

14.5 实例: 卷积神经网络实现手写数字识别

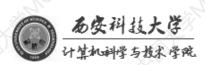
中国大学MOOC

# 14.5 实例: 卷积神经网络实现手写数字识别



### □ 导入库

```
[1]: import tensorflow as tf
         tf. version , tf. keras. version
Out[1]: ('2.0.0', '2.2.4-tf')
In [2]:
         import numpy as np
         import matplotlib. pyplot as plt
In [3]: gpus = tf. config. experimental. list_physical_devices('GPU')
         tf. config. experimental. set_memory_growth(gpus[0], True)
```

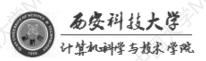


## □ 加载数据集

```
mnist=tf. keras. datasets. mnist
       (train_x, train_y), (test_x, test_y) = mnist.load_data()
[5]:
      print(train x. shape)
       print(train v. shape)
       print(test x. shape)
       print(test v. shape)
                                          In [6]: type(train_x), type(train_y)
       (60000, 28, 28)
       (60000,)
                                           Out[6]:
                                                    (numpy. ndarray, numpy. ndarray)
       (10000, 28, 28)
       (10000,)
                                          In [7]: type(test_x), type(test_y)
                                           Out[7]:
                                                   (numpy. ndarray, numpy. ndarray)
```

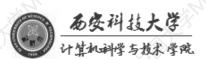
#### □ 数据预处理

```
In [7]: type(test x), type(test y)
Out [7]:
         (numpy. ndarray, numpy. ndarray)
   [8]: X_train, X_test = tf.cast(train_x, dtype=tf.float32)/255.0, tf.cast(test_x, dtype=tf.float32)/255.0
         y train, y test = tf.cast(train_y, dtype=tf.int32), tf.cast(test_y, dtype=tf.int32)
   [9]: X train = train_x. reshape (60000, 28, 28, 1)
                                                            维度变换
         X_test = test_x.reshape(10000, 28, 28, 1)
  [10]:
         print(X_train.shape)
                                                           In [9]: X_train = tf. expand_dims(train_x, 3)
         print(X test. shape)
                                                                     X_test = tf. expand_dims(test_x, 3)
         (60000, 28, 28, 1)
         (10000, 28, 28, 1)
```



## □ 建立模型

```
model=tf.keras.Sequential([
    # unit 1
    tf. keras. layers. Conv2D(16, kernel_size=(3, 3), padding="same", activation=tf.nn.relu, input_shape=(28, 28, 1)),
    tf. keras. layers. MaxPool2D(pool size=(2, 2)),
    # unit 2
    tf.keras.layers.Conv2D(32, kernel size=(3, 3), padding="same", activation=tf.nn.relu),
    tf. keras. layers. MaxPool2D(pool size=(2, 2)),
    # 11nit 3
    tf. keras. layers. Flatten(),
    # unit 4
    tf. keras. layers. Dense (128, activation="relu"),
    tf. keras. layers. Dense (10, activation="softmax")
```



## □ 查看摘要

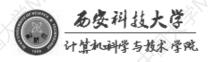
In [12]: model.summary()

Model: "sequential"

Layer (type)	Output	Shape	Param #
conv2d (Conv2D)	(None,	28, 28, 16)	160
max_pooling2d (MaxPooling2D)	(None,	14, 14, 16)	0
conv2d_1 (Conv2D)	(None,	14, 14, 32)	4640
max_pooling2d_1 (MaxPooling2	(None,	7, 7, 32)	0
flatten (Flatten)	(None,	1568)	0
dense (Dense)	(None,	128)	200832
dense_1 (Dense)	(None,	10)	1290
====== <del>(2</del> ===============	=(3)===		

Total params: 206,922 Trainable params: 206,922

Non-trainable params: 0



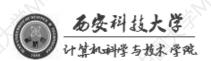
#### ] 配置训练方法

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#### □ 训练模型

```
In [14]: model.fit(X train, y train, batch size=64, epochs=5, validation split=0.2)
       Train on 48000 samples, validate on 12000 samples
       Epoch 1/5
       48000/48000 [============] - 5s 100us/sample - loss: 0.4406 - sparse categorical accuracy: 0.9316 - val loss: 0.0844 - val
       sparse categorical accuracy: 0.9742
       Epoch 2/5
       sparse categorical accuracy: 0.9733
       Epoch 3/5
       48000/48000 [============== ] - 2s 51us/sample - loss: 0.0416 - sparse categorical accuracy: 0.9868 - val loss: 0.0998 - val
       sparse categorical accuracy: 0.9718
       Epoch 4/5
       48000/48000 [============] - 2s 50us/sample - loss: 0.0356 - sparse categorical accuracy: 0.9884 - val loss: 0.0671 - val
       sparse categorical accuracy: 0.9822
       Epoch 5/5
       sparse_categorical_accuracy: 0.9727
Out[14]: (tensorflow.python.keras.callbacks.History at 0x2814c2eac88)
```



### □ 评估模型

In [15]: model.evaluate(X\_test, y\_test, verbose=2)

10000/1 - 1s - loss: 0.0390 - sparse\_categorical\_accuracy: 0.9802

Out[15]: [0.07610834636164945, 0.9802]