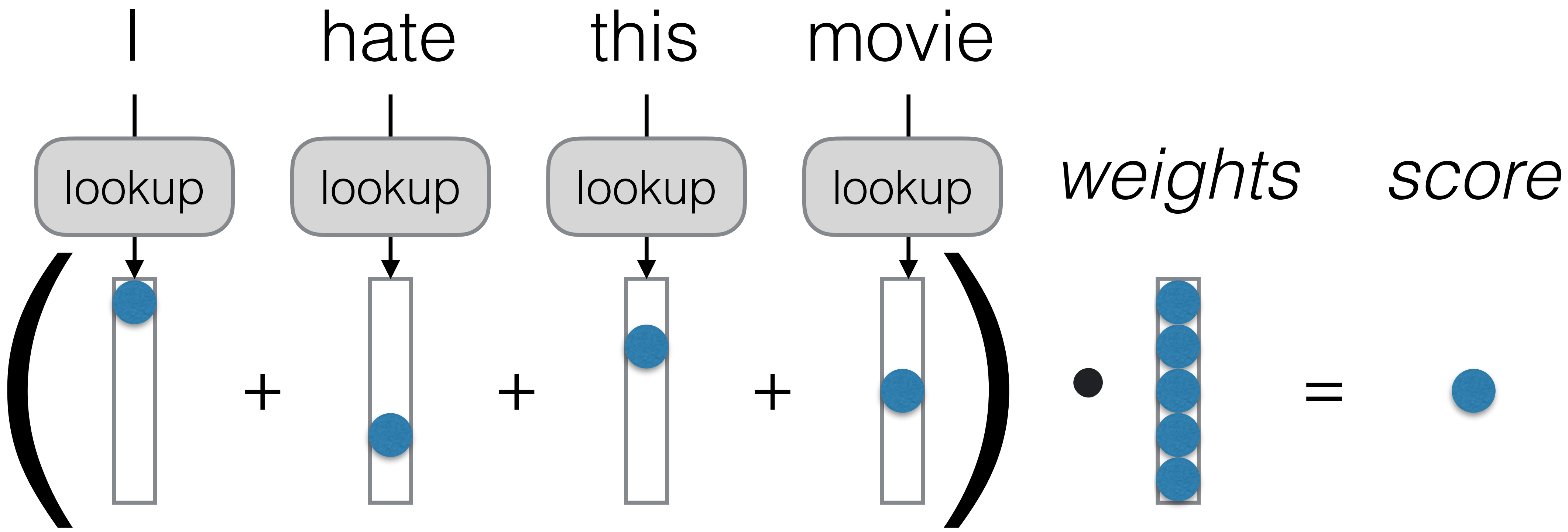
Reminder:
Bag of Words (BOW)



I hate this movie

lookup lookup lookup lookup

weights *score*

Features *f* are based on word identity, weights *w* learned

Which problems mentioned before would this solve?

What’s Missing in BOW?

- Handling of *conjugated or compound words*
  - I **love** this move -> I **loved** this movie

Subword Models

- Handling of *word similarity*
  - I **love** this move -> I **adore** this movie

Word Embeddings

- Handling of *combination features*
  - I **love** this movie -> I **don’t love** this movie
  - I **hate** this movie -> I **don’t hate** this movie

Neural Networks

- Handling of *sentence structure*
  - It has an interesting story, **but** is boring overall

Sequence Models

Subword Models

Basic Idea

- Split less common words into multiple **subword tokens**

the companies are expanding

↓

the **compan _ies** are **expand _ing**

- Benefits:
  - **Share parameters** between word variants, compound words
  - Reduce parameter size, **save compute+memory**

Byte Pair Encoding

(Sennrich+ 2015)

- Incrementally combine together the most frequent token pairs

```
{'l o w </w>': 5, 'l o w e r </w>': 2, 'n e w e s t </w>': 6, 'w i d e s t </w>': 3}

pairs = get_stats(vocab)

[(('e', 's'), 9), (('s', 't'), 9), (('t', '</w>'), 9), (('w', 'e'), 8), (('l', 'o'), 7), …]

vocab = merge_vocab(pairs[0], vocab)

{'l o w </w>': 5, 'l o w e r </w>': 2, 'n e w es t </w>': 6, 'w i d es t </w>': 3}

pairs = get_stats(vocab)

[(('es', 't'), 9), (('t', '</w>'), 9), (('l', 'o'), 7), (('o', 'w'), 7), (('n', 'e'), 6)]

vocab = merge_vocab(pairs[0], vocab)

{'l o w </w>': 5, 'l o w e r </w>': 2, 'n e w est </w>': 6, 'w i d est </w>': 3}
```

Example code:
https://github.com/neubig/anlp-code/tree/main/02-subwords

Unigram Models (Kudo 2018)

- Use a *unigram* LM that generates all words in the sequence independently (more next lecture)
- **Pick a vocabulary** that maximizes the log likelihood of the corpus given a fixed vocabulary size
  - Optimization performed using the EM algorithm (details not important for most people)
- **Find the segmentation** of the input that maximizes unigram probability

SentencePiece

- A highly optimized library that makes it possible to train and use BPE and Unigram models

```
% spm_train --input=<input> \
            --model_prefix=<model_name>
            --vocab_size=8000 --character_coverage=1.0
            --model_type=<type>

% spm_encode --model=<model_file>
             —output_format=piece < input > output
```

- Python bindings also available

https://github.com/google/sentencepiece

Subword Considerations

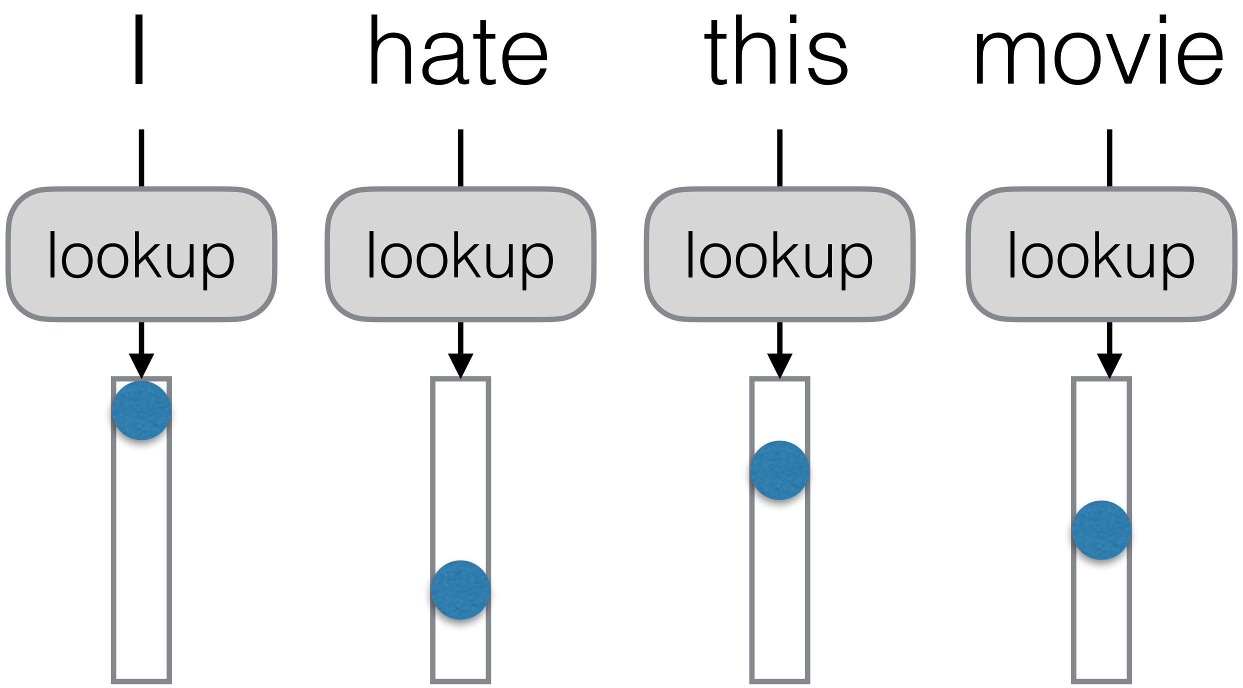
- **Multilinguality:** Subword models are hard to use multilingually because they will over-segment less common languages naively (Ács 2019)
    - *Work-around:* Upsample less represented languages
- **Arbitrariness:** Do we do “es t” or “e st”?
    - *Work-around:* “Subword regularization" samples different segmentations at training time to make models robust (Kudo 2018)

Continuous Word Embeddings

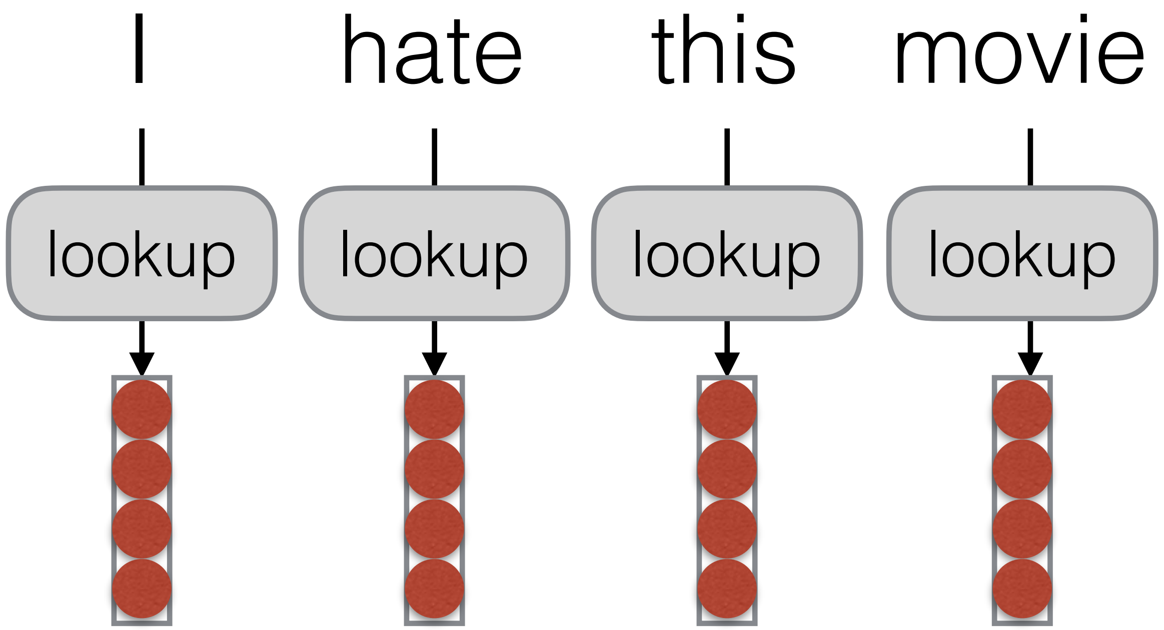
Basic Idea

- Previously we represented words with a *sparse* vector with a single “1” — a **one-hot** vector
- Continuous word embeddings look up a *dense* vector

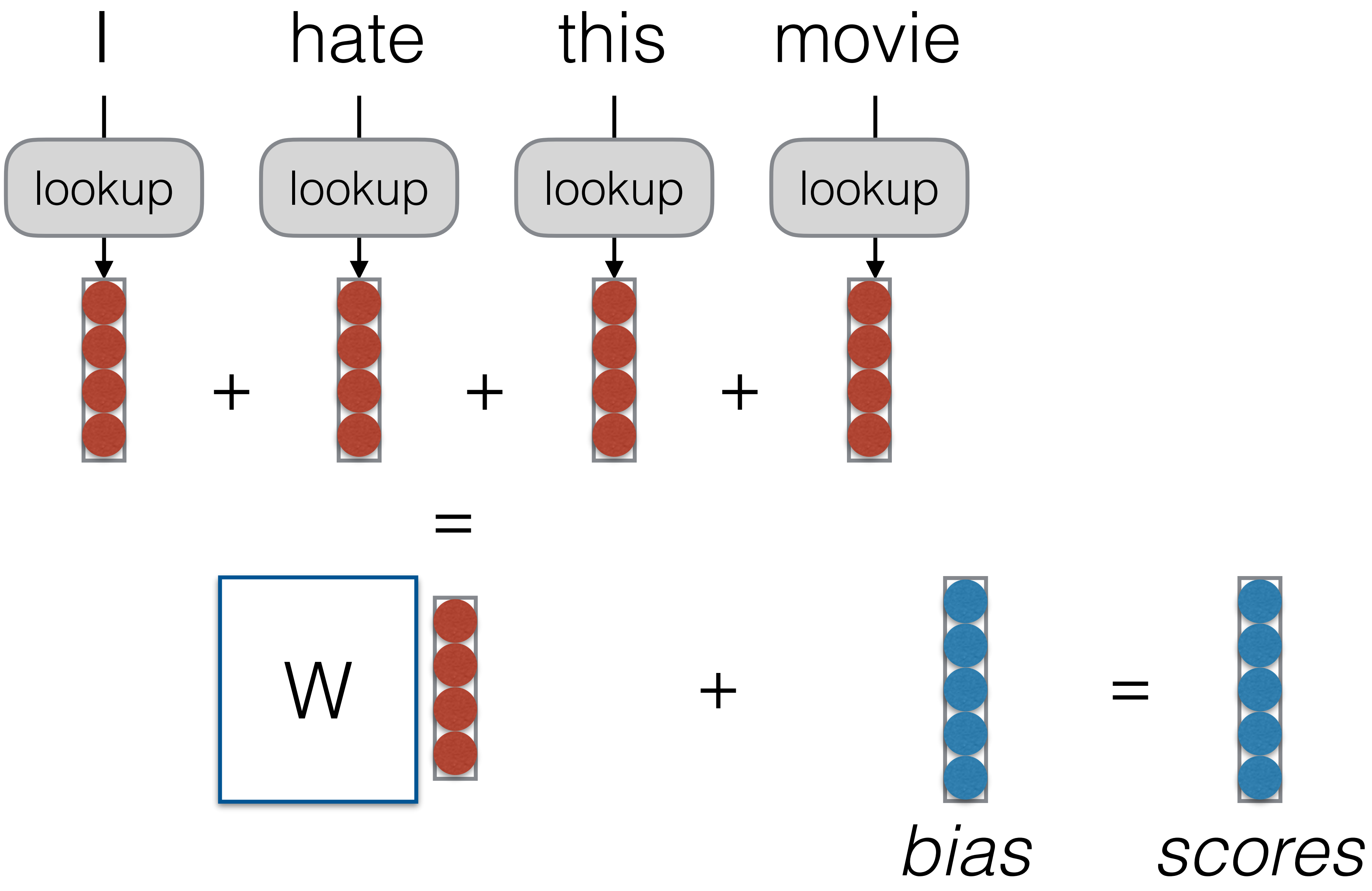
One-hot Representations



Dense Representations

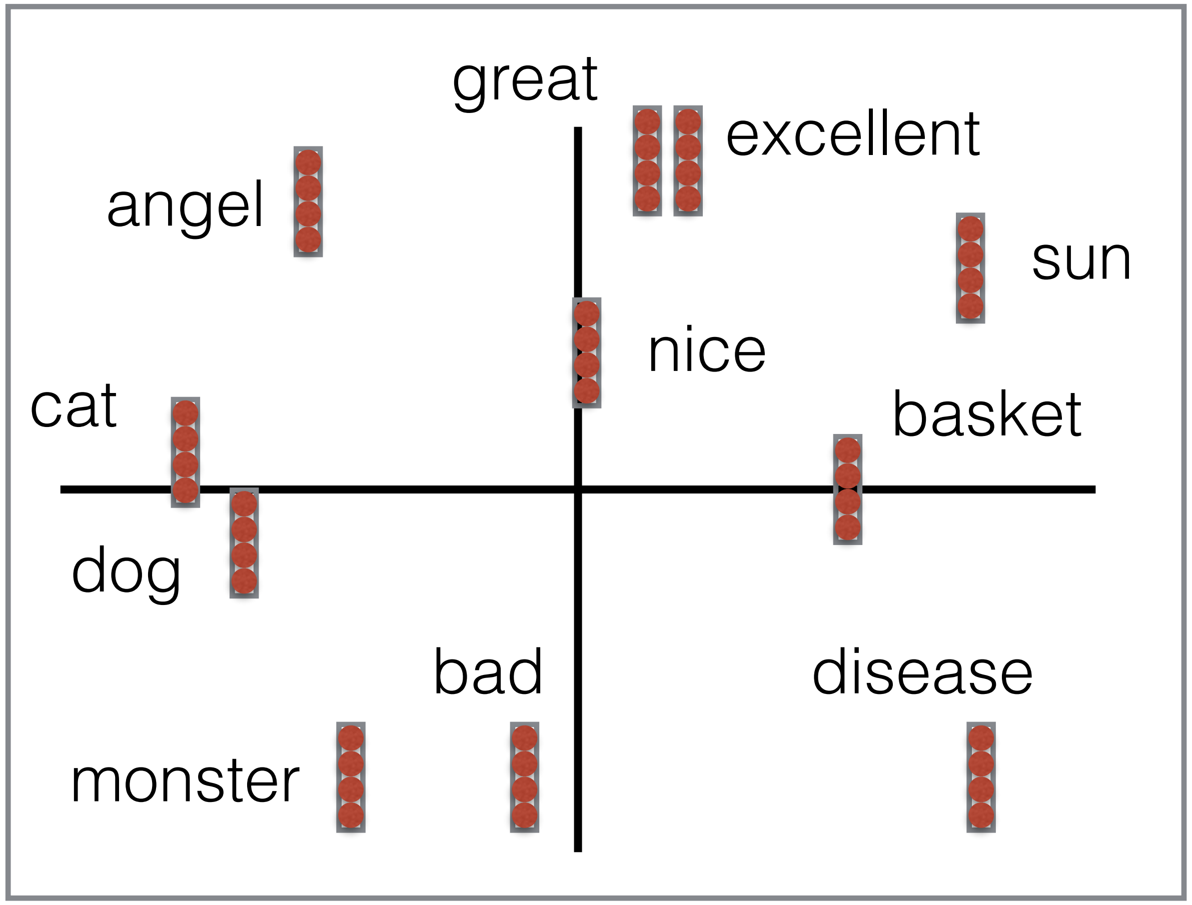


Continuous Bag of Words (CBOW)



What do Our Vectors Represent?

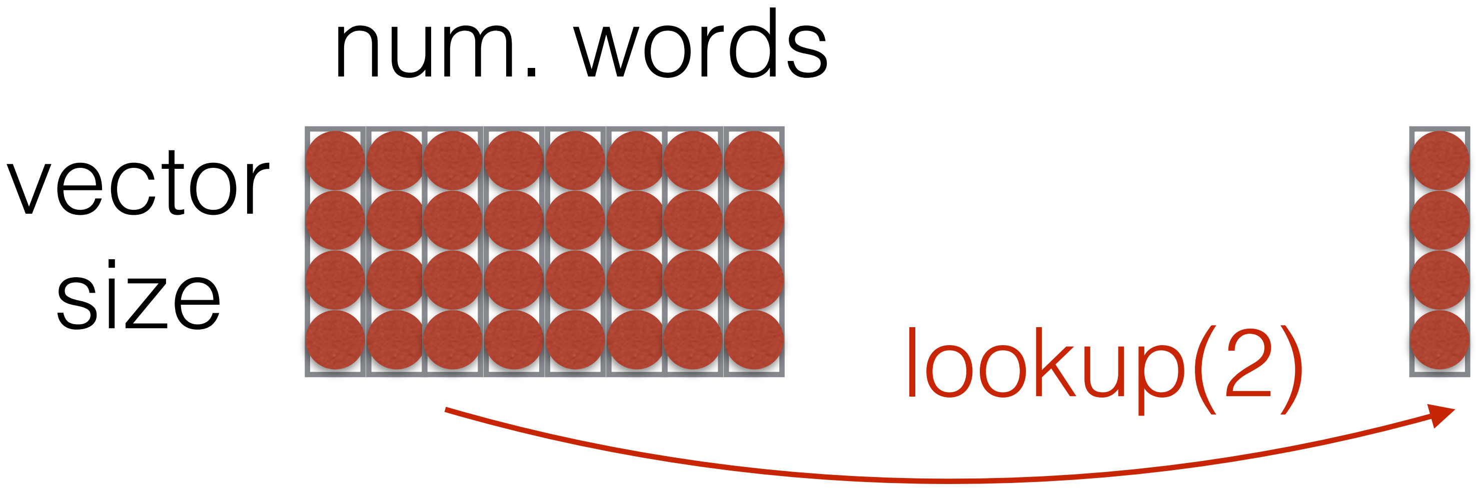
- No guarantees, but we hope that:
  - Words that are **similar** (syntactically, semantically, same language, etc.) are **close** in vector space
  - Each vector element is a **features** (e.g. is this an animate object? is this a positive word, etc.)



Shown in 2D, but in reality we use 512, 1024, etc.

A Note: “Lookup”

- Lookup can be viewed as “grabbing” a single vector from a big matrix of word embeddings

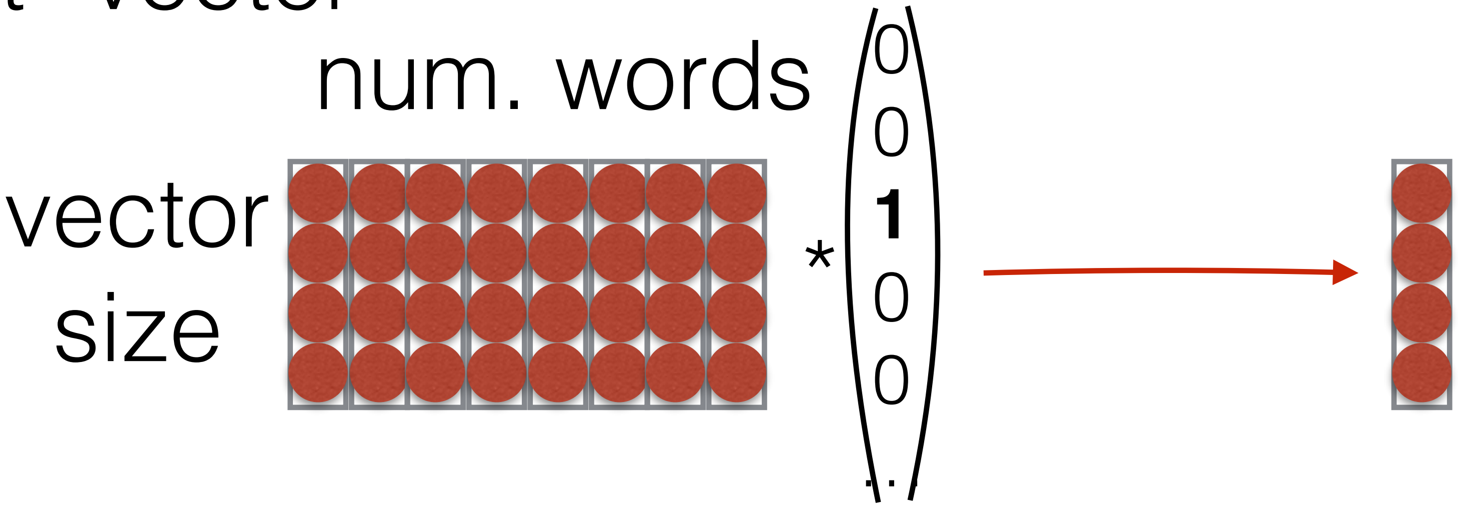


num. words

vector size

lookup(2)

- Similarly, can be viewed as multiplying by a “one-hot” vector



num. words

vector size

- Former tends to be faster

Training a More Complex Model

Reminder: Simple Training of BOW Models

- Use an algorithm called “structured perceptron”

```
feature_weights = {}
for x, y in data:
    # Make a prediction
    features = extract_features(x)
    predicted_y = run_classifier(features)
    # Update the weights if the prediction is wrong
    if predicted_y != y:
        for feature in features:
            feature_weights[feature] = (
                feature_weights.get(feature, 0) +
                y * features[feature]
            )
```

Full Example:
https://github.com/neubig/anlp-code/tree/main/01-simpleclassifier

How do we Train More Complex Models?

- We use *gradient descent*
  - Write down a *loss function*
  - *Calculate derivatives* of the loss function wrt the parameters
  - Move in the parameters in the direction that *reduces the loss function*

Loss Function

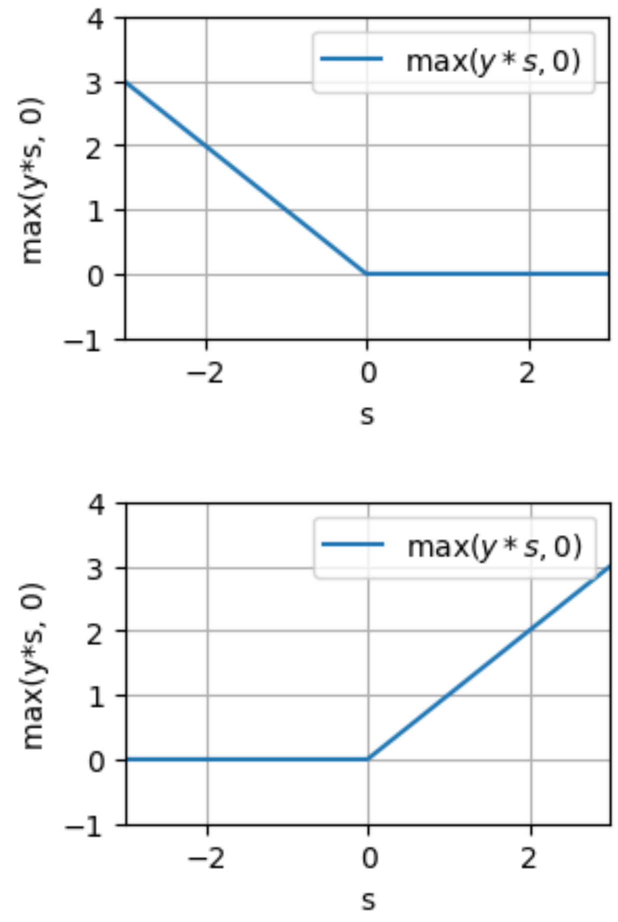
- A value that gets lower as the model gets better
- Examples from binary classification using score *s(x)*

y=1

y=-1

Hinge Loss

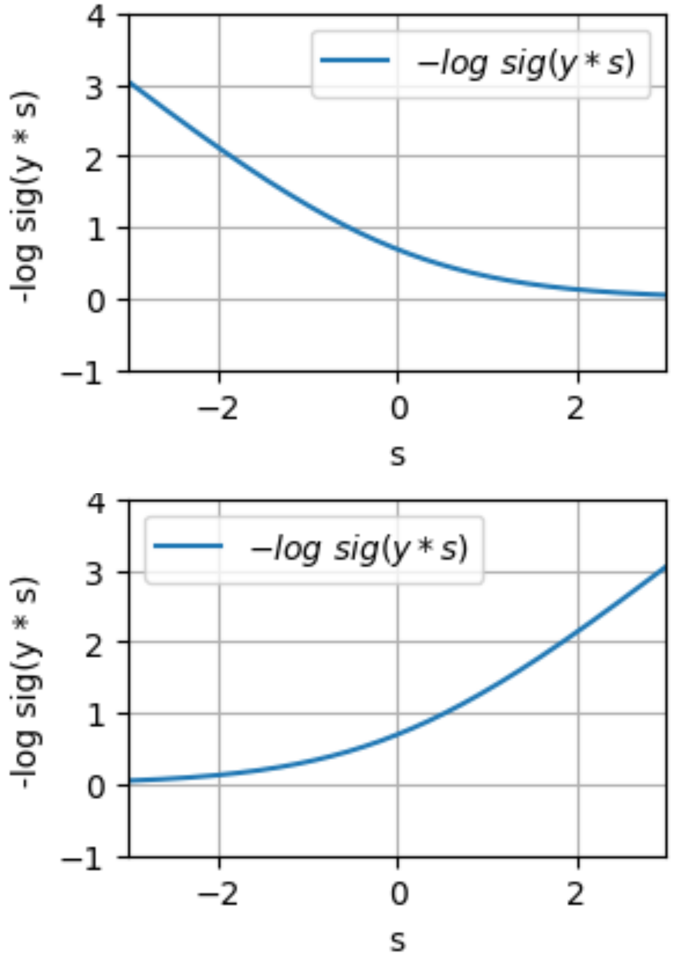
$$\ell = \max(-y * s)$$



more closely linked to acc

Sigmoid + Negative Log Likelihood

$$\sigma(y * s) = \frac{1}{1 + e^{-(y*s)}} \qquad \ell = -\log \sigma(y * s)$$



probabilistic interpretation, gradients everywhere

Calculating Derivatives

- Calculate the derivative of the parameter given the loss function
- Example from BOW model + hinge loss

$$\frac{\partial \max(0, -y * \sum_i^{|\mathcal{V}|} w_i \mathrm{freq}(v_i, x))}{\partial w_i} =$$

$$\begin{cases} -y \cdot \mathrm{freq}(v_i, x) & \text{if } -y \cdot \sum_i^{|\mathcal{V}|} w_i \mathrm{freq}(v_i, x) > 0 \\ 0 & \text{otherwise} \end{cases}$$

Optimizing Gradients

- Standard stochastic gradient descent does

$$g_t = \underset{\text{Gradient of Loss}}{\underline{\nabla_{\theta_{t-1}} \ell(\theta_{t-1})}}$$

$$\theta_t = \theta_{t-1} - \underset{\text{Learning Rate}}{\underline{\eta}} g_t$$

- There are many other optimization options! (see Ruder 2016 in references)

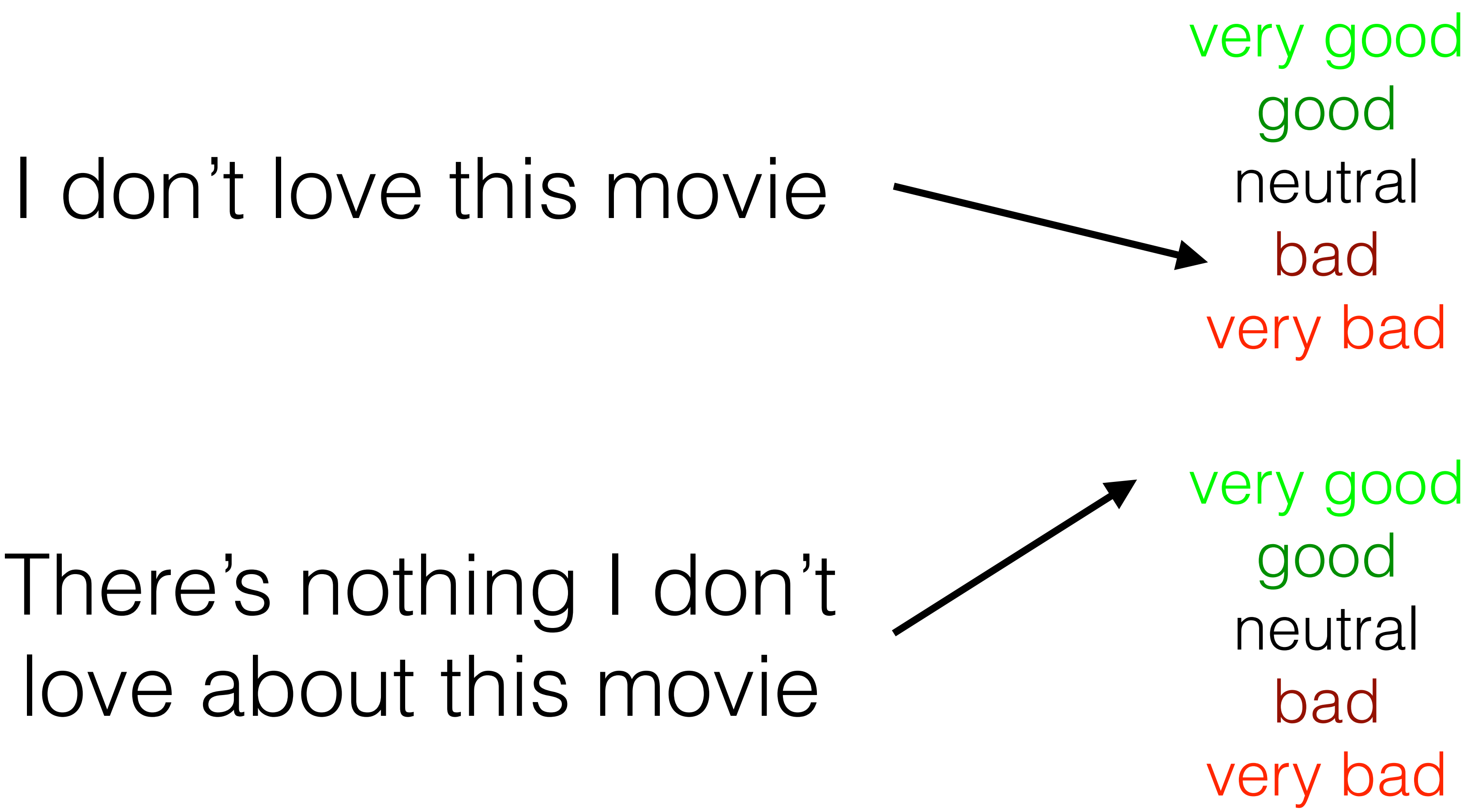
What is this Algorithm?

```
feature_weights = {}
for x, y in data:
    # Make a prediction
    features = extract_features(x)
    predicted_y = run_classifier(features)
    # Update the weights if the prediction is wrong
    if predicted_y != y:
        for feature in features:
            feature_weights[feature] = (
                feature_weights.get(feature, 0) +
                y * features[feature]
            )
```

- **Loss function:** Hinge Loss
- **Optimizer:** SGD w/ learning rate 1

Combination Features

Combination Features



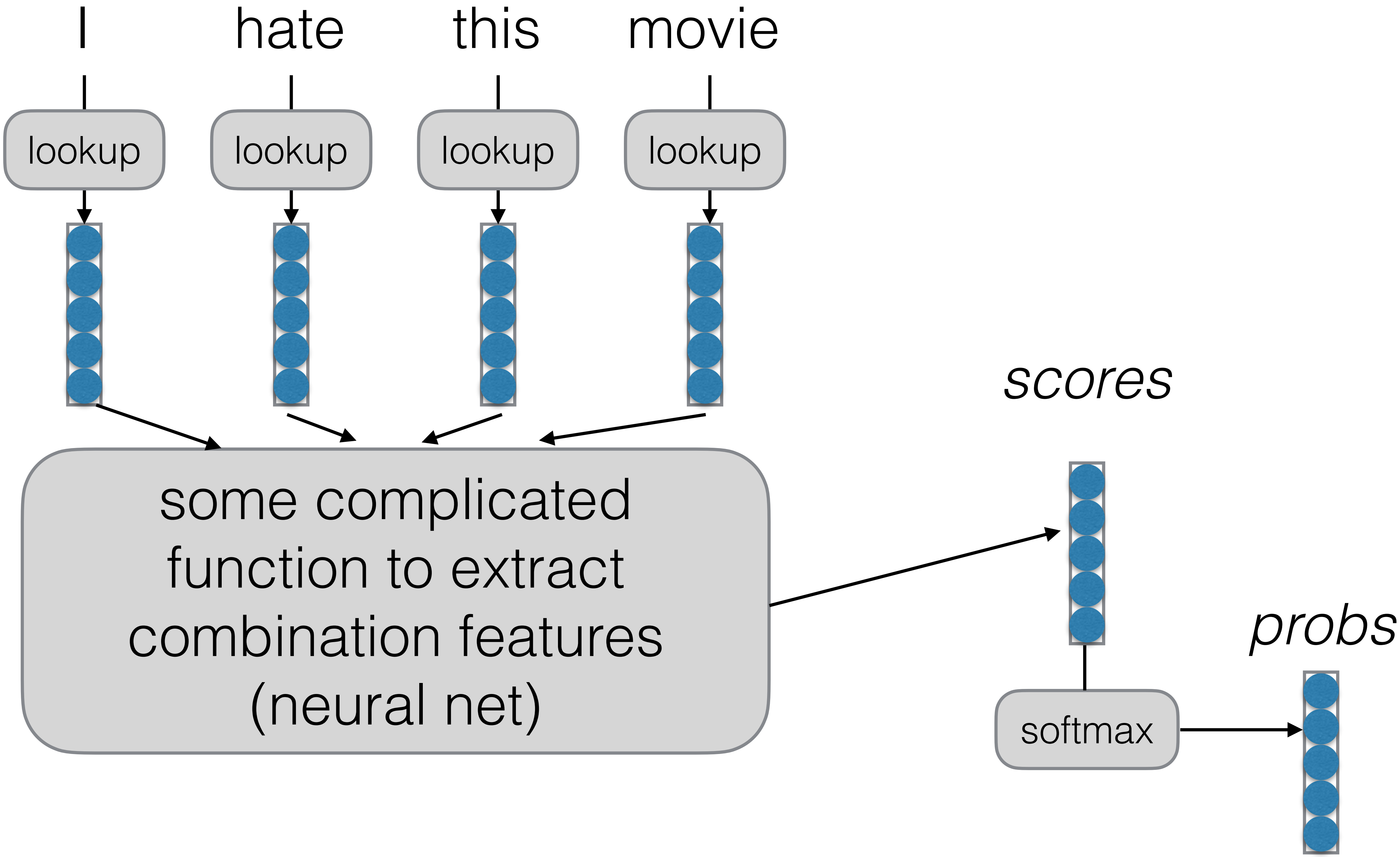
I don’t love this movie

very good
good
neutral
bad
very bad

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

very good
good
neutral
bad
very bad

Basic Idea of Neural Networks (for NLP Prediction Tasks)



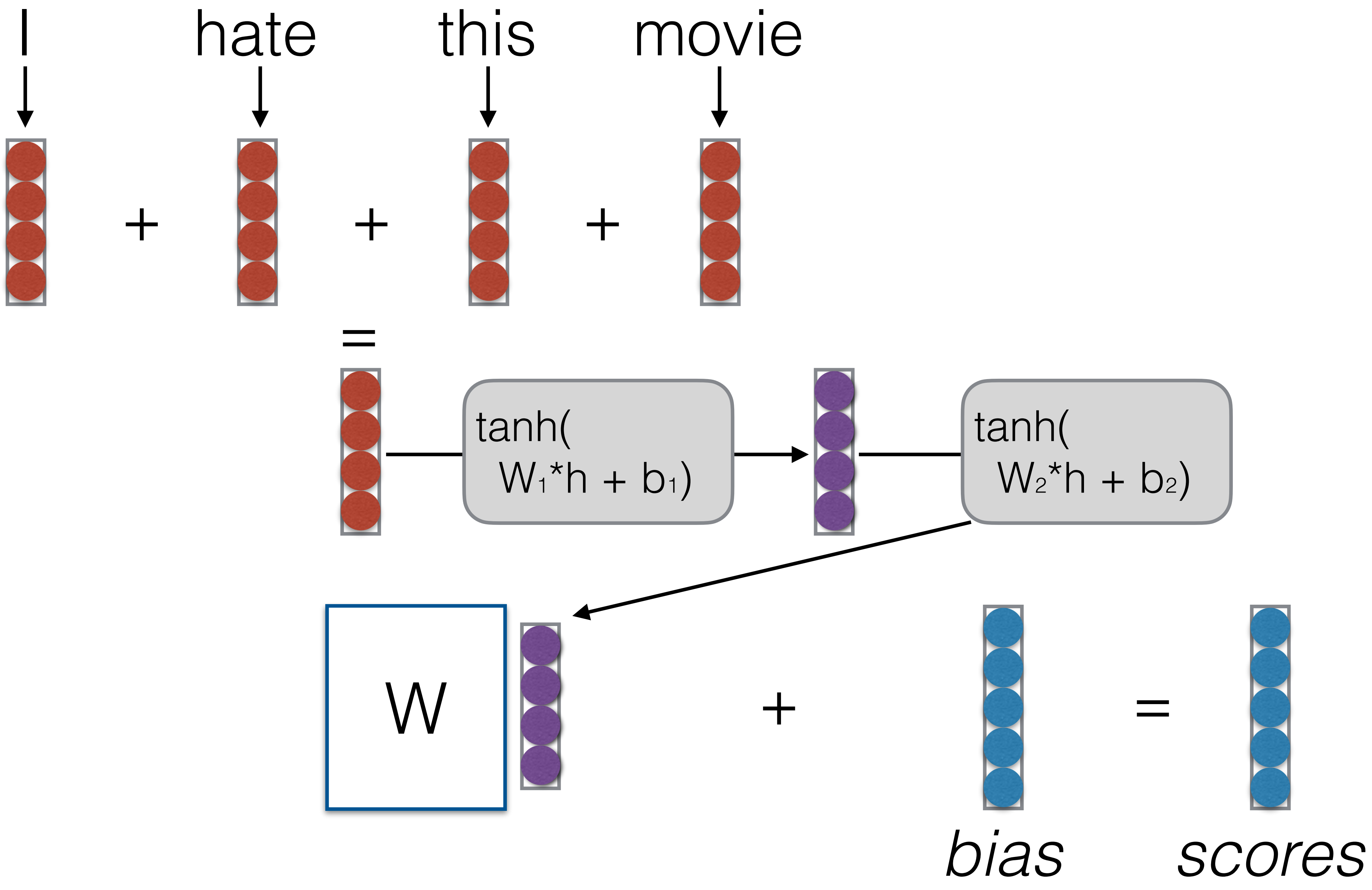
What do Our Vectors Represent?

- Each vector has “features” (e.g. is this an animate object? is this a positive word, etc.)

- We sum these features, then use these to make predictions

- Still no combination features: only the expressive power of a linear model, but dimension reduced

Deep CBOW



I hate this movie

+ + + =

$\tanh(W_1 * h + b_1)$

$\tanh(W_2 * h + b_2)$

W + =

bias

scores

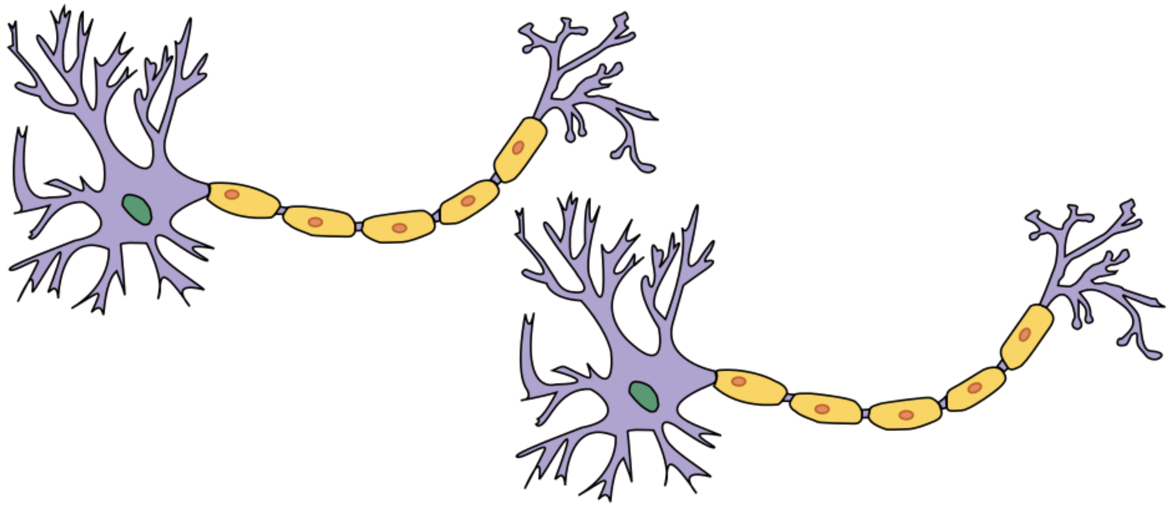
What do Our Vectors Represent?

- Now things are more interesting!
- We can learn feature combinations (a node in the second layer might be “feature 1 AND feature 5 are active”)
- e.g. capture things such as “not” AND “hate”

What is a Neural Net?: Computation Graphs

“Neural” Nets

Original Motivation: Neurons in the Brain



Current Conception: Computation Graphs

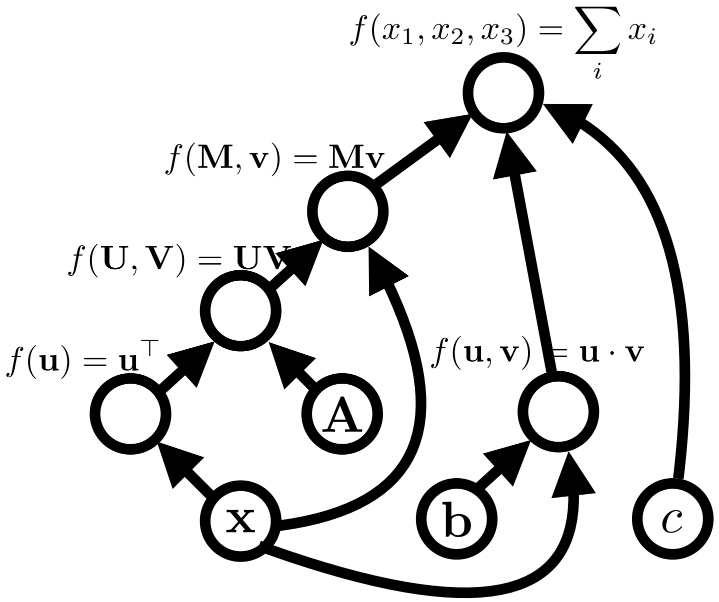


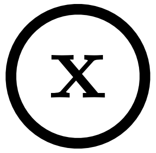
Image credit: Wikipedia

expression:

$\mathbf{x}$

graph:

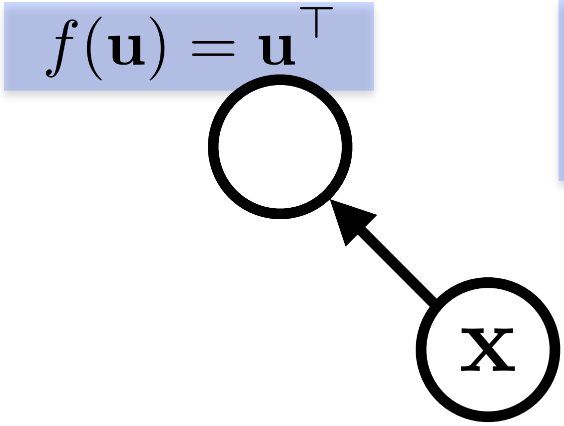
A **node** is a {tensor, matrix, vector, scalar} value



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



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

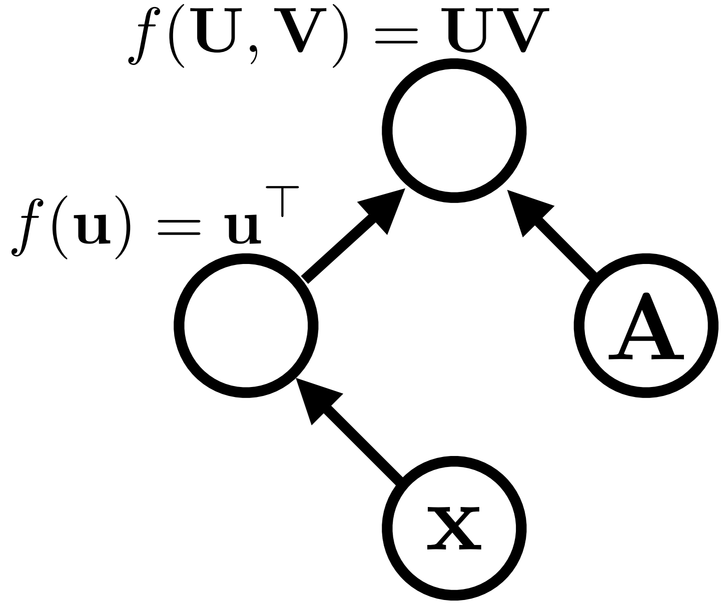
$$\frac{\partial f(\mathbf{u})}{\partial \mathbf{u}} \frac{\partial \mathcal{F}}{\partial f(\mathbf{u})} = \left(\frac{\partial \mathcal{F}}{\partial f(\mathbf{u})} \right)^\top$$

expression:

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

graph:

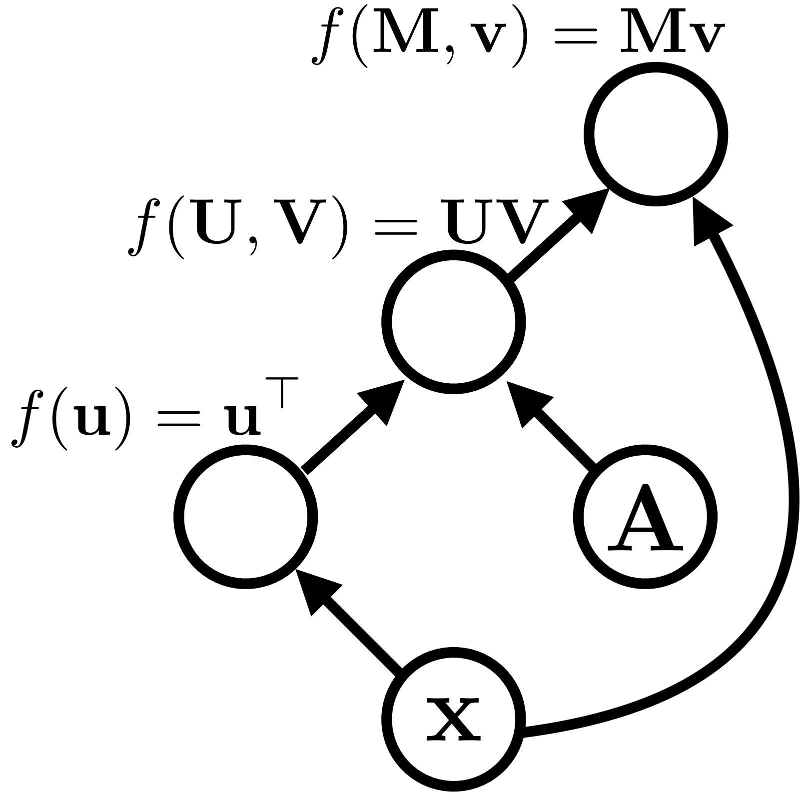
Functions can be nullary, unary, binary, … *n*-ary. Often they are unary or binary.



expression:

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

graph:

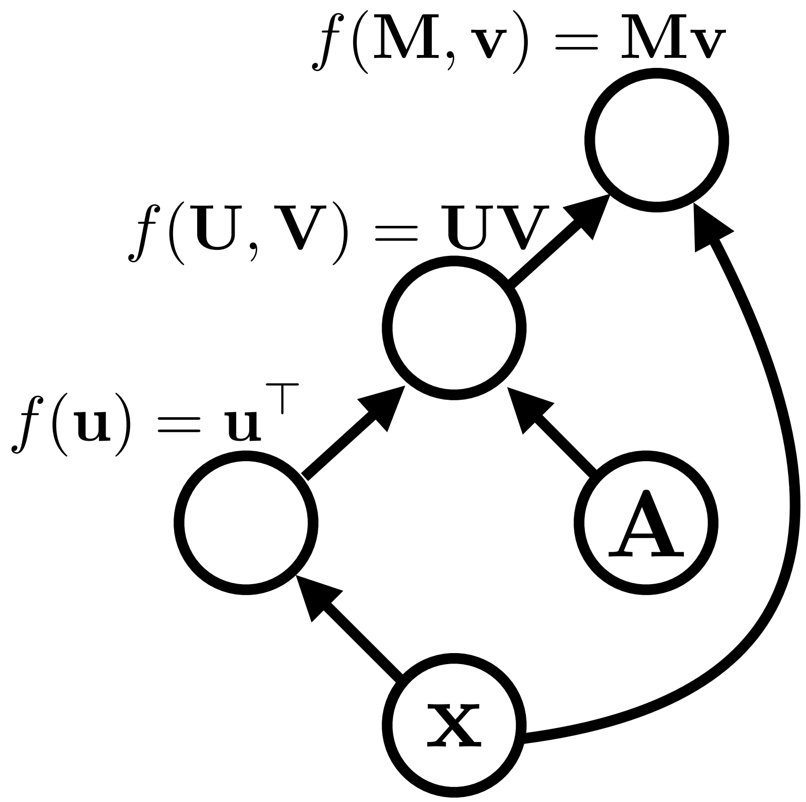


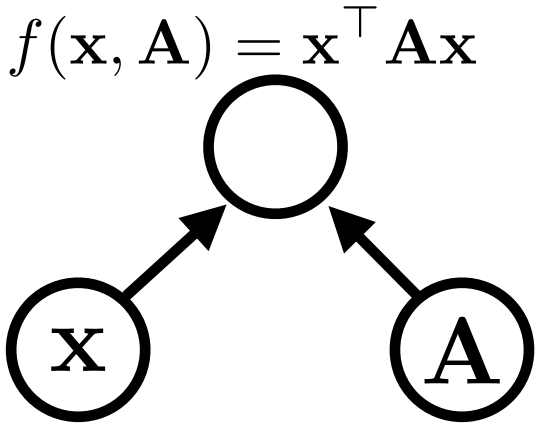
Computation graphs are directed and acyclic (in DyNet)

expression:

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

graph:





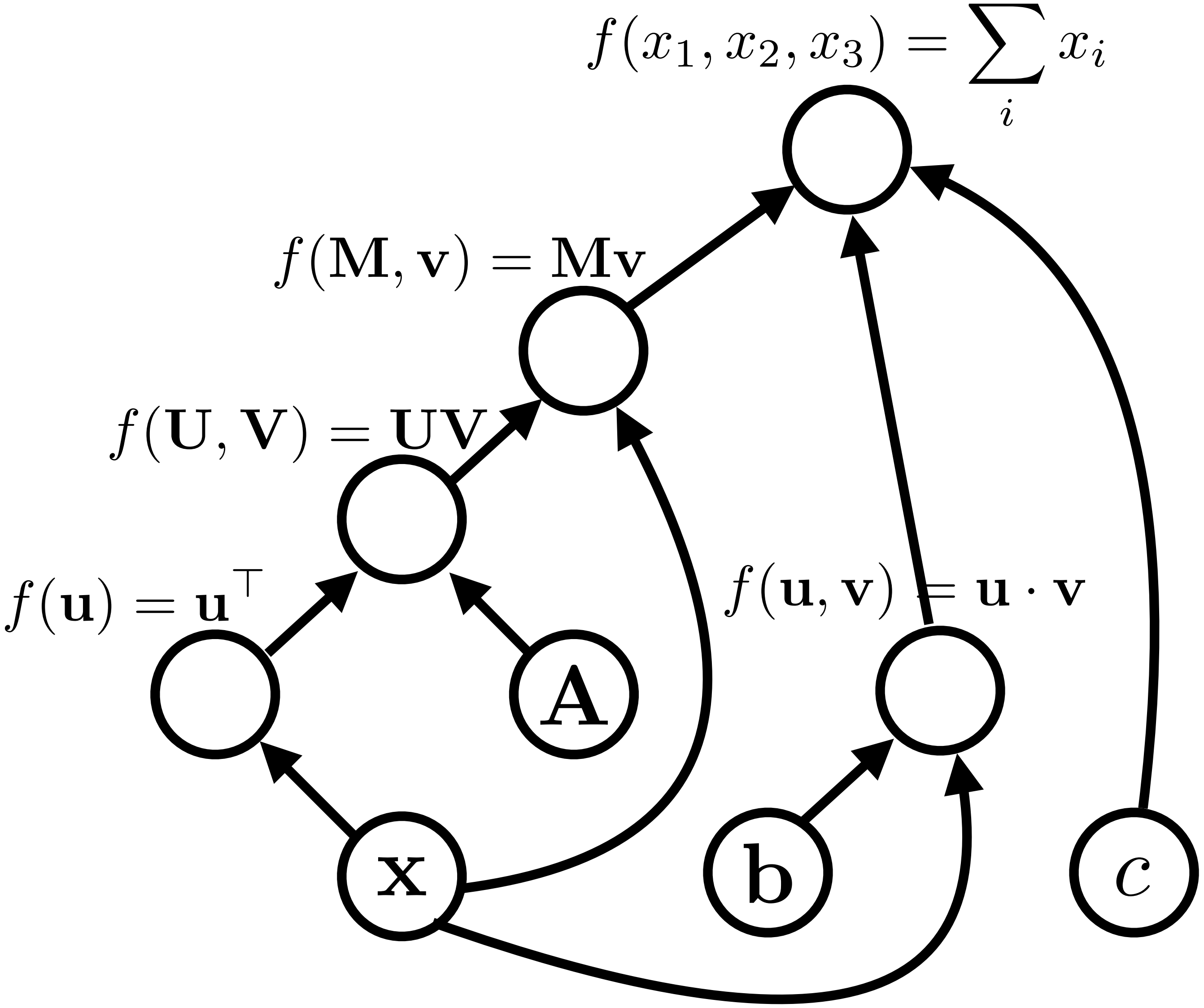
$$\frac{\partial f(\mathbf{x}, \mathbf{A})}{\partial \mathbf{x}} = (\mathbf{A}^\top + \mathbf{A})\mathbf{x}$$

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

expression:

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

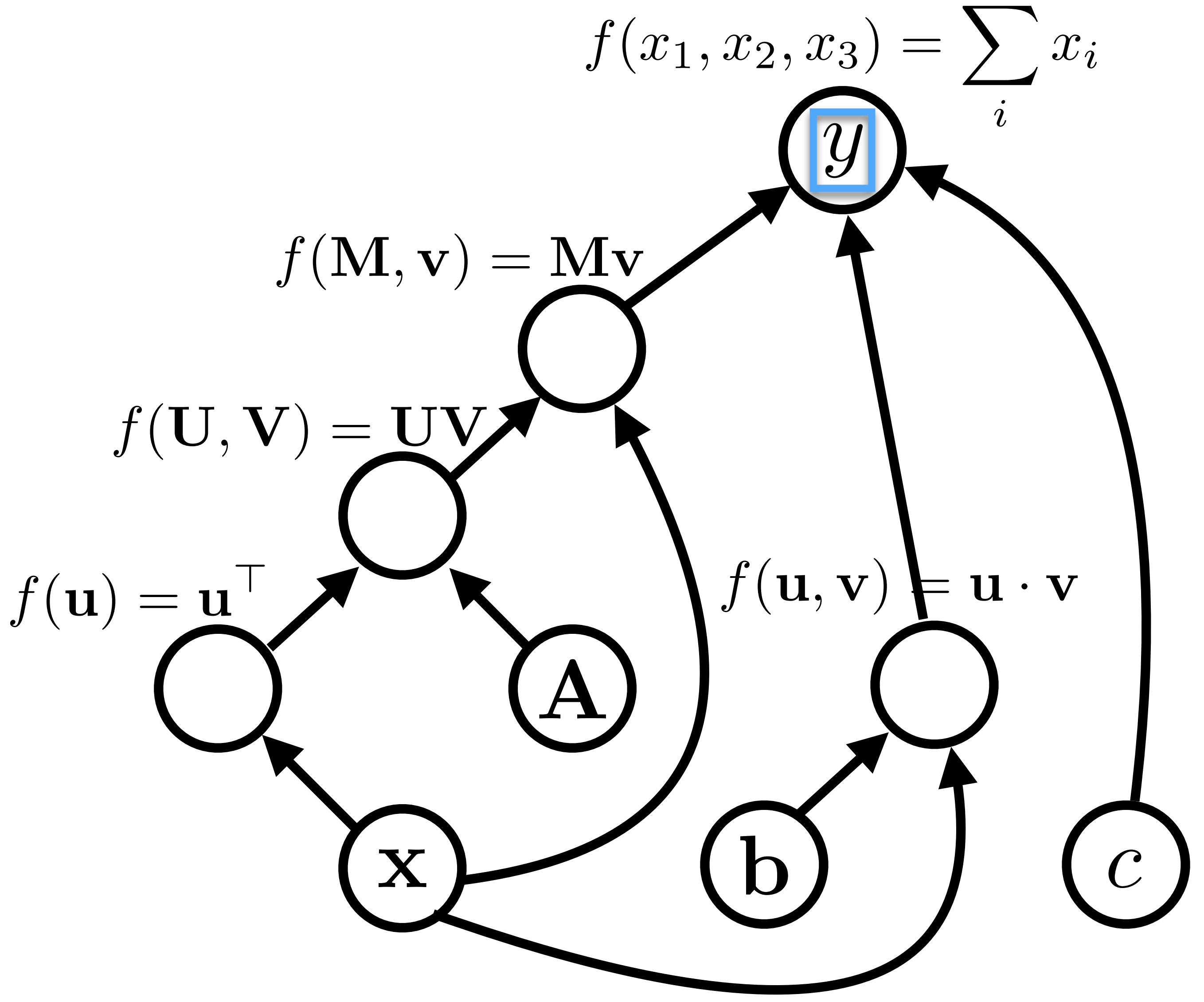
graph:



expression:

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

graph:



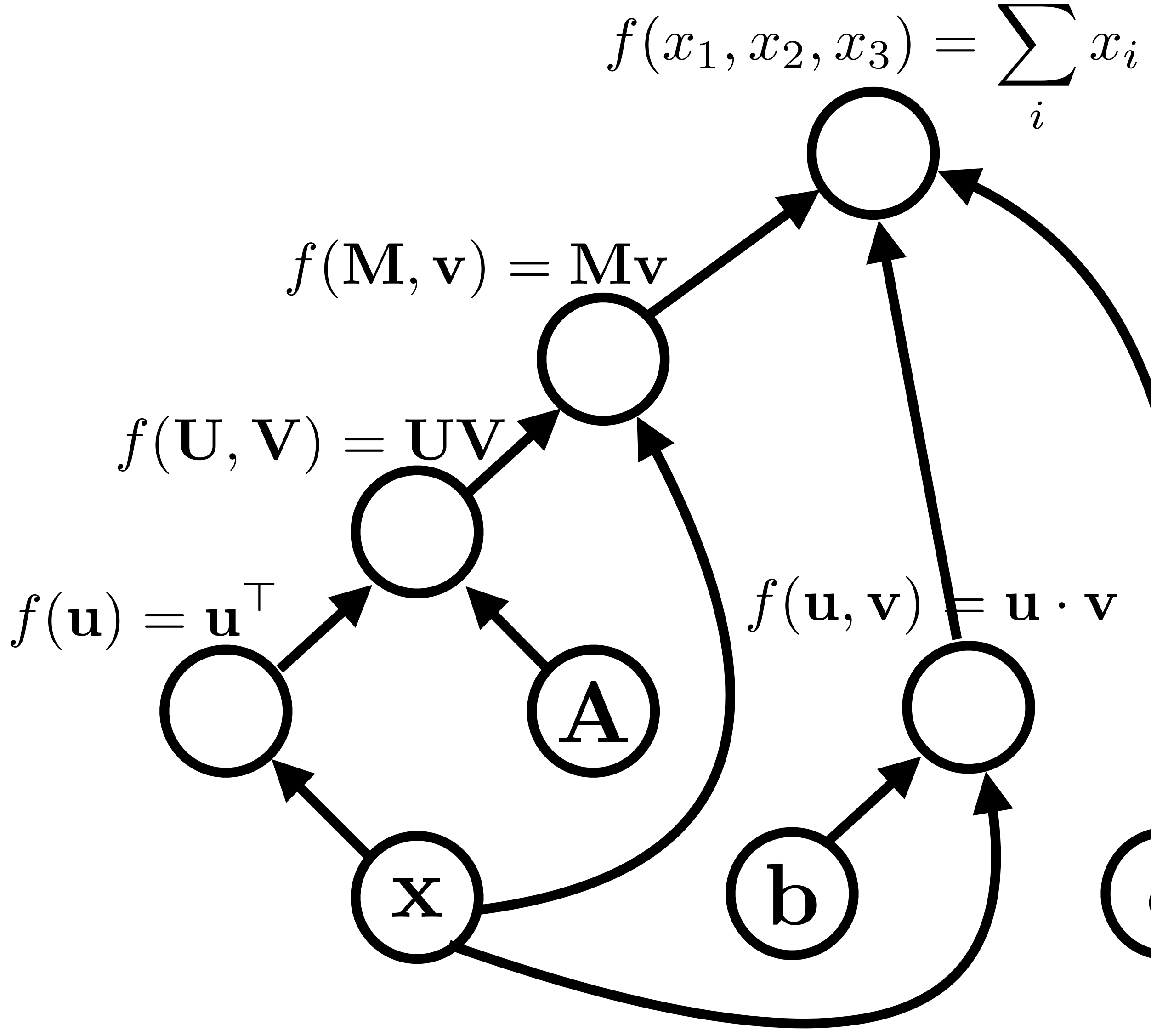
variable names are just labelings of nodes.

Algorithms (1)

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

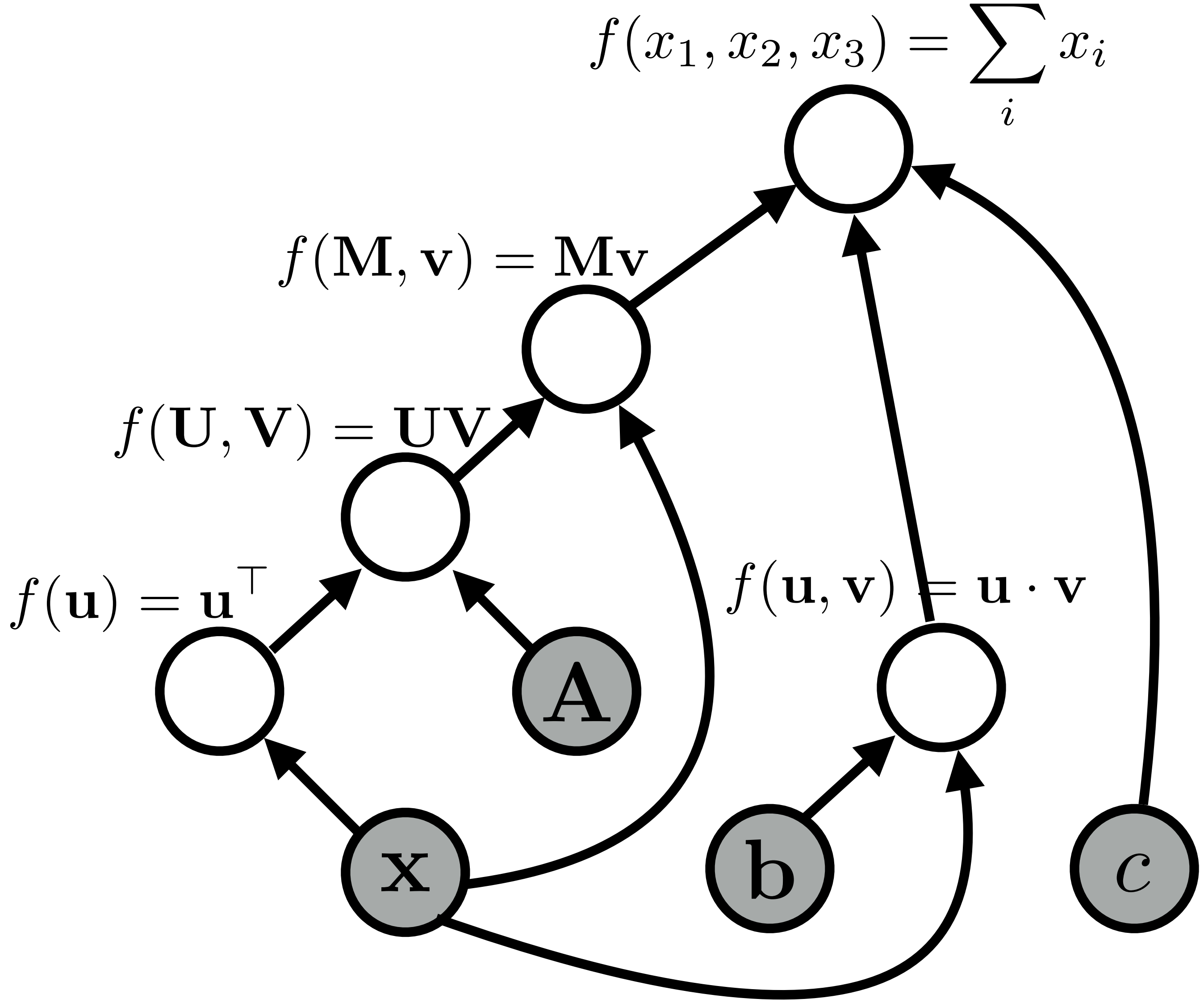
Forward Propagation

graph:



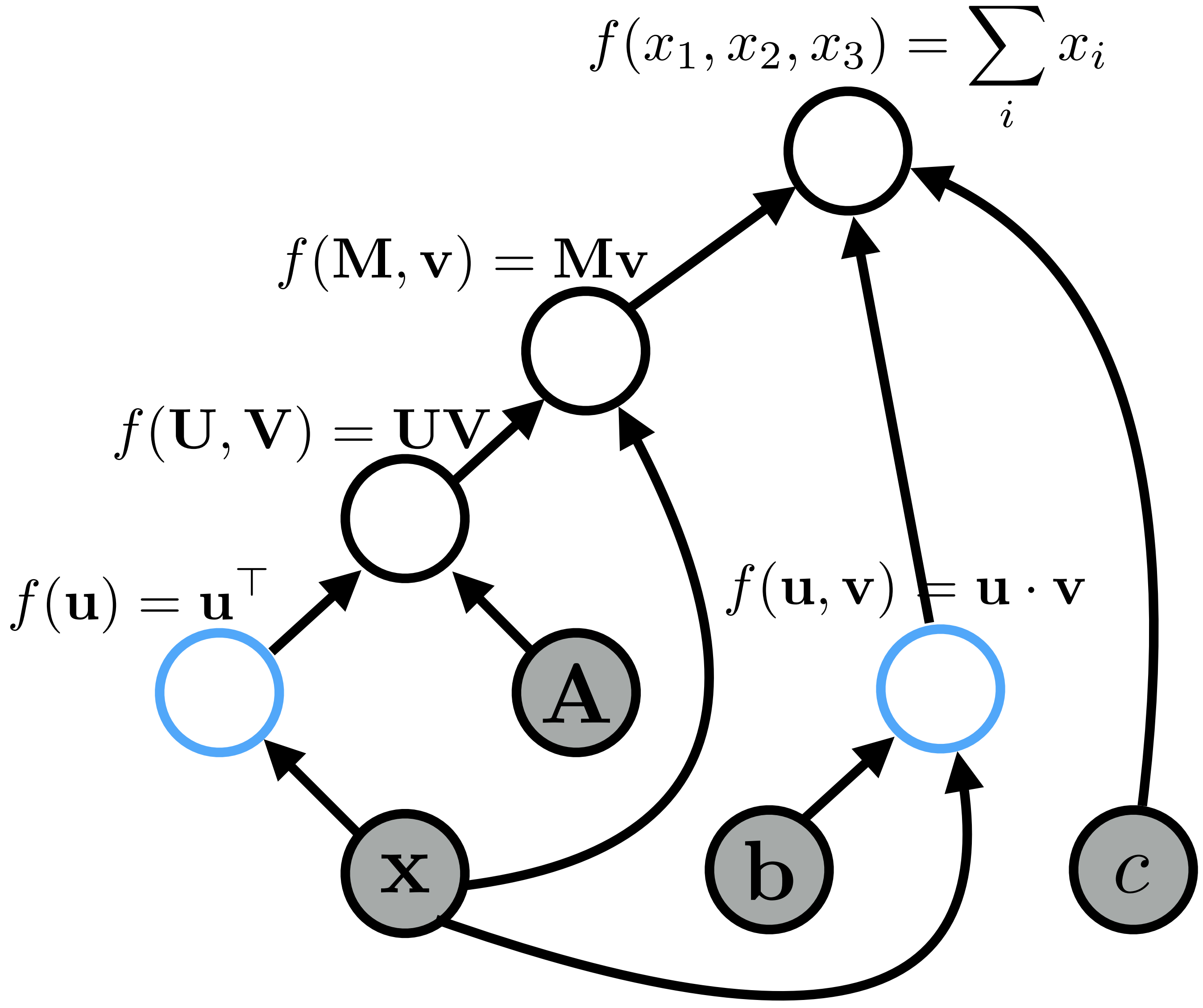
Forward Propagation

graph:



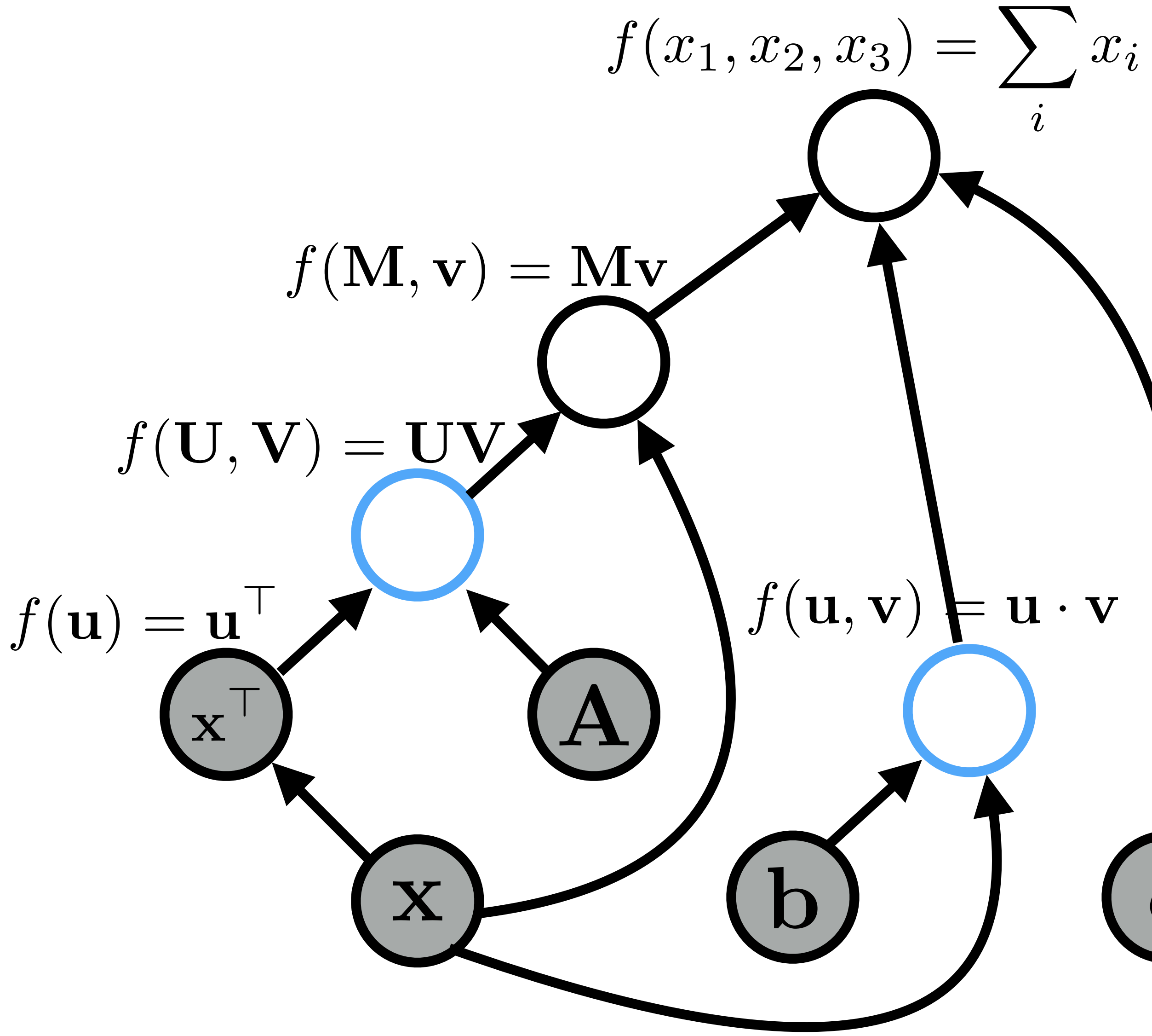
Forward Propagation

graph:



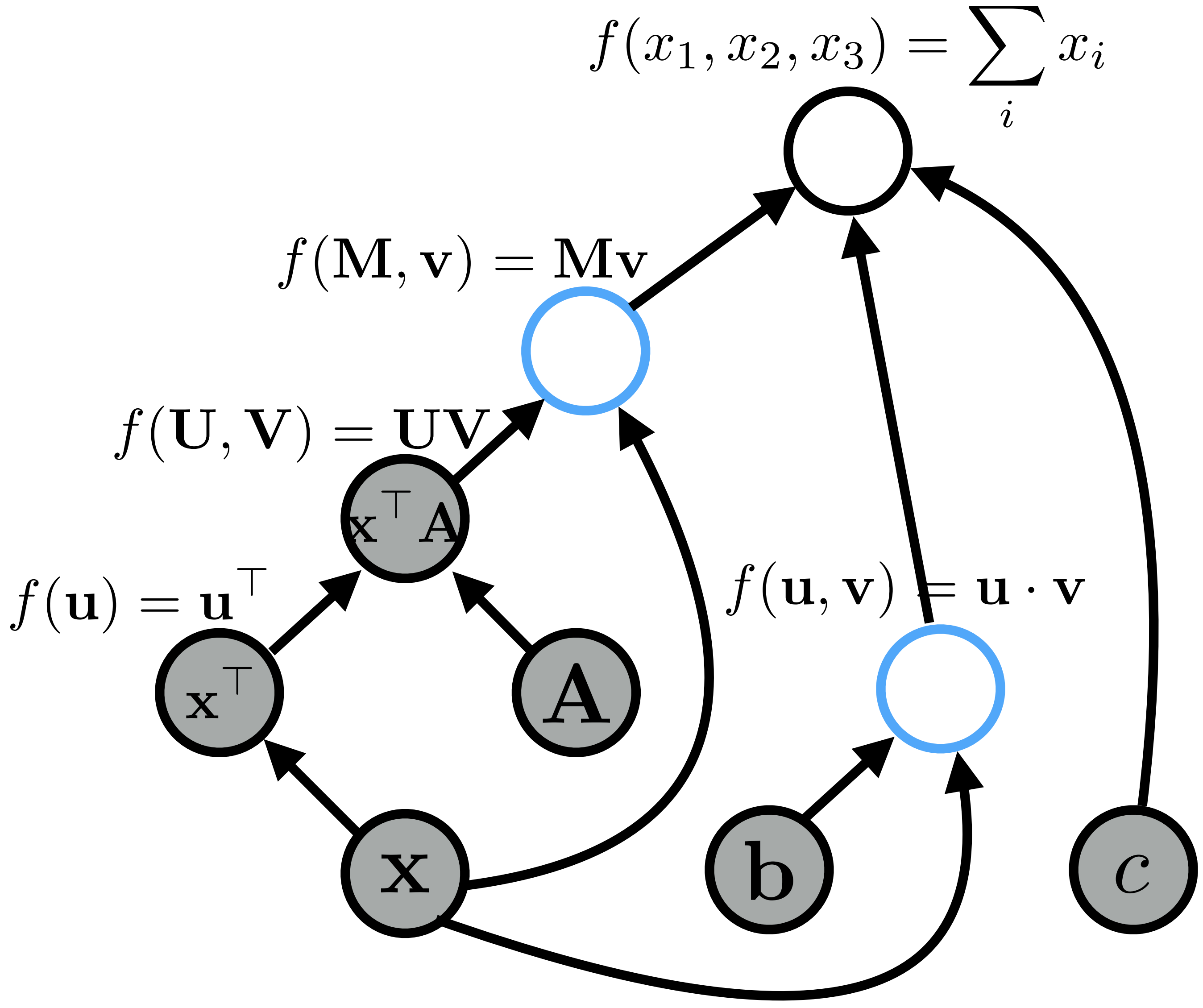
Forward Propagation

graph:



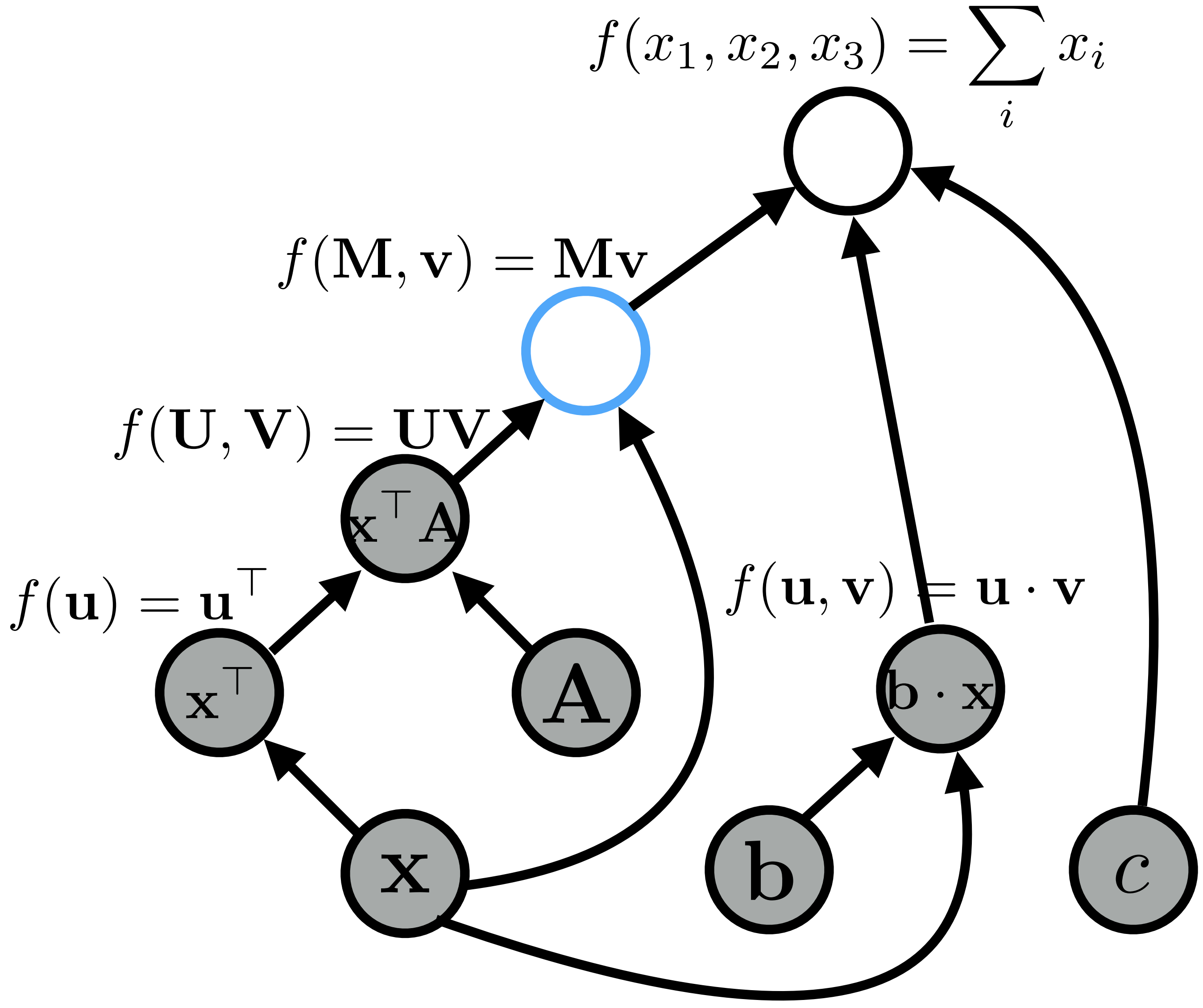
Forward Propagation

graph:



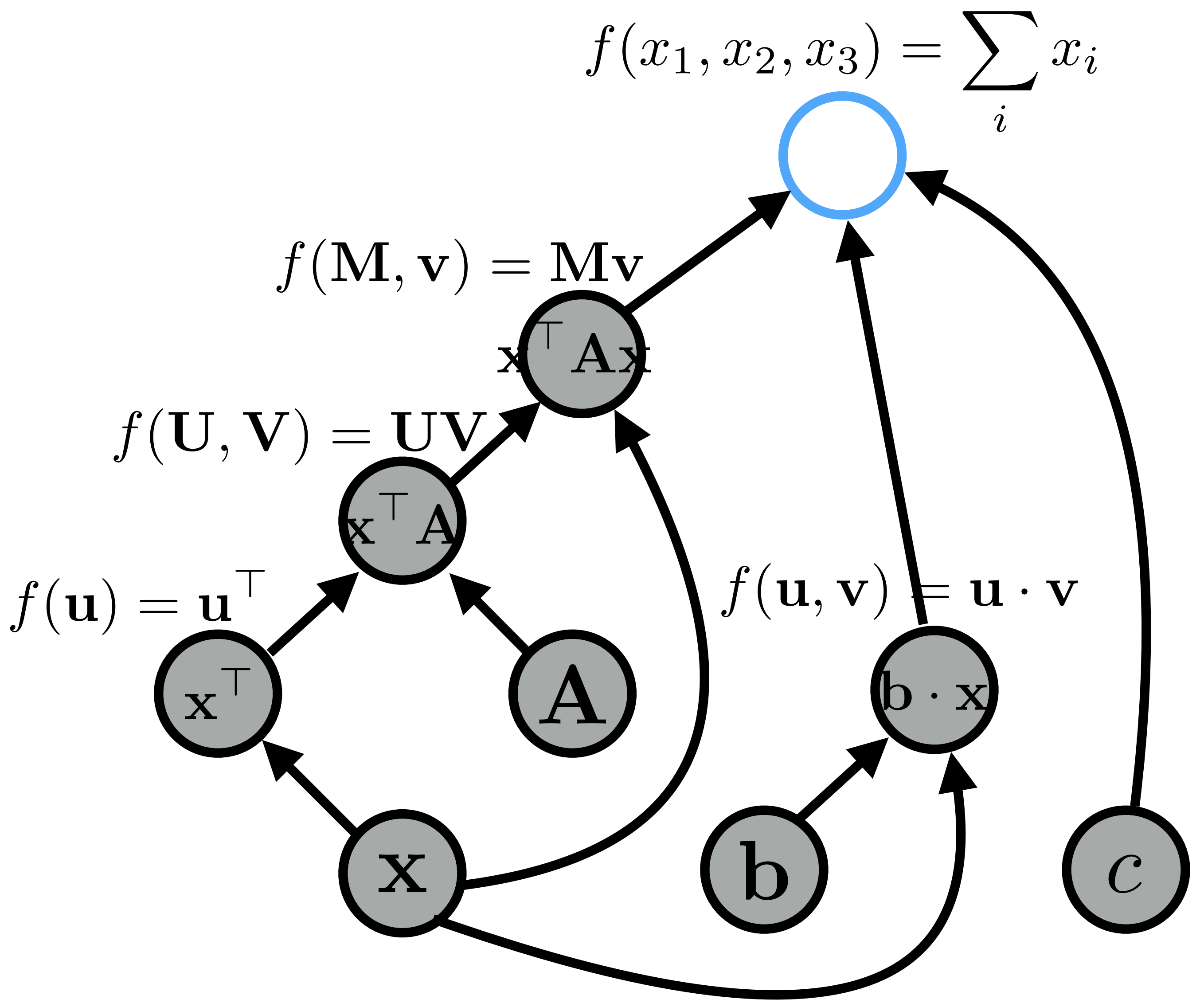
Forward Propagation

graph:



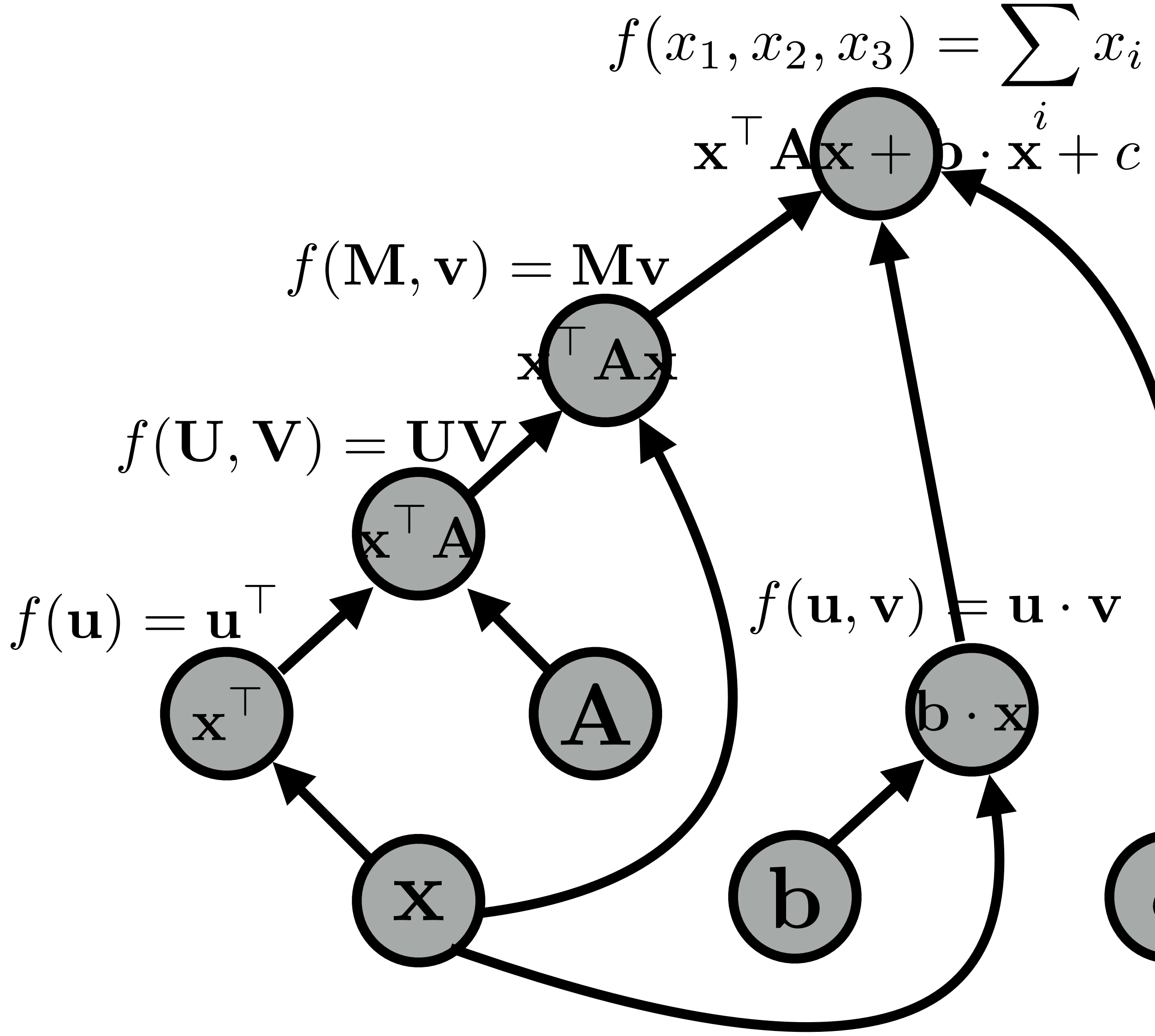
Forward Propagation

graph:



Forward Propagation

graph:

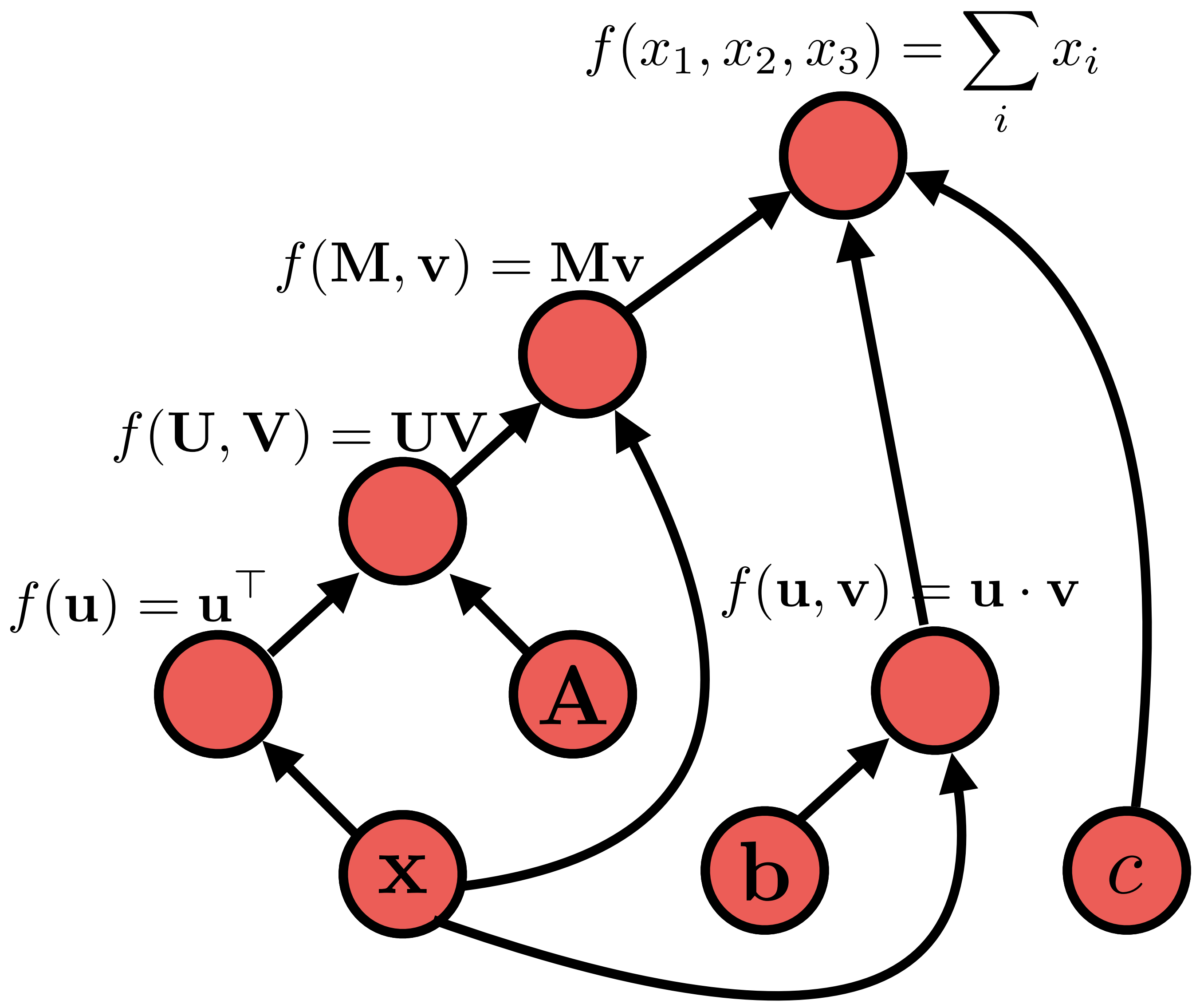


Algorithms (2)

- **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

Back Propagation

graph:



Concrete Implementation Examples

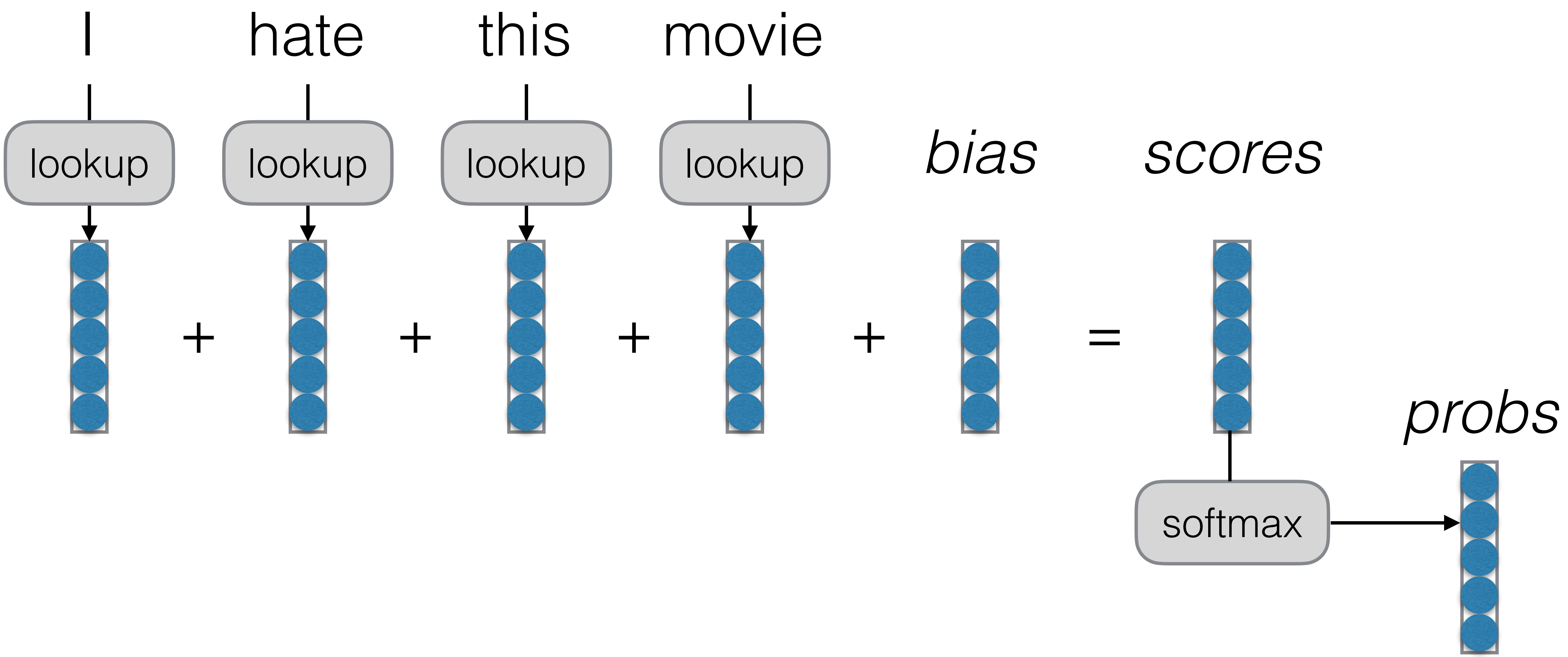
Neural Network Frameworks

PYTORCH	TensorFlow
Developed by FAIR/Meta	Developed by Google
Most widely used in NLP	Used in some NLP projects
Favors dynamic execution	Favors definition+compilation
More flexibility	Conceptually simple parallelization
Most vibrant ecosystem	

Basic Process in Neural Network Frameworks

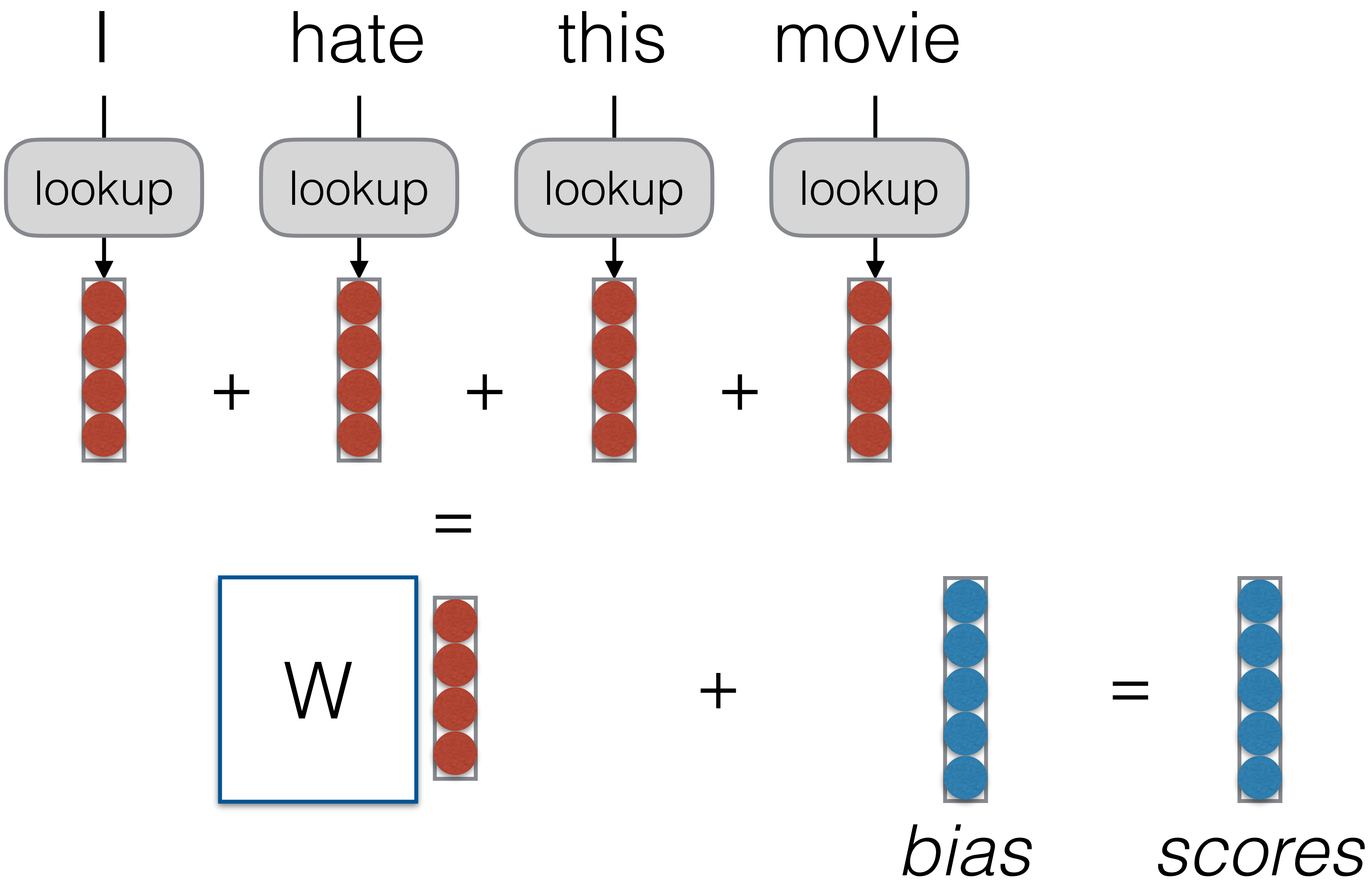
- Create a model
- For each example
  - **create a graph** that represents the computation you want
  - **calculate the result** of that computation
  - if training, perform **back propagation and update**

Bag of Words (BOW)



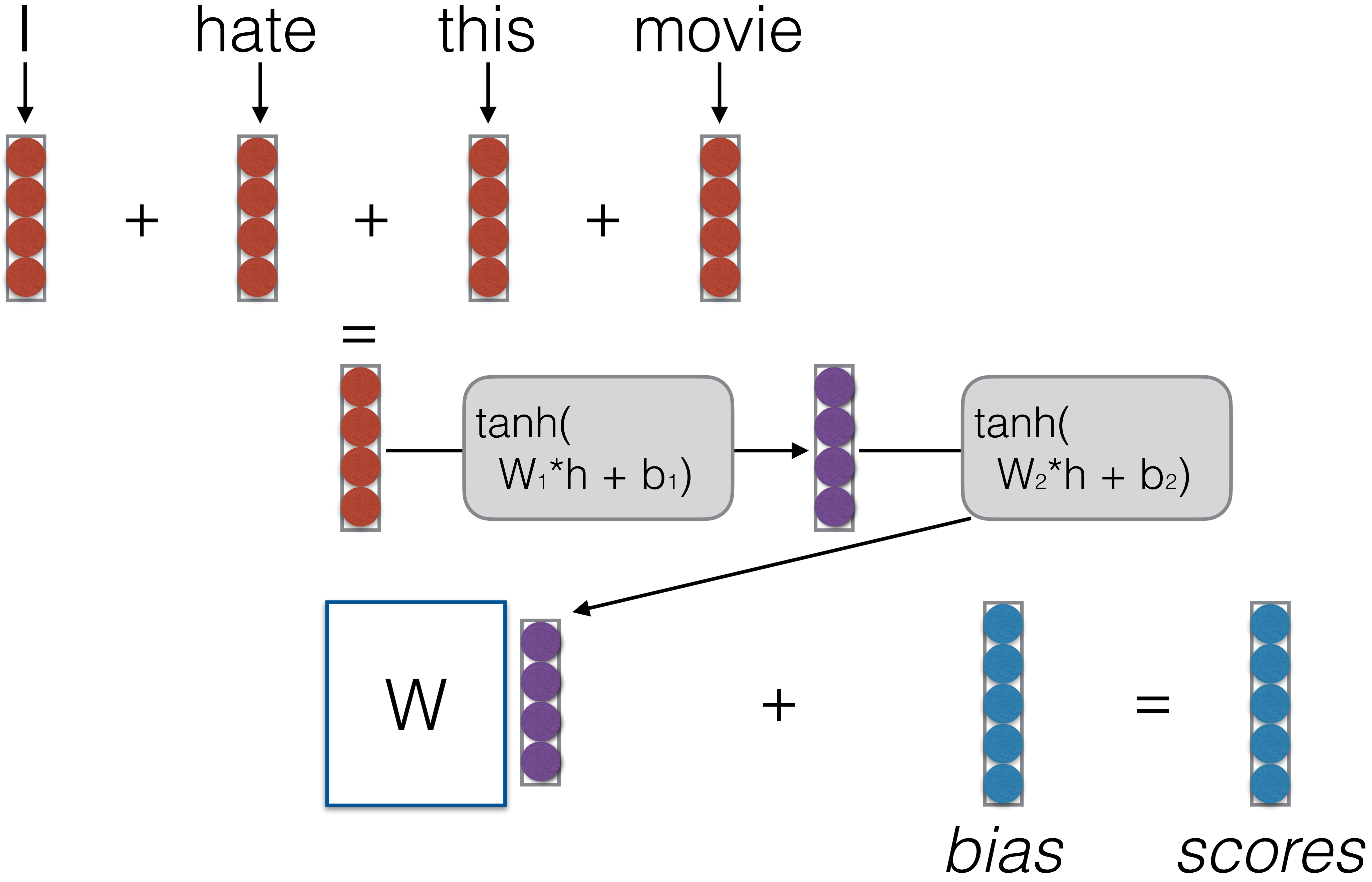
https://github.com/neubig/anlp-code/tree/main/02-textclass

Continuous Bag of Words (CBOW)



https://github.com/neubig/anlp-code/tree/main/02-textclass

Deep CBOW



https://github.com/neubig/anlp-code/tree/main/02-textclass

A Few More Important Concepts

A Better Optimizer: Adam

- Most standard optimization option in NLP and beyond
- Considers rolling average of gradient, and momentum

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

Momentum

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t \odot g_t$$

Rolling Average of Gradient

- Correction of bias early in training

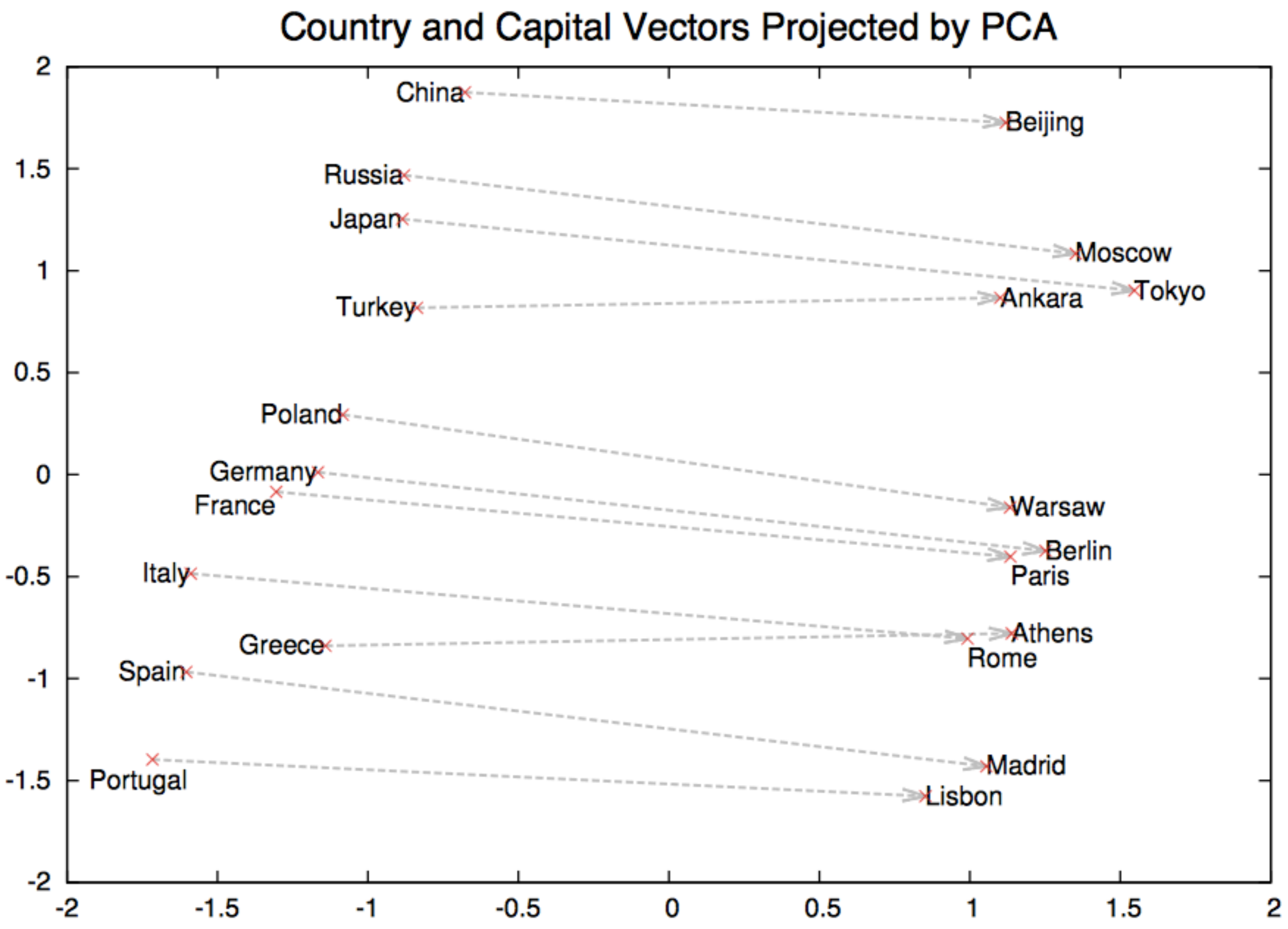
$$\hat{m}_t = \frac{m_t}{1 - (\beta_1)^t} \quad \hat{v}_t = \frac{v_t}{1 - (\beta_2)^t}$$

- Final update

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$$

Visualization of Embeddings

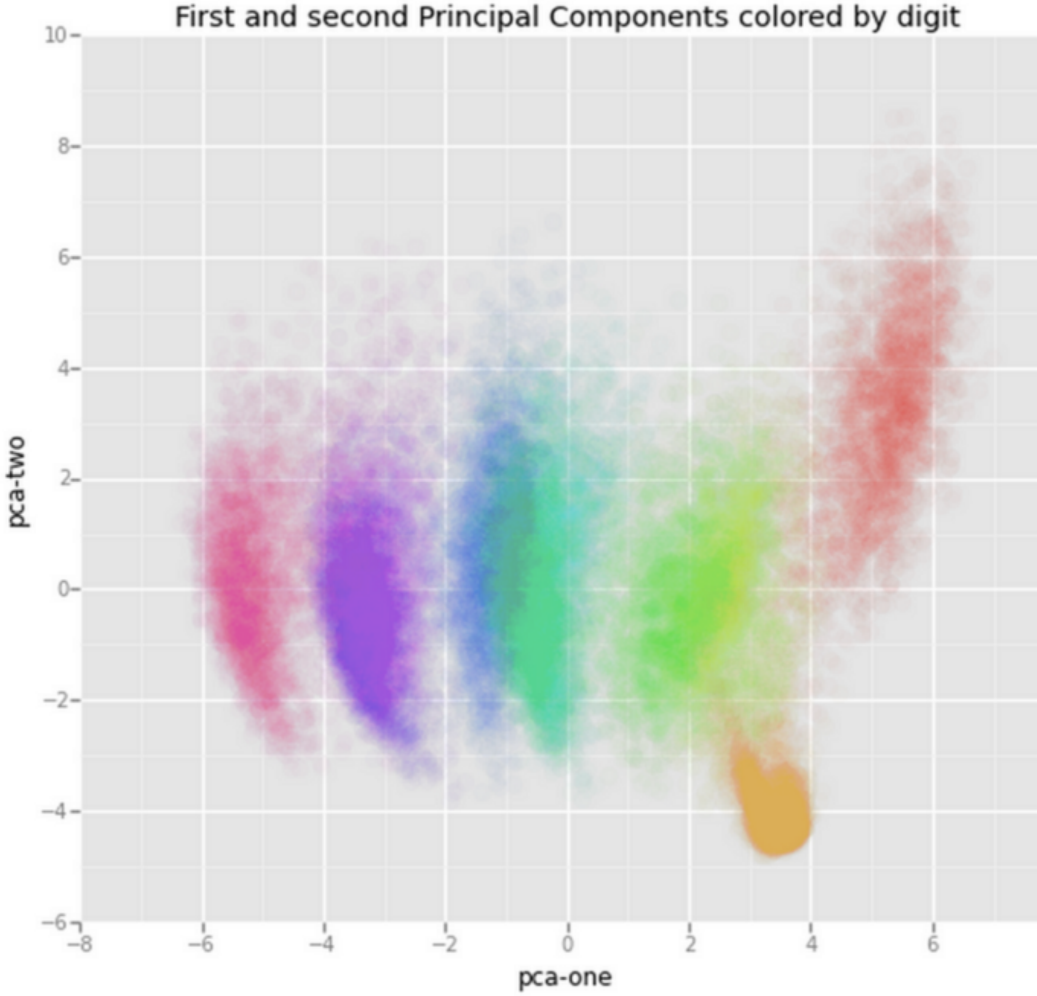
- Reduce high-dimensional embeddings into 2/3D for visualization (e.g. Mikolov et al. 2013)



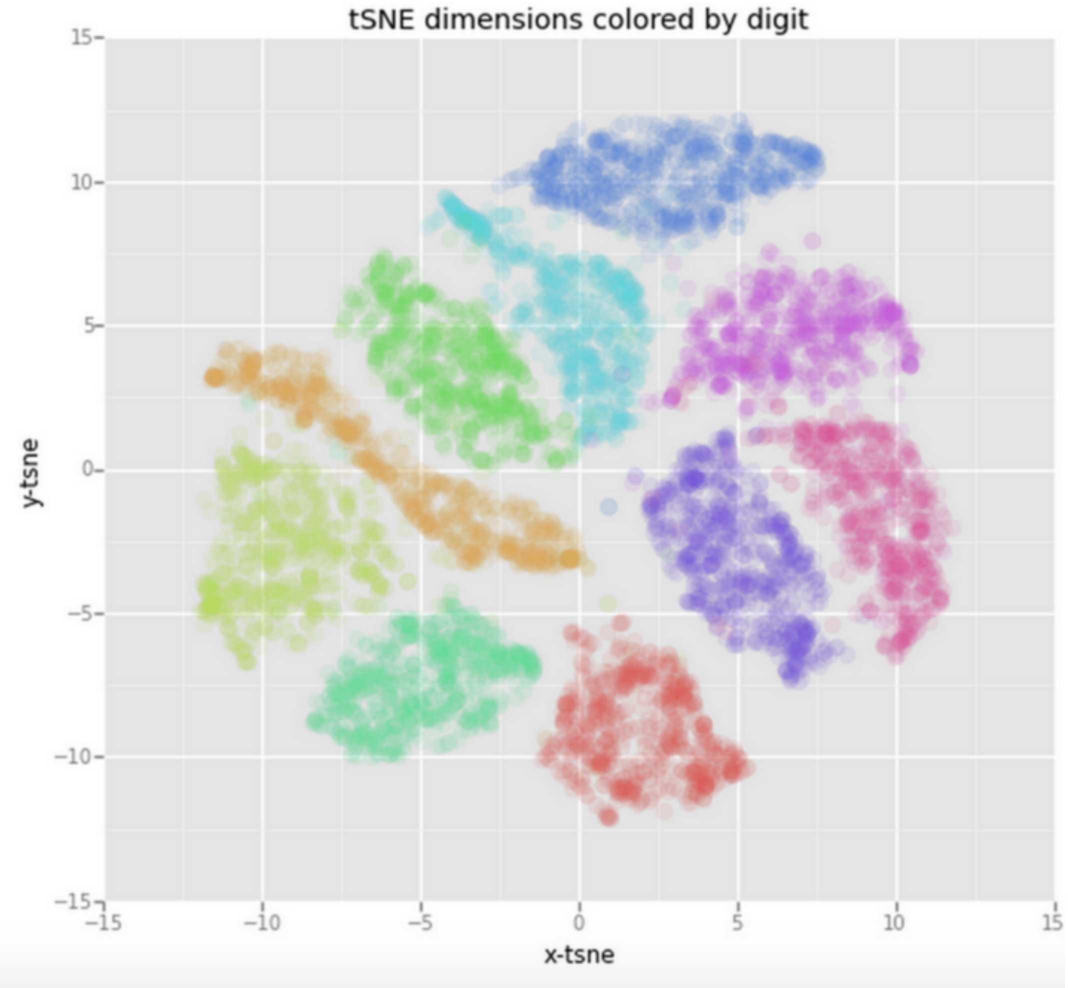
Non-linear Projection

- Non-linear projections group things that are close in high-dimensional space
- e.g. SNE/t-SNE (van der Maaten and Hinton 2008) group things that give each other a high probability according to a Gaussian

PCA



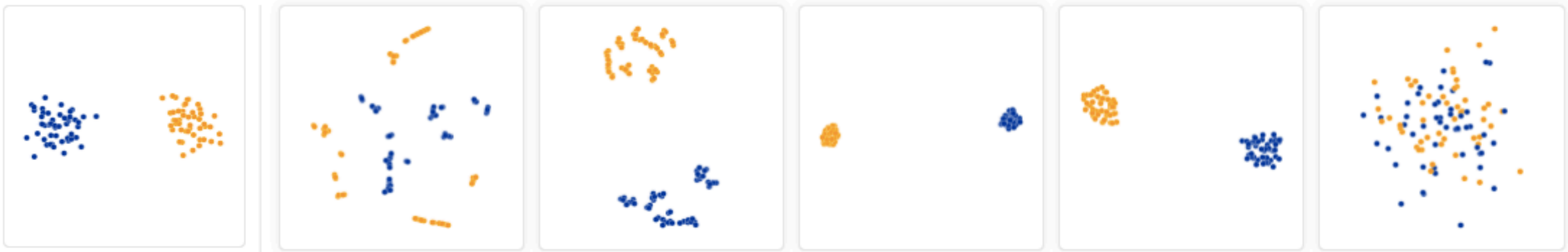
t-SNE



(Image credit: Derksen 2016)

t-SNE Visualization can be Misleading! (Wattenberg et al. 2016)

- Settings matter



Original

Perplexity: 2
Step: 5,000

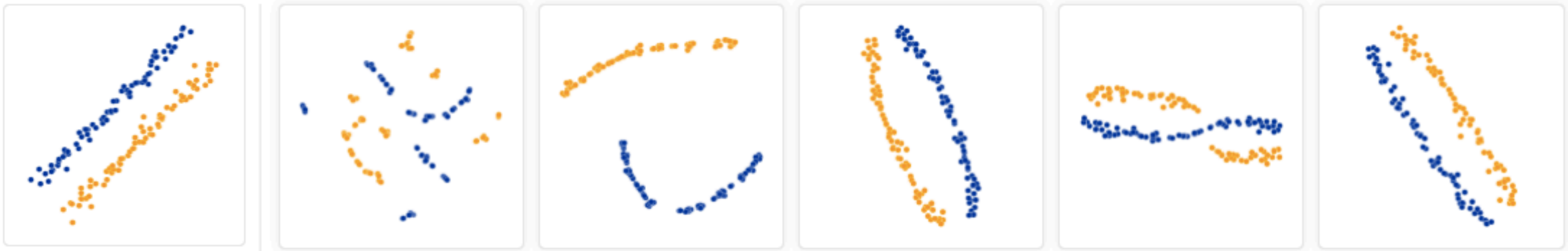
Perplexity: 5
Step: 5,000

Perplexity: 30
Step: 5,000

Perplexity: 50
Step: 5,000

Perplexity: 100
Step: 5,000

- Linear correlations cannot be interpreted



Original

Perplexity: 2
Step: 5,000

Perplexity: 5
Step: 5,000

Perplexity: 30
Step: 5,000

Perplexity: 50
Step: 5,000

Perplexity: 100
Step: 5,000

Any Questions?

(sequence models in next class)