of knowledge in the field of internet science *International Journal of Internet Science, 7*(1), 1–5.

Stork, D. G. (2006). Computer vision, image analysis, and master art: Part 1. *IEEE Multimedia, 13*(3), 16–20.

Yanulevskaya, V., van Gemert, J. C., Roth, K., Herbold, A. K., Sebe, N. & Geusebroek., J. M. (2008). Emotional valence categorization using holistic image features. *Proceedings of the ICIP*, 101–104.