

Deep Learning PhD course: Hand-in assignment 2

Joakim Lindblad

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1 Classification of hand-written digits using a Convolutional Neural Network

*The most common deep learning approach for **image classification** is the use of Convolutional Neural Networks (CNNs). They reduce the number of needed parameters over regular (fully connected) neural networks and provide reduced translation dependence which is welcome in many applications. In a typical setup there will be a sequence of convolutional layers each followed by an activation function such as ReLU or sigmoid, interspersed with spatial pooling (most often maxpooling) layers in order to enlarge the field of view. Towards the end of the network, after several convolutional and pooling layers, the high-level image features are classified by fully-connected (also called dense) layers, where all neurons or nodes are connected to all activations in the previous layer. In the final layer a softmax function maps the non-normalized output of the network to a probability distribution over predicted output classes.*

1.1 Classification of MNIST

In this assignment task you will again perform classification of the MNIST dataset, this time using a convolutional neural network instead of the fully connected network used in assignment 1b. Since it is a bit cumbersome to implement backpropagation for the convolution operations, we will here leave the do-it-yourself coding and move to a deep learning framework of your choice (e.g. PyTorch, Tensorflow, Keras, Matlab (2018b or later), MXNet, Chainer).

Exercise 1.1 *Start by implementing exactly the same (fully connected) network as you designed for the final task in Assignment 1B (Exercise 2.2) in a modern deep-learning framework of your choice (see above for examples). Try to set learning parameters to imitate your Exercise 2.2; it is fine to use the default weight initialization scheme of the framework. Compare performance with your previous results; do you observe similar accuracy? how many times faster/slower was your own implementation? (Make sure to enable GPU support if you have an Nvidia graphics card!)*

Exercise 1.2 *Let us now exchange the Fully connected architecture for a Convolution based one. Construct the network specified below in your DL-environment of choice. Train the network using standard Stochastic Gradient Descent (SGD) on the MNIST dataset. Choose a suitable mini-batch size and number of training epochs (observing a reasonable convergence) and a learning rate which gives you a good convergence without waiting forever. You are expected to reach above 98% accuracy (on the test data partition). How many learnable weights does this network contain? Compare with how many weights you had in the previous exercise.*

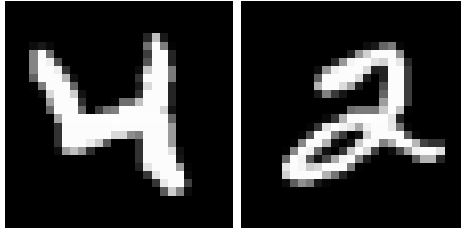


Figure 1: Two example images from the MNIST digit recognition dataset. (a) 4, (b) 2

1) Convolution	8 times $3 \times 3 \times 1$ convolutions with stride 1 and padding 1
2) ReLU	Non-linearity
3) Max Pooling	2×2 max pooling with stride 2
4) Convolution	16 times $3 \times 3 \times 8$ convolutions with stride 1 and padding 1
5) ReLU	Non-linearity
6) Max Pooling	2×2 max pooling with stride 2
7) Convolution	$32 \times 3 \times 3 \times 16$ convolutions with stride 1 and padding 1
8) ReLU	Non-linearity
9) Fully Connected	10 fully connected layer
10) Softmax	Softmax layer
11) Classification Output	Crossentropy with 10 classes

Exercise 1.3 In the previous exercise we first applied the activation function (ReLU in this case) and then performed Max pooling. What would change (accuracy, speed) if you swap the order of these two operations? Test your hypothesis empirically by exchanging layers 2 and 3, resp. layers 5 and 6, such that the pooling operation is performed before the ReLU. The difference is probably more distinct for the hyperbolic tangent activation function, why?

Exercise 1.4 Now change the optimizer, training the network with ADAM instead of SGD. It is fine to pick the default parameters proposed by your framework. (Commonly appearing default values are: GradientDecayFactor (β_1): 0.9000, SquaredGradientDecayFactor (β_2): 0.9990, ϵ : 10^{-8} .) Do you manage to get better results faster than the plain SGD optimization?

Exercise 1.5 Try a few (at least 3) variations based on what you have learned in the course so far; this could be architectural changes, various regularization approaches, change of optimization method, learning-rate scheme, change of activation function, etc. How good performance do you manage to reach?

For each of the exercises above, include in the report:

1. a plot of the training loss,
2. the classification results (on the test data partition) using classification accuracy as performance measure.

For the best performing model, also include a *confusion matrix* of the classification results on the test data partition. Provide a few examples of misclassified images (image, including a note about the real class and predicted class). Make sure to list all your used hyperparameters in the report (including default values of your chosen framework) such that someone else can try to repeat your work (reproducible research).

Information about the MNIST dataset: The MNIST dataset, illustrated in Fig. 1, consists of 60000 training images, and 10000 test images. The dataset has become a classic benchmark dataset for machine learning; do checkout the <http://yann.lecun.com/exdb/mnist/> page for some context. The version you have received is prepackaged into subfolders 'Train' and 'Test', and further into subfolders '0'-'9'. containing a number of images on the form 0000.png-xxxx.png. (Note: Each class does not have exactly the same number of images.) All images are 28×28 pixels and stored in the png-file format.

2 Semantic segmentation of Biomedical images

In *semantic image segmentation* the objective is to assign an object class to each pixel in the image. Such object classes may be foreground and background, or different objects as well as object boundaries.

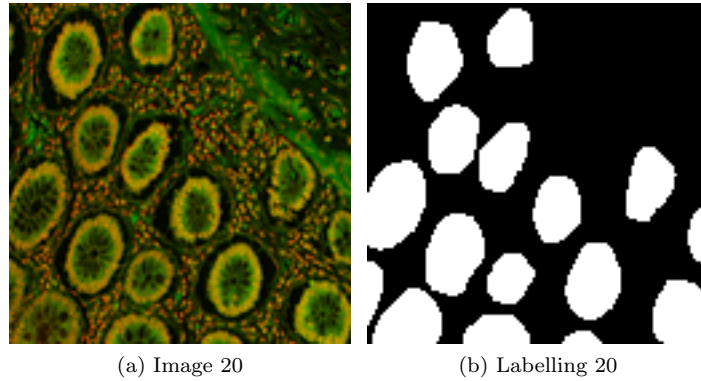


Figure 2: An example image from the Warwick biomedical dataset.

Unlike image classification where we are interested in one global label for the entire image, in segmentation we wish to perform classification of each pixel to get dense pixel-wise predictions and labels from our model.

One problem of re-purposing standard CNN architectures, which were developed for classification tasks, for dense predictions are the fully connected layers present in many architectures as we have to preserve the spatial information for the class maps. In 2014 Long et al. introduced [Fully Convolutional Networks](#) which allowed dense predictions by avoiding all fully connected layers.

Another problem in using CNNs for segmentation lies in the pooling layers. They increase the field of view to be able to aggregate context within an image, but discard a lot of the spatial information. In segmentation however, we need an exact alignment of the object class maps and our image in full spatial resolution as we want to label every pixel in it. One way to overcome this problem is either to replace pooling layers altogether and aggregate context in a bigger field of view with special convolutional layers which are often referred to as 'dilated' or 'atrous' convolutions. Another way to handle the effect of pooling layers is to recover object details in the needed spatial dimensions by so-called decoders which upsample the information which was encoded in the first part of the CNN. Instead of using simple bilinear interpolation, the interpolation can be learnt by special convolutional layers. There exists different names for them in literature: **transposed convolution**, deconvolutional layers, upconvolution, full convolution, or fractionally-strided convolution.

2.1 Segmentation of the Warwick Biomedical Dataset

In this assignment task you will segment images of Hematoxylin and Eosin (H&E) stained microscopy slides of colorectal cancer (see example in Fig. 2). The images show a group of cells that synthesize substances in the human body – so called *glands*. These are important histological structures which are present in most organ systems as the main mechanism for secreting proteins and carbohydrates. The morphology (shape) of glands is used routinely by pathologists to assess the degree of malignancy of several adenocarcinomas, including prostate, breast, lung, and colon cancers.

The dataset (WARWICK.zip) is provided including ground truth annotations by expert pathologists. To provide improved performance, the stains have been unmixed resulting in two-channel images (the blue component in the images is constant equal to zero). The task is to, given an input image, compute an output label-image which has the value one (1) where there is a gland in the image, and zero (0) otherwise.

In order to re-purpose a CNN which was developed for a classification task (e.g. the one used for the MNIST task), a few modifications have to be considered:

- The spatial dimensions of the input which have been reduced by pooling layers have to be recovered by transposed convolutions to gain exact alignment of class maps and the image.
- Do not include any fully-connected layers. The very last fully-connected layer may be replaced by a 1×1 -convolution.
- The softmax has to be taken in the channel-direction to give a class prediction per pixel.
- The loss function has to be adapted to handle a ground truth given by a binary image of the same spatial dimensions as the input image, not a single label for the entire image as in classification.

Exercise 2.1 *Design a network for semantic segmentation of the provided data set, e.g., by modifying the network you used for the MNIST classification task.*

1. *Evaluate and report the results of the segmentation on the test-set using the Sørensen–Dice coefficient as performance measure (you are expected to reach a DSC score above 0.7):*

$$DSC(A, B) = \frac{2|A \cap B|}{|A| + |B|}$$

2. *Visually inspect one of the cases (in the test-set) where the network did not perform well in terms of the evaluation metric, and try to describe what you think makes that instance challenging in comparison to the other instances. Include the examples as images in your report.*

Exercise 2.2 *Evaluate on the same segmentation task three different techniques described in lectures 6 and 7 with an aim to improve the performance on unseen data. Here you probably want to split the training data into training+validation when performing parameter tuning. Complement in the report raw performance figures with your own subjective opinions regarding the different techniques.*

Information about the WARWICK dataset: The WARWICK dataset, illustrated in Fig. 2, as presented for this assignment consists of 85 training images, and 60 test images, each of size 128×128 and with a binary mask indicating Glandular regions in the images. This is a selected and pre-processed part (colors are unmixed and images are resized) of the Warwick-QU dataset (released with the MICCAI'2015 GlaS contest). See <https://warwick.ac.uk/fac/sci/dcs/research/tia/glascontest/download/> for information about the original data.