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Dissecting the Canon: Visual Subject Co-Popularity Networks in Art Research

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Introduction

In Art History and Archaeology scholars use documents to study objects together with their meaning, related people, locations, times and events. Within this effort Art History has been defined as the *history of all man-made things* (Kubler, 1962), which implies a focus on the dynamics of interrelated objects – the growth of what can be seen as the *coral reef of culture* (Gombrich, 1979).

An important question in this domain is the definition or emergence of *canon*, i.e. the set of most popular objects, which everybody knows or supposedly should know in a given area – such as Da Vinci's *Mona Lisa* and Botticelli's *Venus* in painting or the *Colosseum* and the *Pantheon* in architecture.

In this paper we show that canons are identical with the most popular items over a distribution of popularity, which happens to be highly heterogeneous. As a consequence we can explore the meaning of canon by looking at the co-popularity of visual objects in general, no matter if the objects belong to the head or the tail of the popularity distribution.

Background

New research in the area of co-popularity has been facilitated recently by the emergence of relevant datasets, in which tags and other classifications have been used to classify a large number of images and image segments. The work in these projects is either done manually by human editors (Schich 2007, Russell 2008), automatically with the help of pattern recognition algorithms (e.g. http://www. definiens.com) or by human computation, i.e. in a collaborative effort in the form of games such as Peekaboom (Ahn 2006).

The data produced by these efforts can be understood as bi-partite networks connecting image documents and classification criteria. Moreover image documents as well as the classification criteria may feature additional information in the form of trees or ontologies (cf. **figure 1**).

As shown in at least two studies (Schich 2007, Russell 2008), such bi-partite classification networks usually belong to the class of scale-free networks, characterized by a highly heterogeneous connectivity distribution (cf. figure 2). Hence

methods developed in network science can be used to process art research data in search for better definitions of a canon.

Subject Popularity

In this paper we analyze a classic dataset of art research, which collects ancient art and architecture and their Western Renaissance documentation since 1947 (CENSUS 2005):

As we can see in the plot in **figure 2**, there is clearly a long tail of monument popularity, no matter if we look at the Number of Renaissance Documents •, the Number of Depictions/Descriptions in the Documents • or the Total Number of Links Including Overpopulation • (where single depictions are linked to multiple monument parts).

In addition the long tail emerging from the Number of Documents can be dissected into tails of different character, such as Non-Architectural Sculpture + and Everything Else x.

The hitlist in **figure 3** gives a clear idea how **Non-Architectural Sculpture**, Architecture and *Sculptural Architecture* combine to the general canon of ancient monuments in Western Renaissance.

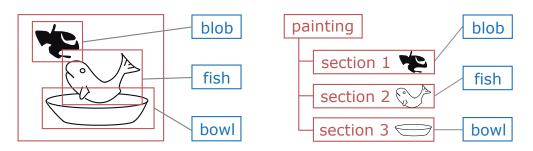


fig. 1 A simple example of a bi-partite image classification network, where paintings and their classified segments are represented as trees, which are connected to classification criteria via the classification link.

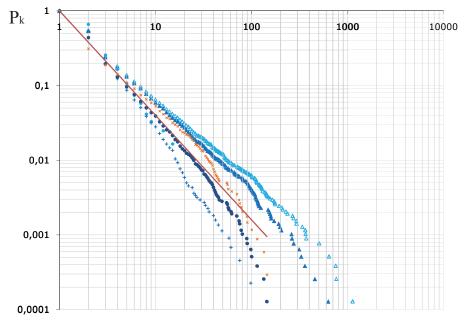


fig. 2 Cumulative distibutions of various types of monument in-degree in the CENSUS 2005 dataset. The plot indicates the probability Pk (y-axis) that a monument node has at least a certain number of connections k (x-axis). See text for the various types of connections. cuments ments

150770 150940 150792 219823 151057 150958 150812 150826 150784 150776 151227 150844	Ancient Monument Arch of Constantine (triumphal arch) Pantheon (temple) Arch of Septimius Severus (triumphal arch) Colosseum (amphitheatre) Laocoon (group of statues) Column of Trajan (honorific column) Arch of Titus (triumphal arch) Baths of Diocletian (thermae) Basilica of Constantine (basilica) Temple of Mars Ultor (temple) Horsetamers (group of statues) Forum of Nerva (forum) Baths of Caracalla (thermae) Theatre of Marcellus (theatre)	134 134 134 114 100 98 90 89 80 78 75 75 74 70 70	457	static strain st	مودلoobniation 112% 20% 129% 40% 0% 39% 41% 61% 35% 113% 1% 59% 84% 79%
151328	Temple of Antoninus and Faustina (temple)	62	160	228	43%
	Equestrian Statue of Marcus Aurelius (equestrian statue) Apollo Belvedere (statue)	61 58	94 66	94 66	0% 0%
	Mausoleum of Hadrian (sepulchral monument)	57	125	142	14%
	Temple of Minerva (temple)	56	149	212	42%
150806	Septizonium (facade)	56	118	124	5%
	Temple of Castor and Pollux (temple)	55	153		35%
	Regisole (equestrian statue)	49	80	80	0%
	Temple of Saturn (temple)	46		145	32%
	Curia Julia (curia) Bacchic Sarcophagus (sarcophagus)	45 45	95 75	112 75	18% 0%
	Temple of Serapis (temple)	44	120	175	46%
	Forum Augustum (forum)	43	90	129	43%
	Forum of Trajan (forum)	42	82	90	10%
	Torso Belvedere (statue)	42	53	53	0%
151143	Basilica Aemilia (basilica)	41	117	176	50%

fig. 3 The Top 30 hitlist of monument popularity, defined by the number of Renaissance documents, clearly corresponds to the expected canon of ancient monuments in Western Renaissance.

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Canons are tails within tails!

Extrapolating from the result that the long tail of ancient monument popularity in Western Renaissance can be dissected into various sub-tails, the general canon of art history can be seen as the head of the long tail distribution of object popularity, where the sub-canon of given specialized areas appears as the head of a self-similar sub-tail of the whole distribution.

In the examples in **figures 4, 5, and 6** we size object images according to their documentation frequency, which provides us with a limiting condition of what objects are contained in various canons emerging from the documents:

The first example in **figures 4 and 5** shows the long tail of Non-Architectural Sculpture in analogy to the + plot and the blue entries in the hitlist in **figures 2 and 3**.

The second example in **figure 6** presents the top 30 monuments of the subtail of Statues Identified as Venus or Aphrodite at some point in history (according to the Census database). Again the long tail appears in the • plot in **figure 2**.

Note: For each monument in figure 4, 5 and 6 we show a directly attached photo or an image of the first document. Question marks indicate that the monument is untraced, i.e. lost since the Renaissance and only verbally documented, or without image information at the first linked document in the database.

fig. 4 The long tail of Non-Architectural Sculpture.

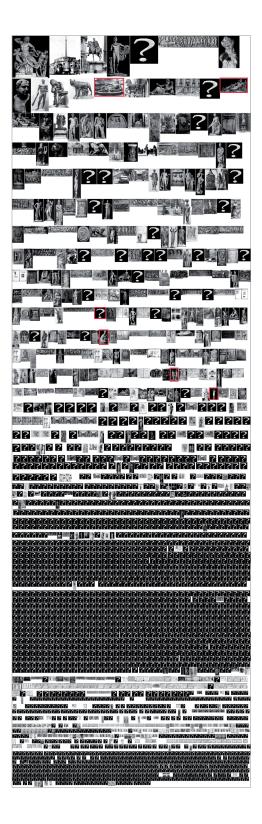




fig. 5 The head of the long tail of Non-Architectural Sculpture is identical to the respective sub-canon as any specialist would expect it. However, the canon is also clarified: in addition to good old friends like the Laokoon, the Horsetamers, the Marc-Aurelius equestrian monument, the Apollo Belvedere, and so on, there are also some surprises, such as five river gods within the top 18.

Note that this canon is not defined by some central authority, but emerges from the documents, whose monument selection varies highly both in genre as well as in number.



fig. 6 The sub-tail of Statues Identified as Venus or Aphrodite has very similar properties as the general long tail of popularity. The same is true for any other chosen sub-tail. There is no average popularity for any class of monuments. Instead, we find long tails of sarcophagi, column bases, temples or any other category.

Visual Subject Co-Popularity

Extending from the question of popularity and canon, we present a new way to explore the related phenomenon of visual subject co-popularity. Starting from a classified/annotated image dataset, we propose a method which combines a bi-partite community-finding algorithm and a method for the production of scalable image matrices in order to construct 2-dimensional overviews.

In order to find interesting areas in the whole network we apply a community-detection algorithm for overlapping bi-cliques introduced by Lehmann et al. (2008), which generalizes on the k-clique community finding algorithm for one-mode networks by Palla et al. (2005).

In a second step the communities found by the algorithm are visualized using a method for the production of scalable image matrices introduced by Schich (2008). Here, node information of a bi-partite classification network is placed in the location of the links in the adjacency matrix of the network, as shown in **figure 7** for the simple paintings example (cf. **figure 1**) and the monument-document network in the CENSUS dataset.

The figures 8a-c provide a proof of concept for our method. The resulting image matrix obviously indicates some reasons of co-popularity of otherwise unrelated monuments - in our case all monuments except for the two superprominent river gods were obviously located in topographical proximity in the mid 16th century.

Note how even this small selection of monuments forms another sub-tail of popularity indicated by the red frames in the **figures 4, 5 and 6**.

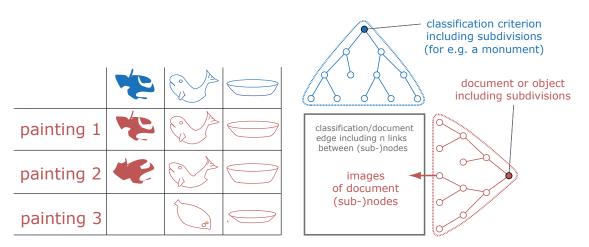
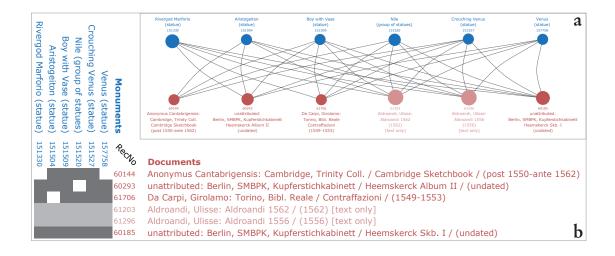


fig. 7 In order to produce 2-dimensional overviews, node information of the image partition is placed in the location of the links in the adjacency matrix (cf. our paintings to the left). While simple in principle, this method can be complicated by the complexity of the node information (cf. CENSUS to the right).



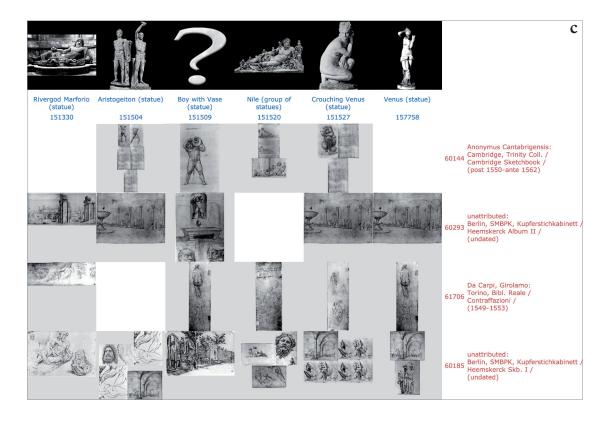


fig. 8 We explore co-popularity in three steps: First, a community of monuments and documents found by the bi-clique community finder (a) is visualized much more clearly as an adjacency matrix (b). After permutation and filtering, the images of subordinate document nodes are finally placed in the location of the links (C). The method scales well to much larger communities.

Discussion

Our approach generalizes the question of canon in art research using the concept of co-popularity, which also applies to the not so well known part of the long tail.

By introducing the network paradigm in art research we open the door for numerous applications on a wide range of art- and archaeology-related datasets. Besides shedding light on the structure of the canon of art, the resulting image matrices can also be used to investigate a canon's dynamics, facilitating the reconstruction of the mostly implicit network of visual citation.

In addition our approach has the potential to augment the usual onedimensional results of image databases and search engines by placing the found image information in a two-dimensional overview, which enables the comparison of multiple classification criteria in multiple images within the context of the network structure.

By using a bi-clique community-finding algorithm our method overcomes the problem of picking the right area in the network, containing a large amount of information while still being useful to the human eye. The approach discovers hidden relationships in the data in a reproducible manner, which otherwise can only be deduced by individual cognitive efforts and which up until now could not be visualized in an objective form.

Future work

The current results are a starting point to explore further issues, such as the superconnected core of co-popularity which seems to be a common feature of the investigated classification networks in art research. We will approach this issue by combining algorithms looking for dense communities, like the one used in the present paper with other algorithms breaking the core into pieces in order to allow for targeted bottom up recombination of fragments.

Another issue is the ambivalent nature of superordinate document and classification entities, which the scalable image matrix method deals with, but for which community finding algorithms have to be adapted.

Finally we plan to investigate not only the structure but also the dynamics of the canons of art history, which includes dealing with the phenomenon of novelty in addition to (co-)popularity (cf. Wu 2008).

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References

G. Kubler (1962): *The Shapes of Time. Remarks* on the History of Things. New Haven/London: Yale University Press.

E.H. Gombrich (1979): *The Sense of Order. A Study in the Psychology of Decorative Art.* Oxford: Phaidon, pp. 209-210.

G. Palla, I. Derényi, I. Farkas, and T. Vicsek (2005): Uncovering the overlapping community structure of complex networks in nature and society. Nature, 435:814, 2005.

CENSUS (2005): Census of Antique Works of Art and Architecture Known in the Renaissance. ed. A. Nesselrath, Verlag Biering & Brinkmann / Stiftung Archäologie, Munich 1997-2005. http://www.dyabola.de

CENSUS (2006...): Census of Antique Works of Art and Architecture Known in the Renaissance. Berlin-Brandenburgische Akademie der Wissenschaften and Humboldt-Universität zu Berlin. http://www. census.de

L. von Ahn, R. Liu, M. Blum (2006): *Peekaboom:* A Game for Locating Objects in Images. CHI 2006 Proceedings. April 22-27, 2006, Montréal, Québec, Canada. http://www.peekaboom.org M. Schich (2007): Rezeption und Tradierung als Komplexes Netzwerk. Der CENSUS und visuelle Dokumente zu den Thermen in Rom. (Diss.) Humboldt-Universität zu Berlin 2007.

B.C. Russell, A. Torralba, K.P. Murphy, W.T. Freeman (2008): *LabelMe: a database and web-based tool for image annotation.* To appear in the International Journal of Computer Vision. Revised January 2, 2008. http://labelme.csail.mit.edu/

M. Schich (2008): Method for producing scalable image matrices. PCT/EP2007/006900 WO/2008/017430 http://www.wipo.int/pctdb/en/wo.jsp?WO=2008017430.

S. Lehmann, M. Schwartz and L.K. Hansen (2008): *Biclique communities*. Phys. Rev. E 78, 016108

F. Wu and B.A. Huberman (2008): *Popularity, novelty and attention.* in: Proceedings of the 9th ACM Conference on Electronic Commerce (Chicago, Il, USA, July 08-12, 2008). EC ,08. ACM, New York, NY, 240-245. DOI= http://doi.acm. org/10.1145/1386790.1386828