

III. ANALYSIS

6. Digital Image Analysis

Prof. Dr. Martin Langner

Kohle (2013) 63–95; Piotr Kuroczyński , Peter Bell and Lisa Dieckmann (eds.), *Computing Art Reader. Einführung in die digitale Kunstgeschichte* (<https://books.ub.uni-heidelberg.de/arthistoricum/catalog/book/413>)



THE ART-HISTORICAL METHOD

- a) Grouping and ordering
- b) Comparing
- c) Interpreting

IMAGE CONTENT AND FORM

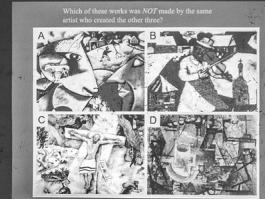
- a) Iconography
- b) Form analysis
- c) Artist attribution
- d) Reconstruction

IMAGE EFFECT AND RECEPTION

- a) Iconology
- b) Reception
- c) Cultural Analytics

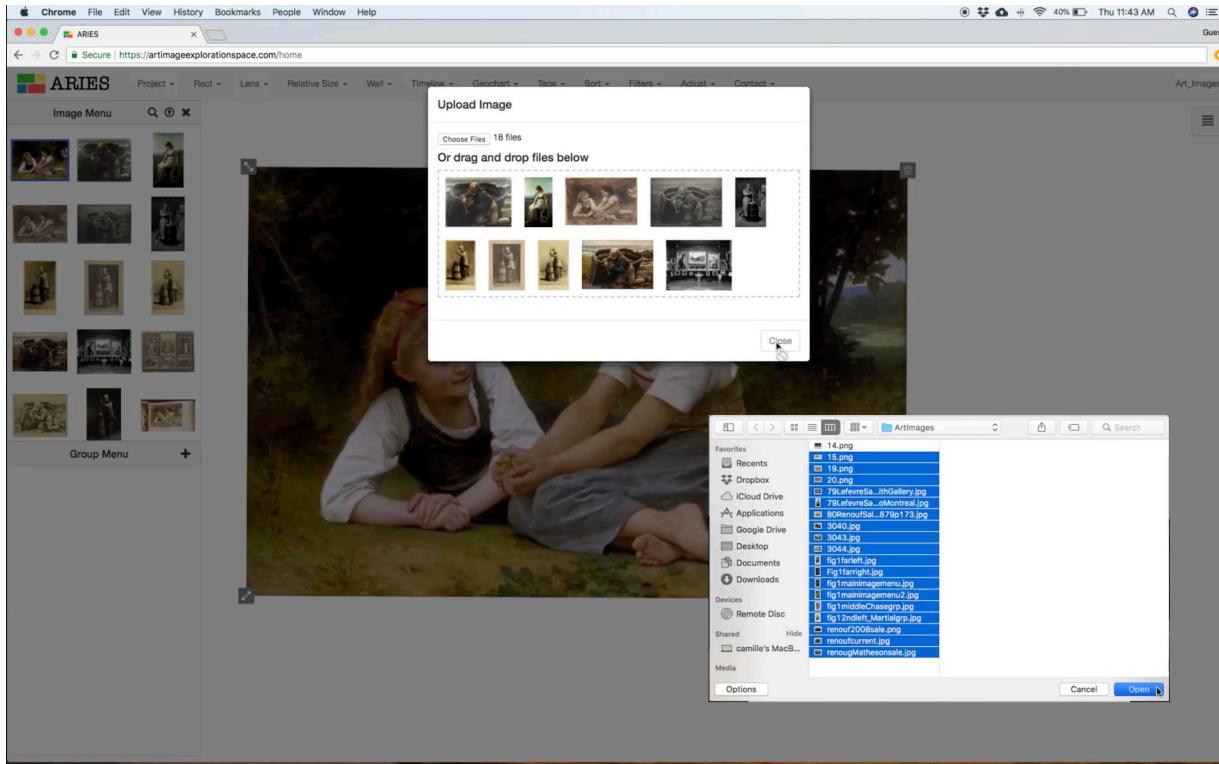


THE ART HISTORICAL METHOD: COMPARING AND ARRANGING PICTURES





DIGITAL PICTURE COMPARISON: ARIES



ARIES ART Image Exploration Space (<https://artimageexplorationspace.com>)



DIGITAL PICTURE COMPARISON: SEARCHING AND GROUPING

The screenshot shows the ARIES ARt Image Exploration Space interface. The top navigation bar includes options like Project, Rect, Lens, Relative Size, Timeline, Geochart, Tags, Sort, Filters, Adjust, and Contact. The main area displays several images of a woman churning butter. One large image is centered, and several smaller versions are overlaid around it. On the left, there's an 'Image Menu' with a grid of thumbnail images and a 'Group Menu' with categories: Nut Gatherers, Churner, and Sappho, each with a corresponding thumbnail.

ARIES ARt Image
Exploration Space
(<https://artimageexplorationspace.com>)



DIGITAL PICTURE COMPARISON: CONFRONTATION

ARIES Project ▾ Rect ▾ Lens ▾ Relative Size ▾ Wall ▾ Timeline ▾ Geochart ▾ Tags ▾ Sort ▾ Filters ▾ Adjust ▾ Contact ▾ Art_Images

Image Menu

Group Menu +

ARIES ART Image Exploration Space (<https://artimageexplorationspace.com>)



DIGITAL PICTURE COMPARISON: OVERLAY COMPARISON

ARIES

[return](#)[Replace Images](#)

ARIES ART Image
Exploration Space
(<https://artimageexplorationspace.com>)



DIGITAL PICTURE COMPARISON: LENS

ARIES

return Match Points Color Change

2530 RENOUF (E.). *Dernier radoub; « mon pauvre ami ! »*



DIGITAL PICTURE COMPARISON: TAGGING

ARIES Project ▾ Rect ▾ Lens ▾ Relative Size ▾ Wall ▾ Timeline ▾ Geochart ▾ Tags ▾ Sort ▾ Filters ▾ Adjust ▾ Contact ▾ ArtImages

Image Menu

Group Menu +

Nut Gatherers Churner

Sappho

hammer

Metadata

Author:

Title:

Year:

Dimensions: x in ↕

Medium:

Technique:

Keywords:

Annotations:

Provenance:

Location:

Tags: hammer



DIGITAL PICTURE COMPARISON: SIZE RATIOS

The screenshot shows a web browser window for 'ARIES' on a Mac OS X system. The title bar includes the standard Apple menu, followed by 'File', 'Edit', 'View', 'History', 'Bookmarks', 'People', 'Window', and 'Help'. The address bar shows a secure connection to 'https://artimageexplorationspace.com/home'. The main content area is titled 'ARIES' and features a navigation menu with 'Project', 'Rect', 'Lens', 'Relative Size', 'Wall', 'Timeline', 'Geochart', 'Tags', 'Sort', 'Filters', 'Adjust', and 'Contact'. On the right side, there is a user profile 'Guest' and a collection name 'MJM_Collection'. Below the menu, five images of artworks are displayed:

- A small image of a painting showing a figure in a dark interior.
- A large image of a landscape painting with a prominent tree and a body of water.
- A painting of a woman in a white dress seated on a chair.
- A small image of a painting showing figures in a workshop or industrial setting.
- A small image of a painting depicting the Virgin Mary holding the Christ Child.

ARIES ARt Image
Exploration Space
(<https://artimageexplorationspace.com>)



DIGITAL PICTURE COMPARISON: TIMELINE

ARIES

Return < >

The screenshot shows the ARIES ARt Image Exploration Space interface. At the top, there are three paintings displayed in separate frames:

- Théodore Rousseau, 1812-1867**
A quiet pool (Landscape)
ca. 1850
- William-Adolphe Bouguereau (1825 – 1905)**
Cupid
ca. 1850 - 1885
- Hector Le Roux**
Sleeping Vestal
ca. 1850 - 1885

Below these frames is a horizontal timeline represented by a series of small thumbnail images of various artworks, spanning from 1835 to 1885. The timeline is marked with years at intervals of 5 years (1835, 1840, 1845, 1850, 1855, 1860, 1865, 1870, 1875, 1880, 1885). A vertical scale bar is positioned to the right of the timeline.

ARIES ARt Image
Exploration Space (<https://artimageexplorationspace.com>)



Finding sections of the image



Manually selecting the portion of an artwork that overlaps with the corresponding alternate image.



Tuscan, 15th century, Harvard Art Museum.



Finding duplicates, copies and image citations



New Match: different work of art. Some children missing, added, changed.

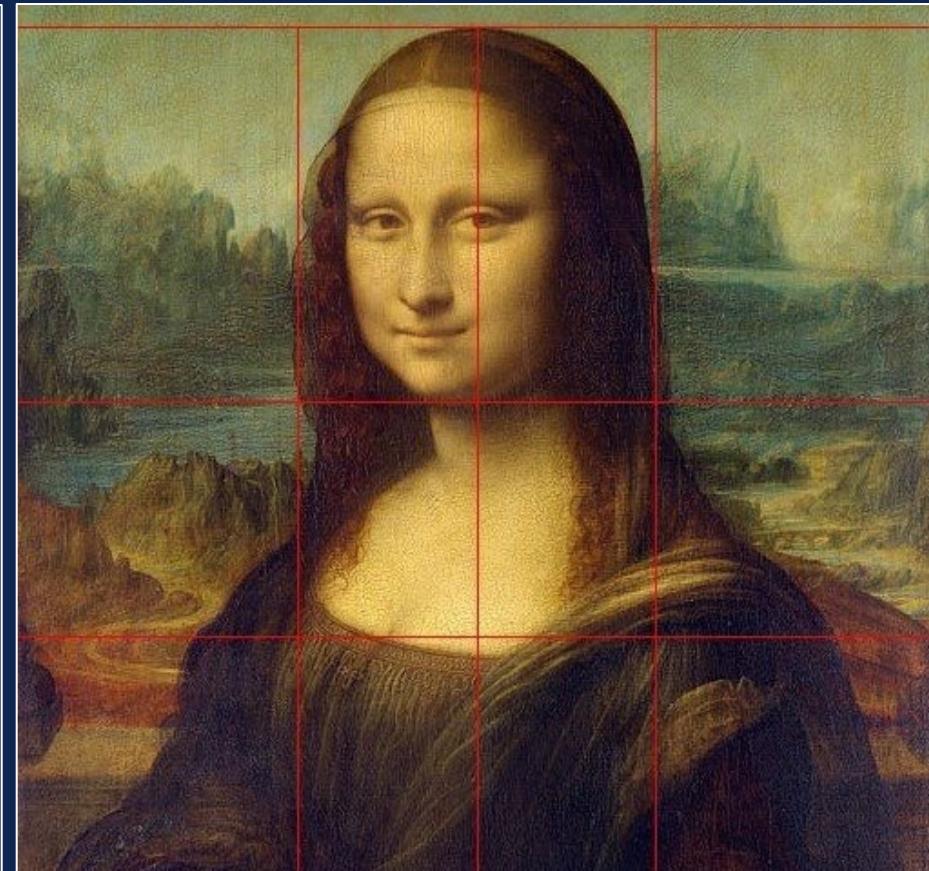
John Resig, Using Computer Vision to Increase the Research Potential of Photo Archives, Journal of Digital Humanities 3 No. 2, Summer 2014

(<http://journalofdigitalhumanities.org/3-2/using-computer-vision-to-increase-the-research-potential-of-photo-archives-by-john-resig/>)



New Match: same work of art, before and after restoration.

IMAGE CONTENT AND FORM



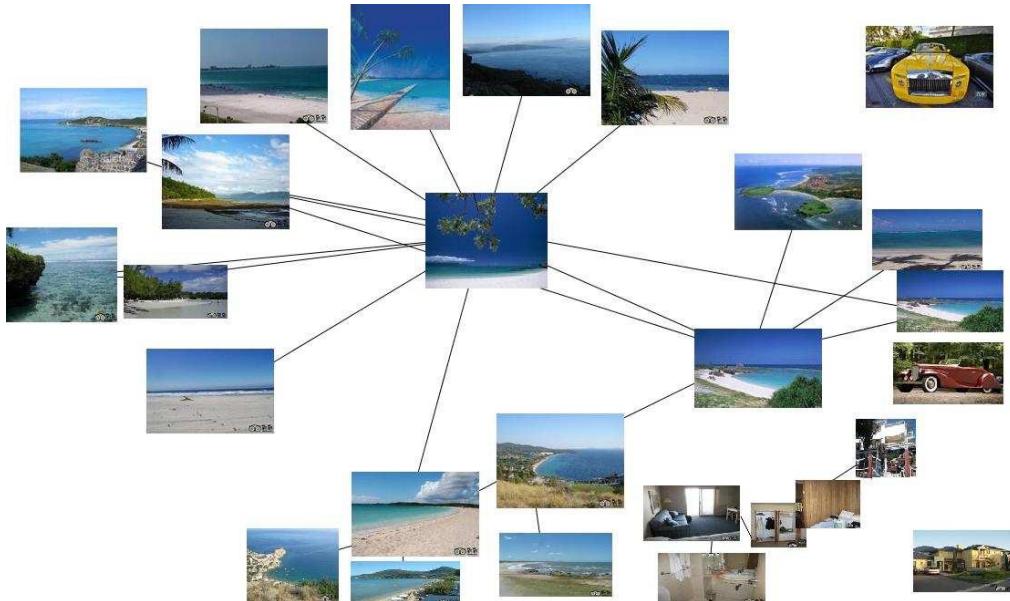
WHO OR WHAT IS DEPICTED?

- Iconography
- Image pattern
recognition (Computer
Vision)



Frank Büttner und Andrea Gottdang, *Einführung in die Ikonographie. Wege zur Deutung von Bildinhalten*, (München: C.H.Beck, 2006)

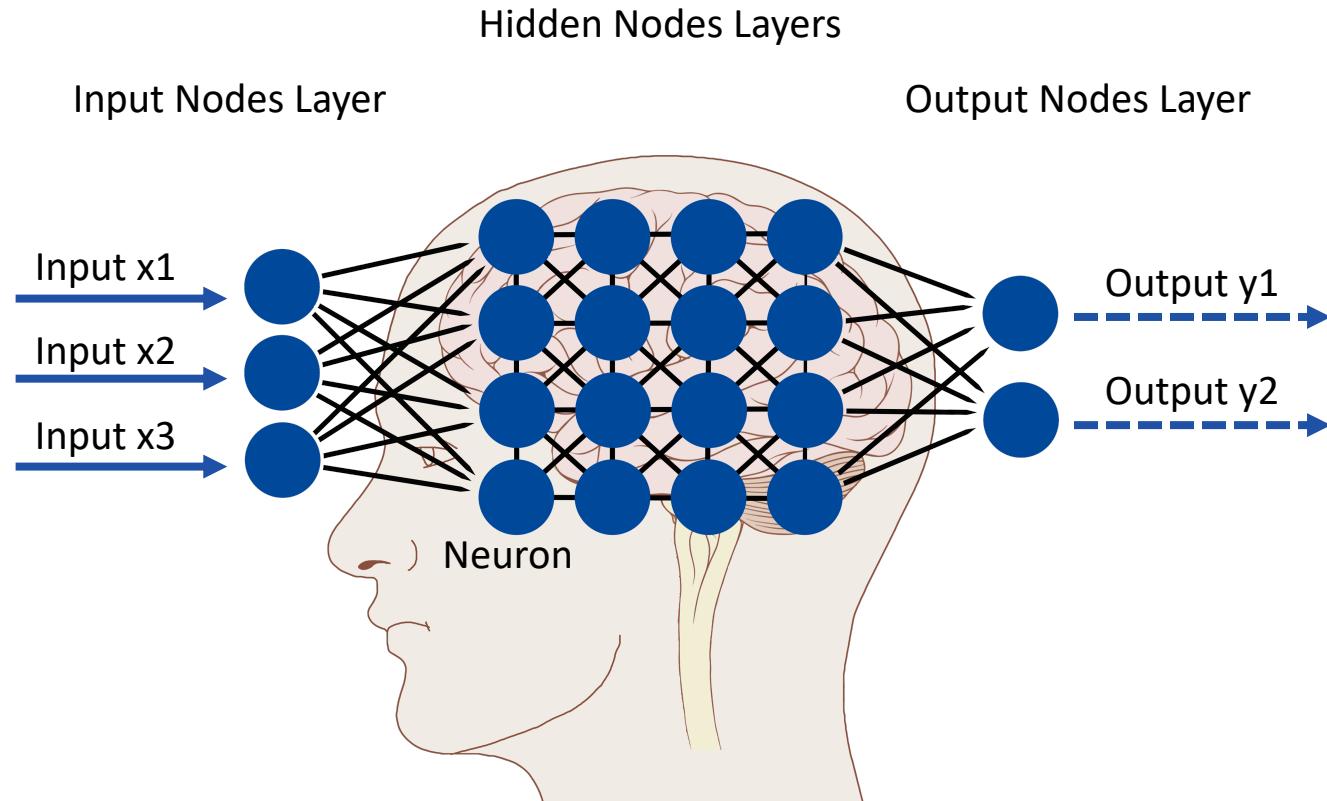
Giulio Romano, Isabella of Aragon



a picture containing sitting, table, indoors, black.



ARTIFICIAL NEURAL NETWORKS





MACHINE LEARNING METHODS

Supervised learning:

- Learning through annotated examples (with the correct, fundamental truth class).
- With each new, unseen example, the model predicts its learning outcome.

Unsupervised learning:

- Learning through own observation (without a given ground truth value).
 - The structure or relationships between different inputs are found independently by clustering "similar" inputs.

Reinforcement Learning:

- The algorithm tries out different approaches by applying try and error and finding out which one brings the greatest success.



TRAINING A NEURAL NETWORK



+



Validation data

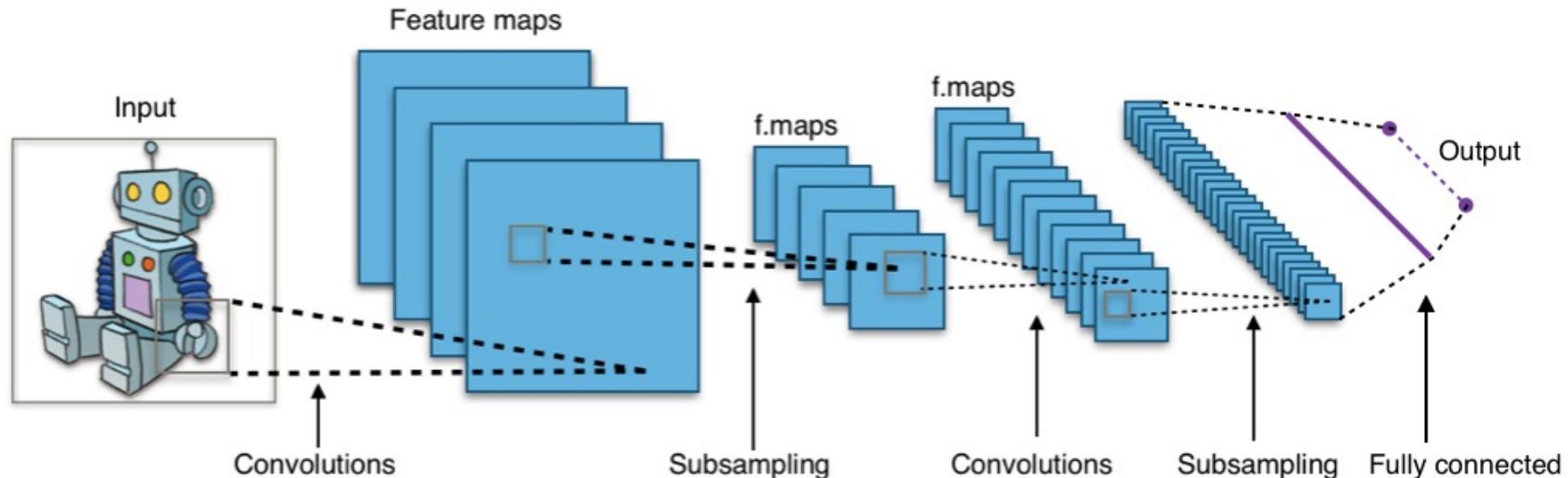
+



Testing data
(Hold-out)



CONVOLUTIONAL NEURONAL NETWORKS

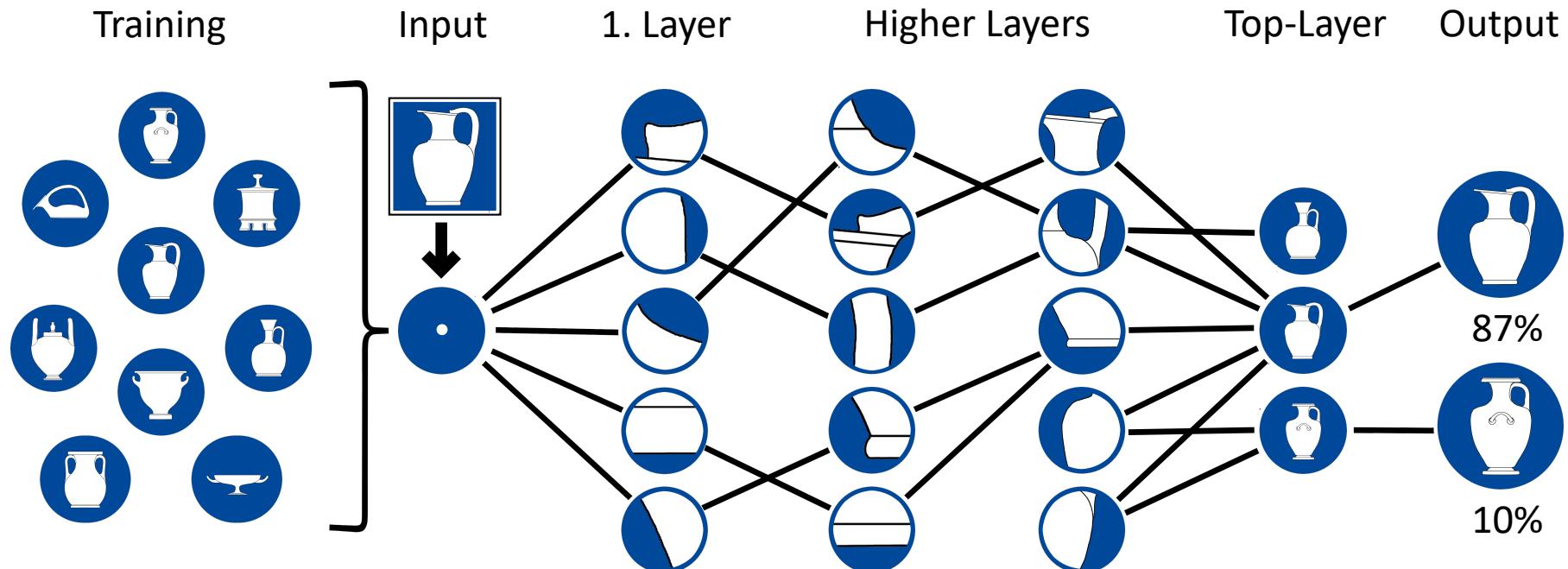


Charu C. Aggarwal, *Neural Networks and Deep Learning. A Textbook* (Cham: Springer, 2018)

https://de.wikipedia.org/wiki/Convolutional_Neural_Network



HOW DO CNNS RECOGNISE A VASE SHAPE IN A PHOTO?





Indexing a large amount of image data to find structural similarities

e.g. the automatic image search for the motif "Capture of St. Peter" in image data from prometheus leads to iconographically correct hits (marked green) and similar compositions.



Peter Bell und Björn Ommer, „Visuelle Erschließung. Computer Vision als Arbeits- und Vermittlungstool,“ in: EVA 2016, 67–74



Comparison of individual scenes at the level of semantic similarity

e.g. comparison of lying persons or gestures in the Sachsenspiegel

Masato Takami, Peter Bell und Björn Ommer, Offline Learning of Prototypical Negatives for Efficient Online Exemplar SVM, in *Proceedings of the IEEE Winter Conference on Applications of Computer Vision*, IEEE, (2014), 377–384

(<http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=6836075>)





Comparison of individual details at the level of semantic similarity



J. Schlecht, B. Carqué and B. Ommer, „Detecting Gestures in Medieval Images“. IEEE International Conference on Image Processing (ICIP 2011), September 11-14, Brussels, Belgium.
<http://ieeexplore.ieee.org/document/6115669/>



Comparison of individual details at the level of semantic similarity



<https://www.instagram.com/p/B-pclo5B-Mq/>



Comparison of individual details at the level of semantic similarity



Bodleian Ballads Search, Visual Geometry Group,
University of Oxford: <http://ballads.bodleian.ox.ac.uk>,
Web demo: <http://zeus.robots.ox.ac.uk/ballads/>

See list view | No text

Query Image

name: MS. Wood E 25(95)

Search Results 1 to 10

MS. Wood E 25(95) MS. Wood E 25(40) MS. Wood E 25(29) Douce Ballads 2(260a)

Detailed matches Detailed matches Detailed matches Detailed matches

#inliers= 48

Boxes Lines Regions [Draw again](#)

name: MS. Wood E 25(95) name: MS. Wood E 25(43)

26



15cILLUSTRATION

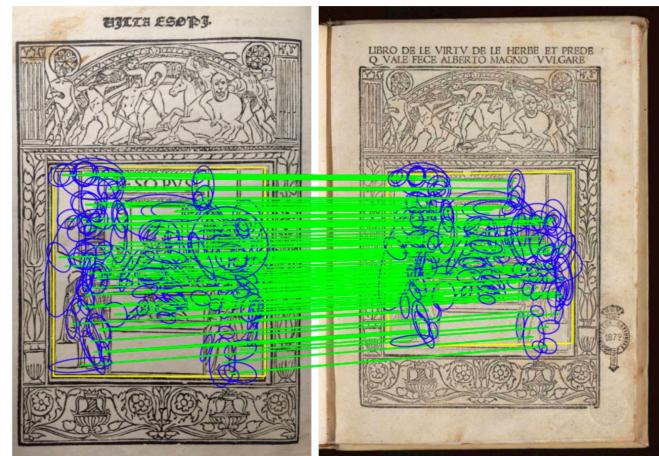
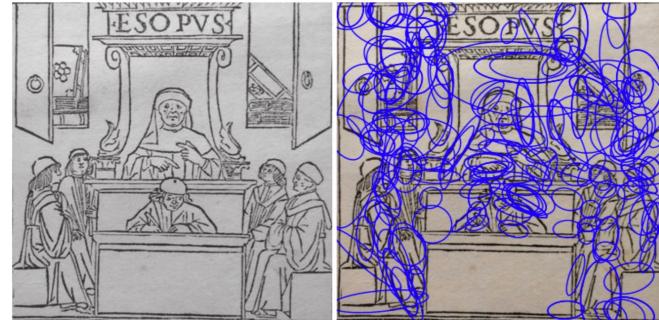
<http://zeus.robots.ox.ac.uk/15cillustration/home>

Query Image Region

• Filename: unknown.jpg (uploaded file)
Note: You can click on the uploaded image (shown on the right hand side) to search using a region in this uploaded file.



Search Result: 1 to 3 [List View](#) [Tile View](#) [Tile View \(images only\)](#)



Cristina Dondi et al., *Printing R-Evolution and Society 1450-1500. Fifty Years that Changed Europe* (Edizioni Ca' Foscari, 2020), 839–869: <http://www.robots.ox.ac.uk/~vgg/publications/2020/dondi20/dondi20.pdf>



Neural networks for classifying image content (such as animals and earrings) in paintings via class-based and instance-based image retrieval:

photographs

dog



Live Demo

You can try out the demo system using one of the following examples or by clicking the demo button:

abstract	arch	baby	beard	bird	boat	button	cap	chair	church
cow	crowd	dog	earrings	fire	flower	forest	fruit	garden	geometric
horse	jug	lace	man	medal	mountain	moustache	road	sand	seascape
sheep	shoe	snow	storm	suit	tower	train	tree	war	woman

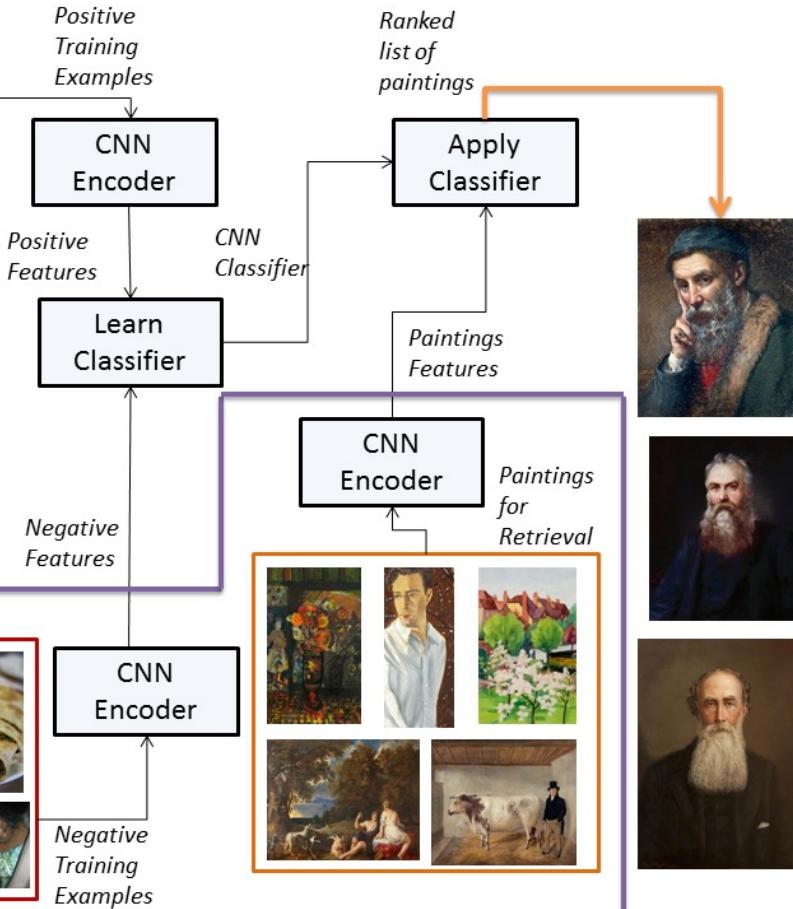
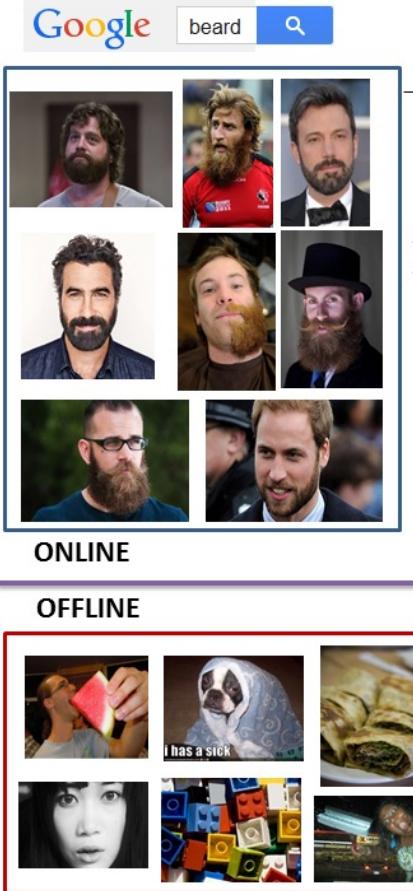
paintings

YOUR
PAINTINGS
> 200,000
Paintings



Access Live Demo

Usage Instructions



Neural networks for classification of image content

E. J. Crowley and A. Zisserman, „In Search of Art,” *Workshop on Computer Vision for Art Analysis*, ECCV, 2014.

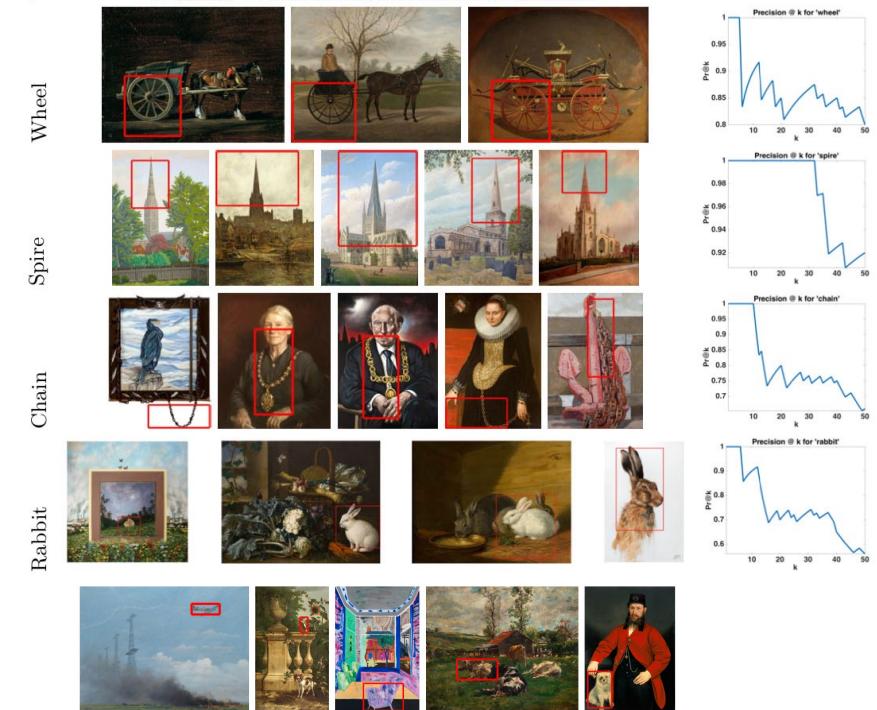
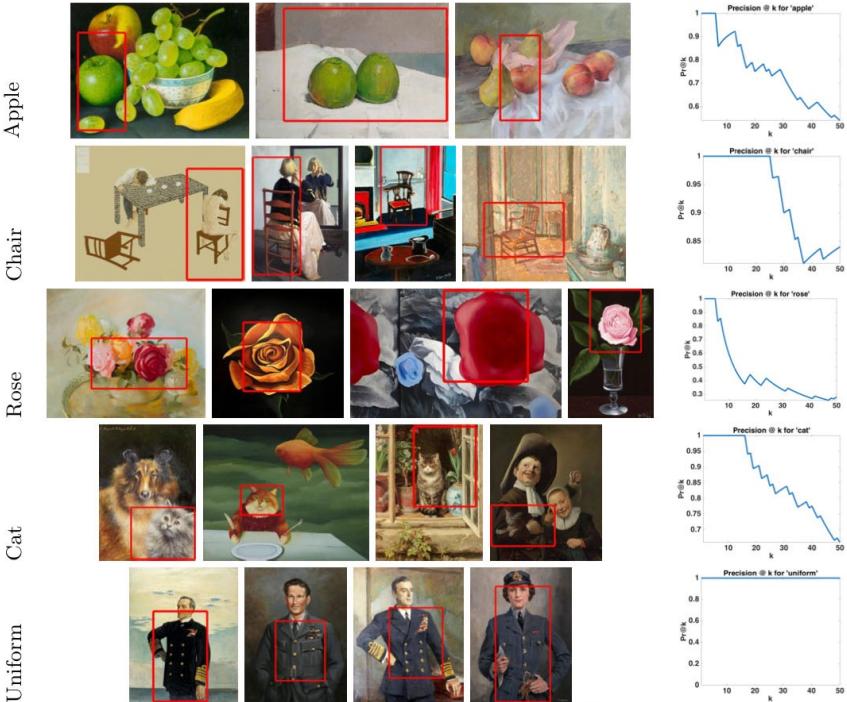
<http://www.robots.ox.ac.uk/~vgg/publications/2014/Crowley14a/crowley14a.pdf>

E. J. Crowley and A. Zisserman, „The State of the Art. Object Retrieval in Paintings using Discriminative Regions,” *British Machine Vision Conference*, 2014.

<http://www.robots.ox.ac.uk/~vgg/publications/2014/Crowley14/crowley14.pdf>



ICONOGRAPHY AND PATTERN RECOGNITION



Elliot. J. Crowley, Visual Recognition in Art using Machine Learning, PhD thesis from University of Oxford (2016):
<http://www.robots.ox.ac.uk/~vgg/publications/2016/Crowley16a/crowley16a.pdf>

Elliot J. Crowley and Andrew Zisserman, The Art of Detection, Workshop on Computer Vision for Art Analysis, ECCV (2016), 1–16: <http://www.robots.ox.ac.uk/~vgg/publications/2016/Crowley16/crowley16.pdf>



The applicability of Convolutional Neural Networks (CNN) for art historical image classification tasks



<https://www.wikiart.org/de>



<https://www.wga.hu>

The applicability of Convolutional Neural Networks (CNN) for art historical image classification tasks



Eva Cetinic, Tomislav Lipic und Sonja Grgic, „Fine-tuning Convolutional Neural Networks for Fine Art Classification,” *Expert Systems with Applications* 114 (2018), 107–118.

The applicability of Convolutional Neural Networks (CNN) for art historical image classification tasks

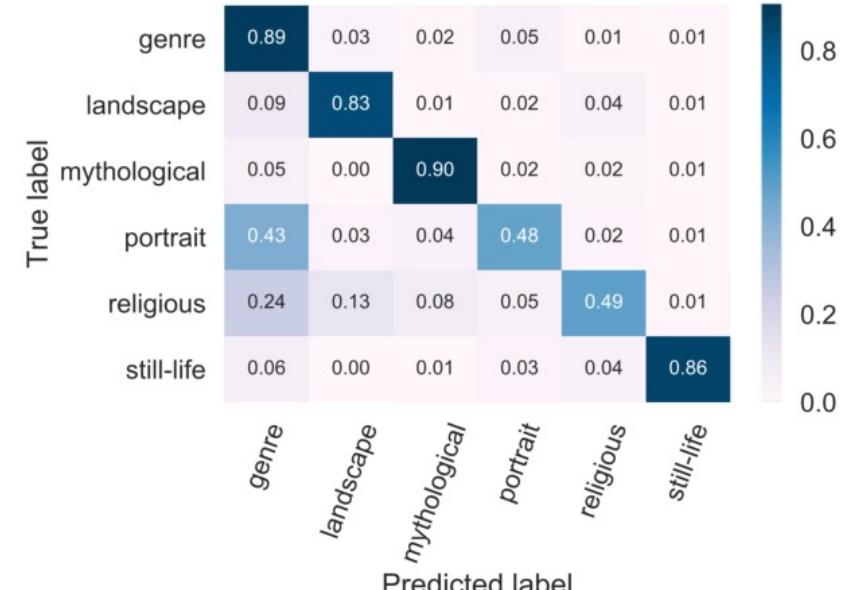
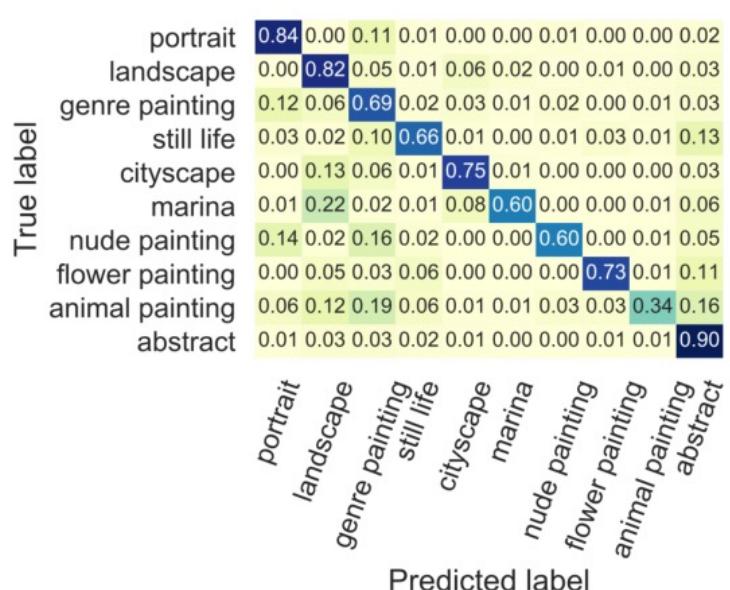


Figure 12. Confusion matrix for WikiArt (left) and WGA (right) **genre** classification

The applicability of Convolutional Neural Networks (CNN) for art historical image classification tasks

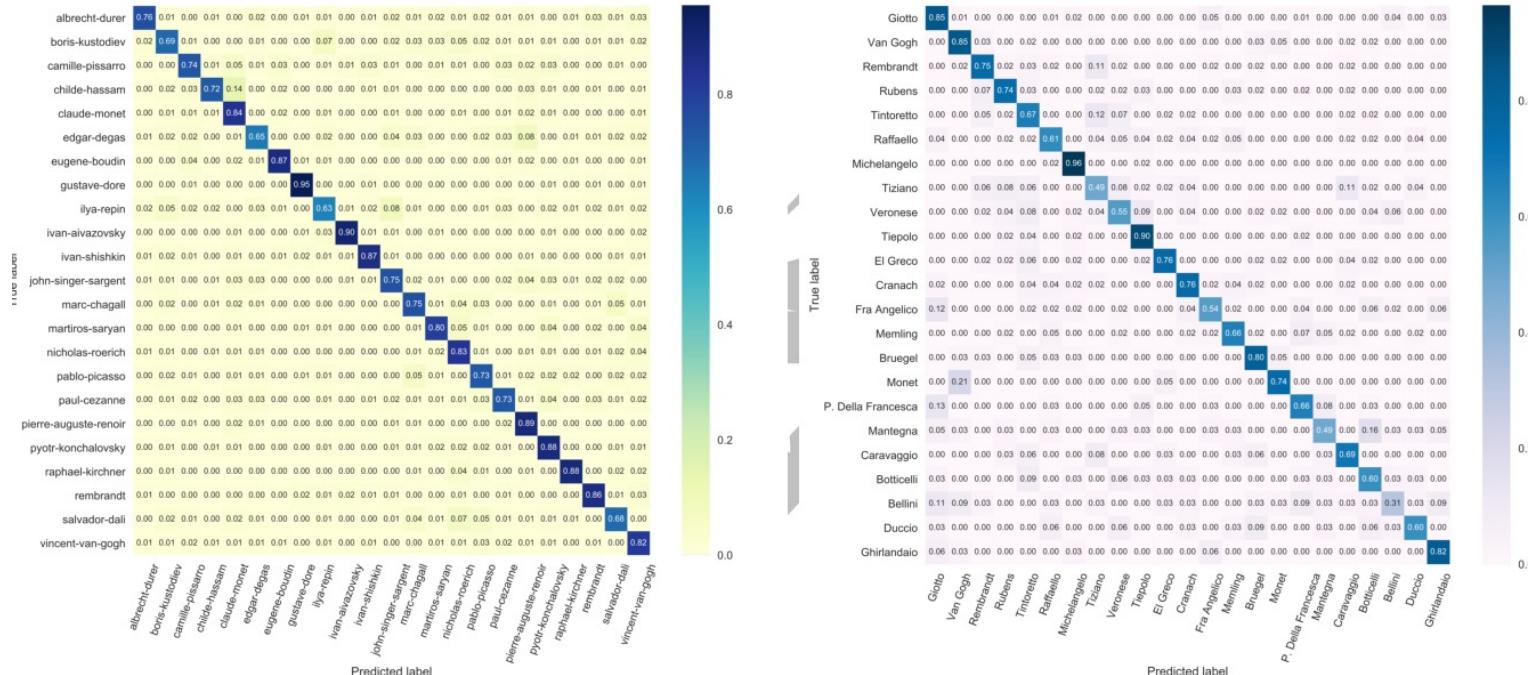


Figure 13. Confusion matrix for WikiArt (left) and WGA (right) artist classification

The applicability of Convolutional Neural Networks (CNN) for art historical image classification tasks

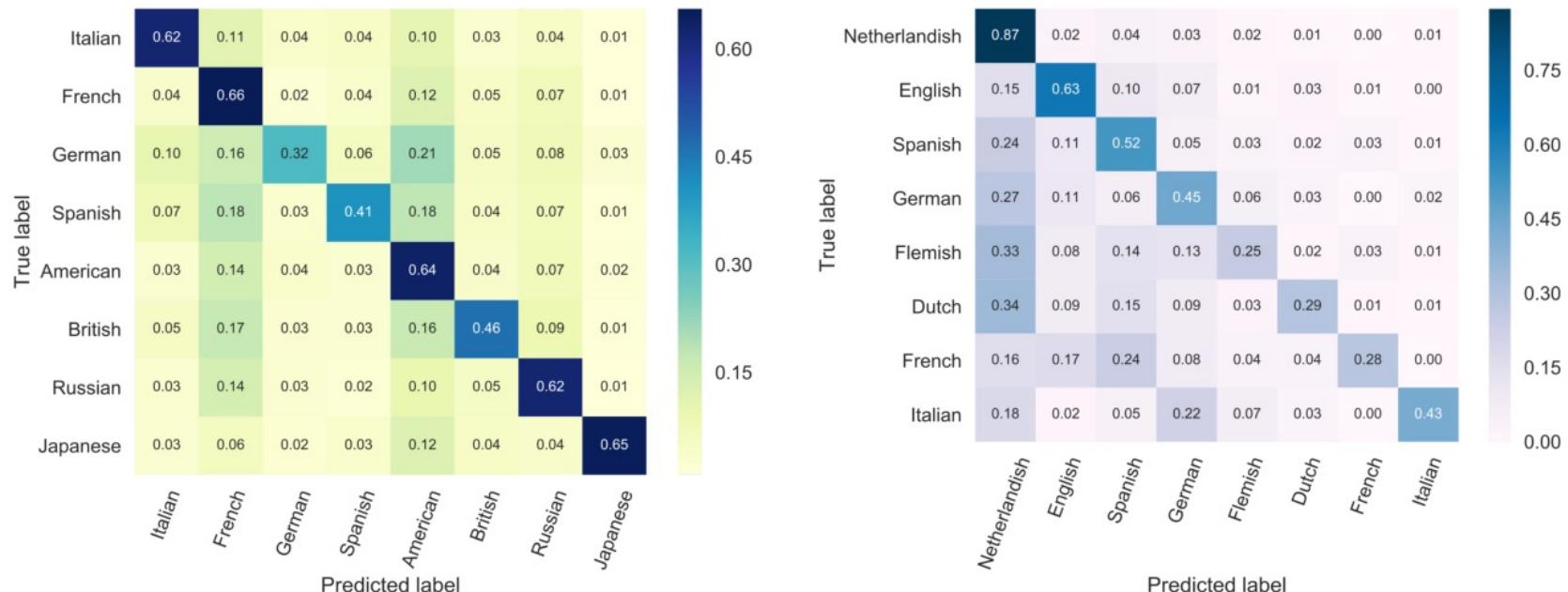
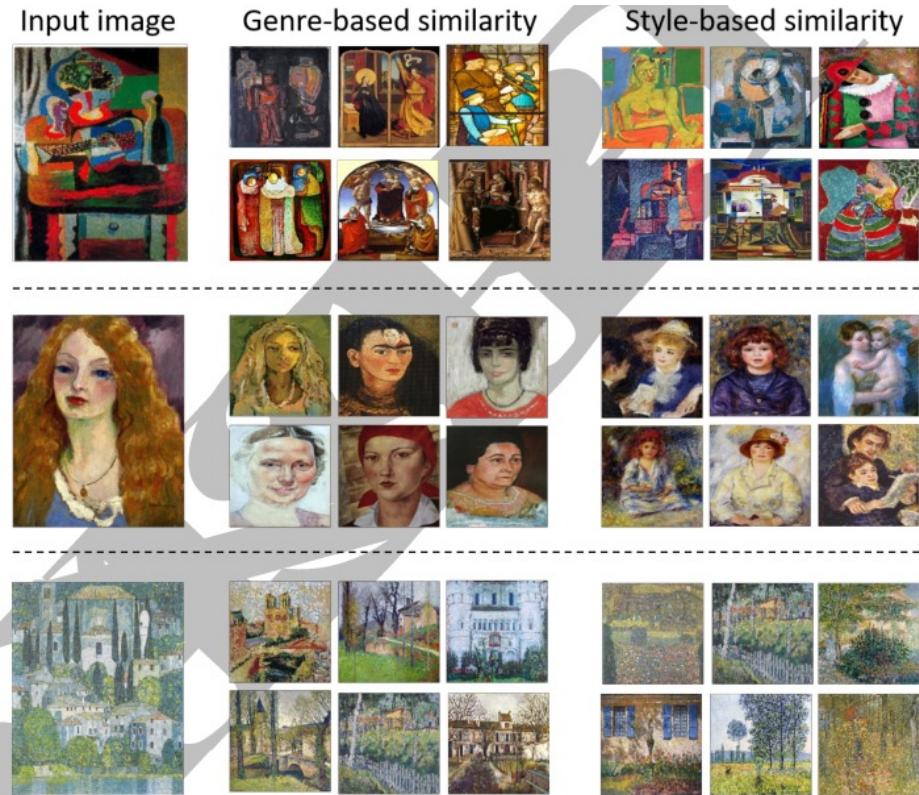


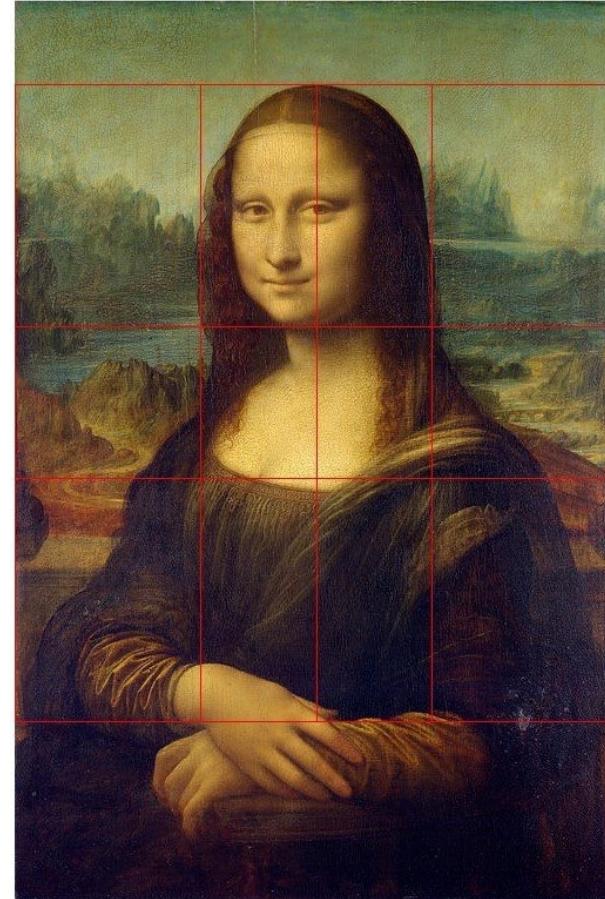
Figure 14. Confusion matrix for WikiArt (left) and WGA (right) **nationality** classification

- Evaluation of CNNs pre-trained for various tasks, ranging from object and scene recognition to mood labelling.
- Analysis of various aspects of image similarity. Fine-tuning models can be used to retrieve images with similar styles or content.



HOW IS THE PICTURE STRUCTURED?

- Compositional Analysis
- Pattern matching, colour measurement, Fourier series, saliency maps



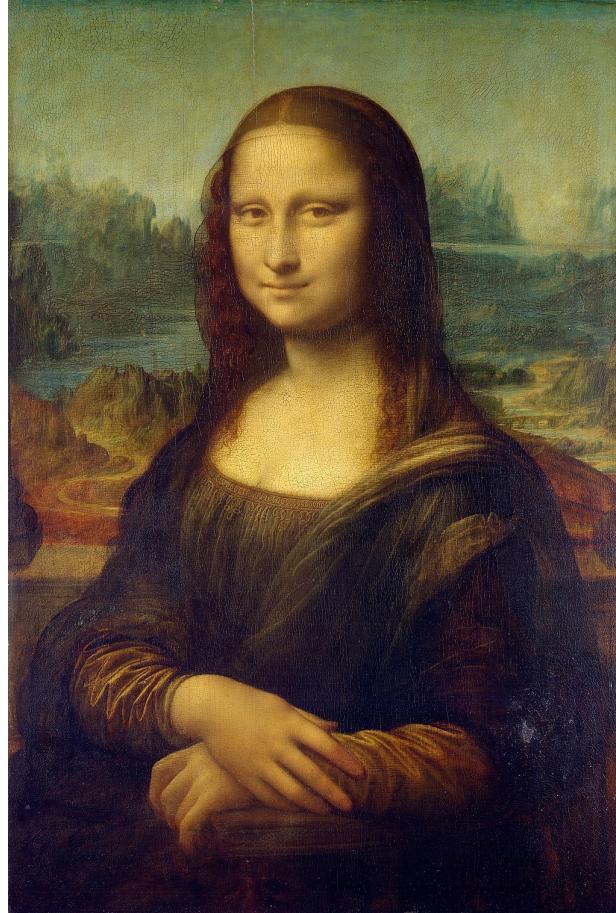
Gillian Rose, *Visual Methodologies. An Introduction to Researching with Visual Materials*, 4th ed. (London: SAGE, 2016), 56–84.



COMPOSITION

is composed of the following elements:

- Shape and line
- Colour
- Texture
- Space
- Arrangement and visual axes





SHAPE AND LINE

geometrically or
organically designed
areas defined by
outlines (edges)
within a work.



Rubens, Weibl. Porträt (ca. 1635-1640), Rotterdam:
https://commons.wikimedia.org/wiki/File:Peter_Paul_Rubens_165.jpg

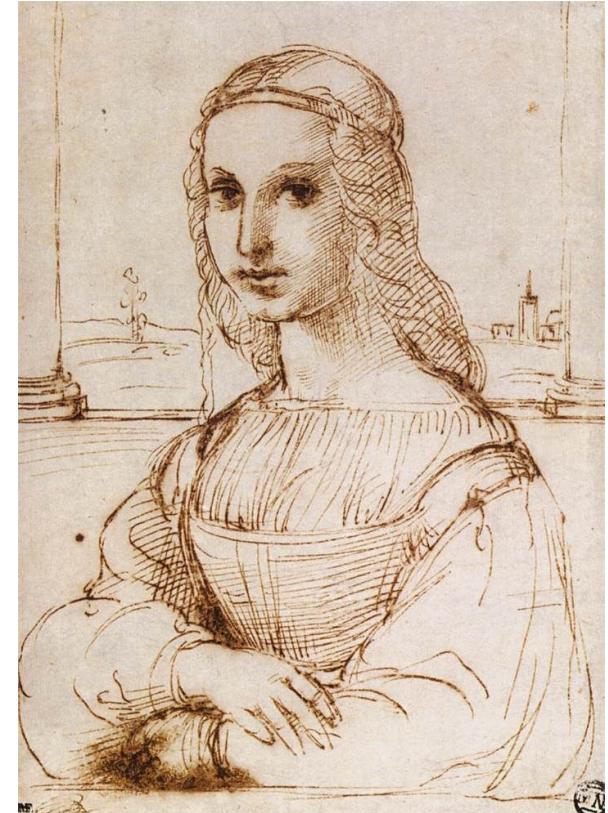
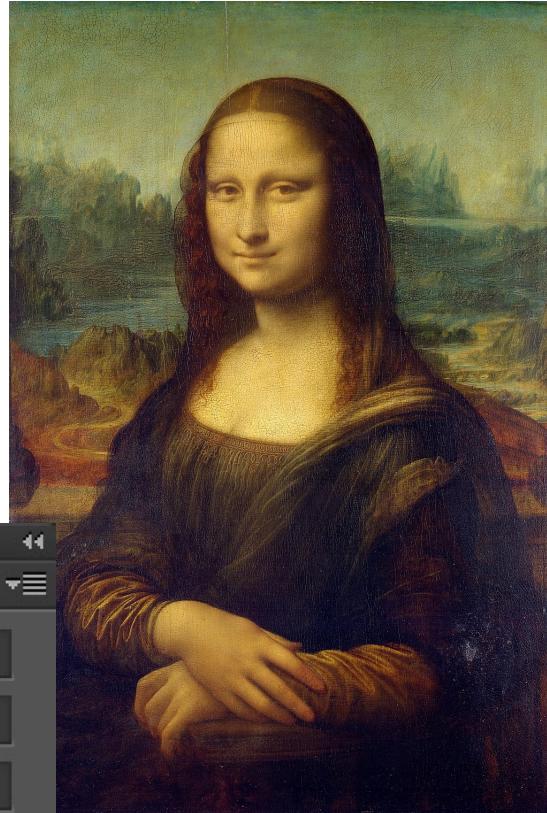


Fig. 3. (a) Johann Anton Ramboux reproduction of (c) Pietro Perugino, *Assumption of the Virgin with four Saints*, 1500 (b) Noise-free contours of the Ramboux reproduction (a) using LoG filters (d) Binary Pb edge-signal of the Perugino (e) Relevant contours of the painting that match to contours of the reproduction. Hence, noisy edges of (d) are suppressed

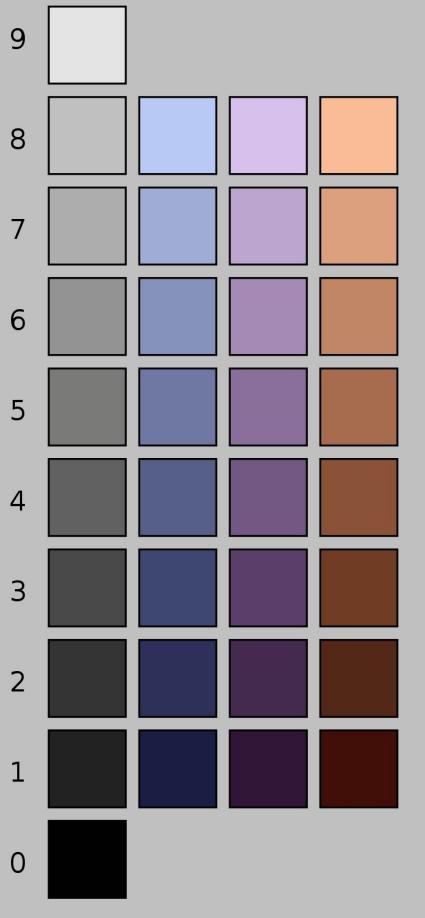


COLOUR

- Hue
- Colour brightness
- Saturation



Zeichnung Raphaels (ca. 1505-07), Louvre 3882:
<https://www.louvre.fr/en/oeuvre-notices/head-and-shoulders-woman-three-quarters-profile-facing-left-folded-arms>



COLOUR BRIGHTNESS

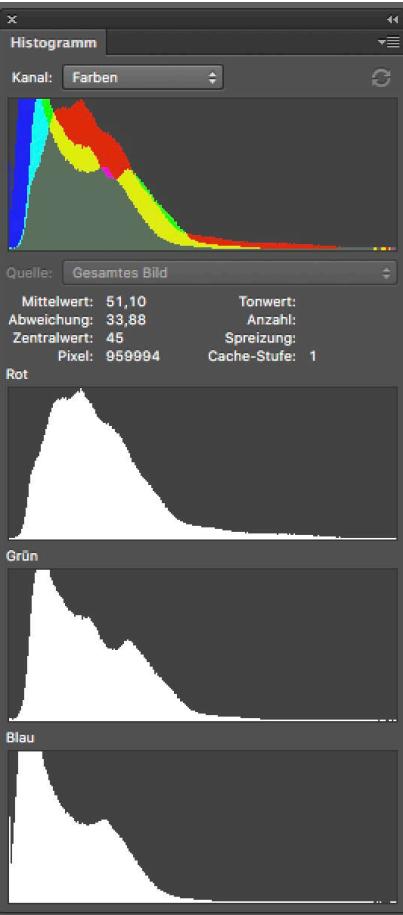
describes how strongly light is reflected by objects of the respective colour. The more light is reflected, the higher the value.

Three shades in the Munsell colour model
<https://en.wikipedia.org/wiki/Lightness>



Claude Monet, Impression, soleil levant, 1872





HISTOGRAM

For each pixel graphic, the colour and brightness distribution can be displayed in a histogram. Visualised as a coordinate system, the X-axis indicates the brightness (the origin of the axis here means maximum darkness). The Y-axis indicates the number of pixels in the image. The coordinate system thus shows how many pixels have which colour value or which brightness.



SATURATION



- describes the quality of the colour shade. A colour has a high saturation when it tends towards the pure colours



COLOURFULLNESS

as a linear combination of colour variance and chroma value (ratio to the brightness and saturation of a similarly illuminated area).

D. Hasler and S.E. Suesstrunk, Measuring colorfulness in natural images, in Proceedings volume 5007, human vision and electronic imaging VIII (Santa Clara: SPIE, 2003), 87–95; P. Obrador and N. Moroney, Low level features for image appeal measurement, in Image Quality and System Performance 6, Proceedings volume 7242 (San Jose: SPIE, 2009), 72420T-1-12.

[https://www.lumas.de/pictures/isabelle_menin/
etude pour un apres midi 06](https://www.lumas.de/pictures/isabelle_menin/etude_pour_un_apres_midi_06)

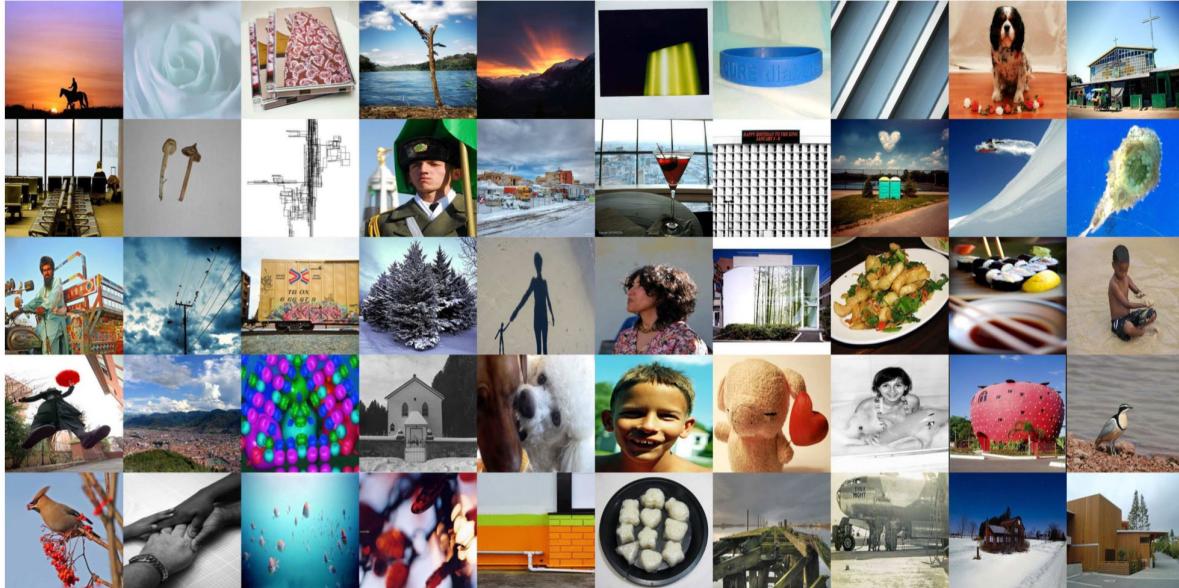


COLOUR HARMONY

<http://www.sessions.edu/color-calculator/>

The interface features a large color wheel on the left with a vertical color bar to its left. A blue square color swatch is selected. Below it is a checked checkbox labeled "Lock". At the bottom left is a dropdown menu set to "RYB Mode".
1. PICK A COLOR: A text input field contains the hex code "#58cdff" with a small blue square swatch next to it. To the right is a "+ Add More" button.
2. CHOOSE A HARMONY: Six harmony types are shown in circles: complementary (two colors opposite each other), monochromatic (variations of one color), analogous (three colors adjacent on the wheel), split complementary (three colors: one central and two on opposite sides of its complement), triadic (three colors forming an equilateral triangle), and tetradic (four colors in a rectangle).
3. SEE RESULTS: Two color swatches are shown with their hex codes: "#7158ff" (blue) and "#58ff8a" (green). Below them is a horizontal bar divided into three colored segments: blue, purple, and green. To the right is a "Get Color Scheme" button.

P. Lu, X.J. Peng, R.F. Li and X.J. Wang, Towards aesthetics of image: A Bayesian framework for color harmony modeling, Signal Processing Image Commun. 39 (2015), 487–498.



■ ■ ■



S. Dhar, V. Ordonez and T.L. Berg, High level describable attributes for predicting aesthetics and interestingness, in: Computer Vision and Pattern Recognition 2011 (Colorado Springs: IEEE, 2011), 1657–1664:

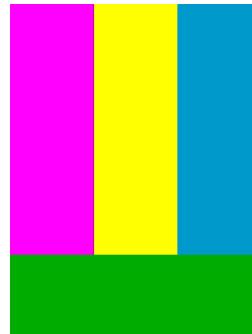
http://www.cs.virginia.edu/~vicente/files/aesthetics_cvpr11.pdf

Y. Ke, X.O. Tang and F. Jing, The design of high-level features for photo quality assessment, in Proceedings of 2006 IEEE computer society conference on computer vision and pattern recognition (New York: IEEE, 2006), 419–426.



COLOUR CONTRASTS

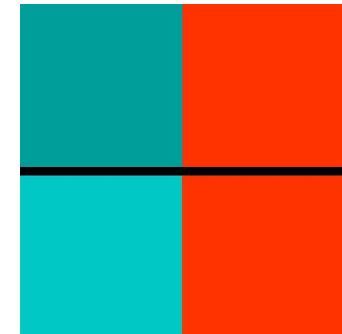
Johannes Itten, *The Art of Color: The Subjective Experience and Objective Rationale of Color.*
(New York: 1961)
[http://de.wikipedia.org/
wiki/Sieben_Farbkontraste](http://de.wikipedia.org/wiki/Sieben_Farbkontraste)



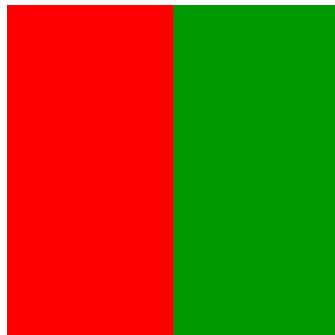
Colour-on-contrast



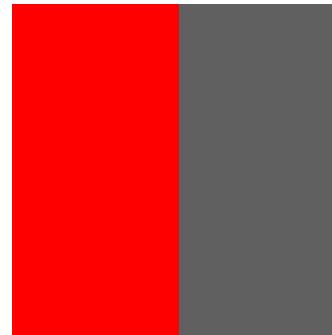
Light-dark contrast



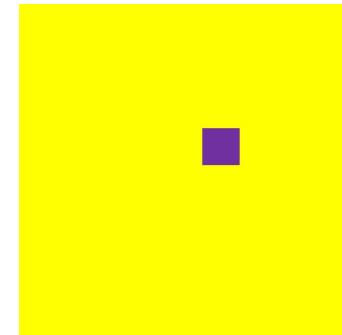
Cold-warm contrast



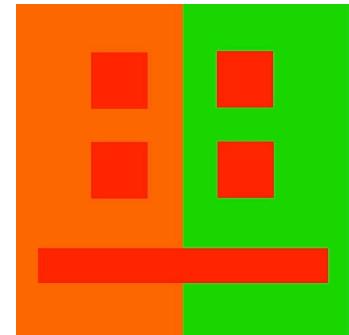
Complementary contrast



Quality contrast



Quantity contrast



Simultaneous contrast



COLOUR CONTRASTS

http://de.wikipedia.org/wiki/Sieben_Farbkontraste



Colour-on-contrast



Light-dark-contrast



Cold-warm-contrast



Complementary contrast



Quality contrast



Quantity contrast



COLOUR CONTRASTS

http://de.wikipedia.org/wiki/Sieben_Farbkontraste



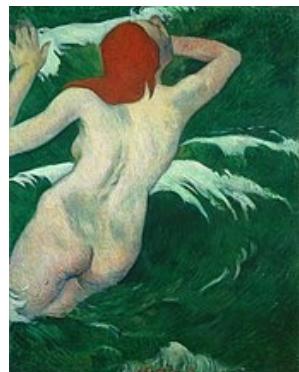
Colour-on-contrast



Light-dark-contrast



Cold-warm-contrast



Complementary contrast



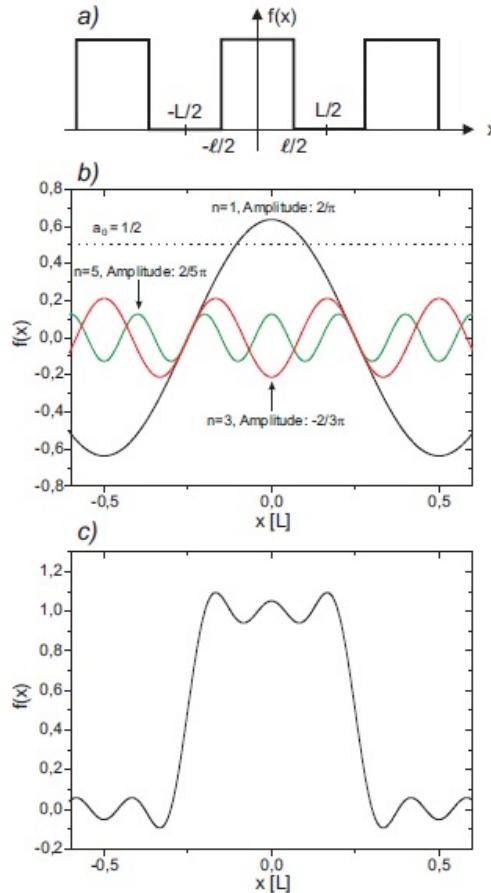
Quality contrast



Quantity contrast



Simultaneous contrast



CONTRAST DISTRIBUTION

Calculation of sharpness based on colour, luminance, focus or edge sharpness

Y. Ke, X.O. Tang and F. Jing, The design of high-level features for photo quality assessment, in Proceedings of 2006 IEEE computer society conference on computer vision and pattern recognition (New York: IEEE, 2006), 419–426.

<https://de.wikipedia.org/wiki/Fourierreihe>



Rectangular functions

(a)



Frequency: low Amplitude: high



Frequency: high Amplitude: high

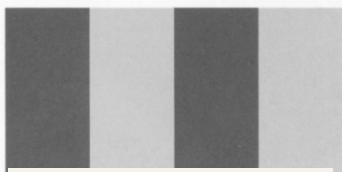


Frequency: high Amplitude: high

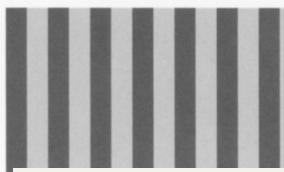


Frequency: high Amplitude: low

(b)



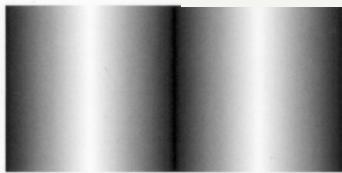
Frequency: low Amplitude: low



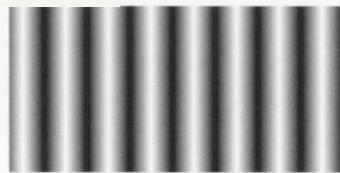
Frequency: high Amplitude: low

Sinusoidal functions

(a)

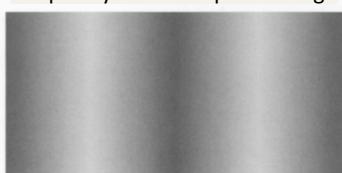


Frequency: low Amplitude: high

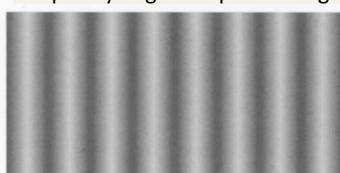


Frequency: high Amplitude: high

(b)



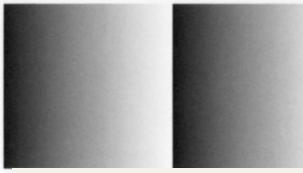
Frequency: low Amplitude: low



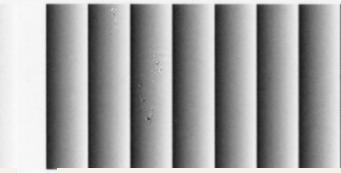
Frequency: high Amplitude: low

Sawtooth functions

(a)

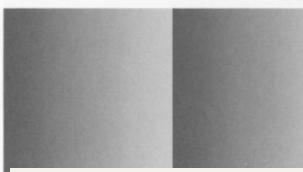


Frequency: low Amplitude: high

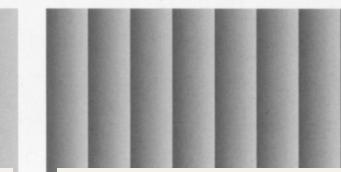


Frequency: high Amplitude: high

(b)



Frequency: low Amplitude: low



Frequency: high Amplitude: low

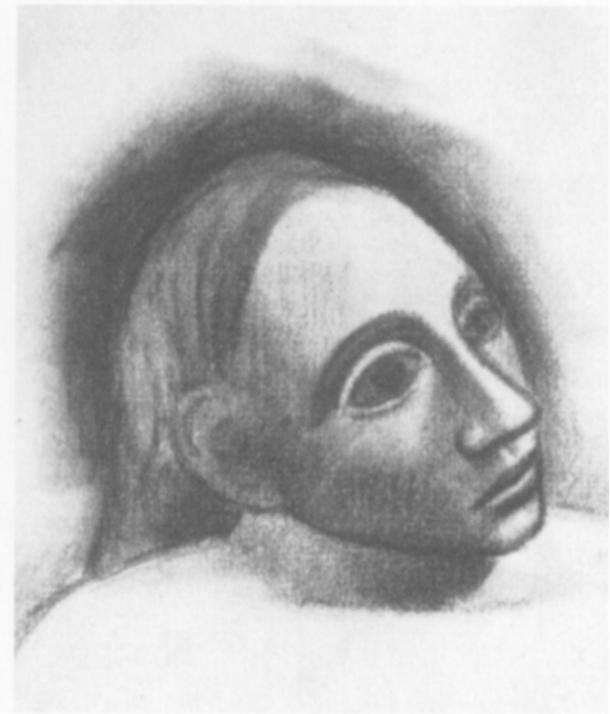
The contrast of a fringe pattern is equal to its amplitude divided by the mean value of the intensity.



Contour drawing with an abrupt change between light and dark
(rectangular function)



continuous transitions
(sinusoidal function)

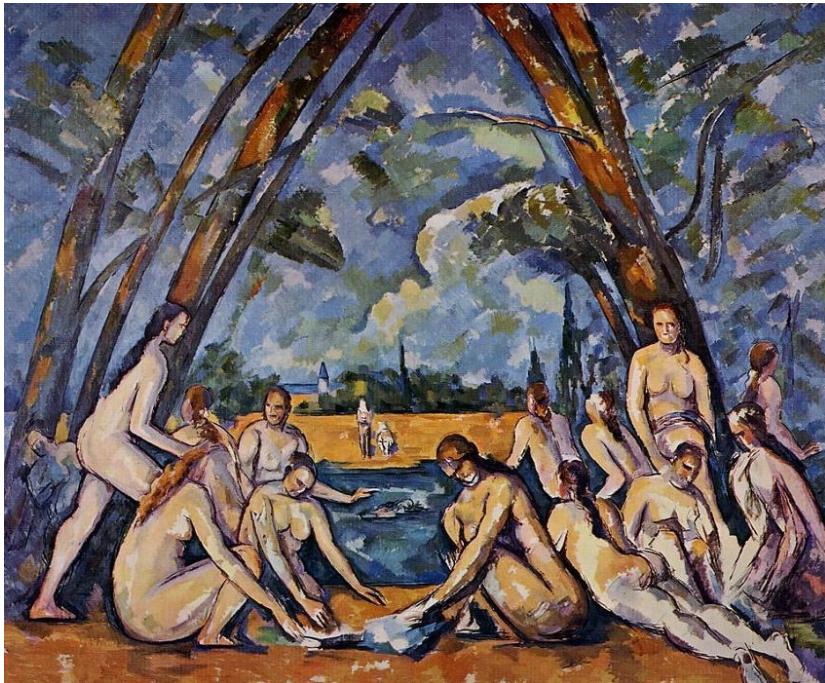


Combination of discrete and continuous transitions
(sawtooth function)



TEXTURE

physical surface qualities that can be realised as optical illusions.



<https://www.instagram.com/p/B0EW6VLi4DH/>



SPACE

three-dimensional extension around, over and within an object

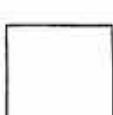
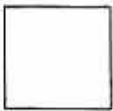
What the situation
is from the side



Image seen from
the front

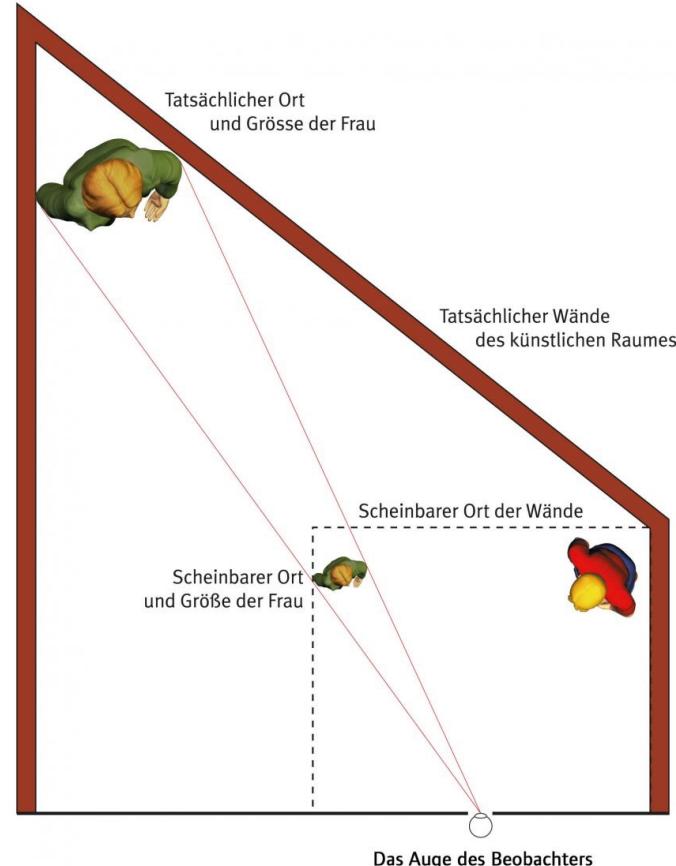


Shape of the
perceived surface





Günther Kebeck, *Bild und Betrachter. Auf der Suche nach Eindeutigkeit* (Regensburg: Schell&Steiner, 2007)





Rembrandt van Rijn, Christus in Emmaus, 1648. The local change of a light source changes the entire picture light.



(a) Original



(b) zwei Lichtquellen

Caravaggio, The Calling of St Matthew, 1599-1600



COMPOSITION: ARRANGEMENT AND VISUAL AXES



<https://www.instagram.com/p/B0EW6VLi4DH/>

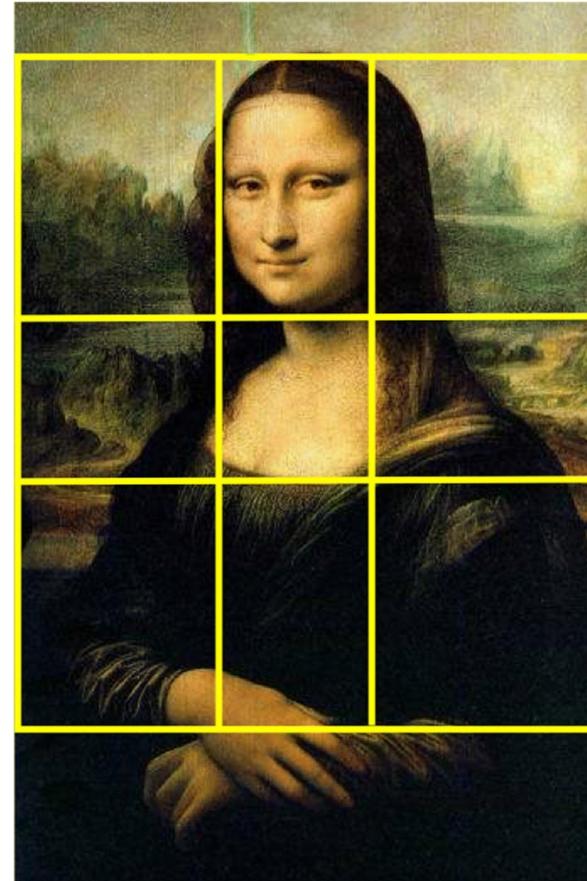


Paul Cezanne, The great bathers 1898-1905



THE GOLDEN RATIO

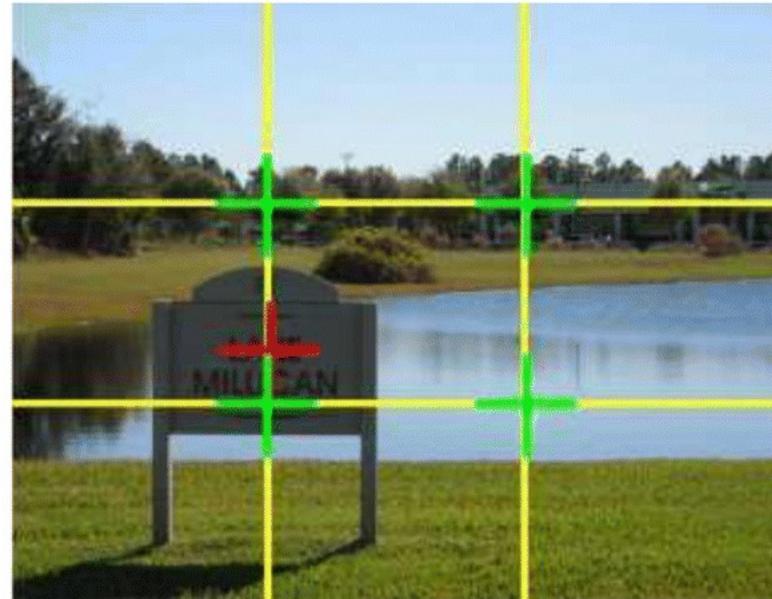
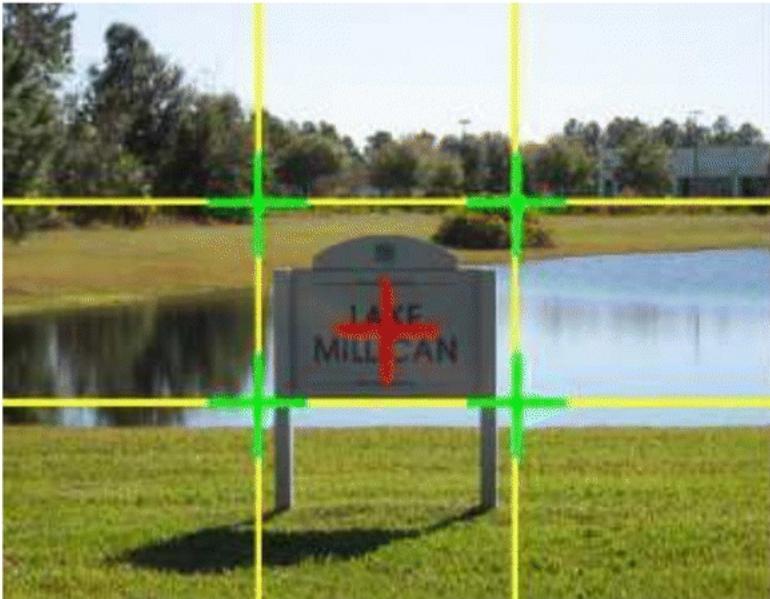
$$\begin{aligned}(a + b) / a \\= a / b \\= (1 + \sqrt{5}) / 2 \\ \approx 1,618\end{aligned}$$



Y.M. Zhou, Y.L. Tan and G.Y. Li, Computational aesthetic measurement of photographs based on multi-features with saliency, in D.S. Huang, V. Bevilacqua and P. Premaratne (eds.), Intelligent computing theory (Cham: Springer, 2014) 357–366.



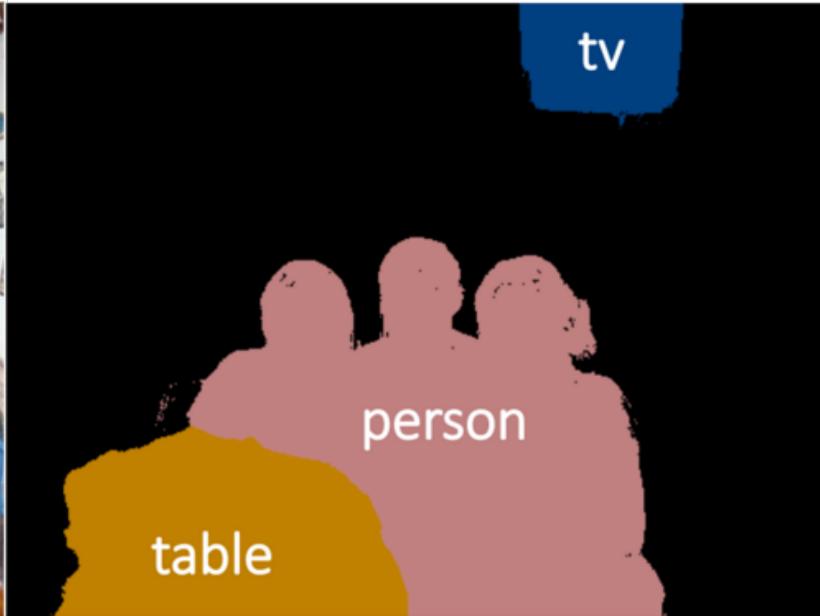
RULE OF THIRDS



Y.M. Zhou, Y.L. Tan and G.Y. Li, Computational aesthetic measurement of photographs based on multi-features with saliency, in D.S. Huang, V. Bevilacqua and P. Premaratne (eds.), Intelligent computing theory (Cham: Springer, 2014) 357–366.



SEGMENTATION OF THE PICTURE INTO REGIONS



<https://medium.com/nanonests/how-to-do-image-segmentation-using-deep-learning-c673cc5862ef>

P. Obrador et al., Towards category-based aesthetic models of photographs, in K. Schoeffmann et al. (eds.), Advances in multimedia modeling (Berlin/Heidelberg: Springer, 2012) 63–76; Yubin Deng et al., Image Aesthetic Assessment: An Experimental Survey (2017): <https://arxiv.org/pdf/1610.00838.pdf>



IMAGE QUALITY ASSESSMENT

- Motif
- Facial expression
- Lighting
- Polls

< Suchfilter

Alle Bilder (9.402) Rauschen (0)

Lizenzyierung
 RS Rights Simplified⁴
 RF Royalty Free¹

Format
 Alle Bilder
 Hochformat
 Querformat
 Quadratisch

Layout

Vorschau
 An / Aus

Ergebnisse pro Seite
30 / 60 / 120

Farbsuche

Konzepte ▾
Zusammen (2.199)
Kindheit (1.502)
Zweisamkeit (1.368)
Verbundenheit (1.352)
Glücklich (1.333)
Alle anzeigen ...

Anzahl Personen ▾
Niemand (2.692)
Einperson (3.708)
Zwei Menschen (1.639)
Drei Menschen (347)
Gruppe (568)
Alle

Abras Lightbox ▾

S. Dhar, V. Ordonez and T.L. Berg, High level describable attributes for predicting aesthetics and interestingness, in: Computer Vision and Pattern Recognition 2011 (Colorado Springs: IEEE, 2011), 1657–1664.
P. Obrador et al., Towards category-based aesthetic models of photographs, in K. Schoeffmann et al. (eds.), Advances in multimedia modeling (Berlin/Heidelberg: Springer, 2012) 63–76.

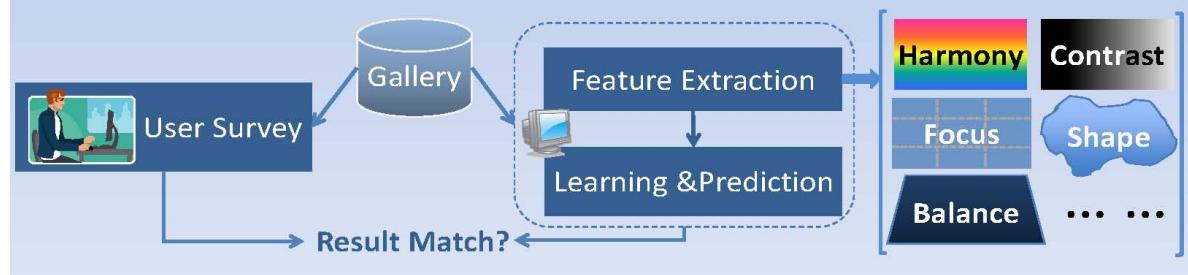


IMAGE QUALITY ASSESSMENT

C. Li and T. Chen, Aesthetic visual quality assessment of paintings, in IEEE J Sel Top Signal Process 3 (2009) 236–252:
<http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.644.6118&rep=rep1&type=pdf>.
<http://chenlab.ece.cornell.edu/people/longcong/research/research.html>

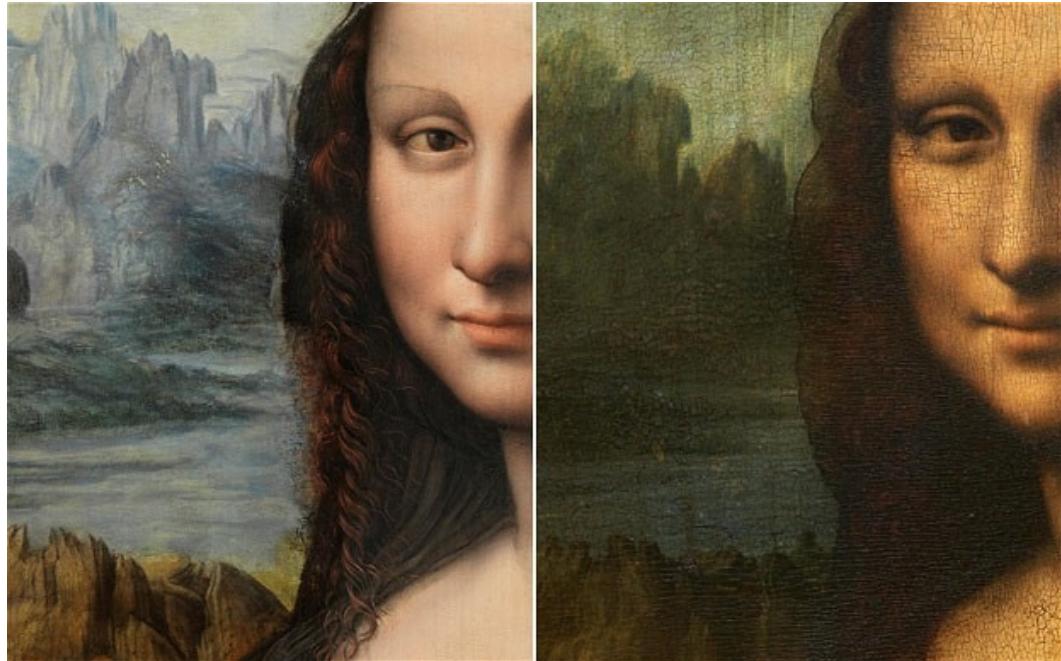


Automatic Aesthetic Visual Quality Assessment of Paintings



WHO PAINTED THE PICTURE? WHEN AND WHERE WAS IT PAINTED?

- ▶ Artist attribution, dating, regional style
- ▶ Stilometry



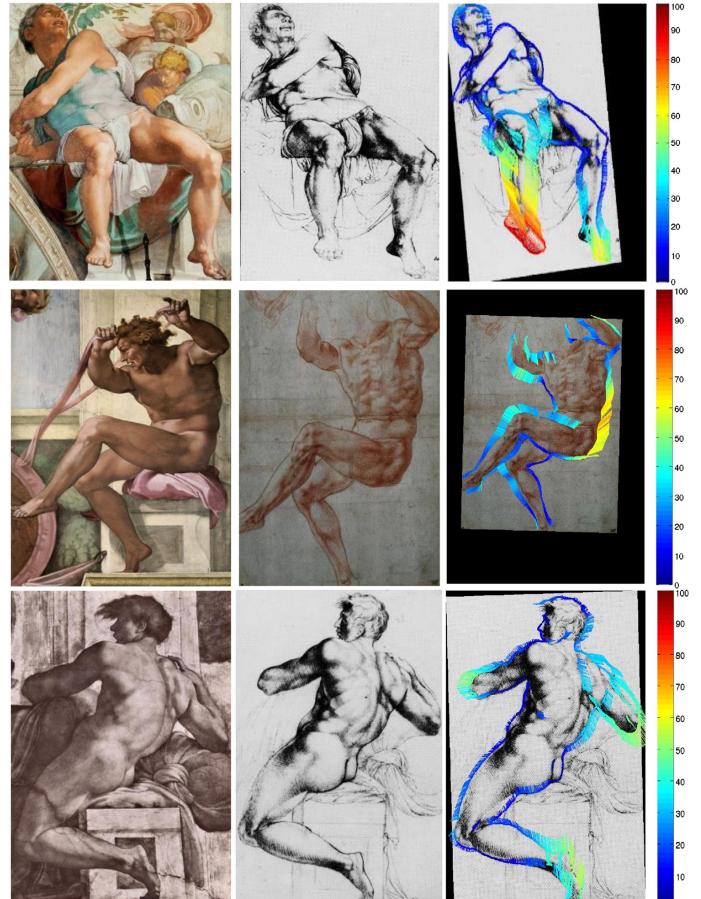
Early copy in the Prado

Hermann Bauer, „Form, Struktur, Stil: Die formanalytischen und formgeschichtlichen Methoden,” in Hans Belting u.a., *Kunstgeschichte. Eine Einführung* (Berlin: Reimer 2008), 157–174.

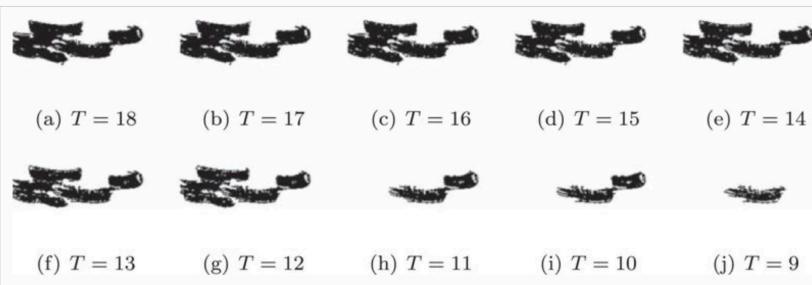
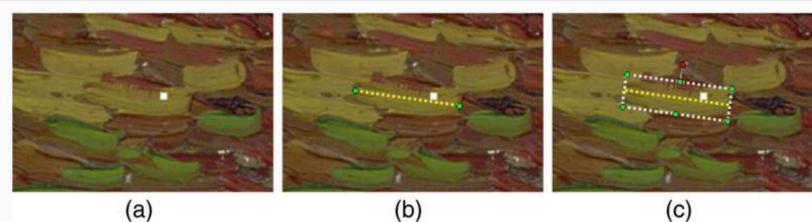
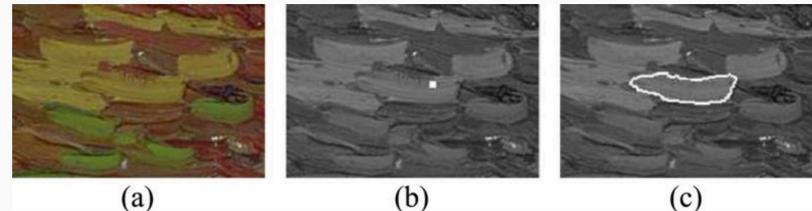
Reconciliation of the differences through precise measurement of the deviations

z.B. Comparison of Michelangelo's frescoes in the Sistine Chapel with copies of his preparatory drawings

Antonio Monroy Monroy / Peter Bell / Björn Ommer,
Morphological analysis for investigating artistic images,
Image and Vision Computing 32(6), 2014, 414–423:
https://hci.iwr.uni-heidelberg.de/sites/default/files/publications/files/1015831446/monroy_ommer.ivc14.pdf



Comparison of technical features (brush strokes, hatching), textures and colours (low level vision)



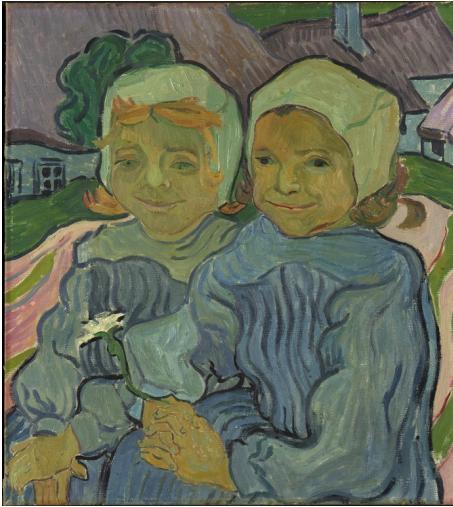
Richard N. Johnson et al., "Image Processing for Artist Identification - Computerized Analysis of Vincent van Gogh's Painting Brushstrokes," July, 2008.

Fabrizio Lamberti, Andrea Sanna and Gianluca Paravati, „Computer-assisted analysis of painting brushstrokes: digital image processing for unsupervised extraction of visible features from van Gogh's works," *EURASIP Journal on Image and Video Processing*, December 2014 (2014), 53 (<https://doi.org/10.1186/1687-5281-2014-53>)

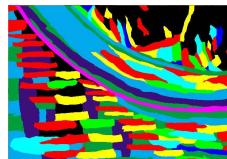
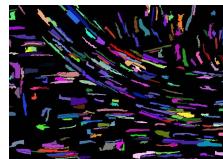
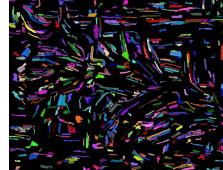
Unüberwachte und annotierte Erkennung der Pinselstriche und Clustering



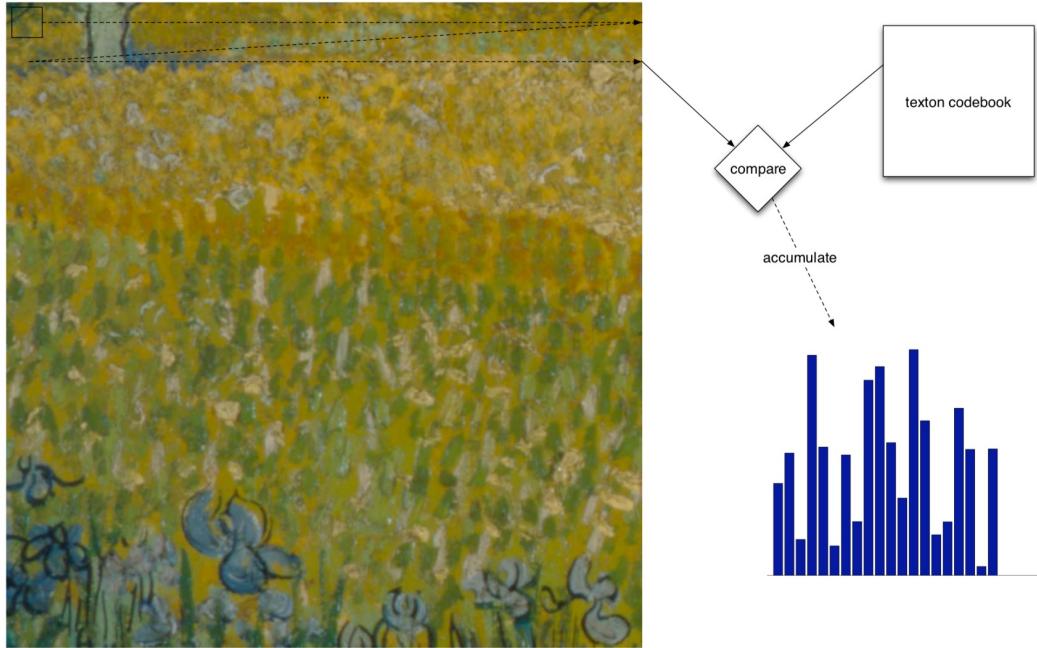
Van Gogh



Cuno Amiet

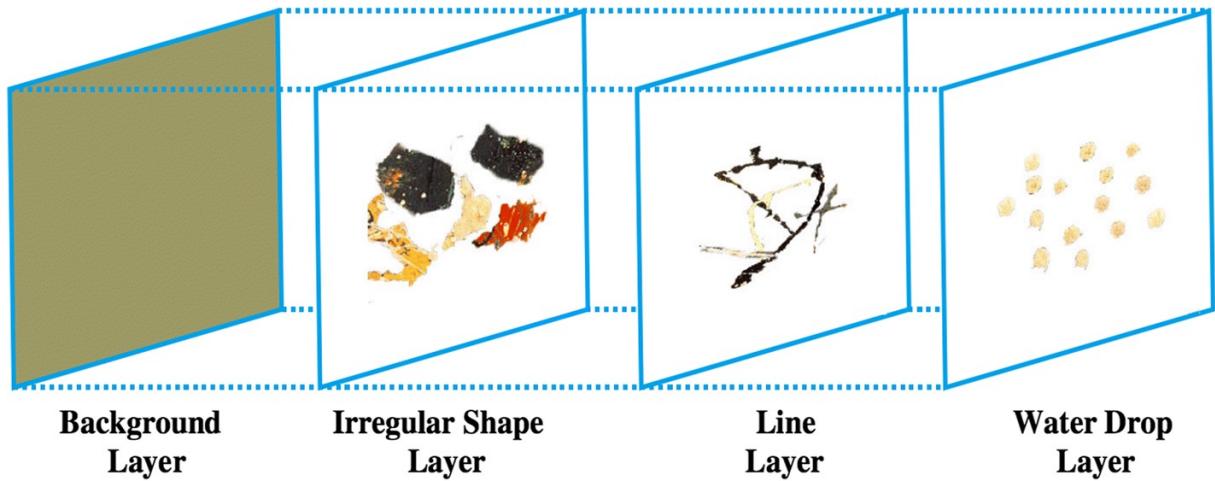


Jia Li et al., Rhythmic Brushstrokes Distinguish van Gogh from His Contemporaries: Findings via Automated Brushstroke Extraction, IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE 2012, 1–17
(<http://infolab.stanford.edu/~wangz/project/imsearch/ART/PAMI11/li.pdf>)

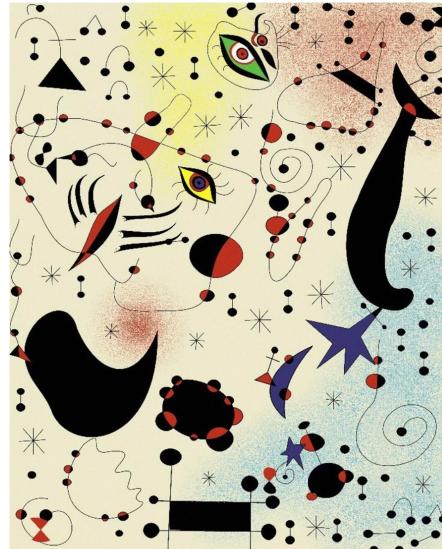
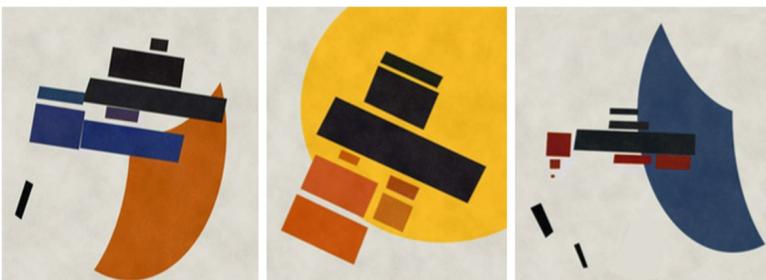
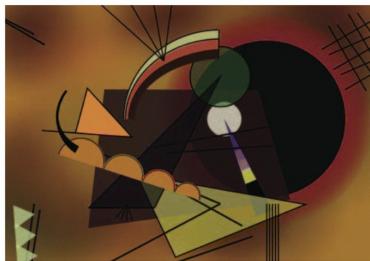
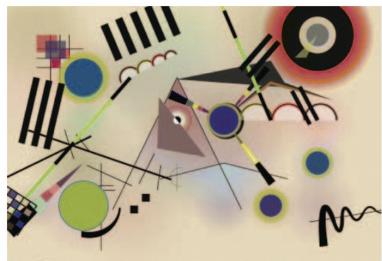


L. van der Maaten, Eric Postma:
Identifying the Real Van Gogh with
Brushstroke Textons, 2009:
<https://lyrawww.uvt.nl/~cenv/ticc/reports/TRvdrMaaten.pdf>

Figure 2: Illustration of the construction of a texton histogram. A window is slid over the texture image, and the histogram bin associated with the most similar codebook texton is incremented at each spatial location. After normalization, the texton histogram represents the relative number of times that a codebook texton appears in the painting.



Y. Zheng et al., Layered modeling and generation of Pollock's drip style,
The Visual Computer 31 (2015), 589–600.



K. Zhang and J.H. Yu,
Generation of Kandinsky art,
Leonardo 49 (2016), 48–55;
L. Xiong and K. Zhang,
Generation of Miro's
surrealism, in Proceedings
of the 9th international
symposium on visual
information communication
and interaction (Dallas:
ACM, 2016), 130–137.

Computer-generated
works in the style of
Kandinsky, Malevich and
Miro.

WHAT DID THE PAINTING ORIGINALLY LOOK LIKE?

- Rekonstruction and Restaurartion
- Optical and chemical processes, digital tone value correction



Günther A. Wagner, Einführung in die Archäometrie, Heidelberg: Springer 2007; Horst Czichos / Oliver Hahn, Was ist falsch am falschen Rembrandt?: Mit High-Tech den Rätseln der Kunstgeschichte auf der Spur, München: Hanser 2011.

<https://blog.world-mysteries.com/science/digital-restoration-of-leonardo-da-vincis-mona-lisa/>



MULTISPECTRAL ANALYSIS



13 photographs

accurately split the light spectrum from ultraviolet to infrared at the limit of the optical laws into 240.000.000 pixels. Generating 22 gigabyte of datas.



ultraviolet
(invisible)

Field of the human vision



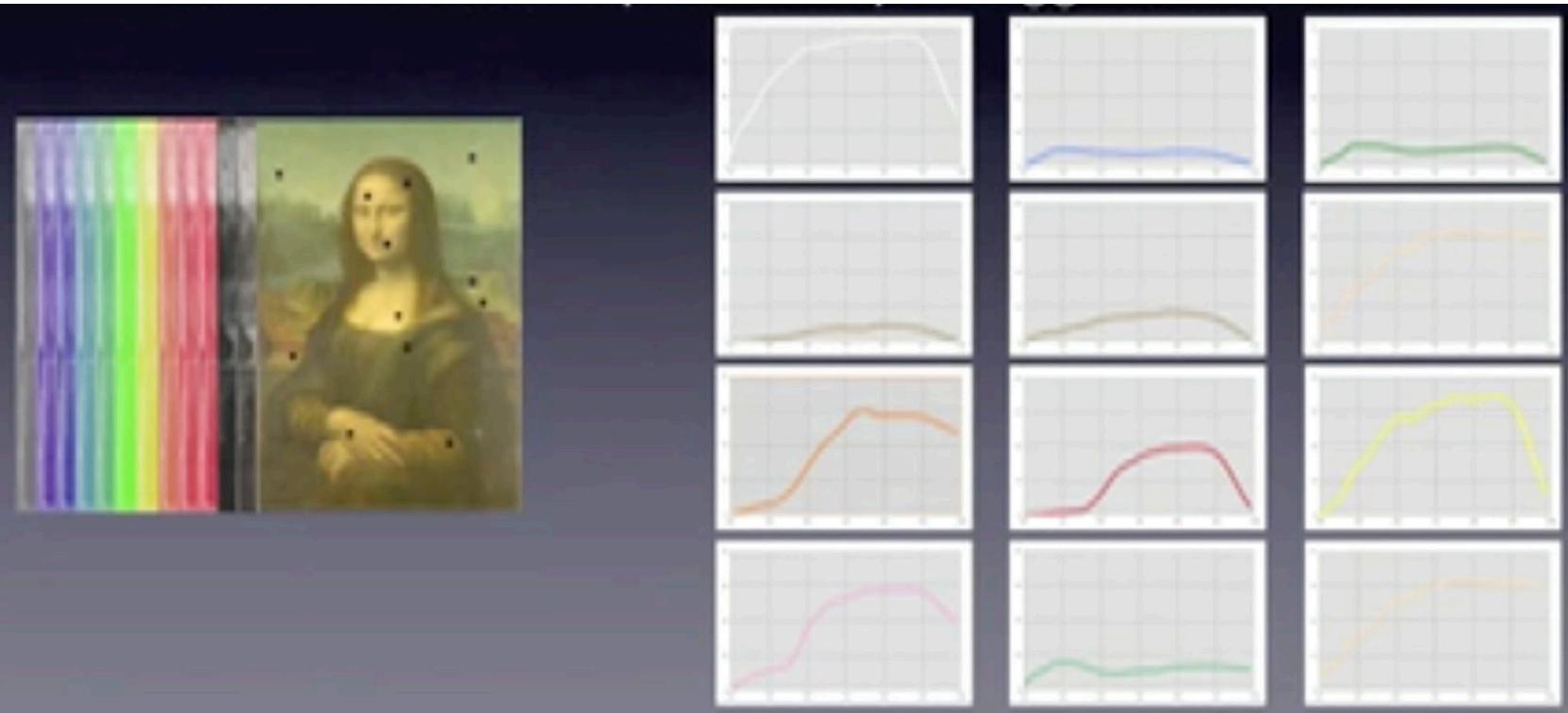
Infrared
(invisible)



Digital multispectral analysis of the Mona Lisa by Lumière Technology:
<https://www.dailymotion.com/video/k3GIpau9WkVvazepCB>



MULTISPECTRAL ANALYSIS





MULTISPECTRAL ANALYSIS

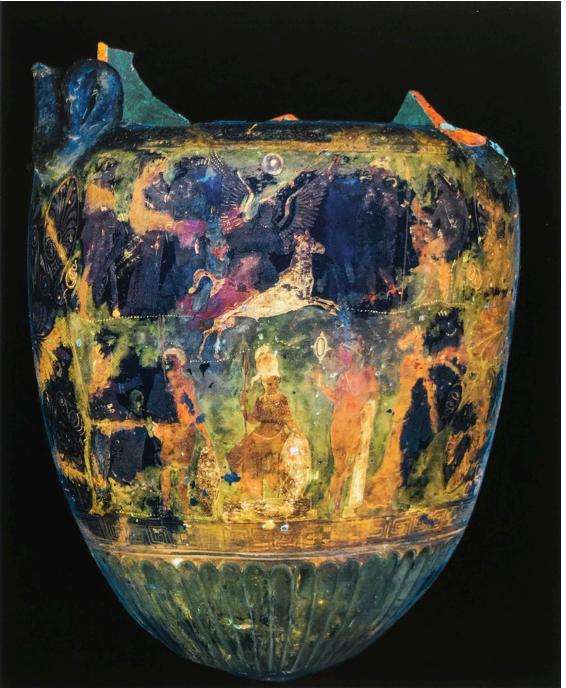
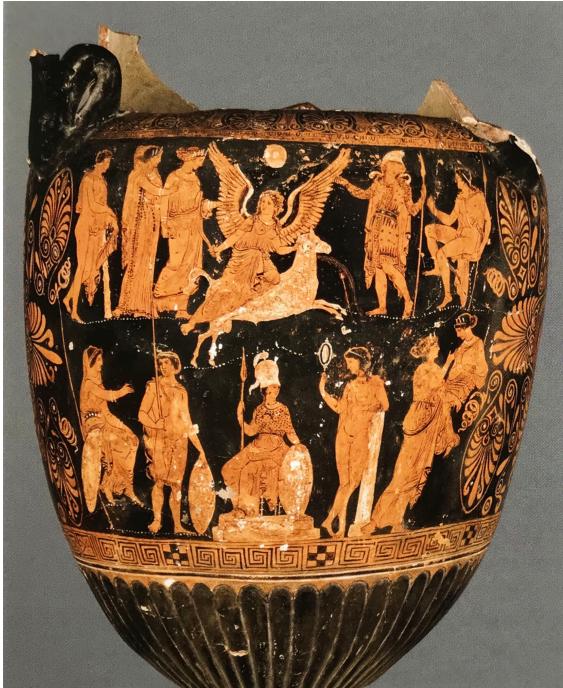
The image illustrates the digital multispectral analysis of the Mona Lisa painting. It features a small thumbnail of the painting in the top left, the full painting in the center, and a color checker card at the bottom. To the right is a grid of color patches used for color calibration and matching. Above the checker card is a spectral library with entries like 'Lapis Lazuli', 'Cendre Meuse', 'Malachite', 'Aurrite', and 'Cendre verte', each accompanied by a corresponding spectral curve.

Digital multispectral analysis of the Mona Lisa by Lumiere Technology:
<https://www.dailymotion.com/video/k3GIpau9WkVvazepCB>



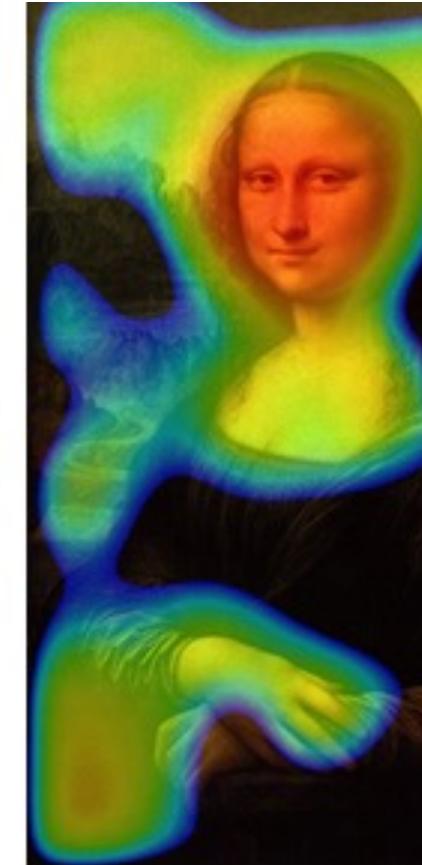
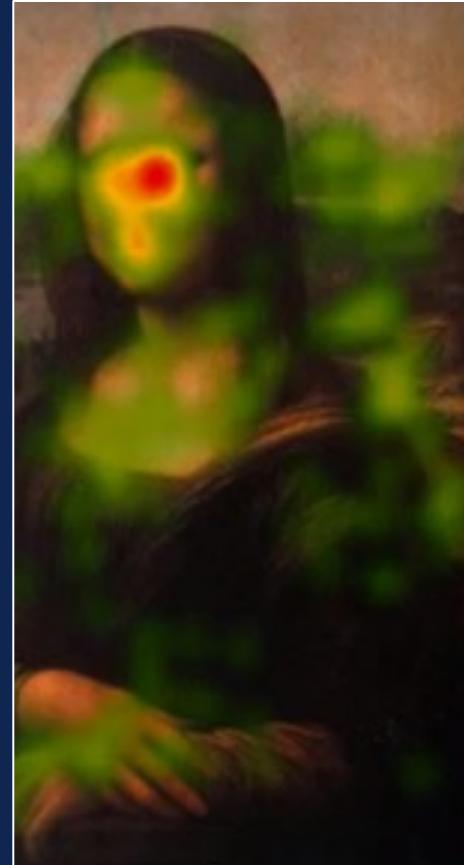
UV-LIGHT

Apul. rf. Volute-krater by the Ilioupersis-P.,
Berlin F 3256 (2008 before Restauration)



Ursula Kastner, David Saunders, Dangerous Perfection: Ancient Funerary Vases from Southern Italy (Malibu 2016) 79

IMAGE EFFECT AND RECEPTION



WHAT DO REPRESENTATION AND DETAILS MEAN AGAINST THE SOCIO-CULTURAL BACKGROUND OF THE TIME?

- Iconological and semiological Analysis
- Statistics and digital source analysis

Hans Belting, Das Werk im Kontext, in: Hans Belting u.a., Kunstgeschichte. Eine Einführung, Berlin: Reimer 2008, 229–246; Gillian Rose, Visual Methodologies, London: SAGE 2016, 106–146



QUANTITATIVE IMAGE TYPE ANALYSIS

- Development of image types through reduction to the central topic
- enables conclusions to be drawn about photojournalistic production and selection patterns as well as about the socio-cultural ideas conveyed with and in images

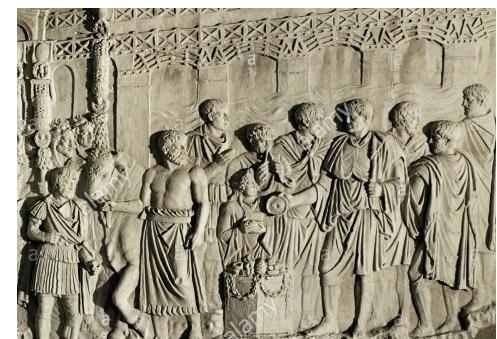


Elke Grittman / Ilona Ammann, Quantitative Bildtypenanalyse, in: Thomas Petersen / Clemens Schwender (Hrsg.), Die Entschlüsselung der Bilder. Methoden zur Erforschung visueller Kommunikation. Ein Handbuch (Köln: Herbert von Halem 2011), 163–177



QUANTITATIVE IMAGE TYPE ANALYSIS

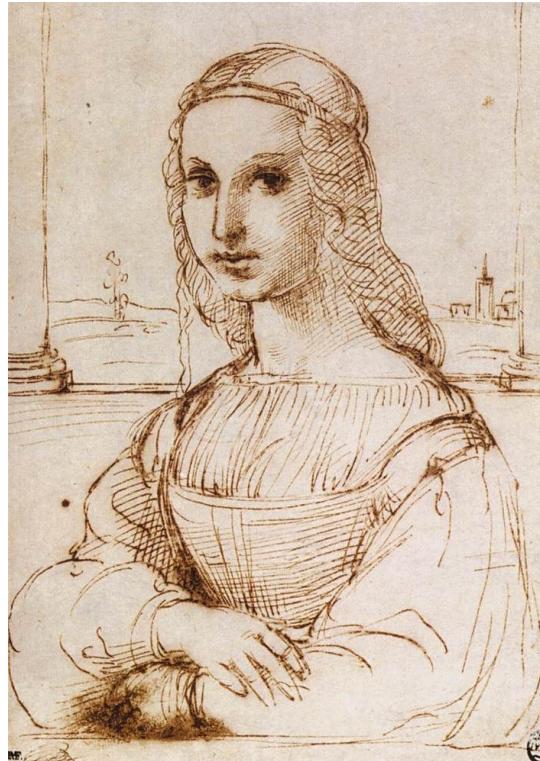
- Example: Trajan's Column



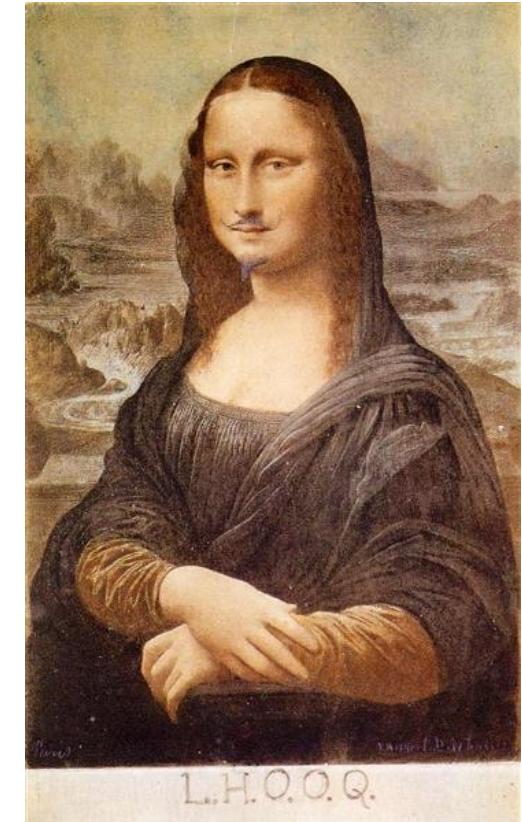
Tonio Hölscher / Lorenz Baumer / Lorenz Winkler,
Narrative Systematik und politisches Konzept in den
Reliefs der Traianssäule, Jahrbuch des Deutschen
Archäologischen Instituts 106, 1991, 261-295.

WHAT EFFECT DID THE PAINTING HAVE?

- Reception analysis
- Image Collection Exploration et al.



Zeichnung Raffaels 1506



Marcel Duchamp 1919

WHAT IS THE BASIC EFFECT OF THE PICTURE ON THE BEHOLDER?

- Perception and attention analysis
- Eyetracking

Karl Clausberg, Neuronale Bildwissenschaften, in: Hans Belting u.a., Kunstgeschichte. Eine Einführung, Berlin: Reimer 2008, 337–362



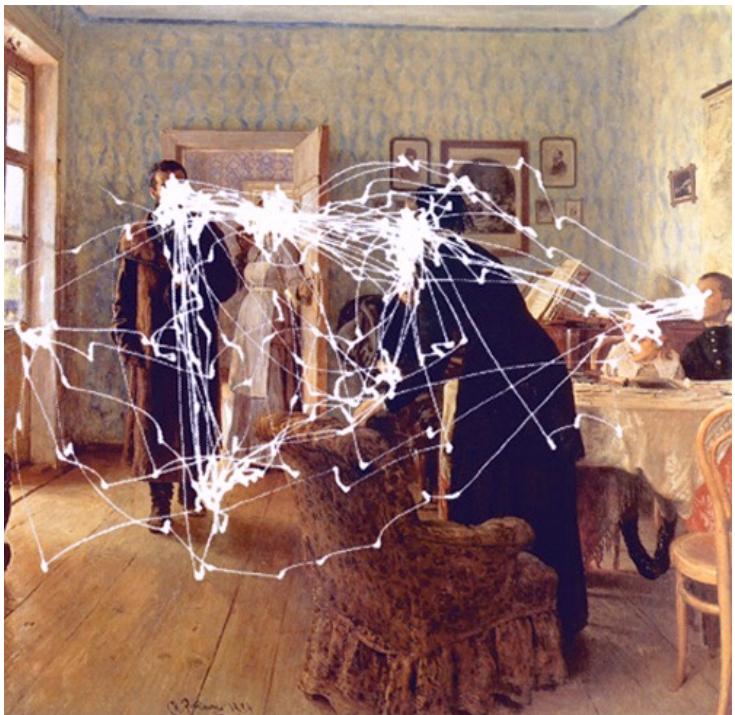
EYETRACKING



<https://mw2013.museumsandtheweb.com/paper/capturing-visitors-gazes-three-eye-tracking-studies-in-museums/>



EYETRACKING



<https://yarbus.eu/attention-effects/>

[https://www.youtube.com/
watch?v=e5Sa3H8QN6c](https://www.youtube.com/watch?v=e5Sa3H8QN6c)



- extensive experiments on CNN fine-tuning



FOR WHICH LINES OF ARGUMENTATION WAS THE IMAGE USED? DID IT UNDERGO A CHANGE OF MEANING?

- ▶ Discourse analysis, history of image use
- ▶ u.a. Image Collection Exploration, Statistics and digital Source Analysis

Barbara Paul, Kunstgeschichte, Feminismus und Gender Studies, in: Hans Belting u.a., Kunstgeschichte. Eine Einführung, Berlin: Reimer 2008, 297–336; Gillian Rose, Visual Methodologies, London: SAGE 2016, 186–252



HOW DO IMAGES GUIDE SEEING, THINKING, FEELING AND KNOWING?

- Cultural history, media studies
- Big Data (Distant Viewing), Content Analysis and Cultural Analytics



Martin Schuster, Wodurch Bilder wirken. Psychologie der Kunst, Köln: DuMont 2003 ;
Gillian Rose, Visual Methodologies, London: SAGE 2016, 85–105

VIKUS VIEWER

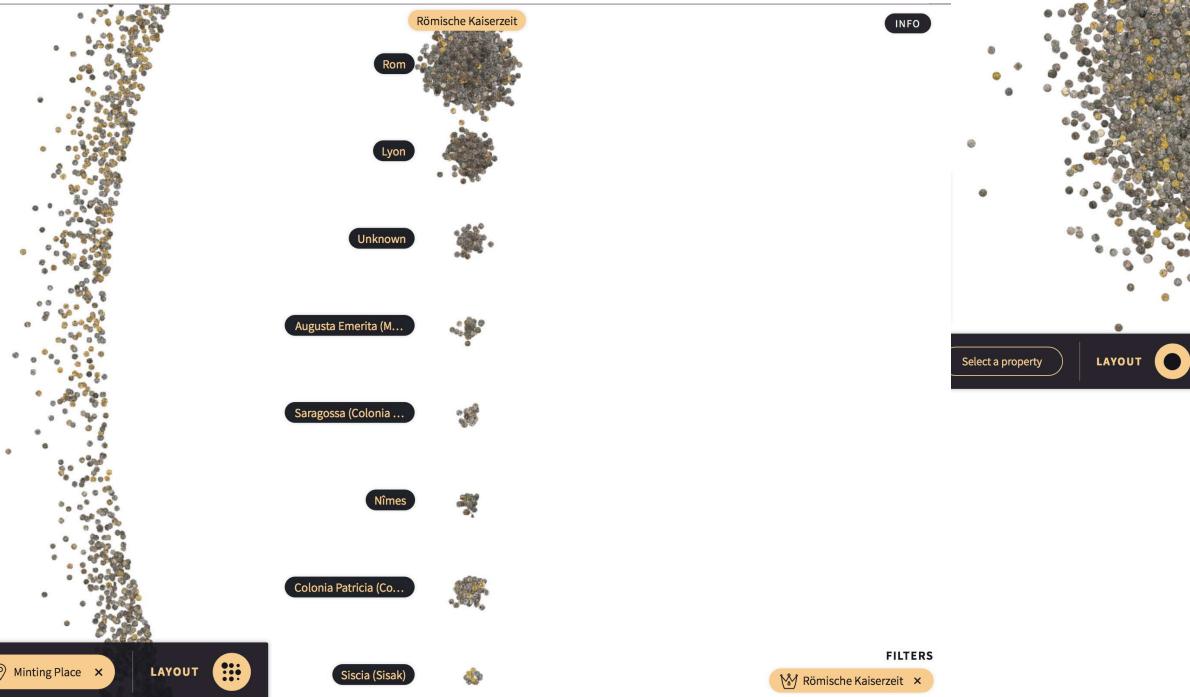
<https://vikusviewer.fh-potsdam.de>

z.B. 986 paintings of van Gogh or
1506 pruss. coins of the 16th to 19th
cent.



COINS

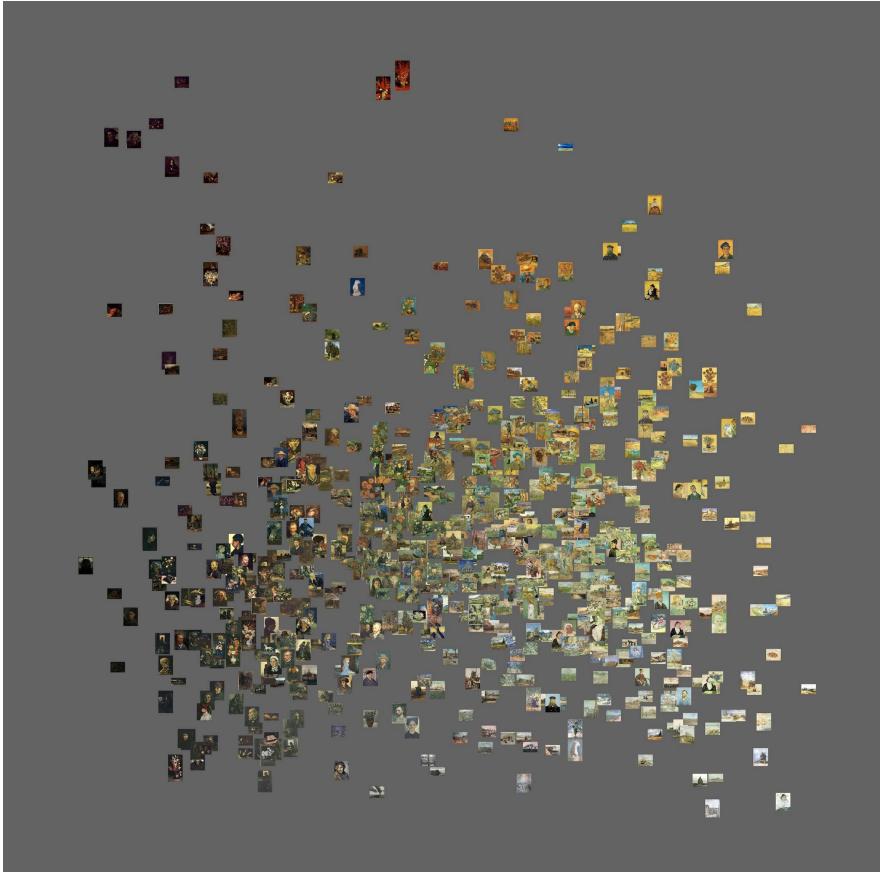
<https://uclab.fh-potsdam.de/coins/>

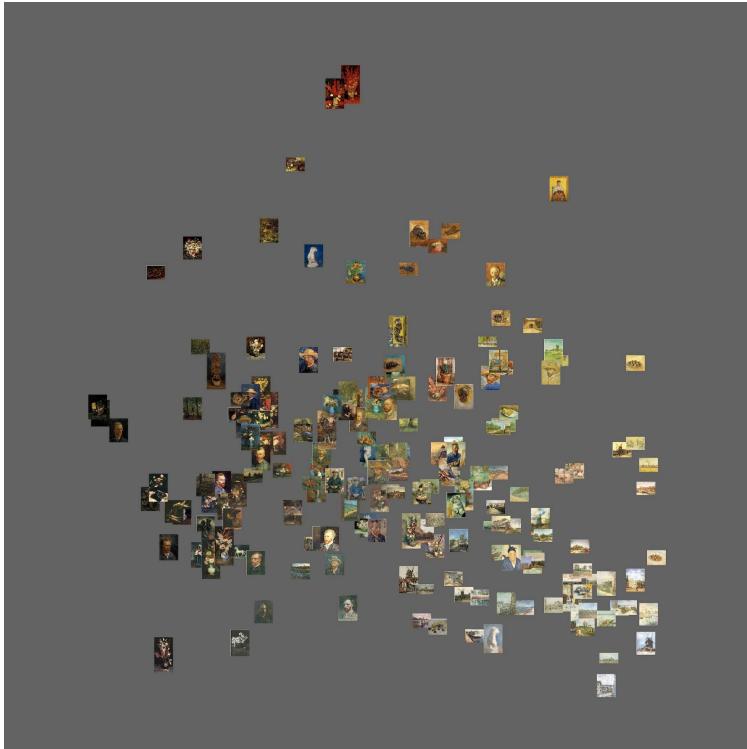


CULTURAL ANALYTICS

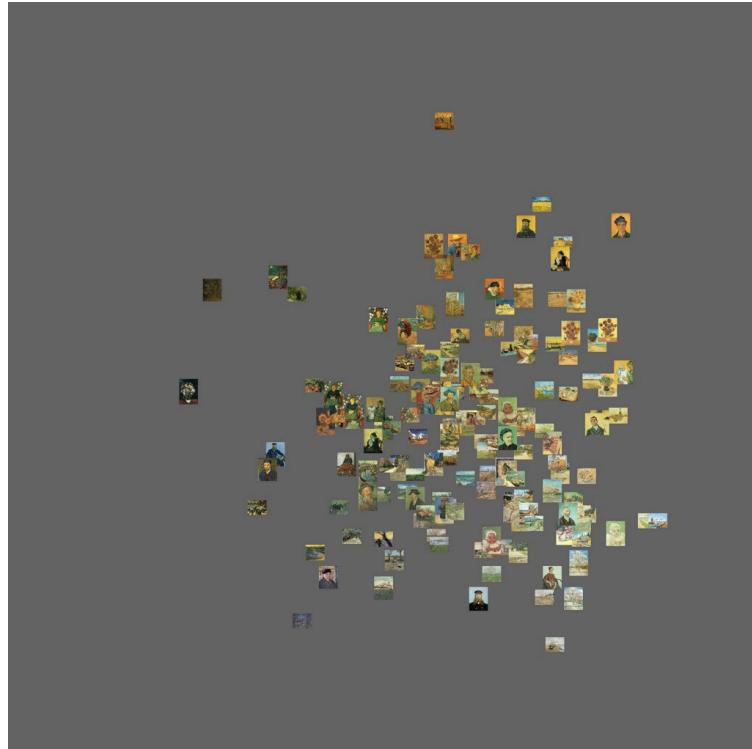


Lev Manovich, Style Space. How to compare image sets and follow their evolution (2011):
http://manovich.net/content/04-projects/073-style-space/70_article_2011.pdf





199 paintings made in Paris (1886-1888)



161 paintings made in Arles (1889)

<http://manovich.net/index.php/projects/tag:Article>

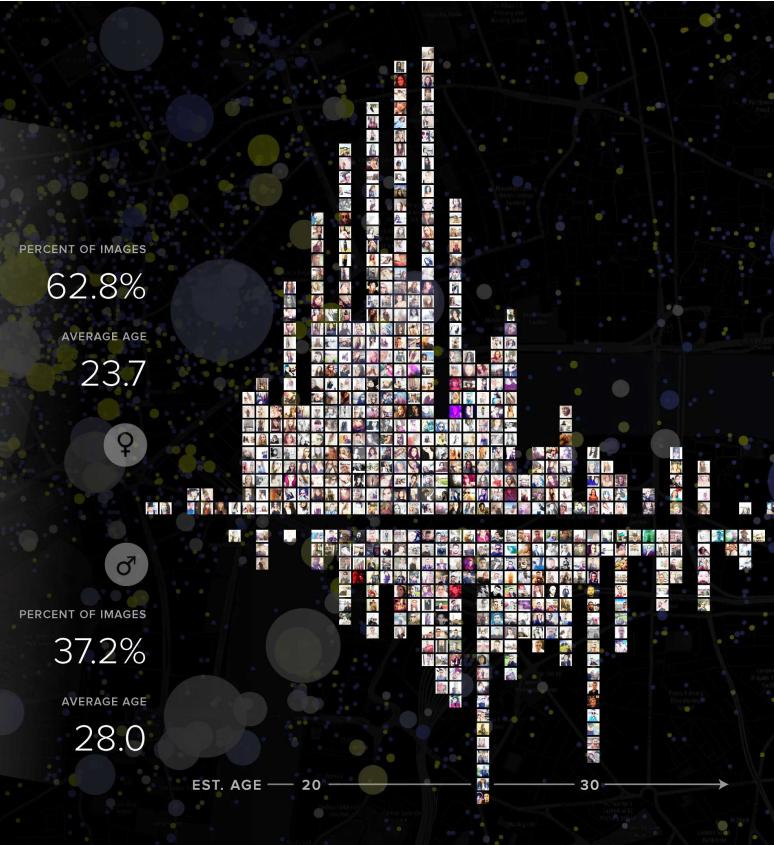
Average brightness (X-axis) vs. average saturation (Y-axis) compared using ImageJ



SELFIECITY LONDON



[HTTP://SELFIECITY.NET/LONDON](http://SELFIECITY.NET/LONDON)



<http://www.selfiecity.net/>

<http://manovich.net/index.php/projects/instagram-and-contemporary-image>



EXAMPLE: FACE RECOGNITION



[http://www.faceplusplus.com/
demo-detect](http://www.faceplusplus.com/demo-detect)



EXAMPLE: FACE RECOGNITION

invisibleaustralians.org

the real face of white australia

home • about

the real face of white australia

The White Australia Policy was about people – people whose lives were monitored and restricted because of the colour of their skin. This experimental browser enables you to explore the records of the White Australia Policy through the faces of those people.

These portraits were extracted from a range of government documents using a [face detection script](#). We've tried to weed out the mistakes, but you may still notice a few oddities. Many portraits are duplicated, as multiple copies of the forms were often kept.

The records are held by the [National Archives of Australia](#). Currently the browser only shows images from Series ST84/1. Other series will be added over time. You can read more about the records at [The Tiger's Mouth](#).

If you click on a portrait you can view the document it came from. You'll also be able to follow a link to explore the context of the document in the National Archives of Australia's [RecordSearch](#) database.

The portraits are presented in random order. You can reverse the order simply by adding `?order=reverse` to the url. You can also browse file by file by adding `?order=file`.

This experimental browser has been developed as part of the [Invisible Australians](#) project.

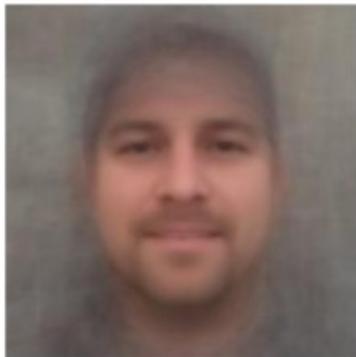
Invisible Australians

<http://invisibleaustralians.org/faces/>



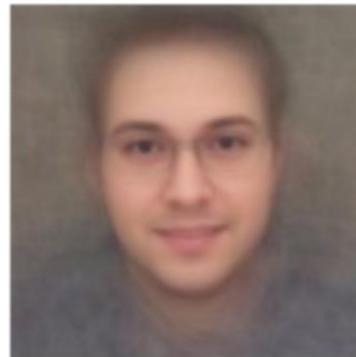
EXAMPLE: FACE RECOGNITION

Composite heterosexual faces

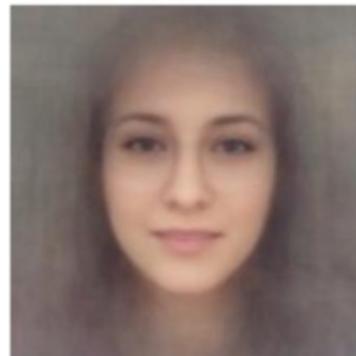
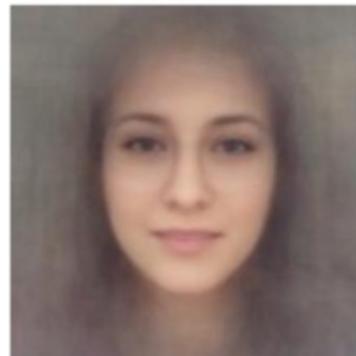
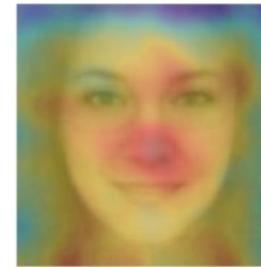
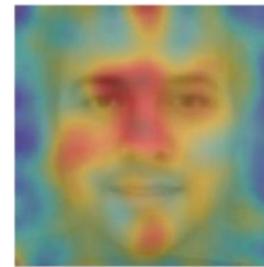


Male

Composite gay faces



Female



Yilun Wang – Michal Kosinski,
Deep neural networks are
more accurate than humans at
detecting sexual orientation
from facial images, Journal of
Personality and Social
Psychology 2017
(<https://osf.io/fk3xr/>)

CRITICISM OF STRUCTURAL RESEARCH



<https://www.dhm.de/lemo/kapitel/ns-regime/innenpolitik/rassenpolitik.html>



CRITICISM OF STRUCTURAL RESEARCH

Neglect of historical conditionality, changeable visual experiences and societal developments, because

- verbal and pictorial expressions do not merely depict reality, but also construct it.
- Socio-cultural realities are not necessarily so, but only a possibility of social development.



Athena and Hera?, North
metope 32 of the Parthenon
(448–442 BC)



Annunciation to Mary,
St. Clement in Ohrid /
Macedonia (ca. 1300)



<https://www.nextrembrandt.com>



PLAY

ABOUT

METHODS

LEARN

PRESS

CONTACT

CALLING BS

Click on the person who is real.



<https://thispersondoesnotexist.com>

<http://www.whichfaceisreal.com>

CHALLENGES FOR DIGITAL IMAGE ANALYSIS

- Further development of image pattern recognition, especially in the historical dimension
- Combination of Distant Viewing and Close Viewing
- Variability and diversity of cultural expressions and processes instead of concentrating on the "typical" and "most popular"

- Possibilities of digital image processing
- Different methods of digital image analysis, their advantages and areas of application
- Good practice examples of digital image comparison
- Big Data approaches in digital image science
- Structure and possible applications of computer vision and convolutional neural networks
- Technical methods for measuring images and viewers

- Practical experience in using an image editing programme (cropping, working in multiple layers, histograms & tonal corrections, use of filters)
- Comparing images digitally
- Developing criteria for creating image sets

Which procedures of digital image analysis do you know?

How do you assess their possibilities?

How do Computational Neural Networks work and what are the advantages of image pattern recognition?

In which areas can computer vision facilitate work with large image archives?

Slide 15 ff., 37 ff., 66 ff., 80 f., 88 ff.

Slide 16–21 et al.

Slide 12–36

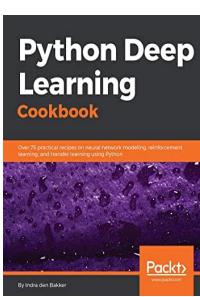
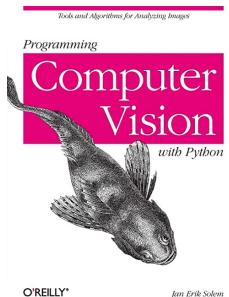
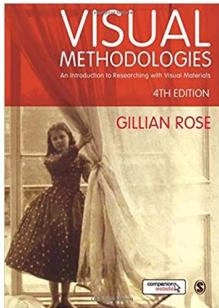
What approach does Lev Manovich take with his Cultural Analytics

Briefly characterise a method for computer-assisted painter attribution.

How do you think image analysis can particularly benefit from the use of computers?

Slide 91-93

Slide 66–72



Gillian Rose, *Visual Methodologies. An Introduction to Researching with Visual Materials*, 4th ed. (London: SAGE, 2016)

Hans Belting u.a., *Kunstgeschichte. Eine Einführung* (Berlin: Reimer, 2008)

Yihang Bo, Jinhui Yu and Kang Zhang, Computational aesthetics and applications, *Visual Computing for Industry, Biomedicine, and Art* 1, no. 6 (2018). <https://doi.org/10.1186/s42492-018-0006-1>

Lev Manovich, *Cultural Analytics* (The MIT Press, 2020)

Jan Erik Solem, *Programming Computer Vision with Python: Tools and algorithms for analyzing images* (O'Reilly, 2012)

Indra den Bakker, *Python Deep Learning Cookbook: Over 75 practical recipes on neural network modeling, reinforcement learning, and transfer learning using Python* (Packt Publishing Ltd, 2017)

Folie 1: <http://www.nextrembrandt.com>

Folie 6: <https://static.messynessy chic.com/wp-content/uploads/2014/06/parissnapshop71.jpg>

Folie 19, 20, 42, 43, 44, 46, 49, 50, 61, 71:

https://upload.wikimedia.org/wikipedia/commons/thumb/e/ec/Mona_Lisa%2C_by_Leonardo_da_Vinci%2C_from_C2RMF_retouched.jpg

Folie 20:

https://upload.wikimedia.org/wikipedia/commons/5/50/Isabella_di_Aragona_as_Mona_Lisa.jpg

Folie 21: http://www.bmoworldwines.com/file/2016/04/11/skypos_1.png

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Inhaltlich verantwortlich:

Prof. Dr. Martin Langner
Institut für Digital Humanities
Georg-August-Universität Göttingen
37073 Göttingen

Martin.Langner@uni-goettingen.de

Telefon 0551 / 3926790

<https://www.uni-goettingen.de/digitalhumanities>

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COMPUTER VISION

- Forschungsfeld der künstlichen Intelligenz und des maschinellen Lernens
- untersucht, wie man aus digitalen Bildern automatisiert ein umfassendes Verständnis des Bildinhalts gewinnen kann.
- automatisierte Extraktion von Informationen aus Bildern (z.B. Bestimmung der Kameraposition, Objekterkennung und -benennung, Gruppieren von Bildinhalten, Bildähnlichkeitssuche).
- Teilbereiche: Image Classification, Object Detection, Image Segmentation und Saliency Detection.



IMAGE CLASSIFICATION (BILDKLASSIFIKATION)

- bringt einem Modell bei, zu erkennen, was sich auf einem bestimmten Bild befindet.



OBJECT DETECTION (OBJEKTERKENNUNG)

- bringt einem Modell bei, eine Instanz eines Objekts aus einem Satz vordefinierter Kategorien zu erkennen, indem eine Bounding Box um jede Instanz einer bestimmten Klasse bereitgestellt wird.



IMAGE SEGMENTATION (BILDSEGMENTIERUNG)

- trainiert ein Modell so, dass es jedes Pixel mit einer Klasse aus einem vordefinierten Satz annotiert, zu der ein bestimmtes Pixel höchstwahrscheinlich gehört.



SALIENCY DETECTION (ERKENNUNG VON AUFFÄLLIGKEITEN)

- trainiert ein Modell so, dass es in der Lage ist, eine Region zu liefern, die höchstwahrscheinlich die Aufmerksamkeit eines Zuschauers auf sich ziehen würde.



BILDVERARBEITUNG (IMAGE PROCESSING)

- erstellt aus einem vorhandenen Bild ein neues Bild, wodurch der Inhalt in der Regel vereinfacht oder auf irgendeine Weise verbessert wird.
- digitale Signalverarbeitung, bei der es nicht darum geht, den Inhalt eines Bildes zu verstehen.

Beispiele:

- Normalisierung der fotometrischen Eigenschaften des Bildes wie Helligkeit oder Farbe
- Beschneiden der Bildgrenzen
- Entfernen von digitalem Rauschen



IKONIK

- bezeichnet die spezifische Wirkkraft des Bildes, besonders im Unterschied zu anderen Formen und Medien menschlicher Kommunikation.
Es geht also um die dem Bild generell inhärenten Ausdrucksmöglichkeiten.