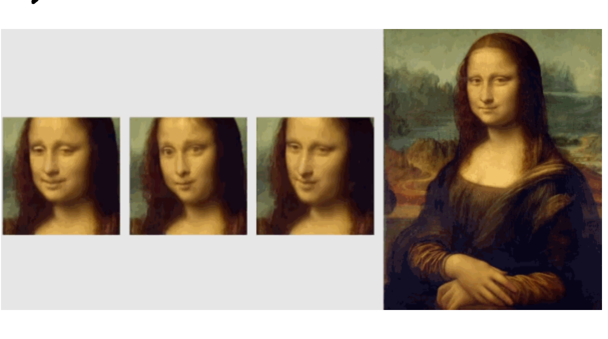
Generative Adversarial Networks (GANs)



Introduction

- Generative Adversarial Networks (GANs)
- How GANs Work
- GANs Process
- Examples

Generative Adversarial Networks (GANs)

Generative Adversarial Networks are used to generate images that never existed before. They learn about the world (objects, animals and so forth) and create new versions of those images that never existed.

They have two components:

- A **Generator** - this creates the images.
- A **Discriminator** - this assesses the images and tells the generator if they are similar to what it has been trained on. These are based off real world examples.

When training the network, both the generator and discriminator start from scratch and learn together.

How GANs Work

G for **Generative** - this is a model that takes an input as a random noise singal and then outputs an image.

A for **Adversarial** - this is the discriminator, the opponent of the generator. This is capable of learning about objects, animals or other features specified. For example: if you supply it with pictures of dogs and non-dogs, it would be able to identify the difference between the two.

Using this example, once the discriminator has been trained, showing the discriminator a picture that isn't a dog it will return a 0. Whereas, if you show it a dog it will return a 1.

N for **Network** - meaning the generator and discriminator are both neural networks.

GANs Process

Step 1 - we input a random noise signal into the generator. The generator creates some images which is used for training the discriminator. We provide the discriminator with some features/images we want it to learn and the discriminator outputs probabilities. These probabilities can be rather high as the discriminator has only just started being trained. The values are then assessed and identified. The error is calculated and these are backpropagated through the discriminator, where the weights are updated.

Next we train the generator. We take the batch of images that it created and put them through the discriminator again. We do not include the feature images. The generator learns by tricking the discriminator into it outputting false positives.

The discriminator will provide an output of probabilities. The values are then assessed and compared to what they should have been. The error is calculated and backpropagated through the generator and the weights are updated.

Step 2 - This is the same as step 1 but the generator and discriminator are trained a little more. Through backpropagation the generator understands its mistakes and starts to make them more like the feature.

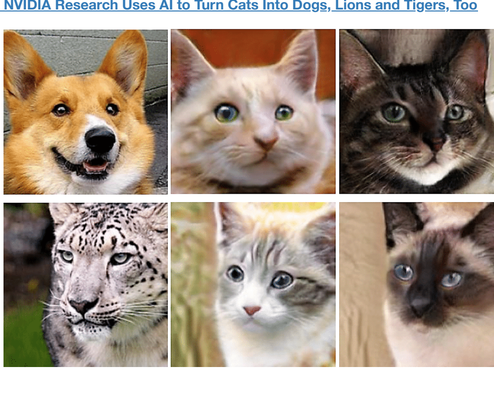
This is created through a *Deconvolutional Neural Network*.

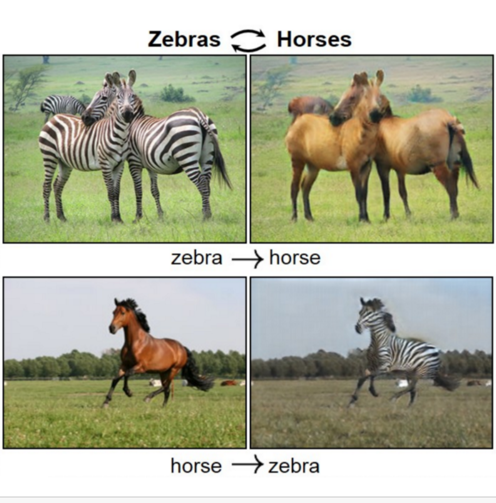
Examples

GANs can be used for the following:

- Generating Images
- Image Modification
- Super Resolution
- Assisting Artists
- Photo-Realistic Images
- Speech Generation
- Face Ageing

[It's Training Cats and Dogs: NVIDIA Research Uses AI to Turn Cats Into Dogs, Lions and Tigers, Too]






```python
import os
print(os.listdir("../input"))
```

Importing the libraries

```python
from __future__ import print_function
import time
import torch
import torch.nn as nn
import torch.nn.parallel
import torch.optim as optim
import torch.utils.data
import torchvision.datasets as dset
import torchvision.transforms as transforms
import torchvision.utils as vutils
from torch.autograd import Variable
import matplotlib.pyplot as plt
import numpy as np
from torch import nn, optim
import torch.nn.functional as F
from torchvision import datasets, transforms
from torchvision.utils import save_image
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from tqdm import tqdm_notebook as tqdm
```

Some dogs

> The Stanford Dogs dataset contains images of 120 breeds of dogs from around the world.

```python
PATH = '../input/all-dogs/all-dogs/'
images = os.listdir(PATH)
print(f'There are {len(os.listdir(PATH))} pictures of dogs.')

fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(12,10))

for indx, axis in enumerate(axes.flatten()):
    rnd_indx = np.random.randint(0, len(os.listdir(PATH)))
    # https://matplotlib.org/users/image_tutorial.html
    img = plt.imread(PATH + images[rnd_indx])
    imgplot = axis.imshow(img)
    axis.set_title(images[rnd_indx])
    axis.set_axis_off()
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
```

Insights

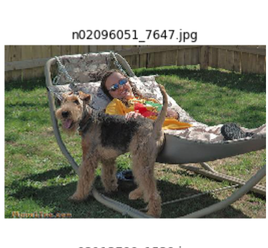
Check this posts:

> Quick data explanation and EDA by @witold1
>
> New Insights

- There are pictures with more than one dog (even with 3 dogs);
- There are pictures with the dog (-s) and person (people);
- There are pictures with more than one person (even with 4 people);
- There are pictures where dogs occupy less than 1/5 of the picture;
- There are pictures with text (magazine covers, from dog shows, memes and pictures with text);
- Even wild predators included, e.g. African wild dog or Dingo, but not wolves.

Examples

n02096051_7647.jpg



n02113799_1539.jpg

n02099849_410.jpg

n02106030_9354.jpg

n02110958_15550.jpg

Image Preprocessing

Check: GAN dogs starter

Initial code ...

```python
batch_size = 32
batchSize = 64
imageSize = 64

# 64x64 images!
transform = transforms.Compose([transforms.Resize(64),
                                transforms.CenterCrop(64),
                                transforms.ToTensor(),
                                transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

train_data = datasets.ImageFolder('../input/all-dogs/', transform=transform)

dataloader = torch.utils.data.DataLoader(train_data, shuffle=True,
                                           batch_size=batch_size)

imgs, label = next(iter(dataloader))
imgs = imgs.numpy().transpose(0, 2, 3, 1)
```

New data Data loader and Augmentations from RaLSGAN dogs

```python
batch_size = 32
image_size = 64

random_transforms = [transforms.ColorJitter(), transforms.RandomRotation(degrees=20)]
transform = transforms.Compose([transforms.Resize(64),
                                transforms.CenterCrop(64),
                                transforms.RandomHorizontalFlip(p=0.5),
                                transforms.RandomApply(random_transforms, p=0.2),
                                transforms.ToTensor(),
                                transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

train_data = datasets.ImageFolder('../input/all-dogs/', transform=transform)
train_loader = torch.utils.data.DataLoader(train_data, shuffle=True,
                                           batch_size=batch_size)

imgs, label = next(iter(train_loader))
imgs = imgs.numpy().transpose(0, 2, 3, 1)
```

```python
for i in range(5):
    plt.imshow(imgs[i])
    plt.show()
```

Weights

Defining the weights_init function

```python
def weights_init(m):
    """
    Takes as input a neural network m that will initialize all its weights.
    """
    classname = m.__class__.__name__
    if classname.find('Conv') != -1:
        m.weight.data.normal_(0.0, 0.02)
    elif classname.find('BatchNorm') != -1:
        m.weight.data.normal_(1.0, 0.02)
        m.bias.data.fill_(0)
```

Generator

```python
class G(nn.Module):
    def __init__(self):
        # Used to inherit the torch.nn Module
        super(G, self).__init__()
        # Meta Module - consists of different layers of Modules
        self.main = nn.Sequential(
                nn.ConvTranspose2d(100, 512, 4, stride=1, padding=0, bias=False),
                nn.BatchNorm2d(512),
                nn.ReLU(True),
                nn.ConvTranspose2d(512, 256, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(256),
                nn.ReLU(True),
                nn.ConvTranspose2d(256, 128, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(128),
                nn.ReLU(True),
                nn.ConvTranspose2d(128, 64, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(64),
                nn.ReLU(True),
                nn.ConvTranspose2d(64, 3, 4, stride=2, padding=1, bias=False),
                nn.Tanh()
                )

    def forward(self, input):
        output = self.main(input)
        return output

# Creating the generator
netG = G()
netG.apply(weights_init)
```

Discriminator

```python
# Defining the discriminator
class D(nn.Module):
    def __init__(self):
        super(D, self).__init__()
        self.main = nn.Sequential(
                nn.Conv2d(3, 64, 4, stride=2, padding=1, bias=False),
                nn.LeakyReLU(negative_slope=0.2, inplace=True),
                nn.Conv2d(64, 128, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(128),
                nn.LeakyReLU(negative_slope=0.2, inplace=True),
                nn.Conv2d(128, 256, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(256),
                nn.LeakyReLU(negative_slope=0.2, inplace=True),
                nn.Conv2d(256, 512, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(512),
                nn.LeakyReLU(negative_slope=0.2, inplace=True),
                nn.Conv2d(512, 1, 4, stride=1, padding=0, bias=False),
                nn.Sigmoid()
                )

    def forward(self, input):
        output = self.main(input)
        # .view(-1) = Flattens the output into 1D instead of 2D
        return output.view(-1)


# Creating the discriminator
netD = D()
netD.apply(weights_init)
```

Another setup

```python
class Generator(nn.Module):
    def __init__(self, nz=128, channels=3):
        super(Generator, self).__init__()

        self.nz = nz
        self.channels = channels

        def convlayer(n_input, n_output, k_size=4, stride=2, padding=0):
            block = [
                nn.ConvTranspose2d(n_input, n_output, kernel_size=k_size, stride=stride, padding=paddin
g, bias=False),
                nn.BatchNorm2d(n_output),
                nn.ReLU(inplace=True),
            ]
            return block

        self.model = nn.Sequential(
            *convlayer(self.nz, 1024, 4, 1, 0), # Fully connected layer via convolution.
            *convlayer(1024, 512, 4, 2, 1),
            *convlayer(512, 256, 4, 2, 1),
            *convlayer(256, 128, 4, 2, 1),
            *convlayer(128, 64, 4, 2, 1),
            nn.ConvTranspose2d(64, self.channels, 3, 1, 1),
            nn.Tanh()
        )

    def forward(self, z):
        z = z.view(-1, self.nz, 1, 1)
        img = self.model(z)
        return img


class Discriminator(nn.Module):
    def __init__(self, channels=3):
        super(Discriminator, self).__init__()

        self.channels = channels

        def convlayer(n_input, n_output, k_size=4, stride=2, padding=0, bn=False):
            block = [nn.Conv2d(n_input, n_output, kernel_size=k_size, stride=stride, padding=padding, b
ias=False)]
            if bn:
                block.append(nn.BatchNorm2d(n_output))
            block.append(nn.LeakyReLU(0.2, inplace=True))
            return block

        self.model = nn.Sequential(
            *convlayer(self.channels, 32, 4, 2, 1),
            *convlayer(32, 64, 4, 2, 1),
            *convlayer(64, 128, 4, 2, 1, bn=True),
            *convlayer(128, 256, 4, 2, 1, bn=True),
            nn.Conv2d(256, 1, 4, 1, 0, bias=False),  # FC with Conv.
        )

    def forward(self, imgs):
        logits = self.model(imgs)
        out = torch.sigmoid(logits)

        return out.view(-1, 1)
```

Training

My training baseline

```python
!mkdir results
!ls
```

```python
EPOCH = 0 # play with me
LR = 0.001
criterion = nn.BCELoss()
optimizerD = optim.Adam(netD.parameters(), lr=LR, betas=(0.5, 0.999))
optimizerG = optim.Adam(netG.parameters(), lr=LR, betas=(0.5, 0.999))
```

This doesn't run because EPOCH = 0, change it and try ;)

```python
for epoch in range(EPOCH):
    for i, data in enumerate(dataloader, 0):
        # 1st Step: Updating the weights of the neural network of the discriminator
        netD.zero_grad()

        # Training the discriminator with a real image of the dataset
        real,_ = data
        input = Variable(real)
        target = Variable(torch.ones(input.size()[0]))
        output = netD(input)
        errD_real = criterion(output, target)

        # Training the discriminator with a fake image generated by the generator
        noise = Variable(torch.randn(input.size()[0], 100, 1, 1))
        fake = netG(noise)
        target = Variable(torch.zeros(input.size()[0]))
        output = netD(fake.detach())
        errD_fake = criterion(output, target)

        # Backpropagating the total error
        errD = errD_real + errD_fake
        errD.backward()
        optimizerD.step()

        # 2nd Step: Updating the weights of the neural network of the generator
        netG.zero_grad()
        target = Variable(torch.ones(input.size()[0]))
        output = netD(fake)
        errG = criterion(output, target)
        errG.backward()
        optimizerG.step()

        # 3rd Step: Printing the losses and saving the real images and the generated images of the mini
batch every 100 steps
        print('[%d/%d][%d/%d] Loss_D: %.4f; Loss_G: %.4f' % (epoch, EPOCH, i, len(dataloader), errD.ite
m(), errG.item()))
        if i % 100 == 0:
            vutils.save_image(real, '%s/real_samples.png' % "./results", normalize=True)
            fake = netG(noise)
            vutils.save_image(fake.data, '%s/fake_samples_epoch_%03d.png' % ("./results", epoch), norma
lize=True)
```

Best public training

- 06/29 RaLSGAN dogs V9
- 06/29 this kernel V5
- some version of this kernel

Parameters

```python
batch_size = 32
LR_G = 0.0005
LR_D = 0.0003

beta1 = 0.5
epochs = 200

real_label = 0.95
fake_label = 0
nz = 128

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

Initialize models and optimizers

```python
netG = Generator(nz).to(device)
netD = Discriminator().to(device)

criterion = nn.BCELoss()

optimizerD = optim.Adam(netD.parameters(), lr=LR_D, betas=(beta1, 0.999))
optimizerG = optim.Adam(netG.parameters(), lr=LR_G, betas=(beta1, 0.999))

fixed_noise = torch.randn(25, nz, 1, 1, device=device)

G_losses = []
D_losses = []
epoch_time = []
```

Plot Loss per EPOCH

> plot_loss()

```python
def plot_loss (G_losses, D_losses, epoch):
    plt.figure(figsize=(10,5))
    plt.title("Generator and Discriminator Loss - EPOCH "+ str(epoch))
    plt.plot(G_losses,label="G")
    plt.plot(D_losses,label="D")
    plt.xlabel("iterations")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()
```

Show generated images

> show_generated_img()

```python
def show_generated_img(n_images=5):
    sample = []
    for _ in range(n_images):
        noise = torch.randn(1, nz, 1, 1, device=device)
        gen_image = netG(noise).to("cpu").clone().detach().squeeze(0)
        gen_image = gen_image.numpy().transpose(1, 2, 0)
        sample.append(gen_image)

    figure, axes = plt.subplots(1, len(sample), figsize = (64,64))
    for index, axis in enumerate(axes):
        axis.axis('off')
        image_array = sample[index]
        axis.imshow(image_array)

    plt.show()
    plt.close()
```

Training Loop

```python
for epoch in range(epochs):

    start = time.time()
    for ii, (real_images, train_labels) in tqdm(enumerate(train_loader), total=len(train_loader)):
        ############################
        # (1) Update D network: maximize log(D(x)) + log(1 - D(G(z)))
        ###########################
        # train with real
        netD.zero_grad()
        real_images = real_images.to(device)
        batch_size = real_images.size(0)
        labels = torch.full((batch_size, 1), real_label, device=device)

        output = netD(real_images)
        errD_real = criterion(output, labels)
        errD_real.backward()
        D_x = output.mean().item()

        # train with fake
        noise = torch.randn(batch_size, nz, 1, 1, device=device)
        fake = netG(noise)
        labels.fill_(fake_label)
        output = netD(fake.detach())
        errD_fake = criterion(output, labels)
        errD_fake.backward()
        D_G_z1 = output.mean().item()
        errD = errD_real + errD_fake
        optimizerD.step()

        ############################
        # (2) Update G network: maximize log(D(G(z)))
        ###########################
        netG.zero_grad()
        labels.fill_(real_label)  # fake labels are real for generator cost
        output = netD(fake)
        errG = criterion(output, labels)
        errG.backward()
        D_G_z2 = output.mean().item()
        optimizerG.step()

        # Save Losses for plotting later
        G_losses.append(errG.item())
        D_losses.append(errD.item())

        if (ii+1) % (len(train_loader)//2) == 0:
            print('[%d/%d][%d/%d] Loss_D: %.4f Loss_G: %.4f D(x): %.4f D(G(z)): %.4f / %.4f'
                  % (epoch + 1, epochs, ii+1, len(train_loader),
                     errD.item(), errG.item(), D_x, D_G_z1, D_G_z2))

    plot_loss (G_losses, D_losses, epoch)
    G_losses = []
    D_losses = []
    if (epoch+1) % 10 == 0:
        show_generated_img()

    epoch_time.append(time.time()- start)

#             valid_image = netG(fixed_noise)
```

```python
print (">> average EPOCH duration = ", np.mean(epoch_time))
```

Generation example

WARNING,THIS CONTAINS IMAGES THAT MAY HURT THE SENSITIVITY OF SOME PEOPLE

```python
show_generated_img(7)
```

```python
if not os.path.exists('../output_images'):
    os.mkdir('../output_images')

im_batch_size = 50
n_images=10000

for i_batch in tqdm(range(0, n_images, im_batch_size)):
    gen_z = torch.randn(im_batch_size, nz, 1, 1, device=device)
    gen_images = netG(gen_z)
    images = gen_images.to("cpu").clone().detach()
    images = images.numpy().transpose(0, 2, 3, 1)
    for i_image in range(gen_images.size(0)):
        save_image(gen_images[i_image, :, :, :], os.path.join('../output_images', f'image_{i_batch+i_im
age:05d}.png'))
```

```python
fig = plt.figure(figsize=(25, 16))
# display 10 images from each class
for i, j in enumerate(images[:32]):
    ax = fig.add_subplot(4, 8, i + 1, xticks=[], yticks=[])
    plt.imshow(j)
```

Submission

```python
import shutil
shutil.make_archive('images', 'zip', '../output_images')
```

Save models

```python
torch.save(netG.state_dict(), 'generator.pth')
torch.save(netD.state_dict(), 'discriminator.pth')
```

MiFID metric

Base code from Demo MiFID metric for Dog image generation comp

In [ ]:

```python
from __future__ import absolute_import, division, print_function
import numpy as np
import os
import gzip, pickle
import tensorflow as tf
from scipy import linalg
import pathlib
import urllib
import warnings
from PIL import Image

class KernelEvalException(Exception):
    pass

model_params = {
    'Inception': {
        'name': 'Inception',
        'imsize': 64,
        'output_layer': 'Pretrained_Net/pool_3:0',
        'input_layer': 'Pretrained_Net/ExpandDims:0',
        'output_shape': 2048,
        'cosine_distance_eps': 0.1
        }
}

def create_model_graph(pth):
    """Creates a graph from saved GraphDef file."""
    # Creates graph from saved graph_def.pb.
    with tf.gfile.FastGFile( pth, 'rb') as f:
        graph_def = tf.GraphDef()
        graph_def.ParseFromString( f.read())
        _ = tf.import_graph_def( graph_def, name='Pretrained_Net')

def _get_model_layer(sess, model_name):
    # layername = 'Pretrained_Net/final_layer/Mean:0'
    layername = model_params[model_name]['output_layer']
    layer = sess.graph.get_tensor_by_name(layername)
    ops = layer.graph.get_operations()
    for op_idx, op in enumerate(ops):
        for o in op.outputs:
            shape = o.get_shape()
            if shape._dims != []:
              shape = [s.value for s in shape]
              new_shape = []
              for j, s in enumerate(shape):
                if s == 1 and j == 0:
                  new_shape.append(None)
                else:
                  new_shape.append(s)
              o.__dict__['_shape_val'] = tf.TensorShape(new_shape)
    return layer

def get_activations(images, sess, model_name, batch_size=50, verbose=False):
    """Calculates the activations of the pool_3 layer for all images.

    Params:
    -- images      : Numpy array of dimension (n_images, hi, wi, 3). The values
                     must lie between 0 and 256.
    -- sess        : current session
    -- batch_size  : the images numpy array is split into batches with batch size
                     batch_size. A reasonable batch size depends on the disposable hardware.
    -- verbose    : If set to True and parameter out_step is given, the number of calculated
                     batches is reported.
    Returns:
    -- A numpy array of dimension (num images, 2048) that contains the
       activations of the given tensor when feeding inception with the query tensor.
    """
    inception_layer = _get_model_layer(sess, model_name)
    n_images = images.shape[0]
    if batch_size > n_images:
        print("warning: batch size is bigger than the data size. setting batch size to data size")
        batch_size = n_images
    n_batches = n_images//batch_size + 1
    pred_arr = np.empty((n_images,model_params[model_name]['output_shape']))
    for i in tqdm(range(n_batches)):
        if verbose:
            print("\rPropagating batch %d/%d" % (i+1, n_batches), end="", flush=True)
        start = i*batch_size
        if start+batch_size < n_images:
            end = start+batch_size
        else:
            end = n_images

        batch = images[start:end]
        pred = sess.run(inception_layer, {model_params[model_name]['input_layer']: batch})
        pred_arr[start:end] = pred.reshape(-1,model_params[model_name]['output_shape'])
    if verbose:
        print(" done")
    return pred_arr


# def calculate_memorization_distance(features1, features2):
#     neigh = NearestNeighbors(n_neighbors=1, algorithm='kd_tree', metric='euclidean')
#     neigh.fit(features2)
#     d, _ = neigh.kneighbors(features1, return_distance=True)
#     print('d.shape=',d.shape)
#     return np.mean(d)

def normalize_rows(x: np.ndarray):
    """
    function that normalizes each row of the matrix x to have unit length.

    Args:
     ``x``: A numpy matrix of shape (n, m)

    Returns:
     ``x``: The normalized (by row) numpy matrix.
    """
    return np.nan_to_num(x/np.linalg.norm(x, ord=2, axis=1, keepdims=True))


def cosine_distance(features1, features2):
    # print('rows of zeros in features1 = ',sum(np.sum(features1, axis=1) == 0))
    # print('rows of zeros in features2 = ',sum(np.sum(features2, axis=1) == 0))
    features1_nozero = features1[np.sum(features1, axis=1) != 0]
    features2_nozero = features2[np.sum(features2, axis=1) != 0]
    norm_f1 = normalize_rows(features1_nozero)
    norm_f2 = normalize_rows(features2_nozero)

    d = 1.0-np.abs(np.matmul(norm_f1, norm_f2.T))
    print('d.shape=',d.shape)
    print('np.min(d, axis=1).shape=',np.min(d, axis=1).shape)
    mean_min_d = np.mean(np.min(d, axis=1))
    print('distance=',mean_min_d)
    return mean_min_d


def distance_thresholding(d, eps):
    if d < eps:
        return d
    else:
        return 1

def calculate_frechet_distance(mu1, sigma1, mu2, sigma2, eps=1e-6):
    """Numpy implementation of the Frechet Distance.
    The Frechet distance between two multivariate Gaussians X_1 ~ N(mu_1, C_1)
    and X_2 ~ N(mu_2, C_2) is
            d^2 = ||mu_1 - mu_2||^2 + Tr(C_1 + C_2 - 2*sqrt(C_1*C_2)).

    Stable version by Dougal J. Sutherland.

    Params:
    -- mu1 : Numpy array containing the activations of the pool_3 layer of the
             inception net ( like returned by the function 'get_predictions')
             for generated samples.
    -- mu2   : The sample mean over activations of the pool_3 layer, precalcualted
               on an representive data set.
    -- sigma1: The covariance matrix over activations of the pool_3 layer for
               generated samples.
    -- sigma2: The covariance matrix over activations of the pool_3 layer,
               precalcualted on an representive data set.

    Returns:
    --   : The Frechet Distance.
    """

    mu1 = np.atleast_1d(mu1)
    mu2 = np.atleast_1d(mu2)

    sigma1 = np.atleast_2d(sigma1)
    sigma2 = np.atleast_2d(sigma2)

    assert mu1.shape == mu2.shape, "Training and test mean vectors have different lengths"
    assert sigma1.shape == sigma2.shape, "Training and test covariances have different dimensions"

    diff = mu1 - mu2

    # product might be almost singular
    covmean, _ = linalg.sqrtm(sigma1.dot(sigma2), disp=False)
    if not np.isfinite(covmean).all():
        msg = "fid calculation produces singular product; adding %s to diagonal of cov estimates" % eps
        warnings.warn(msg)
        offset = np.eye(sigma1.shape[0]) * eps
        # covmean = linalg.sqrtm((sigma1 + offset).dot(sigma2 + offset))
        covmean = linalg.sqrtm((sigma1 + offset).dot(sigma2 + offset))

    # numerical error might give slight imaginary component
    if np.iscomplexobj(covmean):
        if not np.allclose(np.diagonal(covmean).imag, 0, atol=1e-3):
            m = np.max(np.abs(covmean.imag))
            raise ValueError("Imaginary component {}".format(m))
        covmean = covmean.real

    # covmean = tf.linalg.sqrtm(tf.linalg.matmul(sigma1,sigma2))

    print('covmean.shape=',covmean.shape)
    # tr_covmean = tf.linalg.trace(covmean)

    tr_covmean = np.trace(covmean)
    return diff.dot(diff) + np.trace(sigma1) + np.trace(sigma2) - 2 * tr_covmean
    # return diff.dot(diff) + tf.linalg.trace(sigma1) + tf.linalg.trace(sigma2) - 2 * tr_covmean
#-------------------------------------------------------------------------------


def calculate_activation_statistics(images, sess, model_name, batch_size=50, verbose=False):
    """Calculation of the statistics used by the FID.
    Params:
    -- images      : Numpy array of dimension (n_images, hi, wi, 3). The values
                     must lie between 0 and 255.
    -- sess        : current session
    -- batch_size  : the images numpy array is split into batches with batch size
                     batch_size. A reasonable batch size depends on the available hardware.
    -- verbose     : If set to True and parameter out_step is given, the number of calculated
                     batches is reported.
    Returns:
    -- mu    : The mean over samples of the activations of the pool_3 layer of
               the incption model.
    -- sigma : The covariance matrix of the activations of the pool_3 layer of
               the incption model.
    """
    act = get_activations(images, sess, model_name, batch_size, verbose)
    mu = np.mean(act, axis=0)
    sigma = np.cov(act, rowvar=False)
    return mu, sigma, act

def _handle_path_memorization(path, sess, model_name, is_checksize, is_check_png):
    path = pathlib.Path(path)
    files = list(path.glob('*.jpg')) + list(path.glob('*.png'))
    imsize = model_params[model_name]['imsize']

    # In production we don't resize input images. This is just for demo purpose.
    x = np.array([np.array(img_read_checks(fn, imsize, is_checksize, imsize, is_check_png)) for fn in f
iles])
    m, s, features = calculate_activation_statistics(x, sess, model_name)
    del x #clean up memory
    return m, s, features

# check for image size
def img_read_checks(filename, resize_to, is_checksize=False, check_imsize = 64, is_check_png = False):
    im = Image.open(str(filename))
    if is_checksize and im.size != (check_imsize,check_imsize):
        raise KernelEvalException('The images are not of size '+str(check_imsize))

    if is_check_png and im.format != 'PNG':
        raise KernelEvalException('Only PNG images should be submitted.')

    if resize_to is None:
        return im
    else:
        return im.resize((resize_to,resize_to),Image.ANTIALIAS)

def calculate_kid_given_paths(paths, model_name, model_path, feature_path=None):
    ''' Calculates the KID of two paths. '''
    tf.reset_default_graph()
    create_model_graph(str(model_path))
    with tf.Session() as sess:
        sess.run(tf.global_variables_initializer())
        m1, s1, features1 = _handle_path_memorization(paths[0], sess, model_name, is_checksize = True,
is_check_png = True)
        if feature_path is None:
            m2, s2, features2 = _handle_path_memorization(paths[1], sess, model_name, is_checksize = Fa
lse, is_check_png = False)
        else:
            with np.load(feature_path) as f:
                m2, s2, features2 = f['m'], f['s'], f['features']

        print('m1,m2 shape=',(m1.shape,m2.shape),'s1,s2=',(s1.shape,s2.shape))
        print('starting calculating FID')
        fid_value = calculate_frechet_distance(m1, s1, m2, s2)
        print('done with FID, starting distance calculation')
        distance = cosine_distance(features1, features2)
        return fid_value, distance
```

In [ ]:

```
!ls ../output_images
```

I have to fix this :(

In [ ]:

```python
user_images_unzipped_path = '../output_images'
images_path = [user_images_unzipped_path,'../all-dogs/all-dogs/']

model_path = '../input/dog-face-generation-competition-kid-metric-input/classify_image_graph_def.pb'

fid_epsilon = 10e-15

fid_value_public, distance_public = calculate_kid_given_paths(images_path, 'Inception', model_path)
distance_public = distance_thresholding(distance_public, model_params['Inception']['cosine_distance_ep
s'])
print("FID_public: ", fid_value_public, "distance_public: ", distance_public, "multiplied_public: ", fi
d_value_public /(distance_public + fid_epsilon))
```

In [ ]:

References

- DCGAN baseline by Andrew
- RaLSGAN dogs by Vlad
- GAN dogs starter
- GitHub Achronus generative_adversarial_networks
- It's Training Cats and Dogs: NVIDIA Research Uses AI to Turn Cats Into Dogs, Lions and Tigers, Too
- A Beginner's Guide to Generative Adversarial Networks (GANs)

I think I'll keep updating this, I like this comp and GANs :D

btw, If you want to create a x5 team, I'm in :p