

## 数据生成

为什么需要使用数据生成器？答：数据占内存，可能没有足够的内存一下子存储所有数据，生成器可以把小量数据多批次读入内存。虽然花费了时间，但是能够处理很大的数据量。

## 不使用DA

```
In [1]: from keras.preprocessing.image import ImageDataGenerator #从keras
        导入需要需要的包

        IMSIZE=128
        validation_generator = ImageDataGenerator(rescale=1./255).flow_from_directory(
            '/clubear/Lecture 5.1 - Batch Normalization/data/CatDog/validation',
            target_size=(IMSIZE, IMSIZE), #不管数据里的图像大小, 在input统一shape
            batch_size=200, #每一个batch只读取200个数据
            class_mode='categorical') #分类问题
        #简单的制作validation data, rescale 是因为TensorFlow需要倒入的数据值在0-1之间, 而我们拥有的图片是0-255

        train_generator = ImageDataGenerator(rescale=1./255).flow_from_directory(
            '/clubear/Lecture 5.1 - Batch Normalization/data/CatDog/train',
            target_size=(IMSIZE, IMSIZE),
            batch_size=200,
            class_mode='categorical')
```

Using TensorFlow backend.

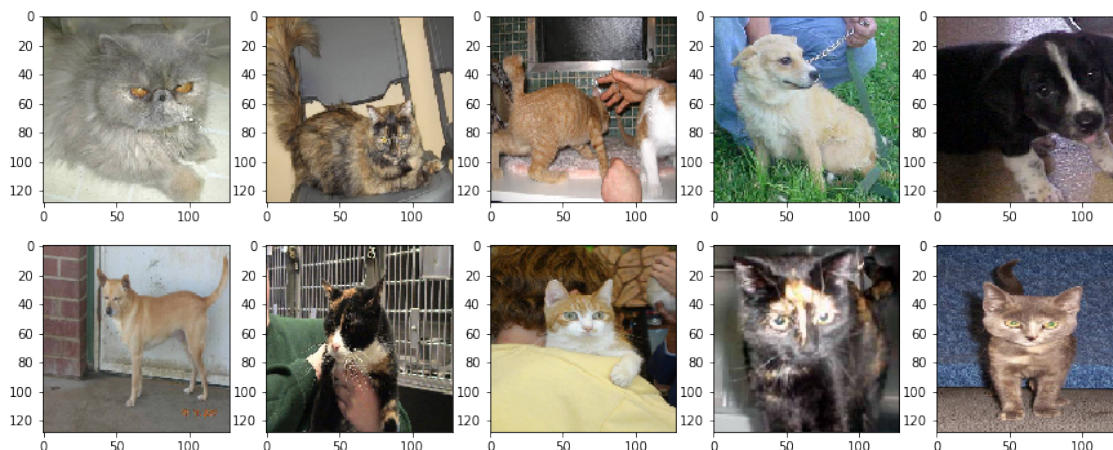
Found 10000 images belonging to 2 classes.

Found 15000 images belonging to 2 classes.

```
In [2]: #数据展示
from matplotlib import pyplot as plt

plt.figure()
fig,ax = plt.subplots(2,5)
fig.set_figheight(6)
fig.set_figwidth(15)
ax=ax.flatten()
X,Y=next(train_generator) #next是一个简单的方程将训练数据添加到x, y上
for i in range(10): ax[i].imshow(X[i,:,:,:])
```

<Figure size 432x288 with 0 Axes>



## 使用DA

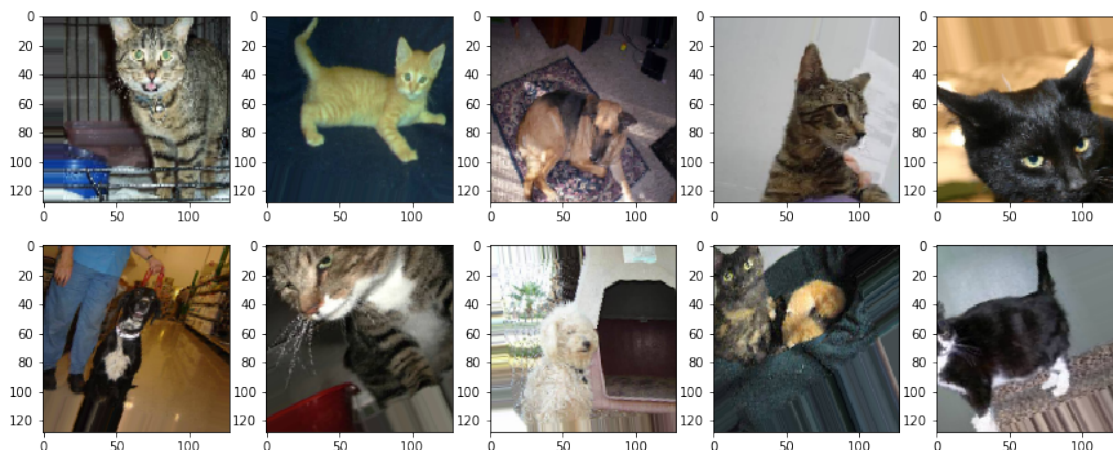
```
In [3]: train_generator1 = ImageDataGenerator(
    rescale=1./255, #tensorflow要求
    shear_range=0.5, #扭曲变形
    rotation_range=30, #旋转
    zoom_range=0.2, #放大
    width_shift_range=0.2, #水平平移
    height_shift_range=0.2, #垂直平移
    horizontal_flip=True).flow_from_directory(
    '/clubear/Lecture 5.1 - Batch Normalization/data/CatDog/train',
    target_size=(IMSIZE, IMSIZE),
    batch_size=200,
    class_mode='categorical')
#这里使用了Data Augmentation技术, 即将图片变形, 使得1) 数据量更大; 2) 在
#现实生活中的图片不可能是全部正面, 通过数据增强可以
#使我们的模型识别到更多变形的图像
#train现在存为了train_generator1
```

Found 15000 images belonging to 2 classes.

```
In [4]: #数据展示
from matplotlib import pyplot as plt

plt.figure()
fig,ax = plt.subplots(2,5)
fig.set_figheight(6)
fig.set_figwidth(15)
ax=ax.flatten()
X,Y=next(train_generator1) #x和y现在从train_generator1中取
for i in range(10): ax[i].imshow(X[i,:,:,:])
```

<Figure size 432x288 with 0 Axes>



## 模型搭建

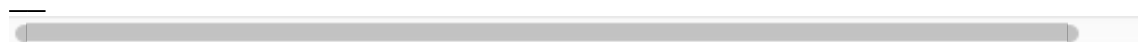
```
In [5]: from keras.layers import Conv2D,Dense,Flatten,Input,MaxPooling2D,Dropout
from keras import Model

input_layer = Input([IMSIZE,IMSIZE,3])
x = input_layer
for _ in range(5):
    x = Conv2D(20,[3,3], activation = 'relu')(x)
    x = MaxPooling2D(pool_size = [2,2], strides = [2,2])(x)

x = Flatten()(x)
x = Dense(84,activation = 'relu')(x)
x = Dense(2,activation = 'softmax')(x)
output_layer=x
model=Model(input_layer,output_layer)
model.summary()
```

Model: "model\_1"

Layer (type)	Output Shape	Param #
=====		
==		
input_1 (InputLayer)	(None, 128, 128, 3)	0
-----		
conv2d_1 (Conv2D)	(None, 126, 126, 20)	560
-----		
max_pooling2d_1 (MaxPooling2D)	(None, 63, 63, 20)	0
-----		
conv2d_2 (Conv2D)	(None, 61, 61, 20)	3620
-----		
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 20)	0
-----		
conv2d_3 (Conv2D)	(None, 28, 28, 20)	3620
-----		
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 20)	0
-----		
conv2d_4 (Conv2D)	(None, 12, 12, 20)	3620
-----		
max_pooling2d_4 (MaxPooling2D)	(None, 6, 6, 20)	0
-----		
conv2d_5 (Conv2D)	(None, 4, 4, 20)	3620
-----		
max_pooling2d_5 (MaxPooling2D)	(None, 2, 2, 20)	0
-----		
flatten_1 (Flatten)	(None, 80)	0
-----		
dense_1 (Dense)	(None, 84)	6804
-----		
dense_2 (Dense)	(None, 2)	170
=====		
==		
Total params: 22,014		
Trainable params: 22,014		
Non-trainable params: 0		



## 参数解释

第一层input layer, 无参数。

for loop中含有5个卷积层和5个池化层, 除去第一个卷积层, 其他卷积层参数为:

conv2D:  $(3 \times 3 \times 20 + 1) \times 20 = 181 \times 20 = 3620$ , 其中3 3 是kernel size, 20是上一层遗留通道数, 20是卷积核个数。

池化使用[2,2]矩形, 步长行列都是2, 没有学习项, 无参数

for loop的第一个卷积层参数计算如下:

$(3 \times 3 \times 3 + 1) \times 20 = 28 \times 20 = 560$ , 其中3 3 是kernel size, 3是上一层遗留通道数, 20是卷积核个数。

压扁, 无参数

Dense1: (hidden)  $80 \times 84 + 84 = 6720 + 84 = 6804$

Dense2:  $84 \times 2 + 2 = 168 + 2 = 170$

所以总共有22014个参数。

没有non-trainable parameters因为BN没有被用到

```
In [6]: from keras.optimizers import Adam
model.compile(loss='categorical_crossentropy', optimizer=Adam(lr=0.01), metrics=['accuracy'])
model.fit_generator(train_generator, epochs=4, validation_data=(validation_generator,))
```

```
Epoch 1/4
75/75 [=====] - 145s 2s/step - loss: 0.6950 - accuracy: 0.5033 - val_loss: 0.6955 - val_accuracy: 0.5000
Epoch 2/4
75/75 [=====] - 148s 2s/step - loss: 0.6933 - accuracy: 0.5015 - val_loss: 0.6926 - val_accuracy: 0.5000
Epoch 3/4
75/75 [=====] - 156s 2s/step - loss: 0.6933 - accuracy: 0.4955 - val_loss: 0.6930 - val_accuracy: 0.5000
Epoch 4/4
75/75 [=====] - 165s 2s/step - loss: 0.6933 - accuracy: 0.4980 - val_loss: 0.6960 - val_accuracy: 0.5000
```

```
Out[6]: <keras.callbacks.callbacks.History at 0x7f6caa8003d0>
```

## 使用BN, 无DA

```
In [7]: from keras.layers import BatchNormalization
input_layer = Input([IMSIZE,IMSIZE,3])
x = input_layer
x=BatchNormalization()(x) #使用BatchNormalisation, 对input的一个batch的数据每一层进行normalisation
for _ in range(5):
    x = Conv2D(20,[3,3], activation = 'relu')(x)
    x = MaxPooling2D(pool_size = [2,2], strides = [2,2])(x)

x = Flatten()(x)
x = Dense(84,activation = 'relu')(x)
x = Dense(2,activation = 'softmax')(x)
output_layer=x
model2=Model(input_layer,output_layer)
model2.summary()
```

Model: "model\_2"

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	(None, 128, 128, 3)	0
batch_normalization_1 (Batch Normalization)	(None, 128, 128, 3)	12
conv2d_6 (Conv2D)	(None, 126, 126, 20)	560
max_pooling2d_6 (MaxPooling2D)	(None, 63, 63, 20)	0
conv2d_7 (Conv2D)	(None, 61, 61, 20)	3620
max_pooling2d_7 (MaxPooling2D)	(None, 30, 30, 20)	0
conv2d_8 (Conv2D)	(None, 28, 28, 20)	3620
max_pooling2d_8 (MaxPooling2D)	(None, 14, 14, 20)	0
conv2d_9 (Conv2D)	(None, 12, 12, 20)	3620
max_pooling2d_9 (MaxPooling2D)	(None, 6, 6, 20)	0
conv2d_10 (Conv2D)	(None, 4, 4, 20)	3620

max_pooling2d_10 (MaxPooling (None, 2, 2, 20))	0
flatten_2 (Flatten)	(None, 80) 0
dense_3 (Dense)	(None, 84) 6804
dense_4 (Dense)	(None, 2) 170
=====	
==	
Total params: 22,026	
Trainable params: 22,020	
Non-trainable params: 6	

## 参数解释

第一层input layer, 无参数。

第二层BatchNormalisation中, 因为每一层/通道都有4个参数,  $3 \times 4 = 12$ ; 但是 $\mu$ 和 $\sigma$ 不需要训练 (因为这两个参数可以从数据总直接计算, 和模型学习没有关系), 所以 non-trainable params 有  $3 \times 2 = 6$ 个。for loop中含有5个卷积层和5个池化层, 除去第一个卷积层, 其他卷积层参数为:

conv2D:  $(3 \times 3 \times 20 + 1) \times 20 = 181 \times 20 = 3620$ , 其中 $3 \times 3$ 是kernel size, 20是上一层遗留通道数, 20是卷积核个数。

池化使用 $[2,2]$ 矩形, 步长行列都是2, 没有学习项, 无参数

for loop的第一个卷积层参数计算如下:

$(3 \times 3 \times 3 + 1) \times 20 = 28 \times 20 = 560$ , 其中 $3 \times 3$ 是kernel size, 3是上一层遗留通道数, 20是卷积核个数。

压扁, 无参数

Dense1: (hidden)  $80 \times 84 + 84 = 6720 + 84 = 6804$

Dense2:  $84 \times 2 + 2 = 168 + 2 = 170$

所以总共有22026个参数, 比没有BN的模型多了12个参数, 其中包含6个non-trainable参数。

没有non-trainable parameters因为BN没有被用到

```
In [8]: model2.compile(loss='categorical_crossentropy',optimizer=Adam(lr
=0.01),metrics=['accuracy'])
model2.fit_generator(train_generator,epochs=4,validation_data=va
lvalidation_generator)
```

```
Epoch 1/4
75/75 [=====] - 170s 2s/step - loss: 0
.6906 - accuracy: 0.5278 - val_loss: 0.6840 - val_accuracy: 0.5
551
Epoch 2/4
75/75 [=====] - 154s 2s/step - loss: 0
.6717 - accuracy: 0.5803 - val_loss: 0.6709 - val_accuracy: 0.5
965
Epoch 3/4
75/75 [=====] - 149s 2s/step - loss: 0
.6330 - accuracy: 0.6447 - val_loss: 0.6960 - val_accuracy: 0.6
154
Epoch 4/4
75/75 [=====] - 153s 2s/step - loss: 0
.6015 - accuracy: 0.6752 - val_loss: 0.5995 - val_accuracy: 0.6
713
```

```
Out[8]: <keras.callbacks.callbacks.History at 0x7f6c28101c10>
```

## 使用DA和BN ¶

```
In [9]: model2.compile(loss='categorical_crossentropy',optimizer=Adam(lr
=0.01),metrics=['accuracy'])
model2.fit_generator(train_generator1,epochs=4,validation_data=v
alvalidation_generator)
#模型用的是加上了BN的LeNet, 训练数据用的是Data Augmentation 以后的trai
n_generator1
```

```
Epoch 1/4
75/75 [=====] - 224s 3s/step - loss: 0
.6362 - accuracy: 0.6325 - val_loss: 0.6261 - val_accuracy: 0.6
455
Epoch 2/4
75/75 [=====] - 196s 3s/step - loss: 0
.6074 - accuracy: 0.6682 - val_loss: 0.5617 - val_accuracy: 0.7
128
Epoch 3/4
75/75 [=====] - 185s 2s/step - loss: 0
.5991 - accuracy: 0.6787 - val_loss: 0.5329 - val_accuracy: 0.7
185
Epoch 4/4
75/75 [=====] - 187s 2s/step - loss: 0
.5815 - accuracy: 0.6949 - val_loss: 0.4817 - val_accuracy: 0.7
279
```

```
Out[9]: <keras.callbacks.callbacks.History at 0x7f6c08713190>
```



# 总结

普通仿LeNet: accuracy 为 0.50 左右, 和一个random guess差不多。

模型with BN: 最后一个epoch的accuracy 为 0.67, 呈增加趋势, 如果epoch再高也许还有更高的精度。

模型with DA & BN: 平均accruacy (在4个epoch里) 达到约0.67, 比只有BN的时候要更精确。