Theano and LSTM for Sentiment Analysis

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Task

This is a classification task where, given a review of a movie, we need to establish whether the movie review is positive or negative. We use the IMDB dataset.

Introduction

High level

Python <- {NumPy/SciPy/libgpuarray} <- Theano <- Pylearn2

- Python: OO coding language
- Numpy: *n*-dimensional array object and scientific computing toolbox
- SciPy: sparse matrix objects and more scientific computing functionality
- libgpuarray: GPU *n*-dimensional array object in C for CUDA and OpenCL
- Theano: compiler/symbolic graph manipulation
- Pylearn2: machine learning framework for researchers

Python

- General-purpose high-level OO interpreted language
- Emphasizes code readability
- Comprehensive standard library
- Dynamic type and memory management
- Slow execution
- Easily extensible with C
- Popular in *web development* and *scientific communities*

NumPy/SciPy

- Python floats are full-fledged objects on the heap
  - Not suitable for high-performance computing!
- NumPy provides an *n*-dimensional numeric array in Python
  - Perfect for high-performance computing
  - Slices of arrays are views (no copying)
- NumPy provides
  - Elementwise computations
  - Linear algebra, Fourier transforms
  - Pseudorandom number generators (many distributions)
- SciPy provides lots more, including
  - Sparse matrices
  - More linear algebra
  - Solvers and optimization algorithms
  - Matlab-compatible I/O
  - I/O and signal processing for images and audio

What's missing?

- Non-lazy evaluation (required by Python) hurts performance
- Bound to the CPU
- Lacks symbolic or automatic differentiation
- No automatic speed and stability optimization

Goal of the stack

Fast to develop
Fast to run

Description

High-level domain-specific language for numeric computation.

- Syntax as close to NumPy as possible
- Compiles most common expressions to C for CPU and/or GPU
- Limited expressivity means more opportunities for optimizations
  - No subroutines -> global optimization
  - Strongly typed -> compiles to C
  - Array oriented -> easy parallelism
  - Support for looping and branching in expressions
- Automatic speed and stability optimizations
- Can reuse other technologies for best performance.
  - BLAS, SciPy, Cython, Numba, PyCUDA, CUDA, ...
- Automatic differentiation and R op
- Sparse matrices (CPU only)
- Extensive unit-testing and self-verification
- Works on Linux, OS X and Windows

Project status?

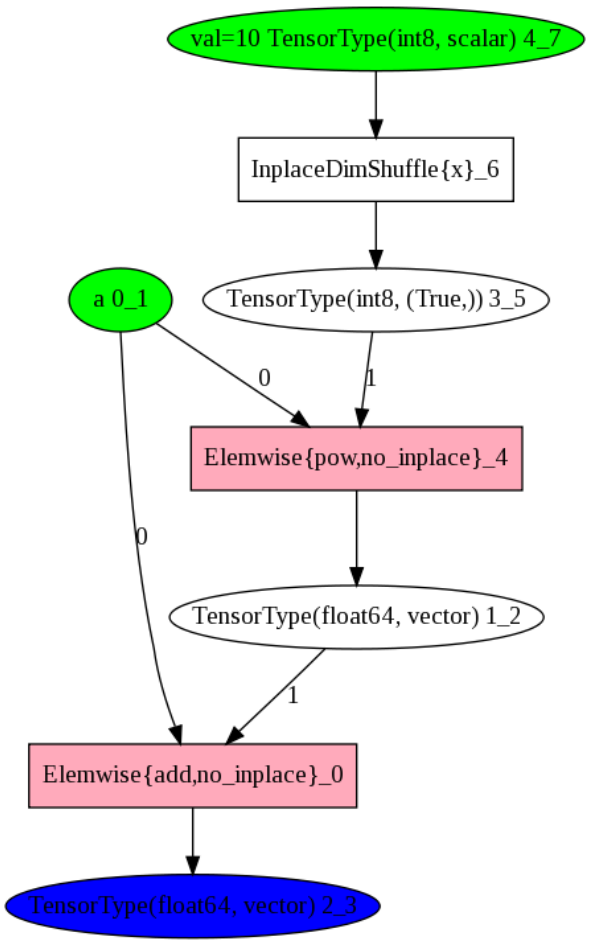
- Mature: Theano has been developed and used since January 2008 (7 yrs old)
- Driven hundreds research papers
- Good user documentation
- Active mailing list with participants from outside our lab
- Core technology for a few Silicon-Valley start-ups
- Many contributors (some from outside our lab)
- Used to teach many university classes
- Has been used for research at big compagnies

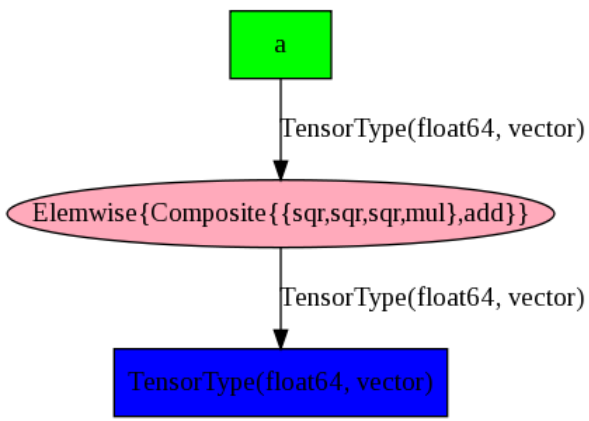
Theano: `deeplearning.net/software/theano/`
Deep Learning Tutorials: `deeplearning.net/tutorial/`

Simple example

```
import theano
# declare symbolic variable
a = theano.tensor.vector("a")

# build symbolic expression
b = a + a ** 10

# compile function
f = theano.function([a], b)

# Execute with numerical value
print f([0, 1, 2])
# prints `array([0, 2, 1026])`
```

Simple example





Overview Language

- Operations on scalar, vector, matrix, tensor, and sparse variables
- Linear algebra
- Element-wise nonlinearities
- Convolution
- Indexing, slicing and advanced indexing.
- Reduction
- Dimshuffle (n-dim transpose)
- Extensible

Scalar math

Some example of scalar operations:

```
import theano
from theano import tensor as T
x = T.scalar()
y = T.scalar()
z = x+y
w = z*x
a = T.sqrt(w)
b = T.exp(a)
c = a ** b
d = T.log(c)
```

Vector math

```
from theano import tensor as T
x = T.vector()
y = T.vector()
# Scalar math applied elementwise
a = x * y
# Vector dot product
b = T.dot(x, y)
# Broadcasting (as NumPy, very powerful)
c = a + b
```

Matrix math

```
from theano import tensor as T
x = T.matrix()
y = T.matrix()
a = T.vector()
# Matrix-matrix product
b = T.dot(x, y)
# Matrix-vector product
c = T.dot(x, a)
```

Tensors

Using Theano:

- Dimensionality defined by length of "broadcastable" argument
- Can add (or do other elemwise op) on two tensors with same dimensionality
- Duplicate tensors along broadcastable axes to make size match

```
from theano import tensor as T
tensor3 = T.TensorType(
    broadcastable=(False, False, False),
    dtype='float32')
x = T.tensor3()
```

Reductions

```
from theano import tensor as T
tensor3 = T.TensorType(
      broadcastable=(False, False, False),
      dtype='float32')
x = tensor3()
total = x.sum()
marginals = x.sum(axis=(0, 2))
mx = x.max(axis=1)
```

Dimshuffle

```
from theano import tensor as T
tensor3 = T.TensorType(
    broadcastable=(False, False, False))
x = tensor3()
y = x.dimshuffle((2, 1, 0))
a = T.matrix()
b = a.T
# Same as b
c = a.dimshuffle((0, 1))
# Adding to larger tensor
d = a.dimshuffle((0, 1, 'x'))
e = a + d
```

Indexing

As NumPy! This mean all slices, index selection return view

```
# return views, supported on GPU
a_tensor[int]
a_tensor[int, int]
a_tensor[start:stop:step, start:stop:step]
a_tensor[::-1] # reverse the first dimension

# Advanced indexing, return copy
a_tensor[an_index_vector] # Supported on GPU
a_tensor[an_index_vector, an_index_vector]
a_tensor[int, an_index_vector]
a_tensor[an_index_tensor, ...]
```

Compiling and running expression

- theano.function
- shared variables and updates
- compilation modes
- compilation for GPU
- optimizations

theano.function

```
>>> from theano import tensor as T
>>> x = T.scalar()
>>> y = T.scalar()
>>> from theano import function
>>> # first arg is list of SYMBOLIC inputs
>>> # second arg is SYMBOLIC output
>>> f = function([x, y], x + y)
>>> # Call it with NUMERICAL values
>>> # Get a NUMERICAL output
>>> f(1., 2.)
array(3.0)
```

Shared variables

- It's hard to do much with purely functional programming
- "shared variables" add just a little bit of imperative programming
- A "shared variable" is a buffer that stores a numerical value for a Theano variable
- Can write to as many shared variables as you want, once each, at the end of the function
- Modify outside Theano function with get_value() and set_value() methods.

Shared variable example

```
>>> from theano import shared
>>> x = shared(0.)
>>> from theano.compat.python2x import OrderedDict
>>> updates = OrderedDict()
>>> updates[x] = x + 1
>>> f = function([], updates=updates)
>>> f()
>>> x.get_value()
1.0
>>> x.set_value(100.)
>>> f()
>>> x.get_value()
101.0
```

Which dict?

- Use theano.compat.python2x.OrderedDict
- Not collections.OrderedDict
  - This isn't available in older versions of python
- Not {} aka dict
  - The iteration order of this built-in class is not deterministic (thanks, Python!) so if Theano accepted this, the same script could compile different C programs each time you run it

Compilation modes

- Can compile in different modes to get different kinds of programs
- Can specify these modes very precisely with arguments to theano.function
- Can use a few quick presets with environment variable flags

Example preset compilation modes

- FAST_RUN: default. Fastest execution, slowest compilation
- FAST_COMPILE: Fastest compilation, slowest execution. No C code.
- DEBUG_MODE: Adds lots of checks. Raises error messages in situations other modes regard as fine.
- optimizer=fast_compile: as mode=FAST_COMPILE, but with C code.
- theano.function(..., mode="FAST_COMPILE")
- THEANO_FLAGS=mode=FAST_COMPILE python script.py

Compilation for GPU

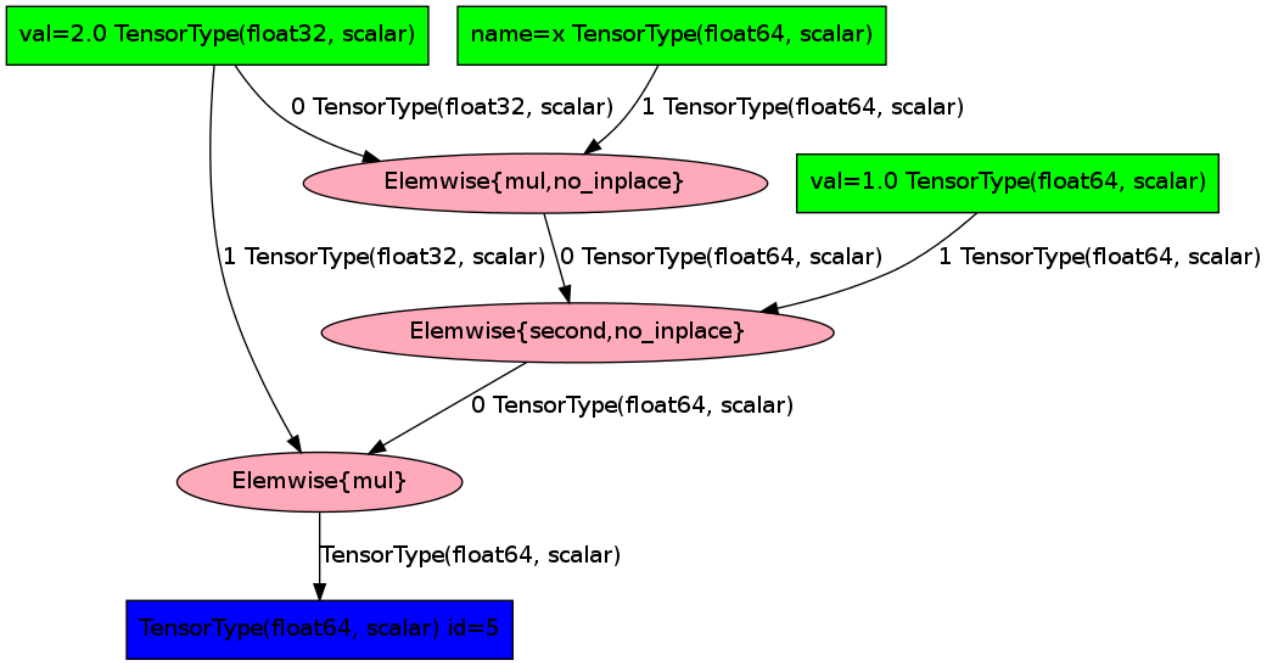
- Theano current back-end only supports 32 bit on GPU
- libgpuarray (new-backend) support all dtype
- CUDA supports 64 bit, but is slow on gamer GPUs
- T.fscalar, T.fvector, T.fmatrix are all 32 bit
- T.scalar, T.vector, T.matrix resolve to 32 bit or 64 bit depending on theano's floatX flag
- floatX is float64 by default, set it to float32
- Set device flag to gpu (or a specific gpu, like gpu0)
- Flag: warn_float64='ignore', 'warn', 'raise', 'pdb'

Modifying expressions

- The grad method
- Others

The grad method

```
>>> x = T.scalar('x')
>>> y = 2. * x
>>> g = T.grad(y, x)
# Print the not optimized graph
>>> theano.printing.pydotprint(g)
```



Others

- R_op, L_op for hessian free
- hessian
- jacobian
- you can navigate the graph if you need (go from the result of computation to its input, recursively)

Debugging

- DEBUG_MODE
- Error message
- theano.printing.debugprint

Error message: code

```
import numpy as np
import theano
import theano.tensor as T
x = T.vector()
y = T.vector()
z = x + x
z = z + y
f = theano.function([x, y], z)
f(np.ones((2,)), np.ones((3,)))
```

Error message: 1st part

```
Traceback (most recent call last):
[...]
ValueError: Input dimension mis-match.
    (input[0].shape[0] = 3, input[1].shape[0] = 2)
Apply node that caused the error:
   Elemwise{add,no_inplace}(<TensorType(float64, vector)>,
                            <TensorType(float64, vector)>,
                            <TensorType(float64, vector)>)
Inputs types: [TensorType(float64, vector),
               TensorType(float64, vector),
               TensorType(float64, vector)]
Inputs shapes: [(3,), (2,), (2,)]
Inputs strides: [(8,), (8,), (8,)]
Inputs scalar values: ['not␣scalar', 'not␣scalar', 'not␣scalar']
```

Error message: 2st part

```
HINT: Re-running with most Theano optimization
disabled could give you a back-traces when this
node was created. This can be done with by setting
the Theano flags optimizer=fast_compile
HINT: Use the Theano flag 'exception_verbosity=high'
for a debugprint of this apply node.
```

Error message: exception_verbosity=high

```
Debugprint of the apply node:
Elemwise{add,no_inplace} [@A] <TensorType(float64, vector)> ''
 |<TensorType(float64, vector)> [@B] <TensorType(float64, vector)>
 |<TensorType(float64, vector)> [@C] <TensorType(float64, vector)>
 |<TensorType(float64, vector)> [@C] <TensorType(float64, vector)>
```

Error message: optimizer=fast_compile

```
Backtrace when the node is created:
  File "test.py", line 7, in <module>
    z = z + y
```

Error message: Traceback

```
Traceback (most recent call last):
  File "test.py", line 9, in <module>
    f(np.ones((2,)), np.ones((3,)))
  File "/u/bastienf/repos/theano/compile/function_module.py",
      line 589, in __call__
    self.fn.thunks[self.fn.position_of_error])
  File "/u/bastienf/repos/theano/compile/function_module.py",
      line 579, in __call__
    outputs = self.fn()
```

debugprint

```
>>> from theano.printing import debugprint
>>> debugprint(a)
Elemwise{mul,no_inplace} [@A] ''
 |TensorConstant{2.0} [@B]
 |Elemwise{add,no_inplace} [@C] 'z'
   |<TensorType(float64, scalar)> [@D]
   |<TensorType(float64, scalar)> [@E]
```

Scan

- Allows looping (for, map, while)
- Allows recursion (reduce)
- Allows recursion with dependency on many of the previous time steps
- Optimize some cases like moving computation outside of scan
- The Scan grad is done via Backpropagation Through Time(BPTT)

When not to use scan

- If you only need it for "vectorization" or "broadcasting". tensor and numpy.ndarray support them natively. This will be much better for that use case.
- If you do a fixed number of iteration that is very small (2,3). You are probably better to just unroll the graph to do it.

Scan Example1: Computing tanh(v.dot(W) + b) * d where b is binomial I

```
import theano
import theano.tensor as T
import numpy as np

# define tensor variables
W = T.matrix("W")
X = T.matrix("X")
b_sym = T.vector("b_sym")

# define shared random stream
trng = T.shared_randomstreams.RandomStreams(1234)
d=trng.binomial(size=W[1].shape)
```

Scan Example1: Computing tanh(v.dot(W) + b) * d where d is binomial (2)

```
results, updates = theano.scan(
    lambda v: T.tanh(T.dot(v, W) + b_sym) * d,
    sequences=X)
f = theano.function(inputs=[X, W, b_sym],
                    outputs=[results],
                    updates=updates)
x = np.eye(10, 2, dtype=theano.config.floatX)
w = np.ones((2, 2), dtype=theano.config.floatX)
b = np.ones((2), dtype=theano.config.floatX)

print f(x, w, b)
```

Scan Example2: Computing pow(A, k)

```
import theano
import theano.tensor as T
theano.config.warn.subtensor_merge_bug = False

k = T.iscalar("k")
A = T.vector("A")

def inner_fct(prior_result, B):
    return prior_result * B
```

Scan Example2: Computing pow(A, k) (2)

```
result, updates = theano.scan(
    fn=inner_fct,
    outputs_info=T.ones_like(A),
    non_sequences=A, n_steps=k)

# Scan provide us with A ** 1 through A ** k.
# Keep only the last value. Scan optimize memory.
final = result[-1]

power = theano.function(inputs=[A, k], outputs=final
                        updates=updates)
print power(range(10), 2)
#[  0.   1.   4.   9.  16.  25.  36.  49.  64.
 81.]
```

Scan signature

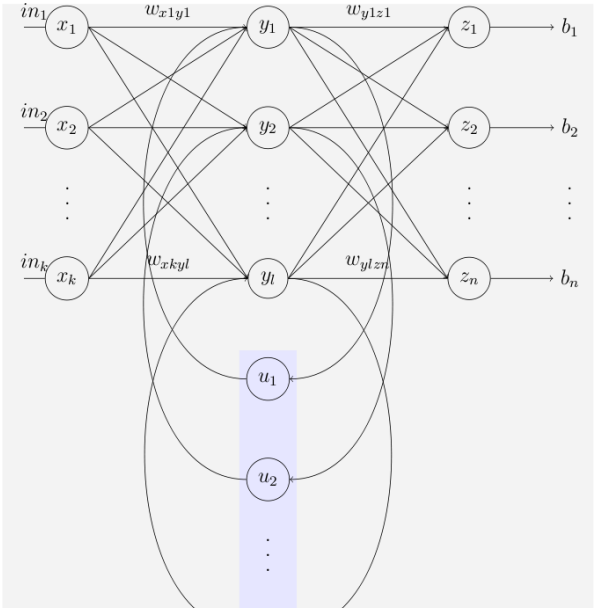
```
result, updates = theano.scan(
    fn=inner_fct,
    sequences=[]
    outputs_info=[T.ones_like(A)],
    non_sequences=A,
    n_steps=k)
```

- Updates are needed if there are random numbers generated in the inner function
  - Pass them to the call theano.function(..., updates=updates)
- The inner function of scan takes arguments like this: scan: sequences, outputs_info, non sequences

Recurrent Neural Network Overview

- RNN is a class of neural network that allows to work with sequences of variable sizes.
- Some layers have recurrent connections to themselves with a time delay.
  - This create an internal state that allows to exhibit dynamic temporal behavior.

Image from wikipedia by Fyedernoggersnodden



Motivation

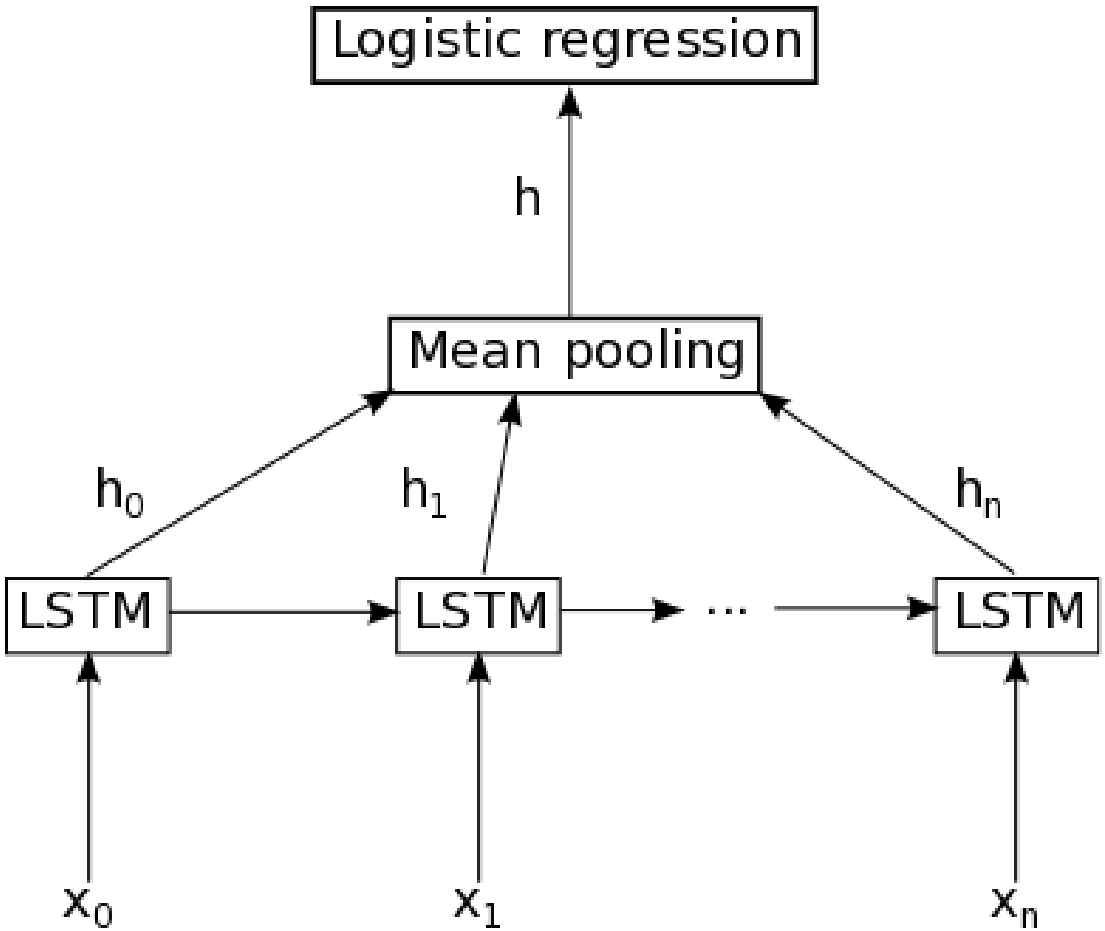
RNN gradient signal end up being multiplied a large number of times (as many as the number of timesteps). This means that, the magnitude of the weights in the transition matrix can have a strong impact on the learning process.

- **vanishing gradients** If the weights in this matrix are small (or, more formally, if the leading eigenvalue of the weight matrix is smaller than 1.0).
- **exploding gradients** If the weights in this matrix are large (or, again, more formally, if the leading eigenvalue of the weight matrix is larger than 1.0),

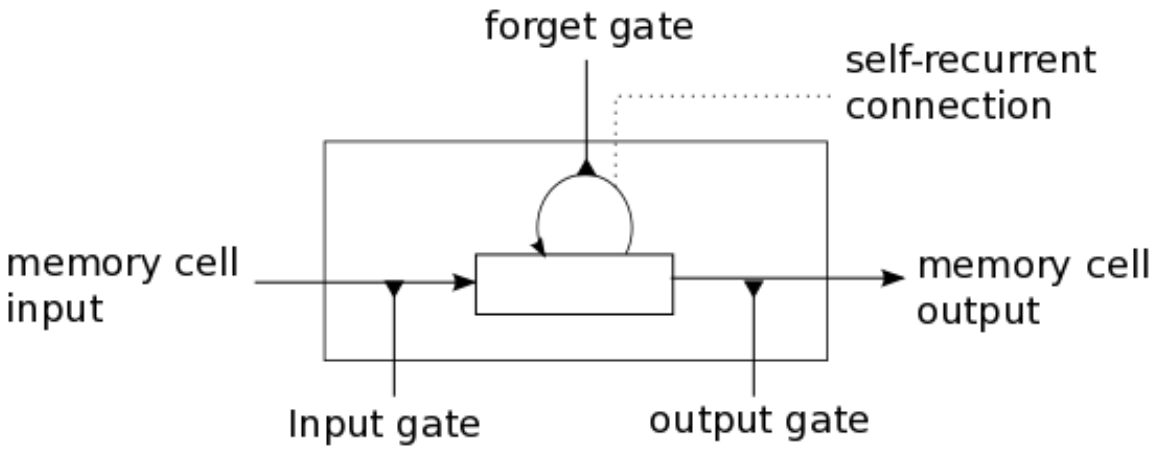
History

- Original version introduced in 1997 by Hochreiter, S., & Schmidhuber, J.
- Forget gate introduced in 2000 by Gers, F. A., Schmidhuber, J., & Cummins, F.
- All people we know use forget gate now.

LSTM overview



LSTM cell


forget gate
self-recurrent
connection
memory cell
input
memory cell
output
Input gate
output gate

LSTM math I

The equations on the next slide describe how a layer of memory cells is updated at every timestep t.
In these equations :

x_t
: is the input to the memory cell layer at time t

W_i, W_f, W_c, W_o, U_i, U_f, U_c, U_o and V_o
: are weight matrices

b_i, b_f, b_c and b_o
: are bias vectors

LSTM math II

First, we compute the values for i_t, the input gate, and $\widetilde{C_t}$ the candidate value for the states of the memory cells at time t :

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{1}$$

$$\widetilde{C_t} = tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{2}$$

Second, we compute the value for f_t, the activation of the memory cells' forget gates at time t :

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{3}$$

LSTM math III

Given the value of the input gate activation i_t, the forget gate activation f_t and the candidate state value $\widetilde{C_t}$, we can compute C_t the memory cells' new state at time t :

$$C_t = i_t * \widetilde{C_t} + f_t * C_{t-1} \tag{4}$$

With the new state of the memory cells, we can compute the value of their output gates and, subsequently, their outputs :

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + V_o C_t + b_1) \tag{5}$$

$$h_t = o_t * tanh(C_t) \tag{6}$$

Tutorial LSTM

The model we used in this tutorial is a variation of the standard LSTM model. In this variant, the activation of a cell's output gate does not depend on the memory cell's state C_t. This allows us to perform part of the computation more efficiently (see the implementation note, below, for details). This means that, in the variant we have implemented, there is no matrix V_o and equation (5) is replaced by equation (7) :

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_1) \tag{7}$$

Implementation Note

In the code included this tutorial, the equations (1), (2), (3) and (7) are performed in parallel to make the computation more efficient. This is possible because none of these equations rely on a result produced by the other ones. It is achieved by concatenating the four matrices W_* into a single weight matrix W and performing the same concatenation on the weight matrices U_* to produce the matrix U and the bias vectors b_* to produce the vector b. Then, the pre-nonlinearity activations can be computed with :

$$z = \sigma(Wx_t + Uh_{t-1} + b)$$

The result is then sliced to obtain the pre-nonlinearity activations for i, f, $\widetilde{C_t}$, and o and the non-linearities are then applied independently for each.

LSTM Tips For Training

- Do not use SGD, but use something like adagrad or rmsprop.
- Initialize any recurrent weights as orthogonal matrices (orth_weights). This helps optimization.
- Take out any operation that does not have to be inside "scan". Theano does many cases, but not all.
- Rescale (clip) the L2 norm of the gradient, if necessary.
- You can use weight noise (try first with $dot(U_c + noise, h_{t-1})$).
- You can use dropout at the output of the recurrent layer.

Exercices

- Theano exercice: Work through the "0[1-4]*" exercices (directory):
  Available at
  "git clone https://github.com/abergeron/ccw_tutorial_theano.git".
- Scan exercices: `http://deeplearning.net/software/theano/tutorial/loop.html#exercise`
- Modif LSTM: Add the V_o parameter and use it.
- Modif LSTM: Reverse the input sequence and try it like that: Sutskever-NIPS2014 (No solutions provided)
- Modif LSTM: Add to have 2 LSTM layers. The new one take the input in the reverse order. Then you concatenate the mean of the outputs of both LSTM to the logistic regression. (No solutions provided)

Deep Learning Tutorial on LSTM:
`http://deeplearning.net/tutorial/lstm.html`

Acknowledgments

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Questions?