Identification and Synthesizing of Raphael Paintings

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Abstract

Raphael was a famous Italian artist in the Renaissance. It is all long difficult to judge whether a painting is credited to Raphael (or other painter). We try to discuss this subject from 28 relative paintings in 3 steps. First extract features using geometric tight frame, then reduce the dimension by ROC curve and forward stage-wise method, and finally build a classifier via 4 different algorithms, namely threshold method, neural network, SVM, and decision tree. Such a model can be trained by cross-validation, and comparing the validation accuracy helps select a presentable classifier. As a consequence, two algorithms stand out: neural network performs best overall (76.2%); whereas threshold method has an accuracy rate of 71.4% but correctly identifies all genuine paintings. Based on the discussion above, we give our prediction on 7 pictures remaining disputed. In addition, we consturct a translation machine of Raphael's style by the method of cycleGAN. That is, given any photo or picture, it could synthesize a similar painting with the same content but in the manner of Raphael.

1 Introduction

Whether in the mists of antiquity or for the lack of preservation, a large number of paintings lost identification of their author. Art authentication is such a subject to identify a painting's author, especially to make judgments on genuine paintings by famous artists, as well as detect forgeries by immitators. This job has long been considered tough because it tradionally relies on the keen eyes and vast experience of experts, who dedicate their whole life to certain artists. There exist evident drawbacks in such a tradional method. Experts have to know a lot about the possible artist, so they usually only judge those paintings relative to some celebrated painters, but have little idea on ordinary ones.

Such being the case, advanced approaches including ultraviolet fluorescence, canvas weave count and statistical means come into use. We call these applications stylometry. Stylometry is based on the assumption that dierent artists have different painting styles, i.e. each artist exhibited particular traces of natural style and habitual physical movements when painting. Therefore, characteristics reecting these manners may be extracted as features to identify the authorship of paintings. Our model succeeds extracting the most several notable features and can predict a new picture's author with various algorithms. In this way, identification becomes effective and efficient. Furthermore, it is a universal method that could also applied to judge an ordinary painting, as long as we have some samples of the relative artist.

In addition, we construct an interesting translation machine of Raphael's style by the method of cycleGAN. That is, given any photo or picture, it could synthesize a similar painting with the same content but in the manner of Raphael. Nowadays, photo filters are popular among young people. Classic filter styles include vivid, dramatic, monochrome, silvertone, noir and so on. Most of them are simply changing the color map, contrast or sharpness. What we are constructing is just like

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designing a new kind of filter style called "Raphael". In this aspect, it is possible to invent any photo filter style unlimited to classic ones.

Section 2 reports the whole process of constructing our model for identification. **Section 2.1** describes how to extract features of Raphael's paintings. **Section 2.1.1** introduces the core algorithm — Gemetric tight frame. Since there might exist noisy features, we reduce the dimension by ROC curve method, which is discussed in **Section 2.1.2**. **Section 2.2** trains the model by cross-validation, and compares the 4 different algorithms: threshold method, neural network, SVM and decision tree. Our predictions on the 7 pictures remaining disputed are shown in **Section 2.3**.

Section 3 is about the translation machine of Raphael's style. **Section 3.1** reviews how GAN works. **Section 3.2** uses cycleGAN for synthesizing, and 10 pairs of pictures with original or Raphael's style are displayed.

Of course, **Section 1** serves here as the sketch, briefly introducing the coming experiment and discussion.

2 Identification

The data provided by Prof. Yang WANG from HKUST12 contains 28 digital paintings of Raphael or forgeries. 21 of them have been known clearly, among which 12 paintings are Raphael's (the positive training set) and 9 forgeries (the negative training set). Our target is to authenticate the genuine from the fake on the remaining 7 paintings (the test set).

2.1 Feature Extraction

The pixels of our paintings vary from 1000 to 6000; furthermore, the data we deal with are informative but diversitive, making it essential to extract proper features in our classification process.

As pointed out in [1], the art authentication problem should be considered as an outlier detection problem. We use **Geometric tight frame** in our feature extraction process.

2.1.1 Geometric Tight Frame

The geometric tight frame can capture the first-and second-order differences in the horizontal, vertical and diagonal directions in every small neighborhood of the paintings. The 1-level geometric tight frame we use has 18 filters $\{\tau_i\}_{i=1}^{18}$ [1].

After convolution, 18 feature matrice are obtained for every single painting, and each matrix is exactly of the same size with the image data matrix. Since the initial features are quite informative and hard to handle, we propose to finely extract the following three statistics as our final features: the mean, standard deviation and the "tail entries". Precisely, for $A^{(i,j)} = \left(a_{l,k}^{(i,j)}\right)$ (the ith painting's feature matrix convoluted by the jth filter, suppose $dim(A^{(i,j)}) = m_i \times n_i$), the three statistics are

$$(1) \quad \mu^{(i,j)} = \frac{1}{m_i n_i} \sum_{l=1}^{m_i} \sum_{k=1}^{n_i} a_{l,k}^{(i,j)}$$

$$(2) \quad \sigma^{(i,j)} = \sqrt{\frac{1}{m_i n_i - 1} \sum_{l=1}^{m_i} \sum_{k=1}^{n_i} \left(a_{l,k}^{(i,j)} - \mu^{(i,j)}\right)^2}$$

$$(3) \quad p^{(i,j)} = \frac{1}{m_i n_i} \#(\hat{A}^{(i,j)})$$

$\#(\hat{A}^{i,j})$ is the number of non-zero entries in the tail matrix $\hat{A}^{(i,j)} = \left(\hat{a}_{l,k}^{(i,j)}\right)$, where

$$\hat{a}_{l,k}^{(i,j)} = \begin{cases} a_{l,k}^{(i,j)}, & \text{if} \quad |a_{l,k}^{(i,j)} - \mu^{(i,j)}| > \sigma^{(i,j)} \\ 0, & \text{otherwise} \end{cases}$$

Thus, we obtain $18 \times 3 = 54$ features for each painting under the geometric tight frame.

2.1.2 Dimension Reduction

In order to exclude the potential noisy features, we implement ROC curve method to reduce the dimension. In conclusion, the ROC (receiver operating characteristic) curve can reflect the effect of a classifier to some extent. And AUC is the area between ROC curve and x-axis; the larger AUC is, the more effective a classifier is.

Suppose the jth feature set of training set $\mathscr{T}^j = \mathscr{P}^j \cup \mathscr{N}^j$, where $\mathscr{P}^j = \{t_i^j\}_{i=1}^n$ is a feature of positive set (n paintings) with label "1" and $\mathscr{N}^j$ is a feature of negative set with label "0″. The **Raphael center** is defined as

$$C = (C^1, C^2, ..., C^n)^T$$

where

$$C^j = \frac{1}{|\mathscr{P}^j|} \sum_{i=1}^{n} t_i^j$$

All that we analysize below are rooted in a **basic assumption**: a painting is more likely to be genuine if its features are more close to the **Raphael center** C. In other words, we believe the paintings drawn by the same artist have a consistency in texture. Mathematically, define the **Raphael distance** of a given painting as

$$d_i = \|F_i - C\|_2$$

where $F_i = \{t_i^j\}_{j=1}^m$ is the feature vector of this painting (m is the number of features); we can judge the genuine or fake based on a given *threshold*; that is, if d_i < *threshold*, then the painting is attributed to genuine, otherwise it is considered fake.

Based on this judgement model, we can generate a series of *threshold* to obtain the ROC curve for different feature subset $\mathscr{A}_t = \{\mathscr{T}^j\}_{j_1,j_2,...,j_t}$ of the totel feature set $\mathscr{T}$, and choose a proper $\mathscr{A}_t$ as our final feature set after dimension reduction.

Considering the number of subsets of $\mathscr{T}$ is up to $54!$, it is barely possible to try all of them respectively. Our solution is to find a relatively proper $\mathscr{A}_t$, by implementing a **forward stage-wise** method, which is a kind of greedy algorithm. (See **Algorithm 1**)

Algorithm 1 Forward Stage-wise

Require: The totel feature set $\mathscr{T} = \{t^j\}_{j=1}^{54}$, the Raphael center$C$
Ensure: A list of local optimal feature subset $\mathscr{A}_t$ for $|\mathscr{A}_t|$ = 1, 2,..., 54.

```
Initialize an empty set 𝒜.
for j = 1 ∼ 54 do
    for k = 1 ∼ 54 do
        if t^k in 𝒜 then
            continue
        end if
        Let ℬ^k = 𝒜 + t^k
        Compute auc^k: the AUC given ℬ^k
    end for
    Find the biggest auc^k, add corresponding t^k to 𝒜
end for
Return 𝒜, whose first nth items make up local optimal feature subset 𝒜_t for n = 1, 2, ··· , 54.
```

The relationship between local maximun AUC and the number of features is shown below:

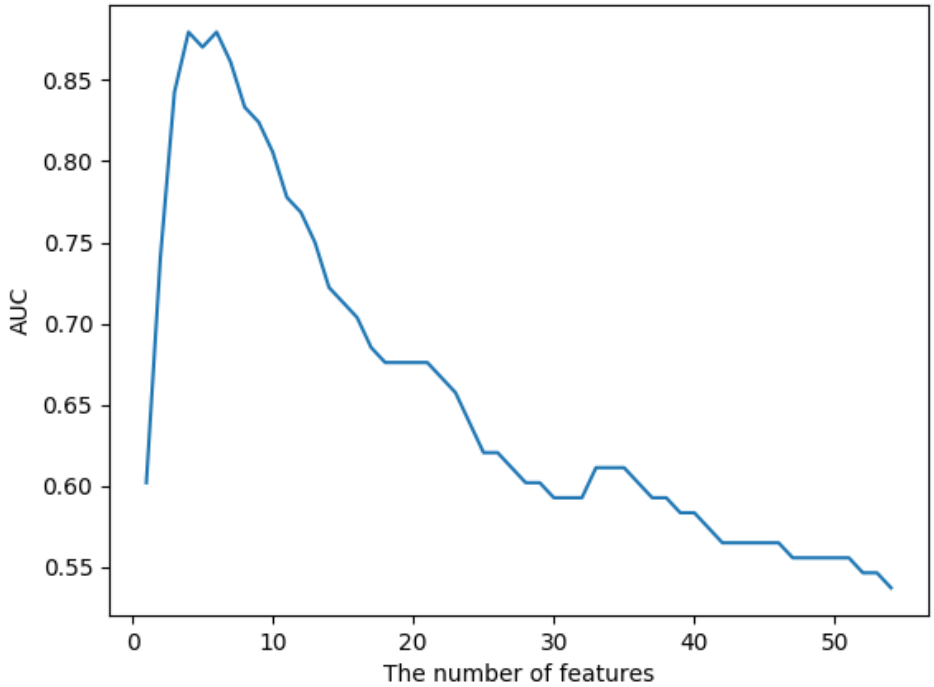

Figure 1: Local maximum AUC against the number of features

The local minimum AUC arrives its maximum 90.0% when $|\mathscr{A}_t| = 4$, and is up to 84.3% when $|\mathscr{A}_t| = 3$. We implement a cross-validation method to choose the number of features. As a result, 3 features performs better than 4, so we set $|\mathscr{A}_t| = 3$.

However, the 3 features are different when the training set changes during cross-validation. Such being the case, we count the frequency that features consisted in $\mathscr{A}_t$ during the 21 times validation:

Table 1: The picking frequency of feature during validation

Feature Index	18	0	43	2	11	25	45	51	29	48	50	others
Picking Frequency	18	17	17	6	4	4	3	3	2	2	2	≤ 1

As shown above, the 18th, 0th and 43th components of initial feature with 54 components become our final feature set after dimension reduction. Below are their attributes:

Table 2: Attributes of the selected 3 features

Feature Index	18	0	43
Filter	τ_1	τ_0	τ_7
Statistics	Standard deviation	Mean	Tail

From [4], we get to know the filter τ_1, τ_7 reflects the feature in vertical and τ_0 the averaging feature, which may indicate the genuine and fake paintings could be separated in vertical direction.

2.2 Training Models

Fit 4 training models by cross-validation method in classification based on the features extracted in **Section 2.1**. They are:

(1) Threshold method: based on the idea in **sec 2.1**; given the parameter *threshold*, if the **Raphael distance** $d < threshold$, then the painting is genuine, or else it is fake.

(2) Neural network: single hidden layer with 10 units

(3) SVM

(4) Decision tree

Before classifying, we divide the training and validation set by the standard deviation of the training set to eliminate the asymmetric influence among the paintings in training set.

The validation accuracy is shown below (TPR: the true positive rate; TNR: the true negative rate):

Table 3: Accuracy of models

Model	TPR	TNR	Accuracy
Threshold method	100%	33.3%	71.4%
Neural network	75.0%	77.8%	76.2%
SVM	75.0%	66.7%	71.4%
Decision tree	75.0%	55.6%	66.7%

The accuracy is not so brilliant for the training set is too small (contains only 20 paintings during cross-validation). We have also tried spliting each painting into 4 parts to increase the sample size, but it turns out to make little difference.

The most practical model is Threshold method, because it is not time-consuming and makes right judgement on all Raphael's painting, identifying some fake paintings successfully although the ability is relatively weak. In application, it can be used to pick some fake out before using other elaborate classifiers.

Figure 2: The 14th painting: it is fake but deceives all our classifiers

2.3 Prediction

Upon all the models, we give our prediction to the 7 pictures remaining disputed:

(1) Positive (Raphael's): 1, 23, 25

(2) Negative (Not Raphael's): 7, 10, 20, 26

But note that the 26th painting has been contaminated! We can even see dark spots clearly on the top half.

Figure 3: The 26th painting: it has been contaminated

Hence we pick the bottom half of it up and repeat our classification. At this time, more experiments also show that the 26th painting is fake, hence our conclusion remains unchanged.

3 Synthesizing Raphael's Style

In this part, we use **cycleGAN**[2]to sythesize a painting of Raphael, i.e. translate a photo or picture into one with Raphael's style. First of all, let's review GAN[3] algorithm.

3.1 Introduction of GAN

GAN (generative adversarial networks) can be applied to generate a fixed style of picture. There are two main components of GAN: generator and discriminator.

Generator $G : X \to Y$ is used to generate a new picture. Here, X and Y are two given spaces, and specifically, Y is the space given samples. (Generally, X is $\mathbb{R}^n$.)

Discriminator $D : Y \to [0, 1]$ is for judging whether a given picture is from the sample space Y or from the generator. We train both X and Y at the same time according to the loss function

$$\text{Loss}(G, D, X, Y) = \mathbb{E}_{y\sim p(y)}[\log D(y)] + \mathbb{E}_{x\sim p(x)}[\log(1 - D(G(x)))]$$

Our goal is to find D^* to maximize the Loss and G^* to minimize the Loss.

3.2 Synthesizing by CycleGAN

Let $\mathcal{X}$ and $\mathcal{Y}$ be two sample spaces which contain two types of graphs. Let $G : \mathcal{X} \to \mathcal{Y}$ and $F : \mathcal{Y} \to \mathcal{X}$ be two generators, and $D_{\mathcal{X}} : \mathcal{X} \to [0, 1]$ and $D_{\mathcal{Y}} : \mathcal{Y} \to [0, 1]$ be two discriminators. F is regarded as the inverse of G, i.e. $F(G(x)) \approx x$ and $G(F(y)) \approx y$. Also, $(G, D_{\mathcal{Y}}, \mathcal{X}, \mathcal{Y})$ and $(F, D_{\mathcal{X}}, \mathcal{Y}, \mathcal{X})$ can be considered as two GANs. So here is the loss function

$$\text{Loss} = \text{Loss}_{G_1} + \text{Loss}_{G_2} + \lambda \text{Loss}_{cyc},$$

where

$$\begin{aligned}
\text{Loss}_{G_1}(G, D_{\mathcal{Y}}, \mathcal{X}, \mathcal{Y}) &= \mathbb{E}_{y\sim p(y)}[\log D_{\mathcal{Y}}(y)] + \mathbb{E}_{x\sim p(x)}[\log(1 - D_{\mathcal{Y}}(G(x)))] \\
\text{Loss}_{G_2}(G, D_{\mathcal{X}}, \mathcal{Y}, \mathcal{X}) &= \mathbb{E}_{x\sim p(x)}[\log D_{\mathcal{X}}(x)] + \mathbb{E}_{y\sim p(y)}[\log(1 - D_{\mathcal{X}}(F(y)))] \\
\text{Loss}_{cyc}(F, G, \mathcal{X}, \mathcal{Y}) &= \mathbb{E}_{x\sim p(x)}[||F(G(x)) - x||_1] + \mathbb{E}_{y\sim p(y)}[||G(F(y)) - y||_1]
\end{aligned}$$

Here, Loss_{G_1} and Loss_{G_2} are the loss of two GANs and Loss_{cyc} is the loss of cycle. And G, F are supposed to minimize the loss and $D_{\mathcal{X}}$, $D_{\mathcal{Y}}$ to maximize the loss. We train the model as is shown in [2]. As a reference, the codes from [5] also help a lot.

The following are our final results.

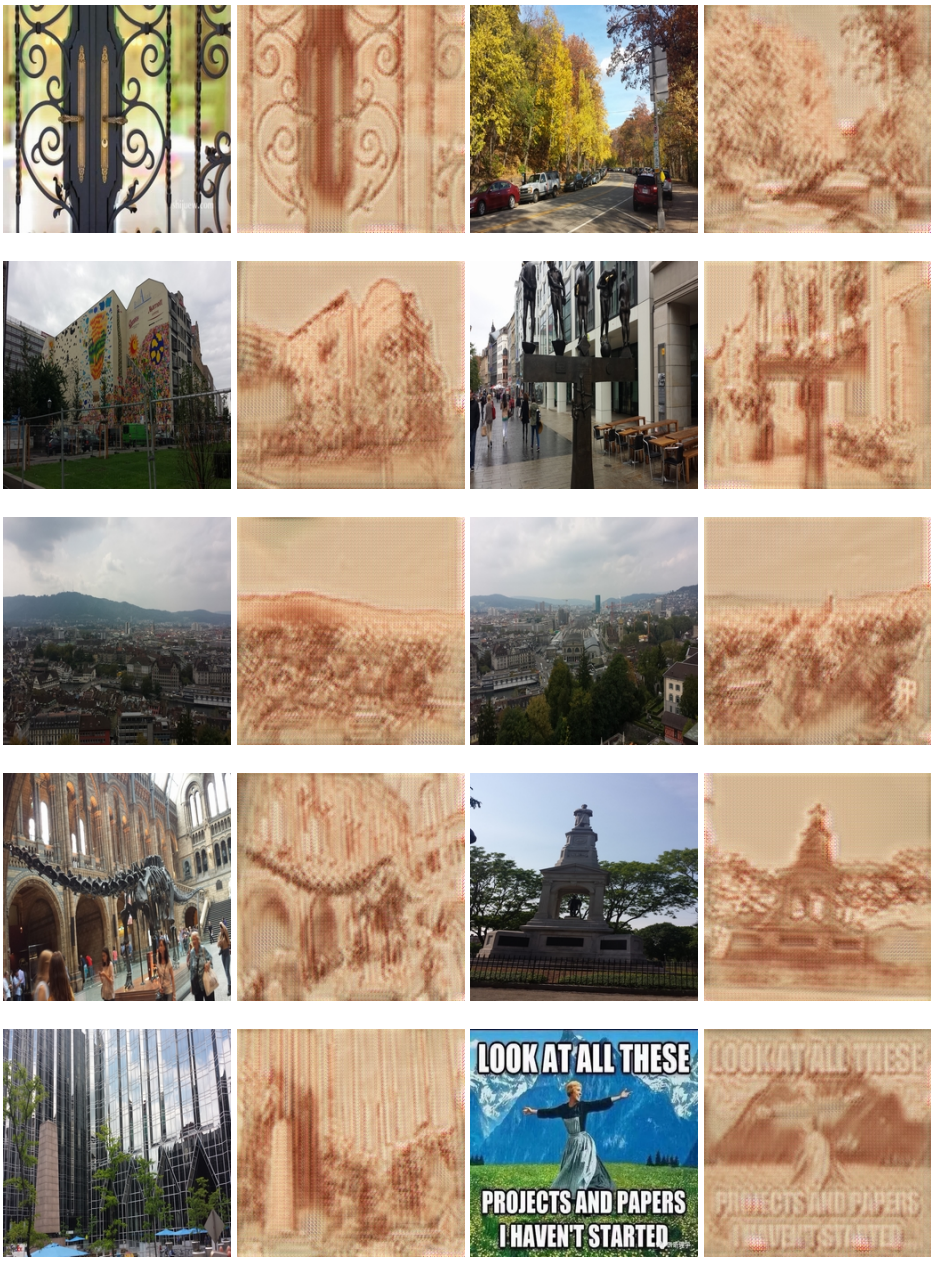

Figure 4: Pictures in pair with original or Raphael's style

References

[1] Liu, H., Chan, R. H., & Yao, Y. (2016). Geometric tight frame based stylometry for art authentication of van gogh paintings. Applied & Computational Harmonic Analysis, 41(2), 590-602.

[2] Zhu, J. Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired image-to-image translation using cycle-consistent adversarial networks.

[3] Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. Computer Science.

[4] http://ieeexplore.ieee.org/document/5680648/

[5] https://github.com/vanhuyz/CycleGAN-TensorFlow

[6] http://ju.outofmemory.cn/entry/326146