Torch7
Scientific computing for Lua(JIT)

www.torch.ch

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- **1: Getting started**

➡ Torch's main site and resources: www.torch.ch
On Github: https://github.com/torch

➡ Torch cheat sheet
https://github.com/torch/torch7/wiki/Cheatsheet

➡ Tutorials for Torch: http://torch.madbits.com
On Github: https://github.com/clementfarabet/torch-tutorials

➡ Lua: http://www.lua.org
LuaJIT: http://luajit.org/luajit.html

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- **Torch has been around since 2000**
  - ➡ Ronan Collobert has been the main dev for all
  - ➡ 4 versions (odd numbers)
  - ➡ Various languages (C, C++, now Lua+C)
  - ➡ A liberal BSD license
  - ➡ Includes lots of packages for neural networks, optimization, graphical models, image processing
  - ➡ More than 50,000 downloads, universities and major industrial labs (Google, Facebook, Twitter)

- **Torch always aimed large-scale learning**
  - ➡ Speech, image and video applications
  - ➡ Large-scale machine-learning applications

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Lua + C

- **Why a mixed language approach?**

  ➡ Complex applications => proper scripting language (LuaJIT)
  ➡ Fast and demanding applications => compiled and optimized backend (C,C++,CUDA,OpenMP)

- **LuaJIT is a great scripting environment**

  ➡ Fastest scripting language, with a transparent JIT compiler
  ➡ Simple, readable (like Python), with clean/consistent constructs
  ➡ The cleanest interface to C (even cleaner/simpler with FFI)
  ➡ Embeddable into any environment (iPhone apps, Video games, web backends ...)

- **Why build Torch around LuaJIT and not simply use Python?**

  ➡ We are obsessed with speed: LuaJIT is very lightweight, and rarely gets in your way (manipulate raw C pointers straight from LuaJIT)

  ➡ We wanted to build applications: the complete Torch framework (Lua included) is self-contained, so you can transform your scripts into easily distributable programs

  ➡ We wanted to easily port our code to any platform: the complete Torch framework runs on iPhone, with no modification to our scripts

  ➡ We wanted easy extensibility: LuaJIT's FFI interface is one of the simplest to learn, it's easy to integrate any library into Torch

- **Lua provides a unique, universal data structure: the table**

  ➡ The Lua table can be used as an array, dictionary (hash table), class, object, struct, list, …

```
my_table = { 1, 2, 3 }
my_table = { my_var = 'hello', my_other_var = 'bye' }
my_table = { 1, 2, 99, my_var = 'hello' }
my_function = function() print('hello world') end
my_table[my_function] = 'this prints hello world'
my_function()
print(my_table[my_function])
```

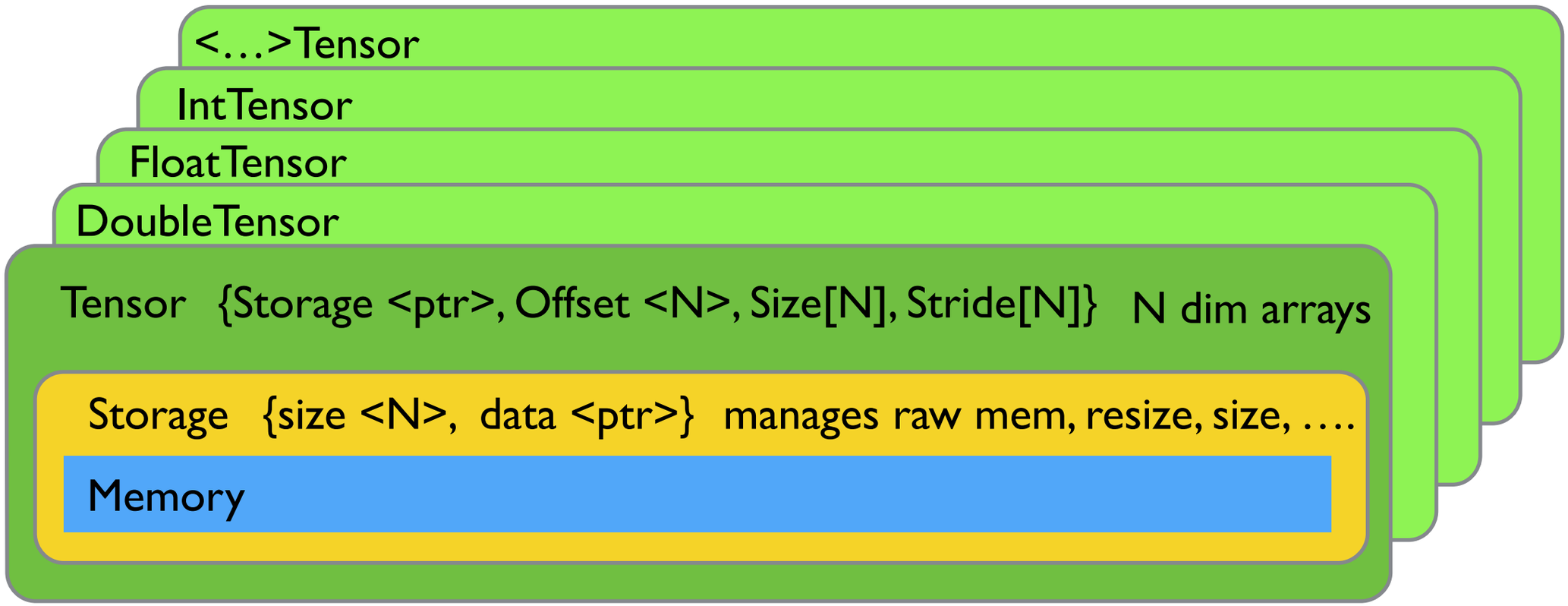
```
Torch 7.0  Copyright (C) 2001-2011 Idiap, NEC Labs, NYU
hello world
this prints hello world
```

- **Lua supports closures**

  ➡ Closures allow very flexible programmatic constructs: on-the-fly object creation, flexible data structure creation, ...

- **Torch7 extends Lua's table with a Tensor object:**

  ➡ An N-Dimensional array type, which supports views
  ➡ A Tensor is a view of a chunk of memory
  ➡ A chunk of memory might have **several views** (Tensors) pointing to it, with different geometries



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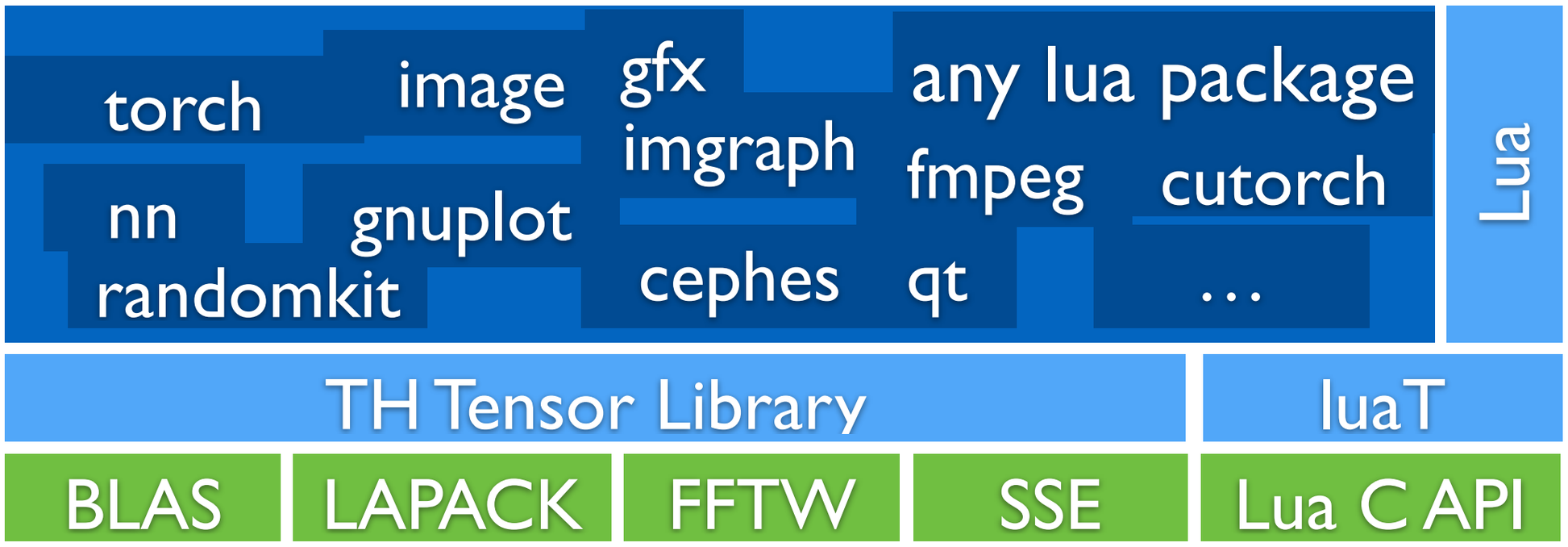
Numeric library

- **Torch7 provides a rich set of packages**

  - ➡ Based on Matlab's common routines (zeros,ones,eye, ...)
  - ➡ Linear algebra stuff
  - ➡ Convolutions, Fourier transform, …
  - ➡ plotting
  - ➡ statistics
  - ➡ …



- **Package Manager**

➡ Many more packages are available via Lua's package manger: `luarocks`

➡ Check out what's available here: github.com/torch/rocks

- **The nn package**

  ➡ When training neural nets, autoencoders, linear regression, convolutional networks, and any of these models, we're interested in gradients, and loss functions

  ➡ The **nn** package provides a large set of transfer functions, which all come with three methods:
  - ➡ `upgradeOutput()  -- compute the output given the input`
  - ➡ `upgradeGradInput()  -- compute the derivative of the loss wrt input`
  - ➡ `accGradParameters()  -- compute the  derivative of the loss wrt weights`

  ➡ The **nn** package provides a set of common loss functions, which all come with two methods:
  - ➡ `upgradeOutput()  -- compute the output given the input`
  - ➡ `upgradeGradInput()  -- compute the derivative of the loss wrt input`

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Efficient backends

- **Optimized backends**

  - ➡ **CPU, using OpenMP + SSE**
  - ➡ **GPU, using CUDA**
    - ➡ **cutorch : TH/torch for CUDA**
    - ➡ **cunn : nn for CUDA**
  - ➡ **wrappers for cuda-convnet**

- **For up-to-date benchmarking comparing caffe/theano/torch/cuda-convet/…**

https://github.com/soumith/convnet-benchmarks

- **Going Further:**

  ➡ **Torch7**:
  http://www.torch.ch/
  https://github.com/torch

  ➡ **Basic Demos**: a bunch of demos/tutorials to get started
  https://github.com/clementfarabet/torch7-demos

  ➡ **Deep-Learning Tutorials**: supervised and unsupervised learning
  http://code.madbits.com

  ➡ **luarocks**: Lua's package manager, to get new packages:
  $ luarocks search --all # list all packages
  $ luarocks install optim # install optim package

  ➡ **Torch Group**: get help!
  https://groups.google.com/forum/?fromgroups#!forum/torch7

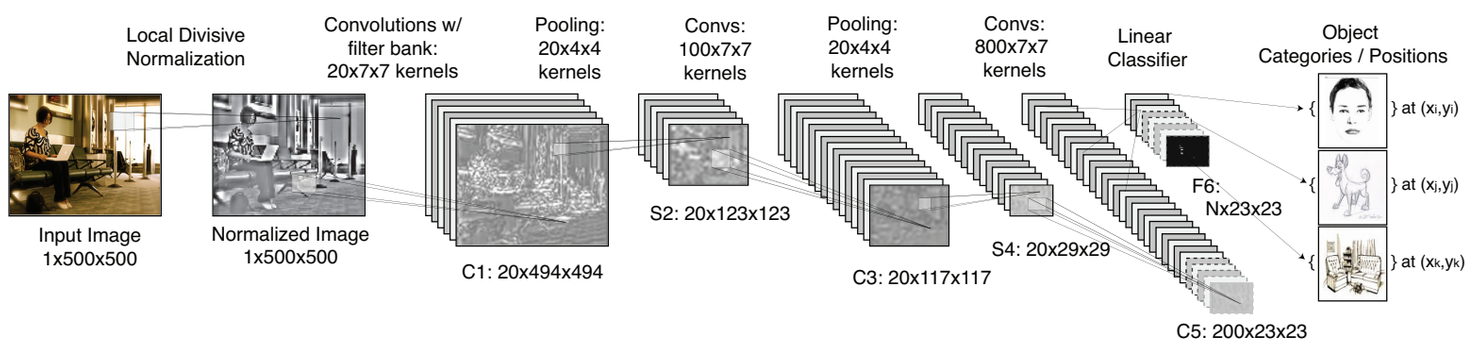
- **2: Supervised Learning**

  ➡ pre-process the (train and test) data, to facilitate learning
  ➡ describe a model to solve a classification task
  ➡ choose a loss function to minimize
  ➡ define a sampling procedure (stochastic, mini-batches), and apply one of several optimization techniques to train the model's parameters
  ➡ estimate the model's performance on unseen (test) data
  ➡ do all the exercises!

- **Example: convolutional network, for natural images**

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

```
model = nn.Sequential()

model:add( nn.SpatialConvolution(3,16,5,5) )
model:add( nn.Tanh() )
model:add( nn.SpatialMaxPooling(2,2,2,2) )
model:add( nn.SpatialContrastiveNormalization(16, image.gaussian(3)) )

model:add( nn.SpatialConvolution(16,64,5,5) )
model:add( nn.Tanh() )
model:add( nn.SpatialMaxPooling(2,2,2,2) )
model:add( nn.SpatialContrastiveNormalization(64, image.gaussian(3)) )

model:add( nn.SpatialConvolution(64,256,5,5) )
model:add( nn.Tanh() )
model:add( nn.Reshape(256) )
model:add( nn.Linear(256,10) )
model:add( nn.LogSoftMax() )
```



- **Example: logistic regression**

  ➡ **step 4/5: define a closure that estimates** `f(x)` **and** `df/dx` **stochastically**

```
08  -- define a closure, that computes the loss, and dloss/dx
09  feval = function()
10     -- select a new training sample
11     _nidx_ = (_nidx_ or 0) + 1
12     if _nidx_ > (#data)[1] then _nidx_ = 1 end
13
14     local sample = data[_nidx_]
15     local inputs = sample[1]
16     local target = sample[2]
17
18     -- reset gradients (gradients are always accumulated,
19     --                  to accomodate batch methods)
20     dl_dx:zero()
21
22     -- evaluate the loss function and its derivative wrt x,
23     -- for that sample
24     local loss_x = criterion:forward(model:forward(inputs), target)
25     model:backward(inputs, criterion:backward(model.output, target))
26
27     -- return loss(x) and dloss/dx
28     return loss_x, dl_dx
29  end
30
```

- **Example: logistic regression**

  ➡ **step 5/5: estimate parameters (train the model), stochastically**

```
31  -- SGD parameters
32  sgd_params = {learningRate = 1e-3, learningRateDecay = 1e-4,
33                weightDecay = 0, momentum = 0}
34
35  -- train for a number of epochs
36  epochs = 1e2
37  for i = 1,epochs do
38     -- this variable is used to estimate the average loss
39     current_loss = 0
40
41     -- an epoch is a full loop over our training data
42     for i = 1,(#data)[1] do
43
44        -- one step of SGD optimization (steepest descent)
45        _,fs = optim.sgd(feval,x,sgd_params)
46
47        -- accumulate error
48        current_loss = current_loss + fs[1]
49     end
50
51     -- report average error on epoch
52     current_loss = current_loss / (#data)[1]
53     print(' current loss = ' .. current_loss)
54  end
```

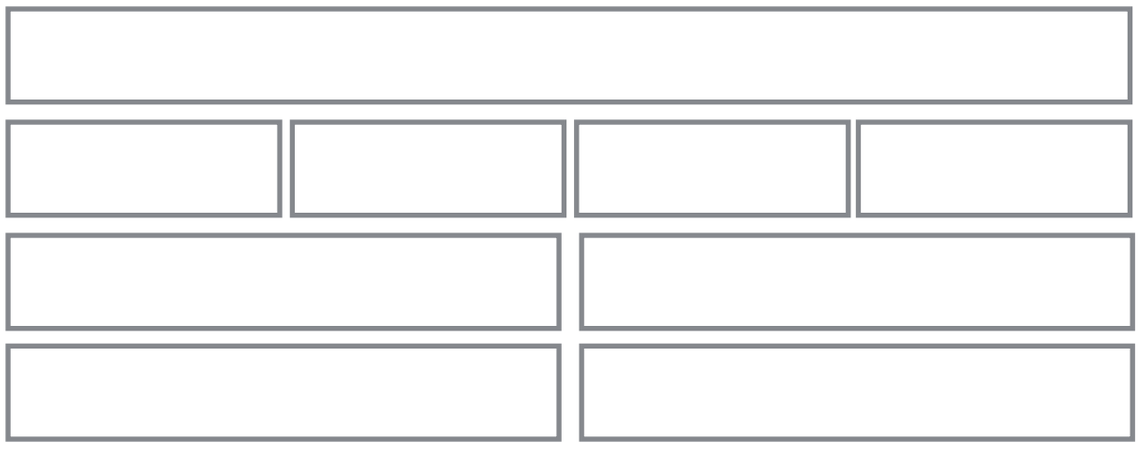
- **Example: optimize differently**

  ➡ **step 5/5: estimate parameters (train the model), using LBFGS**

```
-- LBFGS parameters
lbfgs_params = {lineSearch = optim.lswolfe}

-- train for a number of epochs
epochs = 1e2
for i = 1,epochs do
   -- this variable is used to estimate the average loss
   current_loss = 0

   -- an epoch is a full loop over our training data
   for i = 1,(#data)[1] do

      -- one step of SGD optimization (steepest descent)
      _,fs = optim.lbfgs(feval,x,lbfgs_params)

      -- accumulate error
      current_loss = current_loss + fs[1]
   end

   -- report average error on epoch
   current_loss = current_loss / (#data)[1]
   print(' current loss = ' .. current_loss)
end

```

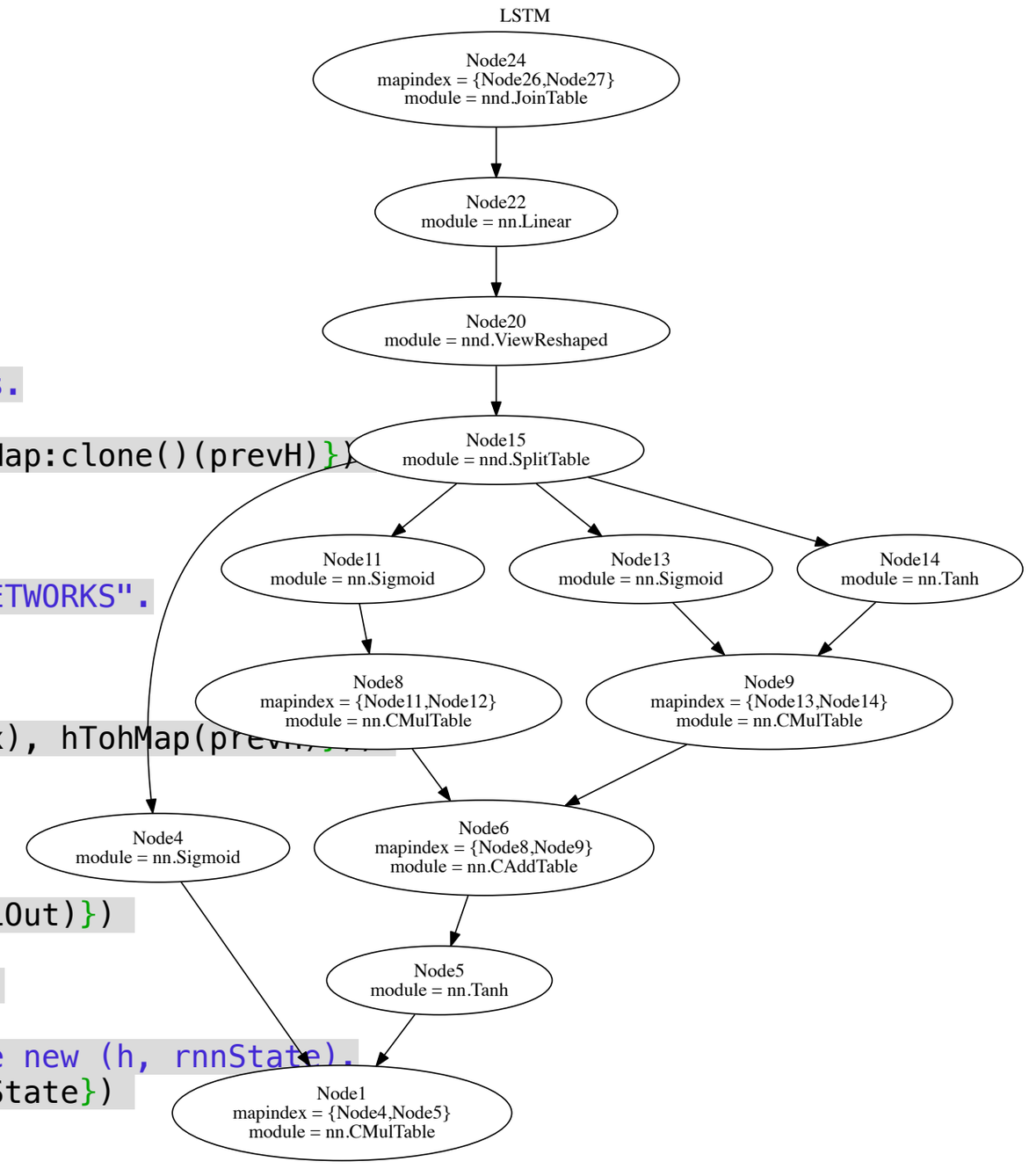
- **Arbitrary models can be constructed using lego-like containers:**

```
nn.Sequential()          -- sequential modules
nn.ParallelTable()       -- parallel modules
nn.ConcatTable()         -- shared modules
nn.SplitTable()          -- (N)dim Tensor -> table of (N-1)dim Tensors
nn.JoinTable()           -- table of (N-1)dim Tensors -> (N)dim Tensor
```



- **Or using graph container directly**

```
function nnd.Lstm(xTohMap, hTohMap)

    local x = nn.Identity()()
    local prevRnnState = nn.Identity()()
    local prevH, prevCell = prevRnnState:split(2)

    -- The input sum produces (Wx + Wh + b).
    -- Each input sum will use different weight matrices.
    local function newInputSum()
        return nn.CAddTable()({xTohMap:clone()(x), hTohMap:clone()(prevH)})
    end

    -- The following are equations (3) to (7) from
    -- "SPEECH RECOGNITION WITH DEEP RECURRENT NEURAL NETWORKS".
    -- The peep-hole connections are not used.
    local inGate = nn.Sigmoid()(newInputSum())
    local forgetGate = nn.Sigmoid()(newInputSum())
    local cellGate = nn.Tanh()(nn.CAddTable()({xTohMap(x), hTohMap(prevH)}))
    local cellOut = nn.CAddTable()({
            nn.CMulTable()({forgetGate, prevCell}),
            nn.CMulTable()({inGate, cellGate})})
    local outGate = nn.Sigmoid()(newInputSum())
    local hOut = nn.CMulTable()({outGate, nn.Tanh()(cellOut)})

    local nextRnnState = nn.Identity()({hOut, cellOut})

    -- The LSTM takes (x, prevRnnState) and computes the new (h, rnnState).
    return nn.gModule({x, prevRnnState}, {hOut, nextRnnState})
end
```



- **Changing the backend: CUDA**

  ➡ **cunn**: that package re-defines lots of **nn** modules with CUDA
  ➡ to use CUDA, Tensors simply need to be cast as CudaTensors

```
01  -- define model
02  model = nn.Sequential()
03  model:add( nn.Linear(100,1000) )
04  model:add( nn.Tanh() )
05  model:add( nn.Linear(1000,10) )
06  model:add( nn.LogSoftMax() )
07
08  -- re-cast model as a CUDA model
09  model:cuda()
10
11  -- define input as a CUDA Tensor
12  input = torch.CudaTensor(100)
13  -- compute model's output (is a CudaTensor as well)
14  output = model:forward(input)
15
16  -- alternative: convert an existing DoubleTensor to a CudaTensor:
17  input = torch.randn(100):cuda()
18  output = model:forward(input)
```

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@Google

- **Torch7 @ Google Deepmind**

  - ➡ Used exclusively for research and prototyping
  - ➡ Unsupervised learning
  - ➡ Supervised learning
  - ➡ Reinforcement Learning
  - ➡ Sequence Prediction

- ➡ Many internal and external open sourced packages
  - ➡ logging
  - ➡ functional programming
  - ➡ datasets
  - ➡ random number generators (randomkit)
  - ➡ statistical distributions
  - ➡ mathematical functions (cephes)
  - ➡ many patches to torch ecosystem

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- **x: Torch at Facebook**

- **We use Torch and LuaJIT at Facebook**
  - ➡ First open contributions released
  - ➡ Improving parallelism for multi-GPUs (model, data, DAG model)
  - ➡ Improving host-device communications (overlapping)
  - ➡ Computation kernels speed (e.g. convolutions in time/freq. domains)

- **See** https://github.com/facebook/fblualib

- **Torch packages released**

  - ➡ **fb.thrift**: fast serialization library
  - ➡ **fb.debugger**: source-level Lua debugger
  - ➡ **fb.python**: bridge between Lua and Python
  - ➡ C++ LuaUtils: collection of C++ utilities for writing Lua extensions
  - ➡ fb.util: collection of low-level Lua utilities
  - ➡ fb.editline: command line editing library based on libedit
  - ➡ fb.trepl: configurable Read-Eval-Print loop with line editing and autocompletion
  - ➡ fb.ffivector: vector of POD types does not count toward the Lua heap limit
  - ➡ fb.mattorch: library for r/w Matlab .mat files from Torch (without Matlab installed)

- **fb.thrift**
  - ➡ Thrift serialization for arbitrary Lua objects
  - ➡ Thrift is the multi-platform, multi-language serialization used in production at FB
  - ➡ Built-in optional compression

- **Serialization / Deserialization of Lua objects**
  - ➡ Supported types: scalars, tables, function with upvalues, torch.Tensor
  - ➡ Arbitrary cyclic object graphs
  - ➡ 3-8x faster speeds than default Torch serialization

- **fb.thrift**
  - ➡ Example

```
01  local thrift = require('fb.thrift')
02
03  local obj = { foo = 2 }  -- arbitrary Lua object
04
05  -- Serialization
06  -- to Lua string
07  local str = thrift.to_string(obj)
08
09  -- to open io.file object
10  local f = io.open('/tmp/foo', 'wb')
11  thrift.to_file(obj, f)
12
13  -- Deserialization
14  -- from Lua string
15  local obj = thrift.from_string(str)
16
17  -- from open io.file object
18  local f = io.open('/tmp/foo')
19  local obj = thrift.from_file(obj)
```

- **fb.debugger**
  - ➡ full-featured source-level Lua debugger
  - ➡ does not require Torch

- **2 modes of operation**
  - ➡ directly within the code

```
01  local debugger = require('fb.debugger')
... ...
    -- At the point of interest, enter the debugger
xy  debugger.enter()
... ...
```

  - ➡ on uncaught errors: with fb.trepl, set the environment variable

```
LUA_DEBUG_ON_ERROR=1
```

- **Debugger inspired by gdb, used similarly**
  - ➡ traditional commands `backtrace | continue | print ...`
  - ➡ list all commands `help`

- **fb.python**
  - ➡ bridge between Lua and Python
  - ➡ enables seamless integration between languages
  - ➡ use SciPy with Lua tensors almost as efficiently as with native numpy arrays
  - ➡ on the fly data conversion, use numpy/scipy/matplotlib with Torch tensors
  - ➡ py.exec(code, locals) executes a given Python code string (no return)
  - ➡ py.eval(code, locals) evaluate a given Python code string (and returns a value)

- **Data model**
  - ➡ Lua and Python do not match exactly, need conversion
  - ➡ data transferred between Lua and Python by **value**
  - ➡ tables are copied **deeply**
  - ➡ tensors **share** data but not metadata
  - ➡ opaque references allow user to

- **fb.python**
  - ➡ Example
  - ➡ '[===[' multiline string syntax (python is sensitive to identation)
  - ➡ values converted automatically between Python and Lua
  - ➡ py.eval creates a local Python environment
  - ➡ with value 'a' of type *'Python float'*
  - ➡ return value of type *'Python float'* is converted to *'Lua int'*
  - ➡ Python to Lua and Lua to Python have specific conversion rules
  - ➡ When existing conversion rules are insufficient, opaque references can be used

```
01  py.exec([=[
02  import numpy as np
03  def foo(x):
04    return x + 1
05  ]=])
06
07  print(py.eval('foo(a) + 10'), {a = 42})  -- prints 53
```

- **fb.python**
  - ➡ opaque references encapsulate any Python object
  - ➡ used in place of Lua values to pass arguments to Python
  - ➡ opaque references support function calls, lookup, arithmetic operations
  - ➡ operations on opaque references always return opaque references
  - ➡ so chaining is possible transparently
  - ➡ need py.eval at the end of an operation chain to convert back to Lua

```
01  -- np is opaque reference to Python numpy module
02  local np = py.import('numpy')
03
04  -- t1 is opaque reference to numpy.ndarray
05  local t1 = np.tri(10).transpose()
06
07  -- t2 is t1 converted to torch Tensor
08  local t2 = py.eval(t1)
09
10  local nltk = py.import('nltk')
11  local tokenized = py.eval(nltk.word_tokenize('Hello world, cats are cool'))
```