

CS11-747 Neural Networks for NLP

Recurrent Neural Networks

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Language Technologies Institute

Site

<https://phontron.com/class/nn4nlp2017/>

NLP and Sequential Data

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 - Words in sentences

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Long-distance Dependencies in Language

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- 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!

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- What is the referent of “it”?

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

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Trophy

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

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Suitcase

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Suitcase

(from Winograd Schema Challenge:

<http://commonsensereasoning.org/winograd.html>)

Recurrent Neural Networks

(Elman 1990)

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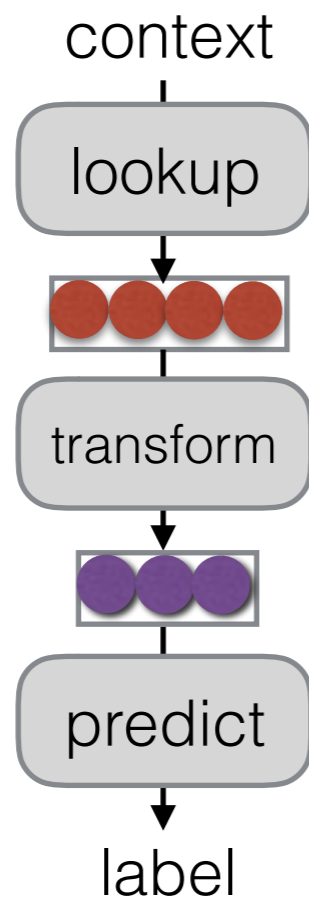
- Tools to “remember” information

Recurrent Neural Networks

(Elman 1990)

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Feed-forward NN

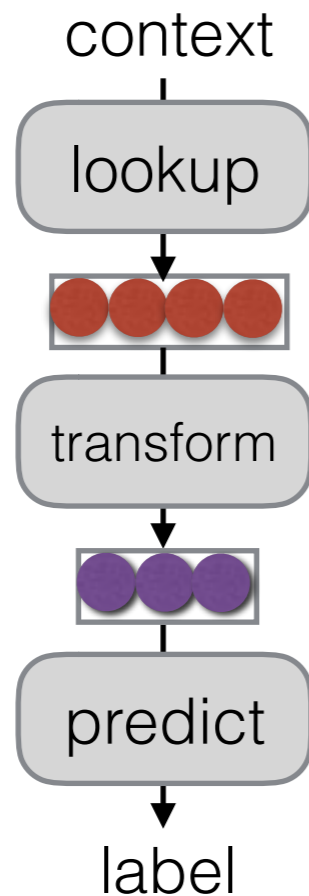


Recurrent Neural Networks

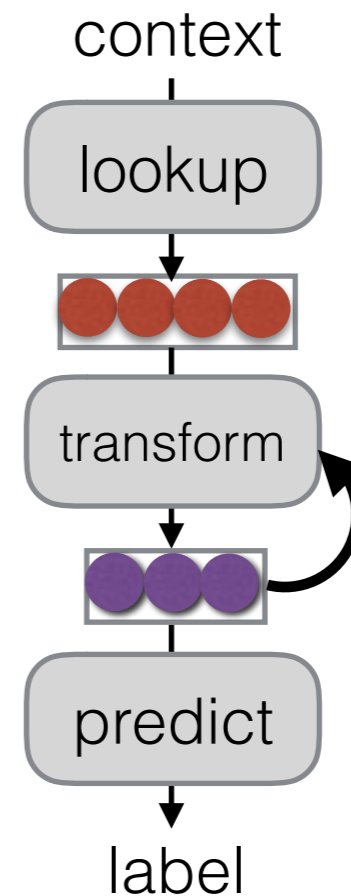
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Feed-forward NN



Recurrent NN



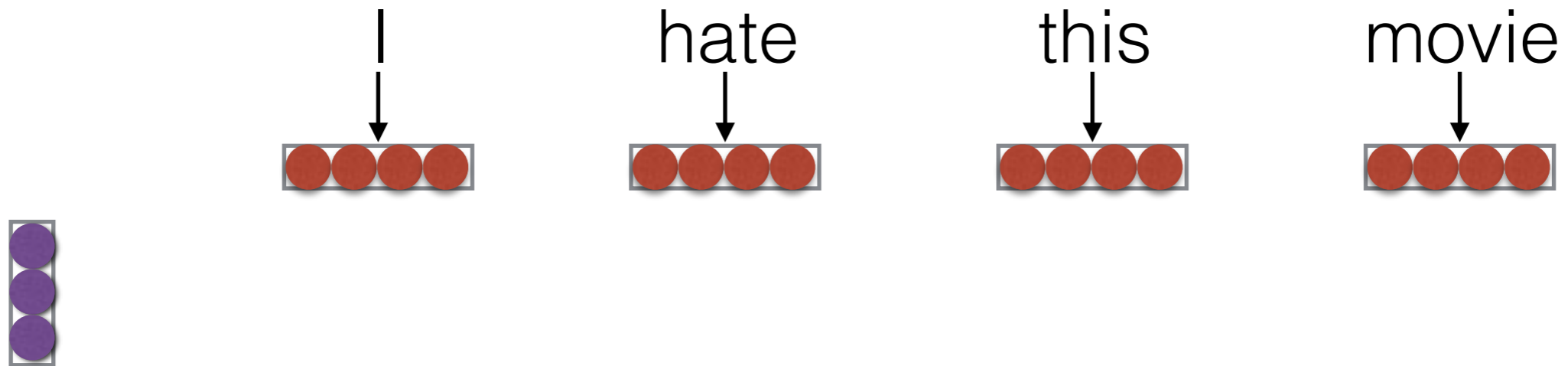
Unrolling in Time

- What does processing a sequence look like?



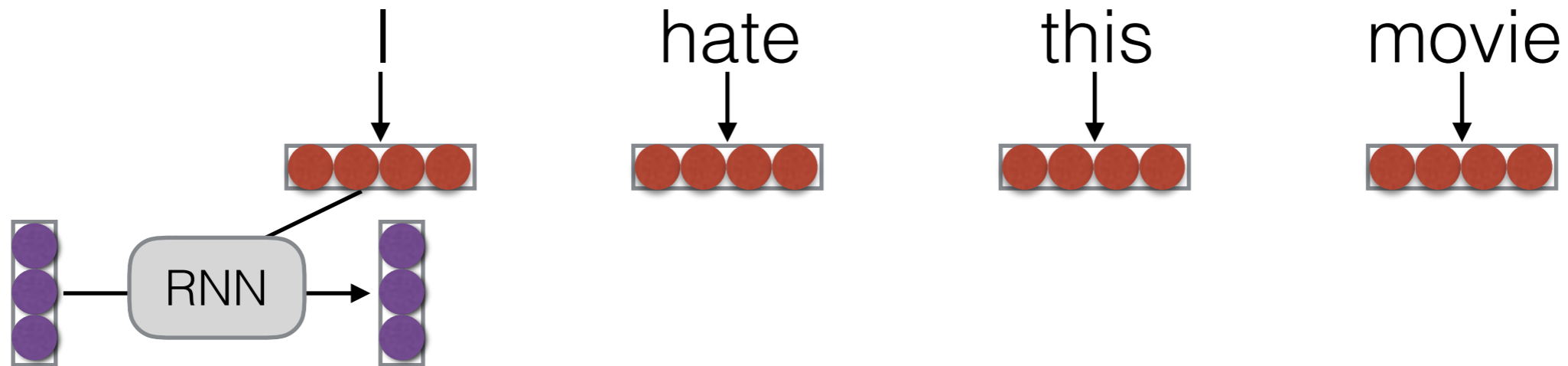
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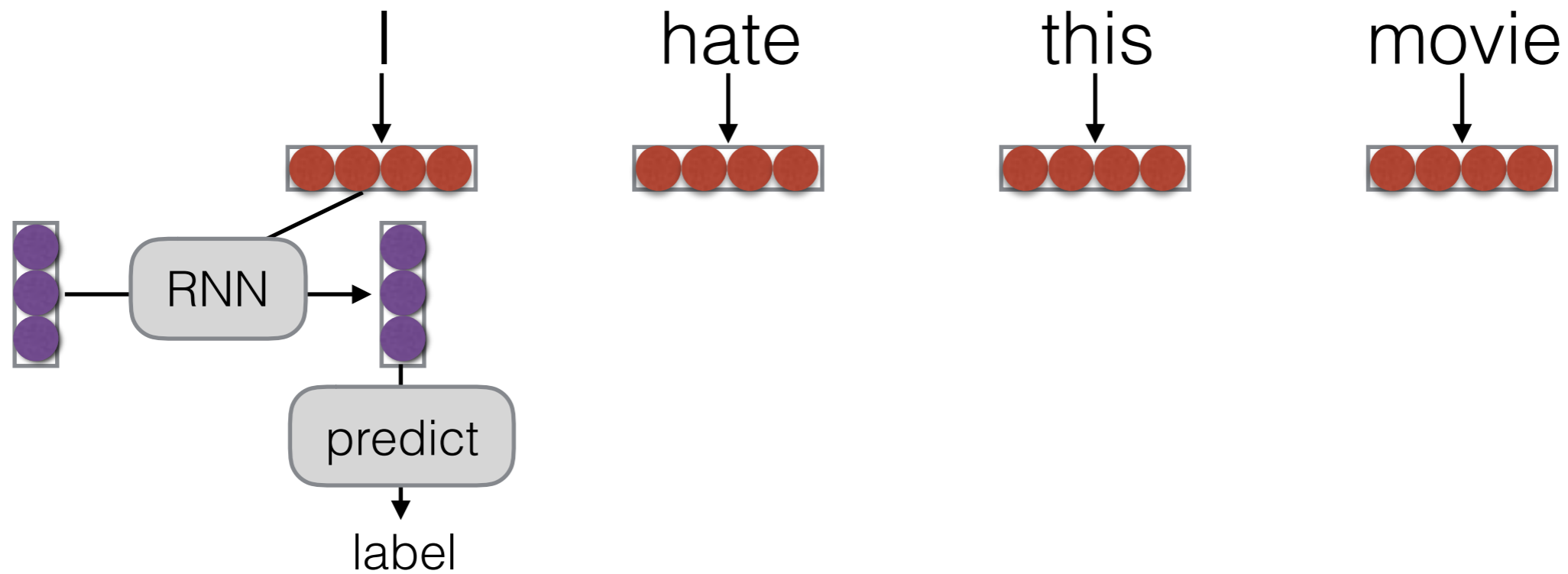
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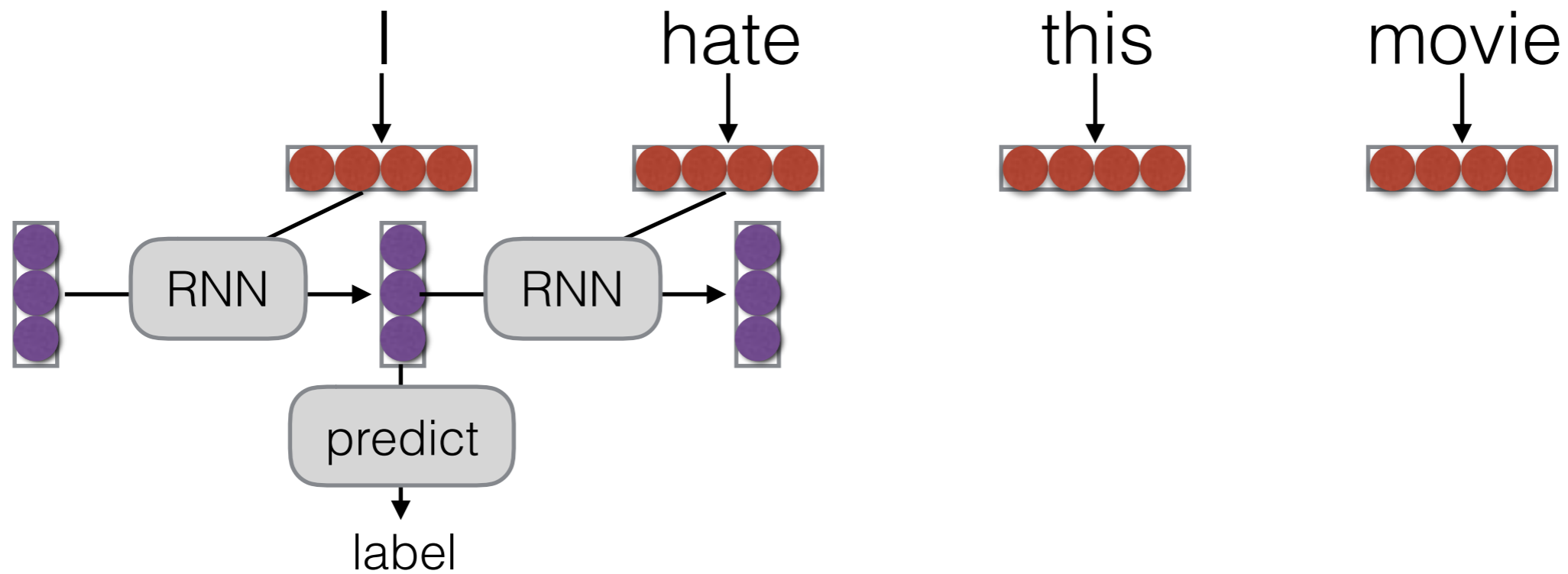
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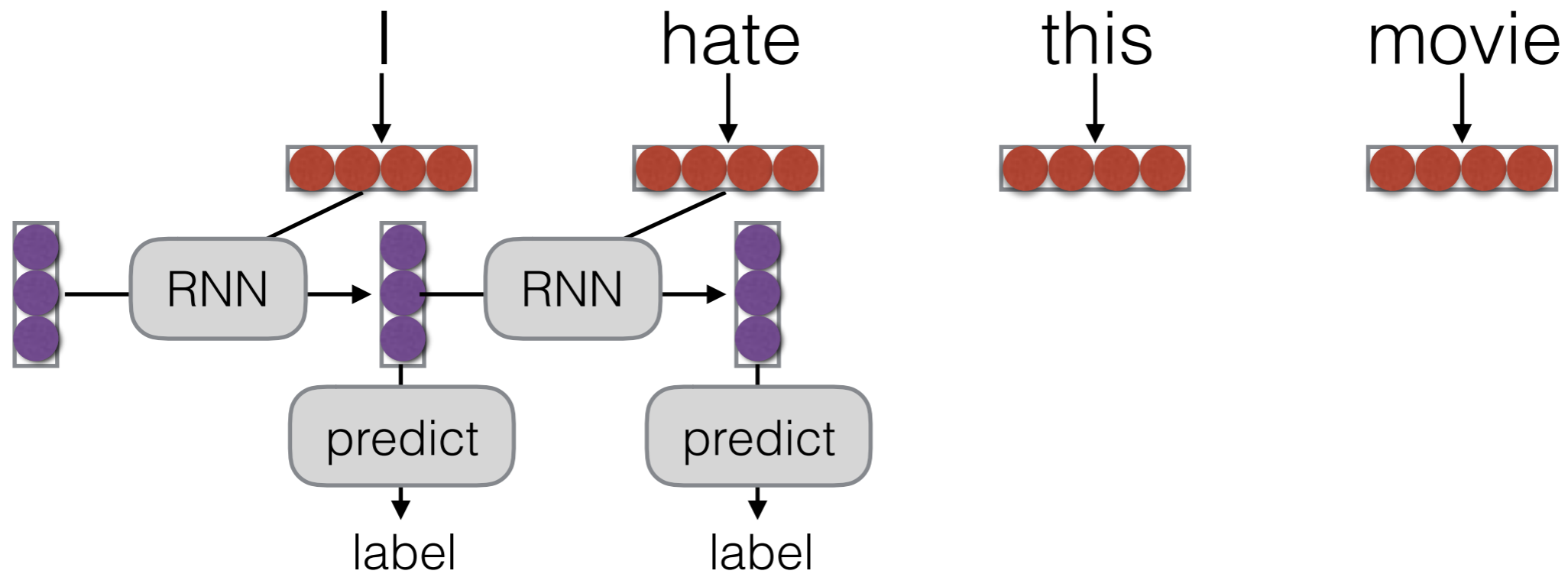
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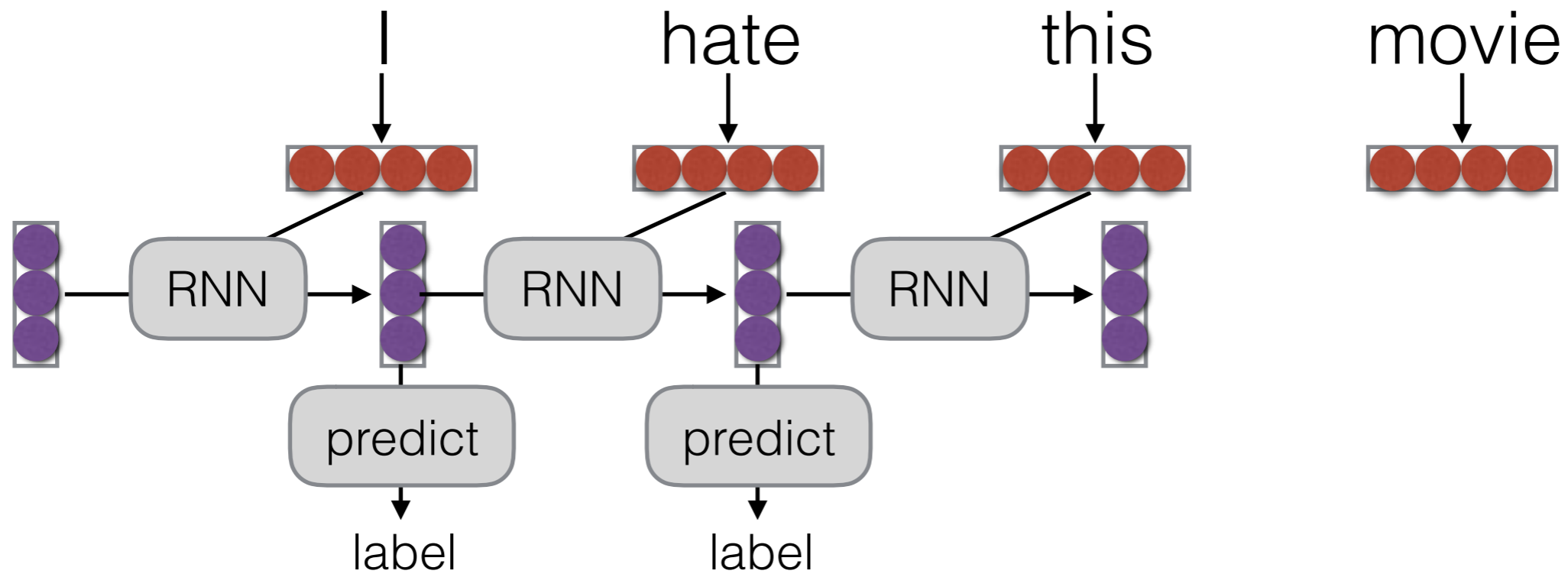
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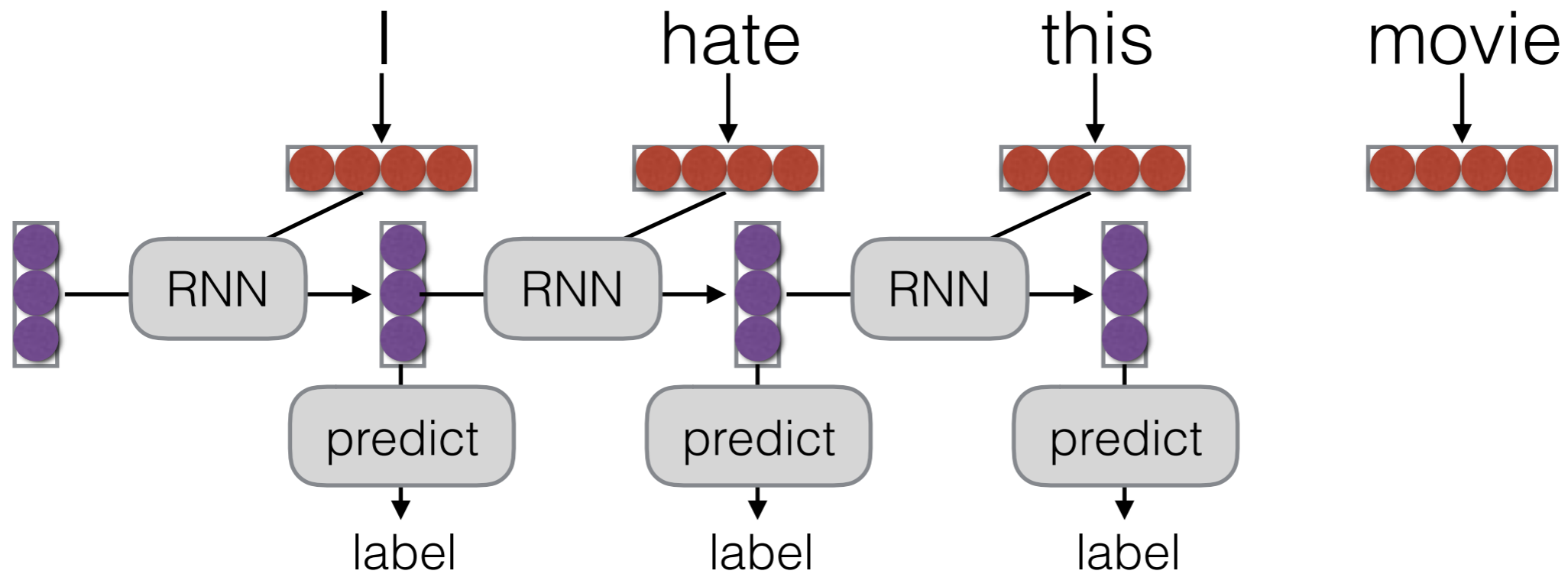
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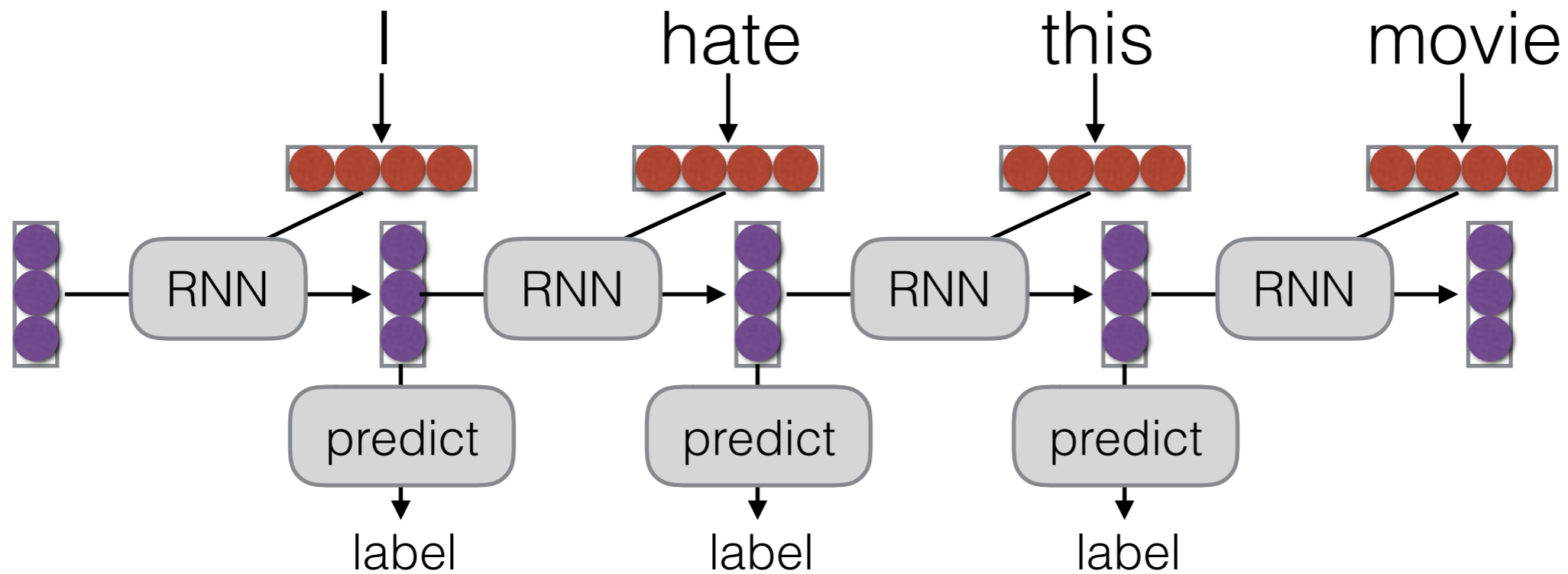
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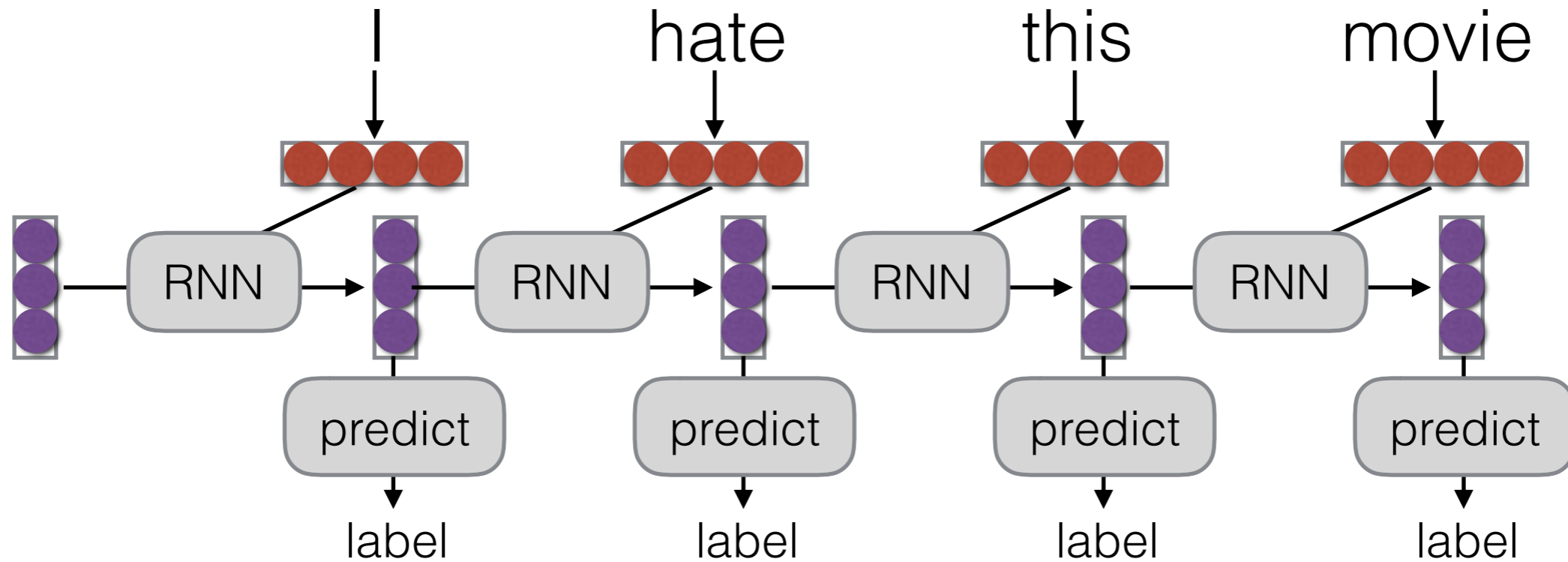
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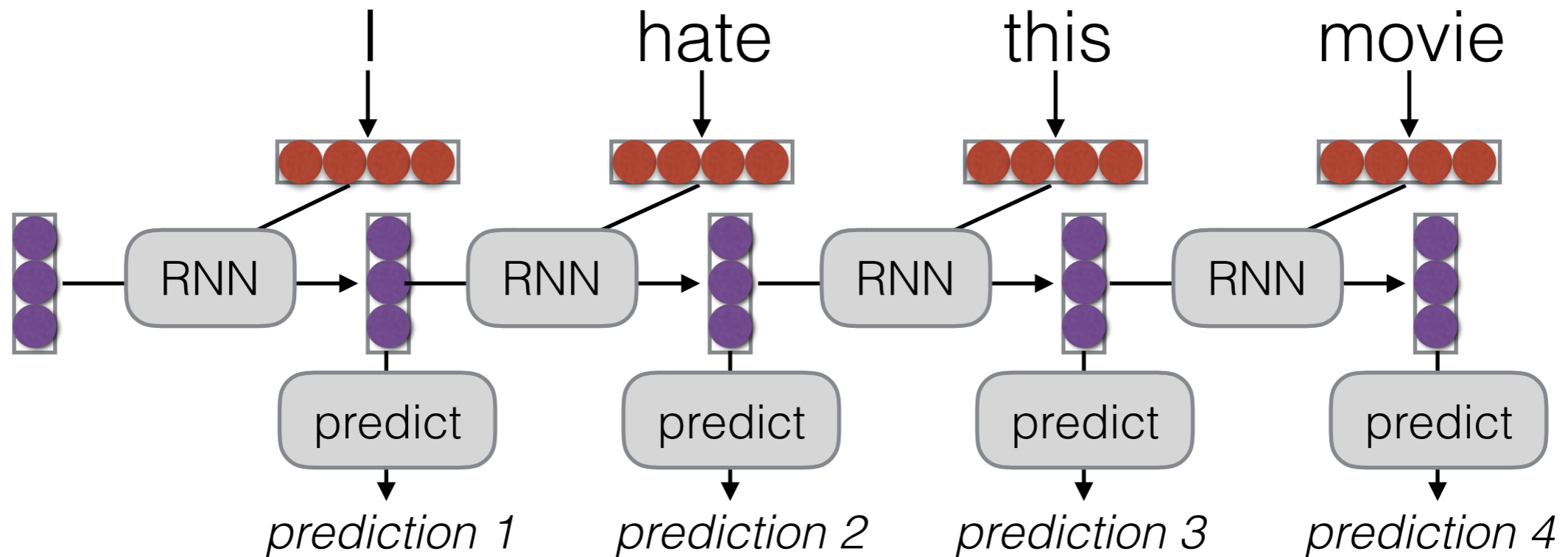


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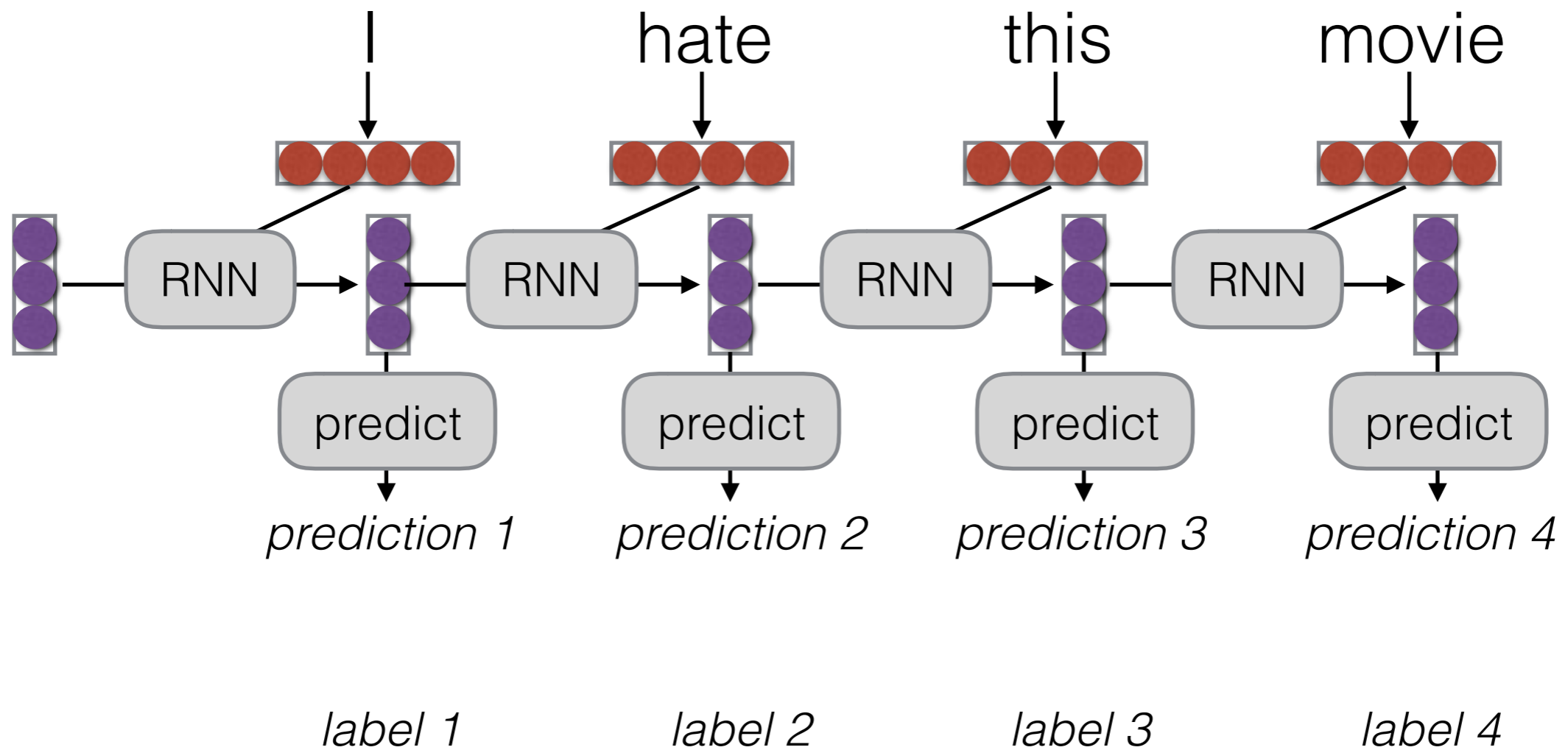
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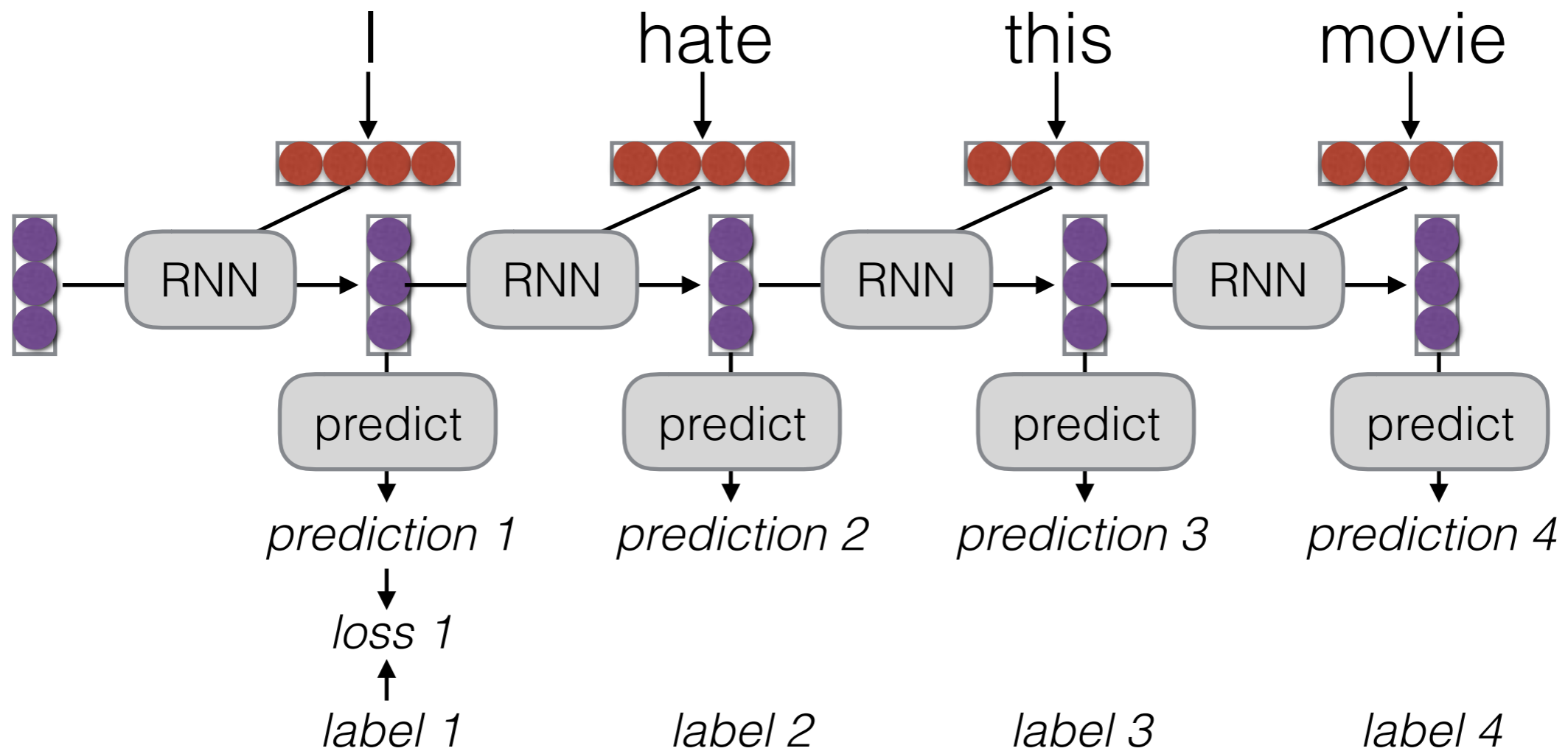
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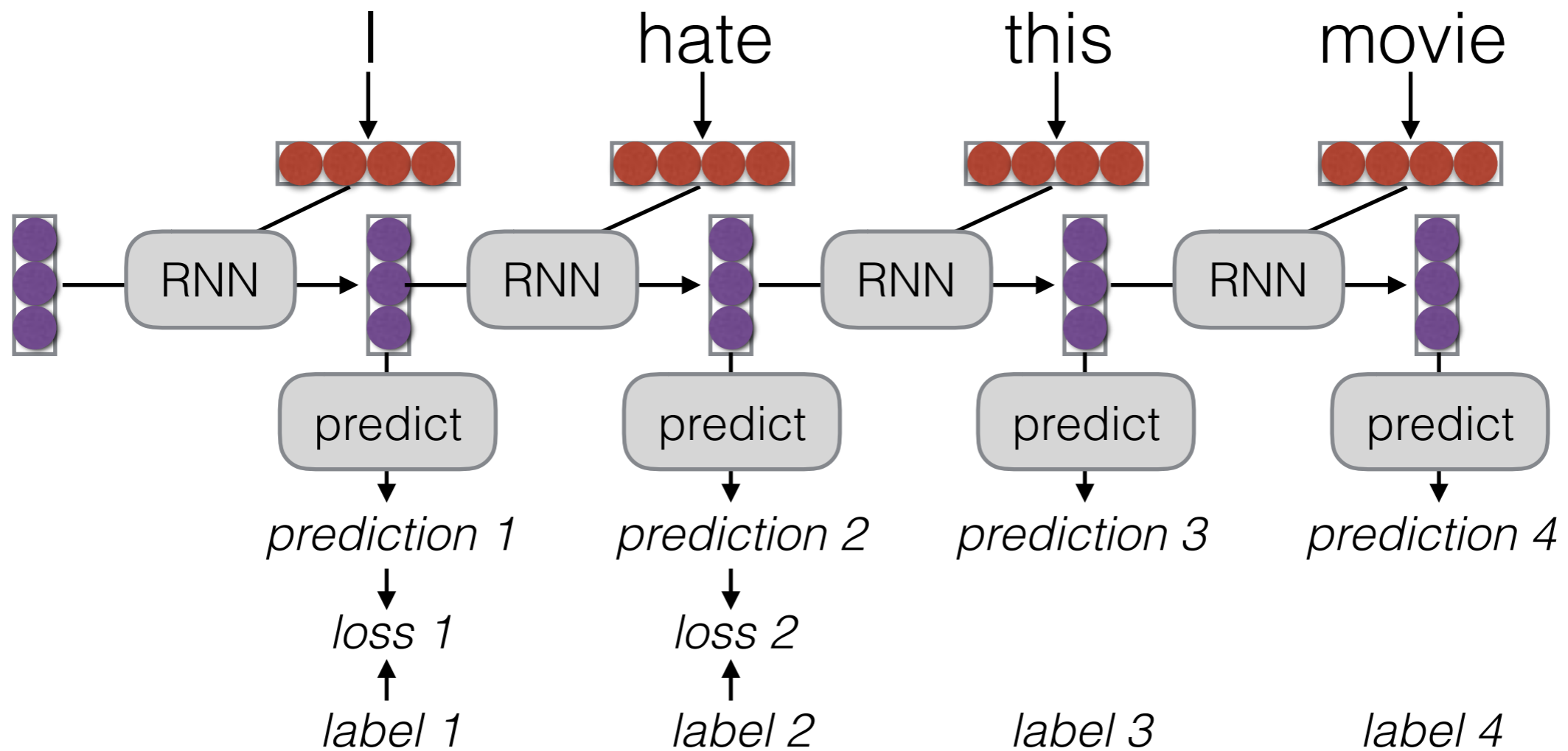
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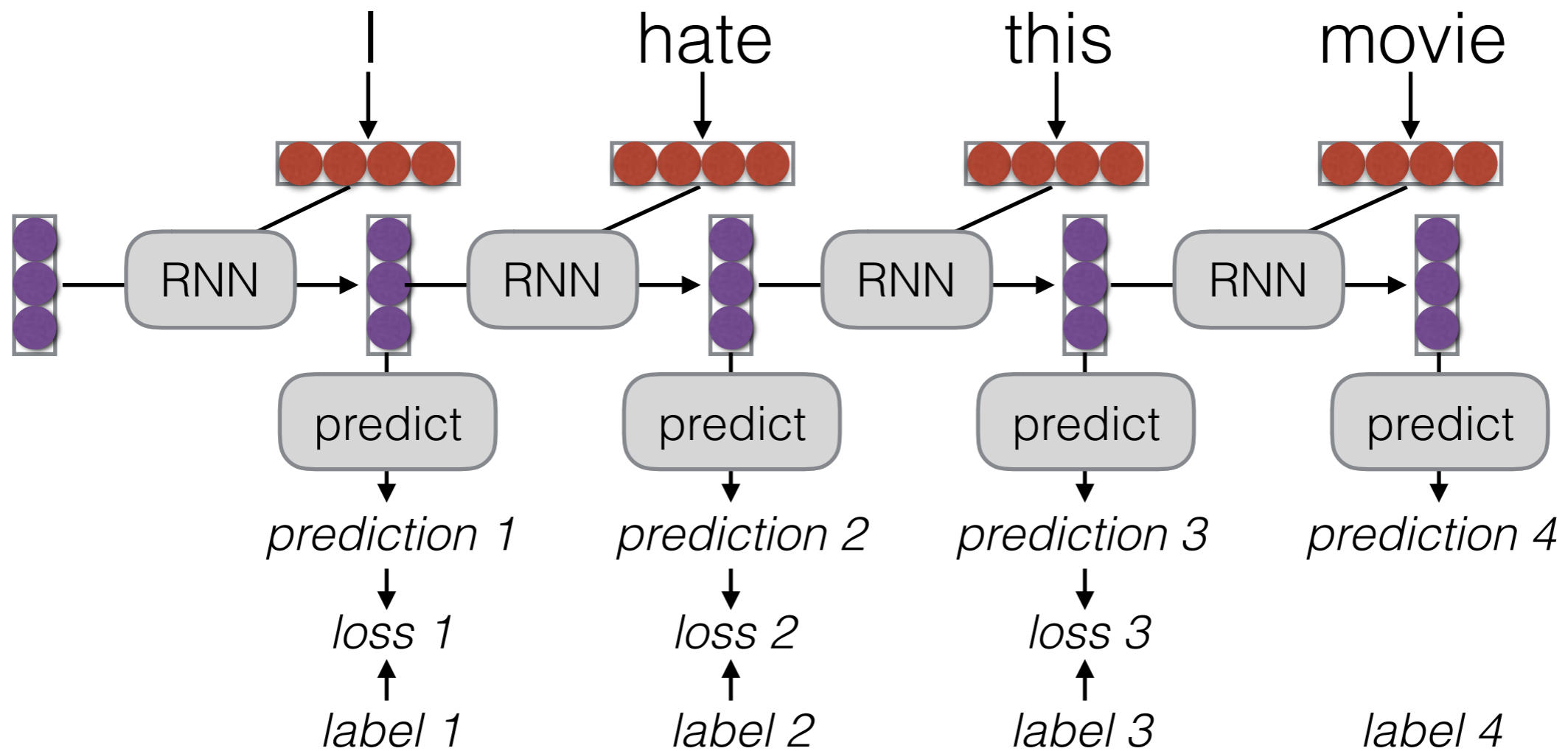
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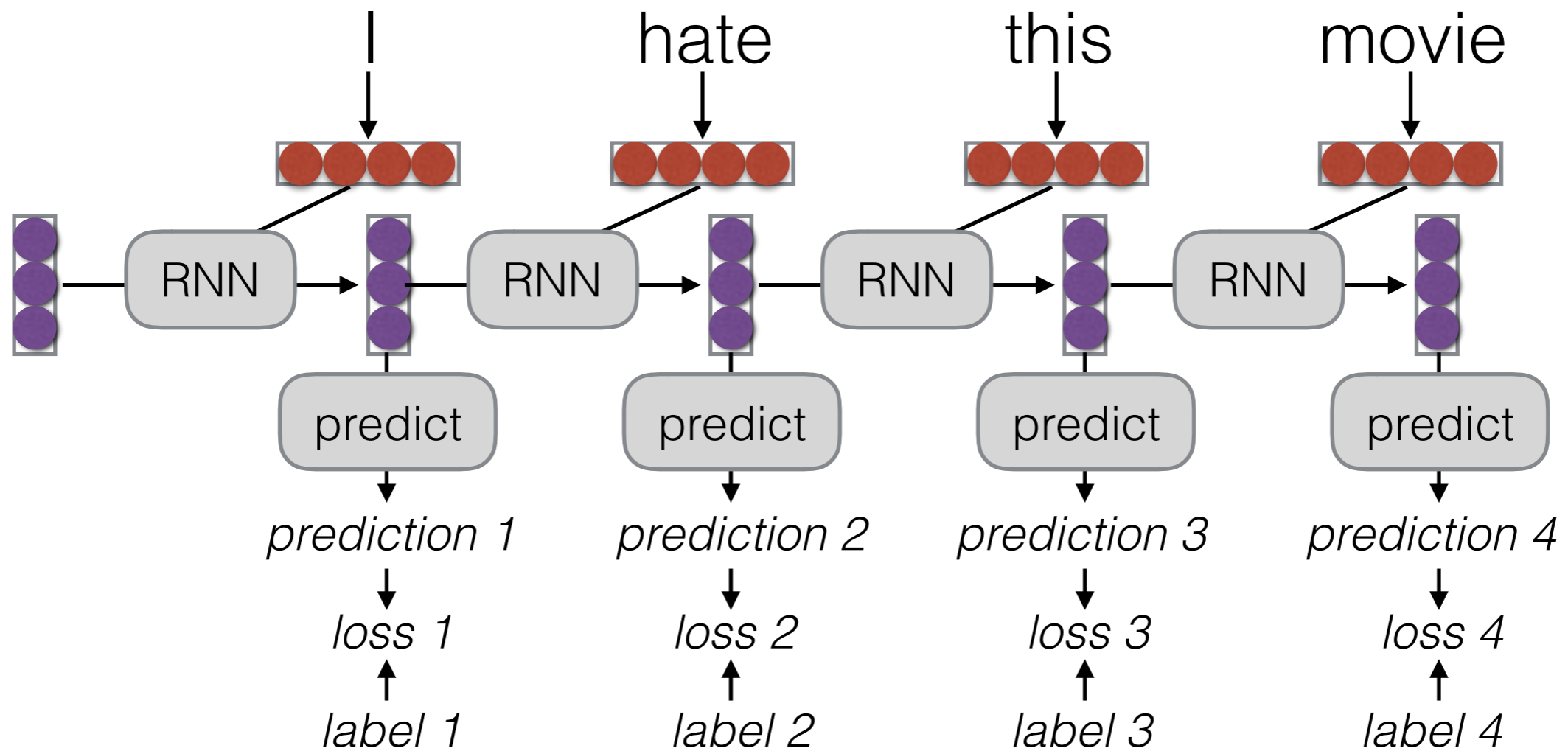
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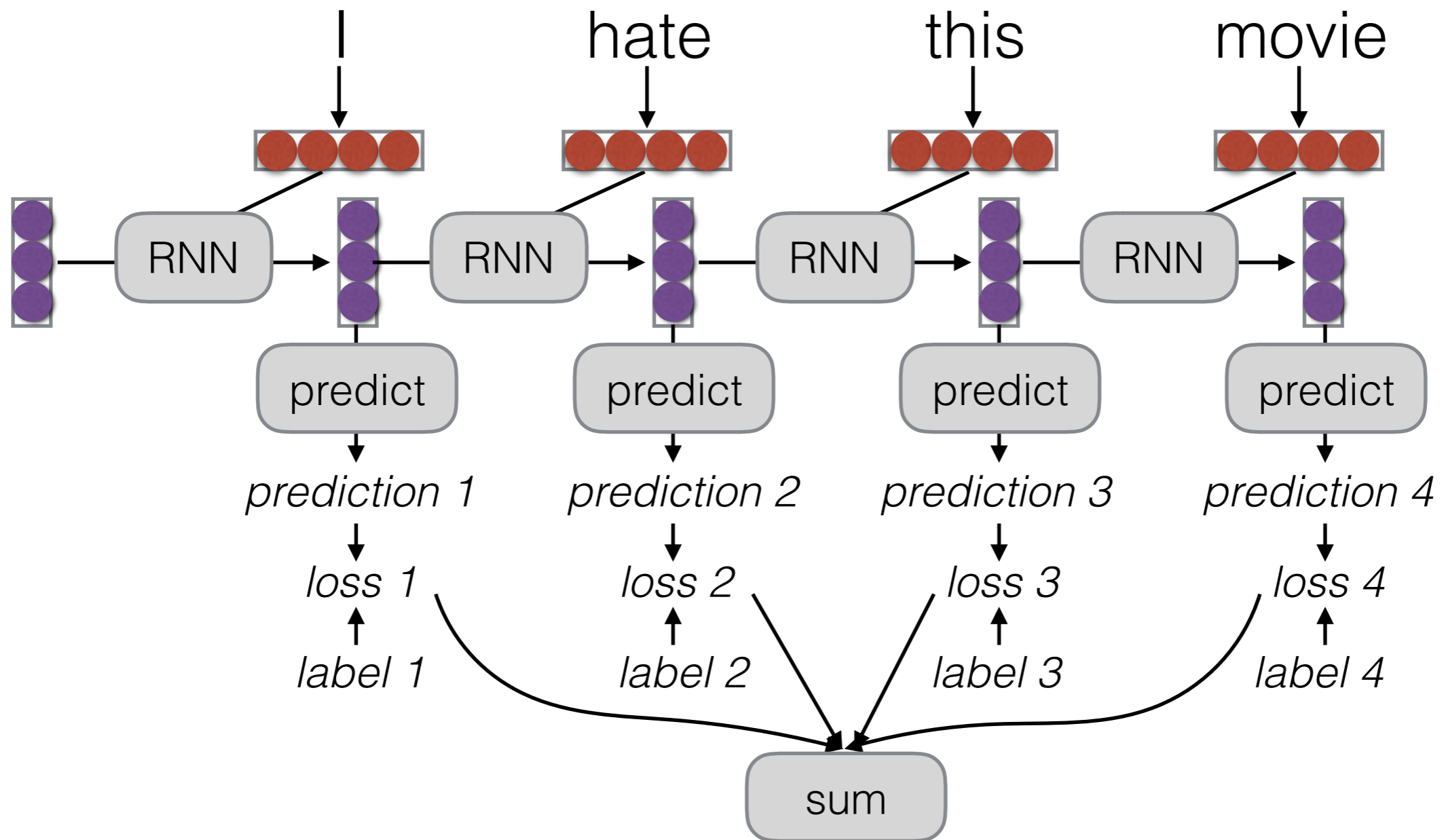
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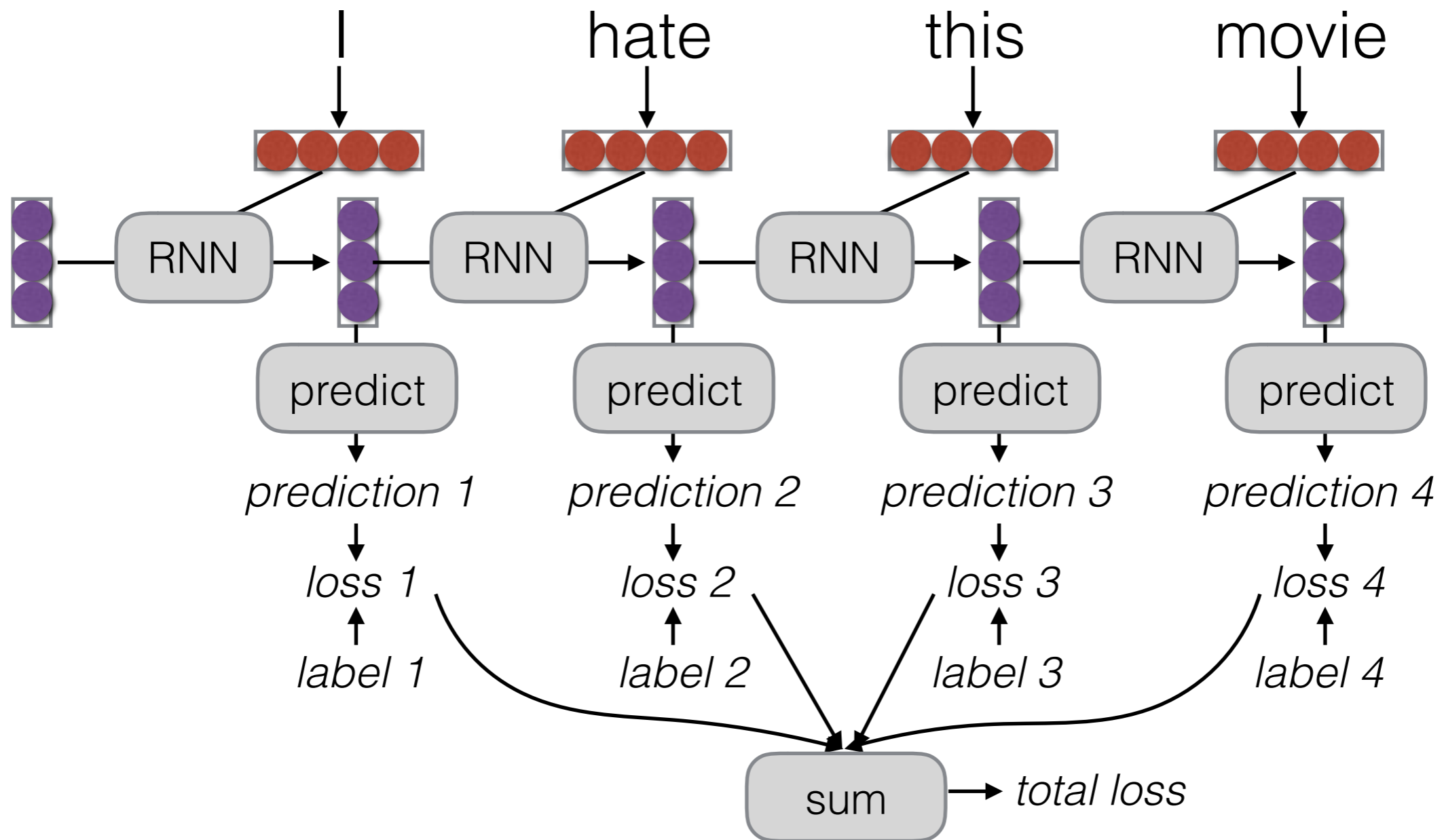
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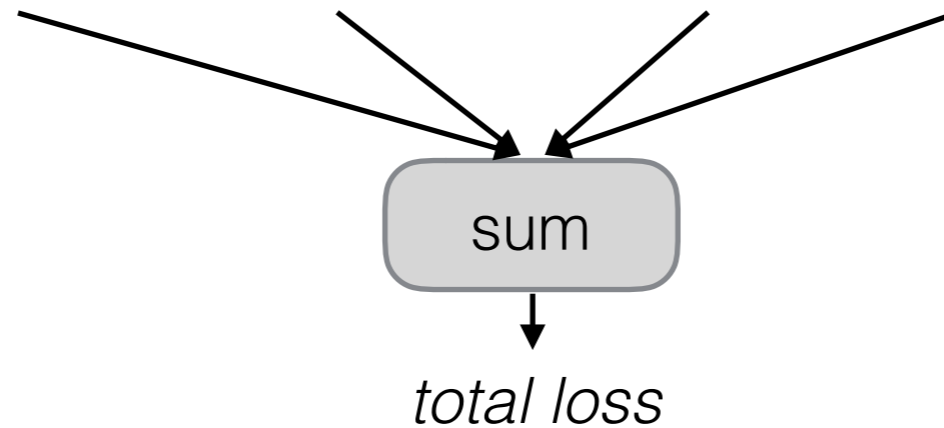
RNN Training

RNN Training

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

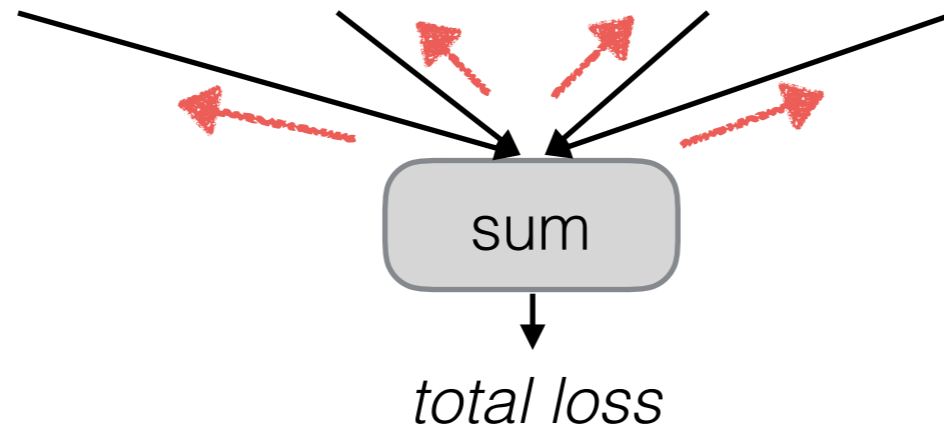
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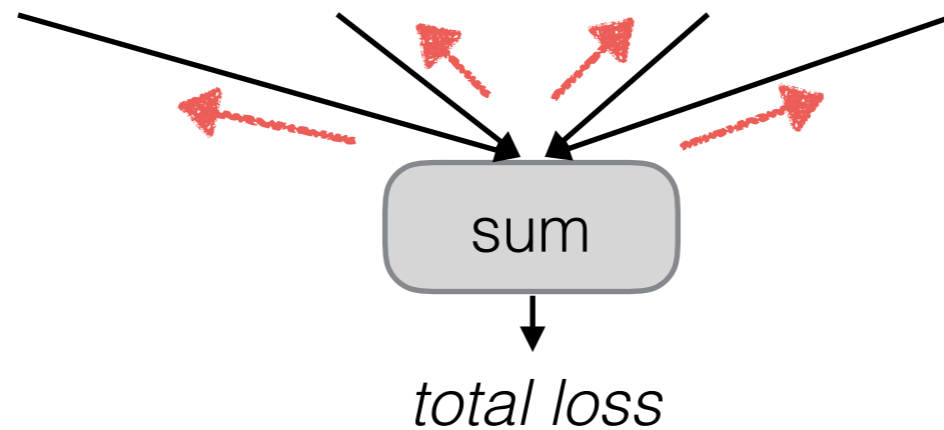
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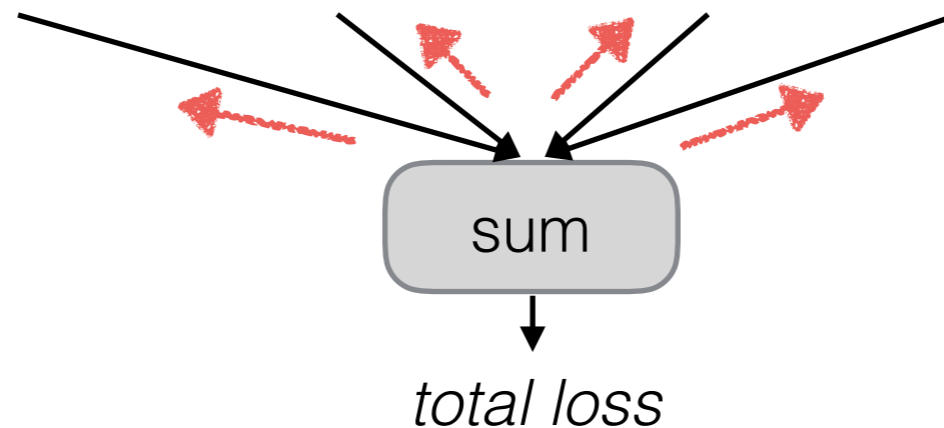
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- Parameters are tied across time, derivatives are aggregated across all time steps

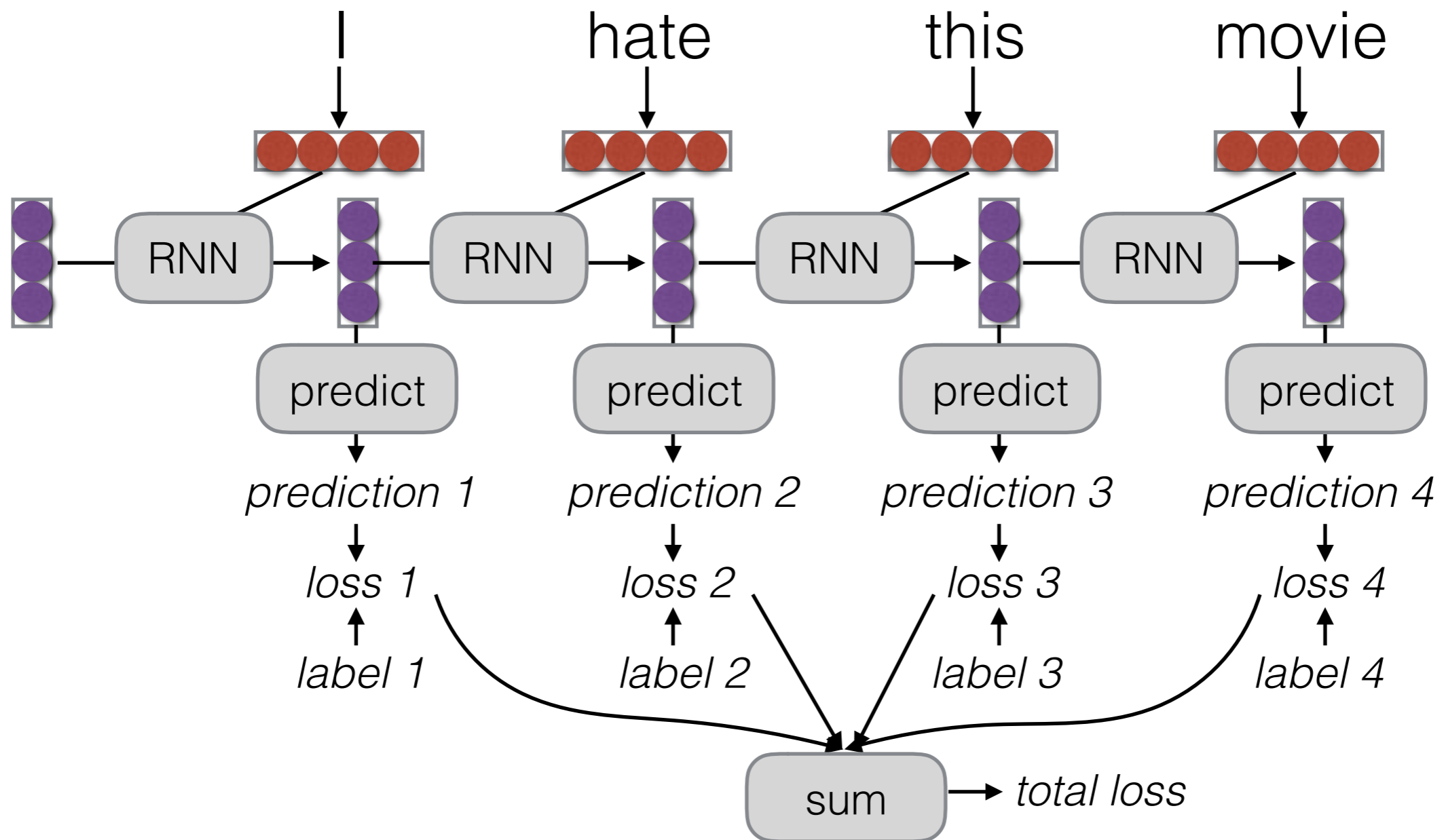
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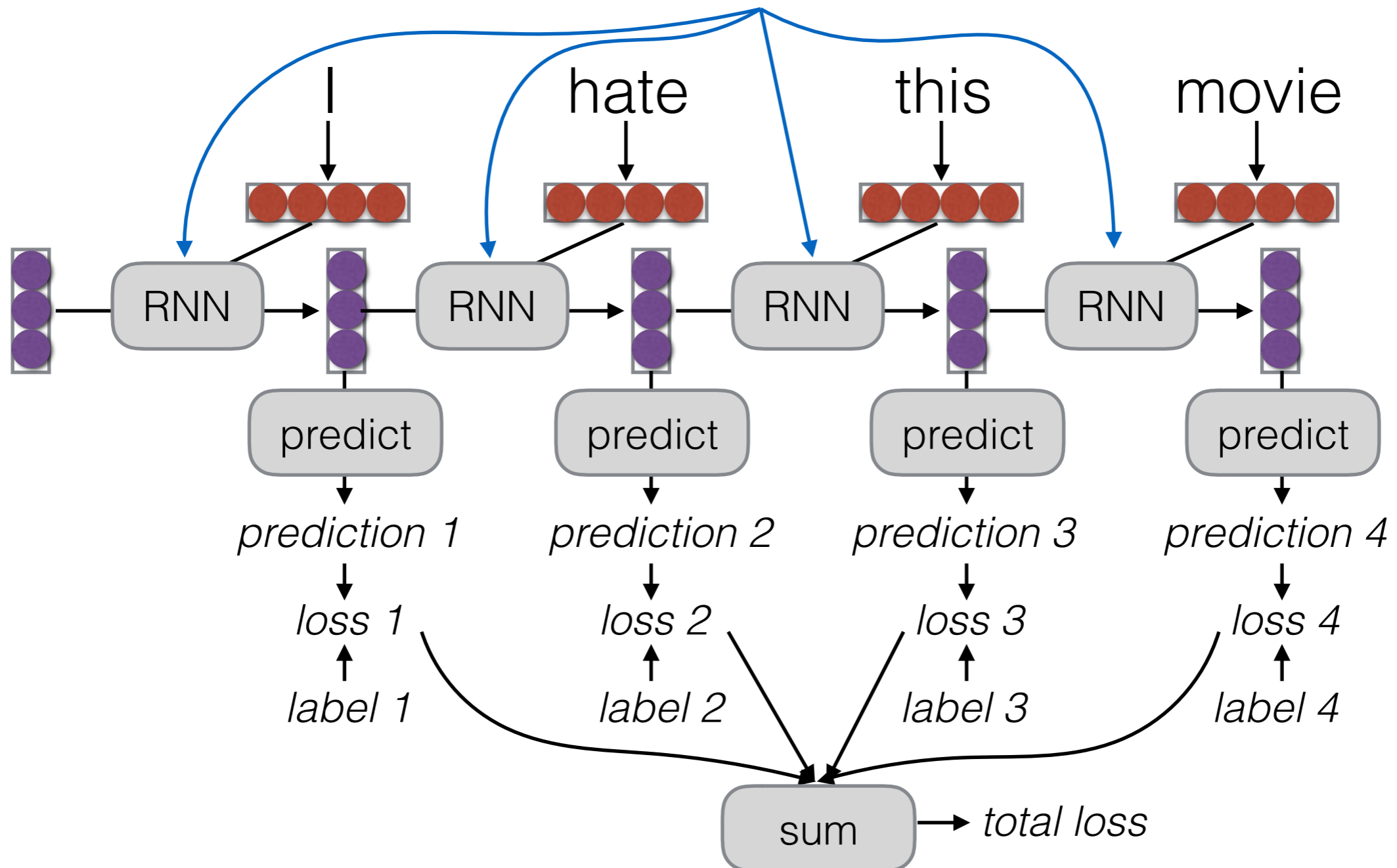
- Parameters are tied across time, derivatives are aggregated across all time steps
- This is historically called “backpropagation through time” (BPTT)

Parameter Tying



Parameter Tying

Parameters are shared! Derivatives are accumulated.



Applications of RNNs

What Can RNNs Do?

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- Represent a sentence

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- Read whole sentence, make a prediction

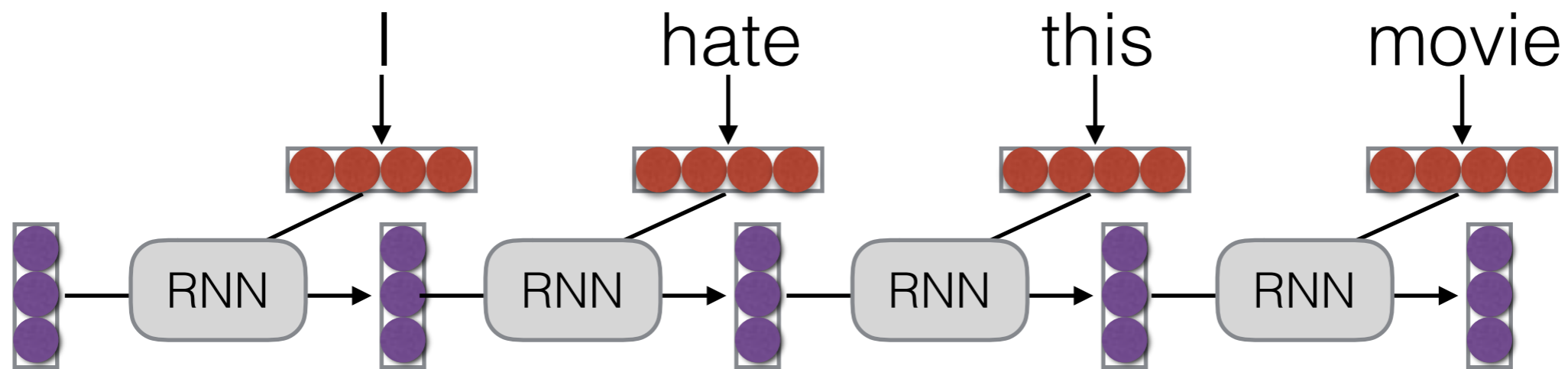
What Can RNNs Do?

- Represent a sentence
 - Read whole sentence, make a prediction
- Represent a context within a sentence

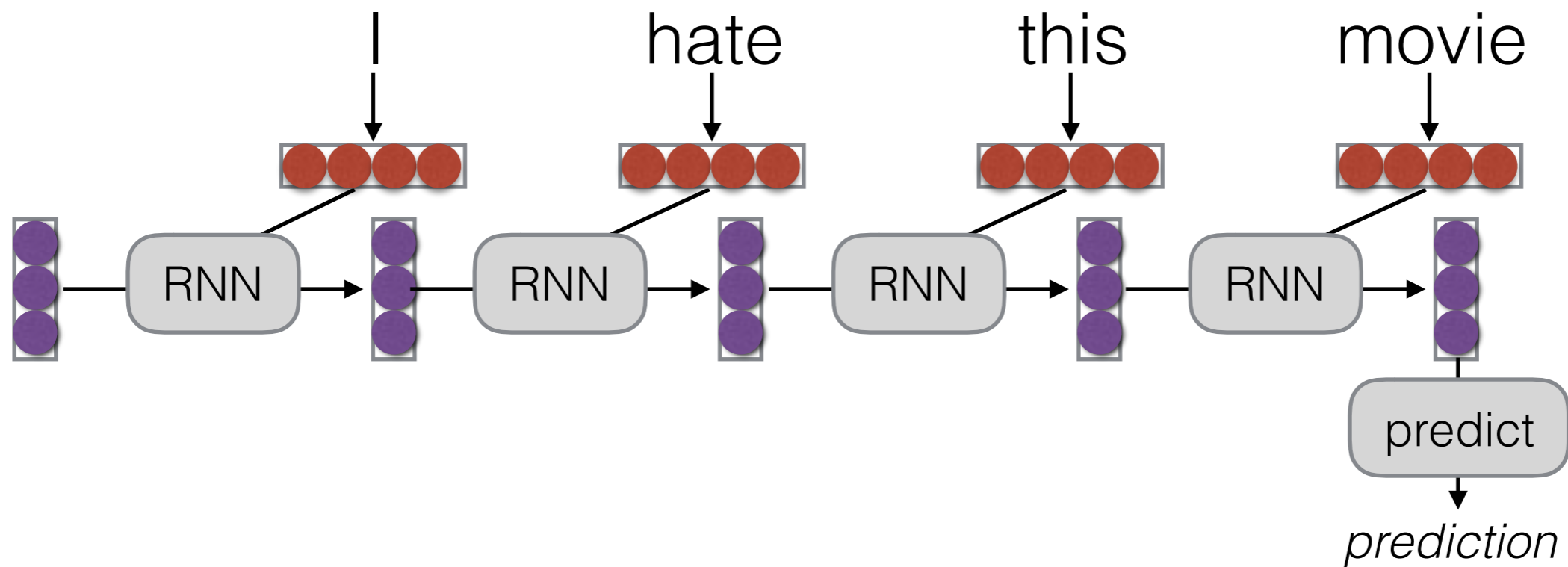
What Can RNNs Do?

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

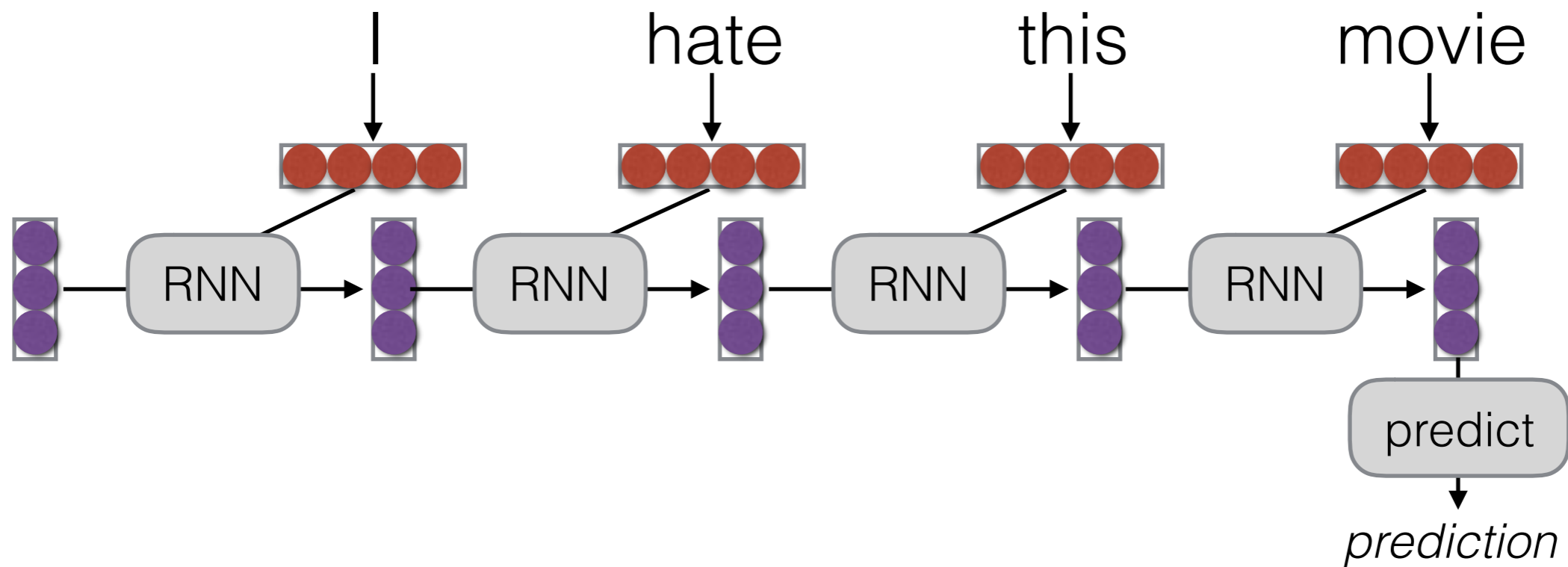
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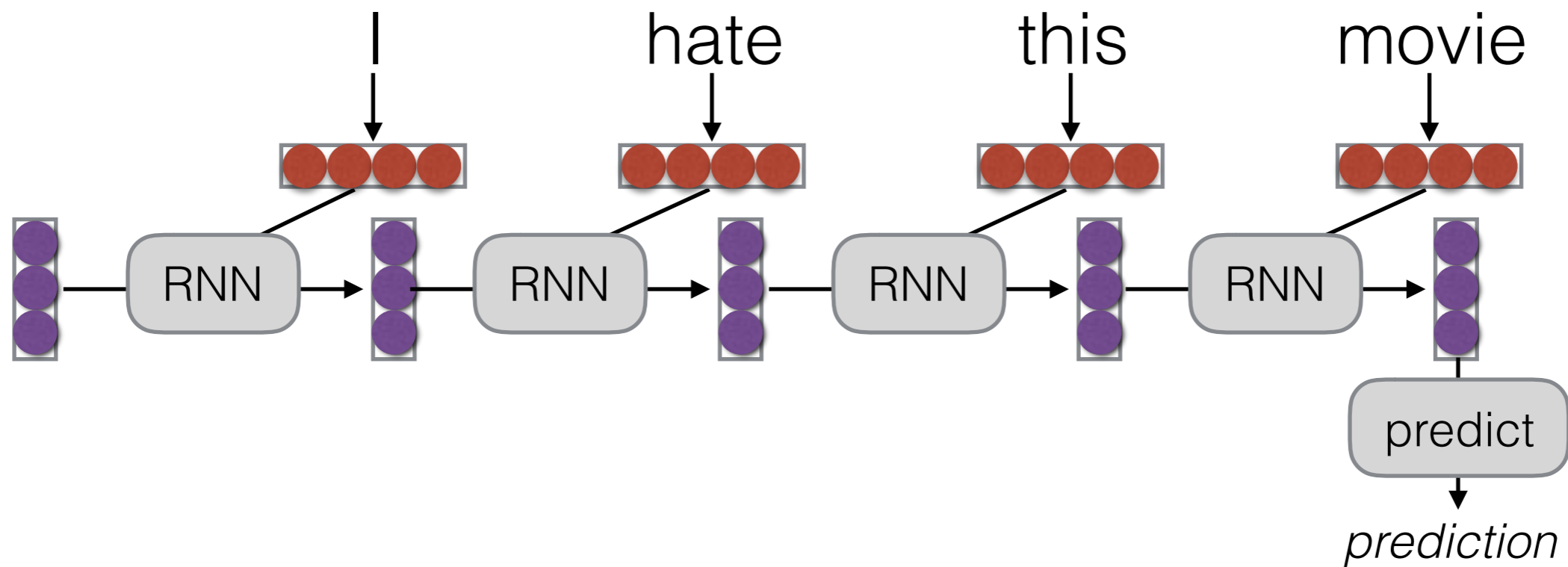


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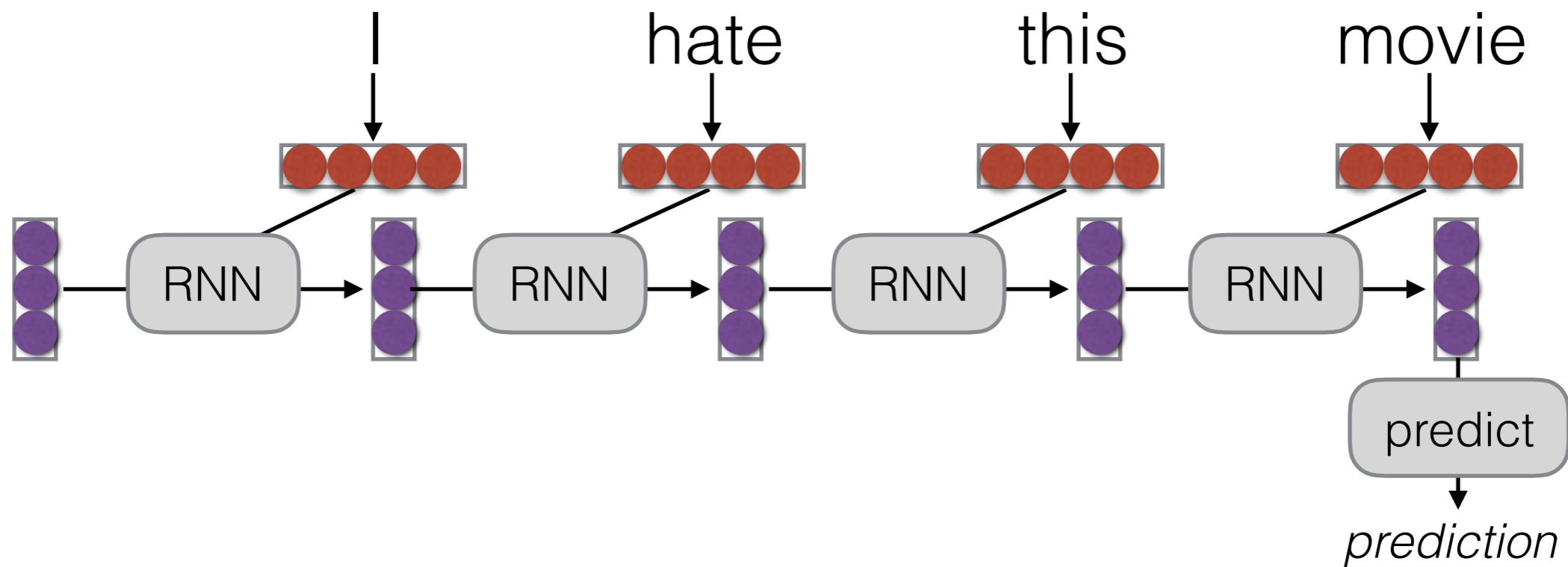
- Sentence classification

Representing Sentences



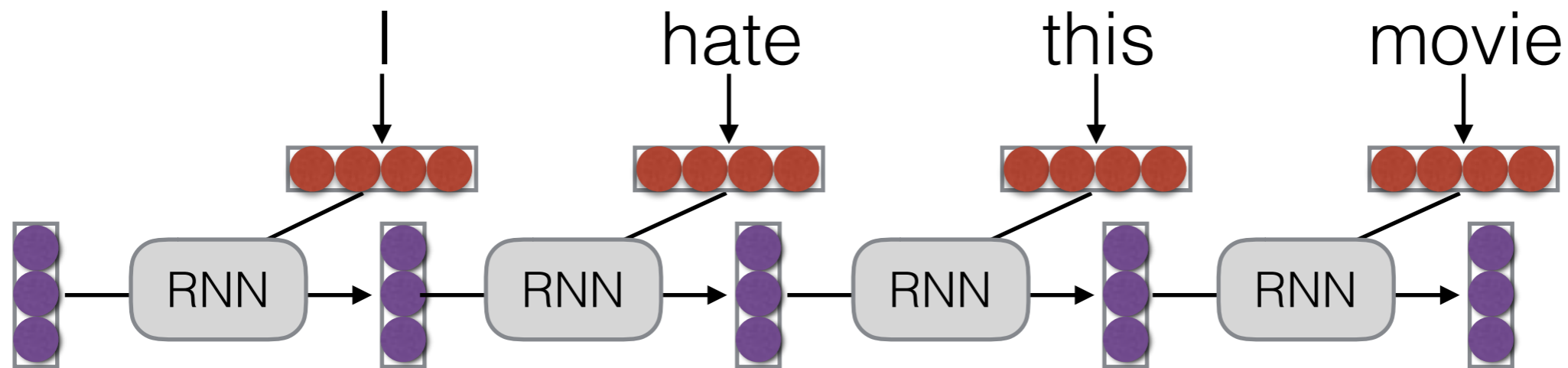
- Sentence classification
- Conditioned generation

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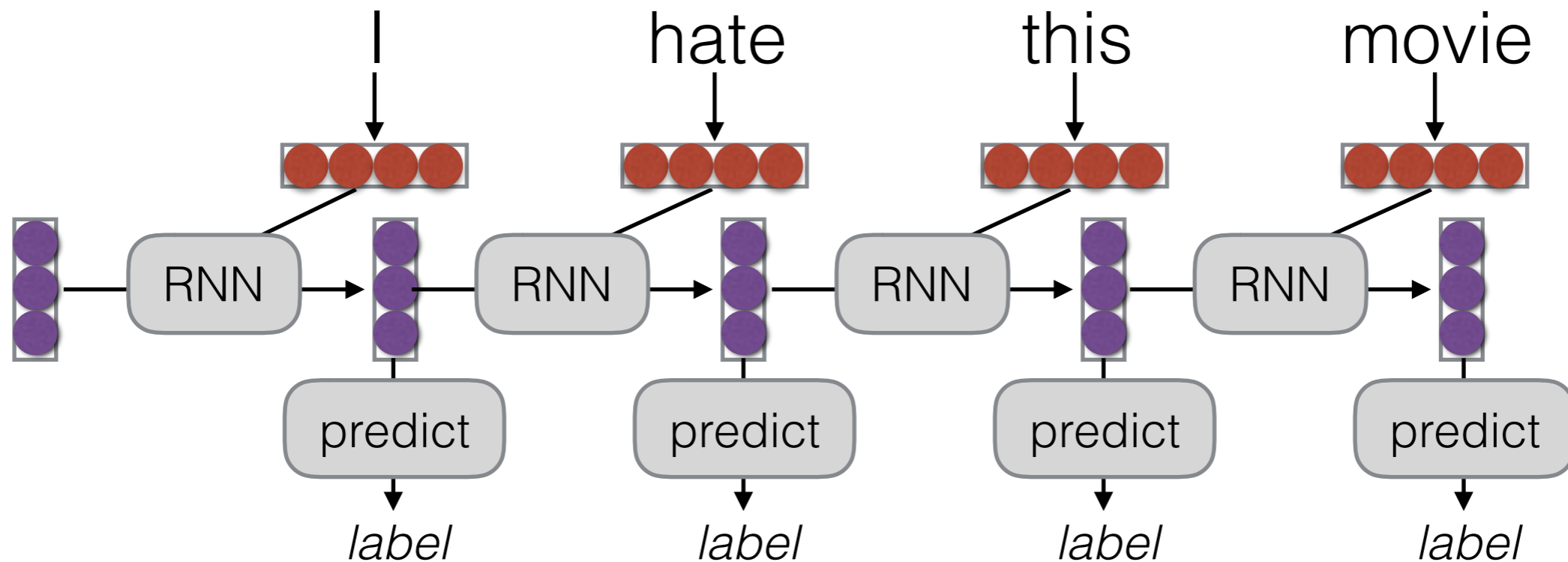


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- Retrieval

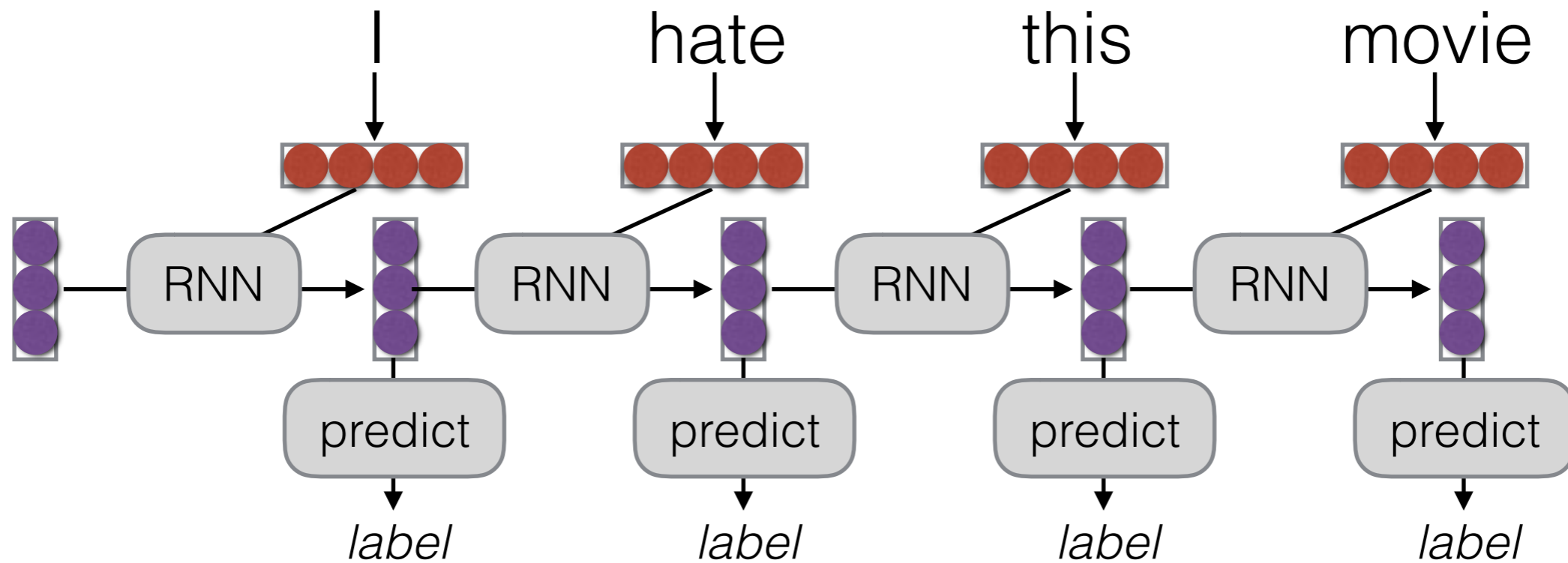
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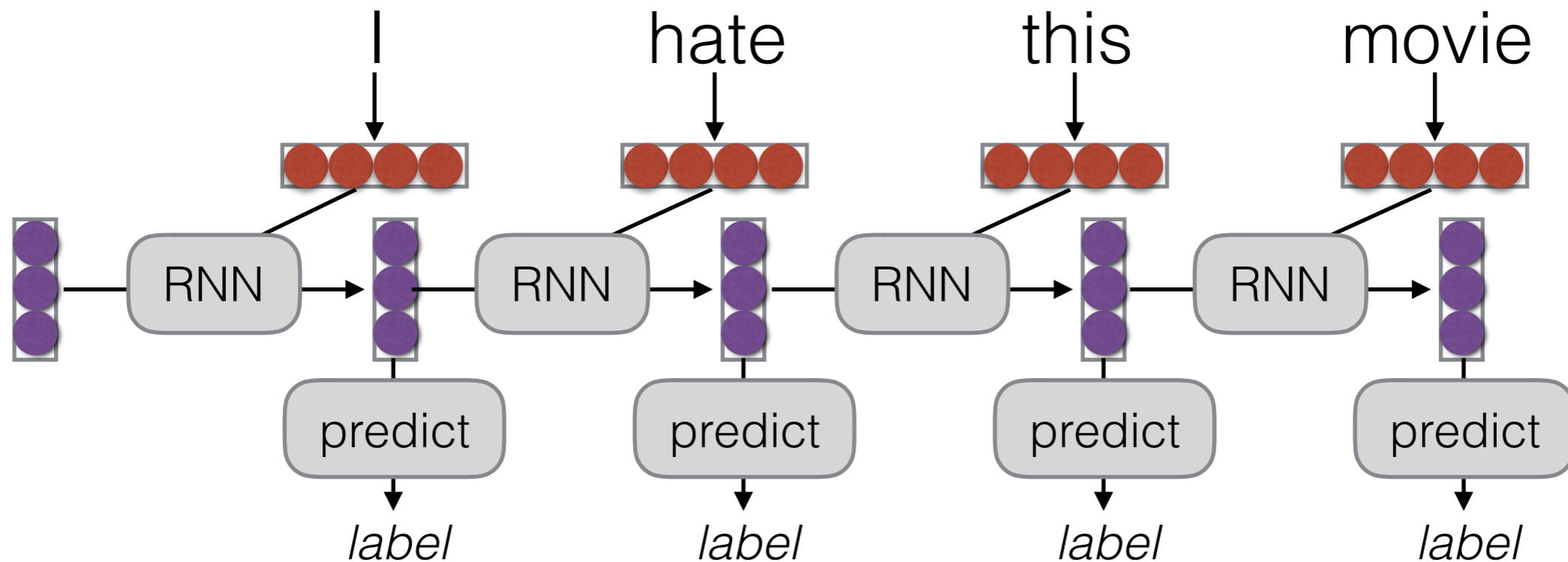


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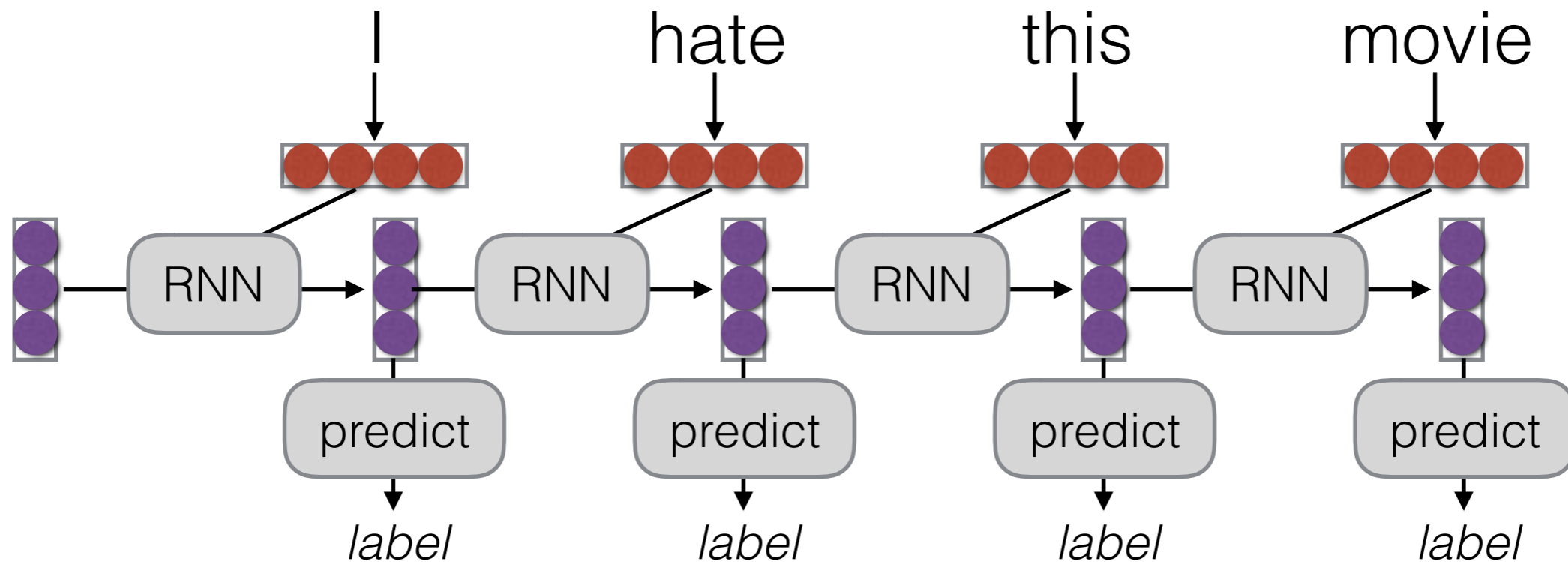
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Representing Contexts



- Tagging
- Language Modeling

Representing Contexts



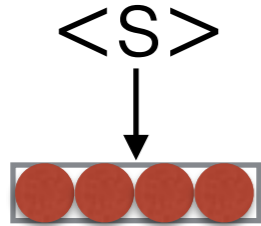
- Tagging
- Language Modeling
- Calculating Representations for Parsing, etc.

e.g. Language Modeling



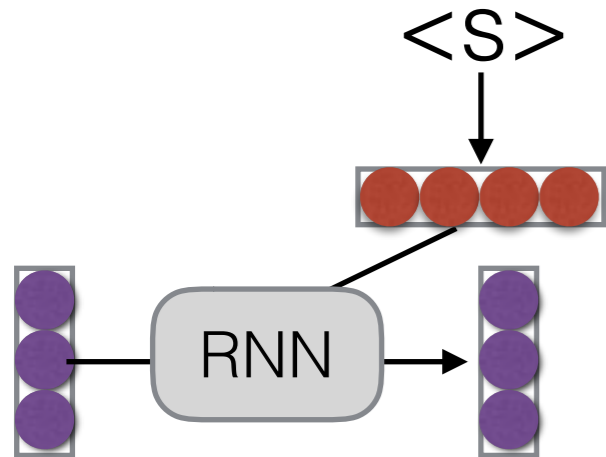
- Language modeling is like a tagging task, where each tag is the next word!

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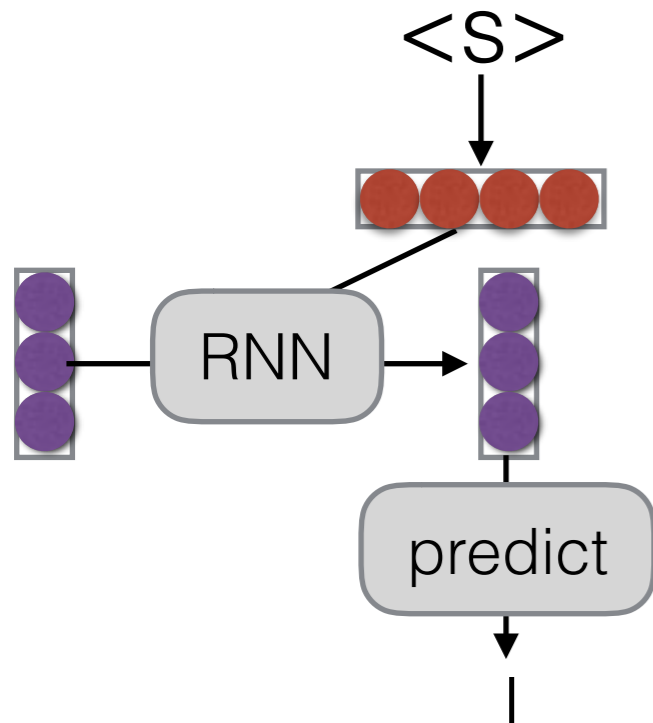
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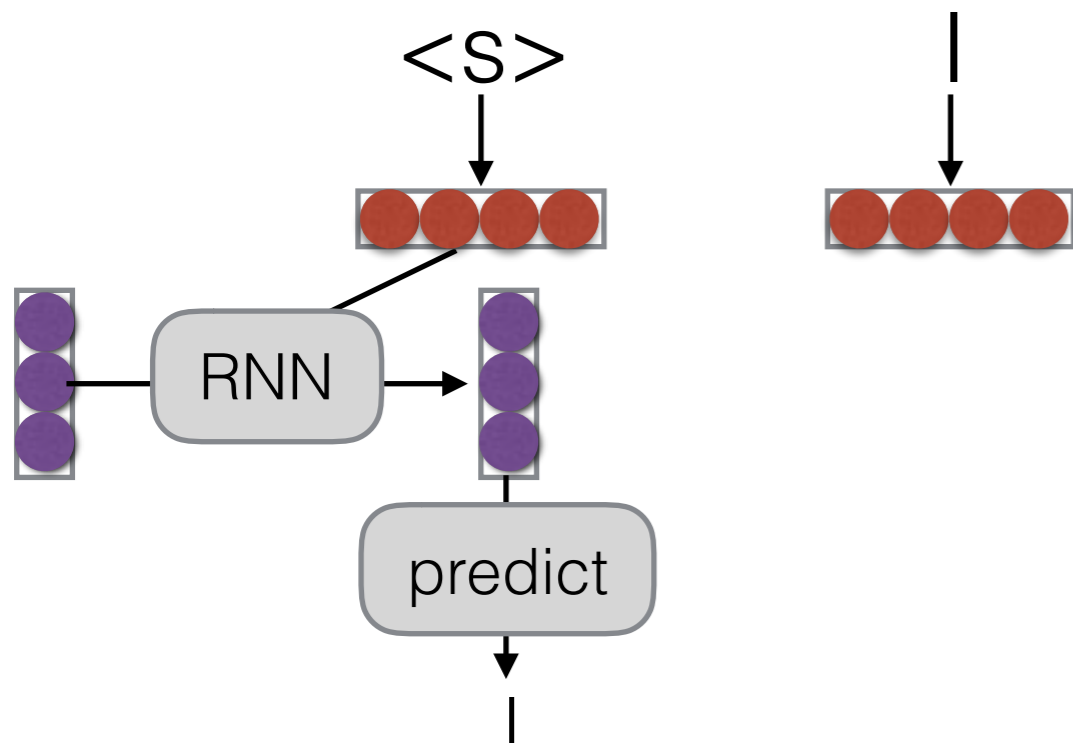
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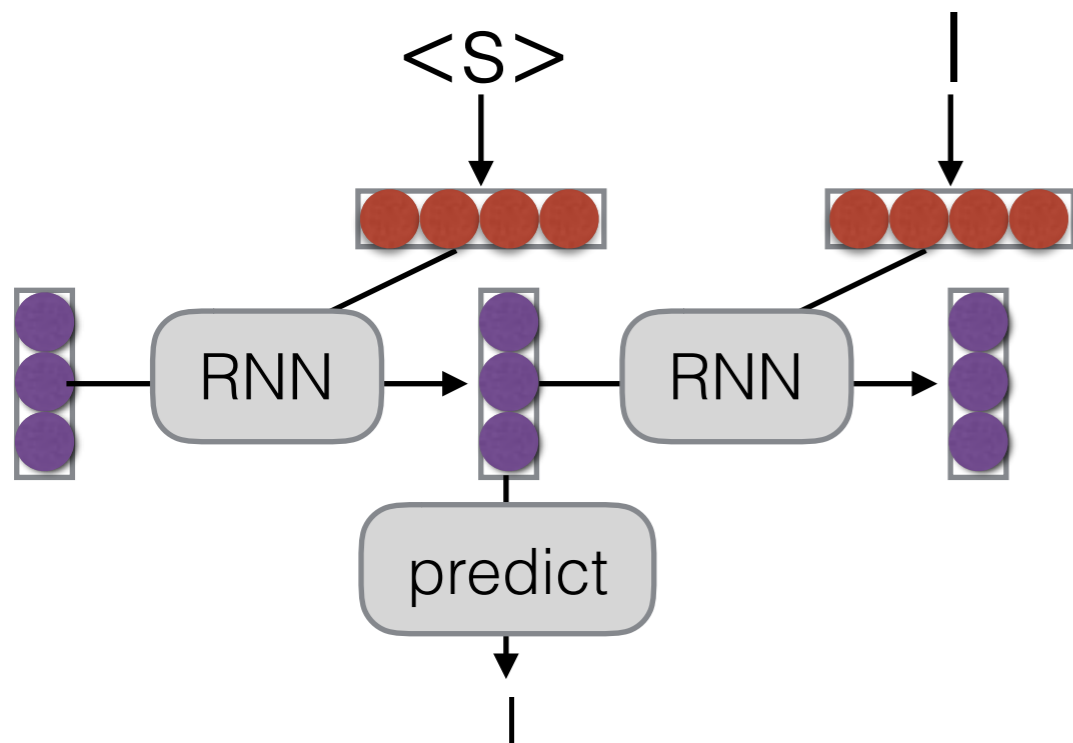
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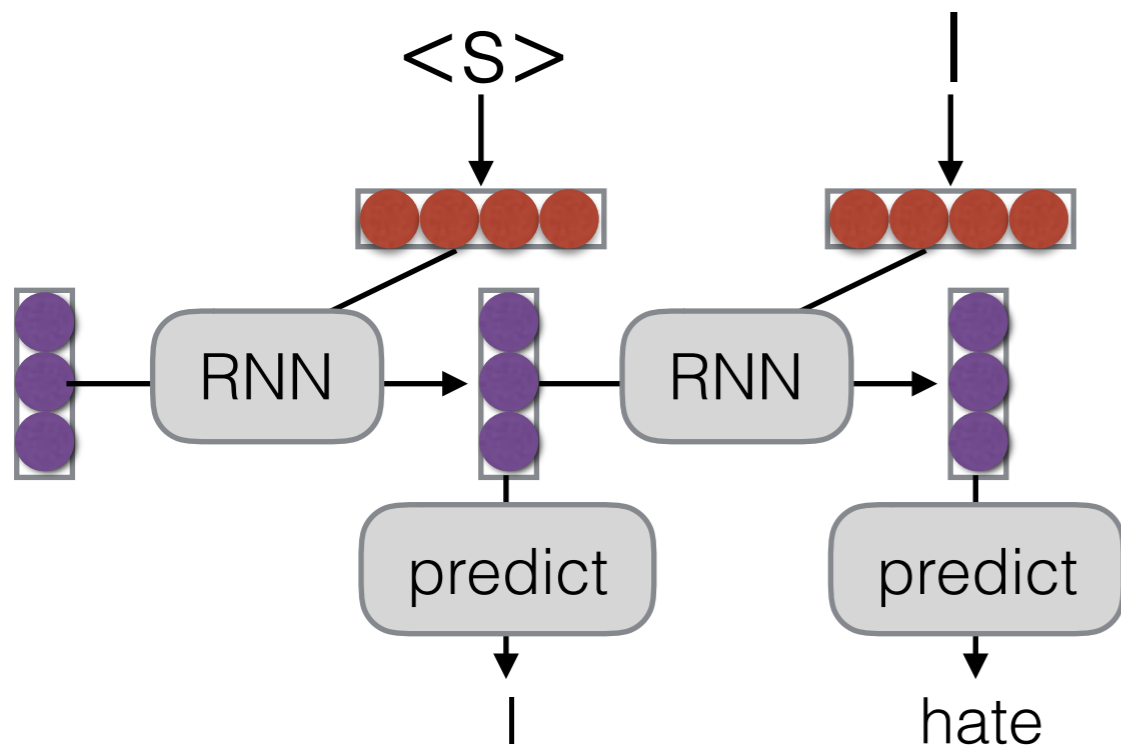
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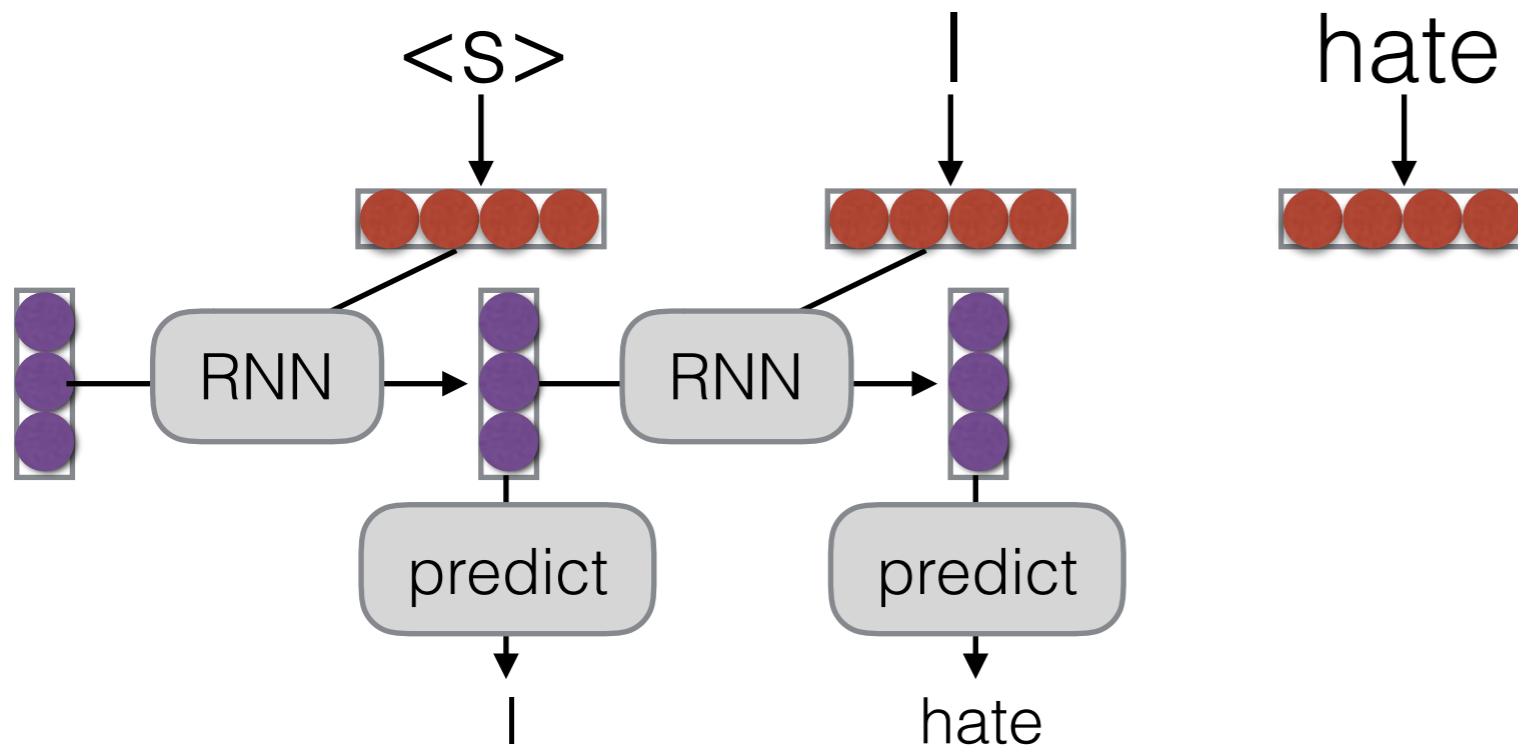
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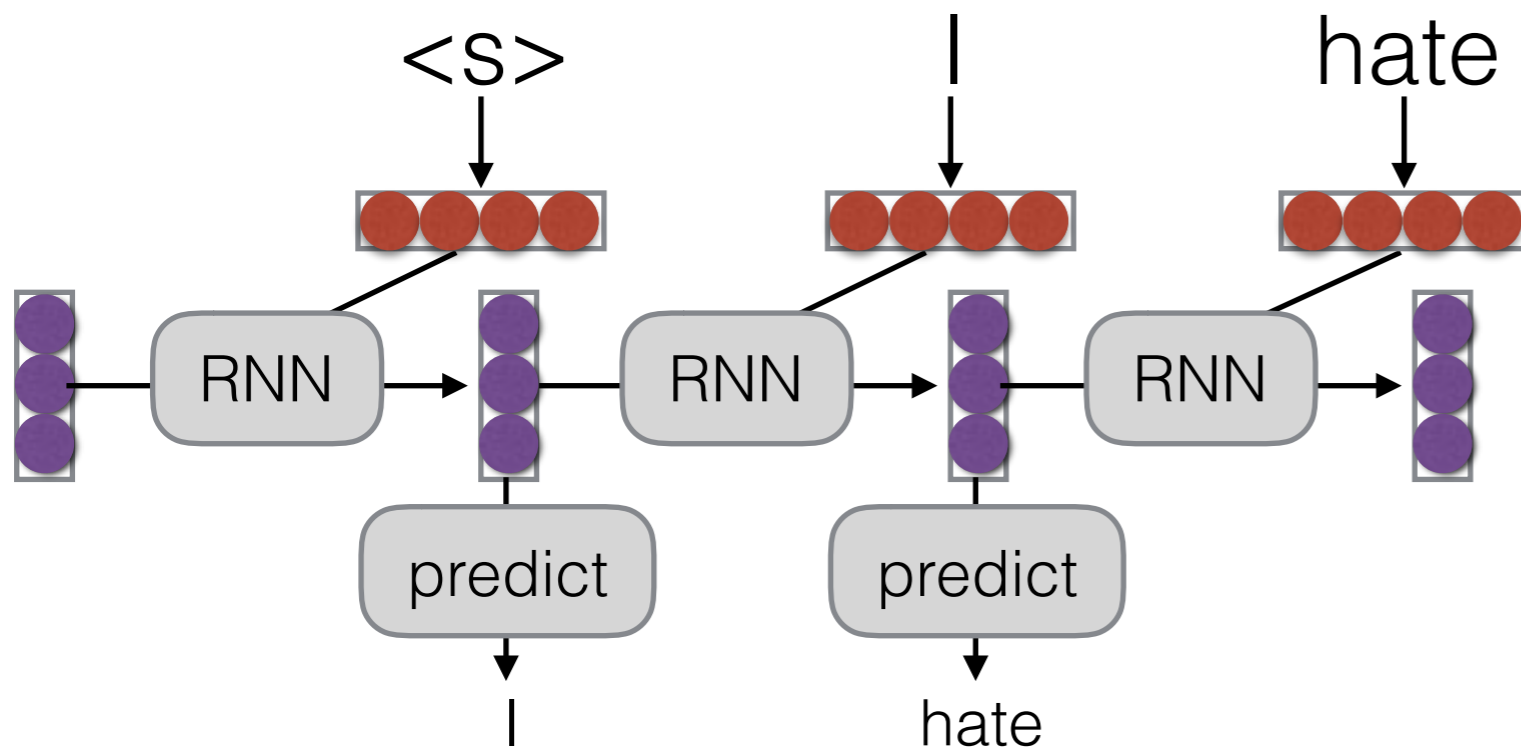
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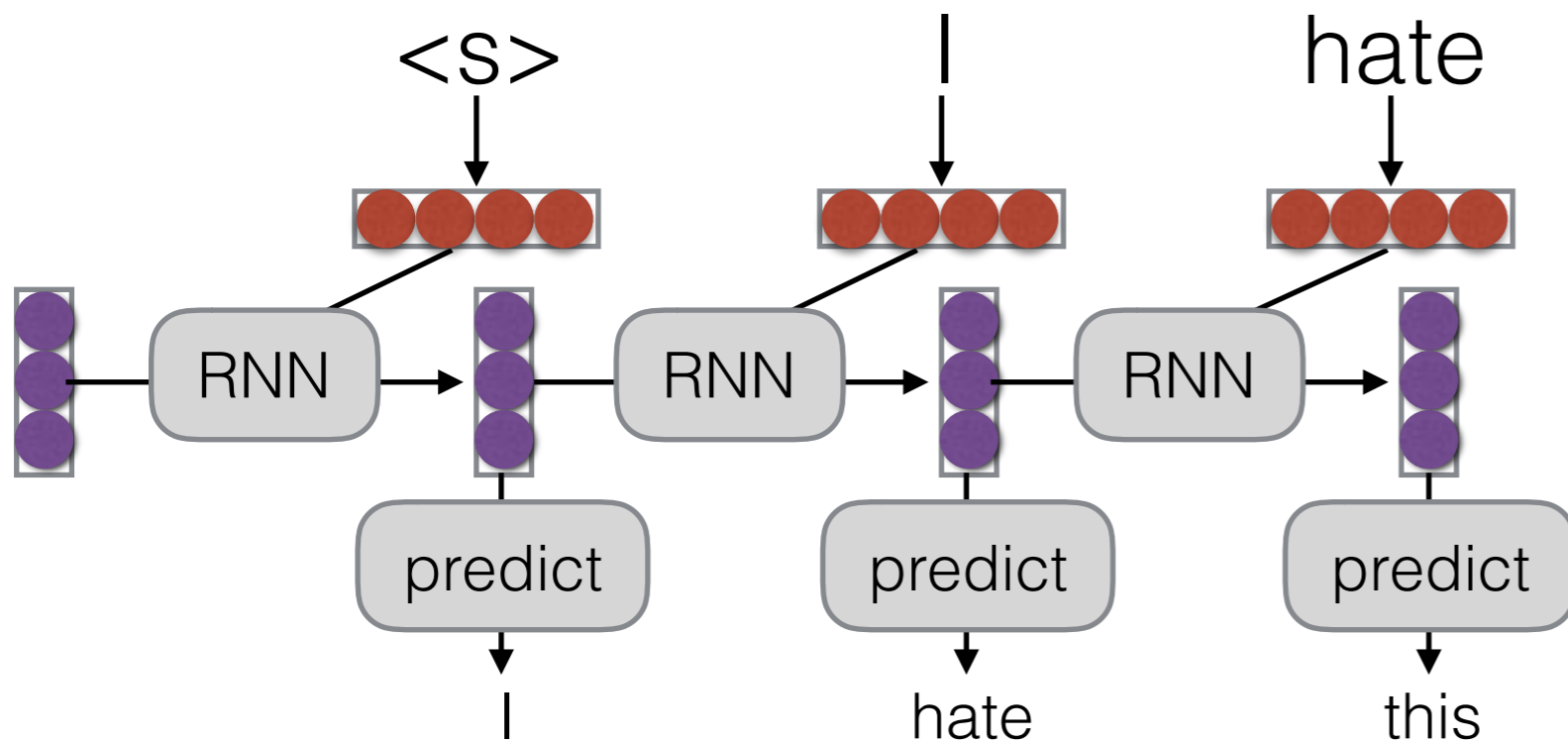
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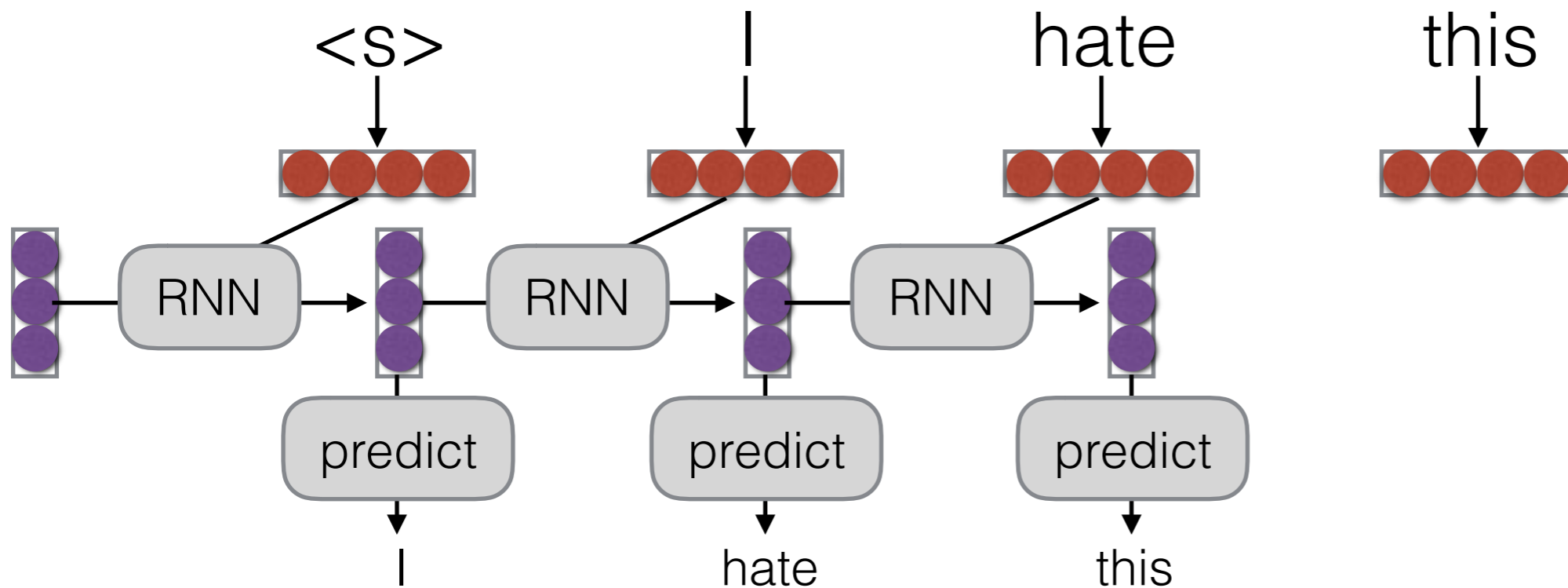
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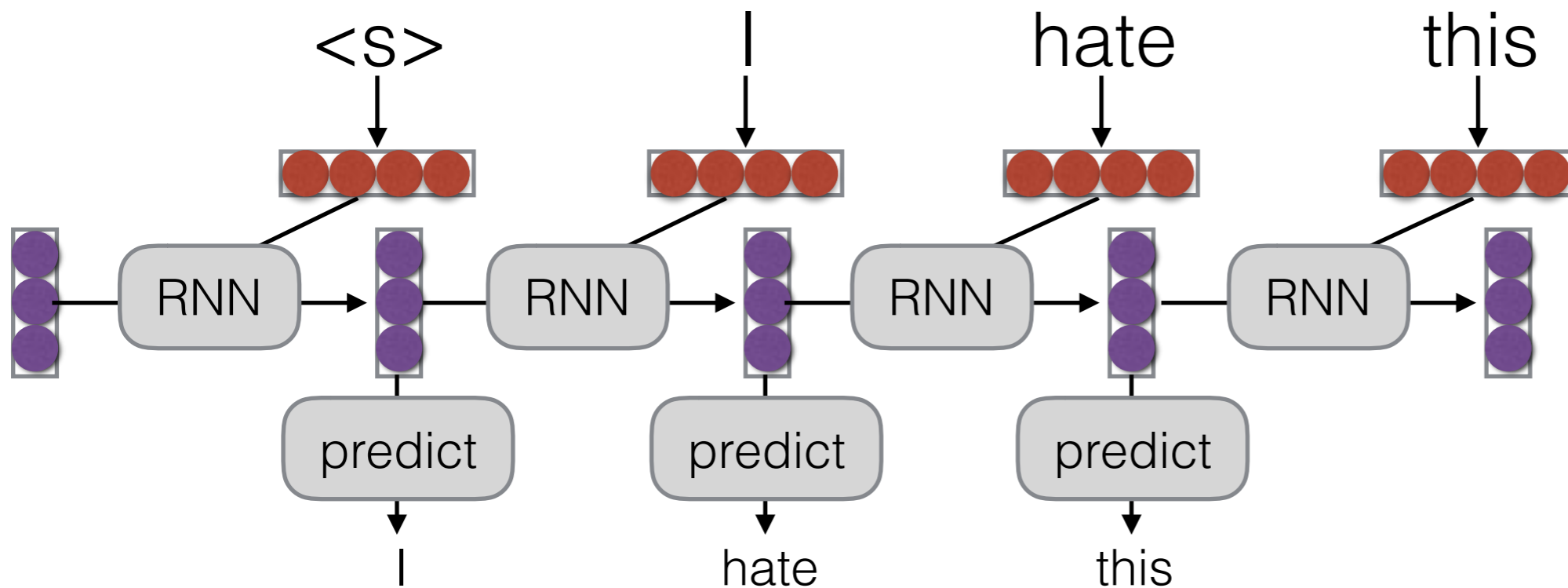
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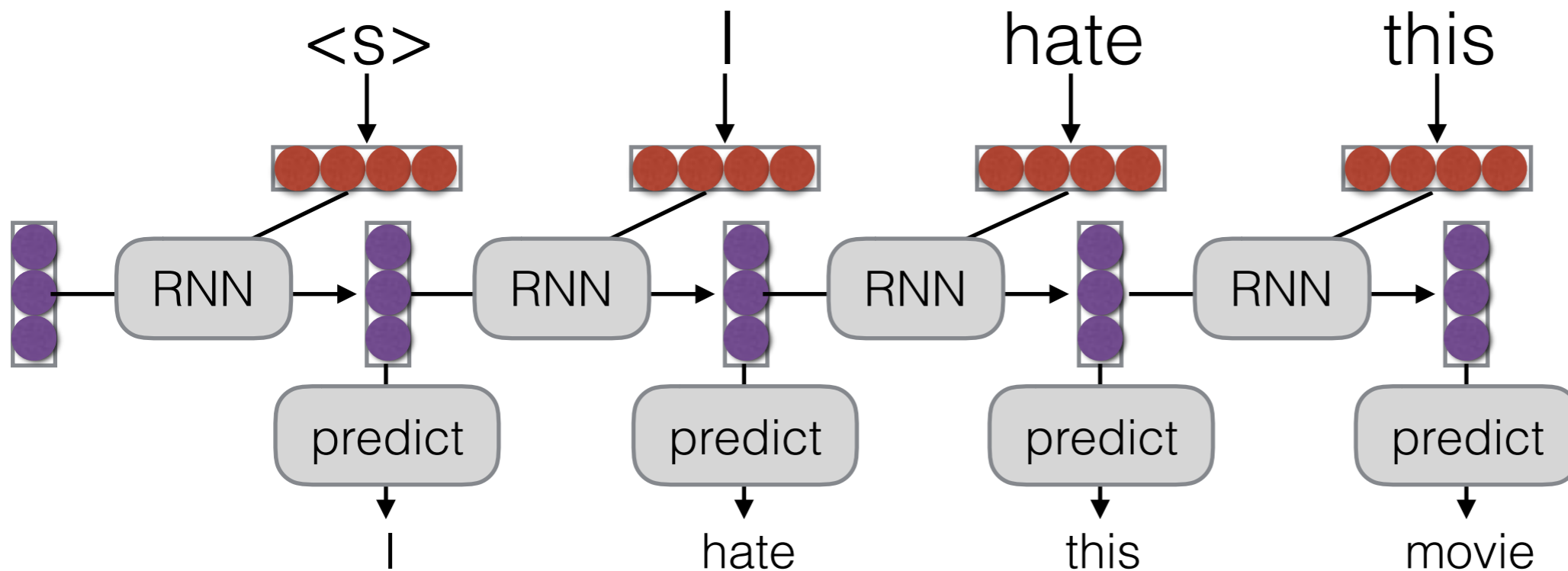
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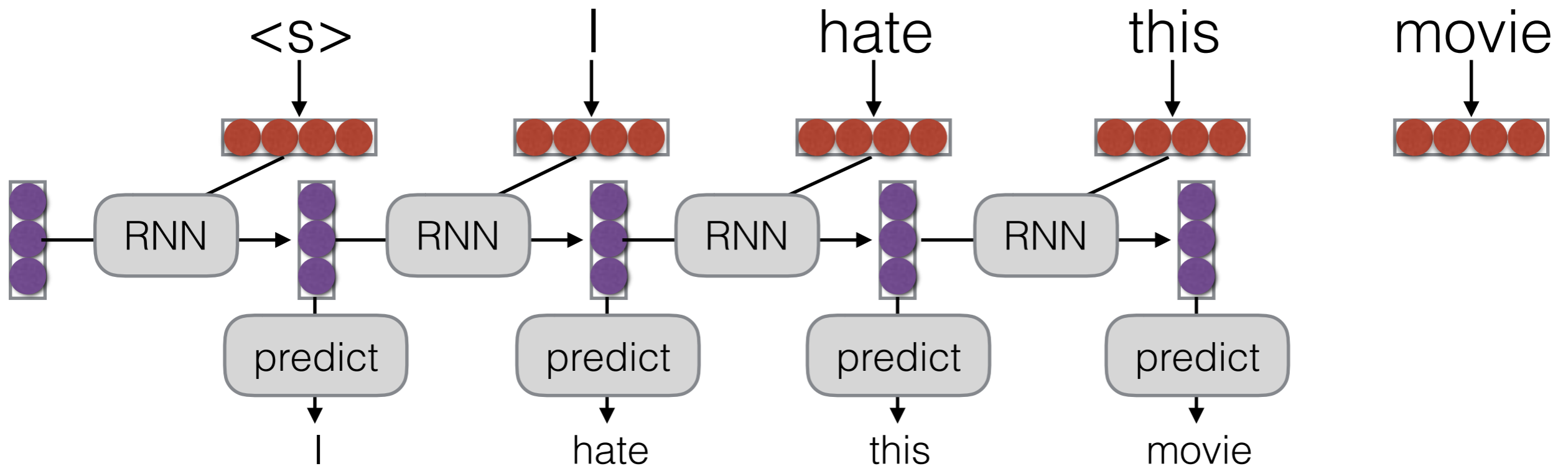
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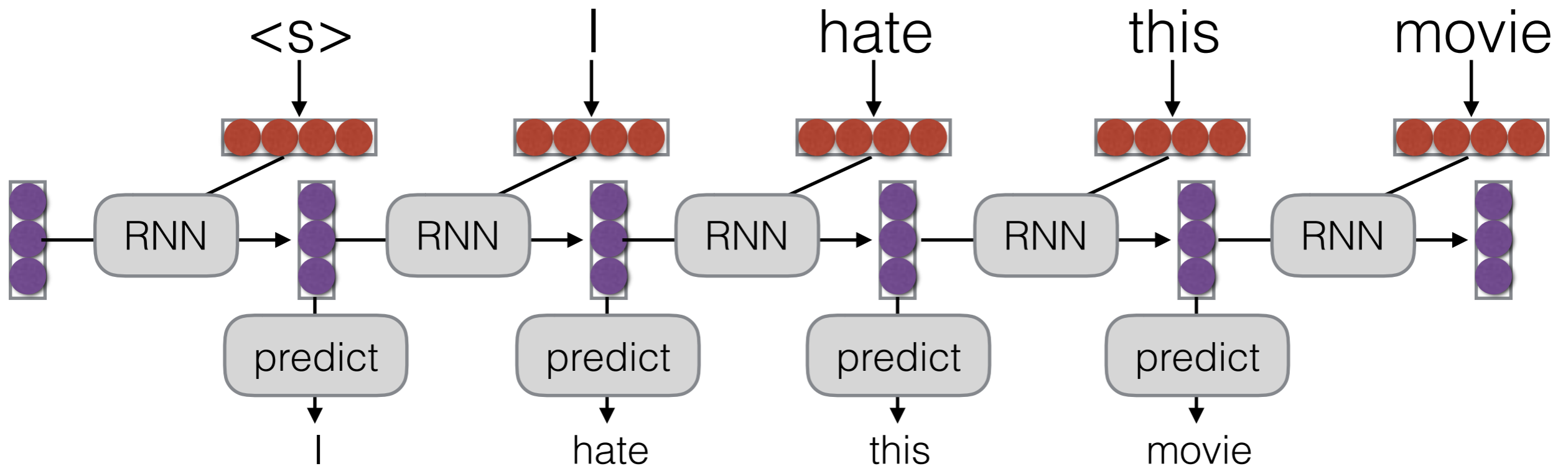
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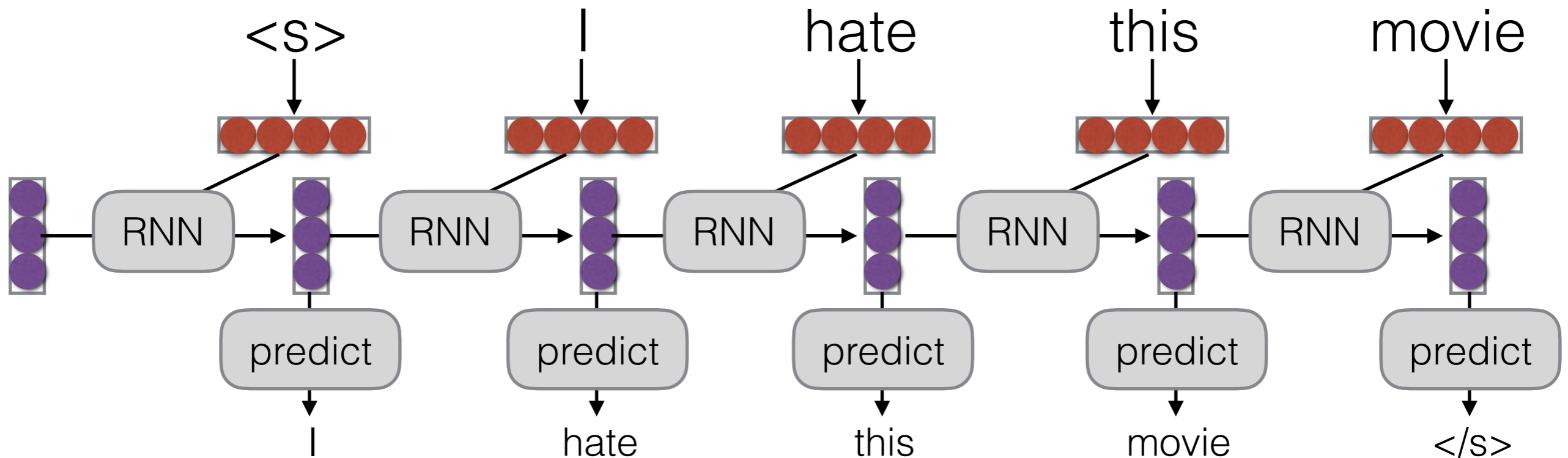
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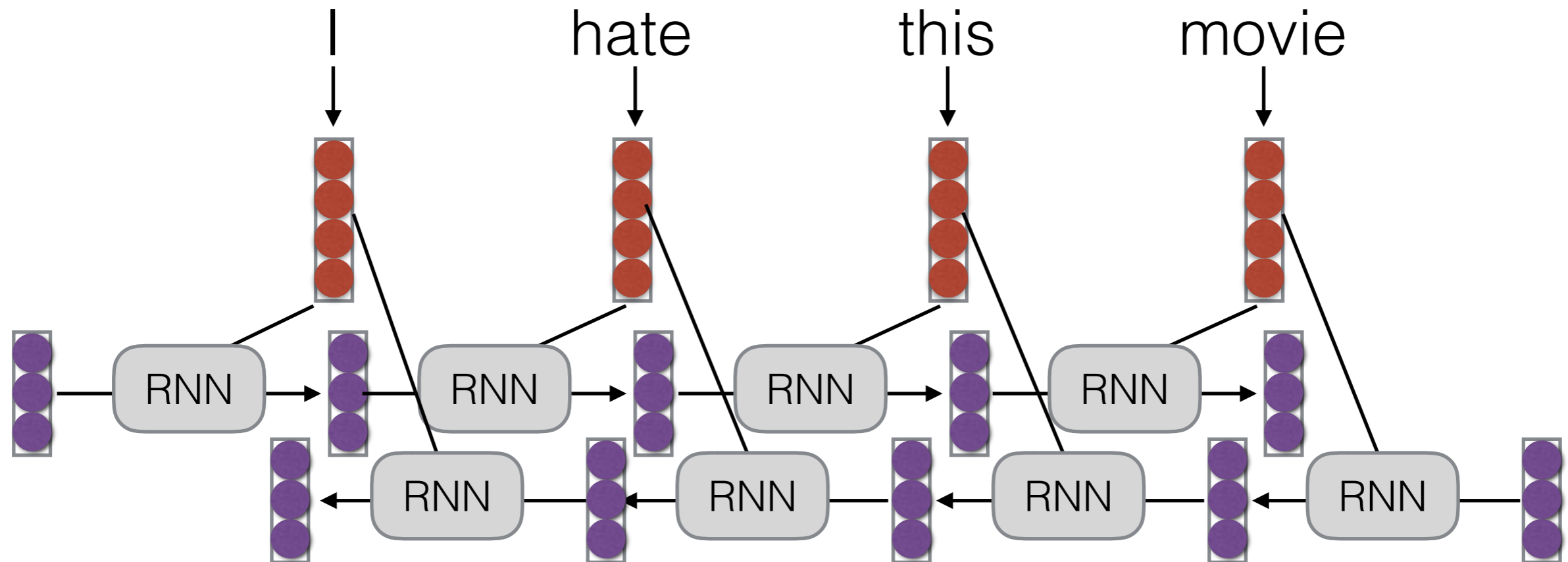
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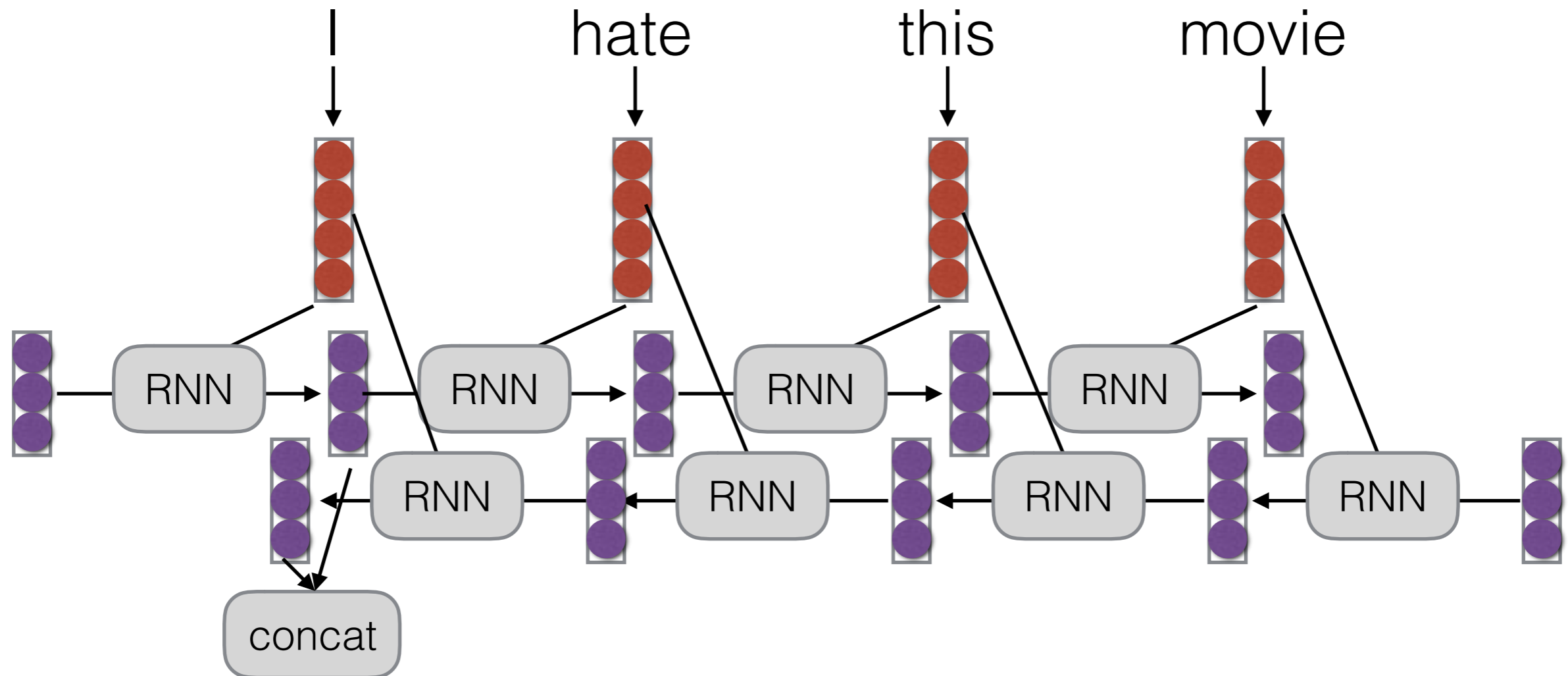
Bi-RNNs

- A simple extension, run the RNN in both directions



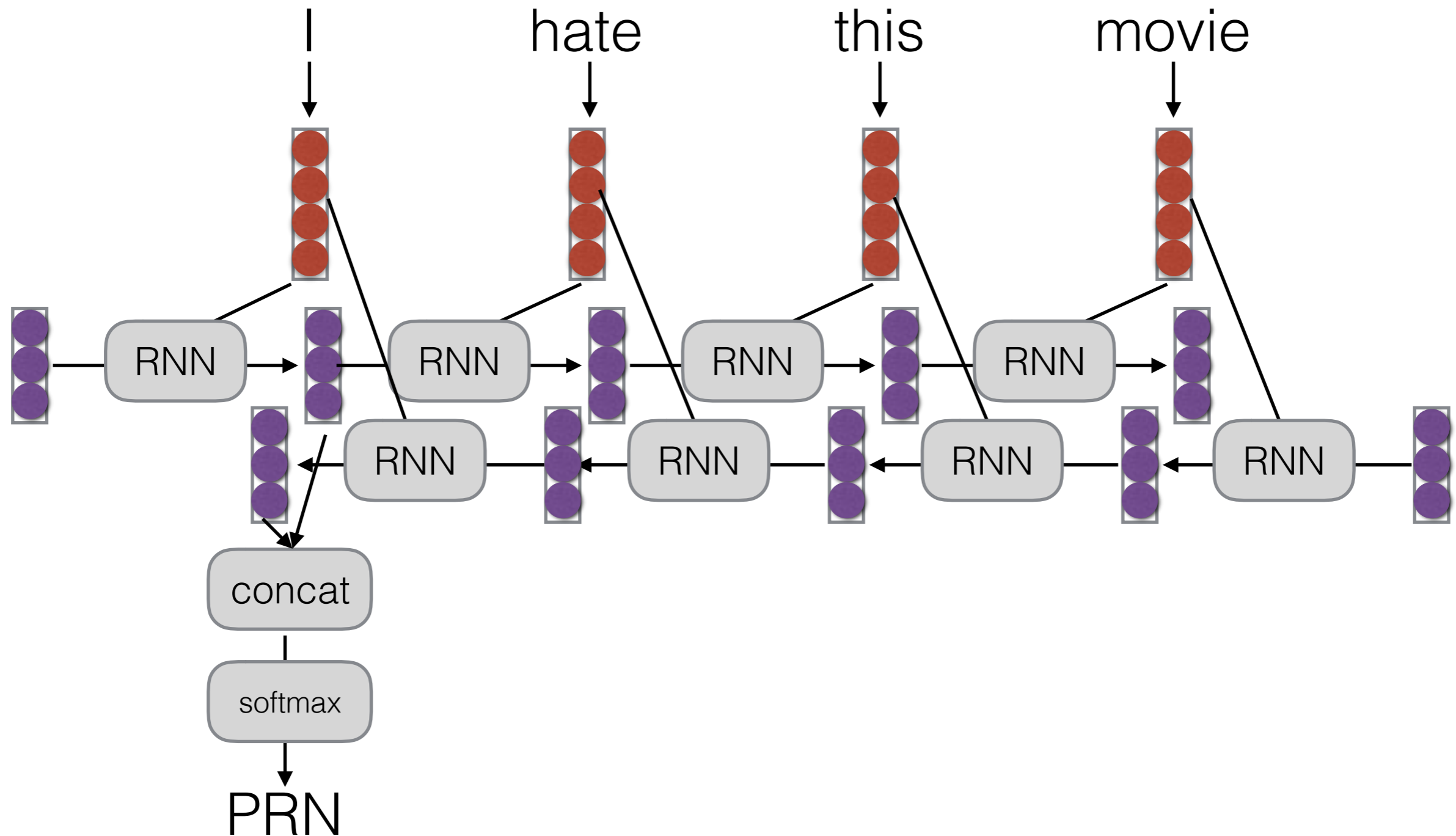
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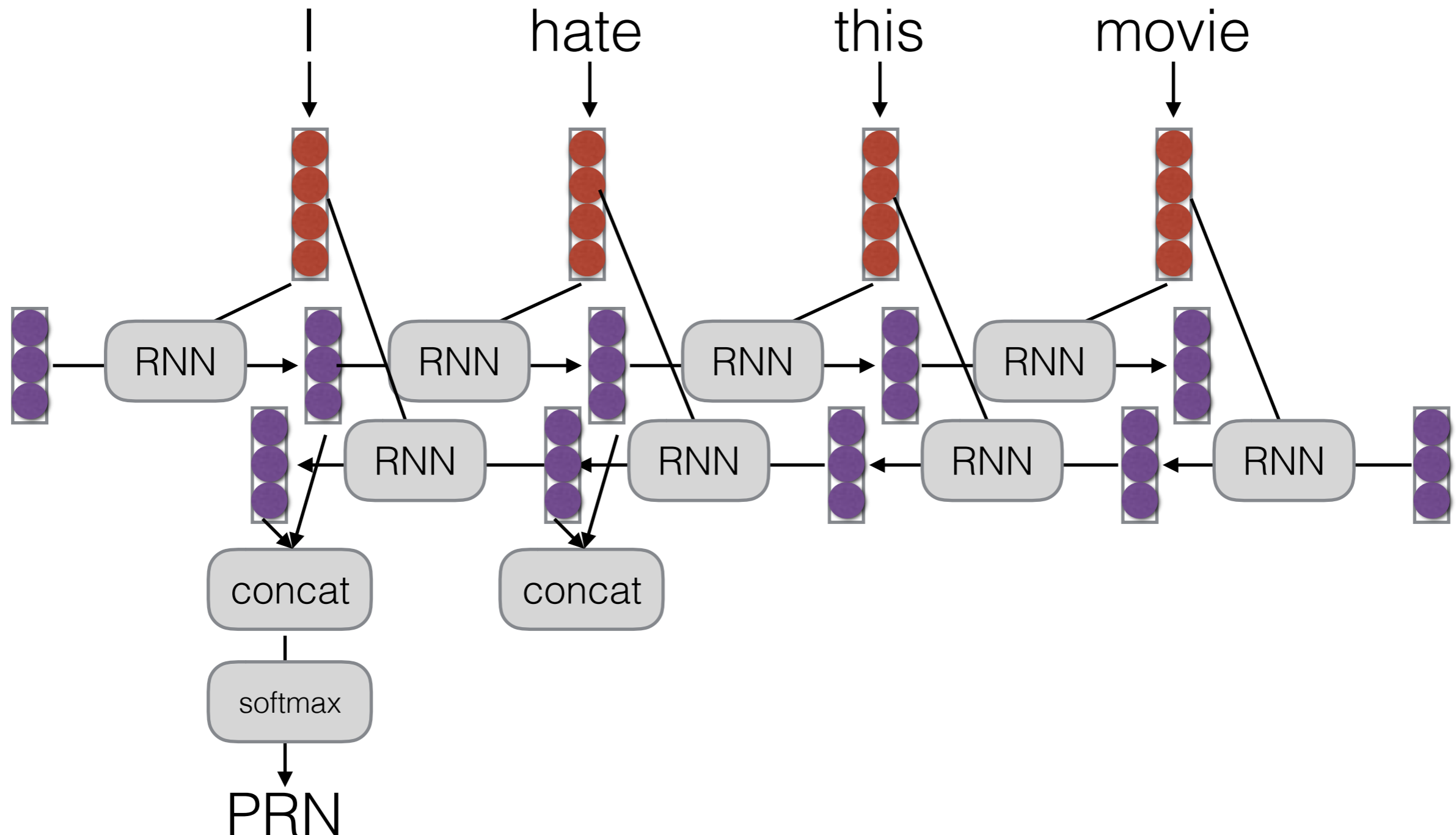
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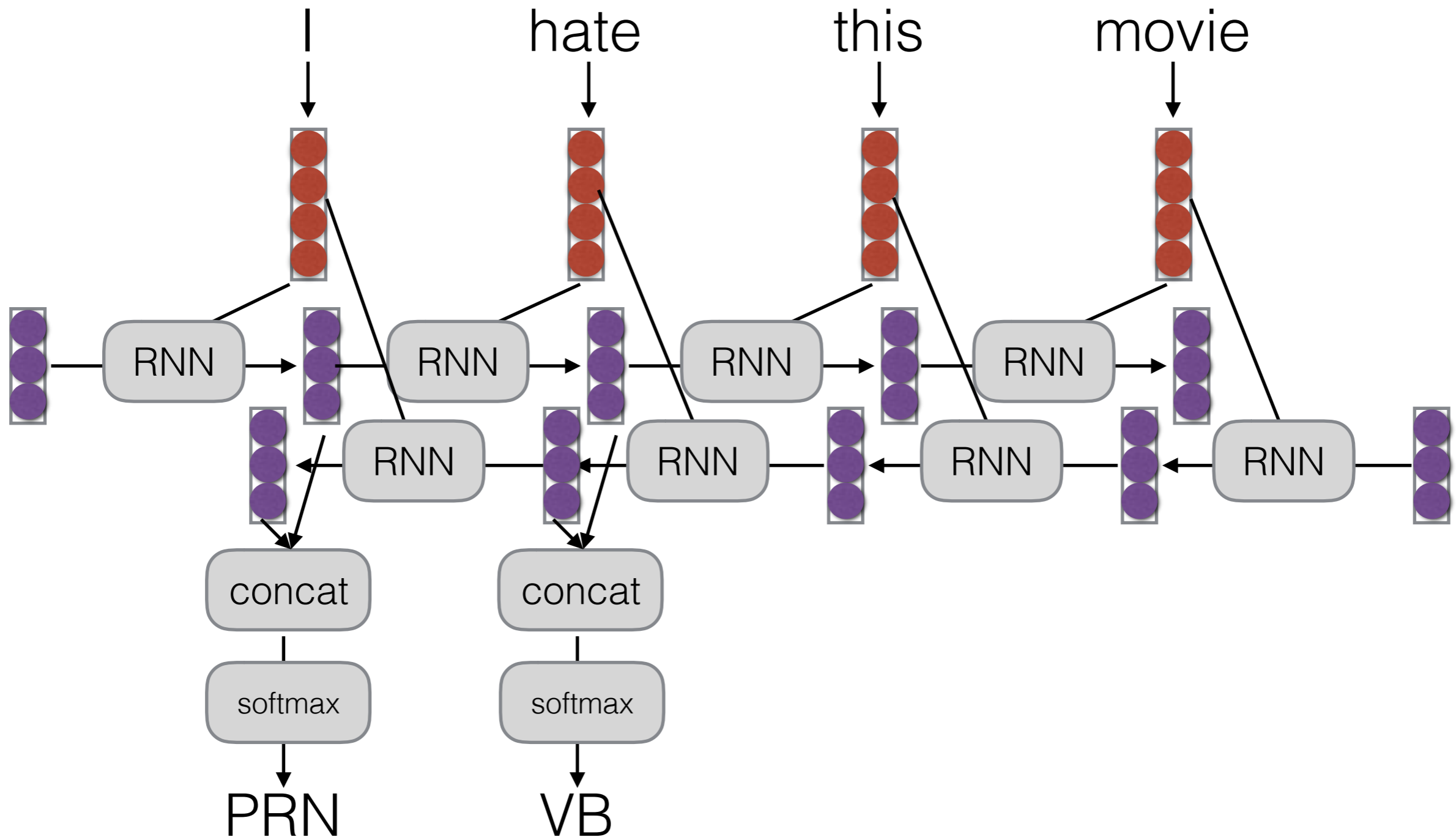
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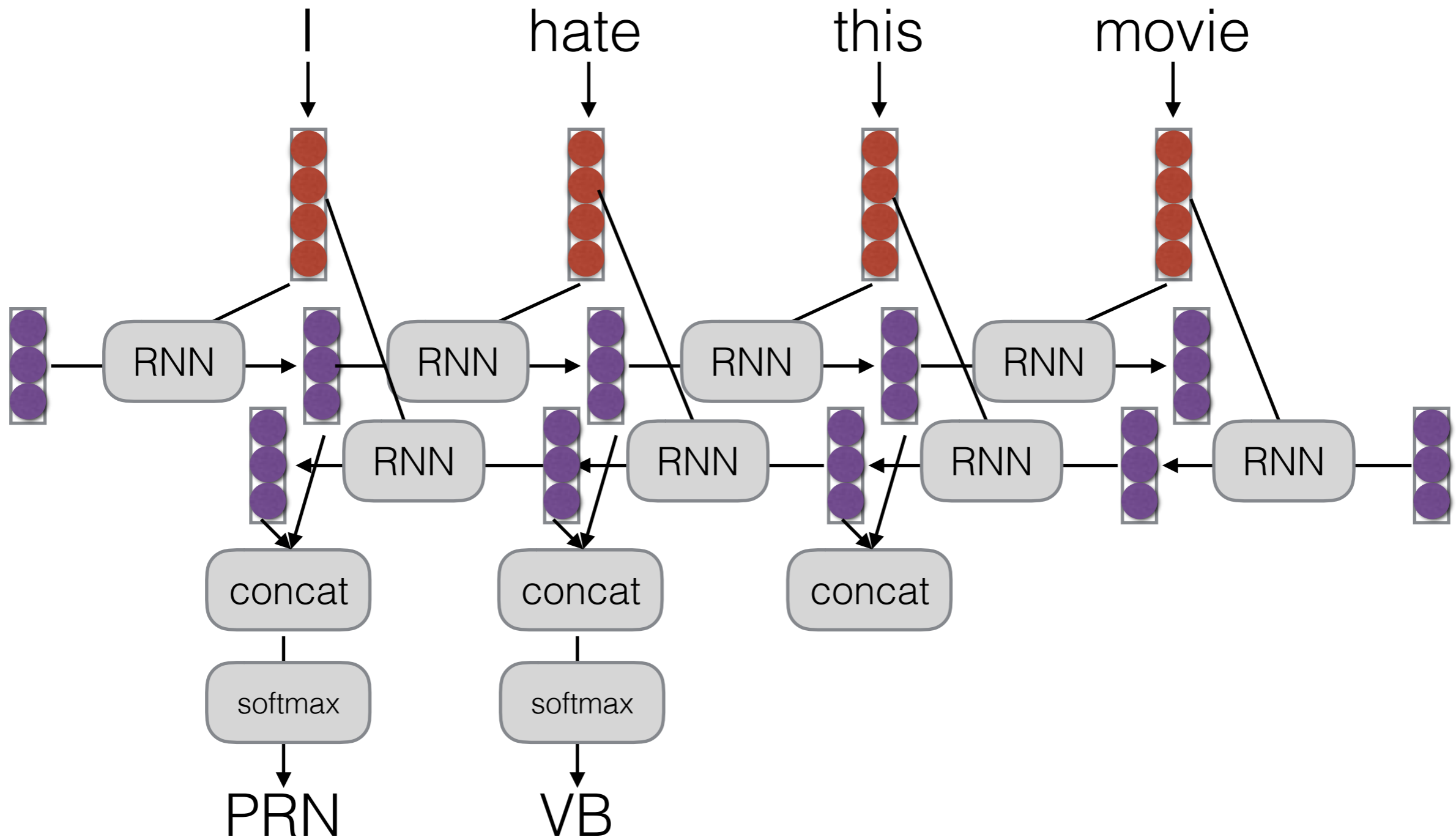
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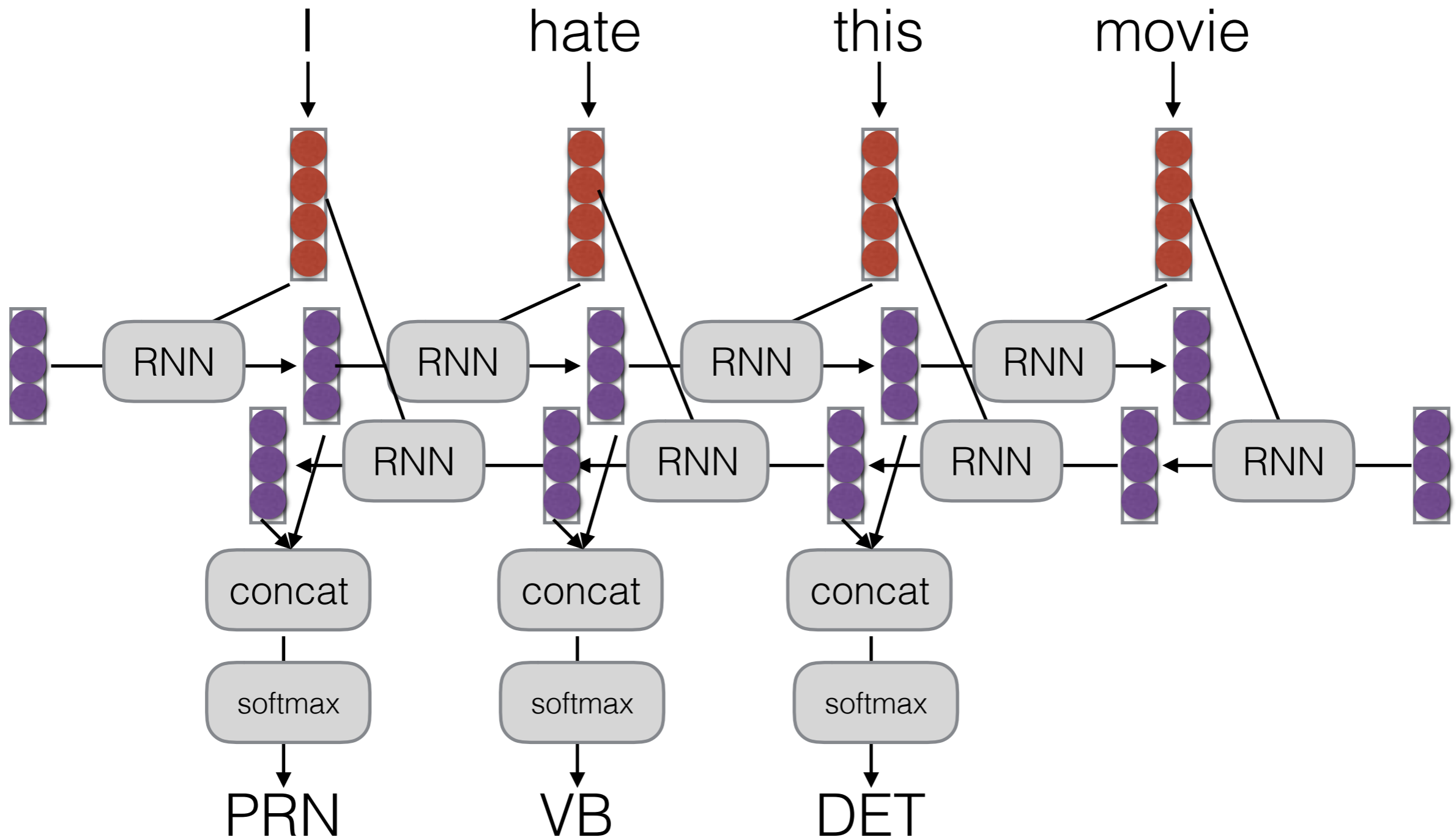
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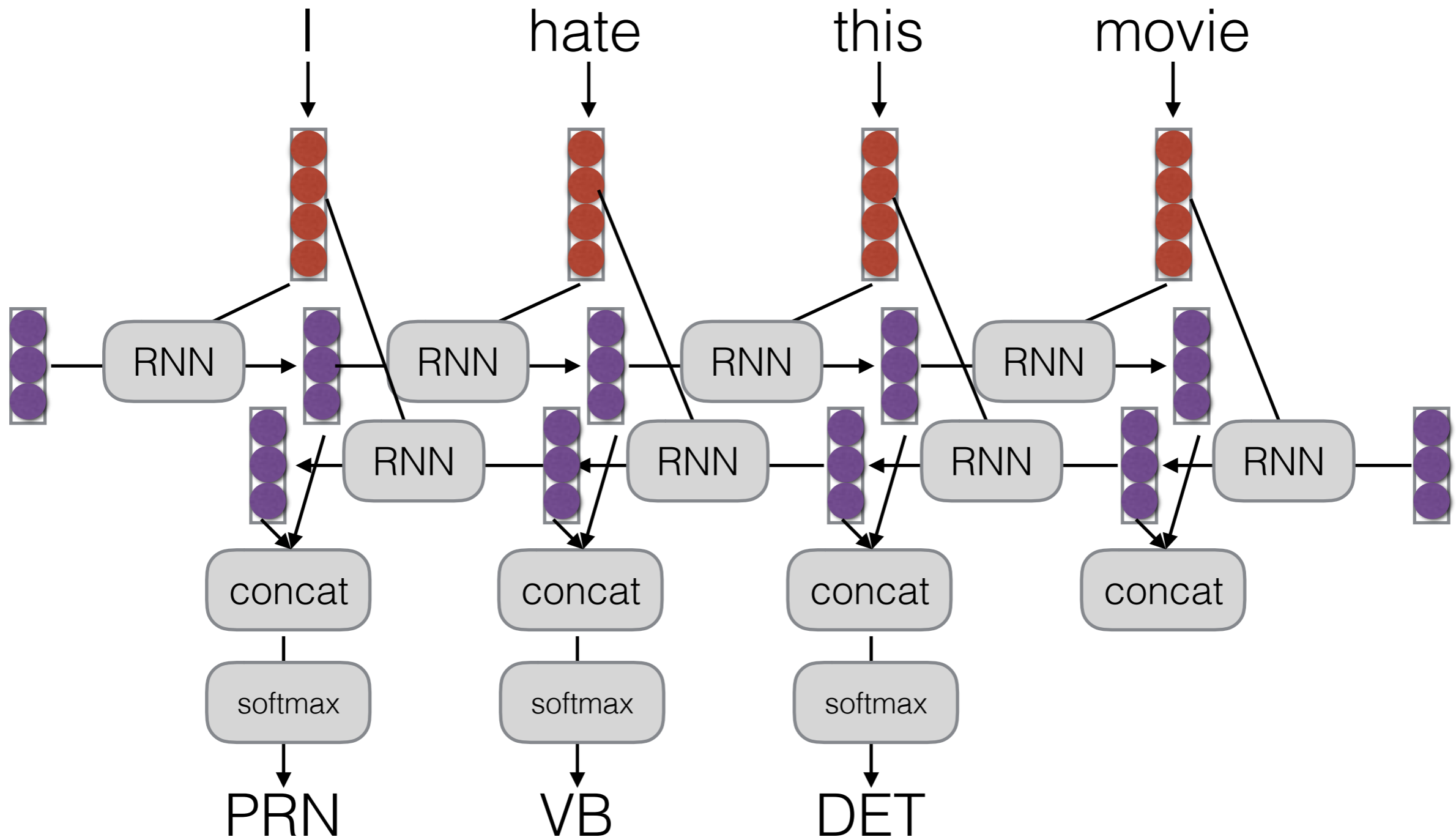
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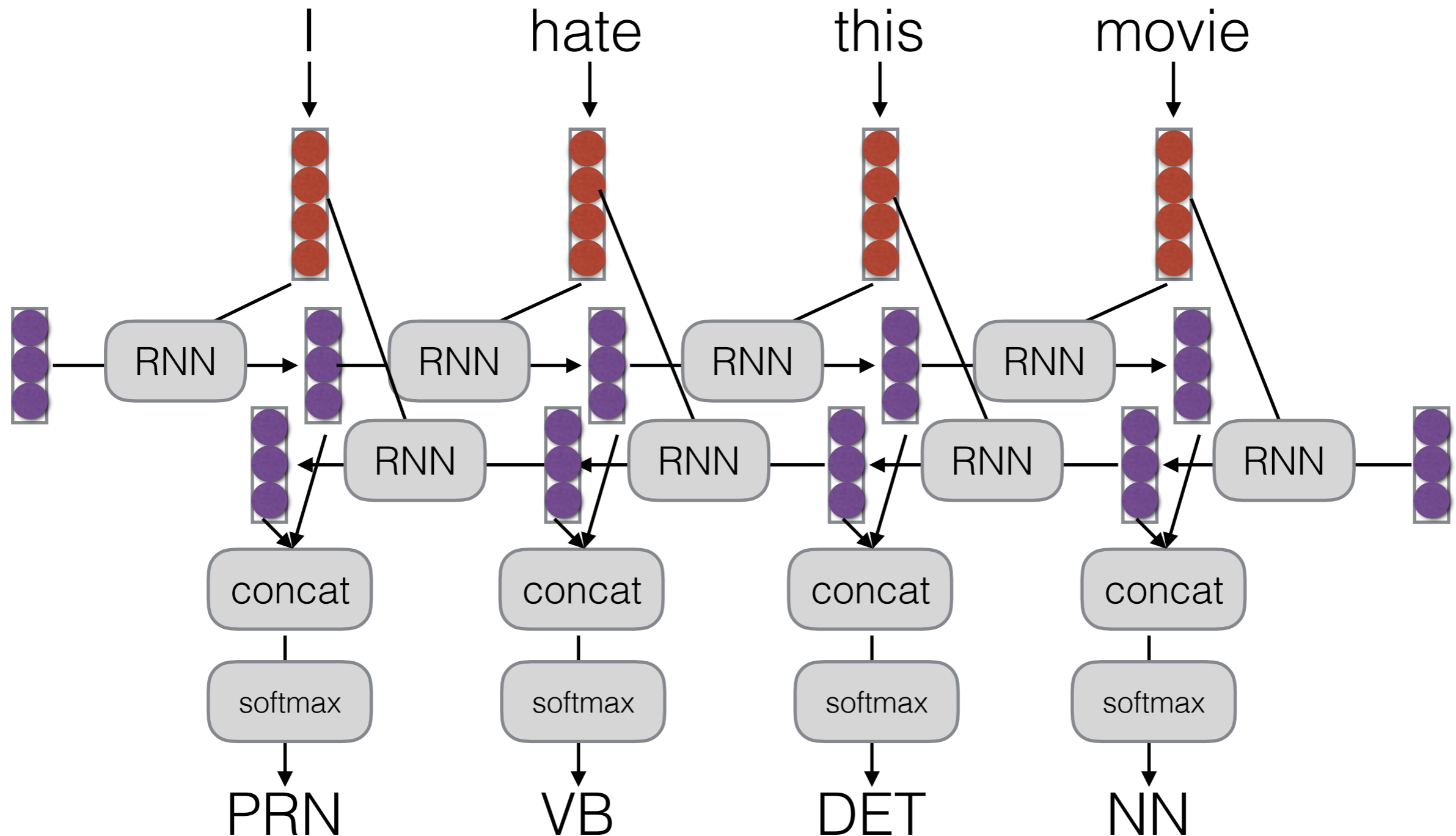
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Let's Try it Out!

Recurrent Neural Networks in DyNet

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- Add parameters to model (once):

```
# LSTM (layers=1, input=64, hidden=128, model)  
RNN = dy.SimpleRNNBuilder(1, 64, 128, model)
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s = RNN.initial_state()
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- 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

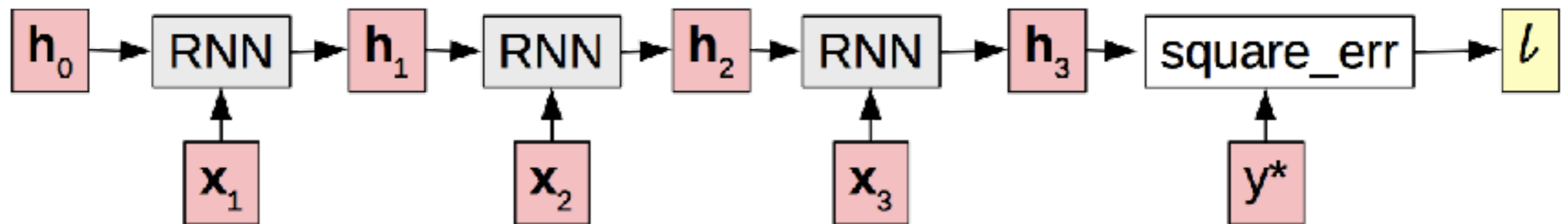
`sentiment-rnn.py`

RNN Problems and Alternatives

Vanishing Gradient

- Gradients decrease as they get pushed back

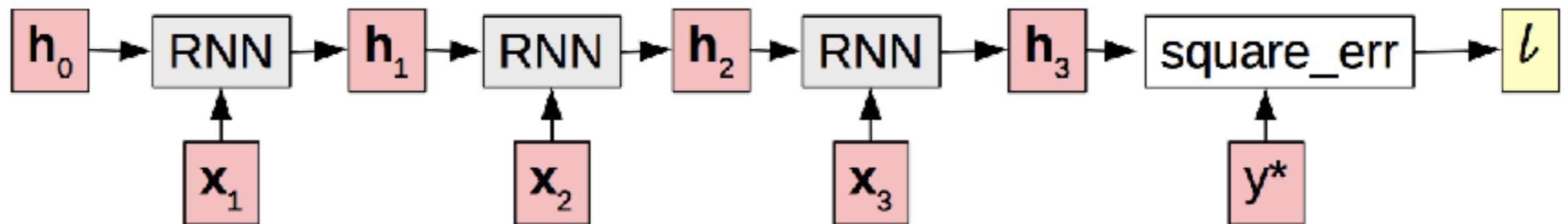
$$\frac{dl}{dh_0} = \text{tiny} \quad \frac{dl}{dh_1} = \text{small} \quad \frac{dl}{dh_2} = \text{med.} \quad \frac{dl}{dh_3} = \text{large}$$



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

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

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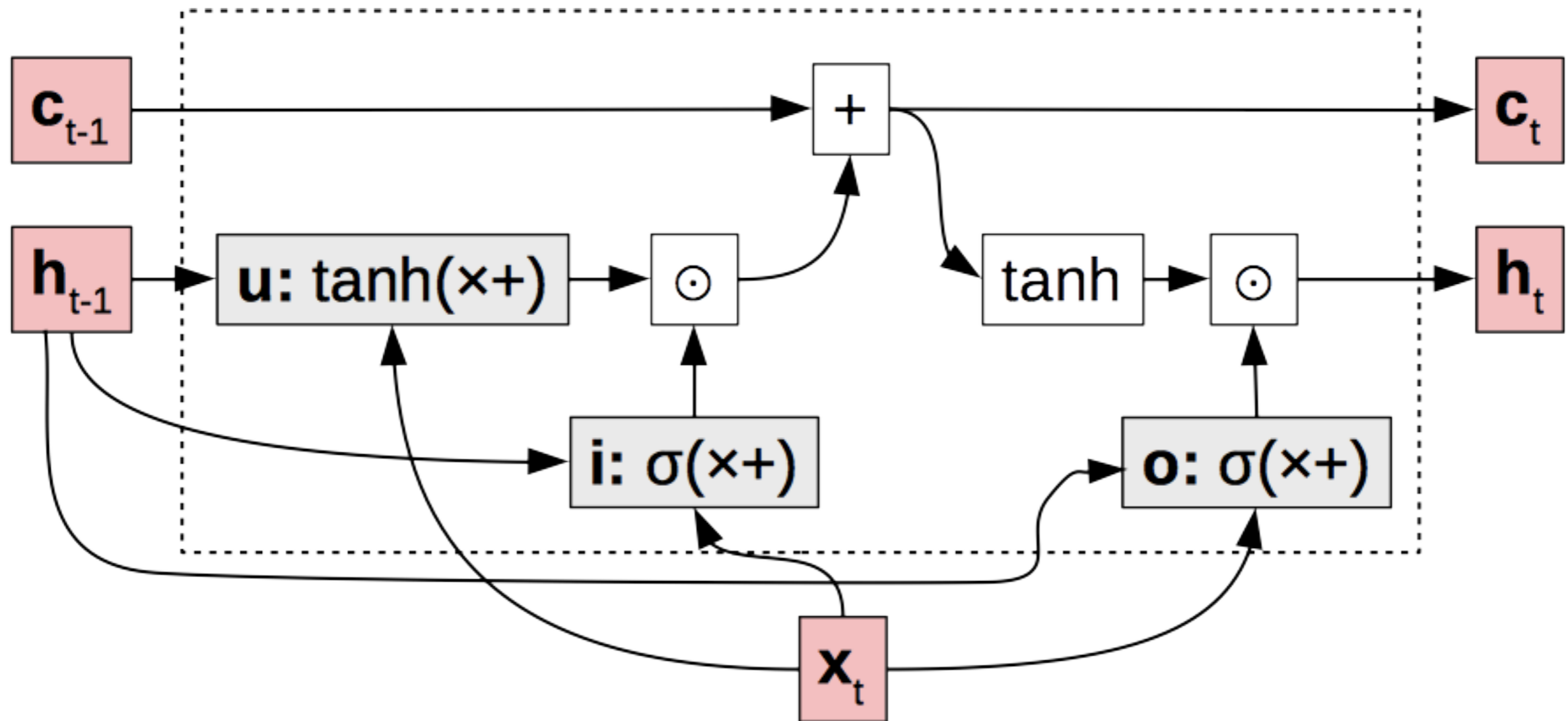
A Solution:

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

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- 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

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- Mini-batching makes things much faster!

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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

```
this is an example </s>  
this is another </s>
```


Mini-batching Method

this	is	an	example	</s>
this	is	another	</s>	</s>

Padding

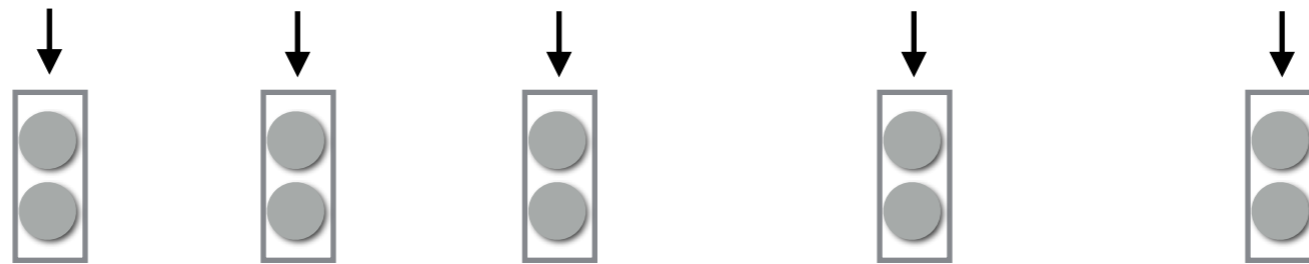
Mini-batching Method

this	is	an	example	</s>
this	is	another	</s>	</s>

Padding

Loss

Calculation



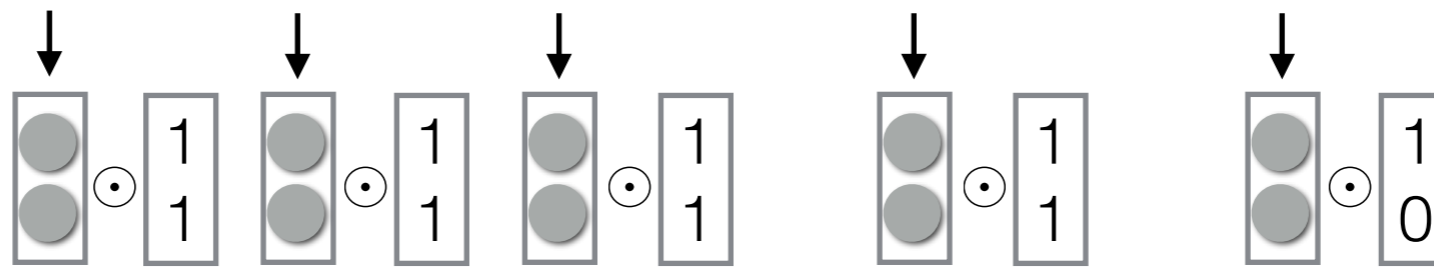
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Mask

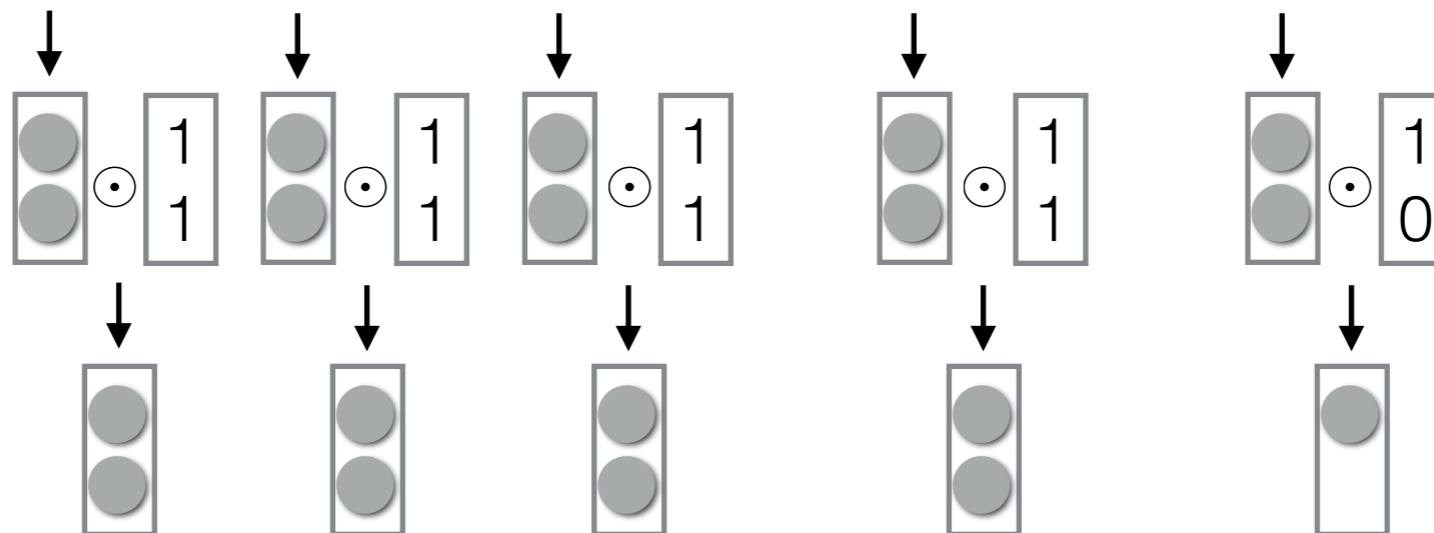
Mini-batching Method

this is an example </s>
this is another </s> **</s>**

Padding

Loss

Calculation



Mask

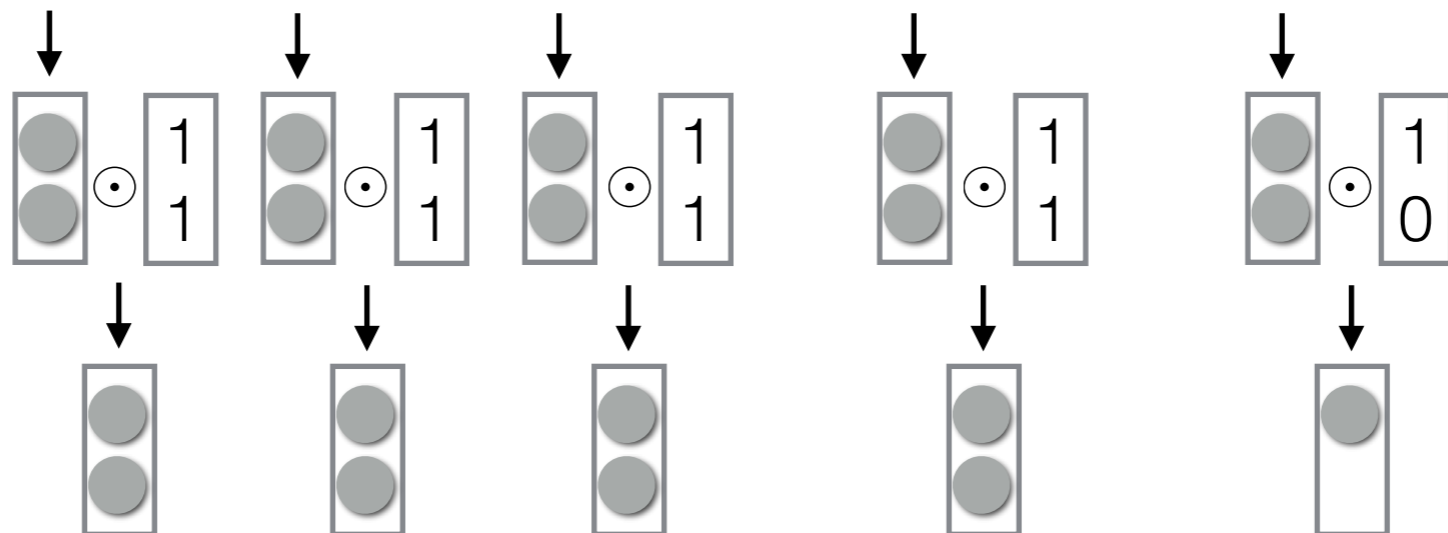
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Padding

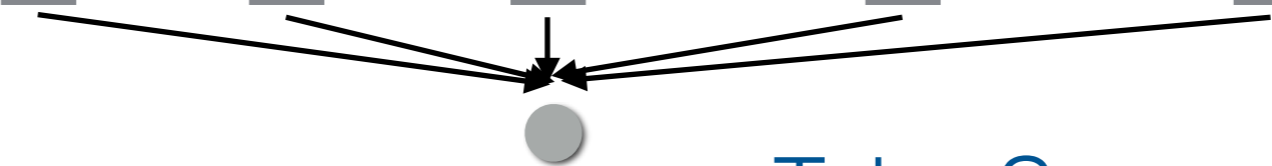
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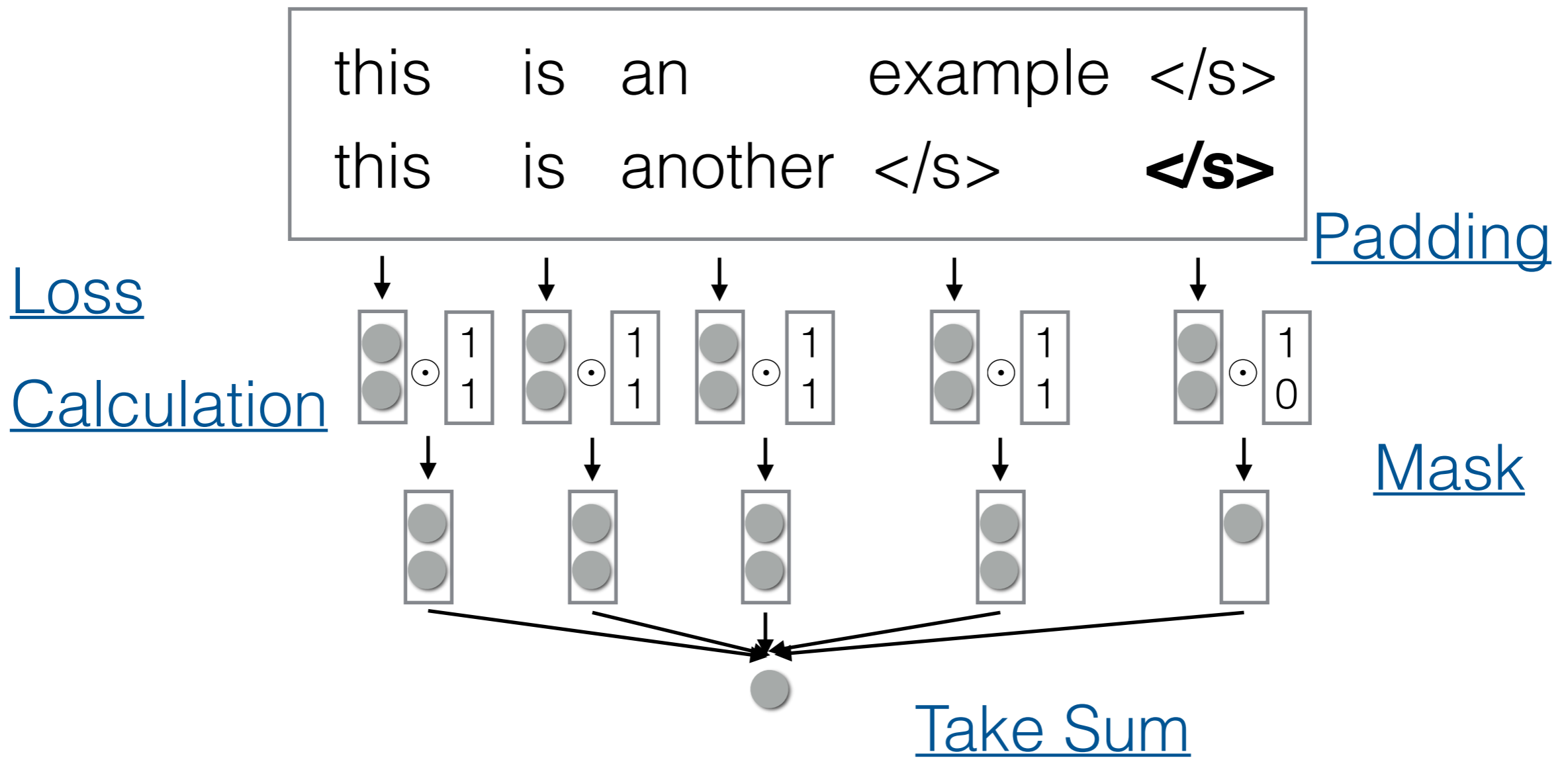


Mask

Take Sum



Mini-batching Method



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

Bucketing/Sorting

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- If we use sentences of different lengths, too much padding and sorting can **result in decreased performance**

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

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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

1st Pass

I hate this movie

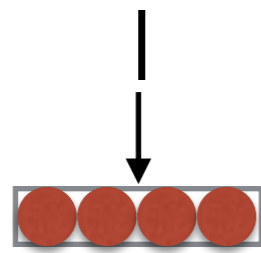
2nd Pass

It is so bad

Truncated BPTT

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1st Pass



hate

this

movie

2nd Pass

It

is

so

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2nd Pass

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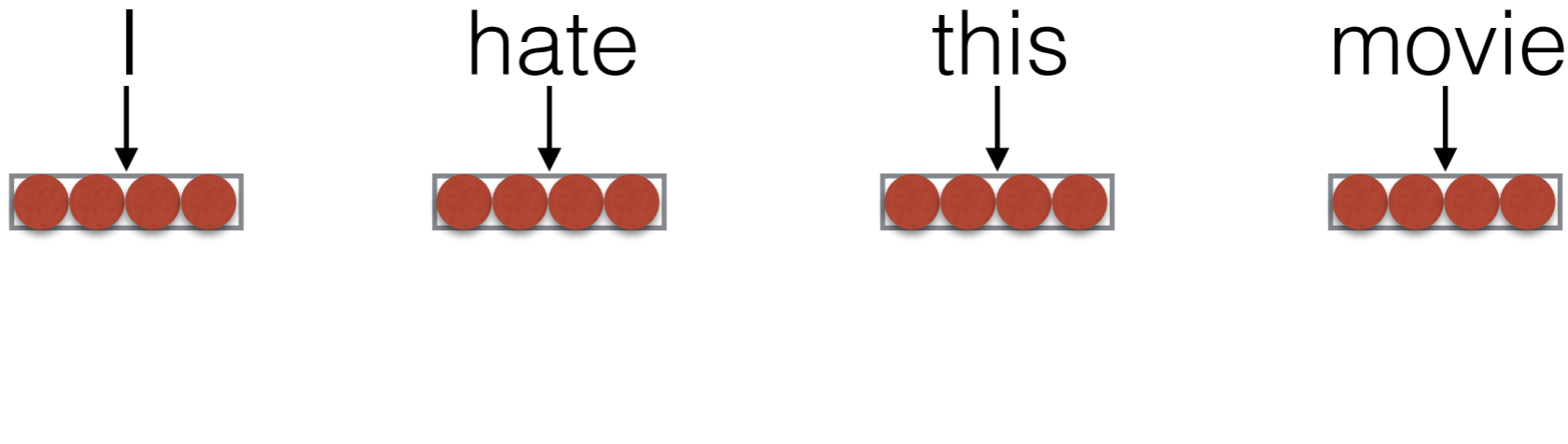
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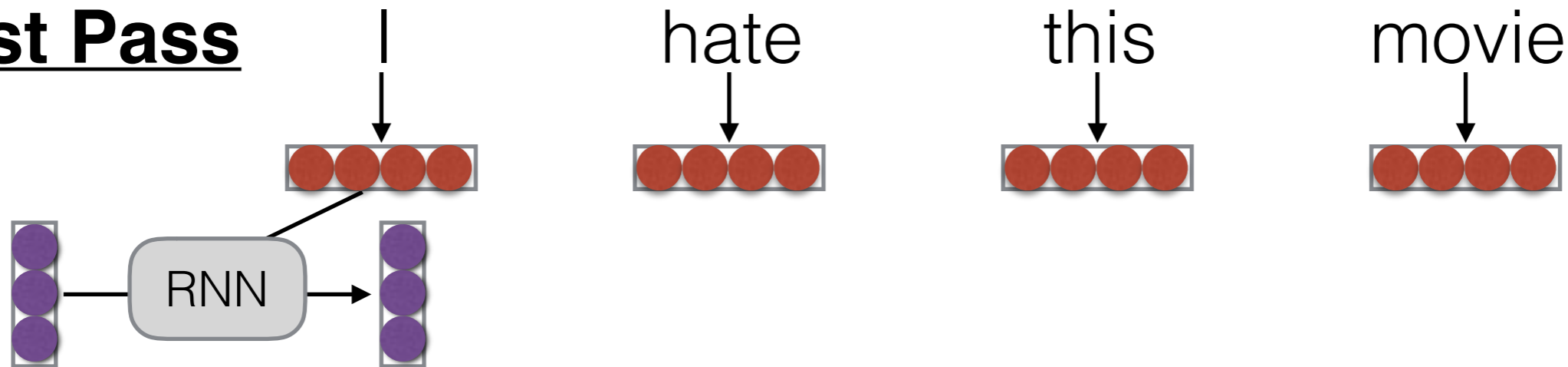
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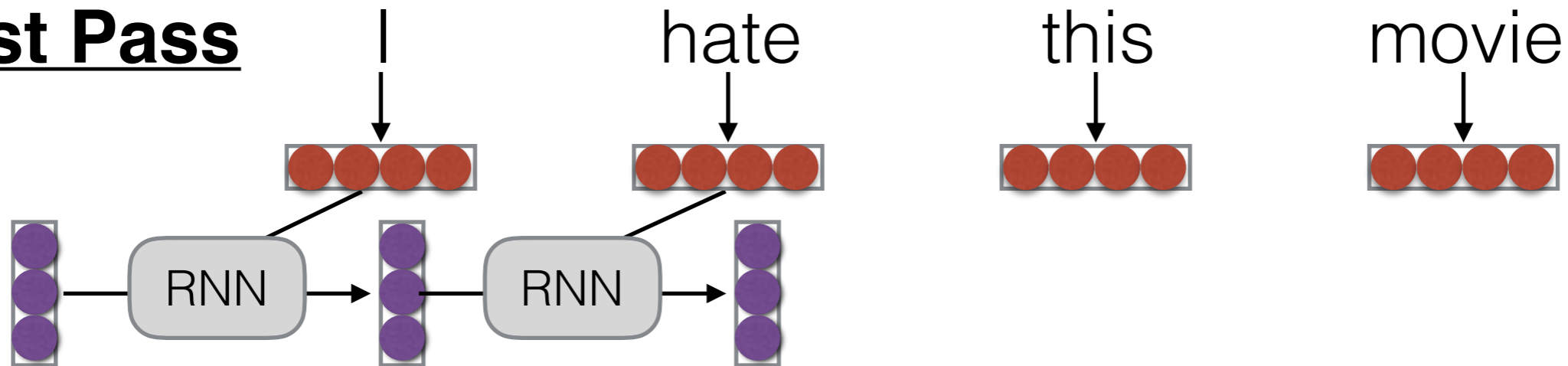
2nd Pass

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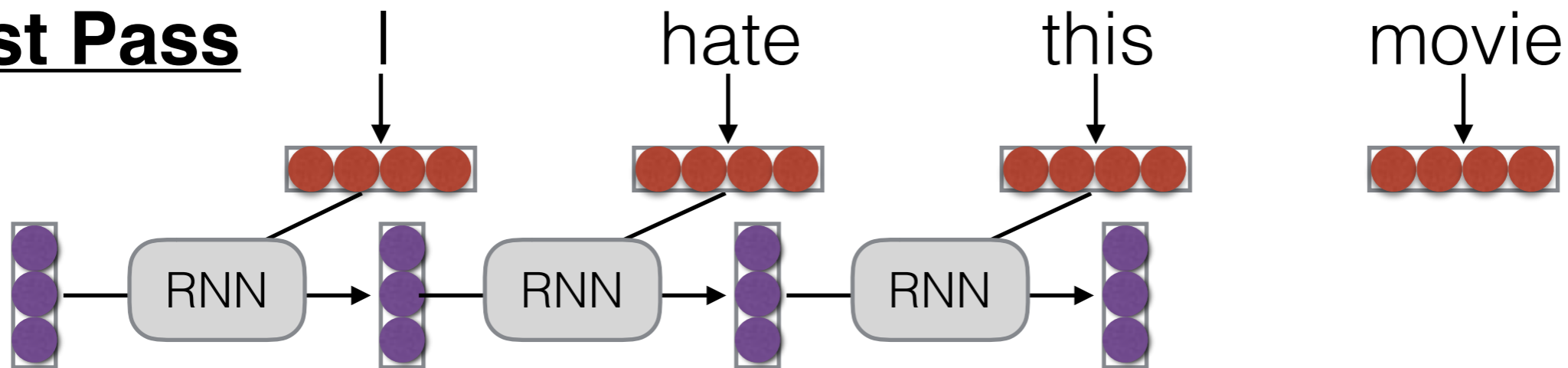
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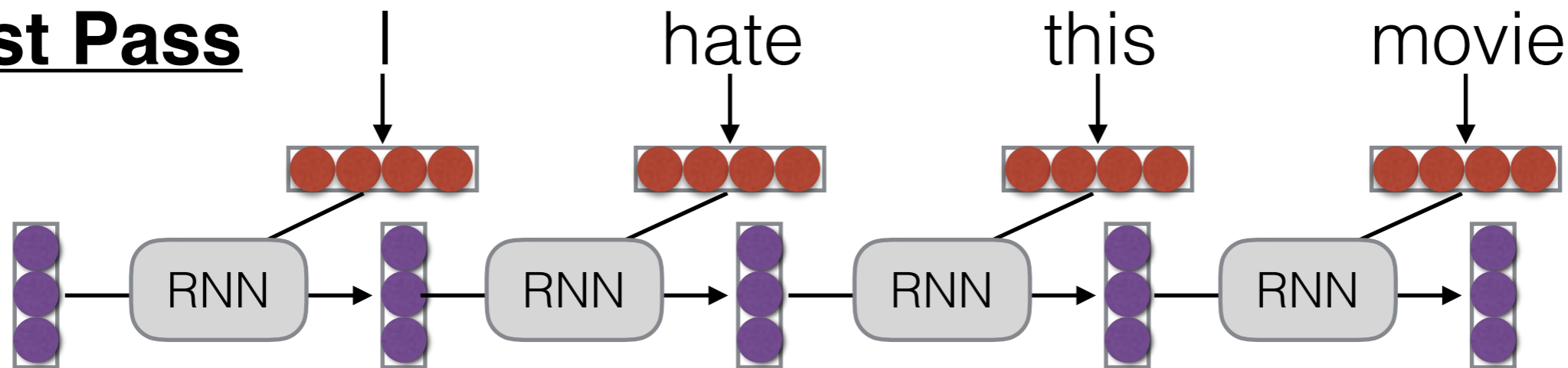
2nd Pass

It is so bad

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1st Pass



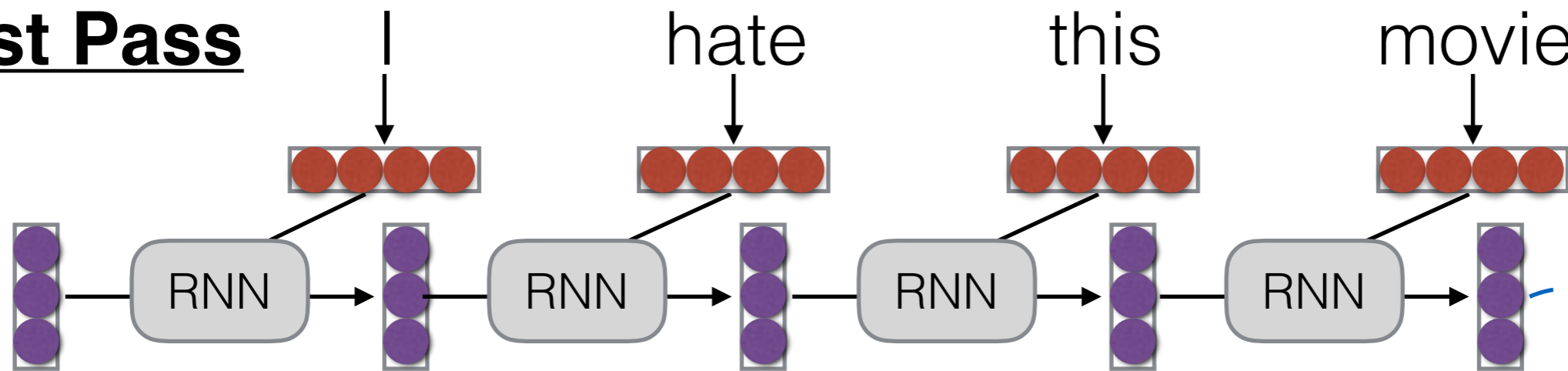
2nd Pass

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1st Pass



2nd Pass

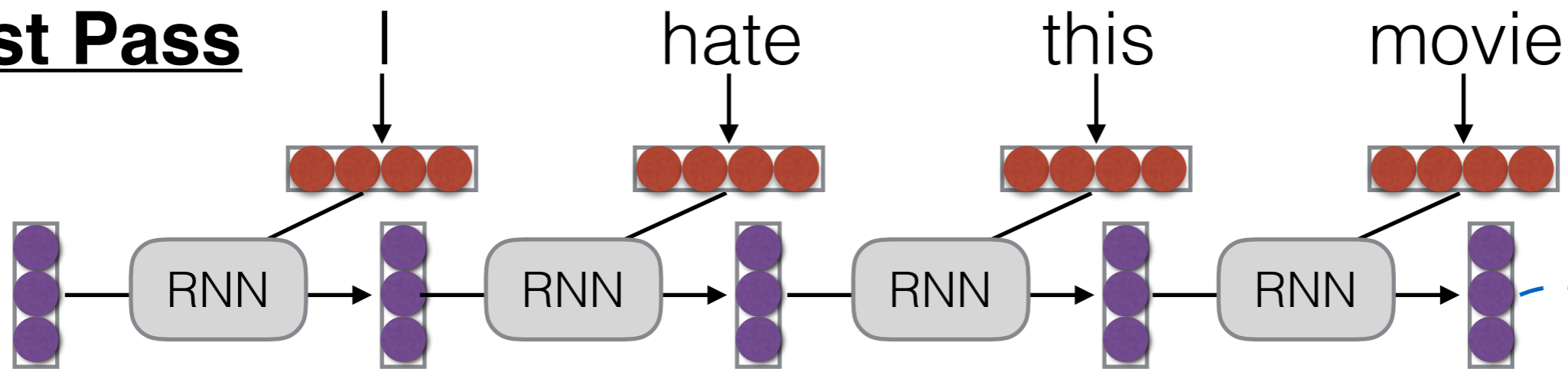
state only, no backprop



Truncated BPTT

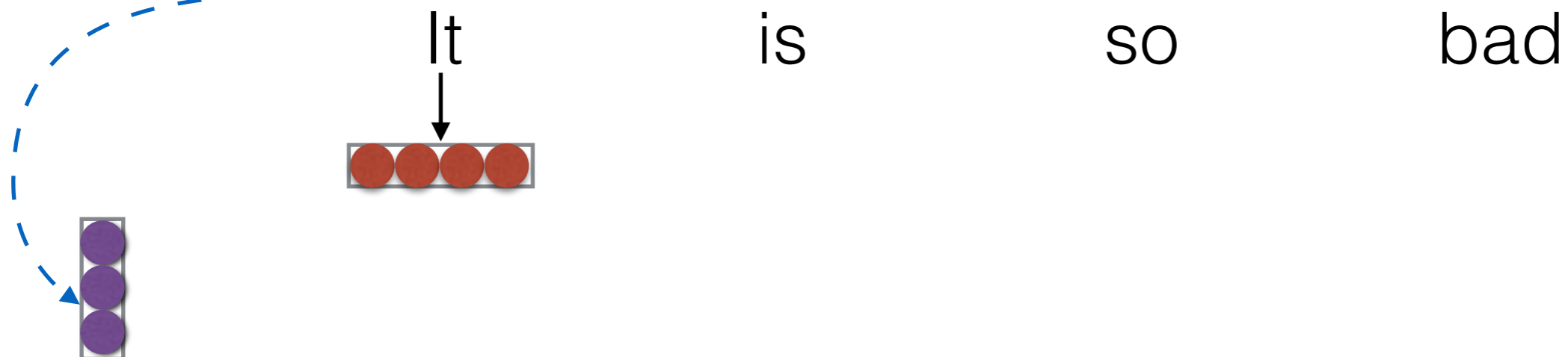
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1st Pass



2nd Pass

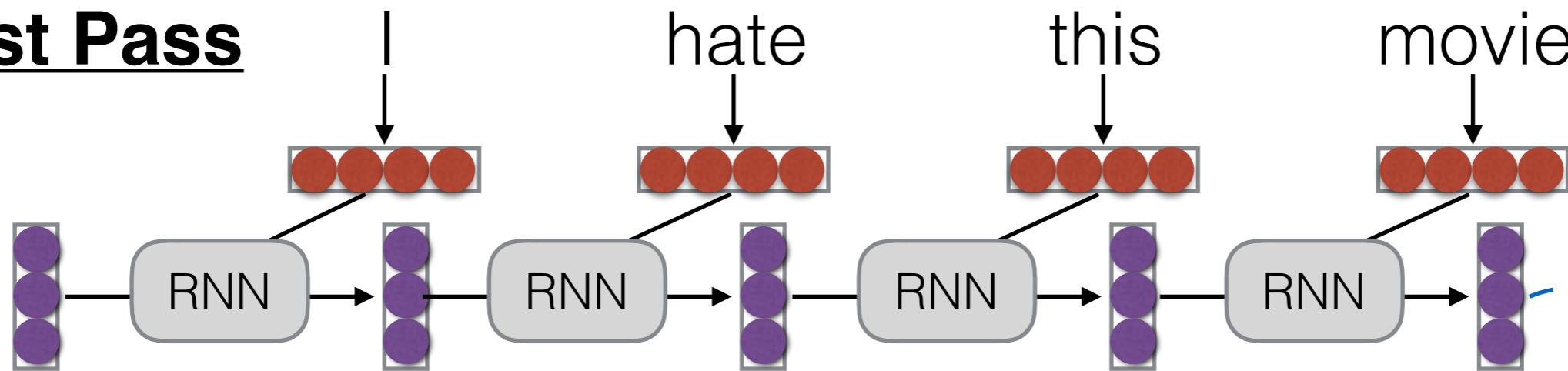
state only, no backprop



Truncated BPTT

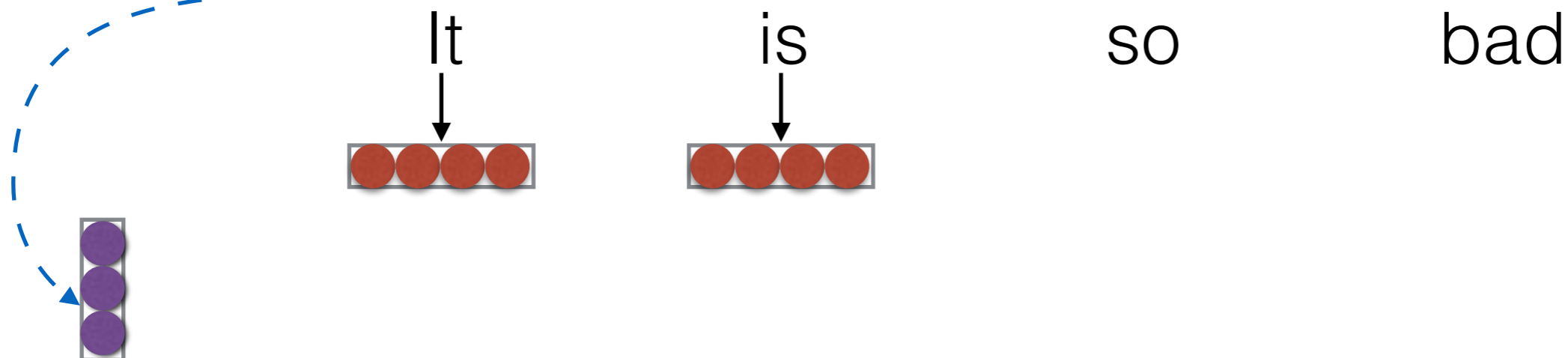
- Backprop over shorter segments, initialize w/ the state from the previous segment

1st Pass



2nd Pass

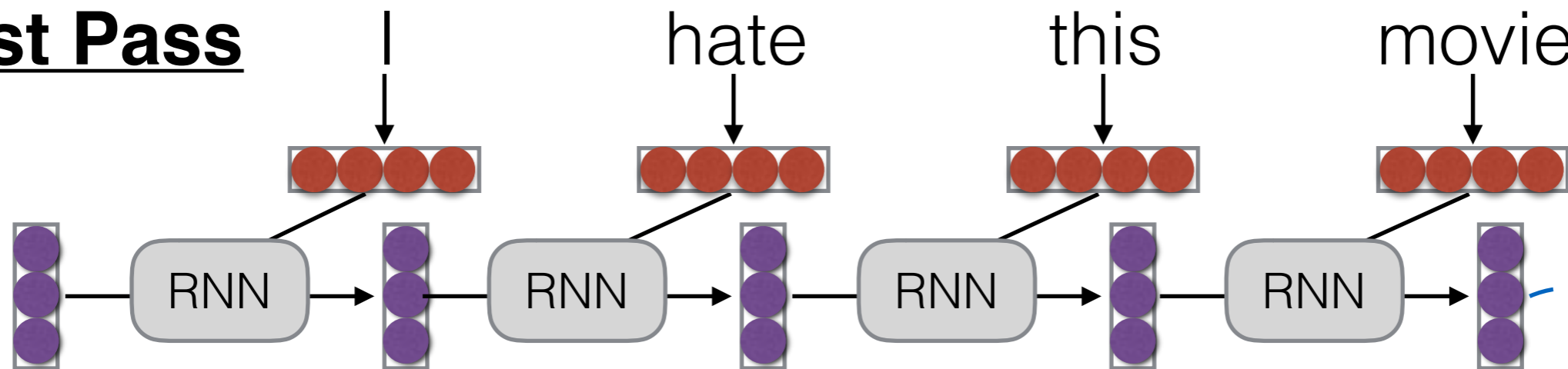
state only, no backprop



Truncated BPTT

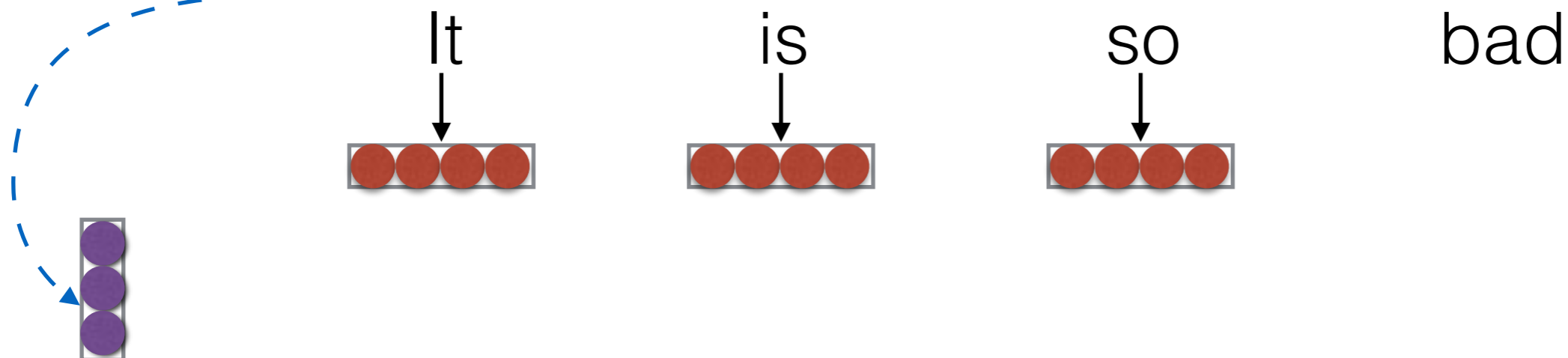
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1st Pass



2nd Pass

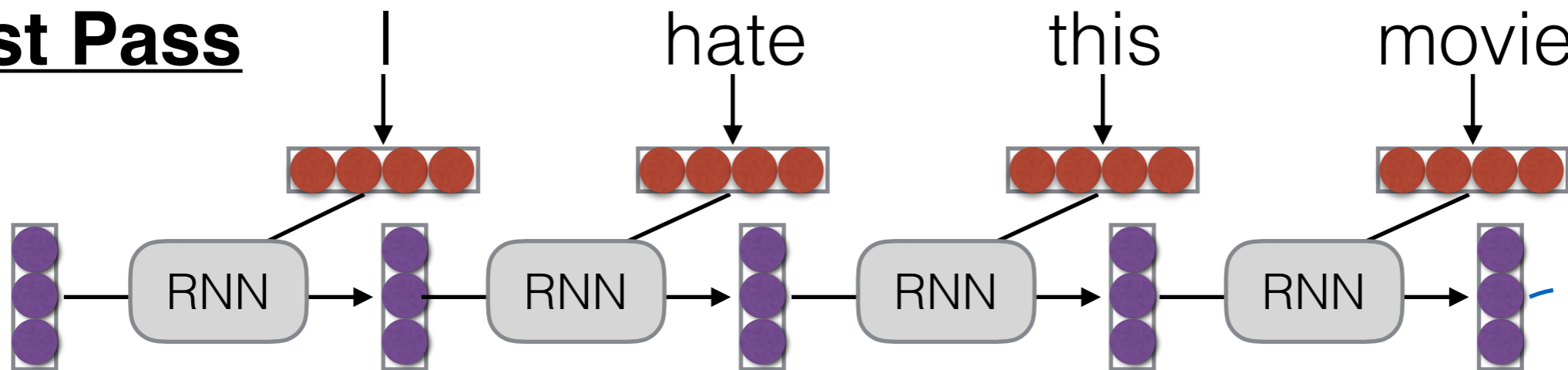
state only, no backprop



Truncated BPTT

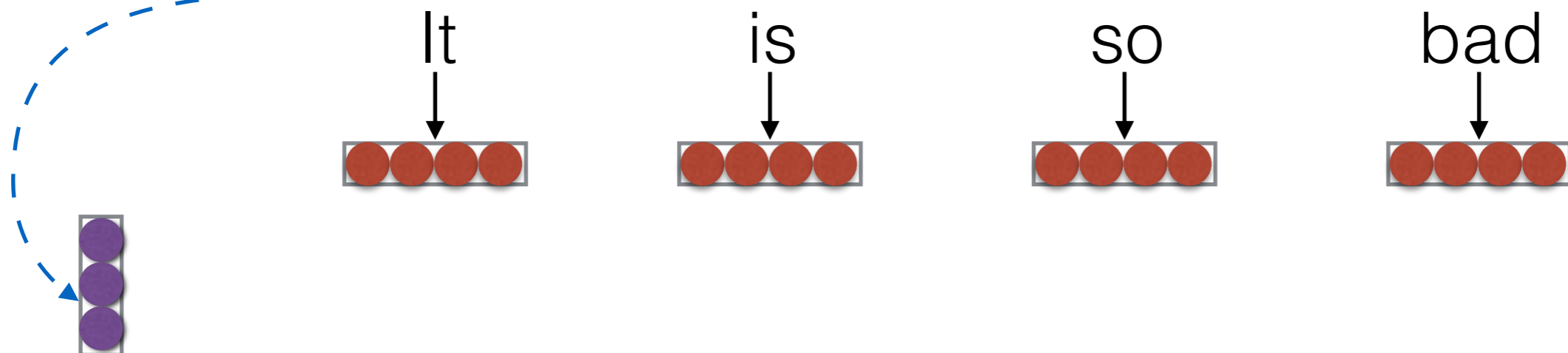
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2nd Pass

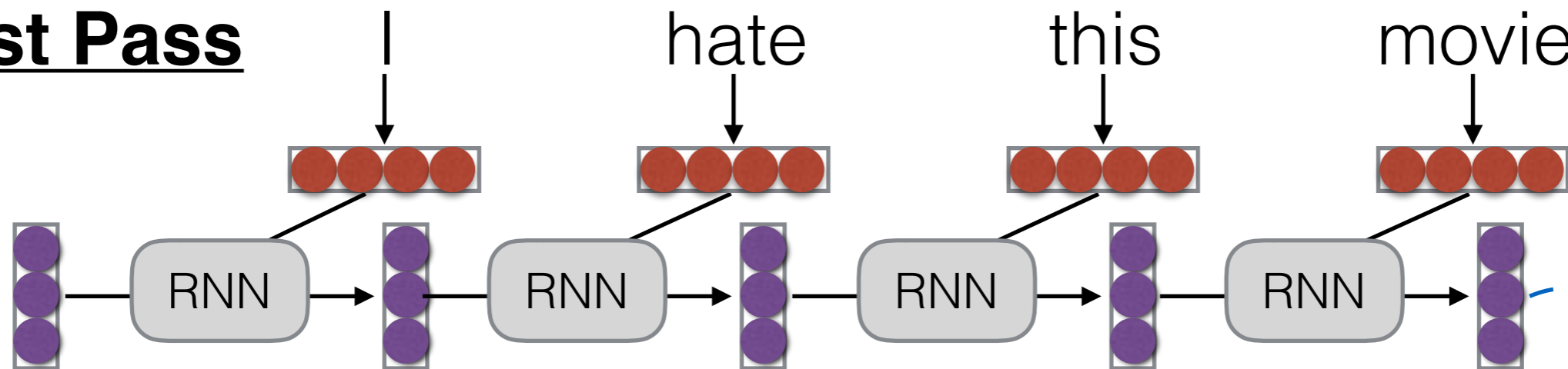
state only, no backprop



Truncated BPTT

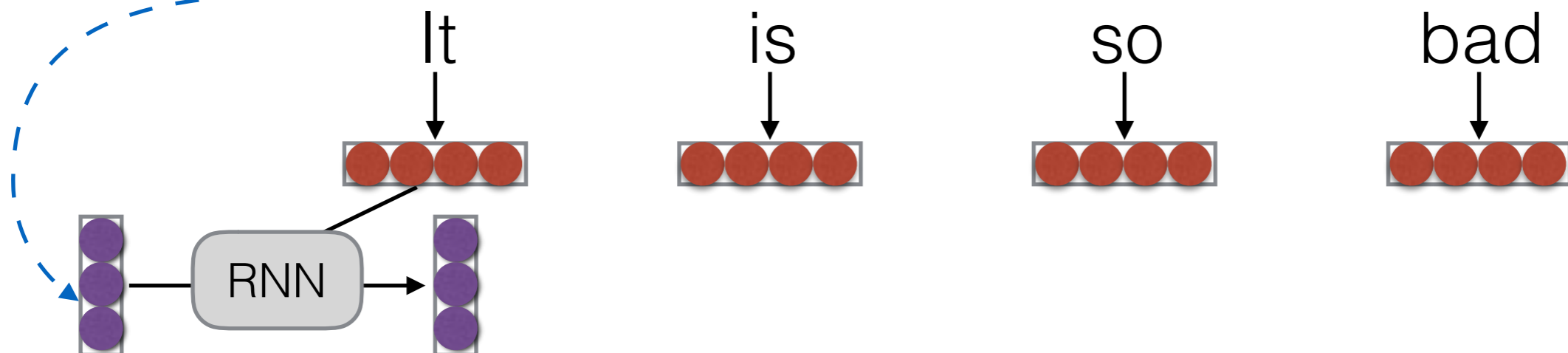
- Backprop over shorter segments, initialize w/ the state from the previous segment

1st Pass



2nd Pass

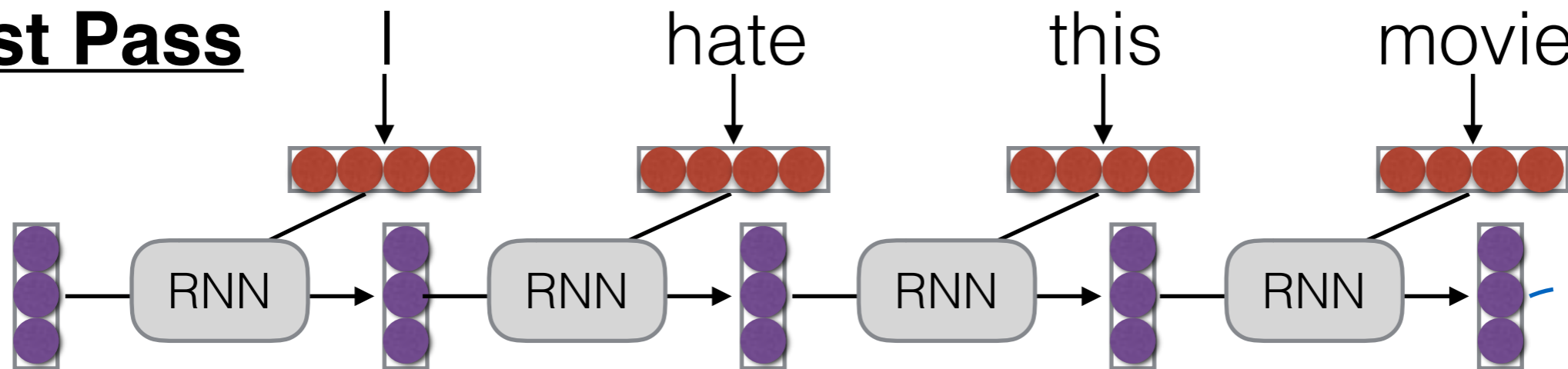
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Truncated BPTT

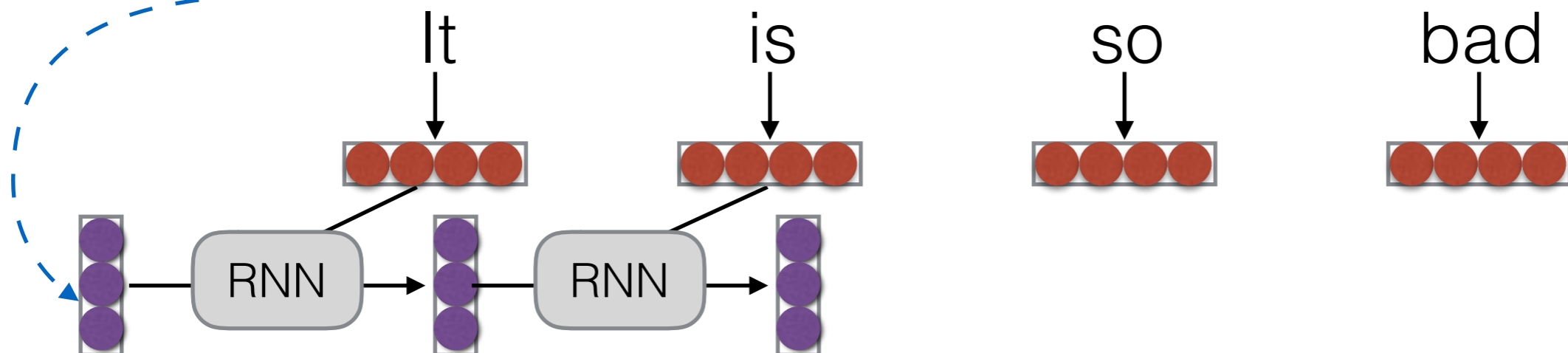
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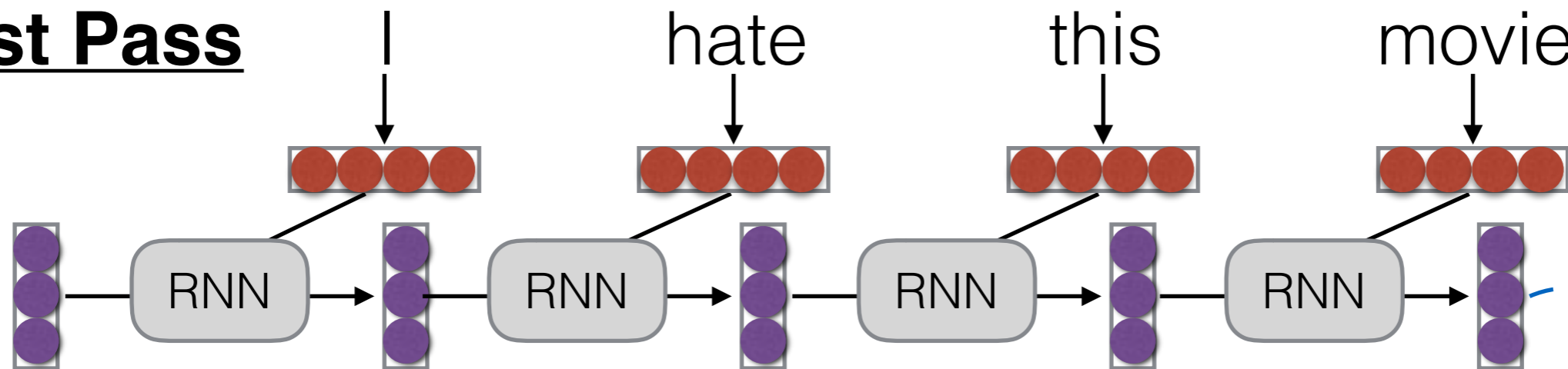
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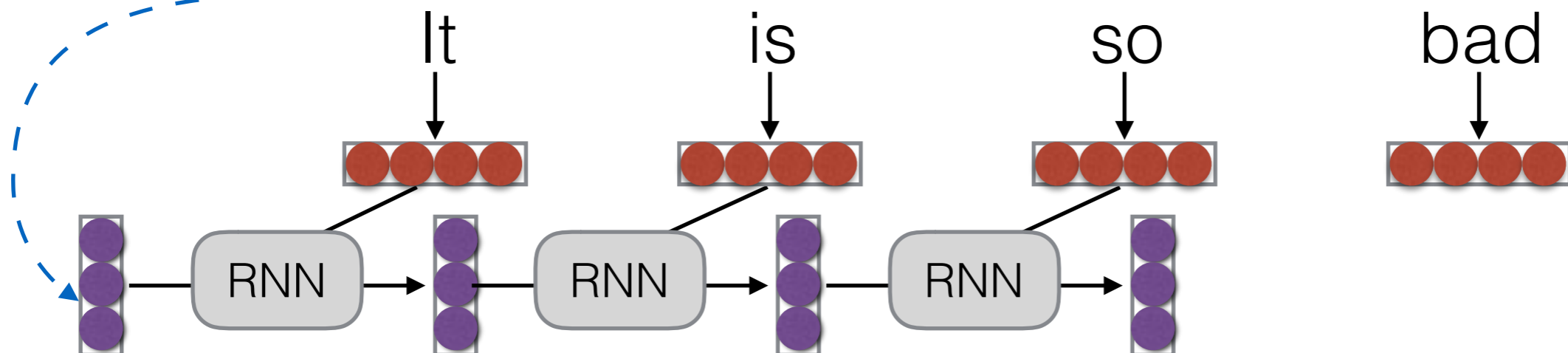
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2nd Pass

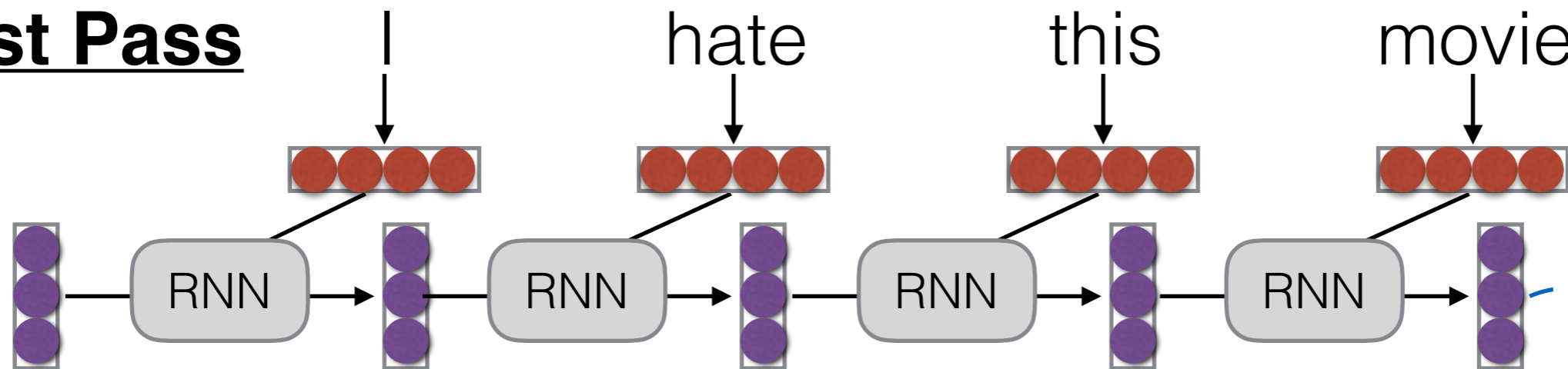
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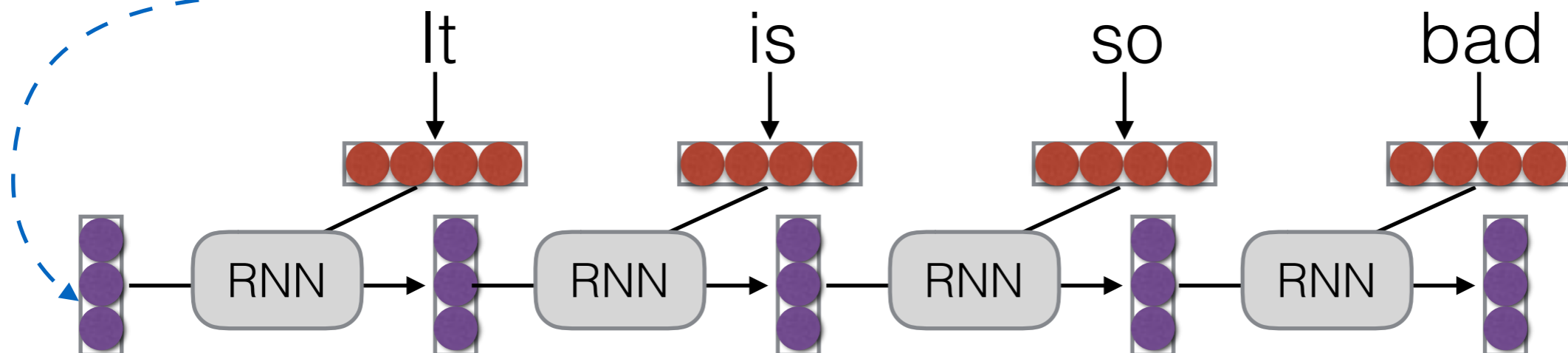
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1st Pass



2nd Pass

state only, no backprop



Pre-training/Transfer for RNNs

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- 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

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- Train for one task, solve another

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- **Pre-training task:** Big data, easy to learn

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 \rightarrow Sentence Classifier

(Luong et al. 2015)

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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?

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

—

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Cell sensitive to position in line:

```
The sole importance of the crossing of the Berezina lies in the fact that it plainly and indubitably proved the fallacy of all the plans for cutting off the enemy's retreat and the soundness of the only possible line of action--the one Kutuzov and the general mass of the army demanded--namely, simply to follow the enemy up. The French crowd fled at a continually increasing speed and all its energy was directed to reaching its goal. It fled like a wounded animal and it was impossible to block its path. This was shown not so much by the arrangements it made for crossing as by what took place at the bridges. When the bridges broke down, unarmed soldiers, people from Moscow and women with children who were with the French transport, all--carried on by vis inertiae--pressed forward into boats and into the ice-covered water and did not surrender.
```

Cell that turns on inside quotes:

```
"You mean to imply that I have nothing to eat out of... On the contrary, I can supply you with everything even if you want to give dinner parties," warmly replied Chichagov, who tried by every word he spoke to prove his own rectitude and therefore imagined Kutuzov to be animated by the same desire.
```

```
Kutuzov, shrugging his shoulders, replied with his subtle penetrating smile: "I meant merely to say what I said."
```

Cell that robustly activates inside if statements:

```
static int __dequeue_signal(struct sigpending *pending, sigset_t *mask, siginfo_t *info)
{
    int sig = next_signal(pending, mask);
    if (sig) {
        if (current->notifier) {
            if (sigismember(current->notifier_mask, sig)) {
                if (! (current->notifier)(current->notifier_data)) {
                    clear_thread_flag(TIF_SIGPENDING);
                    return 0;
                }
            }
        }
        collect_signal(sig, pending, info);
    }
    return sig;
}
```

A large portion of cells are not easily interpretable. Here is a typical example:

```
/* Unpack a filter field's string representation from user-space
 * buffer. */
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)
{
    char *str;
    if (!*bufp || (len == 0) || (len > *remain))
        return ERR_PTR(-EINVAL);
    /* Of the currently implemented string fields, PATH_MAX
     * defines the longest valid length.
     */
```

Cell that turns on inside comments and quotes:

```
/* Duplicate LSM field information. The lsm_rule is opaque, so
 * re-initialized. */
static inline int audit_dupe_lsm_field(struct audit_field *df,
                                     struct audit_field *sf)
{
    int ret = 0;
    char *lsm_str;
    /* Our own copy of lsm_str */
    lsm_str = kstrdup(sf->lsm_str, GFP_KERNEL);
    if (unlikely(!lsm_str))
        return -ENOMEM;
    df->lsm_str = lsm_str;
    /* Our own (refreshed) copy of lsm_rule */
    ret = security_audit_rule_init(df->type, df->op, df->lsm_str,
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    if (ret == -EINVAL) {
        pr_warn("audit rule for LSM '%s' is invalid\n",
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```

Cell that is sensitive to the depth of an expression:

```
#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
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    int i;
    if (classes[class]) {
        for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
            if (mask[i] & classes[class][i])
                return 0;
    }
    return 1;
}
```

Cell that might be helpful in predicting a new line. Note that it only turns on for some "Y":

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     */
    if (len > PATH_MAX)
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    str = kmalloc(len + 1, GFP_KERNEL);
    if (unlikely(!str))
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    memcpy(str, *bufp, len);
    str[len] = 0;
    *bufp += len;
    *remain -= len;
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    *remain -= len;
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}
```

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

Questions?