

A dynamic view of the deep learning world

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Overview

- What is Torch?
- The Community
- Today's Al
- What Next?



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
```



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)

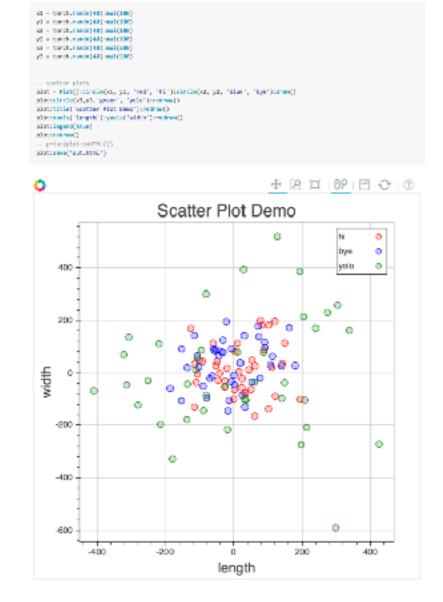
In []: -- matrix-matrix multiplication: syntax 1
    a*b

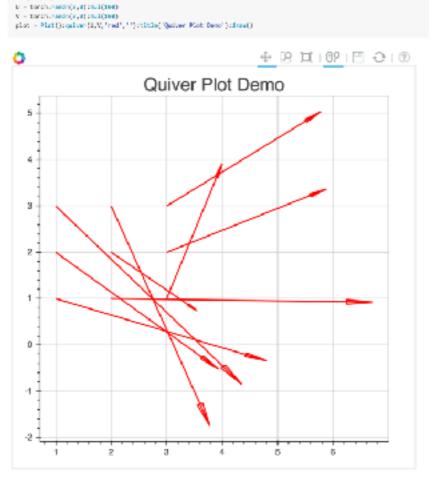
In []: -- matrix-matrix multiplication: syntax 2
    torch.mm(a,b)

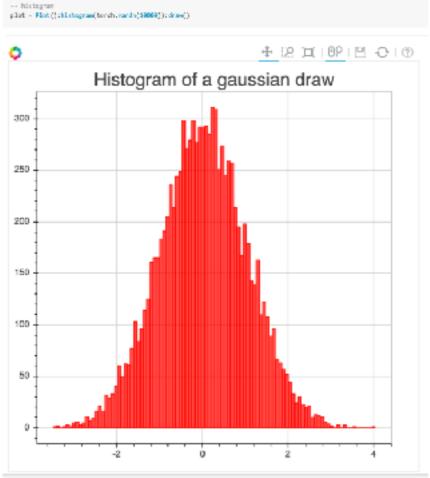
In []: -- matrix-matrix multiplication: syntax 3
    c=torch.Tensor(5,4)
    c:mm(a,b) -- store the result of a*b in c
```



Similar to Matlab / Python+Numpy









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



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
```



Neural Networks

- nn: neural networks made easy
- building blocks of differentiable modules
 - define a model with pre-normalization, to work on raw RGB images:

```
model = nn.Sequential()
01
Ø2
     model:add( nn.SpatialConvolution(3,16,5,5) )
03
     model:add( nn.Tanh() )
     model:add( nn.SpatialMaxPooling(2,2,2,2) )
     model:add( nn.SpatialContrastiveNormalization(16, image.gaussian(3)) )
07
     model:add( nn.SpatialConvolution(16,64,5,5) )
08
     model:add( nn.Tanh() )
     model:add( nn.SpatialMaxPooling(2,2,2,2) )
10
     model:add( nn.SpatialContrastiveNormalization(64, image.gaussian(3)) )
11
12
     model:add( nn.SpatialConvolution(64,256,5,5) )
13
     model:add( nn.Tanh() )
14
     model:add( nn.Reshape(256) )
15
     model:add( nn.Linear(256,10) )
     model:add( nn.LogSoftMax() )
            Local Divisive
                     filter bank:
                                   52: 20x120x120
                                            CS:50xH7xH7
                                                           C6: 200x23x33
```



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)
```



Distributed Learning

- Multi-GPU and Multi-Node
- distlearn by



- MPI-like model
- scales to a large amount of nodes

```
-- 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
 - Easy to understand, think and debug
- Minimal abstraction
 - Thinking linearly
- Maximal Flexibility
 - No constraints on interfaces or classes



































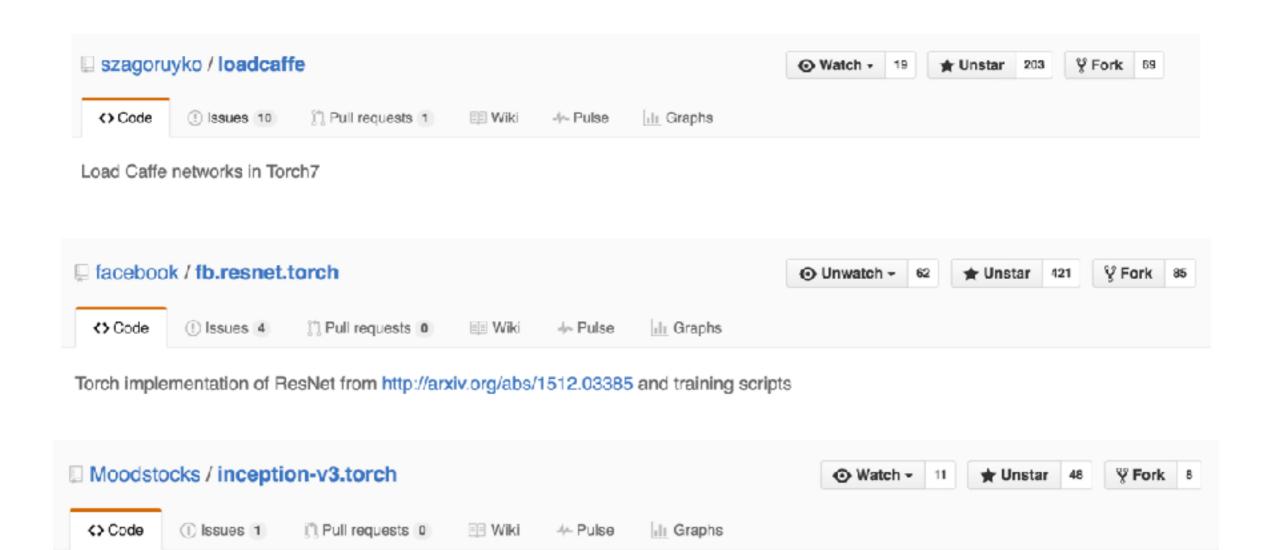












Rethinking the Inception Architecture for Computer Vision http://arxiv.org/abs/1512.00567







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.







Torch implementation of neural style algorithm

neural-style

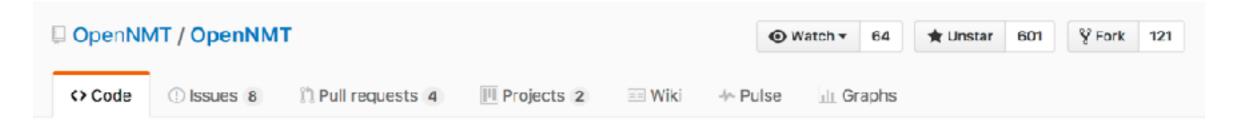
This is a torch implementation of the paper A Neural Algorithm of Artistic Style by Leon A. Gatya, Alexander S. Ecker, and Matthew Retrige.

The paper presents an algorithm for combining the centent 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 compute.





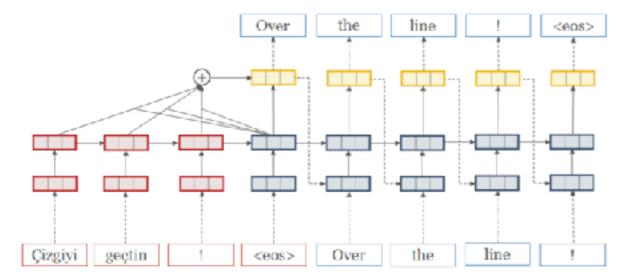




Open-Source Neural Machine Translation in Torch http://opennmt.net/

[∞] OpenNMT: Open-Source Neural Machine Translation

OpenNMT is a full-featured, open-source (MIT) neural machine translation system utilizing the Torch mathematical toolkit.



The system is designed to be simple to use and easy to extend , while maintaining efficiency and state-of-the-art translation accuracy. Features include:

- Speed and memory optimizations for high-performance GPU training.
- Simple general-purpose interface, only requires and source/target data files.
- C++ implementation of the translator for easy deployment.
- Extensions to allow other sequence generation tasks such as summarization and image captioning.







Faster neural doodle

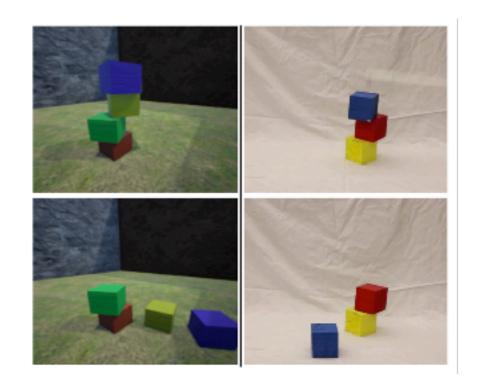








A Torch plugin for Unreal Engine 4.





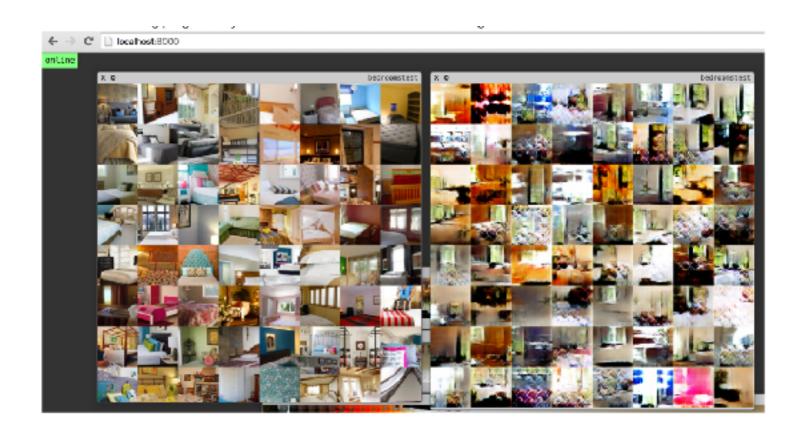
Connecting Torch to StarCraft







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

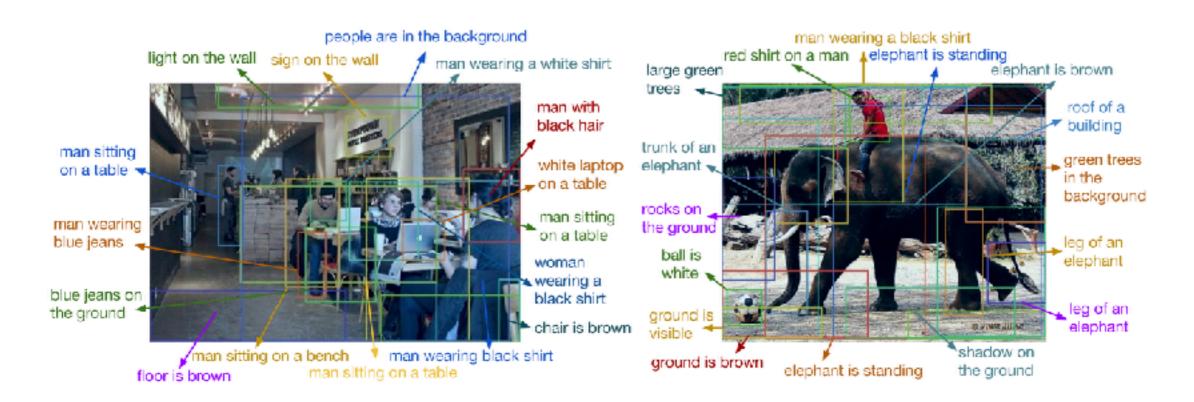




Reasonably solved to be used in production



- Classification and Detection
- in images, videos, volumetric data, sparse datasets



DenseCap: Johnson et. al. https://github.com/jcjohnson/densecap

Segmentation



DeepMask: Pinhero et. al.



- Text Classification (sentiment analysis etc.)
- Text Embeddings
- Graph embeddings
- Machine Translation
- Ads ranking



static datasets + static model structure



static datasets + static model structure

model does not change over training time



static datasets + static model structure

model does not change over training time

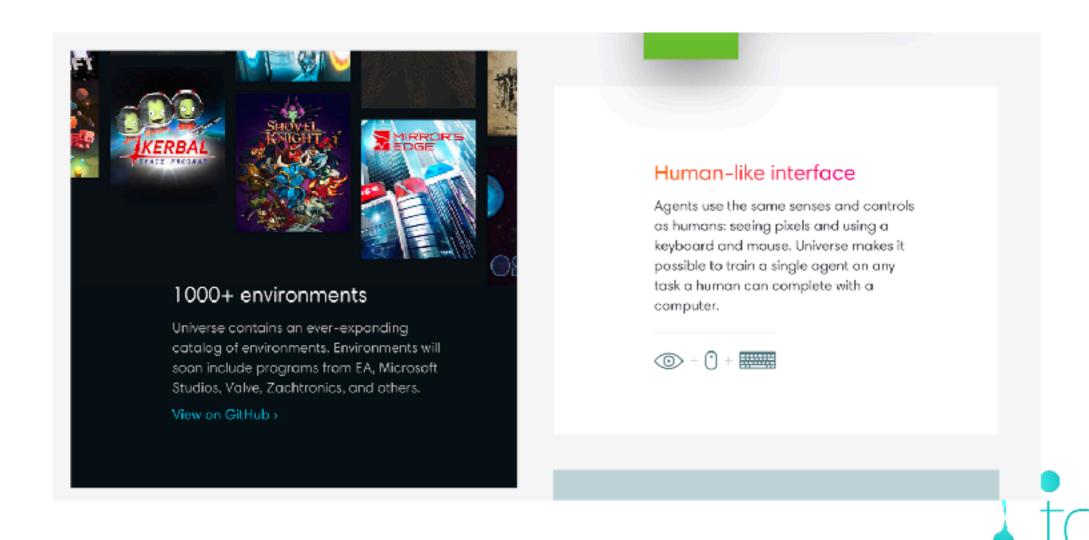
offline learning



Agents training in different and new environments



- RL Agents in different and new environments
 - Example: OpenAl Universe



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 - Example: OpenAl Universe
- Online Learning
 - Example: self-driving cars



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- Dynamic Neural Networks
 - self-adding new memory or layers
 - changing evaluation path based on inputs



- RL Agents in different and new environments
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- Dynamic Neural Networks
 - self-adding new memory or layers
 - changing evaluation path based on inputs
- Structured Prediction
 - Viterbi style decoders



A Next-Gen Framework

- Interop with environments
 - Like Universe, VizDoom, etc.
 - Easy data loaders
- Rich scientific ecosystem (such as SciPy)
 - Neural Networks are not the only methods to be used
- Dynamic Neural Networks
 - with no specific or static structure
- Minimal Abstractions
 - better debugging and low-level programming in the hands of researcher
- Graph Compilers
 - To speed up structured prediction and fuse operations
 - Numba, XLA, Theano



Let's share!

