Frameworks

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Introduction

Slides adapted from Chris Dyer, Yoav Goldberg, Graham Neubig

Neural Nets and Language

Language

Discrete, structured (graphs, trees)

Neural-Nets

Continuous: poor native support for structure

Big challenge: writing code that translates between the {discrete-structured, continuous} regimes

Why not do it yourself?

- Hard to compare with exting models
- Obscures difference between model and optimization
- Debugging has to be custom-built
- Hard to tweak model

Outline

- Computation graphs (general)
- Neural Nets in PyTorch
- Full example

Computation Graphs

Expression

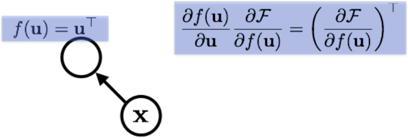
$\vec{x}$

graph:

Computation Graphs

Expression

$\vec{x}^\top$



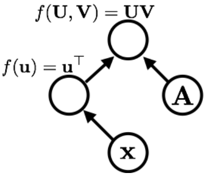
- Edge: function argument / data dependency
- A node with an incoming edge is a function $F \equiv f(u)$ edge's tail node
- A node computes its value and the value of its derivative w.r.t each argument (edge) times a derivative $\frac{\partial f}{\partial u}$

Computation Graphs

Expression

$\vec{x}^\top A$

graph:



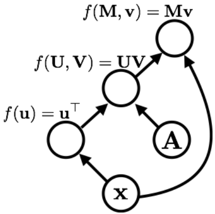
Functions can be nullary, unary, binary, . . . n-ary. Often they are unary or binary.

Computation Graphs

Expression

$\vec{x}^\top A x$

graph:



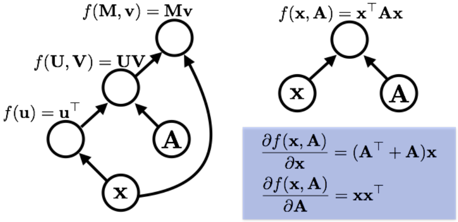
Computation graphs are (usually) directed and acyclic

Computation Graphs

Expression

$\vec{x}^{\top} A x$

graph:

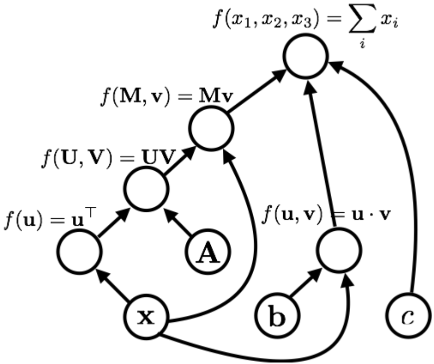


Computation Graphs

Expression

$\vec{x}^\top A x + b \cdot \vec{x} + c$

graph:

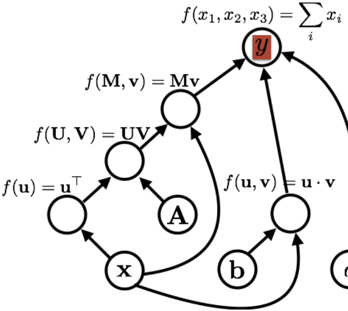


Computation Graphs

Expression

$y = \vec{x}^{\top} A x + b \cdot \vec{x} + c$

graph:

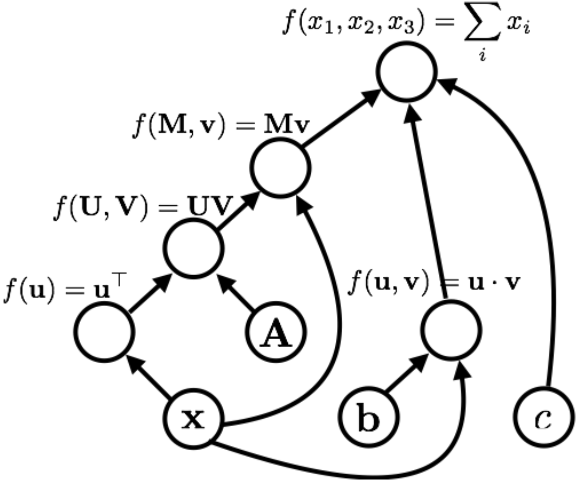


Variable names label nodes

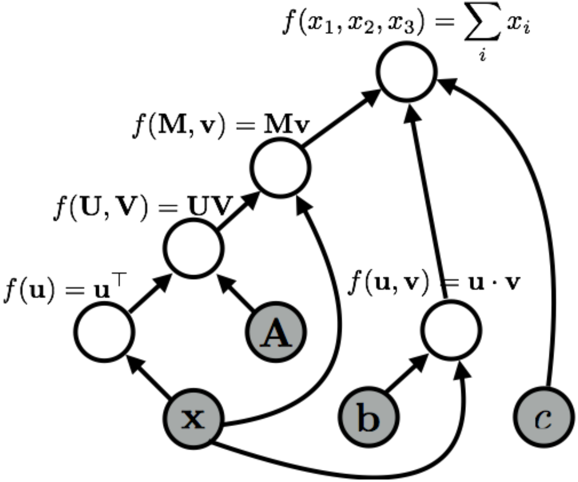
Algorithms

- Graph construction
- Forward propagation
  - Loop over nodes in topological order
  - Compute the value of the node given its inputs
  - Given my inputs, make a prediction (i.e. “error” vs. “target output”)
- Backward propagation
  - Loop over the nodes in reverse topological order, starting with goal node
  - Compute derivatives of final goal node value wrt each edge’s tail node
  - How does the output change with small change to inputs?

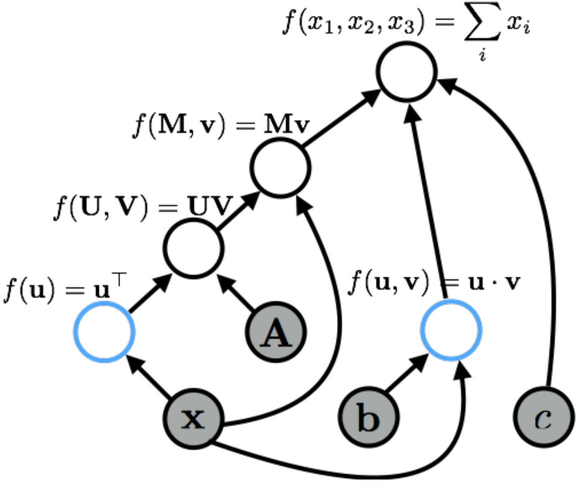
Forward Propagation



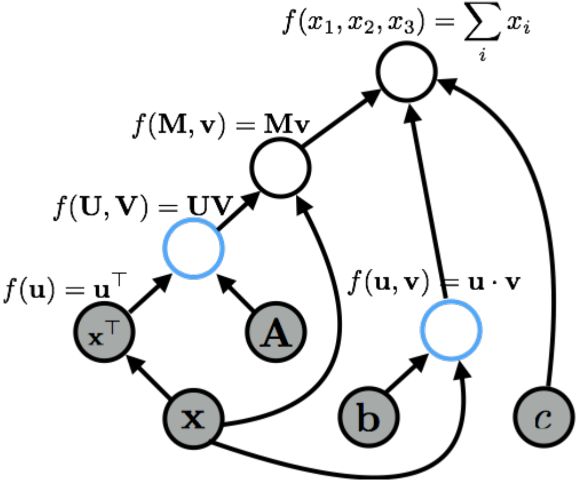
Forward Propagation



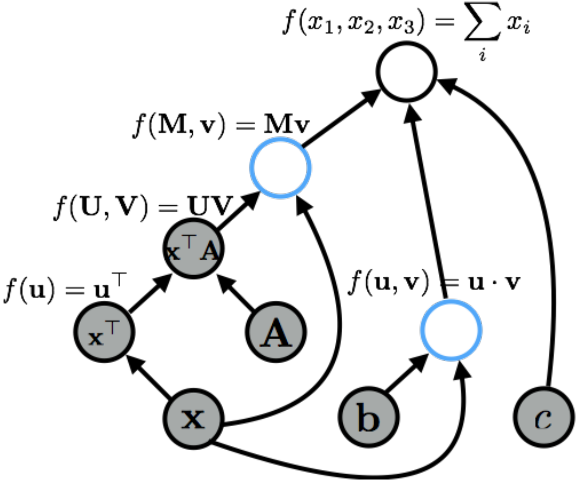
Forward Propagation



Forward Propagation



Forward Propagation



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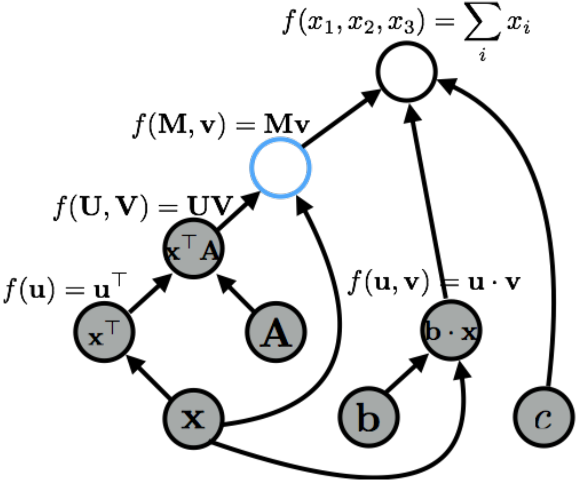

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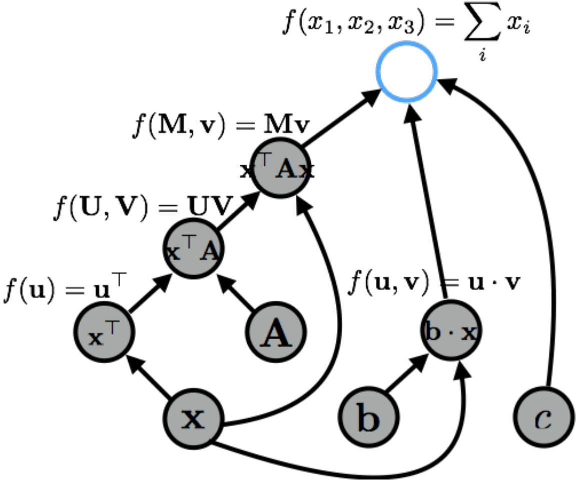

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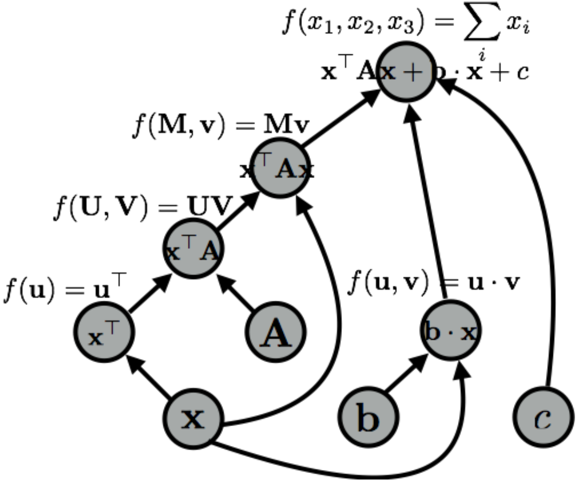

Constructing Graphs

Static declaration

- Define architecture, run data through
- PROS: Optimization, hardware support
- CONS: Structured data ugly, graph language

Theano, Tensorflow

Dynamic declaration

- Graph implicit with data
- PROS: Native language, interleave construction/evaluation
- CONS: Slower, computation can be wasted

Chainer, Dynet, PyTorch

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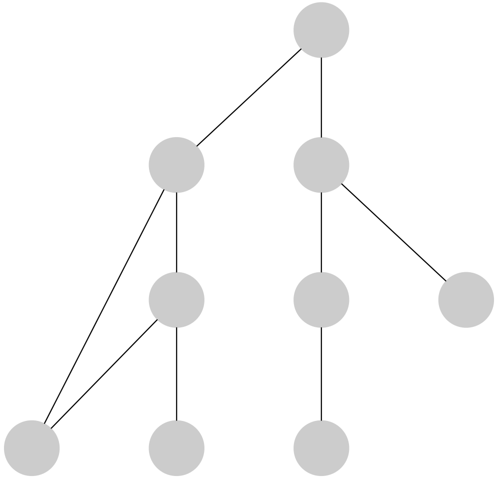
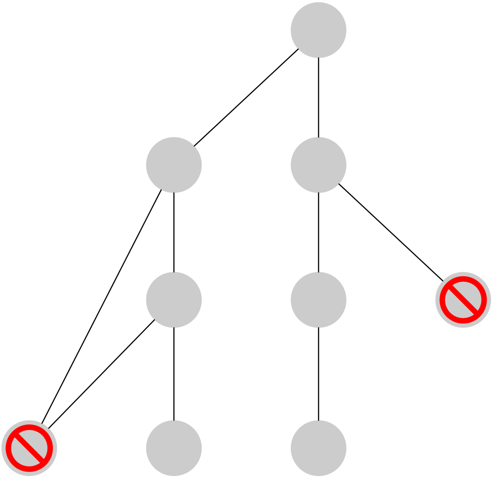
Advantage of Dynamic Declaration



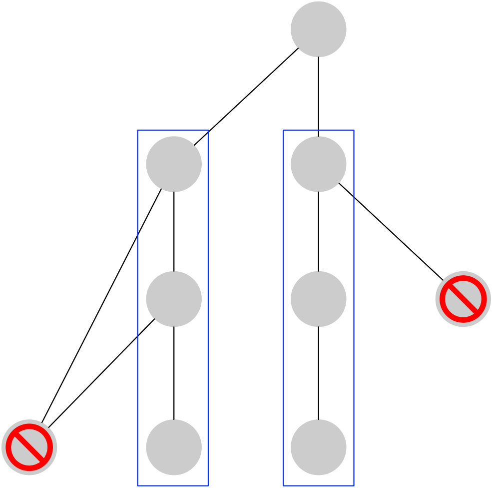
Only get computation graph at runtime

Advantage of Dynamic Declaration



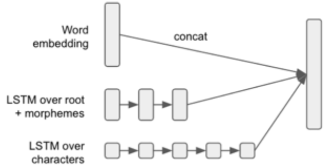
Can find things like zero vectors, unused variables

Advantage of Dynamic Declaration

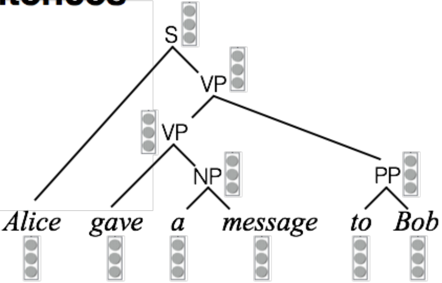


Parallelize on different physical computations

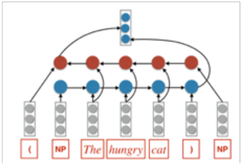
Words



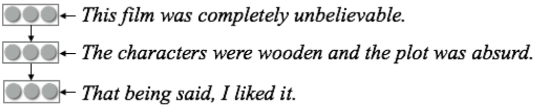
Sentences



Phrases



Documents



Language is Hierarchical

Dynamic Hierarchy in Language

- Language is hierarchical
  - Graph should reflect this reality
  - Traditional flow-control best for processing
- Combinatorial algorithms (e.g., dynamic programming)
- Exploit independencies to compute over a large space of operations tractably

PyTorch

- Torch: Facebook's deep learning framework
- Nice, but written in Lua (C backend)
- Optimized to run computations on GPU
- Mature, industry-supported framework

Why GPU?

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