CS11-711 Advanced NLP

Sequence Modeling and Recurrent Neural Networks

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with slides from Graham Neubig

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Site

https://cmu-anlp.github.io/

NLP and Sequential Data

- NLP is full of sequential data
    - Words in sentences
    - Characters in words
    - Sentences in discourse
    - …

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**.

Can be Complicated!

- What is the referent of “it”?

The trophy would not fit in the brown suitcase because it was too **big**.

Trophy

The trophy would not fit in the brown suitcase because it was too **small**.

Suitcase

(from Winograd Schema Challenge: http://commonsensereasoning.org/winograd.html)

Types of Sequential Prediction Problems

Types of Prediction: Binary, Multi-class, Structured

- Two classes (**binary classification**)

I hate this movie → positive / negative

- Multiple classes (**multi-class classification**)

I hate this movie → very good / good / neutral / bad / very bad

- Exponential/infinite labels (**structured prediction**)

I hate this movie → PRP VBP DT NN

I hate this movie → *kono eiga ga kirai*

Types of Prediction: Unconditioned vs. Conditioned

- **Unconditioned Prediction:** Predict the probability of a single variable $P(X)$

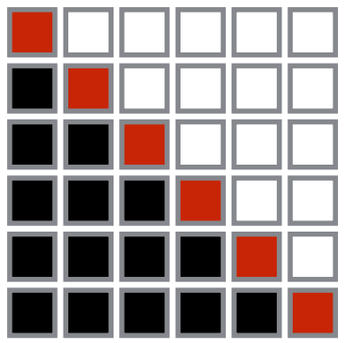
- **Conditioned Prediction:** Predict the probability of an output variable given an input $P(Y|X)$

Types of Unconditioned Prediction

Left-to-right Autoregressive Prediction

$$P(X) = \prod_{i=1}^{|X|} P(x_i | x_1, \ldots, x_{i-1})$$

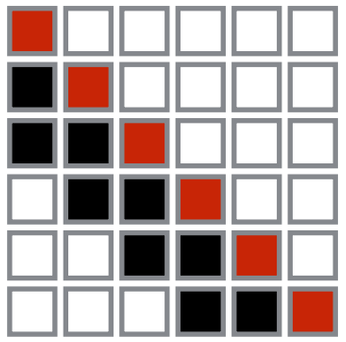
(e.g. RNN LM)



Left-to-right Markov Chain (order n-1*)*

$$P(X) = \prod_{i=1}^{|X|} P(x_i | x_{i-n+1}, \ldots, x_{i-1})$$

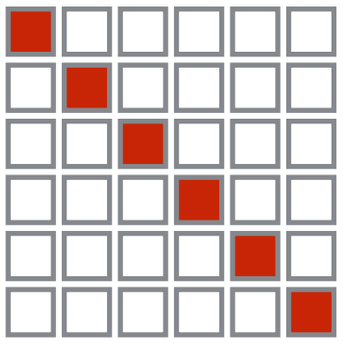
(e.g. n-gram LM, feed-forward LM)



Independent Prediction

$$P(X) = \prod_{i=1}^{|X|} P(x_i)$$

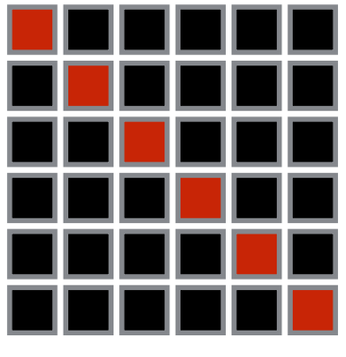
(e.g. unigram model)



Bidirectional Prediction

$$P(X) \neq \prod_{i=1}^{|X|} P(x_i | x_{\neq i})$$

(e.g. masked language model)

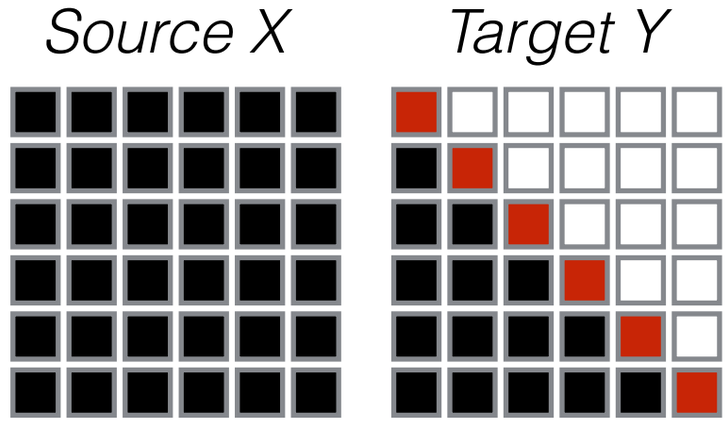


Types of Conditioned Prediction

Autoregressive Conditioned Prediction

$$P(Y|X) = \prod_{i=1}^{|Y|} P(y_i|X, y_1, \ldots, y_{i-1})$$

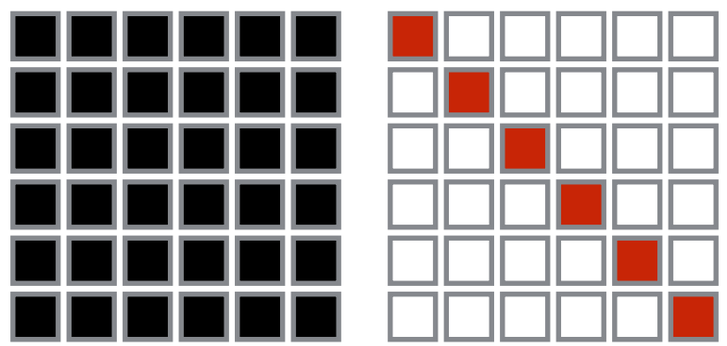
(e.g. seq2seq model)



Non-autoregressive Conditioned Prediction

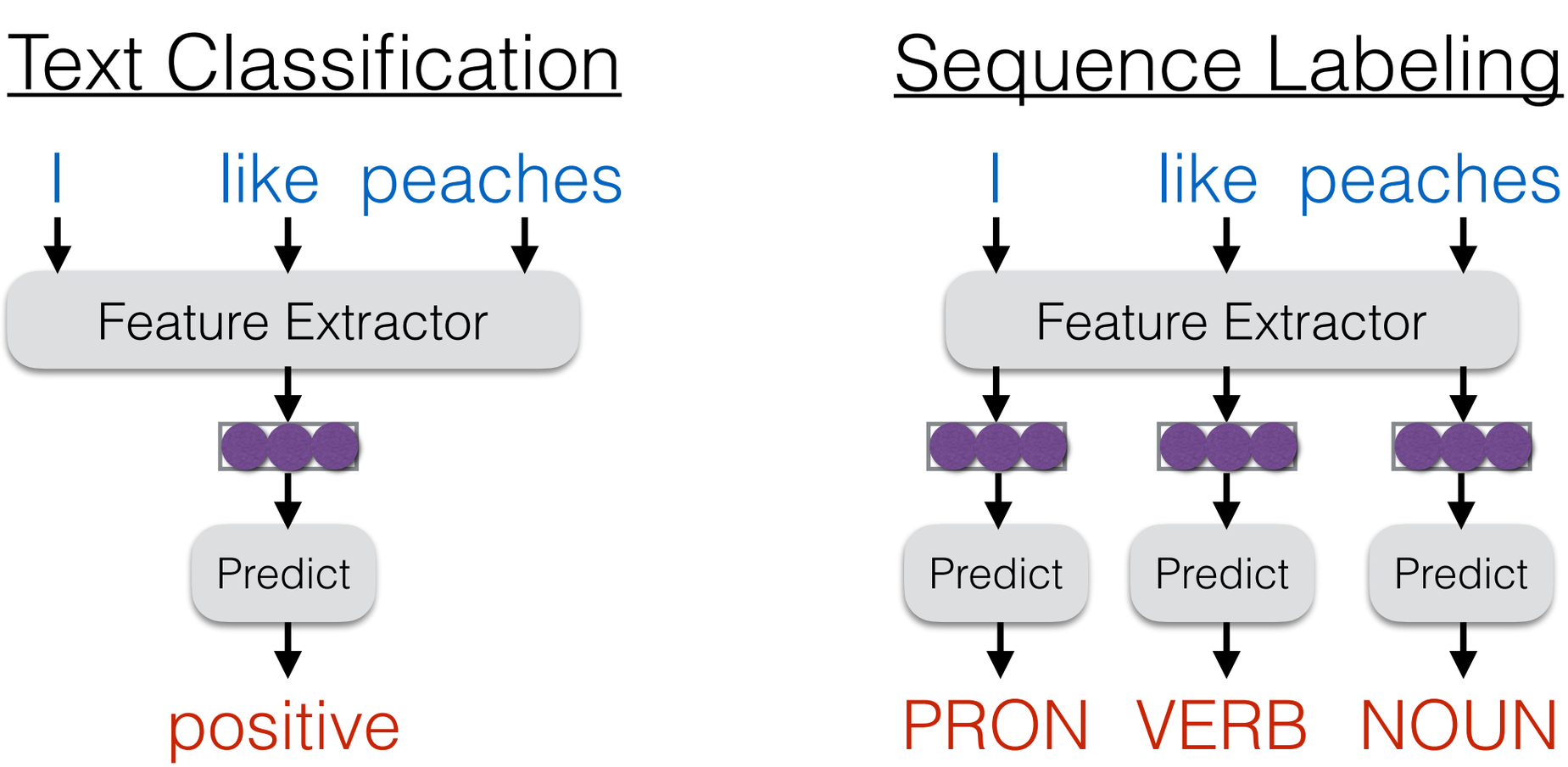
$$P(Y|X) = \prod_{i=1}^{|Y|} P(y_i|X)$$

(e.g. sequence labeling, non-autoregressive MT)



Basic Modeling Paradigm: Extract Features -> Predict

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



An Aside:

More on Sequence Labeling

Sequence Labeling

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

Part of Speech Tagging

He	saw	two	birds
↓	↓	↓	↓
PRON	VERB	NUM	NOUN

Lemmatization

He	saw	two	birds
↓	↓	↓	↓
he	see	two	bird

Morphological Tagging

He	saw	two	birds
↓	↓	↓	↓
PronType=prs	Tense=past, VerbForm=fin	NumType=card	Number=plur

... and more!

Span Labeling

- Given an input text *X*, predict output spans (sequences of words) and labels *Y*.

Named Entity Recognition

Carnegie Mellon University is located in Pittsburgh.

ORG LOC

Syntactic Chunking

Carnegie Mellon University is located in Pittsburgh.

NP VP NP

Semantic Role Labeling

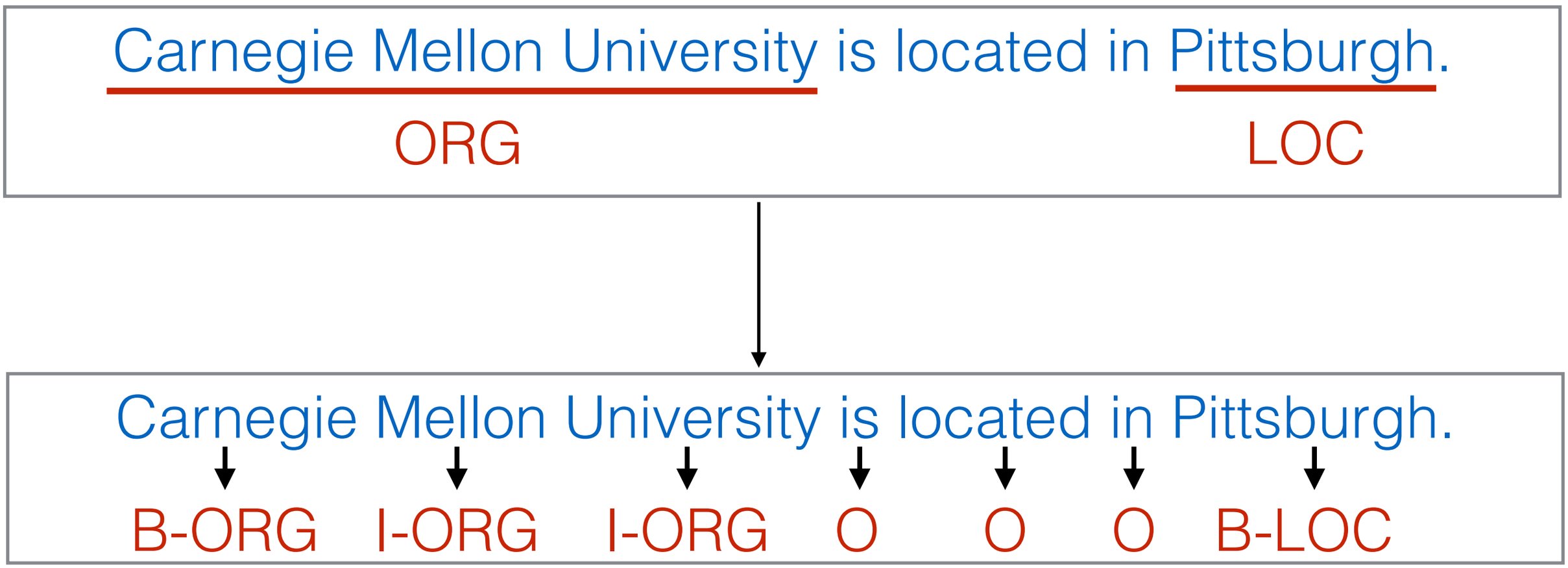
Carnegie Mellon University is located in Pittsburgh.

Argument Predicate Location

... and more!

Span Labeling as Sequence Labeling

- Predict **B**eginning, **I**n, and **O**ut tags for each word in a span



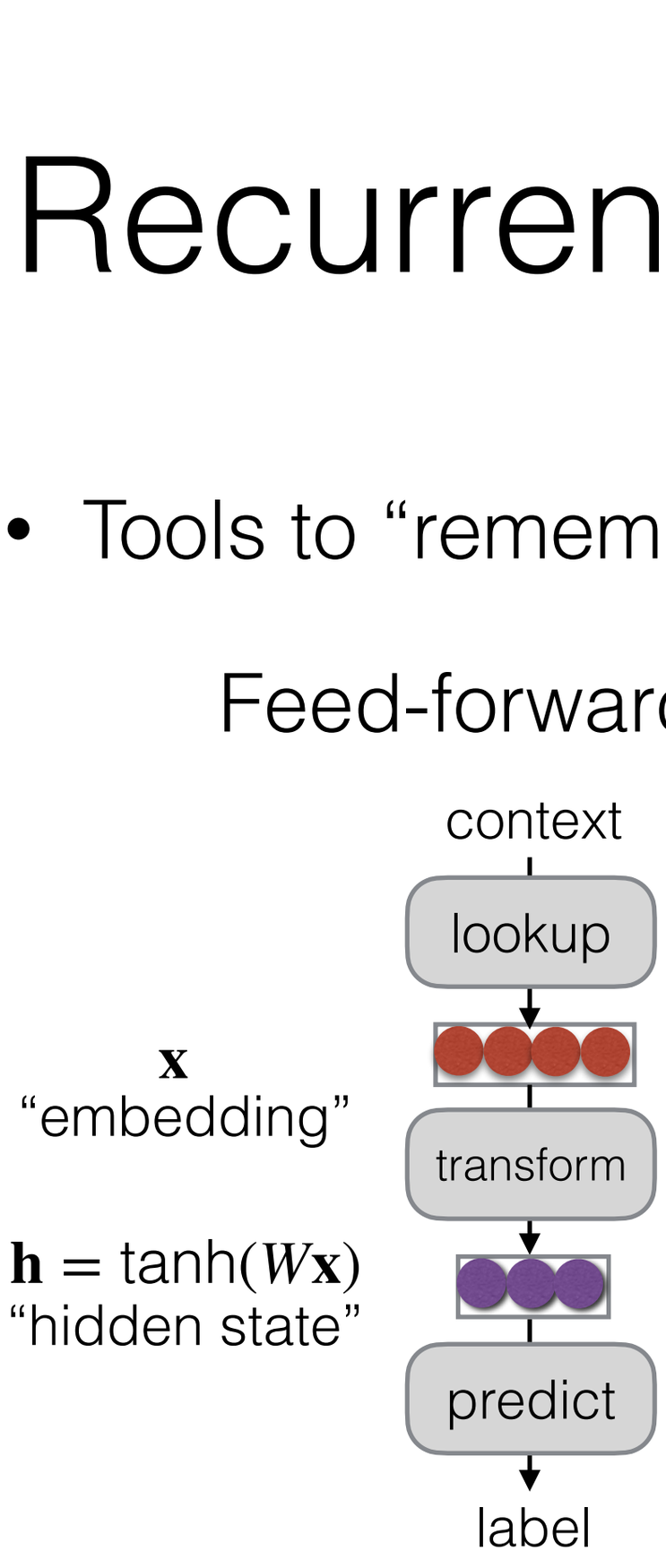
A Sequence Model: Recurrent Neural Networks

Recurrent Neural Networks

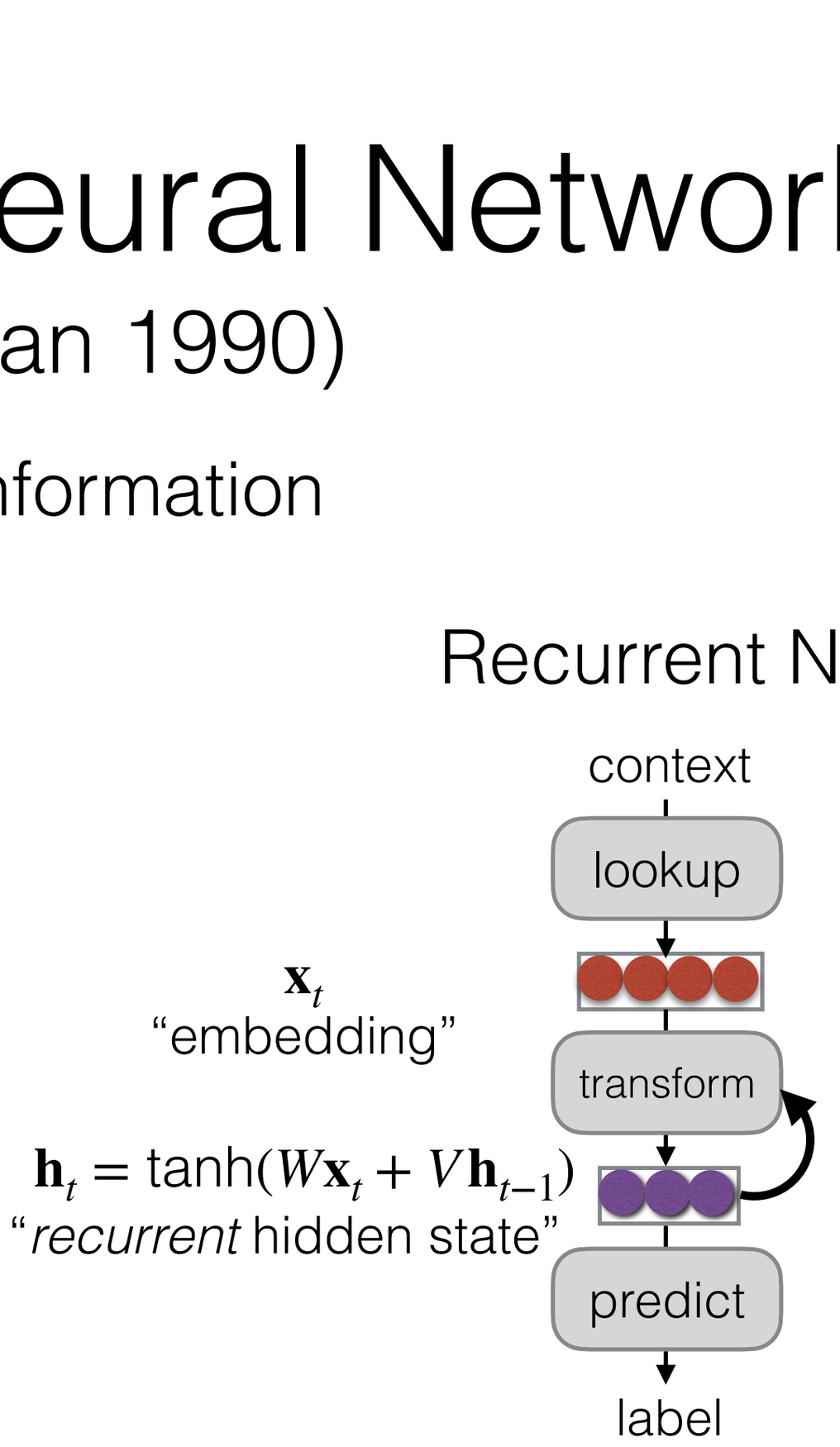
(Elman 1990)

- Tools to "remember" information

Feed-forward NN

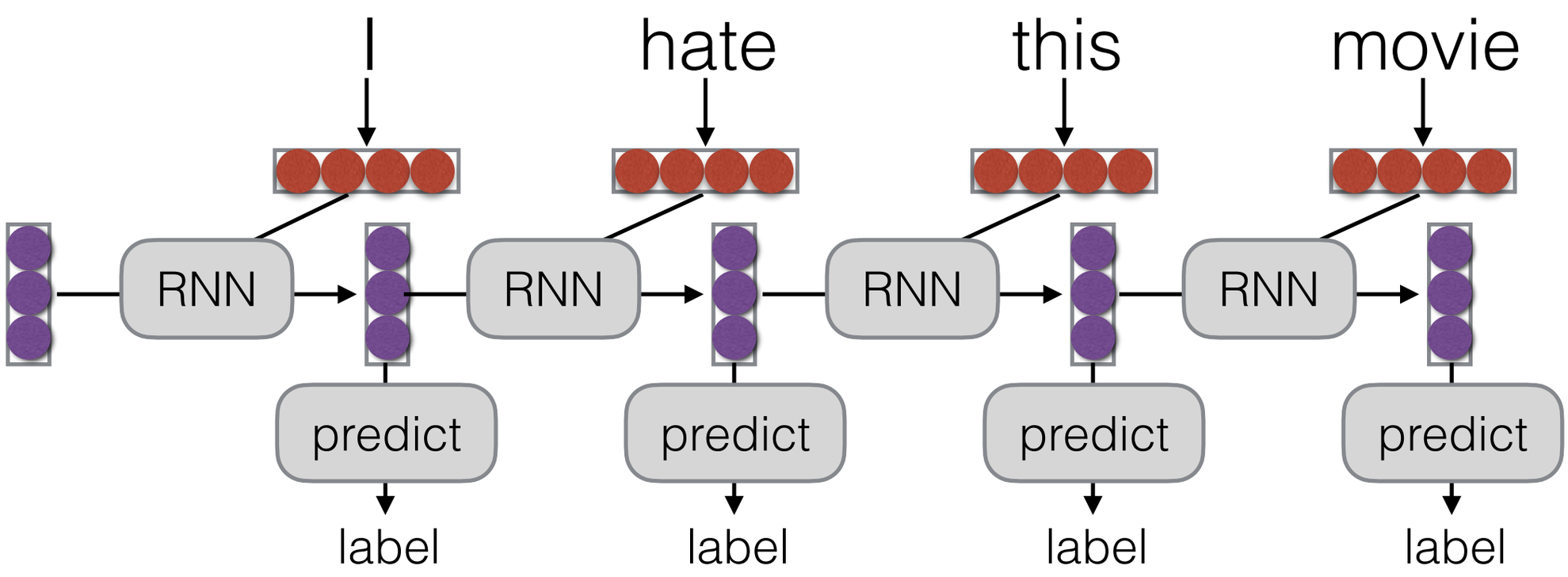


Recurrent NN

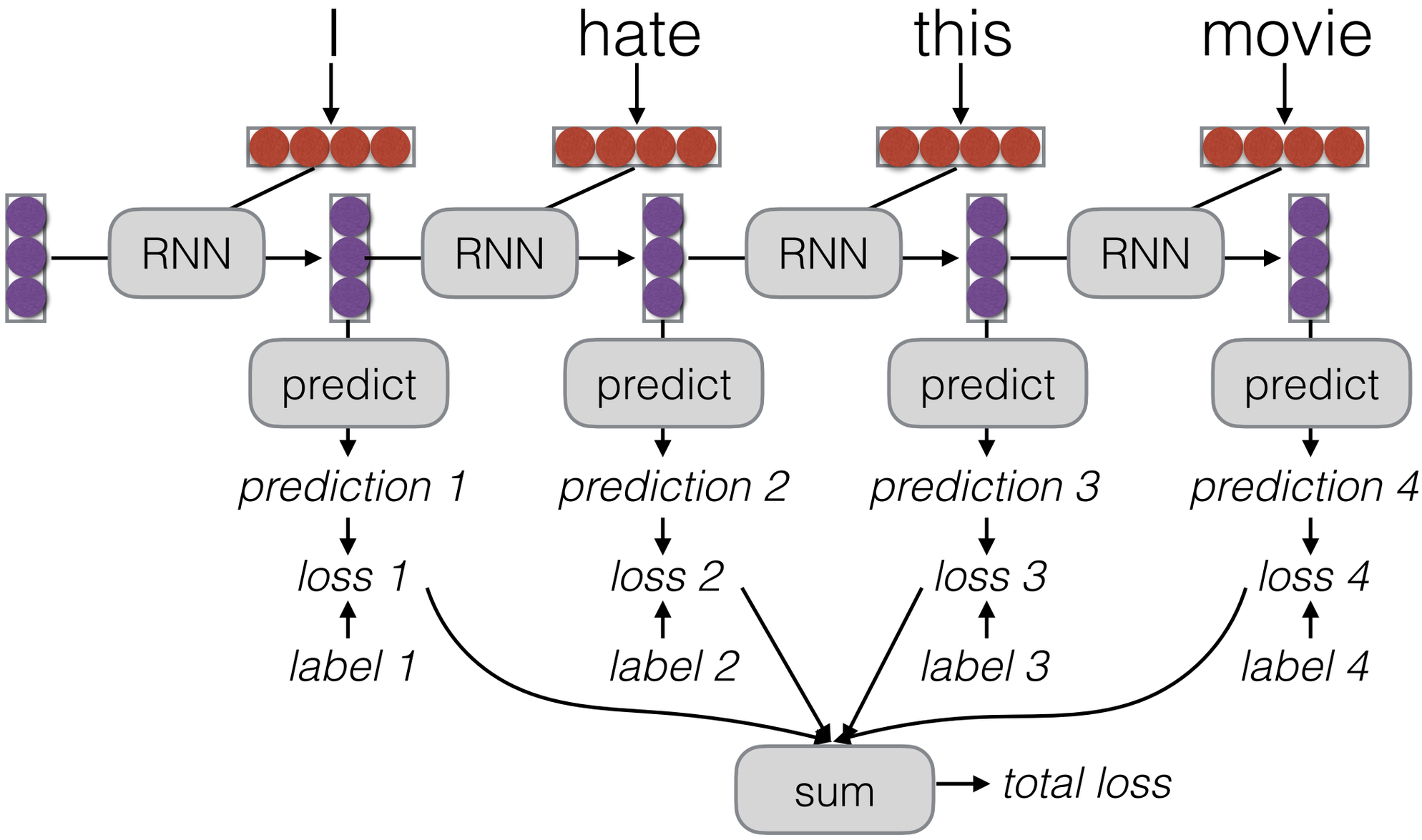


Unrolling in Time

- What does processing a sequence look like?

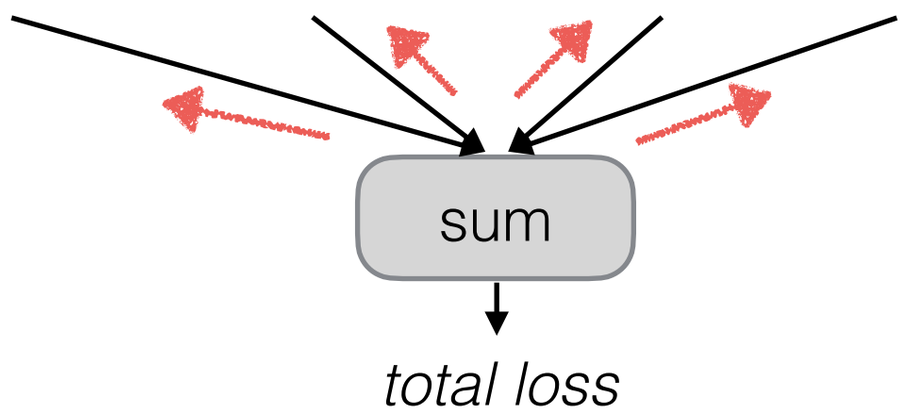


Training RNNs



RNN Training

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



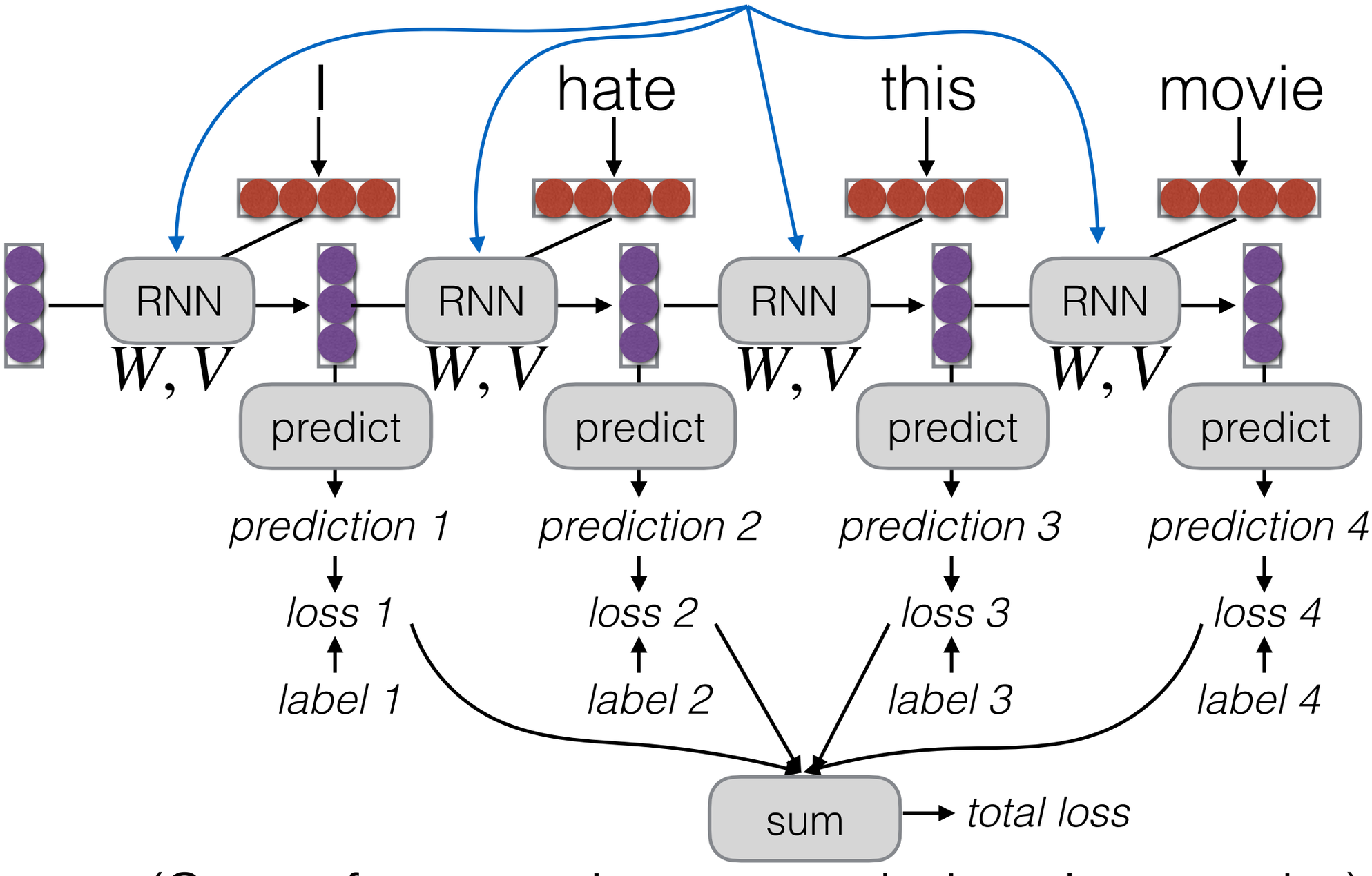
- Parameters are tied across time, derivatives are aggregated across all time steps

- This is historically called “backpropagation through time” (BPTT)

Parameter Tying

$$\mathbf{h}_t = \tanh(W\mathbf{x}_t + V\mathbf{h}_{t-1})$$

Parameters are shared! Derivatives are accumulated.



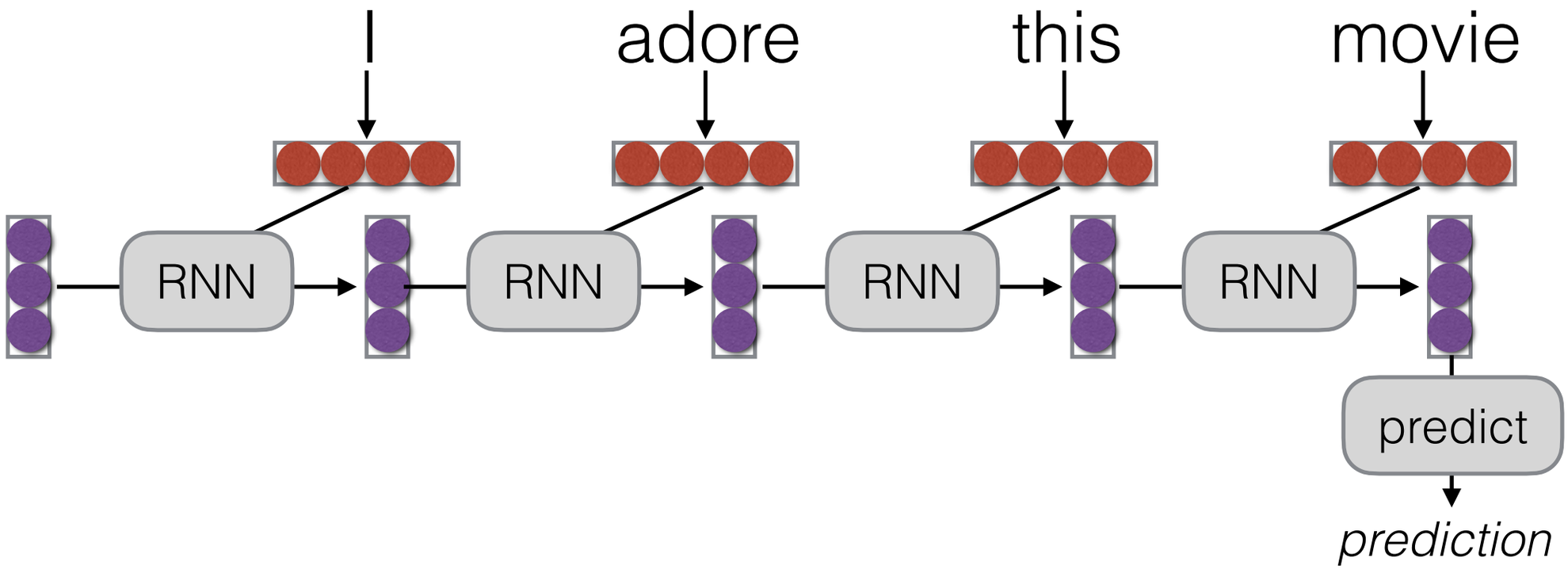
(Same for attention, convolutional networks)

Applications of RNNs

What Can RNNs Do?

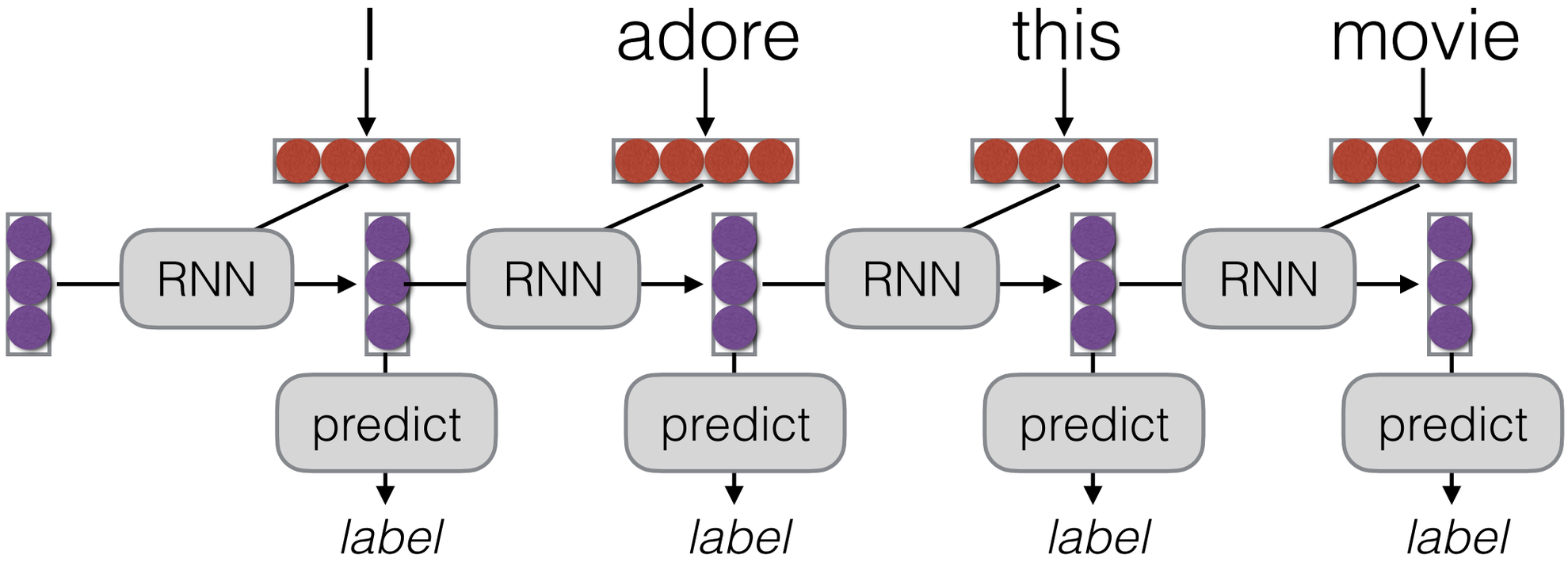
- Represent a sentence
  - Read whole sentence, make a prediction
- Represent a context within a sentence
  - Read context up until that point

Encoding Sentences



- Binary or multi-class prediction
- Sentence representation for retrieval, sentence comparison, etc.

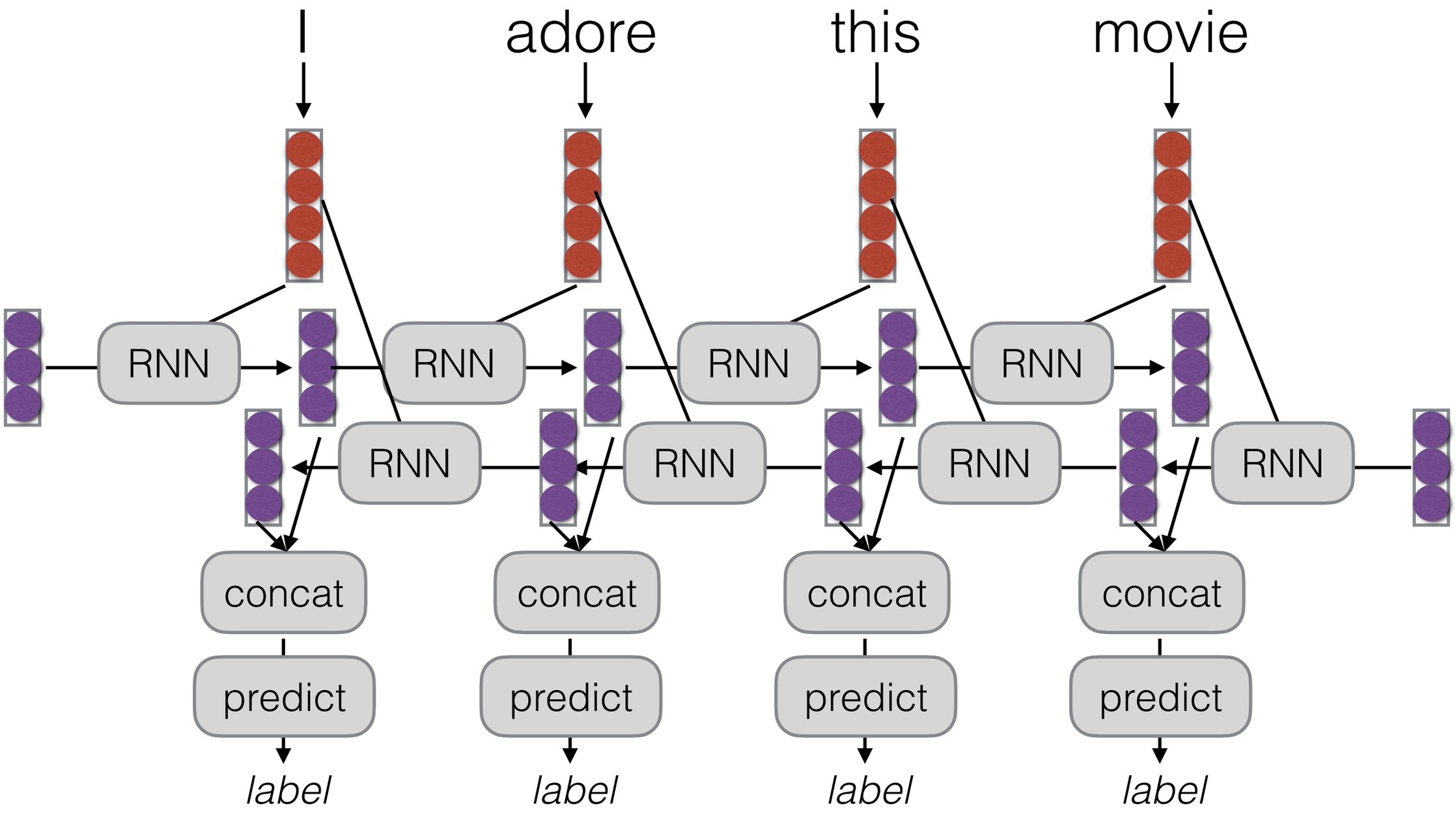
Representing Contexts



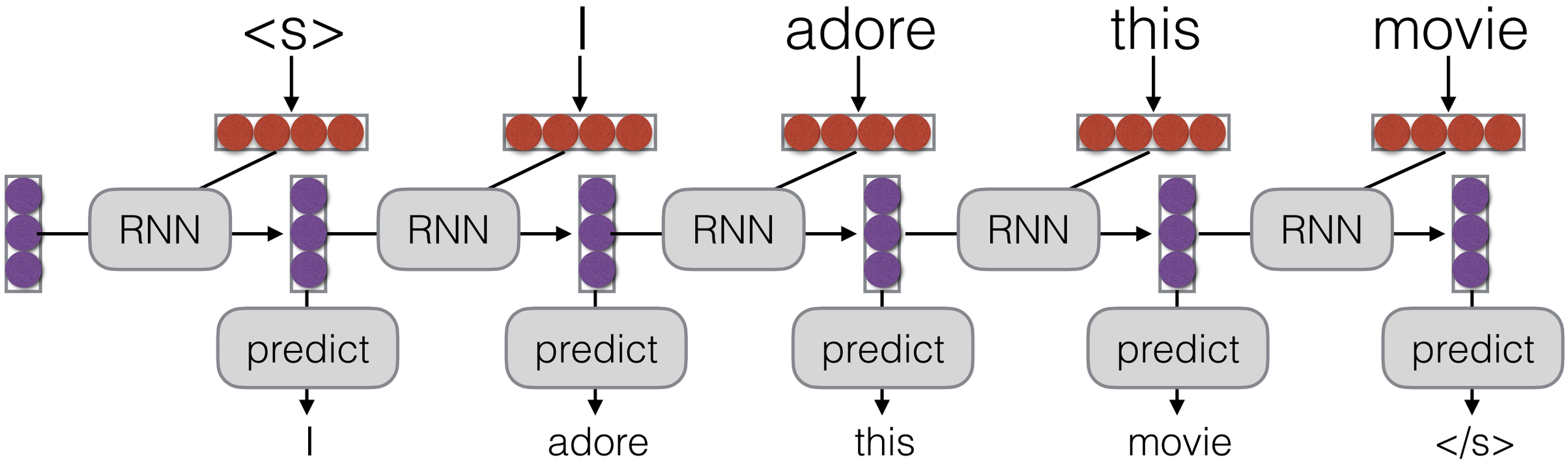
- Sequence labeling
- Calculating representations for parsing, etc.

Bi-RNNs

- A simple extension, run the RNN in both directions



e.g. Language Modeling



- Language modeling is like a tagging task, where each tag is the next word!

- Note: this is an autoregressive model

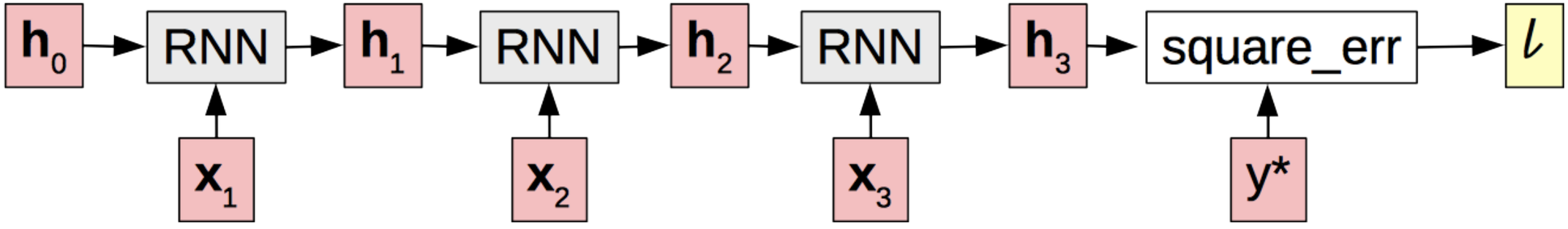
Vanishing Gradients

Based on Slides from Greg Durrett / UT Austin

Vanishing Gradient

- Gradients typically decrease as they get pushed back

$$\frac{dl}{d_{h_0}} = \text{tiny} \quad \frac{dl}{d_{h_1}} = \text{small} \quad \frac{dl}{d_{h_2}} = \text{med.} \quad \frac{dl}{d_{h_3}} = \text{large}$$



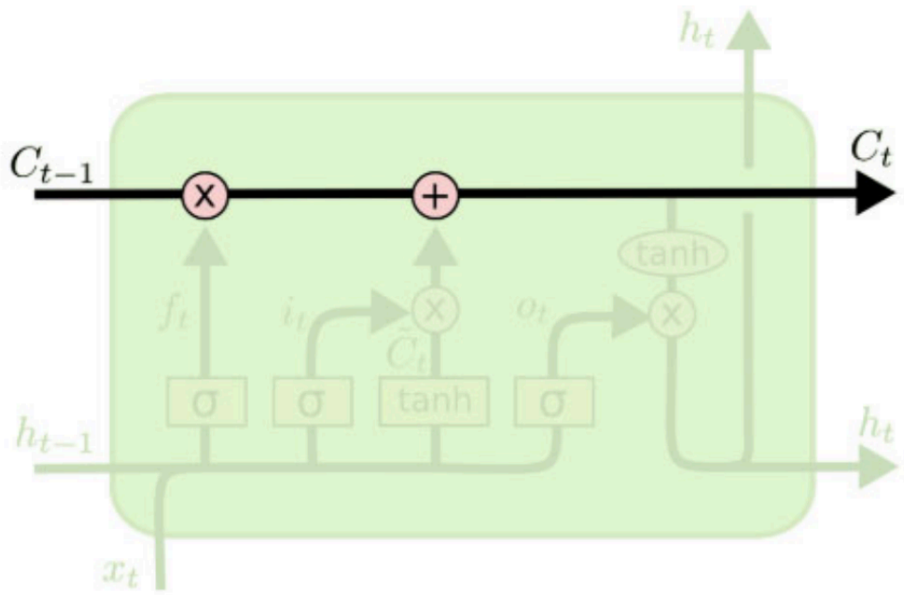
- Why? “Squashed” by non-linearities or small weights in matrices.

A Solution:
Long Short-term Memory
(Hochreiter and Schmidhuber 1997)

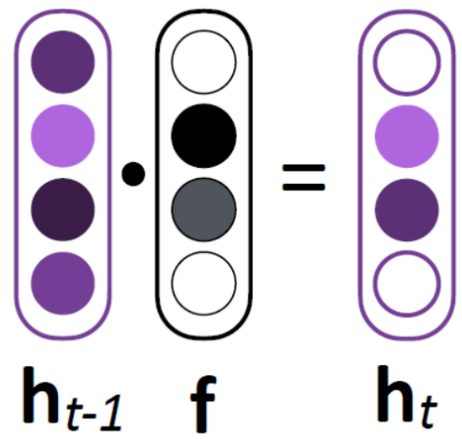
- **Basic idea:** make additive connections between time steps (a “conveyor belt”)

- Addition does not modify the gradient, no vanishing

- Gates to control the information flow



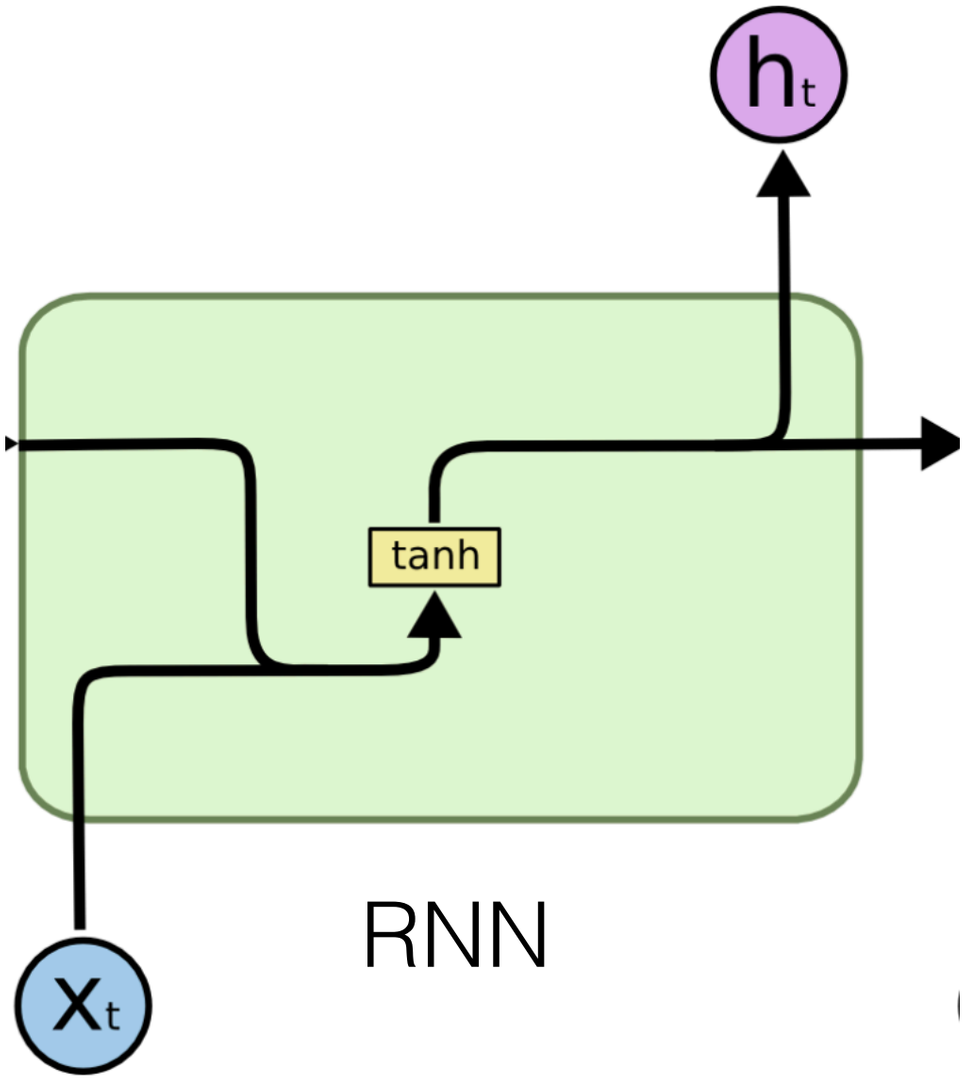
Cell State



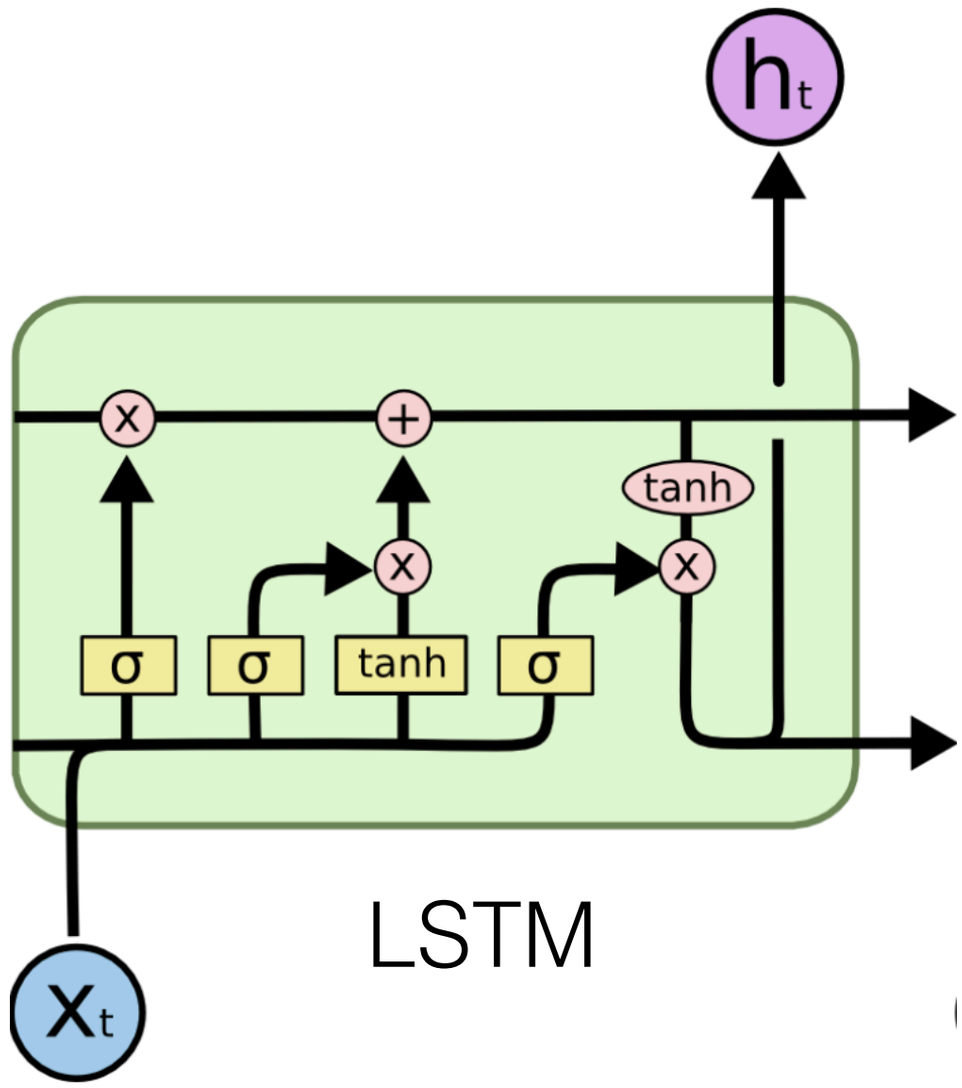
Gating

Image: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

RNN vs LSTM



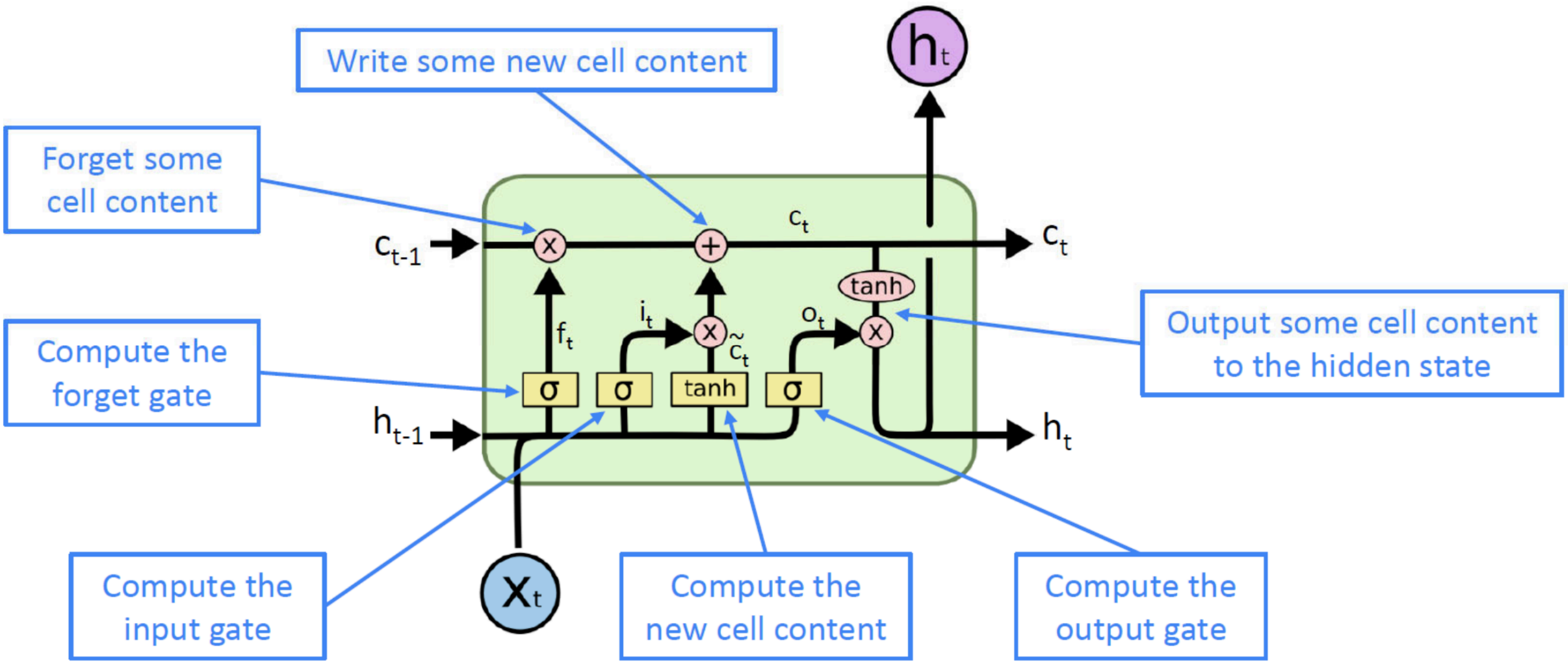
RNN



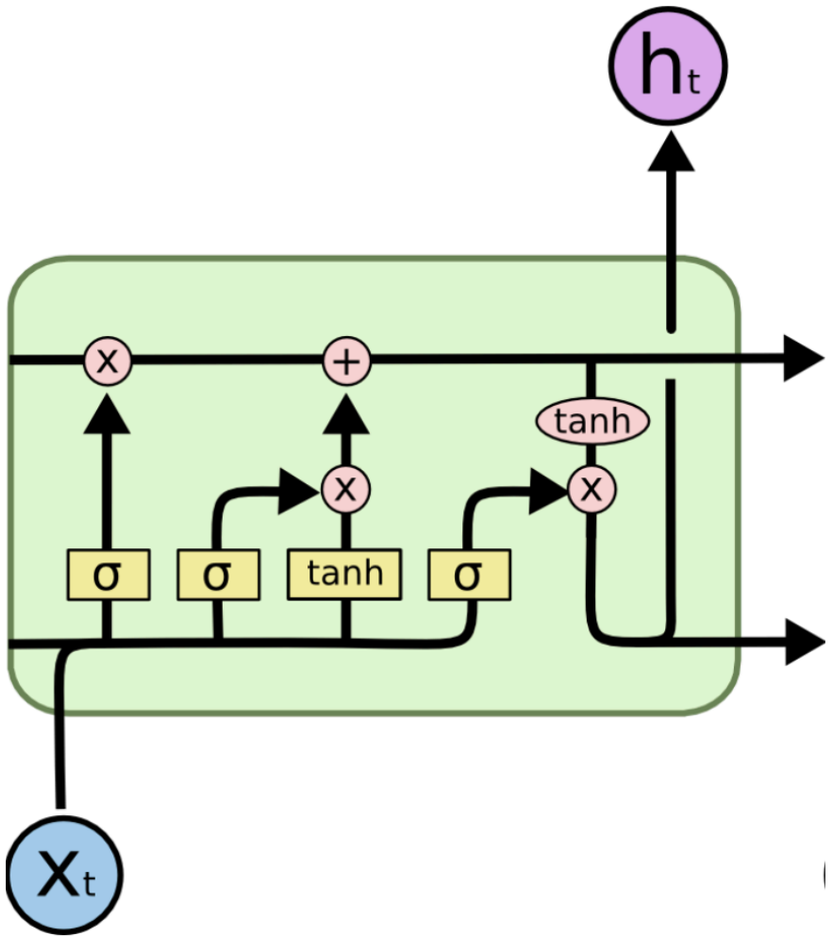
LSTM

https://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTMs


Write some new cell content
Forget some cell content
Compute the forget gate
Compute the input gate
Compute the new cell content
Compute the output gate
Output some cell content to the hidden state
h_t
c_t
c_{t-1}
c_t
h_{t-1}
h_t
x_t
f_t
i_t
$\tilde{c}_t$
o_t
σ
σ
tanh
σ
tanh

LSTMs



- Ignoring recurrent state completely:
  - Gives us a feedforward layer over the token

- Ignoring the input:
  - Let us ignore stop words

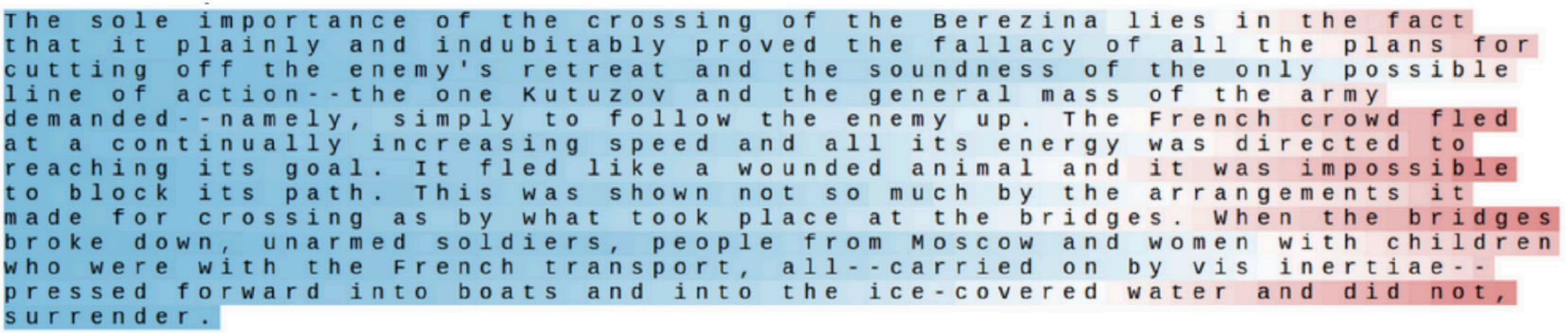
- Summing inputs:
  - Lets us compute a bag-of-words representation

Understanding RNNs

Slides from Greg Durrett / UT Austin

LSTMs Can Model Length

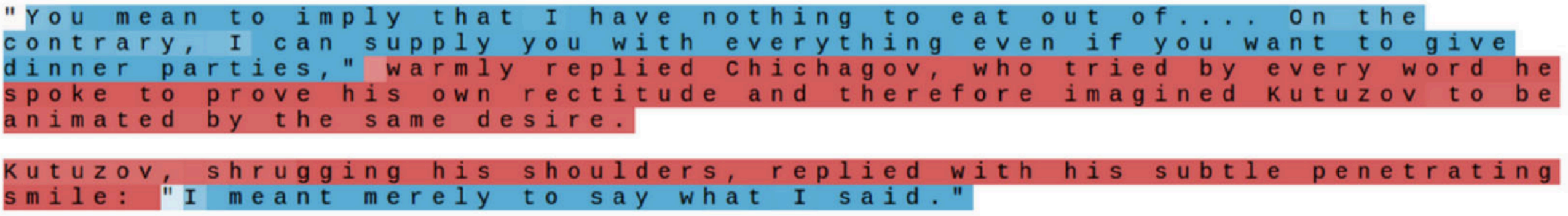
- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells (components of **c**) to understand them
- Counter: know when to generate \n



Karpathy et al. (2015)

LSTMs Can Model Long-Term Bits

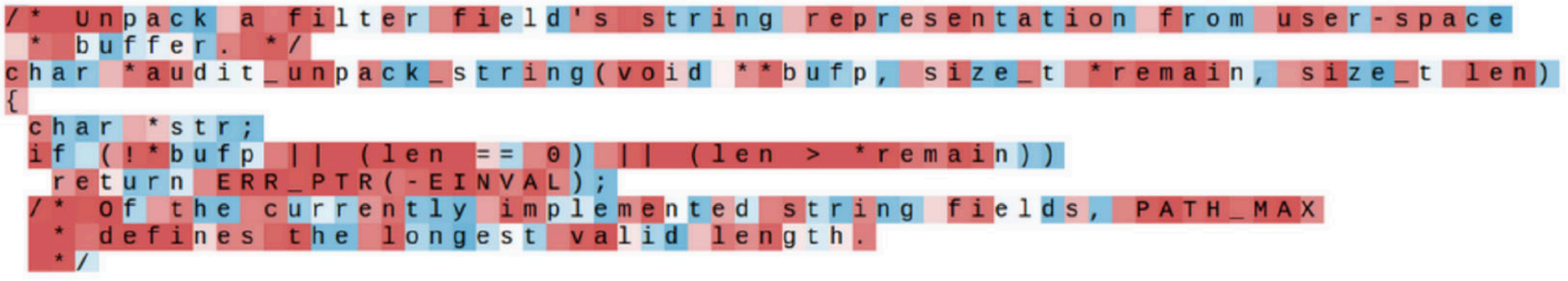
- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells (components of **c**) to understand them
- Binary switch: tells us if we're in a quote or not



Karpathy et al. (2015)

LSTMs Can Be Uninterpretable

- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells (components of **c**) to understand them
- Some cells are uninterpretable: probably doing double-duty, or only make sense in the context of another cell's activations



Karpathy et al. (2015)

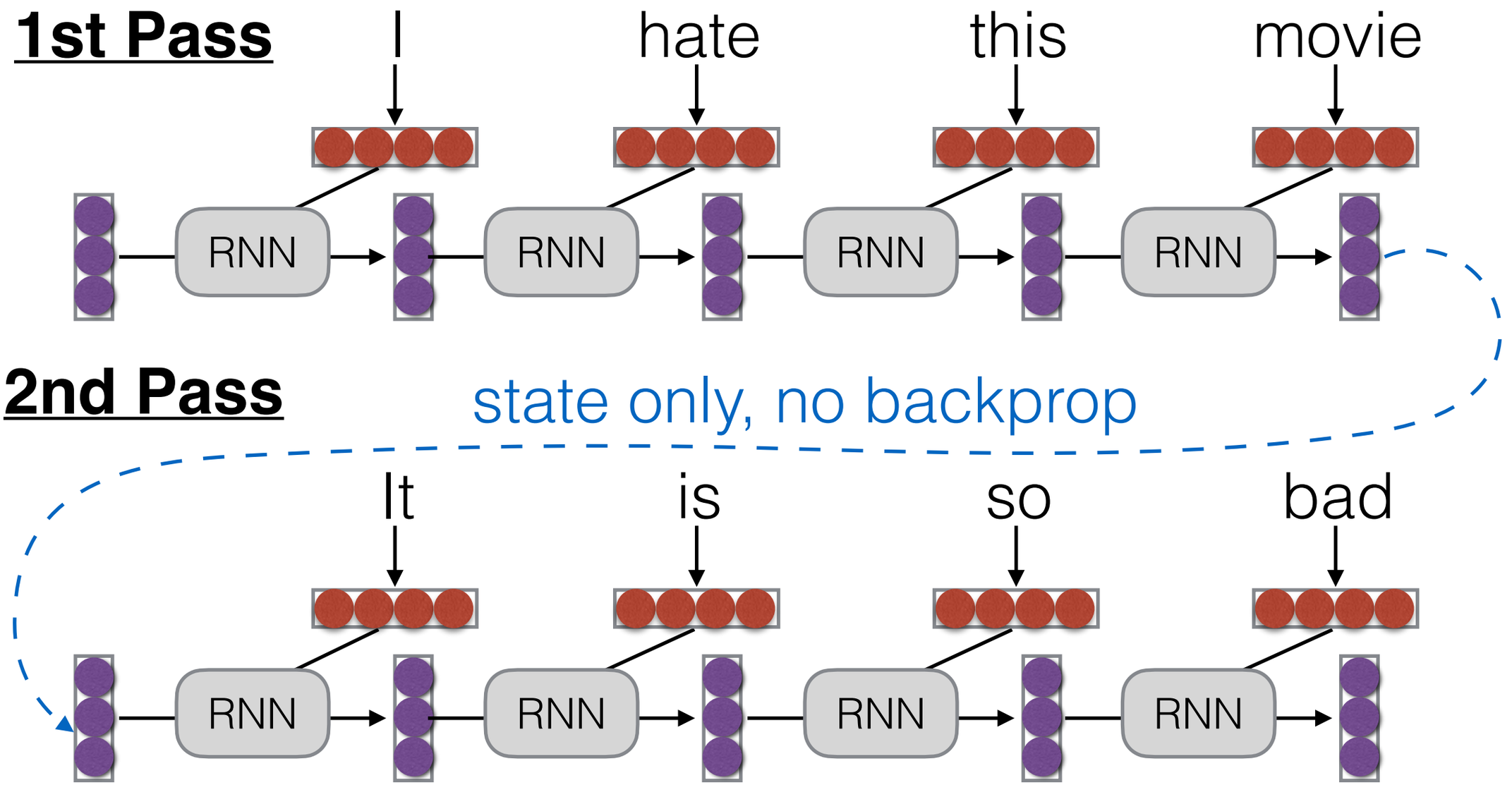
Handling Long Sequences

Handling Long Sequences

- Sometimes we would like to capture long-term dependencies over long sequences
- e.g. words in full documents
- However, this may not fit on (GPU) memory

Truncated BPTT

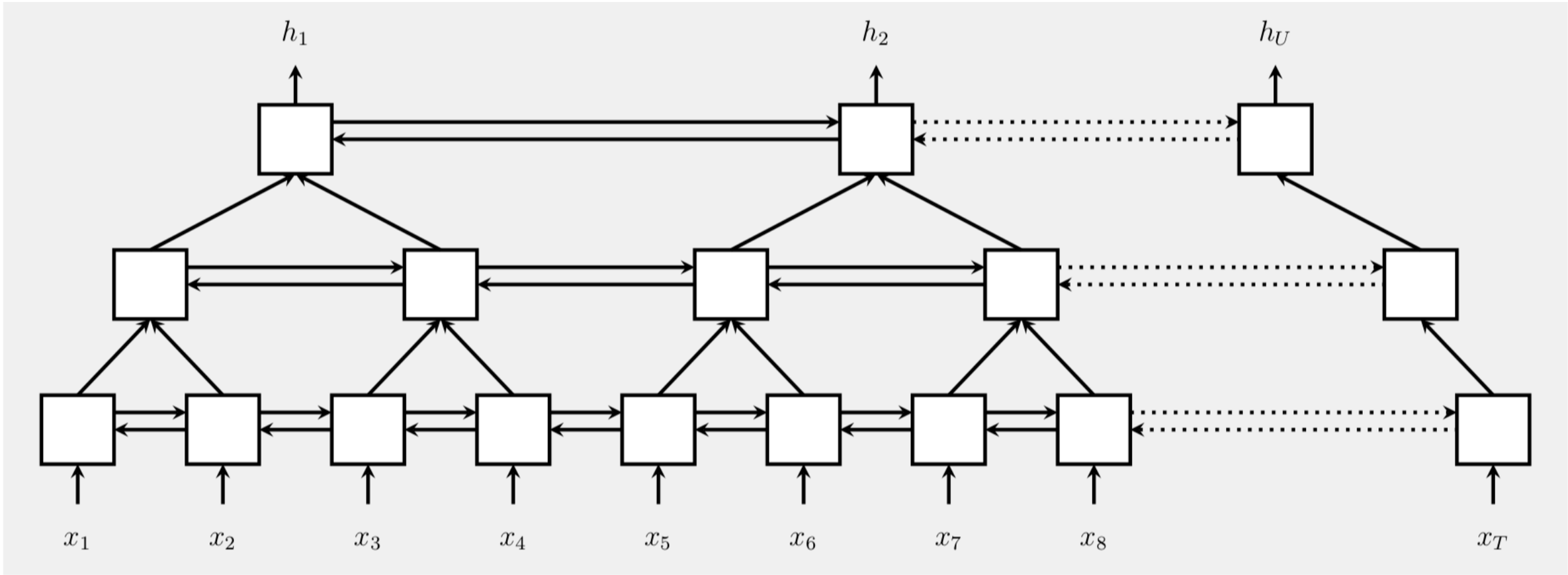
- Backprop over shorter segments, initialize w/ the state from the previous segment



Multi-scale/Pyramidal Architectures

(e.g. Chan et al. 2015)

- Downscale between layers



Types of Prediction
Recurrent Neural Nets
RNN Applications
Vanishing Gradients

Understanding RNNs
Efficiency Tricks
Handling Long Sequences
RNN Variants

Questions?