

mnist with cnn.ipynb

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Files

sample_data

epoch.png

RAM

Disk

85.14 GB available

[1] from keras.datasets import mnist
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz>
11490434/11490434 [=====] - 0s 0us/step

train_images.shape

(60000, 28, 28)

[3] len(train_labels)

60000

[4] train_labels

array([5, 0, 4, ..., 5, 6, 8], dtype=uint8)

[5] from keras import models
from keras import layers
network = models.Sequential()
network.add(layers.Dense(512, activation='relu', input_shape=(28 * 28,)))
network.add(layers.Dense(10, activation='softmax'))

[6] network.compile(optimizer='rmsprop',
loss='categorical_crossentropy',
metrics=['accuracy'])

[7] train_images = train_images.reshape((60000, 28 * 28))
train_images = train_images.astype('float32') / 255
test_images = test_images.reshape((10000, 28 * 28))
test_images = test_images.astype('float32') / 255

[8] from keras.utils import to_categorical
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

[9] network.fit(train_images, train_labels, epochs=6, batch_size=128)

Epoch 1/6
469/469 [=====] - 7s 14ms/step - loss: 0.2614 - accuracy: 0.9241
Epoch 2/6
469/469 [=====] - 5s 11ms/step - loss: 0.1049 - accuracy: 0.9690
Epoch 3/6
469/469 [=====] - 6s 13ms/step - loss: 0.0684 - accuracy: 0.9798
Epoch 4/6
469/469 [=====] - 5s 11ms/step - loss: 0.0501 - accuracy: 0.9851
Epoch 5/6
469/469 [=====] - 5s 10ms/step - loss: 0.0370 - accuracy: 0.9886
Epoch 6/6
469/469 [=====] - 5s 10ms/step - loss: 0.0287 - accuracy: 0.9916
<keras.callbacks.History at 0x7f0e75fd5510>

[10] test_loss, test_acc = network.evaluate(test_images, test_labels)
print('test_acc:', test_acc)

313/313 [=====] - 1s 3ms/step - loss: 0.0680 - accuracy: 0.9801
test_acc: 0.9800999760627747

98% accuracy is not the best, let's try with convnets (conv2D)

[11] model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))

[12] model.summary()

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
conv2d_2 (Conv2D)	(None, 3, 3, 64)	36928

Total params: 55,744
Trainable params: 55,744
Non-trainable params: 0

Now we add flatten 3D outputs to 1D, and then stack on top some dense layers

```
[13] model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
```

```
[14] model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
conv2d_2 (Conv2D)	(None, 3, 3, 64)	36928
flatten (Flatten)	(None, 576)	0
dense_2 (Dense)	(None, 64)	36928
dense_3 (Dense)	(None, 10)	650

=====

Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0

As it can be seen, the (3, 3, 64) outputs are flattened into vectors of shape (576,) before going through two Dense layers

```
[54] [(train_images, train_labels)], (test_images, test_labels) = mnist.load_data()
```

```
[55] train_images = train_images.reshape((60000, 28, 28, 1))
train_images = train_images.astype('float32') / 255
test_images = test_images.reshape((10000, 28, 28, 1))
test_images = test_images.astype('float32') / 255
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
model.fit(train_images, train_labels, epochs=6, batch_size=64, validation_data=(test_images, test_labels))
```

Epoch 1/6
938/938 [=====] - 59s 63ms/step - loss: 0.0055 - accuracy: 0.9987 - val_loss: 0.0691 - val_accuracy: 0.9908
Epoch 2/6
938/938 [=====] - 58s 61ms/step - loss: 0.0024 - accuracy: 0.9994 - val_loss: 0.0769 - val_accuracy: 0.9917
Epoch 3/6
938/938 [=====] - 57s 61ms/step - loss: 0.0033 - accuracy: 0.9990 - val_loss: 0.0672 - val_accuracy: 0.9918
Epoch 4/6
938/938 [=====] - 58s 62ms/step - loss: 0.0031 - accuracy: 0.9992 - val_loss: 0.0758 - val_accuracy: 0.9919
Epoch 5/6
938/938 [=====] - 58s 62ms/step - loss: 0.0034 - accuracy: 0.9992 - val_loss: 0.0799 - val_accuracy: 0.9926
Epoch 6/6
938/938 [=====] - 57s 61ms/step - loss: 0.0023 - accuracy: 0.9995 - val_loss: 0.0878 - val_accuracy: 0.9903
<keras.callbacks.History at 0x7f0e63891f10>

```
test_loss, test_acc = model.evaluate(test_images, test_labels)
test_acc
```

313/313 [=====] - 4s 12ms/step - loss: 0.0878 - accuracy: 0.9903
0.9902999997138977