Lecture 8: RNNs

Alan Ritter

(many slides from Greg Durrett)

Recall: Training Tips

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

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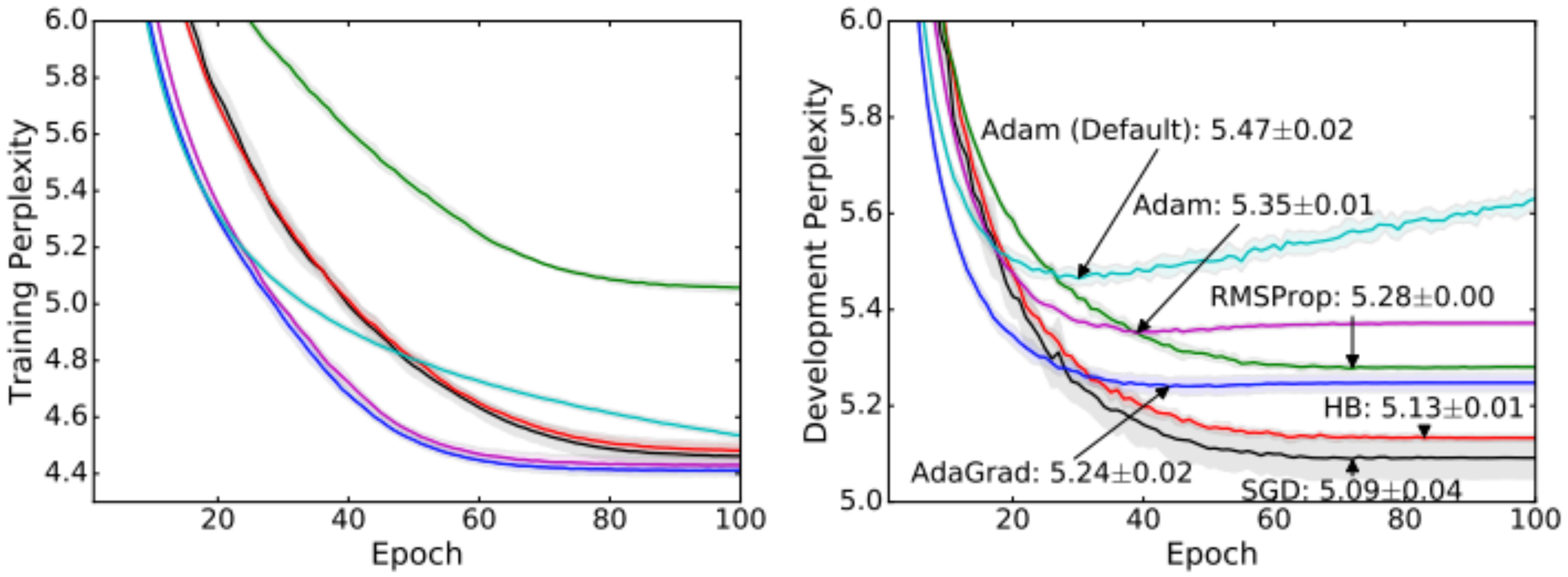
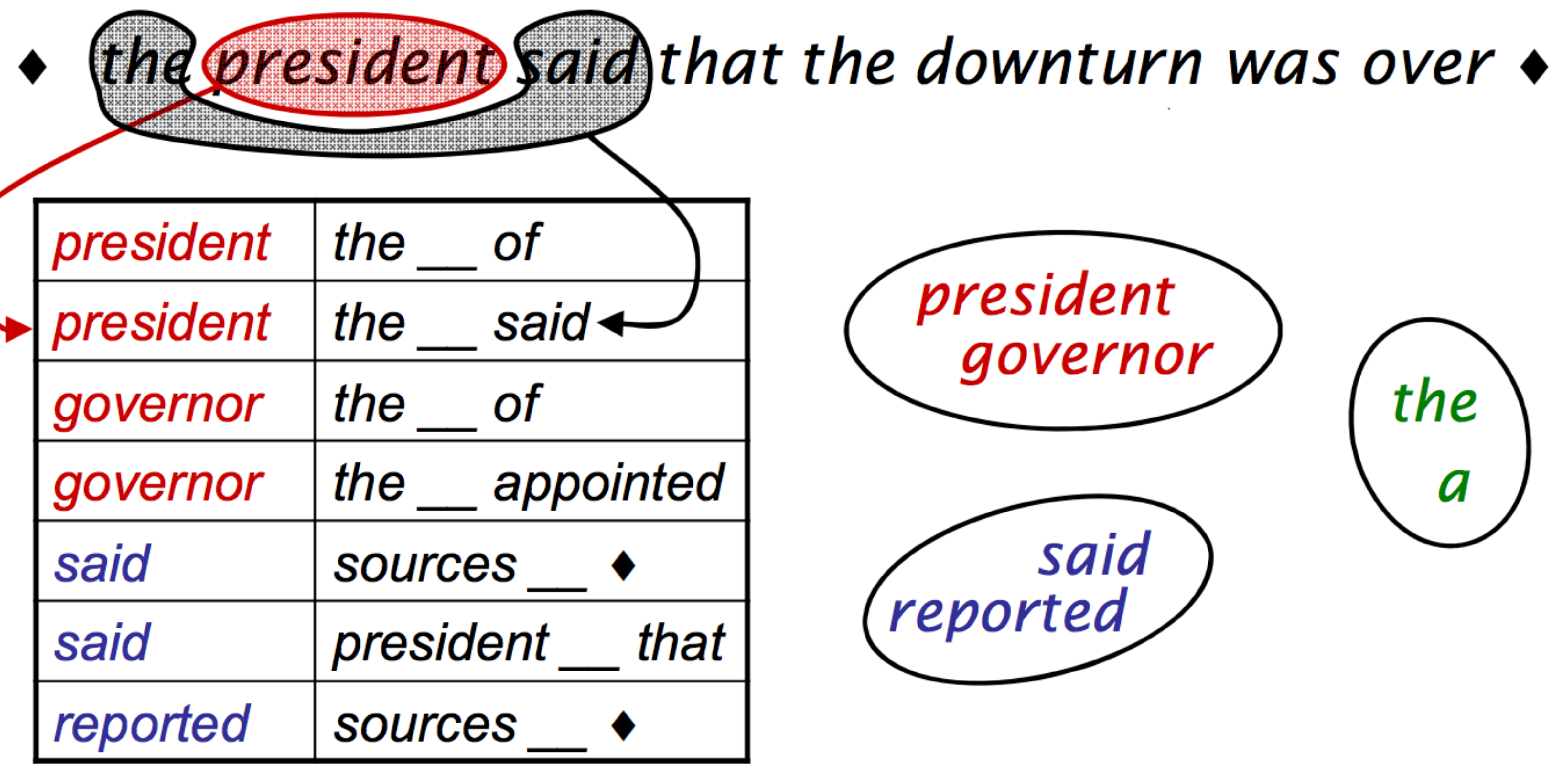
- Dropout is an effective regularizer

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



(e) Generative Parsing (Training Set) (f) Generative Parsing (Development Set)

Recall: Word Vectors



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

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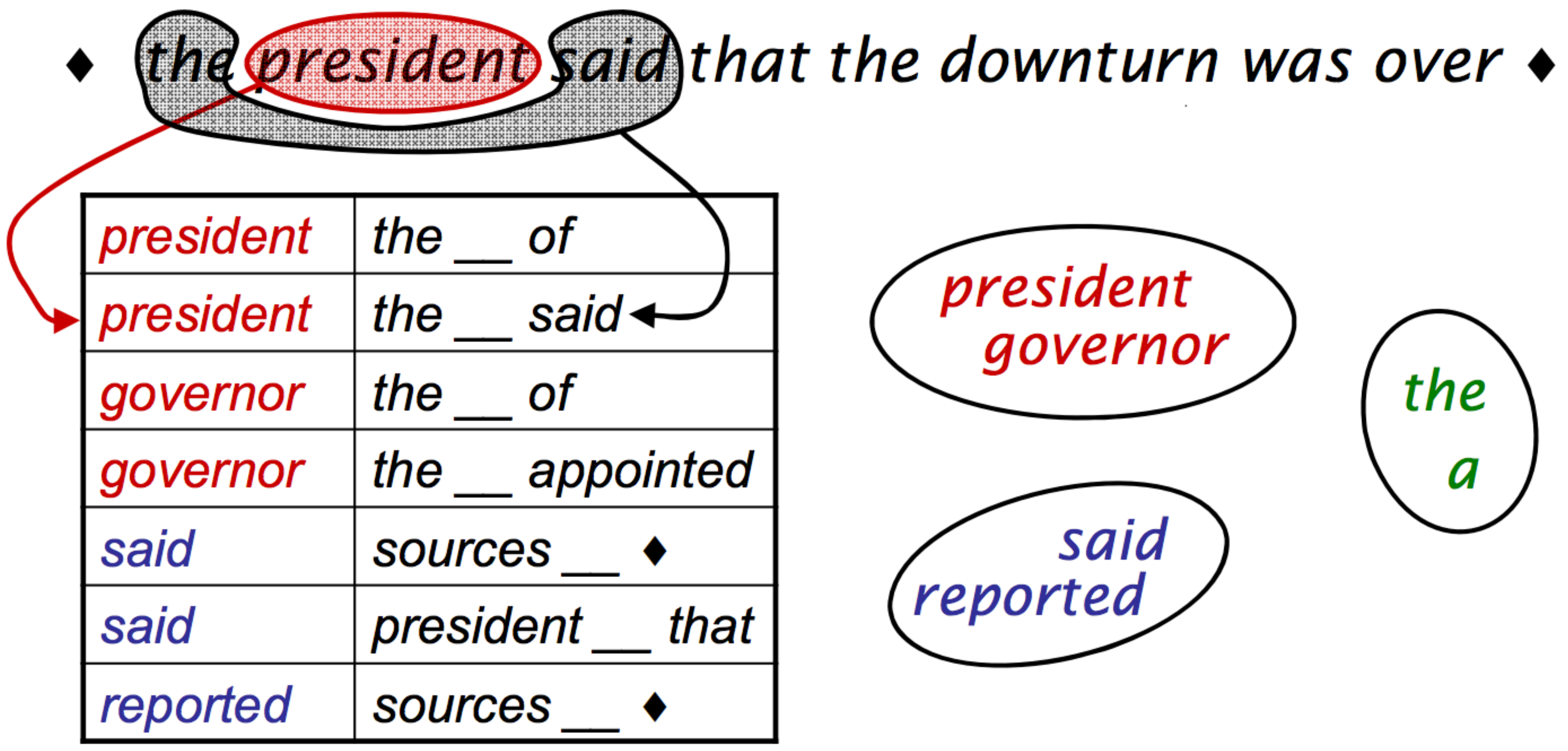
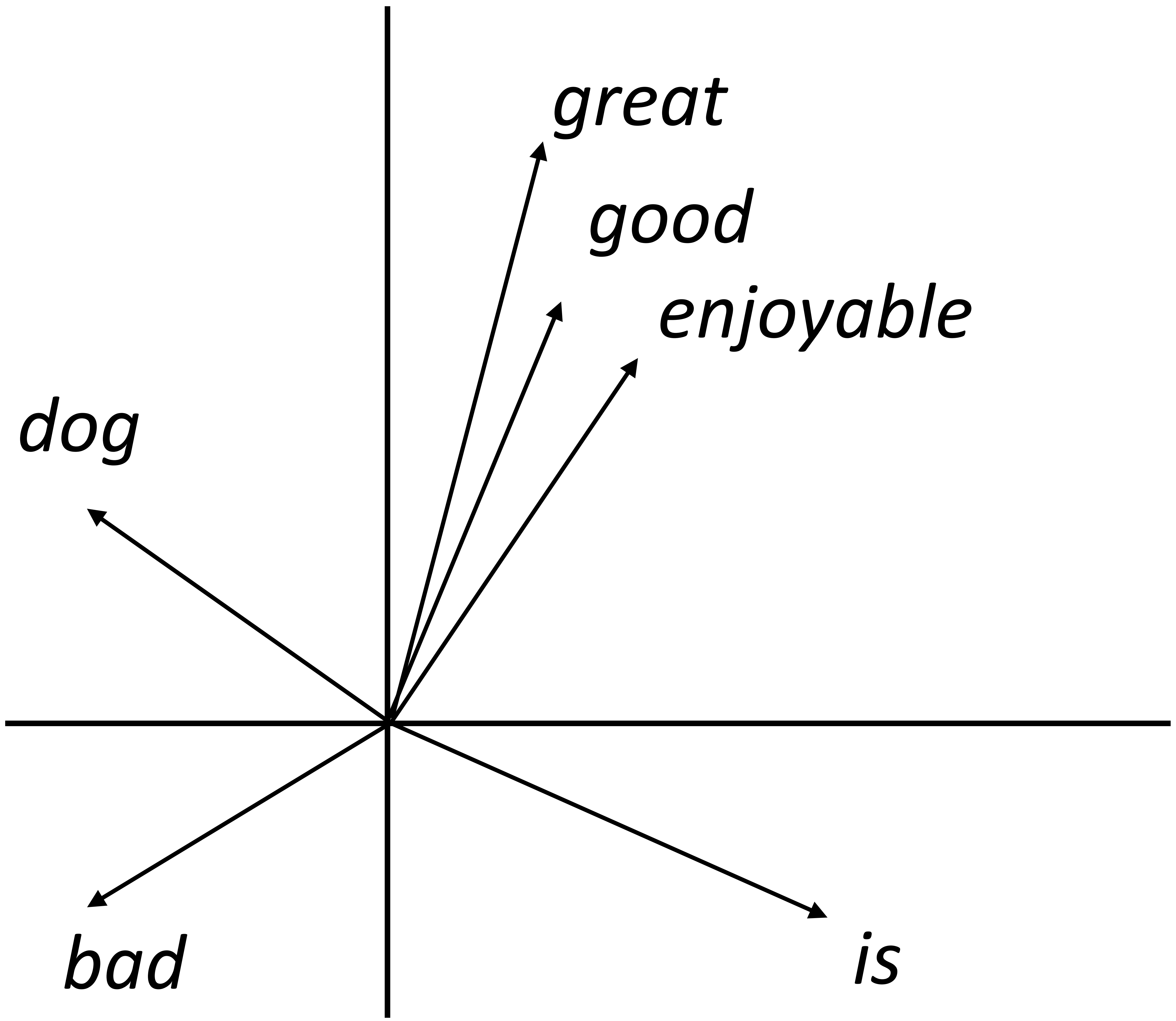


president	the __ of
president	the __ said
governor	the __ of
governor	the __ appointed
said	sources __ ♦
said	president __ that
reported	sources __ ♦

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



Recall: Continuous Bag-of-Words

- Predict word from context

the dog ***bit*** *the man*

Mikolov et al. (2013)

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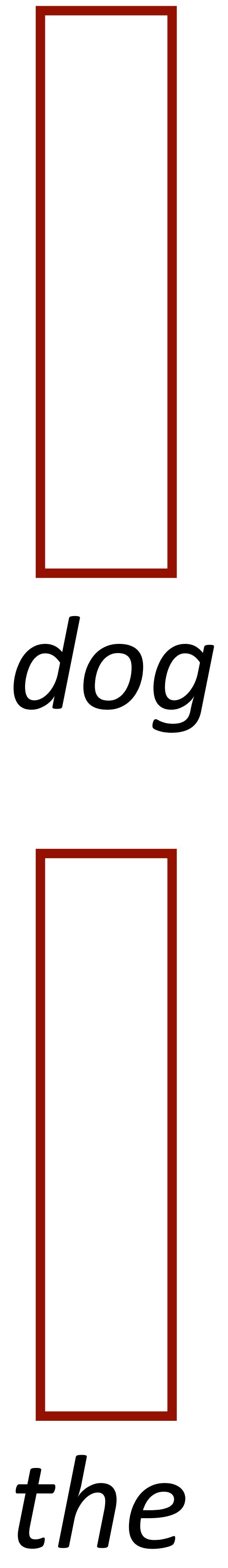

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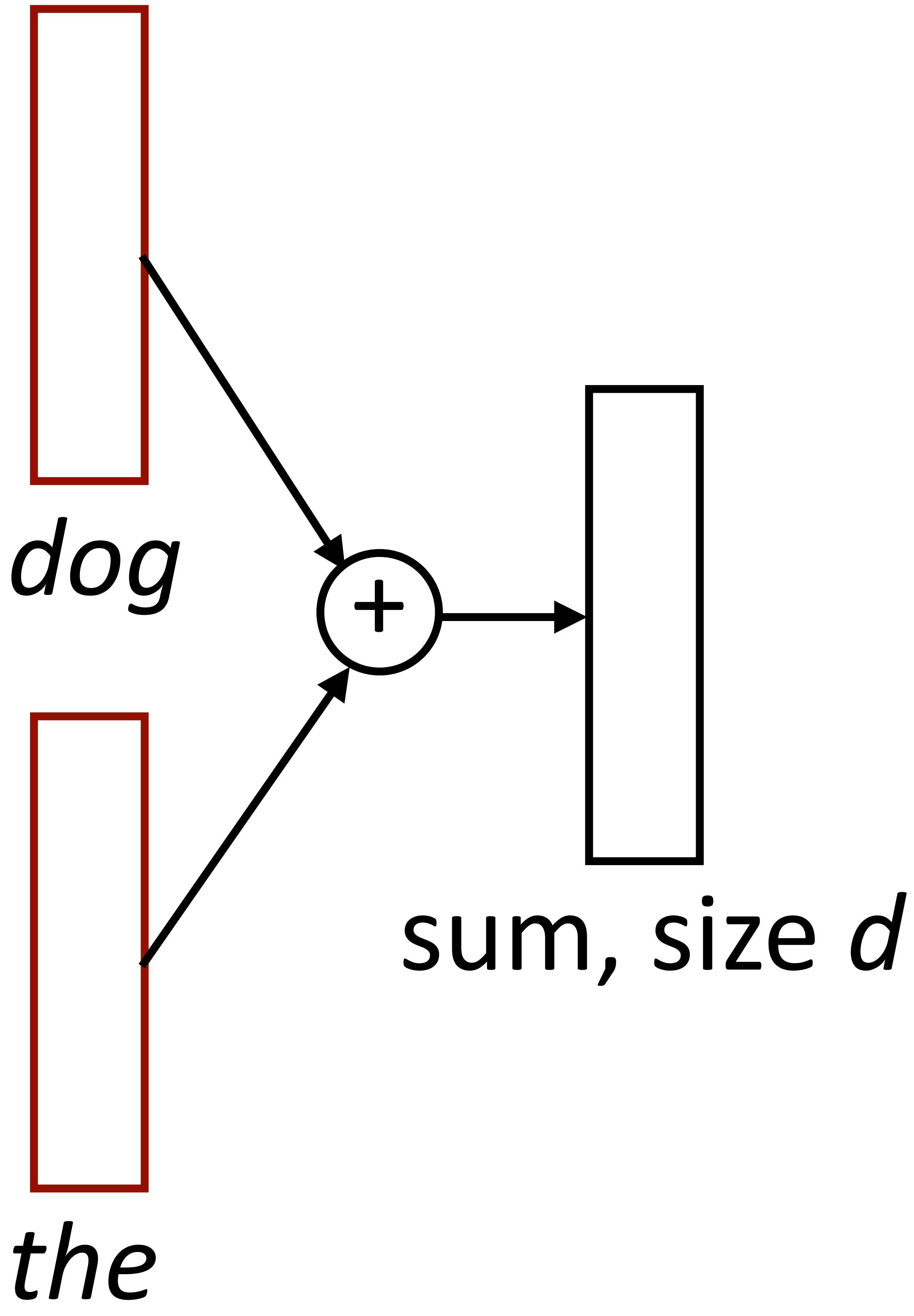

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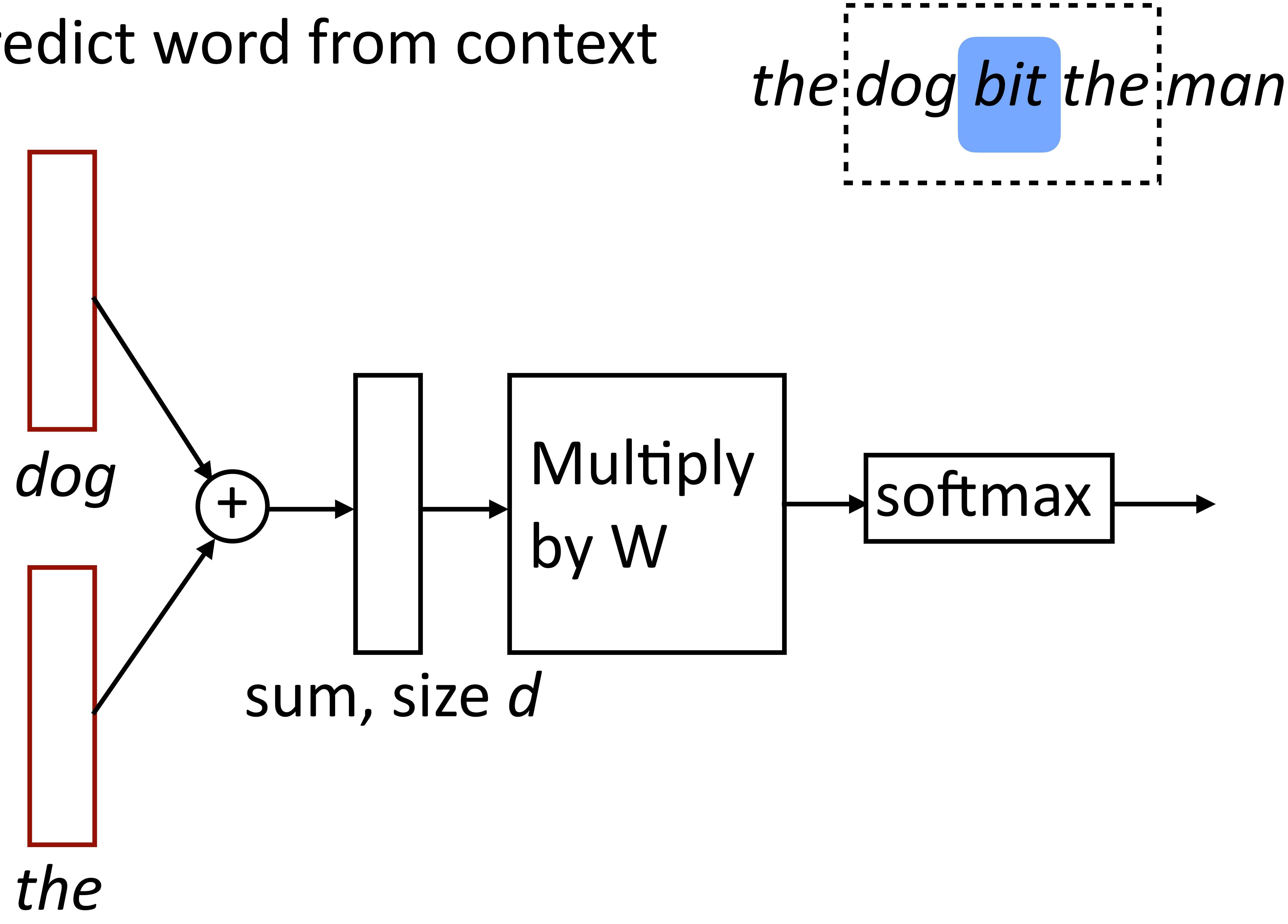

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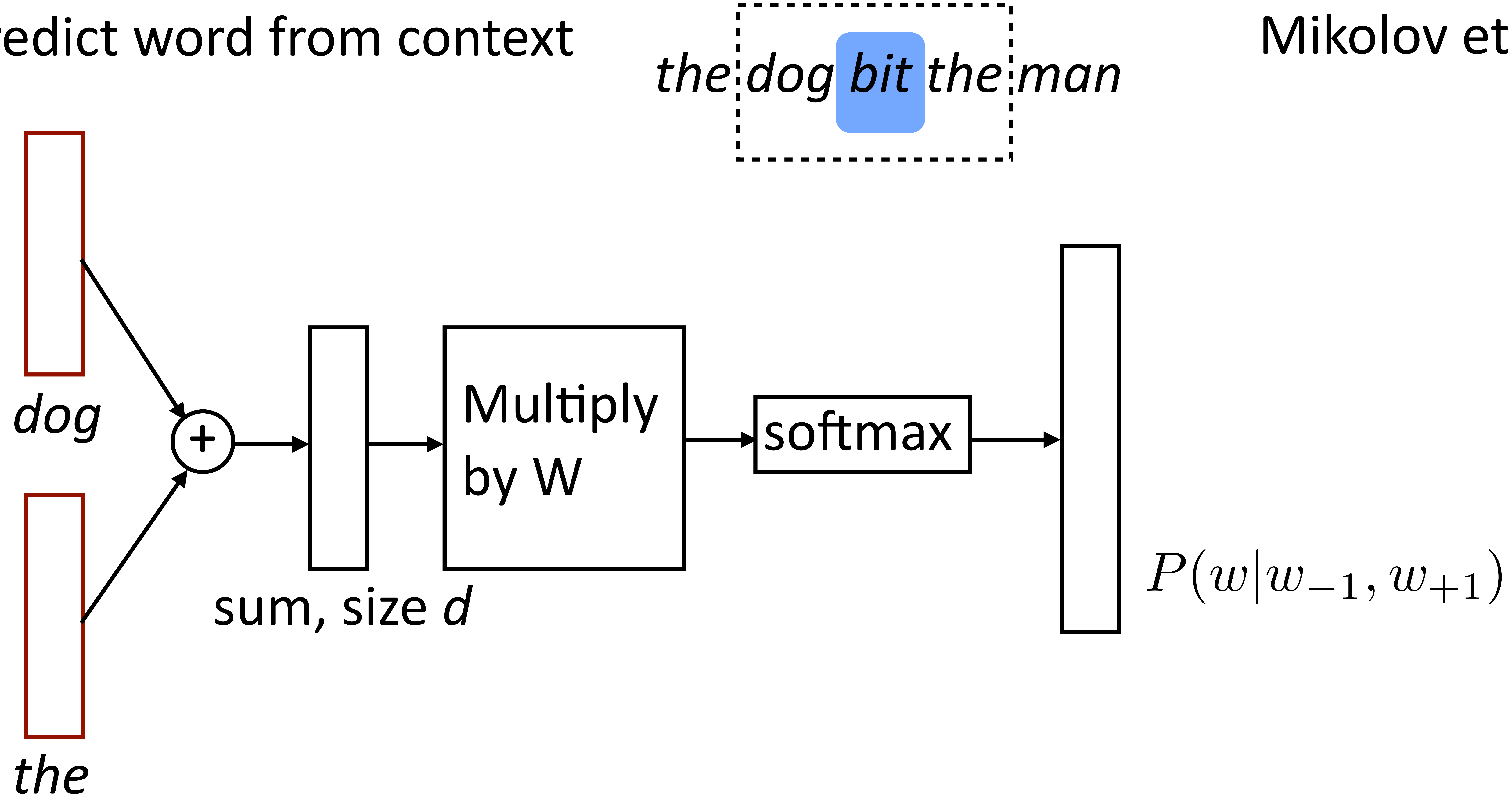

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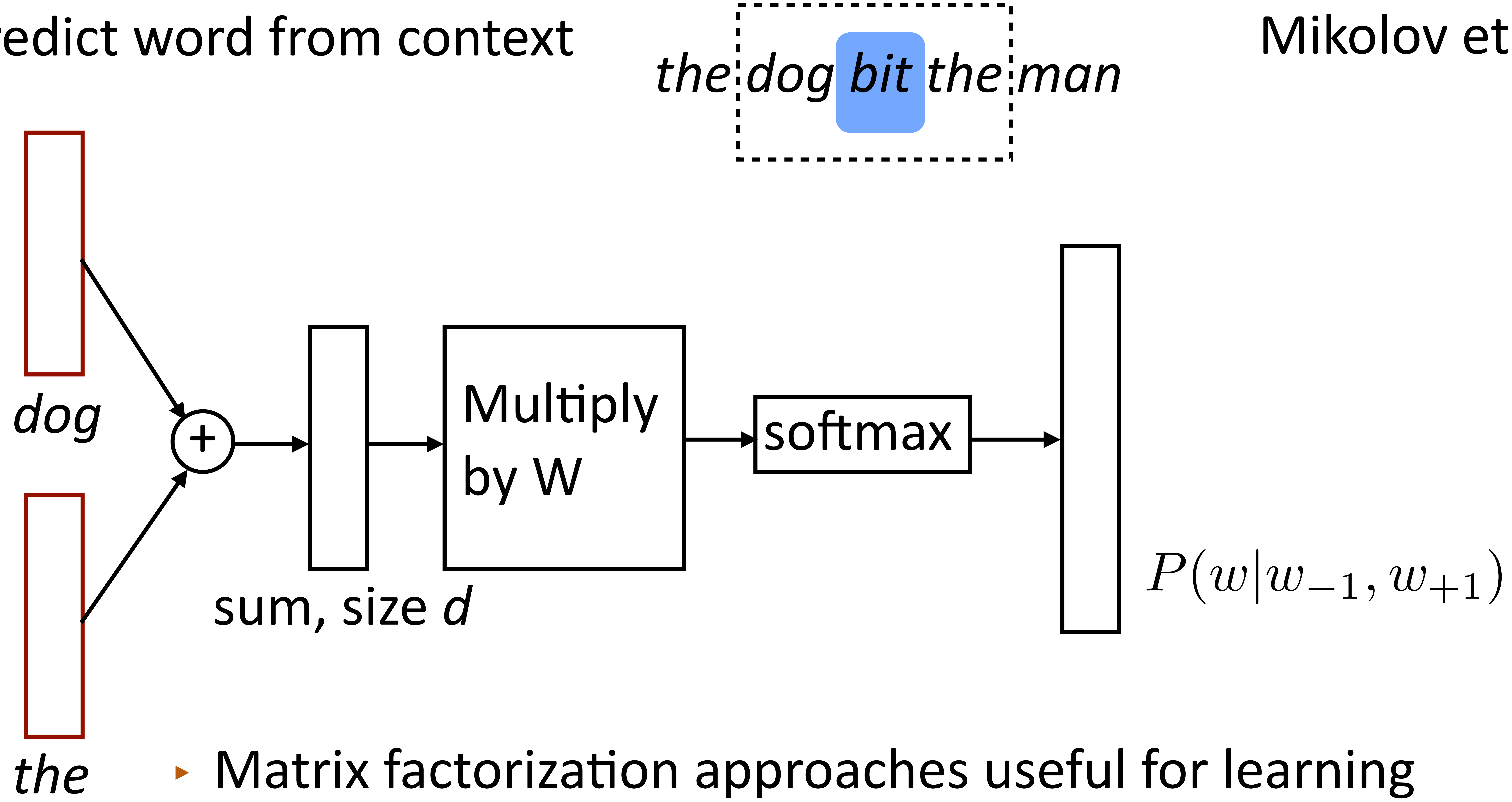
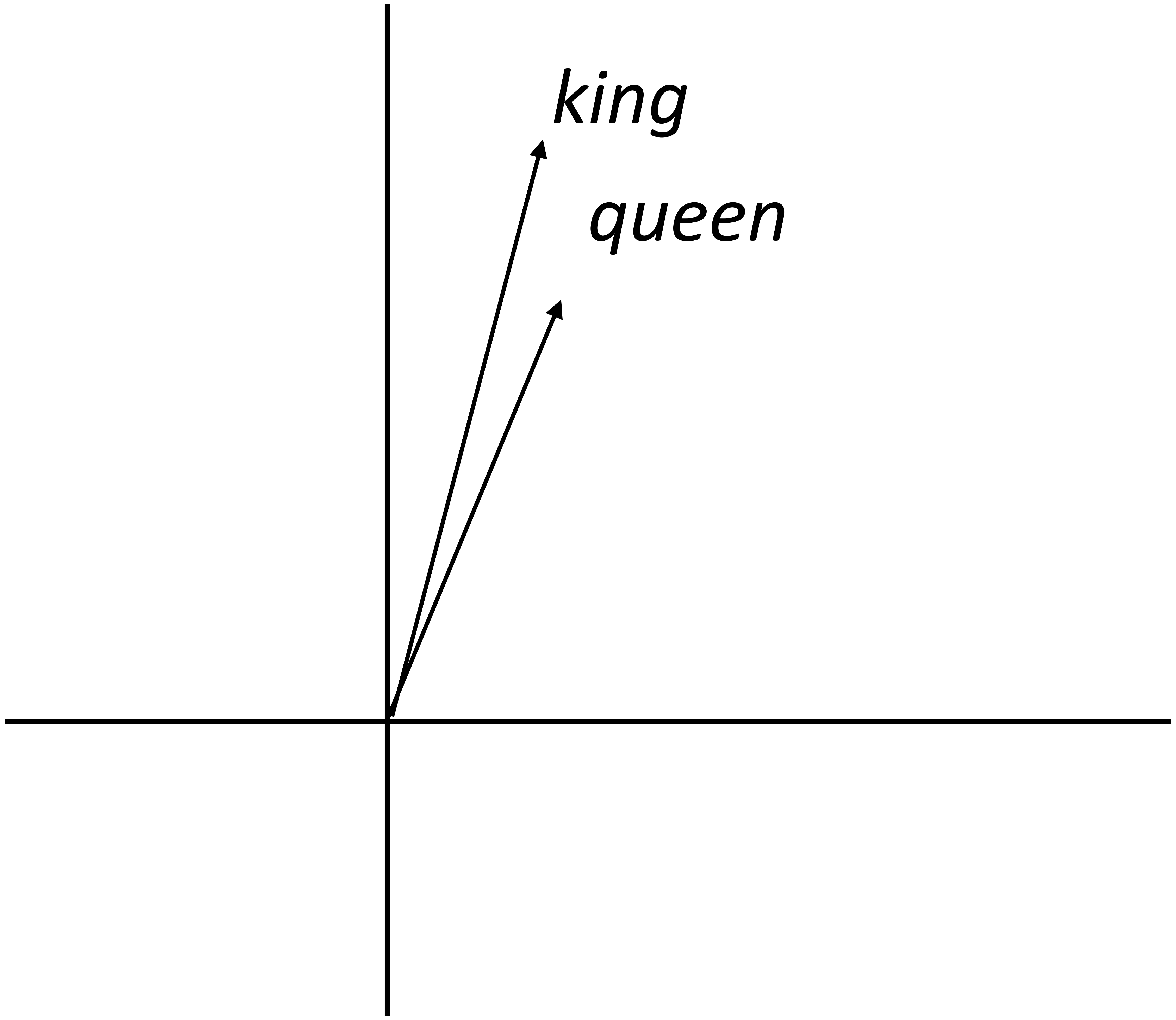


- Matrix factorization approaches useful for learning vectors from really large data

Analogies



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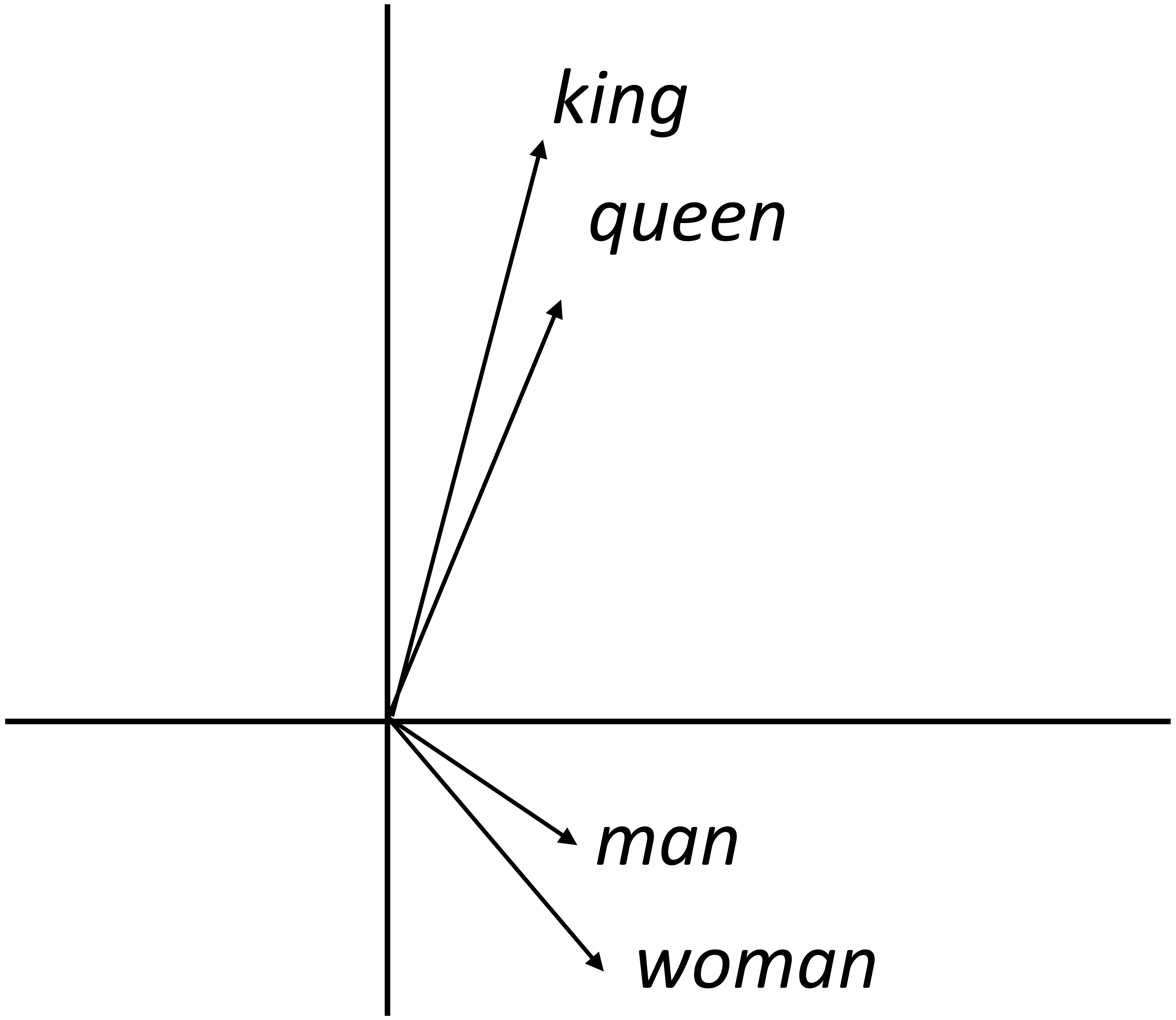
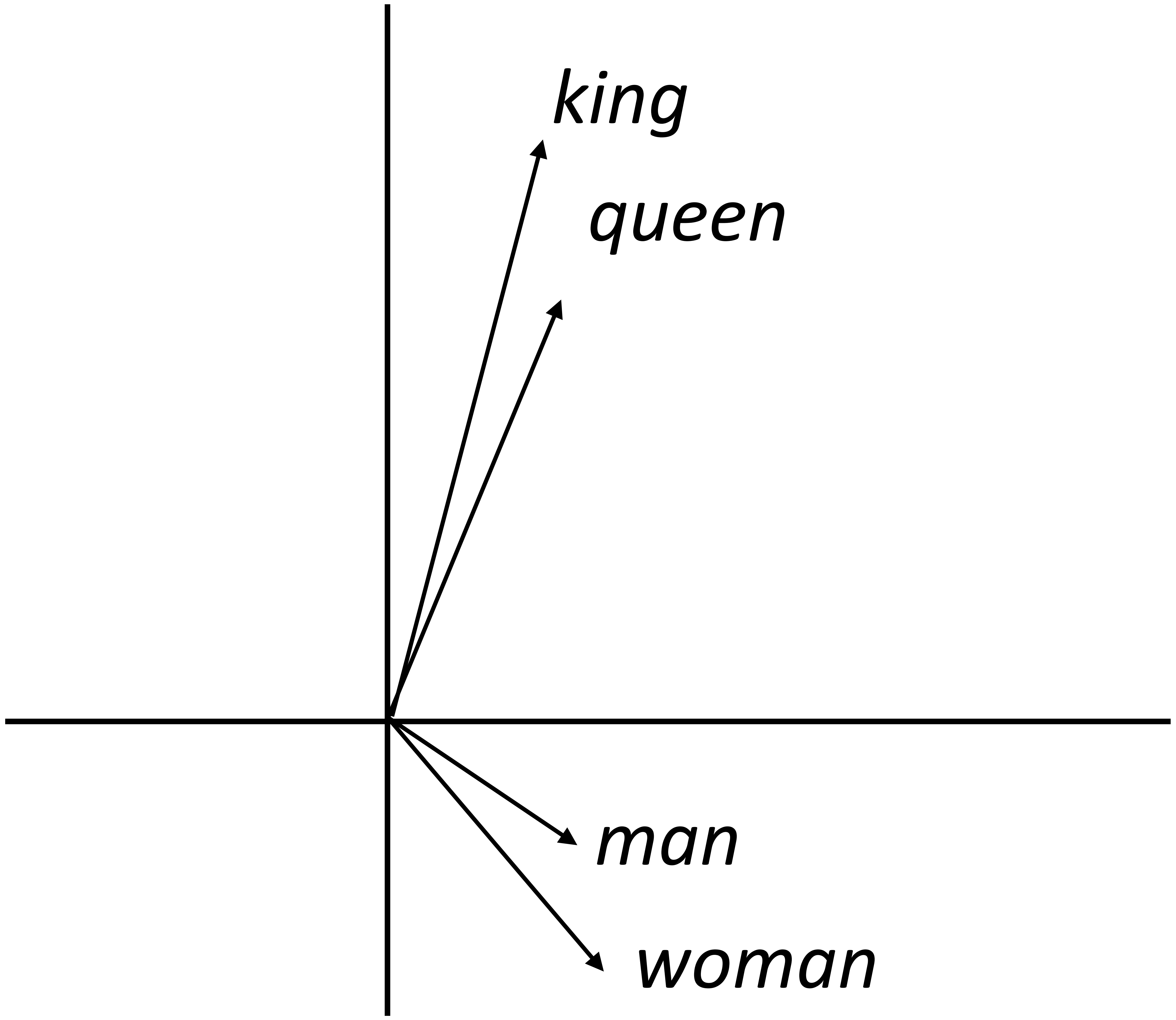


Analogies

(king - man) + woman = queen



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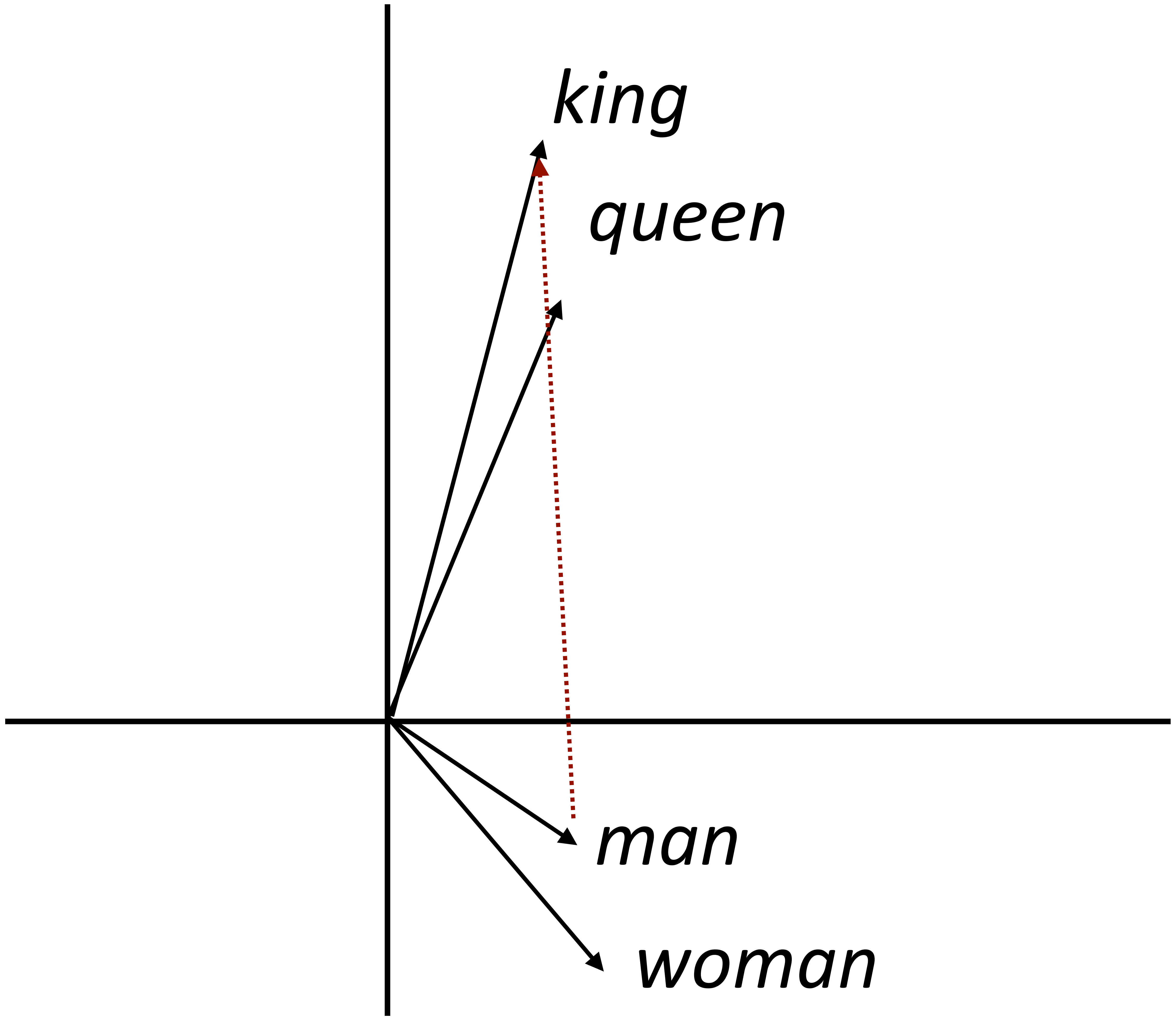

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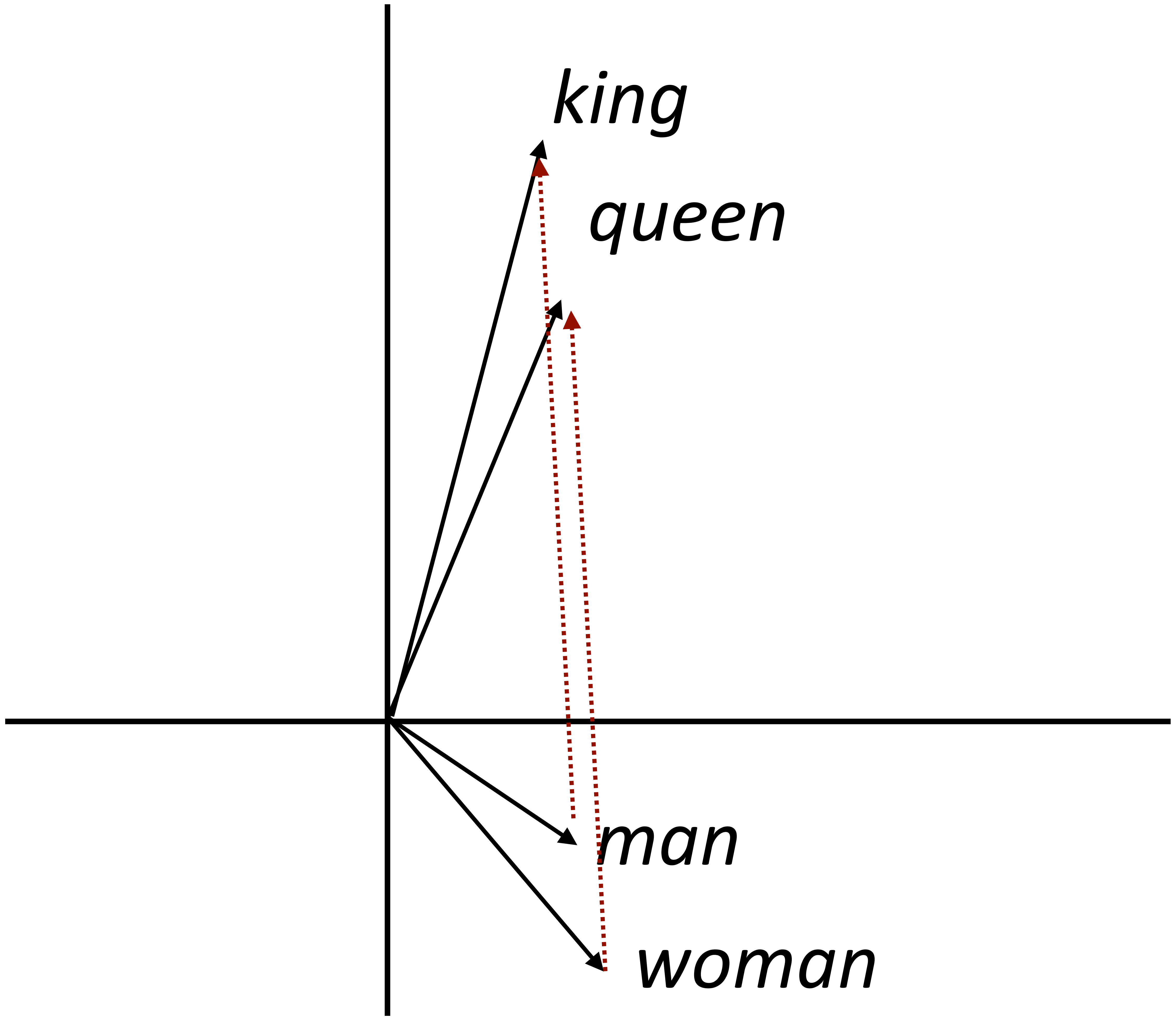

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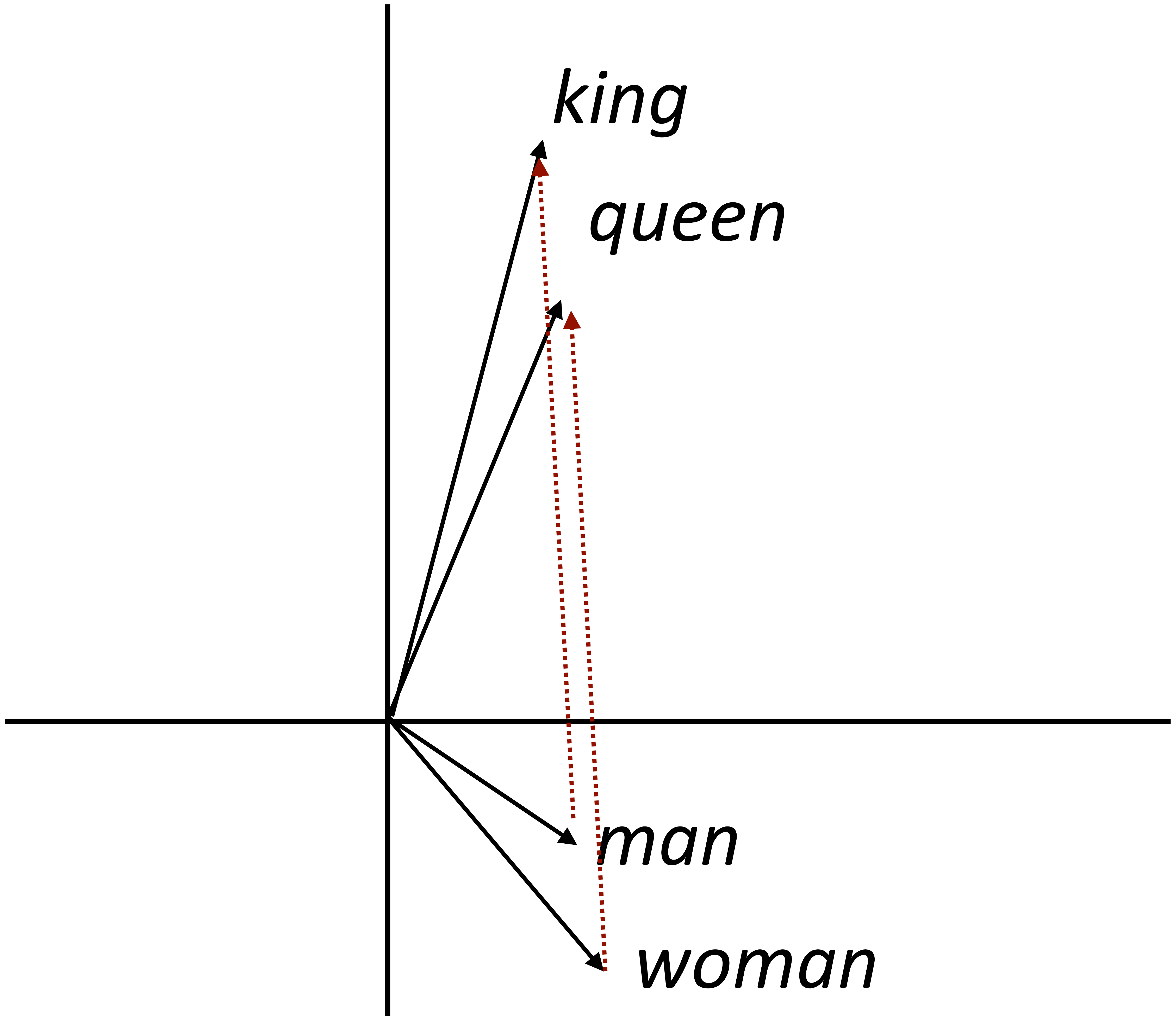

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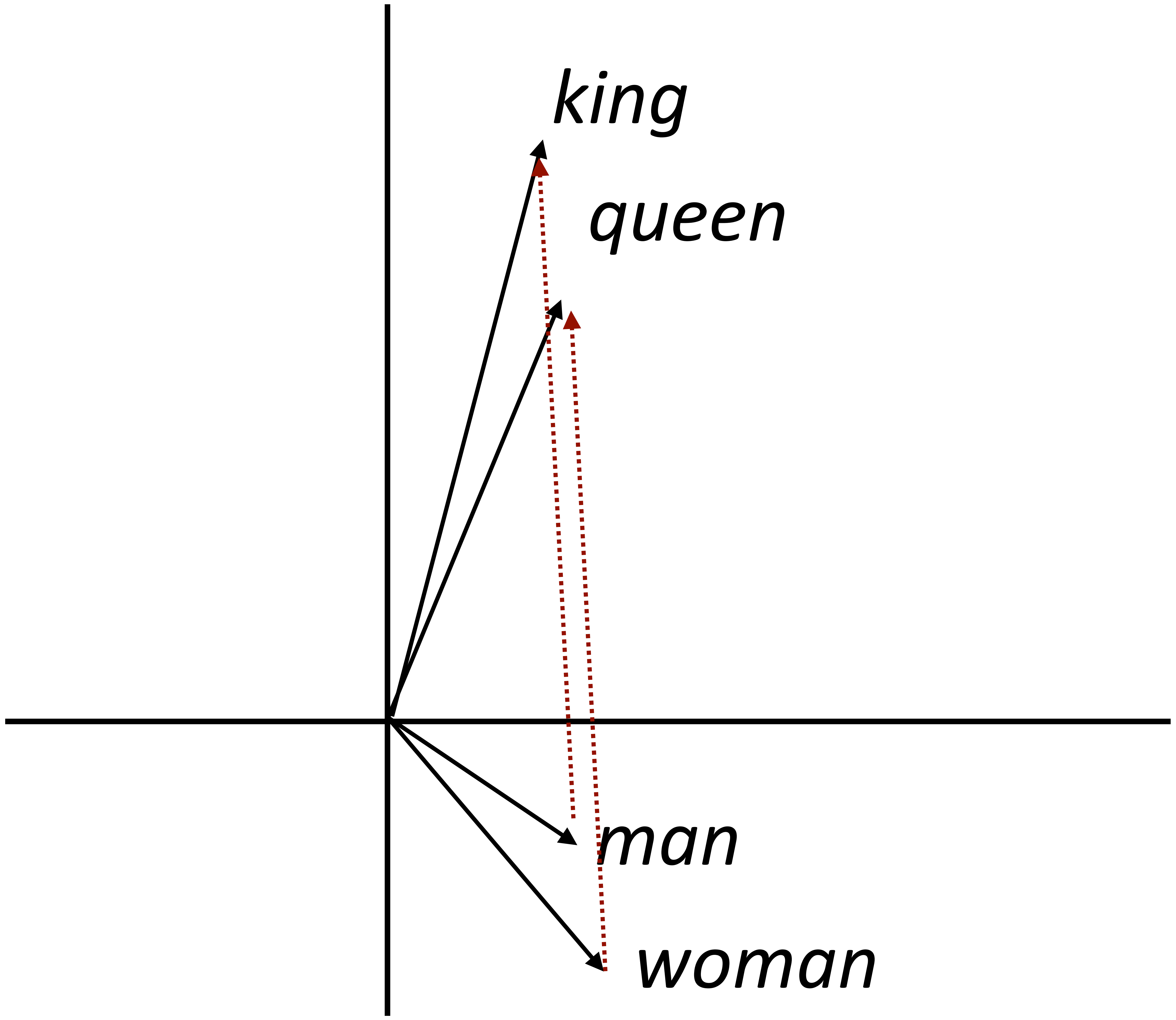

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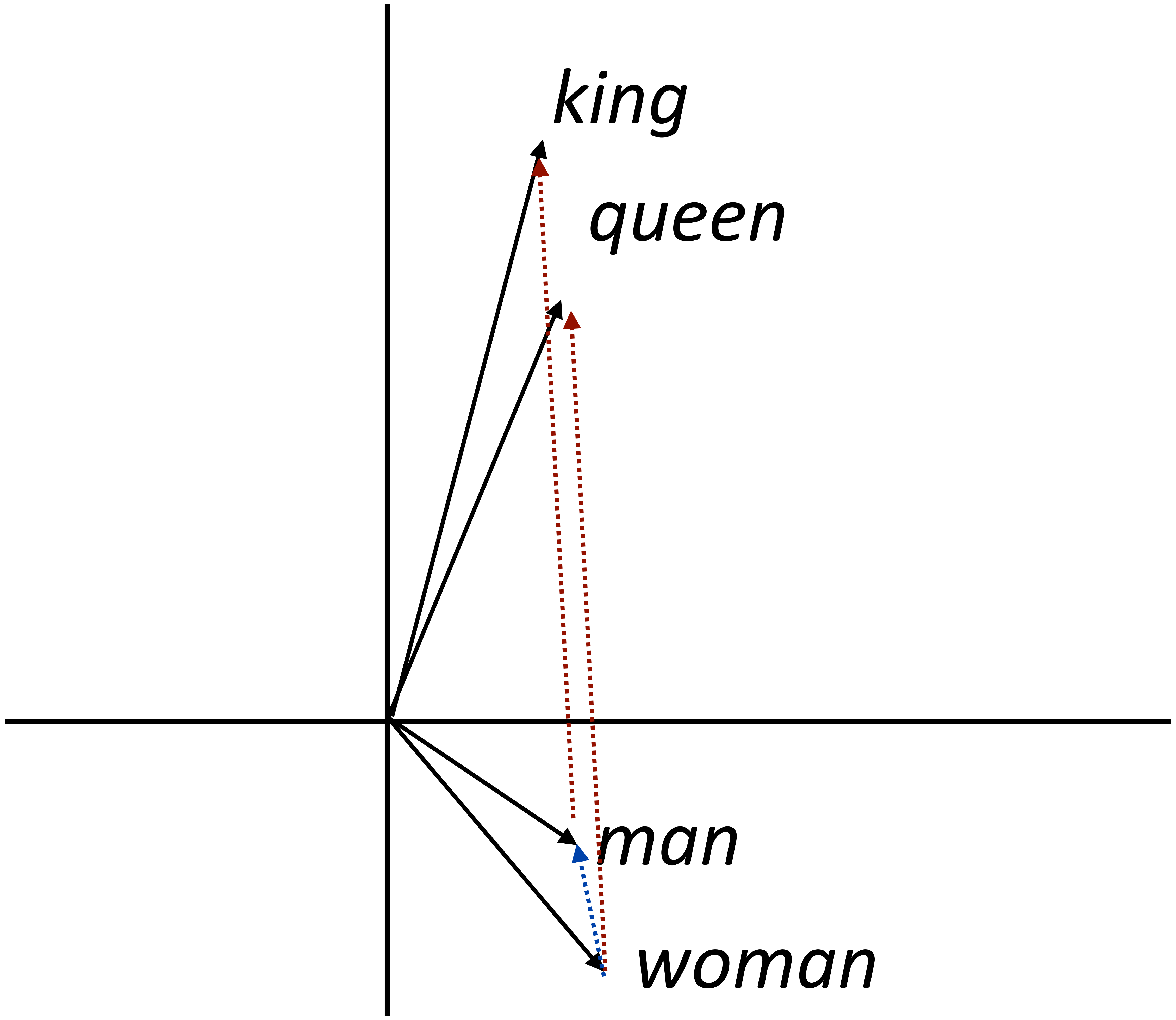

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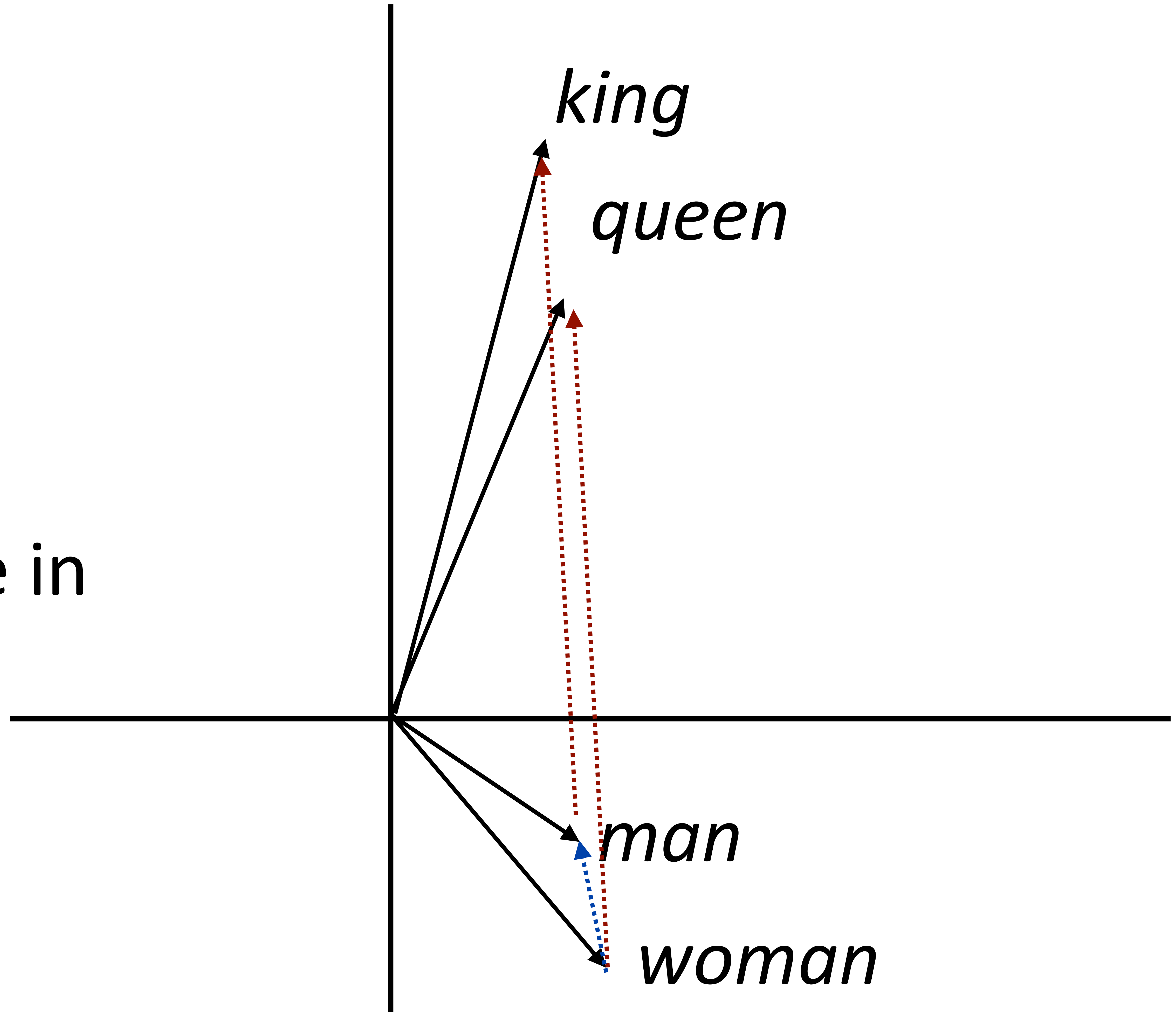

Analogies

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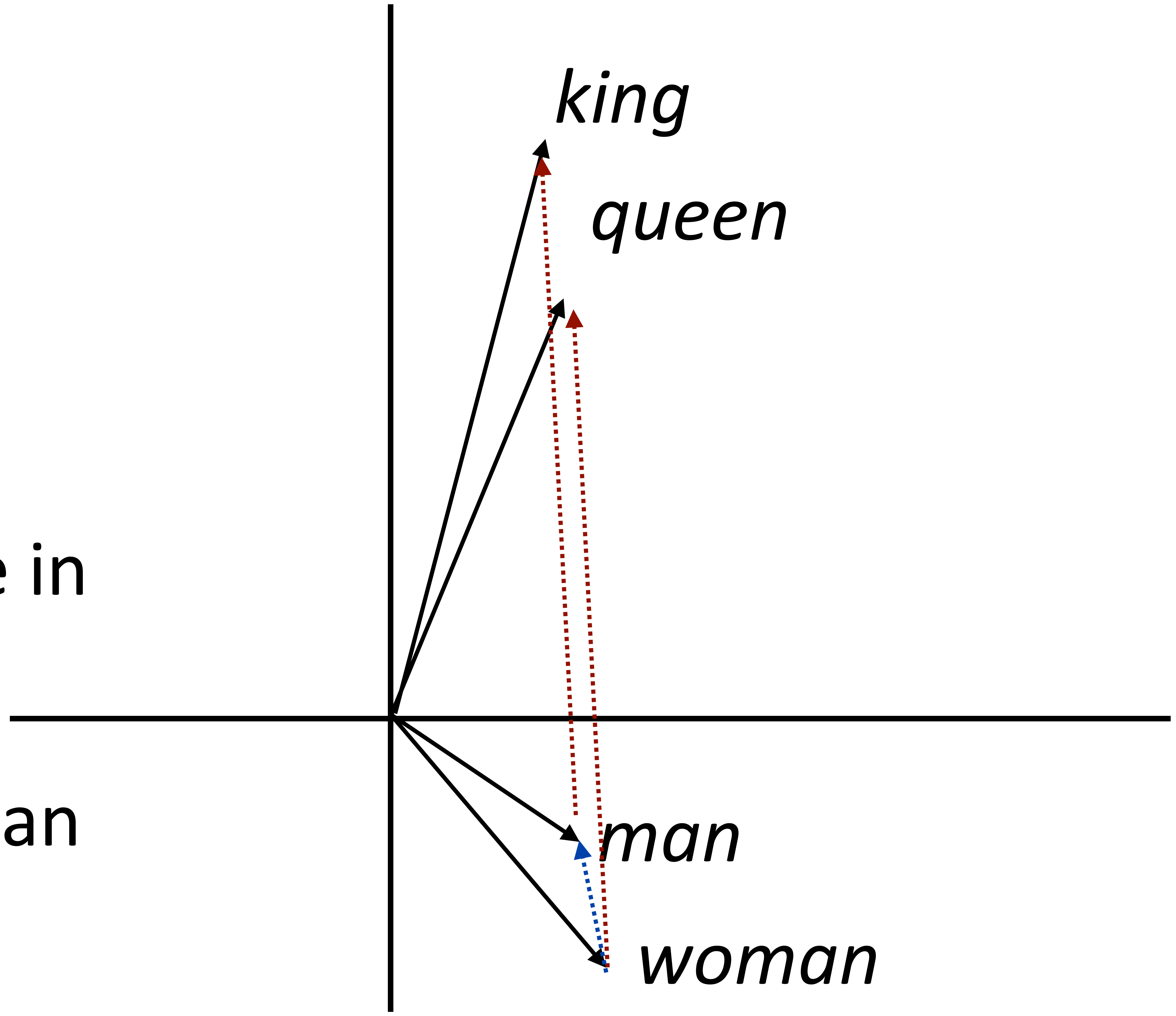
- Why would this be?
- woman - man captures the difference in the contexts that these occur in
- Dominant change: more “he” with man and “she” with woman — similar to difference between king and queen



Analogies

Method	Google Add / Mul	MSR Add / Mul
PPMI	.553 / .679	.306 / .535
SVD	.554 / .591	.408 / .468
SGNS	.676 / **.688**	.618 / **.645**
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Maximizing for *b*: Add = $\cos(b, a_2 - a_1 + b_1)$ Mul = $\dfrac{\cos(b_2, a_2)\cos(b_2, b_1)}{\cos(b_2, a_1) + \epsilon}$

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Using Word Embeddings

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- Approach 2: pretrain using GloVe, keep fixed
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  - 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

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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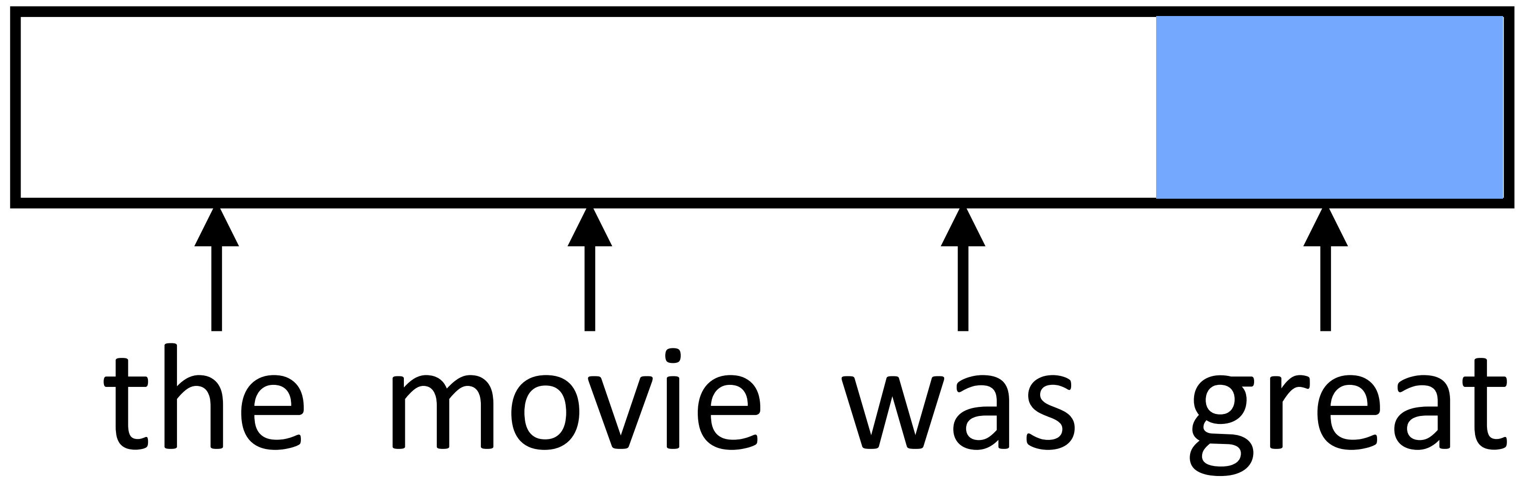

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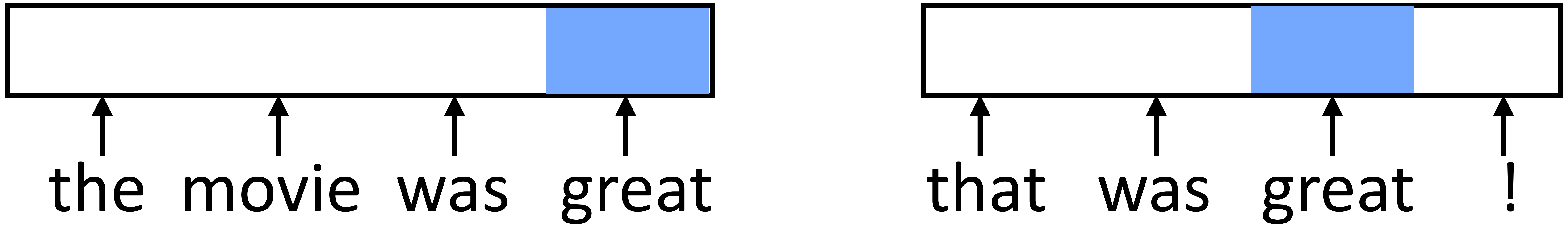

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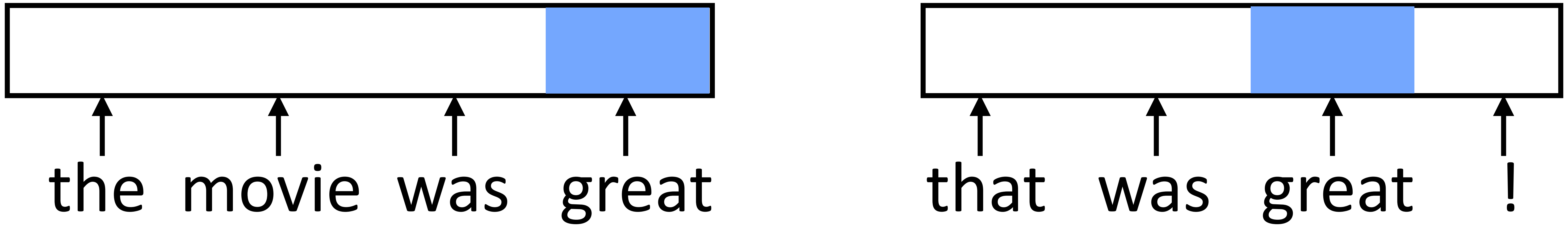

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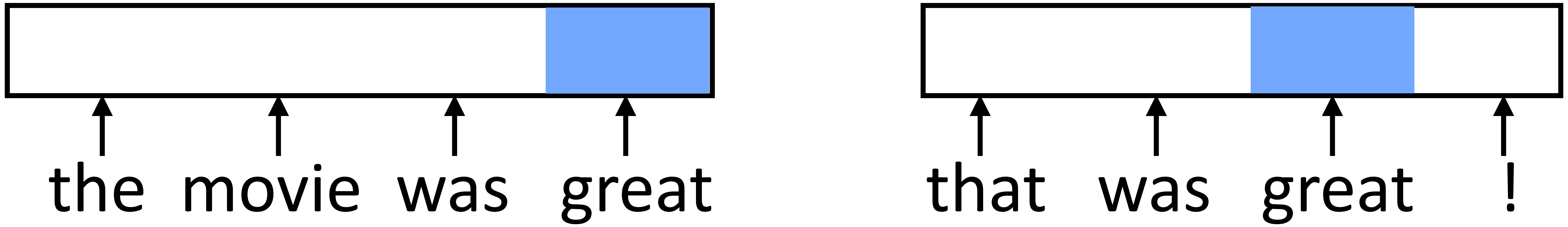

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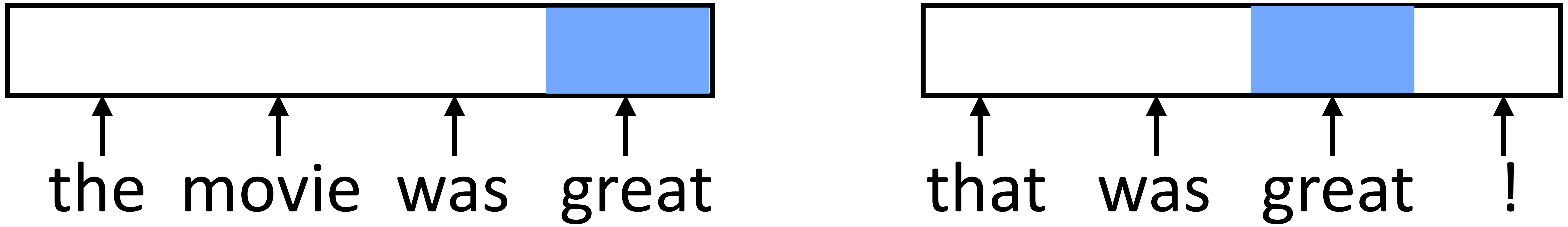

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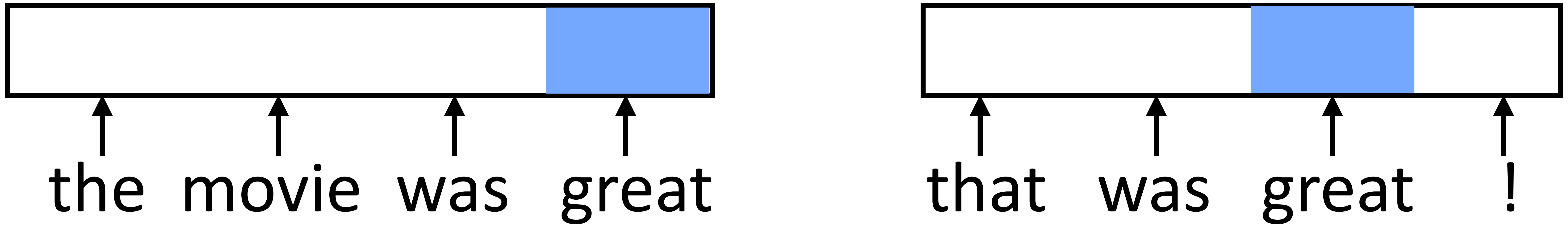


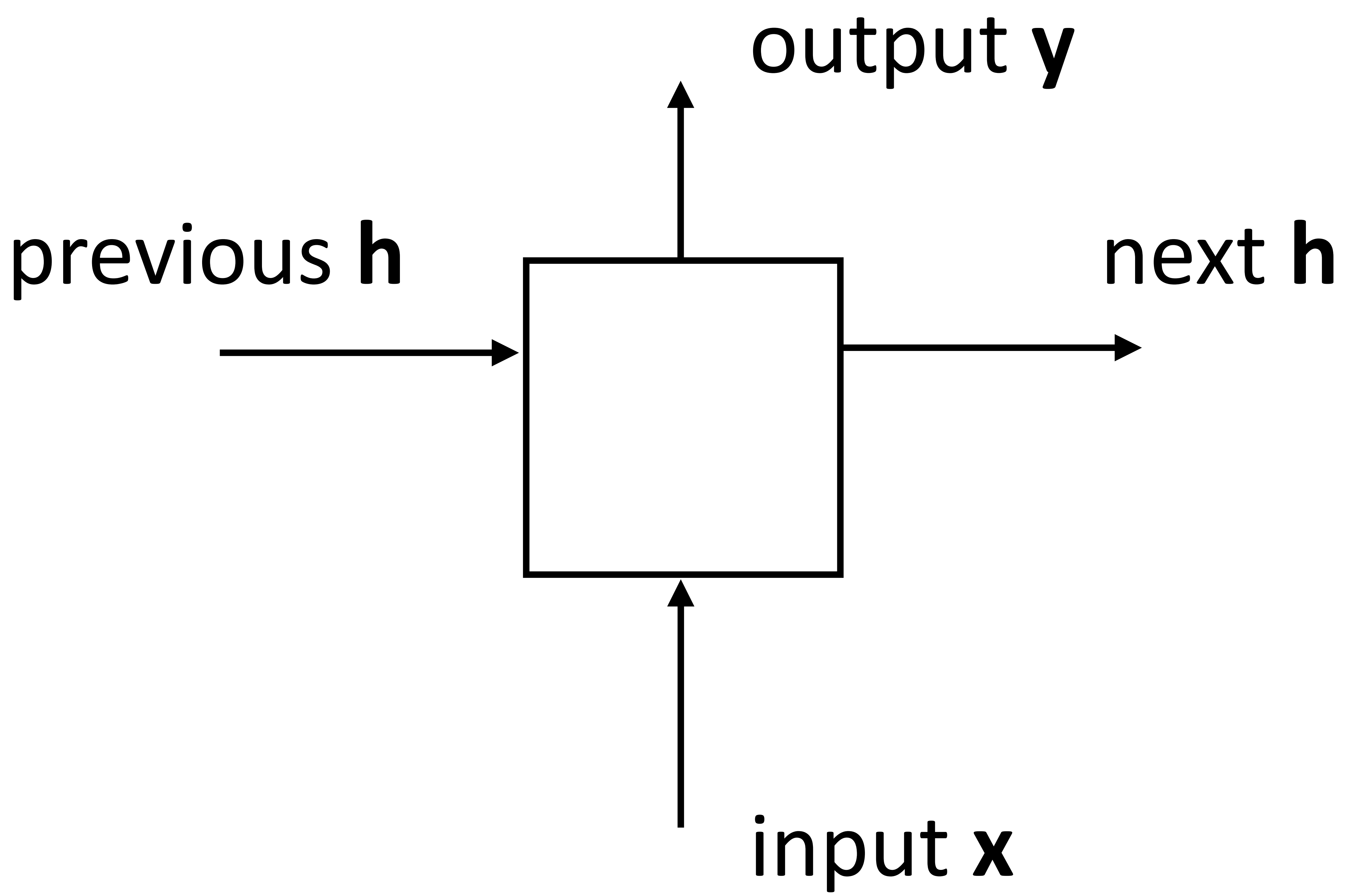
- These don’t look related (*great* is in two different orthogonal subspaces)
- Instead, we need to:

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



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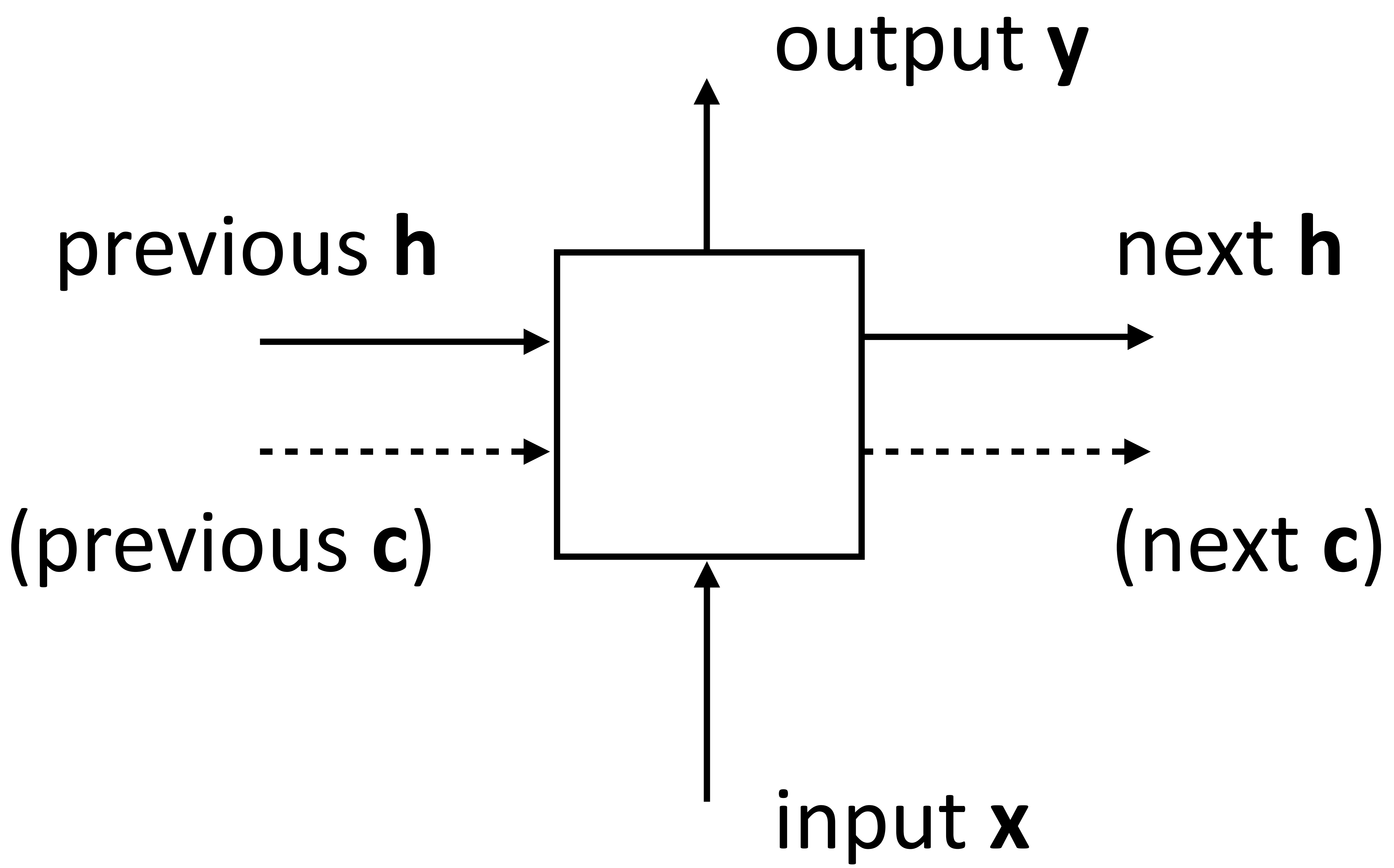
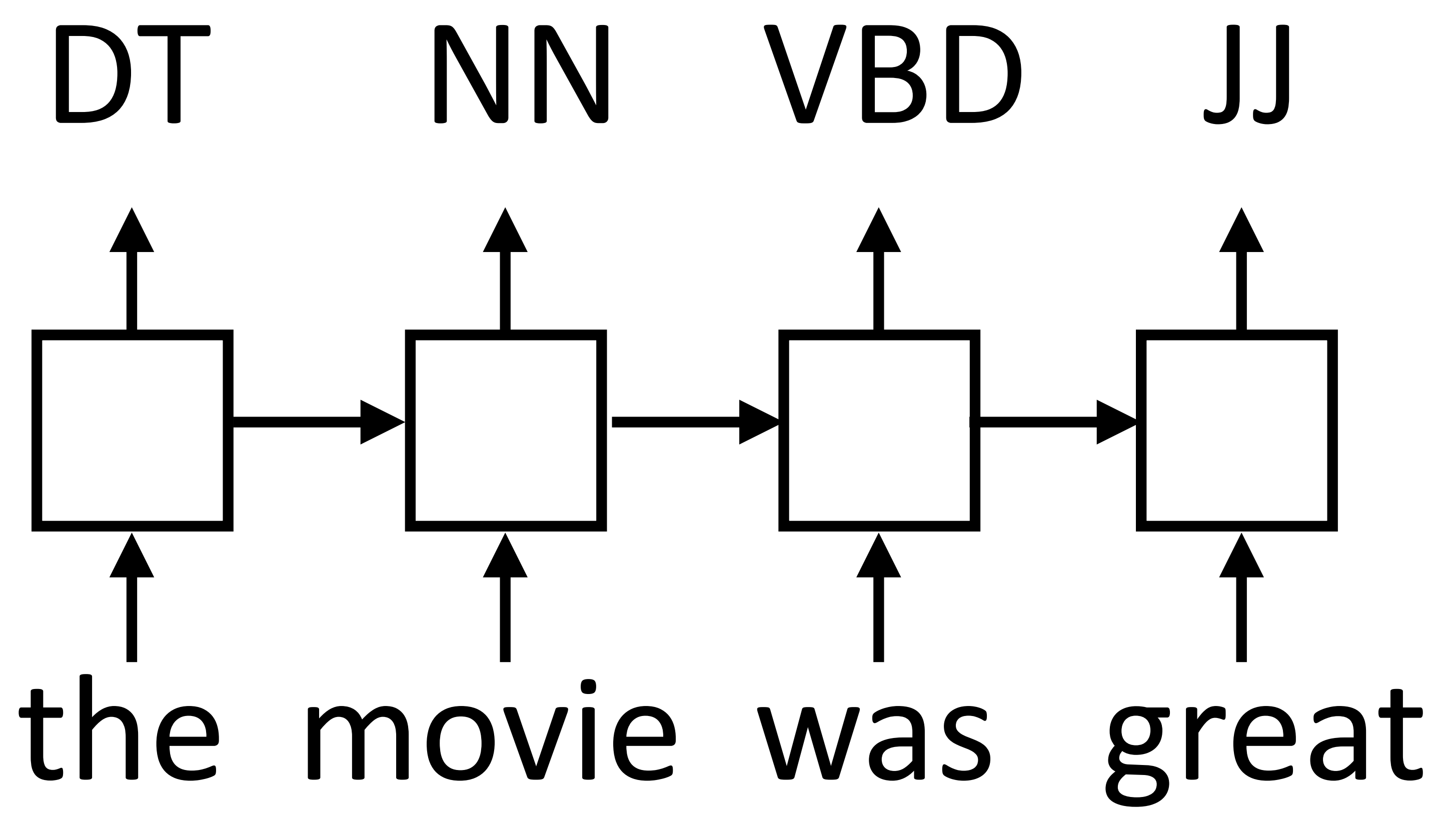


RNN Uses

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



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

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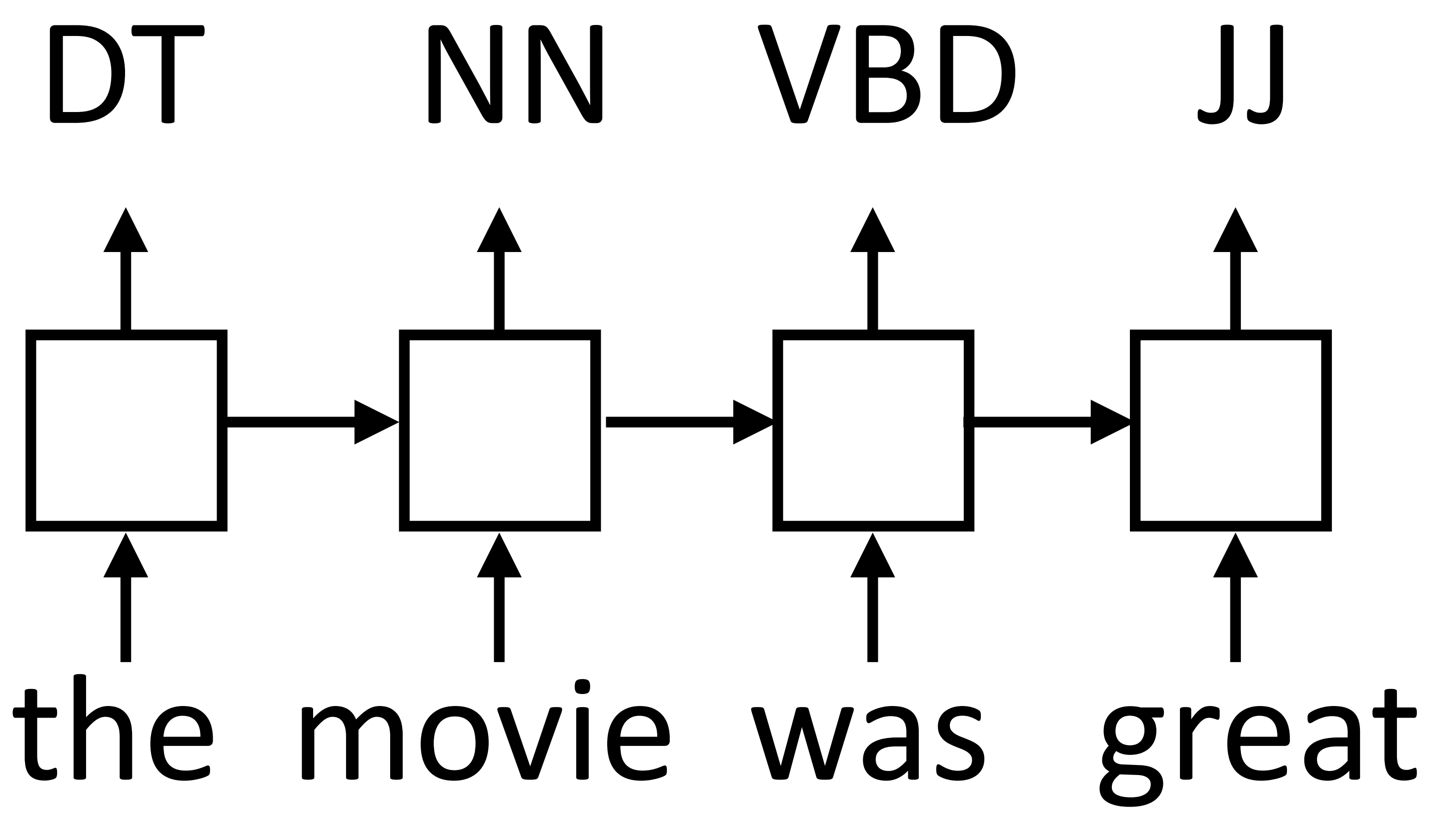

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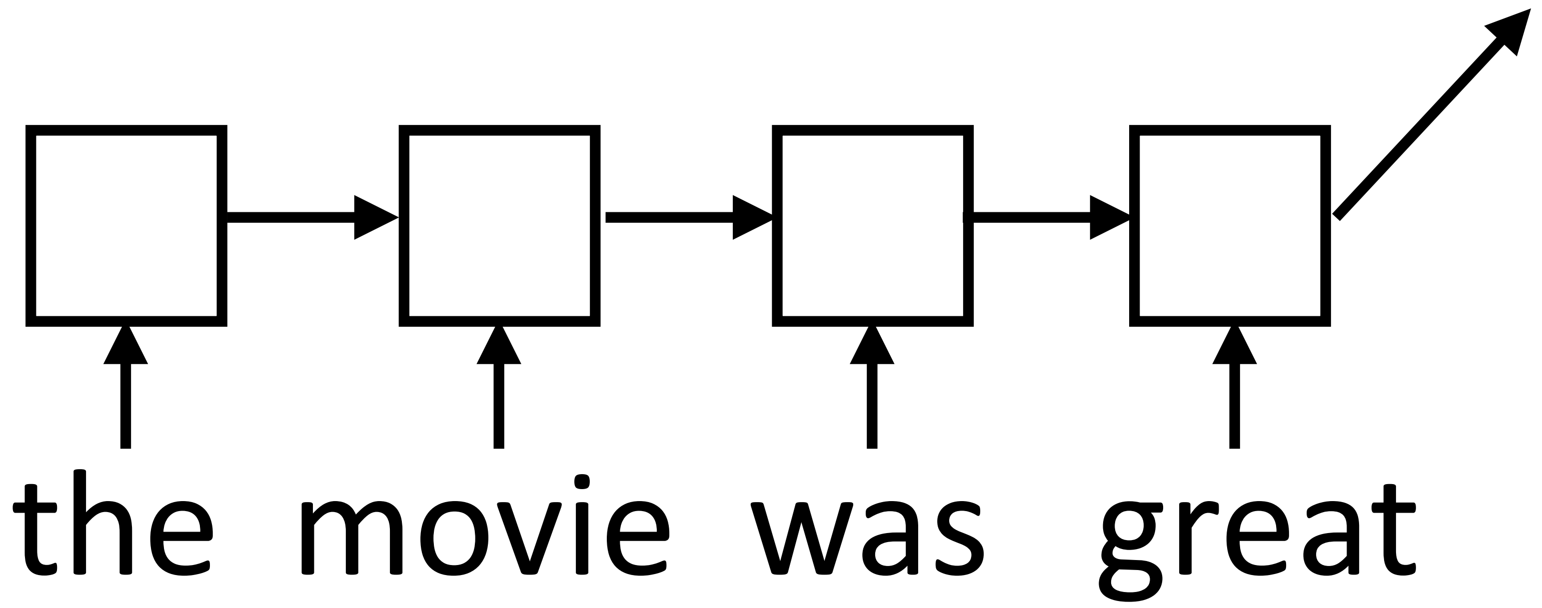
- Acceptor/encoder: encode a sequence into a fixed-sized vector and use that for some purpose

predict sentiment (matmul + softmax)



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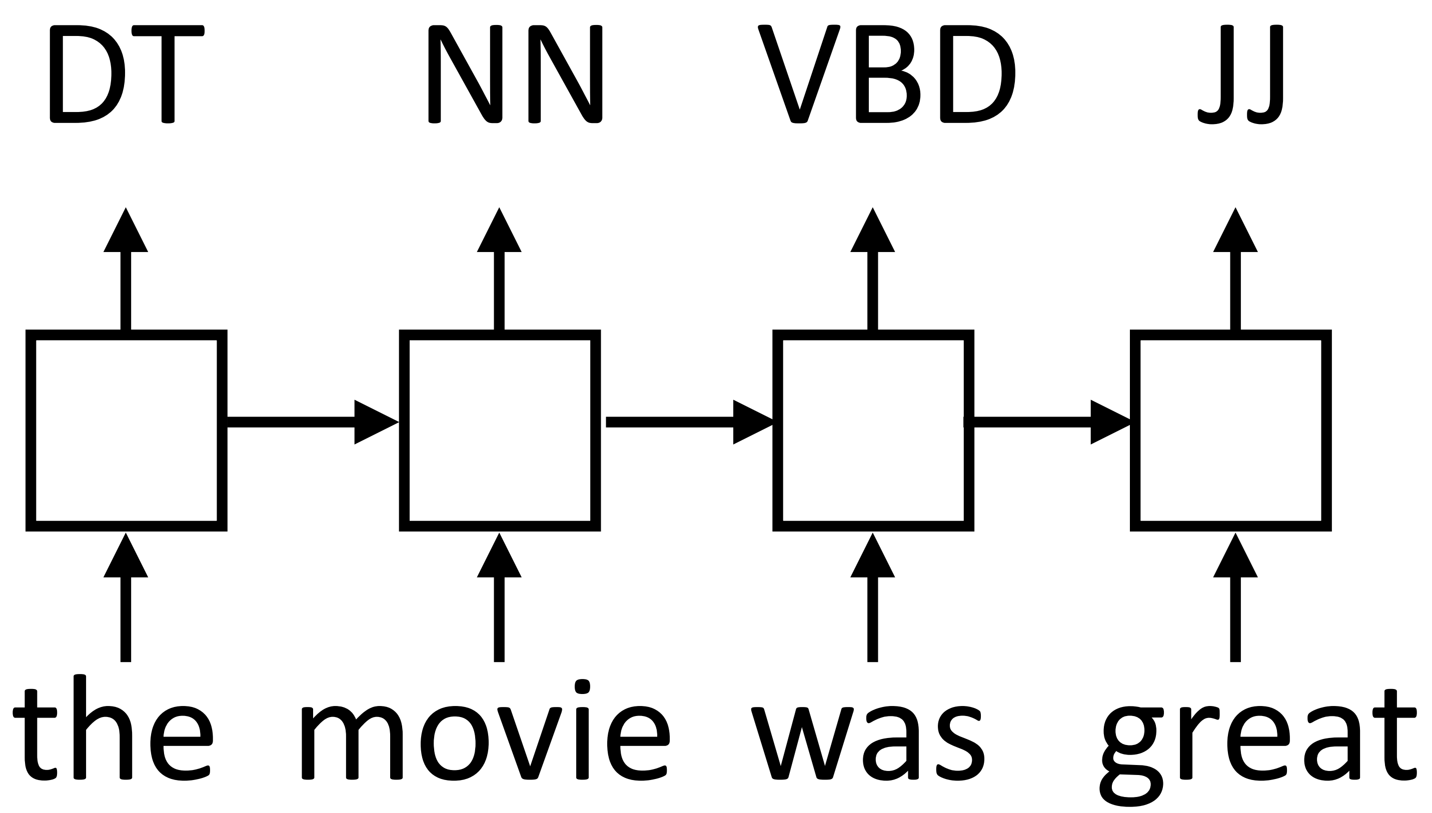

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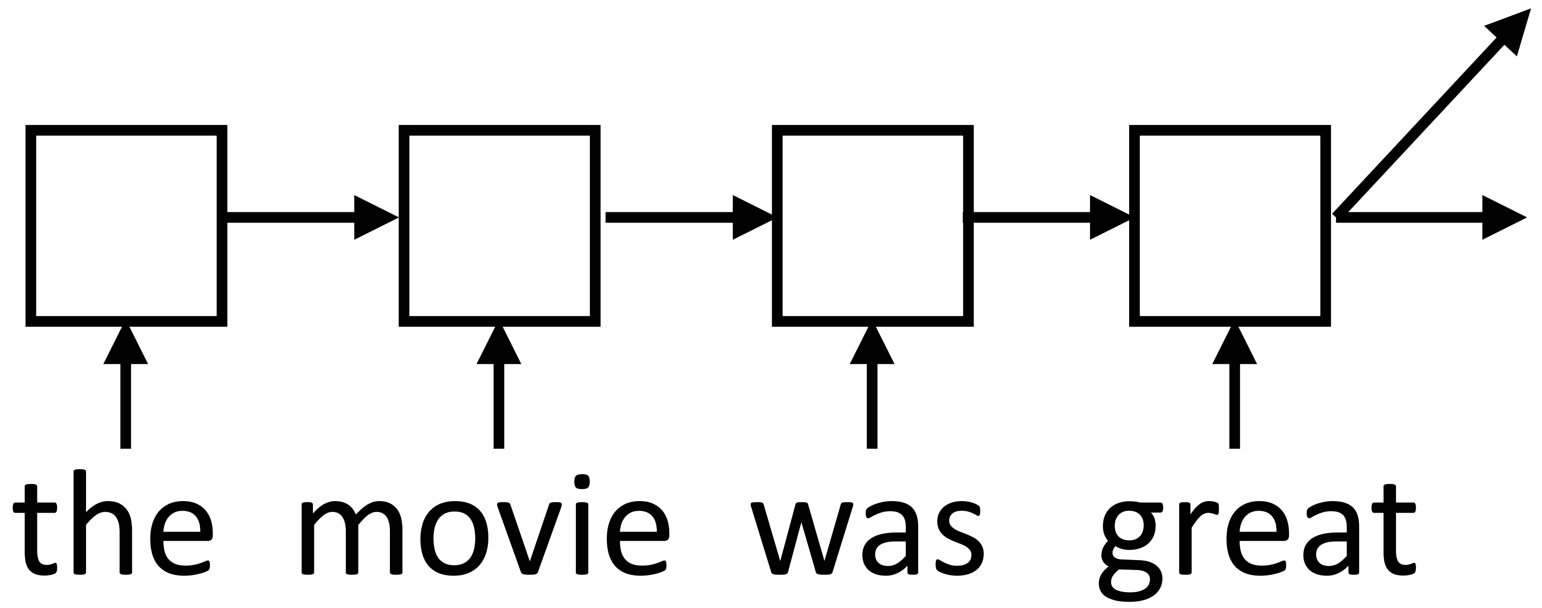

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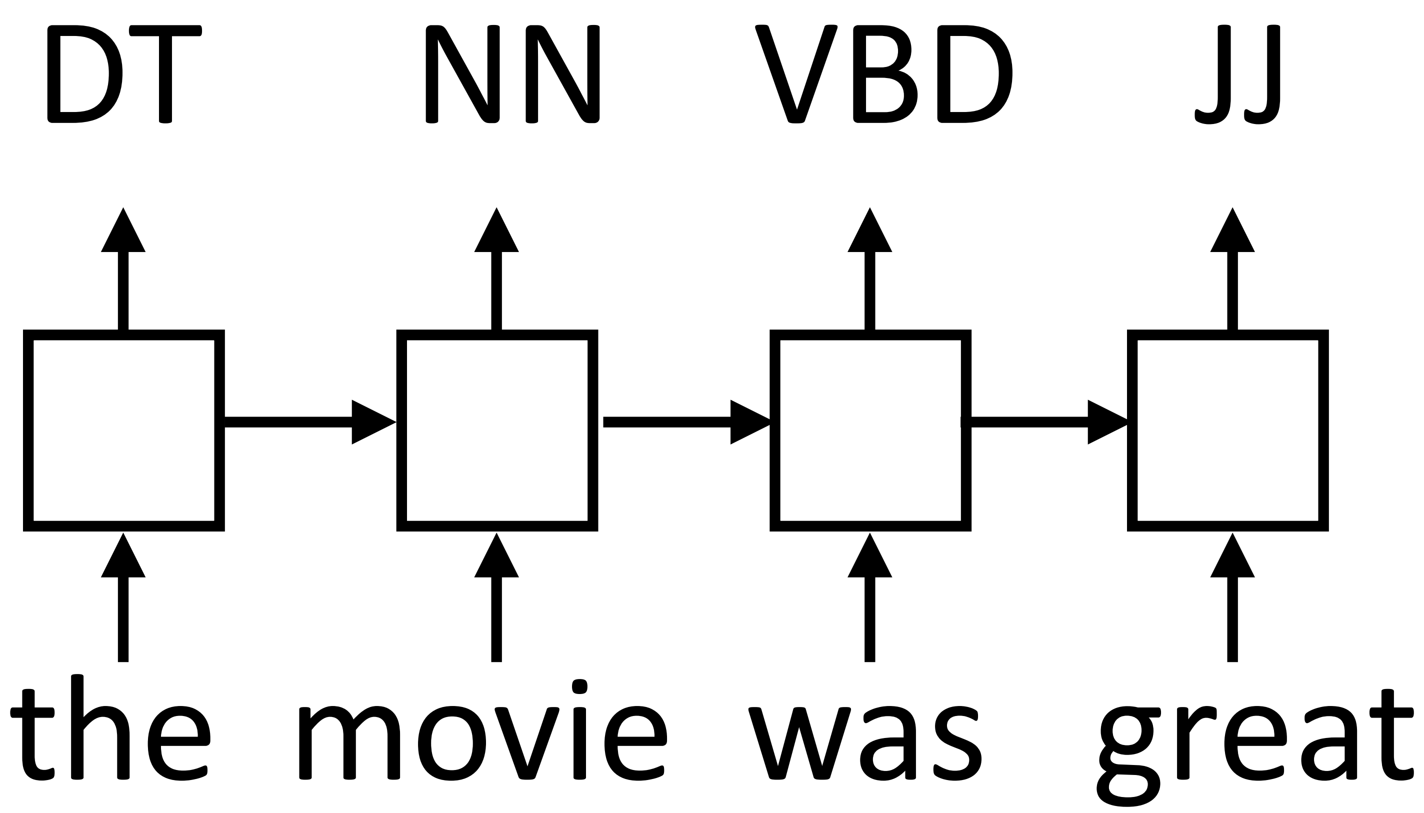

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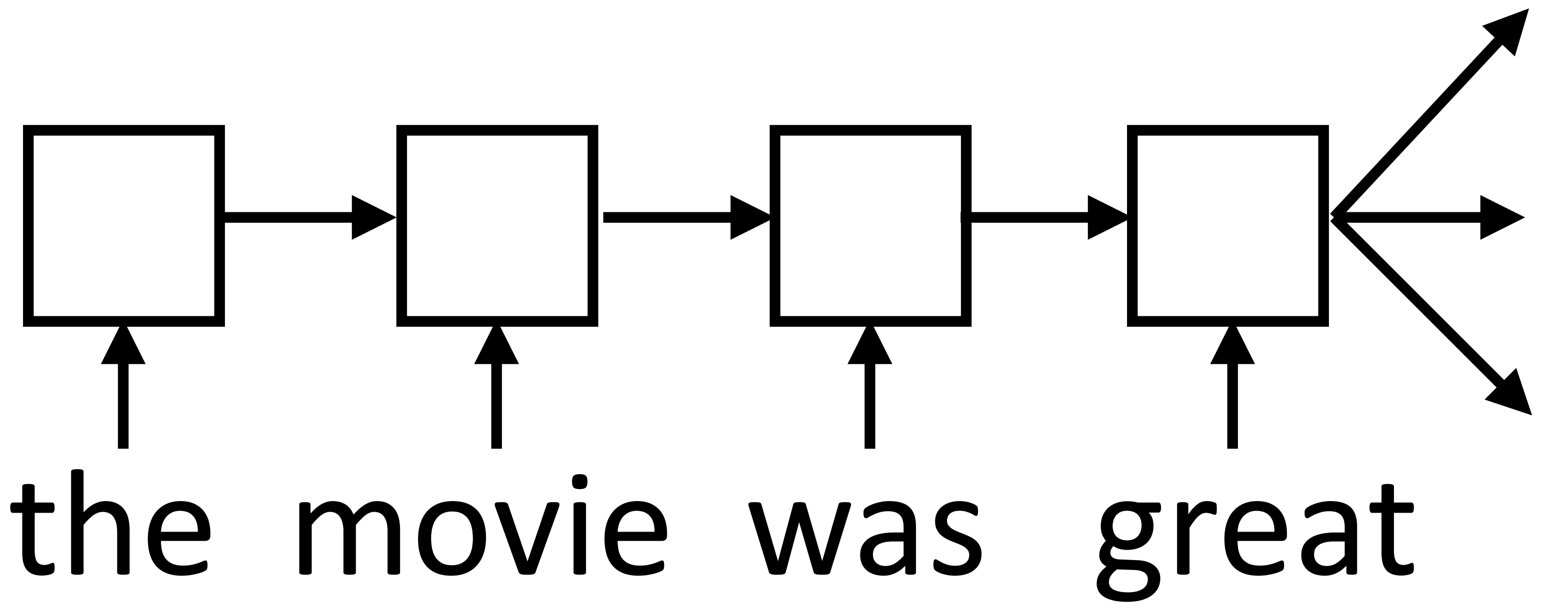

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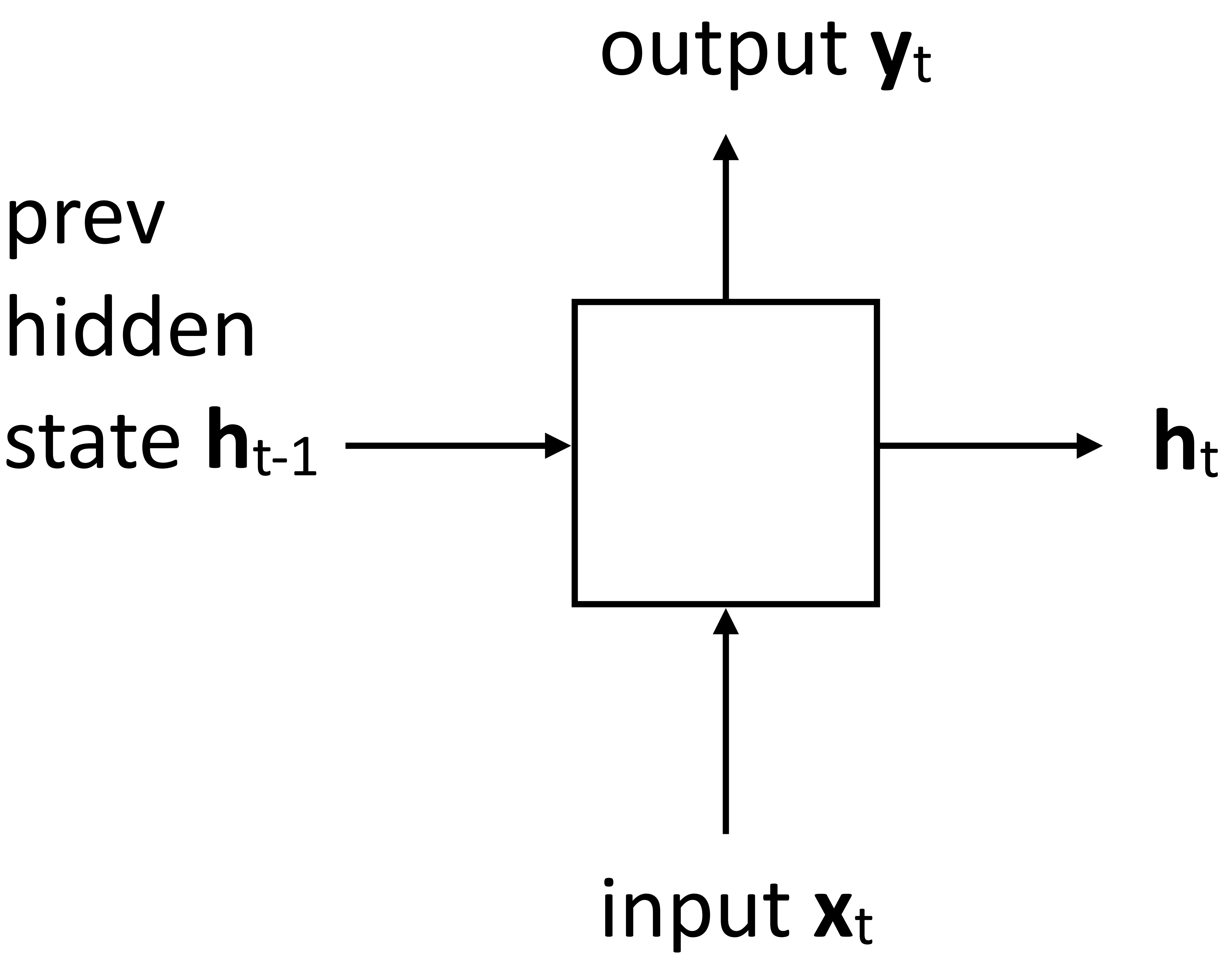
translate

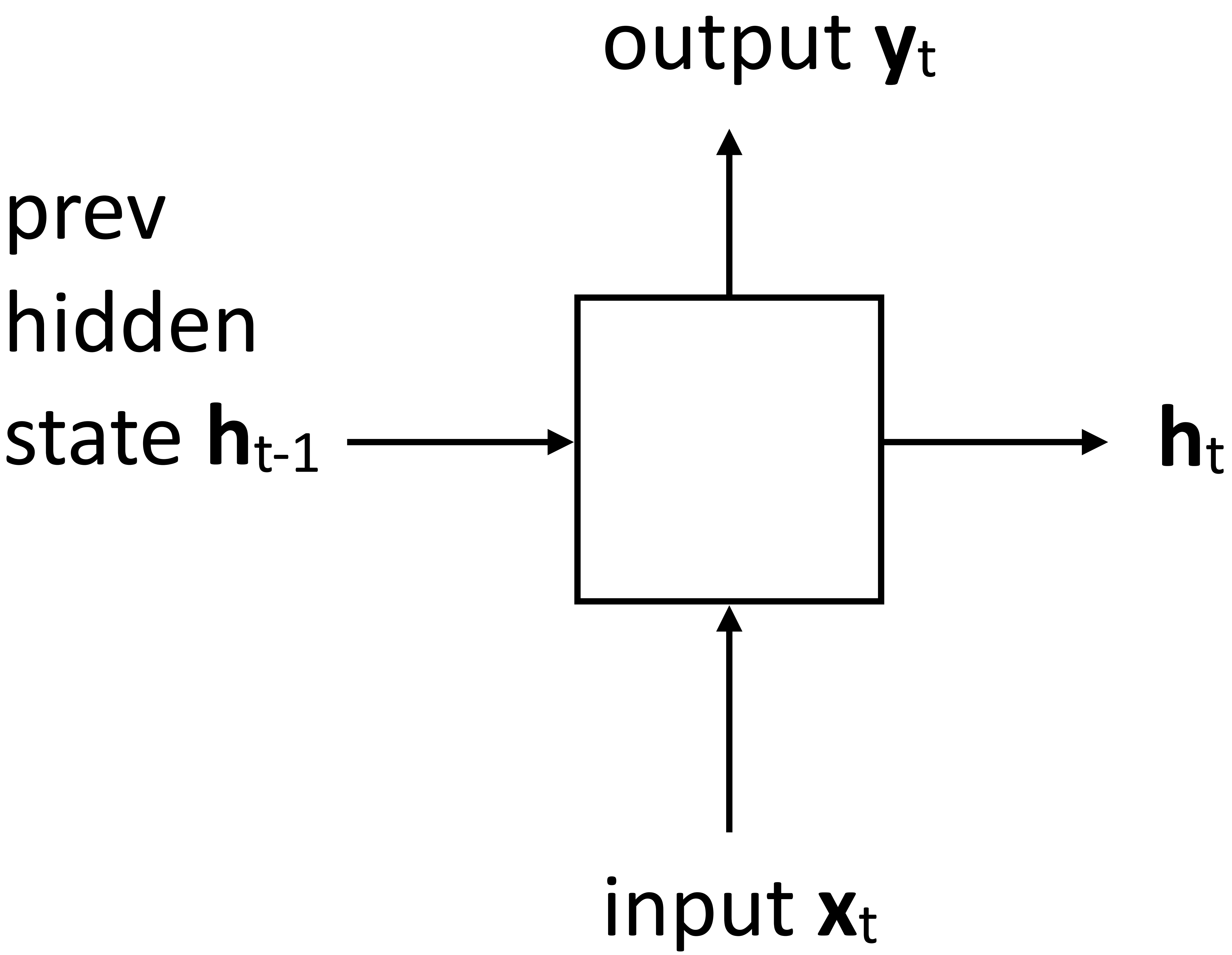
paraphrase/compress

Elman Networks



Elman (1990)

Elman Networks



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- Updates hidden state based on input and current hidden state

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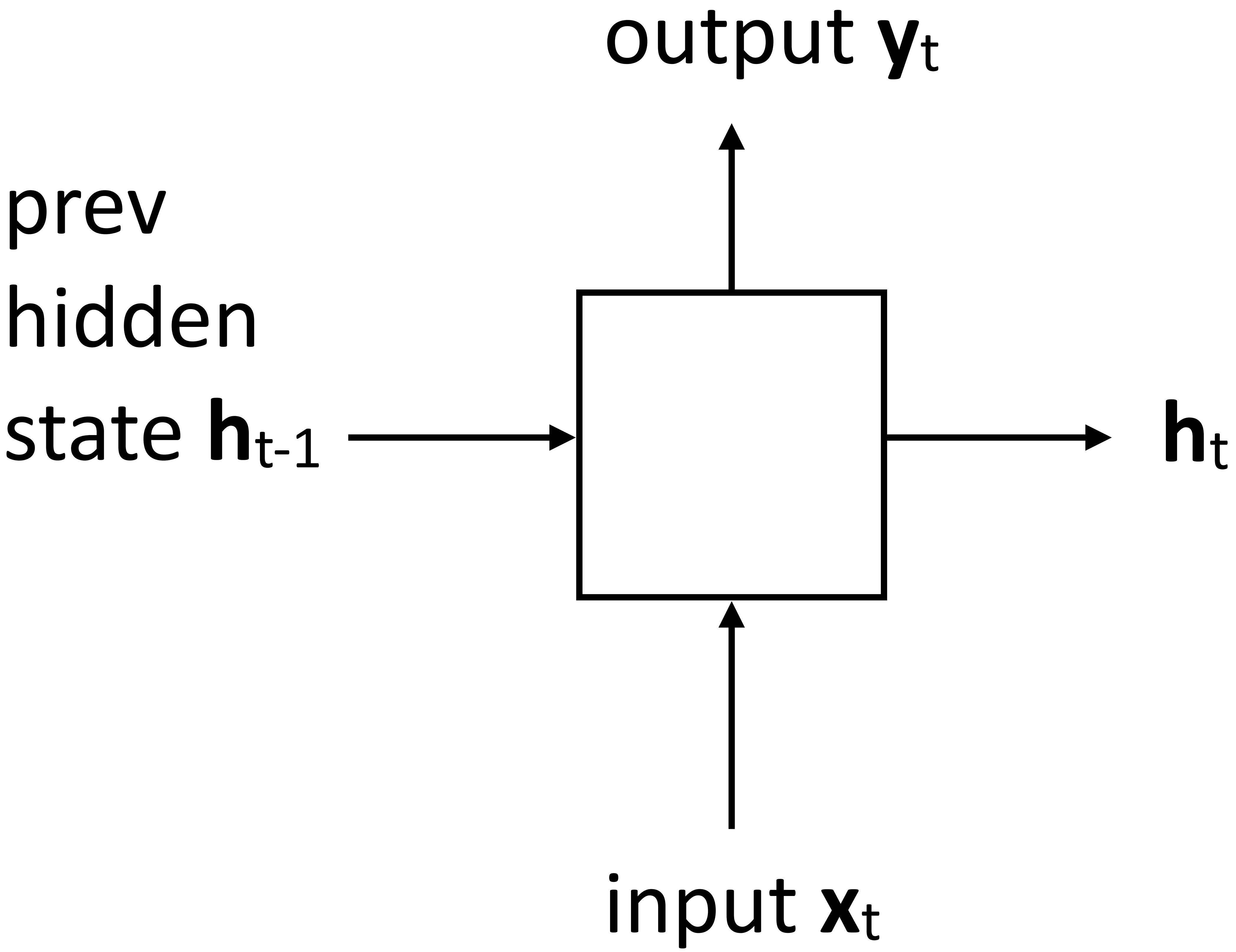

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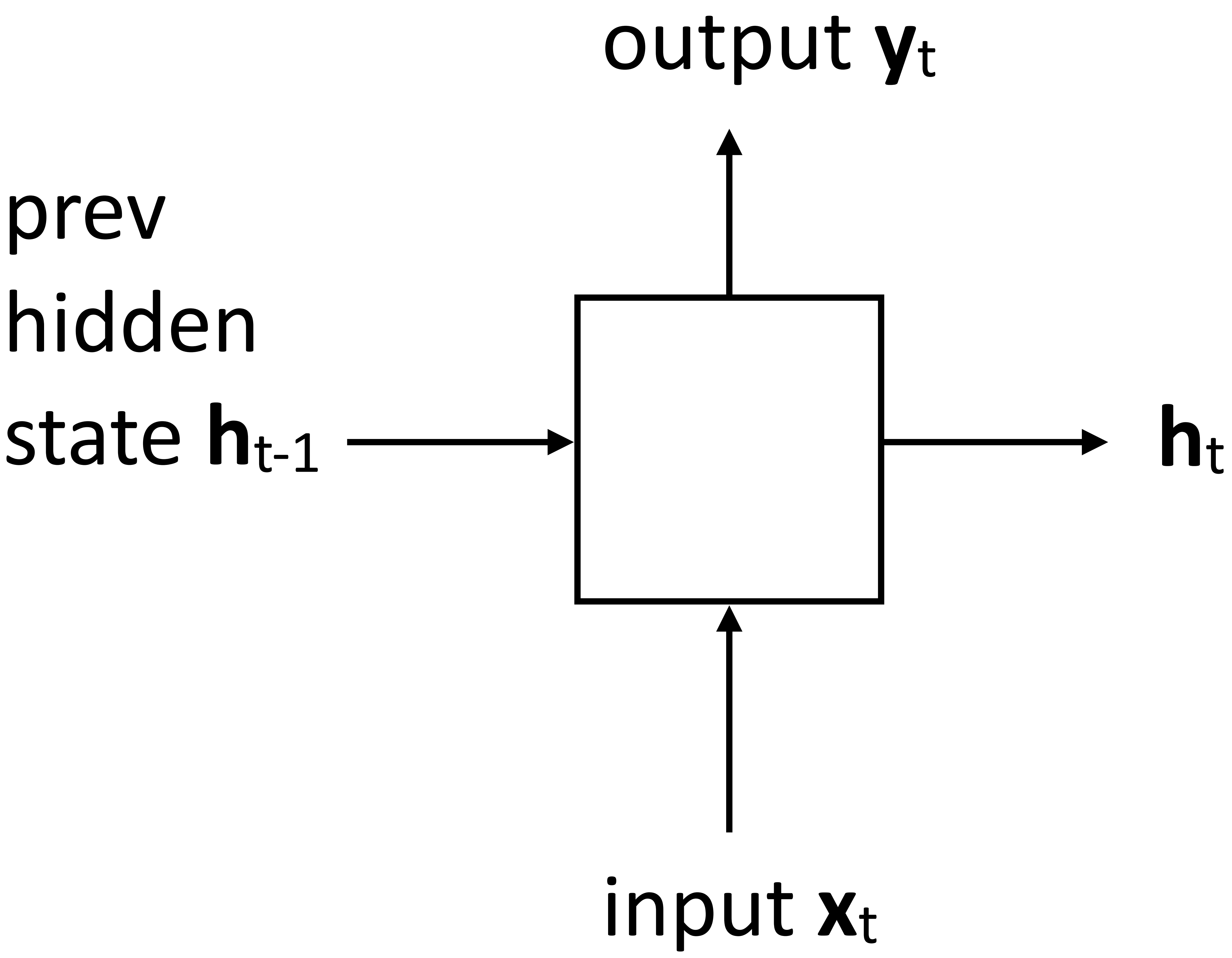

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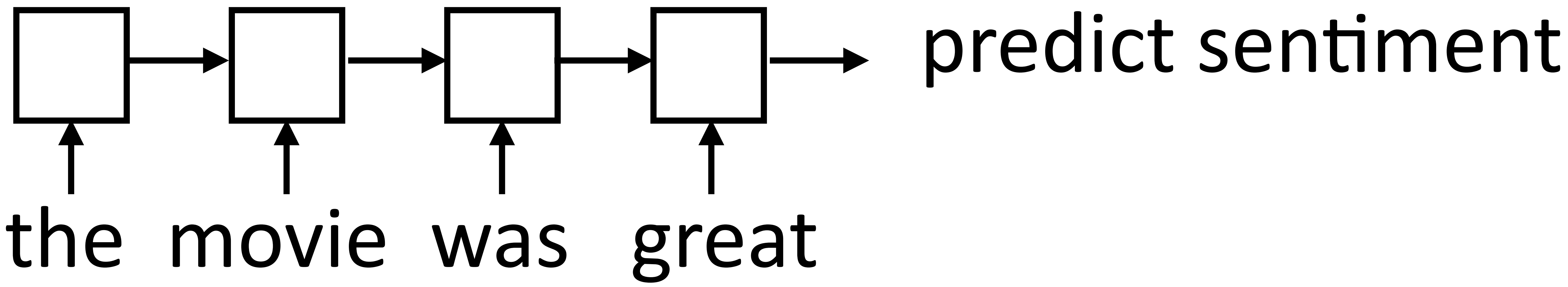
- Long history! (invented in the late 1980s)

Elman (1990)

Training Elman Networks



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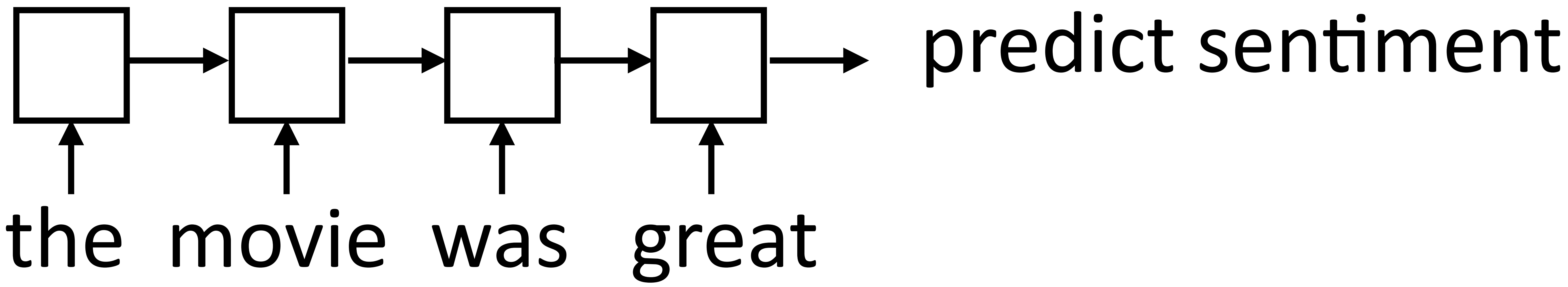

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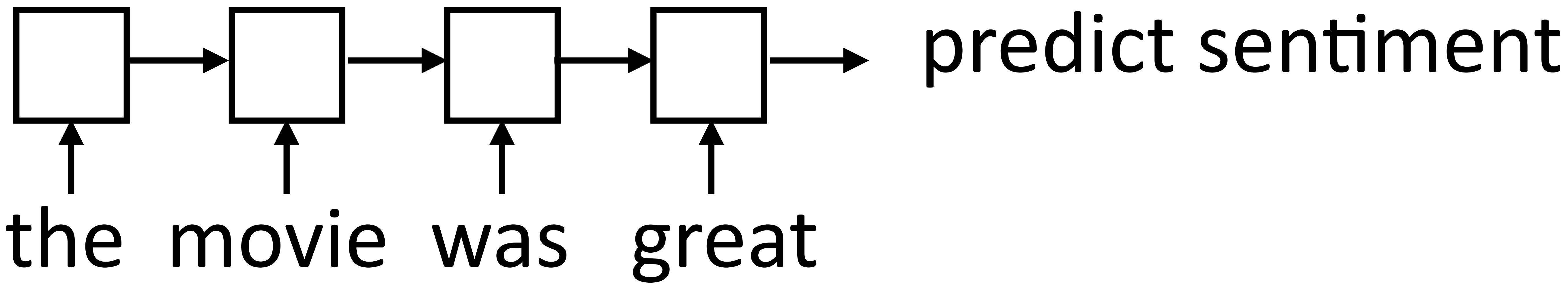

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- RNN potentially needs to learn how to "remember" information for a long time!

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

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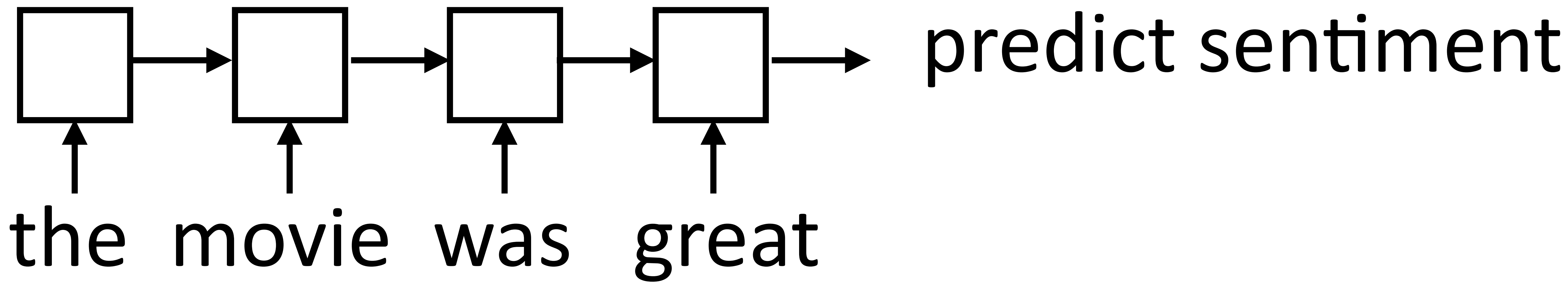

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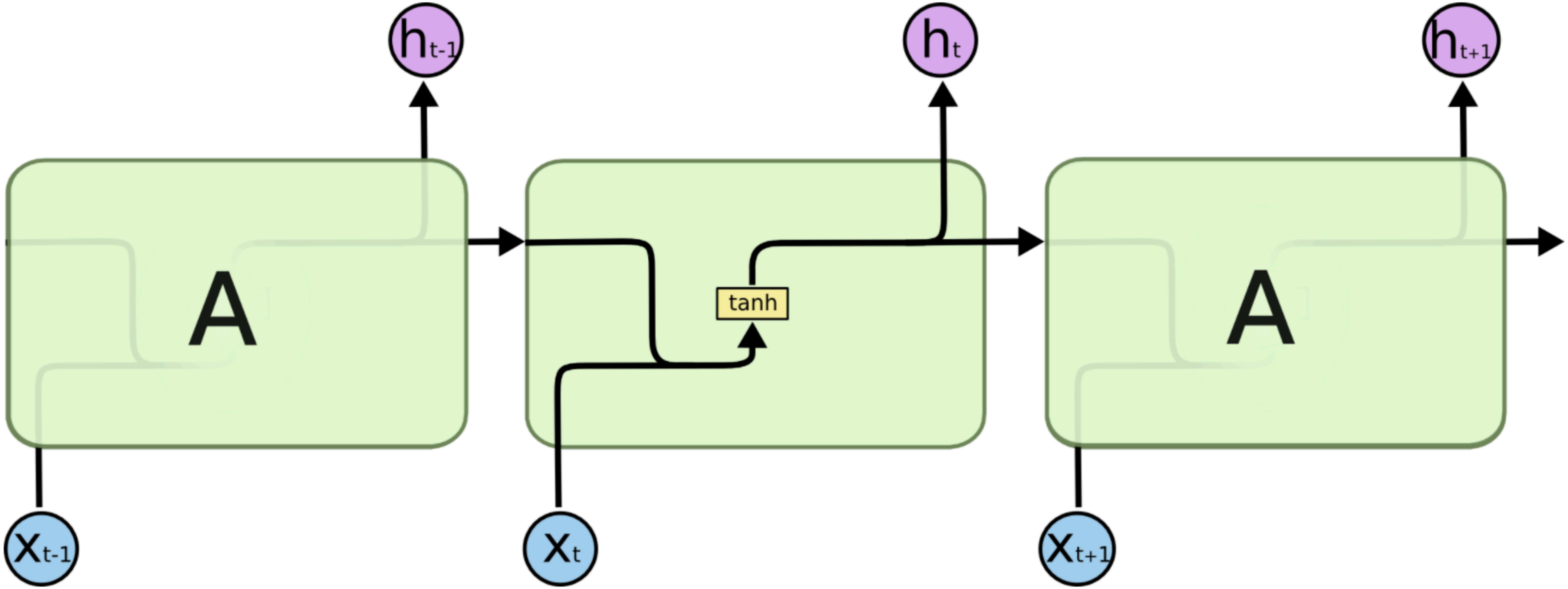
- "Correct" parameter update is to do a better job of remembering the sentiment of *favorite*

Vanishing Gradient



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

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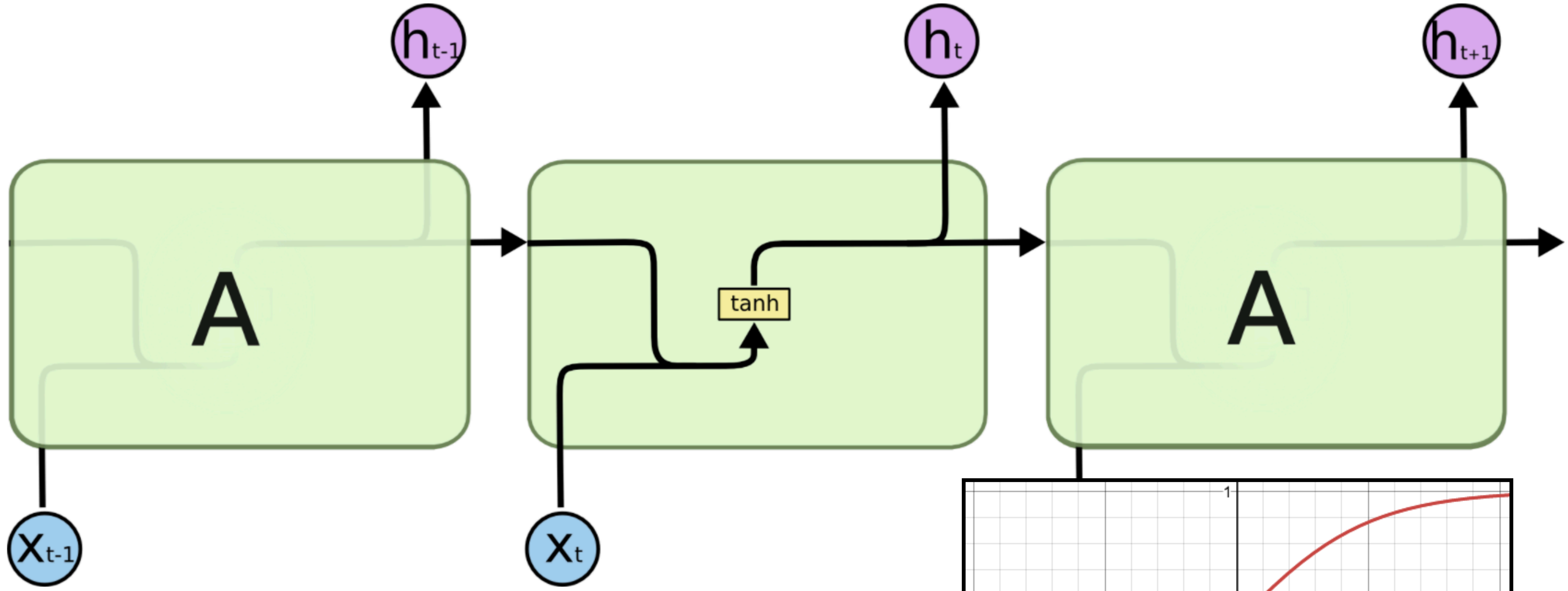

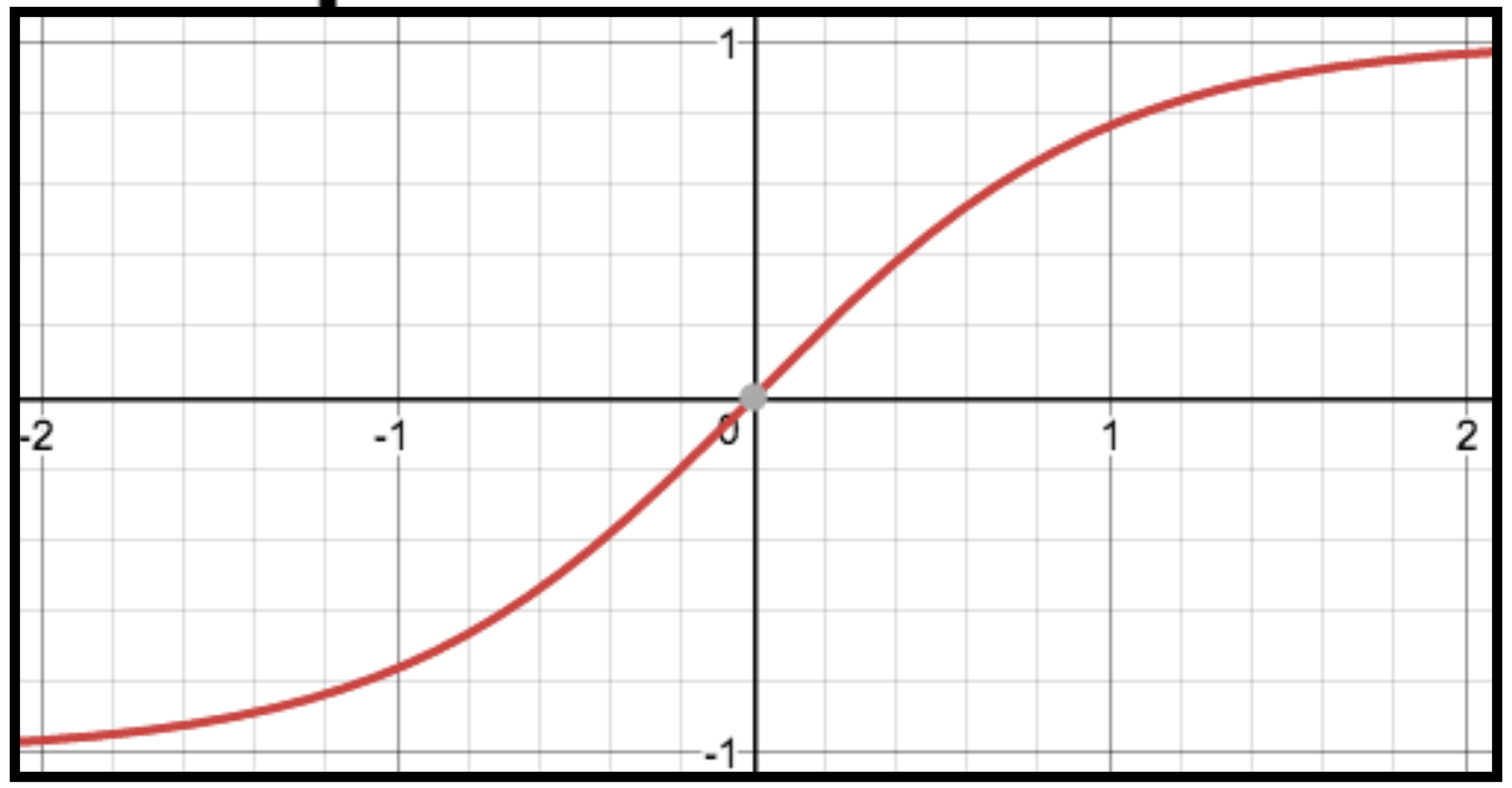

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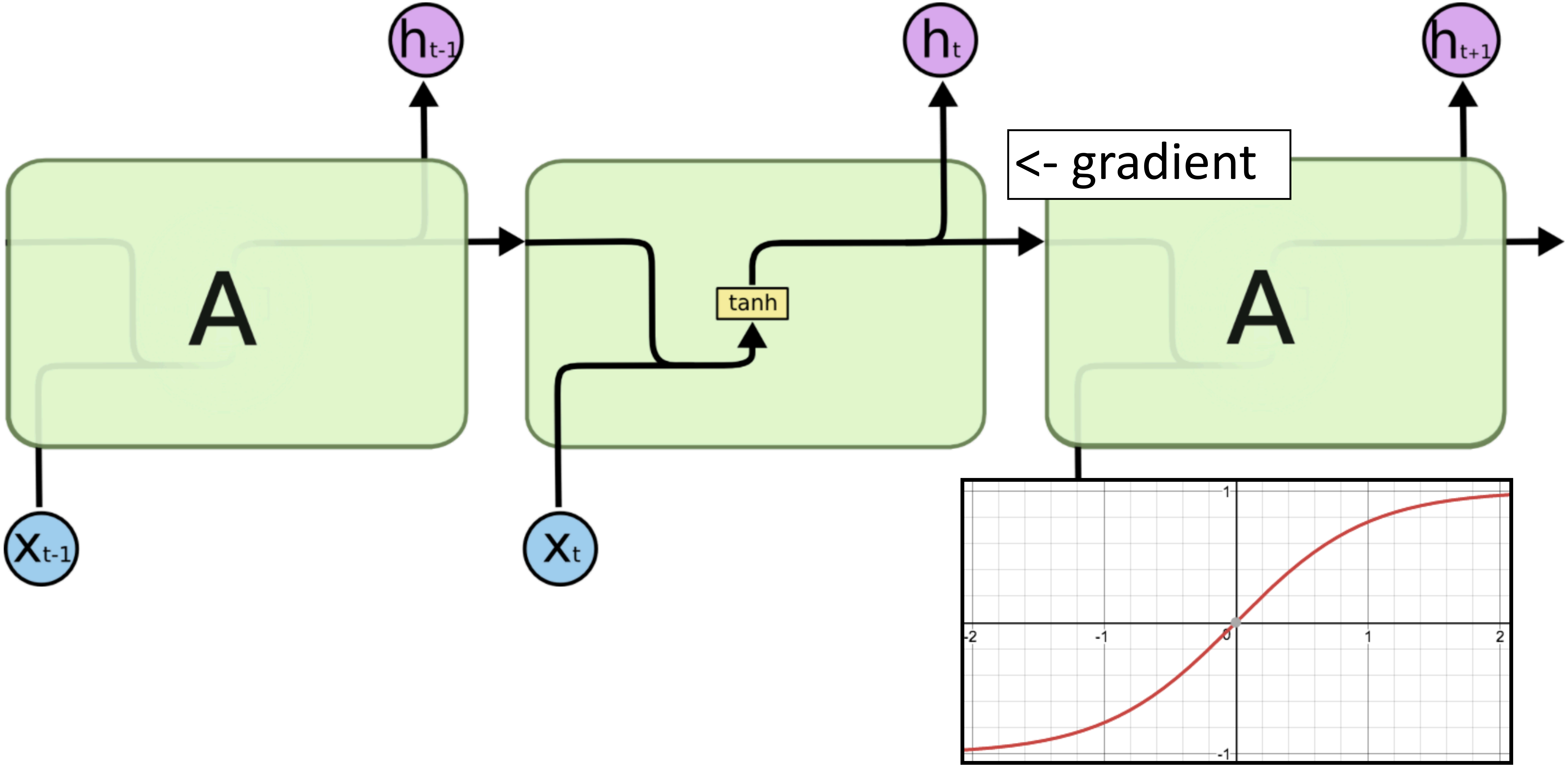

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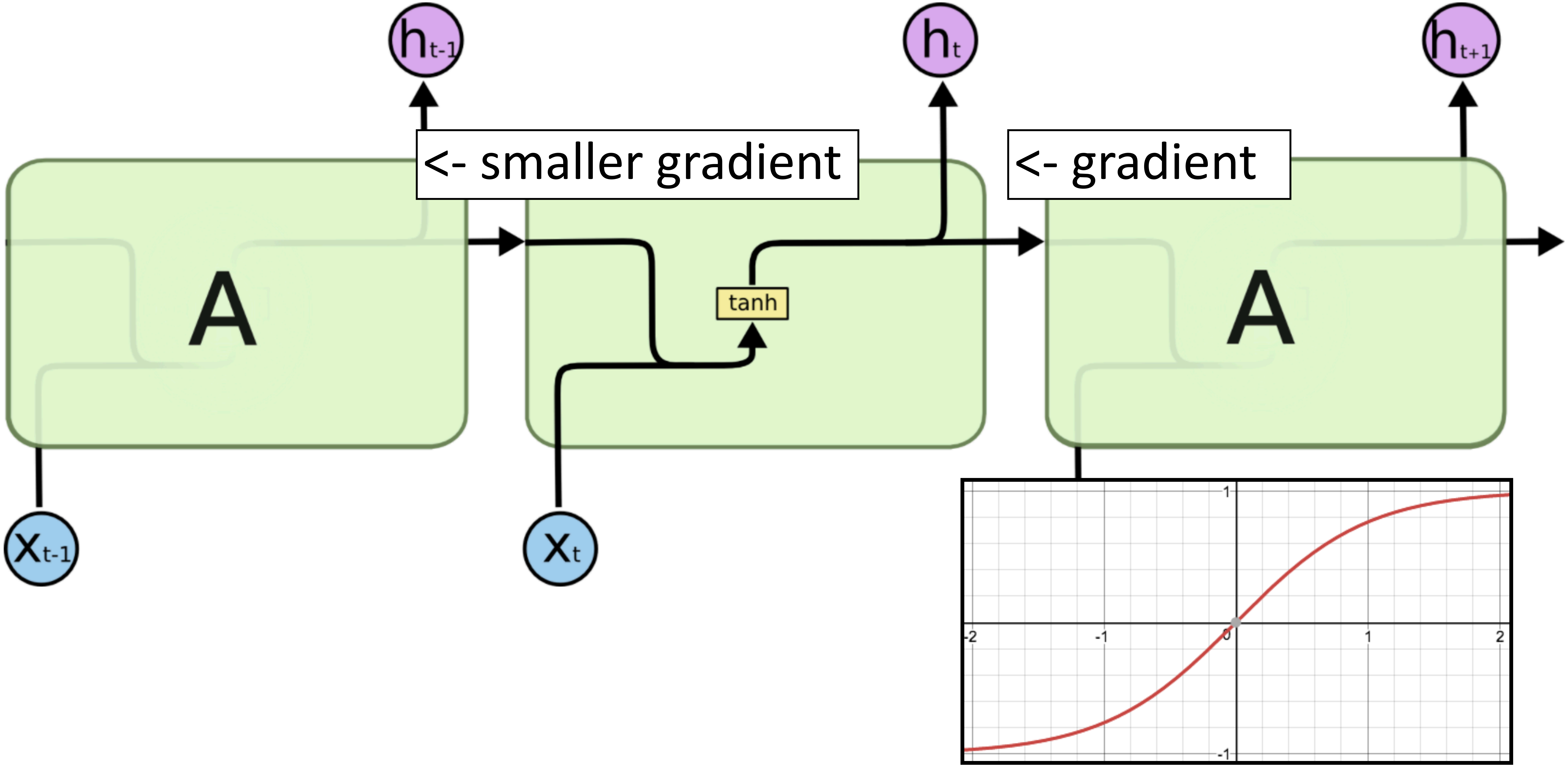

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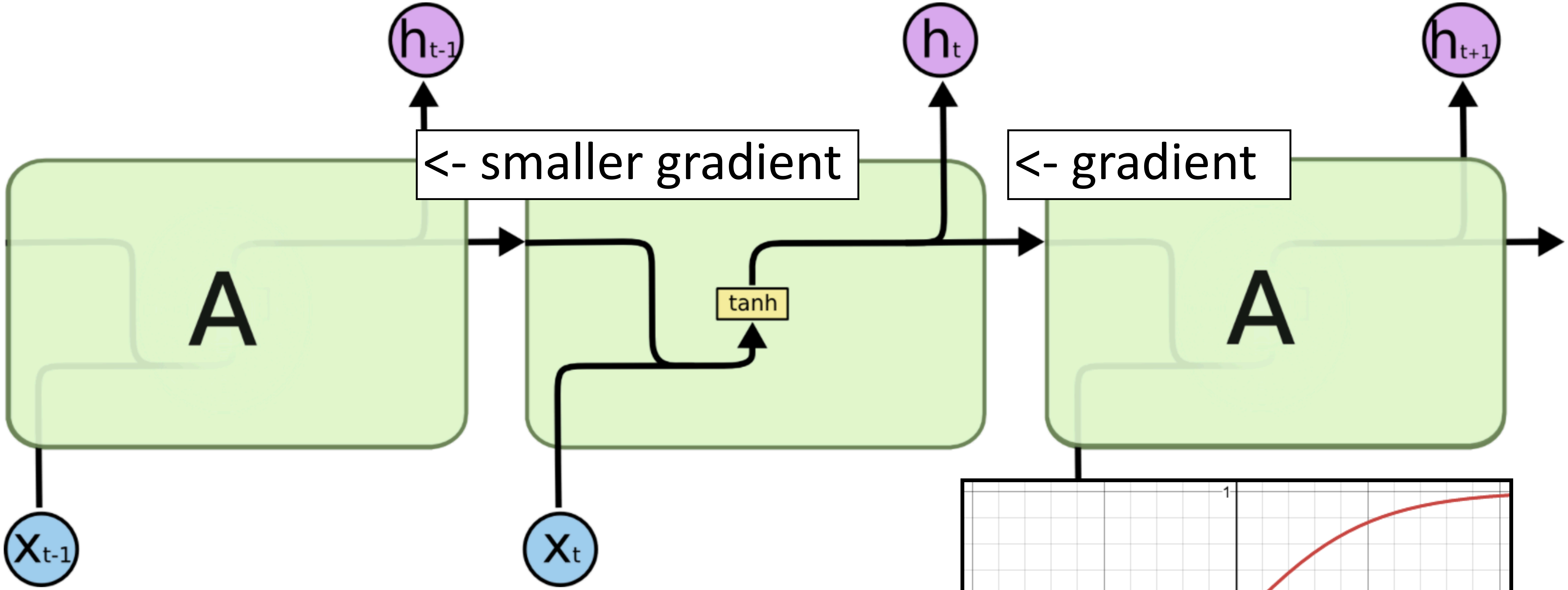

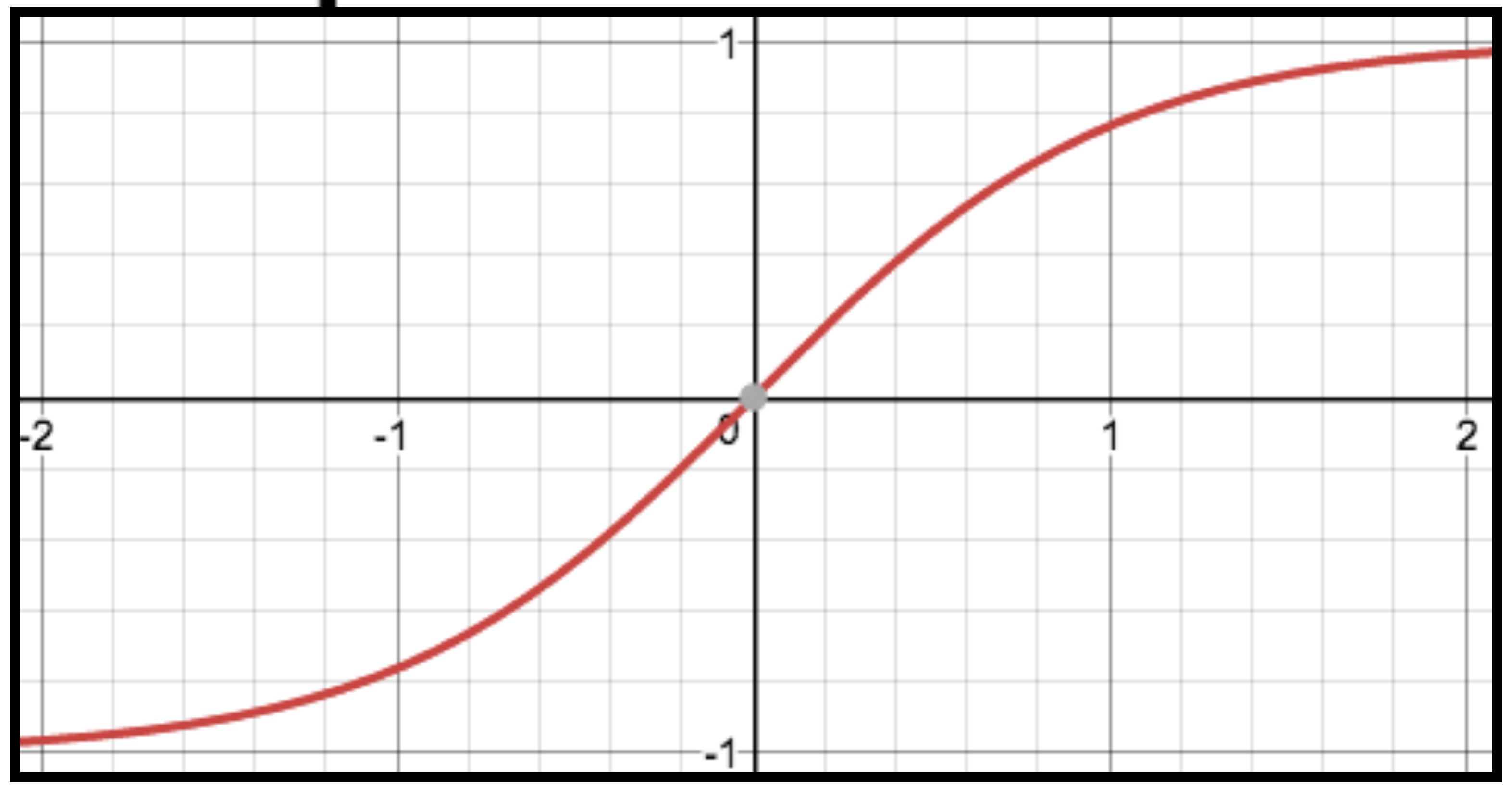

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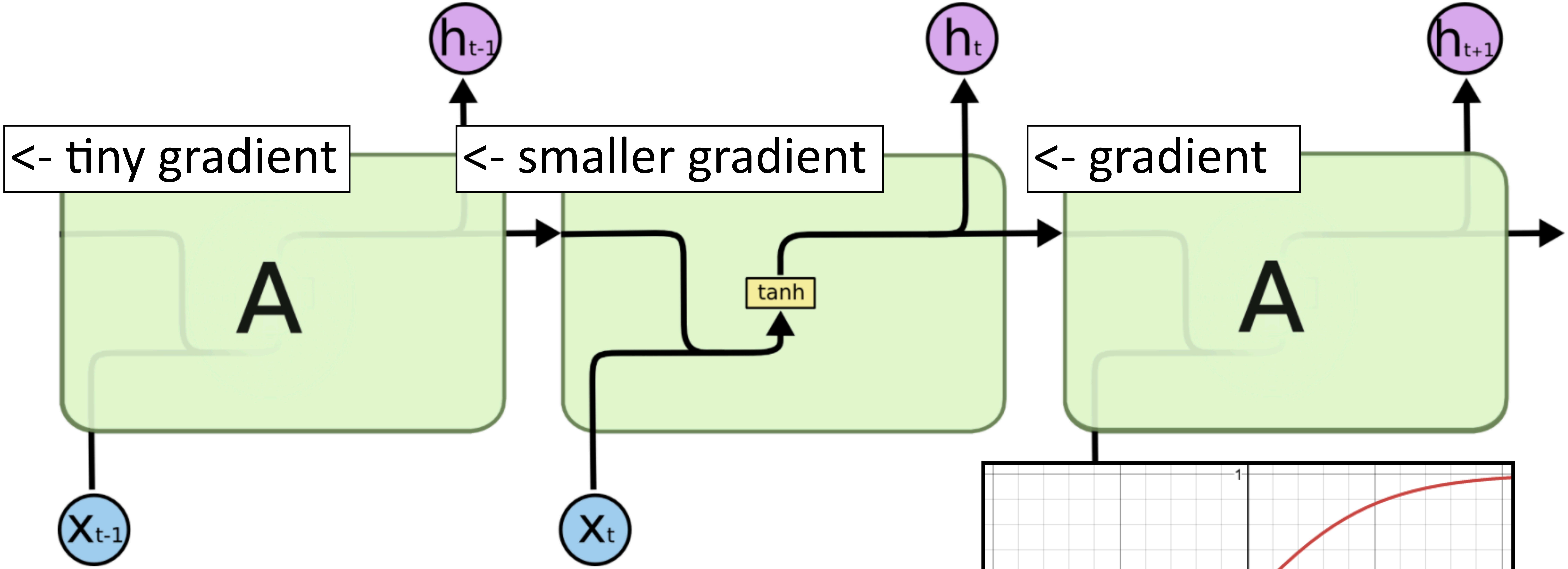
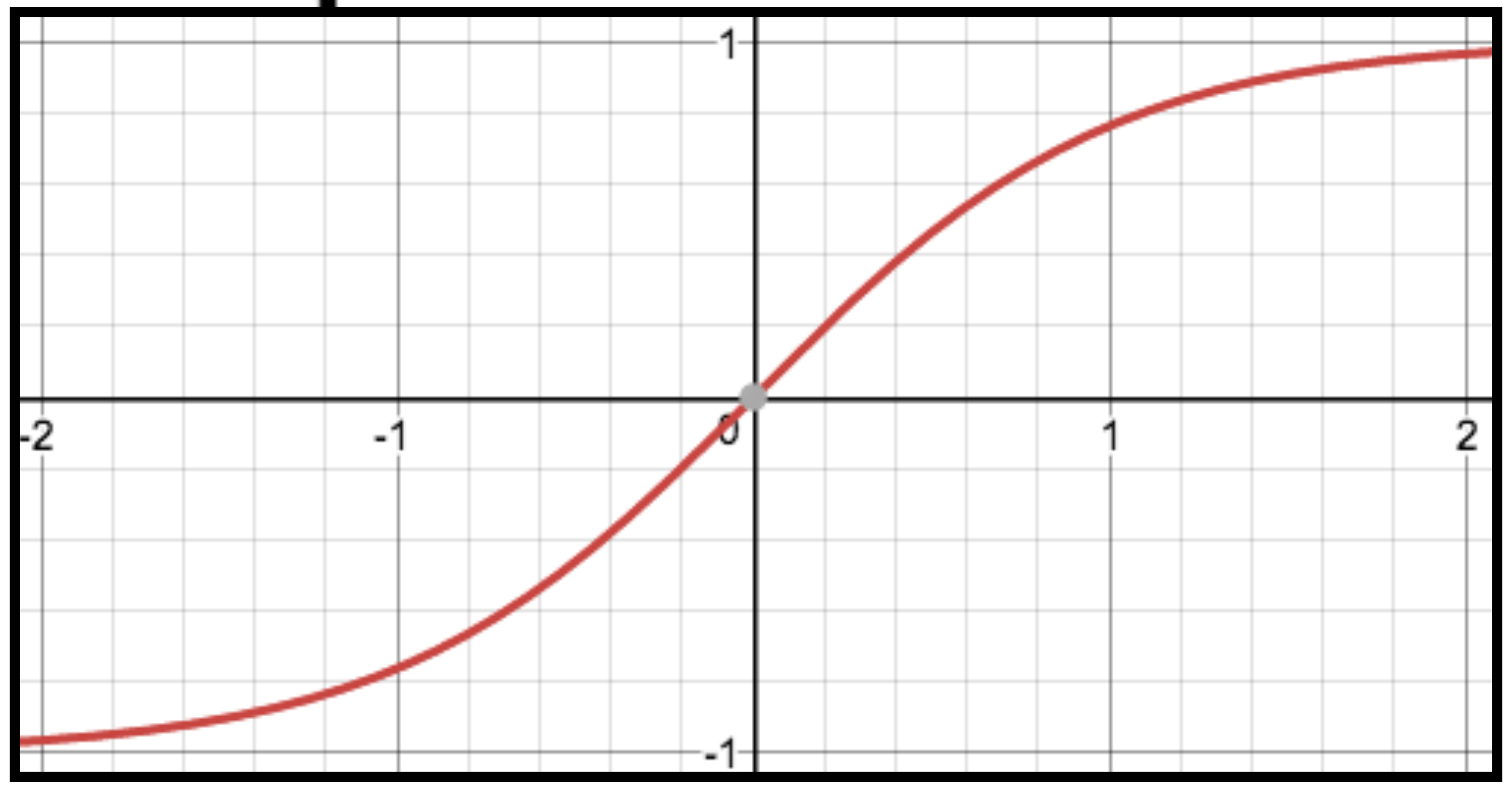


- Gradient diminishes going through tanh; if not in [-2, 2], gradient is almost 0



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

LSTMs/GRUs

Gated Connections

- Designed to fix "vanishing gradient" problem using *gates*

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

gated

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

Elman

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- Vector-valued "forget gate" **f** computed based on input and previous hidden state

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- Sigmoid: elements of **f** are in (0, 1)

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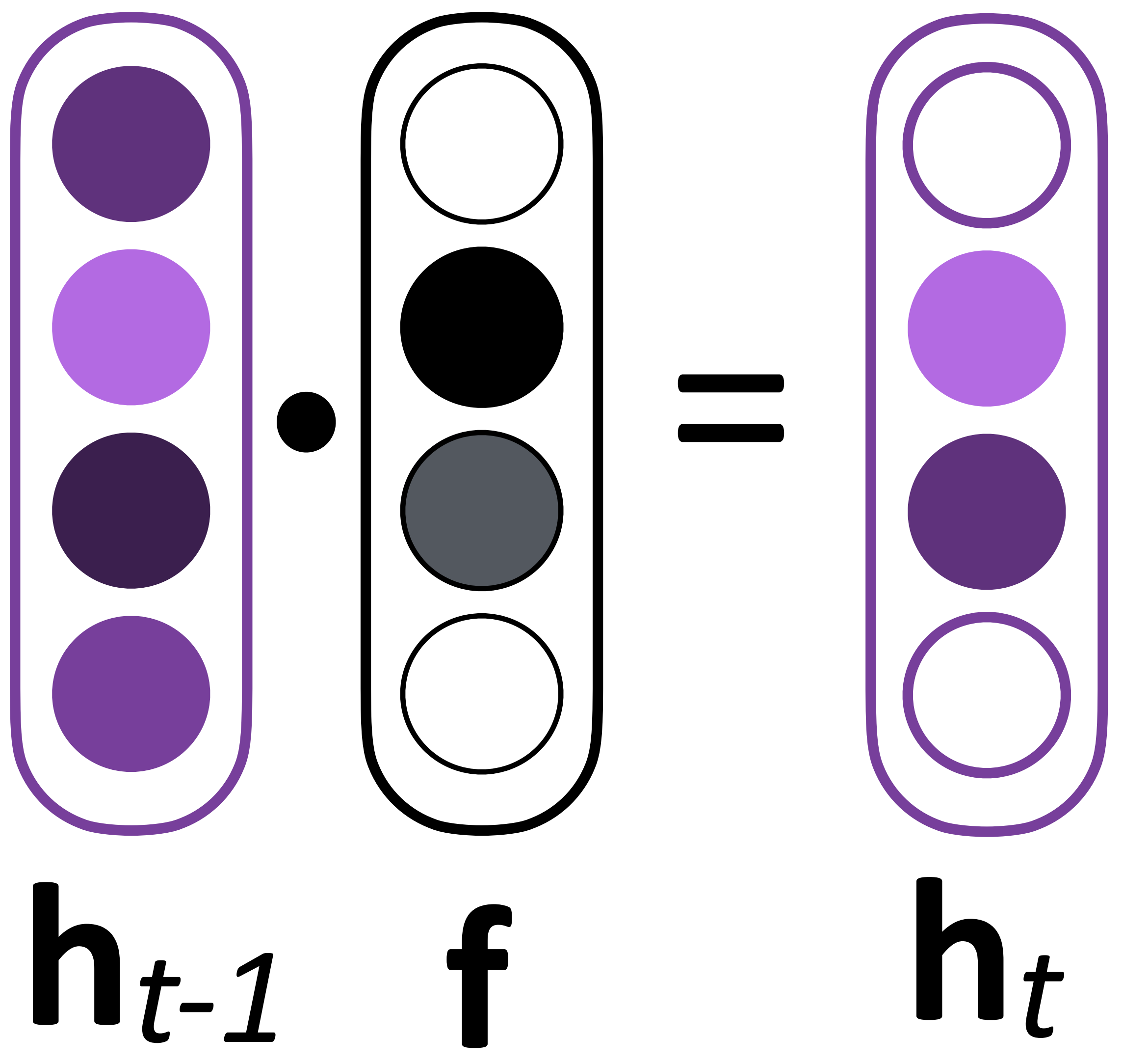

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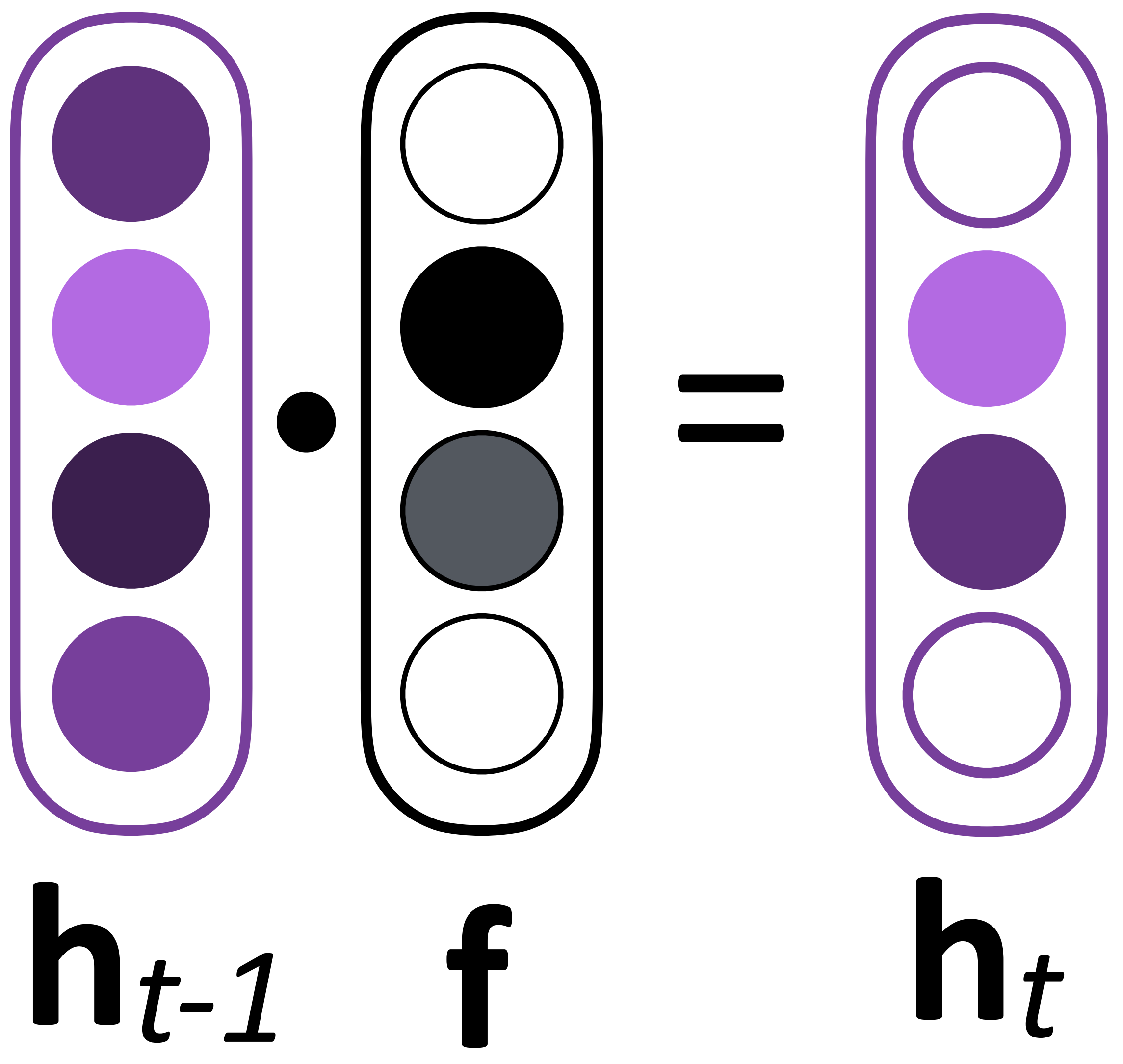

- Sigmoid: elements of **f** are in (0, 1)
- If **f** ≈ **1**, we simply sum up a function of all inputs — gradient doesn't vanish!

LSTMs

- "Cell" **c** in addition to hidden state **h**

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

LSTMs

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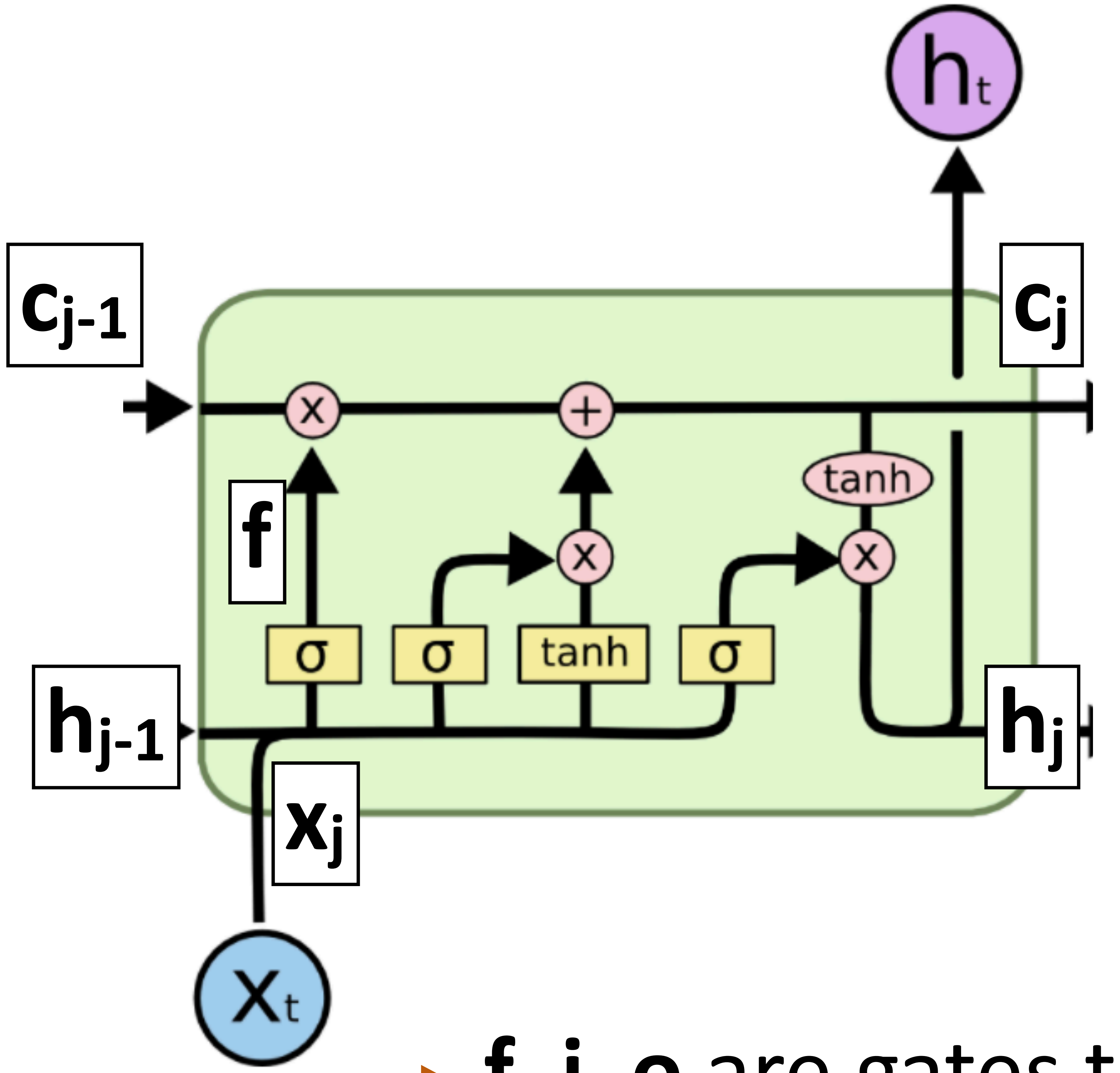
- Basic communication flow: **x** -> **c** -> **h ->** output**,** each step of this process is gated in addition to gates from previous timesteps

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

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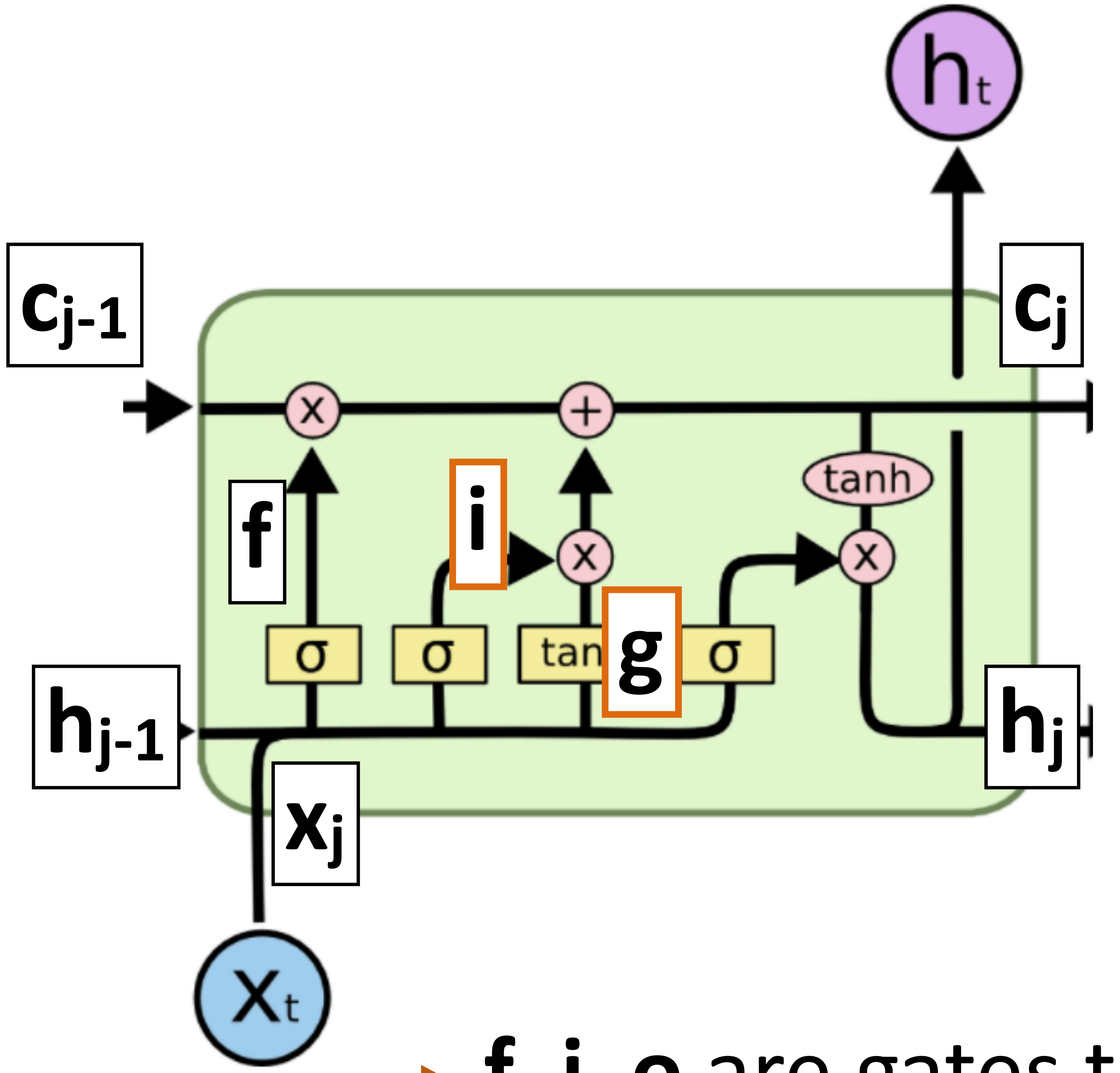
LSTMs



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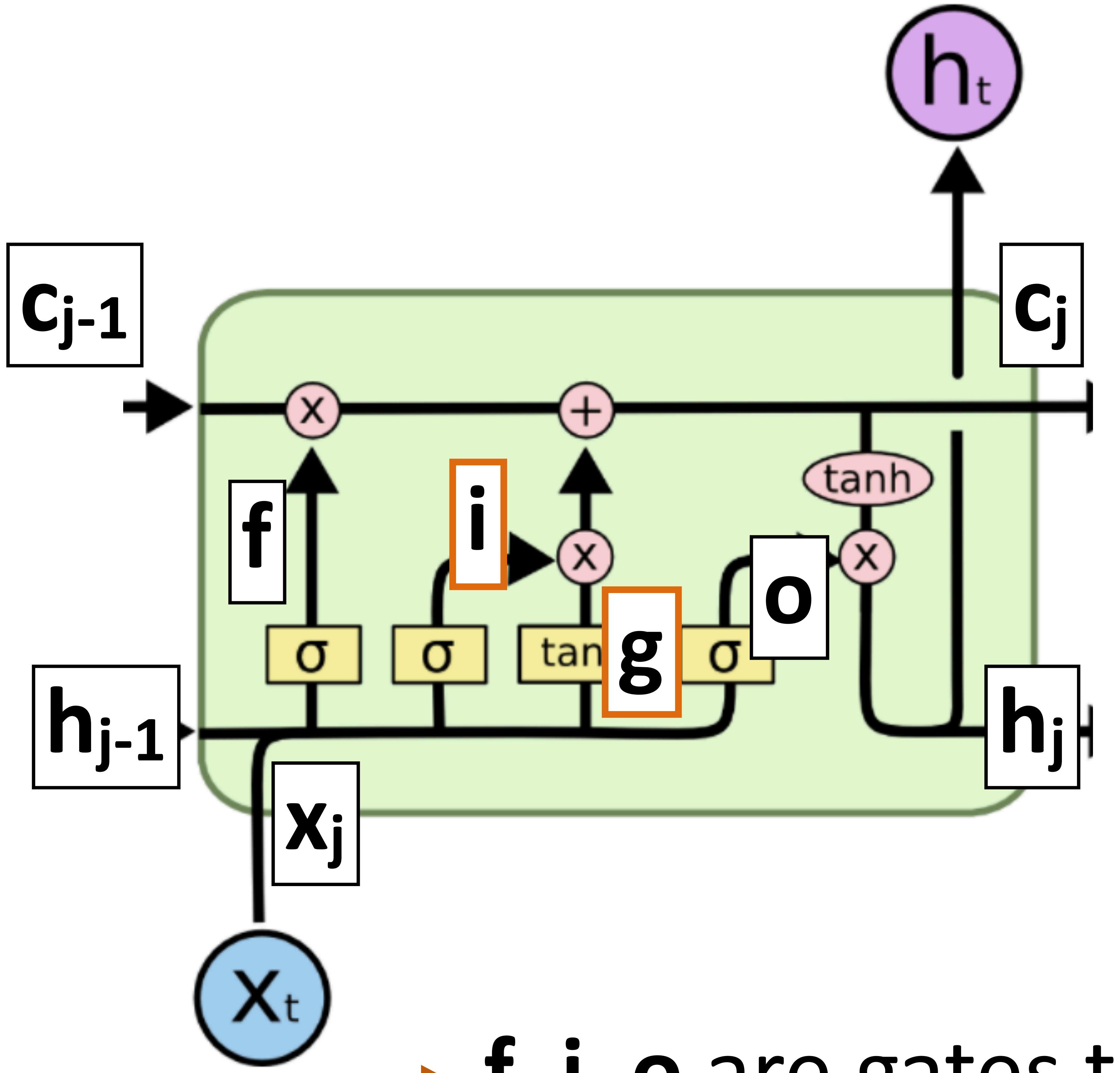
LSTMs



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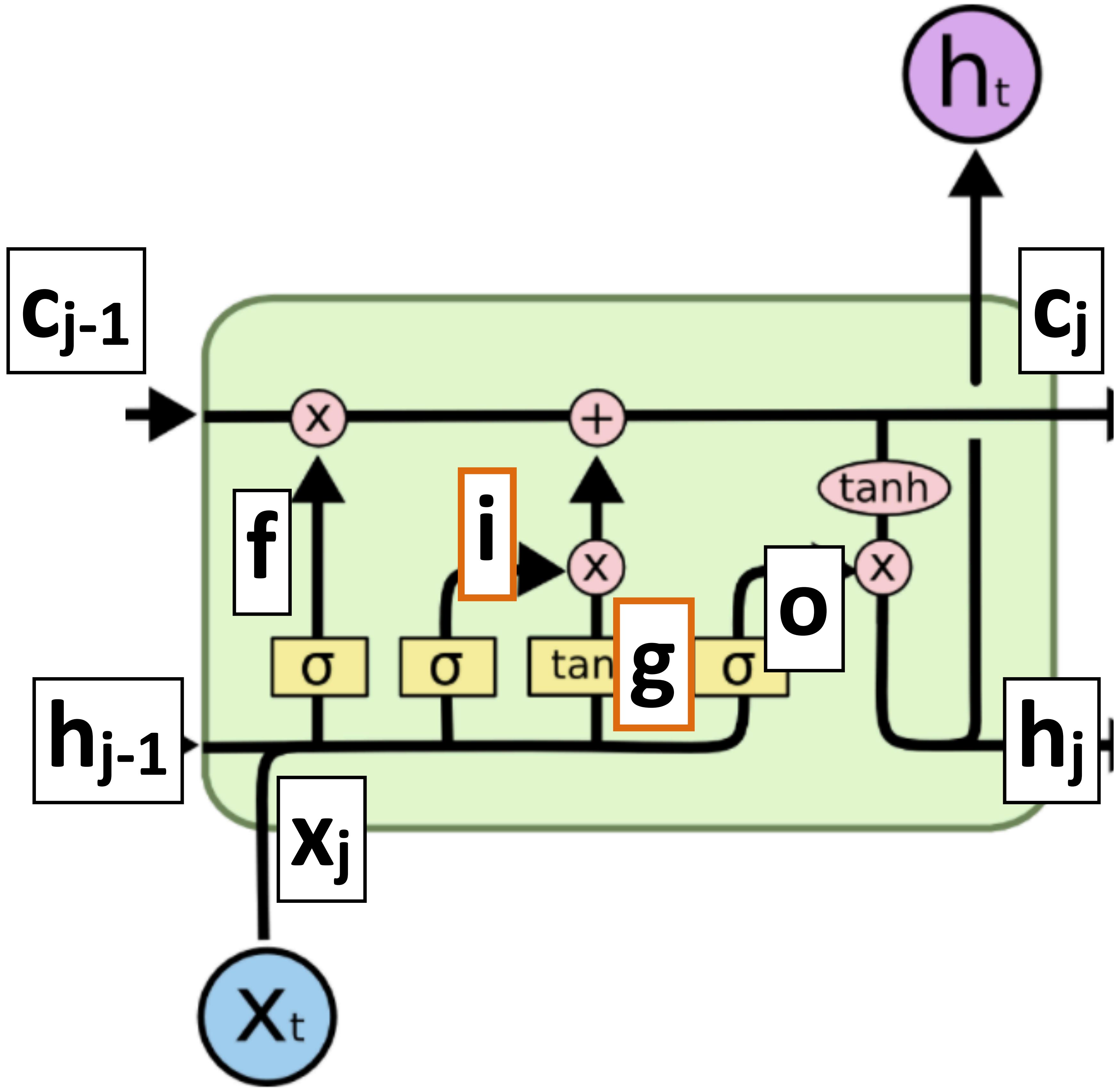
LSTMs



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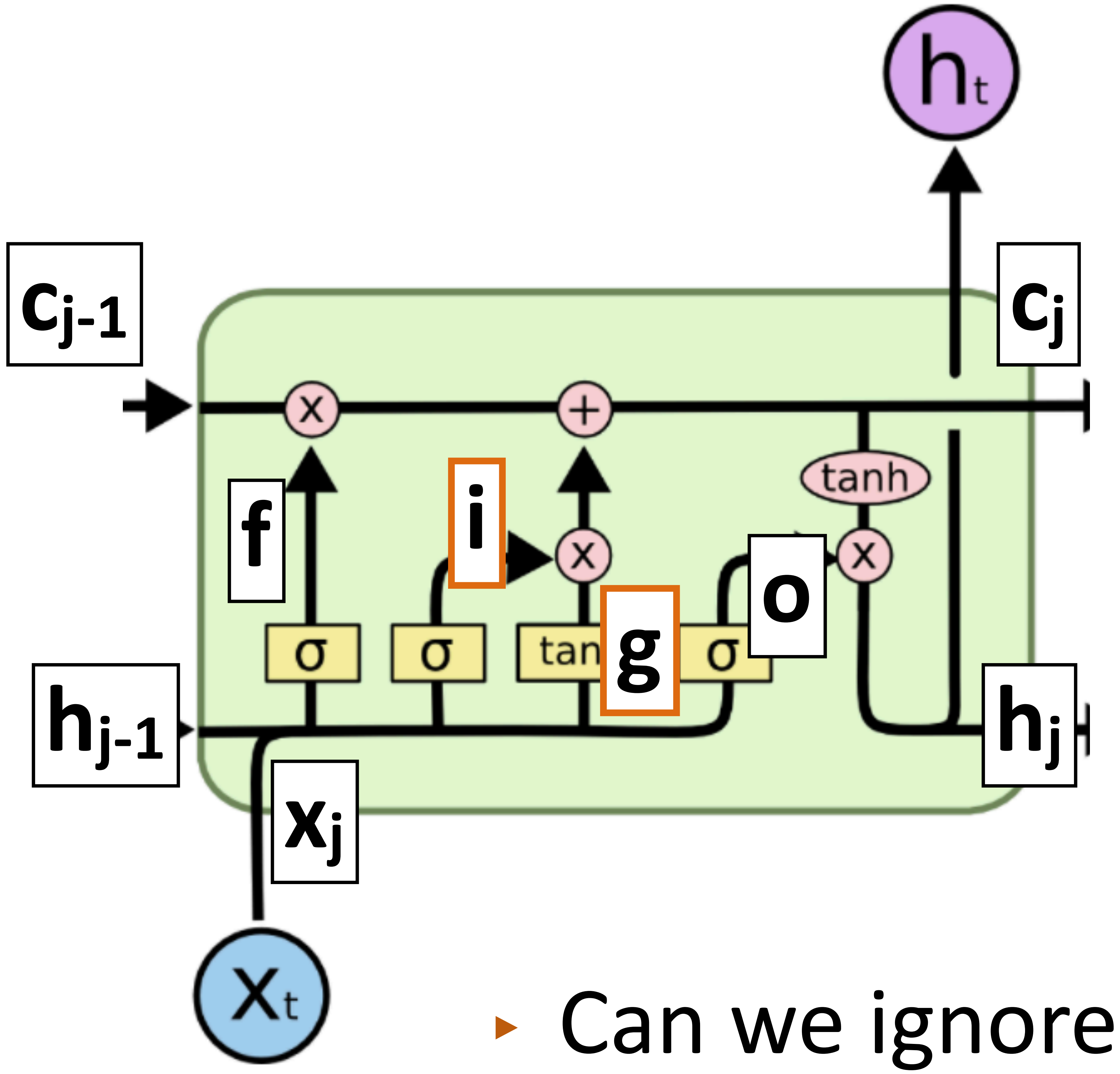
LSTMs



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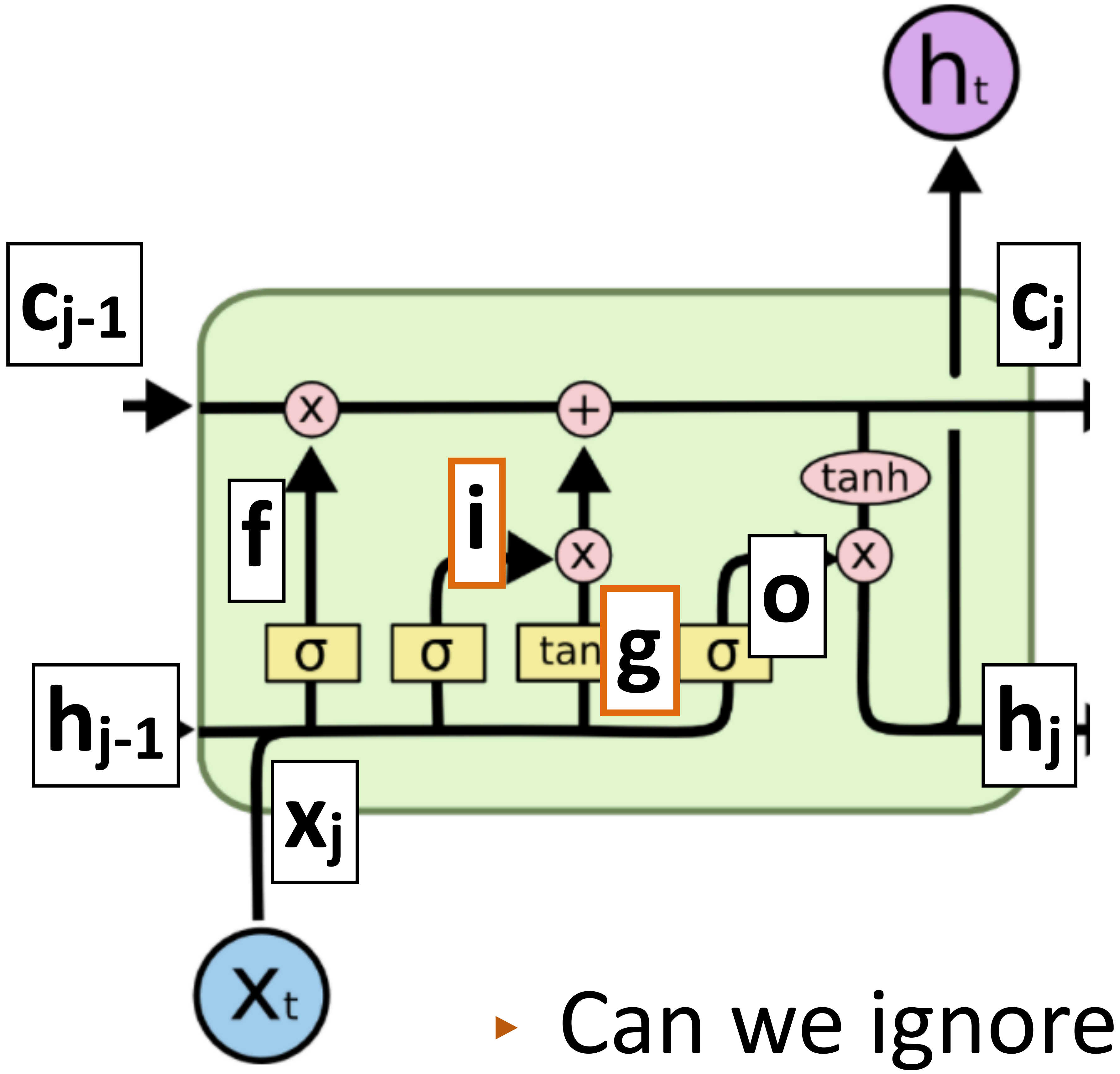
LSTMs



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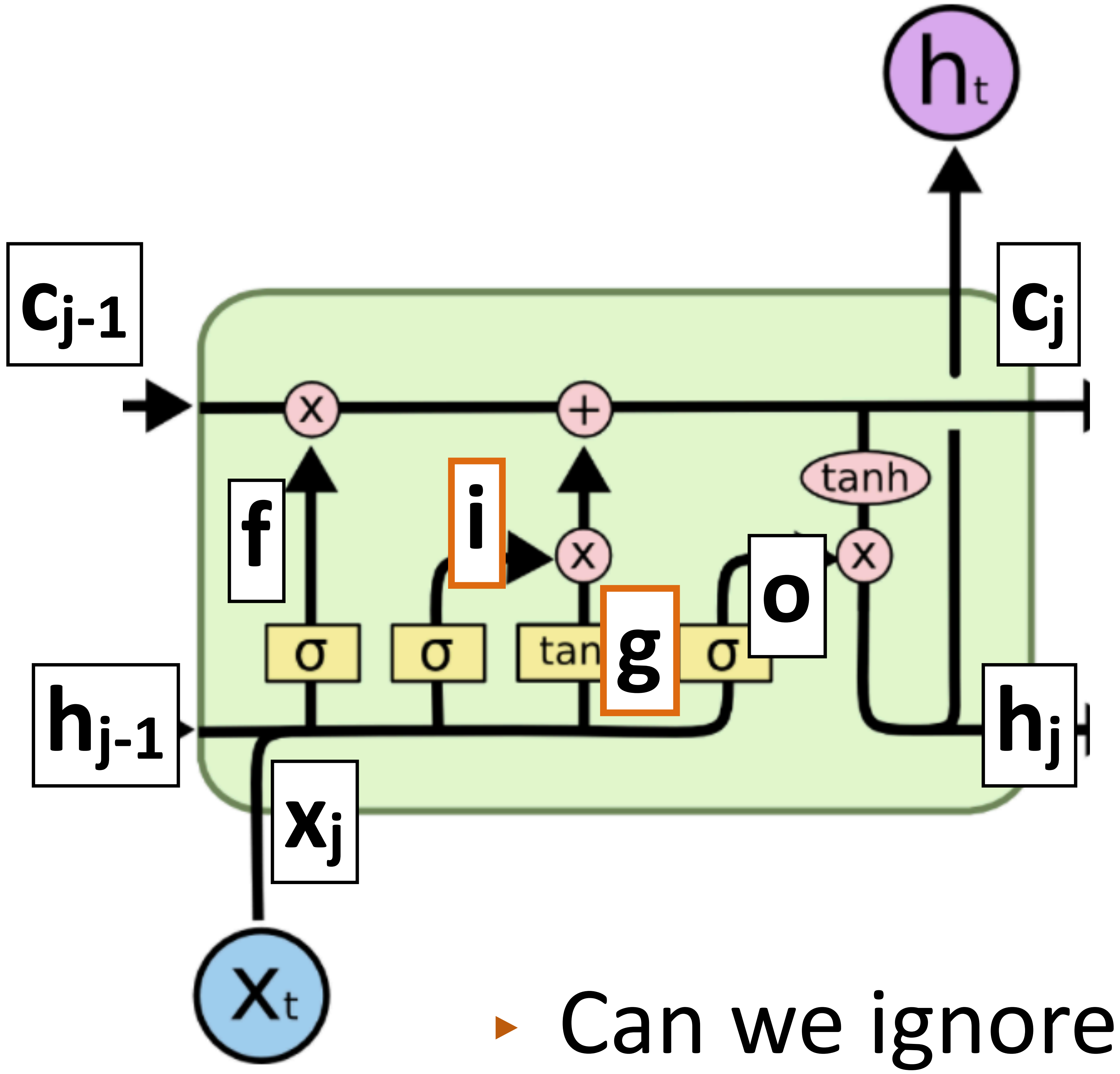
LSTMs



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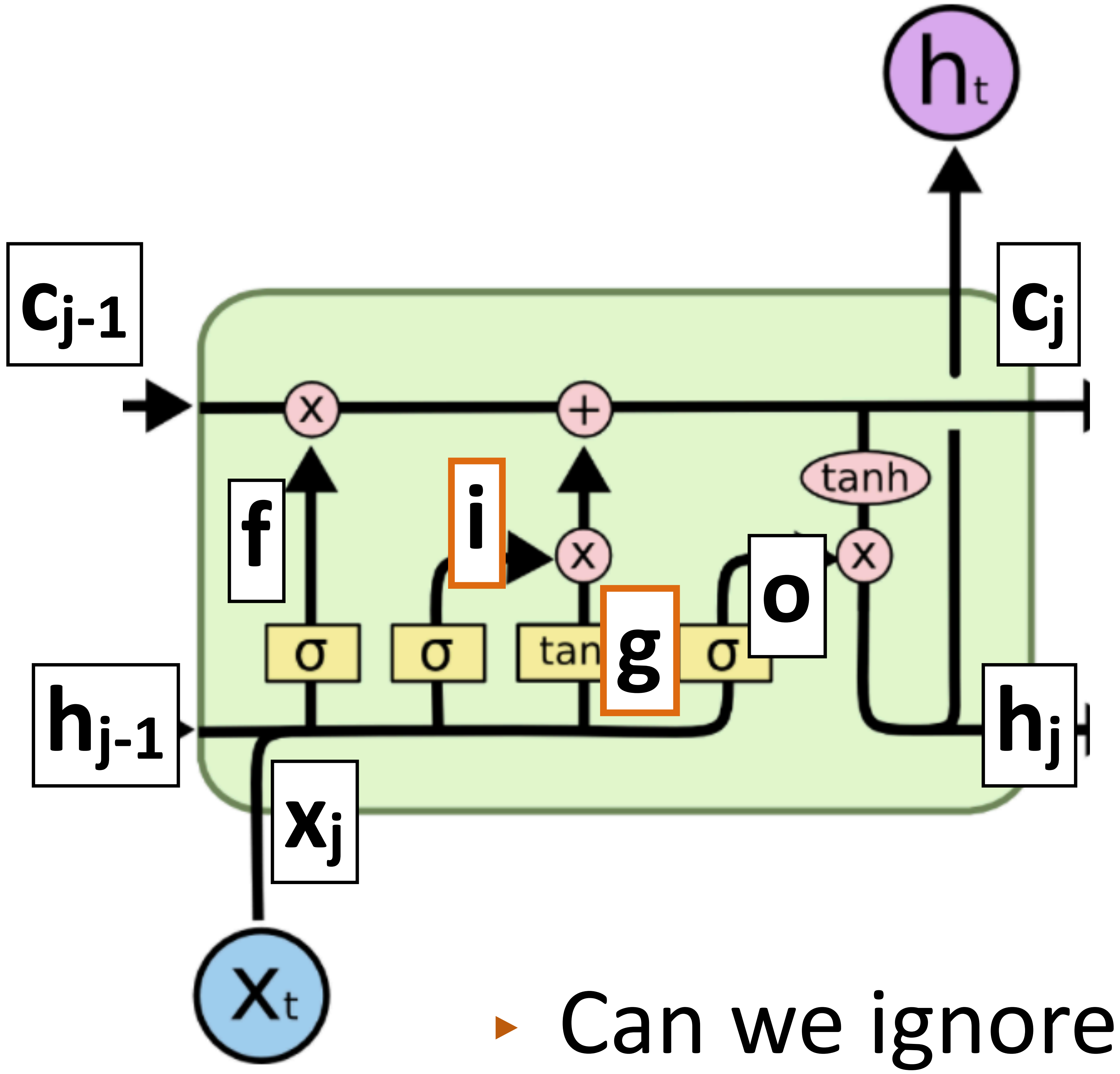
LSTMs



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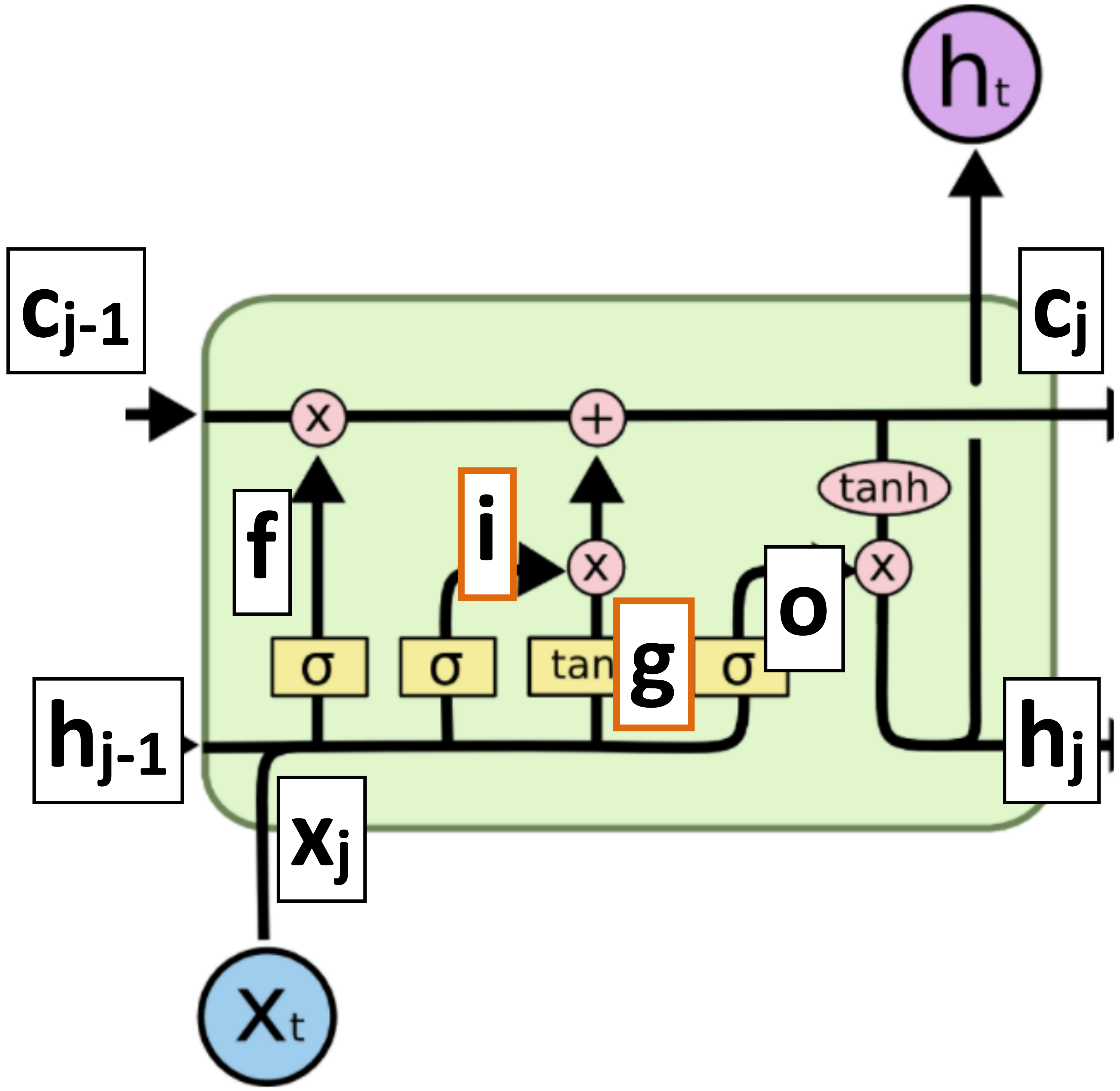
- Can we ignore the old value of **c** for this timestep?
- Can an LSTM sum up its inputs **x**?
- Can we ignore a particular input **x**?
- Can we output something without changing **c**?

LSTMs



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

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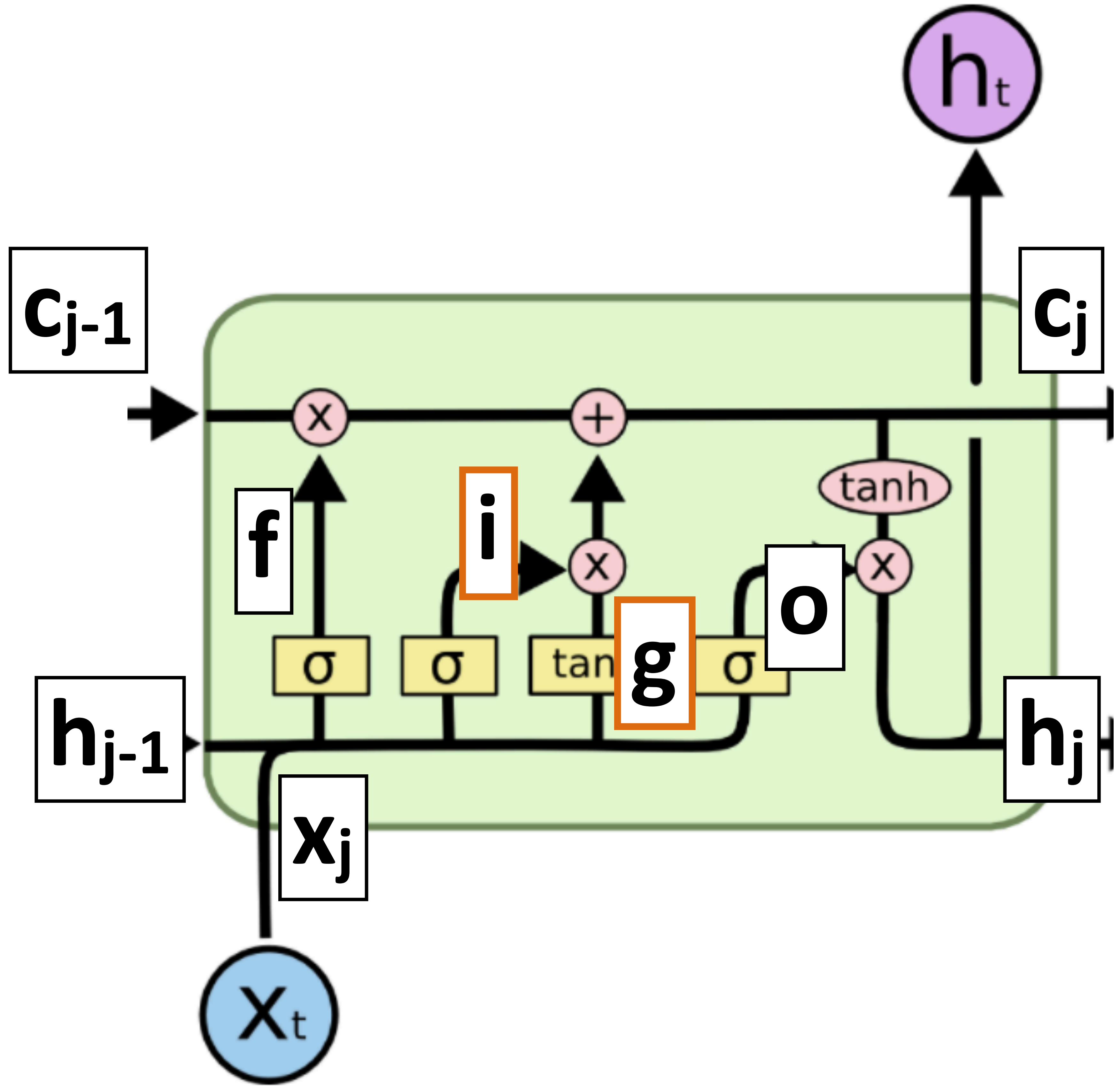
LSTMs



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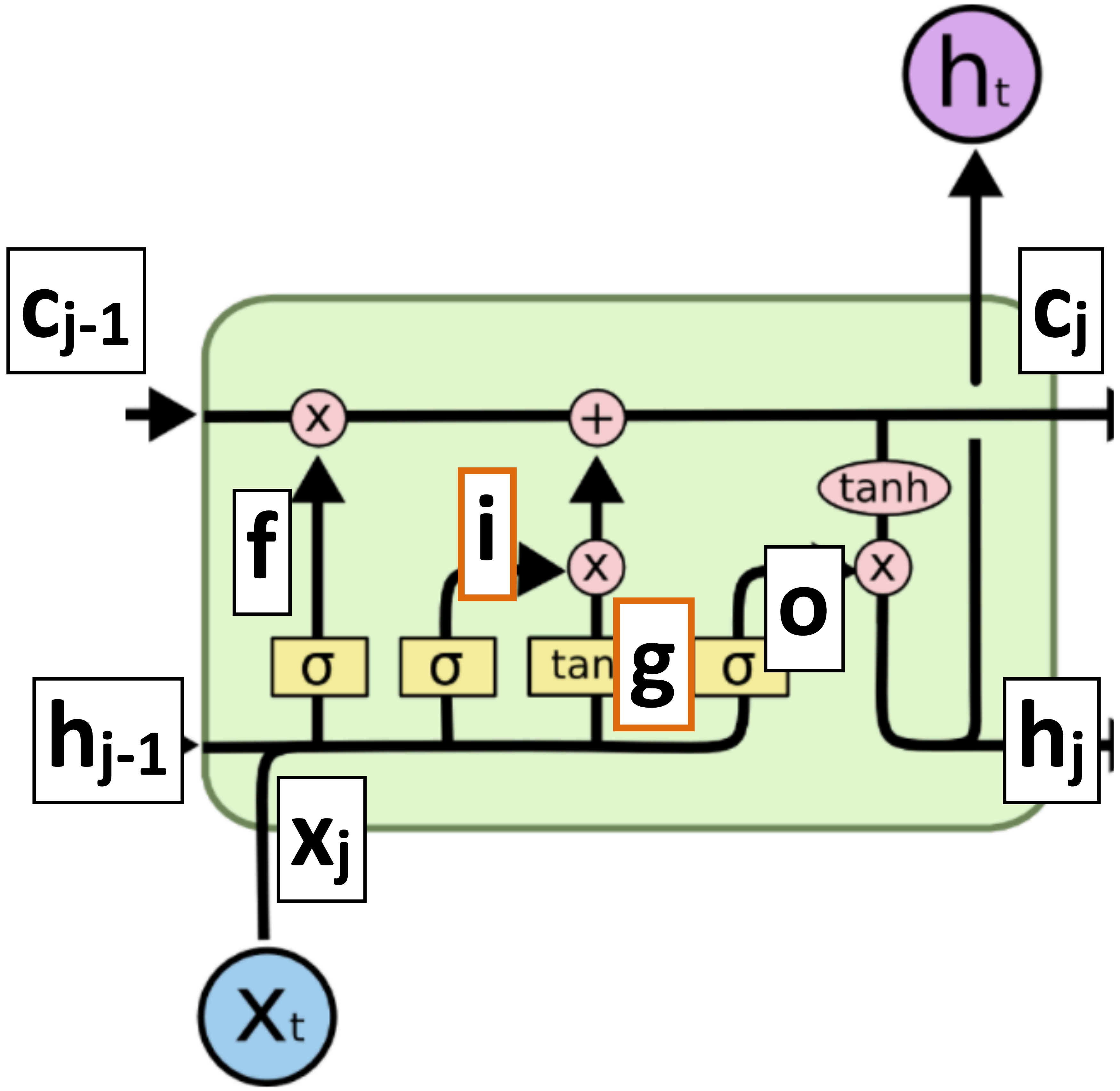
LSTMs



- 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

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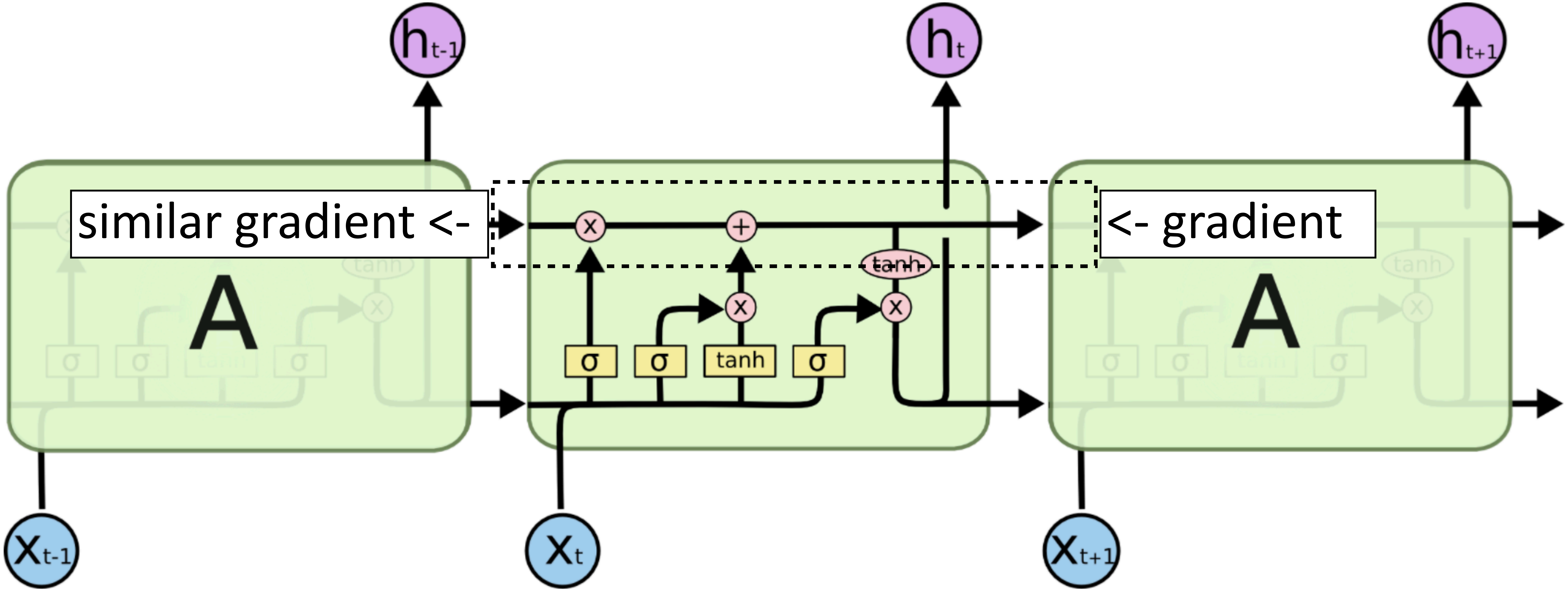
LSTMs



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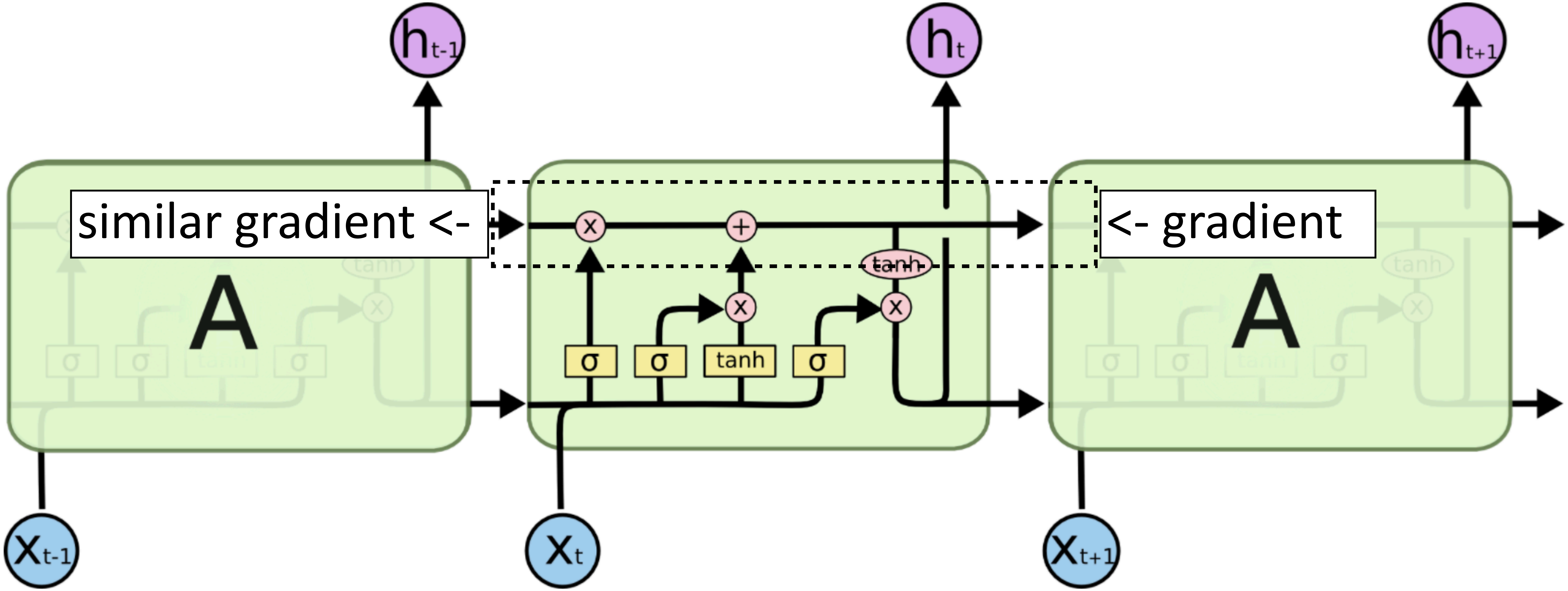
LSTMs



- 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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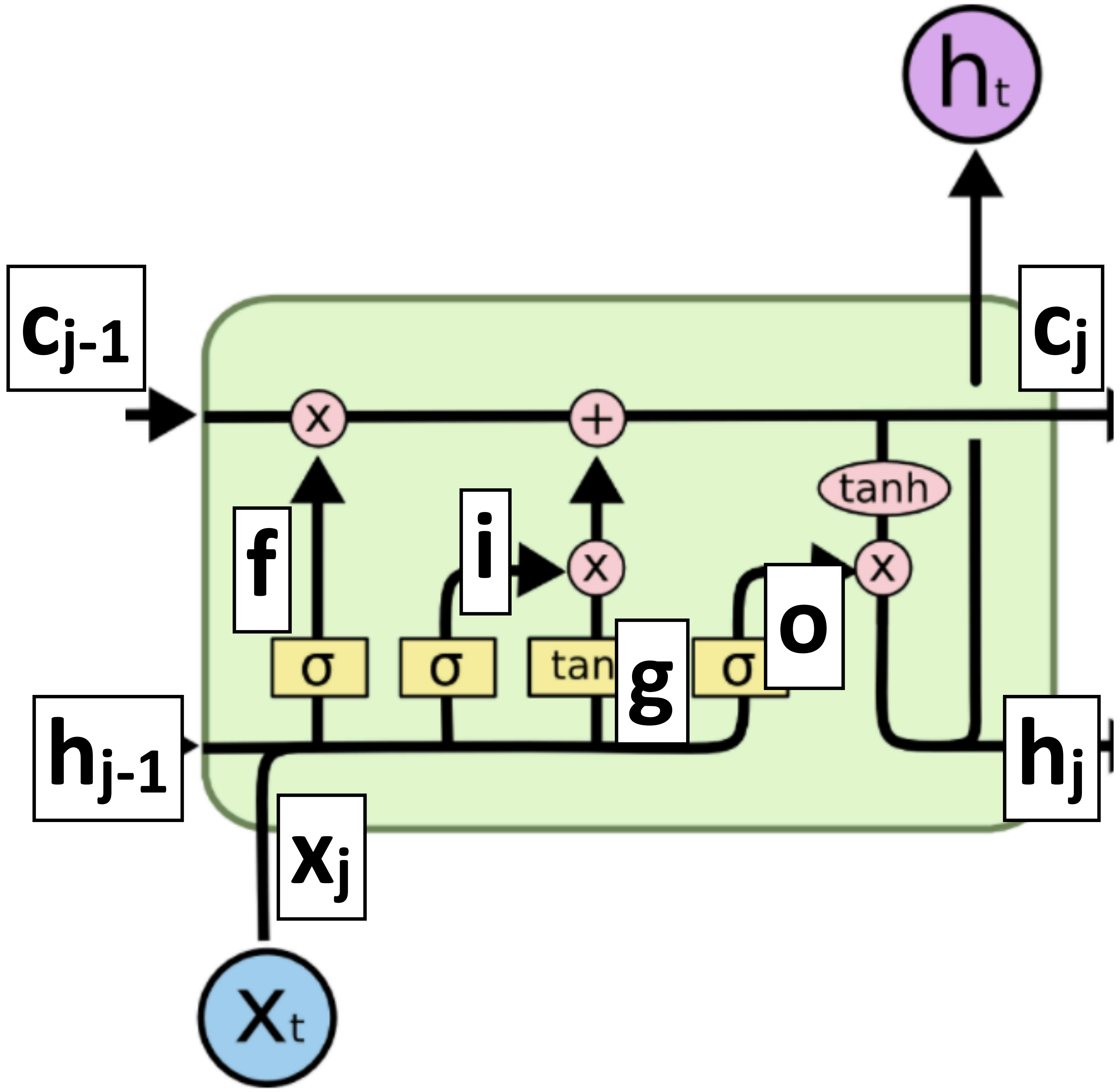
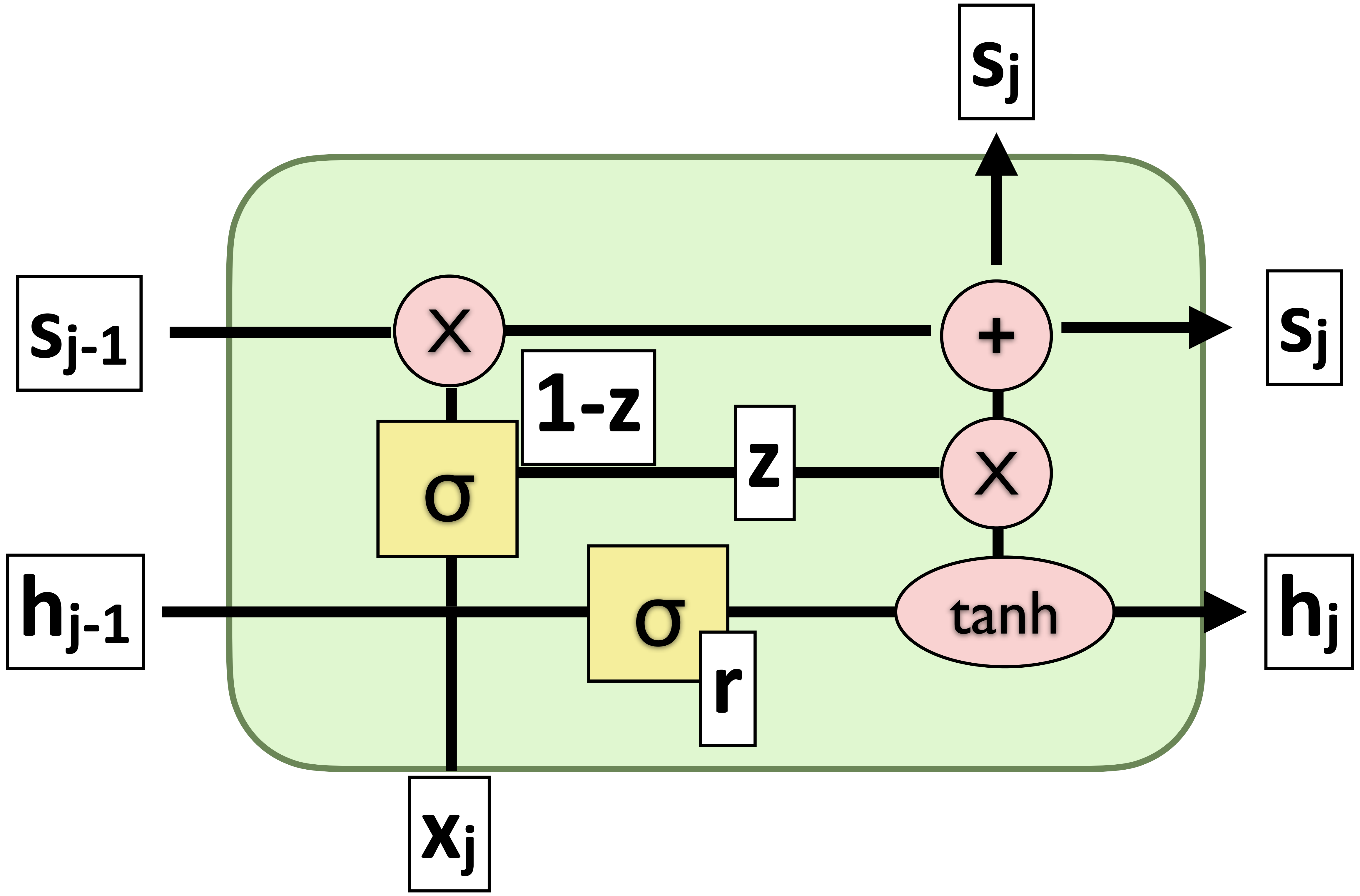
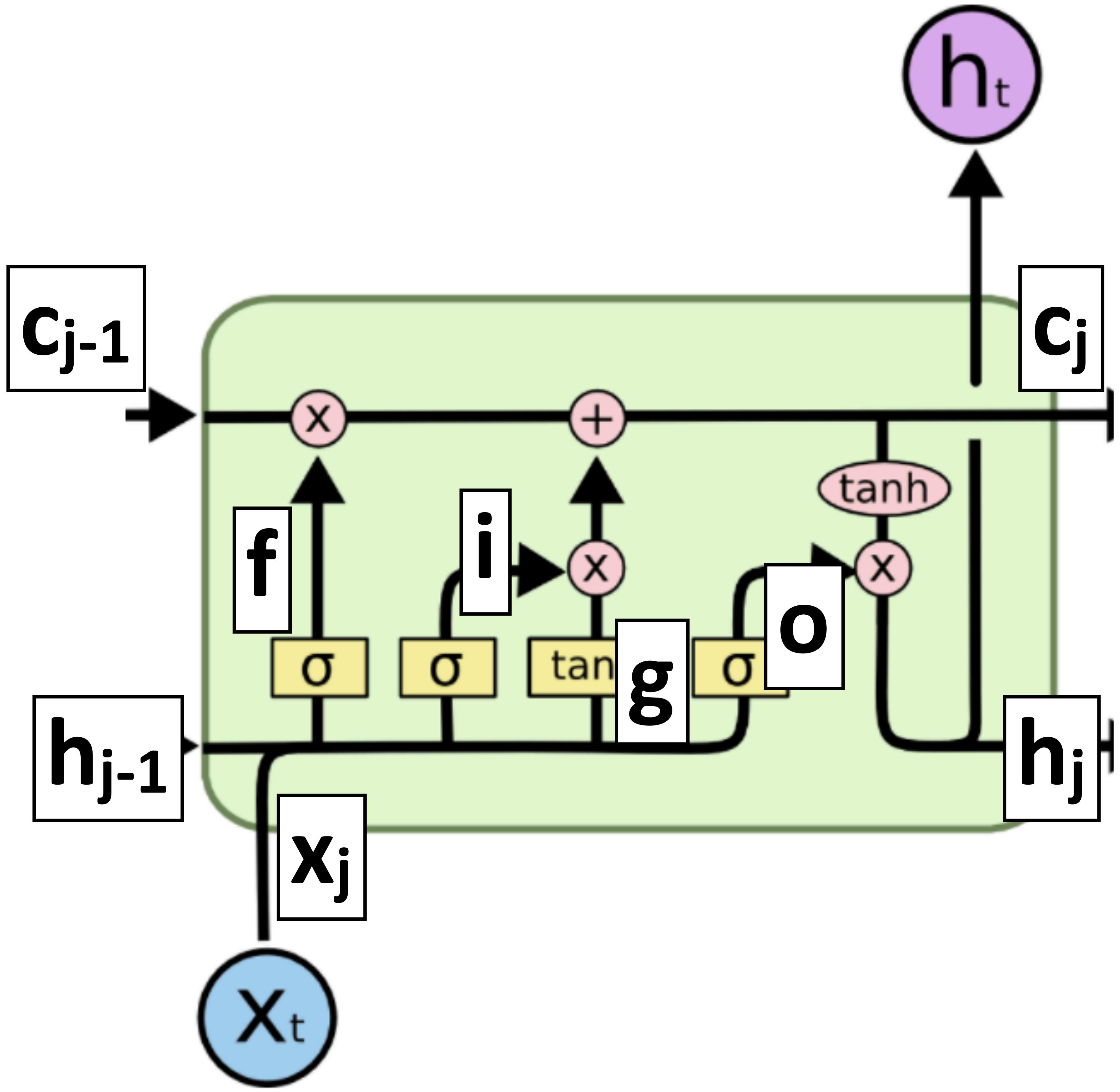
GRUs

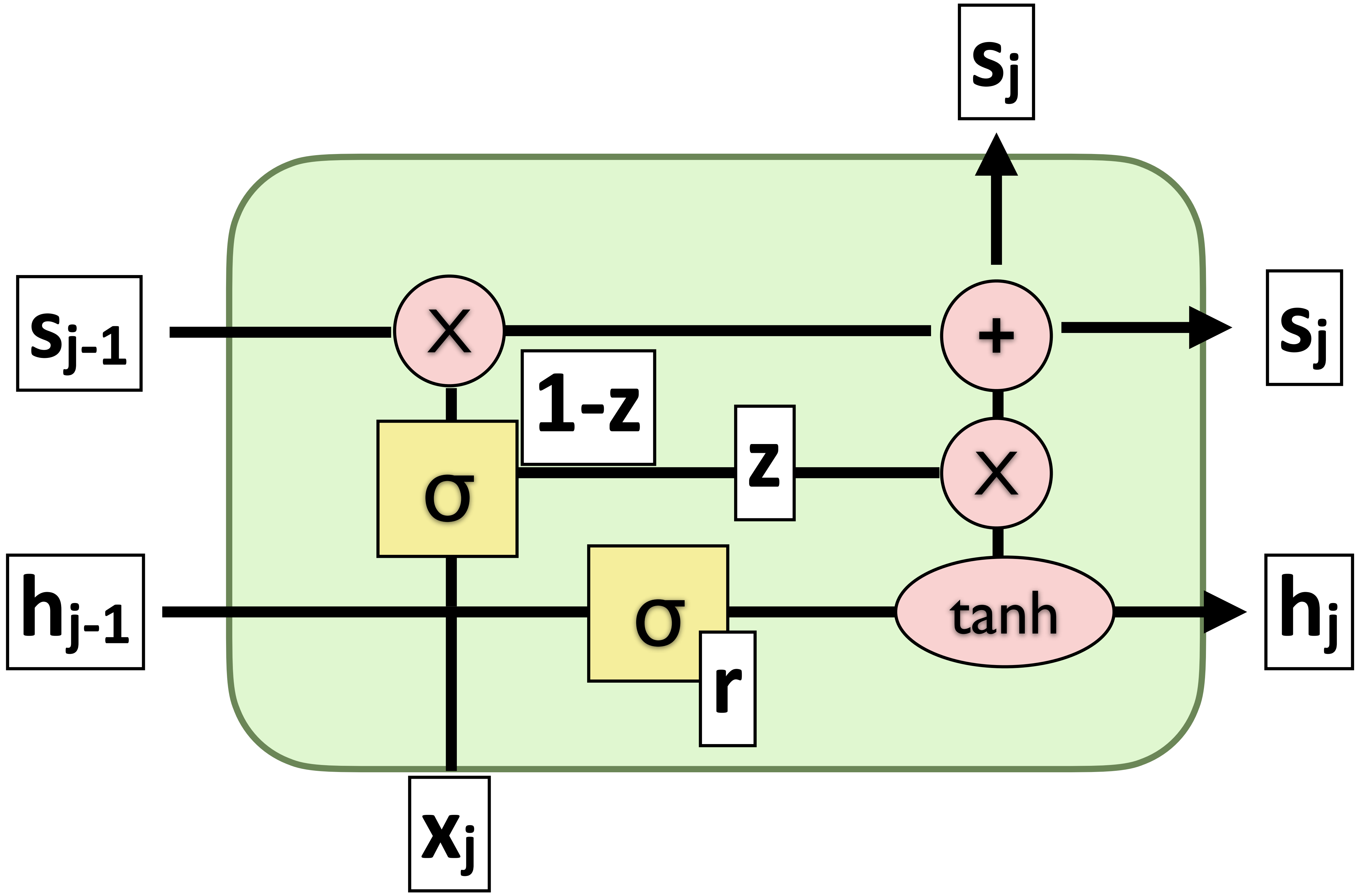




- LSTM: more complex and slower, may work a bit better

GRUs





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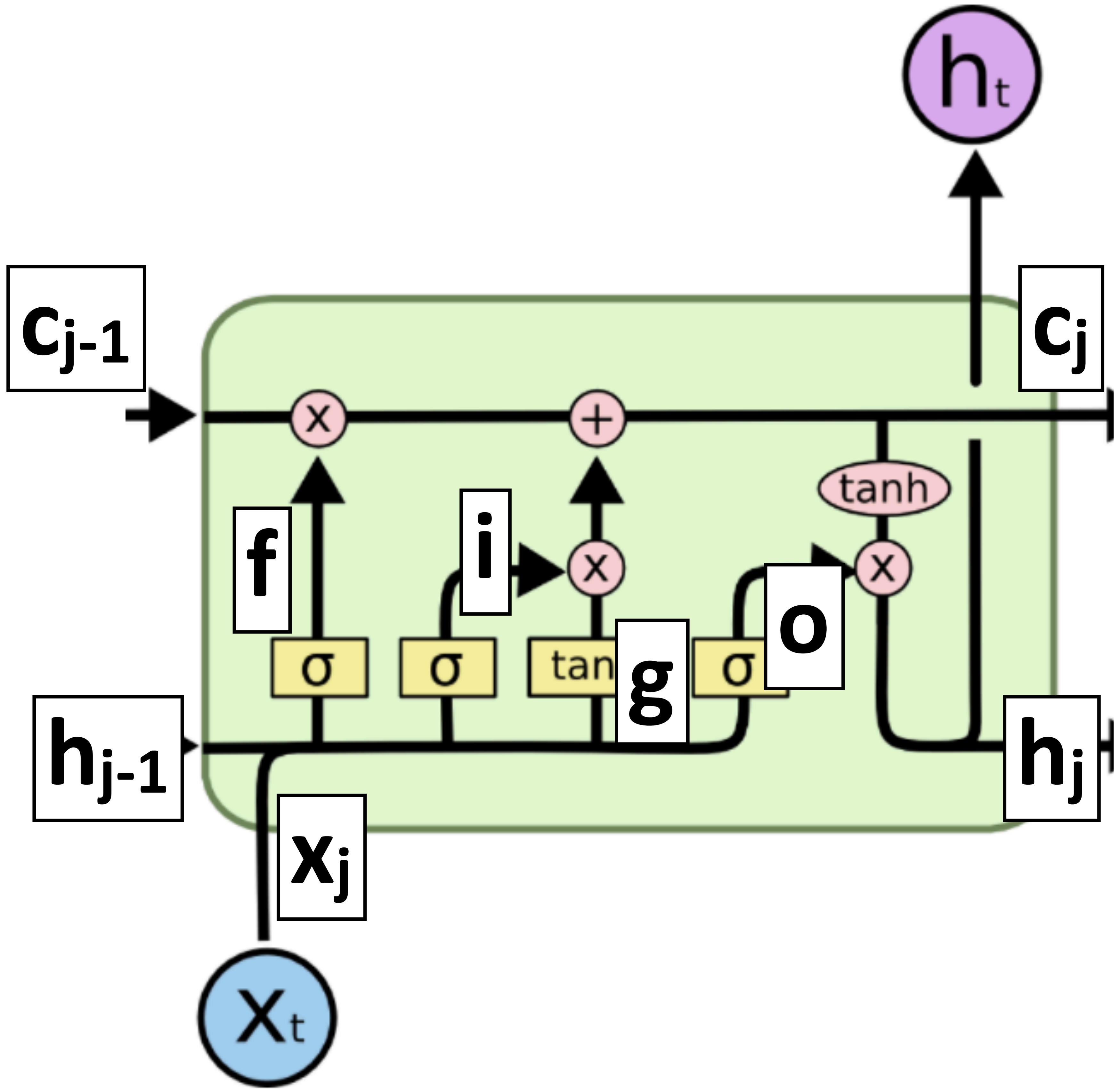
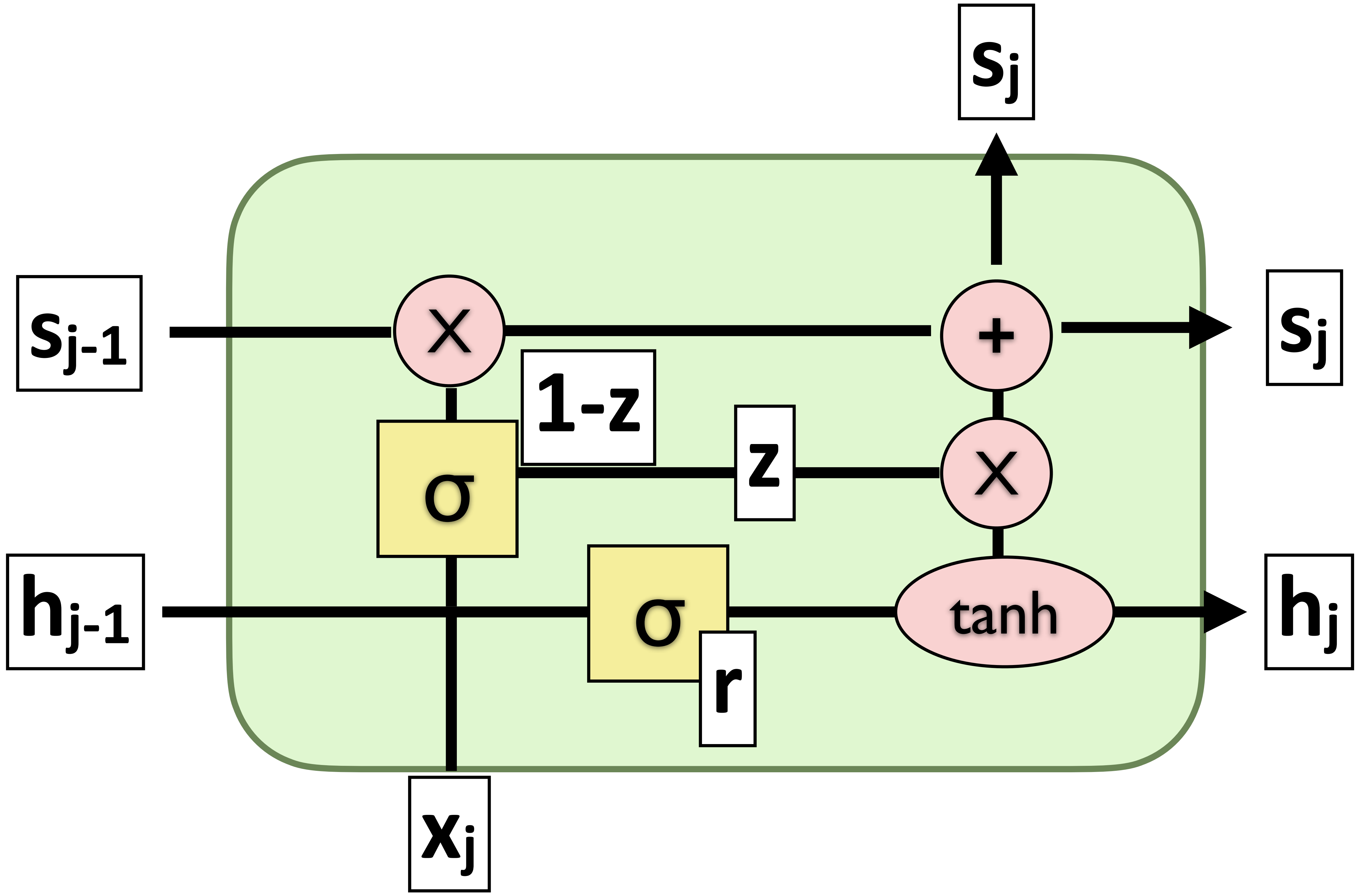
GRUs

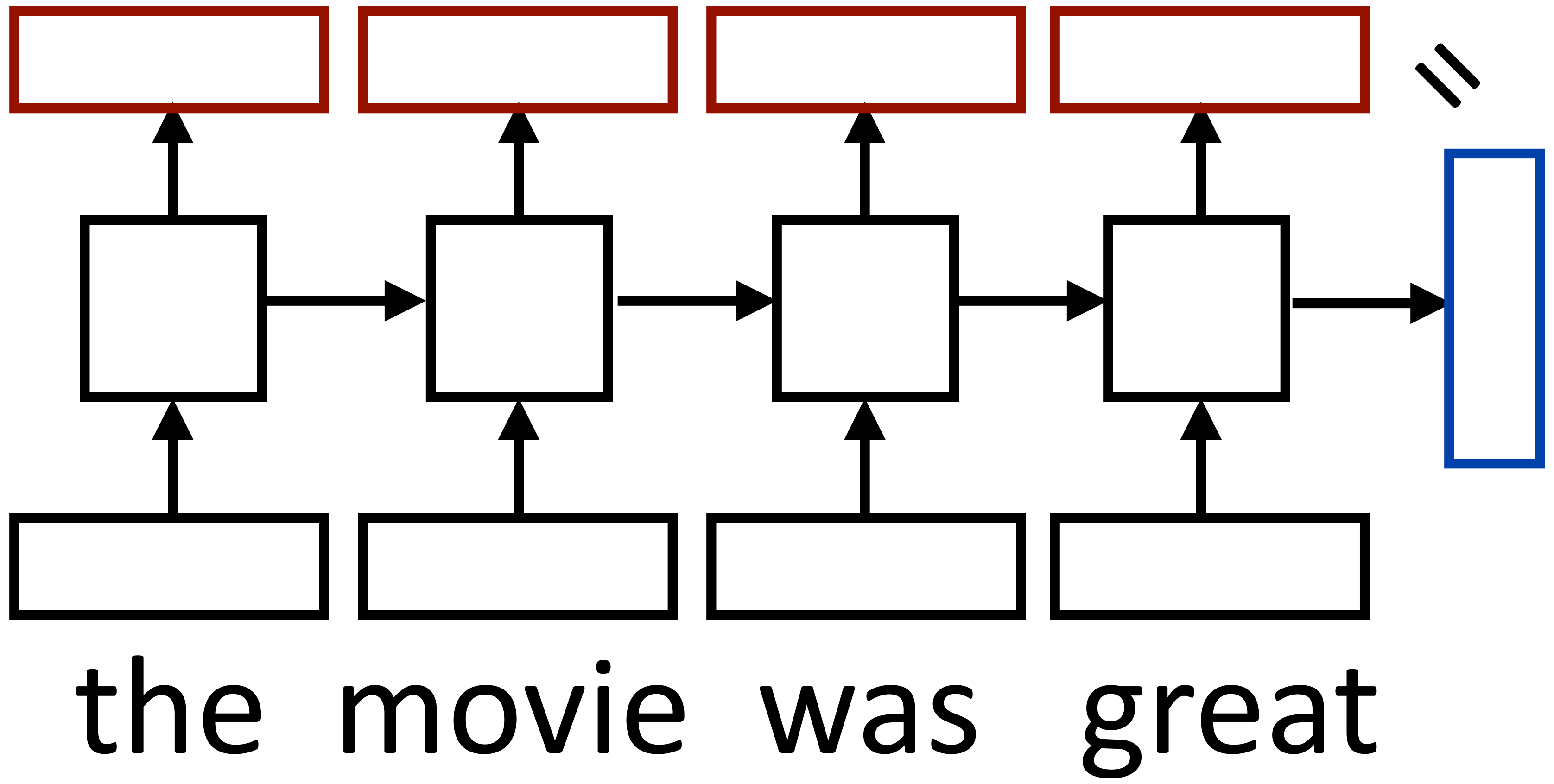




- LSTM: more complex and slower, may work a bit better

- 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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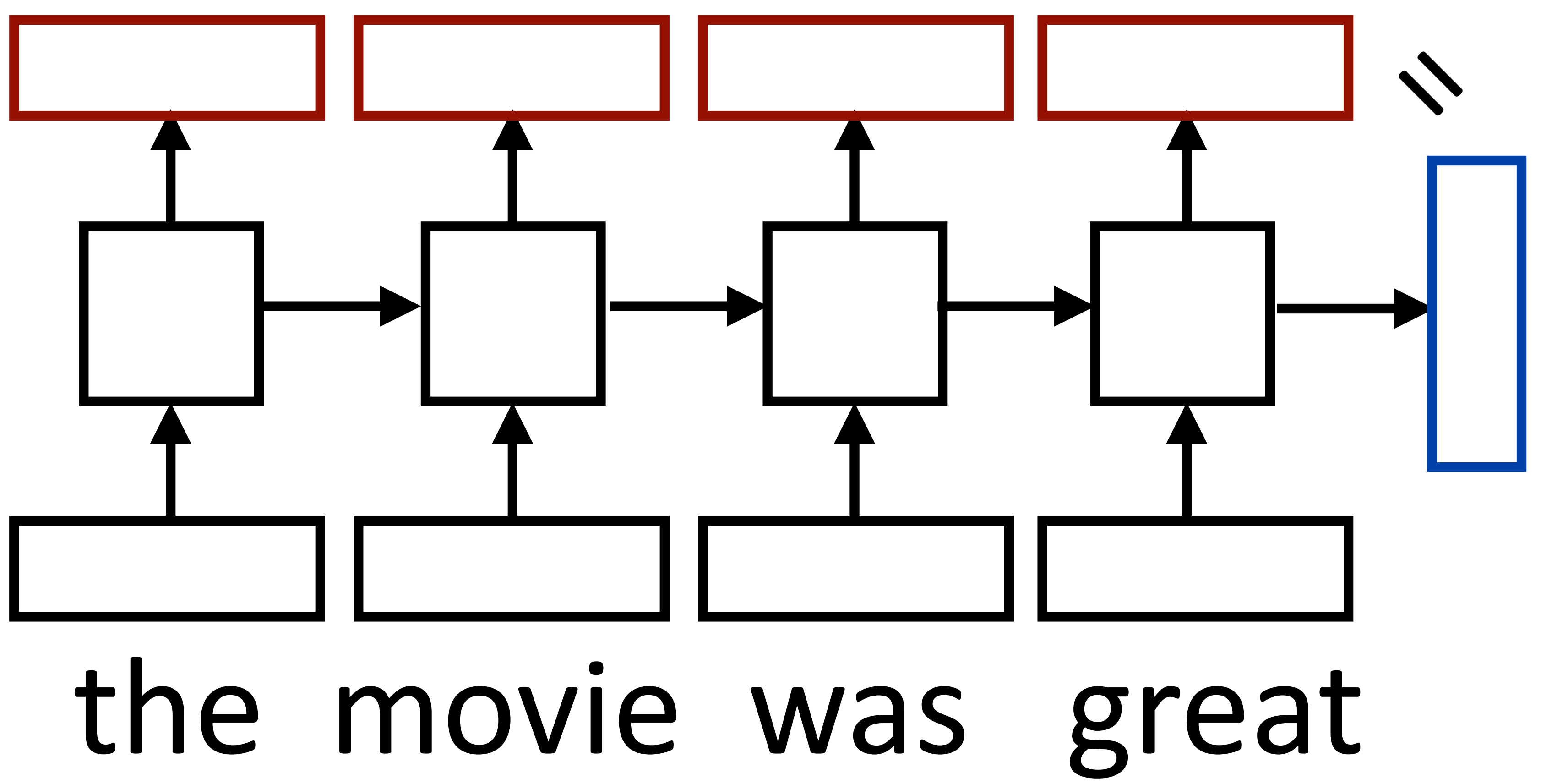

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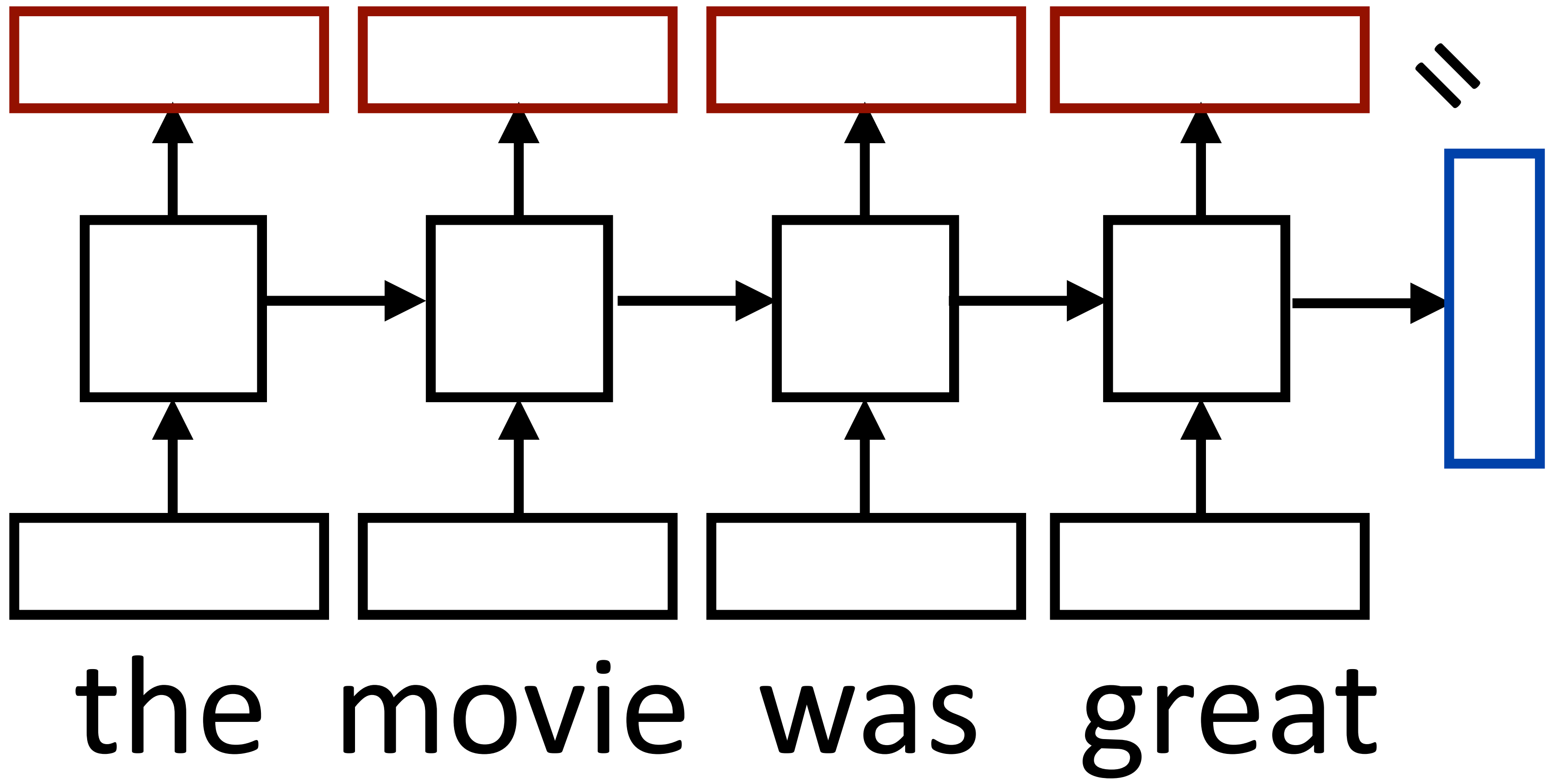
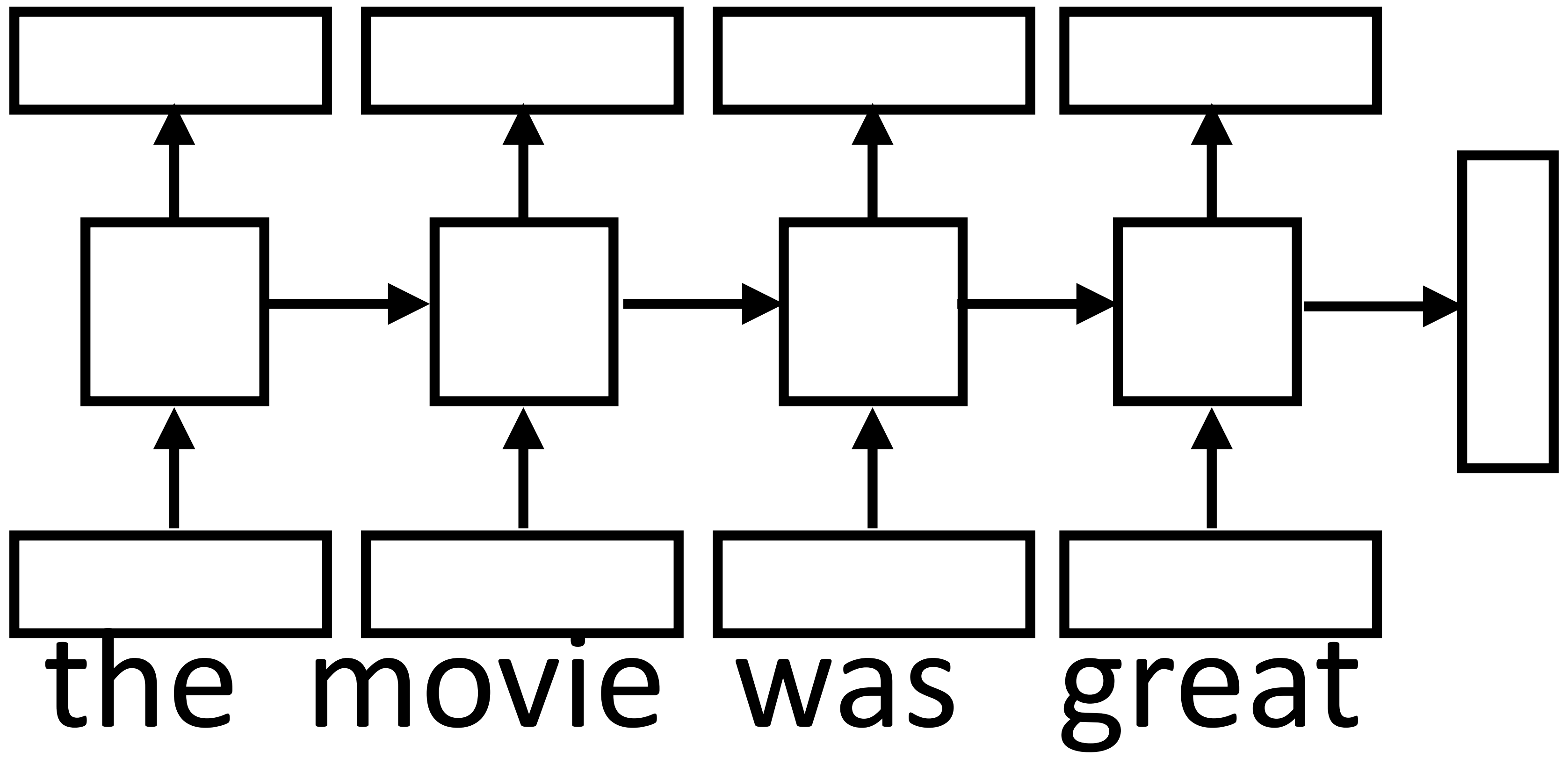


- Encoding of the sentence — can pass this a decoder or make a classification decision about the sentence
- Encoding of each word — can pass this to another layer to make a prediction (can also pool these to get a different sentence encoding)
- RNN can be viewed as a transformation of a sequence of vectors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

Multilayer Bidirectional RNN



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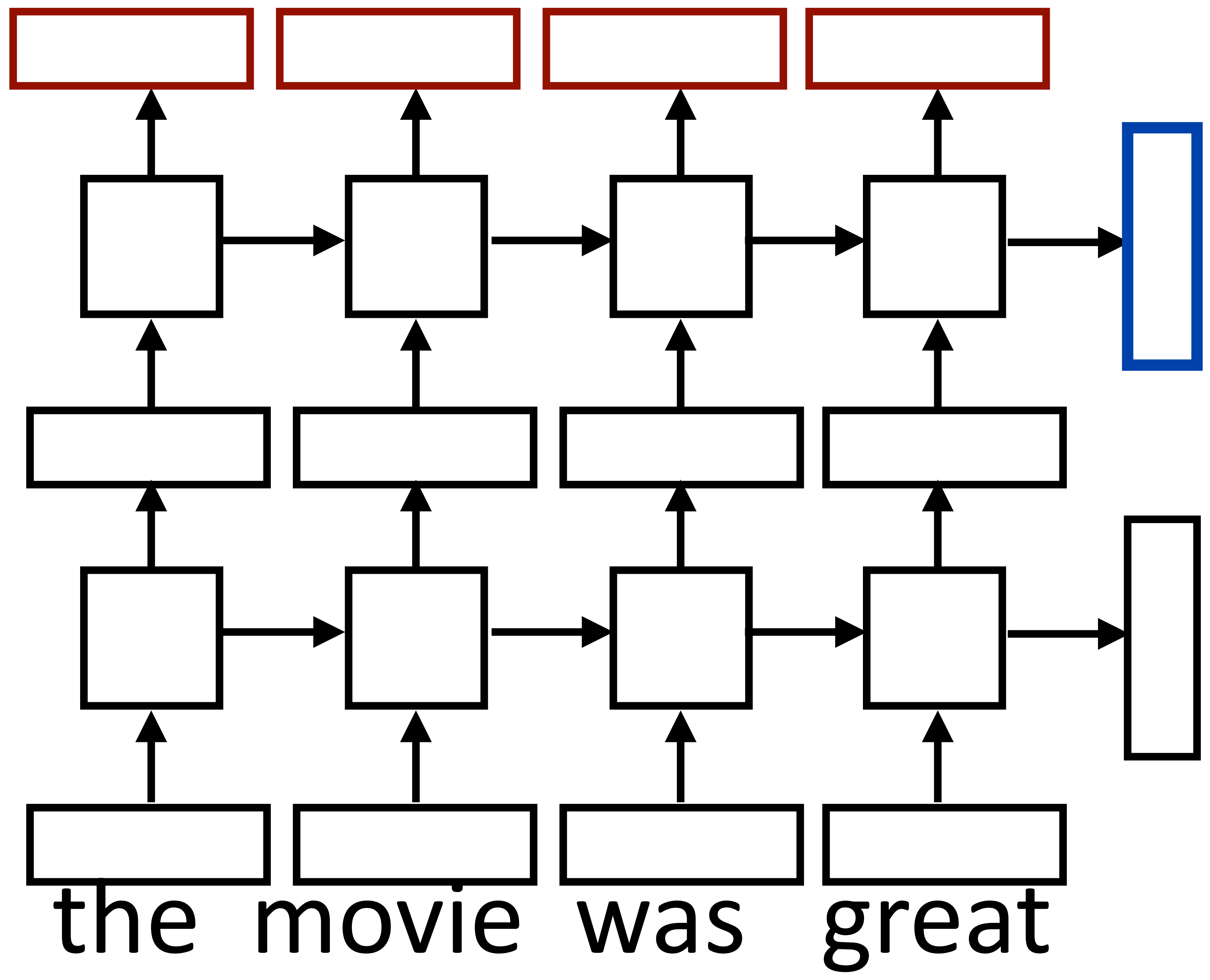

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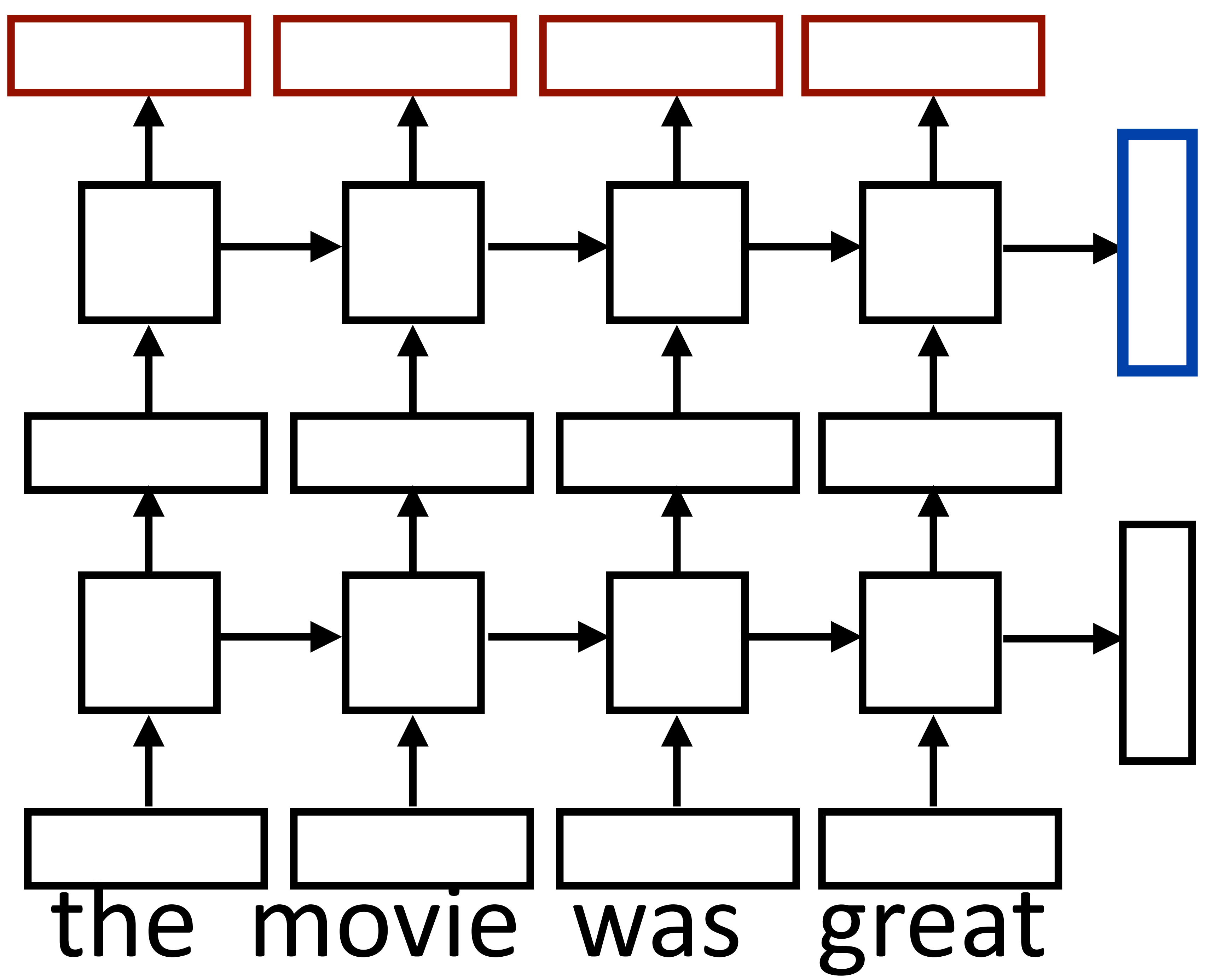

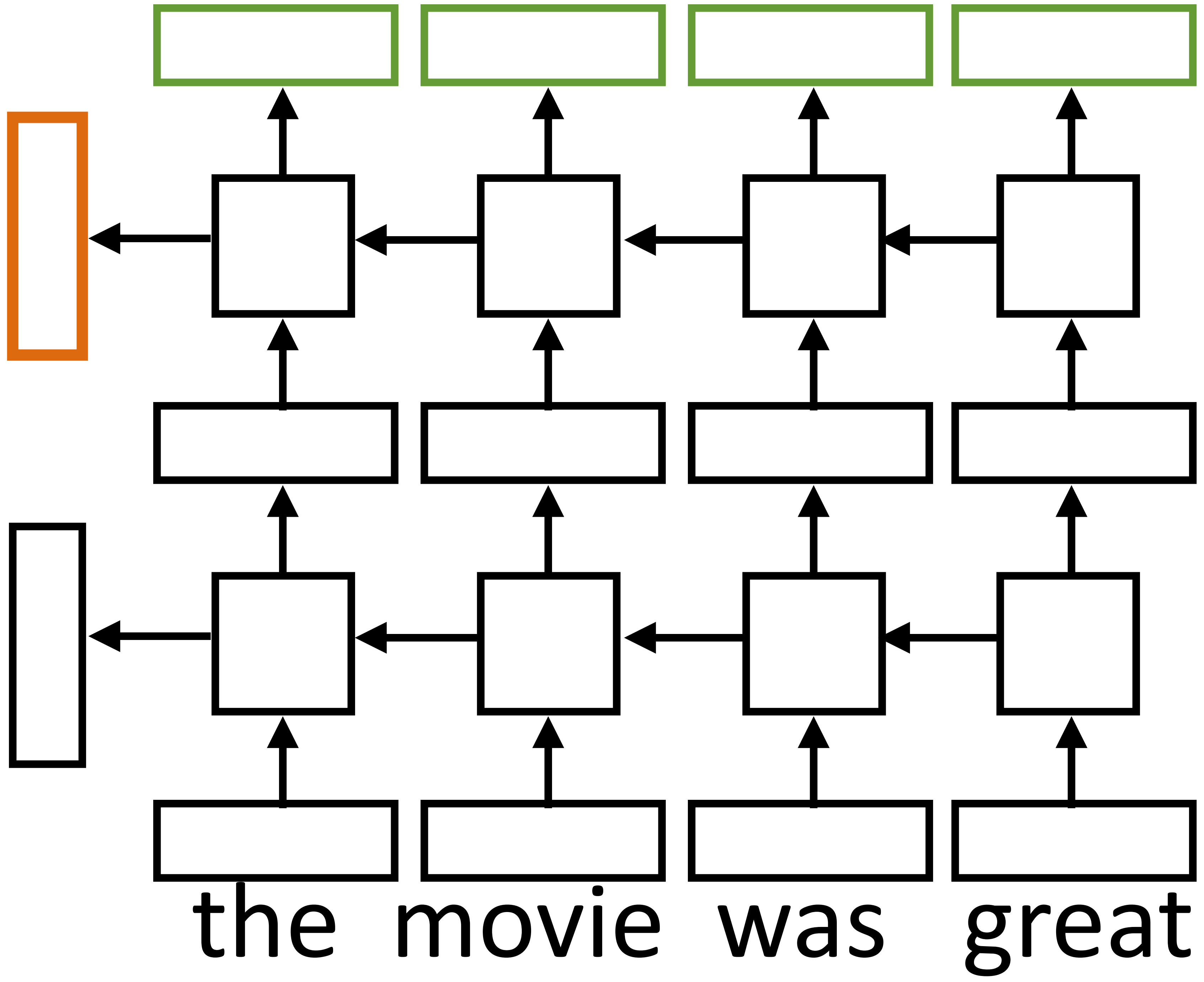

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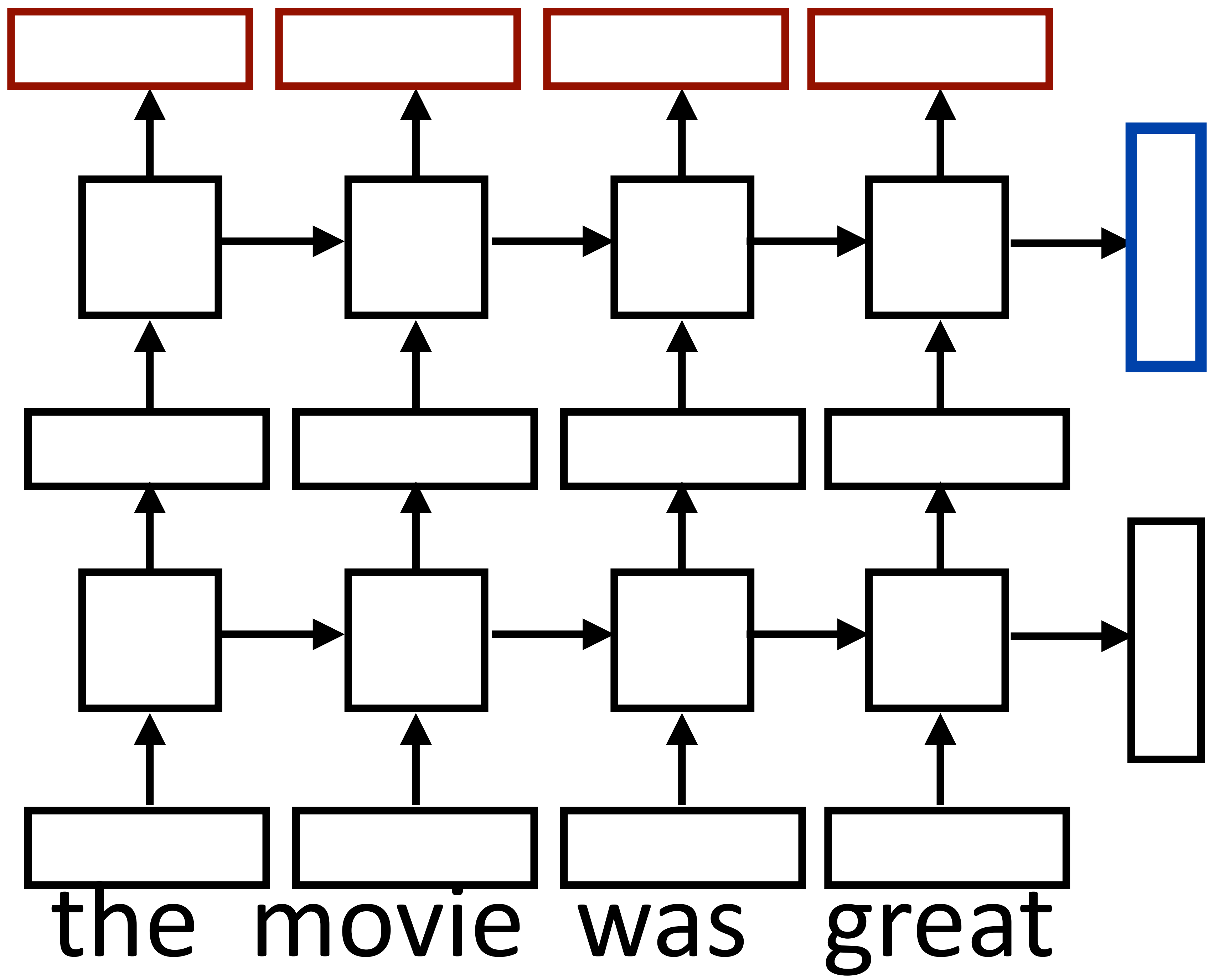
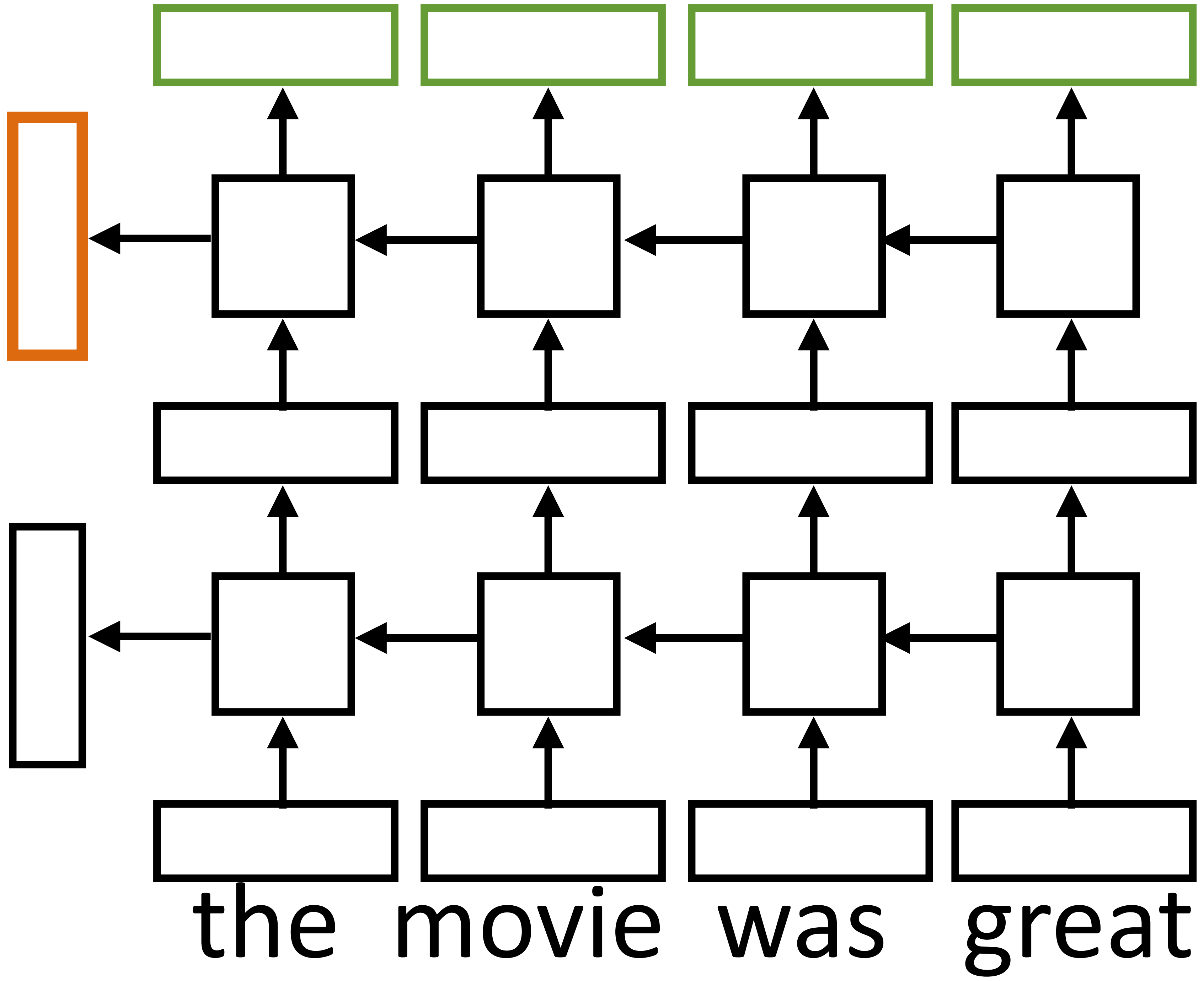
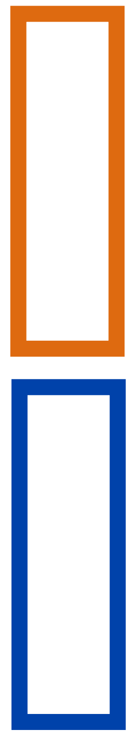




- Sentence classification based on concatenation of both final outputs



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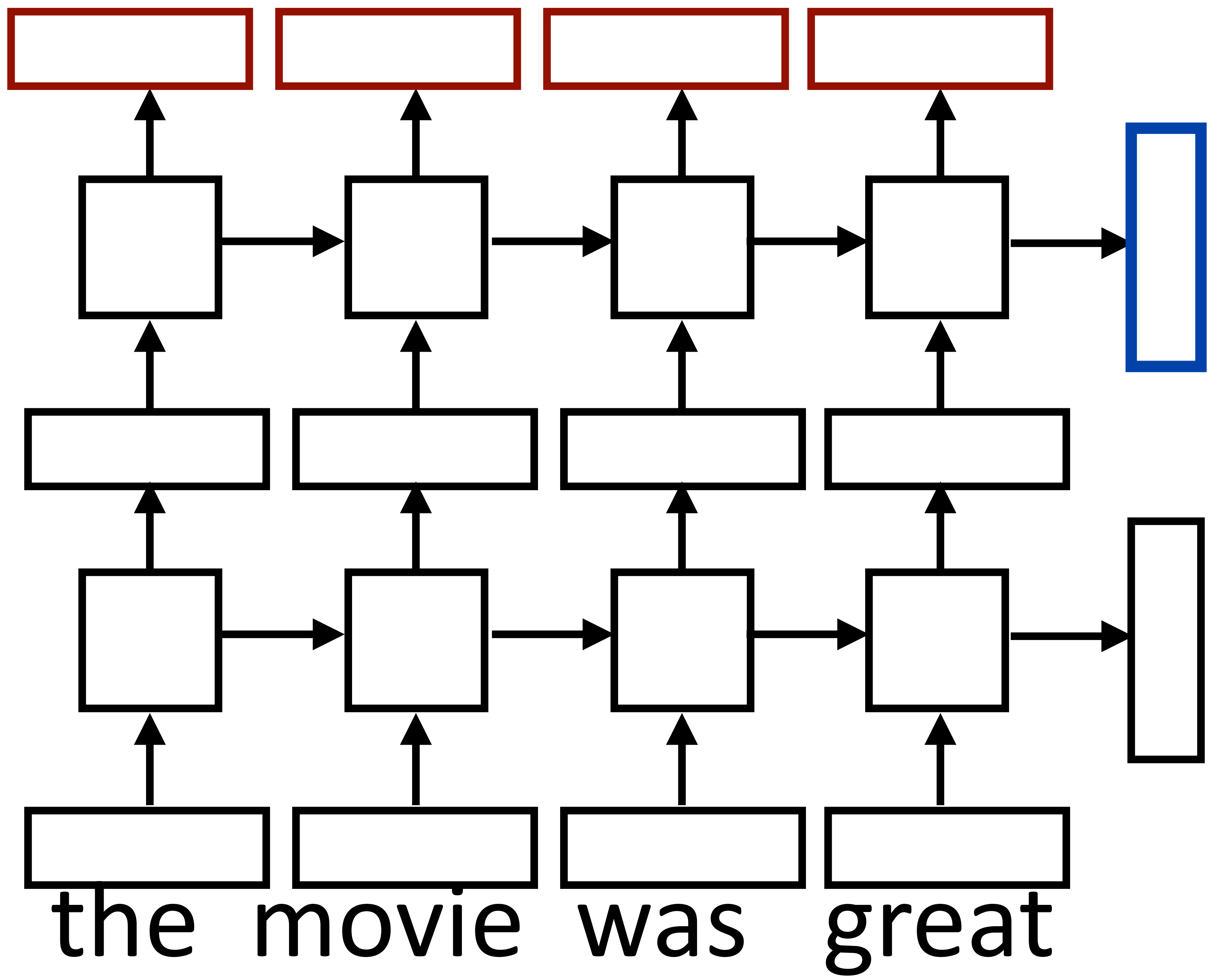

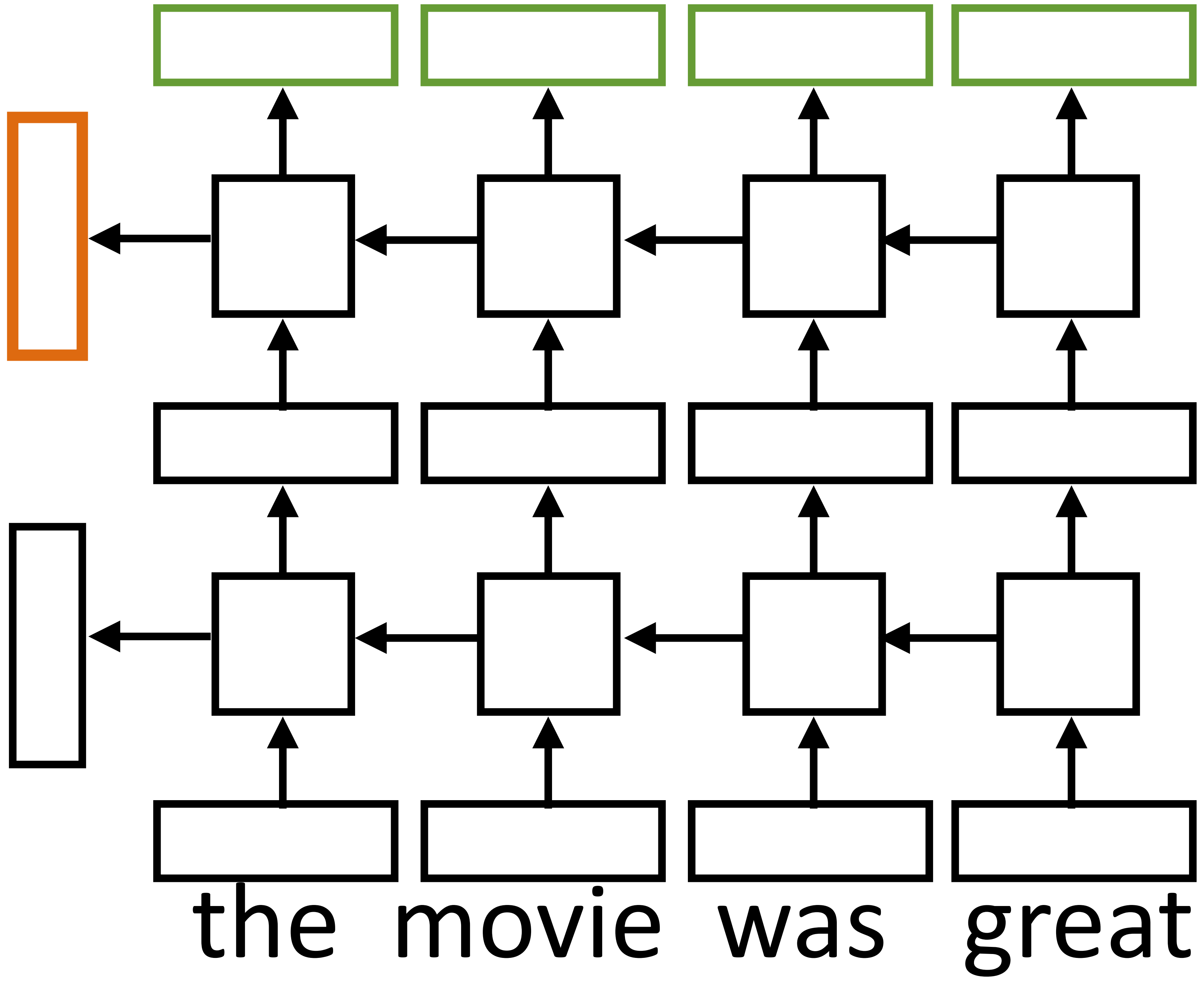

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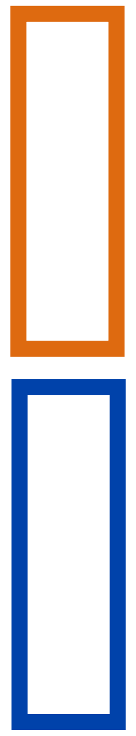
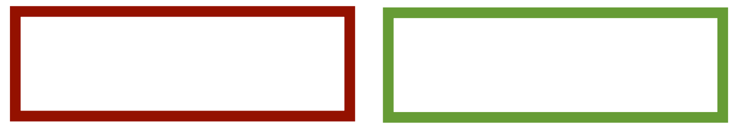
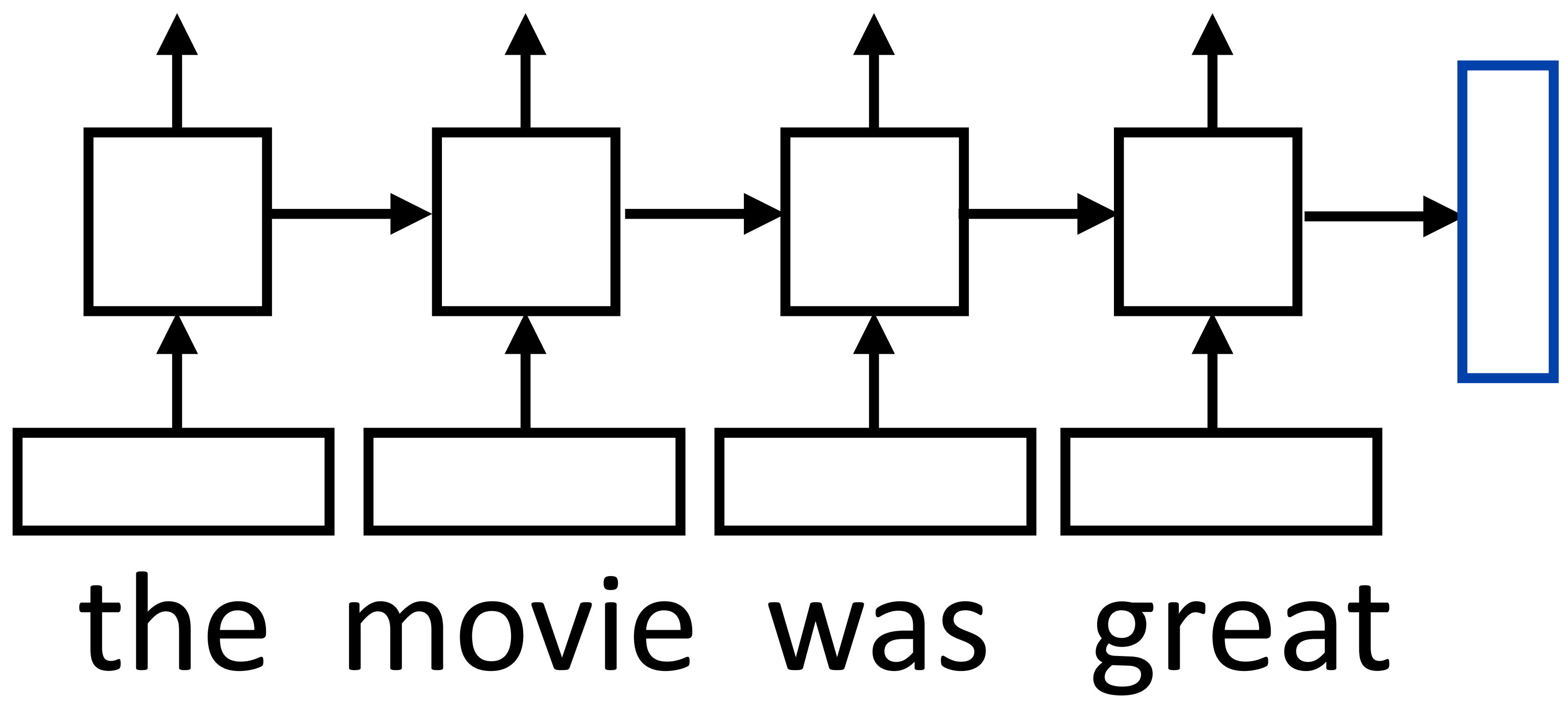


- Token classification based on concatenation of both directions' token representations



Training RNNs



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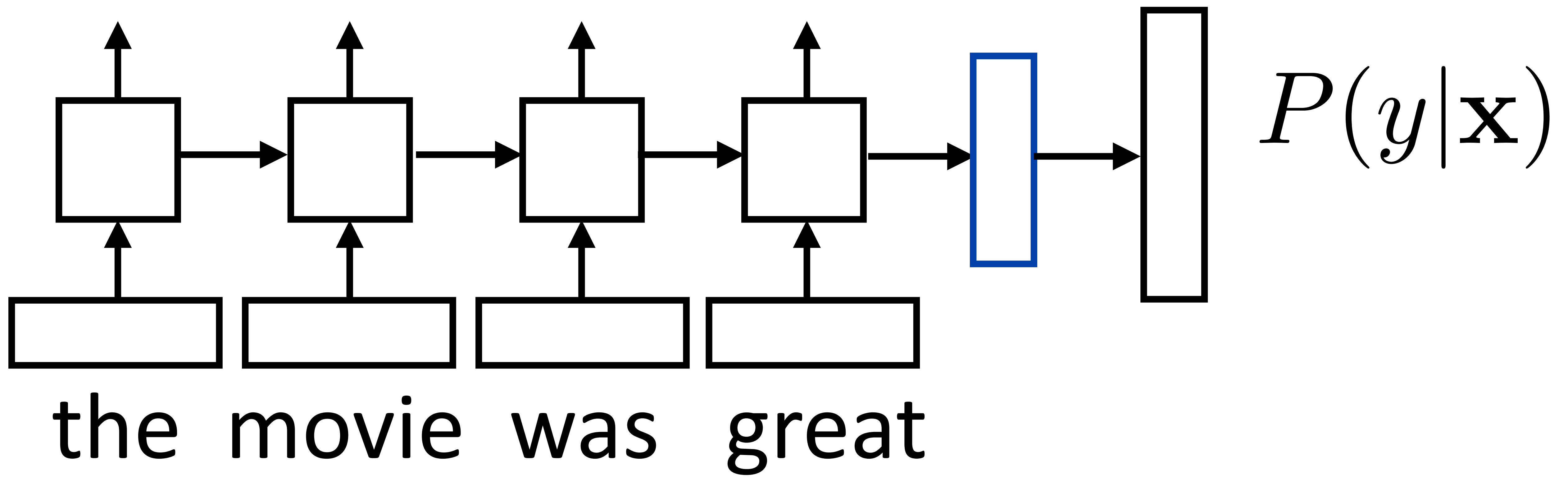

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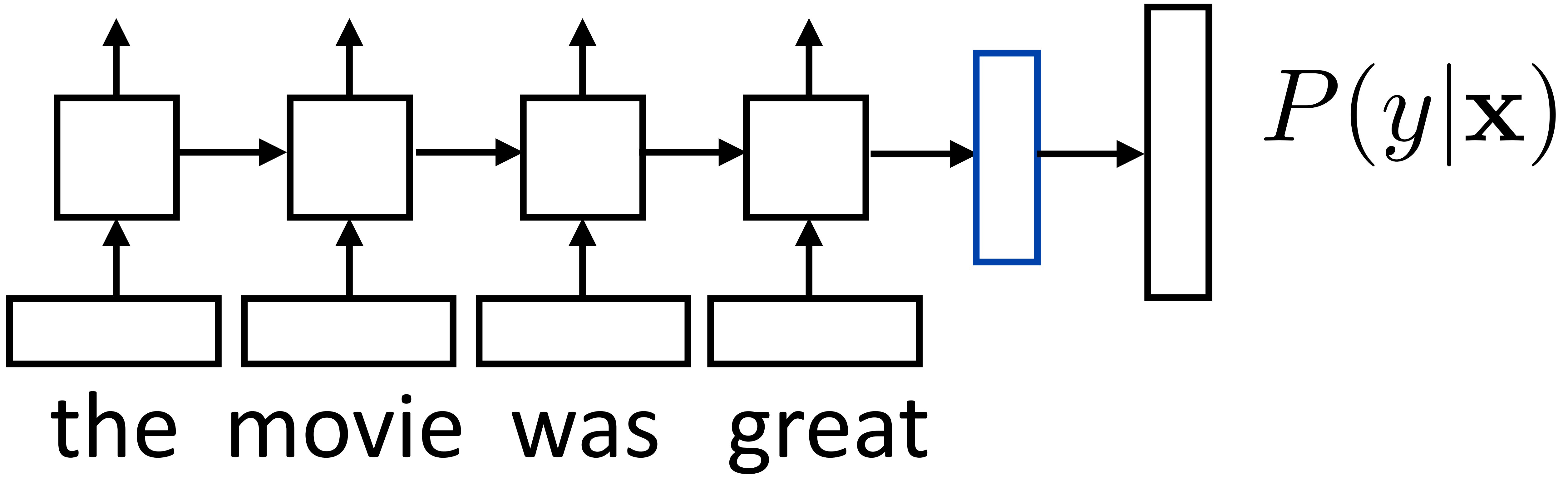

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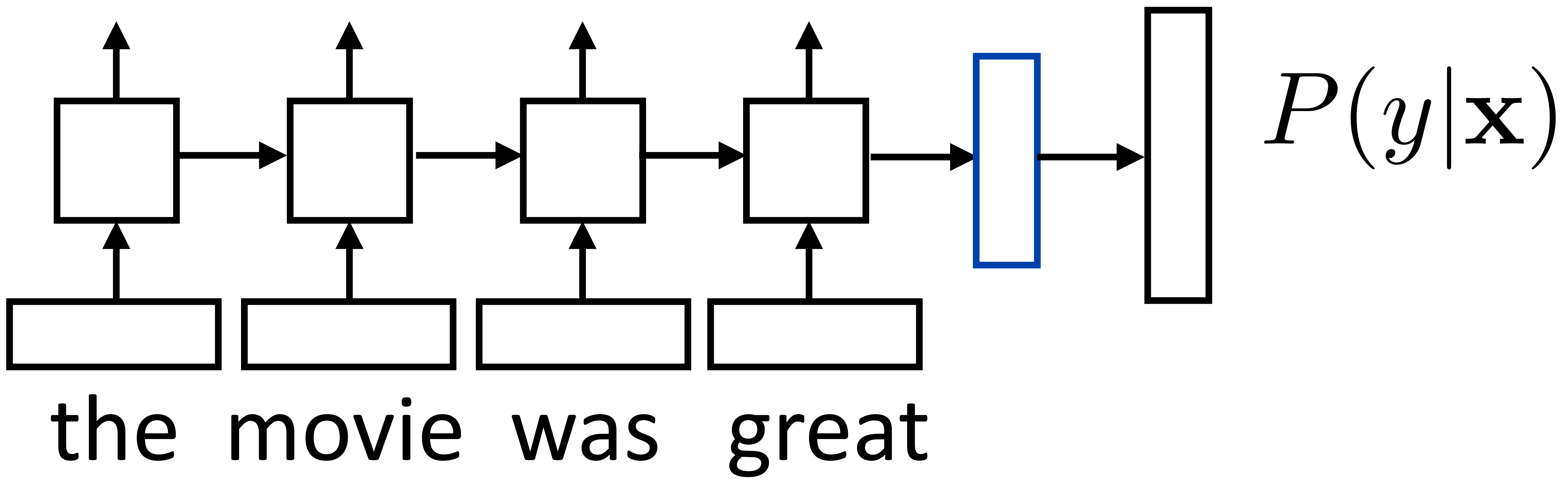

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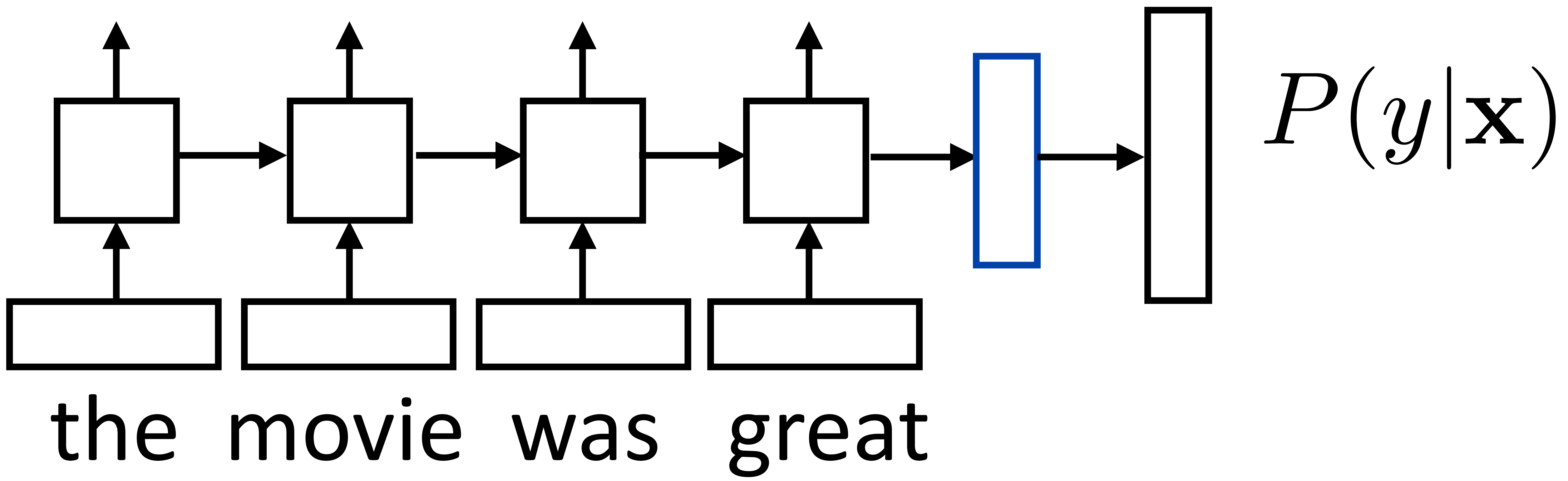
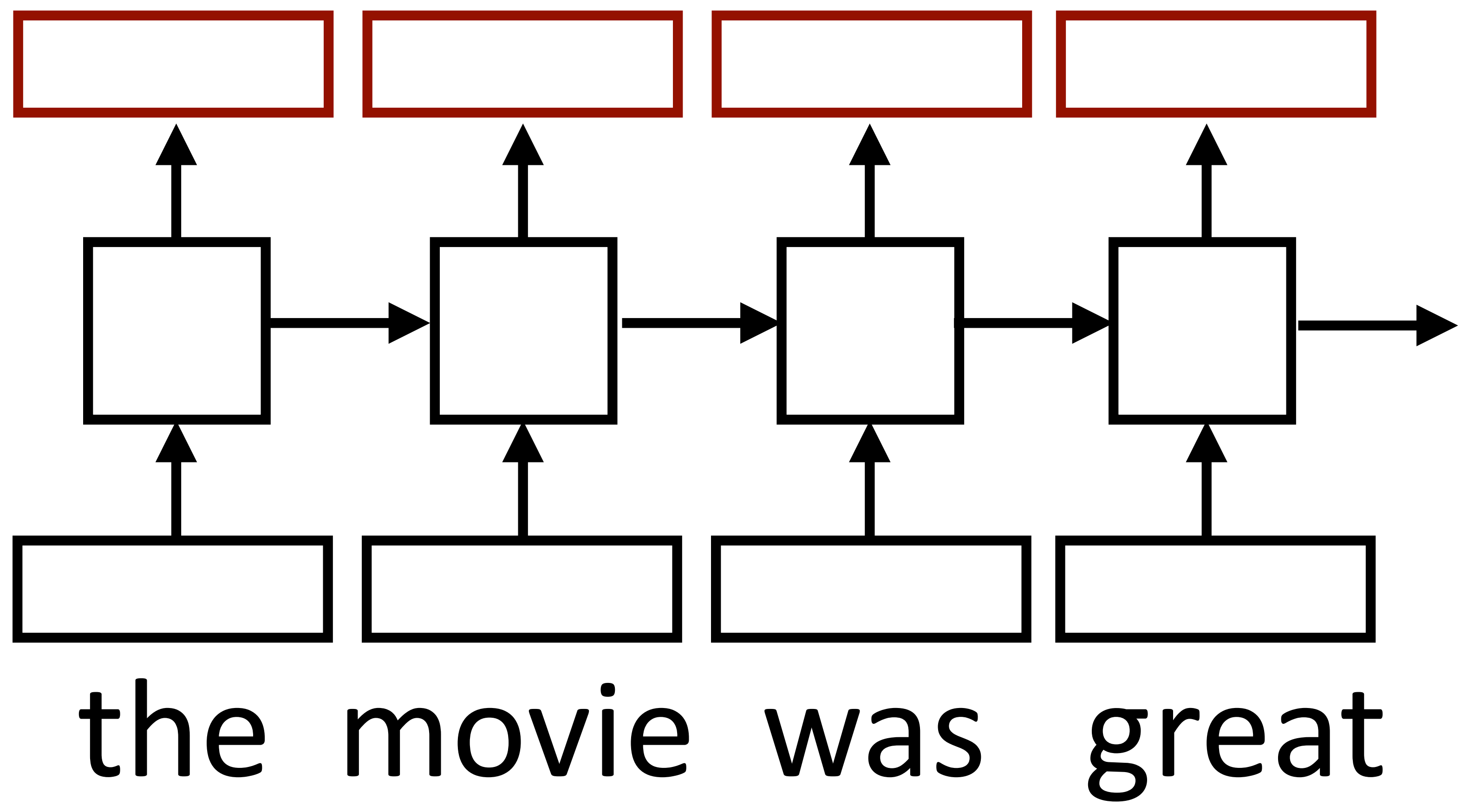
- Backpropagate through entire network

Training RNNs



- Loss = negative log likelihood of probability of gold label (or use SVM or other loss)
- Backpropagate through entire network
- Example: sentiment analysis

Training RNNs



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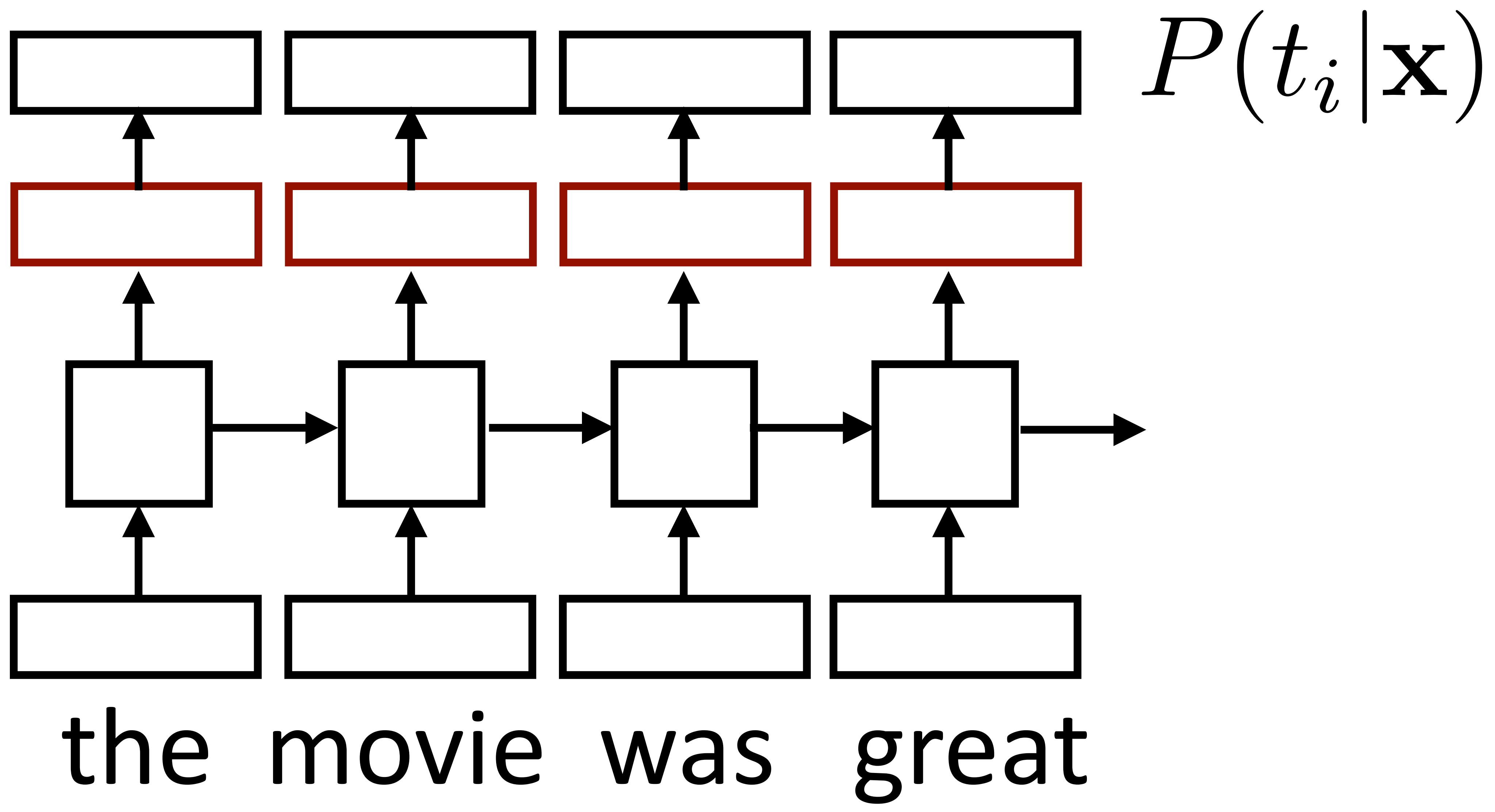

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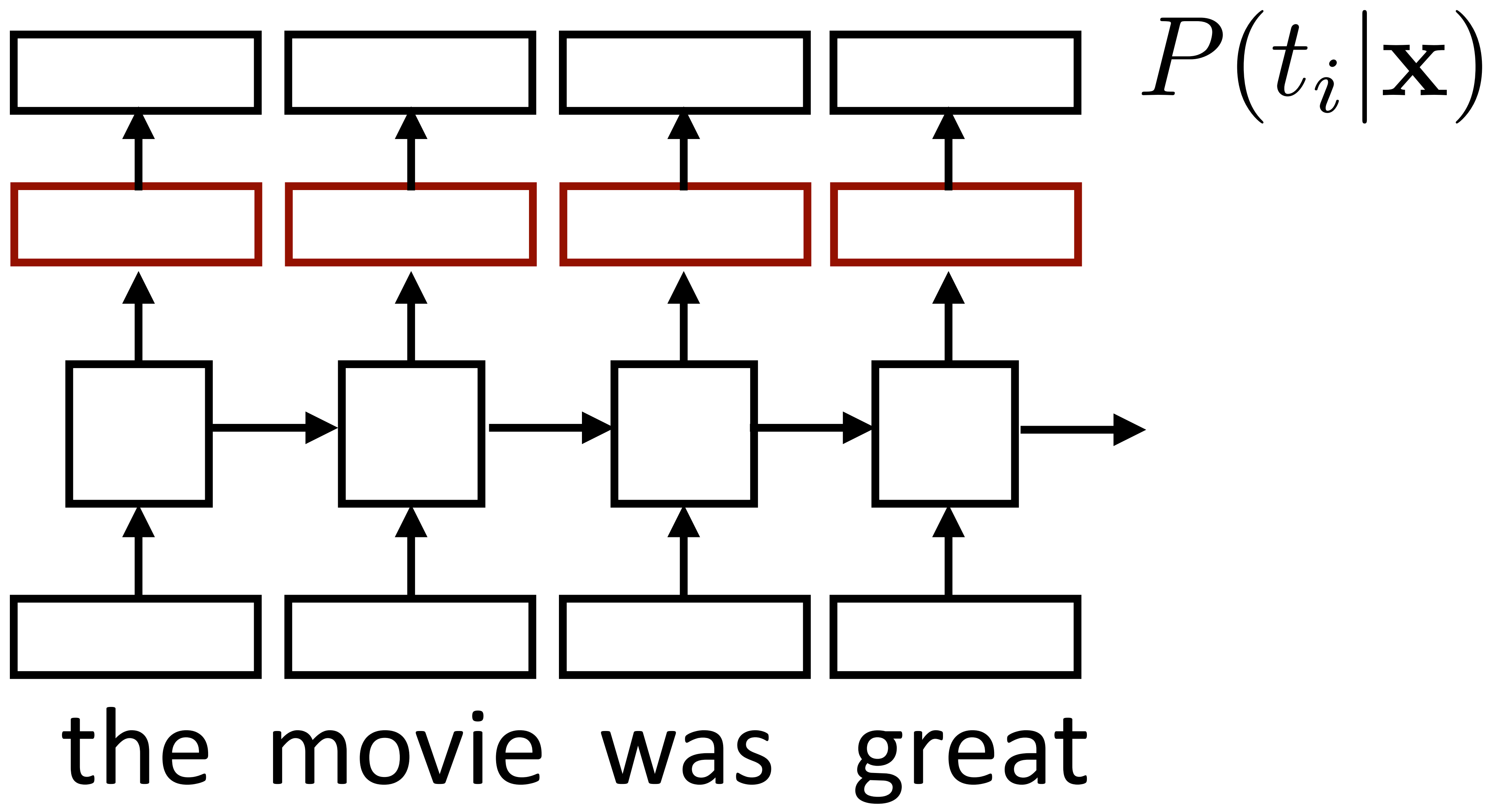
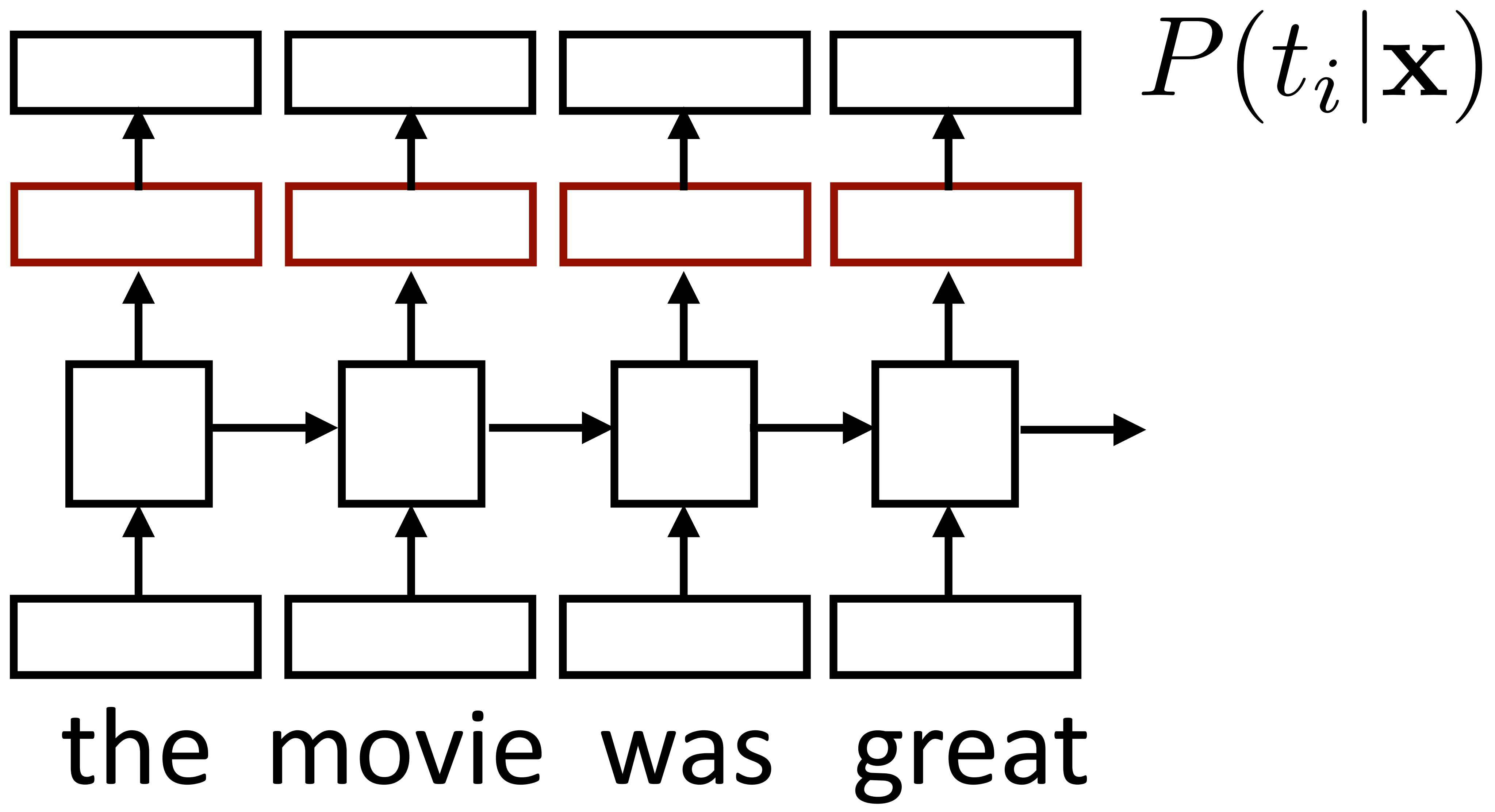


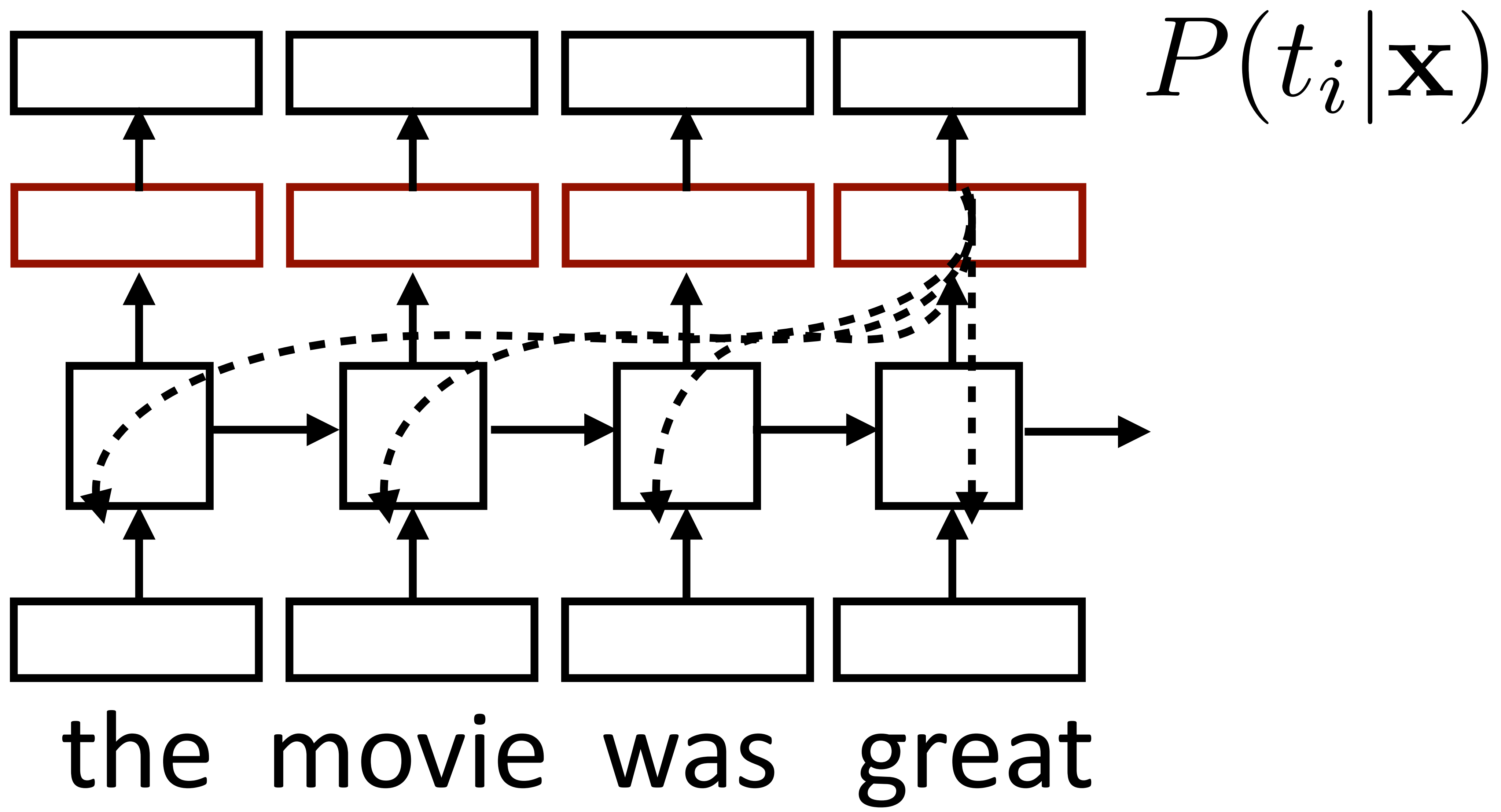
- Loss = negative log likelihood of probability of gold predictions, summed over the tags

Training RNNs



- Loss = negative log likelihood of probability of gold predictions, summed over the tags
- Loss terms filter back through network

Training RNNs



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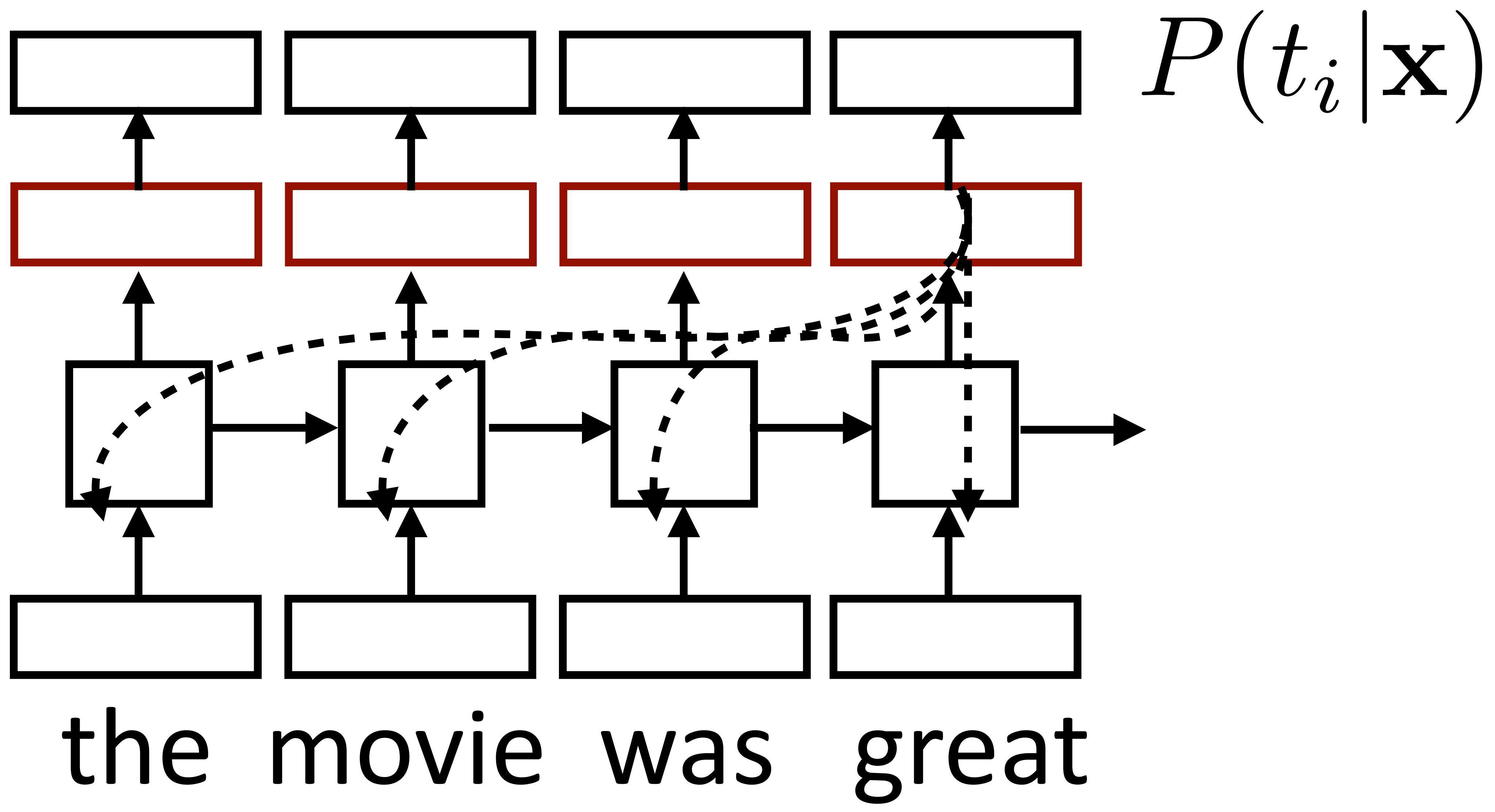

- Loss = negative log likelihood of probability of gold predictions, summed over the tags
- Loss terms filter back through network
- Example: language modeling (predict next word given context)

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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  - 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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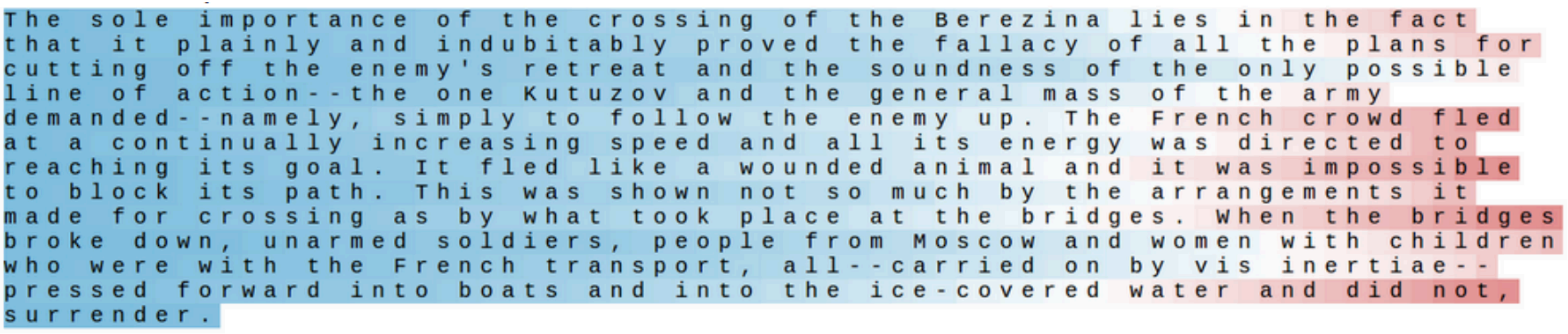

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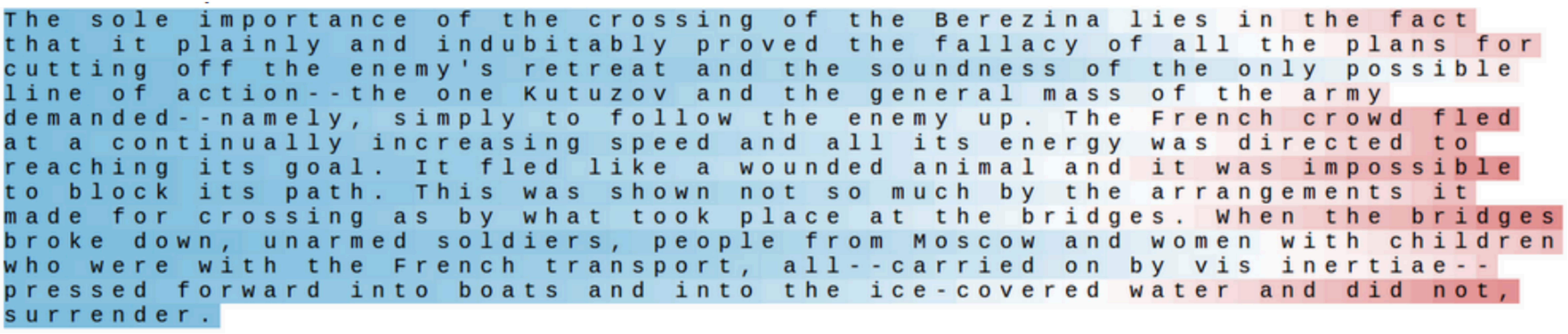
- Counter: know when to generate \n



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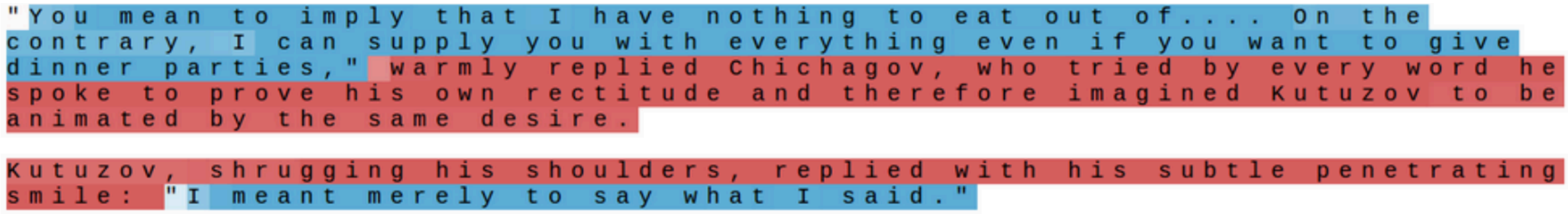

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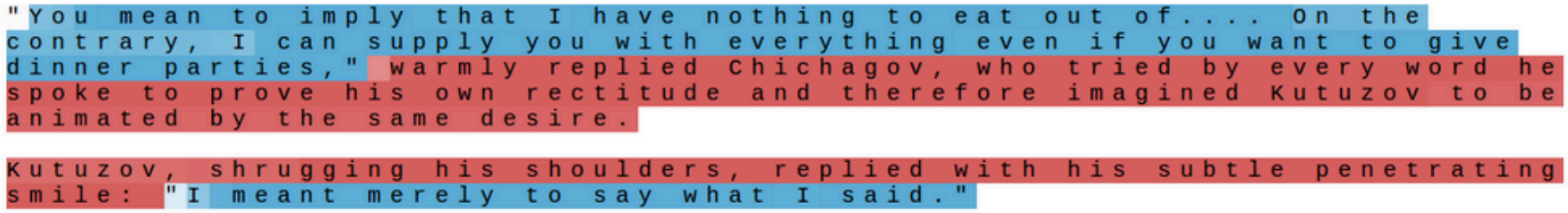
- Binary switch: tells us if we're in a quote or not



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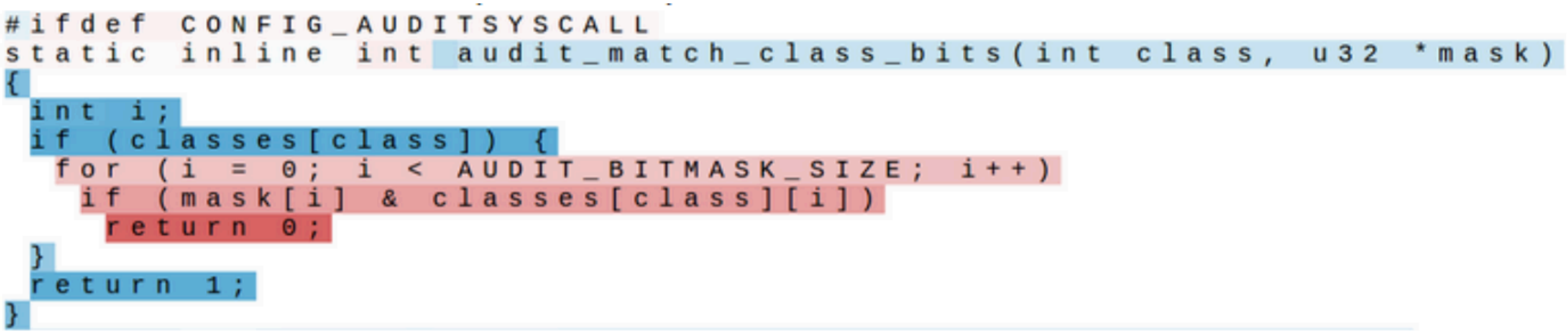

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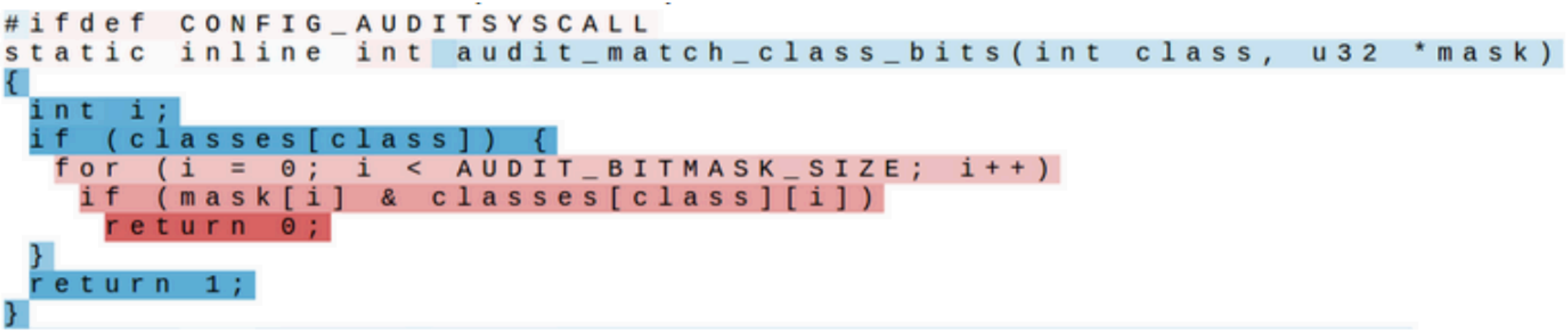
- Stack: activation based on indentation



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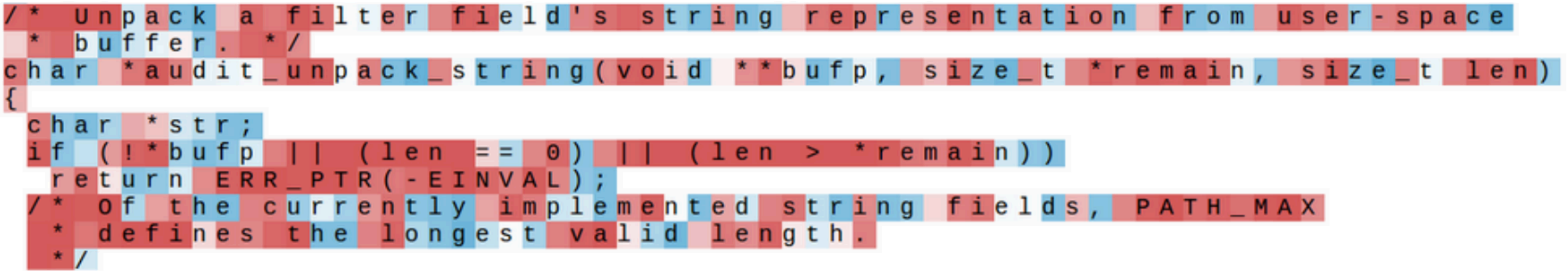
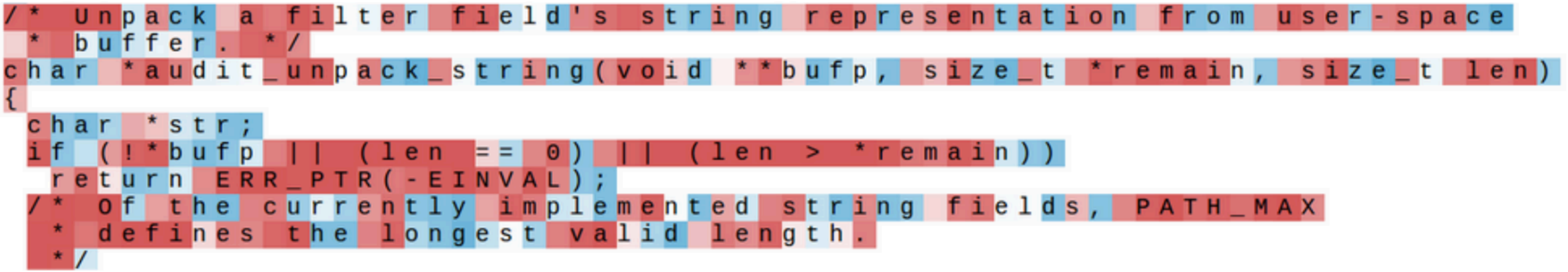


Karpathy et al. (2015)

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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- Textual entailment
  - Encode two sentences, predict

Natural Language Inference

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

Natural Language Inference

Premise		Hypothesis
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

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Premise		Hypothesis
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Premise		Hypothesis
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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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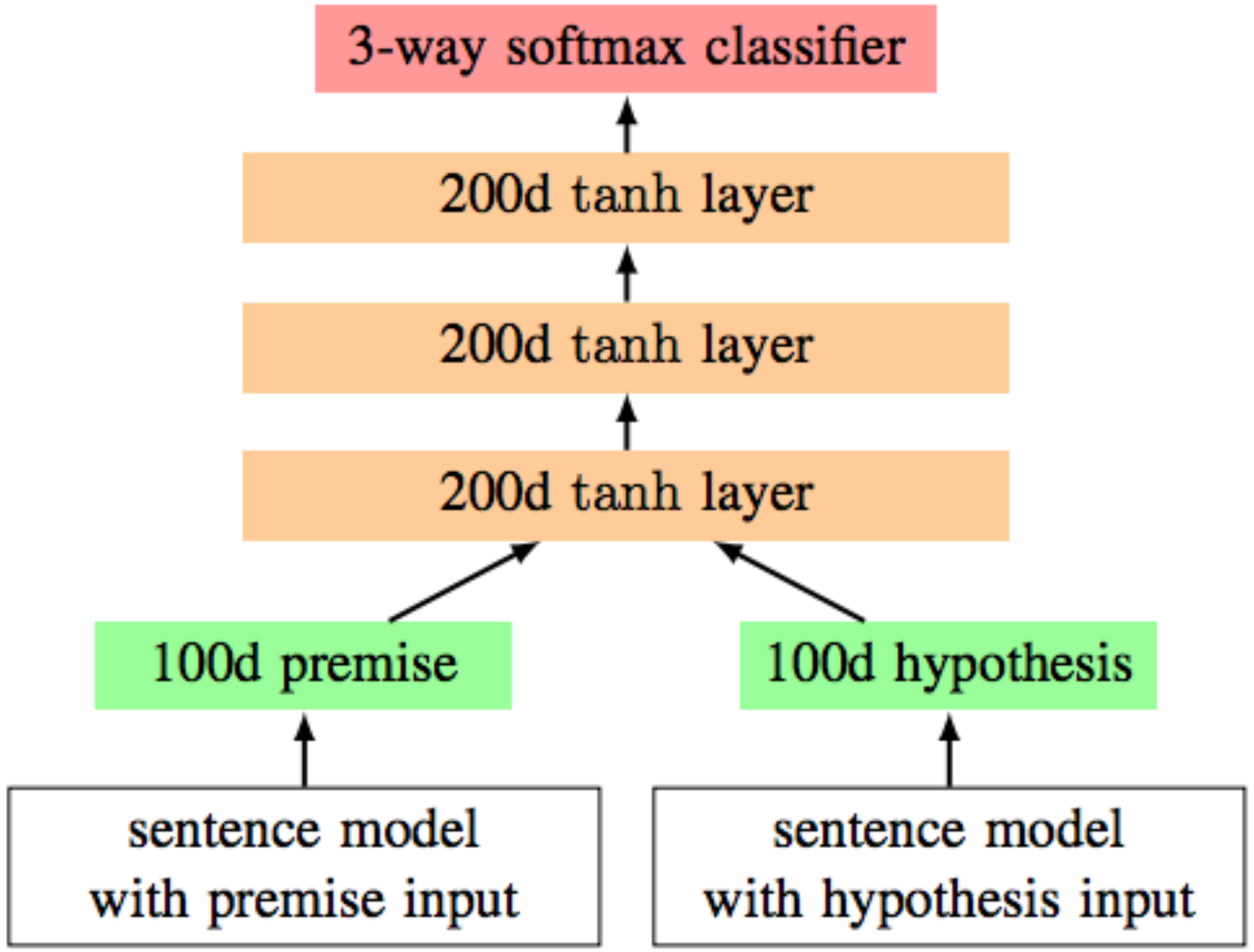

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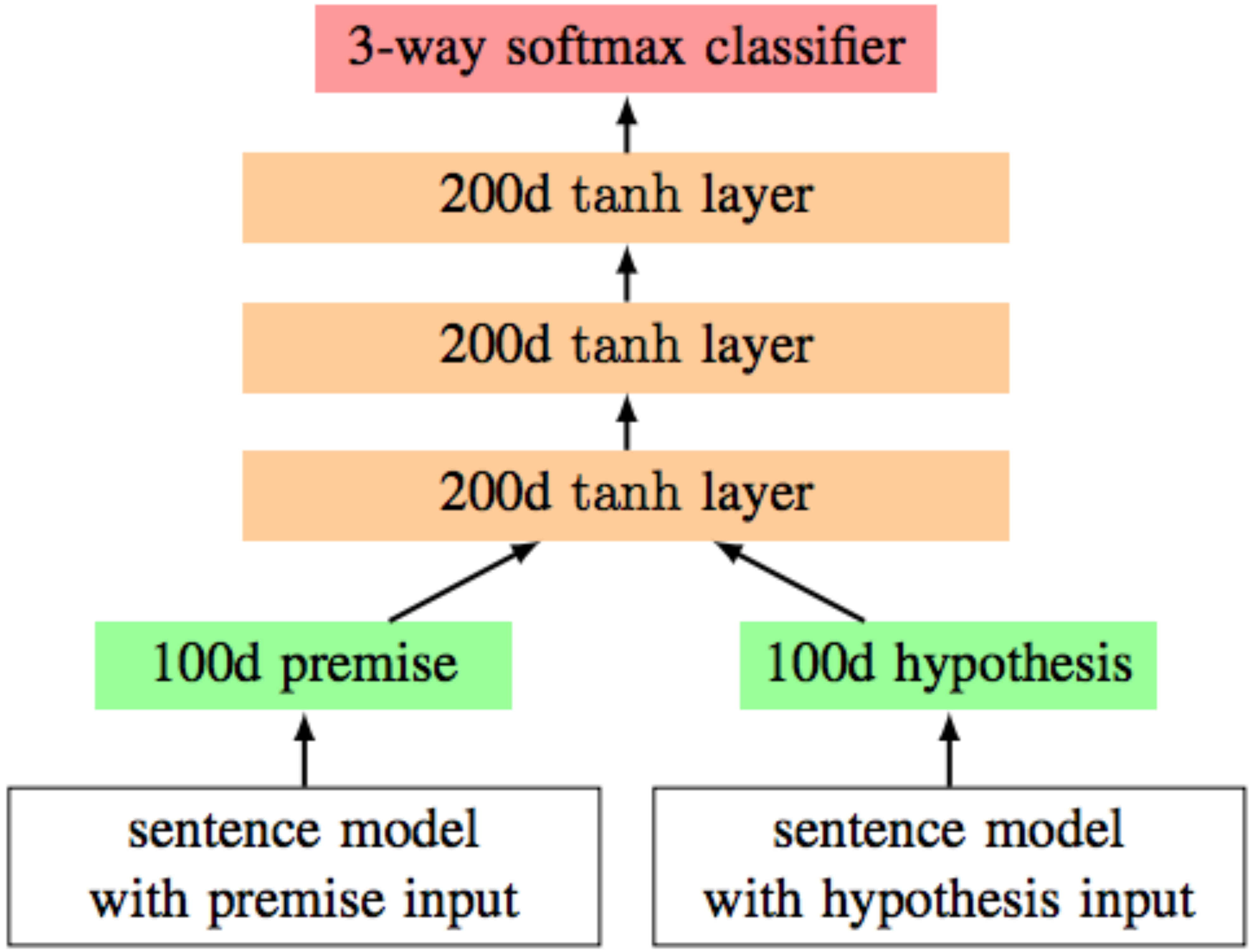

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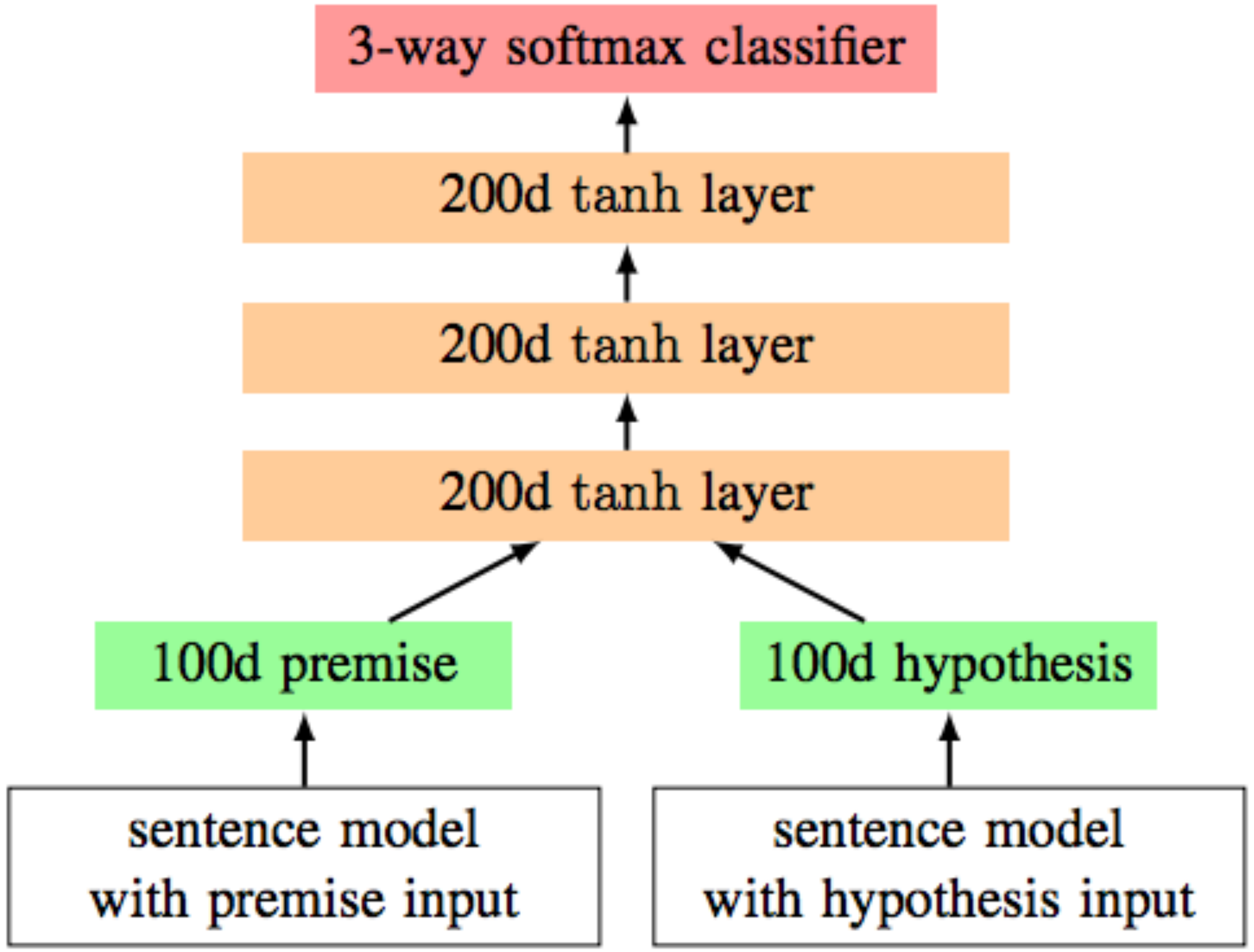
300D LSTM: 80% accuracy

(Bowman et al., 2016)



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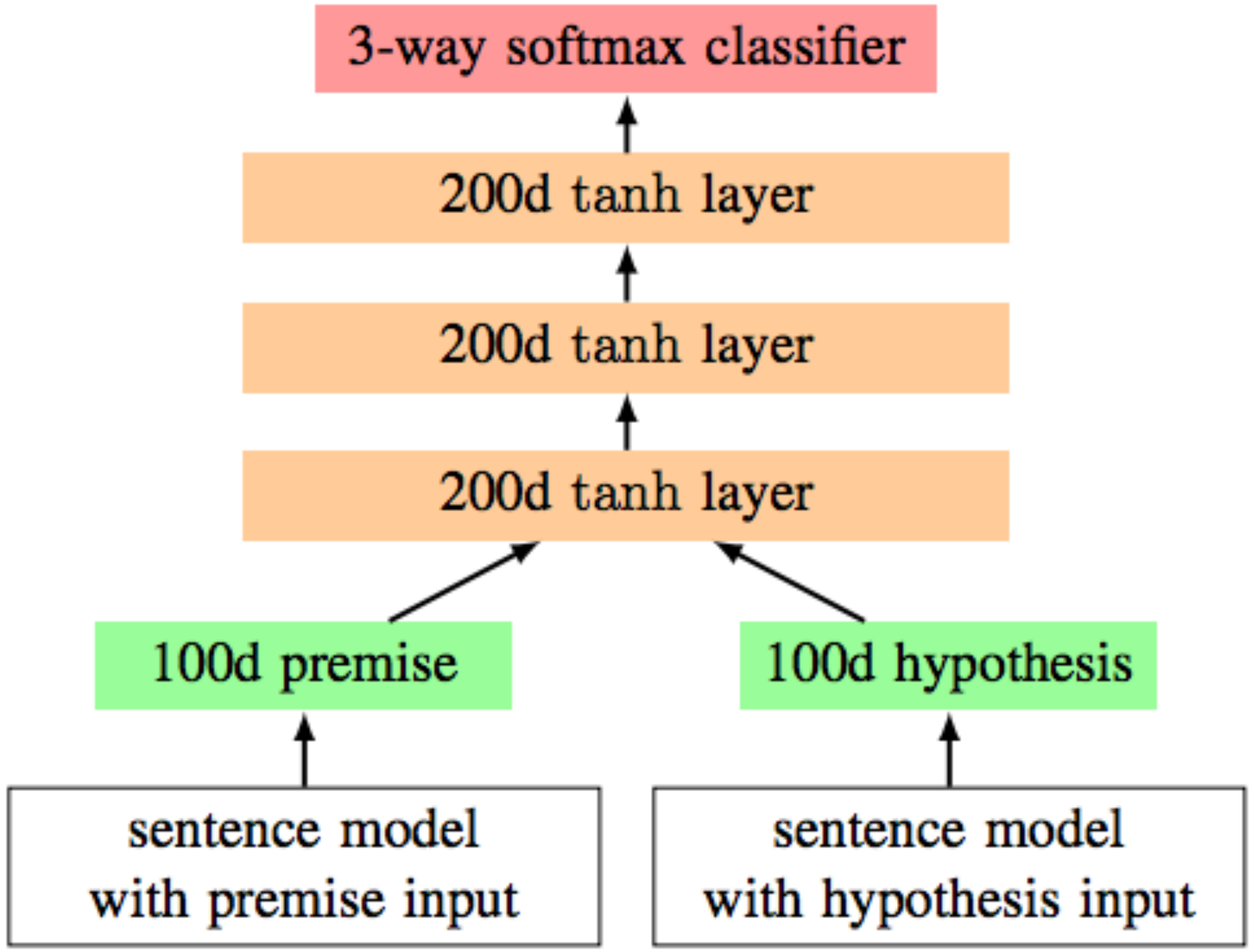
300D BiLSTM: 83% accuracy
(Liu et al., 2016)



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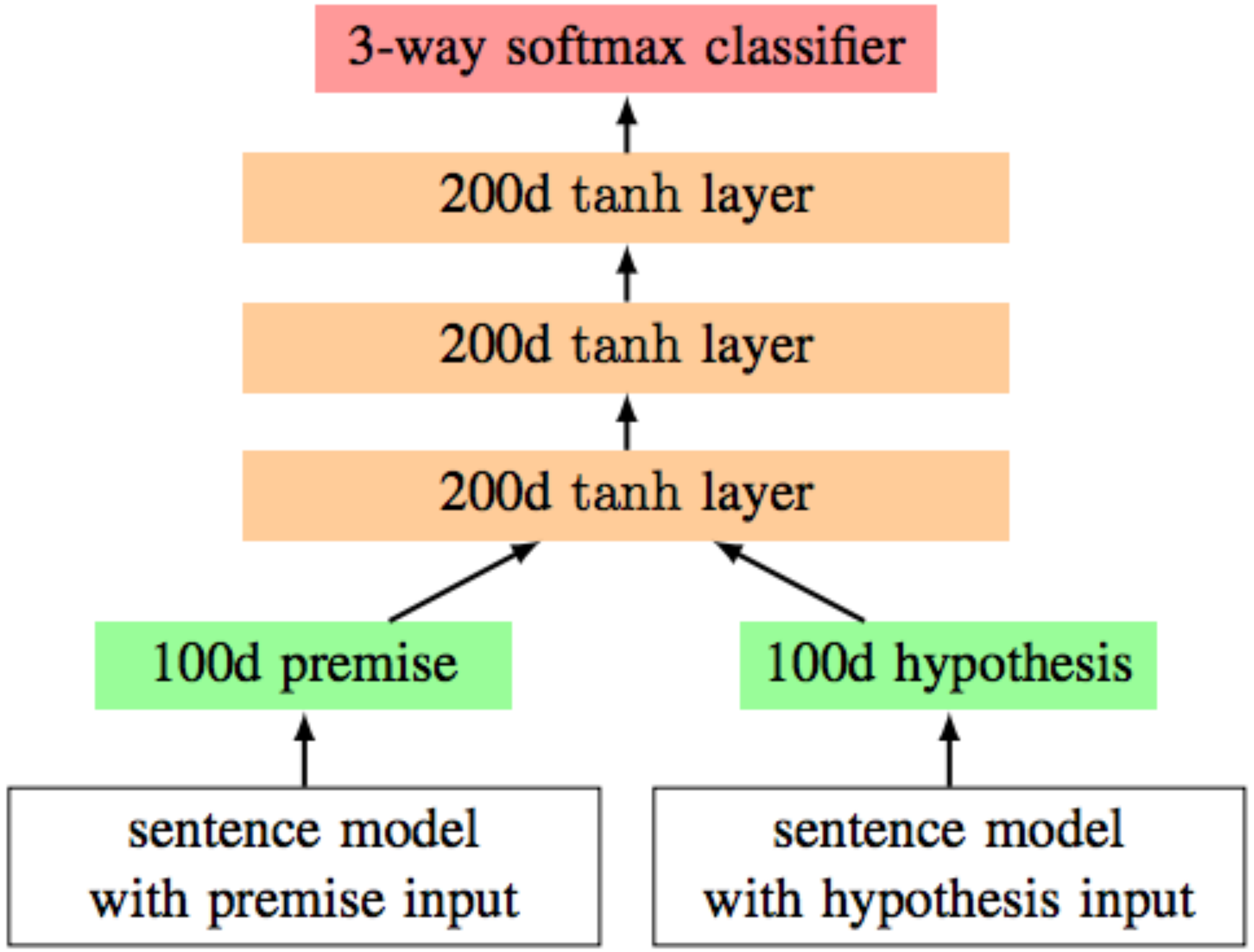
- Later: better models for this



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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