#### Recurrent Neural Networks in Theano

Philémon Brakel Institut des algorithmes d'apprentissage de Montréal Montreal Institute for Learning Algorithms Université de Montréal

August 11th, Deep Learning Summer School 2015, Montréal





#### Recurrent Neural Networks

Neural networks that can process sequences of inputs

- Used to process speech, language, music,...
- Recurrent Neural Networks are very powerful:
  - Non-linear
  - Distributed representations
  - No Markov assumptions
- However:
  - Optimization can be challenging
  - Learning long-term dependencies is difficult
  - Computations are not as easy to parallelize

#### Standard Architecture

$$h_t = q(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$$
  
$$y_t = r(W_{hy}h_t + b_y)$$



Figure : A simple Recurrent Neural Network

Introduction RNNs In Practice

## Long Short-Term Memory (LSTM)



Figure : LSTM: Learn long term dependencies by asserting control over what goes in and out of *memory cells*.<sup>2</sup>

<sup>&</sup>lt;sup>2</sup>Figure Taken from Jozefowicz et al. (2015)

Introduction RNNs In Practice

## Long Short-Term Memory (LSTM)



Figure : Another LSTM<sup>3</sup>

<sup>3</sup>Figure from Graves et al. (2013)

## Update Equations

$$i_{t} = \tanh(W_{xi}x_{t} + W_{hi}h_{t-1} + b_{i})$$

$$j_{t} = \sigma(W_{xj}x_{t} + W_{hj}h_{t-1} + b_{j})$$

$$f_{t} = \sigma(W_{xf}x_{t} + W_{hf}h_{t-1} + b_{f})$$

$$o_{t} = \sigma(W_{xo}x_{t} + W_{ho}h_{t-1} + b_{o})$$

$$c_{t} = f_{t} \otimes c_{t-1} + i_{t} \otimes j_{t}$$

$$h_{t} = \tanh(c_{t}) \otimes o_{t}$$

#### RNNs can be Stacked



Figure : Two Bidirectional Recurrent Neural Networks stacked on top of each other.

#### Parallelizing RNN computations

# Apply RNNs to *batches* of sequences Present the data as a 3D tensor of $(T \times B \times F)$ . Each dynamic update will now be a matrix multiplication.





#### **Binary Masks**

A *mask* matrix may be used to aid with computations that ignore the padded zeros. In Theano this may be required to keep computations *differentiable*.

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0

#### **Binary Masks**

It may be necessary to (partially) sort your data.



#### **Final Notes**

- Fuel has a transformer that automatically padds a batch of sequences and adds a mask
- Since masks are often used for multiplication, their type should often be floating point
- Be careful that your implementation doesn't nest scan nodes

#### **Final Notes**

- Fuel has a transformer that automatically padds a batch of sequences and adds a mask
- Since masks are often used for multiplication, their type should often be floating point
- Be careful that your implementation doesn't nest scan nodes
- Have fun!