TASK目标：本次任务的目的就一个：学习模仿。AlexNet也是DL领域比较早期的经典模型，值得认真学习模仿。

具体而言，本次TASK需要你：

（1）学习模仿这个经典网络，并对每行代码做注释解释；

（2）模仿这个经典模型的基本思想，创造一个属于你自己的CNN模型，并用于前面的性别识别案例，看看最好能做多好，是否有所改进？

（3）请对代码逐行注释，尤其要对model.summary中呈现的参数个数做详细解释。这对帮助大家更好地理解模型结构帮助巨大！

经典CNN网络：AlexNet 介绍

Alexnet 概述

AlexNet是2012年ImageNet竞赛冠军获得者Hinton和他的学生Alex Krizhevsky设计的，其top5预测的错误率为18.9%，远超第二名。,是ImageNet竞赛中第一个使用神经网络的参赛者。在那年之后，更多的更深的神经网路被提出，比如优秀的vgg,GoogLeNet。

Alexnet处理的问题是1000分类问题，AlexNet采用8层的神经网络，5个卷积层和3个全连接层(3个卷积层后面加了最大池化层)，包含6亿3000万个链接，6000万个 参数和65万个神经元。

截止到北京时间2019/3/21,一共被引用37117次。

Alexnet 创新点

1.成功使用ReLU作为CNN的激活函数，验证了其效果在较深的网络中超过了Sigmoid。

2.训练时使用Dropout随机忽略一部分神经元，以避免模型过拟合，一般在全连接层使用。

3.在CNN中使用重叠的最大池化(步长小于卷积核)。

4.提出LRN（Local Response Normalization，即局部响应归一化）层，逐渐被BN（Batch Nomalization）所代替。

5.使用CUDA加速神经网络的训练，利用了GPU强大的计算能力。受限于当时计算能力，Alexnet使用两块GPU进行训练。

6.数据增强，随机的从256×256的图片中截取224×224大小的区域（以及水平翻转的镜像）。

网络结构（详解）

输入层: 227×227×3的图片。

第1层：Conv2D(11×11，96), Stride(4), ReLU, Output: 55×55×96。

第2层：MaxPooling2D(3×3), Stride(2), Output: 27×27×96。

第3层：Conv2D(5×5，256），Same，Output：27×27×256。

第4层：Conv2D(3×3,256），Stride(2)，Output：13×13×256。

第5层：Conv2D(3×3,384），Same，Output：13×13×384。

第6层：Conv2D(3×3,384），Same，Output：13×13×384。

第7层：Conv2D（3×3，256），Same，Output：13×13×256。

第8层：MaxPooling2D（3×3），Stride（2），Output：6×6×256。

输出层：
Flatten，Dense(4096)，Dropout(0.5)，Dense（4096），Dropout（0.5），Output。

Alexnet代码实现

In [1]:

```
import tensorflow as tf
import keras
from keras.layers import Activation,Conv2D, BatchNormalization, Dense    # 导入各种层函数
from keras.layers import Dropout, Flatten, Input, MaxPooling2D, ZeroPadding2D # 导入各种层函数
from keras import Model       # 模型

IMSIZE = 227          # 图片像素
input_layer = Input([IMSIZE,IMSIZE,3])  # 定义一个通道为3的227*227的彩色图片
x = input_layer       # 赋值
x = Conv2D(96,[11,11],strides = [4,4], activation = 'relu')(x)
# 对x做一个2维的96通道的11*11的卷积，步长是4*4

x = MaxPooling2D([3,3], strides = [2,2])(x)    # 最大池化，大小为3*3，步长为2*2
x = Conv2D(256,[5,5],padding = "same", activation = 'relu')(x)    #5*5规则的256个卷积核，步长为2*2
x = MaxPooling2D([3,3], strides = [2,2])(x)    # 最大池化，大小为3*3，步长为2*2
x = Conv2D(384,[3,3],padding = "same", activation = 'relu')(x) # 3个连续的卷积，3*3的规格，1*1的步长，通道的个数为384
x = Conv2D(384,[3,3],padding = "same", activation = 'relu')(x)
x = Conv2D(256,[3,3],padding = "same", activation = 'relu')(x)   # 3个连续的卷积，3*3的规格，1*1的步长，通道的个数为256
x = MaxPooling2D([3,3], strides = [2,2])(x)    # 最大池化，大小为3*3，步长为2*2
x = Flatten()(x)     # 拉直
x = Dense(4096,activation = 'relu')(x)  # 全连接到4096个节点
x = Dropout(0.5)(x)                    # 随机扔掉一半
x = Dense(4096,activation = 'relu')(x)  # 全连接到4096个节点
x = Dropout(0.5)(x)                    # 再次随机扔掉一半
x = Dense(2,activation = 'softmax')(x)   # 输出2个节点
output_layer=x             # 输出
model=Model(input_layer,output_layer)   # 基于以上，构建模型
model.summary()                # 模型结构
```

Using TensorFlow backend.

Model: "model_1"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 227, 227, 3)	0
conv2d_1 (Conv2D)	(None, 55, 55, 96)	34944
max_pooling2d_1 (MaxPooling2	(None, 27, 27, 96)	0

max_pooling2d_1 (MaxPooling2 (None, 27, 27, 96) 0

conv2d_2 (Conv2D) (None, 27, 27, 256) 614656

max_pooling2d_2 (MaxPooling2 (None, 13, 13, 256) 0

conv2d_3 (Conv2D) (None, 13, 13, 384) 885120

conv2d_4 (Conv2D) (None, 13, 13, 384) 1327488

conv2d_5 (Conv2D) (None, 13, 13, 256) 884992

max_pooling2d_3 (MaxPooling2 (None, 6, 6, 256) 0

flatten_1 (Flatten) (None, 9216) 0

dense_1 (Dense) (None, 4096) 37752832

dropout_1 (Dropout) (None, 4096) 0

dense_2 (Dense) (None, 4096) 16781312

dropout_2 (Dropout) (None, 4096) 0

dense_3 (Dense) (None, 2) 8194

Total params: 58,289,538
Trainable params: 58,289,538
Non-trainable params: 0

以上模型参数清点：

输入层: 输入的是227*227像素的3通道的图片, 不消耗任何参数.

第一个卷积层: 输入是3通道, 输出是96通道, 每输出一个通道需要消耗: 输入通道数x卷积核大小+1个截距项 =11x11x3+1=364. 共有364个输出通道, 所以消耗了364x96=34944个参数.

第一个最大池化层: 27*27像素输出96个通道的立体矩阵, 不需要任何参数.

第二个卷积层: 规格大小是27*27，96通道, 每输出一个通道需要消耗: 输入通道数x卷积核大小+1个截距项 =5x5x96+1=2401. 共有256个输出通道, 所以消耗了2401x256=614656个参数.

第二个最大池化层: 13*13像素输出256个通道的立体矩阵, 不需要任何参数.

第三个卷积层: 3*3的卷积层，每输出一个通道需要消耗: 输入通道数x卷积核大小+1个截距项 =3x3x256+1=401. 共有384个输出通道, 所以消耗了885120个参数.

第四个卷积层: 3*3的卷积层，每输出一个通道需要消耗: 输入通道数x卷积核大小+1个截距项 =3x3x256+1=401. 共有384个输出通道, 所以消耗了1327488个参数.

第五个卷积层: 3*3的卷积层，每输出一个通道需要消耗: 输入通道数x卷积核大小+1个截距项 =3x3x256+1=401. 共有384个输出通道, 所以消耗了884992个参数.

第三个最大池化层: 输出的还是6*6像素256的立体矩阵, 不需要任何参数.

**flatten层: 将上一层的256通道矩阵拉直成一个长向量, 输出的是6x6x256=9216的向量, 不需要消耗任何参数.

输出层1：建立一个4096的全连接网络，参数消耗的个数是9216+1，9217*4096=37752832个参数.

删除层1： 不需要任何参数.

输出层2：建立一个4096的全连接网络，参数消耗的个数是（4096+1）*2=16781312个参数.

删除层2： 不需要任何参数.

输出层2：建立一个4096的全连接网络，参数消耗的个数是8194个参数.

合计: 共消耗了:
34944+614656+885120+1327488+884992+37752832+16781312+8194=58289538个参数, 其中所有参数都需要训练. 所以需要训练的参数个数为:58289538，不需要训练的参数个数为：0

数据目录结构

In [2]:

```
%ls ./data/ChineseStyle/
%ls ./data/ChineseStyle/train
%ls ./data/ChineseStyle/test
```

```
test/  train/
lishu/  xingkai/
lishu/  xingkai/
```

数据生成器

In [3]:

```
from keras.preprocessing.image import ImageDataGenerator   # 图像预处理

IMSIZE=227 # 像素

validation_generator = ImageDataGenerator(rescale=1./255).flow_from_directory(
    './data/ChineseStyle/test/',     # 数据路径
    target_size=(IMSIZE, IMSIZE),   # 数据像素（目标大小）
    batch_size=200,                 # 批处理大小
    class_mode='categorical')       # 类模型

train_generator = ImageDataGenerator(rescale=1./255).flow_from_directory(
    './data/ChineseStyle/train',     # 数据路径
    target_size=(IMSIZE, IMSIZE),   # 数据像素（目标大小）
    batch_size=200,                 # 批处理大小
    class_mode='categorical')       # 类模型
```

```
Found 5526 images belonging to 2 classes.
Found 8000 images belonging to 2 classes.
```

数据展示

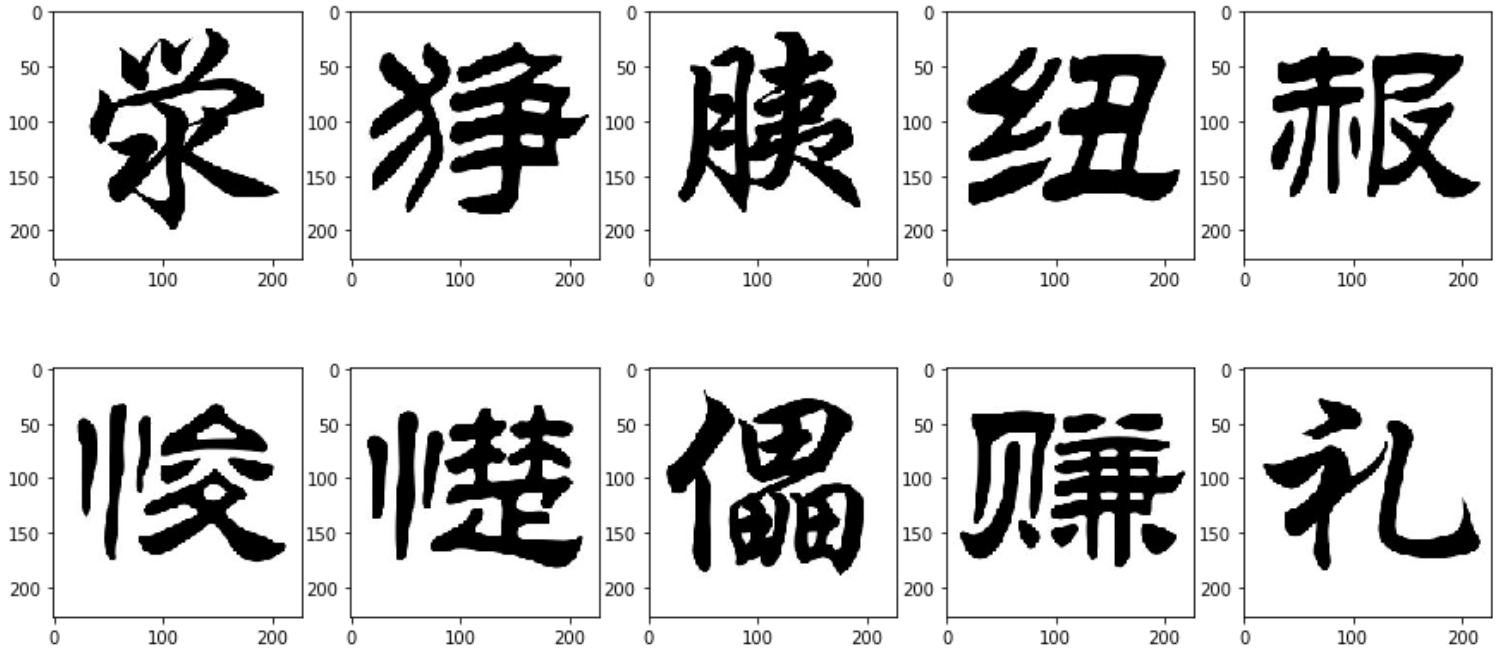
In [4]:

```
from matplotlib import pyplot as plt  # 导入绘图库

plt.figure()  # 初始画板
fig,ax = plt.subplots(2,5)  # 2行5列
fig.set_figheight(7)        # 高度
fig.set_figwidth(15)        # 宽度
```

```
ax=ax.flatten()      # 将ax拉直
X,Y=next(validation_generator)
for i in range(10): ax[i].imshow(X[i,:,:,:])    # 循环展示
```

<Figure size 432x288 with 0 Axes>



In [5]:

```
from keras.optimizers import Adam      # 导入优化器Adam
model.compile(loss='categorical_crossentropy',    #模型编译，损失函数为交叉熵
              optimizer=Adam(lr=0.001),metrics=['accuracy'])  #优化器为Adam，学习速率为0.001 #衡量指标为精度
model.fit_generator(train_generator,epochs=10,       # 训练10轮
                    validation_data=validation_generator) #模型训练，用训练集
```

```
Epoch 1/10
40/40 [==============================] - 33s 828ms/step - loss: 0.9548 - accuracy: 0.5633 - val_loss: 1.3905 - val_accuracy: 0.5094
Epoch 2/10
39/40 [============================>.] - ETA: 0s - loss: 0.6366 - accuracy: 0.6278

---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-5-7f267eb8b529> in <module>
      3              optimizer=Adam(lr=0.001),metrics=['accuracy'])
      4 model.fit_generator(train_generator,epochs=10,
----> 5                     validation_data=validation_generator)

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/keras/legacy/interfaces.py in wrapper(*args, **kwargs)
     89                 warnings.warn('Update your `' + object_name + '` call to the ' +
     90                               'Keras 2 API: ' + signature, stacklevel=2)
---> 91             return func(*args, **kwargs)
     92         wrapper._original_function = func
     93         return wrapper

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/keras/engine/training.py in fit_generator(self, generator, steps_per_epoch, epochs, verbose, callbacks, validation_data, validation_steps, validation_freq, class_weight, max_queue_size, workers, use_multiprocessing, shuffle, initial_epoch)
   1730             use_multiprocessing=use_multiprocessing,
   1731             shuffle=shuffle,
-> 1732             initial_epoch=initial_epoch)
   1733
   1734     @interfaces.legacy_generator_methods_support
```

```
/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/keras/engine/training_generator.py in fit_generator(model, generator, steps_per_epoch, epochs, verbose, callbacks, validation_data, validation_steps, validation_freq, class_weight, max_queue_size, workers, use_multiprocessing, shuffle, initial_epoch)
    240                         validation_steps,
    241                         callbacks=callbacks,
--> 242                         workers=0)
    243                 else:
    244                     # No need for try/except because

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/keras/legacy/interfaces.py in wrapper(*args, **kwargs)
     89                 warnings.warn('Update your `' + object_name + '` call to the ' +
     90                               'Keras 2 API: ' + signature, stacklevel=2)
---> 91             return func(*args, **kwargs)
     92         wrapper._original_function = func
     93         return wrapper

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/keras/engine/training.py in evaluate_generator(self, generator, steps, callbacks, max_queue_size, workers, use_multiprocessing, verbose)
   1789             workers=workers,
   1790             use_multiprocessing=use_multiprocessing,
-> 1791             verbose=verbose)
   1792
   1793     @interfaces.legacy_generator_methods_support

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/keras/engine/training_generator.py in evaluate_generator(model, generator, steps, callbacks, max_queue_size, workers, use_multiprocessing, verbose)
    399             outs = model.test_on_batch(x, y,
    400                                        sample_weight=sample_weight,
--> 401                                        reset_metrics=False)
    402             outs = to_list(outs)
    403             outs_per_batch.append(outs)

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/keras/engine/training.py in test_on_batch(self, x, y, sample_weight, reset_metrics)
   1557             ins = x + y + sample_weights
   1558         self._make_test_function()
-> 1559         outputs = self.test_function(ins)
   1560
   1561         if reset_metrics:

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/tensorflow_core/python/keras/backend.py in __call__(self, inputs)
   3725         value = math_ops.cast(value, tensor.dtype)
   3726       converted_inputs.append(value)
-> 3727     outputs = self._graph_fn(*converted_inputs)
   3728
   3729     # EagerTensor.numpy() will often make a copy to ensure memory safety.

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/tensorflow_core/python/eager/function.py in __call__(self, *args, **kwargs)
   1549       TypeError: For invalid positional/keyword argument combinations.
   1550     """
-> 1551     return self._call_impl(args, kwargs)
   1552
   1553   def _call_impl(self, args, kwargs, cancellation_manager=None):

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/tensorflow_core/python/eager/function.py in _call_impl(self, args, kwargs, cancellation_manager)
```

```
   1589       raise TypeError("Keyword arguments {} unknown. Expected {}.".format(
   1590           list(kwargs.keys()), list(self._arg_keywords)))
-> 1591     return self._call_flat(args, self.captured_inputs, cancellation_manager)
   1592
   1593   def _filtered_call(self, args, kwargs):

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/tensorflow_core/python/eager/function.py in _call
_flat(self, args, captured_inputs, cancellation_manager)
   1690       # No tape is watching; skip to running the function.
   1691       return self._build_call_outputs(self._inference_function.call(
-> 1692           ctx, args, cancellation_manager=cancellation_manager))
   1693     forward_backward = self._select_forward_and_backward_functions(
   1694         args,

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/tensorflow_core/python/eager/function.py in call(s
elf, ctx, args, cancellation_manager)
    543             inputs=args,
    544             attrs=("executor_type", executor_type, "config_proto", config),
--> 545             ctx=ctx)
    546       else:
    547         outputs = execute.execute_with_cancellation(

/anaconda/envs/py37_tensorflow/lib/python3.7/site-packages/tensorflow_core/python/eager/execute.py in quick
_execute(op_name, num_outputs, inputs, attrs, ctx, name)
     59     tensors = pywrap_tensorflow.TFE_Py_Execute(ctx._handle, device_name,
     60                                                op_name, inputs, attrs,
---> 61                                                num_outputs)
     62   except core._NotOkStatusException as e:
     63     if name is not None:

KeyboardInterrupt:
```

```
Epoch 1/10
40/40 [==============================] - 63s 2s/step - loss: 1.0181 - accuracy: 0.5124 - val_loss: 0.6930 - val_accuracy: 0.5000
Epoch 2/10
40/40 [==============================] - 35s 873ms/step - loss: 0.6933 - accuracy: 0.5048 - val_loss: 0.6912 - val_accuracy: 0.5000
Epoch 3/10
40/40 [==============================] - 35s 880ms/step - loss: 0.8379 - accuracy: 0.5472 - val_loss: 0.6573 - val_accuracy: 0.5031
Epoch 4/10
40/40 [==============================] - 35s 870ms/step - loss: 0.3656 - accuracy: 0.8156 - val_loss: 0.0147 - val_accuracy: 0.9857
Epoch 5/10
40/40 [==============================] - 37s 924ms/step - loss: 0.0241 - accuracy: 0.9923 - val_loss: 0.0143 - val_accuracy: 0.9949
Epoch 6/10
40/40 [==============================] - 35s 886ms/step - loss: 0.0093 - accuracy: 0.9966 - val_loss: 3.0953e-04 - val_accuracy: 0.9975
Epoch 7/10
40/40 [==============================] - 37s 916ms/step - loss: 0.0050 - accuracy: 0.9985 - val_loss: 0.0010 - val_accuracy: 0.9980
Epoch 8/10
40/40 [==============================] - 36s 910ms/step - loss: 9.3471e-04 - accuracy: 0.9996 - val_loss: 0.0046 - val_accuracy: 0.9989
Epoch 9/10
40/40 [==============================] - 36s 892ms/step - loss: 0.0019 - accuracy: 0.9994 - val_loss: 4.3206e-04 - val_accuracy: 0.9960
Epoch 10/10
40/40 [==============================] - 38s 941ms/step - loss: 0.0015 - accuracy: 0.9991 - val_loss: 1.9272e-05 - val_accuracy: 0.9976
<keras.callbacks.callbacks.History at 0x7eff342cc890>
```

根据模型预测的精确率来看，0.99的准确率接近于1，所以该模型效果非常棒。

In [1]:

```
import pandas as pd  #导入库
MasterFile=pd.read_csv('F:/大三（上）/深度学习/TASK2.1：AI可以为颜值打分/FaceScore.csv')
#读入参考文件
print(MasterFile.shape) #打印数组维度
MasterFile.head()       #打印前五个
```

(24, 2)

Out[1]:

	Filename	Rating
0	ftw (1).jpg	4.083333
1	mtw (2).jpg	3.666667
2	mtw (3).jpg	1.916667
3	mtw (4).jpg	2.416667
4	mtw (5).jpg	3.166667

In [68]:

```
import numpy as np
from PIL import Image

FileNames=MasterFile['Filename']
N=len(FileNames)
IMSIZE= 100
X=np.zeros([N,IMSIZE,IMSIZE,3])
for i in range(N):
    MyFile=FileNames[i]
    Im=Image.open('F:/大三（上）/深度学习/TASK2.1：AI可以为颜值打分/image/'+MyFile)
    Im=Im.resize([IMSIZE,IMSIZE])  #图像的缩放
    Im=np.array(Im)/255
    X[i,]=Im
```

In [69]:

```
Y=np.zeros([N,2])
for i in range(N):
    gender=FileNames[i][0]
    if gender=='m':
        Y[i,0]=1
    else:
        Y[i,1]=1
```

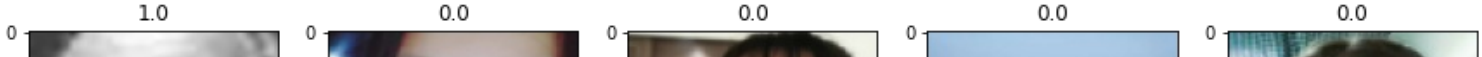
In [70]:

```
import tensorflow as tf
from tensorflow.keras import datasets, Sequential, layers,metrics
from sklearn.model_selection import train_test_split   #构造训练集和测试集
X0,X1,Y0,Y1=train_test_split(X,Y,test_size=0.3,random_state=1)
```

In [71]:

```
from matplotlib import pyplot as plt
plt.figure()                  #导入绘图库
fig,ax=plt.subplots(2,5)       #2行5列
fig.set_figheight(7.5)
fig.set_figwidth(15)
ax=ax.flatten()
for i in range(10):           #展示10张照片的性别
    ax[i].imshow(X0[i,:,:,:])
    ax[i].set_title(Y0[i,0])
```

<Figure size 432x288 with 0 Axes>



In [72]:

```
from keras.layers import Dense, Flatten, Input
from keras.layers import BatchNormalization, Conv2D,MaxPooling2D
from keras import Model
```

In [73]:

```
input_layer = Input([IMSIZE,IMSIZE,3])
x = input_layer
x = BatchNormalization()(x)
x = Conv2D(10,[2,2],activation='relu')(x)
x = MaxPooling2D([3,3])(x)
x = Flatten()(x)
x = Dense(2,activation='softmax')(x)
output_layer = x
model = Model(input_layer,output_layer)
model.summary()
```

Model: "functional_33"

Layer (type)	Output Shape	Param #
input_18 (InputLayer)	[(None, 100, 100, 3)]	0
batch_normalization_4 (Batch	(None, 100, 100, 3)	12
conv2d_31 (Conv2D)	(None, 99, 99, 10)	130
max_pooling2d_28 (MaxPooling	(None, 33, 33, 10)	0
flatten_16 (Flatten)	(None, 10890)	0
dense_27 (Dense)	(None, 2)	21782

Total params: 21,924
Trainable params: 21,918
Non-trainable params: 6

以上模型参数清点：

输入层：输入的是100*100像素的3通道的图片，不消耗任何参数

输入层：输入的是100*100像素的3通道的图片，不消耗任何参数。

batch层：输入100*100像素的3通道图片，消耗12个参数。

卷积层：输入是2通道，输出是3通道，每输出一个通道需要消耗：输入通道数x卷积核大小+1个截距项=2x2x3+1=13. 共有13个输出通道，所以消耗了13x10=130个参数.

最大池化层：99*99像素输出10个通道的立体矩阵，不需要任何参数.

flatten层：将通道矩阵拉直成一个长向量，输出的是6x6x10=10890的向量，不需要消耗任何参数.

输出层：建立一个2通道的全连接网络，参数消耗的个数是19890，10891*2=21782 个参数.

合计：共消耗了:21,924个参数，其中需要训练的参数个数为:21,918，不需要训练的参数个数为：6.

In [74]:

```
from keras.optimizers import Adam
model.compile(optimizer = Adam(0.001),loss = 'categorical_crossentropy',metrics = ['accuracy'])
```

In [75]:

```
model.fit(X0,Y0,validation_data=(X1,Y1),batch_size=20,epochs=10)
```

```
Epoch 1/10
1/1 [==============================] - 0s 178ms/step - loss: 0.4903 - accuracy: 0.8125 - val_loss: 1.830
3 - val_accuracy: 0.7500
Epoch 2/10
1/1 [==============================] - 0s 28ms/step - loss: 0.5956 - accuracy: 0.8750 - val_loss: 2.2959
- val_accuracy: 0.7500
Epoch 3/10
1/1 [==============================] - 0s 25ms/step - loss: 0.6391 - accuracy: 0.8750 - val_loss: 2.3255
- val_accuracy: 0.7500
Epoch 4/10
1/1 [==============================] - 0s 26ms/step - loss: 0.5168 - accuracy: 0.8750 - val_loss: 2.1190
- val_accuracy: 0.7500
Epoch 5/10
1/1 [==============================] - 0s 23ms/step - loss: 0.3155 - accuracy: 0.8750 - val_loss: 1.7779
- val_accuracy: 0.7500
Epoch 6/10
1/1 [==============================] - 0s 31ms/step - loss: 0.1125 - accuracy: 0.8750 - val_loss: 1.3941
- val_accuracy: 0.7500
Epoch 7/10
1/1 [==============================] - 0s 40ms/step - loss: 0.0214 - accuracy: 1.0000 - val_loss: 1.0499
- val_accuracy: 0.7500
Epoch 8/10
1/1 [==============================] - 0s 25ms/step - loss: 0.0045 - accuracy: 1.0000 - val_loss: 0.7659
- val_accuracy: 0.7500
Epoch 9/10
1/1 [==============================] - 0s 29ms/step - loss: 0.0022 - accuracy: 1.0000 - val_loss: 0.5541
- val_accuracy: 0.7500
Epoch 10/10
1/1 [==============================] - 0s 31ms/step - loss: 0.0033 - accuracy: 1.0000 - val_loss: 0.4210
- val_accuracy: 0.8750
```

Out[75]:

```
<tensorflow.python.keras.callbacks.History at 0x1b695239308>
```

模型的预测精度都达到1啦，可见该预测模型很棒！