

Lecture 8: RNNs

Alan Ritter

(many slides from Greg Durrett)

Recall: Training Tips

Recall: Training Tips

- ▶ Parameter initialization is critical to get good gradients, some useful heuristics (e.g., Xavier initializer)

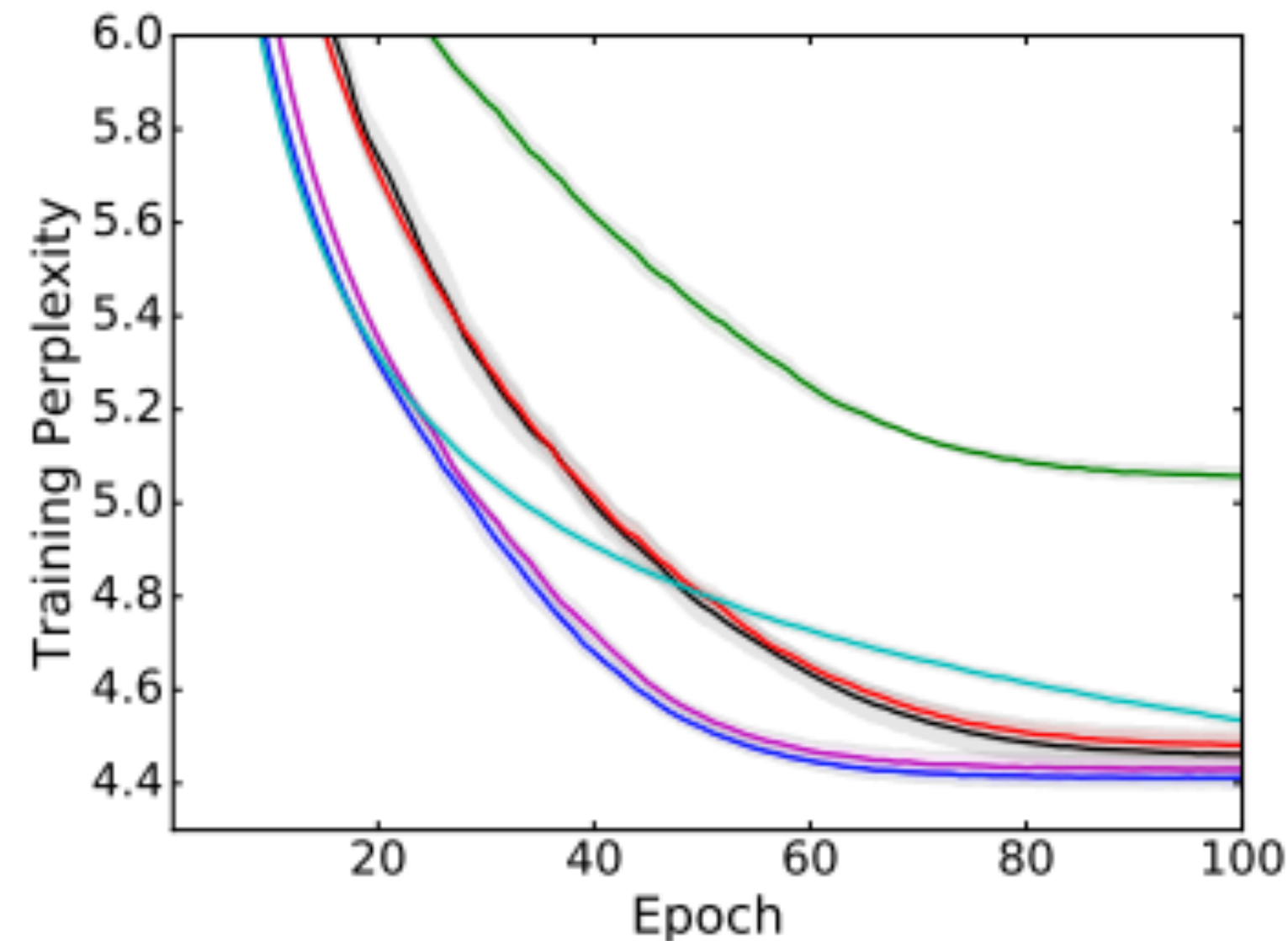
Recall: Training Tips

- ▶ Parameter initialization is critical to get good gradients, some useful heuristics (e.g., Xavier initializer)
- ▶ Dropout is an effective regularizer

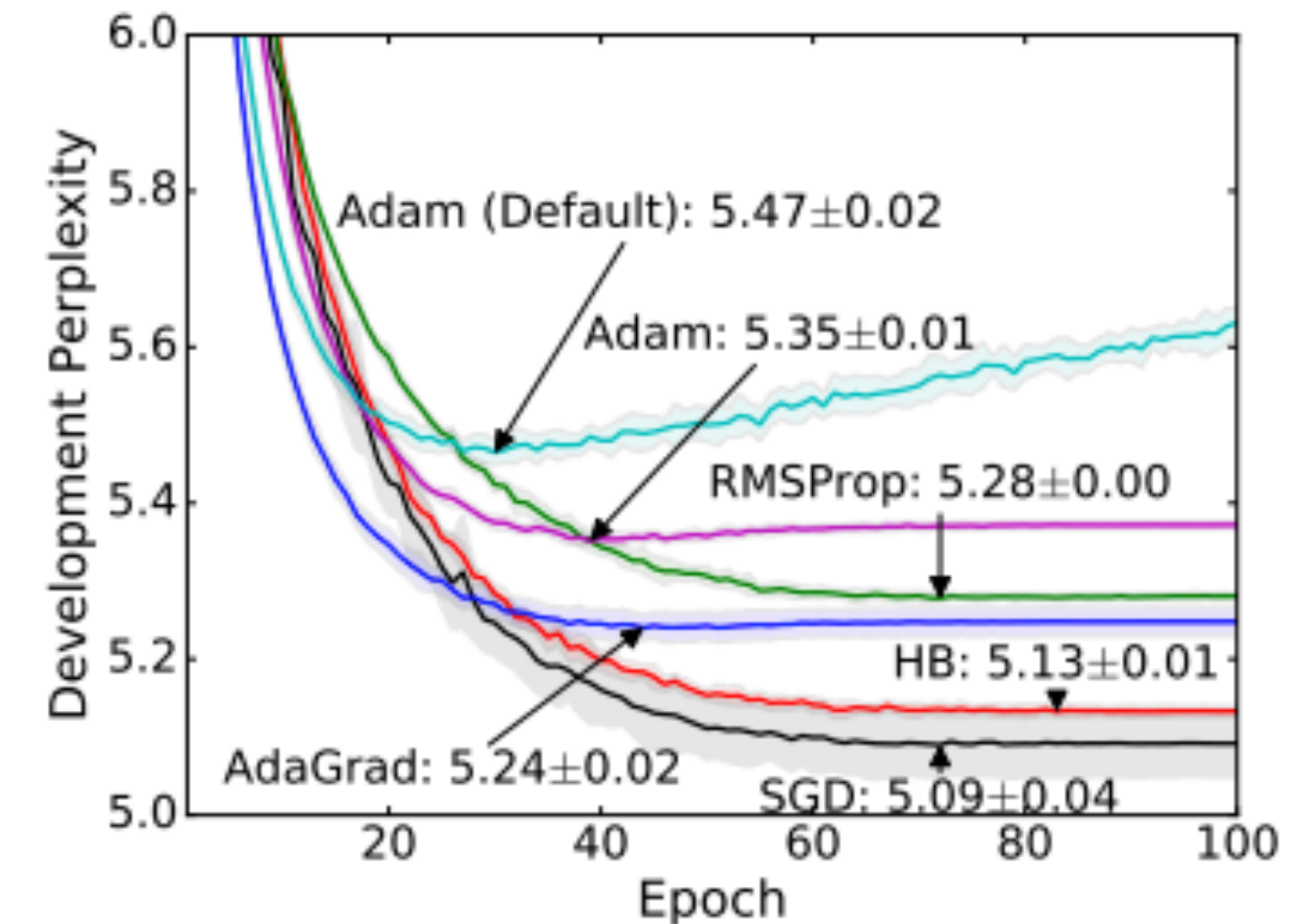
Recall: Training Tips

- ▶ Parameter initialization is critical to get good gradients, some useful heuristics (e.g., Xavier initializer)
- ▶ Dropout is an effective regularizer

- ▶ Think about your optimizer: Adam or tuned SGD work well



(e) Generative Parsing (Training Set)



(f) Generative Parsing (Development Set)

Recall: Word Vectors

◆ *the president said that the downturn was over* ◆

| | |
|------------------|--------------------------|
| <i>president</i> | <i>the __ of</i> |
| <i>president</i> | <i>the __ said</i> ← |
| <i>governor</i> | <i>the __ of</i> |
| <i>governor</i> | <i>the __ appointed</i> |
| <i>said</i> | <i>sources __</i> ◆ |
| <i>said</i> | <i>president __ that</i> |
| <i>reported</i> | <i>sources __</i> ◆ |

president
governor

the
a

said
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[Finch and Chater 92, Shuetze 93, many others]

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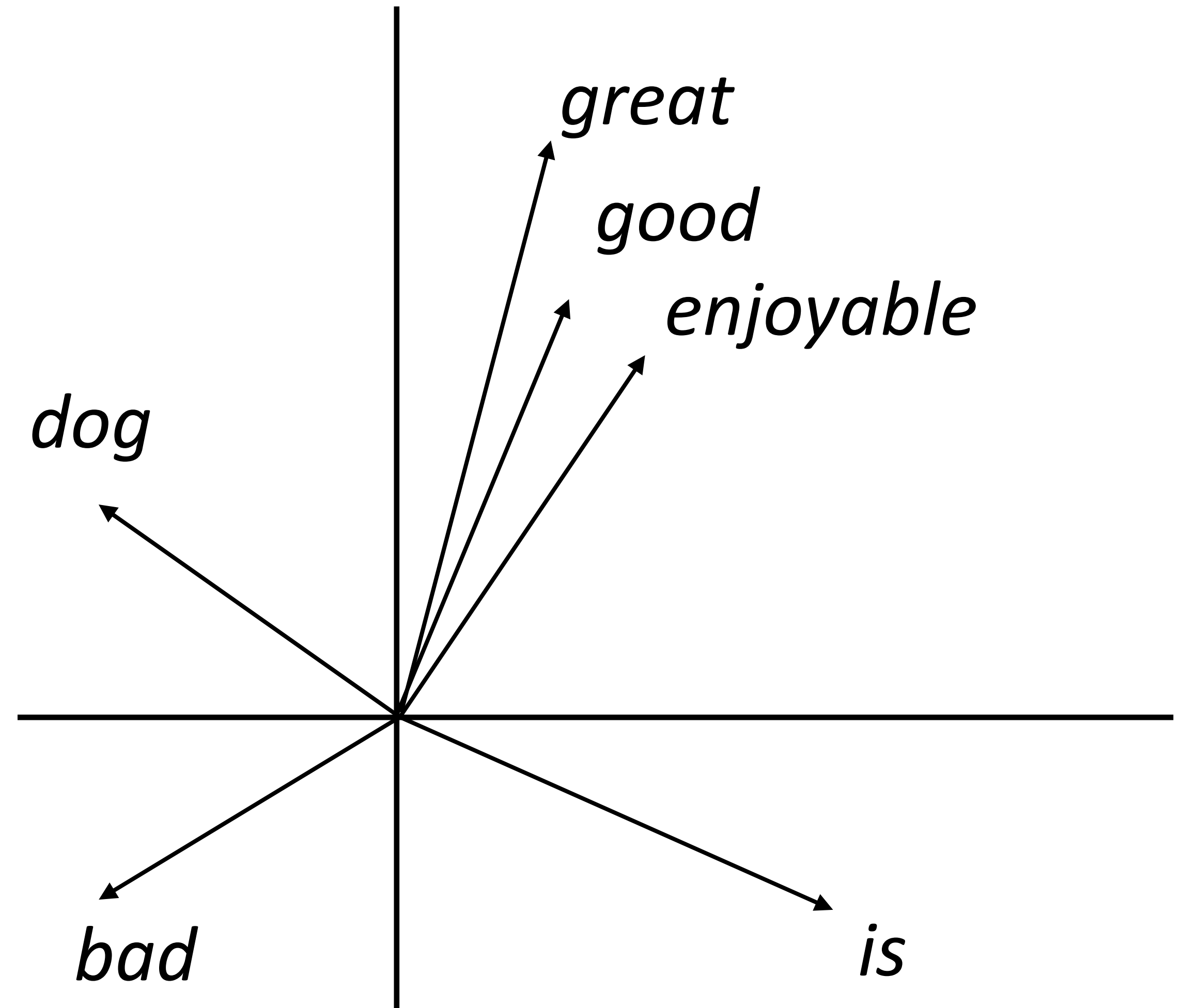
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Recall: Continuous Bag-of-Words

- ▶ Predict word from context

the dog bit the man



Mikolov et al. (2013)


Recall: Continuous Bag-of-Words

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the dog bit the man

The diagram shows the sentence "the dog bit the man" in an italicized font. The word "bit" is highlighted with a solid blue rounded rectangle. A dashed black rectangle encloses the words "dog", "bit", and "the", representing the context used for prediction.

Mikolov et al. (2013)



dog



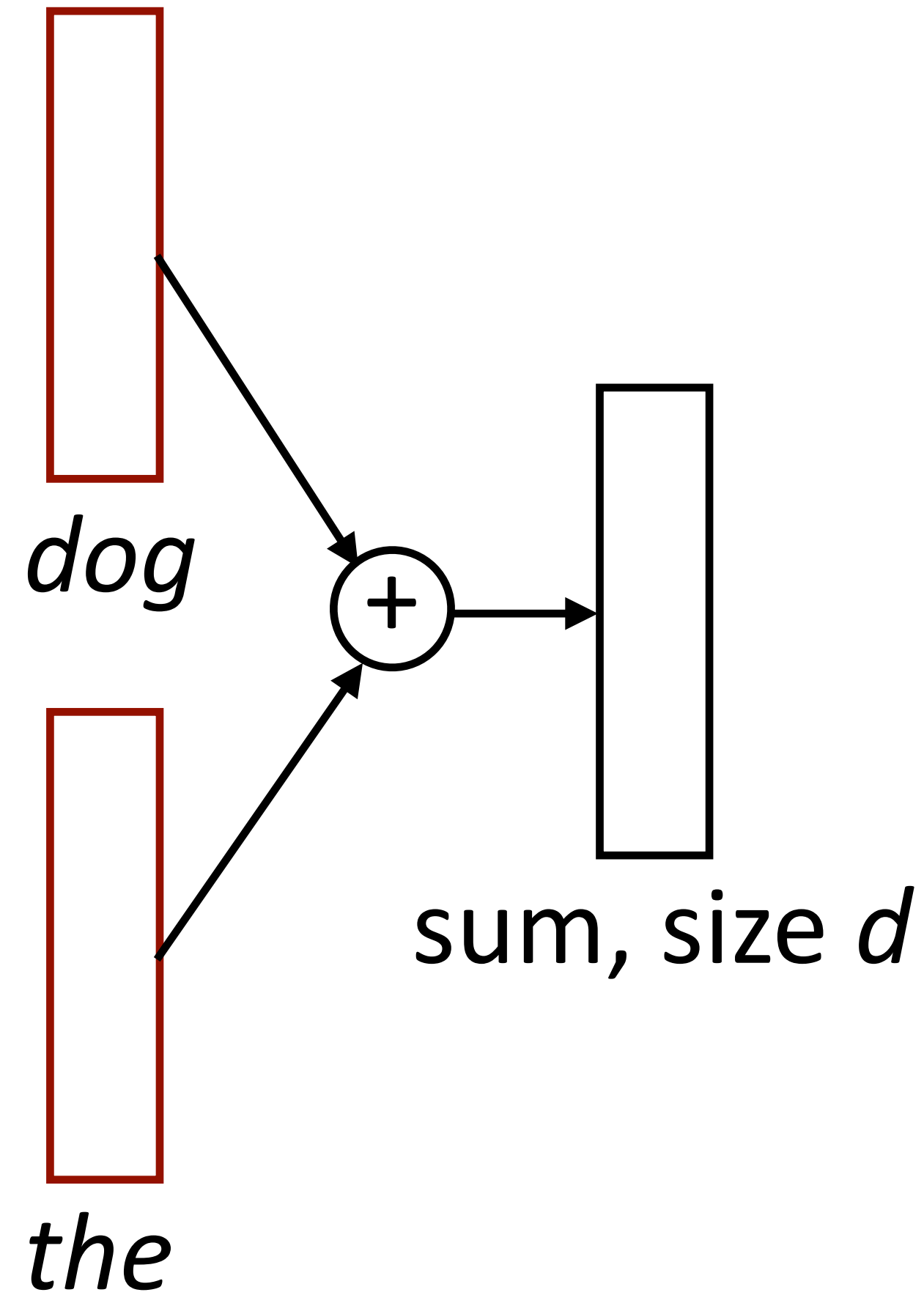
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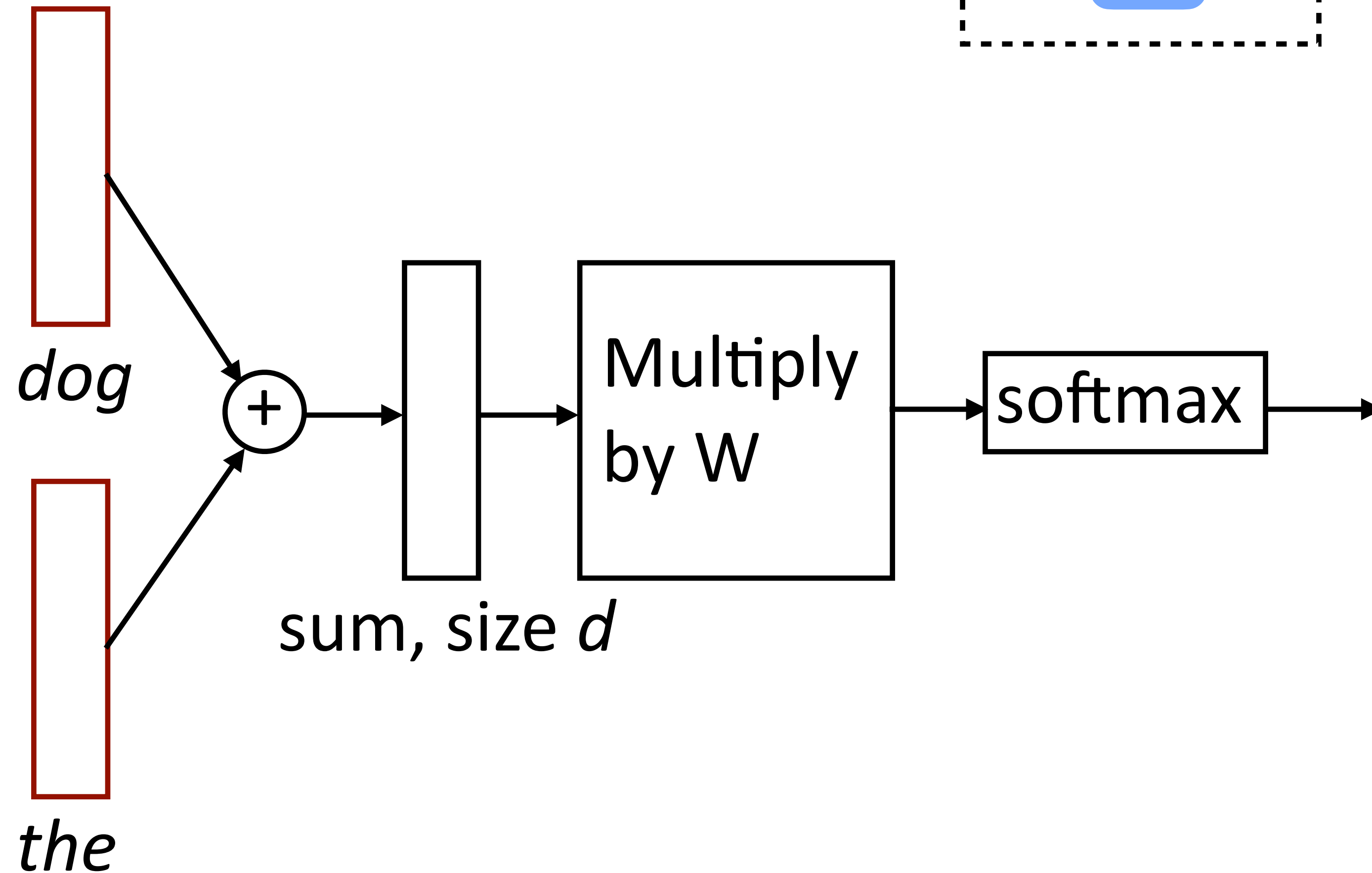


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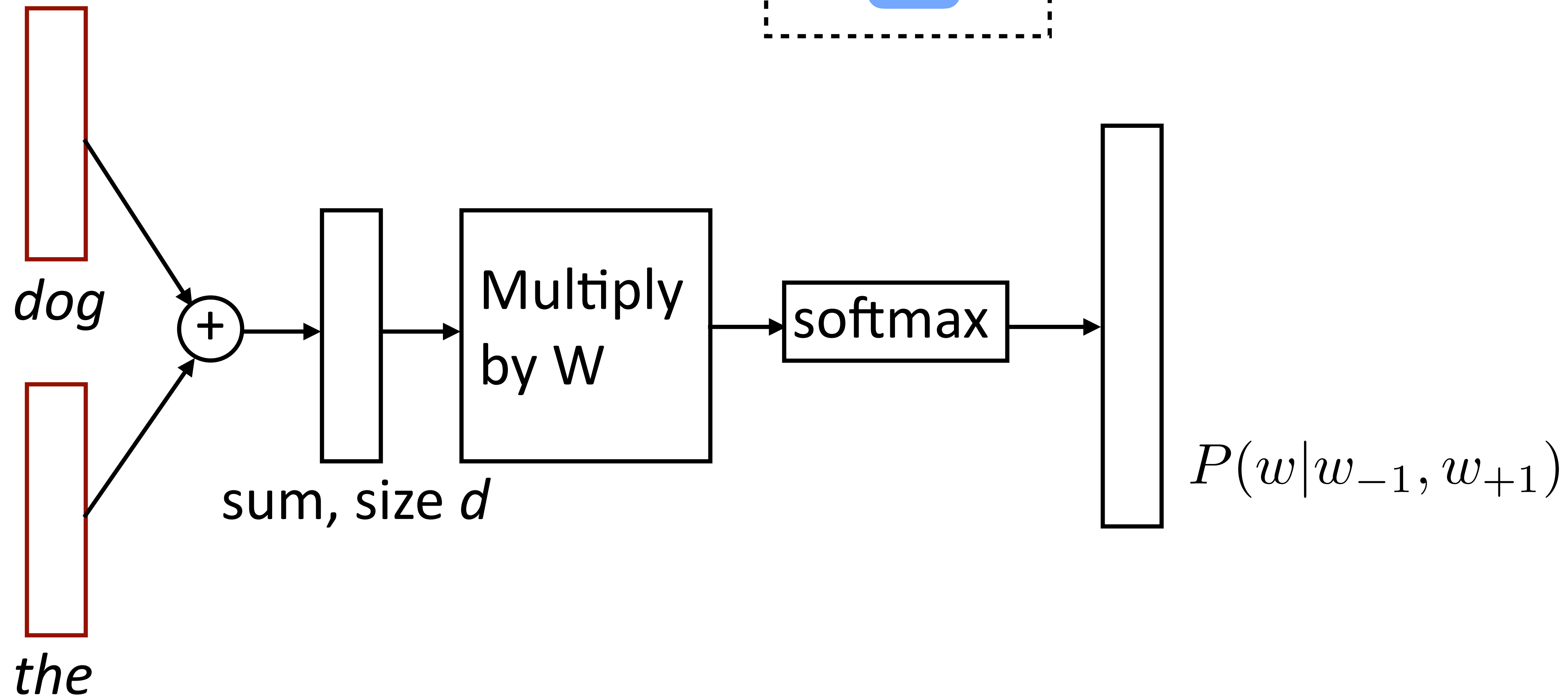


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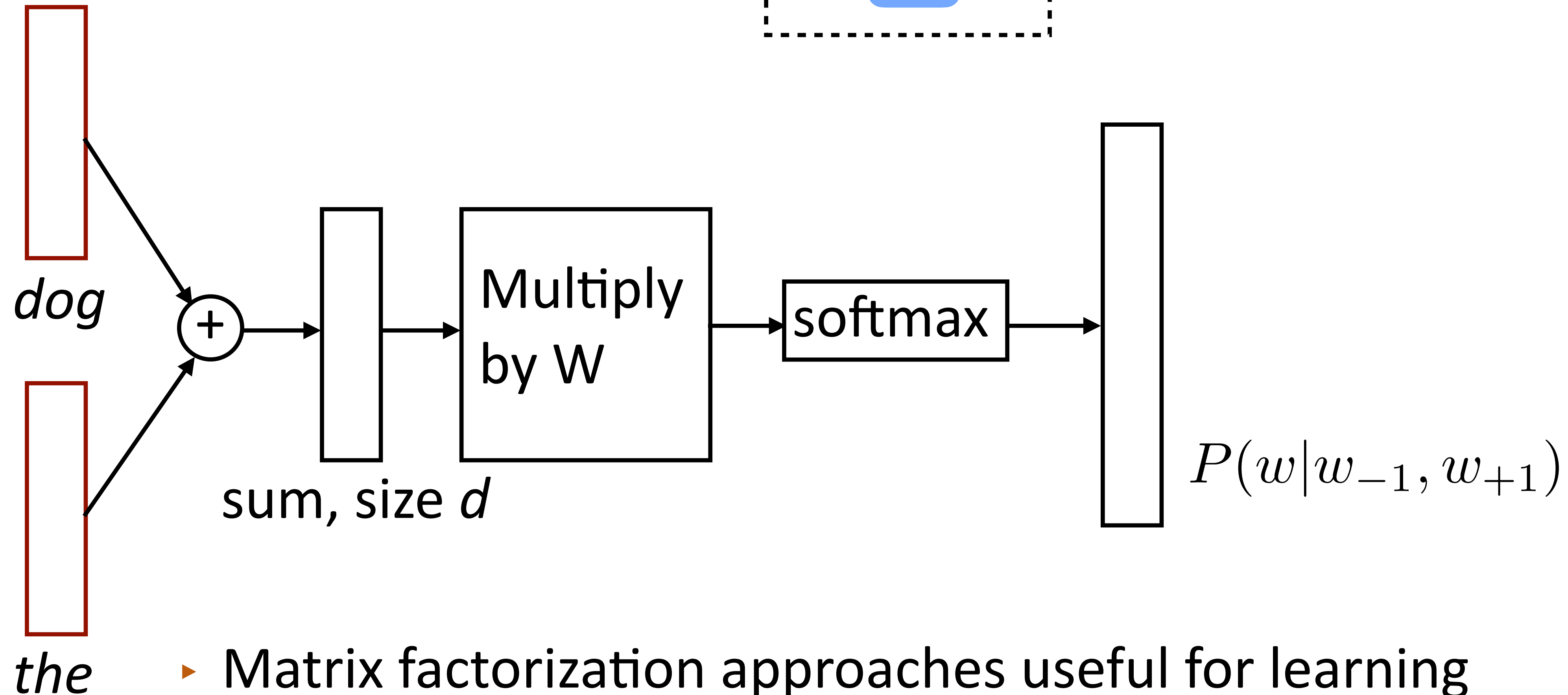


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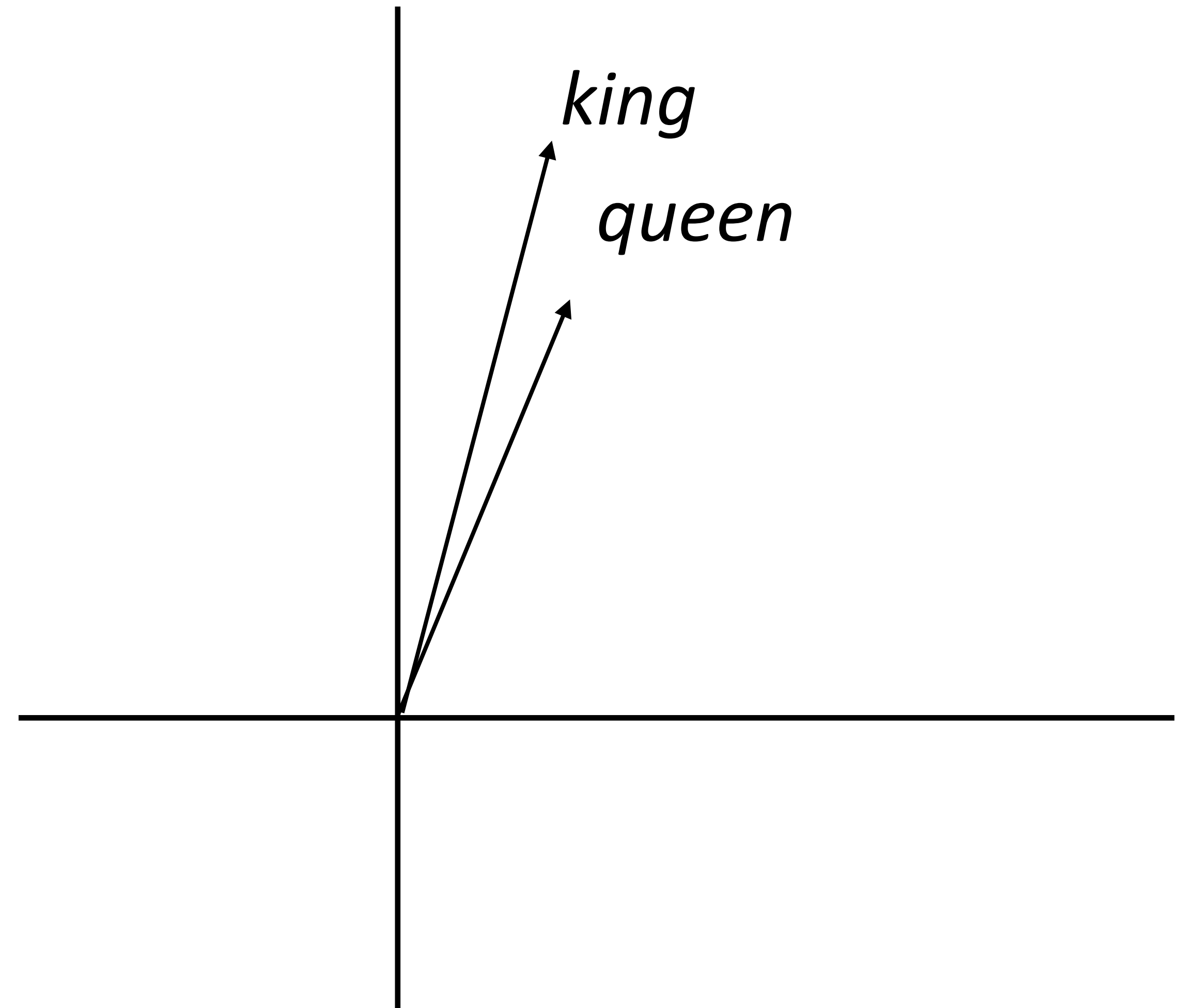
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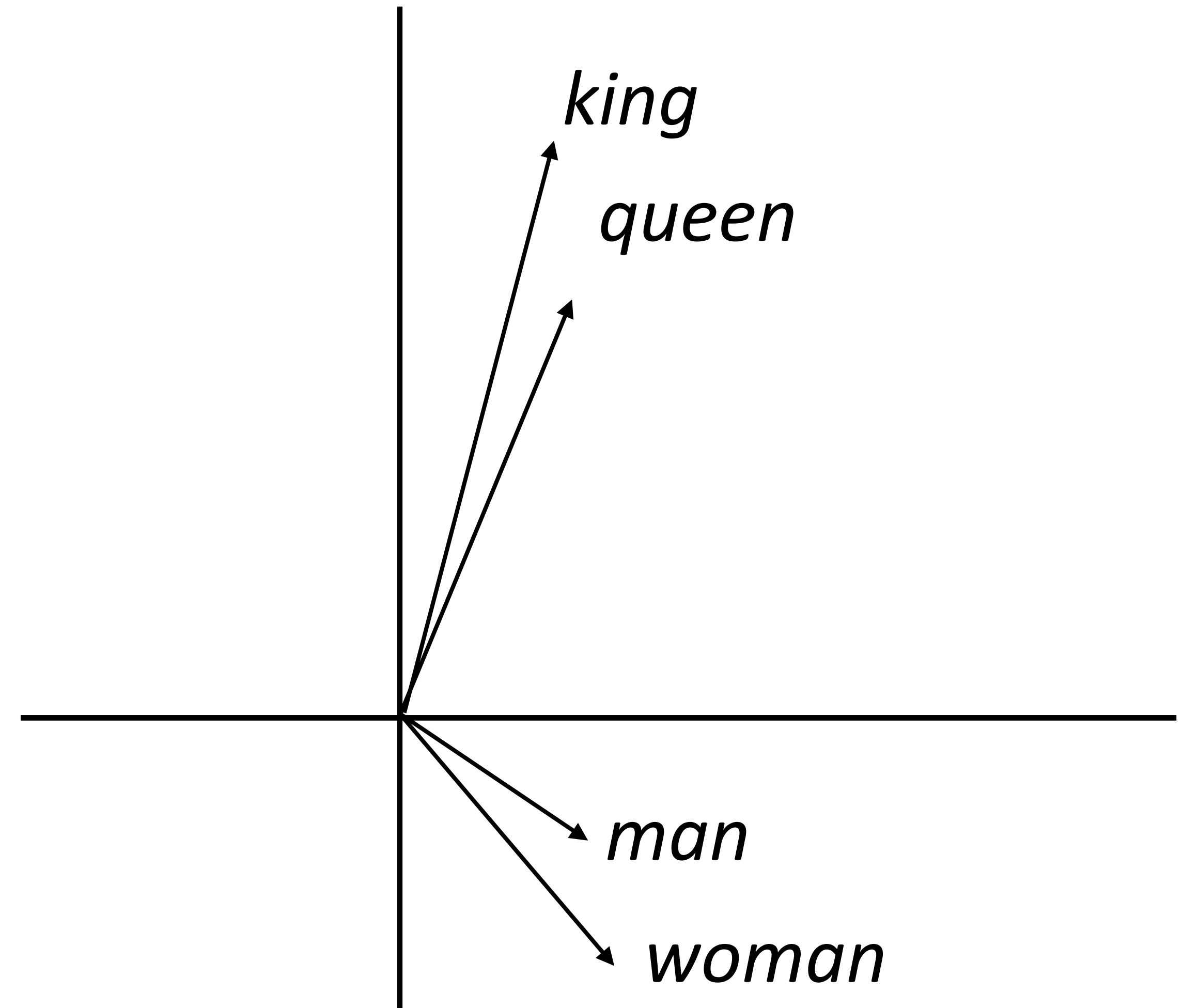


- ▶ Matrix factorization approaches useful for learning vectors from really large data

Analogies

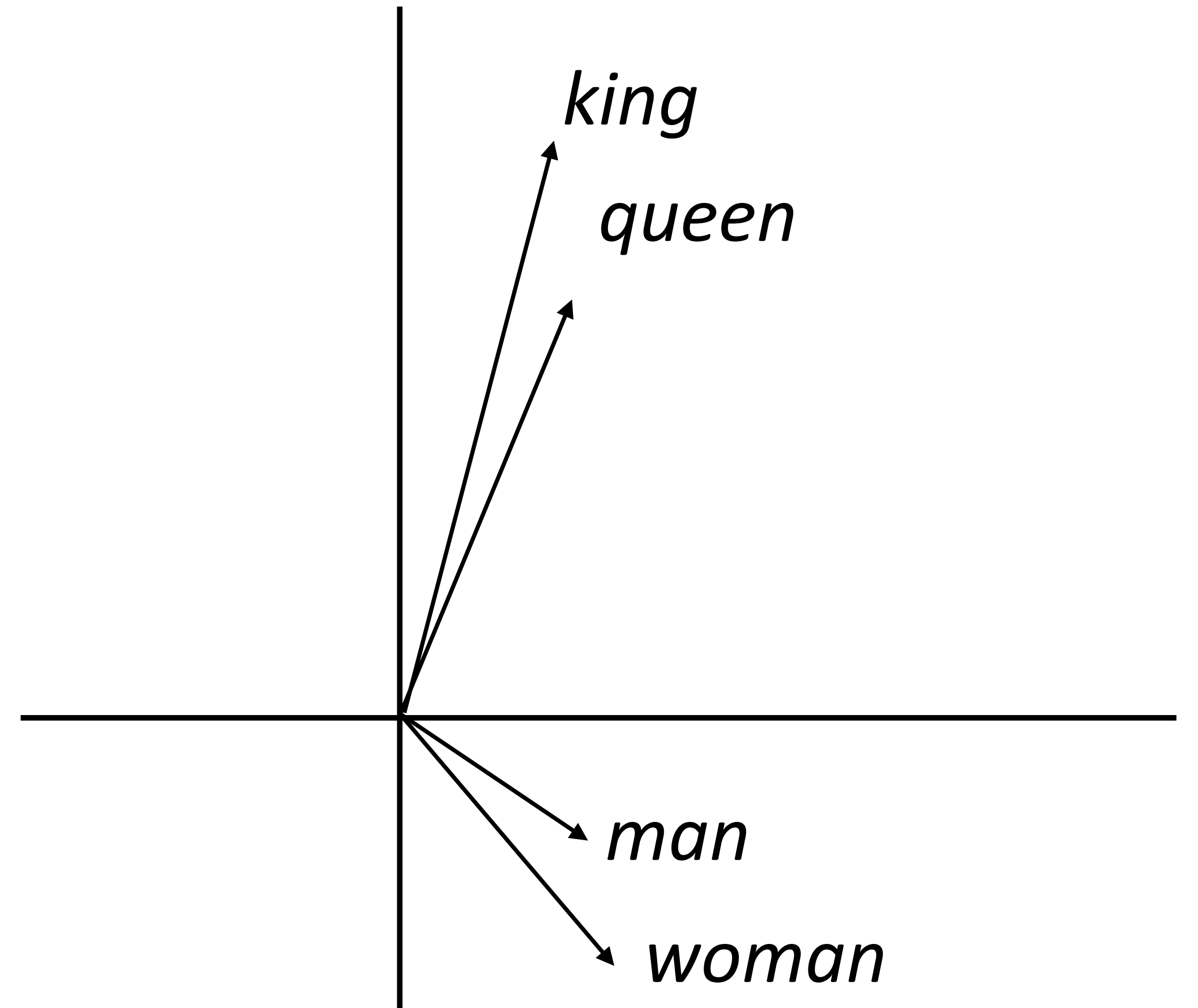


Analogies



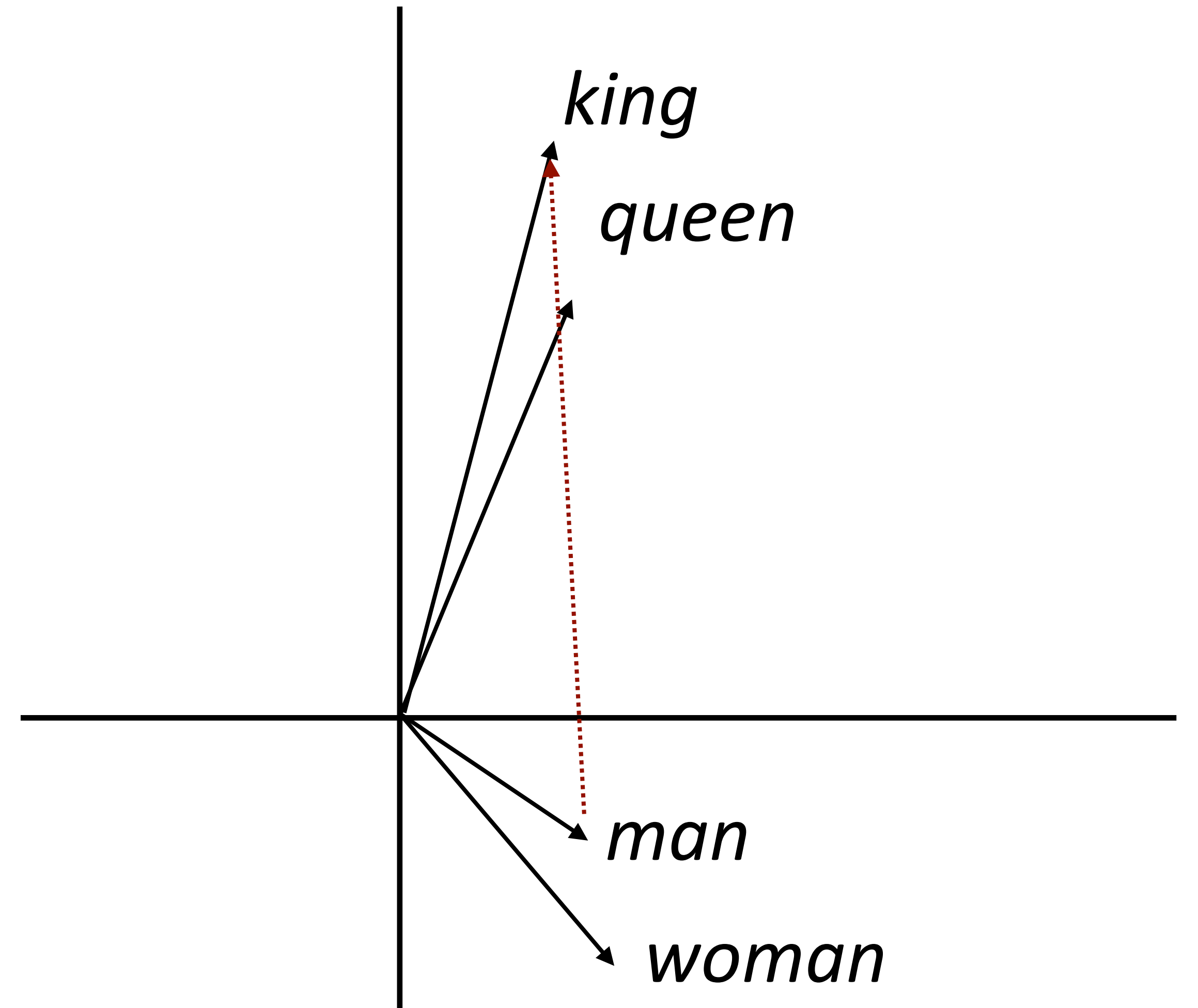
Analogies

(king - man) + woman = queen



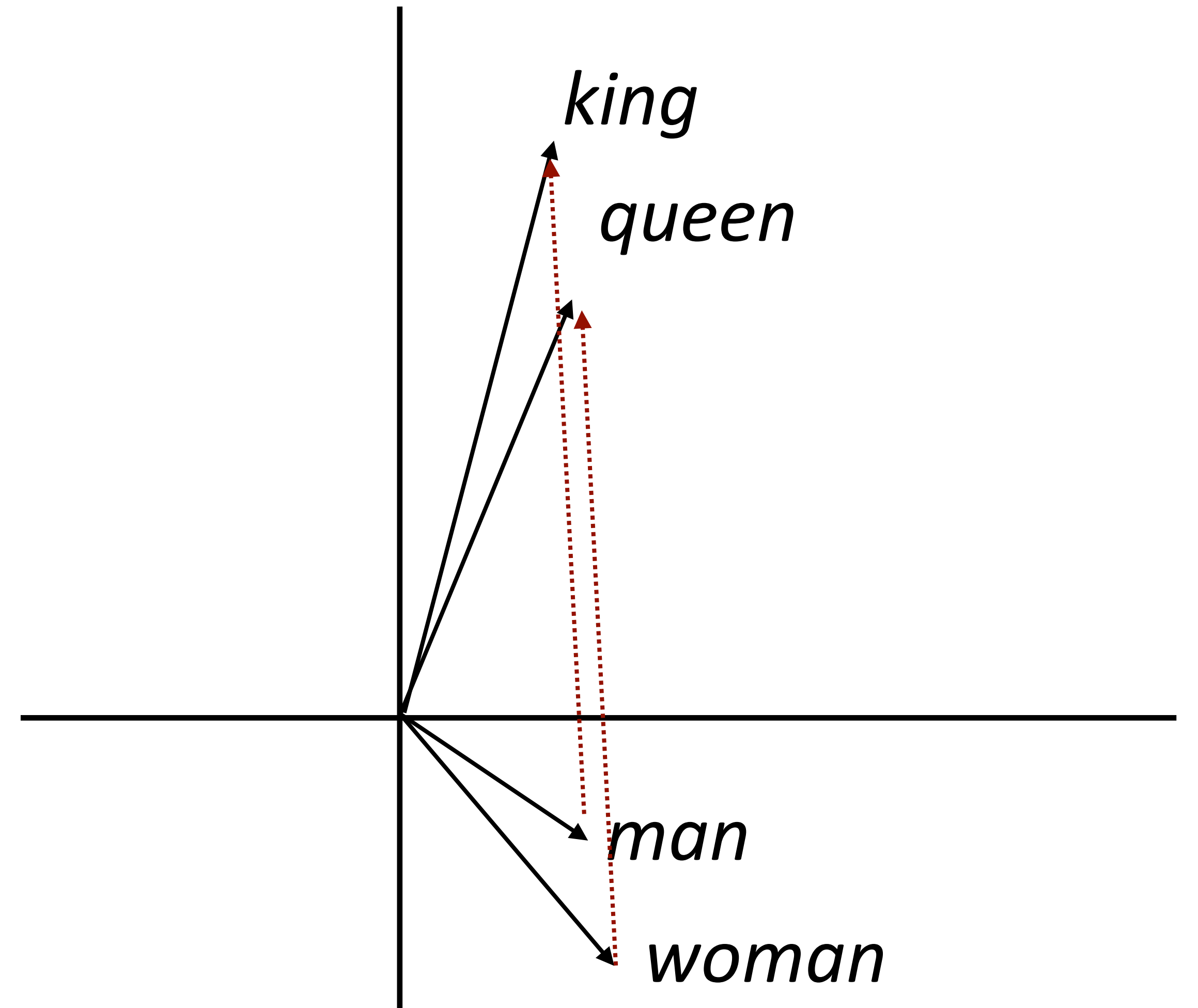
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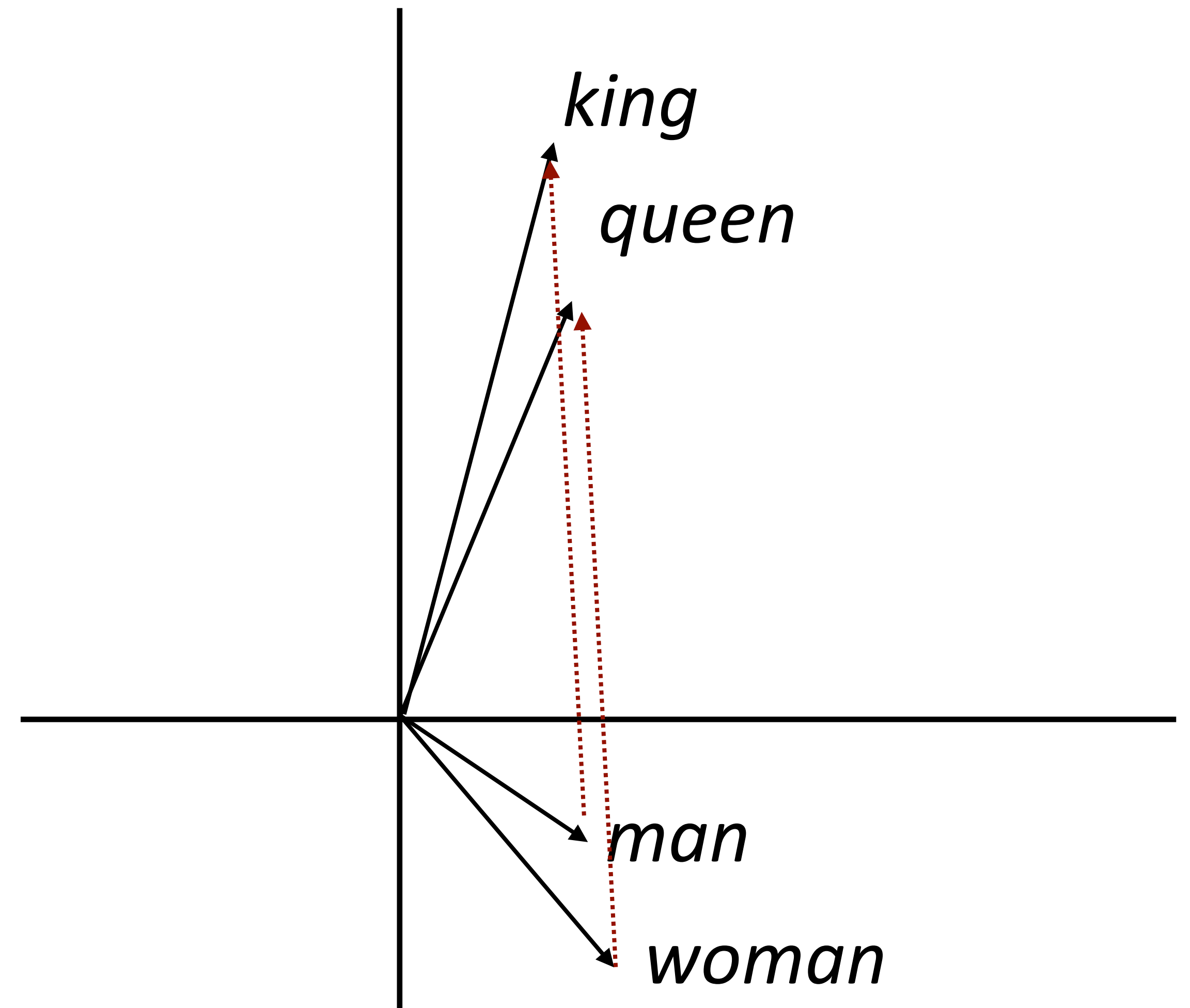
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Analogies

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$king + (woman - man) = queen$

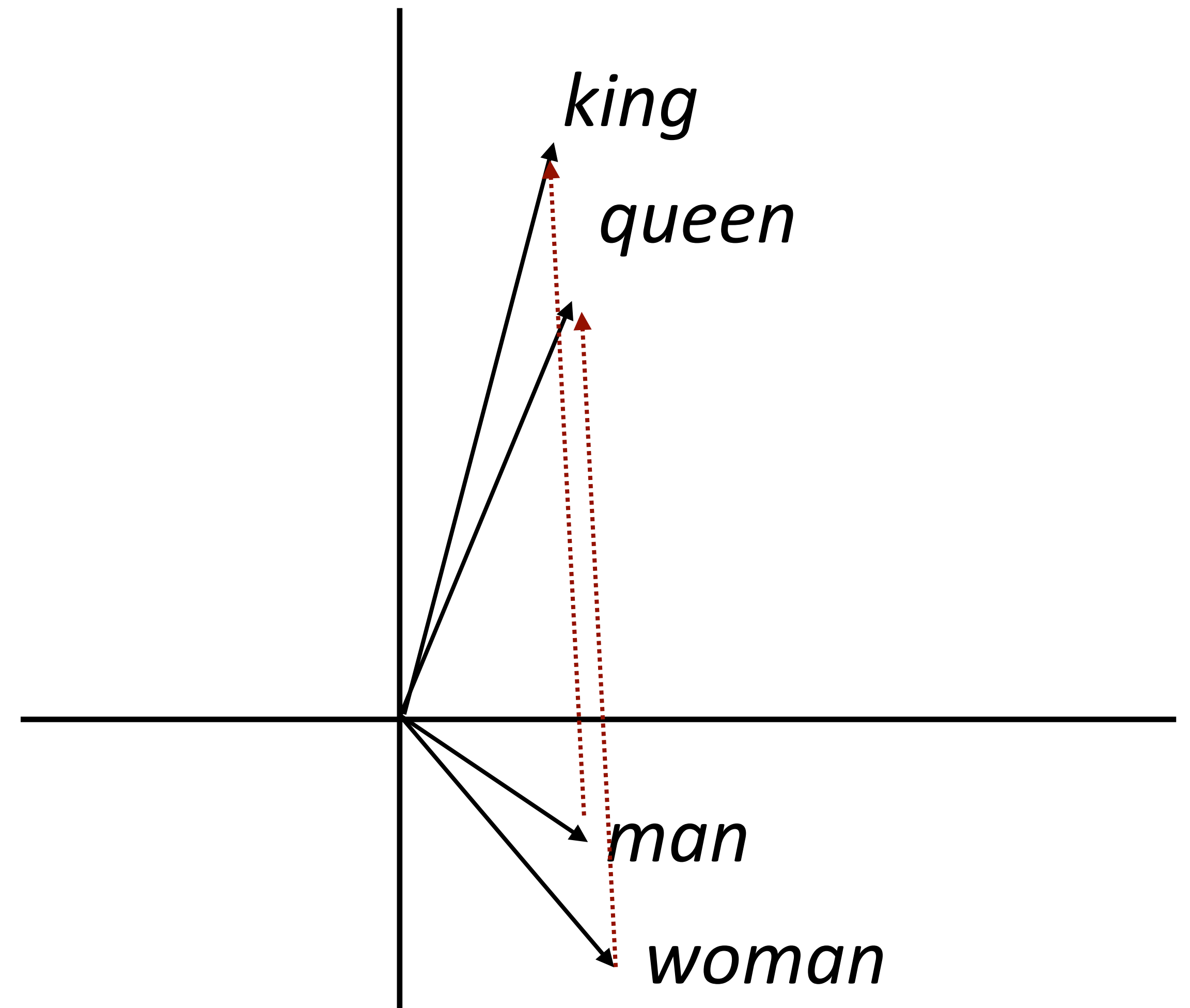


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- ▶ Why would this be?

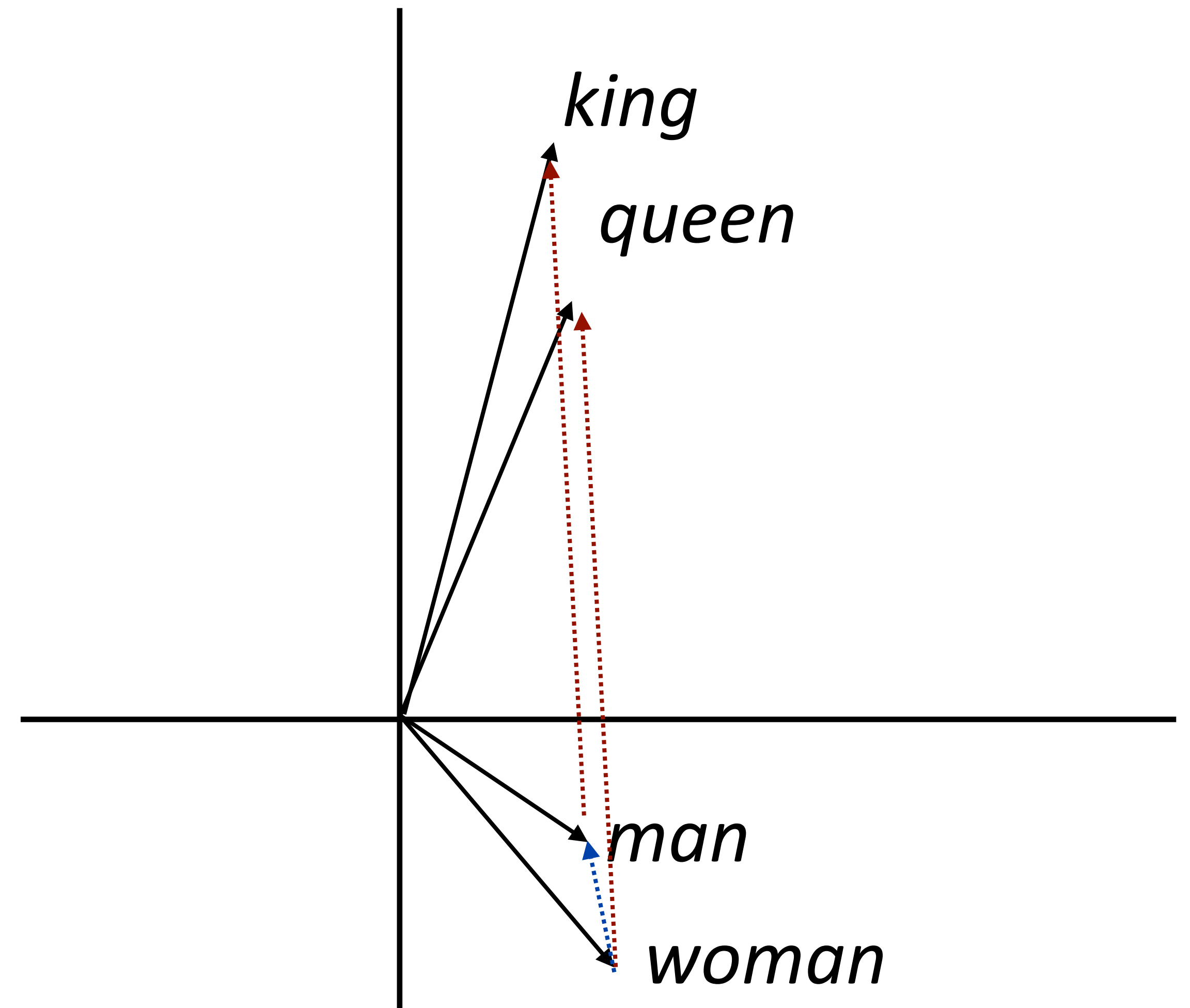


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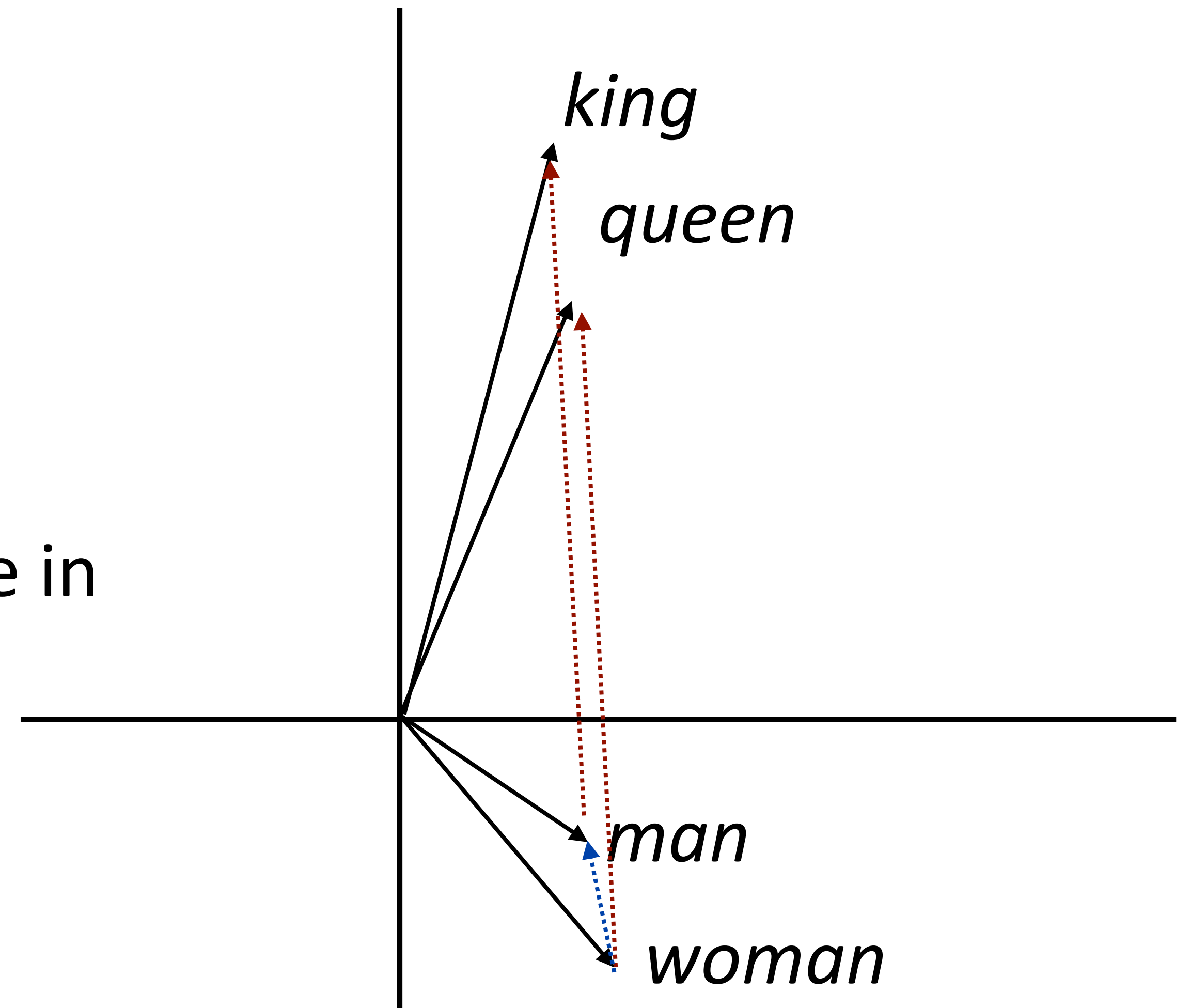


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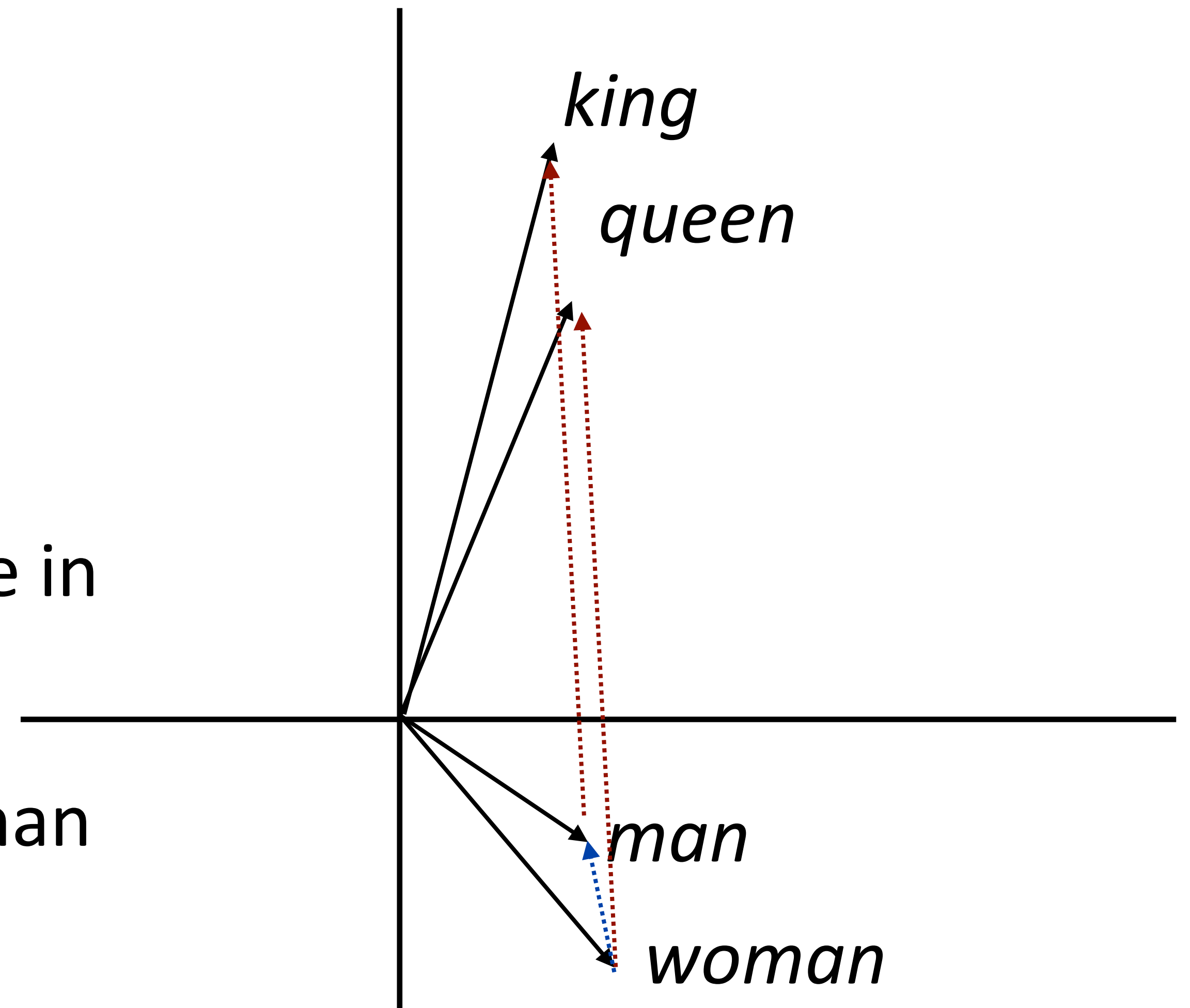


Analogies

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$king + (woman - man) = queen$

- ▶ Why would this be?
- ▶ woman - man captures the difference in the contexts that these occur in
- ▶ Dominant change: more “he” with man and “she” with woman — similar to difference between king and queen



Analogies

| Method | Google | MSR |
|--------|--------------------|--------------------|
| | Add / Mul | Add / Mul |
| PPMI | .553 / .679 | .306 / .535 |
| SVD | .554 / .591 | .408 / .468 |
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$$\text{Maximizing for } b: \text{Add} = \cos(b, a_2 - a_1 + b_1) \quad \text{Mul} = \frac{\cos(b_2, a_2) \cos(b_2, b_1)}{\cos(b_2, a_1) + \epsilon}$$

Levy et al. (2015)

Using Word Embeddings

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 - ▶ Faster because no need to update these parameters
 - ▶ Need to make sure GloVe vocabulary contains all the words you need
- ▶ Approach 3: initialize using GloVe, fine-tune
 - ▶ Not as commonly used anymore

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Compositional Semantics

- ▶ What if we want embedding representations for whole sentences?
- ▶ *Skip-thought* vectors (Kiros et al., 2015), similar to skip-gram generalized to a sentence level
- ▶ Is there a way we can compose vectors to make sentence representations? Summing? RNNs?

This Lecture

- ▶ Recurrent neural networks
- ▶ Vanishing gradient problem
- ▶ LSTMs / GRUs
- ▶ Applications / visualizations

RNN Basics

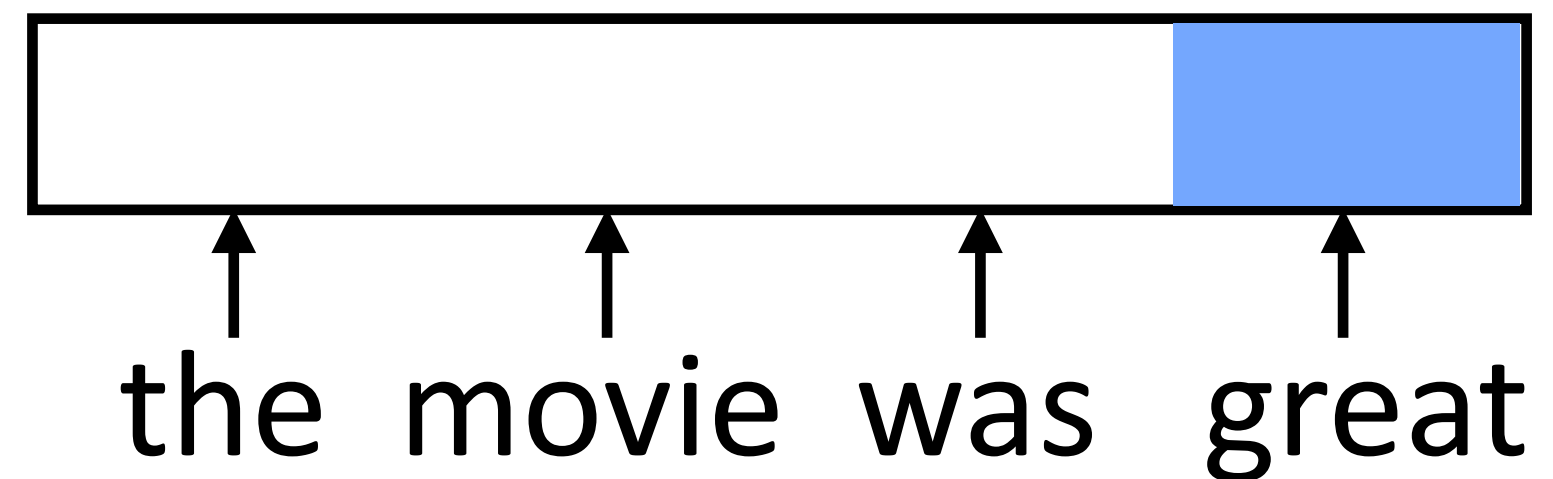
RNN Motivation

- ▶ Feedforward NNs can't handle variable length input: each position in the feature vector has fixed semantics

the movie was great

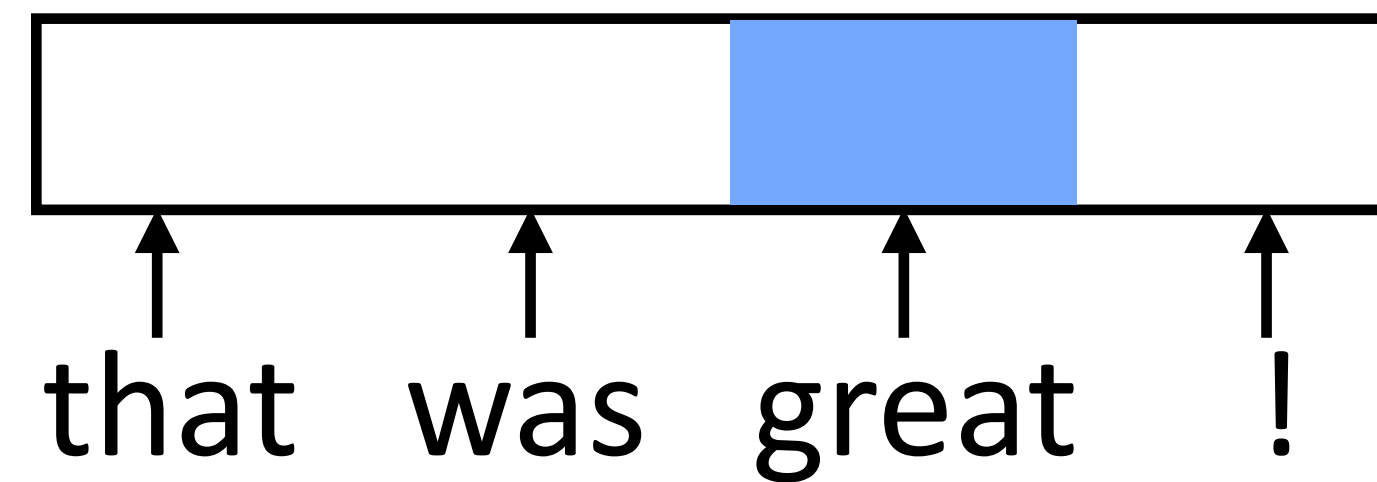
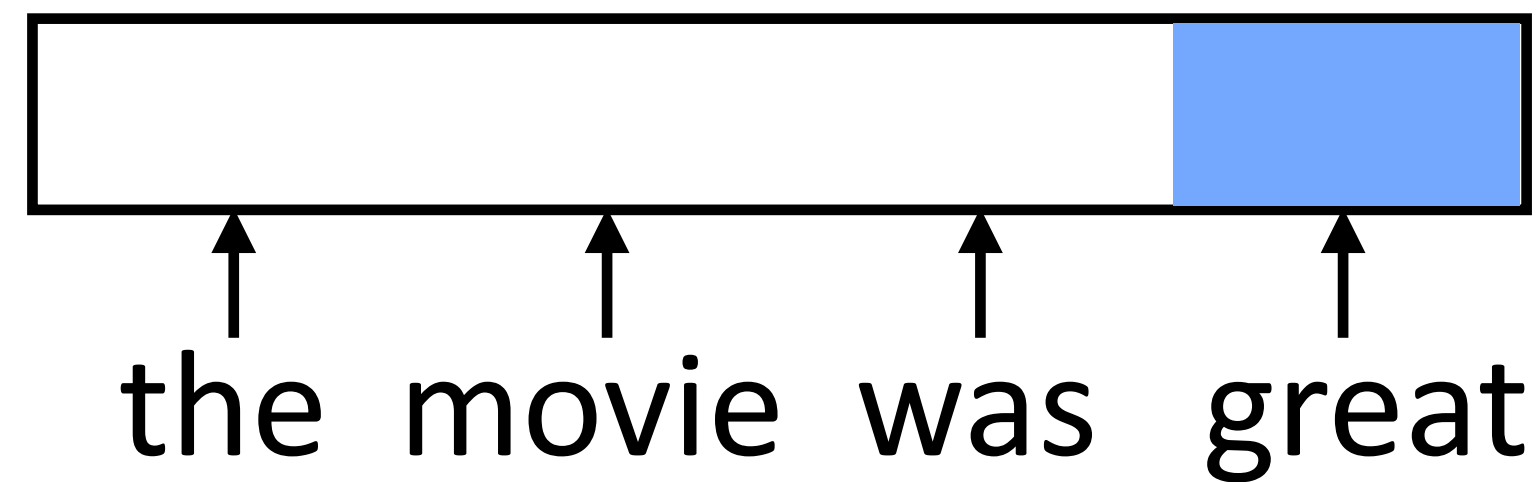
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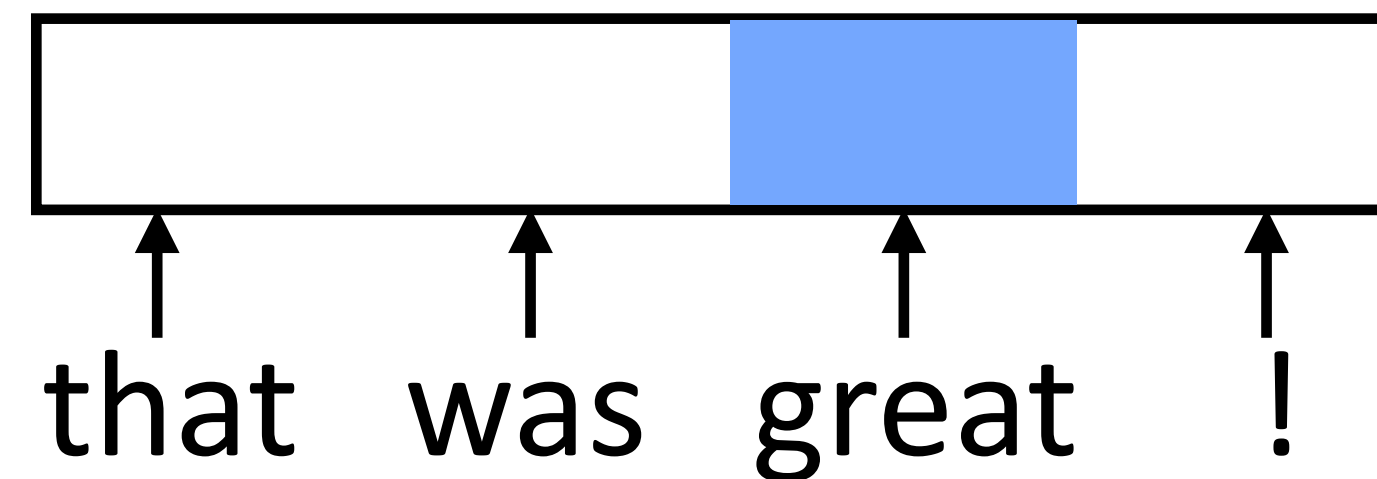
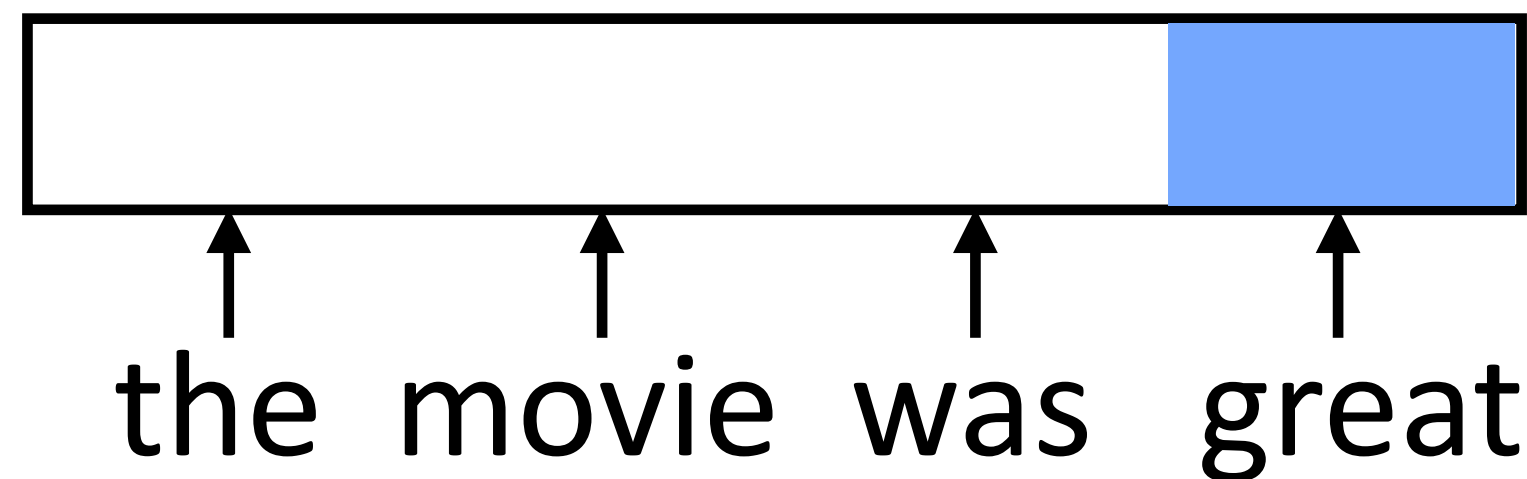
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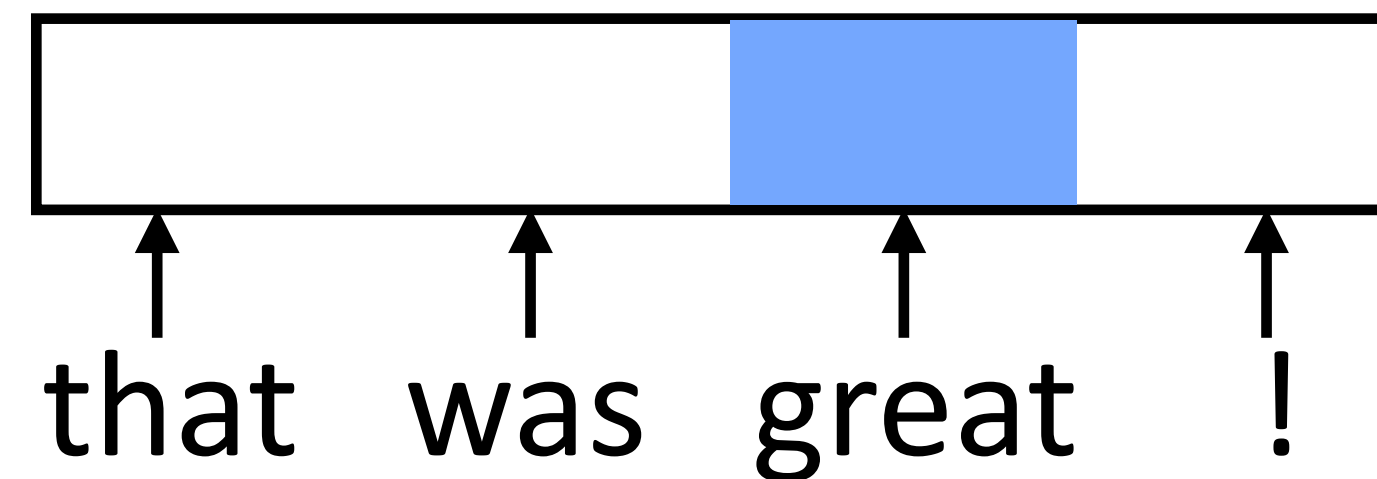
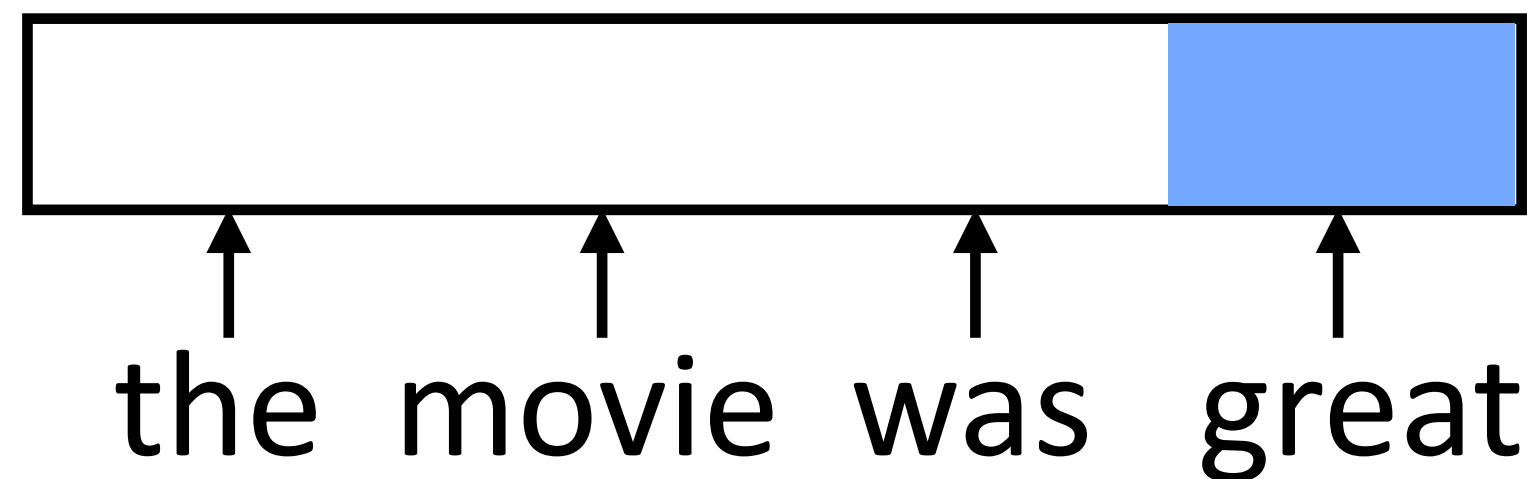
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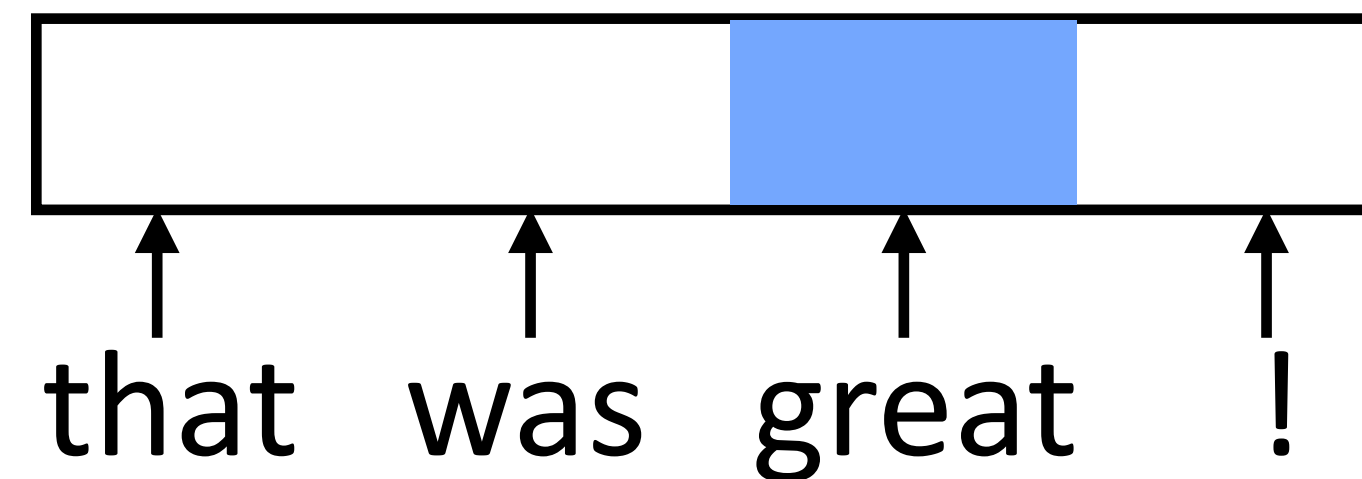
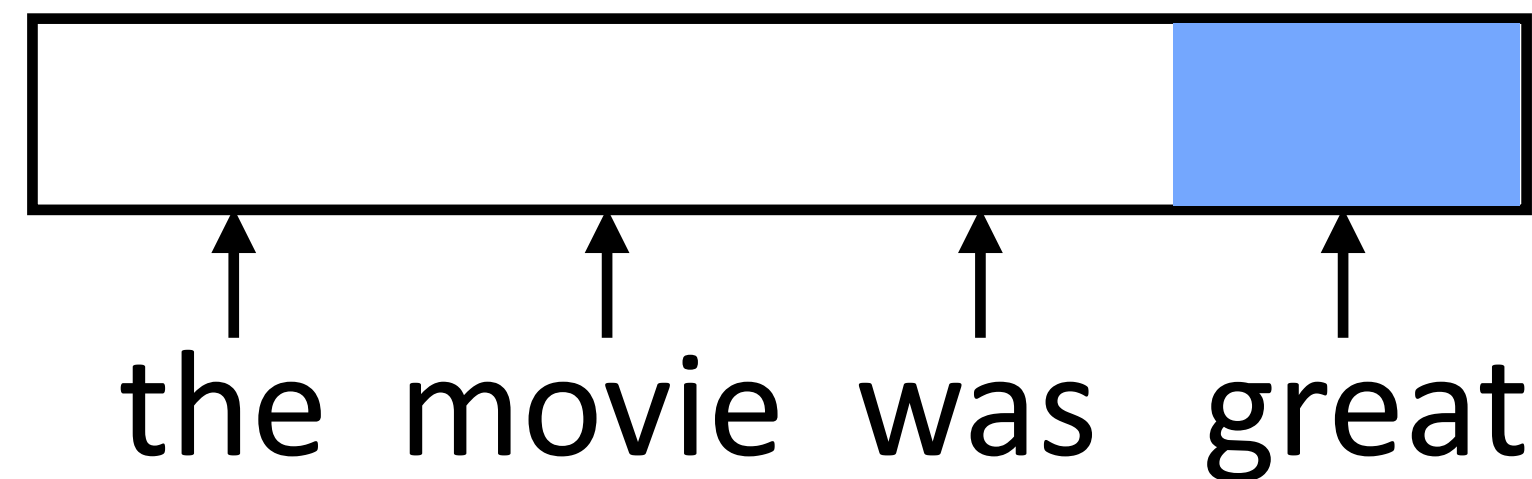
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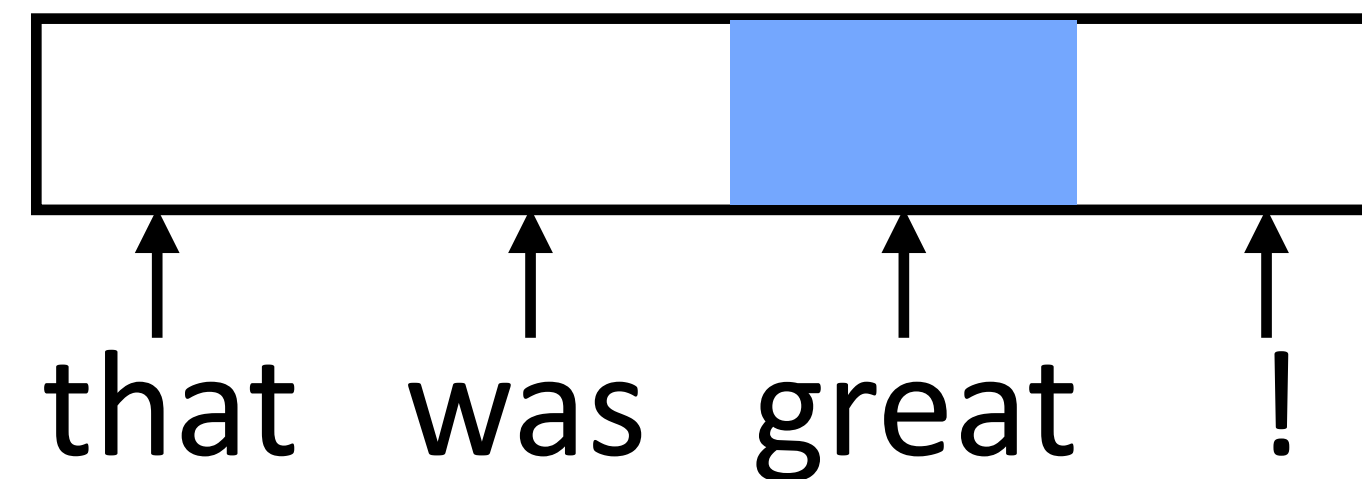
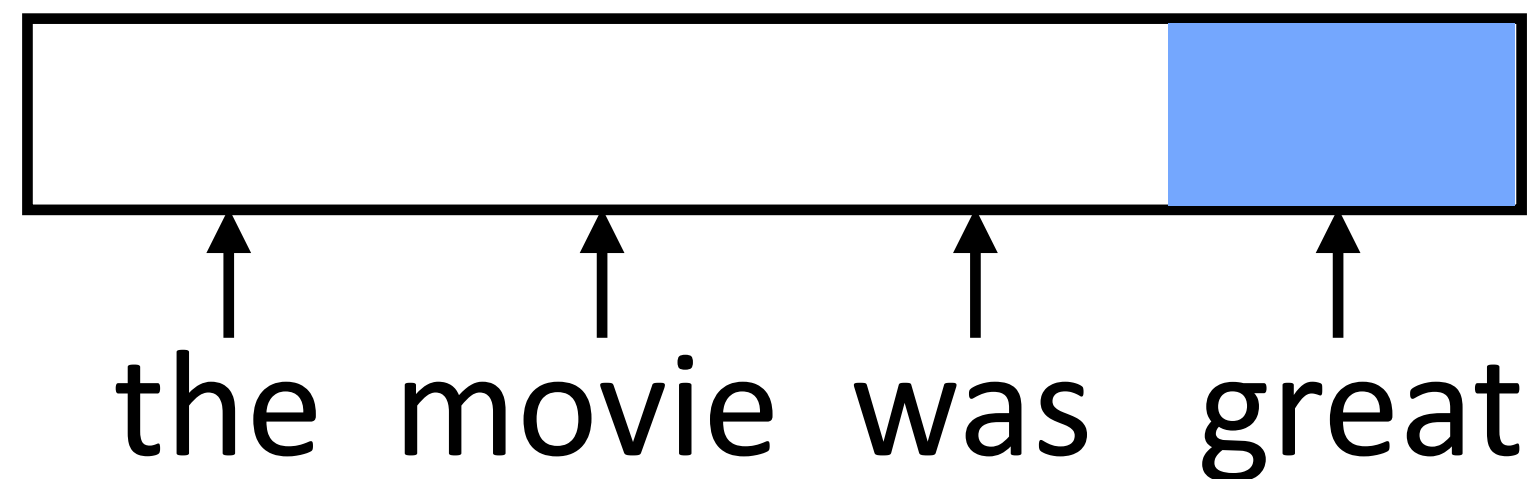
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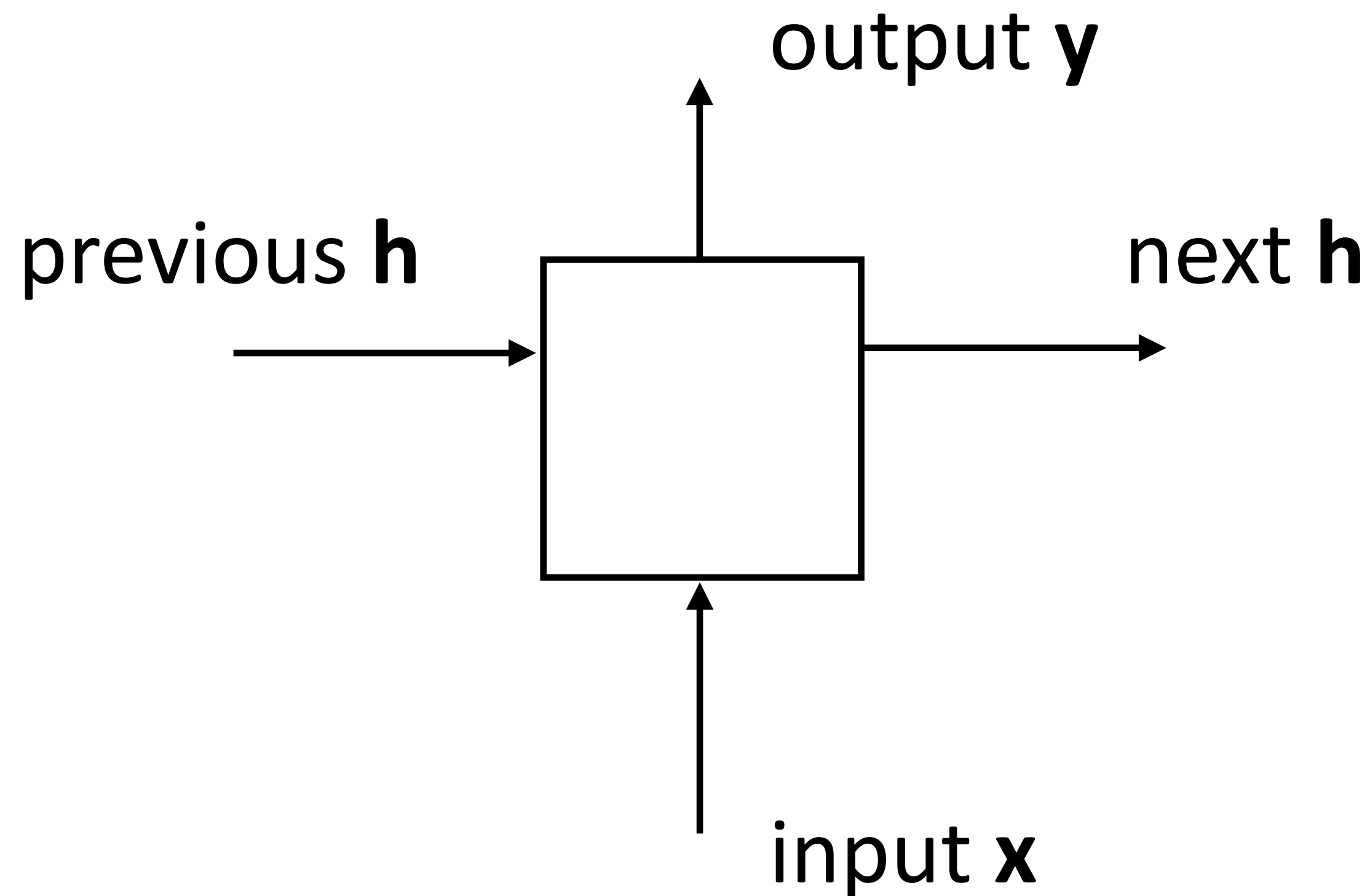
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- ▶ These don't look related (*great* is in two different orthogonal subspaces)
- ▶ Instead, we need to:
 - 1) Process each word in a uniform way
 - 2) ...while still exploiting the context that that token occurs in

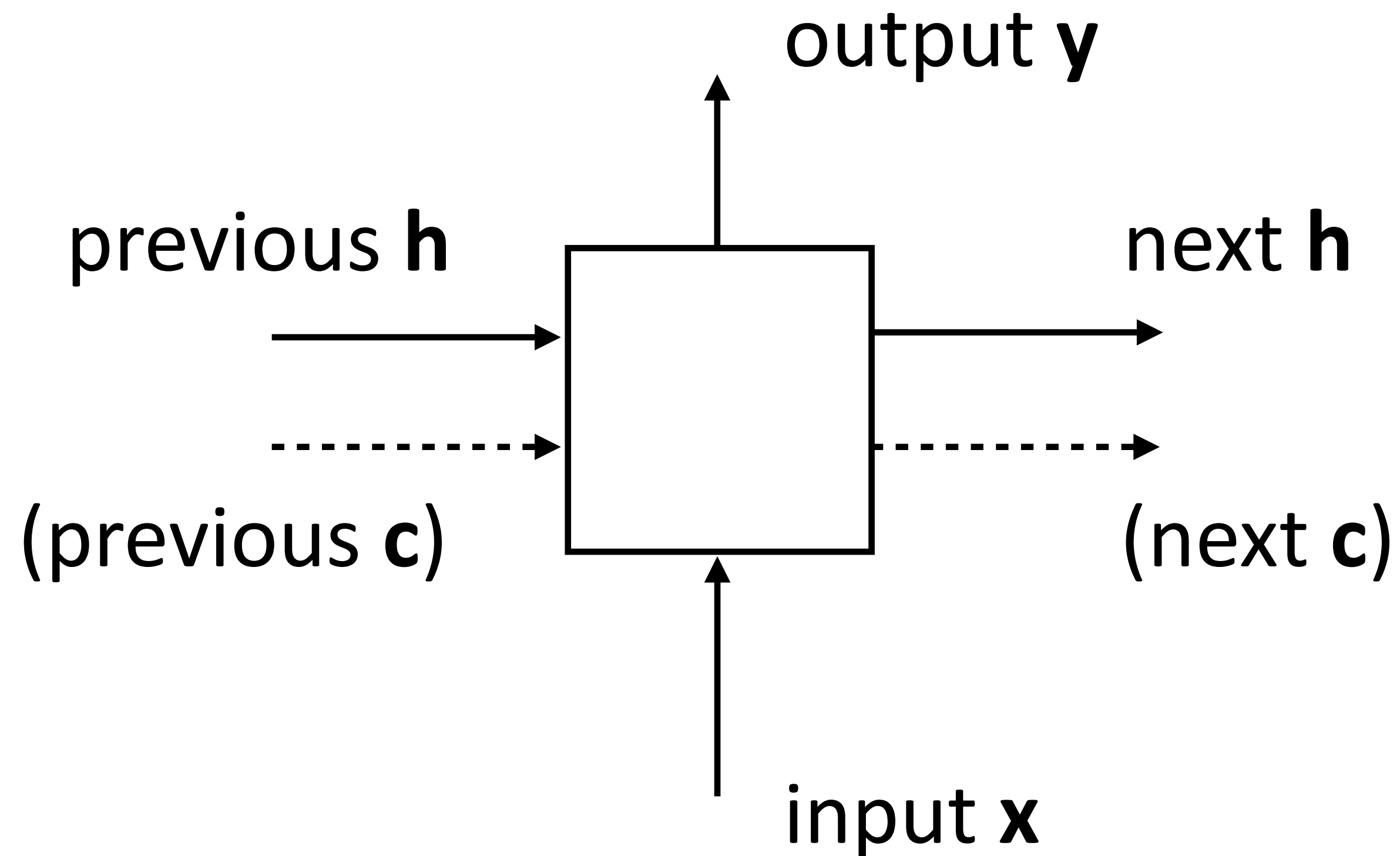
RNN Abstraction

- ▶ Cell that takes some input \mathbf{x} , has some hidden state \mathbf{h} , and updates that hidden state and produces output \mathbf{y} (all vector-valued)



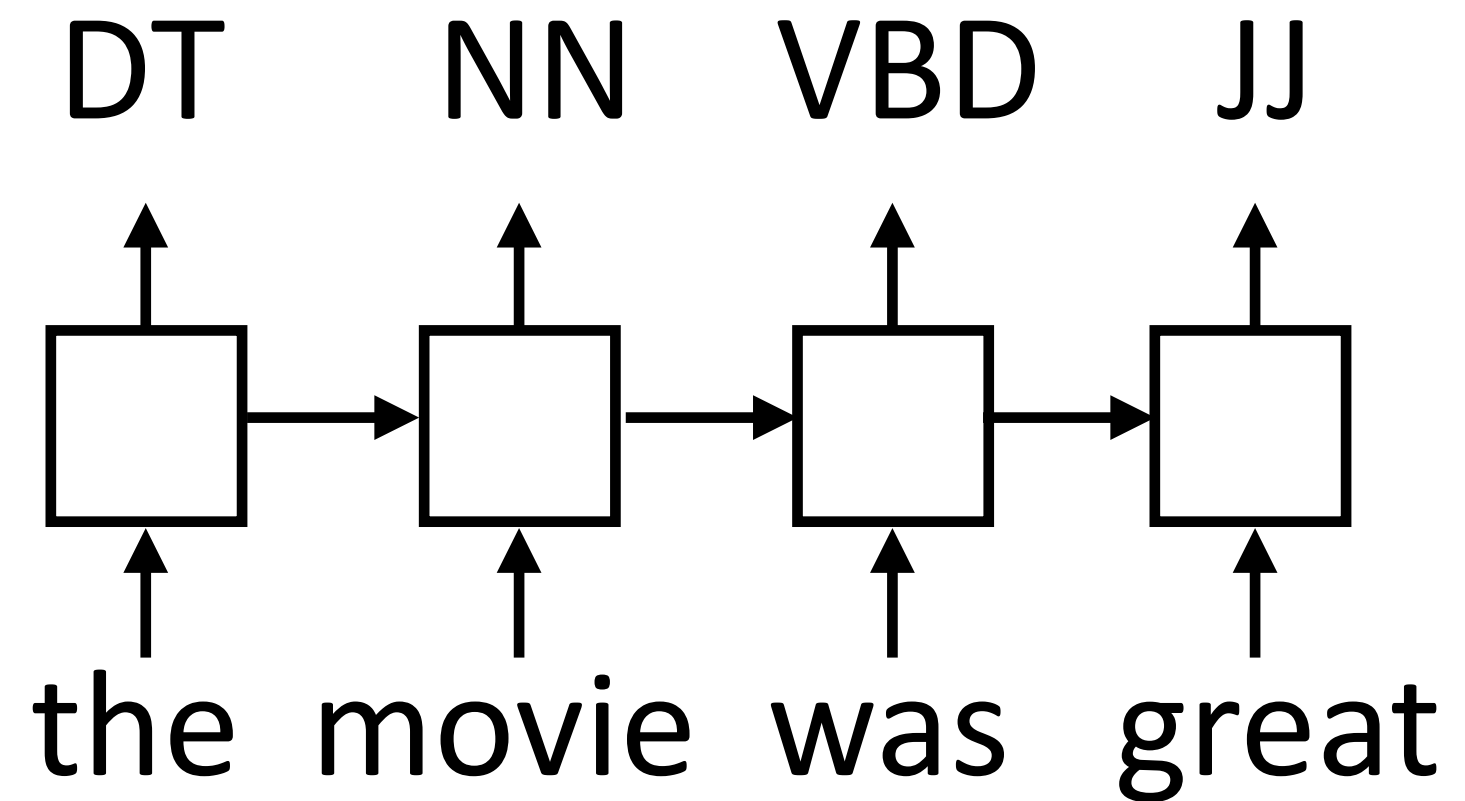
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RNN Uses

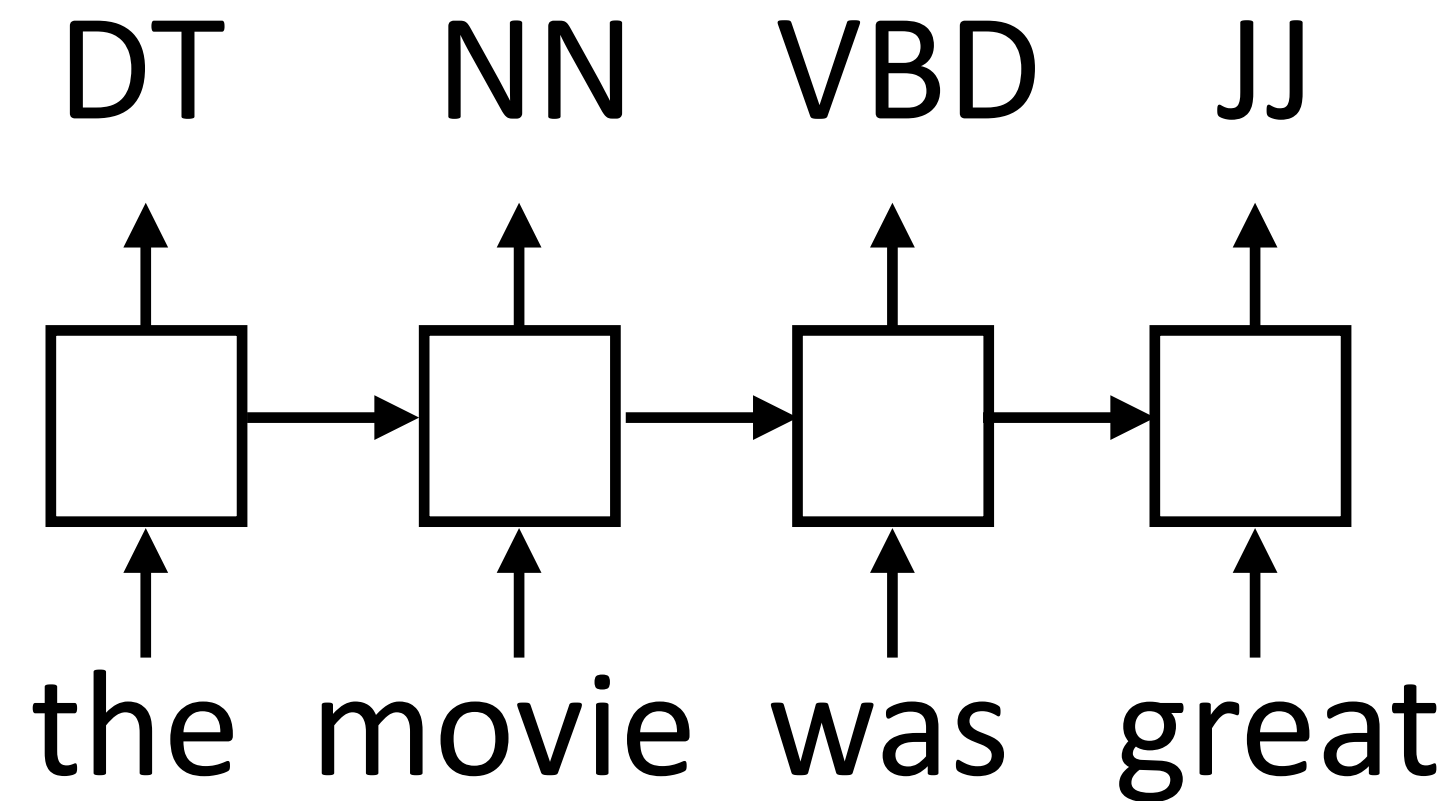
- ▶ Transducer: make some prediction for each element in a sequence



output \mathbf{y} = score for each tag, then softmax

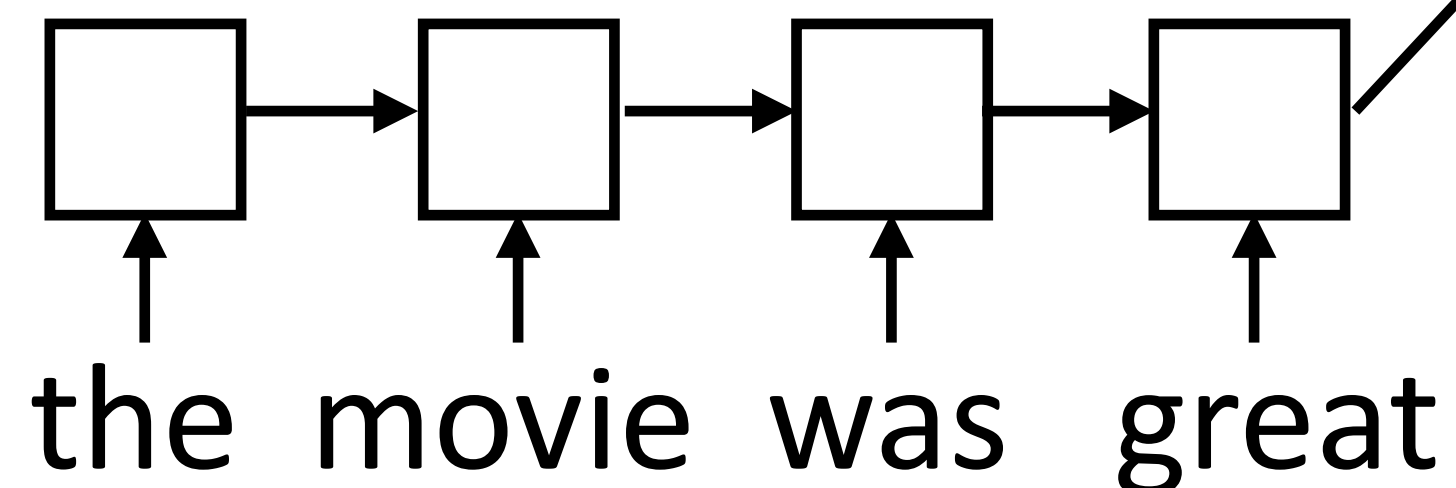
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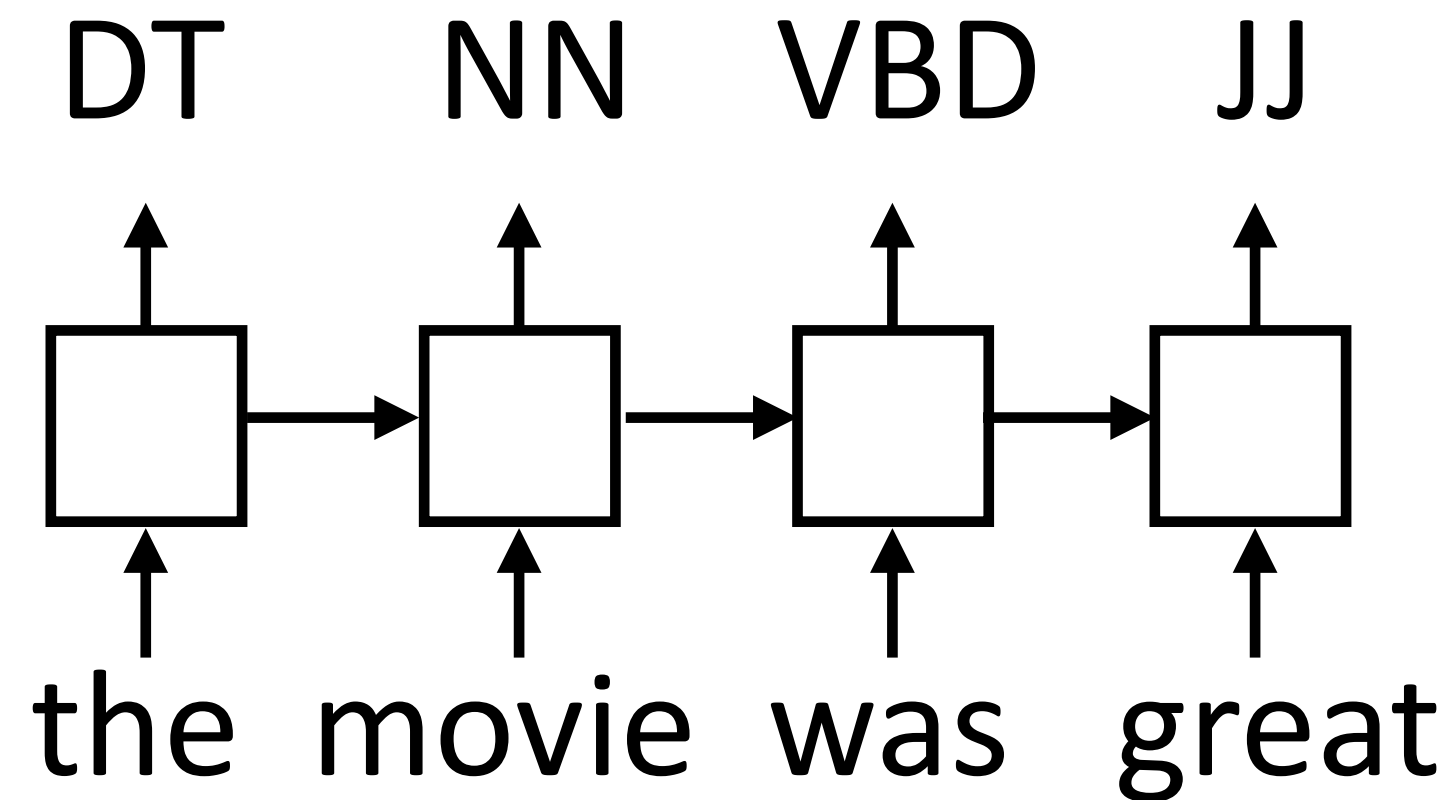
- ▶ Acceptor/encoder: encode a sequence into a fixed-sized vector and use that for some purpose



predict sentiment (matmul + softmax)

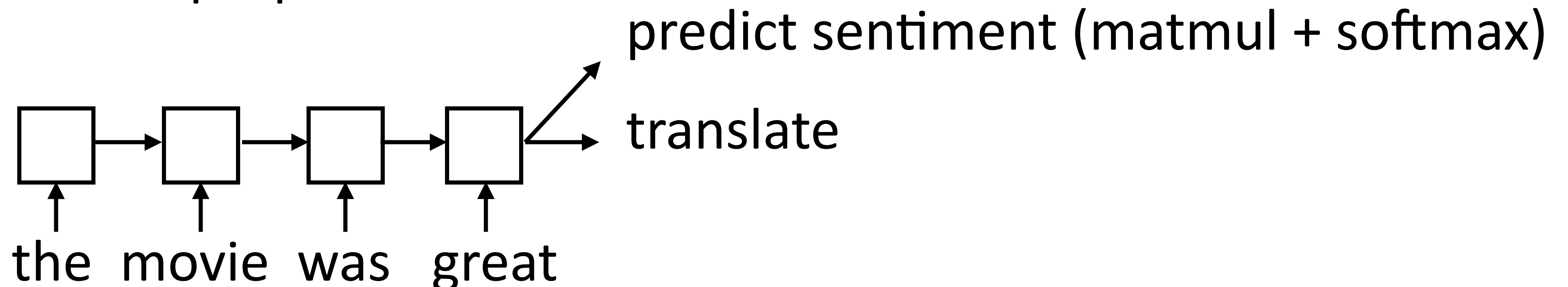
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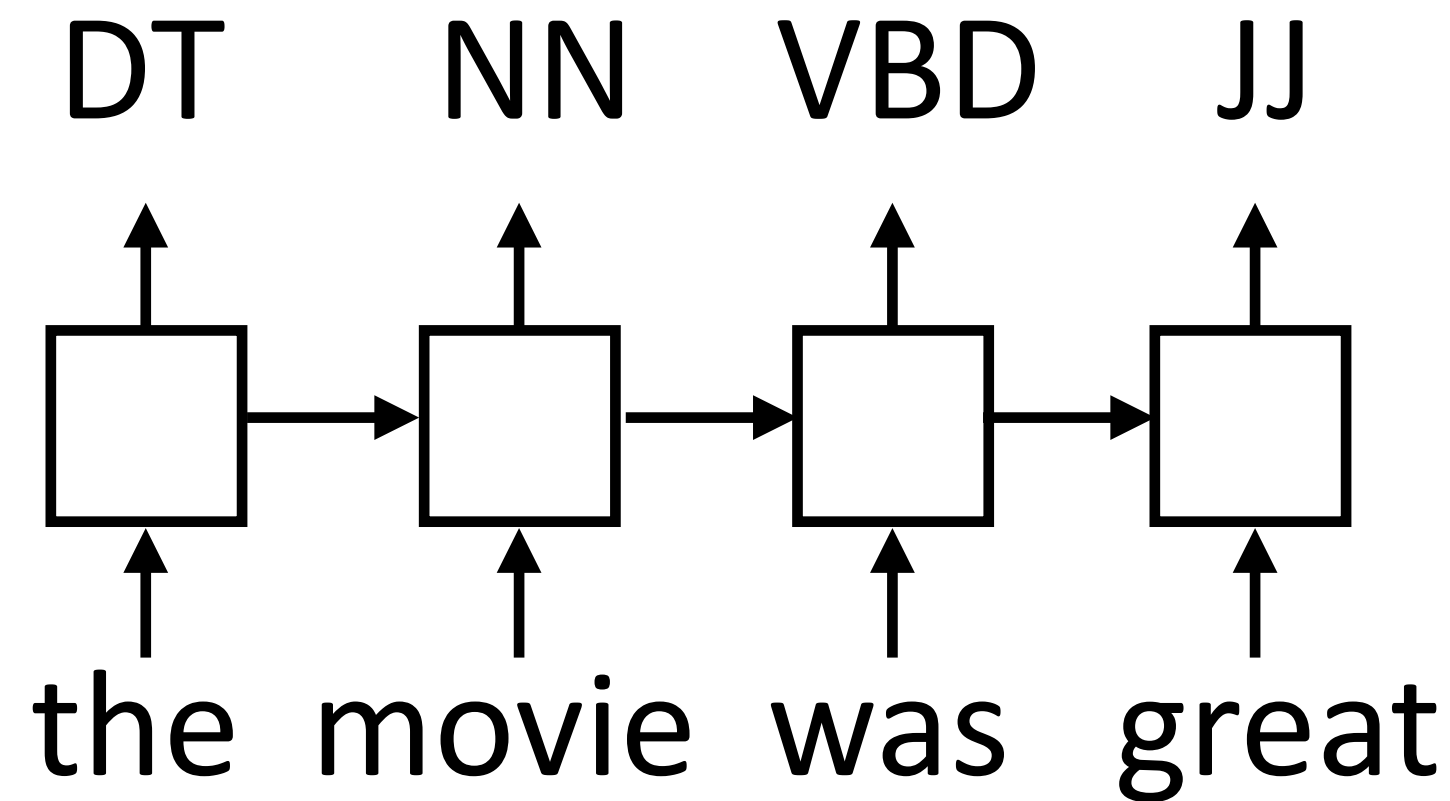
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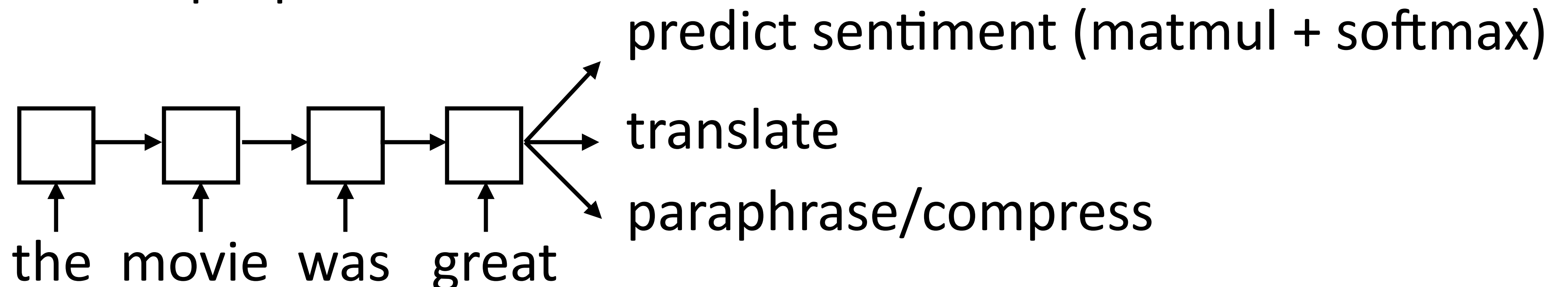
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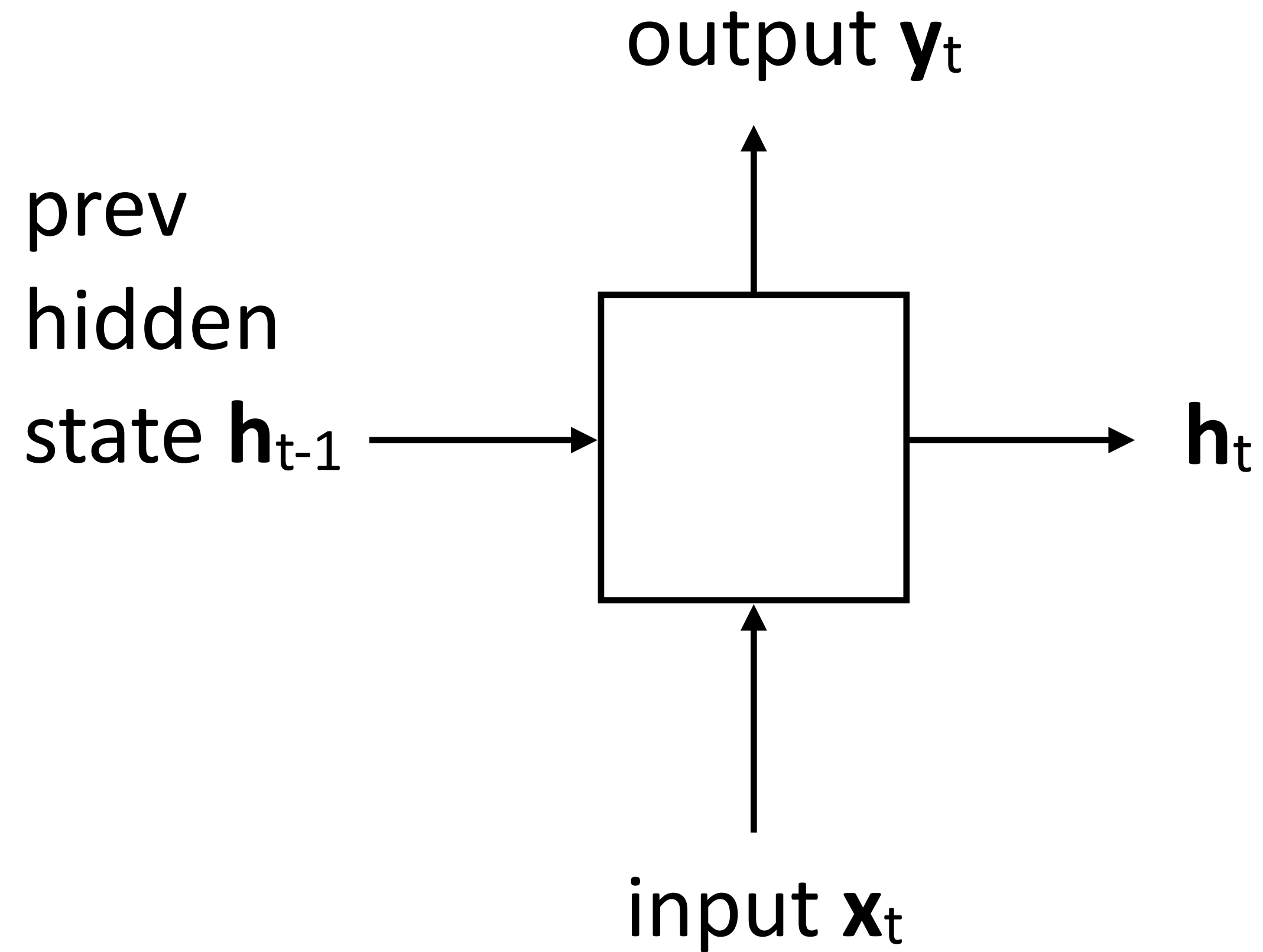


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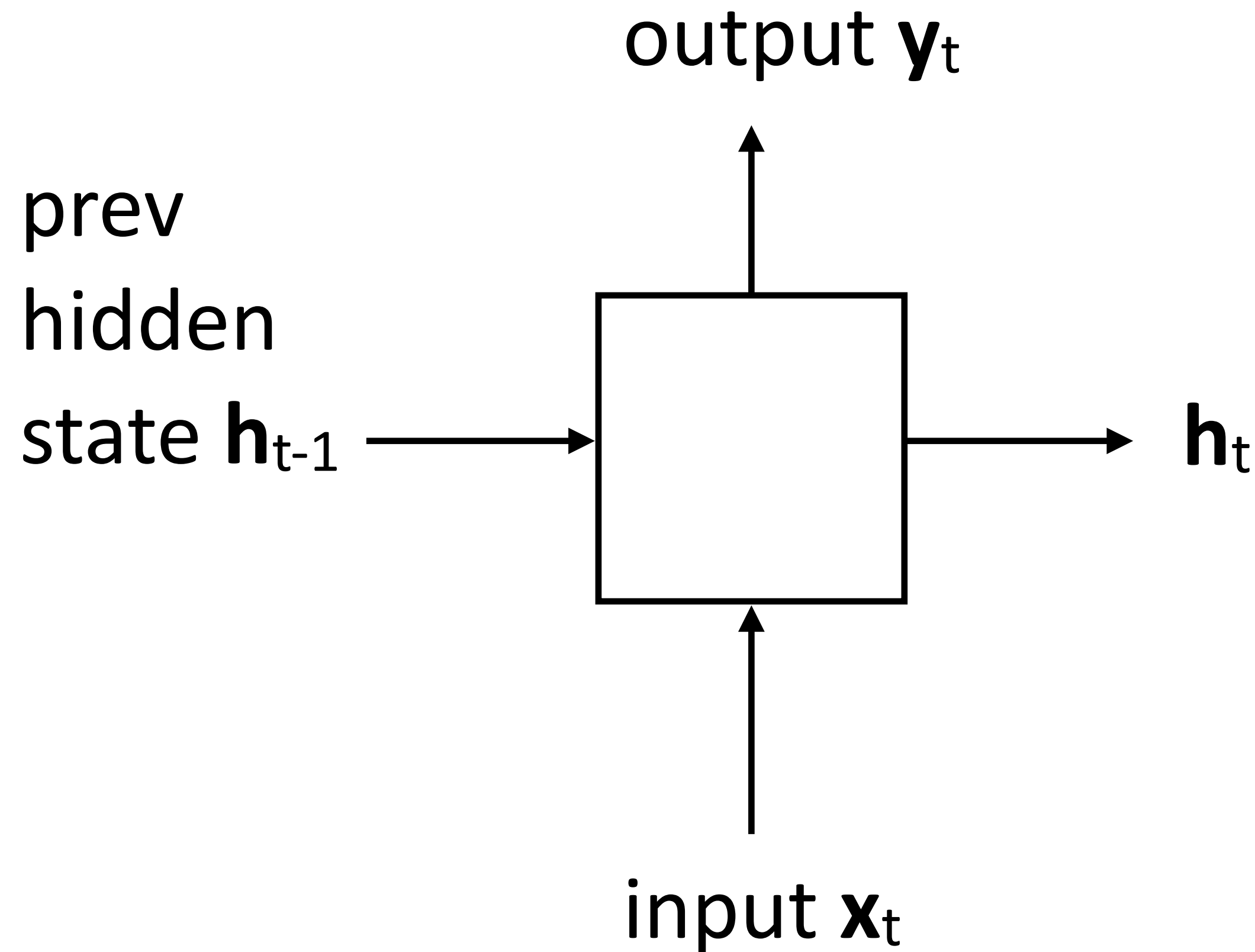
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Elman Networks



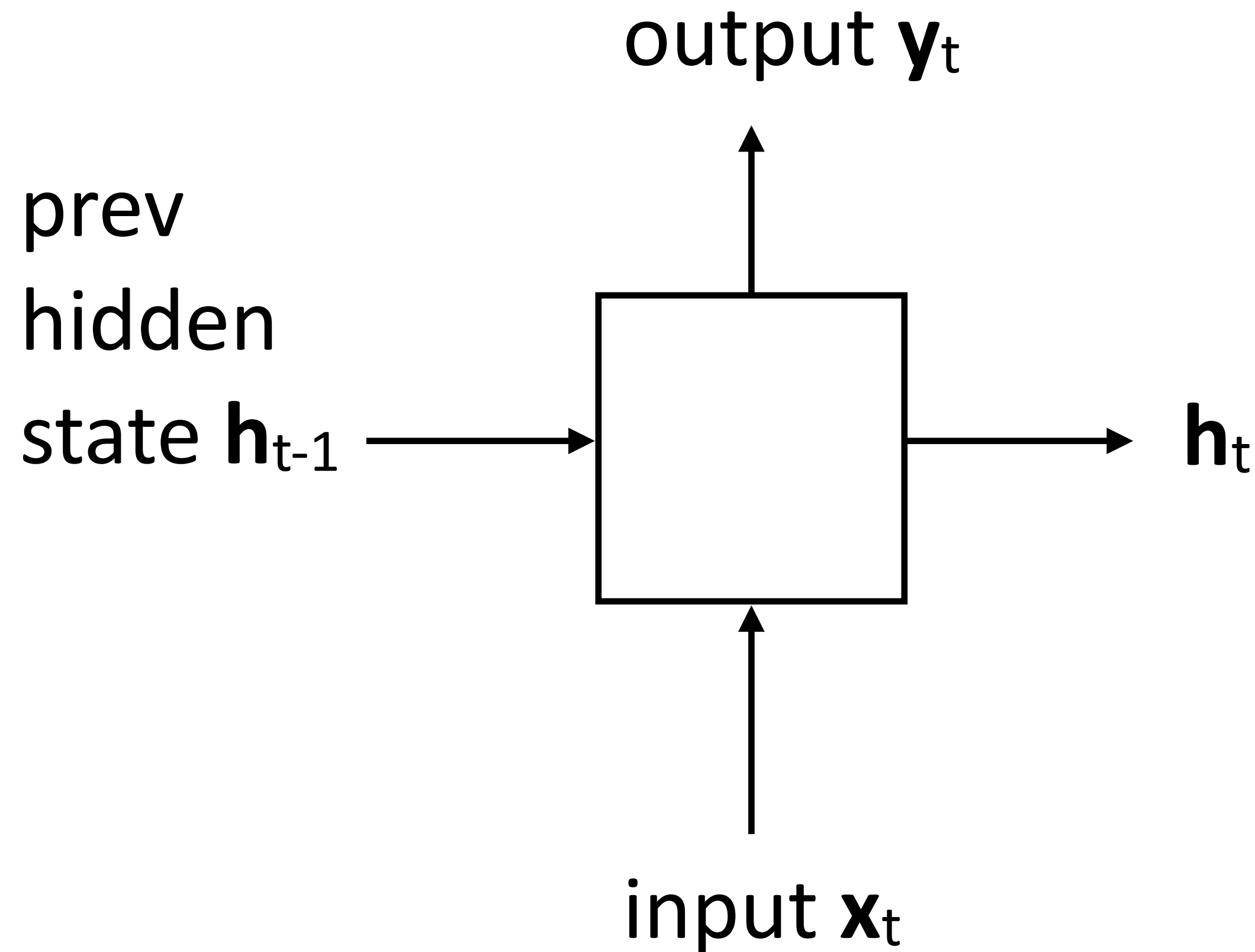
Elman Networks



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

- ▶ Updates hidden state based on input and current hidden state

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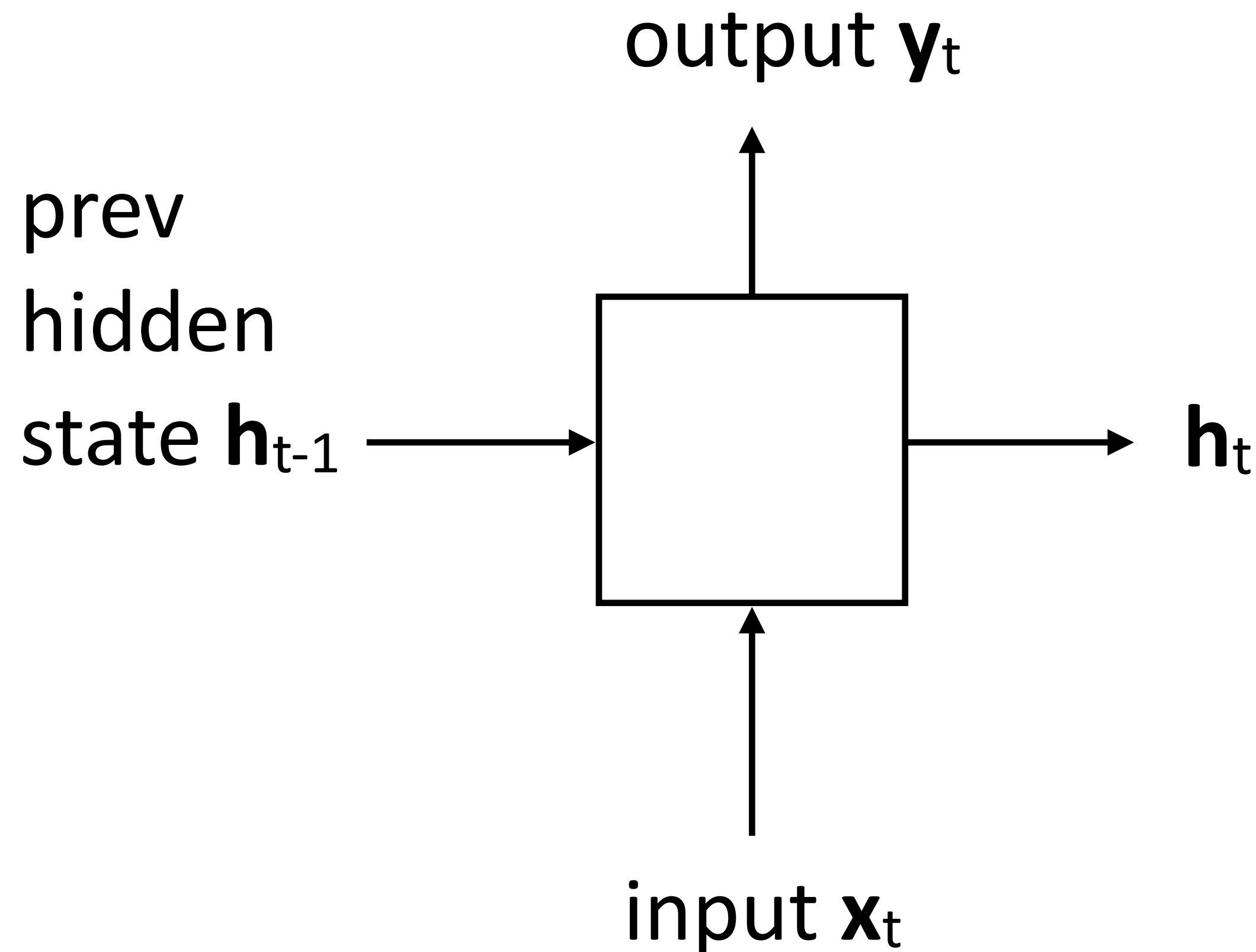
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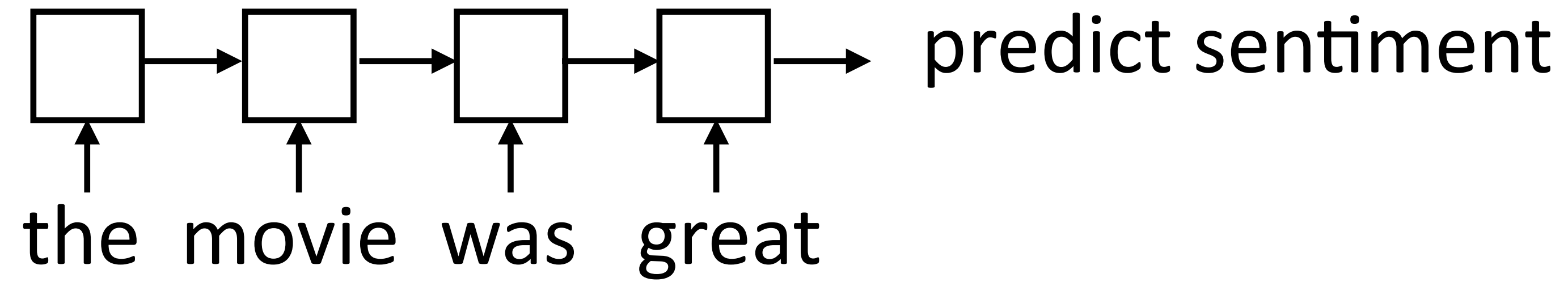
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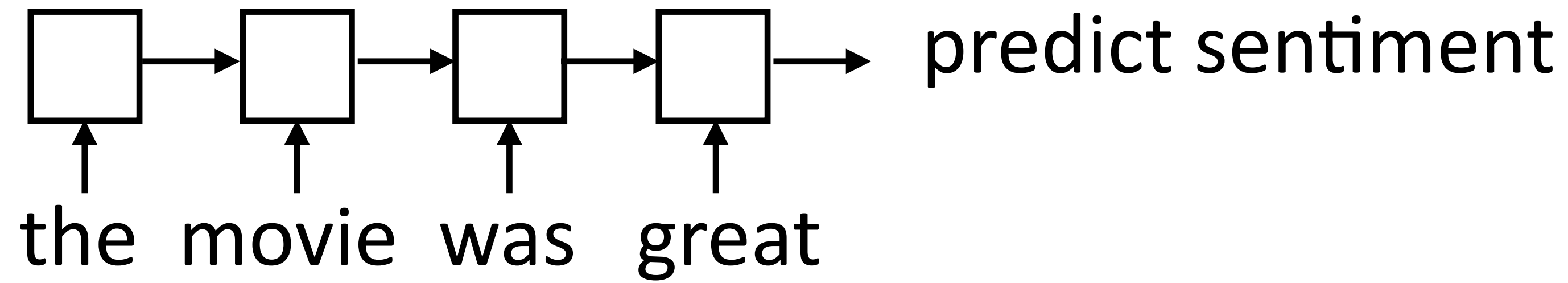
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- ▶ Long history! (invented in the late 1980s)

Training Elman Networks

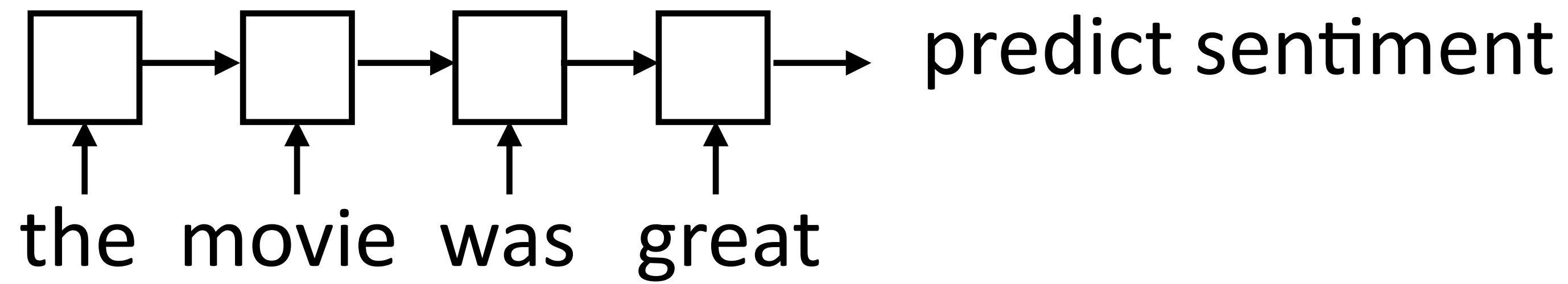


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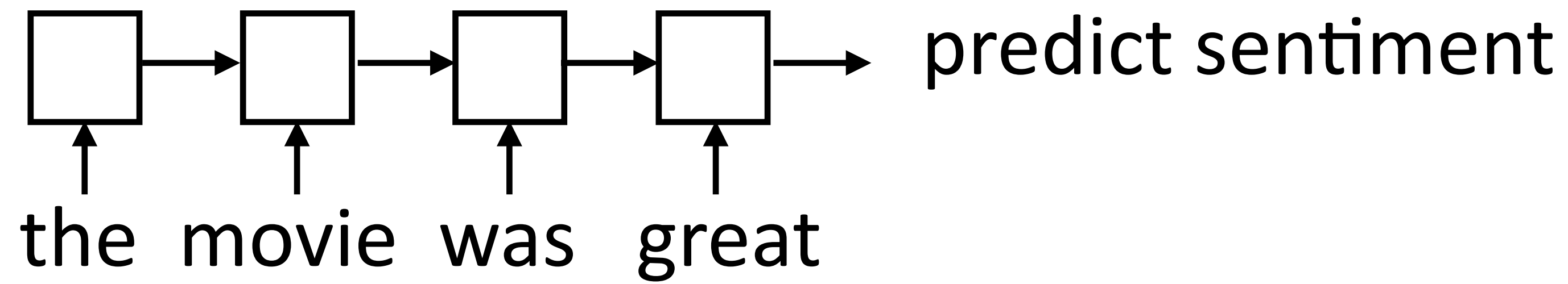
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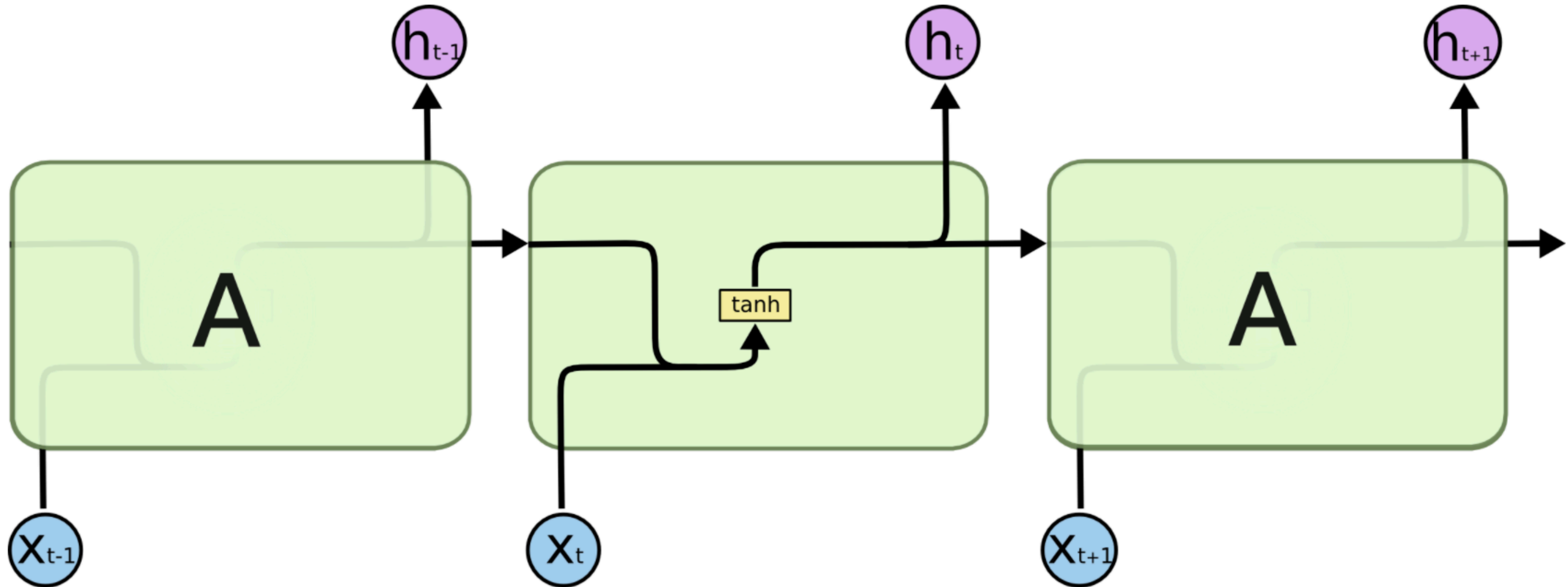
- ▶ “Backpropagation through time”: build the network as one big computation graph, some parameters are shared
 - ▶ RNN potentially needs to learn how to “remember” information for a long time!
- it was my **favorite** movie of 2016, though it wasn't without **problems** -> **+**

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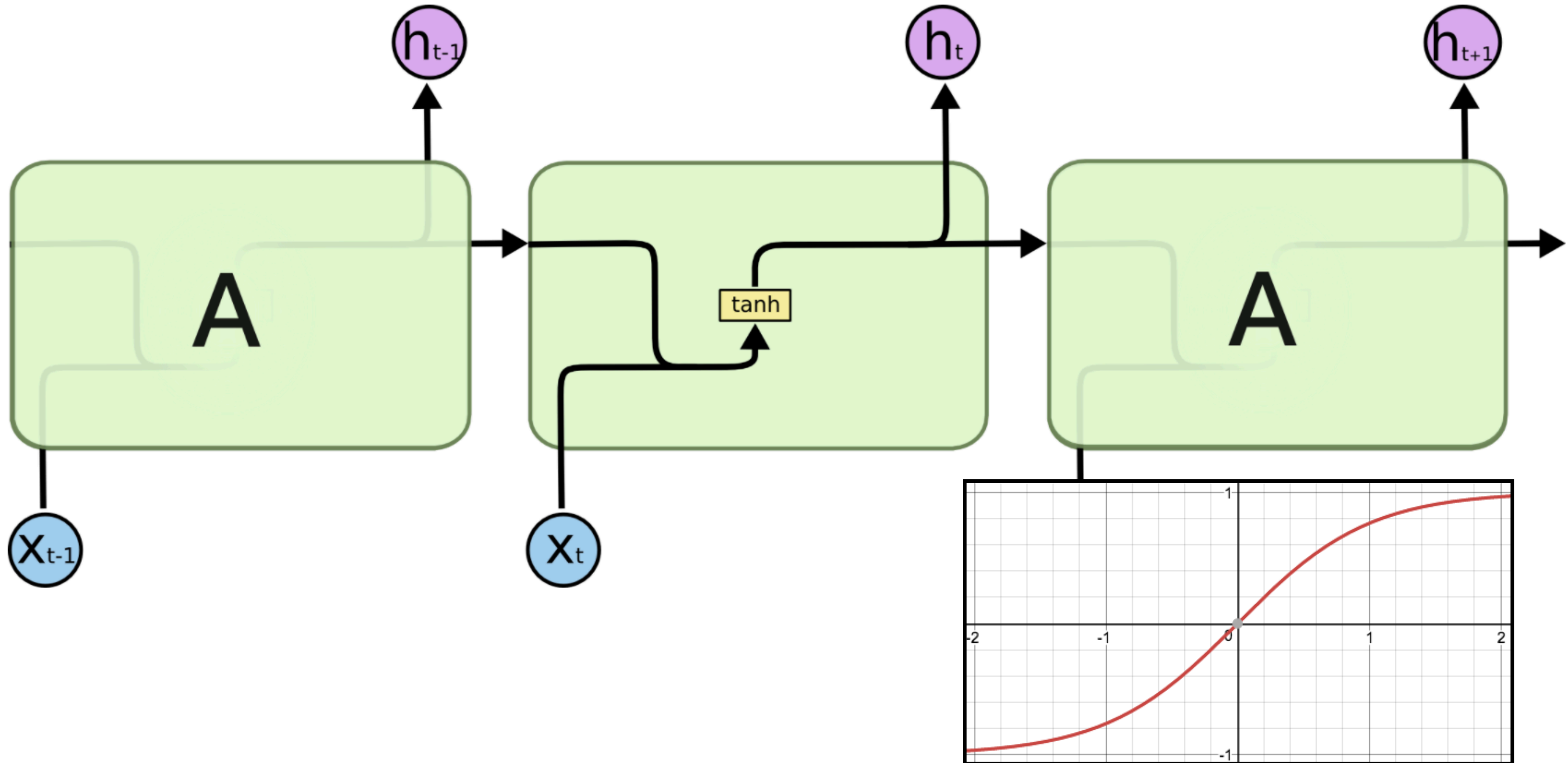


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- it was my **favorite** movie of 2016, though it wasn't without **problems** -> +
- ▶ “Correct” parameter update is to do a better job of remembering the sentiment of *favorite*

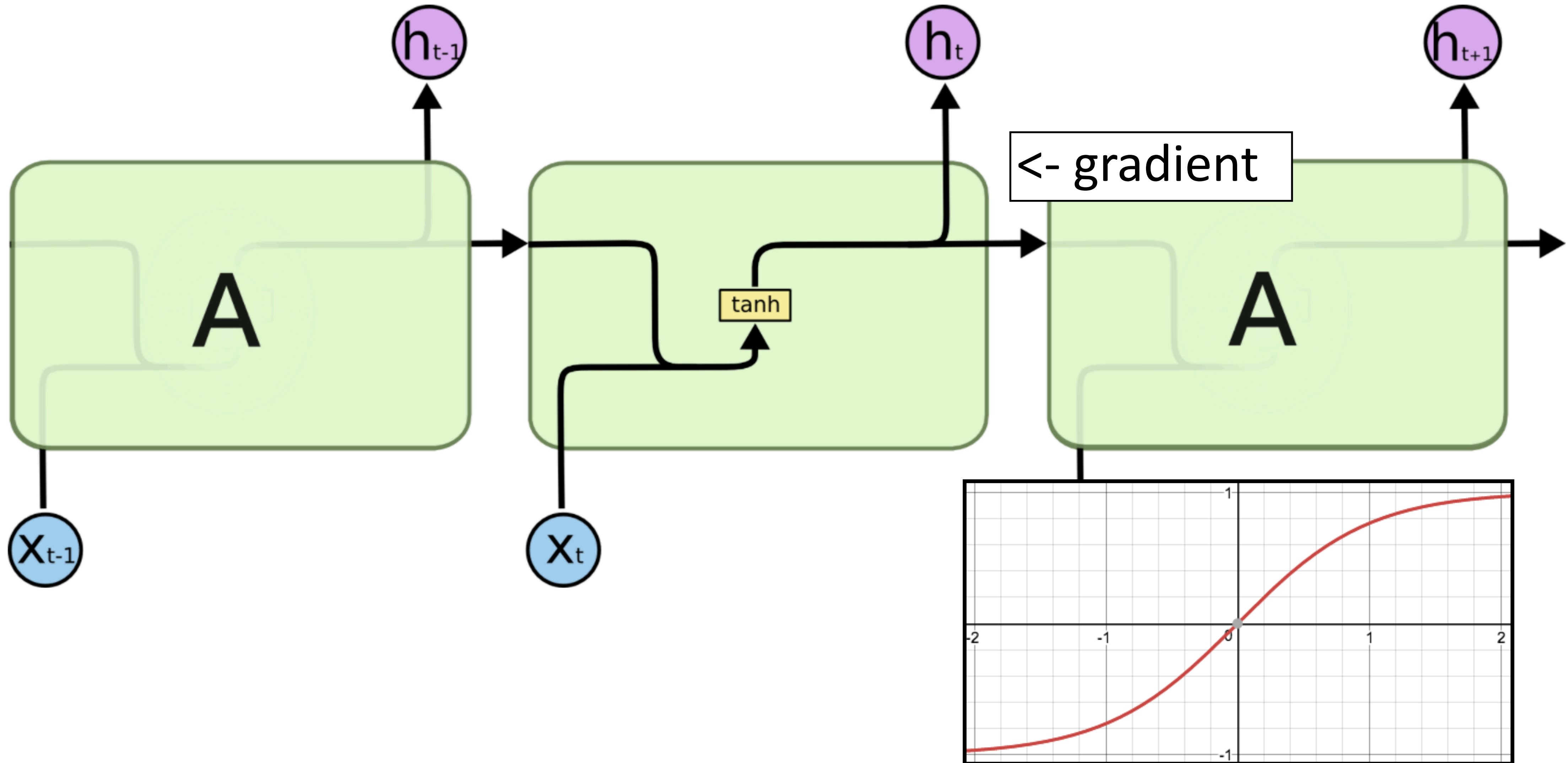
Vanishing Gradient



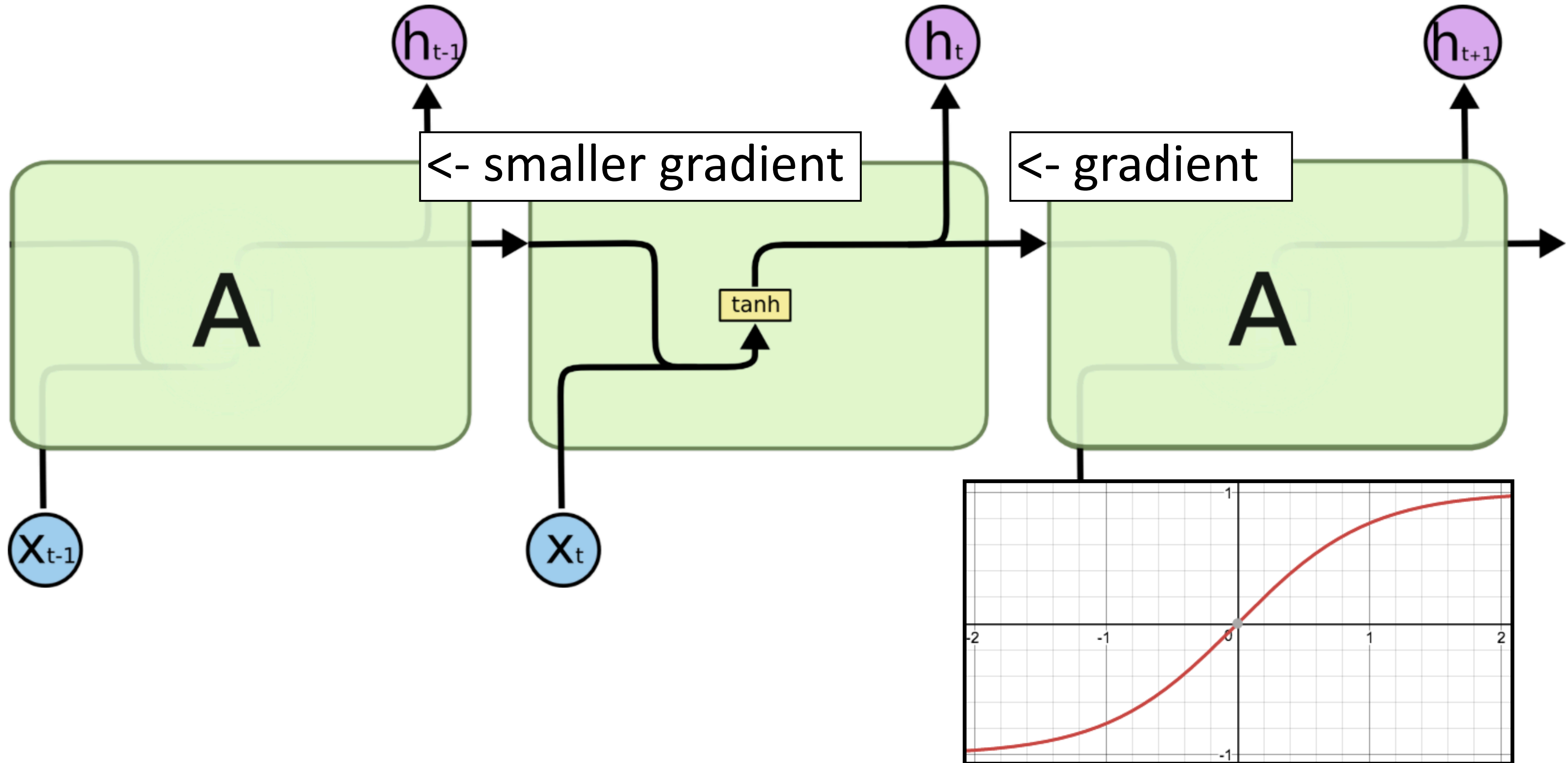
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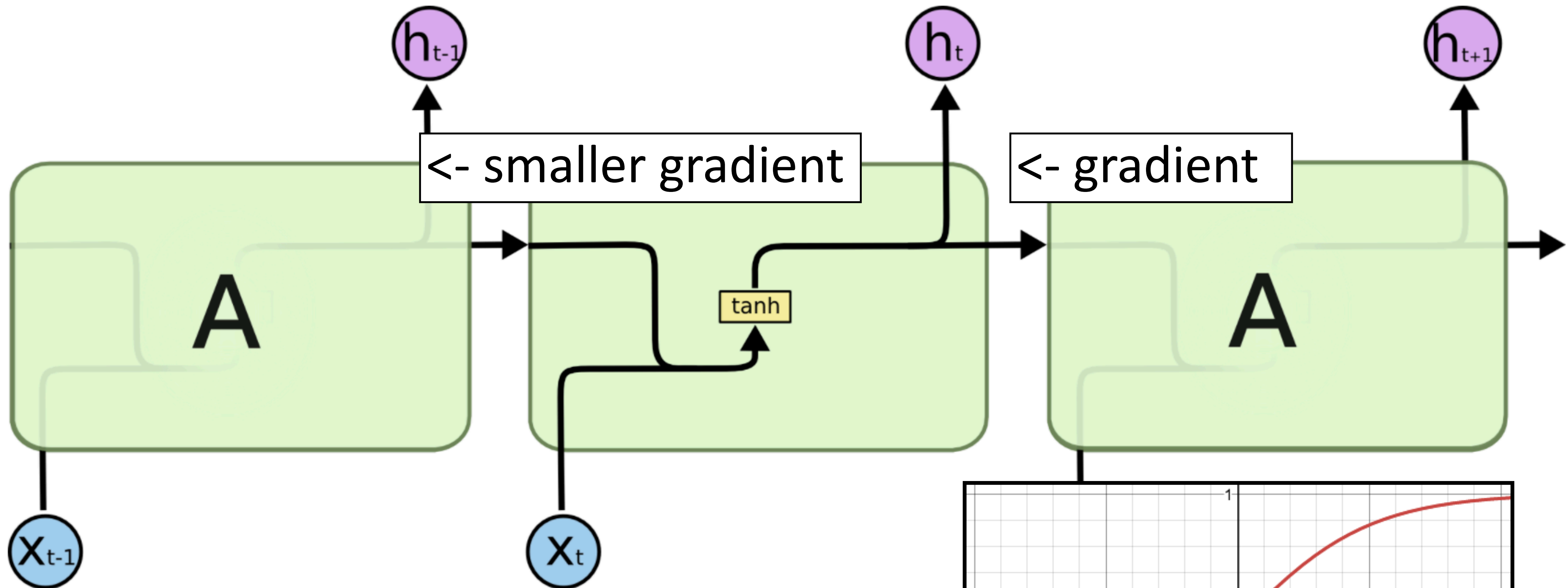
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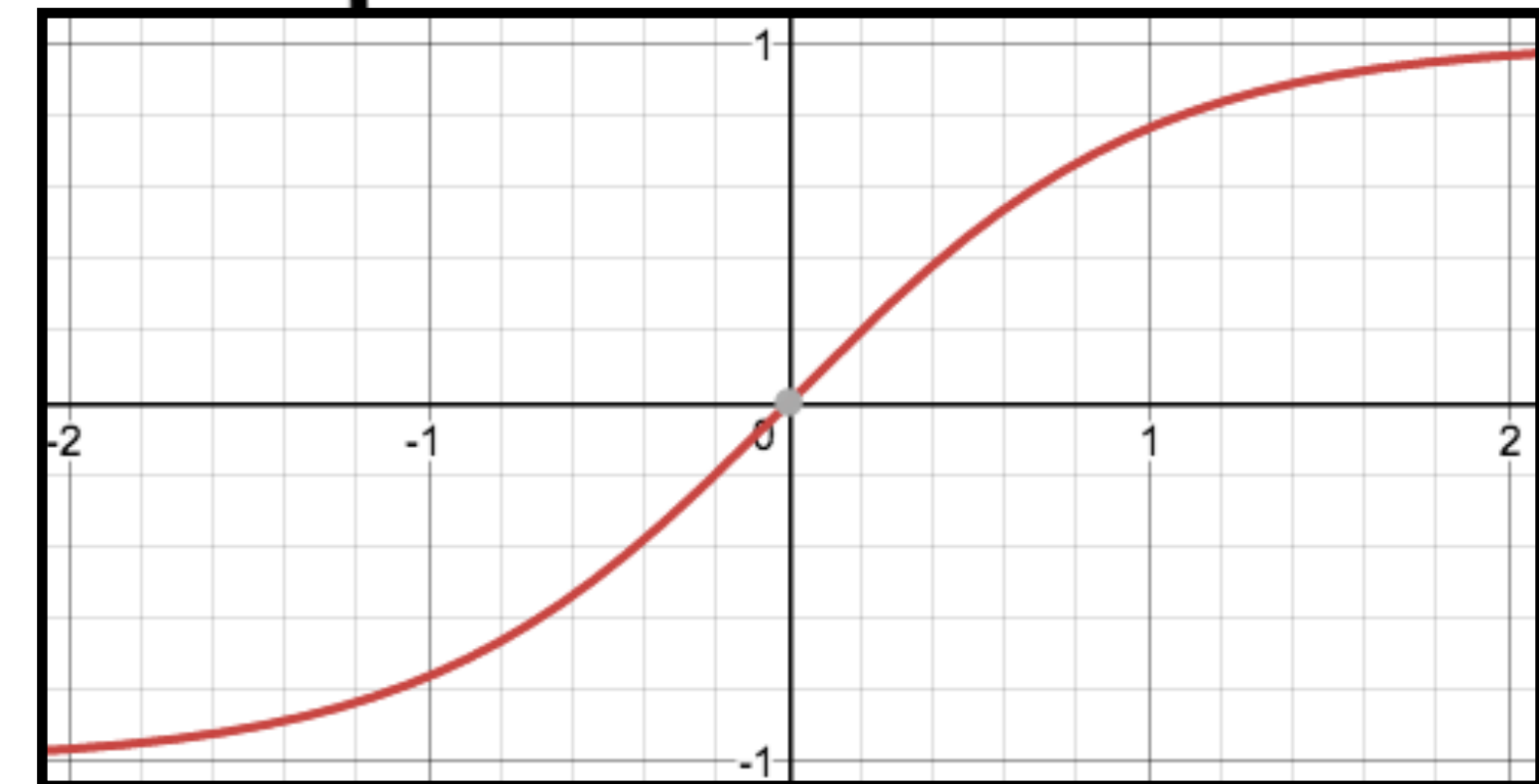
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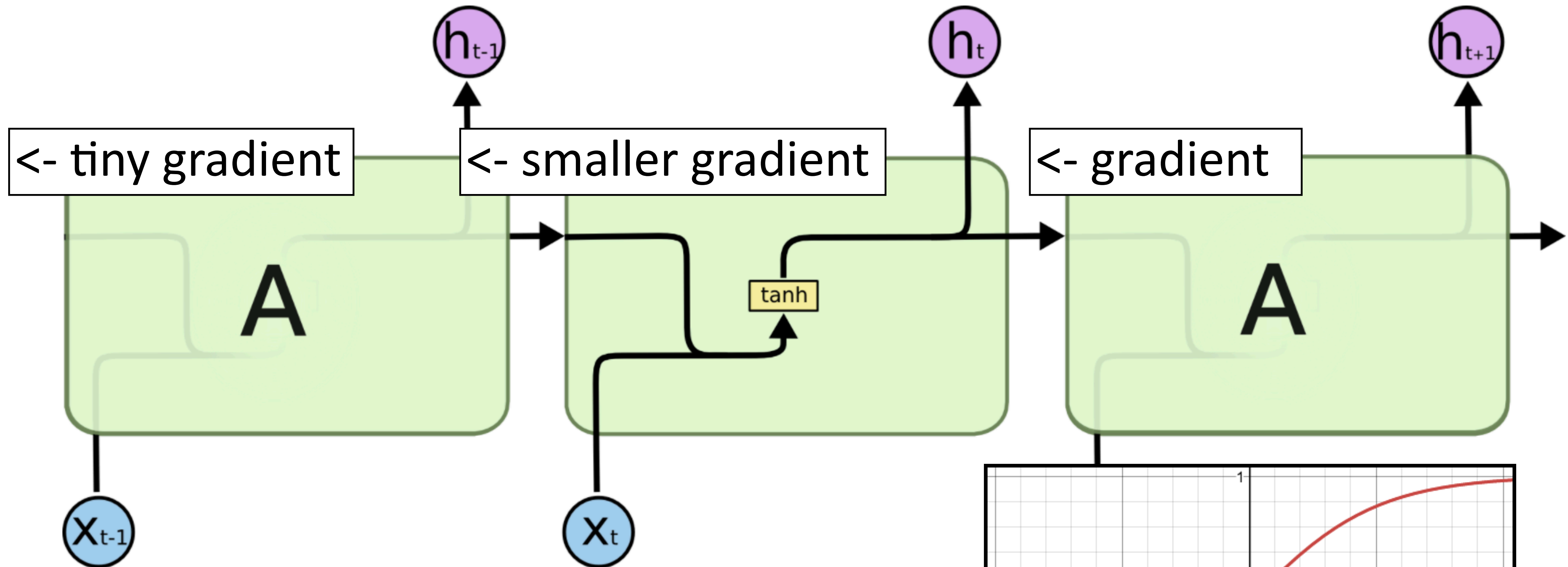
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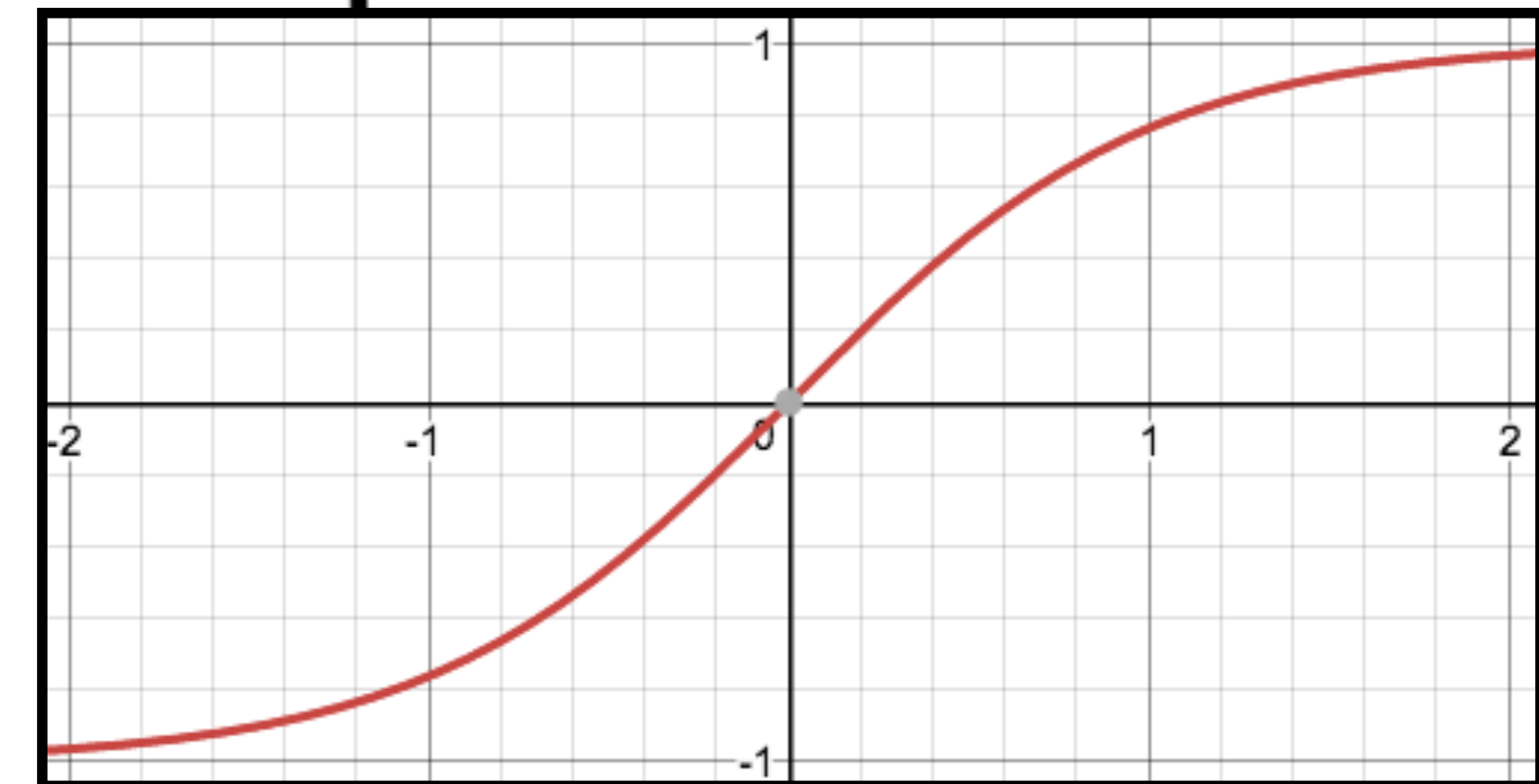
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LSTMs/GRUs

Gated Connections

- ▶ Designed to fix “vanishing gradient” problem using *gates*

$$\mathbf{h}_t = \mathbf{h}_{t-1} \odot \mathbf{f} + \text{func}(\mathbf{x}_t)$$

gated

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Elman

- ▶ Vector-valued “forget gate” \mathbf{f} computed based on input and previous hidden state

$$\mathbf{f} = \sigma(W^{xf}\mathbf{x}_t + W^{hf}\mathbf{h}_{t-1})$$

- ▶ Sigmoid: elements of \mathbf{f} are in $(0, 1)$

Gated Connections

- ▶ Designed to fix “vanishing gradient” problem using *gates*

$$\mathbf{h}_t = \mathbf{h}_{t-1} \odot \mathbf{f} + \text{func}(\mathbf{x}_t)$$

gated

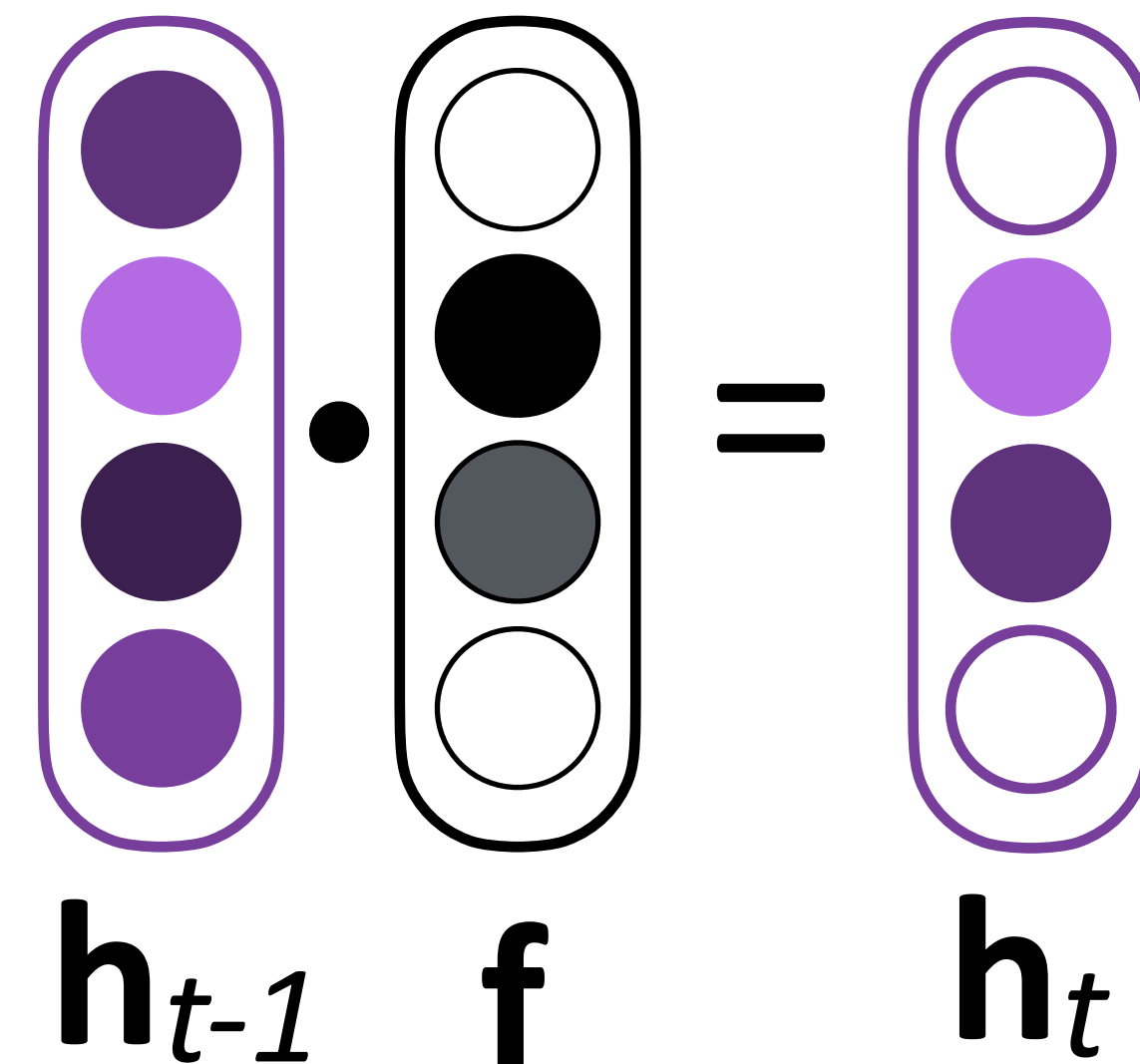
$$\mathbf{h}_t = \tanh(W\mathbf{x}_t + V\mathbf{h}_{t-1} + \mathbf{b}_h)$$

Elman

- ▶ Vector-valued “forget gate” \mathbf{f} computed based on input and previous hidden state

$$\mathbf{f} = \sigma(W^{xf}\mathbf{x}_t + W^{hf}\mathbf{h}_{t-1})$$

- ▶ Sigmoid: elements of \mathbf{f} are in $(0, 1)$



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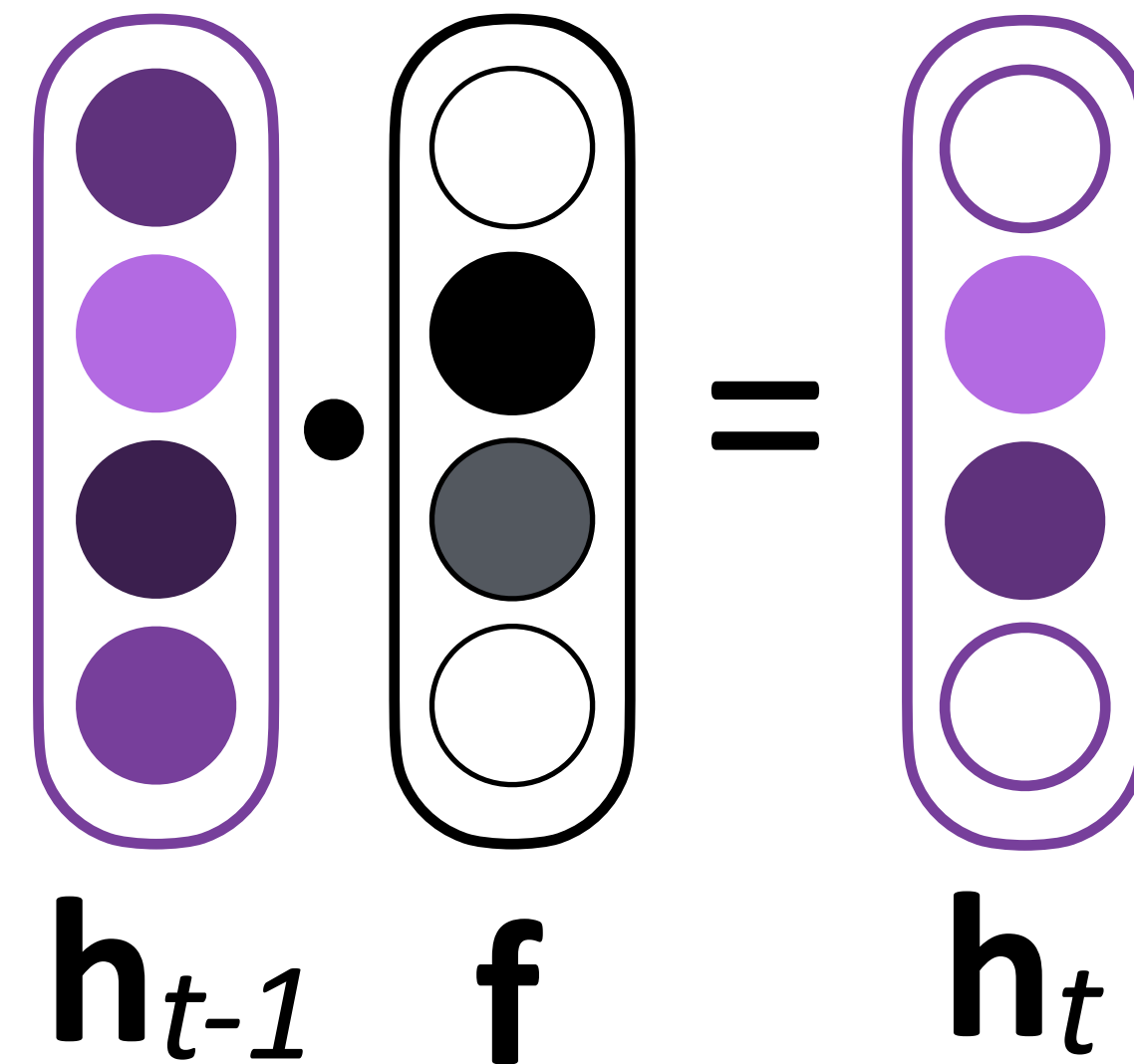
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- ▶ Sigmoid: elements of \mathbf{f} are in $(0, 1)$
- ▶ If $\mathbf{f} \approx \mathbf{1}$, we simply sum up a function of all inputs — gradient doesn’t vanish!



LSTMs

- ▶ “Cell” \mathbf{c} in addition to hidden state \mathbf{h}

$$\mathbf{c}_t = \mathbf{c}_{t-1} \odot \mathbf{f} + \text{func}(\mathbf{x}_t, \mathbf{h}_{t-1})$$

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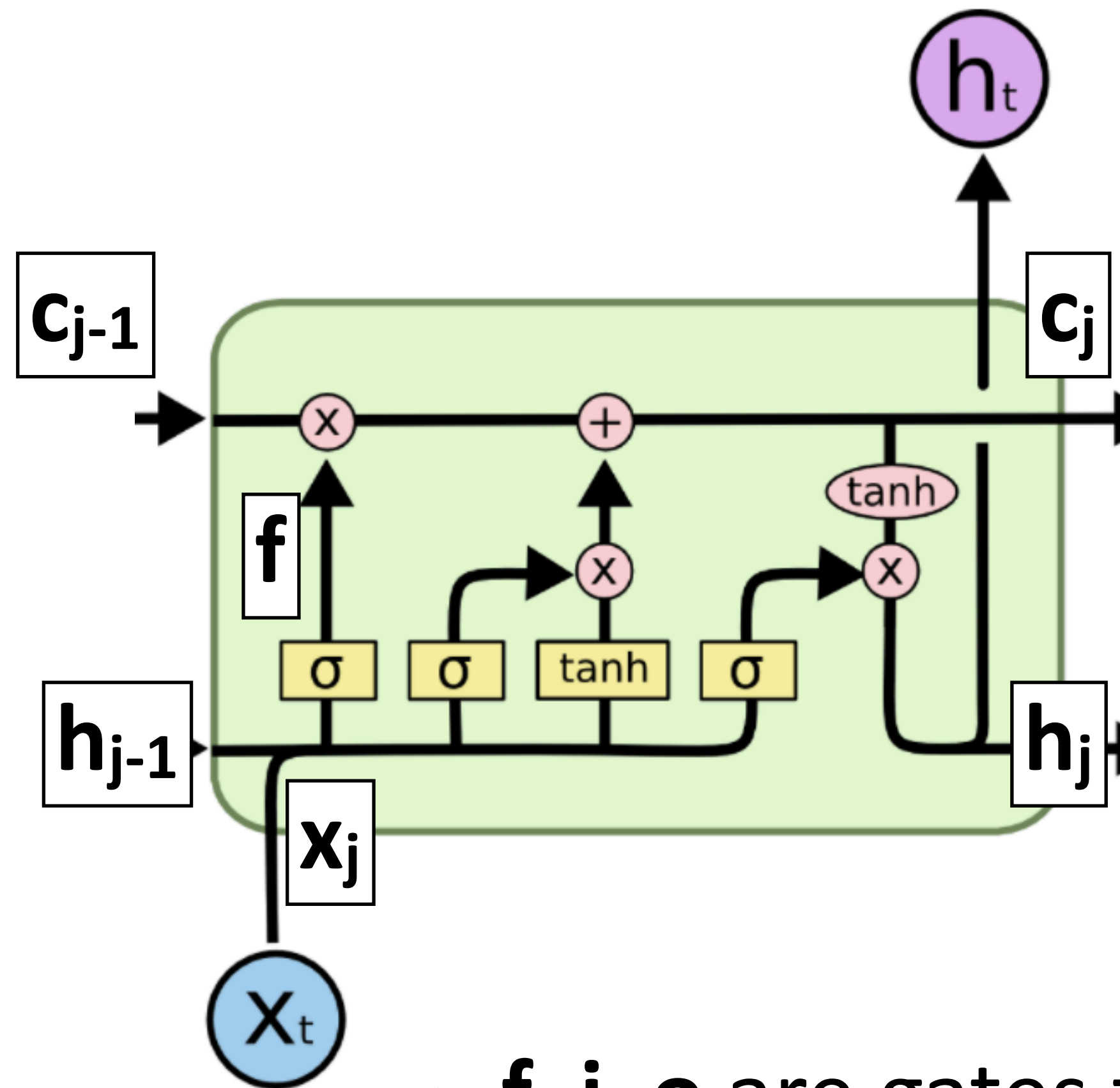
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- ▶ Basic communication flow: $\mathbf{x} \rightarrow \mathbf{c} \rightarrow \mathbf{h} \rightarrow \text{output}$, each step of this process is gated in addition to gates from previous timesteps

LSTMs

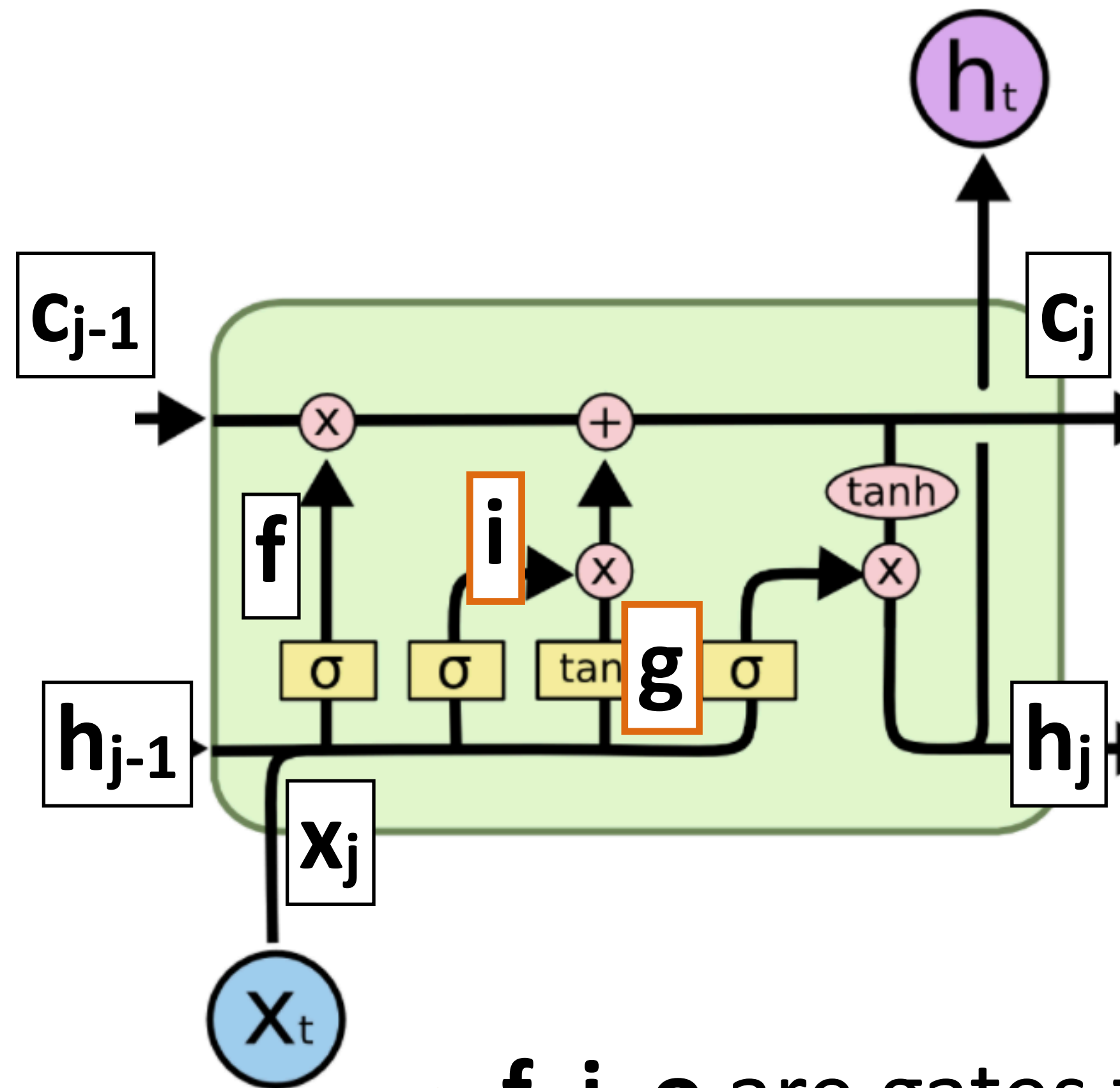


$$c_j = c_{j-1} \odot f + \mathbf{g} \odot \mathbf{i}$$

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- ▶ f , i , o are gates that control information flow
- ▶ g reflects the main computation of the cell

LSTMs



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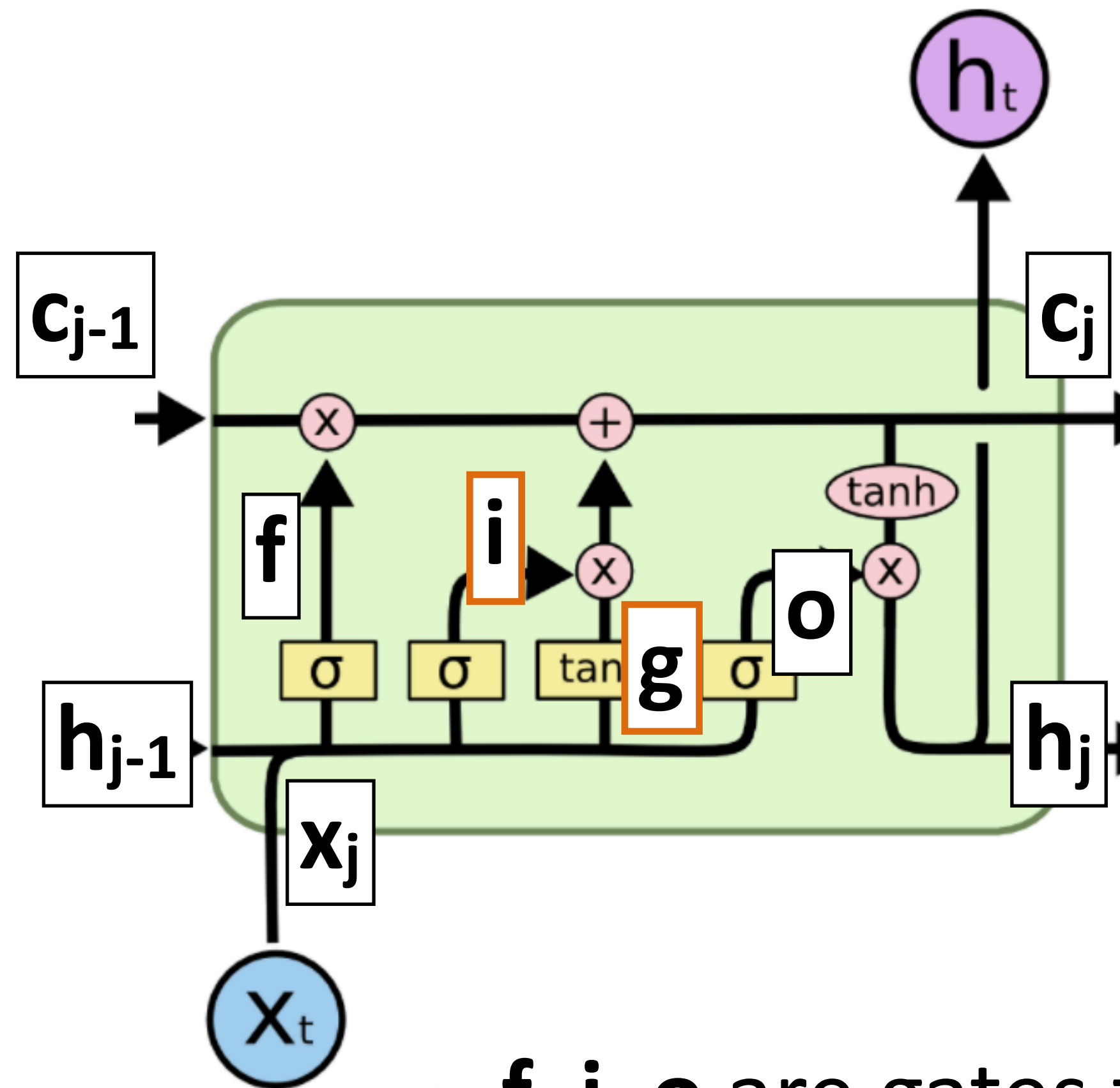
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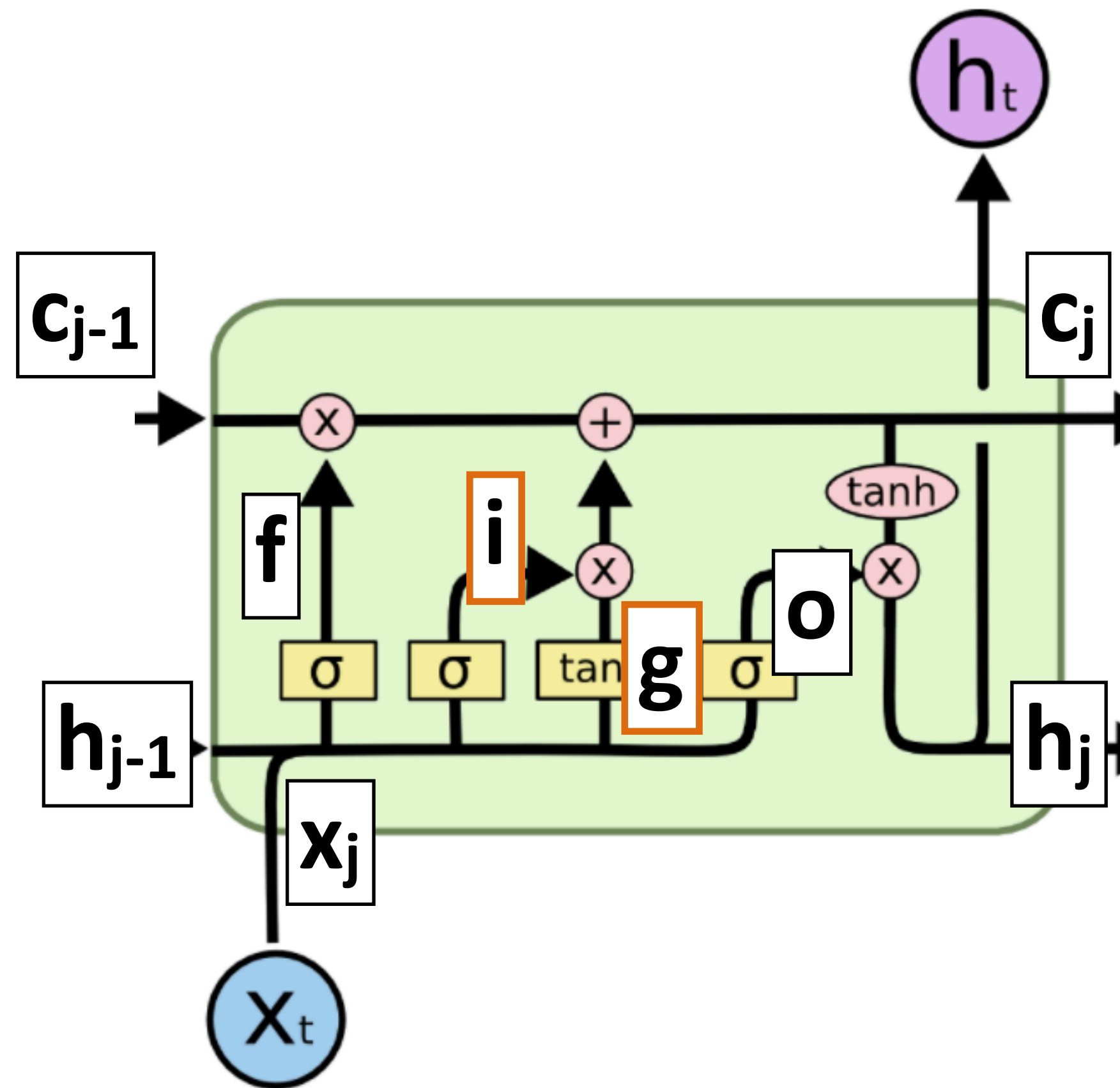
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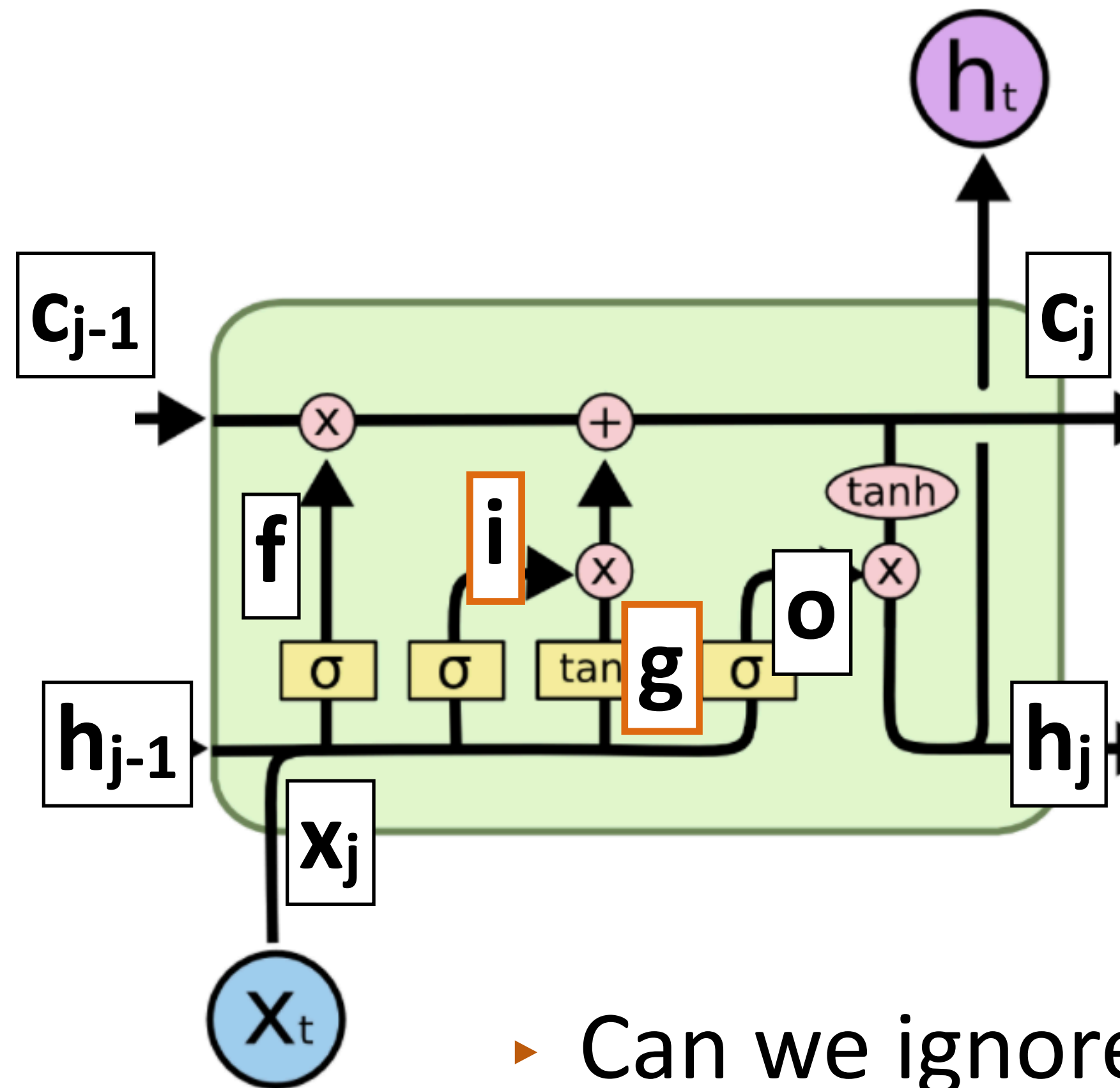
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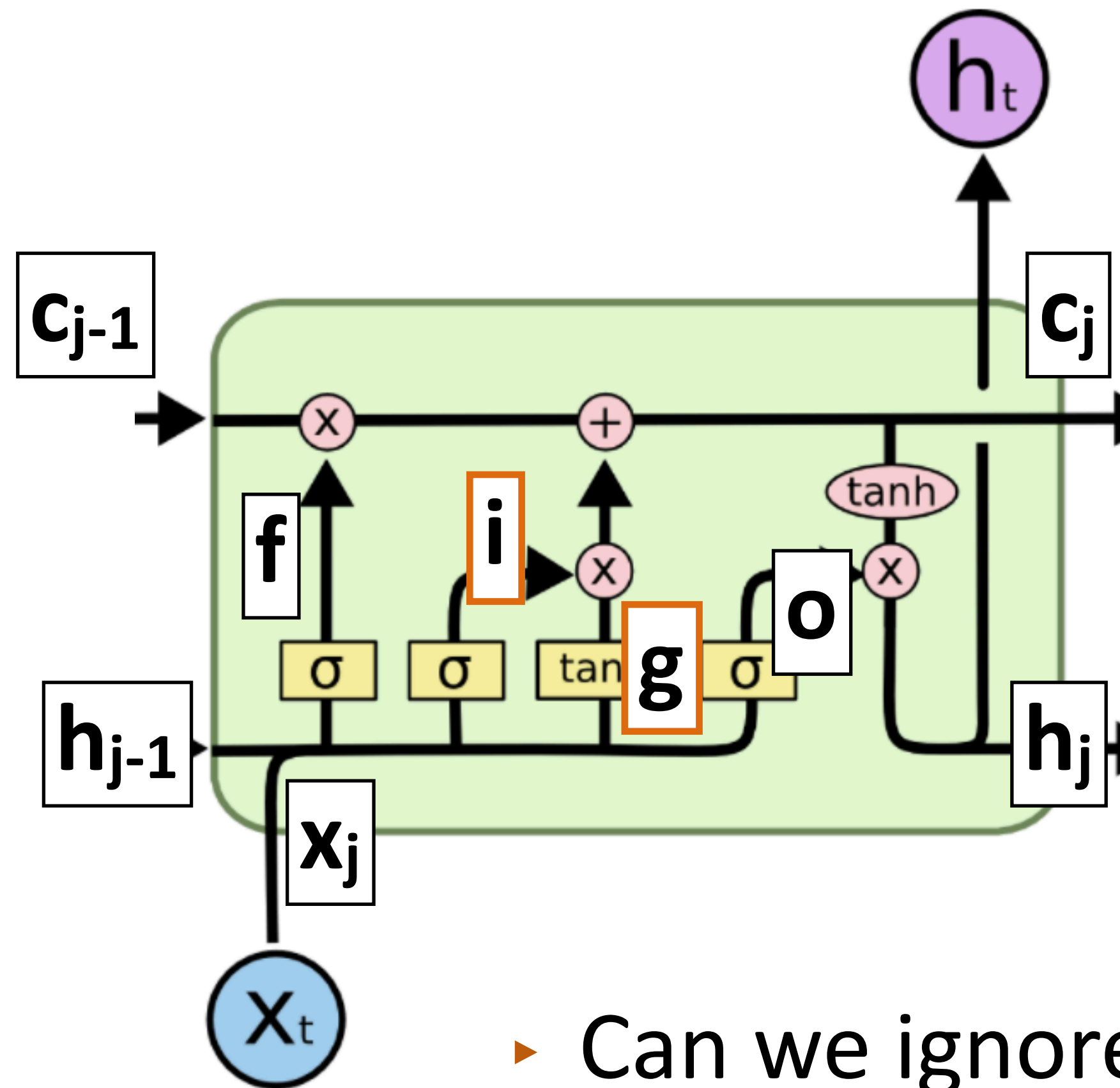
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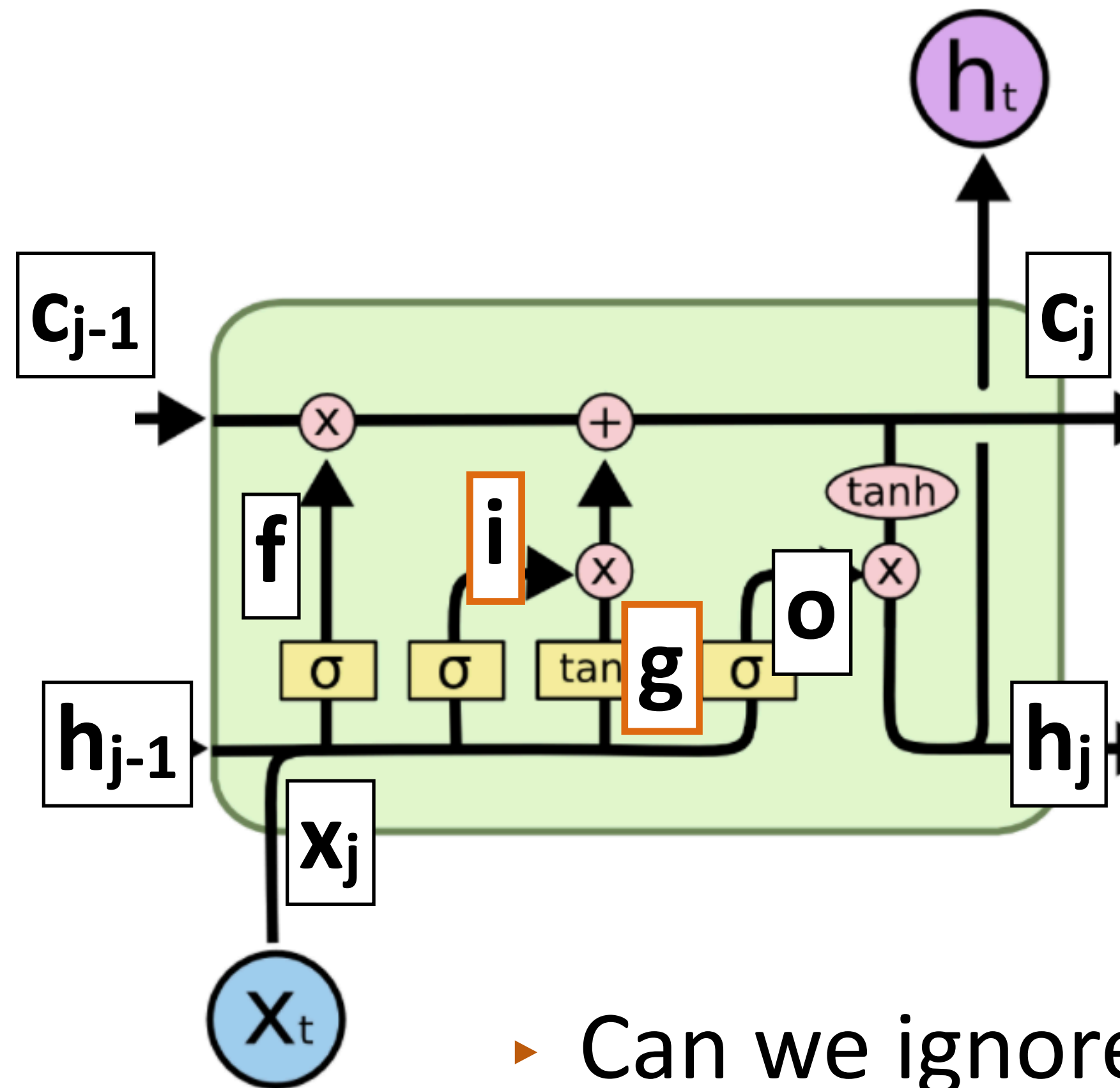
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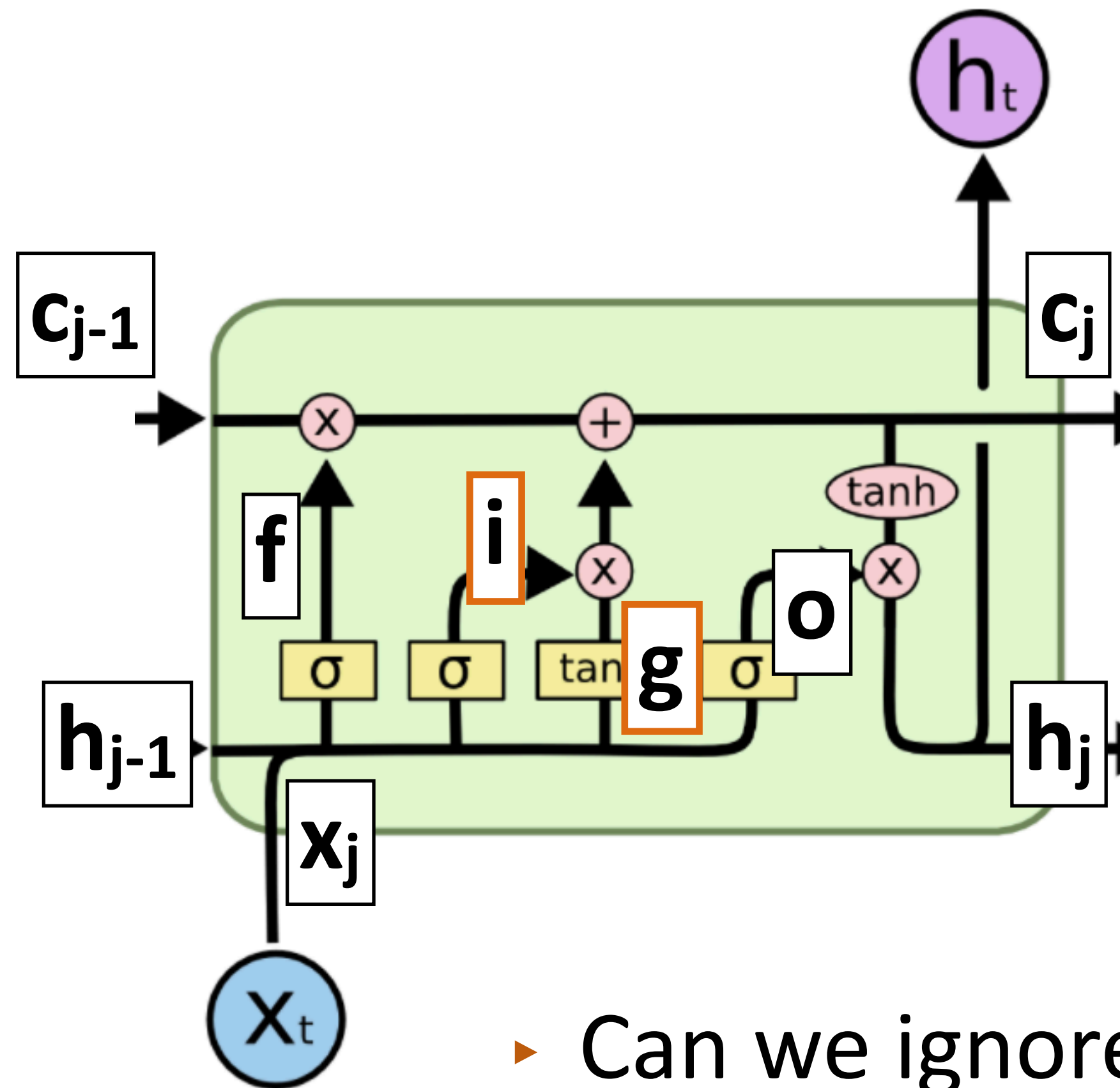
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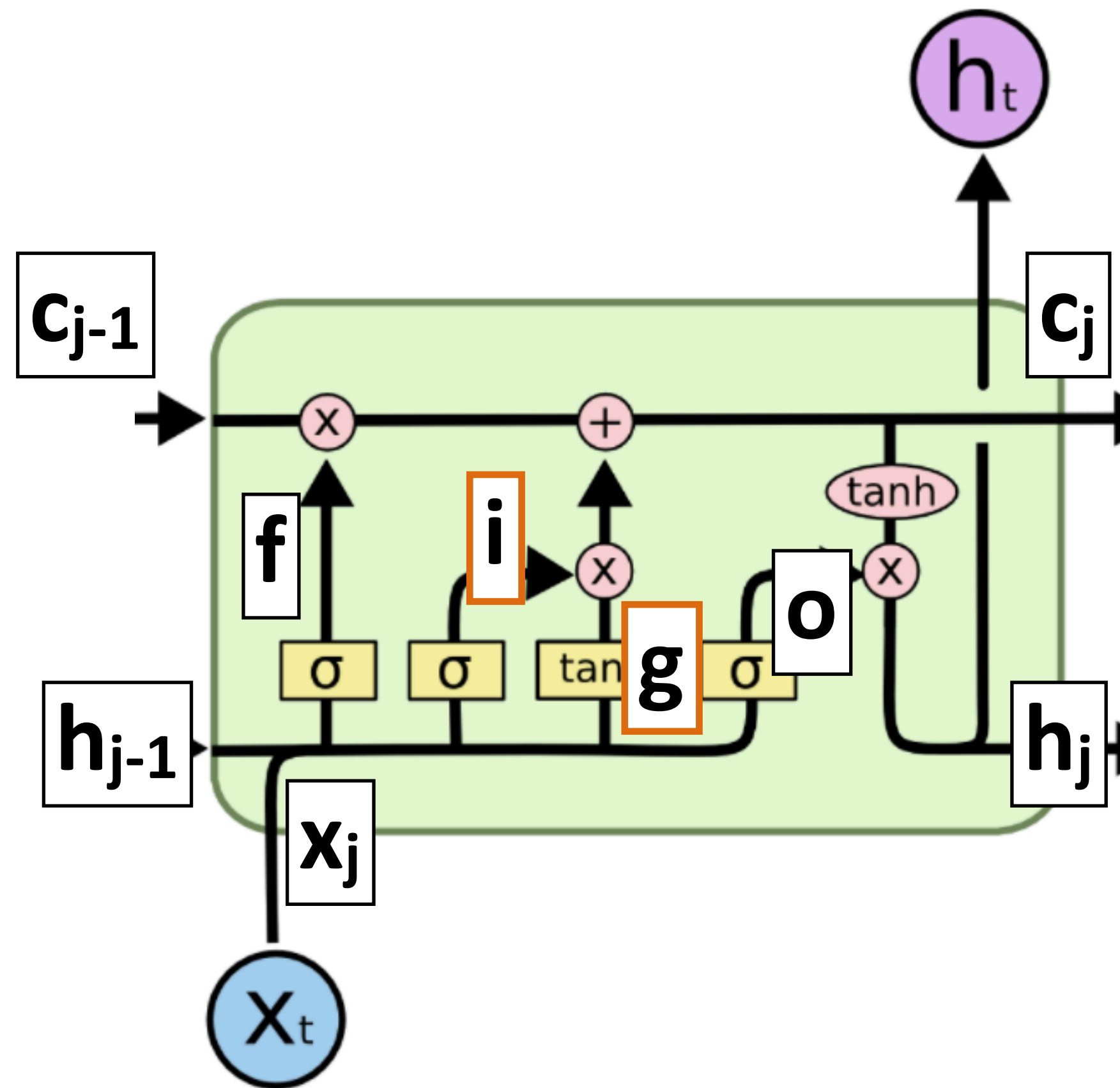
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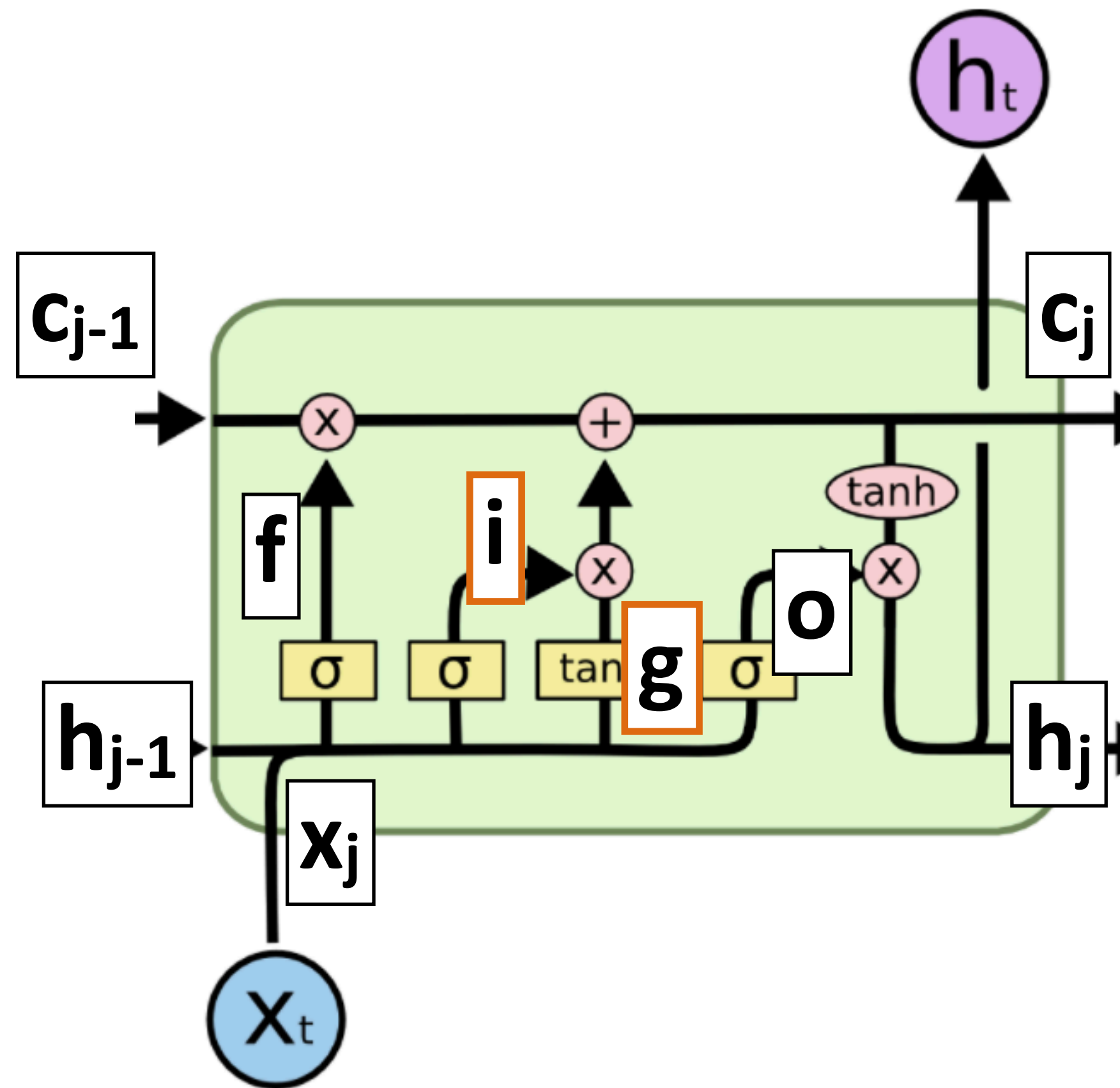
- ▶ Can we ignore the old value of \mathbf{c} for this timestep?
- ▶ Can an LSTM sum up its inputs \mathbf{x} ?
- ▶ Can we ignore a particular input \mathbf{x} ?
- ▶ Can we output something without changing \mathbf{c} ?

LSTMs



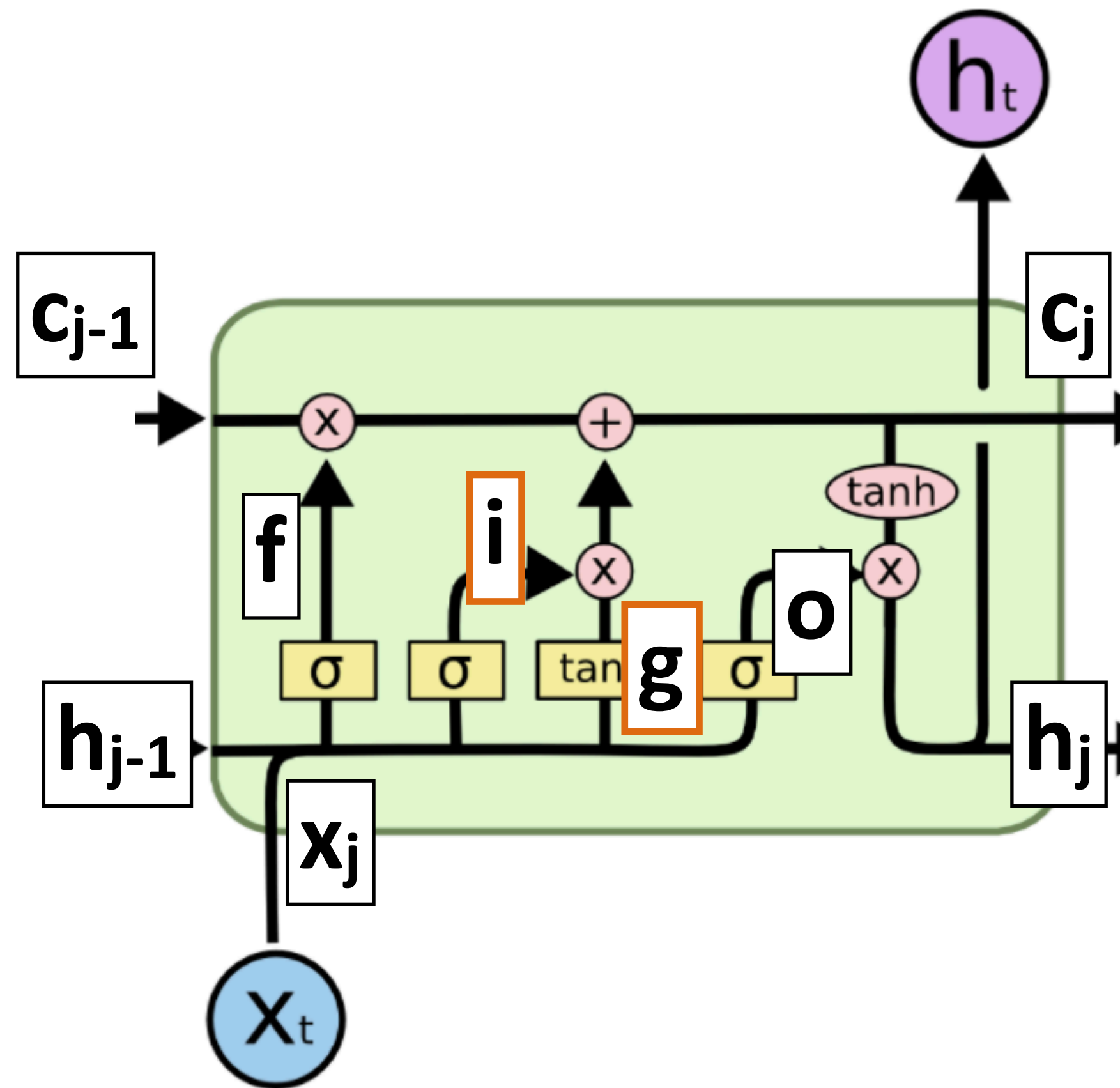
- ▶ Ignoring recurrent state entirely:
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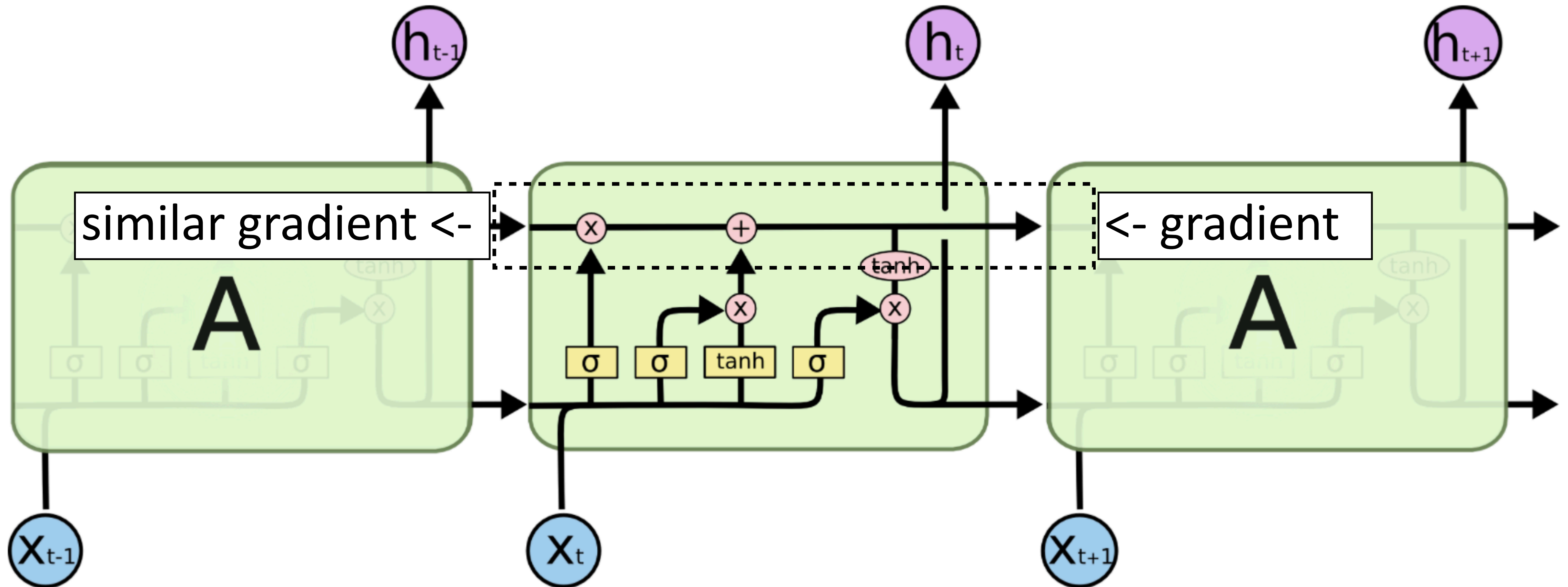
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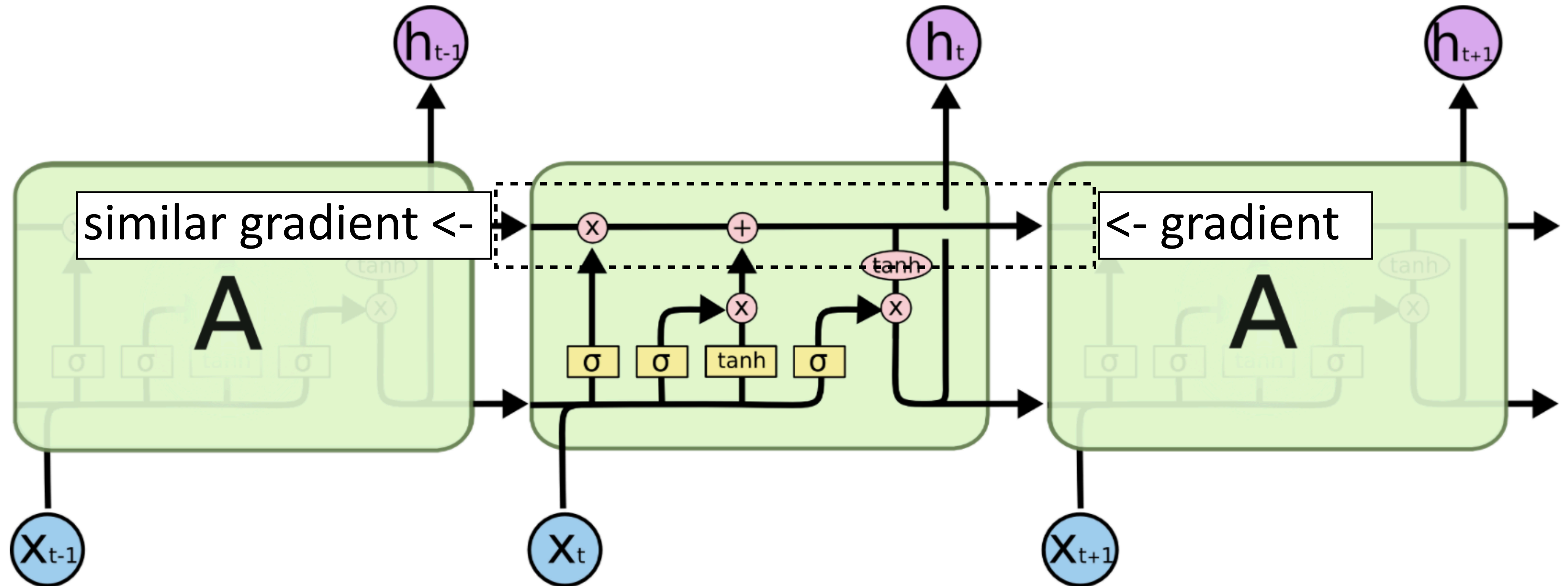


- ▶ Ignoring recurrent state entirely:
 - ▶ Lets us get feedforward layer over token
- ▶ Ignoring input:
 - ▶ Lets us discard stopwords
- ▶ Summing inputs:
 - ▶ Lets us compute a bag-of-words representation

LSTMs

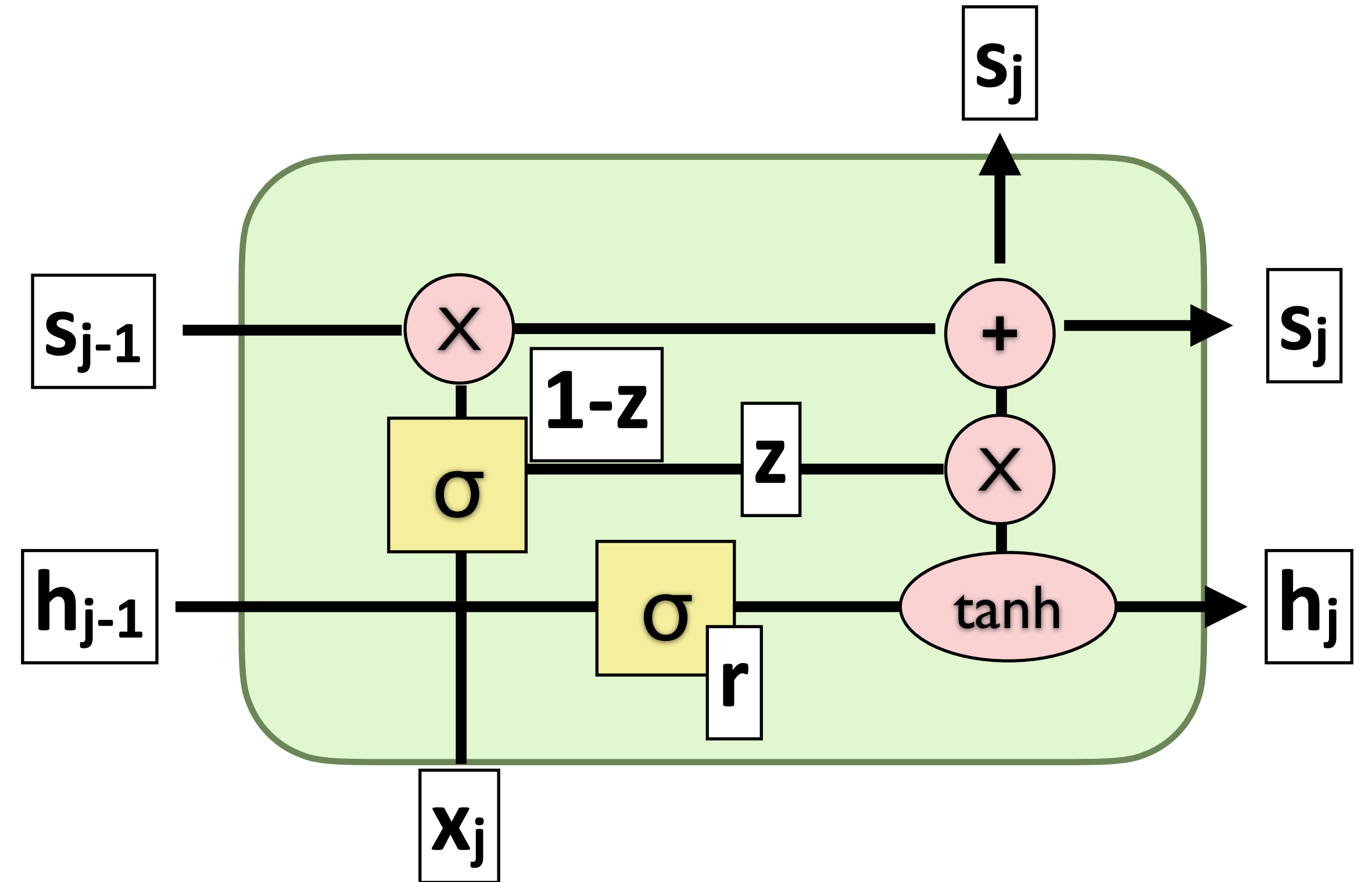
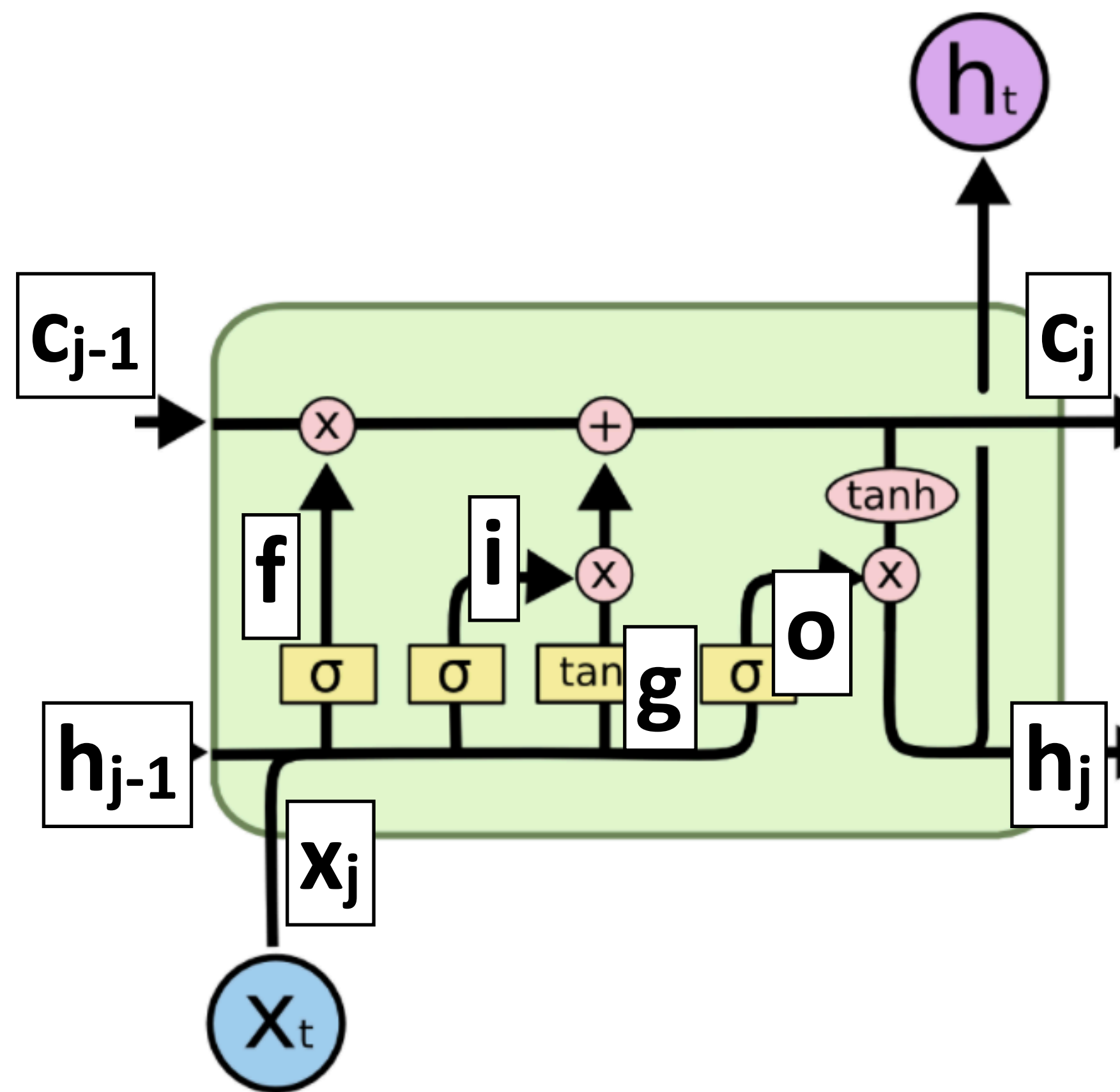


LSTMs



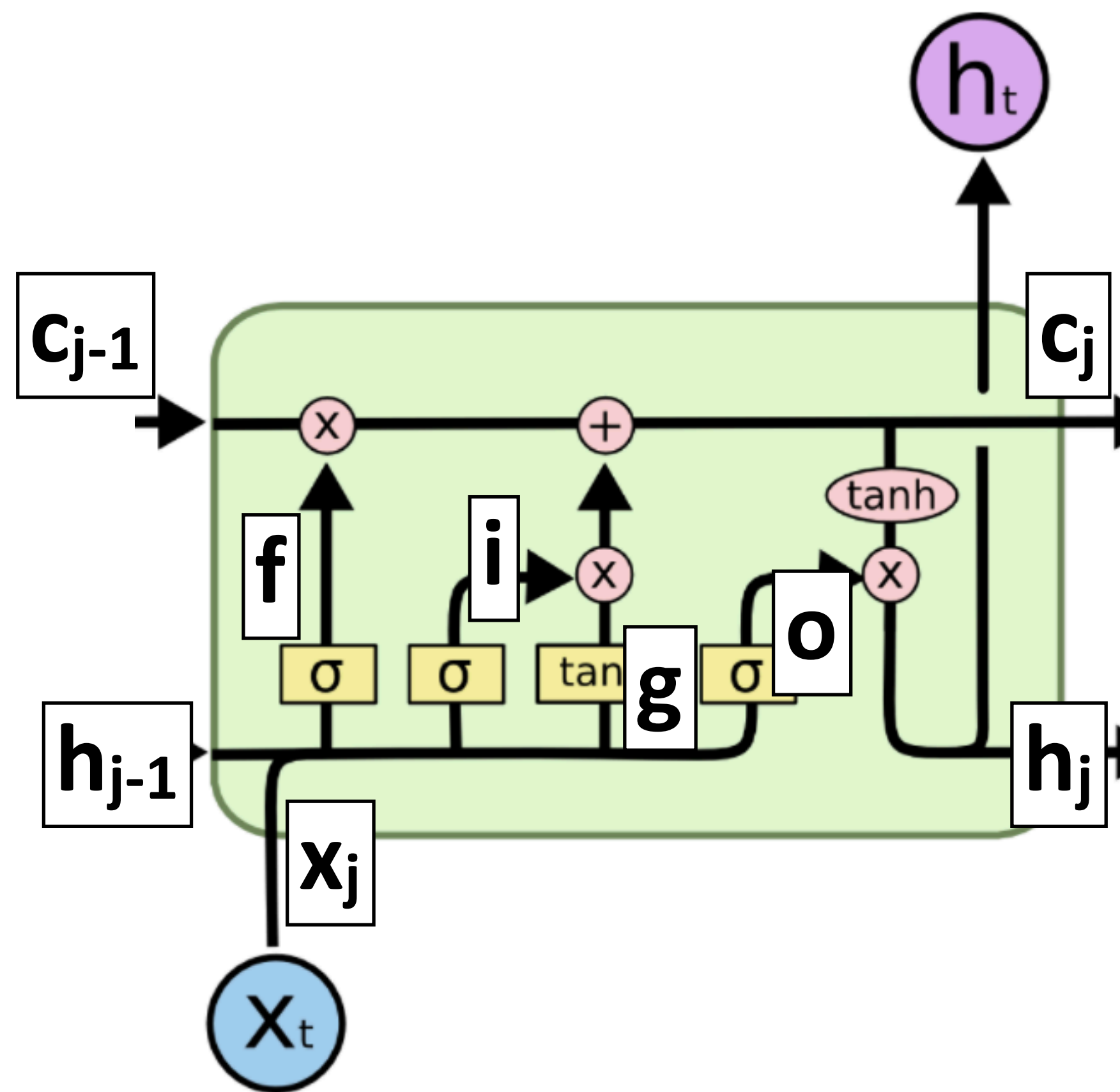
- ▶ Gradient still diminishes, but in a controlled way and generally by less — usually initialize forget gate = 1 to remember everything to start

GRUs

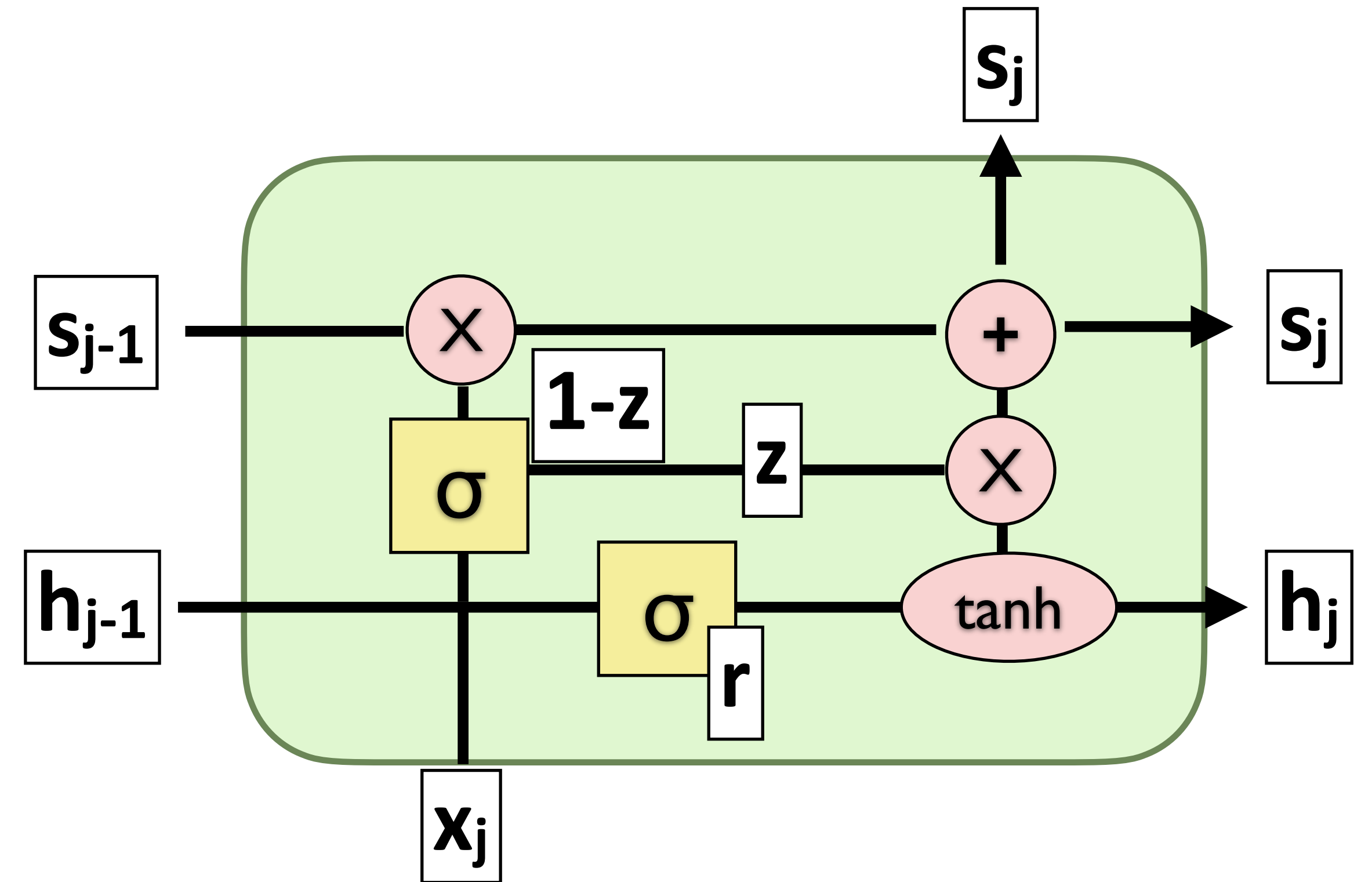


- ▶ LSTM: more complex and slower, may work a bit better

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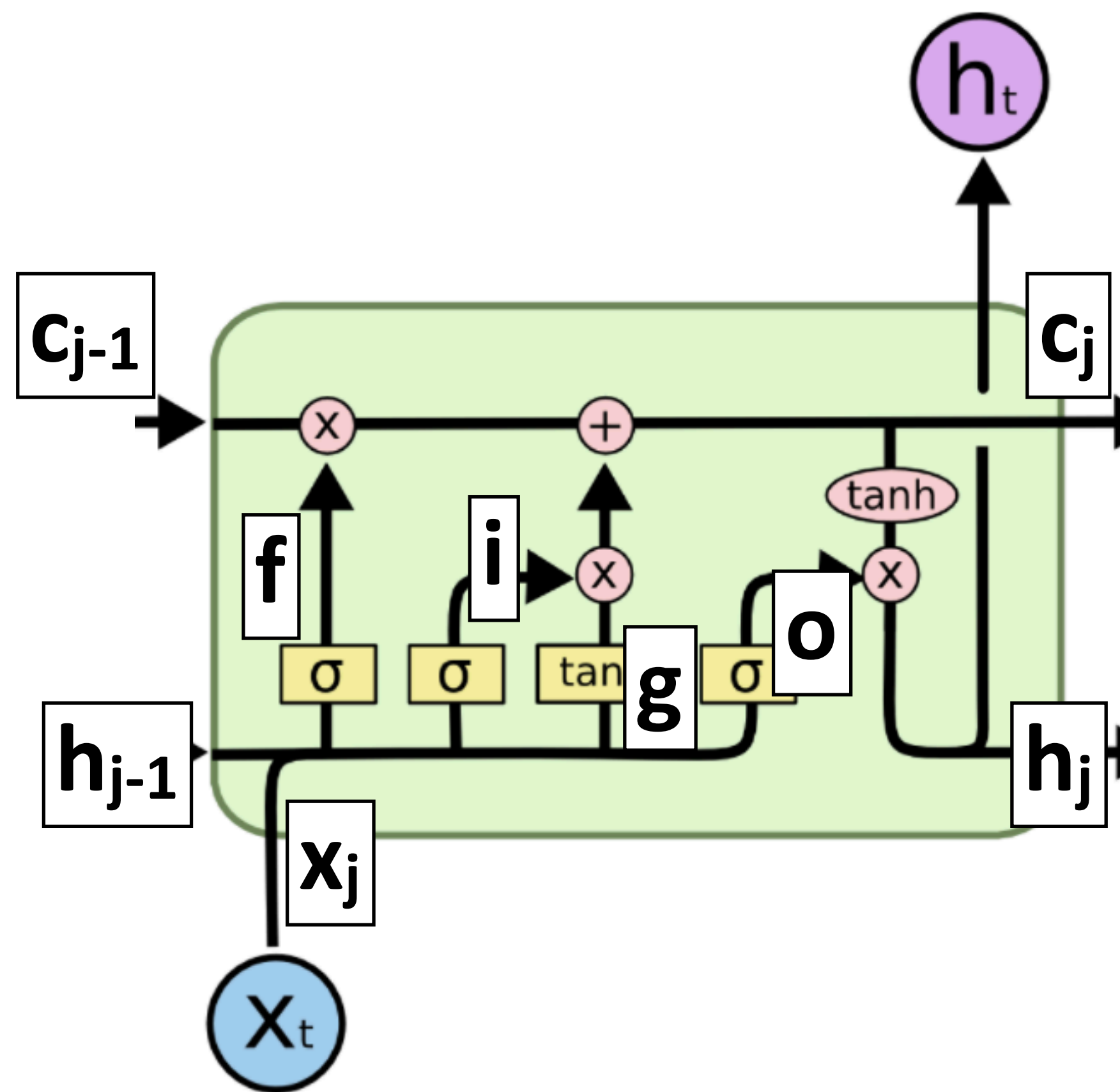


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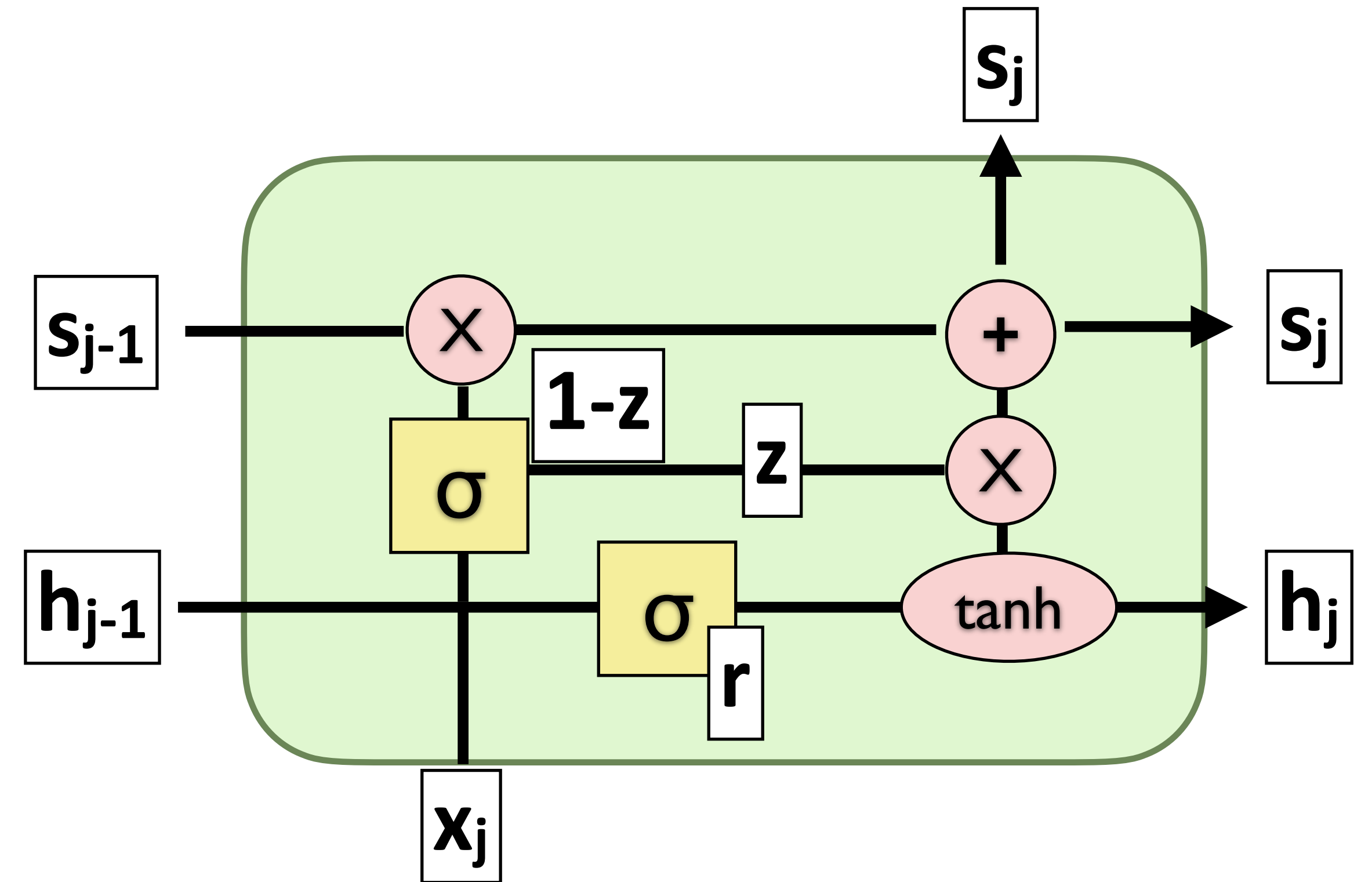


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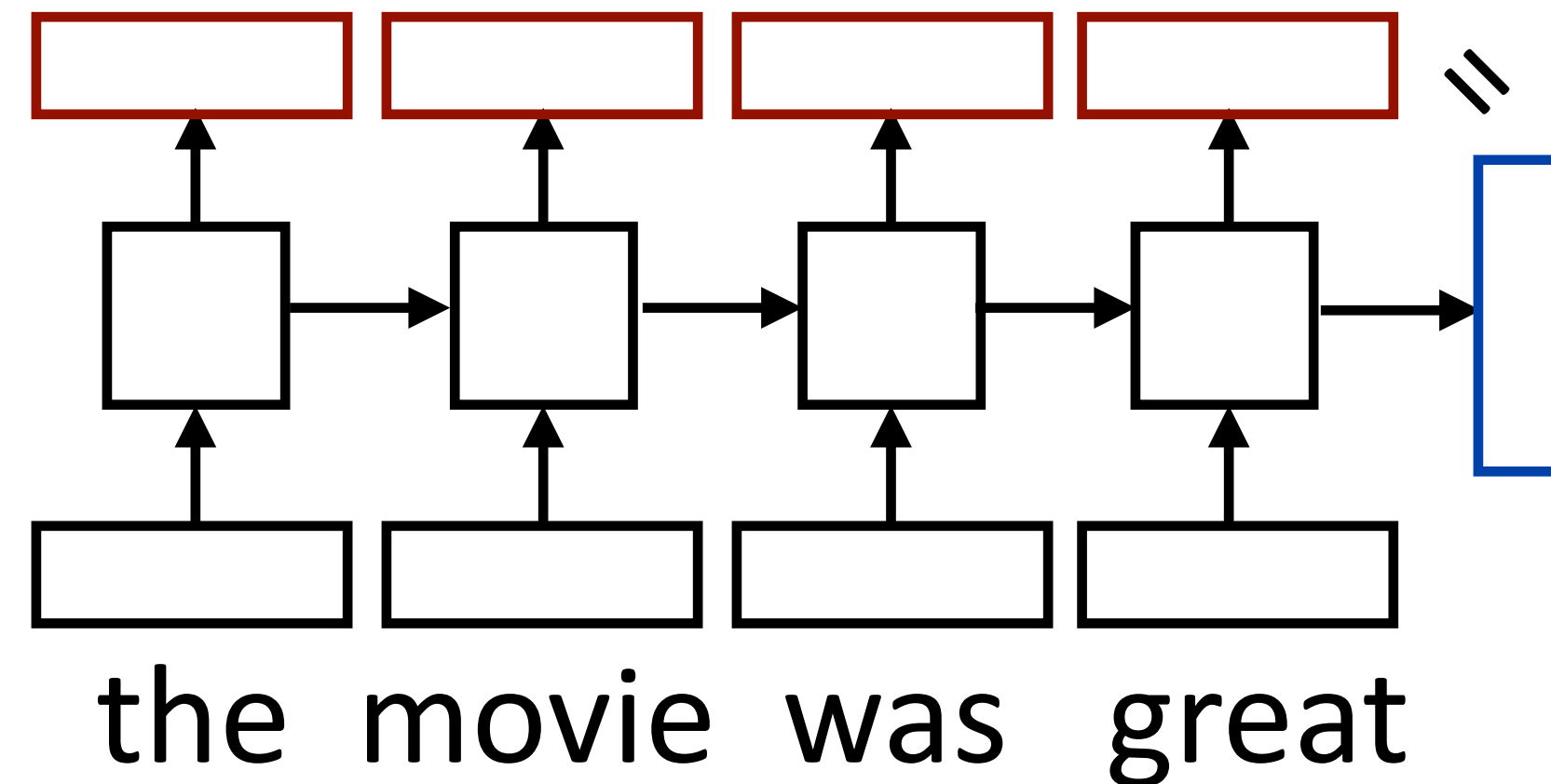


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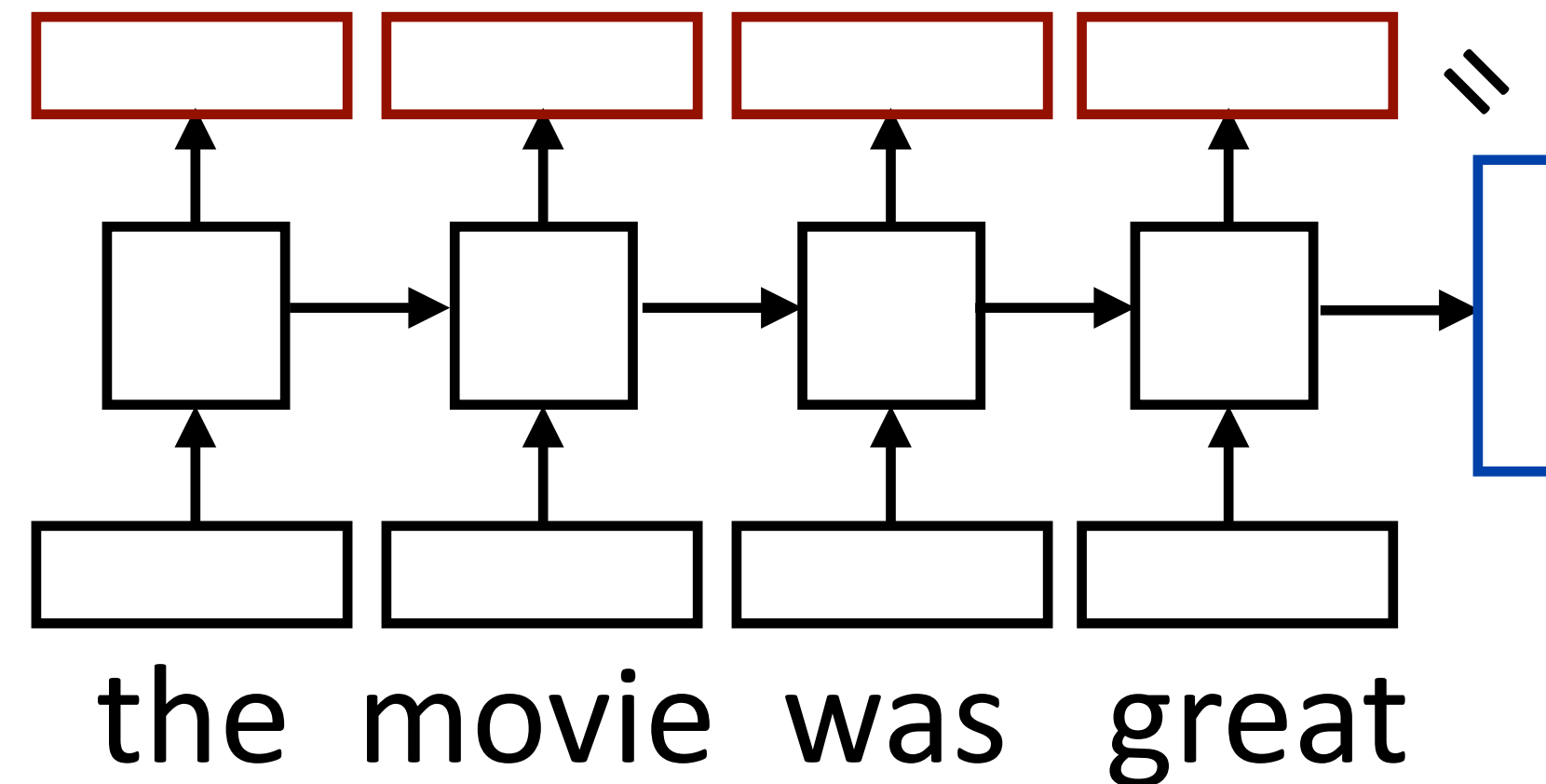
- ▶ GRU: faster, a bit simpler
- ▶ Two gates: z (forget, mixes s and h) and r (mixes h and x)

What do RNNs produce?



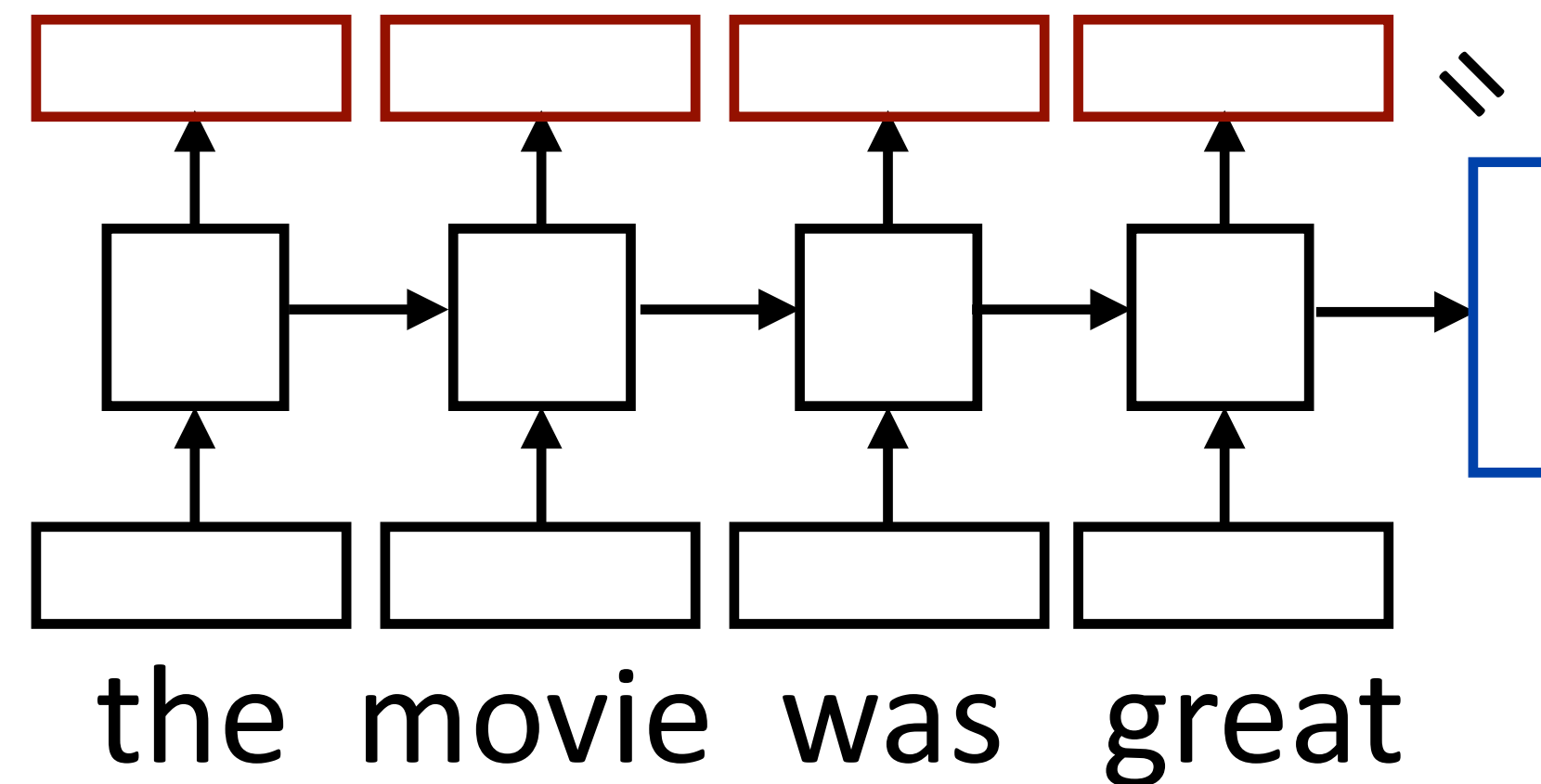
- ▶ **Encoding of the sentence** — can pass this a decoder or make a classification decision about the sentence

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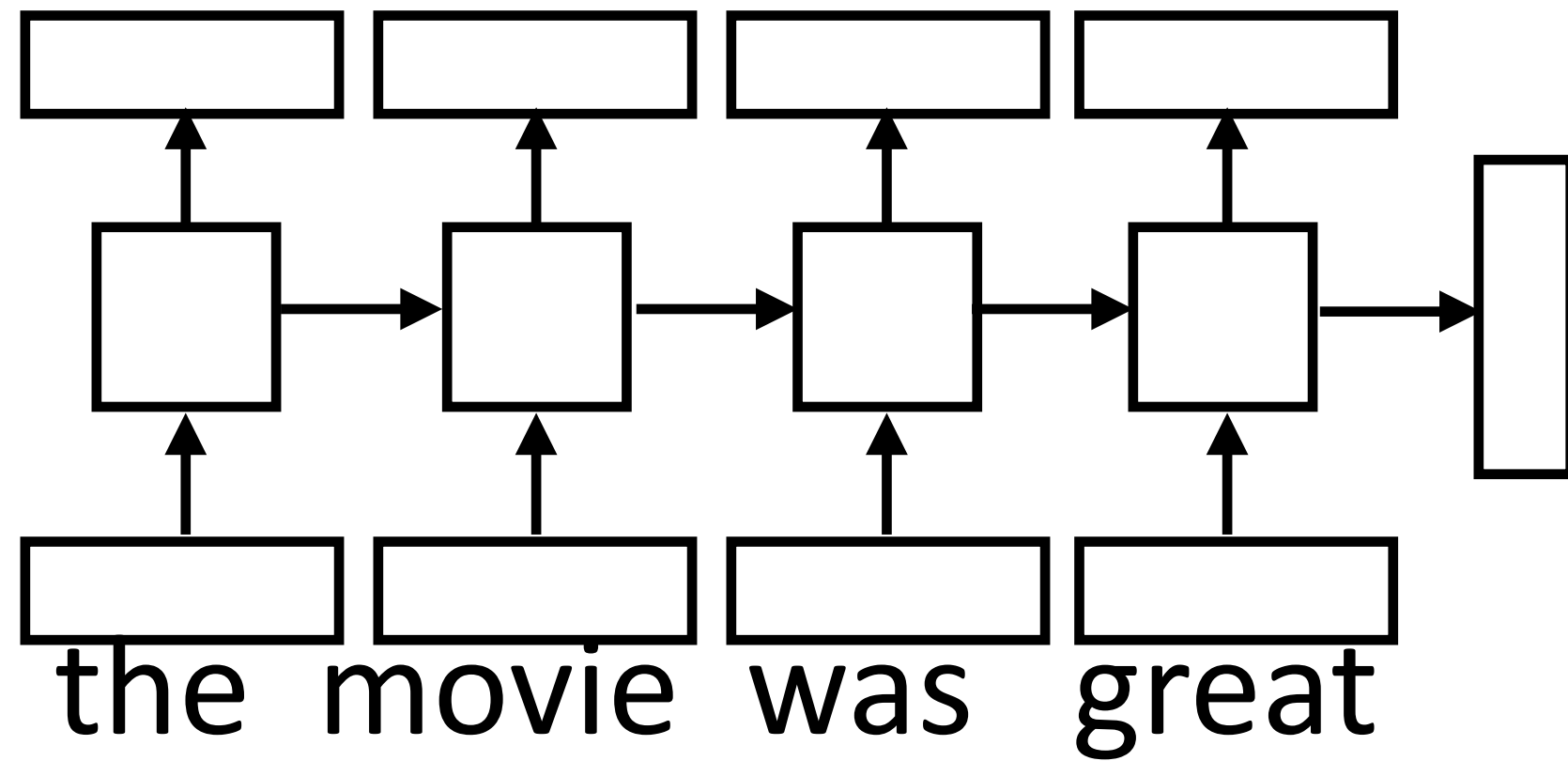
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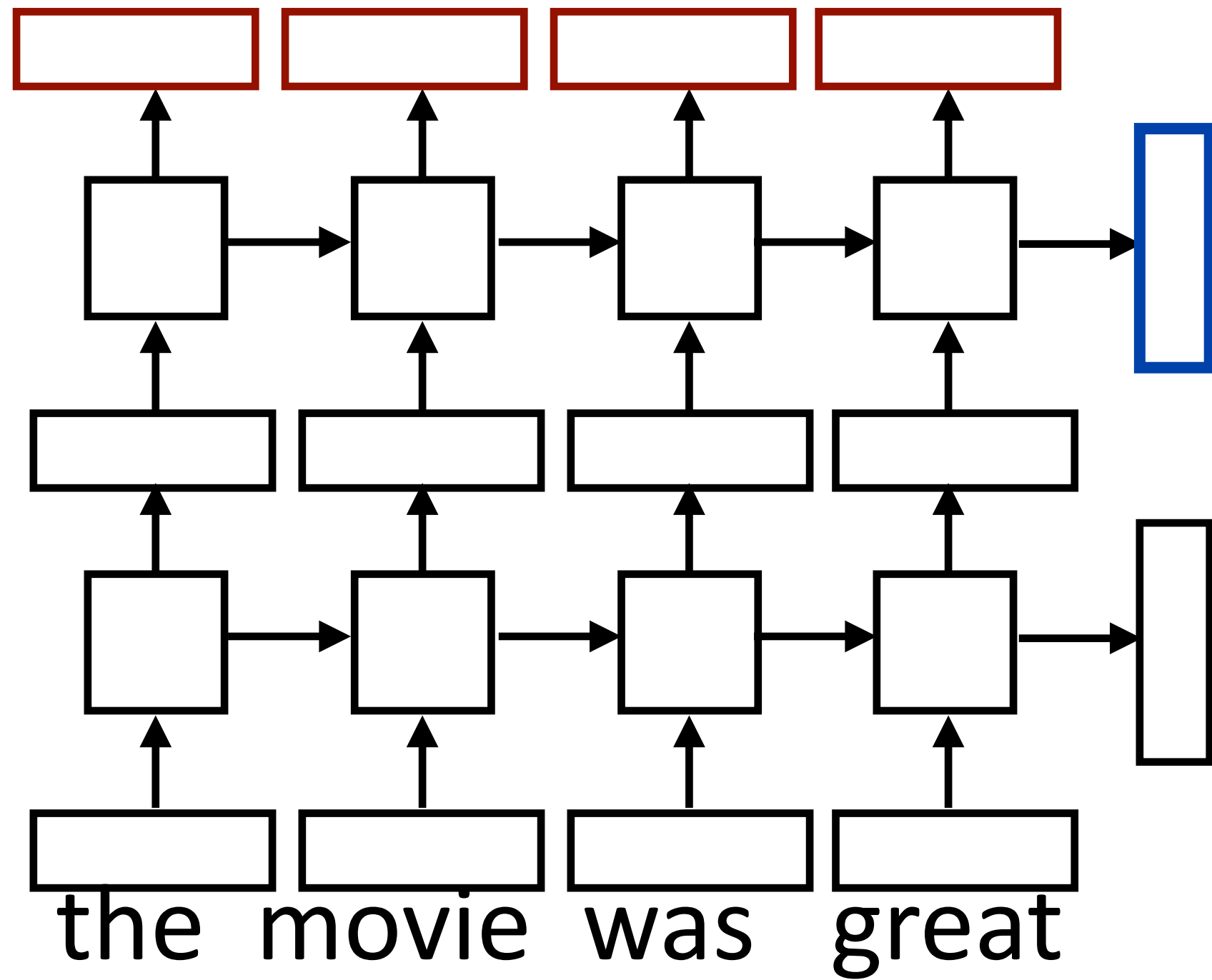


- ▶ **Encoding of the sentence** — can pass this a decoder or make a classification decision about the sentence
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- ▶ RNN can be viewed as a transformation of a sequence of vectors into a sequence of context-dependent vectors

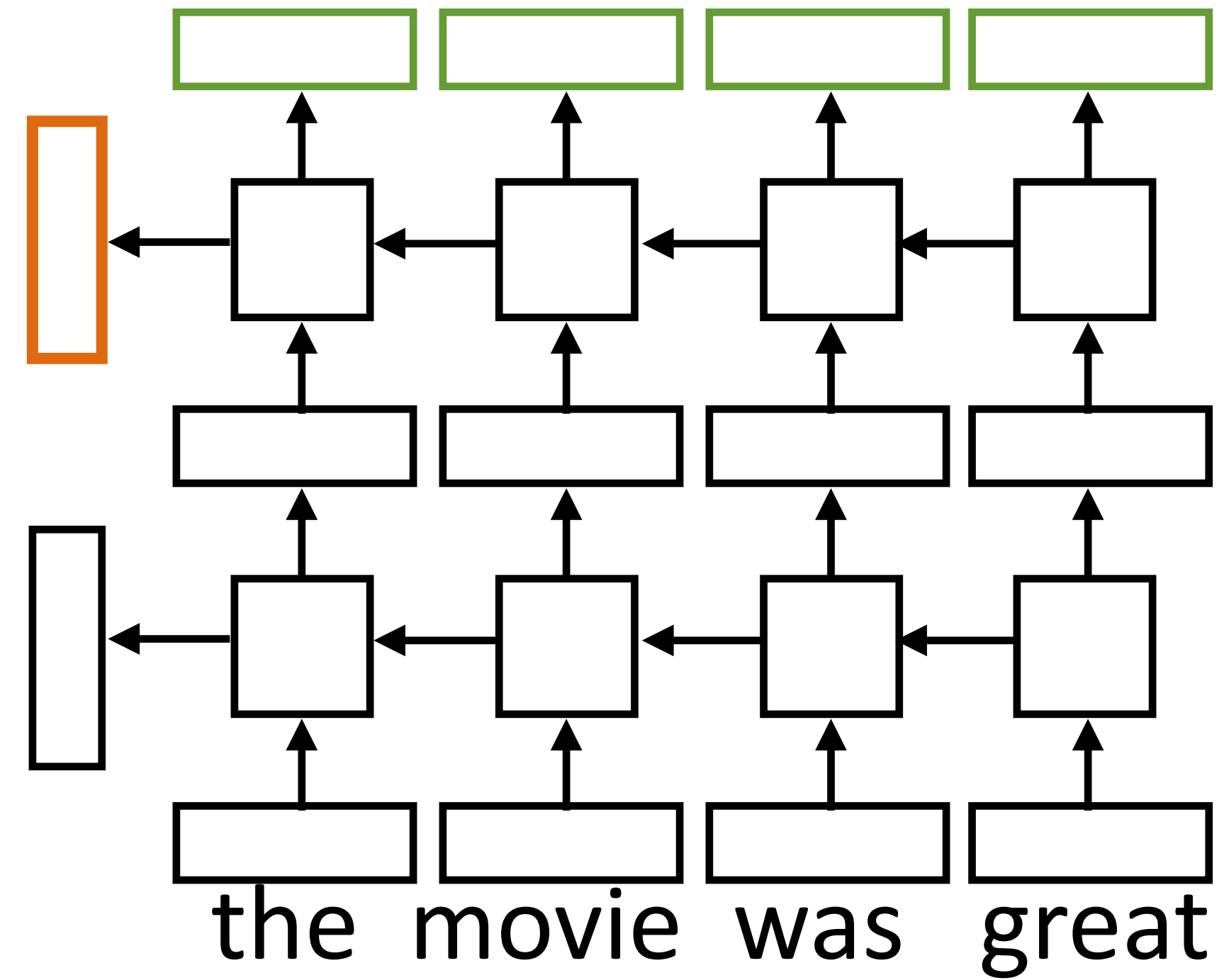
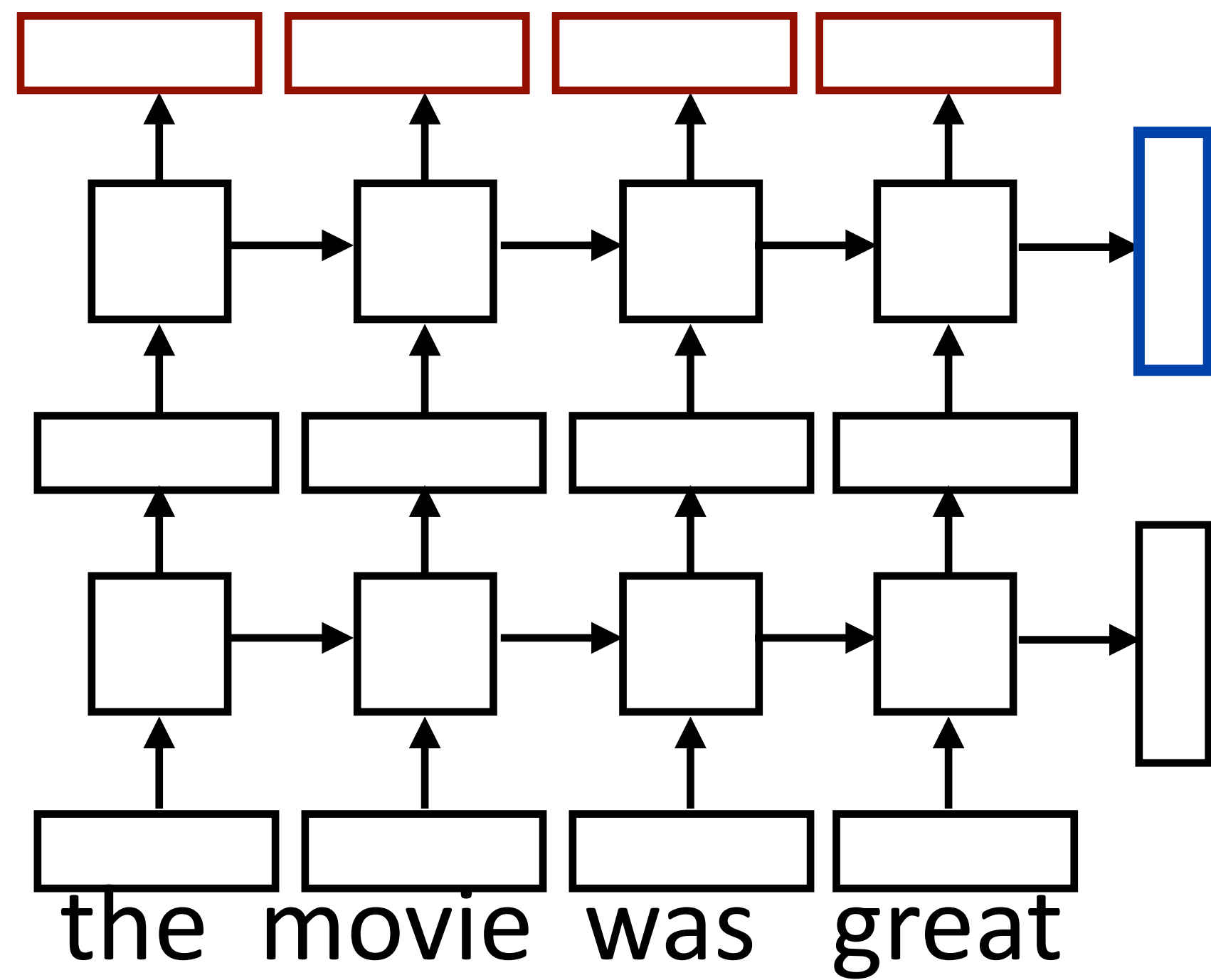
Multilayer Bidirectional RNN



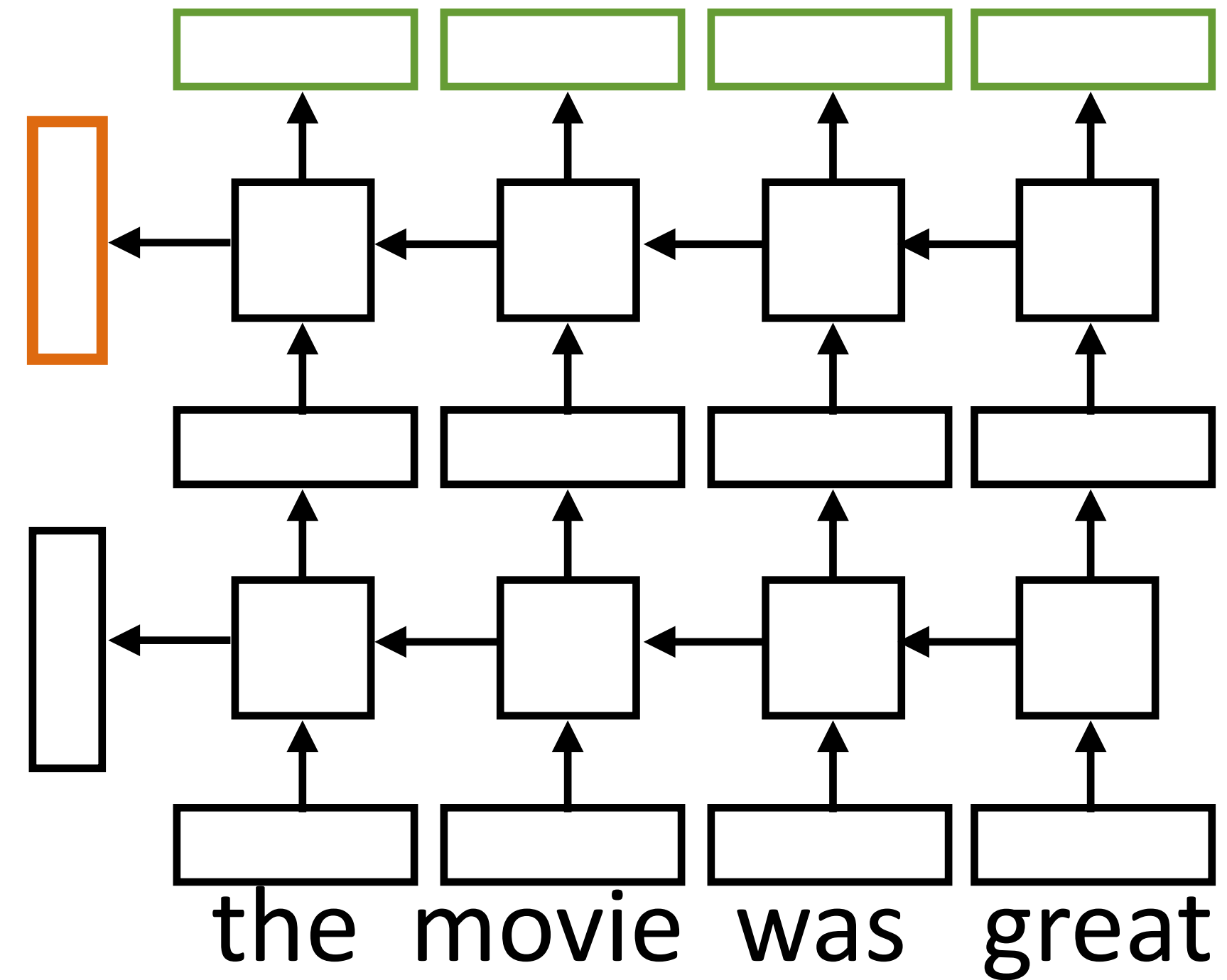
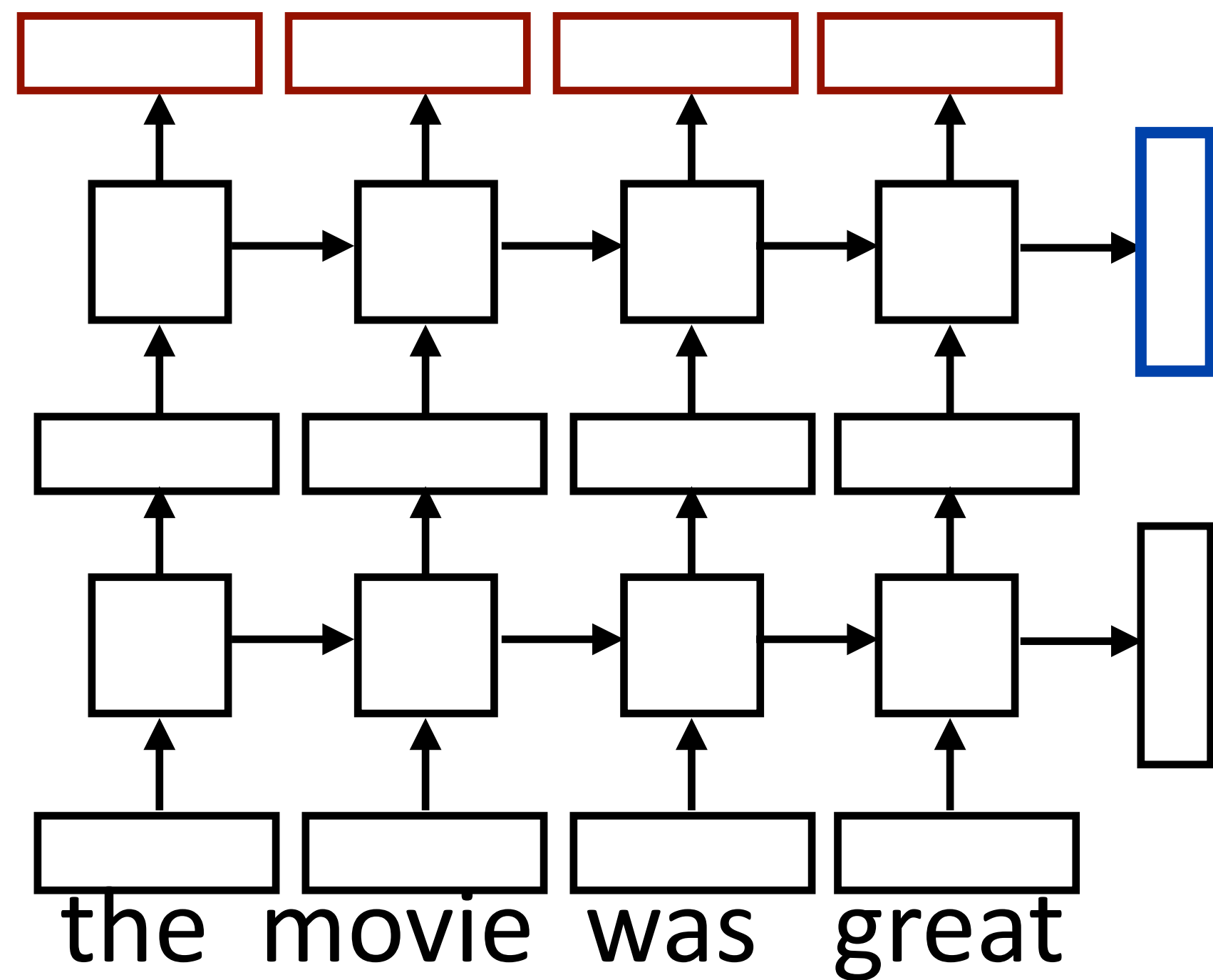
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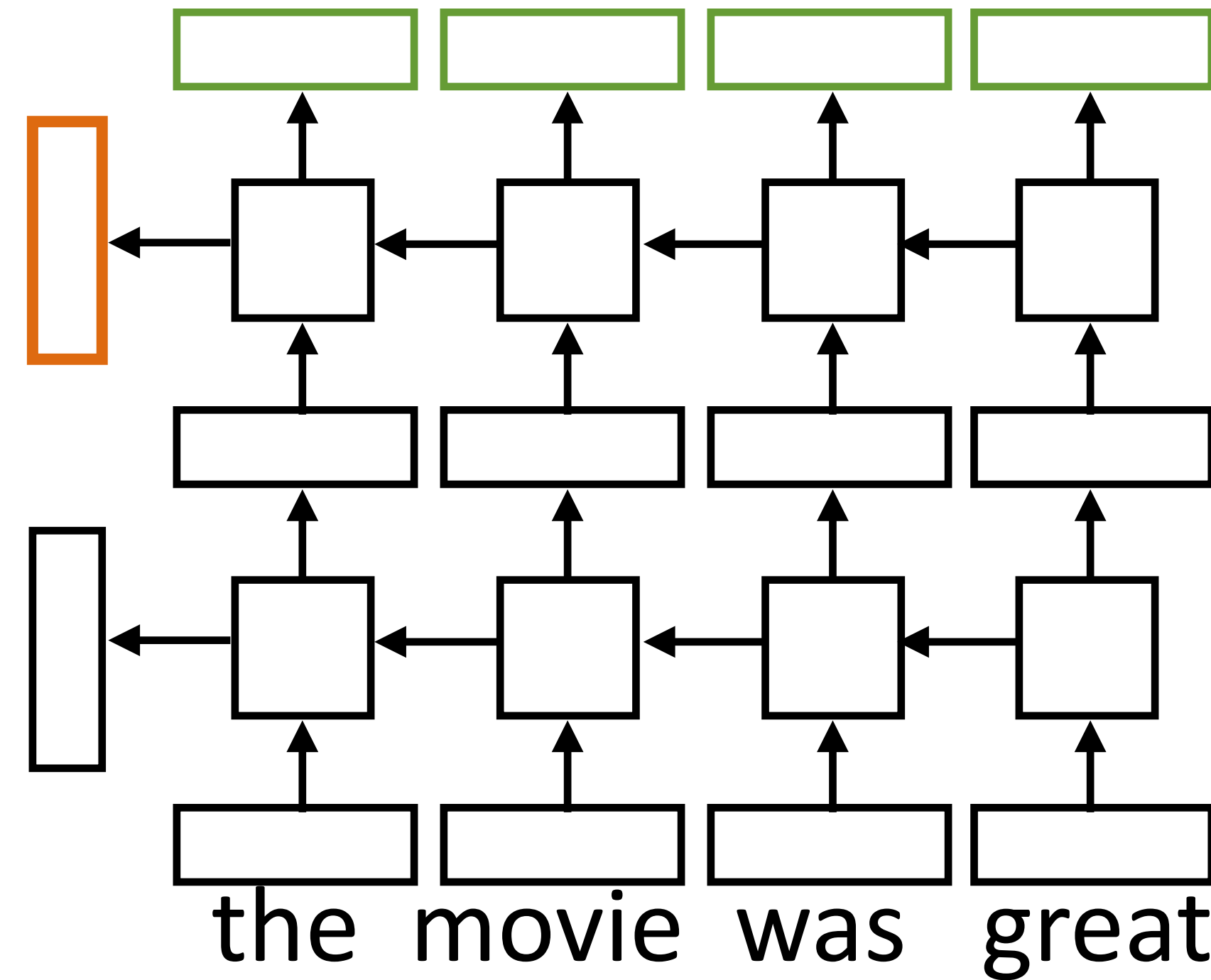
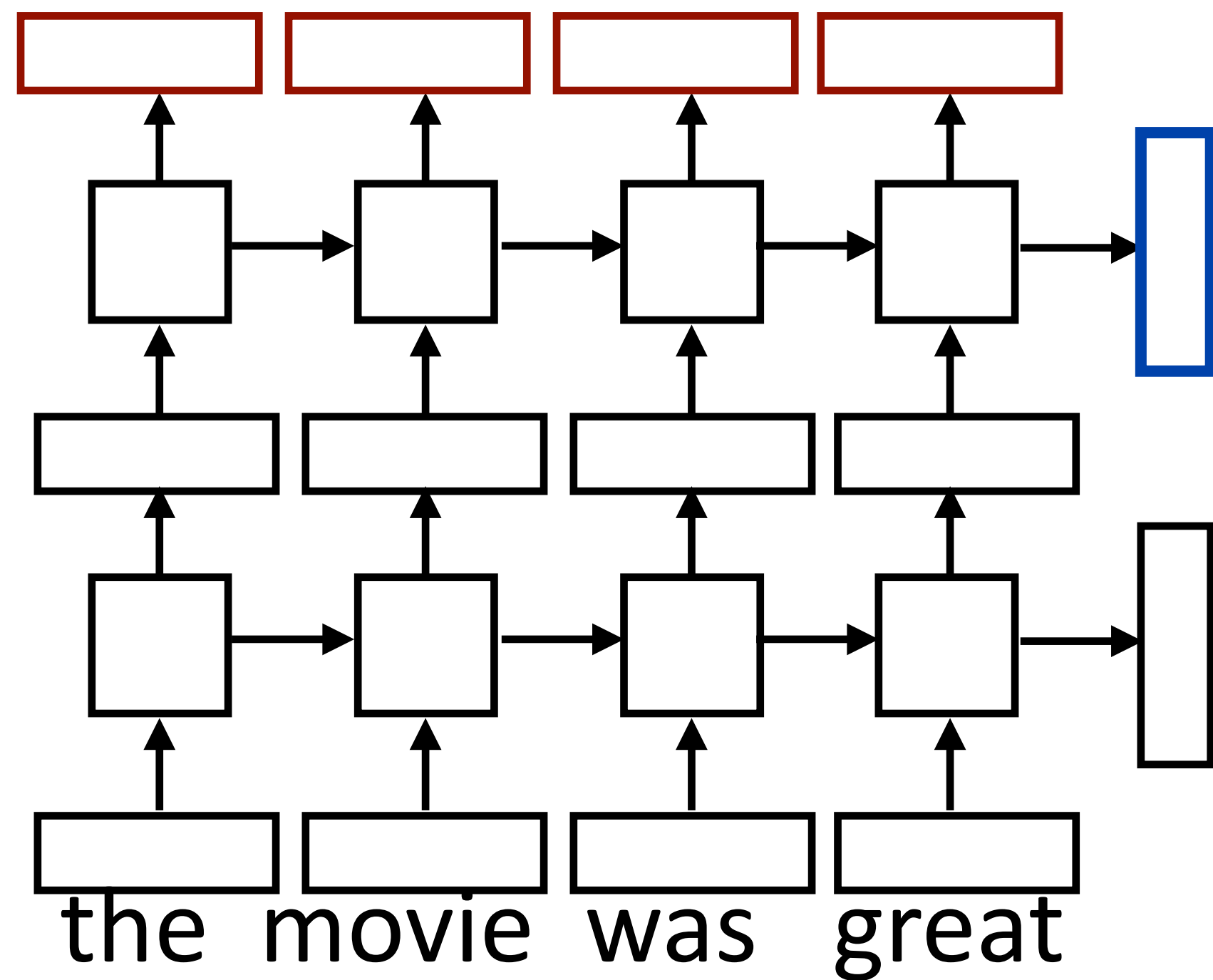
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- ▶ Sentence classification based on concatenation of both final outputs



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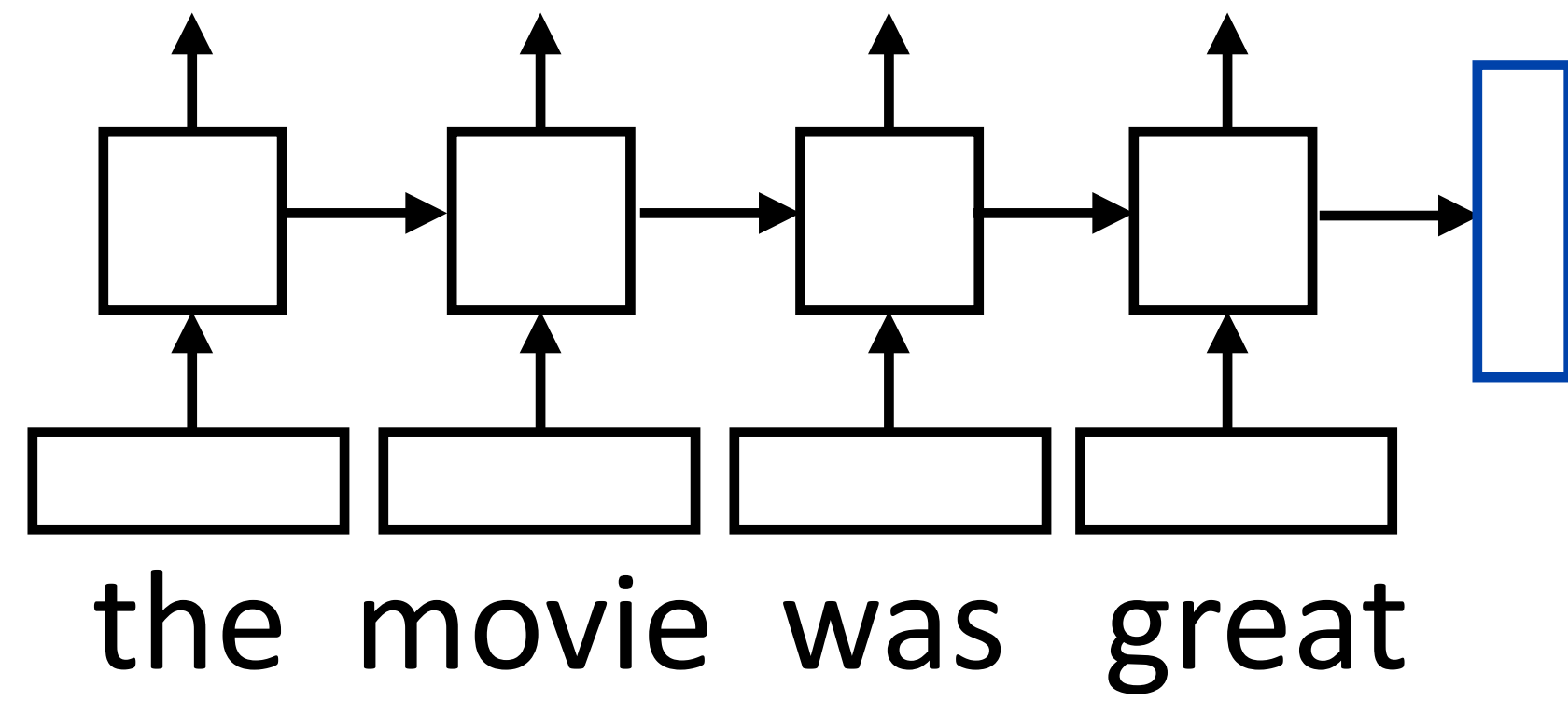
- ▶ Sentence classification based on concatenation of both final outputs



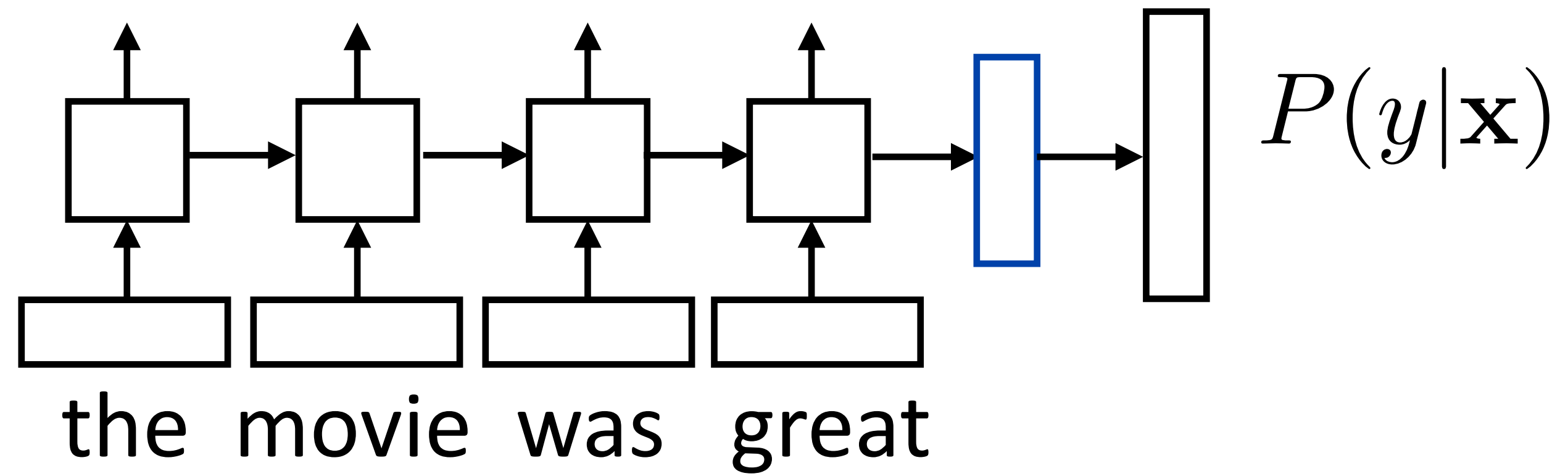
- ▶ Token classification based on concatenation of both directions' token representations



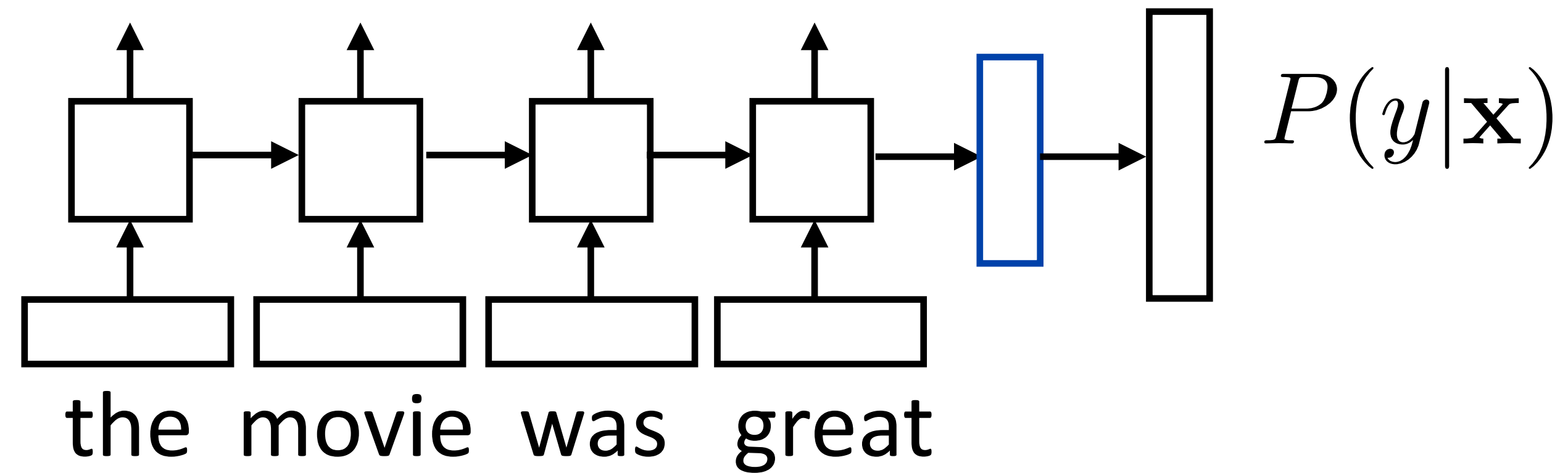
Training RNNs



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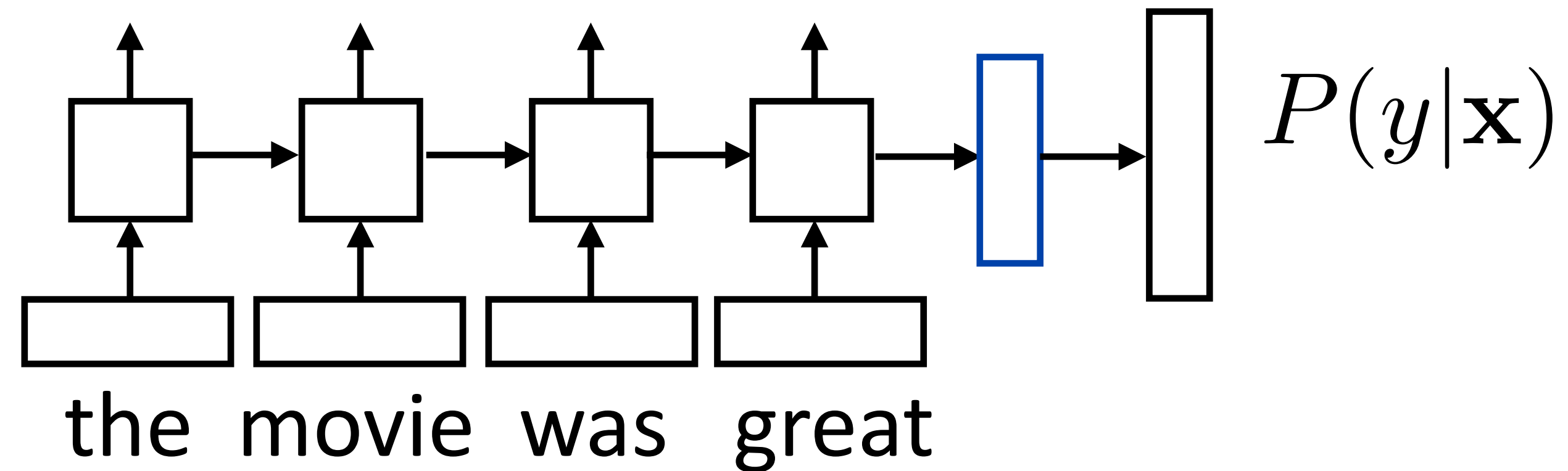


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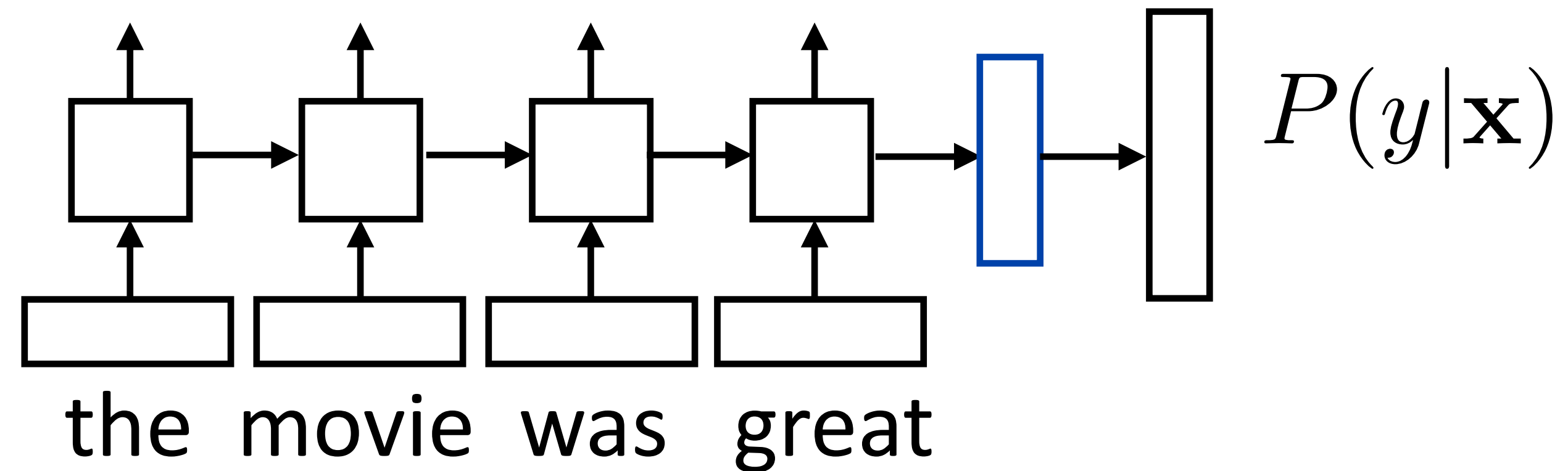
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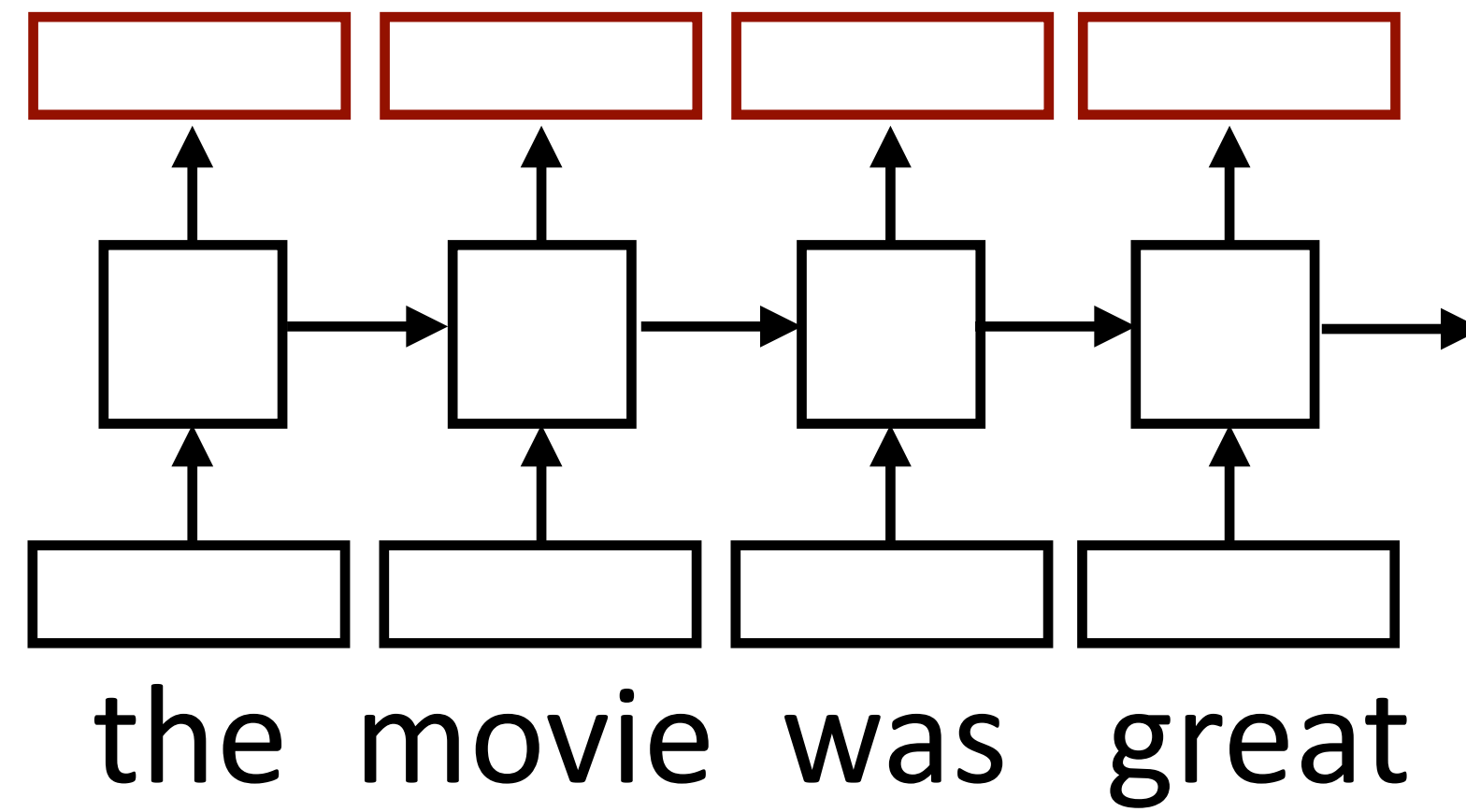
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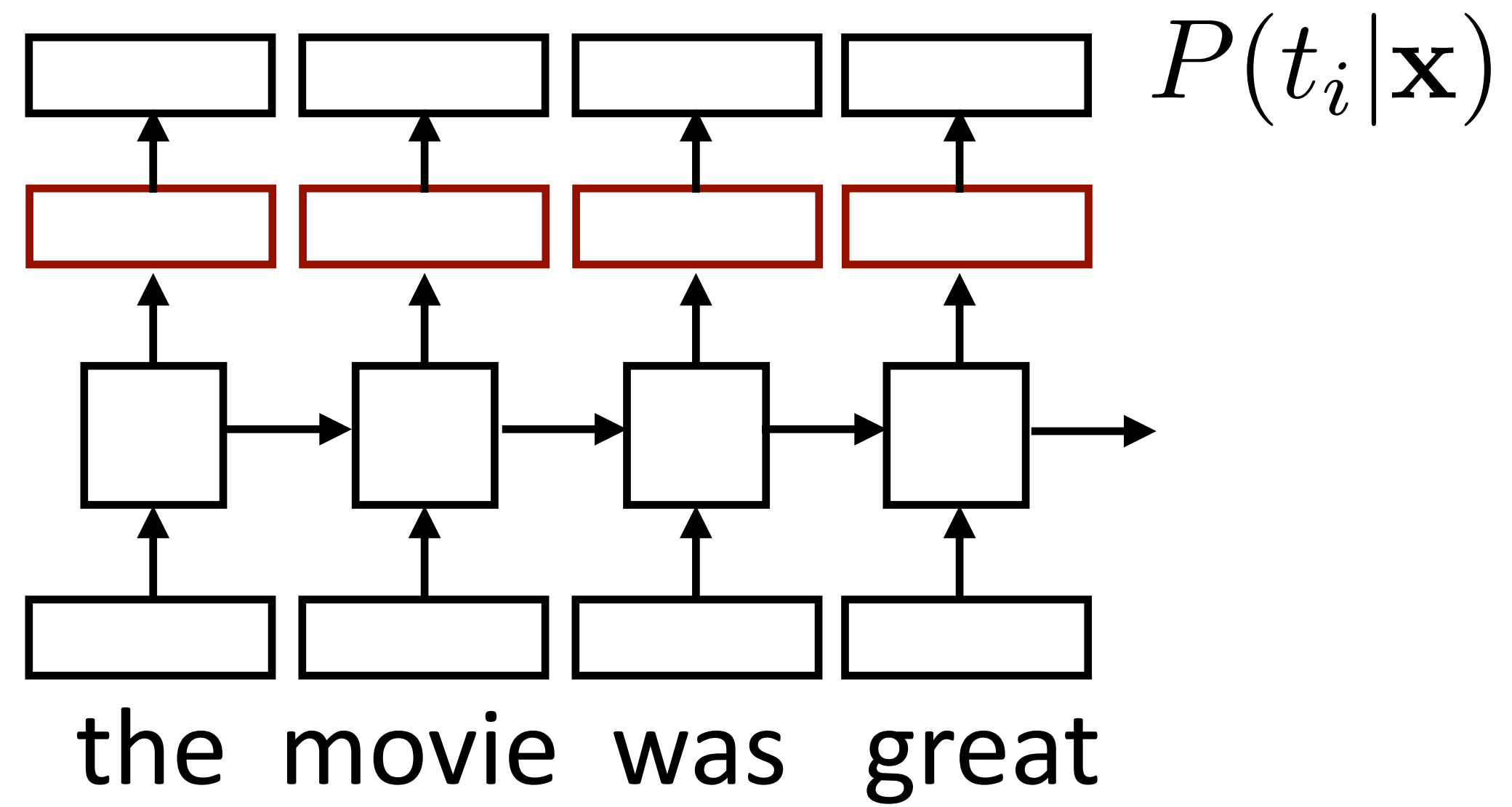


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- ▶ Backpropagate through entire network
- ▶ Example: sentiment analysis

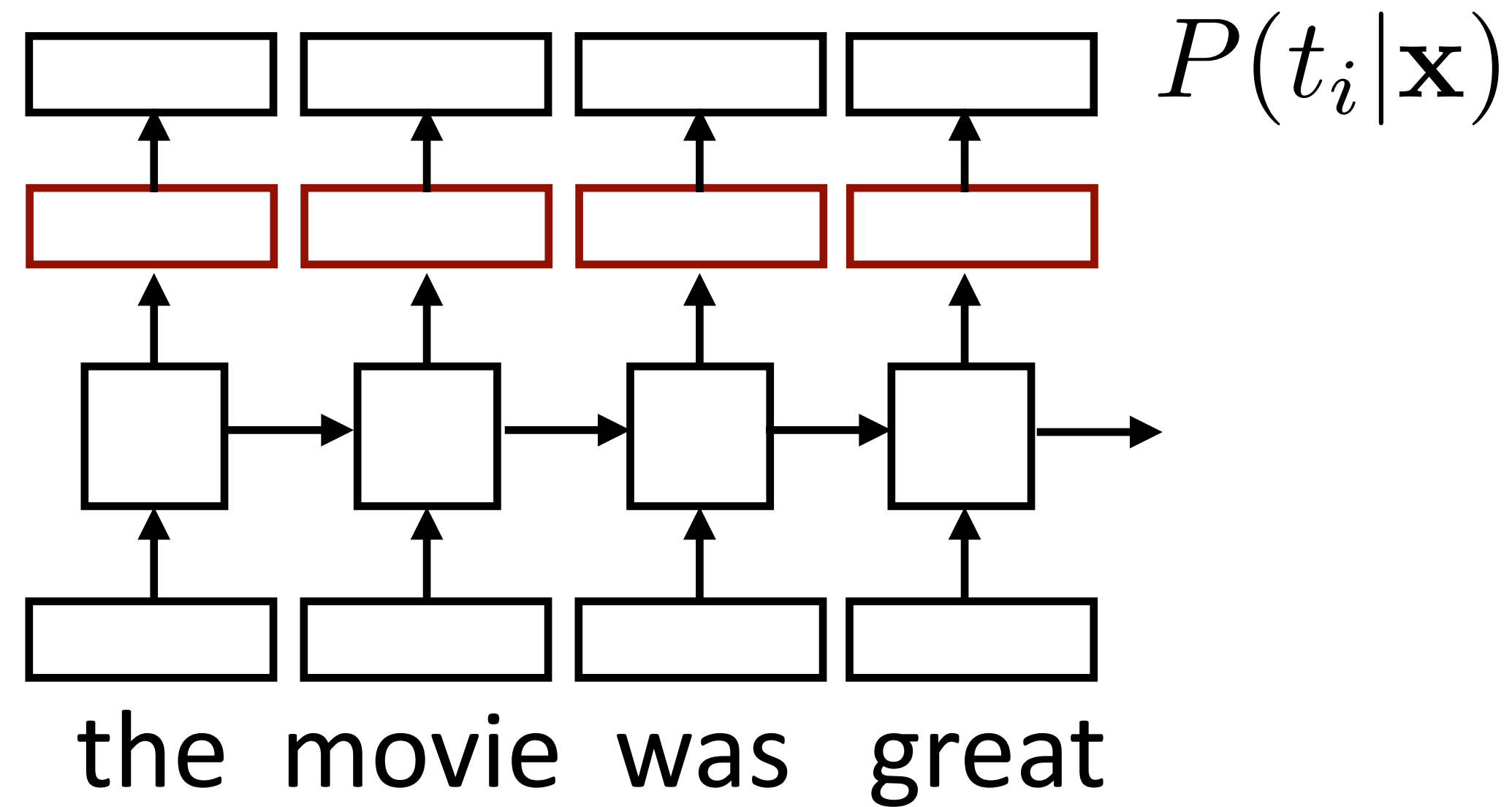
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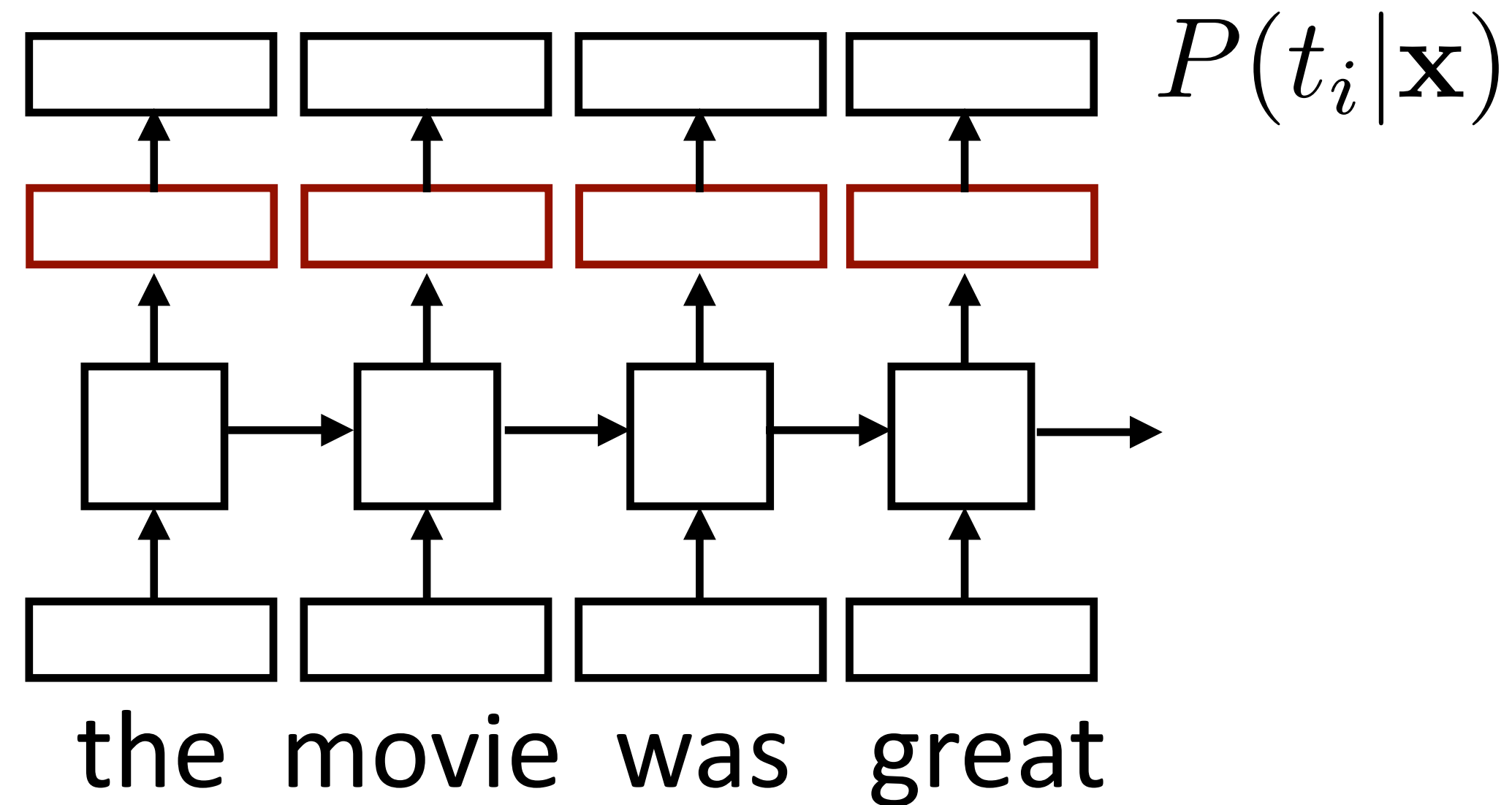


Training RNNs



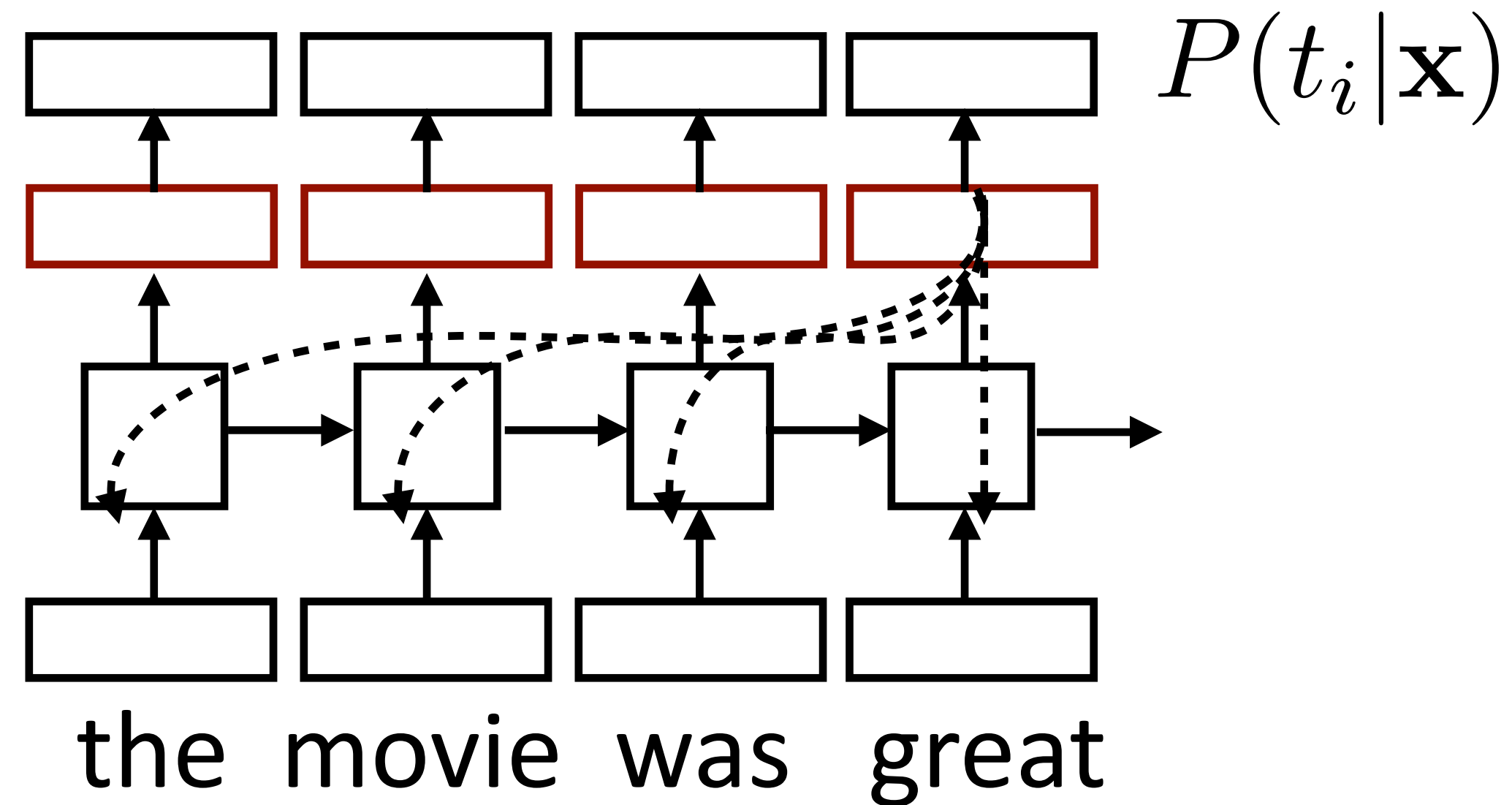
- ▶ Loss = negative log likelihood of probability of gold predictions, summed over the tags

Training RNNs



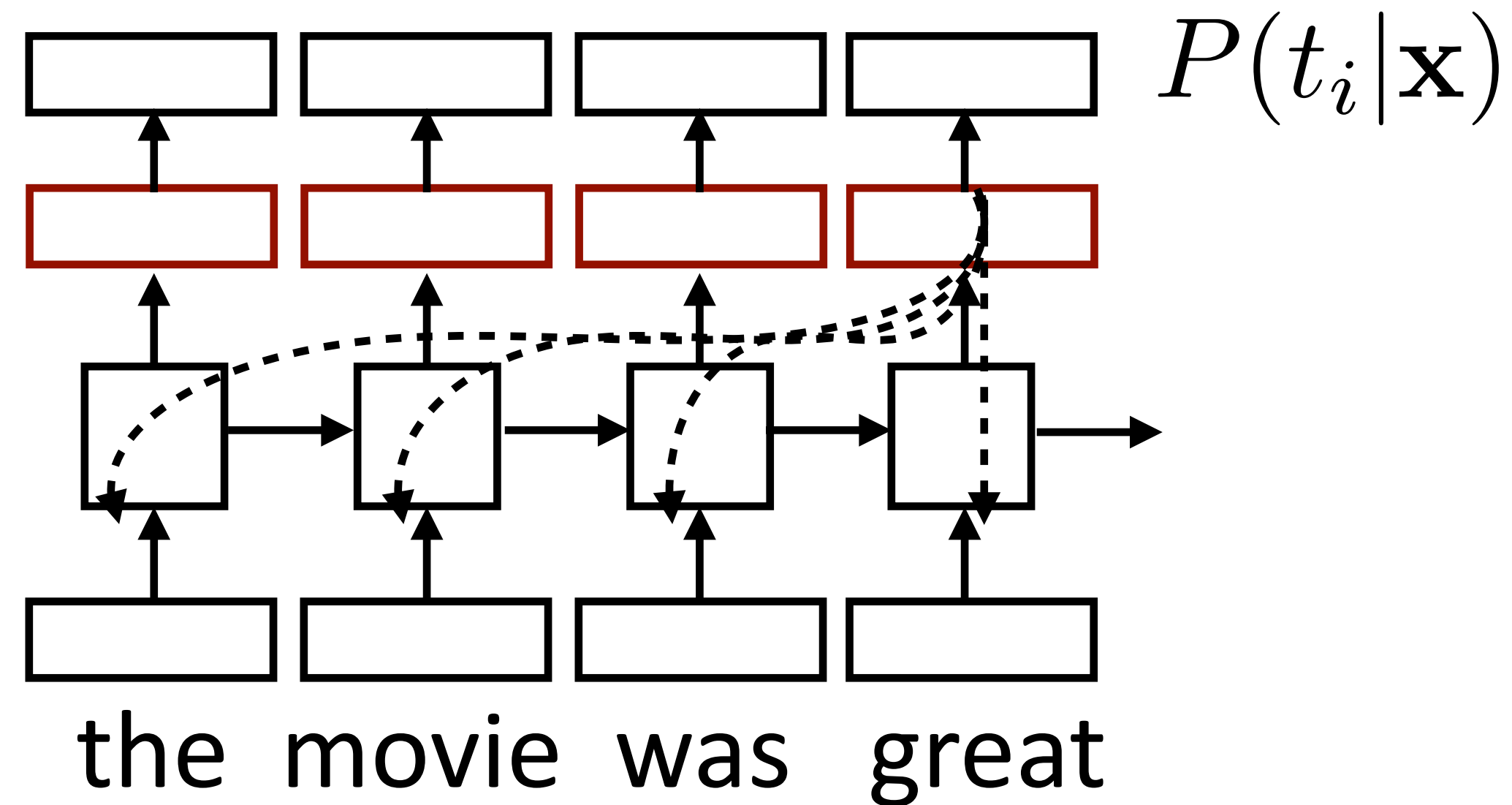
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- ▶ Example: language modeling (predict next word given context)

Applications

What can LSTMs model?

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- ▶ Sentiment
 - ▶ Encode one sentence, predict
- ▶ Language models
 - ▶ Move left-to-right, per-token prediction

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 - ▶ Encode sentence + then decode, use token predictions for attention weights (later in the course)

Visualizing LSTMs

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- ▶ Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code

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- ▶ Counter: know when to generate `\n`

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"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."

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- ▶ Binary switch: tells us if we're in a quote or not

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


Visualizing LSTMs

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- ▶ Stack: activation based on indentation

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    if (classes[class]) {
        for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
            if (mask[i] & classes[class][i])
                return 0;
    }
    return 1;
}
```

Visualizing LSTMs

- ▶ Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- ▶ Visualize activations of specific cells to see what they track

```
/* 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.
     */
}
```

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- ▶ Uninterpretable: probably doing double-duty, or only makes sense in the context of another activation

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What can LSTMs model?

- ▶ Sentiment
 - ▶ Encode one sentence, predict
- ▶ Language models
 - ▶ Move left-to-right, per-token prediction
- ▶ Translation
 - ▶ Encode sentence + then decode, use token predictions for attention weights (next lecture)

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Natural Language Inference

Premise

A boy plays in the snow

Hypothesis

A boy is outside

Natural Language Inference

Premise

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entails

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A man inspects the uniform of a figure

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Natural Language Inference

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A boy plays in the snow

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A man inspects the uniform of a figure

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- ▶ Long history of this task: “Recognizing Textual Entailment” challenge in 2006 (Dagan, Glickman, Magnini)

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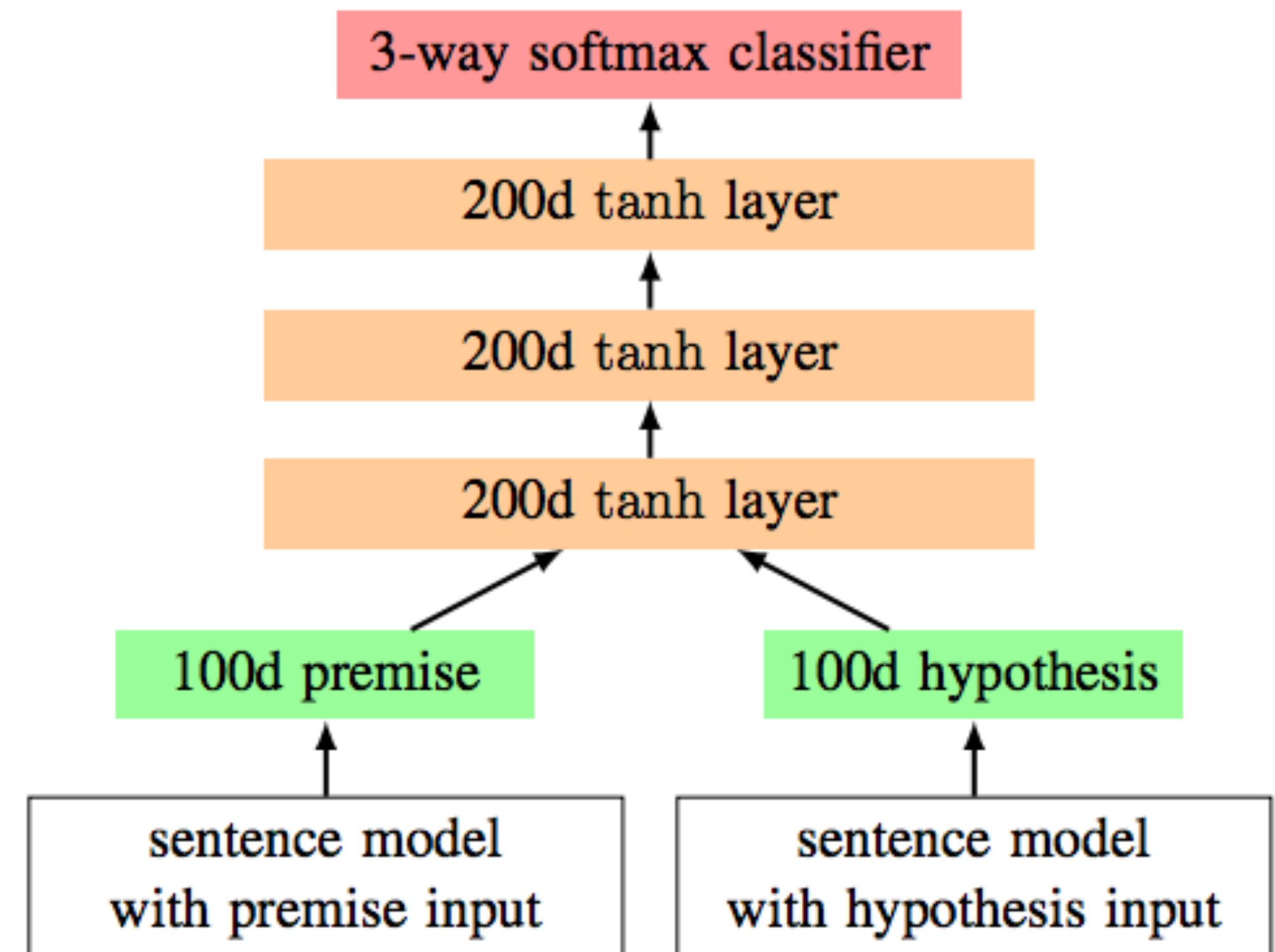
- ▶ Long history of this task: “Recognizing Textual Entailment” challenge in 2006 (Dagan, Glickman, Magnini)
- ▶ Early datasets: small (hundreds of pairs), very ambitious (lots of world knowledge, temporal reasoning, etc.)

SNLI Dataset

- ▶ Show people captions for (unseen) images and solicit entailed / neural / contradictory statements
- ▶ >500,000 sentence pairs

SNLI Dataset

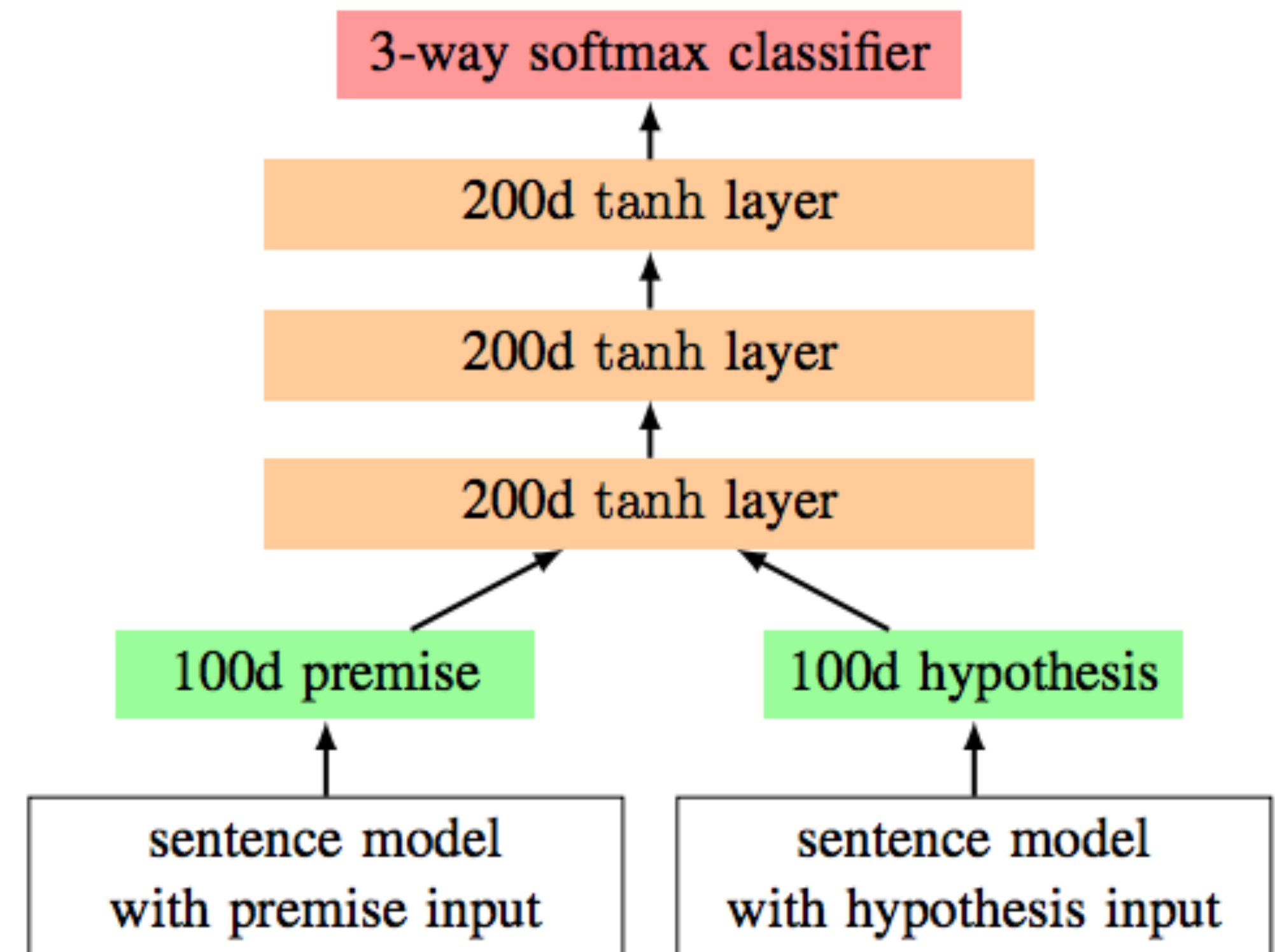
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Bowman et al. (2015)

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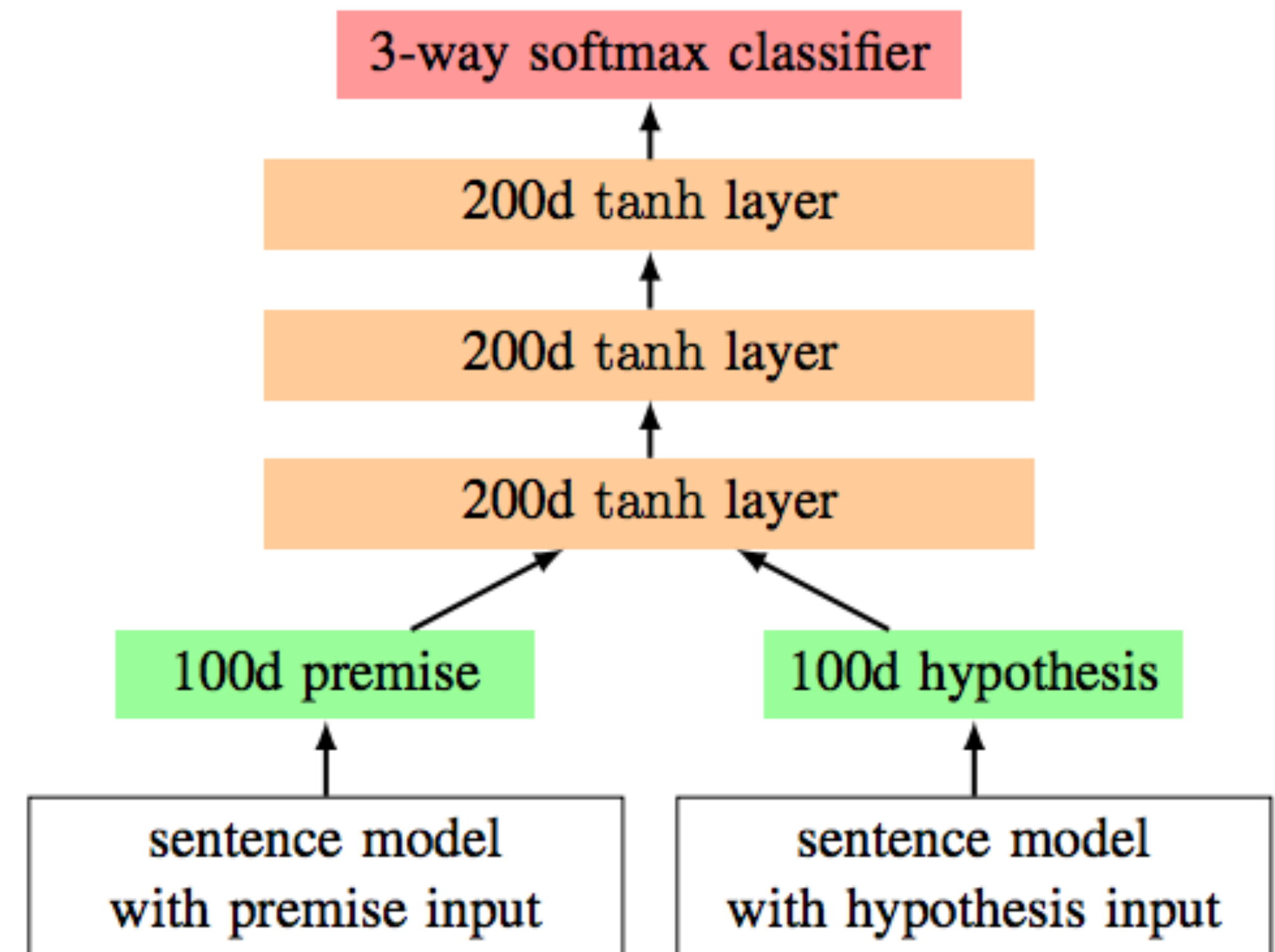
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300D LSTM: 80% accuracy

(Bowman et al., 2016)



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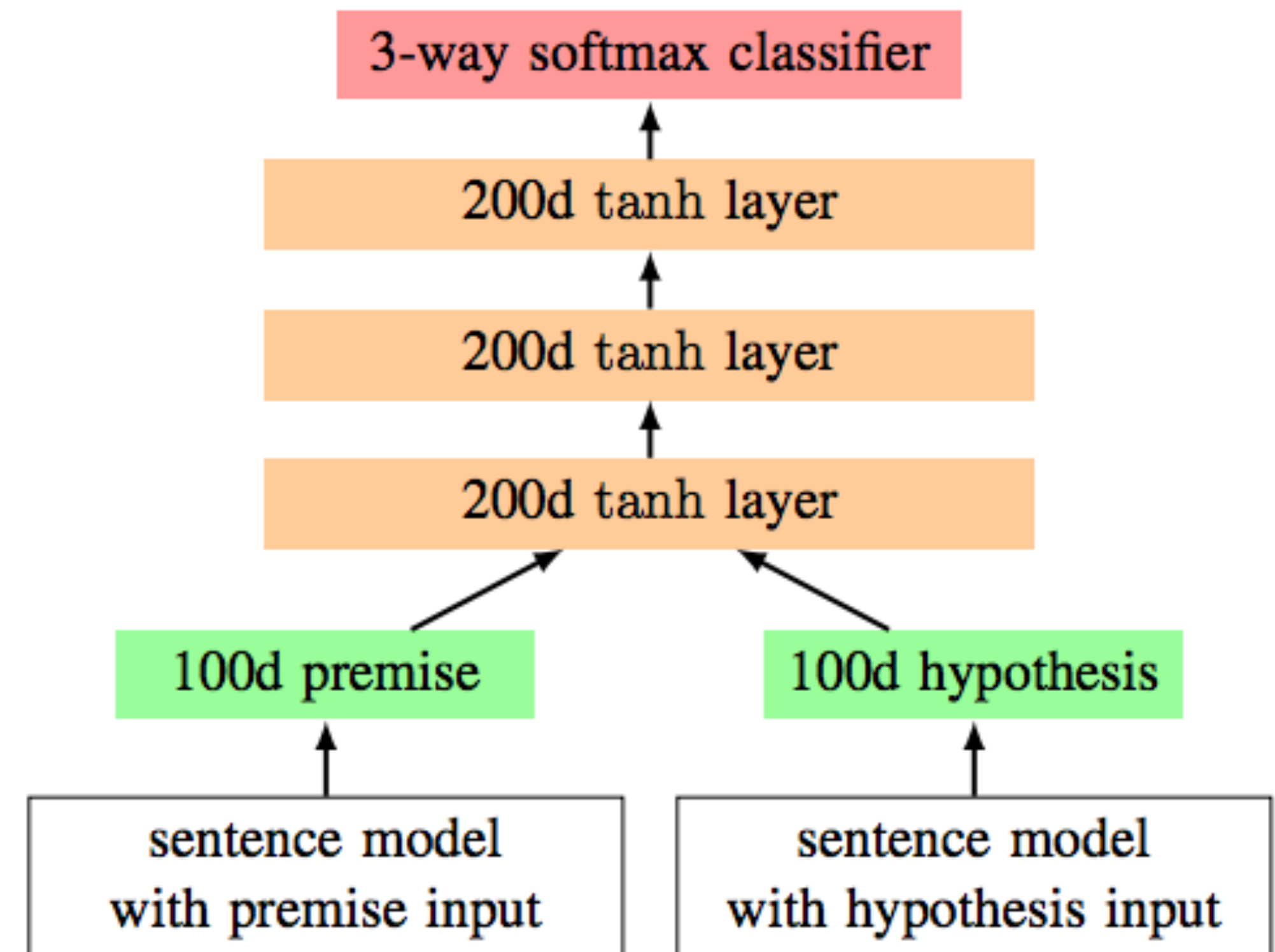
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(Bowman et al., 2016)

300D BiLSTM: 83% accuracy

(Liu et al., 2016)



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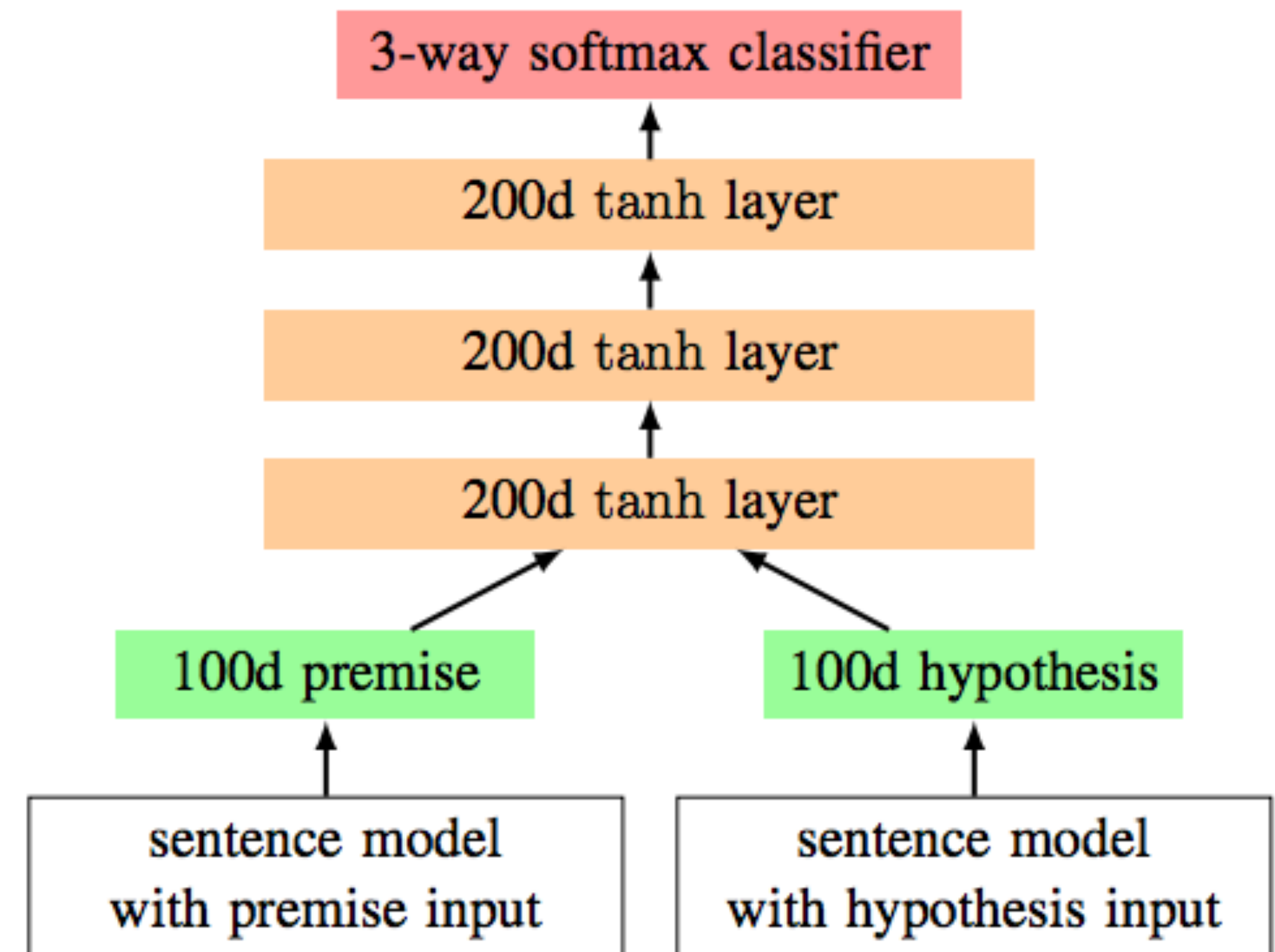
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- ▶ Later: better models for this



Bowman et al. (2015)

Takeaways

- ▶ RNNs can transduce inputs (produce one output for each input) or compress the whole input into a vector
- ▶ Useful for a range of tasks with sequential input: sentiment analysis, language modeling, natural language inference, machine translation
- ▶ Next time: CNNs and neural CRFs