MATH 6380o Mini-Project 1: Feature Extraction and Transfer Learning

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Introduction

Art fraud is common and its identification is extremely difficult. Conventional art forgery detection methods mainly rely on physical examination which can be very complicated and expensive, even can bring the risk of causing irreversible damage to the original art piece. With the development of artificial intelligence, such problems may be solved by a digital approach via deep learning.

In this project, deep neural network ResNet-18 and scattering network (ScatNet) are attempted to predict whether 7 disputed sketches belong to the Italian painter Raphael, one of the trinity of great masters of High Renaissance.

Figure 1. One of Raphael's masterpieces: *The School of Athens.*

Data

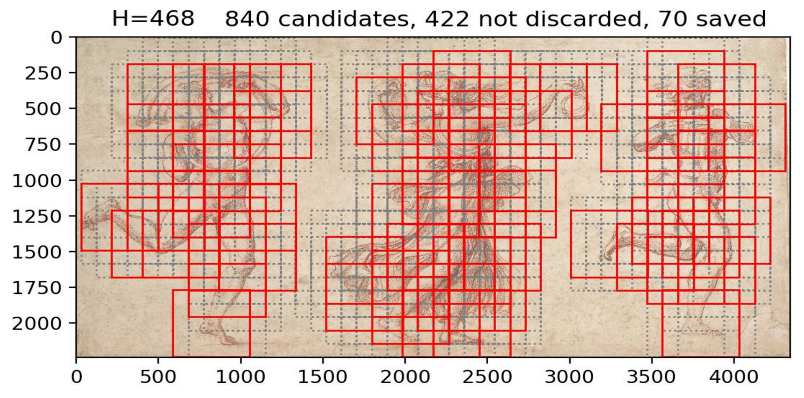
The data provided by Prof. Yang Wang from HKUST, which contains 35 digital sketches of Raphael or forgeries either in .tiff or .jpeg format, 12 of which belong to Raphael, 16 do not and 7 remain disputed.

Data Preparation & Augmentation

With limited prior knowledge on whether local/detailed or global/general characteristics are the key to the classification, we are inspired by methods of multi-scale feature extraction including Spatial Pyramid Pooling, and decide to extract features from various square crops with different sizes. For each specific edge length H, the H × H crop is viewed as a 2-dimensional sliding window shifting on the original image, each time hopping for H/5 pixels. We perform Canny edge detection on all Candidate Crops and discard the empty crops, and then sort the remaining crops by number of edge pixels. Then, we pick up and save the crops in such order, unless more than 9/25 of the crop is overlapped with some previously saved one. In this way, we ensure that crops with most meaningful content of the painting are selected, while not much too duplicated with each other. We select H from the shorter side of the image, and scale H by 2/3 in each iteration until H is smaller than 224. Finally, all crops are rescaled to 224 × 224 to fit the input size of ResNet models pretrained on ImageNet.

In this way, more than **23000** crops of various scales are extracted from the original images, which well augment our data and enable us to discover the impacts of features from different scales on our classification task. Also, we consider to use original images as samples for comparison

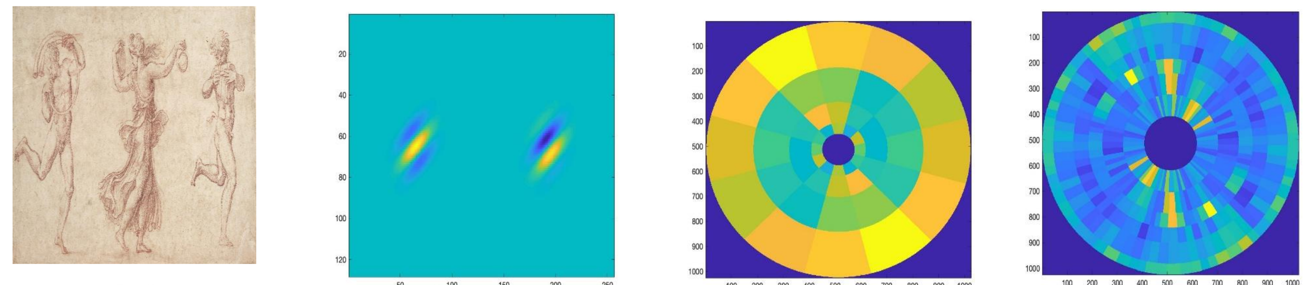
A sample of our crop selection process is given in the Figure, in which candidate crops that are not discarded are marked by grey dotted squares, and the crops selected to be saved are marked by red squares.



Feature Extraction

- **ScatNet**

A wavelet scattering framework enables us to derive, with minimal configuration, low-variance features from the figures. The features extracted from wavelet scattering network are insensitive to input's translations. They are continuous regarding deformations on an invariance scale. With ScatNet package[1], our model are firstly transformed original figures into grey scales then fed into the 2-layer network. The extracted feature vectors are 417 dimensions.



Original figure filter Transform1 Transform2

- **ResNet18**

The Development of transfer learning allows us to transfer the pretrained neural network to work for the new relevant job. Consider the nature of this project is kind of image classification, we introduced pretrained Resnet18 to conduct classification task on Raphael's works, and further perform feature extraction to mine some valuable features for our further unsupervised and supervised learning tasks.

Feature Visualization

To visualize the extracted features, we conduct Principal Component Analysis (PCA) on the 417-column features for ScatNet and 512-column features for Transfer Learning with Resnet18 (using augmented data). The first two main principal components are illustrated and different colors reveal whether the art piece is originated from Raphael or not.

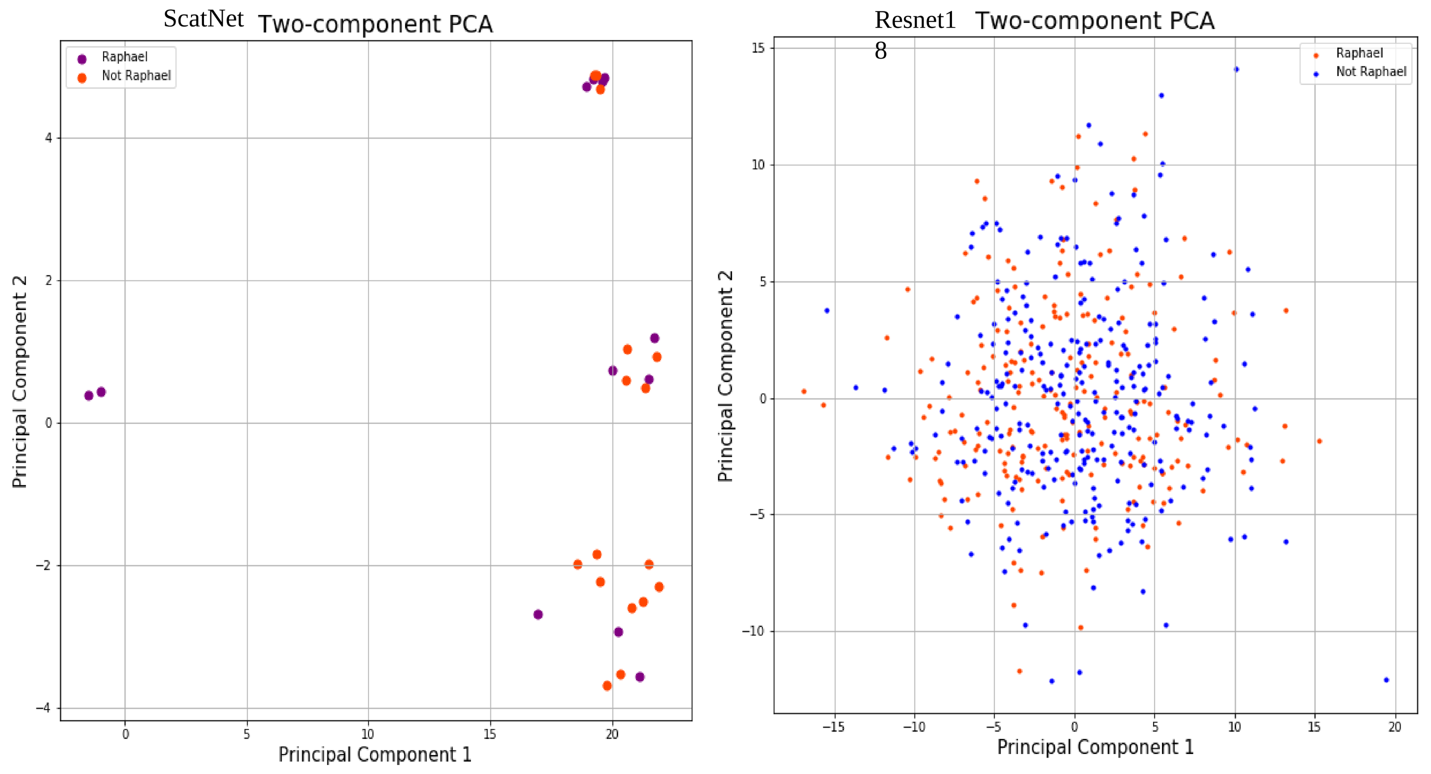
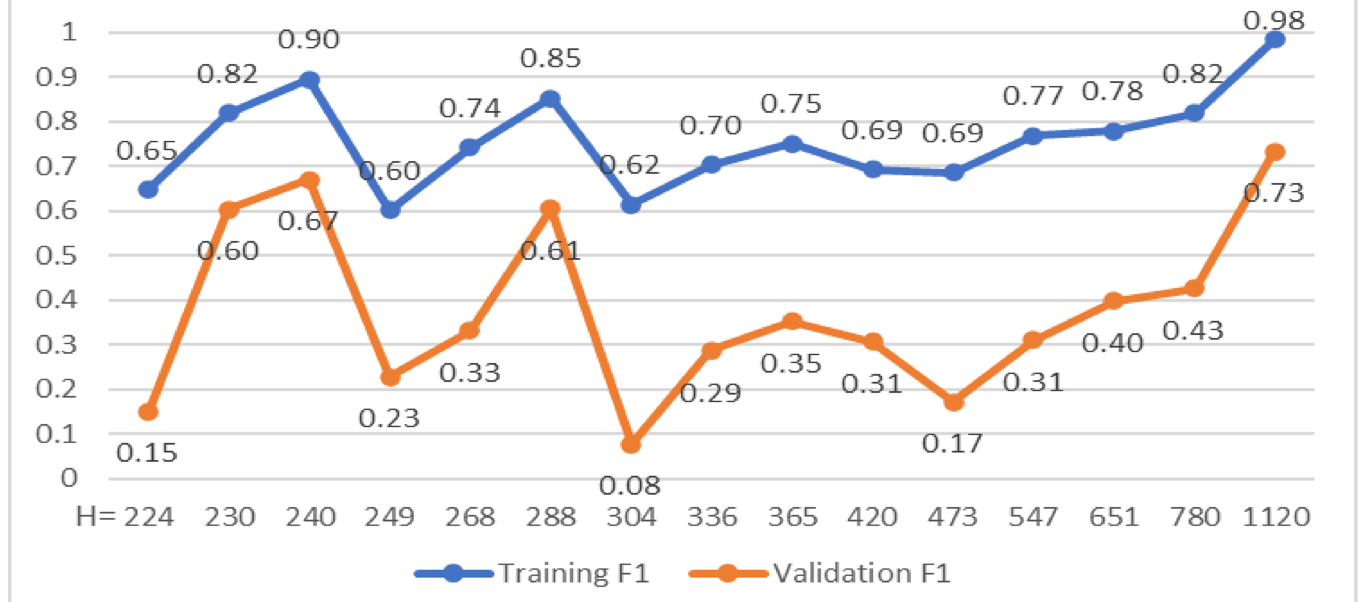


Image Classification

We perform Logistic Regression, Support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and Random Forest on both Resnet18 and Scattering Net features. Results are demonstrated in the following table.

More, we assume that crops with different sizes may have different potential of use for our classification in different ways. Therefore, for each range of size we further train a classifier separately. The ranges are selected so that the sizes of the corresponding training set are balanced to ensure that the comparisons between classifiers are fair.

The results are surprising: as shown in the figure, for some ranges of sizes, the F1-score reaches 0.73, while for others the F1-scores are close to a random guess of 0.5, which indicate that such samples are not useful and may inject noise to our model trained on the entire datasets. More, such findings give us the idea that using a weighted ensemble of classifiers of for different sizes of crops on the disputed painting may give the most convincing results.



MSE	Logistic Regression	SVM	LDA	Random Forrest
Resnet18	0.4521	0.4535	0.4532	0.4782
ScatNet	0.4286	0.5714	0.5714	0.5220

Compared to Resnet18, the ScatNet feature extraction process lacks data augmentation, hence the sample number insufficient for training and classification.

Prediction

We performed prediction on each disputed painting by an ensembled classifier, which is based on weighted votes of logistic regressors trained on ResNet features extracted from different sizes of crops after the augmentation, with their F1 score on dev set as weights. Predicted probabilities of whether the corresponding sample is Raphael are shown in the Table. Samples predicted as Non-Raphael are marked in red.

Sample	Probability
1. 185x354	0.524
7. 243x413	0.566
10. 269x227	0.468
20. 135x390	0.370
23. 84x68	0.557
25. 156x115	0.592
26. 197x187	0.408

Contribution

Mutian He: Data Preparation & Augmentation, Feature extraction using ResNet, Image Classification and Prediction with Augmented Data

Yuxin Tong: Feature extraction by using Wavelet Scattering Network

Qing Yang: Supervised & Unsupervised Learning with Visualization

Ruoyang Hou: Supervised Learning & Poster Editing

Reference

[1] L. Sifre, M. Kapoko, E. Oyallon, V. Lostanlen, Scatnet: a matlab toolbox for scattering networks, 2013.

[2] He, Kaiming, et al. "Deep residual learning for image recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. 2016.