Quantifying historical development of user-generated art during 2001-2010

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Abstract

One of the main questions in the humanities is how cultures and artistic expressions change over time. While a number of researchers have used quantitative methods to study historical changes in literature, music, and cinema, our paper offers the first quantitative analysis of historical changes in visual art created by users of a social online network. We first propose a number of computational methods, including a novel technique inspired by the distance correlation, for the analysis of temporal development of art images. We then apply these methods to a sample of 270,000 artworks created between 2000 and 2010 by users of the most well known social network for art DeviantArt. We investigate changes in subjects, techniques, sizes, proportions and also selected visual characteristics of images. Because these artworks are classified by their creators into two general categories - Traditional Art and Digital Art - we are also able to investigate if the use of digital tools had a significant effect on the content and form of artworks. Our analysis reveals a number of gradual and systematic changes over a ten-year period in artworks in both categories.

Over the last decade, researchers in computer science, social computing and computational social science have published numerous papers analyzing large social and cultural datasets using computational methods (many of the important papers in this area have been presented at ICWSM conferences). The rise of social networks and media sharing sites in the middle of 2000's and the availability of their data was one of the main catalysts for the growth of this research. While this work addresses many questions important for the social sciences, the fundamental concern of the humanities has not yet been systematically addressed: the study of historical changes in human artifacts, norms, ideas, and other dimensions of human culture. Because social media data is so recent, it has not been a good resource for the study social and cultural changes over long periods of time. To use the terms from linguistics, computational studies of social networks have focused more on synchronic as opposed to diachronic dimensions - in other words, the analysis of the system in a given moment rather than its historical evolution. The granularity of available information about social and cultural behavior and much larger sample sizes was traded-in for the traditional "data" used to analyze history with qualitative methods.

Of course, the application of computational quantitative methods is not limited to recently available social networks data. They can be also applied to the gradually growing digitized collections of analog cultural artifacts from the past, such as books, movies and TV programs, songs, or art images. The new field of digital humanities that developed in the late 2000's started to take advantage of the digitization of printed texts. There are already a number of interesting studies of historical patterns across large collections of books and newspapers over the last few centuries. The analysis of historical changes in the use of concepts and names using a sample of a few million of digitized books from Google Books is so far the most well-known example of this research (Michel et al. 2010). However, so far no one has yet used computational methods to analyze historical changes in a larger collection of visual art images, even though such digitized collections have been available for some time. Similarly, no one has yet taken advantage of the massive numbers of born-digital artworks available on both social networks and also peoples web sites for blogs since middle of the 1990's to analyze their temporal development.[1]

To the best of our knowledge, our paper is the first to quantitatively analyze historical changes across hundreds of thousands of art images. We also propose a number of computational methods suitable for quantifying historical development in visual art. We apply our methods to a large real-world dataset: 270,000 images created between 2000 and 2010 by users of DeviantArt, the most popular social network for art.

At the time of this writing, DeviantArt has 32 million members and hundreds of millions of artworks. The descriptions of the network emphasize its democratic character: "We believe that art is for everyone, and we're creating the cultural context for how it is created, discovered, and shared." (DeviantArt).

[1]Note that "visual art" in this paper refers not only to the works created by professional artists and circulating within the professional art world, but any kind of visual images and video, including art created by non-professional and semi-professional artists, photography, illustration, graphic design, motion graphics, etc.

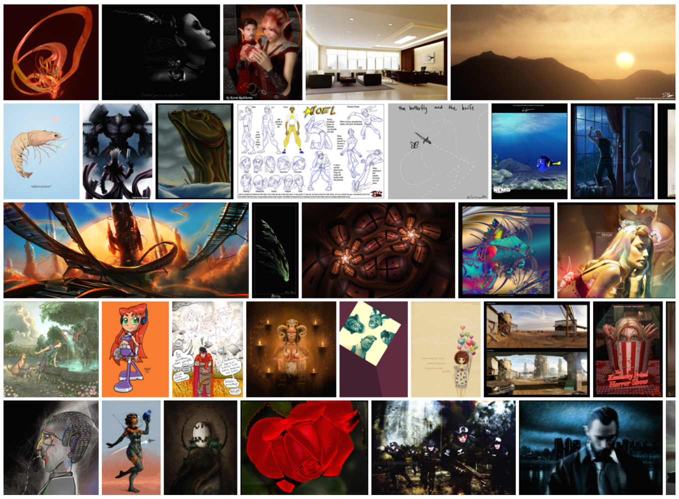

Figure 1: A sample of our DeviantArt dataset showing the diversity of techniques and subjects.

The diversity of art available on this network in terms of techniques, tools, subjects and genres is remarkable. This becomes clear after an informal examination of selected images and the intricate system of over 1,7000 hierarchically organized categories used by DeviantArt members. Figure 1 shows just a few examples of types of images on the site. We also created two interactive visualization which allows exploration of the complete category tree (****). This diversity of content makes DeviantArt challenging for qualitative analysis, and justifies the turn to computational methods. If we consider small image collections where visual changes over time are very strong and only limited to a few dimensions, they would be directly visible to the human eye. As examples, we have visualized large numbers of paintings by artists such as Vincent van Gogh, Piet Mondian, and Mark Rothko by sorting digital images of their paintings by creation dates. These visualizations have shown changes and rates of change in the styles of these artists over time [*** Reference omitted to keep the anonymity of the paper for the review]. But if art datasets are bigger and more diverse, include works by many authors, and the changes are more subtle and/or affect many dimensions in the same time, direct perceptual examination of selected images may no longer help. Therefore, a dataset such as DeviantArt that contains images with all kinds of content and styles offers a good motivation for developing and testing computational methods.

We downloaded a larger sample of 1 million images covering all other categories such as Photography, Design and Interfaces, and Cartoons and Comics, but for this study we chose only Traditional Art and Digital Art categories which together contain 270,000 images created from 2001 to 2010. These categories and their subcategories (portraits, landscapes, etc.) are most compatible with what has been studied in art history and media theory (Manovich 2013; Bolter, Grusin, and Grusin 2000), so we feel that this choice will make our study more relevant to the researchers in these and other fields of humanities. Additionally, having significant number of artworks in two top-level categories of Traditional Art and Digital Art allows us to study how the use of digital tools has influenced content and form of visual artworks during 2001-2010 period. During this period, digital tools have gradually become ubiquitous. Therefore, in addition to being the first paper in what can be called computational art history, we also offer the first example of computational media studies[2].

We will discuss the development of categories, the sizes and proportions of images, and a number of their visual features. The existing research in art history and media theory does not give us reasons to expect that any of the variables we analyze should change in any particular way during the ten year window. However, our analysis reveals that many variables have been changing monotonically. That is, the values of the variables are gradually increasing or decreasing in the same direction over the course of the number of years.

Related Research

For humanities and social sciences, analyzing and explaining historical differences between periods has been central since at least middle of the 19th century. For example, consider three founders of sociology: Karl Marx, Emile Durkheim, and Max Weber. Karl Marx's economic theory postulated a number of different modes of production that replaced each other in turn over many centuries (Marx et al. 1990). Emile Durkheim described evolution of societies as the move from mechanical solidarity to organic solidarity (Durkheim and Halls 1997). Max Weber proposed that the key differences between modernity and traditional societies were rationalisation, secularisation, and disenchantment (Weber and Parsons 2003).

The very names of many humanities fields indicate that they are concerned with history. Besides the discipline of "history" proper, we have art history, architectural history, history of photography, media history, media archeology, music history, history of literature, and so on. For example, consider art history. Similar to the three founders of sociology, the three founders of academic art history were keenly concerned with historical developments in the arts and crafts. Alois Riegls manuscripts of 1890's analyzed stylistic evolution across the entire history of Western art (*Historical grammar of the visual arts*, published posthumously)(Iversen 1980). Heinrich Woelfflins foundational *Principles of Art History* contrasted representations of forms in the 16th century and 17th century Italian art (Wölflin and Hottinger 1950). Erwin Panofskys *Perspective as Symbolic Form* (1927) examined changes in the understanding and representation of spaces between Antiquity, Middle Ages and Renaissance (Panofsky 1991).

Throughout the 19th and 20th centuries, not a single well-known humanities scholar used quantitative methods to study historical changes in their fields. But in the 2000's, this has slowly started to change. The 2005 book by literary

[2]The study of different media technologies and their effects on the content and form of visual media, including digital tools and social networks, is a one of the key concerns of media studies

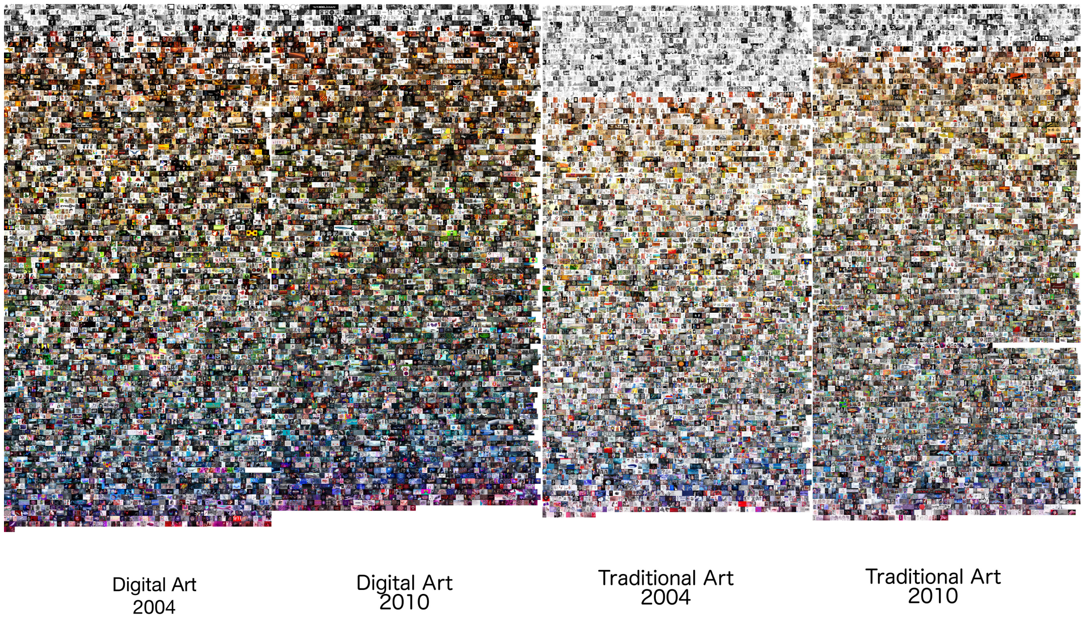

Figure 2: A comparison between 5,000 random samples of Digital and Traditional Art images for 2004 and 2010. The images are sorted by hue, with black and white images appearing on top. This explorative visualization suggests that the changes of Traditional Art between 2004 and 2010 are larger than the changes of Digital Art in the same time period. Figure 8 quantifies these changes.

scholar Franko Moretti (Moretti 2005) and the already mentioned computational analysis of patterns across of a few million digitized books in 2011 (Michel et al. 2010) motivated other researchers to conduct quantitative analysis of historical patterns in various fields of humanities using large datasets. Today, there are publications analyzing changes in literary genres in 18th-19th century (Underwood and Sellers 2012) and 19th century American newspapers (Smith, Cordell, and Dillon 2013) ; a study of changes in popular songs over last 50 years (Serrà et al. 2012); a few publications analyzing changes in feature films from 1900's until now (Cutting et al. 2011); and the analysis of text news archive (Leetaru 2011). However, to the best of our knowledge, no one has yet performed computational analysis of changes in visual art using sufficiently large datasets.

In computer science, there is a size-able literature analyzing visual art, but it does not addresses the questions of historical change. Many earlier papers focused on classification: deciding on whether particular artworks of a famous artist were indeed created by this artist, or automatically classifying artworks into classes (such as art styles) (Lombardi 2005). More recently, the development of social media and crowd sourcing has enabled researchers to obtain aesthetic judgments of artworks and photographs from large sets of people. This has led to another research direction: modelling and predicting aesthetic judgements using quantified characteristics of images (Joshi et al. 2011). Many techniques developed in this research on art images are relevant for the study of temporal changes in visual art.

Methods

Metadata analysis

Images do not exist in isolation. Instead, they are surrounded by many kinds of non-visual metadata. This metadata can be divided into a number of standard data types such as numeric, categorical, unstructured text, geo-spatial, and temporal. The examples of such metadata are names of artists, sizes of artworks, their titles, tags, their descriptions and interpretation in art historical literature, spatial paths of visitors in museums, number of likes or favorites on media sharing sites, and recordings of eye movements, brain activity, or other behavior characteristics of the viewers. In other words, everything which is external to the artworks but is related to their reception, authorship and circulation can be treated as their metadata.

In this paper, we will analyze the following metadata types available in our dataset: number of sub-categories within Traditional and Digital Art categories; numbers of images in these sub-categories, width and height of images, and their proportions.

Image features

Along with the non-image metadata, we can also extract features from images and video. (To simplify the following discussion, in the following we will only consider single images.) The features are numerical summaries of different visual characteristics of images. Global features characterize these characteristics across a whole image (for example, mean brightness, saturation and hue, number of edges, etc).

Typically, in machine learning, practitioners often use a "black box" solution if it offers the best performance. In our case, we want our methods and their applications to art datasets to be meaningful to art historians, artists, museum professionals, and others who are interested in art. The goal is to add quantitative methods to other previously developed research methods in the humanities and social sciences, and not to create an efficient industry application. Although we can imagine such applications - for example, real-time categorization of huge volume of user shared images into types, discovery of their similarity to previously shared images, real-time mapping of worlds digital visual culture, etc. For such applications, efficiency would become quite important. Therefore, in this study we would only use a small number of global features which, in our view, are most interpretable. These features are statistical summaries (mean and standard deviation) and histograms of hue, saturation and value (HSV).

We extract color-based histogram features using the HSV representation of RGB images (Bradski 2000). For each image, we have three sets of n-bin histograms:

$$\begin{aligned} H &= (h_1, \ldots, h_n)^T / \max_i(h_i) \\ S &= (s_1, \ldots, s_n)^T / \max_i(s_i) \\ V &= (v_1, \ldots, v_n)^T / \max_i(v_i) \end{aligned} \tag{1}$$

where each h_i, s_i, v_i for $i \in (1, \ldots, n)$ indicates a specific bin count in the HSV representation respectively. Note that since images can be of different dimensions, the bin counts can vary widely. Therefore, we also scale the histogram features by the maximum bin count $\max_i(\cdot)$ as shown in Equation 1.

Furthermore, we compute the aggregate HSV histogram features by filtering their value with the inverse covariance matrix (that is, a whitening operation (Duda, Hart, and Stork 2000)) and computing the mean for each bin for each year. Note that our final results are not sensitive to the choice of scaling and whitening filters. In the end we have three sets of HSV histogram features for each year.

$$\begin{aligned} H^t &= (\bar{h}_1^t, \ldots, \bar{h}_n^t)^T \\ S^t &= (\bar{s}_1^t, \ldots, \bar{s}_n^t)^T \\ V^t &= (\bar{v}_1^t, \ldots, \bar{v}_n^t)^T \end{aligned} \tag{2}$$

where $t \in (2001, \ldots, 2010)$ and $\bar{h}_i^t$, $\bar{s}_i^t$, and $\bar{v}_i^t$ are the mean bin values after whitening the histograms for Hue, Saturation, and Value respectively.

Pairwise Distance Correlation between Features and Targets

We introduce a novel method that we call Pairwise Distance Correlation. In this paper we will use this method for measuring the changes of HSV features of images over time, but the method itself is more general, and can be applied to any set of features and any targets (e.g, external variables). This method is inspired by (Szkely, Rizzo, and Bakirov 2007), but we introduce the notion of learning the distance metric from data using a Quadratic Program (QP). Other examples of learning distance metrics from data are shown in (Weinberger and Saul 2009; Xiao et al. 2009; Mcfee and Lanckriet 2010).

Consider a set of N features and targets $\{(f_1, t_1), \ldots, (f_N, t_N)\}$. Here the features $f_i \in \Re^n$ are the HSV features we described above in Equation 2 for each year $t_i \in \Re \; \forall i \in (1, \ldots, N)$. We propose that if there is a relationship between features f_i and targets t_i, then this relationship should also be preserved between the distances of pairs of features (f_i, f_j) and pairs of targets (t_i, t_j). Put another way, if there is a relationship between color features and time, then $\exists \epsilon, \delta$ such that $\|f_i - f_j\| \leq \epsilon$ and $\|t_i - t_j\| \leq \epsilon$ for $|i - j| \leq \delta$. Note that this only holds true if the distance between features from years that are farther apart are larger than the distance between features from years that are closer. Effectively we can test this by measuring the correlation between $\|f_i - f_j\|$ and $\|t_i - t_j\|$.

To measure the correlation between $\|f_i - f_j\|$ and $\|t_i - t_j\|$ we need to choose an appropriate distance metric. To establish a general metric, we use the weighted 2-norm $\|f_i - f_j\|_W^2 = (f_i - f_j)^T W (f_i - f_j)$ where the weighting matrix W is learned from data. Note that to ensure that we are using a proper metric, the weighting matrix $W \in S_{++}^{n \times n}$ must be positive semi-definite. Furthermore, to learn the weighting matrix using a QP, we impose an additional constraint on the weighting matrix to be diagonal, that is $W = \text{diag}(w_1, \ldots, w_n)$ and $w_k \geq 0$ for $k = 1, \ldots, k$. To learn the optimal weighting matrix from our data set, we solve the following optimization problem:

$$\begin{aligned} \underset{W}{\text{minimize}} \quad & \sum_{i,j} \left(\|f_i - f_j\|_W^2 - (t_i - t_j)^2 \right)^2 \\ \text{subject to} \quad & W = \text{diag}(w_1, \ldots, w_n) \\ & w_k \geq 0, \; k = 1, \ldots, n. \end{aligned} \tag{3}$$

The objective function in Equation 3 is the sum of squares of differences between $\|f_i - f_j\|_W^2$ and $(t_i - t_j)^2$ for all (i, j) feature and target pairs in the data set. Thus, for the data set of N examples, there are $N(N-1)/2$ terms in the summation. The optimization problem in Equation 3 searches for the weighting matrix W that minimizes this objective function while satisfying the constraints. Note that we can simplify $\|f_i - f_j\|_W^2$ as

$$\begin{aligned} \|f_i - f_j\|_W^2 &= (f_i - f_j)^T \text{diag}(w_1, \ldots, w_n)(f_i - f_j) \\ &= (f_i - f_j)^T \text{diag}(f_i - f_j) w \\ &= d_{i,j}^T w \end{aligned}$$

where $w = (w_1, \ldots, w_n)^T$ and $d_{i,j} = \text{diag}(f_i - f_j)(f_i - f_j)$. We can write Equation 3 equivalently as

$$\begin{aligned} \underset{w}{\text{minimize}} \quad & \sum_{i,j} \left(d_{i,j}^T w - (t_i - t_j)^2 \right)^2 \\ \text{subject to} \quad & w_k \geq 0, \; k = 1, \ldots, n. \end{aligned} \tag{4}$$

which is a least squares problem with positive constraints on the unknown weights (Boyd and Vandenberghe 2004).

This can be solved with numerous QP solvers, for example (Diamond, Chu, and Boyd 2014). The solution to Equation 4 has two benefits: first we are learning the appropriate metric from the data itself to measure distances. Second, the interpretation of the weighting matrix will tell us which dimension of the the features are weighted more (and therefore more important) for correlating with targets. We will demonstrate applying the weights learned from solving Equation 4 below by analyzing HSV features of images from our dataset.

Dataset

DeviantArt defines itself as "The world's largest online art gallery and community." The network was started in August 2000 and it systematically grew since then. In 2011, it was the 13th largest social network in the world. By March 2013, it had more than 25 million members and 246 million submitted artworks (Wikipedia 2015) The network is popular with non-professional and semi-professional artists and also art and media students. In contrast, most artists who belong to the commercial art world as represented by big commercial galleries, auction houses, private collectors, art fairs and museums often avoid putting images of their art online, and also would not participate in online community of "amateurs" such as DeviantArt.

DeviantArt graciously made available our group a one million random sample of artworks from the site for the purpose of academic research. They provided us with the list of the artworks's URLs as well as all metadata publicly available for each artwork on the site. We then used these URLs to downloaded the art images [3]. The one million artworks in our dataset covered the period from the start of the social network in August 2000 until the end of 2010. Because the number of artworks for 2000 is very small, in this paper we omit this year and use all remaining artworks for the 10 year period 2001-2010. The artworks in our sample were created by 30,000 artists from many countries, but although it dominated by the United States. A proportion of artists list their gender and/or country, and the analysis of this data shows that DeviantArt is not dominated by either gender or a narrow age range. However, since our dataset does not have all artworks from the galleries of these artists, in this study we are not comparing artists to each other other, but only analyze the artworks themselves using their metadata and selected visual characteristics.

They key characteristic of DeviantArt art collection is its extreme diversity in terms of genres, subject matter, artistic techniques, visual styles and other characteristics. It is a unique window into contemporary imagination and creativity. For example, media sharing service such as Instagram feature mostly photos and they all have the same size and proportion. At the same time, only a small proportion of Instagram contributors would identify themselves as serious art photographers. In contrast, DeviantArt contributors consider themselves artists (or artists in training). The extreme diversity of DeviantArt is very valuable, but it also makes it challenging to analyze computationally (for example, we can't simply apply standard methods from computational analysis of photographs, since most DeviantArt artworks are not photographs).

[3]Our collaborators have published papers on this dataset, but have not looked at its temporal patterns (Salah and Salah 2013)

Another key and valuable characteristic of DeviantArt is the existence of the detailed system of categories used by the members for the identification of their shared artworks. Most popular media sharing networks use only tags as a way for users to categorize what they share, and since typically a single artifact is given multiple tags, this makes it challenging to understand the content of the artifacts from tags alone. While DeviantArt also has tags, its category system is more important. Our exploratory analysis of the one million dataset has shown that most users understand well the category system and place their artworks within the right subcategories.

Category name	Number of Images
Digital Art/3-Dimensional Art	17374
Digital Art/Drawings	300630
Digital Art/Fractal Art	34618
Digital Art/Miscellaneous	17152
Digital Art/Paintings & Airbrushing	29394
Digital Art/Photomanipulation	29064
Digital Art/Pixel Art	4374
Digital Art/Vector	9087
Traditional Art/Body Art	2794
Traditional Art/Drawings	45511
Traditional Art/Mixed Media	6426
Traditional Art/Paintings	30209
Traditional Art/Sculpture	6738
Traditional Art/Street Art	4417

Table 1: Largest subcategories (number of images greater than 2,000) within Traditional Art and Digital Art categories in our dataset

Since its start in 2000, the number of top-level categories and subcategories systematically grew to accommodate the variety of techniques and subjects in artworks submitted by contributors. The category system is organized as a tree, with a number of top-level categories containing further subcategories. By 2011, many "brunches" of this tree had up to 6 levels of sub-categories under them, and the total number of all subcategories was over 1,700. Examining the structure of this category tree, we see that the first and the second level categories divide art by techniques: for example,Digital Art/3-Dimensional Art or Traditional Art/Sculpture. Subsequent sub-categories often describe subject matter of artworks: for example, Digital Art/3-Dimensional Art/Characters/Animals Creatures or Traditional Art/Sculpture/Figurative. Overall, we have a detailed encyclopedic picture of contemporary creativity, reflecting contributions and interests of millions of artists. This detailed category system is one of the most valuable and unique features of the DeviantArt social network, because it does not exist in the same organized form anywhere else. The analysis of the historical development of the categories structure offers us a unique way to understand how popular art developed during the first decade of the 21st century.

However, while the existence of detailed systems of categories describing various artistic techniques, tools, subjects and genres allows us to study the historical development of these very important aspects of visual art, it does not allow to directly predict the visual characteristics of images. For example, within the "Drawings" subcategory we can find black and white and color works which may have every possible composition and dimensions. Therefore, in addition to analyzing the development of the category system, it is also necessary to analyze all images separately using computational methods, if we want to understand historical patterns in visual form. As explained above, in this study we will look at 270,000 images in Traditional and Digital Art categories.

Results and Discussion

We have analyzed both selected metadata available for 270,000 art images created by users of DeviantArt.com between 2000 and 2010, and HSV features of these images. There is no apriri reason to expect that neither subject matters nor visual characteristics changes in any systematic way in these images over this period. But if there was any changes, we may expect to find it in Digital Art rather than Traditional Art - while the tools and techniques used to make art in the latter category have not changed for many decades, digital tools and platforms (i.e. software such as Photoshop and Painter, and hardware such as desktops, laptops and later in the decade tablets) were rapidly developing in 2000-2010. Computers were getting faster, resolution and the size of RAM were increasing, and storage was getting cheaper, allowing people to create higher resolution images with more complex effects.

The results of our analysis are unexpected. While some aspects of images in Digital Art category did change during the study period, these changes are relatively small. However, images in the Traditional Art category changed in a systematic way during this period, and the amount of these changes is much larger than for Digital Art. Our analysis also reveals other interesting differences between Digital Art and Traditional Art, which were not previously noted by art historians or digital media scholars. In this section, we will go through details of our analysis. We start with quantitative aspects of the category system: growth in the number of images in Digital and Traditional Art, gradual development of hundreds of sub-categories, and changes in image proportions and sizes (in pixels). Finally, we discuss changes in color features we extracted from all images in our dataset, and compare these changes for Digital Art vs. Traditional Art.

Metadata

Categories We compared the numbers of all subcategories for Traditional Art and Digital Art category over the years. While both categories have a similar growth rate, the number of Digital Art subcategories is two times larger than in Traditional Art subcategories. By the end of 2001, Traditional Art had 10 subcategories, while Digital Art had 22; in 2005, these numbers were 81 and 162; in 2010, they were 113 and

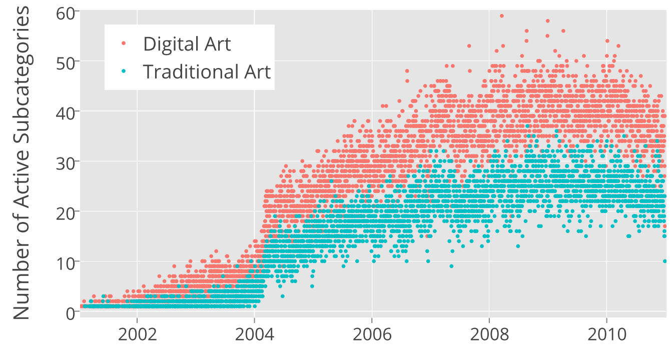

Figure 3: Number of active categories per day

216. Separately from comparing the total number of subcategories created over the years, we also examine how many of these subcategories were active at any given day, or any temporal unit (i.e, users contributed at least one new image in a given subcategory). Figure 3 shows the number of active subcategories in Traditional and Digital Art per day from 2001 to 2010 from dataset. While the numbers are smaller than the total number of all subcategories created (not every subcategory was receiving a new image daily), we see the same pattern: the numbers of active subcategories for Digital Art are systematically larger than the numbers for Traditional Art. Comparing the total number of images placed by users within these two categories once again confirms the same pattern: our sample contains 101,085 images in Traditional Art category, and 177,737 in Digital Art category. (After 2009, the number of newly contributed images became smaller, and correspondingly less categories are active on any given day. We think that the reason for this has to do with rapid growth of other social networks during that time which may be attracting people who previously contributed to DeviantArt.)

Images sizes and proportions Given the systematic changes in software and hardware for digital art creation during the 2000's, we can expect that Digital Art images would get progressively larger (as measured in pixels horizontally and vertically). Additional interesting characteristic which can be analyzed is the proportion between width and height. While both Traditional Art and Digital Art have portraits and landscapes subcategories, they contain only a small proportion of total images. Therefore, we did not have any particular expectations about image ratio, not did we had reasons to expect that they will be different for Traditional and Digital Art.

The analysis of images sizes and proportions also led to surprising findings, which can't be related to any a priori quantitative art historical or media theory analysis. Figure 4 plots width and height (in pixels) of the images. Each image is represented by a point. The smooth curve which acts as the

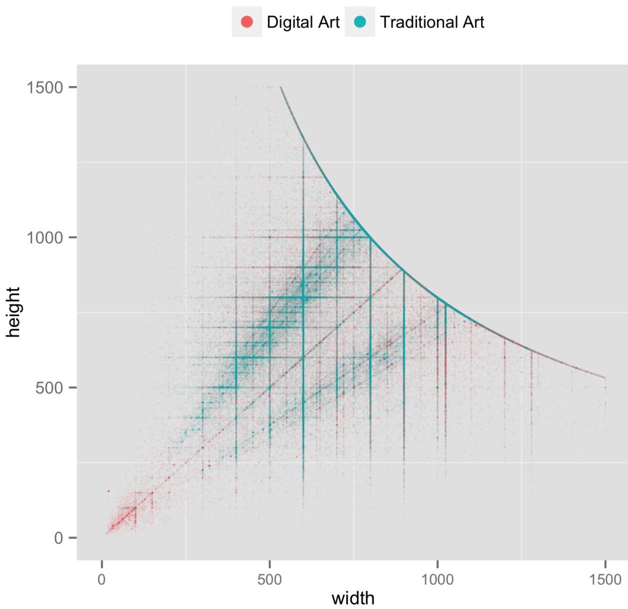

Figure 4: Width and height (in pixels) of the images represented as points

border for a combination of width and height is the result of the deliberate limit of DeviantArt web site which prohibits users from adding images bigger than a particular size - so this is not an interesting finding. But the big difference between clustering of points for Traditional and Digital Art is. While the sizes of Digital Art images vary freely, a larger proportion of sizes for Traditional Art concentrate along a small number of widths and heights. We propose the following explanation for this interesting pattern. When a user of Painter, Photoshop, 3D Studio Max or any other digital software program for photo-editing, painting and drawing or 3D design creates a new image, she can easily choose any size. Equally important, at any time during the creation process, she can easily crop the image or add new area. Each operation requires just a few clicks. But the artworks in Traditional Art category typically begin with physical materials bought in an art store, such as canvases and paper. These materials are sold in a fixed number of sizes and proportions.

Image Features

In this section we extract HSV features from the artworks and measure the temporal evolution of Digital Art and Traditional Art between the years 2001 and 2010. These features include the mean and standard deviation (Std) of the Hue, Saturation and Value of each image. Using these features, we discuss simple yearly summary statistics to measure the temporal changes of these features. In addition, to capture a richer set of features for color, we also extract the 8-bin histograms of HSV. We use Principle Component Analysis of these HSV histograms to visualize the yearly change of HSV features for Digital Art and Traditional Art. Finally, we in-

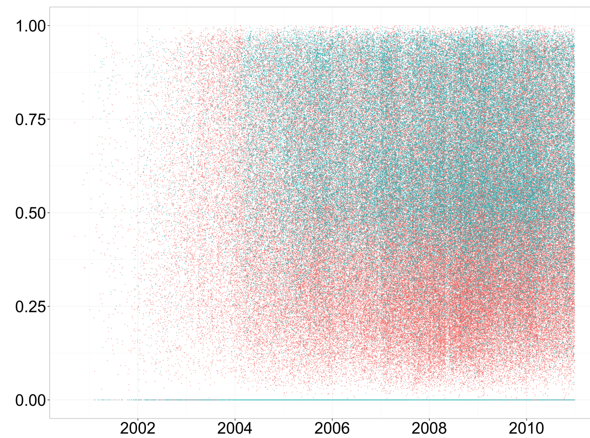

Figure 5: Mean grayscale value of images over time. Red corresponds to Digital Art and green corresponds to Traditional Art as in other figures.

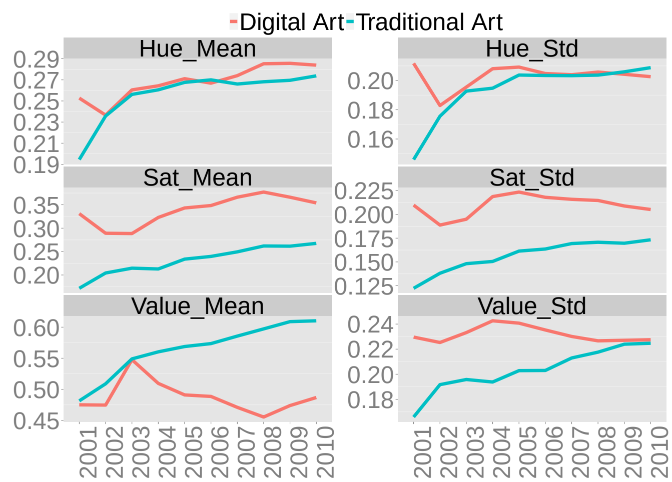

Figure 6: Average HSV features per year

troduce a novel method inspired by the distance correlation statistic to measure the yearly changes in HSV for images.

Aggregates In Figure 5 we show the scatter plot of the average Value (equivalent to gray-scale value of the image) for each artwork in our data set. This figure illustrates that Traditional Art has a much more narrow distribution of grayscale values than Digital Art. Similarly, Figure 6 shows the mean HSV and standard deviation of HSV aggregated using average values for each year. As in Figure 5, we see that the distribution of gray-scale values in Figure 6 (bottom right) for Traditional Art is tighter than for Digital Art. The average distribution of Saturation levels for Digital Art and Traditional appear to be quit different, although we see that by 2010 the standard deviation of Traditional Art saturation approach that of digital art. However, the distribution of Hues (first row of Figure 6) appears that the distribution of Hues for Digital Art and Traditional Art are very sim-

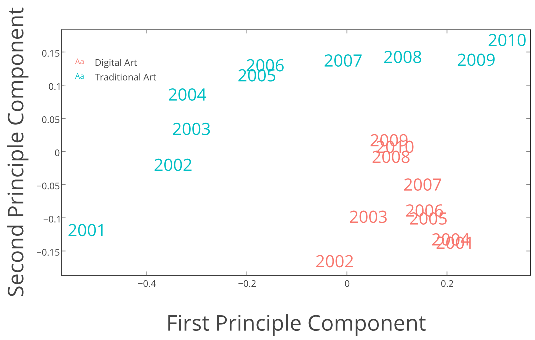

Figure 7: First two PCA components of hue histogram features

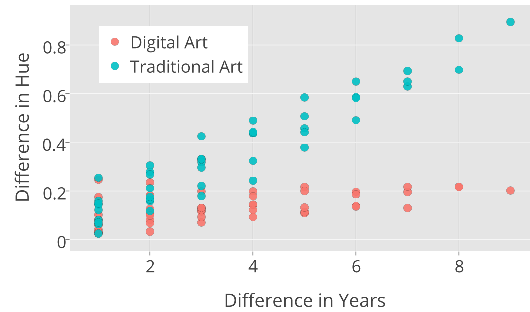

Figure 8: Changes of hue feature histogram vs time differences

ilar. These graphs suggests that HSV characteristics of images are changing over time. However, since they use simple summary statistics which reduce images to just two numbers, we suspect that they don't reveal the full picture.

Principle Component Analysis To analyse colour features at a finer resolution, we extract 8-bin HSV histograms for each image. We then compute the average HSV histograms for each year and normalize each bin component as shown in Equation 2. To visualize this feature set, we use Principle Component Analysis (PCA). Figure 7 shows the top two Principle Components of PCA for the Hue distributions. This figure shows that Digital Art primarily varies along the second PC. Traditional Art, on the other hand, varies a great deal along both the first and second PC.

This suggests that the Hue distributions of Traditional Art varies more than Digital Art. Furthermore, the PCA suggests that Traditional Art has two primary "phases." Before 2005, the majority of variance for Traditional Art is along the second PC. After 2005, the majority of variance for Traditional Art is along the first PC. Digital Art does not exhibit such phases. In fact, from Figure 7 it appears that Digital Art does not have an orderly temporal pattern as Traditional Art does. To quantify these temporal difference and correlation, we use the distance correlation in the next section.

Distance Correlation Here we discuss using Distance Correlation to measure the temporal changes of HSV for artworks. Figure 8 shows a scatter plot of the pairwise distances between the average Hue histogram distributions for every year for the Digital Art and Traditional Art categories. This figure shows that as the difference in the number of years increases, the distance between the Hue distributions also increases. Furthermore, we see that the differences in Hue distributions for Traditional Art are significantly greater than for Digital Art. In other words, the changes in Hue distributions of Traditional Art images from the late 2000's relative to the early 2000's are much larger than for Digital Art. Figure 2 seems to confirm this analysis based on the small random sample that we visualize. That is, examining Figure 2 we get an impression that hue changes of Traditional Art images between 2004 and 2010 are larger than changes in Digital Art in the same time period. But while Figure 2 only suggests that these difference are present, the distance correlation analysis of HSV histogram features allow us to confirm and quantify the degree and patterns of temporal changes. Table 2 shows the average pairwise distances for HSV. Note that the pairwise distances for Traditional Art on average is always bigger than Digital Art.

Category	Hue	Saturation	Value
Digital Art	0.1350021	0.2179323	0.1955803
Traditional Art	0.3621035	0.2858759	0.2943795

Table 2: Average pairwise distances for HSV features. The Hue and Value for Traditional Art is significantly bigger (with $p \leq 0.05$) than Digital Art. The Saturation for Traditional Art is bigger than Digital Art with a $p = 0.06796$. All $p-$values were measured using a one-sided Kolomogorov-Smirnov test.

Note that the result from Figure 8 used the Euclidean norm to measure distance. As discussed in the methods section above, it may be more appropriate to use a weighted metric. In the methods section we introduced a method, as presented in Equation 4, for learning the diagonal weighting matrix from data. More importantly, solving Equation 4 enables us to interpret the results of the Distance Correlation method by telling us which feature components, in this case corresponding to bins in the histogram, are the most important for accounting for temporal changes.

Table 3 shows the weights learned from our data set using only the Hue histograms as computed from Equation 2 for all artworks, and also for artworks that are from a specific category. The items in bold and with asterisks indicate weights that correspond to bins that are most important in generating time differences in hues. In Traditional Art, for example, the bins that have the highest weights are bins 1, 2, and 8. Bin 1 corresponds to black and white images and also images with lots of red. From Figure 2 we qualitatively observe that there are far more black and white images in 2004 than in 2010. This corresponds to the strong weight that we see associated with bin 1 for Traditional Art. For both cat-

Bin	Weights: Both Categories	Weights: Digital Art	Weights: Traditional Art
1	3.11E-05	1.20E-04	**9.20E+01***
2	**1.66E+03***	**2.32E+03***	**4.78E+02***
3	**2.75E+03***	**1.46E+09***	2.22E-08
4	6.96E-04	4.86E-04	2.75E-08
5	7.28E-04	**8.80E+02***	4.46E-08
6	8.05E-04	1.89E-03	1.17E-08
7	8.19E-04	**5.78E+03***	1.05E-08
8	2.14E-04	5.91E-04	**2.78E+02***

Table 3: Changes of hue feature histogram vs time differences using a metric learned from Equation 4

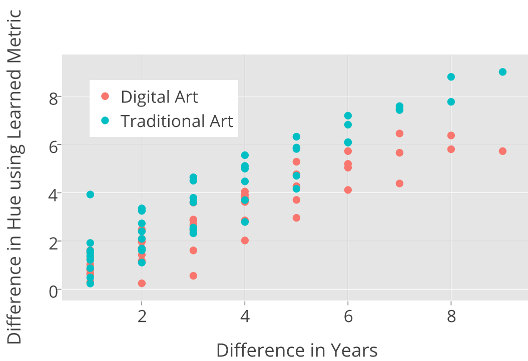

Figure 9: Change of Hue over Time using a learned metric

egories, bins 2 and 3 have the highest weights. These bins correspond to colors between yellow-green and blue-green. Again, looking at Figure 2 these color ranges appear to be the strongest in all 4 cases. Figure 9 shows that if we use the weightings found from both categories (effectively using mostly bins 2 and 3), then our learned metric has found the appropriate distance metric to show how images in both Traditional and Digital categories change with time. However, we observe from Figure 2 that perceptually Traditional Art changes more than Digital Art. Therefore, the main benefit we gain from using the learned metric from Equation 4 is to understand which bins are most responsible for temporal changes. In other words, Figure 9 shows that the method works.

Conclusion and Future Work

In this paper we propose a number of methods for quantitative analysis of historical changes in visual art. These methods are suitable for large art datasets where direct examination of sample images cannot reveal the presence or the amount of changes. We then applied these methods to a sample of 270,000 of artworks created between 2001 and 2010 and shared on DeviantArt network. We looked at the evolution of a category system used by DeviantArt artists to describe genres, techniques and subjects of their artworks, sizes and proportions of artworks, and selected image features (hue, saturation, and value).

Our sample covers two top-level categories used in DeviantArt to classify artworks: Traditional Art and Digital Art. This allowed us to study if the use of digital tools influenced content and form of popular visual art created during the 2001-2010 period. The results of our quantitative analysis were quite surprising. They could not be predicted using existing qualitative art history and media theory. In terms of the visual features we considered, the artworks in Traditional Art category changed more significantly than the artworks in Digital Art categories. The magnitude of the changes for the first category was larger, and the changes were monotonic from year to year. We validated these results using a few methods: analysis of single global features over time, PCA using features histograms, and a new distance correlation method we introduce in this paper.

We also found three other significant differences between the changes in Traditional Art and Digital Art categories during 2001-2010. In retrospective, we can relate these findings to the distinctions between traditional and digital media discussed in media theory. However, purely qualitative media theoretical analysis neither predicted our concrete findings, nor directly discussed these aspects of traditional vs. digital art. Our first finding is that the sizes and proportions of Digital Art images have much more variability than the sizes and proportions of artworks in Traditional Art category. Our second finding concerns the relative number of subcategories in these two categories. The analysis of growth of numbers of subcategories, the numbers of images shared within them, and the number of active subcategories per day revealed gradual monotonic changes. However, all these numbers were approximately twice as big for Digital Art as for Traditional Art. Our possible explanation for this difference is that Digital Art has more categories simultaneously describing specific digital techniques and software programs (Vector Graphics, Pixel Art, 3-Dimensional Art, etc.) and artistic "scenes" corresponding to these authoring techniques and specific software tools or applications. By "scenes" we mean groups of non-professional and semi-professional artists who are passionate about particular techniques and tools, and exchange information and learn from each other using publications, local interest groups and online networks such as DeviantArt. And finally, we discovered that variability of Digital Art images in terms of their value and saturation features (but not hue) is higher than the variability of Traditional Art (Figure 6). This result confirms and quantifies the expectations expressed in one qualitative media theory study of digital art (Manovich 2013).

We are planning new studies which will both expand our methods for analyzing historical change in visual art and apply them to other art datasets. Because of the extreme diversity of techniques, visual styles and subjects used on DeviantArt, we did not want to use mid-level or high-level image features since they only would be relevant to narrow subsets of our dataset. However, if we study historical evolution within a more coherent body of artworks - for example, 20th century modernist black and white photography, paintings of French Impressionists, or millions of Instagram photos shared in global cities around the world (to use examples of the datasets we have already prepared for analysis), the use of middle and high-level image features will be appropriate. These can be popular generic features widely used in computer vision (for example, presence of faces, their characteristics, or type of a scene and subjects in photographs), and also more specific "art features" introduced by researchers such as measures of composition.

However, we think that the most important future direction for research is building bridges between "traditional" qualitative art/media history and quantitative computational analysis. While our paper is the first to offer a quantitative analysis of the historical changes across large sets of art images, a number of researchers already started to analyze qualitatively historical changes in other media using large datasets of novels, popular songs, and feature films. Their findings are often original and novel, but often it is not easy to relate them to the types of concepts developed in non-quantitative literary theory, music theory, and cinema studies, respectively. Building bridges between qualitative and theoretical results is therefore the key issue if the promise of computational study of cultures and art is to be fully realized. From this point of view, we believe that one of the important aspects of our paper is that it starts making the connections between the qualitative and the quantitative for the domain of contemporary visual arts created using both traditional and digital techniques.

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