max planck institut informatik

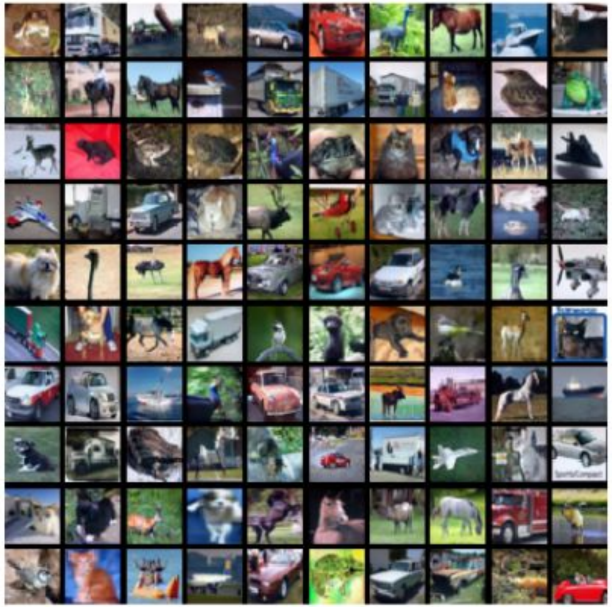
High Level Computer Vision

Exercise 2 | SS 2019

29/04/2019 - Rakshith Shetty

Exercise 2 -- Implement and train neural networks

- Implement a feed-forward neural network to perform image classification



- You will train this network using backpropagation.

- Derive and implement the algorithm.

- Train the network using
    - Stochastic gradient descent.

- Implement the same model using PyTorch

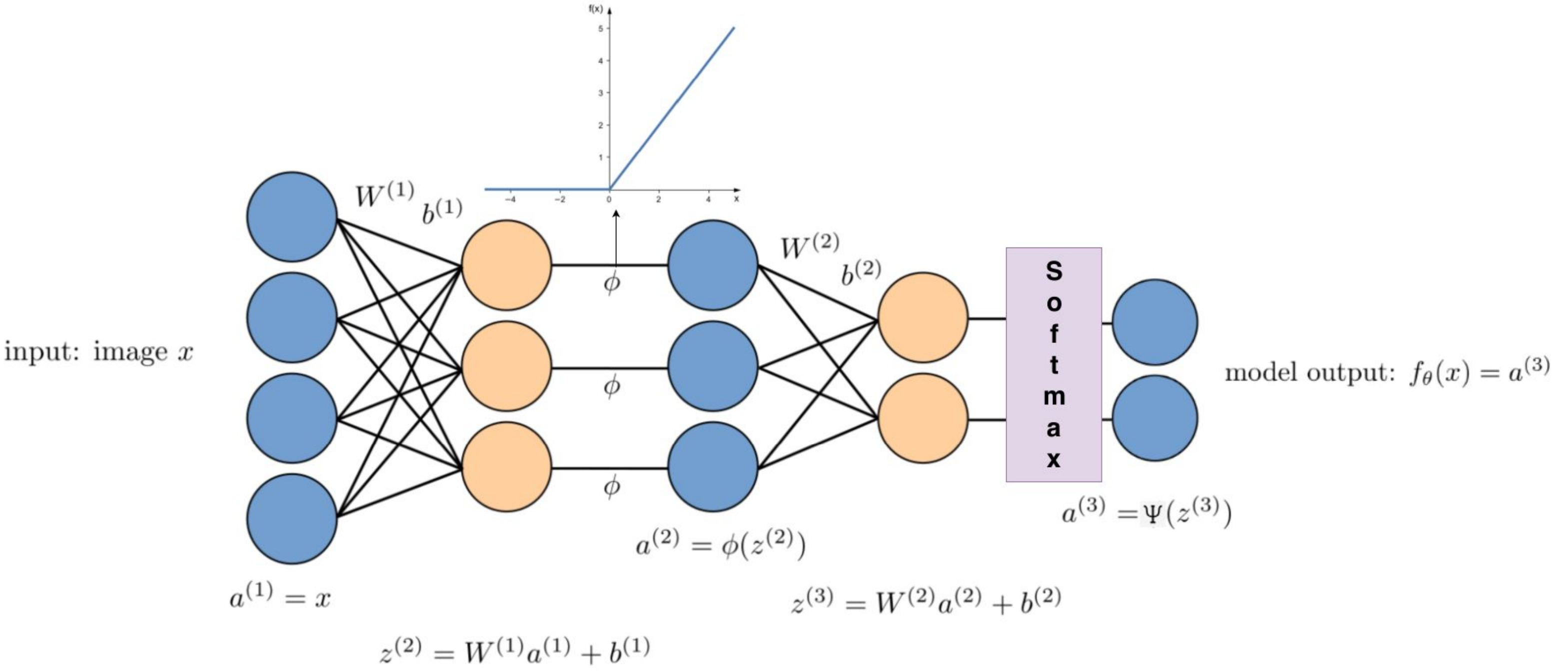
Neural networks are function approximators

- Universal function approximators
    - Networks with at least one hidden layer can **approximate** any function*

- Previously - Feature extract + Classifier

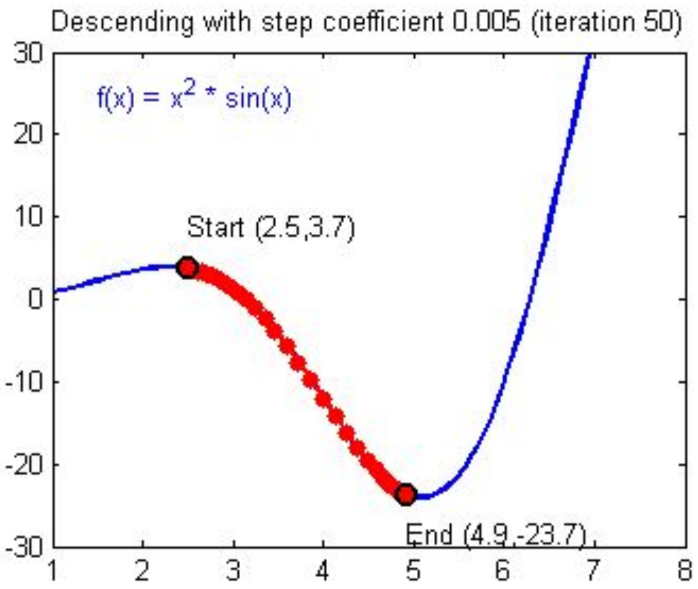
- Now → Let the neural network learn this from scratch.

Network architecture



Function fitting- convex optimization

- Need a loss function to measure the task.
- Smooth convex loss-functions are great!
- We will use stochastic **gradient descent** to optimize our function approximation
- Compute gradients w.r.t to the loss and change the parameters in the direction of steepest descent



Gif from https://hackernoon.com/life-is-gradient-descent-880c60ac1be8

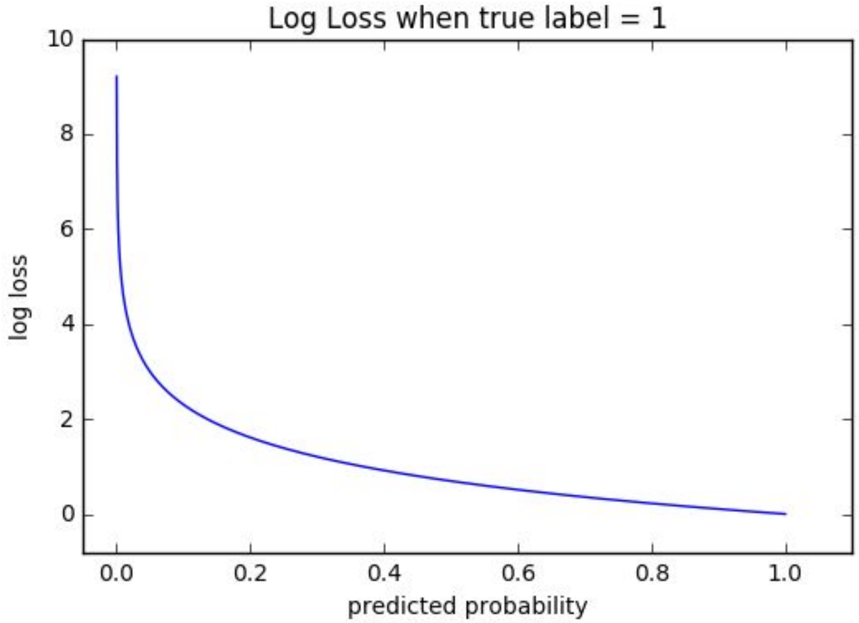
Loss function - Cross Entropy loss

- Cross entropy loss

$$J(u) = \sum_{k=1}^{K} (-y_k \log u_k - (1 - y_k) \log(1 - u_k))$$

- Measures the conditional entropy between predicted label and the true label.

- Lower loss implies predicted and true labels are close to each other.



Side-note → Differentiability

If *f* is smooth and *g* is smooth, then *g* o *f* is also smooth.

"Smooth":

- differentiable, twice differentiable, ..., infinitely differentiable (C^∞).
- continuously differentiable (C^1), twice continuously differentiable (C^2), ..., infinitely differentiable (C^∞).

Our neural network is C^∞.

Slide credit - Seong Joon Oh

Backpropagation

- How do you change the weights to optimize the loss?
  - Since we use gradient descent, we compute the gradient of the loss function w.r.t each weight.

- Simply apply chain rule to compute the gradients.

$$f : \mathbb{R}^M \to \mathbb{R}^N$$
$$g : \mathbb{R}^L \to \mathbb{R}^M$$

$$\left.\frac{\partial\left(f \circ g\right)_i(x)}{\partial x_k}\right|_{x=u} = \sum_{j=1}^{M} \left.\frac{\partial f_i(y)}{\partial y_j}\right|_{y=g(u)} \left.\frac{\partial g_j(x)}{\partial x_k}\right|_{x=u}$$

Slide credit - Seong Joon Oh

Example

$$f : \mathbb{R}^3 \to \mathbb{R}$$
$$g : \mathbb{R}^2 \to \mathbb{R}^3$$

$$f(y) = \sum_{p=1}^{3} y_p^2$$

$$g_p(x) = \sum_{q=1}^{2} w_{pq} x_q^2$$

Example, continued

$$
\begin{aligned}
\frac{\partial f(y)}{\partial y_j} &= \frac{\partial}{\partial y_j}\sum_{p=1}^{3} y_p^2 \\
&= \sum_{p=1}^{3} \frac{\partial}{\partial y_j} y_p^2 \\
&= \sum_{p=1}^{3} 2y_p \delta_{jp} \\
&= 2y_j
\end{aligned}
$$

Slide credit - Seong Joon Oh

Example, continued

$$
\begin{aligned}
\frac{\partial g_j(x)}{\partial x_k} &= \frac{\partial}{\partial x_k} \sum_{q=1}^{2} w_{jq} x_q^2 \\
&= \sum_{q=1}^{2} \frac{\partial}{\partial x_k} \left(w_{jq} x_q^2 \right) \\
&= \sum_{q=1}^{2} \left(2 w_{jq} x_q \delta_{kq} \right) \\
&= 2 w_{jk} x_k
\end{aligned}
$$

Example, continued

$$\begin{aligned}
\left.\frac{\partial\left(f\circ g\right)(x)}{\partial x_k}\right|_{x=u} &= \sum_{j=1}^{3}\left.\frac{\partial f(y)}{\partial y_j}\right|_{y=g(u)}\left.\frac{\partial g_j(x)}{\partial x_k}\right|_{x=u}\\
&= \sum_{j=1}^{3}2g_j(u)\left(2w_{jk}u_k\right)\\
&= 4u_k\sum_{j=1}^{3}w_{jk}g_j(u)\\
&= 4u_k\sum_{j=1}^{3}w_{jk}\sum_{q=1}^{2}w_{jq}u_q^2
\end{aligned}$$

Numerical Gradients

- Wiggle the parameters and compute gradients numerically

$$\frac{\partial \tilde{J}}{\partial \theta_p}(\theta) \approx \frac{\tilde{J}(\theta + \epsilon \mathbf{e}_p) - \tilde{J}(\theta - \epsilon \mathbf{e}_p)}{2\epsilon}$$

- Can do this for all parameters in the network.
- Too slow for practical use in training but great for verifying backpropagation equations.

Batch gradient descent

- Once you have the gradients you can update the parameters.

$$v \leftarrow -\alpha \nabla_{\theta} \tilde{J}(\theta^{(t-1)});$$
$$\theta^{(t)} \leftarrow \theta^{(t-1)} + v;$$

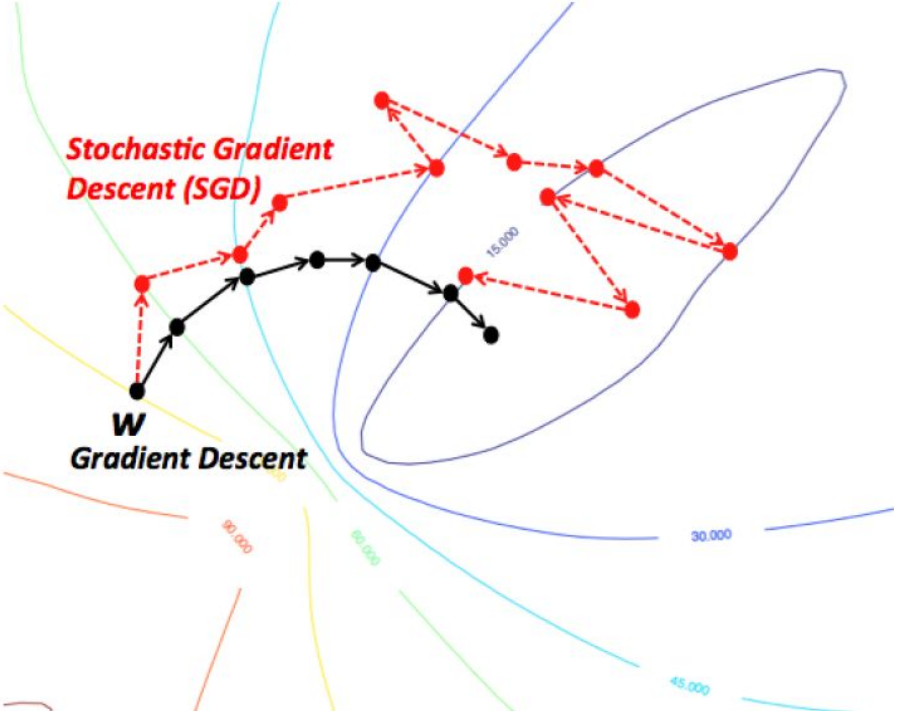
-ve sign to decrease the loss

Averaged over all training samples

- Guaranteed to converge to local minima.
- Very slow since parameters are updated once for each pass on the data.
- Large memory consumption on large datasets.

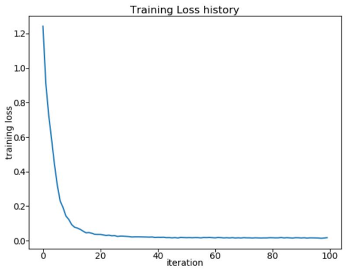
Stochastic Gradient descent

- Compute the gradients for every sample and update instantly.
- Fast and low memory consumption.
- Can be noisy.
- But noise is good! Can again avoid getting stuck in local minima.
- Better generalization properties*

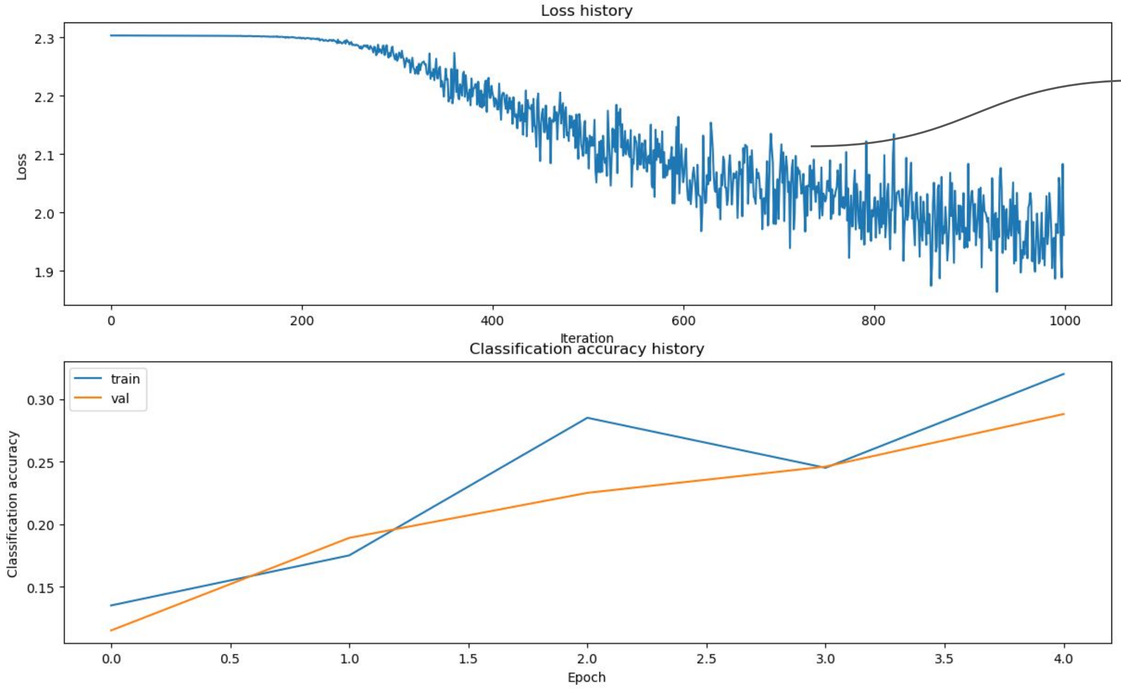


Visualization from https://wikidocs.net/3413

Understanding and debugging training dynamics



On the toy dataset



Stochastic descent

On the CIFAR-10 dataset

Hyper-parameter tuning

- **Underfitting** → Increase model capacity, decrease regularization
- **Overfitting** → Decrease model capacity, increase regularization
- **Slow learning** → increase learning rate, check initialization for saturation
- **Unstable learning** → decrease learning rate

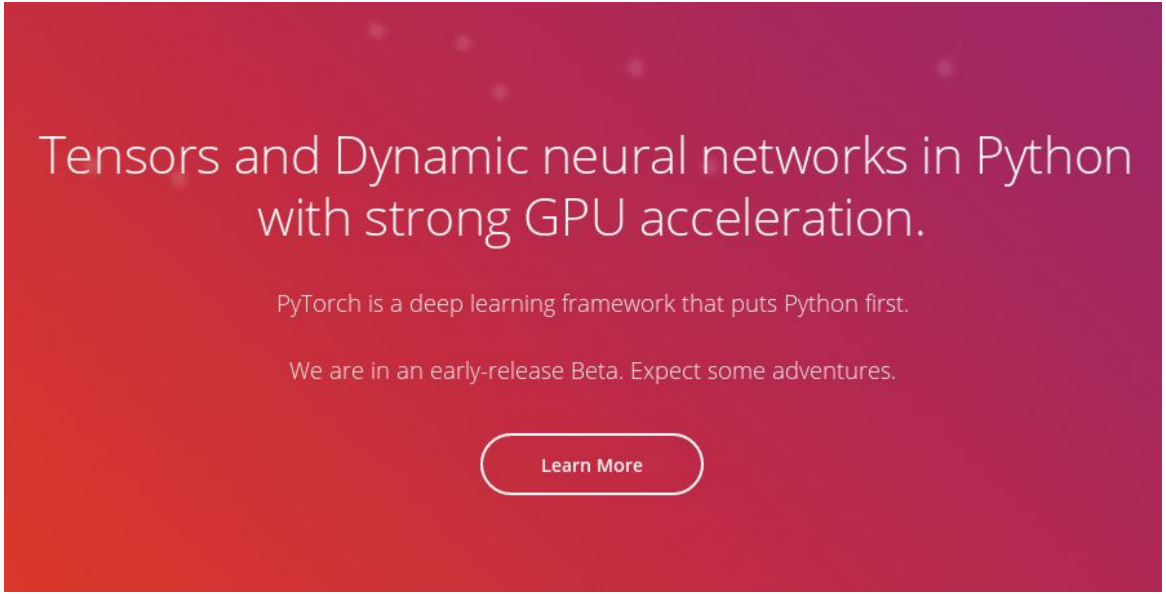
max planck institut
informatik

PyTorch - Quick Introduction

Rakshith Shetty - 29/04/2019

Some slides borrowed from:
http://dl.ee.cuhk.edu.hk/slides/tutorial-pytorch.pdf

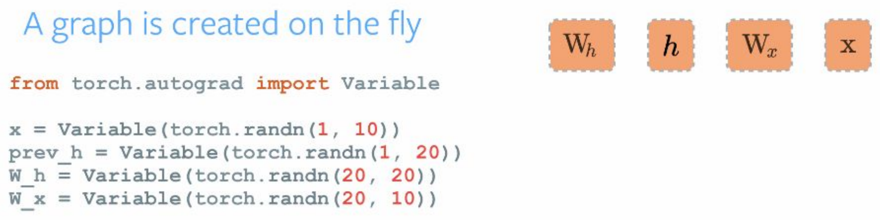
What is it?


Tensors and Dynamic neural networks in Python with strong GPU acceleration.
PyTorch is a deep learning framework that puts Python first.
We are in an early-release Beta. Expect some adventures.
Learn More

What is it?

- A library that allows tensor based computation (like matlab/ numpy)
    - Easily run on GPU or CPU.
    - **Do automatic differentiation! Very useful for backpropagation**
    - One of the fastest (maybe caffe is a bit faster)
    - Several library functions which allows you to quickly

- What’s different to other platforms?
    - **Dynamic computational graphs**
    - Very useful when dealing with recurrent networks or other wacky architectures



Basics

```python
import numpy as np
import torch

# Task: compute matrix multiplication C = AB
d = 3000

# using numpy
A = np.random.rand(d, d).astype(np.float32)
B = np.random.rand(d, d).astype(np.float32)
C = A.dot(B)

# using torch with gpu
A = torch.rand(d, d).cuda()
B = torch.rand(d, d).cuda()
C = torch.mm(A, B)
```

350 ms

0.1 ms

Auto-differentiate

```
import torch
from torch.autograd import Variable

# Task: compute d(||x||^2)/dx
x = Variable(torch.range(1, 5), requires_grad=True)
print(x.data)  # x.data = [1, 2, 3, 4, 5]

f = x.dot(x)
print(f.data)  # f.data = 55

f.backward()
print(x.grad)  # x.grad = [2, 4, 6, 8, 10]
```

Auto-differentiate

```
import torch
from torch.autograd import Variable

# Task: compute d(||x||^2)/dx
x = Variable(torch.range(1, 5), requires_grad=True)
print(x.data)  # x.data = [1, 2, 3, 4, 5]

f = x.dot(x)
print(f.data)  # f.data = 55

f.backward()
print(x.grad)  # x.grad = [2, 4, 6, 8, 10]
```

Components

Package	Description
torch	a Tensor library like NumPy, with strong GPU support
torch.autograd	a tape based automatic differentiation library that supports all differentiable Tensor operations in torch
torch.nn	a neural networks library deeply integrated with autograd designed for maximum flexibility
torch.optim	an optimization package to be used with torch.nn with standard optimization methods such as SGD, RMSProp, LBFGS, Adam etc.
torch.multiprocessing	python multiprocessing, but with magical memory sharing of torch Tensors across processes. Useful for data loading and hogwild training.
torch.utils	DataLoader, Trainer and other utility functions for convenience

Sample Code

Create Layers

Initialize weights

Do forward computations

```python
import torch.utils.data
import torch.nn as nn
from torch.autograd import Variable
from torch import tensor
import numpy as np

class MLP_classifier(nn.Module):
    def __init__(self, params):
        super(MLP_classifier, self).__init__()
        #+1 is to allow padding index
        self.output_size = params.get('num_output_layers',205)
        self.hid_dims = params.get('hidden_widths',[])
        self.inp_size = params.get('pca',-1)


        prev_size = self.inp_size
        self.hid_dims.append(self.output_size)
        self.lin_layers = nn.ModuleList()
        self.non_linearities = nn.ModuleList()
        self.dropouts = nn.ModuleList()
        for i in xrange(len(self.hid_dims)):
            self.lin_layers.append(nn.Linear(prev_size, self.hid_dims[i]))
            self.non_linearities.append(nn.ReLU())
            self.dropouts.append(nn.Dropout(p=params.get('drop_prob',0.25)))
            prev_size = self.hid_dims[i]

        self.softmax = nn.LogSoftmax()
        self.init_weights()
        # we should move it out so that whether to do cuda or not should be upto the user.
        self.cuda()

    def init_weights(self):
        # Weight initializations for various parts.
        a = 0.01
        # LSTM forget gate could be initialized to high value (1.)
        for i in xrange(len(self.hid_dims)):
            self.lin_layers[i].weight.data.uniform_(-a, a)
            self.lin_layers[i].bias.data.fill_(0)

    def forward(self, x, compute_softmax = False):
        x = Variable(x).cuda()
        prev_out = x

        for i in xrange(len(self.hid_dims)-1):
            prev_out = self.dropouts[i](prev_out)
            prev_out = self.non_linearities[i](self.lin_layers[i](prev_out))
        prev_out = self.dropouts[-1](prev_out)
        prev_out = self.lin_layers[-1](prev_out)

        if compute_softmax:
            prob_out = self.softmax(prev_out)
        else:
            prob_out = prev_out

        return prev_out
```

Useful resources

- Official documentation
  - http://pytorch.org/docs/
- Tutorials
  - http://pytorch.org/tutorials/
  - https://github.com/pytorch/tutorials
  - http://pytorch.org/tutorials/beginner/deep_learning_60min_blitz.html (Useful)
- Example projects
  - https://github.com/pytorch/examples

Submission

- Next week, Friday midnight (10/05/2018 23:59)
- Send to rshetty@mpi-inf.mpg.de
- One zip file per team
- Do not send the dataset
- Solutions next tutorial

Questions?