MATH63800 Project 1

Comparing Scattering Network & Resnet-18: A Case Study On Raphael's Sketches

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Introduction

Objective

Statistical and machine learning methods have opened a new door for art authentication. In this project, we aim to compare the performances of Scattering Network and Resnet-18 in terms of their effectiveness of extracting features useful for forgery detection.

Data

Our data contains 28 high-resolution images of sketches (including both JPEG and TIF formats), in which:

- 12 are Raphael's work
- 9 are non-Raphael
- 7 are disputed (i.e. unlabelled)

Methodology

Data Pre-processing

- Random Cropping: In order to augment the data, we randomly crop 200 patches of size 224×224 from each labelled image to obtain a total number of 4200 samples.

Feature Extraction

- Scattering Network: Proposed by Bruna and Mallat [1], it generates a translation invariant representation for each image. Our scattering network contains 2 layers.
- Resnet-18: Proposed by Microsoft [2], this is an 18-layer residual network. For feature extraction, we simply remove its last classification layer and directly use the pre-trained weights in its convolutional layers.

Classification (4 Methods):

- Logistic Regression (LR)
- *k*-Nearest Neighbours (KNN)
- Random Forest (RF)
- Support Vector Machine (SVM)

Evaluation

- Leave-one-out-cross-validation (CV): Due to the small data size, we train our models on all but one labelled images, and obtain the accuracy by testing the model on that one image. This process is repeated for every image in the data set.

Feature Extraction & Visualisation Results

Feature Extraction

We compute two feature vectors for each of the 4200 labelled patches:

- Scattering Net (SN): The images are first transformed in to greyscale before being fed into the network. The resulting feature vectors have 417 dimensions.
- Resnet-18 (R18): The TIF images are first transformed into ordinary RGB ones. The output feature vectors are of 512 dimensions.

Visualisation

We applied 6 dimension reduction techniques to the feature vectors obtained above, which are PCA, MDS, ISOMAP, Standard LLE, Spectral Embedding, and t-SNE.

- R18: Whilst PCA and MDS do not show distinctive clustering, manifold learning methods like TSNE and ISOMAP can demonstrate that images of the same label are indeed grouped together.

- SN: This time, none of the 6 methods show there is distinctive clustering, possibly due to that the points do not lie on a low-dimensional manifold.

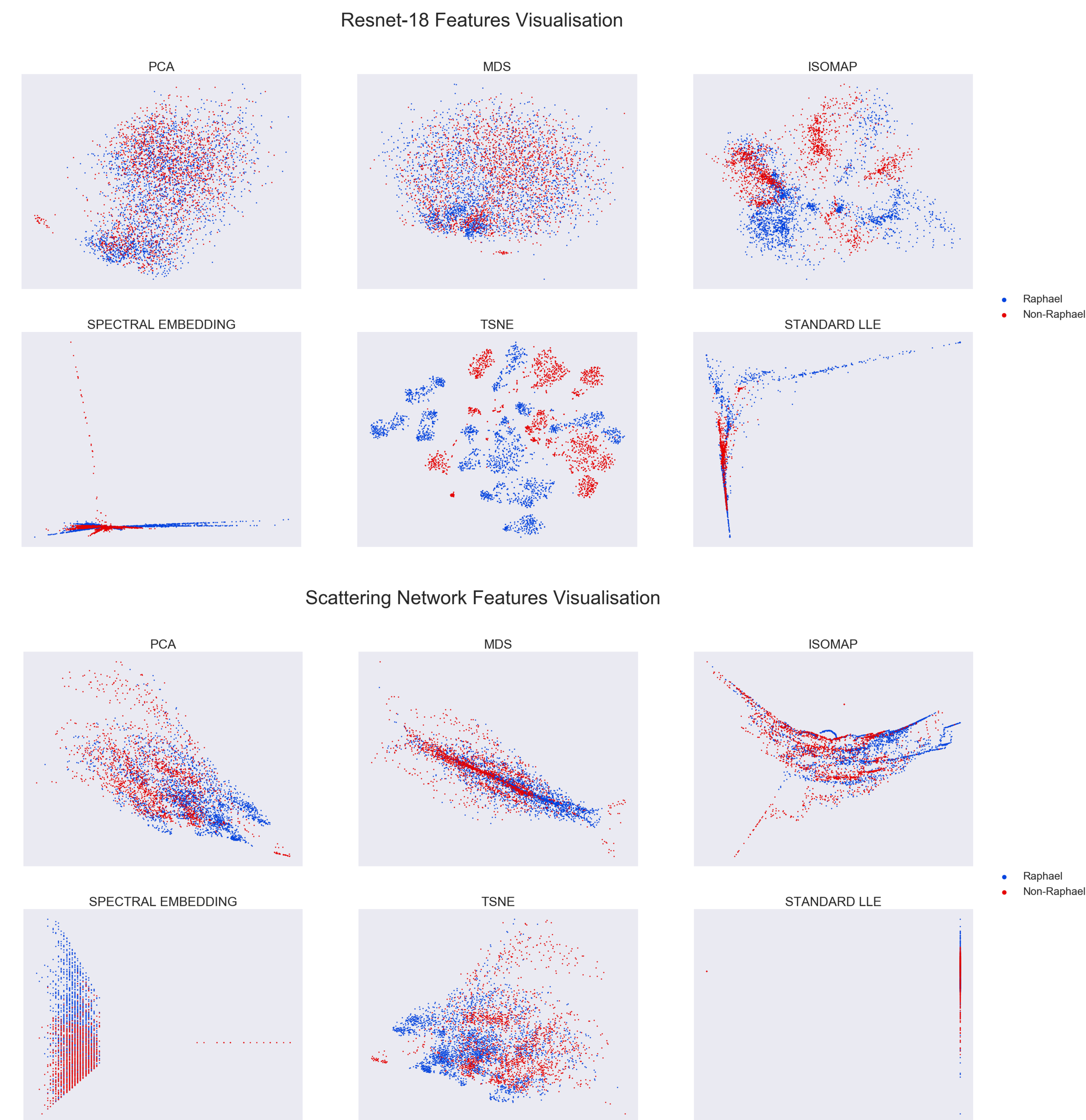

Figure 1. Visualisations of the feature vectors obtained from R18 (upper) and SN (lower). Blue points represent genuine Raphael's sketches, whereas red ones indicate they are non-Raphael.

Classifiers Training Results

As mentioned before, we used CV for model evaluation, and the accuracies are summarised in Table 1. As one can see, R18 gives the most stable results, whereas the accuracies for SN contain a lot of variations. In terms of best performance however, SN+LR gives the best accuracy, at 95.24%.

	Feature Extraction Method							
	R18				SN			
Classifier	LR	KNN	RF	SVM	LR	KNN	RF	SVM
Accuracy	80.95%	85.71%	76.19%	80.95%	95.24%	52.38%	71.42%	90.48%

Table 1. Leave-one-out-cross-validation results.

Authenticating the Disputed Artworks

Now our models have been trained on the 21 labelled images, we are ready to make predictions on the remaining 7 unlabelled ones. From Table 2, we can see image 1 and 23 are predicted to be Raphael's work by most models, and image 10 is predicted to be non-Raphael. However, one cannot draw a definitive conclusion for the other images.

	Feature Extraction Methods							
	R18				SN			
Image ID	LR	KNN	RF	SVM	LR	KNN	RF	SVM
1	✓	✓	✓	✓	✓	✓	✓	✓
7	✗	✗	✓	✓	✓	✗	✗	✓
10	✗	✗	✗	✗	✗	✗	✗	✗
20	✗	✗	✗	✗	✓	✗	✓	✓
23	✗	✓	✓	✗	✓	✗	✗	✓
25	✓	✓	✓	✓	✓	✓	✗	✓
26	✗	✓	✗	✗	✓	✗	✓	✓

Table 2. Predicting the unlabelled images. A tick (✓) means it is classified as Raphael's work, a cross (✗) means it is not.

Figure 2. The unlabelled sketches

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- **SUN Jiaze**: Feature dimension reduction & visualization, poster

References

1. J. Bruna, S. Mallat. *Invariant Scattering Convolution Networks.* arXiv. 2012.
2. K. He, X. Zhang, S. Ren, J. Sun. *Deep Residual Learning for Image Recognition.* arXiv. *2015.* Retrieved from: https://arxiv.org/pdf/1512.03385.pdf.