Practical Neural Networks for NLP (Part 1)

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https://github.com/clab/dynet_tutorial_examples

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EMNLP

Neural Nets and Language

- Tension: Language and neural nets
  - Language is discrete and structured
    - Sequences, trees, graphs
  - Neural nets represent things with continuous vectors
    - Poor “native support” for structure
- The big challenge is writing code that translates between the {discrete-structured, continuous} regimes
- This tutorial is about one framework that lets you **use the power of neural nets without abandoning familiar NLP algorithms**

Outline

- **Part 1**
  - Computation graphs and their construction
  - Neural Nets in DyNet
  - Recurrent neural networks
  - Minibatching
  - Adding new differentiable functions

Outline

- **Part 2: Case Studies**
  - Tagging with bidirectional RNNs
  - Transition-based dependency parsing
  - Structured prediction meets deep learning

Computation Graphs

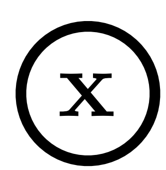
Deep Learning’s Lingua Franca

expression:

$$\mathbf{x}$$

graph:

A **node** is a {tensor, matrix, vector, scalar} value



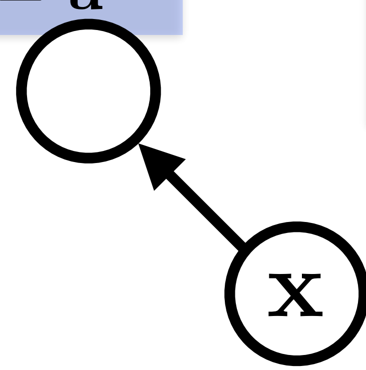
An **edge** represents a function argument (and also an data dependency). They are just pointers to nodes.

A **node** with an incoming **edge** is a **function** of that edge's tail node.

A **node** knows how to compute its value and the *value of its derivative w.r.t each argument (edge) times a derivative of an arbitrary input* $\frac{\partial \mathcal{F}}{\partial f(\mathbf{u})}$.

$$f(\mathbf{u}) = \mathbf{u}^\top$$

$$\frac{\partial f(\mathbf{u})}{\partial \mathbf{u}} \frac{\partial \mathcal{F}}{\partial f(\mathbf{u})} = \left(\frac{\partial \mathcal{F}}{\partial f(\mathbf{u})} \right)^\top$$

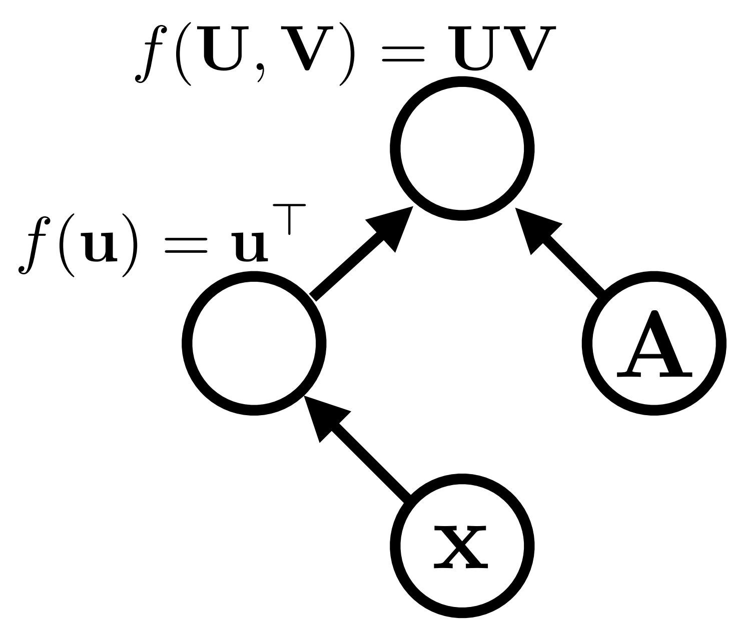


expression:

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

graph:

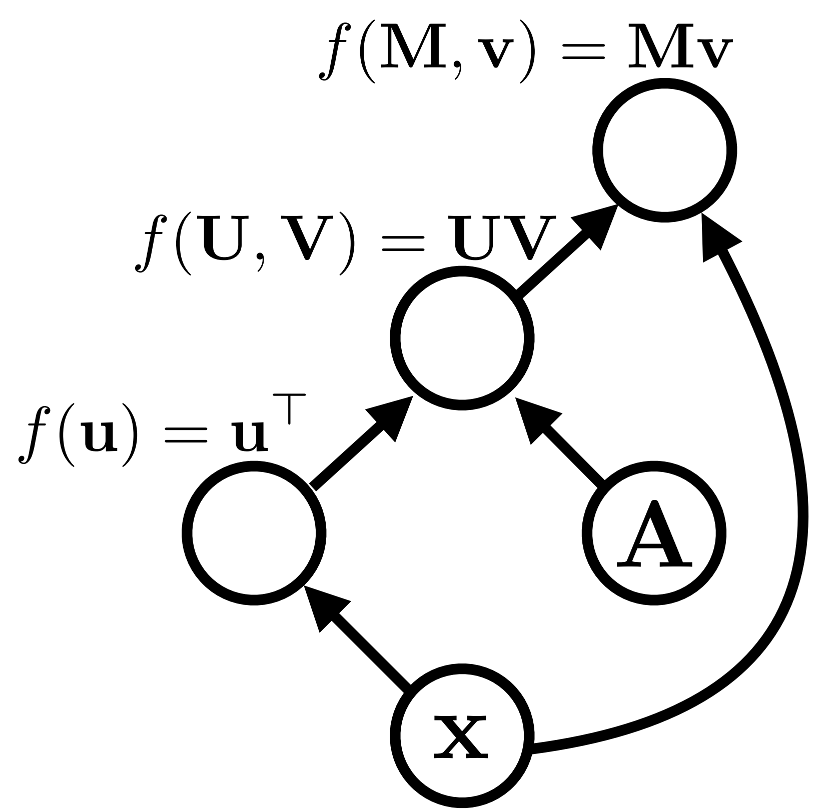
Functions can be nullary, unary, binary, … *n*-ary. Often they are unary or binary.



expression:

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

graph:

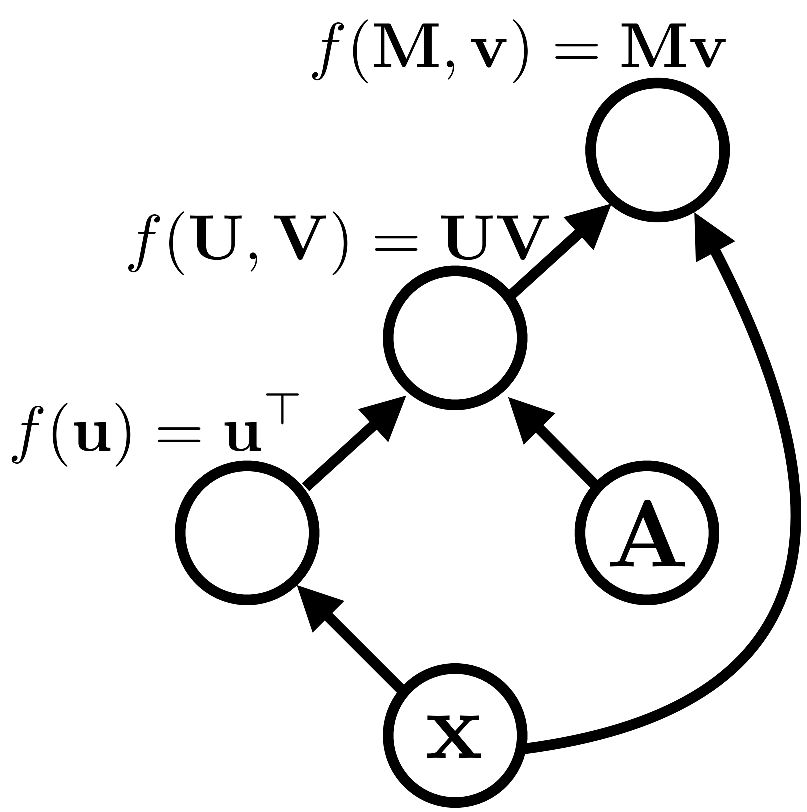


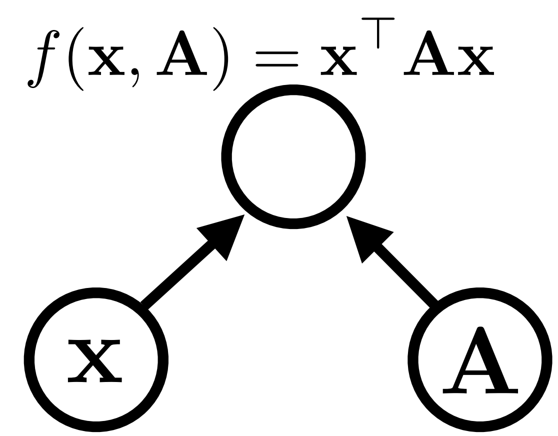
Computation graphs are directed and acyclic (in DyNet)

expression:

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

graph:





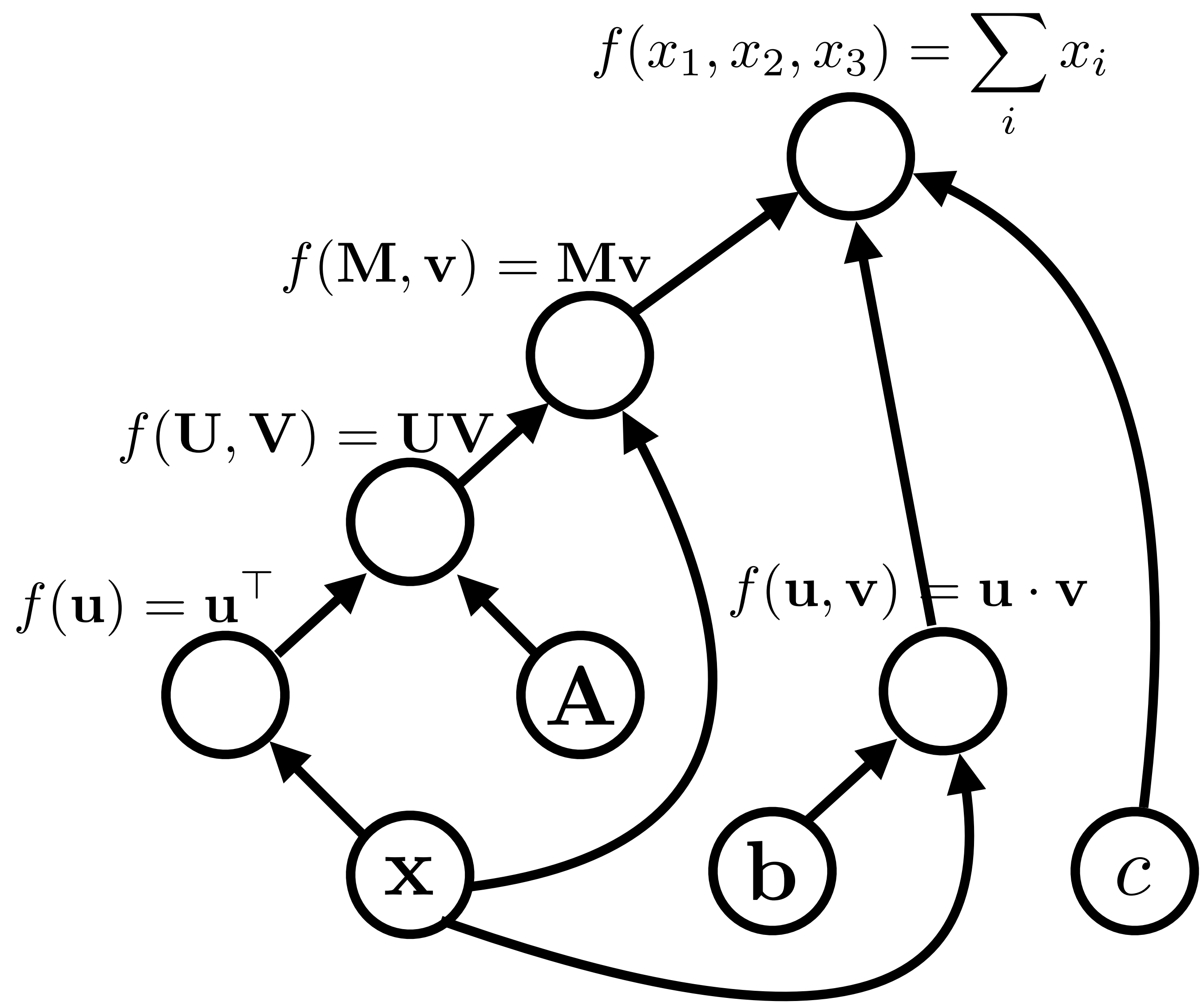
$$\frac{\partial f(\mathbf{x}, \mathbf{A})}{\partial \mathbf{x}} = (\mathbf{A}^\top + \mathbf{A})\mathbf{x}$$

$$\frac{\partial f(\mathbf{x}, \mathbf{A})}{\partial \mathbf{A}} = \mathbf{x}\mathbf{x}^\top$$

expression:

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

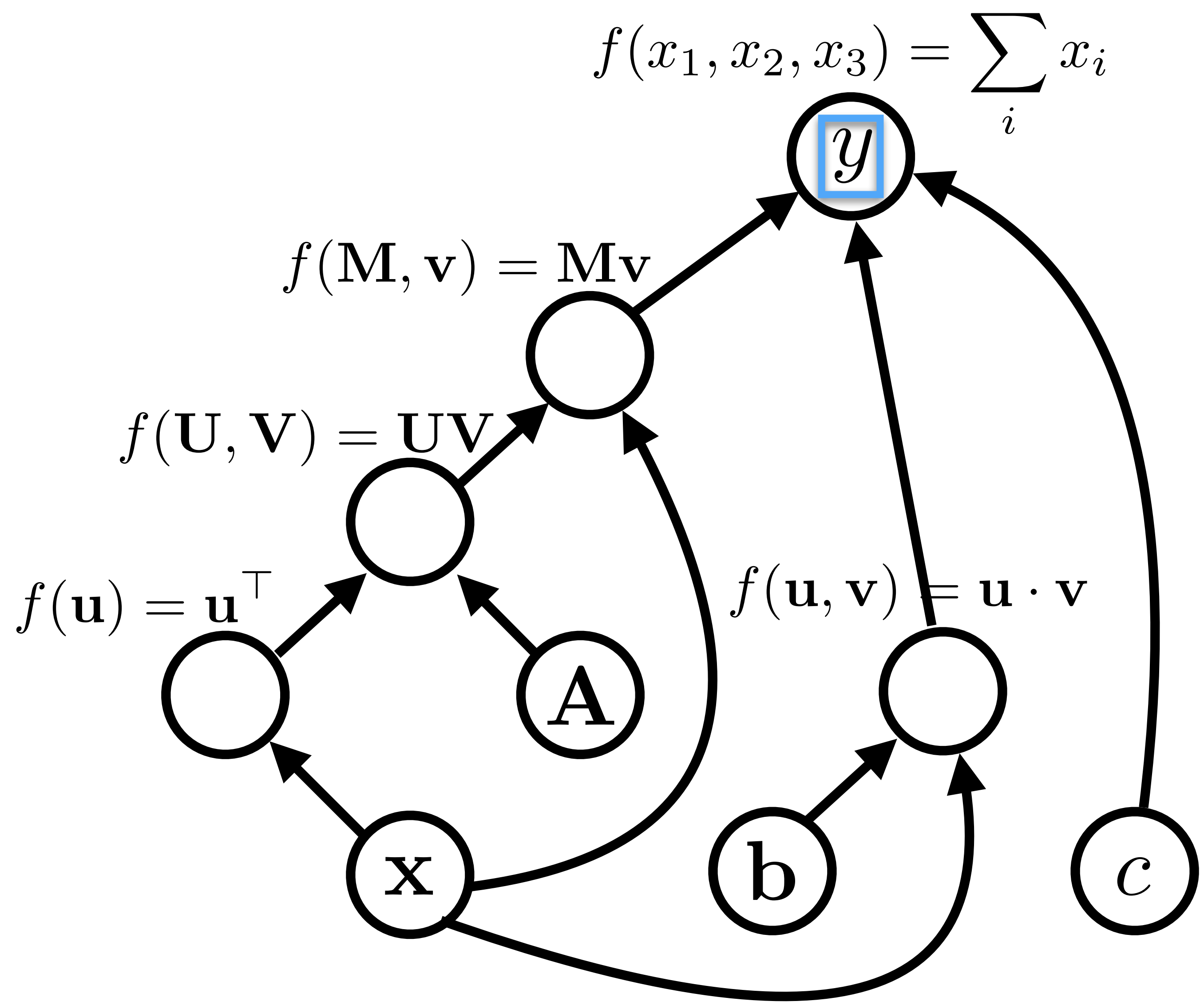
graph:



expression:

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

graph:



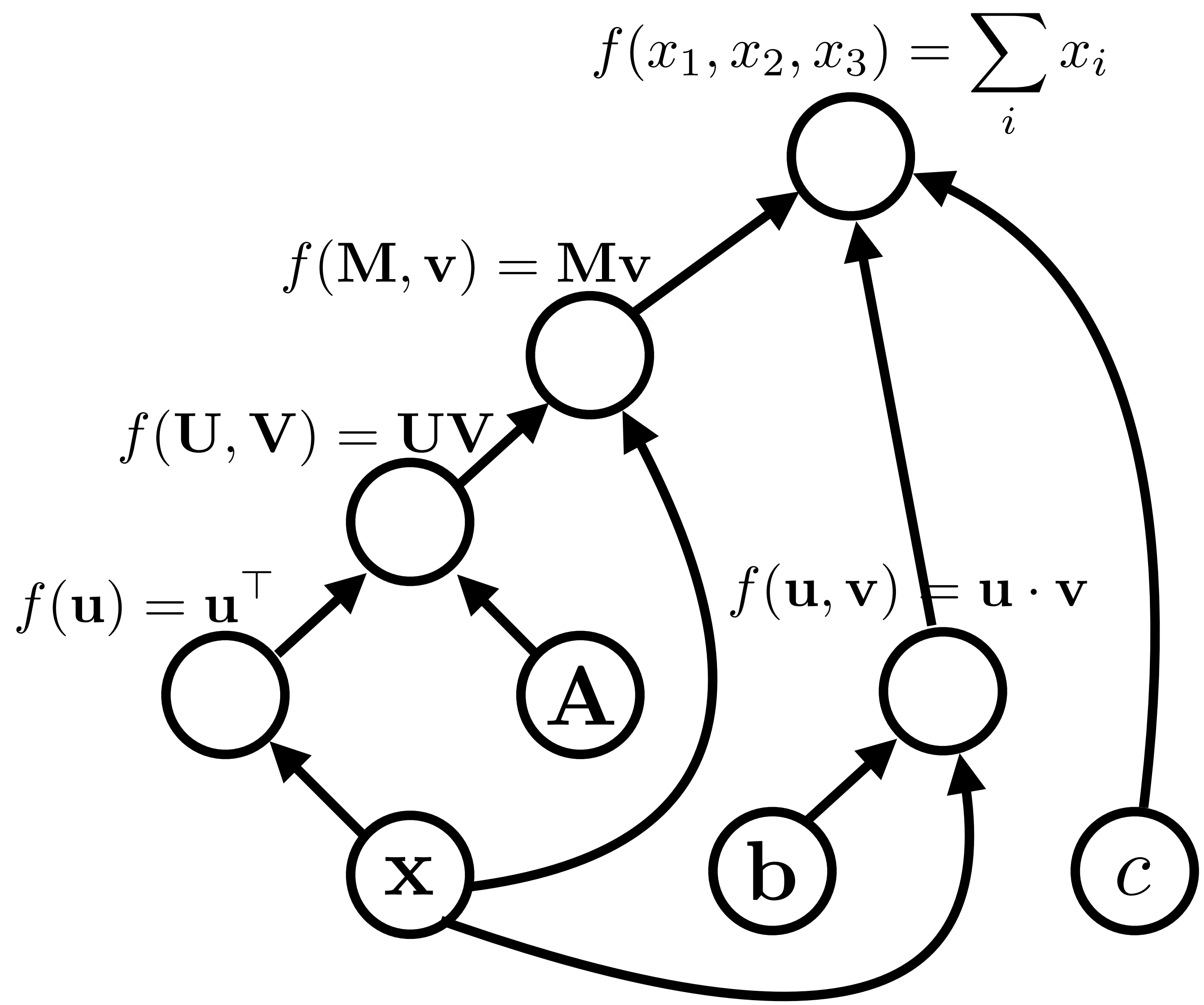
variable names are just labelings of nodes.

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 (or compute an "error" with respect to a "target output")*
- **Backward propagation**
    - Loop over the nodes in reverse topological order starting with a final goal node
        - Compute derivatives of final goal node value with respect to each edge's tail node
    - *How does the output change if I make a small change to the inputs?*

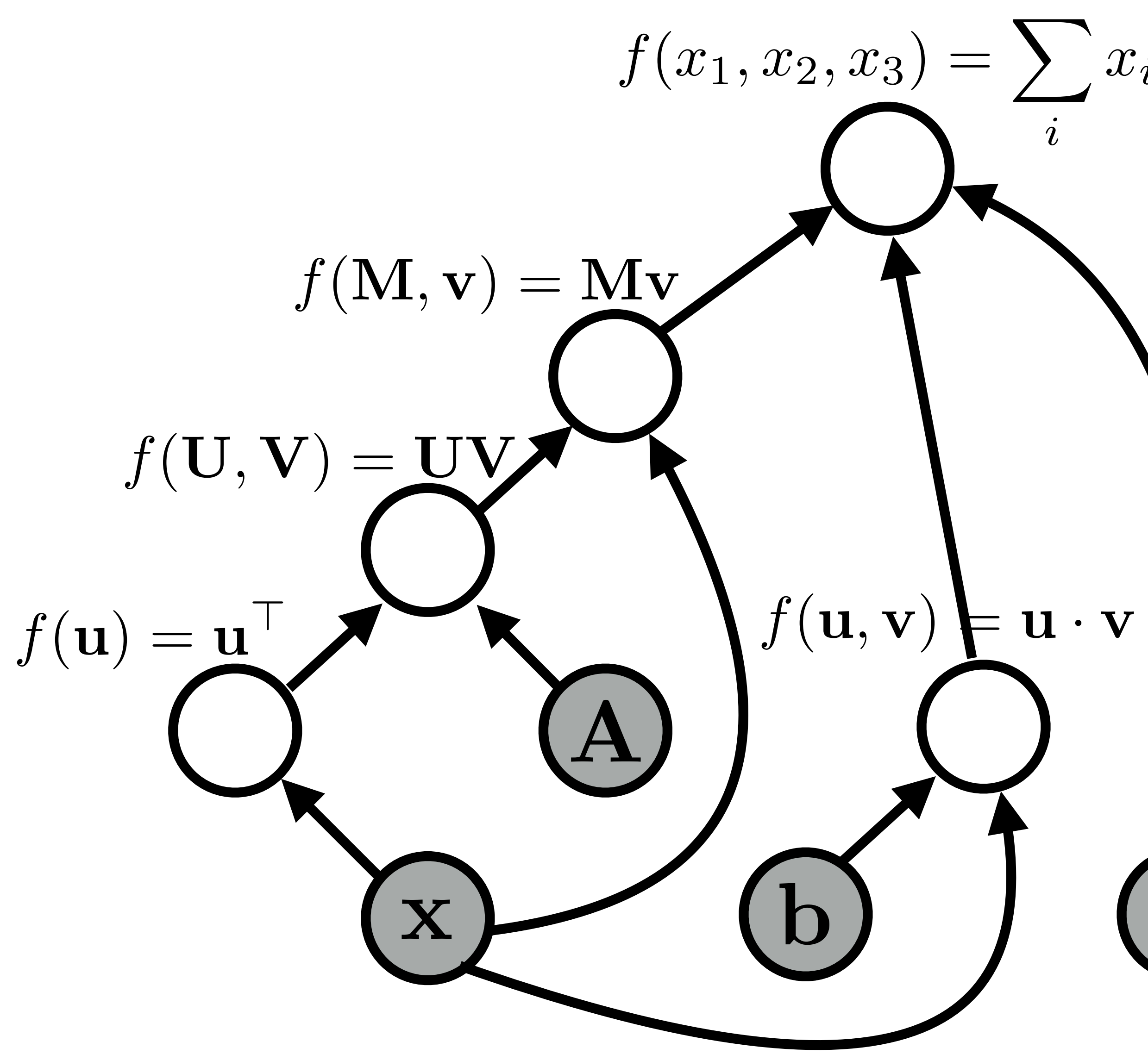
Forward Propagation

graph:



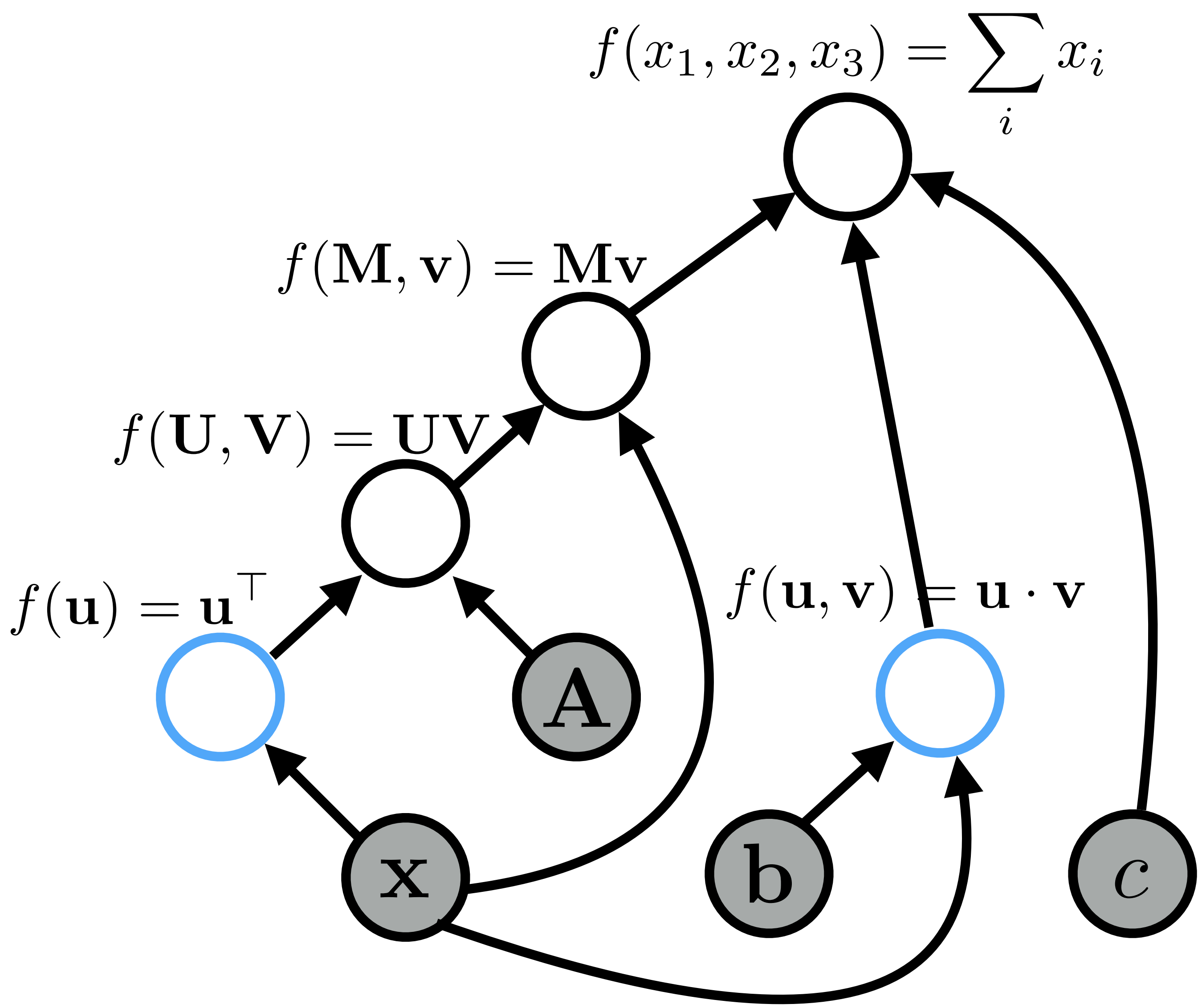
Forward Propagation

graph:



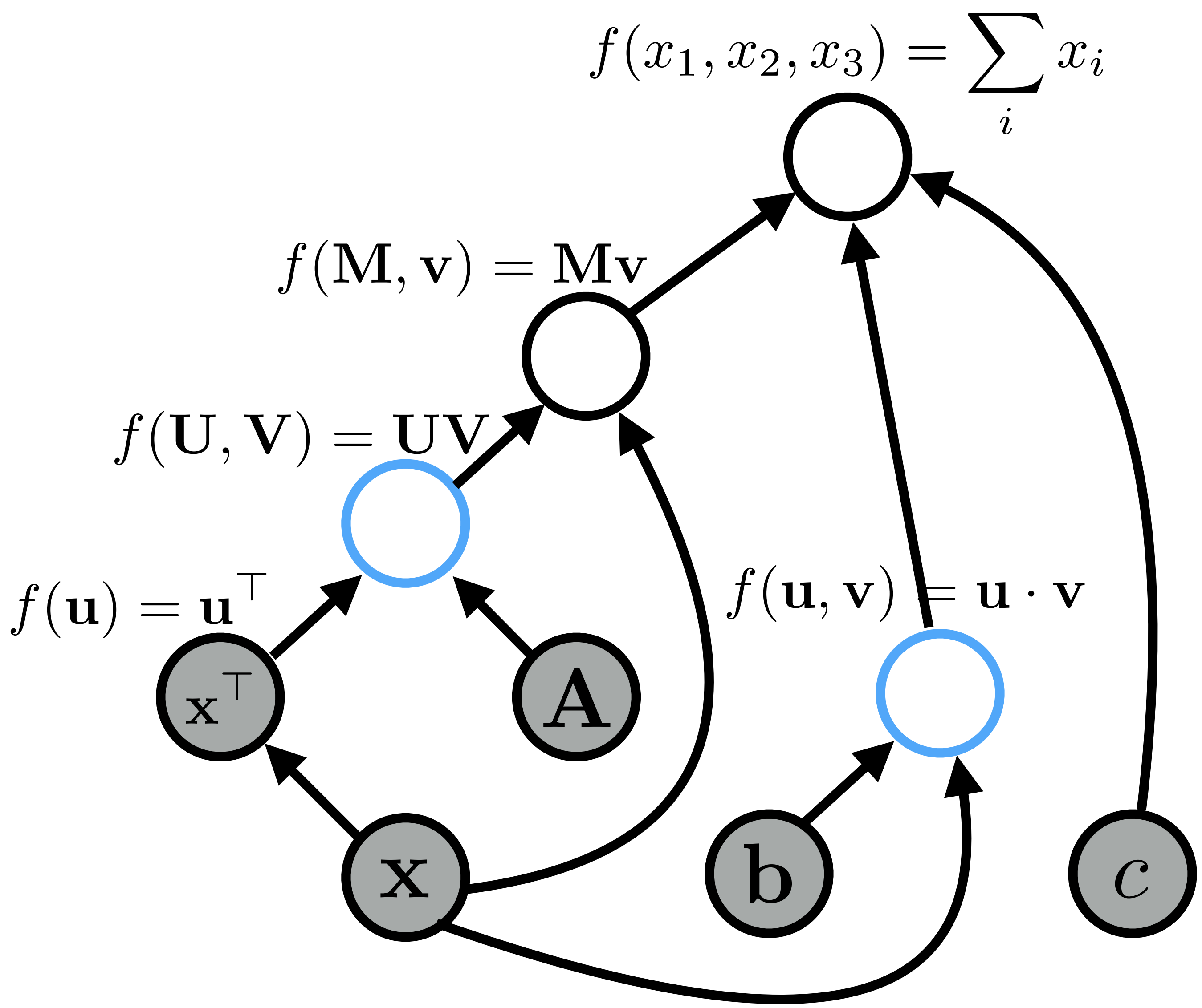
Forward Propagation

graph:



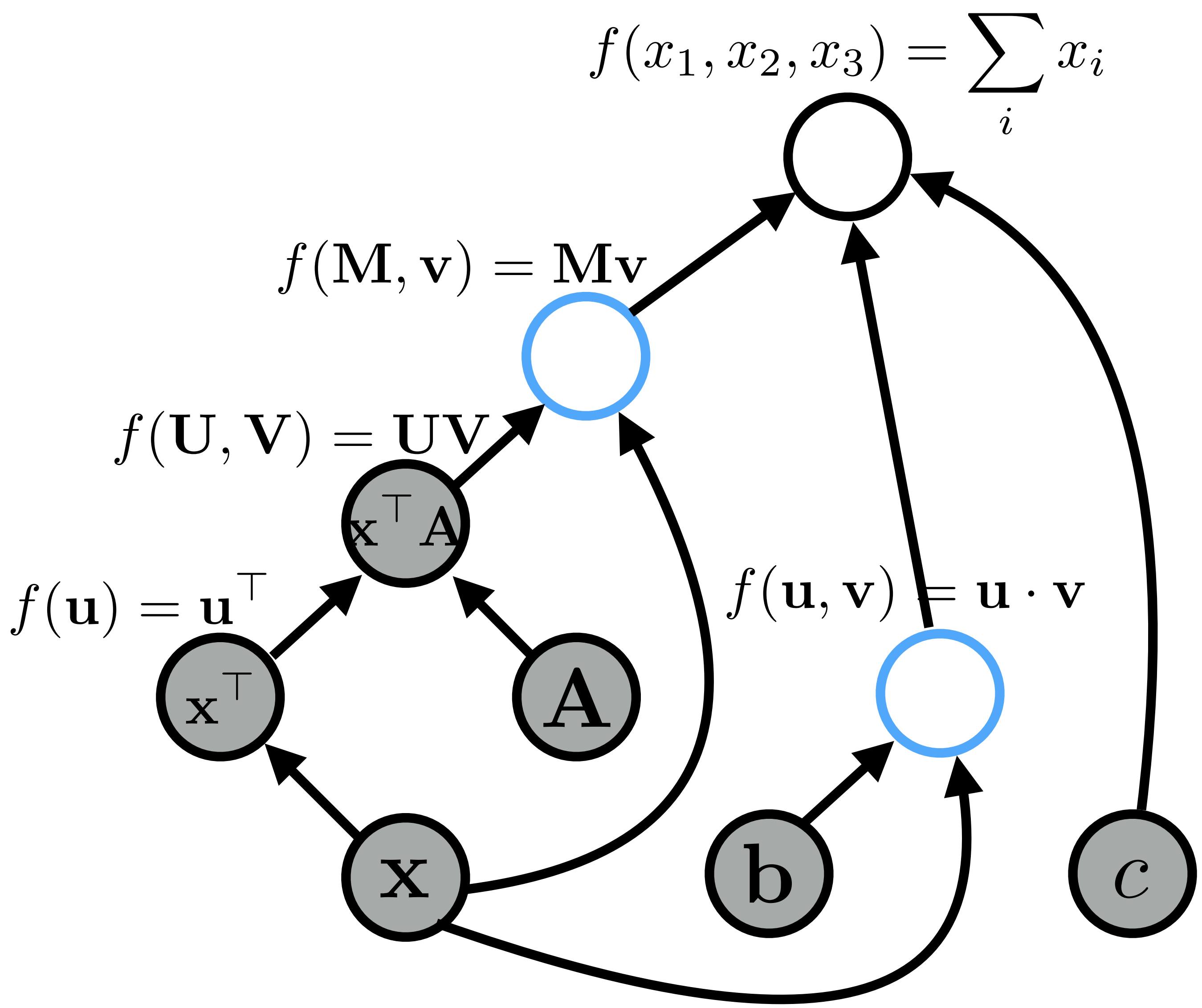
Forward Propagation

graph:



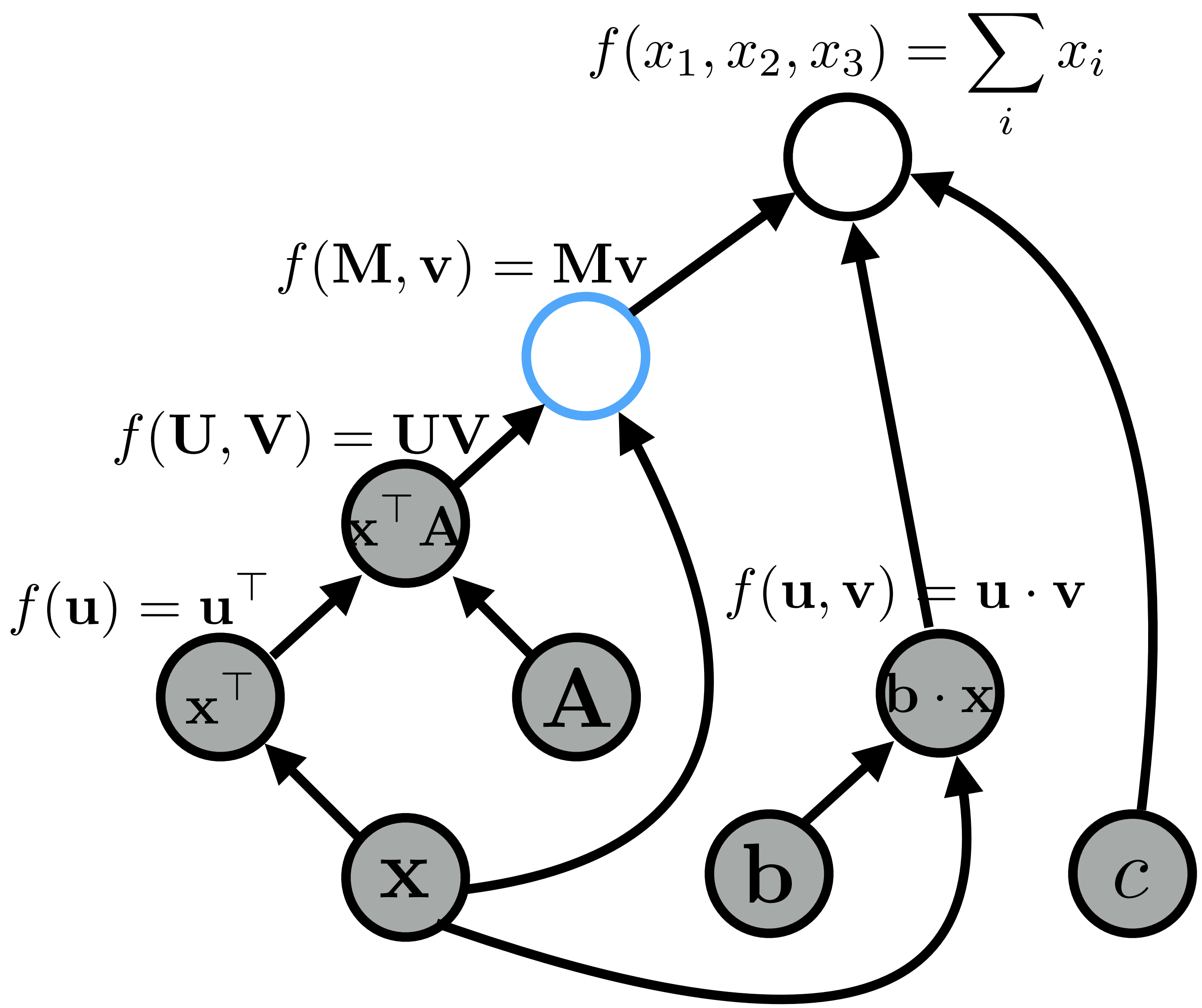
Forward Propagation

graph:



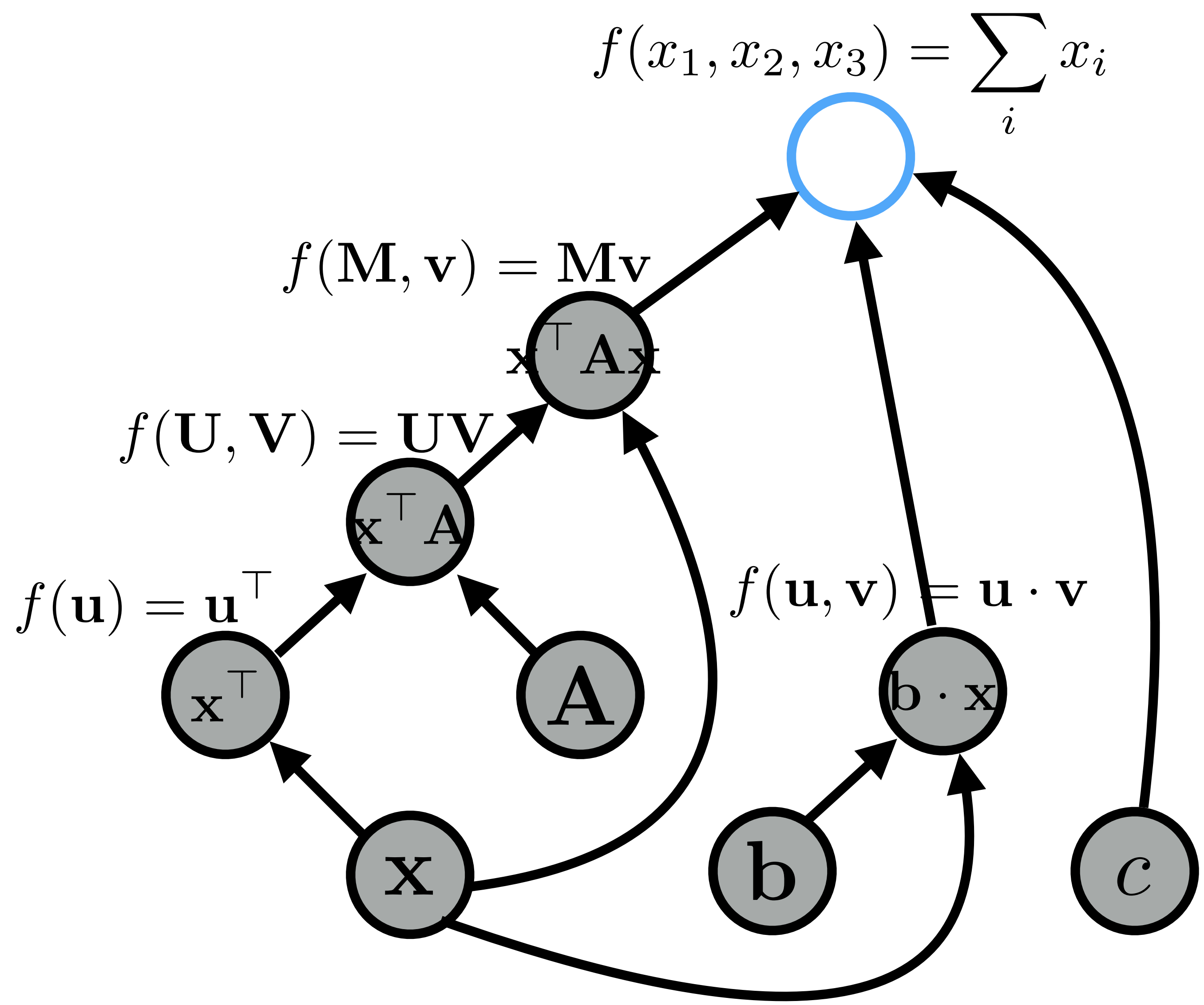
Forward Propagation

graph:



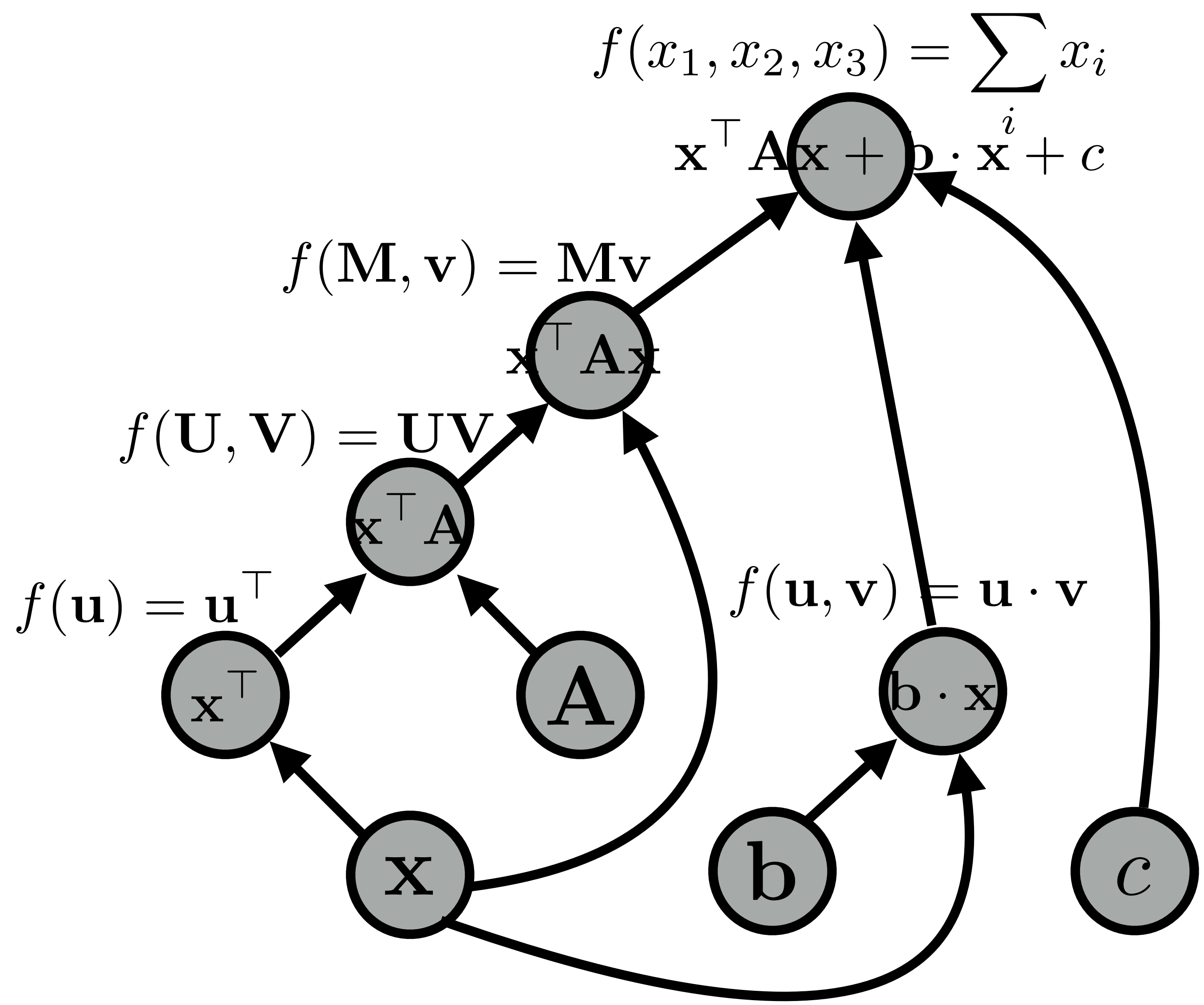
Forward Propagation

graph:



Forward Propagation

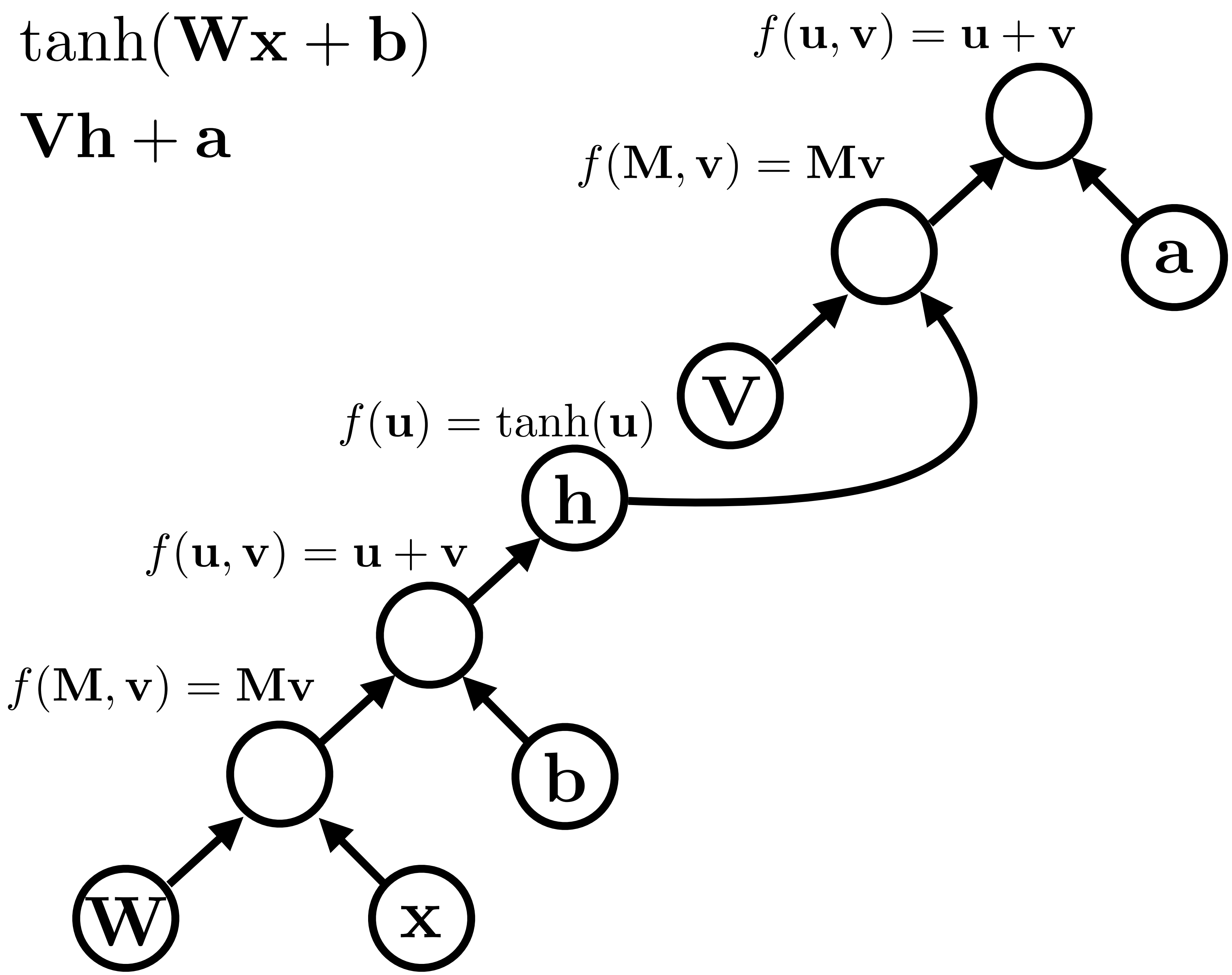
graph:



The MLP

$$\mathbf{h} = \tanh(\mathbf{W}\mathbf{x} + \mathbf{b})$$

$$\mathbf{y} = \mathbf{V}\mathbf{h} + \mathbf{a}$$



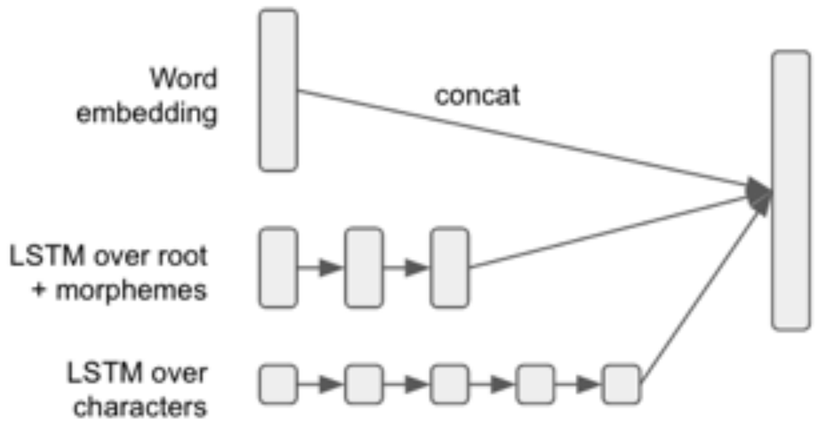
Constructing Graphs

Two Software Models

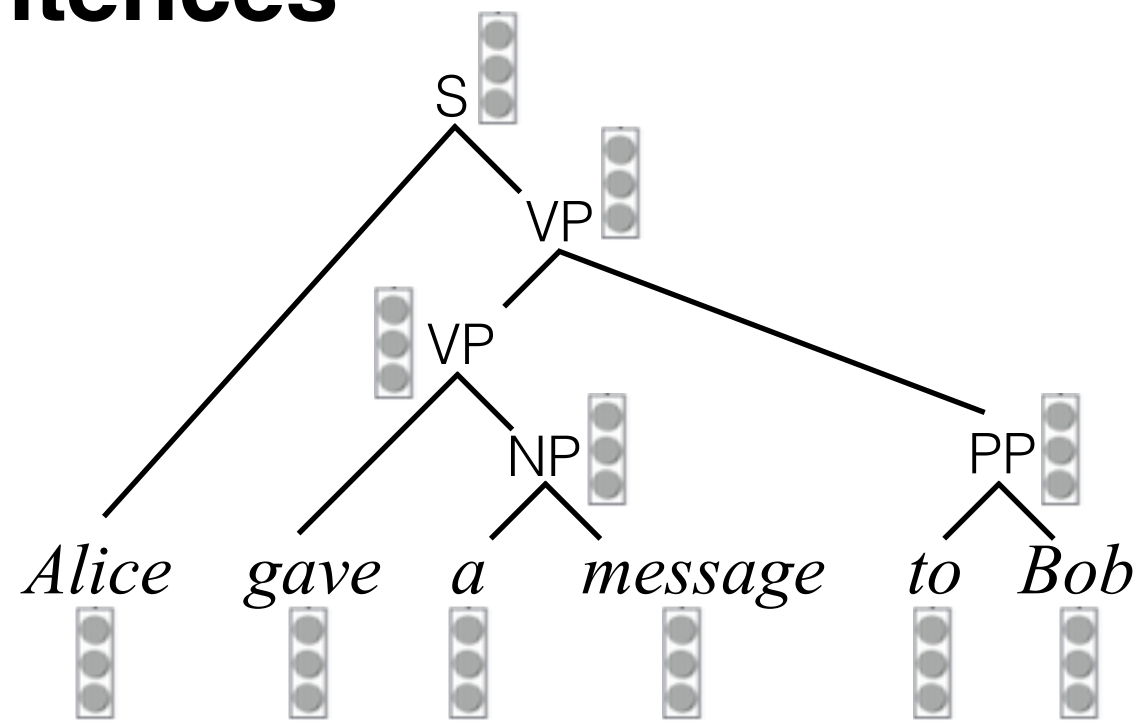
- **Static declaration**
  - Phase 1: define an architecture
    (maybe with some primitive flow control like loops and conditionals)
  - Phase 2: run a bunch of data through it to train the model and/or make predictions
- **Dynamic declaration**
  - Graph is defined implicitly (e.g., using operator overloading) as the forward computation is executed

Hierarchical Structure

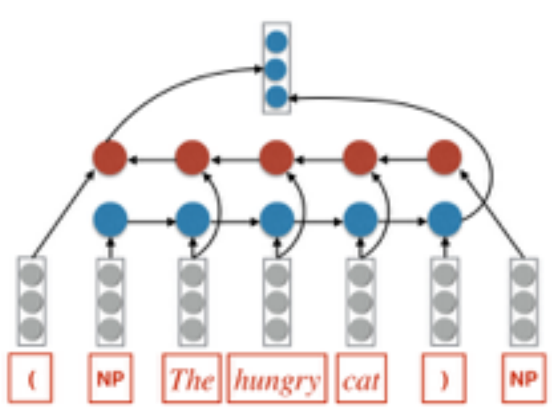
Words



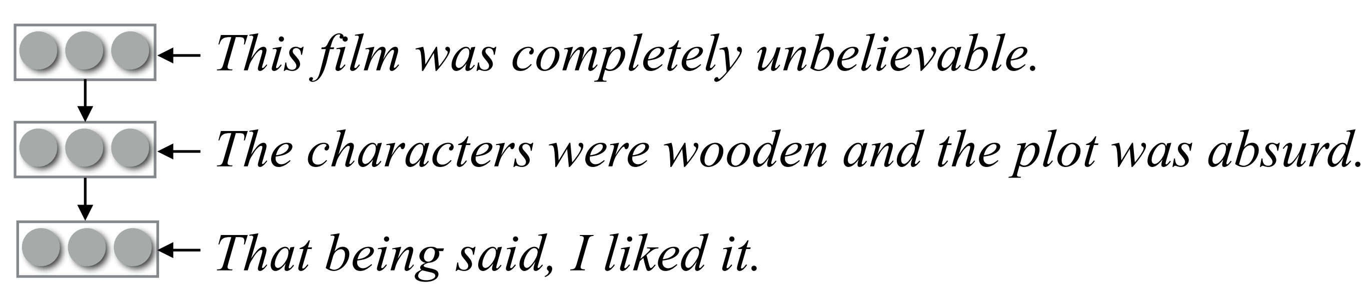
Sentences



Phrases



Documents



Static Declaration

- **Pros**
  - Offline optimization/scheduling of graphs is powerful
  - Limits on operations mean better hardware support
- **Cons**
  - Structured data (even simple stuff like sequences), even variable-sized data, is ugly
  - You effectively learn a new programming language (“the Graph Language”) and you write programs in that language to process data.
- examples: Torch, Theano, TensorFlow

Dynamic Declaration

- **Pros**
  - library is less invasive
  - the forward computation is written in your favorite programming language with all its features, using your favorite algorithms
  - interleave construction and evaluation of the graph
- **Cons**
  - little time for graph optimization
  - if the graph is static, effort can be wasted
- examples: Chainer, *most automatic differentiation libraries,* **DyNet**

Dynamic Structure?

- Hierarchical structures exist in language
  - We might want to let the network reflect that hierarchy
  - Hierarchical structure is easiest to process with traditional flow-control mechanisms in your favorite languages
- Combinatorial algorithms (e.g., dynamic programming)
  - Exploit independencies to compute over a large space of operations tractably

Why DyNet?

- The state of the world before DyNet/cnn
  - AD libraries are fast and good, but don’t have support for deep learning must-haves (GPUs, optimization algorithms, primitives for implementing RNNs, etc.)
  - Deep learning toolkits don’t support dynamic graphs well

t

Why DyNet?

- The state of the world before DyNet/cnn
  - AD libraries are fast and good, but don't have support for deep learning must-haves (GPUs, optimization algorithms, primitives for implementing RNNs, etc.)
  - Deep learning toolkits don't support dynamic graphs well
- DyNet is a hybrid between a generic autodiff library and a Deep learning toolkit
  - It has the flexibility of a good AD library
  - It has most obligatory DL primitives
- (Although the emphasis is dynamic operation, it can run perfectly well in "static mode". It's quite fast too! But if you're happy with that, probably stick to TensorFlow/Theano/Torch.)

How does it work?

- C++ backend based on Eigen
  - Eigen also powers TensorFlow
- Custom (“quirky”) memory management
  - You probably don’t need to ever think about this, but a few well-hidden assumptions make the graph construction and execution very fast.
- Thin Python wrapper on C++ API

Neural Networks in DyNet

The Major Players

- Computation Graph
- Expressions (~ nodes in the graph)
- Parameters
- Model
    - a collection of parameters
- Trainer

Computation Graph and Expressions

```
import dynet as dy

dy.renew_cg() # create a new computation graph

v1 = dy.inputVector([1,2,3,4])
v2 = dy.inputVector([5,6,7,8])
# v1 and v2 are expressions

v3 = v1 + v2
v4 = v3 * 2
v5 = v1 + 1

v6 = dy.concatenate([v1,v2,v3,v5])

print v6
print v6.npvalue()
```

Computation Graph and Expressions

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print v6  expression 5/1
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```

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v6 = dy.concatenate([v1,v2,v3,v5])

print v6
print v6.npvalue()
```

```
array([  1.,   2.,   3.,   4.,   2.,   4.,   6.,   8.,   4.,   8.,  12.,  16.])
```

Computation Graph and Expressions

- Create basic expressions.
- Combine them using *operations*.
- Expressions represent *symbolic computations*.
- Use:

```
.value()
.npvalue()
.scalar_value()
.vec_value()
.forward()
```

to perform actual computation.

Model and Parameters

- **Parameters** are the things that we optimize over (vectors, matrices).
- **Model** is a collection of parameters.
- Parameters **out-live** the computation graph.

Model and Parameters

```
model = dy.Model()

pW = model.add_parameters((20,4))
pb = model.add_parameters(20)


dy.renew_cg()
x = dy.inputVector([1,2,3,4])
W = dy.parameter(pW) # convert params to expression
b = dy.parameter(pb) # and add to the graph

y = W * x + b
```

Parameter Initialization

```
model = dy.Model()

pW = model.add_parameters((4,4))

pW2 = model.add_parameters((4,4), init=dy.GlorotInitializer())

pW3 = model.add_parameters((4,4), init=dy.NormalInitializer(0,1))

pW4 = model.parameters_from_numpu(np.eye(4))
```

Trainers and Backdrop

- Initialize a **Trainer** with a given model.
- Compute gradients by calling `expr.backward()` from a scalar node.
- Call `trainer.update()` to update the model parameters using the gradients.

Trainers and Backdrop

```
model = dy.Model()

trainer = dy.SimpleSGDTrainer(model)

p_v = model.add_parameters(10)

for i in xrange(10):
    dy.renew_cg()

    v = dy.parameter(p_v)
    v2 = dy.dot_product(v,v)
    v2.forward()

    v2.backward()  # compute gradients

    trainer.update()
```

Trainers and Backdrop

```
model = dy.Model()

trainer =

p_v = mode

for i in x
    dy.ren

    v = dy
    v2 = d
    v2.for

    v2.backward()  # compute gradients

    trainer.update()
```

```
dy.SimpleSGDTrainer(model,...)

dy.MomentumSGDTrainer(model,...)

dy.AdagradTrainer(model,...)

dy.AdadeltaTrainer(model,...)

dy.AdamTrainer(model,...)
```

Training with DyNet

- Create model, add parameters, create trainer.
- For each training example:
  - create computation graph for the loss
  - run forward (compute the loss)
  - run backward (compute the gradients)
  - update parameters

Example: MLP for XOR

- Data:

$$\mathrm{xor}(0,0) = 0$$

$$\mathrm{xor}(1,0) = 1$$

$$\mathrm{xor}(0,1) = 1$$

$$\mathrm{xor}(1,1) = 0$$

$$\mathbf{x} \qquad\qquad y$$

- Model form:

$$\hat{y} = \sigma(\mathbf{v} \cdot \tanh(\mathbf{U}\mathbf{x} + \mathbf{b}))$$

- Loss:

$$\ell = \begin{cases} -\log \hat{y} & y = 1 \\ -\log(1 - \hat{y}) & y = 0 \end{cases}$$

$$\hat{y} = \sigma(\mathbf{v} \cdot \tanh(\mathbf{U}\mathbf{x} + \mathbf{b}))$$

```
import dynet as dy
import random

data =[ ([0,1],0),
        ([1,0],0),
        ([0,0],1),
        ([1,1],1) ]

model = dy.Model()
pU = model.add_parameters((4,2))
pb = model.add_parameters(4)
pv = model.add_parameters(4)

trainer = dy.SimpleSGDTrainer(model)
closs = 0.0

for ITER in xrange(1000):
    random.shuffle(data)
    for x,y in data:
        ....
```

```
for ITER in xrange(1000):
  for x,y in data:
```

$$\hat{y} = \sigma(\mathbf{v} \cdot \tanh(\mathbf{Ux} + \mathbf{b}))$$

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```
for ITER in xrange(1000):
  for x,y in data:
    # create graph for computing loss
    dy.renew_cg()
    U = dy.parameter(pU)
    b = dy.parameter(pb)
    v = dy.parameter(pv)
    x = dy.inputVector(x)
    # predict
    yhat = dy.logistic(dy.dot_product(v,dy.tanh(U*x+b)))
    # loss
    if y == 0:
        loss = -dy.log(1 - yhat)
    elif y == 1:
        loss = -dy.log(yhat)

    closs += loss.scalar_value() # forward
    loss.backward()
    trainer.update()
```

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  for x,y in data:
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    dy.renew_cg()
    U = dy.parameter(pU)
    b = dy.parameter(pb)
    v = dy.parameter(pv)
    x = dy.inputVector(x)
    # predict
    yhat = dy.logistic(dy.dot_product(v,dy.tanh(U*x+b)))
    # loss
    if y == 0:
       loss = -dy.log(1 - yhat)
    elif y == 1:
       loss = -dy.log(yhat)

    closs += loss.scalar_value() # forward
    if ITER > 0 and ITER % 100 == 0:
            print "Iter:",ITER,"loss:", closs/400
            closs = 0
```

$$\ell = \begin{cases} -\log \hat{y} & y = 1 \\ -\log(1 - \hat{y}) & y = 0 \end{cases}$$

```python
for ITER in xrange(1000):
  for x,y in data:
      # create graph for computing loss
      dy.renew_cg()
      U = dy.parameter(pU)
      b = dy.parameter(pb)
      v = dy.parameter(pv)
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      # predict
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      loss.backward()
      trainer.update()
```

lets organize the code a bit

```
for ITER in xrange(1000):
 for x,y in data:
    # create graph for computing loss
    dy.renew_cg()
    U = dy.parameter(pU)
    b = dy.parameter(pb)
    v = dy.parameter(pv)
    x = dy.inputVector(x)
    # predict
    yhat = dy.logistic(dy.dot_product(v,dy.tanh(U*x+b)))
    # loss
    if y == 0:
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    elif y == 1:
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    closs += loss.scalar_value() # forward
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```

lets organize the code a bit

```
for ITER in xrange(1000):
  for x,y in data:
     # create graph for computing loss
     dy.renew_cg()

     x = dy.inputVector(x)
     # predict
     yhat = predict(x)
     # loss
     loss = compute_loss(yhat, y)

     closs += loss.scalar_value() # forward
     loss.backward()
     trainer.update()
```

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for ITER in xrange(1000):
  for x,y in data:
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```

$$\hat{y} = \sigma(\mathbf{v} \cdot \tanh(\mathbf{U}\mathbf{x} + \mathbf{b}))$$

```
def predict(expr):
    U = dy.parameter(pU)
    b = dy.parameter(pb)
    v = dy.parameter(pv)
    y = dy.logistic(dy.dot_product(v,dy.tanh(U*expr+b)))
    return y
```

```python
for ITER in xrange(1000):
  for x,y in data:
     # create graph for computing loss
     dy.renew_cg()

     x = dy.inputVector(x)
     # predict
     yhat = predict(x)
     # loss
     loss = compute_loss(yhat, y)

     closs += loss.scalar_value() # forward
     loss.backward()
     trainer.update()
```

```python
def compute_loss(expr, y):
    if y == 0:
        return -dy.log(1 - expr)
    elif y == 1:
        return -dy.log(expr)
```

$$\ell = \begin{cases} -\log \hat{y} & y = 1 \\ -\log(1 - \hat{y}) & y = 0 \end{cases}$$

Key Points

- Create computation graph for each example.
- Graph is built by composing expressions.
- Functions that take expressions and return expressions define graph components.

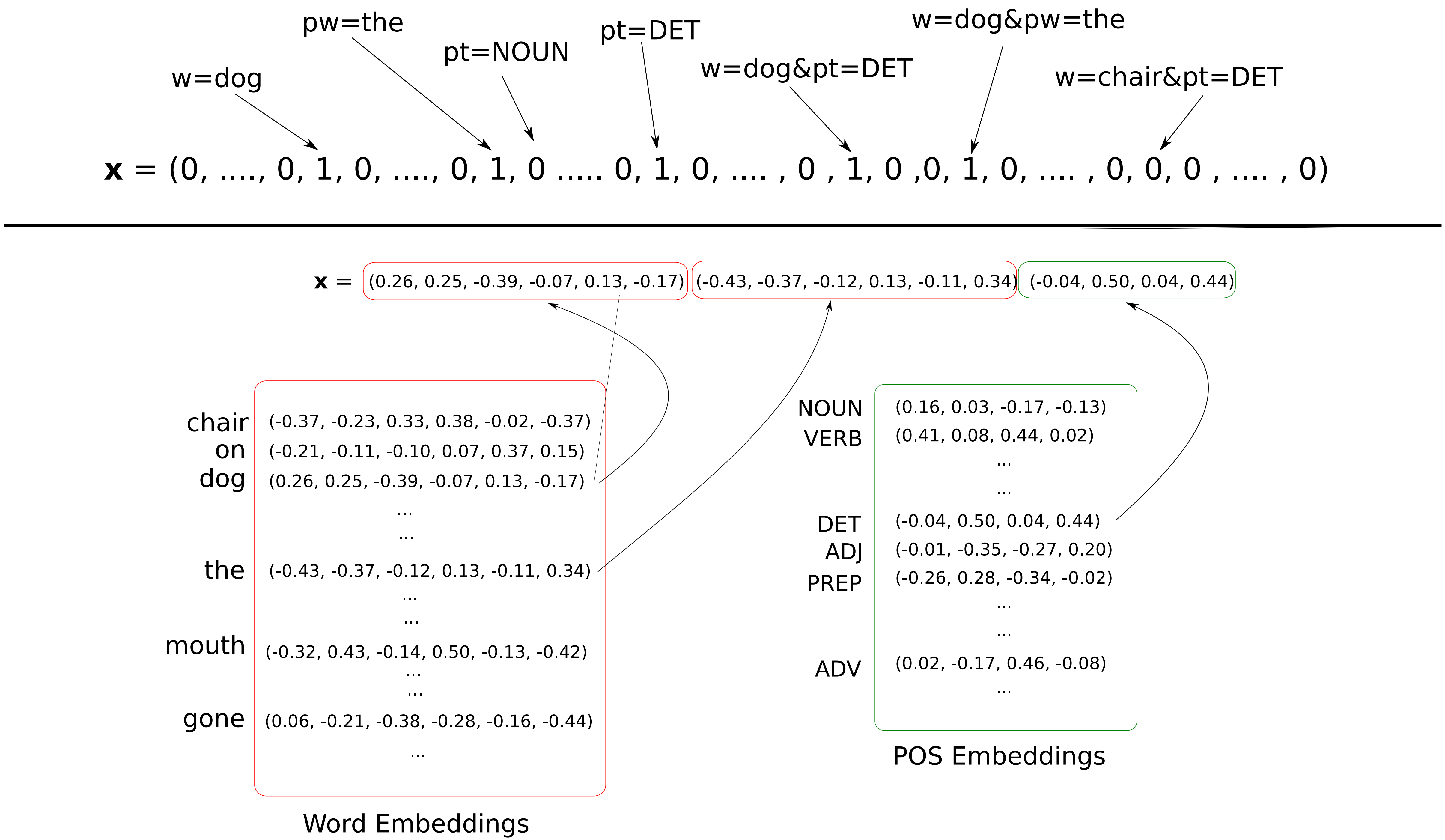
Word Embeddings and LookupParameters

- In NLP, it is very common to use feature embeddings.
- Each feature is represented as a d-dim vector.
- These are then summed or concatenated to form an input vector.
- The embeddings can be pre-trained.
- They are usually trained with the model.

"feature embeddings"

- Each feature is assigned a vector.
- The input is a combination of feature vectors.
- The feature vectors are **parameters of the model** and are trained jointly with the rest of the network.
- **Representation Learning**: similar features will receive similar vectors.

"feature embeddings"



Word Embeddings and LookupParameters

- In DyNet, embeddings are implemented using `LookupParameters`.

```
vocab_size = 10000
emb_dim = 200

E = model.add_lookup_parameters((vocab_size, emb_dim))
```

Word Embeddings and LookupParameters

- In DyNet, embeddings are implemented using `LookupParameters`.

```
vocab_size = 10000
emb_dim = 200

E = model.add_lookup_parameters((vocab_size, emb_dim))

dy.renew_cg()
x = dy.lookup(E, 5)
# or
x = E[5]
# x is an expression
```

Deep Unordered Composition Rivals Syntactic Methods for Text Classification

Mohit Iyyer,[1] **Varun Manjunatha,**[1] **Jordan Boyd-Graber,**[2] **Hal Daumé III**[1]
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[2]University of Colorado, Department of Computer Science
{miyyer,varunm,hal}@umiacs.umd.edu, Jordan.Boyd.Graber@colorado.edu

scores of labels

$$\uparrow$$

$$softmax(\Box)$$

$$\uparrow$$

$$g^2(\mathbf{W}^2\Box + \mathbf{b}^2)$$

$$\uparrow$$

$$g^1(\mathbf{W}^1\Box + \mathbf{b}^1)$$

$$\uparrow$$

$$CBOW(\Box)$$

$$\uparrow$$

$$w_1, ..., w_n$$

"deep averaging network"

$$CBOW(w_1, \ldots, w_n) = \sum_{i=1}^{n} \mathbf{E}[w_i]$$

lets define this network

scores of labels

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$$softmax(\square)$$

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$$g^1 = g^2 = \tanh$$

$$CBOW(w_1, \ldots, w_n) = \sum_{i=1}^{n} \mathbf{E}[w_i]$$

```
pW1 = model.add_parameters((HID, EDIM))
pb1 = model.add_parameters(HID)

pW2 = model.add_parameters((NOUT, HID))
pb2 = model.add_parameters(NOUT)

E = model.add_lookup_parameters((V, EDIM))
```

scores of labels

$$\uparrow$$

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"deep averaging network"

```
for (doc, label) in data:
    dy.renew_cg()
    probs = predict_labels(doc)
```

```
def predict_labels(doc):
    x = encode_doc(doc)
    h = layer1(x)
    y = layer2(h)
    return dy.softmax(y)
```

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$$g^1(\mathbf{W}^1\square + \mathbf{b}^1)$$

$$\uparrow$$

$$CBOW(\square)$$

$$\uparrow$$

$$w_1, ..., w_n$$

"deep averaging network"

```
def layer1(x):
    W = dy.parameter(pW1)
    b = dy.parameter(pb1)
    return dy.tanh(W*x+b)

def layer2(x):
    W = dy.parameter(pW2)
    b = dy.parameter(pb2)
    return dy.tanh(W*x+b)
```

```
for (doc, label) in data:
    dy.renew_cg()
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    W = dy.parameter(pW2)
    b = dy.parameter(pb2)
    return dy.tanh(W*x+b)
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for (doc, label) in data:
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```

```
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    b = dy.parameter(pb2)
    return dy.tanh(W*x+b)
```

```
for (doc, label) in data:
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    probs = predict_labels(doc)
```

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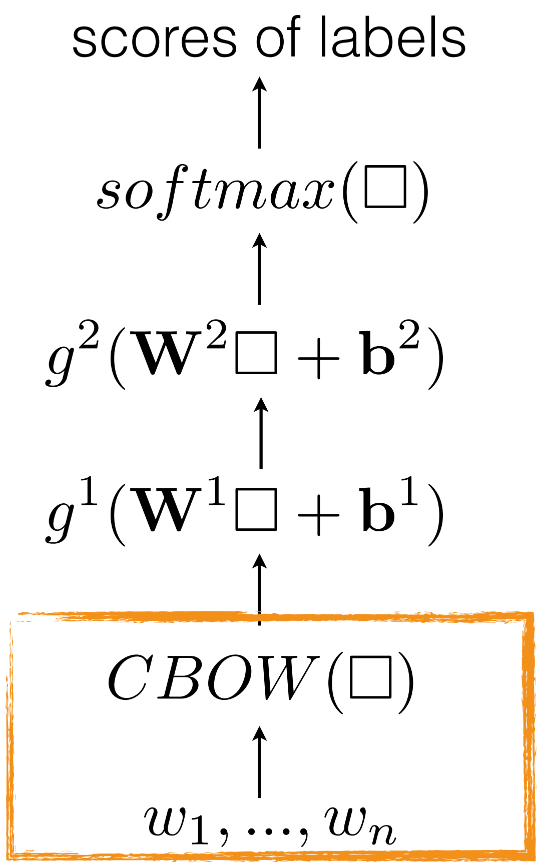
```



"deep averaging network"

```
def layer1(x):
    W = dy.parameter(pW1)
    b = dy.parameter(pb1)
    return dy.tanh(W*x+b)

def layer2(x):
    W = dy.parameter(pW2)
    b = dy.parameter(pb2)
    return dy.tanh(W*x+b)
```

```
for (doc, label) in data:
    dy.renew_cg()
    probs = predict_labels(doc)
```

```
def predict_labels(doc):
    x = encode_doc(doc)
    h = layer1(x)
    y = layer2(h)
    return dy.softmax(y)

def encode_doc(doc):
    doc = [w2i[w] for w in doc]
    embs = [E[idx] for idx in doc]
    return dy.esum(embs)

def layer1(x):
    W = dy.parameter(pW1)
    b = dy.parameter(pb1)
    return dy.tanh(W*x+b)

def layer2(x):
    W = dy.parameter(pW2)
    b = dy.parameter(pb2)
    return dy.tanh(W*x+b)
```

scores of labels

$$\uparrow$$

$$softmax(\square)$$

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$$g^2(\mathbf{W}^2\square + \mathbf{b}^2)$$

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$$\uparrow$$

$$w_1, \ldots, w_n$$

"deep averaging network"

```
for (doc, label) in data:
    dy.renew_cg()
    probs = predict_labels(doc)
```

```
def predict_labels(doc):
    x = encode_doc(doc)
    h = layer1(x)
    y = layer2(h)
    return dy.softmax(y)
```

```
def encode_doc(doc):
    doc = [w2i[w] for w in doc]
    embs = [E[idx] for idx in doc]
    return dy.esum(embs)
```

```
def layer1(x):
    W = dy.parameter(pW1)
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```

```
def layer2(x):
    W = dy.parameter(pW2)
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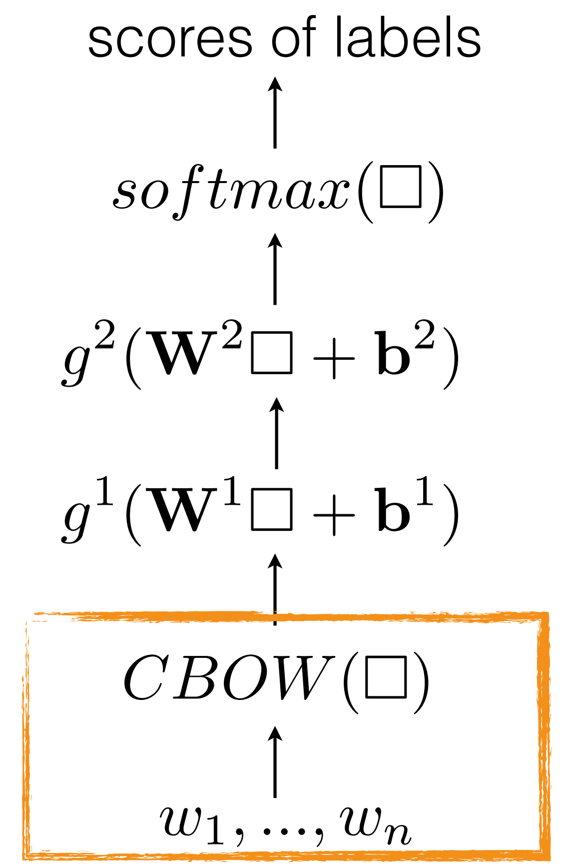
    return dy.tanh(W*x+b)
```



"deep averaging network"

```
for (doc, label) in data:
    dy.renew_cg()
    probs = predict_labels(doc)

    loss = do_loss(probs,label)
    loss.forward()
    loss.backward()
    trainer.update()
```

```python
def predict_labels(doc):
    x = encode_doc(doc)
    h = layer1(x)
    y = layer2(h)
    return dy.softmax(y)
```

scores of labels

$$\uparrow$$

$$softmax(\square)$$

$$\uparrow$$

$$g^2(\mathbf{W}^2\square + \mathbf{b}^2)$$

$$\uparrow$$

$$g^1(\mathbf{W}^1\square + \mathbf{b}^1)$$

$$\uparrow$$

$$CBOW(\square)$$

$$\uparrow$$

$$w_1, ..., w_n$$

"deep averaging network"

```python
def do_loss(probs, label):
    label = l2i[label]
    return -dy.log(dy.pick(probs,label))
```

```python
for (doc, label) in data:
    dy.renew_cg()
    probs = predict_labels(doc)

    loss = do_loss(probs,label)
    loss.forward()
    loss.backward()
    trainer.update()
```

```python
def predict_labels(doc):
    x = encode_doc(doc)
    h = layer1(x)
    y = layer2(h)
    return dy.softmax(y)
```

$$
\begin{array}{c}
\text{scores of labels} \\
\uparrow \\
softmax(\square) \\
\uparrow \\
g^2(\mathbf{W}^2\square + \mathbf{b}^2) \\
\uparrow \\
g^1(\mathbf{W}^1\square + \mathbf{b}^1) \\
\uparrow \\
CBOW(\square) \\
\uparrow \\
w_1, \ldots, w_n
\end{array}
$$

"deep averaging network"

```python
def classify(doc):
    dy.renew_cg()
    probs = predict_labels(doc)

    vals = probs.npvalue()
    return i2l[np.argmax(vals)]
```

TF/IDF?

```
def encode_doc(doc):
    doc = [w2i[w] for w in doc]
    embs = [E[idx] for idx in doc]
    return dy.esum(embs)
```

```
def encode_doc(doc):
    weights = [tfidf(w) for w in doc]
    doc = [w2i[w] for w in doc]
    embs = [E[idx]*w for w,idx in zip(weights,doc)]
    return dy.esum(embs)
```

Encapsulation with Classes

```
class MLP(object):
    def __init__(self, model, in_dim, hid_dim, out_dim, non_lin=dy.tanh):
        self._W1 = model.add_parameters((hid_dim, in_dim))
        self._b1 = model.add_parameters(hid_dim)
        self._W2 = model.add_parameters((out_dim, hid_dim))
        self._b2 = model.add_parameters(out_dim)
        self.non_lin = non_lin

    def __call__(self, in_expr):
        W1 = dy.parameter(self._W1)
        W2 = dy.parameter(self._W2)
        b1 = dy.parameter(self._b1)
        b2 = dy.parameter(self._b2)
        g = self.non_lin
        return W2*g(W1*in_expr + b1)+b2
```

```
x = dy.inputVector(range(10))

mlp = MLP(model, 10, 100, 2, dy.tanh)

y = mlp(v)
```

Summary

- Computation Graph
- Expressions (~ nodes in the graph)
- Parameters, LookupParameters
- Model (a collection of parameters)
- Trainers
- **Create a graph for each example**, then compute loss, backdrop, update.

Outline

- **Part 1**
    - Computation graphs and their construction
    - Neural Nets in DyNet
    - Recurrent neural networks
    - Minibatching
    - Adding new differentiable functions

Recurrent Neural Networks

- NLP is full of sequential data
  - Words in sentences
  - Characters in words
  - Sentences in discourse
  - …
- **How do we represent an arbitrarily long history?**

Recurrent Neural Networks

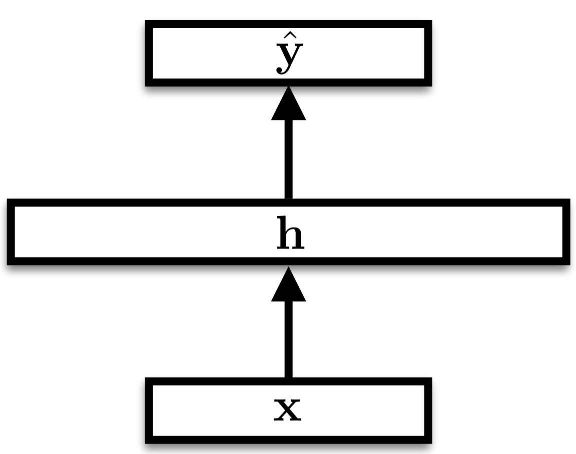
- NLP is full of sequential data
  - Words in sentences
  - Characters in words
  - Sentences in discourse
  - …
- **How do we represent an arbitrarily long history?**
  - we will train neural networks to build a representation of these arbitrarily big sequences

Recurrent Neural Networks

Feed-forward NN

$$\mathbf{h} = g(\mathbf{V}\mathbf{x} + \mathbf{c})$$

$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{h} + \mathbf{b}$$



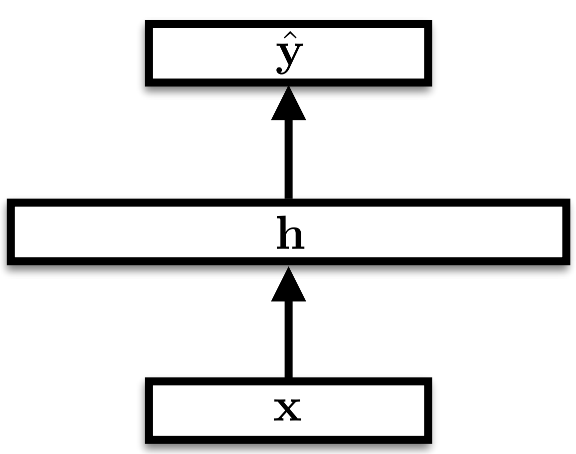
Recurrent Neural Networks

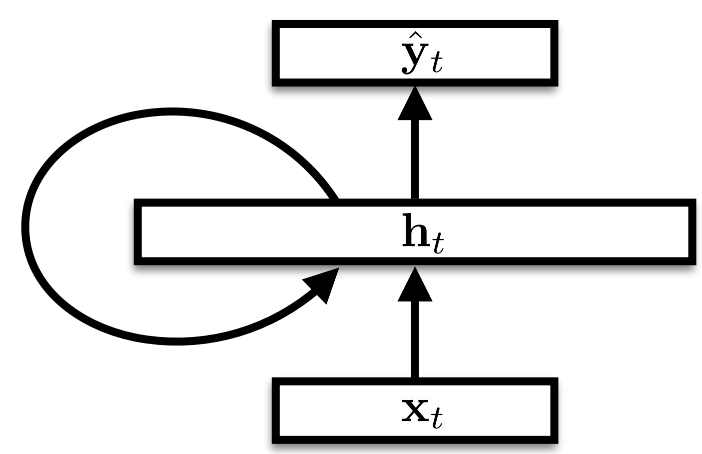
Feed-forward NN

$$\mathbf{h} = g(\mathbf{V}\mathbf{x} + \mathbf{c})$$
$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{h} + \mathbf{b}$$

Recurrent NN

$$\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})$$
$$\hat{\mathbf{y}}_t = \mathbf{W}\mathbf{h}_t + \mathbf{b}$$





Recurrent Neural Networks

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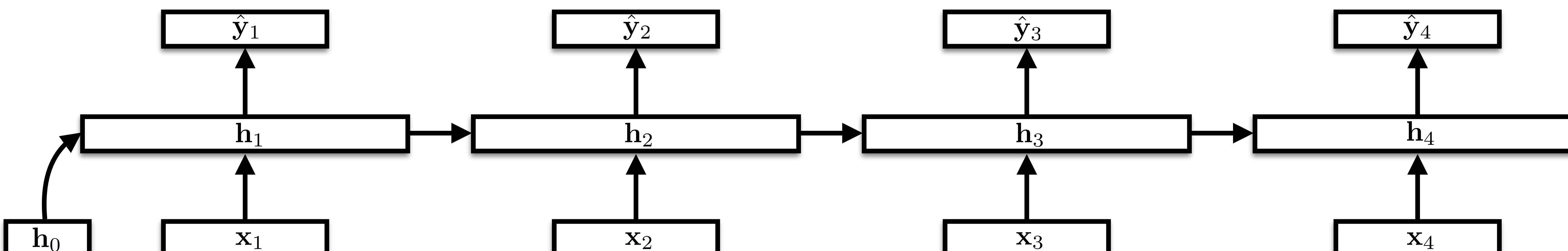
How do we train the RNN's parameters?



Recurrent Neural Networks

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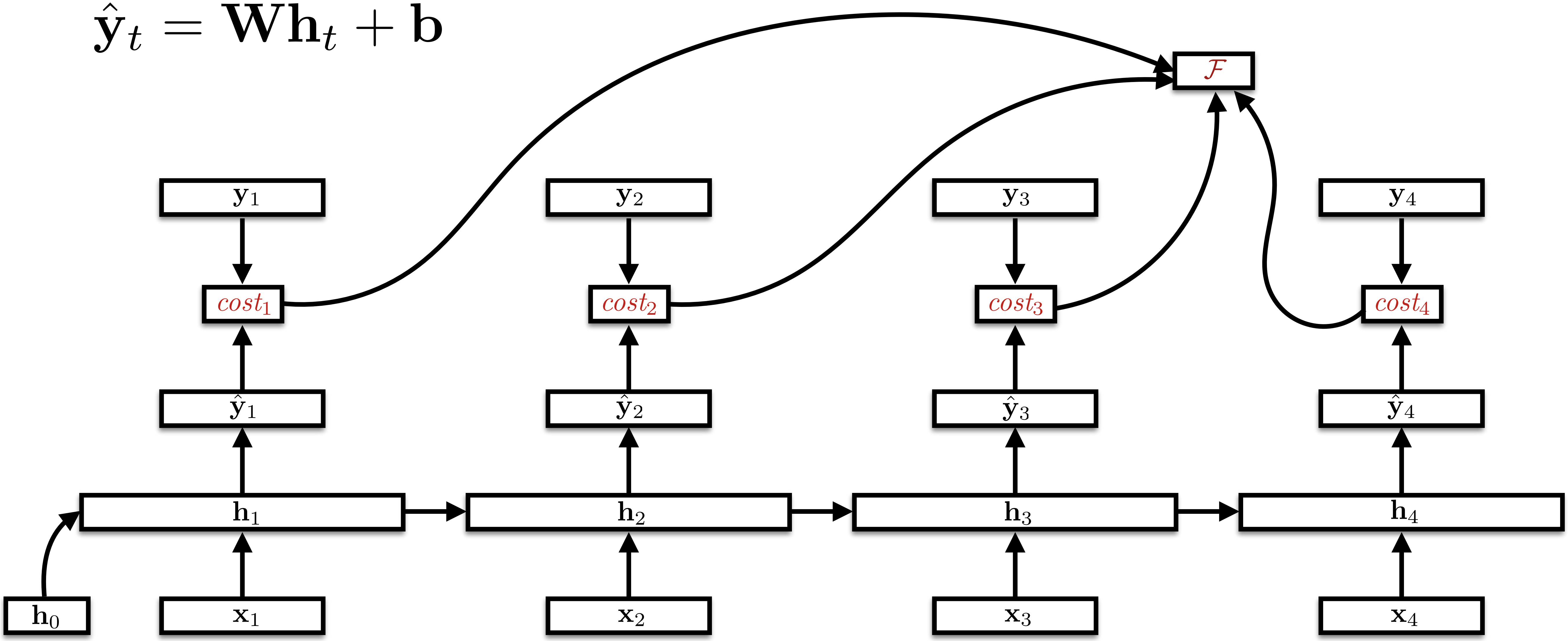
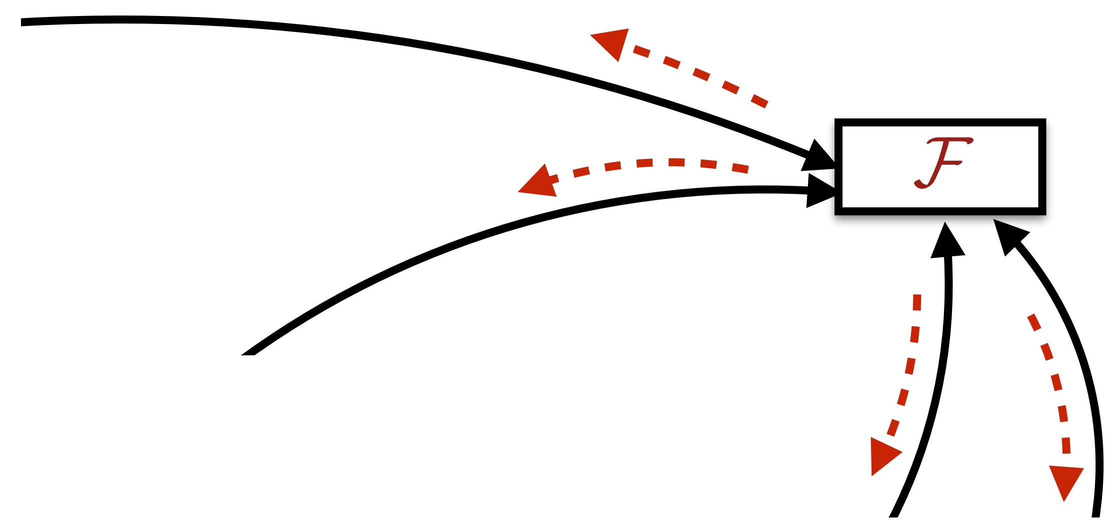


Recurrent Neural Networks

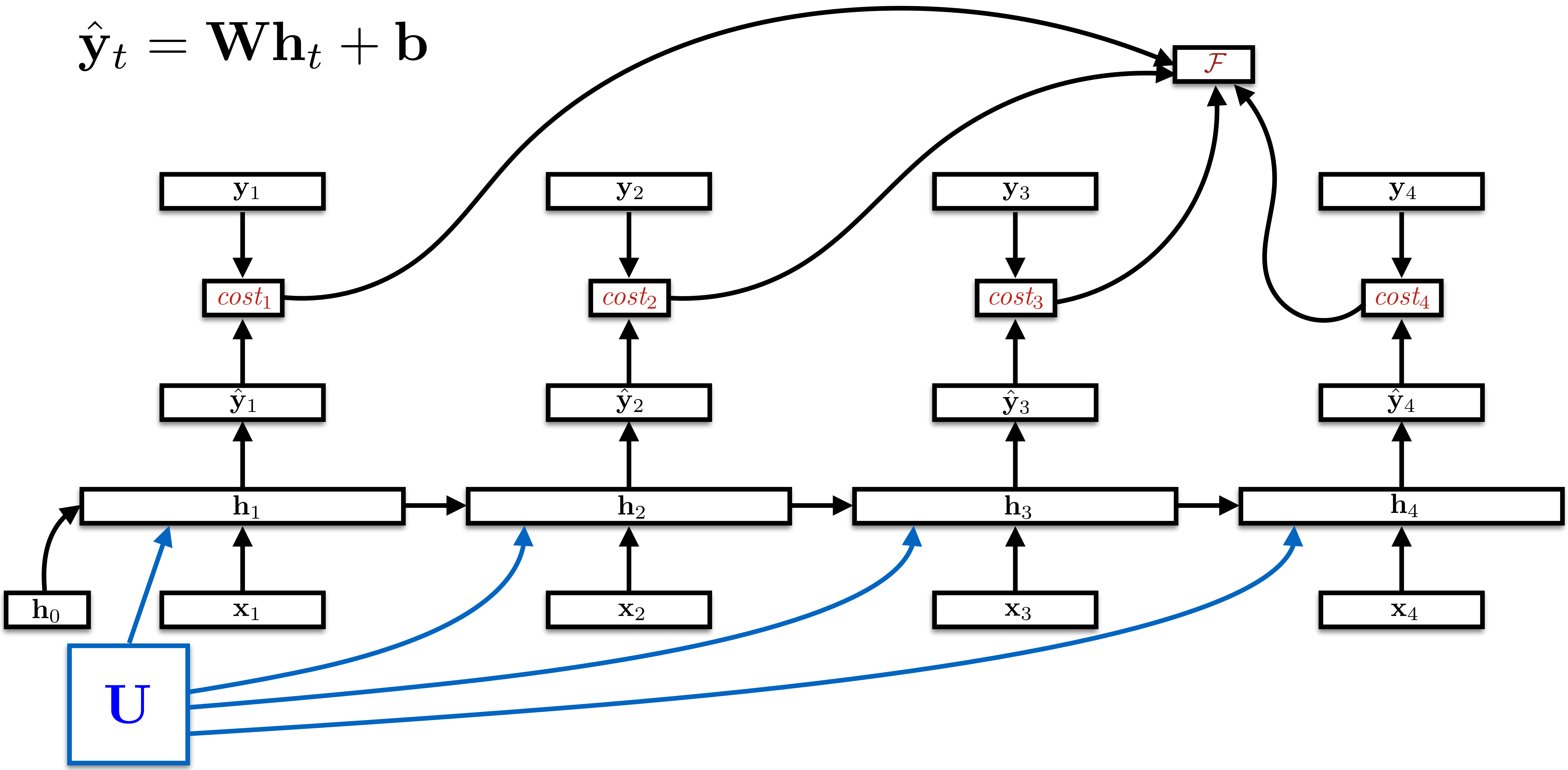


- The unrolled graph is a well-formed (DAG) computation graph—we can run backprop
  - Parameters are tied across time, derivatives are aggregated across all time steps
  - This is historically called “backpropagation through time” (BPTT)

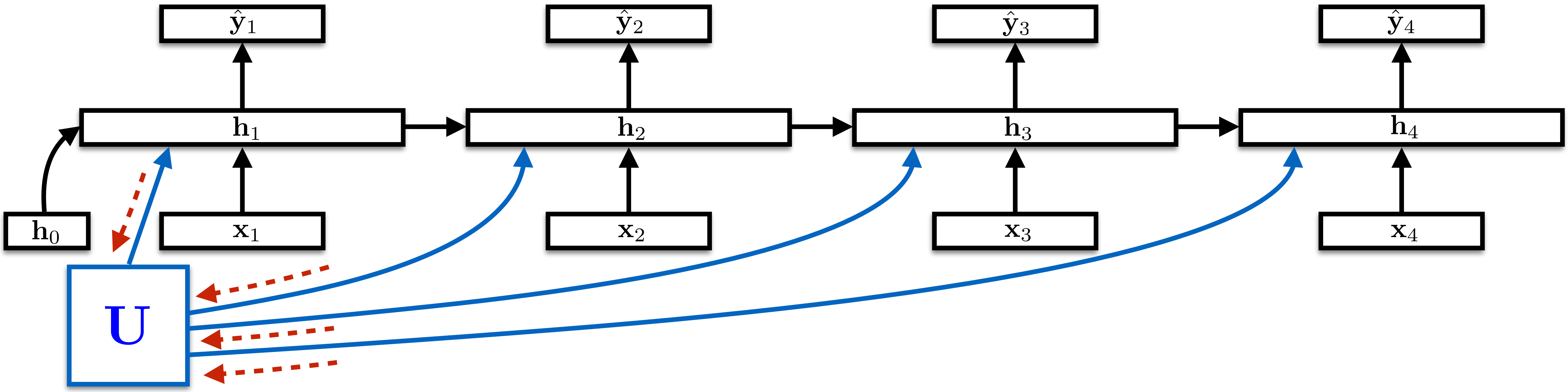
Parameter Tying

$$\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})$$

$$\hat{\mathbf{y}}_t = \mathbf{W}\mathbf{h}_t + \mathbf{b}$$



Parameter Tying

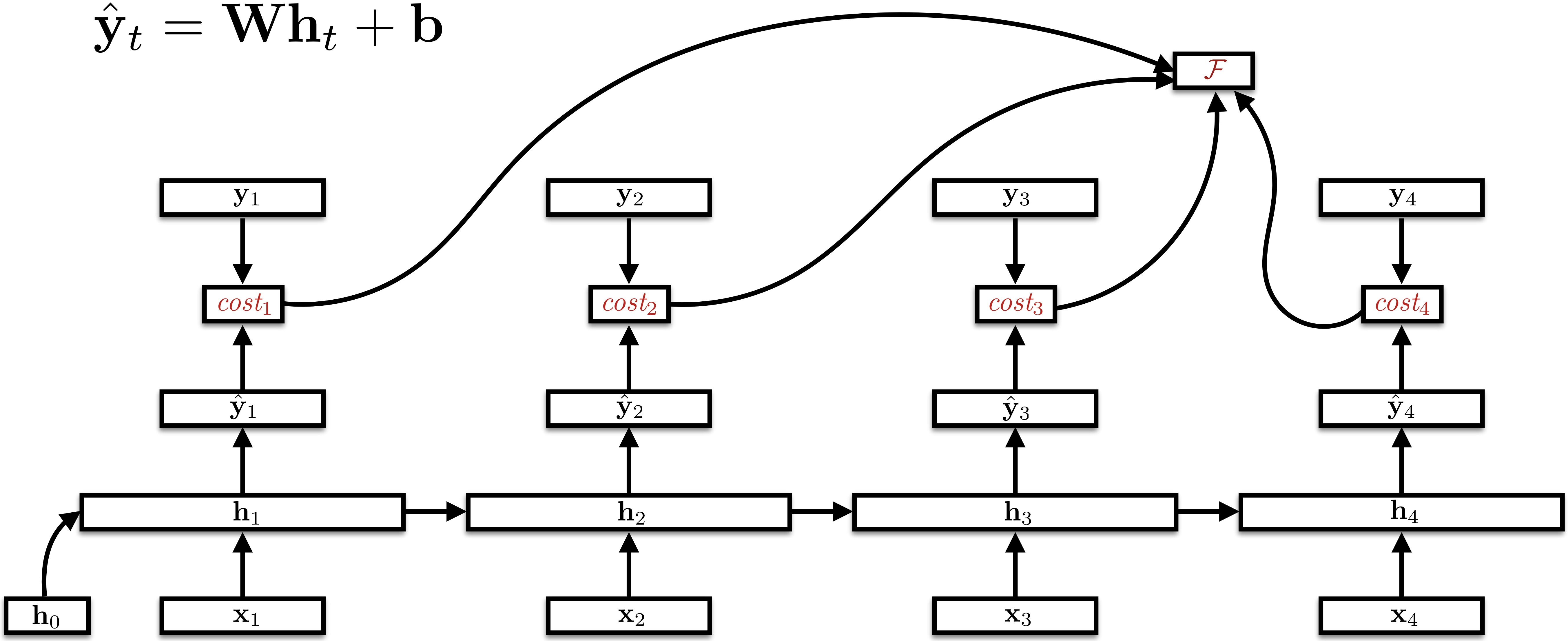


$$\frac{\partial \mathcal{F}}{\partial \mathbf{U}} = \sum_{t=1}^{4} \frac{\partial \mathbf{h}_t}{\partial \mathbf{U}} \frac{\partial \mathcal{F}}{\partial \mathbf{h}_t}$$

What else can we do?

$$\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})$$

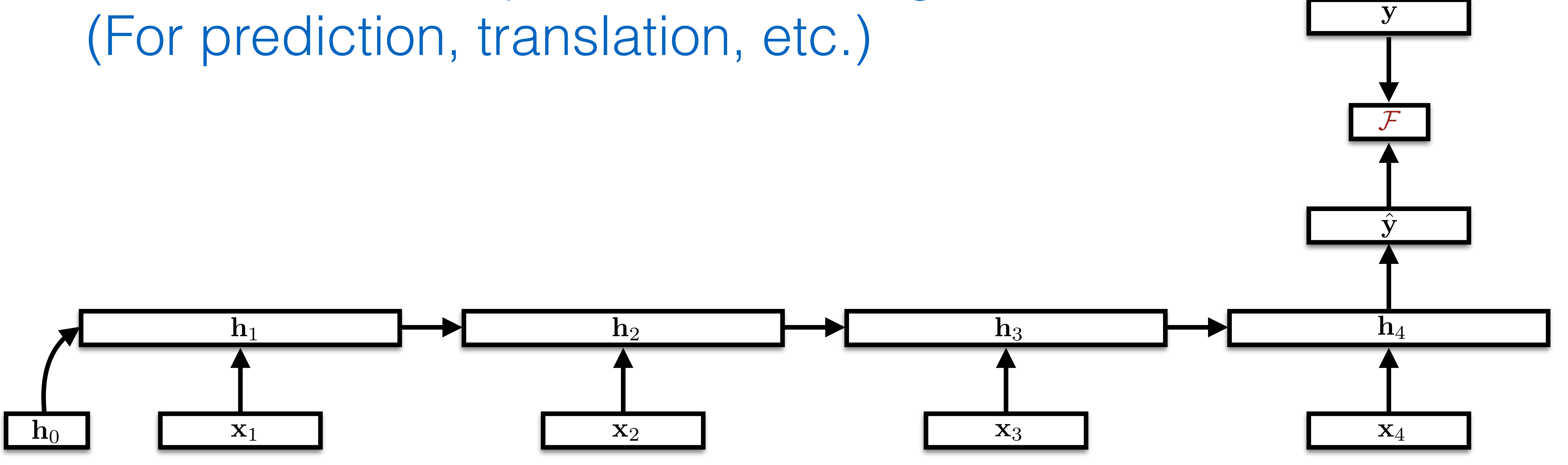
$$\hat{\mathbf{y}}_t = \mathbf{W}\mathbf{h}_t + \mathbf{b}$$



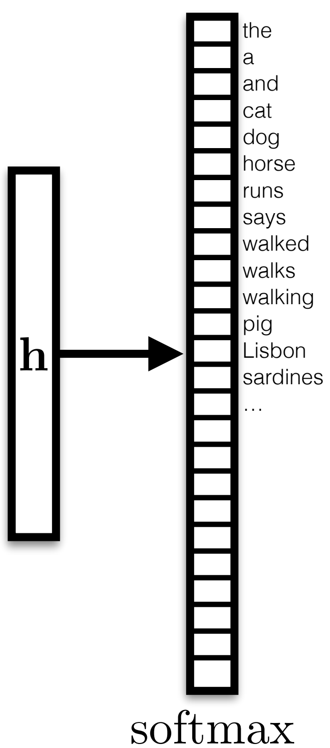
“Read and summarize”

$$\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})$$
$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{h}_{|\boldsymbol{x}|} + \mathbf{b}$$

Summarize a sequence into a single vector.
(For prediction, translation, etc.)



Example: Language Model



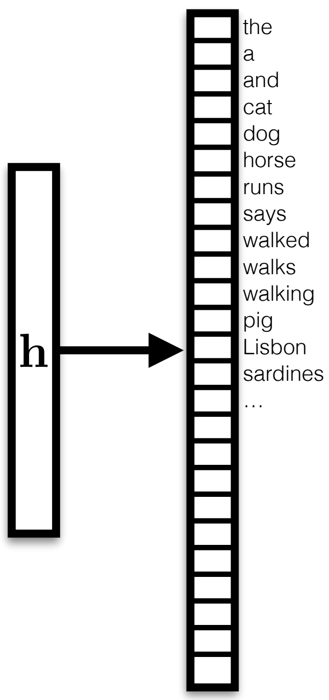
$$\mathbf{u} = \mathbf{W}\mathbf{h} + \mathbf{b}$$

$$p_i = \frac{\exp u_i}{\sum_j \exp u_j}$$

$$\mathbf{h} \in \mathbb{R}^d$$

$$|V| = 100,000$$

Example: Language Model



softmax

$$\mathbf{u} = \mathbf{W}\mathbf{h} + \mathbf{b}$$

$$p_i = \frac{\exp u_i}{\sum_j \exp u_j}$$

$$\mathbf{h} \in \mathbb{R}^d$$

$$|V| = 100{,}000$$

$$\begin{aligned} p(\boldsymbol{e}) = & p(e_1) \times \\ & p(e_2 \mid e_1) \times \\ & p(e_3 \mid e_1, e_2) \times \\ & p(e_4 \mid e_1, e_2, e_3) \times \\ & \cdots \end{aligned}$$

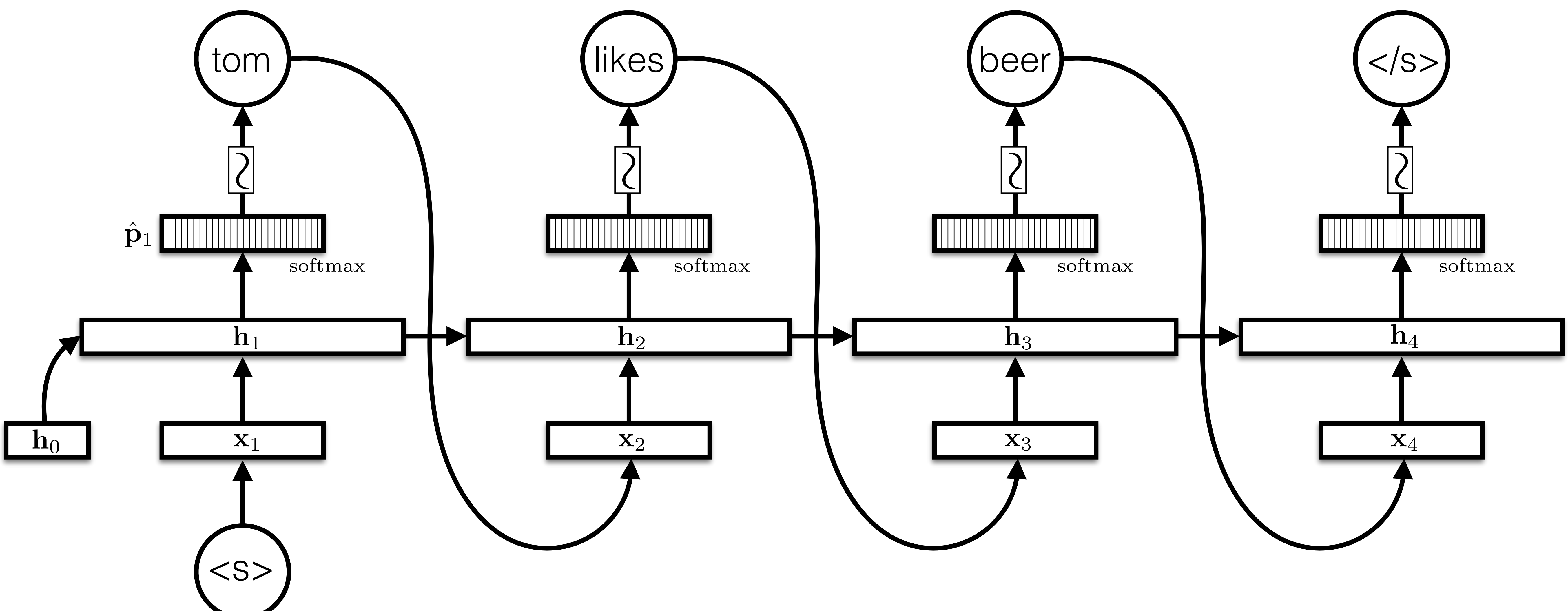
histories are sequences of words…

Example: Language Model

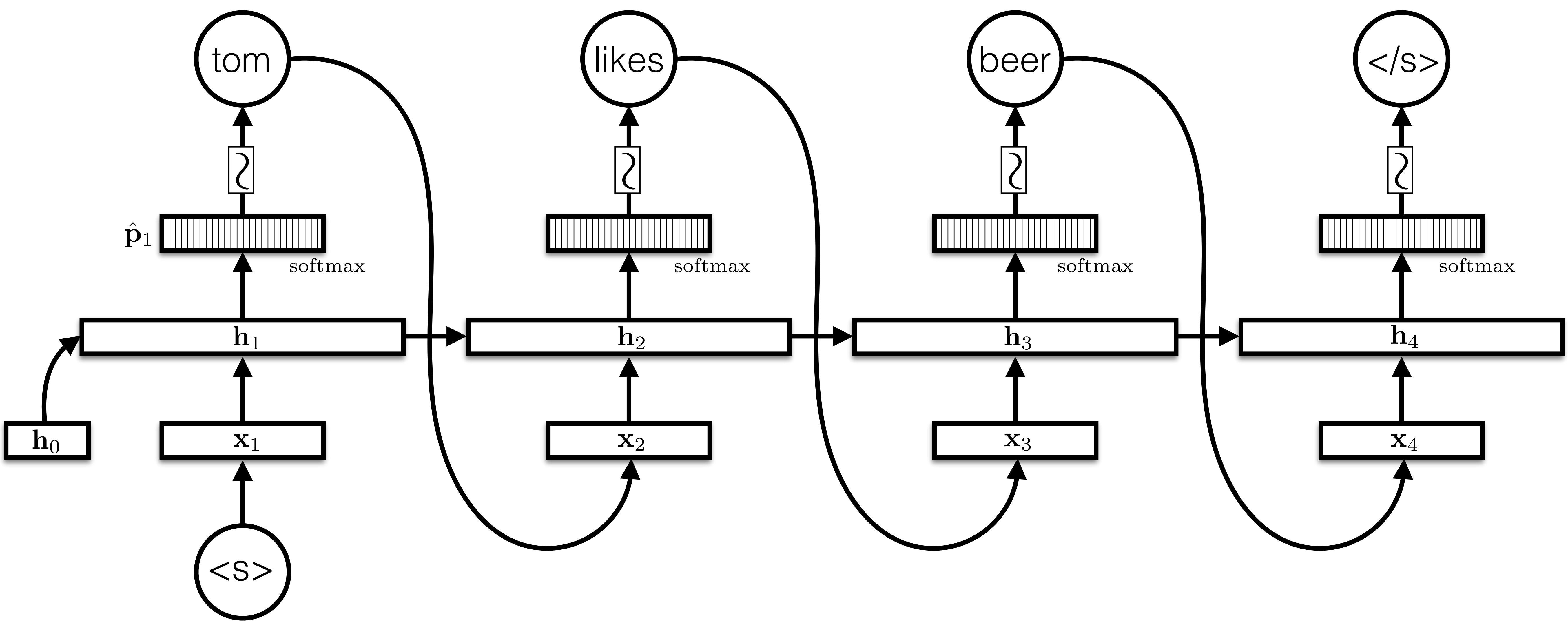
$$p(tom \mid \langle \mathbf{s} \rangle) \times p(likes \mid \langle \mathbf{s} \rangle, tom)$$

$$\times p(beer \mid \langle \mathbf{s} \rangle, tom, likes)$$

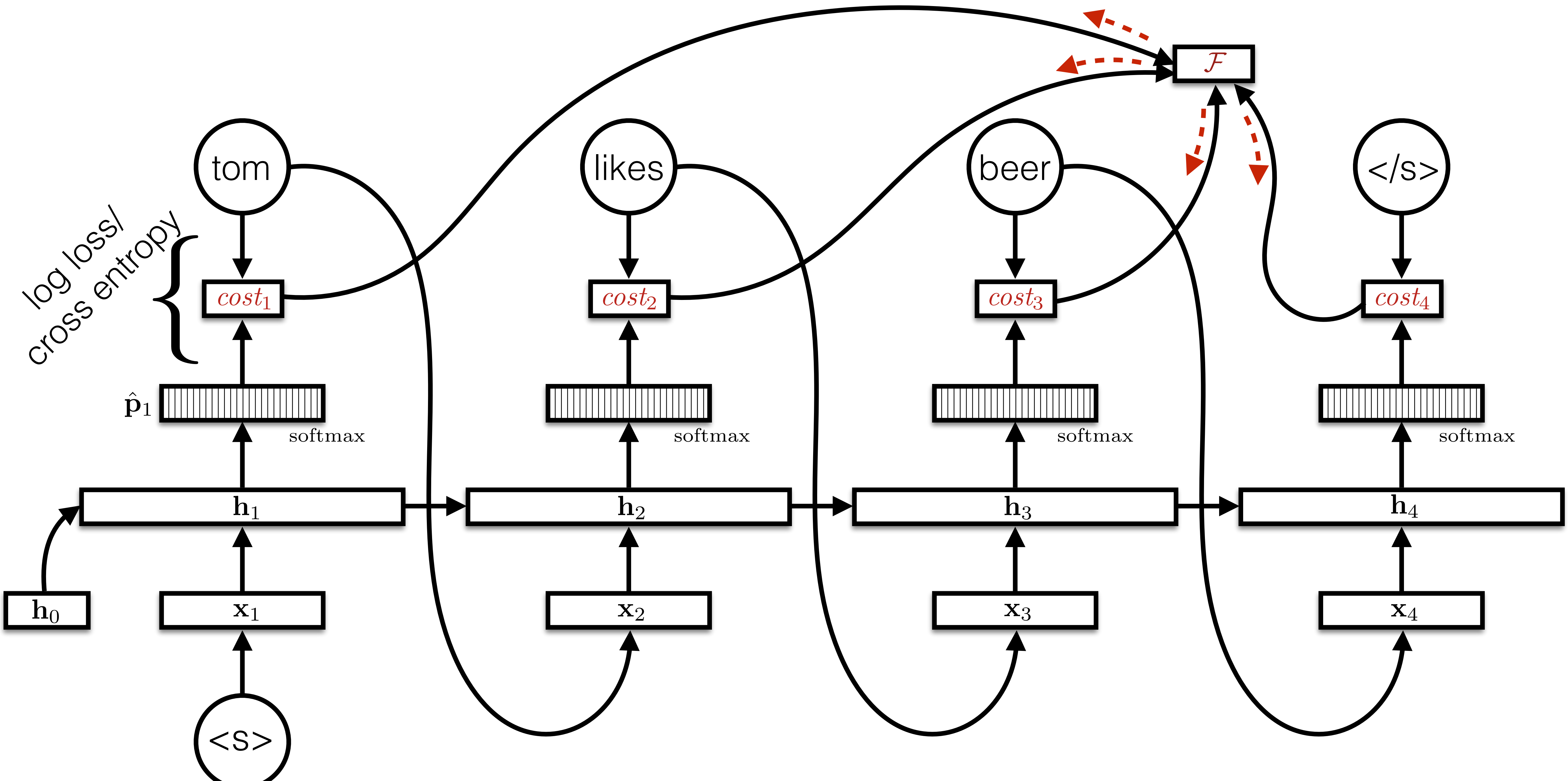
$$\times p(\langle /\mathbf{s} \rangle \mid \langle \mathbf{s} \rangle, tom, likes, beer)$$



Language Model Training



Language Model Training



Alternative RNNs

- Long short-term memories (LSTMs; Hochreiter and Schmidthuber, 1997)
- Gated recurrent units (GRUs; Cho et al., 2014)
- All follow the basic paradigm of “take input, update state”

Recurrent Neural Networks in DyNet

- Based on “*Builder” class (*=SimpleRNN/LSTM)

- Add parameters to model (once):

```
# LSTM (layers=1, input=64, hidden=128, model)
RNN = dy.LSTMBuilder(1, 64, 128, model)
```

- Add parameters to CG and get initial state (per sentence):

```
s = RNN.initial_state()
```

- Update state and access (per input word/character):

```
s = s.add_input(x_t)
h_t = s.output()
```

RNNLM Example: Parameter Initialization

```
# Lookup parameters for word embeddings
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 64))

# Word-level LSTM (layers=1, input=64, hidden=128, model)
RNN = dy.LSTMBuilder(1, 64, 128, model)

# Softmax weights/biases on top of LSTM outputs
W_sm = model.add_parameters((nwords, 128))
b_sm = model.add_parameters(nwords)
```

RNNLM Example: Sentence Initialization

```
# Build the language model graph
def calc_lm_loss(wids):
    dy.renew_cg()

    # parameters -> expressions
    W_exp = dy.parameter(W_sm)
    b_exp = dy.parameter(b_sm)

    # add parameters to CG and get state
    f_init = RNN.initial_state()

    # get the word vectors for each word ID
    wembs = [WORDS_LOOKUP[wid] for wid in wids]

    # Start the rnn by inputting "<s>"
    s = f_init.add_input(wembs[-1])

                    …
```

RNNLM Example: Loss Calculation and State Update

…

```python
# process each word ID and embedding
losses = []
for wid, we in zip(wids, wembs):

    # calculate and save the softmax loss
    score = W_exp * s.output() + b_exp
    loss = dy.pickneglogsoftmax(score, wid)
    losses.append(loss)

    # update the RNN state with the input
    s = s.add_input(we)

# return the sum of all losses
return dy.esum(losses)
```

Mini-batching

Implementation Details: Minibatching

- Minibatching: group together multiple similar operations
- Modern hardware
  - pretty fast for elementwise operations
  - very fast for matrix-matrix multiplication
  - has overhead for every operation (esp. GPUs)
- Neural networks consist of
  - lots of elementwise operations
  - lots of matrix-vector products

Minibatching

Single-instance RNN

$$\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})$$

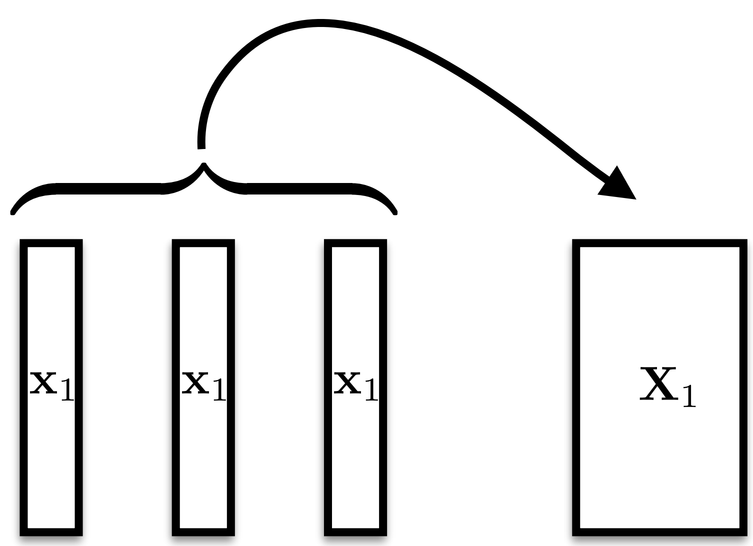
$$\hat{\mathbf{y}}_t = \mathbf{W}\mathbf{h}_t + \mathbf{b}$$

Minibatch RNN

$$\mathbf{H}_t = g(\mathbf{V}\mathbf{X}_t + \mathbf{U}\mathbf{H}_{t-1} + \mathbf{c})$$

$$\hat{\mathbf{Y}}_t = \mathbf{W}\mathbf{H}_t + \mathbf{b}$$

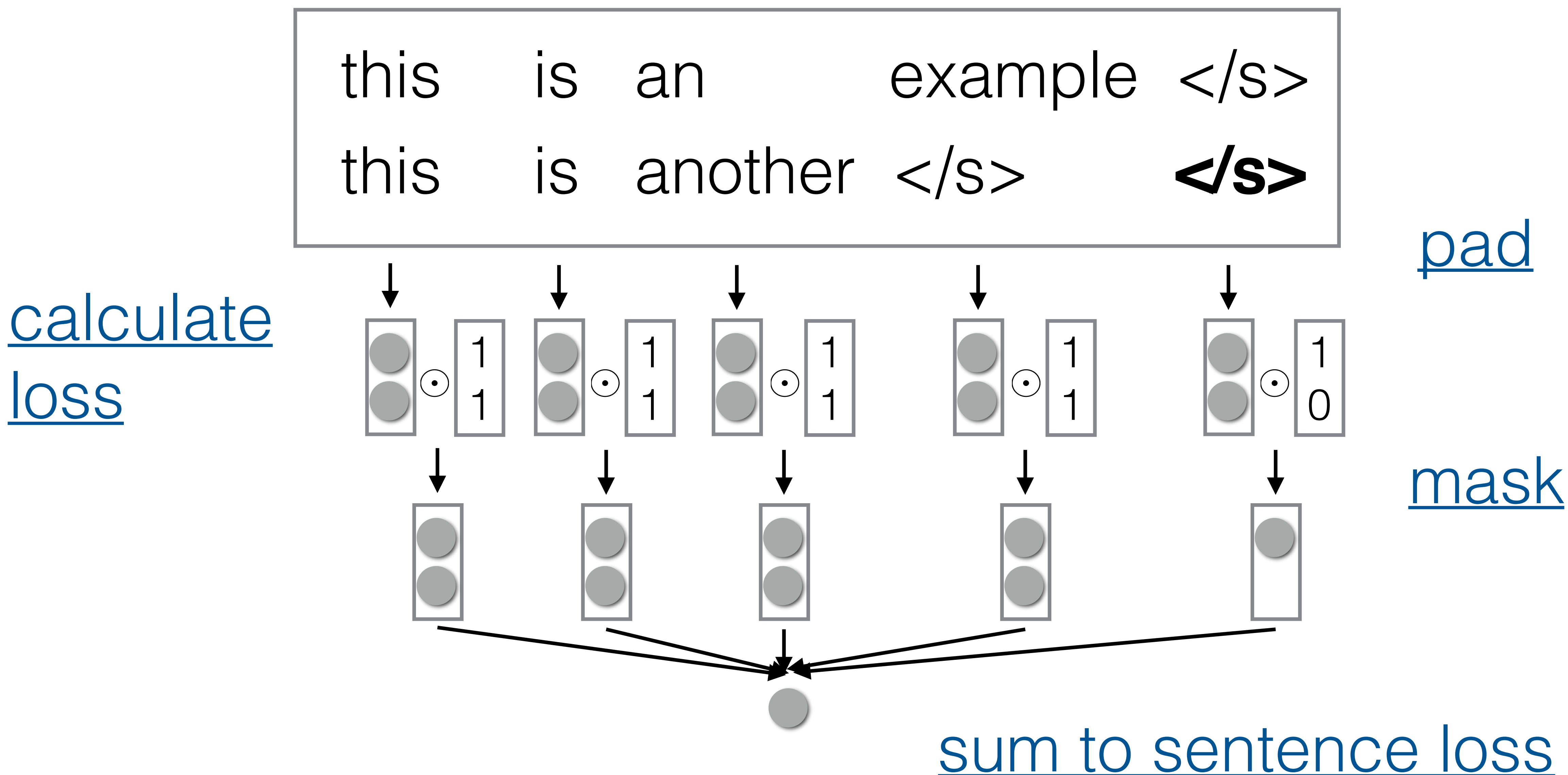
anything wrong here?



We batch across instances,
not across time.

Minibatching Sequences

- How do we handle sequences of different lengths?



Mini-batching in Dynet

- DyNet has special minibatch operations for lookup and loss functions, everything else automatic
- You need to:
  - Group sentences into a mini batch (optionally, for efficiency group sentences by length)
  - Select the “t”th word in each sentence, and send them to the lookup and loss functions

Function Changes

```
wid = 5
wemb = WORDS_LOOKUP[wid]
loss = dy.pickneglogsoftmax(score, wid)
```

```
wids = [5, 2, 1, 3]
wemb = dy.lookup_batch(WORDS_LOOKUP, wids)
loss = dy.pickneglogsoftmax_batch(score, wids)
```

Implementing Functions

Standard Functions

addmv, affine_transform, average, average_cols, binary_log_loss, block_dropout, cdiv, colwise_add, concatenate, concatenate_cols, const_lookup, const_parameter, contract3d_1d, contract3d_1d_1d, conv1d_narrow, conv1d_wide, cube, cwise_multiply, dot_product, dropout, erf, exp, filter1d_narrow, fold_rows, hinge, huber_distance, input, inverse, kmax_pooling, kmh_ngram, l1_distance, lgamma, log, log_softmax, logdet, logistic, logsumexp, lookup, max, min, nobackprop, noise, operator*, operator+, operator-, operator/, pairwise_rank_loss, parameter, pick, pickneglogsoftmax, pickrange, poisson_loss, pow, rectify, reshape, select_cols, select_rows, softmax, softsign, sparsemax, sparsemax_loss, sqrt, square, squared_distance, squared_norm, sum, sum_batches, sum_cols, tanh, trace_of_product, transpose, zeroes

What if I Can't Find my Function?

- e.g. Geometric mean

```
y = sqrt(x_0 * x_1)
```

- **Option 1:** Connect multiple functions together

- **Option 2:** Implement forward and backward functions directly
→ C++ implementation w/ Python bindings

Implementing Forward

- Backend based on Eigen operations

$$\mathrm{geom}(x_0, x_1) := \sqrt{x_0 * x_1}$$

nodes.cc

```
template<class MyDevice>
void GeometricMean::forward_dev_impl(const MyDevice & dev,
                                     const vector<const Tensor*>& xs,
                                     Tensor& fx) const {
  fx.tvec().device(*dev.edevice) =
        (xs[0]->tvec() * xs[1]->tvec()).sqrt();
}
```

dev: which device — CPU/GPU
xs: input values
fx: output value

Implementing Backward

- Calculate gradient for all args $\frac{\partial \text{geom}(x_0, x_1)}{\partial x_0} = \frac{x_1}{2 * \text{geom}(x_0, x_1)}$

nodes.cc

```
template<class MyDevice>
void GeometricMean::backward_dev_impl(const MyDevice & dev,
                                      const vector<const Tensor*>& xs,
                                      const Tensor& fx,
                                      const Tensor& dEdf,
                                      unsigned i,
                                      Tensor& dEdxi) const {
  dEdxi.tvec().device(*dev.edevice) +=
                                xs[i==1?0:1] * fx.inv() / 2 * dEdf;
}
```

dev: which device, CPU/GPU
xs: input values
fx: output value

dEdf: derivative of loss w.r.t f
i: index of input to consider
dEdxi: derivative of loss w.r.t. x[i]

Other Functions to Implement

- nodes.h: class definition
- nodes-common.cc: dimension check and function name
- expr.h/expr.cc: interface to expressions
- dynet.pxd/dynet.pyx: Python wrappers

Gradient Checking

- Things go wrong in implementation (forgot a “2” or a “-“)
- Luckily, we can check forward/backward consistency automatically
- Idea: small steps (*h*) approximate gradient

$$\underbrace{\frac{\partial f(x)}{\partial x}}_{\text{Uses Backward}} \approx \underbrace{\frac{f(x+h) - f(x-h)}{2h}}_{\text{Only Forward}}$$

- Easy in DyNet: use GradCheck(cg) function

Questions/Coffee Time!