# **Deep Learning**

# 3007/7059 Artificial Intelligence

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#### Required packages:

- Python version 3.5
- numpy version 1.10 or later: http://www.numpy.org/
- scipy version 0.16 or later: http://www.scipy.org/
- matplotlib version 1.4 or later: http://matplotlib.org/
- pandas version 0.16 or later: http://pandas.pydata.org
- scikit-learn version 0.15 or later: http://scikit-learn.org
- keras version 2.0 or later: http://keras.io
- tensorflow version 1.0 or later: https://www.tensorflow.org
- ipython/jupyter version 4.0 or later, with notebook support

#### Optional packages:

- pyyaml
- hdf5 and h5py (required if you use model saving/loading functions in keras)
- NVIDIA cuDNN if you have NVIDIA GPUs on your machines. https://developer.nvidia.com/rdp/cudnn-download
- Anaconda (from Continuum) has most of the packages above.

In [1]:

import numpy as np

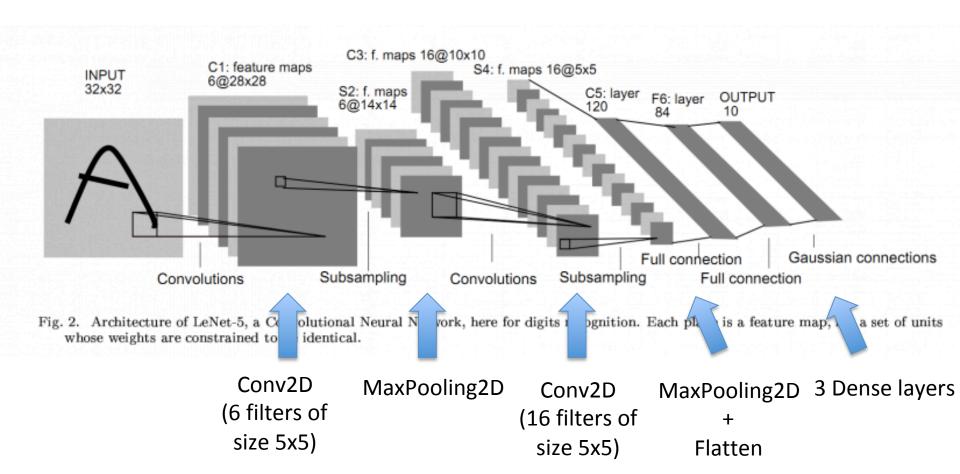
- ./jupyter notebook
- Test your packages

```
import scipy as sp
        import pandas as pd
        import matplotlib
        import matplotlib.pyplot as plt
        import matplotlib
        import IPython
        import sklearn
        import keras
        Using TensorFlow backend.
In [2]: print('numpy:', np. version_)
        print('scipy:', sp. version )
        print('matplotlib:', matplotlib. version )
        print('iPython:', IPython. version )
        print('scikit-learn:', sklearn. version )
        print('keras: ', keras. version )
        import tensorflow as tf
        print('Tensorflow: ', tf. version )
        numpy: 1.13.3
        scipy: 1.0.0
        matplotlib: 2.1.0
        iPython: 6.2.1
        scikit-learn: 0.19.1
        keras: 2.1.2
        Tensorflow: 1.4.0
```

Load Keras packages for the CNN layers

```
In [3]: from keras.datasets import mnist
  from keras.models import Sequential
  from keras.layers import Dense, Flatten
  from keras.layers import Conv2D, MaxPooling2D
  from keras import backend as K
```

- mnist has the MNIST dataset
- Sequential model is a linear stack of layers
- Dense, Flatten, Conv2D and MaxPooling2D are the layer types we will use



- 1. Why feature maps change sizes during convolution? How can I avoid that?
- 2. How is the 2D convolution done with 6 channels of 14x14 inputs?

#### Training parameters

- batch\_size: number of images at each step of gradient descent
- num\_classes: number of MNIST classes (10)
- epochs: number of times the whole training set is used for training
- img\_rows, img\_cols: image size

```
In [4]: # batch size for gradient descent
batch_size = 128
# number of MNIST classes
num_classes = 10
# number of epochs (1 epoch = amount of iterations that covers the whole training set)
epochs = 3 # try a larger number of epochs here (for example 10 or larger)
# input image dimensions
img_rows, img_cols = 28, 28
```

Loading the data, and adjusting image dimensions

```
In [5]: # the data, split between train and test sets
   (x_train, y_train), (x_test, y_test) = mnist.load_data()

In [6]: # adjust training image format
   if K.image_data_format() == 'channels_first':
        x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
        x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
        input_shape = (1, img_rows, img_cols)
   else:
        x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
        x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
        input_shape = (img_rows, img_cols, 1)
```

- Type casting input to be float32
- Normalizing gray values to be in [0,1]
- Verifying training and testing sets

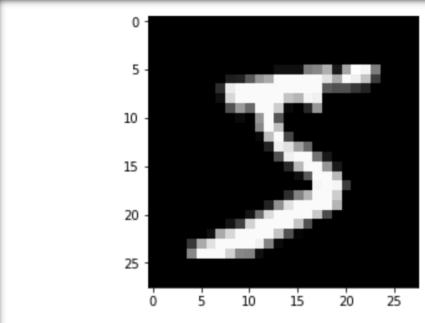
10000 test samples

```
In [7]: x_train = x_train.astype('float32')
    x_test = x_test.astype('float32')
    x_train /= 255
    x_test /= 255
    print('x_train shape:', x_train.shape)
    print(x_train.shape[0], 'train samples')
    print(x_test.shape[0], 'test samples')

x_train shape: (60000, 28, 28, 1)
    60000 train samples
```

Visualizing the dataset

```
In [8]: for i in range(10):
    first_image = x_train[i,:,:,0]
    first_image = np.array(first_image, dtype='float')
    pixels = first_image.reshape((28, 28))
    plt.imshow(pixels, cmap='gray')
    plt.show()
```



Convert labels to one-hot vectors

```
In [9]: # convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)
```

- Example
  - $-4 \rightarrow [0000100000]$
  - $-9 \rightarrow [000000001]$

 Cross-entropy loss function – see explanation on the board.

#### Create Model

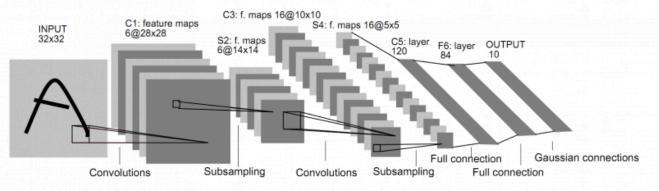
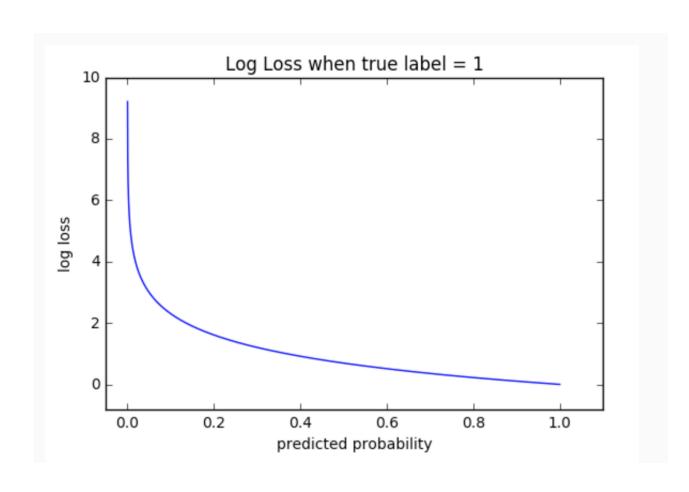


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

- Configuring the learning process:
  - An optimizer. This could be the string identifier of an existing optimizer (such as rmsprop or adagrad), or an instance of the Optimizer class. See: optimizers.
  - A loss function. This is the objective that the model will try to minimize. It can be the string identifier of an existing loss function (such as categorical\_crossentropy or mse), or it can be an objective function. See: losses.
  - A list of metrics. For any classification problem you will want to set this to metrics=['accuracy']. A metric could be the string identifier of an existing metric or a custom metric function.

# Cross entropy loss when true label is 1



Training... finally!

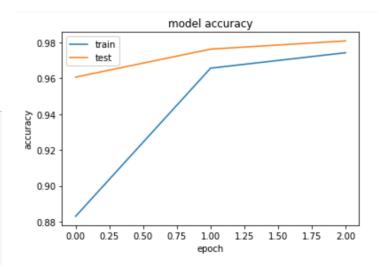
Running the classifier

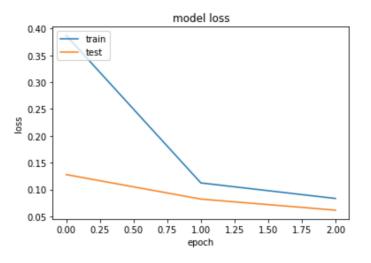
```
In [13]: score = model.evaluate(x_test, y_test, verbose=0)
    print('Test loss:', score[0])
    print('Test accuracy:', score[1])

Test loss: 0.0736543145942
    Test accuracy: 0.9751
```

#### Plot graphs

```
In [15]: # summarize history for accuracy
         plt.plot(history.history['acc'])
         plt.plot(history.history['val acc'])
         plt.title('model accuracy')
         plt.ylabel('accuracy')
         plt.xlabel('epoch')
         plt.legend(['train', 'test'], loc='upper left')
         plt.show()
         # summarize history for loss
         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 left')
         plt.show()
```





### **LSTMs**

 Let's look at a couple of LSTM examples – just for fun, this is not going to be in your exam...