CS11-737 Multilingual NLP

Text Classification and Sequence Labeling

Lei Li

https://lileicc.github.io/course/11737mnlp23fa/



Carnegie Mellon University

Language Technologies Institute

Text Classification

 Given an input text X, predict an output label y
 Topic Classification

I like peaches and

food
politics

music

politics like peaches and herk

politics music

food

<u>_anguage Identification</u>

like peaches and pears

English
Japanese
German

桃と梨が好き

English

Japanese

German

Sentiment Analysis (sentence/document-level)

like peaches and pears

positive

neutral

hate peaches and pears

negative

positive

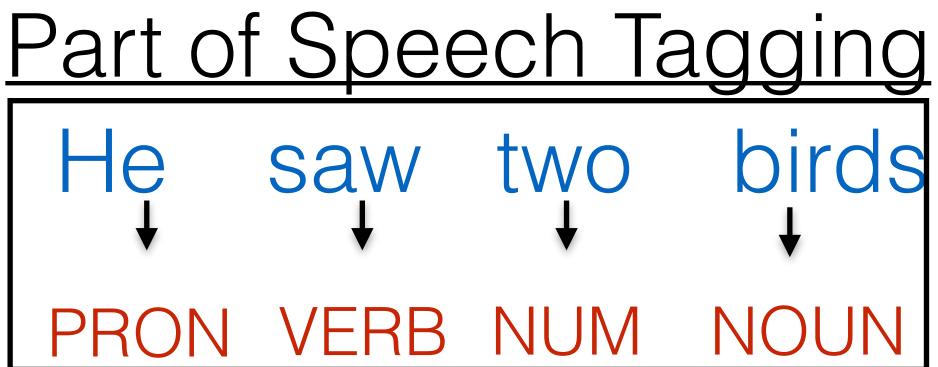
neutral

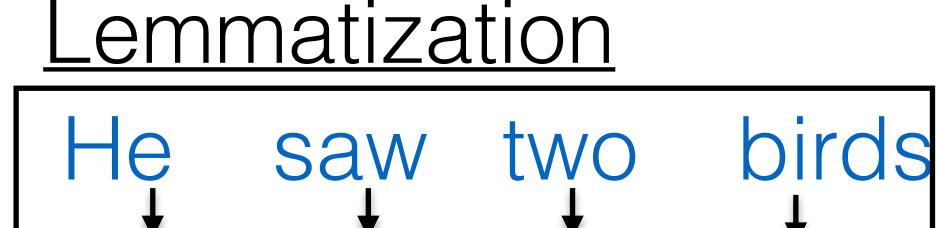
... and many many more!

<u>negative</u>

Sequence Labeling

Given an input text X, predict an output label sequence Y of equal length!







Morphological Tagging

```
Hesawtwobirds↓↓↓PronType=prsTense=past,<br/>VerbForm=finNumType=card<br/>Number=plur
```

... and more!

bird

Span Labeling

• Given an input text X, predict an output spans and labels Y.

Named Entity Recognition

```
Leo Messi plays for Inter Miami CF PER ORG
```

Syntactic Chunking

```
Leo Messi plays for Inter Miami CF NP VP NP
```

Semantic Role Labeling

```
<u>Leo Messi plays for Inter Miami CF</u>

Agent Predicate Theme
```

... and more!

Span Labeling as Sequence Labeling

 Predict Beginning, In, and Out tags for each word in a span

```
Leo Messi plays for Inter Miami CF
PER ORG
```



```
Leo Messi plays for Inter Miami CF
B-PER I-PER O O B-ORG I-ORG
```

Text Segmentation

Given an input text X, split it into segmented text Y.
 Tokenization

```
A well-conceived "thought exercise."
```

A well - conceived " thought exercise .

Word Segmentation (very important for web search)



Morphological Segmentation

```
Kopekier

Köpek ler

Hog Number=Plural

Köpekle r

Hog dog paddle Tense=Aorist
```

Rule-based (statistical), or span labeling models

Modeling for Sequence Labeling/ Classification

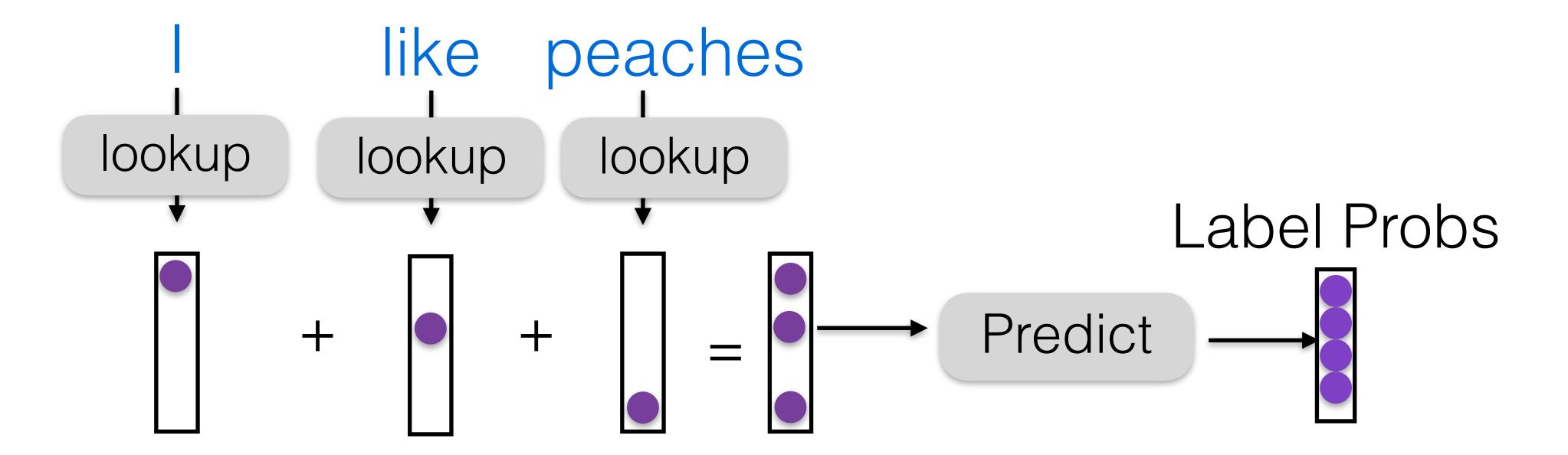
How do we Make Predictions?

- Given an input text X
- Extract features H
- Predict labels Y
 Text Classification

Predict
Predict
Feature Extractor
I | he peaches

A Simple Feature Extractor: Bag of Words (BOW)

Each word has a vector of weights for each tag



A Simple Predictor: Linear Transform+Softmax

$$p = softmax(W*h+b)$$

Softmax converts arbitrary scores into probabilities

$$p_{i} = \frac{e^{s_{i}}}{\sum_{j} e^{s_{j}}} \qquad \text{s=} \begin{pmatrix} 0.2 \\ -2.9 \\ 1.0 \\ 2.2 \\ 0.6 \end{pmatrix} \longrightarrow \text{p=} \begin{pmatrix} 0.002 \\ 0.003 \\ 0.329 \\ 0.444 \\ 0.090 \end{pmatrix}$$

Problem: Language is not a Bag of Words!

I don't love pears

There's nothing I don't love about pears

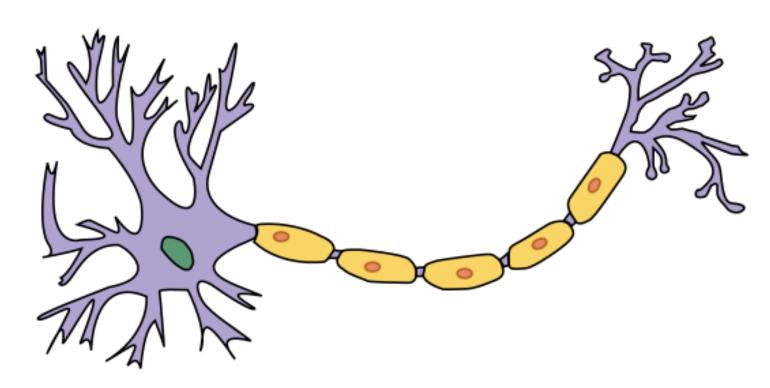
Better Featurizers

- Bag of n-grams
- Syntax-based features (e.g. subject-object pairs)
- Neural networks
 - Recurrent neural networks
 - Convolutional networks
 - Self attention

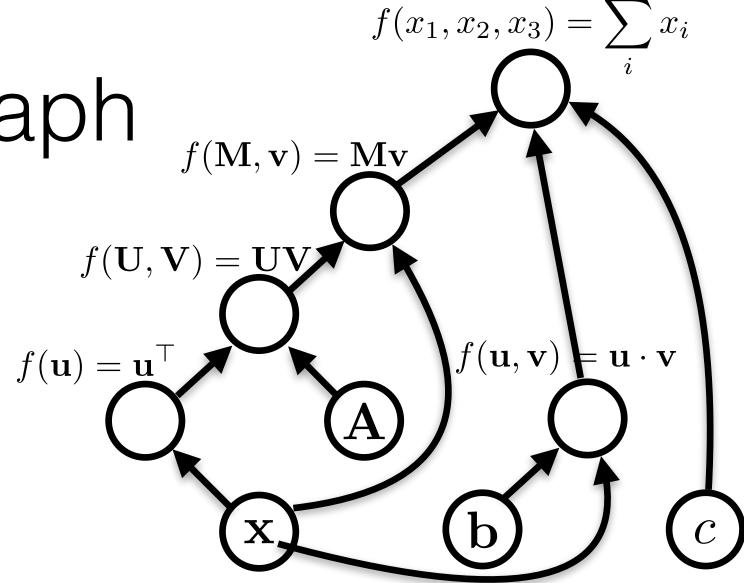
What is a Neural Net?: Computation Graphs

"Neural" Nets

Original Motivation: The Neurons in Brain



Neural Network is a Computational graph



 \mathbf{X}

graph:

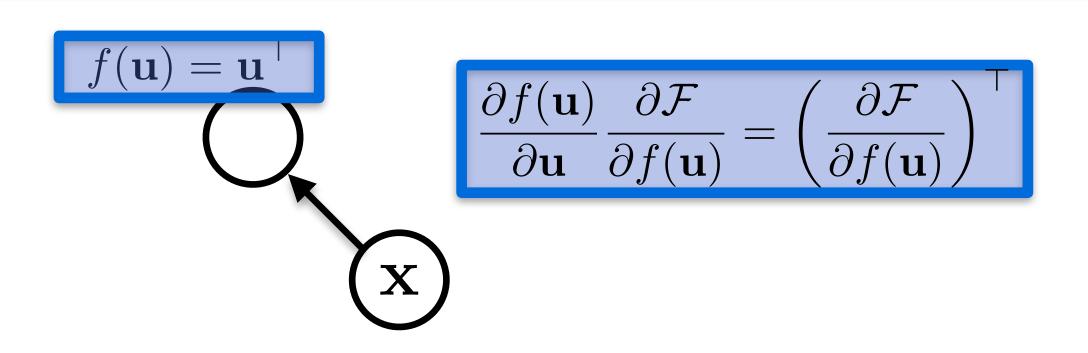
A node is a {tensor, matrix, vector, scalar} value



An edge represents a function argument.

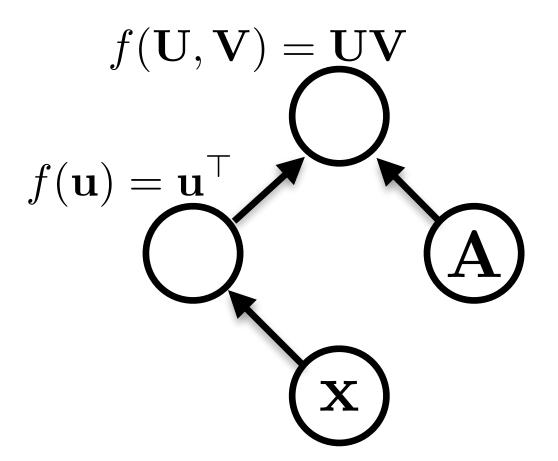
A **node** with an incoming **edge** is a **function** of that edge's tail node.

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



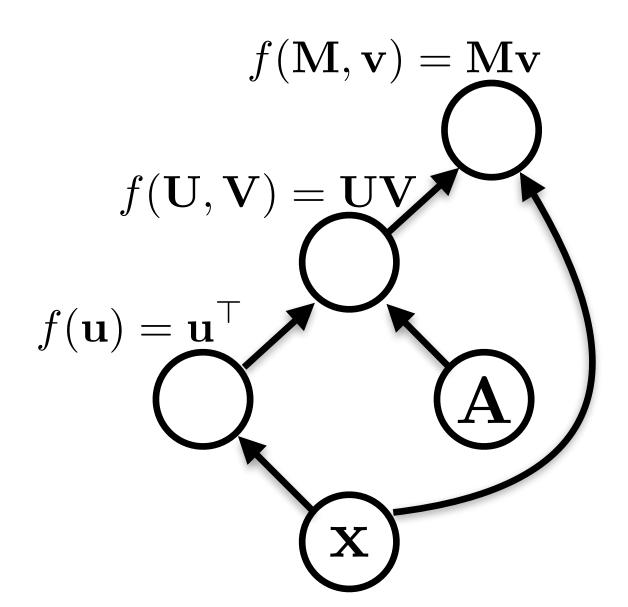
$$\mathbf{x}^{\top}\mathbf{A}$$

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



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

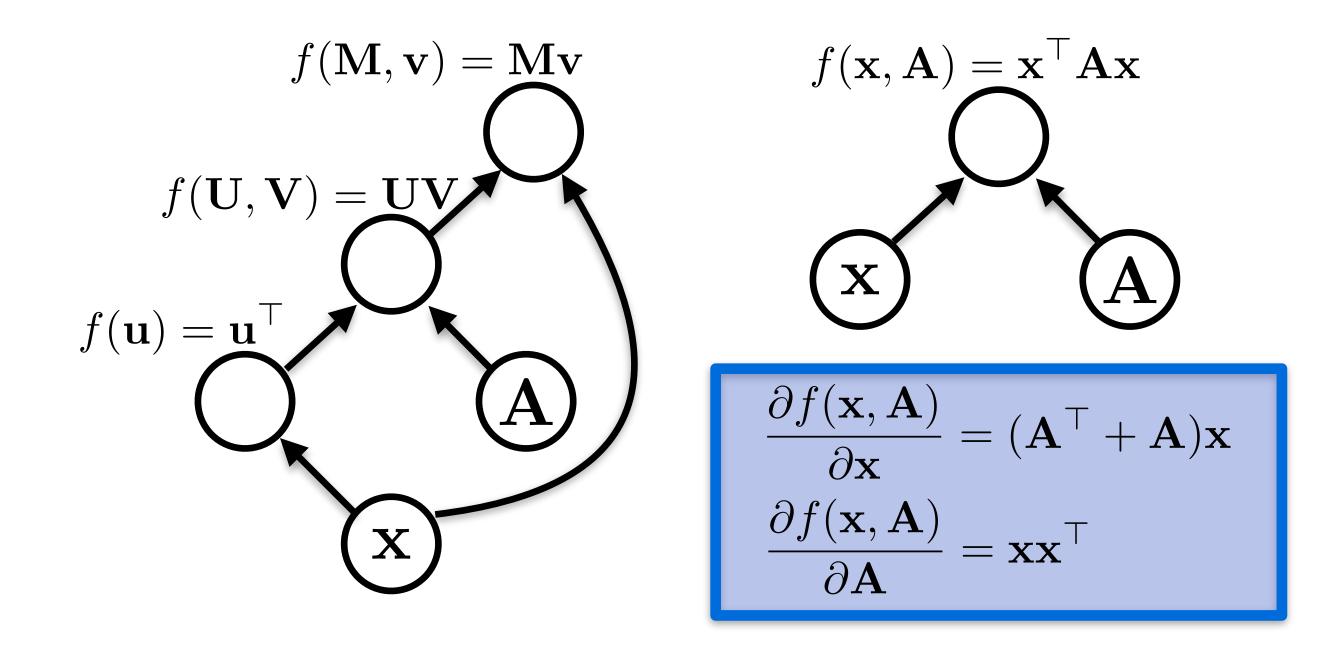
graph:



Computation graphs are generally directed and acyclic

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

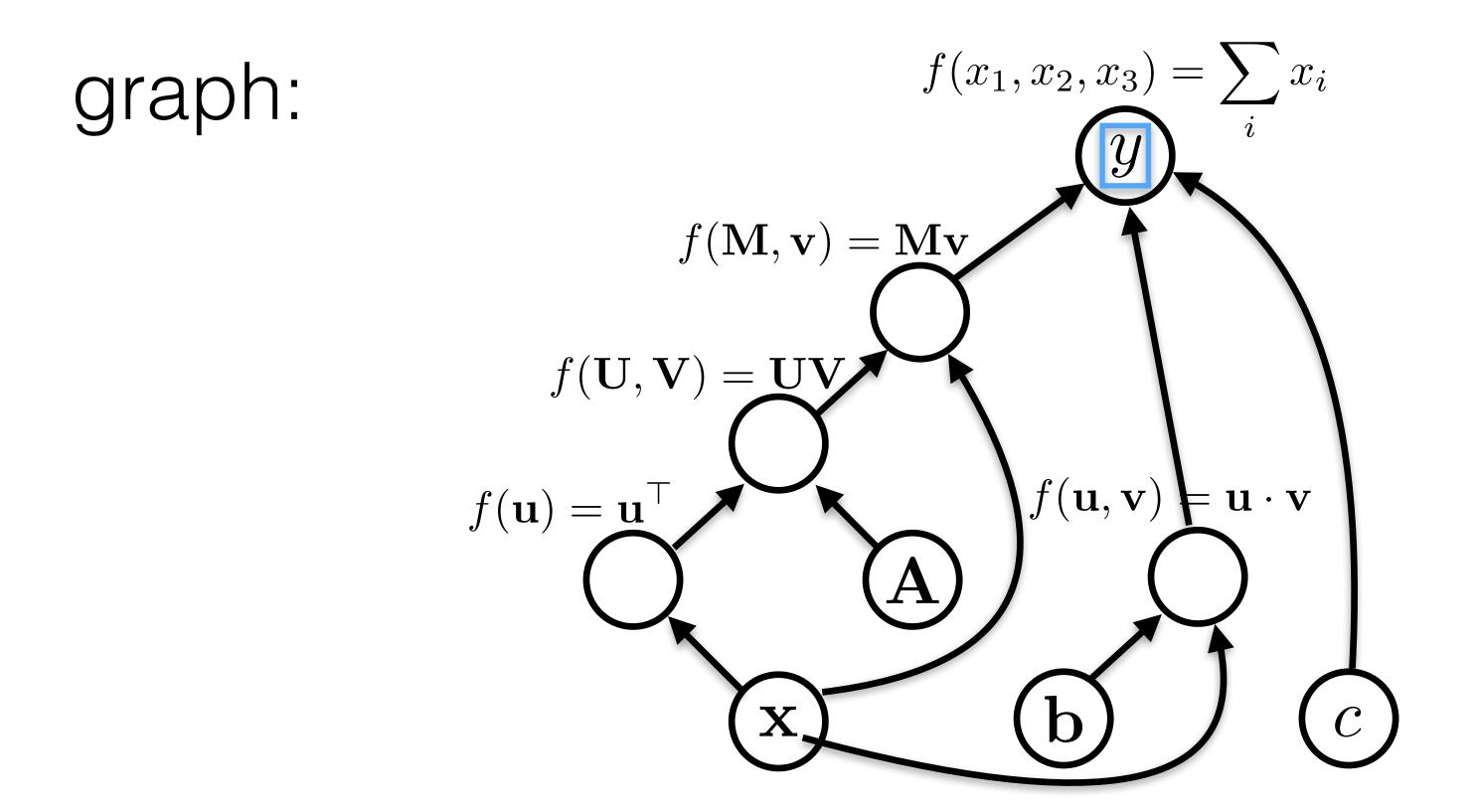
graph:



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

 $f(x_1, x_2, x_3) = \sum_{i} x_i$ graph: $f(\mathbf{M}, \mathbf{v}) = \mathbf{M}\mathbf{v}$ $f(\mathbf{U}, \mathbf{V}) = \mathbf{U}\mathbf{V}$ $f(\mathbf{u}, \mathbf{v}) \models \mathbf{u} \cdot \mathbf{v}$ $f(\mathbf{u}) = \mathbf{\underline{u}}^{\top}$

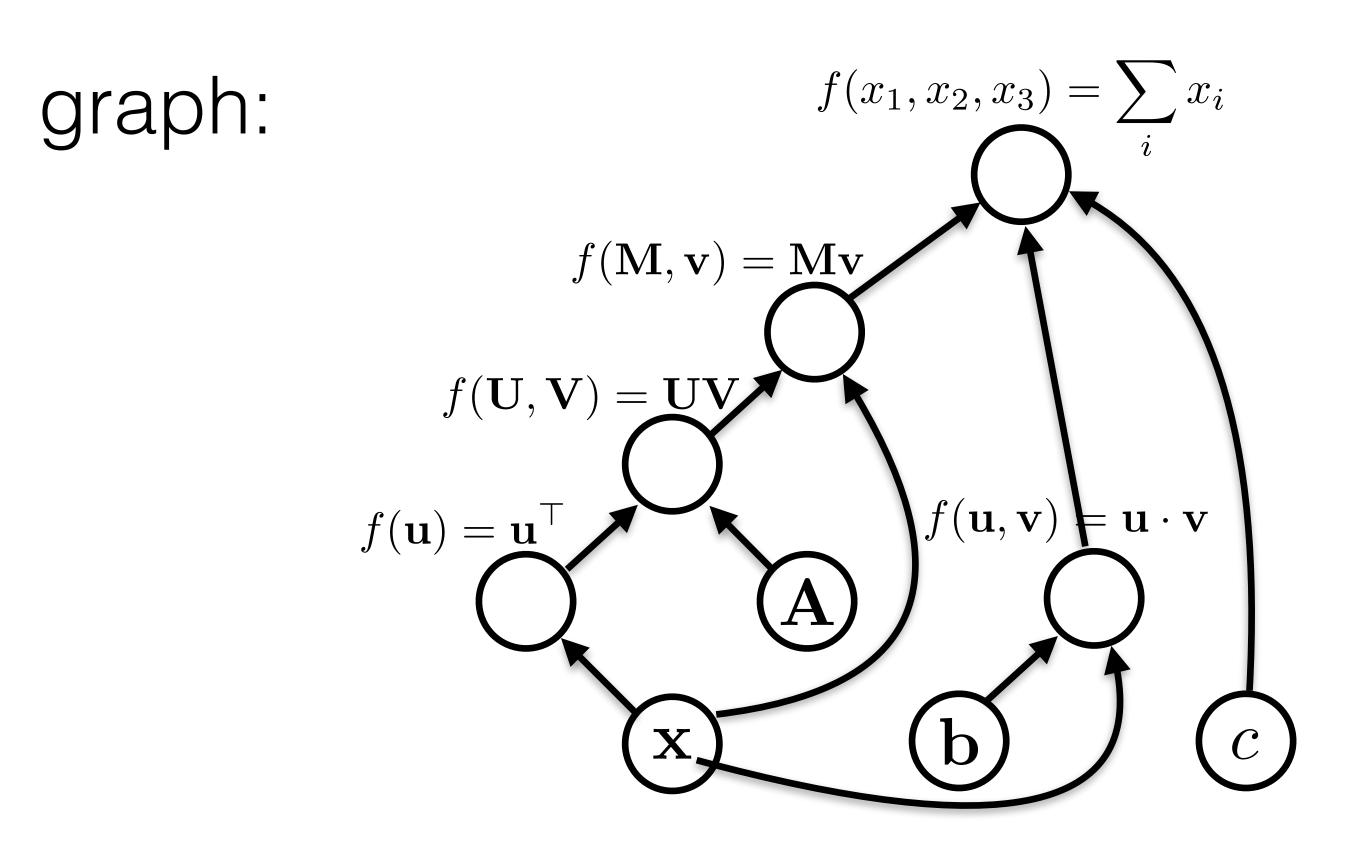
$$y = \mathbf{x}^{\mathsf{T}} \mathbf{A} \mathbf{x} + \mathbf{b} \cdot \mathbf{x} + c$$

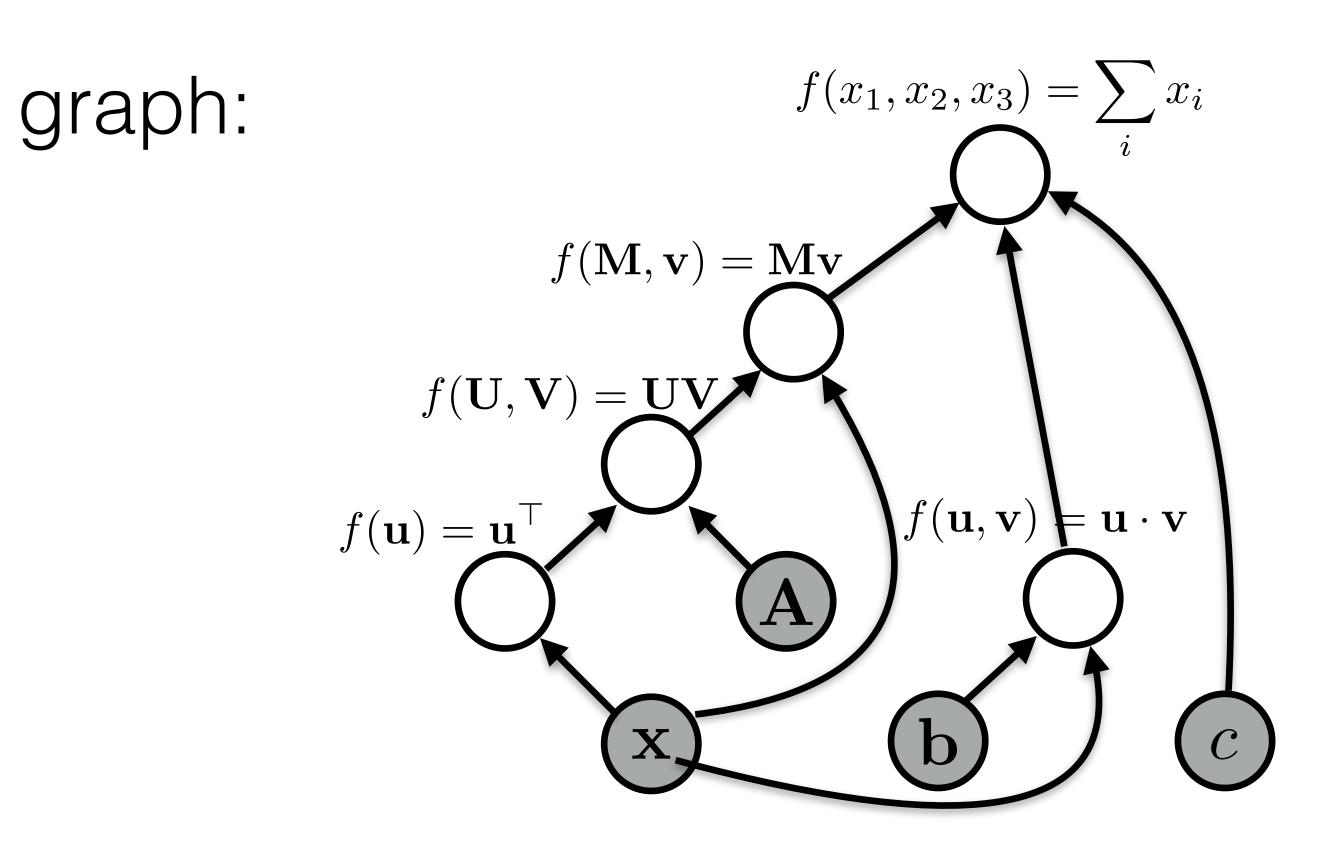


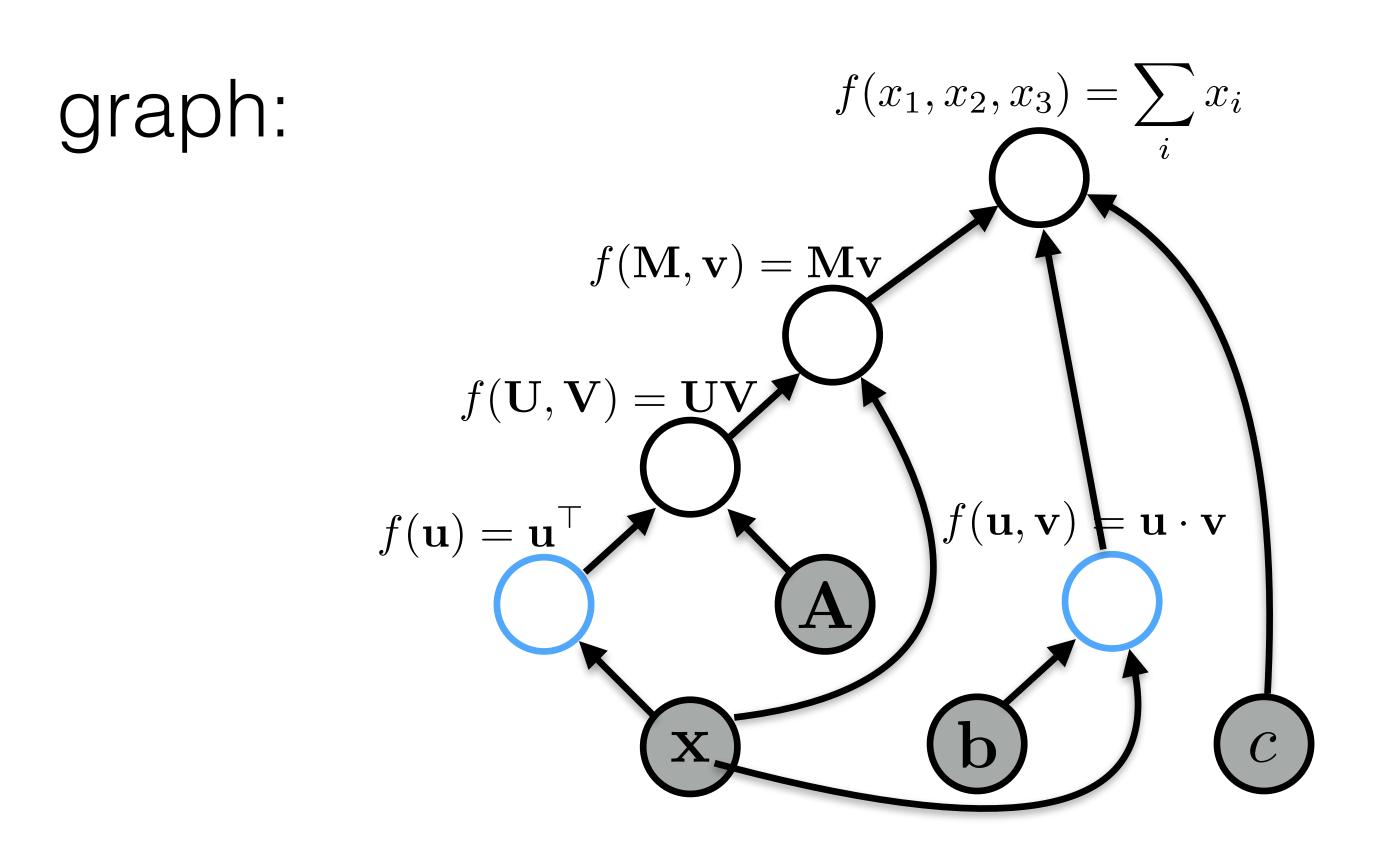
variable names are just labelings of nodes.

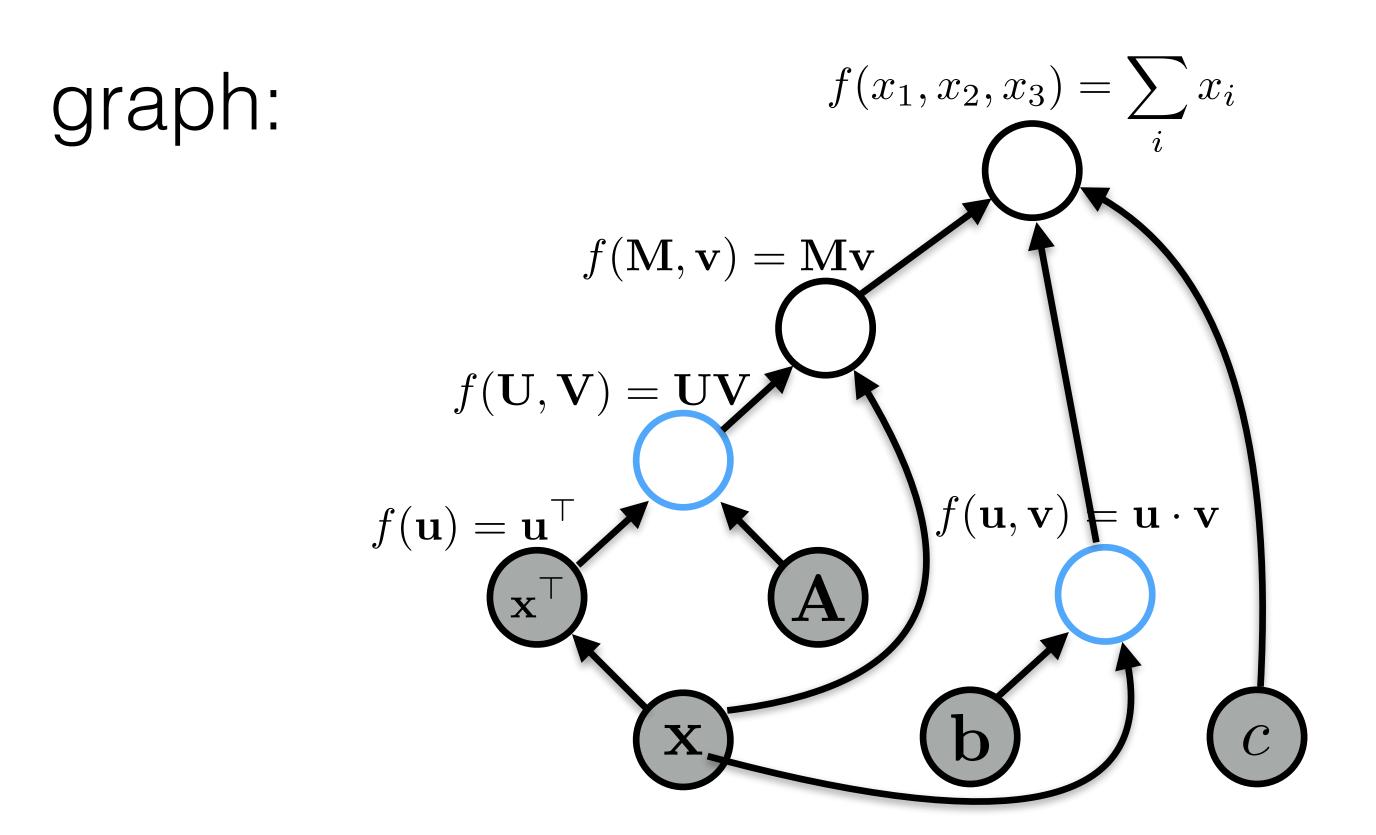
Algorithms (1)

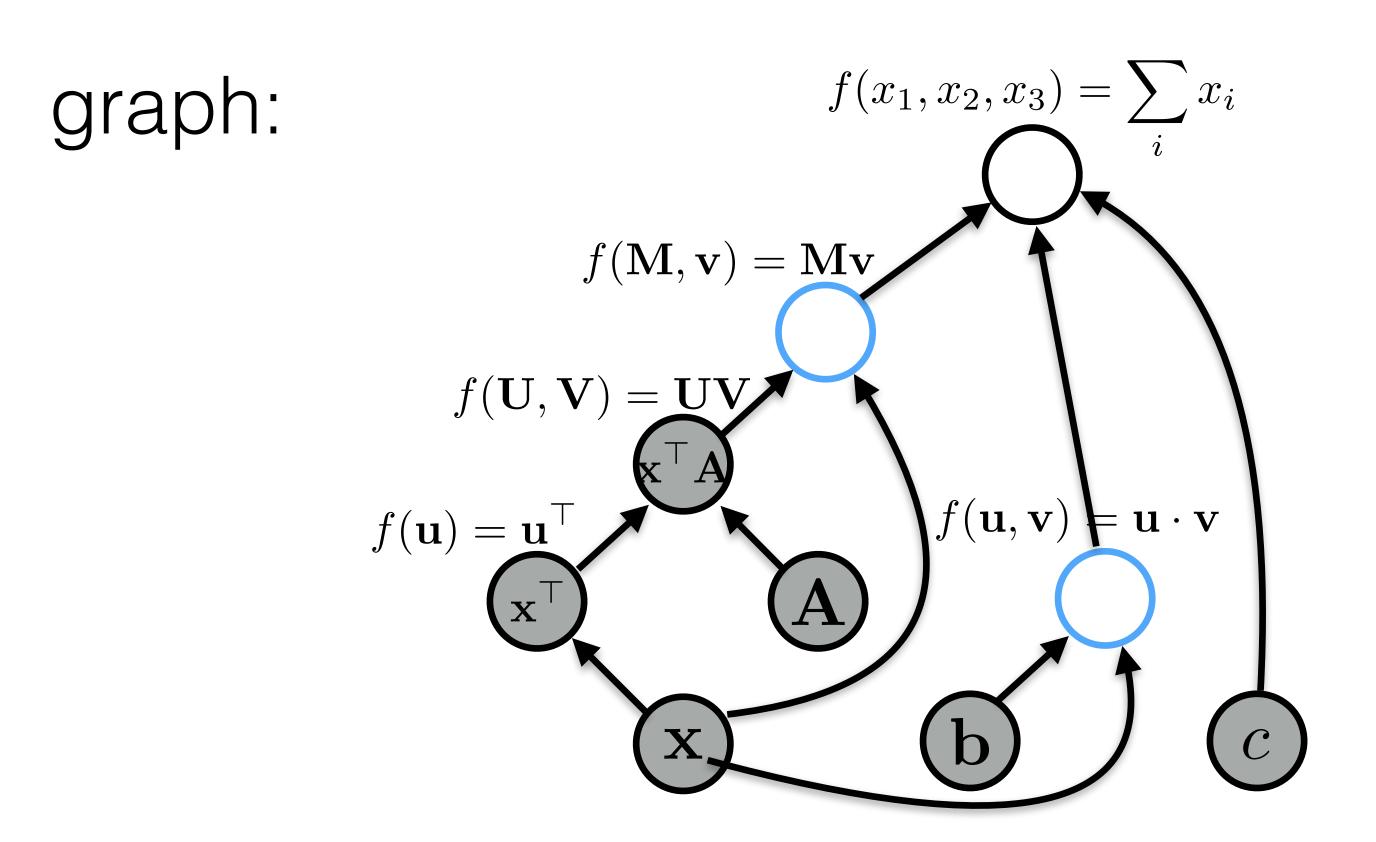
- Graph construction
- Forward propagation
 - In topological order, compute the value of the node given its inputs

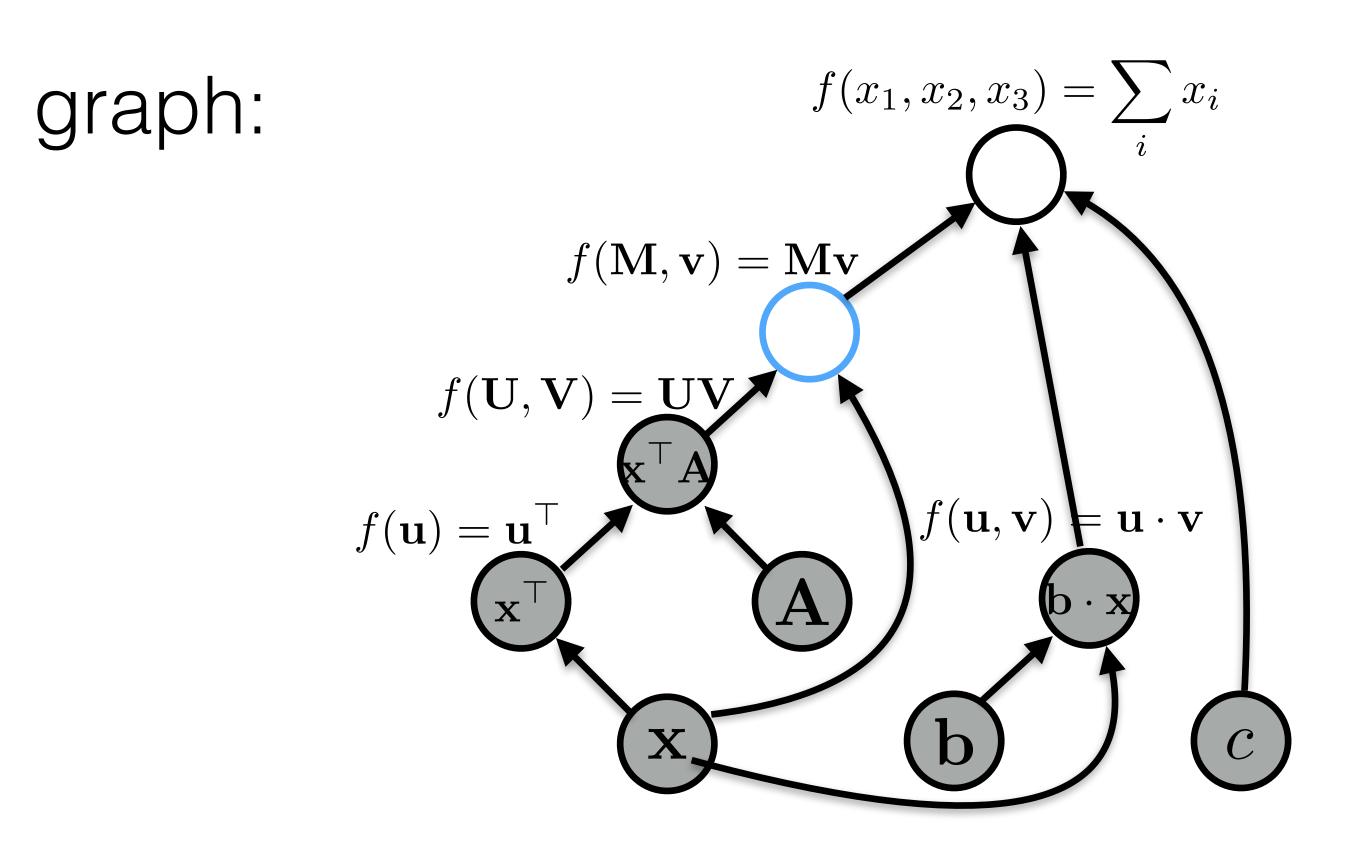


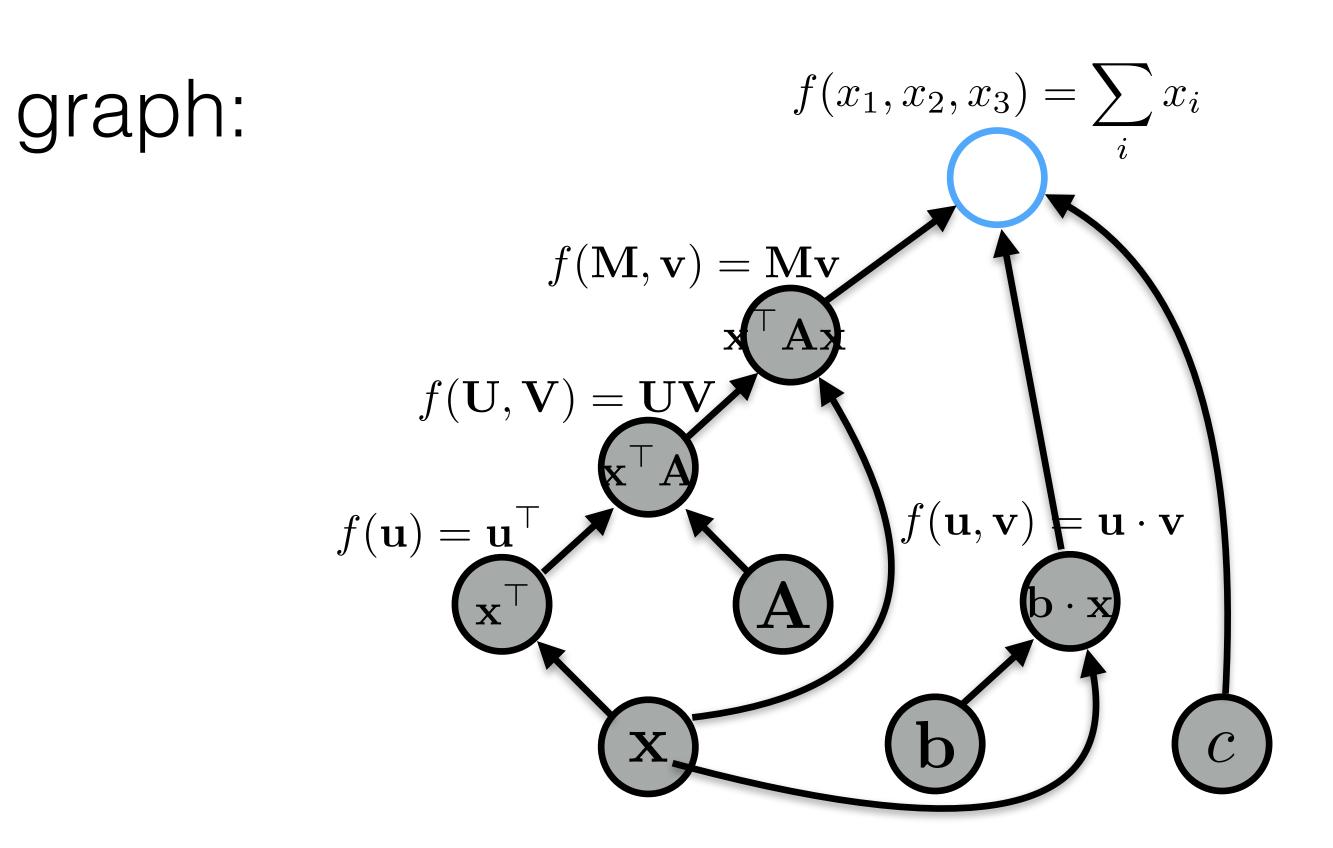


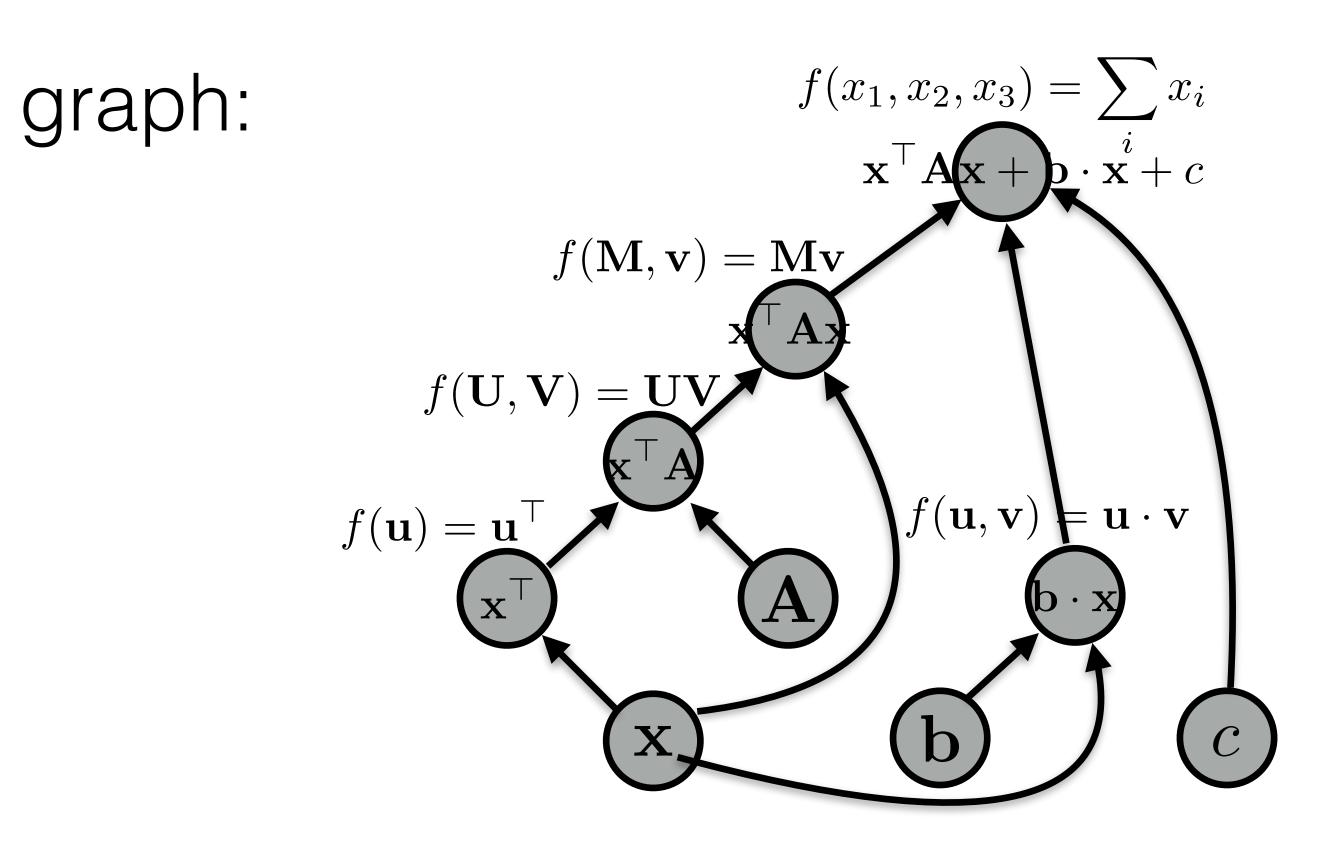












Algorithms (2)

- 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 $W \rightarrow \alpha * dI/dW$

Back Propagation

 $f(x_1, x_2, x_3) = \sum x_i$ graph: $f(\mathbf{M}, \mathbf{v}) = \mathbf{M}\mathbf{v}$ $f(\mathbf{U}, \mathbf{V}) = \mathbf{U}\mathbf{V}$ $f(\mathbf{u}, \mathbf{v}) \models \mathbf{u} \cdot \mathbf{v}$ $f(\mathbf{u}) = \mathbf{\underline{u}}^{\top}$

Neural Network Frameworks



Examples in this class





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

Pytorch Quick Tutorial

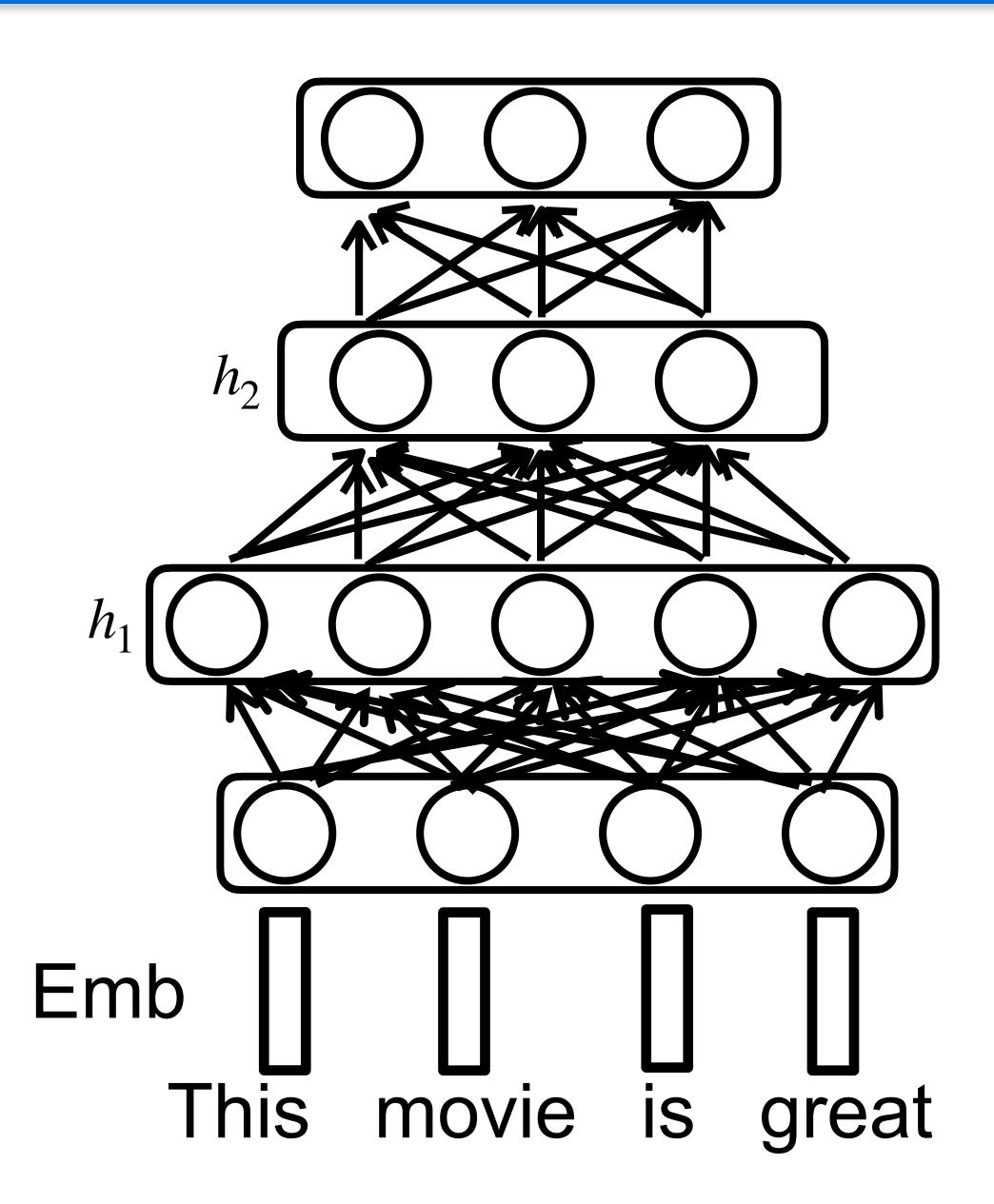
https://pytorch.org/tutorials/beginner/basics/intro.html

Feedforward Neural Net (FFN)

- also known as multilayer perceptron (MLP)
- Layers are connected sequentially
- Each layer has full-connection (each unit is connected to all units of next layer)
 - Linear project followed by
 - an element-wise nonlinear activation function

$$h = \sigma(w \cdot x + b)$$

 There is no connection from output to input



Recurrent Neural Networks

Long-distance Dependencies in Language

• Agreement in number, gender, etc.

He does not have very much confidence in himself.

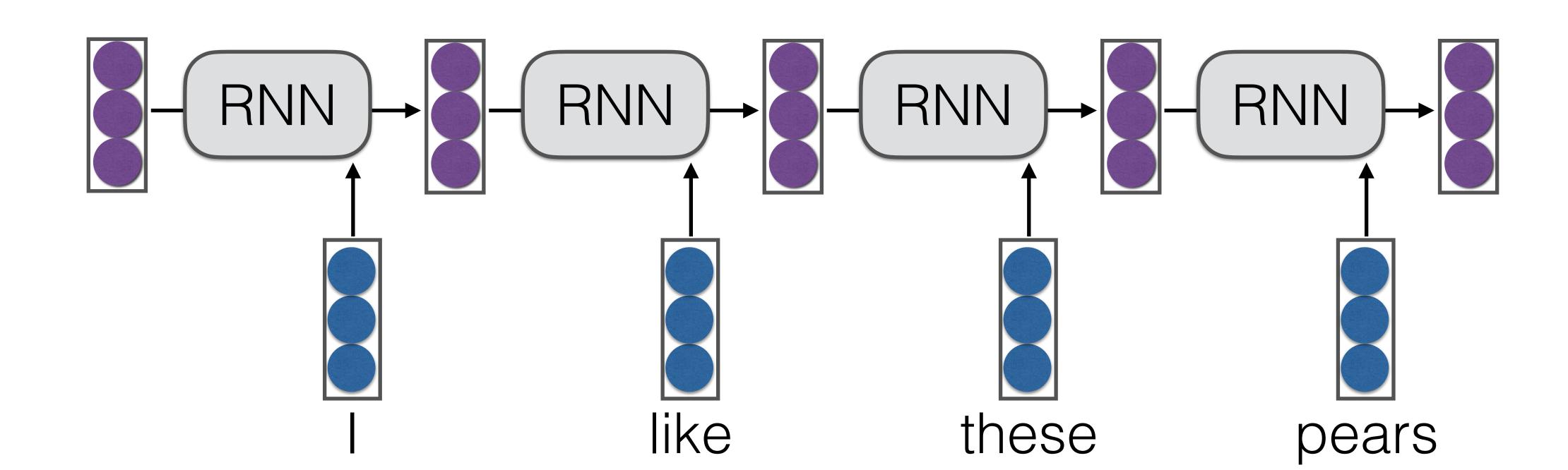
She does not have very much confidence in herself.

Selectional preference

The **reign** has lasted as long as the life of the **queen**. The **rain** has lasted as long as the life of the **clouds**.

Recurrent Neural Networks (Elman 1990)

Tools to "remember" information

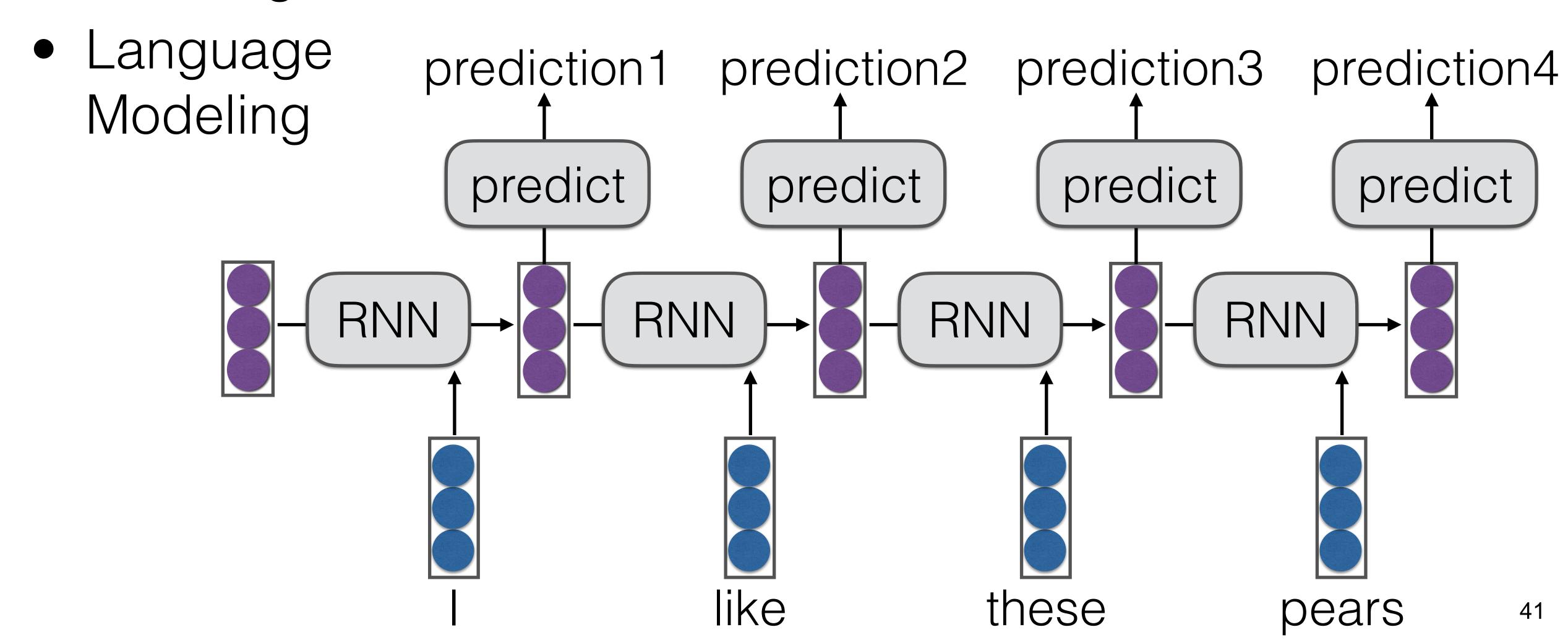


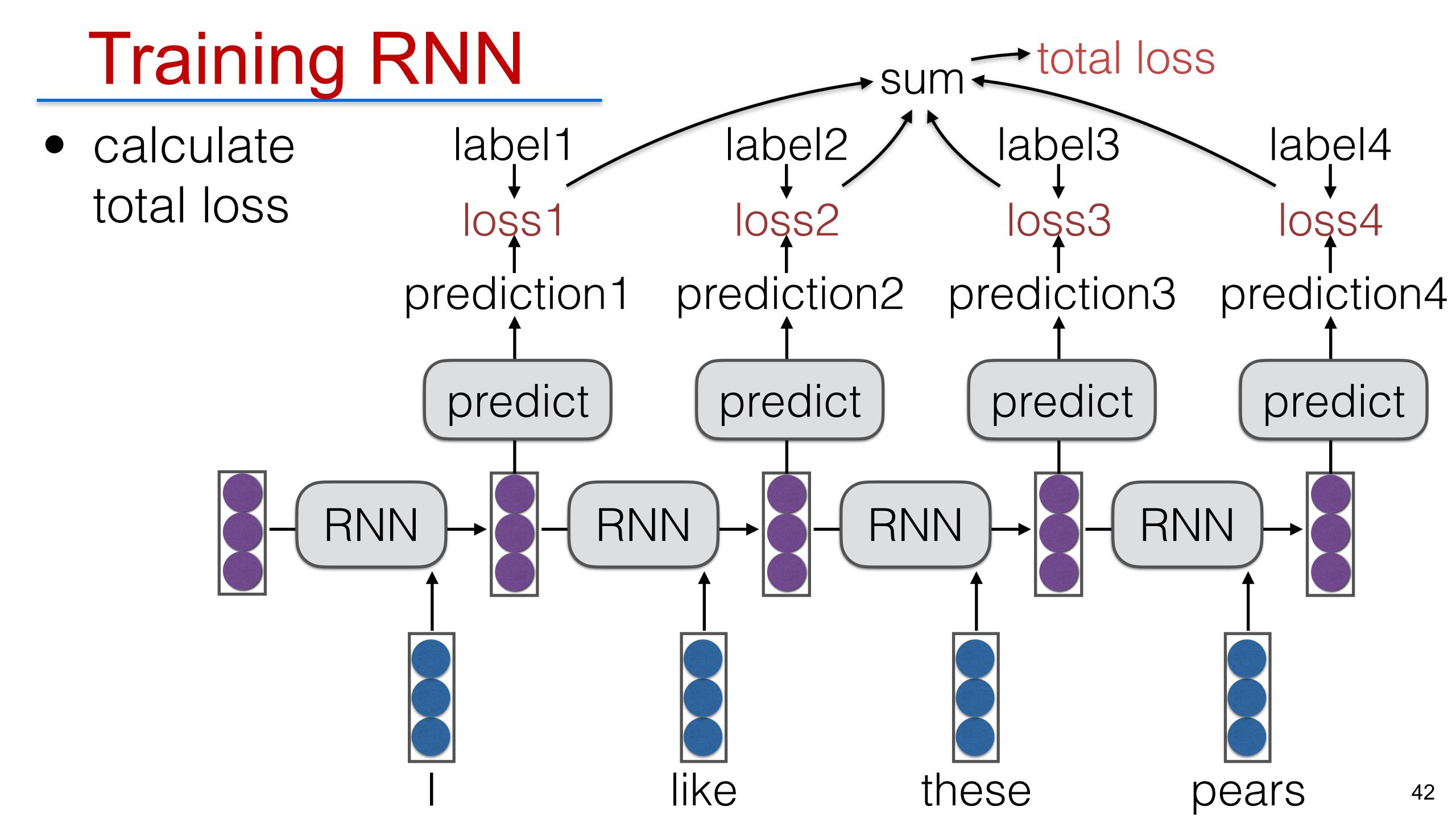
Sentence Representation for Downstream Tasks

- Text classification
- Conditional generation
- Sentense retrieval prediction predict RNN RNN RNN RNN like these pears 40

Representing Words

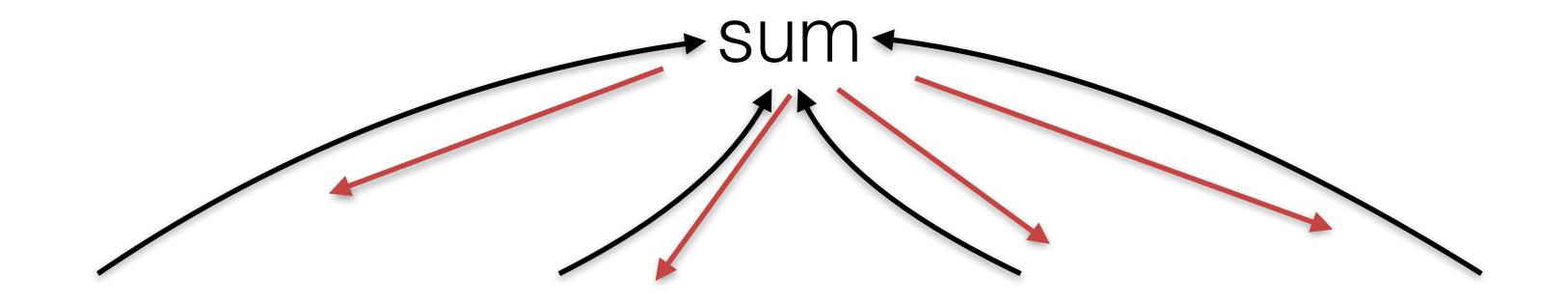
SequenceLabeling



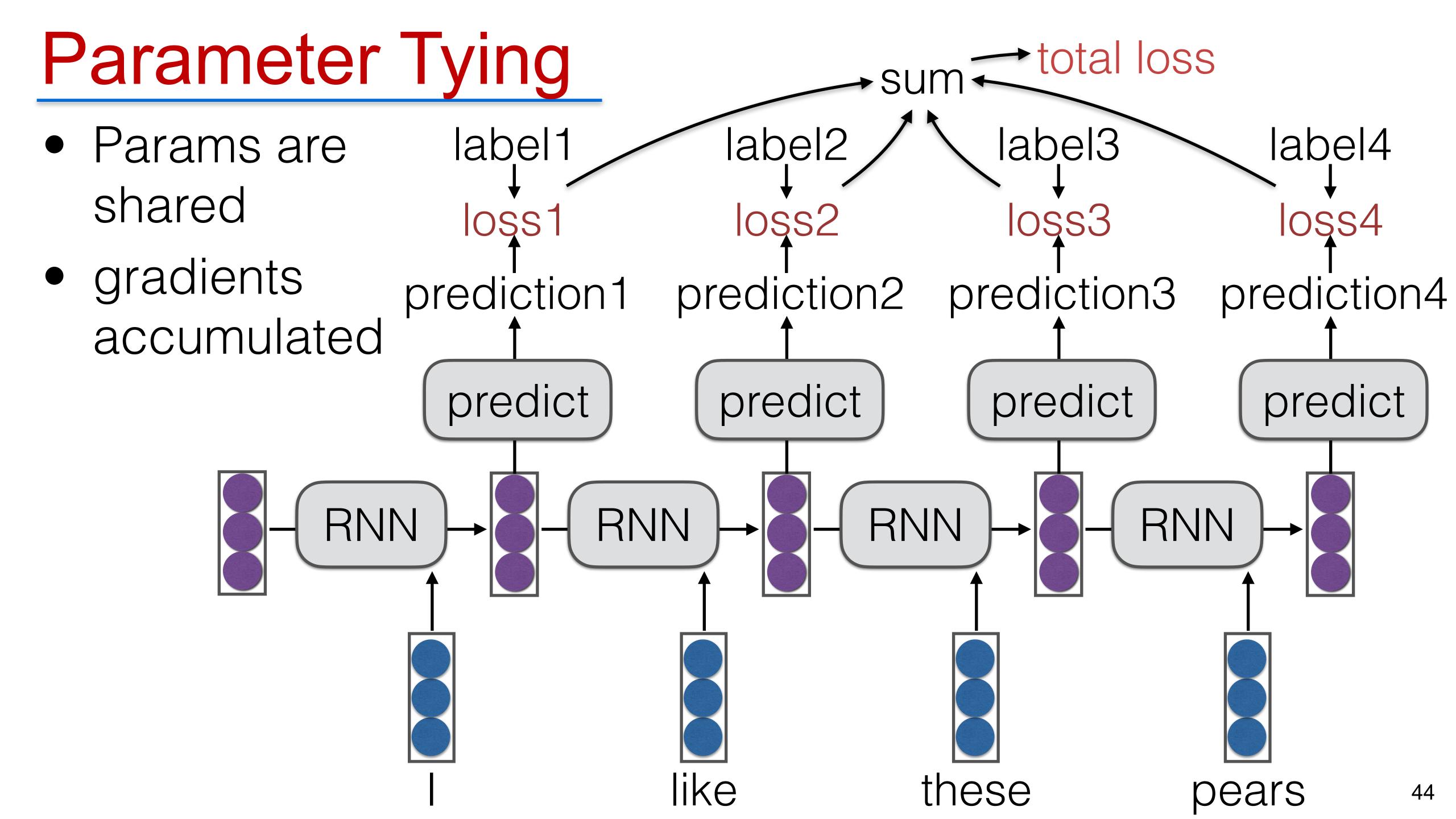


RNN Training

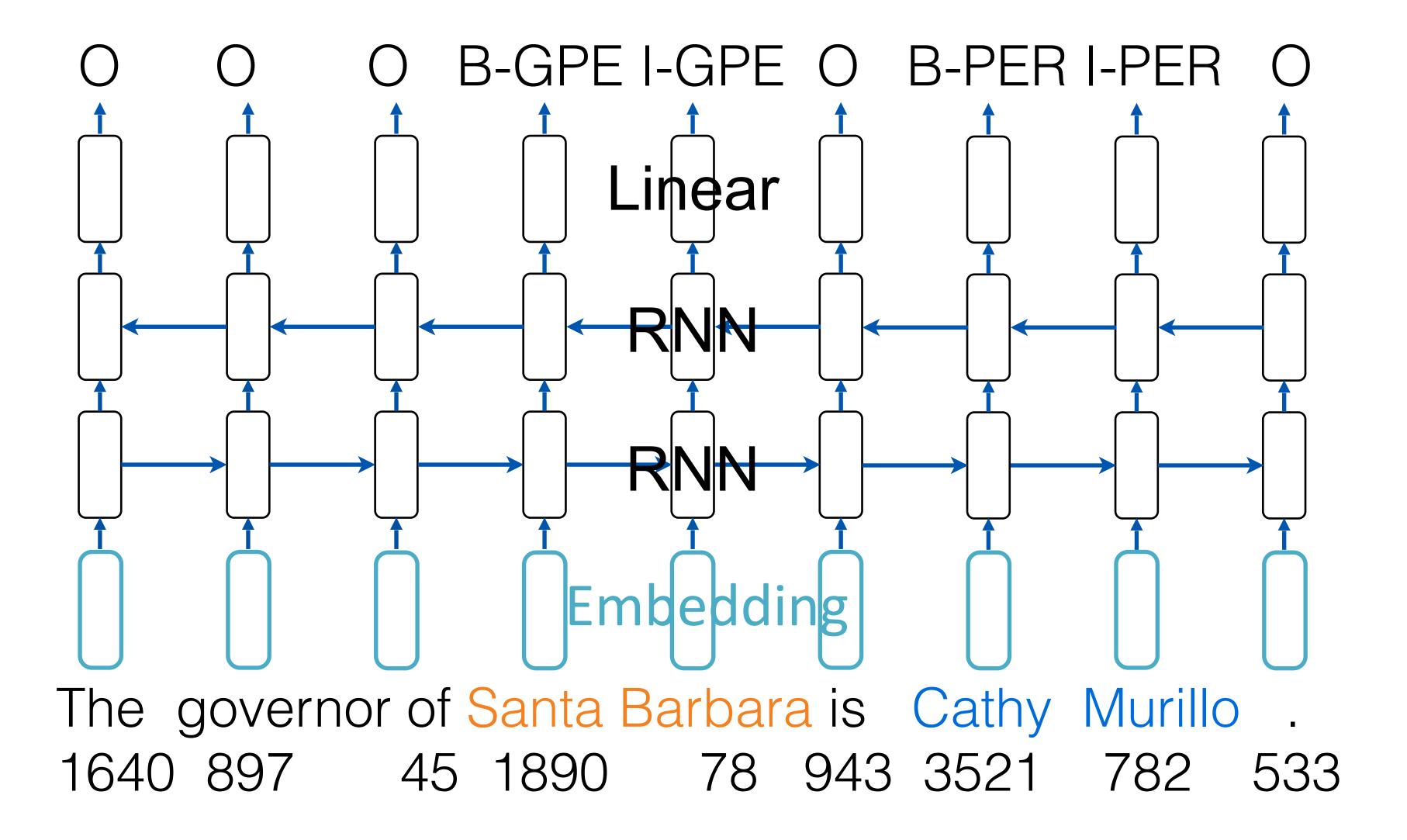
 The unrolled graph is a well-formed (DAG) computation graph—we can run backprop



- Parameters are tied across time, derivatives are aggregated across all time steps
- This is historically called "backpropagation through time" (BPTT)



Bi-directional RNN



Multilingual Labeling/Classification Data and Models

Language Identification

LTI Language Identification Corpus http://www.cs.cmu.edu/~ralf/langid.html

Benchmark on 1152 languages from a variety of free sources

langid.py

https://github.com/saffsd/langid.py

Off-the-shelf language ID system for 90+ languages

Automatic Language Identification in Texts: A Survey https://arxiv.org/pdf/1804.08186.pdf

Text Classification

Very broad field, many different datasets

MLDoc: A Corpus for Multilingual Document Classification in Eight Languages

https://github.com/facebookresearch/MLDoc

Topic classification, eight languages

PAWS-X: Paraphrase Adversaries from

https://github.com/google-research-datasets/paws/tree/

Paraphrase detection (sentence pair classification)

Cross-lingual Natural Language Inference (XNLI) corpus

https://cims.nyu.edu/~sbowman/

Textual entailment prediction (sentence pair classification)

Cross-lingual Sentiment Classification

Available from: https://github.com/ccsasuke/

Chinese-English cross-lingual sentiment dataset

Part of Speech/Morphological Tagging

- Part of universal dependencies treebank https://universaldependencies.org/
- Contains parts of speech and morphological features for 90 languages
- Standardized "Universal POS" and "Universal Morphology" tag sets make things consistent
- Several pre-trained models on these datasets:
 - Udify: https://github.com/Hyperparticle/udify
 - Stanza: https://stanfordnlp.github.io/stanza/

Named Entity Recognition

- "Gold standard" data
 - CoNLL 2002/2003 Language Independent Named Entity Recognition
 - https://www.clips.uantwerpen.be/conll2003/ner/
 - English, German, Spanish, Dutch human annotated data
- "Silver Standard"
 - WikiAnn Entity Recognition/Linking in 282 Languages
 - https://www.aclweb.org/anthology/P17-1178/
 - Available from: https://github.com/google-research/xtreme
 - Data automatically extracted from Wikipedia using inter-page links

Composite Benchmarks

- Benchmarks that aggregate many different sequence labeling/classification tasks
- XTREME: A Massively Multilingual Multi-task Benchmark for Evaluating Cross-lingual Generalization
 - 10 different tasks, 40 different languages
 - https://github.com/google-research/xtreme
- XGLUE: A New Benchmark Dataset for Cross-lingual Pretraining, Understanding and Generation
 - https://microsoft.github.io/XGLUE/
 - 11 tasks over 19 languages (including generation)

Discussion Today

Assignment 1 introduction

Code walk