First (serious) training of a Neural Network!

Disclaimer: large parts of the lab are taken from [Deep Learning with PyTorch: A 60 Minute Blitz] by [Soumith Chintala] and lectures material of [Sebastian Goldt].

```
### Some starting stuff ####

%matplotlib inline

import numpy as np

import torch
import torch.nn as nn # Importing the neural network library
from torchvision import datasets, transforms # Transformation contains, i.e., normalization

import matplotlib as mpl
import matplotlib.pyplot as plt

# To plot in a better way
plt.rc("font", **{"size": 12})
plt.rc("lines", linewidth=2.0)
mpl.rcParams['lines.markersize'] = 12
mpl.rcParams['lines.markeredgewidth'] = 2
```

Definition of Neural Networks by means of `PyTorch`

The `torch.nn` package is used to define and train a Neural Network (model definition). The package depends on `autograd` that performs the differentiation.

A Neural Network is defined as `nn.Module` (that is a class) and its main features are, we need to define some functions, inside, such as:

- the layers, --> struction that gives me idea in which way the layer are connected
- the `forward` method that process the `input` to predict an `output`.

The main passages of the training procedure are:

- The definition of the neural network and of its learnable parameters (weights, bias, regulaitrations)
- Perform a prediction over some `inputs` by means of a law (weighted layers and activation functions)
- evaluate the loss (i.e. a measure to understand the distance between the prediction and the `output`)
- use back propagation on the trainable paramters parameters
- update the trainable parameters (gradient descent-based startegies).

Summarizing:

1. Forward
2. Loss
3. Backpropagation
4. Repeat again and again untile you get the right value of loss

What is means Regularization? Change the function that you want to minimize to penalize stuff in different way --> you are constraining to go along a direction or onother

Let us define the Network

```
import torch
import torch.nn as nn
import torch.nn.functional as F


# Build the net inheriting  the data from nn.Module
class Net(nn.Module):

    def __init__(self): # In the constructor we define the layer of the NN
        super(Net, self).__init__()
        # 3 Layer
        self.fc1 = nn.Linear(784, 100) # Linear one where 784 are the initial pixel 28 x 28 (fully connected)
        self.fc2 = nn.Linear(100, 100)
        self.fc3 = nn.Linear(100, 10) # Where 10 are the different final label that I want to predict
        # self.apply(self._init_weights) # If you want to initialize the weight

    """
    def _init_weights(self, module):
        if isinstance(module, nn.Linear):
            module.weight.data.normal_(mean=0.0, std=1.0)
            if module.bias is not None:
                module.bias.data.zero_()
    """

    # Activation
    def forward(self, x):   ### Forward law ----> prediction
        x = F.relu(self.fc1(x)) # The input is transformed, thanks to the ReLu in the result of the first layer
        x = F.relu(self.fc2(x))

        # So I have 3 layer with 2 ReLu and after a Identity function
        x = self.fc3(x) # Identity --> we do NOT apply the ReLu

        return x
```

```
seed_num = 0
torch.manual_seed(seed_num)
net = Net()
print(net)

# By defoult I have the bias
```

```
Net(
  (fc1): Linear(in_features=784, out_features=100, bias=True)
  (fc2): Linear(in_features=100, out_features=100, bias=True)
  (fc3): Linear(in_features=100, out_features=10, bias=True)
)
```

Only the defintion of the function `forward` is needed, since the backward is directly defined for you by `autograd`. The `forward` function is a law where all the Tensors operations are admitted.

Let us give a look to the parameters in `net.parameters()`

```
params = list(net.parameters()) # All the parameters put in a list: weight and bias for each layer (3 x 2 = 6)
print(len(params))
print(params[0].size())  # fc1 .weight
print(params[1].size())
print(params[2].size())
print(params[3].size())
print(params[4].size())
print(params[5].size())
```

```
6
torch.Size([100, 784])
torch.Size([100])
torch.Size([100, 100])
torch.Size([100])
torch.Size([10, 100])
torch.Size([10])
```

Tipo di cella non supportato. Fai doppio clic per ispezionare/modificare i contenuti.

Question time!: why is the number of parameters 6? We have only three layers...

Let give it a try: we define a random 28x28 = 784 `input`.

Question time!: why do we need a 28x28 = 784 `input`?

```
input = torch.randn(1, 784) # Dimension that I need to give in input to perform an evaluation
out = net(input)
print(out)
```

```
tensor([[ 0.1824,  0.0367, -0.1264, -0.1809,  0.0431, -0.0219,  0.0701,  0.0807,
          0.1693, -0.0903]], grad_fn=<AddmmBackward0>)
```

We now use the function `zero_grad` to set the gradient at zero. It is a good practise because for each mini-batch we want to forget the information about the gradient (otherwise it is accumulated). We now use back propagation over a random gradient.

```
net.zero_grad() # With zero_grad() we reset the gradients of the neural network parameters
                # that have been accumulated previously
out.backward(torch.randn(1, 10))
```

Be careful! `torch.nn` is able to only work with batches (i.e. more than one `input` with some features). If you want to work with a single sample, use the command `input.unsqueeze(0)` to add a fake dimension related to the batch size.

A brief recap: the features we are dealing with are...

- `torch.Tensor`: the `PyTorch` *multi-dimensional array* that supports `autograd` (and, thus, `backward()` operation).
- `nn.Module`: it is the *definition of the Neural Network* with information about parameters, layers and forward law.
- `nn.Parameter`: a Tensor with all the parameters (the bias are present by default!) authomatically generated from the layers.

A brief recap: we...

- defined the net
- postprocessed the input thanks to the forward law
- have been able to compute gradients

There is something missing though!

- The loss --> functional of the optimization problem
- the update of the parameters.

The Loss

The loss is a function that evaluates how far the prediction is from the target (i.e. the *known output* of the dataset). The `Torch.nn` has many losses, give a look! The most common is the `nn.MSELoss`, i.e. the mean-squared error between the prediction and the given data.

```
output = net(input)
target = torch.randn(10)  # a dummy target, for example --> random number
print(target.shape)
target = target.view(1, 10)  # make it the same shape as output of the net, you can use target.view(1, -1) [equivalent]
```

```
# MSE the most common and most intuitive, but not used in general
criterion = nn.MSELoss() # Import the loss from torch (there are a lot of defined loss in this package)

loss = criterion(output, target)
print(loss) # Tell us the discrepancy: we're printing output of the MSE apply to this case
```

```
torch.Size([10])
tensor(1.3280, grad_fn=<MseLossBackward0>)
```

Backpropagation

To perform backpropagation on the loss we have to call `loss.backward()`. But, as already said, first thing first: clear the existing gradients to avoid accumulating existing information.

```
# Reset the data before backpropagation

net.zero_grad()     # zeroes the gradient
print('fc1.bias.grad before backward')
print(net.fc1.bias.grad)

loss.backward()

print('fc1.bias.grad after backward')
print(net.fc1.bias.grad)
```

```
fc1.bias.grad before backward
None
fc1.bias.grad after backward
tensor([ 0.0058,  0.0000,  0.0281,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
         0.0000,  0.0000,  0.0000,  0.0302, -0.0170,  0.0000, -0.0098,  0.0006,
         0.0120,  0.0000,  0.0000,  0.0000, -0.0157,  0.0286, -0.0168, -0.0034,
         0.0000,  0.0006, -0.0182,  0.0000,  0.0175,  0.0000,  0.0000,  0.0000,
         0.0000, -0.0089,  0.0000, -0.0038,  0.0000,  0.0000,  0.0119, -0.0102,
         0.0000, -0.0144,  0.0266,  0.0000,  0.0079, -0.0142, -0.0155, -0.0121,
         0.0107,  0.0000,  0.0145,  0.0000,  0.0000,  0.0000,  0.0157,  0.0007,
         0.0164,  0.0000,  0.0125, -0.0099, -0.0070,  0.0000, -0.0291,  0.0274,
         0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0381,  0.0000,  0.0083,
         0.0355, -0.0167, -0.0361,  0.0167,  0.0000,  0.0000, -0.0113,  0.0068,
        -0.0195,  0.0000, -0.0136,  0.0000, -0.0003,  0.0317,  0.0495,  0.0291,
         0.0039,  0.0000,  0.0000,  0.0000, -0.0158,  0.0000, -0.0426,  0.0099,
         0.0000,  0.0000,  0.0000,  0.0000])
```

The update

We have seen that the simplest way to update the parameters is the Stochastic Gradient Descent:

```
``weight = weight - learning_rate * weight_gradient``
``bias = bias - learning_rate * bias``
```

We can implement it by hand as

```
learning_rate = 0.01
for p in net.parameters():
    p.data.sub_(p.grad.data * learning_rate)
```

However, there are many rules to update the parameters: SGD, Nesterov-SGD, Adam (most used), RMSProp (very fast in convergence), etc. --> better to use this that are optimize and performe better

We can use the package `torch.optim` to choose them. The sintax is very simple:

```
import torch.optim as optim

# create your optimizer
optimizer = optim.SGD(net.parameters(), lr=0.01) # Definition of the optimizer

# in your training loop:
optimizer.zero_grad()   # zero the gradient
output = net(input)
loss = criterion(output, target)
loss.backward() # Compute the gradient with the backward
optimizer.step() # Does the update --> optimization done NOT by hand, but with the Stochastic Gradient Descent (definition line 4)
```

That'a all folks!

Your Turn: train the MNIST dataset with Pytorch!

First of all, let us collect the data from the package `torchvision`. Our goal is to train *an image classifier*. Given a hand-written digit, we want to associate a number.

Please, follow these tasks:

1. Load and normalize the training and test dataset (MNIST) using `torchvision` and visualize them (together).
2. Define the Neural Network `Net()`. --> NET

3. Define the loss function (give a look to `nn.CrossEntropyLoss()`) and choose an optimizer (give the probability distrubution of the label class: at the end you will have the vector containing the probability of belonging to the different classe). --> LOSS
4. Train the Network on the training data. --> TRAIN
5. Test the Network on the test data (together). --> TEST

```
import torch
import torch.nn as nn
from torchvision import datasets, transforms # In orderd to import DataLoader: usefull to import
                                            # data from torch and compute transformation on them
```

Task 1: In the following we load the data in the `DataLoader` that is a peculiar structure that allows many operations on the data in a *smarter way*. See the documentation. --> To devide the data, and preprocessing them

Dataset: MNIST images. The MNIST dataset contains 28x28 grayscale images of handwritten digits from 0 to 9. The training set has 60,000 samples, the test set has 10,000 samples. The output is an interger label from 0 to 9.

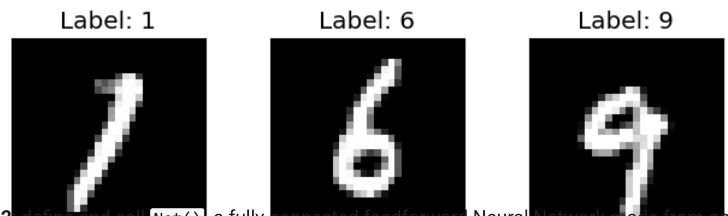
Dataset class in pytorch recasts the data in a tuple in other to create the dataloader class which can be used to shuffle, apply Mini-Batch Gradient Descent and more.

```
transform = transforms.Compose([transforms.ToTensor()]) # Composition of transformation (in this case only one,
                            # in general more than one): the data has to be set in torch array (i.e, no numpy)

# Import the dataset (trianing part)
mnist_trainset = datasets.MNIST(root='./data', train=True, download=True, transform=transform)
train_loader = torch.utils.data.DataLoader(mnist_trainset, batch_size=10, shuffle=True) # shuffle=True
                                            # --> takes the batches and mix together, to have more informarmation during the train

# The same for the test
mnist_testset = datasets.MNIST(root='./data', train=False, download=True, transform=transform)
test_loader = torch.utils.data.DataLoader(mnist_testset, batch_size=10, shuffle=True)
```

```
100%|████████████████████████████████████████| 9.91M/9.91M [00:01<00:00, 5.31MB/s]
100%|████████████████████████████████████████| 28.9k/28.9k [00:00<00:00, 311kB/s]
100%|████████████████████████████████████████| 1.65M/1.65M [00:00<00:00, 1.96MB/s]
100%|████████████████████████████████████████| 4.54k/4.54k [00:00<00:00, 2.37MB/s]
```

Let us visualize some of the digits.

```
import matplotlib.pyplot as plt

# get some random training images
dataiter = iter(train_loader)
images, labels = next(dataiter)


fig = plt.figure()
for i in range(3):
  plt.subplot(1,3,i+1)
  plt.tight_layout()
  plt.imshow(images[i][0], cmap='gray', interpolation='none')
  plt.title("Label: {}".format(labels[i]))
  plt.xticks([])
  plt.yticks([])
```



Task 2: define and call `Net()`, a fully connected feedforward Neural Network made from an input layer (*what is the dimension of the input?*), hidden layers, and an output layer. The structure is [`input_dim`, 100, 50, `output_dim`] (*what is the dimension of the output?*) Moreover, the internal neurons have feature a `Tanh` *activation function action*, while the output layer is subjected to `ReLU`.

Dimensions.

- **Input**: 28x28=784 represents the pixel that the photo has at the beginning
- **Output**: 10 represents the differen classes

Be careful!: a reshape of the input is needed!

```
# Build the NET as usual
class Net(nn.Module):
    def __init__(self): # Constractor
        super(Net,self).__init__()

        # Layer of the net
        self.linear1 = nn.Linear(28*28, 100) # First layer
        self.linear2 = nn.Linear(100,50)  # Middle layer
        self.final = nn.Linear(50,10) # Final layer

        # Activation function that we will use and call in the forward function
        self.tanh = nn.Tanh() # More uesd because we have both positive and negative value
        self.relu = nn.ReLU()

        ## self.apply(self._init_weights) # To define the initial weights (if you want,
        # as done in the previous lab - "Gradient_descent")

    """
```

```
    def HERE YOU CAN DEFINE THE WEIGHTS (look above)
    """

    def forward(self, img): #convert + flatten
        x = img.view(-1, 28*28)

        # Application of the activation function to the different layer of out net
        x = self.tanh(self.linear1(x))
        x = self.tanh(self.linear2(x))
        x = self.relu(self.final(x))

        return x

seed_num = 1
torch.manual_seed(seed_num)
net = Net() # Creation of the net
```

Task 3 and 4: define the loss (`nn.CrossEntropyLoss()`) and choose an optimizer (*Let us start with SGD?*). Fix the learning rate. When we work with mini-batches, we can iterate over the DataLoarder (6000 iterations for a mini-batch of dimention 10) for some epochs, say 10. Complete the following cell. --> We're looking 10-by-10 value

We have two counter:

1. Epochs
2. Minibatches -> how long I go through the data at each epoch

Can you trace the loss and plot it with respect to the number of iterations (different from epochs)?

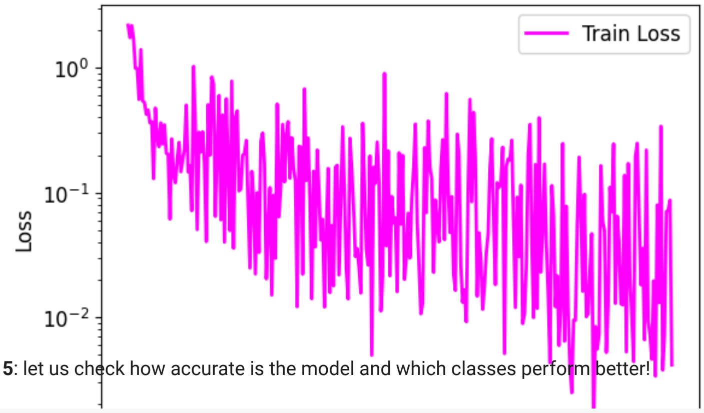
```
my_loss = nn.CrossEntropyLoss() # Definition of the loss
optimizer = torch.optim.SGD(net.parameters(), lr=0.01) # Stochastic Gradient Descent to optimize the parameter

epoch = 10
i = 0

#### Useful quantities ####

train_losses = []

for ep in range(epoch):
    net.train() # Function of torch that set the training phase

    # For each data, we go though the data 10 times (10-by-10)
    for data in train_loader: # train_loader all data devided in minibatches
          i += 1
          x, y = data

          ### set zero grad on the optimizer
          optimizer.zero_grad()

          ## compute output
          output = net(x) # The evaluation of the net over the input

          # compute the loss
          loss = my_loss(output, y)

          #compute the gradients
          loss.backward() # Backpropagation step

          # optimizer update
          optimizer.step() # Optimization step

          if i % 200 == 199:    # print every 10*200 = 2000 mini-batches
              print('[%d, %5d] loss: %.3f' %
                    (ep + 1, i + 1, loss.item()))
              running_loss = 0.0
              train_losses.append(loss.item())
    # i = 0
```

```
[1,   200] loss: 2.201
[1,   400] loss: 1.749
[1,   600] loss: 2.188
[1,   800] loss: 1.706
[1,  1000] loss: 0.994
[1,  1200] loss: 0.990
[1,  1400] loss: 0.557
[1,  1600] loss: 1.403
[1,  1800] loss: 0.543
[1,  2000] loss: 0.528
[1,  2200] loss: 0.424
[1,  2400] loss: 0.459
[1,  2600] loss: 0.362
[1,  2800] loss: 0.370
[1,  3000] loss: 0.129
[1,  3200] loss: 0.476
[1,  3400] loss: 0.272
[1,  3600] loss: 0.233
[1,  3800] loss: 0.362
[1,  4000] loss: 0.245
[1,  4200] loss: 0.349
[1,  4400] loss: 0.206
[1,  4600] loss: 0.203
[1,  4800] loss: 0.061
[1,  5000] loss: 0.270
[1,  5200] loss: 0.137
[1,  5400] loss: 0.120
[1,  5600] loss: 0.183
[1,  5800] loss: 0.252
```

```
[1,  6000] loss: 0.147
[2,  6200] loss: 0.181
[2,  6400] loss: 0.223
[2,  6600] loss: 0.503
[2,  6800] loss: 0.146
[2,  7000] loss: 0.164
[2,  7200] loss: 0.071
[2,  7400] loss: 1.029
[2,  7600] loss: 0.358
[2,  7800] loss: 0.050
[2,  8000] loss: 0.305
[2,  8200] loss: 0.211
[2,  8400] loss: 0.307
[2,  8600] loss: 0.169
[2,  8800] loss: 0.040
[2,  9000] loss: 0.507
[2,  9200] loss: 0.199
[2,  9400] loss: 0.847
[2,  9600] loss: 0.742
[2,  9800] loss: 0.064
[2, 10000] loss: 0.219
[2, 10200] loss: 0.601
[2, 10400] loss: 0.060
[2, 10600] loss: 0.419
[2, 10800] loss: 0.040
[2, 11000] loss: 0.565
[2, 11200] loss: 0.159
[2, 11400] loss: 0.049
```

```python
fig = plt.figure()
plt.semilogy(range(len(train_losses)), train_losses, color='magenta')
plt.legend(['Train Loss'], loc='upper right')
plt.xlabel('Number of training examples seen')
plt.ylabel('Loss')

# The plot has such that shape because we have shuffle the data, so maybe he start to learn, but after
# something change (like go to another number) and so is not quite good as before
# BUT the important thing is that we can see a downward trend
```

```
Text(0, 0.5, 'Loss')
```

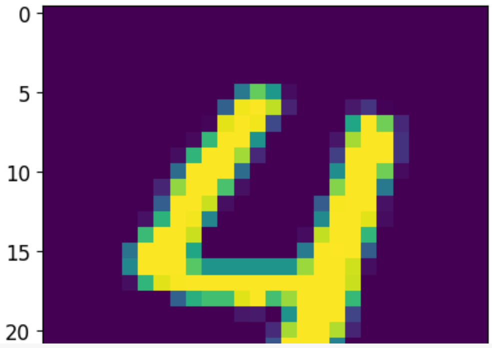


Task 5: let us check how accurate is the model and which classes perform better!

```python
correct = 0
total = 0

with torch.no_grad():
    for data in test_loader:
        x, y = data
        output = net(x)
        # print(output)

        for idx, i in enumerate(output):
            # This is a prediction that is correct
            if torch.argmax(i) == y[idx]:  #### idx indicates which sample I am taking from the mini-batch.
                                # The Output is a a vector of floats, the biggest is the one with higher probability
                correct +=1
            total +=1

print('Accuracy of the network on the 10000 test images: %d %%' % (
    100 * correct / total))

# The result is related to the entropy (loss) that we use
# OPEN QUESTION - How we can decide the correct loss?
```

```
Accuracy of the network on the 10000 test images: 96 %
```

```python
plt.imshow(x[3].view(28, 28))
plt.show()
print(torch.argmax(net(x[3].view(-1, 784))[0]))
```



```python
# Compute the accuracy for each of the class to understand if some digits are well classified wrt the other
class_correct = list(0. for i in range(10))
class_total = list(0. for i in range(10))
classes = ('0', '1', '2', '3',
           '4', '5', '6', '7', '8', '9')

with torch.no_grad():
    for data in test_loader:
        images, labels = data
        images = images.reshape(-1, 784)
        outputs = net(images)
        _, predicted = torch.max(outputs, 1) ### returning the indices
        c = (predicted == labels).squeeze()

        for i in range(10):
            label = labels[i]
            class_correct[label] += c[i].item()
            class_total[label] += 1


for i in range(10): # Print the accuracy for each class
    print('Accuracy of %5s : %2d %%' % (
        classes[i], 100 * class_correct[i] / class_total[i]))
```

```
Accuracy of     0 : 98 %
Accuracy of     1 : 98 %
Accuracy of     2 : 96 %
Accuracy of     3 : 96 %
Accuracy of     4 : 95 %
Accuracy of     5 : 95 %
Accuracy of     6 : 97 %
Accuracy of     7 : 96 %
Accuracy of     8 : 97 %
Accuracy of     9 : 96 %
```