HW5-Conv

May 21, 2020

[1]:

```python
# imports for array-handling and plotting
import numpy as np
import matplotlib
matplotlib.use('agg')
import matplotlib.pyplot as plt
%matplotlib inline

# let's keep our keras backend tensorflow quiet
import os
# for testing on GPU
#os.environ['TF_CPP_MIN_LOG_LEVEL']='3'
# for testing on CPU
os.environ['CUDA_VISIBLE_DEVICES'] = ''

# keras imports for the dataset and building our neural network
from keras.datasets import mnist
from keras.models import Sequential, load_model
from keras.layers.core import Dense, Dropout, Activation, Dense
from keras.utils import np_utils
from keras import backend as K

from keras.layers import Conv2D, MaxPooling2D, Flatten
from keras.preprocessing.image import ImageDataGenerator
```

```
Using TensorFlow backend.
```

[2]:

```python
# dimensions of our images.
img_width, img_height = 30, 30

train_data_dir = 'DITS-classification/classification train'
test_data_dir = 'DITS-classification/classification test'
nb_train_samples = 7489
nb_test_samples = 1159
epoche = 30
batch_size = 128
split_per_validazione=0.2

# this is the augmentation configuration we will use for training
```

```
train_datagen = ImageDataGenerator(
    rescale=1. / 255,
    shear_range=0.2,
    zoom_range=0.2,
    validation_split=split_per_validazione,
    #rotation_range=20,
    #width_shift_range=0.05,
    #height_shift_range=0.05,
    #fill_mode="nearest",
    horizontal_flip=True)

# this is the augmentation configuration we will use for testing:
# only rescaling
test_datagen = ImageDataGenerator(rescale=1. / 255.)
```

[3]:

```
train_generator = train_datagen.flow_from_directory(
    train_data_dir,
    target_size=(img_width, img_height),
    color_mode="rgb",
    batch_size=int(nb_train_samples*(1-split_per_validazione)),
    class_mode='categorical',
    subset='training')

validation_generator = train_datagen.flow_from_directory(
    train_data_dir,
    target_size=(img_width, img_height),
    color_mode="rgb",
    batch_size=int(nb_train_samples*split_per_validazione),
    class_mode='categorical',
    subset='validation')

test_generator = test_datagen.flow_from_directory(
    test_data_dir,
    target_size=(img_width, img_height),
    color_mode="rgb",
    batch_size=nb_test_samples,
    class_mode="categorical")

X_train = train_generator[0][0]
Y_train = train_generator[0][1]
X_validation = validation_generator[0][0]
Y_validation = validation_generator[0][1]
X_test = test_generator[0][0]
Y_test = test_generator[0][1]
```

```
Found 5992 images belonging to 59 classes.
Found 1497 images belonging to 59 classes.
```

```
Found 1159 images belonging to 59 classes.
```

[4]:
```python
#Stampa di alcuni esempi con le relative digits
for i in range(9):
  plt.subplot(3,3,i+1)
  plt.tight_layout()
  plt.imshow(X_train[i], interpolation='none')
  plt.title("Digit: {}".format(np.where(Y_test[i]==1)[0][0]))
  plt.xticks([])
  plt.yticks([])
plt.show()
```

[5]:
```python
#Trasformazioni
y_train = np.empty(len(Y_train),dtype=int)
y_test = np.empty(len(Y_test),dtype=int)
for i in range(len(Y_train)):
    #print(i, "/", len(Y_train), end='\r')
    y_train[i]=(np.where(Y_train[i]==1)[0][0])
for j in range(len(Y_test)):
    #print(j, "/", len(Y_test), end='\r')
    y_test[j]=(np.where(Y_test[j]==1)[0][0])

print(np.unique(y_train, return_counts=True)[0]) #Stampa le classi
print(np.unique(y_train, return_counts=True)[1]) #Stampa le nuove quantità
```

```python
#Quest'ultima cosa serve per la stampa finale
immaginiPerLaStampaFinale=X_test
```

```
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
 48 49 50 51 52 53 54 55 56 57 58]
[ 24  12  48 504 156  36  60  24  24  60  12 192  24  12 336  36 264  12
 264 204 261  24 204  60  72 168  12  48 144  24  60 168  84  48 167 204
 108 251  84  24 372  48  12  12 360  72  36  24  12  24  12  36  48  24
  24  48 188  12 108]
```

[6]:

```python
# building a linear stack of layers with the sequential model
def prepare_model():
    model = Sequential()
    model.add(Conv2D(128,kernel_size=(7,␣
 ↪7),activation='relu',input_shape=(img_width, img_height, 3)))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Conv2D(128,kernel_size=(5, 5),activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Conv2D(128,kernel_size=(3, 3),activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Flatten())
    model.add(Dense(59, activation='relu'))
    model.add(Dense(59, activation='softmax'))
    model.
 ↪compile(loss="categorical_crossentropy",optimizer="adam",metrics=['accuracy'])
    return model
```

[7]:

```python
model = prepare_model()
history = model.fit(X_train, Y_train,
                    batch_size=batch_size,
                    epochs=epoche,
                    verbose=2,
                    validation_data=(X_validation, Y_validation))



# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
```

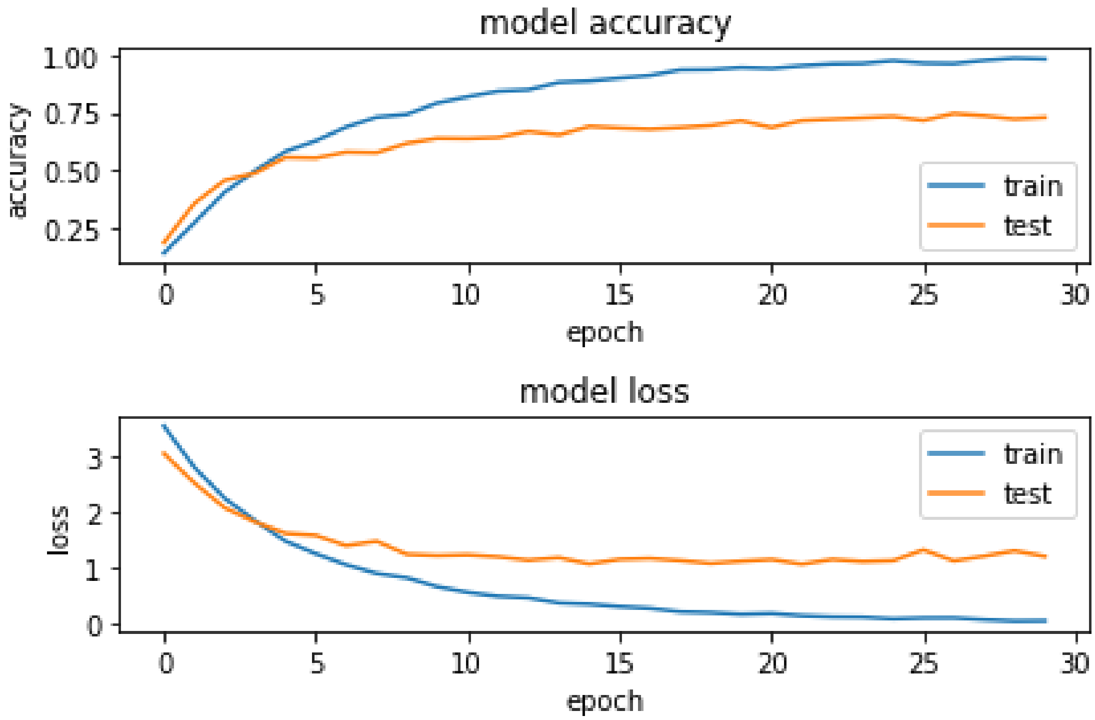
```python
plt.subplot(2,1,2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')

plt.tight_layout()

fig
```

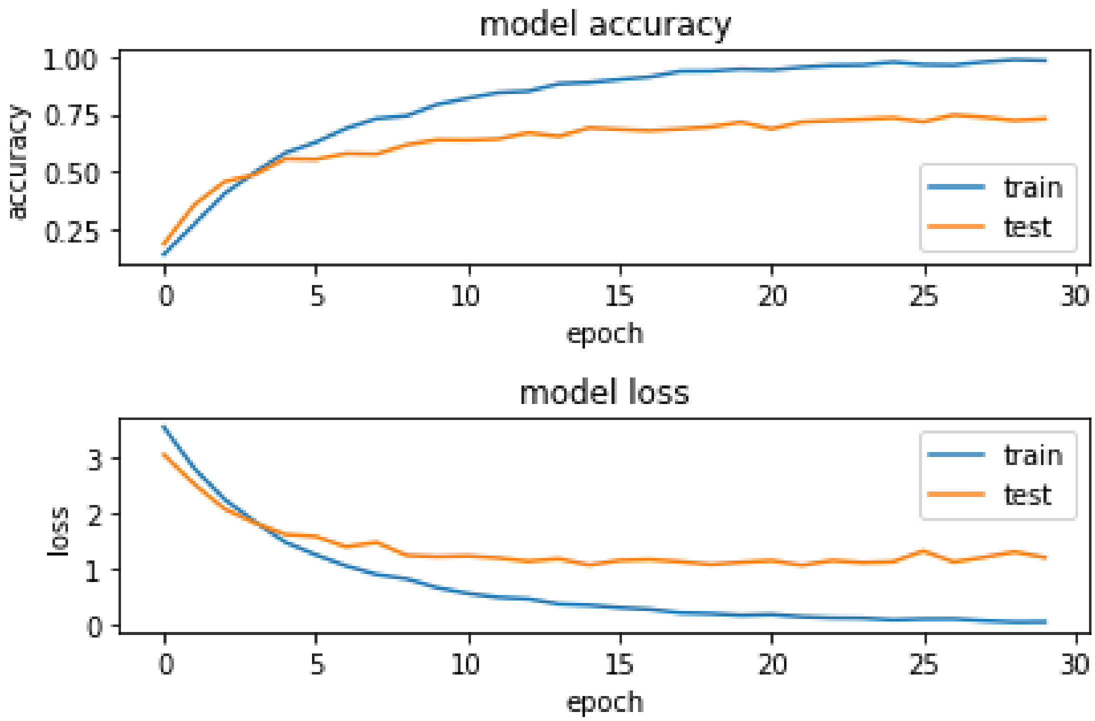
```
Train on 5991 samples, validate on 1497 samples
Epoch 1/30
 - 15s - loss: 3.5288 - accuracy: 0.1414 - val_loss: 3.0405 - val_accuracy:
0.1870
Epoch 2/30
 - 13s - loss: 2.7982 - accuracy: 0.2717 - val_loss: 2.5170 - val_accuracy:
0.3560
Epoch 3/30
 - 12s - loss: 2.2445 - accuracy: 0.4046 - val_loss: 2.0746 - val_accuracy:
0.4569
Epoch 4/30
 - 12s - loss: 1.8449 - accuracy: 0.4974 - val_loss: 1.8229 - val_accuracy:
0.4876
Epoch 5/30
 - 11s - loss: 1.4809 - accuracy: 0.5819 - val_loss: 1.6199 - val_accuracy:
0.5558
Epoch 6/30
 - 12s - loss: 1.2573 - accuracy: 0.6276 - val_loss: 1.5833 - val_accuracy:
0.5531
Epoch 7/30
 - 13s - loss: 1.0603 - accuracy: 0.6875 - val_loss: 1.3995 - val_accuracy:
0.5792
Epoch 8/30
 - 12s - loss: 0.9054 - accuracy: 0.7301 - val_loss: 1.4774 - val_accuracy:
0.5765
Epoch 9/30
 - 12s - loss: 0.8273 - accuracy: 0.7424 - val_loss: 1.2455 - val_accuracy:
0.6172
Epoch 10/30
 - 12s - loss: 0.6698 - accuracy: 0.7915 - val_loss: 1.2243 - val_accuracy:
0.6386
Epoch 11/30
 - 13s - loss: 0.5697 - accuracy: 0.8186 - val_loss: 1.2368 - val_accuracy:
0.6373
Epoch 12/30
```

```
 - 12s - loss: 0.4991 - accuracy: 0.8429 - val_loss: 1.2017 - val_accuracy:
0.6420
Epoch 13/30
 - 13s - loss: 0.4720 - accuracy: 0.8491 - val_loss: 1.1430 - val_accuracy:
0.6687
Epoch 14/30
 - 12s - loss: 0.3797 - accuracy: 0.8812 - val_loss: 1.1869 - val_accuracy:
0.6533
Epoch 15/30
 - 12s - loss: 0.3589 - accuracy: 0.8870 - val_loss: 1.0759 - val_accuracy:
0.6900
Epoch 16/30
 - 12s - loss: 0.3148 - accuracy: 0.8997 - val_loss: 1.1578 - val_accuracy:
0.6834
Epoch 17/30
 - 13s - loss: 0.2854 - accuracy: 0.9109 - val_loss: 1.1732 - val_accuracy:
0.6780
Epoch 18/30
 - 12s - loss: 0.2232 - accuracy: 0.9351 - val_loss: 1.1347 - val_accuracy:
0.6854
Epoch 19/30
 - 12s - loss: 0.2093 - accuracy: 0.9361 - val_loss: 1.0849 - val_accuracy:
0.6941
Epoch 20/30
 - 12s - loss: 0.1788 - accuracy: 0.9451 - val_loss: 1.1231 - val_accuracy:
0.7148
Epoch 21/30
 - 12s - loss: 0.1934 - accuracy: 0.9409 - val_loss: 1.1547 - val_accuracy:
0.6854
Epoch 22/30
 - 12s - loss: 0.1533 - accuracy: 0.9524 - val_loss: 1.0714 - val_accuracy:
0.7154
Epoch 23/30
 - 12s - loss: 0.1338 - accuracy: 0.9606 - val_loss: 1.1558 - val_accuracy:
0.7214
Epoch 24/30
 - 12s - loss: 0.1293 - accuracy: 0.9624 - val_loss: 1.1176 - val_accuracy:
0.7275
Epoch 25/30
 - 11s - loss: 0.0981 - accuracy: 0.9750 - val_loss: 1.1340 - val_accuracy:
0.7335
Epoch 26/30
 - 12s - loss: 0.1143 - accuracy: 0.9639 - val_loss: 1.3245 - val_accuracy:
0.7161
Epoch 27/30
 - 12s - loss: 0.1158 - accuracy: 0.9621 - val_loss: 1.1302 - val_accuracy:
0.7462
Epoch 28/30
```

```
 - 11s - loss: 0.0829 - accuracy: 0.9760 - val_loss: 1.2138 - val_accuracy:
0.7361
Epoch 29/30
 - 13s - loss: 0.0605 - accuracy: 0.9858 - val_loss: 1.3087 - val_accuracy:
0.7221
Epoch 30/30
 - 12s - loss: 0.0645 - accuracy: 0.9820 - val_loss: 1.2098 - val_accuracy:
0.7295
```

[7]:





[8]:

```
save_dir = "results/"
model_name = 'HW5Conv.h5'
model_path = os.path.join(save_dir, model_name)
model.save(model_path)
print('Saved trained model at %s ' % model_path)
```

```
Saved trained model at results/HW5Conv.h5
```

[9]:

```
modello_cartelli = load_model("results/HW5Conv.h5")
loss_and_metrics = modello_cartelli.evaluate(X_test, Y_test, verbose=2)

print("Test Loss", loss_and_metrics[0])
print("Test Accuracy", loss_and_metrics[1])
```

```
Test Loss 2.908780539827783
Test Accuracy 0.6376186609268188
```

[10]:

```
# Creazione delle predizioni sul test set sulla base del modello caricato
carica_model = load_model('results/HW5Conv.h5')
predicted_classes = carica_model.predict_classes(X_test)

# Distinguo cosa è stato predetto bene e cosa no
correct_indices = np.nonzero(predicted_classes == y_test)[0]
incorrect_indices = np.nonzero(predicted_classes != y_test)[0]
```

```python
print()
print(len(correct_indices)," classified correctly")
print(len(incorrect_indices)," classified incorrectly")

# adapt figure size to accomodate 18 subplots
plt.rcParams['figure.figsize'] = (7,14)

figure_evaluation = plt.figure()

# Stampa delle 9 predizioni corrette
for i, correct in enumerate(correct_indices[:9]):
    plt.subplot(6,3,i+1)
    plt.imshow(immaginiPerLaStampaFinale[correct], interpolation='none')
    plt.title(
      "Predicted: {}, Truth: {}".format(predicted_classes[correct],
                                        y_test[correct]))
    plt.xticks([])
    plt.yticks([])

# Stampa delle 9 predizioni incorrette
for i, incorrect in enumerate(incorrect_indices[:9]):
    plt.subplot(6,3,i+10)
    plt.imshow(immaginiPerLaStampaFinale[incorrect], interpolation='none')
    plt.title(
      "Predicted {}, Truth: {}".format(predicted_classes[incorrect],
                                       y_test[incorrect]))
    plt.xticks([])
    plt.yticks([])

figure_evaluation
```

```
739  classified correctly
420  classified incorrectly
```

[10]:


Predicted: 52, Truth: 52
Predicted: 4, Truth: 4
Predicted: 3, Truth: 3
Predicted: 34, Truth: 34
Predicted: 40, Truth: 40
Predicted: 41, Truth: 41
Predicted: 4, Truth: 4
Predicted: 55, Truth: 55
Predicted: 16, Truth: 16
Predicted 12, Truth: 49
Predicted 6, Truth: 12
Predicted 35, Truth: 33
Predicted 33, Truth: 25
Predicted 55, Truth: 21
Predicted 56, Truth: 52
Predicted 35, Truth: 37
Predicted 24, Truth: 20
Predicted 47, Truth: 5


Predicted: 52, Truth: 52
Predicted: 4, Truth: 4
Predicted: 3, Truth: 3
Predicted: 34, Truth: 34
Predicted: 40, Truth: 40
STOP
Predicted: 41, Truth: 41
Predicted: 4, Truth: 4
Predicted: 55, Truth: 55
Predicted: 16, Truth: 16
Predicted 12, Truth: 49
Predicted 6, Truth: 12
Predicted 35, Truth: 33
10
Predicted 33, Truth: 25
Predicted 55, Truth: 21
Predicted 56, Truth: 52
Predicted 35, Truth: 37
50
Predicted 24, Truth: 20
Predicted 47, Truth: 5