Deep Learning — Assignment 2 (update 2020.09.10)

Second assignment for the 2020 Deep Learning course (NWI-IMC058) of the Radboud University.

Twan van Laarhoven (tvanlaarhoven@cs.ru.nl) and Gijs van Tulder (g.vantulder@cs.ru.nl)

September 2020

Names: Mick Tuit, Maurice Verbrugge

Group: 1

Instructions:

- Fill in your names and the name of your group.
- Answer the questions and complete the code where necessary.
- Re-run the whole notebook before you submit your work.
- Save the notebook as a PDF and submit that in Brightspace together with the `.ipynb` notebook file.
- The easiest way to make a PDF of your notebook is via File > Print Preview and then use your browser's print option to print to PDF.

Objectives

In this assignment you will

1. Learn how to define and train a neural network with pytorch
2. Experiment with convolutional neural networks
3. Investigate the effect of dropout and batch normalization

Required software

If you haven't done so already, you will need to install the following additional libraries:

- `torch` and `torchvision` for PyTorch,
- `d2l` , the library that comes with [Dive into deep learning (https://d2l.ai)](https://d2l.ai) book,
- `sounddevice` to play audio,
- `python_speech_features` to compute MFCC features.

All libraries can be installed with `pip install` .

In [52]:

```
%matplotlib inline

!pip install d2l
!pip install python_speech_features
```

```
Requirement already satisfied: d2l in /usr/local/lib/python3.6/dist-
packages (0.14.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dis
t-packages (from d2l) (1.18.5)
Requirement already satisfied: jupyter in /usr/local/lib/python3.6/d
ist-packages (from d2l) (1.0.0)
Requirement already satisfied: pandas in /usr/local/lib/python3.6/di
st-packages (from d2l) (1.0.5)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.
6/dist-packages (from d2l) (3.2.2)
Requirement already satisfied: nbconvert in /usr/local/lib/python3.
6/dist-packages (from jupyter->d2l) (5.6.1)
Requirement already satisfied: ipykernel in /usr/local/lib/python3.
6/dist-packages (from jupyter->d2l) (4.10.1)
Requirement already satisfied: ipywidgets in /usr/local/lib/python3.
6/dist-packages (from jupyter->d2l) (7.5.1)
Requirement already satisfied: jupyter-console in /usr/local/lib/pyt
hon3.6/dist-packages (from jupyter->d2l) (5.2.0)
Requirement already satisfied: notebook in /usr/local/lib/python3.6/
dist-packages (from jupyter->d2l) (5.3.1)
Requirement already satisfied: qtconsole in /usr/local/lib/python3.
6/dist-packages (from jupyter->d2l) (4.7.7)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python
3.6/dist-packages (from pandas->d2l) (2018.9)
Requirement already satisfied: python-dateutil>=2.6.1 in /usr/local/
lib/python3.6/dist-packages (from pandas->d2l) (2.8.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python
3.6/dist-packages (from matplotlib->d2l) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/p
ython3.6/dist-packages (from matplotlib->d2l) (1.2.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.
0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->d2l)
(2.4.7)
Requirement already satisfied: entrypoints>=0.2.2 in /usr/local/lib/
python3.6/dist-packages (from nbconvert->jupyter->d2l) (0.3)
Requirement already satisfied: pygments in /usr/local/lib/python3.6/
dist-packages (from nbconvert->jupyter->d2l) (2.6.1)
Requirement already satisfied: jupyter-core in /usr/local/lib/python
3.6/dist-packages (from nbconvert->jupyter->d2l) (4.6.3)
Requirement already satisfied: bleach in /usr/local/lib/python3.6/di
st-packages (from nbconvert->jupyter->d2l) (3.1.5)
Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/pyth
on3.6/dist-packages (from nbconvert->jupyter->d2l) (4.3.3)
Requirement already satisfied: nbformat>=4.4 in /usr/local/lib/pytho
n3.6/dist-packages (from nbconvert->jupyter->d2l) (5.0.7)
Requirement already satisfied: defusedxml in /usr/local/lib/python3.
6/dist-packages (from nbconvert->jupyter->d2l) (0.6.0)
Requirement already satisfied: mistune<2,>=0.8.1 in /usr/local/lib/p
ython3.6/dist-packages (from nbconvert->jupyter->d2l) (0.8.4)
Requirement already satisfied: testpath in /usr/local/lib/python3.6/
dist-packages (from nbconvert->jupyter->d2l) (0.4.4)
Requirement already satisfied: pandocfilters>=1.4.1 in /usr/local/li
b/python3.6/dist-packages (from nbconvert->jupyter->d2l) (1.4.2)
Requirement already satisfied: jinja2>=2.4 in /usr/local/lib/python
3.6/dist-packages (from nbconvert->jupyter->d2l) (2.11.2)
Requirement already satisfied: ipython>=4.0.0 in /usr/local/lib/pyth
on3.6/dist-packages (from ipykernel->jupyter->d2l) (5.5.0)
Requirement already satisfied: jupyter-client in /usr/local/lib/pyth
on3.6/dist-packages (from ipykernel->jupyter->d2l) (5.3.5)
Requirement already satisfied: tornado>=4.0 in /usr/local/lib/python
3.6/dist-packages (from ipykernel->jupyter->d2l) (5.1.1)
```

```
Requirement already satisfied: widgetsnbextension~=3.5.0 in /usr/loc
al/lib/python3.6/dist-packages (from ipywidgets->jupyter->d2l) (3.5.
1)
Requirement already satisfied: prompt-toolkit<2.0.0,>=1.0.0 in /usr/
local/lib/python3.6/dist-packages (from jupyter-console->jupyter->d2
l) (1.0.18)
Requirement already satisfied: Send2Trash in /usr/local/lib/python3.
6/dist-packages (from notebook->jupyter->d2l) (1.5.0)
Requirement already satisfied: terminado>=0.8.1 in /usr/local/lib/py
thon3.6/dist-packages (from notebook->jupyter->d2l) (0.8.3)
Requirement already satisfied: ipython-genutils in /usr/local/lib/py
thon3.6/dist-packages (from notebook->jupyter->d2l) (0.2.0)
Requirement already satisfied: pyzmq>=17.1 in /usr/local/lib/python
3.6/dist-packages (from qtconsole->jupyter->d2l) (19.0.2)
Requirement already satisfied: qtpy in /usr/local/lib/python3.6/dist
-packages (from qtconsole->jupyter->d2l) (1.9.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/
dist-packages (from python-dateutil>=2.6.1->pandas->d2l) (1.15.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.
6/dist-packages (from bleach->nbconvert->jupyter->d2l) (20.4)
Requirement already satisfied: webencodings in /usr/local/lib/python
3.6/dist-packages (from bleach->nbconvert->jupyter->d2l) (0.5.1)
Requirement already satisfied: decorator in /usr/local/lib/python3.
6/dist-packages (from traitlets>=4.2->nbconvert->jupyter->d2l) (4.4.
2)
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in /usr/loca
l/lib/python3.6/dist-packages (from nbformat>=4.4->nbconvert->jupyte
r->d2l) (2.6.0)
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/py
thon3.6/dist-packages (from jinja2>=2.4->nbconvert->jupyter->d2l)
(1.1.1)
Requirement already satisfied: pexpect; sys_platform != "win32" in /
usr/local/lib/python3.6/dist-packages (from ipython>=4.0.0->ipykerne
l->jupyter->d2l) (4.8.0)
Requirement already satisfied: pickleshare in /usr/local/lib/python
3.6/dist-packages (from ipython>=4.0.0->ipykernel->jupyter->d2l) (0.
7.5)
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/py
thon3.6/dist-packages (from ipython>=4.0.0->ipykernel->jupyter->d2l)
(50.3.0)
Requirement already satisfied: simplegeneric>0.8 in /usr/local/lib/p
ython3.6/dist-packages (from ipython>=4.0.0->ipykernel->jupyter->d2
l) (0.8.1)
Requirement already satisfied: wcwidth in /usr/local/lib/python3.6/d
ist-packages (from prompt-toolkit<2.0.0,>=1.0.0->jupyter-console->ju
pyter->d2l) (0.2.5)
Requirement already satisfied: ptyprocess; os_name != "nt" in /usr/l
ocal/lib/python3.6/dist-packages (from terminado>=0.8.1->notebook->j
upyter->d2l) (0.6.0)
Requirement already satisfied: python_speech_features in /usr/local/
lib/python3.6/dist-packages (0.6)
```

In [53]:

```
!git clone https://github.com/Jakobovski/free-spoken-digit-dataset
```

```
fatal: destination path 'free-spoken-digit-dataset' already exists a
nd is not an empty directory.
```

In [54]:

```
import os
import numpy as np
from d2l import torch as d2l
import torch
from torch import nn
from scipy.io import wavfile
```

2.1 Digits dataset

The d2l book uses a dataset of images as a running example (FashionMNIST). In this assignment we will investigate CNNs in a completely different domain: speech recognition.

The dataset we use is the free spoken digits dataset, which can be found on https://github.com/Jakobovski/free-spoken-digit-dataset (https://github.com/Jakobovski/free-spoken-digit-dataset). This dataset consists of the digits 0 to 9, spoken by different speakers. The data comes as .wav files.

Use `git clone` to download the dataset.

Below is a function to load the data. We pad/truncate each sample to the same length. The raw audio is usually stored in 16 bit integers, with a range -32768 to 32767, where 0 represents no signal. Before using the data, it should be normalized. A common approach is to make sure that the data is between 0 and 1 or between -1 and 1.

Update the below code to normalize the data to a reasonable range

In [55]:

```
samplerate = 8000
def load_waveform(file, size = 6000):
    samplerate, waveform = wavfile.read(file)
    # Take first 6000 samples from waveform. With a samplerate of 8000 that corr
esponds to 3/4 second
    # Pad with 0s if the file is shorter
    waveform = np.pad(waveform,(0,size))[0:size]
    # Normalize waveform
    # DONE: Your code here.
    # using RMS
    # waveform = waveform / (np.sqrt(np.sum(waveform ** 2)) + 1e-16)
    # to [-1:1]
    max_wav = max(waveform)
    waveform = waveform / max_wav
    return waveform
```

The following code loads all .wav files in a directory, and makes it available in a pytorch dataset.

Load the data into a variable `data`

In [56]:

```
class SpokenDigits(torch.utils.data.Dataset):
    def __init__(self, data_dir):
        digits_x = []
        digits_y = []
        for file in os.listdir(data_dir):
            if file.endswith(".wav"):
                waveform = load_waveform(os.path.join(data_dir, file))
                label = int(file[0])
                digits_x.append(waveform)
                digits_y.append(label)
        # convert to torch tensors
        self.x = torch.from_numpy(np.array(digits_x, dtype=np.float32))
        self.x = self.x.unsqueeze(1) # One channel
        self.y = torch.from_numpy(np.array(digits_y))

    def __len__(self):
        return len(self.x)

    def __getitem__(self, idx):
        return self.x[idx], self.y[idx]

# DONE: Your code here.
data = SpokenDigits("free-spoken-digit-dataset/recordings")
help(data)
print("Length of dataset is: ", len(data))
print("Dimension of a sample is: ", data.x[0].shape)
print("Number of classes are: ", len(torch.unique(data.y)))
```

```
Help on SpokenDigits in module __main__ object:

class SpokenDigits(torch.utils.data.dataset.Dataset)
 |  An abstract class representing a :class:`Dataset`.
 |
 |  All datasets that represent a map from keys to data samples shou
ld subclass
 |  it. All subclasses should overwrite :meth:`__getitem__`, support
ing fetching a
 |  data sample for a given key. Subclasses could also optionally ov
erwrite
 |  :meth:`__len__`, which is expected to return the size of the dat
aset by many
 |  :class:`~torch.utils.data.Sampler` implementations and the defau
lt options
 |  of :class:`~torch.utils.data.DataLoader`.
 |
 |  .. note::
 |    :class:`~torch.utils.data.DataLoader` by default constructs a
index
 |    sampler that yields integral indices.  To make it work with a
map-style
 |    dataset with non-integral indices/keys, a custom sampler must
be provided.
 |
 |  Method resolution order:
 |      SpokenDigits
 |      torch.utils.data.dataset.Dataset
 |      builtins.object
 |
 |  Methods defined here:
 |
 |  __getitem__(self, idx)
 |
 |  __init__(self, data_dir)
 |      Initialize self.  See help(type(self)) for accurate signatur
e.
 |
 |  __len__(self)
 |
 |  ----------------------------------------------------------------
------
 |  Methods inherited from torch.utils.data.dataset.Dataset:
 |
 |  __add__(self, other)
 |
 |  ----------------------------------------------------------------
------
 |  Data descriptors inherited from torch.utils.data.dataset.Datase
t:
 |
 |  __dict__
 |      dictionary for instance variables (if defined)
 |
 |  __weakref__
 |      list of weak references to the object (if defined)

Length of dataset is:  3000
Dimension of a sample is:  torch.Size([1, 6000])
Number of classes are:  10
```

Describe the dataset: how many samples are there, what is their dimensionality? How many classes are there?

DONE: your answer here.

The dataset contains 3000 samples. The dimension of a sample is [1, 6000] and the number of different classes is 10.

Here is code to play samples from the dataset to give you an idea what it "looks" like.

In [57]:

```
# import sounddevice as sd
# # errors on Deepnote

# def play(sample):
#     sd.play(sample[0][0], samplerate)
#     print(sample[1])
# play(data[0])
```

In [58]:

```
train_prop = 2/3
train_count = int(len(data) * train_prop)
train, test = torch.utils.data.random_split(data, [train_count, len(data)-train_
count])
```

The code above is code to split the data into a training and test set. It uses 2/3 of the data for training.

Discuss an advantage and disadvantage of using more of the data for training

DONE: your answer here.

An advantage of using more data for the training would be that it results in faster learning. A disadvantage would be that you are more likely to overfit on the training set.

Finally, we split the data into batches:

In [59]:

```
data_params = {'batch_size': 32}
train_iter = torch.utils.data.DataLoader(train, **data_params)
test_iter  = torch.utils.data.DataLoader(test,  **data_params)
```

2.2 One dimensional convolutional neural network

We will now define a network architecture. We will use a combination of convolutional layers and pooling. Note that we use 1d convolution and pooling here, instead of the 2d operations used for images.

Complete the network architecture, look at the d2l book chapters 6 and 7 for examples

In [62]:

```
net = torch.nn.Sequential(
    nn.Conv1d(1, 4, kernel_size=5), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    # TODO: Add three more convolutional layers, ReLU layers and pooling layers;
    #       doubling the number of channels each time
    # TODO: Your code here.
    nn.Conv1d(4, 8, kernel_size=5), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    nn.Conv1d(8, 16, kernel_size=5), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    nn.Conv1d(16, 32, kernel_size=5), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    nn.Flatten(),
    nn.Linear(11872, 128), nn.ReLU(),
    nn.Linear(128, 64), nn.ReLU(),
    nn.Linear(64, 10))
```

In [63]:

```
# print(summary(net, (1, 6000)))
# does not work in colab
```

The first fully connected layer has input dimension 11872, where does that number come from?

DONE: your answer here

Through the convolutions and pooling layers the dimensions of the data is changed. At the first layer, the input size of 6000 is reduced by the kernel size + 1, which gives 6000-5+1=5996. The pooling layer effectively divides this by 2, resulting in 5996/2=2998. Next layers do the same, leading to 371x32=11872 parameters. Below the whole calculation is written out using tensorflow summary for ease of use.If you multiply the dimensions (32 x 371) (the flatten operation) of the the last layer before the fully connected layer you get the number 11872.

```
# This is formatted as code
Conv1d-1              [-1, 4, 5996]              24
              ReLU-2              [-1, 4, 5996]               0
         AvgPool1d-3              [-1, 4, 2998]               0
            Conv1d-4              [-1, 8, 2994]             168
              ReLU-5              [-1, 8, 2994]               0
         AvgPool1d-6              [-1, 8, 1497]               0
            Conv1d-7             [-1, 16, 1493]             656
              ReLU-8             [-1, 16, 1493]               0
         AvgPool1d-9              [-1, 16, 746]               0
           Conv1d-10              [-1, 32, 742]           2,592
             ReLU-11              [-1, 32, 742]               0
        AvgPool1d-12              [-1, 32, 371]               0
          Flatten-13               [-1, 11872]               0
           Linear-14                 [-1, 128]       1,519,744
             ReLU-15                 [-1, 128]               0
           Linear-16                  [-1, 64]           8,256
             ReLU-17                  [-1, 64]               0
           Linear-18                  [-1, 10]             650
================================================================
Total params: 1,532,090
Trainable params: 1,532,090
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.02
Forward/backward pass size (MB): 1.92
Params size (MB): 5.84
Estimated Total Size (MB): 7.78
----------------------------------------------------------------
```

How many parameters are there in the model? I.e. the total number of weights and biases

In [64]:

```
# DONE: Compute the number of parameters
# Hint: use net.parameters() and param.nelement()

print('Amount of parameters in network is:', sum([param.nelement() for param in
net.parameters()]))
```

```
Amount of parameters in network is: 1532090
```

Suppose that instead of using convolutions, we had used only fully connected layers. How many parameters would be needed in that case approximately?

DONE: your answer here

When using fully connected layers the dimensions of a layer are not being changed and would remain the same. So you would get (4, 5996) after the first Convolution, this would then be the same for the next 3 layers. This would mean you would have 4 *(4* \ 5996) parameters. Then from 23984 to 128 in a fully connected layer, then (128, 64), then a layer with (64, 10). This results in a total of 31,747,20 parameters.

The FashionMNIST dataset used in the book has 60000 training examples. How large is our training set? How would the difference affect the number of epochs that we need? Compare to chapter 6.6 and 7.1 of the book.

How many epochs do you think are needed?

Answer: We have 3000 training examples. The FashionMNIST training size is a factor 20 larger than our dataset, so for approximations sake we will say the number of epochs also needs to increase by a factor of 20 resulting in $10 * 20 = 200$, assuming the learning rate is the same.

In [65]:

```
lr, num_epochs = 0.01, 200
```

We will use the code from the d2l book to train the network. In particular, the `train_ch6` function, defined in [chapter 6.6 (http://d2l.ai/chapter_convolutional-neural-networks/lenet.html#training)](http://d2l.ai/chapter_convolutional-neural-networks/lenet.html#training). This function is available in the `d2l` library. However, this function has a bug: it only initializes the weights for 2d convolutional layers, not for 1d convolutional layers.

Make a copy of the train_ch6 function, and correct the error

In [66]:

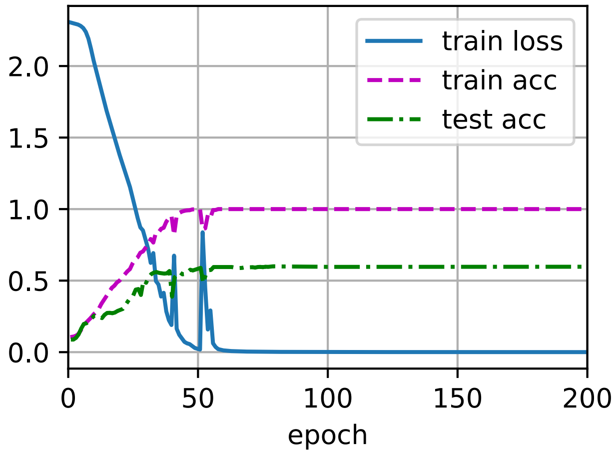
```
def train(net, train_iter, test_iter, num_epochs, lr, device=d2l.try_gpu()):
    # DONE: your code here (copied and corrected from train_ch6)
    """Train a model with a GPU (defined in Chapter 6)."""
    def init_weights(m):
        if type(m) == nn.Linear or type(m) == nn.Conv1d:
            torch.nn.init.xavier_uniform_(m.weight)
    net.apply(init_weights)
    print('training on', device)
    net.to(device)
    optimizer = torch.optim.SGD(net.parameters(), lr=lr)
    loss = nn.CrossEntropyLoss()
    animator = d2l.Animator(xlabel='epoch', xlim=[0, num_epochs],
                            legend=['train loss', 'train acc', 'test acc'])
    timer = d2l.Timer()
    for epoch in range(num_epochs):
        # Sum of training loss, sum of training accuracy, no. of examples
        metric = d2l.Accumulator(3)
        for i, (X, y) in enumerate(train_iter):
            timer.start()
            net.train()
            optimizer.zero_grad()
            X, y = X.to(device), y.to(device)
            y_hat = net(X)
            l = loss(y_hat, y)
            l.backward()
            optimizer.step()
            with torch.no_grad():
                metric.add(l * X.shape[0], d2l.accuracy(y_hat, y), X.shape[0])
            timer.stop()
            train_loss = metric[0]/metric[2]
            train_acc = metric[1]/metric[2]
            if (i + 1) % 50 == 0:
                animator.add(epoch + i / len(train_iter),
                             (train_loss, train_acc, None))
        test_acc = d2l.evaluate_accuracy_gpu(net, test_iter)
        animator.add(epoch+1, (None, None, test_acc))
    print(f'loss {train_loss:.3f}, train acc {train_acc:.3f}, '
          f'test acc {test_acc:.3f}')
    print(f'{metric[2] * num_epochs / timer.sum():.1f} examples/sec '
          f'on {str(device)}')
```

Now train the network.

In [67]:

```
train(net, train_iter, test_iter, num_epochs, lr)
```

```
loss 0.000, train acc 1.000, test acc 0.597
8828.0 examples/sec on cuda:0
```



Is the training converged?

If the training has not converged, maybe you need to change the number of epochs and/or the learning rate.

DONE: steps with the initial lr=0.01 and 200 epochs the training converges.

1. initial nr of epochs is 200, can be reduced to 150 (in the run used for this answer, in a lucky case convergence is achieved faster), after this nr of epchs the test accuracy doesn't improve. The initial learning rate was 0.01 for step 2 we reduced this to 0.001.
2. The network learns slow, too slow. So the learning rate should be higher. Lets try 0.005.
3. that doesn't work either.
4. back to the inital values, it is interesting to see that convergence commences already within 10 epochs

2.3 Questions and evaluation

Does the network look like it is overfitting or underfitting?

In [67]:

```

```

DONE: it overfits, because the training loss goes to zero, however the test accuracy stays behind.

Is what we have here a good classifier? Could it be used in a realistic application?

DONE: So, no this not a good classifier, it will not be applicable to a realistic application, because when used on unseen data it isn't accurate.

Do you think there is enough training data compared to the dimensions of the data and the number of parameters?

DONE: the rule of thumb is to have the same order of samples compared to the number of parameters. This is not the case 1.5M vs 0.003M

How could the classifier be improved?

DONE: prune connections by using dropout, so the fit is 'made less strong'.

The free spoken digits datasets has recordings from several different speakers. Is the test set accuracy a good measure of how well the trained network would perform for recognizing the voice of a new speaker? And if not, how could that be tested instead?

DONE: you should have a training batch of speaker X and then have a different speaker for the test. You could for instance use one speaker exclusively for the test set. Another approach is randomization of all the samples, by change the test sets will than have various speakers.

> Indented block

2.4 Variations

One way in which the training might be improved is with dropout or with batch normalization.

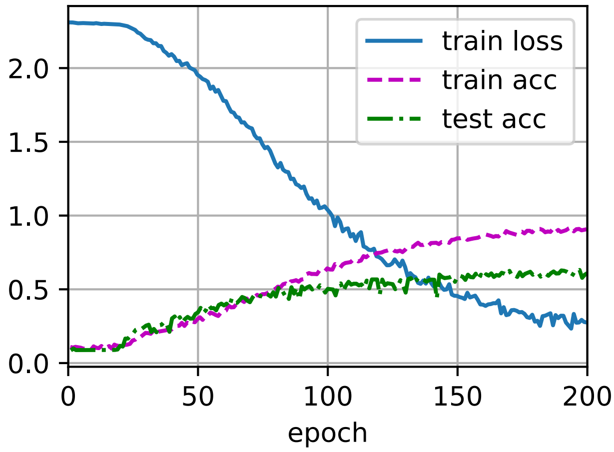
Make a copy of the network architecture below, and add dropout

Hint: see chapter 7.1 (http://d2l.ai/chapter_convolutional-modern/alexnet.html#architecture) for an example that uses dropout.

In [68]:

```
net_dropout = torch.nn.Sequential(
    nn.Conv1d(1, 4, kernel_size=5), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    # TODO: Add three more convolutional layers, ReLU layers and pooling layers;
    #       doubling the number of channels each time
    # TODO: Your code here.
    nn.Conv1d(4, 8, kernel_size=5), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    nn.Conv1d(8, 16, kernel_size=5), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    nn.Conv1d(16, 32, kernel_size=5), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    nn.Flatten(),
    nn.Linear(11872, 128), nn.ReLU(),
    nn.Dropout(p=0.5),

    nn.Linear(128, 64), nn.ReLU(),
    nn.Dropout(p=0.5),

    nn.Linear(64, 10))

train(net_dropout, train_iter, test_iter, num_epochs, lr)
```

```
loss 0.280, train acc 0.907, test acc 0.610
8548.4 examples/sec on cuda:0
```



How does dropout change the results?

DONE: the training now shows a jumpy behaviour, because 50% of the connections is thrown away every minibatch. Furthermore, if you look closely the test accuracy worsens around 150 epochs (in the instance we checked). And last but not least, this network performs better, the final test accuracy is 74% (that is more than 20% extra)

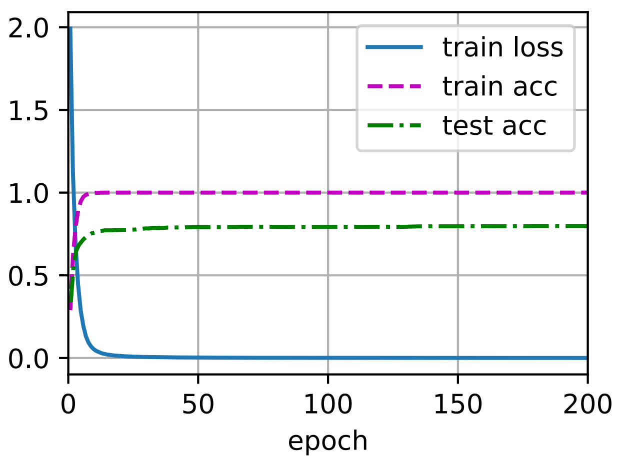
Make a copy of the original network architecture, and add batch normalization to all convolutional and linear layers.

Hint: see [chapter 7.5 (http://d2l.ai/chapter_convolutional-modern/batch-norm.html#concise-implementation)](http://d2l.ai/chapter_convolutional-modern/batch-norm.html#concise-implementation) for an example.

In [69]:

```
net_batchnorm = torch.nn.Sequential(
    nn.Conv1d(1, 4, kernel_size=5),
    nn.BatchNorm1d(4), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    # TODO: Add three more convolutional layers, ReLU layers and pooling layers;
    #       doubling the number of channels each time
    # TODO: Your code here.
    nn.Conv1d(4, 8, kernel_size=5), nn.ReLU(),
    nn.BatchNorm1d(8), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    nn.Conv1d(8, 16, kernel_size=5), nn.ReLU(),
    nn.BatchNorm1d(16), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    nn.Conv1d(16, 32, kernel_size=5), nn.ReLU(),
    nn.BatchNorm1d(32), nn.ReLU(),
    nn.AvgPool1d(kernel_size=2, stride=2),

    nn.Flatten(),
    nn.Linear(11872, 128), nn.ReLU(),
    nn.Linear(128, 64), nn.ReLU(),
    nn.Linear(64, 10))

train(net_batchnorm, train_iter, test_iter, num_epochs, lr)
```

```
loss 0.000, train acc 1.000, test acc 0.798
6554.6 examples/sec on cuda:0
```



How does batch normalization change the results?

DONE: the Batch Normalisation 'accelates convergence' extremely, you could reduce the nr of epochs safely to 50. The network however still overfits but a test accuracy of 81% is the best so far.

2.5 Bonus: feature extraction

Given enough training data a deep neural network can learn to extract features from raw data like audio and images. However, in some cases it is still necesary to do manual feature extraction. For speech recognition, a popular class of features are [MFCCs (https://en.wikipedia.org/wiki/Mel-frequency_cepstrum)](https://en.wikipedia.org/wiki/Mel-frequency_cepstrum).

Here is code to extract these features. You will need to install the `python_speech_features` first.

In [70]:

```
from python_speech_features import mfcc

def load_waveform_mfcc(file, size = 6000):
    samplerate, waveform = wavfile.read(file)
    waveform = np.pad(waveform,(0,size))[0:size] / 32768
    return np.transpose(mfcc(waveform, samplerate))
```

Implement a variation of the dataset that uses these features

In [71]:

```
class SpokenDigitsMFCC(torch.utils.data.Dataset):
    # DONE: Your code here.
    def __init__(self, data_dir):
        digits_x = []
        digits_y = []
        for file in os.listdir(data_dir):
            if file.endswith(".wav"):
                waveform = load_waveform_mfcc(os.path.join(data_dir, file))
                label = int(file[0])
                digits_x.append(waveform)
                digits_y.append(label)
        # convert to torch tensors
        self.x = torch.from_numpy(np.array(digits_x, dtype=np.float32))
        self.y = torch.from_numpy(np.array(digits_y))

    def __len__(self):
        return len(self.x)

    def __getitem__(self, idx):
        return self.x[idx], self.y[idx]
    pass

data_mfcc = SpokenDigitsMFCC("free-spoken-digit-dataset/recordings") # DONE: you
r data directory here
train_count_mfcc = int(len(data_mfcc) * train_prop)
train_mfcc, test_mfcc = torch.utils.data.random_split(data, [train_count_mfcc, l
en(data_mfcc)-train_count_mfcc])
train_iter_mfcc = torch.utils.data.DataLoader(train_mfcc, **data_params)
test_iter_mfcc  = torch.utils.data.DataLoader(test_mfcc,  **data_params)
```

The MFCC features will have 13 channels instead of 1 (the `unsqueeze` operation is not needed).

Inspect the shape of the data, and define a new network architecture that accepts data with this shape

In [72]:

```
print("Length of dataset is: ", len(data_mfcc))
print("Dimension of a sample is: ", data_mfcc.x[0].shape)
print("Number of classes are: ", len(torch.unique(data_mfcc.y)))
```

```
Length of dataset is:  3000
Dimension of a sample is:  torch.Size([13, 74])
Number of classes are:  10
```

Train the network with the mfcc features.

In [73]:

```
mfcc_epochs = 50
```

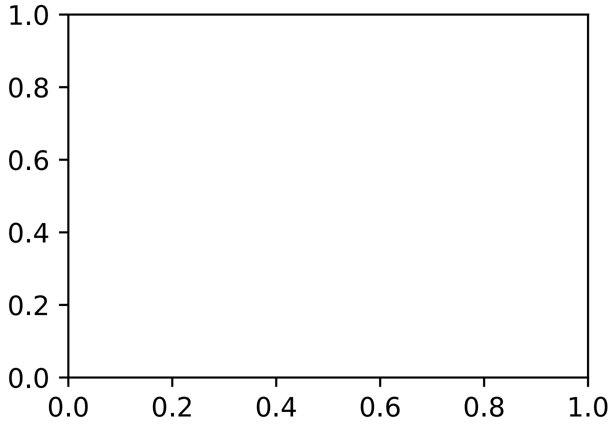
In [74]:

```
# Your code here.
net_mfcc = torch.nn.Sequential(
    nn.Conv2d(1, 4, kernel_size=3),
    nn.BatchNorm1d(4), nn.ReLU(),
    # nn.AvgPool1d(kernel_size=2, stride=2),

    # DONE: Add three more convolutional layers, ReLU layers and pooling layers;
    #       doubling the number of channels each time
    # DONE: Your code here.
    # nn.Conv1d(4, 8, kernel_size=5), nn.ReLU(),
    # nn.BatchNorm1d(8), nn.ReLU(),
    # nn.AvgPool1d(kernel_size=2, stride=2),

    # nn.Conv1d(8, 16, kernel_size=5), nn.ReLU(),
    # nn.BatchNorm1d(16), nn.ReLU(),
    # nn.AvgPool1d(kernel_size=2, stride=2),

    # nn.Conv1d(16, 32, kernel_size=5), nn.ReLU(),
    # nn.BatchNorm1d(32), nn.ReLU(),
    # nn.AvgPool1d(kernel_size=2, stride=2),

    nn.Flatten(),
    # nn.Linear(11872, 128), nn.ReLU(),
    nn.Linear(792, 128), nn.ReLU(),
    nn.Linear(128, 64), nn.ReLU(),
    nn.Linear(64, 10))

train(net_mfcc, train_iter_mfcc, test_iter_mfcc, mfcc_epochs, lr)
```

```
training on cuda:0
```

```
---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
<ipython-input-74-3d556574767d> in <module>()
     26     nn.Linear(64, 10))
     27 
---> 28 train(net_mfcc, train_iter_mfcc, test_iter_mfcc, mfcc_epochs, lr)

<ipython-input-66-a6f3b0b1b73f> in train(net, train_iter, test_iter, num_epochs, lr, device)
     21             optimizer.zero_grad()
     22             X, y = X.to(device), y.to(device)
---> 23             y_hat = net(X)
     24             l = loss(y_hat, y)
     25             l.backward()

/usr/local/lib/python3.6/dist-packages/torch/nn/modules/module.py in _call_impl(self, *input, **kwargs)
    720             result = self._slow_forward(*input, **kwargs)
    721         else:
--> 722             result = self.forward(*input, **kwargs)
    723         for hook in itertools.chain(
    724                 _global_forward_hooks.values(),

/usr/local/lib/python3.6/dist-packages/torch/nn/modules/container.py in forward(self, input)
    115     def forward(self, input):
    116         for module in self:
--> 117             input = module(input)
    118         return input
    119 

/usr/local/lib/python3.6/dist-packages/torch/nn/modules/module.py in _call_impl(self, *input, **kwargs)
    720             result = self._slow_forward(*input, **kwargs)
    721         else:
--> 722             result = self.forward(*input, **kwargs)
    723         for hook in itertools.chain(
    724                 _global_forward_hooks.values(),

/usr/local/lib/python3.6/dist-packages/torch/nn/modules/conv.py in forward(self, input)
    417 
    418     def forward(self, input: Tensor) -> Tensor:
--> 419         return self._conv_forward(input, self.weight)
    420 
    421 class Conv3d(_ConvNd):

/usr/local/lib/python3.6/dist-packages/torch/nn/modules/conv.py in _conv_forward(self, input, weight)
    414                             _pair(0), self.dilation, self.groups)
    415         return F.conv2d(input, weight, self.bias, self.stride,
--> 416                         self.padding, self.dilation, self.groups)
    417 
    418     def forward(self, input: Tensor) -> Tensor:
```

```
RuntimeError: Expected 4-dimensional input for 4-dimensional weight
 [4, 1, 3, 3], but got 3-dimensional input of size [32, 1, 6000] ins
tead
```



Is there a neural-network based alternative to mfcc features?

TODO: your answer here