

Gugelmann Galaxy. An Unexpected Journey through a collection of Schweizer Kleinmeister

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Abstract: GLAM¹ institutions all over the world are digitizing their collections. As the number of items in such a collection amounts to tens or even hundreds of thousands, providing comprehensible access and presentation becomes increasingly difficult. At the same time, a steadily growing amount of this data is openly available. This gives rise to various projects approaching the hidden treasures in these collections with computational tools. The project presented here, Gugelmann Galaxy, lets the user explore an entire collection of digitized images and their textual metadata in an immersive three-dimensional cloud, whose configuration can be rearranged according to different criteria. The project questions traditional models of categorization and curating and implements alternative approaches prototypically.

Keywords: art collection, computer vision, machine learning, 3D visualization, curating

Introduction

The Gugelmann Galaxy project presented in this article touches two main issues of working with collections of art works. The first one is presentation and curation of the collection and the second is the understanding of the content of single items of the collection. Both these tasks are about organization, about the installation of rule sets and metrics to tell items apart and make subsets of items from the entire collection. In both areas exist many very interesting approaches. I would like to highlight a few of them here in order to situate the presented work.

As examples for the presentation of art collections serve the projects WikiArt (WikiArt 2010) and ArtStack (Konvitz 2012). These portals behave like static archives, showing the result of standard database queries as lists of thumbnails. Possible choices for a sorting on WikiArt are the hard coded categories style, genre and technique. Proposed similar items only include works by the same author or the same contributor. The platform artsy.net (Cleveland and Cwilich 2010) tries to go one step further with their Art Genome Project. A team of art historians and experts assigns tags to works out of a catalogue containing more than 1'000 different characteristics. They refer to these characteristics as genes.

Figure 1: Detail of Fig. 2, showing images with a tree in the left foreground.

Gugelmann Galaxy

The project Curiator (Erbuer and Boonstoppel 2012) joined forces with Curalytics, whose Steffon Davis defines curation on his blog (Davis 2013) as “Curation: the subjective selection, categorization, and arrangement of content”. Curiator allows to create what they call rooms, individual collections curated by its users. The partner Curalytics applies a machine-learning algorithm called collaborative filtering, used by recommender systems known from media providers like Amazon or Netflix. It assumes that if two items are put in a room together by at least two different users, they have something in common. Analyzing all the rooms of all the users lets them on the one hand identify taste leaders and on the other hand control what shows up in the you-might-also-like-section.

Computer vision departments all over the world were approached in recent years with the question of image understanding in art works. The Visual Geometry Group at Oxford University dedicates itself to object detection in fine art paintings (Crowley and Zissermann 2014b). The results in terms of precision and recall are very promising. The downside is that only objects occurring very frequently in a lot of paintings, like trains, sheep, dogs, horses or chairs, offer a sufficient amount of samples for training a model. The range of detectable objects broadens when a combination of artworks and images from the Internet are used to train the model (Crowley and Zissermann 2014a). Researchers at the University

of Heidelberg work on tasks such as object detection (Yarlagadda et al. 2012) and hand gesture estimation in medieval paintings (Schlecht, Carqué, and Ommer 2011). These tasks are highly complex, because the objects to be received (e.g. crowns) vary drastically in shape and color over the entire collection of images available. In addition, to be able to train a reliable classifier, a large collection of already labeled training samples must be available.

And finally somewhere in between the two – because they work both on features extracted from single items and the relationship network among all the items in the collection – are situated the researchers from Rutgers University. They made interesting studies on genre classification (Saleh and Elgammal 2015), creativity networks (Elgammal and Saleh 2015) or artistic influence (Saleh et al. 2014) in the WikiArt dataset. A combination of features and labels contained in available metadata and others extracted from the images by means of computer vision algorithms allows for training successful classification models.

Project

The Gugelmann Galaxy project grew out of a two days hackathon, a marathon for hackers. The First Swiss Open Cultural Data Hackathon was organized by opendata.ch, the Swiss chapter of the Open Knowledge Foundation. It took place on February

Gugelmann Galaxy

27th and 28th 2015 at the Swiss National Library (SNL) in Berne. Some 100 computer scientists, artists, researchers, and members of the heritage sector gathered to explore more than 30 open data sets, provided by over 20 different GLAM institutions with the aim to put this cultural data to wider use. One of the datasets provided by the SNL itself is the Gugelmann Collection.² The dataset was brought to the hackathon with the goal of raising its public awareness.

Our group, consisting of Nikola Marinčić, Jorge Orozco and myself³ was joined by art historian Sonja Gasser to form an interdisciplinary team covering a broad field of interests and skills. The foundation of the project was developed during these two days by the team. Successive developments like the adoption to various platforms or the addition of alternative options are the result of my own research.

Problem

The collection was not easily accessible to the general public before. Even though the pictures in high resolution were available on Wikimedia Commons, one can only scroll through seemingly endless tables of thumbnails, ordered alphabetically by the authors' last names. In addition to the digital images, the collection provides an XML-file containing some metadata. The record for each item contains the records signature (corresponding to the filename and something like the unique identifier),

title, author(s) and – if available – date, technique and a short description. Further fields hold information about the collector, the source and the legal permission but they are identical for all the items, as they all belong to the same collection. From the pure and unprocessed metadata alone, the items could linearly be sorted by date with the goal to unveil developments over time, similar to what Florian Kräutli (Kräutli 2015) showed with the MoMA collection (MoMA 2015). But the majority of the items in the Gugelmann Collection are from a relatively narrow range of time between 1750 and 1850 and so to investigate a development over time is difficult. Alternatively, one could try to group the items by technique. Because there did not seem to be a uniform naming convention, this cannot be done directly but needs some further processing of the raw data as we will see later.

Question

How can a user get an overview of the content of this collection, when one has to flick through these tables clicking “next” twelve times? Our goal is to provide a different form of access to this body of work by rethinking conventional ways of sorting and questioning concepts of curating. Items need no longer be stringed together linearly along a time or alphabetical axis. There is no necessity for items to be classified in pre-labeled drawers, obeying fixed, hierarchical ontologies. Instead of hard-edged categories, configurations

Gugelmann Galaxy

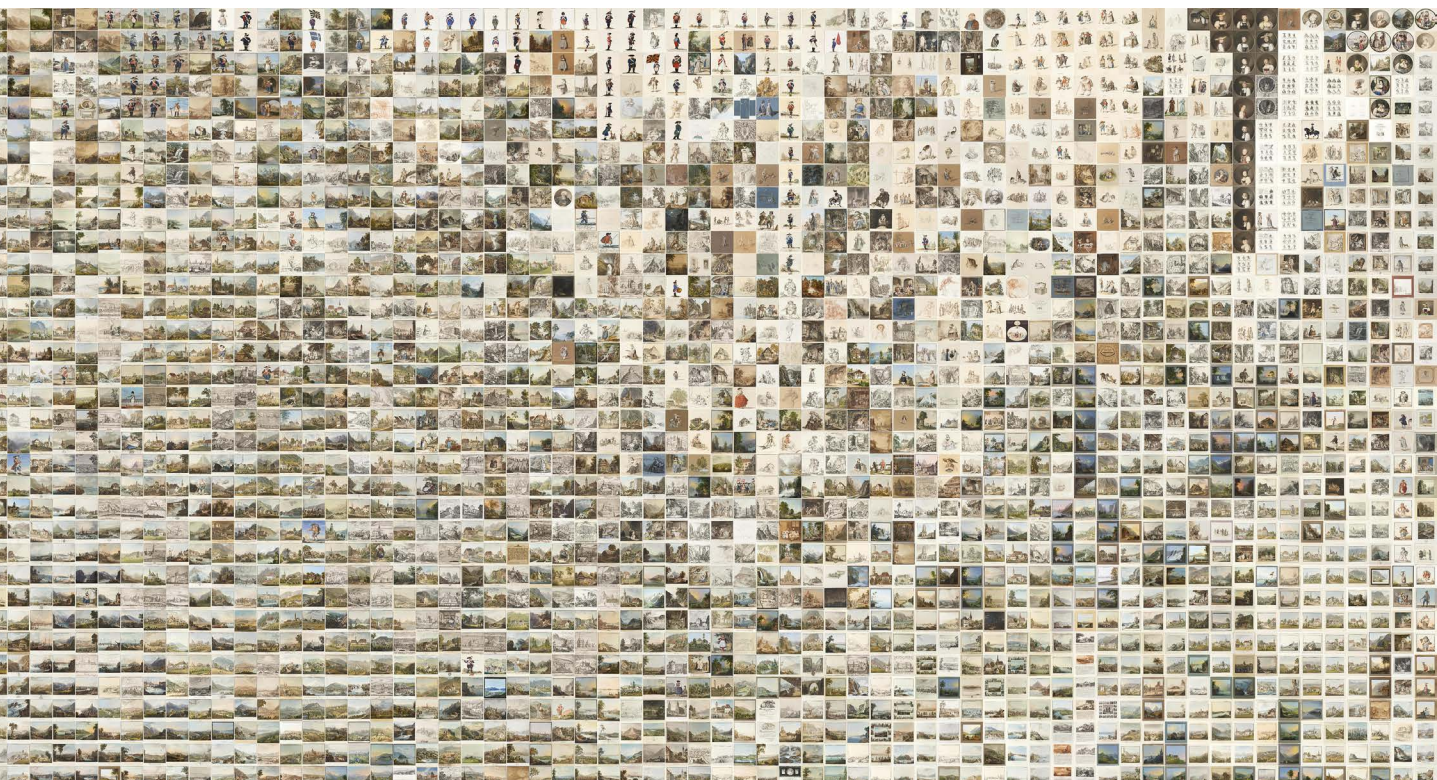
can arrange freely, densifying to clusters at some points while spanning open voids at others. Binary decisions whether or not an item is for example colorful, are replaced by assigning to it a certain degree of colorfulness.

Method

The project Gugelmann Galaxy provides four different criteria for arrangement, based on four different similarity measures between the items. Two are based on textual data contained in the metadata (TECHNIQUE and DESCRIPTION) and two are based on attributes⁴ extracted from the digital images using computer vision algorithms (COLOR and COMPOSITION). Each of these four criteria, its attempt and method of feature engineering shall now be described.

TECHNIQUE attempts a topological grouping of the information contained in the “Technik” field. Some annotations are very consistent, as there is 605 times the entry “Aquarell”, 478 times “Umrisradierung, koloriert” or 456 times “Aquatinta, koloriert”. But there is a long tail of a total of 82 different descriptions that are not supposed to make up a category on their own. For example one item’s technique is described with “schwarze und weisse Kreide auf blauem Papier” and another one’s “Kohle und weisse Kreide auf grau eingefäbtem Papier”. A human reader can easily concede a high degree of similarity between the two, since they both contain “weiss” (white), “Kreide” (chalk/crayon) and are drawn on colored paper. For a computer, this is less obvious. Therefore, we compiled a list of 22 words⁵ and checked, whether

Figure 2: Clustering of images by compositional concepts, 2d grid plot.



Gugelmann Galaxy

or not that word was contained in the description. This resulted in a 22 dimensional binary vector for each item, having a 1 for the presence and 0 for the absence of every word in the list. A 22-dimensional vector, each item a point in 22-dimensional space, thus represents the items. The selection of words is a first guess. One possible improvement is to work with word parts instead of full words only. This would allow an item described as “Kreidelithographie” to get a check for both “Kreide” and “Lithographie”. Another improvement could be to automatically assign more global tags like drawing to items containing “Tusche”, “Rötel”, “Kreide” or “Bleistift”, even if the word “Zeichnung” is not contained in the text. The elaboration of this list requires a lot of expert knowledge from art historians and can hardly be automated. A well composed set of words leads to a more fine grained distinction between items and thereby sheds some lights on what techniques were often combined together, instead of assigning two separate categories. Works produced using “Aquatinta, unkoloriert” are in proximity of the ones using “Aquatinta, koloriert” who again are close to the ones using “Umrissradierung, koloriert”.

The DESCRIPTION sorting aims to extract concepts from the three fields title, description and place. For this purpose, the text of all the three fields is concatenated, punctuation and numbers removed and the individual words extracted⁶. After removal of stop words (von, und, mit, der, die, das etc.),

the list of the most frequent words is Bern (373), Kirche (323), Pfarrhaus (307), Blick (151), links / rechts (both 133), Schloss (128) and Ansicht (127). Words that occur in almost every description are not good indicators to measure the difference between two items. A method frequently used in natural language processing (NLP) called TF-IDF⁷ is applied to account for that. Items are described as roughly 2300-dimensional vectors of reciprocal distance measures. The sorting resulting from this similarity measure reveals higher level concepts represented in the images, independent of author, date or technique.

The COLOR sorting is an attempt to compare images not only by their average color (one single value for hue or saturation) but rather the distribution of different colors. The feature vector extracted for that purpose is 300-dimensional, namely the red, green and blue channel of a thumbnail image down-sampled to 10 by 10 pixels. This sorting can distinguish coarse categories like landscapes (bluish in the upper, greenish in the lower part) or traditional dresses studies (column of colors in the center on bright background). It also unveils clusters of very specific palettes used by one painter to represent different landscapes.

And finally, COMPOSITION describes every image as a series of eight orientations with their relative intensity in 64 different regions (8x8 tiles) of the image, resulting in a

Gugelmann Galaxy

512-dimensional vector. This is called a HOG descriptor, for histogram of oriented gradients (Dalal and Triggs 2005). This feature vector describes an image by the directions dominant in different regions, independent from colors and allows therefore clustering the collection by composition of the images.

For every item, various sets of relevant features have been extracted

that describe it as an n-dimensional vector. As was shown, anything can become a dimension, easily accessible numerical data like date or size, over low level features like color distribution or word counts up to high level features like edges or textures. Each item constitutes one data point in this n-dimensional space, with similar items being closer to each other. We are used to seeing two-dimensional scatterplots, where one feature (read: dimension) of

Figure 3: (l) Image with its eight closest neighbors in color distribution embedding: same palette, different places. (r) Same image with its eight closest neighbors in description embedding: Lucerne thematic cluster,



Gugelmann Galaxy

every item is plotted against one other feature. But how can 2300-dimensional space (for the DESCRIPTION sorting) be represented, visualized and made accessible? How can a user explore this space? Sophisticated algorithms from the domain of manifold learning (Pedregosa et al. 2011) are used to project the original high-dimensional space onto a lower-dimensional space, in this case three dimensions. For DESCRIPTION and COMPOSITION,

the algorithm used is t-SNE (van der Maarten and Hinton 2008). For the other two, Isomap (Tenenbaum, de Silva, and Langford 2000) proved to give good results. Proximity relations are maintained so that neighbors in the original high-dimensional space remain neighbors in the lower dimensional embedding. It is important to note that the axes of the resulting space don't have any meaning. They do not map individual numerical at-



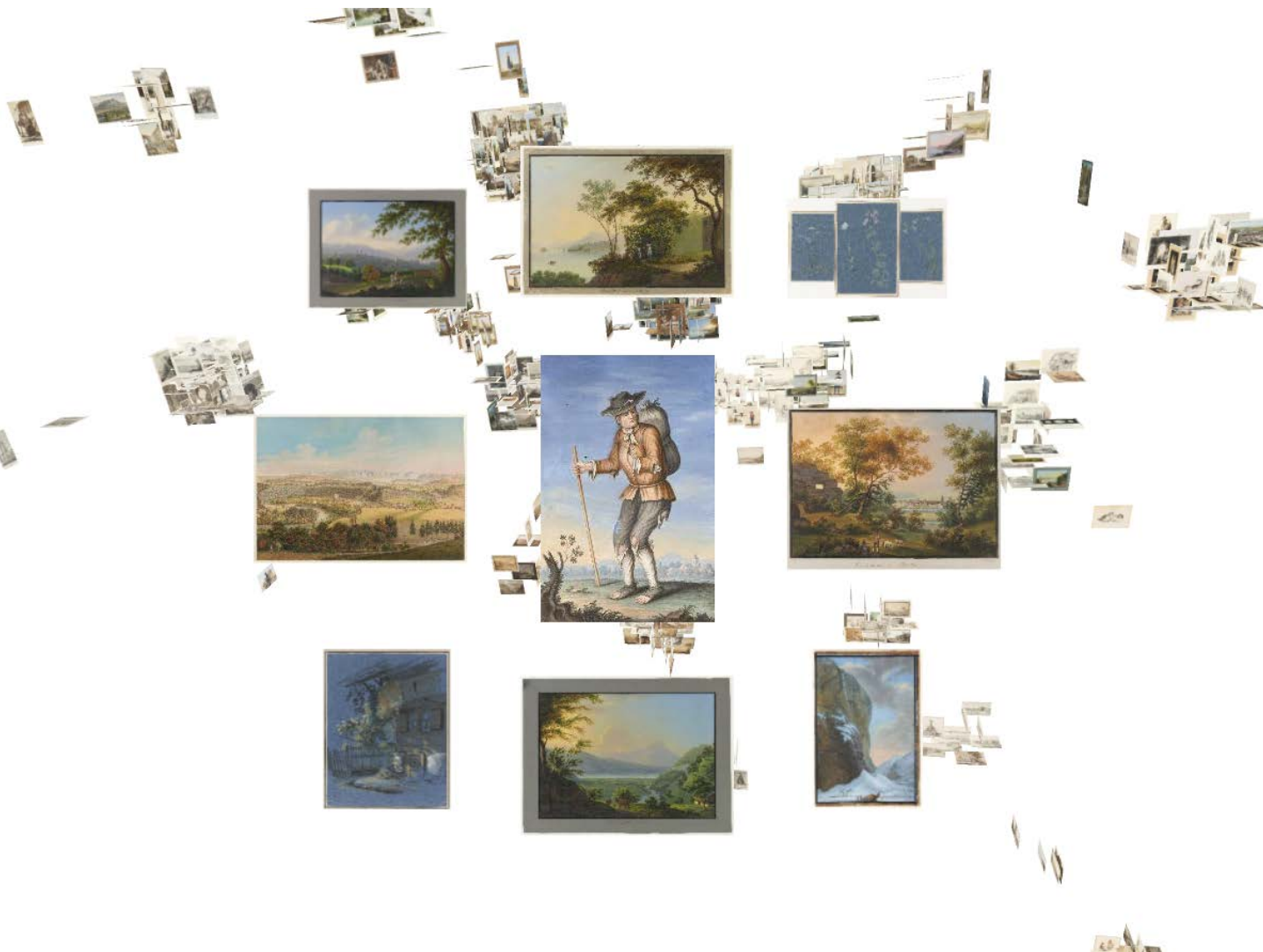
Gugelmann Galaxy

tributes like hue against saturation or size against time. The position of an item in that space therefore doesn't say anything about that very item. But instead items are expressed in terms of the relational network of neighborhoods they are embedded in. Niches are not treated as anomalies but preserved as richness. Class affiliations can be deduced but are not presumed. Also, there is no intention to extract means from the entire collection

like the average painting. In order to illustrate this emergence of clusters beyond categories, I would like to explain in a bit more detail one of the findings of this method, for the COMPOSITION sorting.

Figure 2 is not a visualization from the Gugelmann Galaxy, but shows the two-dimensional embedding with the points to an orthogonal grid (to avoid mutual occlusion) using a rather

Figure 4: (l) Image with eight others of the same technique. (r) Same image with its eight closest neighbors in composition embedding: upright figure (person or waterfall) in the center.



Gugelmann Galaxy

simple method. There exist much more elaborate algorithms for that purpose, e.g. RasterFairy (Klingemann 2016) or IsoMatch (Fried et al. 2015) that I was unfortunately not aware of at the time of working on the project.

Some compositional concepts become obvious at first sight, such as the circular vignettes in the top right corner, upright figures on a neutral background a bit farther left,

wide landscapes in the bottom left or images maintaining a frame despite the cropping in the bottom right. Some of these clusters (landscapes, soldiers on white background or the women portraits in folk costumes) already emerged from the sorting according to color distribution. A notable improvement can be illustrated by a group of images at the bottom, a bit left of the center.



Gugelmann Galaxy

All the colored thumbnails⁸ show a tree on the left side in the foreground and an open landscape, often with a lake, in the background. The similarity of these images' composition could by no means be discovered in the metadata. The images are by different authors, date from different years and represent different places. Also the color clustering would not arrange them in close proximity because they are very different in sky color and overall tonality. Even a very light

pencil sketch (2nd row, right) can be found in this cluster, something that from a computer vision system point of view – that is, dealing uniquely with a matrix of numbers for red, green and blue values – really is something different than a full colored painting.

Figure 5: Stills from YouTube video (https://youtu.be/3O6OfSyn7_4): (l) The author wearing a VR headset. (r) Render from within the goggles with right and left eye view.



Gugelmann Galaxy

Results

As a final product, these three-dimensional projections are rendered as a cosmos of free floating images. The first version was called Schweizer Kleinmeister – An Unexpected Journey (Bernhard et al. 2015), was developed on the occasion of the hackathon and is a desktop application created in Processing⁹. The user can freely navigate by rotating, zooming and panning through the cloud. Figures

3 and 4 show exemplary stills from that version. Once an image is selected, it can be displayed surrounded by its eight closest neighbors in the currently selected embedding.

With the aim of making the experience even more immersive and physical, the second version was made in a game engine called Unity¹⁰. The Gugelmann Galaxy can now be explored by means of a virtual reality headset called Oculus Rift.



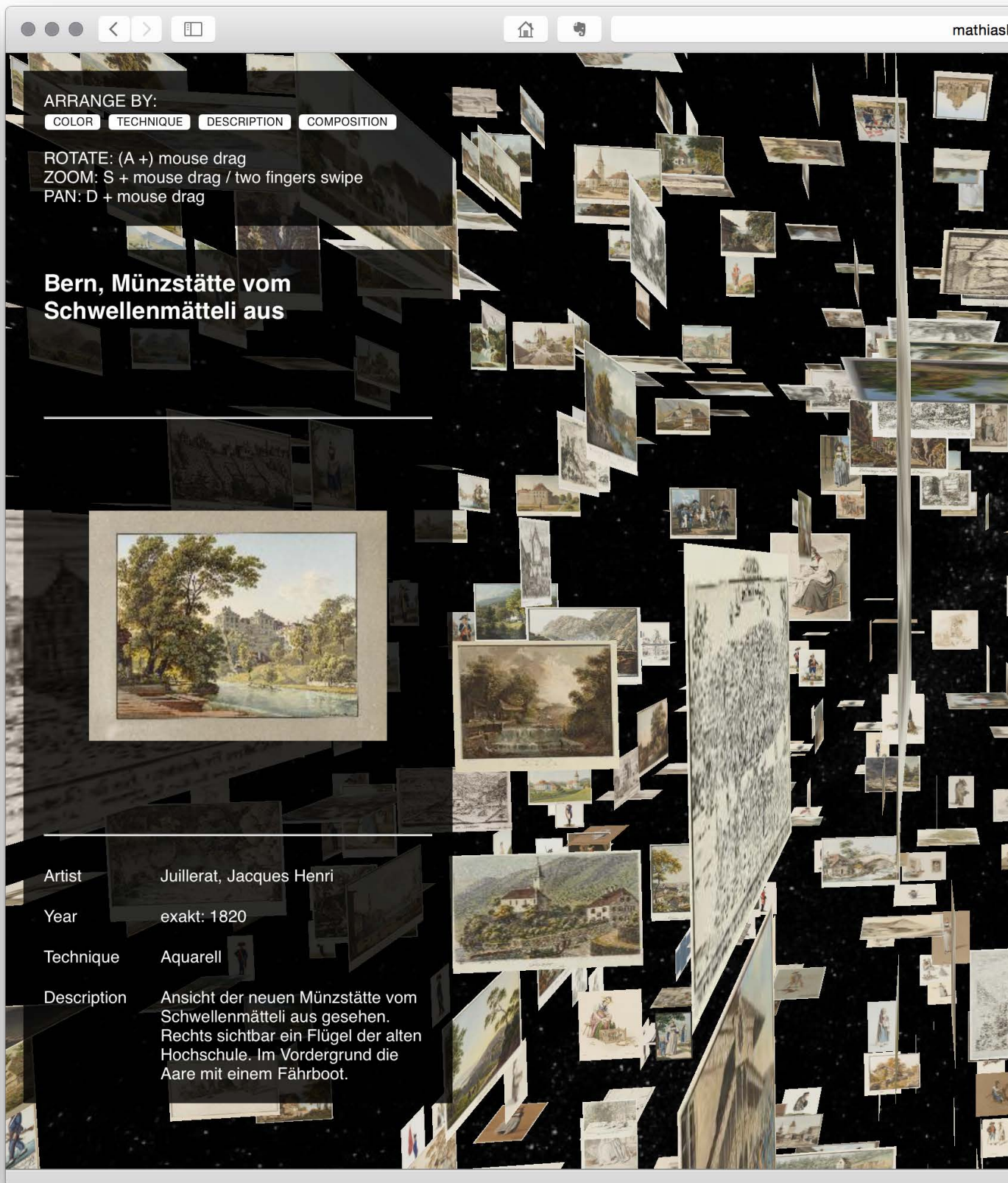


Figure 6: Screenshot of browser application "Gugelmann Galaxy"



Gugelmann Galaxy

To meet the demand for increased accessibility, I created a third version of the Gugelmann Galaxy running in the online. It can be accessed from anywhere by anyone without the need to install software, just by pointing the browser to the address www.mathiasbernhard.ch/gugelmann. The user can navigate through the galaxy by rotating, zooming and panning and can rearrange the configuration according to the four different criteria described above. When the mouse hovers over an item in space, it is highlighted and a frame on the left lists a higher resolution version of the image and the available metadata (see Figure 6: screenshot of browser application “Gugelmann Galaxy”).

The four different views on the collection (TECHNIQUE, DESCRIPTION, COLOR and COMPOSITION) are meant to be only prototypical implementations, demonstrating a methodology. Many more questions can of course be formulated, limited solely by the curiosity of the users. Whatever the interest, the collection can be projected into an arrangement specific for that very query.

Conclusion

Elaine Gurian begins her paper *THE ESSENTIAL MUSEUM* (Gurian 2006) with the question “What if our profession created a museum in which visitors could comfortably search for answers to their own questions regardless of the importance placed on

such questions by others?” She goes on in describing it as “another kind of museum, one that arises not from organized presentations by those in control, but one that puts control into the hands of the user. [...]Unfettered browsing of objects will be the main organizing motif in this museum and to facilitate that, the majority of the museum’s objects will be on view.” Such a proposal questions the role of the curator and the installed hierarchies. This idea is further elaborated in our magazine article *ANY-FOLD: On Curation, Literacy and Space* (Bernhard, Marincić, and Orozco 2015). A project like the Gugelmann Galaxy can in many ways provide loose ends to connect to in order to pursue this goal. It is not bound to a physical location like a museum building – a potential mental barrier for many audiences. It does not impose one specific and unchangeable organization. Instead, it facilitates access and empowers curious minds to dig for personal nuggets. It does not assume an infeasible set of categories but relies on gradual statistical correlations. Statistics show up in artists’ work every now and then. There is for example the collective Guerilla Girls, who furnish evidence for the gender gap with percent figures. (Freeland 2001) Or the Russian-American conceptualist artist duo Vitaly Komar and Alexander Melamid who made professional polls in various countries asking people for their favorite color, format or motif in an artwork. Evaluating the results, they created the most wanted and most unwanted paintings of these countries, co-authored by the majority vote.

Gugelmann Galaxy

But while inevitably a certain weird interestingness has to be attested to the lonely George Washington standing in front of a lake with meadowing deers (Komar and Melamid 1994), probably nobody really finds his or her particular interest reflected in it because everybody's interest is supposed to be reflected. The assumption leading to this meaninglessness is that the features are all independent. They even publish the numerical results on their website but only the sums. Looking at correlation of the various features one could make more specific conclusions. The absurdity of making everything flat and unspecific is what the artists play with and should be taken with a grain of salt. With projects like the Gugelmann Galaxy, statistical approaches to an entire collection of artworks, the interest is neither in the examination of a single item, nor in boiling it down to some global insight. The marvel such a framework offers us is to observe individuality always within and defined by the position within all the others.

Little Big Data

The focus of this second issue of the DAH Journal is Visualizing Big Image Data. I think it is necessary to relativize the hyped, ubiquitous and watery term of big data. The Gugelmann collection, which serves as a base for the work presented here, contains roughly 2300 items. In orders of magnitudes that is 10^3 items. Other collections of art works available are in the range of 10^5 items. There are

101'086 items in the WikiArt (formerly WikiPaintings) dataset (Karayev 2013), which for Saleh and Elgammal (2015) "to the best of our knowledge, is the largest online public collection of digitized artworks". Further, there are the roughly 200'000 items in the YourPaintings (BBC 2014) collection or the 120'000 records on items at the Museum of Modern Art (MoMA 2015) recently published on GitHub. The Gugelmann collection dataset is hence a rather small one among the art collection datasets. However, the datasets used by search engines or social media companies to train their classifiers are again 2-4 orders of magnitude bigger. The dataset provided for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) contains 14'197'122 (10^7) images labeled with thousands of categories (ImageNet 2010). The body of image raw material Facebook can work with is estimated to amount to 200'000 images uploaded every minute (Horaczek 2013). So to summarize it drastically, twice as many images are uploaded to Facebook every minute than WikiArt collected from 800 years of art history. As Peter Norvig, head of Google research points out in his lecture The Unreasonable Effectiveness of Data (Norvig 2011), for a lot of tasks the search engine giant has to deal with, more is more. The scientific method, feature engineering and more conventional machine learning algorithms that work well for smaller datasets get easily outperformed by algorithms such as multi-layer neural networks through the mere number of training samples available.

Outlook

User behavior like detail views or fly routes can be recorded to further improve the network of links between the items, similar to how search engines like Google learn from user clicks what a suitable answer to a query might be. After having looked at or even liked, starred, favored (what ever the evaluation metrics in place) enough paintings, such a system could even learn my taste and make a ranking or proposals beyond any category. Why am I only given the choice to love or hate all of photography? Why do I have to decide upon one specific century to make a choice – let alone how should I know what –ism¹¹ suits me best before I know anything about styles? To keep the motivation high, the user needs the feeling to be in control. It is rewarding to be able to make new discoveries. No absolute treasure is hidden in the archives and collections until we ask our very specific questions. As more and more researches from different fields join forces and create more and more elaborate systems, digital art history heads for a very interesting future.

Notes

1 Galleries, libraries, archives and museums

2 Since 1982, the SNL has been home to the Gugelmann Collection, consisting of over 2300 drawings, prints and paintings by the Schweizer Kleinmeister - Swiss 18th century masters - assembled by Annemarie Gugelmann and her brother Rudolf. It is one of the most valuable donations the NL has ever received. This unique collection is continually being expanded with significant new acquisitions, and constitutes the essential core of Swiss iconography.

3 All three are architects, computer scientists and PhD students at the chair for Computer Aided Architectural Design at ETH Zurich.

4 Following the proposal of Lev Manovich in the first issue of this journal (Manovich 2015), I will also refer to these attributes as features. Features can be integers, floating point numbers or text and they are organized in the data table's columns. Individual images are called items or samples of the dataset and are organized in rows. In a later section, I will not write about features but about dimensions instead. This should facilitate the understanding of the concept multi-dimensional spaces and vectors.

5 The words are: aquarell, aquatinta, gouachiert, koloriert, unkoloriert, bleistift, roetel, farbkupferstich, federzeichnung, laviert, gouachemalerei, holzschnitt, kohle, kreide, kupferstich, lithographie, pinselzeichnung, radierung, sepia, stahlstich, tuschezeichnung and umrissradierung

6 Similar as for TECHNIK described above, 1 if the word is present, 0 if it is not

7 TF-IDF short for term frequency-inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. It is often used as a weighting factor in information retrieval and text mining. The TF-IDF value increases proportionally to the number of times a word appears in the document, but is offset by the frequency of the word in the corpus, which helps to adjust for the fact that some words appear more frequently in general. (Wikipedia)

8 The grayed and blurry images are similar as well, maybe without the tree. Their appearance could be the result of the inferior quality algorithm used to push the items to a grid layout.

9 www.processing.org Processing is a flexible software sketchbook and a language for learning how to code within the context of the visual arts. (Processing website)

10 www.unity3d.com Unity is a cross-platform game engine developed by Unity Technologies and used to develop video games for PC, consoles, mobile devices and websites. (Wikipedia)

11 There are 83 –isms among a total of 164 styles distinguished by the WikiArt platform.

Bibliography

- BBC. 2014. "YourPaintings." Accessed 6. Aug. <http://www.bbc.co.uk/arts/yourpaintings/paintings/search>.
- Bernhard, Mathias, Nikola Marinčić, and Jorge Orozco. 2015. "ANY-FOLD: On Curation, Literacy & Space." *trans*, 84-87.
- Bernhard, Mathias, Nikola Marinčić, Jorge Orozco, and Sonja Gasser. 2015. "Schweizer Kleinmeister: An Unexpected Journey." *opendata.ch*. http://make.opendata.ch/wiki/project:schweizer_kleinmeister:an_unexpected_journey.
- Cleveland, Carter, and Sebastian Cwilich. 2010. "The Art Genome Project." <https://www.artsy.net/about/the-art-genome-project>.
- Crowley, Elliot J., and Andrew Zissermann. 2014a. "In Search of Art." In *Workshop on Computer Vision for Art Analysis, ECCV*.
- Crowley, Elliot J., and Andrew Zissermann. 2014b. "The State of the Art: Object Retrieval in Paintings using Discriminative Regions." British Machine Vision Conference.
- Dalal, N, and B Triggs. 2005. "Histograms of Oriented Gradients for Human Detection." IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Diego, CA, USA.
- Elgammal, Ahmed, and Babak Saleh. 2015. "Quantifying Creativity in Art Networks." The Art and Artificial Intelligence Laboratory, Department of Computer Science, Rutgers University.
- Erbuer, Moenen, and Tobias Boonstoppel. 2012. *Curator - The World's Greatest Collaborative Art Collection* New York, NY.
- Freeland, Cynthia A. 2001. *But Is It Art?* Oxford, New York: Oxford University Press.
- Fried, Ohad, Stephen DiVerdi, Maciej Halber, Elena Sizikova, and Adam Finkelstein. 2015. "IsoMatch: Creating Informative Grid Layouts." *Computer Graphics Forum (Proc. Eurographics)* 34 (2).
- Gurian, Elaine Heumann. 2006. "The Essential Museum." Museums Aotearoa Conference, Hawke's Bay, New Zealand.
- Horaczek, Stan. 2013. "How Many Photos Are Uploaded to The Internet Every Minute?" *Popular Photography*, 6. Aug. <http://www.popphoto.com/news/2013/05/how-many-photos-are-uploaded-to-internet-every-minute>.
- ImageNet. 2010. "Summary and Statistics." Last Modified April 30, 2010 Accessed 6. Aug. <http://www.image-net.org/about-stats>.
- Karayev, Sergey. 2013. "Vislab - Computer Vision Group." Berkeley, University of California Accessed 6. Aug. <http://vislab.berkeleyvision.org/tutorial.html>.
- RasterFairy 1.0.2. Klingemann, Mario (Quasimondo), GitHub.
- Komar, Vitaly, and Alexander Melamid. 1994. UNITED STATES: MOST WANTED PAINTING. Dia Center for the Arts.
- Konvitz, Ezra. 2012. ArtStack.
- Kräutli, Florian. 2015. "MoMA on GitHub." *YYYY-MM-DD Time/Data/Visualization*. <http://research.kraeutli.com/index.php/2015/09/moma-on-github/>.

Gugelmann Galaxy

- Manovich, Lev. 2015. "Data Science and Digital Art History." *International Journal for Digital Art History* (1).
- MoMA. 2015. The Museum of Modern Art (MoMA) collection data. doi:10.5281/zenodo.21147.
- Norvig, Peter. 2011. *The Unreasonable Effectiveness of Data*. YouTube: UBCCPSC.
- Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. "Scikit-learn: Machine Learning in Python." *Journal of Machine Learning Research* 12:2825-2830.
- Saleh, Babak, Kanako Abe, Ravneet Singh Arora, and Ahmed Elgammal. 2014. "Toward Automated Discovery of Artistic Influence." In *Multimedia Tools and Applications*. Springer US.
- Saleh, Babak, and Ahmed Elgammal. 2015. "Large-scale Classification of Fine-Art Paintings: Learning The Right Metric on The Right Feature." Department of Computer Science, Rutgers University.
- Schlecht, Joseph, Bernd Carqué, and Björn Ommer. 2011. "Detecting Gestures in Medieval Images." IEEE International Conference on Image Processing (ICIP 2011), Brussels, Belgium.
- Tenenbaum, Joshua B., Vin de Silva, and John C. Langford. 2000. "A Global Geometric Framework for Nonlinear Dimensionality Reduction." *Science* 290 (5500):2319-2323. doi: 10.1126/science.290.5500.2319.
- van der Maarten, L.J.P., and G. E. Hinton. 2008. "Visualizing High-Dimensional Data Using t-SNE." *Journal of Machine Learning Research* 9:2579-2605.
- WikiArt. 2010. WikiArt - Encyclopedia of fine arts. <http://www.wikiart.org>.
- Yarlagadda, Pradeep, Antonio Monroy, Bernd Carqué, and Björn Ommer. 2012. "Towards a Computer-Based Understanding of Medieval Images." In *Scientific Computing and Cultural Heritage*.

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Gugelmann Galaxy

