新冠肺炎CT图像识别

案例目标:通过迁移学习识别感染和未感染新冠的CT图像

教学目的: (1) 学习使用数据生成器进行训练集和测试集的生成; (2) 掌握迁移学习模型的使用(3) 对感染了新冠肺炎和未感染新冠肺炎的CT进行自动识别; (4) 尝试使用不同的迁移学习模型进行训练并对比不同模型的效果

相关知识点: (1) ImageDataGenerator的使用; (2) 数据增强处理的基本技巧; (3) 迁移学习Inception V3模型; (4) 对给定的CT图像进行预测,判断其感染新冠肺炎的概率

一、背景介绍

新冠肺炎疫情自爆发以来迅速在全球蔓延,毒株的变异更是增强了新冠肺炎病毒的传播能力,欧美地区感染人数仍在飞速增加,中国部分地区也出现多轮疫情反复,新冠肺炎疫情仍然影响着人们的正常生活,威胁着人们的生命健康。本案例使用SARS-CoV-2 CT-scan公开数据集(https://www.kaggle.com/datasets/plameneduardo/sarscov2-ctscan-dataset (https://www.kaggle.com/datasets/plameneduardo/sarscov2-ctscan-dataset/),通过构建迁移学习模型(Inception V3)对CT图像进行分类,尝试高效区分感染和未感染新冠肺炎的CT图像。

二、数据准备

SARS-CoV-2 CT-scan数据集是收集自巴西圣保罗医院真实患者的公开数据集,该数据集的图片以.png格式存储,共包含感染新冠肺炎的CT图片1252张,未感染新冠肺炎的CT图片1229张。所有数据存储在data文件夹下,首先展示目录存储结构,之所以这样进行数据存储,是为了后续构建数据生成器。

```
In [1]: import os
print(os.listdir('./data')) #展示data文件夹
print(os.listdir('./data/train')) #展示train文件夹
print(os.listdir('./data/validation')) #展示validation
文件夹

['train', 'validation']
['COVID-negative', 'COVID-positive']
['COVID-negative', 'COVID-positive']
```

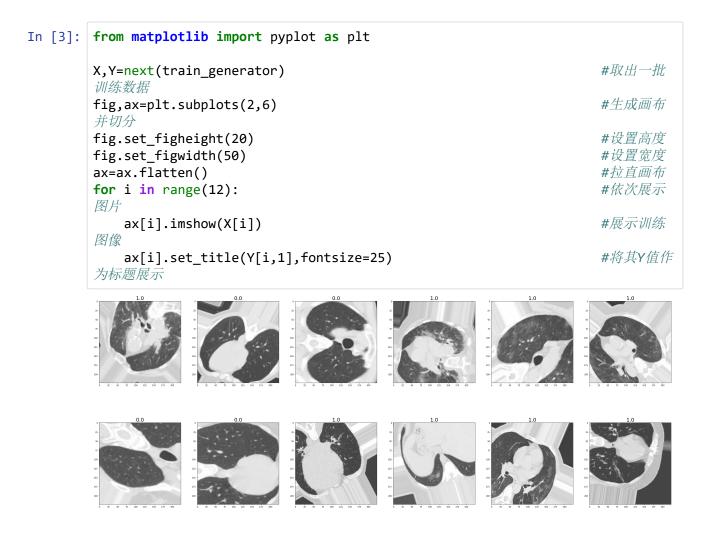
由于数据量太大,无法一次性读入显存,因此需要建立一个数据生成器,其中训练数据集的生成器需要做数据增强操作,而校验集的数据生成器不需要。

from keras.preproce	essing.image import ImageDataGenerator	
IMAGE_SIZE = 224 片大小		#设置图
train_generator =] 数据生成器(需要进行	[mageDataGenerator(数据增强)	#训练集
像素取值转换至0-1之间	rescale=1./255,	#将图片
	rotation_range=360,	#图片旋
转	width_shift_range=0.2,	#水平方
向平移	height_shift_range=0.2,	#竖直方
向平移		
放	zoom_range=0.2,	#图片缩
平翻转	<pre>horizontal_flip=True,</pre>	#随机水
	<pre>vertical_flip=True).flow_from_directory(</pre>	#随机数
值翻转	'./data/train',	#设置该
取路径	<pre>target_size=(IMAGE_SIZE,IMAGE_SIZE),</pre>	#将图片
调整至统一大小		
样本量设置为256	batch_size=64,	#每批次
类问题	<pre>class_mode='categorical',</pre>	#声明分
乱	shuffle = True)	#随机打
	or=ImageDataGenerator(# <i>校验集</i>
数据生成器 (无需数据		#将图片
像素取值转换至0-1之间		
取路径	'./data/validation',	#设置该
调整至统一大小	<pre>target_size=(IMAGE_SIZE,IMAGE_SIZE),</pre>	#将图片
	batch_size=64,	#每批次日
样本量设置为256	class_mode='categorical',	#声明为
分类问题	shuffle=False)	#不在每
个epoch之前打乱排序	· ·	#111L H

Found 1737 images belonging to 2 classes. Found 744 images belonging to 2 classes.

深度学习代码实践中经常涉及到非常复杂的数据处理。疏漏错误实在难免。因此,所有的数据读取过程,最好都需要一个可视化肉眼核实确认的环节。为此,我们选取一个批次的部分训练集数据进行展示。其中1为感染新冠,0为未感染新冠。

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三、模型训练: 迁移学习Inception V3

"迁移学习"是指将某个领域或任务上学习到的知识或模式运用到不同、但相关的领域或问题中。我们可以使用 Keras中的迁移学习模型,站在前人的肩膀上,将别人的模型结构和参数训练结果应用在自己的模型中,从而 快速且相对准确地得到预测结果。本案例中,我们迁移Inception V3作为基础模型,将基础模型的输出继续输入 全局池化层、BN层、Dropout层和全连接层进行相应操作后,得到模型的最终输出。

```
In [8]: from tensorflow.keras.applications.inception_v3 import InceptionV3
       from tensorflow.keras import Model
       from tensorflow.keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPoo
       12D, BatchNormalization, AveragePooling2D, GlobalAveragePooling2D, Activati
       from tensorflow.keras.optimizers import Adam,SGD
       base_model = InceptionV3(weights='imagenet', include_top=False) #基础模型In
        ception V3,设置迁移的模型不包含全连接层
       x = base model.output
                                                                   #取基础模型
        的输出
       x = GlobalAveragePooling2D()(x)
                                                                   #全局池化
       x = BatchNormalization()(x)
                                                                   #BN层
       x = Dropout(0.7)(x)
                                                                   #Dropout避
        免过拟合,修改为0.7
       x = Dense(256, activation='relu')(x)
                                                                   #第一个全连
        接层
                                                                   #再次进行BN
       x = BatchNormalization()(x)
       操作
       x = Dropout(0.7)(x)
                                                                    #修改为0.7
       predictions = Dense(2, activation = 'softmax')(x)
                                                                   #第二个全连
        接层,得到输出
       model = Model(inputs = base_model.input, outputs = predictions) #建立模型,
        声明输入、输出
       for layer in base_model.layers:
           layer.trainable = False
                                                                   #直接迁移训
        练好的Inception V3模型,设置基础模型每一层的参数都不需要训练
       model.summary()
                                                                   #打印模型概
        要表
```

Model: "model_2"

Layer (type)		Output	·			Param #	Connected
input_3 (InputLayer)		[(None,					
conv2d_188 (Conv2D) [0][0]		(None,	None,	None,	3	864	input_3
batch_normalization_193 ([0][0]	(BatchN	(None,	None,	None,	3	96	conv2d_188
activation_188 (Activation_193[0][0]	on)	(None,	None,	None,	3	0	batch_norm
conv2d_189 (Conv2D) _188[0][0]		(None,	None,	None,	3	9216	activation
batch_normalization_194 ([0][0]	(BatchN	(None,	None,	None,	3	96	conv2d_189
activation_189 (Activation_194[0][0]	on)	(None,	None,	None,	3	0	batch_norm
conv2d_190 (Conv2D) _189[0][0]		(None,	None,	None,	6	18432	activation
batch_normalization_195 ([0][0]	(BatchN	(None,	None,	None,	6	192	conv2d_190
activation_190 (Activation_195[0][0]	on)	(None,	None,	None,	6	0	batch_norm
max_pooling2d_8 (MaxPooli _190[0][0]	ing2D)	(None,	None,	None,	6	0	activation
conv2d_191 (Conv2D) g2d_8[0][0]		(None,	None,	None,	8	5120	max_poolin
batch_normalization_196 ([0][0]	(BatchN	(None,	None,	None,	8	240	conv2d_191

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activation_191 (Activation) alization_196[0][0]	(None,	None,	None,	8	0	batch_norm
conv2d_192 (Conv2D) _191[0][0]	(None,	None,	None,	1	138240	activation
batch_normalization_197 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_192
activation_192 (Activation) alization_197[0][0]	(None,	None,	None,	1	0	batch_norm
max_pooling2d_9 (MaxPooling2D) _192[0][0]	(None,	None,	None,	1	0	activation
conv2d_196 (Conv2D) g2d_9[0][0]	(None,	None,	None,	6	12288	max_poolin
batch_normalization_201 (BatchN [0][0]	(None,	None,	None,	6	192	conv2d_196
activation_196 (Activation) alization_201[0][0]	(None,	None,	None,	6	0	batch_norm
conv2d_194 (Conv2D) g2d_9[0][0]	(None,	None,	None,	4	9216	max_poolin
conv2d_197 (Conv2D) _196[0][0]	(None,	None,	None,	9	55296	activation
batch_normalization_199 (BatchN [0][0]	(None,	None,	None,	4	144	conv2d_194
batch_normalization_202 (BatchN [0][0]	(None,	None,	None,	9	288	conv2d_197
activation_194 (Activation) alization_199[0][0]	(None,	None,	None,	4	0	batch_norm
activation_197 (Activation) alization_202[0][0]	(None,	None,	None,	9	0	batch_norm

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average_pooling2d_18 (Average g2d_9[0][0]	ePo (None,	None,	None,	1	0	max_poolin
conv2d_193 (Conv2D) g2d_9[0][0]	(None,	None,	None,	6	12288	max_poolin
conv2d_195 (Conv2D) _194[0][0]	(None,	None,	None,	6	76800	activation
conv2d_198 (Conv2D) _197[0][0]	(None,	None,	None,	9	82944	activation
conv2d_199 (Conv2D) oling2d_18[0][0]	(None,	None,	None,	3	6144	average_po
batch_normalization_198 (Batch_0][0]	chN (None,	None,	None,	6	192	conv2d_193
batch_normalization_200 (Batch_0][0]	chN (None,	None,	None,	6	192	conv2d_195
batch_normalization_203 (Batcon_10)[0]	chN (None,	None,	None,	9	288	conv2d_198
batch_normalization_204 (Batch_0][0]	chN (None,	None,	None,	3	96	conv2d_199
activation_193 (Activation) alization_198[0][0]	(None,	None,	None,	6	0	batch_norm
activation_195 (Activation) alization_200[0][0]	(None,	None,	None,	6	0	batch_norm
activation_198 (Activation) alization_203[0][0]	(None,	None,	None,	9	0	batch_norm
activation_199 (Activation) alization_204[0][0]	(None,	None,	None,	3	0	batch_norm
mixed0 (Concatenate) _193[0][0]	(None,	None,	None,	2	0	activation

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_195[0][0]						activation
						activation
_198[0][0]						activation
_199[0][0]						
conv2d_203 (Conv2D) [0][0]	(None,	None,	None,	6	16384	mixed0
batch_normalization_208 (BatchN [0][0]	(None,	None,	None,	6	192	conv2d_203
activation_203 (Activation) alization_208[0][0]	(None,	None,	None,	6	0	batch_norm
conv2d_201 (Conv2D) [0][0]	(None,	None,	None,	4	12288	mixed0
conv2d_204 (Conv2D) _203[0][0]	(None,	None,	None,	9	55296	activation
batch_normalization_206 (BatchN [0][0]	(None,	None,	None,	4	144	conv2d_201
batch_normalization_209 (BatchN [0][0]	(None,	None,	None,	9	288	conv2d_204
activation_201 (Activation) alization_206[0][0]	(None,	None,	None,	4	0	batch_norm
activation_204 (Activation) alization_209[0][0]	(None,	None,	None,	9	0	batch_norm
average_pooling2d_19 (AveragePo [0][0]	(None,	None,	None,	2	0	mixed0
conv2d_200 (Conv2D) [0][0]	(None,	None,	None,	6	16384	mixed0
	(None,	None,	None,	6	76800	activation

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conv2d_205 (Conv2D) _204[0][0]	(None,	None,	None,	9	82944	activation
conv2d_206 (Conv2D) oling2d_19[0][0]	(None,	None,	None,	6	16384	average_po
batch_normalization_205 (Bat [0][0]	chN (None,	None,	None,	6	192	conv2d_200
batch_normalization_207 (Bat [0][0]	chN (None,	None,	None,	6	192	conv2d_202
batch_normalization_210 (Bat [0][0]	chN (None,	None,	None,	9	288	conv2d_205
batch_normalization_211 (Bat [0][0]	chN (None,	None,	None,	6	192	conv2d_206
activation_200 (Activation) alization_205[0][0]	(None,	None,	None,	6	0	batch_norm
activation_202 (Activation) alization_207[0][0]	(None,	None,	None,	6	0	batch_norm
activation_205 (Activation) alization_210[0][0]	(None,	None,	None,	9	0	batch_norm
activation_206 (Activation) alization_211[0][0]	(None,	None,	None,	6	0	batch_norm
mixed1 (Concatenate) _200[0][0]	(None,	None,	None,	2	0	activation
_202[0][0]						activation
						activation
_205[0][0] _206[0][0]						activation
conv2d_210 (Conv2D) [0][0]	(None,	None,	None,	6	18432	mixed1
batch_normalization_215 (Bat [0][0]	chN (None,	None,	None,	6	192	conv2d_210

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activation_210 (Activation) alization_215[0][0]	(None,	None,	None,	6	0	batch_norm
conv2d_208 (Conv2D) [0][0]	(None,	None,	None,	4	13824	mixed1
conv2d_211 (Conv2D) _210[0][0]	(None,	None,	None,	9	55296	activation
batch_normalization_213 (Bat[0][0]	tchN (None,	None,	None,	4	144	conv2d_208
batch_normalization_216 (Bat[0][0]	tchN (None,	None,	None,	9	288	conv2d_211
activation_208 (Activation) alization_213[0][0]	(None,	None,	None,	4	0	batch_norm
activation_211 (Activation) alization_216[0][0]	(None,	None,	None,	9	0	batch_norm
average_pooling2d_20 (Average[0][0]	gePo (None,	None,	None,	2	0	mixed1
conv2d_207 (Conv2D) [0][0]	(None,	None,	None,	6	18432	mixed1
conv2d_209 (Conv2D) _208[0][0]	(None,	None,	None,	6	76800	activation
conv2d_212 (Conv2D) _211[0][0]	(None,	None,	None,	9	82944	activation
conv2d_213 (Conv2D) oling2d_20[0][0]	(None,	None,	None,	6	18432	average_po
batch_normalization_212 (Bat[0][0]	tchN (None,	None,	None,	6	192	conv2d_207
batch_normalization_214 (Bat[0][0]	tchN (None,	None,	None,	6	192	conv2d_209

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batch_normalization_217 (BatchN [0][0]	(None,	None,	None,	9	288	conv2d_212
batch_normalization_218 (BatchN [0][0]	(None,	None,	None,	6	192	conv2d_213
activation_207 (Activation) alization_212[0][0]	(None,	None,	None,	6	0	batch_norm
activation_209 (Activation) alization_214[0][0]	(None,	None,	None,	6	0	batch_norm
activation_212 (Activation) alization_217[0][0]	(None,	None,	None,	9	0	batch_norm
activation_213 (Activation) alization_218[0][0]	(None,	None,	None,	6	0	batch_norm
mixed2 (Concatenate) _207[0][0]	(None,	None,	None,	2	0	activation
_209[0][0]						activation
_212[0][0]						activation
_213[0][0]						activation
conv2d_215 (Conv2D) [0][0]	(None,	None,	None,	6	18432	mixed2
batch_normalization_220 (BatchN [0][0]	(None,	None,	None,	6	192	conv2d_215
activation_215 (Activation) alization_220[0][0]	(None,	None,	None,	6	0	batch_norm
conv2d_216 (Conv2D) _215[0][0]	(None,	None,	None,	9	55296	activation
batch_normalization_221 (BatchN [0][0]	(None,	None,	None,	9	288	conv2d_216

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<pre>activation_216 (Activation) alization_221[0][0]</pre>	(None,	None,	None,	9	0	batch_norm
conv2d_214 (Conv2D) [0][0]	(None,	None,	None,	3	995328	mixed2
conv2d_217 (Conv2D) _216[0][0]	(None,	None,	None,	9	82944	activation
batch_normalization_219 (BatchN [0][0]	(None,	None,	None,	3	1152	conv2d_214
batch_normalization_222 (BatchN [0][0]	(None,	None,	None,	9	288	conv2d_217
activation_214 (Activation) alization_219[0][0]	(None,	None,	None,	3	0	batch_norm
activation_217 (Activation) alization_222[0][0]	(None,	None,	None,	9	0	batch_norm
max_pooling2d_10 (MaxPooling2D) [0][0]	(None,	None,	None,	2	0	mixed2
mixed3 (Concatenate) _214[0][0]	(None,	None,	None,	7	0	activation
_217[0][0]						<pre>activation max_poolin</pre>
g2d_10[0][0]						
conv2d_222 (Conv2D) [0][0]	(None,	None,	None,	1	98304	mixed3
batch_normalization_227 (BatchN [0][0]	(None,	None,	None,	1	384	conv2d_222
activation_222 (Activation) alization_227[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_223 (Conv2D) _222[0][0]	(None,	None,	None,	1	114688	activation

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<pre>batch_normalization_228 (Ba [0][0]</pre>	atchN (None	, None,	None,	1	384	conv2d_223
activation_223 (Activation) alization_228[0][0]	(None	, None,	None,	1	0	batch_norm
conv2d_219 (Conv2D) [0][0]	(None	, None,	None,	1	98304	mixed3
conv2d_224 (Conv2D) _223[0][0]	(None	, None,	None,	1	114688	activation
batch_normalization_224 (Ba	atchN (None	, None,	None,	1	384	conv2d_219
batch_normalization_229 (Ba	atchN (None	, None,	None,	1	384	conv2d_224
activation_219 (Activation) alization_224[0][0]	(None	, None,	None,	1	0	batch_norm
activation_224 (Activation) alization_229[0][0]) (None	, None,	None,	1	0	batch_norm
conv2d_220 (Conv2D) _219[0][0]	(None	, None,	None,	1	114688	activation
conv2d_225 (Conv2D) _224[0][0]	(None	, None,	None,	1	114688	activation
batch_normalization_225 (Ba	atchN (None	, None,	None,	1	384	conv2d_220
batch_normalization_230 (Ba	atchN (None	, None,	None,	1	384	conv2d_225
activation_220 (Activation) alization_225[0][0]	(None	, None,	None,	1	0	batch_norm
activation_225 (Activation) alization_230[0][0]	(None	, None,	None,	1	0	batch_norm

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<pre>average_pooling2d_21 (AverageF [0][0]</pre>	Po (None,	None,	None,	7	0	mixed3
conv2d_218 (Conv2D) [0][0]	(None,	None,	None,	1	147456	mixed3
conv2d_221 (Conv2D) _220[0][0]	(None,	None,	None,	1	172032	activation
conv2d_226 (Conv2D) _225[0][0]	(None,	None,	None,	1	172032	activation
conv2d_227 (Conv2D) oling2d_21[0][0]	(None,	None,	None,	1	147456	average_po
batch_normalization_223 (Batch [0][0]	nN (None,	None,	None,	1	576	conv2d_218
batch_normalization_226 (Batch [0][0]	nN (None,	None,	None,	1	576	conv2d_221
batch_normalization_231 (Batch [0][0]	nN (None,	None,	None,	1	576	conv2d_226
batch_normalization_232 (Batch [0][0]	nN (None,	None,	None,	1	576	conv2d_227
activation_218 (Activation) alization_223[0][0]	(None,	None,	None,	1	0	batch_norm
activation_221 (Activation) alization_226[0][0]	(None,	None,	None,	1	0	batch_norm
activation_226 (Activation) alization_231[0][0]	(None,	None,	None,	1	0	batch_norm
activation_227 (Activation) alization_232[0][0]	(None,	None,	None,	1	0	batch_norm
mixed4 (Concatenate) _218[0][0]	(None,	None,	None,	7	0	activation
_221[0][0]						accivacion

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_226[0][0]						activation
_227[0][0]						activation
conv2d_232 (Conv2D) [0][0]	(None,	None,	None,	1	122880	mixed4
batch_normalization_237 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_232
activation_232 (Activation) alization_237[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_233 (Conv2D) _232[0][0]	(None,	None,	None,	1	179200	activation
batch_normalization_238 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_233
activation_233 (Activation) alization_238[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_229 (Conv2D) [0][0]	(None,	None,	None,	1	122880	mixed4
conv2d_234 (Conv2D) _233[0][0]	(None,	None,	None,	1	179200	activation
batch_normalization_234 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_229
batch_normalization_239 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_234
activation_229 (Activation) alization_234[0][0]	(None,	None,	None,	1	0	batch_norm
activation_234 (Activation) alization_239[0][0]	(None,	None,	None,	1	0	batch_norm
 conv2d_230 (Conv2D) _229[0][0]	(None,	None,	None,	1	179200	activation

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conv2d_235 (Conv2D) _234[0][0]	(None,	None,	None,	1	179200	activation
batch_normalization_235 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_230
batch_normalization_240 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_235
activation_230 (Activation) alization_235[0][0]	(None,	None,	None,	1	0	batch_norm
activation_235 (Activation) alization_240[0][0]	(None,	None,	None,	1	0	batch_norm
average_pooling2d_22 (AveragePo [0][0]	(None,	None,	None,	7	0	mixed4
conv2d_228 (Conv2D) [0][0]	(None,	None,	None,	1	147456	mixed4
conv2d_231 (Conv2D) _230[0][0]	(None,	None,	None,	1	215040	activation
conv2d_236 (Conv2D) _235[0][0]	(None,	None,	None,	1	215040	activation
conv2d_237 (Conv2D) oling2d_22[0][0]	(None,	None,	None,	1	147456	average_po
batch_normalization_233 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_228
batch_normalization_236 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_231
batch_normalization_241 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_236
batch_normalization_242 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_237

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activation_228 (Activation) alization_233[0][0]	(None,	None,	None,	1	0	batch_norm
activation_231 (Activation) alization_236[0][0]	(None,	None,	None,	1	0	batch_norm
activation_236 (Activation) alization_241[0][0]	(None,	None,	None,	1	0	batch_norm
activation_237 (Activation) alization_242[0][0]	(None,	None,	None,	1	0	batch_norm
mixed5 (Concatenate) _228[0][0]	(None,	None,	None,	7	0	activation activation
_231[0][0]						activation
_236[0][0]						activation
_237[0][0]						
conv2d_242 (Conv2D) [0][0]	(None,	None,	None,	1	122880	mixed5
batch_normalization_247 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_242
activation_242 (Activation) alization_247[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_243 (Conv2D) _242[0][0]	(None,	None,	None,	1	179200	activation
batch_normalization_248 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_243
activation_243 (Activation) alization_248[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_239 (Conv2D) [0][0]	(None,	None,	None,	1	122880	mixed5

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conv2d_244 (Conv2D) _243[0][0]	(None,	None,	None,	1	179200	activation
batch_normalization_244 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_239
batch_normalization_249 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_244
activation_239 (Activation) alization_244[0][0]	(None,	None,	None,	1	0	batch_norm
activation_244 (Activation) alization_249[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_240 (Conv2D) _239[0][0]	(None,	None,	None,	1	179200	activation
conv2d_245 (Conv2D) _244[0][0]	(None,	None,	None,	1	179200	activation
batch_normalization_245 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_240
batch_normalization_250 (BatchN [0][0]	(None,	None,	None,	1	480	conv2d_245
activation_240 (Activation) alization_245[0][0]	(None,	None,	None,	1	0	batch_norm
activation_245 (Activation) alization_250[0][0]	(None,	None,	None,	1	0	batch_norm
average_pooling2d_23 (AveragePo [0][0]	(None,	None,	None,	7	0	mixed5
conv2d_238 (Conv2D) [0][0]	(None,	None,	None,	1	147456	mixed5
conv2d_241 (Conv2D) _240[0][0]	(None,	None,	None,	1	215040	activation

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conv2d_246 (Conv2D) _245[0][0]	(None,	None,	None,	1	215040	activation
conv2d_247 (Conv2D) oling2d_23[0][0]	(None,	None,	None,	1	147456	average_po
batch_normalization_243 (BatchN[0][0]	N (None,	None,	None,	1	576	conv2d_238
batch_normalization_246 (BatchN[0][0]	N (None,	None,	None,	1	576	conv2d_241
batch_normalization_251 (BatchN[0][0]	N (None,	None,	None,	1	576	conv2d_246
batch_normalization_252 (BatchN [0][0]	N (None,	None,	None,	1	576	conv2d_247
activation_238 (Activation) alization_243[0][0]	(None,	None,	None,	1	0	batch_norm
activation_241 (Activation) alization_246[0][0]	(None,	None,	None,	1	0	batch_norm
activation_246 (Activation) alization_251[0][0]	(None,	None,	None,	1	0	batch_norm
activation_247 (Activation) alization_252[0][0]	(None,	None,	None,	1	0	batch_norm
mixed6 (Concatenate) _238[0][0]	(None,	None,	None,	7	0	activation
_241[0][0]						activation
_246[0][0]						activation
_247[0][0]						activation
 conv2d_252 (Conv2D) [0][0]	(None,	None,	None,	1	147456	mixed6
batch_normalization_257 (BatchN [0][0]	N (None,	None,	None,	1	576	conv2d_252

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activation_252 (Activation) alization_257[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_253 (Conv2D) _252[0][0]	(None,	None,	None,	1	258048	activation
batch_normalization_258 (Batch [0][0]	N (None,	None,	None,	1	576	conv2d_253
activation_253 (Activation) alization_258[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_249 (Conv2D) [0][0]	(None,	None,	None,	1	147456	mixed6
conv2d_254 (Conv2D) _253[0][0]	(None,	None,	None,	1	258048	activation
batch_normalization_254 (Batch [0][0]	N (None,	None,	None,	1	576	conv2d_249
batch_normalization_259 (Batch [0][0]	N (None,	None,	None,	1	576	conv2d_254
activation_249 (Activation) alization_254[0][0]	(None,	None,	None,	1	0	batch_norm
activation_254 (Activation) alization_259[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_250 (Conv2D) _249[0][0]	(None,	None,	None,	1	258048	activation
conv2d_255 (Conv2D) _254[0][0]	(None,	None,	None,	1	258048	activation
batch_normalization_255 (Batch [0][0]	N (None,	None,	None,	1	576	conv2d_250
batch_normalization_260 (Batch [0][0]	N (None,	None,	None,	1	576	conv2d_255

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activation_250 (Activation) alization_255[0][0]	(None,	None,	None,	1	0	batch_norm
activation_255 (Activation) alization_260[0][0]	(None,	None,	None,	1	0	batch_norm
average_pooling2d_24 (AveragePo	None,	None,	None,	7	0	mixed6
conv2d_248 (Conv2D) [0][0]	(None,	None,	None,	1	147456	mixed6
conv2d_251 (Conv2D) _250[0][0]	(None,	None,	None,	1	258048	activation
conv2d_256 (Conv2D) _255[0][0]	(None,	None,	None,	1	258048	activation
conv2d_257 (Conv2D) oling2d_24[0][0]	(None,	None,	None,	1	147456	average_po
batch_normalization_253 (BatchN [0][0]	I (None,	None,	None,	1	576	conv2d_248
batch_normalization_256 (BatchN [0][0]	I (None,	None,	None,	1	576	conv2d_251
batch_normalization_261 (BatchN [0][0]	l (None,	None,	None,	1	576	conv2d_256
batch_normalization_262 (BatchN [0][0]	l (None,	None,	None,	1	576	conv2d_257
activation_248 (Activation) alization_253[0][0]	(None,	None,	None,	1	0	batch_norm
activation_251 (Activation) alization_256[0][0]	(None,	None,	None,	1	0	batch_norm
activation_256 (Activation) alization_261[0][0]	(None,	None,	None,	1	0	batch_norm

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activation_257 (Activation) alization_262[0][0]	(None,	None,	None,	1	0	batch_norm
mixed7 (Concatenate) _248[0][0]	(None,	None,	None,	7	0	activation
_251[0][0]						activation
_256[0][0]						activation
_257[0][0]						activation
conv2d_260 (Conv2D) [0][0]	(None,	None,	None,	1	147456	mixed7
batch_normalization_265 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_260
activation_260 (Activation) alization_265[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_261 (Conv2D) _260[0][0]	(None,	None,	None,	1	258048	activation
batch_normalization_266 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_261
activation_261 (Activation) alization_266[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_258 (Conv2D) [0][0]	(None,	None,	None,	1	147456	mixed7
conv2d_262 (Conv2D) _261[0][0]	(None,	None,	None,	1	258048	activation
batch_normalization_263 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_258
batch_normalization_267 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_262

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<pre>activation_258 (Activation) alization_263[0][0]</pre>	(None,	None,	None,	1	0	batch_norm
activation_262 (Activation) alization_267[0][0]	(None,	None,	None,	1	0	batch_norm
conv2d_259 (Conv2D) _258[0][0]	(None,	None,	None,	3	552960	activation
conv2d_263 (Conv2D) _262[0][0]	(None,	None,	None,	1	331776	activation
batch_normalization_264 (BatchN [0][0]	(None,	None,	None,	3	960	conv2d_259
batch_normalization_268 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_263
activation_259 (Activation) alization_264[0][0]	(None,	None,	None,	3	0	batch_norm
activation_263 (Activation) alization_268[0][0]	(None,	None,	None,	1	0	batch_norm
max_pooling2d_11 (MaxPooling2D) [0][0]	(None,	None,	None,	7	0	mixed7
mixed8 (Concatenate) _259[0][0]	(None,	None,	None,	1	0	activation activation
_263[0][0] g2d_11[0][0]						max_poolin
conv2d_268 (Conv2D) [0][0]	(None,	None,	None,	4	573440	mixed8
batch_normalization_273 (BatchN [0][0]	(None,	None,	None,	4	1344	conv2d_268
activation_268 (Activation) alization_273[0][0]	(None,	None,	None,	4	0	batch_norm

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conv2d_265 (Conv2D) [0][0]	(None,	None,	None,	3	491520	mixed8
conv2d_269 (Conv2D) _268[0][0]	(None,	None,	None,	3	1548288	activation
batch_normalization_270 (BatchN [0][0]	(None,	None,	None,	3	1152	conv2d_265
batch_normalization_274 (BatchN [0][0]	(None,	None,	None,	3	1152	conv2d_269
activation_265 (Activation) alization_270[0][0]	(None,	None,	None,	3	0	batch_norm
activation_269 (Activation) alization_274[0][0]	(None,	None,	None,	3	0	batch_norm
conv2d_266 (Conv2D) _265[0][0]	(None,	None,	None,	3	442368	activation
conv2d_267 (Conv2D) _265[0][0]	(None,	None,	None,	3	442368	activation
conv2d_270 (Conv2D) _269[0][0]	(None,	None,	None,	3	442368	activation
conv2d_271 (Conv2D) _269[0][0]	(None,	None,	None,	3	442368	activation
average_pooling2d_25 (AveragePo [0][0]	(None,	None,	None,	1	0	mixed8
conv2d_264 (Conv2D) [0][0]	(None,	None,	None,	3	409600	mixed8
batch_normalization_271 (BatchN [0][0]	(None,	None,	None,	3	1152	conv2d_266
batch_normalization_272 (BatchN [0][0]	(None,	None,	None,	3	1152	conv2d_267

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<pre>batch_normalization_275 (BatchN [0][0]</pre>	(None,	None,	None,	3	1152	conv2d_270
batch_normalization_276 (BatchN [0][0]	(None,	None,	None,	3	1152	conv2d_271
conv2d_272 (Conv2D) oling2d_25[0][0]	(None,	None,	None,	1	245760	average_po
batch_normalization_269 (BatchN [0][0]	(None,	None,	None,	3	960	conv2d_264
activation_266 (Activation) alization_271[0][0]	(None,	None,	None,	3	0	batch_norm
activation_267 (Activation) alization_272[0][0]	(None,	None,	None,	3	0	batch_norm
activation_270 (Activation) alization_275[0][0]	(None,	None,	None,	3	0	batch_norm
activation_271 (Activation) alization_276[0][0]	(None,	None,	None,	3	0	batch_norm
batch_normalization_277 (BatchN [0][0]	(None,	None,	None,	1	576	conv2d_272
activation_264 (Activation) alization_269[0][0]	(None,	None,	None,	3	0	batch_norm
mixed9_0 (Concatenate) _266[0][0]	(None,	None,	None,	7	0	activation
_267[0][0]						activation
concatenate_4 (Concatenate) _270[0][0] _271[0][0]	(None,	None,	None,	7	0	activation
activation_272 (Activation) alization_277[0][0]	(None,	None,	None,	1	0	batch_norm

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mixed9 (Concatenate) _264[0][0]	(None,	None,	None,	2	0	activation
[0][0]						mixed9_0
e_4[0][0]						concatenat
_272[0][0]						activation
conv2d_277 (Conv2D) [0][0]	(None,	None,	None,	4	917504	mixed9
batch_normalization_282 (Batchl	N (None,	None,	None,	4	1344	conv2d_277
activation_277 (Activation) alization_282[0][0]	(None,	None,	None,	4	0	batch_norm
conv2d_274 (Conv2D) [0][0]	(None,	None,	None,	3	786432	mixed9
conv2d_278 (Conv2D) _277[0][0]	(None,	None,	None,	3	1548288	activation
batch_normalization_279 (Batchl	N (None,	None,	None,	3	1152	conv2d_274
batch_normalization_283 (Batch	N (None,	None,	None,	3	1152	conv2d_278
activation_274 (Activation) alization_279[0][0]	(None,	None,	None,	3	0	batch_norm
activation_278 (Activation) alization_283[0][0]	(None,	None,	None,	3	0	batch_norm
conv2d_275 (Conv2D) _274[0][0]	(None,	None,	None,	3	442368	activation
conv2d_276 (Conv2D) _274[0][0]	(None,	None,	None,	3	442368	activation
conv2d_279 (Conv2D) _278[0][0]	(None,	None,	None,	3	442368	activation

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conv2d_280 (Conv2D) _278[0][0]		(None,	None,	None,	3	442368	activation
average_pooling2d_26 (A [0][0]	veragePo	(None,	None,	None,	2	0	mixed9
conv2d_273 (Conv2D) [0][0]		(None,	None,	None,	3	655360	mixed9
batch_normalization_280 [0][0]	(BatchN	(None,	None,	None,	3	1152	conv2d_275
batch_normalization_281 [0][0]	(BatchN	(None,	None,	None,	3	1152	conv2d_276
batch_normalization_284 [0][0]	(BatchN	(None,	None,	None,	3	1152	conv2d_279
batch_normalization_285 [0][0]	(BatchN	(None,	None,	None,	3	1152	conv2d_280
conv2d_281 (Conv2D) oling2d_26[0][0]		(None,	None,	None,	1	393216	average_po
batch_normalization_278 [0][0]	(BatchN	(None,	None,	None,	3	960	conv2d_273
activation_275 (Activat alization_280[0][0]	ion)	(None,	None,	None,	3	0	batch_norm
activation_276 (Activat alization_281[0][0]	ion)	(None,	None,	None,	3	0	batch_norm
activation_279 (Activat alization_284[0][0]	ion)	(None,	None,	None,	3	0	batch_norm
activation_280 (Activat alization_285[0][0]	ion)	(None,	None,	None,	3	0	batch_norm
batch_normalization_286 [0][0]	(BatchN	(None,	None,	None,	1	576	conv2d_281

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activation_273 (Activation) alization_278[0][0]	(None,	None,	None,	3	0	batch_norm
mixed9_1 (Concatenate) _275[0][0]	(None,	None,	None,	7	0	activation activation
_276[0][0]						activation
concatenate_5 (Concatenate) _279[0][0]	(None,	None,	None,	7	0	activation
_280[0][0]						activation
activation_281 (Activation) alization_286[0][0]	(None,	None,	None,	1	0	batch_norm
mixed10 (Concatenate) _273[0][0]	(None,	None,	None,	2	0	activation
[0][0]						mixed9_1
e_5[0][0]						concatenat
_281[0][0]						activation
global_average_pooling2d_2 (Glo [0][0]	(None,	2048)			0	mixed10
batch_normalization_287 (BatchN rage_pooling2d_2[0][0]	(None,	2048)			8192	global_ave
dropout_5 (Dropout) alization_287[0][0]	(None,	2048)			0	batch_norm
dense_5 (Dense) [0][0]	(None,	256)			524544	dropout_5
batch_normalization_288 (BatchN [0][0]	(None,	256)			1024	dense_5
dropout_6 (Dropout) alization_288[0][0]	(None,	256)			0	batch_norm
					-	

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接下来做模型训练,可以模型看到在15个epoch循环后,达到70%左右的精度。

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```
Epoch 1/30
curacy: 0.7265 - val_loss: 0.5038 - val_accuracy: 0.7460
Epoch 2/30
28/28 [=============== ] - 17s 429ms/step - loss: 0.5437 - ac
curacy: 0.7427 - val_loss: 0.5116 - val_accuracy: 0.7487
Epoch 3/30
curacy: 0.7524 - val loss: 0.5148 - val accuracy: 0.7446
28/28 [================ ] - 16s 428ms/step - loss: 0.5015 - ac
curacy: 0.7565 - val_loss: 0.5084 - val_accuracy: 0.7527
Epoch 5/30
28/28 [================ ] - 16s 425ms/step - loss: 0.5100 - ac
curacy: 0.7478 - val_loss: 0.5129 - val_accuracy: 0.7379
Epoch 6/30
curacy: 0.7455 - val_loss: 0.5133 - val_accuracy: 0.7500
Epoch 7/30
28/28 [=================== ] - 16s 416ms/step - loss: 0.5014 - ac
curacy: 0.7559 - val_loss: 0.5171 - val_accuracy: 0.7352
Epoch 8/30
curacy: 0.7582 - val_loss: 0.5129 - val_accuracy: 0.7460
Epoch 9/30
curacy: 0.7599 - val_loss: 0.5056 - val_accuracy: 0.7567
Epoch 10/30
curacy: 0.7547 - val_loss: 0.5047 - val_accuracy: 0.7648
Epoch 11/30
curacy: 0.7547 - val_loss: 0.5035 - val_accuracy: 0.7527
Epoch 12/30
curacy: 0.7605 - val_loss: 0.5030 - val_accuracy: 0.7513
Epoch 13/30
curacy: 0.7651 - val_loss: 0.5140 - val_accuracy: 0.7352
Epoch 14/30
curacy: 0.7841 - val_loss: 0.5165 - val_accuracy: 0.7406
Epoch 15/30
curacy: 0.7668 - val_loss: 0.5167 - val_accuracy: 0.7473
Epoch 16/30
curacy: 0.7444 - val_loss: 0.5293 - val_accuracy: 0.7218
Epoch 17/30
curacy: 0.7686 - val_loss: 0.5259 - val_accuracy: 0.7164
Epoch 18/30
28/28 [=============== ] - 16s 427ms/step - loss: 0.4984 - ac
curacy: 0.7530 - val_loss: 0.5188 - val_accuracy: 0.7406
Epoch 19/30
```

```
curacy: 0.7542 - val_loss: 0.5267 - val_accuracy: 0.7272
Epoch 20/30
28/28 [=============== ] - 16s 434ms/step - loss: 0.5078 - ac
curacy: 0.7617 - val_loss: 0.5080 - val_accuracy: 0.7446
Epoch 21/30
28/28 [=============== ] - 16s 443ms/step - loss: 0.5148 - ac
curacy: 0.7513 - val_loss: 0.5140 - val_accuracy: 0.7339
Epoch 22/30
28/28 [================ ] - 15s 404ms/step - loss: 0.5004 - ac
curacy: 0.7691 - val_loss: 0.5136 - val_accuracy: 0.7446
Epoch 23/30
28/28 [=============== ] - 16s 407ms/step - loss: 0.5148 - ac
curacy: 0.7478 - val_loss: 0.5082 - val_accuracy: 0.7500
28/28 [=============== ] - 15s 403ms/step - loss: 0.4930 - ac
curacy: 0.7559 - val_loss: 0.5071 - val_accuracy: 0.7513
Epoch 25/30
28/28 [================ ] - 16s 431ms/step - loss: 0.4853 - ac
curacy: 0.7680 - val_loss: 0.5098 - val_accuracy: 0.7513
Epoch 26/30
28/28 [================ ] - 16s 423ms/step - loss: 0.4963 - ac
curacy: 0.7634 - val_loss: 0.5173 - val_accuracy: 0.7392
Epoch 27/30
28/28 [================ ] - 16s 408ms/step - loss: 0.4907 - ac
curacy: 0.7622 - val_loss: 0.5066 - val_accuracy: 0.7567
Epoch 28/30
28/28 [=============== ] - 15s 377ms/step - loss: 0.4822 - ac
curacy: 0.7761 - val_loss: 0.4978 - val_accuracy: 0.7581
Epoch 29/30
28/28 [================ ] - 16s 413ms/step - loss: 0.4837 - ac
curacy: 0.7714 - val loss: 0.4997 - val accuracy: 0.7554
28/28 [================ ] - 16s 440ms/step - loss: 0.4825 - ac
curacy: 0.7645 - val_loss: 0.5032 - val_accuracy: 0.7594
```

Out[11]: <keras.callbacks.History at 0x7f6964f29280>

四、模型评估

绘制ROC曲线并计算AUC取值。

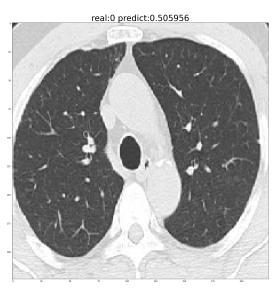
首先将测试集图片并带入模型进行预测。

```
In [18]: Yscore = model.predict(validation_generator)[:,1] ##入模型进行
预测得输出概率
Ytrue=validation_generator.classes #数据的真实标
签
```

```
In [39]: import numpy as np
         X,Y=next(validation_generator)
                                                                              #取出
         一批训练数据
                                                                         #生成画布
         fig,ax=plt.subplots(2,2)
         并切分
         fig.set_figheight(50)
                                                                         #设置高度
         fig.set_figwidth(50)
                                                                         #设置宽度
         ax=ax.flatten()
                                                                         #拉直画布
         ax[0].imshow(X[0])
                                                                         #展示图像
         ax[0].set_title("real:%d predict:%f"%(Y[0,1],model.predict(X[:1])[:,1]),fon
         tsize=40)
         ax[1].imshow(X[1])
                                                                         #展示图像
         ax[1].set_title("real:%d predict:%f"%(Y[1,1],model.predict(X[1:2])[:,1]),fo
         ntsize=40)
         ax[2].imshow(X[-1])
                                                                          #展示图像
         ax[2].set_title("real:%d predict:%f"%(Y[-1,1],model.predict(X[-1:])[:,1]),f
         ontsize=40)
         ax[3].imshow(X[-2])
                                                                          #展示图像
         ax[3].set_title("real:%d predict:%f"%(Y[i,1],model.predict(X[-2:-1])[:,1]),
         fontsize=40)
         print()
```









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针对二分类的问题,通常会将样本分为以下四种情况:

- (1) 真阳(TP): 实例是阳性,被预测为阳性;
- (2) 假阴(FN): 实例是阳性,被预测为阴性;
- (3) 假阳(FP): 实例是阴性,被预测为阳性;
- (4) 真阴(TN): 实例是阴性,被预测为阴性。

基于此,模型评估时,常考虑以下几个指标:

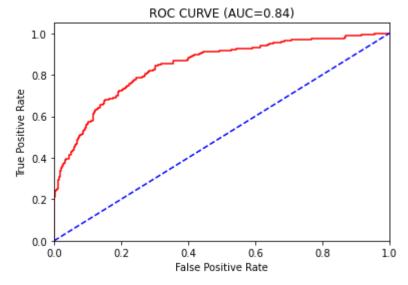
True Positive Rate真阳率TPR=TP/(TP+FN)

False Positive Rate假阳率FPR=FP/(FP+TN)

Precision精度PRE=TP/(TP+FP)

下面,我们首先基于TPR和FPR绘制ROC曲线,随后计算最佳阈值,最后再给出各评估指标的数值。

```
In [19]:
        import pandas as pd
         import matplotlib.pyplot as plt
         from sklearn.metrics import roc_curve,auc
         fpr, tpr, threshold = roc_curve(Ytrue, Yscore)
                                                               #利用内置函数计算用
         于绘制曲线的fpr和tpr坐标
         roc_auc = auc(fpr, tpr)
                                                               #计算auc的值
         #ROC曲线绘制
         plt.figure()
         plt.title('ROC CURVE (AUC={:.2f})'.format(roc_auc))
                                                               #设置图表标题
         plt.xlabel('False Positive Rate')
                                                               #横纵坐标轴标签
         plt.ylabel('True Positive Rate')
                                                               #横纵坐标轴取值范围
         plt.xlim([0.0,1.0])
         plt.ylim([0.0,1.05])
         plt.plot(fpr,tpr,color='r')
                                                               #绘制ROC曲线
         plt.plot([0, 1], [0, 1], color='b', linestyle='--')
         plt.show()
```



理想的最佳阈值,应使TPR尽量大且FPR尽量小,即二者差值最大;因此,我们选取ROC图像中TPR与FPR之差最大的点对应的阈值为最佳阈值。

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```
In [20]:
            import numpy as np
            optimal_threshold = threshold[np.argmax(tpr-fpr)]
                                                                     #求出最佳阈值
            print('最佳阈值: ',round(optimal_threshold,4))
                                                                     #打印最佳阈值
                                                                     #利用最佳阈值给出新
            Yhat=1.0*(Yscore>optimal_threshold)
            的预测标签
            TPR=np.sum(Yhat*Ytrue)/np.sum(Ytrue)
                                                                     #计算True Positive
            FPR=np.sum(Yhat*(1-Ytrue))/np.sum(1-Ytrue)
                                                                     #计算False Positiv
            e Rate
            PRE=np.sum(Yhat*Ytrue)/np.sum(Yhat)
                                                                     #计算Precision
            print('TPR', round(TPR,4))
                                                                     #打印
            print('FPR',round(FPR,4))
            print('PRE', round(PRE, 4))
            最佳阈值: 0.3573
            TPR 0.84
            FPR 0.3008
            PRE 0.7394
task2: sensitivity:真阳性人数/ (真阳性人数+假阴性人数) *100% 即TPR=TP/ (TP+ FN)
specificity:真阴性人数/(真阴性人数+假阳性人数)) *100% 即TNR= TN / (FP + TN)
PPV=TP/(TP+FP)
NPV=TN / (FN + TN)
   In [22]: | sensitivity=np.sum(Yhat*Ytrue)/np.sum(Ytrue)
            specificity=np.sum((1-Yhat)*(1-Ytrue))/np.sum(1-Ytrue)
            PPV=np.sum(Yhat*Ytrue)/np.sum(Yhat)
            NPV=np.sum((1-Yhat)*(1-Ytrue))/np.sum(1-Yhat)
            print("sensitivity", round(sensitivity, 4))
            print("specificity", round(specificity, 4))
            print("PPV", round(PPV,4))
            print("NPV", round(NPV,4))
            sensitivity 0.84
            specificity 0.6992
            PPV 0.7394
            NPV 0.8113
```

思考: 你还可以把模型的精度训练的更高么?

```
In [ ]:
```