Social Networks in Digital Art

Matthew Zbikowski

Agenda

1. Quantifying reputation and success in art
   a. Topic & Applications
   b. Data
   c. Methods
   d. Results
   e. Conclusions
   f. Evaluation
2. Importance of social networks in digital art
   a. Hypothesis
   b. Data
   c. Software & Methods
   d. Results
   e. Conclusions
   f. Takeaways

Quantifying reputation and success in art

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Topic & Applications

- Value of art vs. value of artist
- Qualitative nature of art popularity
- Institutional effects
- Measure artistic career trajectory
- Model for artist success

Data

- Dataset from Magnus
    - Roughly 500,000 artists
    - N = 9392 institutions ranked A to D
    - 36 years of data
- Key assumptions
    - Institution prestige is objective and largely static over time
    - Exhibited artists vs. artworks exhibited

Methods

- Graph development
  - Node: museums and galleries
  - Edge: movement of artist’s work, directed
- Artists grouped by prestige of first 5 exhibits
- Simulation of careers based on dataset facts

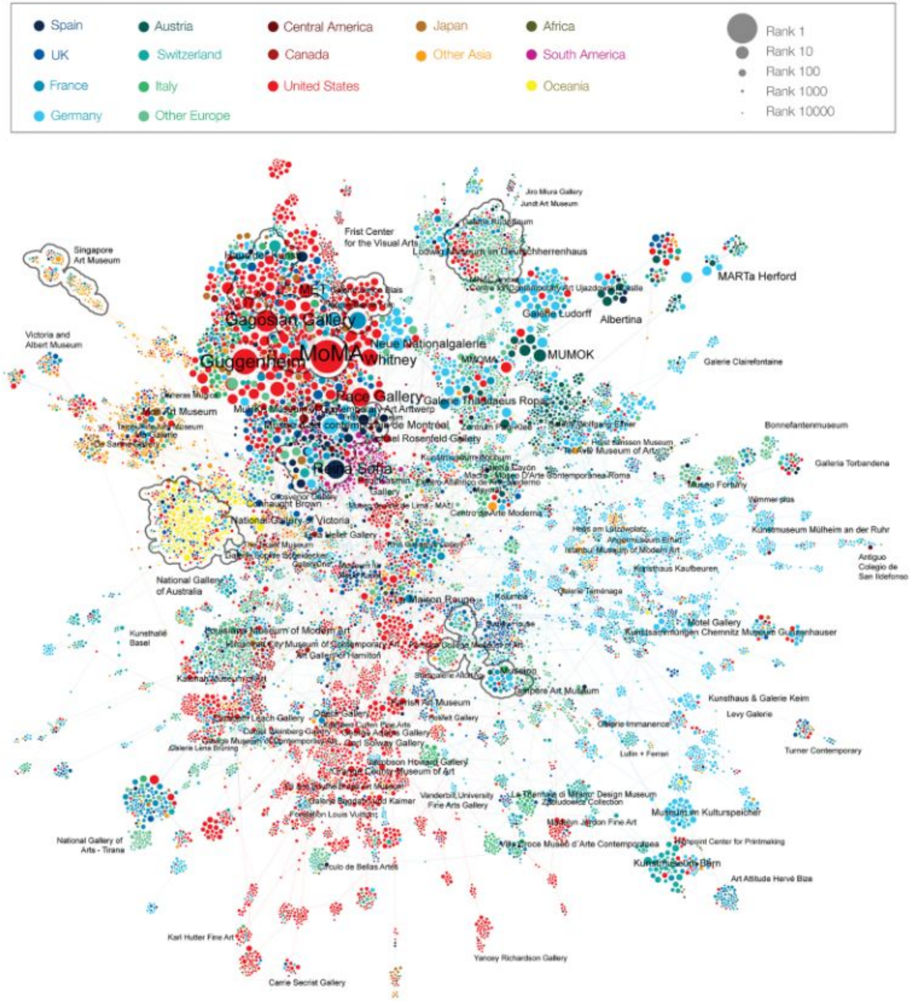
Results

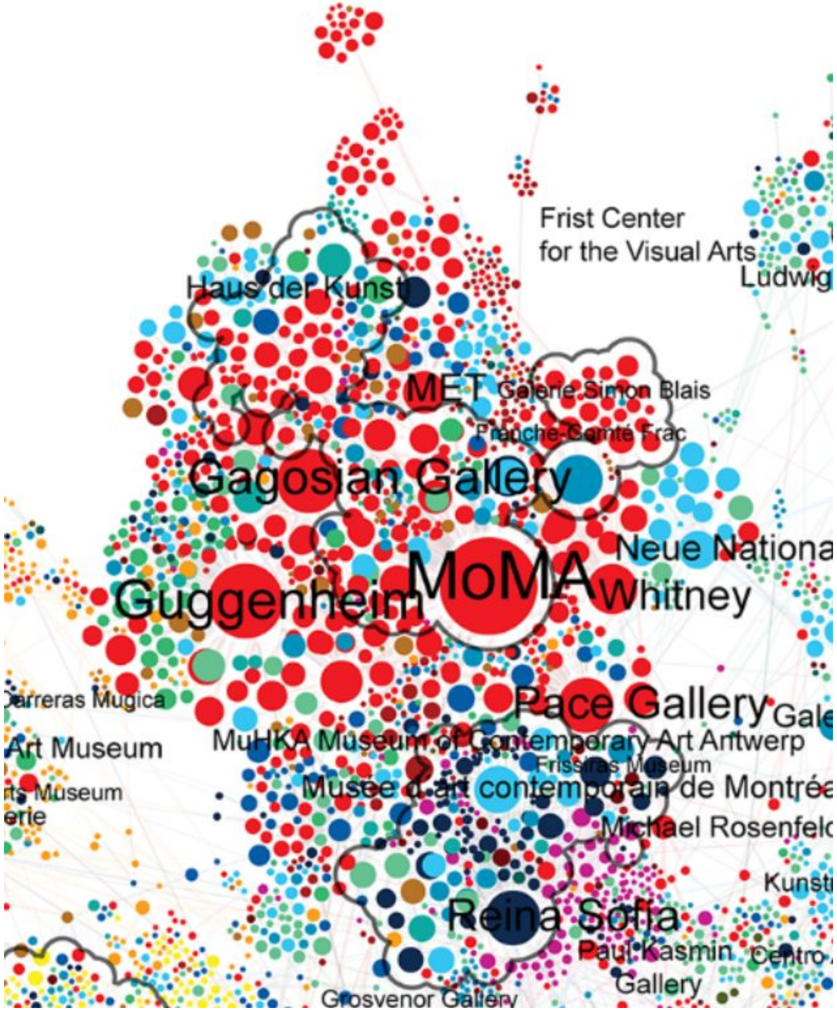
- Probability an artist moves from previous exhibition to new exhibition gives memory term mu:

$$\mu\left[\pi_{i_{\tau+1}}; m_\tau\right] = \frac{p\left[\pi_{i_{\tau+1}} \middle| m_\tau\right]}{p\left[\pi_{i_{\tau+1}}\right]}$$

- Where m_{tau} is average reputation, representing average exhibition prestige

$$m_\tau = \frac{1}{\tau}\sum_{k=1}^{n_\tau} \pi_{i_{\tau-k+1}}$$


Spain
UK
France
Germany
Austria
Switzerland
Italy
Other Europe
Central America
Canada
United States
Japan
Other Asia
Africa
South America
Oceania
Rank 1
Rank 10
Rank 100
Rank 1000
Rank 10000
MoMA
Guggenheim
Gagosian Gallery
Whitney
Neue Nationalgalerie
MUMOK
Albertina
MARTa Herford
Singapore Art Museum
Victoria and Albert Museum
Frist Center for the Visual Arts
National Gallery of Australia
National Gallery of Victoria
Bonnefantenmuseum
Galleria Torbandena
Kunsthalle Basel
National Gallery of Arts - Tirana
Karl Hutter Fine Art
Carrie Secrist Gallery
Yancey Richardson Gallery
Turner Contemporary
Levy Galerie
Kunsthaus & Galerie Keim
Art Attitude Hervé Bize
Galerie Clairefontaine


Frist Center
for the Visual Arts
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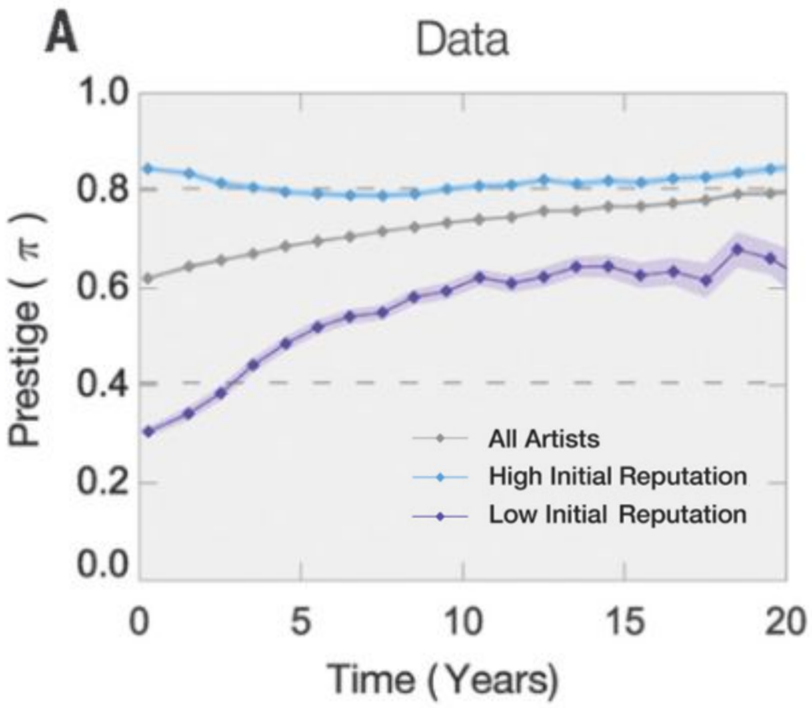
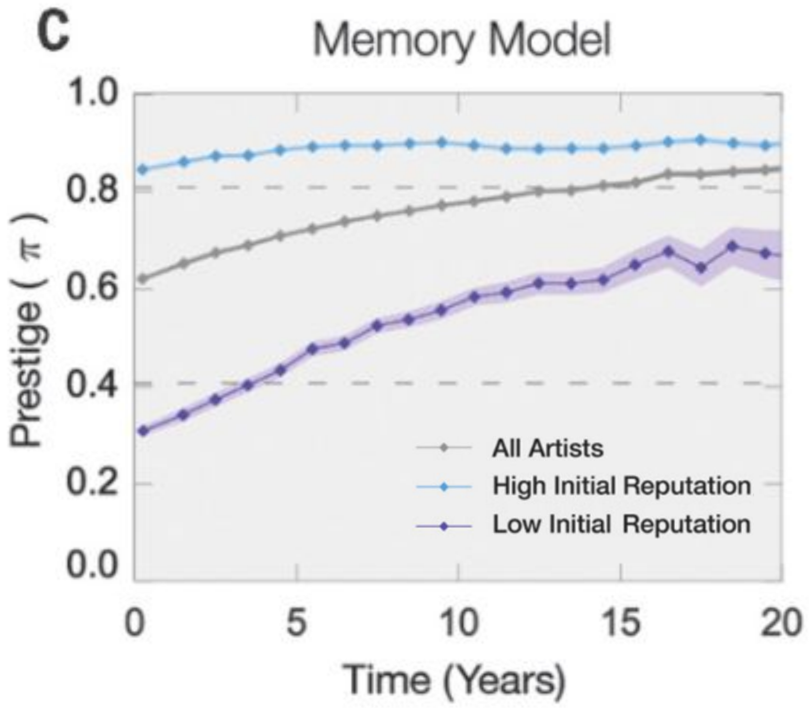
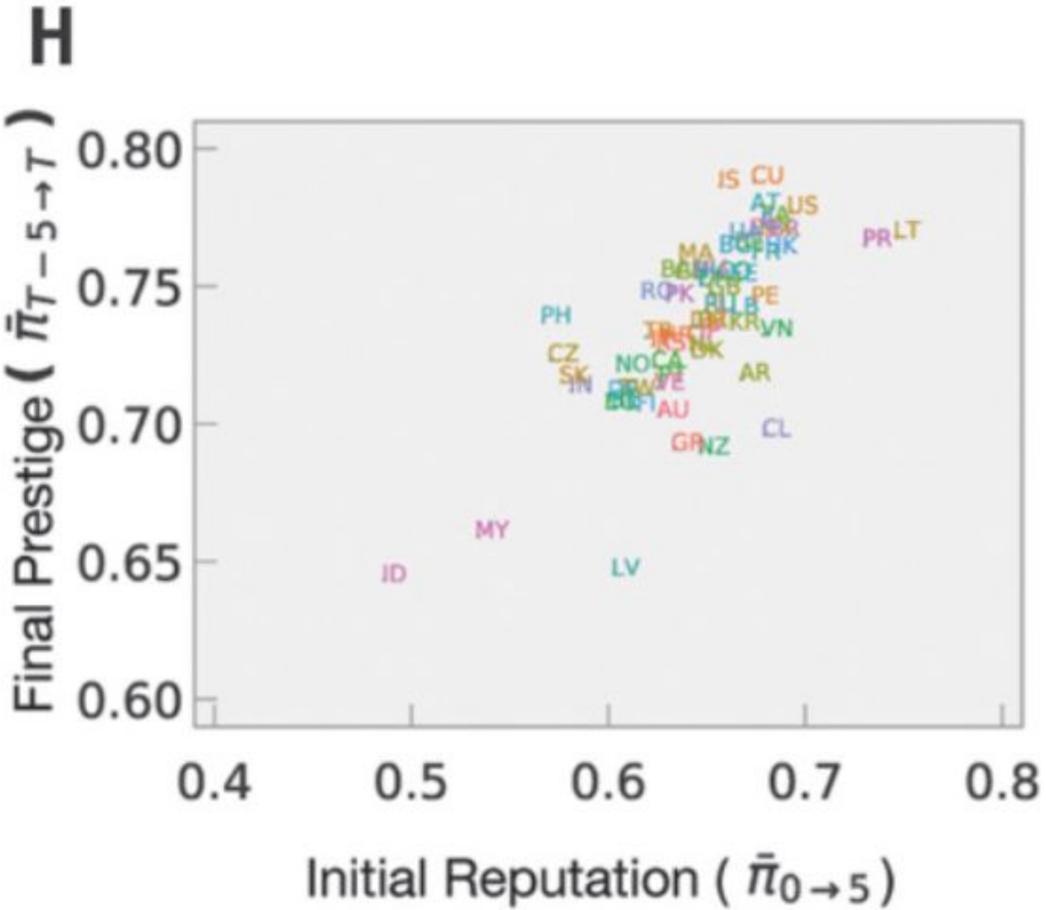
MET
Galerie Simon Blais
Franche-Comté Frac
Gagosian Gallery
Neue Nationa
MoMA
Guggenheim
Whitney
Pace Gallery
arreras Mugica
Art Museum
MuHKA Museum of Contemporary Art Antwerp
Frissiras Museum
Musée d'art contemporain de Montréa
Michael Rosenfel
Reina Sofia
Paul Kasmin
Gallery
Grosvenor Gallery

Observed



Modeled




H
Final Prestige ($\bar{\pi}_{T-5\to T}$)
0.80
0.75
0.70
0.65
0.60
0.4
0.5
0.6
0.7
0.8
Initial Reputation ($\bar{\pi}_{0\to 5}$)
IS
CU
US
PR
LT
MA
PE
PH
VN
CZ
AR
AU
CL
NZ
MY
LV
ID

Conclusions

- Low previous reputation ➔ 17x higher likelihood of low prestige institution next, 42x opposite
- Past 12 exhibitions offer optimal memory for future prediction
- Artists who break through low reputations do so in the first 10 years of their career
- More distinct institutions generally correlates with better trajectory
- Artist’s talent uncorrelated with country of origin, but some countries have better access to the art network

Evaluation

- Succeeds in codifying art success
- Bias
  - Dataset bias (noted as negligible)
  - Underrepresentation of non-object art
- Repeatability

Importance of social networks in digital art

Hypothesis

- Key differences
    - Importance of social networks/artists as opposed to institutions
    - Digital art is quantifiable, focus on relations
- Scope limitation
    - Single website, deviantArt.com
    - Snapshot as opposed to trajectory
    - Proof-of-concept

If a digital artist is “watched” by people with more popular portfolios, then said artist’s creations will be more popular.

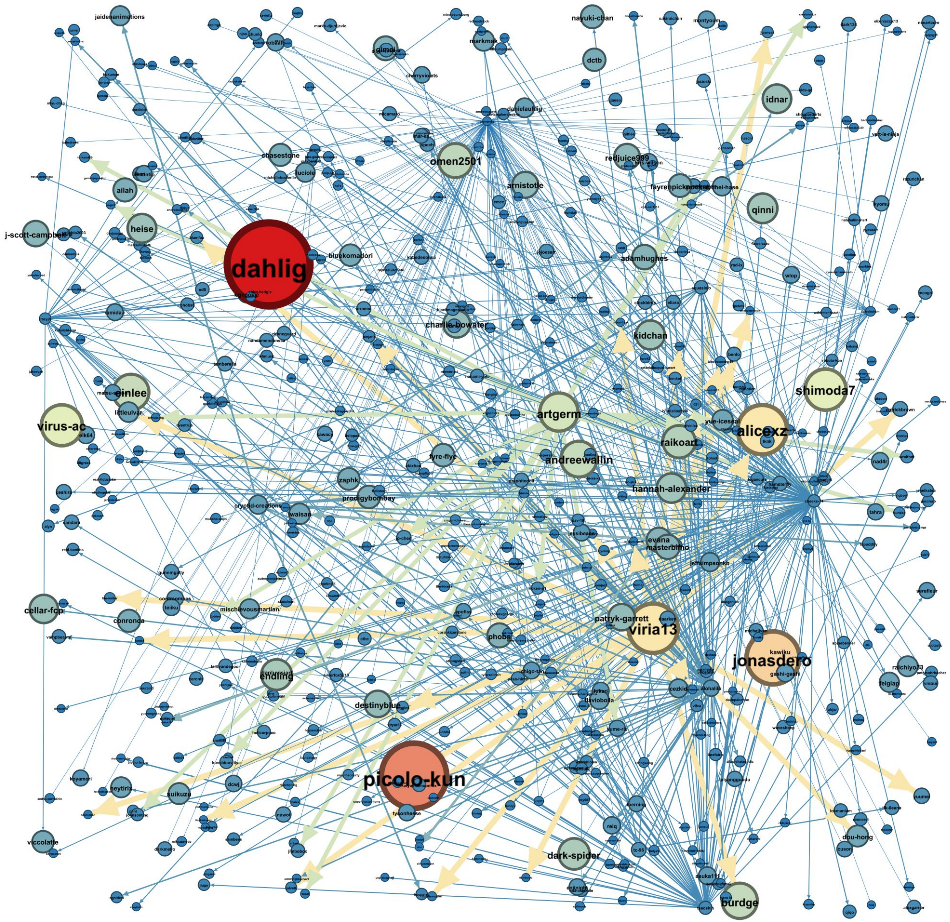
Data

- deviantArt API
- Key factors
  - Node: artist
  - Node weight: popularity
  - Directional edge: “is watching” artist, i.e. follows
- Dataset
  - Approximately 200,000 artists considered
  - Initial “seed artists” could create bias
  - “Popularity” = average favorites on 24 newest submissions
  - Artists below popularity threshold (5000) discarded

Software & Methods

- Data collection
  - Python
  - API, web scraping
- Network visualization
  - Gephi
- Qualitative analysis
  - Clique identification
  - Cross-discipline interaction
  - Usage of platform

Results



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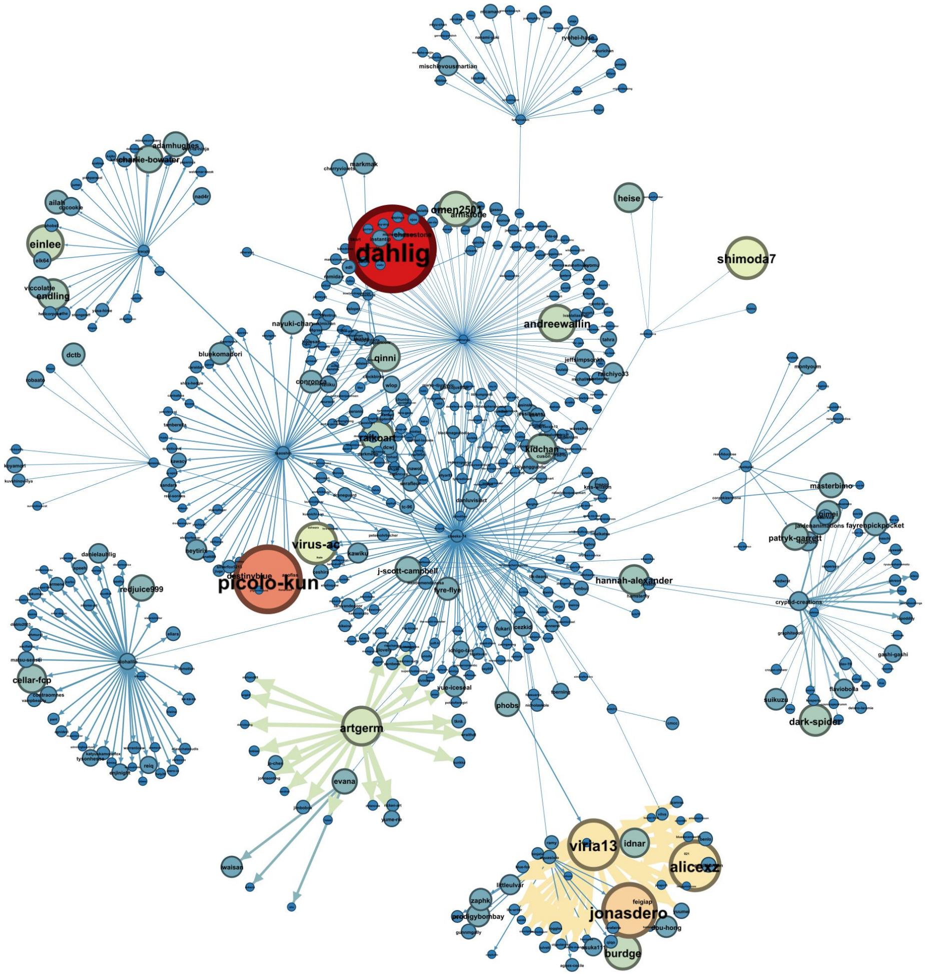
cellar-fcp
viccolatte
destinyblue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charlie-bowater
adamhughes
heise
dctb
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cherryviolets
nayuki-chan
bluekomadori
conronca
aikoart
kidchan
j-scott-campbell
hannah-alexander
masterbimo
patryk-garrett
jaldenanimations
fayrenpickpocket
crypid-creations
dark-spider
suikuzu
flaviobolla
gashi-gashi
redjuice999
cellar-fcp
danielaufflig
evana
iwaisan
phobs
idnar
burdge
zaphk
prodigybombay
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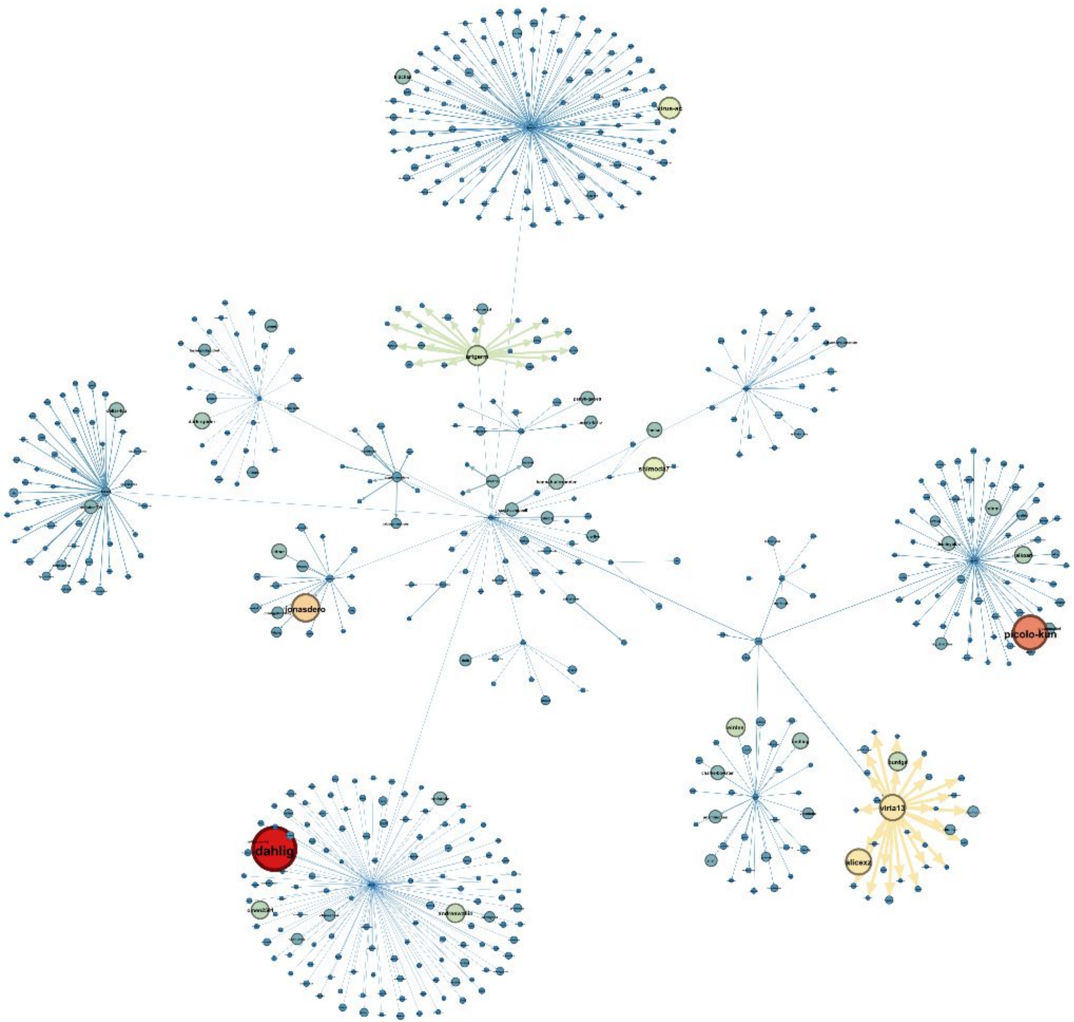

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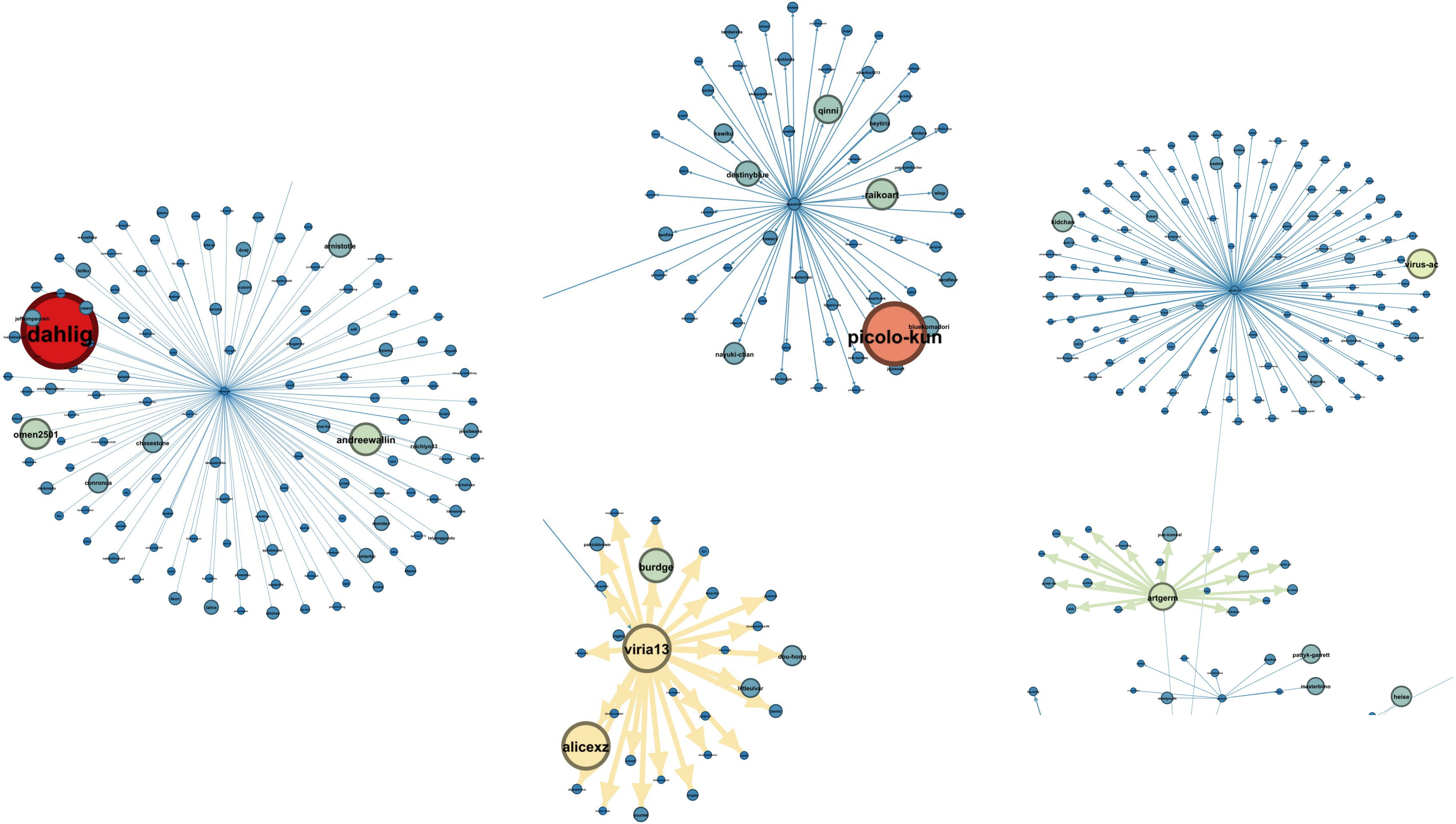
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artgerm
yue-iceseal
patryk-garrett
masterbimo
heise

Conclusions

- Proof-of-concept for determining social impact on digital art popularity
- Initial hypothesis disproved (qualitative)
  - Quantity of followers > quality of followers
  - High-popularity artists follow fewer artists on average, little overlap between upper echelon
  - Higher “following” count could be indicative of the user being an amateur artist looking for inspiration
  - High-popularity artists shift from “user” to “influencer,” using the site to build a social network and gain popularity
- More data needed for further analysis

Takeaways

- Hangups with data collection
- Collect multiple data snapshots
  - Artist popularity over time
  - Shift of social networks
- Multiple websites
- Virality
- Categorization