ZENTRUM FÜR
INFORMATIONSMODELLIERUNG
AUSTRIAN CENTRE FOR
DIGITAL HUMANITIES

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State of the Art?

Computer Vision Projects in the Digital Humanities

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Graz,
10.02.2023

Overview

1. Computer Vision oder Distant Viewing?
2. What's the state of the art?
3. The different sub-fields who use CV in DH
    - The study of visual culture
    - Art history
    - Computer art and aesthetics
    - Archaeology
    - Media studies
    - History
    - Historical maps
    - Archives
    - Computational Social Science
    - Ethics & inequality
    - Document Analysis

Computer Vision oder Distant Viewing?

Distant Viewing

- analogous to *Distant Reading* (Moretti 2013)
- Distant Viewing Toolkit adopts this analogous name (T. B. Arnold and Tilton 2019)
  - *`distantviewing.org`*
  - Python package
  - created for media/video studies but annotators can be used for historical images too

What’s the state of the art?

A literature overview i

van Noord 2022, 3

> [There is a] growing body of computational work that is guided and inspired by theories and challenges related to the study of visual culture... ”

- **mostly inspired by the recent publication:** Nanne van Noord. “A survey of computational methods for iconic image analysis”. In: *Digital Scholarship in the Humanities* (2022). fqac003. DOI: *10.1093/llc/fqac003*, 3
- the paper distinguished the following categories:
  - **the study of visual culture** (Johnson et al., 2008; Stork, 2009; Crowley and Zisserman, 2013; Elgammal et al., 2018; Impett et al., 2018; Lang and Ommer, 2018; Arnold and Tilton, 2019; Chávez Heras and Blanke, 2020; Münster and Terras, 2020; Wevers and Smits, 2020; Azar et al., 2021)
  - **early works with a focus on art history** (van den Herik and Postma, 2000; Criminisi et al., 2005; Johnson et al., 2008; Yarlagadda et al., 2013)
  - **computer art and aesthetics** (Noll, 1966; Dietrich, 1986; Manovich, 1994)

A literature overview ii

- **archaeology** (da Gama Leitao and Stolfi, 2002; Kampel and Melero, 2003; van der Maaten et al., 2006)
- **media studies** (Gehl et al., 2017; Arnold and Tilton, 2019; Thomas, 2020; Matud et al., 2021)
- **history** (Smits, 2017; Wevers and Smits, 2020)
- **historical maps** (Budig et al., 2016; Weinman et al., 2019; Hosseini et al., 2021; Uhl and Duan, 2021)
- **archives** (Chung et al., 2015; van Noord et al., 2021)
- **Computational Social Science** (Olesen, 2015; Wevers et al., 2018; Bocyte and Oomen, 2020; Masson et al., 2020)
- **ethics and inequality** (Jo and Gebru, 2020; Mohamed et al., 2020; Offert and Bell, 2020; Parisi, 2020).

- More examples:
  - other work by the Oxford Visual Geometry Group / Giles Bergel on the computer vision analysis of early modern print (Dutta, Bergel, and Zisserman 2021)
  - Or some of our own... (Götzelmann 2022; Vogeler et al. 2022)

What are the research questions in the DH field of *Distant Viewing*?

- we will look at what types of research questions are
- keeping the following categories:
  1. the study of visual culture
  2. early works with a focus on art history
  3. computer art and aesthetics
  4. archaeology
  5. media studies
  6. history
  7. historical maps
  8. archives
  9. Computational Social Science
  10. ethics and inequality
- look at a few examples
- but also look at some methods to understand who is using what (helping you to know where to look for inspiration for your own work

The different sub-fields who use CV in DH

The study of visual culture i

- **Computer vision and computer graphics analysis of paintings and drawings: An introduction to the literature** (Stork 2009)
- **Of Gods and Goats: Weakly Supervised Learning of Figurative Art** (Crowley and Zisserman 2013):
  - Data – the Beazley Vase Archive - a publicly available pottery database containing around 50,000 vase entries with one or more associated images
  - use of text mining to select sets of images that are visually consistent for a god; Keywords such as verbs and nouns are used to determine the clusters, and stop-words are ignored.
  - reducing the search space by eliminating irrelevant image regions
  - the image regions are used to train a Deformable Parts Model (DPM) sliding window classifier, which is used to annotate all vases (the candidate region is used to train a HOG sliding window classifier
- **The Shape of Art History in the Eyes of the Machine** (Elgammal et al. 2018): discusses Lev Manovich's theory that digital methods continue Humanities methodologies

The study of visual culture ii

- This study used the WikiArt dataset of 81,449 paintings from 1,119 artists to train, validate, and test networks for style classification. The number of style classes was reduced to 20, and the symbolism style class was ignored due to erroneous labeling.
- This paper examines the accuracy of style labels in the WikiArt collection, the largest publicly available collection, and compares it to other smaller collections.
- It also uses another datasets, Artchive (1485 images of paintings from 1400-2000AD by 60 artists), to visualize and analyze the learned representations.
- also compares the performance of three deep convolutional networks, AlexNet, VGGNet, and ResNet, for the task of style classification.
- The results suggest that visual similarity is the main factor that forces a smooth temporal representation to evolve, and highlights the potential role of data science and machine learning in art history. It also confirms existing knowledge in an empirical way and provides insights into the characteristics and functions of style.

- **Attesting similarity: Supporting the organization and study of art image collections with computer vision** (Lang and Ommer 2018)
- **On machine vision and photographic imagination** (Heras and Blanke 2020): importance of lens aesthetics in photography, NN classifies focal lengths

The study of visual culture iii

- **The visual side of digital humanities: a survey on topics, researchers, and epistemic cultures** (Münster and Terras 2019): Review article on 'visual literacy' in DH
- **Introduction: ways of machine seeing** (Azar, Cox, and Impett 2021): Perceptual bias; political consequences of human-machine relations: With the advent of deep convolutional neural networks, the risk of unintended discrimination has increased.
- **Historical data. A portrait** (Fafinski 2020): Critical blogpost about a huge fail published in *Nature*

The study of visual culture iv

A fail because Computer Science on Humanities Data without Humanists

> The authors attempted to analyse how “trustworthiness” changes over time using machine learning. To this end they have analysed historical portraiture in order to identify facial features that correlate with “trustworthiness” (Fafinski 2020).

Art history (early works)

- **Image processing for artist identification** (Johnson et al. 2008): identify Van Gogh's brushwork
- **Towards a Computer-Based Understanding of Medieval Images** (Yarlagadda et al. 2012): category retrieval, detect object instances in large-scale datasets (SVM)

Computer art and aesthetics

- Human or Machine: A Subjective Comparison of Piet Mondrian's "Composition with Lines" (1917) and a Computer-Generated Picture (Noll 1966)
- Visual Intelligence: The First Decade of Computer Art (1965-1975) (Manovich 1994)

Archaeology

- **A Multiscale Method for the Reassembly of Two-Dimensional Fragmented Objects** (Gama Leitao and Stolfi 2002): Fragment matching/pairing given observed fragment outlines
- **Computer vision and machine learning for archaeology** (van der Maaten et al. 2006): exploring potentials like content based retrieval, type classification (for various objects) or restoring highly degraded artifacts
- **Implementing State-of-the-Art Deep Learning Approaches for Archaeological Object Detection in Remotely-Sensed Data: The Results of Cross-Domain Collaboration** (Olivier and Vaart 2021)
- **A deep-learning model for predictive archaeology and archaeological community detection** (Resler et al. 2021)

Media studies

- **Training Computers to See Internet Pornography: Gender and Sexual Discrimination in Computer Vision Science** (Gehl, Moyer-Horner, and Yeo 2016): pornography filtering
- **Distant viewing: analyzing large visual corpora** (T. Arnold and Tilton 2019): This article applies the idea of *Distant Reading* to Computer Vision, coining the term *Distant Viewing*. It shows the DVT Python toolkit (media) and two examples (television shows, image clustering).
- **A survey of computational methods for iconic image analysis** (van Noord 2022): Special type of 'iconic images' (of historical events / special meanings) cannot be understood without context, what to do about that? They are special in production, distribution and reception contexts.
- **The Computational Memorability of Iconic Images.** (Saleh and Noord 2022): Are those images as memorable for computer as they are for us?

History

- **The visual digital turn: Using neural networks to study historical images** (Wevers and Smits 2019): CNNs for historical visual sources, such as digitized Dutch newspapers, calling for a 'visual turn' in DH.
- **Towards Multimodal Computational Humanities. Using CLIP to Analyze Late-Nineteenth Century Magic Lantern Slides** (Smits and Kestemont 2021): multi-modal deep learning for binary classification, pretrained model much better than BERT
- **Automatic Identification and Classification of Portraits in a Corpus of Historical Photographs.** (T. Arnold, Tilton, and Wigard 2022): between Humanities annotation and CV – can the algorithm detect and classify portrait photography? Different types are investigated.

Historical maps

- **Deep Neural Networks for Text Detection and Recognition in Historical Maps** (Weinman et al. 2019): Demonstration that NN can be used for the complex data that are historical maps.
- **Maps of a Nation? The Digitized Ordnance Survey for New Historical Research** (Hosseini et al. 2021)
- **Automating Information Extraction from Large Historical Topographic Map Archives: New Opportunities and Challenges** (Uhl and Duan 2020)

Archives

- **Re-presentations of Art Collections** (van Noord et al. 2021): Aid art historians in analyzing large collections, use image level descriptors for category-based clustering, identify illustrations from the same source by instance matching.
- **Automatic Annotations and Enrichments for Audiovisual Archives** (van Noord et al. 2021): Audiovisual Processing (AVP) tools for heritage institutions; examples: pose analysis, automatic speech recognition.

- **Exploring Digitised Moving Image Collections: The SEMIA Project, Visual Analysis and the Turn to Abstraction** (Masson et al. 2020)
  - The Sensory Moving Image Archive project (SEMIA), first results
  - Sensory features are essential to users experiences of audiovisual heritage objects but inadequately captured by verbal description.
  - The Sensory Moving Image Archive (SEMIA) project aimed to explore how sensory object features such as colour, shape, visual complexity and movement can be used to explore digitised audiovisual collections, rather than relying solely on search and retrieval of single items.

Ethics & inequality i

- **Perceptual bias and technical metapictures: critical machine vision as a humanities challenge** (Offert and Bell 2020)
  - machine vision systems are inherently biased not only because of their reliance on biased datasets, but also because of their specific way of representing the visual world, which gives rise to a new type of bias called perceptual bias.
  - It examines how perceptual bias affects the interpretability of machine vision systems, using a visualization technique called feature visualization. It argues that both dataset bias and perceptual bias need to be considered in the critical analysis of machine vision systems
  - critical machine vision = important transdisciplinary challenge at the intersection of computer science and visual studies.
  - feature visualizations should be understood as technical metapictures, as images about (machine) seeing (ref: W. J. T. Mitchell (Mitchell 1995))
  - perceptual bias = problem of representation and interpretation
- **Negative optics in vision machines** (Parisi 2020)
- **The agency of computer vision models as optical instruments** (Smits and Wevers 2021):

Ethics & inequality ii

- six widely cited benchmark datasets (Caltech 101, Caltech 256, PASCAL VOC, ImageNet, MS COCO and Google Open Images)
- $\rightarrow$ explores the power and subjective choices of its creators and the labor of crowd workers.
- The selection of categories is not based on any general notion of visuality, but depends heavily upon perceived practical applications and the availability of downloadable images.
- Additionally, the reliance on Flickr for data collection introduces a temporal bias in computer vision datasets.
- Computer vision models are optical instruments that shape contemporary visuality, and that their decisions are influenced by the desires of computer scientists and the labour of crowd workers.

- **Training Computers to See Internet Pornography: Gender and Sexual Discrimination in Computer Vision Science** (Gehl, Moyer-Horner, and Yeo 2016): pornography filtering. Article argues that computer scientists (by majority straight & male) apply a 'male gaze' to their algorithms which this paper wants fixed.

Ethics & inequality iii

- **Historical data. A portrait** (Fafinski 2020): Critical blogpost about a huge fail published in *Nature*

A fail because Computer Science on Humanities Data without Humanists

> The authors attempted to analyse how "trustworthiness" changes over time using machine learning. To this end they have analysed historical portraiture in order to identify facial features that correlate with "trustworthiness" (Fafinski 2020).

Document Analysis i

- **Computational Methods in Studying Late Medieval Charters** (Vogeler et al. 2022) = Graz Didip project
- **Bilderschätze, Bildersuchen: Digitale Auswertung von Illustrationswiederverwendungen im Buchdruck des 16. Jahrhunderts** (Götzelmann 2022)
- Portrait classification and identification in historical photos (T. Arnold, Tilton, and Wigard 2022)
- Analyse visual style in sitcoms (T. Arnold, Tilton, and Berke 2019)
- Can we teach machines a 'curatorial gaze'? (Bönisch 2021)
- Page Segmentation for historical document images (Chen and Seuret 2017)
- 19th century illustrated newspapers (Fyfe and Ge 2018)
- Automatic gesture annotation & human-machine collaboration (Ienaga et al. 2022)

Document Analysis ii

- Classify historical newspaper (Kleppe, Smits, and Faber 2019)
- Date estimation for scanned photo for image retrieval (Molina et al. 2021)
- When was this picture taken? (Müller, Springstein, and Ewerth 2017)
- Anguelos Nicolaou's TorMentor (Nicolaou et al. 2022)
- Deep Learning for archaeological remote sensing (Olivier and Vaart 2021)
- Archaeologiacal predictions (Resler et al. 2021)
- Semi-supervised pose estimation in historical images (Springstein et al. 2022)
- Tagging the Met Museums Data (Villaespesa and Crider 2021)
- CV for Museum Collections (Villaespesa and Murphy 2021)

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