# Abstractions and Frameworks for Deep Learning: a Discussion

Caffe, Torch, Theano, TensorFlow, et al.

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# Finding Parameters of a Function (supervised)

- Notations
  - Input *i*
  - Output o
  - $\blacksquare$  Function f given
  - $\blacksquare$  Parameters  $\theta$  to be learned
  - lacksquare We suppose:  $o=f_{ heta}(i)$
- How to optimize it: how to find the best  $\theta$ ?
  - need some regularity assumptions
  - usually, at least differentiability
- Remark: a more generic view

$$lacksquare o = f_{ heta}(i) = f( heta,i)$$

#### **Gradient Descent**

- We want to find the best parameters
  - lacksquare we suppose:  $o=f_{ heta}(i)$
  - lacktriangle we have examples of inputs  $i^n$  and target output  $t^n$
  - lacksquare we want to minimize the sum of errors  $L( heta) = \sum_n L(f_ heta(i^n), t^n)$
  - lacktriangle we suppose f and L are differentiable
- Gradient descent (gradient = vector of partial derivatives)
  - $\blacksquare$  start with a random  $\theta^0$
  - lacksquare compute the gradient and update  $heta^{t+1} = heta^t \gamma 
    abla_{ heta} L( heta)$
- Variations
  - stochastic gradient descent (SGD)
  - conjugate gradient descent
  - BFGS
  - L-BFGS
  - **...**

# Finding Parameters of a "Deep" Function

- Idea
  - lacksquare f is a composition of functions
  - lacksquare 2 layers:  $o=f_{ heta}(i)=f_{ heta^2}^2(f_{ heta^1}^1(i))$
  - lacksquare 3 layers:  $o=f_{ heta}(i)=f_{ heta^3}^3(f_{ heta^2}^2(f_{ heta^1}^1(i)))$
  - lacksquare K layers:  $o=f_ heta(i)=f_{ heta^K}^K(...f_{ heta^3}^3(f_{ heta^2}^2(f_{ heta^1}^1(i)))...)$
  - with all  $f_l$  differentiable
- How can we optimize it?
- The chain rule!
- ullet Many versions (with  $F=f\circ g$ )
  - $\bullet (f \circ g)' = (f' \circ g) \cdot g'$
  - $\bullet F'(x) = f'(g(x))g'(x)$
  - $lacksquare rac{df}{dx} = rac{df}{dq} \cdot rac{dg}{dx}$

# Finding Parameters of a "Deep" Function

- ullet Reminders: K layers:  $o=f_ heta(i)=f_{ heta^K}^K(...f_{ heta^3}^3(f_{ heta^2}^2(f_{ heta^1}^1(i)))...)$ 
  - lacksquare minimize the sum of errors  $L( heta) = \sum L(f_{ heta}(i^n), t^n)$
  - lacksquare chain rule  $\dfrac{df}{dx}=\dfrac{df}{da}\cdot\dfrac{dg}{dx}$
- ullet Goal: compute  $abla_{ heta} L$  for gradient descent

$$lacksquare 
abla_{ heta^K} L = rac{dL}{d_{ heta^K}} = rac{dL}{df^K} rac{df^K}{d_{ heta^K}}$$

$$lacksquare 
abla_{ heta^{K-1}}L = rac{dL}{d_{ heta^{K-1}}} = rac{dL}{df^K} rac{df^K}{df^{K-1}} rac{df^{K-1}}{d_{ heta^{K-1}}}$$

$$lackbox{lack} 
abla_{ heta^1} L = rac{dL}{d_{ heta^1}} = rac{dL}{df^K} rac{df^K}{df^{K-1}} \cdots rac{df^2}{df^1} rac{df^1}{d_{ heta^1}}$$

- $\frac{dL}{df^K}$ : gradient of the loss with respect to its input 🗸
- $lacksquare \frac{df^k}{df^{k-1}}$ : gradient of a function with respect to its input  $\checkmark$
- $\frac{df^k}{d_{ok}}$ : gradient of a function with respect to its parameters  $\checkmark$

### **Deep Learning and Composite Functions**

- Deep Learning?
  - NN can be deep, CNN can be deep
  - "any" composition of differentiable function can be optimized with gradient descent
  - some other models are also deep... (hierarchical models, etc)
- ullet Evaluating a composition  $f_ heta(i) = f_{ heta^K}^K(...f_{ heta^3}^3(f_{ heta^2}^2(f_{ heta^1}^1(i)))...)$ 
  - "forward pass"
  - evaluate successively each function
- ullet Computing the gradient  $abla_{ heta}L$  (for gradient descent)
  - compute the input (\$0) gradient (from the output error)
  - lacksquare for each  $f_1$ ,  $f_2$ , ...
  - compute the parameter gradient (from the output gradient)
  - compute the input gradient (from the output gradient)

# Back to "seeing parameters as inputs"

- Parameters  $(\theta^k)$
- ullet Just another input of  $f_k$
- ullet Can be rewritten, e.g. as  $f_k( heta_k,x)$
- More generic
  - inputs can be constant
  - inputs can be parameters
  - lacktriangle inputs can be produced by another function (e.g. f(g(x),h(x)))



# Function/Operator/Layer

- ullet The functions that we can use for  $f_k$
- Many choices
  - fully connected layers
  - convolutions layers
  - activation functions (element-wise)
  - soft-max
  - pooling
  - **...**
- Loss Functions: same with no parameters
- In the wild
  - Torch module
  - Theano operator

#### Data/Blob/Tensor

- The data: input, intermediate result, parameters, gradient, ...
- Usually a tensor (n-dimensional matrices)
- In the wild
  - Torch tensor
  - Theano tensor, scalars, numpy arrays



#### **Contenders**

- Caffe
- Torch
- Theano
- Lasagne
- Tensor Flow
- Deeplearning4j
- ...

#### **Overview**

- Basics
  - install CUDA/Cublas/OpenBlas
  - blob/tensors, blocks/layers/loss, parameters
  - cuDNN
  - open source
- Control flow
  - define a composite function (graph)
  - choice of an optimizer
  - forward, backward
- Extend
  - write a new operator/module
  - "forward"
  - "backward": gradParam, gradInput

#### Caffe

- "made with expression, speed, and modularity in mind"
- "developed by the Berkeley Vision and Learning Center (BVLC)"
- "released under the BSD 2-Clause license"
- (++
- layers-oriented http://caffe.berkeleyvision.org/tutorial /layers.html
- plaintext protocol buffer schema (prototxt) to describe models (and so save them too)
- 1,068 / 7,184 / 4,077

#### Torch7

- By
  - Ronan Collobert (Idiap, now Facebook)
  - Clement Farabet (NYU, now Madbits now Twitter)
  - Koray Kavukcuoglu (Google DeepMind)
- Lua (+ C)
  - need to learn
  - easy to embed
- Layer-oriented
  - easy to use
  - difficult to extend, sometimes (merging sources)
- 418 / 3,267 / 757

#### Theano

- "is a Python library"
- "allows you to define, optimize, and evaluate mathematical expressions"
- "involving multi-dimensional arrays"
- "efficient symbolic differentiation"
- "transparent use of a GPU"
- "dynamic C code generation"
- Use symbolic expressions: reasoning on the graph
  - write numpy-like code
  - no forced "layered" architecture
  - computation graph
- 263 / 2,447 / 878

# Lasagne (Keras, etc)

- Overlay to Theano
- Provide layer API close to caffe/torch etc
- Layer-oriented
- 133 / 1,401 / 342

#### **Tensor Flow**

- By Google, Nov. 2015
- Selling points
  - easy to move from a cluster to a mobile phone
  - easy to distribute
- Currently slow?
- Not fully open yet?
- 1,303 / 13,232 / 3,375

## Deeplearning4j

- "Deep Learning for Java, Scala & Clojure on Hadoop, Spark & GPUs"
- Apache 2.0-licensed
- Java
- High level (layer-oriented)
- Typed API
- 236 / 1,648 / 548



# Be creative! anything differentiable can be tried!

# How to choose a framework?

# Any experience to share?

