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网络结构

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 128, 128, 3)	0
conv2d_1 (Conv2D)	(None, 64, 64, 64)	3136
leaky_re_lu_1 (LeakyReLU)	(None, 64, 64, 64)	0
conv2d_2 (Conv2D)	(None, 32, 32, 128)	131200
batch_normalization_1 (Batch Normalization)	(None, 32, 32, 128)	512
leaky_re_lu_2 (LeakyReLU)	(None, 32, 32, 128)	0
conv2d_3 (Conv2D)	(None, 16, 16, 256)	524544
batch_normalization_2 (Batch Normalization)	(None, 16, 16, 256)	1024

leaky_re_lu_3 (LeakyReLU)	(None, 16, 16, 256)	0
conv2d_4 (Conv2D)	(None, 8, 8, 512)	2097664
batch_normalization_3 (Batch Normalization)	(None, 8, 8, 512)	2048
leaky_re_lu_4 (LeakyReLU)	(None, 8, 8, 512)	0
conv2d_5 (Conv2D)	(None, 4, 4, 1024)	8389632
batch_normalization_4 (Batch Normalization)	(None, 4, 4, 1024)	4096
leaky_re_lu_5 (LeakyReLU)	(None, 4, 4, 1024)	0
flatten_1 (Flatten)	(None, 16384)	0
dense_1 (Dense)	(None, 128)	2097280
=====		
Total params: 13,251,136		
Trainable params: 13,247,296		
Non-trainable params: 3,840		

Layer (type)	Output Shape	Param #	Connected to
=====			
input_2 (InputLayer)	(None, 128)	0	
dense_2 (Dense)	(None, 16384)	2113536	input_2[0][0]
reshape_1 (Reshape)	(None, 4, 4, 1024)	0	dense_2[0][0]
dense_3 (Dense)	(None, 128)	16512	input_2[0][0]
dense_5 (Dense)	(None, 128)	16512	input_2[0][0]
batch_normalization_5 (Batch Normalization)	(None, 4, 4, 1024)	2048	reshape_1[0][0]
dense_4 (Dense)	(None, 1024)	132096	dense_3[0][0]

dense_6 (Dense)	(None, 1024)	132096	dense_5[0][0]
scale_shift_1 (ScaleShift)	[(None, 4, 4, 1024), 0		
batch_normalization_5[0][0]			dense_4[0][0]
			dense_6[0][0]
activation_1 (Activation)	(None, 4, 4, 1024)	0	
scale_shift_1[0][0]			
conv2d_transpose_1 (Conv2DTrans	(None, 8, 8, 512)	8389120	activation_1[0][0]
dense_7 (Dense)	(None, 128)	16512	input_2[0][0]
dense_9 (Dense)	(None, 128)	16512	input_2[0][0]
batch_normalization_6 (BatchNor	(None, 8, 8, 512)	1024	
conv2d_transpose_1[0][0]			
dense_8 (Dense)	(None, 512)	66048	dense_7[0][0]
dense_10 (Dense)	(None, 512)	66048	dense_9[0][0]
scale_shift_2 (ScaleShift)	[(None, 8, 8, 512), 0		
batch_normalization_6[0][0]			dense_8[0][0]
			dense_10[0][0]
activation_2 (Activation)	(None, 8, 8, 512)	0	
scale_shift_2[0][0]			
conv2d_transpose_2 (Conv2DTrans	(None, 16, 16, 256)	2097408	activation_2[0][0]
dense_11 (Dense)	(None, 128)	16512	input_2[0][0]

dense_13 (Dense)	(None, 128)	16512	input_2[0][0]
batch_normalization_7 (BatchNormal conv2d_transpose_2[0][0])	(None, 16, 16, 256)	512	
dense_12 (Dense)	(None, 256)	33024	dense_11[0][0]
dense_14 (Dense)	(None, 256)	33024	dense_13[0][0]
scale_shift_3 (ScaleShift) batch_normalization_7[0][0]	[(None, 16, 16, 256) 0		dense_12[0][0] dense_14[0][0]
activation_3 (Activation) scale_shift_3[0][0]	(None, 16, 16, 256) 0		
conv2d_transpose_3 (Conv2DTrans [0])	(None, 32, 32, 128)	524416	activation_3[0]
dense_15 (Dense)	(None, 128)	16512	input_2[0][0]
dense_17 (Dense)	(None, 128)	16512	input_2[0][0]
batch_normalization_8 (BatchNormal conv2d_transpose_3[0][0])	(None, 32, 32, 128)	256	
dense_16 (Dense)	(None, 128)	16512	dense_15[0][0]
dense_18 (Dense)	(None, 128)	16512	dense_17[0][0]
scale_shift_4 (ScaleShift) batch_normalization_8[0][0]	[(None, 32, 32, 128) 0		dense_16[0][0]

			dense_18[0][0]
<hr/>			
activation_4 (Activation) scale_shift_4[0][0]	(None, 32, 32, 128)	0	
<hr/>			
conv2d_transpose_4 (Conv2DTrans [0]	(None, 64, 64, 64)	131136	activation_4[0][0]
<hr/>			
dense_19 (Dense)	(None, 128)	16512	input_2[0][0]
<hr/>			
dense_21 (Dense)	(None, 128)	16512	input_2[0][0]
<hr/>			
batch_normalization_9 (BatchNor conv2d_transpose_4[0][0]	(None, 64, 64, 64)	128	
<hr/>			
dense_20 (Dense)	(None, 64)	8256	dense_19[0][0]
<hr/>			
dense_22 (Dense)	(None, 64)	8256	dense_21[0][0]
<hr/>			
scale_shift_5 (Scaleshift) batch_normalization_9[0][0]	[(None, 64, 64, 64), 0		
			dense_20[0][0]
			dense_22[0][0]
<hr/>			
activation_5 (Activation) scale_shift_5[0][0]	(None, 64, 64, 64)	0	
<hr/>			
conv2d_transpose_5 (Conv2DTrans [0]	(None, 128, 128, 3)	3075	activation_5[0][0]
<hr/>			
activation_6 (Activation) conv2d_transpose_5[0][0]	(None, 128, 128, 3)	0	
<hr/>			
=====			
=====			
Total params: 13,939,651			
Trainable params: 13,935,683			
Non-trainable params: 3,968			
<hr/>			
<hr/>			

Layer (type)	Output Shape	Param #	Connected to
=====			
input_4 (InputLayer)	(None, 128)	0	
=====			
model_2 (Model)	(None, 128, 128, 3)	13939651	input_4[0][0]
=====			
input_3 (InputLayer)	(None, 128, 128, 3)	0	
=====			
lambda_1 (Lambda)	(None, 128, 128, 3)	0	model_2[1][0]
=====			
model_1 (Model)	(None, 128)	13251136	input_3[0][0] model_2[1][0] lambda_1[0][0]
=====			
=====			
Total params: 27,190,787			
Trainable params: 27,182,979			
Non-trainable params: 7,808			

源码阅读

读取数据集(glob、shuffle)

```
imgs = glob.glob('D:\\Storage\\datasets\\lfw\\*\\*.jpg')
np.random.shuffle(imgs)
```

老苏使用了glob.glob的方式读取数据。

glob

读取到的imgs其实只是每一个图片的路径

```
['D:\\Storage\\datasets\\lfw\\Aaron_Eckhart\\Aaron_Eckhart_0001.jpg',
'D:\\Storage\\datasets\\lfw\\Aaron_Guie1\\Aaron_Guie1_0001.jpg'....]
```

后序，实际读入python对象的时候，我们需要借助另外的函数(misc.imread、misc.imresize)

shuffle

从后序使用了np.random.shuffle将读入的图片路径打散，以下附上shuffle的用法

```
arr = np.arange(10)
np.random.shuffle(arr)
arr
```

```
[1 7 5 2 9 4 3 6 0 8]
```

```
arr = np.arange(9).reshape((3, 3))
np.random.shuffle(arr)
arr
```

```
array([[3, 4, 5],
       [6, 7, 8],
       [0, 1, 2]])
```

可以看出shuffle可以只打乱numpy数组的第一维

misc

```
img_dim = 128

def imread(f):
    x = misc.imread(f, mode='RGB')
    print(x.shape)
    x = misc.imresize(x, (img_dim, img_dim))
    x = x.astype(np.float32)
    return x / 255 * 2 - 1

imgs = glob.glob('D:\\Storage\\datasets\\lfw\\*\\*.jpg')
f = imgs[0]
data = imread(f)
print(data.shape)
```

```
(250, 250, 3)
(128, 128, 3)
```

使用misc.imread 以三通道的方式读取图片，f就是传入图片的路径。

可见最初的图片大小是250x250x3，但是使用imresize之后，可以统一大小为128x128x3

数据的预处理

img_dim 处理为 num_layers(卷积层、逆卷积层个数),max_num_channels(单个卷积层和逆卷积层的卷积输出通道数)

```
img_dim = 128
z_dim = 128
batch_size = 64

num_layers = int(np.log2(img_dim)) - 3
max_num_channels = img_dim * 8
f_size = img_dim // 2 ** (num_layers + 1)
```

np.log2 是对numpy数组元素进行取对数的操作

```
>>> x = np.array([0, 1, 2, 2**4])
>>> np.log2(x)
array([-Inf,  0.,  1.,  4.])
```

num_layers

$$NumLayer = (int)(\log_2(ImageDim)) - 3$$

num_layers 与 img_dim 呈现正相关，只要图片的维度越高，num_layers 数值越大，而 num_layers 本身可能代表的是网络的层数。

在这里 img_dim = 128，则 num_layers = 7 - 3 = 4

1. 作用于 f_size
2. 作用于解码器的卷积层数
3. 作用于生成器的卷积层数

max_num_channels

$$MaxNumChannels = ImageDim * 8$$

在这里 max_num_channels 同样与 img_dim 正相关。就等于 img_dim * 8

此处的 max_num_channels = 1024

1. 作用于生成器的每一个逆卷积层的输出通道
2. 作用于解码器的每一个卷积层的输出通道

f_size

$$Fsize = ImageDim / 2^{Numlayers+1}$$

f_size 在此处等于 128/(32) = 4

f_size 是生成器初始层参数个数的重要参数

```
z_in = Input(shape=(z_dim,))
z = z_in

z = Dense(f_size ** 2 * max_num_channels,
          kernel_initializer=RandomNormal(0, 0.02))(z)
z = Reshape((f_size, f_size, max_num_channels))(z)
```

$$zDim \rightarrow f^2 * channels \rightarrow (f, f, channels)$$

编码器

编码器的代码

```
# 编码器
x_in = Input(shape=(img_dim, img_dim, 3))
x = x_in

for i in range(num_layers + 1):
    num_channels = max_num_channels // 2 ** (num_layers - i)
    x = Conv2D(num_channels,
                (4, 4),
                strides=(2, 2),
                padding='same',
                kernel_initializer=RandomNormal(0, 0.02))(x)
    if i > 0:
        x = BatchNormalization()(x)
    x = LeakyReLU(0.2)(x)

x = Flatten()(x)
x = Dense(z_dim,
           kernel_initializer=RandomNormal(0, 0.02))(x)

e_model = Model(x_in, x)
e_model.summary()
```

$$numChannels = maxNumChannels / 2^{numLayers - i}$$

```
num_channels = max_num_channels // 2 ** (num_layers - i)
```

num_channels

num_channels的取值变化。首先i的取值是 [0,1,...,layers]

那么numLayers - i 的取值是[layers,layers - 1, ... ,1 , 0]

注意的是此处num_layers= 4

所以我们可以推出numChannels的取值是 [64,128,256,512,1024]

数据形状

我们发现这样使用最少的代码来构建不断压缩的卷积网络。图片的大小经过该五层网络后，则按如下规律变化

$$128- > 64- > 32- > 16- > 8- > 4$$

无论卷积核大小为多少，只要strides = 2，padding选择 same。

那么就可以实现每次大小缩减一半。

生成器

生成器的代码

```
# 生成器
```

```

z_in = Input(shape=(z_dim,))
z = z_in

z = Dense(f_size ** 2 * max_num_channels,
          kernel_initializer=RandomNormal(0, 0.02))(z)
z = Reshape((f_size, f_size, max_num_channels))(z)
z = SelfModulatedBatchNormalization(z, z_in)
z = Activation('relu')(z)

for i in range(num_layers):
    num_channels = max_num_channels // 2 ** (i + 1)
    z = Conv2DTranspose(num_channels,
                        (4, 4),
                        strides=(2, 2),
                        padding='same',
                        kernel_initializer=RandomNormal(0, 0.02))(z)
    z = SelfModulatedBatchNormalization(z, z_in)
    z = Activation('relu')(z)

z = Conv2DTranspose(3,
                    (4, 4),
                    strides=(2, 2),
                    padding='same',
                    kernel_initializer=RandomNormal(0, 0.02))(z)
z = Activation('tanh')(z)

g_model = Model(z_in, z)
g_model.summary()

```

值得注意的是生成器在最开始的维度就被拓展为了

$$\text{维度} = fSize^2 * maxNumChannels$$

i 的取值范围是[0,1,2,3]

num_channels的取值范围是[512,256,128,64]

初始维度是4 x 4 x 1024，使用逆卷积，对应上之前的num_channels

维度变化为

```
8 x 8 x 512 -> 16 x 16 x 256 -> 32 x 32 x 128 -> 64 x 64 x 64
```

最后经过一次转置

```
64 x 64 x 64 -> 128 x 128 x 3
```

整合模型（生成器和编码器）

模型整合部分

```

# 整合模型
x_in = Input(shape=(img_dim, img_dim, 3))
z_in = Input(shape=(z_dim,))

x_real = x_in

```

```

x_fake = g_model(z_in)
x_fake_ng = Lambda(K.stop_gradient)(x_fake)

z_real = e_model(x_real)
z_fake = e_model(x_fake)
z_fake_ng = e_model(x_fake_ng)

train_model = Model([x_in, z_in],
                    [z_real, z_fake, z_fake_ng])

z_real_mean = K.mean(z_real, 1, keepdims=True)
z_fake_mean = K.mean(z_fake, 1, keepdims=True)
z_fake_ng_mean = K.mean(z_fake_ng, 1, keepdims=True)

```

这里需要理解一下x_fake_ng, 这是x_fake求梯度得到的结果。

keras.backend.stop_gradient可以求的所传入参数的梯度

至于使用Lambda层, 不太清楚不使用Lambda层会有什么后果。

z_real 与 z_fake 都是 (?, 128) 形状, 而z_real_mean 是 (?, 1)的形状

损失函数部分

```

t1_loss = z_real_mean - z_fake_ng_mean
t2_loss = z_fake_mean - z_fake_ng_mean
z_corr = correlation(z_in, z_fake)
qp_loss = 0.25 * t1_loss[:, 0] ** 2 / K.mean((x_real - x_fake_ng) ** 2, axis=[1, 2, 3])

train_model.add_loss(K.mean(t1_loss + t2_loss - 0.5 * z_corr) + K.mean(qp_loss))
train_model.compile(optimizer=RMSprop(1e-4, 0.99))
train_model.metrics_names.append('t1_loss')
train_model.metrics_tensors.append(K.mean(t1_loss))
train_model.metrics_names.append('z_corr')
train_model.metrics_tensors.append(K.mean(z_corr))

```

z_{in} 经过 $model_g$ 再经过 $model_z$ 得到 z_{fake} 。我们需要比较 z_{in} 与 z_{fake} 的 *correlation*

```

def correlation(x, y):
    x = x - K.mean(x, 1, keepdims=True)
    y = y - K.mean(y, 1, keepdims=True)
    x = K.l2_normalize(x, 1)
    y = K.l2_normalize(y, 1)
    return K.sum(x * y, 1, keepdims=True)

```

其中l2_normalize函数的作用如下

$$x = [1, 2, 3] \text{ 对其求 } l2 - \text{normalize 的结果是: } \left[\frac{1}{1^2 + 2^2 + 3^2}, \frac{2}{1^2 + 2^2 + 3^2}, \frac{3}{1^2 + 2^2 + 3^2} \right]$$

其运算意义, 只知道最终这个是一个相关性

t1_loss 本来就是 (?, 1) 形状的tensor

$$ave[x_{Real} - (x_{Fake})']^2$$

训练模型

创建generator

主要是__iter__方法返回迭代器
__len__方法返回：训练集训练完毕（N个batch）需要多少步

```
class img_generator:
    def __init__(self, imgs, mode='gan', batch_size=64):
        self.imgs = imgs
        self.batch_size = batch_size
        self.mode = mode
        if len(imgs) % batch_size == 0:
            self.steps = len(imgs) // batch_size
        else:
            self.steps = len(imgs) // batch_size + 1

    def __len__(self):
        return self.steps

    def __iter__(self):
        x = []
        while True:
            np.random.shuffle(self.imgs)
            for i, f in enumerate(self.imgs):
                x.append(imread(f, self.mode))
                if len(x) == self.batch_size or i == len(self.imgs) - 1:
                    x = np.array(x)
                    if self.mode == 'gan':
                        z = np.random.randn(len(x), z_dim)
                        yield [x, z], None
                    elif self.mode == 'fid':
                        yield x
            x = []
```

使用fit_generator

```
img_data = img_generator(imgs, 'gan', batch_size)
train_model.fit_generator(img_data.__iter__(),
                          steps_per_epoch=len(img_data),
                          epochs=1000,
                          callbacks=[trainer])
```

注意

这里注意，在'gan'模式下，generator 返回的迭代器是一个 ([X, Z], None) 形式的返回值

```
train_model = Model([x_in, z_in],
                    [z_real, z_fake, z_fake_ng])
```

这里对应的是规划训练模型的时候，使用了这个结构