assignment06-1_muley_tushar

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Assignment: Assignment 6-1

Date:January 9, 2022

Assignment 6.1 Using section 5.1 in Deep Learning with Python as a guide (listing 5.3 in particular), create a ConvNet model that classifies images in the MNIST digit dataset.

[1]:
```
from keras import layers
from keras import models
```

[2]:
```
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'))
```

[3]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
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 (MaxPooling2 (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
_________________________________________________________________
```

Listing 5.2. Adding a classifier on top of the convnet

[4]:
```
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
```

[5]:
```
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
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 (MaxPooling2 (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 3, 3, 64)          36928
_________________________________________________________________
flatten (Flatten)            (None, 576)               0
_________________________________________________________________
dense (Dense)                (None, 64)                36928
_________________________________________________________________
dense_1 (Dense)              (None, 10)                650
=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
_________________________________________________________________
```

Listing 5.3. Training the convnet on MNIST images

[6]:
```
from keras.datasets import mnist
from keras.utils import to_categorical
```

[7]:
```
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
```

[8]:
```
train_images = train_images.reshape((60000, 28, 28, 1))
train_images = train_images.astype('float32') / 255
```

[9]:
```
test_images = test_images.reshape((10000, 28, 28, 1))
test_images = test_images.astype('float32') / 255
```

[10]:
```
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
```

[12]:
```
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

[16]:
```
# validation set
val_images = train_images[:10000,:]
val_labels = train_labels[:10000,:]

partial_train_images = train_images[10000:,:]
partial_train_labels = train_labels[10000:,:]

partial_train_images.shape, val_images.shape
```

[16]:
```
((50000, 28, 28, 1), (10000, 28, 28, 1))
```

[18]:
```
# train the model
history=model.fit(train_images,
                  train_labels,
                  epochs=5,
                  batch_size=64,
                  validation_data=(val_images, val_labels))
```

```
Epoch 1/5
938/938 [==============================] - 35s 36ms/step - loss: 0.0154 -
accuracy: 0.9953 - val_loss: 0.0124 - val_accuracy: 0.9962
Epoch 2/5
938/938 [==============================] - 44s 47ms/step - loss: 0.0128 -
accuracy: 0.9964 - val_loss: 0.0080 - val_accuracy: 0.9974
Epoch 3/5
938/938 [==============================] - 45s 48ms/step - loss: 0.0100 -
accuracy: 0.9970 - val_loss: 0.0045 - val_accuracy: 0.9987
Epoch 4/5
938/938 [==============================] - 43s 46ms/step - loss: 0.0077 -
accuracy: 0.9977 - val_loss: 0.0045 - val_accuracy: 0.9985
Epoch 5/5
938/938 [==============================] - 40s 43ms/step - loss: 0.0076 -
accuracy: 0.9977 - val_loss: 0.0068 - val_accuracy: 0.9976
```

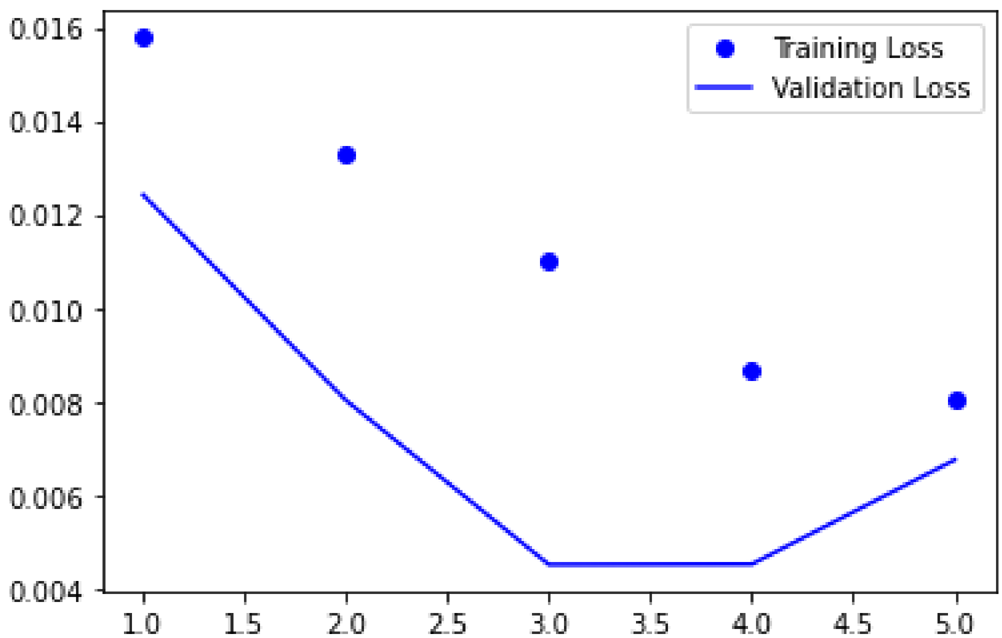
[19]:
```
history_dict = history.history
history_dict.keys()
```

[19]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

Plot

Training and Validation Loss

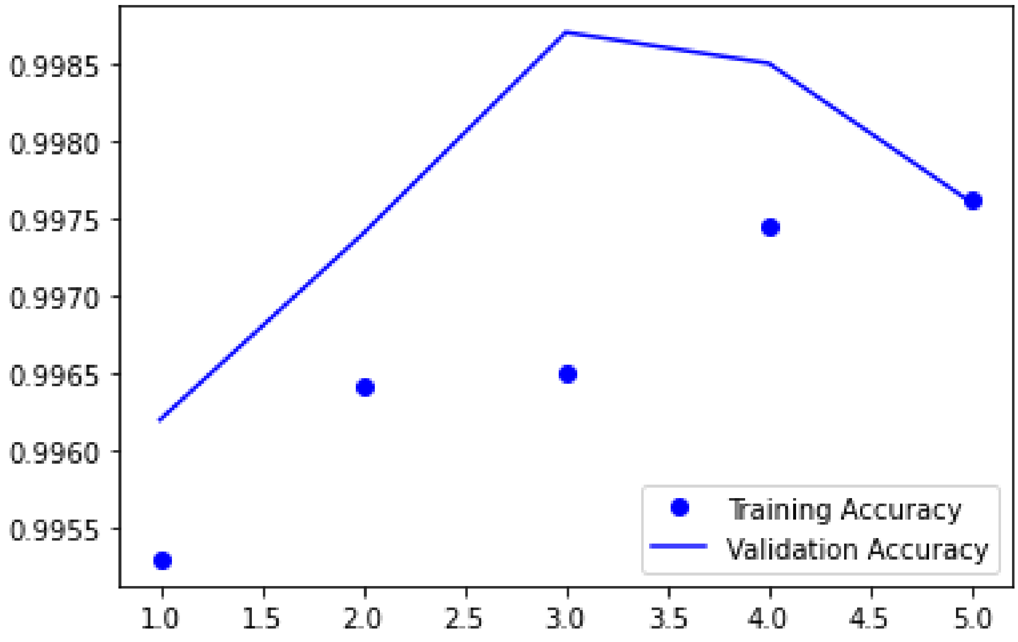
[21]:
```
import matplotlib.pyplot as plt
history_dict = history.history
loss_val = history_dict["loss"]
val_loss_val = history_dict["val_loss"]
epochs= range(1, len(loss_val) +1)
plt.plot(epochs, loss_val, "bo", label="Training Loss")
plt.plot(epochs, val_loss_val, "b", label="Validation Loss")
plt.plot(title = "Training and Validation Loss")
plt.plot(xlabel="Epochs")
plt.plot(ylabel="Loss")
plt.legend()
plt.show()
```



Training and Validation Accuracy

[22]:
```
history_dict = history.history
acc = history_dict["accuracy"]
val_acc = history_dict["val_accuracy"]
epochs= range(1, len(loss_val) +1)
plt.plot(epochs, acc, "bo", label="Training Accuracy")
plt.plot(epochs, val_acc, "b", label="Validation Accuracy")
plt.plot(title = "Training and Validation Accuracy")
plt.plot(xlabel="Epochs")
plt.plot(ylabel="Accuracy")
plt.legend()
```

```
plt.show()
```



Retrain model

[26]:
```
model.compile(optimizer='rmsprop',
              loss = 'categorical_crossentropy',
              metrics = ['accuracy'])

model.fit(train_images, train_labels, epochs=3, batch_size=512)

results=model.evaluate(test_images, test_labels)
```

```
Epoch 1/3
118/118 [==============================] - 30s 248ms/step - loss: 0.0018 -
accuracy: 0.9993
Epoch 2/3
118/118 [==============================] - 34s 283ms/step - loss: 6.9039e-04 -
accuracy: 0.9997
Epoch 3/3
118/118 [==============================] - 33s 276ms/step - loss: 5.5668e-04 -
accuracy: 0.9998
313/313 [==============================] - 3s 8ms/step - loss: 0.0373 -
accuracy: 0.9927
```

[27]:
```
results
```

[27]:
```
[0.03726635128259659, 0.9926999807357788]
```

[28]:
```python
model.predict(test_images)
```

[28]:
```
array([[1.17138473e-18, 1.52956668e-14, 1.89267655e-13, …,
         1.00000000e+00, 2.82987699e-16, 9.99412358e-13],
        [3.89941445e-19, 2.53855212e-17, 1.00000000e+00, …,
         6.27537656e-27, 4.38832692e-20, 1.33996726e-29],
        [5.93215256e-13, 1.00000000e+00, 1.57812270e-11, …,
         8.91156648e-10, 1.22106908e-10, 1.01484397e-10],
        …,
        [2.81409270e-33, 1.80594282e-24, 6.73015316e-29, …,
         2.94729163e-23, 3.30883150e-21, 8.33329335e-22],
        [5.74947273e-21, 1.00544685e-23, 1.31905212e-29, …,
         4.42883865e-28, 1.92395280e-13, 1.18429775e-18],
        [3.33153792e-15, 6.87902423e-18, 2.37463993e-14, …,
         9.12308501e-30, 2.69159071e-13, 1.71166226e-21]], dtype=float32)
```

[ ]: