Style Transfer

CS 20: TensorFlow for Deep Learning Research

Lecture 9

2/9/2017

Announcements

Assignment 2 is out. It’s fun, but tricky. Start early.

Sign up for check-ins/IGs with the course staff!
cs20-win1718-staff@lists.stanford.edu

Guest lectures next week

Alec Radford
OpenAI
Topic: GANs
2/9

Danijar Hafner
Google Brain
Topic: Variational Autoencoder
2/14

Agenda

TFRecord

Getting to know each other!

Style Transfer

TFRecord

What’s TFRecord

1. The recommended format for TensorFlow
2. Binary file format

What’s TFRecord

1. The recommended format for TensorFlow
2. Binary file format
   a serialized tf.train.Example protobuf object

Why binary

- make better use of disk cache

Why binary

- make better use of disk cache
- faster to move around

Why binary

- make better use of disk cache
- faster to move around
- can handle data of different types
  e.g. you can put both images and labels in one place

Convert to TFRecord format

- Feature: an image
- Label: a number

Convert to TFRecord format

```
# Step 1: create a writer to write tfrecord to that file
writer = tf.python_io.TFRecordWriter(out_file)

# Step 2: get serialized shape and values of the image
shape, binary_image = get_image_binary(image_file)

# Step 3: create a tf.train.Features object
features = tf.train.Features(feature={'label': _int64_feature(label),
                                      'shape': _bytes_feature(shape),
                                      'image': _bytes_feature(binary_image)})

# Step 4: create a sample containing of features defined above
sample = tf.train.Example(features=features)

# Step 5: write the sample to the tfrecord file
writer.write(sample.SerializeToString())
writer.close()
```

Convert to TFRecord format

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Serialize different data type into byte strings

Convert to TFRecord format

```
def _int64_feature(value):
    return tf.train.Feature(int64_list=tf.train.Int64List(value=[value]))

def _bytes_feature(value):
    return tf.train.Feature(bytes_list=tf.train.BytesList(value=[value]))
```

Read TFRecord

Using TFRecordDataset

Read TFRecord

```
dataset = tf.data.TFRecordDataset(tfrecord_files)
dataset = dataset.map(_parse_function)
```

Parse each tfrecord_file into different features that we want

In this case, a tuple of (label, shape, image)

Read TFRecord

```
dataset = tf.data.TFRecordDataset(tfrecord_files)
dataset = dataset.map(_parse_function)

def _parse_function(tfrecord_serialized):
    features={'label': tf.FixedLenFeature([], tf.int64),
              'shape': tf.FixedLenFeature([], tf.string),
              'image': tf.FixedLenFeature([], tf.string)}

    parsed_features = tf.parse_single_example(tfrecord_serialized, features)

    return parsed_features['label'], parsed_features['shape'], parsed_features['image']
```

See 08_tfrecord_example.py

Assignment 2: Style Transfer

Bringing Impressionism to Life with Neural Style Transfer in *Come Swim*

Bhautik J Joshi*
Research Engineer, Adobe

Kristen Stewart
Director, *Come Swim*

David Shapiro
Producer, Starlight Studios

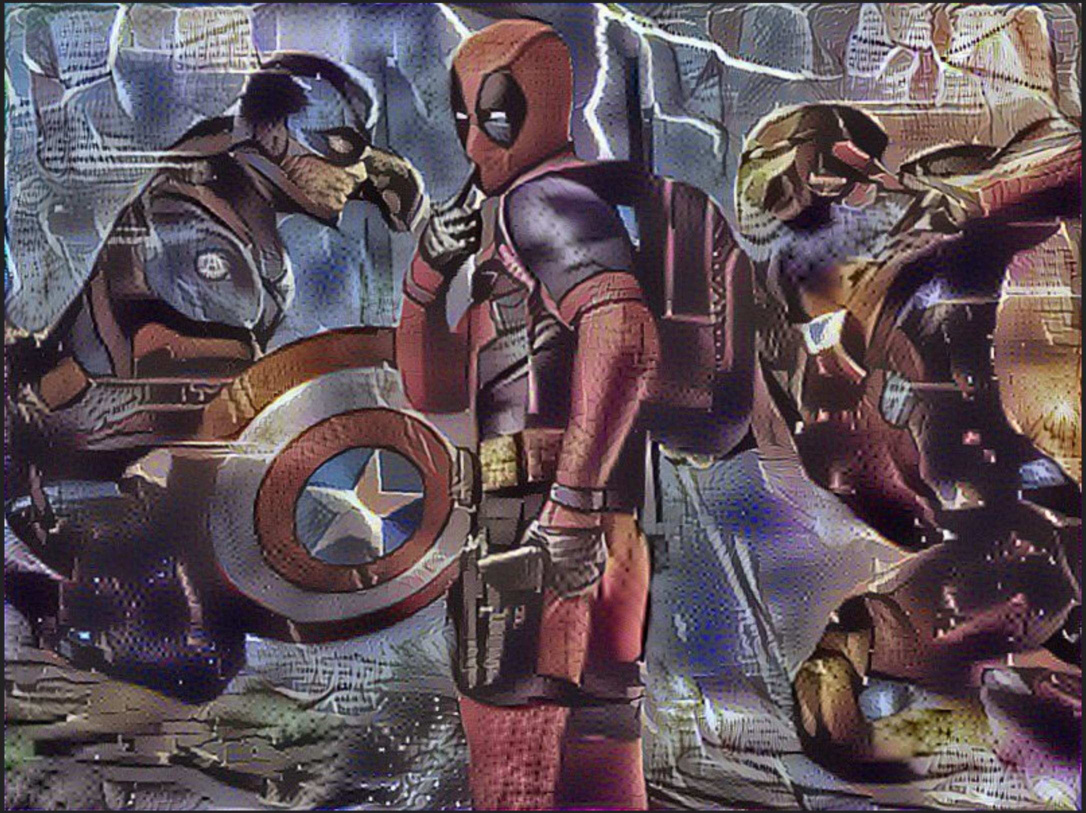
Figure 1: *Usage of Neural Style Transfer in Come Swim; left: content image, middle: style image, right: upsampled result. Images used with permission, (c) 2017 Starlight Studios LLC & Kristen Stewart.*

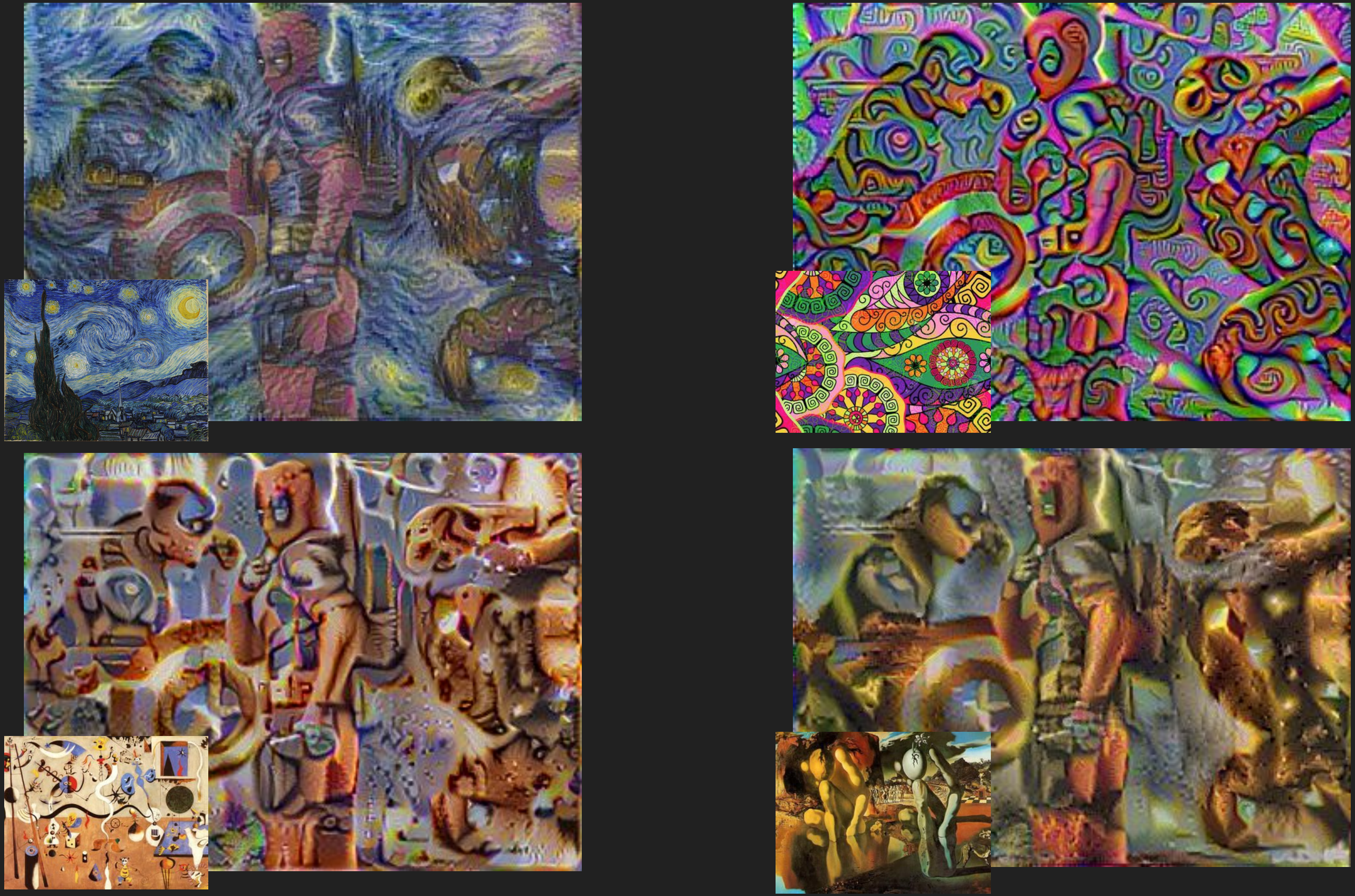
Yes, that Kristen Stewart!

Deadpool

Guernica

Deadpool and Guernica





Logan Engstrom’s fast-style-transfer @ GitHub

Style Transfer

The math is aight
but the implementation is tricky

Mathy stuff

Find a new image:

- whose content is closest to the content image and
- whose style is closest to the style image

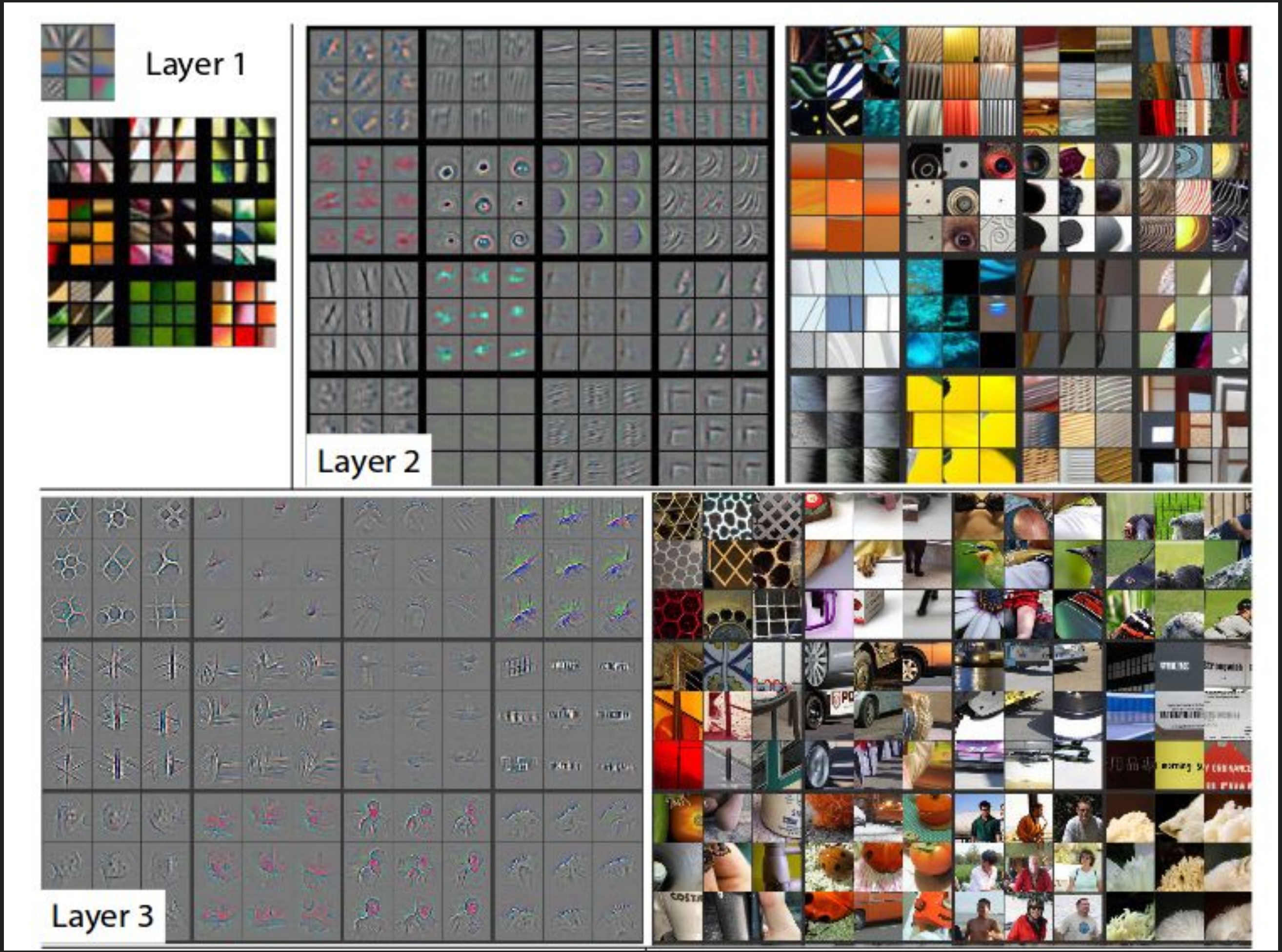
It's all about the loss functions

- Content loss
  Measure the content loss between the content of the generated image and the content of the content image
- Style loss
  Measure the style loss between the style of the generated image and the style of the style image


WHAT'S CONTENT?
WHAT'S STYLE?

Feature maps

A convolutional network has many layers, each layer is a function that extracts certain features



Zeiler, Matthew D., and Rob Fergus. "Visualizing and understanding convolutional networks." European conference on computer vision. Springer, Cham, 2014.

Content/style of an image

Feature visualization have shown that:

- lower layers extract features related to content
- higher layers extract features related to style

Loss functions revisited

- Content loss
  Measure the loss between **the feature maps in the content layer** of the generated image and the content image
- Style loss
  Measure the loss between **the feature maps in the style layers** of the generated image and the style image

Loss functions revisited

- Content loss

  To measure the content loss between **the feature map in the content layer** of the generated image and the content image

  Paper: 'conv4_4'

- Style loss

  To measure the style loss between **the gram matrices of feature maps in the style layers** of the generated image and the style image

  Paper: ['conv1_1', 'conv2_1', 'conv3_1', 'conv4_1' and 'conv5_1']

Loss functions revisited

- Content loss

  To measure the content loss between **the feature map in the content layer** of the generated image and the content image

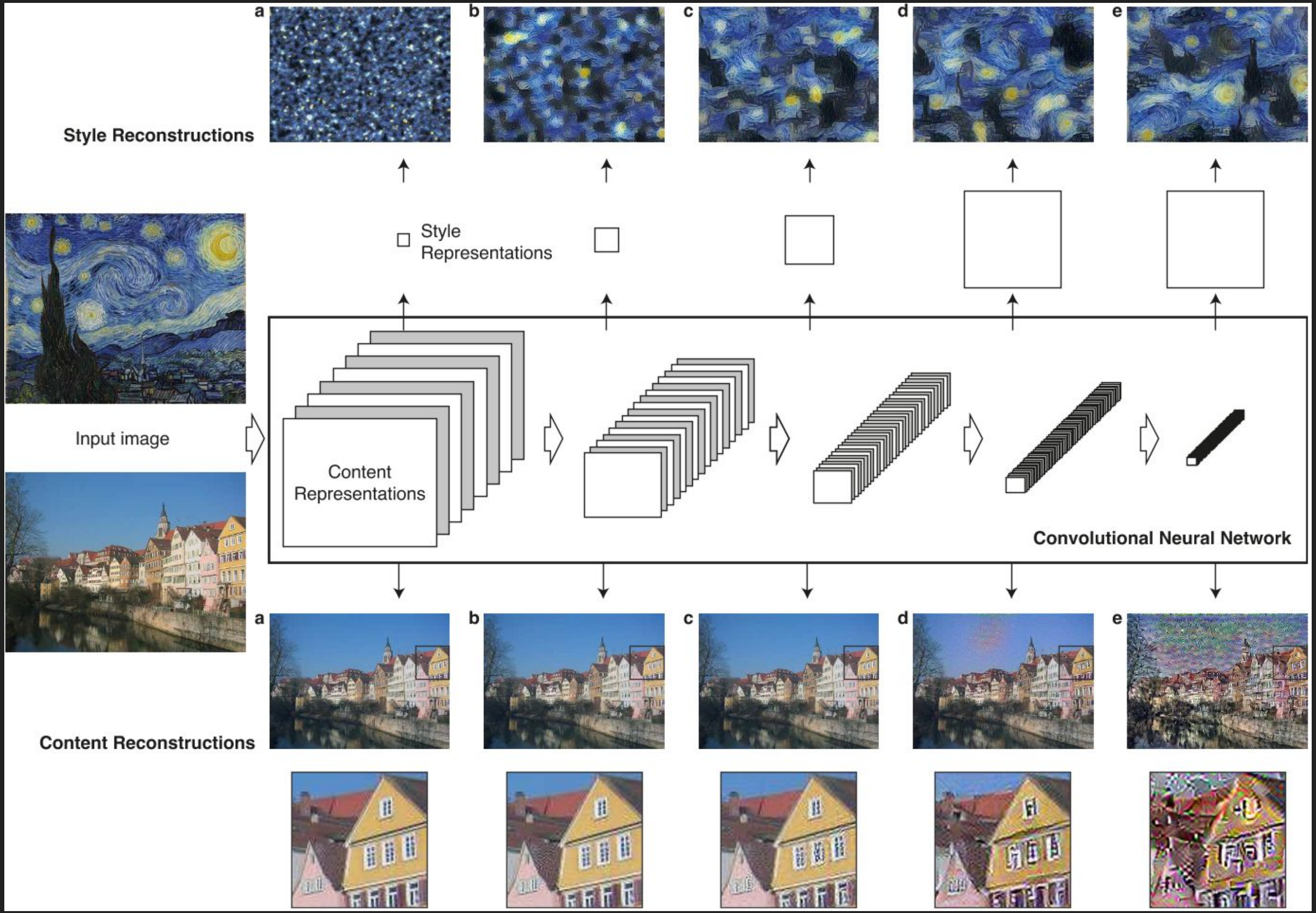
  Paper: ‘conv4_4’

- Style loss

  To measure the style loss between **the gram matrices of feature maps in the style layers** of the generated image and the style image

  Paper: [‘conv1_1’, ‘conv2_1’, ‘conv3_1’, ‘conv4_1’ and ‘conv5_1’]

  Weighted sum. Give more weight to deeper layers
  E.g. 1.0 for ‘conv1_1’, 2.0 for ‘conv2_1’, ...



Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. "A neural algorithm of artistic style." arXiv preprint arXiv:1508.06576 (2015).

How to find these magic feature maps?

Use pretrained weights (functions) such as VGG, AlexNet, GoogleNet

Loss functions revisited

- Content loss

$$\mathcal{L}_{content}(\vec{p}, \vec{x}, l) = \frac{1}{2} \sum_{i,j} \left(F_{ij}^l - P_{ij}^l\right)^2$$

- Style loss

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} \left(G_{ij}^l - A_{ij}^l\right)^2$$

$$\mathcal{L}_{style}(\vec{a}, \vec{x}) = \sum_{l=0}^{L} w_l E_l$$

Optimizer

Optimizes the initial image to minimize the combination of the two losses

$$\mathcal{L}_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{content}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{style}(\vec{a}, \vec{x})$$

Do not optimize the weights!

Tricky implementation details

1. Train input instead of weights

Tricky implementation details

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2. Multiple tensors share the same variable to avoid assembling identical subgraphs

Tricky implementation details

1. Train input instead of weights
2. Multiple tensors share the same variable to avoid assembling identical subgraphs
3. Use pre-trained weights (from VGG-19)
   a. Weights and biases already loaded for you
   b. They are numpy, so need to be converted to tensors
   c. Must not be trainable!!

Progress

Cool story, bro. So what?

Fun applications

- Snapchat filters
- Google photos
- Movies!!!

Is art exclusively a human domain?

Next class

GANs by Alec Radford!

Feedback: chiphuyen@cs.stanford.edu

Thanks!