作业一:基于深度神经网络的猫狗图像分类

- 一、实验目的
 - 1. 掌握卷积神经网络、循环神经网络等深度学习的各项基本技术。
 - 2. 加强对pytorch、tensorflow等深度学习框架的使用能力。
- 二、实验要求
 - 1. 任选一个深度学习框架,实现在给定数据集上的基于DNN、CNN、RNN的图片分类模型。

三、数据集介绍

猫狗分类,即对给定的图片用模型来判断其是猫还是狗,本质上是一个二分类的图像分类任务。本次实验所用的数据集提供在了附件的data.rar中,train和val文件夹下分别是2000张和500张猫狗图片用于训练和测试模型。这些图片都来自于kaggle竞赛数据集,**如果设备充足,有兴趣做完整数据集的**,也可以从下面的链接下载数据集来使用。

四、任务说明

- 1. 由于自然语言处理任务普遍要使用词向量来完成,但课程进度还未达到。因此,我们第一次作业以一个计算机视觉领域里的典型任务来让大家更好地掌握使用深度学习几个基本网络和框架的能力。
- 2. 请分别使用DNN、CNN、RNN**三种模型**来实现猫狗分类任务,具体网络结构不进行要求,可以根据自己上课的理解来进行设计。
- 3. 由于猫狗图片数目完全一致,因此测评指标采用各个类别的准确率即可。实验完 毕后,请提交自己的代码以及一份实验报告(不要求具体长度),报告中可以说明自己使用的网络结构、所得到的结果,以及自己的一些问题和思考(如果有)等。

一、基础设置

包导入

```
from tensorflow.keras.models import Sequential,Model
from tensorflow.keras.layers import Dense, Flatten, Dropout,
Activation,Bidirectional,SimpleRNN
from tensorflow.keras.preprocessing.image import ImageDataGenerator,
img_to_array, load_img
from livelossplot.keras import PlotLossesCallback
import tensorflow as tf
from keras import regularizers
import numpy as np
import matplotlib.image as mpimg
from keras.optimizers import adam_v2
import matplotlib.pyplot as plt
from keras.layers import Activation, Dropout, Flatten, Dense,Input,LSTM,
GlobalMaxPooling2D, Conv2D, MaxPooling2D,ConvLSTM1D
```

```
training_data_dir = '../data/train_set'
validation_data_dir = "../data/valid_set"
test_data_dir = '../data/test_set'
RNN_WEIGHTS_DOGS_VS_CATS = r'output/RNN/cats_vs_dogs_rnn.h5'

IMAGE_SIZE = 256
IMAGE_WIDTH, IMAGE_HEIGHT = IMAGE_SIZE, IMAGE_SIZE
nb_train_samples = 1500
nb_test_samples = 500
EPOCHS = 20
BATCH_SIZE = 16
LR = 0.001
TRAINING_LOGS_FILE = "output/RNN/training_logs_rnn.csv"
MODEL_SUMMARY_FILE = "output/RNN/model_summary_rnn.txt"
```

二、数据预处理

```
# 数据增强
training_data_generator = ImageDataGenerator(
    rescale=1. / 255,
    shear_range=0.1,
    zoom_range=0.1,
    horizontal_flip=True)
validation_data_generator = ImageDataGenerator(rescale=1. / 255)
test_data_generator = ImageDataGenerator(rescale=1. / 255)
# 数据准备
training_generator = training_data_generator.flow_from_directory(
    training_data_dir,
    target_size=(IMAGE_WIDTH, IMAGE_HEIGHT),
    batch_size=BATCH_SIZE,
    class_mode="binary")
validation_generator = validation_data_generator.flow_from_directory(
    validation_data_dir,
    target_size=(IMAGE_WIDTH, IMAGE_HEIGHT),
    batch_size=BATCH_SIZE,
    class_mode="binary")
test_generator = test_data_generator.flow_from_directory(
    test_data_dir,
    target_size=(IMAGE_WIDTH, IMAGE_HEIGHT),
    batch_size=1,
    class_mode="binary",
    shuffle=False)
```

二、网络结构

DNN

```
input_shape = (IMAGE_WIDTH, IMAGE_HEIGHT, 3)
model = Sequential()
model.add(Flatten(input_shape=input_shape))
model.add(Dense(256))
model.add(Activation('relu'))
model.add(Dropout(0.5))
```

```
model.add(Dense(128))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(1))
model.add(Activation('sigmoid'))

model.compile(optimizer='rmsprop',loss='binary_crossentropy',metrics=
['accuracy'])
```

Model: "sequential"			
Layer (type)	Output	·	Param #
flatten (Flatten)		196608)	0
dense (Dense)	(None,	256)	50331904
activation (Activation)	(None,	256)	0
dropout (Dropout)	(None,	256)	0
dense_1 (Dense)	(None,	128)	32896
activation_1 (Activation)	(None,	128)	0
dropout_1 (Dropout)	(None,	128)	0
dense_2 (Dense)	(None,	64)	8256
activation_2 (Activation)	(None,	64)	0
dropout_2 (Dropout)	(None,	64)	0
dense_3 (Dense)	(None,	1)	65
activation_3 (Activation)	(None,	1)	0
Total params: 50,373,121 Trainable params: 50,373,121 Non-trainable params: 0			

CNN

```
input_shape = (IMAGE_WIDTH, IMAGE_HEIGHT, 3)
model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=input_shape))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
```

```
model.add(Conv2D(128, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(256, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())
model.add(Dense(256))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dropout(0.5))
model.add(Dense(1))
model.add(Activation('sigmoid'))

model.compile(loss='binary_crossentropy',optimizer='rmsprop', metrics=
['accuracy'])
```

Model: "sequential"			
Layer (type)	Output	Shape	Param #
conv2d (Conv2D)		254, 254, 32)	896
activation (Activation)	(None,	254, 254, 32)	0
max_pooling2d (MaxPooling2D)	(None,	127, 127, 32)	0
conv2d_1 (Conv2D)	(None,	125, 125, 64)	18496
activation_1 (Activation)	(None,	125, 125, 64)	0
max_pooling2d_1 (MaxPooling2	(None,	62, 62, 64)	0
conv2d_2 (Conv2D)	(None,	60, 60, 128)	73856
activation_2 (Activation)	(None,	60, 60, 128)	0
max_pooling2d_2 (MaxPooling2	(None,	30, 30, 128)	0
conv2d_3 (Conv2D)	(None,	28, 28, 256)	295168
activation_3 (Activation)	(None,	28, 28, 256)	0
max_pooling2d_3 (MaxPooling2	(None,	14, 14, 256)	0
flatten (Flatten)	(None,	50176)	0
dense (Dense)	(None,	256)	12845312
activation_4 (Activation)	(None,	256)	0
dropout (Dropout)	(None,	256)	0
dense_1 (Dense)	(None,	1)	257

RNN (在CNN层中间添加LSTM层)

```
input_shape = (IMAGE_WIDTH, IMAGE_HEIGHT, 3)
model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=input_shape))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(128, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(ConvLSTM1D(256,3,activation='relu',return_sequences=True))
model.add(ConvLSTM1D(128,3,activation='relu',return_sequences=True))
model.add(ConvLSTM1D(64,3,activation='relu',return_sequences=True))
model.add(Flatten())
model.add(Dense(256))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(1))
model.add(Activation('sigmoid'))
adam = adam_v2.Adam(learning_rate=LR)
model.compile(optimizer=adam,loss='categorical_crossentropy', metrics=
['accuracy'])
```

Layer (type)	Output	Shape	Param #
conv2d (Conv2D)	(None,	254, 254, 32)	896
activation (Activation)	(None,	254, 254, 32)	0
max_pooling2d (MaxPooling2D)	(None,	127, 127, 32)	0
conv2d_1 (Conv2D)	(None,	125, 125, 64)	18496
activation_1 (Activation)	(None,	125, 125, 64)	0
max_pooling2d_1 (MaxPooling2	(None,	62, 62, 64)	0
conv2d_2 (Conv2D)	(None,	60, 60, 128)	73856
activation_2 (Activation)	(None,	60, 60, 128)	0

max_pooling2d_2 (MaxPooling2	(None,	30, 30, 128)	0
conv_lst_m1d (ConvLSTM1D)	(None,	30, 28, 256)	1180672
conv_lst_m1d_1 (ConvLSTM1D)	(None,	30, 26, 128)	590336
conv_lst_m1d_2 (ConvLSTM1D)	(None,	30, 24, 64)	147712
flatten (Flatten)	(None,	46080)	0
dense (Dense)	(None,	256)	11796736
activation_3 (Activation)	(None,	256)	0
dropout (Dropout)	(None,	256)	0
dense_1 (Dense)	(None,	1)	257
activation_4 (Activation)	(None,	1)	0
Total params: 13,808,961 Trainable params: 13,808,961 Non-trainable params: 0			

三、模型训练

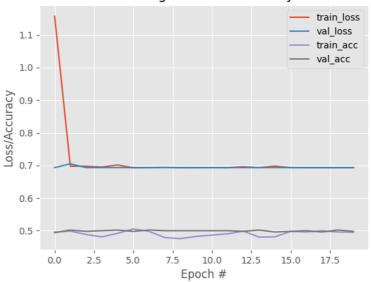
```
H = model.fit_generator(
    training_generator,
    steps_per_epoch=len(training_generator.filenames) // BATCH_SIZE,
    epochs=EPOCHS,
    validation_data=validation_generator,
    validation_steps=len(validation_generator.filenames) // BATCH_SIZE,
    verbose=1)
model.save_weights(RNN_WEIGHTS_DOGS_VS_CATS)
```

四、效果可视化

```
N = np.arange(0, EPOCHS)
plt.style.use("ggplot")
plt.figure()
plt.plot(N, H.history["loss"], label="train_loss")
plt.plot(N, H.history["val_loss"], label="val_loss")
plt.plot(N, H.history["accuracy"], label="train_acc")
plt.plot(N, H.history["val_accuracy"], label="val_acc")
plt.plot(N, H.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.savefig('output/(D\C)RNN/(c/d)rnn_plot.png')
plt.show()
```

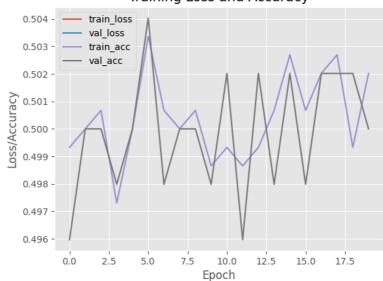
DNN: 损失率在0.7左右,准确率在0.5左右,效果较差。

Training Loss and Accuracy



RNN: 准确率大约在0.5左右,效果跟DNN差不多。

Training Loss and Accuracy



CNN: 损失率在0.5上下波动,准确率在0.7上下波动,较DNN和RNN有明显提升。

Training Loss and Accuracy

