CS11-747 Neural Networks for NLP

Recurrent Neural Networks

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Site
https://phontron.com/class/nn4nlp2018/

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**.

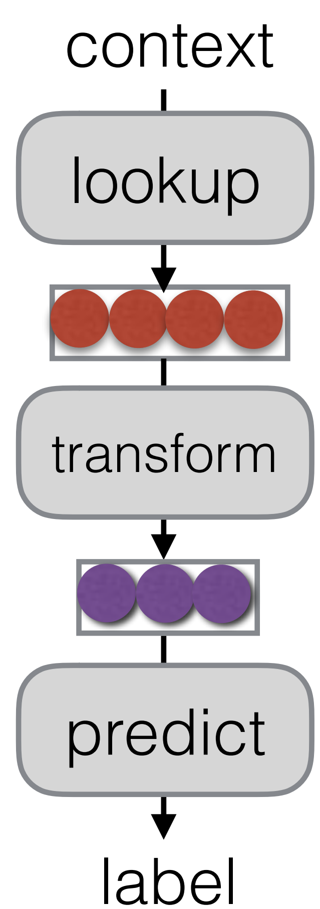
Suitcase

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

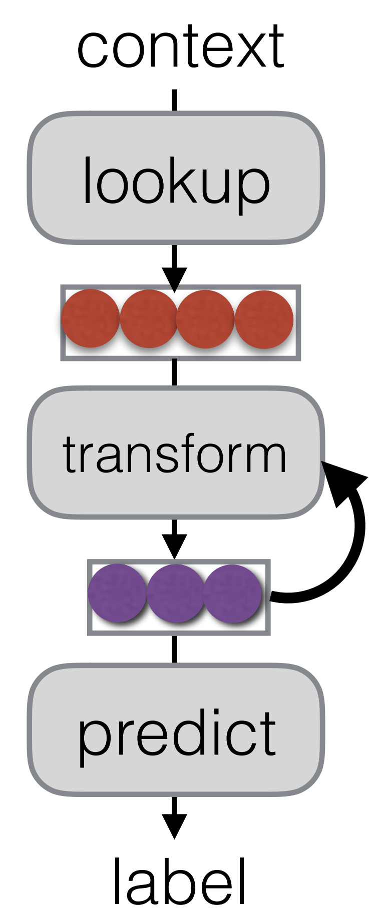
Recurrent Neural Networks
(Elman 1990)

- Tools to “remember” information

Feed-forward NN

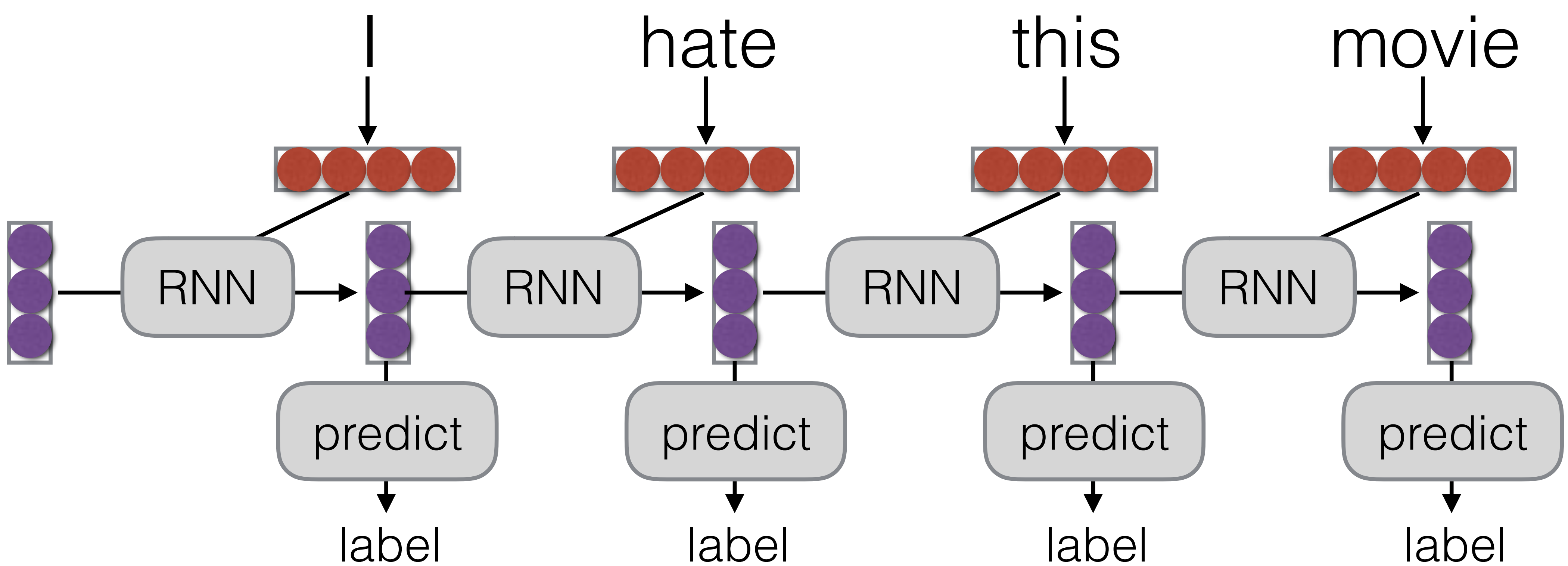


Recurrent NN

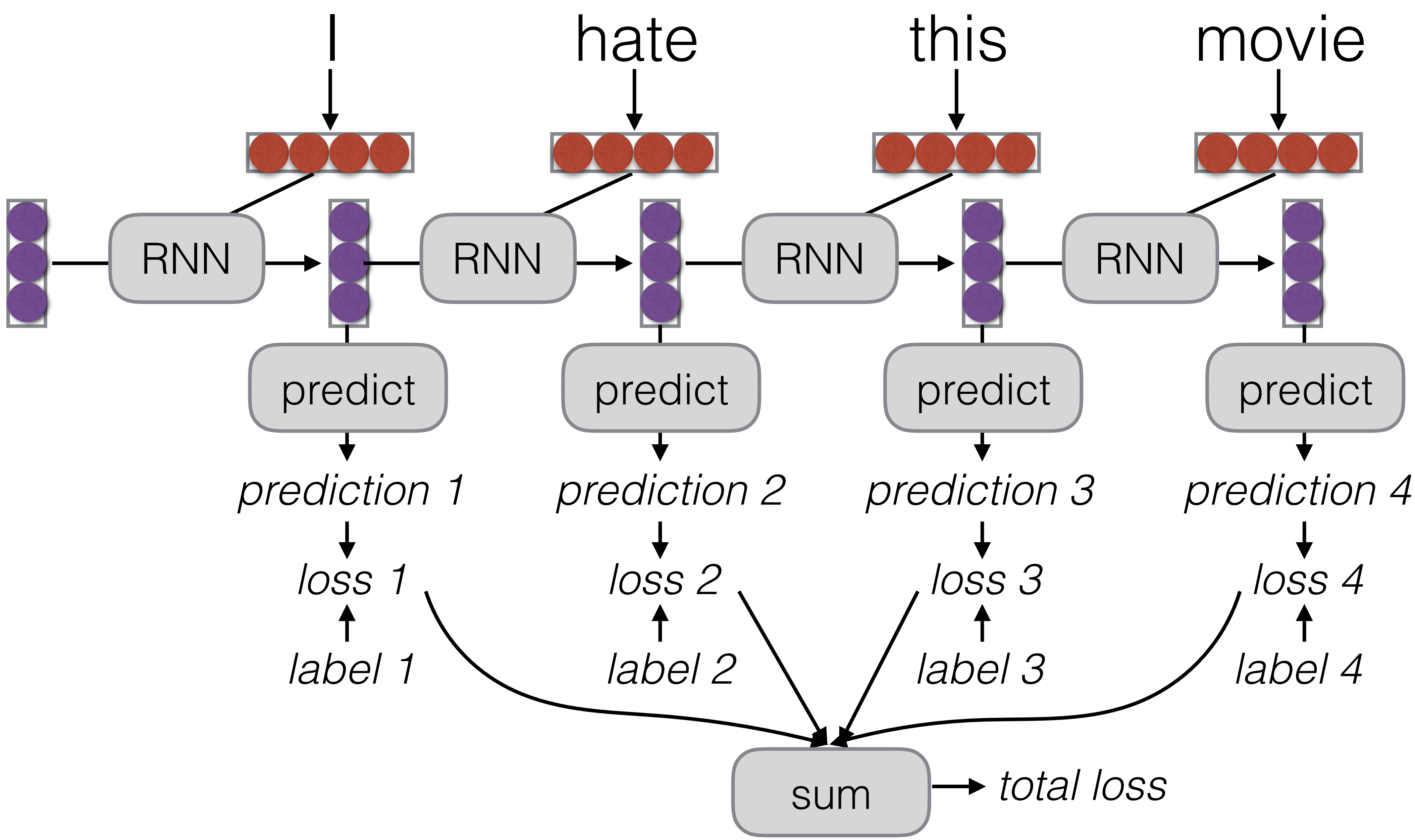


Unrolling in Time

- What does processing a sequence look like?

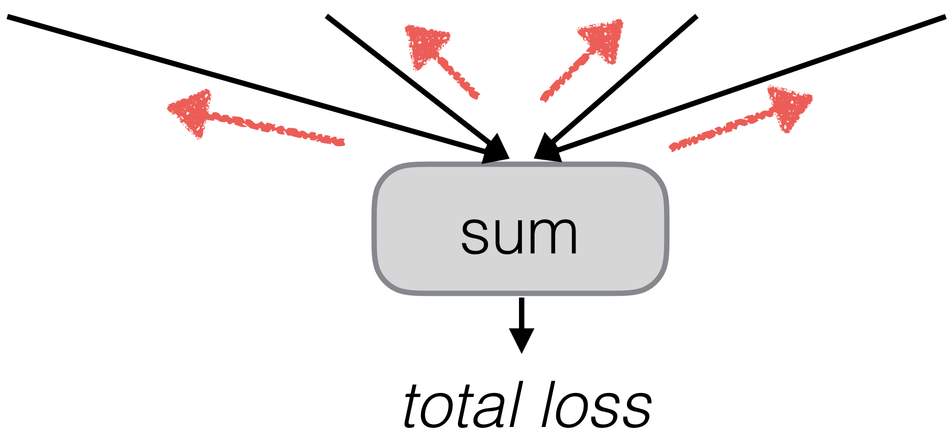


Training RNNs



RNN Training

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

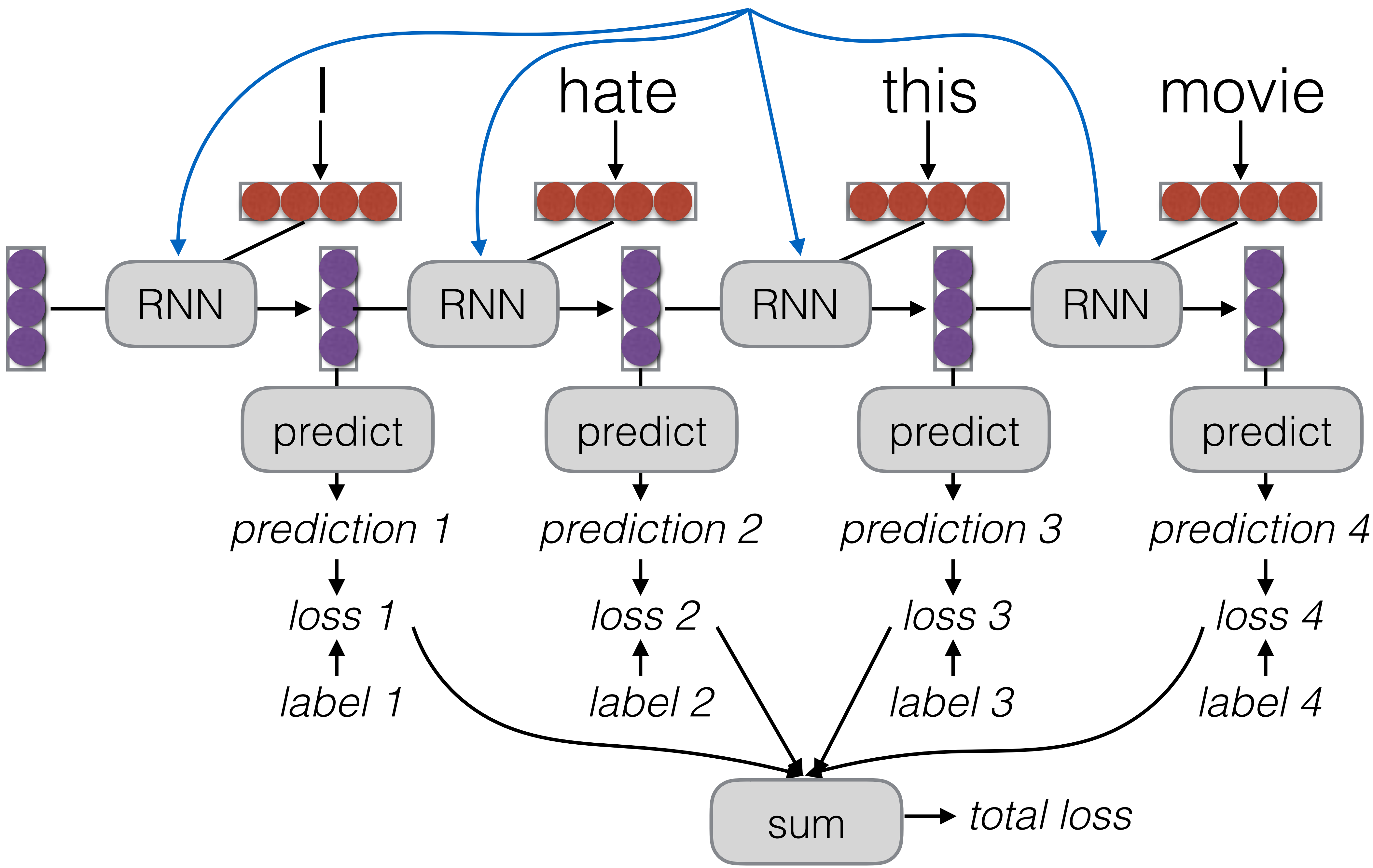


- Parameters are tied across time, derivatives are aggregated across all time steps

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

Parameter Tying

Parameters are shared! Derivatives are accumulated.

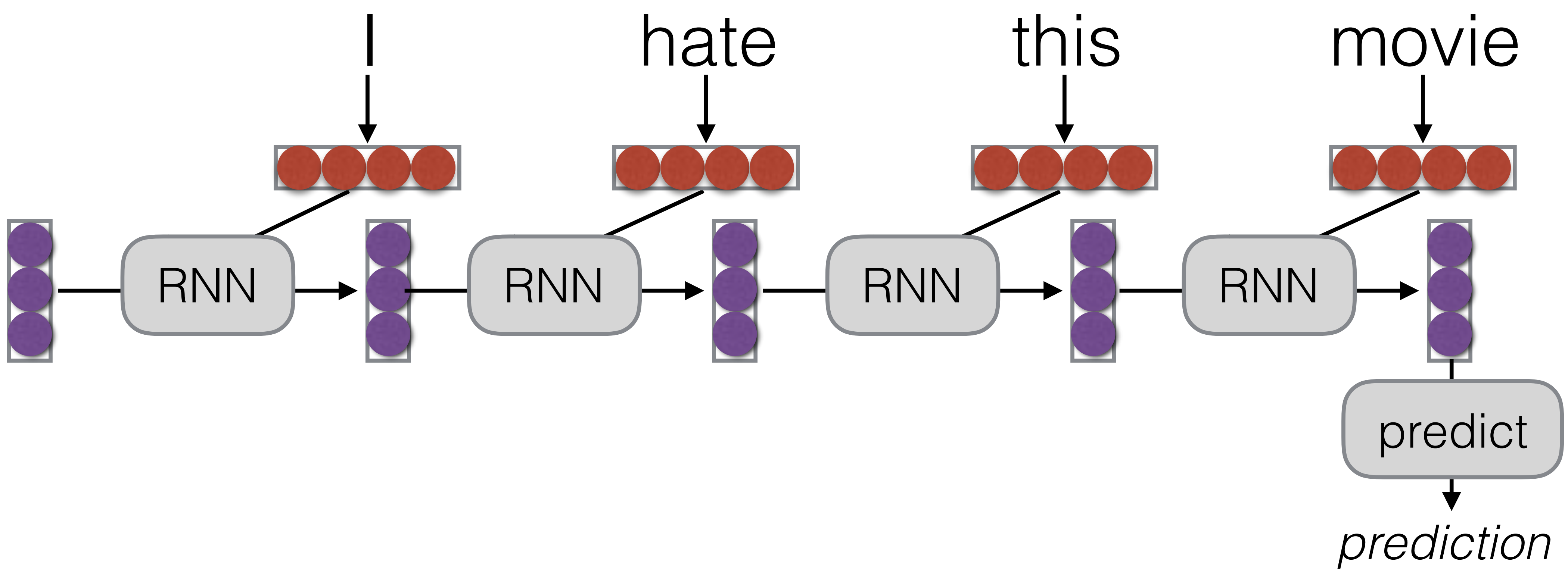


Applications of RNNs

What Can RNNs Do?

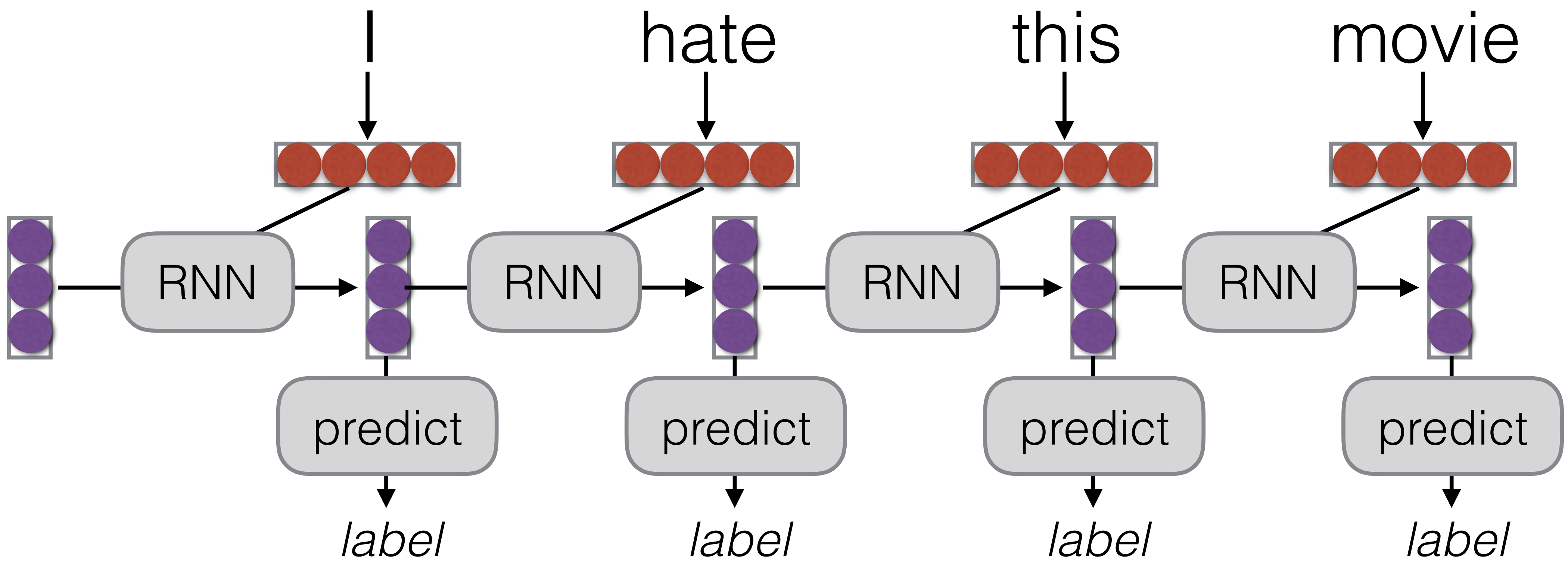
- Represent a sentence
  - Read whole sentence, make a prediction
- Represent a context within a sentence
  - Read context up until that point

Representing Sentences



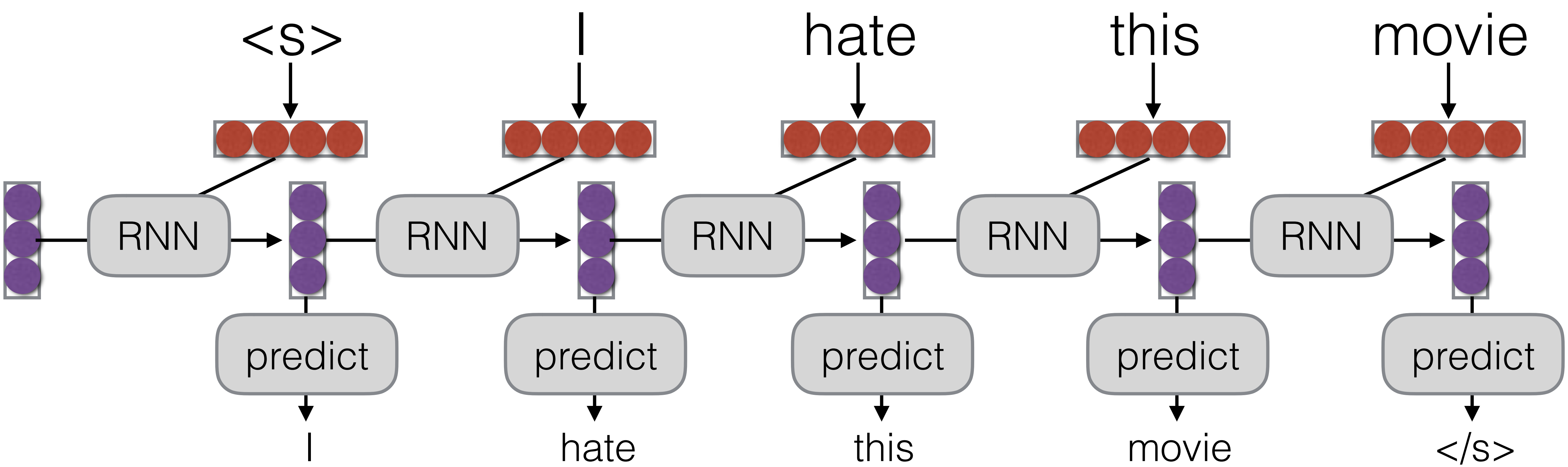
- Sentence classification
- Conditioned generation
- Retrieval

Representing Contexts



- Tagging
- Language Modeling
- Calculating Representations for Parsing, etc.

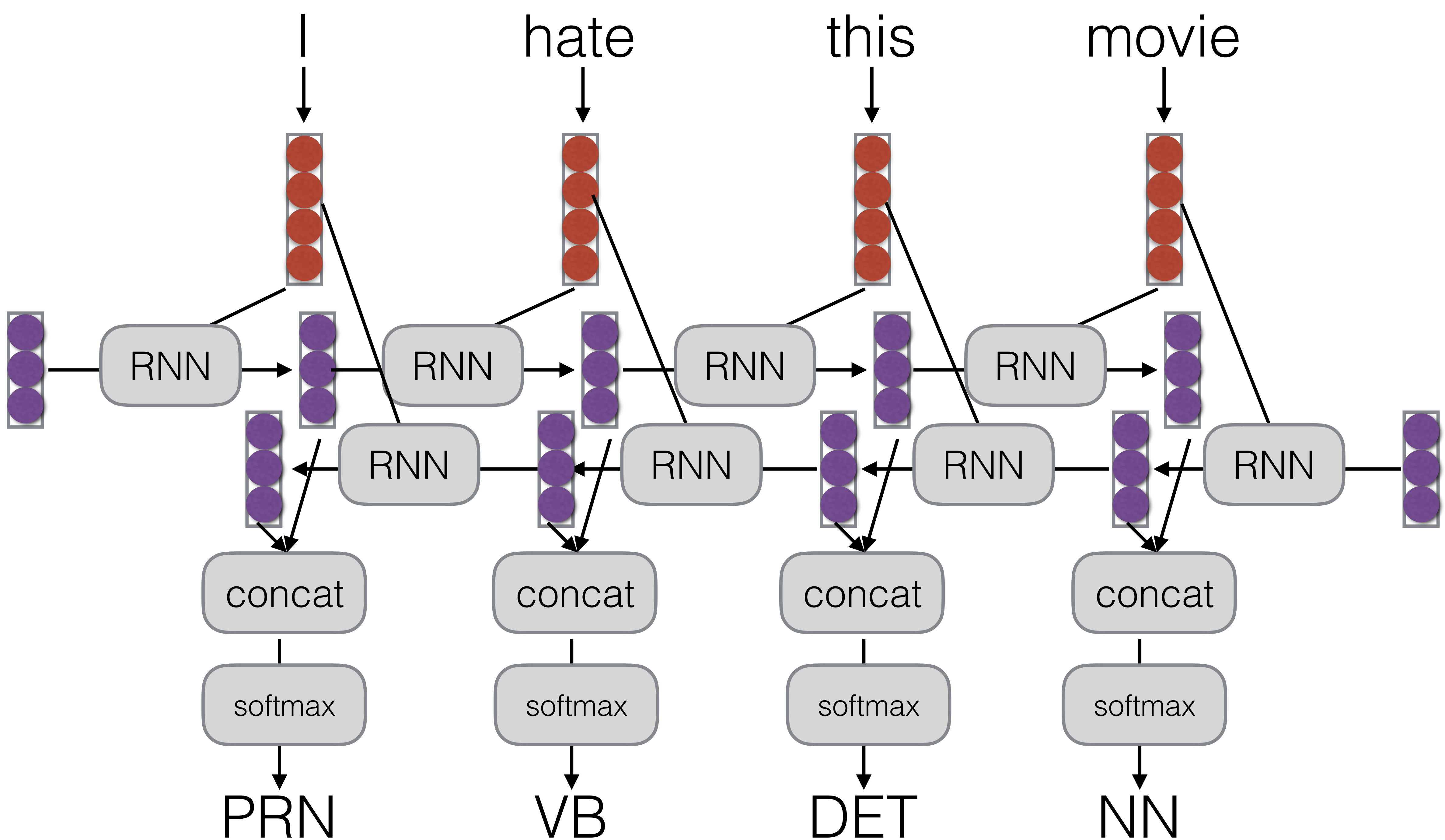
e.g. Language Modeling



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

Bi-RNNs

- A simple extension, run the RNN in both directions



Let’s Try it Out!

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.SimpleRNNBuilder(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 RNN (layers=1, input=64, hidden=128, model)
RNN = dy.SimpleRNNBuilder(1, 64, 128, model)

# Softmax weights/biases on top of RNN 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

…

```
# 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)
```

Code Examples

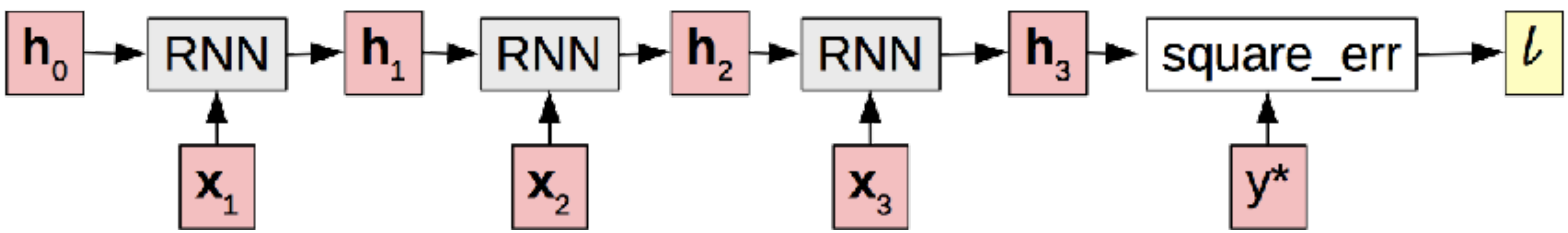
`sentiment-rnn.py`

RNN Problems and Alternatives

Vanishing Gradient

- Gradients decrease as they get pushed back

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

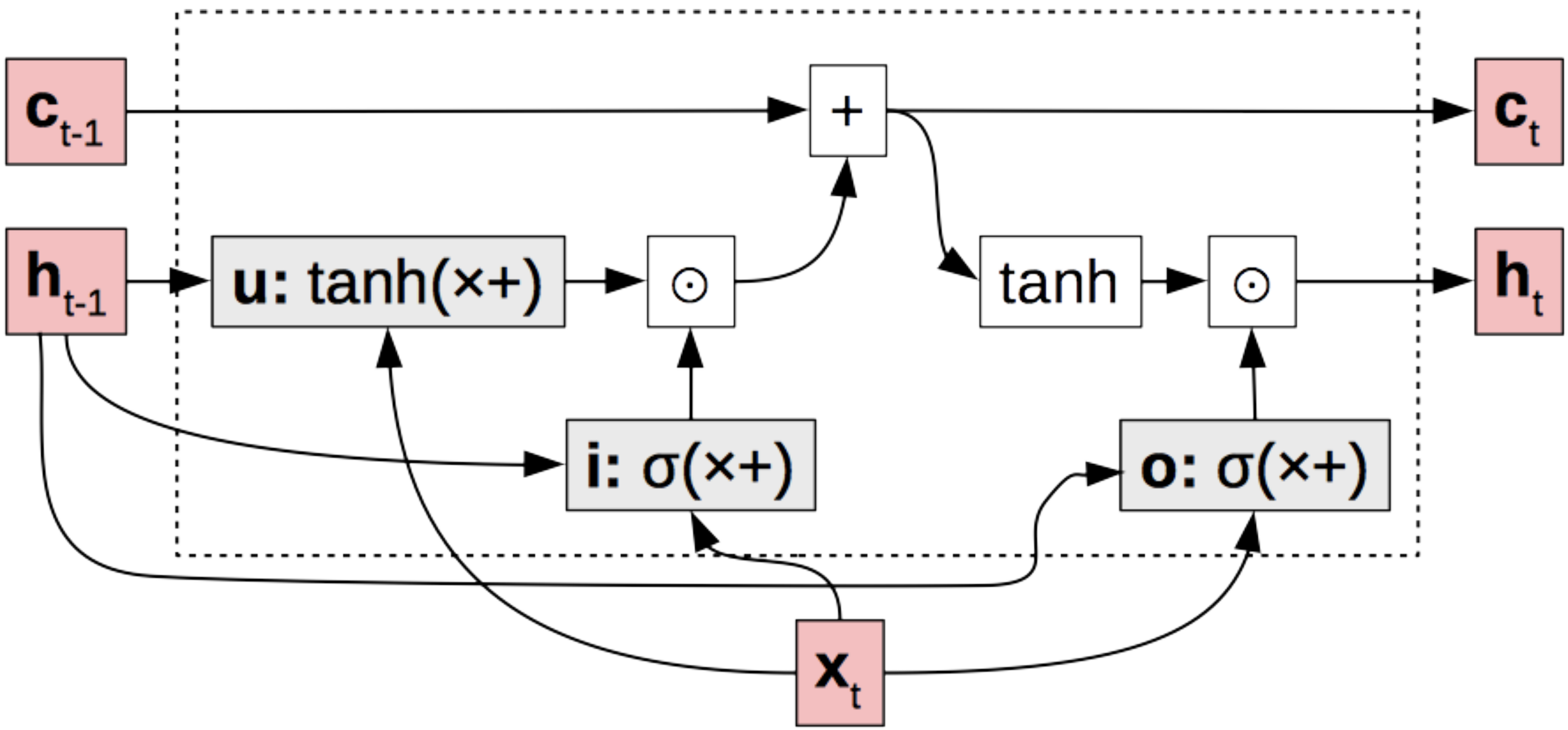


- Why? “Squashed” by non-linearities or small weights in matrices.

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

- **Basic idea:** make additive connections between time steps
- Addition does not modify the gradient, no vanishing
- Gates to control the information flow

LSTM Structure



update **u**: what value do we try to add to the memory cell?
input **i**: how much of the update do we allow to go through?
output **o**: how much of the cell do we reflect in the next state?

Other Alternatives

- Lots of variants of LSTMs (Hochreiter and Schmidhuber, 1997)

- Gated recurrent units (GRUs; Cho et al., 2014)

- All follow the basic paradigm of “take input, update state”

Code Examples

`sentiment-lstm.py`

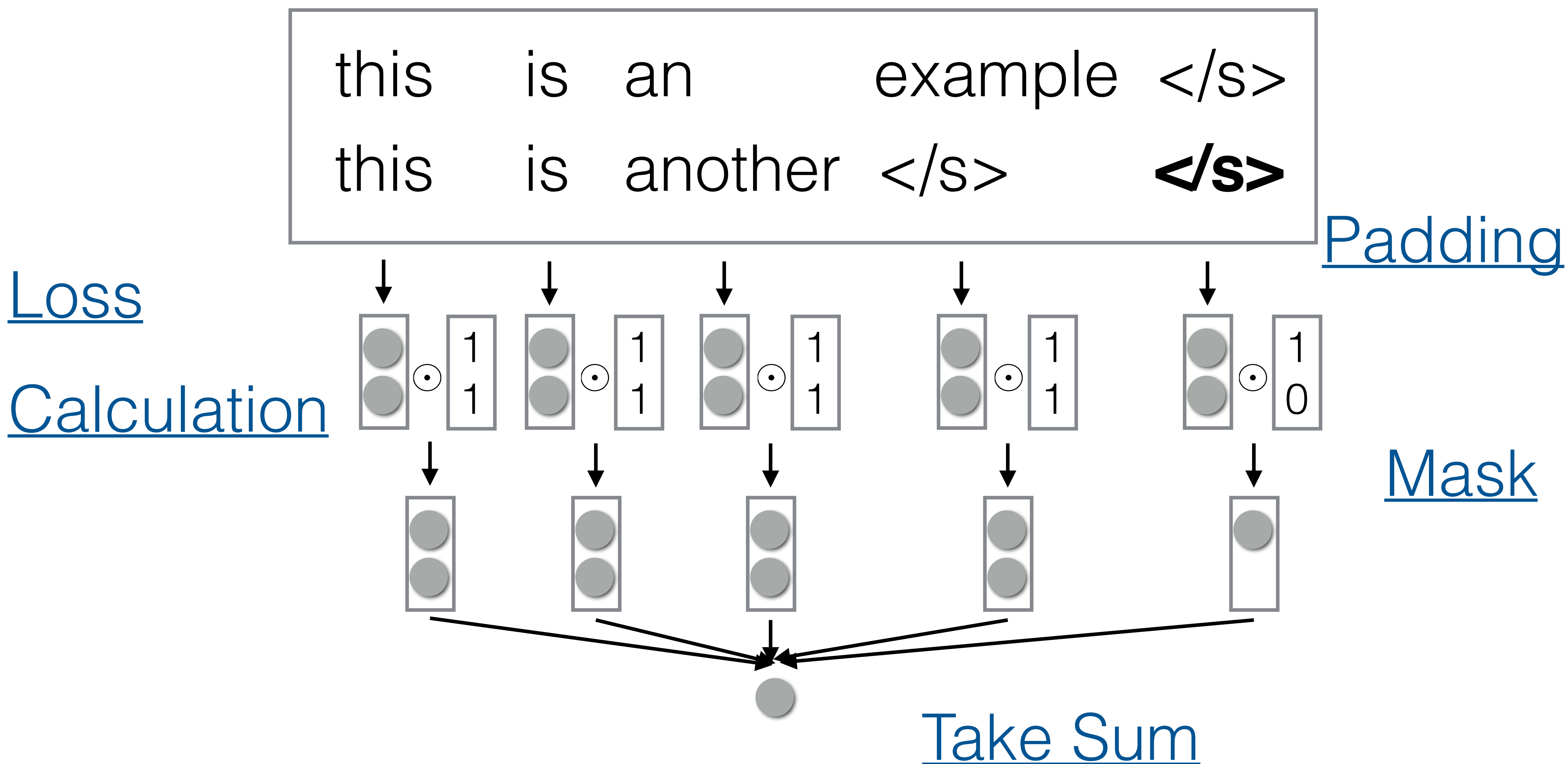
`lm-lstm.py`

Efficiency/Memory Tricks

Handling Mini-batching

- Mini-batching makes things much faster!
- But mini-batching in RNNs is harder than in feed-forward networks
    - Each word depends on the previous word
    - Sequences are of various length

Mini-batching Method



(Or use DyNet automatic mini-batching, much easier but a bit slower)

Bucketing/Sorting

- If we use sentences of different lengths, too much padding and sorting can **result in decreased performance**
- To remedy this: **sort sentences** so similarly-lengthed sentences are in the same batch

Code Example

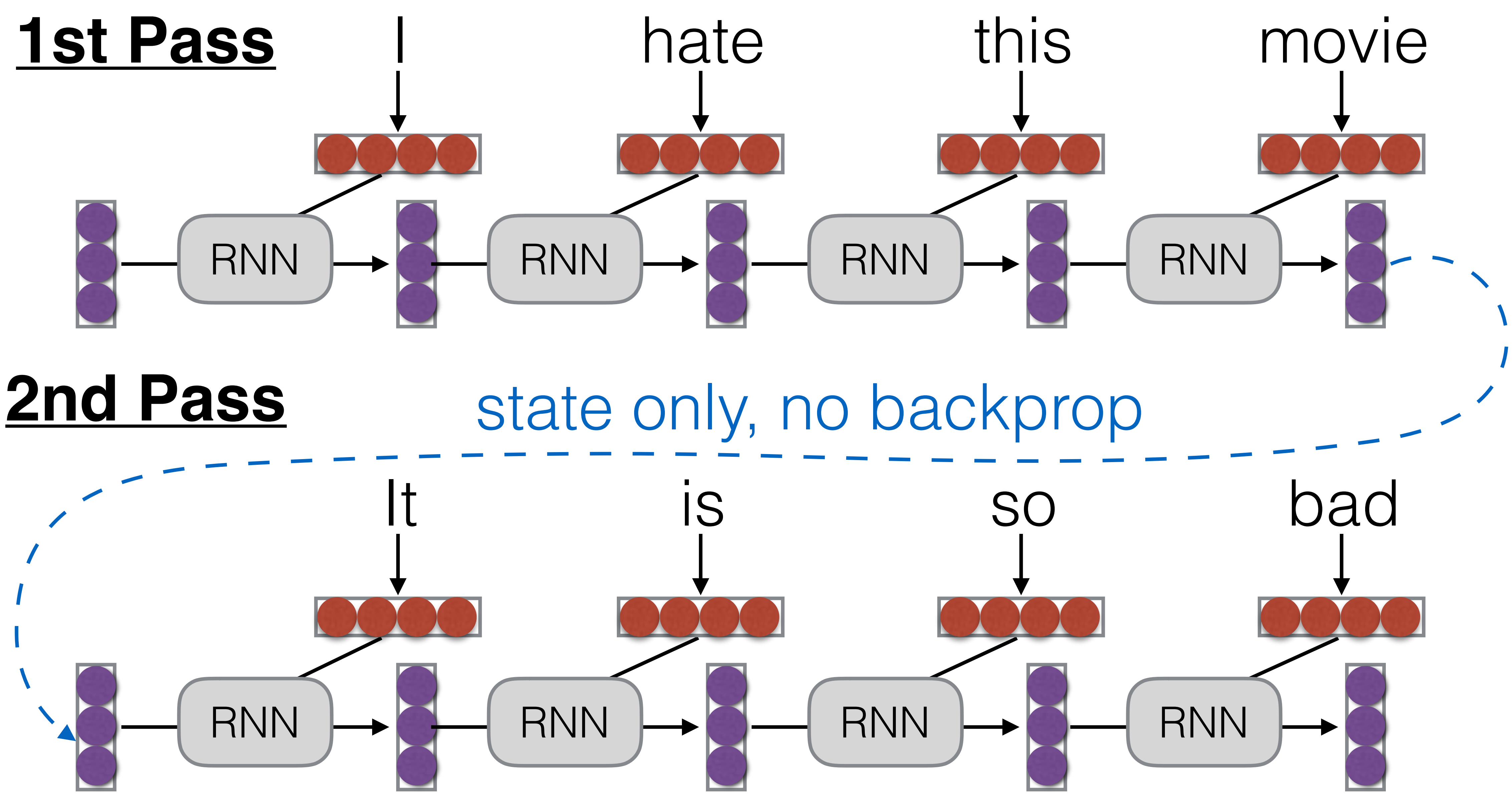
`lm-minibatch.py`

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



Pre-training/Transfer for RNNs

RNN Strengths/Weaknesses

- RNNs, particularly deep RNNs/LSTMs, are **quite powerful and flexible**
- But they **require a lot of data**
- Also have trouble with **weak error signals** passed back from the end of the sentence

Pre-training/Transfer

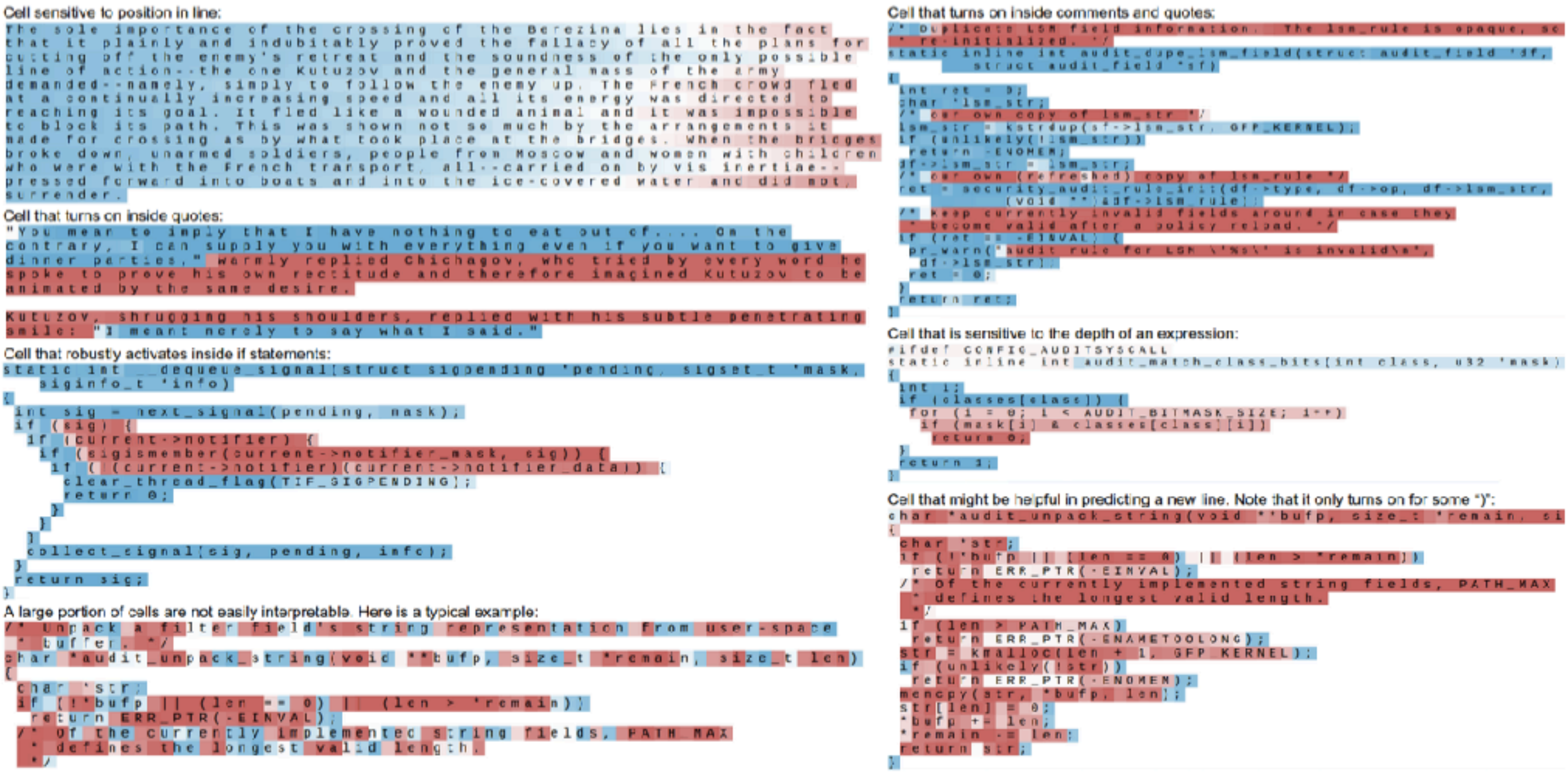
- Train for one task, solve another
- **Pre-training task:** Big data, easy to learn
- **Main task:** Small data, harder to learn

Example:
LM -> Sentence Classifier
(Luong et al. 2015)

- Train a **language model first**: lots of data, easy-to-learn objective
- **Sentence classification**: little data, hard-to-learn objective
- Results in much better classifications, competitive or better than CNN-based methods

Why Pre-training?

- The model learns consistencies in the data (Karpathy et al. 2015)



- Model learns syntax (Shi et al. 2017) or semantics (Radford et al. 2017)

Questions?