Growing a research platform for cutting edge AI

Soumith Chintala
Facebook AI Research

Overview

- What is Torch?
- The Community
- Common use
- Core Philosophy
- Key drivers of adoption
- Questions

What is torch ?

- Interactive Scientific computing framework

Strings, numbers, tables - a tiny introduction

```
In [ ]: a = 'hello'

In [ ]: print(a)

In [ ]: b = {}

In [ ]: b[1] = a

In [ ]: print(b)

In [ ]: b[2] = 30

In [ ]: for i=1,#b do -- the # operator is the length operator in Lua
            print(b[i])
        end
```

torch

What is torch ?

- Interactive Scientific computing framework

Tensors

In [ ]:
```
a = torch.Tensor(5,3) -- construct a 5x3 matrix, uninitialized
```

In [ ]:
```
a = torch.rand(5,3)
print(a)
```

In [ ]:
```
b=torch.rand(3,4)
```

In [ ]:
```
-- matrix-matrix multiplication: syntax 1
a*b
```

In [ ]:
```
-- matrix-matrix multiplication: syntax 2
torch.mm(a,b)
```

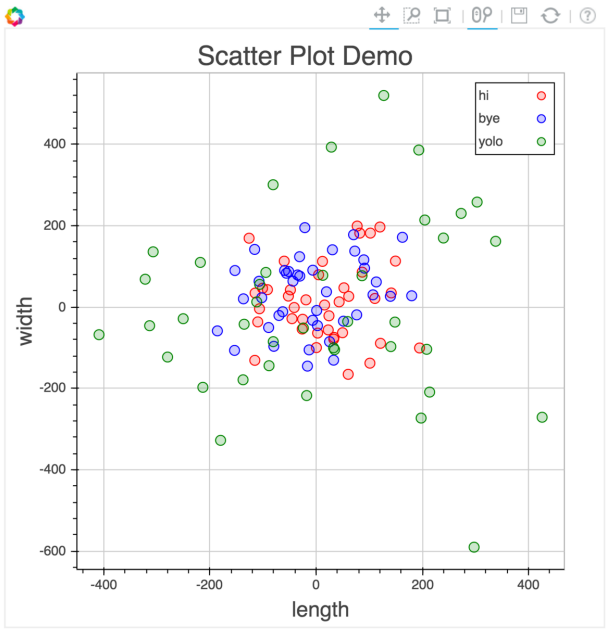
In [ ]:
```
-- matrix-matrix multiplication: syntax 3
c=torch.Tensor(5,4)
c:mm(a,b) -- store the result of a*b in c
```

torch

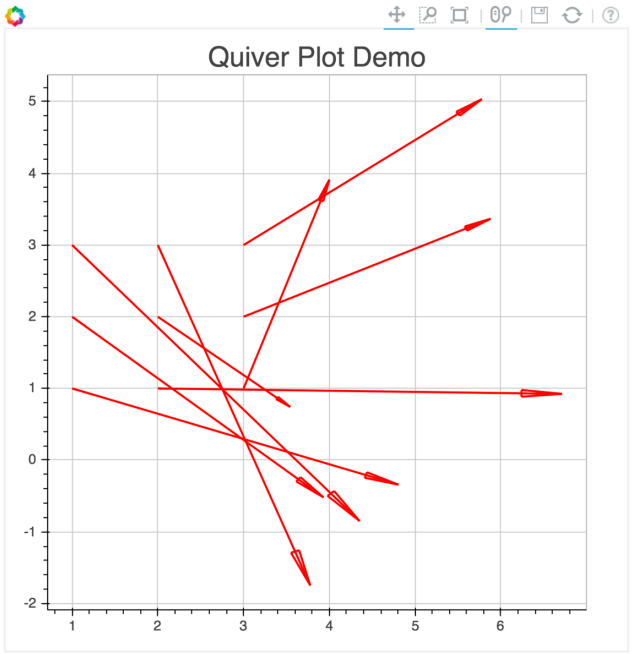
What is torch ?

- Similar to Matlab / Python+Numpy

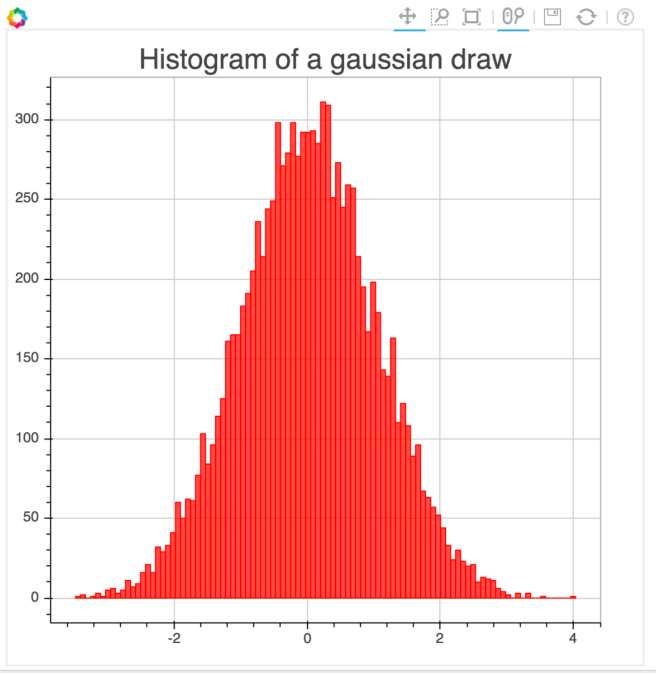
```
x1 = torch.randn(40):mul(100)
y1 = torch.randn(40):mul(100)
x2 = torch.randn(40):mul(100)
y2 = torch.randn(40):mul(100)
x3 = torch.randn(40):mul(200)
y3 = torch.randn(40):mul(200)


-- scatter plots
plot = Plot():circle(x1, y1, 'red', 'hi'):circle(x2, y2, 'blue', 'bye'):draw()
plot:circle(x3,y3,'green', 'yolo'):redraw()
plot:title('Scatter Plot Demo'):redraw()
plot:xaxis('length'):yaxis('width'):redraw()
plot:legend(true)
plot:redraw()
-- print(plot:toHTML())
plot:save('out.html')
```



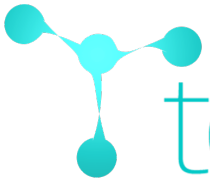

```
-- quiver plots
U = torch.randn(3,3):mul(100)
V = torch.randn(3,3):mul(100)
plot = Plot():quiver(U,V,'red',''):title('Quiver Plot Demo'):draw()
```




```
-- histogram
plot = Plot():histogram(torch.randn(10000)):draw()
```



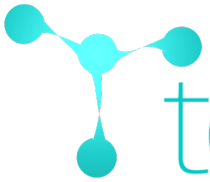
torch

What is  ?

- Little language overhead compared to Python / Matlab
- JIT compilation via LuaJIT
  - Fearlessly write for-loops

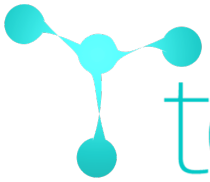
Code snippet from a core package

```
function NarrowTable:updateOutput(input)
   for k,v in ipairs(self.output) do self.output[k] = nil end
   for i=1,self.length do
      self.output[i] = input[self.offset+i-1]
   end
   return self.output
end
```

What is  ?

- Easy integration into and from C
- Example: using CuDNN functions

```
for g = 0, self.groups - 1 do
    errcheck('cudnnConvolutionForward', cudnn.getHandle(),
             one:data(),
             self.iDesc[0], input:data() + g*self.input_offset,
             self.weightDesc[0], self.weight:data() + g*self.weight_offset,
             self.convDesc[0], self.fwdAlgType[0],
             self.extraBuffer:data(), self.extraBufferSizeInBytes,
             zero:data(),
             self.oDesc[0], self.output:data() + g*self.output_offset);
end
```

What is  ?

- Strong GPU support

CUDA Tensors

Tensors can be moved onto GPU using the :cuda function

In [ ]:
```
require 'cutorch';
a = a:cuda()
b = b:cuda()
c = c:cuda()
c:mm(a,b) -- done on GPU
```


torch
Community
Google DeepMind
Facebook AI Research
UNIVERSITY OF OXFORD
École des Ponts ParisTech
NYU
NVIDIA
Inria
Stanford University
PURDUE UNIVERSITY
IIIT-H
canary
idiap RESEARCH INSTITUTE
VisionLabs visual recognition company
Etsy
Yandex
element
Moodstocks
AMD
IBM
MULTICOREWARE
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Community

szagoruyko / **loadcaffe**

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Load Caffe networks in Torch7

facebook / **fb.resnet.torch**

Unwatch 62 | Unstar 421 | Fork 85

Code | Issues 4 | Pull requests 0 | Wiki | Pulse | Graphs

Torch implementation of ResNet from http://arxiv.org/abs/1512.03385 and training scripts

Moodstocks / **inception-v3.torch**

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Rethinking the Inception Architecture for Computer Vision http://arxiv.org/abs/1512.00567

Community

karpathy / neuraltalk2

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Efficient Image Captioning code in Torch, runs on GPU

NeuralTalk2

Recurrent Neural Network captions your images. Now much faster and better than the original NeuralTalk. Compared to the original NeuralTalk this implementation is **batched, uses Torch, runs on a GPU, and supports CNN finetuning**. All of these together result in quite a large increase in training speed for the Language Model (~100x), but overall not as much because we also have to forward a VGGNet. However, overall very good models can be trained in 2-3 days, and they show a much better performance.

This is an early code release that works great but is slightly hastily released and probably requires some code reading of inline comments (which I tried to be quite good with in general). I will be improving it over time but wanted to push the code out there because I promised it to too many people.

This current code (and the pretrained model) gets ~0.9 CIDEr, which would place it around spot #8 on the codalab leaderboard. I will submit the actual result soon.

You can find a few more example results on the demo page. These results will improve a bit more once the last few bells and whistles are in place (e.g. beam search, ensembling, reranking).

There's also a fun video by @kcimc, where he runs a neuraltalk2 pretrained model in real time on his laptop during a walk in Amsterdam.

Community

jcjohnson / **neural-style**

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Torch implementation of neural style algorithm

neural-style

This is a torch implementation of the paper A Neural Algorithm of Artistic Style by Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge.

The paper presents an algorithm for combining the content of one image with the style of another image using convolutional neural networks. Here's an example that maps the artistic style of The Starry Night onto a night-time photograph of the Stanford campus:

Community

DmitryUlyanov / **fast-neural-doodle**

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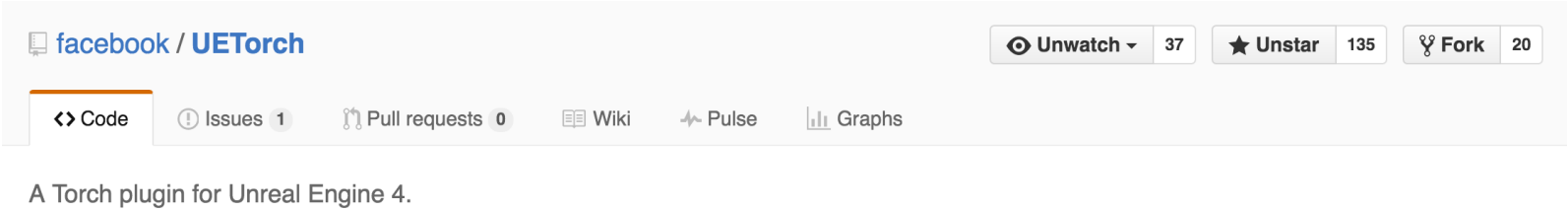
Faster neural doodle


torch

Community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Fork 20
Code
Issues 1
Pull requests 0
Wiki
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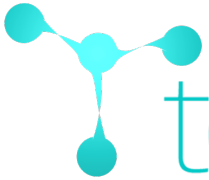
Graphs
A Torch plugin for Unreal Engine 4.


torch



Community

willwhitney / **understanding-visual-concepts**

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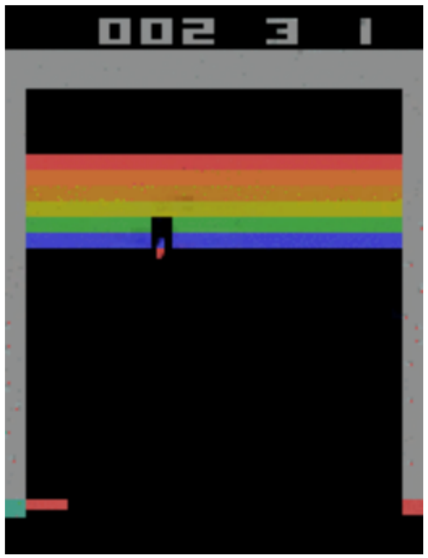
Unsupervised learning of visual concepts from video http://willwhitney.github.io/understanding-visual-concepts/

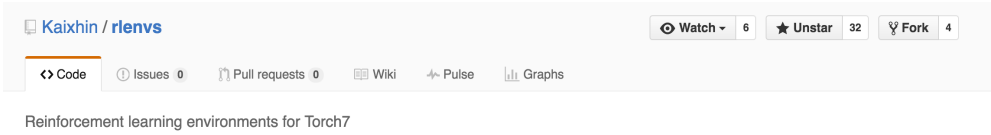
Moving the paddle.



Counting remaining lives.

Animating the aliens.

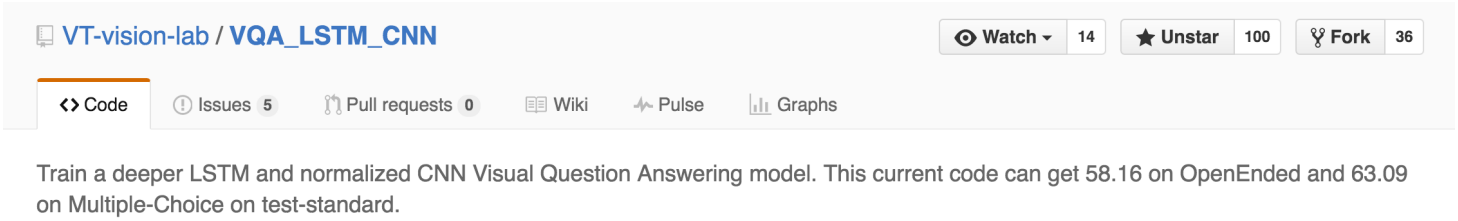
Community



Reinforcement learning environments for Torch7, inspired by RL-Glue [1]. Supported environments:

- rlenvs.Acrobot [2]
- rlenvs.Atari (Arcade Learning Environment)* [3]
- rlenvs.Blackjack [4]
- rlenvs.CartPole [5]
- rlenvs.Catch [6]
- rlenvs.CliffWalking [7]
- rlenvs.DynaMaze [8]
- rlenvs.GridWorld [9]
- rlenvs.JacksCarRental [7]
- rlenvs.MountainCar [10]
- rlenvs.MultiArmedBandit [11, 12]
- rlenvs.RandomWalk [13]
- rlenvs.Taxi [14]
- rlenvs.WindyWorld [7]

Community



Deeper LSTM+ normalized CNN for Visual Question Answering

Train a deeper LSTM and normalized CNN Visual Question Answering model. This current code can get **58.16** on Open-Ended and **63.09** on Multiple-Choice on **test-standard** split. You can check Codalab leaderboard for more details.

Community

Neural Conversational Model in Torch

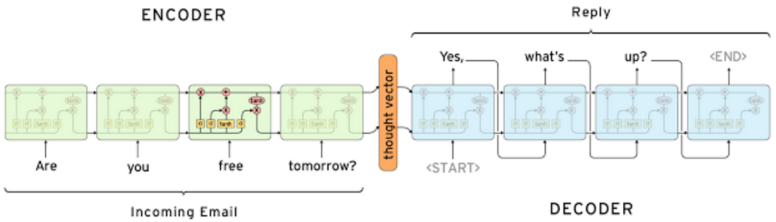
This is an attempt at implementing Sequence to Sequence Learning with Neural Networks (seq2seq) and reproducing the results in A Neural Conversational Model (aka the Google chatbot).

The Google chatbot paper became famous after cleverly answering a few philosophical questions, such as:

> **Human:** What is the purpose of living?
> **Machine:** To live forever.

How it works

The model is based on two LSTM layers. One for encoding the input sentence into a "thought vector", and another for decoding that vector into a response. This model is called Sequence-to-sequence or seq2seq.



Source: http://googleresearch.blogspot.ca/2015/11/computer-respond-to-this-email.html

Community

soumith / **dcgan.torch**

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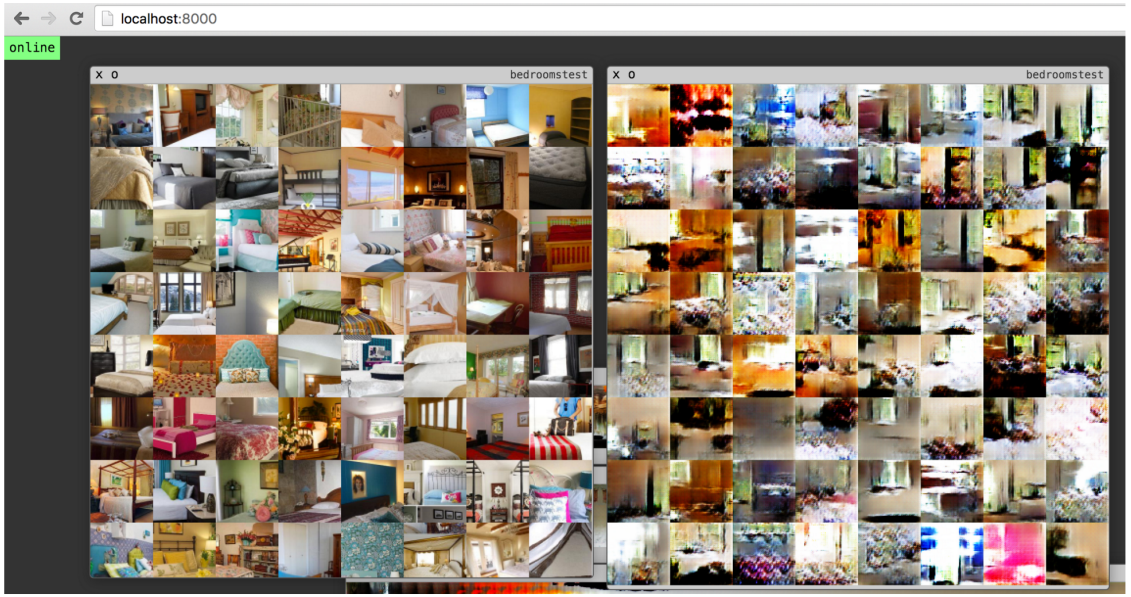
A torch implementation of http://arxiv.org/abs/1511.06434 — Edit

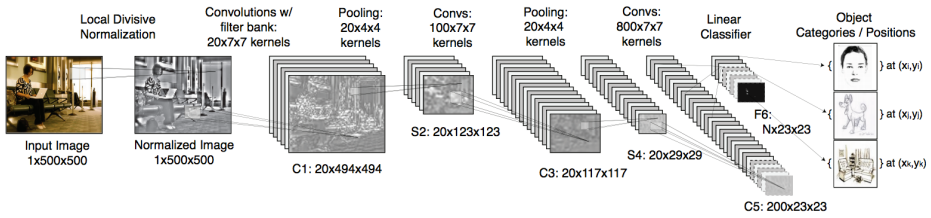


Neural Networks

- nn: neural networks made easy
- building blocks of differentiable modules

➡ **define a model with pre-normalization, to work on raw RGB images:**

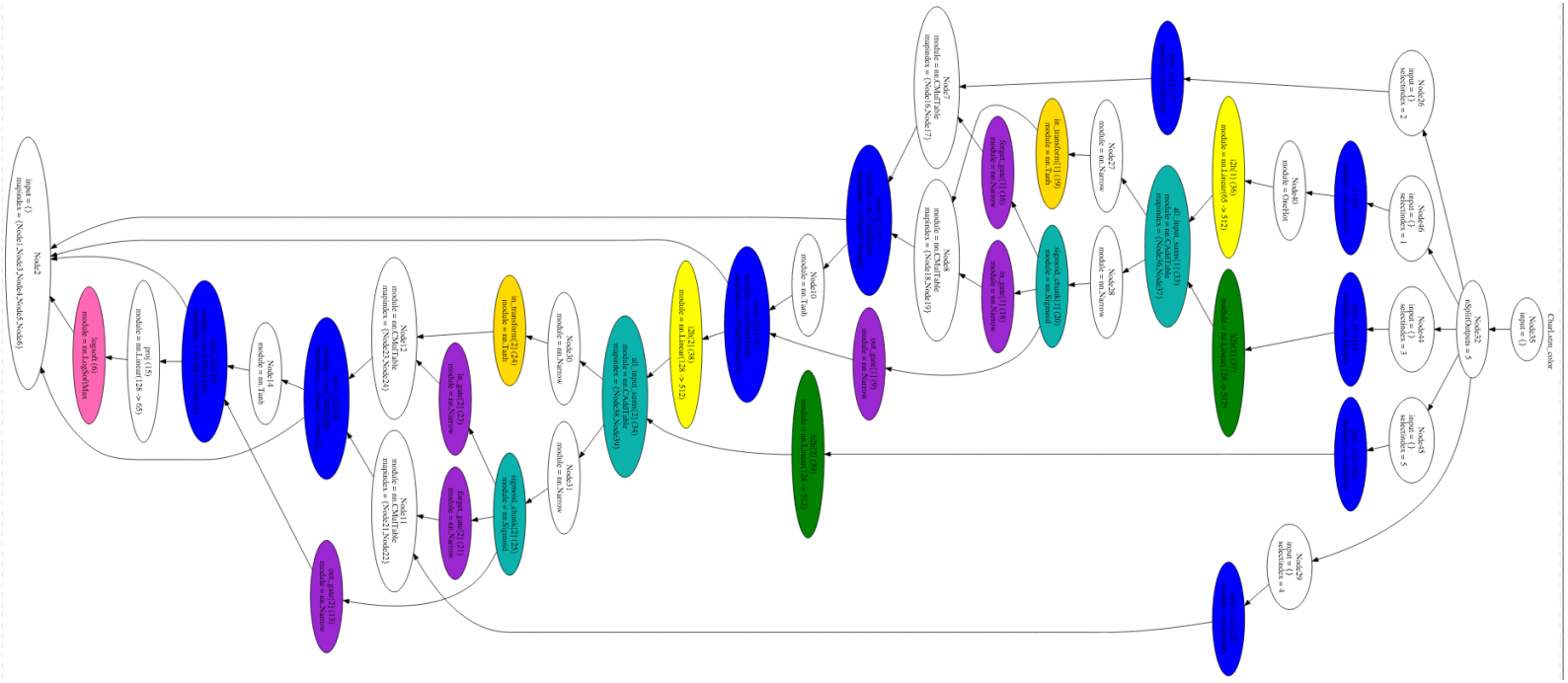
```
01  model = nn.Sequential()
02
03  model:add( nn.SpatialConvolution(3,16,5,5) )
04  model:add( nn.Tanh() )
05  model:add( nn.SpatialMaxPooling(2,2,2,2) )
06  model:add( nn.SpatialContrastiveNormalization(16, image.gaussian(3)) )
07
08  model:add( nn.SpatialConvolution(16,64,5,5) )
09  model:add( nn.Tanh() )
10  model:add( nn.SpatialMaxPooling(2,2,2,2) )
11  model:add( nn.SpatialContrastiveNormalization(64, image.gaussian(3)) )
12
13  model:add( nn.SpatialConvolution(64,256,5,5) )
14  model:add( nn.Tanh() )
15  model:add( nn.Reshape(256) )
16  model:add( nn.Linear(256,10) )
17  model:add( nn.LogSoftMax() )
```



torch

Advanced Neural Networks

- nngraph
  - easy construction of complicated neural networks



autograd by 

- Write imperative programs
- Backprop defined for every operation in the language

```
neuralNet = function(params, x, y)
   local h1 = t.tanh(x * params.W[1] + params.b[1])
   local h2 = t.tanh(h1 * params.W[2] + params.b[2])
   local yHat = h2 - t.log(t.sum(t.exp(h2)))
   local loss = - t.sum(t.cmul(yHat, y))
   return loss
end

-- gradients:
dneuralNet = grad(neuralNet)

-- some data:
x = t.randn(1,100)
y = t.Tensor(1,10):zero() y[1][3] = 1

-- compute loss and gradients wrt all parameters in params:
dparams, loss = dneuralNet(params, x, y)
```

torch

Distributed Learning

- in-built multi-GPU (data and model parallel)
- distlearn by 
  - multi-node parallelism

```
-- Use a tau of 10 and an alpha of 0.2
local allReduceEA = require 'distlearn.AllReduceEA'(tree, 10, 0.2)
-- Make sure all the nodes start with the same parameter values
allReduceEA.synchronizeParameters(params)
for _ = 1,epochs do
   for _ = 1,steps
      -- Compute your gradients as normal
      local grads = computeYourGrads(...)
      -- Do your SGD as normal
      SGD(params, grads)
      -- Average the params
      allReduceEA.averageParameters(params)
   end
   -- Make sure the center's haven't drifted too far due to
   -- floating point precision error build up
   allReduceEA.synchronizeCenter(params)
   -- Validate...
end
```

Core Philosophy

- Interactive computing
  - No compilation time
- Imperative programming
  - Write code like you always did, not computation graphs in a hacked up DSL
- Minimal abstraction
  - Thinking linearly
- Maximal Flexibility
  - No constraints on interfaces or classes

There is no silver bullet

D4J etc.

TensorFlow

Torch

Caffe

Neon

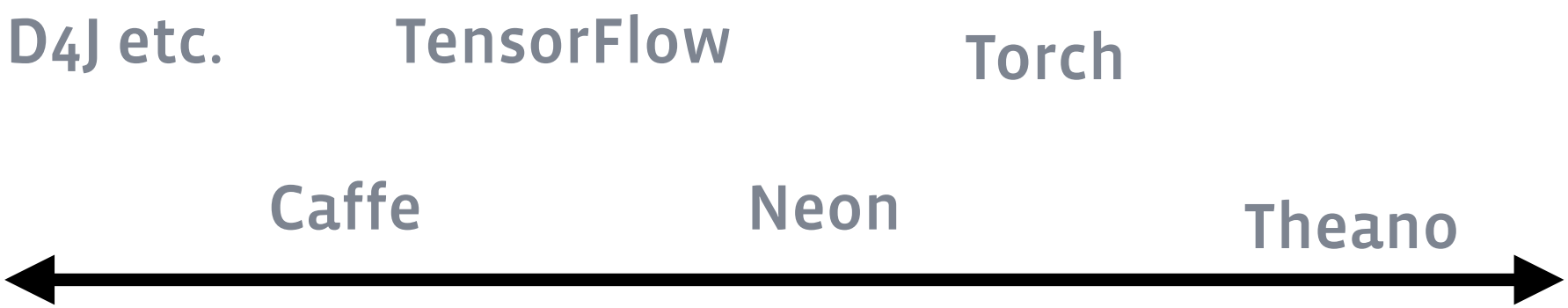
Theano

Industry:
Stability
Scale & speed
Data Integration
Relatively Fixed

Research:
Flexible
Fast Iteration
Debuggable
Relatively bare bone

Slide credit: Yangqing Jia

There is no silver bullet



Industry:
Stability
Scale & speed
Data Integration
Relatively Fixed

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Slide credit: Yangqing Jia

torch

There is no silver bullet

convnet-benchmarks

Easy benchmarking of all public open-source implementations of convnets. A summary is provided in the section below.

Machine: `6-core Intel Core i7-5930K CPU @ 3.50GHz` + `NVIDIA Titan X` + `Ubuntu 14.04 x86_64`

Industry:
Stability
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There is no silver bullet

convnet-benchmarks

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GoogleNet V1 - Input 128x3x224x224

Library	Class	Time (ms)	forward (ms)	backward (ms)
Nervana-neon-fp16	ConvLayer	230	72	157
Nervana-neon-fp32	ConvLayer	270	84	186
CuDNN[R4]-fp16 (Torch)	cudnn.SpatialConvolution	462	112	349
CuDNN[R4]-fp32 (Torch)	cudnn.SpatialConvolution	470	130	340
Chainer	Convolution2D	687	189	497
TensorFlow	conv2d	905	187	718
Caffe	ConvolutionLayer	1935	786	1148
CL-nn (Torch)	SpatialConvolutionMM	7016	3027	3988
Caffe-CLGreenTea	ConvolutionLayer	9462	746	8716

Industry:
Stability
Scale & speed
Data Integration
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Research:
Flexible
ast Iteration
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y bare bone

torch

Slide credit: Yangqing Jia

Key Drivers of Adoption

- Tutorials and support
  - Pre-trained models
  - High-quality open-source projects
- Deeply integrated GPU goodness
- Minimal abstractions
- Imperative programming
- Zero compile-time

Questions!

L6121 - Applied Deep Learning for Vision and Natural Language with Torch7

Nicholas Leonard (Research Engineer, Element Inc.)
This hands-on tutorial targets machine learning enthusiasts and researchers and will cover applying deep learning techniques on classifying images and natural language data. The session is driven in Torch: a scientific computing platform that has great toolboxes for deep learning and optimization among others, and fast CUDA backends with multi-GPU support. Torch is supported by Facebook, Google, Twitter, and a strong community who actively open-source their code and packages. **This lab utilizes GPU resources in the cloud, you are required to bring your own laptop.**

Session Level: Beginner
Session Type: Hands-on Lab
Tags: Deep Learning & Artificial Intelligence; Computer Vision & Machine Vision; Tools & Libraries

Day: Wednesday, 04/06
Time: 15:30 - 17:00
Location: Room 210A