TensorFlow实现线性回归: 颜值评分作业

In [2]:

import pandas as pd # 载入pandas包并命名为pd

MasterFile=pd.read csv('./FaceScore.csv') # 从当前notebook所在文件夹读入FaceScore.csv并重命名为Mast erFile

print(MasterFile.shape) # 输出MasterFile数据集的行数与列数

MasterFile[0:5] # 输出MasterFile的前五条记录

(5500, 2)

Out[2]:

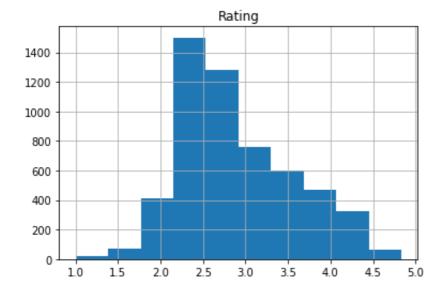
	Filename	Rating
0	ftw1.jpg	4.083333
1	ftw10.jpg	3.666667
2	ftw100.jpg	1.916667
3	ftw101.jpg	2.416667
4	ftw102.jpg	3.166667

In [3]:

MasterFile.hist() # 绘制MasterFile中Rating变量的频数分布直方图

Out[3]:

array([[<AxesSubplot:title={'center':'Rating'}>]], dtype=object)



import numpy as np # 载入numpy包并重命名为np

FileNames=MasterFile['Filename'] # 将MasterFile数据框中的Filename所在列的数据存在FileNames变量中 N=len(FileNames) # 记录FileNames文件中的记录条数

Y=np.array(MasterFile['Rating']).reshape([N,1]) # 选取MaterFile数据框中的Rating变量对应数据并将其存储形 式改为含有N个小list的大list,每个小list只含有一个元素,最后转化为nparray

#Y=(Y-np.mean(Y))/np.std(Y) # 对Y做标准化处理

In [5]:

In [4]:

```
from PIL import Image # 从PIL包中载入Image类
IMSIZE=128 # 限定图片大小参数为128像素
X=np.zeros([N,IMSIZE,IMSIZE,3]) # 生成一个N*IMSIZE*IMSIZE*3大小的高维纯0矩阵并命名为X
for i in range(N): #生成0到N-1的连续正整数
  MyFile=FileNames[i] # 选择FileNames中下标为i的元素记录为MyFile
  Im=Image.open('./images/'+MyFile) # 打开上层文件夹中的images文件夹并取出名为MyFile的图片重命名为I
m
  Im=Im.resize([IMSIZE,IMSIZE]) # 将Im的大小调整为128*128
  Im=np.array(Im)/255 # 将Im对应像素矩阵中的0-255的色值元素变换到0-1之间
  X[i,]=lm # 将lm添加到X矩阵第一维度的i位置
In [71]:
X_pred=np.zeros([N,IMSIZE,IMSIZE,3]) # 生成一个N*IMSIZE*IMSIZE*3大小的高维纯0矩阵并命名为X pred
for i in range(8): # 生成0到7的连续正整数
  name = str(i+1)
  Im=Image.open('./predict_images/'+name+'.png') # 打开上层文件夹中的images文件夹并取出名为MyFile的
图片重命名为Im
  Im=Im.resize([IMSIZE,IMSIZE]) # 将Im的大小调整为128*128
  Im=np.arrav(Im)/255 # 将Im对应像素矩阵中的0-255的色值元素变换到0-1之间
  X pred[i,]=Im # 将Im添加到X矩阵第一维度的i位置
In [6]:
from matplotlib import pyplot as plt # 从matplotlib 包里载入pyplot类并重命名为plt
plt.figure() # 初始化一个Figure类的实例作为所有绘图元素的最高级容器
fig,ax=plt.subplots(2,5) # 为当前的Figure类实例添加子图,以行数为2,列数为5的排列方式呈现,并返回axes
类型变量命名为fig或ax,由于subplot()缺少参数index,此处的axes是整个子图的坐标轴
fig.set_figheight(7.5) # 限制图像高度为7.5
fig.set figwidth(15) # 限制图像宽度为15
ax=ax.flatten() # 将ax由n*m的Axes组展平成1*nm的Axes组,以便通过下标循环取用
for i in range(10): # 生成0-9的连续正整数
  ax[i].imshow(X[i,:.::]) # 将X中第一纬度下标为i的三维色值元素矩阵绘制出来
  ax[i].set title(np.round(Y[i],2)) # 为axes组中的每一个子图axes设置标题为对应Rating保留两位小数
d:\anaconda3\envs\tensorflow_gpu_36\lib\site-packages\matplotlib\text.py:1163: FutureWarning: elementwise c
omparison failed; returning scalar instead, but in the future will perform elementwise comparison
if s != self. text:
<Figure size 432x288 with 0 Axes>
        [4.08]
                                            [1.92]
                          [3.67]
                                                              [2.42]
                                                                                [3.17]
 20
                                     20
                                                       20
                                                                        20
 40
                                                       60
 60
                                     60
                                                                        60
 80
                   80
                                     80
                                                       80
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                  100
                                    100
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                                                                        100
100
                  120
120
                                    120
                                                      120
                                                                        120
        [2.42]
                          [2.67]
                                            [2.67]
                                                              [3.08]
                                                                                [3.75]
 20
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In [7]

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from sklearn.model_selection import train_test_split # 从sklearn包中的model_selection模块载入 train_test__ split函数 X0,X1,Y0,Y1=train test split(X,Y,test size=0.5,random state=0) # 按照0.5的比例划分测试集[X1,Y1]与训练集 [X0, Y0]

In [37]:

from keras.layers import Dense, Flatten, Input # 从keras包中的layers模块载入Dense, Flatten, Input类 from keras import Model # 从keras 包中载入Model类

input layer=Input([IMSIZE,IMSIZE,3]) # 用IMSIZE(length),IMSIZE(width),3(channel)初始化输入层对象 x=input_layer # 将input_layer命名为x

x=Flatten()(x) #将輸入层从矩阵形式降维成一维向量

x=Dense(1)(x) # 设置一个输出元素数量为1的全连接层

output layer=x # 将x重命名为out layer

model=Model(input_layer,output_layer) # 用input_layer,output_layer来初始化一个model实例

model.summary() # 输出model的基本信息

Model: "sequential_11"

Layer (type)	Output Shape	Param #	
flatten_7 (Flatten)	(None, 49152)	0	
dense_12 (Dense)	(None, 1)	49153	

Total params: 49,153 Trainable params: 49,153 Non-trainable params: 0

In [38]:

from keras.optimizers import Adam # 从keras包的optimizer模块中载入Adam类 model.compile(loss='mse',optimizer=Adam(lr=0.001),metrics=['mse']) # 调用model类的compile方法设置损失 函数为均方损失,优化算法为学习率为0.001的Adam算法,设置测试集上的评估标准为均方损失

In [39]:

model.fit(X0,Y0,validation data=(X1,Y1),batch size=100,epochs=100) #训练模型,输入训练集X0,Y0,验证▲ 集[X1,Y1],每批处理100张图片,一共完成100轮批处理训练

```
Epoch 1/100
```

6222 - val mse: 17.6222

Epoch 2/100

28/28 [========= =======] - 1s 28ms/step - loss: 6.3022 - mse: 6.3022 - val_loss: 1.2458 - v

al_mse: 1.2458 Epoch 3/100

28/28 [====== ======] - 1s 26ms/step - loss: 0.9062 - mse: 0.9062 - val loss: 0.6136 - v

al mse: 0.6136 Epoch 4/100

=======] - 1s 27ms/step - loss: 0.4550 - mse: 0.4550 - val loss: 0.4508 - v 28/28 [======

al mse: 0.4508 Epoch 5/100

al mse: 0.4554 Epoch 6/100

al mse: 0.3901

Epoch 7/100

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al mse: 0.3642
Epoch 8/100
al mse: 0.3533
Epoch 9/100
al_mse: 0.3728
Epoch 10/100
al_mse: 0.3755
Epoch 11/100
al mse: 0.3351
Epoch 12/100
al mse: 0.3541
Epoch 13/100
al_mse: 0.3530
Epoch 14/100
al mse: 0.3278
Epoch 15/100
al_mse: 0.4012
Epoch 16/100
al mse: 0.3233
Epoch 17/100
al_mse: 0.3547
Epoch 18/100
al mse: 0.3799
Epoch 19/100
al mse: 0.3228
Epoch 20/100
al mse: 0.3540
Epoch 21/100
al_mse: 0.3491
Epoch 22/100
al_mse: 0.3398
Epoch 23/100
al mse: 0.3119
Epoch 24/100
al_mse: 0.3170
Epoch 25/100
al mse: 0.3373
Epoch 26/100
al_mse: 0.3359
Epoch 27/100
al mse: 0.4568
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Epoch 28/100
al_mse: 0.3111
Epoch 29/100
28/28 [======
      al mse: 0.3224
Epoch 30/100
al mse: 0.3227
Epoch 31/100
al mse: 0.4817
Epoch 32/100
al mse: 0.3229
Epoch 33/100
28/28 [===============] - 1s 24ms/step - loss: 0.2678 - mse: 0.2678 - val_loss: 0.3163 - v
al_mse: 0.3163
Epoch 34/100
al mse: 0.3352
Epoch 35/100
28/28 [===============] - 1s 26ms/step - loss: 0.2898 - mse: 0.2898 - val_loss: 0.3384 - v
al_mse: 0.3384
Epoch 36/100
al_mse: 0.3076
Epoch 37/100
al mse: 0.4840
Epoch 38/100
al mse: 0.3220
Epoch 39/100
28/28 [===============] - 1s 23ms/step - loss: 0.2535 - mse: 0.2535 - val_loss: 0.4018 - v
al_mse: 0.4018
Epoch 40/100
al_mse: 0.3090
Epoch 41/100
al mse: 0.3142
Epoch 42/100
al mse: 0.3076
Epoch 43/100
al_mse: 0.4695
Epoch 44/100
al_mse: 0.3679
Epoch 45/100
al mse: 0.3186
Epoch 46/100
al_mse: 0.3092
Epoch 47/100
28/28 [======
             ====] - 1s 23ms/step - loss: 0.2430 - mse: 0.2430 - val loss: 0.3258 - v
al mse: 0.3258
Epoch 48/100
28/28 [_____
               --1 - 1e 23me/etan - lose: 0.3347 - mea: 0.3347 - val. lose: 0.3538 - v
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O, – O 1–
al_mse: 0.3538
Epoch 49/100
al mse: 0.3433
Epoch 50/100
al_mse: 0.3721
Epoch 51/100
al mse: 0.4220
Epoch 52/100
al_mse: 0.4301
Epoch 53/100
al mse: 0.5660
Epoch 54/100
al_mse: 0.4648
Epoch 55/100
al_mse: 0.4847
Epoch 56/100
al_mse: 1.0380
Epoch 57/100
28/28 [===============] - 1s 23ms/step - loss: 0.3854 - mse: 0.3854 - val_loss: 0.5994 - v
al mse: 0.5994
Epoch 58/100
al_mse: 0.3307
Epoch 59/100
al mse: 0.4636
Epoch 60/100
al mse: 0.7949
Epoch 61/100
al mse: 0.3130
Epoch 62/100
al_mse: 0.3122
Epoch 63/100
al mse: 0.3194
Epoch 64/100
al mse: 1.5285
Epoch 65/100
al mse: 0.9031
Epoch 66/100
al_mse: 0.4893
Epoch 67/100
al_mse: 0.4022
Epoch 68/100
al mse: 1.1930
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al_mse: 1.1469
Epoch 70/100
al_mse: 0.8159
Epoch 71/100
al_mse: 0.8203
Epoch 72/100
al mse: 0.4048
Epoch 73/100
al mse: 0.4734
Epoch 74/100
al_mse: 1.3928
Epoch 75/100
al mse: 0.4407
Epoch 76/100
al mse: 0.8241
Epoch 77/100
al_mse: 4.1613
Epoch 78/100
al_mse: 0.6738
Epoch 79/100
al_mse: 0.3500
Epoch 80/100
al mse: 2.9902
Epoch 81/100
al_mse: 0.9963
Epoch 82/100
al mse: 1.3101
Epoch 83/100
al_mse: 0.6791
Epoch 84/100
al_mse: 0.4360
Epoch 85/100
al_mse: 0.8352
Epoch 86/100
al mse: 1.2777
Epoch 87/100
al_mse: 0.3723
Epoch 88/100
al_mse: 0.3478
Epoch 89/100
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ai_mse: 0.7995
Epoch 90/100
al mse: 0.3735
Epoch 91/100
al mse: 0.4968
Epoch 92/100
al_mse: 0.6237
Epoch 93/100
al mse: 0.5410
Epoch 94/100
al_mse: 0.5406
Epoch 95/100
al_mse: 3.6290
Epoch 96/100
al_mse: 0.3450
Epoch 97/100
al mse: 0.4859
Epoch 98/100
al mse: 2.1161
Epoch 99/100
al_mse: 0.4606
Epoch 100/100
al mse: 1.9373
```

Out[39]:

<tensorflow.python.keras.callbacks.History at 0x28bb166ec88>

In [73]:

Out[73]:

array([[0.3103053]], dtype=float32)

如果给我们朋友们的颜值打分,他们会不高兴

In [72]:

plt.figure() # 初始化一个Figure类的实例作为所有绘图元素的最高级容器 fig,ax=plt.subplots(2,4) # 为当前的Figure类实例添加子图,以行数为2,列数为5的排列方式呈现,并返回axes fig.set_figheight(7.5) # 限制图像高度为7.5
fig.set_figwidth(15) # 限制图像宽度为15
ax=ax.flatten() # 将ax 由n*m的Axes组展平成1*nm的Axes组,以便通过下标循环取用
for i in range(8): # 生成0-9的连续正整数
ax[i].imshow(X_pred[i,:,:,:]) # 将X中第一纬度下标为i的三维色值元素矩阵绘制出来
ax[i].set_title(model.predict((np.array(X_pred[i,:,:,:]).reshape((1,IMSIZE,IMSIZE,3))))) # 为axes组中的每一

<Figure size 432x288 with 0 Axes>

个子图axes设置标题为对应Rating保留两位小数



我的预测模型 (利用Sequential)

In [74]:

from keras.models import Sequential # 我的预测模型

my_model= Sequential([Input([IMSIZE,IMSIZE,3]),Flatten(),Dense(units=1,use_bias=**True**)]) # 使用sequential容器(有点类似dplyr的管道函数)配置训练模型 my_model.summary() # 输出model的基本信息

Model: "sequential_12"

Layer (type)	Output Shape	Param #
flatten_8 (Flatten)	(None, 49152)	0
dense_13 (Dense)	(None, 1)	49153

Total params: 49,153 Trainable params: 49,153 Non-trainable params: 0

In [75]:

from keras.optimizers import Adam # 从keras包的optimizer模块中载入Adam类my_model.compile(loss='mse',optimizer=Adam(lr=0.001),metrics=['mse']) # 调用model类的compile方法设置损失函数为均方损失,优化算法为学习率为0.001的Adam算法,设置测试集上的评估标准为均方损失

al maa: 0.4750

```
In [76]:
my_model.fit(X0,Y0,validation_data=(X1,Y1),batch_size=100,epochs=100) #训练模型,输入训练集X0,Y0, 🔳
验证集[X1,Y1],每批处理100张图片,一共完成100轮批处理训练
Epoch 1/100
00 - val_mse: 2.6400
Epoch 2/100
al_mse: 2.8223
Epoch 3/100
al_mse: 0.4742
Epoch 4/100
al mse: 0.4381
Epoch 5/100
al mse: 0.4092
Epoch 6/100
al mse: 0.4012
Epoch 7/100
al_mse: 0.4866
Epoch 8/100
al mse: 0.4186
Epoch 9/100
al mse: 0.4490
Epoch 10/100
28/28 [==============] - 1s 25ms/step - loss: 0.3377 - mse: 0.3377 - val_loss: 0.3652 - v
al_mse: 0.3652
Epoch 11/100
al_mse: 0.3583
Epoch 12/100
al mse: 0.3609
Epoch 13/100
al mse: 0.3518
Epoch 14/100
al_mse: 0.3439
Epoch 15/100
al mse: 0.3923
Epoch 16/100
al mse: 0.3799
Epoch 17/100
al mse: 0.3402
Epoch 18/100
al_mse: 0.6007
Epoch 19/100
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ai 11136. U.4130
Epoch 20/100
al mse: 0.4376
Epoch 21/100
al_mse: 0.3295
Epoch 22/100
al_mse: 0.3645
Epoch 23/100
al_mse: 0.3308
Epoch 24/100
28/28 [===============] - 1s 23ms/step - loss: 0.2877 - mse: 0.2877 - val_loss: 0.3252 - v
al mse: 0.3252
Epoch 25/100
al_mse: 0.4499
Epoch 26/100
al mse: 0.3494
Epoch 27/100
al_mse: 0.3444
Epoch 28/100
al mse: 0.3951
Epoch 29/100
al_mse: 0.3342
Epoch 30/100
al mse: 0.5568
Epoch 31/100
al mse: 0.3371
Epoch 32/100
al mse: 0.3405
Epoch 33/100
al_mse: 0.3298
Epoch 34/100
al mse: 0.3326
Epoch 35/100
28/28 [===============] - 1s 24ms/step - loss: 0.2642 - mse: 0.2642 - val_loss: 0.3842 - v
al mse: 0.3842
Epoch 36/100
al_mse: 0.7570
Epoch 37/100
28/28 [===============] - 1s 24ms/step - loss: 0.3279 - mse: 0.3279 - val_loss: 0.4890 - v
al_mse: 0.4890
Epoch 38/100
al_mse: 0.3921
Epoch 39/100
al mse: 0.3908
Epoch 40/100
```

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28/28 [=====
              =j - 18 24ms/step - loss: 0.2907 - mse: 0.2907 - vai_loss: 0.5781 - v
al_mse: 0.5781
Epoch 41/100
      28/28 [======
al_mse: 0.3265
Epoch 42/100
al mse: 0.3354
Epoch 43/100
al mse: 0.4445
Epoch 44/100
28/28 [===============] - 1s 27ms/step - loss: 0.2708 - mse: 0.2708 - val_loss: 0.3614 - v
al_mse: 0.3614
Epoch 45/100
al_mse: 0.7607
Epoch 46/100
al mse: 0.4197
Epoch 47/100
al_mse: 0.3172
Epoch 48/100
al mse: 0.4526
Epoch 49/100
al_mse: 0.3150
Epoch 50/100
al mse: 0.6752
Epoch 51/100
al_mse: 0.3154
Epoch 52/100
al_mse: 0.4881
Epoch 53/100
al mse: 0.4428
Epoch 54/100
al_mse: 0.3213
Epoch 55/100
28/28 [===============] - 1s 25ms/step - loss: 0.4996 - mse: 0.4996 - val_loss: 0.3489 - v
al_mse: 0.3489
Epoch 56/100
al_mse: 0.4538
Epoch 57/100
al mse: 0.7987
Epoch 58/100
al_mse: 0.4096
Epoch 59/100
           ======] - 1s 28ms/step - loss: 0.7144 - mse: 0.7144 - val loss: 0.3284 - v
28/28 [======
al mse: 0.3284
Epoch 60/100
al_mse: 1.2868
```

```
Epoch 61/100
28/28 [===============] - 1s 25ms/step - loss: 0.6644 - mse: 0.6644 - val_loss: 0.3505 - v
al mse: 0.3505
Epoch 62/100
al_mse: 0.5139
Epoch 63/100
al mse: 0.4132
Epoch 64/100
al mse: 1.2611
Epoch 65/100
al mse: 0.4161
Epoch 66/100
al_mse: 0.4190
Epoch 67/100
al_mse: 2.1776
Epoch 68/100
al_mse: 1.1426
Epoch 69/100
al mse: 1.9352
Epoch 70/100
al_mse: 1.6372
Epoch 71/100
al_mse: 2.2914
Epoch 72/100
al mse: 0.7847
Epoch 73/100
al mse: 0.3190
Epoch 74/100
al_mse: 0.9897
Epoch 75/100
al mse: 0.9127
Epoch 76/100
al mse: 0.3299
Epoch 77/100
al mse: 0.8650
Epoch 78/100
al_mse: 0.5772
Epoch 79/100
al mse: 0.4003
Epoch 80/100
28/28 [===============] - 1s 24ms/step - loss: 0.8833 - mse: 0.8833 - val_loss: 0.5307 - v
al_mse: 0.5307
Epoch 81/100
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al_mse: 0.9742
Epoch 82/100
al_mse: 1.4449
Epoch 83/100
al_mse: 1.4230
Epoch 84/100
al mse: 0.3657
Epoch 85/100
al mse: 0.5416
Epoch 86/100
al mse: 0.3514
Epoch 87/100
al mse: 0.8550
Epoch 88/100
al mse: 0.6653
Epoch 89/100
al mse: 0.3568
Epoch 90/100
al mse: 0.7849
Epoch 91/100
al mse: 0.3435
Epoch 92/100
al_mse: 0.3474
Epoch 93/100
al mse: 0.5525
Epoch 94/100
al mse: 0.6396
Epoch 95/100
al mse: 0.6573
Epoch 96/100
al mse: 2.3367
Epoch 97/100
al_mse: 0.5517
Epoch 98/100
al mse: 0.3603
Epoch 99/100
al mse: 0.6866
Epoch 100/100
al_mse: 1.6267
```

Out[76]:

In [78]:

plt.figure() # 初始化一个Figure类的实例作为所有绘图元素的最高级容器
fig,ax=plt.subplots(2,4) # 为当前的Figure类实例添加子图,以行数为2,列数为5的排列方式呈现,并返回axes
类型变量命名为fig或ax,由于subplot()缺少参数index,此处的axes是整个子图的坐标轴
fig.set_figheight(7.5) # 限制图像高度为7.5
fig.set_figwidth(15) # 限制图像宽度为15
ax=ax.flatten() # 将ax由n*m的Axes组展平成1*nm的Axes组,以便通过下标循环取用
for i in range(8): # 生成0-9的连续正整数
ax[i].imshow(X_pred[i,:,:,:]) # 将X中第一纬度下标为i的三维色值元素矩阵绘制出来
ax[i].set_title(my_model.predict((np.array(X_pred[i,:,:,:]).reshape((1,IMSIZE,IMSIZE,3))))) # 为axes组中的
每一个子图axes设置标题为对应Rating保留两位小数
■

<Figure size 432x288 with 0 Axes>



In []: