

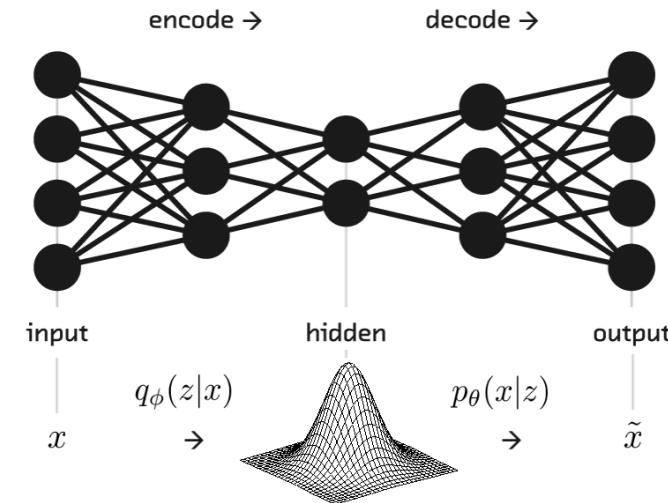
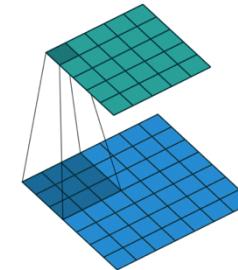
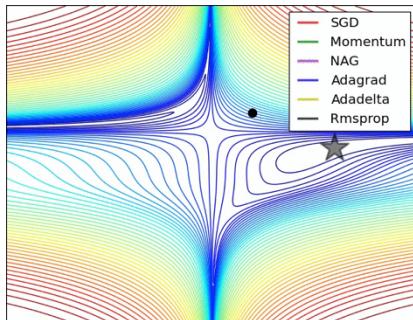
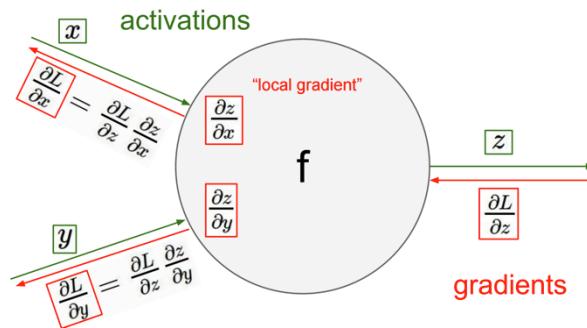
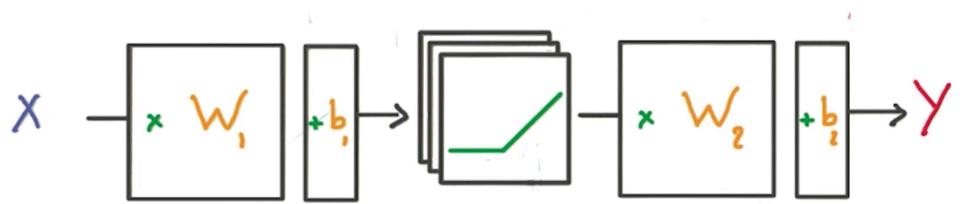
Deep Learning Software

Arsenii Ashukha



Aug 17th, 2017

Earlier



The point of deep learning frameworks

- Easily build big computational graphs
- Easily compute gradients in computational graphs
- Run it all efficiently on GPU (wrap cuDNN, cuBLAS, etc)

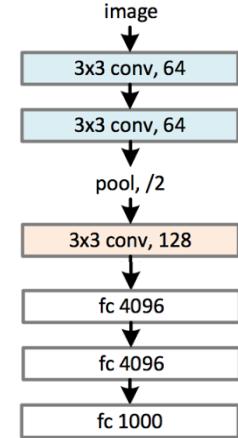
All frameworks do the same thing

but in different ways!

Standard Pipeline to Train your DNN

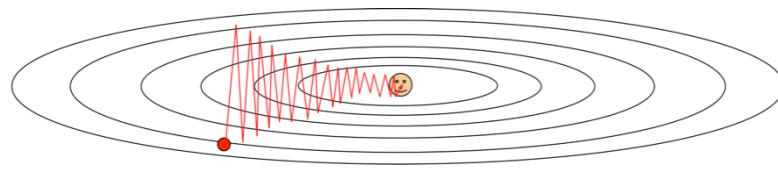
Before training:

- Get your training/validation data
- Define the model

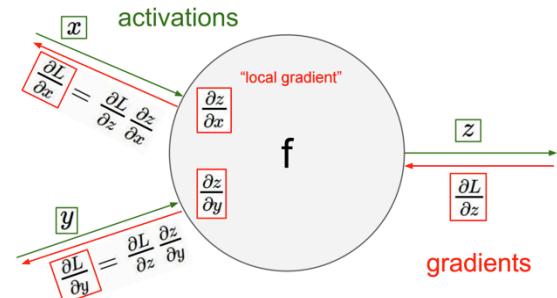


A lot of times:

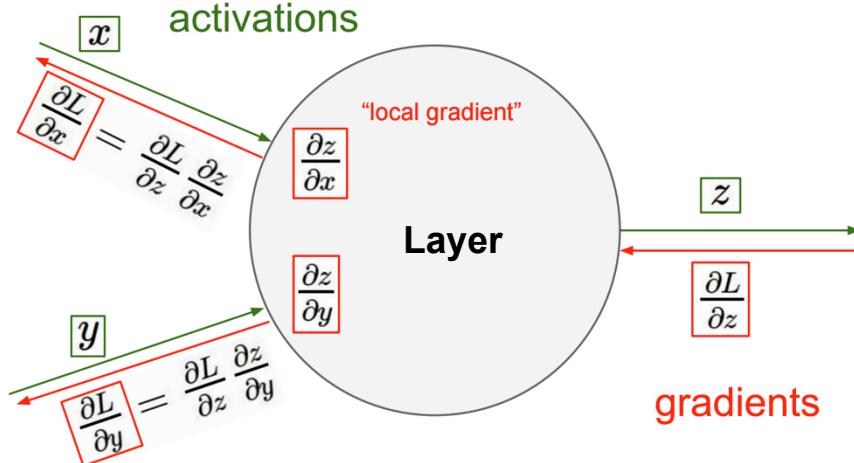
- Sample a batch (subset) of images/labels
- Evaluate the Gradient of the Loss function
- Update the parameters using the Gradient



$$\frac{\partial L}{\partial w_i} \quad L = \underbrace{\frac{1}{N} \sum_i L_i}_{\text{data loss}} + \underbrace{\lambda R(W)}_{\text{regularization loss}}$$



What is the simplest way to create a DL Library?



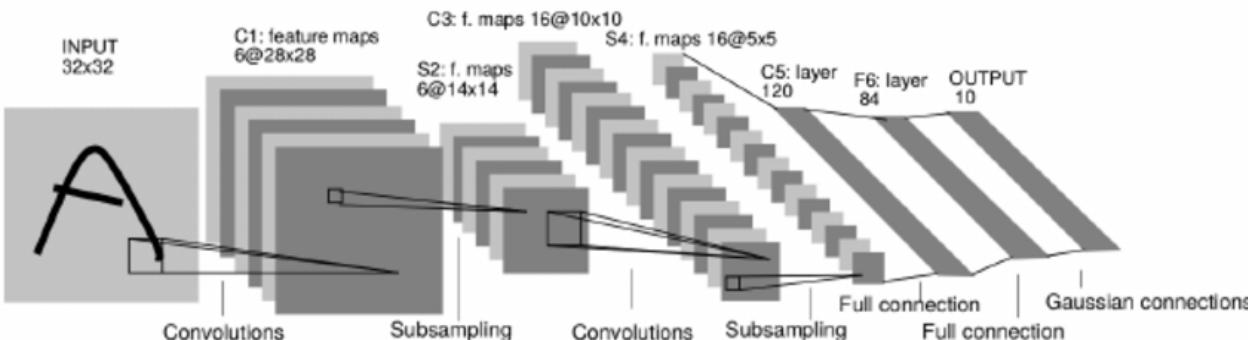
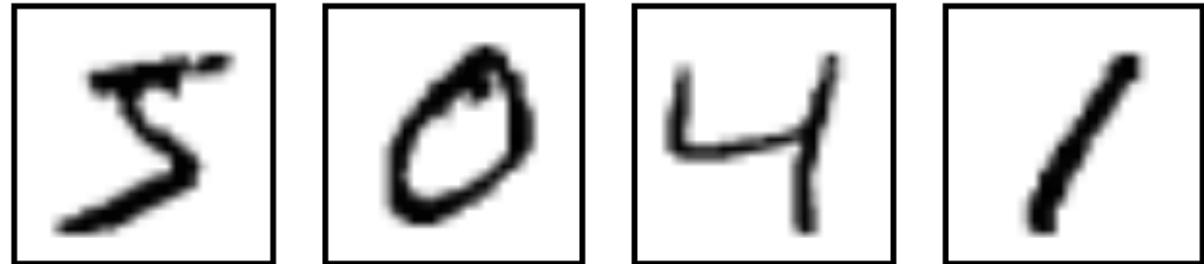
```
void Layer<Dtype>::Forward_gpu(  
    const vector<Blob<Dtype>*>& bottom,  
    const vector<Blob<Dtype>*>& top) {  
    ...  
    % Compute Layer Output efficiently  
    % on your own with C++ and CUDA  
}  
}
```

```
void Layer<Dtype>::Backward_gpu(  
    const vector<Blob<Dtype>*>& top,  
    const vector<bool>& propagate_down,  
    const vector<Blob<Dtype>*>& bottom) {  
    ...  
    % Compute Layer Gradients  
}  
}
```

- You have to write C++ code if you want to define a new layer
 - + Standard models with no coding at all
 - + A lot of computer vision things are made with Caffe

Caffe

Caffe Example



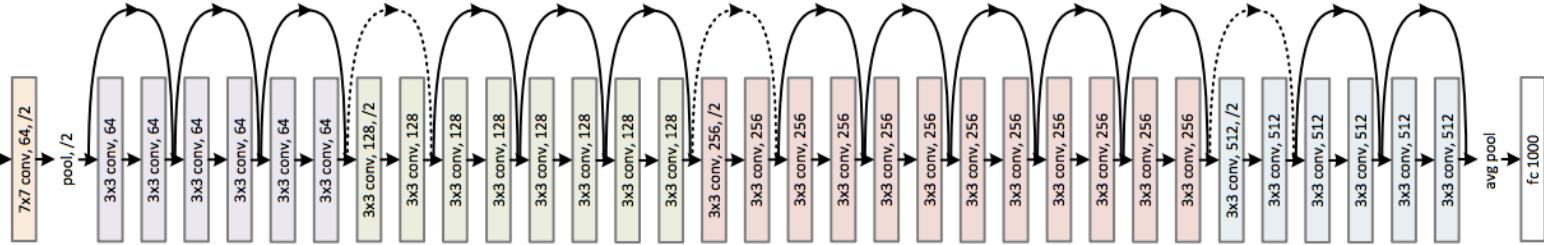
```
name: "LeNet"
layer {
    name: "conv1"
    type: "Convolution"
    bottom: "data"
    top: "conv1"
    param {lr_mult: 1}
    param {lr_mult: 2}
    convolution_param {
        num_output: 20
        kernel_size: 5
        stride: 1
        weight_filler {
            type: "xavier"
        }
    }
}
```

130 lines

Caffe Example



34-layer residual



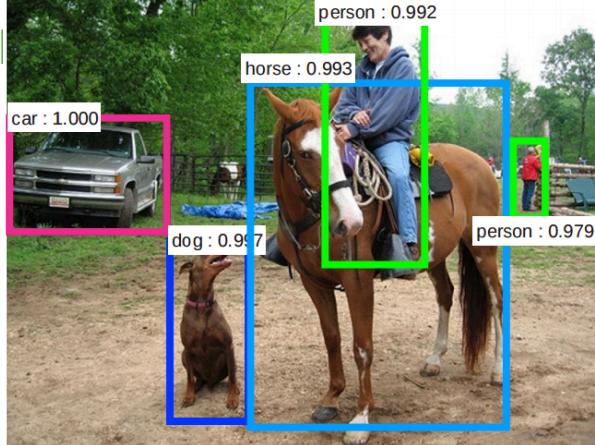
6776 lines (6104 sloc) | 95.7 KB

```
1 name: "ResNet-152"
2 input: "data"
3 input_dim: 1
4 input_dim: 3
5 input_dim: 224
6 input_dim: 224
7
8 layer {
9     bottom: "data"
10    top: "conv1"
```

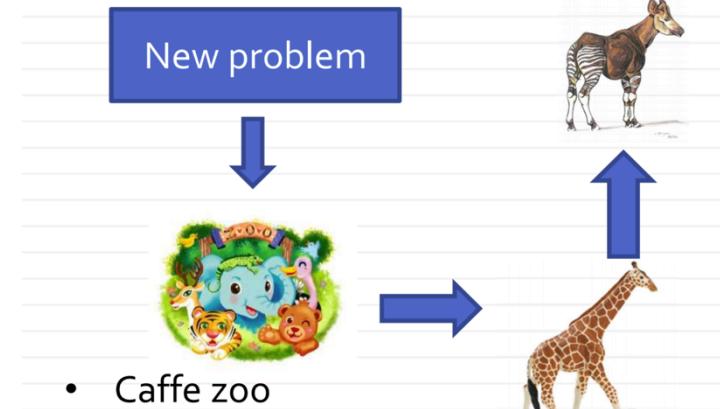
6776 lines

CaffeProtobuf language

- Hard to create your own layers (C++, CUDA, Recompile, ...)
- Hard to debug
- Easy to deploy, you can convert caffe models to pure C++
- De facto standard in Computer Vision tasks
- Rich



Applying CNN in practice



<https://github.com/BVLC/caffe/wiki/Model-Zoo>

Lenet Caffe vs Theano

130 lines (129 sloc) 1.7 KB

```
name: "LeNet"
layer {
    name: "data"
    type: "Input"
    bottom: "data"
    input_param { shape: { dim: 64 dim: 1 dim: 28 dim: 28 } }
}
layer {
    name: "conv1"
    type: "Convolution"
    bottom: "data"
    top: "conv1"
    param {
        lr_mult: 1
    }
    param {
        lr_mult: 2
    }
    convolution_param {
        num_output: 20
        kernel_size: 5
        stride: 1
        weight_filler {
            type: "xavier"
        }
        bias_filler {
            type: "constant"
        }
    }
}
layer {
    name: "pool1"
    type: "Pooling"
    bottom: "conv1"
    top: "pool1"
    pooling_param {
        pool: MAX
        kernel_size: 2
        stride: 2
    }
}
layer {
    name: "conv2"
    type: "Convolution"
    bottom: "pool1"
    top: "conv2"
    param {
        lr_mult: 1
    }
    param {
        lr_mult: 2
    }
    convolution_param {
        num_output: 50
        kernel_size: 5
        stride: 1
        weight_filler {
            type: "xavier"
        }
        bias_filler {
            type: "constant"
        }
    }
}
layer {
    name: "pool2"
    type: "Pooling"
    bottom: "conv2"
    top: "pool2"
    pooling_param {
        pool: MAX
        kernel_size: 2
        stride: 2
    }
}
layer {
    name: "ip1"
    type: "InnerProduct"
    bottom: "pool2"
    top: "ip1"
    param {
        lr_mult: 1
    }
    param {
        lr_mult: 2
    }
    inner_product_param {
        num_output: 500
        weight_filler {
            type: "xavier"
        }
        bias_filler {
            type: "constant"
        }
    }
}
layer {
    name: "relu1"
    type: "ReLU"
    bottom: "ip1"
    top: "relu1"
}
layer {
    name: "ip2"
    type: "InnerProduct"
    bottom: "relu1"
    top: "ip2"
    param {
        lr_mult: 1
    }
    param {
        lr_mult: 2
    }
    inner_product_param {
        num_output: 10
        weight_filler {
            type: "xavier"
        }
        bias_filler {
            type: "constant"
        }
    }
}
layer {
    name: "prob"
    type: "Softmax"
    bottom: "ip2"
    top: "prob"
}
```

Caffe
130 lines

37 lines (26 sloc) 1.18 KB

```
from __future__ import print_function
import warnings
from nets import objectives
from nets import optimizers
from nets import layers
from experiments.util import run_experiment
from lasagne.layers.dnn import Conv2DNNLayer as ConvLayer
warnings.simplefilter('ignore')

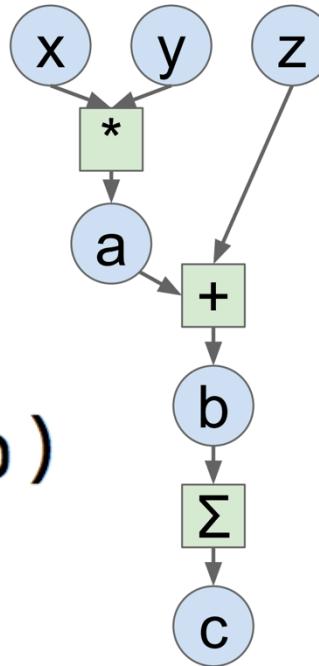
def net_leenet(input_shape, nclass):
    input_x, target_y, Winit = T.tensor4("input"), T.vector("target")
    net = ll.InputLayer(input_shape, input_x)
    net = ConvLayer(net, 20, 5, Winit.Normal())
    net = NonlinearityLayer(net, 20, 5, Winit.Normal())
    net = ConvLayer(net, 50, 5, Winit.Normal())
    net = MaxPool2DLayer(net, 2)
    net = DenseLayer(net, 500, Winit.Normal())
    net = NonlinearityLayer(net, 500, Winit.Normal(), nonlinear=rectify)
    return net, input_x, target_y, 1

num_epochs, batch_size, verbose, dataset = 200, 100, 1, 'mnist'
opt = AdamOptimizer()
net = run_experiment(
    dataset, num_epochs, batch_size, arch, objectives.sqvl,
    verbose, opt, opt.optimizer_type.adam, daTr)
```

Theano
37 lines

Static Computational Graph

```
a = x * y  
b = a + z  
c = np.sum(b)
```



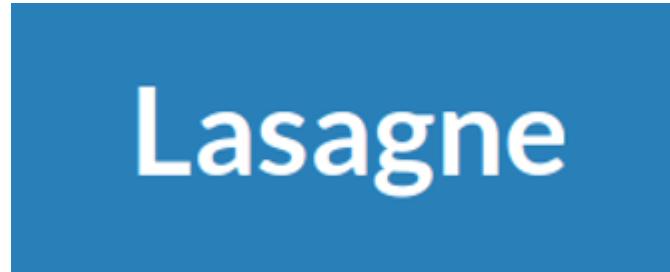
- + Easy to build nets and eval gradients
- + We can optimize the Graph
- Graph is static during training
- Need time to compile/optimize
- Hard to debug

theano and

TensorFlow™

Wrappers

From basic operation **sum, mul, log** to **layers!**



TensorFlow-Slim

TF-Slim is a lightweight library for defining, training and evaluating complex models in TensorFlow. Components of tf-slim can be freely mixed with native tensorflow, as well as other frameworks, such as tf.contrib.learn.

Tensor Board

TensorBoard SCALARS IMAGES AUDIO GRAPHS DISTRIBUTIONS HISTOGRAMS EMBEDDINGS C ⚙️ ?

Write a regex to create a tag group X

Split on underscores

Histogram Mode

OVERLAY **OFFSET**

Offset Time Axis

STEP RELATIVE WALL

Runs

Write a regex to filter runs

TOGGLE ALL RUNS

/tmp/tensorflow/mnist/log

layer1

layer1/biases/summaries/histogram

layer1/dropout/summaries/histogram

layer1/out/summaries/histogram

layer1/weights/summaries/histogram

layer1/z/summaries/histogram

5

Embeddings Visualization

projector.tensorflow.org

PyTorch



Andrej Karpathy ✅

@karpathy

Following

I've been using PyTorch a few months now and I've never felt better. I have more energy. My skin is clearer. My eye sight has improved.

Dynamic Computational Graph



A graph is created on the fly

```
from torch.autograd import Variable  
  
x = Variable(torch.randn(1, 10))  
prev_h = Variable(torch.randn(1, 20))  
W_h = Variable(torch.randn(20, 20))  
W_x = Variable(torch.randn(20, 10))
```



- Dynamic graph is hard to optimize
- Very young and still a bit raw
- + Step-by-step debugging
- + Changing architecture on the fly

How did we get over the head theano

We were happy with theano
Until we started working on ImageNet



We were happy with pytorch
Until we started working with Numerical Unusable code



Still trying to work with TF

Comparison

	Caffe	theano	TensorFlow	PyTorch
Paradigm	Declarative	Declarative	Declarative	Imperative
Language	Protobuf, C++	Python, C	Python, C++	Python, C++
Deployment	Easy to deploy		Easy to deploy	
Model size		Good for small models	Good for large models	Good for large models
CV inside	Good for CV		Good for CV	
Stability	Yes		Not yet	Not yet

Theano

```
import theano  
import theano.tensor as T
```

Imports

```
n = T.scalar(dtype='float32')  
f = T.power(n, 2)  
df = theano.grad(f, n)
```

Create scalar node

Create operation @power for n and constant node

Create an expression df / dn

```
sq_function = theano.function(inputs=[n], outputs=f)  
gr_function = theano.function(inputs=[n], outputs=df)
```

Compile graphs: input, result -> computable function

Log Reg Theano

```
import theano
import numpy as np
import theano.tensor as T
from sklearn.datasets import load_digits
```

```
Xtr, Ytr = load_digits(2, return_X_y=True)
Ytr = 2 * (Ytr - 0.5) # [0, 1] -> [-1, 1]
```

```
X = T.matrix()
y = T.vector()
W = theano.shared(np.zeros(64))
```

```
logit = X.dot(W)
ppred = 1.0 / (1.0 + np.exp(logit))
```

```
datL = T.log(1 + T.exp(y * ppred)).sum()
regL = T.power(W, 2).sum()

L = datL + 1e-4 * regL
```

```
dW = T.grad(L, W)
up = {W: W - 1e-3*dW}
```

```
train_func = theano.function([X, y], L, updates=up)
predi_func = theano.function([X], ppred)
```



$$f(x_i, W, b) = Wx_i + b$$

$$L = \underbrace{\frac{1}{N} \sum_i L_i}_{\text{data loss}} + \underbrace{\lambda R(W)}_{\text{regularization loss}}$$

$$\nabla_W L$$

Log Reg Theano

```
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test = train_test_split(Xtr, Ytr)

for i in range(31):
    loss_i = train_func(X_train,y_train)
    if i % 5 == 0:
        print ' loss at iter %i: %.4f' % (i, loss_i),
        print ' tr auc: %.2f' % roc_auc_score(y_train, predi_func(X_train)),
        print ' te auc: %.2f' % roc_auc_score(y_test, predi_func(X_test))
```



What goes wrong?

```
loss at iter 0: 193.0345  tr auc: 0.10  te auc: 0.10
loss at iter 5: 135.5271  tr auc: 0.00  te auc: 0.00
loss at iter 10: 135.3691  tr auc: 0.00  te auc: 0.00
loss at iter 15: 135.2518  tr auc: 0.00  te auc: 0.00
loss at iter 20: 135.2101  tr auc: 0.00  te auc: 0.00
loss at iter 25: 135.1875  tr auc: 0.00  te auc: 0.00
loss at iter 30: 135.1733  tr auc: 0.00  te auc: 0.00
```

Lasagne

theano

Lasagne

latest

$$\begin{aligned}i_t &= \sigma_i(x_t W_{xi} + h_{t-1} W_{hi} + w_{ci} \odot c_{t-1} + b_i) \\f_t &= \sigma_f(x_t W_{xf} + h_{t-1} W_{hf} + w_{cf} \odot c_{t-1} + b_f) \\c_t &= f_t \odot c_{t-1} + i_t \odot \sigma_c(x_t W_{xc} + h_{t-1} W_{hc} + b_c) \\o_t &= \sigma_o(x_t W_{xo} + h_{t-1} W_{ho} + w_{co} \odot c_t + b_o) \\h_t &= o_t \odot \sigma_h(c_t)\end{aligned}$$

```
W = T.matrix()
b = T.vector()
T.max(0, T.dot(W, X) + b))
```

```
lasagne.DenseLayer(X)
```

```
lasagne.layers
```

```
lasagne.updates
```

```
lasagne.init
```

```
lasagne.nonlinearities
```

```
lasagne.objectives
```

```
lasagne.regularization
```

```
lasagne.random
```

```
lasagne.utils
```

Lasagne: Simplest Network

```
from mnist import load_dataset
X_train, y_train, X_val, y_val, X_test, y_test = load_dataset()

input_X, target_y = T.tensor4('X'), T.vector('y', dtype='int32')

inputl = ll.InputLayer((None, 1, 28, 28), input_X)

net = ll.Conv2DLayer(inputl, 20, 5)
net = ll.Pool2DLayer(net, 2)
net = ll.DenseLayer(net, 100)

outputl = ll.DenseLayer(net, num_units=10, nonlinearity=nl.softmax)

predicted = ll.get_output(outputl)
weights = ll.get_all_params(outputl)

loss = lo.categorical_crossentropy(predicted, target_y).mean()
opt = lasagne.updates.rmsprop(loss, weights, learning_rate=0.01)

train_fun = theano.function([input_X, target_y], [loss], updates=opt)

num_epochs, batch_size = 10, 50
for epoch in range(num_epochs):
    for inputs, targets in iterate_minibatches(X_train, y_train, batch_size):
        train_err_batch = train_fun(inputs, targets)
        print '%.2f' % train_err_batch[0]
```

- ← Read Dataset
- ← Create X, y variables
- ← Define your DNN
- ← Define loss and opt
- ← Compile the Graph
- ← Iterate over batches

Theano Install and Run

```
1 pip install numpy  
2 pip install --upgrade https://github.com/Theano/Theano/archive/rel-0.9.0.zip  
3 pip install --upgrade https://github.com/Lasagne/Lasagne/archive/master.zip
```

```
1 export THEANO_FLAGS='floatX=float32,device=gpu3,lib.cnmem=0.5'  
2 ipython2 notebook
```

```
import theano  
import lasagne  
import theano.tensor as T  
from lasagne.layers import *
```

WARNING (theano.sandbox.cuda): The cuda backend is deprecated and will be removed in the next release (v0.10). Please switch to the gpuarray backend. You can get more information about how to switch at this URL:
<https://github.com/Theano/Theano/wiki/Converting-to-the-new-gpu-backend%28gpuarray%29>

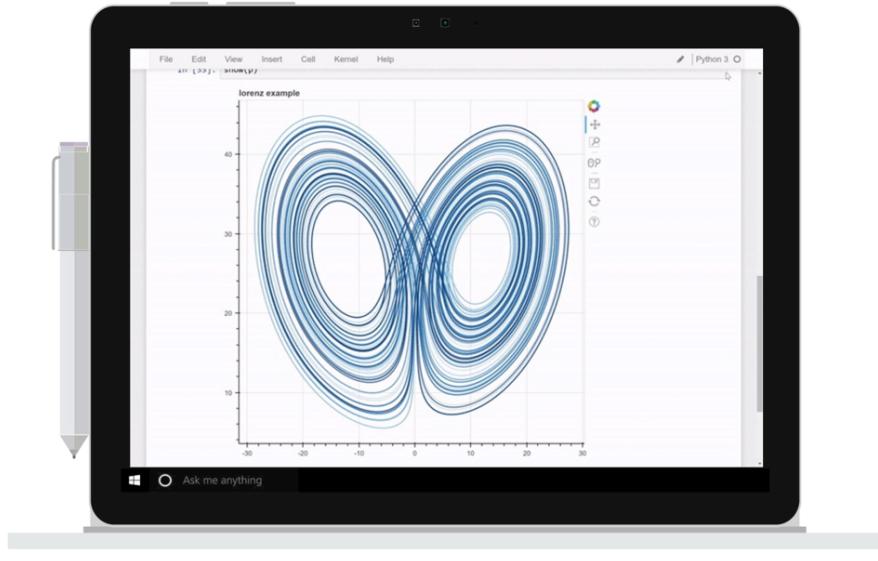
Using gpu device 3: Tesla K40m (CNMeM is enabled with initial size: 80.0% of memory, cuDNN 5105)

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<https://notebooks.azure.com>

Summary

- All frameworks do the same thing but in different ways!
- Good idea is to choose framework for your requirements
 - Caffe seems good only if you are in Computer Vision
 - TF or PyTorch are good default choice, but they still have a couple of troubles (optimization, rawness, ...)
 - Theano is good only for small nets and easy prototyping

Caffe  theano a power^{TensorFlow™} graph optimization PYTORCH