



## Deep learning with PyTorch

Elements of Machine Learning

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with content from Deep Learning with PyTorch,

Eli Stevens and Luca Antiga



### About this lecture

- Covering content from Deep learning with PyTorch, Eli Stevens and Luca Antiga, chapters 1-5
- further reading at http://pytorch.org/docs and https://pytorch.org/tutorials/beginner/deep\_ learning\_60min\_blitz.html

We assume familarity with Python, NumPy...



## Deep learning with PyTorch

#### What is PyTorch

- Python library which
  - facilitates deep learning
  - allows easy use of both GPUs and CPUs (switching requires nothing more than a function call)

#### Why PyTorch as opposed to TensorFlow?

- (+) More pythonic and PyTorch tensors are similar to NumPy arrays, so may be easier to learn, use, extend, and debug (opinions are like ...)
- (+) Dynamic graph as opposed to static graph (TensorFlow 2.0 also has dynamic graphs)
- Adopted more in research and less in industry



# Immediate versus deferred execution (Dynamic/Static)

Immediate execution / dynamic computation graph / eager mode

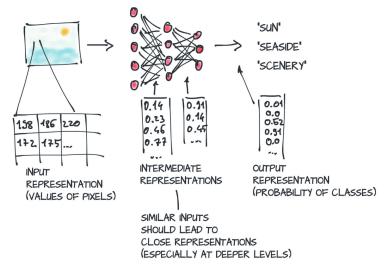
 When problems arise, interpreter and debugger have direct access to Python objects involved.

Deferred execution / static computation graph

Code can be compiled to machine code (performance)



## Handling data in DL networks - PyTorch tensors





## PyTorch tensors

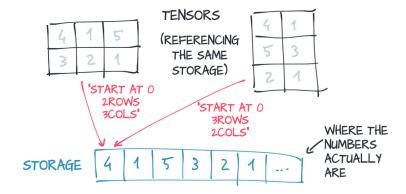
3 
$$\begin{bmatrix} 4 \\ 1 \\ 5 \end{bmatrix} \begin{bmatrix} 4 & 6 & 7 \\ 7 & 3 & 9 \\ 1 & 2 & 5 \end{bmatrix} \begin{bmatrix} 5 & 7 & 1 \\ 3 & 4 & 3 \\ 3 & 5 & 2 \end{bmatrix}$$
SCALAR VECTOR MATRIX TENSOR TENSOR
$$X[2]=5 \quad X[1,0]=7 \quad X[0,2,1]=2 \quad X[1,3,...,2]=4$$
od AD 2D 3D

N-D DATA  $\Rightarrow$  N INDICES

- Seamless interoperability with NumPy
  - Allows easy integration with existing scientific libraries (SciPy, Scikit-learn, Pandas...)

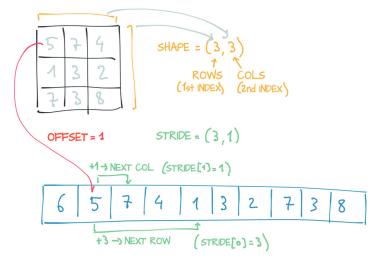


## PyTorch tensors - views over a Storage instance





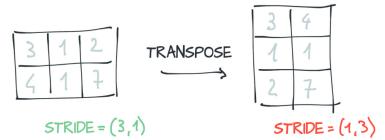
## PyTorch tensors - views over a Storage instance

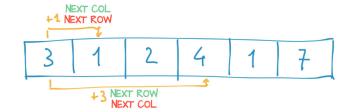


#### Open 1\_tensors.slides.html



## PyTorch tensors - transpose example



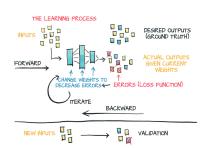




## Learning with PyTorch

Given input and groundtruth output, iterate over

- forward pass: compute error given weights
- backward pass: compute how much we need to change each weight to decrease error.
- update weights accordingly

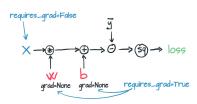




## Learning with PyTorch

Given input and groundtruth output, iterate over

- forward pass: compute error given weights
- backward pass: compute gradients, or partial derivatives of the loss with respect to each parameter, w and b in this example.
  - In PyTorch, these are stored in the .grad attribute of each tensor
- update weights accordingly



#### loss.backward()



## Autograd

Gradients are computed automatically using Autograd.

- Graph (DAG) recording all operations that created the data as you execute operations
  - forward pass
  - requires\_grad = True
- By tracing this graph from roots to leaves, gradients are computed using the chain rule
  - backward\_pass
- Note the graph is created from scratch in every iteration
  - What you run is what you differentiate!

Open 2\_autograd.slides.html



## PyTorch optimizers and training loop

PyTorch comes with optimizers, open 3\_optimizers.slides.html for an example of how to use them.



## Neural networks in PyTorch

Critical to implementing neural networks are activation and loss functions.

Open 4\_neural\_networks.slides.html



## Convolutional neural networks in PyTorch

We will go through the example from the PyTorch 60 minutes tutorial https://colab.research.google.com/drive/1B-NPM6i6U0sU\_bFQzDmMN27ZqTpmgMwC.



## Questions?

