CS11-747 Neural Networks for NLP

Intro/
Why Neural Nets for NLP?

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Site
https://phontron.com/class/nn4nlp2017/

Neural Networks:
A Tool for Doing Hard Things

An Example Prediction Problem: Sentence Classification

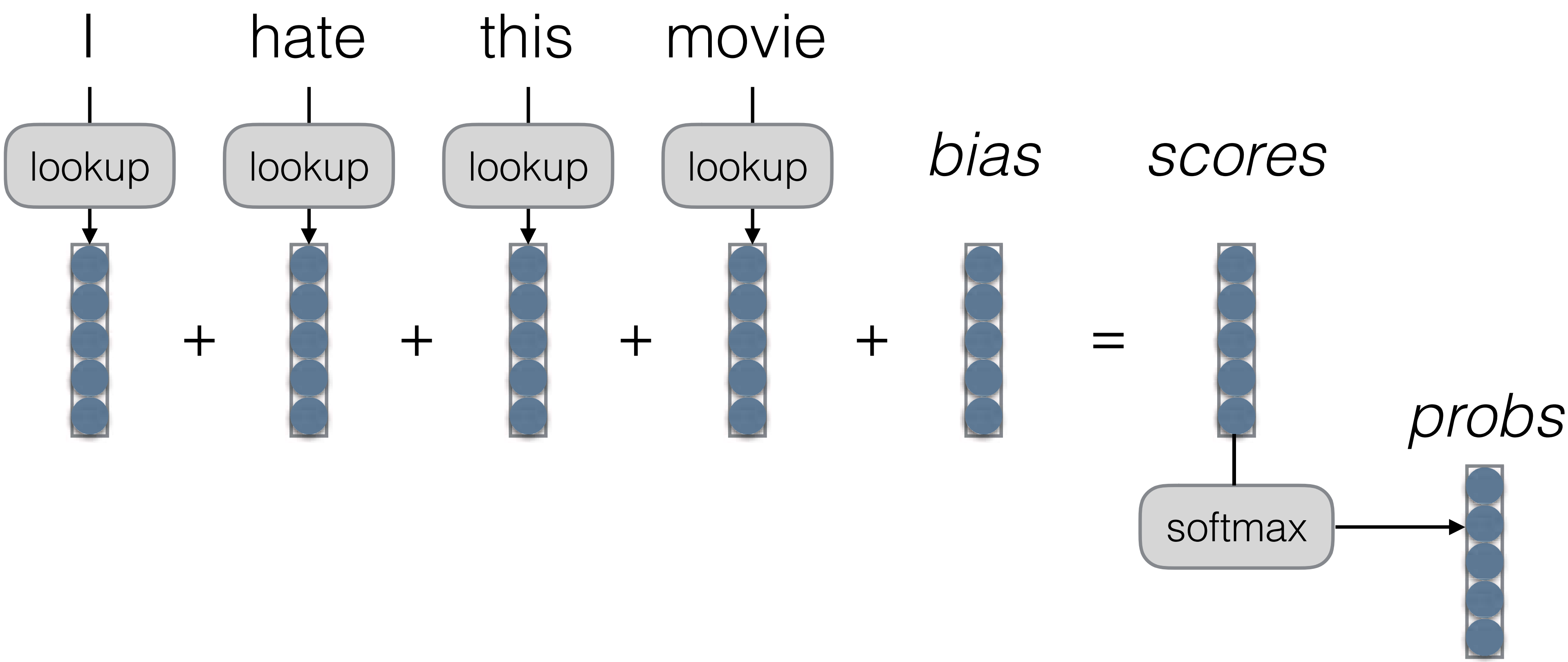
I hate this movie → very bad

very good
good
neutral
bad
very bad

I love this movie → very good

very good
good
neutral
bad
very bad

A First Try: Bag of Words (BOW)



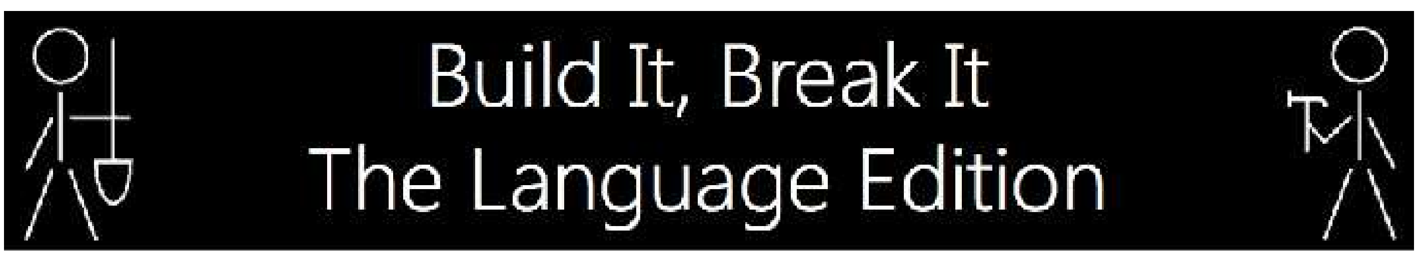
Build It, Break It

I don’t love this movie

very good
good
neutral
bad
very bad

There’s nothing I don’t love about this movie

very good
good
neutral
bad
very bad

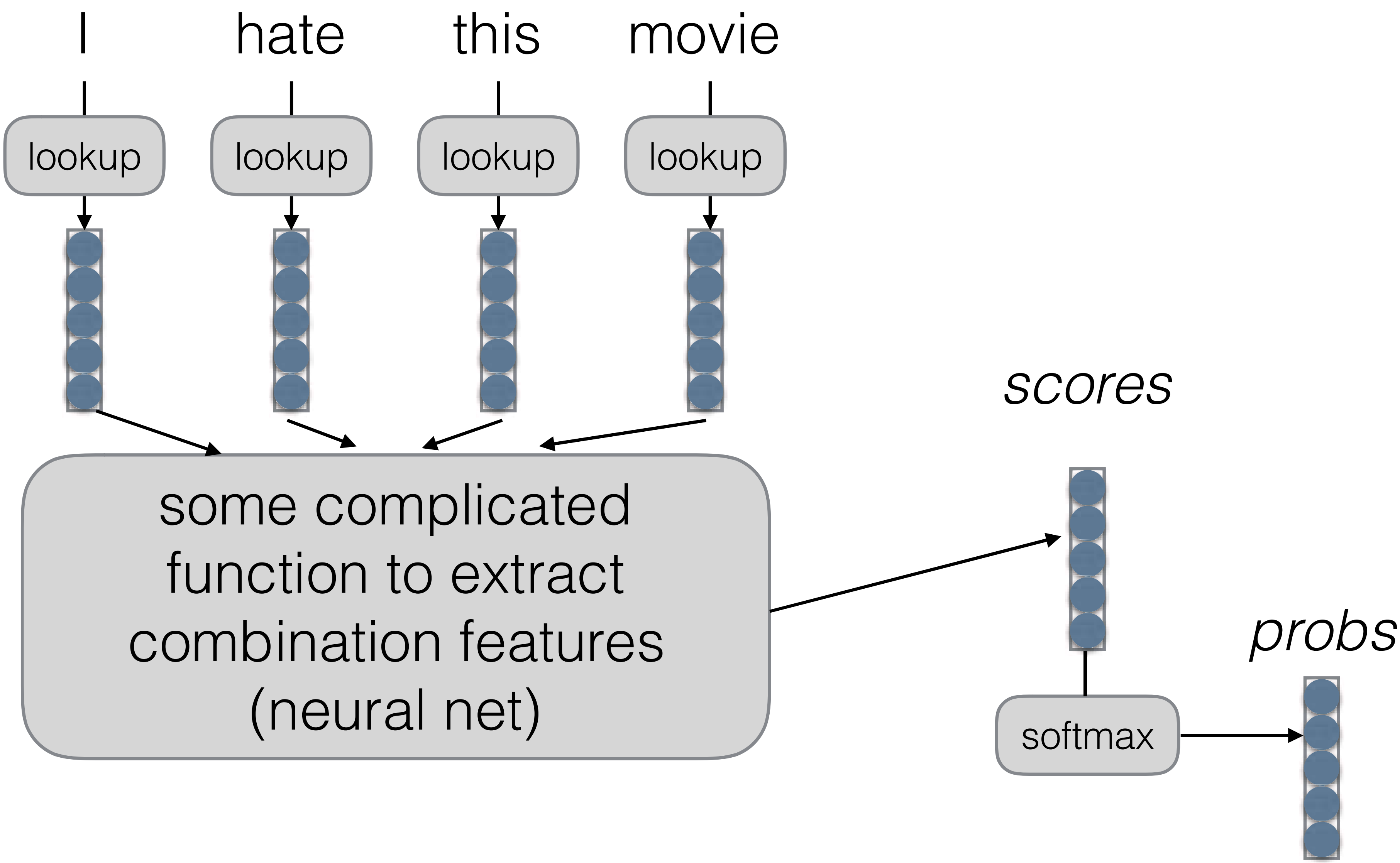


https://bibinlp.umiacs.umd.edu

Combination Features

- Does it contain “don’t” and “love”?
- Does it contain “don’t”, “i”, “love”, and “nothing”?

Basic Idea of Neural Networks (for NLP Prediction Tasks)



Computation Graphs

The Lingua Franca of Neural Nets

expression:

$$\mathbf{x}$$

graph:

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

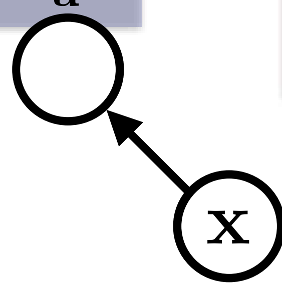
$$\mathbf{x}$$

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* $\frac{\partial \mathcal{F}}{\partial f(\mathbf{u})}$.

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



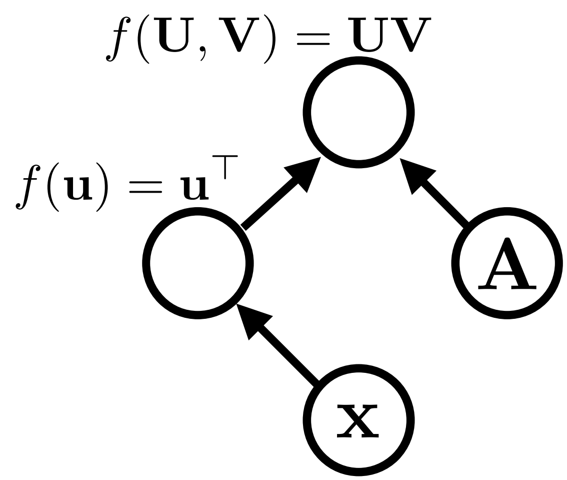
$$\frac{\partial f(\mathbf{u})}{\partial \mathbf{u}} \frac{\partial \mathcal{F}}{\partial f(\mathbf{u})} = \left(\frac{\partial \mathcal{F}}{\partial f(\mathbf{u})} \right)^\top$$

expression:

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

graph:

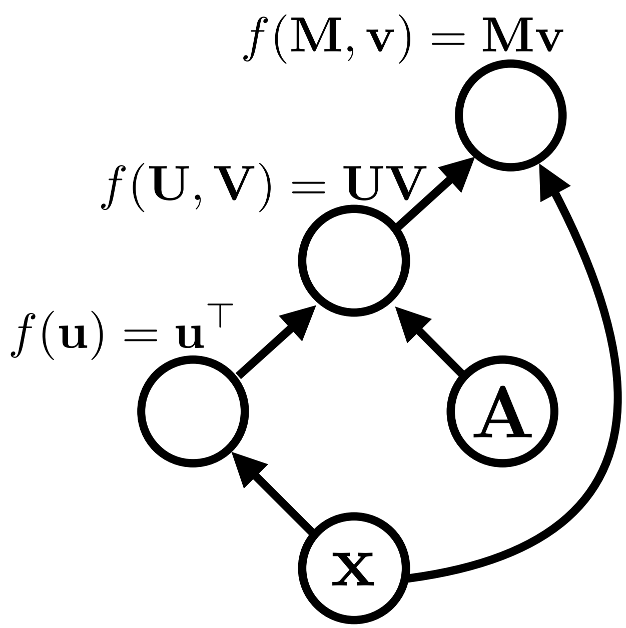
Functions can be nullary, unary, binary, … *n*-ary. Often they are unary or binary.



expression:

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

graph:

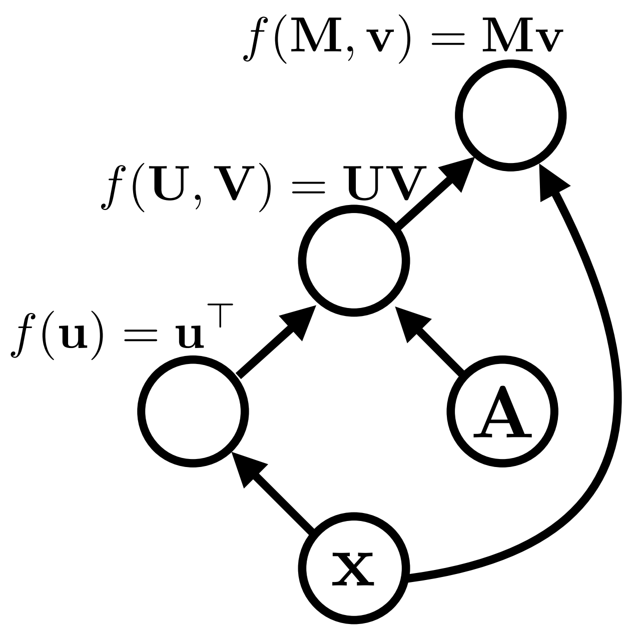


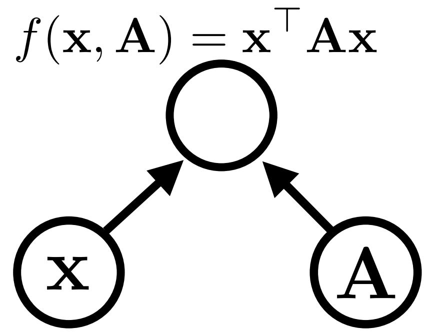
Computation graphs are directed and acyclic (in DyNet)

expression:

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

graph:





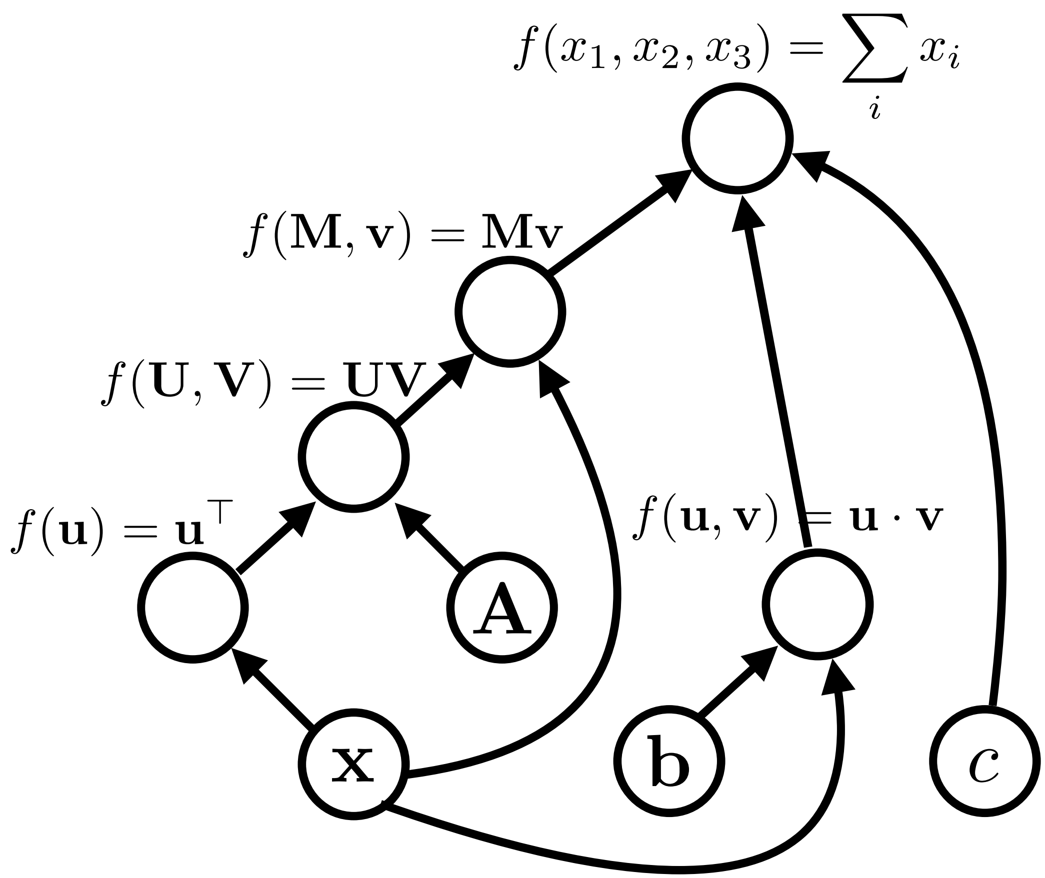
$$\frac{\partial f(\mathbf{x}, \mathbf{A})}{\partial \mathbf{x}} = (\mathbf{A}^\top + \mathbf{A})\mathbf{x}$$

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

expression:

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

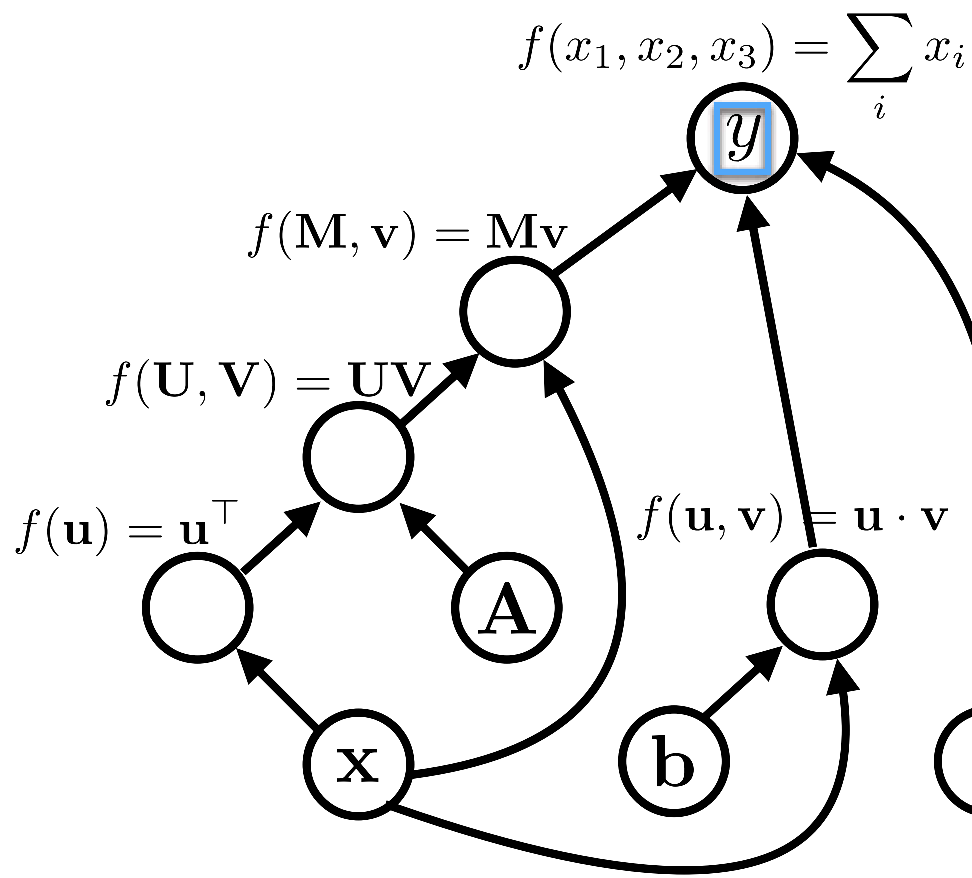
graph:



expression:

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

graph:



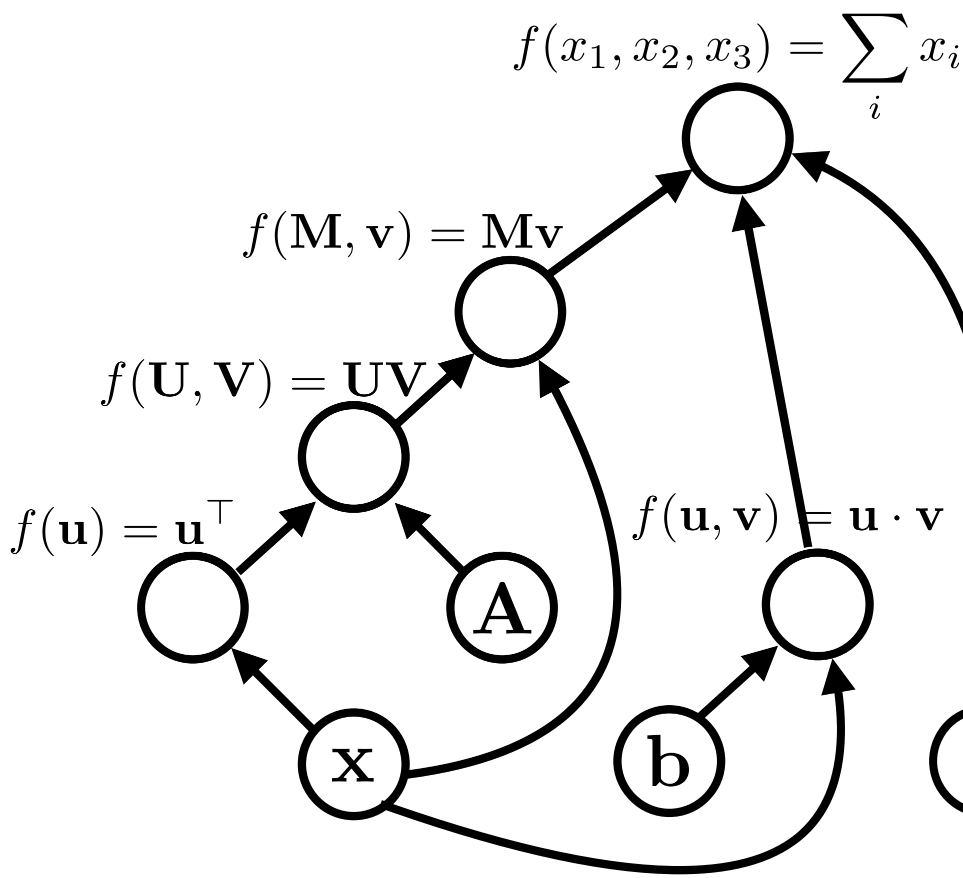
variable names are just labelings of nodes.

Algorithms (1)

- **Graph construction**
- **Forward propagation**
  - In topological order, compute the **value** of the node given its inputs

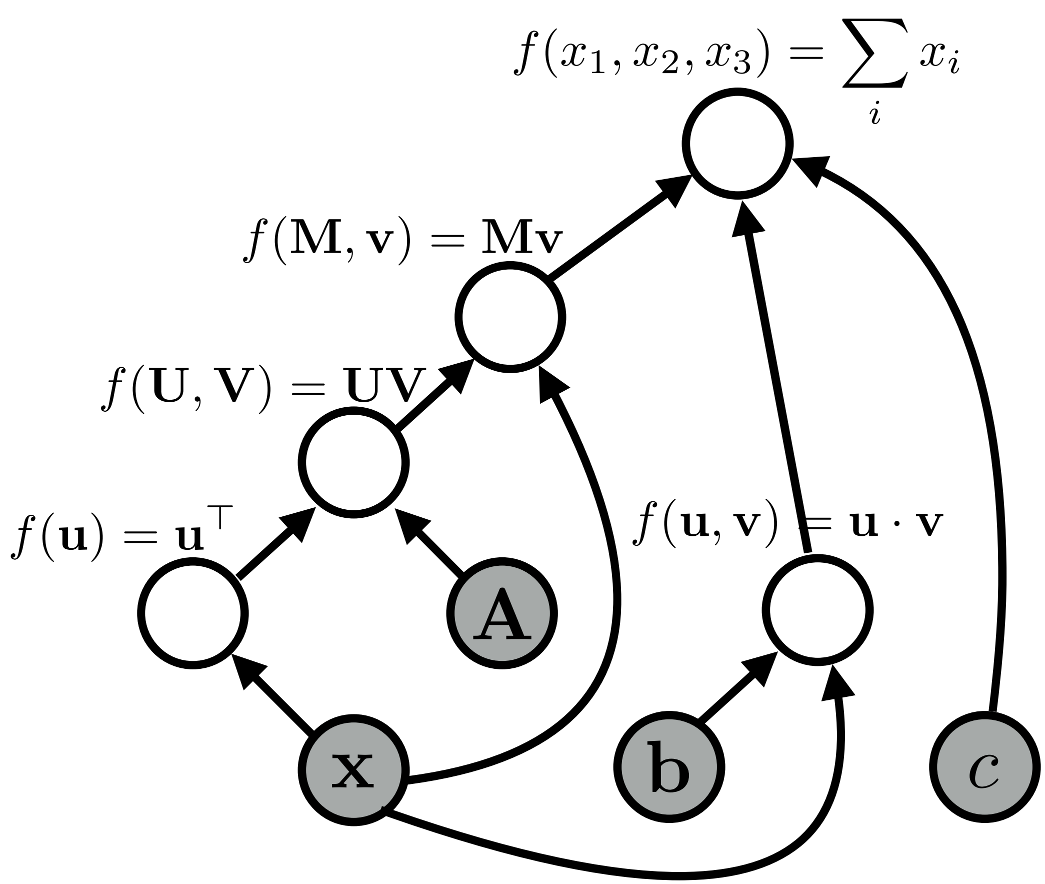
Forward Propagation

graph:



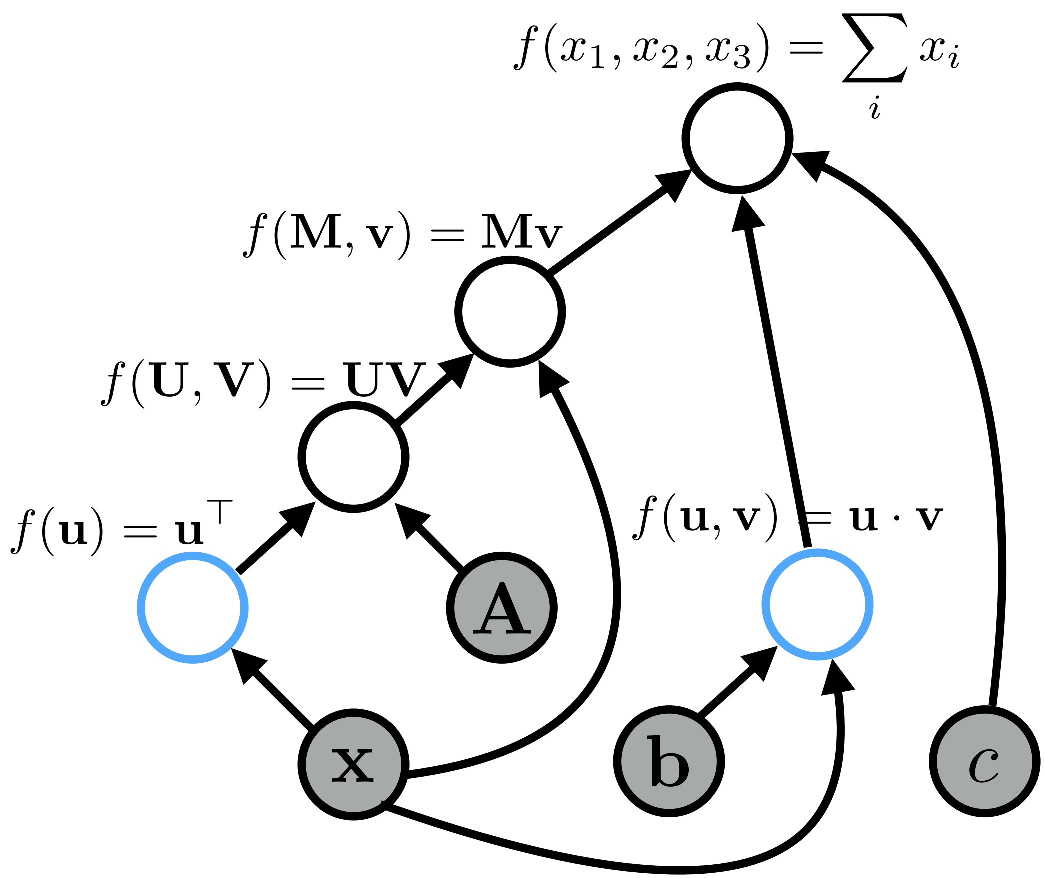
Forward Propagation

graph:



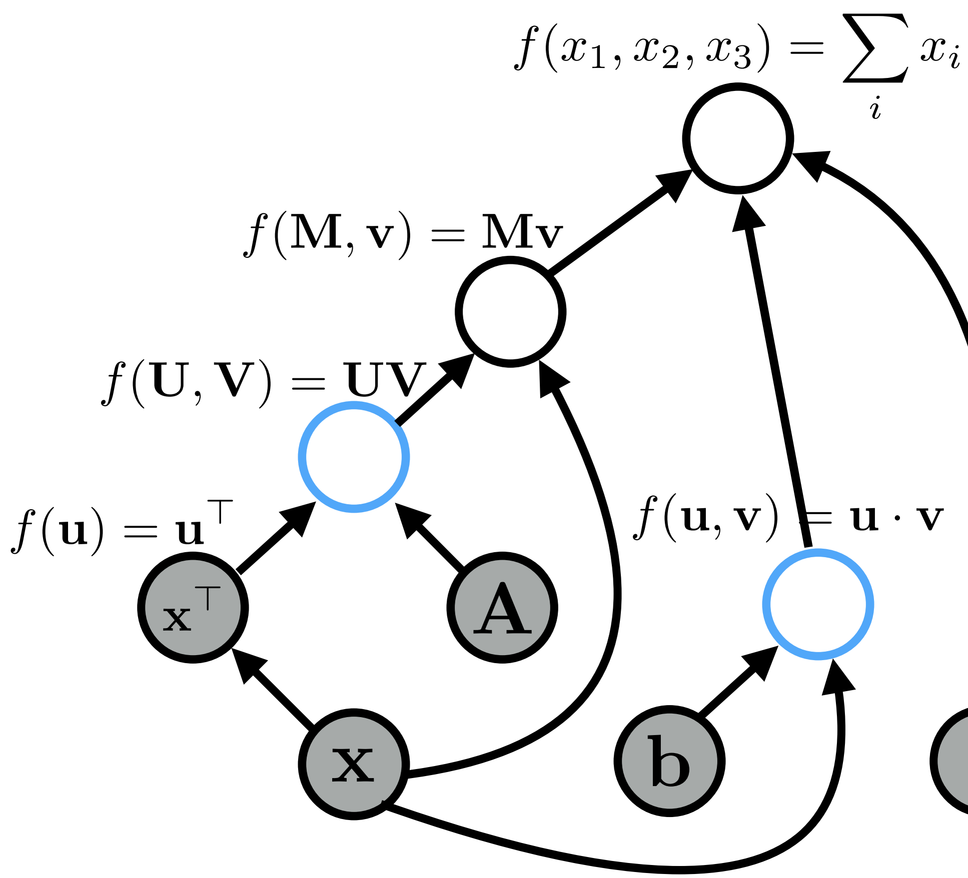
Forward Propagation

graph:



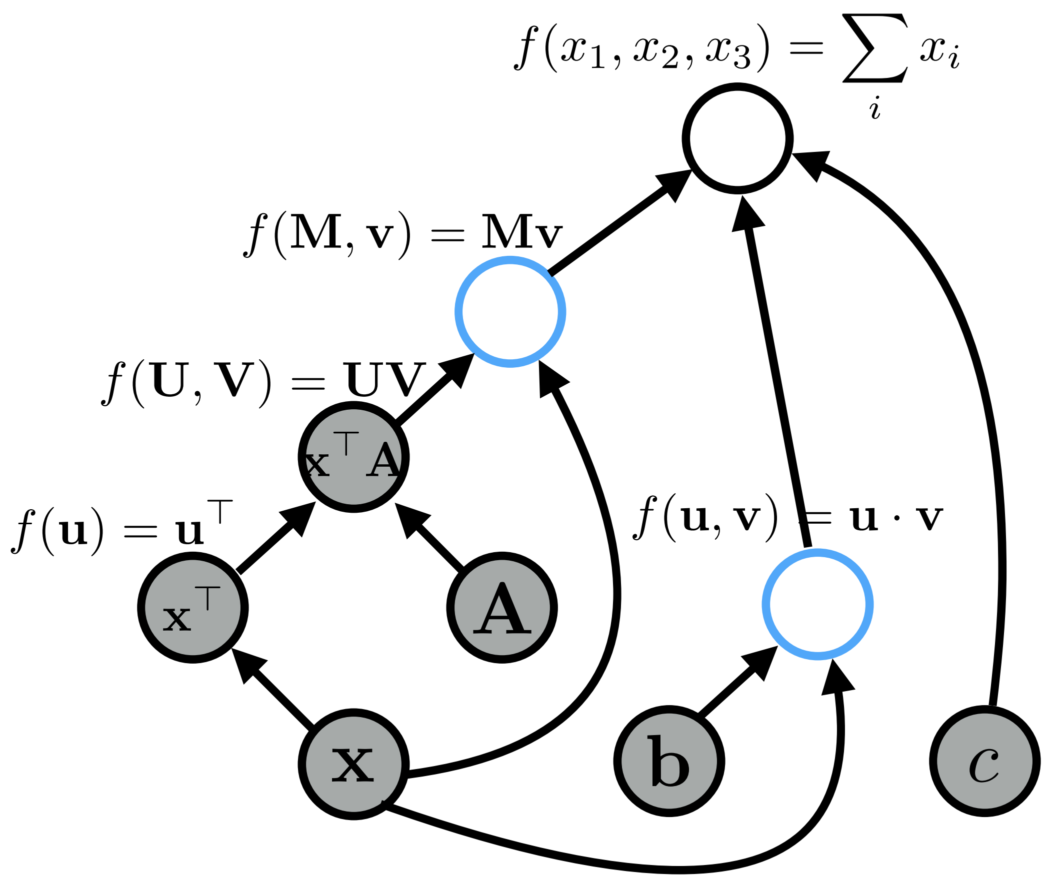
Forward Propagation

graph:



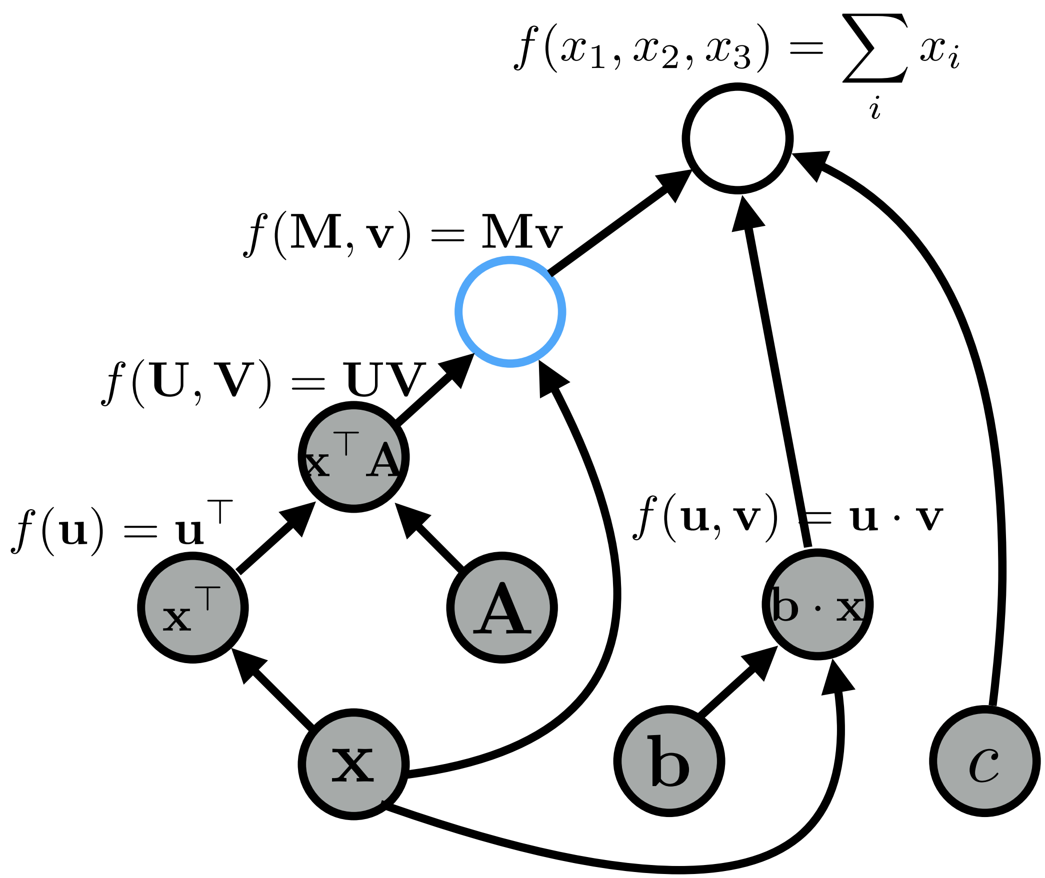
Forward Propagation

graph:



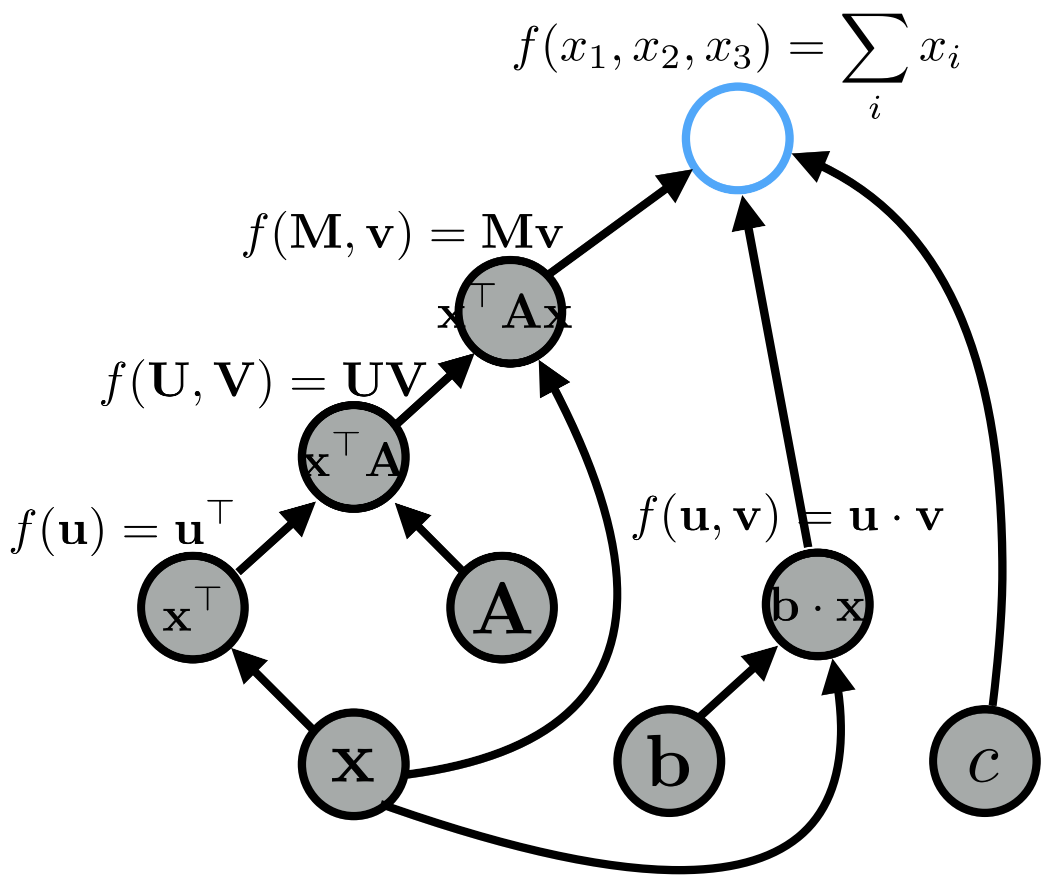
Forward Propagation

graph:



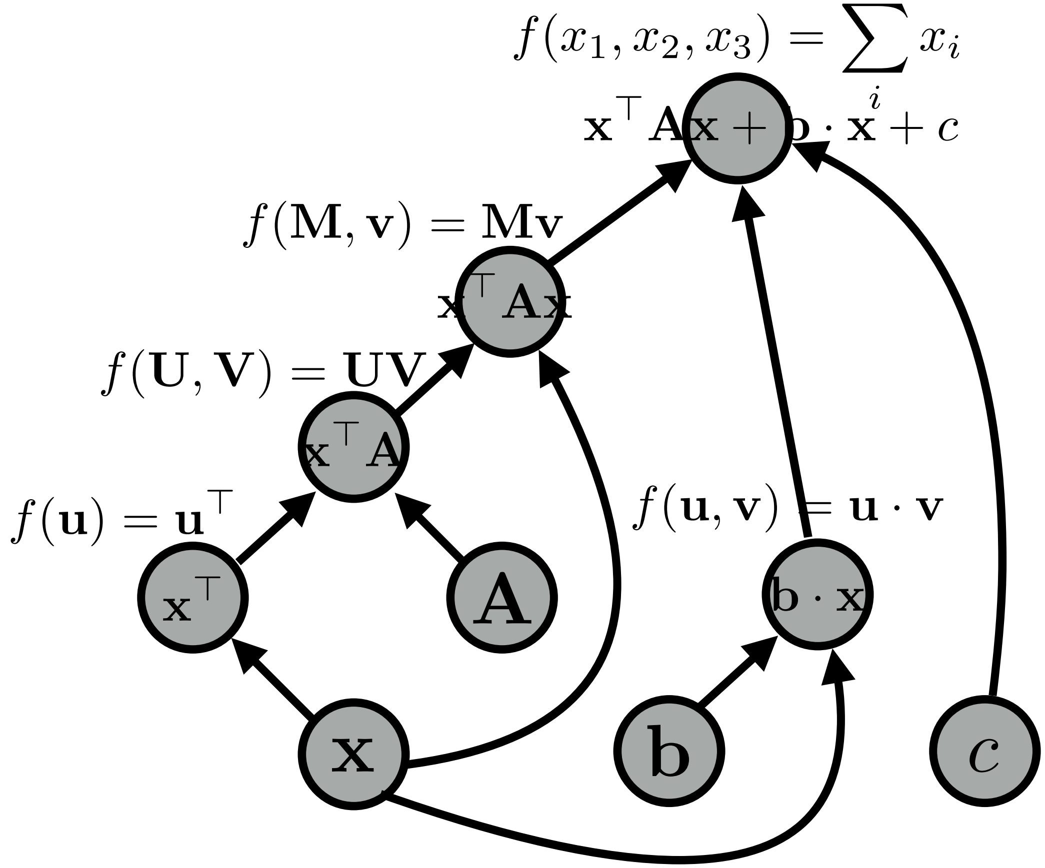
Forward Propagation

graph:



Forward Propagation

graph:



Algorithms (2)

- **Back-propagation:**
  - Process examples in reverse topological order
  - Calculate the derivatives of the parameters with respect to the final value
    (This is usually a “loss function”, a value we want to minimize)
- **Parameter update:**
  - Move the parameters in the direction of this derivative

    W -= α * dl/dW

Basic Process in Dynamic Neural Network Frameworks

- Create a model
- For each example
  - **create a graph** that represents the computation you want
  - **calculate the result** of that computation
  - if training, perform **back propagation and update**

DyNet

- Examples in this class will be in DyNet:
  - **intuitive**, program like you think (c.f. TensorFlow, Theano)
  - **fast for complicated networks** on CPU (c.f. autodiff libraries, Chainer, PyTorch)
  - has **nice features to make efficient implementation easier** (automatic batching)

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()
```

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expression 5/1

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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,...)

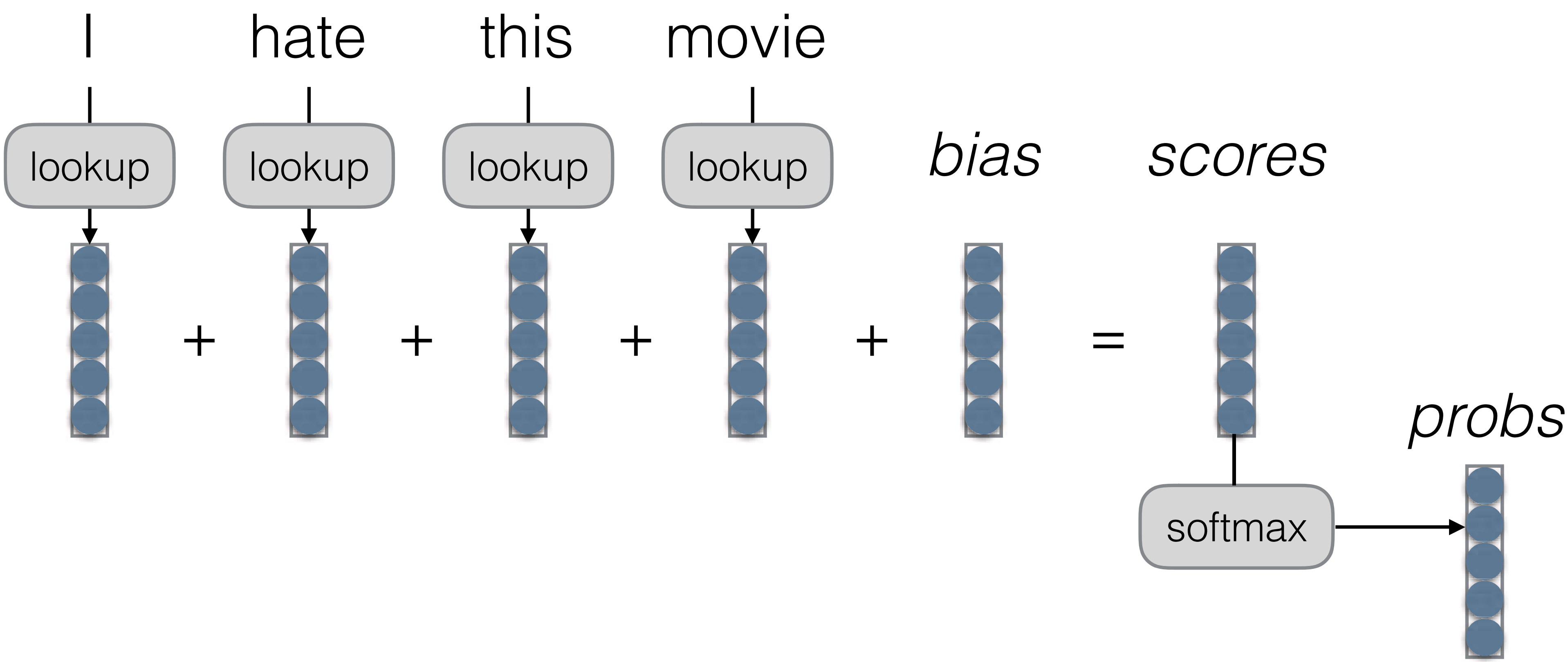
dy.AdamTrainer(model,...)
```

Training with DyNet

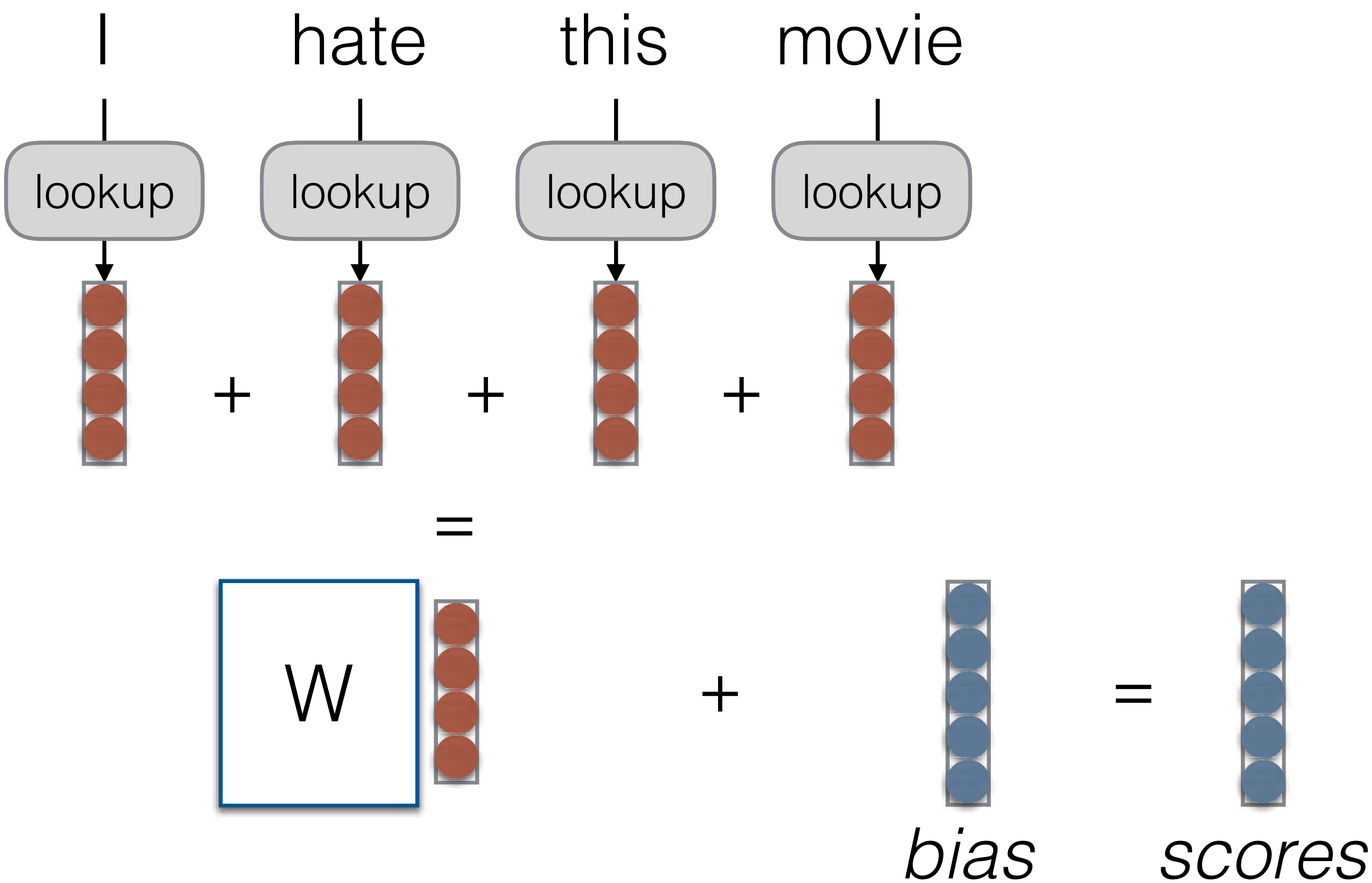
- Create model, add parameters, create trainer.
- For each training example:
    - create computation graph for the loss
    - run forward (compute the loss)
    - run backward (compute the gradients)
    - update parameters

Example Implementation
(in DyNet)

Bag of Words (BOW)



Continuous Bag of Words (CBOW)



Deep CBOW