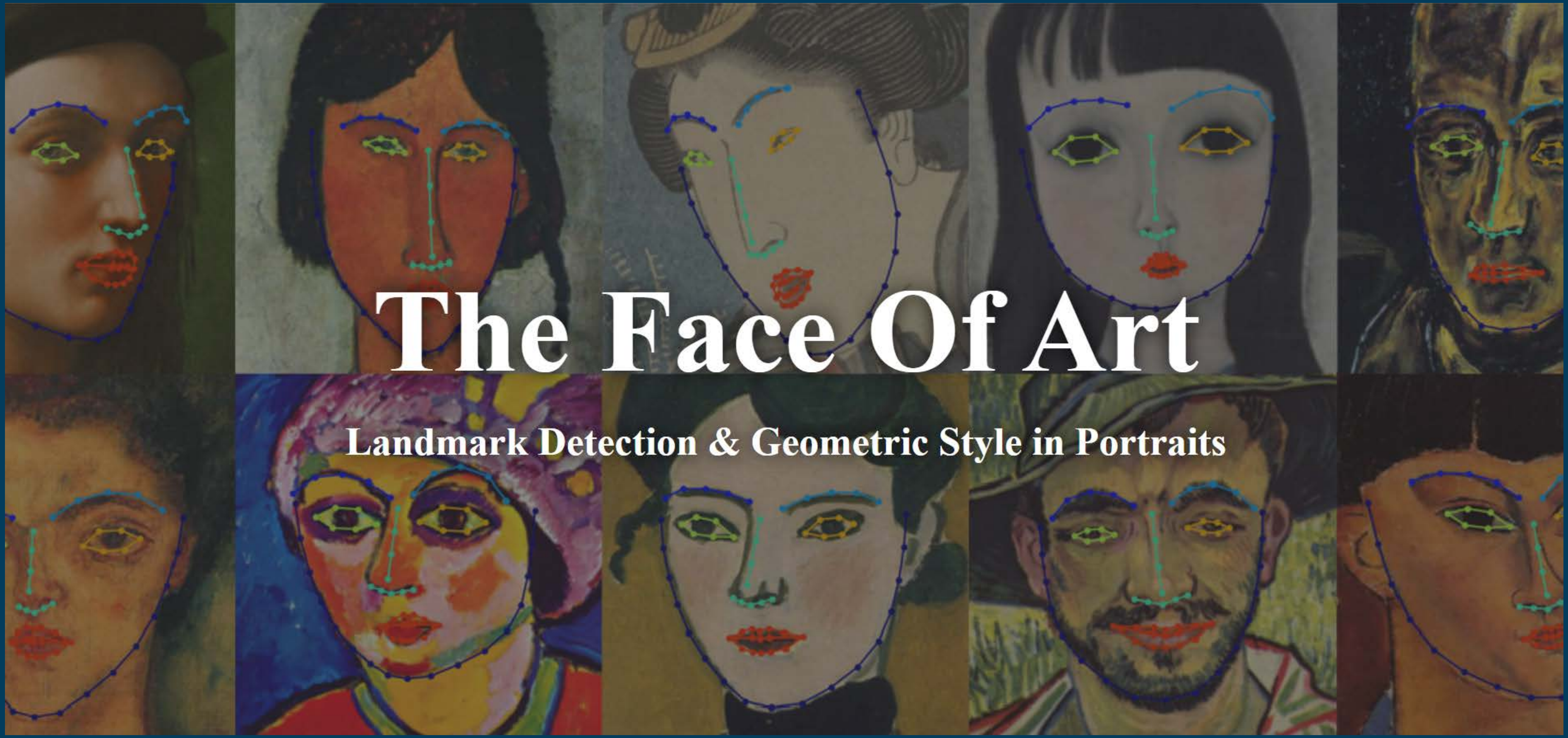
Seminar Presentation

Research Center for Technology and Art



01 Art Statement

02 Background

03 Methodology

04 Demo/Connection

Artificial Intelligence Art

Art Statement

Facial Landmark detection in natural images is a very active research domain. Compared to natural face images, artistic portraits are much more diverse. They contain a much wider style variation in both geometry and texture and are more complex to analyze. This study propose a method for artistic augmentation of natural face images that enables training deep neural networks for landmark detection in artistic portraits. We utilize conventional facial landmarks datasets, and transform their content from natural images into "artistic face" images.

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Background

The Artistic-Faces Dataset is mainly drawn from the Painter By Numbers (PBN) dataset, which consists of 103,250 artworks.

Samples from the Artistic-Faces Dataset including landmarks (3rd from right is from Girl in Bath, 1963 ©Estate of Roy Lichtenstein)

Samples from the Artistic-Faces Dataset including landmarks. From left to right:
(1) Portrait of Jeanne Hebuterne, 1919 by Amedeo Modigliani,
(2) Portrait of Eduard Kosmack, Frontal, with Clasped Hands, 1910 by Egon Schiele,
(3) The Red Madras Headdress, 1907 by Henri Matisse,
(4) Saint Elizabeth of Thuringia, c. 1475/1480 by Israhel van Meckenem,
(5) Woman in white, 1923 by Pablo Picasso,
(6) Portrait of the Young Pietro Bembo, 1504 by Raphael,
(8) Girl in Bath, 1963 by Roy Lichtenstein,
(9) Actor and Woman on a Riverbank, 1820 1830 by Utagawa Kunisada,
(10) La Mousme seduta, 1888 by Vincent van Gogh

http://www.faculty.idc.ac.il/arik/site/foa/artistic-faces-dataset.asp

Background

Source:

Van Gogh Museum, Amsterdam

The Metropolitan Museum of Art, New York

National Gallery of Art, Washington DC

Nasjonalmuseet, Oslo

Tate Gallery, London

WIKI Art

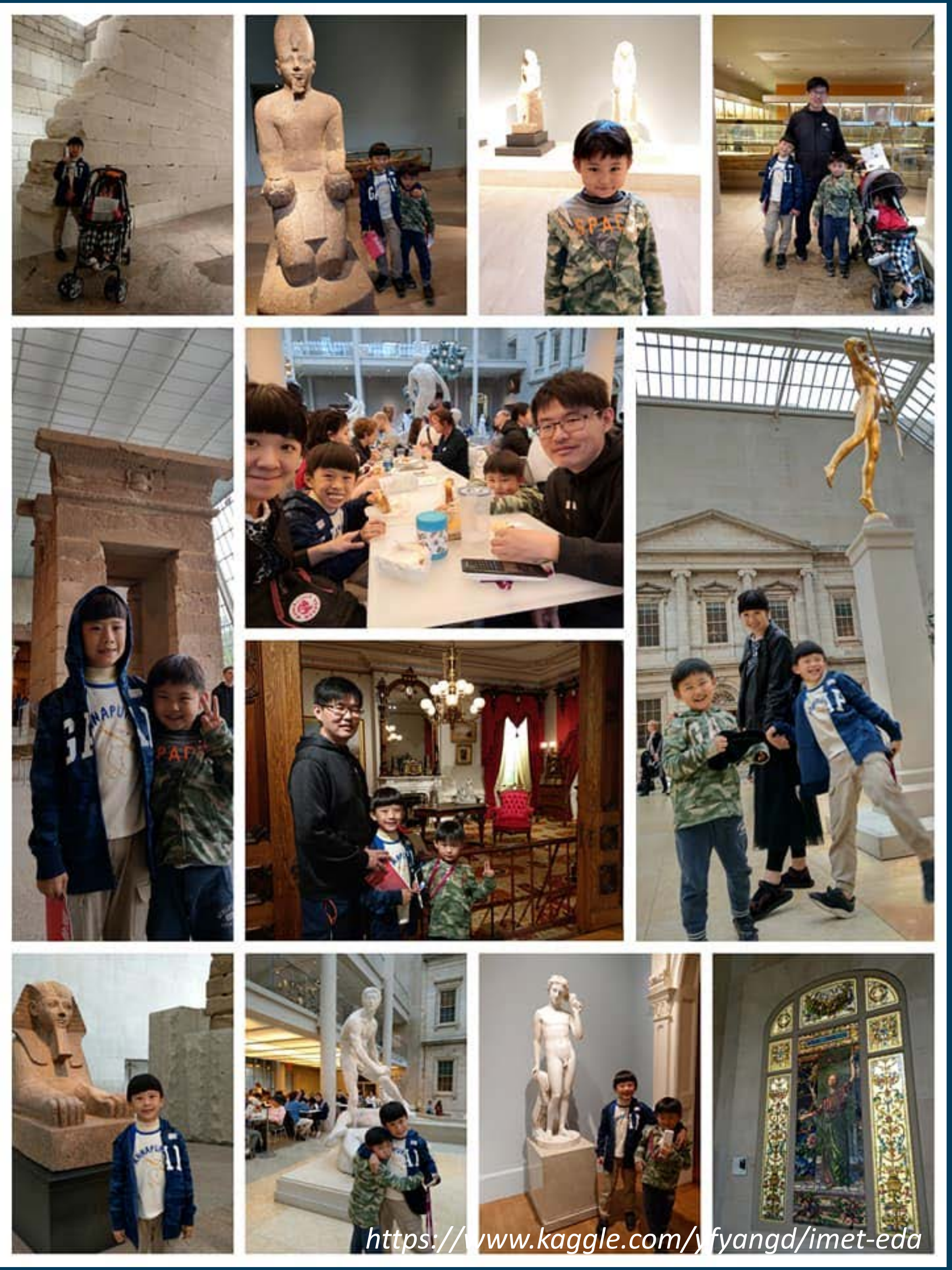
Google Image Datasets

ImageDuplicator by Roy Lichtenstein

The Metropolitan Museum of Art in New York, also known as The Met , is the largest art museum in the United States. With 6,953,927 visitors in 2018. Its permanent collection contains over two million works of which over 200K have been digitized with imagery.

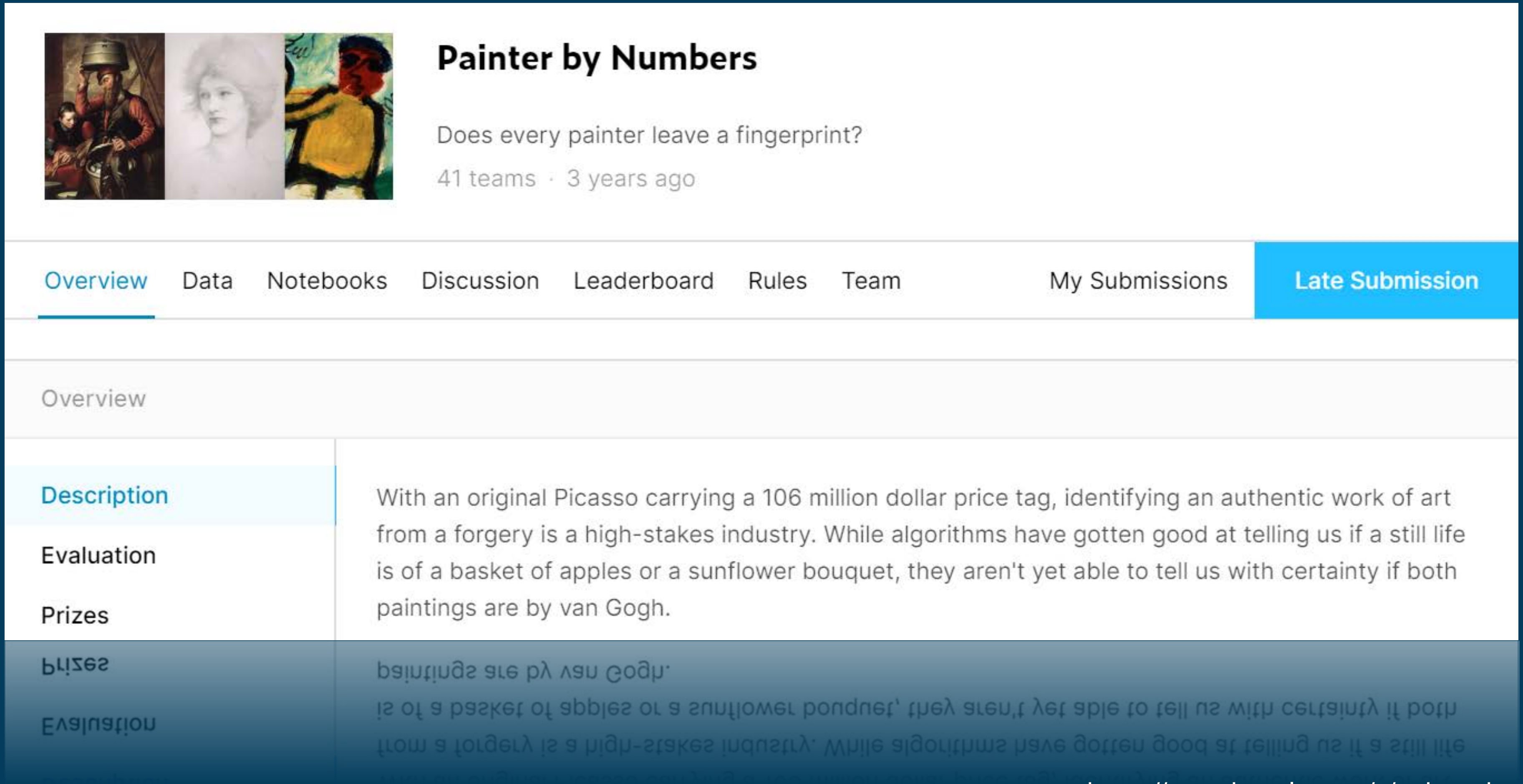
The online cataloguing information is generated by Subject Matter Experts (SME) and includes a wide range of data. SME can also be indirect in describing finer-grained attributes from the museum-goer's understanding. Adding fine-grained attributes to aid in the visual understanding of the museum objects will enable the ability to search for visually related objects.

In this study, we tried to extract the feature of image and analysis the feature by each attributes. Simple method (Random Forest) was performed and I hope it is useful for Machine Learningers.



https://www.kaggle.com/yfyangd/imet-eda

The Painter By Numbers competition challenges Kagglers to examine pairs of paintings and predict whether the paintings are by the same artist. The exciting thing about constructing the competition in this way is that instead of learning to label paintings as 'van Gogh' or 'Rembrandt', the algorithm is learning how to distinguish between artists. This means that the algorithm can be used to extrapolate to artists whose work it has never been trained on.



https://www.kaggle.com/c/painter-by-numbers/overview

One of the contributor got 90% accuracy, but in his dataset …

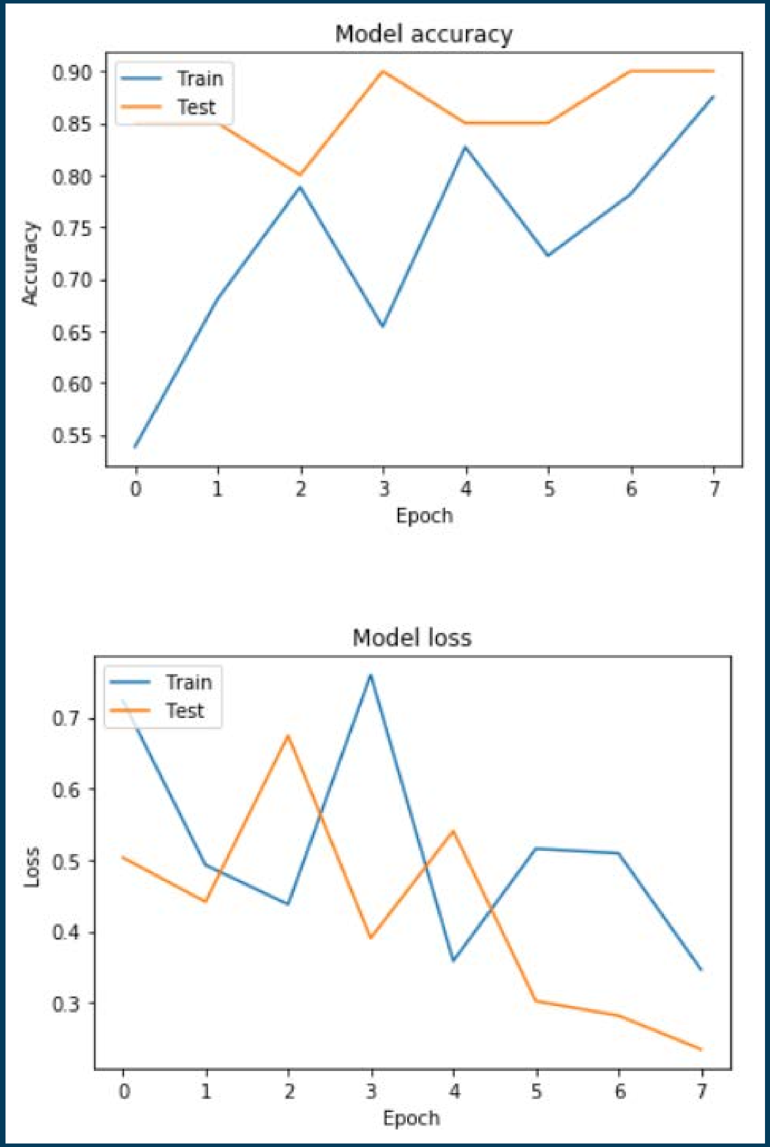
Picasso-Not-Picasso

Python notebook using data from multiple data sources · 1,701 views · 1y ago

beginner, deep learning, cnn, +2 more

```
# now let's set up the first layers
model.add(ResNet50(    # add a whole ResNet50 model
  include_top=False,          # without the last layer
  weights=weights_notop_path, # and with the "notop" weights file
  pooling='avg' # means collapse extra "channels" into 1D tensor by t
aking an avg across channels
))


# Now lets add a "Dense" layer to make predictions
model.add(Dense(
  num_classes, # this last layer just has 2 nodes
  activation='softmax' # apply softmax function to turn values of th
is layer into probabilities
))
```



https://www.kaggle.com/mfekadu/picasso-not-picasso/log

Picasso-Not-Picasso
Python notebook using data from multiple data sources · 1,701 views · 1y ago
beginner, deep learning, cnn, +2 more

Picasso:

Not Picasso:

Challenge: Van Meegeren (1889-1947) and Vermeer (1632-1675)

沒有登入 討論 貢獻 建立帳號 登入

維基百科
自由的百科全書

條目 討論 臺灣正體

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分類索引
特色內容
新聞動態
近期變更
隨機條目
資助維基百科

說明

說明
維基社群
方針與指引
互助客棧
知識問答
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維基百科愛好者交流群（Telegram：@wikipedia_zh_n、Discord及IRC：#wikipedia-zh 連線互聯）歡迎大家加入。 [關閉]

漢·范米格倫 [編輯]

維基百科，自由的百科全書

亨里克斯·安東尼烏斯·「漢」·范米格倫（Henricus Antonius "Han" van Meegeren，荷蘭語發音：[ɦɛnˈrikes an ˈtoːnies ˈɦan van ˈmeːɣərə(n)]、1889年10月10日－1947年12月30日[1]）是一位荷蘭畫家，被認為是20世紀最聰明的藝術偽造者之一[2]。儘管他犯了詐欺罪，但是在第二次世界大戰結束後，范米格倫成為民族英雄。他在納粹德國佔領荷蘭期間，他曾出售過一幅偽造的維梅爾畫作給帝國元帥赫爾曼·戈林[3]。

目錄 [隱藏]

生平 [編輯]

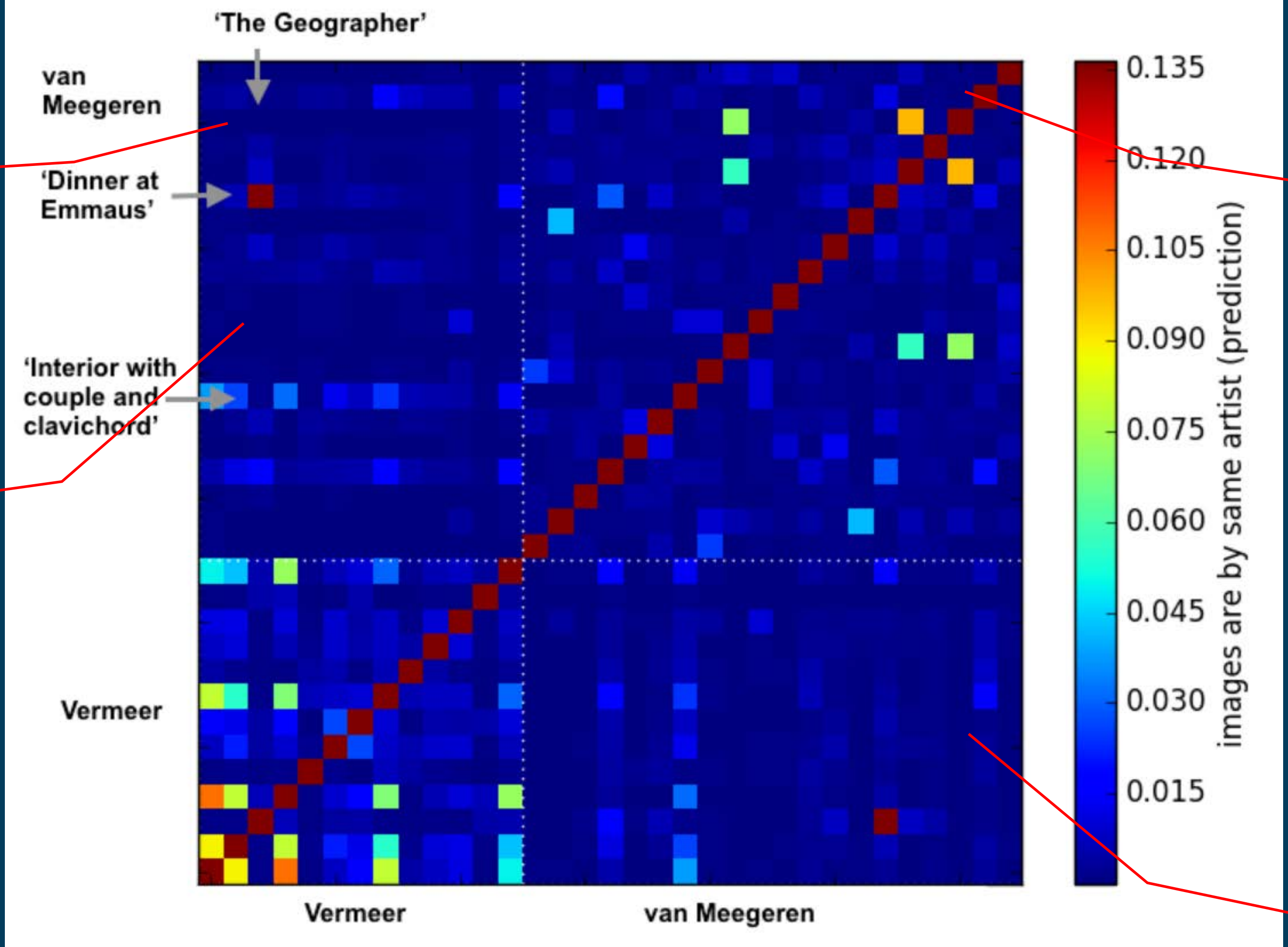
漢·范米格倫

1945年的漢·范米格倫，因向德國納粹兜售*國寶*《耶穌與通姦的女王》後被判為叛國罪，為證明自己的偽畫技巧正在獄中作人生中最後一幅畫《年輕的耶穌及眾長老》

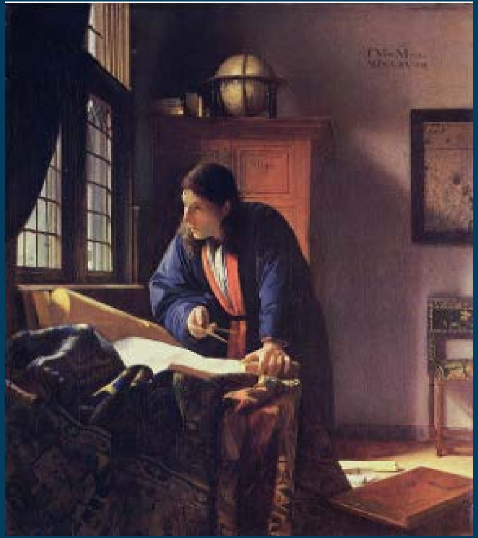
The pairwise comparison table for first-place winner orange-nejc's predictions for van Meegeren and Vermeer paintings in the test set

Dinner at Emmaus (van Meegeren)

Interior with couple and clavichord (van Meegeren)



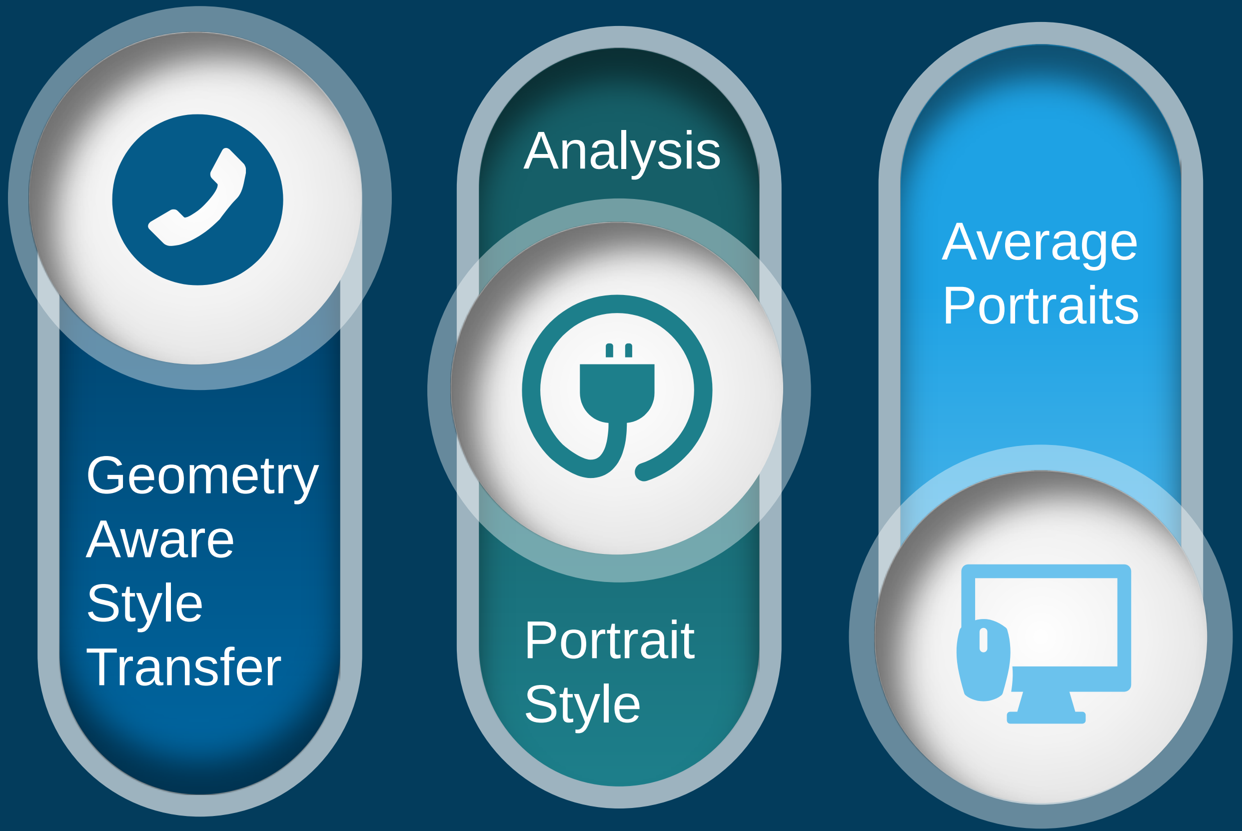
The Milkmaid (Vermeer)



The Geographer (Vermeer)

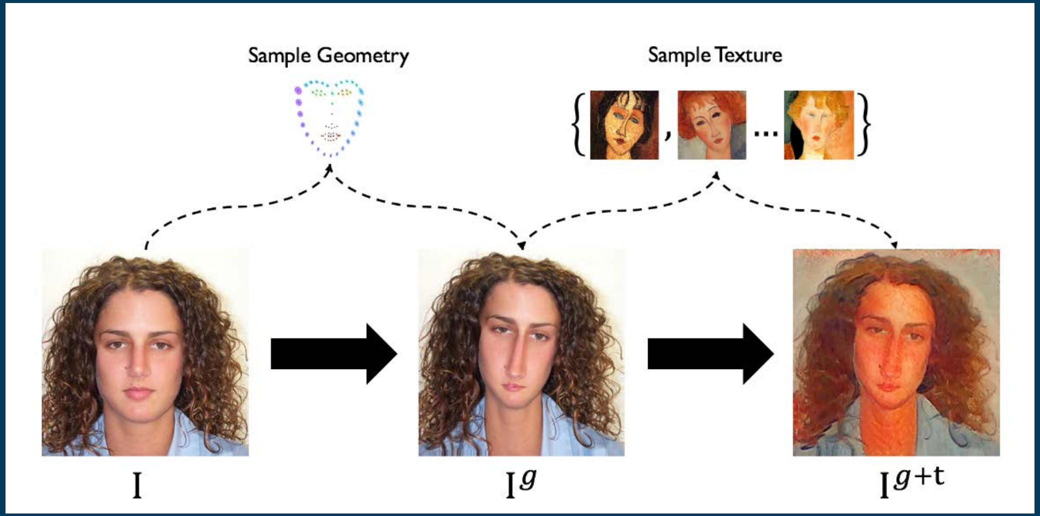
Methodology

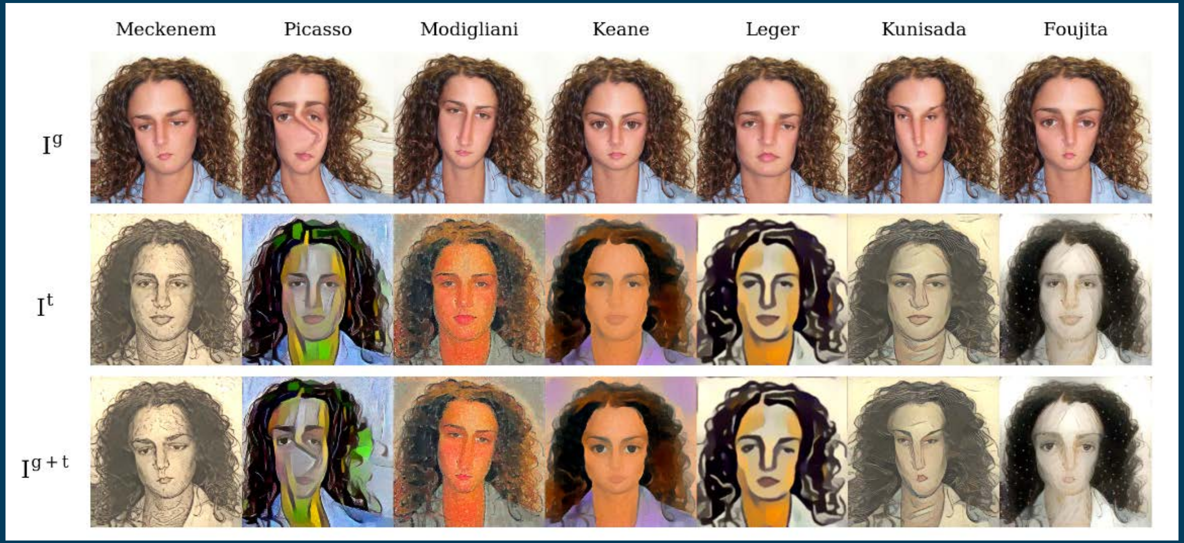
To motivate and plan the adaptation of existing algorithms to detect landmarks of artistic portraits, we need to understand the key differences between natural face images and artistic portraits. The differences between the two domains are revealed by two main aspects: geometric and textural. Given an input face image, the landmark detection result is obtained in three steps of estimation, correction and tuning. The Estimation Step aims to compute a global localization of each landmark based on the peak response points in the response maps, which are learned using a fully convolutional network.



Geometry Aware Style Transfer

This study present a method for Geometry-aware style transfer and show results of various artistic models. Our geometry-aware style transfer is performed using a portrait image bank for texture style transfer, and the artist-specific geometric-style model for geometric style transfer.
For geometric stylization, we use the artists' portrait image bank, and build the geometric style model $\mathcal{P}_{artist}$ (similar to artist distributions). $\mathcal{P}_{artist}$ is then sampled to produce a set of stylized landmarks. The input image is than warped to the stylized landmarks using TPS interpolation, resulting in I^g - a geometrically stylized image.
For texture style transfer we use the algorithm proposed by Gatys et al., where I^g serves as the content image, and a random sample from the portrait collection serves as the style image, resulting in a portrait that is stylized in both geometry and texture I^{g+t}.





Geometry Aware Style Transfer

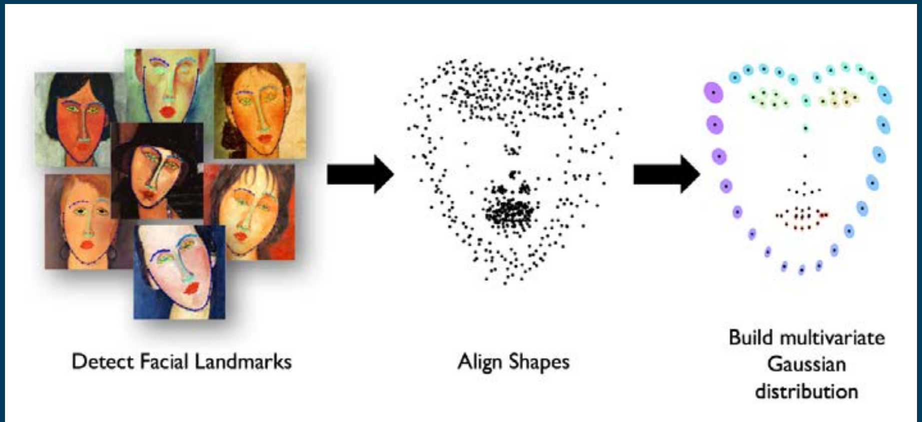
In this figure, we show results of automatically stylizing photographs using our method on different faces. We can identify the signature geometric style of each artist: a small face with large eyes for Keane, a wide chin and large distance between the eyes for Leger, an elongated face and nose for Modigliani, distorted spatial locations of the different facial features for Picasso. Notice the second to last image, we can identify the signature Picasso style of integrating a profile into a frontal face drawing. In the last row, notice the signature style of Foujita; round, child-like face, with pointy chin, small mouth and large distance between the eyes.

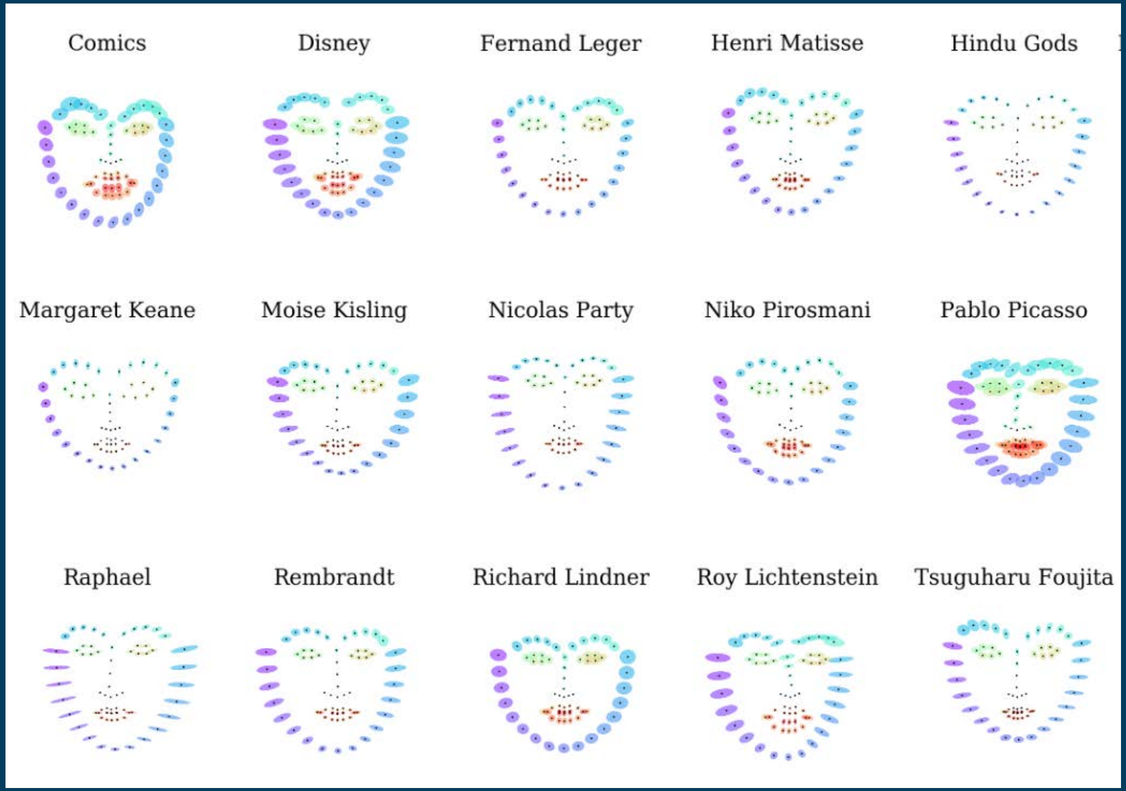
Portrait Style Analysis

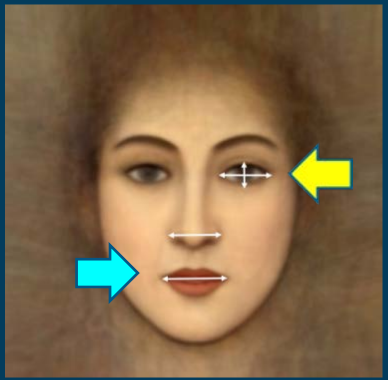
To define a mathematical model of the geometric style of an artist, we use our landmark detection framework to extract facial landmarks from a collection of portraits by each artist. We uniformly normalize the size of the faces and align their center points (the point on the tip of the nose). We calculate the mean vector for the set of portraits of each artist μ_{artist} and the covariance matrix Σ_{artist}. Lastly, we fit a Multivariate Gaussian Model to the artist data $P_{artist} \sim N(\mu_{artist}, \Sigma_{artist})$.

Here we show the distribution (mean and covariance) of each landmark point for the different artists. Observing these distributions, we can identify the signature geometric style of the artist. For example, elongated face and nose for Modigliani, a short face with wide chin and large distance between the eyes for Leger, a small face with large eyes for Keane, etc. This kind of analysis can help understand artistic styles, and aid in finding similarities or differences between the different artists.

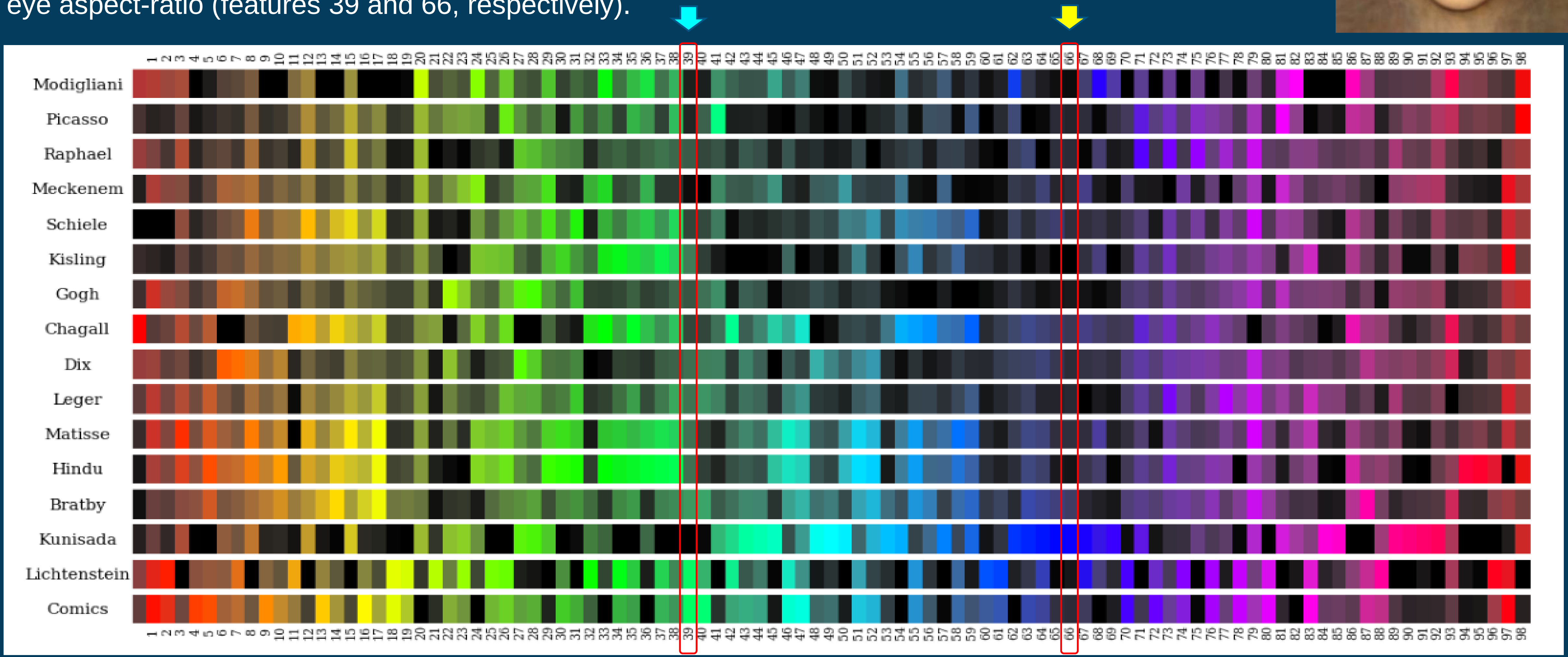
Artist Landmarks Distribution







This study define a vector of 99 dimensions as the *geometric style signature* of a portrait. This signature vector includes many size, proportion and location measurements of facial features. We also include facial proportions that have been reported to have correlation with beauty and attractiveness .
In this figure we show two example ratios included in the signature- mouth to nose width ratio and right eye aspect-ratio (features 39 and 66, respectively).



Geometric Style Signature Legend:
totally define a vector of 99 dimensions as the *geometric style signature* of a portrait

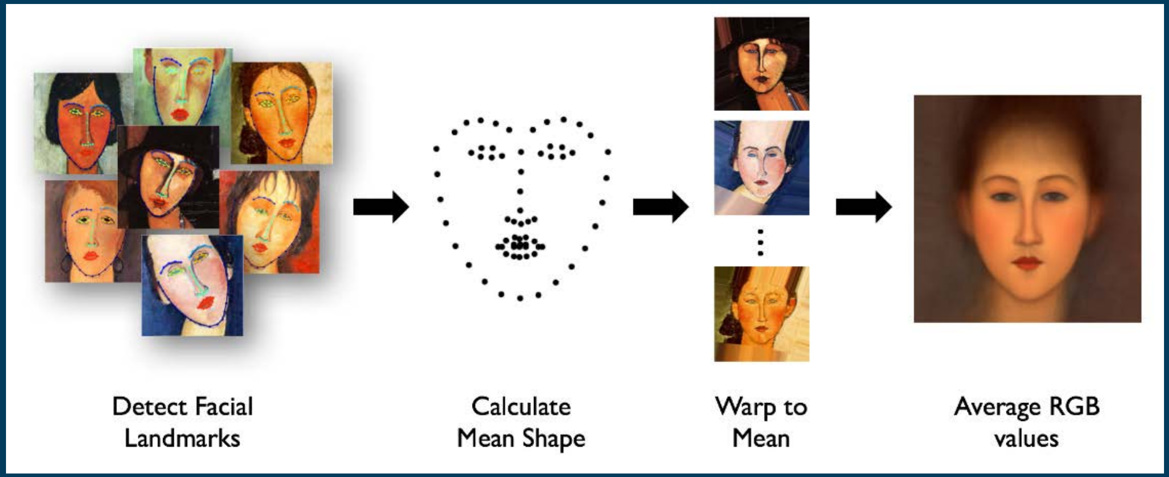
Index	Description	Type
0	height(Left Eyebrow) / height(Right Eyebrow)	Part Proportion
1	height(Left Eyebrow) / height(Left Eye)	Part Proportion
2	height(Left Eyebrow) / height(Right Eye)	Part Proportion
3	height(Left Eyebrow) / height(Mouth)	Part Proportion
4	height(Left Eyebrow) / height(Nose)	Part Proportion
5	height(Left Eyebrow) / height(Jaw)	Part Proportion
6	height(Right Eyebrow) / height(Left Eye)	Part Proportion
7	height(Right Eyebrow) / height(Right Eye)	Part Proportion
8	height(Right Eyebrow) / height(Mouth)	Part Proportion
9	height(Right Eyebrow) / height(Nose)	Part Proportion
10	height(Right Eyebrow) / height(Jaw)	Part Proportion
11	height(Left Eye) / height(Right Eye)	Part Proportion
12	height(Left Eye) / height(Mouth)	Part Proportion
13	height(Left Eye) / height(Nose)	Part Proportion
14	height(Left Eye) / height(Jaw)	Part Proportion
15	height(Right Eye) / height(Mouth)	Part Proportion
16	height(Right Eye) / height(Nose)	Part Proportion
17	height(Right Eye) / height(Jaw)	Part Proportion
18	height(Mouth) / height(Nose)	Part Proportion
19	height(Mouth) / height(Jaw)	Part Proportion
20	height(Nose) / height(Jaw)	Part Proportion

⋮

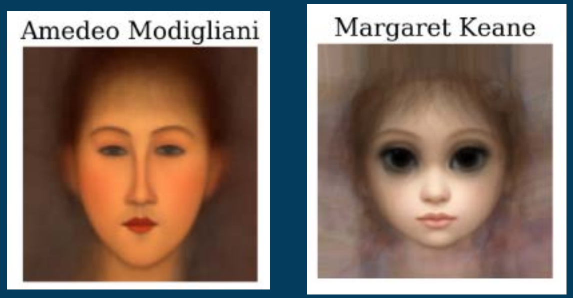
Index	Description	Type
81	nose width to face width	Aesthetic Proportions
82	nose length to lower face length	Aesthetic Proportions
83	inner eye corners distance to nose width	Aesthetic Proportions
84	inner eye corners distance to left eye width	Aesthetic Proportions
85	inner eye corners distance to right eye width	Aesthetic Proportions
86	Inter-pupil distance to inner eye corners distance	Aesthetic Proportions
87	mouth width to inner eye corners distance	Aesthetic Proportions
88	mouth-chin distance to nose width	Aesthetic Proportions
89	inner eye corners distance to mouth length	Aesthetic Proportions
90	nose width to left eye width	Aesthetic Proportions
91	nose width to right eye width	Aesthetic Proportions
92	nose width to mouth length	Aesthetic Proportions
93	mouth-chin distance to inner eye corners distance	Aesthetic Proportions
94	left eye width to nose-mouth distance	Aesthetic Proportions
95	right eye width to nose-mouth distance	Aesthetic Proportions
96	mouth length to nose-mouth distance	Aesthetic Proportions
97	lower face length to mouth-chin distance	Aesthetic Proportions
98	nose width to nose-mouth distance	Aesthetic Proportions

Average Portraits

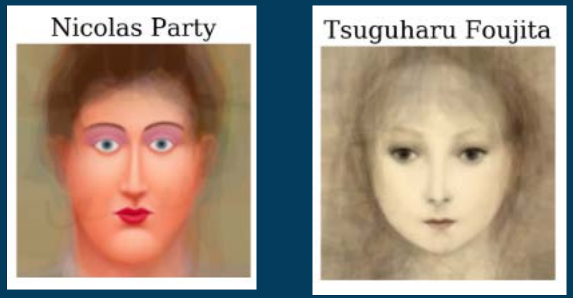
Using our detection framework to obtain an annotated dataset. we can calculate the artist mean facial shape μ artist (similar to artist distributions), and create an average portrait representing the different artists. To create an average portrait, we simply warp the collection of annotated portraits to the artists mean shape μ artist and calculate the mean RGB values of the warped portraits collection. Here we show several average portraits of different artists. Using these images we gain some interesting insights regarding the artist's style preferences



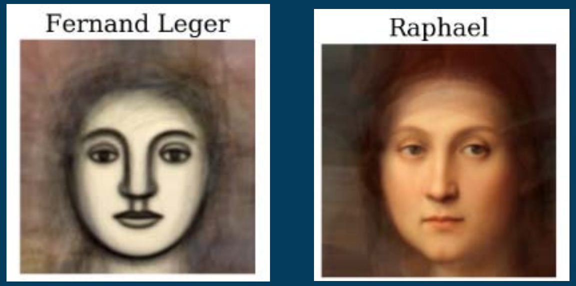
color schemes (warm colors for Modigliani, cool colors for Keane),



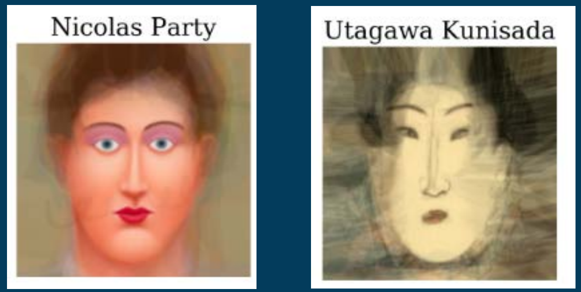
colorfulness (saturated colors for Party, dull colors for Foujita)



abstraction level (abstract portraits for Leger, realistic, detailed portraits for Rafael)



textures (smooth portraits for Party, rough textured portraits for Kokoschka)



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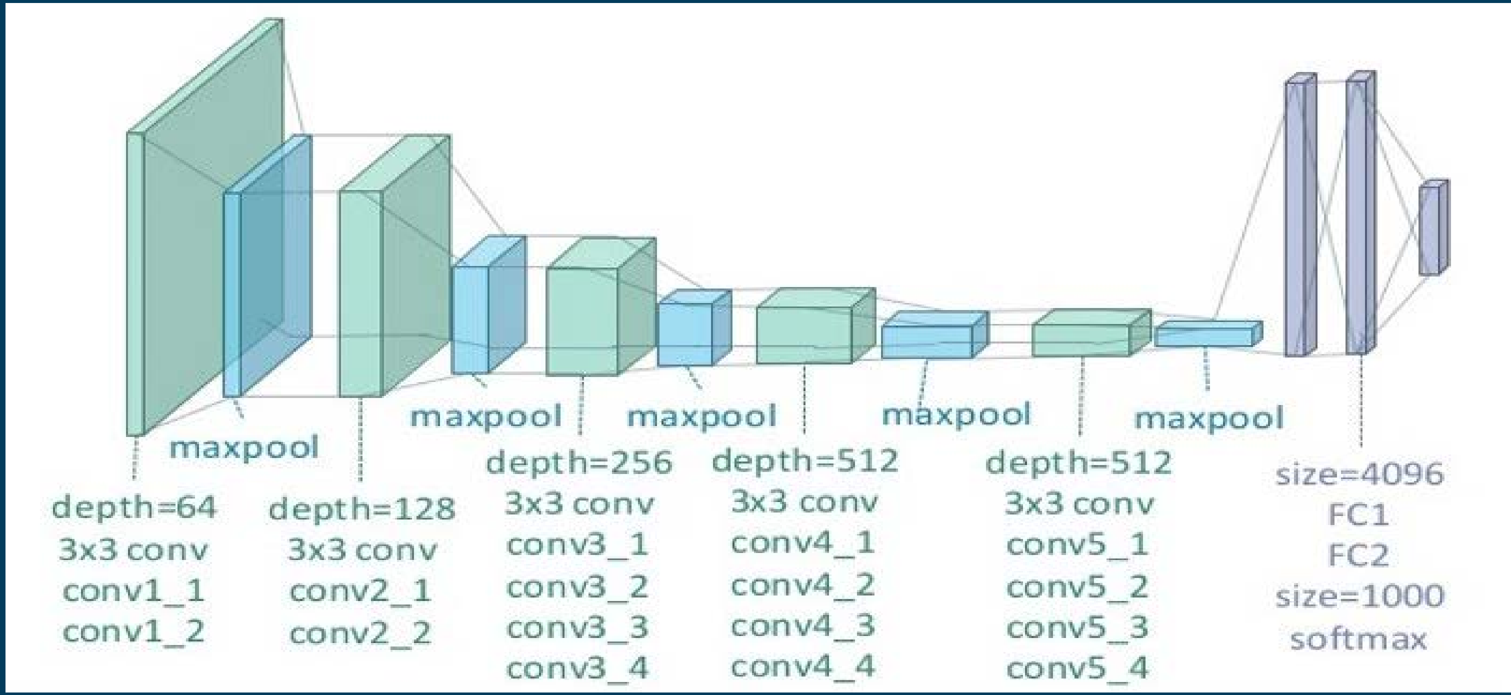
Artificial Intelligence Art

Demo Model: VGG-19

- VGG-19 is a deep convolutional neural network developed by researchers from the Visual Geometry Group at Oxford University and Google DeepMind (ILSVRC'14 2nd).
- Architecture:
  14 Convolution layer, 5 Pooling layer, and 2 Fully connection layer
  - More deep (10 hidden layer)
  - Activation function: ReLU
  - With drop out function



Deep Learning to Painting Styles

Un dimanche après-midi à l'Île de la Grande Jatte, 1884, Georges Seurat,
傑特島的星期日下午, ,法國畫家喬治·修拉

Deep Learning to Painting Styles

Input

Original Picture

Model: VGG19
Iteration: 100
Pooling: Max

Feature Extraction

Van Gogh- Starry Night

Output

Van Gogh Style

content lost: 2.56 e6
style loss: 1.44 e06
total loss: 4.2 0e06

Deep Learning to Painting Styles

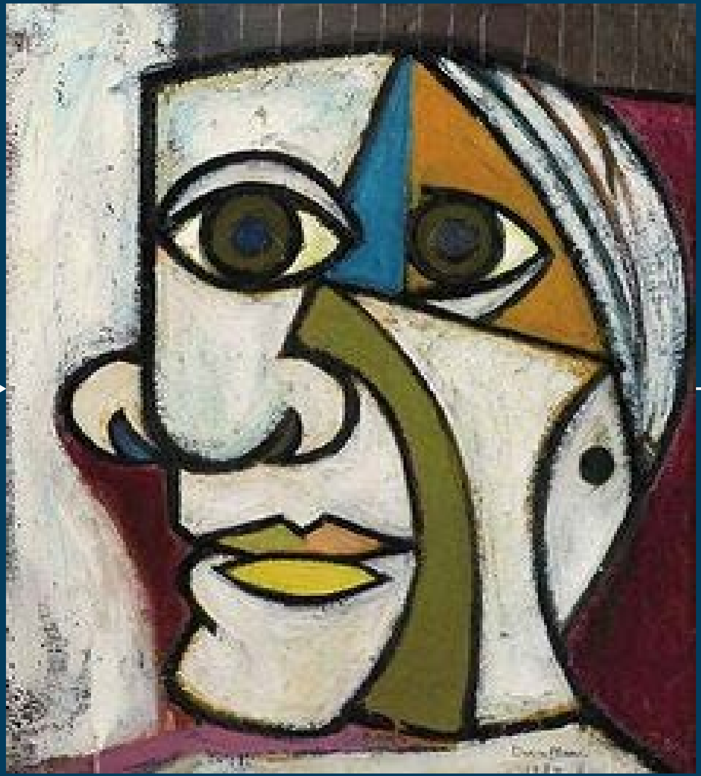
Input

Original Picture

Model: VGG19
Iteration: 100
Pooling: Max

Feature Extraction

Picasso- Dora Maar



Output

Picasso Style

content lost: 2.20 e6
style loss: 1.42 e06
total loss: 3.62 e06

Deep Learning to Painting Styles

Input	Feature Extraction	Output
Original Picture	水墨畫	水墨畫 Style

Model: VGG19
Iteration: 100
Pooling: Max

content lost: 2.25 e6
style loss: 1.62 e06
total loss: 4.0 0e06

Connection

A.I. 偽畫鑑定, 畫跡偵測
(Descriminator)

A.I. 偽畫創作, 畫跡模仿
(Genarator)

Application: 美肌美顏/一鍵上妝
Makeup Learning
(Texture Learning, without Geometry)

Wolfgang Beltracchi

https://www.sohu.com/a/236539684_660999

Connection

- A.I. 偽畫鑑定, 畫跡偵測 (Descriminator)
- A.I. 偽畫創作, 畫跡模仿 (Genarator)
- Application: 美肌美顏/一鍵上妝 Makeup Learning (Texture Learning, without Geometry)

Real Image　　Fake Image

Connection

A.I. 偽畫鑑定, 畫跡偵測
(Descriminator)

A.I. 偽畫創作, 畫跡模仿
(Genarator)

Application: 美肌美顏/一鍵上妝
Makeup Learning
(Texture Learning, without Geometry)