

Artistic Style Transfer Implementation with Tensorflow

GR5242 Advanced Machine Learning Final Project

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1 Introduction

1.1 Project background

1.2 Related works

1.3 Development environment and hardware information

2 Mathematical Foundation

2.1 Covolutional neural network

2.2 VGG-network

2.3 Loss function

3 Tensorflow Implementation

3.1 System overview

The style transfer system is implemented mainly with Python Tensorflow, with auxiliary packages including NumPy, SciPy, and Pillows. A flowchart of the system overview is provided in Fig. 3–1.

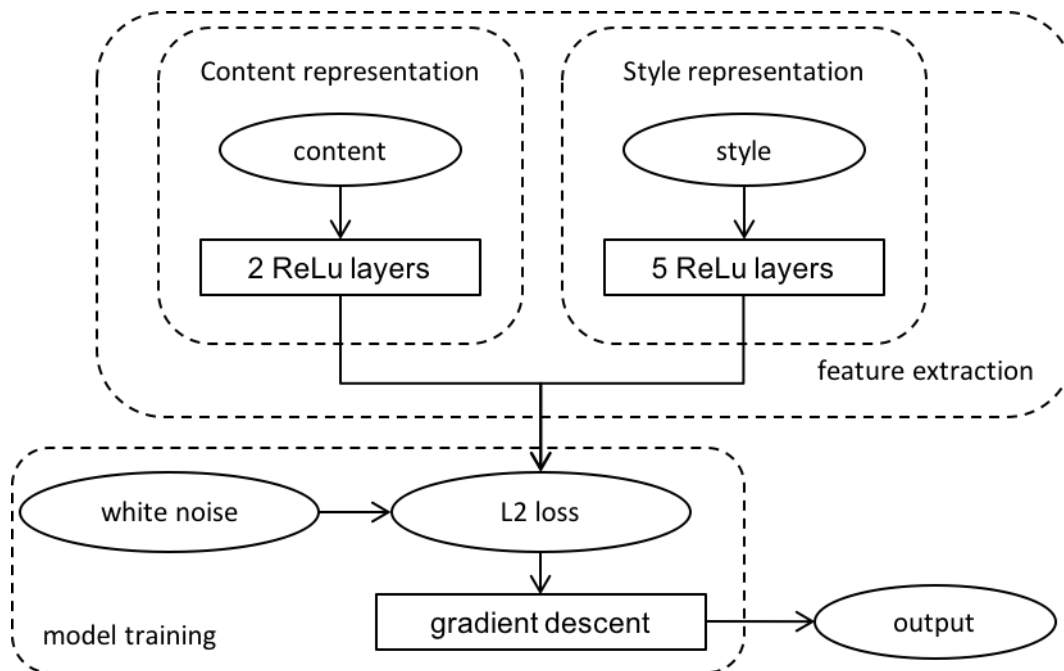


Figure 3–1: Tensorflow implementation system overview

In feature extraction part, the pre-trained VGG network is used for both content representation and style representation. One ReLu layers (relu4_2) is for content feature extraction and five ReLu layers (relu1_1, relu2_1, relu3_1, relu4_1, relu5_1) are for style representation, which are different from the original work [1].

In model training part, the final output is initialized with a white noise picture, and a gradient-based optimization methodology known as Adam is used. As is described in [2], Adam optimizer is based on first-order gradient. Other optimizers including traditional gradient descent method can also be implemented.

3.2 Pre-defined parameters

Some tuning parameters are hard-wired in the system. Most of the choices follow the original work [1], or the reference [3] and some are modified.

There is plenty of room with cross-validation optimization for performance improvement (see Sec 5.1 for more details). For simplicity, they are fixed in this system for now and the user can easily modify part of them in `constants.py` following instruction in A.

Some pre-defined parameters are listed below in Table 3–1. The ratio of content loss and style loss is arbitrarily set while [1] explores different loss ratios and corresponding output results. Parameters can always be modified and optimized with techniques like cross-validation.

| parameter type | parameter value |
|------------------------|-----------------|
| content weight | 5 |
| style weight | 500 |
| total variation weight | 100 |
| Adam learning rate | 10 |
| Adam β_1 | 0.9 |
| Adam β_2 | 0.999 |
| Adam ϵ | 10^{-8} |
| maximum iteration | 1000 |
| pooling layer method | max |

Table 3–1: Pre-defined model parameters

Apart from model parameters, neural network choice in this work is also different.

| | | layers used |
|------------------------|---------------|---|
| content representation | this work | relu4_2 |
| | original work | conv1_1, conv4_2 |
| | Anish work | relu4_2, relu5_2 (weight adjustable) |
| style representation | this work | relu1_1, relu2_1, relu3_1, relu4_1, relu5_1 |
| | original work | conv1_1, conv2_1, conv3_1, conv4_1, conv5_1 |
| | Anish work | relu1_1, relu2_1, relu3_1, relu4_1, relu5_1 |

Table 3–2: Pre-defined feature extraction layers

Specifically, all layers in style representation are equally weighted. The random initialization, i.e. process to generate the white noise graph is arbitrary as well but has little impact on the output results, and thus is omitted here.

4 Sample Results

4.1 When New York meets Van Gogh

4.2 More examples

5 Discussion

5.1 Tuning parameters optimization

5.2 Running time optimization

A Code Manuscript

Please refer to <https://github.com/tian-gao/AdvML-fall17-project> for detailed instructions. All source code are provided.

The following table shows the required directories and files to use the system.

| | folder or file name | usage |
|------------------|------------------------------|---|
| folders | input | put content picture and style picture inside |
| | output | store output pictures |
| neural network | visual_geometry_group.py | pre-process the trained VGG network data |
| Tensorflow model | neural_network.py | feature extraction and model training with Tensorflow |
| system | style_transfer.py | main function to accept arguments |
| utility | utils.py | utility functions |
| | constants.py | VGG network layers and pre-defined parameters |
| | settings.py | file paths definition |
| | logger.py | formatted standard screen output |
| data | imagenet-vgg-verydeep-19.mat | VGG network data |

Table A–1: Project directory

In order to carry out style transfer, do

```
python style_transfer.py --content content.jpg --style style.jpg --output output.jpg
```

to transfer “style” to “content” and get the “output”.

Instructions to run the Python code and download the data are all explained in details on the GitHub repository.

B Python Code

B.1 style_transfer.py

```
1 import os
2 import sys
3 import time
4 import scipy.misc
5 from argparse import ArgumentParser
6 from utils import read_image, save_image
7
8 from logger import logger
9 from settings import PATH_INPUT_STYLE, PATH_INPUT_CONTENT, PATH_OUTPUT, TRAINED_NETWORK_DATA
10 from constants import (
11     CONTENT_WEIGHT, STYLE_WEIGHT, TV_WEIGHT, POOLING,
12     LEARNING_RATE, BETA1, BETA2, EPSILON, MAX_ITERATION
13 )
14 from visual_geometry_group import VGG
15 from neural_network import NeuralNetwork
16
17
18 def style_transfer(
19     content_name, style_name, output_name, content_weight, style_weight, tv_weight,
20     pooling, learning_rate, beta1, beta2, epsilon, max_iteration, check_point):
21     time_start = time.time()
22
23     # read images
24     content = read_image(PATH_INPUT_CONTENT + content_name)
25     style = read_image(PATH_INPUT_STYLE + style_name)
26     style = scipy.misc.imresize(style, content.shape[1] / style.shape[1])
27
28     # initialize objects
29     vgg = VGG(TRAINED_NETWORK_DATA, pooling)
30     nn = NeuralNetwork(content, style, vgg, content_weight, style_weight, tv_weight)
31
32     # train model
33     for k, output_image in nn.train_model(learning_rate, beta1, beta2, epsilon,
34         max_iteration, check_point):
35         name_list = output_name.split('.')
36         image_name = PATH_OUTPUT + '.'.join(name_list[:-1]) + '_{}.{}'.format(str(k) if not
37             k % check_point else 'final', name_list[-1])
38         save_image(output_image, image_name)
39
40     time_end = time.time()
41     logger.info('Time elapsed: {} seconds'.format(round(time_end - time_start)))
```

```
42 def build_parser():
43     parser = ArgumentParser()
44     parser.add_argument('--content', dest='content', required=True,
45                         help='Content image, e.g. "input.jpg"')
46     parser.add_argument('--style', dest='style', required=True,
47                         help='Style image, e.g. "style.jpg"')
48     parser.add_argument('--output', dest='output', required=True,
49                         help='Output image, e.g. "output.jpg"')
50     return parser
51
52
53 if __name__ == '__main__':
54     parser = build_parser()
55     args = parser.parse_args()
56
57     # check if network data file exists
58     if not os.path.isfile(TRAINED_NETWORK_DATA):
59         logger.error('Cannot find pre-trained network data file!')
60         sys.exit()
61
62     style_transfer(
63         content_name=args.content,
64         style_name=args.style,
65         output_name=args.output,
66
67         content_weight=CONTENT_WEIGHT,
68         style_weight=STYLE_WEIGHT,
69         tv_weight=TV_WEIGHT,
70         pooling=POOLING,
71
72         learning_rate=LEARNING_RATE,
73         beta1=BETA1,
74         beta2=BETA2,
75         epsilon=EPSILON,
76         max_iteration=MAX_ITERATION,
77         check_point=MAX_ITERATION / 10
78     )
```

B.2 neural_network.py

```
1 import numpy as np
2 import tensorflow as tf
3 from functools import reduce
4 from operator import mul
5
6 from logger import logger
7 from constants import CONTENT_LAYERS, STYLE_LAYERS
8 from utils import process_image, unprocess_image
9
10
11 class NeuralNetwork(object):
12     """NeuralNetwork provides an interface to formulate the Tensorflow neural network model
13     and perform style transfer algorithm"""
14     def __init__(self, content, style, vgg, content_weight, style_weight, tv_weight):
15         logger.info('Initializing neural network.....')
16         self.content = content
17         self.style = style
18         self.vgg = vgg
19
20         self.content_weight = content_weight
21         self.style_weight = style_weight
22         self.tv_weight = tv_weight
23
24         self.content_shape, self.style_shape, self.content_layer_weights, self.
25             style_layer_weights = self.get_parameters()
26         self.content_features, self.style_features = self.get_features()
27
28     def get_parameters(self):
29         logger.info('Fetching images parameters.....')
30         content_shape = (1, ) + self.content.shape
31         style_shape = (1, ) + self.style.shape
32
33         # get content layer weights
34         content_layer_weights = {}
35         content_layer_weights['relu4_2'] = 1.0
36         content_layer_weights['relu5_2'] = 0.0
37
38         # get style layer weights
39         style_layer_weights = {}
40         for style_layer in STYLE_LAYERS:
41             style_layer_weights[style_layer] = 1.0 / len(STYLE_LAYERS)
42
43         return content_shape, style_shape, content_layer_weights, style_layer_weights
44
45     def get_features(self):
46         content_features = self._get_content_feature()
47         style_features = self._get_style_feature()
```

```
47         return content_features, style_features
48
49     def _get_content_feature(self):
50         logger.info('Fetching content features.....')
51         content_features = {}
52         graph = tf.Graph()
53         with graph.as_default(), graph.device('/cpu:0'), tf.Session() as session:
54             content_image = tf.placeholder('float', shape=self.content_shape)
55             content_net = self.vgg.load_net(content_image)
56             content_pre = np.array([
57                 process_image(self.content, self.vgg.mean_pixel)])
58             for content_layer in CONTENT_LAYERS:
59                 content_features[content_layer] = content_net[content_layer].eval(feed_dict
60                     ={content_image: content_pre})
61
62         return content_features
63
64     def _get_style_feature(self):
65         logger.info('Fetching style features.....')
66         style_features = {}
67         graph = tf.Graph()
68         with graph.as_default(), graph.device('/cpu:0'), tf.Session() as session:
69             style_image = tf.placeholder('float', shape=self.style_shape)
70             style_net = self.vgg.load_net(style_image)
71             style_pre = np.array([
72                 process_image(self.style, self.vgg.mean_pixel)])
73             for style_layer in STYLE_LAYERS:
74                 feature = style_net[style_layer].eval(feed_dict={style_image: style_pre})
75                 feature = np.reshape(feature, (-1, feature.shape[3]))
76                 gram = feature.T.dot(feature) / feature.size
77                 style_features[style_layer] = gram
78
79         return style_features
80
81     def train_model(self, learning_rate, beta1, beta2, epsilon, max_iteration, check_point):
82         with tf.Graph().as_default():
83             # initialize with random guess
84             logger.info('Initializing tensorflow graph with random guess.....')
85             noise = np.random.normal(size=self.content_shape, scale=np.std(self.content) *
86                 0.1)
87             initial_guess = tf.random_normal(self.content_shape) * 0.256
88             input_image = tf.Variable(initial_guess)
89             parsed_net = self.vgg.load_net(input_image)
90
91             # calculate loss
92             content_loss = self._calculate_content_loss(parsed_net)
93             style_loss = self._calculate_style_loss(parsed_net)
94             tv_loss = self._calculate_tv_loss(input_image)
95             loss = content_loss + style_loss + tv_loss
```

```
94
95     # summary statistics
96     tf.summary.scalar('content_loss', content_loss)
97     tf.summary.scalar('style_loss', style_loss)
98     tf.summary.scalar('tv_loss', tv_loss)
99     tf.summary.scalar('total_loss', loss)
100     summary_loss = tf.summary.merge_all()
101
102     # initialize optimization
103     train_step = tf.train.AdamOptimizer(learning_rate, beta1, beta2, epsilon).
        minimize(loss)
104
105     with tf.Session() as session:
106         summary_writer = tf.summary.FileWriter('logs/neural_network', session.graph)
107         logger.info('Saving graph.....')
108
109         session.run(tf.global_variables_initializer())
110         logger.info('Initializing optimization.....')
111         logger.info('Current total loss: {}'.format(loss.eval()))
112
113         for k in range(max_iteration):
114             logger.info('Iteration {} total loss {}'.format(str(k+1), loss.eval()))
115             train_step.run()
116             summary = session.run(summary_loss)
117             summary_writer.add_summary(summary, k)
118
119             # save intermediate images at checkpoints
120             if (check_point and (not k % check_point)) or k == max_iteration - 1:
121                 output_temp = input_image.eval()
122                 output_image = unprocess_image(output_temp.reshape(self.
                    content_shape[1:]), self.vgg.mean_pixel)
123                 yield k, output_image
124
125     def _calculate_content_loss(self, parsed_net):
126         logger.info('Calculating content loss.....')
127         losses = []
128         for content_layer in CONTENT_LAYERS:
129             losses += [
130                 self.content_layer_weights[content_layer] * self.content_weight * (
131                     2 * tf.nn.l2_loss(
132                         parsed_net[content_layer] - self.content_features[content_layer]
133                     ) / self.content_features[content_layer].size)]
134         return reduce(tf.add, losses)
135
136     def _calculate_style_loss(self, parsed_net):
137         logger.info('Calculating style loss.....')
138         losses = []
139         for style_layer in STYLE_LAYERS:
140             layer = parsed_net[style_layer]
```



```
141         _, height, width, number = map(lambda x: x.value, layer.get_shape())
142         size = height * width * number
143         feats = tf.reshape(layer, (-1, number))
144         gram = tf.matmul(tf.transpose(feats), feats) / size
145         style_gram = self.style_features[style_layer]
146         losses += [
147             self.style_layer_weights[style_layer] * 2 * tf.nn.l2_loss(gram - style_gram)
148             / style_gram.size]
149     return self.style_weight * reduce(tf.add, losses)
150
151 def _calculate_tv_loss(self, image):
152     # total variation denoising
153     logger.info('Calculating total variation loss.....')
154     tv_y_size = self._get_tensor_size(image[:, 1:, :, :])
155     tv_x_size = self._get_tensor_size(image[:, :, 1:, :])
156     tv_loss = self.tv_weight * 2 * ((
157         tf.nn.l2_loss(image[:, 1:, :, :] - image[:, :, self.content_shape[1]-1, :, :]) /
158         tv_y_size) + (
159         tf.nn.l2_loss(image[:, :, 1:, :] - image[:, :, :, self.content_shape[2]-1, :]) /
160         tv_x_size))
161     return tv_loss
162
163 def _get_tensor_size(self, tensor):
164     return reduce(mul, (d.value for d in tensor.get_shape()), 1)
```

B.3 visual_geometry_group.py

```
1 import numpy as np
2 import scipy.io
3 import tensorflow as tf
4
5 from logger import logger
6 from constants import VGG19_LAYERS
7
8
9 class VGG(object):
10     """VGG provides an interface to extract parameter from pre-trained neural network
11     and formulate Tensorflow layers"""
12     def __init__(self, trained, pooling):
13         logger.info('Loading pre-trained network data.....')
14         self.network = scipy.io.loadmat(trained)
15         self.layers, self.mean_pixel = self.init_net()
16         self.pooling = pooling
17
18     def init_net(self):
19         mean_mat = self.network['normalization'][0][0][0] # shape: (224, 224, 3)
20         mean_pixel = np.mean(mean_mat, axis=(0, 1)) # length: 3
21         layers = self.network['layers'].reshape(-1) # length: 43
22         return layers, mean_pixel
23
24     def load_net(self, input_image):
25         # construct layers using parameters
26         logger.info('Parsing layers.....')
27         parsed_net = {}
28         current_image = input_image
29
30         for layer_name, input_layer in zip(VGG19_LAYERS, self.layers):
31             layer_kind = layer_name[:4]
32
33             if layer_kind == 'conv':
34                 current_image = self._get_conv_layer(current_image, input_layer)
35             elif layer_kind == 'relu':
36                 current_image = self._get_relu_layer(current_image)
37             elif layer_kind == 'pool':
38                 current_image = self._get_pool_layer(current_image)
39             parsed_net[layer_name] = current_image
40
41         assert len(parsed_net) == len(VGG19_LAYERS)
42         return parsed_net
43
44     def _get_conv_layer(self, input_image, input_layer):
45         # get kernel and bias
46         # matconvnet: weights are [width, height, in_channels, out_channels]
47         # tensorflow: weights are [height, width, in_channels, out_channels]
```

```
48     kernels, bias = input_layer[0][0][0][0]
49     kernels = np.transpose(kernels, (1, 0, 2, 3))
50     bias = bias.reshape(-1)
51
52     # formulate conv layer
53     conv = tf.nn.conv2d(input_image, tf.constant(kernels), strides=(1, 1, 1, 1), padding
54                        = 'SAME')
55     layer = tf.nn.bias_add(conv, bias)
56     return layer
57
58 def _get_relu_layer(self, input_image):
59     return tf.nn.relu(input_image)
60
61 def _get_pool_layer(self, input_image):
62     if self.pooling == 'avg':
63         layer = tf.nn.avg_pool(input_image, ksize=(1, 2, 2, 1), strides=(1, 2, 2, 1),
64                               padding='SAME')
65     elif self.pooling == 'max':
66         layer = tf.nn.max_pool(input_image, ksize=(1, 2, 2, 1), strides=(1, 2, 2, 1),
67                               padding='SAME')
68     return layer
```

References

- [1] Leon A Gatys, Alexander S Ecker, and Matthias Bethge. Image Style Transfer Using Convolutional Neural Networks. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2414–2423. IEEE, 2016.
- [2] Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.
- [3] Anish Athalye. Neural style. <https://github.com/anishathalye/neural-style>, 2015.