Lecture 8: RNNs

Alan Ritter

(many slides from Greg Durrett)

Administrivia

- Reading: RNNs
  - Goldberg 10, 11
  - Jurafsky and Martin, Chapter 9
- Homework 3 Due Next week on Monday
- Guest lecture next week on Wednesday
- Midterm is next week on Friday
  - Will cover everything up to this Friday
  - Practice Questions:
    - https://docs.google.com/document/d/1eidU29ni8ZeTlBcrTyQ67duurxU74vk7I16fUok_X8s/edit?usp=sharing

Recall: Training Tips

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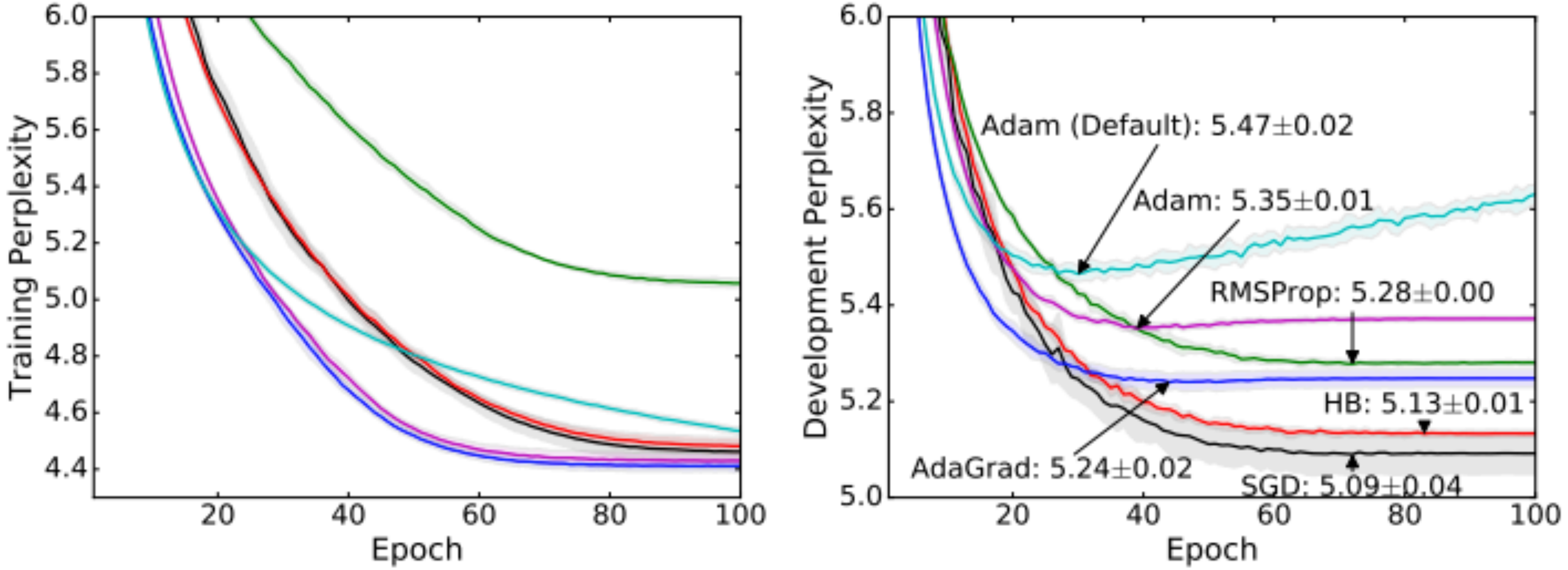
- Parameter initialization is critical to get good gradients, some useful heuristics (e.g., Xavier initializer)

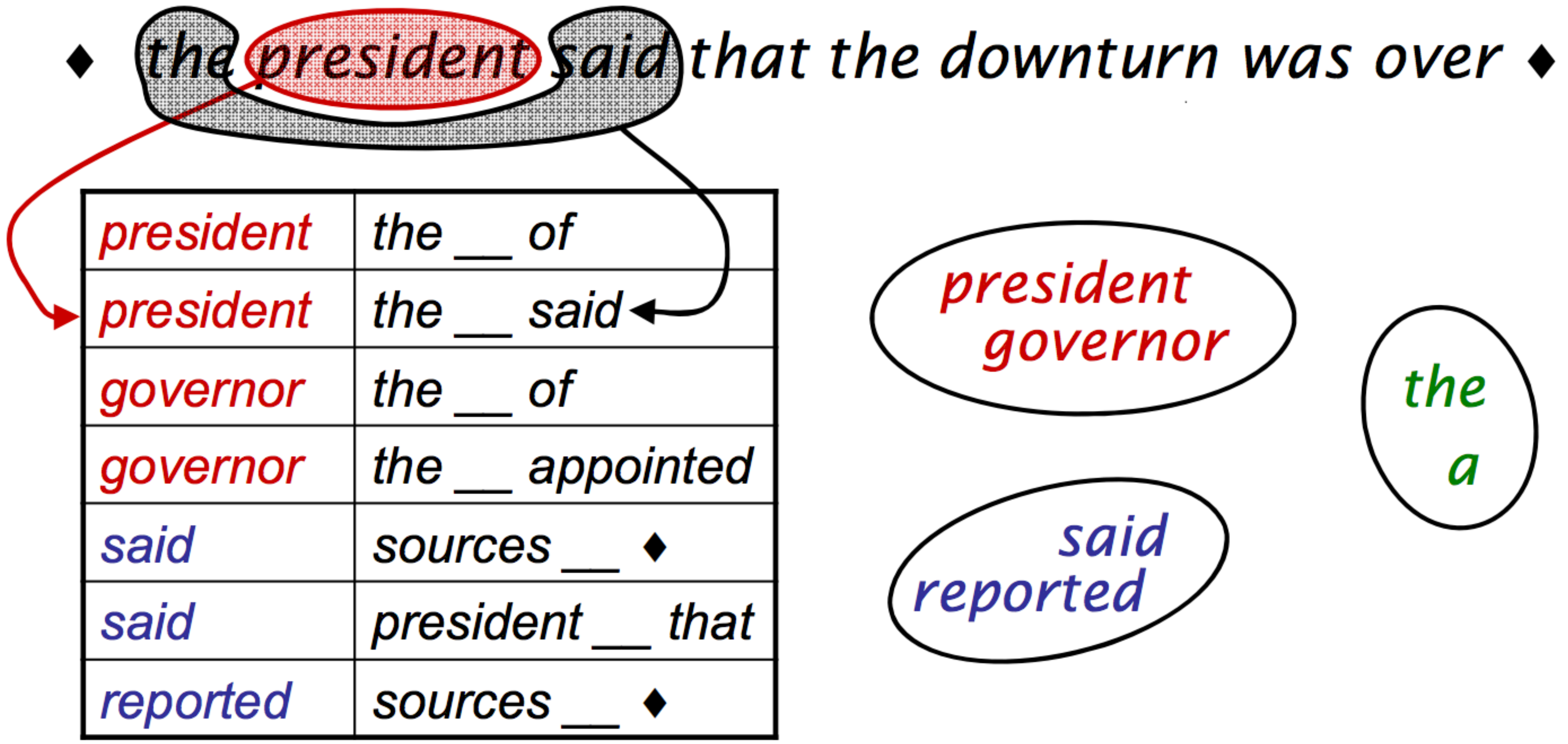
- Dropout is an effective regularizer

- 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 downtown was over* ♦

president	*the __ of*
president	*the __ said*
governor	*the __ of*
governor	*the __ appointed*
said	*sources __ ♦*
said	*president __ that*
reported	*sources __ ♦*

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

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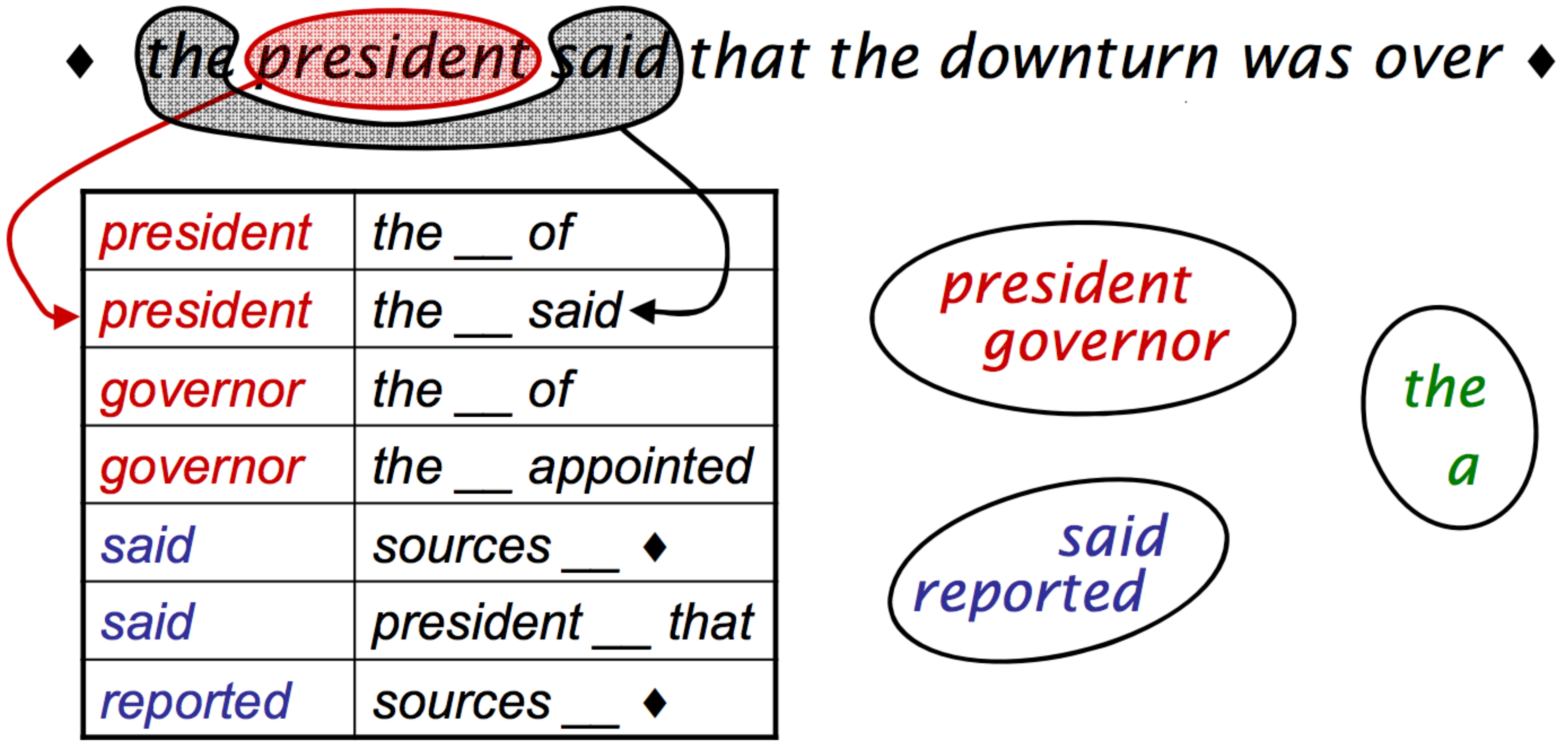

♦ *the president said that the downturn was over* ♦

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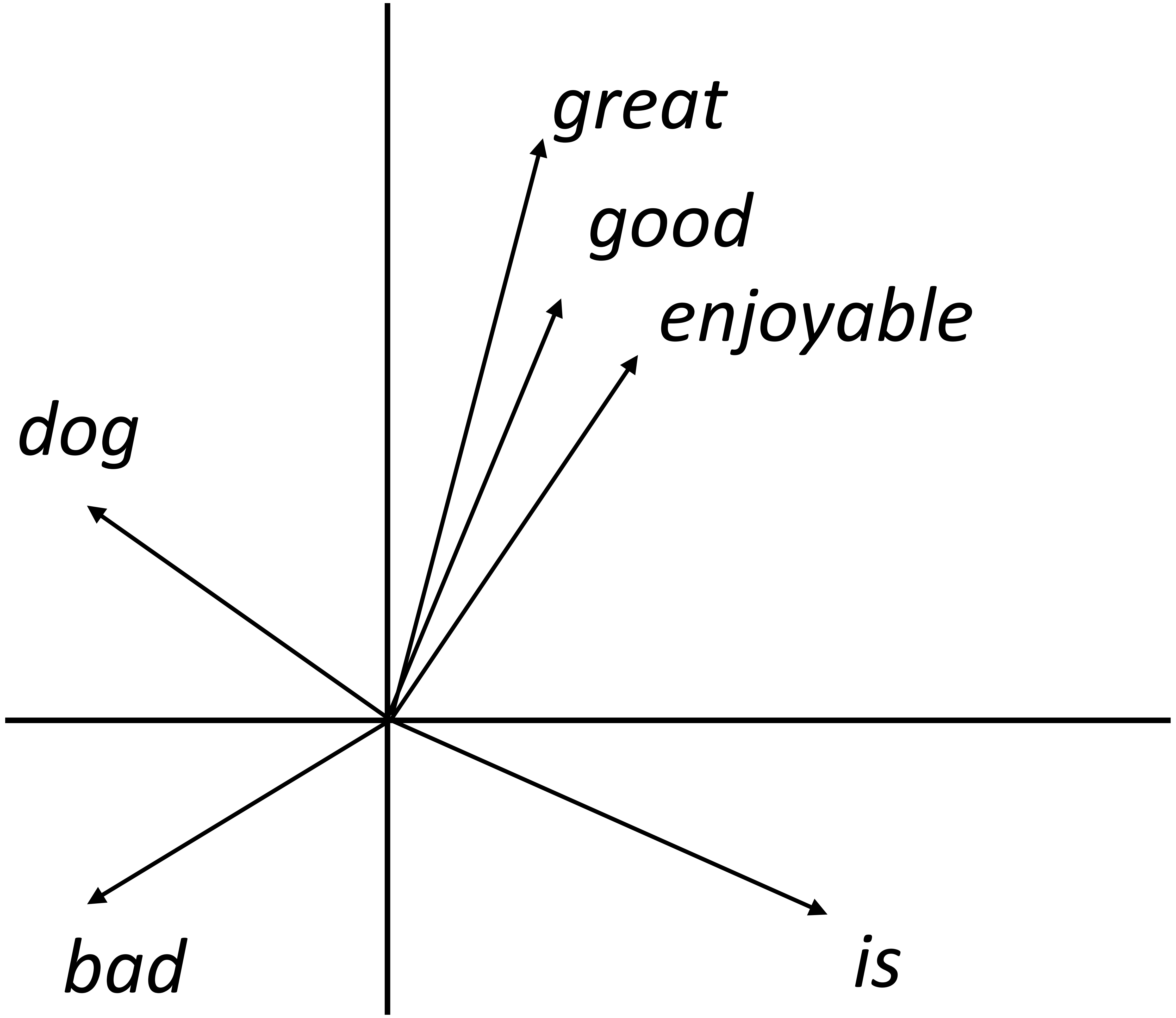
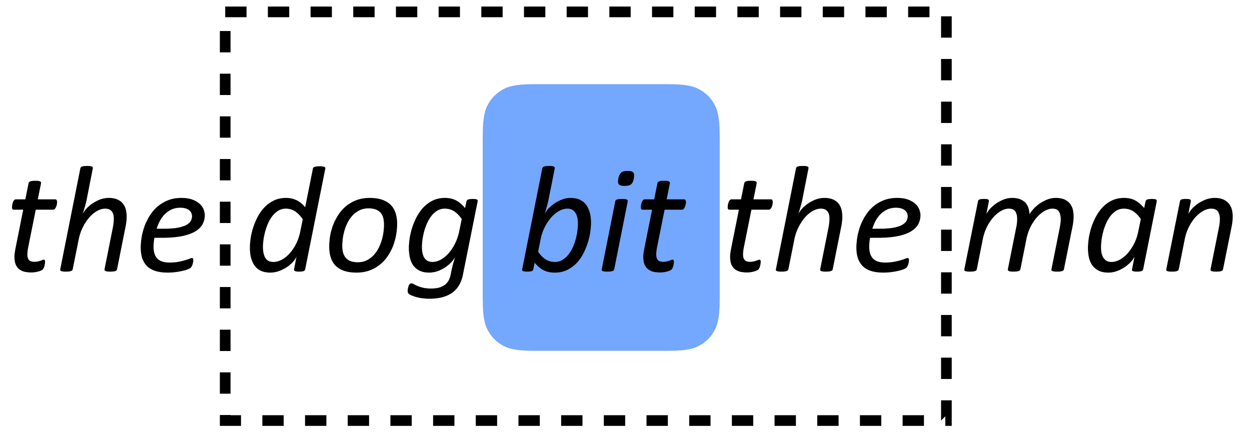


Recall: Continuous Bag-of-Words

- Predict word from context



the dog bit the man

Mikolov et al. (2013)

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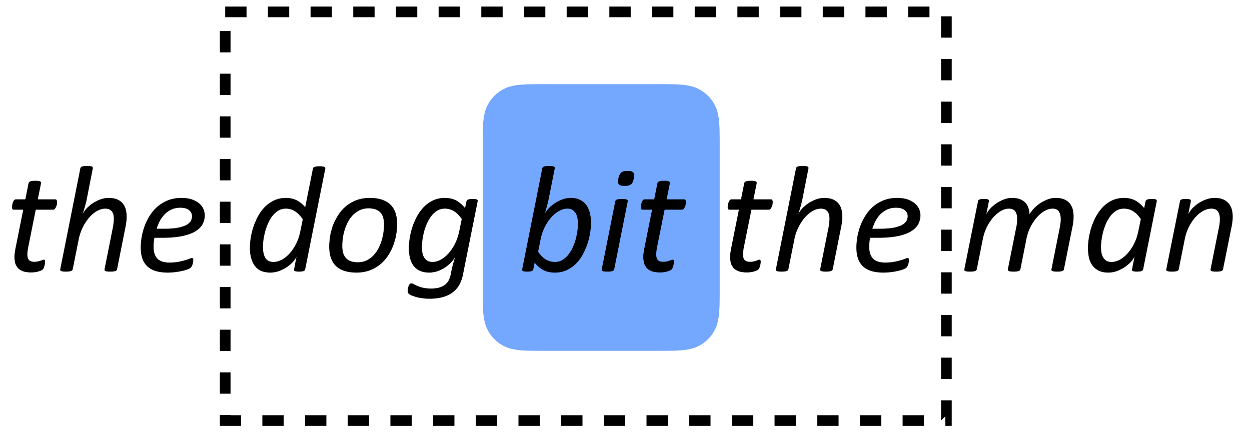
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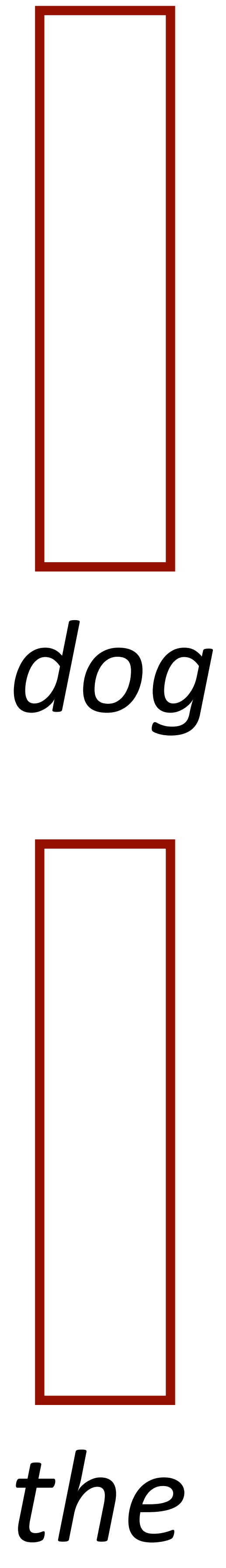
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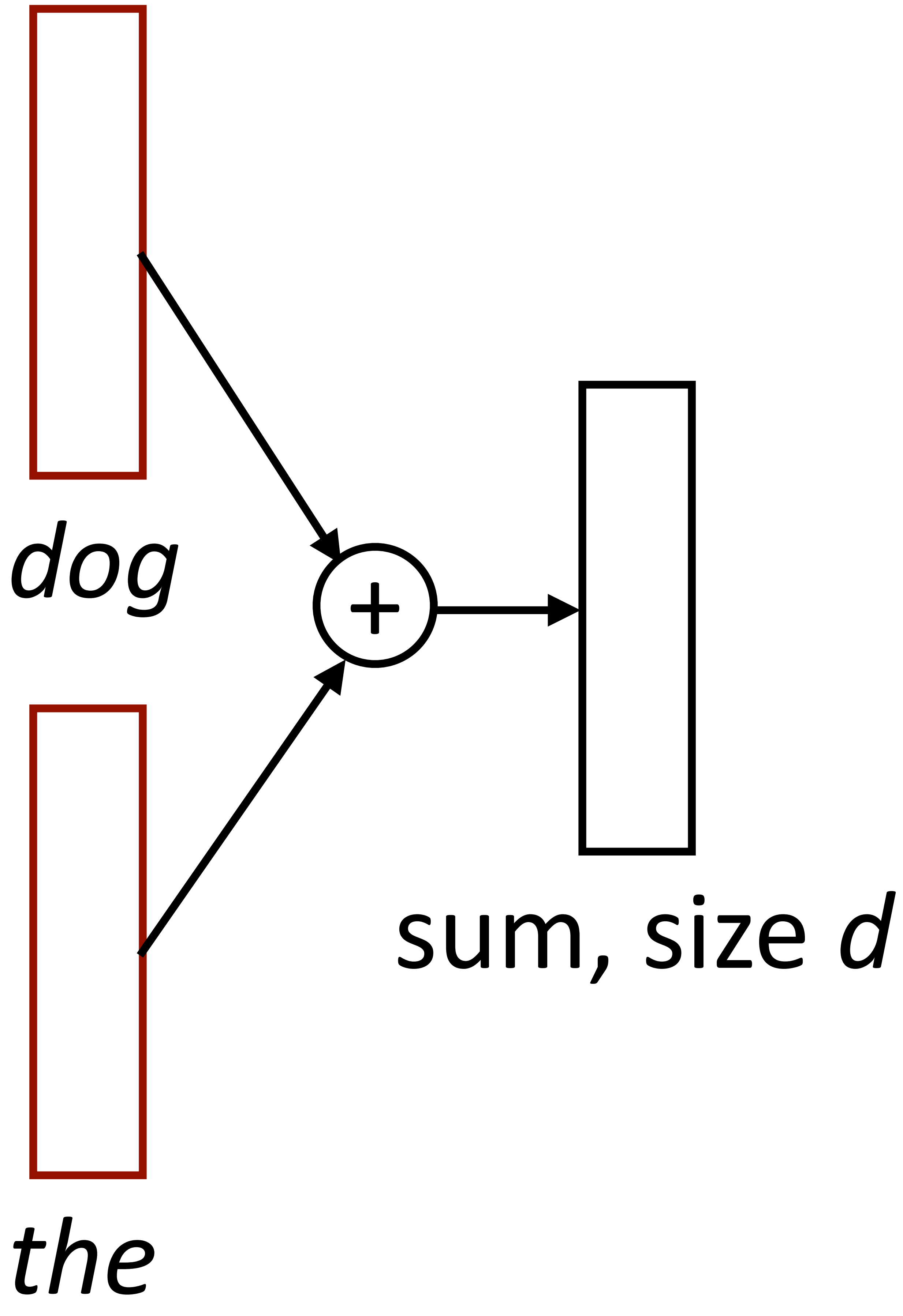

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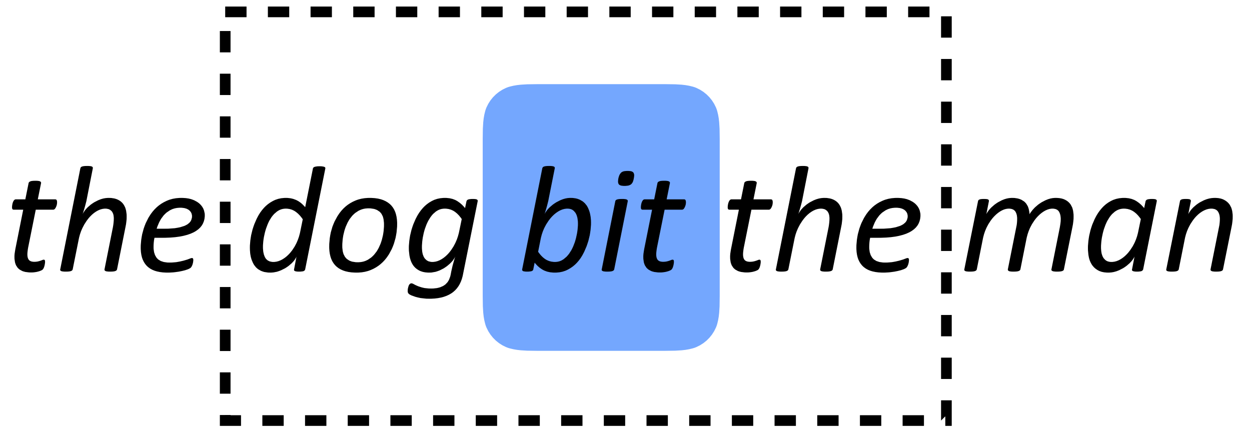

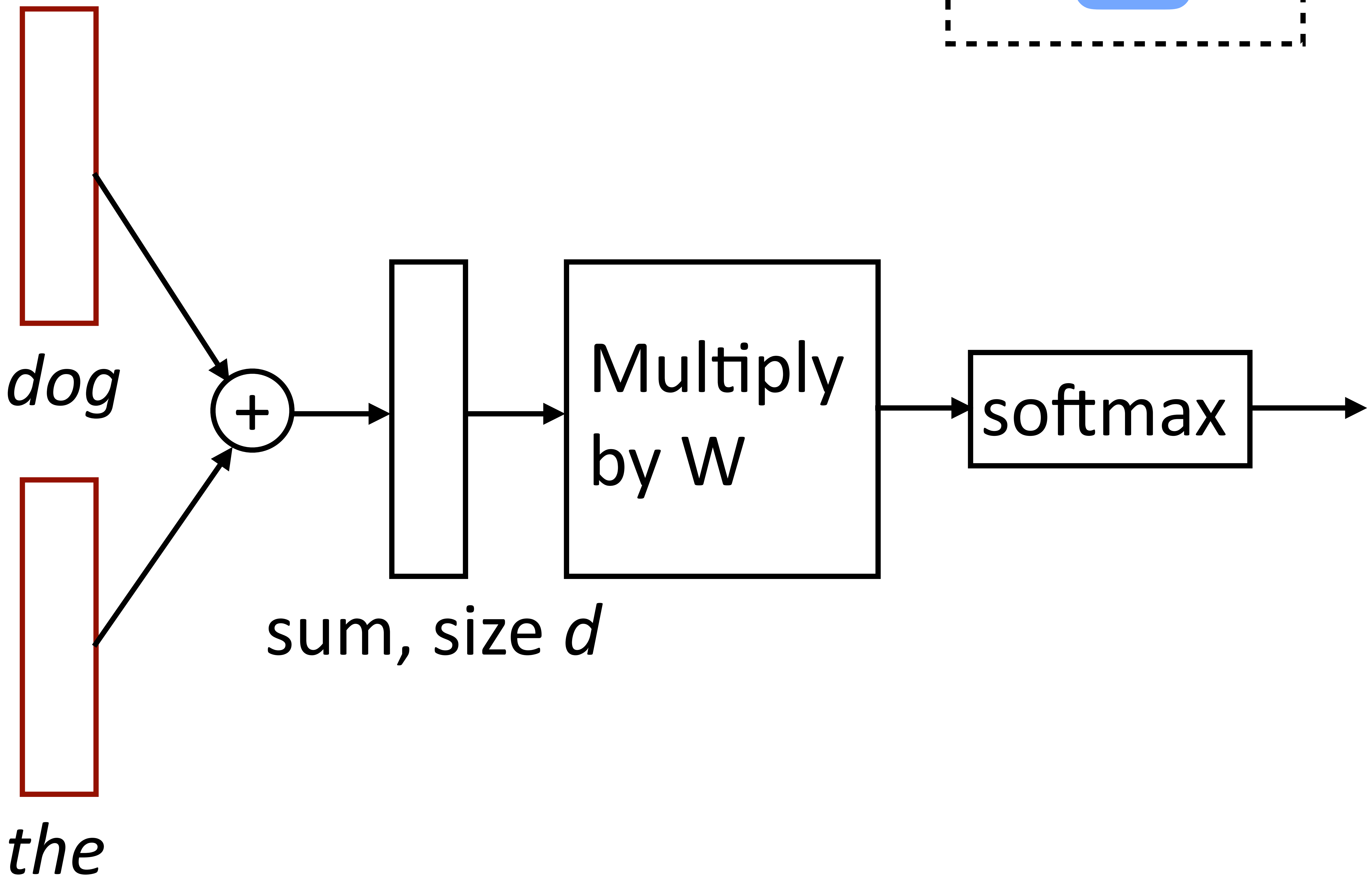

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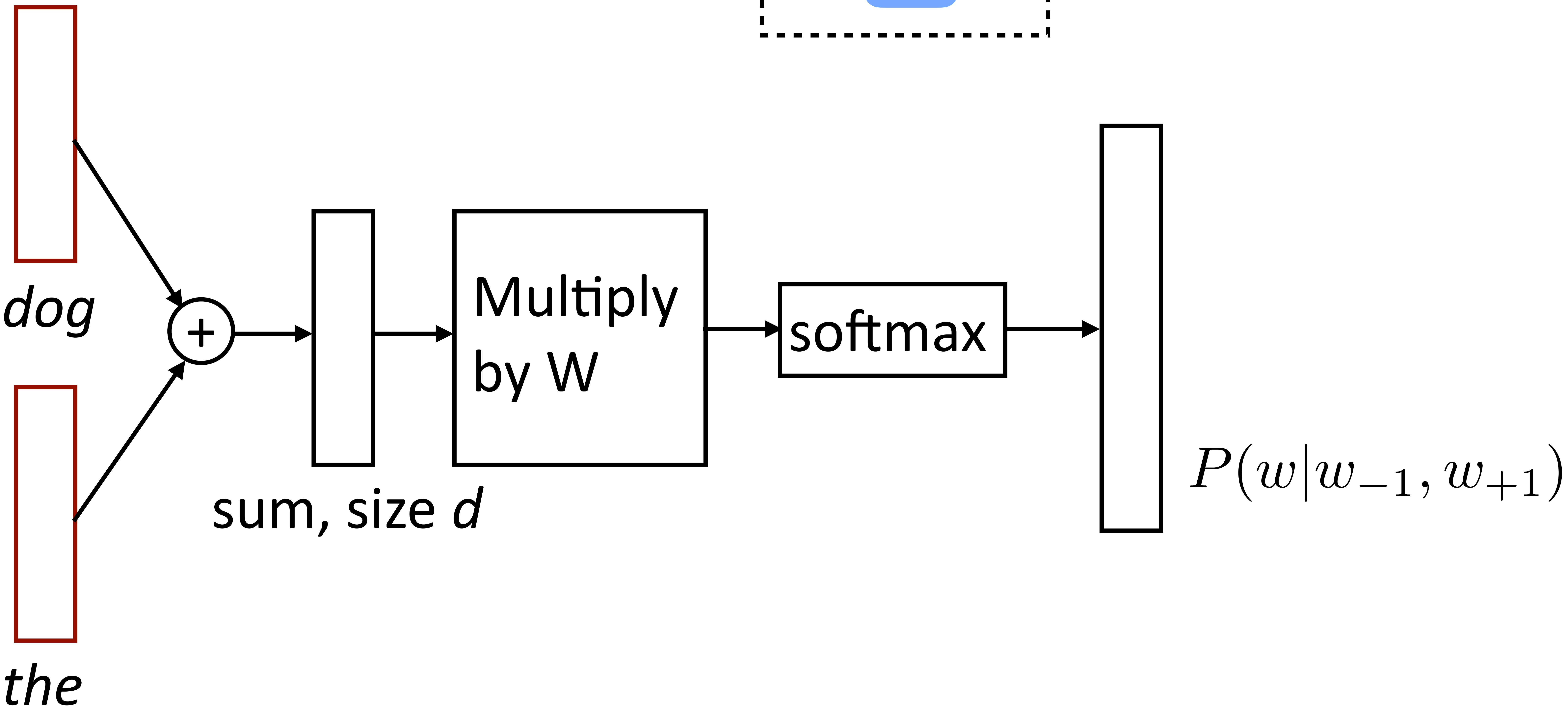

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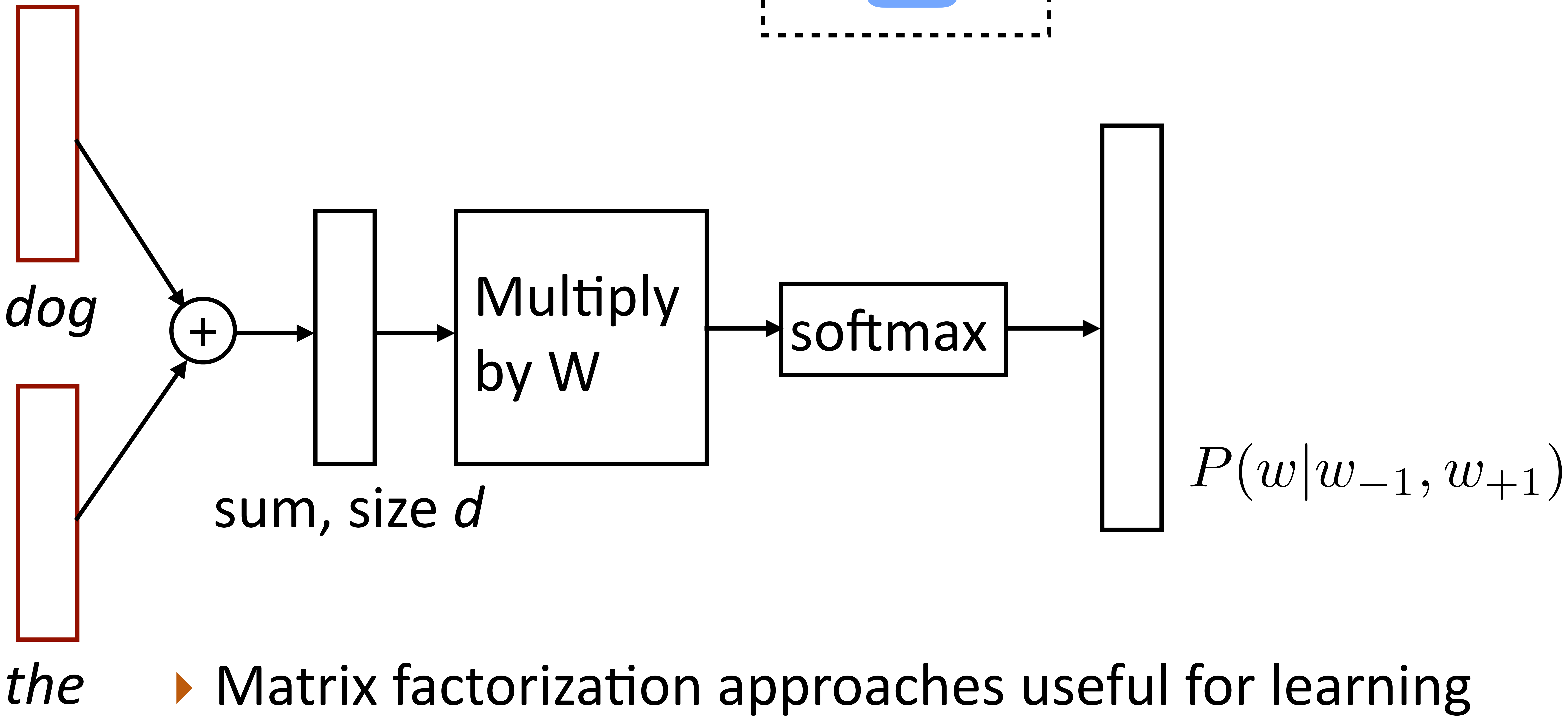

- Matrix factorization approaches useful for learning vectors from really large data

Using Word Embeddings

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- Approach 2: pretrain using GloVe, keep fixed
  - 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

Compositional Semantics

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- Skip-*thought* vectors (Kiros et al., 2015), similar to skip-gram generalized to a sentence level (more later)

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 (more later)
- 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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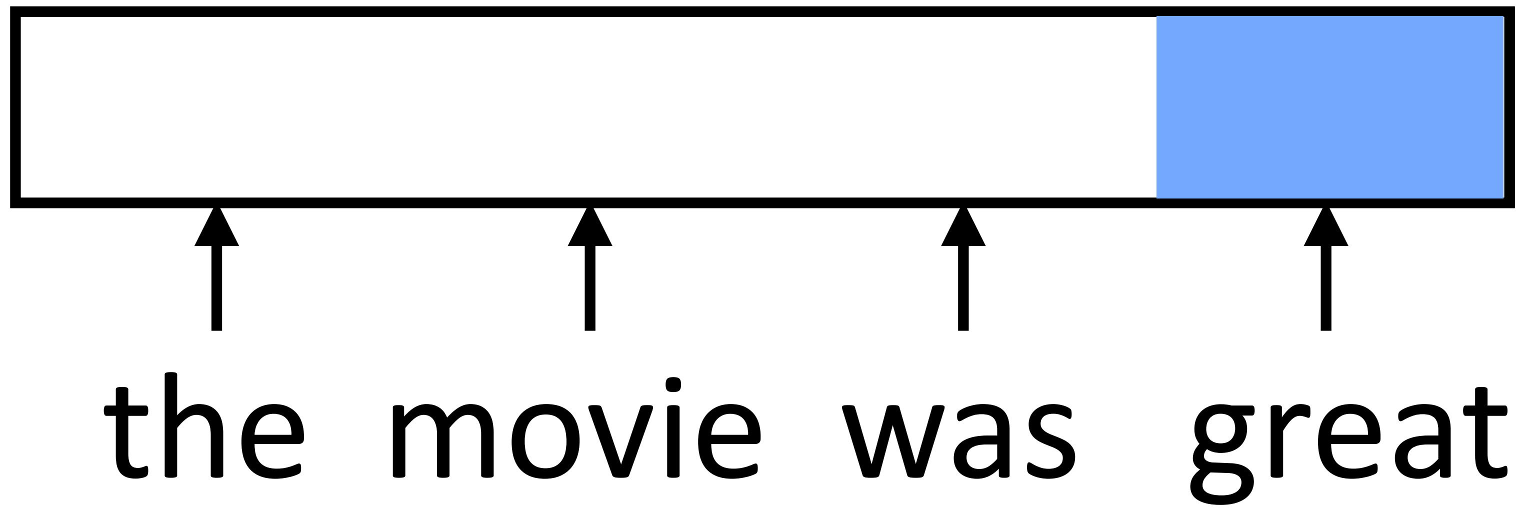

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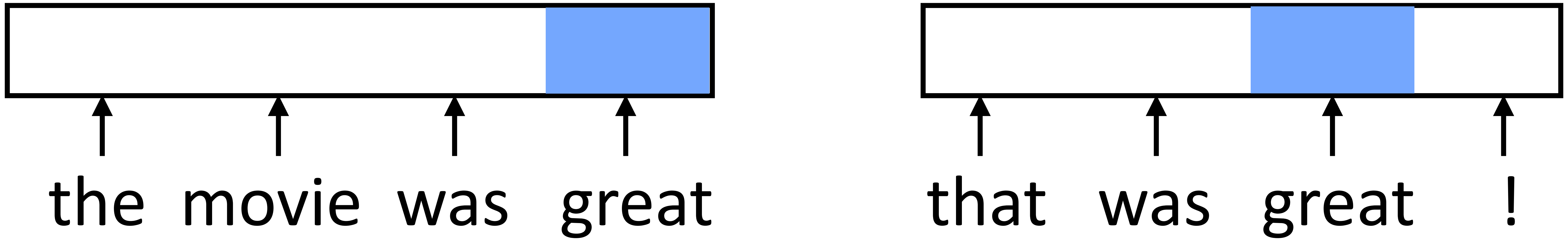

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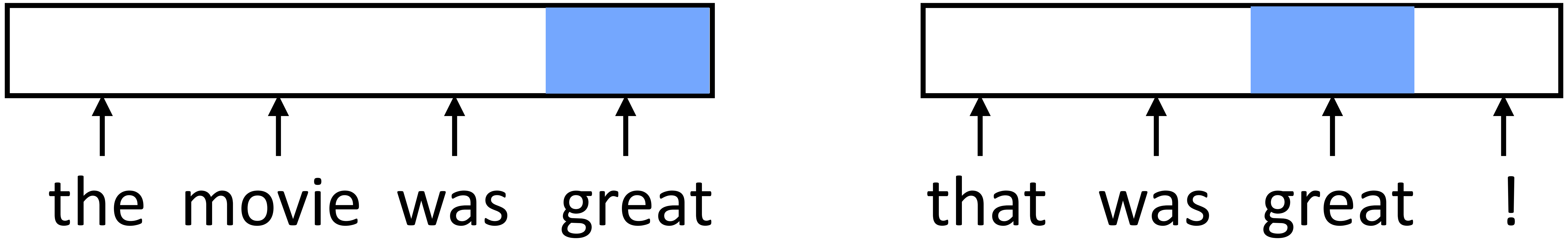

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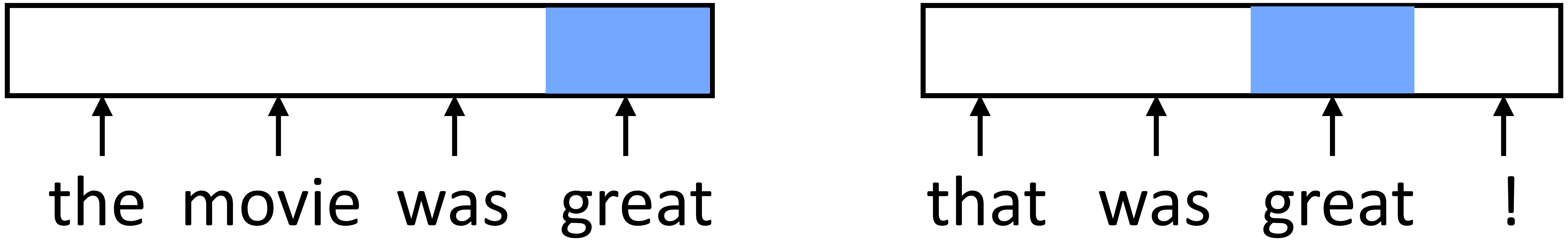

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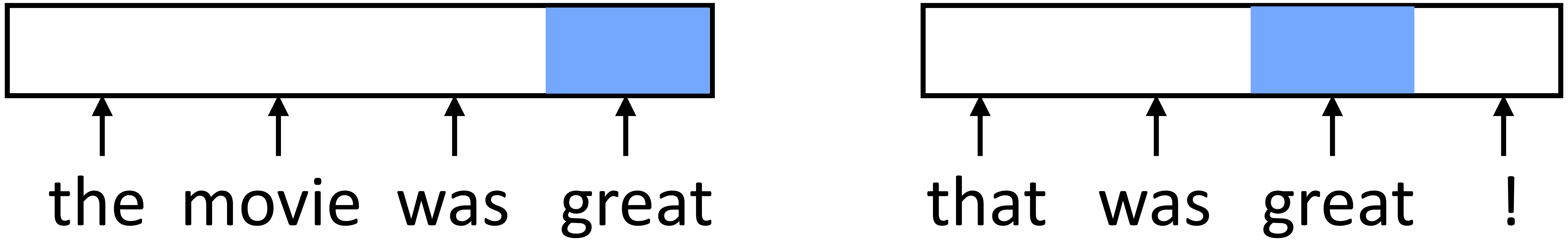

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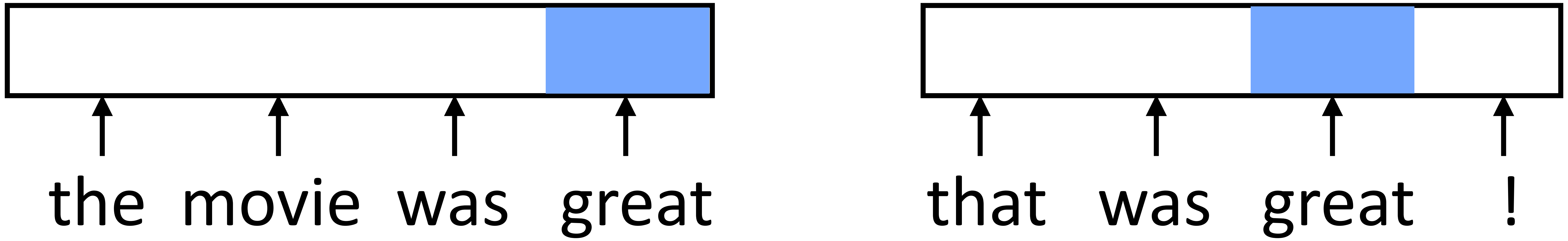

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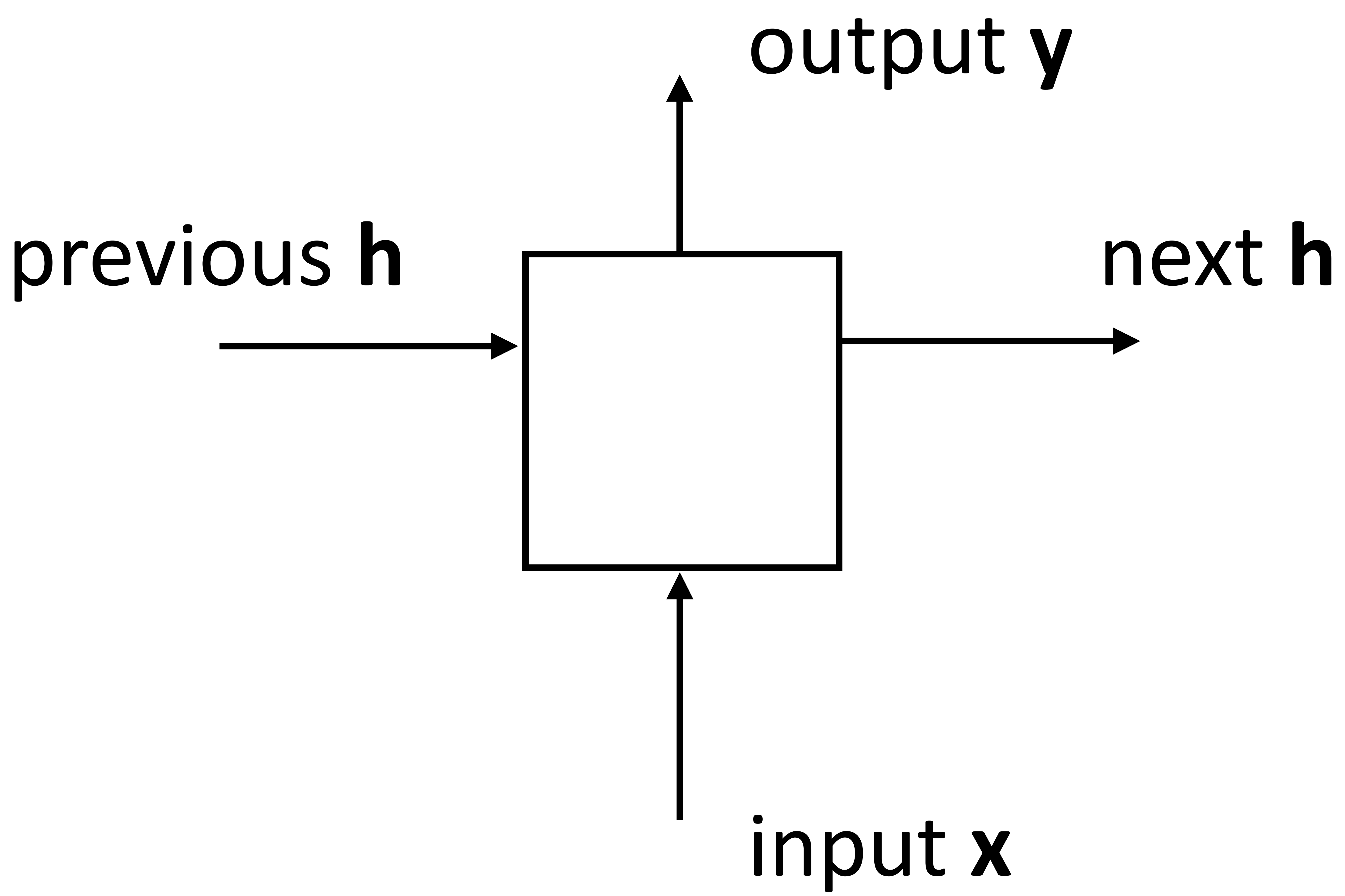
- Instead, we need to:

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 **x**, has some hidden state **h**, and updates that hidden state and produces output **y** (all vector-valued)



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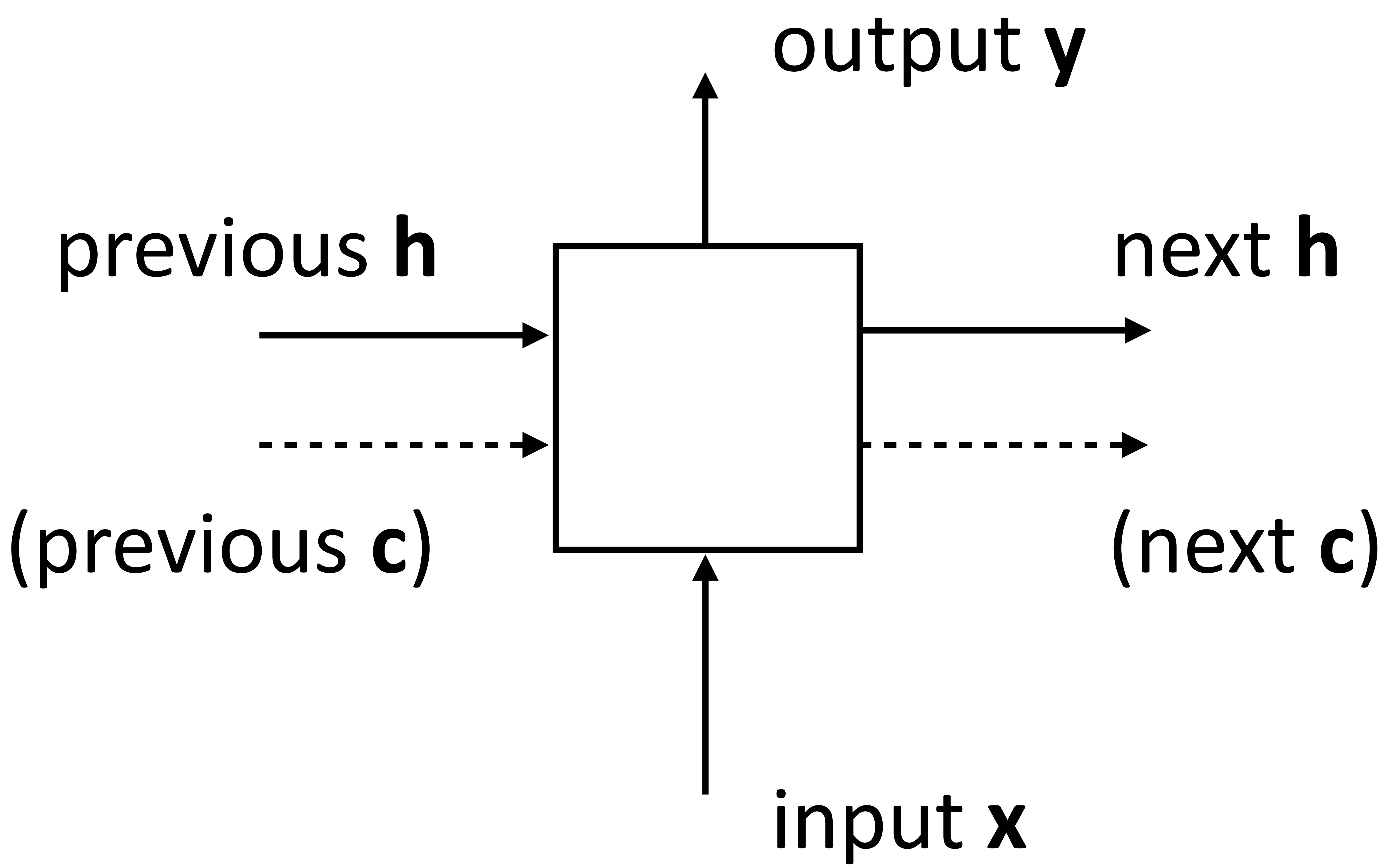
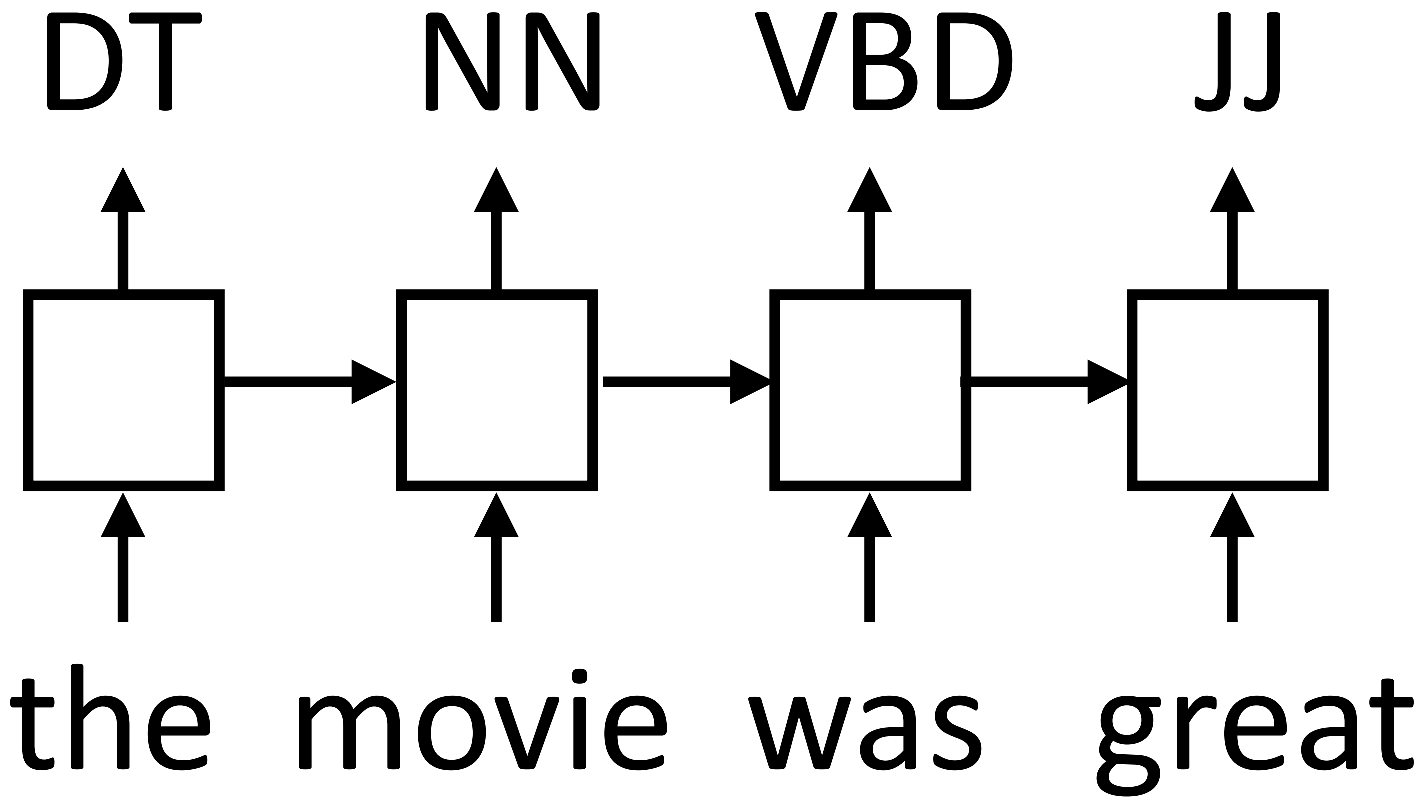


RNN Uses

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



output **y** = score for each tag, then softmax

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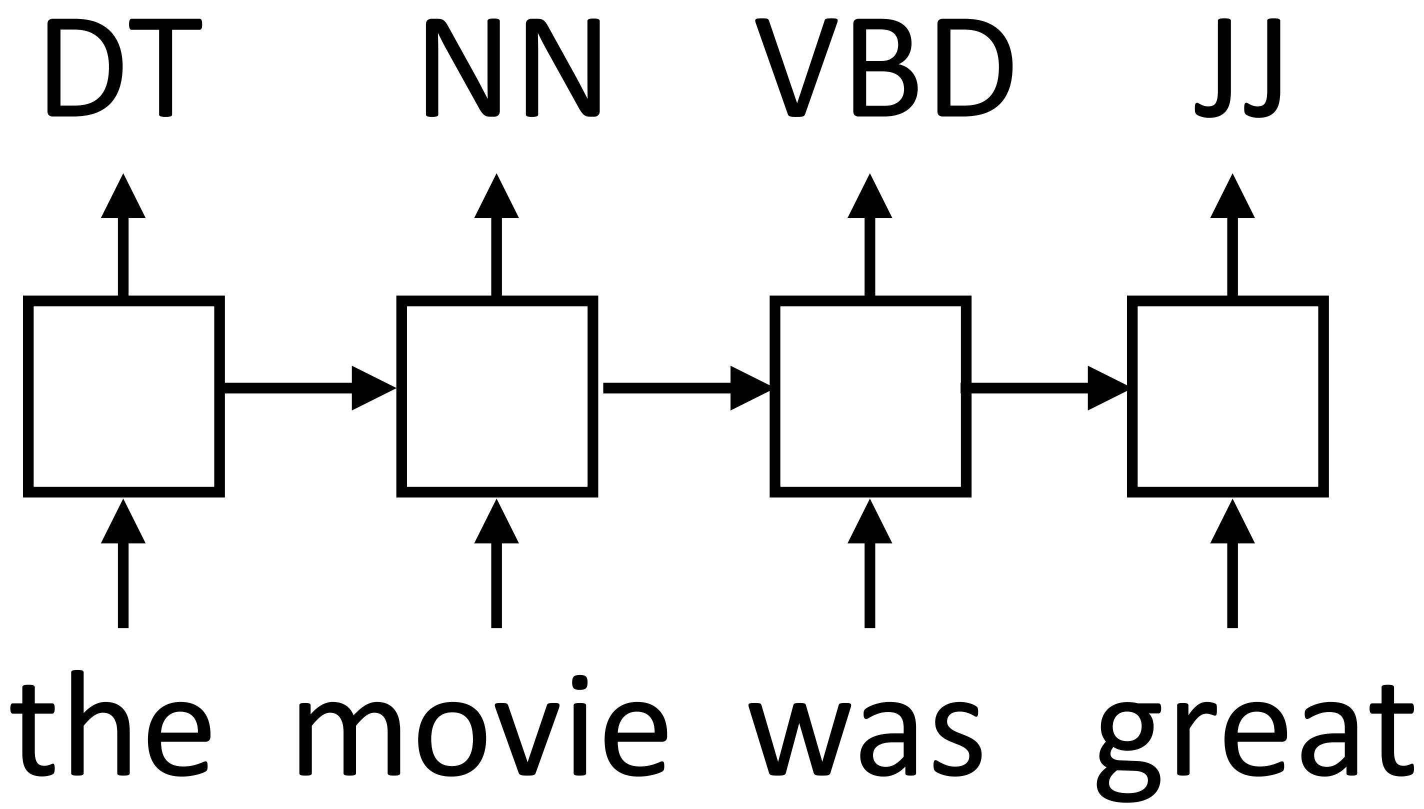

DT NN VBD JJ

the movie was great

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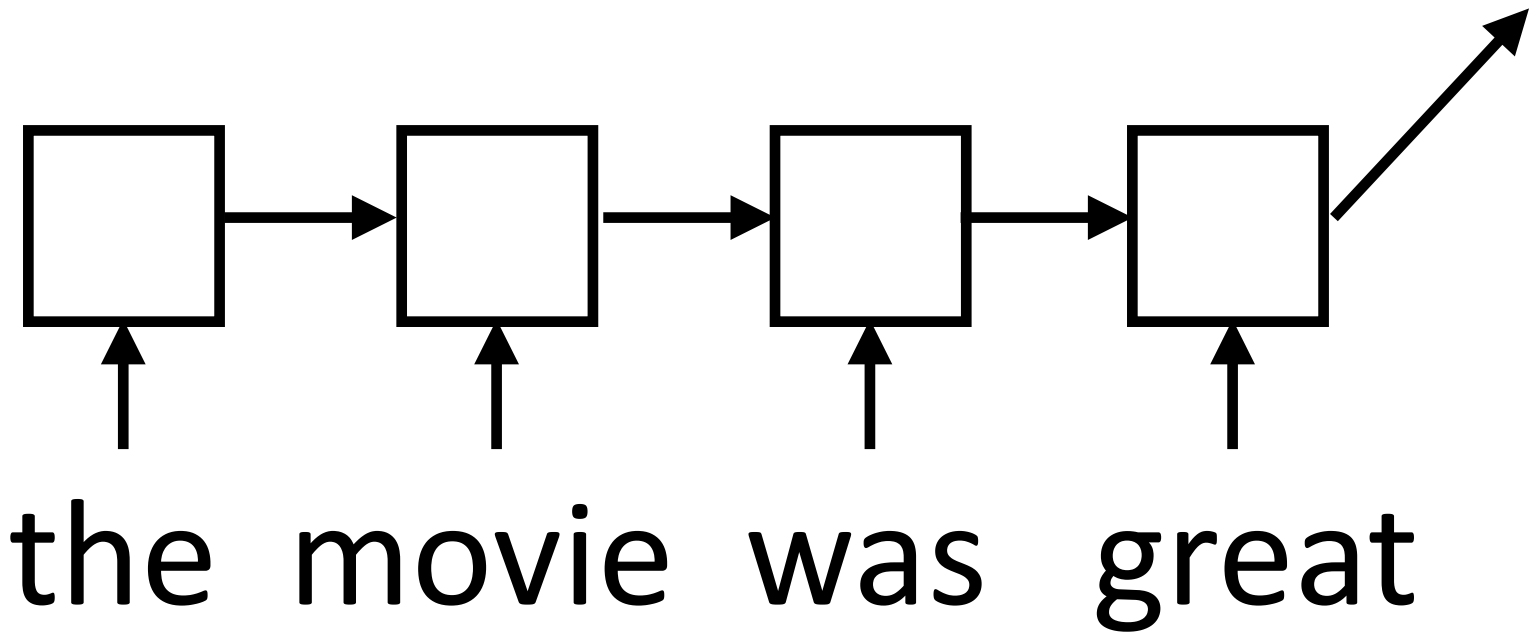

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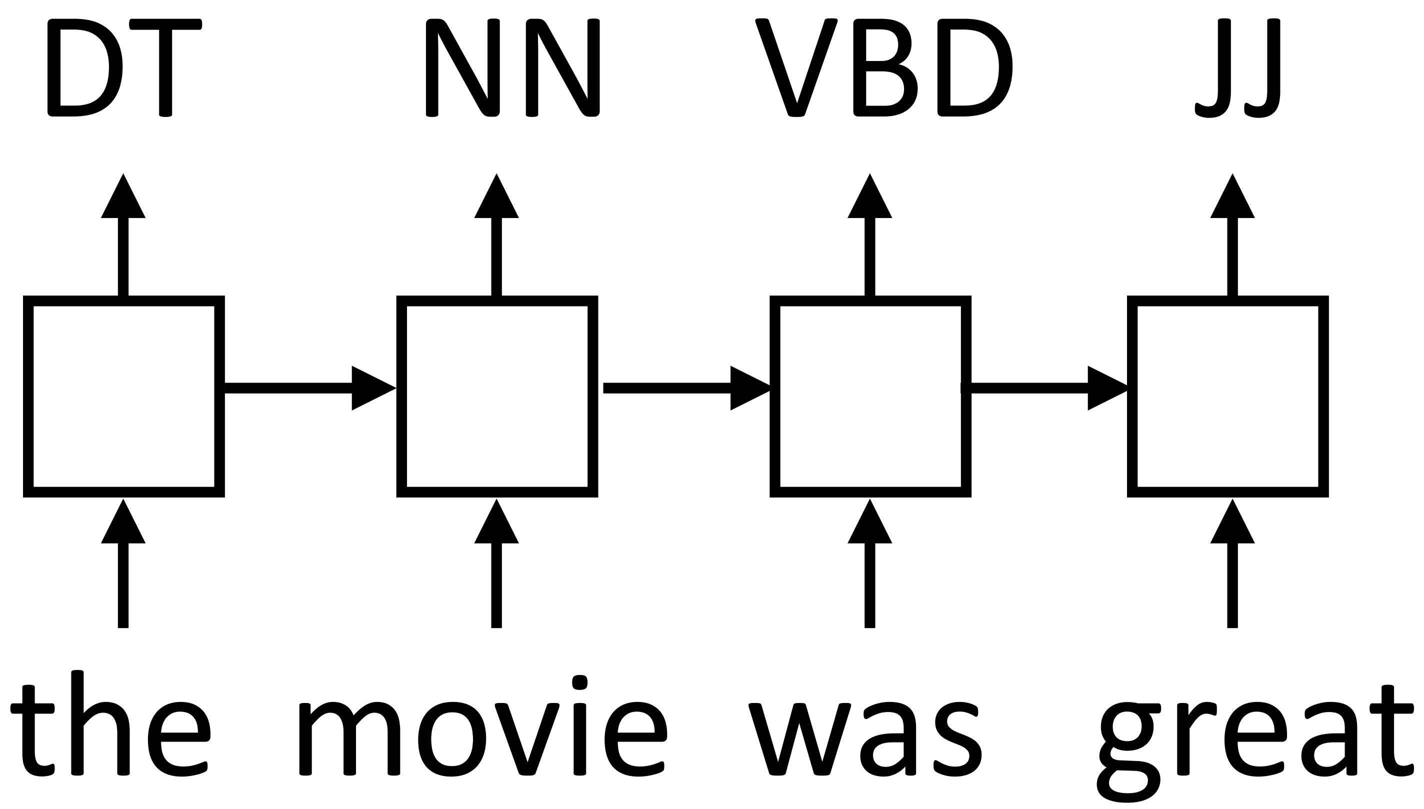

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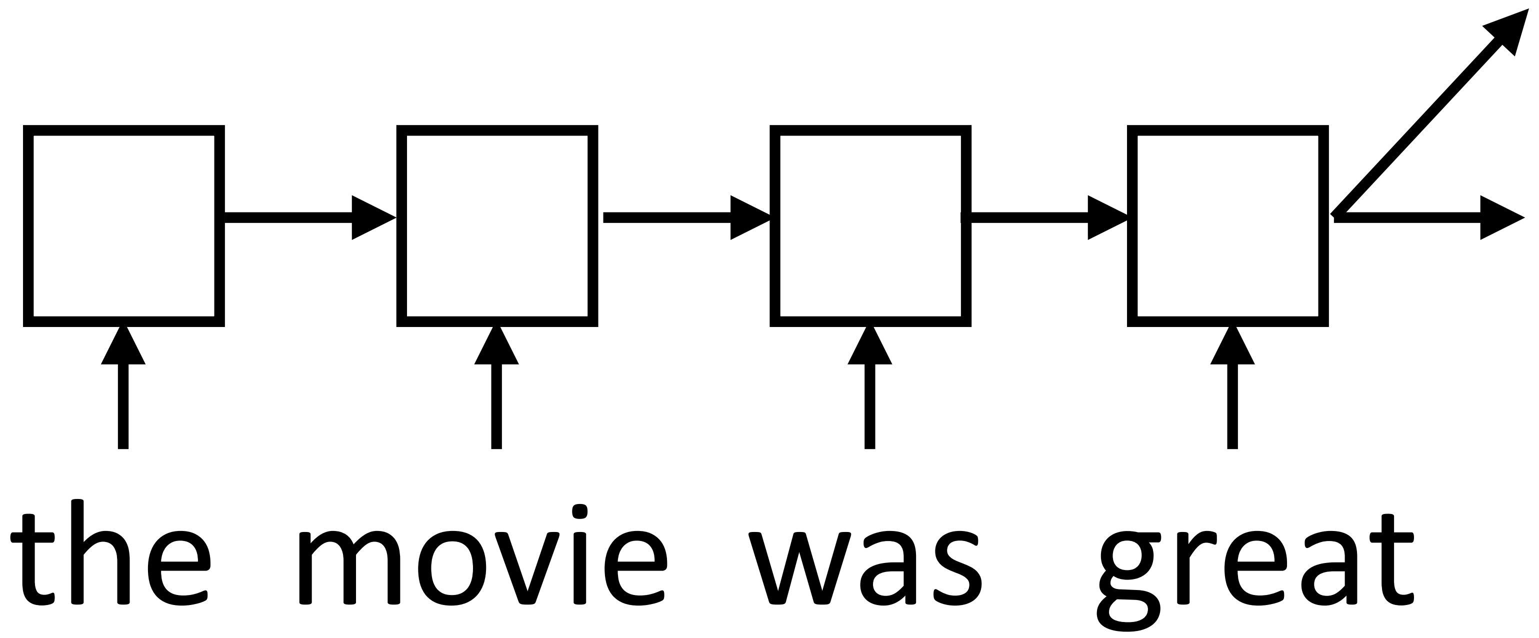

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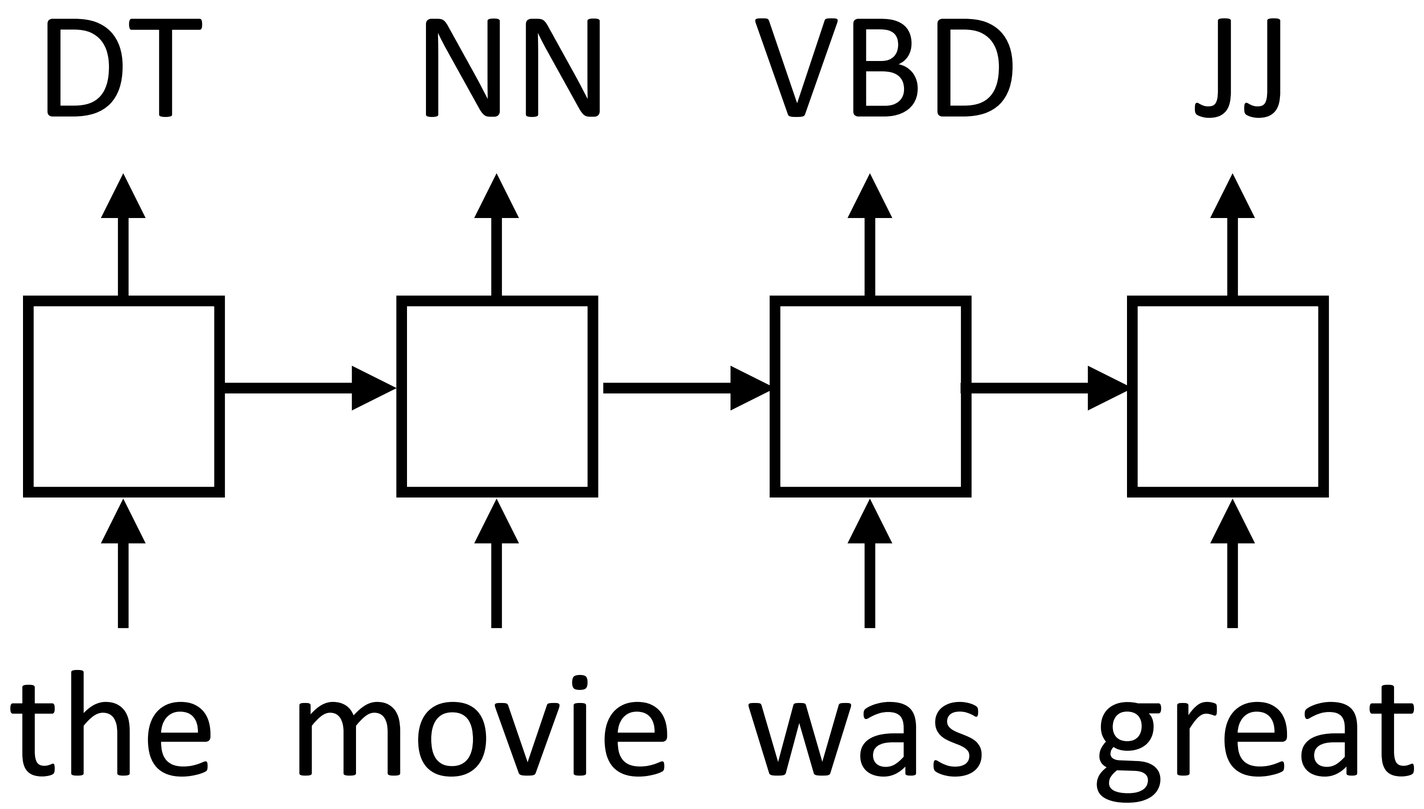

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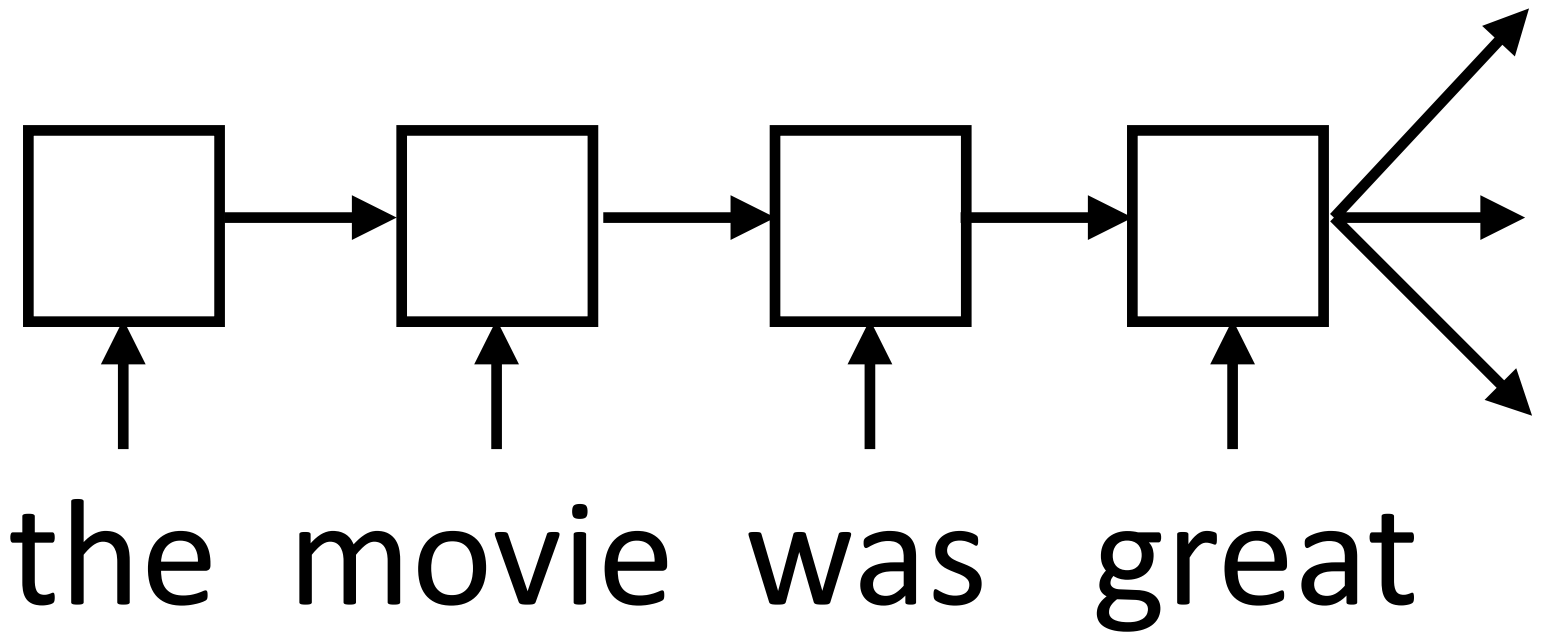

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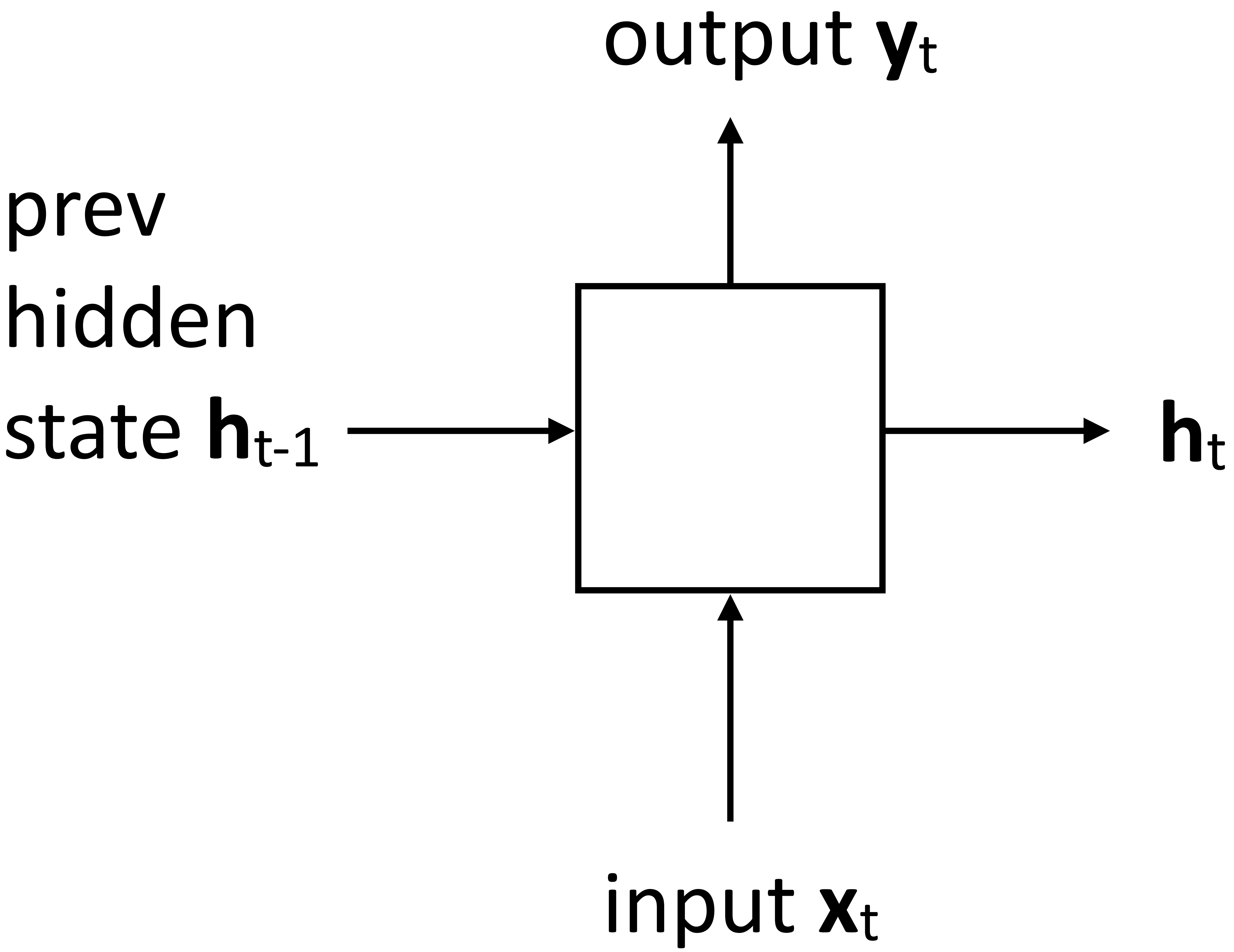
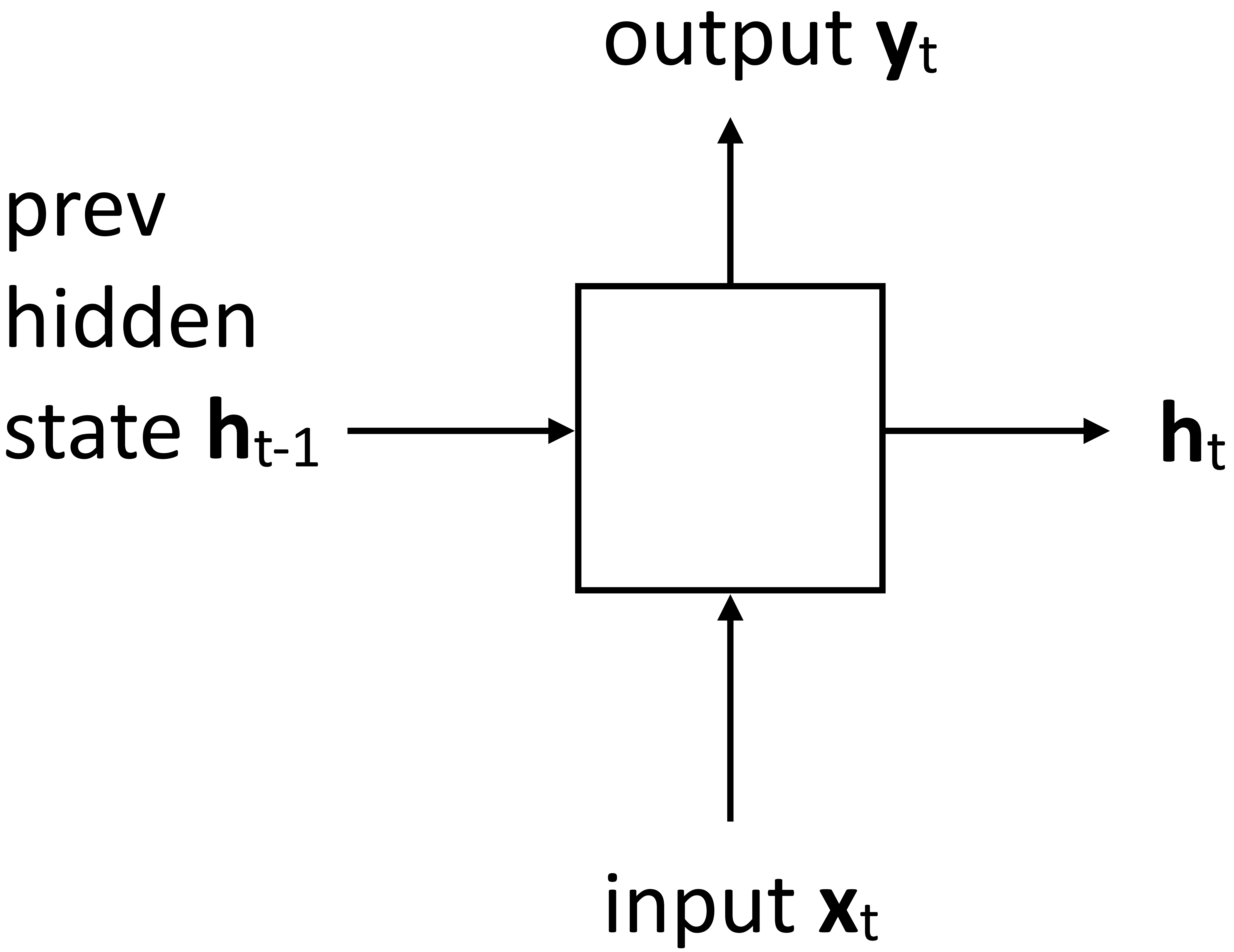
paraphrase/compress

Elman Networks



Elman (1990)

Elman Networks



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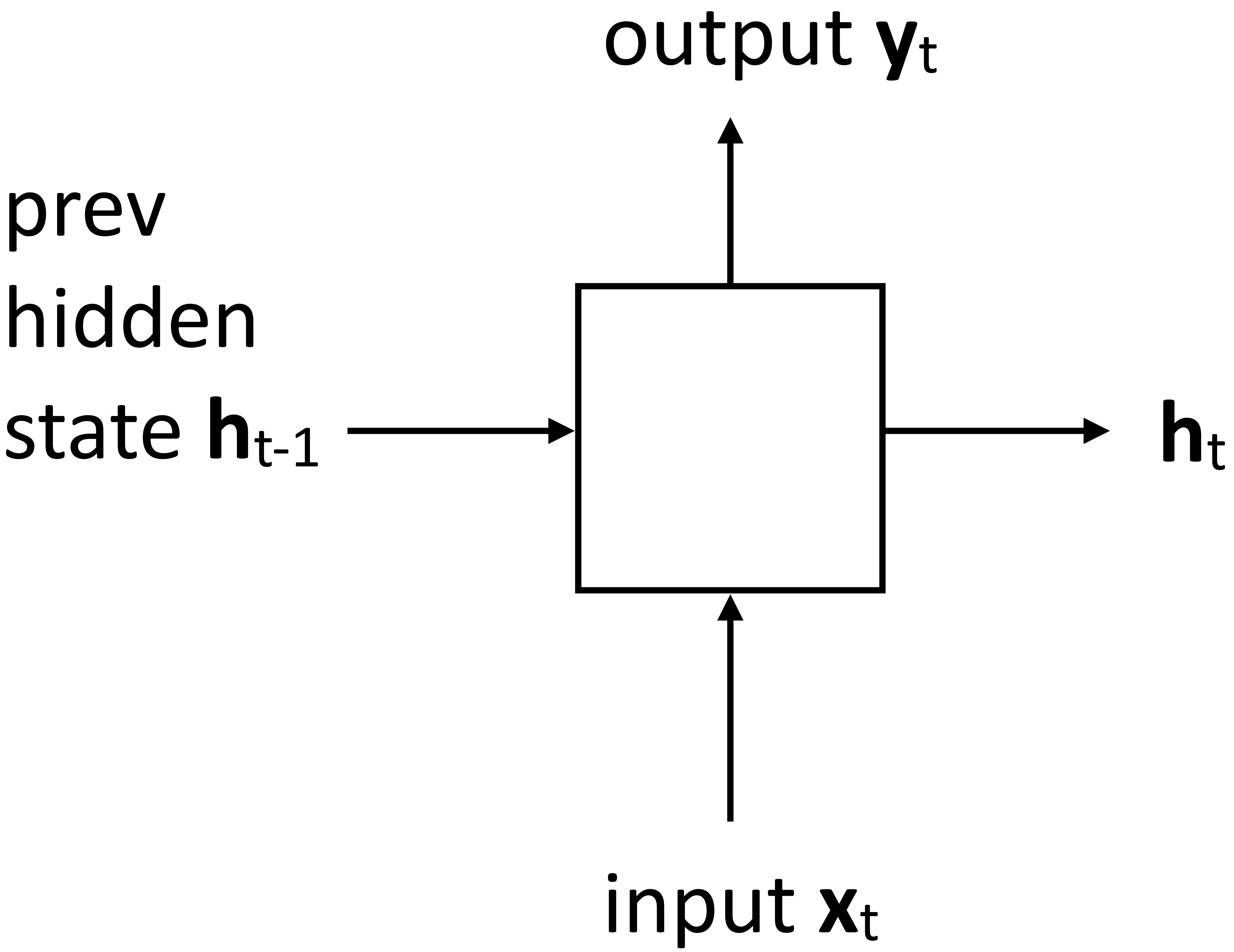

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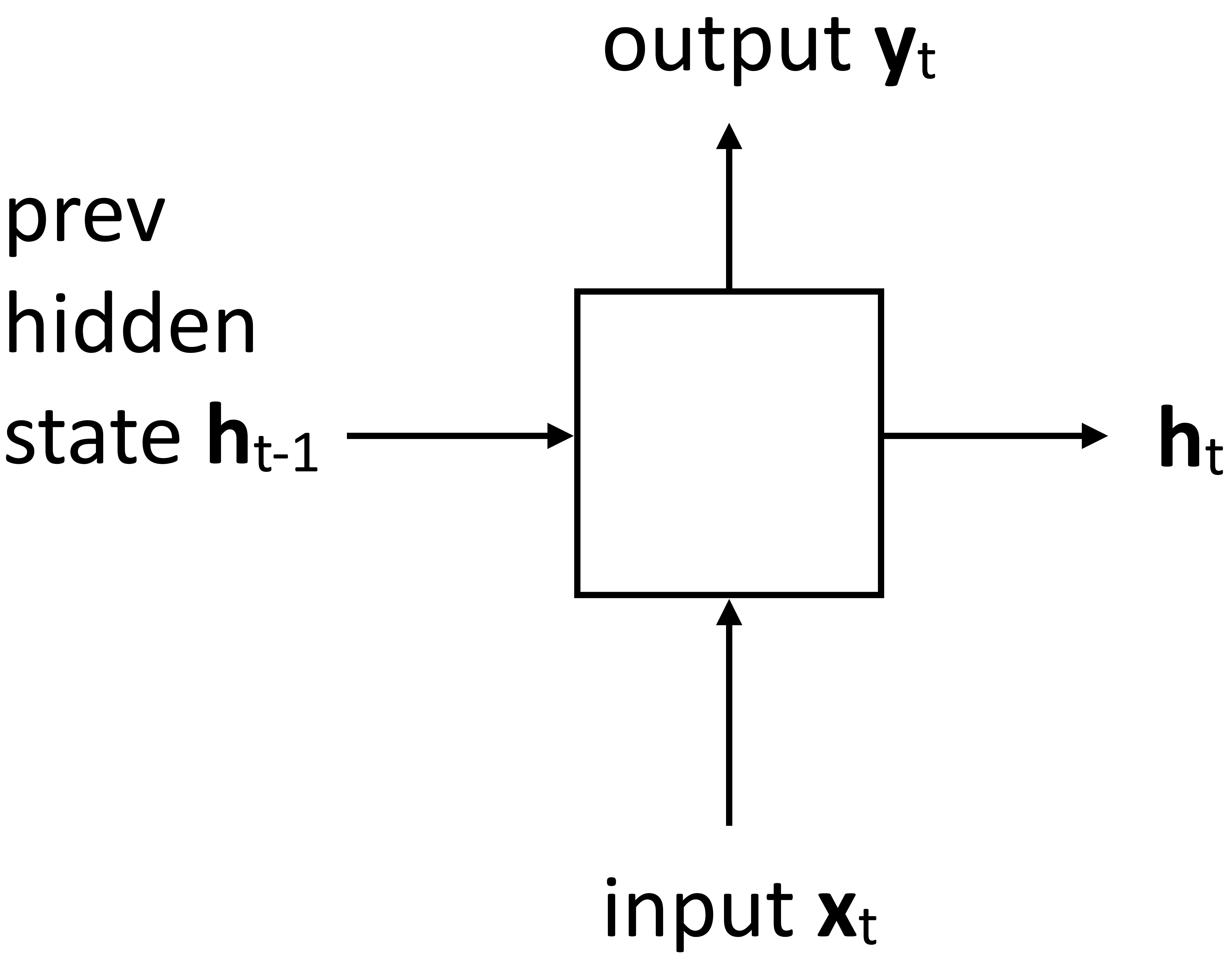

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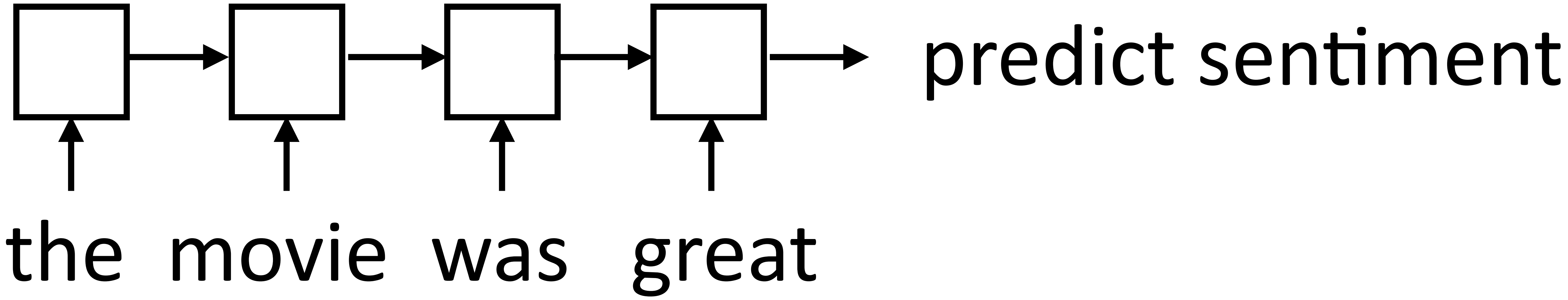
- Long history! (invented in the late 1980s)

Elman (1990)

Training Elman Networks



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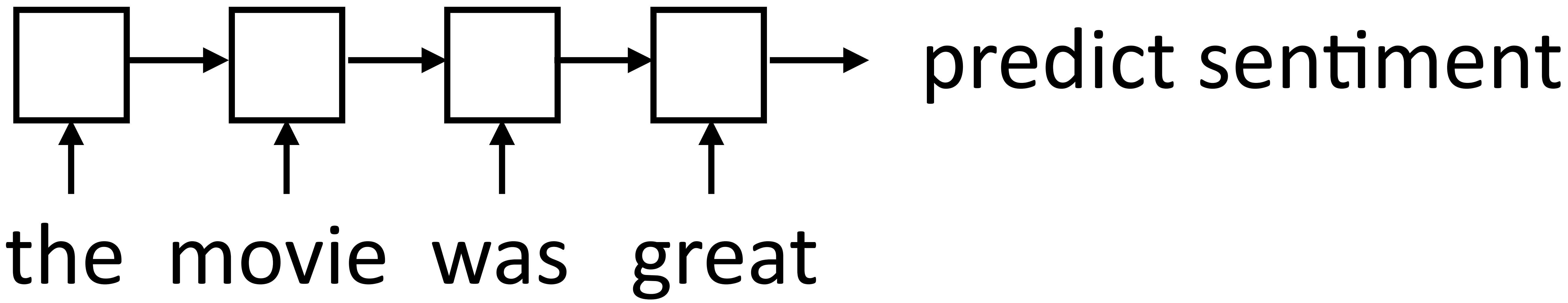

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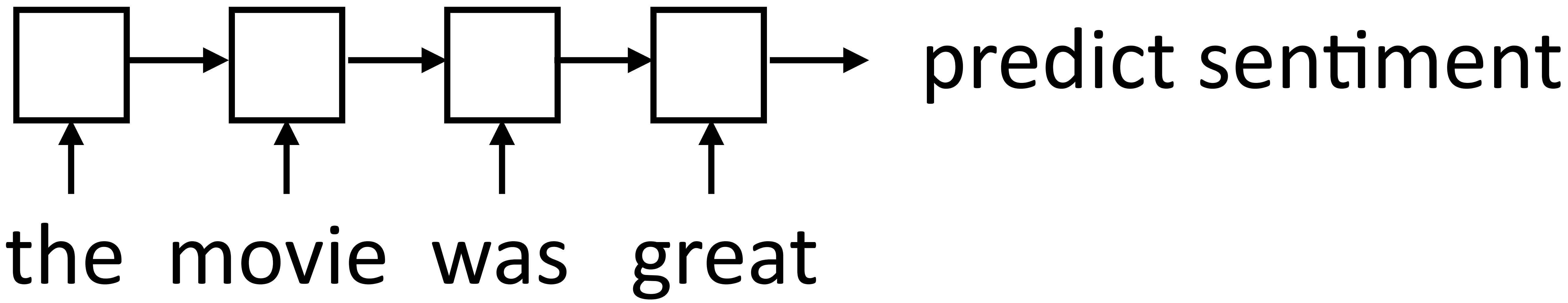

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it was my favorite movie of 2016, though it wasn’t without problems -> **+**

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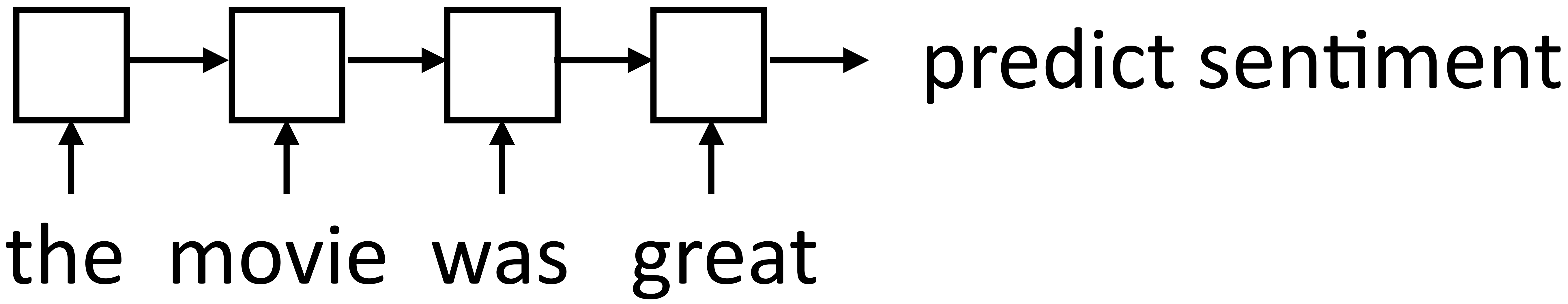

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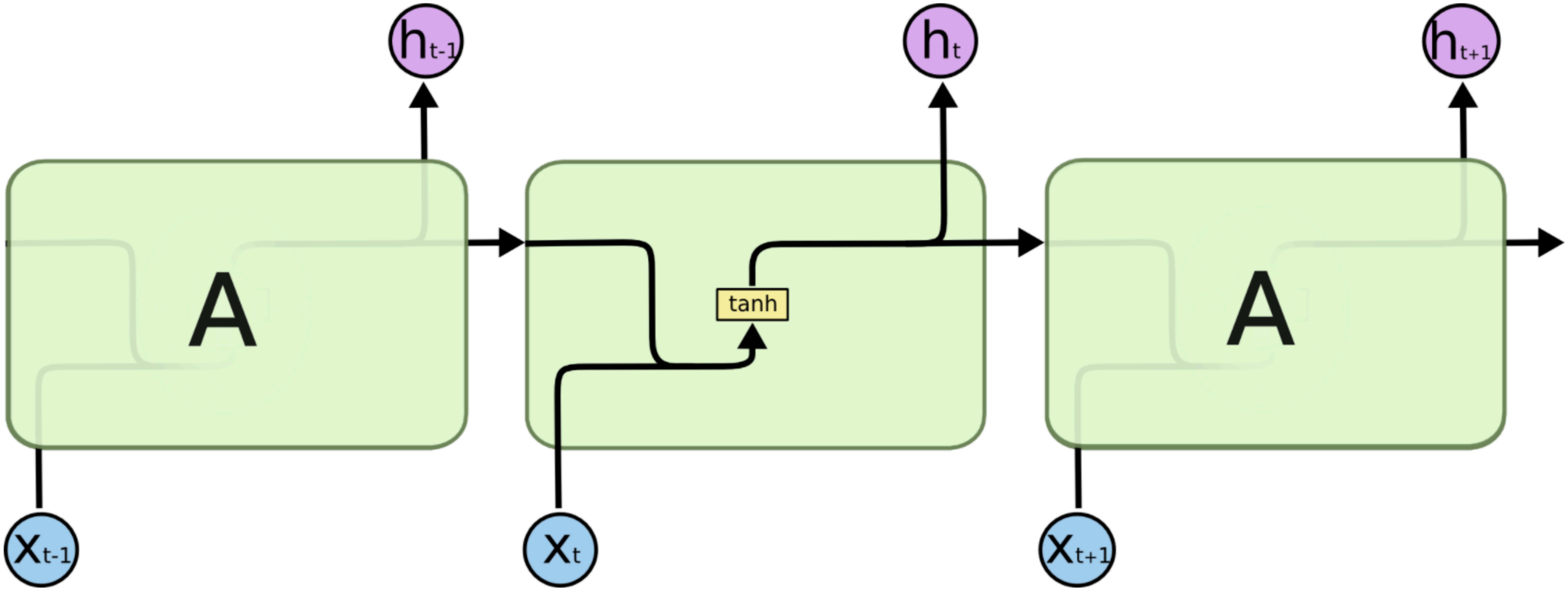
- “Correct” parameter update is to do a better job of remembering the sentiment of *favorite*

Vanishing Gradient



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

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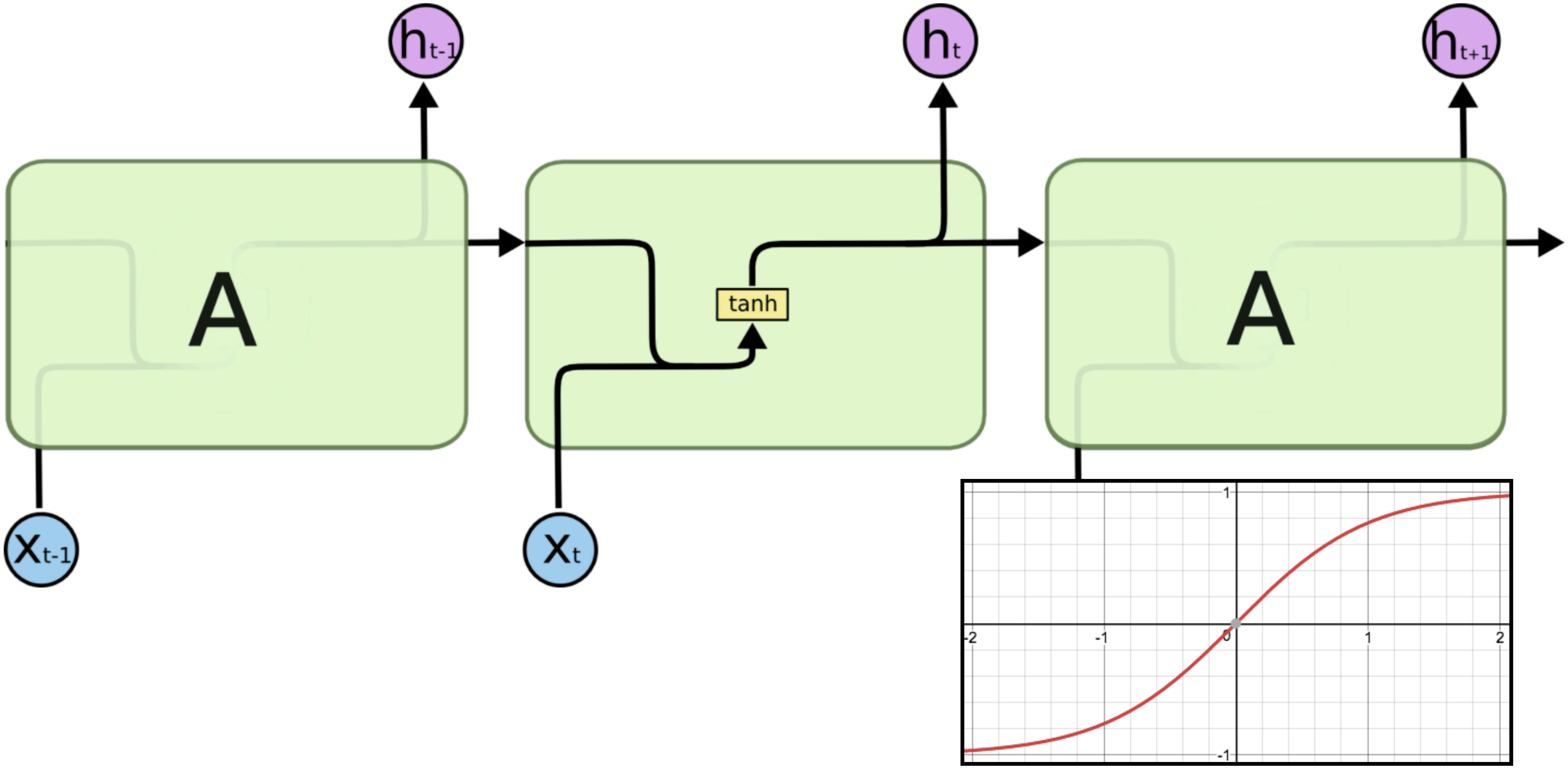

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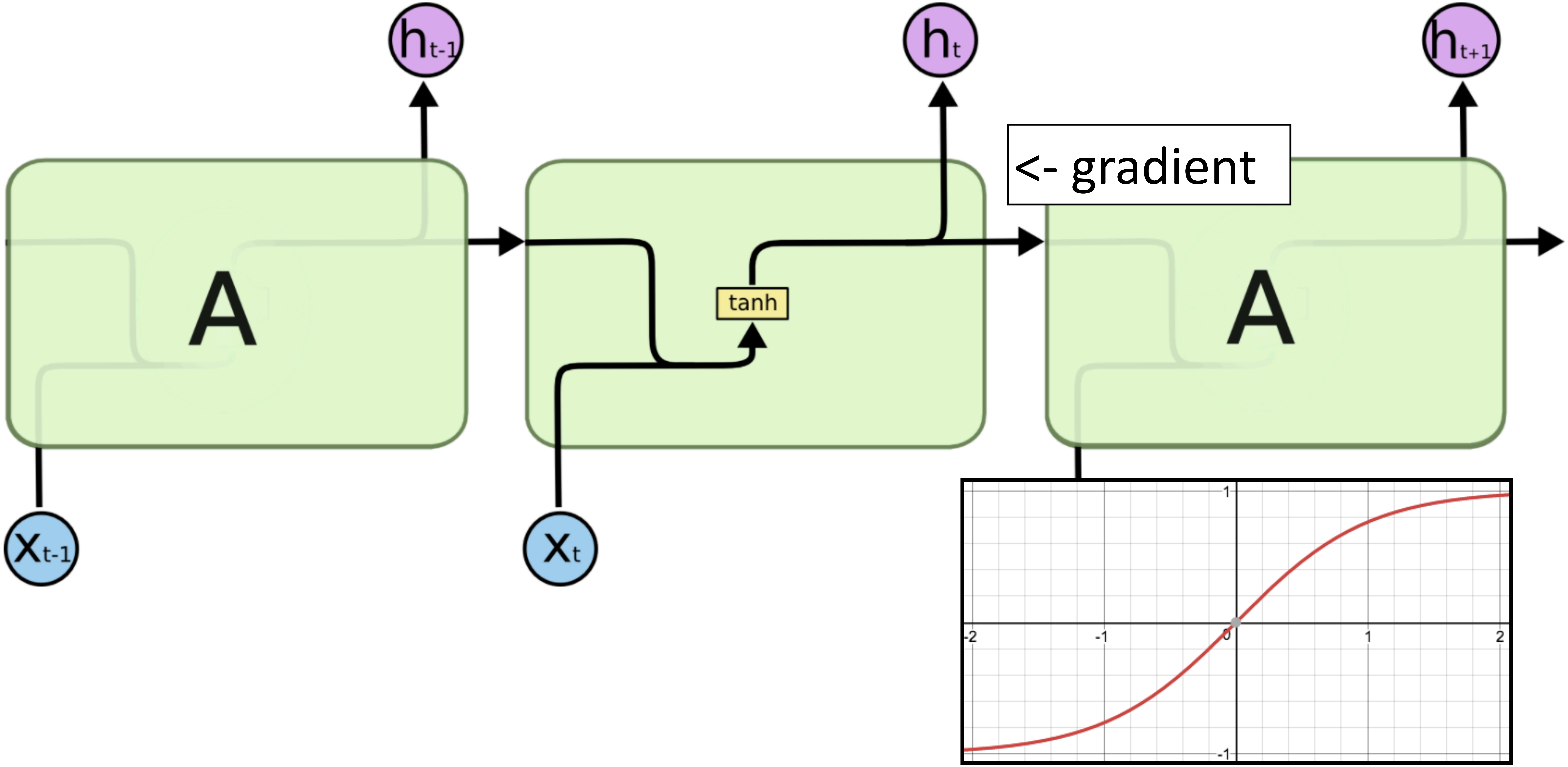

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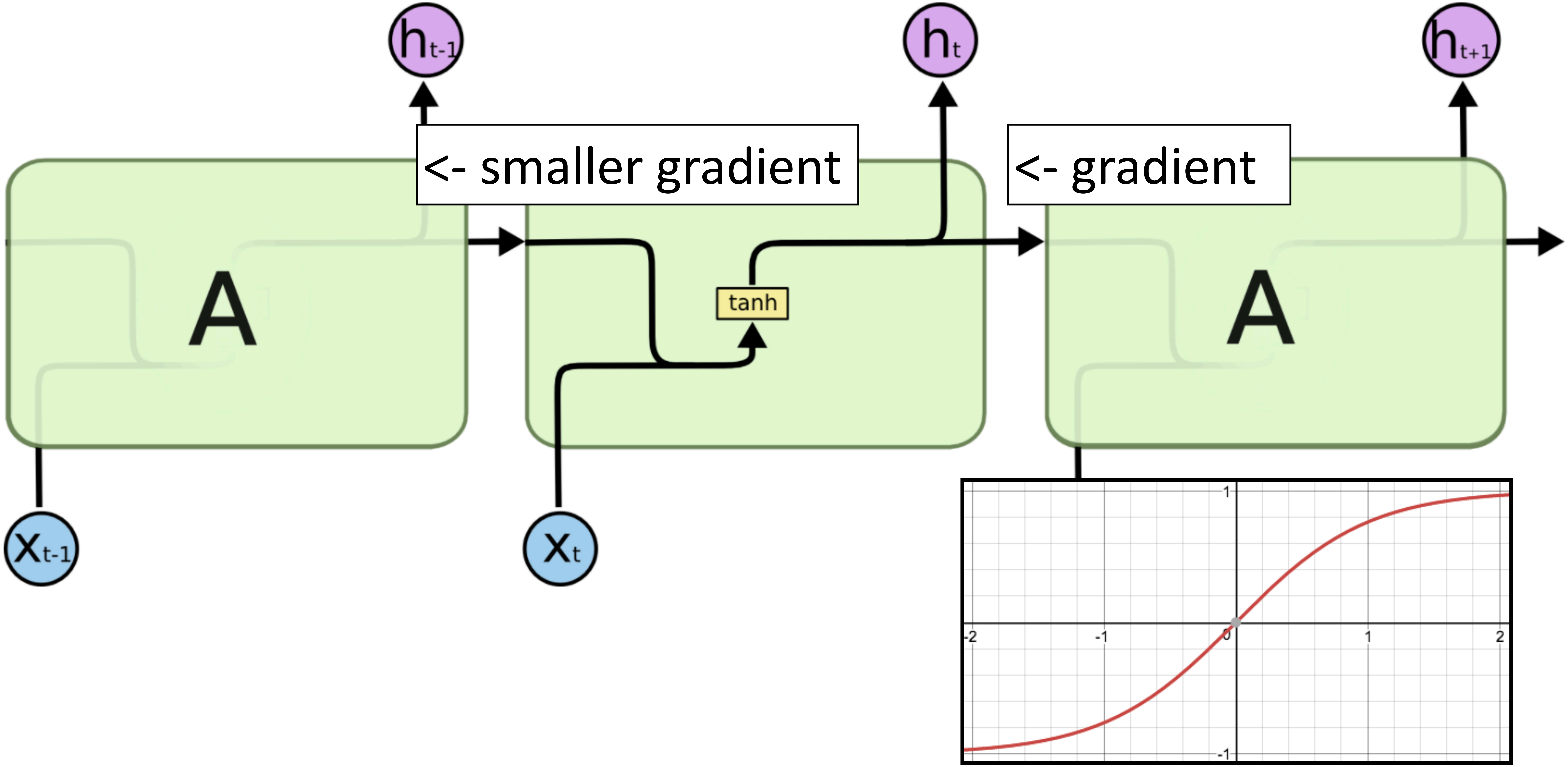

<- smaller gradient

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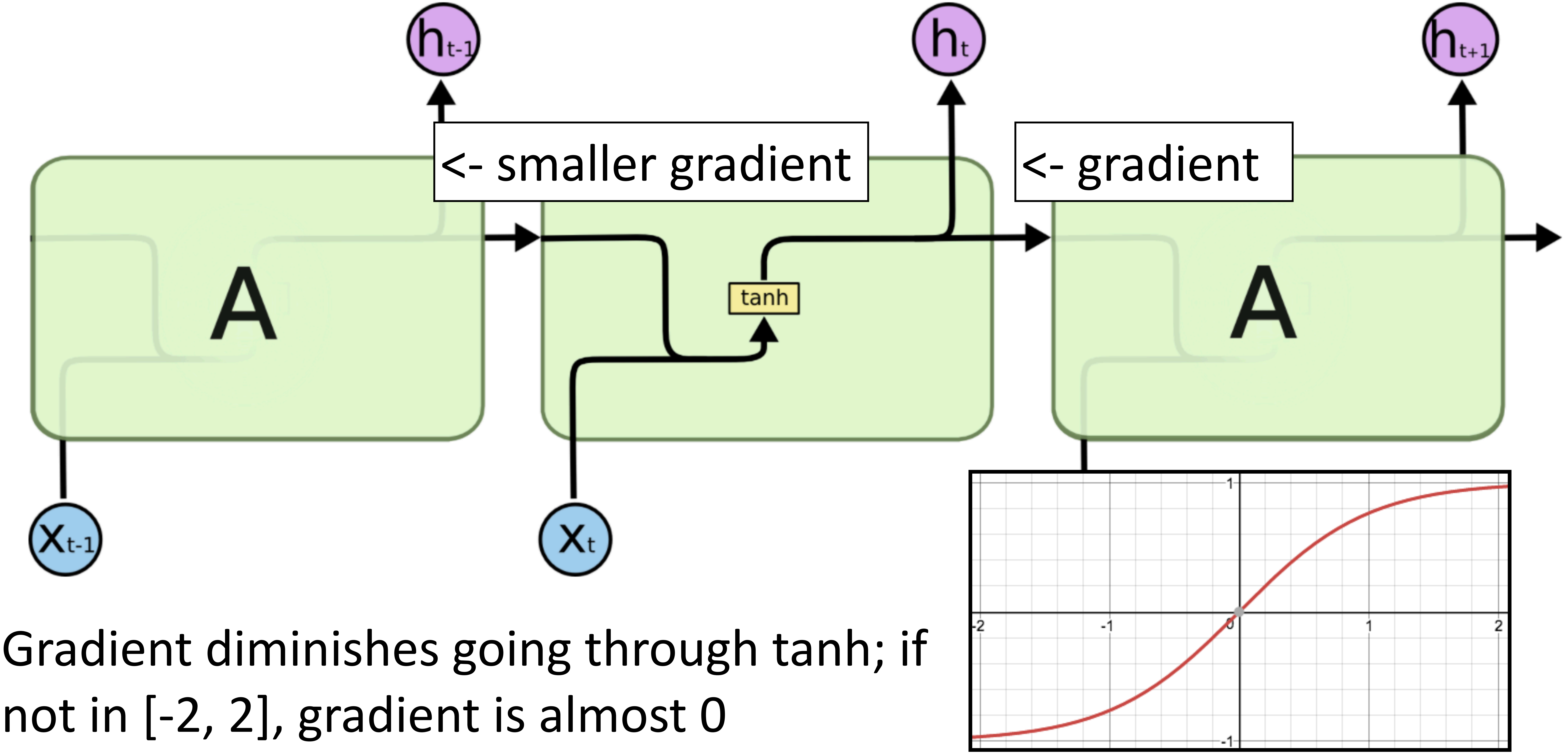

- Gradient diminishes going through tanh; if not in [-2, 2], gradient is almost 0

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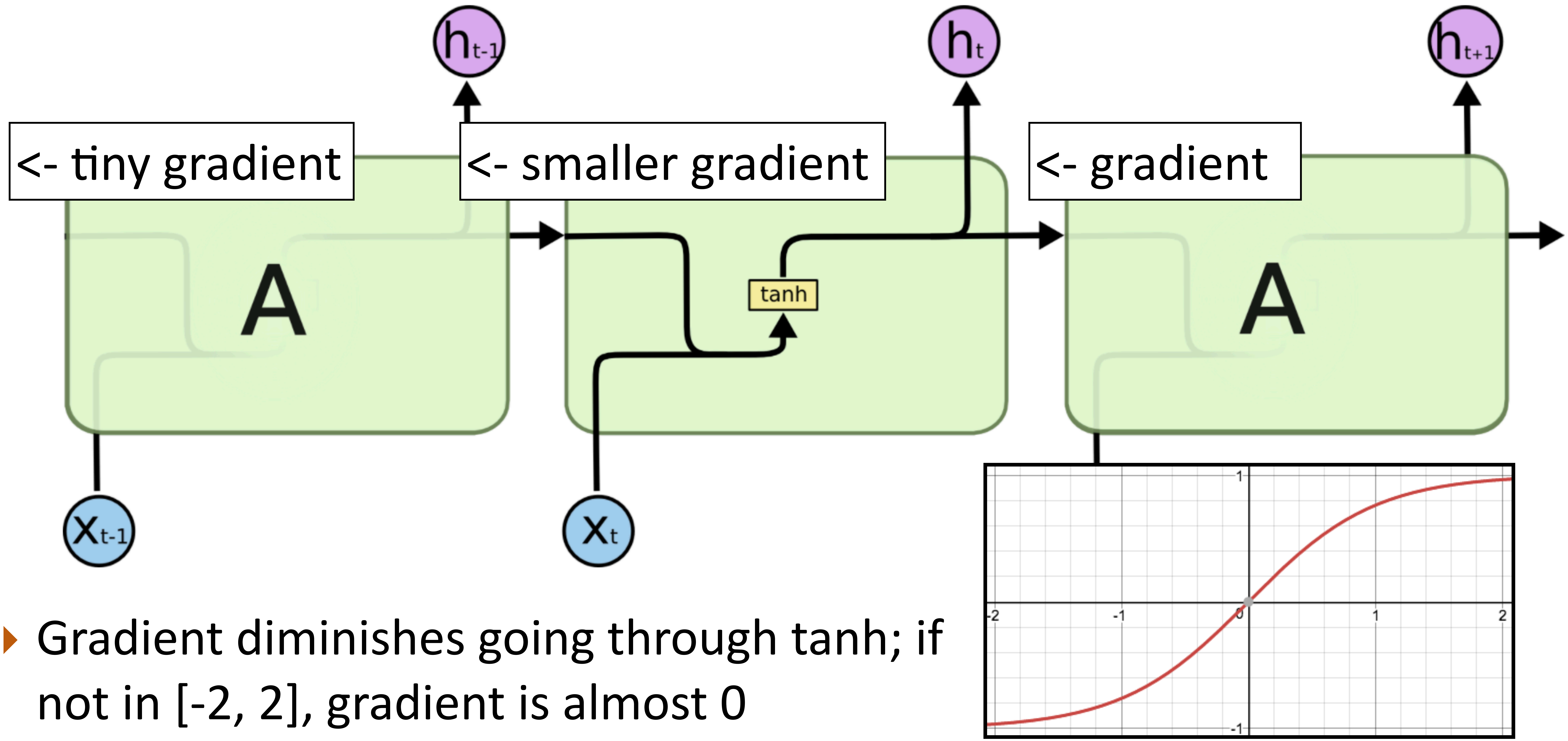

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LSTMs/GRUs

Gated Connections

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

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gated

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Elman

- Vector-valued "forget gate" **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 **f** are in (0, 1)

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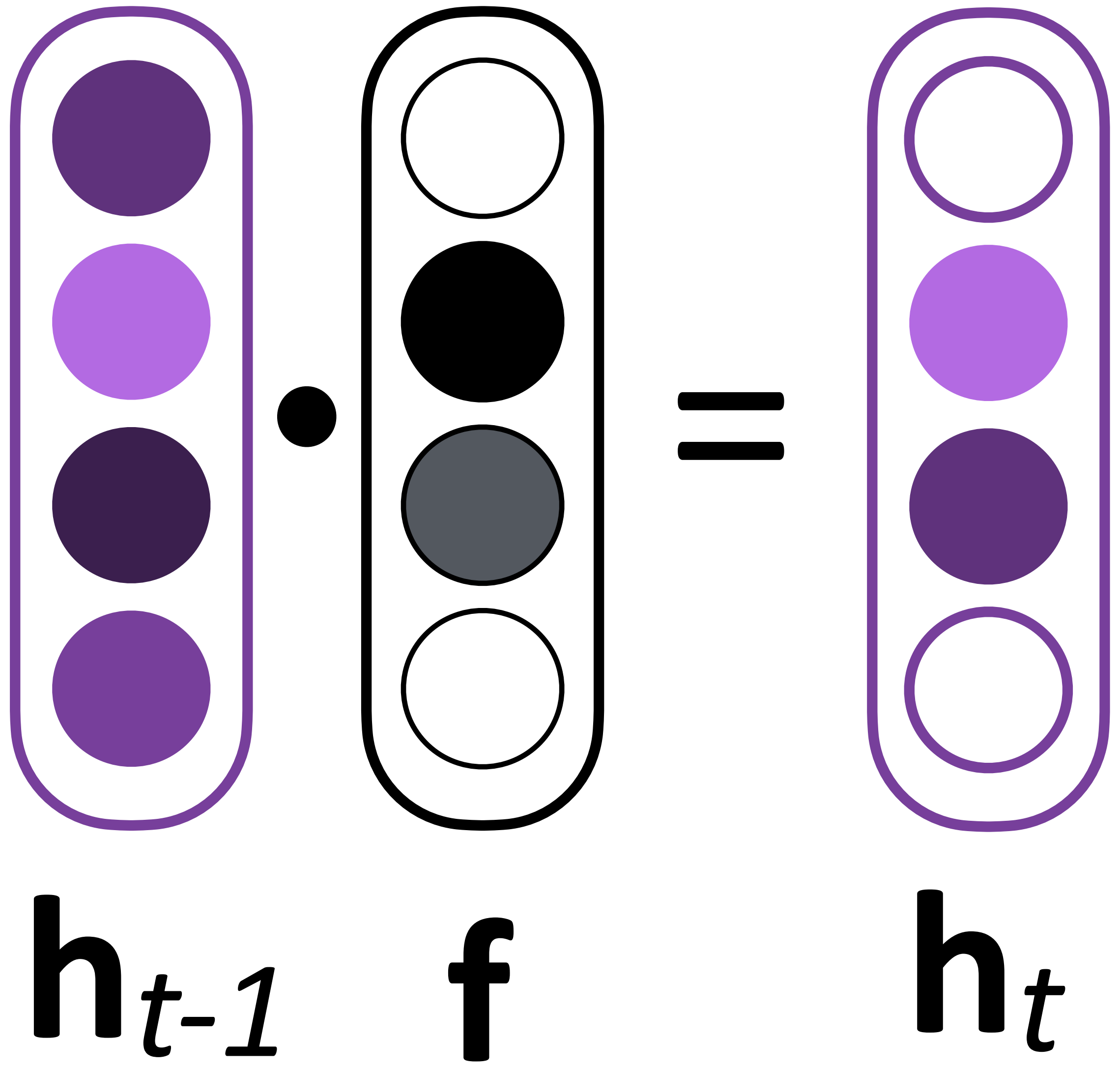

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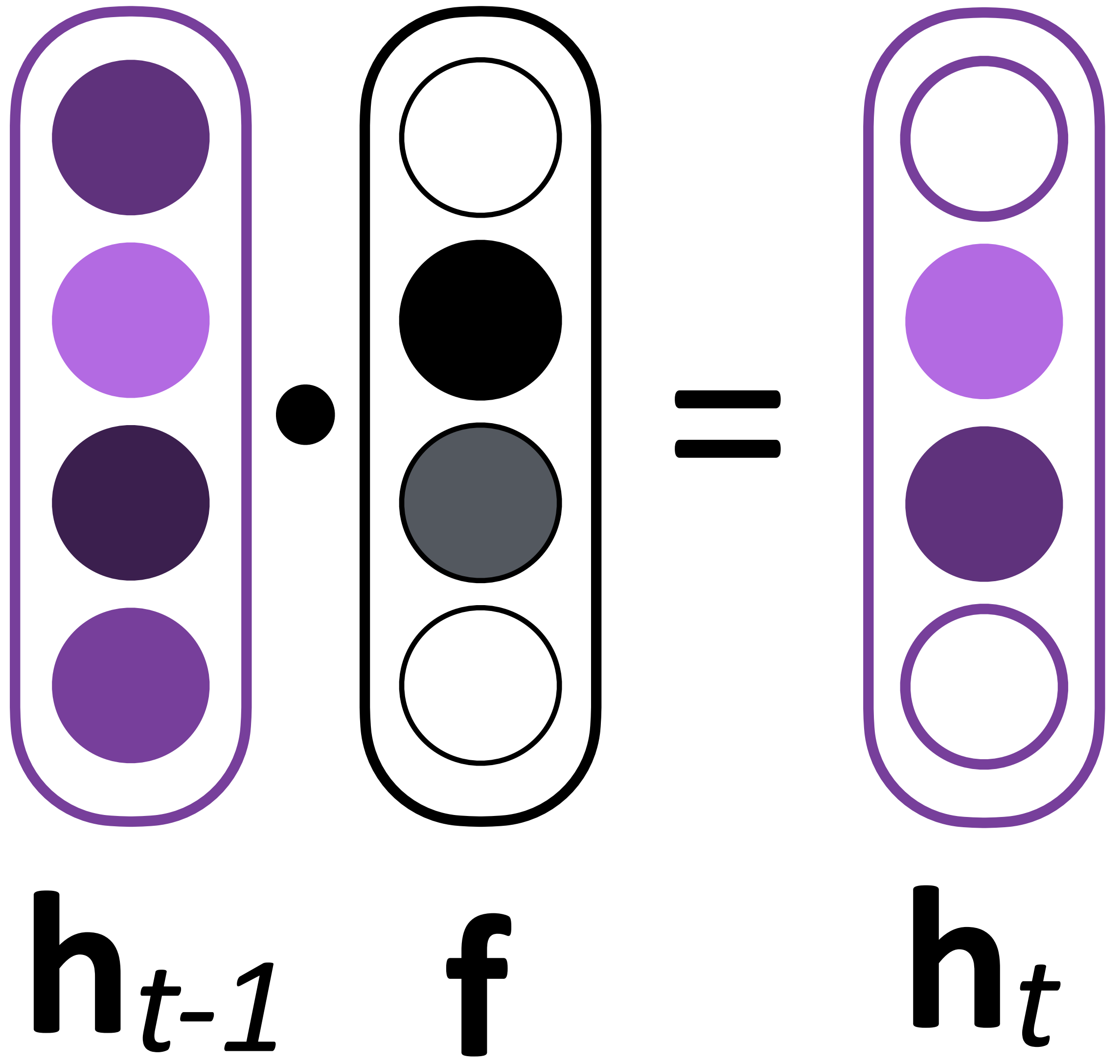

- Sigmoid: elements of **f** are in (0, 1)
- If **f** ≈ **1**, we simply sum up a function of all inputs — gradient doesn't vanish!

LSTMs

- “Cell” **c** in addition to hidden state **h**

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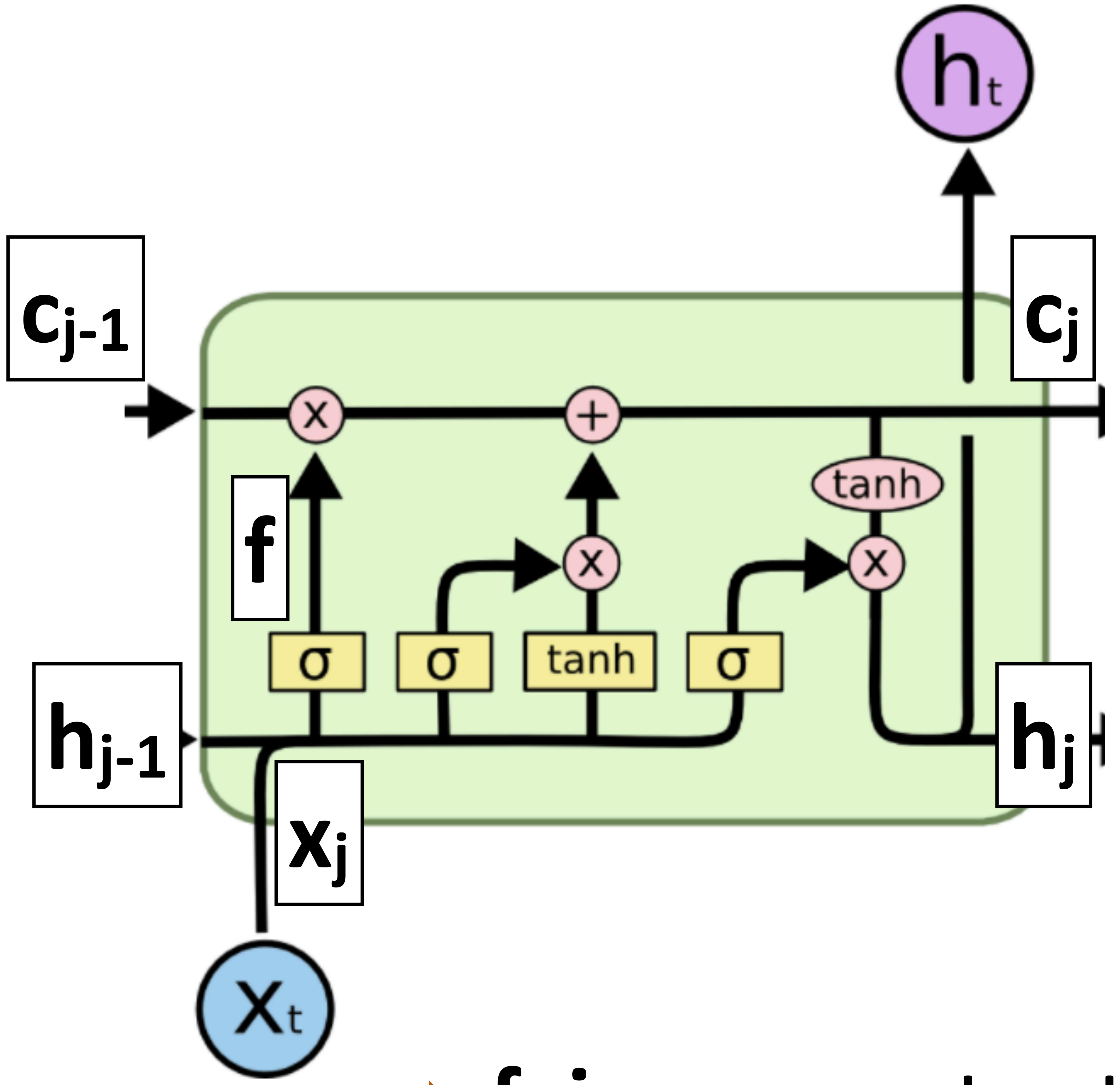
- Basic communication flow: **x** -> **c** -> **h ->** output**,** each step of this process is gated in addition to gates from previous timesteps

LSTMs



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

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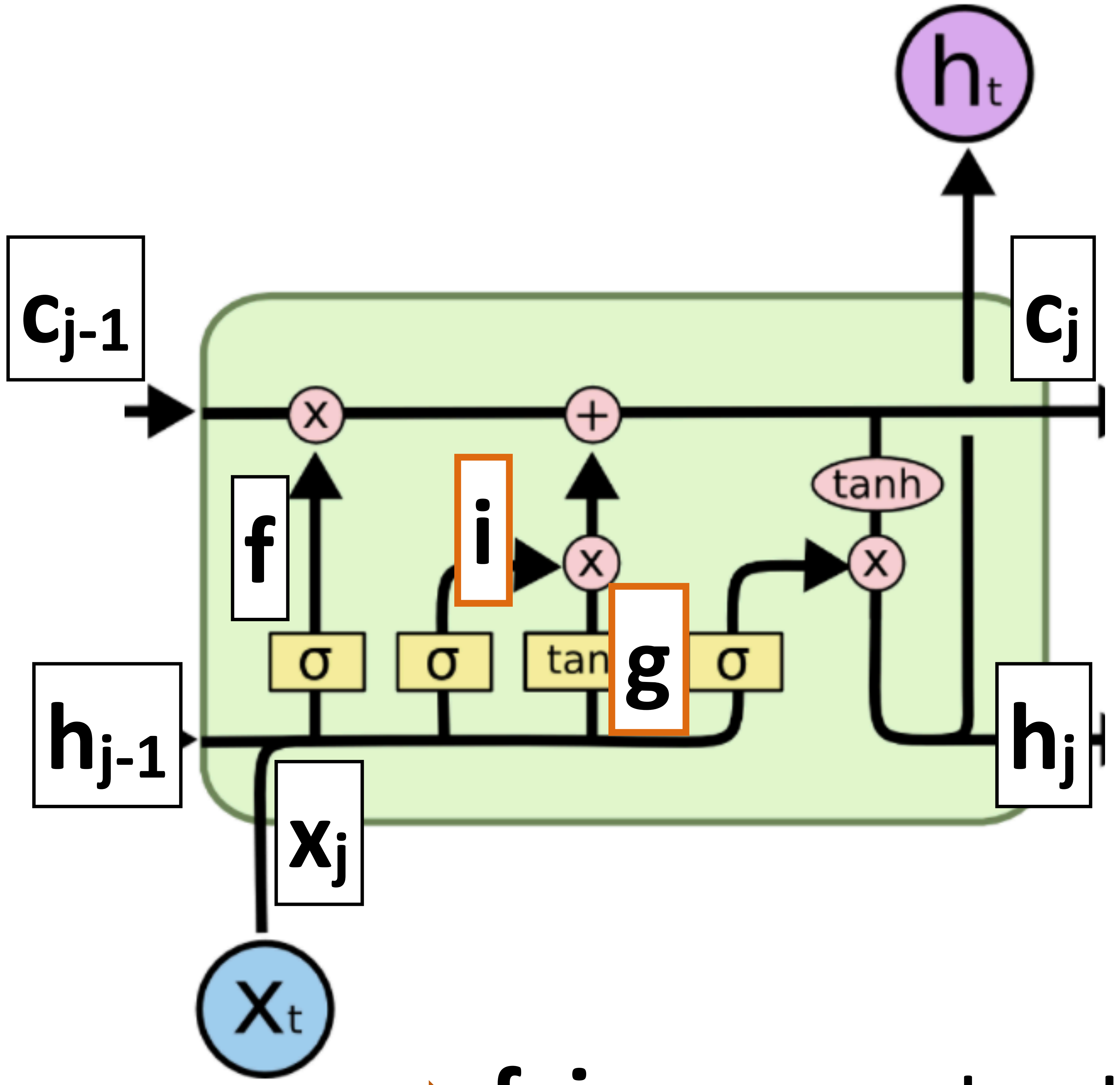
- **f**, **i**, **o** are gates that control information flow
- **g** reflects the main computation of the cell

Goldberg lecture notes

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

LSTMs



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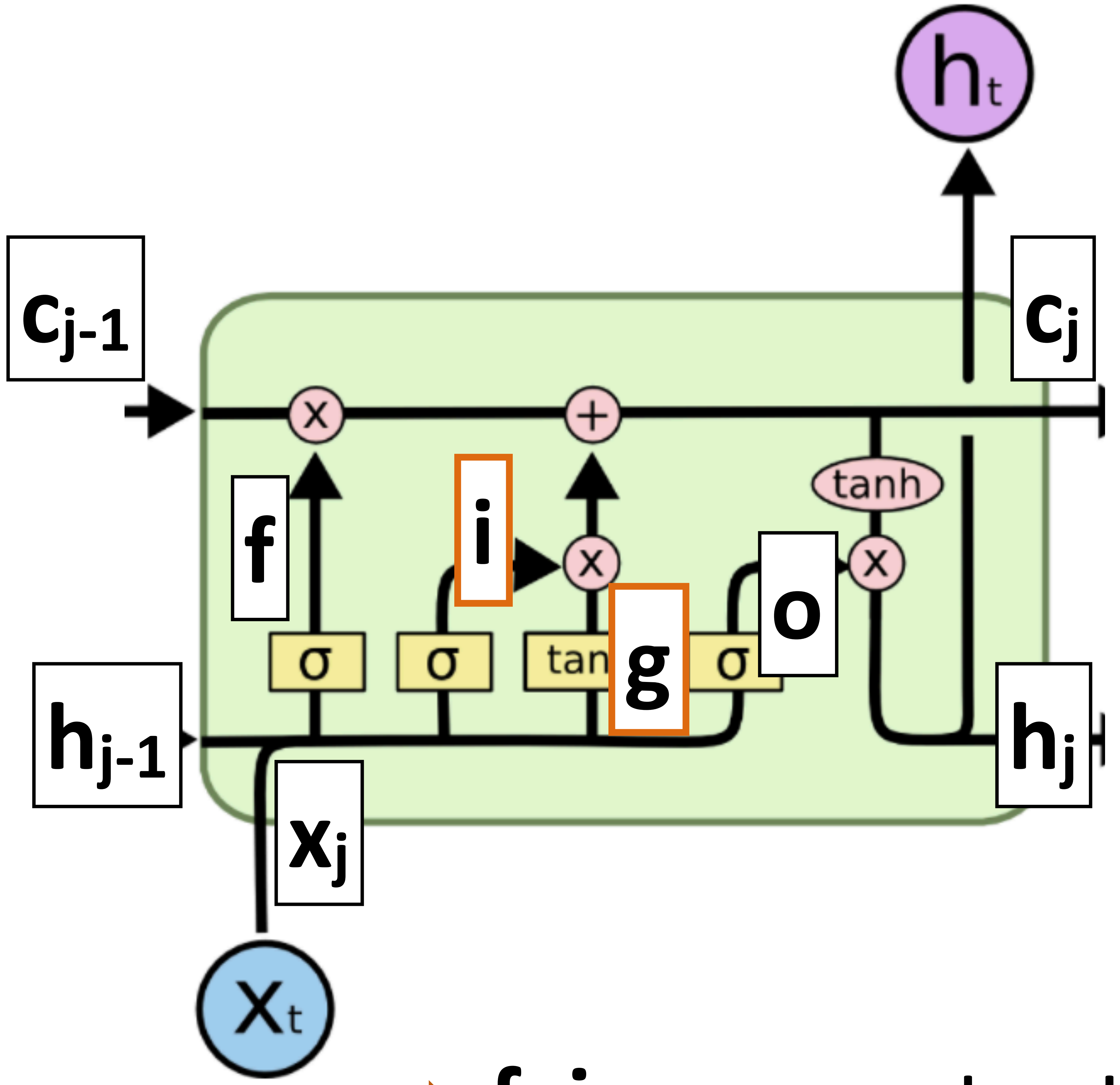

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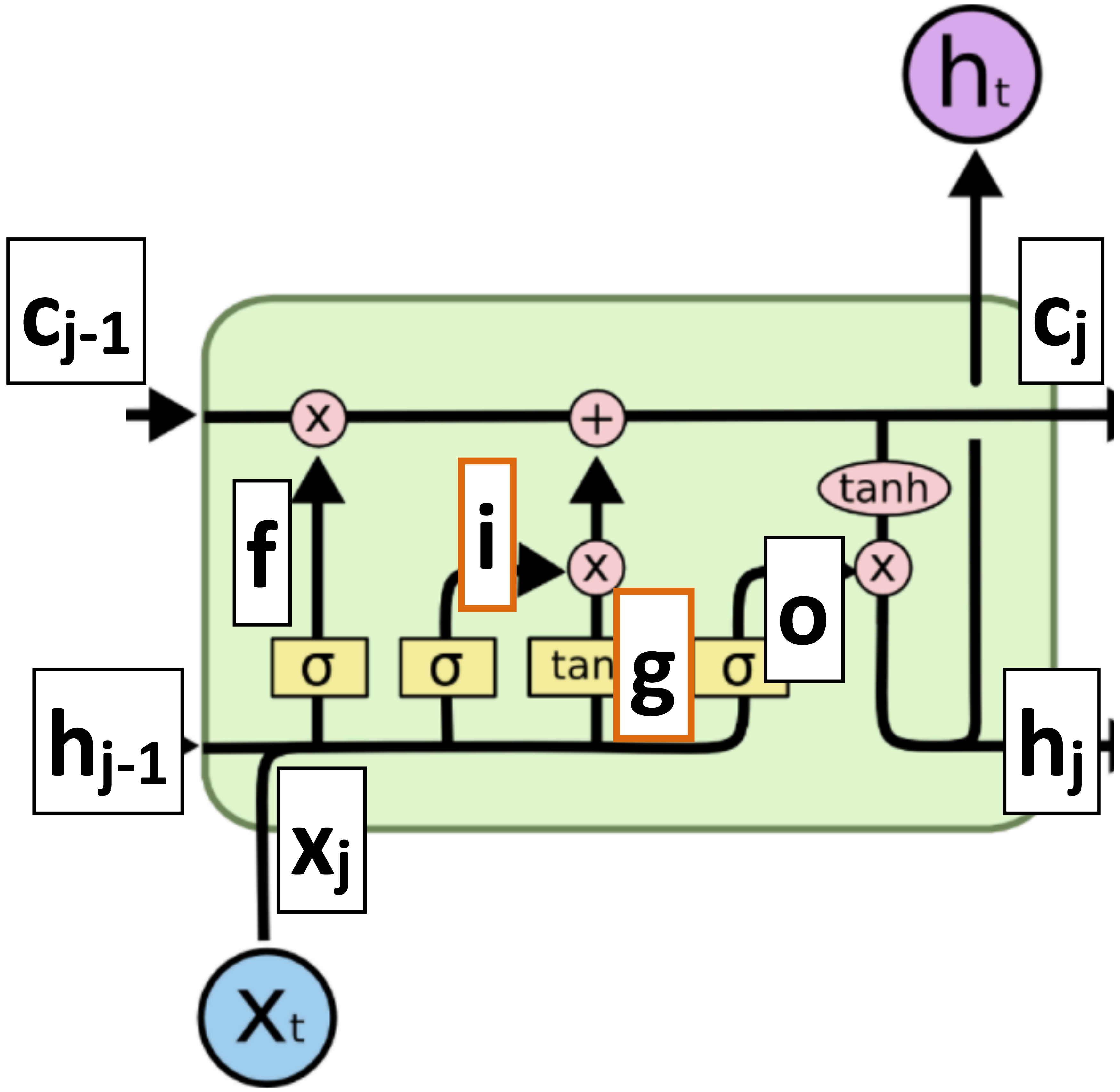

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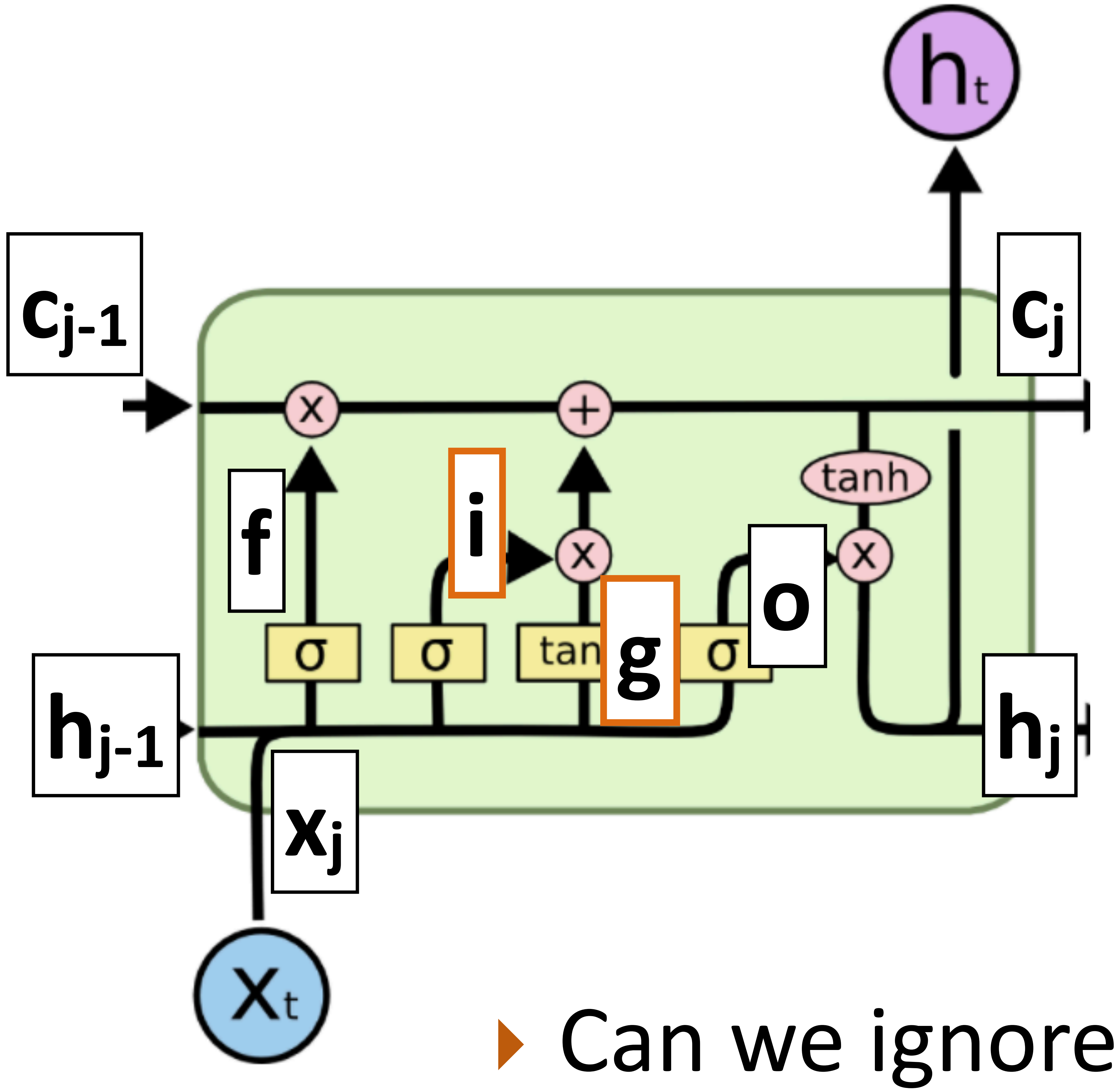

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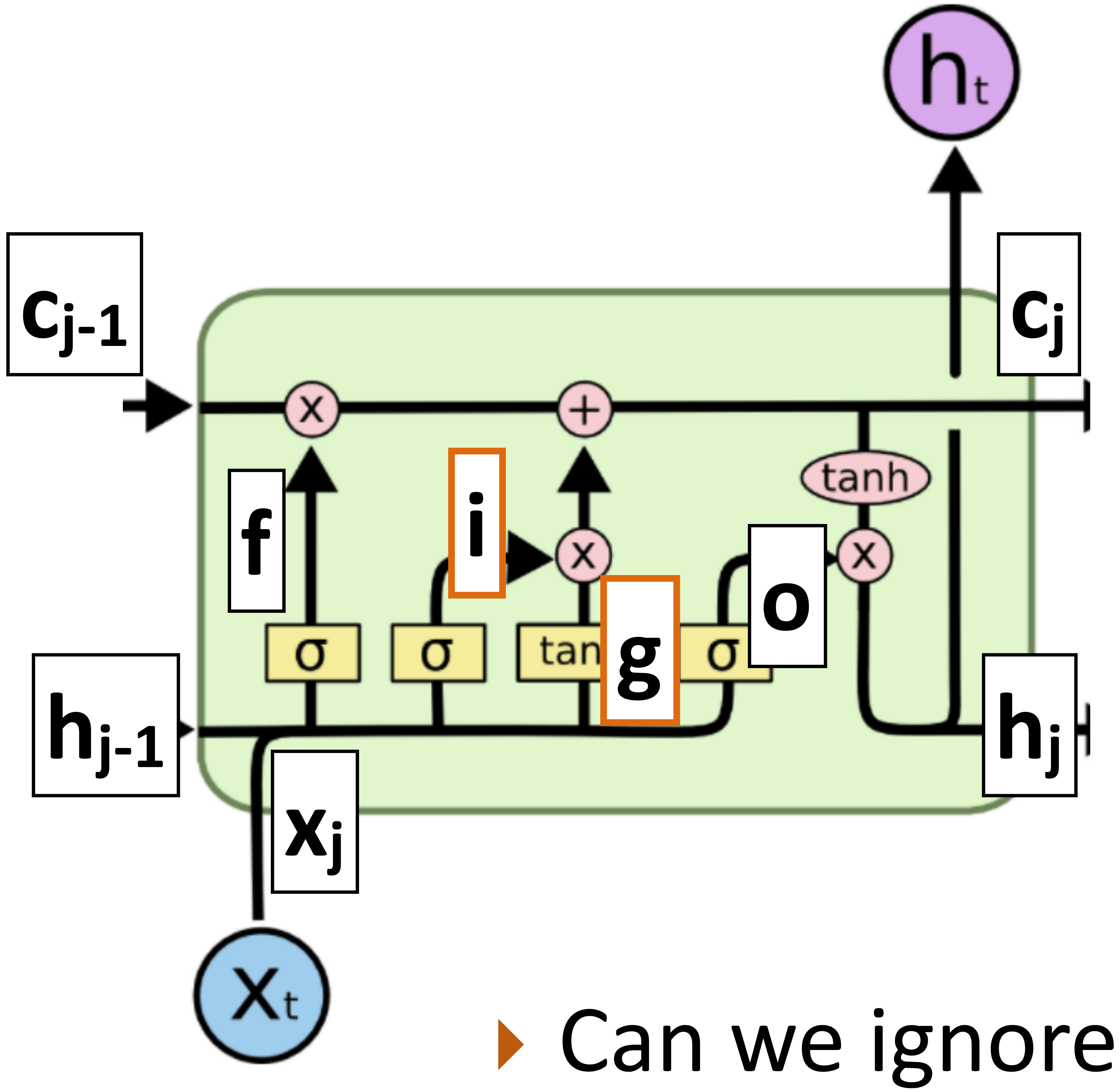
- Can we ignore the old value of **c** for this timestep?

LSTMs



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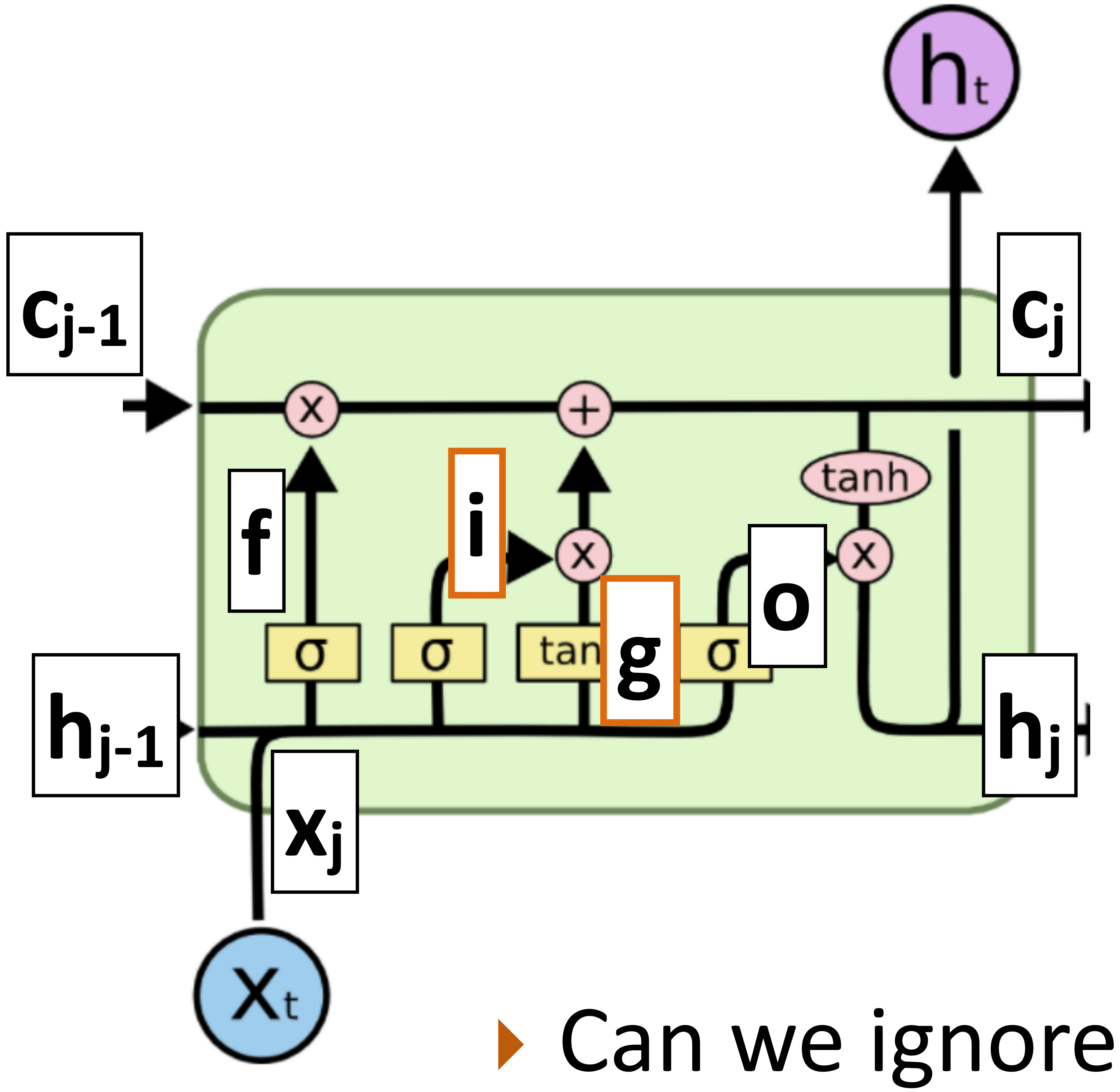
LSTMs



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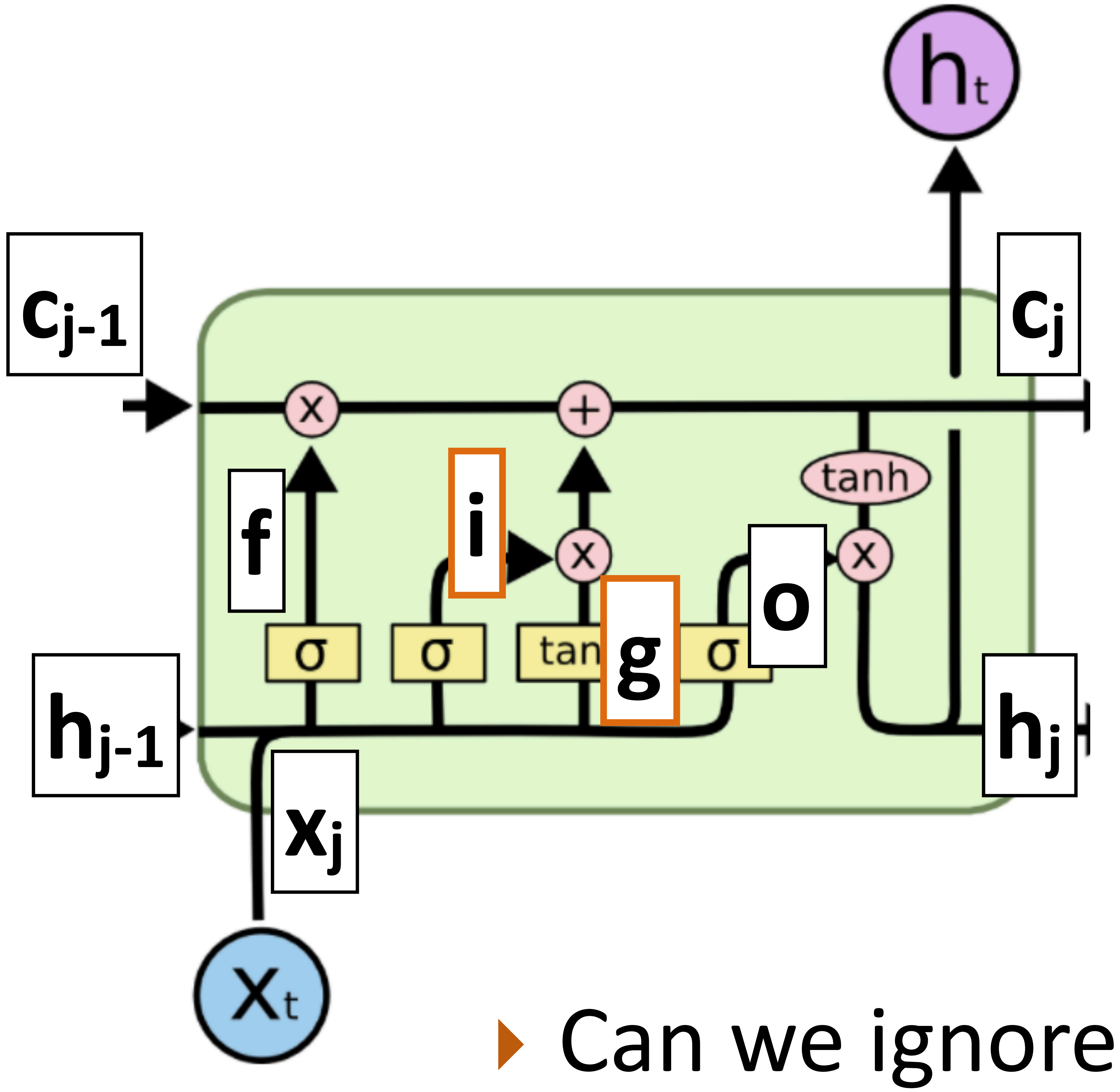
LSTMs



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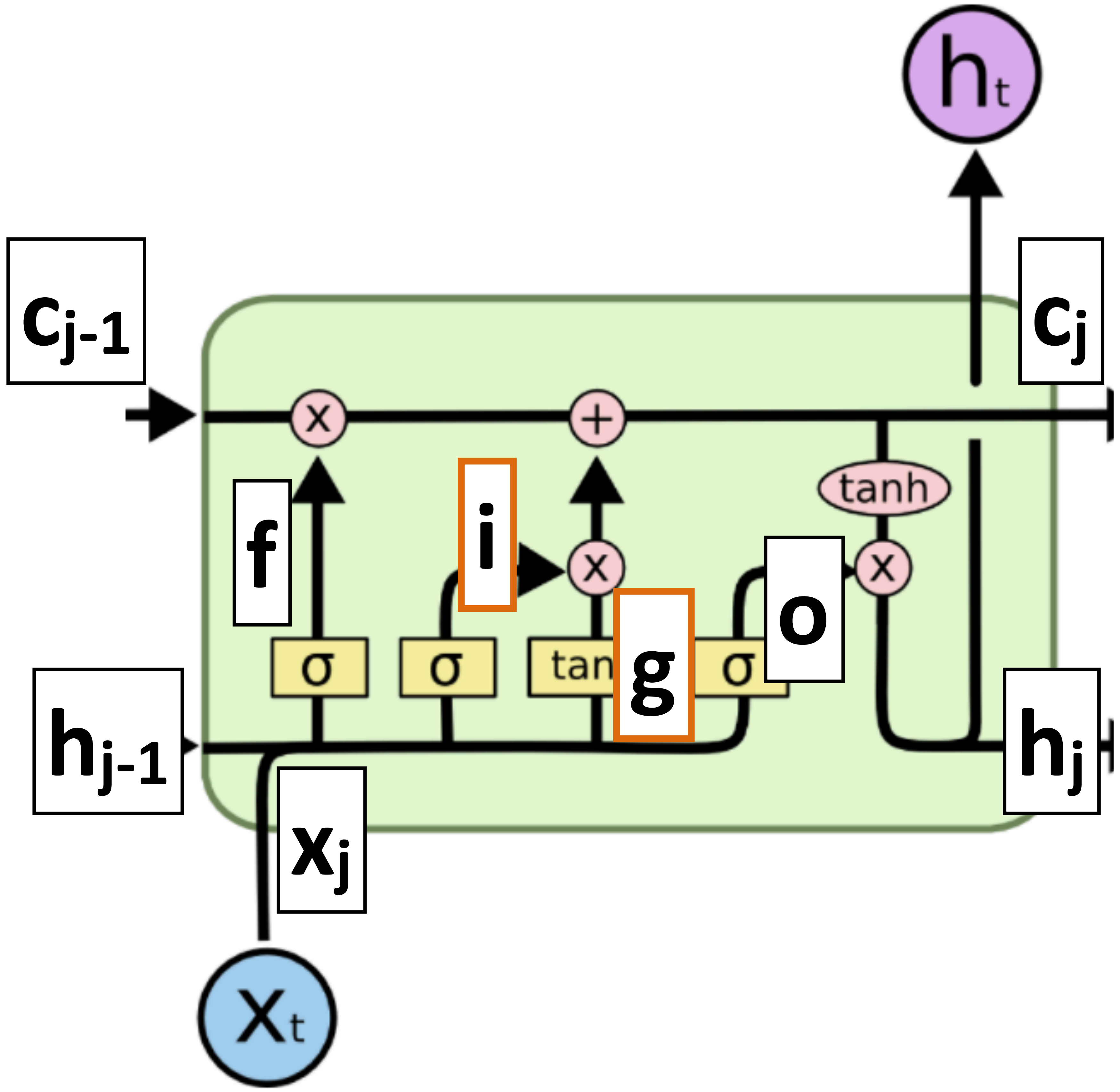
- Can we ignore the old value of **c** for this timestep?
- Can an LSTM sum up its inputs **x**?
- Can we ignore a particular input **x**?
- Can we output something without changing **c**?

LSTMs



- Ignoring recurrent state entirely:
  - Lets us get feedforward layer over token

Goldberg lecture notes

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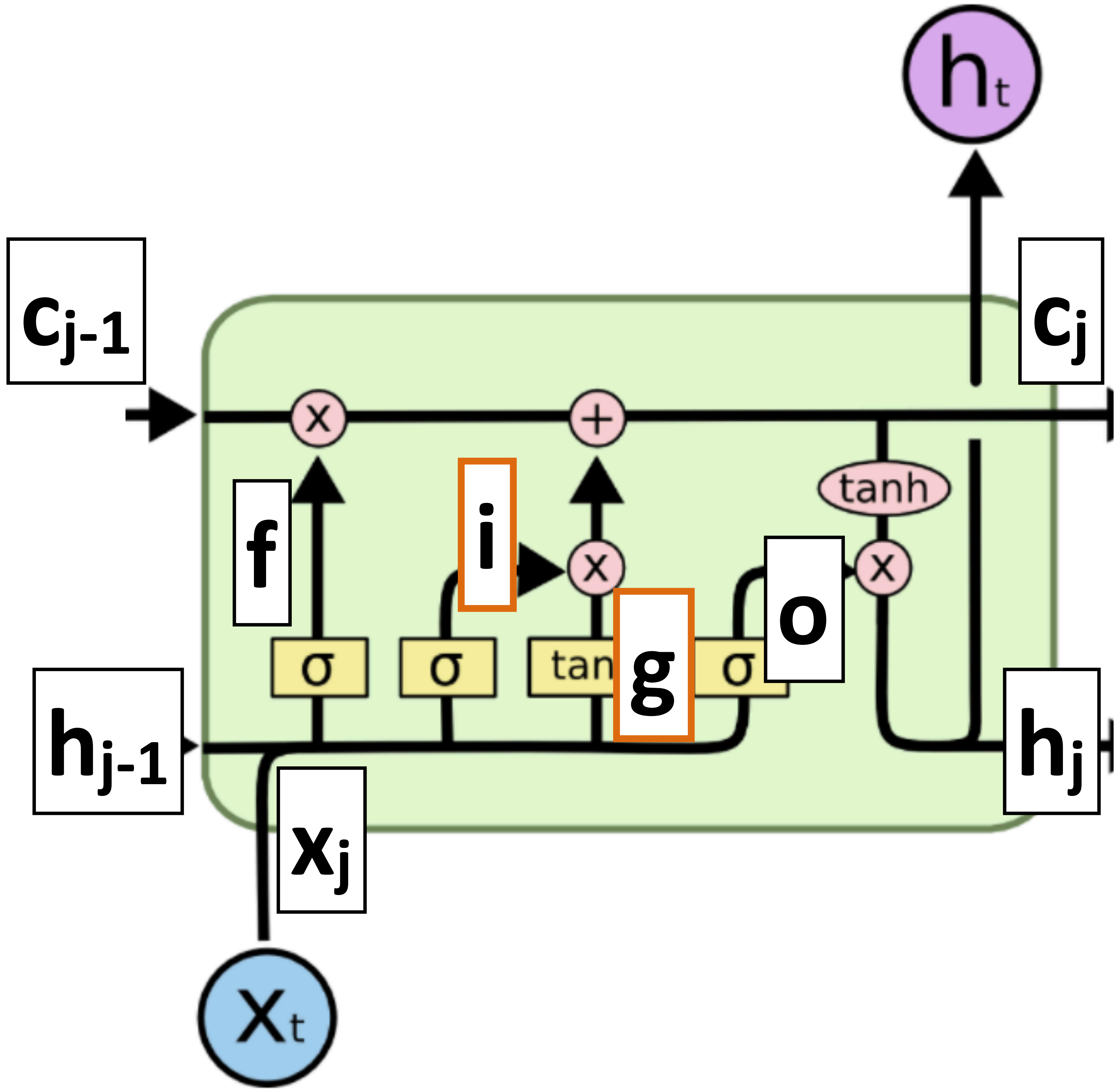
LSTMs



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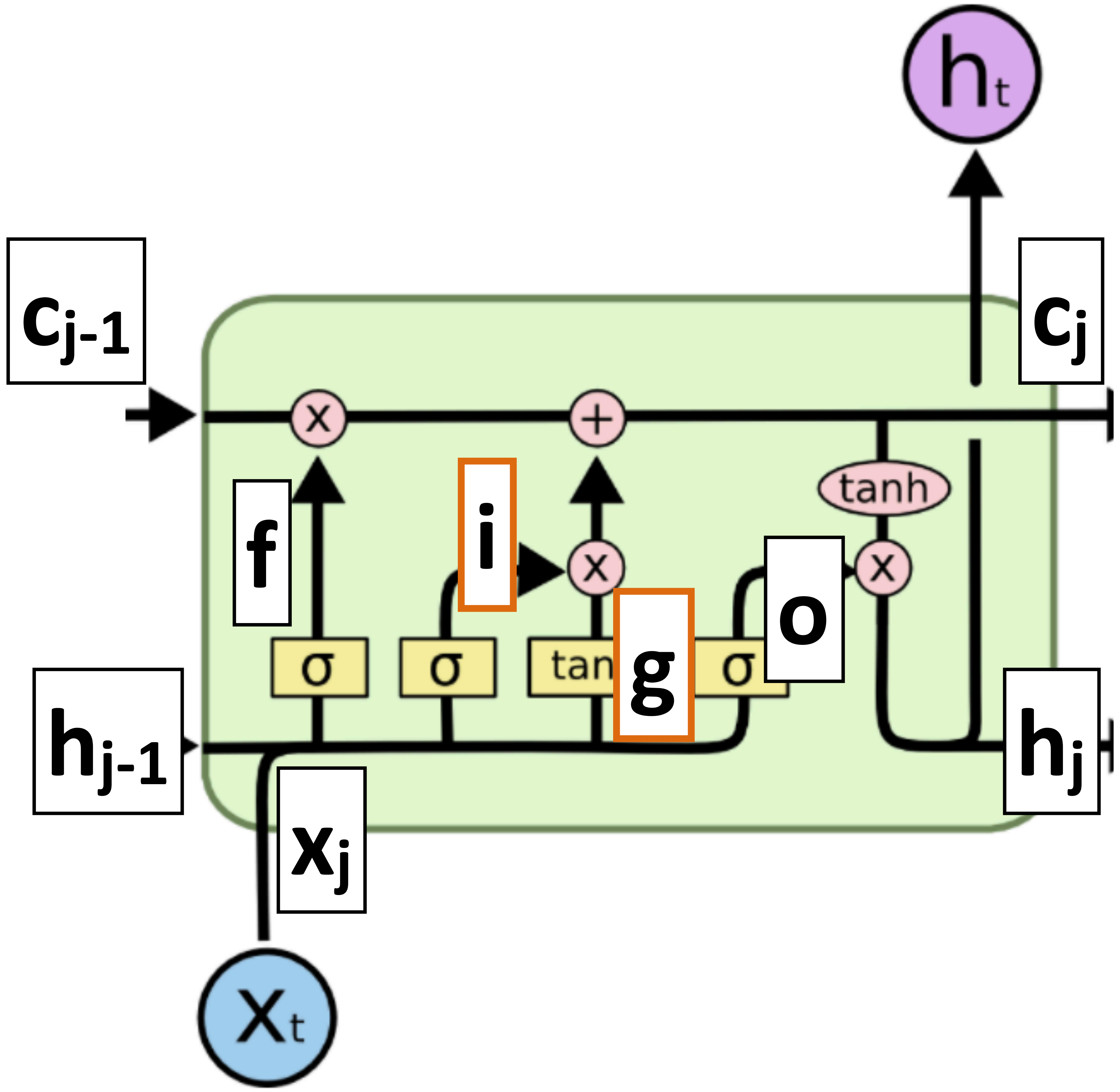
LSTMs



- Ignoring recurrent state entirely:
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- Ignoring input:
  - Lets us discard stopwords
- Summing inputs:
  - Lets us compute a bag-of-words representation

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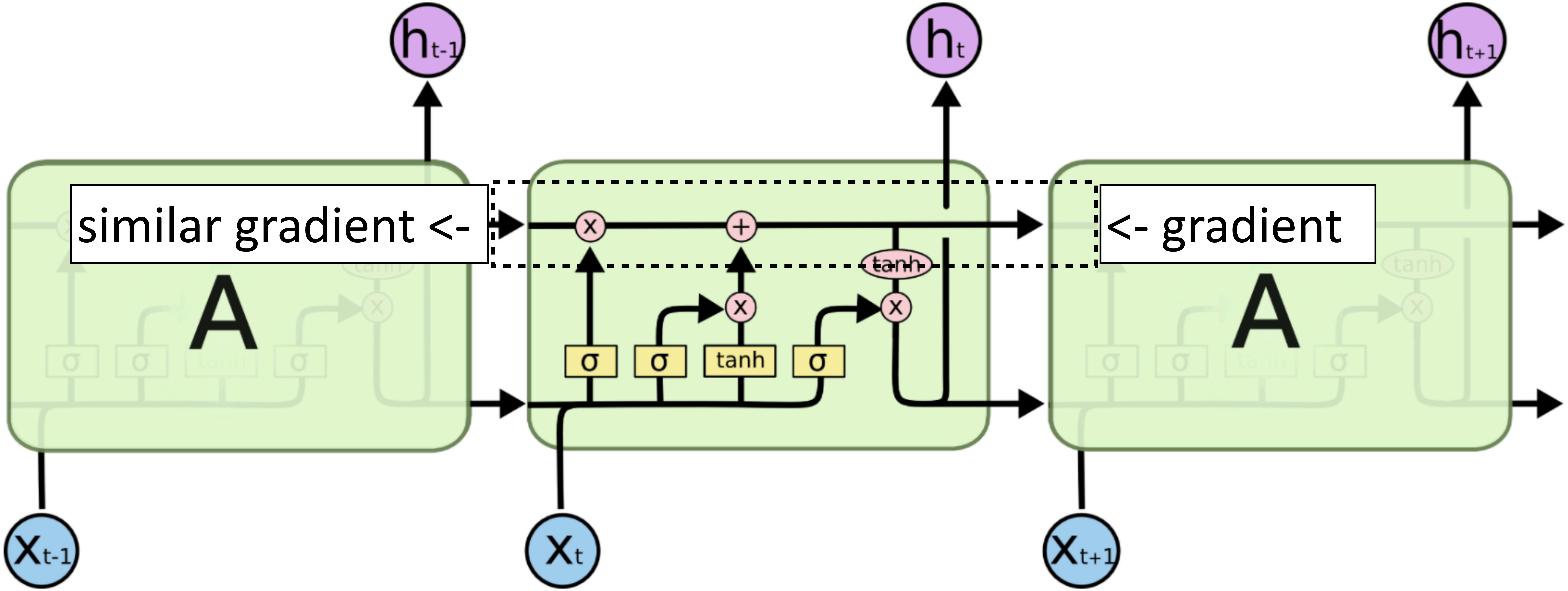
LSTMs



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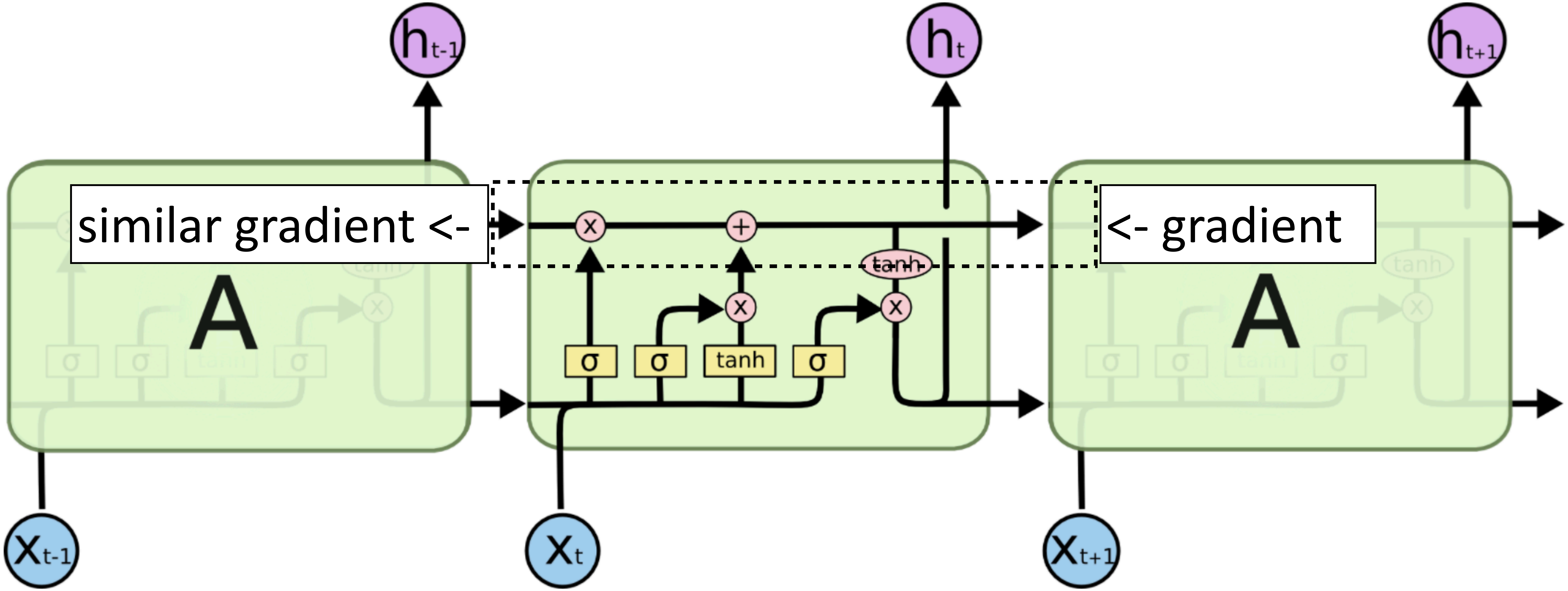
LSTMs



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

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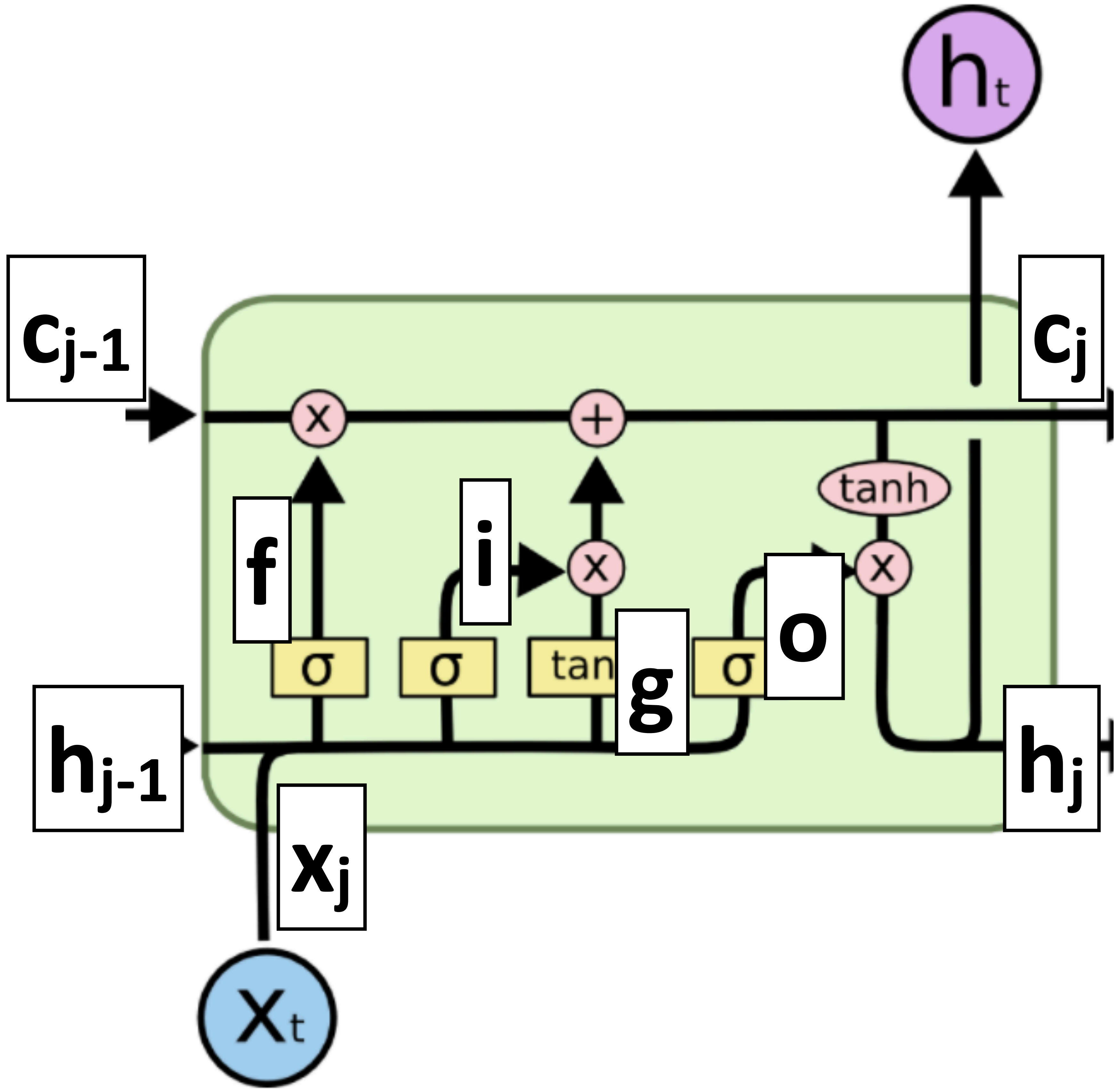
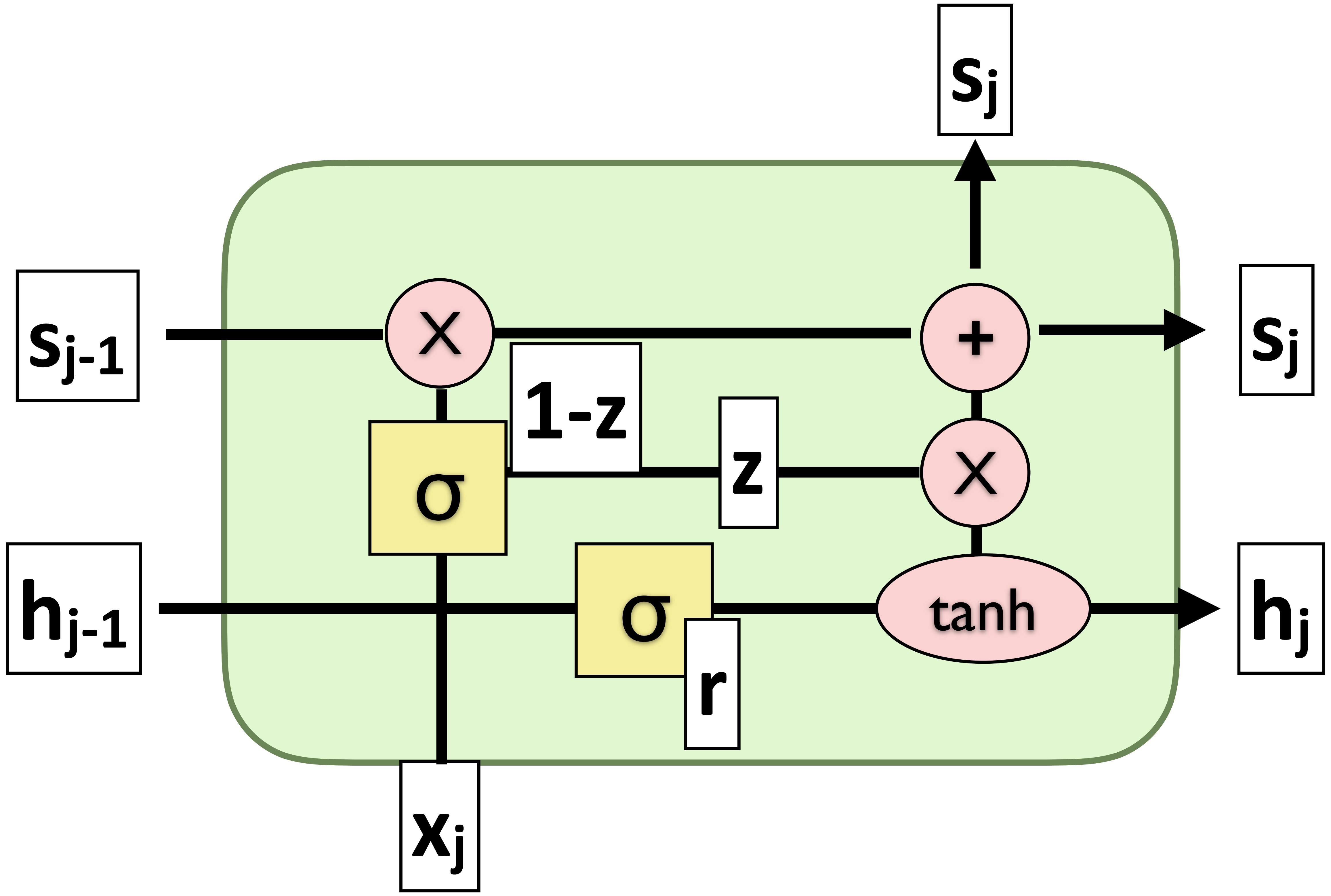
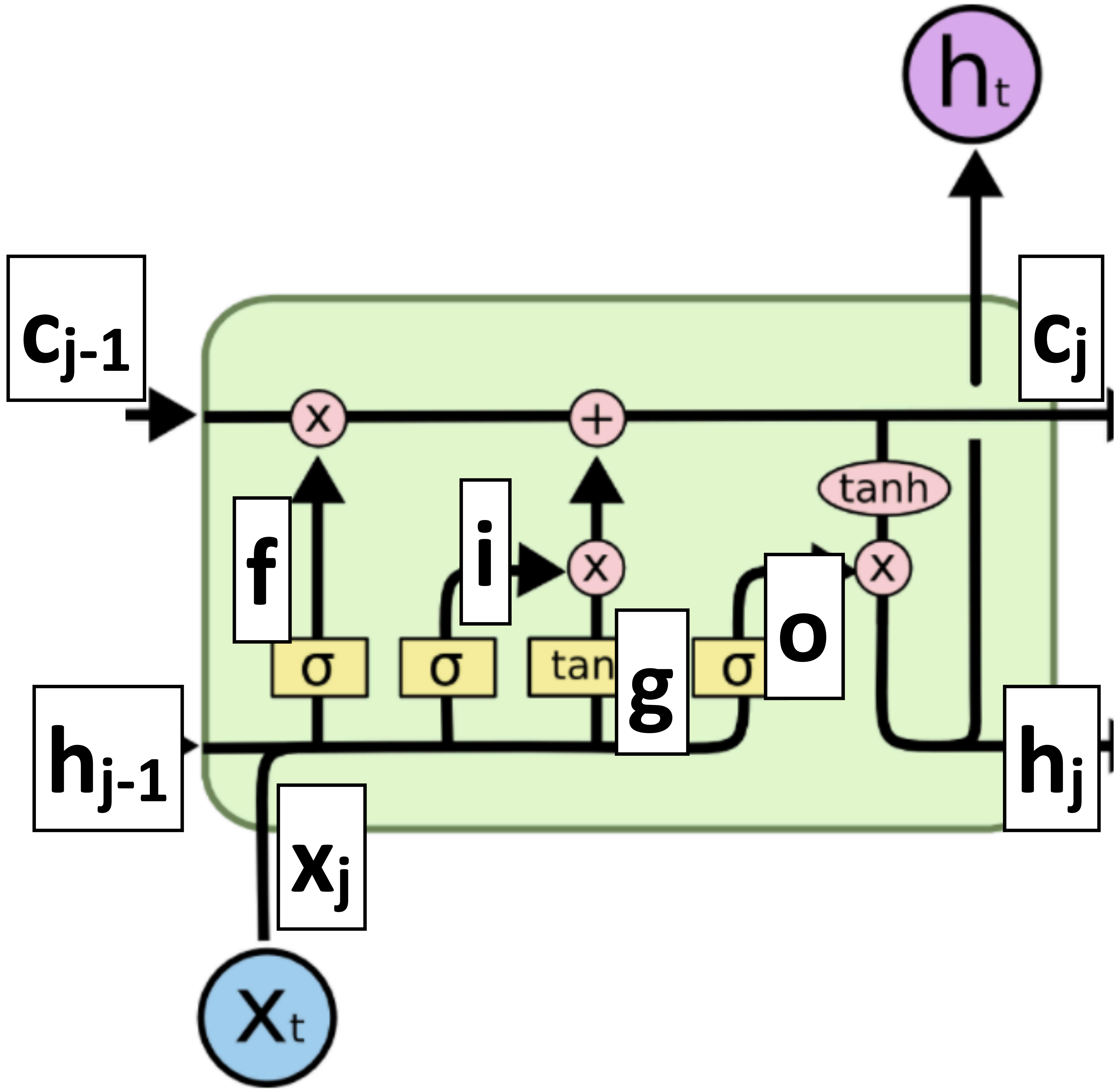
GRUs

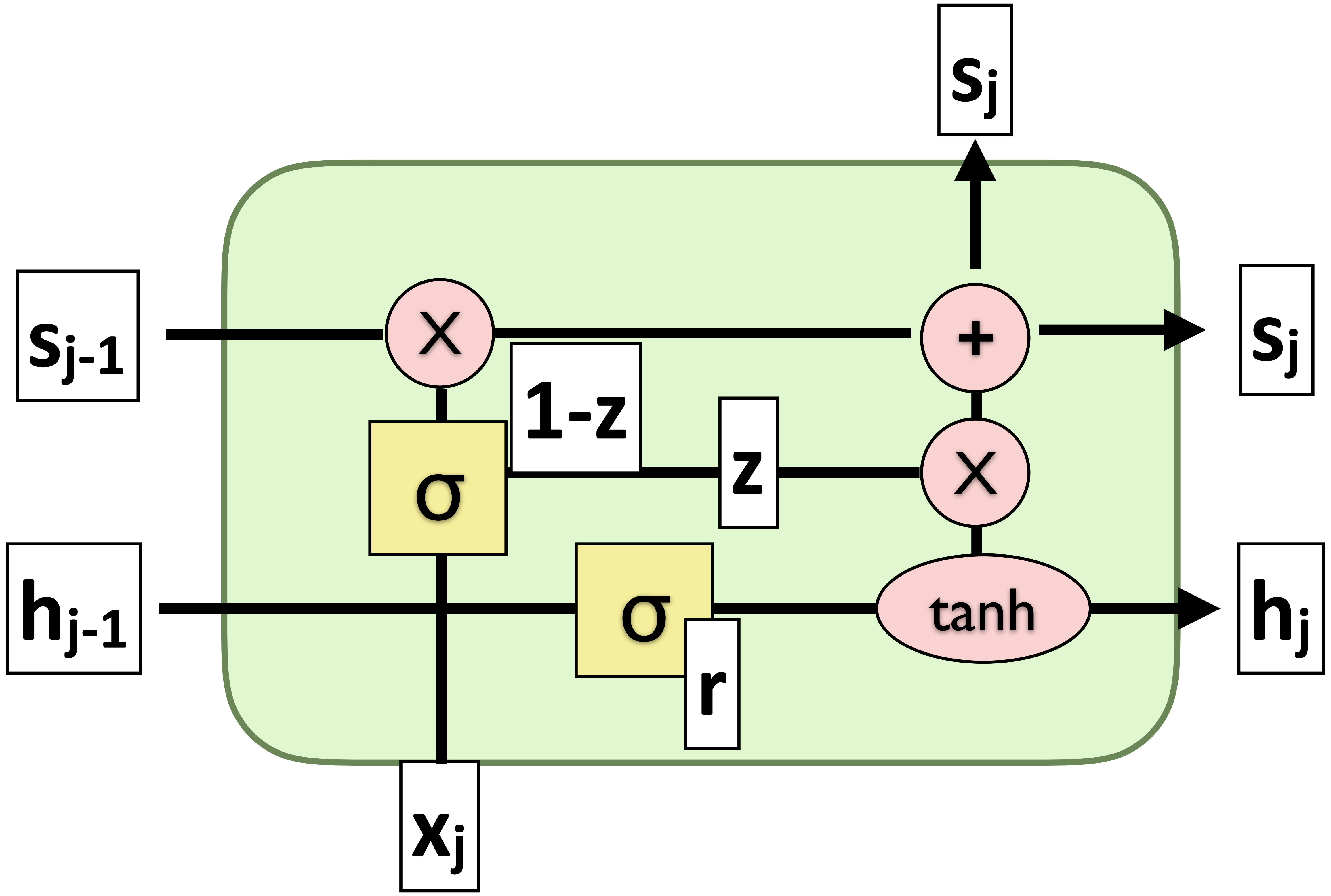




- LSTM: more complex and slower, may work a bit better

GRUs





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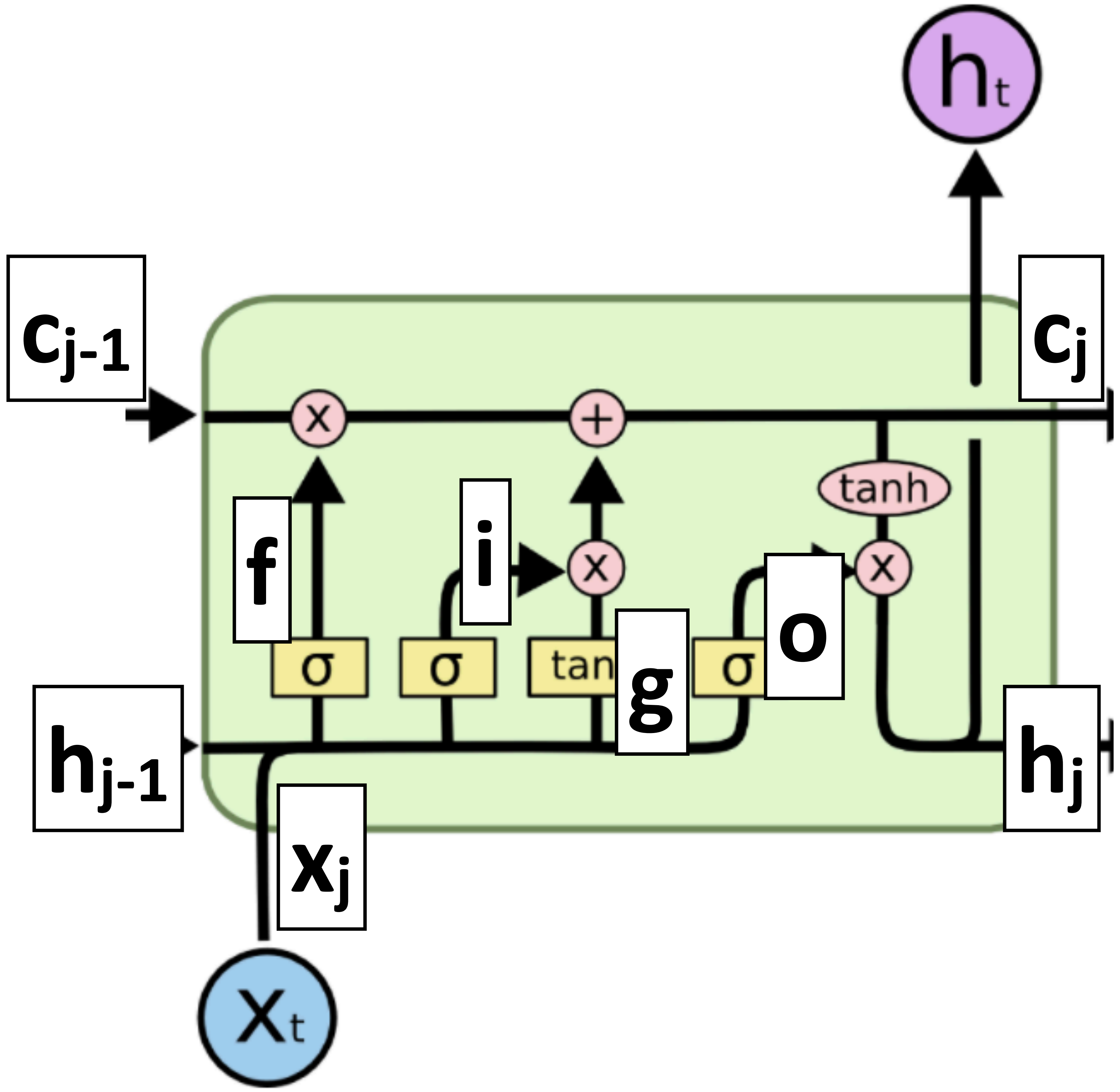
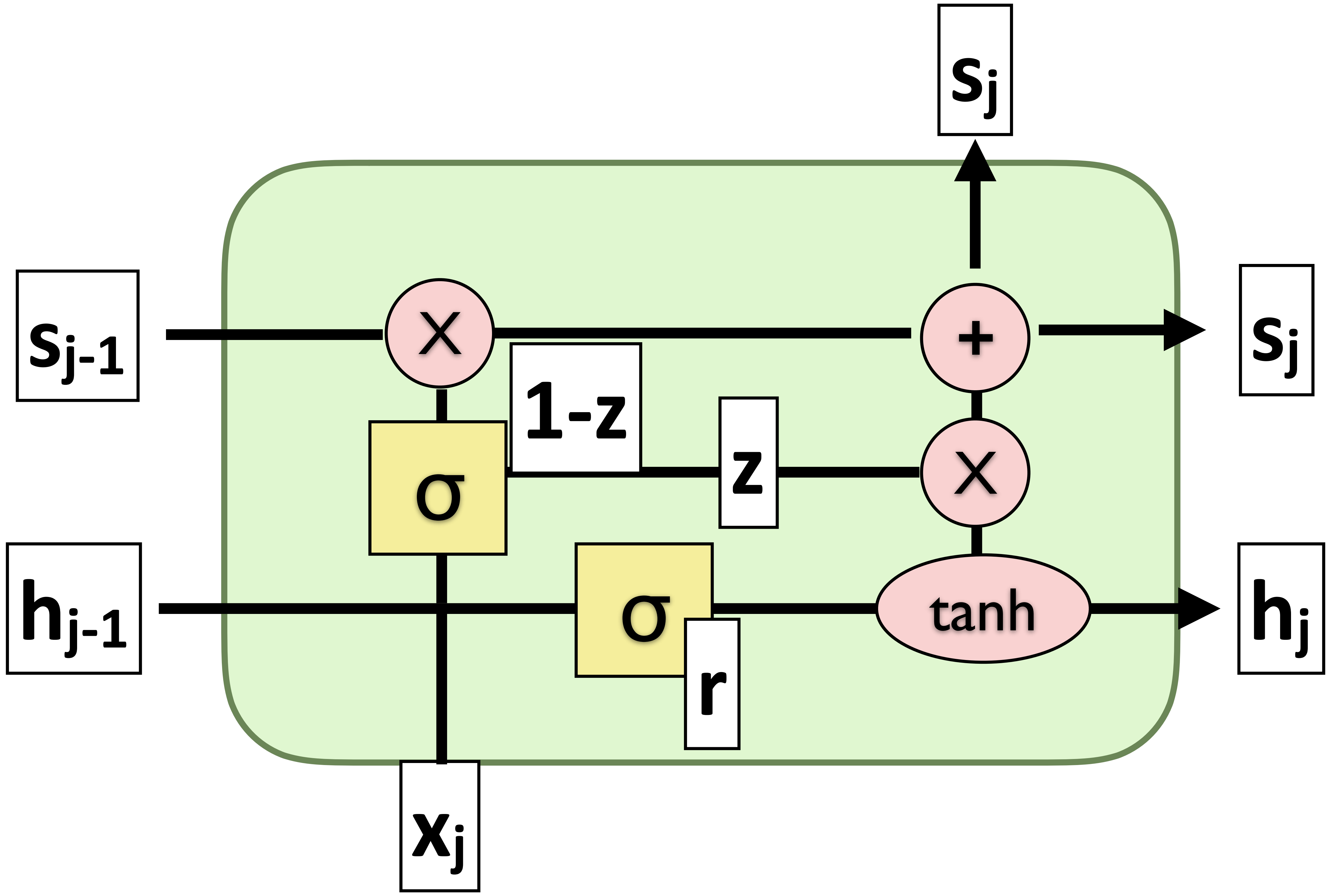
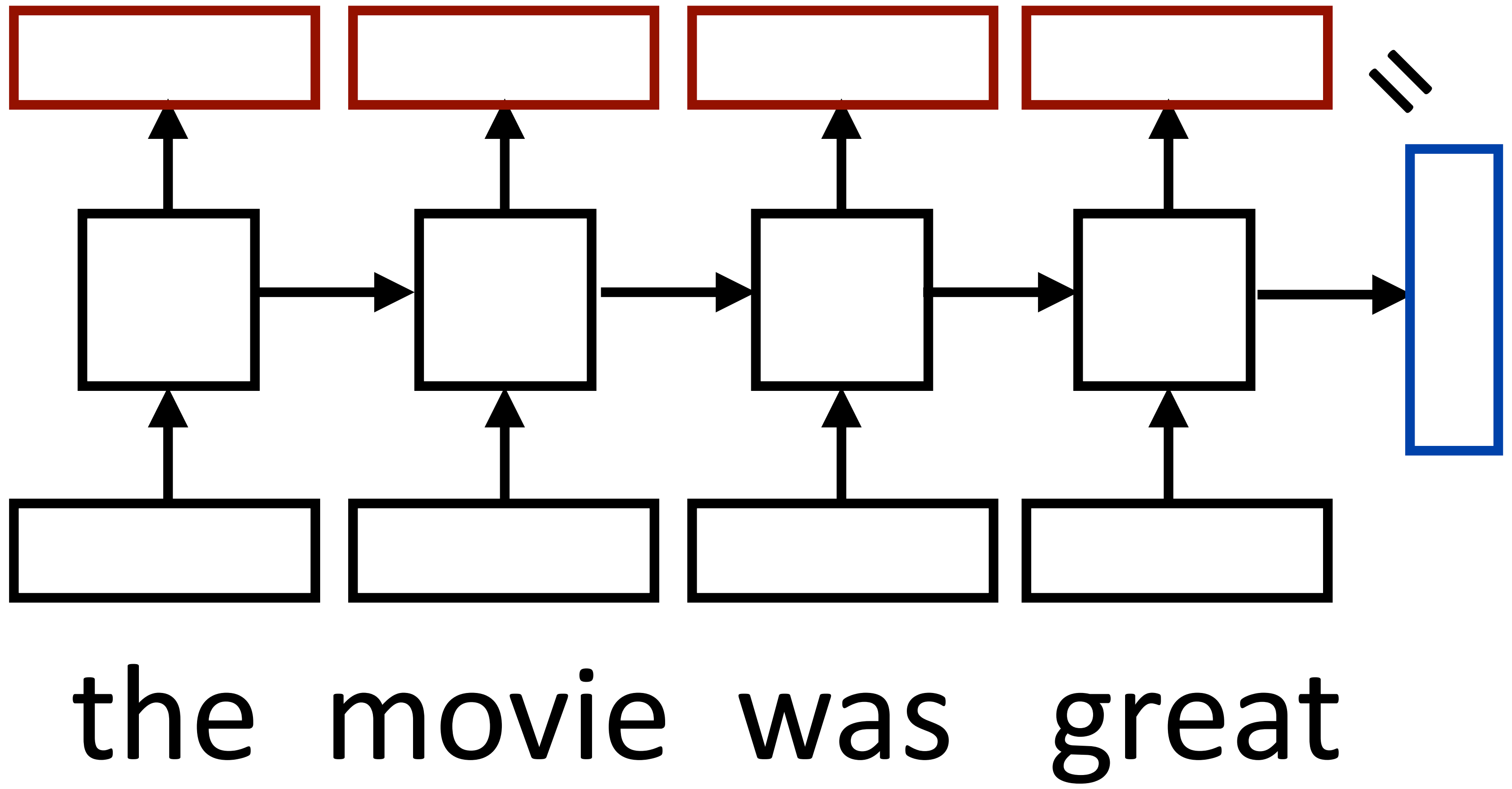




- LSTM: more complex and slower, may work a bit better

- 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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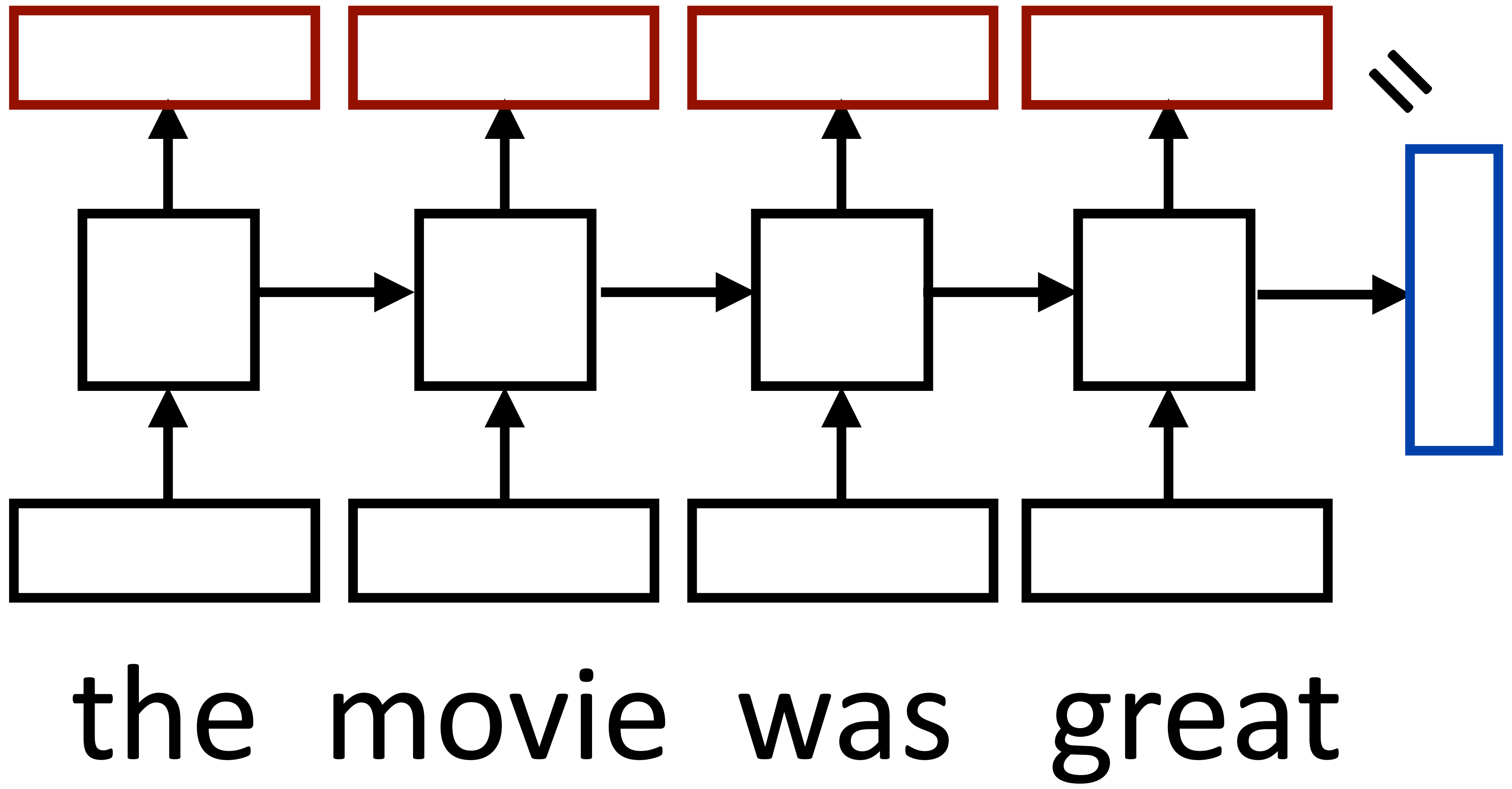

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- Encoding of each word — can pass this to another layer to make a prediction (can also pool these to get a different sentence encoding)

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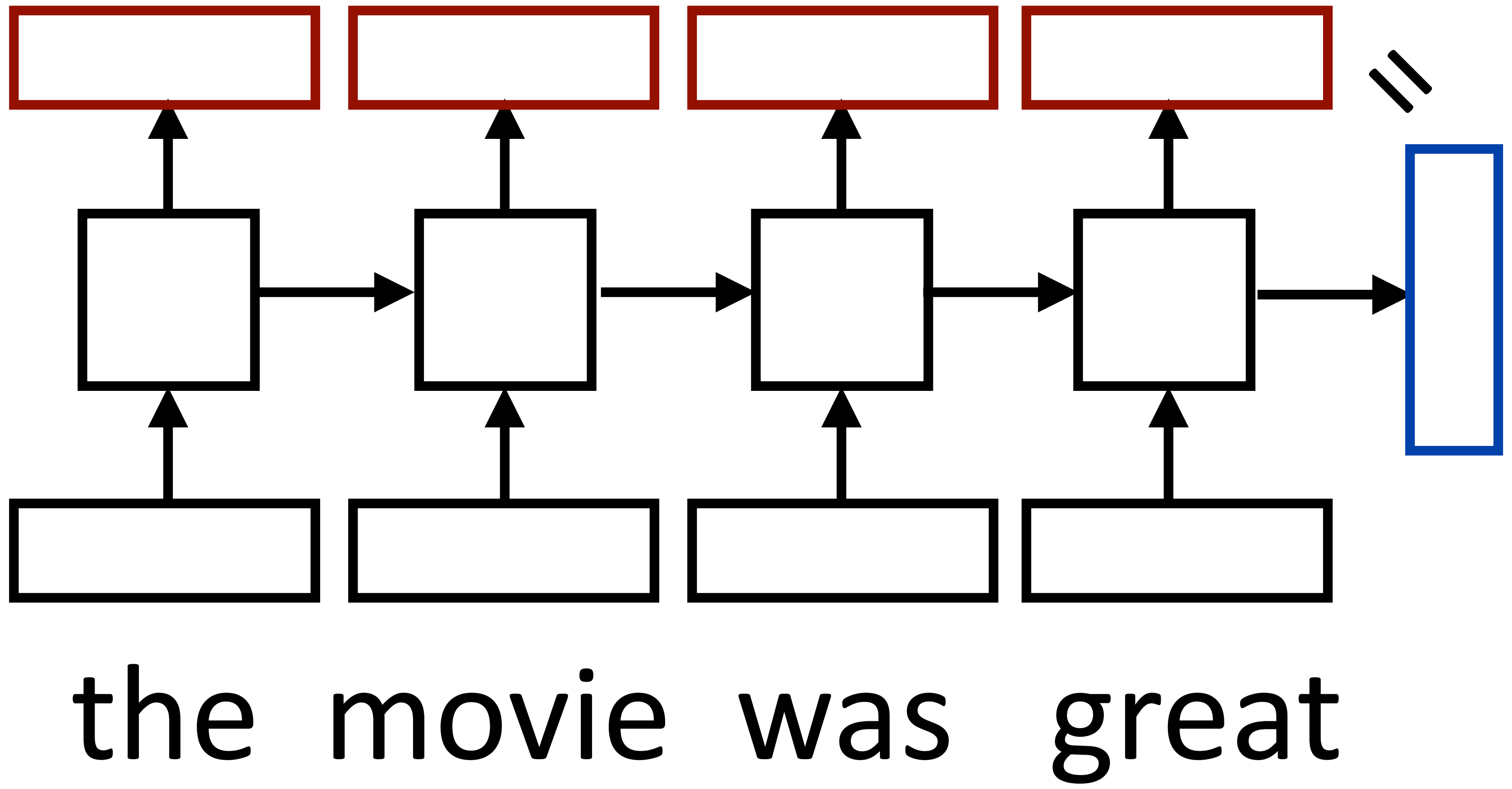
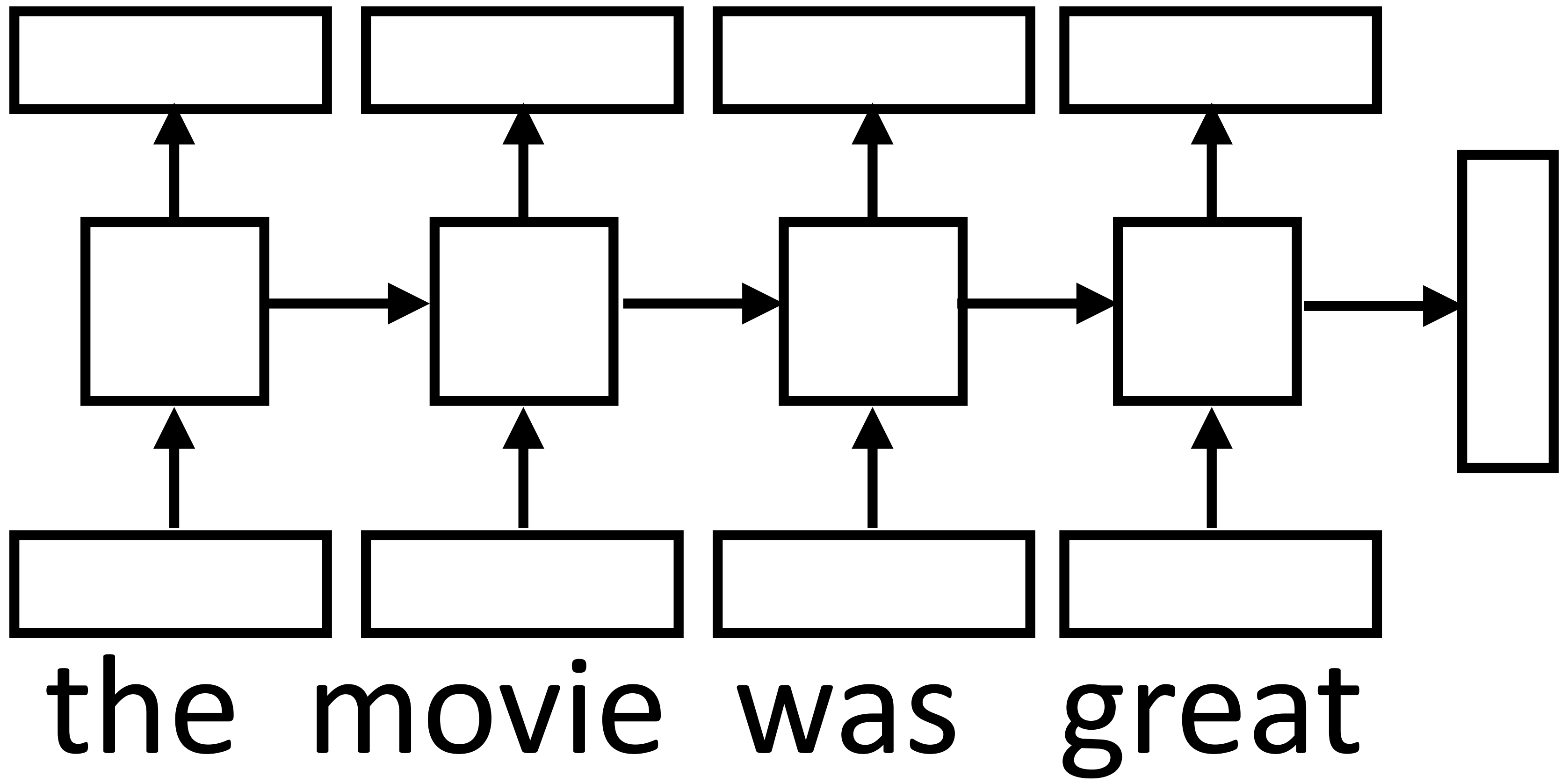


- Encoding of the sentence — can pass this a decoder or make a classification decision about the sentence
- Encoding of each word — can pass this to another layer to make a prediction (can also pool these to get a different sentence encoding)
- RNN can be viewed as a transformation of a sequence of vectors into a sequence of context-dependent vectors

Multilayer Bidirectional RNN



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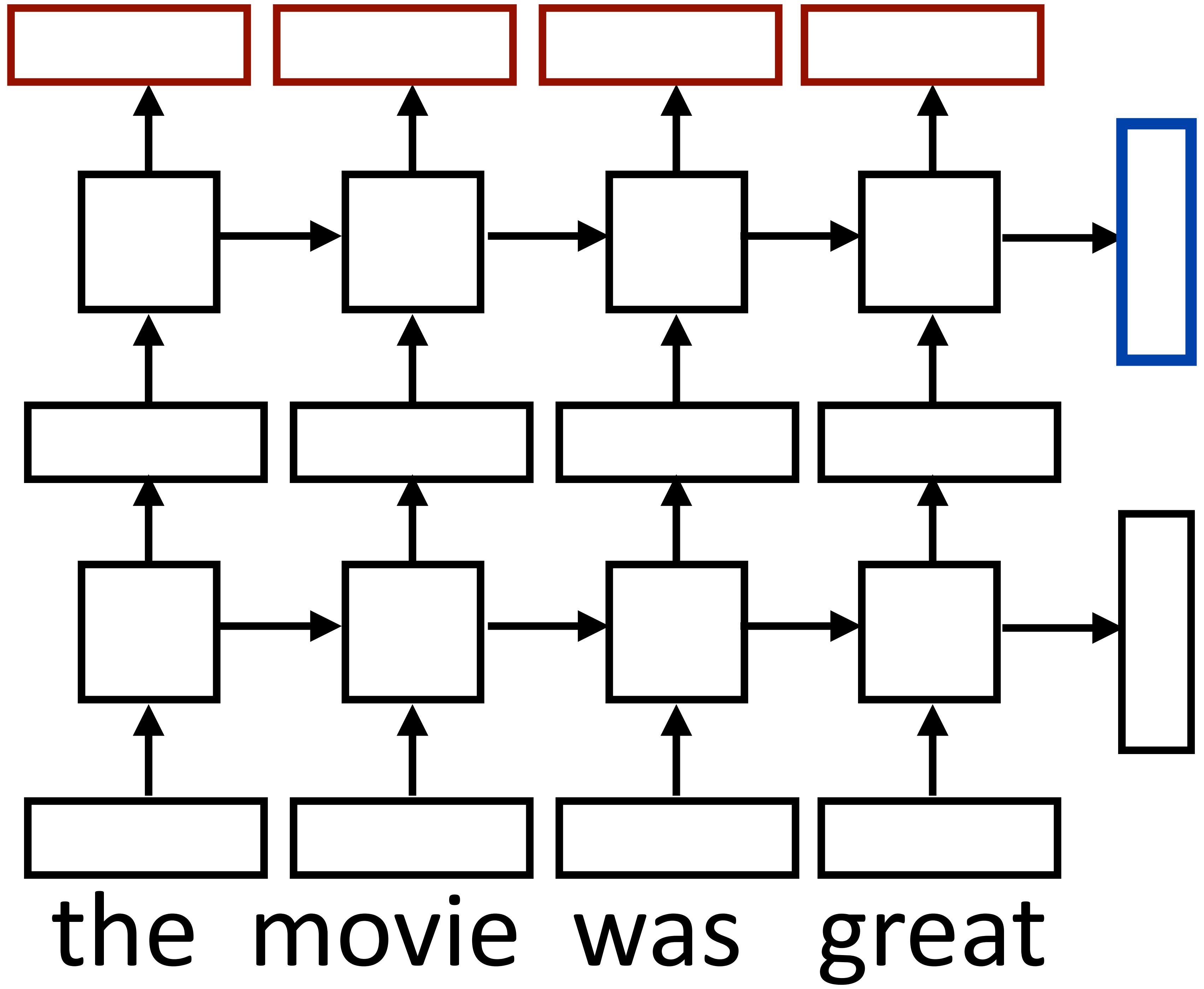

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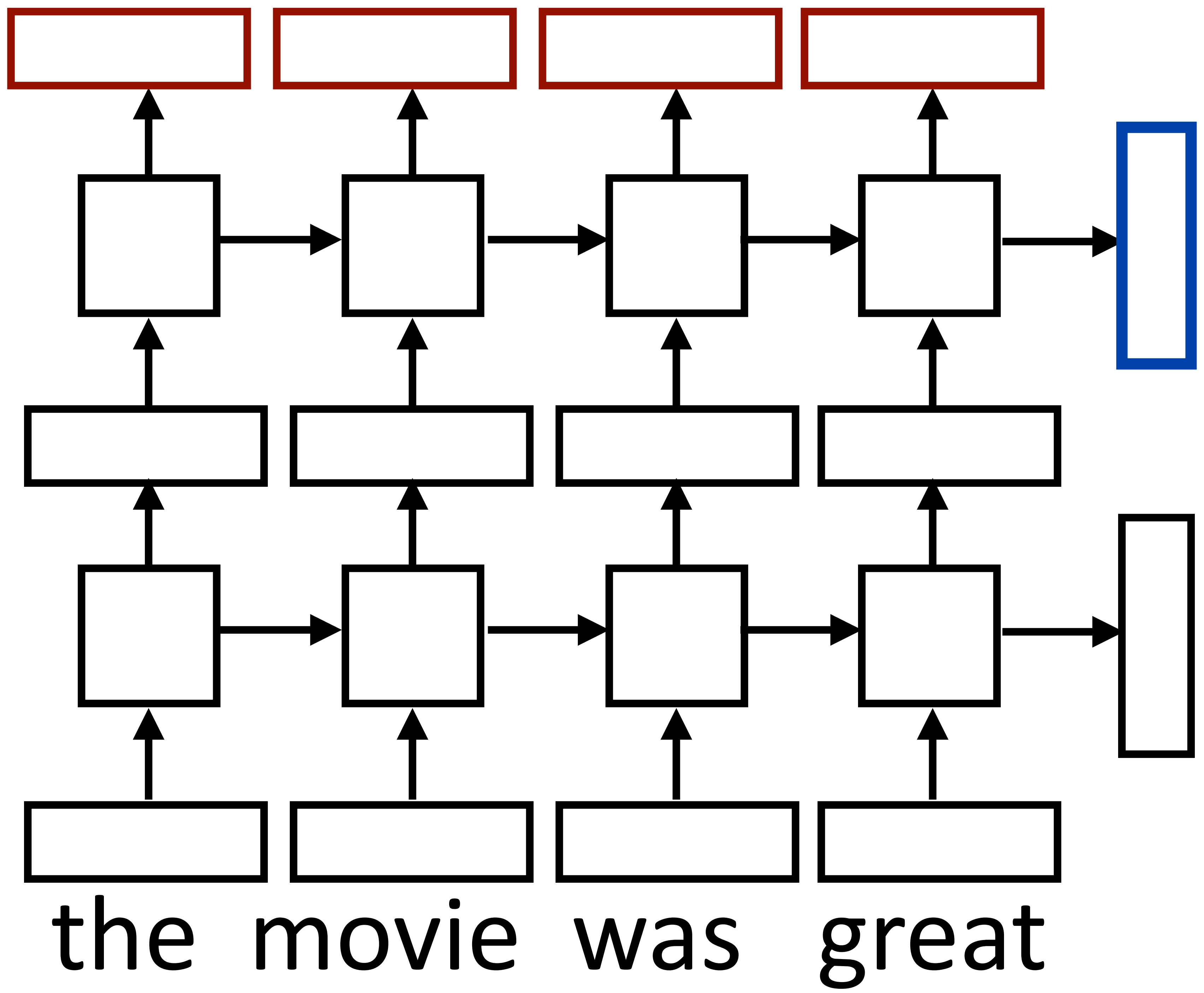

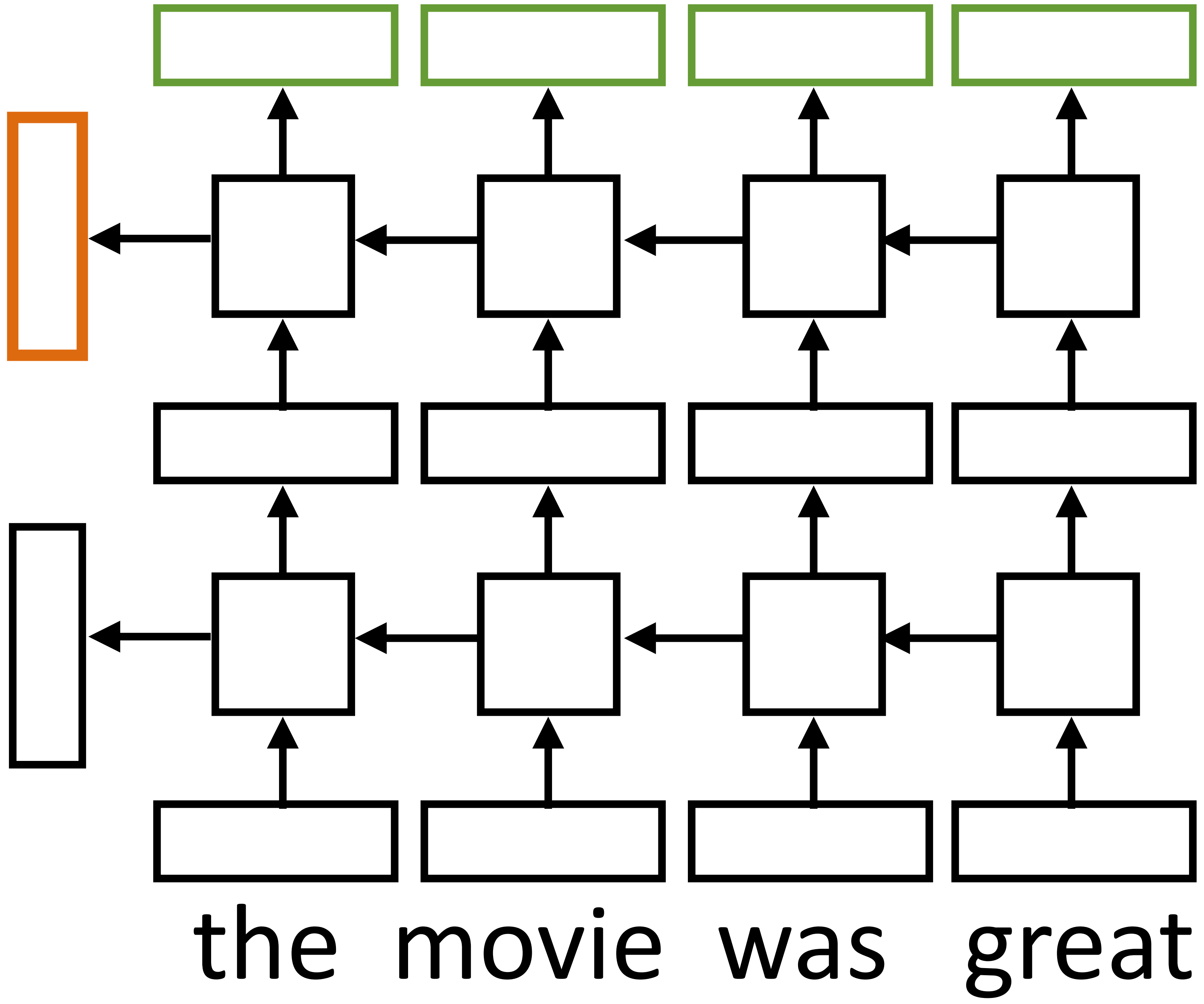

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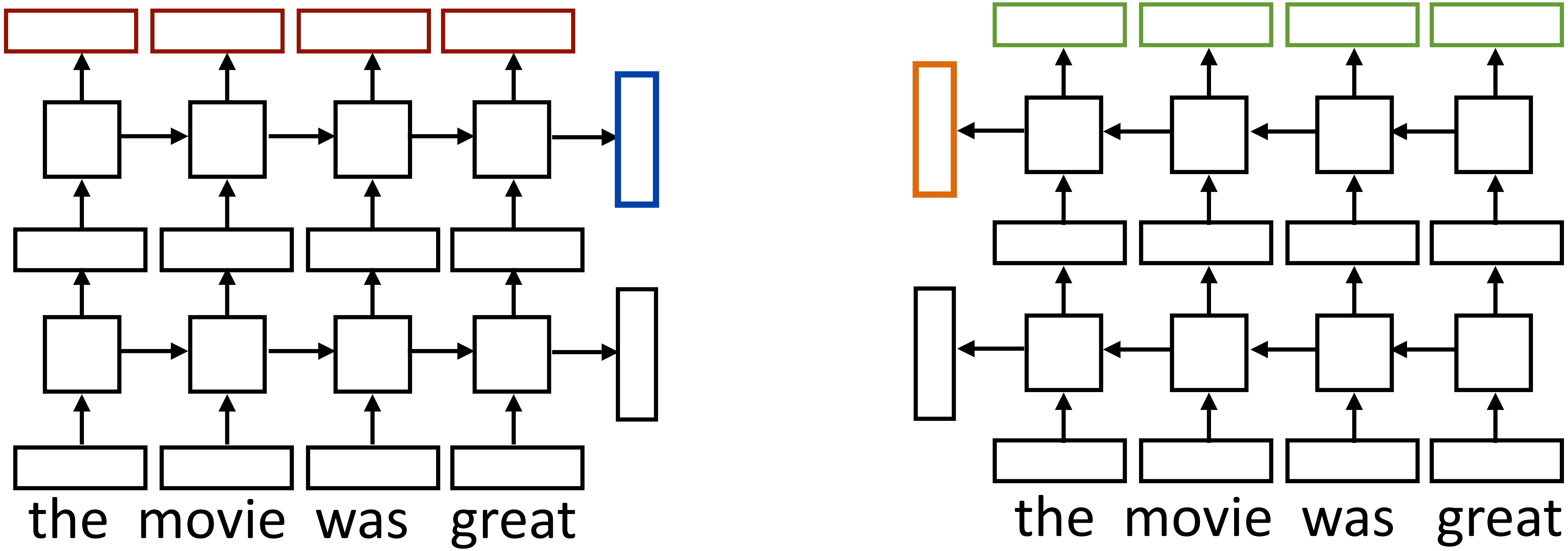
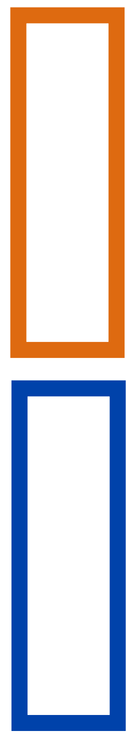


- Sentence classification based on concatenation of both final outputs



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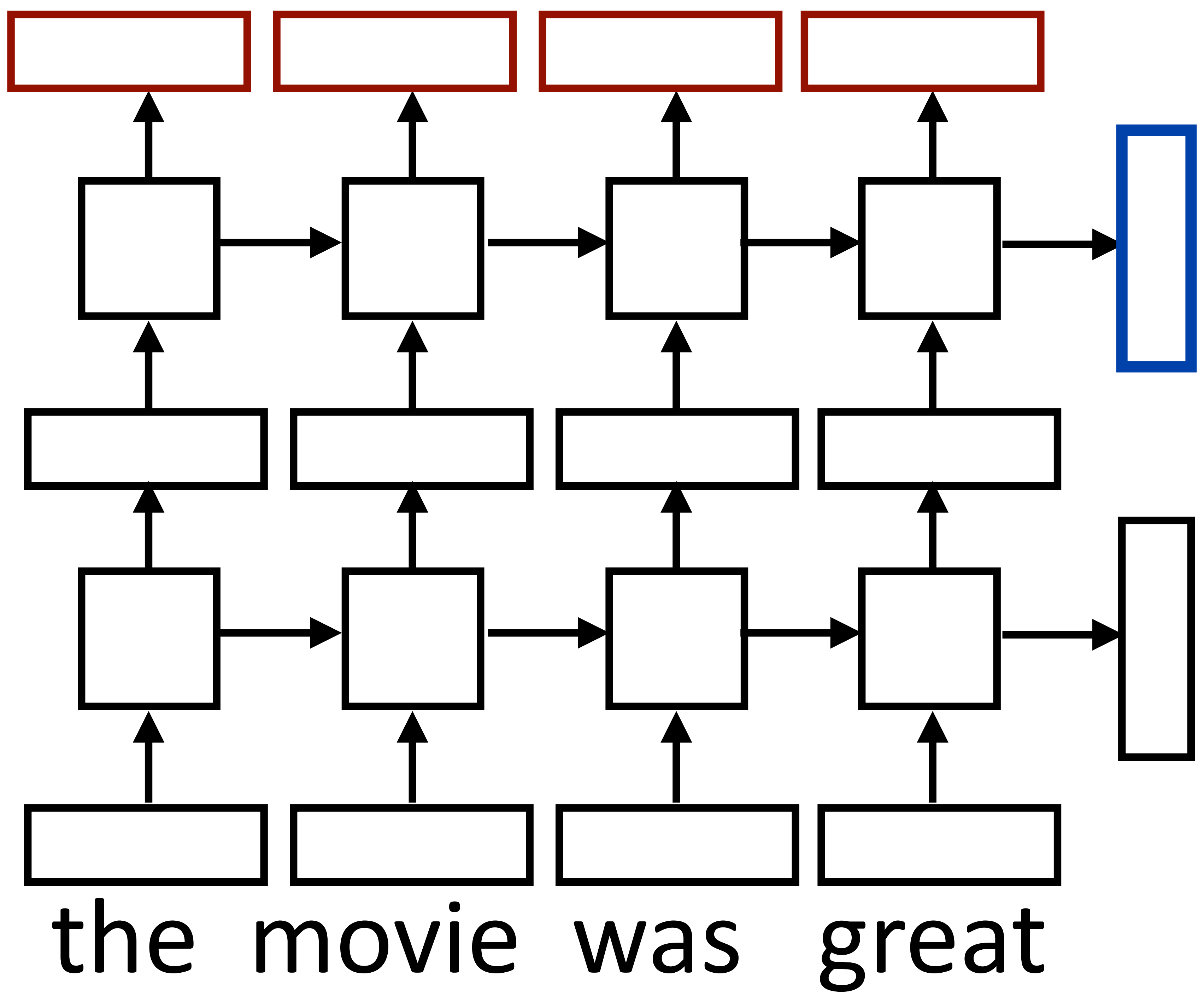

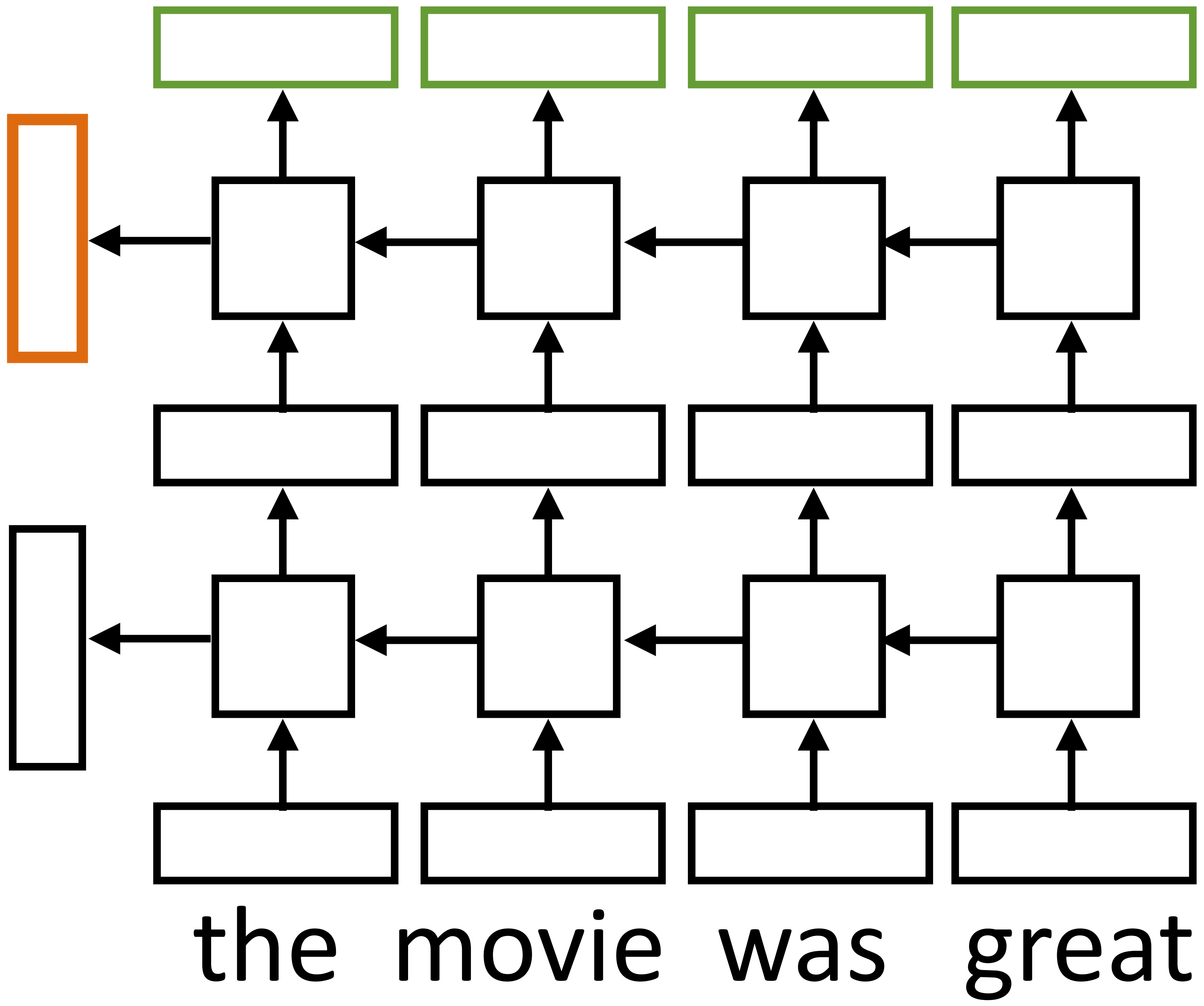

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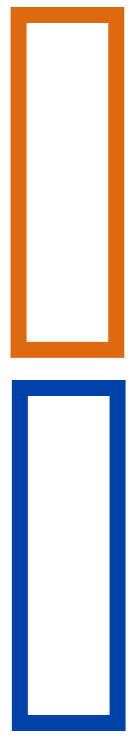
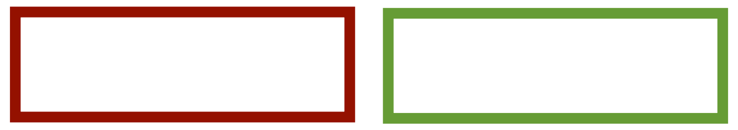
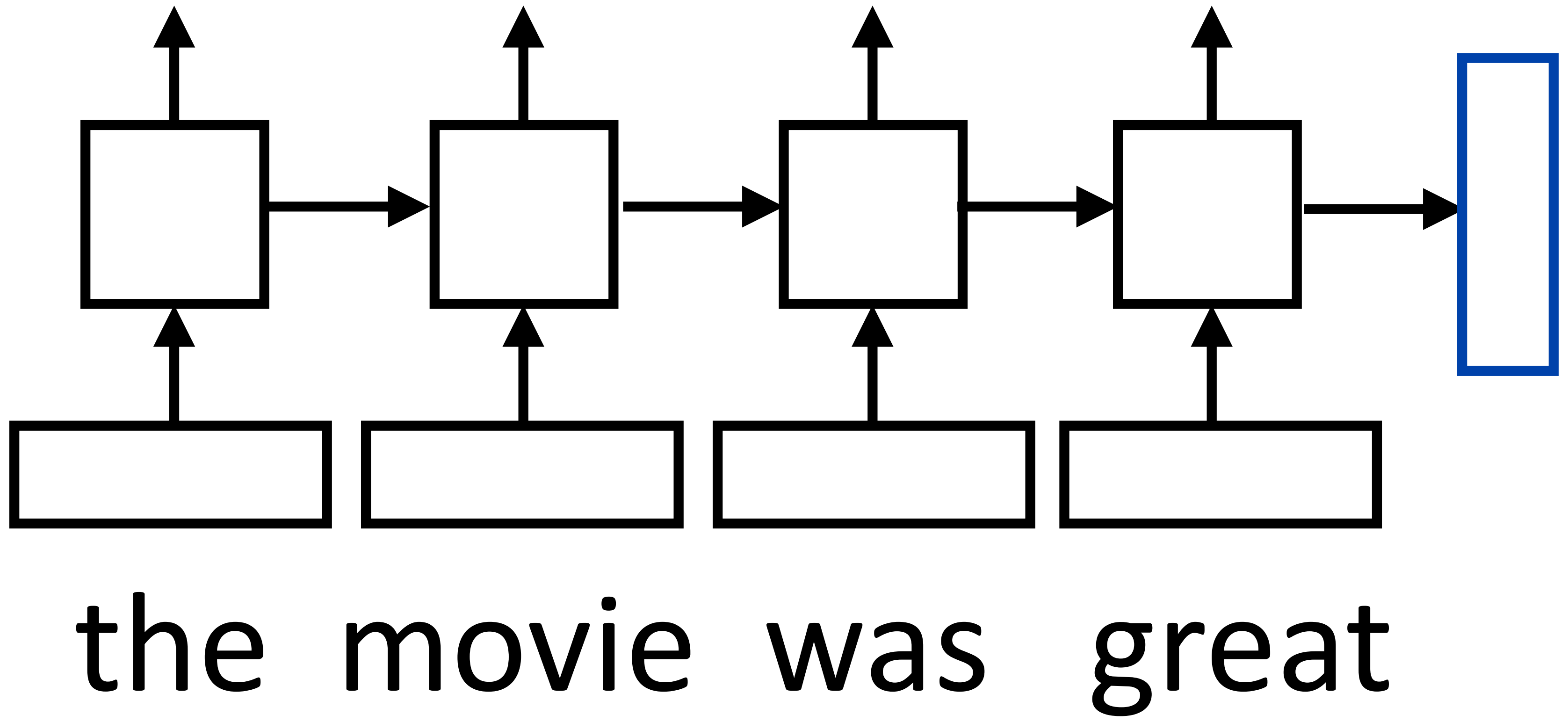


- Token classification based on concatenation of both directions' token representations



Training RNNs



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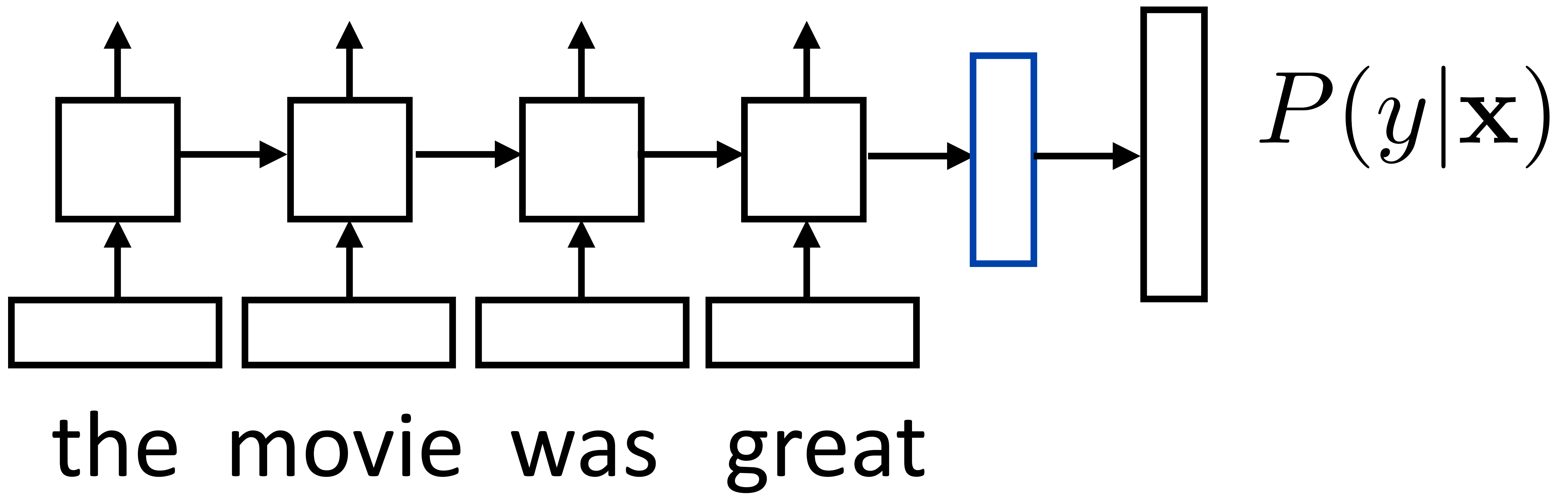

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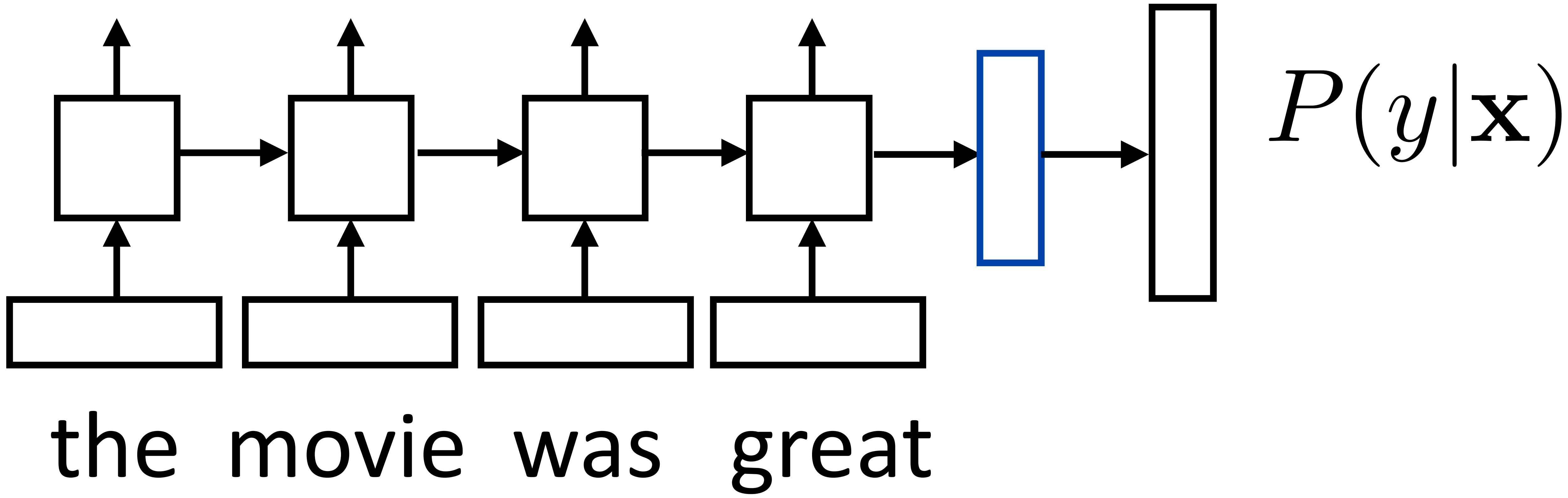

- Loss = negative log likelihood of probability of gold label (or use SVM or other loss)

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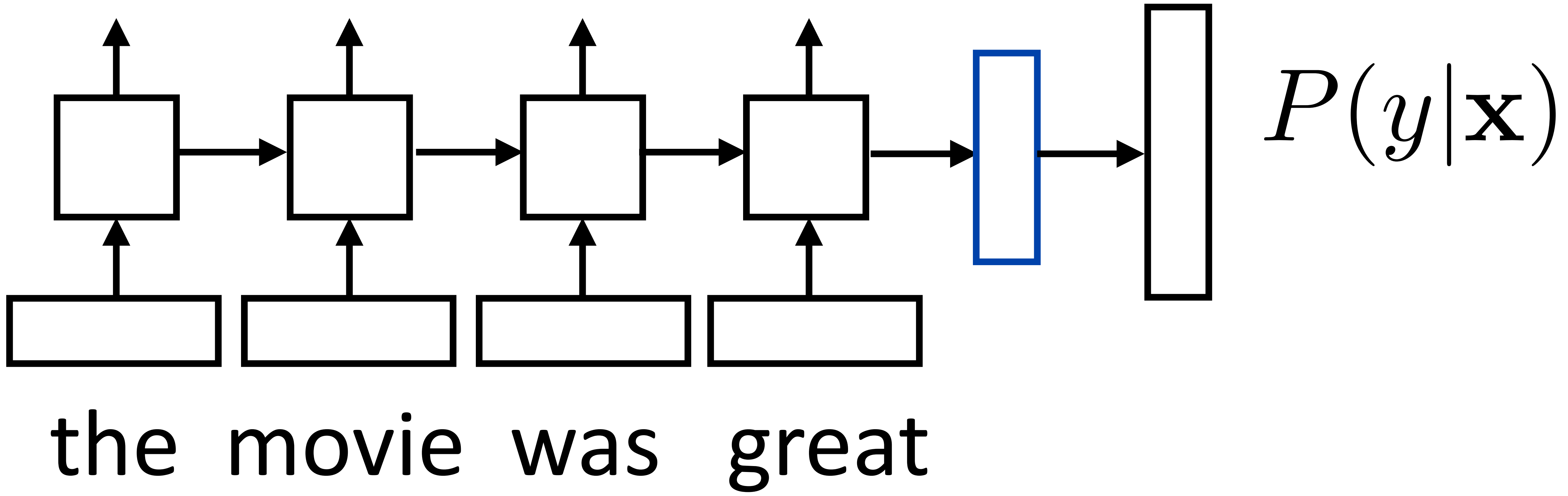

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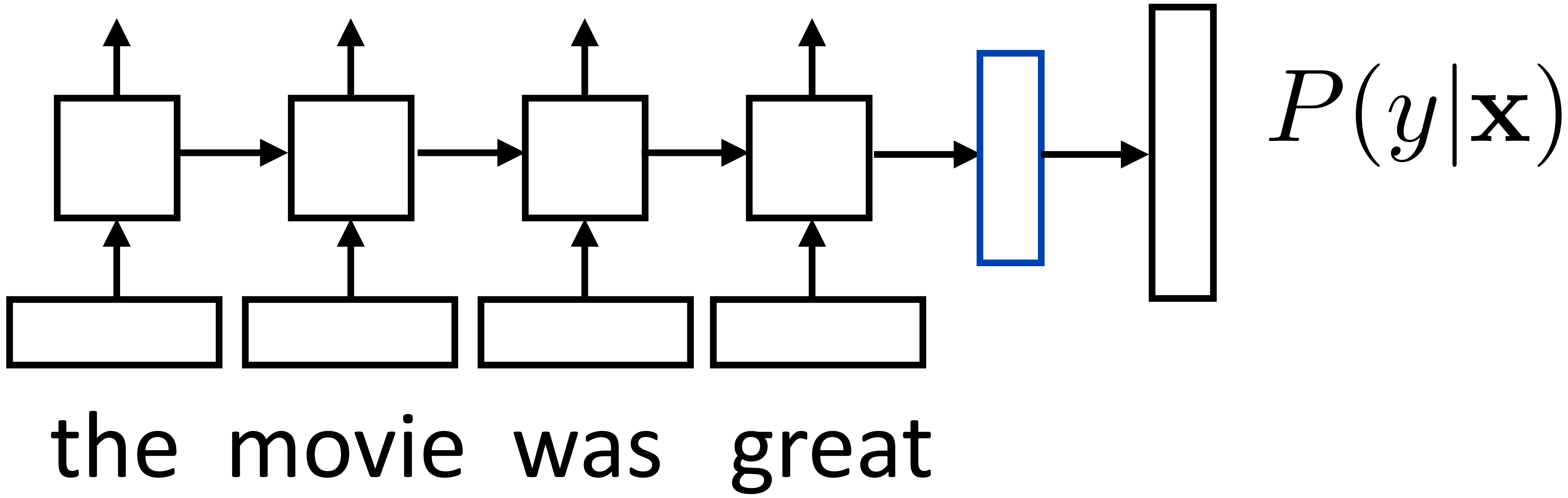

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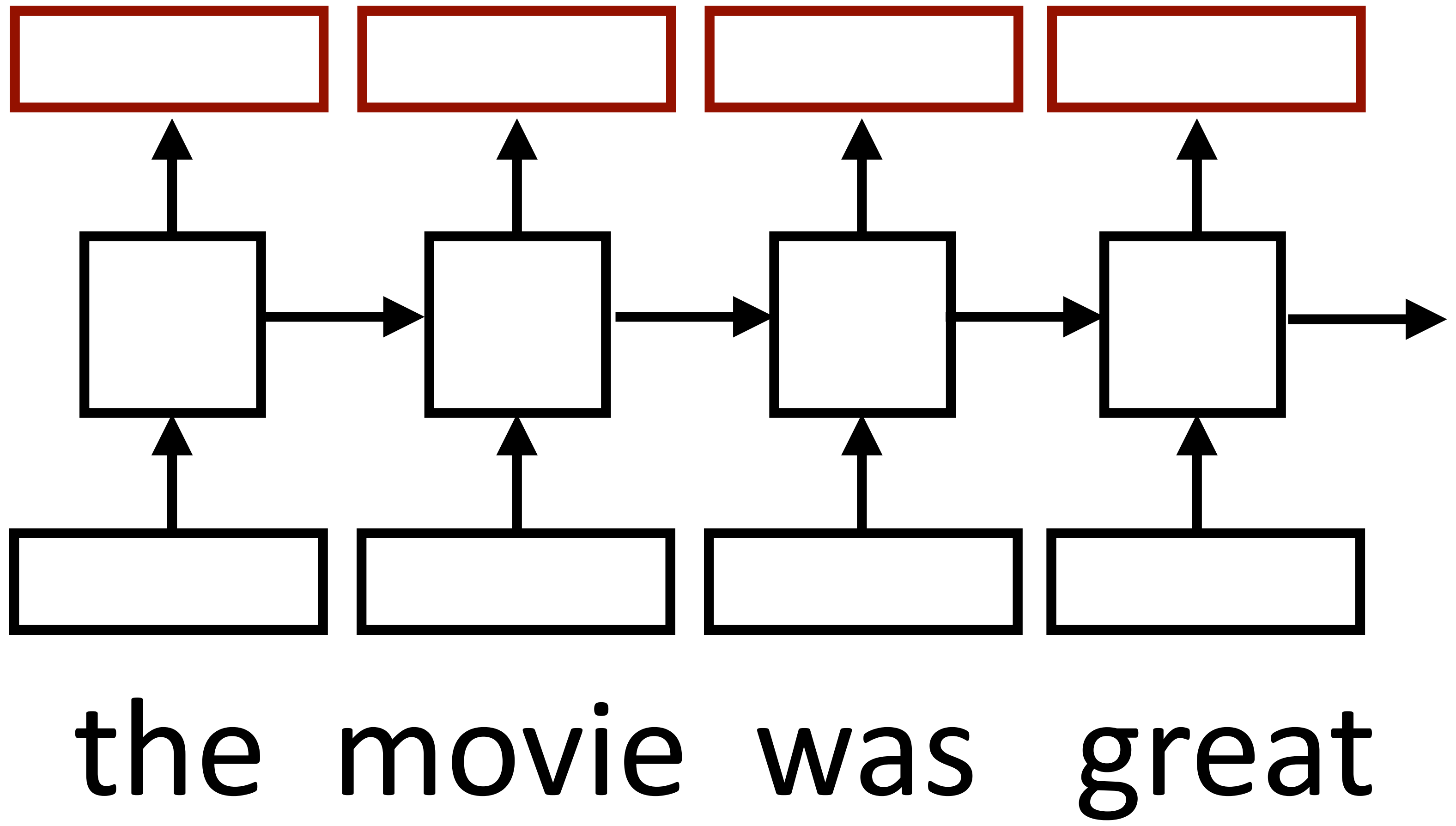
- Example: sentiment analysis

Training RNNs



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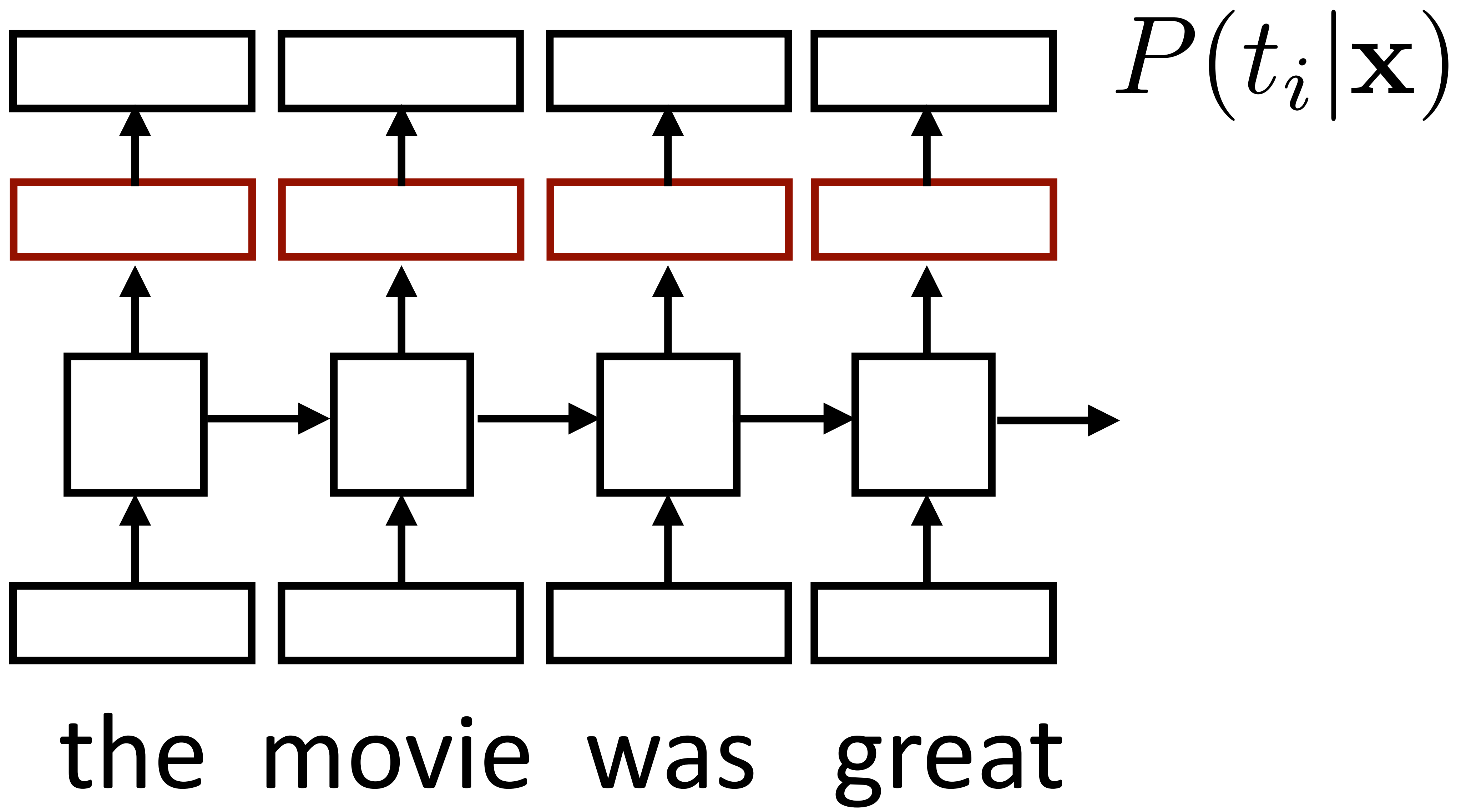

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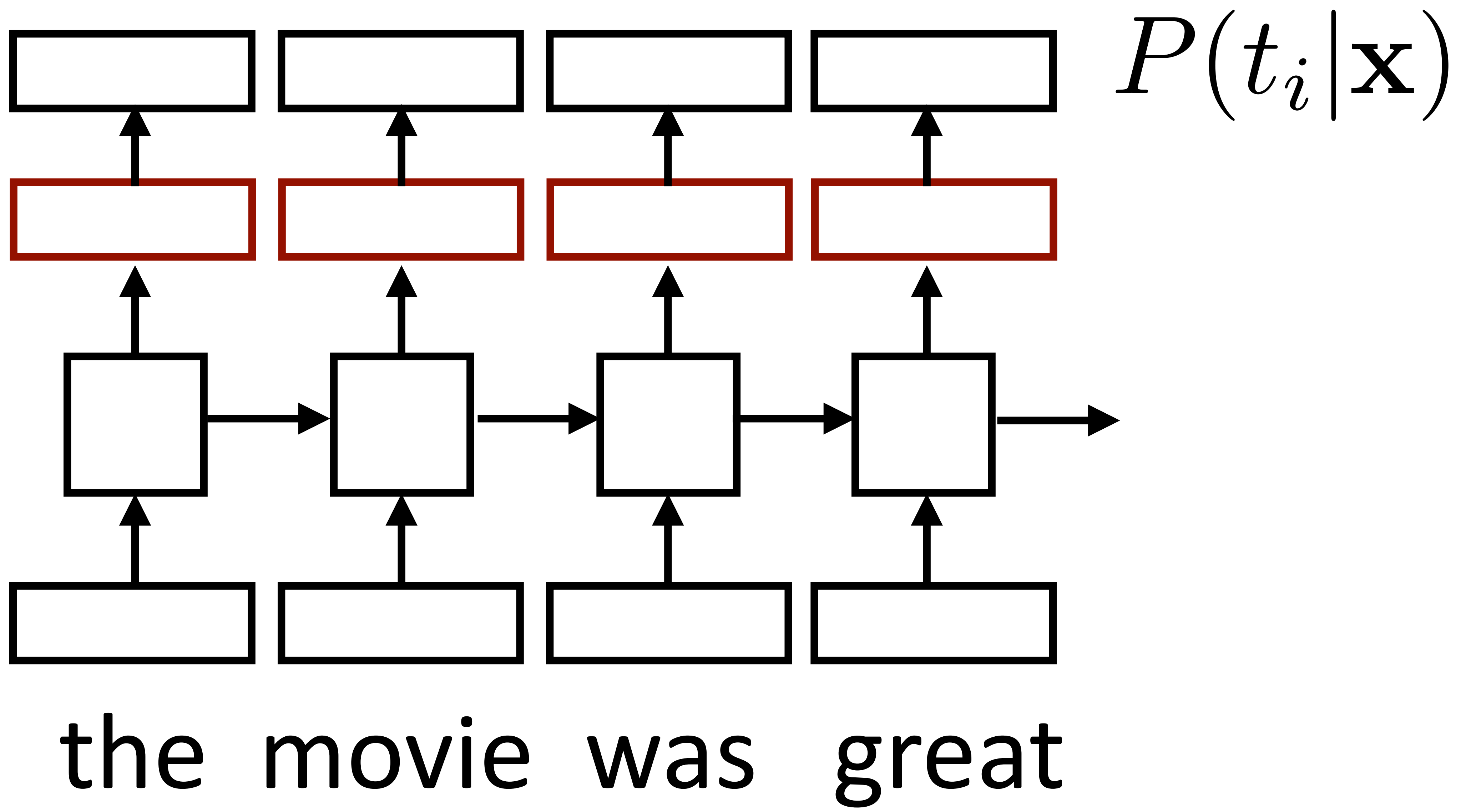

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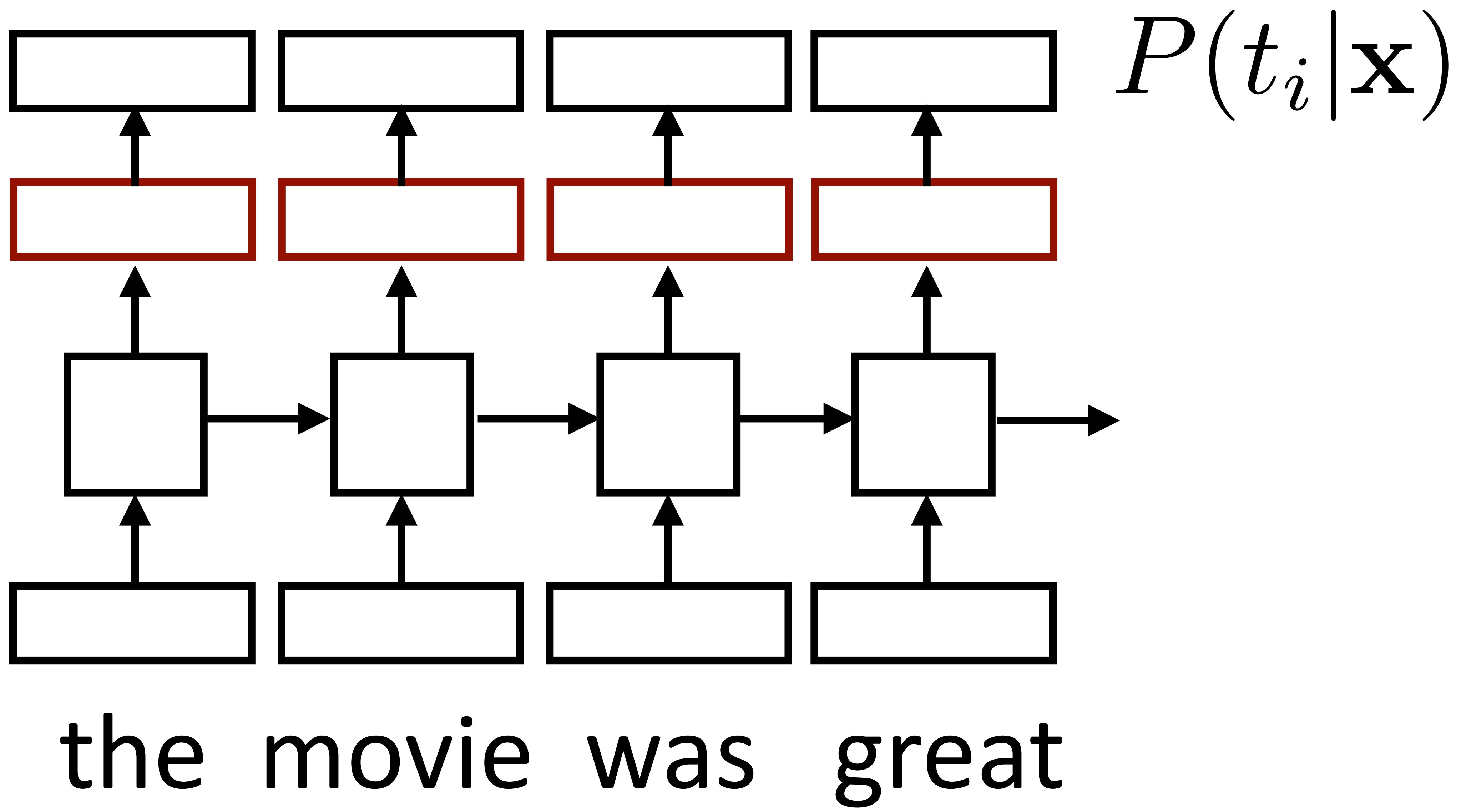

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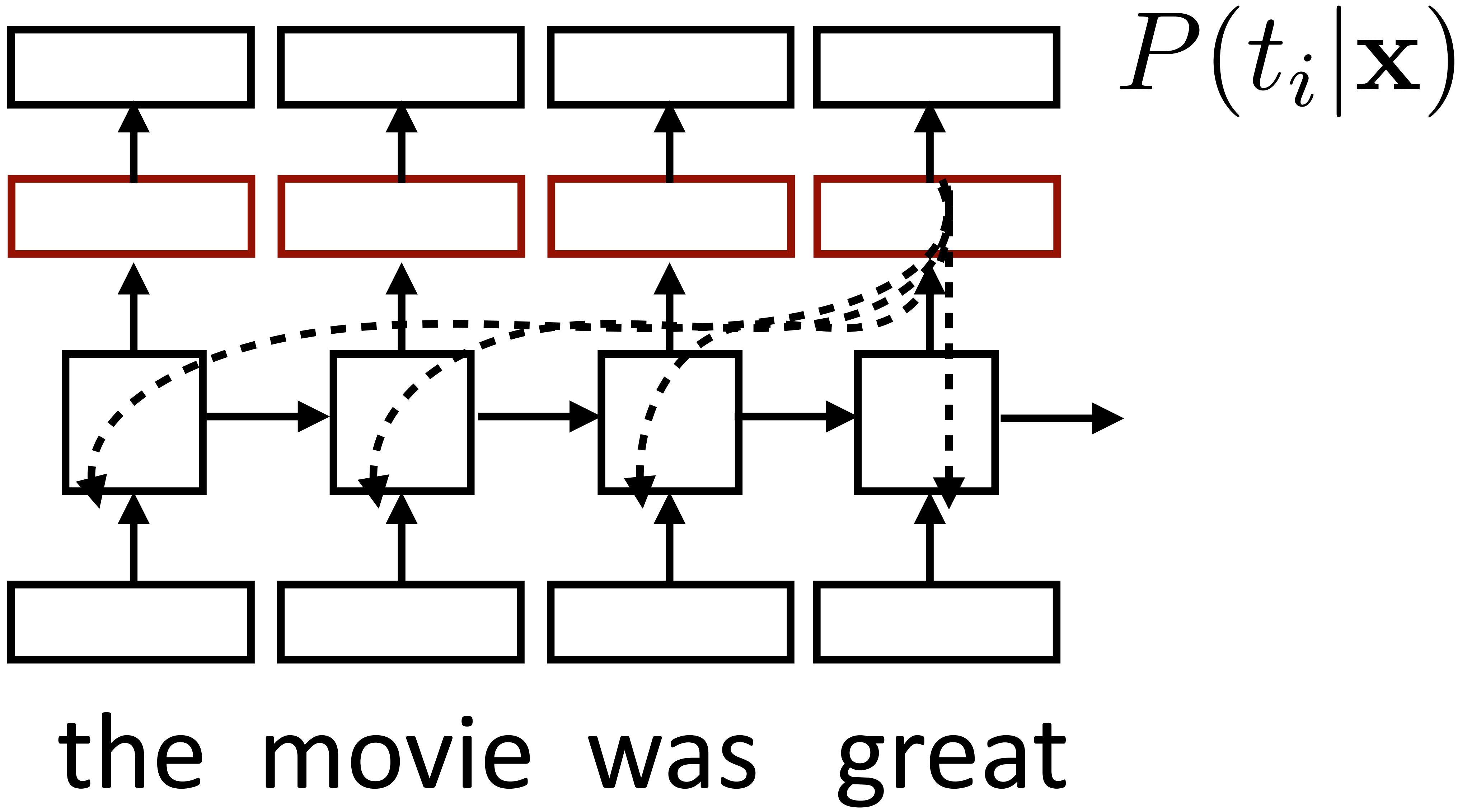

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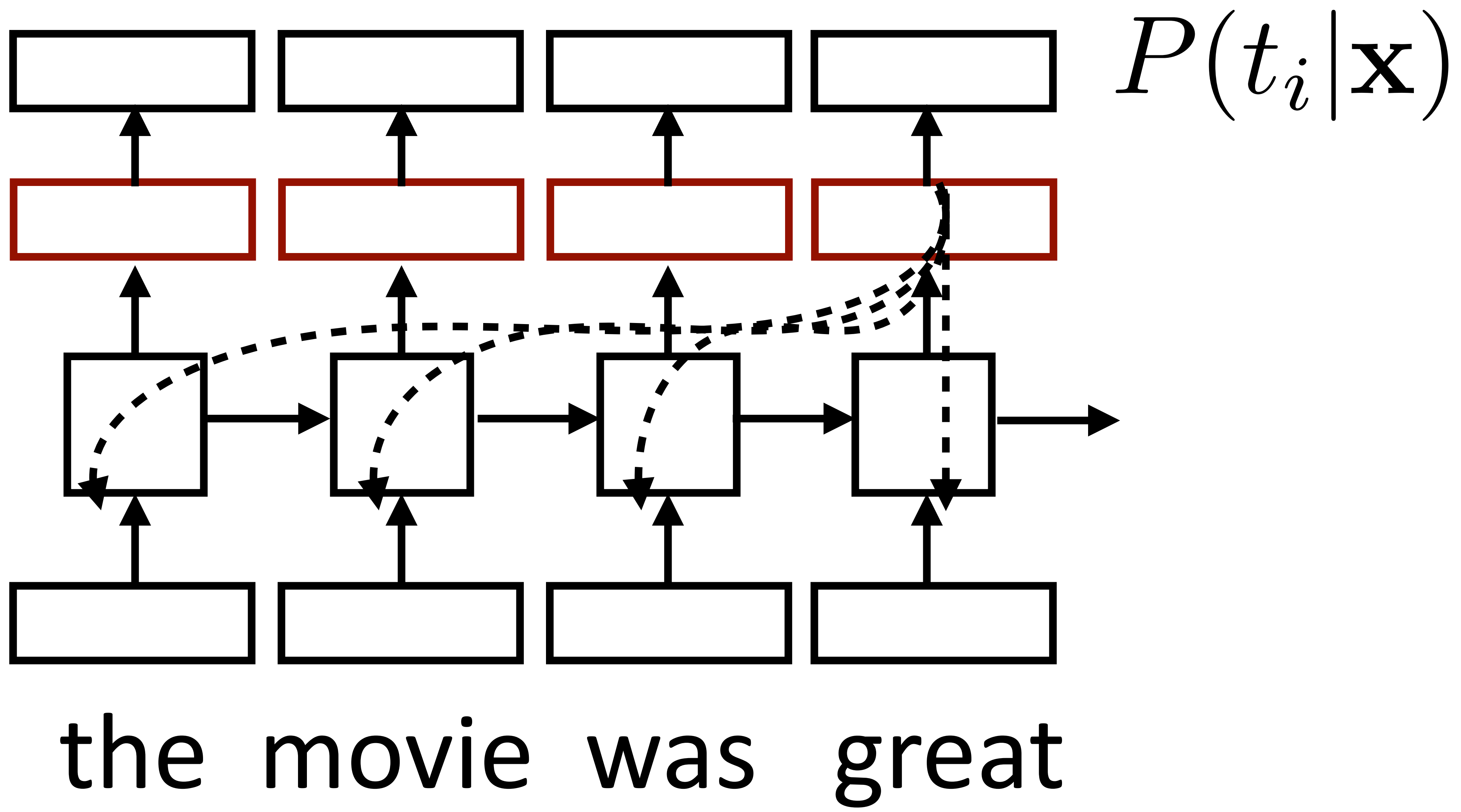

- Loss = negative log likelihood of probability of gold predictions, summed over the tags
- Loss terms filter back through network
- Example: language modeling (predict next word given context)

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

Visualizing LSTMs

Karpathy et al. (2015)

Visualizing LSTMs

- 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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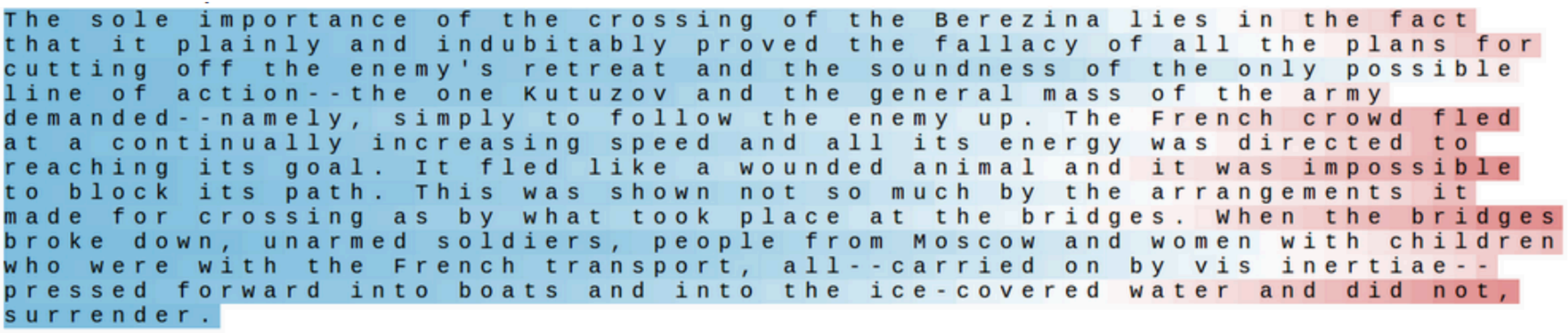
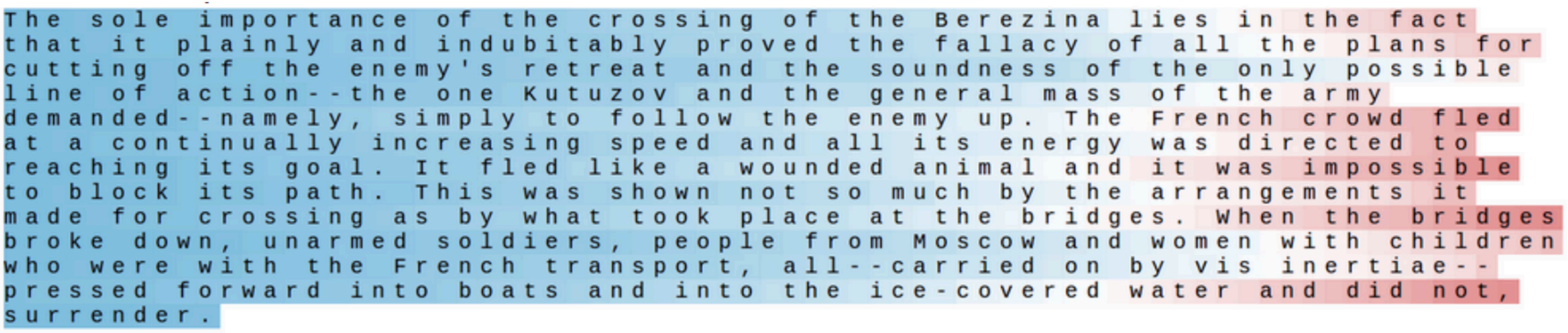


The sole importance of the crossing of the Berezina lies in the fact
that it plainly and indubitably proved the fallacy of all the plans for
cutting off the enemy's retreat and the soundness of the only possible
line of action--the one Kutuzov and the general mass of the army
demanded--namely, simply 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.

Karpathy et al. (2015)

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 (components of **c**) to understand them
- Counter: know when to generate \n



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
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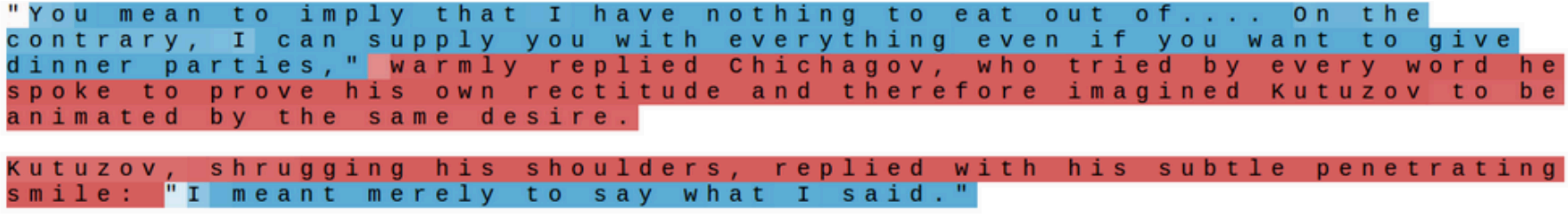

"You mean to imply that I have nothing to eat out of.... On the contrary, I can supply you with everything even if you want to give dinner parties," warmly replied Chichagov, who tried by every word he spoke to prove his own rectitude and therefore imagined Kutuzov to be animated by the same desire.

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

Karpathy et al. (2015)

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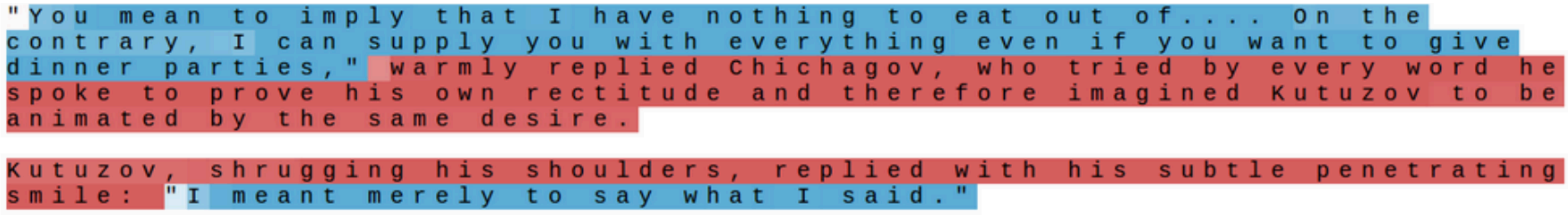
- Binary switch: tells us if we're in a quote or not



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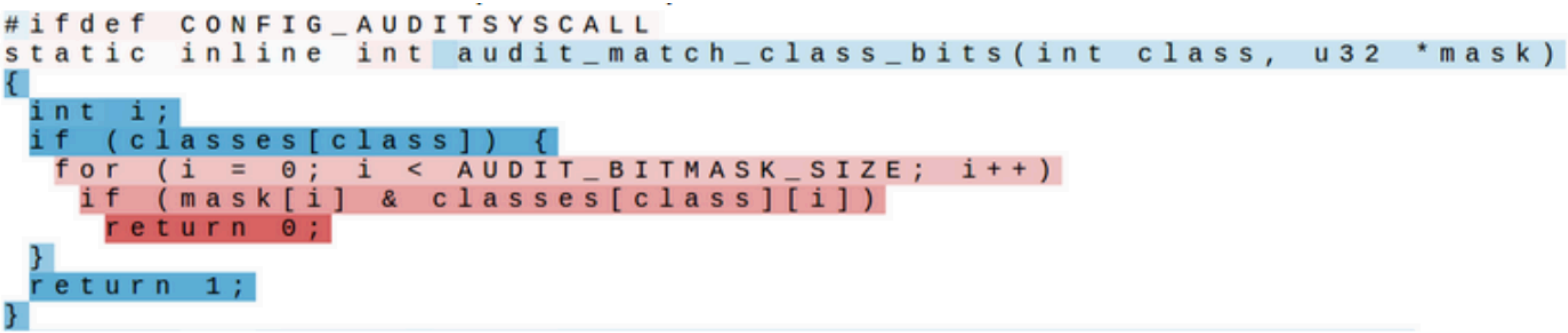

```
#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
{
 int i;
 if (classes[class]) {
  for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
   if (mask[i] & classes[class][i])
    return 0;
 }
 return 1;
}
```

Karpathy et al. (2015)

Visualizing LSTMs

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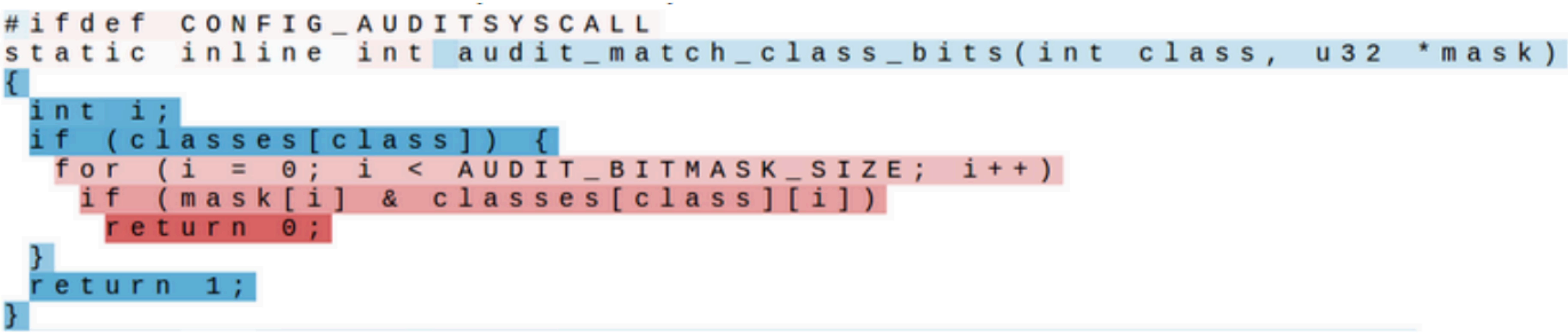
- Visualize activations of specific cells to see what they track
- Stack: activation based on indentation



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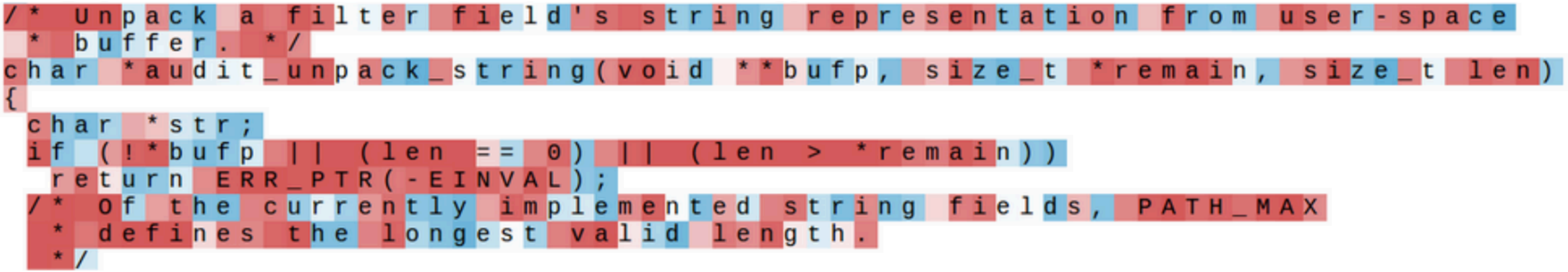

```
/* Unpack a filter field's string representation from user-space
 * buffer. */
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)
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 char *str;
 if (!*bufp || (len == 0) || (len > *remain))
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 /* Of the currently implemented string fields, PATH_MAX
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  */
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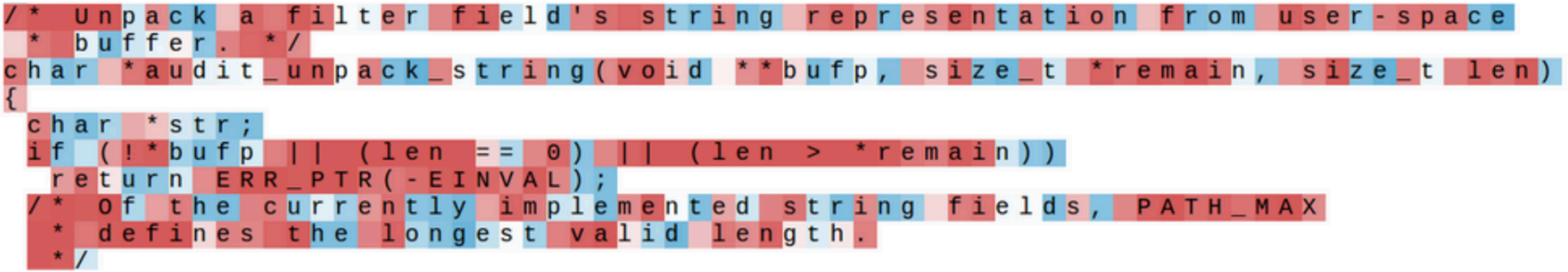
Karpathy et al. (2015)

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

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



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Karpathy et al. (2015)

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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- Textual entailment
  - Encode two sentences, predict

Natural Language Inference

Premise	Hypothesis
A boy plays in the snow	A boy is outside

Natural Language Inference

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A boy plays in the snow	*entails*	A boy is outside

Natural Language Inference

Premise		Hypothesis
A boy plays in the snow	*entails*	A boy is outside
A man inspects the uniform of a figure		The man is sleeping

Natural Language Inference

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A boy plays in the snow	*entails*	A boy is outside
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An older and younger man smiling		Two men are smiling and laughing at cats playing

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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

Bowman et al. (2015)

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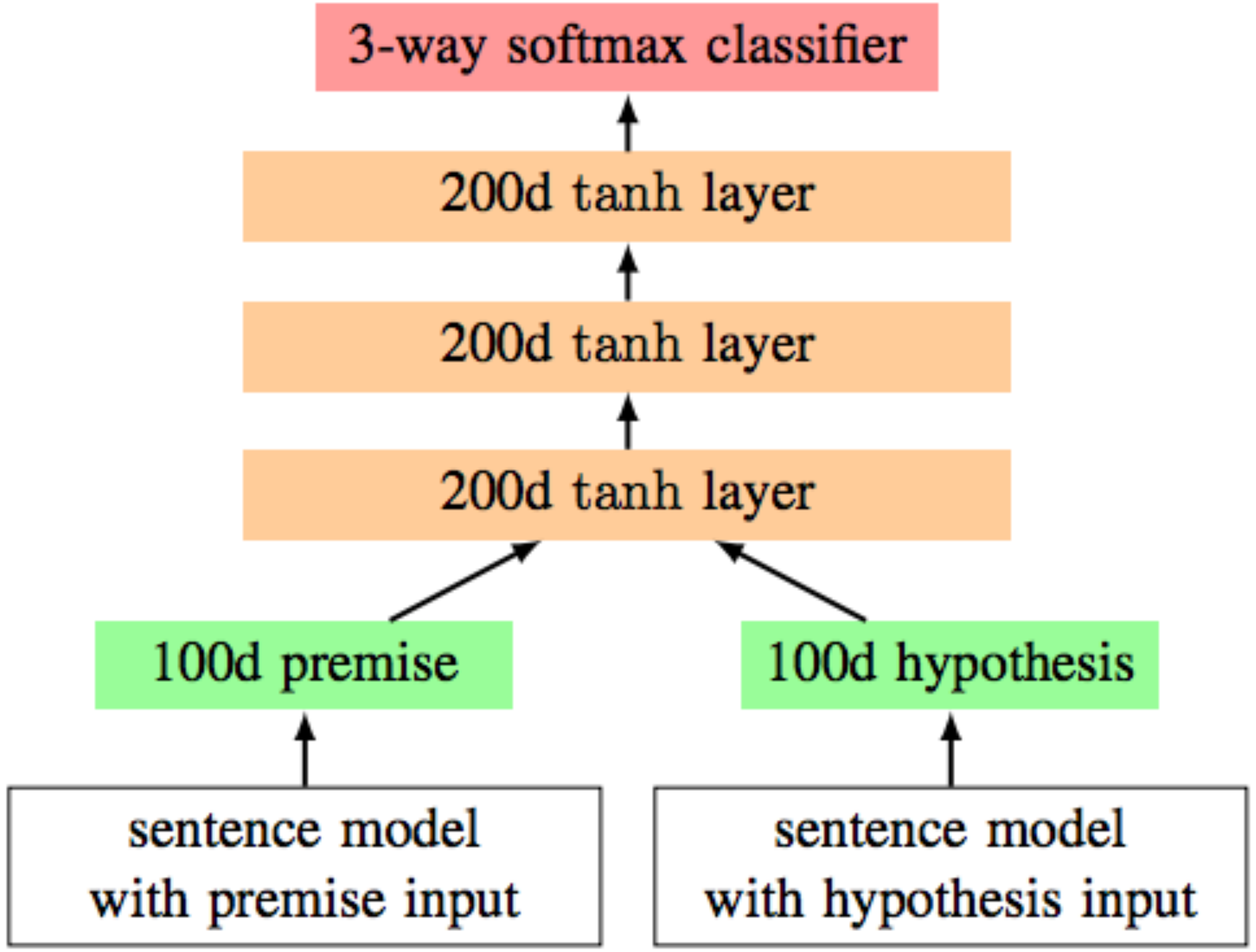

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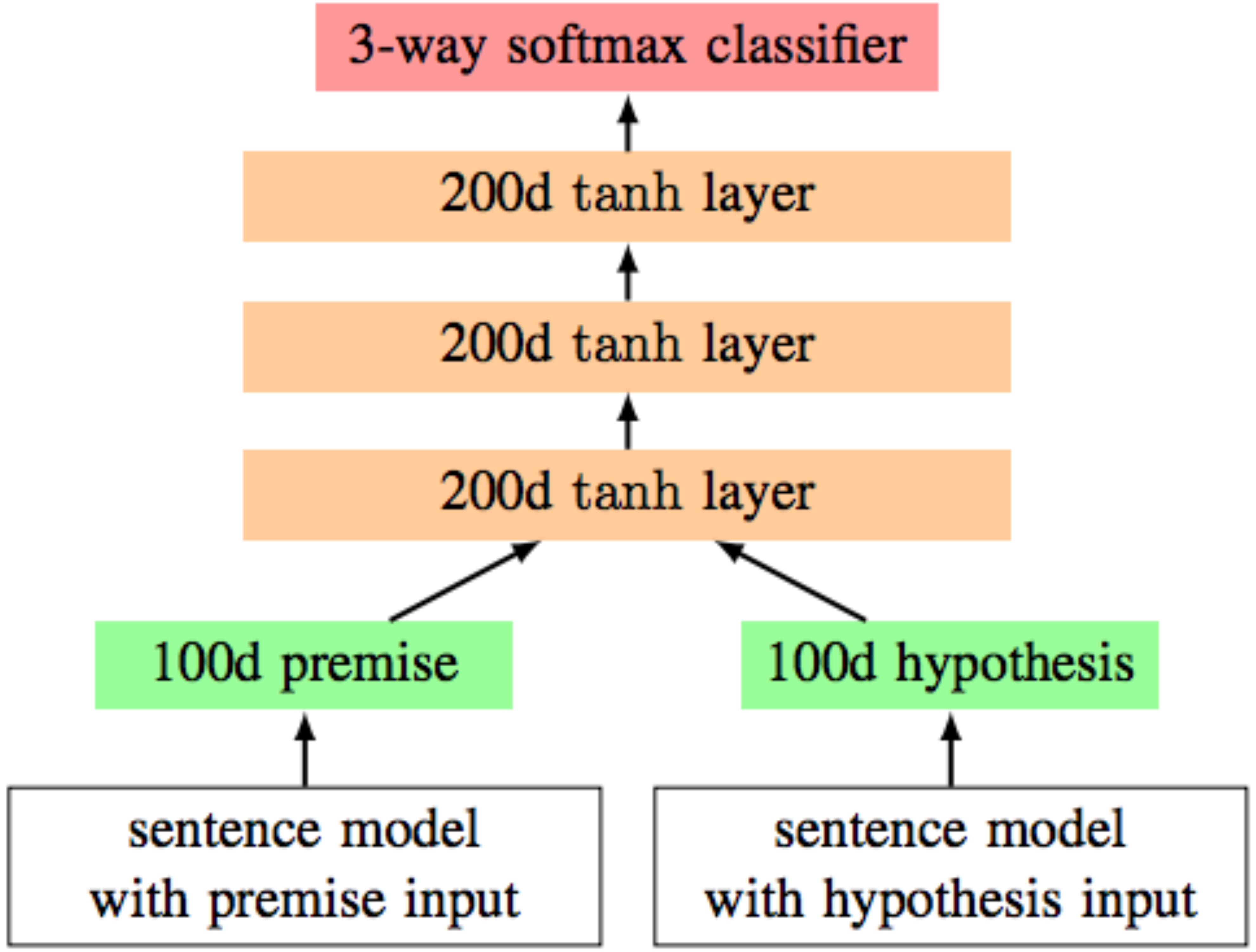
100D LSTM: 78% accuracy



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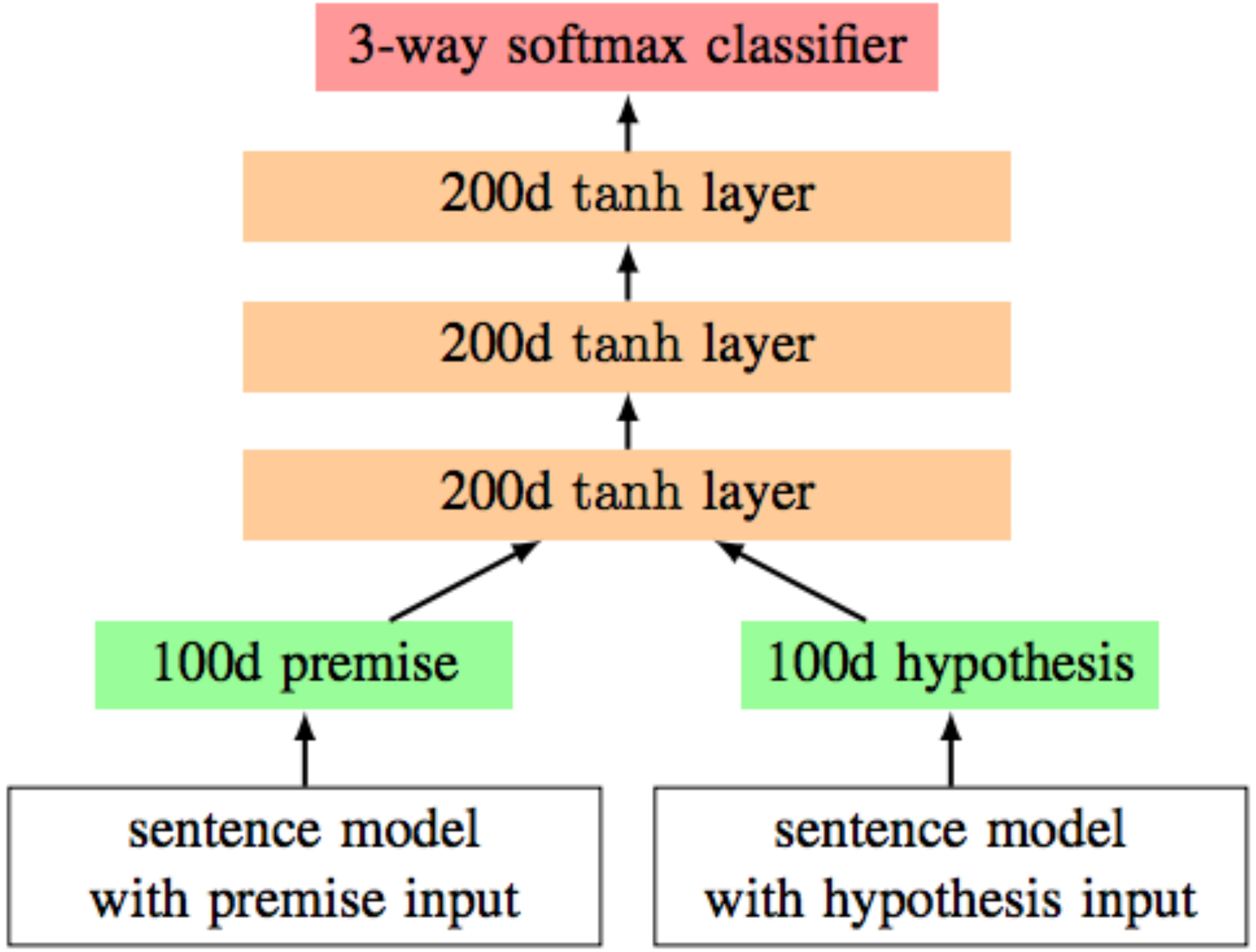
300D LSTM: 80% accuracy

(Bowman et al., 2016)



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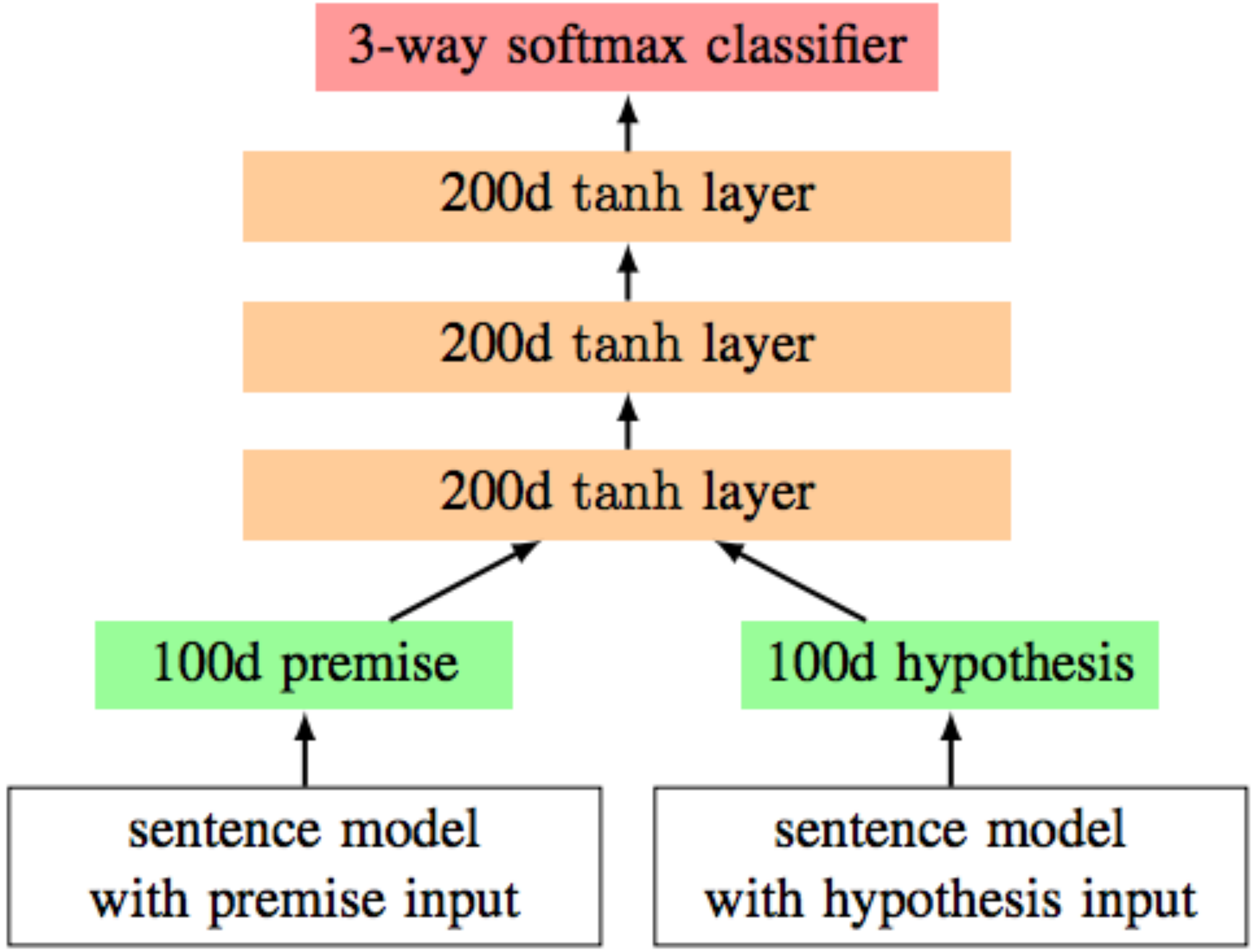
300D BiLSTM: 83% accuracy
(Liu et al., 2016)



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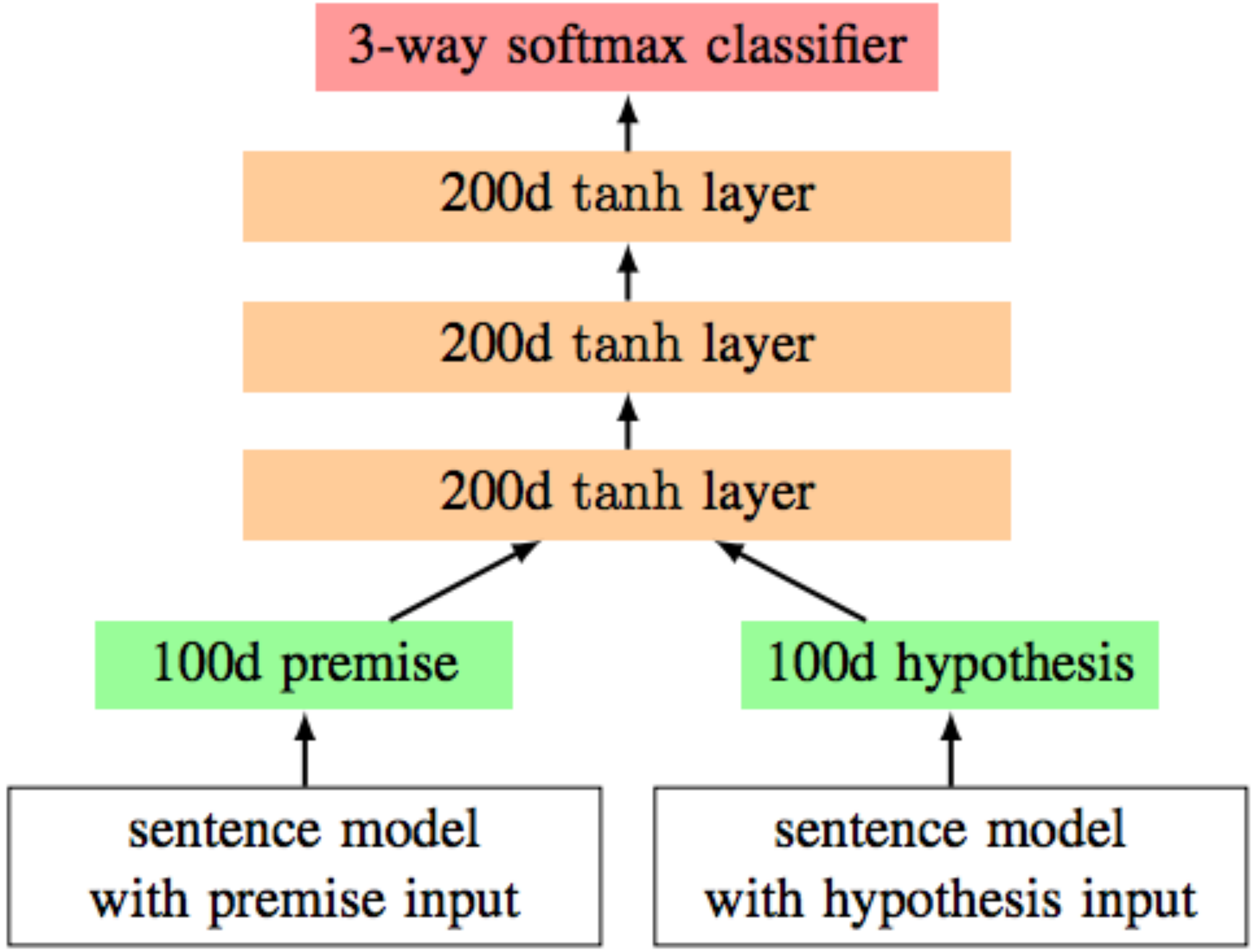
- Later: better models for this



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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