fast-neural-style :city_sunrise: :rocket:
This repository contains a pytorch implementation
of an algorithm for artistic style transfer. The
algorithm can be used to mix the content of an
image with the style of another image. For example,
here is a photograph of a door arch rendered in the
style of a stained glass painting.

The model uses the method described in [Perceptual Losses for Real-Time Style Transfer and Super-Resolution](https://arxiv.org/abs/1603.08155) along with [Instance Normalization](https://arxiv.org/pdf/1607.08022.pdf). The saved-models for examples shown in the README can be downloaded from [here] (https://www.dropbox.com/s/lrvwfehqdcxoza8/saved_models.zip?dl=0).

Requirements

The program is written in Python, and uses [pytorch] (http://pytorch.org/), [scipy](https://www.scipy.org). A GPU is not necessary, but can provide a significant speed up especially for training a new model. Regular sized images can be styled on a laptop or desktop using saved models.

```
## Usage
Stylize image
```

python neural_style/neural_style.py eval --contentimage </path/to/content/image> --model </path/to/ saved/model> --output-image </path/to/output/image> --cuda 0

- * `--content-image`: path to content image you want to stylize.
- * `--model`: saved model to be used for stylizing the image (eg: `mosaic.pth`)
- * `--output-image`: path for saving the output image.
- * `--content-scale`: factor for scaling down the content image if memory is an issue (eg: value of 2 will halve the height and width of content-image) * `--cuda`: set it to 1 for running on GPU, 0 for CPU.

Train model
```bash
python neural\_style/neural\_style.py train --dataset
</path/to/train-dataset> --style-image </path/to/
style/image> --save-model-dir </path/to/save-model/
folder> --epochs 2 --cuda 1

There are several command line arguments, the important ones are listed below

\* `--dataset`: path to training dataset, the path should point to a folder containing another folder with all the training images. I used COCO 2014

Training images dataset [80K/13GB] [(download)] (http://mscoco.org/dataset/#download).

\* `--style-image`: path to style-image.

\* `--save-model-dir`: path to folder where trained model will be saved.

\* `--cuda`: set it to 1 for running on GPU, 0 for

CPU.

Refer to ``neural style/neural\_style.py`` for other command line arguments. For training new models you might have to tune the values of `--content-weight` and `--style-weight`. The mosaic style model shown above was trained with `--content-weight le5` and `--style-weight 1e10`. The remaining 3 models were also trained with similar order of weight parameters with slight variation in the `--styleweight` (`5e10` or `1e11`). ## Models Models for the examples shown below can be downloaded from [here](https://www.dropbox.com/s/ lrvwfehqdcxoza8/saved\_models.zip?dl=0) or by running the script ``download saved models.py``. <div align='center'> <img src='images/content-images/amber.jpg'</pre> height="174px"> </div> <div align='center'> <img src='images/style-images/mosaic.jpg'</pre> height="174px"> <img src='images/output-images/amber-mosaic.jpg'</pre> height="174px"> <img src='images/output-images/amber-candy.jpg'</pre> height="174px"> <img src='images/style-images/candy.jpg'</pre> height="174px"> <br><img src='images/style-images/rain-princess-</pre>

<img src='images/output-images/amber-rain-</pre>

cropped.jpg' height="174px">

princess.jpg' height="174px">

```
<img src='images/output-images/amber-udnie.jpg'</pre>
height="174px">
 <img src='images/style-images/udnie.jpg'</pre>
height="174px">
</div>
import os
import zipfile
PyTorch 1.1 moves download url to file
 from torch.utils.model zoo to torch.hub
PyTorch 1.0 exists another _download_url_to_file
 2 argument
TODO: If you remove support PyTorch 1.0 or older,
 You should remove torch.utils.model zoo
#
 Ref. PyTorch #18758
#
 https://github.com/pytorch/pytorch/pull/
#
18758/commits
try:
 from torch.utils.model zoo import
download url to file
except ImportError:
 from torch.hub import _download_url_to_file
def unzip(source filename, dest dir):
 with zipfile.ZipFile(source filename) as zf:
 zf.extractall(path=dest dir)
if name == ' main ':
 _download_url_to_file('https://www.dropbox.com/
s/lrvwfehqdcxoza8/saved models.zip?dl=1',
'saved models.zip', None, True)
 unzip('saved models.zip', '.')
```

```
import argparse
import os
import sys
import time
import re
import numpy as np
import torch
from torch.optim import Adam
from torch.utils.data import DataLoader
from torchvision import datasets
from torchvision import transforms
import torch.onnx
import utils
from transformer net import TransformerNet
from vgg import Vgg16
def check paths(args):
 try:
 if not os.path.exists(args.save model dir):
 os.makedirs(args.save model dir)
 if args.checkpoint model dir is not None
and not (os.path.exists(args.checkpoint model dir)):
 os.makedirs(args.checkpoint model dir)
 except OSError as e:
 print(e)
 sys.exit(1)
def train(args):
 device = torch.device("cuda" if args.cuda else
"cpu")
 np.random.seed(args.seed)
 torch.manual seed(args.seed)
```

```
transform = transforms.Compose([
 transforms.Resize(args.image_size),
 transforms.CenterCrop(args.image size),
 transforms.ToTensor(),
 transforms.Lambda(lambda x: x.mul(255))
 1)
 train dataset =
datasets.ImageFolder(args.dataset, transform)
 train loader = DataLoader(train dataset,
batch size=args.batch size)
 transformer = TransformerNet().to(device)
 optimizer = Adam(transformer.parameters(),
args.lr)
 mse_loss = torch.nn.MSELoss()
 vgg = Vgg16(requires grad=False).to(device)
 style transform = transforms.Compose([
 transforms.ToTensor(),
 transforms.Lambda(lambda x: x.mul(255))
 1)
 style = utils.load image(args.style image,
size=args.style size)
 style = style_transform(style)
 style = style.repeat(args.batch_size, 1, 1,
1).to(device)
 features style =
vgg(utils.normalize batch(style))
 gram style = [utils.gram matrix(y) for y in
features style]
 for e in range(args.epochs):
 transformer.train()
 agg content loss = 0.
 agg_style_loss = 0.
```

```
count = 0
 for batch_id, (x, _) in
enumerate(train loader):
 n batch = len(x)
 count += n batch
 optimizer.zero grad()
 x = x.to(device)
 y = transformer(x)
 y = utils.normalize batch(y)
 x = utils.normalize batch(x)
 features y = vgg(y)
 features x = vgg(x)
 content loss = args.content weight *
mse_loss(features_y.relu2_2, features_x.relu2_2)
 style loss = 0.
 for ft y, gm s in zip(features_y,
gram style):
 gm y = utils.gram matrix(ft y)
 style loss += mse loss(gm y,
gm s[:n batch, :, :])
 style_loss *= args.style_weight
 total loss = content loss + style loss
 total loss.backward()
 optimizer.step()
 agg content loss += content loss.item()
 agg style loss += style loss.item()
 if (batch id + 1) % args.log interval
== 0:
 mesg = "{} \tEpoch {} : \t[{}/{})
```

```
\tcontent: \{:.6f}\tstyle: \{:.6f}\ttotal: \{:.
6f}".format(
 time.ctime(), e + 1, count,
len(train dataset),
agg content loss / (batch id + 1),
 agg_style loss /
(batch id + 1),
 (agg content loss
+ agg_style_loss) / (batch_id + 1)
 print(mesq)
 if args.checkpoint model dir is not
None and (batch id + 1) % args.checkpoint interval
== 0:
 transformer.eval().cpu()
 ckpt_model_filename = "ckpt epoch "
+ str(e) + "_batch_id_" + str(batch_id + 1) + ".pth"
 ckpt model path =
os.path.join(args.checkpoint model dir,
ckpt model filename)
torch.save(transformer.state dict(),
ckpt model path)
 transformer.to(device).train()
 # save model
 transformer.eval().cpu()
 save model filename = "epoch " +
str(args.epochs) + " " +
str(time.ctime()).replace(' ', '_') + "_" + str(
 args.content weight) + "" +
str(args.style_weight) + ".model"
 save model path =
os.path.join(args.save model dir,
save model filename)
```

```
torch.save(transformer.state dict(),
save model path)
 print("\nDone, trained model saved at".
save model path)
def stylize(args):
 device = torch.device("cuda" if args.cuda else
"cpu")
 content image =
utils.load_image(args.content_image,
scale=args.content scale)
 content transform = transforms.Compose([
 transforms.ToTensor(),
 transforms.Lambda(lambda x: x.mul(255))
 1)
 content_image = content_transform(content_image)
 content image =
content image.unsqueeze(0).to(device)
 if args.model.endswith(".onnx"):
 output = stylize onnx caffe2(content image,
args)
 else:
 with torch.no grad():
 style_model = TransformerNet()
 state dict = torch.load(args.model)
 # remove saved deprecated running *
keys in InstanceNorm from the checkpoint
 for k in list(state dict.keys()):
 if re.search(r'in\d+\.running (mean)
var)$', k):
 del state dict[k]
 style_model.load_state_dict(state_dict)
 style model.to(device)
```

```
if args.export onnx:
 assert
args.export onnx.endswith(".onnx"), "Export model
file should end with .onnx"
 output =
torch.onnx. export(style model, content image,
args.export onnx).cpu()
 else:
 output =
style model(content image).cpu()
 utils.save image(args.output image, output[0])
def stylize onnx caffe2(content image, args):
 Read ONNX model and run it using Caffe2
 assert not args.export onnx
 import onnx
 import onnx caffe2.backend
 model = onnx.load(args.model)
 prepared_backend =
onnx caffe2.backend.prepare(model, device='CUDA' if
args.cuda else 'CPU')
 inp = {model.graph.input[0].name:
content image.numpy()}
 c2 out = prepared backend.run(inp)[0]
 return torch.from numpy(c2 out)
def main():
 main arg parser =
```

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argparse.ArgumentParser(description="parser for
fast-neural-style")
 subparsers =
main arg parser.add subparsers(title="subcommands",
dest="subcommand")
 train_arg_parser =
subparsers.add_parser("train", help="parser for
training arguments")
 train_arg_parser.add_argument("--epochs",
type=int, default=2,
 help="number of
training epochs, default is 2")
 train arg parser.add argument("--batch-size",
type=int, default=4,
 help="batch size
for training, default is 4")
 train_arg_parser.add_argument("--dataset",
type=str, required=True,
 help="path to
training dataset, the path should point to a folder
 "containing
another folder with all the training images")
 train_arg_parser.add_argument("--style-image",
type=str, default="images/style-images/mosaic.jpg",
 help="path to
style-image")
 train_arg_parser.add_argument("--save-model-
dir", type=str, required=True,
 help="path to
folder where trained model will be saved.")
 train arg parser.add argument("--checkpoint-
model-dir", type=str, default=None,
 help="path to
folder where checkpoints of trained models will be
saved")
```

```
train arg parser.add argument("--image-size",
type=int, default=256,
 help="size of
training images, default is 256 X 256")
 train arg parser.add argument("--style-size",
type=int, default=None,
 help="size of
style-image, default is the original size of style
image")
 train_arg_parser.add_argument("--cuda",
type=int, required=True,
 help="set it to 1
for running on GPU, 0 for CPU")
 train_arg_parser.add_argument("--seed",
type=int, default=42,
 help="random seed
for training")
 train arg parser.add argument("--content-
weight", type=float, default=1e5,
 help="weight for
content-loss, default is 1e5")
 train_arg_parser.add_argument("--style-weight",
type=float, default=1e10,
 help="weight for
style-loss, default is 1e10")
 train_arg_parser.add_argument("--lr",
type=float, default=1e-3,
 help="learning
rate, default is 1e-3")
 train arg parser.add argument("--log-interval",
type=int, default=500,
 help="number of
images after which the training loss is logged,
default is 500")
 train_arg_parser.add_argument("--checkpoint-
interval", type=int, default=2000,
 help="number of
```

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batches after which a checkpoint of the trained
model will be created")
 eval arg parser = subparsers.add parser("eval",
help="parser for evaluation/stylizing arguments")
 eval arg parser.add argument("--content-image",
type=str, required=True,
 help="path to
content image you want to stylize")
 eval arg parser.add argument("--content-scale",
type=float, default=None,
 help="factor for
scaling down the content image")
 eval arg_parser.add_argument("--output-image",
type=str, required=True,
 help="path for
saving the output image")
 eval_arg_parser.add_argument("--model",
type=str, required=True,
 help="saved model
to be used for stylizing the image. If file ends
in .pth - PyTorch path is used, if in .onnx -
Caffe2 path")
 eval arg parser.add argument("--cuda",
type=int, required=True,
 help="set it to 1
for running on GPU, 0 for CPU")
 eval arg parser.add argument("--export onnx",
type=str,
 help="export ONNX
model to a given file")
 args = main arg parser.parse args()
 if args.subcommand is None:
 print("ERROR: specify either train or eval")
 sys.exit(1)
```

```
if args.cuda and not torch.cuda.is available():
 print("ERROR: cuda is not available, try
running on CPU")
 sys.exit(1)
 if args.subcommand == "train":
 check_paths(args)
 train(args)
 else:
 stylize(args)
if __name__ == "__main__":
 main()
import torch
class TransformerNet(torch.nn.Module):
 def __init__(self):
 super(TransformerNet, self). init ()
 # Initial convolution layers
 self.conv1 = ConvLayer(3, 32,
kernel size=9, stride=1)
 self.in1 = torch.nn.InstanceNorm2d(32,
affine=True)
 self.conv2 = ConvLayer(32, 64,
kernel size=3, stride=2)
 self.in2 = torch.nn.InstanceNorm2d(64,
affine=True)
 self.conv3 = ConvLayer(64, 128,
kernel size=3, stride=2)
 self.in3 = torch.nn.InstanceNorm2d(128,
affine=True)
 # Residual layers
 self.res1 = ResidualBlock(128)
 self.res2 = ResidualBlock(128)
 self.res3 = ResidualBlock(128)
```

```
self.res4 = ResidualBlock(128)
 self.res5 = ResidualBlock(128)
 # Upsampling Layers
 self.deconv1 = UpsampleConvLayer(128, 64,
kernel size=3, stride=1, upsample=2)
 self.in4 = torch.nn.InstanceNorm2d(64,
affine=True)
 self.deconv2 = UpsampleConvLayer(64, 32,
kernel size=3, stride=1, upsample=2)
 self.in5 = torch.nn.InstanceNorm2d(32,
affine=True)
 self.deconv3 = ConvLayer(32, 3,
kernel_size=9, stride=1)
 # Non-linearities
 self.relu = torch.nn.ReLU()
 def forward(self, X):
 y = self.relu(self.in1(self.conv1(X)))
 y = self.relu(self.in2(self.conv2(y)))
 y = self.relu(self.in3(self.conv3(y)))
 v = self.resl(v)
 y = self.res2(y)
 y = self.res3(y)
 v = self.res4(v)
 y = self.res5(y)
 y = self.relu(self.in4(self.deconv1(y)))
 y = self.relu(self.in5(self.deconv2(y)))
 v = self.deconv3(v)
 return v
class ConvLayer(torch.nn.Module):
 def __init__(self, in_channels, out channels,
kernel size, stride):
 super(ConvLayer, self).__init__()
 reflection padding = kernel_size // 2
 self.reflection pad =
```

```
torch.nn.ReflectionPad2d(reflection padding)
 self.conv2d = torch.nn.Conv\overline{2}d(in channels,
out channels, kernel size, stride)
 def forward(self, x):
 out = self.reflection pad(x)
 out = self.conv2d(out)
 return out
class ResidualBlock(torch.nn.Module):
 """ResidualBlock
 introduced in: https://arxiv.org/abs/1512.03385
 recommended architecture: http://torch.ch/blog/
2016/02/04/resnets.html
 0.00
 def __init_ (self, channels):
 super(ResidualBlock, self).__init__()
 self.conv1 = ConvLayer(channels, channels,
kernel_size=3, stride=1)
 self.in1 =
torch.nn.InstanceNorm2d(channels, affine=True)
 self.conv2 = ConvLayer(channels, channels,
kernel size=3, stride=1)
 self.in2 =
torch.nn.InstanceNorm2d(channels, affine=True)
 self.relu = torch.nn.ReLU()
 def forward(self, x):
 residual = x
 out = self.relu(self.in1(self.conv1(x)))
 out = self.in2(self.conv2(out))
 out = out + residual
 return out
```

```
class UpsampleConvLayer(torch.nn.Module):
 """UpsampleConvLayer
 Upsamples the input and then does a
convolution. This method gives better results
 compared to ConvTranspose2d.
 ref: http://distill.pub/2016/deconv-
checkerboard/
 def init (self, in channels, out channels,
kernel size, stride, upsample=None):
 super(UpsampleConvLayer, self). init ()
 self.upsample = upsample
 reflection padding = kernel size // 2
 self.reflection pad =
torch.nn.ReflectionPad2d(reflection padding)
 self.conv2d = torch.nn.Conv2d(in channels,
out channels, kernel size, stride)
 def forward(self, x):
 x in = x
 if self.upsample:
 x in =
torch.nn.functional.interpolate(x in,
mode='nearest', scale_factor=self.upsample)
 out = self.reflection pad(x in)
 out = self.conv2d(out)
 return out
import torch
from PIL import Image
def load image(filename, size=None, scale=None):
 img = Image.open(filename)
 if size is not None:
 img = img.resize((size, size),
Image.ANTIALIAS)
```

```
elif scale is not None:
 img = img.resize((int(img.size[0] / scale),
int(img.size[1] / scale)), Image.ANTIALIAS)
 return ima
def save image(filename, data):
 img = data.clone().clamp(0, 255).numpy()
 img = img.transpose(1, 2, 0).astype("uint8")
 img = Image.fromarray(img)
 img.save(filename)
def gram matrix(y):
 (b, ch, h, w) = y.size()
 features = y.view(b, ch, w * h)
 features t = features.transpose(1, 2)
 gram = features.bmm(features t) / (ch * h * w)
 return gram
def normalize batch(batch):
 # normalize using imagenet mean and std
 mean = batch.new_tensor([0.485, 0.456,
[0.406]).view(-1, 1, \overline{1})
 std = batch.new tensor([0.229, 0.224,
0.225]).view(-1, 1, 1)
 batch = batch.div (255.0)
 return (batch - mean) / std
from collections import namedtuple
import torch
from torchvision import models
class Vgg16(torch.nn.Module):
 def init (self, requires grad=False):
```

```
super(Vgg16, self).__init__()
 vgg pretrained features =
models.vgg16(pretrained=True).features
 self.slice1 = torch.nn.Sequential()
 self.slice2 = torch.nn.Sequential()
 self.slice3 = torch.nn.Sequential()
 self.slice4 = torch.nn.Sequential()
 for x in range(4):
 self.slice1.add_module(str(x),
vgg pretrained features[x])
 for x in range(4, 9):
 self.slice2.add module(str(x),
vgg_pretrained_features[x])
 for x in range(9, 16):
 self.slice3.add module(str(x),
vgg pretrained features[x])
 for x in range(16, 23):
 self.slice4.add module(str(x),
vgg_pretrained_features[x])
 if not requires grad:
 for param in self.parameters():
 param.requires grad = False
 def forward(self, X):
 h = self.slice1(X)
 h relu12 = h
 h = self.slice2(h)
 h relu22 = h
 h = self.slice3(h)
 h relu33 = h
 h = self.slice4(h)
 h relu43 = h
 vgg_outputs = namedtuple("VggOutputs",
['relu1 2', 'relu2 2', 'relu3 3', 'relu4 3'])
 out = vgg_outputs(h_relu1 2, h relu2 2,
h relu3 3, h relu4 3)
 return out
```