Deep Learning with PyTorch

Advance Machine Learning 2024/2025

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Deep Learning with PyTorch

- **Prerequisites:**
  - Object Oriented Programming
  - Python
  - Numpy
  - Basic understanding of Deep Learning

Deep Learning Frameworks

Caffe 2
(Facebook AI)

TensorFlow
(Google, tensorflow.org)

PyTorch
(Facebook AI, pytorch.org)

K Keras
Python Deep Learning API
(keras.io)

JAX
(Google, https://github.com/google/jax)

Several Others..

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Our Choice

(Facebook AI, pytorch.org)

(Python as main programming language)

- Why PyTorch?

Our Choice

(Facebook AI, pytorch.org)

(Python as main programming language)

- Why PyTorch?
  - **Pythonic Nature**:
    - Follows standard Python conventions,
    - Python developers should feel more confident with PyTorch than with any other DL framework

Our Choice

(Facebook AI, pytorch.org)

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- Why PyTorch?
  - **Pythonic Nature: ...**
  - **Easy to learn**: intuitive syntax and similar to Numpy

Our Choice

PyTorch +

(Facebook AI, pytorch.org)

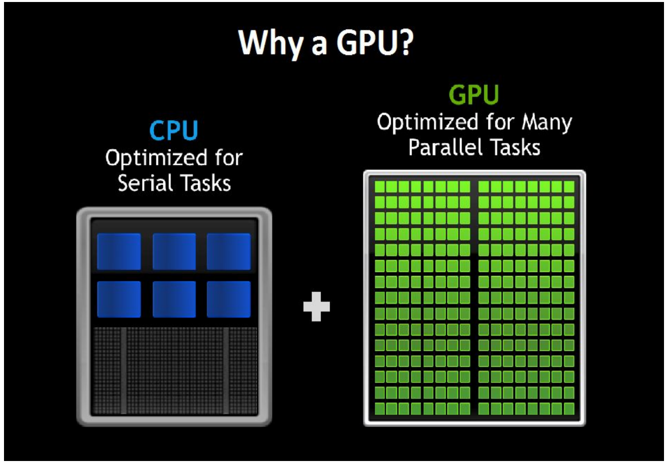
(Python as main programming language)

- Why PyTorch?
  - **Pythonic Nature: ...**
  - **Easy to learn**: intuitive syntax and similar to Numpy
  - **Strong Community**: Find help on https://discuss.pytorch.org

PyTorch

https://pytorch.org/tutorials/beginner/blitz/tensor_tutorial.html#what-is-pytorch

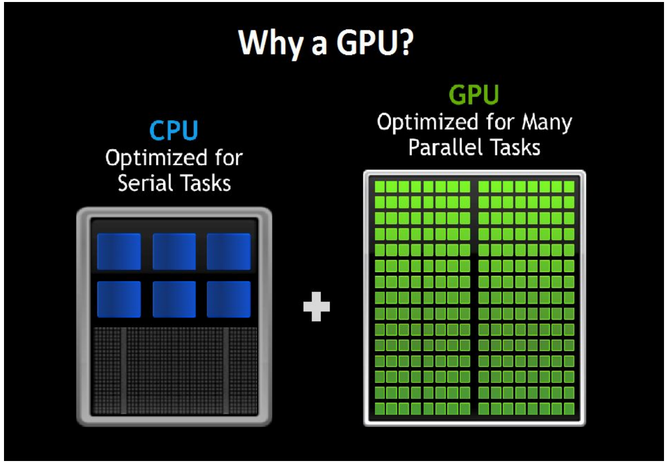
- An Open Source Framework for Deep Learning (and Machine Learning)
- **Deep Learning:**
  - Mathematical computing on **Multidimensional Arrays (aka Tensors)**
  - Highly benefit from **Parallel Computing**



PyTorch

https://pytorch.org/tutorials/beginner/blitz/tensor_tutorial.html#what-is-pytorch

- **Exploit Parallel Computing**
- **CPU:** few cores that can handle a few threads at a time - not ideal for DL
- GPU:
  - **Increased level of parallelism**
  - Hundreds of cores that can handle thousands of threads simultaneously
  - e.g. NVIDIA RTX 3090 has **10496 CUDA cores!**



PyTorch

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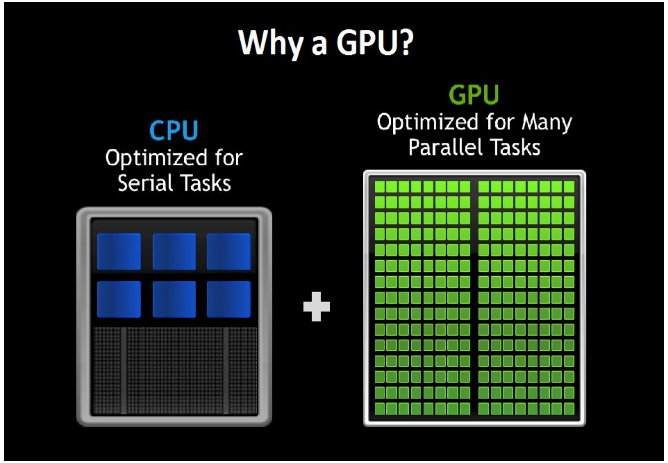
- **PyTorch let us easily exploit GPUs' power**
- Thus being a '**replacement for Numpy to exploit the parallelism offered by GPUs'**
- **Offering**
    - Strong performance
    - Automatic Differentiation
    - High Flexibility



Tensors

- Tensors are the PyTorch **counterpart of Numpy arrays**
- Contain *only numerical values*
- Used to encode:
  - **Signal to process** (e.g. images, strings of text, videos, ...)
  - **Internal states and parameter** of neural networks
- **All of PyTorch computation takes place on Tensors**

```
#                        R    G    B
img = tensor([[[ 48,  80,  79],
               [175, 104, 207],
               [162,  24, 224],
               [ 97,  27,  28],
               [ 51, 137,  60],
               [124, 214, 249]],
                ...
             ]])
t.size() ==> [256, 256, 3]
t.device ==> gpu:0
t.dtype ==> torch.float32
```

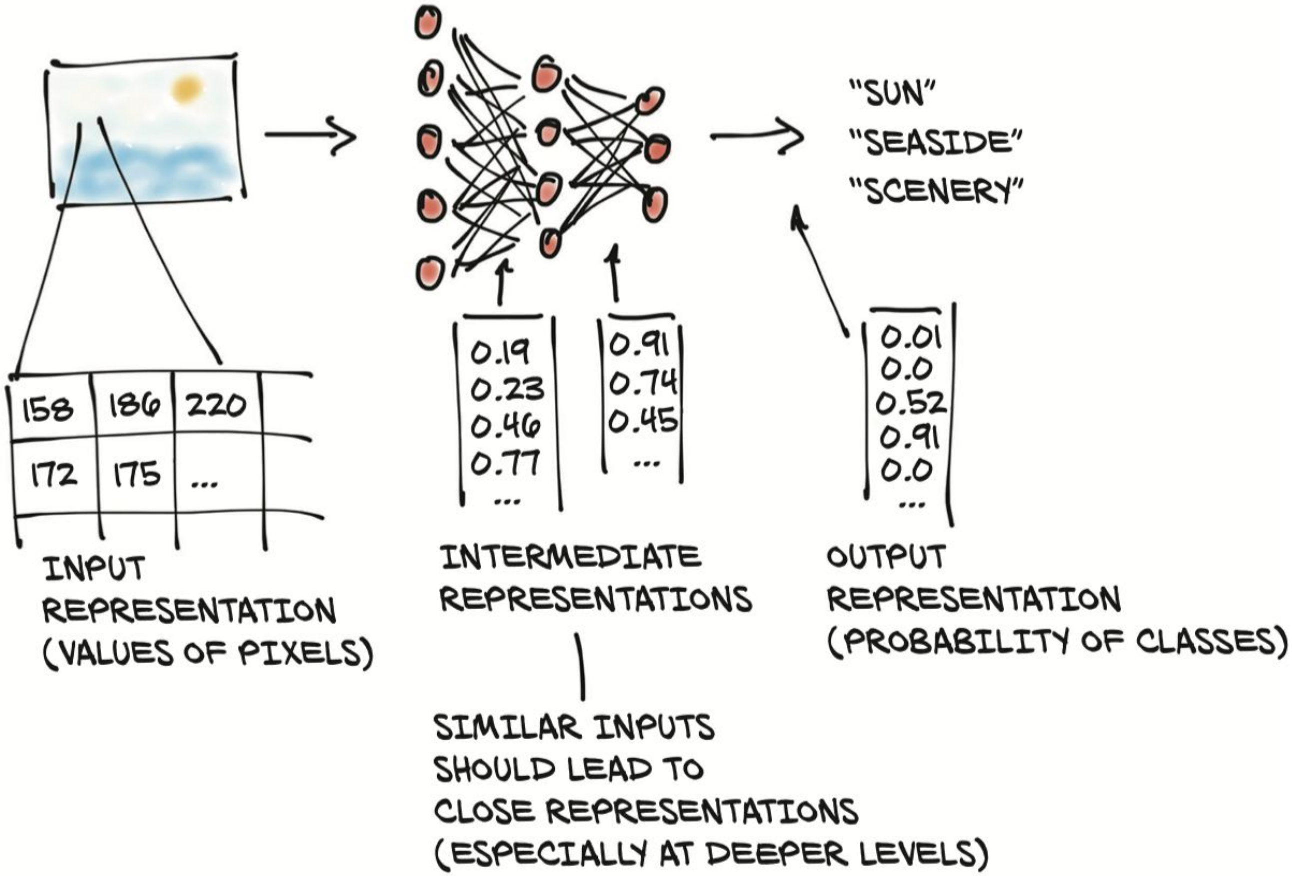


Figure 3.1 A deep neural network learns how to transform an input representation to an output representation. (Note: The numbers of neurons and outputs are not to scale.)

Tensors

- **Create a Tensor 't' of size (2,3) from scratch:**
  - Zeros init:
    t = torch.zeros(size=(2,3), dtype=torch.float32)
  - Ones init:
    t = torch.ones(size=(2,3), dtype=torch.float32)
  - Random init:
    t = torch.rand(size=(2,3), dtype=torch.float32)
- **Properties:**
  - **t.size()** - returns its shape - OSS. size() is a method of the Tensor class! (not a property)
  - **t.device** - whether it is store on CPU or GPU (+index)
  - **t.dtype** - values type (e.g. torch.int8, torch.float32, torch.bool, ...)

1. Create a tensor from scratch in PyTorch

```
In [10]: torch.zeros(size=(2,3), dtype=torch.float32)
Out[10]:
tensor([[0., 0., 0.],
        [0., 0., 0.]])

In [11]: torch.ones(size=(2,3), dtype=torch.float32)
Out[11]:
tensor([[1., 1., 1.],
        [1., 1., 1.]])

In [12]: torch.rand(size=(2,3), dtype=torch.float32)
Out[12]:
tensor([[0.5818, 0.3530, 0.5550],
        [0.4265, 0.1131, 0.5708]])
```

2. Check tensor 't' properties

```
In [21]: print(t)
tensor([[0.2330, 0.1985, 0.6867],
        [0.3123, 0.6324, 0.1508]])

In [22]: t.size()
Out[22]: torch.Size([2, 3])

In [23]: t.device
Out[23]: device(type='cpu')

In [24]: t.dtype
Out[24]: torch.float32
```

Tensors

- **From NumPy array to Tensor:**
    - use **torch.from_numpy()** static method
    - line 36
- **From Tensor to NumPy array:**
    - use tensor.**numpy()** method
    - line 38
- **Move tensor between CPU and GPU**:
    - Tensor are initialized on CPU by default
    - **tensor.device** to check where it is stored
    - **tensor.cuda()** to move it on GPU:0
    - **tensor.cpu()** to move it on CPU

3. Numpy bridge

```
In [33]: import torch, numpy as np

In [34]: np_arr = np.random.rand(2, 3)

In [35]: np_arr.shape
Out[35]: (2, 3)

In [36]: t = torch.from_numpy(np_arr)

In [37]: t.size()
Out[37]: torch.Size([2, 3])

In [38]: np_arr_theReturn = t.numpy()

In [39]: np_arr_theReturn.shape
Out[39]: (2, 3)

In [40]: np_arr_theReturn
Out[40]:
array([[0.20823187, 0.55286813, 0.37927967],
       [0.31437054, 0.21745502, 0.22156234]])
```

4. Move tensor to GPU, you need a CUDA capable device

```
In [18]: print(t,", device: ", t.device)
tensor([[0.6417, 0.4857, 0.9736],
        [0.1095, 0.5623, 0.1343]]) , device:  cpu

In [19]: t = t.cuda() # move to gpu!

In [20]: print(t,", device: ", t.device)
tensor([[0.6417, 0.4857, 0.9736],
        [0.1095, 0.5623, 0.1343]], device='cuda:0') , device:  cuda:0
```

Neural networks and Backpropagation

- **Define the neural network architecture**
- While training:

Neural networks and Backpropagation

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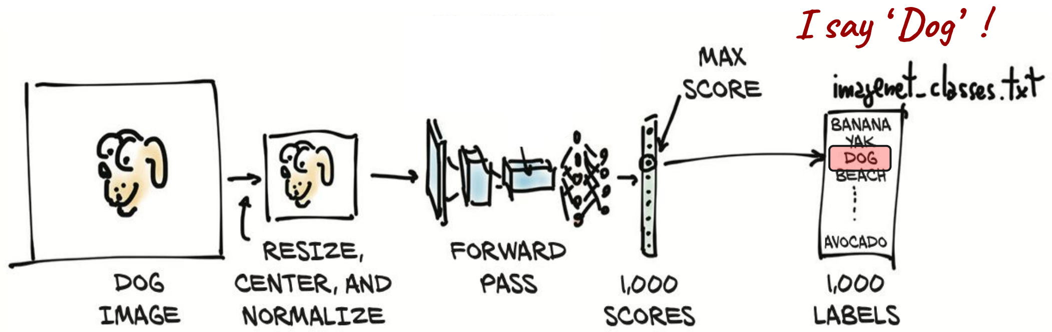
- While training:
    1. **Forward pass**: feed input data to the network to obtain the Network Prediction



Neural networks and Backpropagation

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  4. **Update** the network parameters **(PyTorch Optimizer)**

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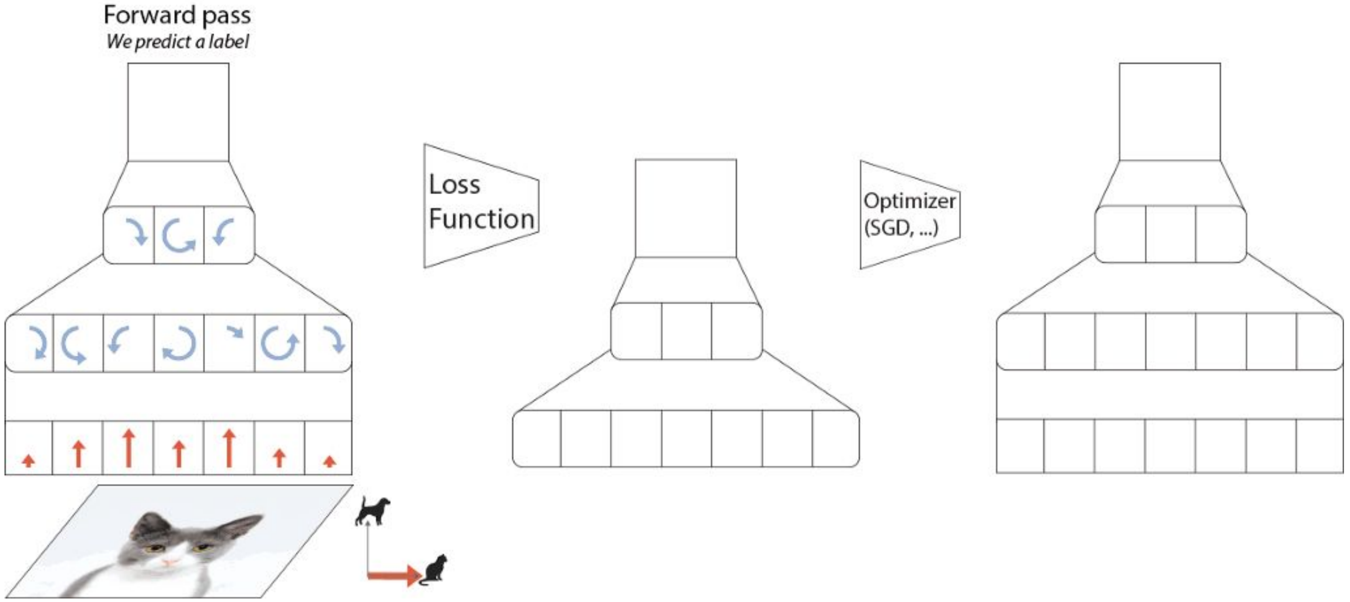
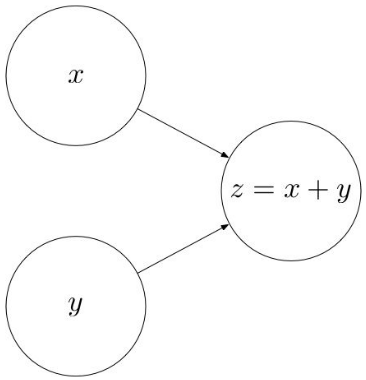
  ➢ *Repeat from 1… until convergence*

Neural networks and Backpropagation



Computational Graph

- The **Computational Graph** is a directed graph keeping track of all Operations performed on Variables
- To **support 'Forward Pass' and 'Backward Pass'**
- **Nodes** represent:
    - **Variables:** can feed their output into operations
    - **Operations:** can feed their output into other operations



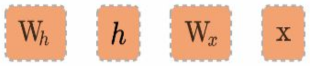
PyTorch Autograd

- **Do we need to build a Computational Graph by ourselves?**
- No, **Autograd takes care of it!**
- Every operations applied to Variables is tracked by PyTorch through the Autograd tape
- Thus providing **automatic differentiation**

A graph is created on the fly

```python
from torch.autograd import Variable

x = Variable(torch.randn(1, 10))
prev_h = Variable(torch.randn(1, 20))
W_h = Variable(torch.randn(20, 20))
W_x = Variable(torch.randn(20, 10))
```



PyTorch - Basic Components

- **Network Architecture**
  - Define a subclass of ‘torch.nn.Module’
- **Dataset**
  - Define a subclass of ‘torch.utils.data.Dataset’
- **Loss Function + Optimizer**
  - Network Prediction penalization + Update Network parameters
- **Training Loop**
  - Simple python script: sort of main function interconnecting all components

Network

- All neural networks (and layers) in PyTorch are a subclass of the torch Module class
    - **torch.nn.Module:** base class for all neural network modules
    - Modules can also contain other Modules, allowing to nest them in a tree structure
    - https://pytorch.org/docs/stable/nn.html#torch.nn.Module
- Pre-defined models for addressing different tasks
    - https://pytorch.org/vision/stable/models.html

Network from Scratch

- Define a simple MLP
  - Two Fully Connected layers spaced out by ReLU activation function

```
import torch.nn as nn

# Fully connected neural network with one hidden layer
class NeuralNet(nn.Module):
    def __init__(self, input_size, hidden_size, num_classes):
        super(NeuralNet, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.relu = nn.ReLU()
        self.fc2 = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        out = self.fc1(x)
        out = self.relu(out)
        out = self.fc2(out)
        return out
```

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initialization:
instantiate linear layers and relu (encapsulated)

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        out = self.relu(out)
        out = self.fc2(out)
        return out
```

forward function:
describe the flow of input data (x) through the network layers

Network from Scratch

- Instantiate the neural network object

Instantiate network object ⇒ model

```
input_size, hidden_size, num_classes = 784, 500, 10
model = NeuralNet(input_size=input_size, hidden_size=hidden_size, num_classes=num_classes)
print('Our model:')
print(model)
```

```
Our model:
NeuralNet(
  (fc1): Linear(in_features=784, out_features=500, bias=True)
  (relu): ReLU()
  (fc2): Linear(in_features=500, out_features=10, bias=True)
)
```

```
# FORWARD
forward_res = model(img)
```

Network from Scratch

- Instantiate the neural network object
- Invoke forward on data

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)
```

```
# FORWARD
forward_res = model(img)
```

calls network forward function on ‘img’ ⇒ logits

Data Reading

- Define Preprocessing
  - https://pytorch.org/docs/stable/torchvision/transforms.html

- Create a Dataset class
  - https://pytorch.org/docs/stable/data.html#torch.utils.data.Dataset

- Choose a Sampling Strategy
  - https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader

Dataset Class

In [8]:
```python
import torch
import pandas as pd
from torch.utils.data import DataLoader, Dataset
from torchvision import transforms

class DatasetMNIST(Dataset):

    def __init__(self, file_path, transform=None):
        self.data = pd.read_csv(file_path)
        self.transform = transform

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

    def __getitem__(self, index):
        # load image as ndarray type (Height * Width * Channels)
        # be carefull for converting dtype to np.uint8 [Unsigned integer (0 to 255)]
        # in this example, i don't use ToTensor() method of torchvision.transforms
        # so you can convert numpy ndarray shape to tensor in PyTorch (H, W, C) --> (C, H, W)
        image = self.data.iloc[index, 1:].values.astype(np.uint8).reshape((1, 28, 28))
        label = self.data.iloc[index, 0]

        if self.transform is not None:
            image = self.transform(image)

        return image, label
```

Dataset Class

- **torch.data.Dataset:** base class for all datasets
- **Basic Methods to override:**
  - init(): initial processing, loading data in memory, ...
  - len(): returns the total number of samples in the dataset
  - getitem(idx): given and index return a data sample from the dataset
- **Transforms:** pre-processing or data-augmentation to be applied on each sample

```
In [9]: transform = transforms.Compose([
            transforms.ToPILImage(), # because the input dtype is numpy.ndarray
            transforms.RandomHorizontalFlip(0.5), # because this method is used for PIL Image dtype
            transforms.ToTensor(), # because inpus dtype is PIL Image
        ])

        train_dataset = DatasetMNIST(file_path='../input/train.csv', transform=transform)
```

Example: Instantiating an object Dataset

DataLoader

- PyTorch provides an efficient way to iterate a Dataset through **DataLoader** *(torch.utils.data.DataLoader)*
- Its **constructor takes as input an object of type Dataset**
- Provides:
  - **Data Batching**: we want to forward to our network batches of data (e.g. 32 images at a time)
  - **Data Shuffling**
  - **Parallel Data Loading**: multiple threads/workers loading data in parallel

DataLoader

- Constructor takes as input an object of type Dataset

```
train_loader = torch.utils.data.DataLoader(
  torchvision.datasets.MNIST('/files/', train=True, download=True,
                             transform=torchvision.transforms.Compose([
                               torchvision.transforms.ToTensor(),
                               torchvision.transforms.Normalize(
                                 (0.1307,), (0.3081,))
                             ])),
  batch_size=batch_size_train, shuffle=True)
```

Example: Instantiating a DataLoader object

Loss

- In PyTorch there are some predefined Loss Function that we can use
- Examples are **torch.nn.CrossEntropyLoss** (classification) and **torch.nn.MSELoss** (regression)

Instantiate loss

```
In [1]: import torch

In [2]: import torch.nn

In [3]: loss_fn = torch.nn.CrossEntropyLoss()

In [4]: # define some stub tensors for network pred and ground truth

In [5]: pred = torch.rand(3, 5, requires_grad=True)

In [6]: ground_truth = torch.empty(3, dtype=torch.long).random_(5)

In [7]: # compute loss

In [8]: loss = loss_fn(pred, ground_truth)

In [9]: # now backward

In [10]: loss.backward()
```

```
In [12]: print("pred: ", pred)
pred:  tensor([[0.7878, 0.1673, 0.6948, 0.4985, 0.4380],
        [0.8667, 0.6241, 0.0718, 0.2107, 0.5227],
        [0.0934, 0.7967, 0.5874, 0.6695, 0.9948]], requires_grad=True)

In [13]: print(pred.shape)
torch.Size([3, 5])

In [14]: print("ground_truth: ", ground_truth)
ground_truth:  tensor([0, 3, 4])

In [15]: print(ground_truth.shape)
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```

CrossEntropyLoss example - *CrossEntropyLoss takes as input the network logits since it encapsulates a softmax op. inside!*

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CrossEntropyLoss example - *CrossEntropyLoss takes as input the network logits since it encapsulates a softmax op. inside!*

Optimizer

- Updates network parameters depending on the gradients computed at the backward step *(**loss.backward()** in previous slide)*
- Optimizer constructor takes as inputs at least:
  - **parameters** : parameters to optimize (e.g. a neural network)
  - **lr** : learning rate to use in the update rule
- Basic method:
  - **step()** : update model parameters - **do this only after the *loss.backward()***

Instantiate Optimizer

```
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)
optimizer = optim.Adam([var1, var2], lr=0.0001)
```

doc: https://pytorch.org/docs/stable/optim.html

Optimization Step

```
for input, target in dataset:
    optimizer.zero_grad()
    output = model(input)
    loss = loss_fn(output, target)
    loss.backward()
    optimizer.step()
```

Training loop example

- Just code..

```python
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)

for epoch in range(100): # loop over the dataset multiple times
    tot_loss, tot_samples = 0.0, 0
    for i, data in enumerate(train_dataloader):
        # Step 1: Retrieving a batch of input from the dataloader
        inputs, labels = data
        tot_samples += inputs.size(0)

        # Step 2: Zeroing the parameter gradients - always do this before doing loss.backward()!!!
        optimizer.zero_grad()
        # Step 3: forward (get network prediction)
        outputs = model(inputs)

        # Step 4: compute loss
        loss = criterion(outputs, labels)
        # Step 5: Compute gradients for each of the model learnable parameters
        loss.backward()
        # Step 4: Update model parameters according to the gradients
        optimizer.step()

        # logging, accumulating loss value for current epoch...
        tot_loss += (loss.data[0] * inputs.size(0))
    # End epoch here
    print("Epoch %d loss is: %.6f" % (epoch, (tot_loss * 1.0 / float(tot_samples))))
# End Training here
```

It's your turn!

https://colab.research.google.com/drive/1jwBxRTNnu0oxkx6xGQ44UHxJWVYw3jeX?usp=sharing