lab1

January 21, 2025

1 Digit recognition with a CNN

Code to initiliaze Tensorflow 2.0 in Colab

[1]:
```
from __future__ import absolute_import, division, print_function,␣
↪unicode_literals
# %tensorflow_version 2.x
import tensorflow as tf
%load_ext tensorboard
import datetime
import numpy as np
import matplotlib.pyplot as plt
```

```
2025-01-21 22:30:47.615947: I tensorflow/core/util/port.cc:153] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn them
off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2025-01-21 22:30:47.616890: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:32]
Could not find cuda drivers on your machine, GPU will not be used.
2025-01-21 22:30:47.623159: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:32]
Could not find cuda drivers on your machine, GPU will not be used.
2025-01-21 22:30:47.642046: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:477] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
E0000 00:00:1737495047.673600  178167 cuda_dnn.cc:8310] Unable to register cuDNN
factory: Attempting to register factory for plugin cuDNN when one has already
been registered
E0000 00:00:1737495047.683101  178167 cuda_blas.cc:1418] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
2025-01-21 22:30:47.714122: I tensorflow/core/platform/cpu_feature_guard.cc:210]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other
operations, rebuild TensorFlow with the appropriate compiler flags.
```

Import the MNIST dataset. The default loader will return tensors for the train/test partitions of the images and the labels.

[2]:
```
mnist = tf.keras.datasets.mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train = x_train[:,:,:,np.newaxis]/255.0   # our images are 4 dimensional␣
↪(NumImages, Height, Width, Channels) - these images are grayscale so we only␣
↪have 1 channel
x_test = x_test[:,:,:,np.newaxis]/255.0
```

[TODO] Check the size of the loaded tensors

[3]:
```
print(f'Dimension of X_train: {x_train.shape}') # 6000 images used as training␣
↪set, each with size 28x28 and only one channel cause they are in greyscale
print(f'Dimension of X_test: {x_test.shape}') # 1000 images used as test set
print(f'Dimension of Y_train: {y_train.shape}') # 6000 labels
print(f'Dimension of Y_test: {y_test.shape}') # 1000 labels
```

```
Dimension of X_train: (60000, 28, 28, 1)
Dimension of X_test: (10000, 28, 28, 1)
Dimension of Y_train: (60000,)
Dimension of Y_test: (10000,)
```

Prepare Keras callback for Tensorboard

[4]:
```
logdir = "logs/scalars/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
%tensorboard --logdir logs
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=logdir,␣
↪update_freq='batch')
```

```
<IPython.core.display.HTML object>
```

[TODO] Define a Keras Sequential model with the convolutional neural network

[5]:
```
# we are performing images classification, so given a dataset of labeled images␣
↪(supervised learning) we want that our model understand how to extract␣
↪features and then use these to predict the class of the image
# for the process of features extraction we use convolutional layers, that␣
↪performs F different filters on the same image in order to obtain a map␣
↪associated to each filter. These maps correspond to some features
# extracted from the images. These process of features extraction is called␣
↪convolutional encoding, cause through the convolutional layers we are␣
↪ectracting more and more details from the image and we are reducing
# the size of the image. In our case we use 'same' padding, this means that the␣
↪on the input image are added new pixels in the border, so the convolution␣
↪can return an image with the same size. This new pixels can
# be added equals to 0 (zero padding), or with the same values of the real␣
↪borders (symmetric padding), or with the same values just over the border␣
↪(reflection padding). We could decide to not perform any padding,
```

```
# so we give to the convolutional layer the original image, this method is␣
↪called valid padding and the returned output will be the image reduced of 2␣
↪pixels on each dimension.
# While we are going deeper in the NN, the convolutional layers should extract␣
↪more features cause we want to extract more and more complex features. Note␣
↪that a pixel in the output image of convolutional layer is
# is evaluated on a perceptive field of the size of the kernel used by the␣
↪convolution, so while we are going deeper each pixel contains the␣
↪information of more pixels.
# Between the layers we are also performing Batch Normalization, this is␣
↪important cause it normalize (by standardization) the input values by␣
↪considering the statistics (mean and standard devietion) of a batch
# of the data. This is important cause it reduce the effect of too low value␣
↪that could bring to vanishing gradient, and too high value that could bring␣
↪to exploding gradient.
# The we use an activation function, that recives the input values and perform␣
↪on them the ReLu activation function. The activation function perform an␣
↪operation of the input. Is important that this function is
# non linear, cause if it was linear it will perform the same operations on␣
↪each input, and so we loose the advantages of having multiple layers cause␣
↪they are all performing the same action.
# We can decide between sigmoid, ReLu and Leaky ReLu for applying the non␣
↪linear activation function. Sigmoid function is the worst, cause all the low␣
↪input are forced to 0 and all the high input are forced to 1,
# this cause saturation of the outputs and so vanishing gradient. ReLu is a␣
↪linear function (y=x) on positive inputs, but it force all the negative␣
↪inputs to 0. Leaky ReLu is the same but it doesn't force
# the negative input to 0 but it set them with a linear function (y=x/10).
# Between the convolutional layers we are also performing Pooling, these␣
↪operations reduces the dimension of the image (not of the features) by␣
↪selecting a specific value (max, min, avarege) on the kernel.
# For applying the classification we use softmax function that returns a pdf␣
↪between all the 10 possible classes. Before doing so, softmax function need␣
↪a vector as input, so we have to flat the matrix into a
# vector by using Flatten layer. From the pdf of the softmax we read the class␣
↪with the higher probability. This is how a convolutional encoder works for␣
↪performing image classification.
# Before deciding the class i've added a new layer that perform dropout. This␣
↪will remove randomly 50% of the neurons from the trained network and then␣
↪try to train the other neurons to perform the same.
# This method reduces the dimension of the neural network but it increases the␣
↪values of the parameters. Parameters increases of 1/(1-p), where p is the␣
↪percentage of neurons freed. Having high values of the
# parameters could be not good, cause high weights made the model very sen␣
↪sistive on input channges. So we could also perform regularization to give␣
↪penalty on the cost function for high weights.
```

```
# I have tested that the model with the regularization perform worst than the␣
↪model without it, so i decided to remove regularization.
# Note that the NN is divided into two steps, before it applies features␣
↪extraction and then it performs decision making on those.
model = tf.keras.models.Sequential([
    # tf.keras.layers.Conv2D(32, (3,3), padding='same', kernel_regularizer=tf.
↪keras.regularizers.L2(0.01)),  # extracts basics features from the image by␣
↪using a convolutional kernel (3x3) and 32 filters, so we get 32 feature maps.
↪ With the regularization the cost function receive a penalty that follows␣
↪the square norm of the weights.
    tf.keras.layers.Conv2D(32, (3,3), padding='same'),
    tf.keras.layers.BatchNormalization(), # this layer normalize the output by␣
↪applying standardization by using the statistics evaluated on a batch␣
↪extracted from the training dataset. Used to avoid exploding and vanishing␣
↪gradient
    tf.keras.layers.ReLU(), # non linear activation function. All the negative␣
↪input are forced to 0, the positive ones are setted following a linear␣
↪function y=x
    tf.keras.layers.MaxPooling2D((2,2)),     # halve the size of the image by␣
↪taking the maximum value from a 2x2 square
    # tf.keras.layers.Conv2D(64, (3,3), padding='same', kernel_regularizer=tf.
↪keras.regularizers.l2(0.01)),   # we increase the number of filters to 64,␣
↪so we get 64 feature maps. This layer will extract more complex features
    tf.keras.layers.Conv2D(32, (3,3), padding='same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.ReLU(),
    tf.keras.layers.MaxPooling2D((2,2)),     # halve the size of the image by␣
↪taking the maximum value from a 2x2 square
    # tf.keras.layers.Conv2D(128, (3,3), padding='same', kernel_regularizer=tf.
↪keras.regularizers.l2(0.01)),   # we extract again more complex features
    tf.keras.layers.Conv2D(32, (3,3), padding='same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.ReLU(),
    tf.keras.layers.Flatten(),  # we flatten the 3D tensor to a 1D tensor,␣
↪because Dense layer only accepts 1D tensor
    tf.keras.layers.Dropout(0.5),   # we use dropout to avoid overfitting, this␣
↪layer randomly set 0 some neurons, then the NN is forced to train with the␣
↪remeining ones how to work as previous
    tf.keras.layers.Dense(10, activation='softmax') # softmax activation␣
↪function is used to get the probabilities of each class, so the output is a␣
↪vector of 10 probabilities (one for each class) summed to 1
])
```

```
W0000 00:00:1737495058.276980  178167 gpu_device.cc:2344] Cannot dlopen some GPU
libraries. Please make sure the missing libraries mentioned above are installed
properly if you would like to use GPU. Follow the guide at
https://www.tensorflow.org/install/gpu for how to download and setup the
```

```
required libraries for your platform.
Skipping registering GPU devices…
```

[TODO] Compile the Keras model: specify the optimization algorithm, the loss function and the test metric

[6]:
```
# Train a NN means trying to find the best weights and biases (parameters of␣
 ↪the NN) that can explain in the best way possible the relations between␣
 ↪inputs and outputs. For doing so we must evaluate we amount
# of error made by our model, so we can understand how far we are from the␣
 ↪desired result. This evaluation is done through the cost function, that␣
 ↪could be the MSE (mean square error) or the cross entropy
# evaluated between the desired output and the one that our NN returns. After␣
 ↪having evaluated the amount error through the cost function, we have to␣
 ↪understand how to change the parameters in order to reduce the
# error. This could be done by evaluating the gradient, so we derive the cost␣
 ↪function on each parameter and we obtain a vector in the space of the␣
 ↪function that indicates to us the direction where we have to move
# for reducing the error. Our goal is to arrive to the minimum point of this␣
 ↪function by exploiting the gradient, so we evaluate the cost function and␣
 ↪then we update the parameters with the gradiet until we reach
# a convergence. This algorithm is called gradient descending, and it ensures␣
 ↪that we could reach a local minimum point, but not that it is the global␣
 ↪minimum. We could start from random parameters and see where
# the algorithm brings us. Then we can try again with other random parameter␣
 ↪and see if the gradient descend converge on better minimum. This is the way␣
 ↪how we can increase the prbability of reaching the global
# minimum. Note that the gradient gives us only the direction where we have to␣
 ↪move, but not the amount of step that we should perform. For finding this␣
 ↪value we should evaluate the second derivative, but this mean
# to evaluate (number of parameters)^2 derivative of the cost function, too␣
 ↪complex in system with many parameters as the NN. So what we can do is to␣
 ↪estimate the amount of step through a learning rate.
# A too big step can cause jumping over minimum point and so guide on the wrong␣
 ↪direction the algorithm, instead a too short step could slow down the␣
 ↪covergence of the algorithm.
# We know that the cost function after having applied the step should be lower␣
 ↪that the actual value: C(w + Δw) - C(w) = -η _w (C), where η is the learning␣
 ↪rate.
# At each iteration gradient descending must read the entire dataset for␣
 ↪evaluating the cost function and then update the parameters with the␣
 ↪gradient. An optimization is the Stocastic Gradient Descending, that
# performs the same actions but it doesn't load the entire dataset but it␣
 ↪extract from it a batch and then it doesn't put it back. So at each␣
 ↪iteration the cost function is evaluated on the extracted batch, and
```

```
# the size of the training set decreases of the batch size. The number of␣
↪epochs rappresent the number of times that the algorithm should see the␣
↪entire training set, so the total number of iterations performed
# by this algorithm is (n / b) * e, where n is the size of the training set, b␣
↪is the size of the batch and e is the number of epochs.
# Adam oprimizer is an optmization of the stochastic gradient descent, that␣
↪changes the learnig rate through the iterations by considering the␣
↪statistics of the gradient.
lr = 0.01   # learning rate
model.compile(optimizer = tf.keras.optimizers.Adam(lr), loss =␣
↪'sparse_categorical_crossentropy', metrics=['accuracy'])
```

[TODO] Train the Keras model

[7]:
```
model.fit(x_train, y_train, batch_size=128, epochs=5,␣
↪callbacks=[tensorboard_callback])
```

```
Epoch 1/5
469/469              41s 78ms/step -
accuracy: 0.8818 - loss: 0.4391
Epoch 2/5
469/469              34s 72ms/step -
accuracy: 0.9778 - loss: 0.0691
Epoch 3/5
469/469              32s 68ms/step -
accuracy: 0.9824 - loss: 0.0551
Epoch 4/5
469/469              31s 66ms/step -
accuracy: 0.9841 - loss: 0.0504
Epoch 5/5
469/469              32s 67ms/step -
accuracy: 0.9865 - loss: 0.0437
```

[7]:
```
<keras.src.callbacks.history.History at 0x79aa808ff6a0>
```

[TODO] Print model summary

[8]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 32)	320
batch_normalization (BatchNormalization)	(None, 28, 28, 32)	128

```
re_lu (ReLU)                    (None, 28, 28, 32)                 0

max_pooling2d (MaxPooling2D)    (None, 14, 14, 32)                 0

conv2d_1 (Conv2D)               (None, 14, 14, 32)             9,248

batch_normalization_1           (None, 14, 14, 32)               128
(BatchNormalization)

re_lu_1 (ReLU)                  (None, 14, 14, 32)                 0

max_pooling2d_1 (MaxPooling2D)  (None, 7, 7, 32)                   0

conv2d_2 (Conv2D)               (None, 7, 7, 32)               9,248

batch_normalization_2           (None, 7, 7, 32)                 128
(BatchNormalization)

re_lu_2 (ReLU)                  (None, 7, 7, 32)                   0

flatten (Flatten)               (None, 1568)                       0

dropout (Dropout)               (None, 1568)                       0

dense (Dense)                   (None, 10)                    15,690
```

```
 Total params: 104,288 (407.38 KB)

 Trainable params: 34,698 (135.54 KB)

 Non-trainable params: 192 (768.00 B)

 Optimizer params: 69,398 (271.09 KB)
```

[TODO] Test the Keras model by computing the accuracy the whole test set

[9]:
```
model.evaluate(x_test, y_test)
```

```
313/313              3s 7ms/step -
accuracy: 0.9712 - loss: 0.1088
```

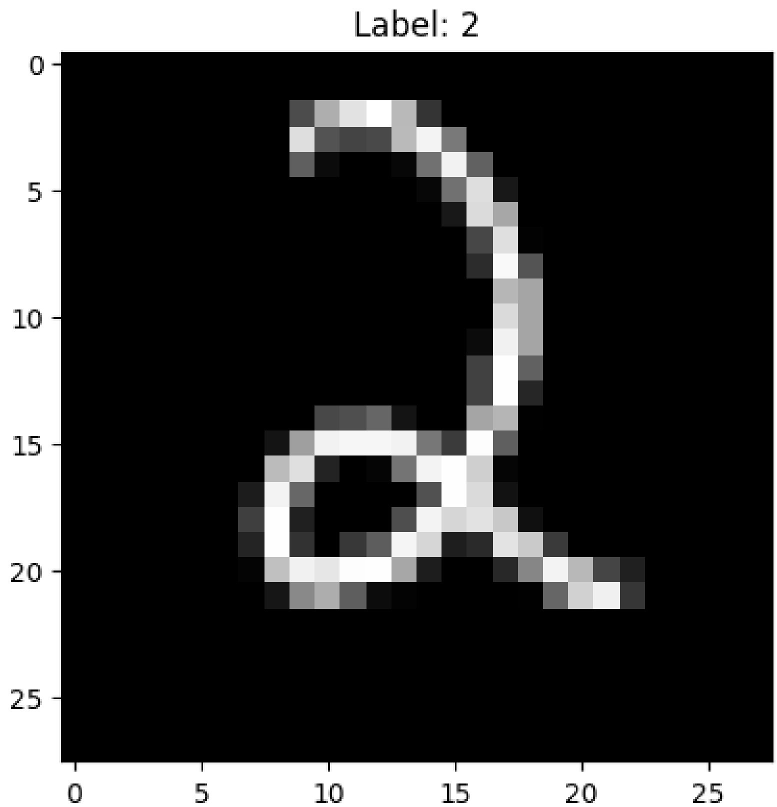
[9]:
```
[0.09016285091638565, 0.9763000011444092]
```

[TODO] Visualize test image number 47 and the prediction from the neural network

[10]:

```python
plt.imshow(x_test[47].reshape(28, 28), cmap='gray')
plt.title(f'Label: {y_test[47]}')
plt.show()

y_pred = model.predict(x_test[47][np.newaxis, :, :, :])
print(f'Predicted label: {np.argmax(y_pred)}')
```




```
1/1              0s 221ms/step
Predicted label: 2
```