

Raphael Painting Analysis

Transfer learning and Visualization

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Outline

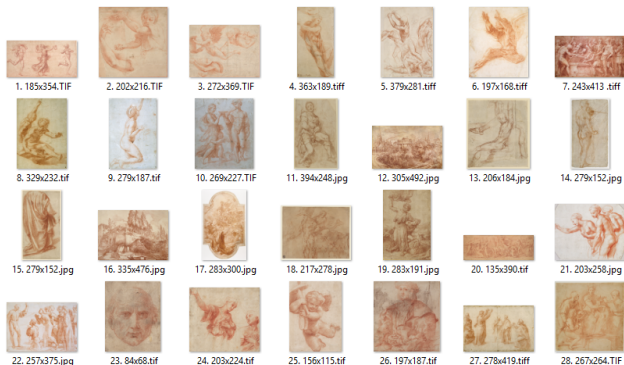
1 Data Description

2 Methodology

3 Visualization

Data Description

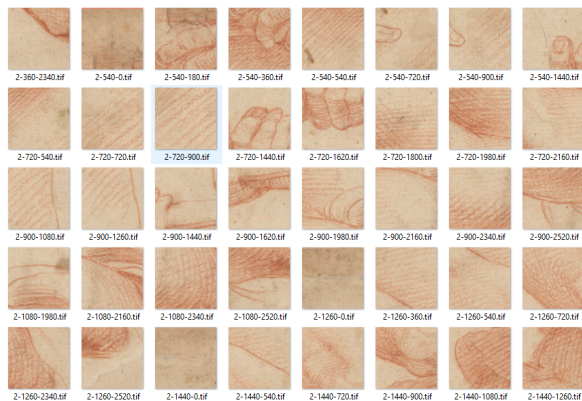
Raphael Paintings: 12 authentic, 9 fake and 7 disputed paintings.



Goal: Investigate the secret of Raphael!

Data Description

Preprocessing: crop (224, 224) patches from original paintings, remove almost blank parts (simply thresholding at variance of patches).



Data Description

Sequentially cropping v.s. random cropping

```
crop_size = (224, 224)
picture_dir = 'Raphael_Project'
disputed_id = [1, 7, 10, 20, 23, 25, 26]
authentic_id = [2, 3, 4, 5, 6, 8, 9, 21, 22, 24, 27, 28]
fake_id = [11, 12, 13, 14, 15, 16, 17, 18, 19]
labels = dict(**{str(x): 'fake' for x in fake_id}, **{str(x): 'disputed' for x in disputed_id},
              **{str(x): 'authentic' for x in authentic_id})
low_var_filter = True
low_var_threshold = 200

%load_ext autoreload
%autoreload 2
```

```
from Crop_Images import crop_Images
crop = crop_Images(picture_dir, labels, low_var_filter, low_var_threshold)
```

```
crop.random_crop(crop_size, n_multiple = 2)
```

```
folder: data/train/disputed does not exists, creating
folder: data/train/authentic does not exists, creating
folder: data/train/fake does not exists, creating
totally 18072 pictures created
```

```
crop.sequential_crop(crop_size, offset=(180, 180))
```

```
Folder: data/train\disputed does not exist, creating
Folder: data/train\authentic does not exist, creating
Folder: data/train\fake does not exist, creating
totally 12034 pictures created, we ignore 1055 low variance pictures
```

Data Description

Both validation and test sets consist of one authentic and one fake paintings.

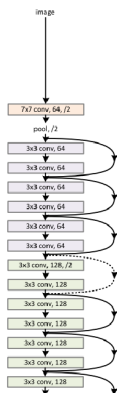
```
crop.shuffle()
```

```
take 24 and 12 as validation pictures  
take 3 and 16 as test pictures
```

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Transfer Learning



We borrow pretrained ResNet18 from PyTorch, reset FC layer.

Transfer Learning

```
(layer2): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d (64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True)
    (relu): ReLU(inplace)
    (conv2): Conv2d (128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True)
    (downsample): Sequential(
      (0): Conv2d (64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True)
    )
  )
  (1): BasicBlock(
    (conv1): Conv2d (128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True)
    (relu): ReLU(inplace)
    (conv2): Conv2d (128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True)
  )
)
```

Resnet18 has 4 such Layers. Next, we shall tune the number of freeze Layers.

Results

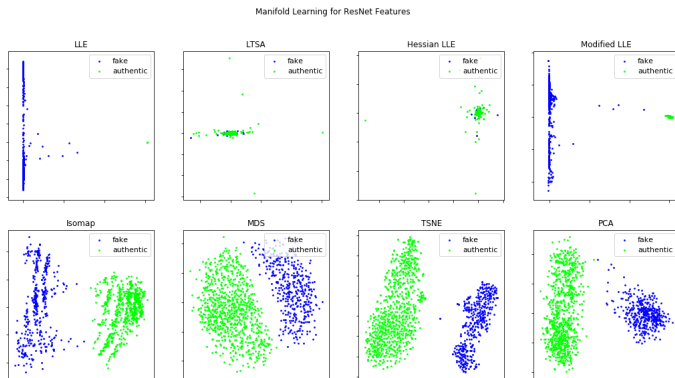
Typical models	Good model			Bad model		
	train	val	test	train	val	test
FC layer	86.98	97.98	98.15	97.08	78.11	57.06
Layer 4, FC layer	93.87	99.36	99.66	99.99	83.38	54.95
Layers 3 & 4, FC layer	99.90	99.79	99.50	99.96	86.15	74.46

Good model: Val: 21,18 Test:9,12

Bad model: Val:24, 12 Test:3,16

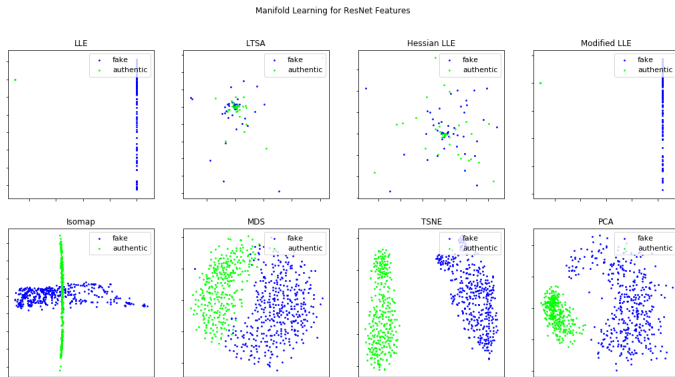
Manifold Learning

We compare 8 popular methods in Manifold Learning on the test sets. The result of the Good model (Layers 3, 4 and FC layer) is as follows:



Manifold Learning

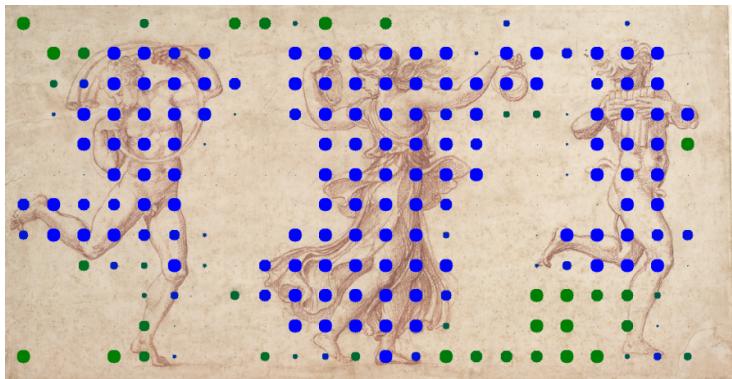
The result of the bad model (Layers 3 & 4, FC layer) is as follows:



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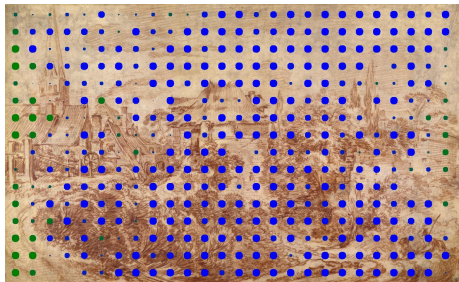
Visualization directly on painting



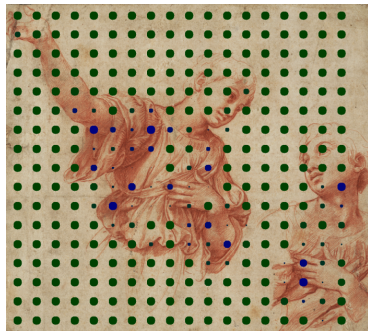
Motivation

- ▶ The performance of model highly depends on the choice of data segmentation.
- ▶ Lack of data - prior knowledge - visualization.
- ▶ Visualization bridge the gap between art master and data scientist.

Bad Model: Validation

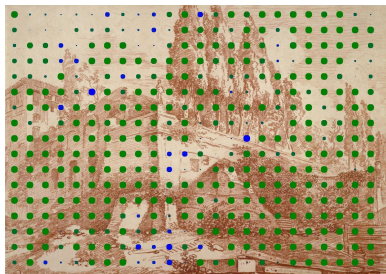


(a) #12 Fake

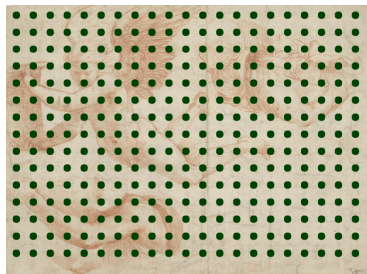


(b) #24 Authentic

Bad Model: Test



(c) #16 Fake



(d) #3 Authentic

Possible Reasons



(e) #12

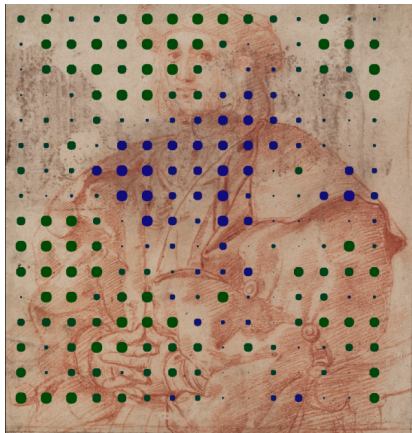


(f) #16

Figure: Landscape

- ▶ These are the only 2 landscape paintings in datasets.
- ▶ Model did not learn any features for landscape painting.

Disputed



- ▶ Our model gives 48% of patches to be real.
- ▶ Model mis-recognize contaminated patches.