CS3485

Deep Learning for Computer Vision

Lec 5: Pytorch I – MLPs

(Tentative) Lecture Roadmap

Basics of Deep Learning

- Intro to Computer Vision
- Linear Classifiers and Perceptron
- Multilayer Perceptron
- Optimization in Deep Learning
- Pytorch I – MLPs
- Pytorch II – Images and Regularization
- Convolutional Neural Networks
- Data Augmentation and Deep CNNs
- Transfer Learning and Residual Nets
- Inception Net and what CNNs learn
- Adversarial Examples and Self-supervision

Deep Learning and Computer Vision in Practice

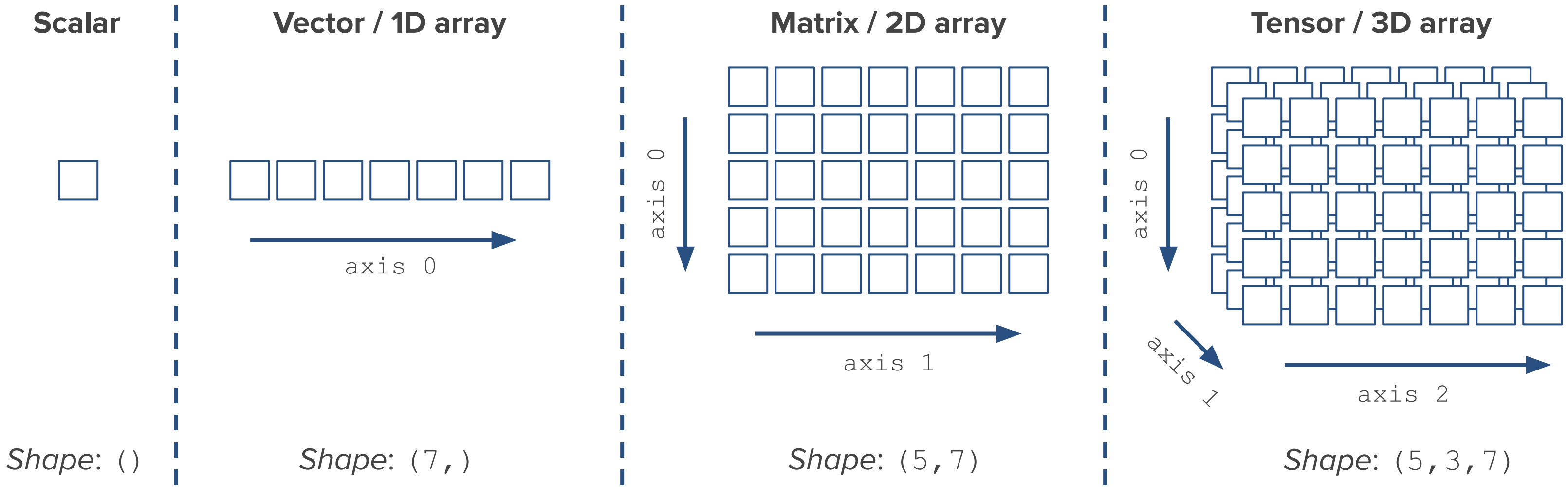
- Intro to MLOps
- Intro to Object Detection
- Fast Object Detection
- Intro to Image Segmentation
- Applications of Detection and Segmentation
- Autoencoders
- Image Generation with GANs
- Advanced GANs
- The Attention Mechanism
- Transformers and ChatGPT
- Image Generation by Prompt
- Misc. Topics

PyTorch

- After we learned all this previous theory on Deep Learning, it is finally time to implement it and solve real problem.
- To that goal, we'll use a Python library called **PyTorch**, which provides many more features, and it is much more optimized for Deep Learning development than Scikit-learn, which we used previously.
- Created in 2016 by Facebook, PyTorch has become the de facto library for DL in many industries and most of the Artificial Intelligence research is done with it nowadays.

Tensors

- The main data structure used in PyTorch is a **tensor**, which is a generalization of vectors and matrices:



- We can create tensors / arrays of more dimensions (4, 5, ...) following the same principle.

Initializing a tensor

- We initialize a tensor by calling `torch.tensor()` on a list of numerical elements:

```
import torch
x = torch.tensor([[1,2]])
y = torch.tensor([[1],[2]])
```

- Just like in Numpy, we can access the tensors' shapes and data types:

```
print(x.shape, y.shape)
print(x.dtype)
```

```
torch.Size([1,2]) torch.Size([2,1])
torch.int64
```

- The data type of all elements within a tensor **is the same**! If a tensor contains data of different data types, entire tensor is coerced to the most generic data type: `float`.

```
x = torch.tensor([False, 1, 2.0])
print(x)
```

```
tensor([0., 1., 2.])
```

Initializing a tensor

- Just like Numpy and usually with the same command names, we can initialize tensors with built-in functions. For example, in the following example different tensors of size $3{\times}4$ are created using these functions:

```
t1 = torch.zeros((3, 4))      # tensor of zeros
t2 = torch.ones((3, 4))       # tensor of ones
t3 = torch.randint(low=0, high=10, size=(3,4)) # tensor of random integers between 0 and 10
t4 = torch.rand(3, 4)         # tensor of random floats 0 and 1
t5 = torch.randn((3,4))       # tensor of random floats normally distributed
```

- Finally, one can convert a Numpy array into a Pytorch tensor and vice-versa:

```
x = np.array([[10,20,30],[2,3,4]])
y = torch.tensor(x)
z = y.numpy()
print(type(x), type(y), type(z))
```

```
<class 'numpy.ndarray'> <class 'torch.Tensor'> <class 'numpy.ndarray'>
```

Operations in tensors

- There are many useful operations we can do with tensors, most of them similar to how Numpy works:
  - Addition and multiplication by a scalar:

```
x = torch.tensor([[1,2,3,4],
                  [5,6,7,8]])
print(x + x)
print(x * 10)
```

```
tensor([[ 2,  4,  6,  8],
        [10, 12, 14, 16]])
tensor([[10, 20, 30, 40],
        [50, 60, 70, 80]])
```

  - Matrix transposition and multiplication (example below uses `x` from above):

```
print(torch.matmul(x, x.T)) # or x @ x.T
```

```
tensor([[ 30,  70],
        [ 70, 174]])
```

  - Indexing and concatenation (example below uses `x` from above):

```
y = torch.tensor([9, 10, 11, 12])
print(torch.cat([x[1, :], y], axis = 0))
```

```
tensor([ 5,  6,  7,  8,  9, 10, 11, 12])
```

Operations in tensors

- Tensor reshaping:

```
y = torch.tensor([[2, 3], [1, 0]])
z = y.view(4,1)  # 4 rows and 1 column
w = y.view(-1,4) # The other dimension is inferred if using "-1"
print(z)
print(w)
```

```
tensor([[2],
        [3],
        [1],
        [0]])
tensor([[2, 3, 1, 0]])
```

- Maximum value and index:

```
x = torch.arange(16).view(4,4)
print(x)
print(x.max()) # Maximum over the whole tensor

vals, indx = x.max(dim=1) # Maximum over each row
print(vals)
print(indx) # We could use "argmax()" to get just the indices
```

```
tensor([[ 0,  1,  2,  3],
        [ 4,  5,  6,  7],
        [ 8,  9, 10, 11],
        [12, 13, 14, 15]])
tensor(15)
tensor([ 3,  7, 11, 15])
tensor([3, 3, 3, 3])
```

- Standard mathematical operations: `abs`, `floor`, `sin`, `cos`, `exp`, `mean`, `round`...

Gradients with Autograd

- One of the main operations in PyTorch is to **compute the gradients** of a tensor object.
- It uses a technique called **Automatic Differentiation (Autograd)**, which enables us to do it by evaluating the derivative of a function **specified by a computer program**.
- In PyTorch, the way we to use it starts by specifying that a tensor requires a gradient to be calculated via the parameter `requires_grad`:

```
x = torch.tensor([2., -1.], requires_grad=True)
```

- Say you have the following function of x = $[x_1, x_2]$:

$$f(x_1, x_2) = x_1^2 + x_2^2$$

which can be computed in PyTorch as:

```
f = x.pow(2).sum()
```

Gradients with Autograd

- Now, we know that the gradient of f is $[2x_1, 2x_2]$.
- We get this in PyTorch by first using the (very important) function `backward()`:

```
f.backward()
```

(As the name of it hints at, `backward()` is where the backpropagation in NN happens).

- Now we compute the gradient of f at the point x from the previous slide with `x.grad`:

```
ans = x.grad
print(ans)
```

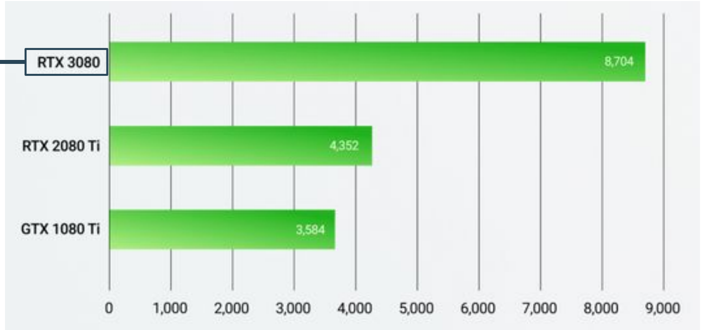
```
tensor([ 4., -2.])
```

- There's one catch with PyTorch autograd: the function you want to compute the gradient of **should return a scalar**. Loss functions fit in that category.

PyTorch's tensors vs NumPy's arrays

- Despite the similarities, PyTorch performs certain mathematical operations more quickly than Numpy.
- This is mainly due to the fact that PyTorch tensor is optimized to work with a **Graphics Processing Unit (GPU)**, instead of a Central Processing Unit (CPU), although they also work in CPUs.
- GPUs make **parallelizable operations** (such as matrix multiplication) much quicker, because of the sheer amount of computational cores it has available (between 700 and 9000).
- A usual CPU (which, in general, have less than 64 cores) would be much slower than a GPU.

Number of cores per GPU model



PyTorch's tensors vs NumPy's arrays

- Let's check that with an experiment. Create random matrices with PyTorch and Numpy:

```
x_t, y_t = torch.rand(1, 6400), torch.rand(6400, 5000)
x_n, y_n = np.random.random((1, 6400)),  np.random.random((6400, 5000))
```

- Then check if **CUDA (a parallel computing platform)** is available to be used.

```
device = 'cuda' if torch.cuda.is_available() else 'cpu'     # If CUDA isn't available, we use the CPU.
```

- We can store our PyTorch tensors in the GPU (if it is available) with `.to(device)`, and in the CPU (with `.cpu()`) and compare their performances with regular Numpy:

```
x, y = x_t.to(device), y_t.to(device)
%timeit z = x@y
```

```
100 loops: 515 µs per loop
```

```
x, y = x_t.cpu(), y_t.cpu()
%timeit z = x@y
```

```
100 loops: 9.04 ms per loop
```

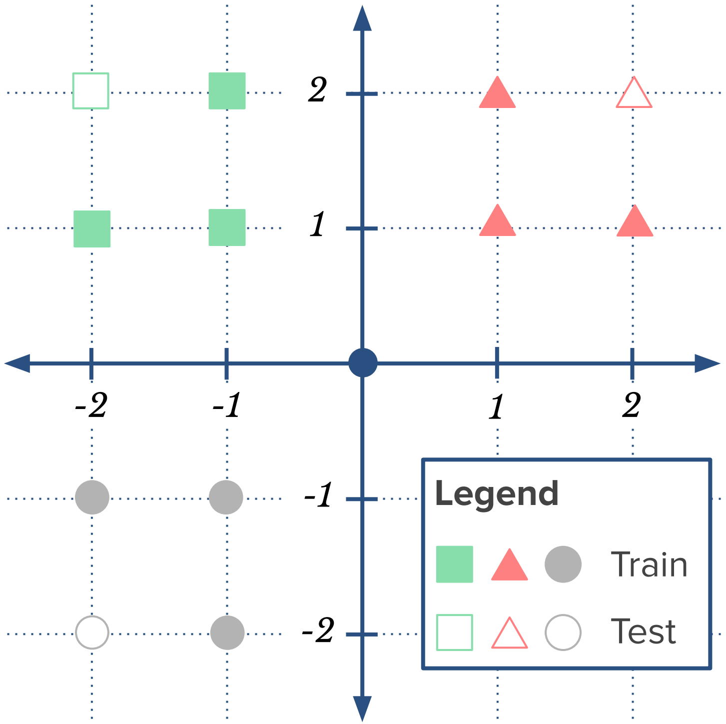
```
%timeit z = np.matmul(x_n,y_n)
```

```
100 loops: 18.8 ms per loop
```

Our First Neural Network: Dataset

- Now we are ready to build and train our first neural network in PyTorch!
- We'll first instantiate the training data on the right with what we saw so far:

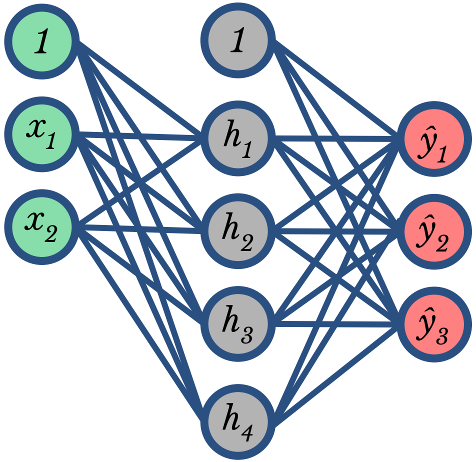
```
x_train = [[-2,-1], [-1,-1], [-1,-2],
            [2,-1],  [1,-1],  [1,-2],
            [2,1],   [1,1],   [1,2]]
y_train = [[1, 0, 0], [1, 0, 0], [1, 0, 0],
            [0, 1, 0], [0, 1, 0], [0, 1, 0],
            [0, 0, 1], [0, 0, 1], [0, 0, 1]]

X_train = torch.tensor(x_train).float()
Y_train = torch.tensor(y_train).float()

device = 'cuda' if torch.cuda.is_available() else 'cpu'
X_train = X_train.to(device)
Y_train = Y_train.to(device)
```



Our First Neural Network: Architecture

- Let’s define our network. For simplicity, we’d like a network with
  - **One hidden layer** with **four units** (*shown below*),
  - **ReLU activation functions** between the hidden and the output layer.
- In Torch, we have to create a class for our network that inherits `torch`’s nn.Module.
- That class should implement the constructor and `forward()` methods:

```
import torch.nn as nn
class MyNeuralNet(nn.Module):
    def __init__(self):
        super().__init__()
        self.input_to_hidden_layer = nn.Linear(2,4)
        self.hidden_layer_activation = nn.ReLU()
        self.hidden_to_output_layer = nn.Linear(4,3)
    def forward(self, x):
        x = self.input_to_hidden_layer(x)
        x = self.hidden_layer_activation(x)
        x = self.hidden_to_output_layer(x)
        return x
```



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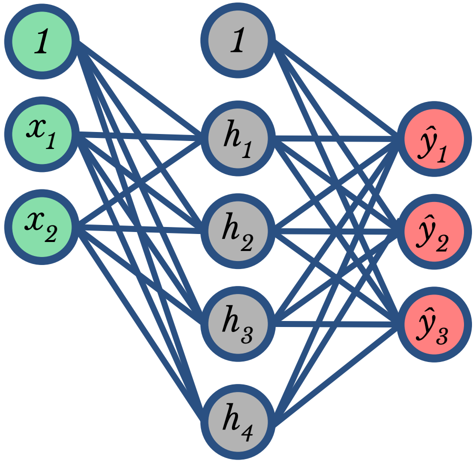
        x = self.hidden_layer_activation(x)
        x = self.hidden_to_output_layer(x)
        return x
```

In the constructor, you should declare the layers and functions you need.

In `forward()`, you explain how the layer would be composed such that to transform the network input `x` into the output in `return`.



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        x = self.hidden_to_output_layer(x)
        return x
```
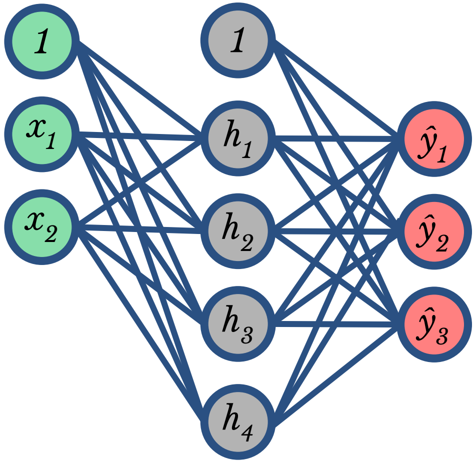

A `Linear` layer is the type of layer that connects all layer inputs to all layer outputs. Notice that you have to specify how many inputs and outputs.

Notice: no softmax!



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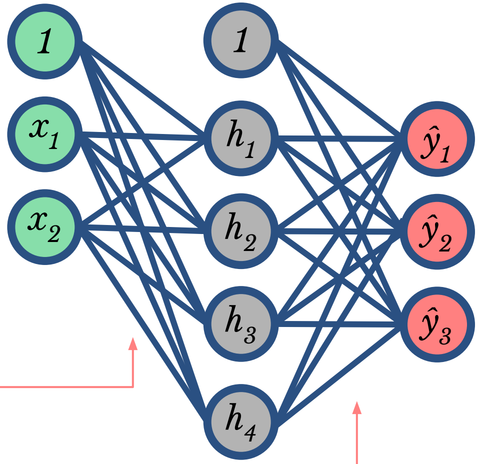


Our First Neural Network: Optimizer and Loss

- The next step is to **instantiate a network** of the class `MyNeuralNet`:

```
mynet = MyNeuralNet().to(device)
```

Here we also register the network **weights (which are tensors)** to the device.

- Then we need to **define the loss function** that we optimize for. Since we have three classes, we'll use Cross Entropy, which can be used in PyTorch as:

```
loss_func = nn.CrossEntropyLoss()
```

(again, this loss also computes the softmax operation to its inputs).

- Finally, we define our optimizer. For now, let's use our simplest option: Stochastic Gradient Descent (SGD).

```
from torch.optim import SGD
opt = SGD(mynet.parameters(), lr = 0.001) # "lr" is the learning rate.
```

Our First Neural Network: Training!

- Good! Now, we are ready to train our network on our dataset!
- For now, we will not consider mini-batches, so we'll use all the data to compute one step in gradient descent.
- When training a network in PyTorch, we have to go over *4* main steps in a `for` loop:
  1. **Zero the gradients** saved in the optimizer: PyTorch accumulates them by default.
  2. **Compute the loss** for current set of data: the current data is the whole dataset for now.
  3. **Compute the new gradients**: this operation is done via the AutoGrad's `backward()`.
  4. **Make a gradient descent step**: this operation is done via `opt.step()`.
- Then we repeat it for a given amount of epochs. Here's how it looks like:

```
n_epochs = 1000
for _ in range(n_epochs):
    opt.zero_grad()              # flush the previous epoch's gradients
    loss_value = loss_func(mynet(X_train),Y_train) # compute loss
    loss_value.backward()        # perform back-propagation
    opt.step()                   # update the weights according to the gradients computed
```

Our First Neural Network: Training!

- How well we are doing during training? We can track the loss value over the epochs ...

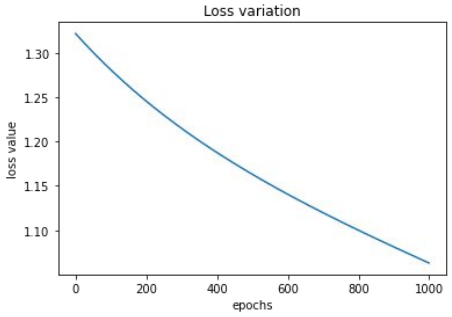
```
n_epochs = 1000
loss_history = []
for   in range(n_epochs):
   opt.zero_grad()
   loss_value = loss_func(mynet(X_train),Y_train)
   loss_value.backward()
   opt.step()

   loss_history.append(loss_value.detach().cpu().numpy())
```

Why is it so complicated? We just want a number! Well, `loss_value` is a tensor on the GPU that can be used to compute gradients. We need to remove all that to get the loss value (a number). So we do:

- `detach()` removes `requires_grad`.
- `cpu()` moves the tensor to the cpu.
- `numpy()` converts the tensor to an array.

... and plot it using Matplotlib:

```
import matplotlib.pyplot as plt
plt.plot(loss_history)
plt.title('Loss variation')
plt.xlabel('epochs')
plt.ylabel('loss value')
```



Our First Neural Network: Checking Parameters

- We can use `mynet.parameters()` to check what weights we've learned after training:

```
for par in mynet.parameters():
    print(par)
```

```
Parameter containing:
tensor([[ 0.0207,  0.6736],
        [-0.6257, -0.1910],
        [ 0.1345,  0.4238],
        [-0.0057, -0.0278]], device='cuda:0', requires_grad=True)
Parameter containing:
tensor([ 0.3481, -0.5513, -0.5184, -0.0614], device='cuda:0',
       requires_grad=True)
Parameter containing:
tensor([[-0.3208, -0.1217,  0.3756, -0.0855],
        [-0.0237, -0.1747, -0.2482, -0.2043],
        [ 0.0442, -0.1720, -0.3428,  0.2704]], device='cuda:0',
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Parameter containing:
tensor([-0.3330, -0.0685, -0.2763], device='cuda:0', requires_grad=True)
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```

Weights from the input layer to the hidden layer.

Biases on the input layer.

Weights from the hidden layer to the output layer.

Biases on the hidden layer.

Our First Neural Network: Testing!

- Let’s test how our network performs on the test data. First, let’s get the test data:

```
x_test = [[-2,-2], [2,-2], [2,2]]
y_test = [[1, 0, 0], [0, 1, 0], [0, 0, 1]] # This means that the test labels are [0, 1, 2]

X_test, Y_test = torch.tensor(x_test).float().to(device), torch.tensor(y_test).float().to(device)
```

- Now, we simply need to **feed the test data to the network** and get the predictions:

```
Y_pred = mynet(X_test)
print(Y_pred.cpu().detach().numpy())
print(torch.argmax(Y_pred, dim=1).cpu().numpy())
```

```
[[ 0.69065624  0.26163384  0.29026318]
 [-0.01491237  0.0594516   0.10389088]
 [ 0.13534957  0.03114225  0.16994081]]
[0 2 2]
```

Note that we don’t get the softmax’s probabilities as we never added that layer in. This is okay, since our final predictions are the indices where the max prediction occur*.

- **In this run**, we didn’t get all points correctly classified. How can we improve?

* If you want the softmaxes anyway, you first define the softmax function as `softmax = nn.Softmax()` and the apply it to `Y_pred`.

Exercise (*In pairs*)

Click here to open code in Colab

- Change the previous experiment by the following ways:
  - Keeping the same network as before, increase the number of epochs.
  - Keeping the one hidden layers and number of epochs, add more units to it.
  - Keeping the same number of units per layer and number of epochs, increase the number of hidden layers.
- Graph the loss variation of epochs on those experiments.
- Create an MLP that learns to classify the data in this dataset (from a few lectures ago):

```
from sklearn.datasets import make_blobs
from sklearn.model_selection import train_test_split
x, y = make_blobs(n_samples=400, centers=4, cluster_std=2, random_state=10)
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=2)
```

Train the network on you training data and test it on your test data. Add an `accuracy()` function that computes final classification accuracy. You'll need to use the function `torch.nn.functional.one_hot()` from Pytorch (*More on it here*).

Video: Go AlphaGo!