Learning Deep Learning with PyTorch

(3) Knowing PyTorch

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Deep Learning Platform Competition Final

PYTORCH vs. TensorFlow

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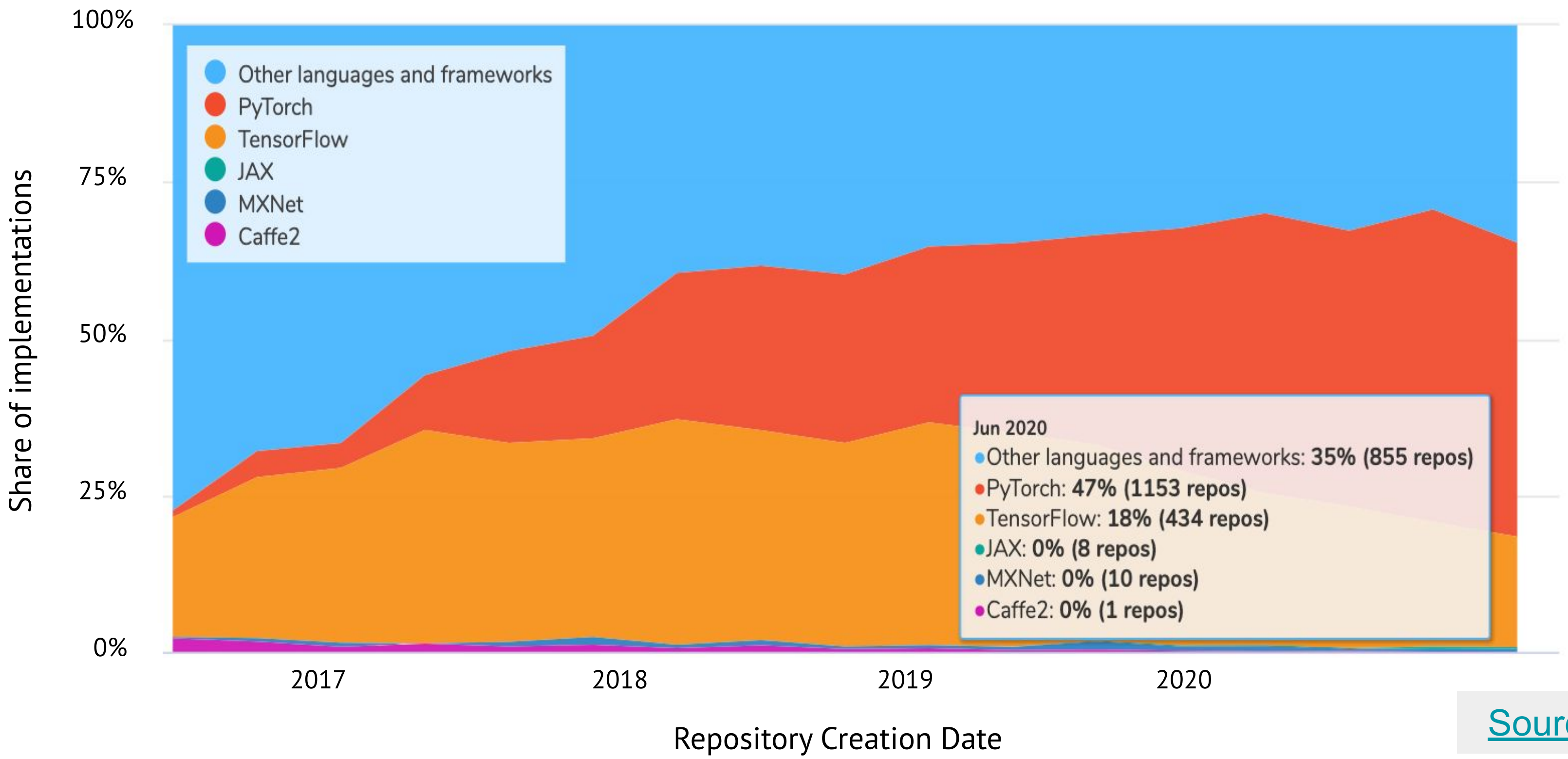
Frameworks used in paper implementations on GitHub



Jun 2020
●Other languages and frameworks: **35% (855 repos)**
●PyTorch: **47% (1153 repos)**
●TensorFlow: **18% (434 repos)**
●JAX: **0% (8 repos)**
●MXNet: **0% (10 repos)**
●Caffe2: **0% (1 repos)**

Source

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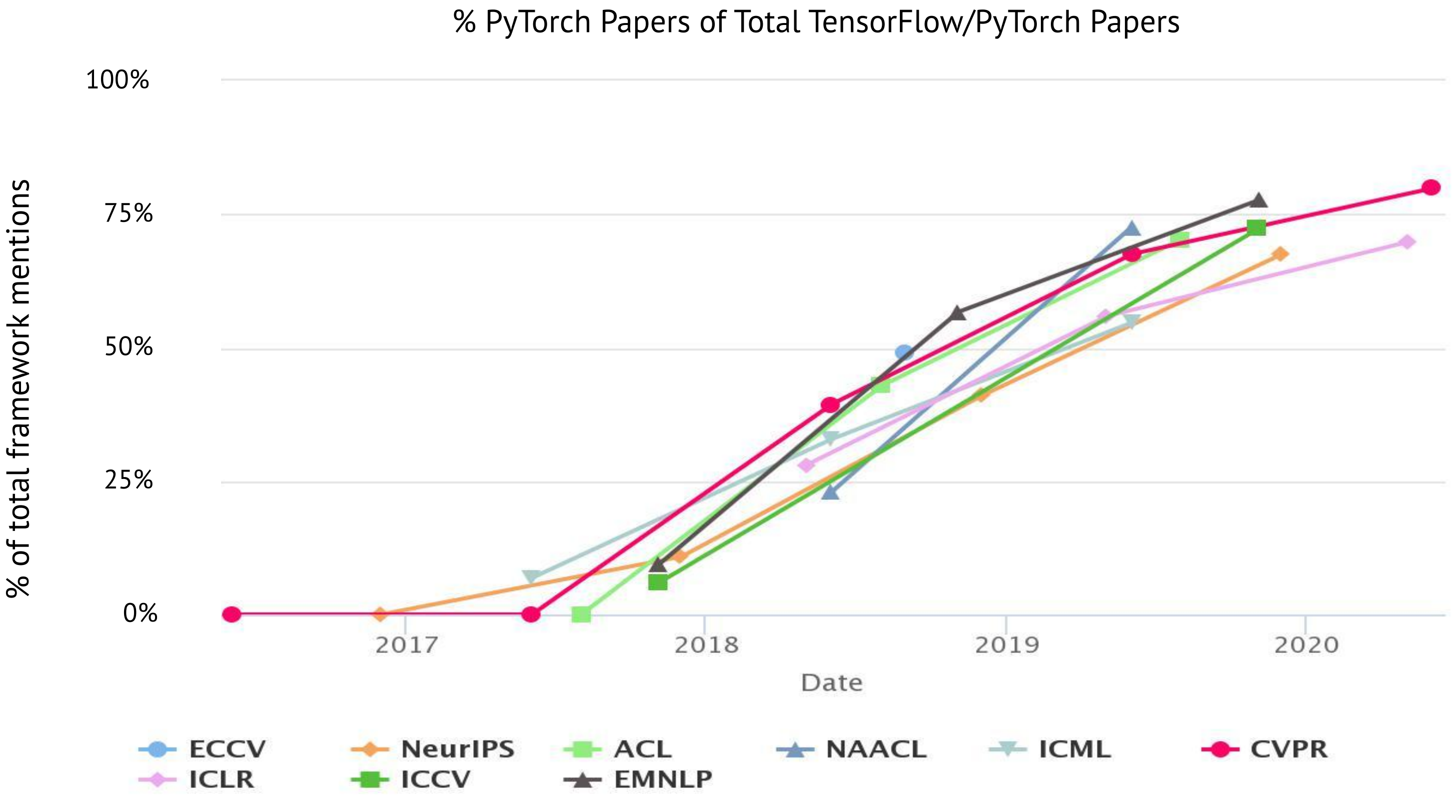
PyTorch is increasing dominance in research



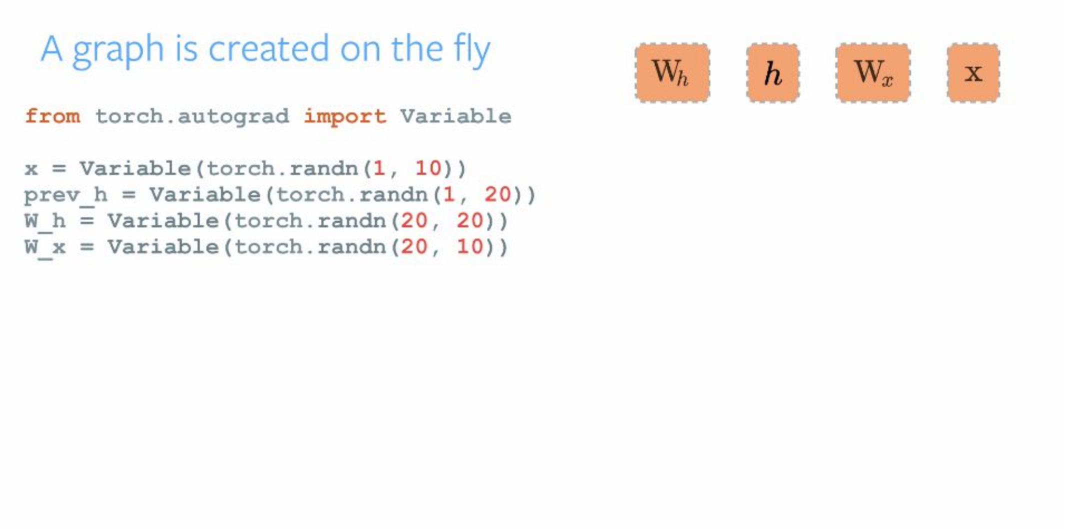
Source

What is PYTORCH

- An open-source Python-based deep learning framework
  - Primarily developed by Facebook's AI Research lab (FAIR)
  - Replacement for Numpy with supporting GPUs, ROCm, TPUs (?)
  - A full set of deep learning libraries
- History
  - Lua-based Torch (2002 - 2011)
  - PyTorch 0.1 (2016): THNN
  - PyTorch 1.0 (2018): merging Caffe2
  - PyTorch 1.6.0 (July 28, 2020) release note
- PyTorch as a backend building block
  - Keras-like: PyTorch Lightening, PyTorch Ignite, tensorlayers, fast.ai
  - For specific domains: NiftyTorch, Flair, Skorch, ELF, Detectron2

Why PYTORCH

- Simplicity
  - Feels like Numpy
  - Consistent & great APIs
- Flexibility
  - Defining the model
  - Modifying the model
- Immediate execution mode
  - Defined by run
  - Tape-based autograd
  - Awesome debugging
- Catching up hybrid front-end
  - JIT: TorchScript, Tracing
    - Seamlessly switch between Modes, Distributed training, Mobile deployment



A graph is created on the fly

```
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))
```

Tensors as building blocks

$$1$$

Scalar

0-D

$$X = 1$$

$$\begin{bmatrix} 2 \\ 5 \\ 4 \end{bmatrix}$$

Vector

1-D

$$X[1] = 5$$

$$\begin{bmatrix} 2 & 1 & 3 \\ 5 & 7 & 9 \\ 4 & 8 & 6 \end{bmatrix}$$

Matrix

2-D

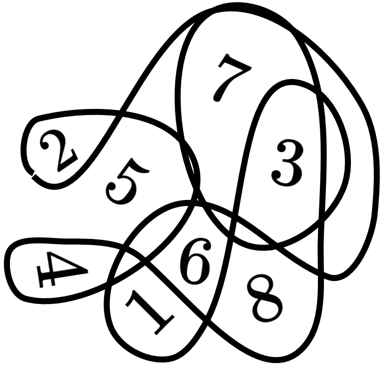
$$X[2,1] = 8$$

$$\begin{bmatrix} 4 & 6 & 9 \\ 1 & 2 & 5 \\ 8 & 7 & 3 \end{bmatrix}$$

Tensor

3-D

$$X[0,1,2] = 5$$



Tensor

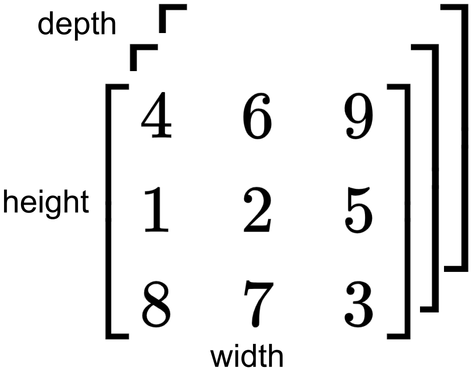
n-D

$$X[\underbrace{2,3,\ldots,1}_{N \text{ indices}}] = 6$$

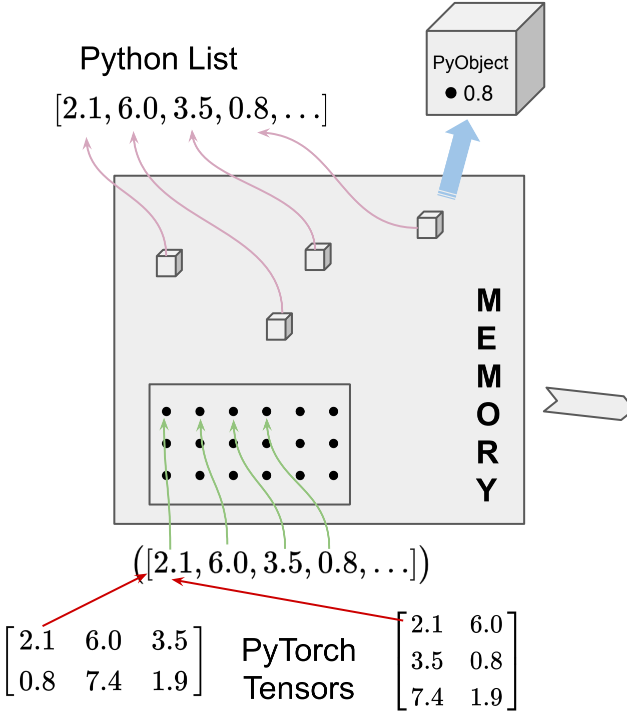
Tensor, Storage and Views

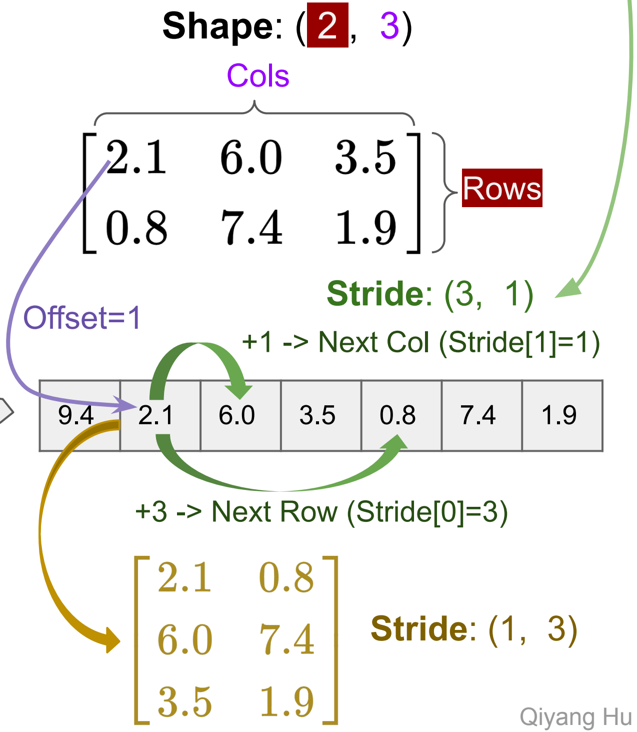
$$M(i,j) = \text{offset} + \text{stride}[0]\cdot i + \text{stride}[1]\cdot j$$

- Data and Metadata
- Contiguous & Unboxed
- Offset, size, stride



sizes	(D,H,W)
dtype	integer
device	cuda:0
layout	strided
strides	(H*W,W,1)





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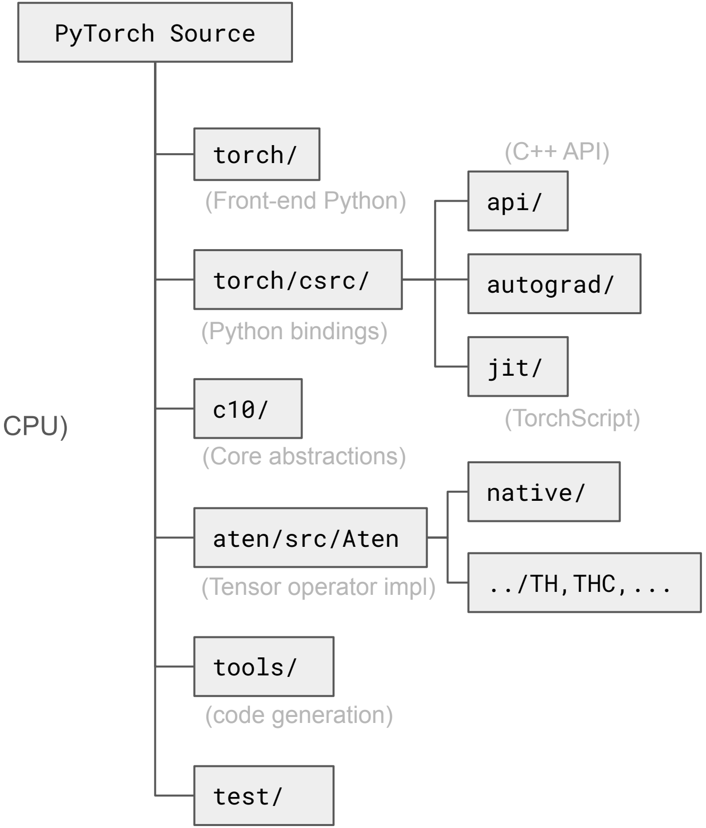
“Py” and “Non-Py” in PyTorch

- Tensor extensions
  - Beyond strided tensors:

    sparse, quantized, encrypted, MKLDNN, TPU tensors etc.
  - Tensor wrapper: device ❌ layout ❌ dtype
- Works with Numpy arrays
  - Easy conversion
  - Zero copy: share their underlying memory locations (if on CPU)
- PyTorch = Python + C/C++ + CUDA
  - Python extension objects in C/C++
  - Code base components:
    - The core Torch libraries: TH, THC, THNN, THCUNN
    - Vendor libraries: CuDNN, NCCL
    - Python Extension libraries
    - Additional 3rd-party libraries: NumPy, MKL, LAPACK, DLPack



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Colab Hands-on

bit.ly/LDL_01

Automatic differentiation

- Autograd package
  - Track all operations of tensors
  - Compute derivatives analytically via back-prop
  - Natively loaded in torch module
  - Can be used in other scientific domains

- Simple usage
  - Set tensor's .requires_grad as TRUE
  - Call .backward()
    - Gradient accumulated into .grad attribute
    - Tensor's creation function recorded in .grad_fn attribute

- Stop a tensor from tracking history
  - .detach()
  - Wrap the code block in with torch.no_grad()

Neural Networks in PyTorch

- torch.nn package
  - Contains all building blocks for NN architectures
  - All blocks subclassed from nn.Module (e.g. nn.Linear)
- Define a network
  - For simple networks:
    - concatenate modules through a nn.Sequential container
  - For complex networks:
    - Subclassing nn.Module
- nn.Module package expects first index as first batch size of samples
  - Need to reshape the input by .unsqueeze()
- Loss functions in torch.nn:
  - L1Loss, MSELoss, CrossEntropyLoss, MarginRankingLoss, ...

Optimizers in PyTorch

- torch.optim package
  - Provides various optimization algorithms
  - Need to move model to GPU before constructing optimizers
  - Must zero the gradient explicitly:
    - optimizer.zero_grad()
  - Take an optimization step:
    - optimizer.step() in GD method
    - optimizer.step(closure) in CG or LBFGS method
  - Optional: adjust the learning rate based on the number of epochs.
    - optimizer.lr_scheduler

Don’t forget to

- Github Repo:
  - https://github.com/huqy/idre-learning-deep-learning-pytorch
- Slack workspace:
  - bit.ly/Join-LDL
- Contact me
  - huqy@idre.ucla.edu
  - Direct message in Slack