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

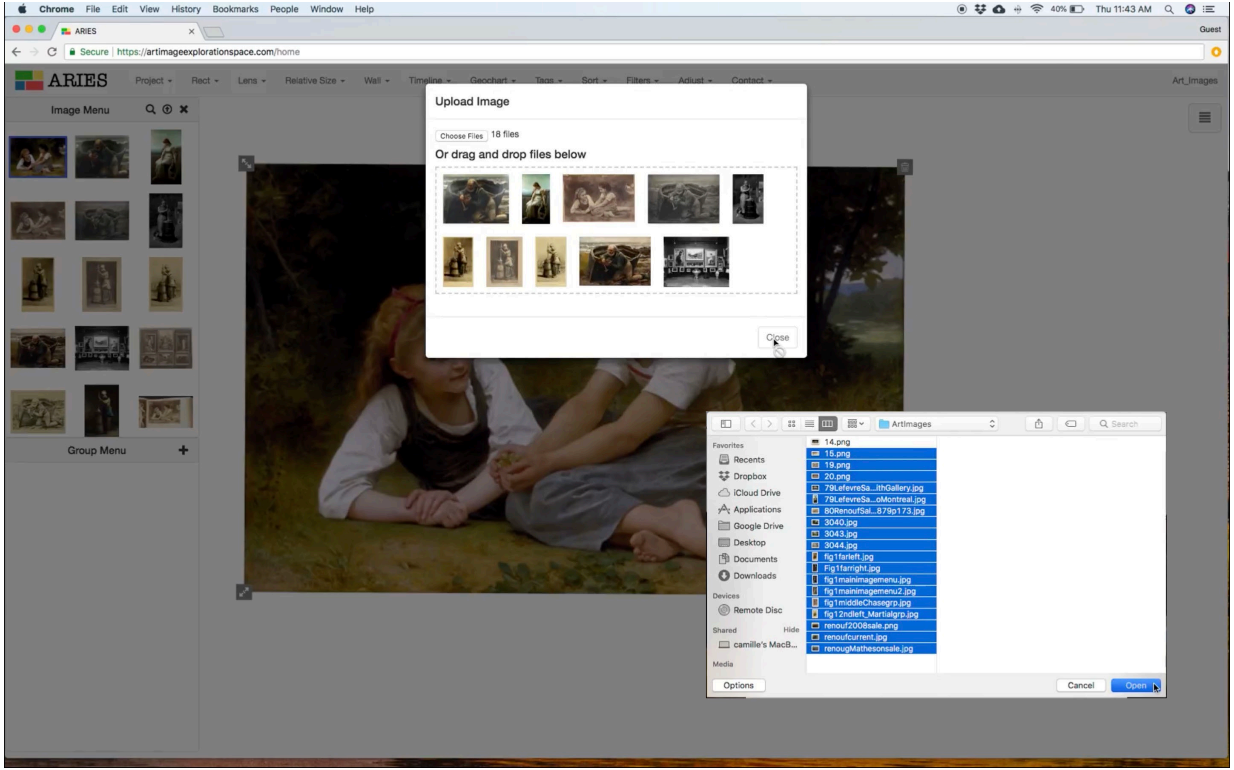
b) Reception

c) Cultural Analytics

THE ART HISTORICAL METHOD:

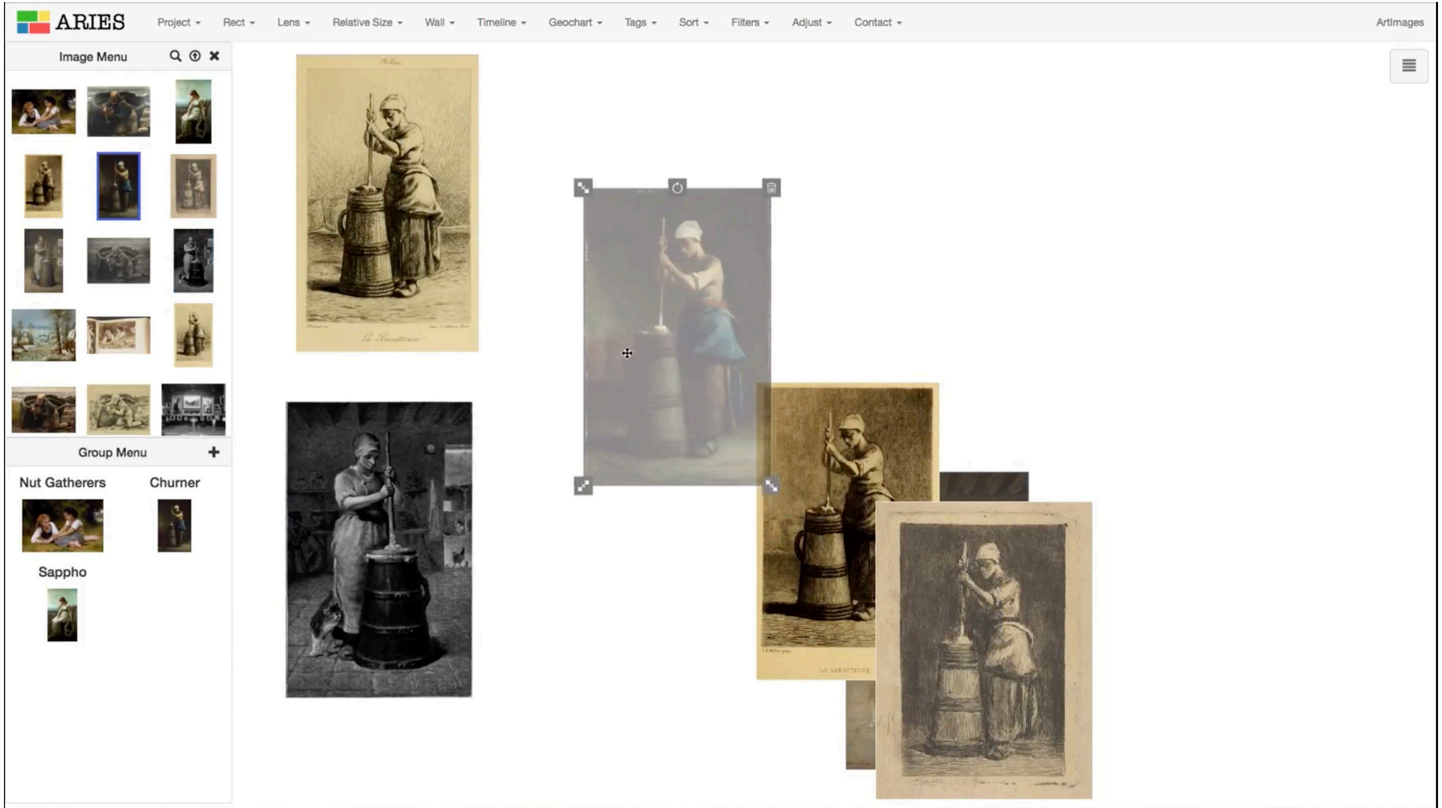
COMPARING AND ARRANGING PICTURES

DIGITAL PICTURE COMPARISON: ARIES



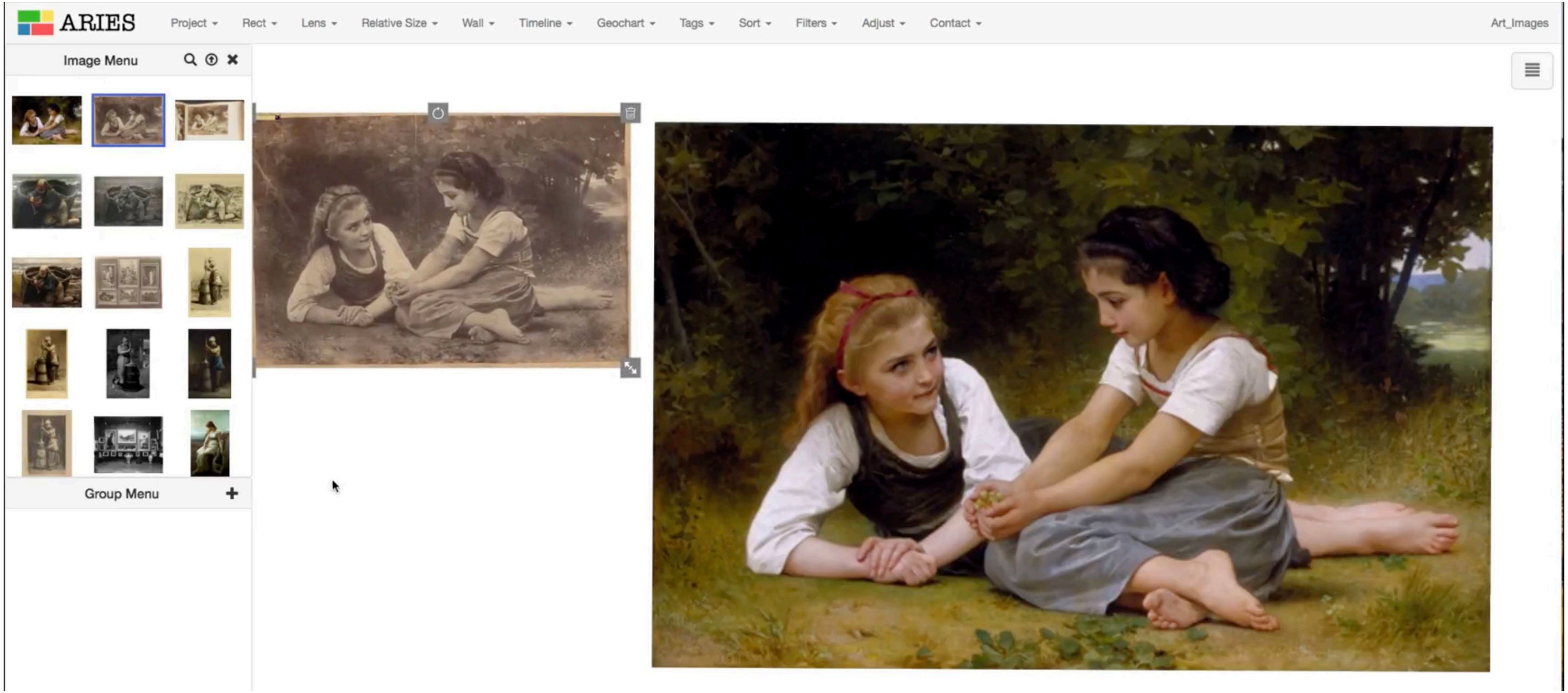
ARIES ARt Image Exploration Space (https://artimageexplorationspace.com)

DIGITAL PICTURE COMPARISON: SEARCHING AND GROUPING



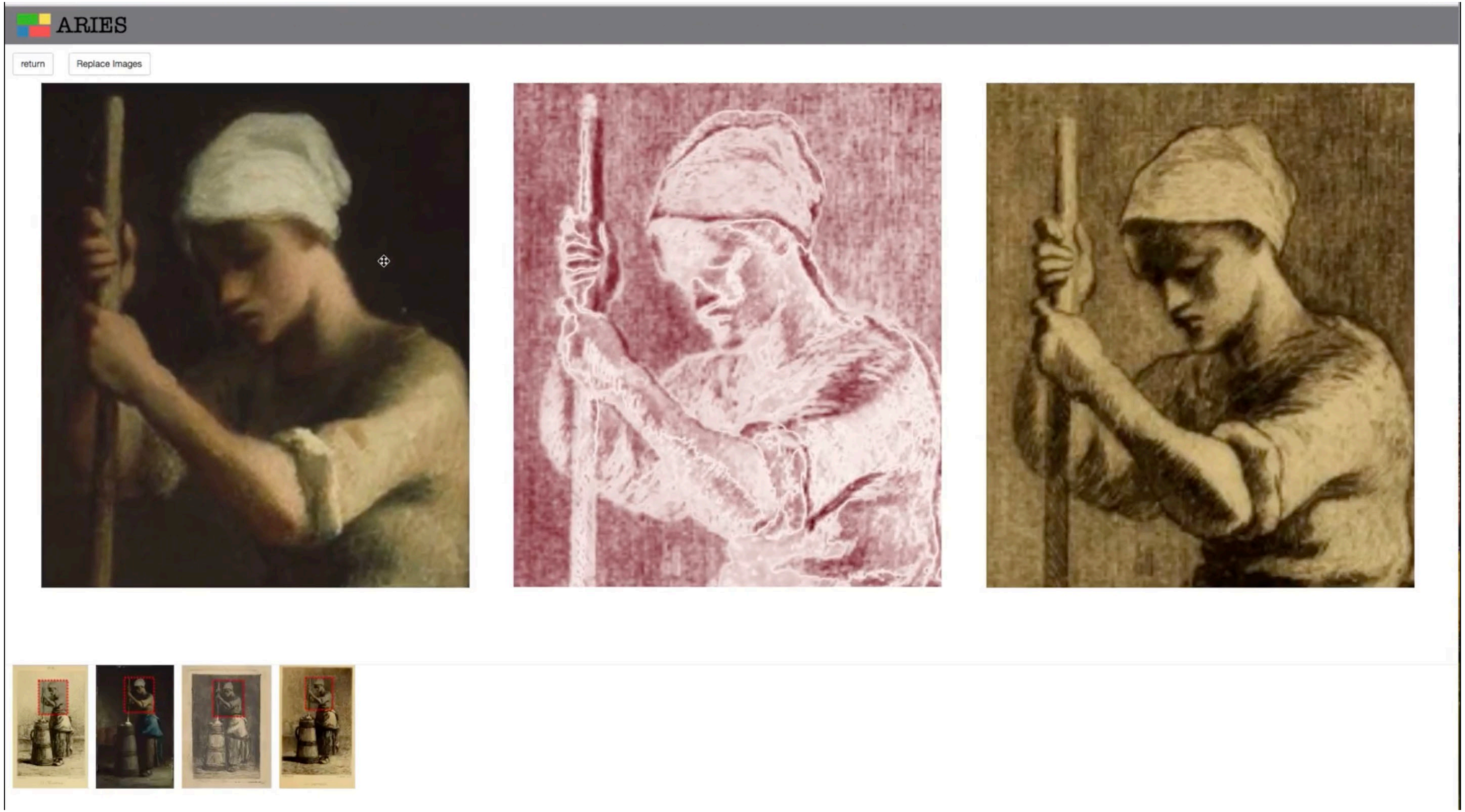
ARIES ARt Image Exploration Space (https://artimageexplorationspace.com)

DIGITAL PICTURE COMPARISON: CONFRONTATION



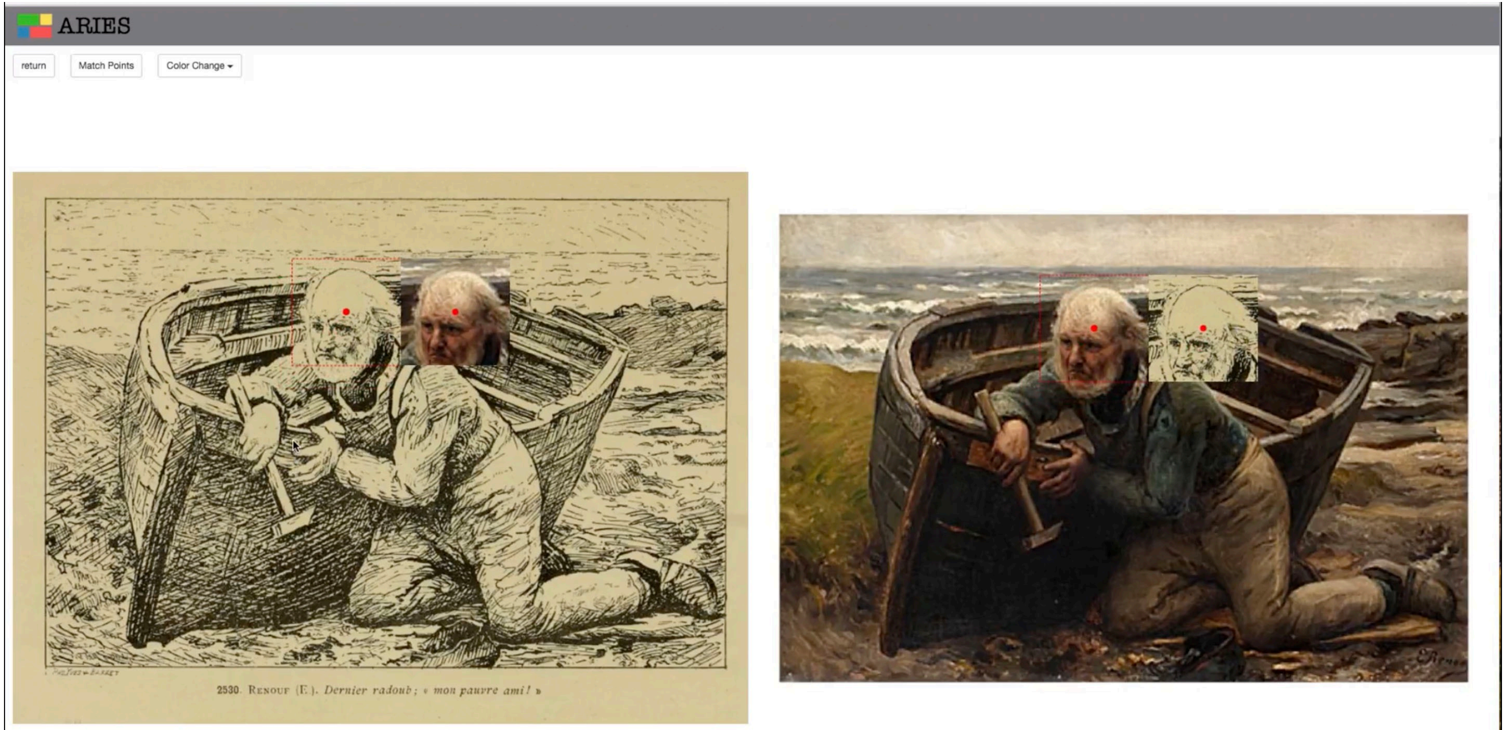
ARIES ARt Image Exploration Space (https://artimageexplorationspace.com)

DIGITAL PICTURE COMPARISON: OVERLAY COMPARISON



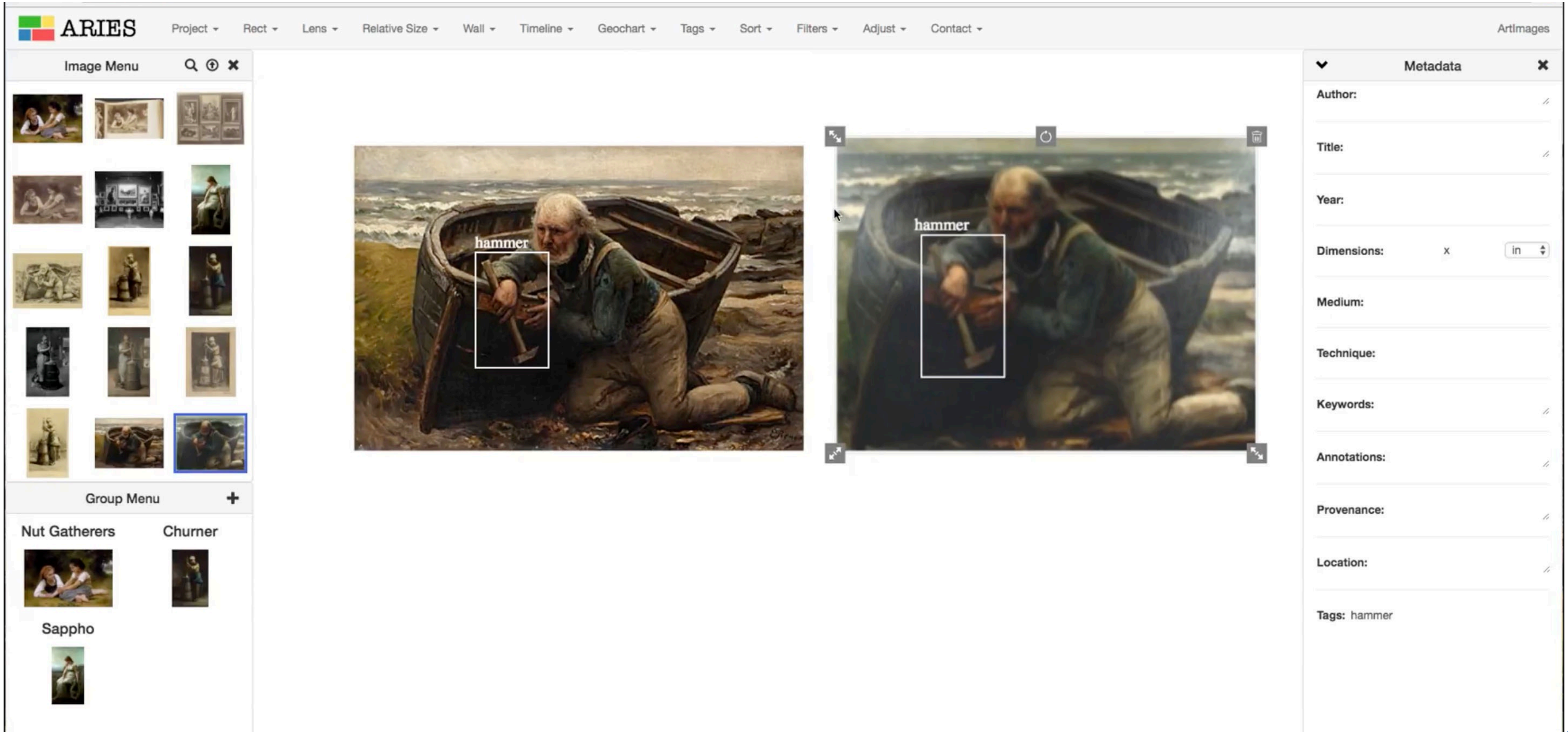
ARIES ARt Image Exploration Space (https://artimageexplorationspace.com)

DIGITAL PICTURE COMPARISON: LENS

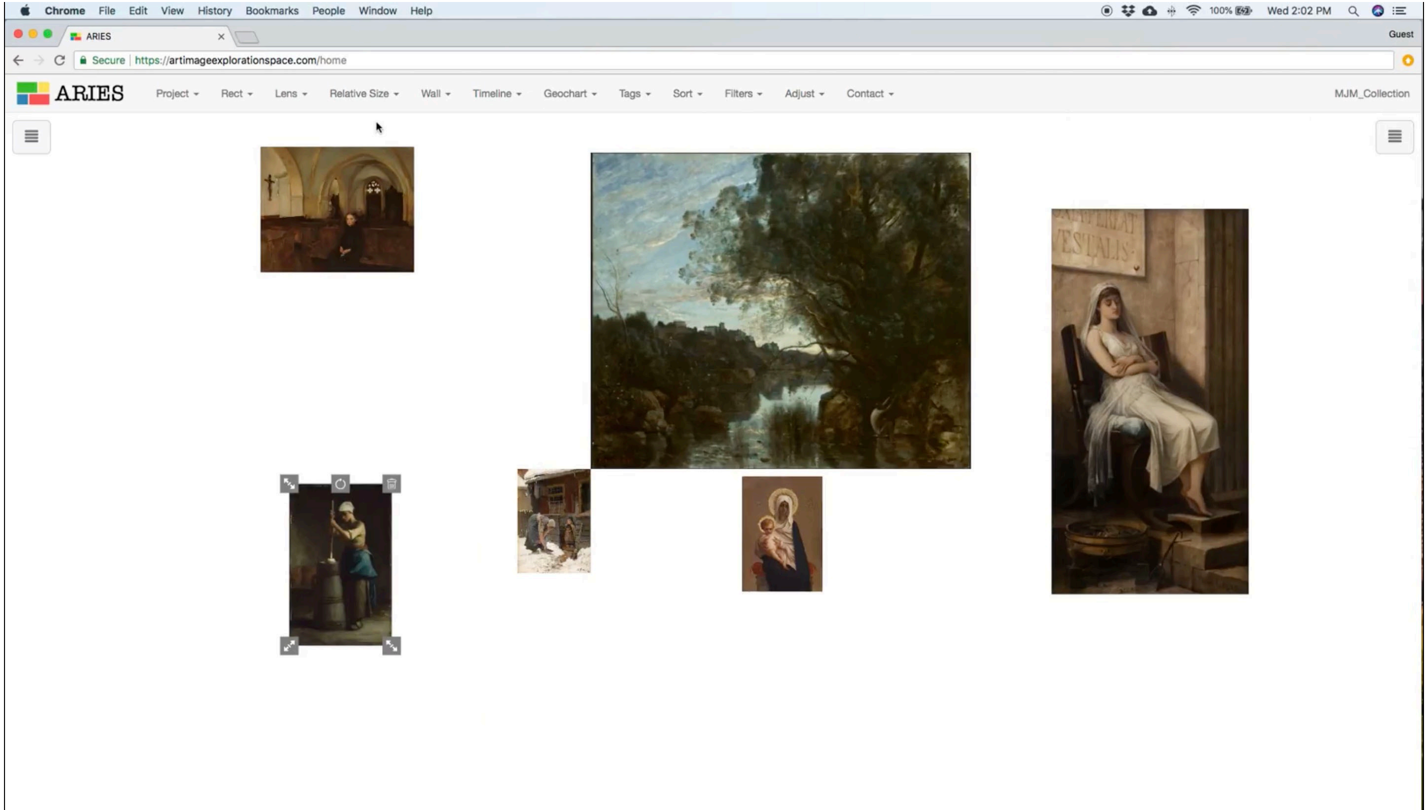


ARIES ARt Image Exploration Space (https://artimageexplorationspace.com)

DIGITAL PICTURE COMPARISON: TAGGING

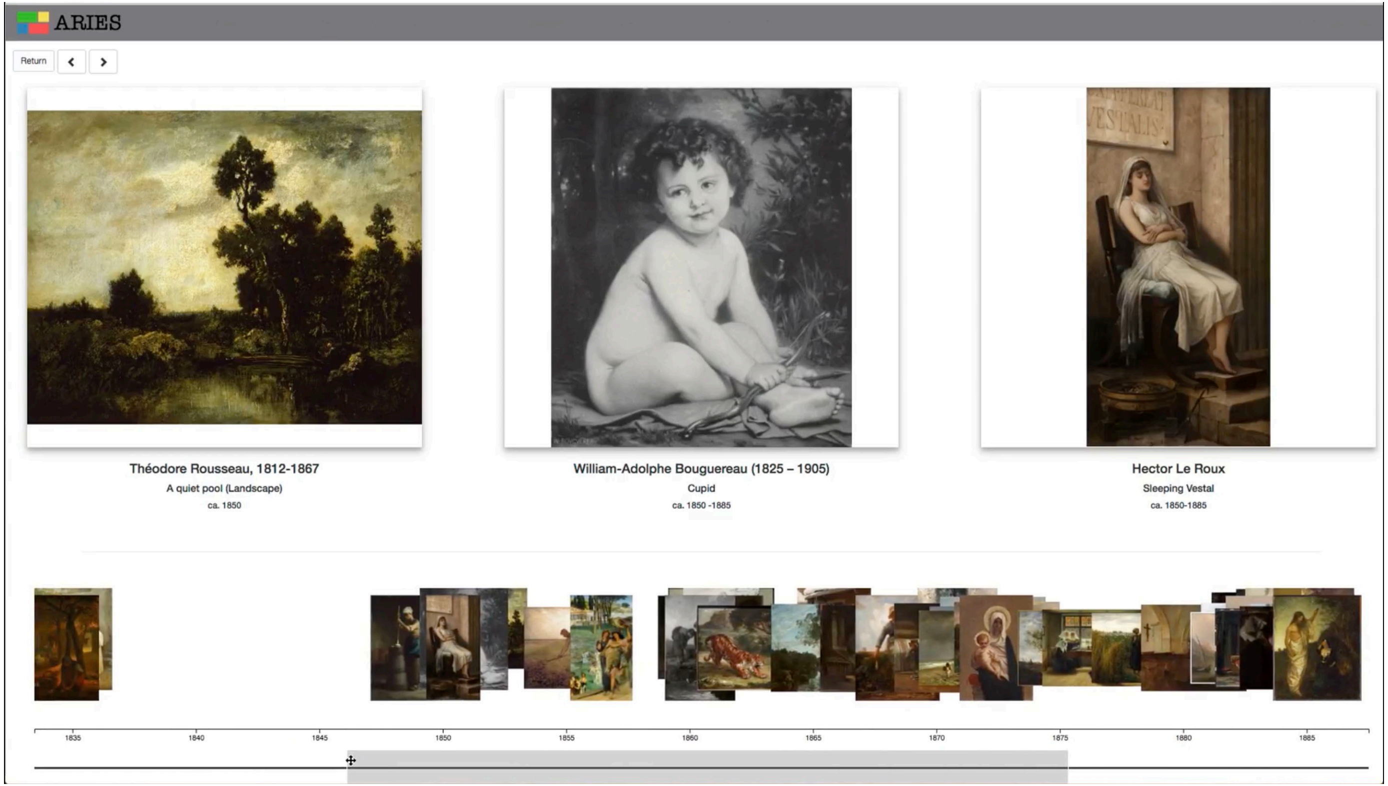


DIGITAL PICTURE COMPARISON: SIZE RATIOS



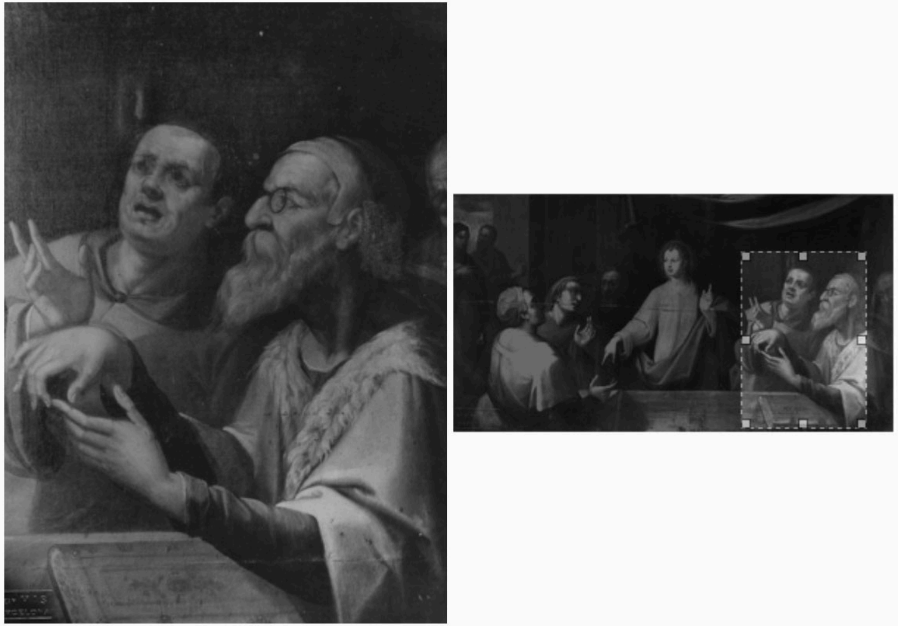
ARIES ARt Image Exploration Space (https://artimageexplorationspace.com)

DIGITAL PICTURE COMPARISON: TIMELINE

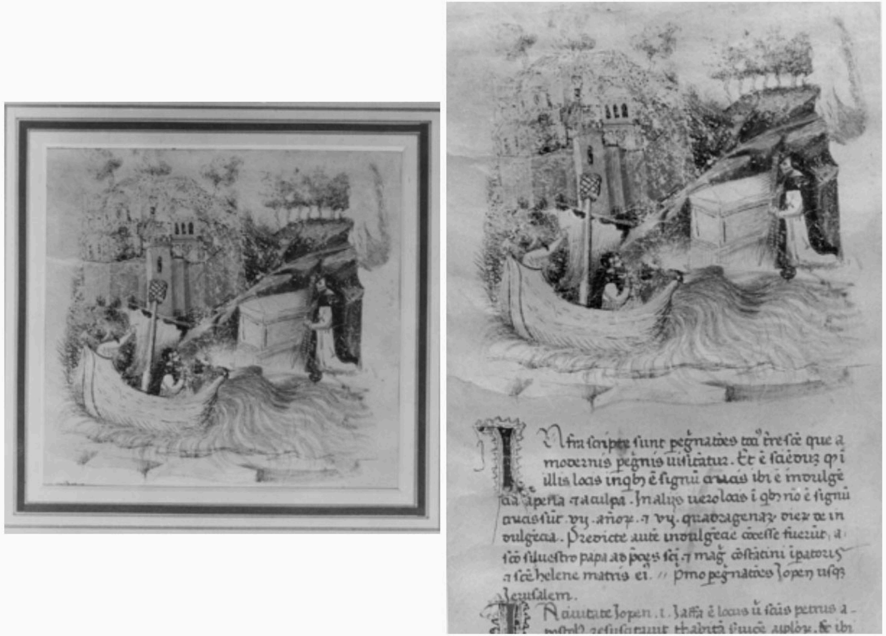


ARIES ARt Image Exploration Space (https://artimageexplorationspace.com)

Findung sections of the image



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



Tuscan, 15th century, Harvard Art Museum.

John Resig, „Using Computer Vision to Increase the Research Potential of Photo Archives," *Journal of Digital Humanities* 3 No. 2 (2014): http://journalofdigitalhumanities.org/3-2/using-computer-vision-to-increase-the-research-potential-of-photo-archives-by-john-resig/

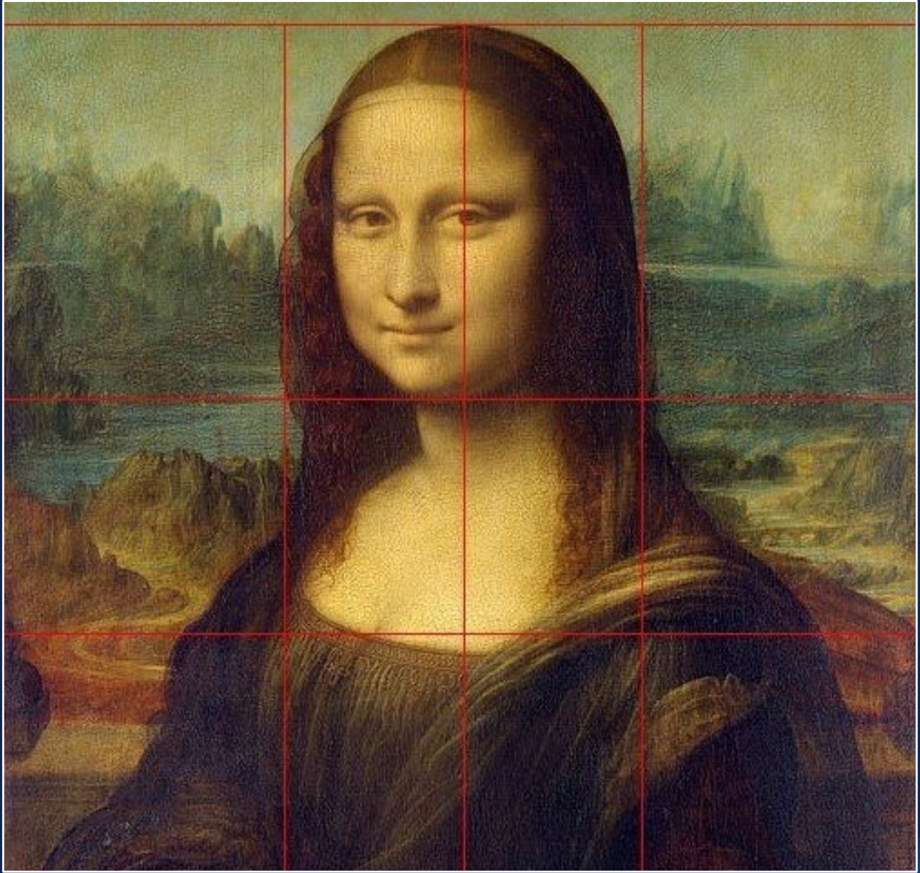
Finding duplicates, copies and image citations

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

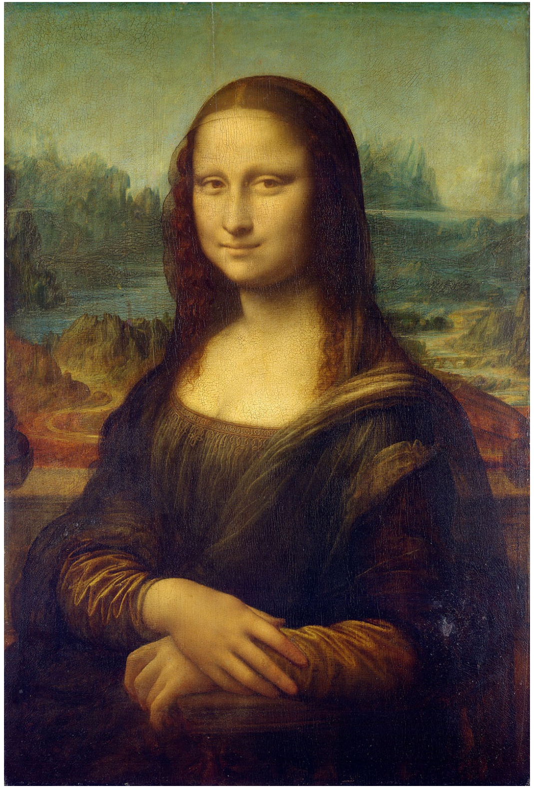


WHO OR WHAT IS DEPICTED?

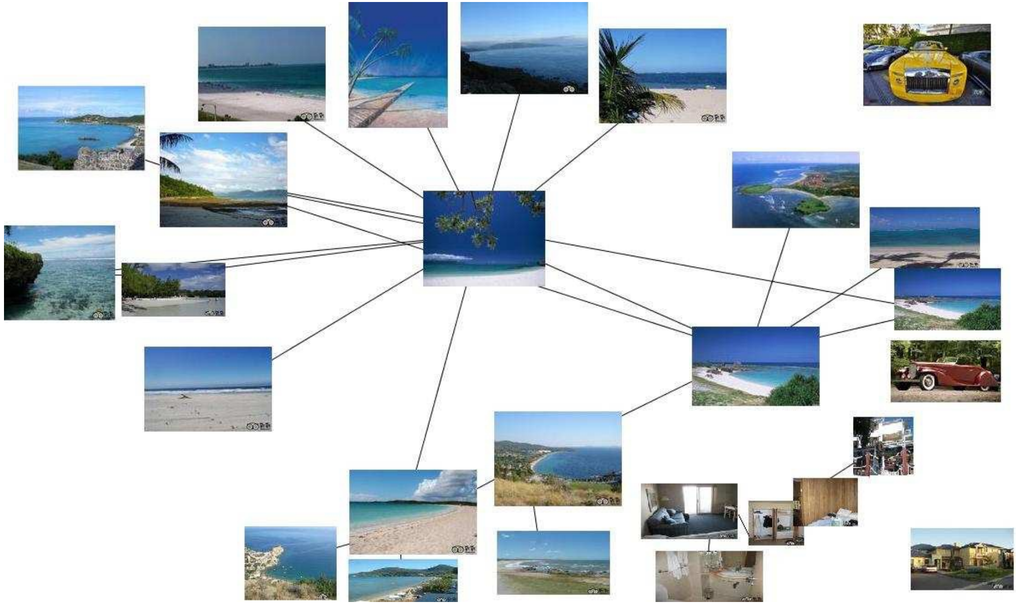
- ➤ Iconography

- ➤ Image pattern recognition (Computer Vision)

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

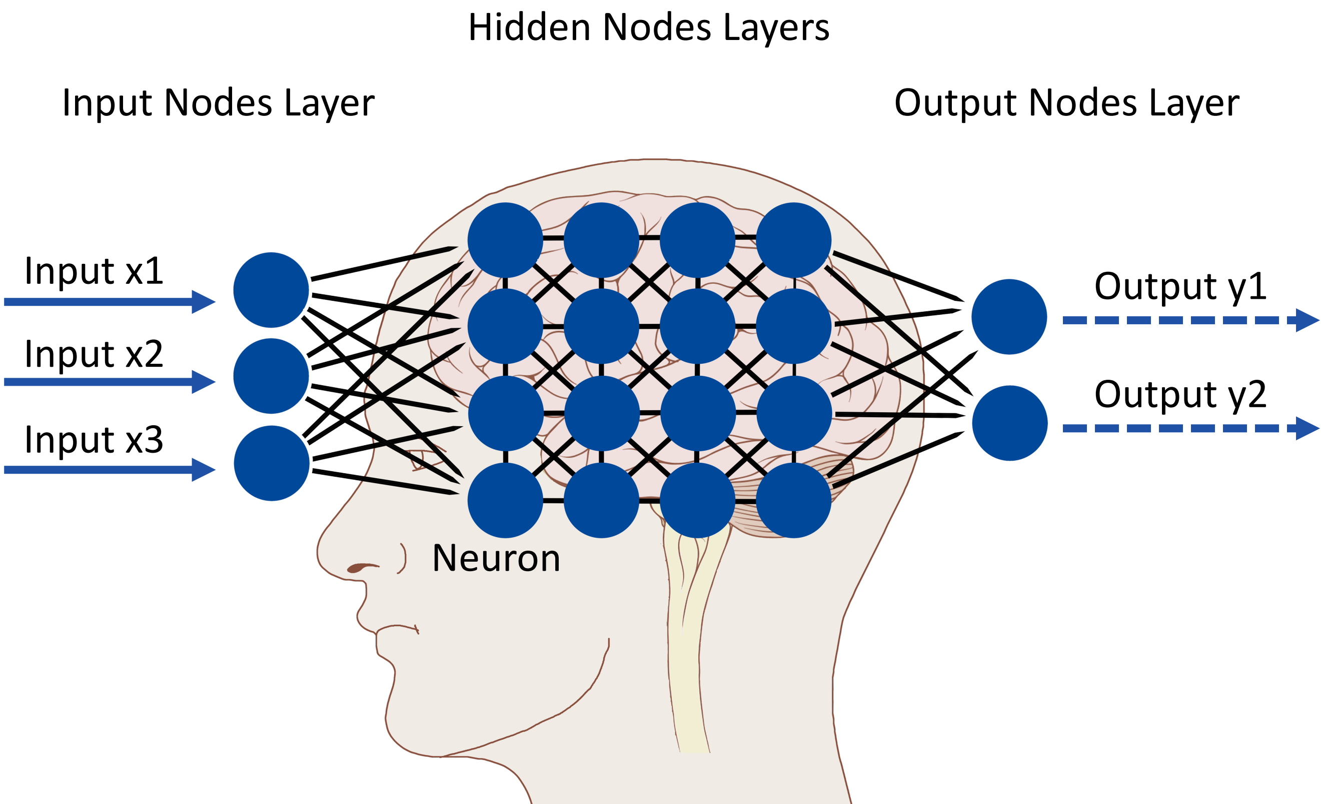


Giulio Romano, Isabella of Aragon



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.

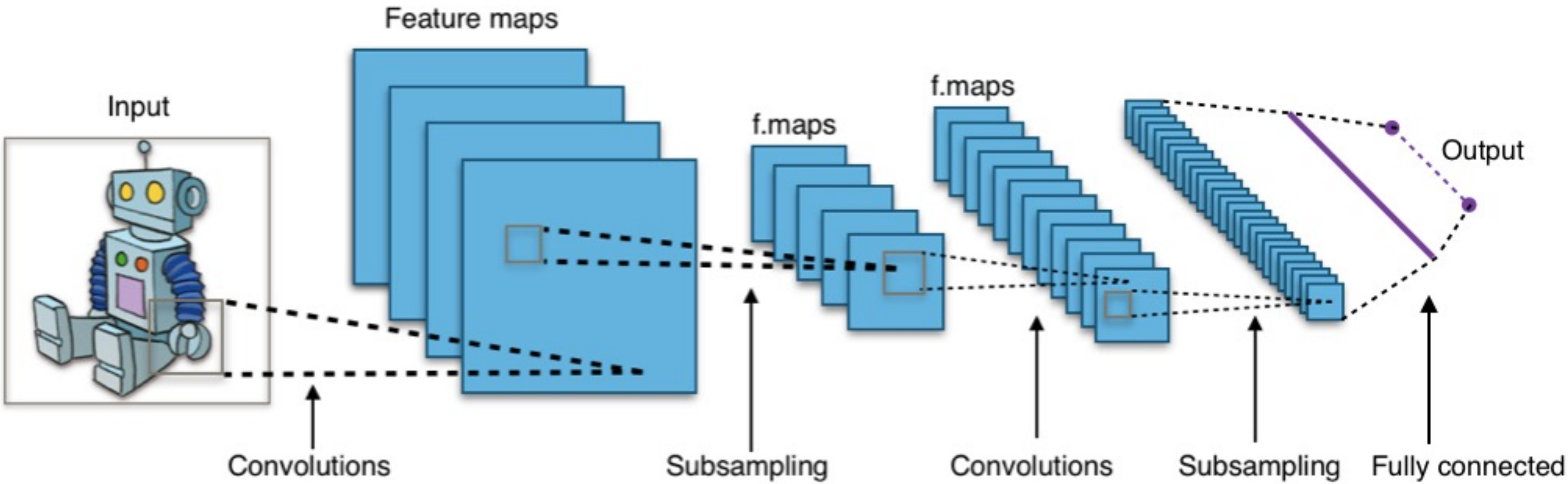
Reinforcement Learning:

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

TRAINING A NEURAL NETWORK

Training data + Validation data + Testing data (Hold-out)

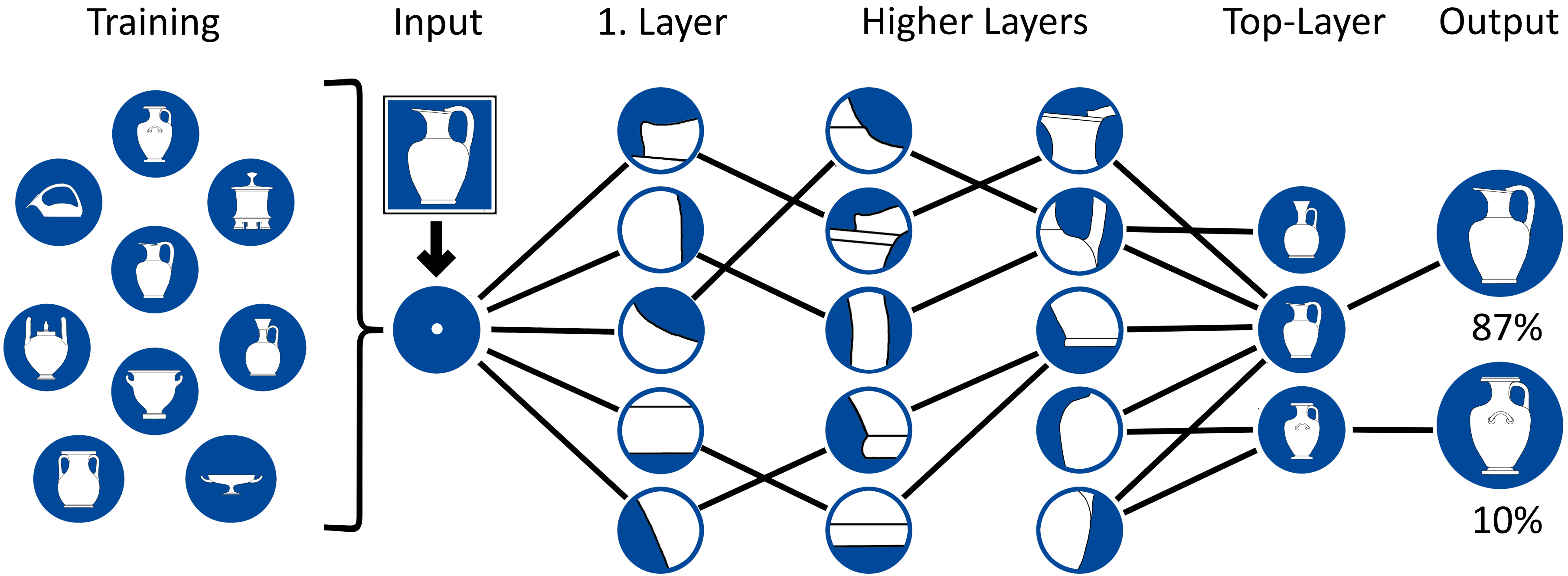
CONVOLUTIONAL NEURONAL NETWORKS



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

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

HOW DO CNNS RECOGNISE A VASE SHAPE IN A PHOTO?



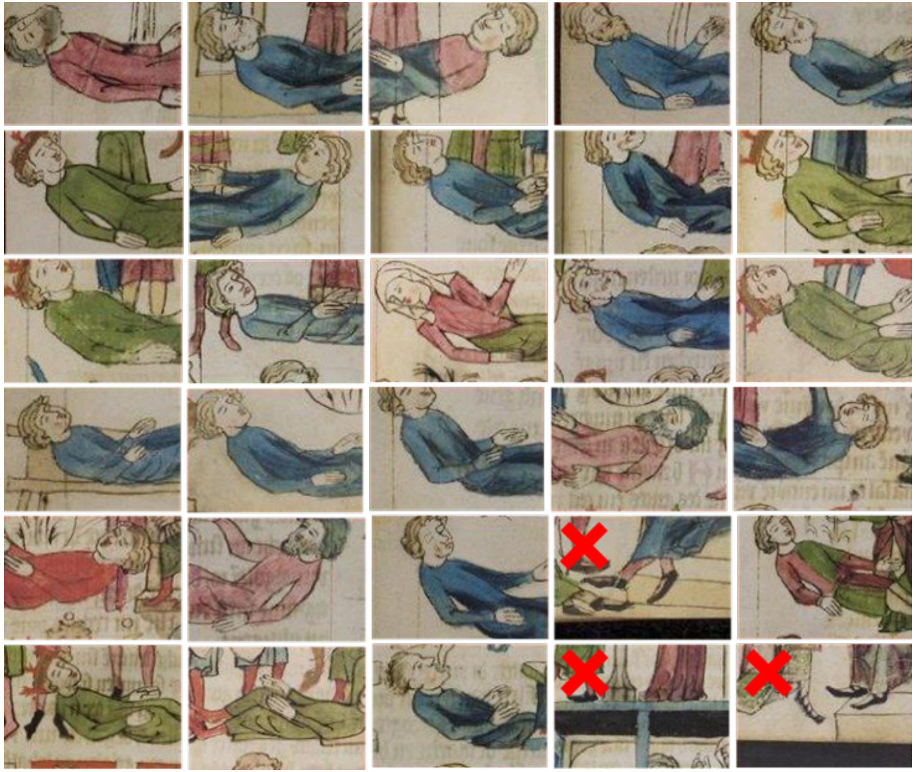
Indexing a large amount of image data to find structural similarities

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

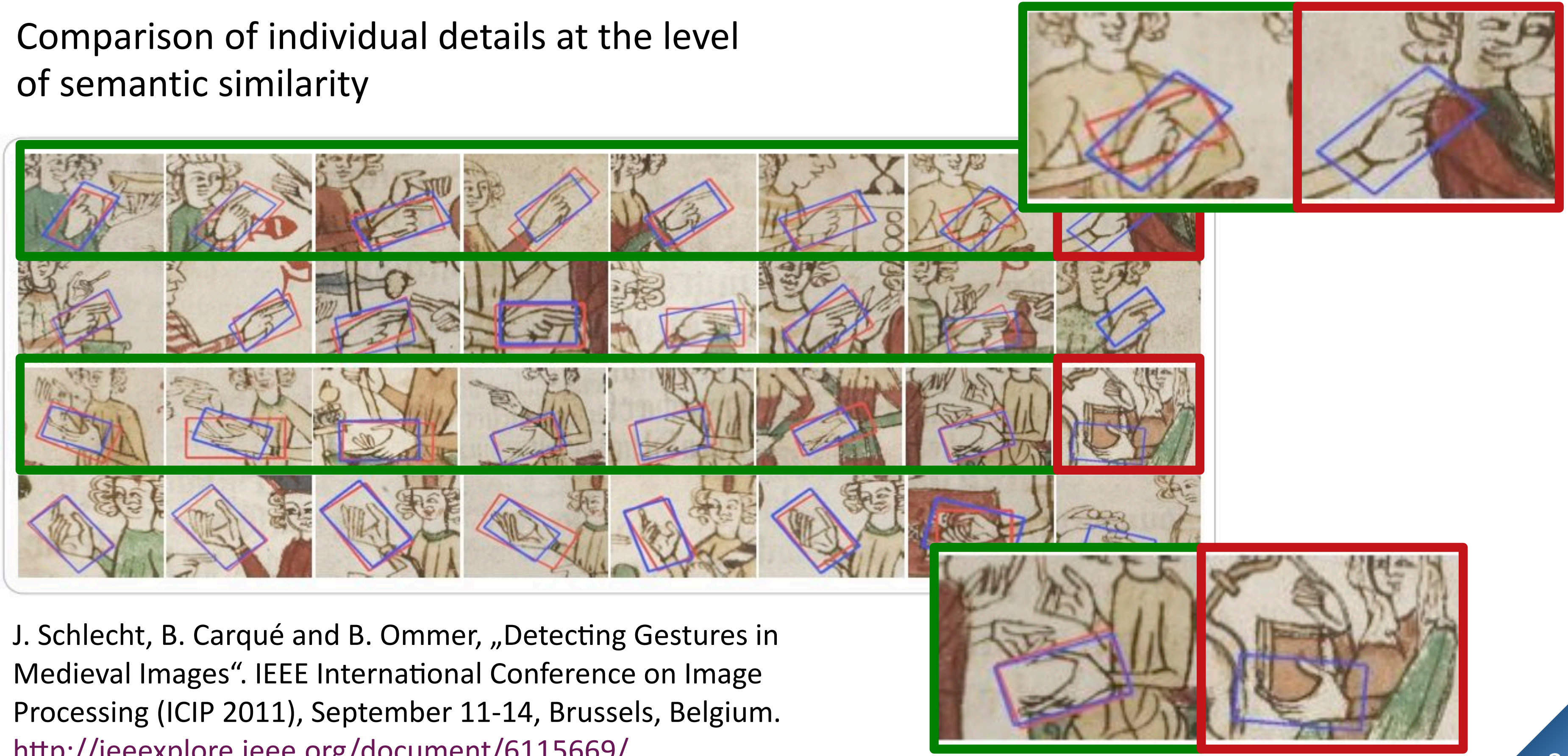
Comparison of individual scenes at the level of semantic similarity

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

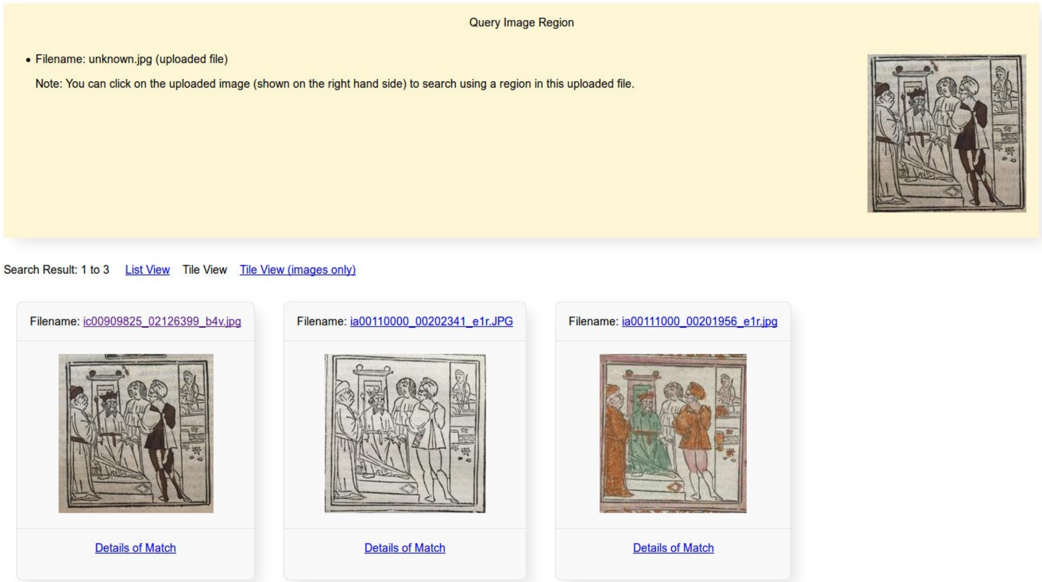
https://www.instagram.com/p/B-pclo5B-Mq/

Comparison of individual details at the level of semantic similarity

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

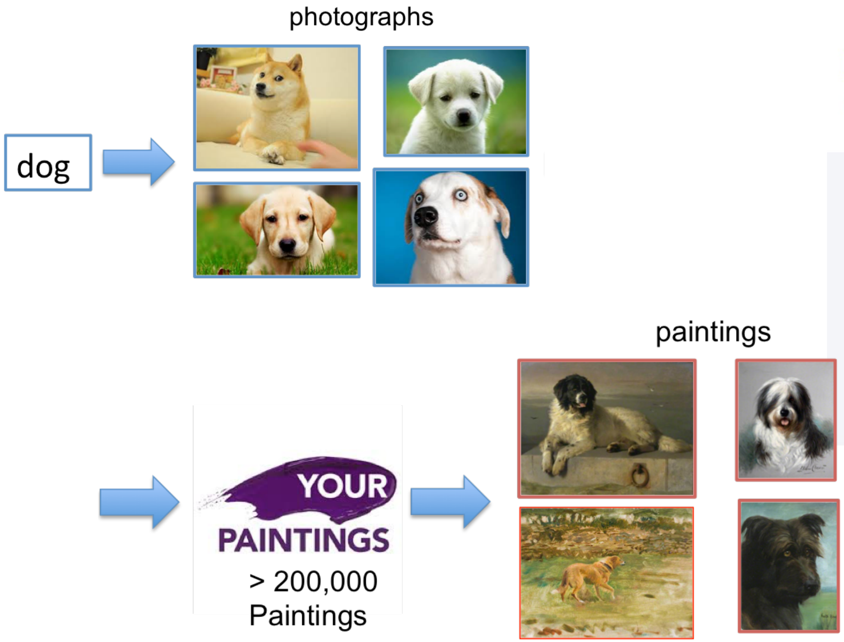
15cILLUSTRATION

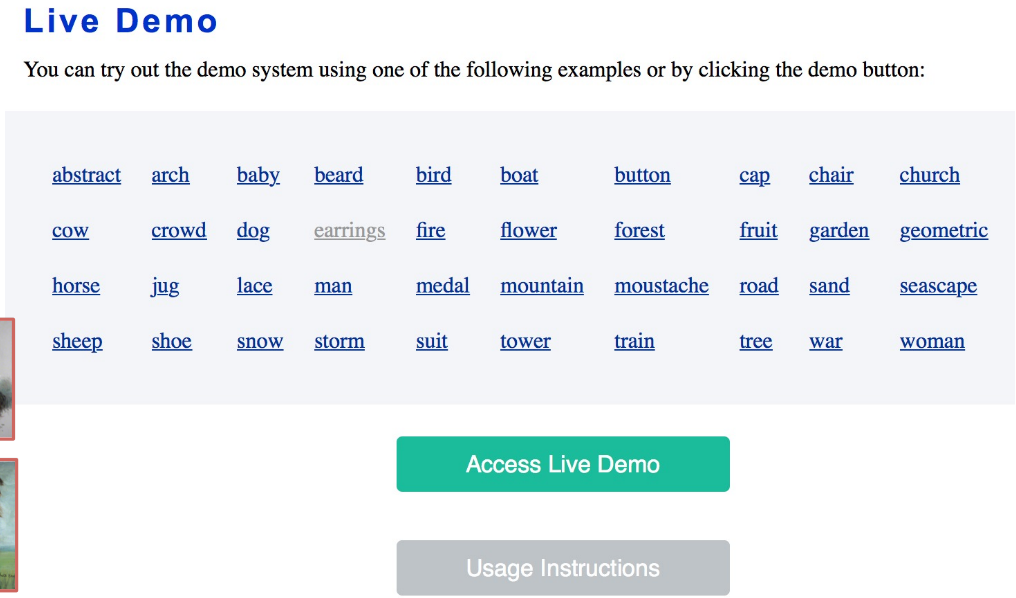
http://zeus.robots.ox.ac.uk/15cillustration/home



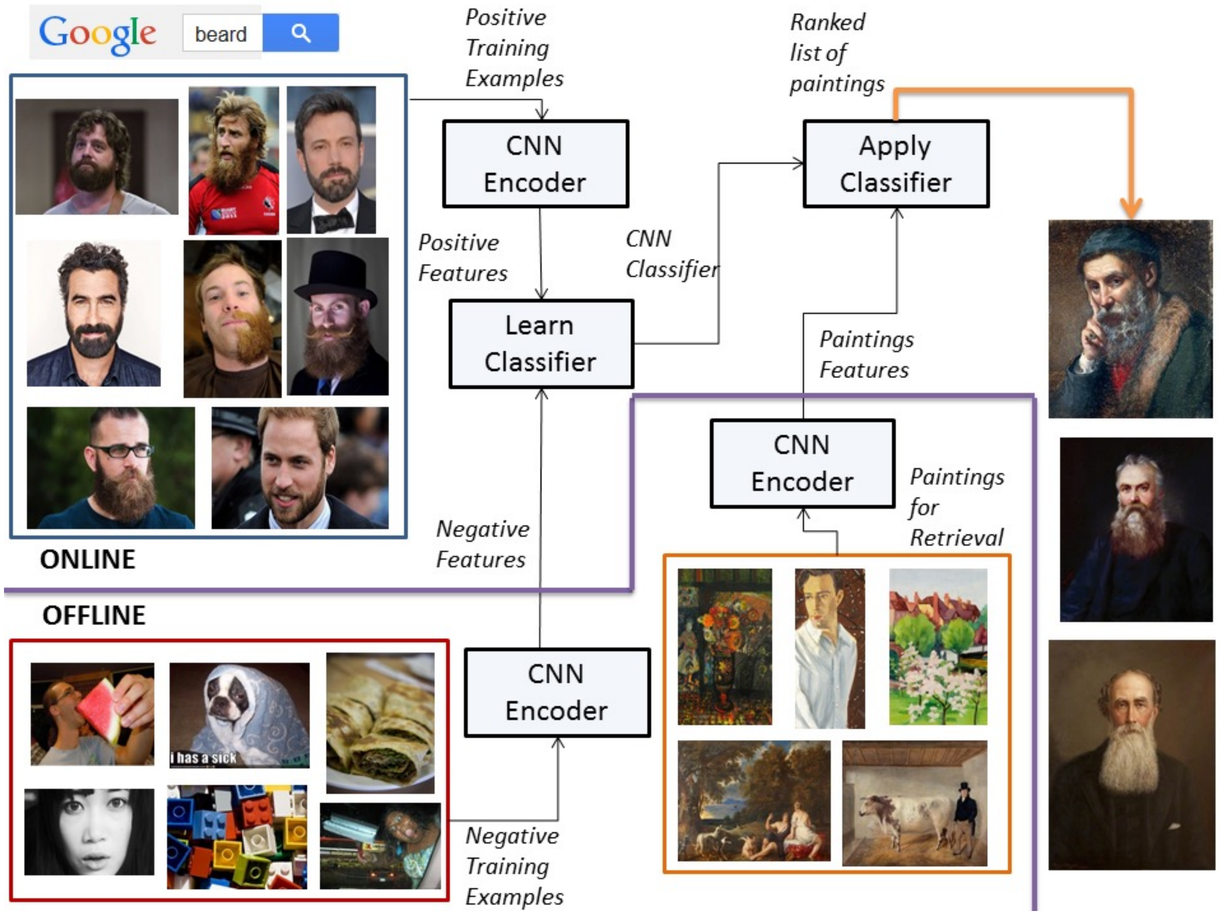
Cristina Dondi et al., Printing R-Evolution and Society 1450-1500. Fifty Years that Changed Europe (Edizioni Ca'Foscari, 2020), 839–869: http://www.robots.ox.ac.uk/~vgg/publications/2020/dondi20/dondi20.pdf

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





http://www.robots.ox.ac.uk/~vgg/research/art_search/

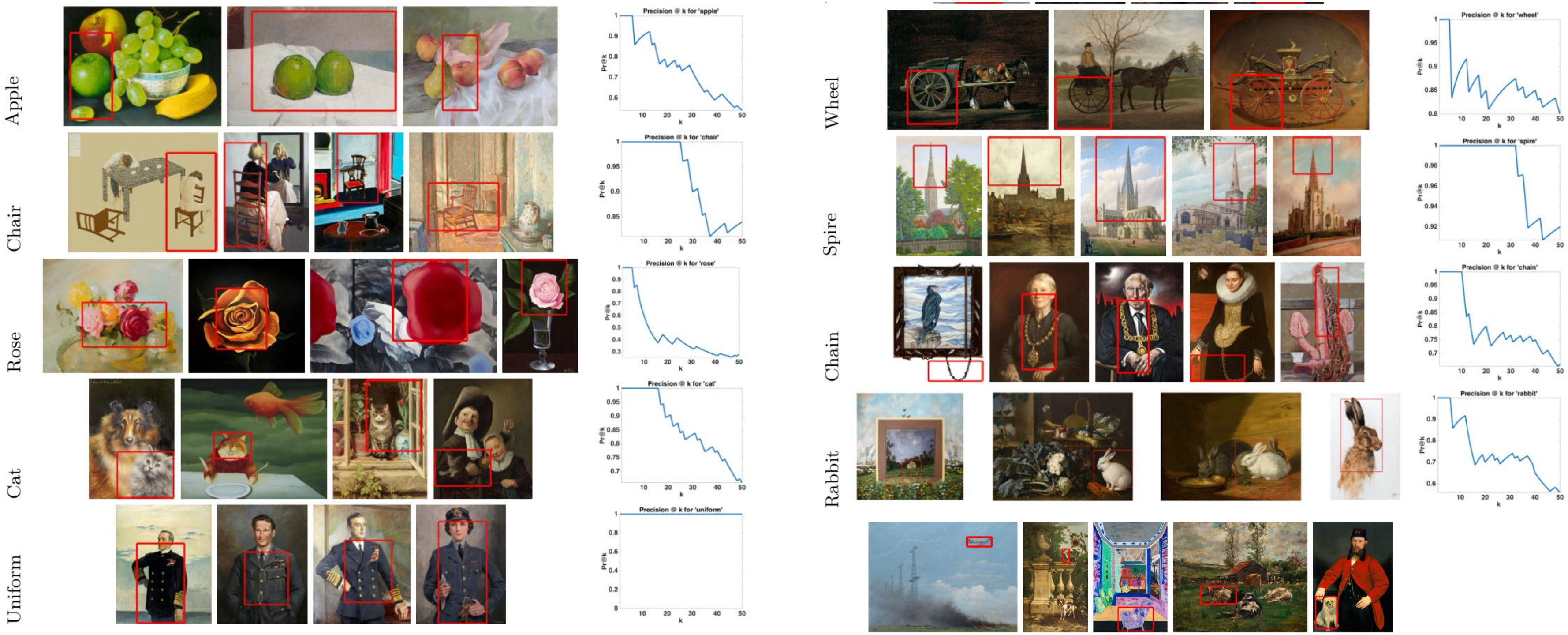


Neural networks for classification of image content

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

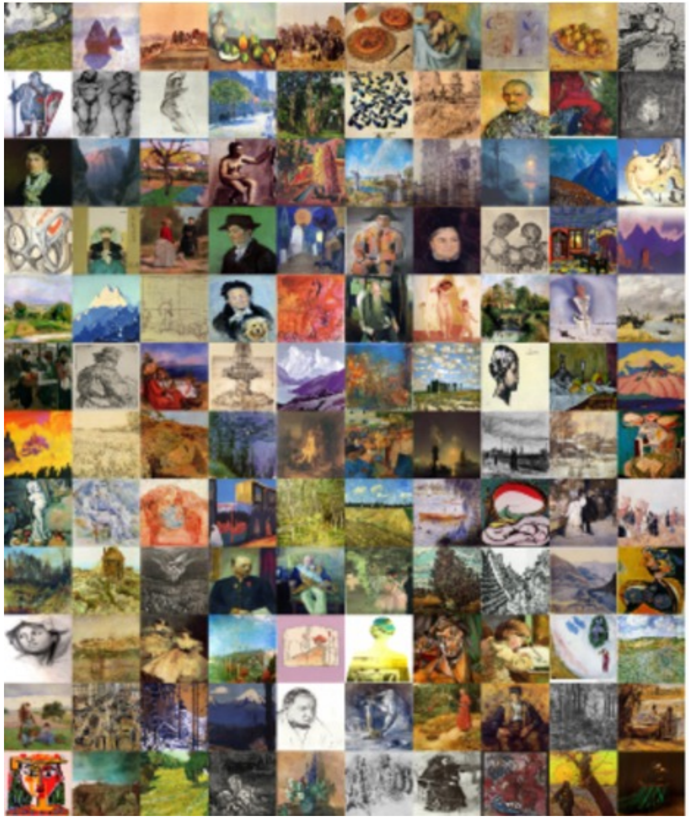
E. J. Crowley and A. Zisserman, „The State of the Art. Object Retrieval in Paintings using Discriminative Regions," *British Machine Vision Conference*, 2014. http://www.robots.ox.ac.uk/~vgg/publications/2014/Crowley14/crowley14.pdf

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

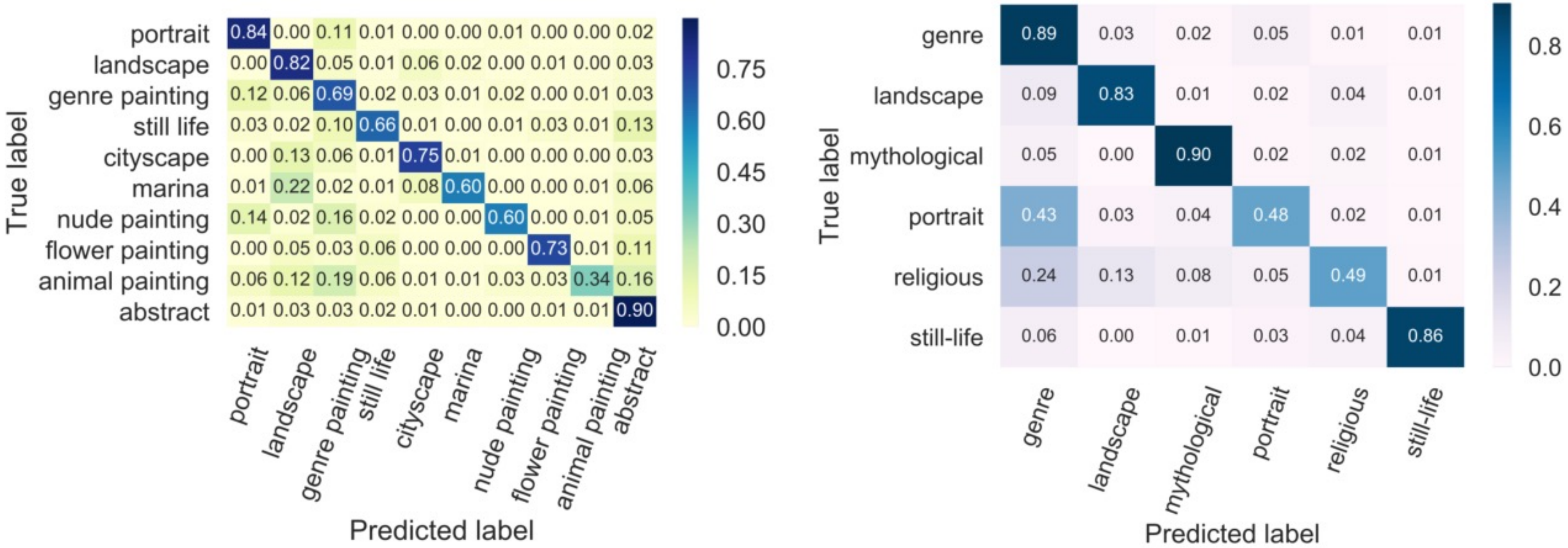
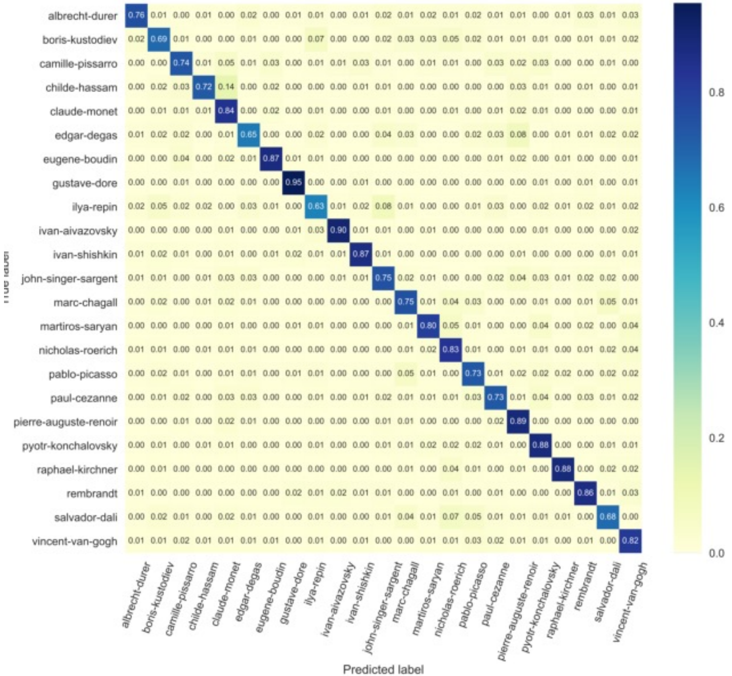


Figure 12. Confusion matrix for WikiArt (left) and WGA (right) **genre** classification

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



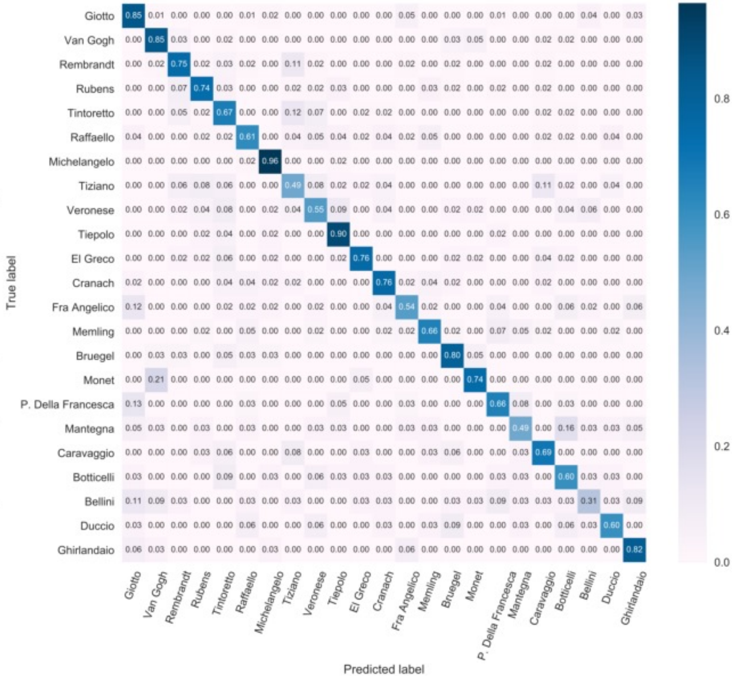


Figure 13. Confusion matrix for WikiArt (left) and WGA (right) **artist** classification

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

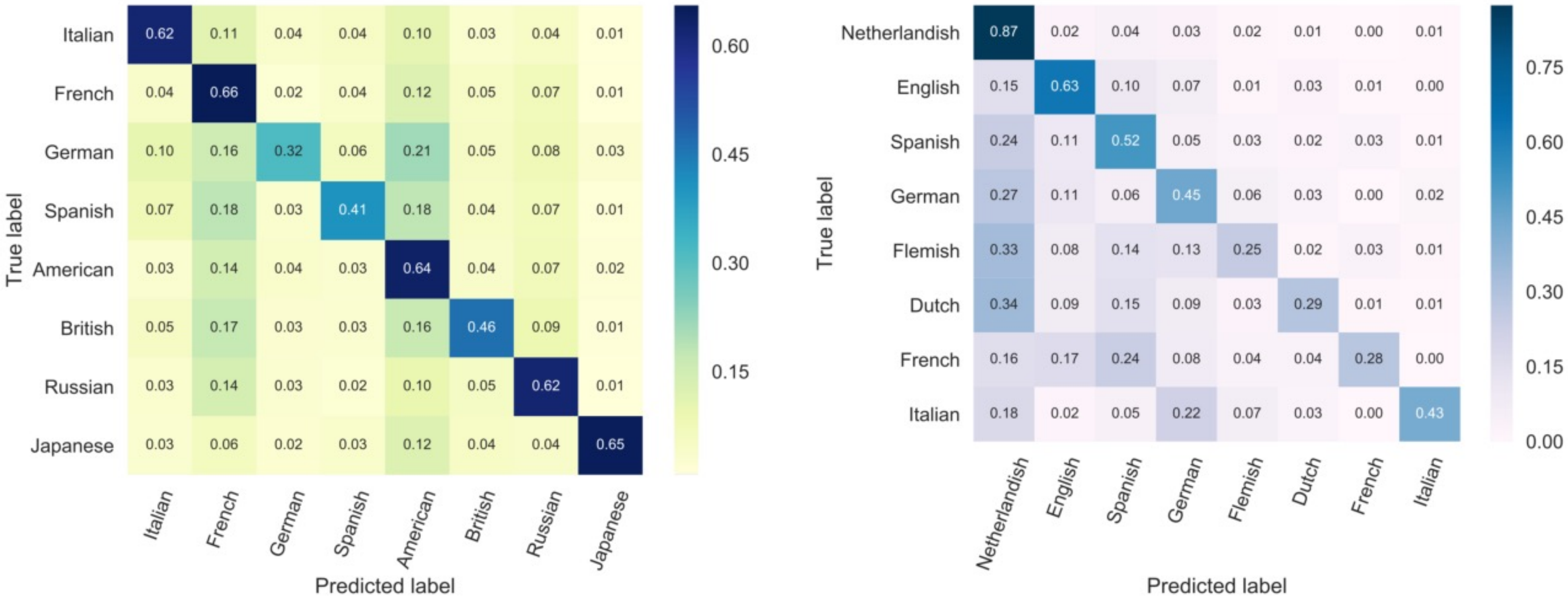


Figure 14. Confusion matrix for WikiArt (left) and WGA (right) **nationality** classification

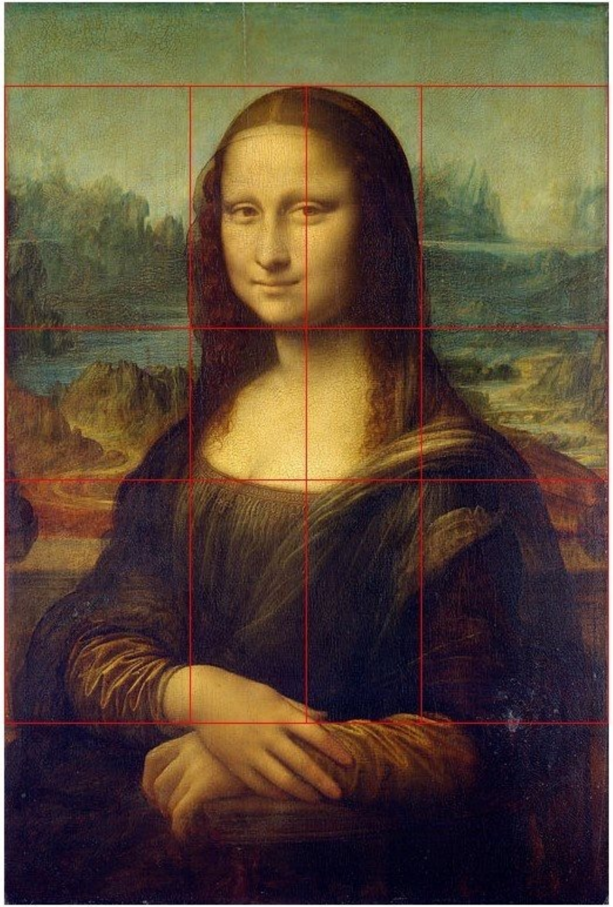
- Evaluation of CNNs pre-trained for various tasks, ranging from object and scene recognition to mood labelling.
- Analysis of various aspects of image similarity. Fine-tuning models can be used to retrieve images with similar styles or content.

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

HOW IS THE PICTURE STRUCTURED?

- Compositional Analysis

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

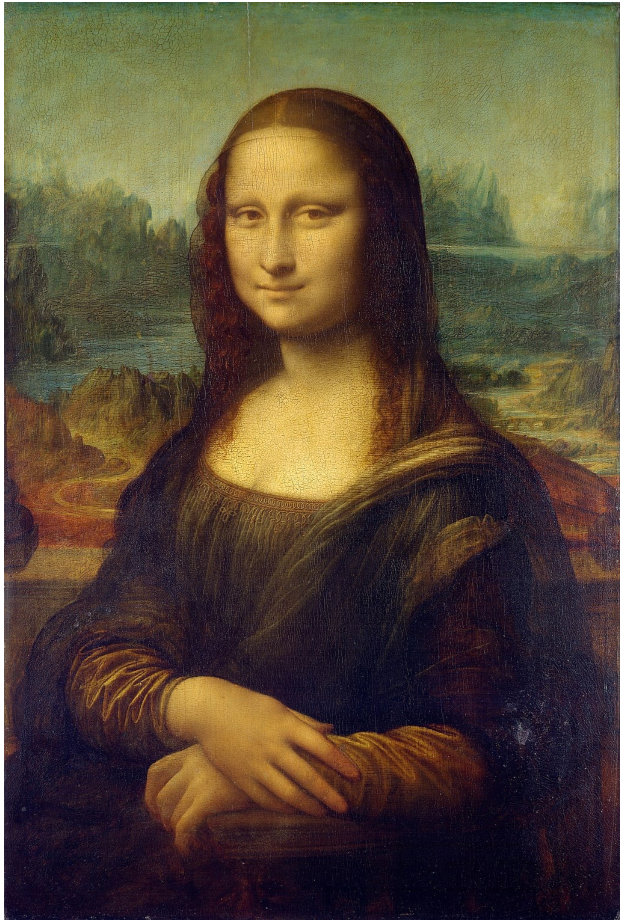


Gillian Rose, *Visual Methodologies. An Introduction to Researching with Visual Materials,* 4th ed. (London: SAGE, 2016), 56–84.

COMPOSITION

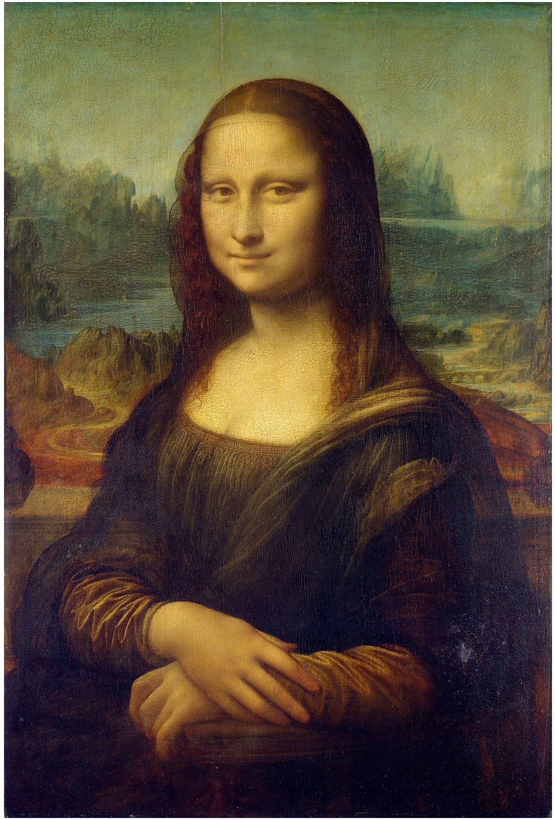
is composed of the following elements:

- 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

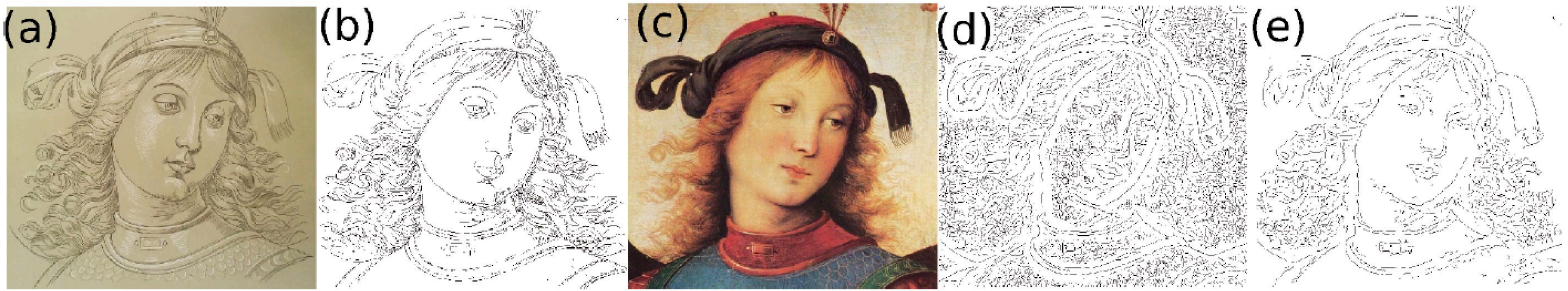
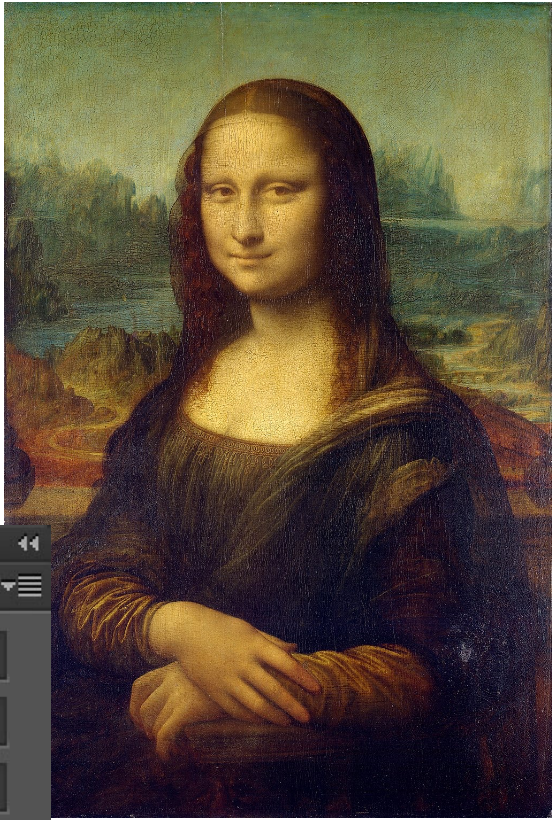


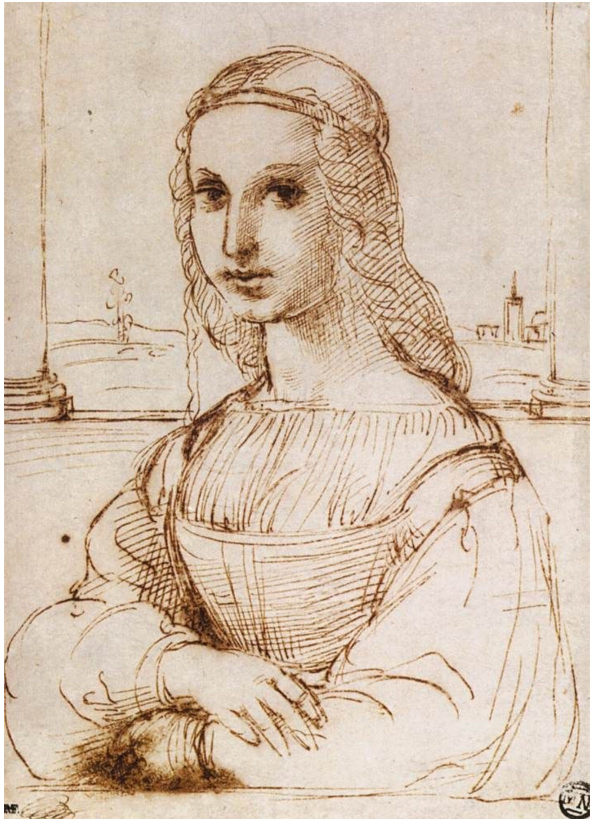
Fig. 3. (a) Johann Anton Ramboux reproduction of (c) Pietro Perugino, *Assumption of the Virgin with four Saints*, 1500 (b) Noise-free contours of the Ramboux reproduction (a) using LoG filters (d) Binary Pb edge-signal of the Perugino (e) Relevant contours of the painting that match to contours of the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

Antonio Monroy, Peter Bell und Björn Ommer, „Morphological analysis for investigating artistic images,"
Image and Vision Computing 32 (2014), 414–423

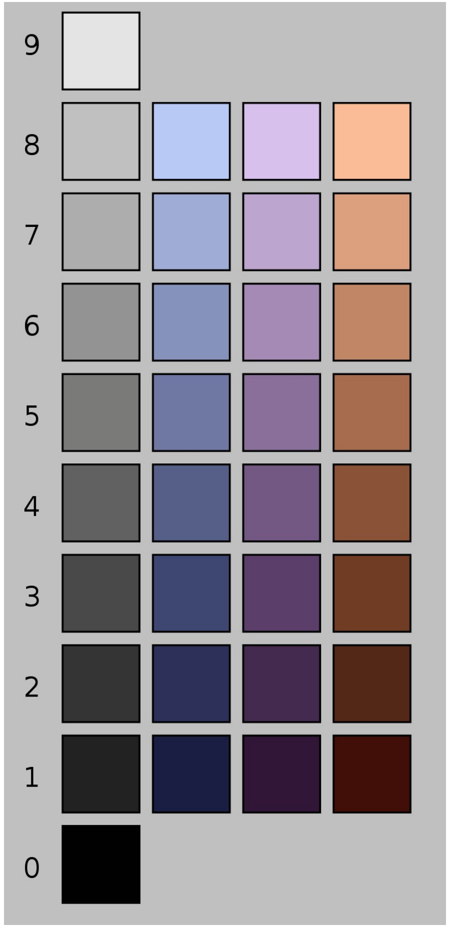
COLOUR

- Hue
- Colour brightness
- Saturation





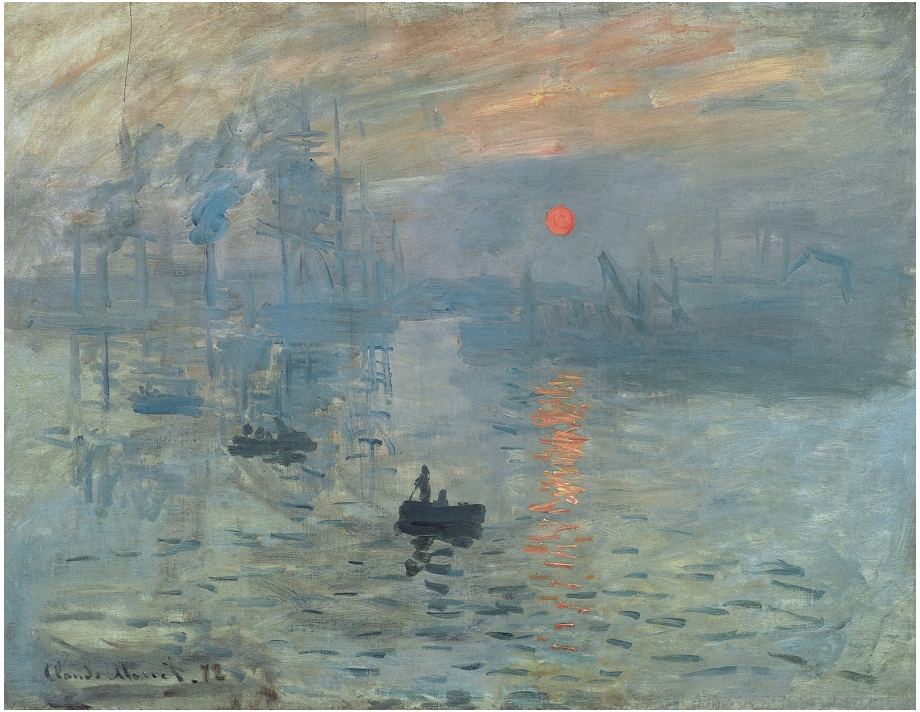
Zeichnung Raphaels (ca. 1505-07), Louvre 3882:
https://www.louvre.fr/en/oeuvre-notices/head-and-shoulders-woman-three-quarters-profile-facing-left-folded-arms



COLOUR BRIGHTNESS

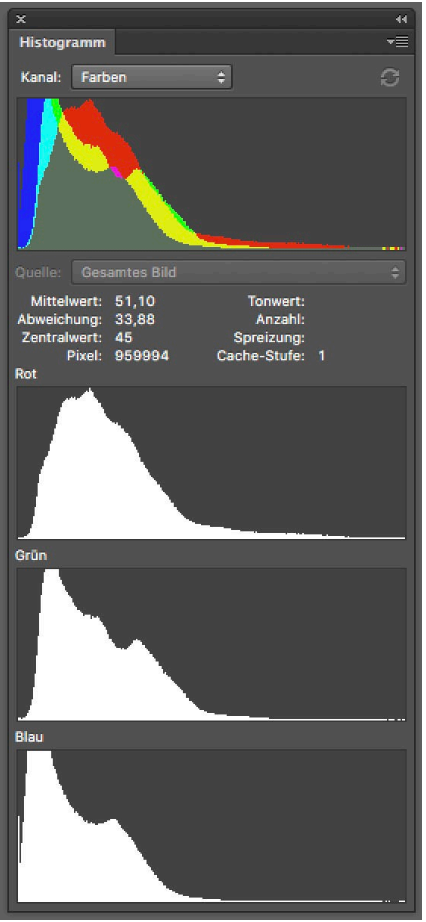
describes how strongly light is reflected by objects of the respective colour. The more light is reflected, the higher the value.

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



Claude Monet, Impression, soleil levant, 1872

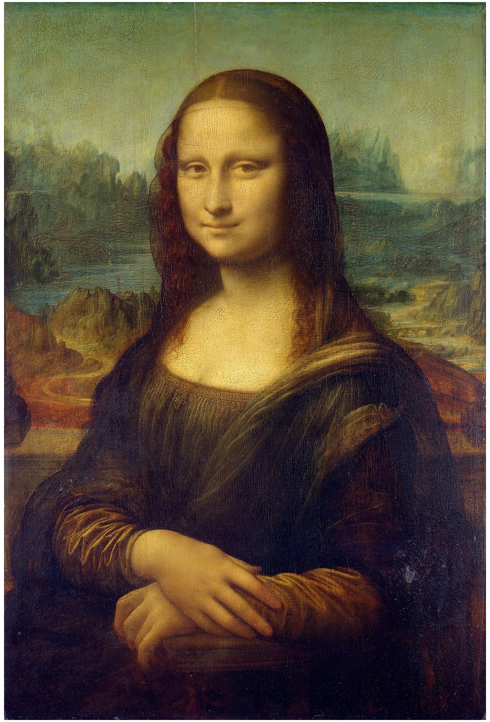
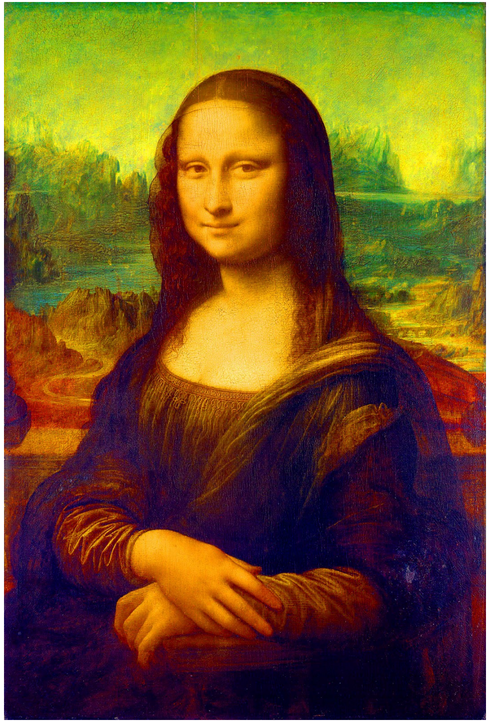
https://upload.wikimedia.org/wikipedia/commons/5/54/Claude_Monet%2C_Impression%2C_soleil_levant.jpg



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

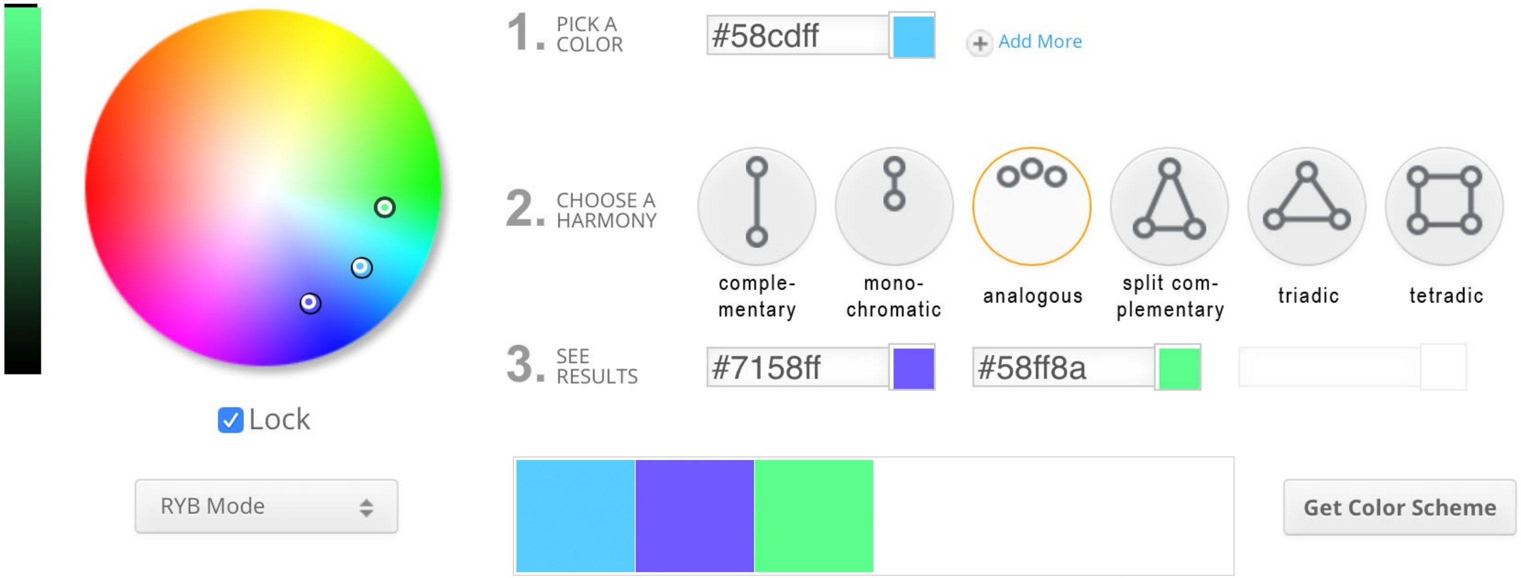
as a linear combination of colour variance and chroma value (ratio to the brightness and saturation of a similarly illuminated area).

D. Hasler and S.E. Suesstrunk, Measuring colorfullness 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

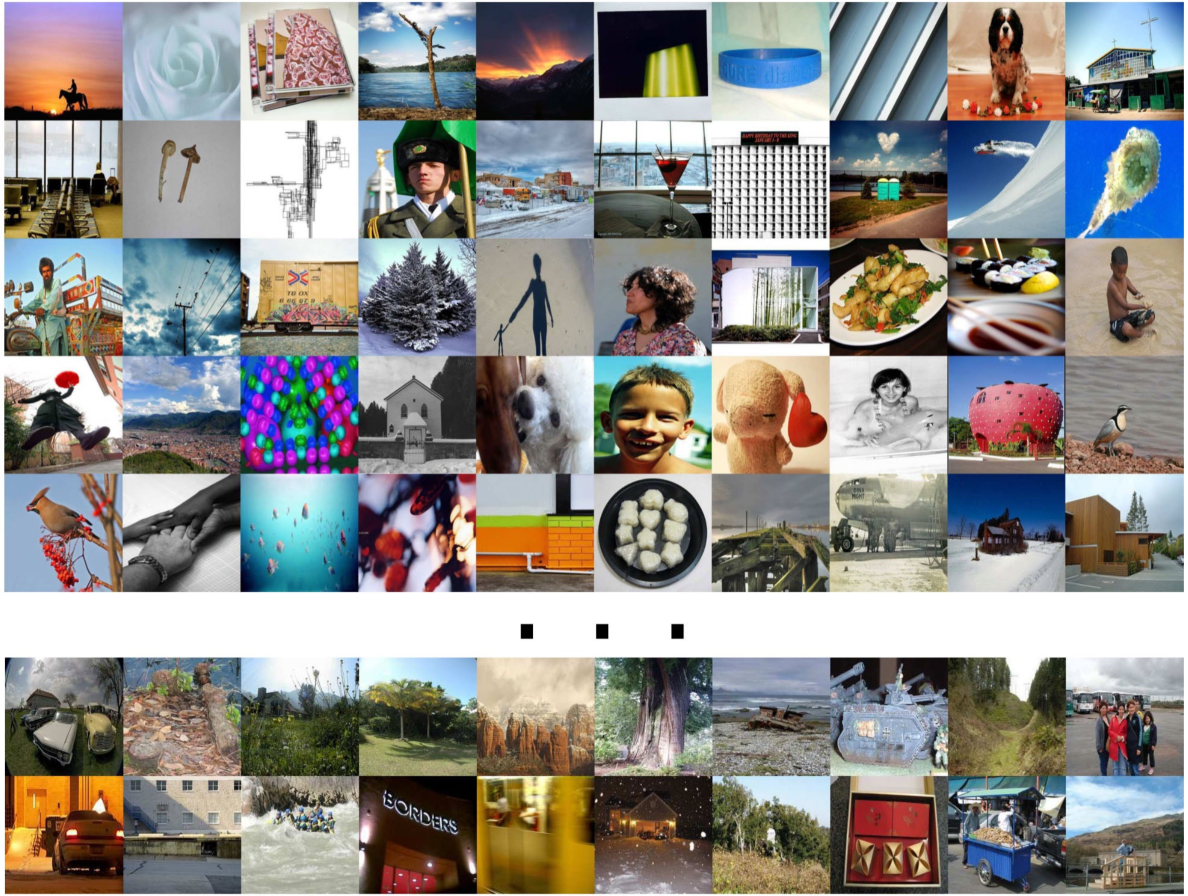
COLOUR HARMONY

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



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.

COMPOSITION: COLOUR CONTRASTS

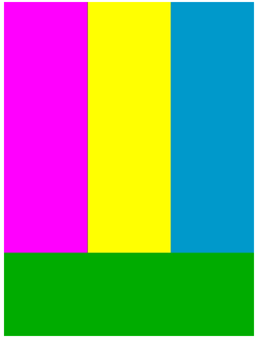


S. Dhar, V. Ordonez and T.L. Berg, High level describable attributes for predicting aesthetics and interestingness, in: Computer Vision and Pattern Recognition 2011 (Colorado Springs: IEEE, 2011), 1657–1664: http://www.cs.virginia.edu/~vicente/files/aesthetics_cvpr11.pdf

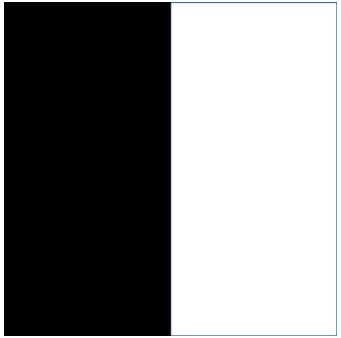
Y. Ke, X.O. Tang and F. Jing, The design of high-level features for photo quality assessment, in Proceedings of 2006 IEEE computer society conference on computer vision and pattern recognition (New York: IEEE, 2006), 419–426.

COLOUR CONTRASTS

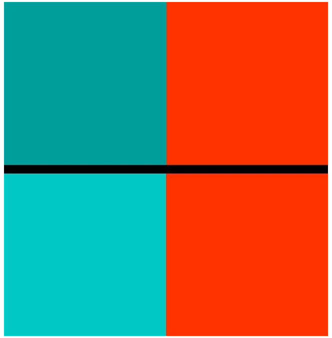
Johannes Itten, *The Art of Color: The Subjective Experience and Objective Rationale of Color*. (New York: 1961)
http://de.wikipedia.org/wiki/Sieben_Farbkontraste



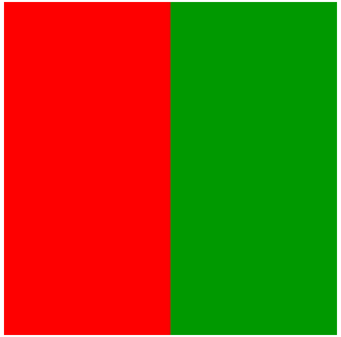
Colour-on-contrast



Light-dark contrast

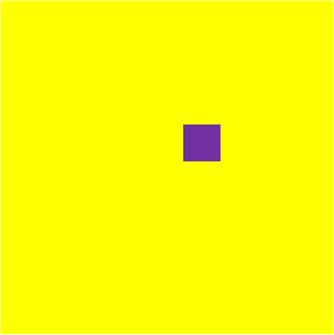


Cold-warm contrast



Complementary contrast

Quality contrast



Quantity contrast

Simultaniouscontrast

COLOUR CONTRASTS

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

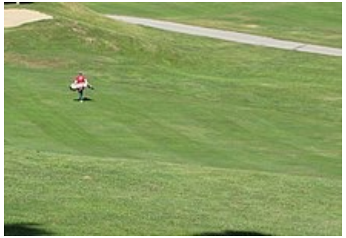
Colour-on-contrast

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

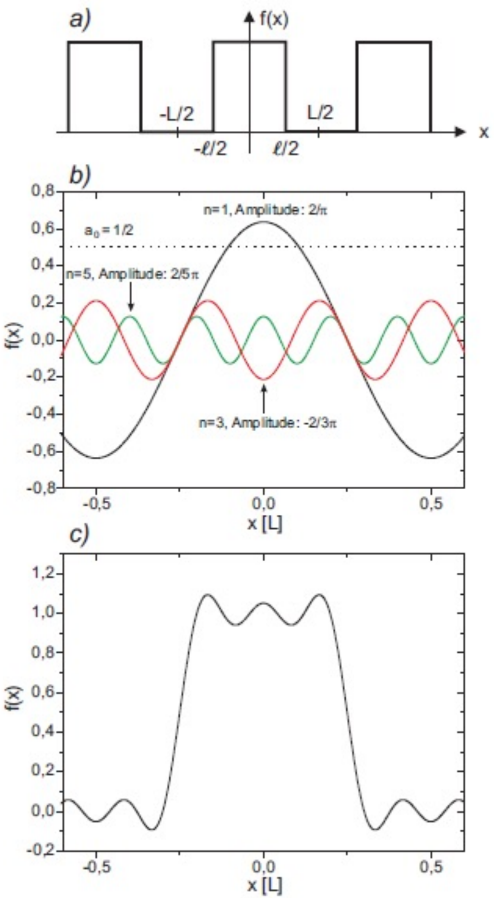
Cold-warm-contrast

Complementary contrast

Quality contrast

Quantity contrast

Simultaniouscontrast

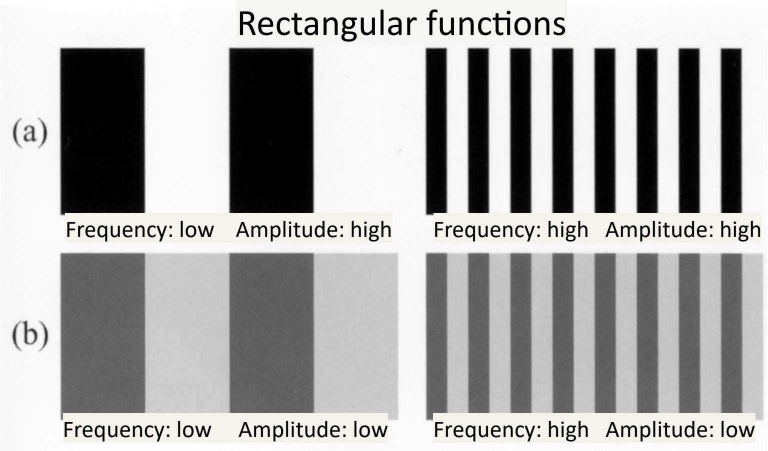


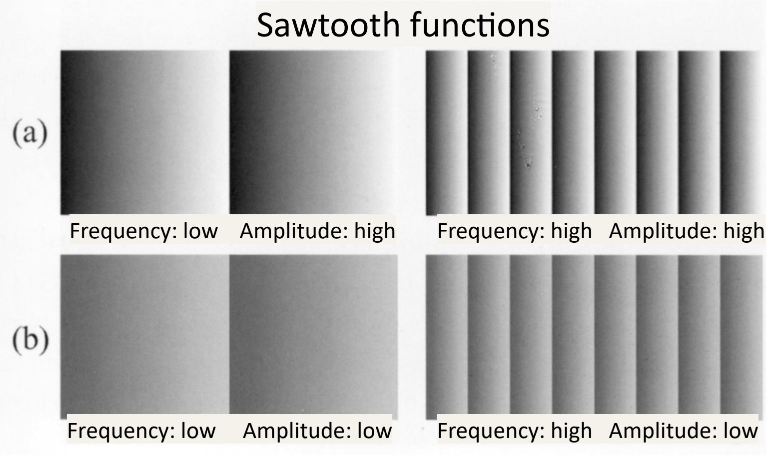
CONTRAST DISTRIBUTION

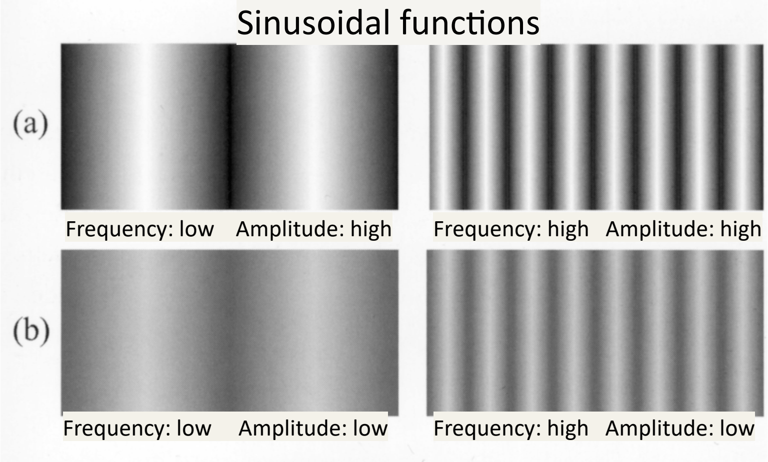
Calculation of sharpness based on colour, luminance, focus or edge sharpness

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







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

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

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

continuous transitions (sinusoidal function)

Combination of discrete and continuous transitions (sawtooth function)

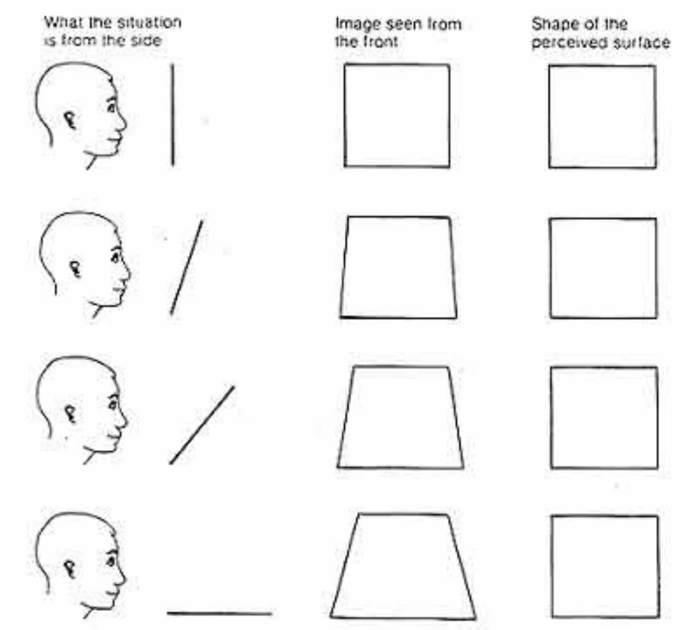
TEXTURE

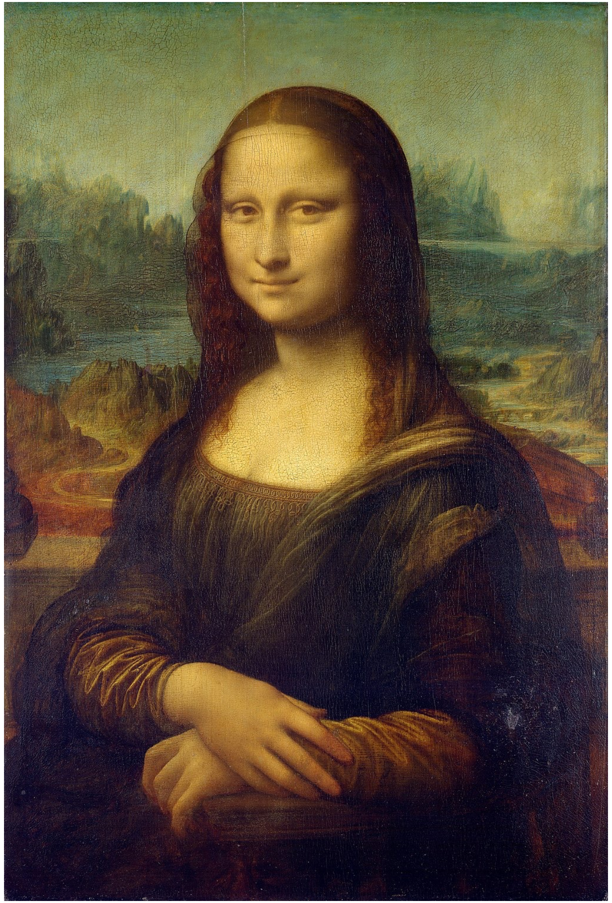
physical surface qualities that can be realised as optical illusions.

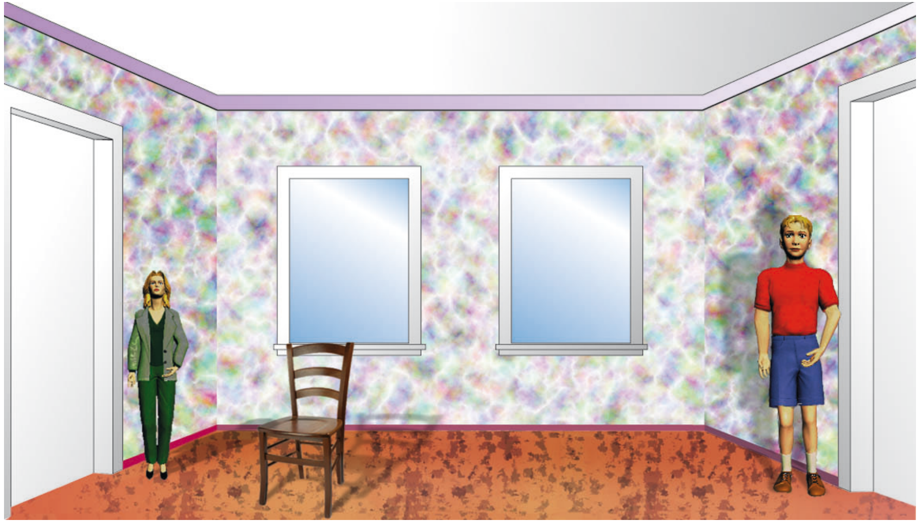
https://www.instagram.com/p/B0EW6VLi4DH/

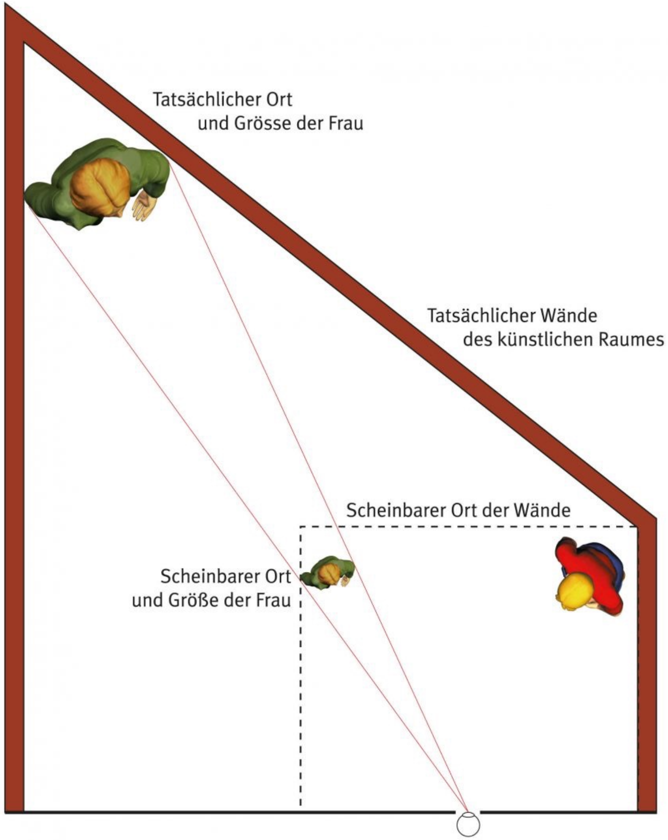
SPACE

three-dimensional extension around, over and within an object









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

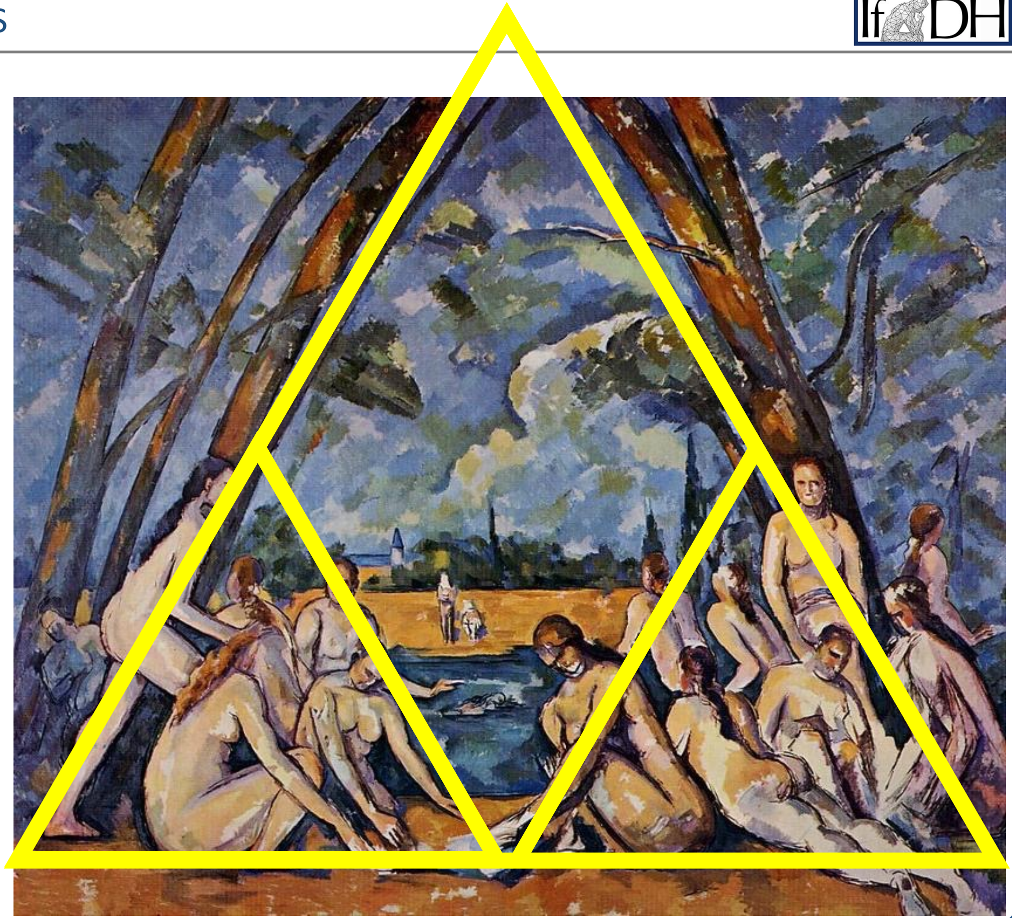
Rembrandt van Rijn, Christus in Emmaus, 1648. The local change of a light source changes the entire picture light.

(a) Original

(b) zwei Lichtquellen

Caravaggio, The Calling of St Matthew, 1599-1600

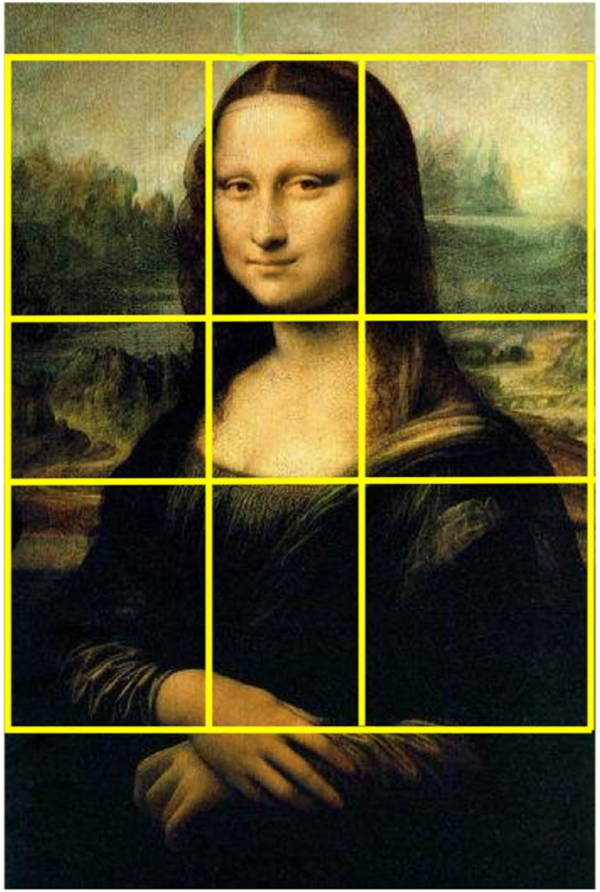
https://www.instagram.com/p/B0EW6VLi4DH/



Paul Cezanne, The great bathers 1898-1905

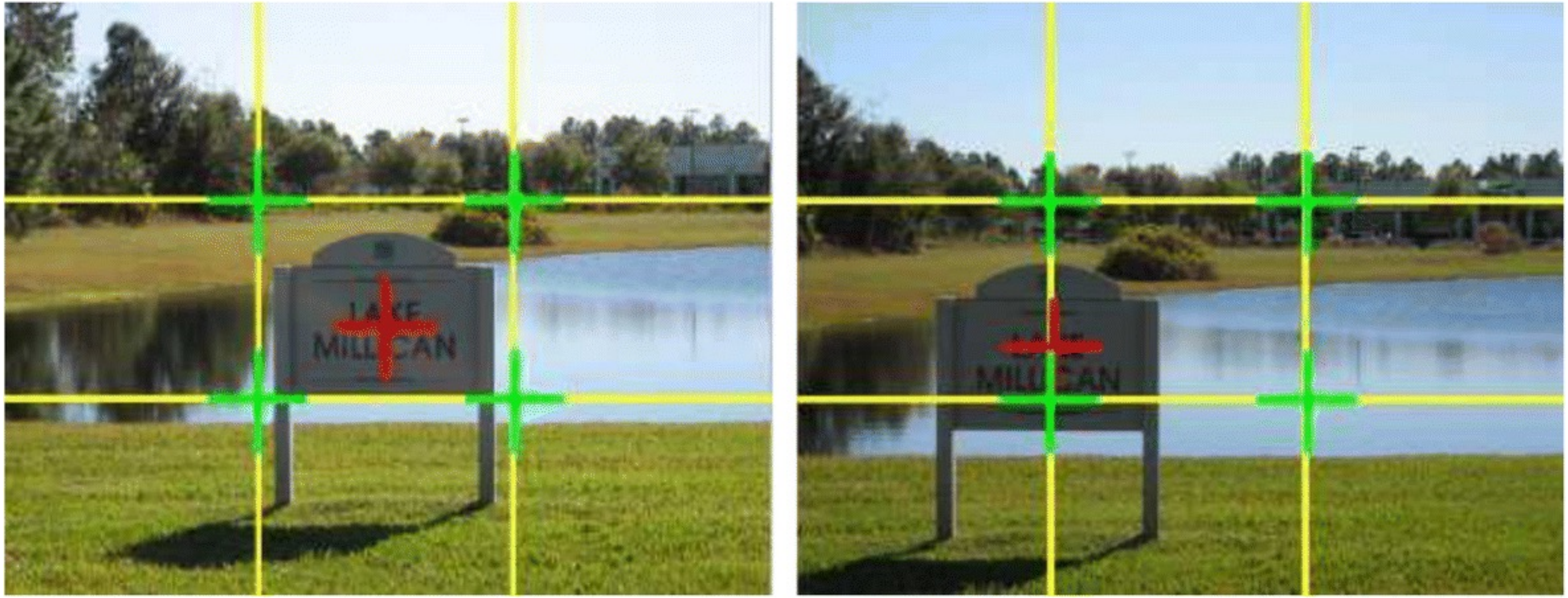
THE GOLDEN RATIO

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



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.

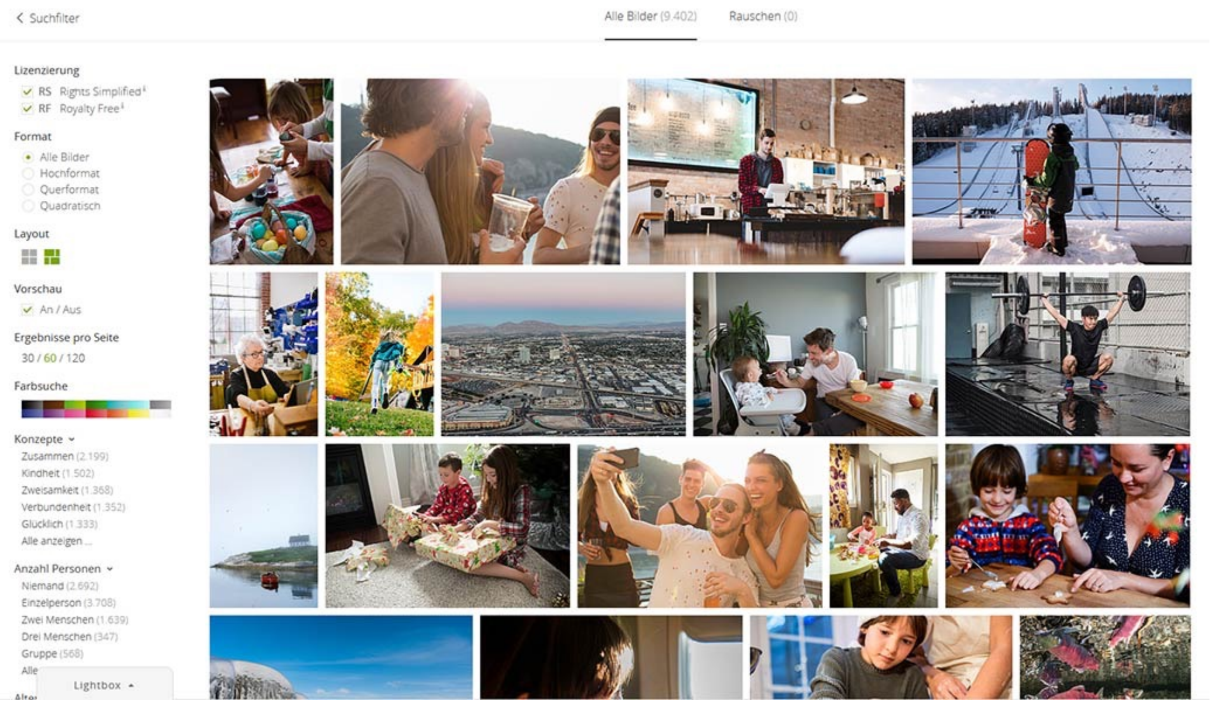
SEGMENTATION OF THE PICTURE INTO REGIONS

https://medium.com/nanonets/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

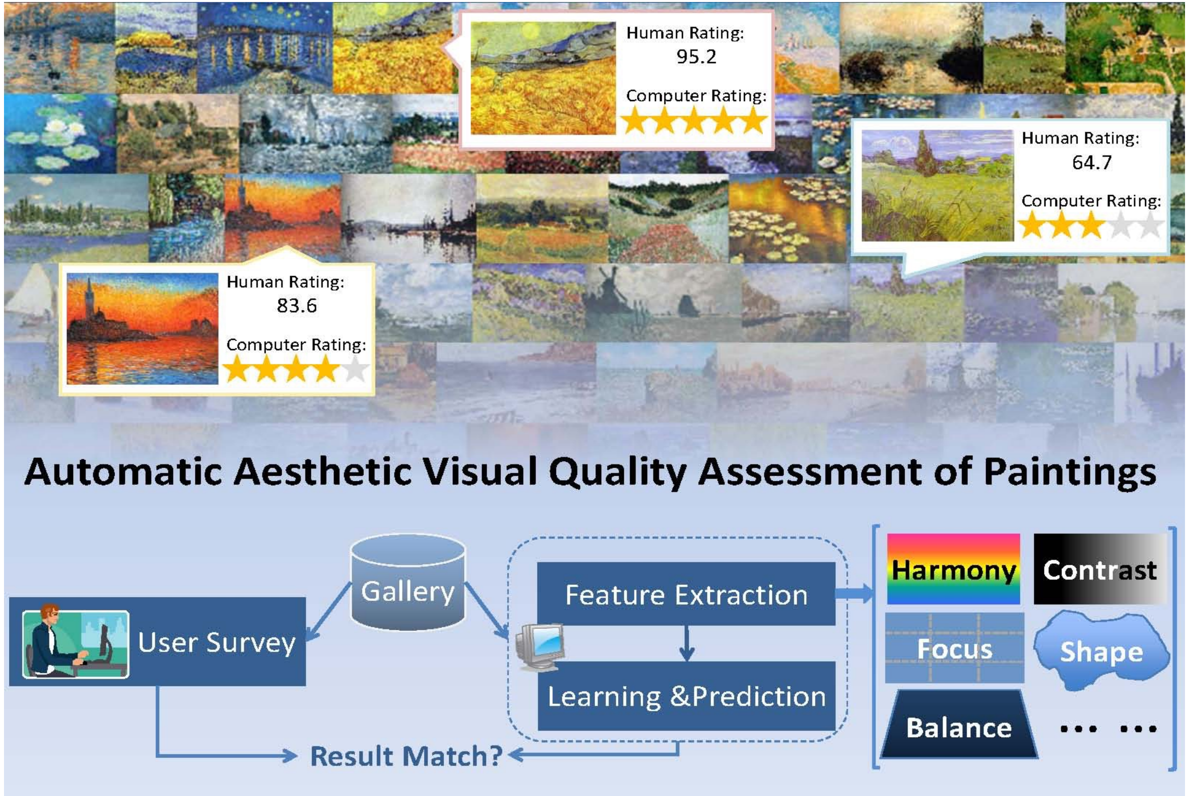
- Motif
- Facial expression
- Lighting
- Polls



https://www.plainpicture.com/de

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/congcong/research/research.html

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

- Artist attribution, dating, regional style
- Stilometry

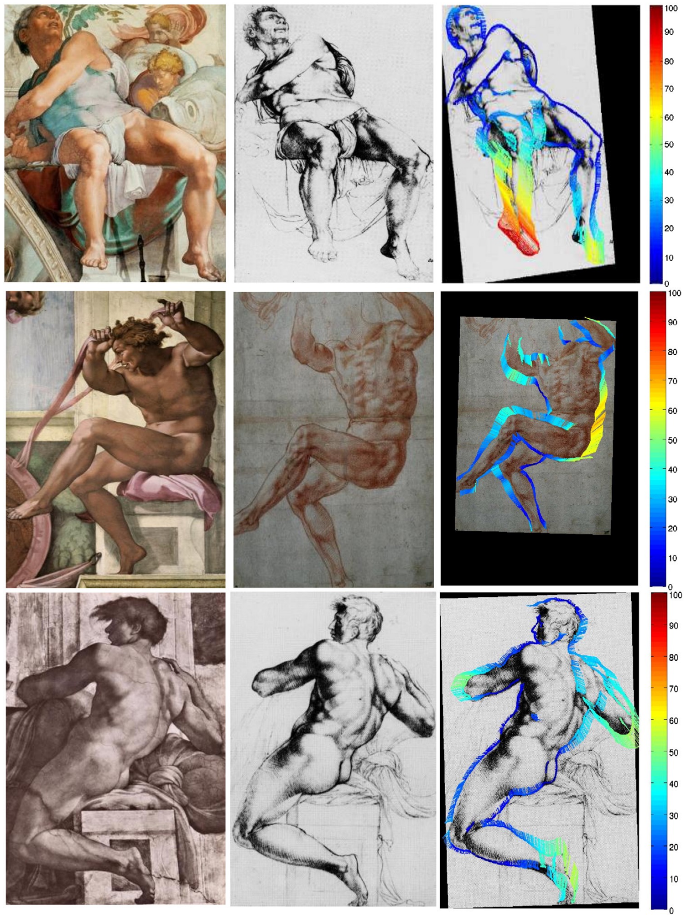
Early copy in the Prado

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

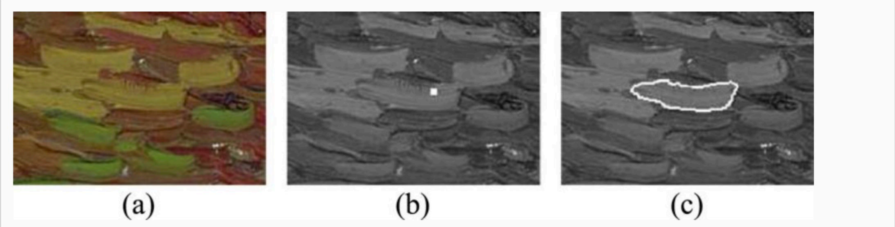
Reconciliation of the differences through precise measurement of the deviations

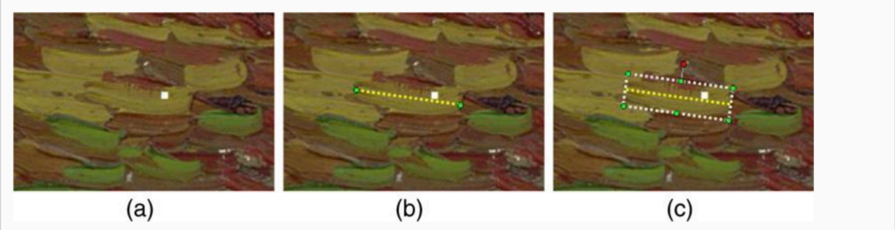
z.B. Comparison of Michelangelo's frescoes in the Sistine Chapel with copies of his preparatory drawings

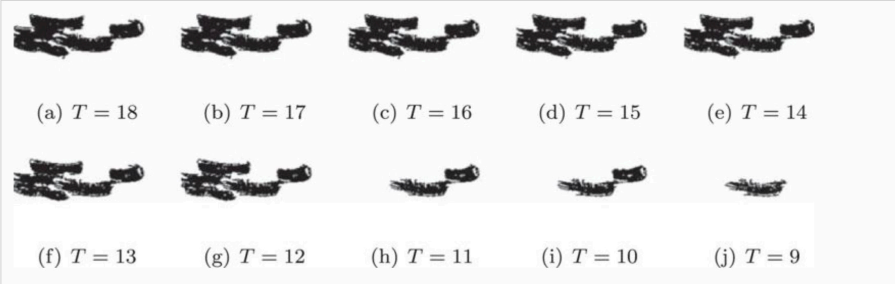
Antonio Monroy Monroy / Peter Bell / Björn Ommer, Morphological analysis for investigating artistic images, Image and Vision Computing 32(6), 2014, 414–423: https://hci.iwr.uni-heidelberg.de/sites/default/files/publications/files/1015831446/monroy_ommer.ivc14.pdf



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







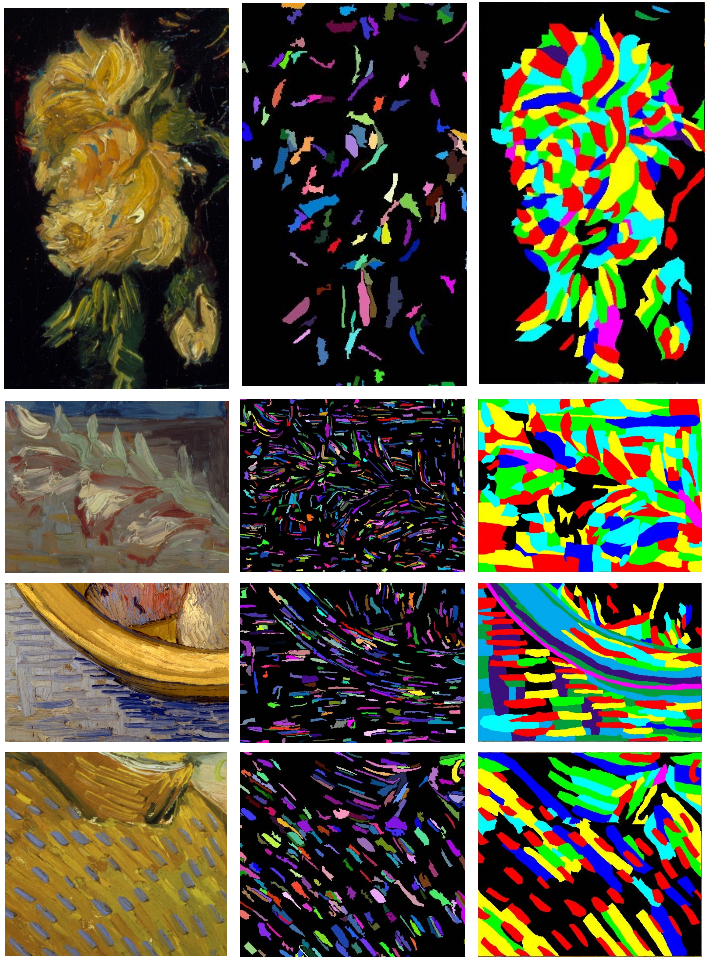
Unüberwachte und annotierte Erkennung der Pinselstriche und Clustering

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)

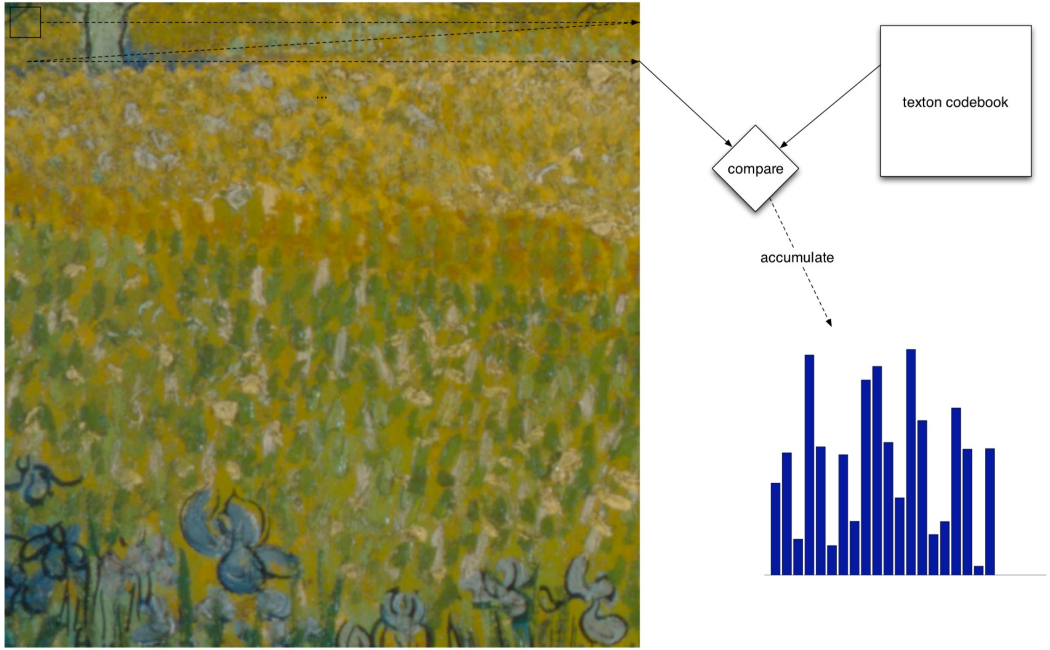
ARTIST ASSIGNMENT THROUGH PATTERN RECOGNITION

Van Gogh

Cuno Amiet

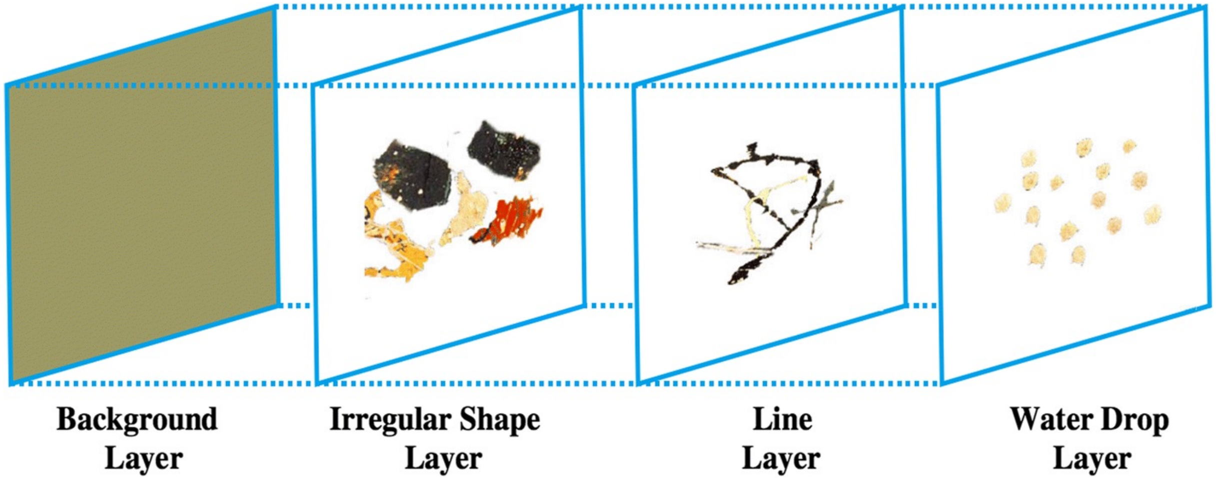


Jia Li et al., Rhythmic Brushstrokes Distinguish van Gogh from His Contemporaries: Findings via Automated Brushstroke Extraction, IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE 2012, 1–17 (http://infolab.stanford.edu/~wangz/project/imsearch/ART/PAMI11/li.pdf)

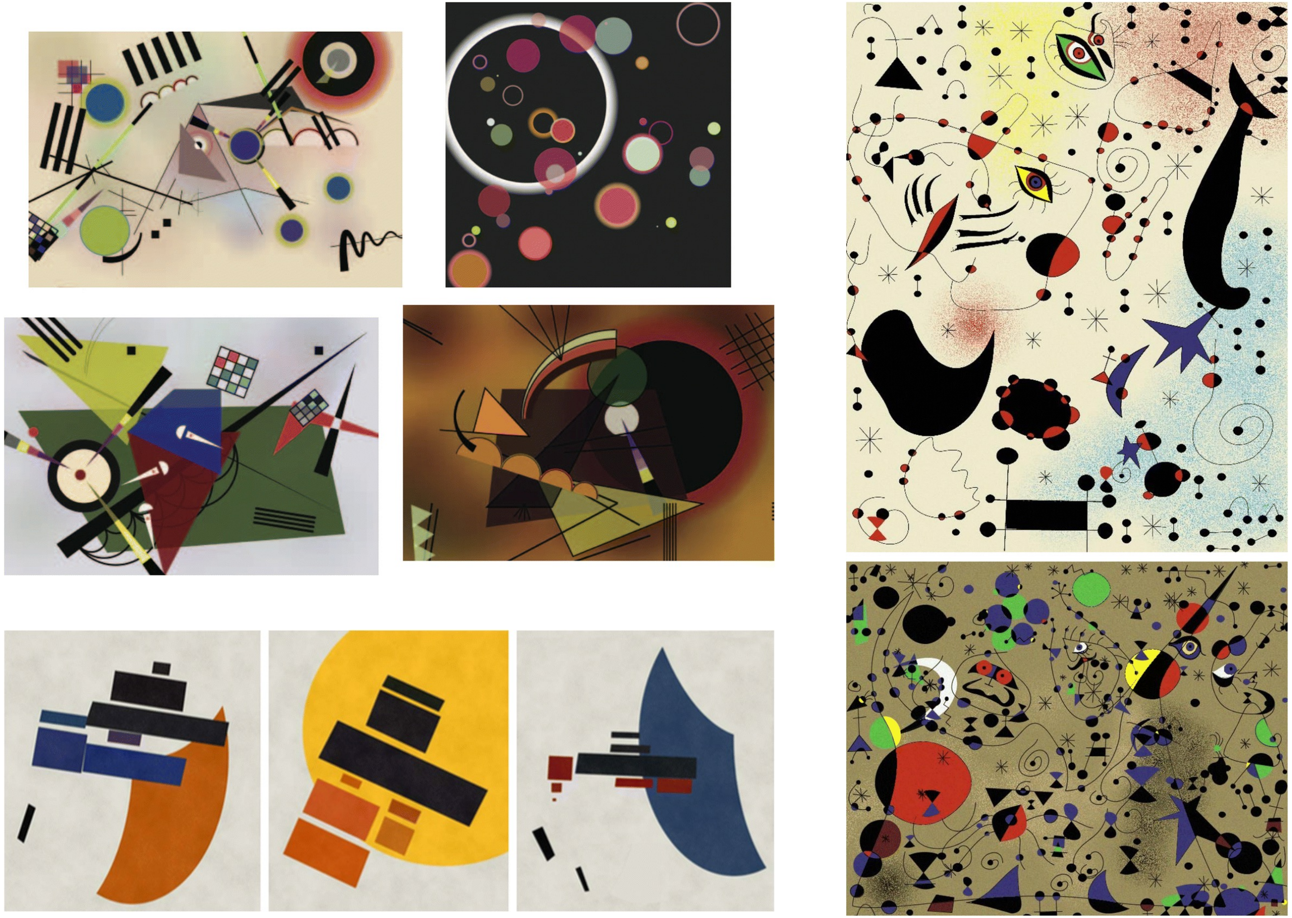


L. van der Maaten, Eric Postma: Identifying the Real Van Gogh with Brushstroke Textons, 2009: https://lyrawww.uvt.nl/~cenv/ticc/reports/TRvdrMaaten.pdf

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.



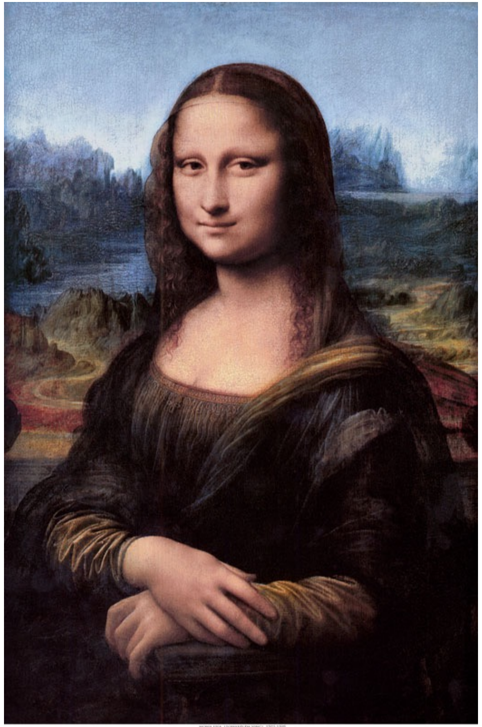
K. Zhang and J.H. Yu, Generation of Kandinsky art, Leonardo 49 (2016), 48–55; L. Xiong and K. Zhang, Generation of Miro's surrealism, in Proceedings of the 9th international symposium on visual information communication and interaction (Dallas: ACM, 2016), 130–137.

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

WHAT DID THE PAINTING ORIGINALLY LOOK LIKE?

- Rekonstruction and Restauration

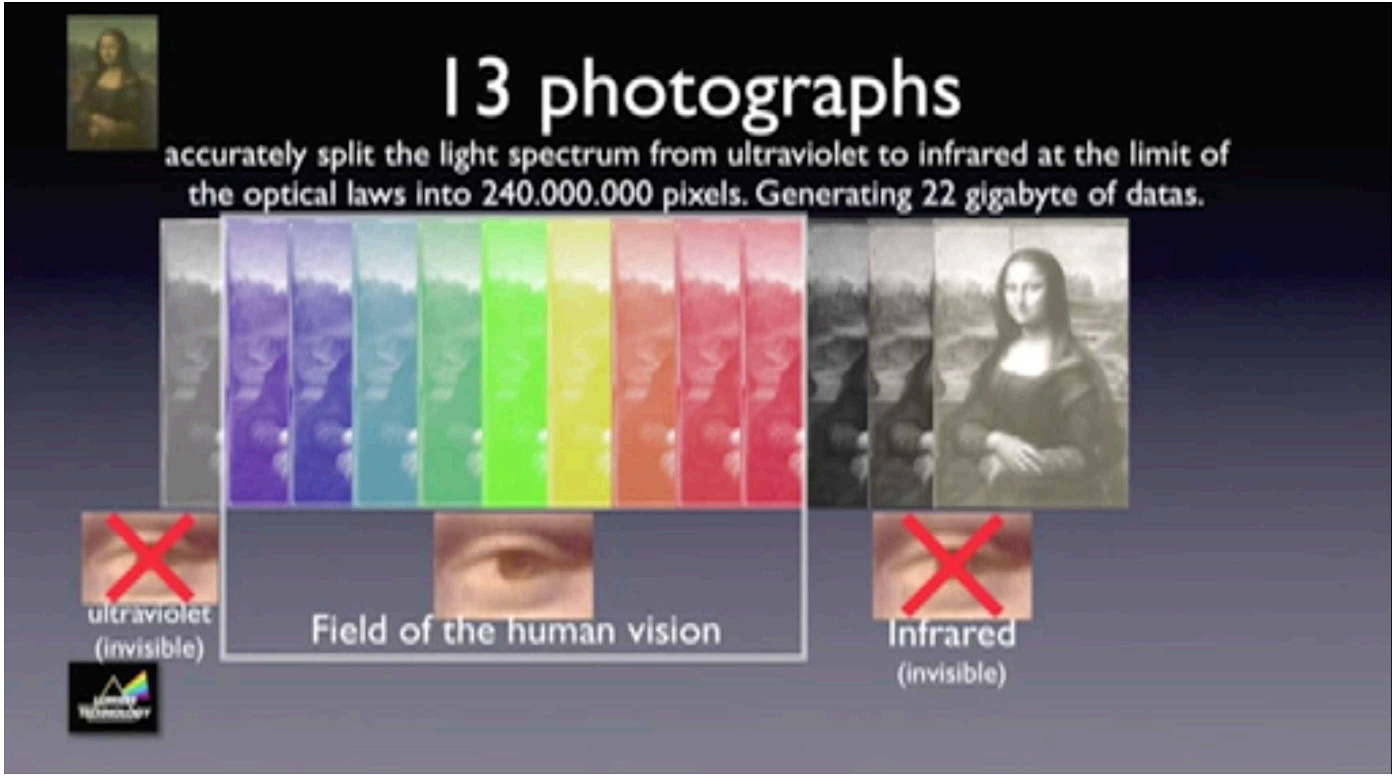
- Optical and chemical processes, digital tone value correction



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

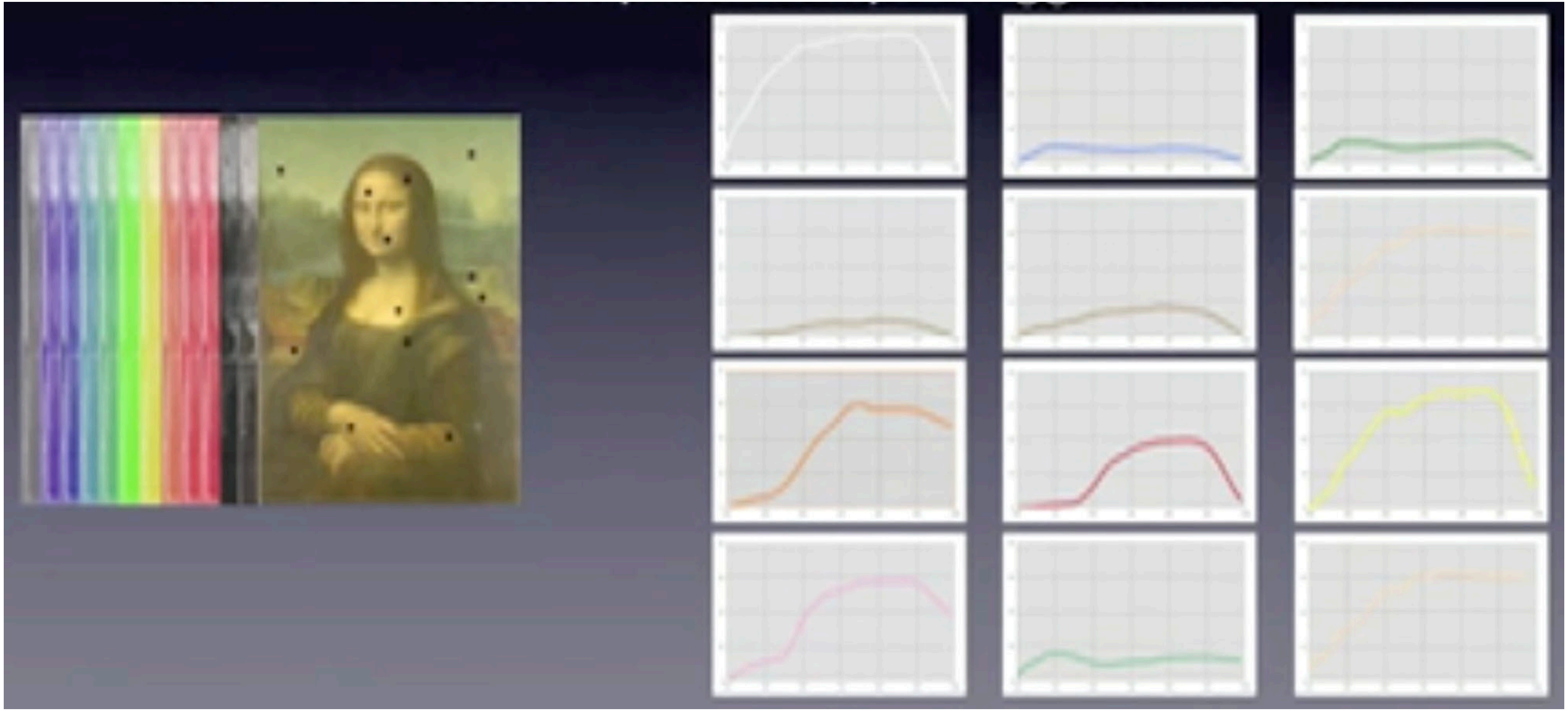
Günther A. Wagner, Einführung in die Archäometrie, Heidelberg: Springer 2007; Horst Czichos / Oliver Hahn, Was ist falsch am falschen Rembrandt?: Mit High-Tech den Rätseln der Kunstgeschichte auf der Spur, München: Hanser 2011.

MULTISPECTRAL ANALYSIS

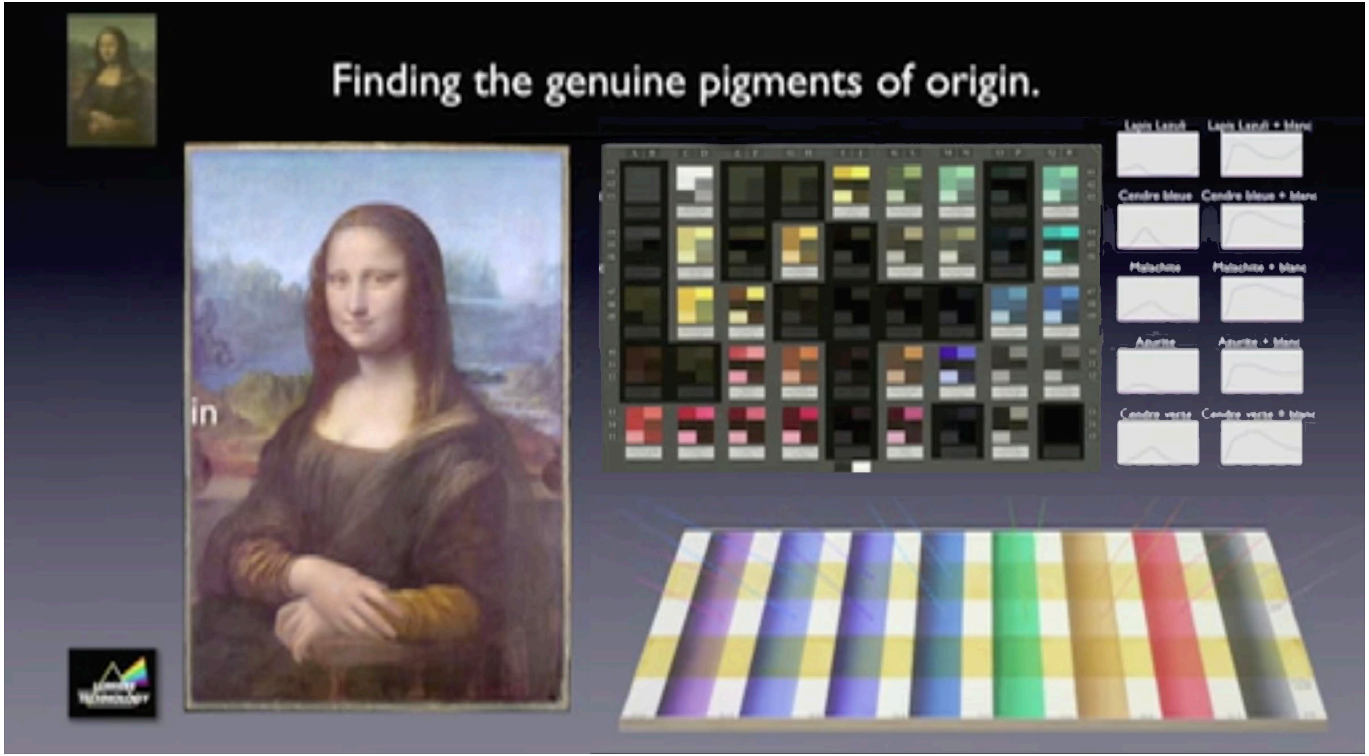


Digital multispectral analysis of the Mona Lisa by Lumiere Technology: https://www.dailymotion.com/video/k3GIpau9WkVvazepCB

MULTISPECTRAL ANALYSIS



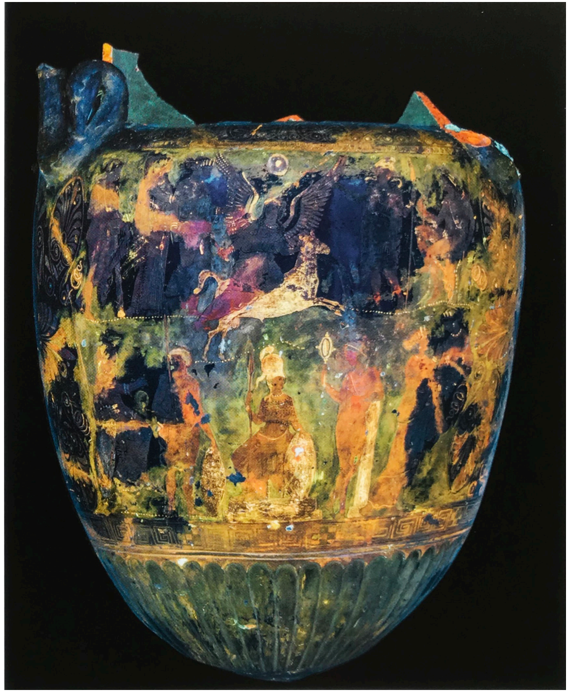
MULTISPECTRAL ANALYSIS



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

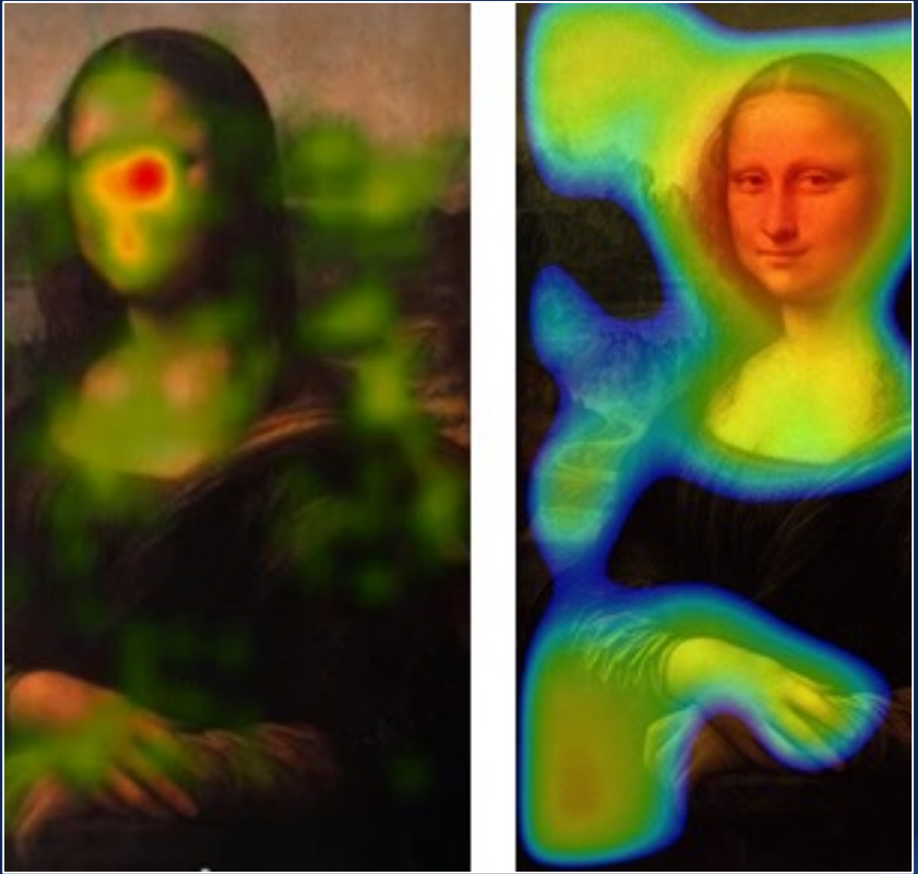
UV-LIGHT

Apul. rf. Volute-krater by the Ilioupersis-P.,
Berlin F 3256 (2008 beforer 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 Grittmann / 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

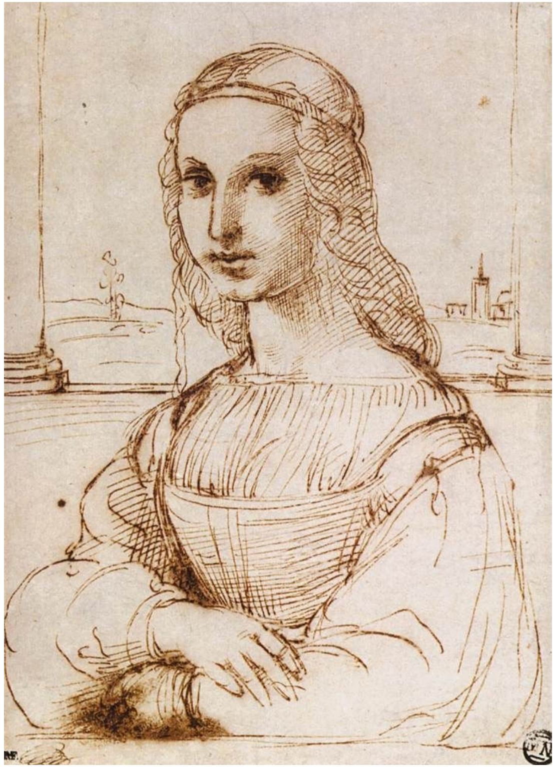
QUANTITATIVE IMAGE TYPE ANALYSIS

- Example: Traian‘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

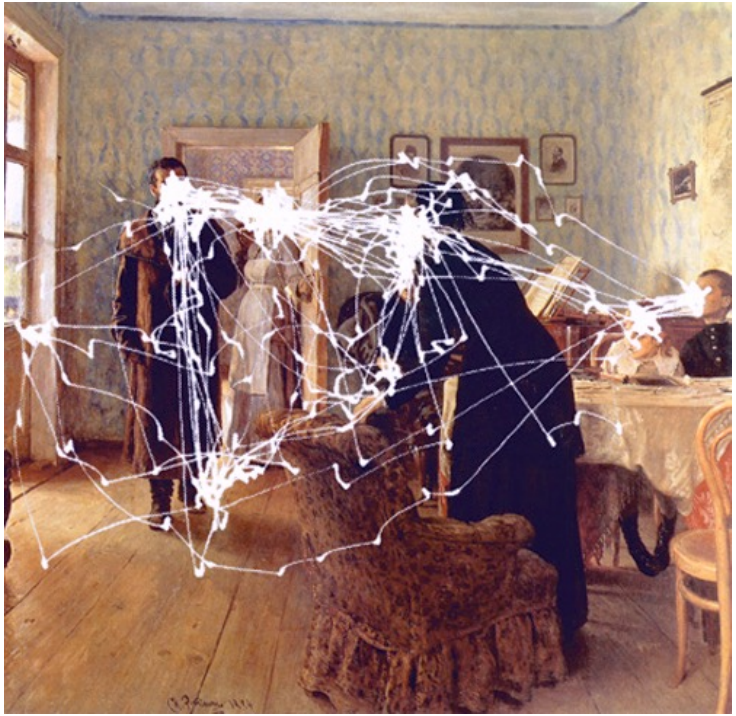
Karl Clausberg, Neuronale Bildwissenschaften, in: Hans Belting u.a., Kunstgeschichte. Eine Einführung, Berlin: Reimer 2008, 337–362

EYETRACKING

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

EYETRACKING

https://www.youtube.com/watch?v=e5Sa3H8QN6c



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

- extensive experiments on CNN fine-tuning

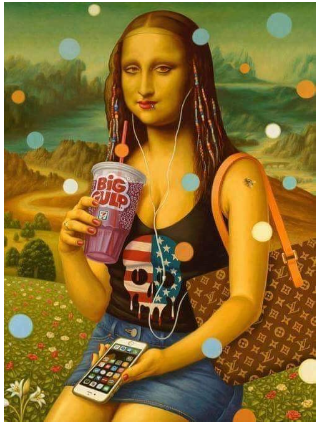
Víctor Camposa, Brendan Joub, Xavier Giró-i-Nietoc, From Pixels to Sentiment. Fine-tuning CNNs for Visual Sentiment Prediction, https://arxiv.org/abs/1604.03489

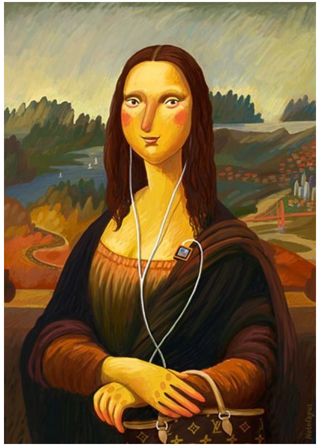
FOR WHICH LINES OF ARGUMENTATION WAS THE IMAGE USED? DID IT UNDERGO A CHANGE OF MEANING?

- ➤ 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

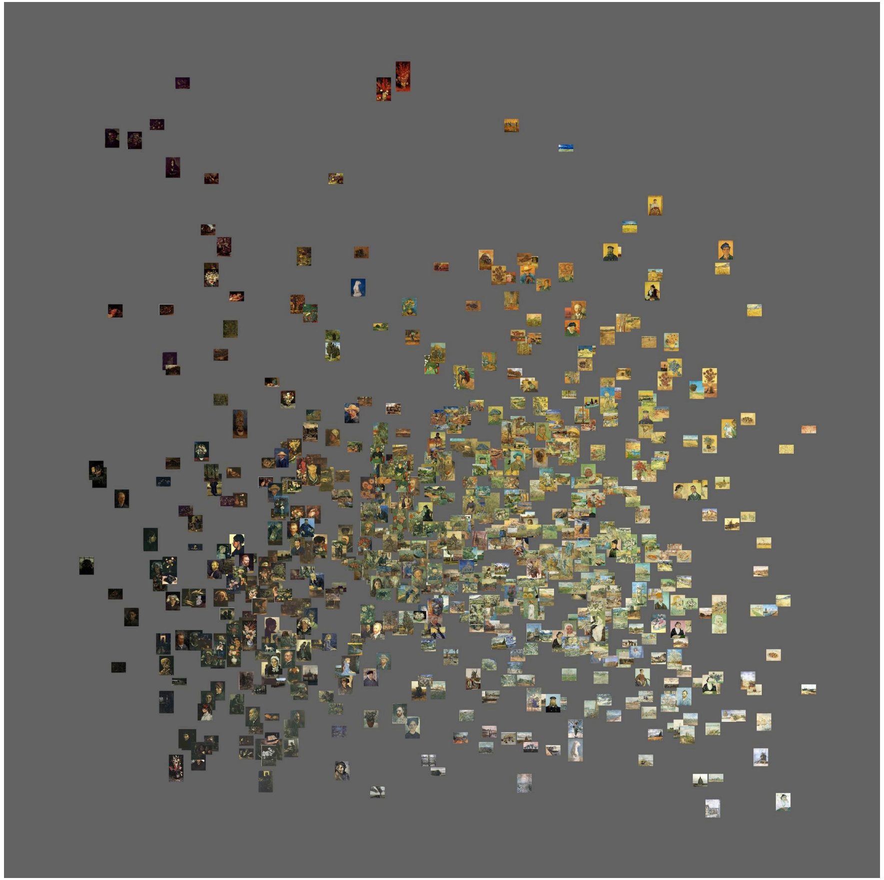
z.B. 986 paintings of van Gogh or 1506 pruss. coins of the 16th to 19th cent.

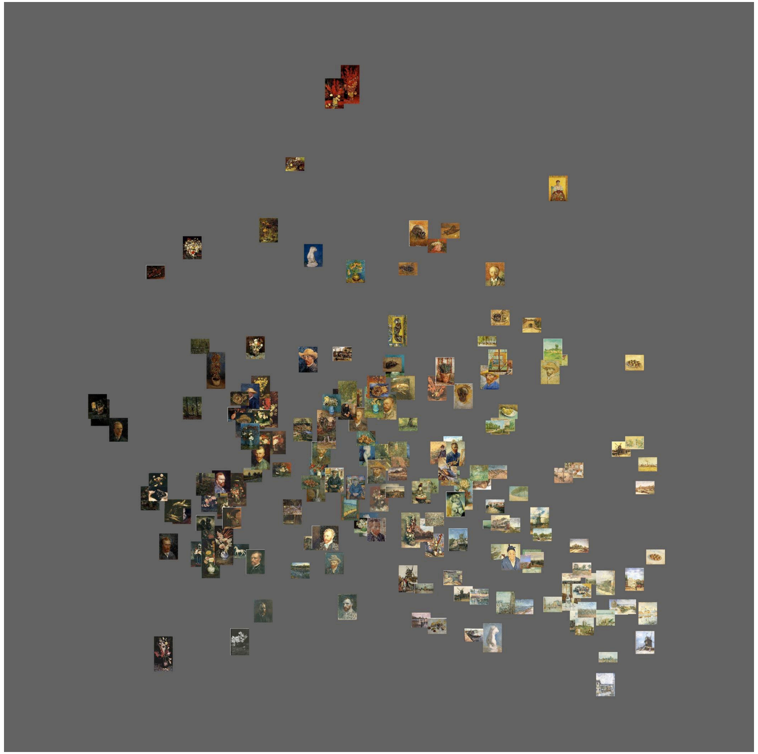
COINS

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

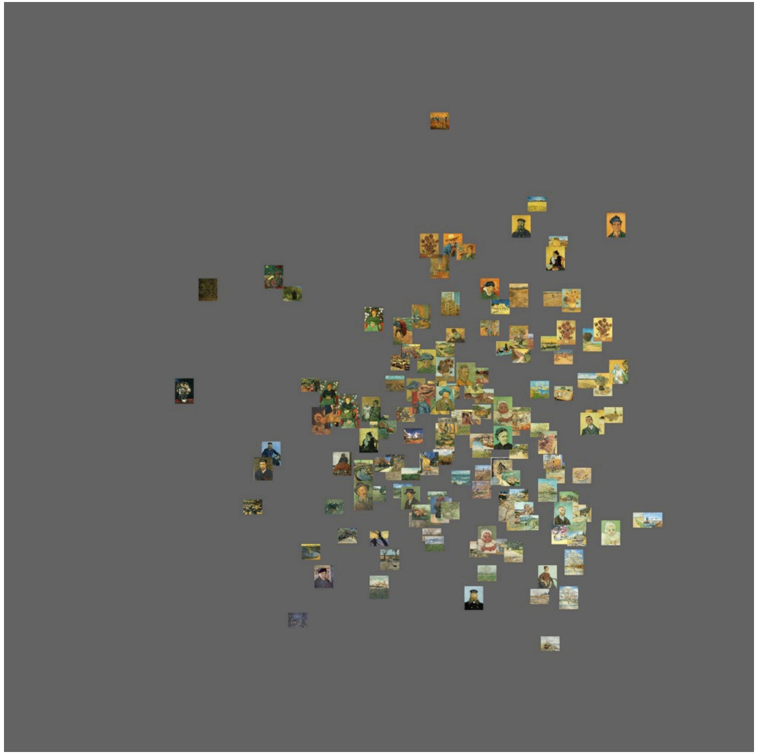
CULTURAL ANALYTICS

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





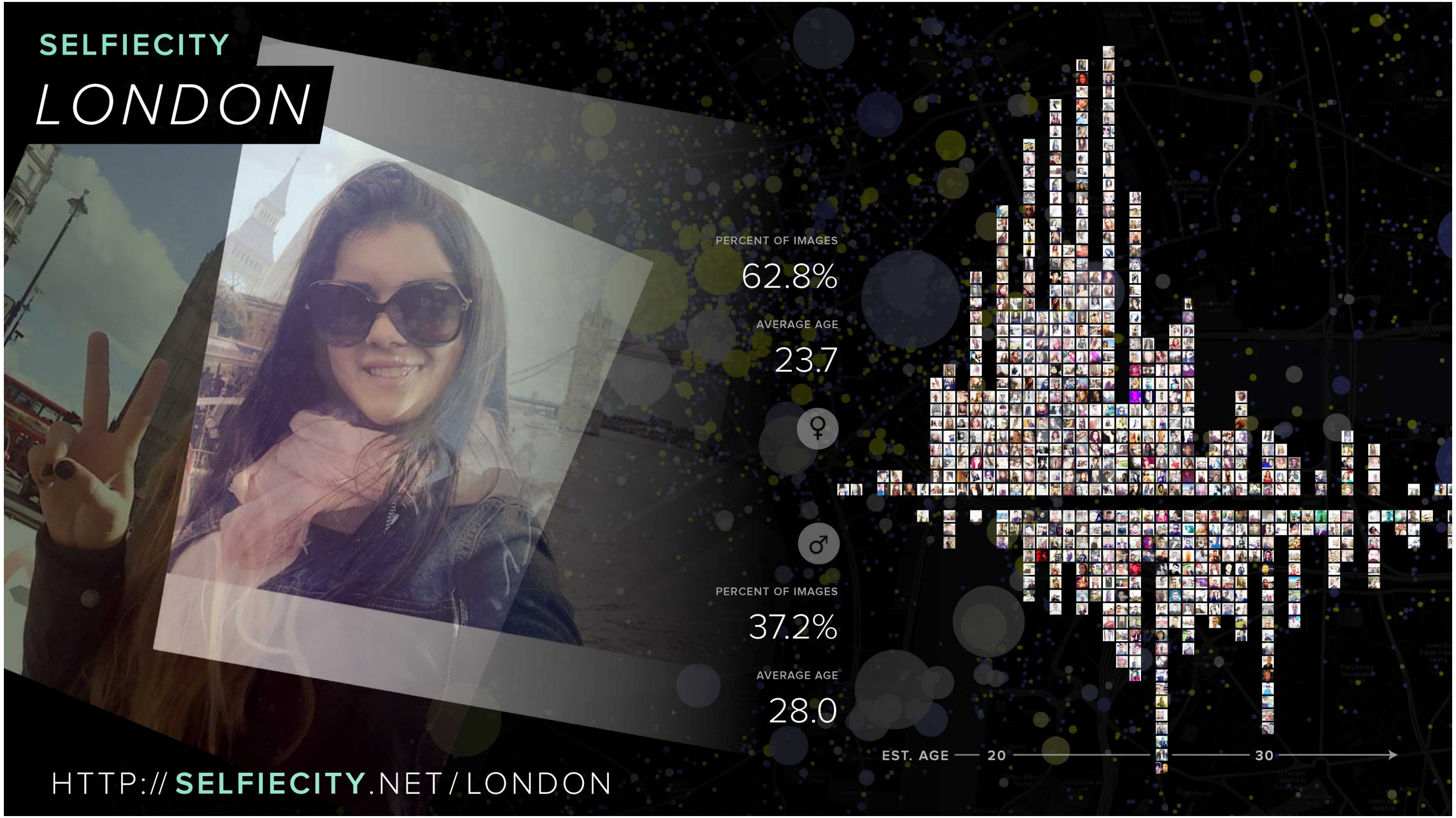
199 paintings made in Paris (1886-1888)



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



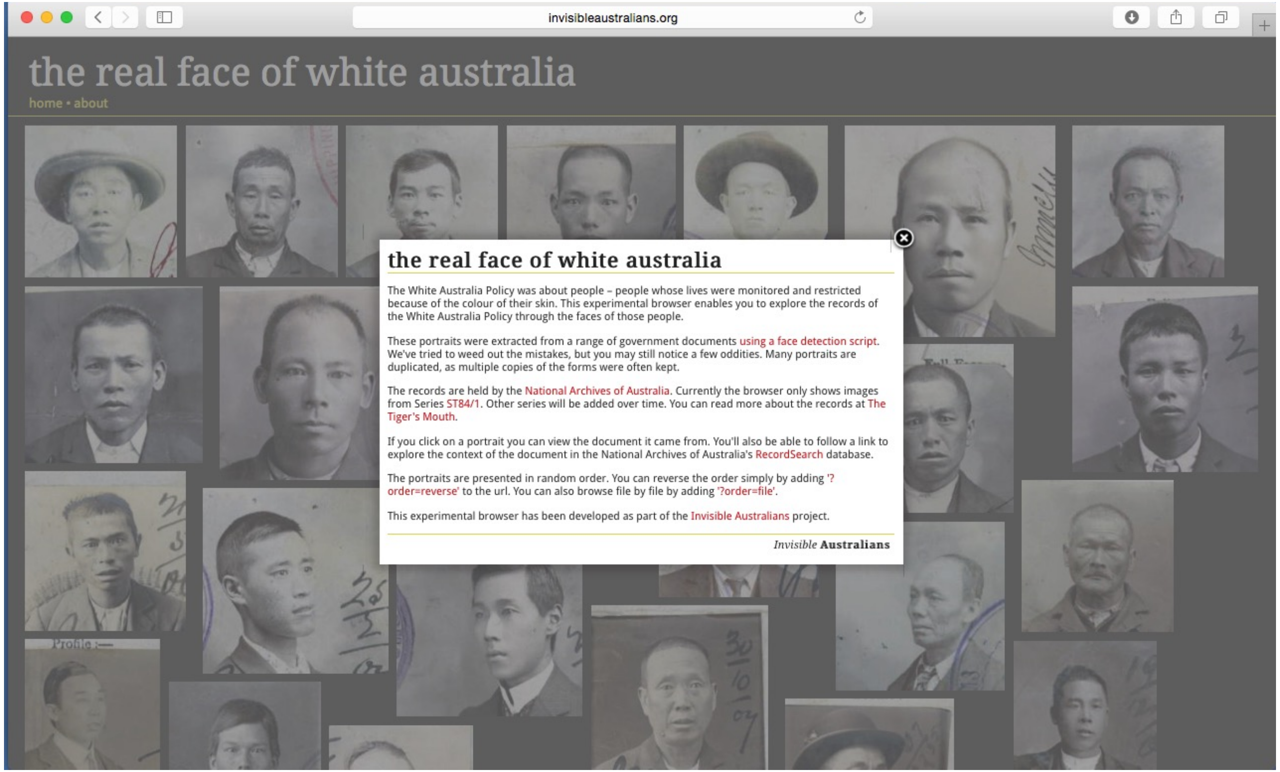
http://www.selfiecity.net/

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

EXAMPLE: FACE RECOGNITION

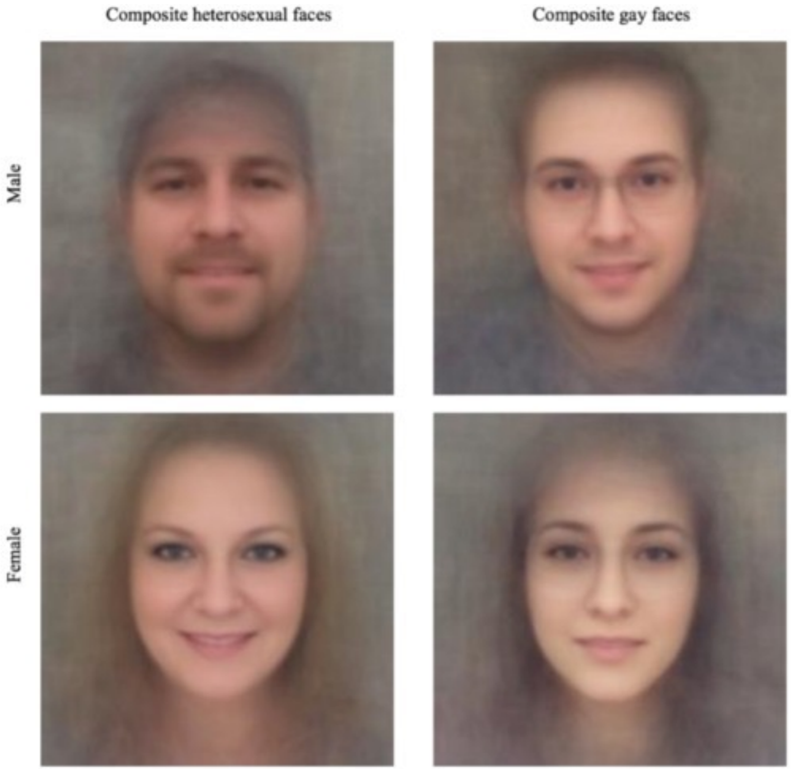
http://www.faceplusplus.com/demo-detect

EXAMPLE: FACE RECOGNITION



http://invisibleaustralians.org/faces/

EXAMPLE: FACE REGOCNITION



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?

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

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

Slide 16–21 et al.

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

Slide 12–36

What approach does Lev Manovich take with his Cultural Analytics

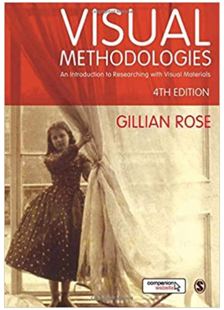
Slide 91-93

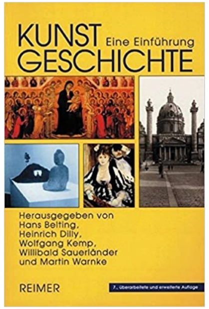
Briefly characterise a method for computer-assisted painter attribution.

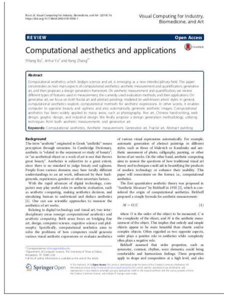
Slide 66–72

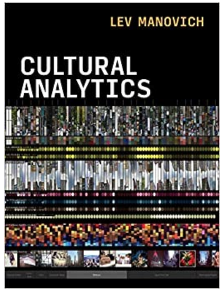
How do you think image analysis can particularly benefit from the use of computers?

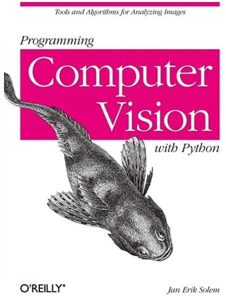
LITERATUR

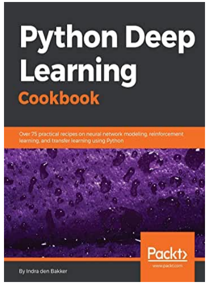












Gillian Rose, Visual Methodologies. An Introduction to Researching with Visual Materials, 4th ed. (London: SAGE, 2016)

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)

i ABBILDUNGSNACHWEIS

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

Folie 6: https://static.messynessychic.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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IMPRESSUM

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Nutzungsbedingungen:

Haftungshinweis:

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.