DHQ: Digital Humanities Quarterly
2008
Volume 2 Number 1

As You Can See: Applying Visual Collaborative Filtering to Works of Art

Gerhard Jan Nauta <G_dot_J_dot_Nauta at let_dot_leidenuniv_dot_nl>, Leiden University

Abstract

Art historically relevant visual knowledge can be deconstructed and the resulting components of this visual knowledge — visual discernments — lend themselves to be socially negotiated. Individual visual experts (like connoisseurs) do not share some grand and undividable cognitive cataloguing system; they are attentive to piecemeal visual discernments and the patterns in which these occur in reality. In conventional scholarly communication sophisticated tools to discuss perceptual patterns are lacking. This paper not only proposes a theoretical model of visual knowledge accumulation, but also describes a practical implementation, *Art.Similarities*, which is designed as a prototype of such a sophisticated tool. Using a custom-made interface it records visual behavior: the non-verbally expressed visual similarity judgments of distributed individuals. Users can be assigned to groups according to the qualities of their judgments. These qualities may be distilled from emerging similarity patterns. The implications of individual judgments in different user groups may vary considerably. Emerging patterns can be assessed both according to human analysis and statistical procedures. Most studies on art evaluation are attentive to either the characteristics of works, or the characteristics of observers. In this study both are considered as interdependent entities consistently.

Introduction

Without being aware of the underlying technologies, our behavior is frequently recorded, assessed, and fed back to us via today's Web interfaces. Information systems are now far more advanced in mirroring preferences, curiosities, and yes, *knowledge*, than they were, say, five years ago. The example which is familiar to us all is Amazon.com.[1] The world's largest bookstore makes clever use of the newest collaborative filtering technology.[2] From a complex database of recorded consumer behavior persuasive, personalized web pages are generated. The idea behind the process is that statistically combining traces of user behavior will yield knowledge about user interests.[3] If you have ever ordered a book that was suggested to you by Amazon, that forms the best proof of the success of the collaborative filtering approach. 1

Looking at the basic idea behind collaborative filtering systems, one may wonder whether this concept is applicable to the humanities, where the expression of value judgments (as against stating incontrovertible facts) is of such importance. Building a collaborative filtering tool involves first establishing what are supposed to be relevant data, and then modeling the way these data may be recorded and organized, in order to turn data into information, and perhaps collaborative knowledge.[4] 2

This paper discusses a field test in collaboratively establishing visual similarities, a topic of concern in art history. *Art.Similarities* is the experimental application used to sample visual similarity judgments.[5] The experiment could be relevant for other disciplines than the history of art, both inside and outside the humanities. 3

The bulk of research in distributed cognition is text-based — as we shall see in the next paragraph. For this type of research in information science and cognitive psychology an example in the domain of visual cognition may be advantageous. In particular crossing off the intermediary function of verbal language, may encourage the development of scenarios for combining transactional data (partial observations of visual artifacts) to construct emergent knowledge 4 (holistic representations). This is why I believe that in its consequences this field test could support cross-cultural comparisons in visual cognition.

I also expect that the project may shine a new light on the relation between the cultural interpretation of images and words on one side, and the relation between such cultural interpretations and objective image data, e.g. as produced by content-based image retrieval technologies [Eakins & Graham 1999], on the other side. In other words: it could help tracing the line between objective visual facts (as captured for instance in a color histogram) and more interpretive "truths". 5

In the practical sphere, because visual attention becomes partly measurable and comparable, the project may contribute to the development of educational applications, in which students learn to reflect on culture as a determinant of visual cognition. And because the interconnectedness of base distinctions and more evolved cultural knowledge is worked out computationally, it becomes conceivable that by means of technology subjects will be offered the tools to vary the compositional elements of a visual configuration, just as when you add or remove query strings based on intermediate search results, when searching large volumes of texts. 6

I presume that the latent possibilities of the *Art.Similarities* experiment will only come to the fore when we do not discuss it in isolation. Therefore consider in advance that interesting alternatives may evolve when varying such dimensions as: 7

- the scale on which the application is used (small, maybe local communities versus large, global crowds);
- a focus on gathering coherent large scale data versus a focus on developing various applications (to be populated with different sets of data);
- the application in isolation versus the application as a building block in more complicated dedicated software (e.g. as one of the options to organize visual materials in image databases or image processing software).

Such dimensions are important in assessing the usefulness of the experiment. Just to get an idea of the kind of problem addressed here, consider these two works of art, dating from the early 1930s: 8

Figure 1. Georgia O'Keeffe, *Black and White*, 1930, oil on canvas. Whitney Museum of American Art, New York. © c/o Pictoright Amsterdam 2008.

Figure 2. Edward Weston, *Sand Dunes, Oceano*, 1934, gelatin silver print. Center for Creative Photography, Tucson AZ. © c/o CCP Tucson AZ 2008

Both images show a striking overall similarity. Experienced observers seeing these works of art, may draw conclusions about artistic influences. And indeed, artists are observers by profession, adopting typical ways of expressing visual thoughts in new visual configurations. The history of art has documented innumerable instances of both explicit and implicit borrowing of formal traits and configurations.[6] This is partly motivated by the common assumption that visual phenomena in cultural artifacts are indices of material, personal and social conditions during the time of creation. 9

Establishing visual similarities is part of the groundwork in the field of art history, but making these similarity observations verifiable is precisely where the conventional systems of scholarly communication fail, since neither do we have an effective way of discussing visual similarities, nor do we have the means to trace observed similarities in large collections of images.[7] 10

Collaborative Knowledge

In recent years we have seen several attempts at constructing frameworks for the study of collaborative knowledge. The subject was variously denoted with terms such as “distributed cognition”, “social cognition”, “situated cognition”, or “group cognition”. The urge to develop theory in this field has increased dramatically since the waves of hypertext enthusiasm in the late 1980s and early 1990s, the subsequent rise of the world wide web and later semantic web, and the popularization, recently, of social software, of which the collaborative filtering systems mentioned earlier are an omnipresent example. In theories of collaborative knowledge the psychology of Lev Vygotsky, who may have been one of the first to envision a socially constructed mind, is frequently referred to. His *Mind in Society* dates back to 1930 [Vygotsky 1976]. Gavriel Salomon stressed the importance of the complementary concepts of “shared cognition” (knowledge of the world which is continuously established through live interactions among individuals) and “off-loaded cognition” (recording and processing cognitive facts and functions to realia, such as concept maps) [Salomon 1996]. In 1995 Edwin Hutchins published another influential book, *Cognition in the Wild*, where the author uses the metaphor of 11 ship navigation to pinpoint the cultural nature of cognition: no single individual from the ship's crew is capable of managing all the complex operations that are necessary to sail [Hutchins 1995].

Important building blocks of frameworks for collaborative knowledge are: thought processes, as distributed amongst a group of individuals, representations of these thought processes, as captured in external realia, and mediating processes (i.e. computer systems) that are capable of coordinating both internal and external representations and lifting the newly generated forms of knowledge above the level of consciousness of the individual. 12

A recent attempt to theorize in this field is Gerry Stahl's book *Group Cognition: Computer Support for Building Collaborative Knowledge* [Stahl 2006]. On the basis of a series of experiments, in which the promise of computer supported knowledge negotiation has been tested, Stahl analyses the mechanisms of collaborative knowledge building and ends by presenting a tentative theory of group cognition. In Stahl's model the sphere of personal understanding is opposed to and merges with a cycle of social knowledge building. Individuals articulate – in public statements – personal perspectives, which in a process of argumentation and rationale are being assimilated with the perspectives of other individuals into collaborative knowledge. This collaborative knowledge is formalized and objectified in cultural artifacts that can be observed and known by individuals. Et cetera. Stahl's model may help pointing out the stages of the process of knowledge construction and thus facilitate the design of specific forms of computer support [Stahl 2006, 207]. 13

Typical for Stahl's approach is his focus on verbal discourse. Although in some of his experiments schematic representations of e.g. floor plans or network architectures are crucial to the tasks of his subjects, in most of the experiments he uses chat-like conversations and threaded discussions to unfold his theory. But the kind of knowledge being researched here is visual knowledge constructed by visual means. As yet I have found no models of distributed cognition covering this particular domain. In my model the visual discernments ("personal focus") of individuals are expressed ("off-loaded") in visual images, where the computer records and mediates ("negotiation of perspectives"). 14

Basic Assumptions

It is taken for granted in this study that the visual appearance of a cultural artifact, and thus its potential similarity to other artifacts, is resolvable into literally innumerable formal qualities. Two artifacts may share any number of formal qualities, and these are thought to somehow account for their similarity. Two (visually) identical (=maximally similar) artifacts share immense quantities of visual characteristics, whereas for two very dissimilar artifacts the number of shared visual traits is minimal. In between the extremes the rule would be that *the more two cultural artifacts share a set of singular formal/visual attributes/traits, the more they are experienced as being similar to one another.* [8] In other words: the actually perceived similarity is defined as the function of an unspecified number of trait-to-trait similarities. 15

In order to avoid endless image dissections, another assumption adopted here is that the overall visual appearance of a cultural artifact in fact approximates to the weighted sum of relatively few, but *distinctive* formal/visual attributes/traits. So I assume that culture is a decisive factor in subjects focusing on specific image characteristics: the threat of an infinite number of physical features is being balanced by cultural determinants.[9] 16

Observers have a number of options to denote a visual concept [Nauta 2001]. In most of these options abstract symbols (words, numbers, etc.) signify visual similarities. Two options, however, concern iconic references. One focuses on the simultaneous display of multiple instances of similar artifacts along one or several specific attribute(s). For instance, Santini, Gupta and Jain discuss an experimental interface in which the user is allowed "to manipulate not only the individual images, but also the relation between them" [Santini et al. 2001]. An example of fairly successful content-based image retrieval is the system developed by D.P. Huijsmans et al. for the *Leiden 19th-Century Portrait Database* (LCPD), a database of Dutch carte-de-visite studio portraits (1860-1914). One of the options for consulting the LCPD is a so-called "relevance feedback" interface. After each retrieval action the user is presented a table of results. Feedback is given by just clicking the photographs that are close to what the user was looking for, whereupon the system — using pre-calculated image characteristics — offers a new set of images, ideally closer matching the user's preferences. Et cetera. [Huijsmans & Smeulders 1999] In the other type of iconic denotation, the one elaborated here, image similarities are indicated by simple images exemplifying a restricted set of formal attributes.[10] These simple images are thus 17 conceived as visual denotats.[11] So where Santini et al. avoid immediate deconstruction of holistic appearances, this paper will explicitly *analyze* similarities in considering *iconic* denotations.[12] In this way, problematic verbal denomination issues will be evaded. Present-day computers are perfectly suited to create systems for communicating pronouncements on matters of visual similarities through instant presentation of instances.[13]

Another assumption concerning the similarity of artifacts has to do with the quantity of common visual traits. Where two visual artifacts share a substantial number of different visual traits, we say that these artifacts manifest *multi-trait similarity*. The notion of "style" may be akin to this concept. In the vocabulary of this article style could be defined as *multi-trait similarity occurring across multiple images.* 18

Apart from considering the number of visual traits two artifacts have in common, it is important to recognize that the *relative weight* of these visual traits is of interest: the more observers indicate they have discerned one particular trait, the more relevant this trait will be in any function defining the visual similarity of the artifact to any other artifact. Of course it should be kept in mind that relevance is dependent on the *group* these observers belong to. We are *not* considering facts. We need individual human observers to assess the visual qualities of artifacts. And assessments may either apply to the entire surface of a visual artifact or to only a segment of that surface. Once these assessments are recorded they can be analyzed. And the more individuals are involved in assessing visual qualities, the greater the cultural relevance of these assessments will be. Patterns in individual assessments, *calculated* for social groups, may reveal "high order" notions (such as — perhaps — *stylistic notions)*. That an individual observer giving individual assessments need not be conscious of these high order notions is a fascinating idea. 19

Hypothesis

The following hypothesis aims at focusing the points made so far: The social formation of opinions concerning the visual similarity of cultural artifacts amongst a group of motivated observers can be modeled and recorded *without* the application of verbal descriptors, using information technology (web technology, databases, statistics), in such a way as to make real use of archived records for purposes like: getting to know broad classes of image attributes; retrieving related images; and learning the preferences and perceptual biases of user classes and individual users. 20

Experimental Setup

In order to test the hypothesis an experimental application — *Art.Similarities* — had to be developed, offering access to a modest quantity of digital images. The application interface had to be constructed in such a way that it would be relatively easy for observers to link visual icons from a restricted but varied set to the digital objects in the collection. Every transaction involving the database would have to be recorded to be able to quantitatively compare the visual discernments of different observers. 21

Here is an approximation of the processes the application should ideally support: 22

1. Users identify themselves. New users may be asked to submit a *preprocessing user profile*, containing data such as: name, age, sex, professional affiliation, etc. Returning users just log in.
2. Novice users are assigned Level 1 privileges, meaning that they are allowed to assess single trait similarities (artifact-icon associations; explained below).
3. A sequence of artifacts is being displayed, one by one, in random order. The Level 1 user is invited to select an appealing work.
4. The selected artifact is presented together with a set of uniform, but visually maximally diverse icons.
5. Level 1 users distinguish single trait similarities between the simple ("attenuated") images (icons) and ("replete") artifact reproductions, and fix these similarities by means of icon-artifact attributions (one by one).[14]
6. Attribution data are recorded, together with user IDs, date stamps, etc.
7. The preceding steps (i.e. the attribution process) can be repeated, until the user indicates he/she wishes to stop interactions.

8. Since the artifact similarity measures are precisely quantified, statistical procedures may be applied to the records in the database. This will yield *artifact profiles*.
9. Over time, artifact profiles will be generated/recorded, consisting of sets of icon references related to individual images, together with user IDs.
10. Artifact profiles may be displayed. Repeated artifact-icon associations will become apparent immediately.
11. Artifact similarity measures may be deduced from artifact profiles. These similarities are either single trait (t=1) or multiple trait (t=N) similarities.
12. Based on similarity measures the system can retrieve and display artifacts “like” the one the user started with (~similarity-groups; s-groups).
13. The profile (in terms icons referred to) of any one of the retrieved artifacts can be inspected individually. This way the user will be able to examine multiple formal perspectives relevant for a given artifact.
14. The user must be able to ask for recorded data concerning each and every artifact-icon association.
15. The more artifact-icon assignments a user makes, the more precise a *post processing user profile* will freeze his visual cognition (behavior).
16. Following a preconceived algorithm the coherence of both preprocessing and post processing user profiles may be analyzed. The outcome may be fed into a process of user classification.
17. Either based on the preprocessing user profile only, or based on the analysis just mentioned, some users may gain the status of Level 2 users (~superpeers).
18. Level 2 users assess high-order artifact qualifications (profiles), thus either implicitly or explicitly approving both perceived inter-artifact similarities and Level 1 user articulations.

Technical Elaboration

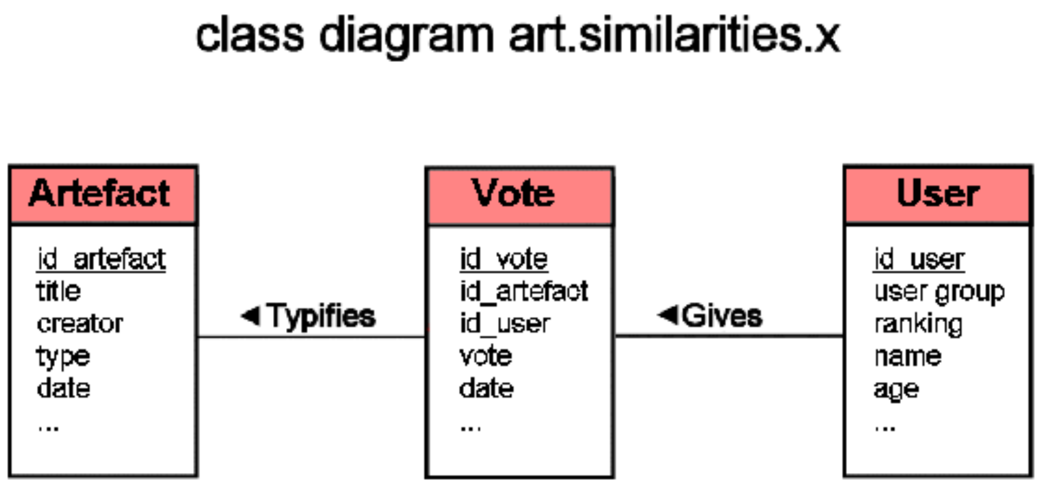
Object Modeling and Database Design

Although the combinatorial nature of calculating visual similarities may eventually lead to a data explosion, the actual number of object classes in this experiment is limited. There are *users/observers*, *visual artifacts*, and *votes*, expressed by means of icons that are indicative of perceived visual traits.[15] For the object types in the experiment open standards were adhered to wherever possible: 23

- Visual *artifacts* were catalogued using the CDWA metadata scheme [Baca & Harpring 2005]. Among the attributes in the database are creator name, title, date, etc. In the class diagram below only a subset of the full set has been incorporated.
- *Users/observers* were classified according to common attributes like name and other personal data such as address, gender, age, etc. Specific attributes indicative of observer classes are: education, profession and expertise.[16]
- To keep it simple *votes* were initially recorded with only a minimum of attributes: a key referring to one of the icons, references to the table of users (user name) and artifacts (object id), and a date (and time) stamp.[17]

The basic design of the database consisted of only three related tables. Two of these (the *artifacts* and *votes* table, see below) were so arranged as to be able to log all transactions. The third table (the *user* table) serves the purpose of identifying specific users and — in the next phase — recording the results of an analysis of performance data.[18] 24

Figure 3 shows a class diagram of the system: 25



Interface Design

In this experimental pilot the interface was designed as straightforward as possible, with a firm eye on both database design and the basic tasks the users of the application should be able to perform. As to these tasks the decision has been to keep two different activities clearly separated: editing and browsing/searching. These activities were reflected in two different interface modes: *editing mode* and *serendipity mode*. The design of these modes was based on slightly different principles. Switching from one mode to the other, however, had to be self-explanatory. Within each of the modes media objects, metadata, and interaction controls were placed within one and the same screen (no overlapping windows). Still in both modes a clear balance was sought between the object/artifact of the user's present focus/attention and images for comparison, whether these would be simple icons or replete (thumbnails of) artifacts. 26

Textual data were kept to a minimum. For navigation of the data collection the decision was to rely on either *random presentations* (e.g. on starting an interactive session) or *pointing and clicking*. Although the underlying database of artifacts did in fact enable it, no textual search options were offered. Since throughout a session the identity of the user should be known, the first step of working with the program was authentication. 27

Here are two screendumps from *Art.Similarities*: 28

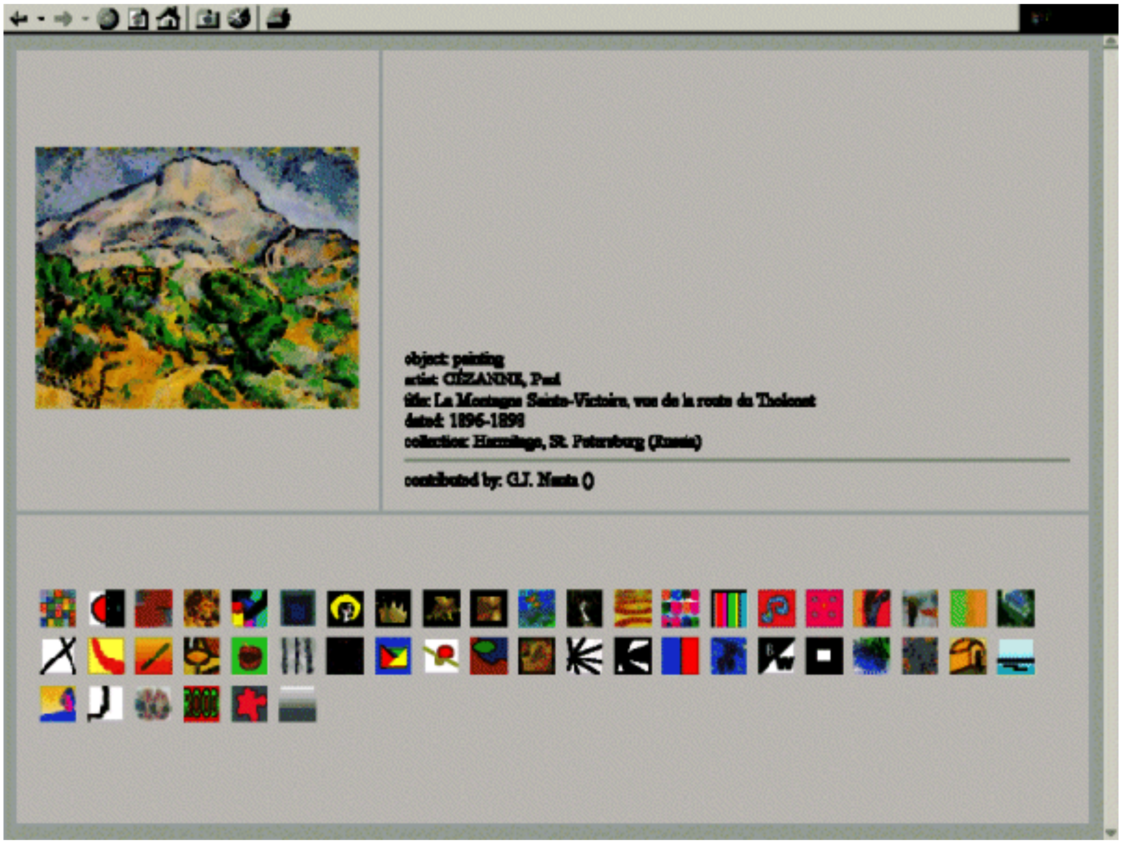


Figure 4. Editing mode: Together with a selected work of art, a collection of icons is on display. The task at hand is to check out the icon representing the most outstanding visual trait of the artifact, by simply clicking one of the icons. The association of artifact and icon is stored in the database.

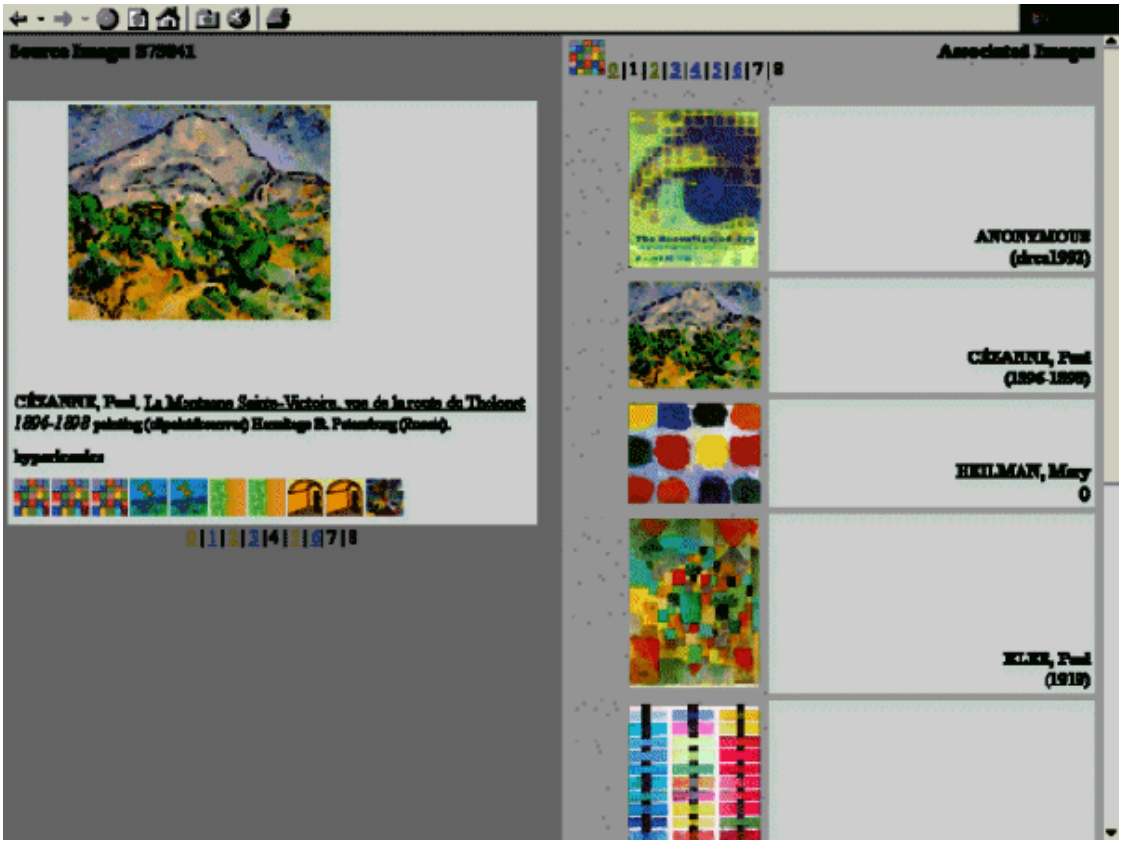


Figure 5. Serendipity mode: By clicking any of the icons assigned to a particular artifact (left) the application will display an overview of other artifacts to which this particular icon has been attributed. In this example the listing is sorted according to one of the values of the descriptive metadata. An alternative would be sorting according to the number of times a particular icon has been assigned to the individual entities.

Implementation

For the population of the artifact file a collection of about 400 reproductions of 2D artifacts and matching descriptive 29
metadata was imported into the database. This special purpose data set was compiled to have a research collection, with a variety of provenances, media types, and formal characteristics. The controlled addition of test pairs of similar images was considered, but to avoid complexity it was decided to elaborate on this line of thought in a follow-up.[19]

For pragmatic reasons in the experimental setup a more or less justifiable set of icons was used. Students produced 30
icons in dedicated assignments; others were created by the author or were found on the Internet. Undoubtedly this will bring some bias to the experiment. I will come back to the selection of indexing items in the final section.

The number and size of icons had to be decided upon as well. Since for some time to come the major impediment to 31
rich visual comparisons will be the size and resolution of display devices the use of large sets of icons of considerable pixel dimensions, would go at the expense of the space available for the presentation of the artifact under consideration. Since the simultaneous display of both icons and artifact was considered desirable, the provisional layout was fixed at 1 artifact and 100 icons.

Use

In five subsequent years (2003-2007) BA students in the history of art tested the *Art.Similarities* application. Students 32
could approach the system from any PC connected to the Internet. Some 4000 interactions (icon-artifact pairs) on a total of about 200 users were logged, so the average number of indexing results per user in this pilot is about 20. Since the design philosophy was to make the application as simple as possible, no help function was offered. And indeed, students had no difficulties in using the program. The analysis below is based on the database logs of this pilot. Some evidence comes from an additional paper survey.

An Analysis of Results

Since the experiment considers three object types — observers, artifacts, icons — and since these object types are systematically interrelated — observers assign icons to works of art — the analysis may extend into at least three fields of semantic relevance. The primary concern is with how artifacts will be typified or defined as being more or less similar to one another. But an analysis of patterns in observer behavior and the covariance of icon-image assignments can equally yield interesting results. 33

Before we turn to an inspection of the collected data, however, a few words must be added on the representativeness of the sample. The following analysis of data is explorative. In comparison with today's large-scale commercial data warehouses the couple of thousand of records in my transaction database is very small. In the real world data mining techniques will not be used on data sets of this size. Add to this that data were not collected systematically: subjects were not asked to visually tag a fixed number of artifacts; they were free to start or stop tagging any time, and artifacts were presented at random. The only choice the subjects had was to skip an artifact and go on with the next object displayed. As a result the choice of artifacts and the distribution of visual tags across the objects represented in the database cannot be fully representative. Still it was decided not to normalize data routinely. The meaning of differing tagging frequencies could be relevant. Below the results of the *Art.Similarities* experiment will mostly be explored on the basis of raw data, especially where the similarity of artifacts is under consideration. 34

The setup of the test application is fairly simple. Nevertheless an analysis of database logs already requires substantial pre-processing and the application of sophisticated algorithms to extract measures of central tendency from the rapidly growing files. Just to compare one artifact and its related icons with all other artifacts, one needs to know both how many icons any pair of artifacts has in common, and the number of times any shared icon has been assigned to both artifacts. Below are some indications of what lies hidden in these database tables. My approach is a combination of searching for patterns in the data and doing empirical checks, in particular in the form of a visual assessment of artifacts and icons. Other methods of relating data and reality could be asking subjects (experts) to assess the results of manipulating transaction data, or even in some cases using content-based image retrieval technology to evaluate matches of artifacts. 35

Artifact Characterizations

To control for bias caused by low numbers, most of the analyses of image similarity was done on the top 100 artifacts according to tagging frequencies. This subset provided for 1834 (out of 3917) tags, so the average number of tags per artifact was about 18. The co-occurrences for this dataset were computed (n=28100). Starting from the table of co-occurrences a number of measures could be extracted, the most immediate being the absolute number of co-occurrences per pair of artifacts. This was taken as a rough measure of artifact similarity. 36

Similarity Based on Absolute Numbers

An empirical (visual) inspection of the top 25 of similar pairs according to the absolute number of co-occurrences yielded no surprising results. The visual characteristics corresponding to computed similarities were quite obvious: strong primary colors (red, yellow, etc.), peculiar shapes (whirls, extreme converging and/or parallel lines), or overall organizational configurations (rectangular subdivisions, compositions balanced around two or three main compositional elements). As stated above the subjects in this experiment were free to skip artifacts in the process of tagging, so they probably preferred obvious image characteristics. Frequencies of tag scores — number of tags, number of co-occurrences, and number of associated artifacts — seem to support that interpretation. Below I will have a closer look at this. 37

The relative importance of vortex-like shapes was remarkable. Two post-impressionist paintings — the *Starry Night* by Vincent van Gogh (1889) and *Portrait of Felix Feneon* by Paul Signac (1890-91), both in the Museum of Modern Art, New York, co-occurred as much as 270 times. These works appeared in the top of the list in association with another rather non-ambiguous "whirly" image: a picture by fractal artist Forest Kenton Musgrave (aka "Doc Mojo"): *Fractal Berry 01* (1997). The Van Gogh painting also appeared in the top of the list related to a photograph of a platoon of cyclists, 38 driving along a winding road in the Alps, and to another painting by Van Gogh, *Cornfield (with cypresses)* (1889), now in the Bürle Collection, Zürich. Maybe vortex-like configurations are eye-catching,[20] though an alternative explanation could be that the vocabulary in use (i.e. the set of 100 icons) was particularly suited to tag vortex-like shapes. A possible *vocabulary bias* must be taken into account.

Here is an example of two visually “similar” artifacts, according to the raw database logs: 39

Figure 6. Raphael (Raffaello Sanzio), *School of Athens*, between 1509-1511, fresco. Vatican (Stanza della Segnatura), Rome.

Figure 7. Marcel Molle, *Dean Hamer (rechts) en Steven Rose in Amsterdam*, 1999, photograph (De Volkskrant, June 12, 1999). © Marcel Molle Amsterdam.

The number of icon-artifact associations for this pair was distributed like this: 40

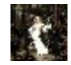
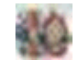
									
Raphael, *School of Athens*	8	5	1	1	0	1	1	1	18
Molle, *Dean Hammer*	7	2	2	1	1	0	0	0	13
	15	7	3	2	1	1	1	1	31

Table 1.

The number of co-occurrences computed for these artifacts was 69. The distribution of icons shows that the Raphael 41
painting has been tagged more often. Normalization would have given a different ranking for this pair of artifacts.

Similarity Based on Weighted Co-occurrences

For the top 100 sample data a number of weighted co-occurrences were computed, in essence by multiplying each 42
icon-artifact combination by a factor based on the number of tags assigned to that artifact. Here is an example of two artifacts that rose on the list of calculated similarities as compared to the unweighted data:

Figure 8. Peter Jenny, *“Die minimalen farblichen Abweichungen (...) werden in der formalen Reduktion zum bildbestimmenden Thema”* . In *Bildkonzepte: das wohlgeordnete Durcheinander*. Mainz: Verlag Hermann Schmidt, 2000.

Figure 9. Sol Lewitt, *Four Basic Colors and all their Combinations*, 1984, indian ink. Private collection (Sol LeWitt) USA. © c/o Pictoright Amsterdam 2008.

The number of icon-artifact associations, *after weighting*, was distributed like this: 43

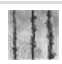
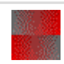
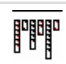
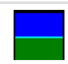
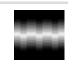
										
Jenny, *Untitled*	15	2	4	2	2	0	1	1	1	28
Lewitt, *Four Basic Colors*	33	3	0	0	0	3	0	0	0	39
	48	5	4	2	2	3	1	1	1	67

Table 2.

What is most striking in this table is the high frequency of one particular icon shared by both artifacts *and* the relatively large number of icons indicating a difference in the images they refer to. The Jenny picture has an unmistakably horizontal articulation, which is lacking in the Lewitt piece. The tagging behavior of subjects in the experiment appears to be visually sound, but our crude computational procedures do not fully reflect that. 44

The number of co-occurrences for the Lewitt and Jenny artifacts was 501 (167 if the raw data were used). A remarkable shift of this pair of artifacts in the weighted charts was caused by the relative distance between the frequencies of assigned icons: 28 versus 13. Broadly speaking however, in the subset chosen here the differences in approach did rarely result in spectacular shifts. More research is needed to refine the still rudimentary similarity measures. 45

One Artifact and its Neighbors

Another approach to the inspection of the transaction database is to take one artifact and calculate what in Last.fm terms would be referred to as its *neighbors*.[21] We did just that for the Raphael painting presented above (tag frequency: 18). Keeping one value in the comparison constant understandably reduces the effect of weighting. In the top rankings calculated only two pairs of artifacts changed position after weighting. 46

Again our sample resulted in rather obvious combinations of artifacts. The look of the Raphael painting is strongly determined by the arch across the full width of the painting, which is reflected in a succession of smaller arches in the axis of the picture plane. More than half of the neighbors displayed such arch-like shapes. Another salient feature of the calculated neighbors is precisely this repetitive quality of shapes containing shapes. Here is an illustrative example of an artifact that co-occurred with the School of Athens: 47

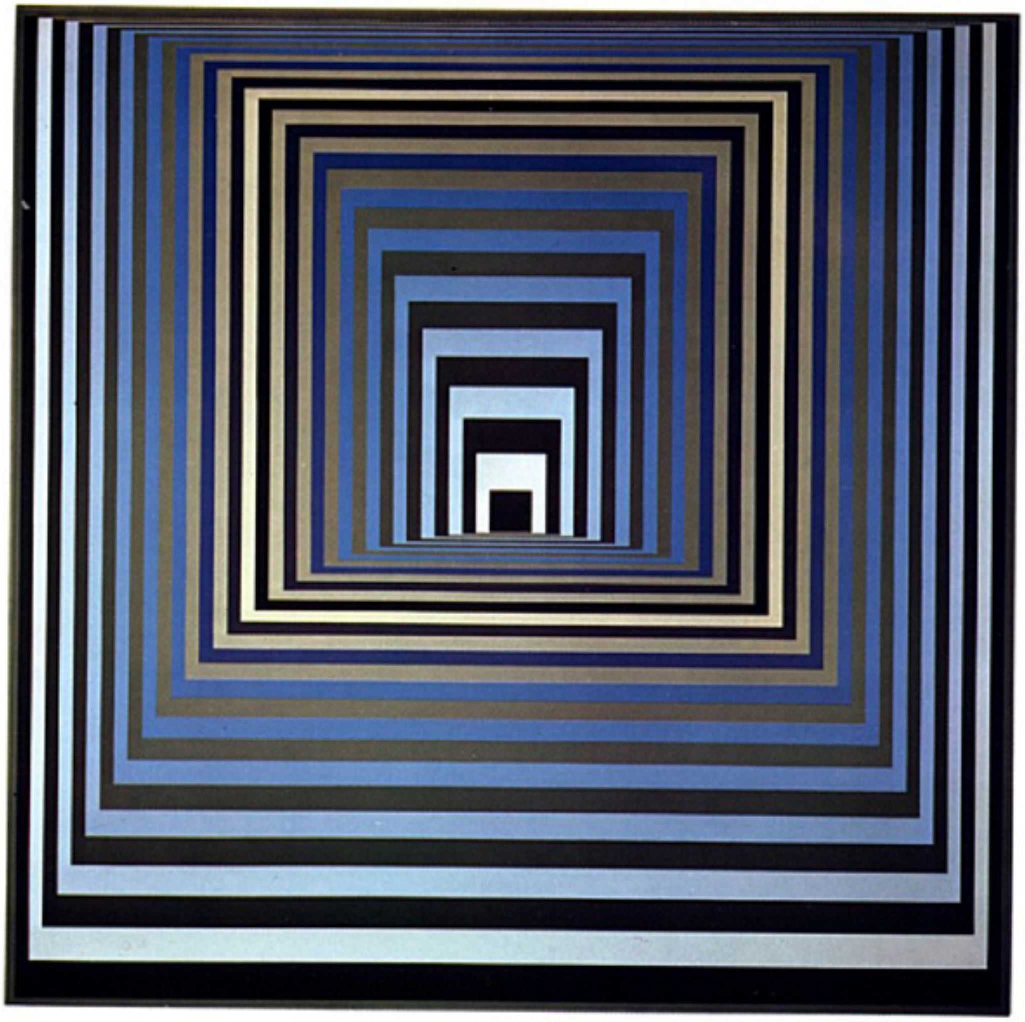


Figure 10. Victor Vasarely, *Vonal-Ksz.*, 1968 vinyl. Private collection. © c/o Pictoright Amsterdam 2008.

This association may at first surprise us, but nevertheless the diagrammatic similarity is apparent. If we look up the 48
corresponding distribution of icon-artifact associations it appears that the high similarity score is completely dependent on the shared icon of two congruent rectangles, connected at the corners by four straight converging lines.

		…	
Raphael, *School of Athens*	5		18
Vasarely, *Vonal-Ksz.*	8	…	33
	13	…	51

Table 3.

Please note that the Vasarely painting has been denoted by a relatively large number of icons *not shared* by the 49
Raphael piece. Somehow the icons any two artifacts do *not* share should be weighed in a formal definition of similarity. In the next paragraph I will momentarily alter the focus of my analysis and discuss an equation in which both the number and distribution of shared icons and the icons *not* shared are considered.

A Formula Describing a Similarity Measure for Pairs of Artifacts

The discussion above was based on an overall analysis of a co-occurrence table and crude distance measures taking 50
the number of shared icons into account. Another approach to similarity measurement is taking any pair of artifacts to compare the corresponding patterns of icon-artifact assignments. If two artifacts share an icon this must add to the

overall similarity value. The more icons two artifacts have in common, the more the similarity value should increase. Conversely icons not shared (but used for one of the artifacts in the comparison) should diminish the overall similarity measure. Furthermore the ratio of co-occurrences must also be taken into account. This amounts to weighting the straightforward numbers: if both artifacts in a comparison have an equal number of one particular icon in common, the weight of the corresponding part in the equation could be multiplied by 1 (n:n); if one of the artifacts has been tagged twice as much, the equation could be multiplied by 1/2 (n:2n) and so on. (Of course the numbers must be weighted to optimize results. See below.) So the similarity (o) might be expressed in the following descriptive formula:

$$o = ((\sum_{1}^{n}(\theta_n/N * s/l) - \sum_{1}^{m}\alpha_m/N) + 1)/2$$

Here n is the number of shared icons, θ is (per icon shared by both artifacts) the total number of occurrences, s is the minimum and l is the maximum number of occurrences for each icon. The number of icons not shared (per artifact) is m. The number (per icon) of icons not shared by both artifacts is α. N is the sum total of occurrences of icons assigned to both artifacts. As a result of this: if two artifacts do not share any icon, the similarity equals to 0. 51

Applying the formula to the (non-normalized) data for the artifacts of figures 6 and 7 this is the outcome: 52

$$o = ((15/31 * 7/8 + 7/31 * 2/5 + 3/31 * 1/2 + 2/31 * 1/1 - 4/31) + 1)/2 = 0.7488$$

For the artifacts in figures 8 and 9 *before normalization* o would become: 53

$$o = ((26/41 * 11/15 + 3/41 * 1/2 - 12/41) + 1)/2 = 0.6045$$

Because in the formula s/l is the ratio of the smallest and largest number (per pair of artifacts) the effect of applying the formula to non-normalized data will lead to a pronounced bias. Obviously normalization is a necessary step in preprocessing the raw data if we use the formula.[22] 54

Fake Similarities

Up to now we have focused on similarity measures that become understandable if we empirically compare the associated icons and artifacts. In the sample data however there are indications of problems caused by the ambiguity of visual tags (icons). Here is an extract of the (normalized) artifact x artifact co-occurrence table, showing only 5 artifacts that were tagged exactly 24 times. 55

	S18500	S23715	S75116	S75122	S75308	
S18500	137					137
S23715		25	48	10		83
S75116			64	1		65
S75122				41		41
S75308					92	92
						418

Table 4.

In the row and column headings we have the IDs of the five artifacts, while in the table cells there are eight co-occurrence values, five of them being values indicating the number of times an artifact co-occurred with itself. (We will get back to this in the next paragraph.) The three remaining values express co-occurrences of *different* artifacts. E.g. S75116 and S23715 refer to waterscape paintings by Claude Monet. The association (n=48) visually makes sense. The other values seem to suggest a similarity between another artifact (S75122) and the two Monet paintings. On closer consideration, however, the icon responsible for the co-occurrence scores appears to have been selected for its bluish appearance in case of the Monet waterscapes, and for its sophisticated color gradients and peculiar configuration of rectilinear lines in case of the other artifact: a painting from the series *Homage to the Square: Apparition* (1959), by 56

Josef Albers. In fact the co-occurrence is an “artifact of the method”. Here is the icon responsible for the confusion:

Figure 11.

This must be taken as a warning. Apart from the *vocabulary bias* mentioned earlier, ambiguities in the vocabulary in use 57
— our 100 icons — may cause “fake similarities”. I will refer to this as *vocabulary ambiguity*. (In a section below the inverse of this problem will be discussed, viz. the confusion caused by partly redundant visual tags.)

Measures Qualifying Individual Artifacts and/or Visual Tags

Doubts about the appropriateness of the particular set of icons used in the experiment forced me to take a closer look at 58
the numbers associated with individual artifacts. Again the objective is to verify empirically what numbers in the co-occurrence tables stand for. And again the analysis was done on the top 100 subset in terms of co-occurrences. This time however the values in the pivot table were normalized. Artifacts were ordered according to the total number of co-occurrences, the number of “self co-occurrences” (a multiple of the number of times an artifact was tagged with one or more icons — see above), and the number of co-occurring artifacts (per artifact). Maximum and minimum values, and average, mode and median were also computed.

Data point out that the number of co-occurrences roughly co-varies with the number of self co-occurrences. The same is 59
true if we first subtract the number of self co-occurrences from the number of co-occurrences. But unfortunately this finding will not bring us near a paradigm shift.

More interesting was the outcome that the number of self co-occurrences for a particular artifact negatively co-varied 60
with the number of artifacts associated with that artifact (correlation coefficient: -0.6753)[23]. In other words: the more often an icon (or small set of icons) was assigned to an artifact (in relative terms) the less often that particular artifact could be related to other artifacts. All the same the number of co-occurrences with these few artifacts tended to be high. Another paraphrase of this could be: the smaller the number of partial similarities, the more an artifact “approaches to” one of the icons used. It is clear that this qualifies both artifact and icon (set). The implication of these findings would be that a mere (automatic) analysis of transaction data can be used to improve the set of icons. (See below.)

If we have a look at the top 10 of artifacts scoring high on “self co-occurrence”, we might discern two broad classes of 61
objects: artifacts that are schematic (or: diagrammatic) in appearance, and “rich” (non-schematic) artifacts that have one conspicuous formal feature. Because subjects were asked to “check out the icon that you think matches *any singular* outstanding visual characteristic of the piece most of all available icons” the conspicuous traits must have been magnified.

Given the present set of icons this appeared to be a painting difficult to “describe” unambiguously: 62

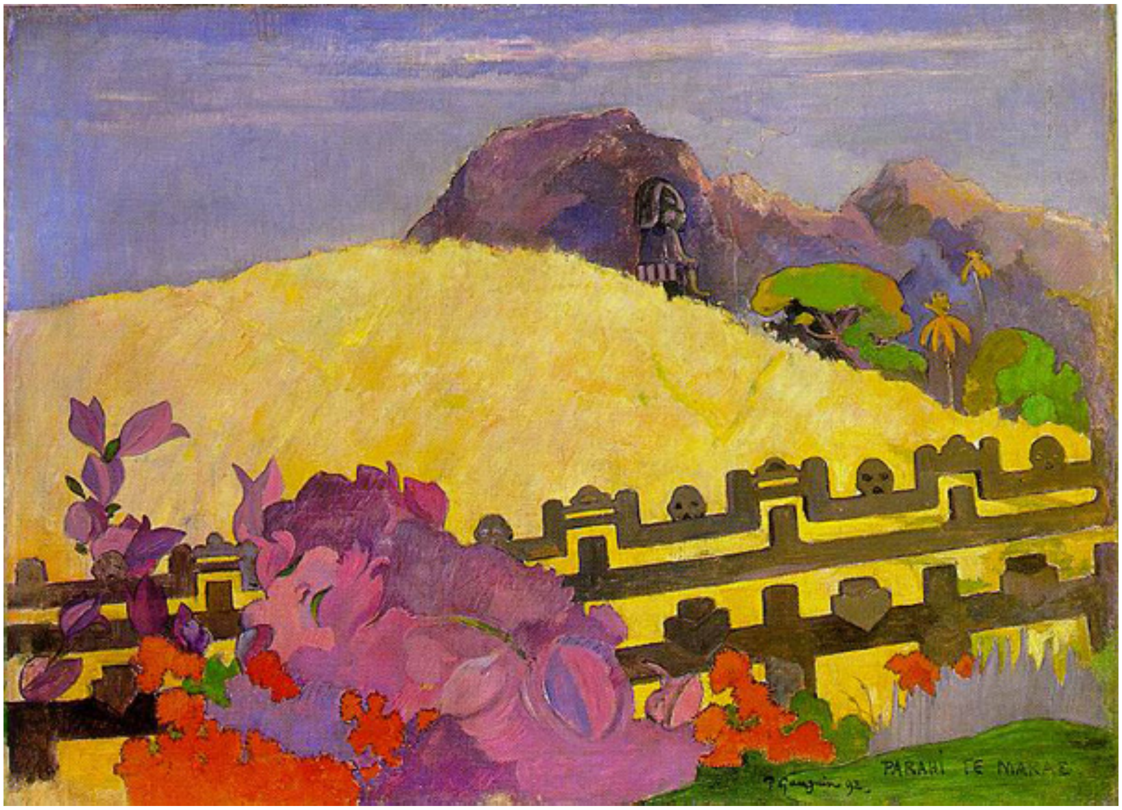


Figure 12. Paul Gauguin, *The Sacred Mountain (Parahi Te Marae)*, 1892, oil on canvas. Philadelphia Museum of Art: Gift of Mr. and Mrs. Rodolphe Meyer de Schauensee, 1980

Several icons seem to have been chosen to indicate the colorfulness of the painting: both the variety of colors and the 63
striking yellow and purple image regions. Others presumably refer to the composition of the picture in three horizontal planes and/or the use of diagonals, the irregular size and shape of color regions. Still others, according to my interpretation, are intended to denote the complementary color contrasts and the “painterliness” of the surface. Anyway it is evident that subjects in the *Art.Similarities* experiment were not unanimous in using the visual diagrams offered to tag the Gauguin painting.

The interpretation of data so far suggests looking at a few other summaries. From the full artifacts x icons table were 64
extracted (per icon) the maximum number of times it was assigned to any artifact. If we divide this maximum value by the grand total for a specific icon, we might have a rough measure of the efficacy of the icon. Values ranged from 0.05 (low efficacy) to 0.5 (high efficacy). According to this approach the most and least “problematic” icons in the set (if we skip very low grand totals — say below 25) are these:

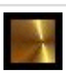
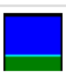
	where n=43; efficacy score=0.05
	where n=40; efficacy score=0.48

Table 5.

Of course such numbers should be handled with care: maximum values could be outliers. Perhaps other measures of 65
central tendency (average, median) give better results or could be used to arrive at conclusions that are more firm.

Falsifications

The empirical verification of similarity measures — number of co-occurrences, similarity measure (o) — also made clear 66
that some unmistakably similar artifacts were not recognized as such. Here is a telling example:

Figure 13. Keith Carter, *Silhouette*, 1994, photograph. San Jose Museum of Art: Partial and promised gift of Arthur J. Goodwin. © Keith Carter 2008.

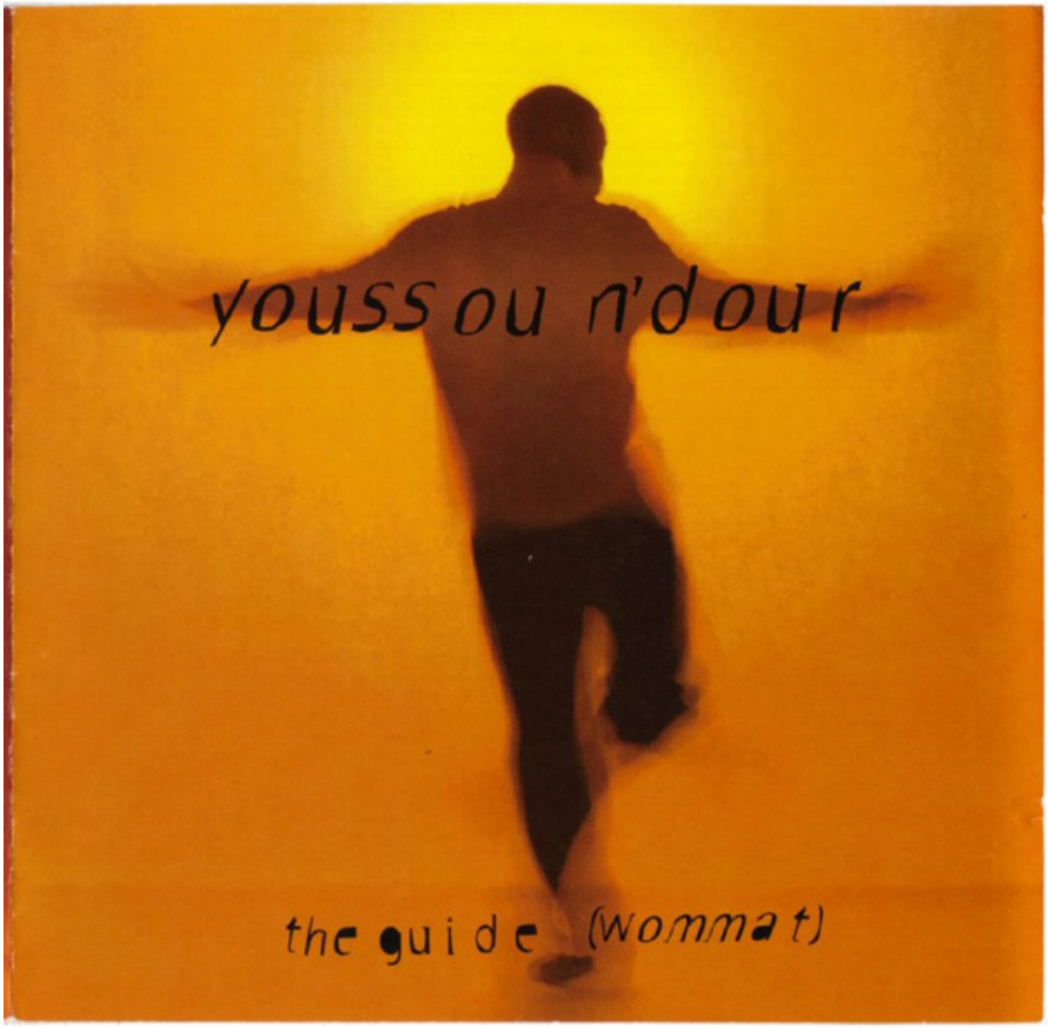


Figure 14. Tracy Boychuk (design), Andrew Eccles (photography), Christopher Austopchuk (art direction), *youssou n'dour, "the guide (wommat)"* , 1994, CD Sleeve design. ©1994 Sony BMG.

The similarity of both images is striking, but they co-occurred only once. Why is that so? If we review the available tags it appears that there is no single icon fit to express the cross-shaped configuration that according to many is the primary similarity feature here. One of the icons seems to be a candidate — and it has indeed been related to the Carter photograph twice; it is a representational black-and-white icon, displaying an umbrella depicted in silhouette: 67

Figure 15.

Perhaps the conceptual distance between an umbrella and a human figure disqualified this icon.[24] The fact that the Carter photograph is a grayscale image, on the other hand, may have diminished this conceptual distance. Other empirical findings seem to support the importance of color in visual tagging. Half of the icons associated with the Boychuk picture were dominantly orange colored; the color palette of eight out of ten was very similar to the palette of the photograph.[25] 68

Apart from the (cross-shaped) compositional features that both images have in common, and the dominant color characteristics that — perhaps as a second most conspicuous feature — set them apart, both artifacts apparently share another formal trait, one that — in iconographical terms — may be described as a *silhouette*. In the visual vocabulary of *Art.Similarities* there are quite a few icons that could be used to denote this image characteristic, but most of these are in black-and-white and show sharp outlines. That could be an explanation for the missing match in this case. Both 69 images show vague outlines (conspicuous similarity feature number four). In fact there is one icon with the representation of a human figure, which could be qualified as a silhouette, and it was used to tag the Boychuk artifact. But it has an orangish background, which apparently disqualifies it for the Carter photograph.

My rather lengthy discussion of this one falsification casus is intended to introduce a few speculations about the promises of using visual tags. It makes clear that successful tagging is dependent on a balanced set of visual tags (icons). The size and the number of these visual tags are clearly decisive for effective tagging. Furthermore the following principles should be taken into account: 70

- Color phenomena may have a strong impact on efficient tagging.
- The presence of basic compositional features in the tag set is decisive.
- Representational elements may interfere with the tagging of formal artifact characteristics.

And finally: 71

- Refined overall local features, as in the qualification “vagueness” (of contour), will be hard to express unambiguously.

Observer Behavior

Even in the simple prototype application discussed here, it is possible to retrieve all the image-icon assignments of one particular person. It is fascinating to inspect the recorded visual discernments of individuals, because they seem to give away observer habits. A sound follow-up procedure would be to compare central tendencies in the discernments of several observers. The outcomes can be stored in the database as *performance data*. If two observers have made similar image-icon associations, then possibly they resemble one another in the way their mental processes organize the visual world. What if one of these individuals is recognized as an authority? Would that somehow qualify the other? And if two qualified art historians agree on what is typical of a series of artifacts, would that be the beginning of “proof”? 72

I made the point earlier, and I shall make it again, that the random presentation of artifacts in this experiment must have affected similarity scores. Another restriction is that subjects (n=204) were free to tag images. The top tagger assigned icons 141 times and 19 subjects only tagged once. Obviously absolute pronouncements based on these figures cannot be made. This is all the more true where as to the dimension of subject characteristics — prior knowledge, professional merits, age, race, etc. — an empirical verification of analysis outcomes would have implied a more extensive survey. This was beyond the ambitions of the current experiment. 73

So the dataset in this experiment is too restricted to justify a thorough analysis of the behavior of subjects. With 400 artifacts and 100 icons we have 40.000 possible combinations. In the database only 2242 combinations occurred on a total of 3918 records, giving an average of less than 2 hits per combination. It is clear that few co-occurrence scores can be computed from these numbers. After the grouping of observers by artifact-icon combinations I calculated 5317 co-occurrences for all subjects, the highest number being 15. In principle such numbers can be used to compute similar observers, but given the restricted data I will not elaborate on these data now. 74

Inspecting the voter x voter pivot table I noticed one peculiar phenomenon: the rows and columns of some subjects displayed a striking low number of co-occurrence scores. This appeared to be independent of the number of tags assigned by these subjects. What could be the cause of these outliers? One explanation is that the outliers correspond to subjects noticing visual subtleties that remain hidden for other observers. Another, I think more plausible explanation is that the outliers were caused by “clumsy” individuals, unable to make up their mind about the most *outstanding visual characteristics* of the artifacts on display, or even worse maybe, by subjects unable to understand the task at hand. 75

One might expect a correlation between the number of co-occurrences and the number of unique icon-artifact assignments. For a sample of 10 subjects in the middle range of tag frequencies (n=41–63) I computed for each individual in the transaction table the ratio of the number of tags assigned and the number of unique icon-artifact assignments. For obvious reasons there was a strong correlation with the ratio of the sum of all co-occurrence values and the number of co-occurrence values (r=0.94). 76

77 A quick-and-dirty reality check pointed out that my outliers were caused by students with rather feeble study results, whereas — conversely — a highly successful student was responsible for the top score. Especially the latter finding seems to suggest that a good student in art history is able to discern visual features that are in conformity with the discernments of his or her peers. Of course we must be very careful with generalizations of this kind. It would be more profitable to search for correlations related to an individual's preferences on dimensions like: time period, geographical location, or even iconographical subjects.

Icon Covariance

78 In my experiment the selection of icons was non-arbitrary.[26] In fact a priori visual knowledge was used to compile an effective (i.e. varied) set of icons, starting from a base collection of about 500 diagrams. There is a drawback to this non-evolutionary approach. The process may become biased. I may have unknowingly excluded options for expressing specific visual concepts. And indeed, the discussion of falsifications in the previous section gave an example of such a probable omission. I will now consider the opposite phenomenon, viz. *vocabulary redundancy*, which is here defined as a lack of efficacy in the icon set due to the existence of icons that are apparently used to denote same or almost same visual concepts.[27]

79 The assumption is that icons appropriate to refer to a specific visual feature will co-occur more often than may be expected in the case of purely disjointed icons. Of course there is the risk that the set of artifacts used in this experiment displays a few “real world” conjunctions — as a matter of fact I have an example of that below. Therefore I repeat that my data analysis can only be indicative. Nevertheless I think that from the results of the present experiment some generalizations can be made.

80 This time in the original transaction table I grouped the icons that had been assigned to each individual artifact. For the resulting subsets of icons co-occurrences were computed. The sum of all possible pairs is $(100^2+100)/2=5050$, since we have 100 icons and since co-occurrences of same icons are relevant as well. In the transaction database 3137 unique combinations occurred. Only 7 icons were never assigned more than once to a particular artifact.[28] The sum total of icon pairs in our database was 24.826. So the average number of co-occurrences — if we skip the zero-values — is about 8. Here is the top 5 of pairs of icons in terms of co-occurrences:

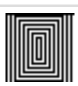
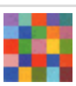
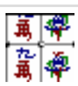
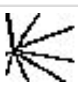
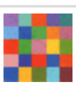
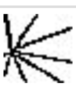
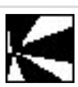
Icon pairs	Co-occurrences
 and 	204
 and 	136
 and 	119
 and 	116
 and 	114

Table 6.

81 This way of visualizing co-occurrences may create the impression that redundancies in our vocabulary indeed exist. The fact that mere numbers seem to indicate an overlap in the visual features of a set of schematic images is captivating. None of our subjects ever alleged this! So could the manipulation of visual things by individuals amount to some sort of collaborative visual knowledge, a knowledge that emerges from our transaction database?

82 Just to check on this I zoomed in on co-occurrences for the pair of icons for which n=114. Here are the results:

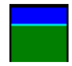
										
	119	114	89	46	29	26	20	19	18	16

Table 7.

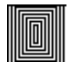
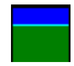
										
	114	84	29	23	21	17	13	13	13	12

Table 8.

83 In this particular experiment we must be cautious: the relatively small number of objects in the database could affect the number of co-occurrences computed. As a matter of fact there are two possible causes of high frequencies for co-occurrences:

1. Icons in the tag set are visually similar. (I would suggest they are redundant.)
2. A particular combination of visual characteristics is prevailing in the artifacts considered.

84 It is tempting to forget about the reality these icons refer to, and to read each table as a summary of the alternative interpretations of the icons on the left. On the other hand, the more the co-occurring icons classify the icon on the left, the more redundancy we presumably have in the set. Furthermore I expect that the similarity between the icon being analyzed and the co-occurring icons diminishes from left to right. In the table just above the first icon in the row — the one with the spokes — is ostensibly similar to the icon of our focus. The appearance of a green-and-blue icon however is less obvious in an immediate comparison. An empirical check gives away that the co-occurrence value here is caused by pictures of landscapes with an easily tractable vanishing point and guidelines.

85 Unfortunately I have no data at hand to support this line of thought. Still I think it is safe to say that the mere number of co-occurrences with other icons in the tagging set suggests that the icons are partly redundant indeed.[29] Knowledge of this kind can be used to improve the (initial) set of icons. What than could be a rule for detecting redundancies in the set of icons? I think such a rule should both consider the number of co-occurrences and the number and distribution of other icons in the neighborhood of the icons compared, e.g.:

86 *If two icons are in the top n of co-occurrences, and the top n of co-occurrences for these icons is composed of the same icons, than the icons are at least partly redundant and a “merge operation” to get rid of the redundancy is justified.*

87 The challenge for future research is to make such rules for an automated analysis explicit.

Conclusions

88 As was contended in the Introduction, advocates of humanities computing stressed the fact that computational techniques may have the collateral benefit of indicating where in the domain of scholarly research “there are holes in your sketch, [and] where it breaks down” [Unsworth 2001]. Add to this that in the humanities the process of fine tuning personal interests and cognitive schemata is paramount. There are few if any final answers as to meaning in the visual arts: “the process is often at least as important as the product, and the process itself produces new knowledge and understanding” [Jörgensen 1999, 315]. That is exactly why I have good hopes that applications like *Art.Similarities* will be beneficial in art/art history education. More in general I think that the experiment has demonstrated that Web 2.0 technologies can offer new opportunities in humanities research.

89 From the analysis section we learned:

- that meaningful perspectives on visual artifacts can be pointed out by visual means;
- that useful similarity measures can be derived from multiple (simple) similarity expressions;

- that the composition of efficient visual vocabularies may benefit from visual tagging.

Stock-taking here was primarily aimed at indicating the essential possibilities of a visual labeling and harvesting paradigm for art historically relevant visual traits. But our field test also indicated some limitations of visual labeling. Color is problematic; the size of our displays units is (still) limiting; the power to differentiate between stylistically similar works of art is still indeterminate; we have no sharp idea of what an ideal set of visual denotats may look like; we don't know in what degree such a set could be universal. Nevertheless *Art.Similarities* also suggested possible directions for future research. 90

One drawback of collaborative filtering systems is their tendency not to cover the extreme cases [Chen & McCleod 2005], [Sierra 2007]. This issue also came up with the visual voting system proposed here. How can we direct the system to encode the significance of valuable exceptions to the rule, and how can we make it ignore cheating, trivialities and clichés? Some data mining protocol for judging automatically traced deviant votes (outliers) and blowing up or playing down their relative importance would be a valuable extension to *Art.Similarities*.[30] 91

Another extension would be the coordination of different solutions to the retrieval of information about same object types. This paper offered rough sketches of a method of classifying visual artifacts independently of other classifying options. But the interdependency of different classification systems is worth considering. Iconographical descriptions ("aboutness") and descriptions of visual qualities ("offness") belong to separate notational spheres [Panofsky 1970], [Bätschmann 1986], [Nauta 1993], [Shatford Layne 2002]. Still there is an apparent covariance of these description options: if two artifacts are depictions of a particular theme, chances are that both artifacts share a considerable number of visual characteristics. Such partial description parallels also exist for other types of metadata. For example: once an object has been classified as an "engraving" (qua technique), it is usually redundant to file the artifact as a "grayscale" picture, or as a picture "having linear qualities". So we could fine tune the current approach by introducing restrictions: if images are in grayscale, don't offer colored icons, and vice versa. Eventually this may lead to the use of exchangeable icon sets, and the related question of how to select these sets of visual icons. 92

Conventional scholarly communication in art history amounts to a textual exchange of information in perhaps 95% of the cases. With that in mind the idea might come up that somehow the results of visual voting actions should be translated back into textual arguments. Now how will we ever get back to words? Since today's information technology is truly interactive in nature, conclusions based on coordinated visual discernments can be immediately communicated back to the communities involved in the process. One group of observers could be involved in visual voting, while the results from this "subroutine" may be fed back to another part — say the "Next Level" users — of the population. If the second group uses some sort of verbal labeling interface, like the one developed by the Steve.museum initiative [Wyman et al. 2006], promising cross-fertilizations become possible. With the adoption of appropriate standards, an integration of textual annotations, reviews, or the discussion of remarkable patterns in visual behavior becomes possible. In a way the collaborative visual filtering system enables noticing, labeling and re-labeling phenomena, thus giving shape to an augmented social construction of knowledge [Barrett 1989]. The role of a scholar in designing these filtering systems will not be the role of an author of scholarly articles or monographs, but the role of a broker in art historical knowledge, the director of an intricate process of knowledge mediation [Stubenrauch 1993]. 93

If it is assumed that there is no reason to strive for a one-fits-all collection of visual denotats, extended research might be focused on the matching of specific collections of visual artifacts and appropriate sets of icons. Such research efforts could start from the assumption that when the medium of expression is fixed, observers (experts and/or lay people) will just express themselves in the reference materials at hand, focusing in these denotats on what are their peculiar points for attention. This actually simplifies research, since developers need not be explicit about suitable reference options. A myriad of further extensions to the basic visual voting model is now conceivable. Observers from particular user groups, for instance, might be enabled to work with sets of dedicated icons ("private alphabets"). We predict that as a matter of course these series will be composed according to common sense principles, like maximum diversity, sufficient coverage, etc. 94

Extensions of the voting system may include additional functionalities. One might be the possibility to define subsets of 95 artifacts, based on singular or multiple corresponding artifact-icon associations; these subsets would thus be true collaborative products. Based on an analysis of patterns in voting behavior (or, alternatively, explicit observer profiles), the system could also gradually evolve into a system displaying only the preferences (both artifacts and/or votes) of a particular user group. Finally, since somehow artifacts co-organize icons, the labels (icons) in the interface may be grouped (i.e. organized) by their co-occurence patterns; perhaps these may be taken as so-called *emergent semantics* [Aberer et al. 2004].

Hopefully this orientation has made clear that the social formation of opinions concerning the visual similarity of cultural artifacts amongst a group of motivated observers *can* with the use of information technology be modeled and recorded *without* the application of verbal descriptors, and that interesting data processing options exist for collaboratively and visually characterized artifacts. This offers many starting points for further research. 96

Notes

[1] Other interesting examples: Connotea, LibraryThing, MovieLens, Last.fm, Steve.museum. The list is open-ended.

[2] "Collaborative filtering is the method of making automatic predictions (filtering) about the interests of a user by collecting taste information from many users (collaborating)" (http://en.wikipedia.org/wiki/Collaborative_filtering). For more extensive reading, refer to [Bra & Neijdl 2004], [Heylighen 1999] and [Lynch 2001].

[3] A question indicative of ever shifting intellectual property concerns is whether surreptitious measurements of user behavior should be considered a breach of copyright laws. That someone's purchasing behavior is a creative act may be defendable.

[4] The value of such an exercise could be in testing the methods of the field under consideration. Advocates of humanities computing like John Unsworth have stressed the fact that computational techniques may have the collateral benefit of indicating where are methodological flaws in scholarly research:

> "The implementation of a spec in a program appears as a kind of critique of the text of the spec" — which is to say, when you sketch what you think you understand, and then try to turn that sketch into a series of instructions a computer can execute, you find out where there are holes in your sketch, where it breaks down. Similarly, when you design an information structure and then try to fit the actual information into it, you find out where the structure doesn't fit. That's the back and forth between part and whole, rule and instance. [Unsworth 2001]

[5] For a comprehensive project on collaborative *verbal* tagging (in the context of museum information systems), refer to the Steve.museum project. Cf. [Bearman & Trant 2005] and [Wyman et al. 2006]. See also [Ross et al. 2004, 145–179] for contextual materials. A more general verbal tagging application, much discussed, is *Google Image Labeler*, based on the work of Luis von Ahn. Cf. [O'Reilly 2006].

[6] For a classic study refer to [Wölfflin 1950].

[7] Here the word "effective" is used in the sense of "being able to get at the record" [Bush 1945], which is a modest objective. One of the rare attempts to communicate in a systematic way about certain (compositional) features of works of art is Erle Loran's controversial book on Cézanne's composition [Loran 2006]. Loran developed a diagrammatic language to point at organizational principles in the paintings of Cézanne. His diagrams, however, are fairly dependent on the oeuvre being studied. For the present experiment they are not sufficiently simple. It is my aim to use more "attenuated" diagrammatic images in order to communicate less specific image characteristics.

[8] In a sense this is a loose generalization of what as early as 1950 was concluded by Fred Attneave after a series of experiments using simple visual stimuli [Attneave 1950]. Attneave's findings initiated a prolific line of research in the domain of cognitive psychology and computer vision.

[9] Some support for this assumption I found in Jörgensen [Jörgensen 1999, 305].

[10] Russel A. Kirsch defined these as "intermediate sources" [Kirsch 1984].

[11] A visual *denotat* is defined here as an actual feature or formal characteristic of a visual artifact, which an observer regards as meaningful and communicable, and which may be referred to by a visual abstraction of that feature. It may be contrasted with the *connotat*, which is any emotional or otherwise associative response to an artifact which, though meaningful privately, cannot be meaningfully communicated in abstractable visual form.

[12] Consider this as a special type of visual similarity, where one image is *replete* and the other *simple* (or, as Goodman worded it, *attenuated*). The relationship is *unbalanced.* The simple image might be said to *clarify* one trait in the replete image, acting this way as a visual denominator. Cf. [Goodman 1988]. See note 14 in this article.

[13] It might be objected that even a simple (iconic) image may be (visually) ambiguous, up to the point where the nature of its similarity to a replete visual artifact becomes obscure. This objection is refutable by proposing that whenever associations are ambiguous it is the presentation *context* that will determine the probability of specific readings. Compare this to the ambiguity of a word like "Bank", where "Bank" + "of England" <> "Bank" + "under water".

[14] "Replete" is the word used by Nelson Goodman to indicate that (in certain images, particularly works of art) every namable trait is or may be decisive for the overall aesthetic effect. The opposite of "replete" in Goodman's vocabulary is "attenuated" [Goodman 1988, 230n]. The concept is used here to distinguish full, rich, multi-trait artifacts from simple (attenuated) icons. See also [Elkins 1999, 70].

[15] Subsequent research may lead to systems where another type of object is involved, viz. the *textual argumentation* of individuals, worded ad hoc or in the manner of familiar ontologies.

[16] In future systems additional attributes can be added in separate tables to record various kinds of *performance data*.

[17] Here are two examples of additional attributes of votes that might or even should be incorporated in future versions of the system. First, normalized picture coordinates: these might be stored to record regions of interest in cases where outstanding features are distinctly localized. And second, the kind of task involved: asking an observer to indicate what is the most salient image characteristic will lead to a very different significance of voting behavior results as compared to asking for giving votes to some trivial or even any image feature.

[18] An exhaustive discussion of data dictionaries falls outside the scope of this paper.

[19] The inclusion of choice pairs of replete images sharing some apparent visual configuration was considered, e.g. two highly symmetrical images, two images pronounced to be similar according to a widely respected art historian, or even two copies of the same work. The only "testers" actually included are a pair of almost identical artifact reproductions — a painting by Seurat (*Bathers at Asnières*, 1883) and a preparatory sketch of the same piece (*Final Study for "Bathers at Asnières"* , 1883), and two similar images from a textbook on pictorial concepts [Jenny 2000, 98–99]. It is a quick-and-dirty setup to see if these image pairs would be indexed in a predictable manner. They were.

[20] "Eye-catching", to put it plainly, implies a response of contemporary observers. The historicity of my approach will be discussed in a separate publication.

[21] Cf. http://www.last.fm/help/faq/.

[22] Following this adaption the similarity measure for figures 6 and 7 would become: 0.7319 (a slight decrease in value). For figures 8 and 9 o after normalization would be: 0.5832 (also a slight decrease).

[23] Compare this to the correlation coefficient for the sum of "non-self" co-occurrences and the number of associated artifacts, which is -0.1504.

[24] Time and again I found that as soon as pictures could be perceived as depictions, the objective of tagging formal image characteristics was not fulfilled.

[25] I compared histogram values of the Boychuk picture and all of the associated icons taken together: mean and median for the hue channel were exactly the same: mean=23, median=22.

[26] Starting from the premise that the *actual* manipulation of indexing terms would take a meaningful form, reflecting visual habits/knowledge in the observer group, the initial plan was to supply the community with a set of *random* visual signs. From an analysis of the icon use logs, after a substantial amount of time, would emerge traces of visual thinking. The whole process might be made evolutionary. Some icons might be used too often, reducing informational value; some might never be used at all; some icons might tend to appear together in most of the cases. There might be pairs of icons co-appearing with another icon, where the latter one could be taken as a merge (component) icon of both the others, and so on. The initial set of icons might be restricted or extended based upon results from the analysis. This way the effectiveness of the visual vocabulary in use would be improved, while the relevant visual notions could surface.

[27] *Vocabulary bias* and *vocabulary ambiguity* were considered in an earlier section of this paper.

[28] Notwithstanding the fact that our sample is modest, I assume that a relatively low number of self co-occurrences may also count as a crude

measure of icon efficacy. Compare this to the earlier paragraph on icon efficacy. If we take the ratio of the number of times an icon co-occurred with itself and the frequency of that same icon as a measure of efficacy, the icons in our earlier example become 0.16 (for the "golden glow" icon) and 4.45 (for the "low horizon" icon) on a scale ranging from 0.07 to 6.86.

[29] The *differences* in both sets of co-occurring icons on the other hand are informative as well. The vortex-like shape having a high co-occurrence value in the upper table does not show up in the lower table, and in the lower table we have a checker board which would be visually unsound in the upper table. These differences are immediate qualifications of the icons being compared.

[30] For *Art.Similarities* work in progress is focused on "detecting Level 2" observers and approval recording. Refer to steps 16–18 from the experimental setup. See also Luis von Ahn's "games with a purpose" [Ahn 2006].

Works Cited

Aberer et al. 2004 AbererKarl, Philippe Cudré-Maroux and Aris M. Ouksel, eds. *Emergent Semantics Principles and Issues*. IFIP 2.6 Working Group on Data Semantics: Research Group of Distributed Information Systems (SID), University of Zaragoza, 2004. http://sid.cps.unizar.es/PUBLICATIONS/POSTSCRIPTS/dasfaa04.pdf.

Ahn 2006 Ahn, Luis von. "Games With a Purpose". *Computer* 39: 6 (2006), pp. 92-94.

Attneave 1950 Attneave, Fred. "Dimensions of similarity". *American Journal of Psychology* 63: 4 (1950), pp. 516-556.

Baca & Harpring 2005 Baca, Murtha, and Patricia Harpring. *Categories for the Description of Works of Art (CDWA)*. Los Angeles, CA: J. Paul Getty Trust and College Art Association, Inc, 2005.

Barrett 1989 Barrett, Edward. "Introduction: Thought and Language in a Virtual Environment". In Edward Barrett, ed., *The Society of Text: Hypertext, Hypermedia, and the Social Construction of Information*. Cambridge, MA: MIT Press, 1989.

Bearman & Trant 2005 Bearman, David, and Jennifer Trant. "Social Terminology Enhancement through Vernacular Engagement: Exploring Collaborative Annotation to Encourage Interaction with Museum Collections". *D-Lib Magazine* 11: 9 (2005).

Bra & Neijdl 2004 de BraPaul, and Wolfgang Neijdl, eds. *Adaptive Hypermedia and Adaptive Web-Based Systems*. Vol. 3137. *Lecture Notes in Computer Science*. Berlin: Springer, 2004. http://www.springerlink.com/content/r21696v81c2a/.

Bush 1945 Bush, Vannevar. "As We May Think". *Atlantic Monthly* 176: 1 (1945), pp. 641-649.

Bätschmann 1986 Bätschmann, Oskar. *Einführung in die kunstgeschichtliche Hermeneutik: Die Auslegung von Bildern*. Darmstadt: Wissenschaftliche Buchgesellschaft, 1986.

Chen & McCleod 2005 Chen, Anne Yun-An, and Dennis McCleod. "Collaborative Filtering for Information Recommendation Systems". In *Encyclopedia of Data Warehousing and Mining*. Idea Group, 2005.

Eakins & Graham 1999 EakinsJohn P., and Margaret E. Graham. *Content-based Image Retrieval: A report to the JISC Technology Applications Programme*. Newcastle: Institute for Image Data Research, University of Northumbria at Newcastle, , 1999.

Elkins 1999 Elkins, James. *The Domain of Images*. Ithaca and London: Cornell University Press, 1999.

Finch 1974 Finch, Margaret. *Style in Art History*. Metuchen, NJ: Scarecrow Press, 1974.

Goodman 1988 Goodman, Nelson. *Languages of Art*. Indianapolis: Hackett Publishing Company, 1988.

Heylighen 1999 HeylighenFrancis. *Collaborative Filtering*. *Principia Cybernetica Web*. Principia Cybernetica Project, 1999. http://pespmc1.vub.ac.be/COLLFILT.html.

Huijsmans & Smeulders 1999 Huijsmans, Dionysius P, and Arnold Smeulders. *Visual Information and Information Systems: Third International Conference*. *Visual'99*. *Lecture Notes in Computer Science*. *Vol. 1614*. Berlin: Springer, 1999.

Hutchins 1995 Hutchins, Edwin. *Cognition in the Wild*. Cambridge, MA: MIT Press, 1995.

Jenny 2000 Jenny, Peter. *Bildkonzepte: das wohlgeordnete Durcheinander*. Mainz, Germany: Verlag Hermann Schmidt, 2000.

Jörgensen 1999 Jörgensen, Corinne. "Access to Pictorial Material: A Review of Current Research and Future Prospects". *Computers and the Humanities* 33: 4 (1999), pp. 293-318.

Kirsch 1984 Kirsch, Russell A. "Making Art Historical Sources Visible to Computers: Pictures as Primary Sources for Computer-based Art History Data". Presented at *Automatic Processing of Art History Data and Documents*. (1984).

Loran 2006 Loran, Erle. *Cézanne's Composition: Analysis of His Form with Diagrams and Photographs of His Motifs*. Berkeley and Los Angeles: University of California Press, 2006.

Lynch 2001 Lynch, Clifford. "Personalization and Recommender Systems in the Larger Context: New Directions and Research Questions". *http://www.ercim.org/publication/ws-proceedings/DelNoe02/CliffordLynchAbstract.pdf*. Presented at *Second DELOS Network of Excellence Workshop on Personalisation and Recommender Systems in Digital Libraries*. (2001).

Nauta 1993 NautaGerhard Jan. "HyperIconics: Hypertext and the Social Construction of Information about the History of Artistic Notions". *Knowledge Organization* 20: 1 (1993), pp. 35-46. http://www.let.leidenuniv.nl/arthis/website/staf/nauta/archive/NautaGJ_Hypericonics_1993_300dpi.pdf.

Nauta 2001 Nauta, Gehrard Jan. "Nicolaas Cornelis de Gijselaar, Bladzijde uit een prenten-plakboek, midden negentiende eeuw". In Nelke Bartelings, ed., *Uit het Leidse Prentenkabinet*. Leiden: Primavera Pers, 2001.

O'Reilly 2006 O'Reilly, Tim. *Google Image Labeler, the ESP Game, and Human-Computer Symbiosis*. *O'Reilly Radar (weblog)*. 2006. http://radar.oreilly.com/archives/2006/09/more_on_google_image_labeler.html.

Panofsky 1970 Panofsky, Erwin. "Iconography and Iconology: An Introduction to the Study of Renaissance Art". In *Meaning in the Visual Arts*. Harmondsworth: Penguin Books, 1970. pp. 51-81.

Ross et al. 2004 Ross, Seamus, Martin Donnelly and Milena Dobreva. "DigiCULT Technology Watch Report 2". *http://www.digicult.info/downloads/twr_2_2004_final_low.pdf*. Presented at *Core Technologies For the Cultural and Scientific Heritage Sector*. (2004).

Salomon 1996 Salomon, Gavrie. *Distributed Cognitions: Psychological and Educational Considerations, Learning in Doing: Social, Cognitive and Computational Perspectives*. Cambridge: Cambridge University Press, 1996.

Santini et al. 2001 Santini, Simone, Armanth Gupta and Ramesh Jain. "Emergent Semantics Through Interaction in Image Databases". *IEEE Transactions on Knowledge and Data Engineering* 13: 3 (2001), pp. 337-351.

Shatford Layne 2002 Shatford Layne, Sara. "Subject Access to Art Images". In Murtha Baca, ed., *Introduction to Art Image Access: Tools, Standards, and Strategies*. Los Angeles, CA: Getty Research Institute, 2002.

Sierra 2007 Sierra, Kathy. *The 'Dumbness of Crowds'*. *Creating Passionate Users (weblog)*. 2007. http://headrush.typepad.com/creating_passionate_users/2007/01/the_dumbness_of.html.

Stahl 2006 Stahl, Gerry. *Group Cognition: Support for Building Collaborative Knowledge*. Cambridge, MA: MIT Press, 2006.

Stubenrauch 1993 Stubenrauch, Robert, Frank Kappe and Keith Andrews. "Large Hypermedia Systems: The End of the Authoring Era". Presented at *Educational Multimedia and Hypermedia Annual*. (1993).

Tufte 1998 Tufte, Edward Rolf. *Visual Explanations: Images and Quantities, Evidence and Narrative*. Cheshire, CT: Graphics Press, 1998.

Unsworth 2001 Unsworth, John. "Knowledge Representation in Humanities Computing". In *Lecture I in the eHumanities: NEH Lecture Series on Technology and the Humanities*. Washington, D.C.: 2001.

Vygotsky 1976 Vygotsky, Lev. *Mind in Society: The Development of Higher Psychological Processes*. Cambridge, MA: Harvard University Press, 1976.

Wenger et al. 2002 Wenger, Etienne, Richard McDermott and William M. Snyder. *Cultivating Communities of Practice*. Cambridge, MA: Harvard Business School Press, 2002.

Wyman et al. 2006 Wyman, Bruce, Susan Chun, Rich Cherry, Doug Hiwiller and Jennifer Trant. "Steve.museum: An Ongoing Experiment in Social Tagging, Folksonomy, and Museums". In *Papers Museums and the Web 2006*. Pittsburgh: Archives and Museum Informatics, 2006.

Wölfflin 1950 Wölfflin, Heinrich. *Principles of Art History: The Problem of the Development of Style in Later Art*. Mineola, NY: Dover, 1950.