Deep Learning Libraries

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- I have refered few slides of Prof. Fei-Fei Li and Prof. Anoop M. Namboodiri.
- This presentation is meant for educational purpose only.















Introduction
 Caffe
 Torch







Deep Network: CNN

- Similar framework to LeCun'98 but:
 - Bigger model (7 hidden layers, 60,000,000 params)
 - More data (10⁶ vs 10³ images)
 - GPU implementation (50x speedup over CPU)
 - Trained on two GPUs for a week

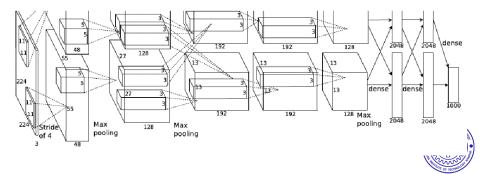
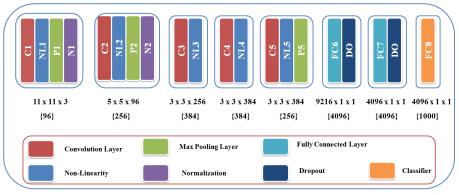


Image credit: A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012.

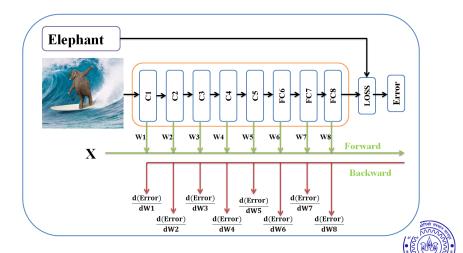
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Deep Learning Libraries

Deep Network: CNN







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- Code the optimizer/solver (SGD?)
- Several tricks to improve learning (Batch-norm, Dropout, etc.)
- Do this on CPU/GPU/Distributed-systems

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- Train in batches of 64 images
- Use the following learning rate schedule



• Easily configure a network(Sequential and parallel conntction)



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- Easily Add and remove layers in a network



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- Easily Add and remove layers in a network
- Make use of GPUs, CPUs
- Easily train a network
- Change various parameter



• Torch [Lua]



- Torch [Lua]
- Theano [Python]



- Torch [Lua]
- Theano [Python]
- Caffe

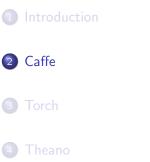


- Torch [Lua]
- Theano [Python]
- Caffe
- TensorFlow



- Torch [Lua]
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- Caffe
- TensorFlow
- Matconvnet









Badri Patro (IITK)

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- Written in C++, Python wrappers.



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- Created at UC Berkeley
- Written in C++, Python wrappers.
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- In short
 - Simple and fast
 - Very easy for beginners/users



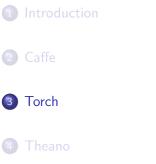
Pros:

- Good for feedforward networks
- Good for finetuning existing networks
- Train models without writing any code!
- Python interface is pretty useful!

Cons:

- \bullet Need to write C++ / CUDA for new GPU layers
- Not good for recurrent networks
- Not Good big networks (GoogLeNet, ResNet)









- Developed at NYU and IDIAP
- Written in C and Lua.
- Current Version: Torch7 (1,3,5,7)
- Current Maintainers:
 - Ronan Collobert: Facebook [IDIAP]
 - Clement Farabert: Twitter [NYU]
 - Koray Kavukcuoglu: Google DeepMind
 - Soumith Chintala: Facebook
- In short
 - Flexible and fast



Main data structure:

- table in Lua; like object in Javascript
- tensor in Torch: like Numpy array in Python
- Core Torch just has Tensors; others in packages
 - neural network layers in nn package
 - optimizers in optim package
 - nngraph for complex archiectures
- Torch layers are called modules; operate on Tensor



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- Update: Make a gradient descent step



Torch: Training

1 -- Step 0:----- Load all the necessary packages-----2 require 'cutorch' 3 require 'cunn' 4 require 'optim' 5 regulre 'anuplot' 6 -- load file which have user defined functions 7 dofile './util.lua 9 -- step 1:----- Initilize variables------18 11 --Batch size, input dimension, hidden dimension, number of classes 12 local batch_size, input_data_dim, No_of_neurons_hidden_layer, no_of_classes = 100, 1000, 100, 10 14 -- step 2:-----Build Network-: two layer ReLU Network-----15 16 -- note: variable cann't start with number. 21 network== worng, correct one is 12 network. 17 local 12 networks = nn.Sequential() 18 l2 networks:add(nn.Linear(input data dim. No of neurons hidden laver)) 19 l2 networks:add(nn.ReLU()) 20 12 networks:add(nn.Linear(No of neurons hidden layer, no of classes)) 21 22 -- step 3:-----Get Weight and gradient for entire Network------24 -- Collect all the weights and gradients in a single tensor 25 local weights, gradient_weights = l2_networks:getParameters() 26 27 -- step 4:-------Use Softmax Loss function------28 29 -- loss function are called criterions 30 local criterion= nn.CrossEntropyCriterion() --Softmax loss 31 32 -- step 5:------Generate Randon Data------33 34 -- Generate some Random input Data 35 local input x = torch.randn(batch size, input data dim) 36 local output y= torch.Tensor(batch size):random(no of classes) 37 38 -- step 6:------Forward pass -: compute scores and loss------39 40 local scores = 12 networks:forward(input x) 41 local loss = criterion:forward(scores.output v) 42 43 -- step 7:-----Backward pass-: Compute gradients-----44 45 gradient weights:zero()-- set gradient weight to zero 46 47 local dscores = criterion:backward(scores.output v) --ist find grad of loss functionn then 48 local dx = 12 networks:backward(input x.dscores) -- find grad of network 49 50 -- step 8:------update weights-: Make a gradient descent step------52 local learning_rate = 1e-3 53 weights:add(-learning_rate,gradient_weights)



Pros:

- Lots of modular pieces that are easy to combine
- Easy to write your own layer types and run on GPU
- Most of the library code is in Lua, easy to read
- Lots of pretrained models!

Cons:

Lua

- Less plug-and-play than Caffe
- You usually write your own training code
- Not great for RNNs





2 Caffe









Badri Patro (IITK)

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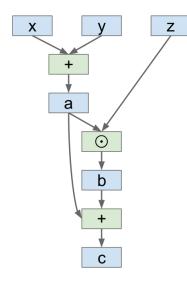
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- In short
 - Complex code to do simple things
 - High-level wrappers: Keras, Lasagne



Theano: Computational Graphs



```
import theano
import theano.tensor as T
# Define symbolic variables
x = T.matrix('x')
y = T.matrix('y')
z = T.matrix('z')
# Compute some other values symbolically
a = x + y
b = a * z
c = a + b
# Compile a function that computes c
f = theano.function(
      inputs=[x, y, z],
      outputs=c
# Evaluate the compiled function
# on some real values
xx = np.random.randn(4, 5)
yy = np.random.randn(4, 5)
zz = np.random.randn(4, 5)
print f(xx, vv, zz)
# Repeat the same computation
# explicitly using numpy ops
aa = xx + yy
bb = aa * zz
cc = aa + bb
```



Image courtesy: Fei-Fei Li et al.

print cc

Theano: Computational Graphs code

```
require 'torch'
  require 'nn'
5 -- Batch size, input dim, hidden dim, num classes
6 local N, D, H, C = 100, 1000, 100, 10
8 -- Build a one-layer ReLU network
9 local net = nn.Sequential()
 net:add(nn.Linear(D, H))
 net:add(nn.ReLU())
 net:add(nn.Linear(H, C))
 local weights, grad weights = net:getParameters()
 local crit = nn.CrossEntropyCriterion() -- Softmax loss
0 -- Generate some random input data
 local x = torch.randn(N. D)
  local y = torch.Tensor(N):random(C)
 -- Forward pass: Compute scores and loss
 local scores = net:forward(x)
6 local loss = crit:forward(scores, y)
 grad weights:zero()
 local dscores = crit:backward(scores, v)
 local dx = net:backward(x, dscores)
4 local learning rate = 1e-3
 weights:add(-learning rate, grad weights)
```

Image credit: Fei-Fei Li. et al.

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Theano: Pros / Cons

Pros:

- Python + numpy
- Computational graph is nice abstraction
- RNNs fit nicely in computational graph
- High level wrappers (Keras, Lasagne) ease the pain

Cons:

- Raw Theano is somewhat low-level
- Error messages can be unhelpful
- Large models can have long compile times
- Much "fatter" than Torch; more magic
- Patchy support for pretrained models





2 Caffe









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- In short
 - Good for large, distributed systems
 - Data and model parallelism



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TensorFlow: Tensorboard

Start Tensorboard server, and we get graphs!

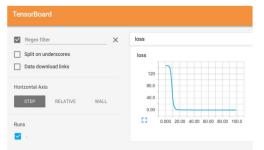






Image courtesy: Fei-Fei Li et al.

Tensorboard shows the graph!

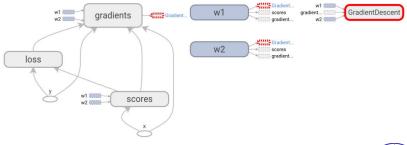




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TensorFlow: TensorBoard

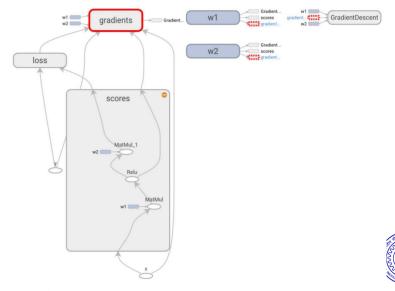
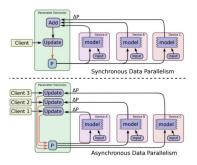


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Data parallelism: synchronous or asynchronous



Model parallelism: Split model across GPUs

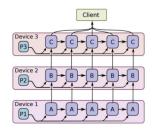
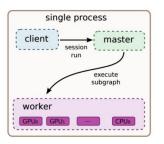




Image courtesy: Fei-Fei Li et al.

Badri Patro (IITK)

Single machine: Like other frameworks



Many machines: Not open source (yet) =(

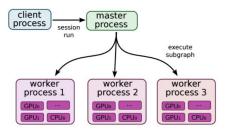
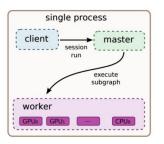




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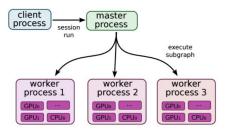




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Pros:

- Python + numpy
- Computational graph abstraction, like Theano; great for RNNs
- Much faster compile times than Theano
- Slightly more convenient than raw Theano?
- TensorBoard for visualization
- Data AND model parallelism; best of all frameworks

Cons:

- Distributed models, but not open-source yet
- Slower than other frameworks right now
- Much "fatter" than Torch; more magic
- Not many pretrained models



	Caffe	Torch	Theano	TensorFlow
Language	C++,Python	Lua	Python	Python
Pretrained	Very good	Very good	OK	Poor
Multi-GPU:	Yes	Yes	Ok	Yes
Data parallel				
Multi-GPU:	No	Yes	Experimental	Yes
Model parallel				(best)
Readable	Yes(C++)	Yes(lua)	V. Poor	V. Poor
Good at RNN	No	Mediocre	Yes	Yes
				(best)
Visualization	No	OK	No	Yes
Automatic	No	Yes(nngraph)	Yes	Yes and the second
differentiation				

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- Segmentation? (Classify every pixel)
 - Need pretrained model (Caffe, Torch, Lasagna)
 - If loss function exists in Caffe: Use Caffe
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 - $\bullet \ \ Use \ Caffe \ + \ \ Python \ or \ \ Torch$
- Implement BatchNorm?
 - Don't want to derive gradient? Theano or TensorFlow
 - Implement efficient backward pass? Use Torch



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- Language modeling with new RNN structure?
 - Need easy recurrent nets (NOT Caffe, Torch)
 - No need for pretrained models
 - Use Theano or TensorFlow



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- Simple parallelism required? Torch or Caffe
- Reinforcement learning? Torch or Tensorflow



• Feature extraction / finetuning existing models: Use Caffe



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- Complex uses of pretrained models: Use Lasagne or Torch



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- Crazy RNNs: Use Theano or Tensorflow
- Huge model, need model parallelism: Use TensorFlow



Thank you.

