Introduction to Theano

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Outline

- Overview of library (3 min)
- Building expressions (30 min)
- Compiling and running expressions (30 min)
- Modifying expressions (25 min)
- Debugging (30 min)
- Citing theano (2 min)

Overview of Library

- Theano is many things
 - Language
 - Compiler
 - Python library

Overview

- Theano language:
 - Operations on scalar, vector, matrix, tensor, and sparse variables
 - Linear algebra
 - Element-wise nonlinearities
 - Convolution
 - Extensible

Overview

- Using Theano:
 - ullet define expression f(x,y)=x+y
 - compile expression

```
int f(int x, int y) {
    return x + y;
}
```

execute expression

```
>>> f(1,2)
3
>>>
```

Building expressions

- Scalars
- Vectors
- Matrices
- Tensors
- Reductions
- Dimshuffle

Scalar math

from theano import tensor as T

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
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

- 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 = 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), dtype='float32')
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
```

Exercises

Work through the
 "01_building_expressions" directory now

Compiling and running expressions

- 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 function with get_value and set_value

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, and will limit the portability of your code
- 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. Spends a lot of time on compilation to get an executable that runs fast.
- FAST_COMPILE: Doesn't spend much time compiling. Executable usually uses python instead of compiled C code. Runs slow.
- DEBUG_MODE: Adds lots of checks.
 Raises error messages in situations other modes regard as fine.

Compilation for GPU

- Theano only supports 32 bit on GPU
 - CUDA supports 64 bit, but is slow
 - 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)

Optimizations

- Theano changes the symbolic expressions you write before converting them to C code
- It makes them faster
 - (x+y)+(x+y) -> 2 (x + y)
- It makes them more stable
 - exp(a)/exp(a).sum()->softmax(a)

Optimizations

 Sometimes optimizations discard error checking and produce incorrect output rather than an exception

```
>>> x = T.scalar()
>>> f = function([x], x/x)
>>> f(0.)
array(1.0)
```

Exercises

 Work through the "02_compiling_and_running" directory now

Modifying expressions

- The grad method
- Variable nodes
- Types
- Ops
- Apply nodes

The grad method

```
>>> x = T.scalar('x')
>>> y = 2. * x
>>> g = T.grad(y, x)
>>> from theano.printing import min_informative_str
>>> print min_informative_str(g)
A. Elemwise { mul }
B. Elemwise { second, no_inplace }
 C. Elemwise { mul, no_inplace }
 D. TensorConstant {2.0}
 E. x
 F. TensorConstant { 1.0 }
< D >
```

Theano Variables

- A Variable is a theano expression
- Can come from T.scalar, T.matrix, etc.
- Can come from doing operations on other Variables
- Every Variable has a type field, identifying its
 Type
 - e.g. TensorType((True, False), 'float32')
- Variables can be thought of as nodes in a graph

Ops

- An Op is any class that describes a mathematical function of some variables
- Can call the op on some variables to get a new variable or variables
- An Op class can supply other forms of information about the function, such as its derivatives

Apply nodes

- The Apply class is a specific instance of an application of an Op
- Notable fields:
 - op:The Op to be applied
 - inputs: The Variables to be used as input
 - outputs: The Variables produced
- Variable.owner identifies the Apply that created the variable
- Variable and Apply instances are nodes and owner/ inputs/outputs identify edges in a Theano graph

Exercises

 Work through the "03_modifying" directory now

Debugging

- DEBUG_MODE
- compute_test_value
- min_informative_str
- DebugPrint
- Accessing the FunctionGraph

compute_test_value

```
>>> from theano import config
>>> config.compute_test_value = 'raise'
>>> x = T.vector()
>>> import numpy as np
>>> x.tag.test_value = np.ones((2,))
>>> y = T.vector()
>>> y.tag.test_value = np.ones((3,))
>>> X + \Lambda
ValueError: Input dimension mis-match.
(input[0].shape[0] = 2, input[1].shape[0] = 3)
```

min_informative_str

```
>>> x = T.scalar()
>>> y = T.scalar()
>>> z = x + y
>>> z.name = 'z'
>>> a = 2. * z
>>> from theano.printing import min_informative_str
>>> print min_informative_str(a)
A. Elemwise{mul,no_inplace}
B. TensorConstant{2.0}
C. z
```

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]
```

Accessing a function's fgraph

Exercises

 Work through the "04_debugging" directory now

Citing Theano

- Please cite both of the following papers in all work that uses Theano:
- Bastien, Frédéric, Lamblin, Pascal, Pascanu, Razvan, Bergstra, James, Goodfellow, Ian, Bergeron, Arnaud, Bouchard, Nicolas, and Bengio, Yoshua. Theano: new features and speed improvements. Deep Learning and Unsupervised Feature Learning NIPS 2012 Workshop, 2012.
- Bergstra, James, Breuleux, Olivier, Bastien, Frédéric, Lamblin, Pascal, Pascanu, Razvan, Desjardins, Guillaume, Turian, Joseph, Warde-Farley, David, and Bengio, Yoshua. Theano: a CPU and GPU math expression compiler. *In Proceedings of the Python for Scientific Computing Conference (SciPy)*, June 2010. Oral Presentation.

Example acknowledgments

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