CS695-002 Special Topics in NLP

Language Modeling, Smoothing, and Recurrent Neural Networks

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https://cs.gmu.edu/~antonis/course/cs695-fall20/

Slides are taken from Graham Neubig's CMU NN4NLP course

Are These Sentences OK?

- Jane went to the store.
- store to Jane went the.
- Jane went store.
- Jane goed to the store.
- The store went to Jane.
- The food truck went to Jane.

Calculating the Probability of a Sentence

Jane went to the store .

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But word order and context matters!

Calculating the Probability of a Sentence

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$$\begin{aligned}
P(\text{Jane went to the store}) = {} & P(Jane \mid <s>) \times P(went \mid Jane) \times \\
& P(to \mid went) \times P(the \mid to) \times \\
& P(store \mid the) \times P(. \mid store) \\
& P(</s> \mid .)
\end{aligned}$$

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The big problem: How do we predict

$$P(x_i \mid x_1, \ldots, x_{i-1})$$

?!?!

Count-based Language Models

Count-based Language Models

- Count up the frequency and divide:

$$P_{ML}(x_i \mid x_{i-n+1}, \ldots, x_{i-1}) := \frac{c(x_{i-n+1}, \ldots, x_i)}{c(x_{i-n+1}, \ldots, x_{i-1})}$$

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Corpus:

The cat sat on the mat .
A dog chased the cat .
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The mouse ran under a mat .

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$$p(chased \mid dog) = ? \quad p(cat \mid the) = ? \quad p(the \mid <s>) = ?$$

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$$p(chased \mid dog) = \frac{1}{1} = 1 \quad p(cat \mid the) = \frac{1}{4} = 0.25 \quad p(the \mid <s>) = 0.5$$

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p(A cat chased the mouse .) =

$$p(<s>|A) \times$$
$$p(cat\,|\,a) \times$$
$$p(chased\,|\,cat) \times$$
$$p(the\,|\,chased) \times$$
$$p(mouse\,|\,the) \times$$
$$p(\,.\,|\,mouse)$$

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- Add smoothing to deal with zero counts:

$$p(x_i | x_{i-n+1:i-1}) = \frac{c(x_{i-n+1:i}) + \alpha}{c(x_{i-n+1:i-1}) + \alpha |V|}$$

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$$|V| = |\{the, a, cat, sat, \dots\}| = 15 \qquad \alpha = 1$$

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$p($A cat chased the mouse .$) =$

$$p(<s> \| A) \times$$
$$p(cat \mid a) \times$$
$$p(chased \mid cat) \times$$
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$$p(\,.\mid mouse)$$

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- Another way to smooth: skip some words

$$\begin{aligned} P(x_i \mid x_{i-n+1}, \ldots, x_{i-1}) =& \lambda P_{ML}(x_i \mid x_{i-n+1}, \ldots, x_{i-1}) \\ &+ (1-\lambda) P(x_i \mid x_{1-n+2}, \ldots, x_{i-1}) \end{aligned}$$

Evaluation

- **Log-likelihood:**

$$LL(\mathcal{E}_{test}) = \sum_{E \in \mathcal{E}_{test}} \log P(E)$$

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- **Per-word Log Likelihood:**

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- **Per-word (Cross) Entropy:**

$$H(\mathcal{E}_{test}) = \frac{1}{\sum_{E \in \mathcal{E}_{test}} |E|} \sum_{E \in \mathcal{E}_{test}} - \log_2 P(E)$$

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- **Perplexity:**

$$ppl(\mathcal{E}_{test}) = 2^{H(\mathcal{E}_{test})} = e^{-WLL(\mathcal{E}_{test})}$$

Evaluation

What does “My LM achieves a perplexity of 23” mean?

https://sjmielke.com/comparing-perplexities.htm

What Can we Do w/ LMs?

- Score sentences:

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(same as calculating loss for training)

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- Generate sentences:

while didn't choose end-of-sentence symbol:
  calculate probability
  sample a new word from the probability distribution

Problems and Solutions?

- Cannot share strength among **similar words**

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for tennis class he wanted to buy his own racquet

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→ solution: cache, trigger, topic, syntactic models, etc.

An Alternative:
Featurized Log-Linear Models

An Alternative: Featurized Models

- Calculate features of the context
- Based on the features, calculate probabilities
- Optimize feature weights using gradient descent, etc.

Example:

Previous words: “giving a"

Example:

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a
the
talk
gift
hat
…

Words we’re predicting

Example:

Previous words: “giving a"

a	
the	
talk	$b = \begin{pmatrix} 3.0 \\ 2.5 \\ -0.2 \\ 0.1 \\ 1.2 \\ \ldots \end{pmatrix}$
gift	
hat	
…	
Words we’re predicting	How likely are they?

Example:

Previous words: "giving a"

a the talk gift hat …	$b=\begin{pmatrix}3.0\\2.5\\-0.2\\0.1\\1.2\\\ldots\end{pmatrix}$	$w_{1,a}=\begin{pmatrix}-6.0\\-5.1\\0.2\\0.1\\0.5\\\ldots\end{pmatrix}$
Words we're predicting	How likely are they?	How likely are they given prev. word is "a"?

Example:

Previous words: “giving a"

$$\begin{array}{c} \text{a} \\ \text{the} \\ \text{talk} \\ \text{gift} \\ \text{hat} \\ \dots \end{array} \qquad b=\begin{pmatrix} 3.0 \\ 2.5 \\ -0.2 \\ 0.1 \\ 1.2 \\ \dots \end{pmatrix} \quad w_{1,a}=\begin{pmatrix} -6.0 \\ -5.1 \\ 0.2 \\ 0.1 \\ 0.5 \\ \dots \end{pmatrix} \quad w_{2,giving}=\begin{pmatrix} -0.2 \\ -0.3 \\ 1.0 \\ 2.0 \\ -1.2 \\ \dots \end{pmatrix}$$

Words we’re predicting

How likely are they?

How likely are they given prev. word is “a”?

How likely are they given 2nd prev. word is “giving”?

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$$
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b=\begin{pmatrix} 3.0 \\ 2.5 \\ -0.2 \\ 0.1 \\ 1.2 \\ \ldots \end{pmatrix}
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\quad
s=\begin{pmatrix} -3.2 \\ -2.9 \\ 1.0 \\ 2.2 \\ 0.6 \\ \ldots \end{pmatrix}
$$

Words we’re predicting	How likely are they?	How likely are they given prev. word is “a”?	How likely are they given 2nd prev. word is “giving”?	Total score

Softmax

- Convert scores into probabilities by taking the exponent and normalizing (softmax)

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$$P(x_i \mid x_{i-n+1}^{i-1}) = \frac{e^{s(x_i \mid x_{i-n+1}^{i-1})}}{\sum_{\tilde{x}_i} e^{s(\tilde{x}_i \mid x_{i-n+1}^{i-1})}}$$

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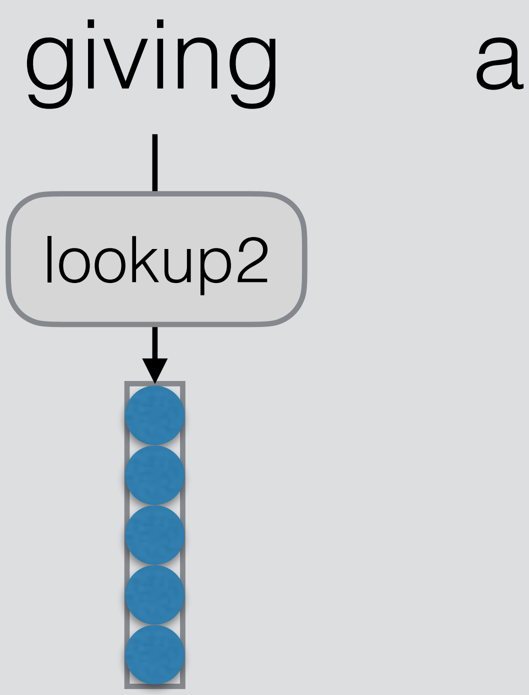
$$\text{s}=\begin{pmatrix} -3.2 \\ -2.9 \\ 1.0 \\ 2.2 \\ 0.6 \\ \dots \end{pmatrix} \longrightarrow \text{p}=\begin{pmatrix} 0.002 \\ 0.003 \\ 0.329 \\ 0.444 \\ 0.090 \\ \dots \end{pmatrix}$$

A Computation Graph View

giving a

Each vector is size of output vocabulary

A Computation Graph View



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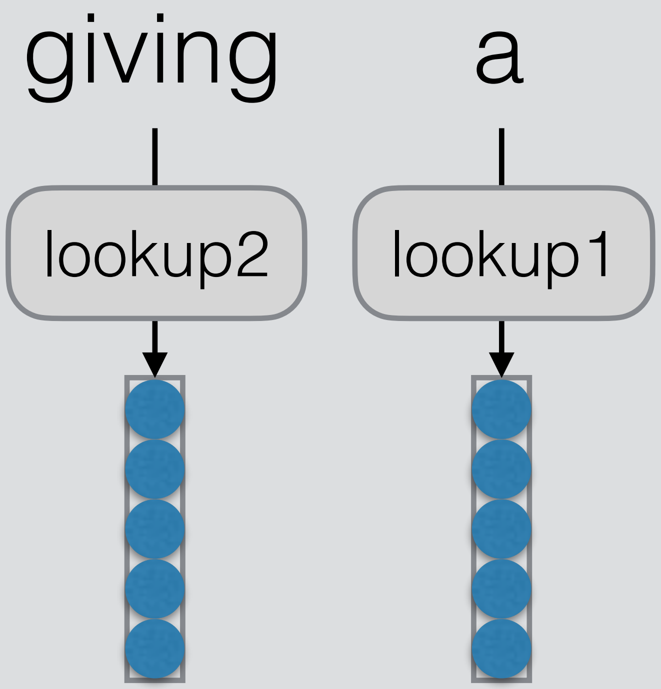

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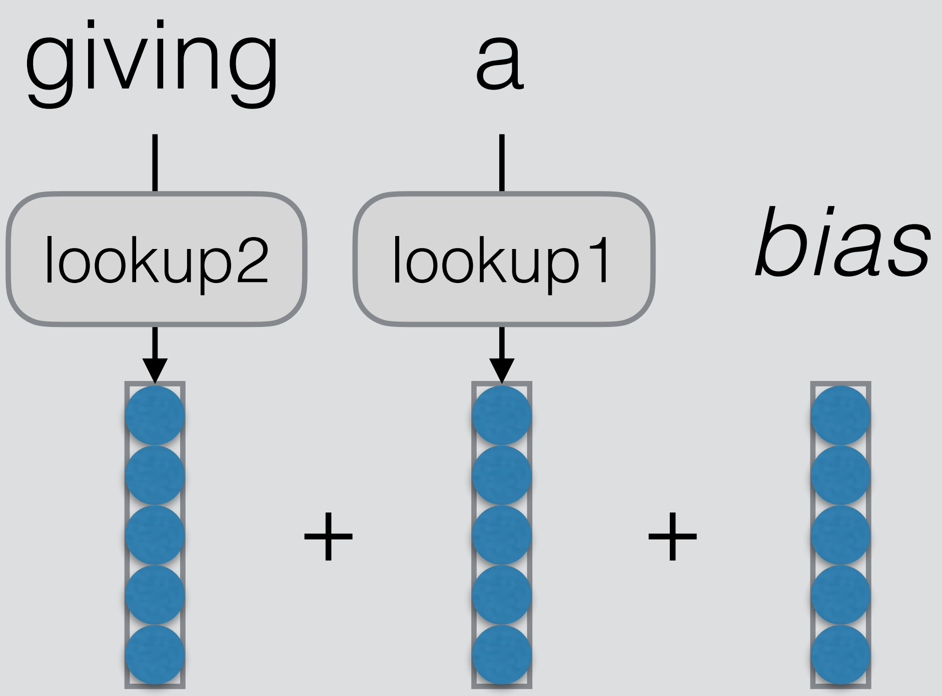

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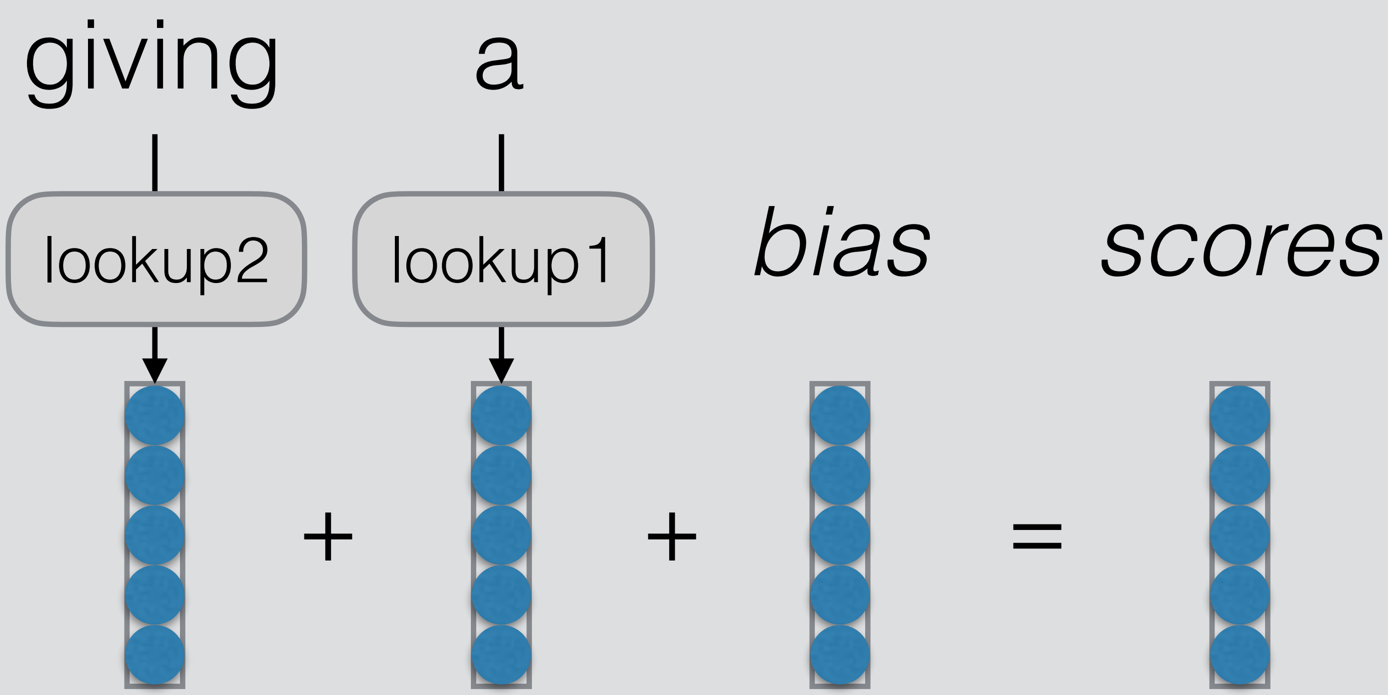

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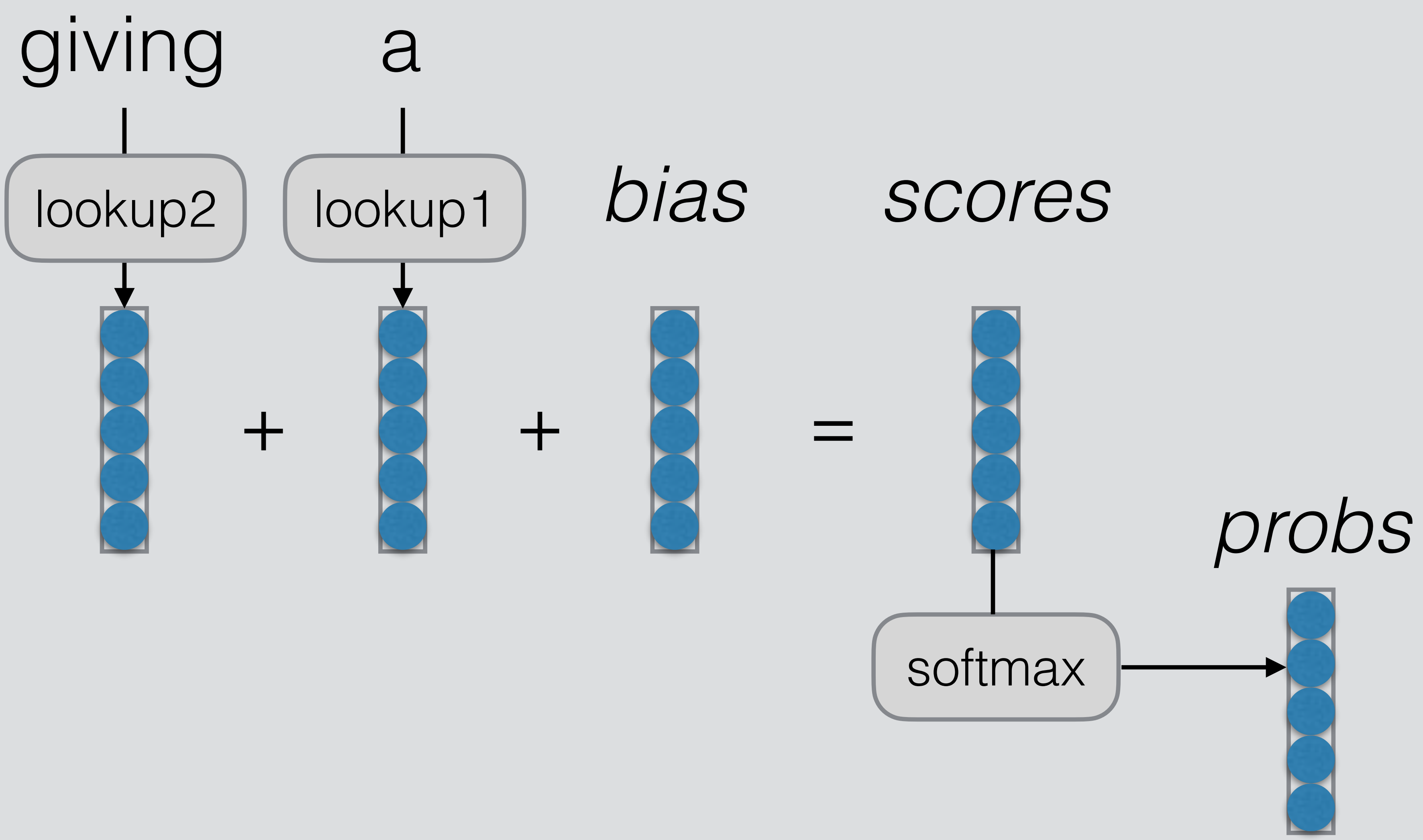

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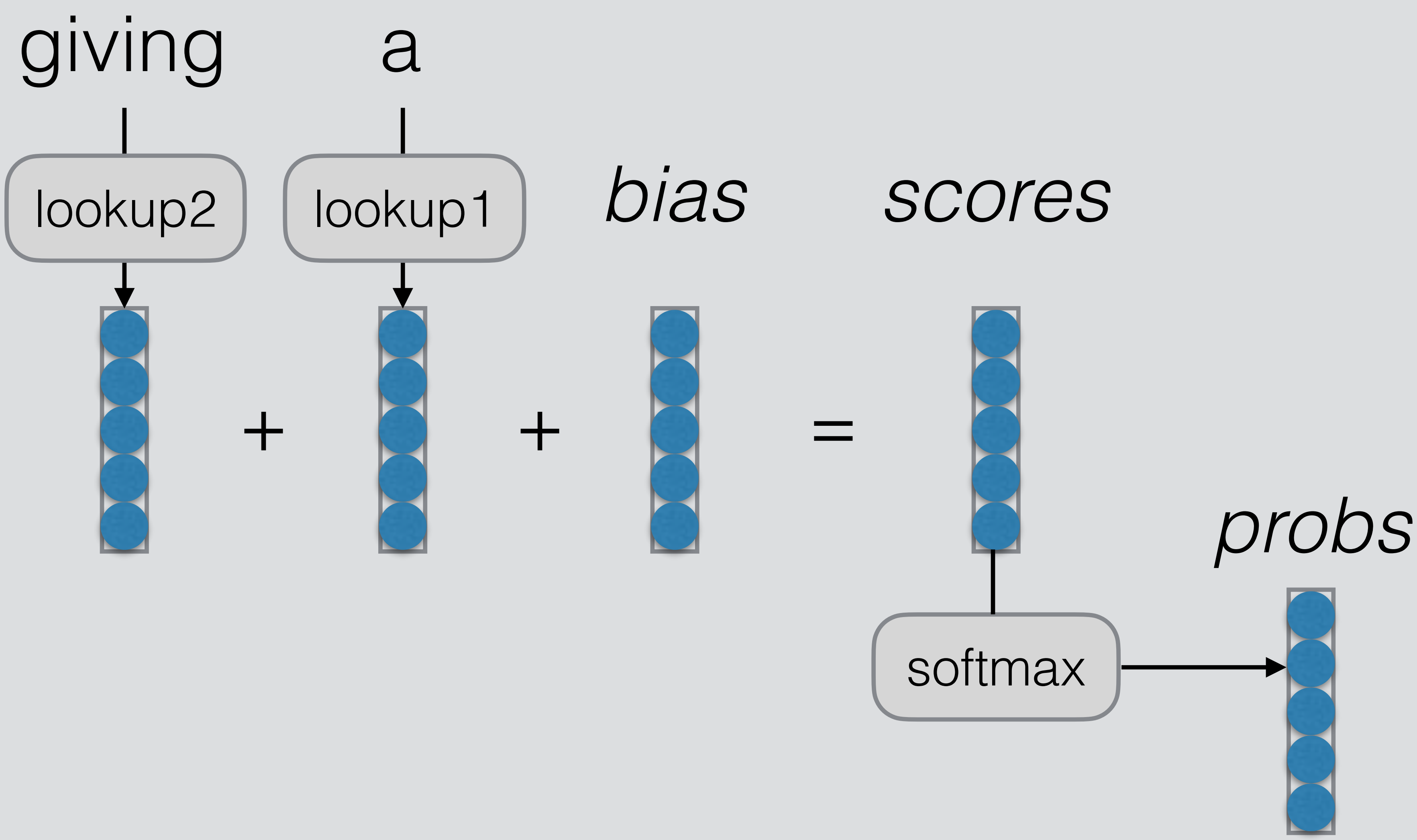
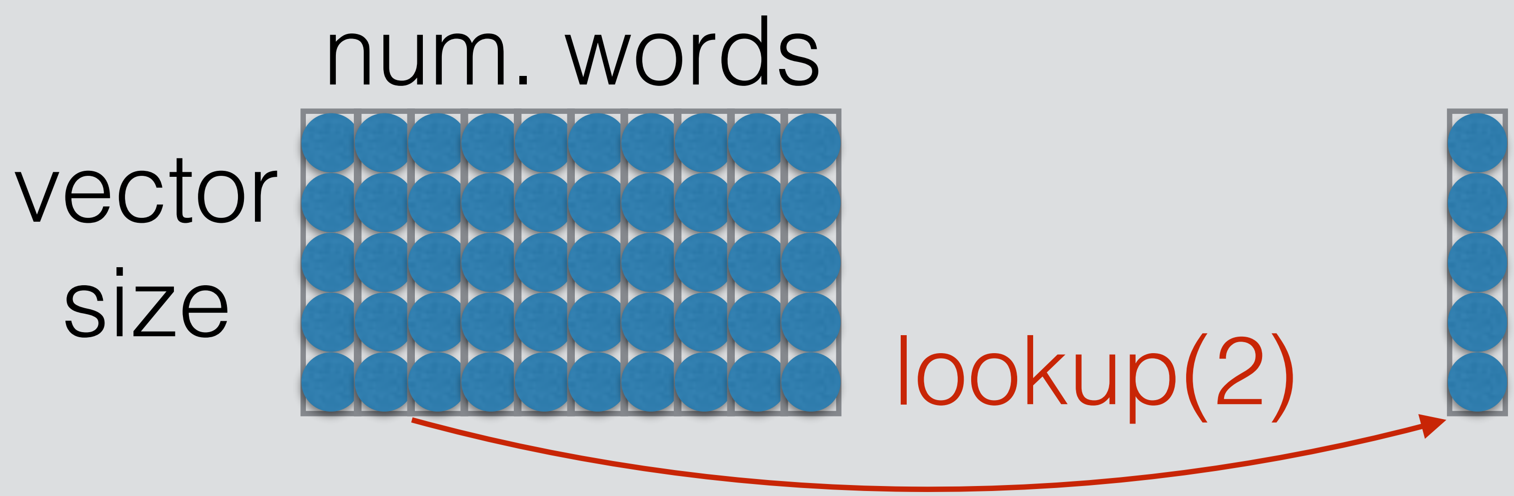


Each vector is size of output vocabulary

A Note: "Lookup"

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



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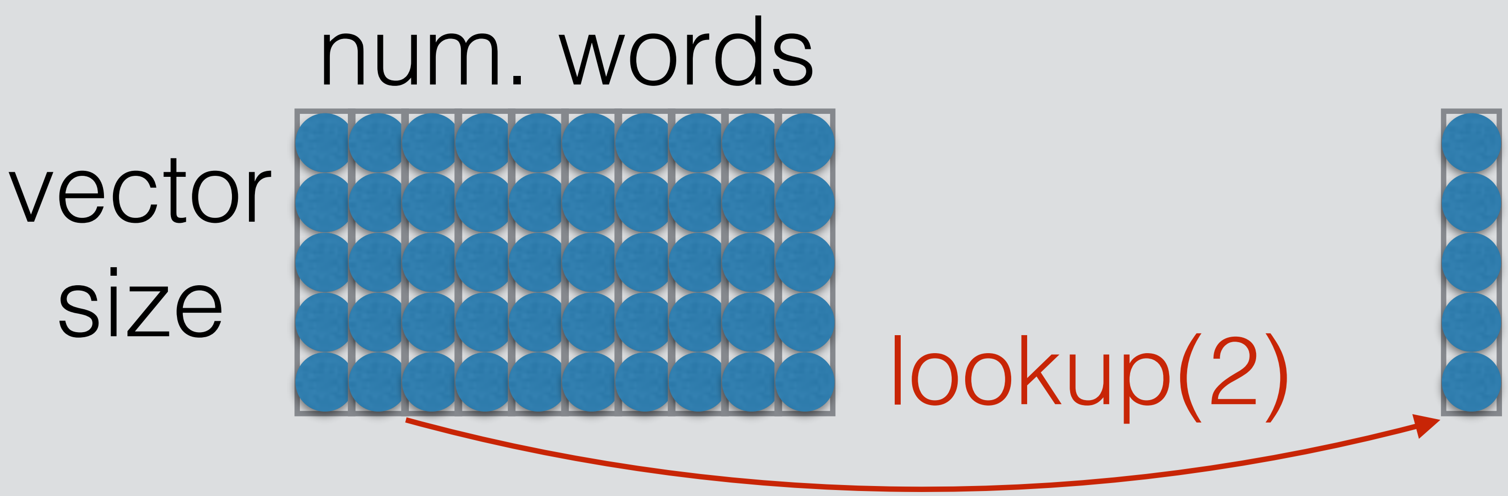
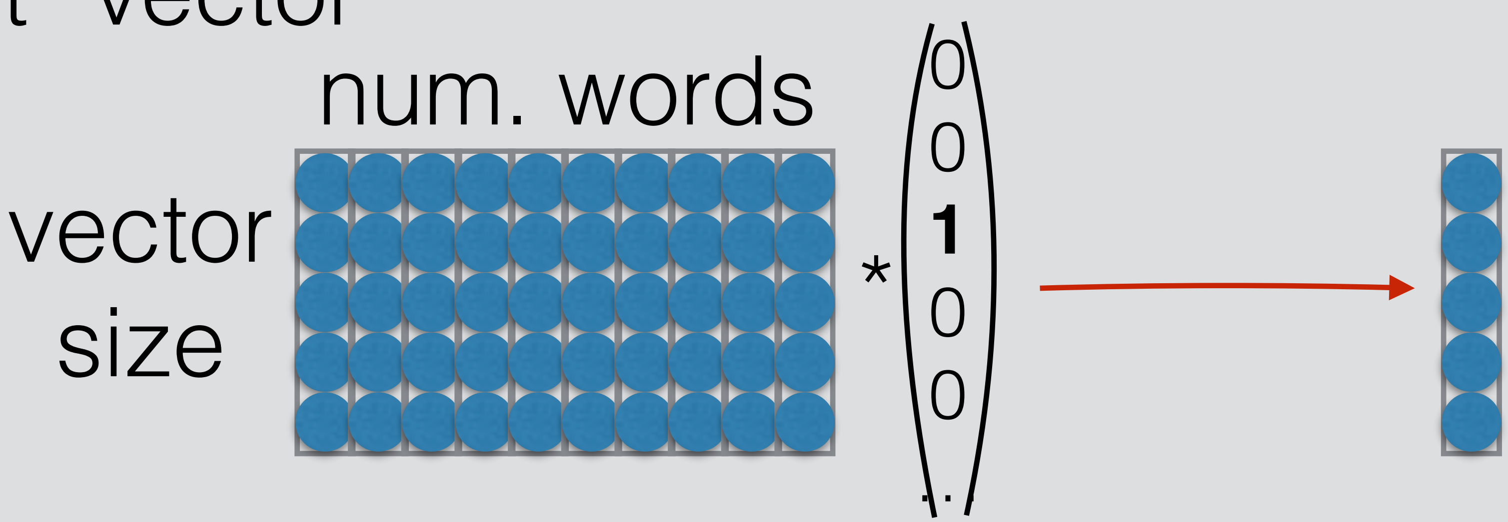


- Similarly, can be viewed as multiplying by a "one-hot" vector



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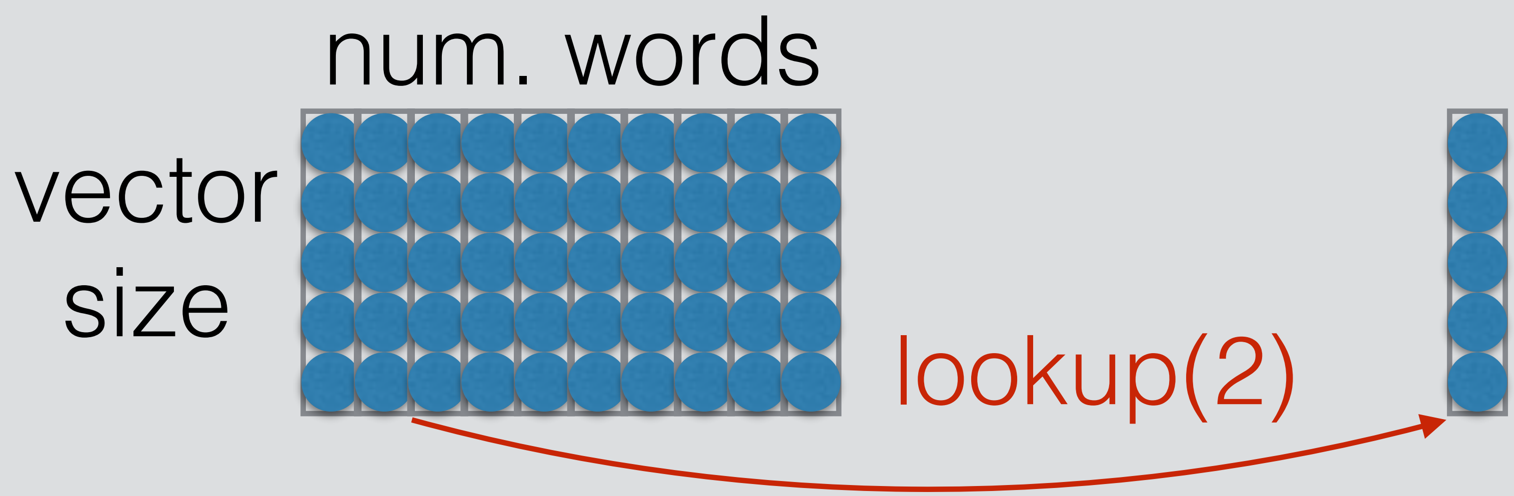

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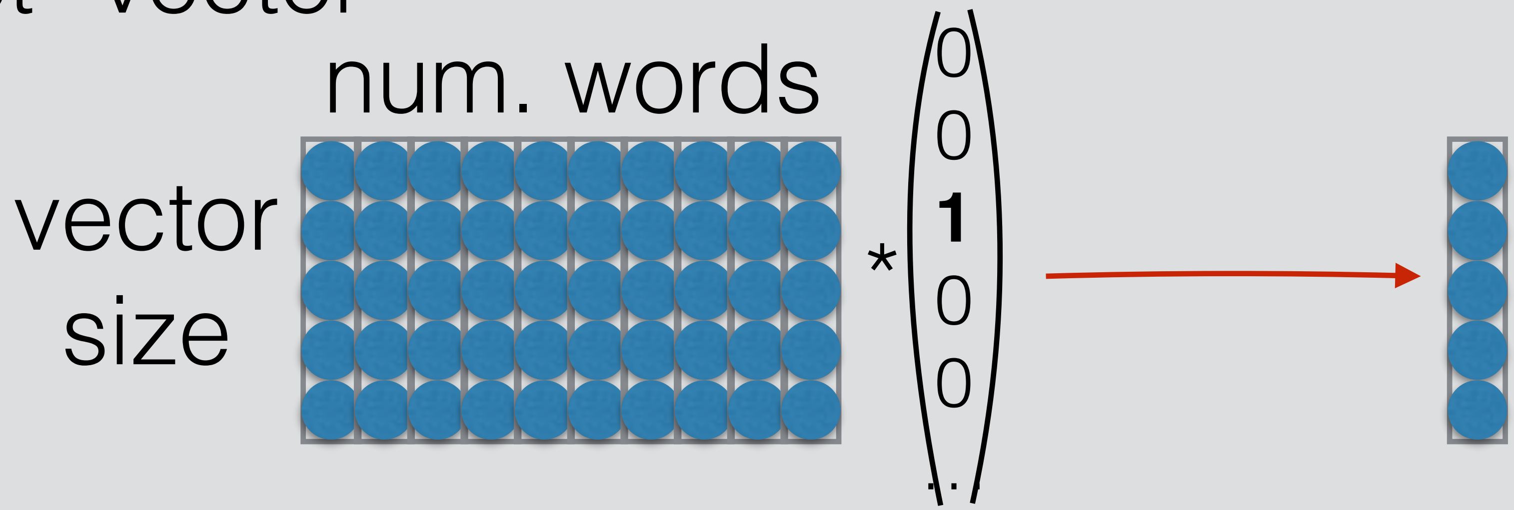

- Former tends to be faster

Training a Model

- **Reminder:** to train, we calculate a "loss function" (a measure of how bad our predictions are), and move the parameters to reduce the loss
- The most common loss function for probabilistic models is "negative log likelihood"

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If element 3 (or zero-indexed, 2) is the correct answer:

$$p = \begin{pmatrix} 0.002 \\ 0.003 \\ \boxed{0.329} \\ 0.444 \\ 0.090 \end{pmatrix} \qquad 0.329 \xrightarrow{-\log} 1.112$$

$\ldots$

Parameter Update

- Back propagation allows us to calculate the derivative of the loss with respect to the parameters

$$\frac{\partial \ell}{\partial \boldsymbol{\theta}}$$

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- Simple stochastic gradient descent optimizes parameters according to the following rule

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \alpha \frac{\partial \ell}{\partial \boldsymbol{\theta}}$$

Choosing a Vocabulary

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  - Frequency threshold (usually UNK <= 1)
  - Rank threshold

Unknown Words

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truecase + tokenize

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Find rare words (e.g. with freq<2)

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Substitute with UNK

Evaluation and Vocabulary

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- **Important:** the vocabulary must be the same over models you compare
- Or more accurately, all models must be able to generate the test set (it’s OK if they can generate *more* than the test set, but not less)
  - e.g. Comparing a character-based model to a word-based model is fair, but not vice-versa

What Problems are Handled?

- Cannot share strength among **similar words**

she bought a car	she bought a bicycle
she purchased a car	she purchased a bicycle

- Cannot condition on context with **intervening words**

Dr. Jane Smith   Dr. Gertrude Smith

- Cannot handle **long-distance dependencies**

for tennis class he wanted to buy his own racquet

for programming class he wanted to buy his own computer

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Break
Beyond Linear Models

Linear Models can't Learn Feature Combinations

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farmers eat steak → **high**

Linear Models can't Learn Feature Combinations

farmers eat steak → **high**

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farmers eat steak → **high**

farmers eat hay → **low**

cows eat steak → **low**

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Linear Models can't Learn Feature Combinations

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- These can't be expressed by linear features

Linear Models can't Learn Feature Combinations

farmers eat steak → **high**
farmers eat hay → **low**

cows eat steak → **low**
cows eat hay → **high**

- These can't be expressed by linear features
- What can we do?
  - Remember combinations as features (individual scores for "farmers eat", "cows eat")

Linear Models can't Learn Feature Combinations

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    → Feature space explosion!
  - Neural nets

Neural Language Models

- (See Bengio et al. 2004)

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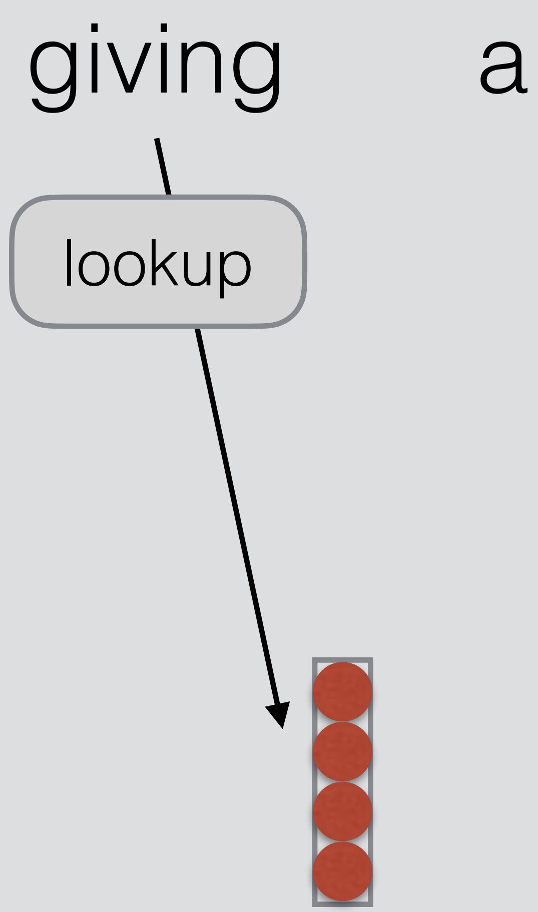
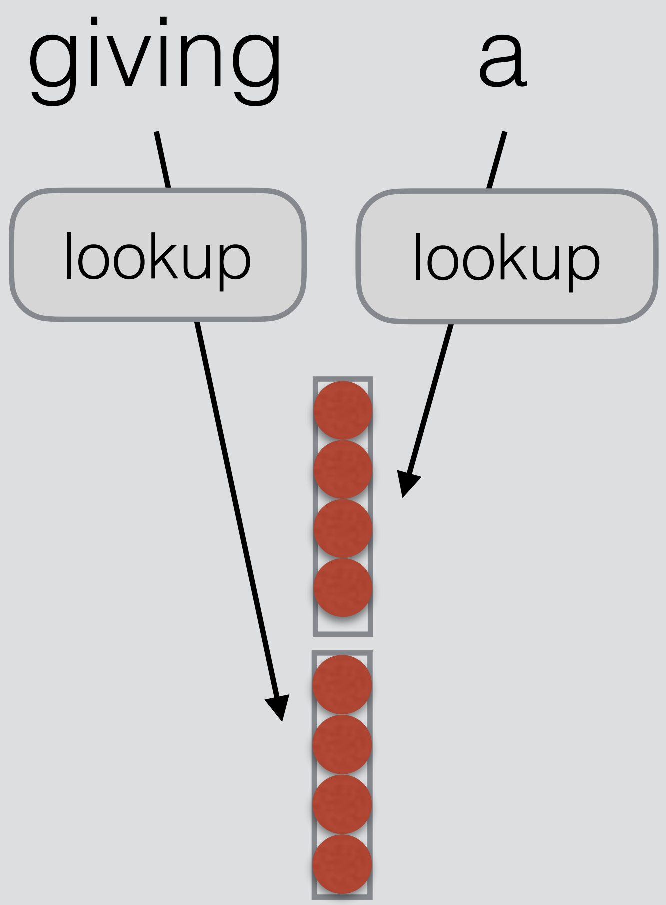


Neural Language Models



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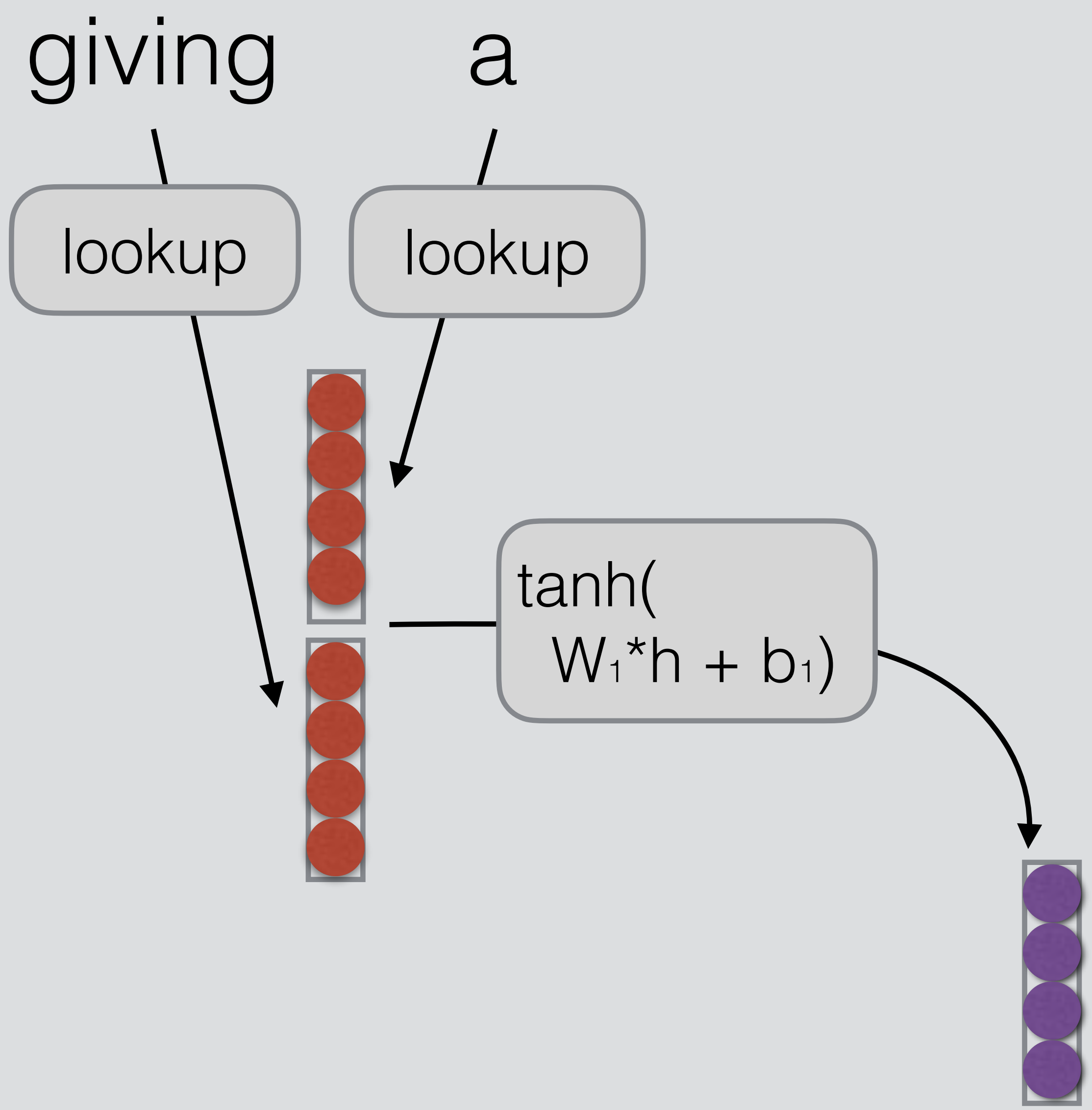

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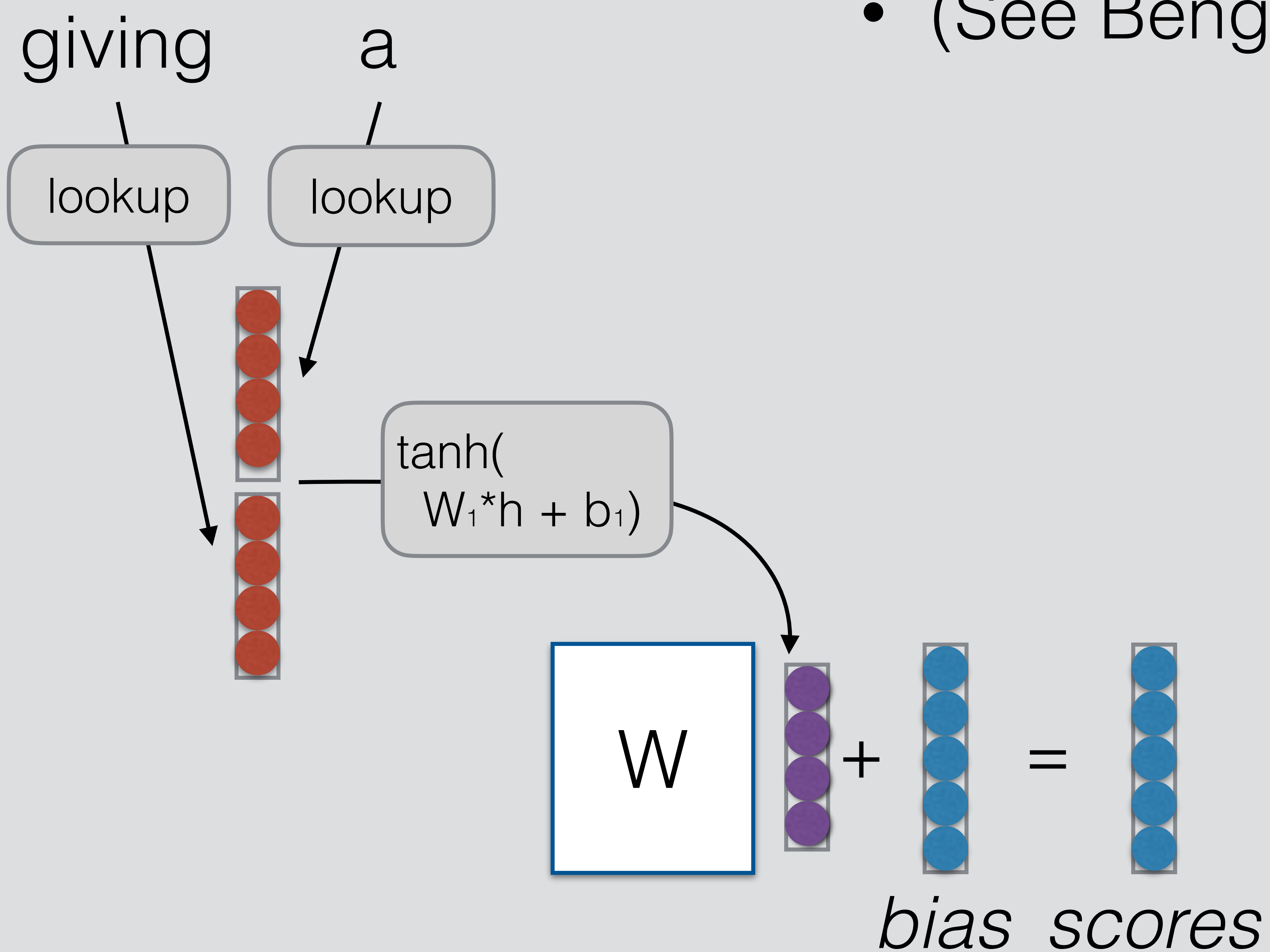

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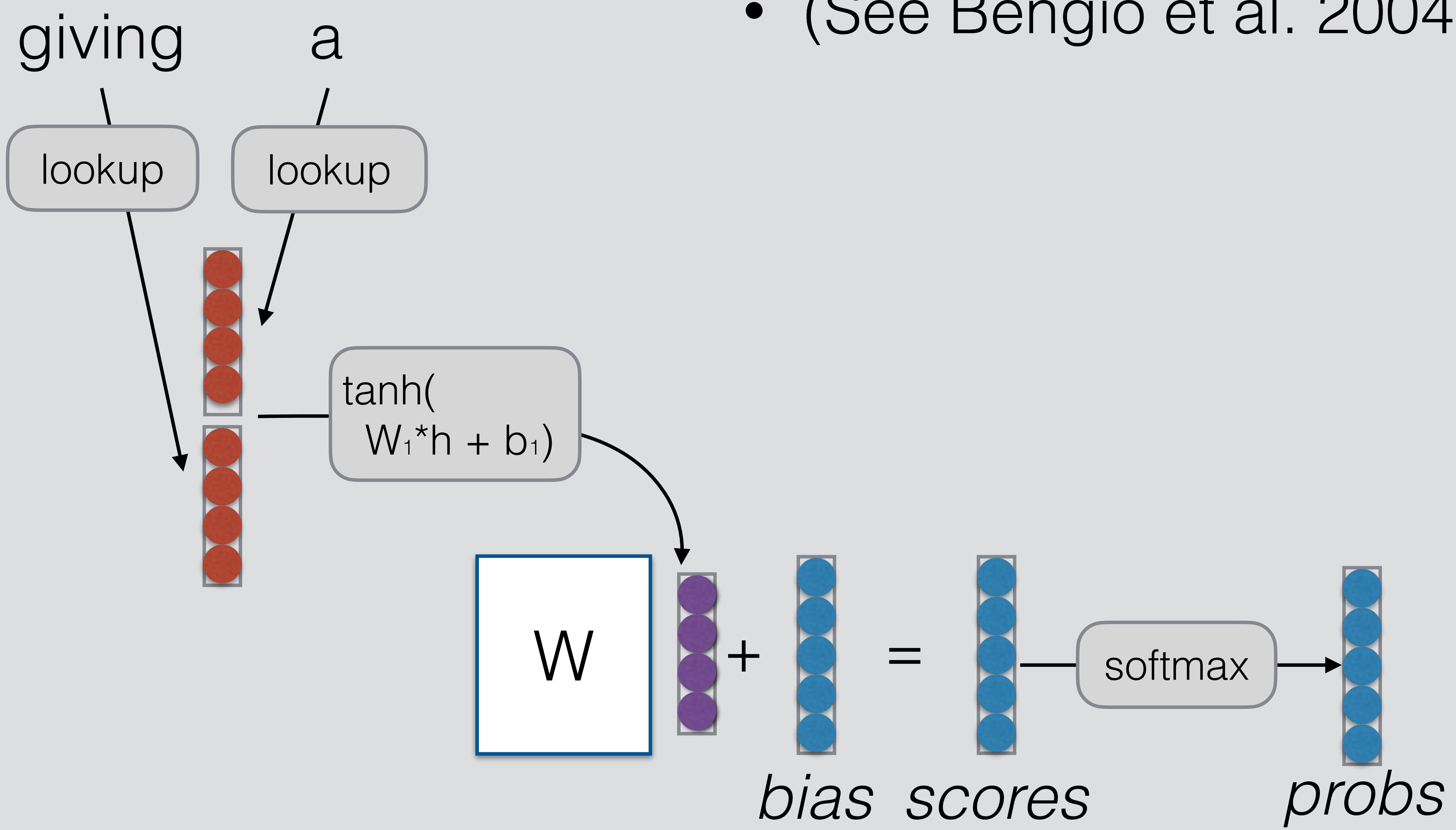

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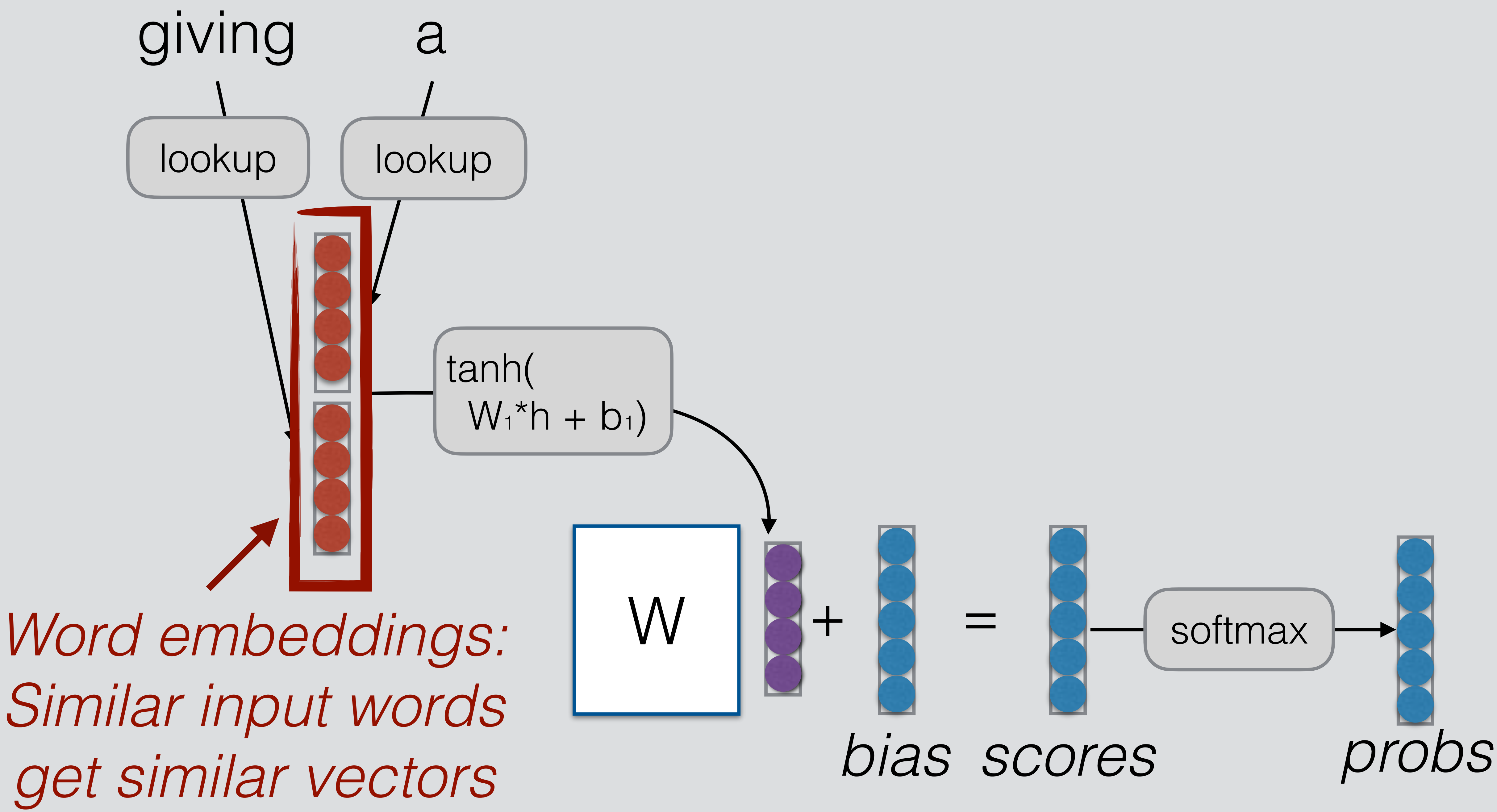

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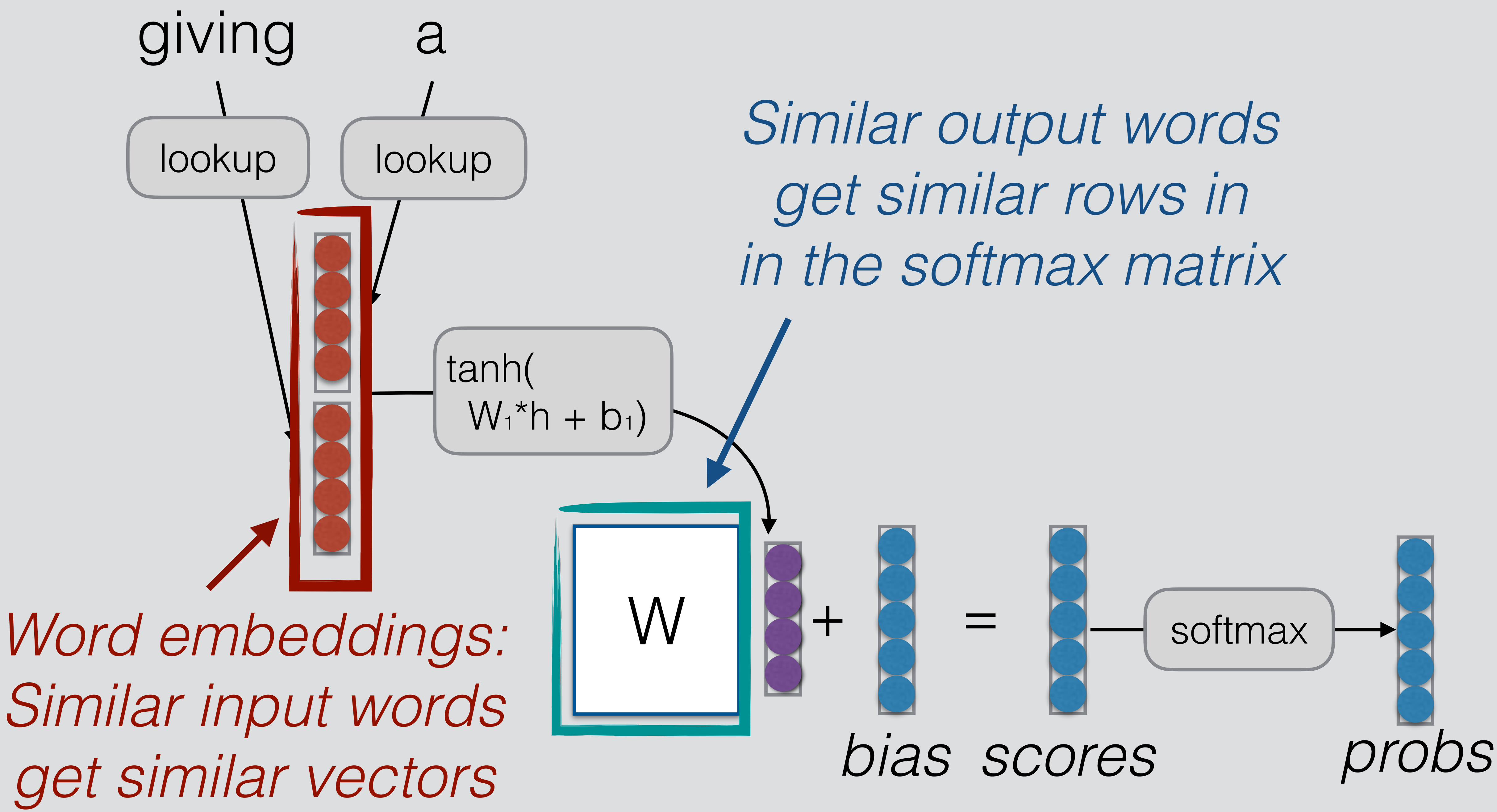

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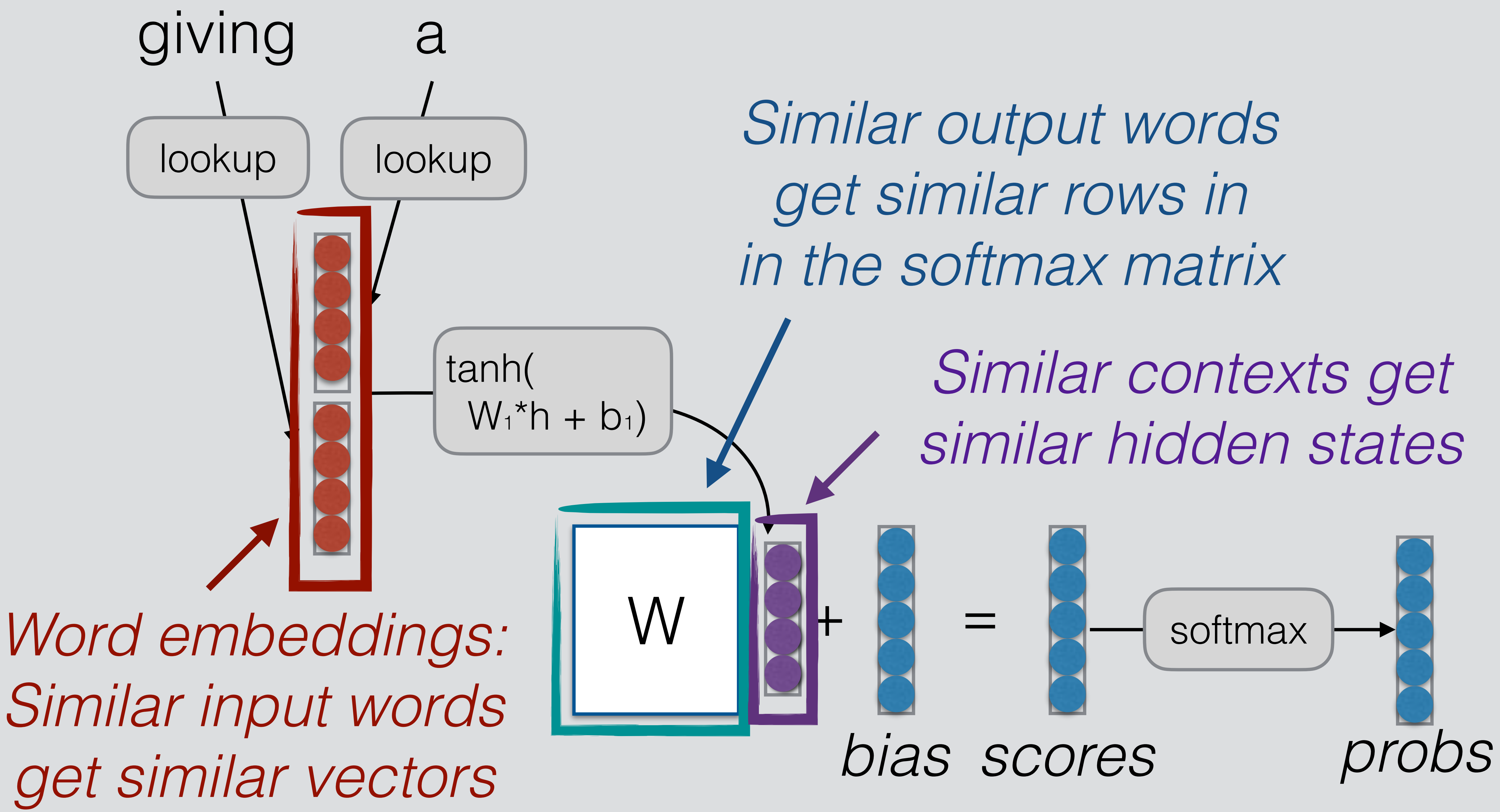


What Problems are Handled?

- Cannot share strength among **similar words**

she bought a car she purchased a car	she bought a bicycle she purchased a bicycle

→ solved, and similar contexts as well! 😀

- Cannot condition on context with **intervening words**

Dr. Jane Smith   Dr. Gertrude Smith

→ solved! 😀

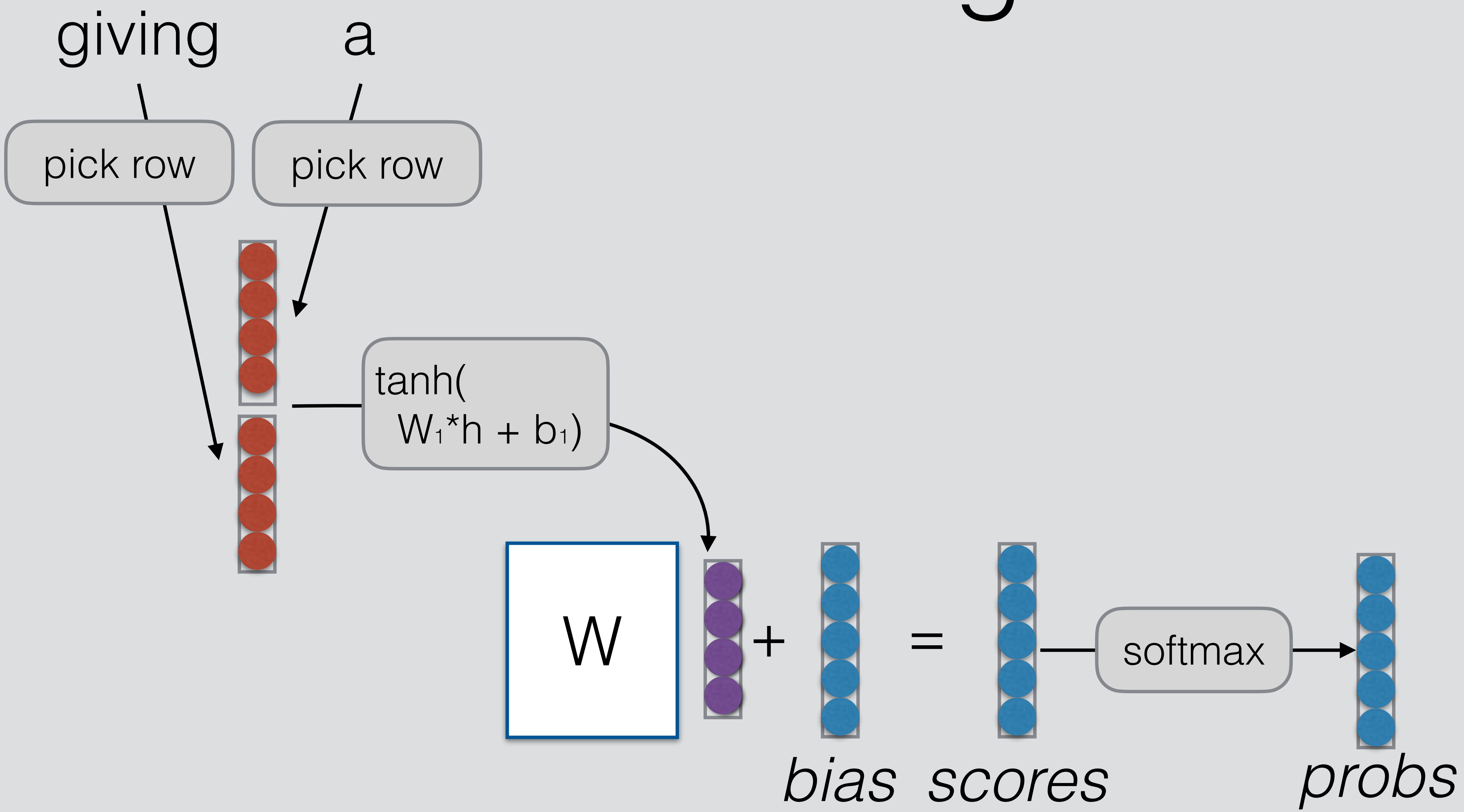
- Cannot handle **long-distance dependencies**

for tennis class he wanted to buy his own racquet

for programming class he wanted to buy his own computer

→ not solved yet 😞

Tying Input/Output Embeddings



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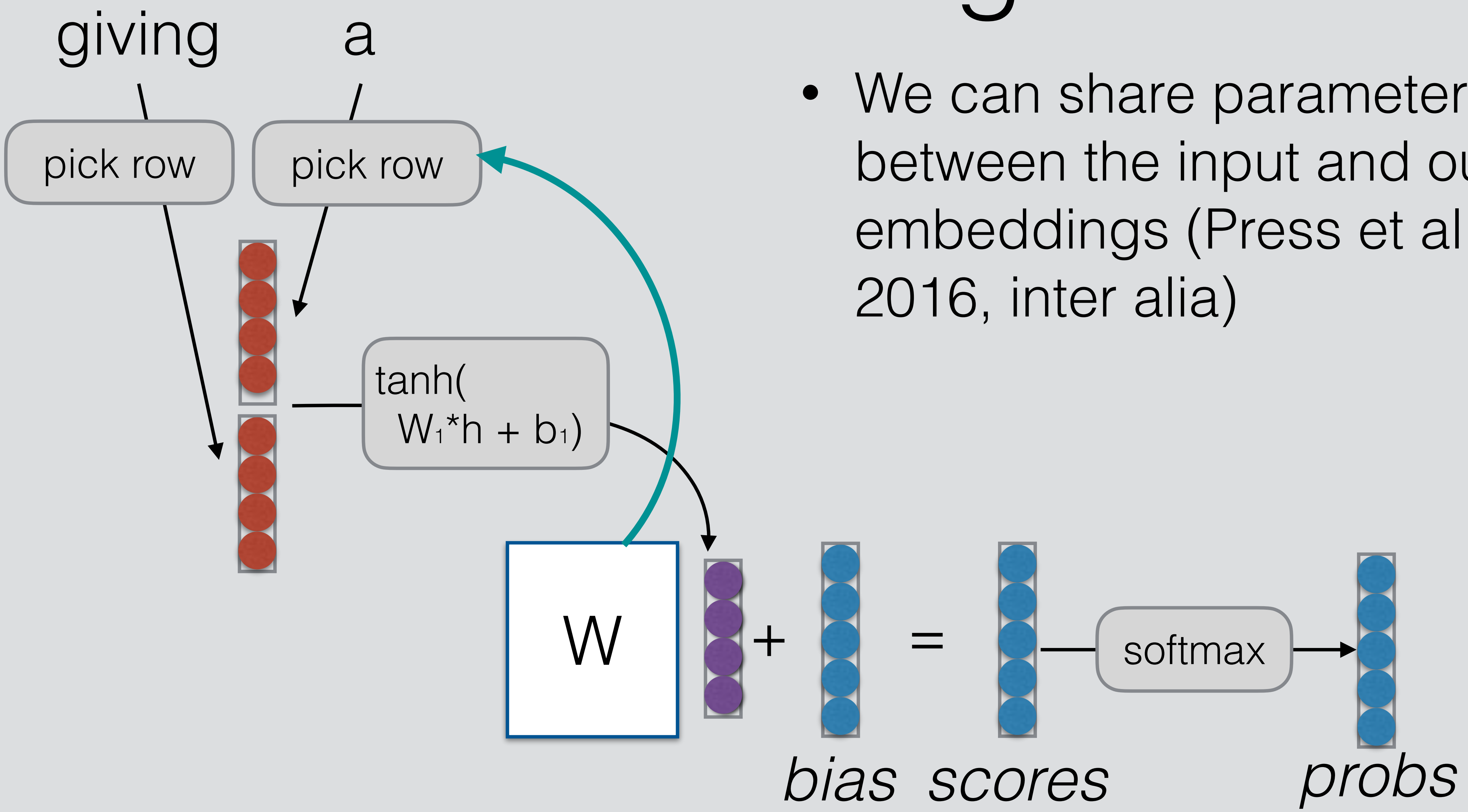

- We can share parameters between the input and output embeddings (Press et al. 2016, inter alia)

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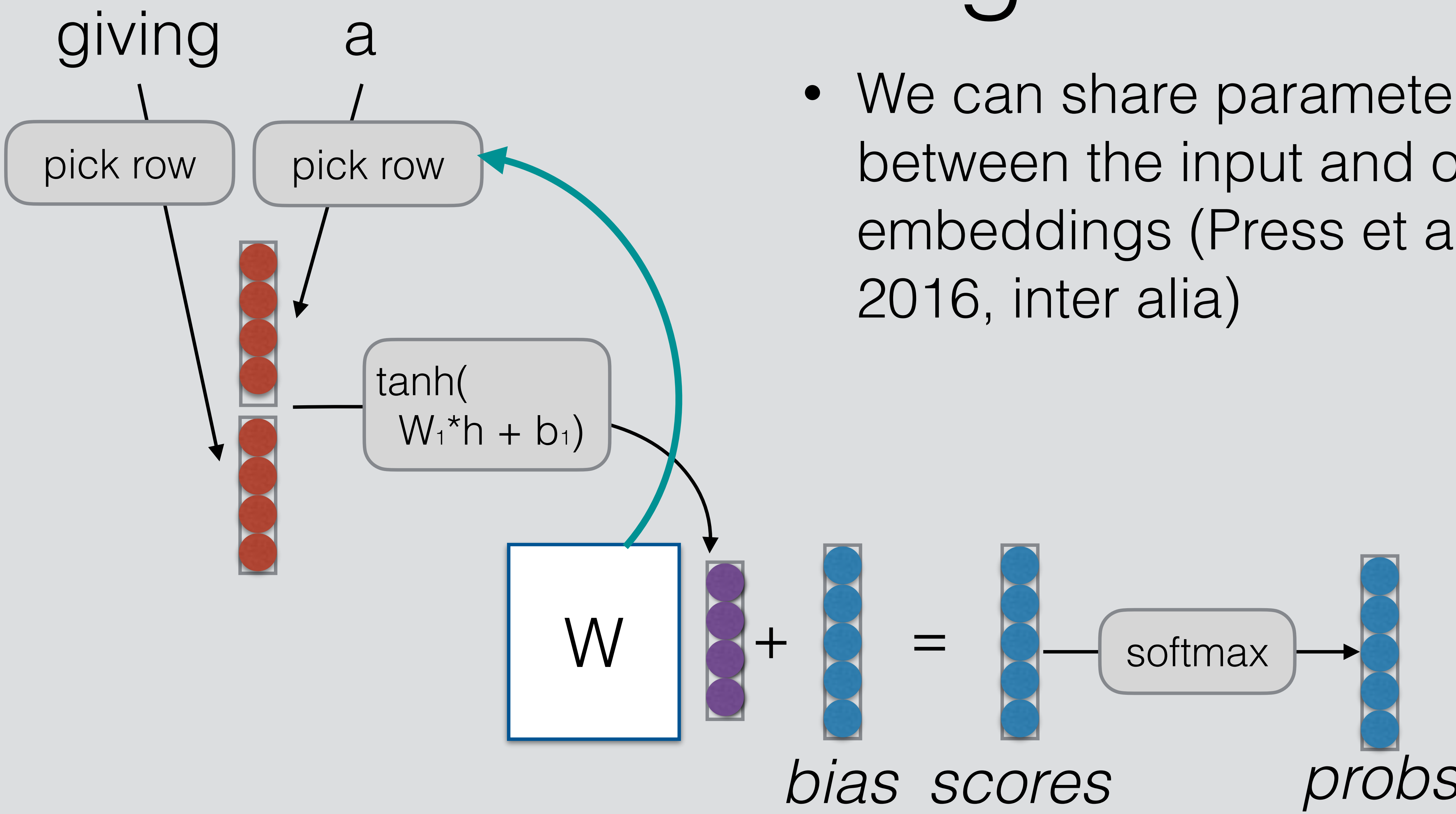

Want to try? Delete the input embeddings, and instead pick a row from the softmax matrix.

Training Tricks

Shuffling the Training Data

- Stochastic gradient methods update the parameters a little bit at a time

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    - What if we have the sentence “I love this sentence so much!” at the end of the training data 50 times?

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- Stochastic gradient methods update the parameters a little bit at a time
    - What if we have the sentence “I love this sentence so much!” at the end of the training data 50 times?
- To train correctly, we should randomly shuffle the order at each time step

Other Optimization Options

- **SGD with Momentum:** Remember gradients from past time steps to prevent sudden changes

- **Adagrad:** Adapt the learning rate to reduce learning rate for frequently updated parameters (as measured by the variance of the gradient)

- **Adam:** Like Adagrad, but keeps a running average of momentum and gradient variance

- **Many others:** RMSProp, Adadelta, etc.
(See Ruder 2016 reference for more details)

Early Stopping, Learning Rate Decay

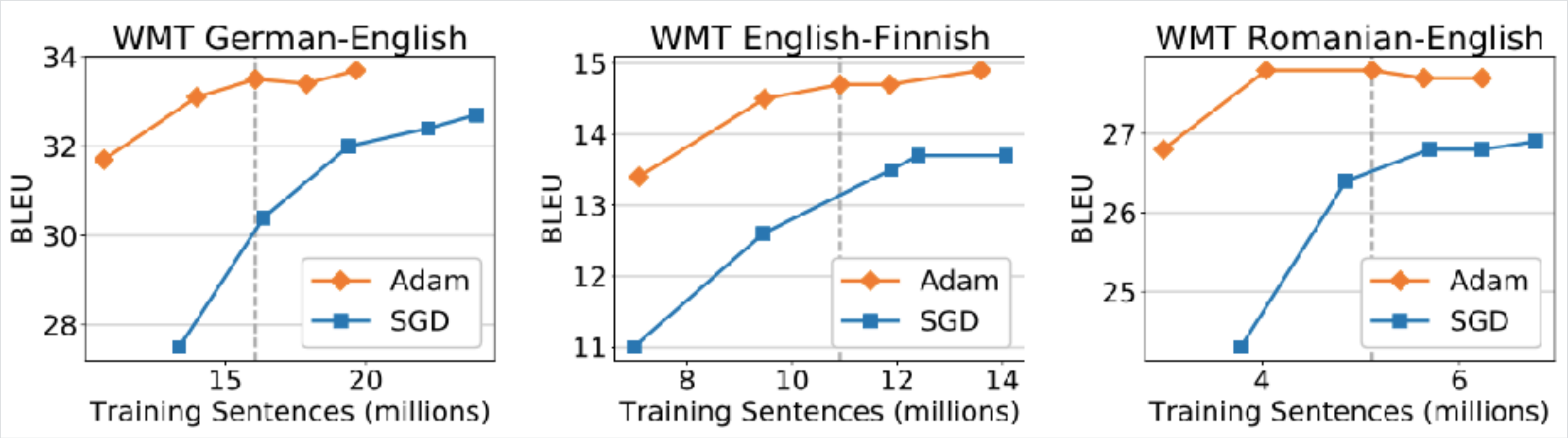
- Neural nets have tons of parameters: we want to prevent them from over-fitting

- We can do this by monitoring our performance on held-out development data and stopping training when it starts to get worse

- It also sometimes helps to reduce the learning rate and continue training

Which One to Use?

- Adam is usually fast to converge and stable
- But simple SGD tends to do very will in terms of generalization (Wilson et al. 2017)
- You should use learning rate decay, (e.g. on Machine translation results by Denkowski & Neubig 2017)



Dropout

(Srivastava+ 14)

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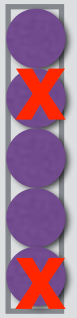

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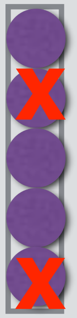


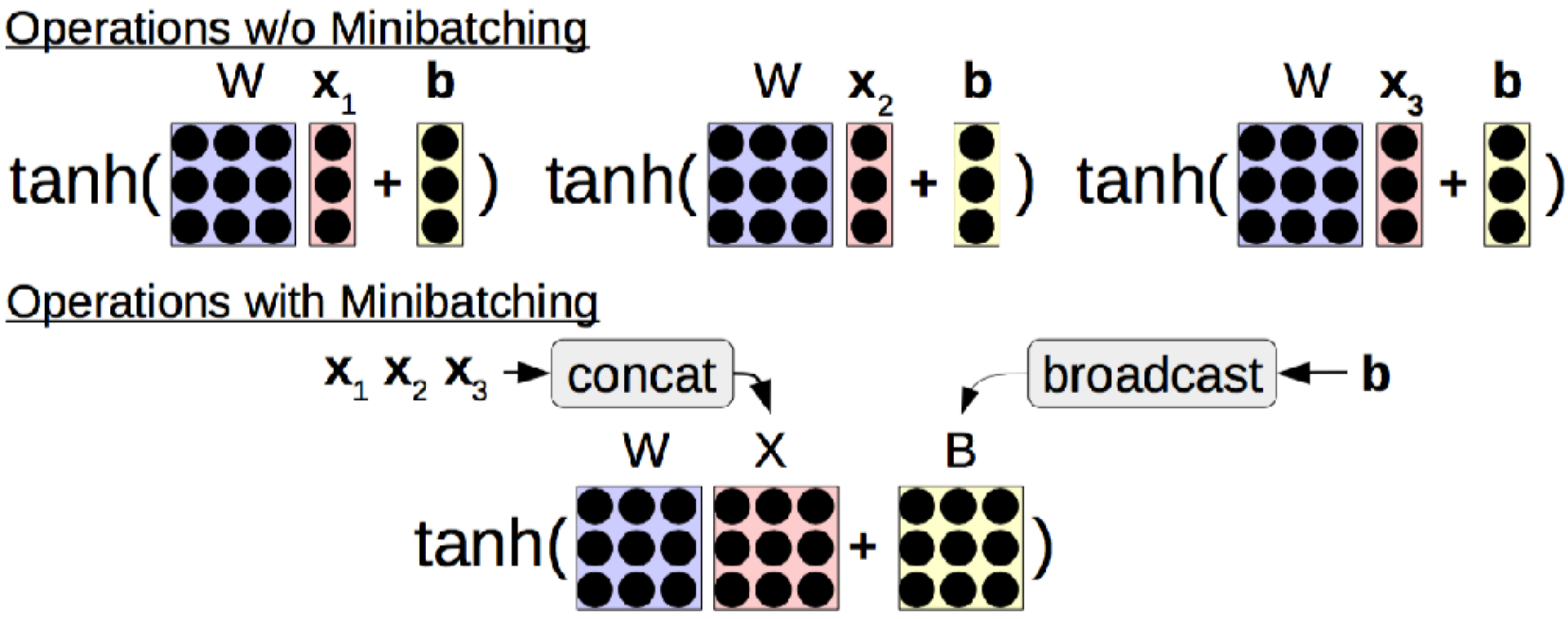
- Because the number of nodes at training/test is different, scaling is necessary:
    - **Standard dropout:** scale by *p* at test time
    - **Inverted dropout:** scale by 1/(1-*p*) at training time
- An alternative: **DropConnect** (Wan+ 2013) instead zeros out weights in the NN

Efficiency Tricks: Operation Batching

Efficiency Tricks: Mini-batching

- On modern hardware 10 operations of size 1 is **much slower than** 1 operation of size 10
- Minibatching combines together smaller operations into one big one

Minibatching



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- How this works depends on toolkit
  - Most toolkits require you to add an extra dimension representing the batch size
  - DyNet has special minibatch operations for lookup and loss functions, everything else automatic
  - In PyTorch (almost) all operations already automatically support batches

Mini-batched Code Example

```
# in_words is a tuple (word_1, word_2)
# out_label is an output label
word_1 = E[in_words[0]]
word_2 = E[in_words[1]]
scores_sym = W*dy.concatenate([word_1, word_2])+b
loss_sym = dy.pickneglogsoftmax(scores_sym, out_label)
```

(a) Non-minibatched classification.

```
# in_words is a list [(word_{1,1}, word_{1,2}), (word_{2,1}, word_{2,2}), ...]
# out_labels is a list of output labels [label_1, label_2, ...]
word_1_batch = dy.lookup_batch(E, [x[0] for x in in_words])
word_2_batch = dy.lookup_batch(E, [x[1] for x in in_words])
scores_sym = W*dy.concatenate([word_1_batch, word_2_batch])+b
loss_sym = dy.sum_batches( dy.pickneglogsoftmax_batch(scores_sym, out_labels) )
```

(b) Minibatched classification.

A Case Study:
Regularizing and Optimizing LSTM Language Models (Merity et al. 2017)

Regularizing and Optimizing LSTM Language Models (Merity et al. 2017)

- Uses LSTMs as a backbone (discussed later)
- A number of tricks to improve stability and prevent overfitting:
  - DropConnect regularization
  - SGD w/ averaging triggered when model is close to convergence
  - Dropout on recurrent connections and embeddings
  - Weight tying
  - Independently tuned embedding and hidden layer sizes
  - Regularization of activations of the network
- Strong baseline for language modeling, SOTA at the time (without special model, just training methods)

Break
Next: Recurrent Neural Networks

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**.

Long-distance Dependencies in Language

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He does not have very much confidence in **himself**.
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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!

- What is the referent of “it”?

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

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

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Suitcase

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

Recurrent Neural Networks

(Elman 1990)

- Tools to “remember” information

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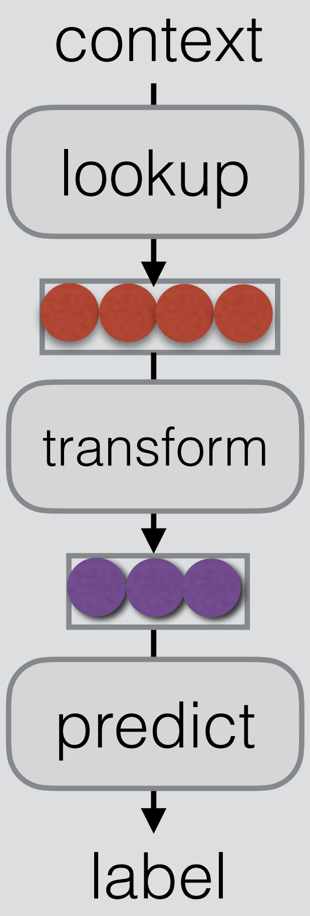
Feed-forward NN



Recurrent Neural Networks
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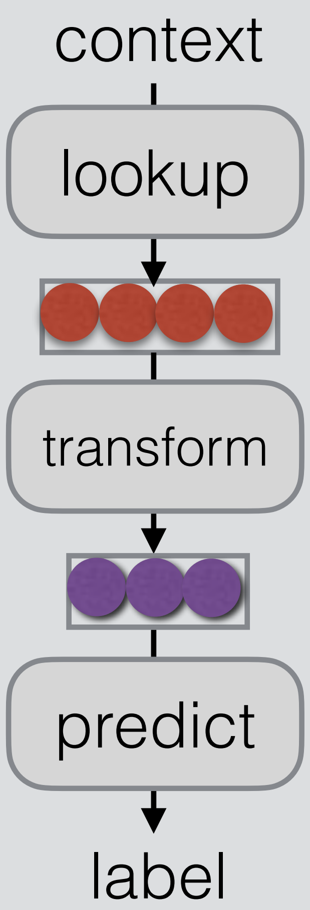
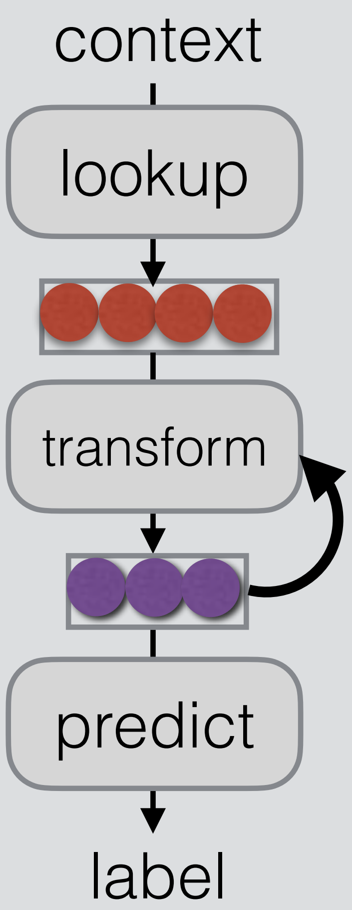
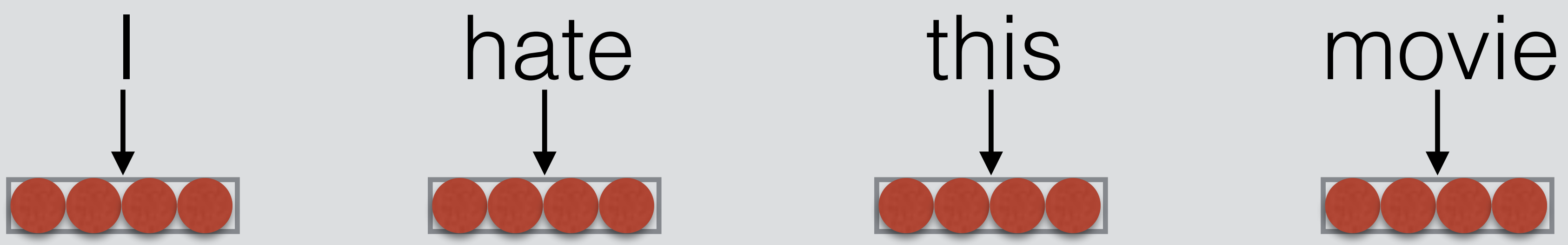


Recurrent NN



Unrolling in Time

- What does processing a sequence look like?



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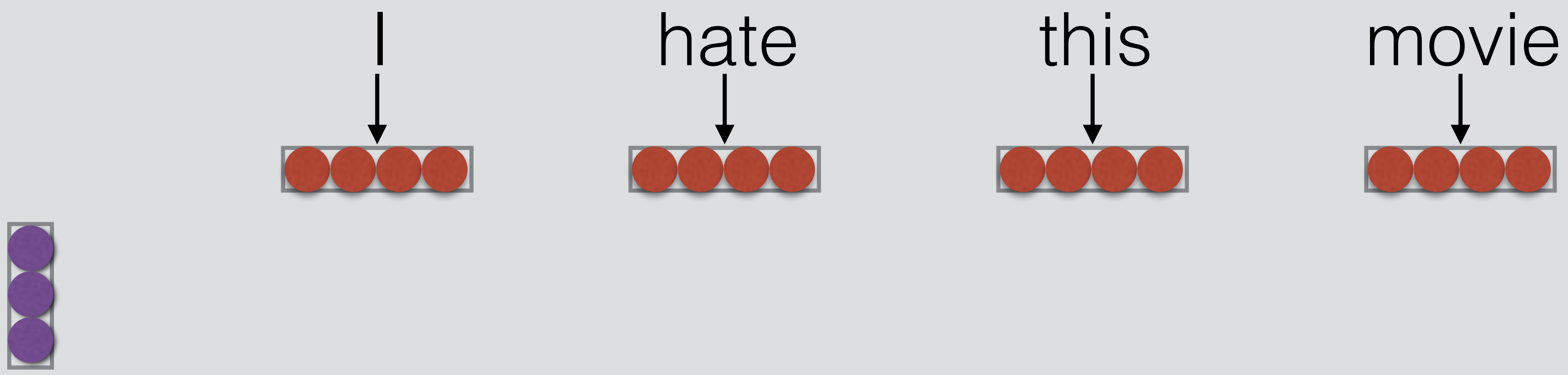

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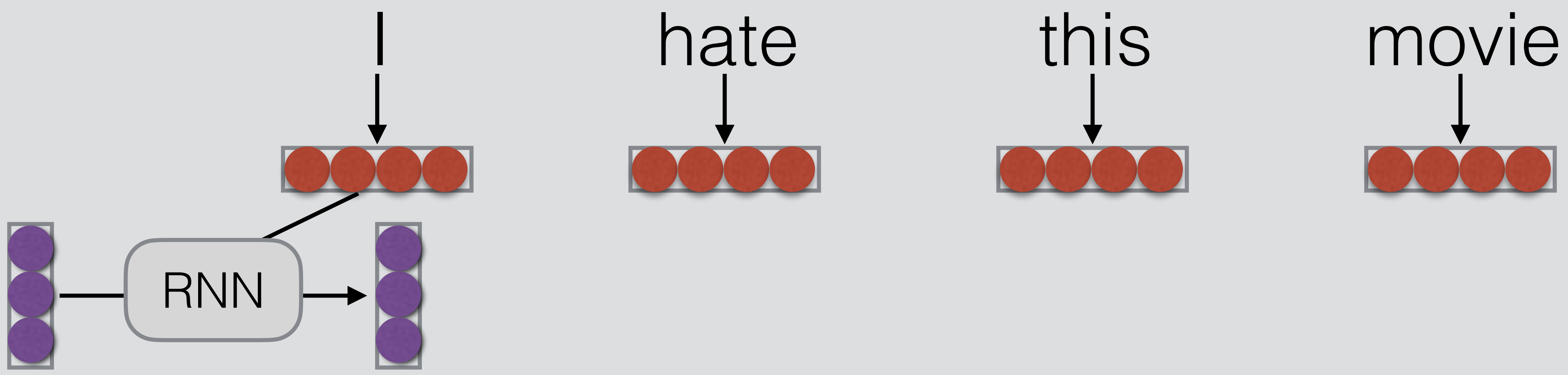

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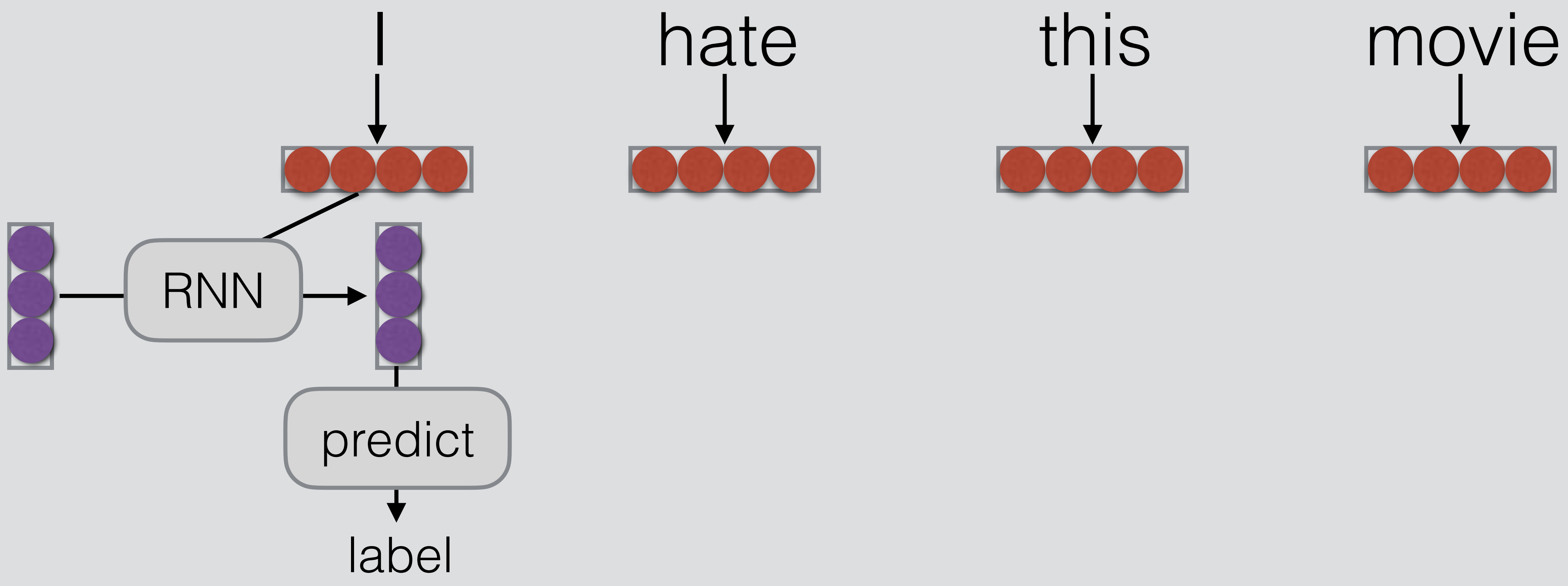

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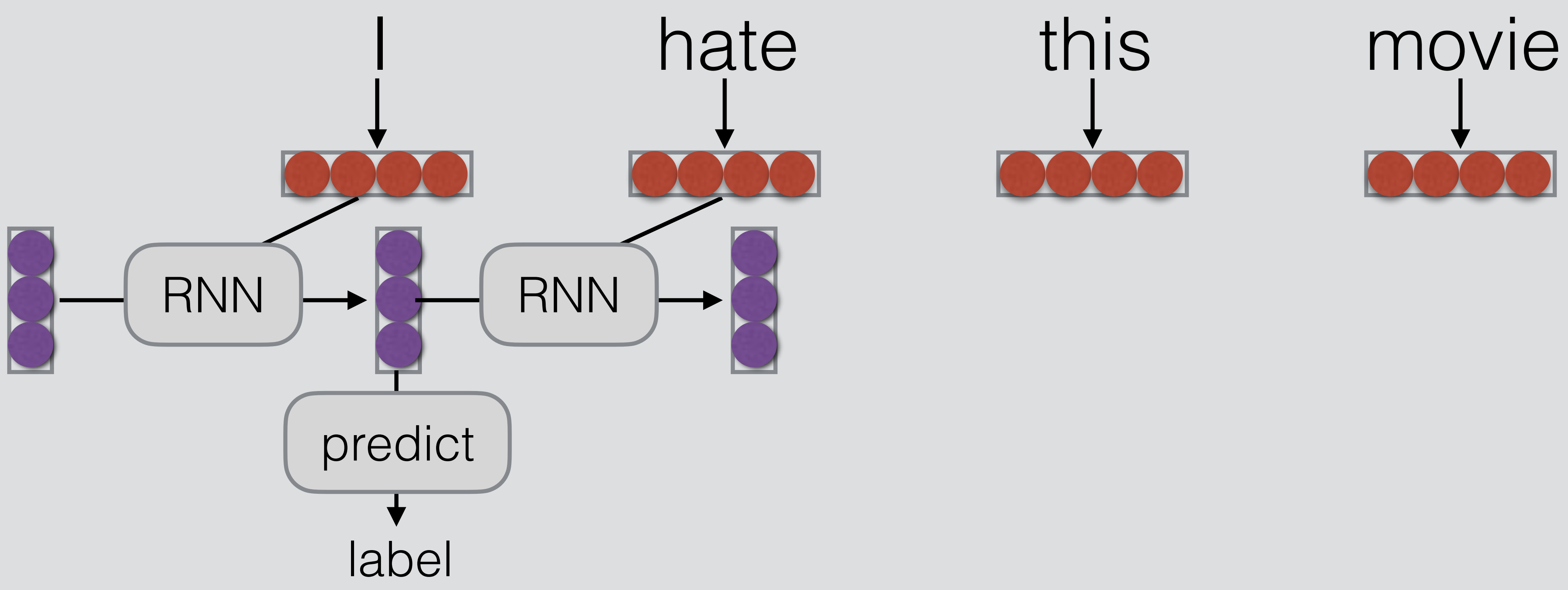

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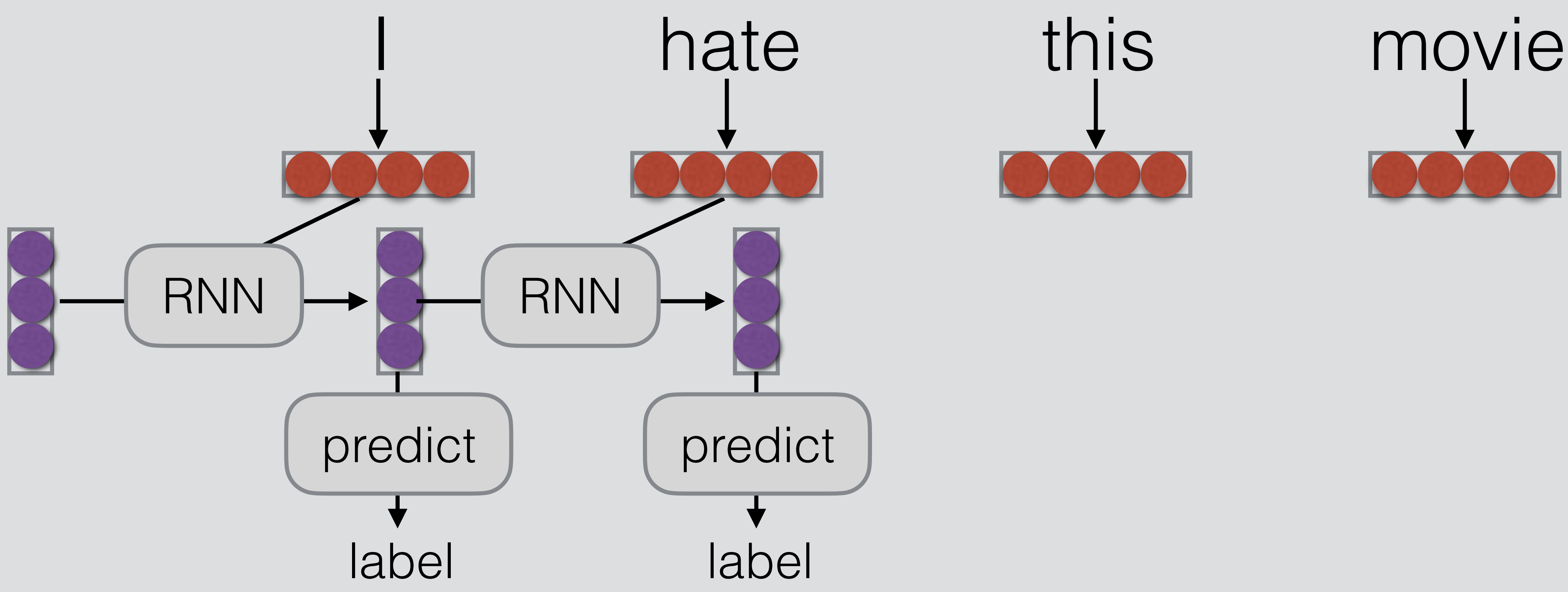

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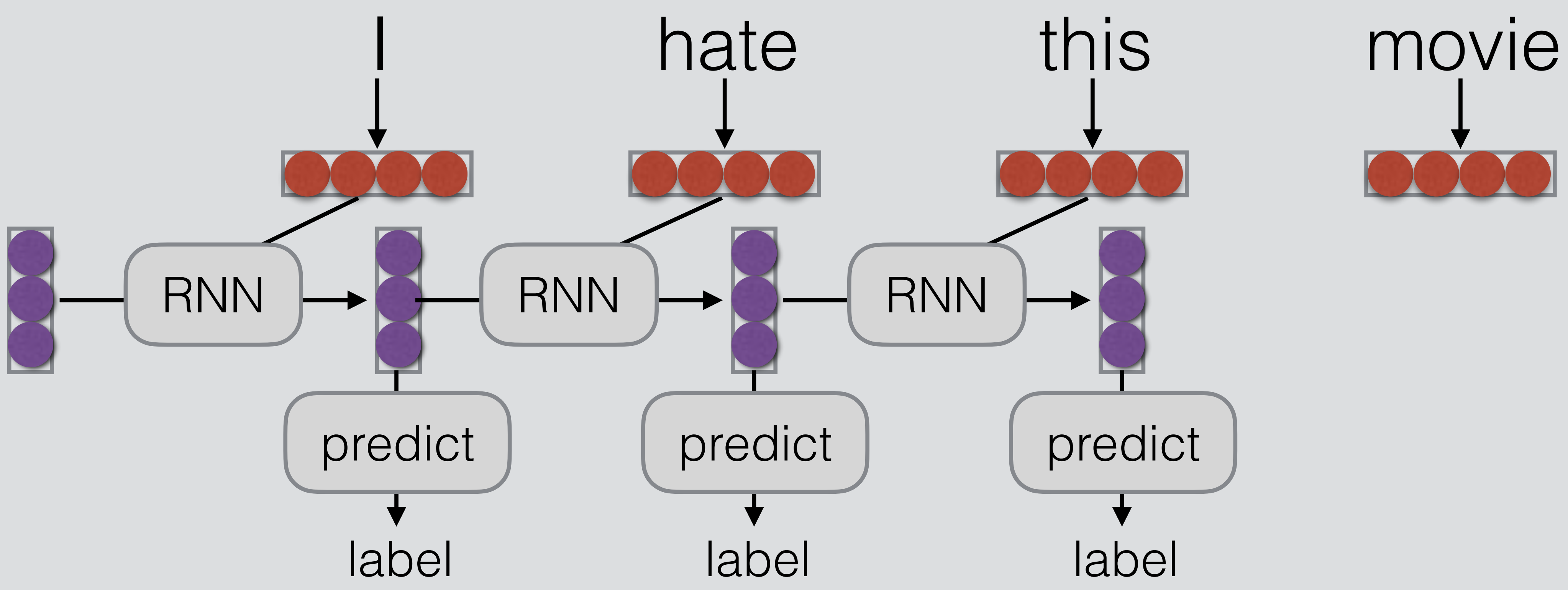

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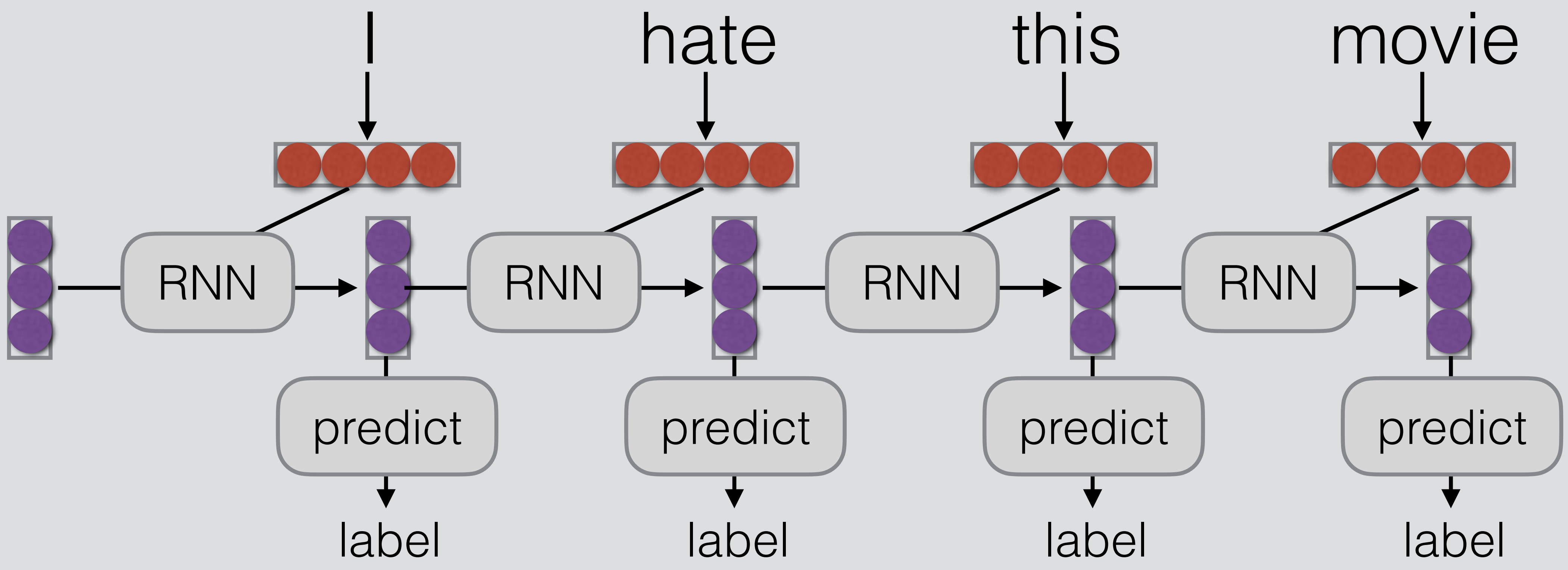
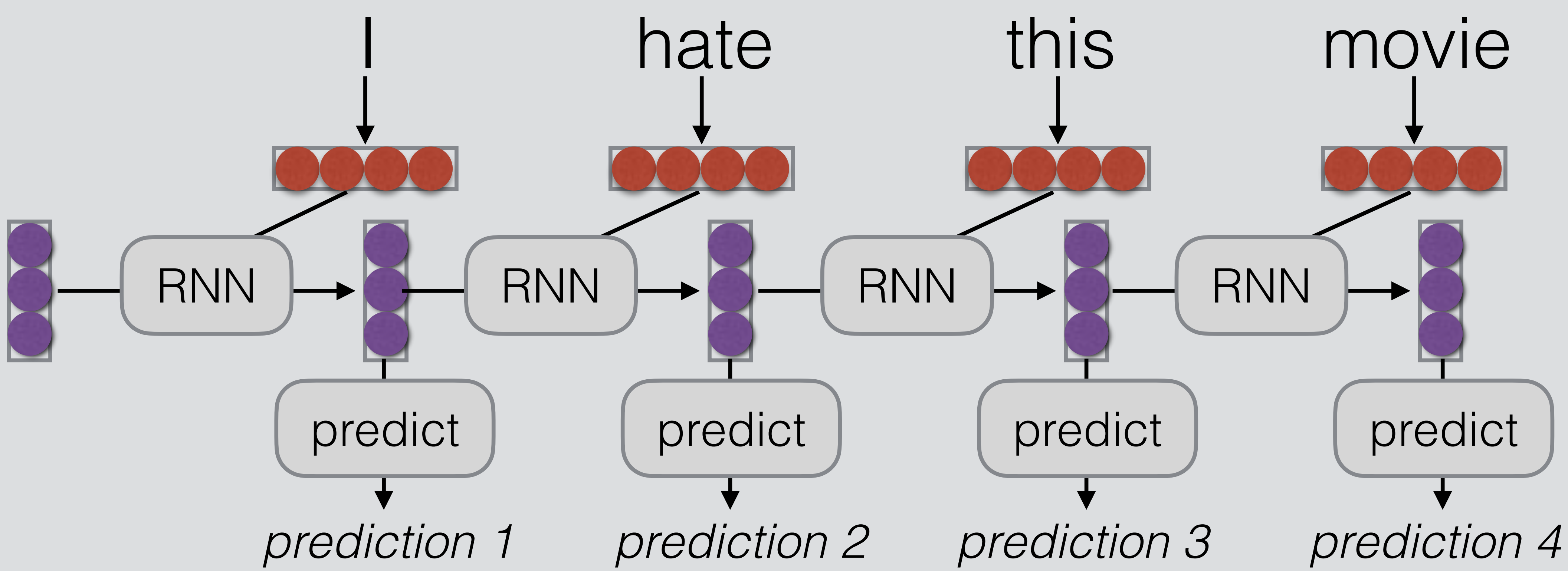


Training RNNs



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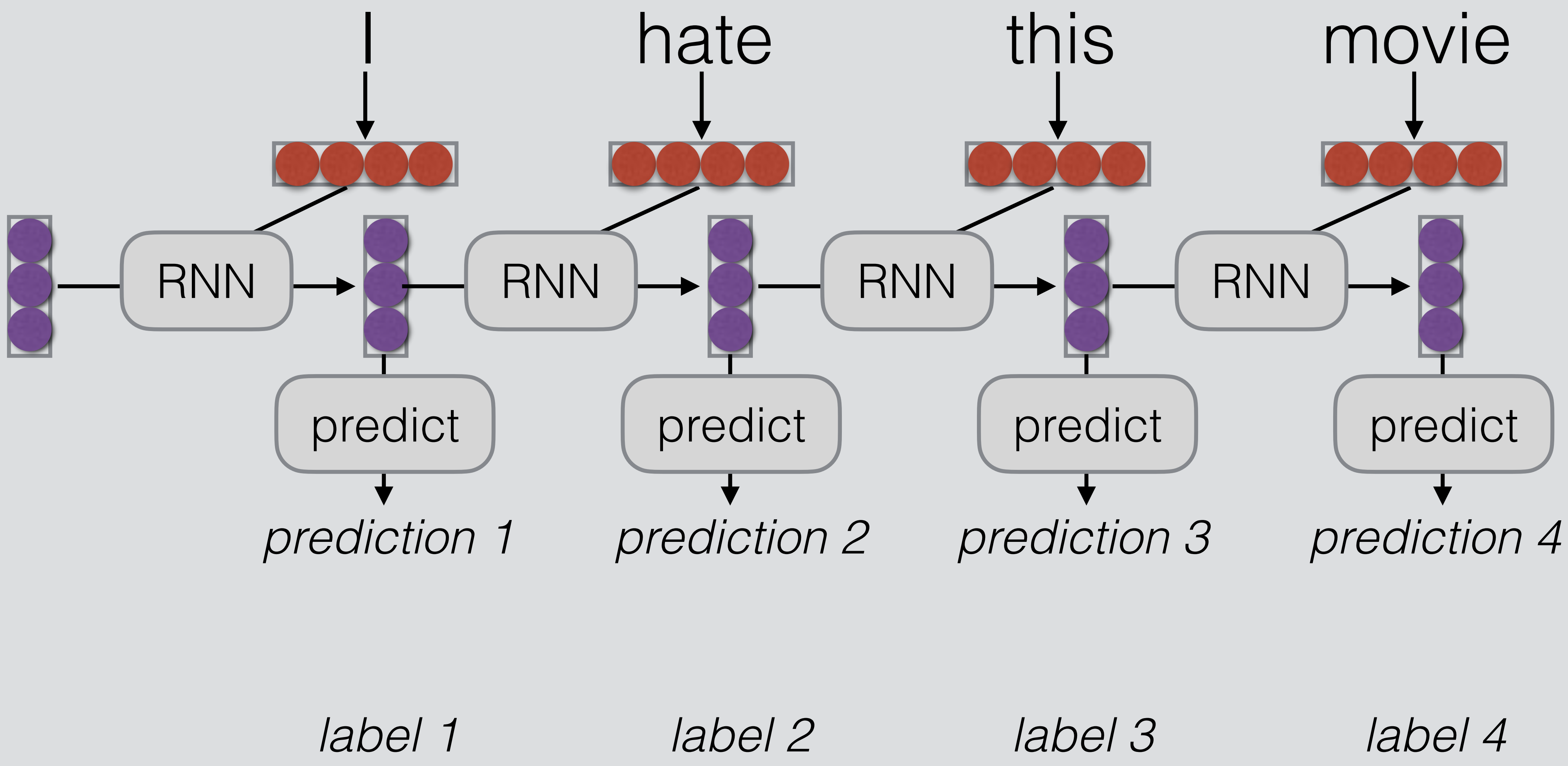

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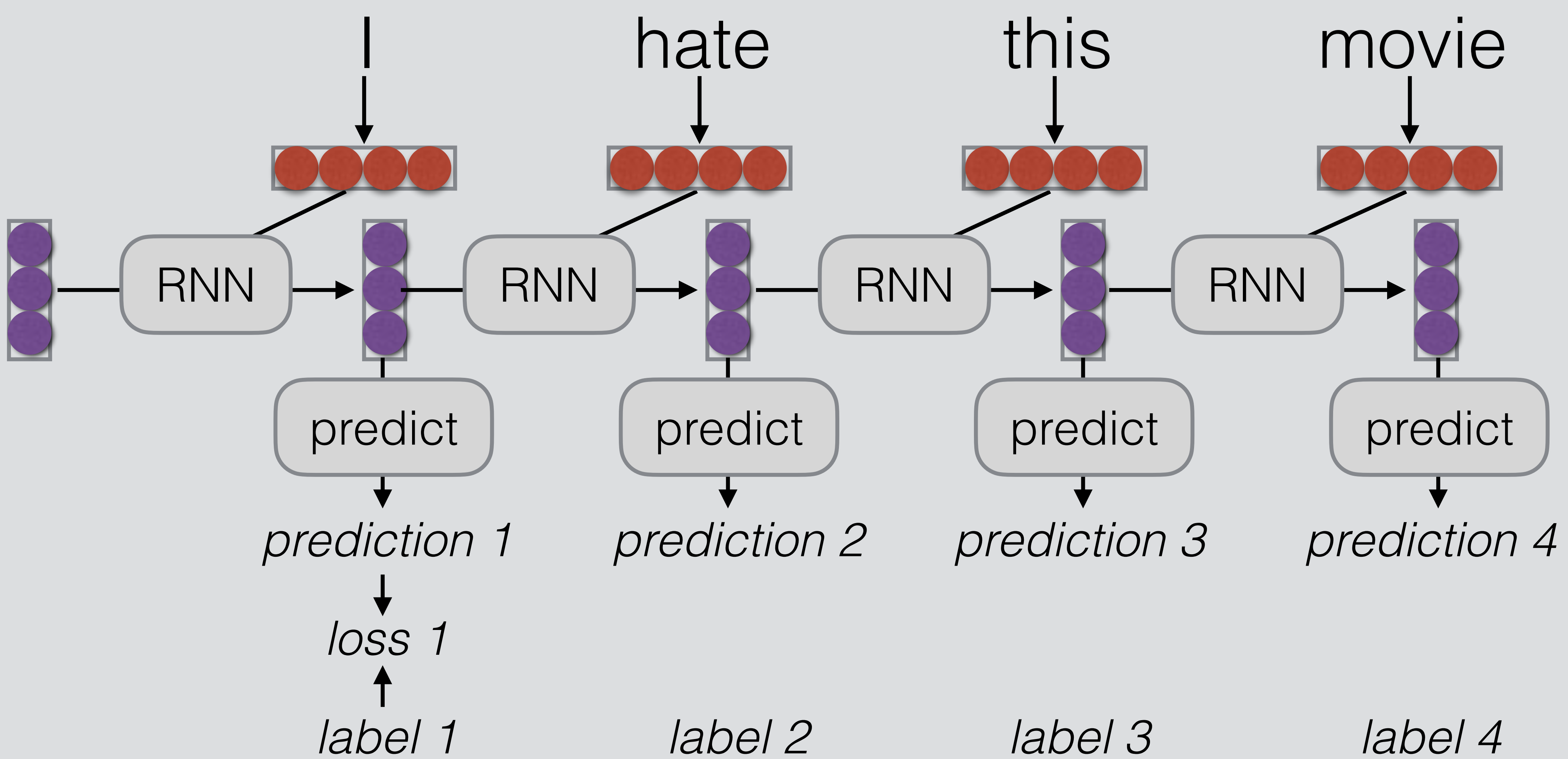

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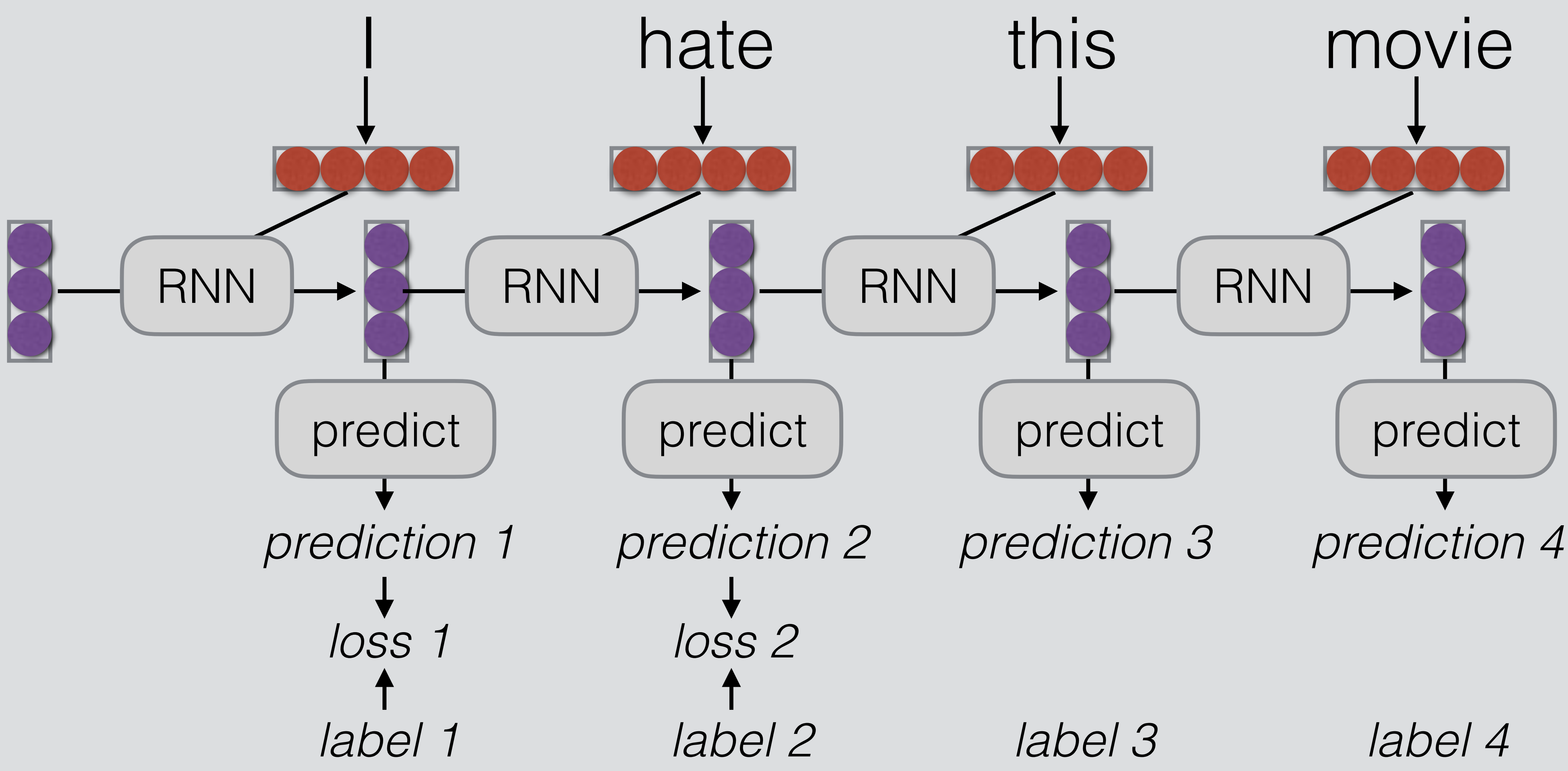

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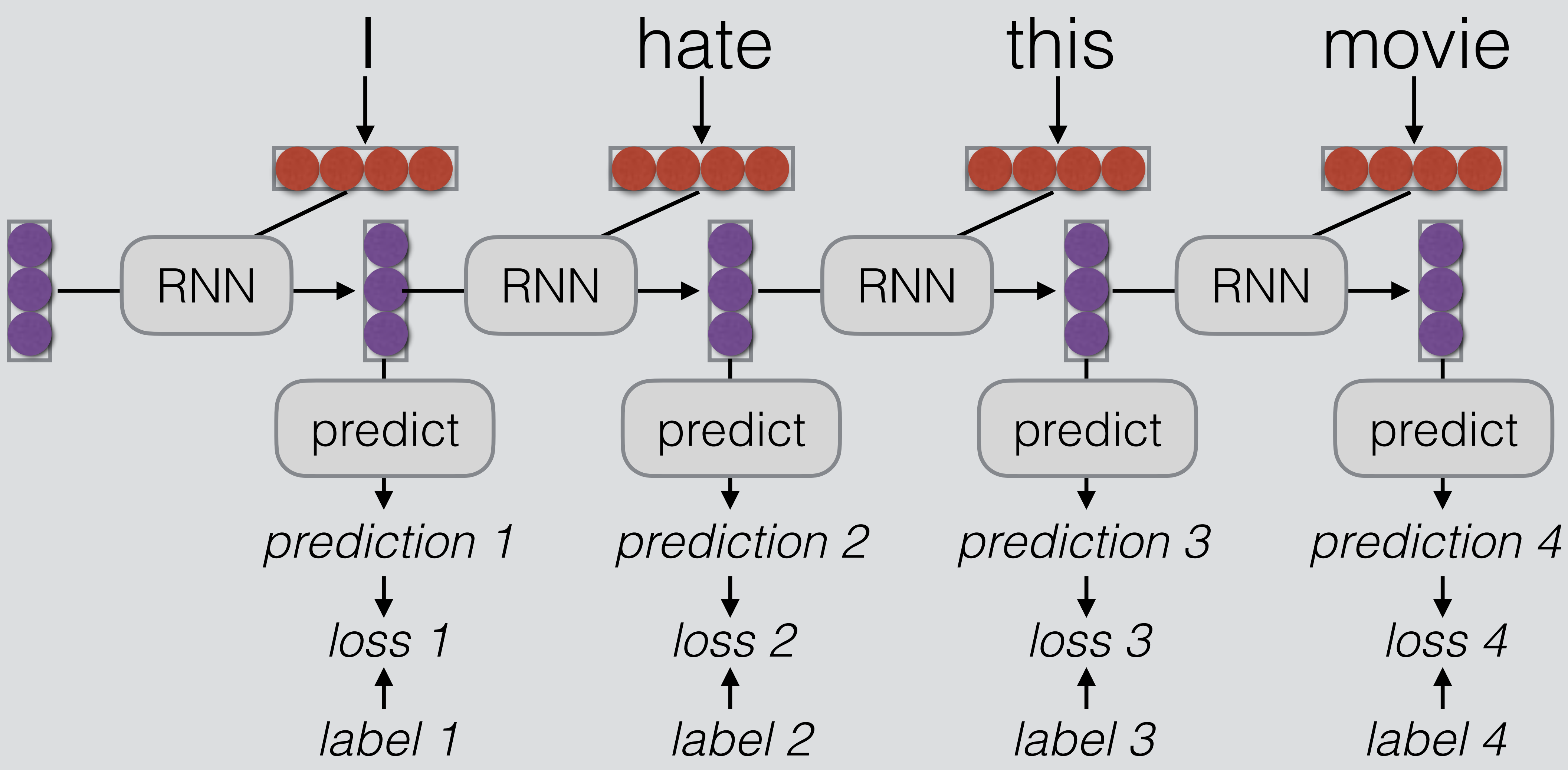

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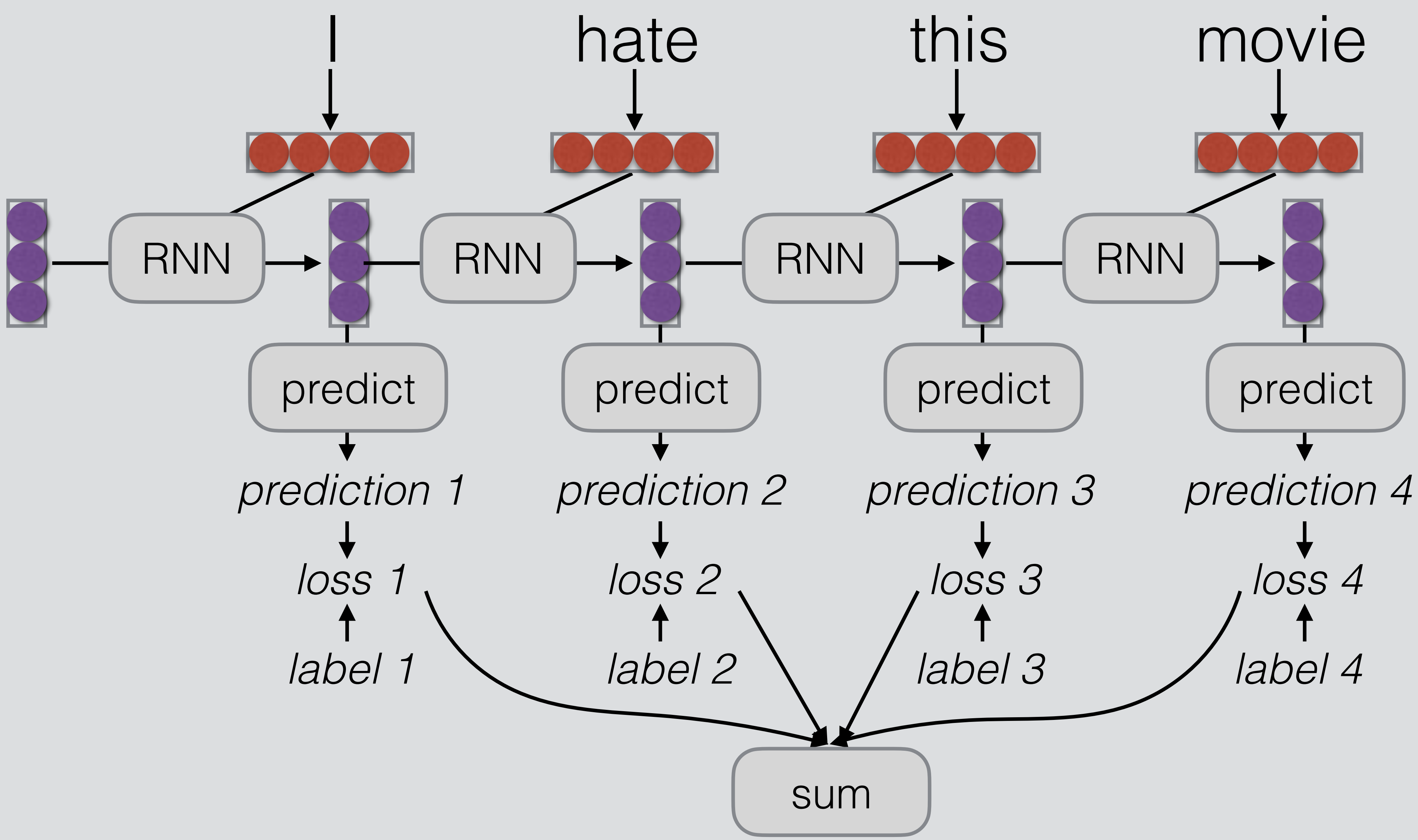

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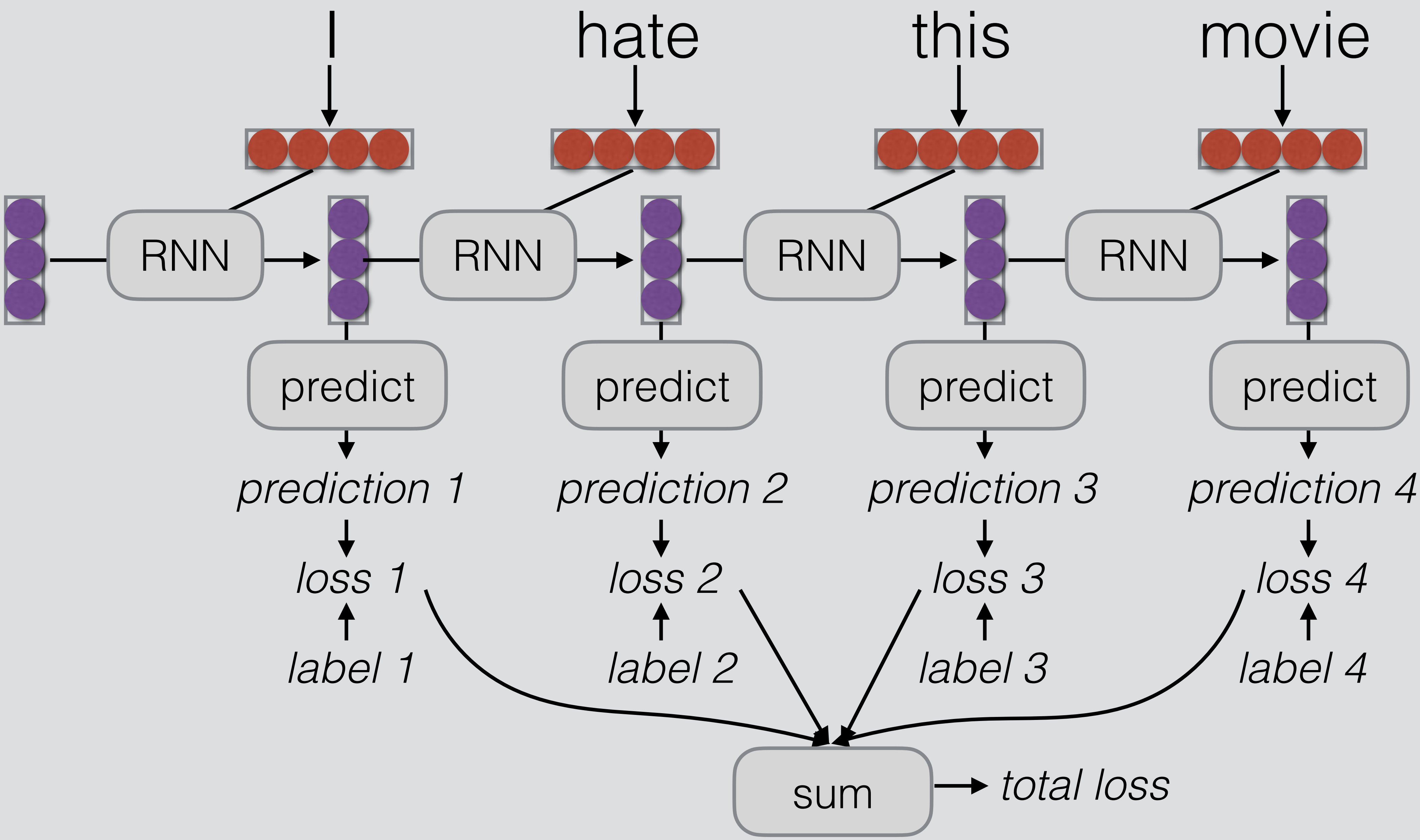

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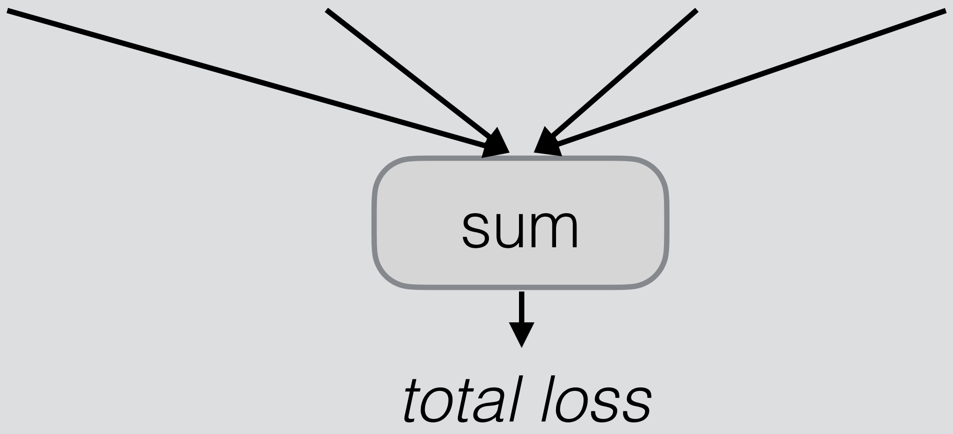

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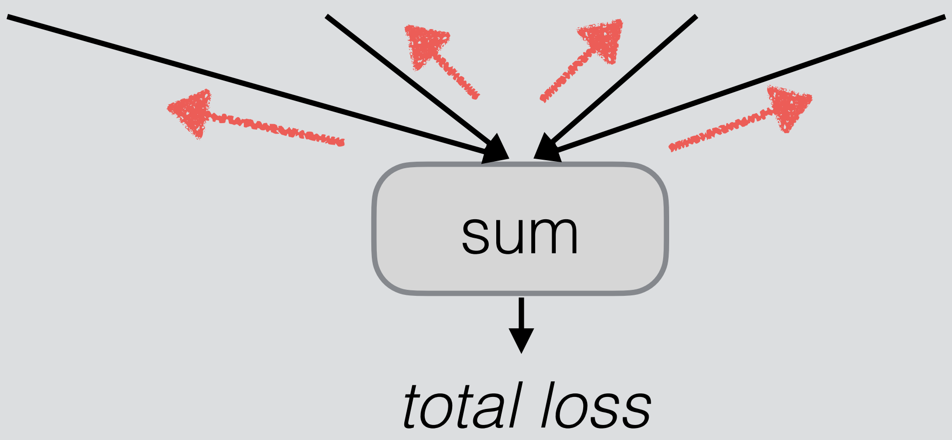

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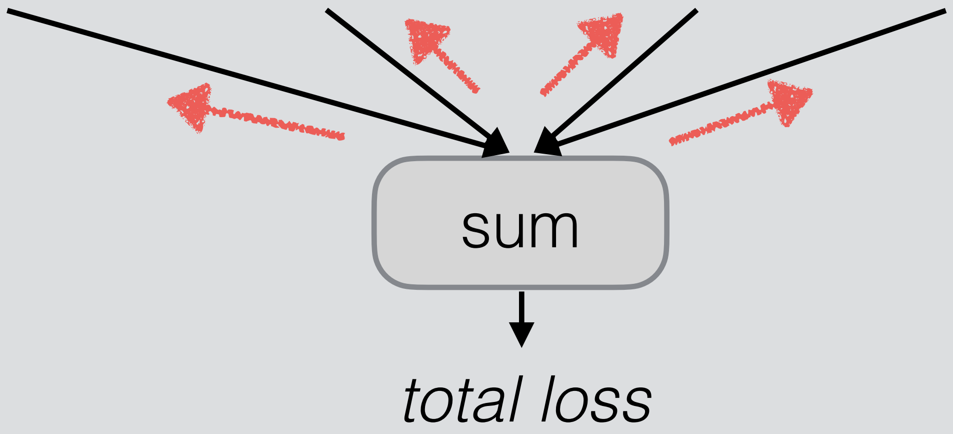

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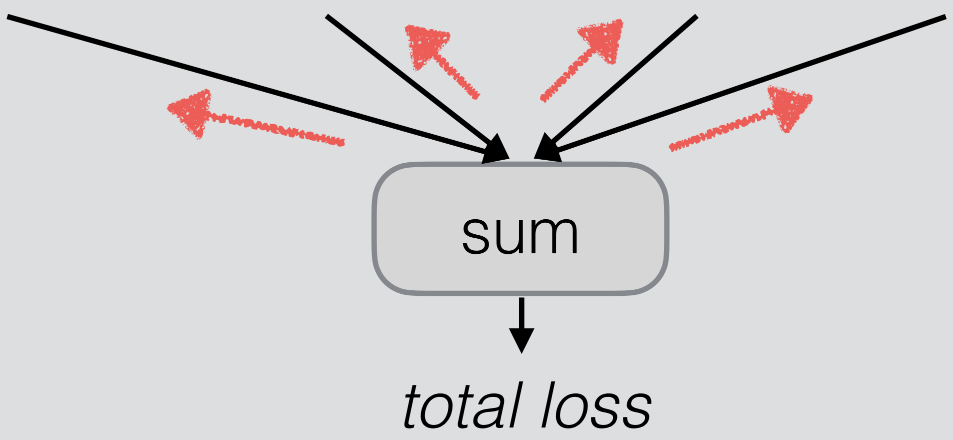
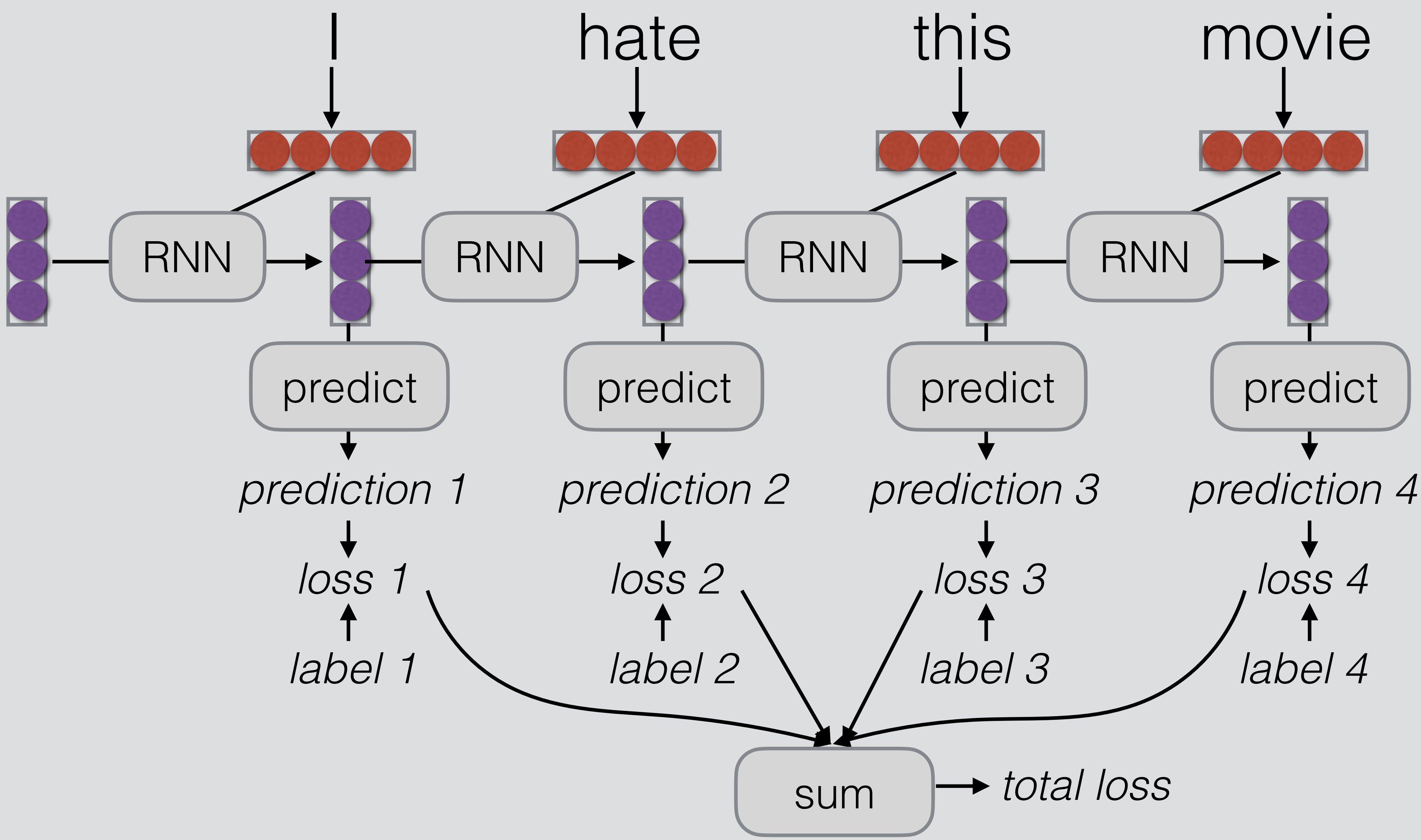


- Parameters are tied across time, derivatives are aggregated across all time steps

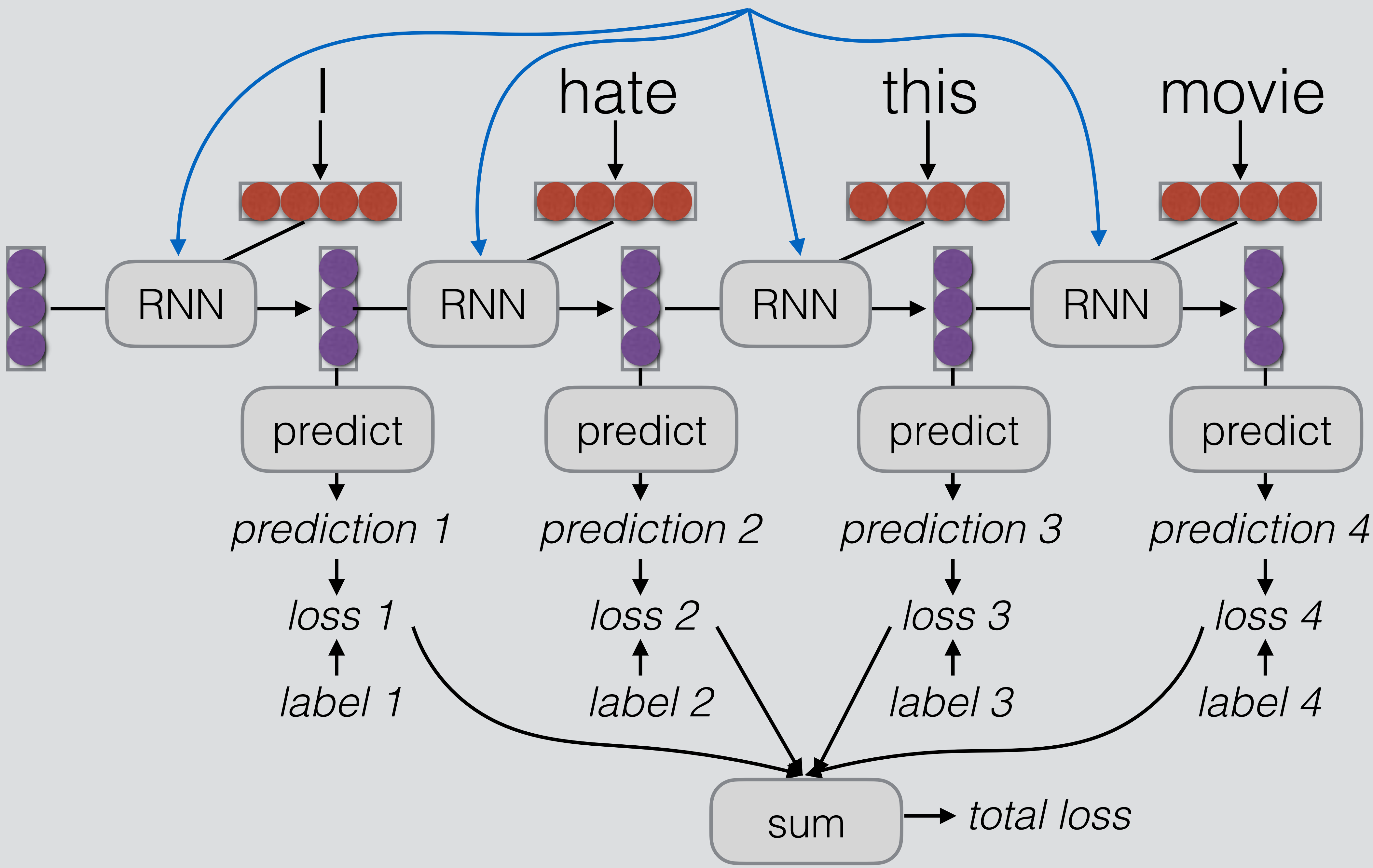
- This is historically called “backpropagation through time” (BPTT)

Parameter Tying



Parameter Tying

Parameters are shared! Derivatives are accumulated.

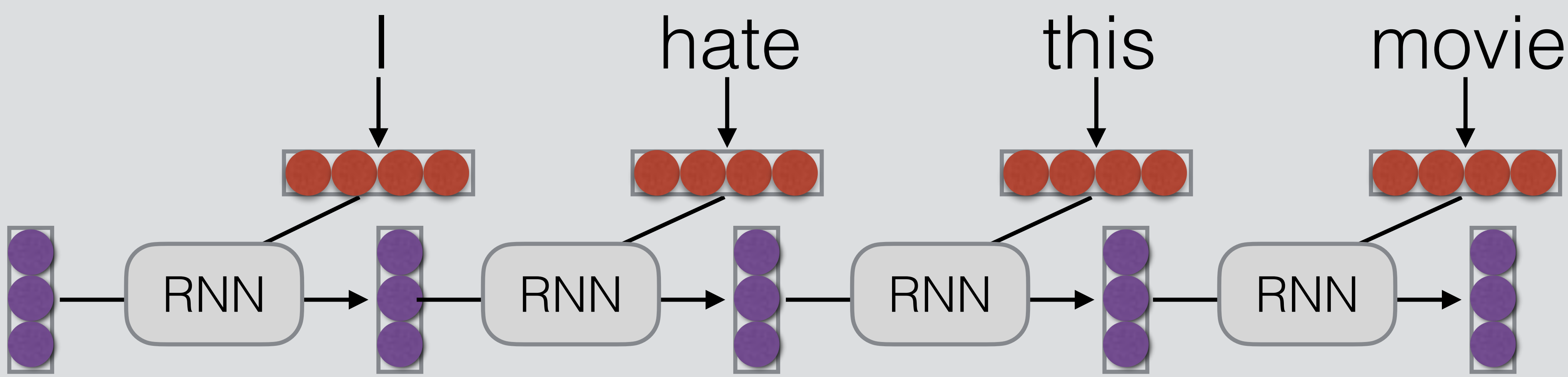


Applications of RNNs

What Can RNNs Do?

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

Representing Sentences



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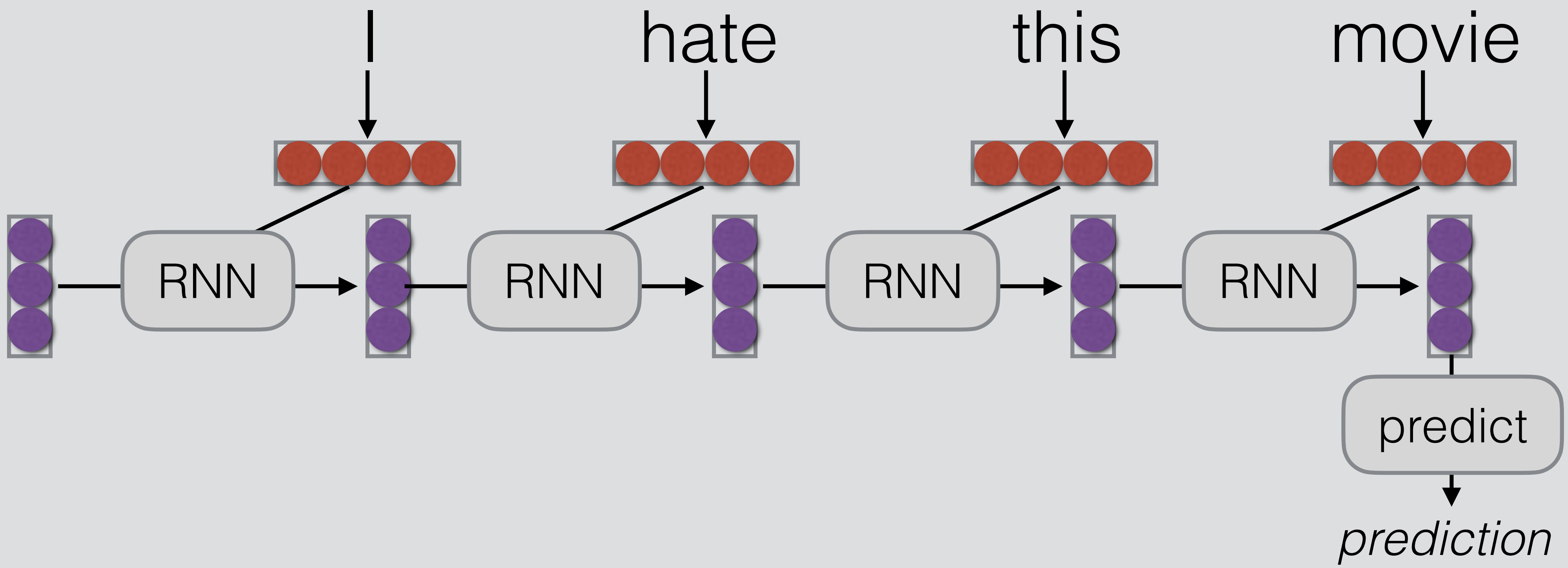

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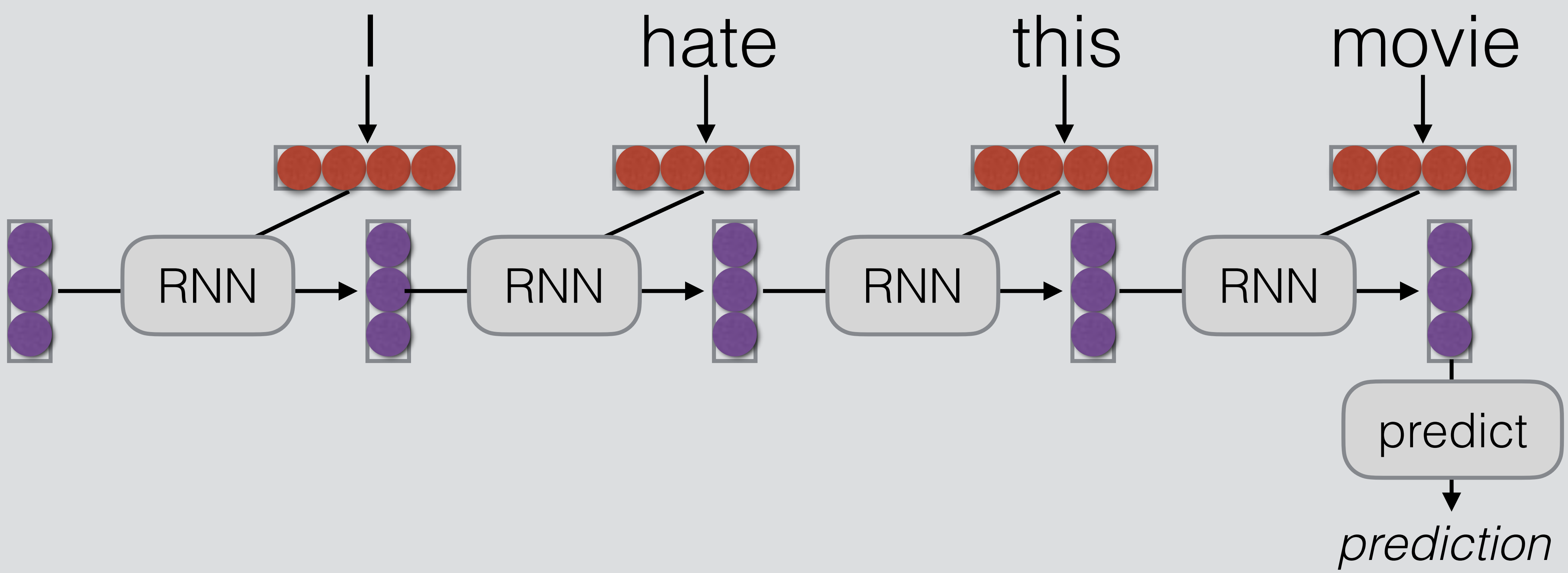
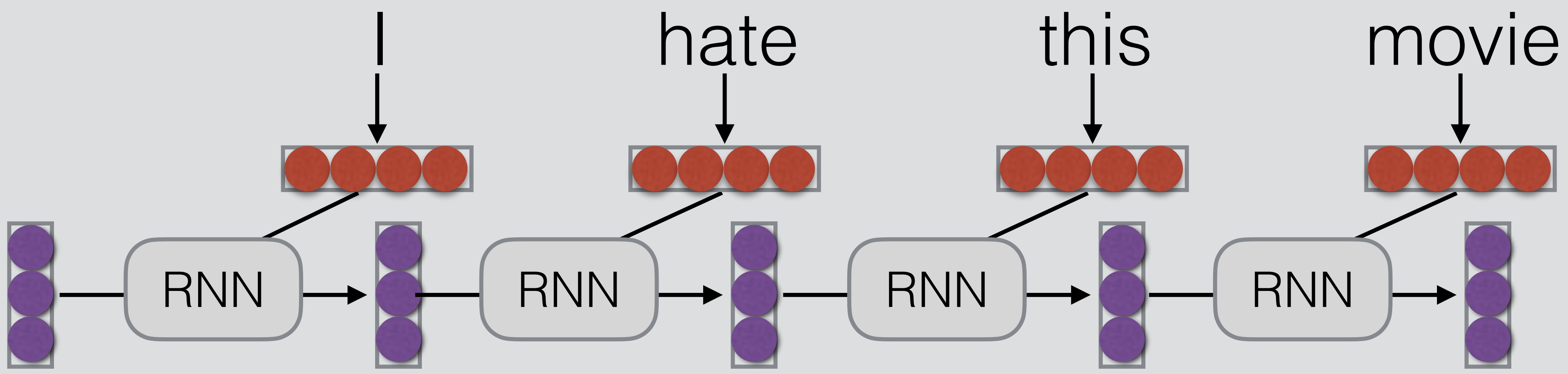


- Sentence classification
- Conditioned generation
- Retrieval

Representing Contexts



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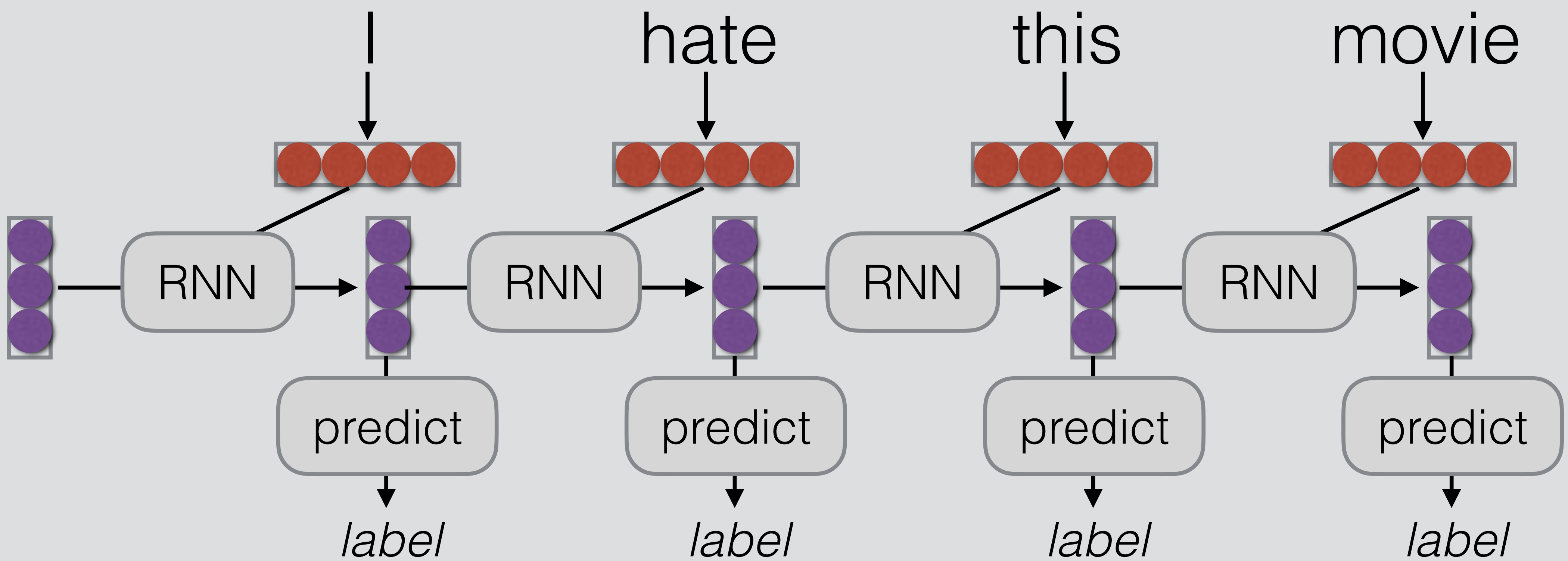
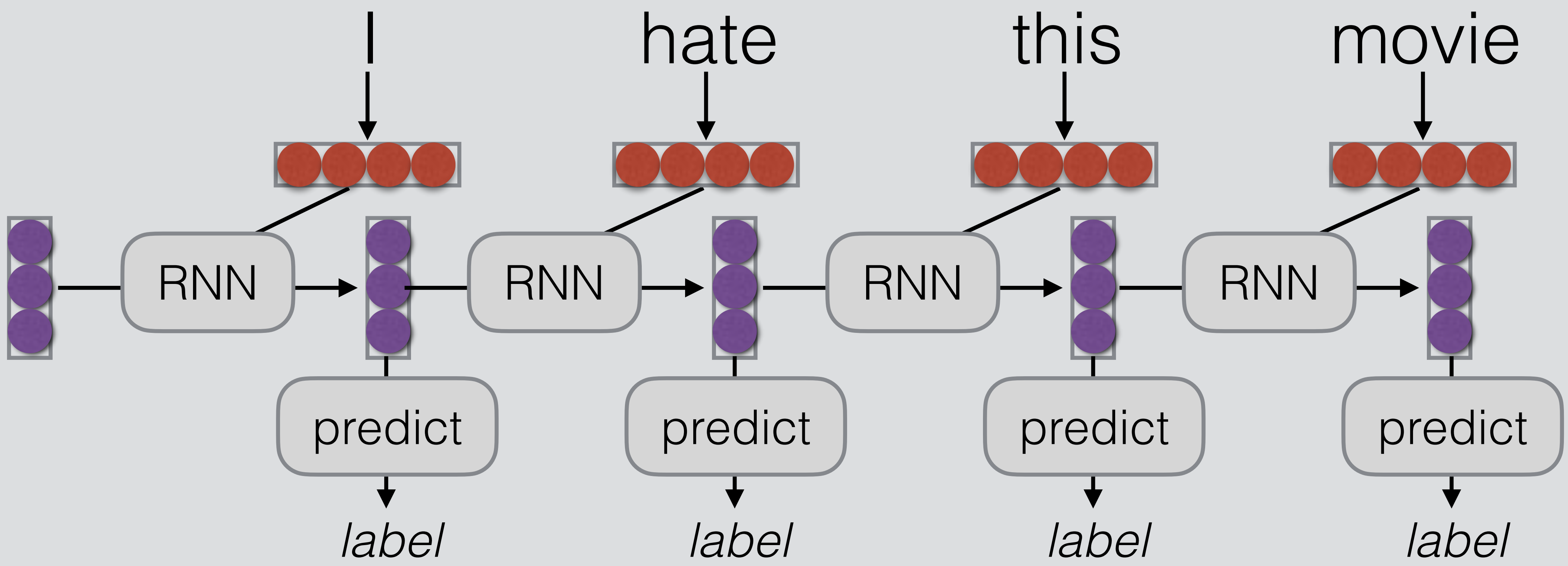
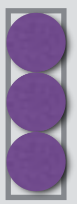


Representing Contexts



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

e.g. Language Modeling



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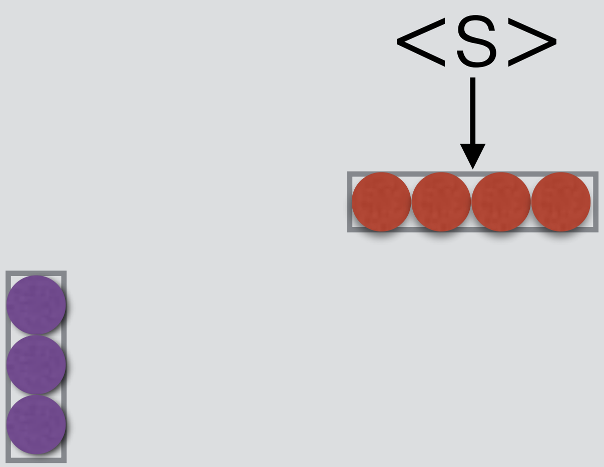

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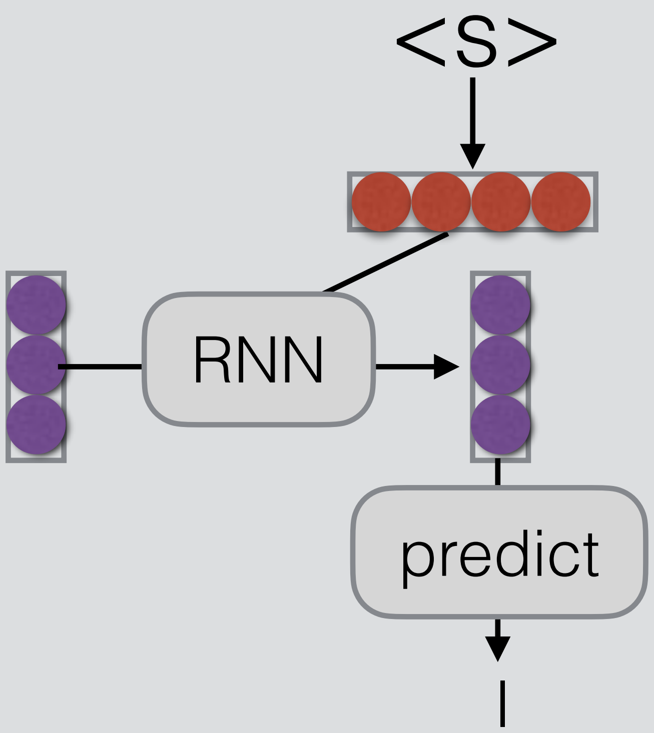

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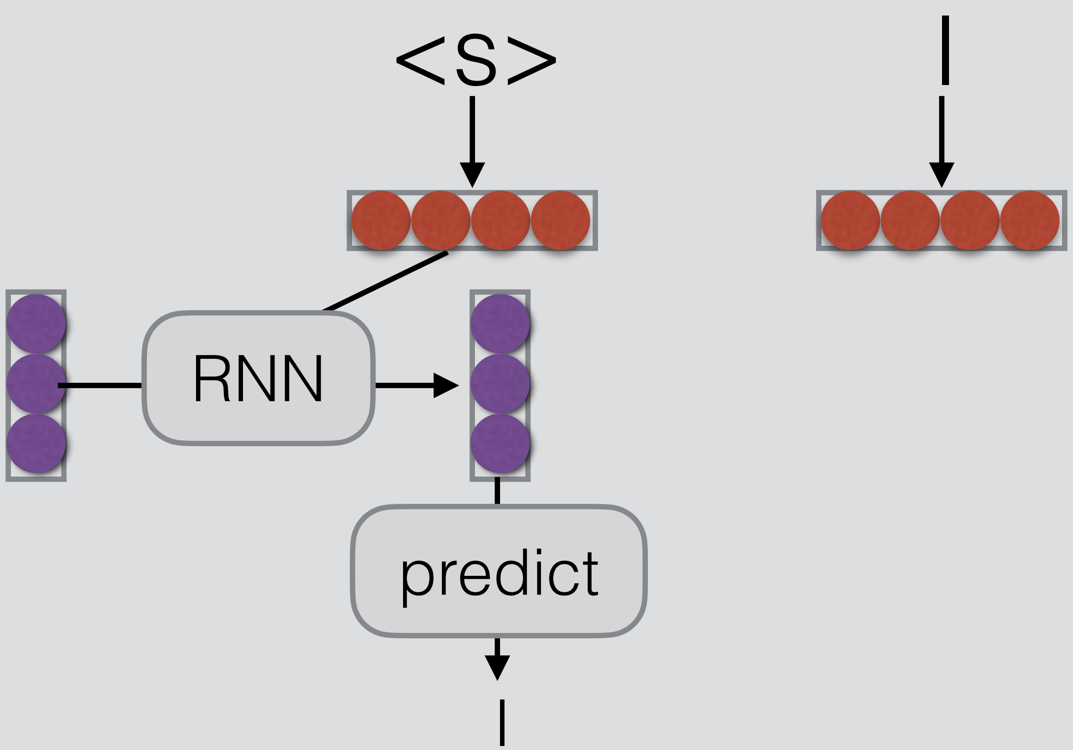
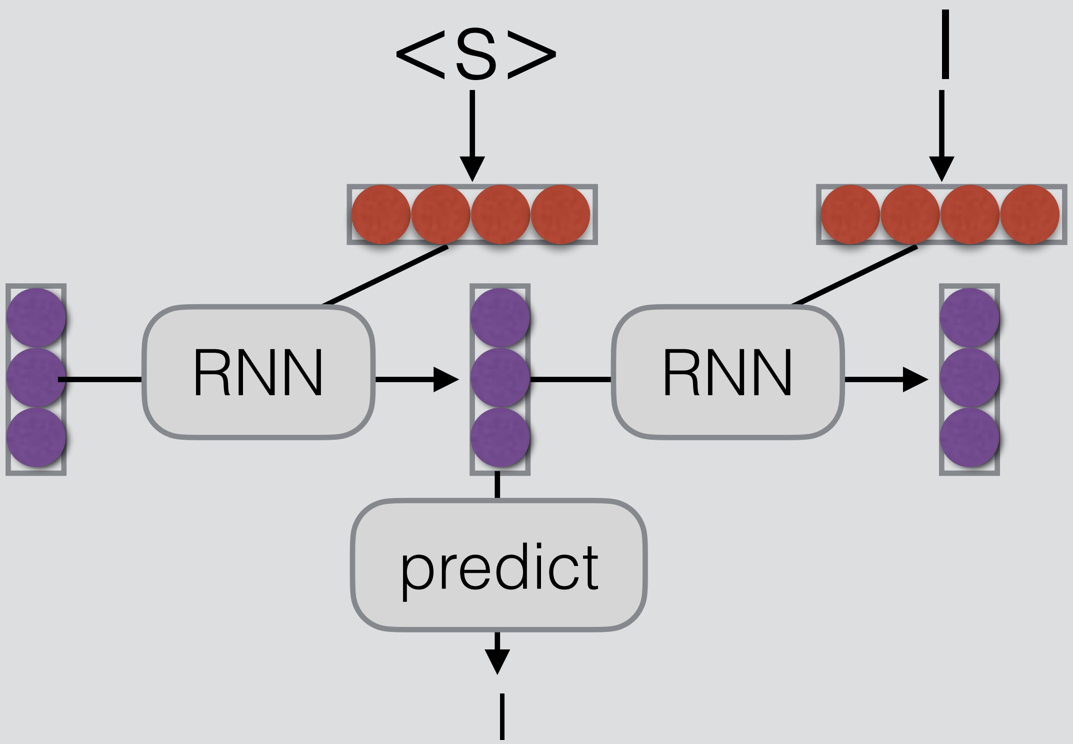


e.g. Language Modeling



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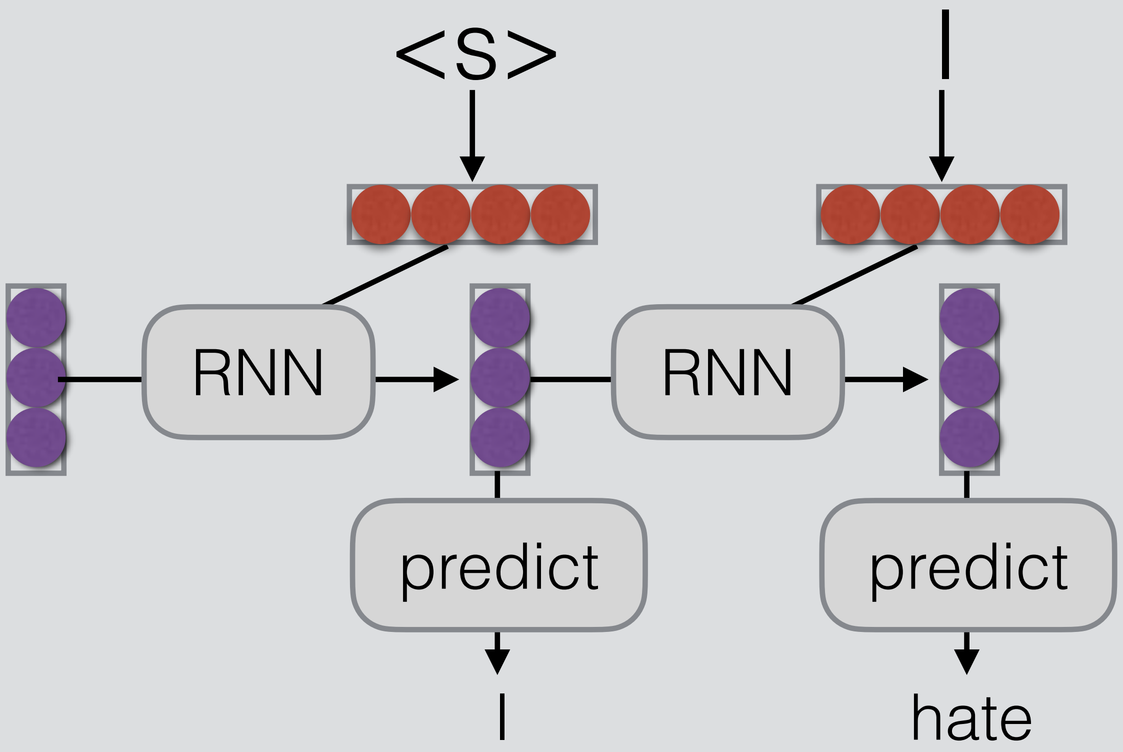

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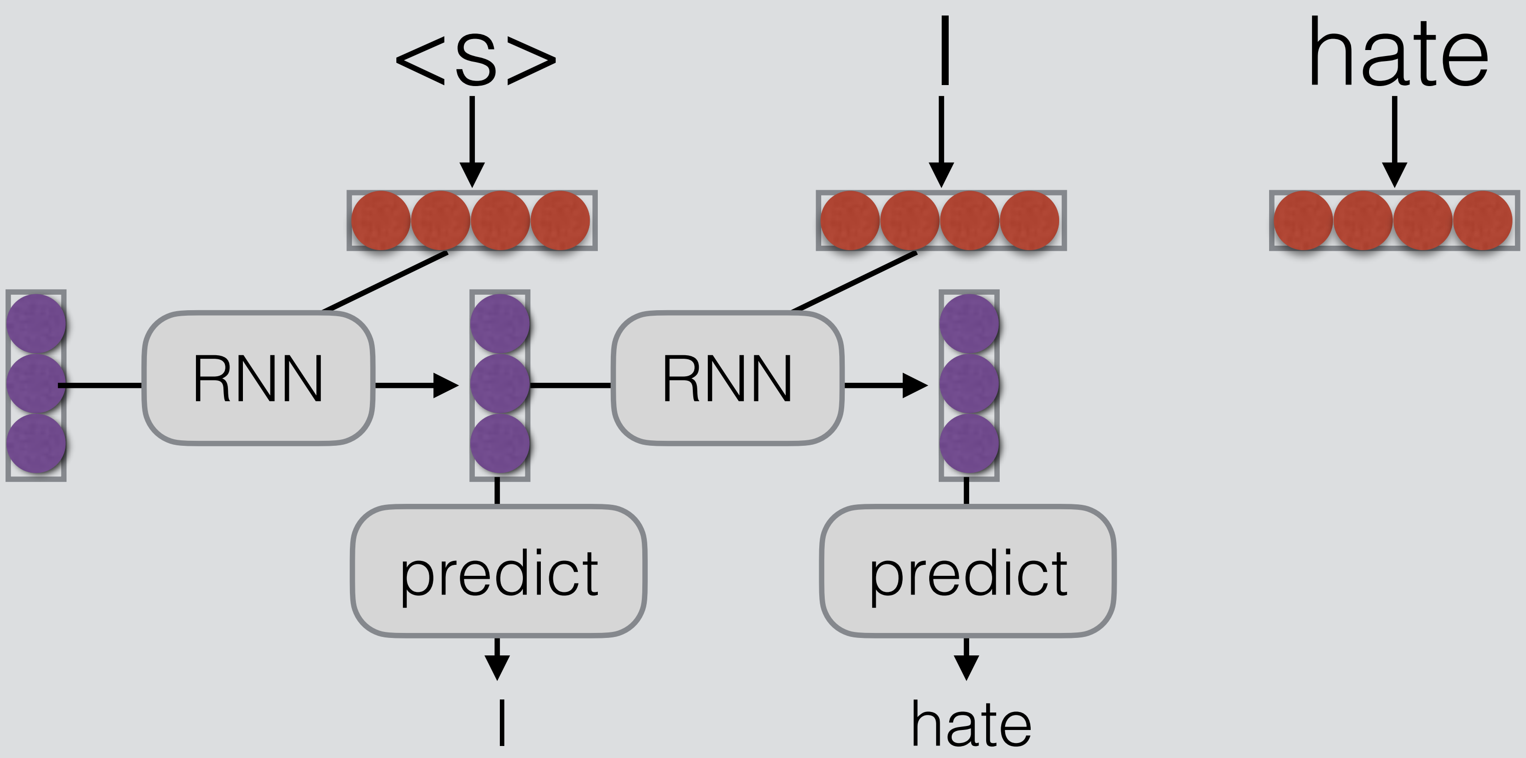

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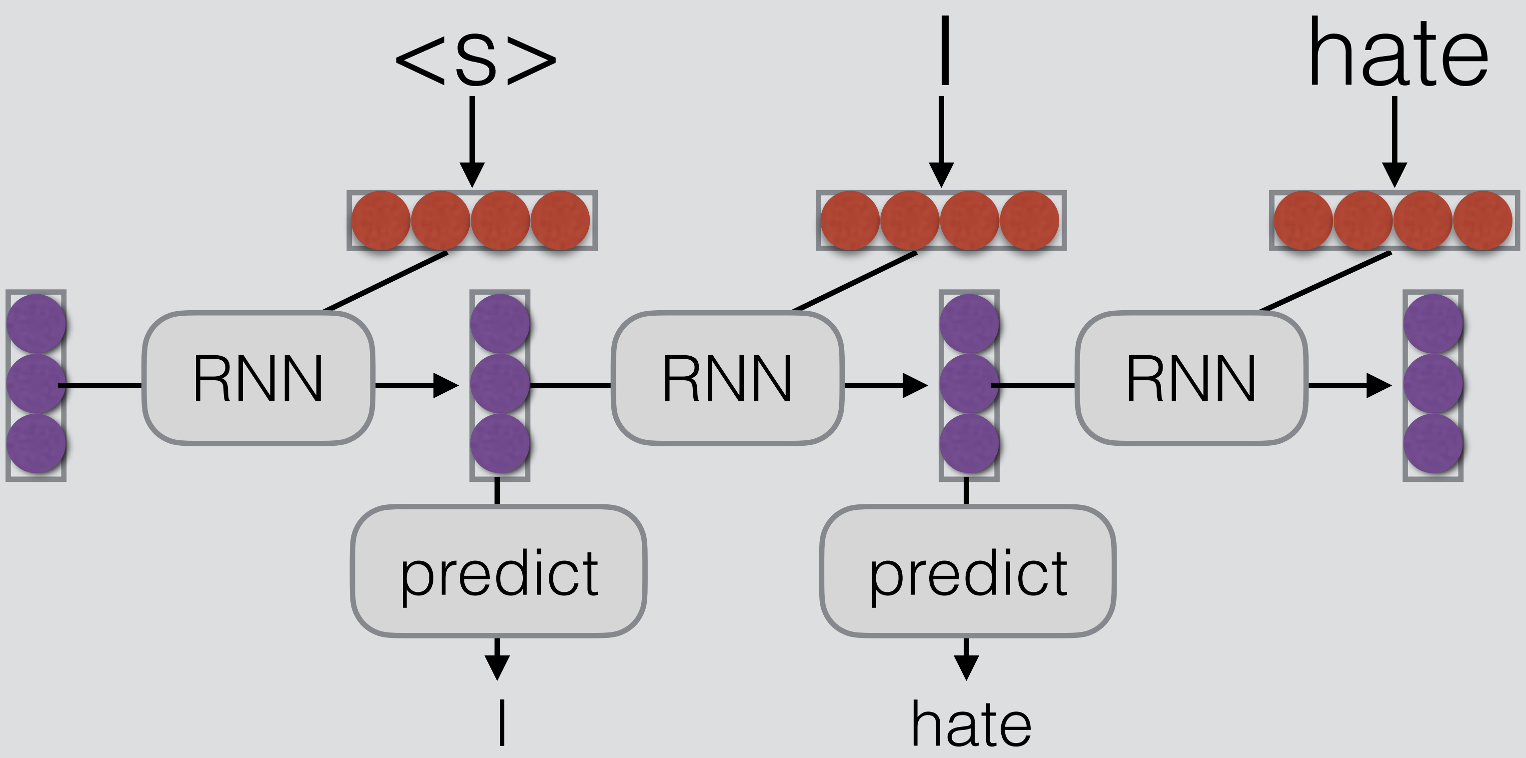

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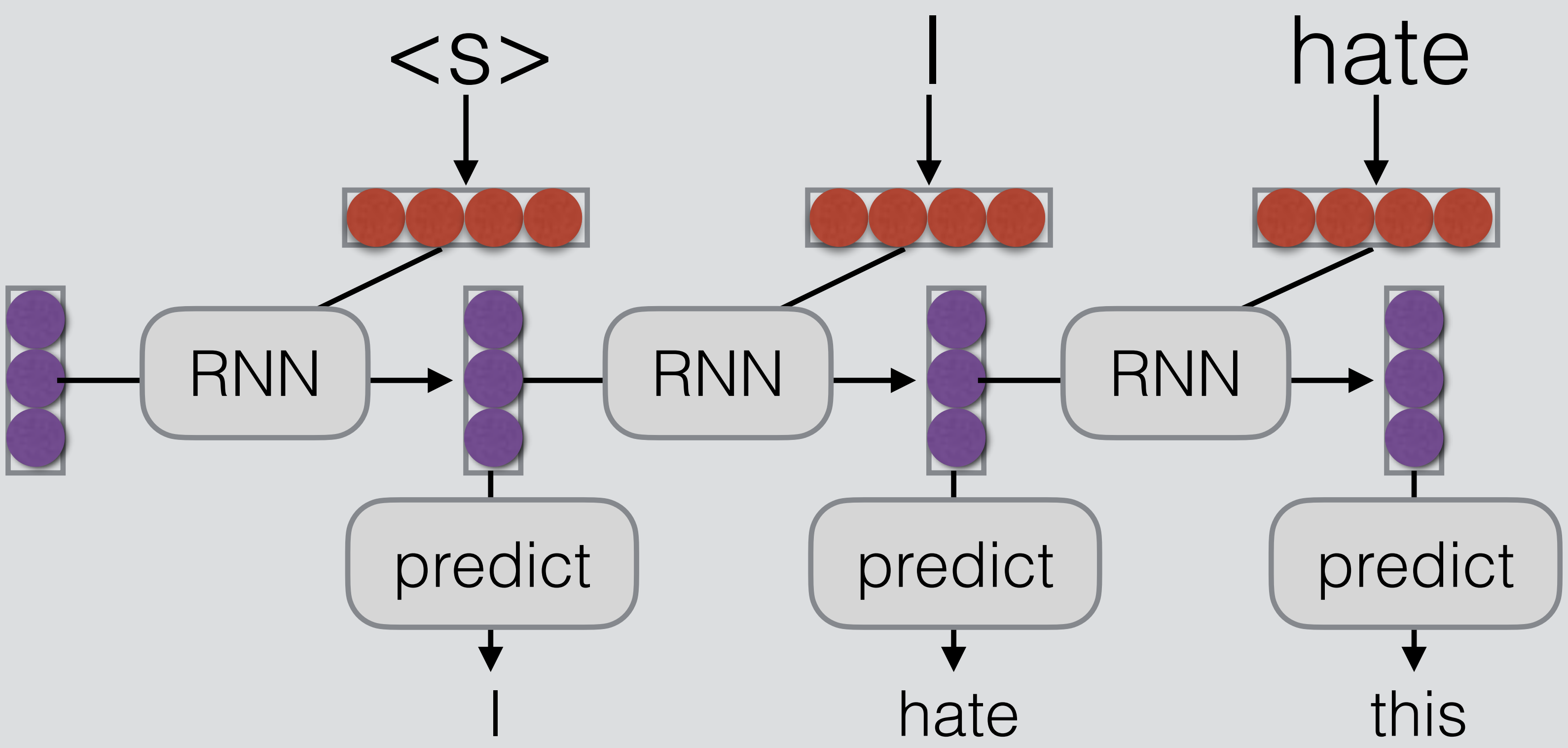

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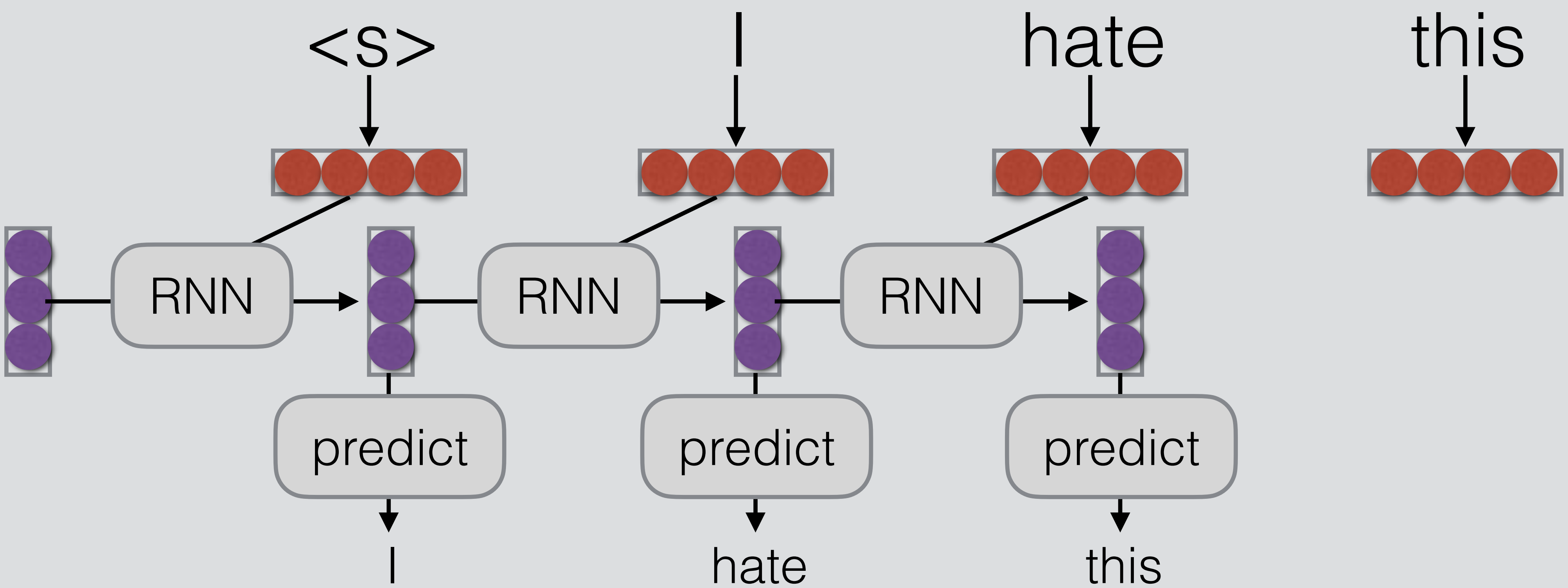

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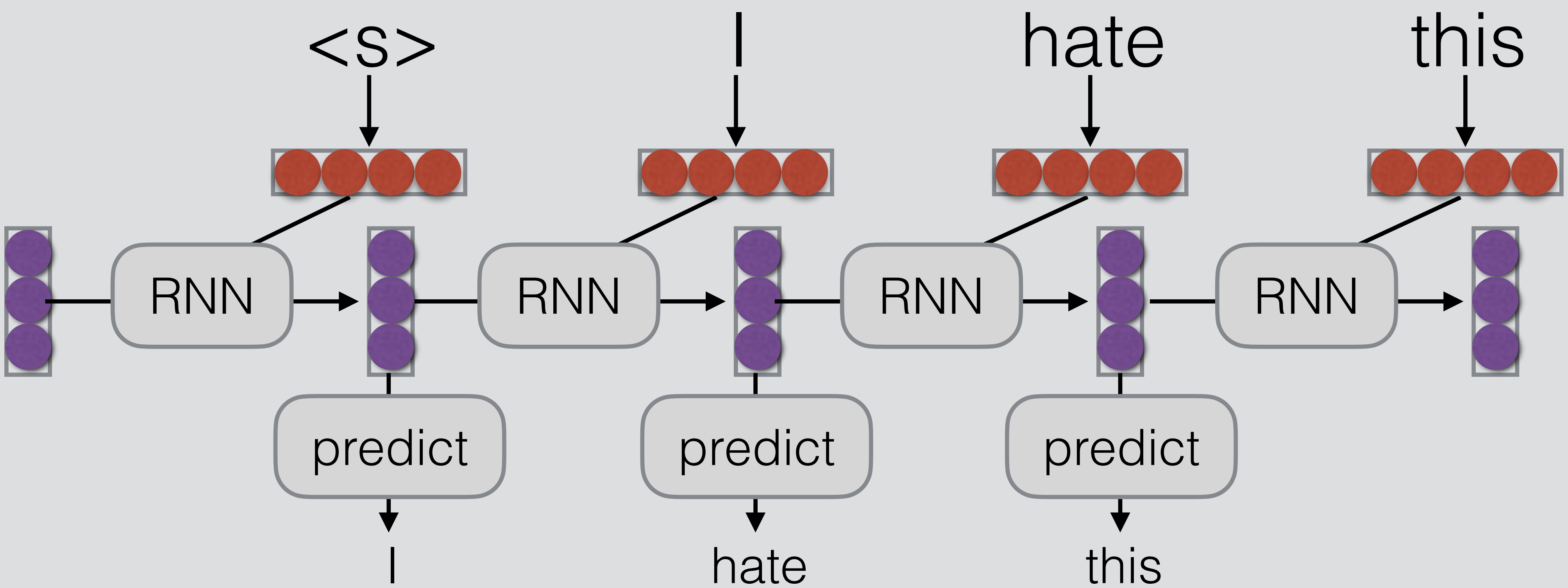

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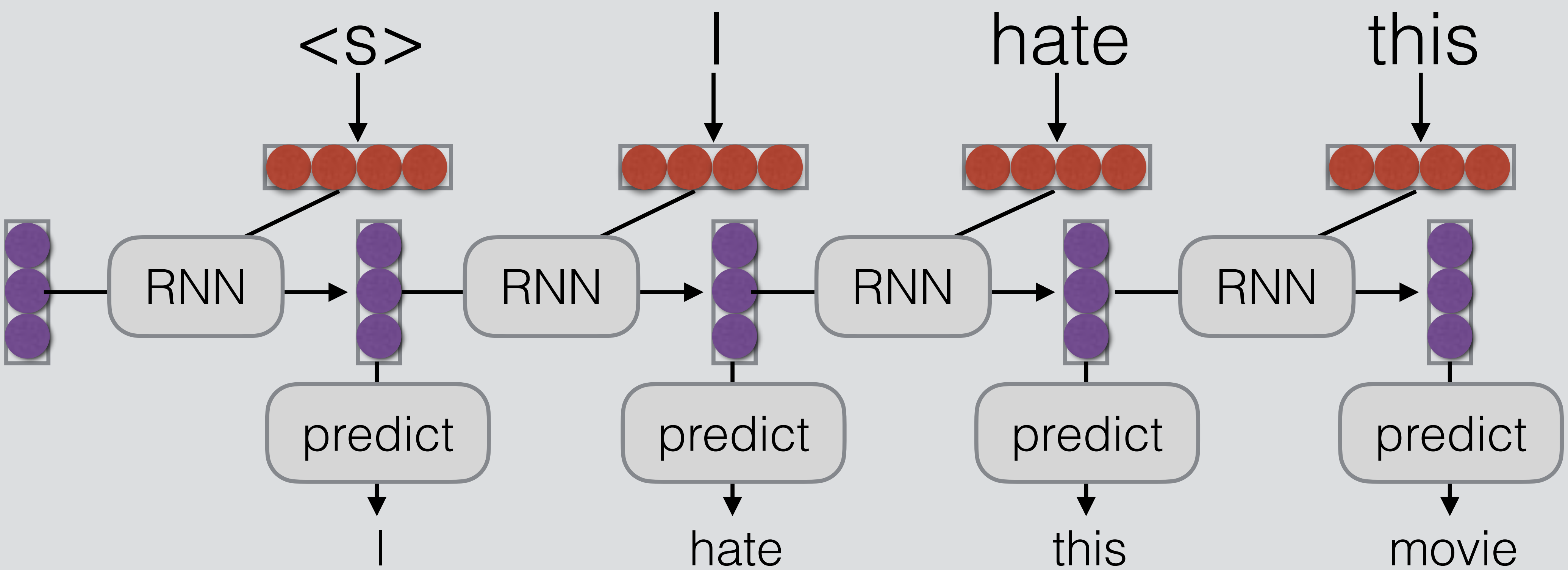

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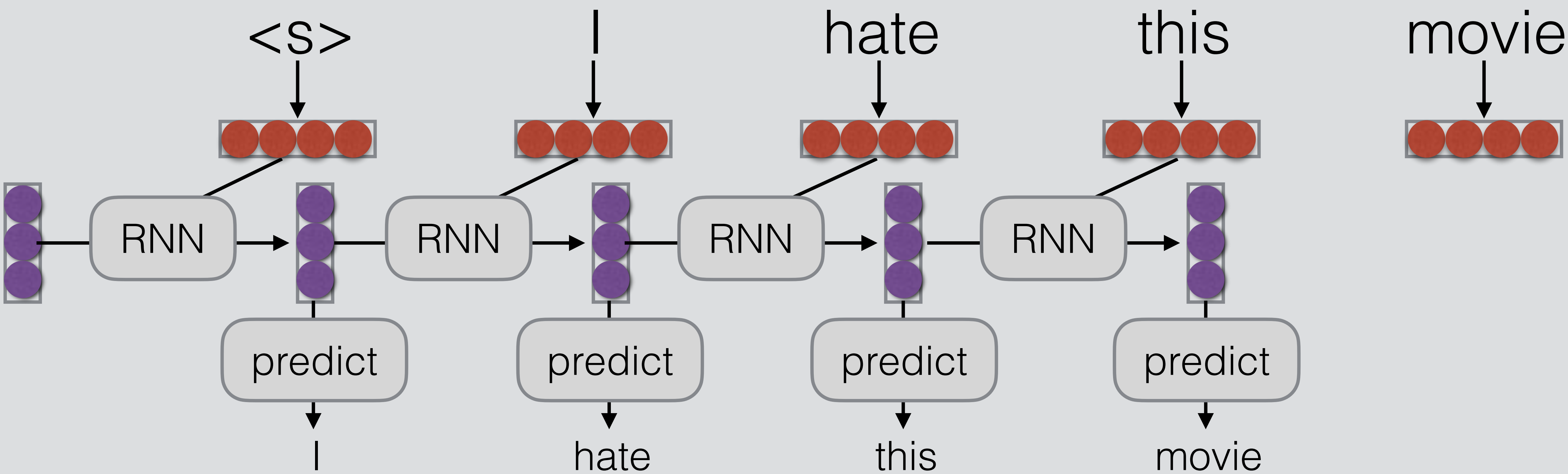

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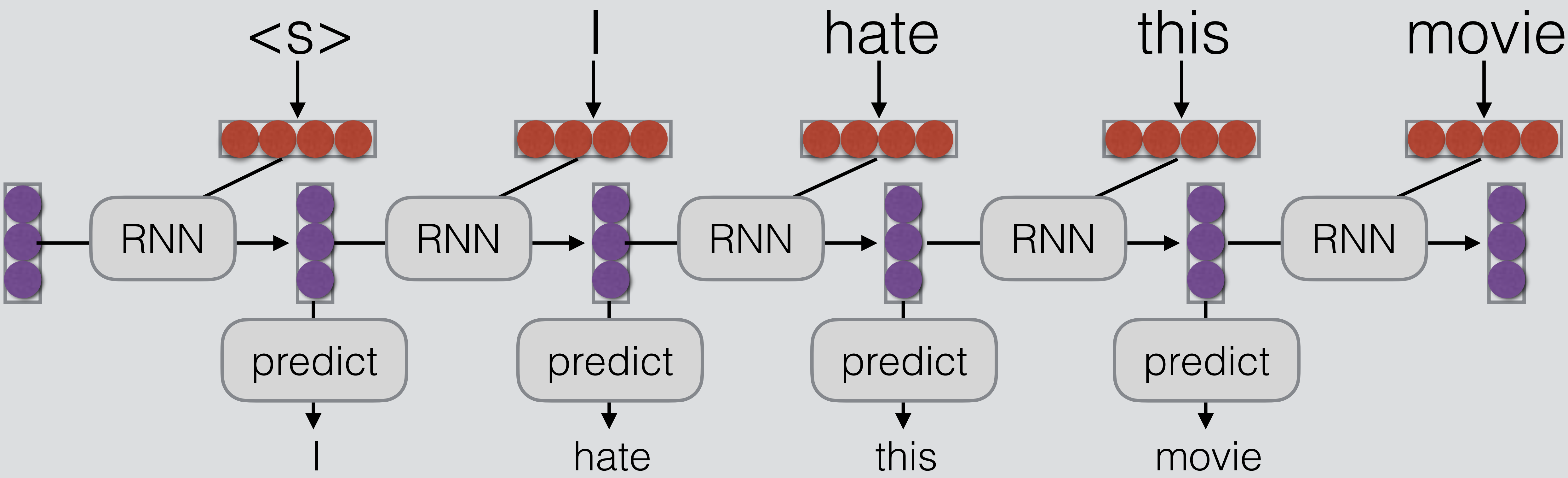

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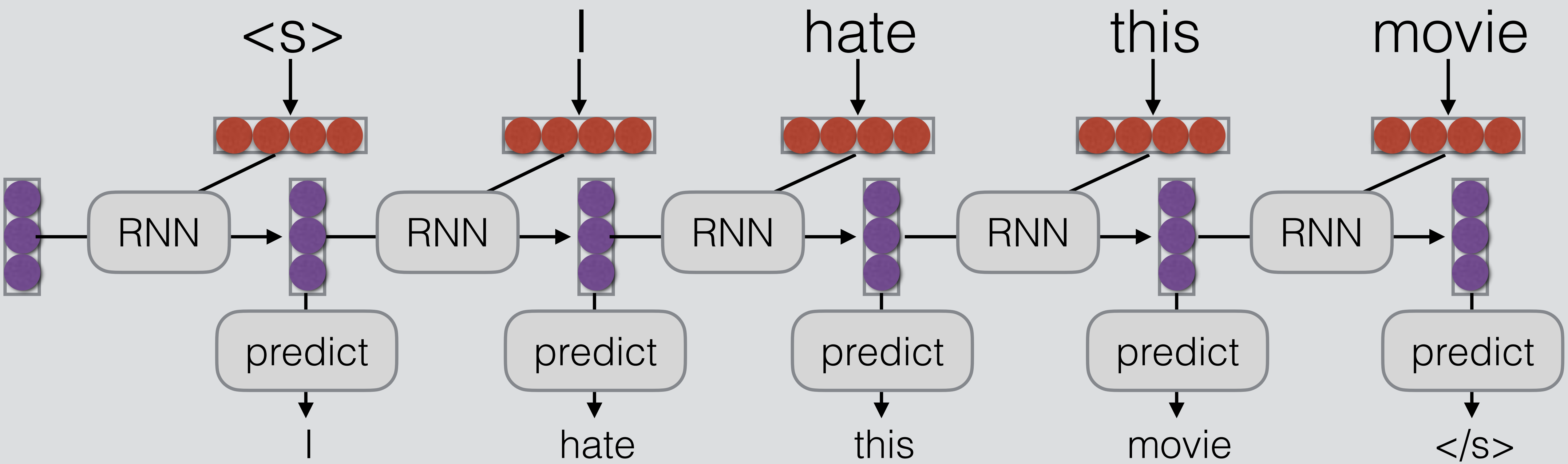

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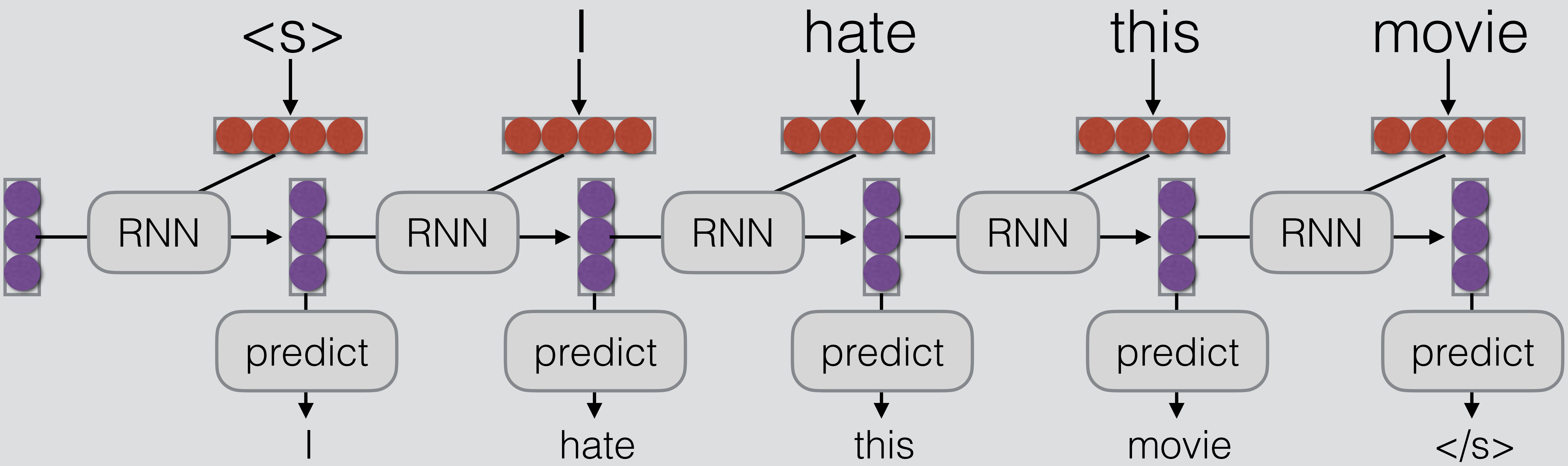
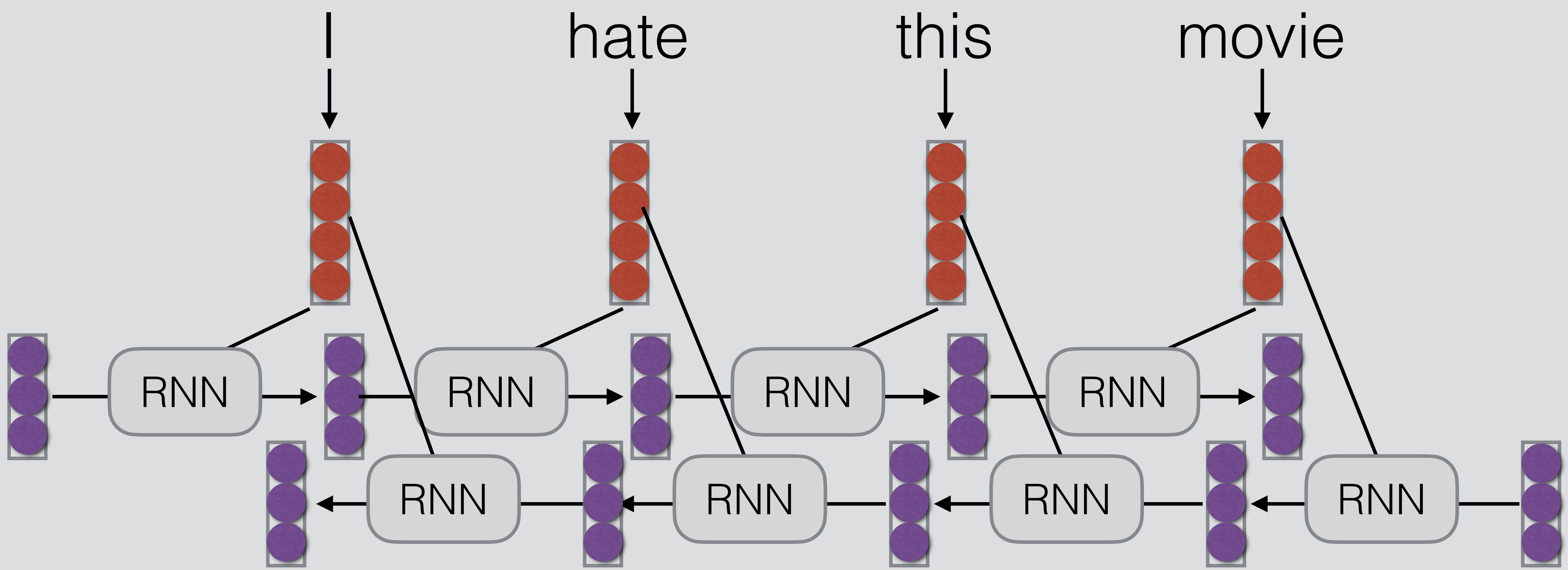


- Language modeling is like a tagging task, where each tag is the next word!

Bi-RNNs

- A simple extension, run the RNN in both directions



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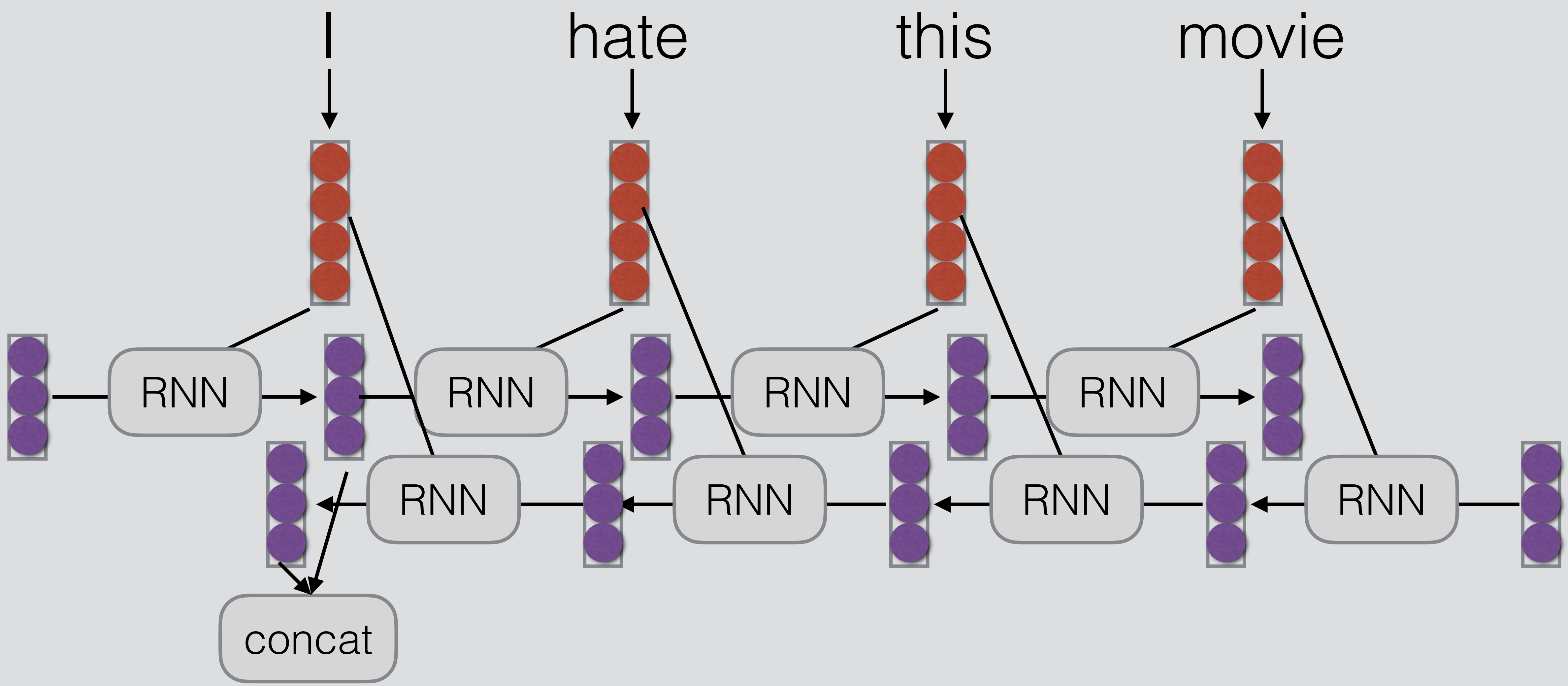

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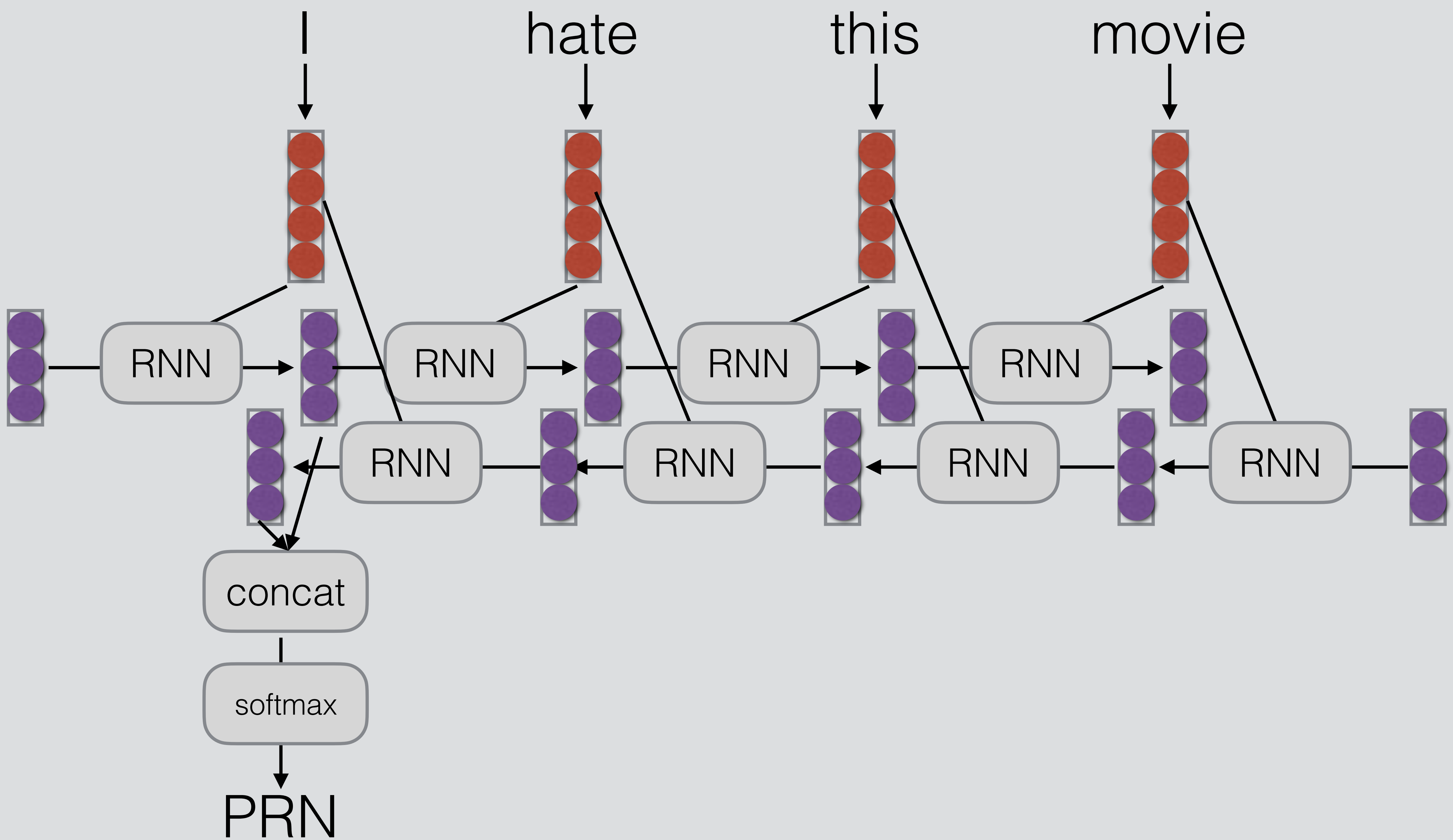

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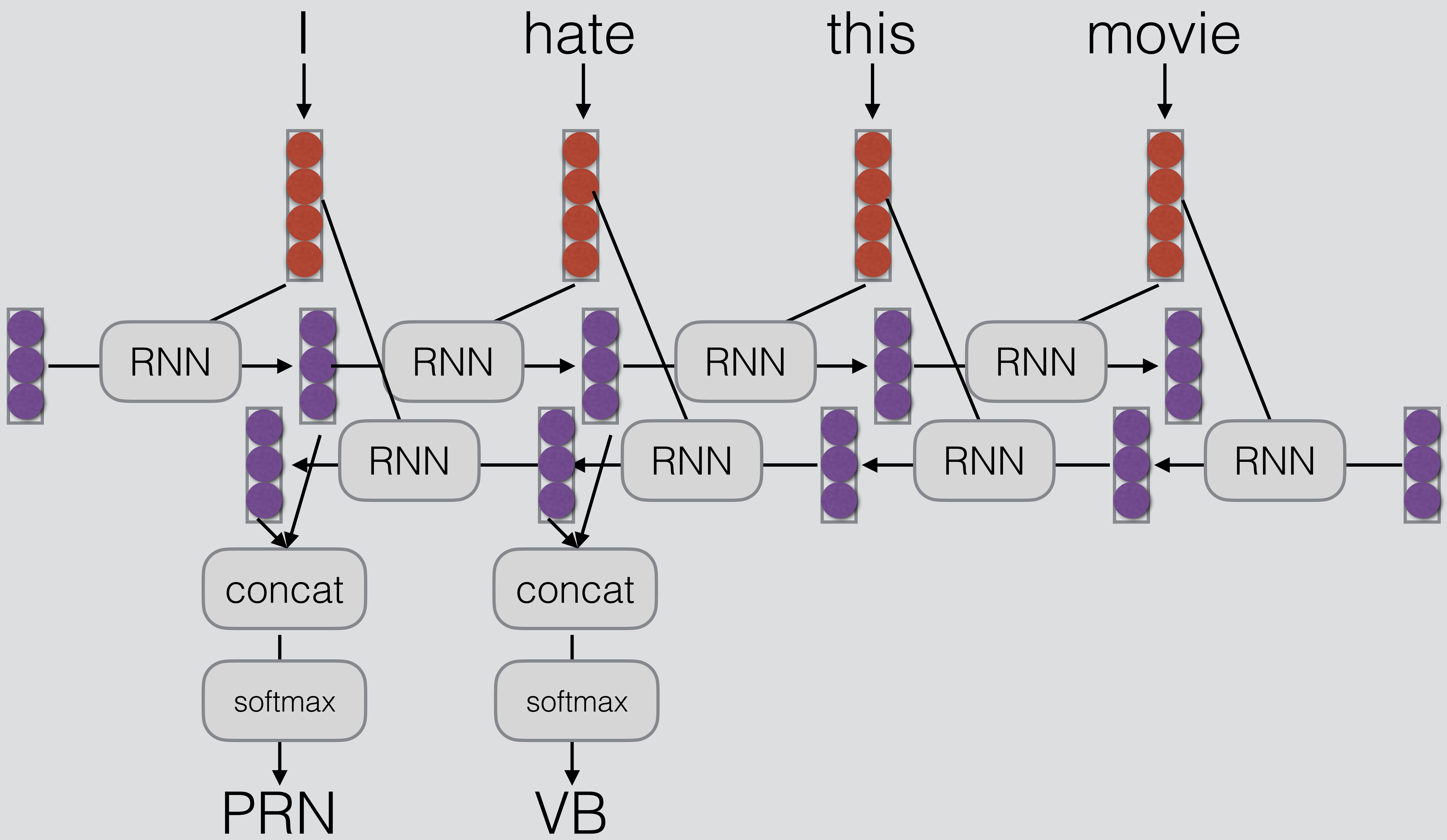

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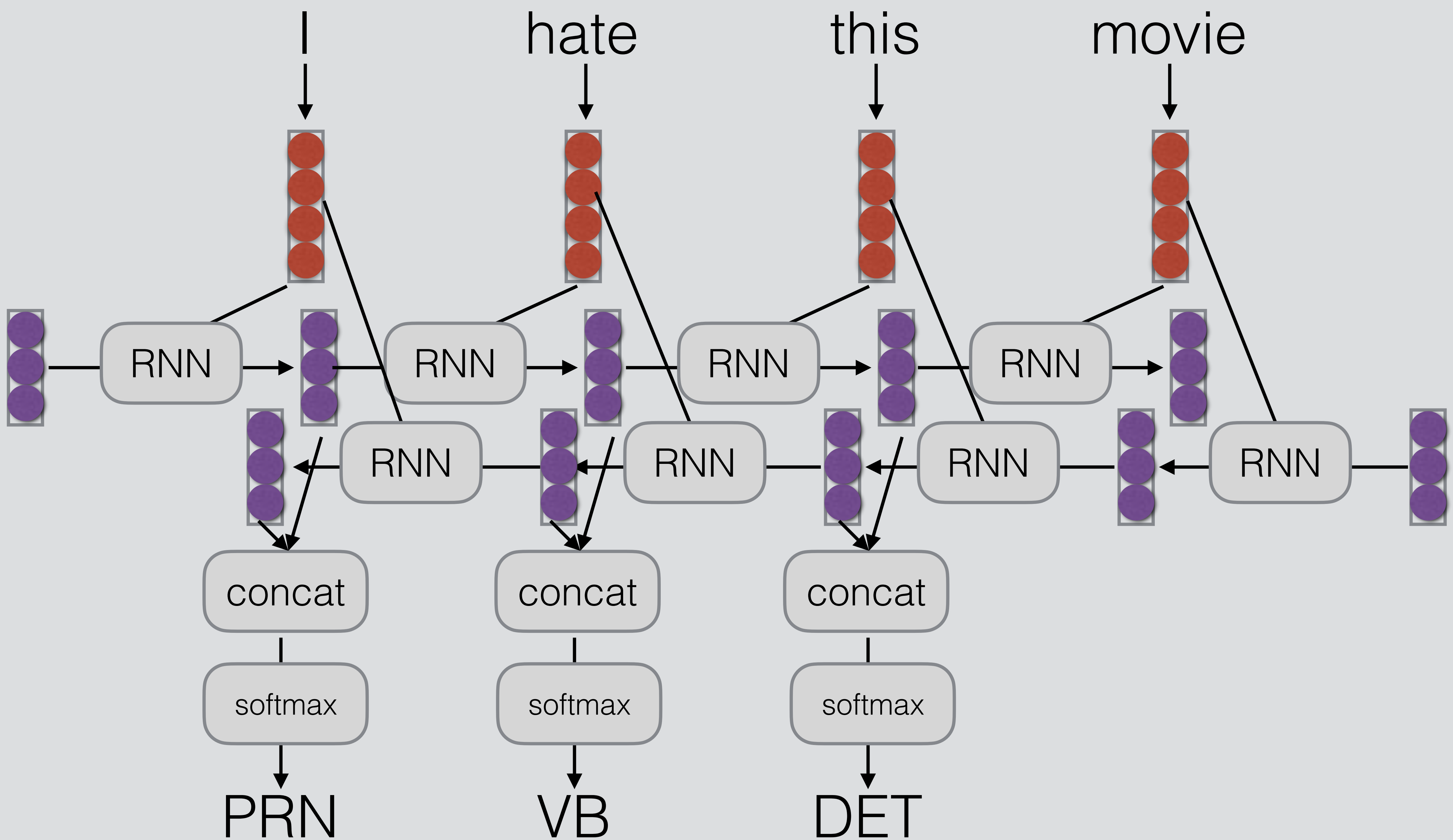

Bi-RNNs

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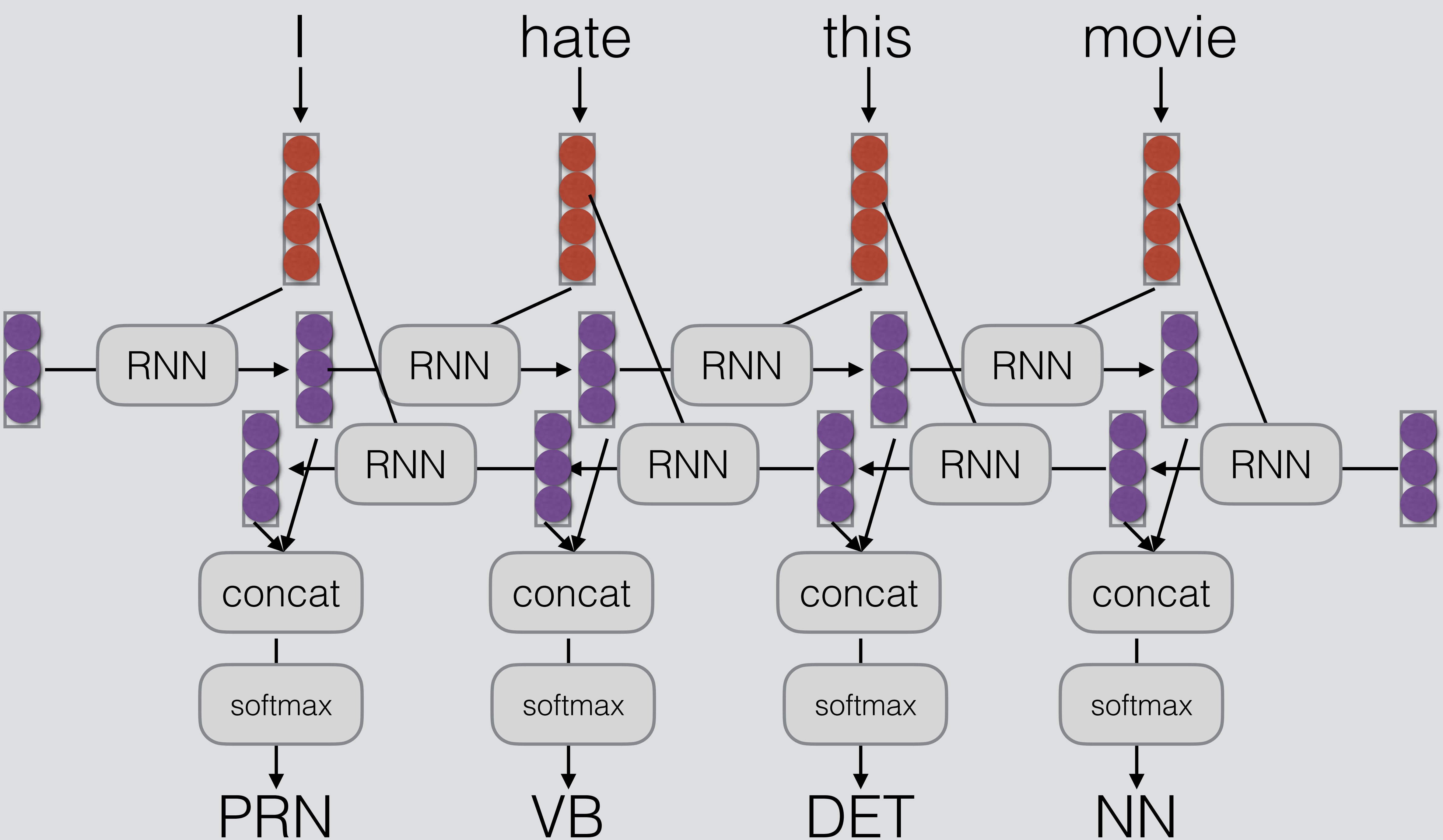
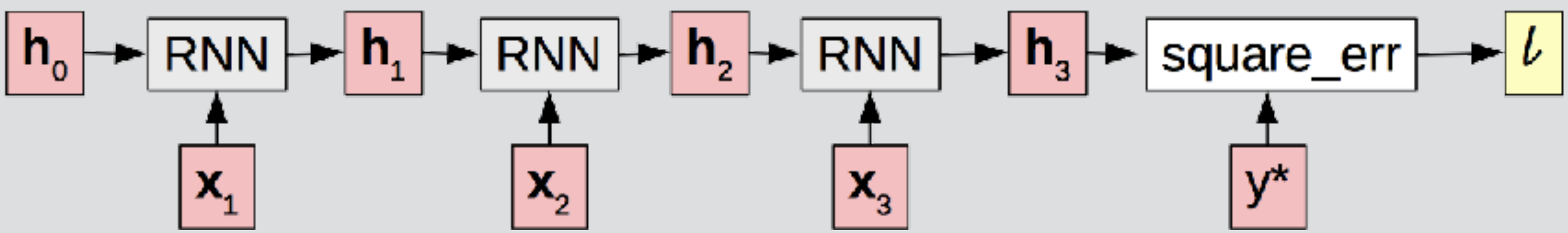


Vanishing Gradients

Vanishing Gradient

- Gradients decrease as they get pushed back

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



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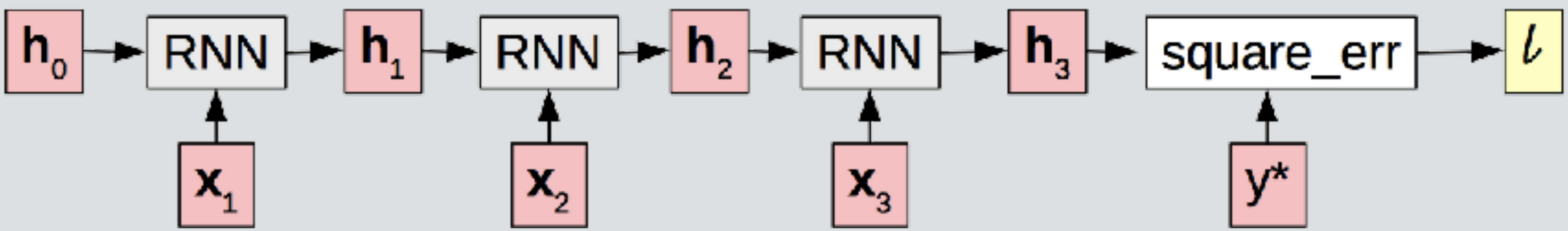
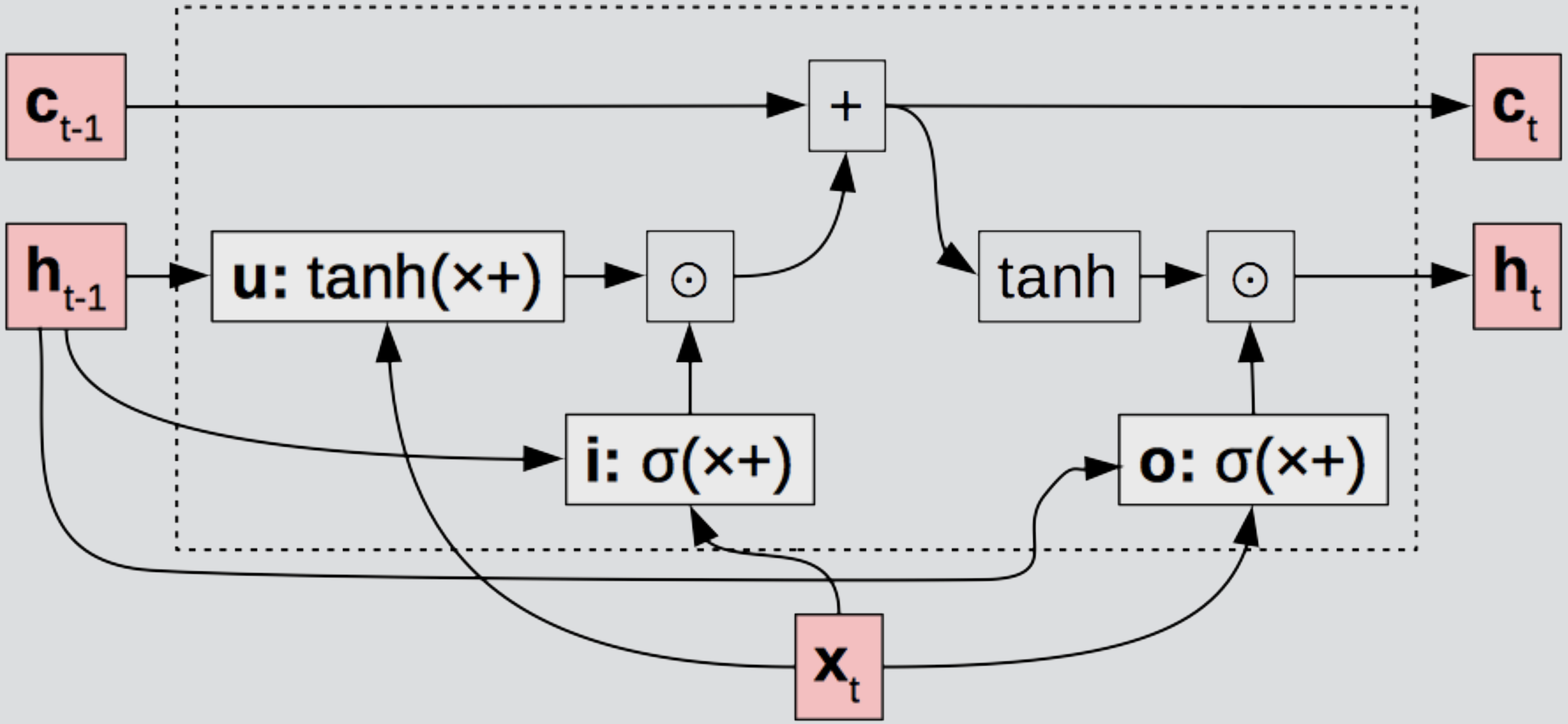


- Why? "Squashed" by non-linearities or small weights in matrices.

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

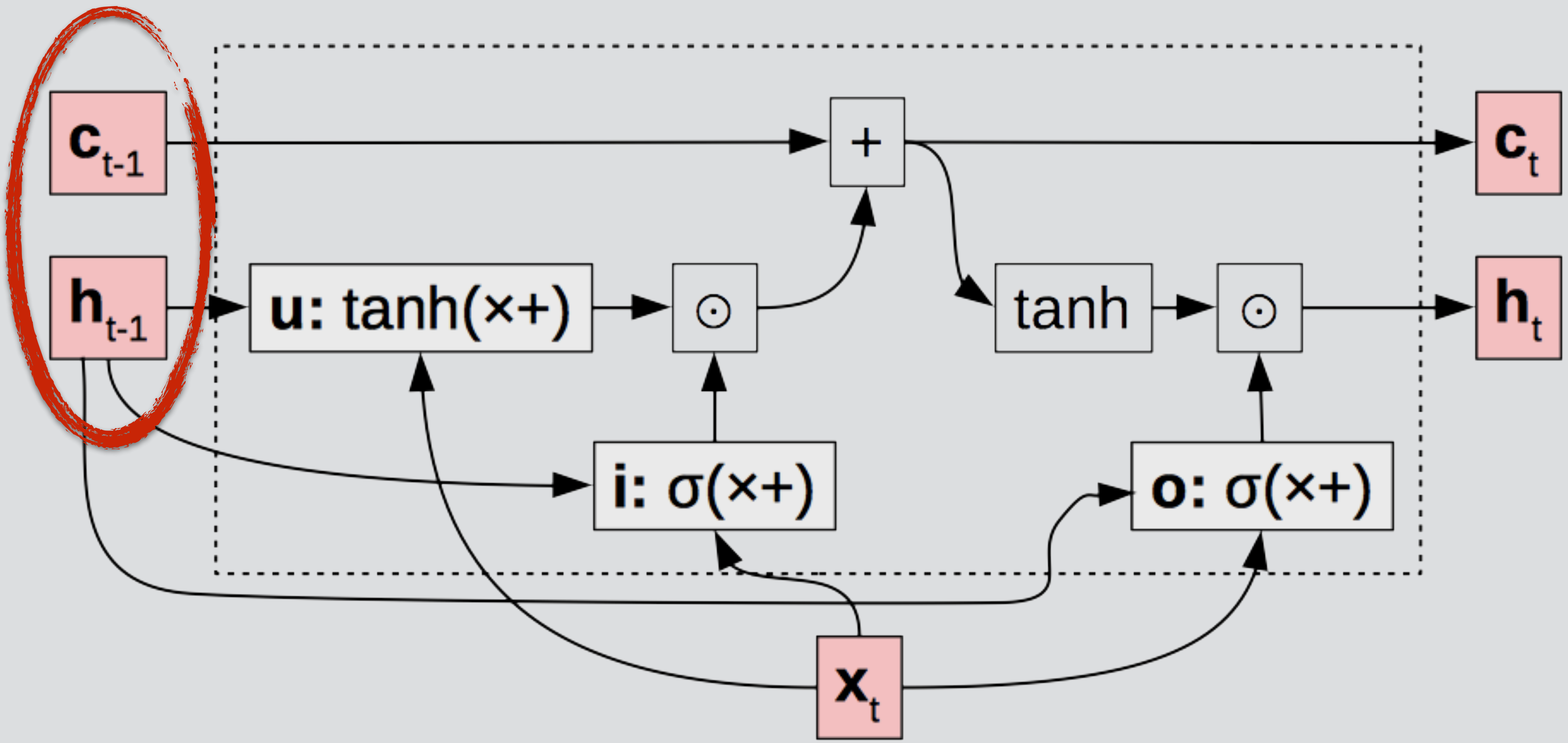
- **Basic idea:** make additive connections between time steps
- Addition does not modify the gradient, no vanishing
- Gates to control the information flow

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?

LSTM Structure



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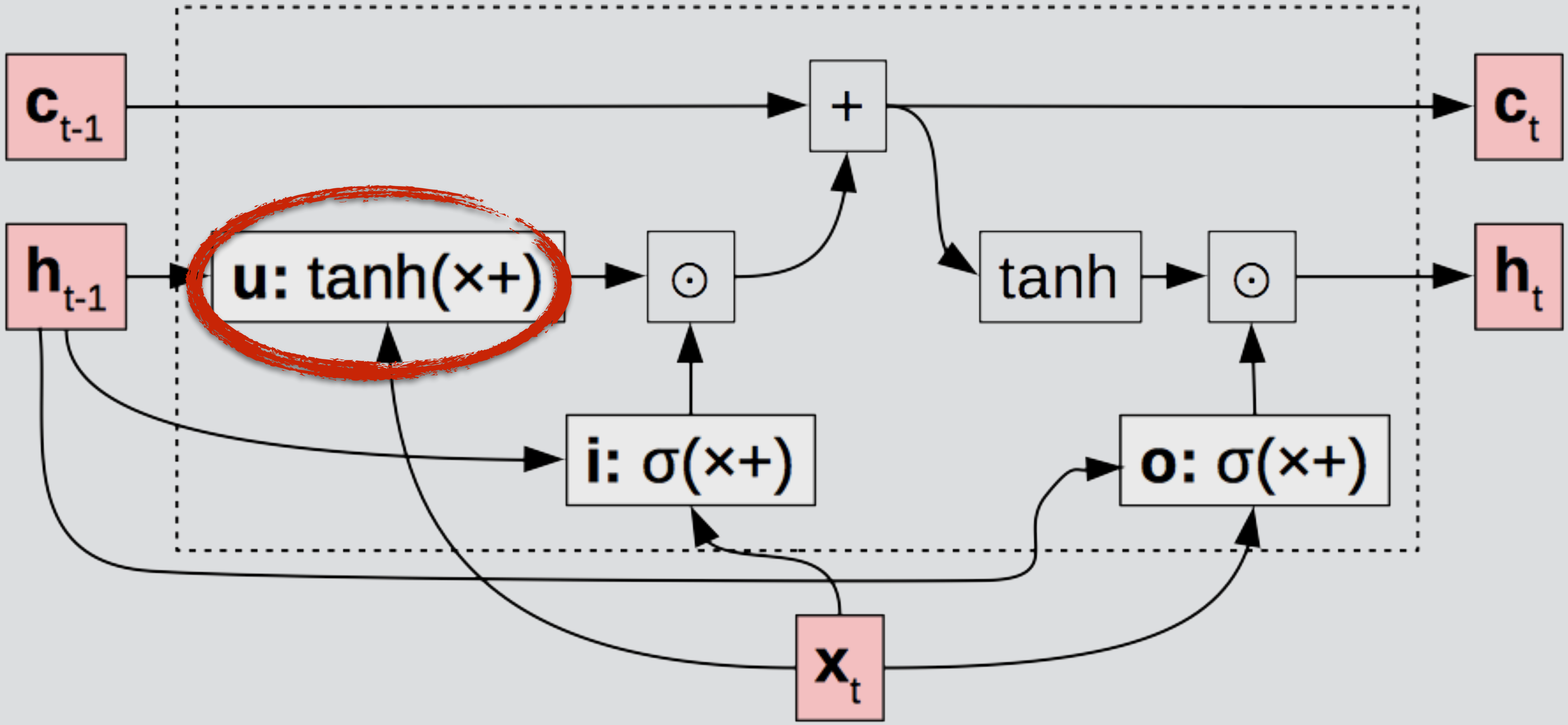

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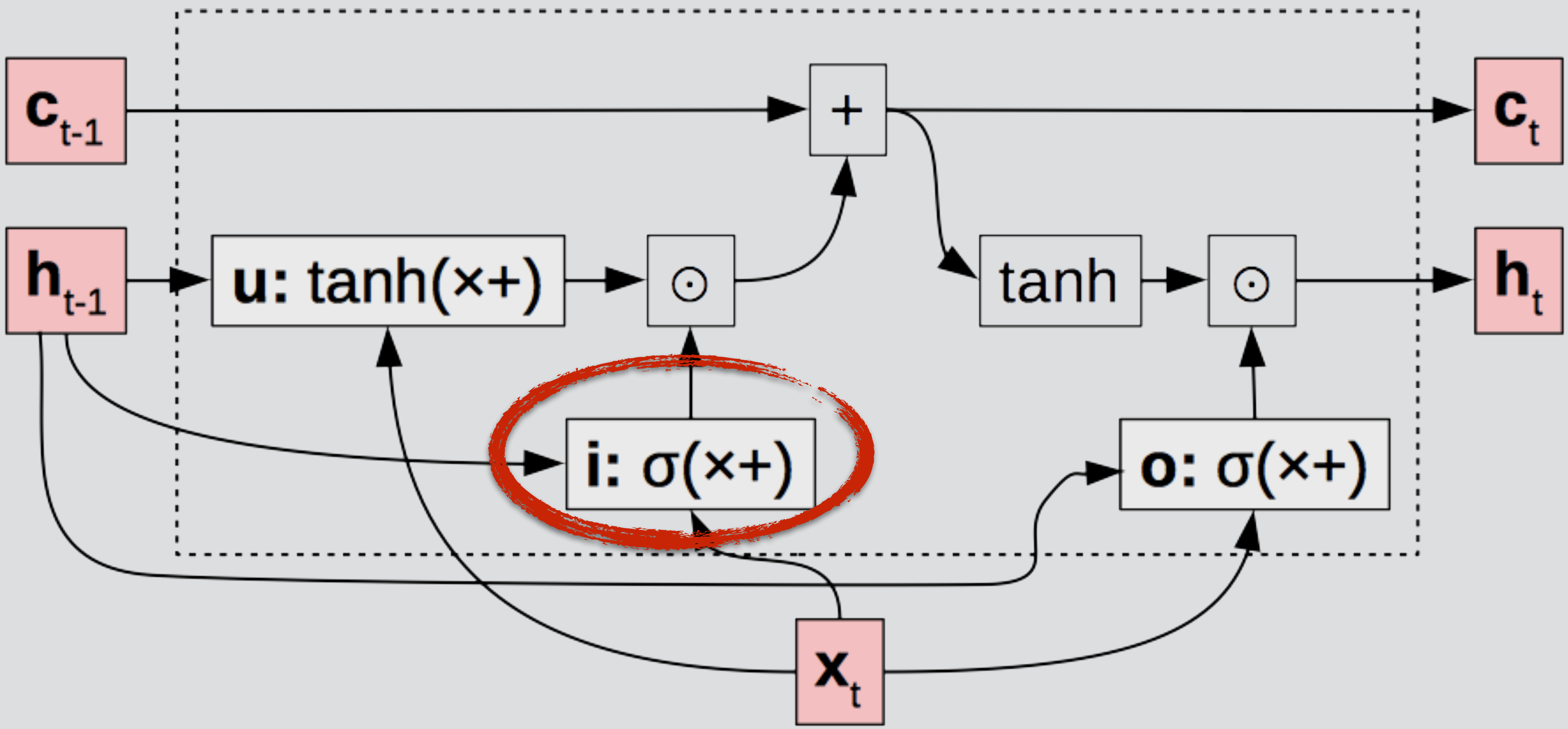

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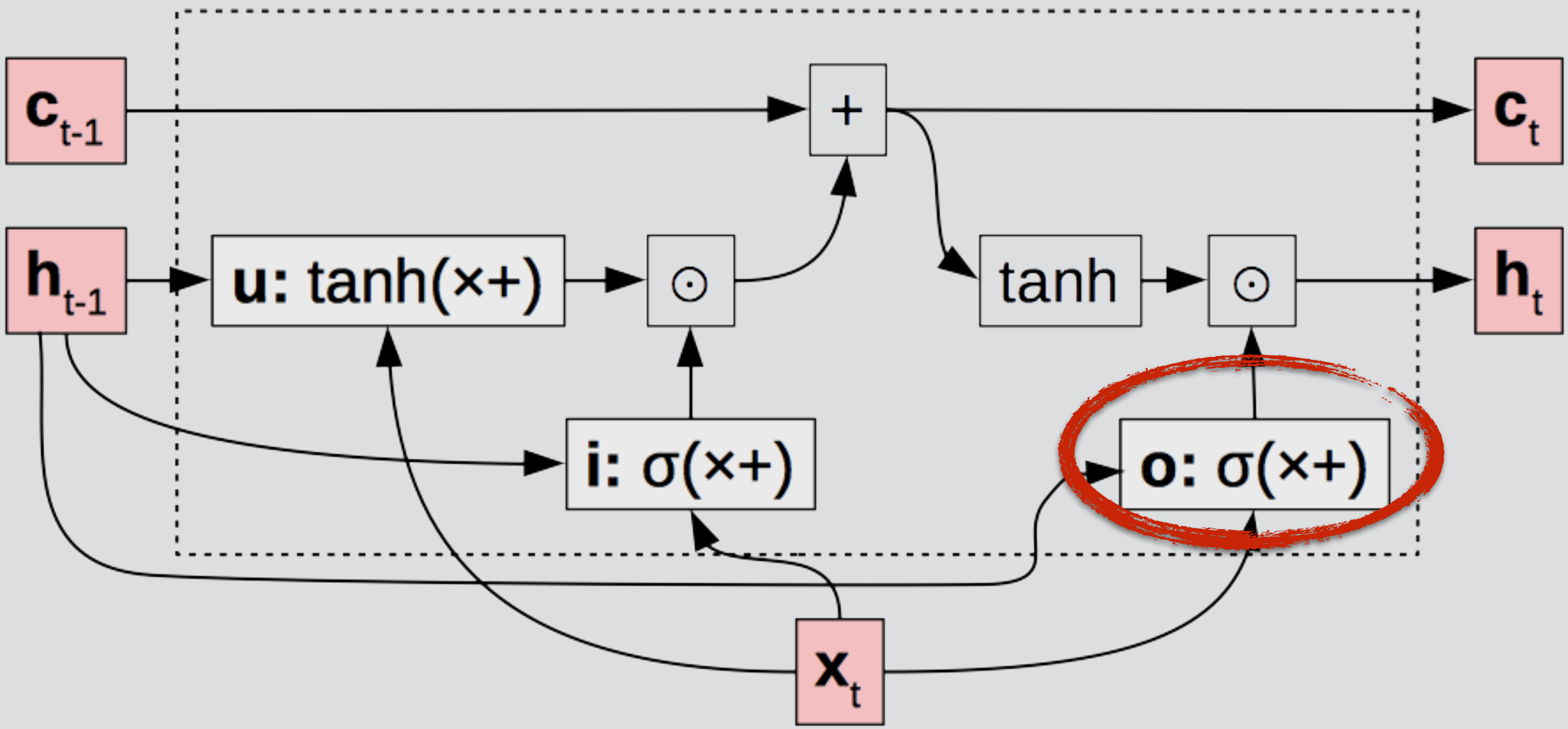

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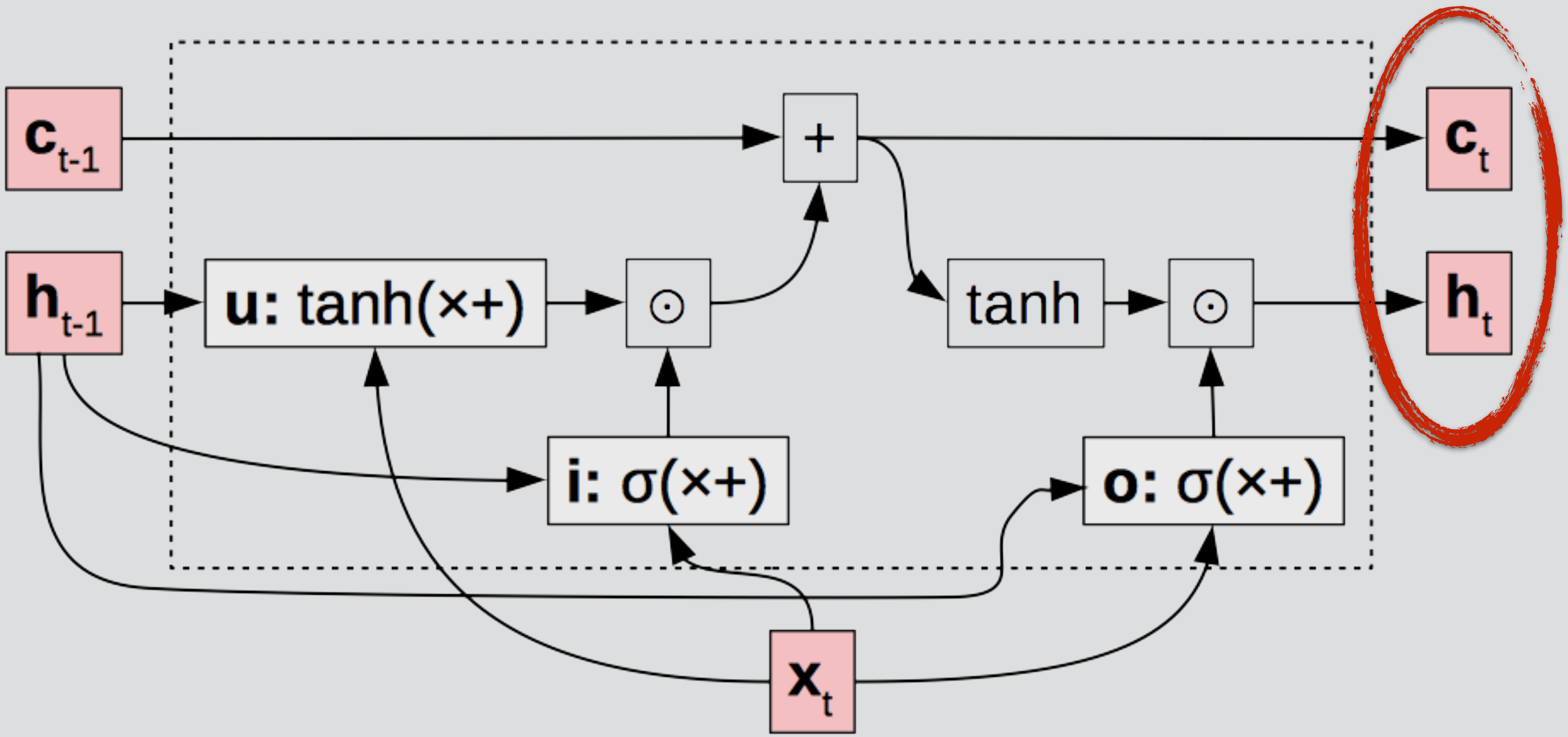

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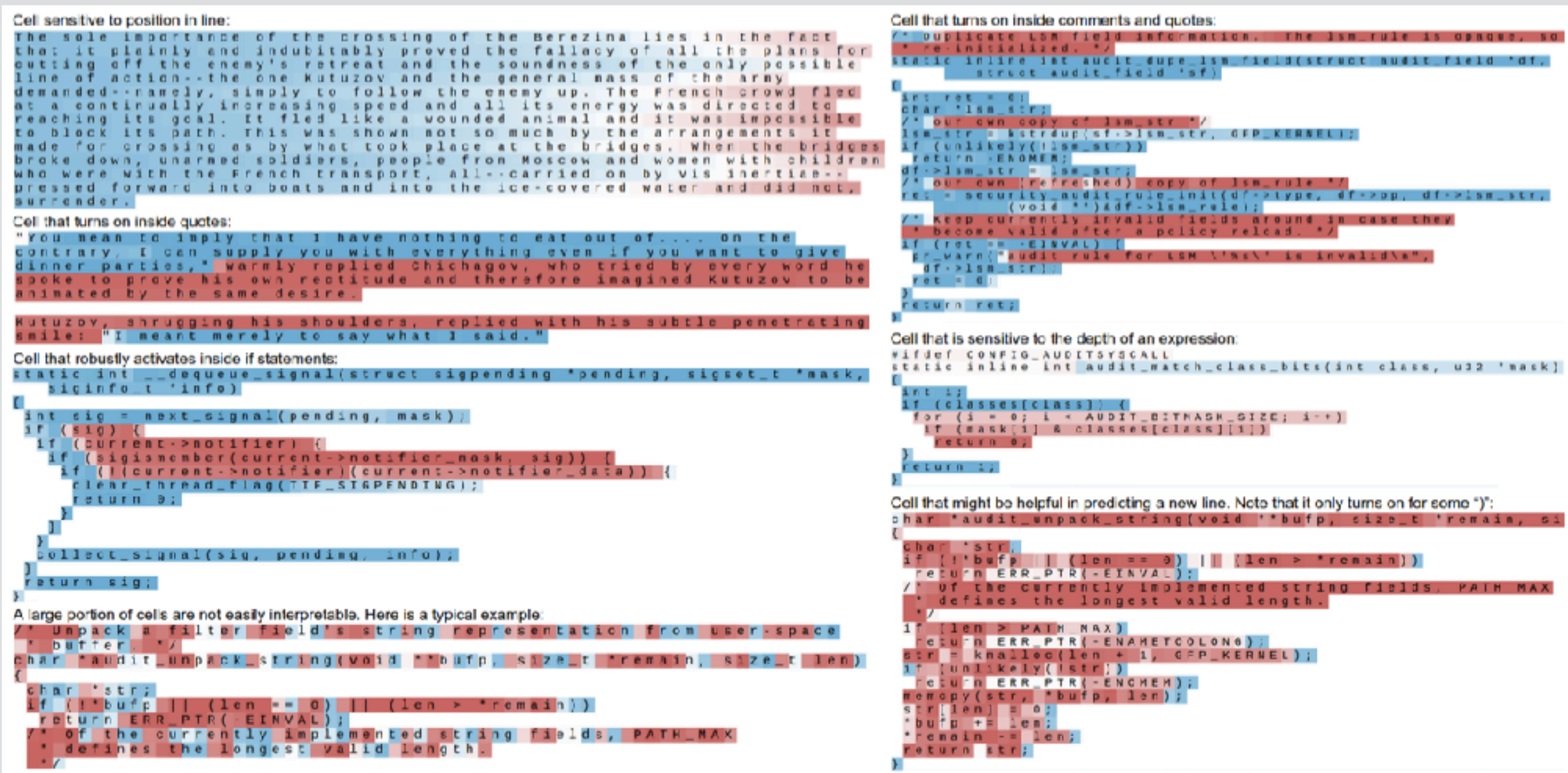
What can LSTMs Learn? (1)

(Karpathy et al. 2015)

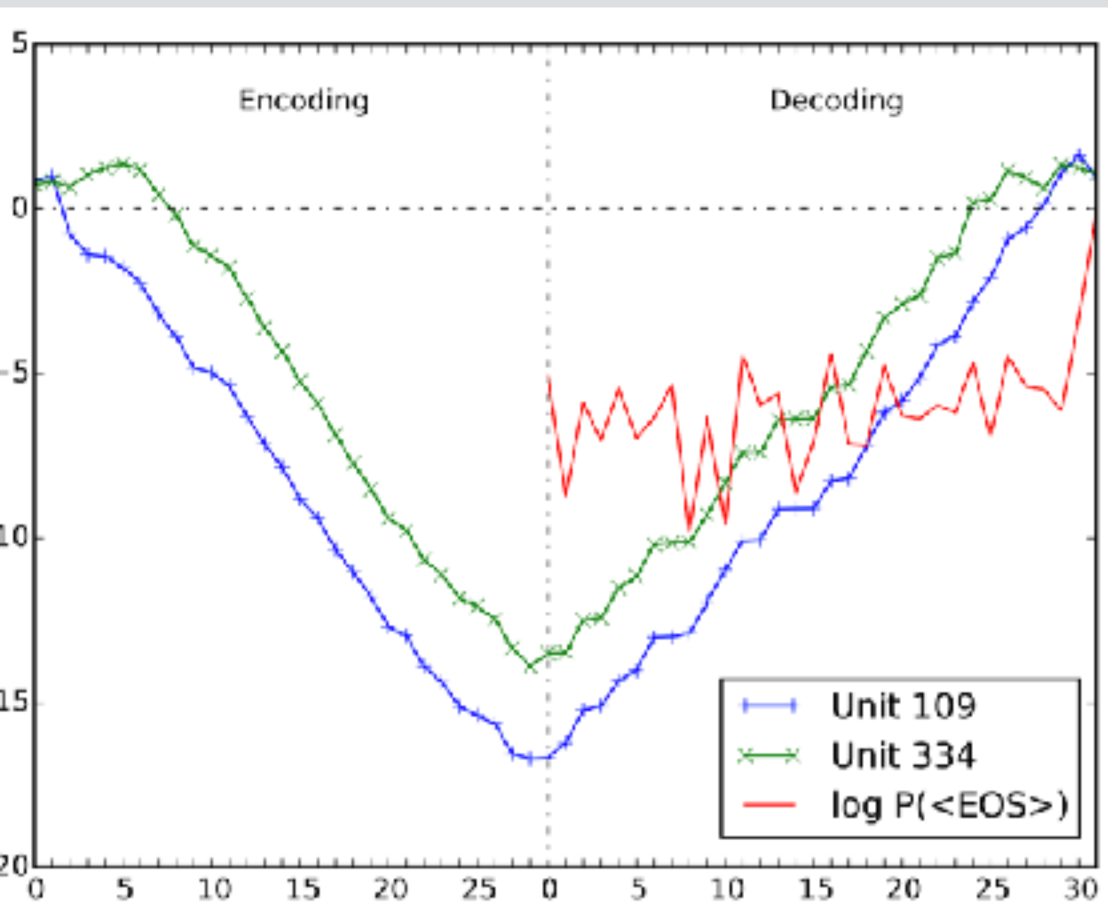
- Additive connections make single nodes surprisingly interpretable



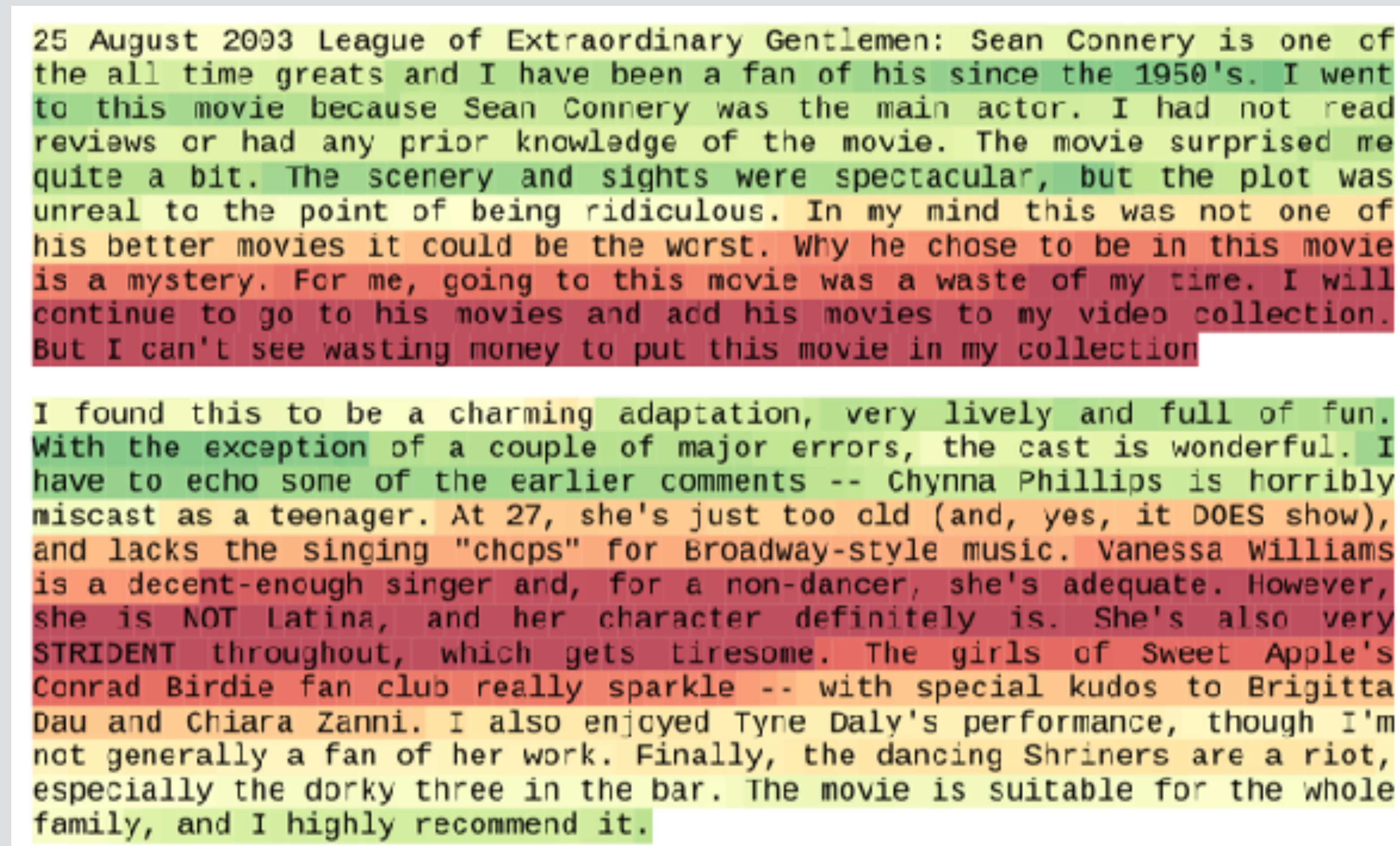
What can LSTMs Learn? (2)

(Shi et al. 2016, Radford et al. 2017)

Count length of sentence



Sentiment



Efficiency Tricks

Handling Mini-batching

- Mini-batching makes things much faster!

Handling Mini-batching

- Mini-batching makes things much faster!
- But mini-batching in RNNs is harder than in feed-forward networks

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

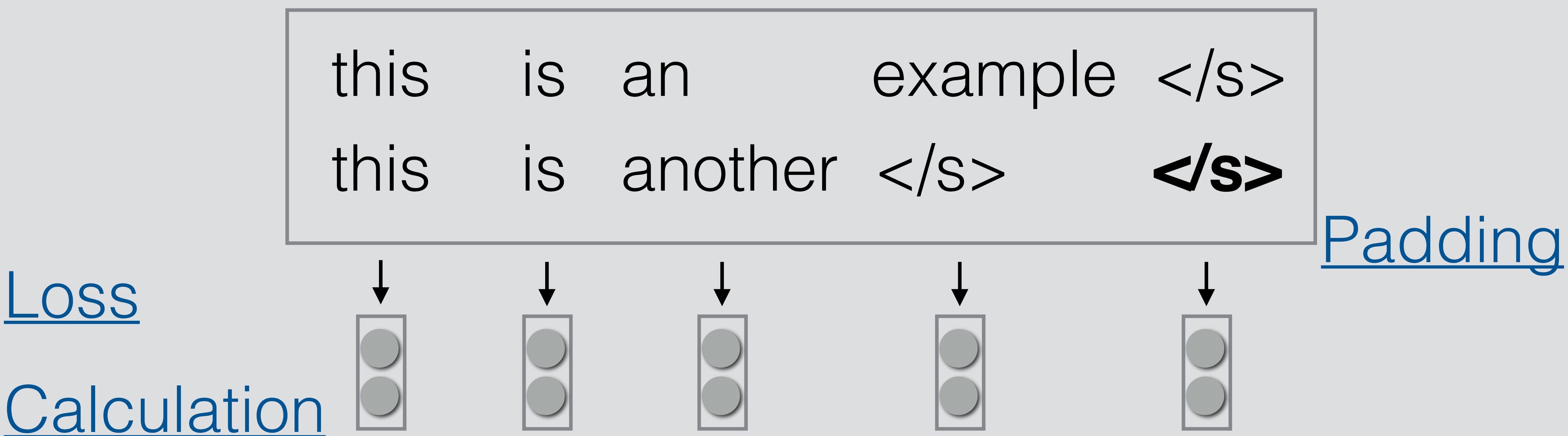
this	is	an	example	</s>
this	is	another	</s>	

Mini-batching Method

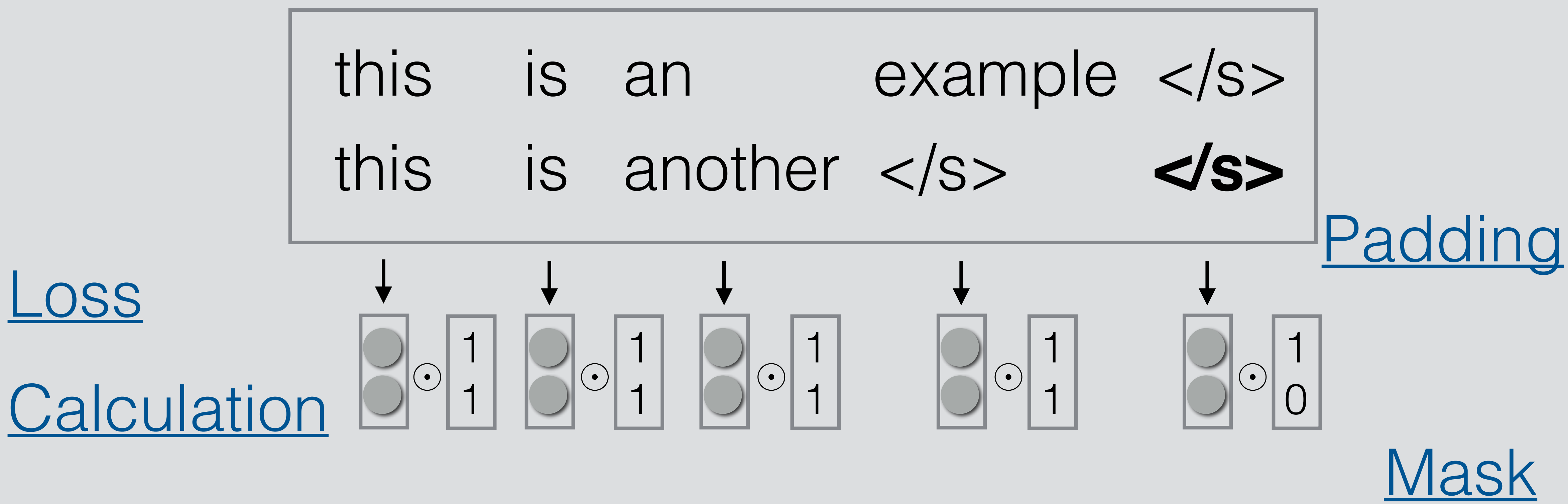
this	is	an	example	</s>
this	is	another	</s>	**</s>**

Padding

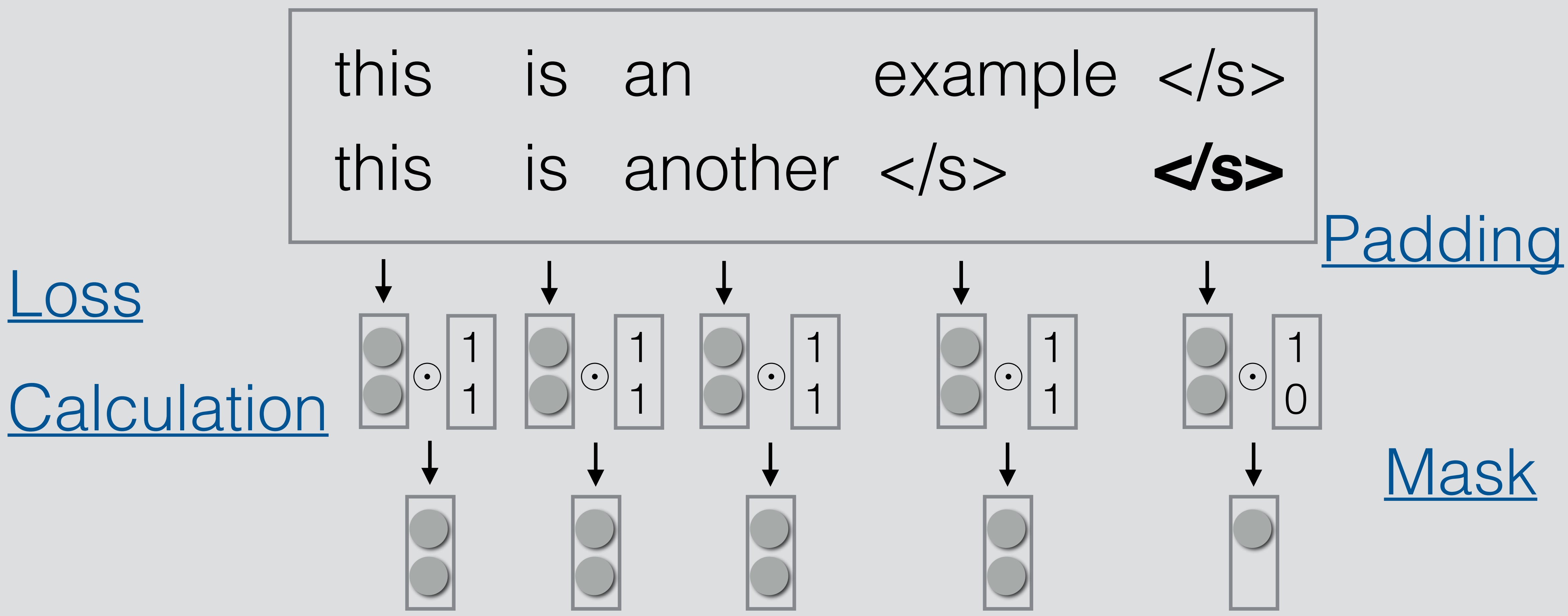
Mini-batching Method



Mini-batching Method



Mini-batching Method



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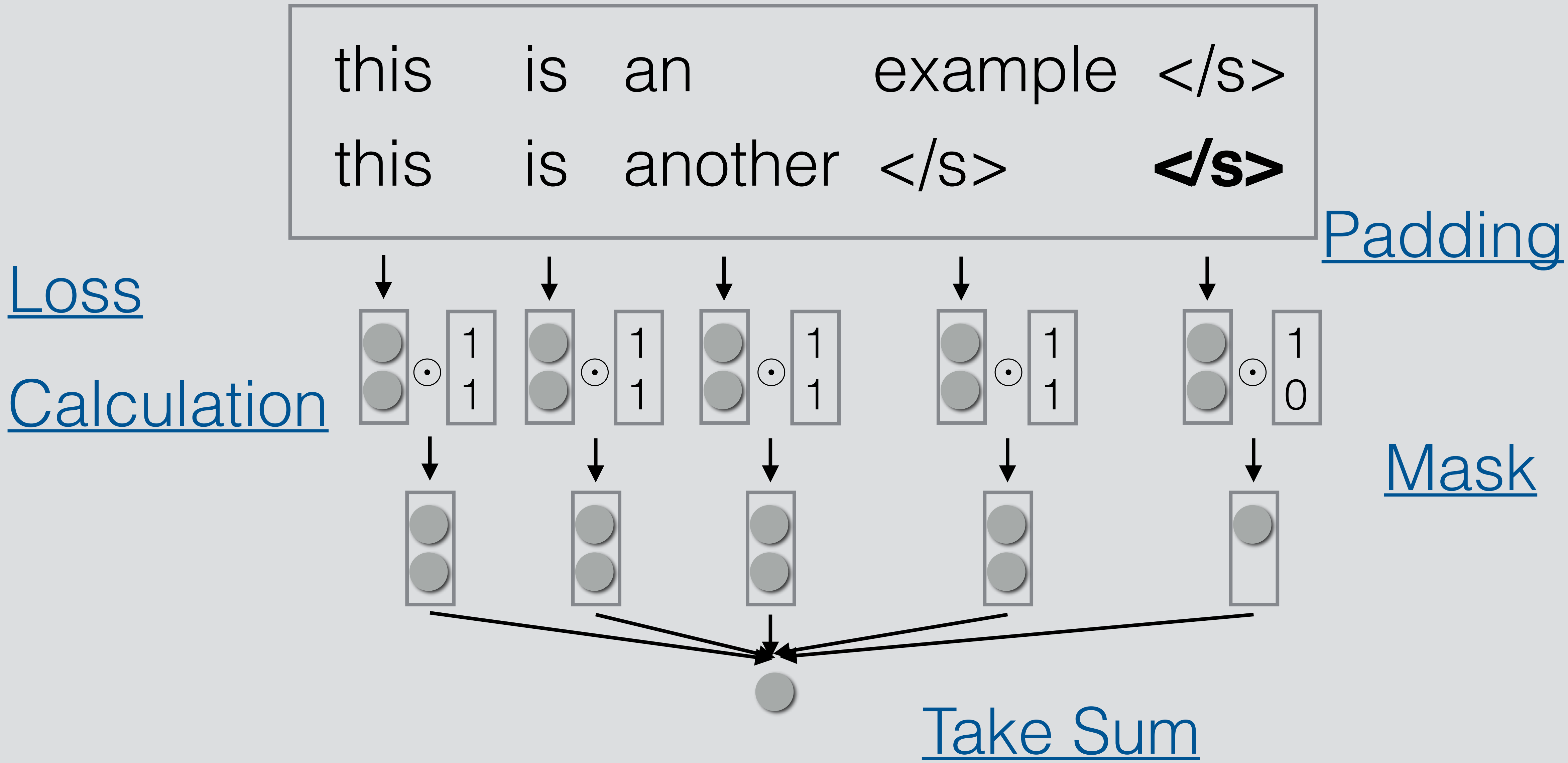

Bucketing/Sorting

- 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

RNN Variants

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(Greffen et al. 2015)

- Gated Recurrent Units
  (GRU; Cho et al 2014)

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- Gated Recurrent Units (GRU; Cho et al 2014)

$$z_t = \sigma_g(W_z x_t + U_z h_{t-1} + b_z)$$

$$r_t = \sigma_g(W_r x_t + U_r h_{t-1} + b_r)$$

$$h_t = \boxed{(1 - z_t)} \circ h_{t-1} + \boxed{z_t} \circ \sigma_h(W_h x_t + U_h(r_t \circ h_{t-1}) + b_h)$$

Additive or Non-linear

RNN Variants
(Greffen et al. 2015)

- Gated Recurrent Units
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Additive or Non-linear

- **Note:** GRUs cannot do things like simply count

RNN Variants
(Greffen et al. 2015)

- Gated Recurrent Units (GRU; Cho et al 2014)
- Many different types of architectures tested for LSTMs (Greffen et al. 2015)

NIG: No Input Gate: $\mathbf{i}^t = \mathbf{1}$
NFG: No Forget Gate: $\mathbf{f}^t = \mathbf{1}$
NOG: No Output Gate: $\mathbf{o}^t = \mathbf{1}$
NIAF: No Input Activation Function: $g(\mathbf{x}) = \mathbf{x}$
NOAF: No Output Activation Function: $h(\mathbf{x}) = \mathbf{x}$
CIFG: Coupled Input and Forget Gate: $\mathbf{f}^t = \mathbf{1} - \mathbf{i}^t$
NP: No Peepholes:

$$\begin{aligned}
\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} + \mathbf{b}_i \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} + \mathbf{b}_f \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} + \mathbf{b}_o
\end{aligned}$$

FGR: Full Gate Recurrence:

$$\begin{aligned}
\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} + \mathbf{p}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i \\
&\quad + \mathbf{R}_{ii}\mathbf{i}^{t-1} + \mathbf{R}_{fi}\mathbf{f}^{t-1} + \mathbf{R}_{oi}\mathbf{o}^{t-1} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} + \mathbf{p}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f \\
&\quad + \mathbf{R}_{if}\mathbf{i}^{t-1} + \mathbf{R}_{ff}\mathbf{f}^{t-1} + \mathbf{R}_{of}\mathbf{o}^{t-1} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} + \mathbf{p}_o \odot \mathbf{c}^{t-1} + \mathbf{b}_o \\
&\quad + \mathbf{R}_{io}\mathbf{i}^{t-1} + \mathbf{R}_{fo}\mathbf{f}^{t-1} + \mathbf{R}_{oo}\mathbf{o}^{t-1}
\end{aligned}$$

RNN Variants

(Greffen et al. 2015)

- Gated Recurrent Units (GRU; Cho et al 2014)
- Many different types of architectures tested for LSTMs (Greffen et al. 2015)
- **Conclusion:** basic LSTM quite good, other variants (e.g. coupled input/forget gates) reasonable

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NFG: No Forget Gate: $\mathbf{f}^t = \mathbf{1}$
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\bar{\mathbf{o}}^t &= \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} + \mathbf{b}_o
\end{aligned}
$$

FGR: Full Gate Recurrence:

$$
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\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} + \mathbf{p}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i \\
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\bar{\mathbf{f}}^t &= \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} + \mathbf{p}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f \\
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&\quad + \mathbf{R}_{io}\mathbf{i}^{t-1} + \mathbf{R}_{fo}\mathbf{f}^{t-1} + \mathbf{R}_{oo}\mathbf{o}^{t-1}
\end{aligned}
$$

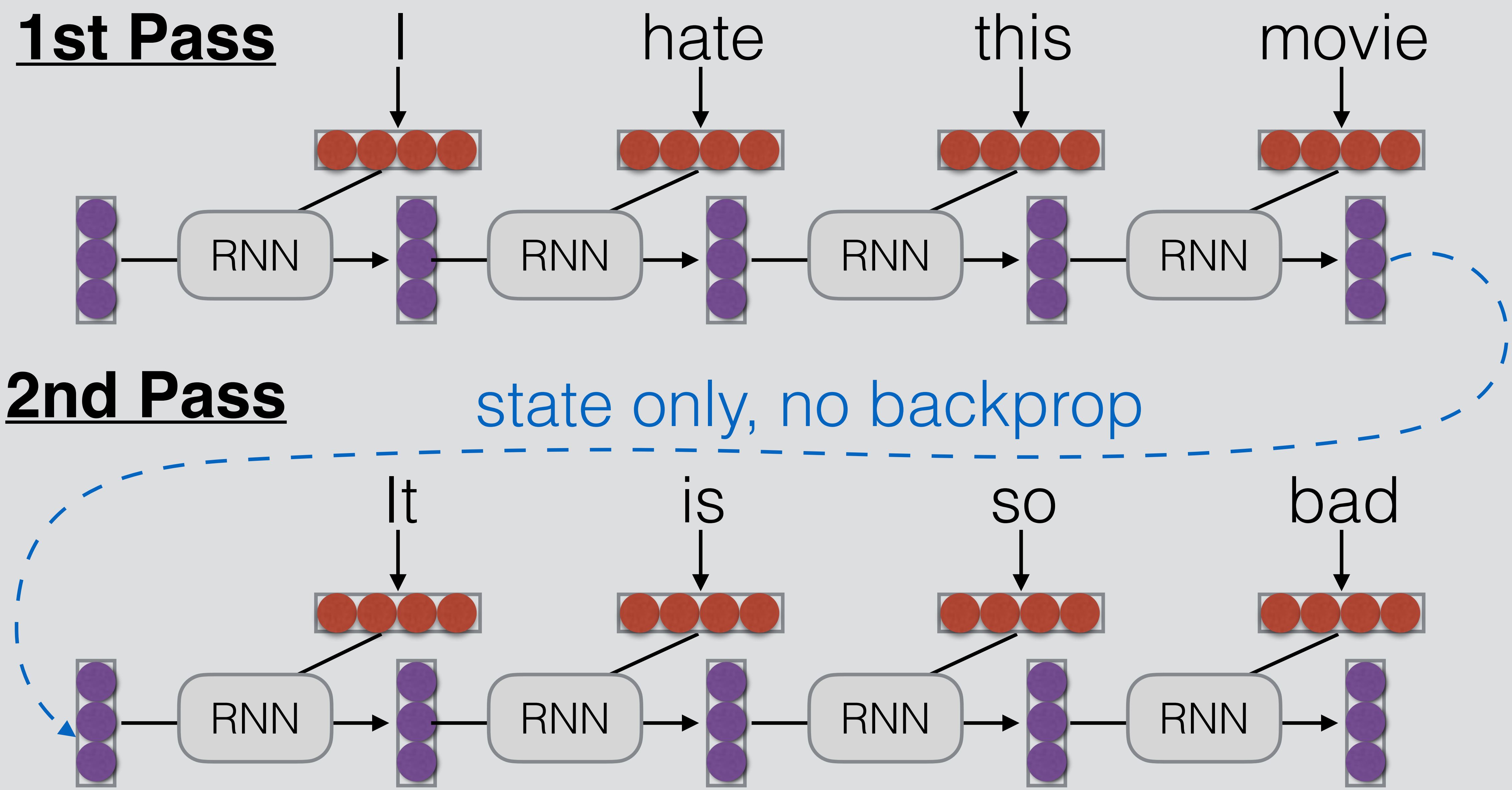
Handling Long Sequences

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



Questions?
(see extra slides)

Simple Implementation of RNNs (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`