Summary / Review

LING 574 Deep Learning for NLP
Shane Steinert-Threlkeld

Announcements

- Course evaluations open **only until Friday** (more later)

Today's Plan

- Survey of what we covered in the class
  - Core progression
  - Guest lectures
  - Assignments
- Some pointers to what's next
- Question time

Learning Objectives

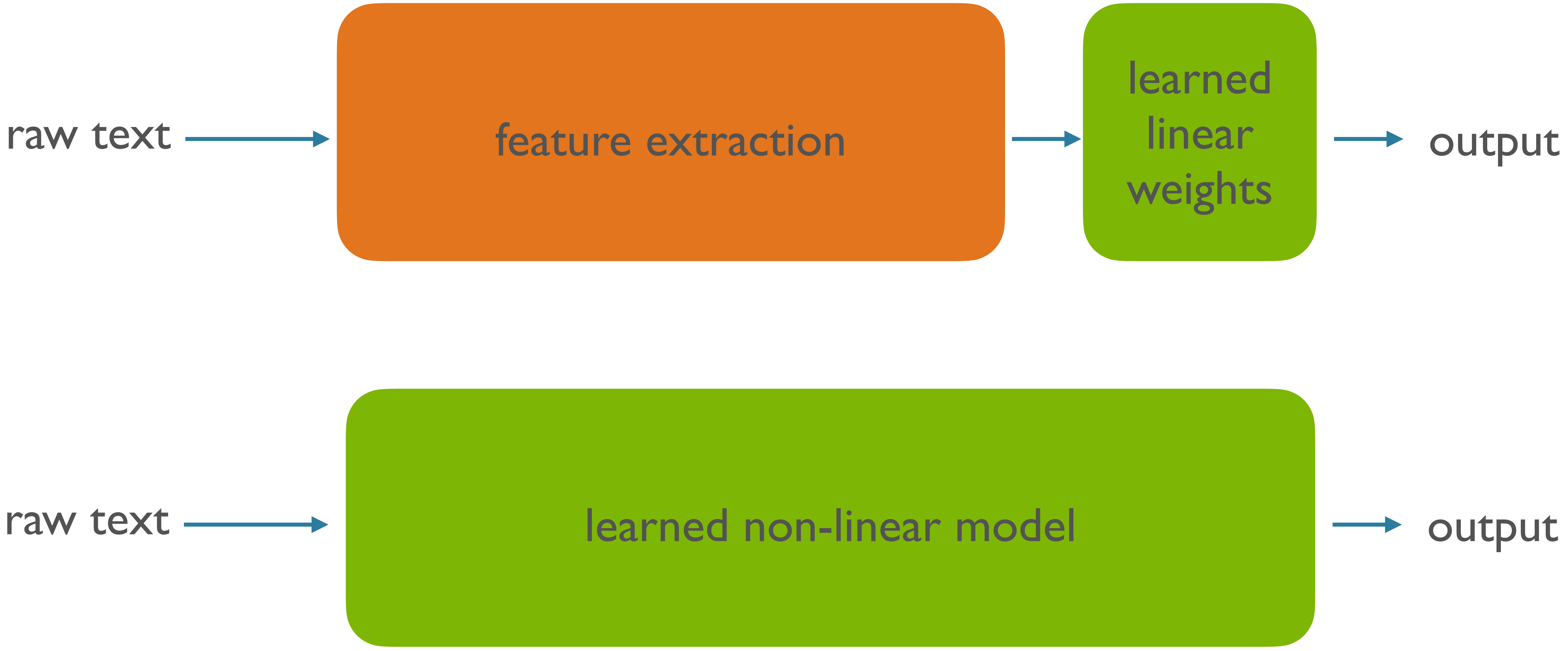
- Provide hands-on experience with building neural networks and using them for NLP tasks
- Theoretical understanding of building blocks
  - Computation graphs + gradient descent
  - Forward/backward API
    - Chain rule for computing gradients [backpropagation]
  - Various network architectures; their structure and biases

Topics Covered

Getting Started

- History
- Gradient descent optimization
  - Regularization, mini-batches, etc.
- Word vectors / word2vec
- Main tasks: classification (sentiment analysis), language modeling

Very potted history



The SGNS Model

$$P(1 \mid w, c) = \sigma\left(E_w \cdot C_c\right)$$

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Target word
embedding

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Target word embedding

Context word embedding

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Target word embedding

Context word embedding

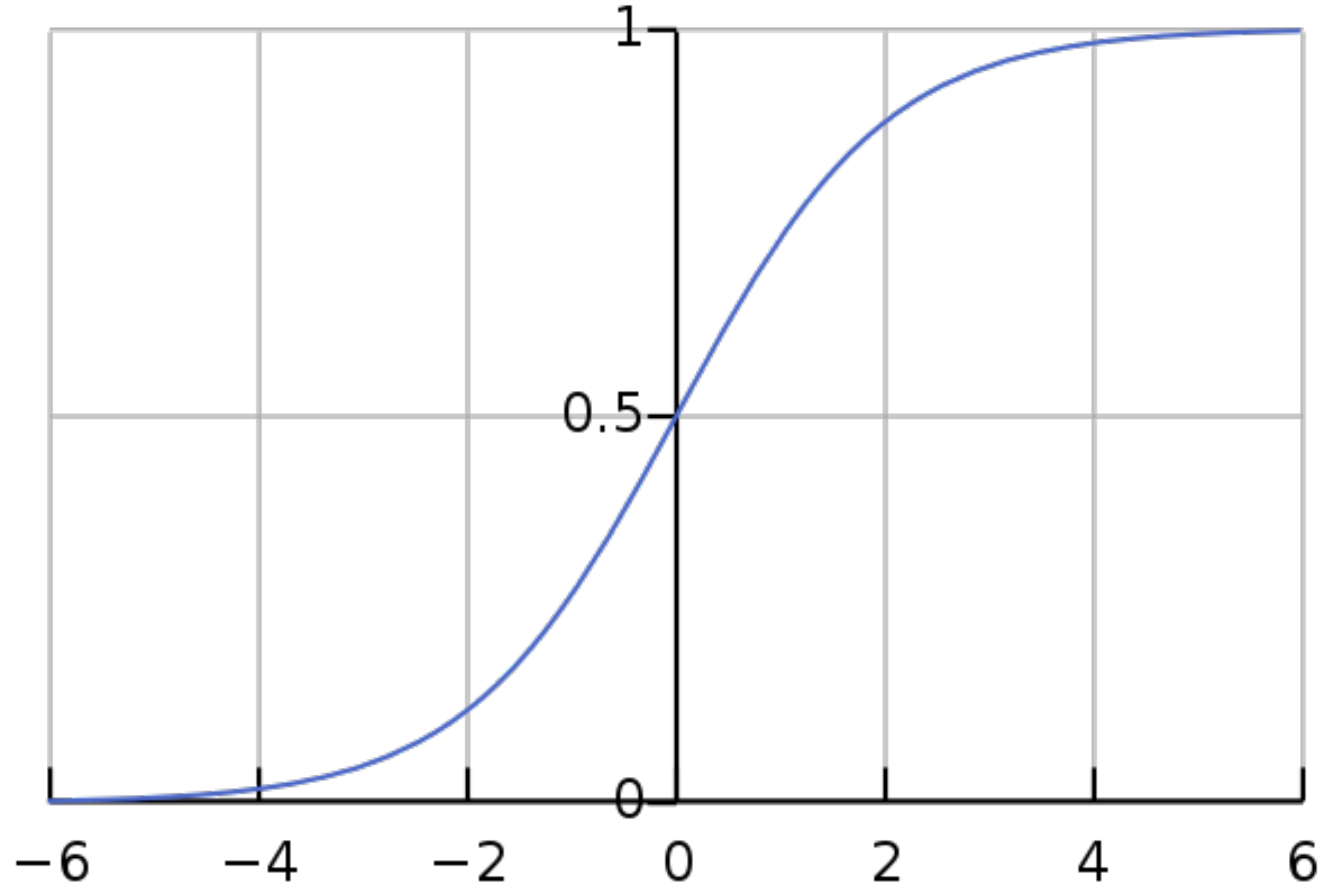
Similarity (dot-product)

The SGNS Model

$$P(1 \mid w, c) = \sigma\left(E_w \cdot C_c\right)$$

sigmoid

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$



Target word embedding

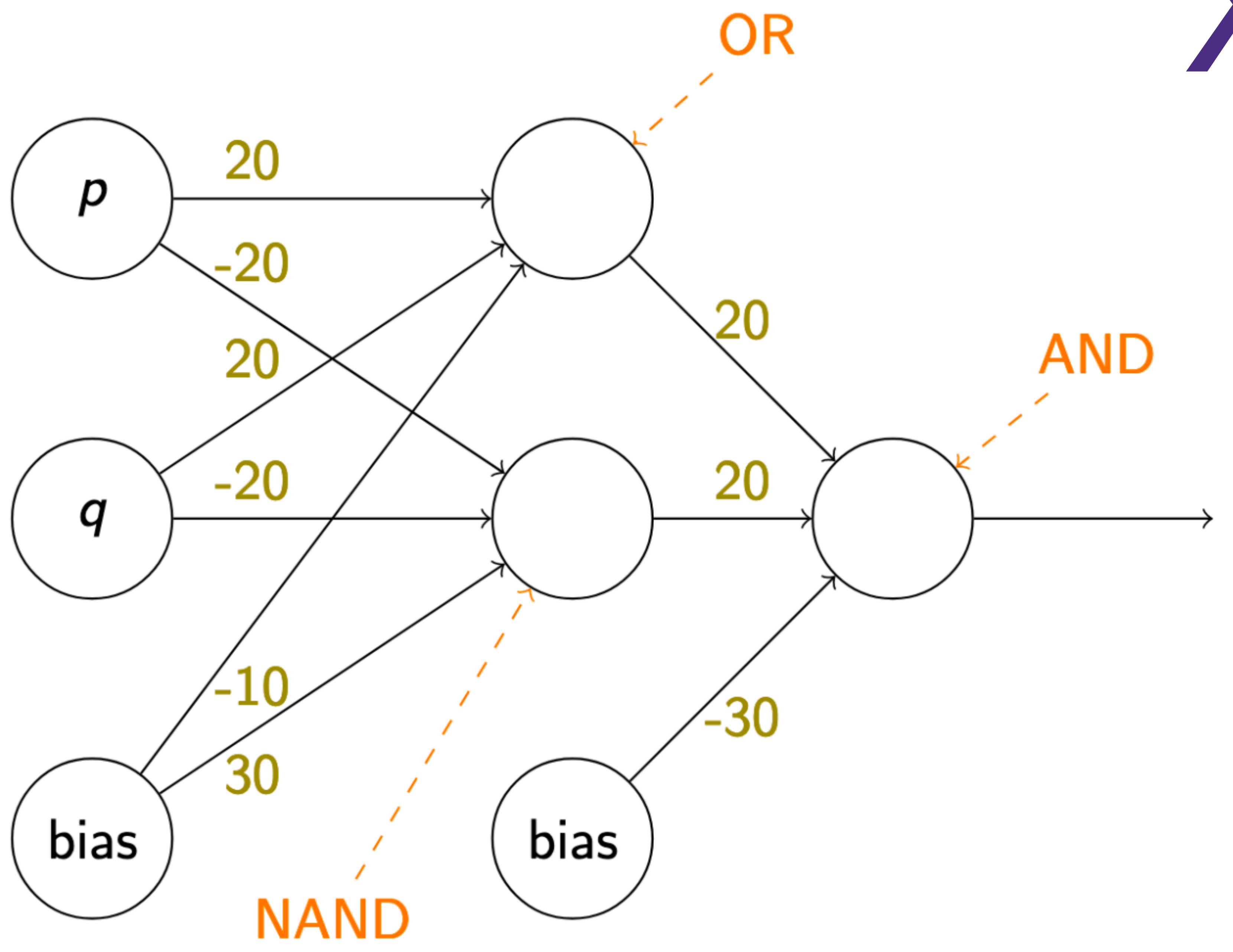
Context word embedding

Similarity (dot-product)

Neural Networks: Foundations

- Neural networks: intro
  - Expressive power / limitations
- Computation graph abstraction
- Backpropagation

XOR Network

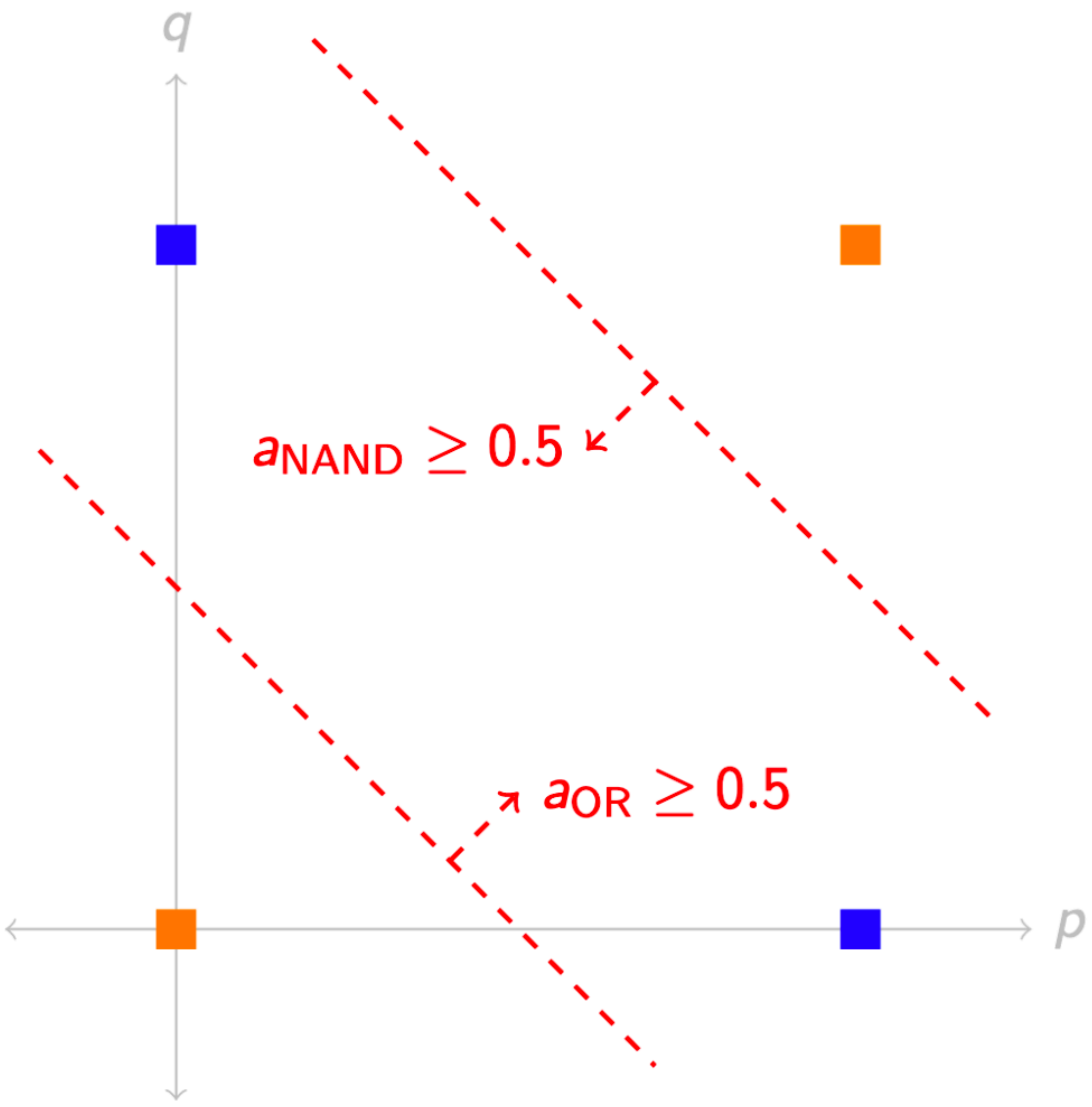


$$a_{\text{and}} = \sigma\left(w^{\text{and}}_{\text{or}} \cdot a_{\text{or}} + w^{\text{and}}_{\text{nand}} \cdot a_{\text{nand}} + b^{\text{and}}\right)$$

$$= \sigma\left(\begin{bmatrix} a_{\text{or}} & a_{\text{nand}} \end{bmatrix} \begin{bmatrix} w^{\text{and}}_{\text{or}} \\ w^{\text{and}}_{\text{nand}} \end{bmatrix} + b^{\text{and}}\right)$$

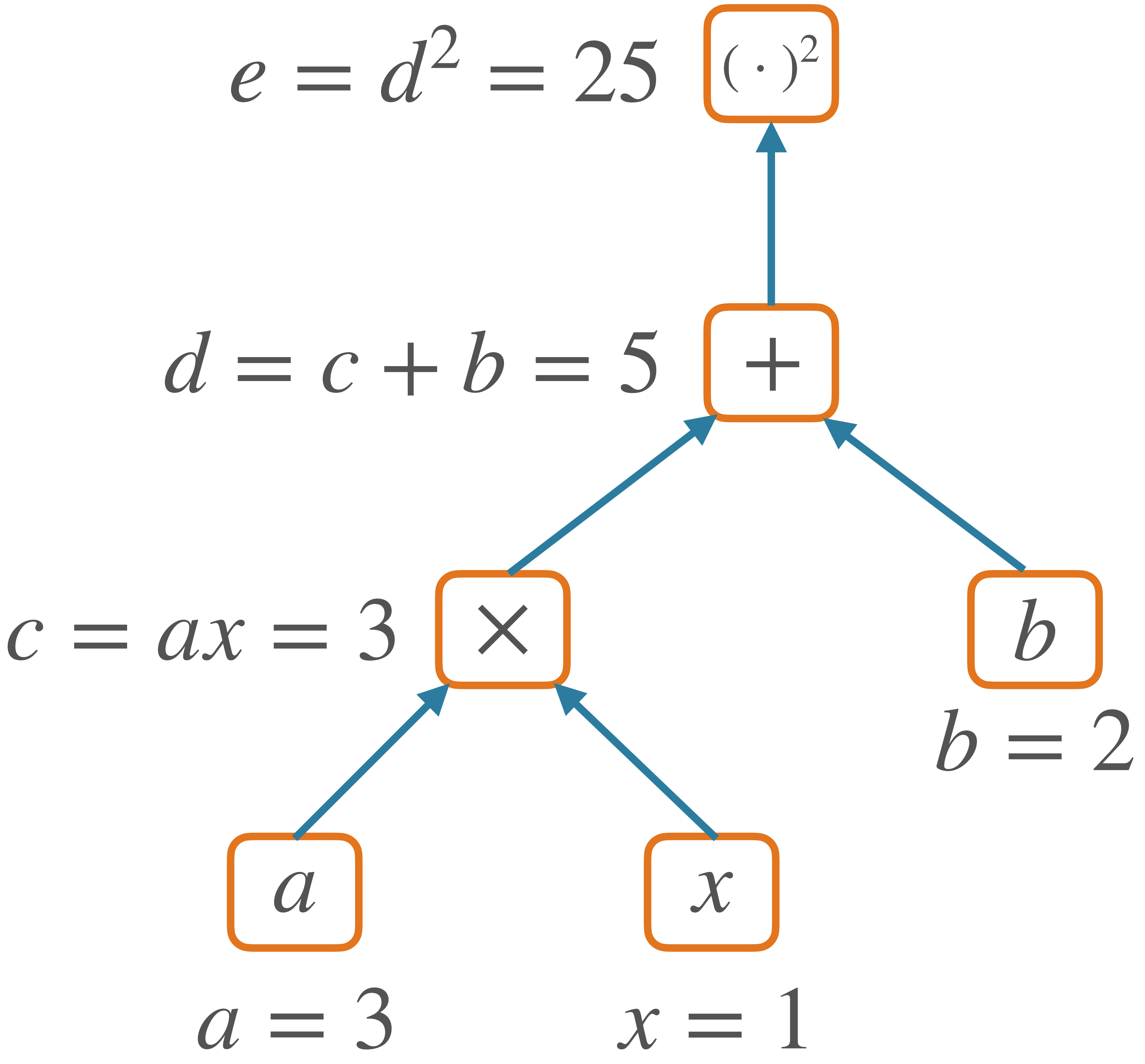
$$a_{\text{and}} = \sigma\left(\sigma\left(\begin{bmatrix} a_p & a_q \end{bmatrix} \begin{bmatrix} w^{\text{or}}_p & w^{\text{nand}}_p \\ w^{\text{or}}_q & w^{\text{nand}}_q \end{bmatrix} + \begin{bmatrix} b^{\text{or}} & b^{\text{nand}} \end{bmatrix}\right) \begin{bmatrix} w^{\text{and}}_{\text{or}} \\ w^{\text{and}}_{\text{nand}} \end{bmatrix} + b^{\text{and}}\right)$$

Computing XOR (not linearly-separable)



Backpropagation Example

$$f(x; a, b) = (ax + b)^2$$



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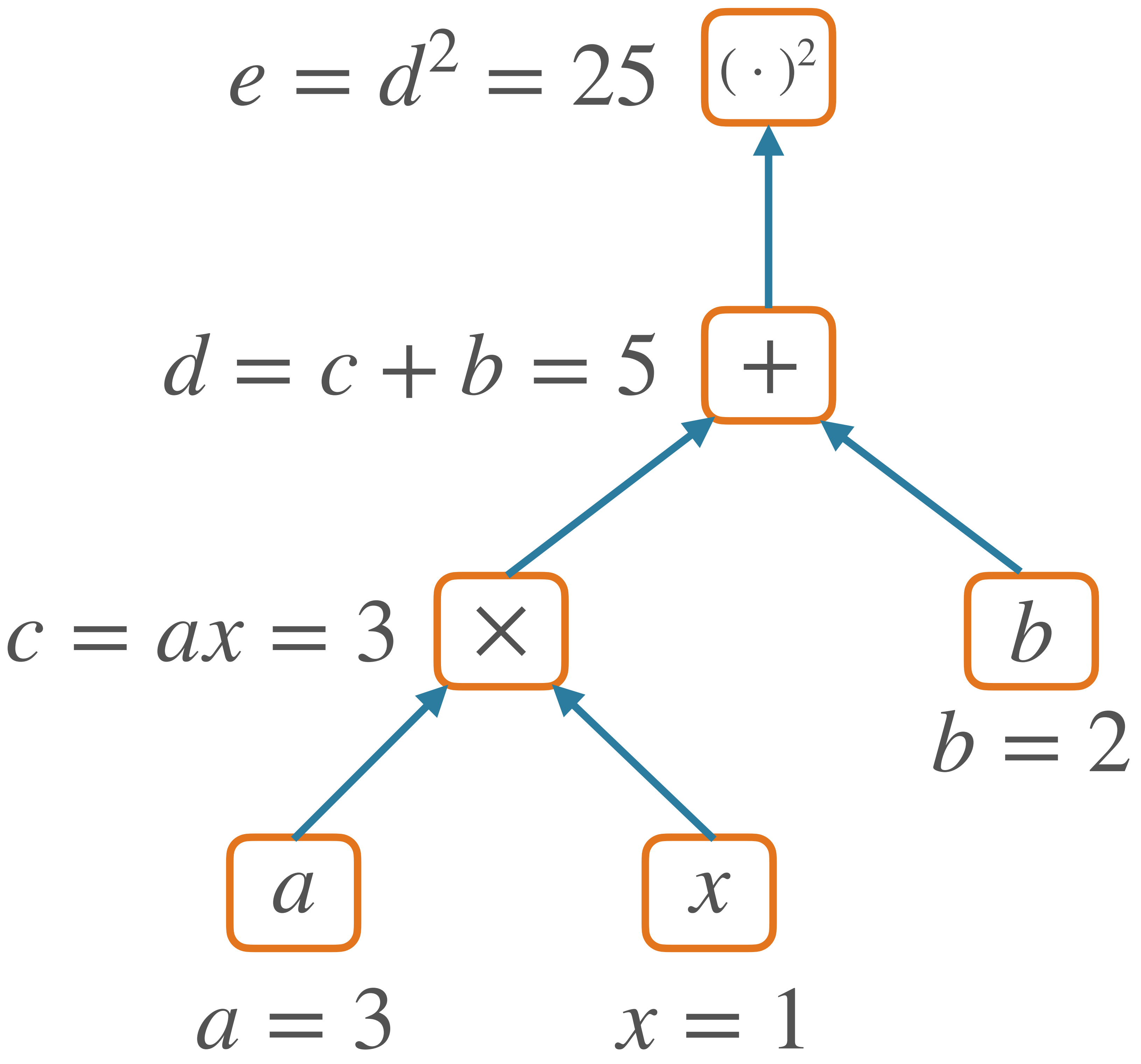

$$\frac{\partial e}{\partial e} = 1$$

Backpropagation Example

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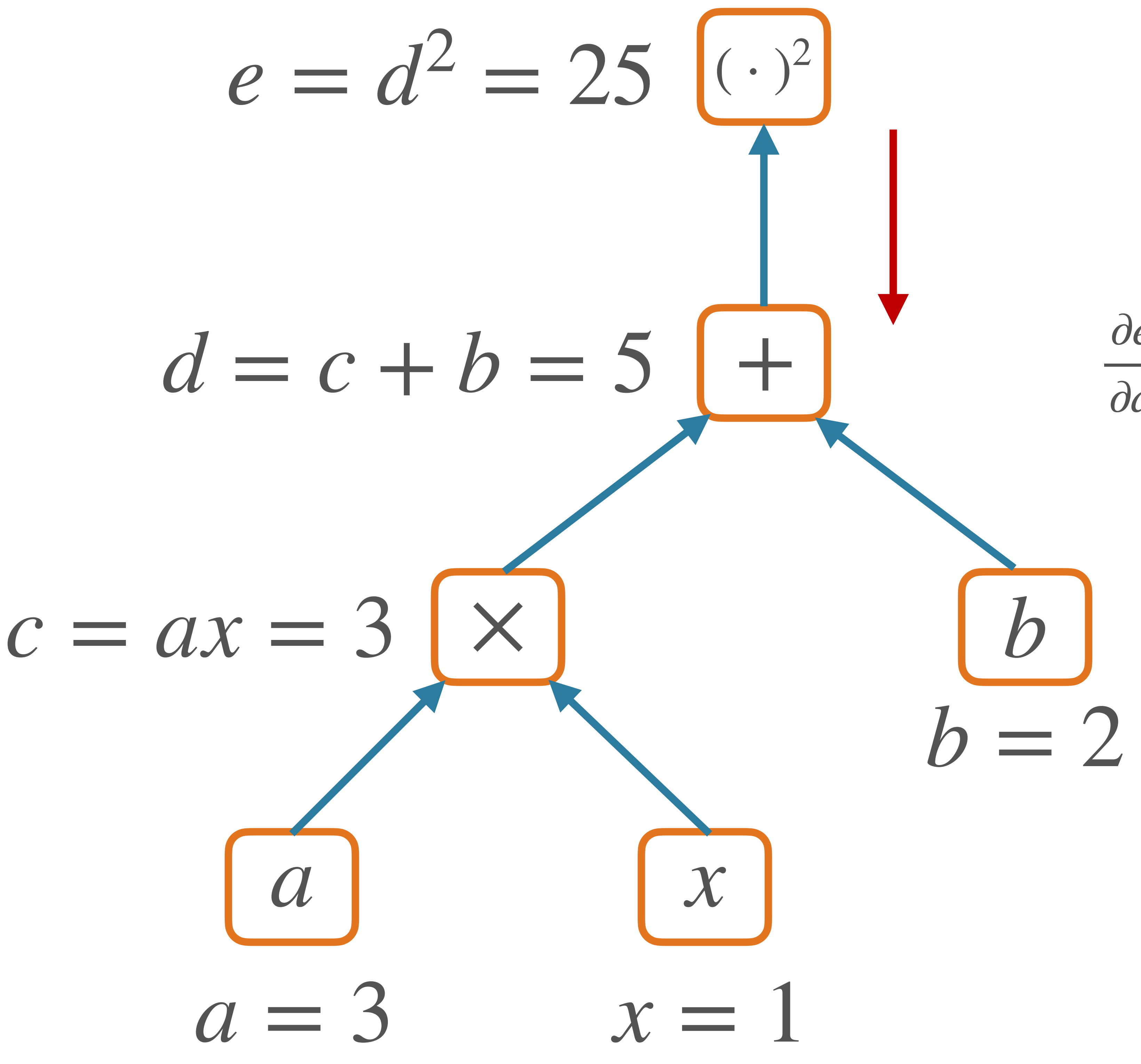

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$$\frac{\partial e}{\partial d} = 2d\frac{\partial e}{\partial e} = 10$$

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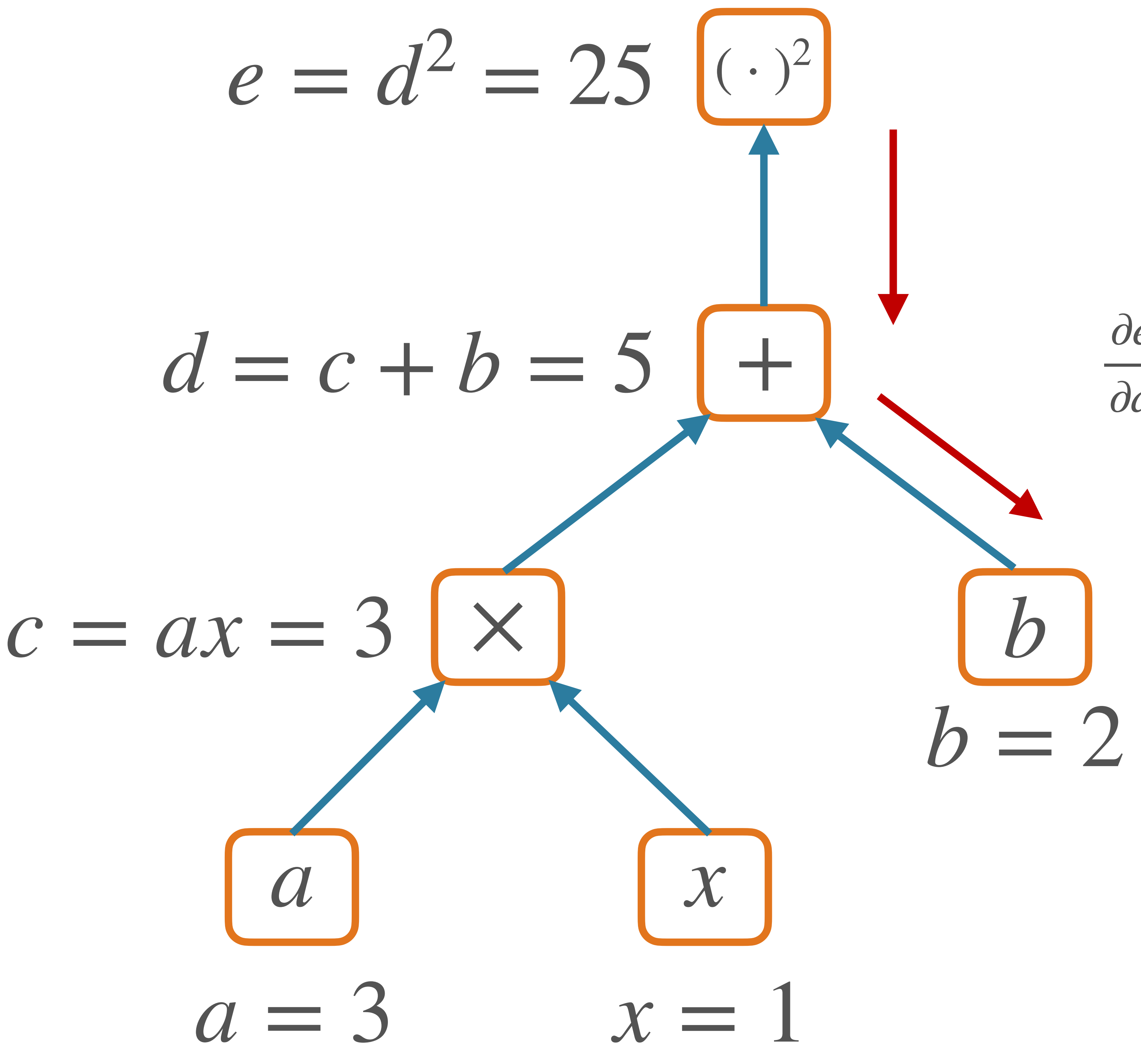

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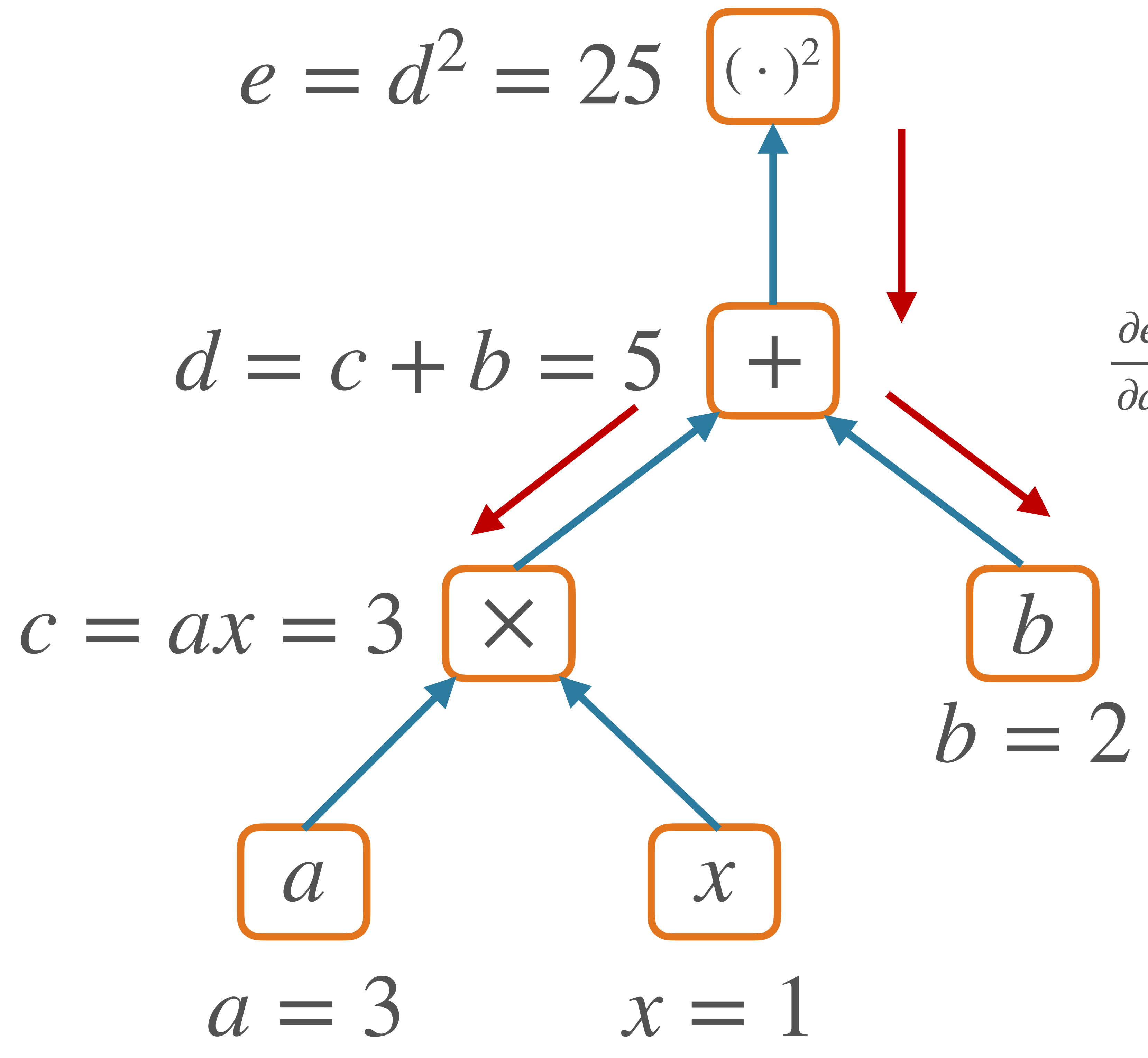

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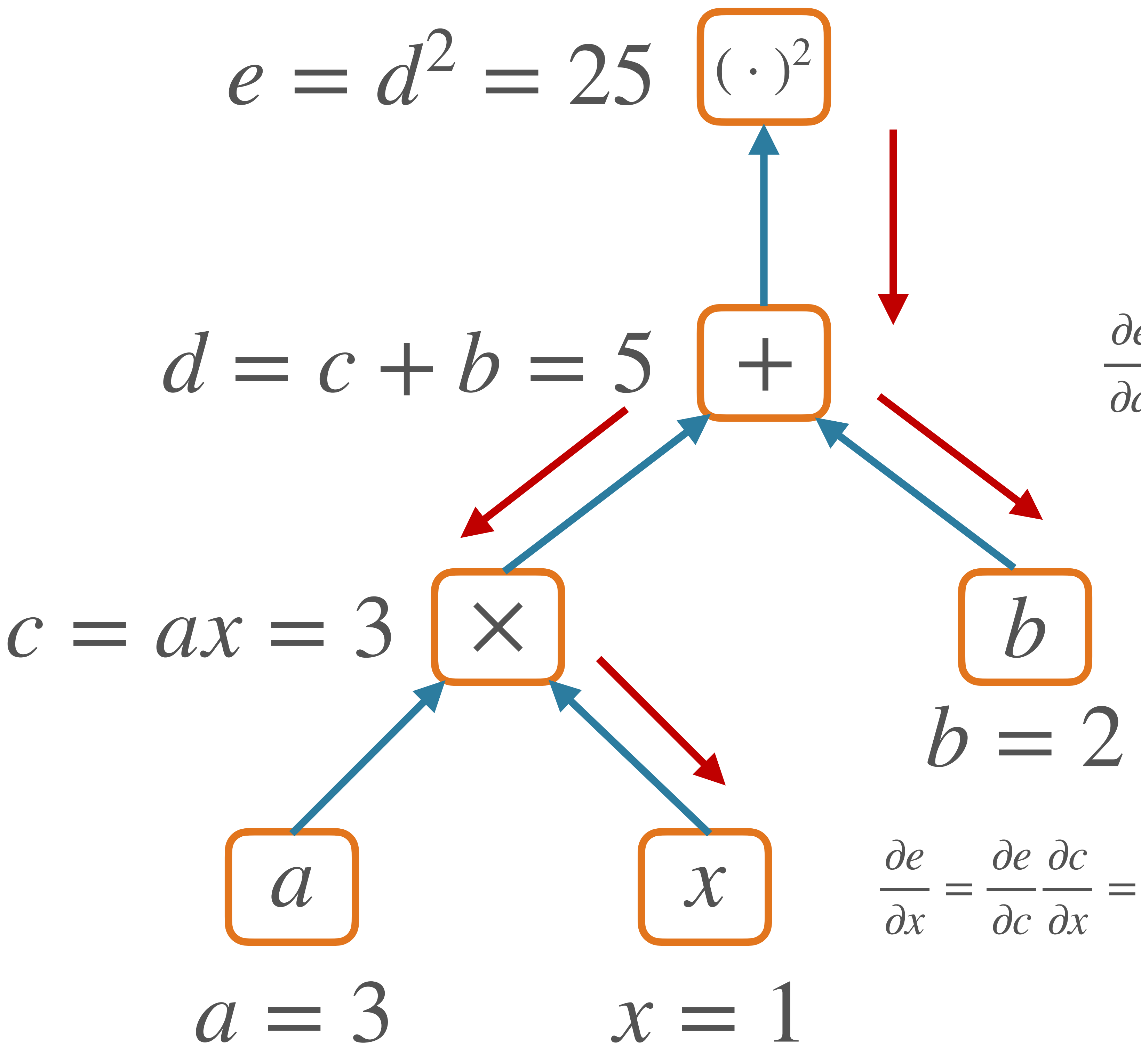

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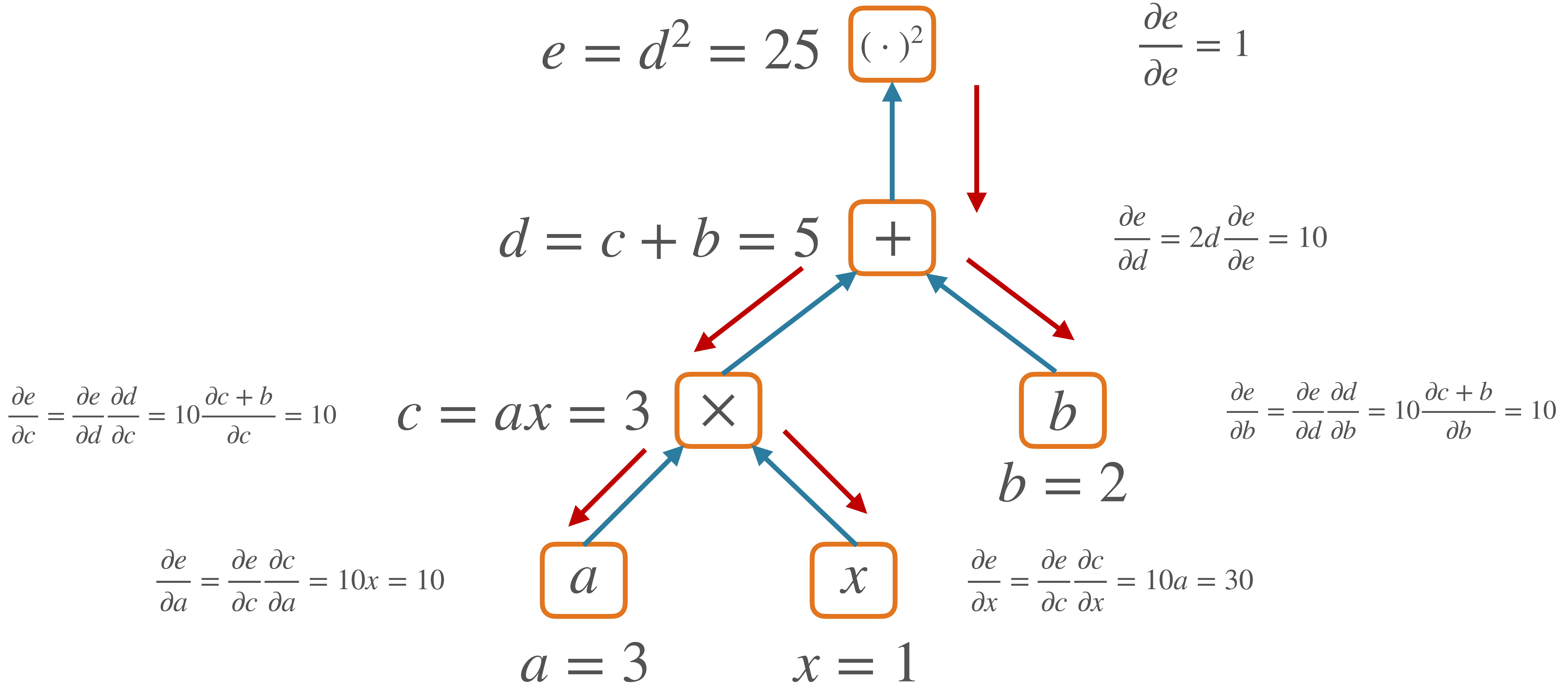
$$\frac{\partial e}{\partial x} = \frac{\partial e}{\partial c}\frac{\partial c}{\partial x} = 10a = 30$$

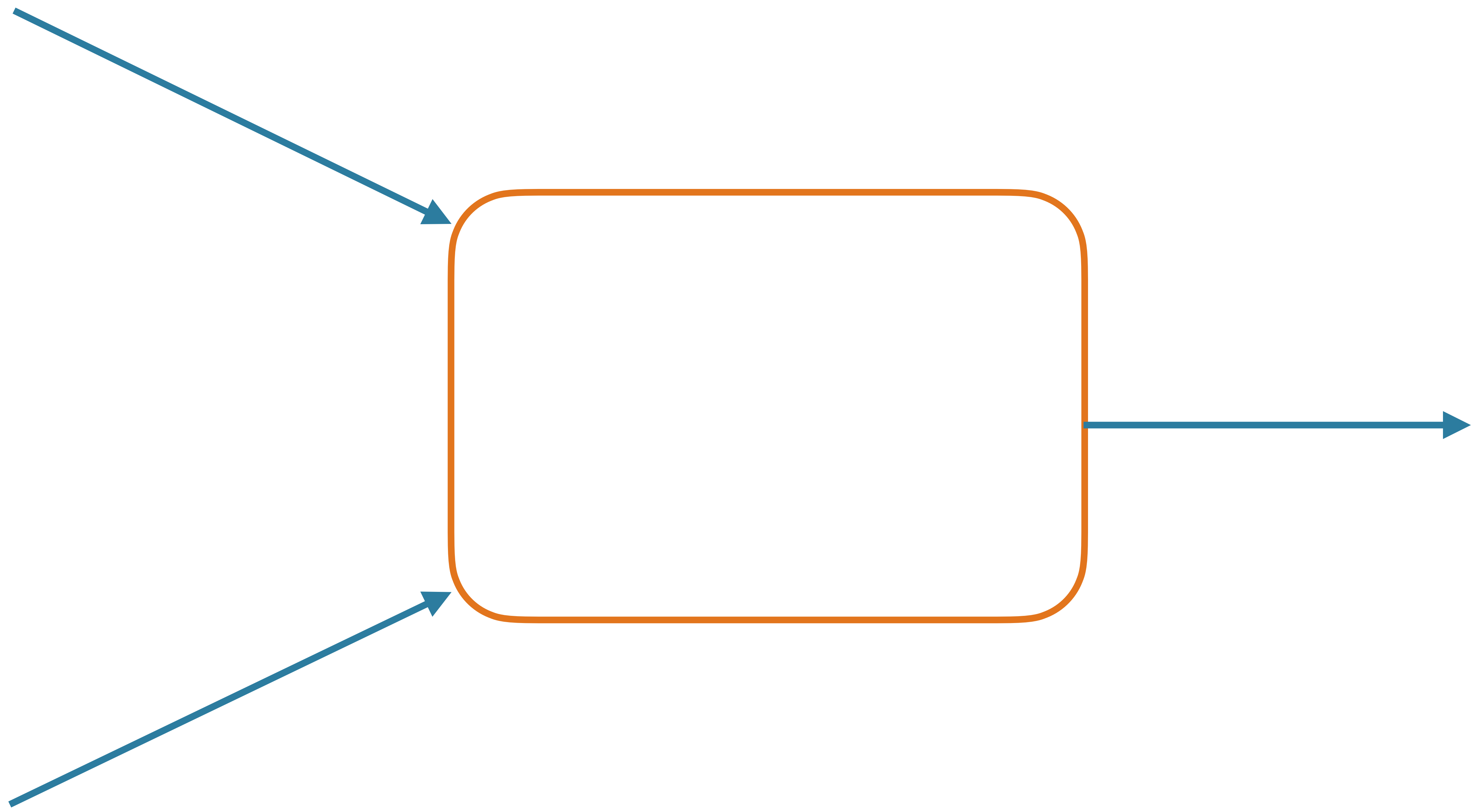
Backpropagation Example

$$f(x; a, b) = (ax + b)^2$$



Nodes in Computational Graph

- Forward pass:
  - Compute value given parents' values
- Backward pass:
  - Compute parents' gradients given children's



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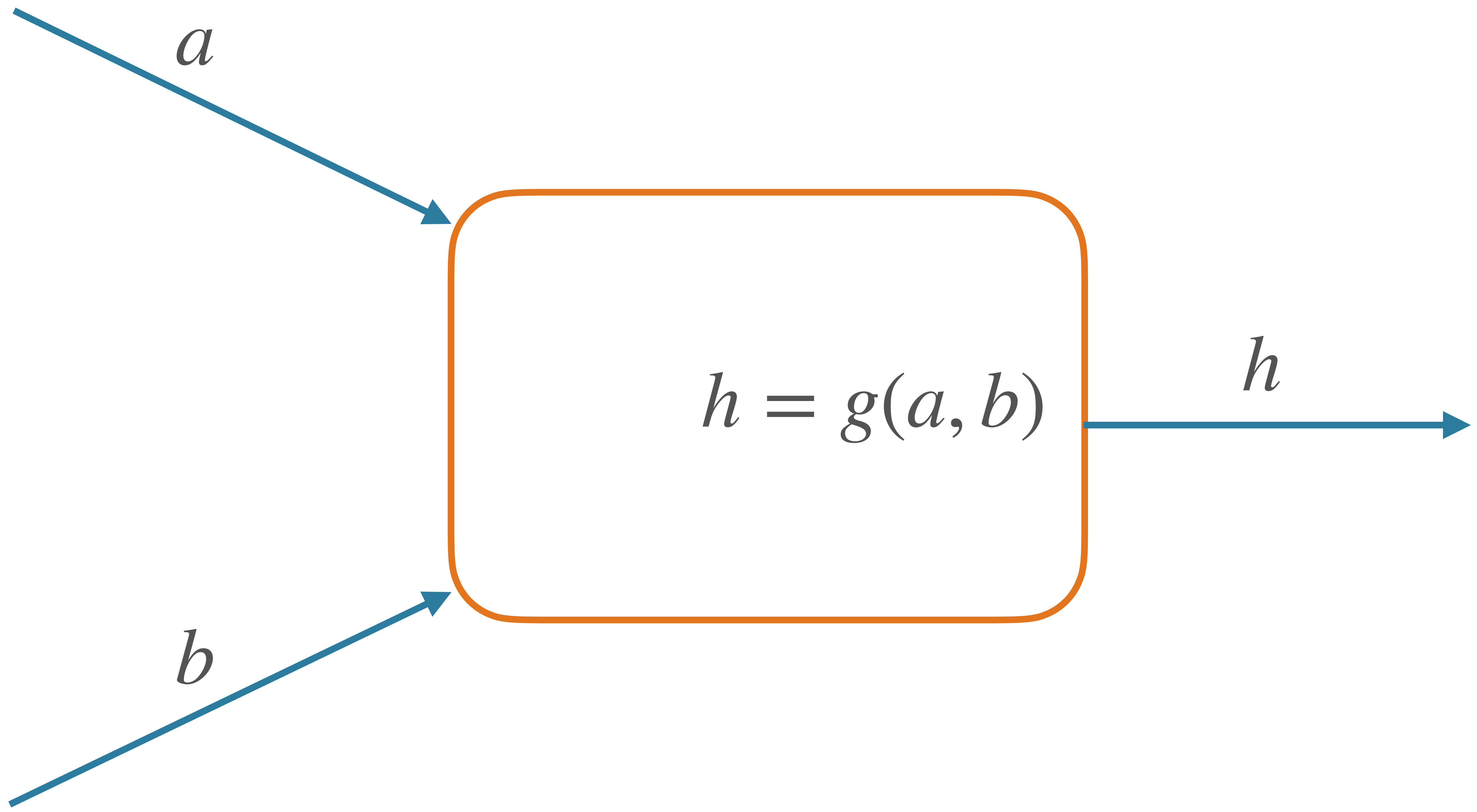

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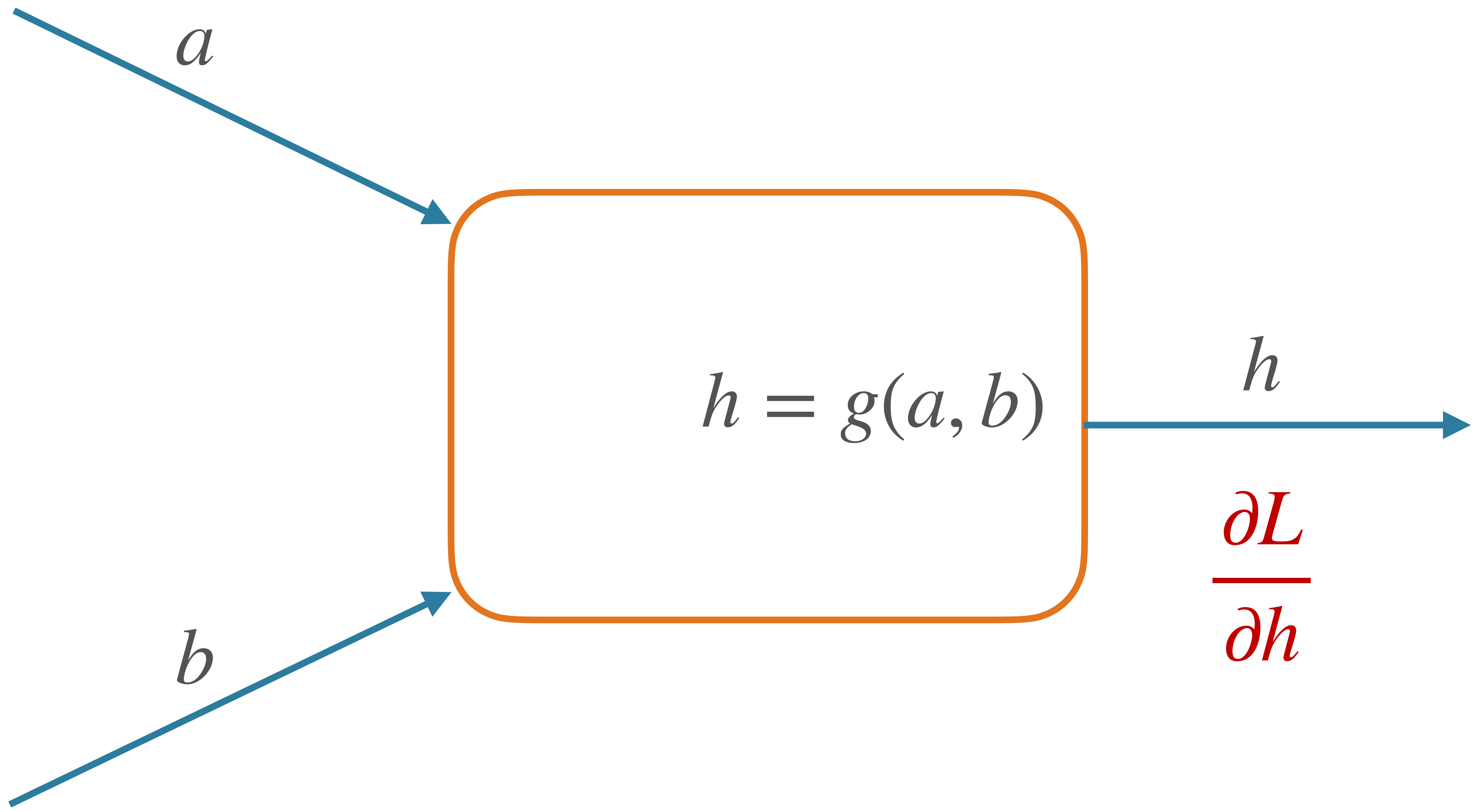

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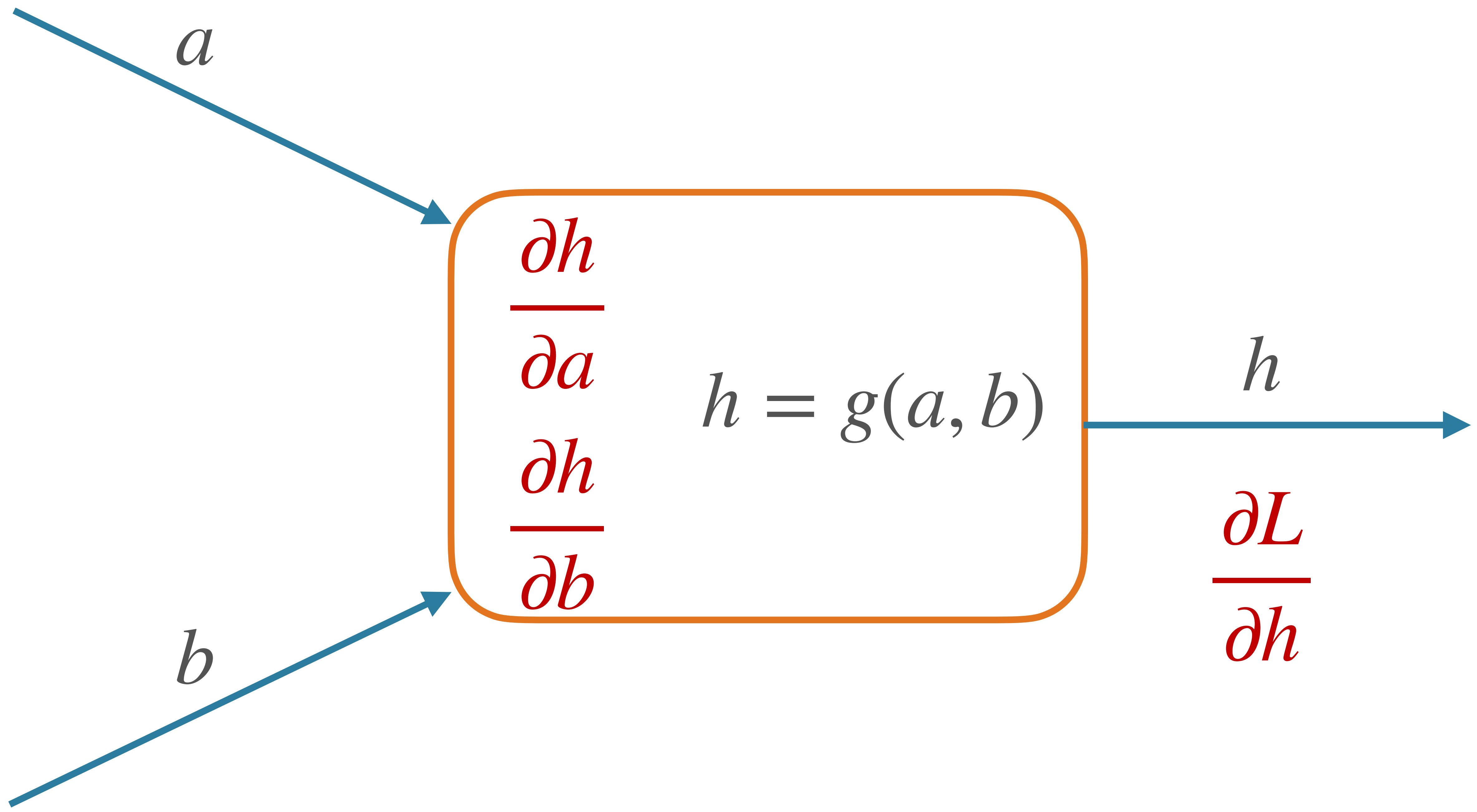

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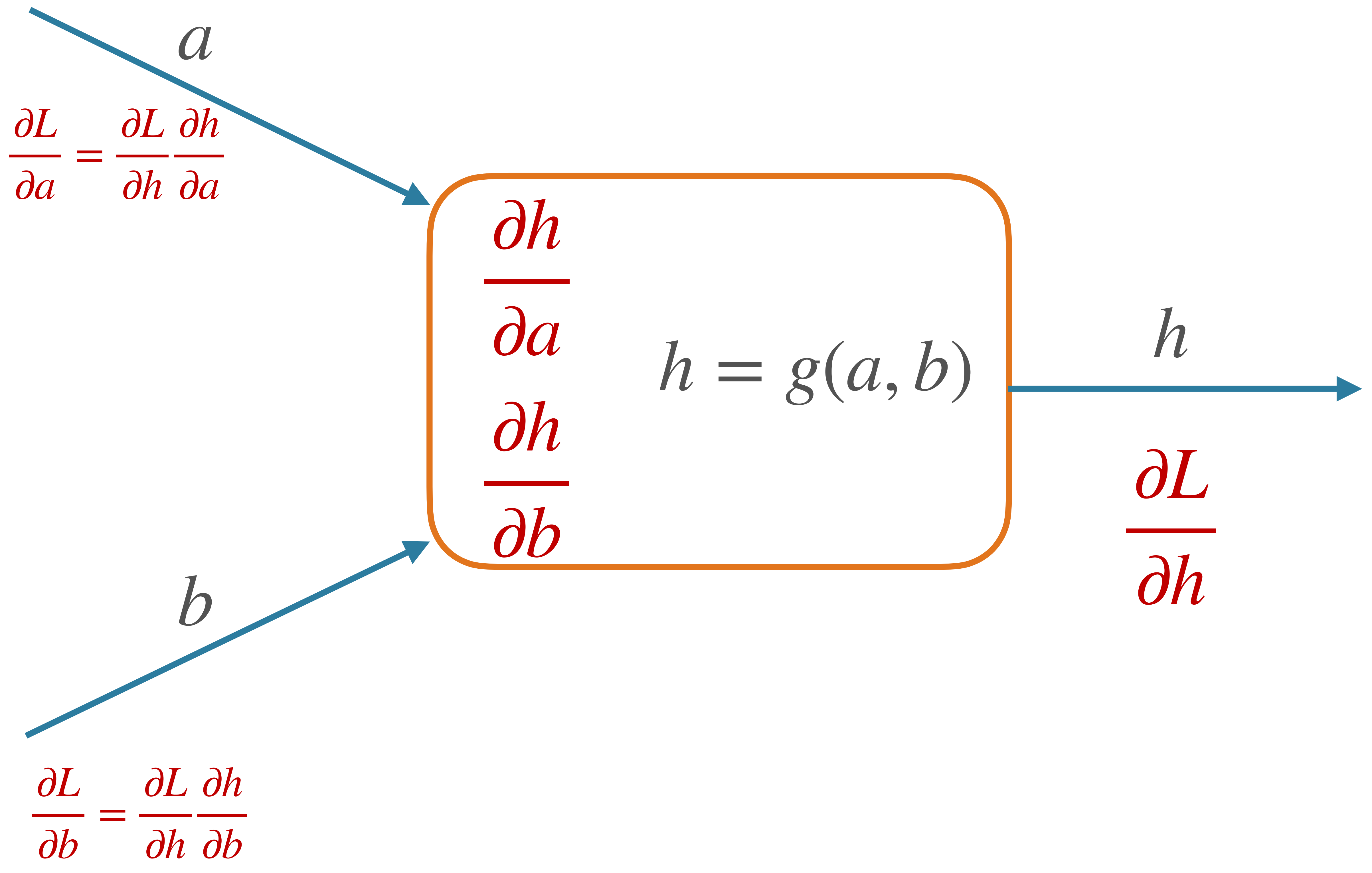

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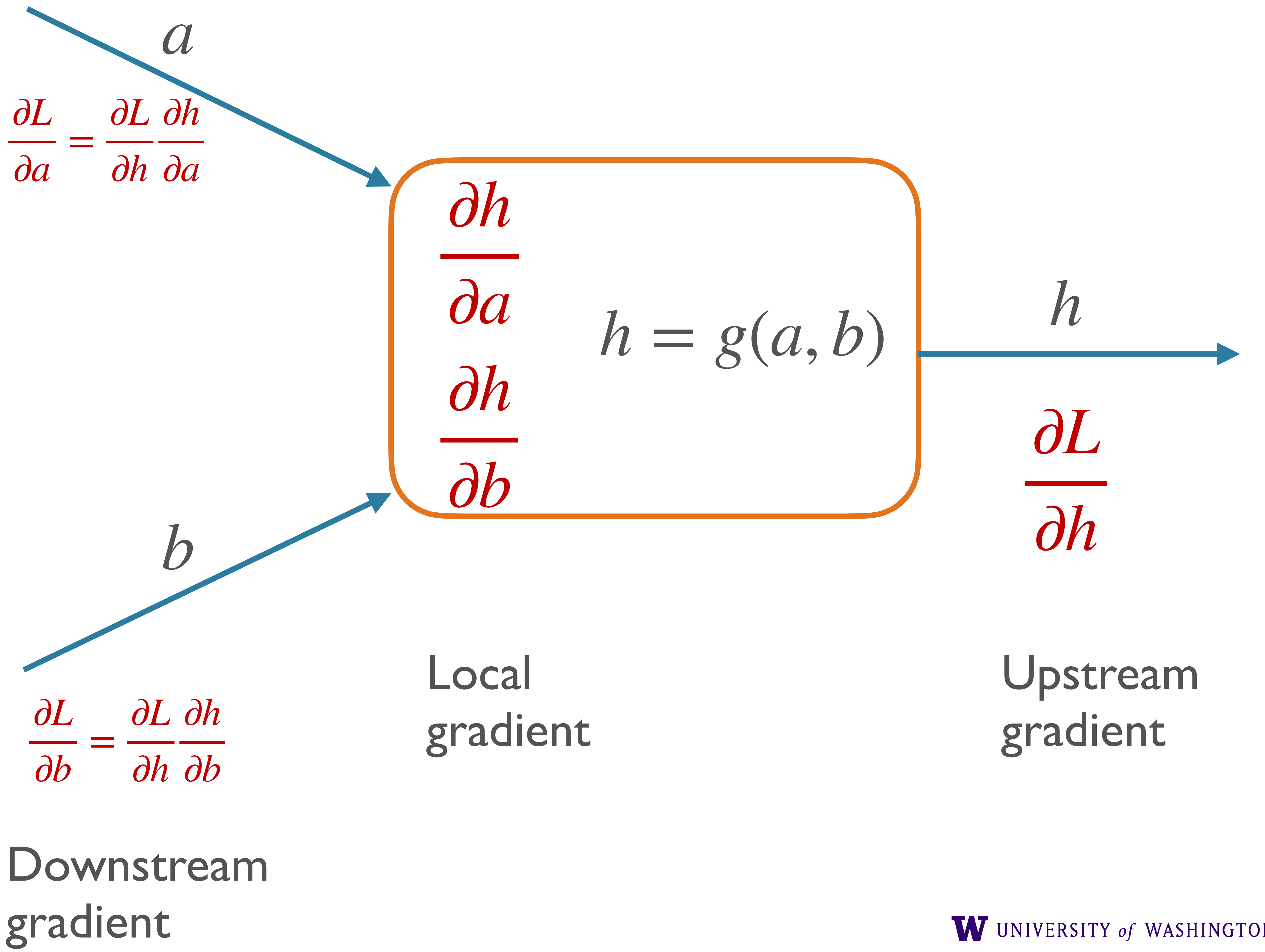

Example: ReLU

```python
@tensor_op
class relu(Operation):
    @staticmethod
    def forward(ctx, value):
        new_val = np.maximum(0, value)
        ctx.append(new_val)
        return new_val

    @staticmethod
    def backward(ctx, grad_output):
        value = ctx[-1]
        return [(value > 0).astype(float) * grad_output]
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Save and retrieve the input value!

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local gradient times upstream gradient

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Save and retrieve the input value!

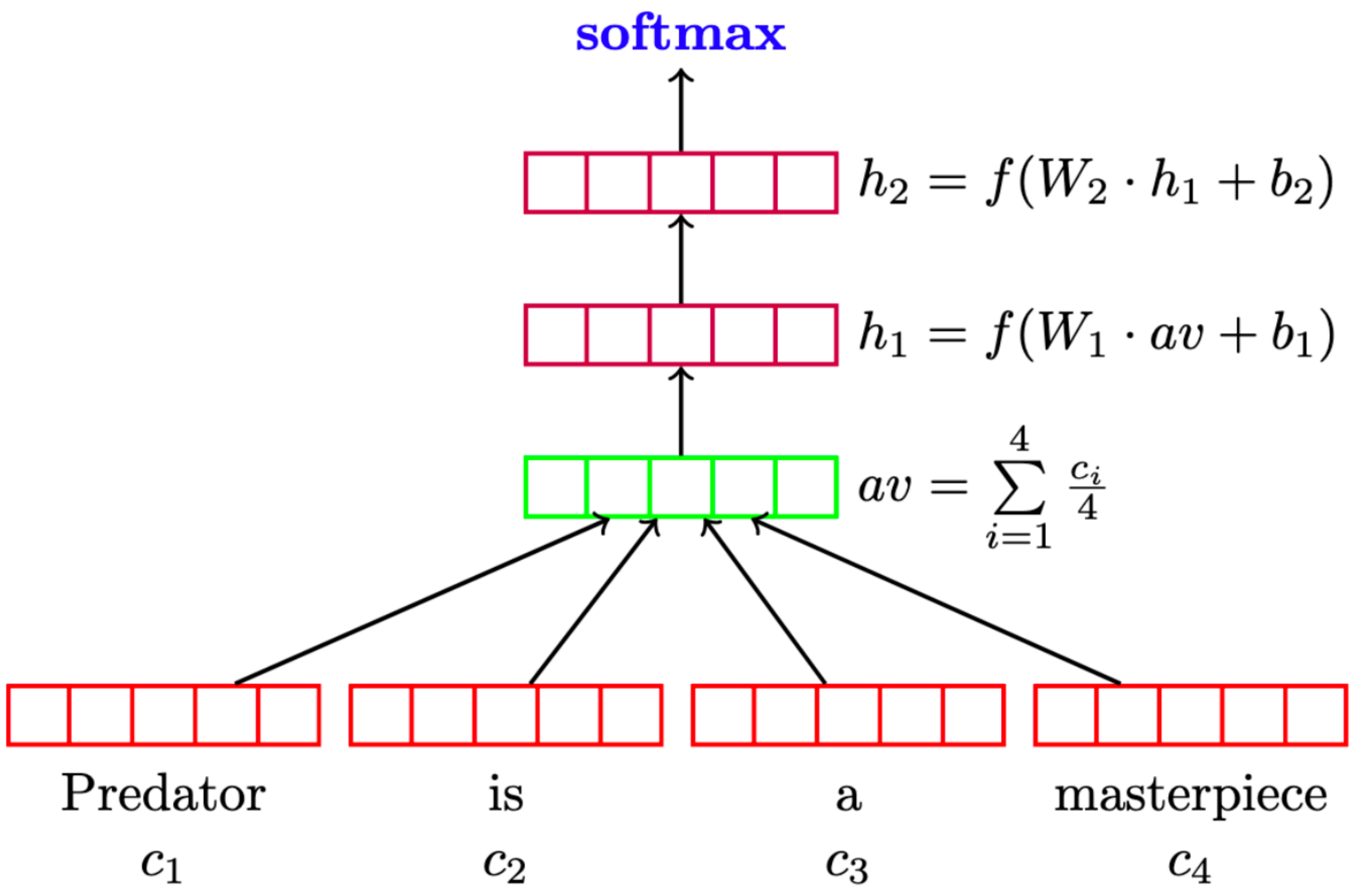
NB: list, one downstream gradient per input (in this case, one)

local gradient times upstream gradient

Neural Networks, I

- Feed-forward networks
  - Fixed size: average, fixed window of prep tokens
- Recurrent neural networks: sequence processors
  - Vanishing gradients, gated variants (LSTM)
  - Encoder-decoder / seq2seq architecture and tasks
    - Attention mechanism

Model Architecture, One Input



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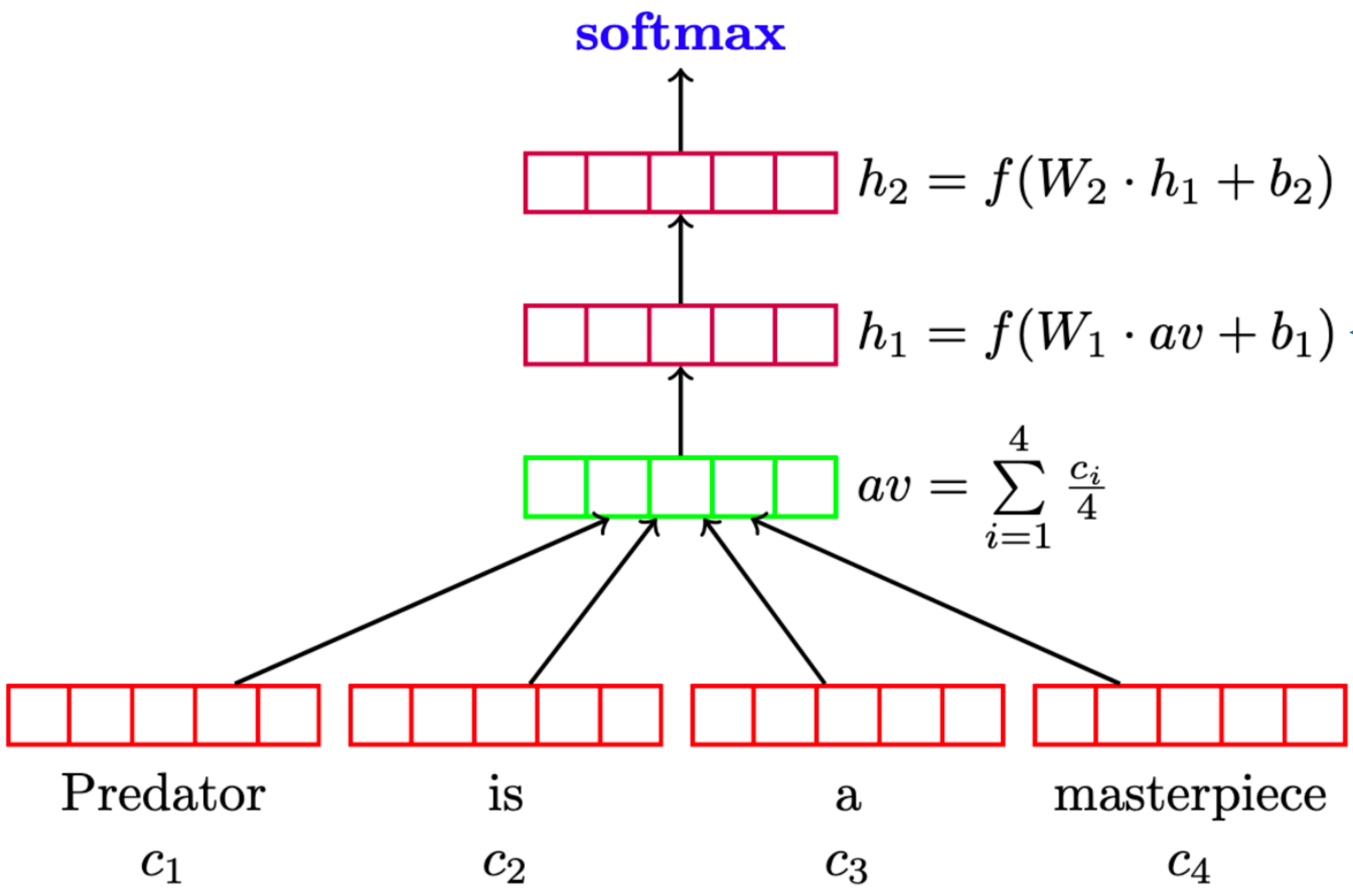
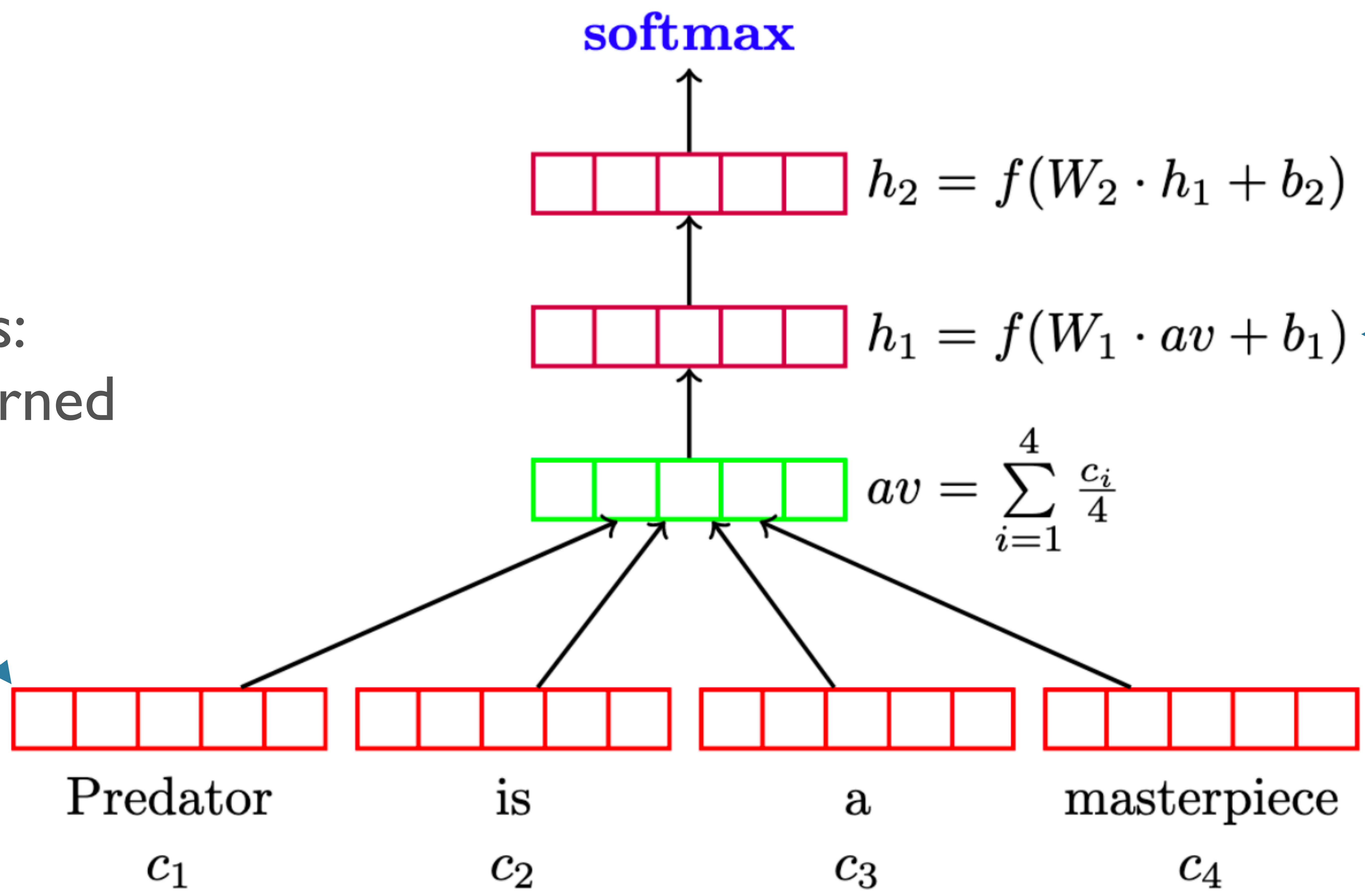


$f(\mathrm{av}W^1 + b^1)$

Model Architecture, One Input

Word embeddings:
Pre-trained or learned



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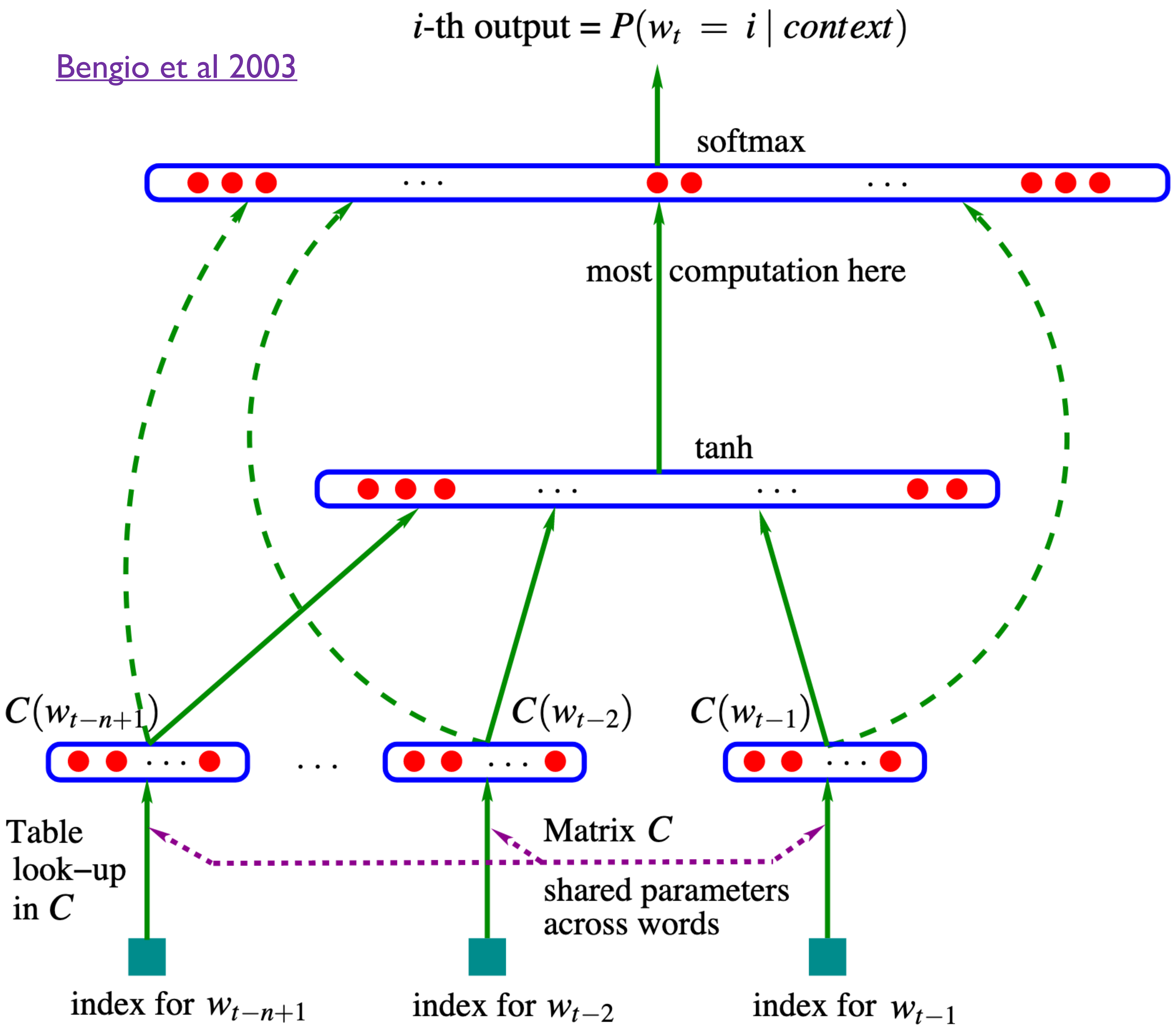
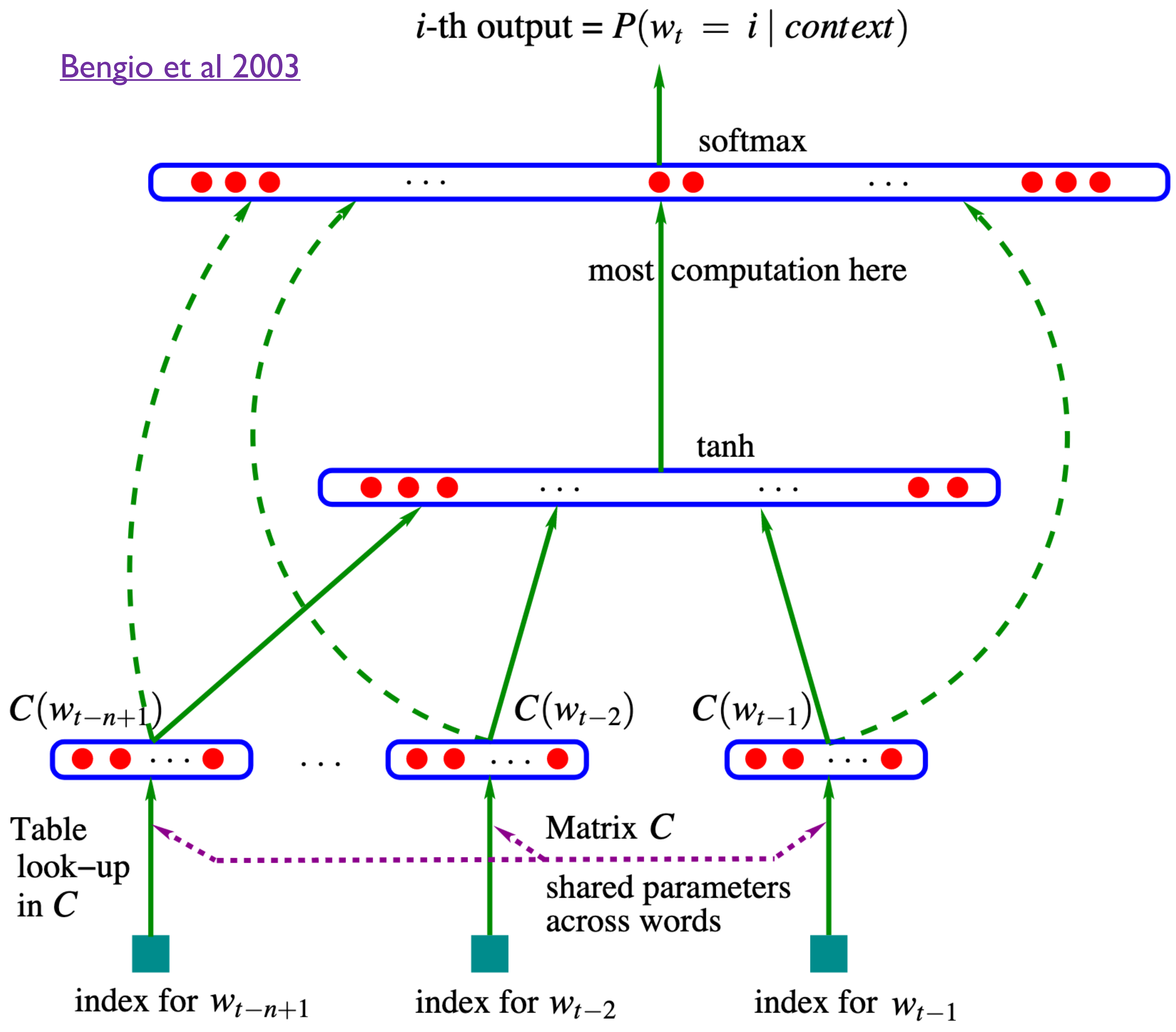
Neural LM Architecture

Bengio et al 2003



Neural LM Architecture

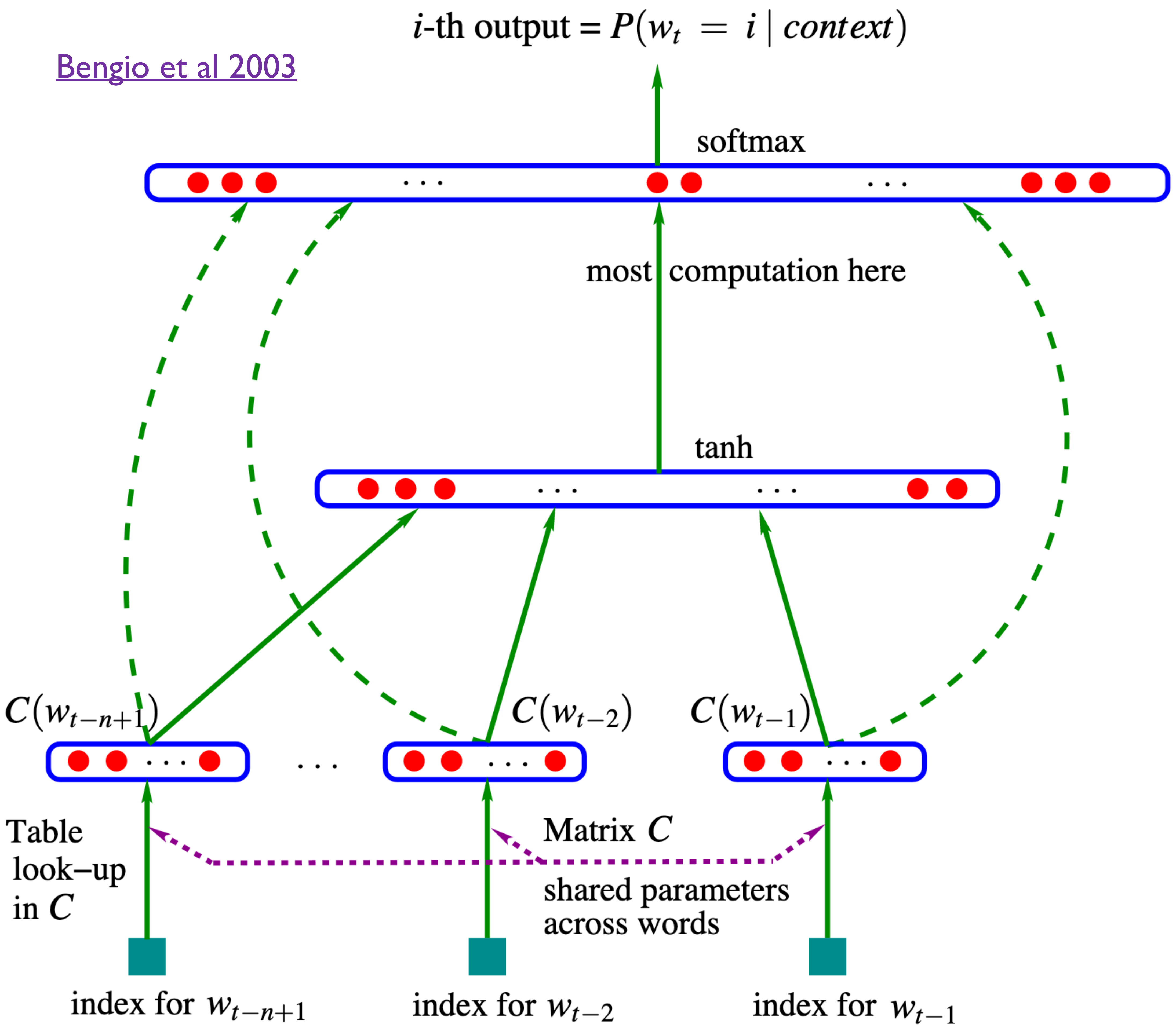
[Bengio et al 2003](#)



w_t: one-hot vector

Neural LM Architecture

[Bengio et al 2003]

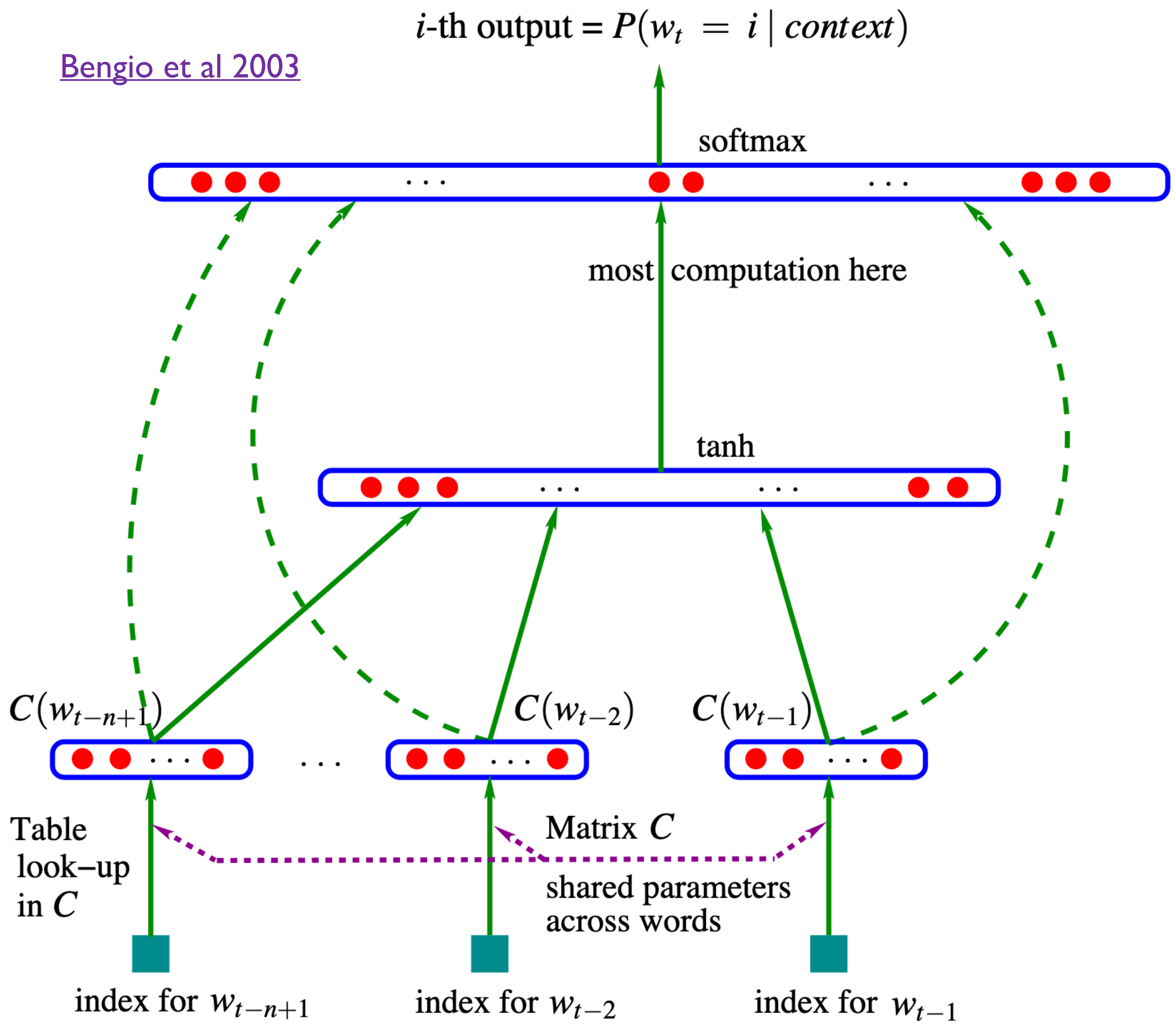


embeddings = concat$(w_{t-1}C, w_{t-2}C, \ldots, w_{t-(n+1)}C)$

w_t: one-hot vector

Neural LM Architecture

[Bengio et al 2003]



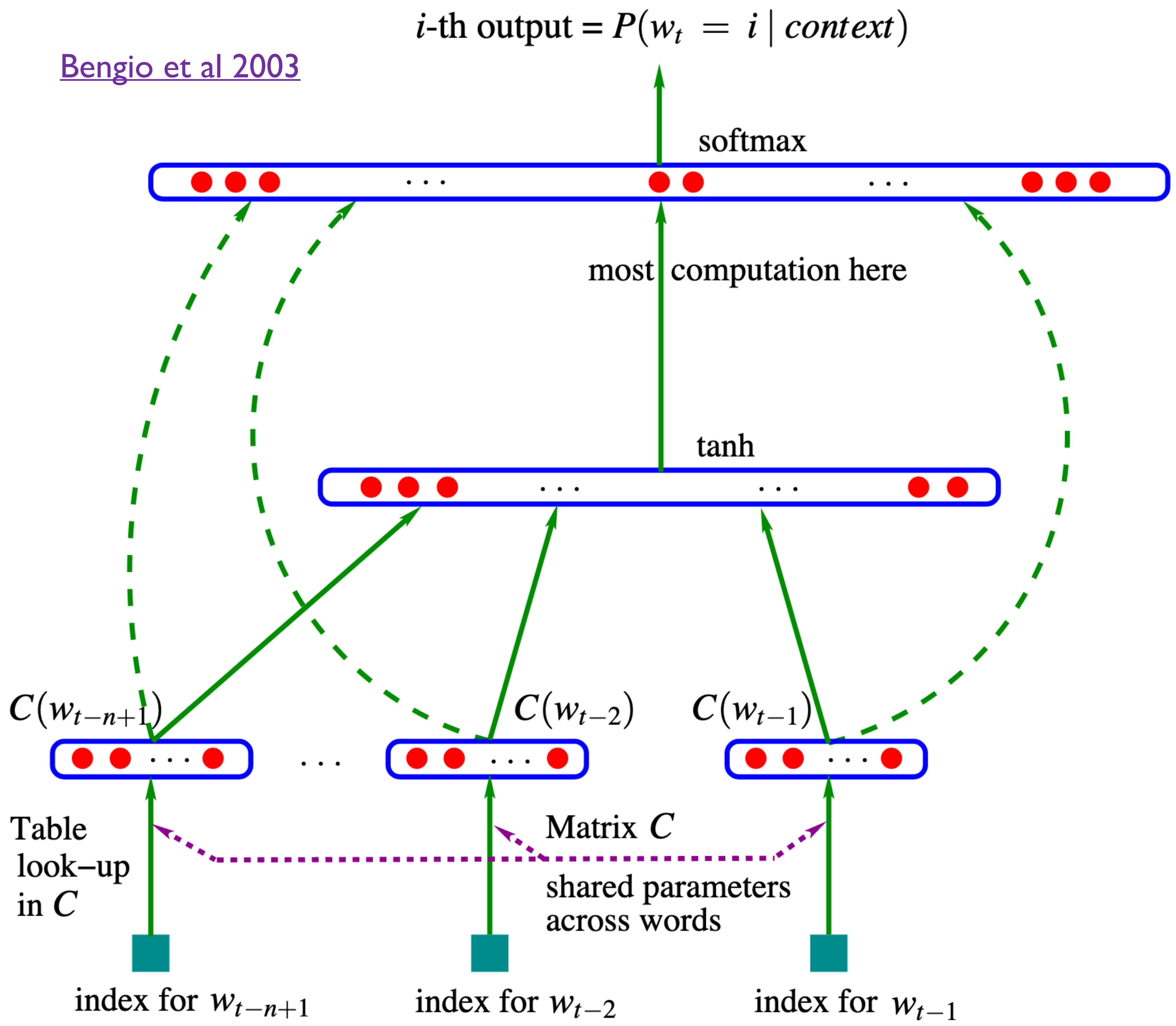
$$\text{hidden} = \tanh(\text{embeddings}W^1 + b^1)$$

$$\text{embeddings} = \text{concat}(w_{t-1}C, w_{t-2}C, \ldots, w_{t-(n+1)}C)$$

w_t: one-hot vector

Neural LM Architecture

Bengio et al 2003



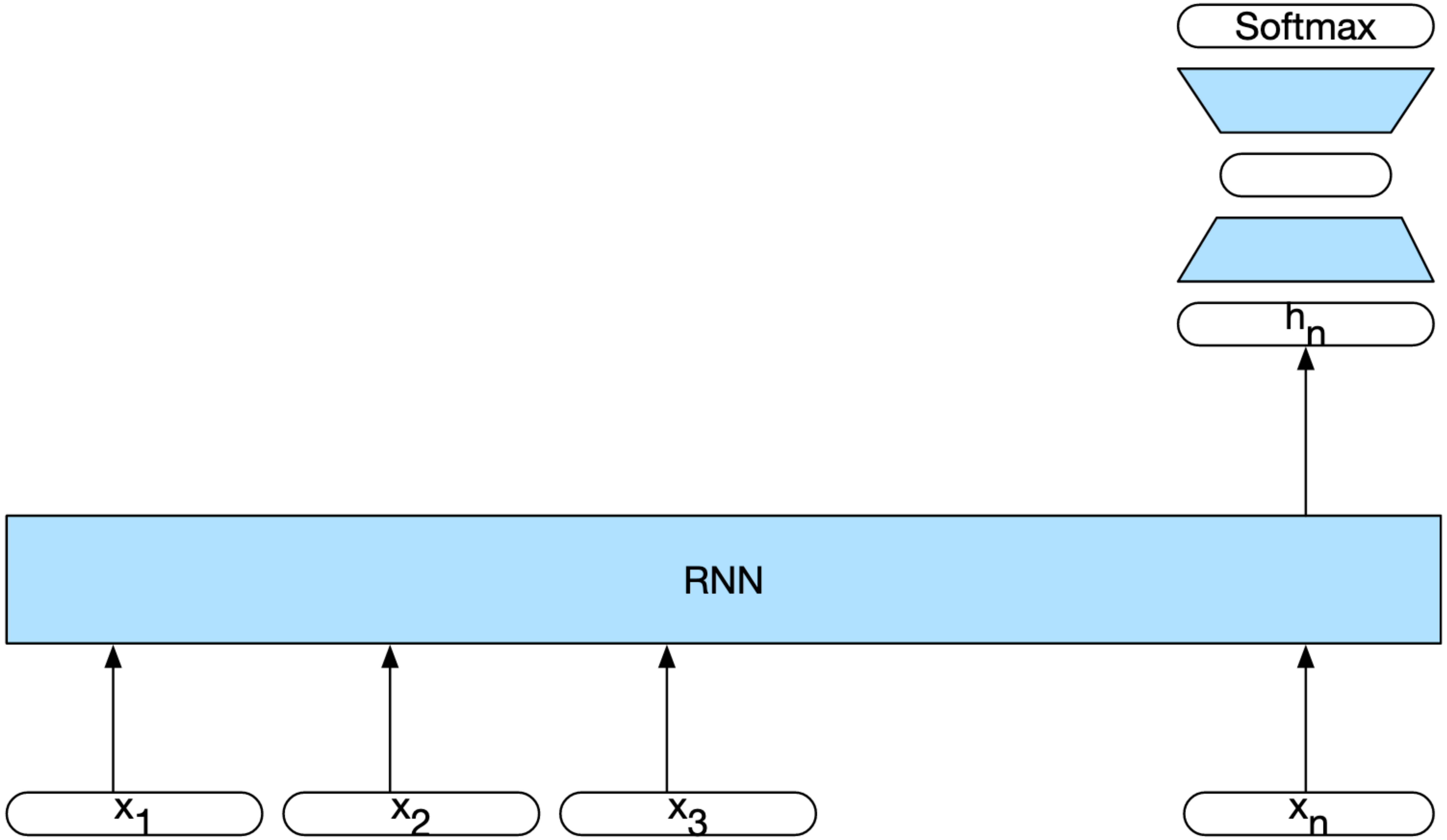
$$\text{probabilities} = \text{softmax}(\text{hidden}W^2 + b^2)$$

$$\text{hidden} = \tanh(\text{embeddings}W^1 + b^1)$$

$$\text{embeddings} = \text{concat}(w_{t-1}C, w_{t-2}C, \ldots, w_{t-(n+1)}C)$$

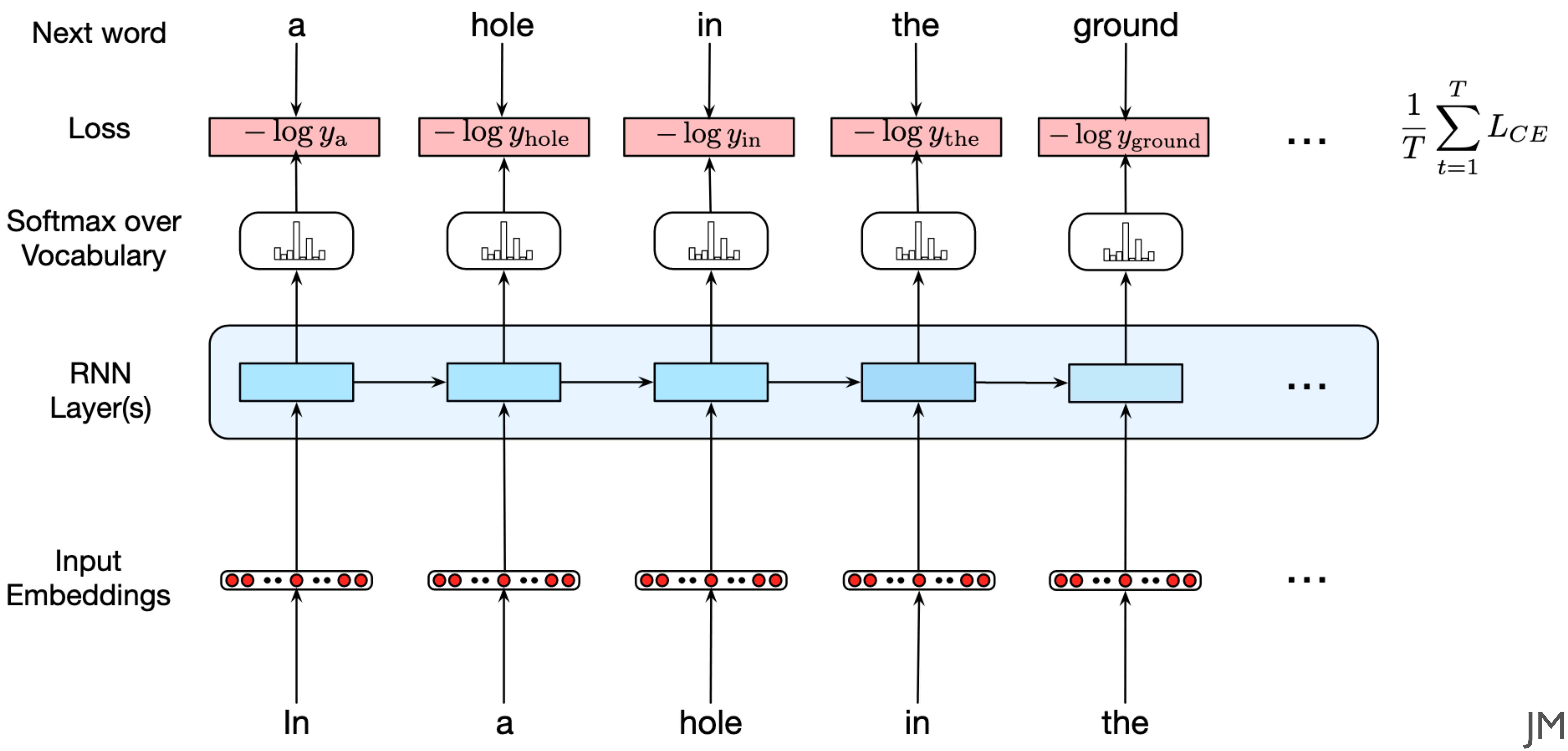
w_t: one-hot vector

RNN for Text Classification



JM sec 9.2.5

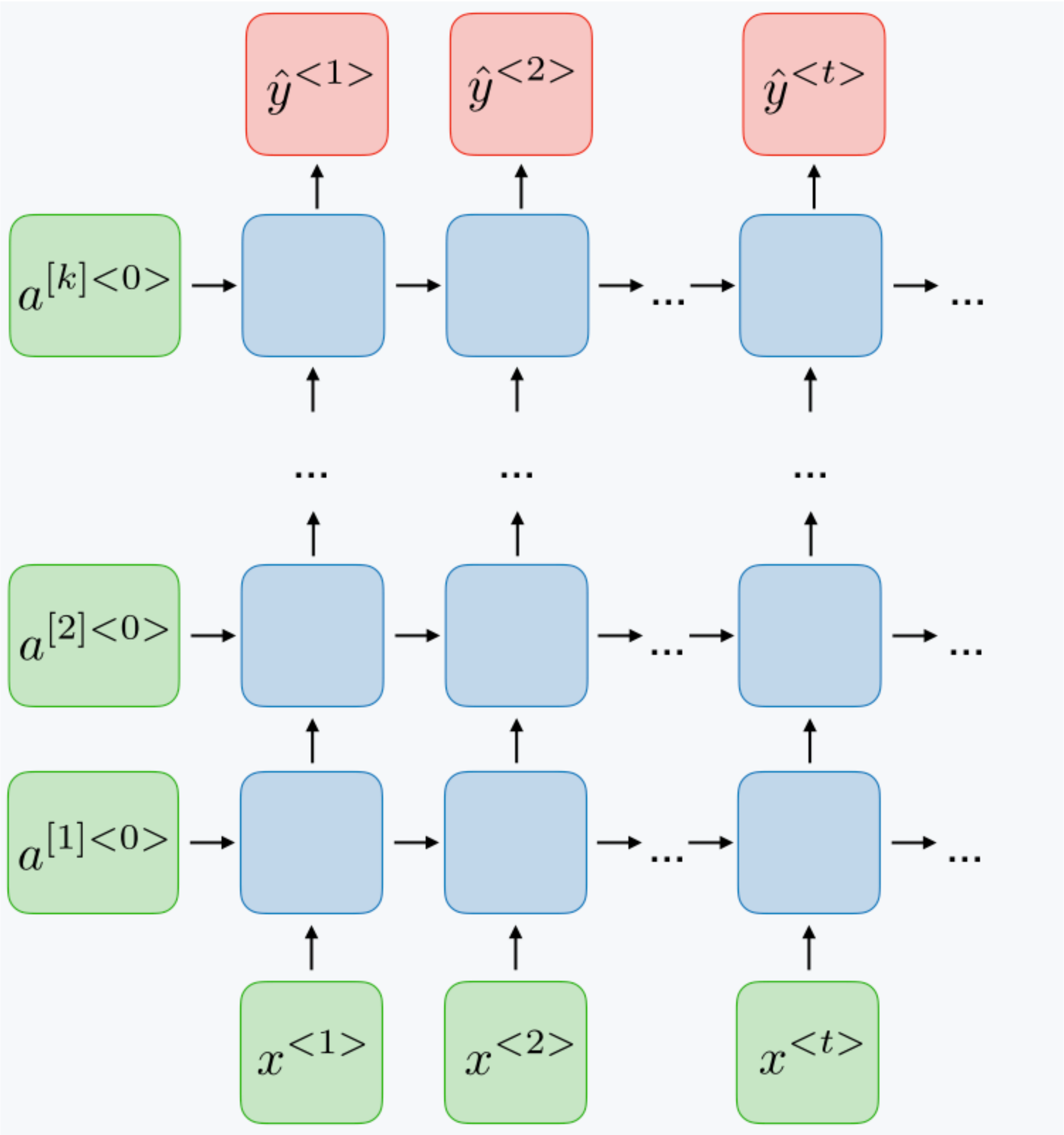
RNNs for Language Modeling



JM sec 9.2.3

Two Extensions

- Deep RNNs:



Source: RNN cheat sheet

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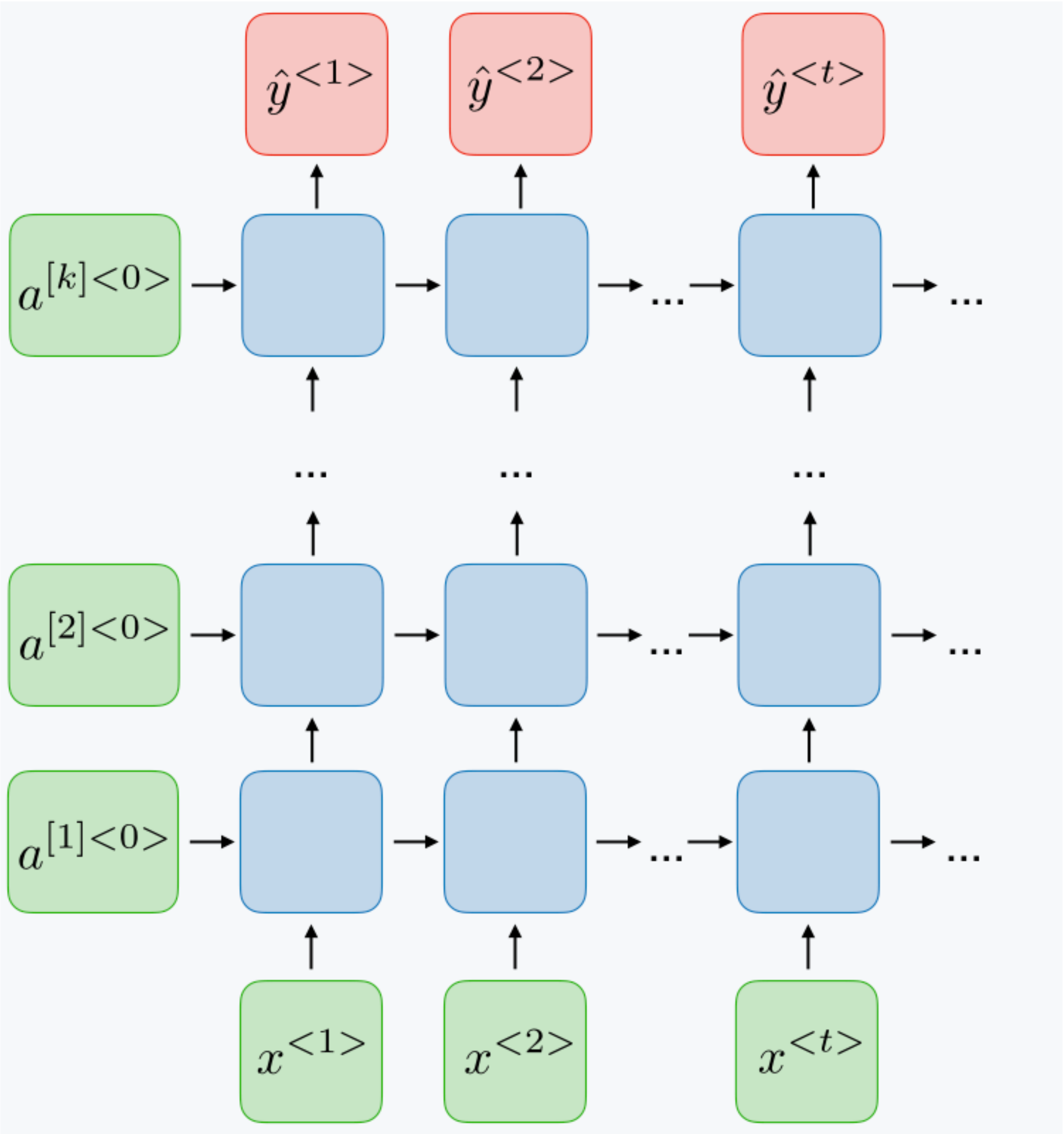
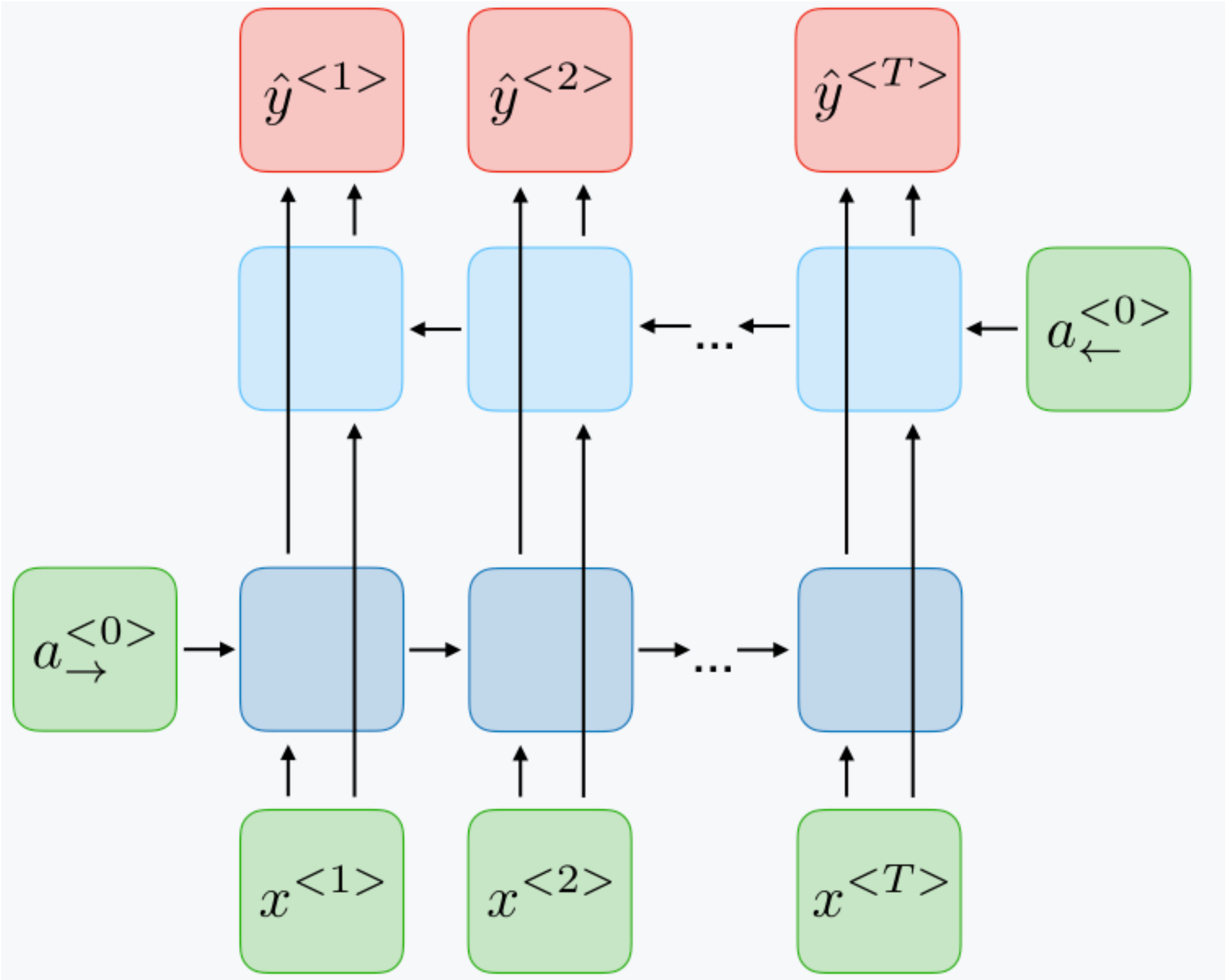


- Bidirectional RNNs:



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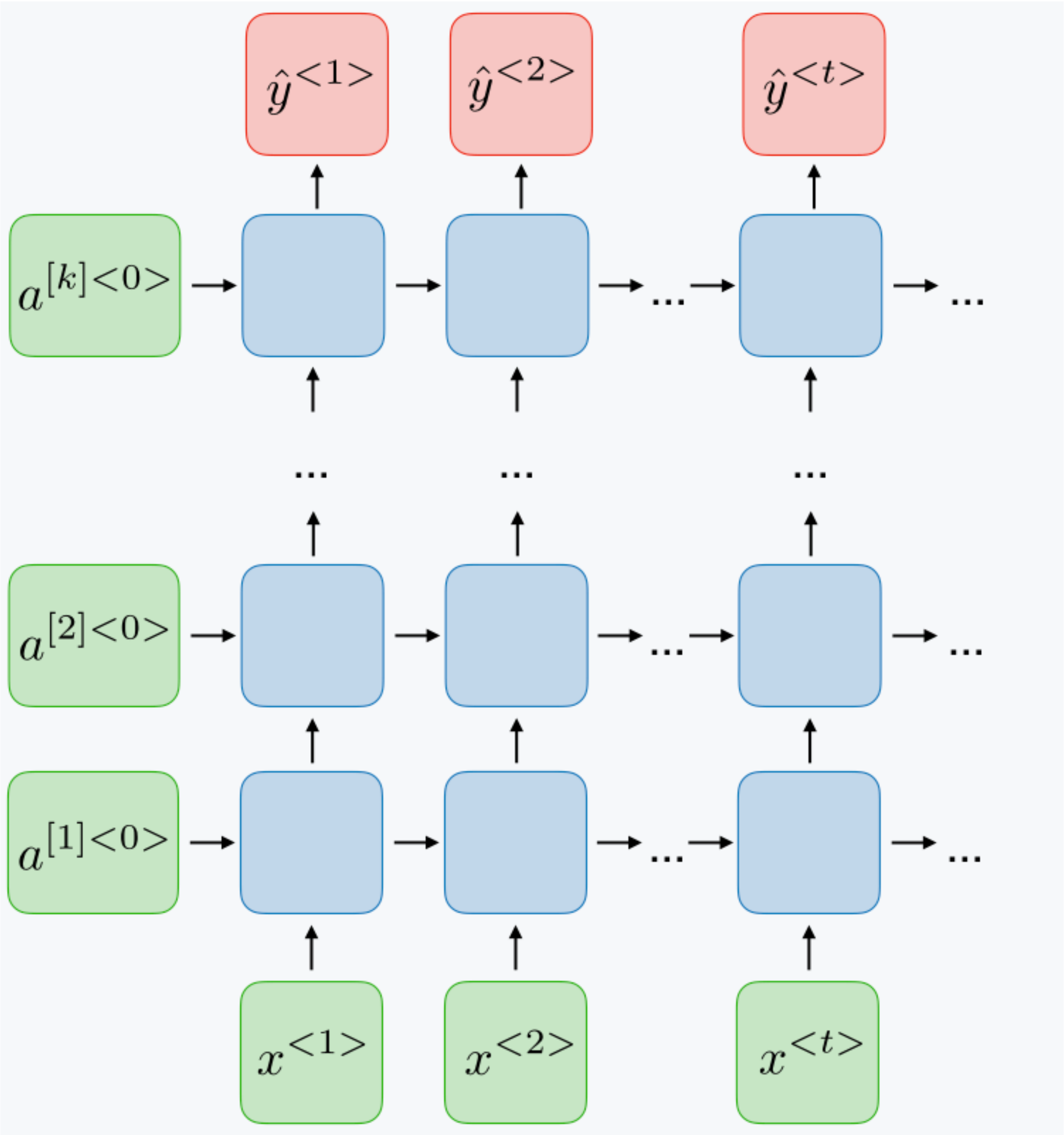
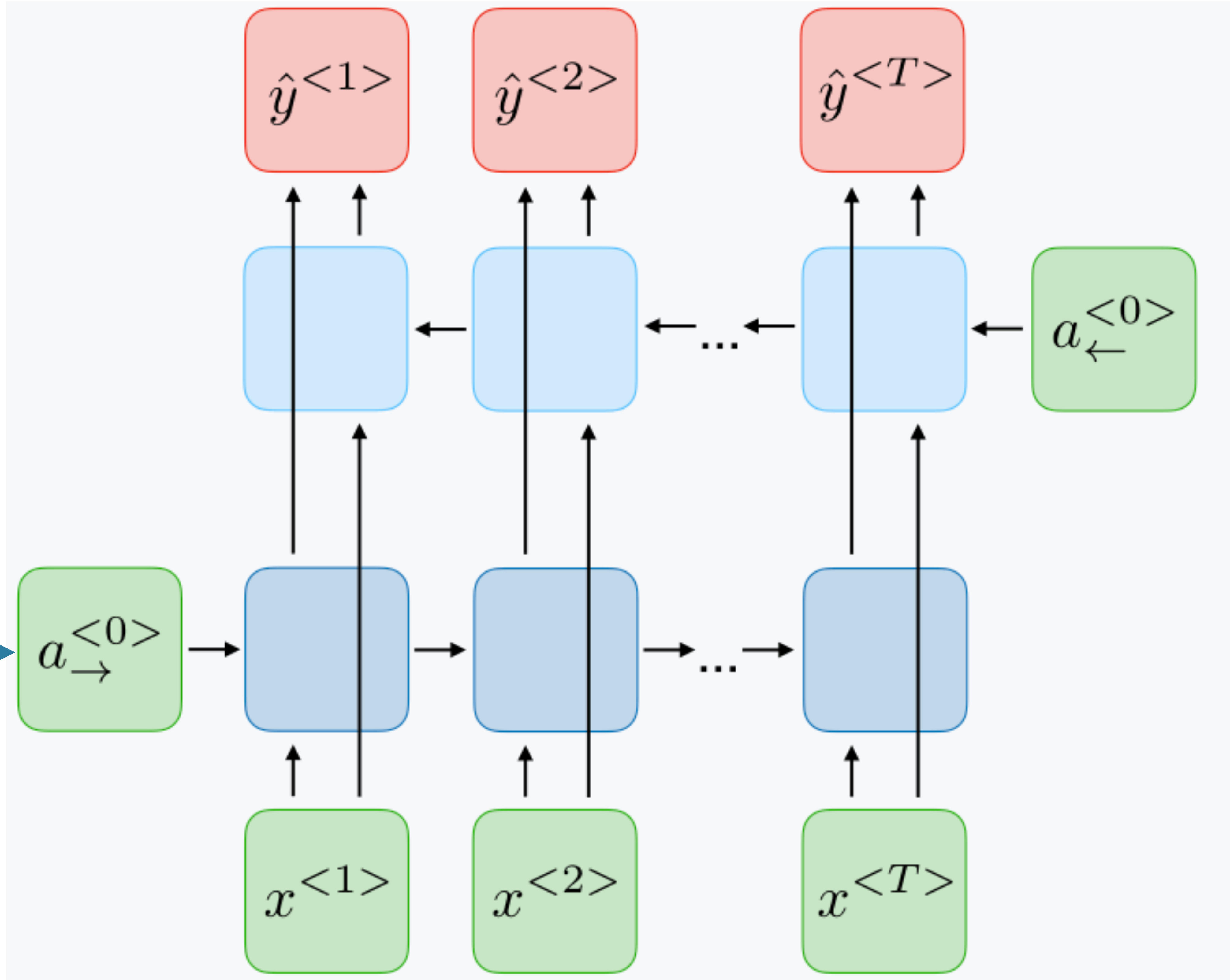


- Bidirectional RNNs:

Forward RNN



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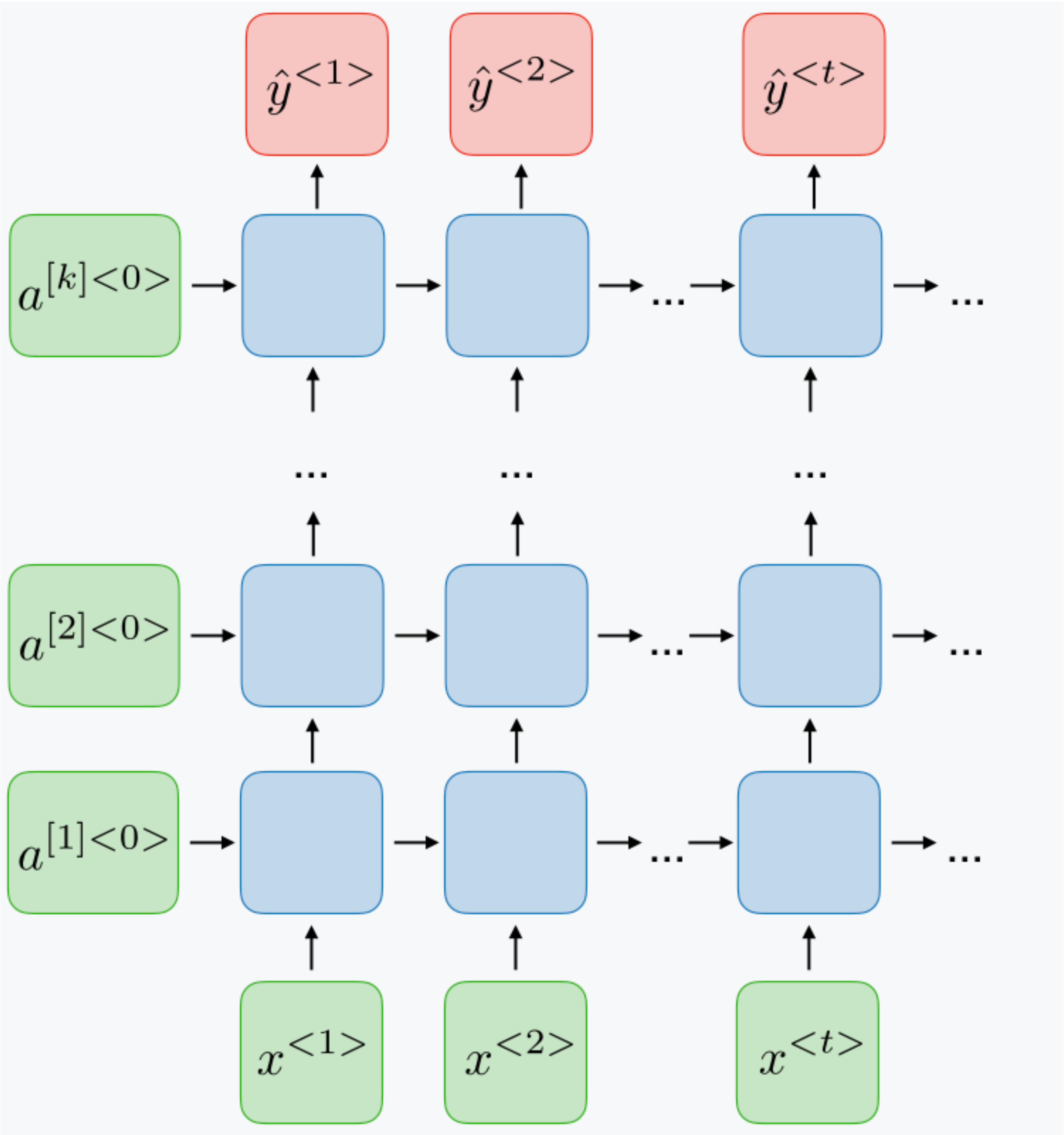

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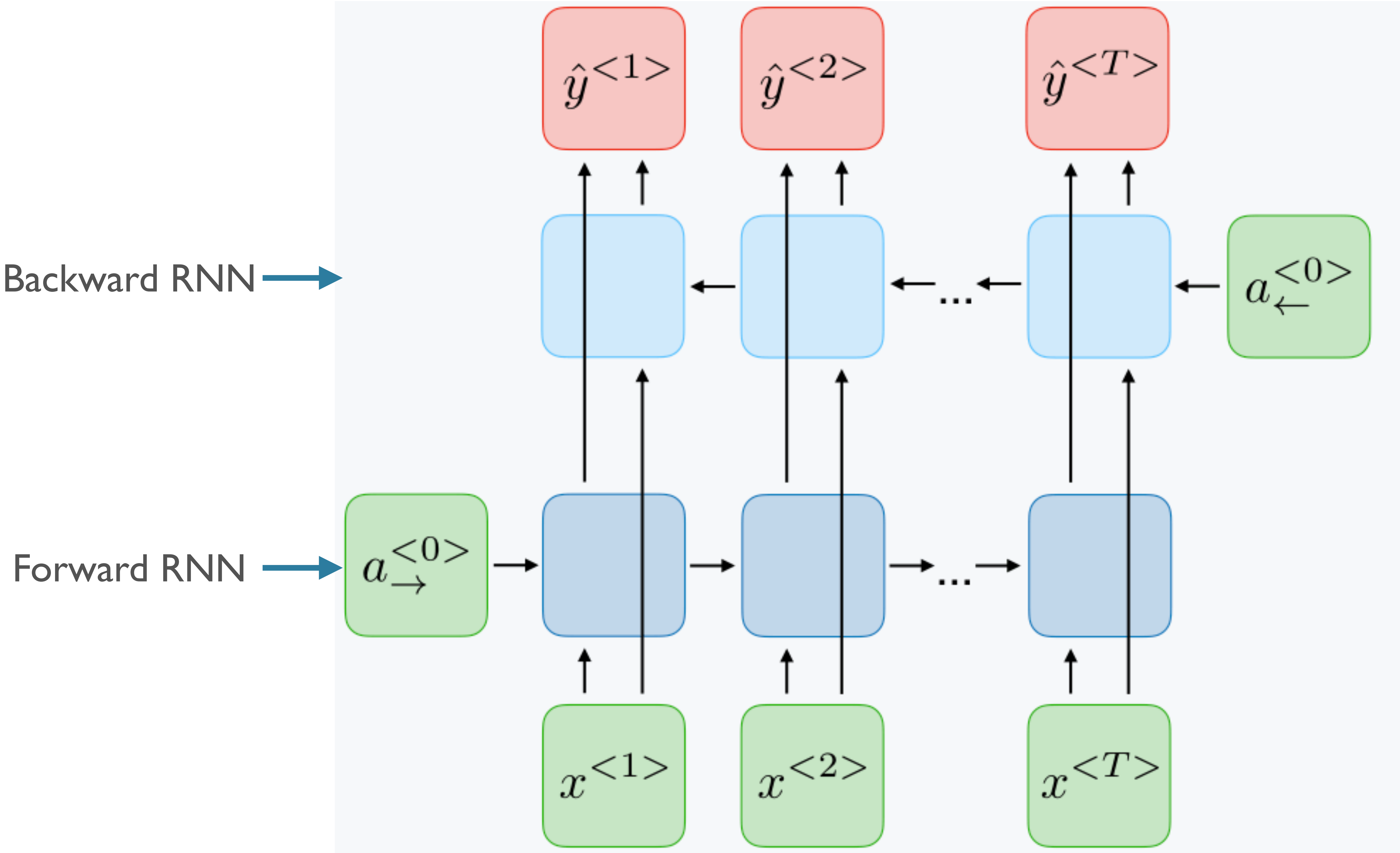

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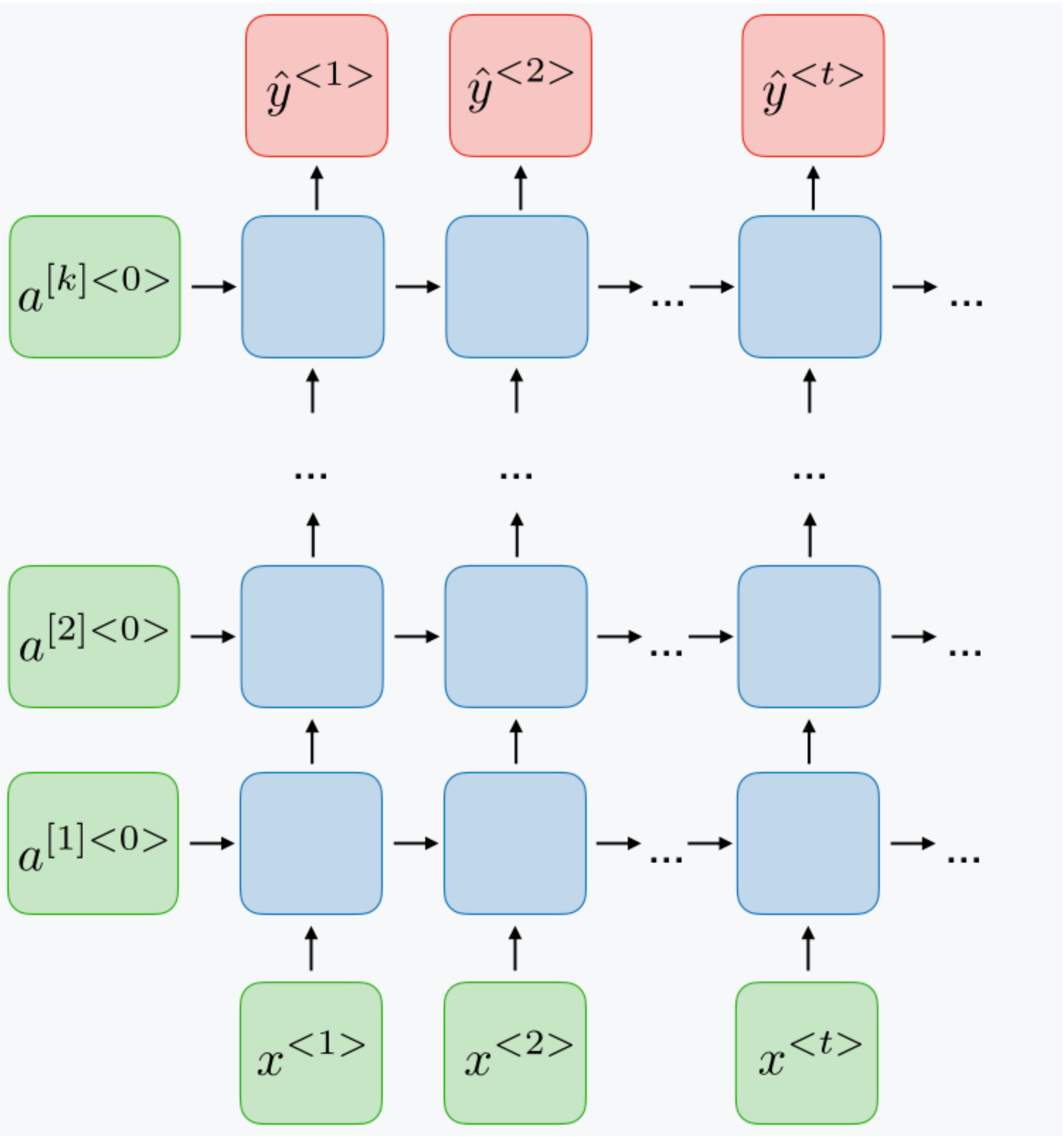

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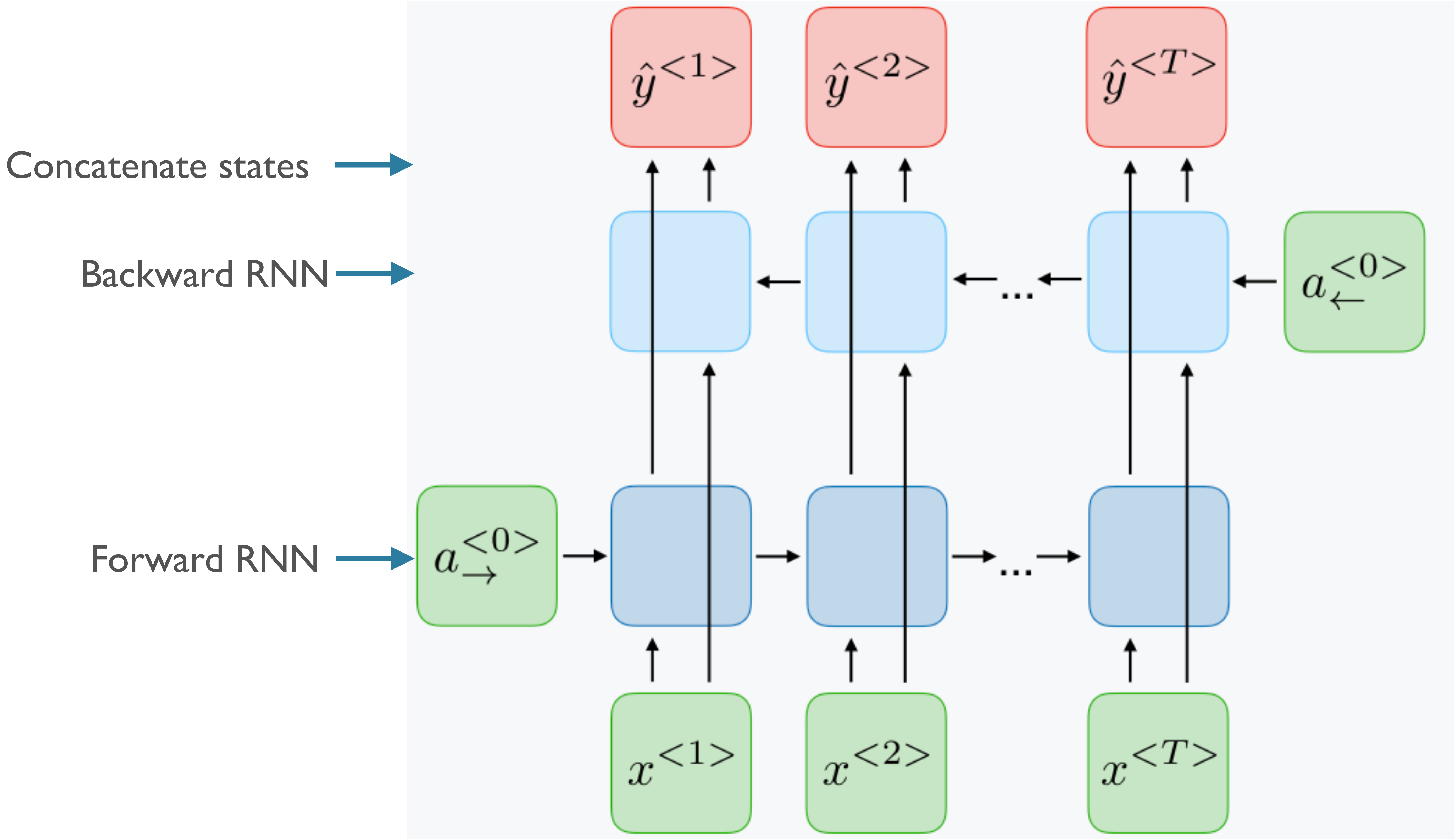
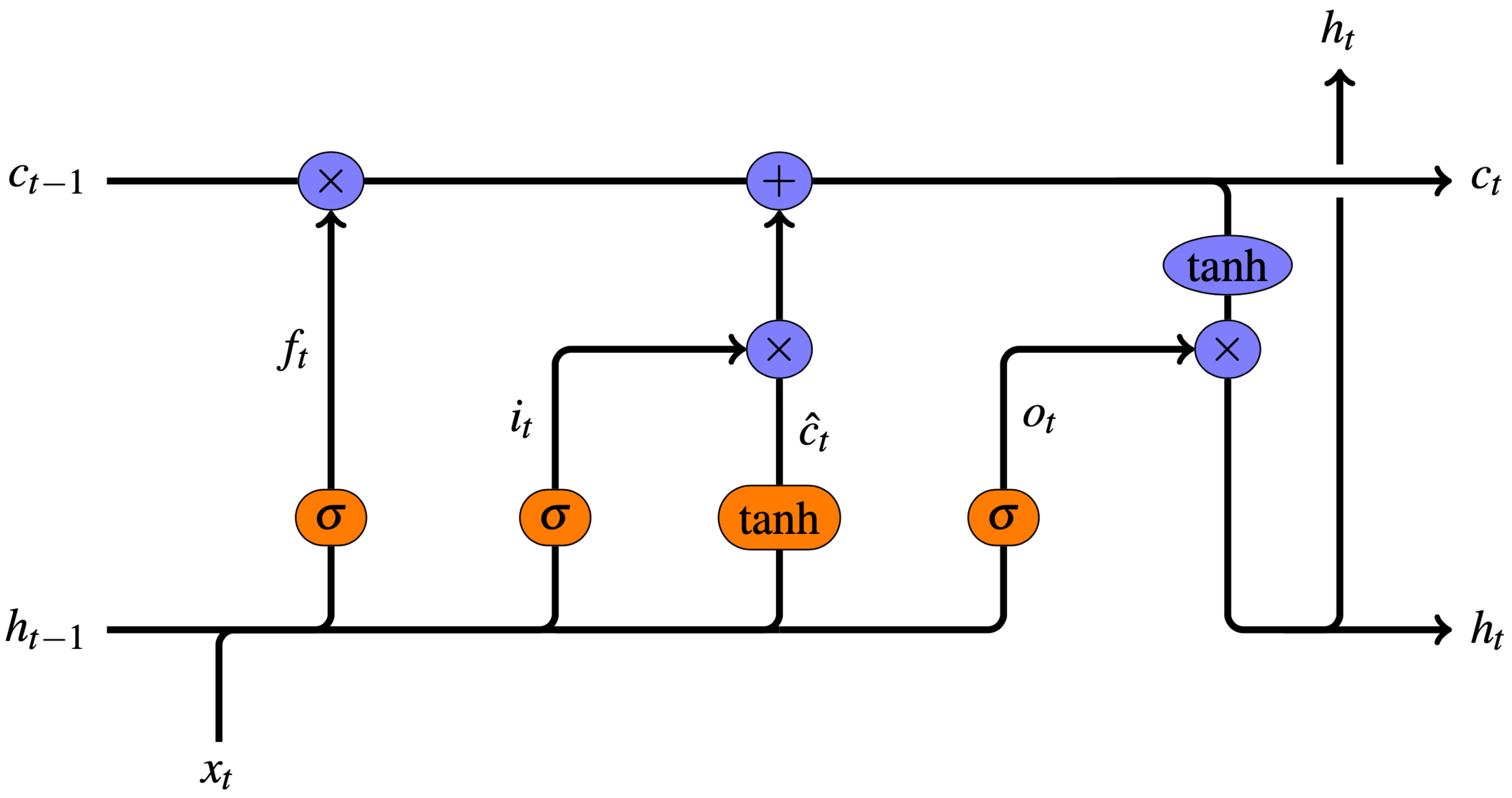


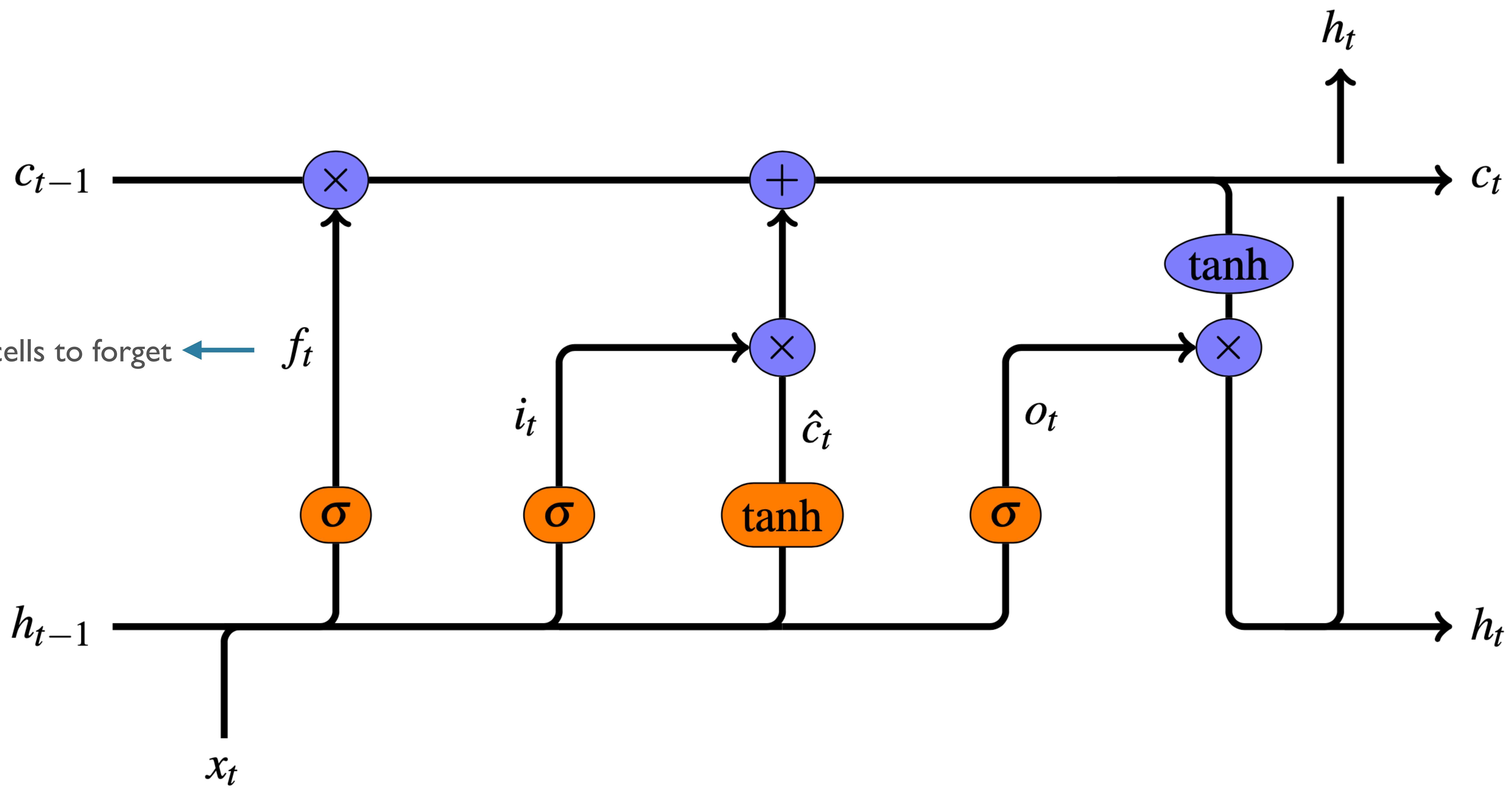
Source: RNN cheat sheet

LSTMs



LSTMs

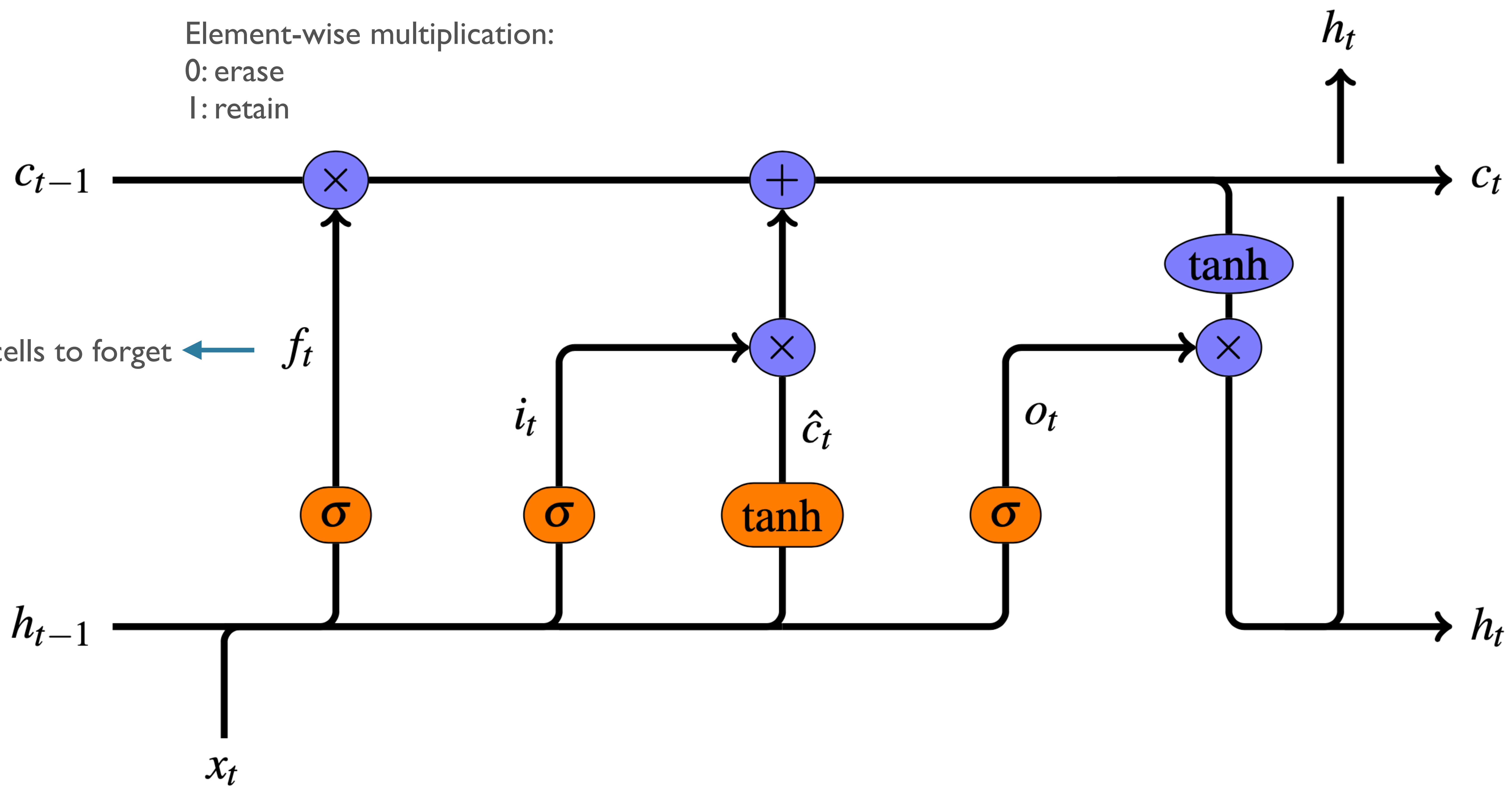
$f_t \in [0,1]^m$: which cells to forget



LSTMs

Element-wise multiplication:
0: erase
1: retain

$f_t \in [0,1]^m$: which cells to forget



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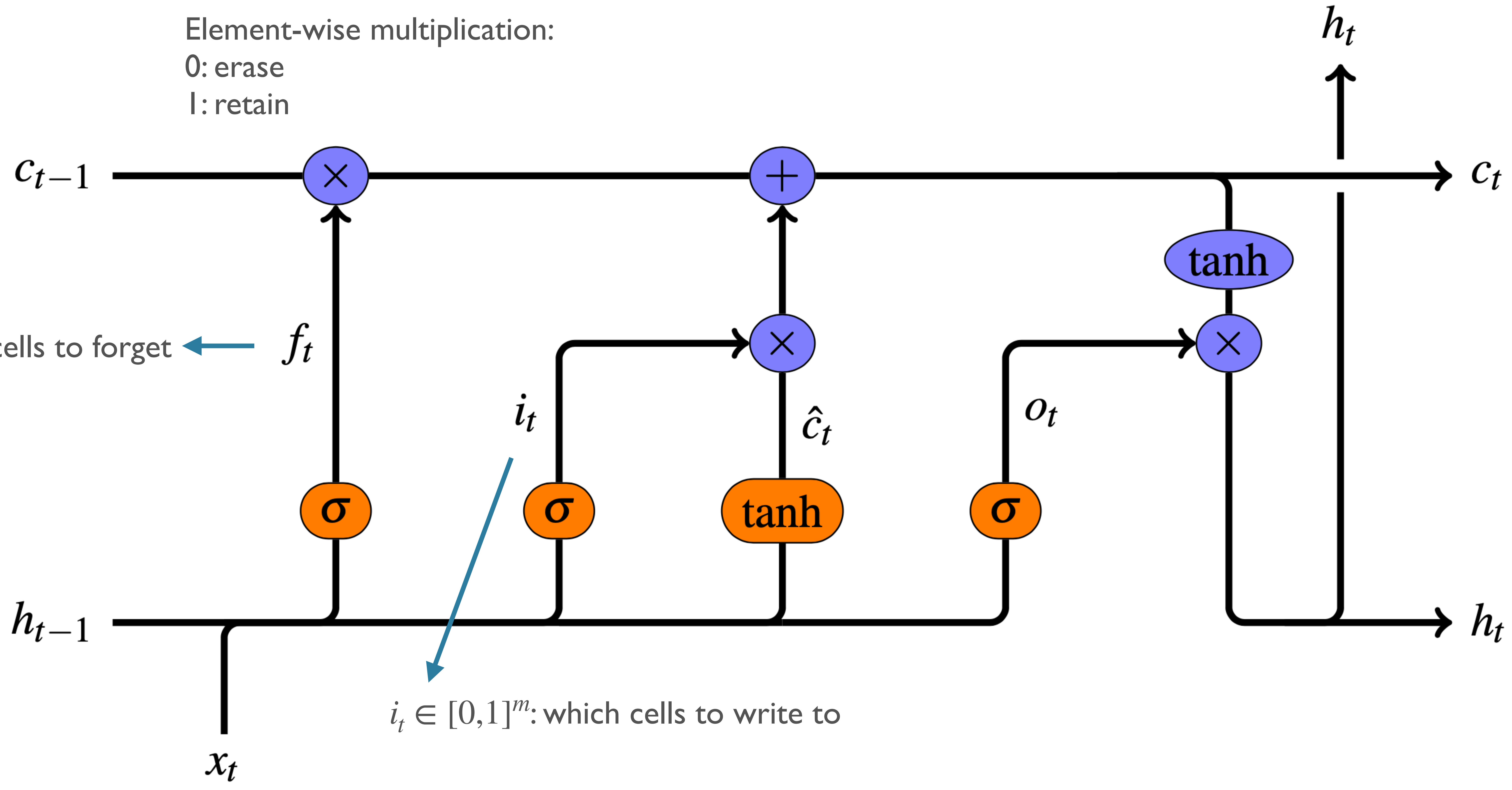
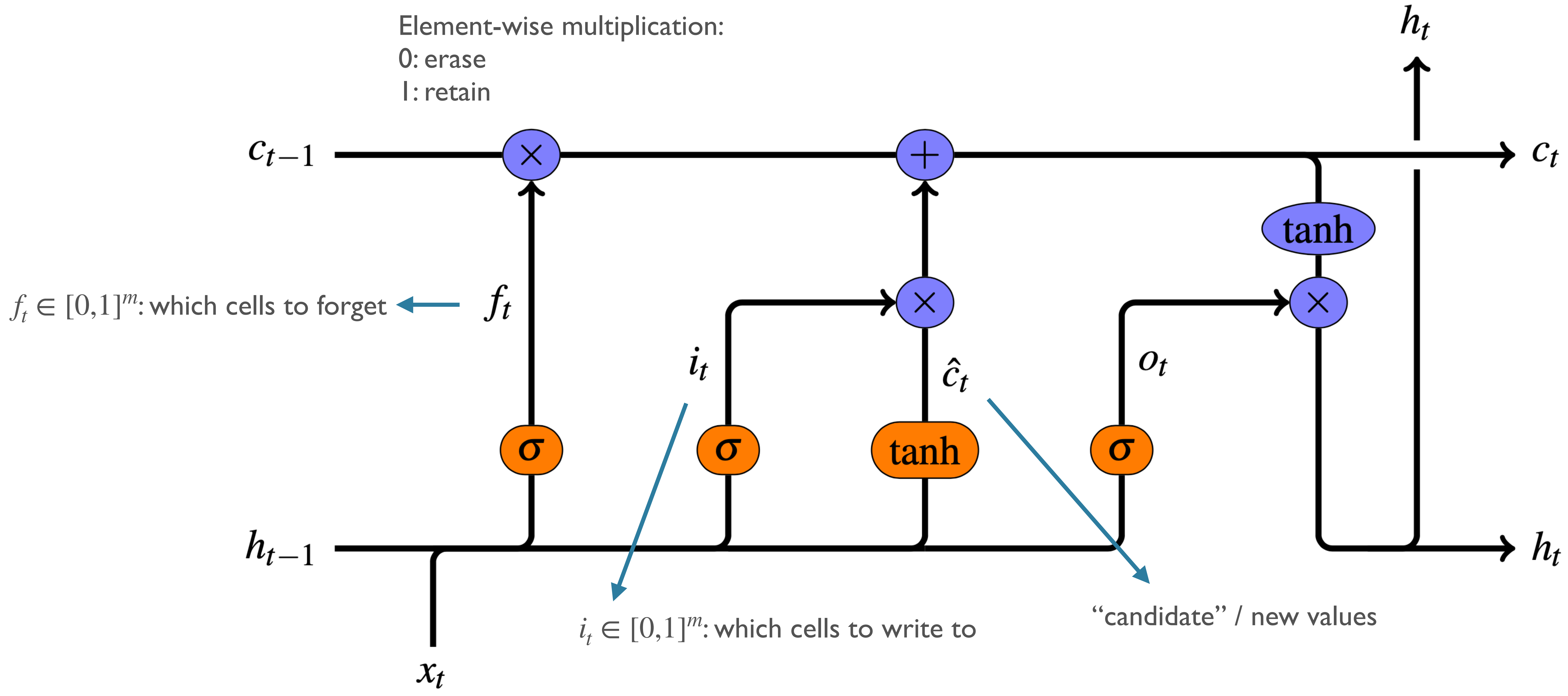


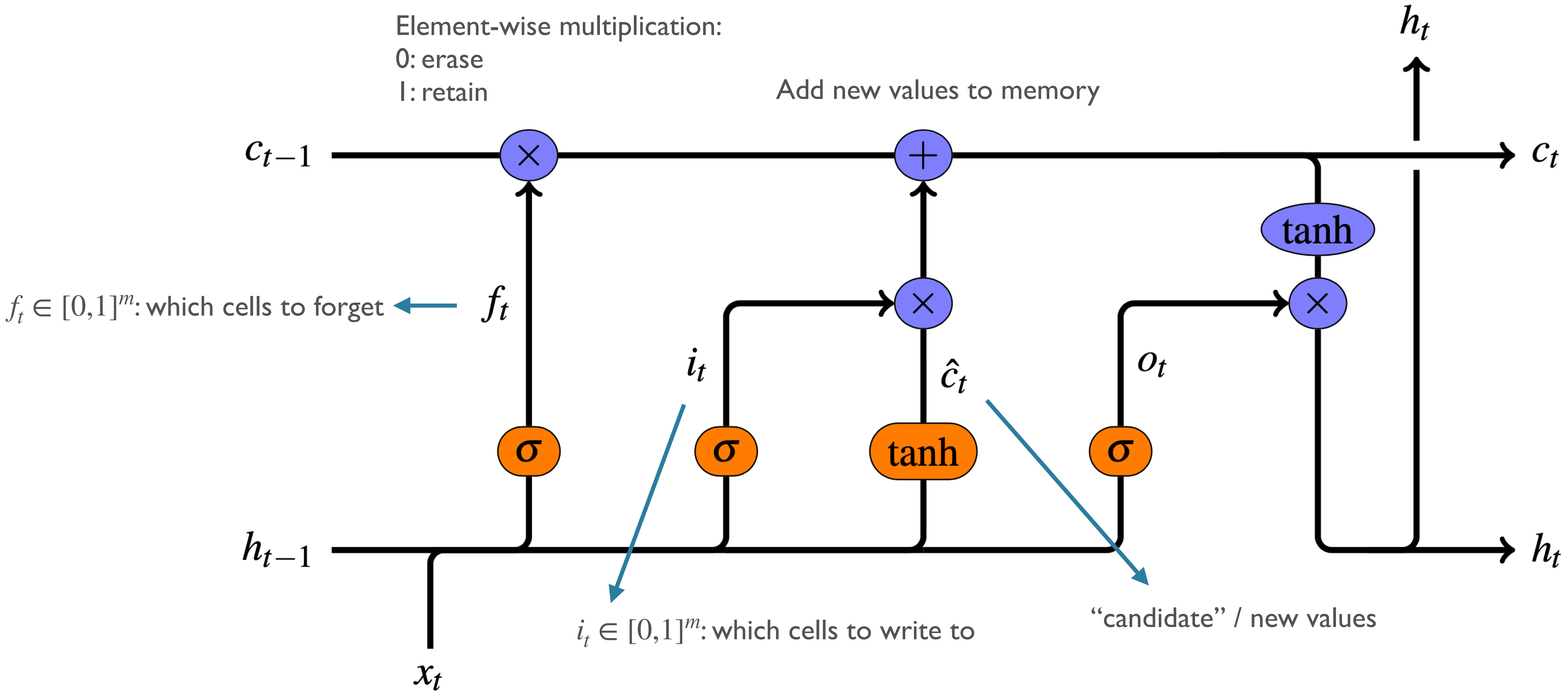
$i_t \in [0,1]^m$: which cells to write to

LSTMs



Element-wise multiplication:
0: erase
1: retain
c_{t-1}
c_t
h_t
h_{t-1}
h_t
x_t
f_t
i_t
$\hat{c}_t$
o_t
σ
σ
tanh
σ
tanh
$f_t \in [0,1]^m$: which cells to forget
$i_t \in [0,1]^m$: which cells to write to
"candidate" / new values

LSTMs



Element-wise multiplication:
0: erase
1: retain
Add new values to memory
h_t
c_{t-1}
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$f_t \in [0,1]^m$: which cells to forget
f_t
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x_t

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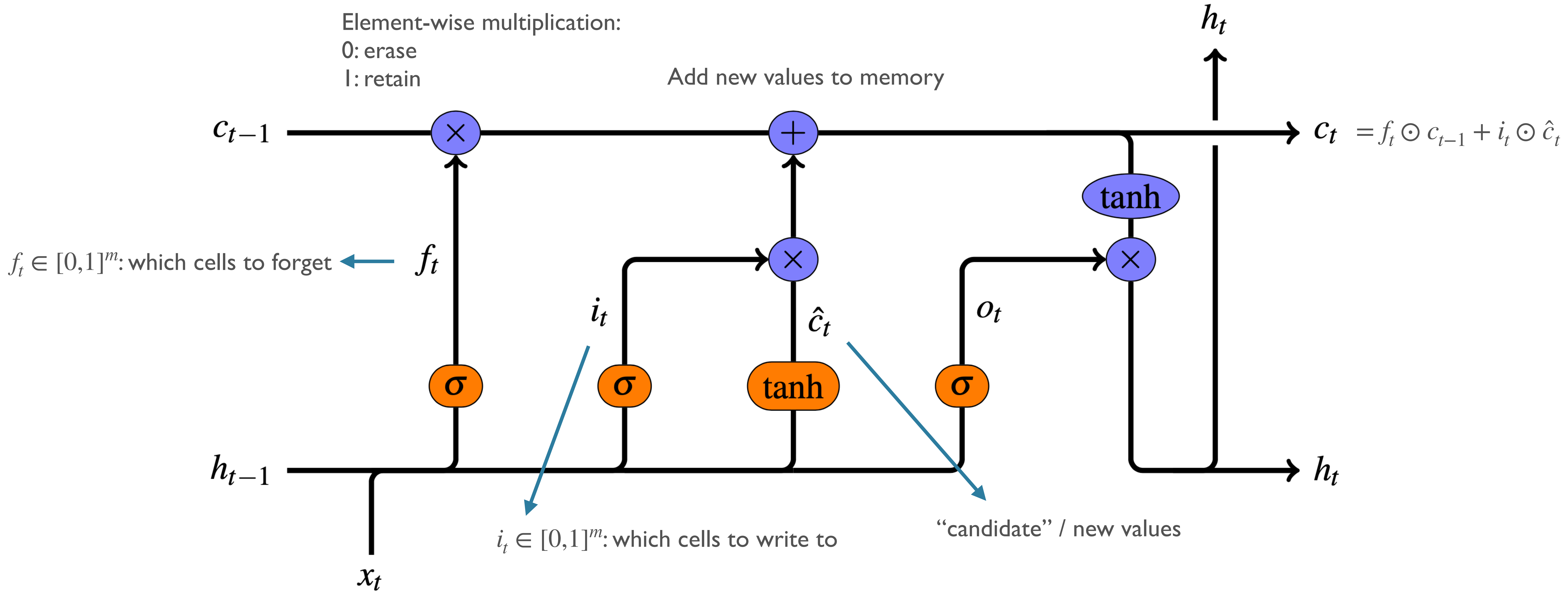
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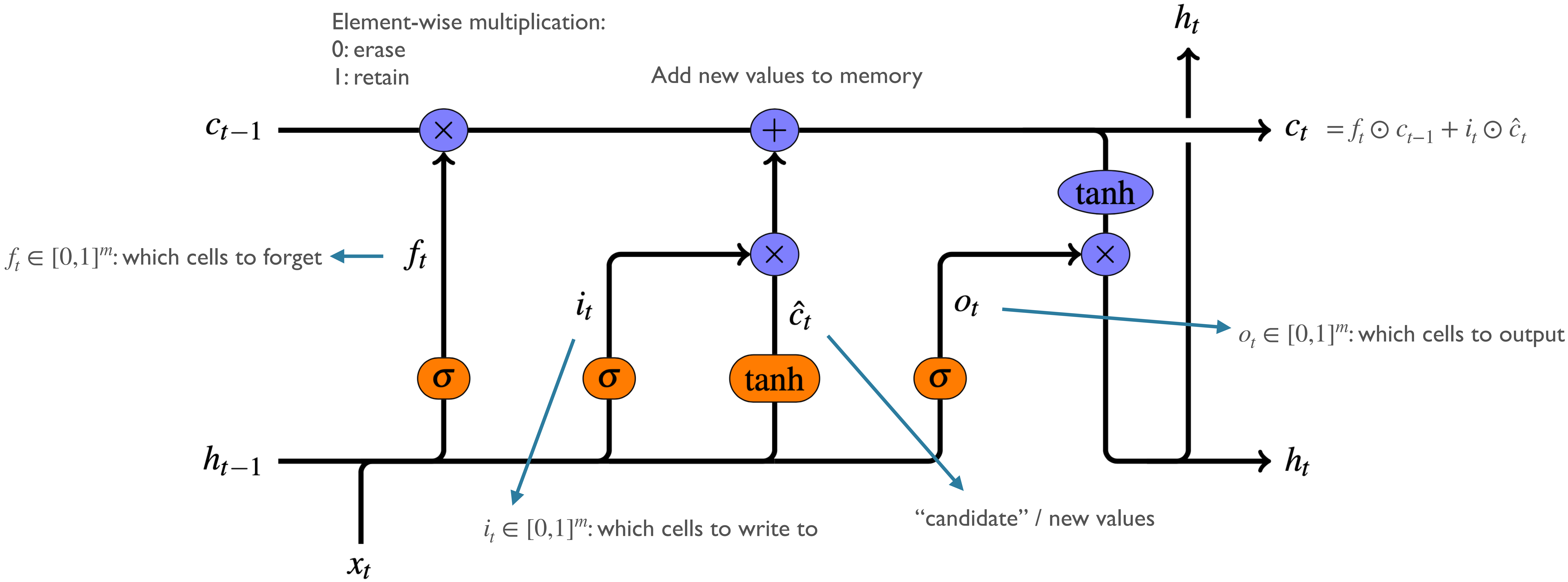

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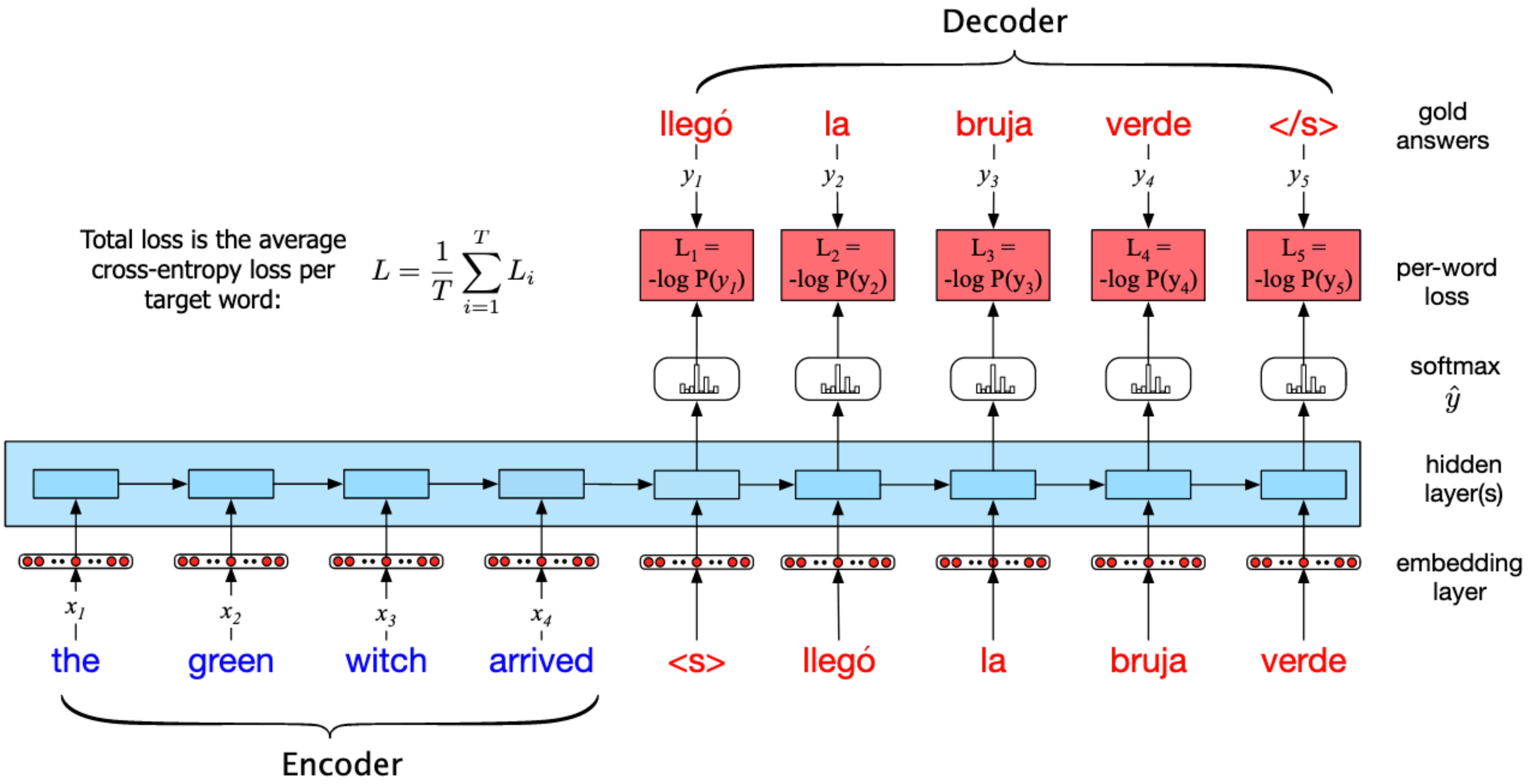
$\hat{c}_t$
o_t
$o_t \in [0,1]^m$: which cells to output
σ
σ
tanh
σ
h_{t-1}
h_t
$i_t \in [0,1]^m$: which cells to write to
"candidate" / new values
x_t

Training an encoder-decoder RNN

Total loss is the average cross-entropy loss per target word:

$$L = \frac{1}{T}\sum_{i=1}^{T} L_i$$



JM 11.3.1

Alignment, example

	Ceci	n’	est	pas	une	pipe
This	■					
is			■			
not		■		■		
a					■	
pipe						■

Alignment, example

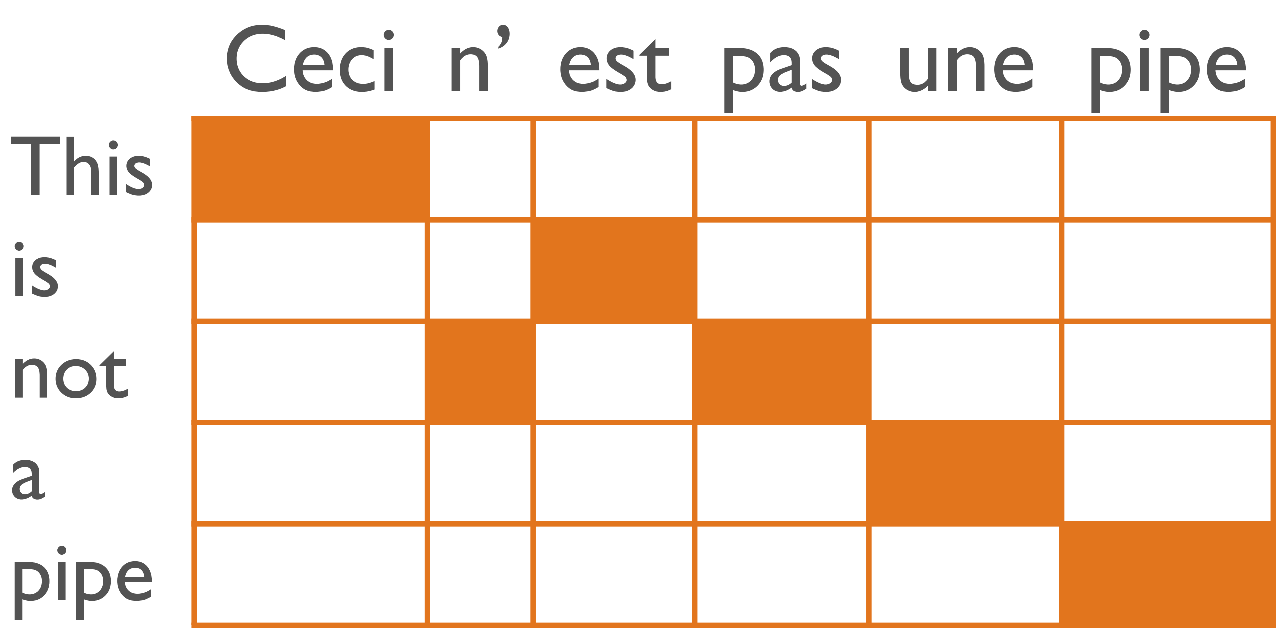
Ceci n' est pas une pipe

	Ceci	n'	est	pas	une	pipe
This	■					
is			■			
not		■		■		
a					■	
pipe						■

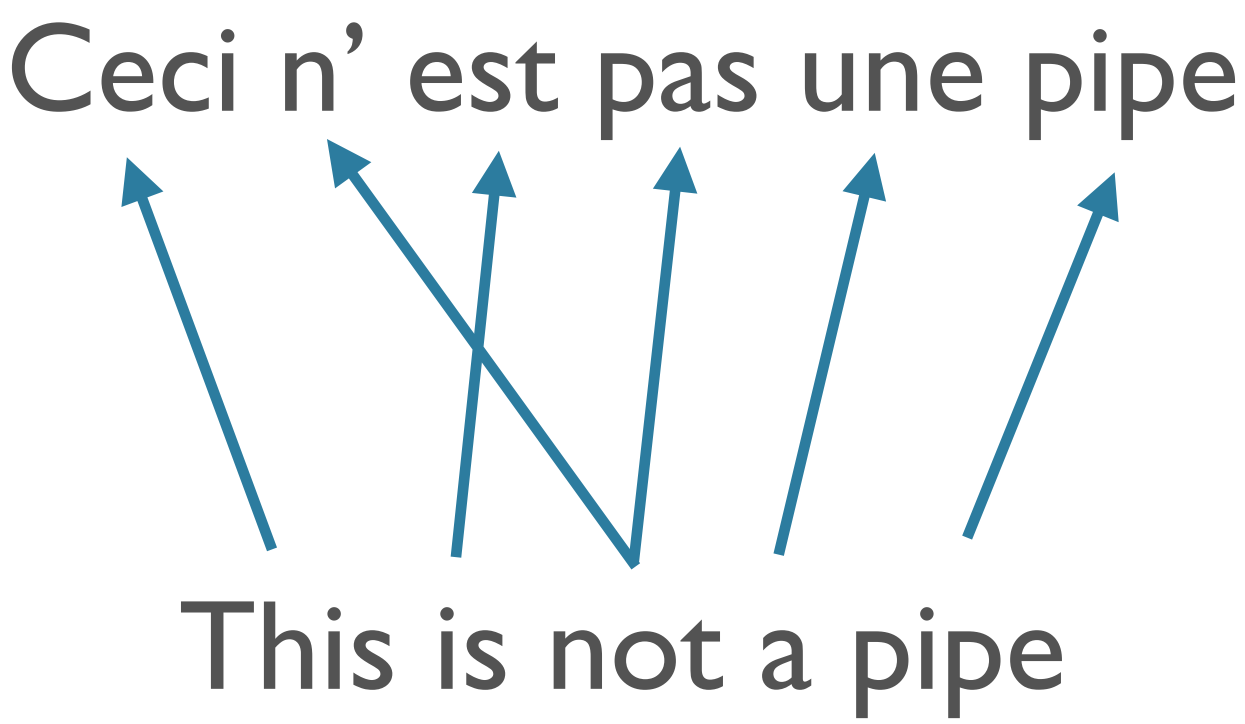
Alignment, example

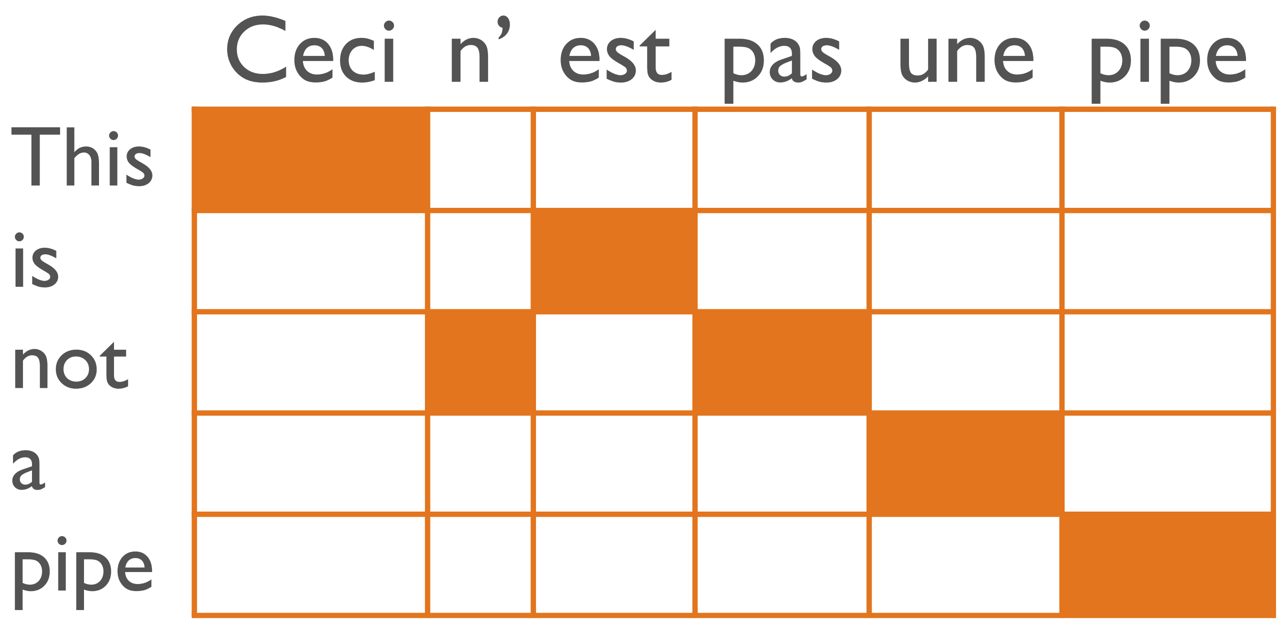
Ceci n’ est pas une pipe

This is not a pipe

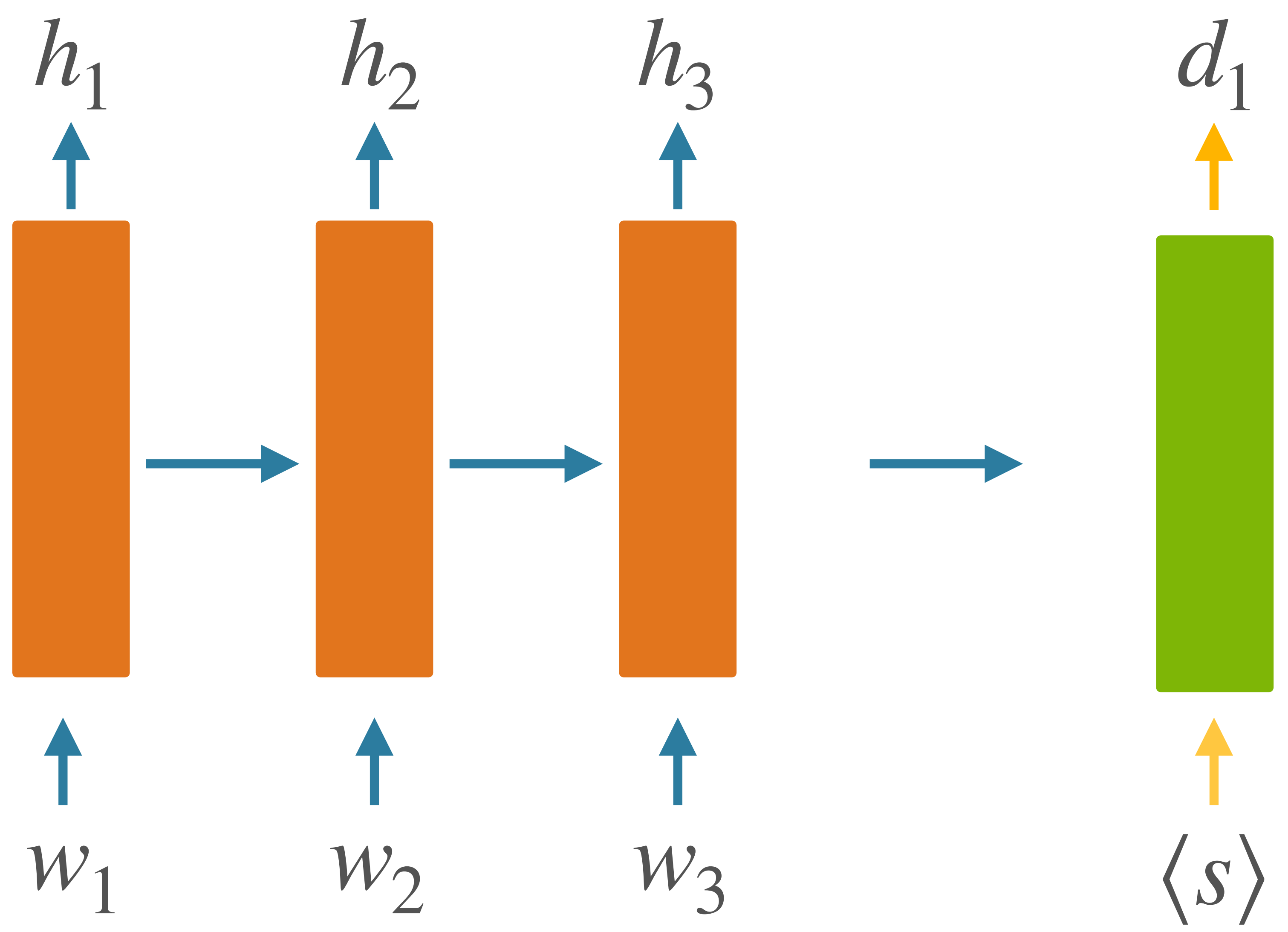


Alignment, example



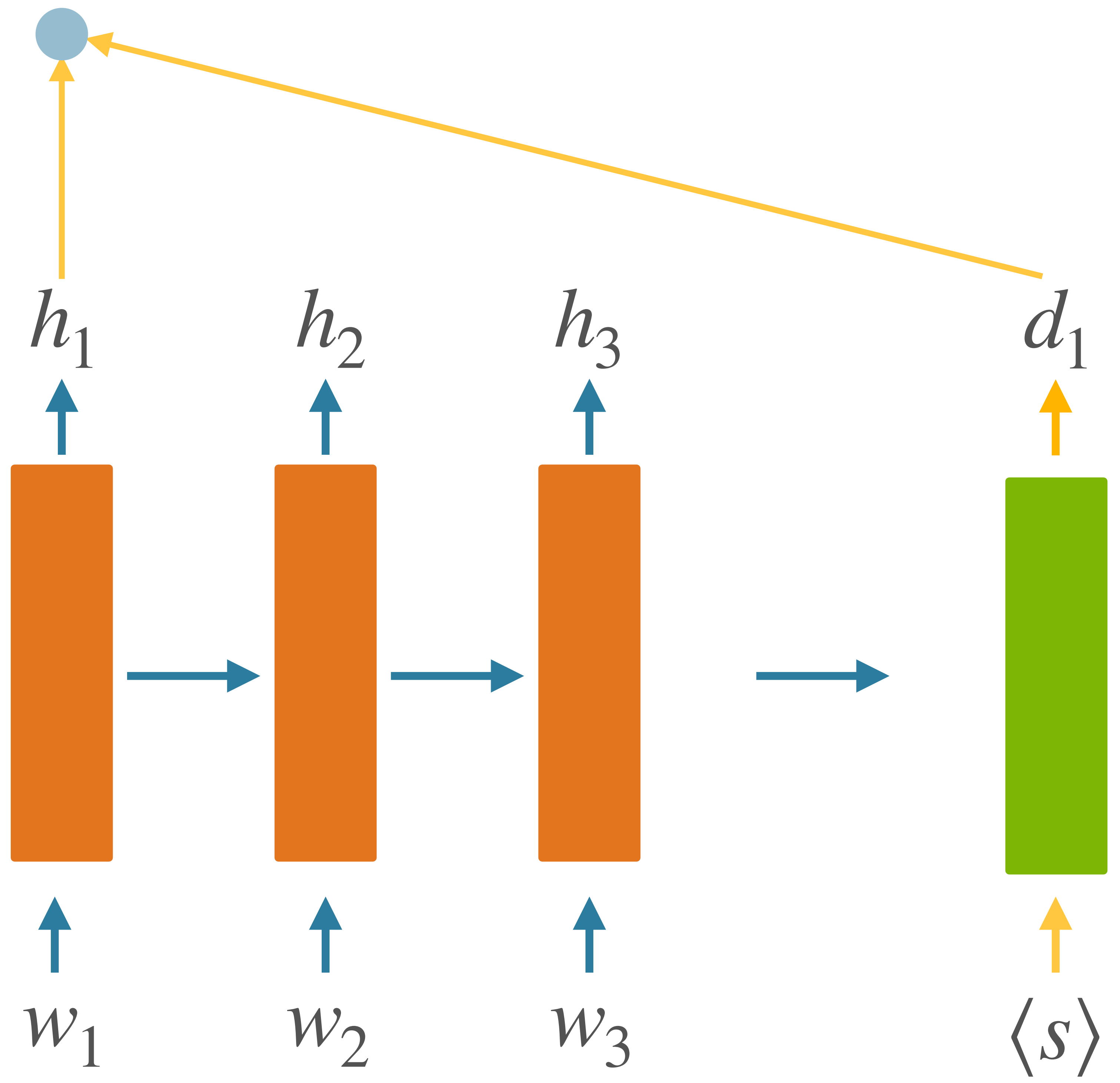


Adding Attention



Badhanau et al 2014

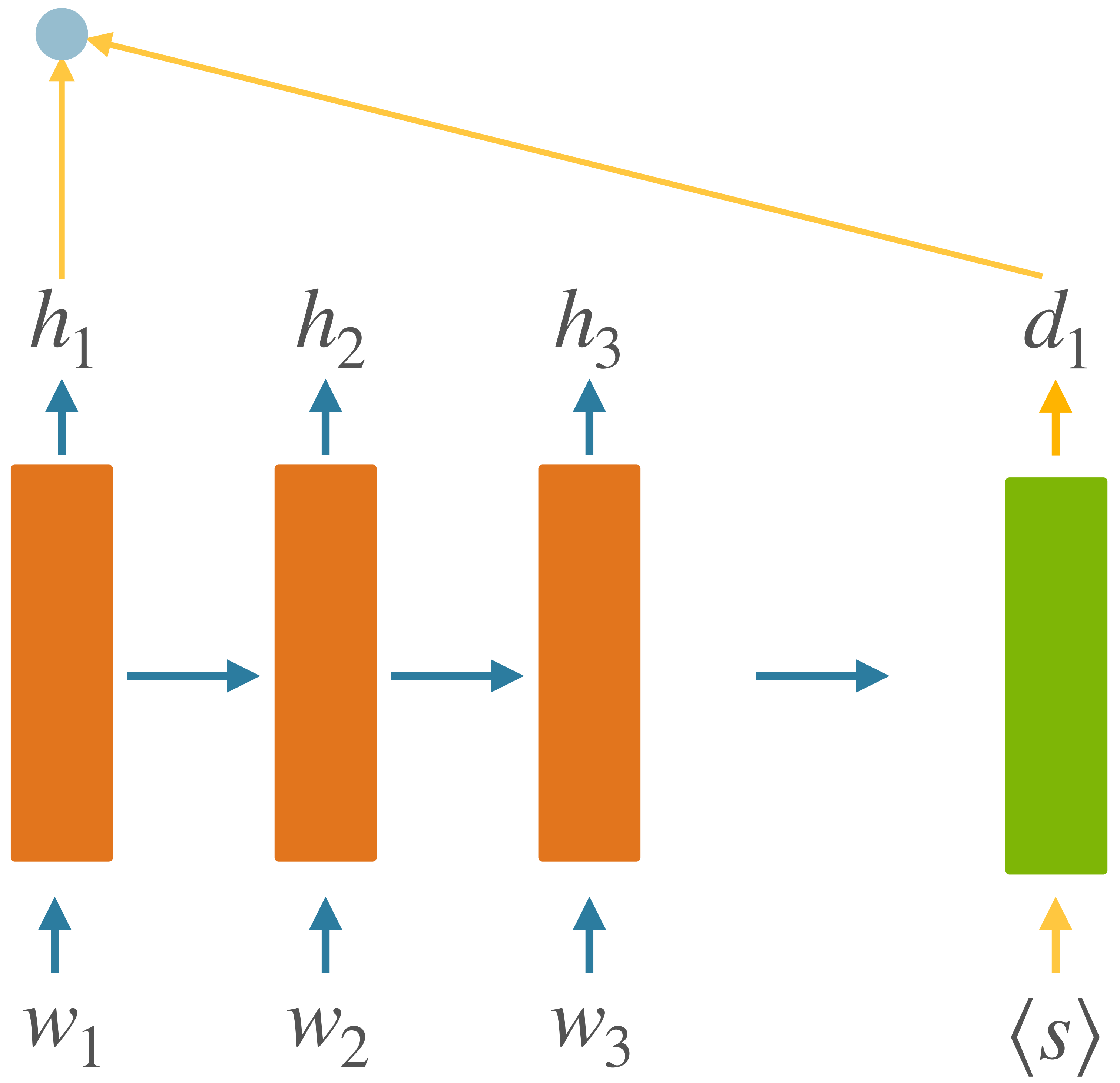
Adding Attention



Badhanau et al 2014

Adding Attention

$\alpha_{ij} = a(h_j, d_i)$
(dot product usually)



Badhanau et al 2014

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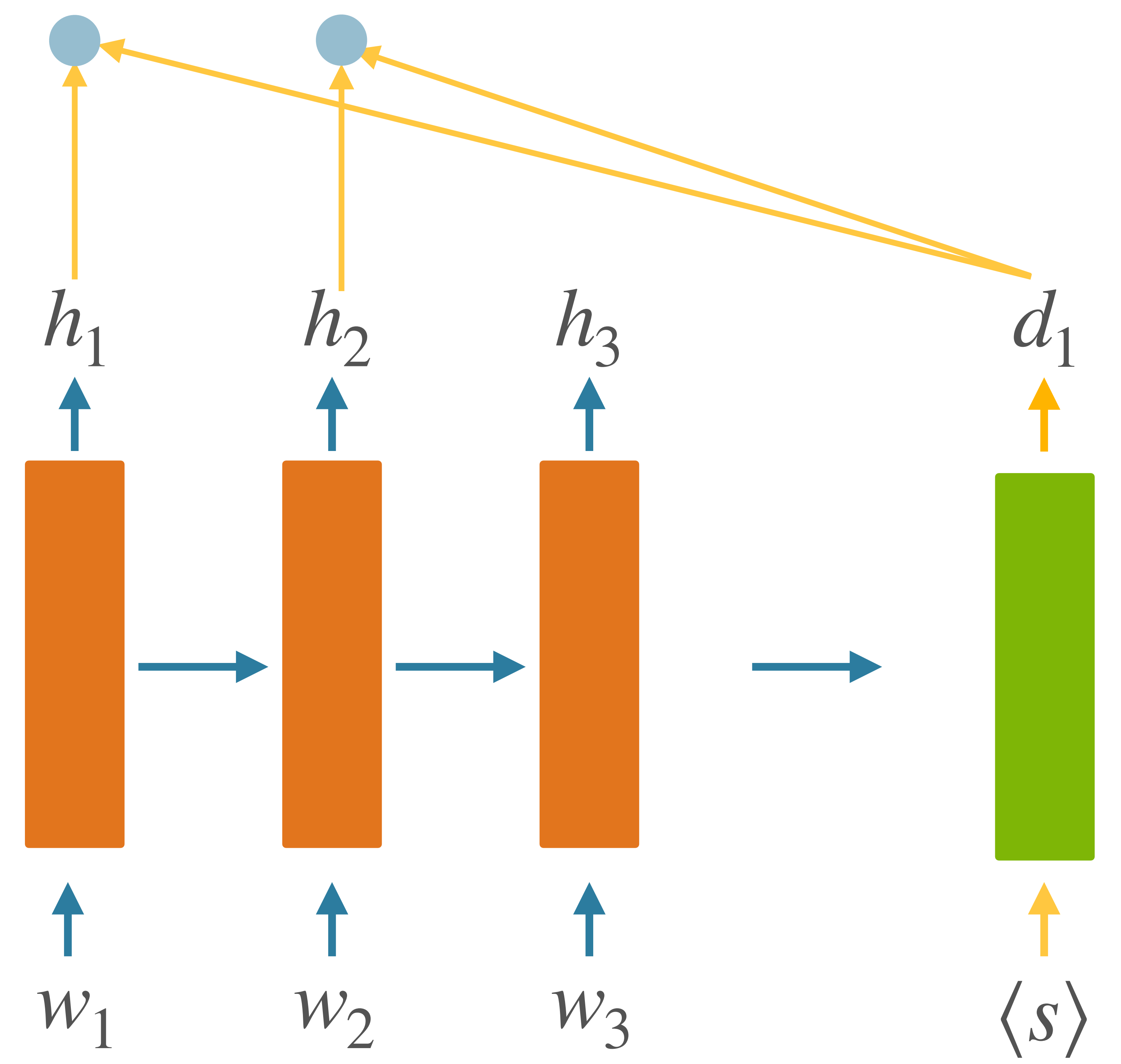

Badhanau et al 2014

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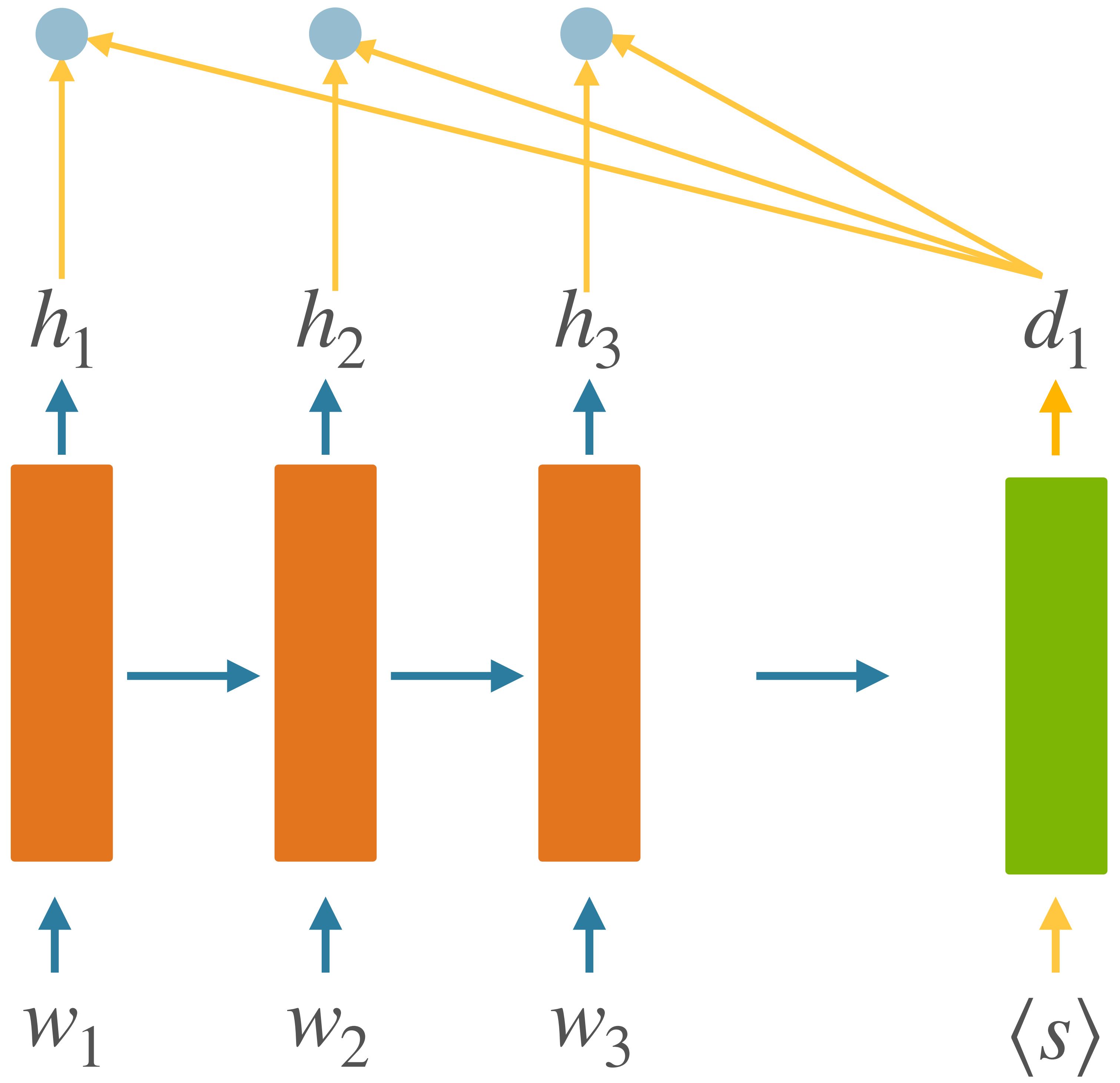
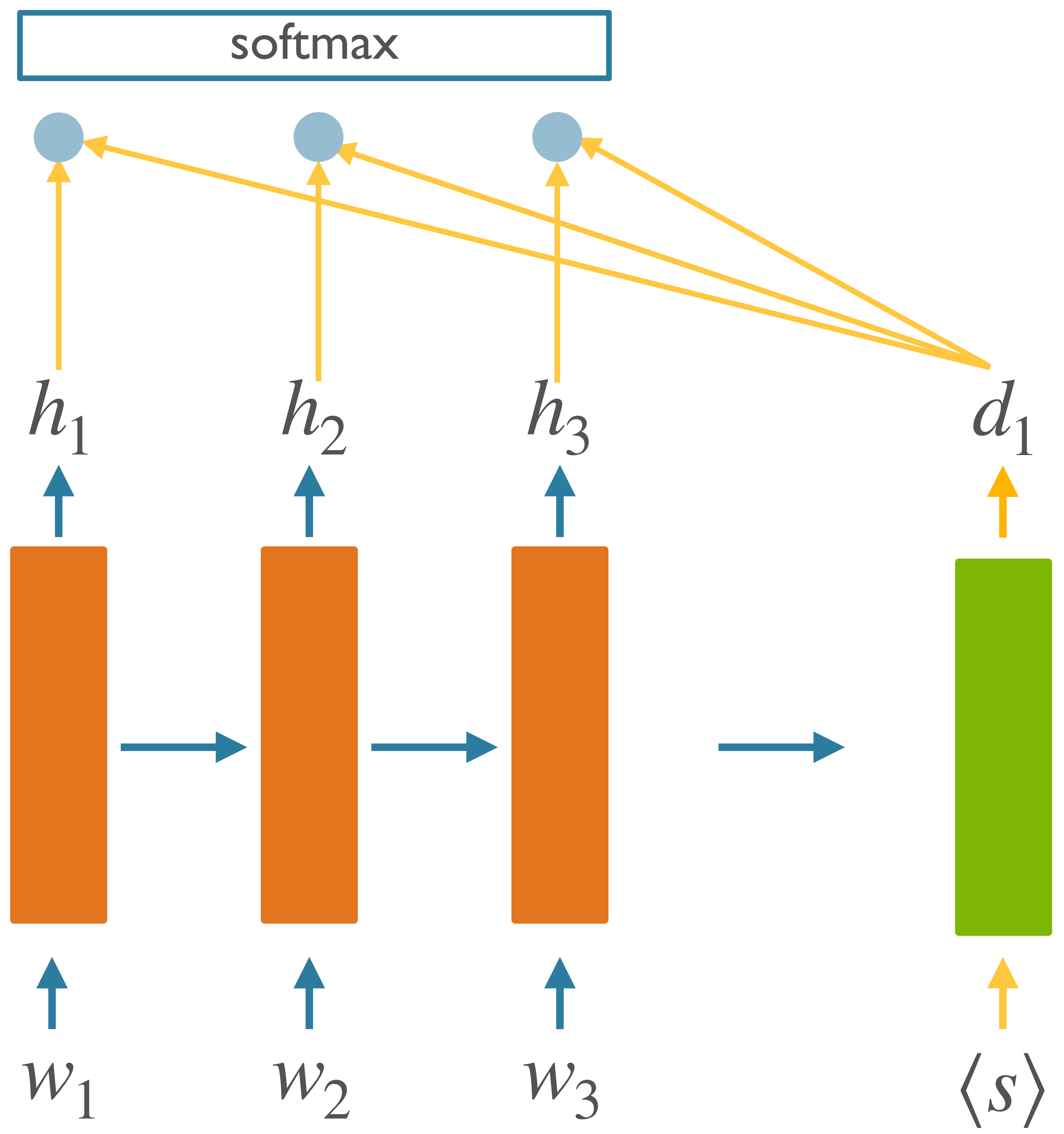


Badhanau et al 2014

Adding Attention

$e_{ij} = \text{softmax}(\alpha)_j$

$\alpha_{ij} = a(h_j, d_i)$
(dot product usually)



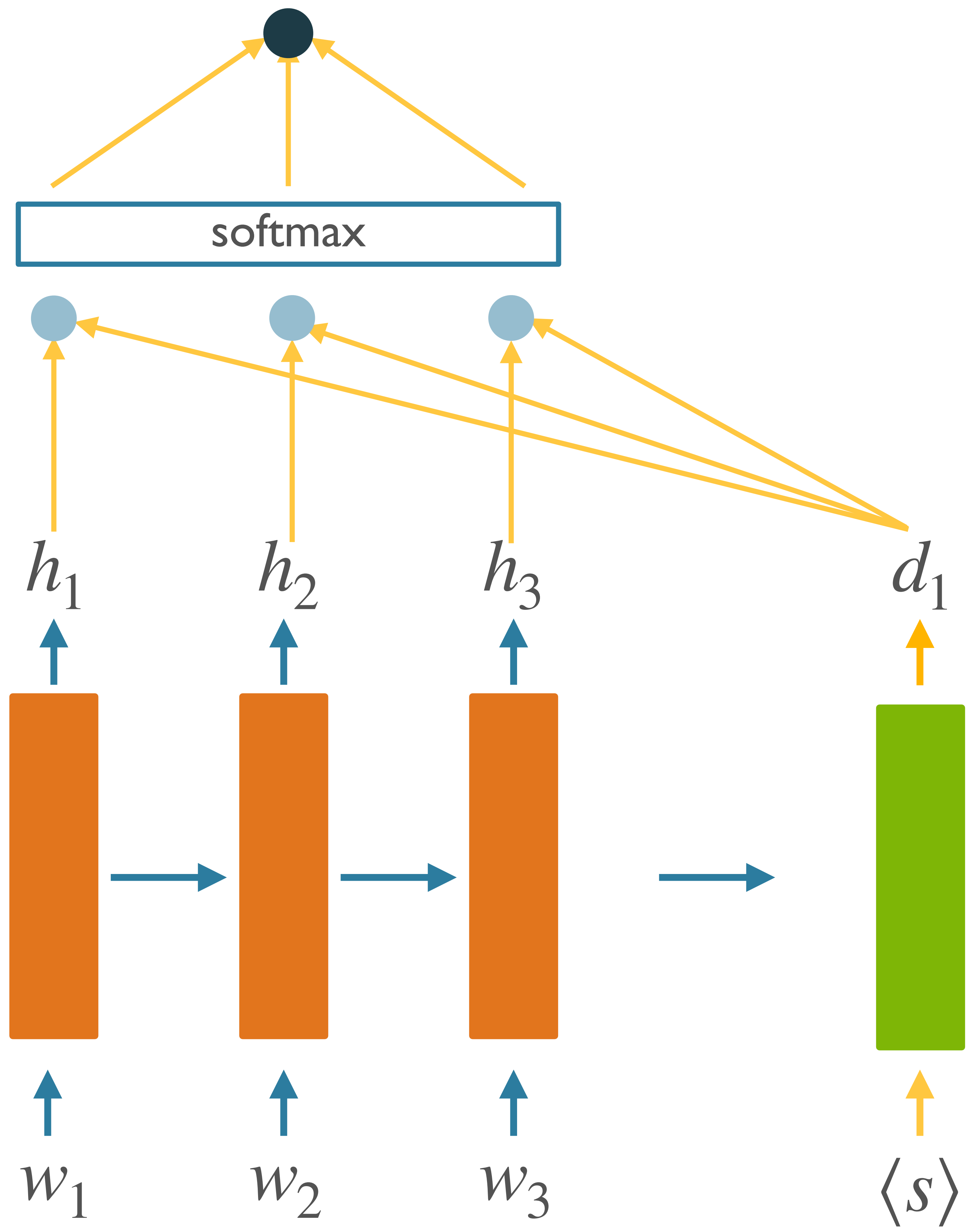
Badhanau et al 2014

Adding Attention

$c_i = \Sigma_j e_{ij} h_j$

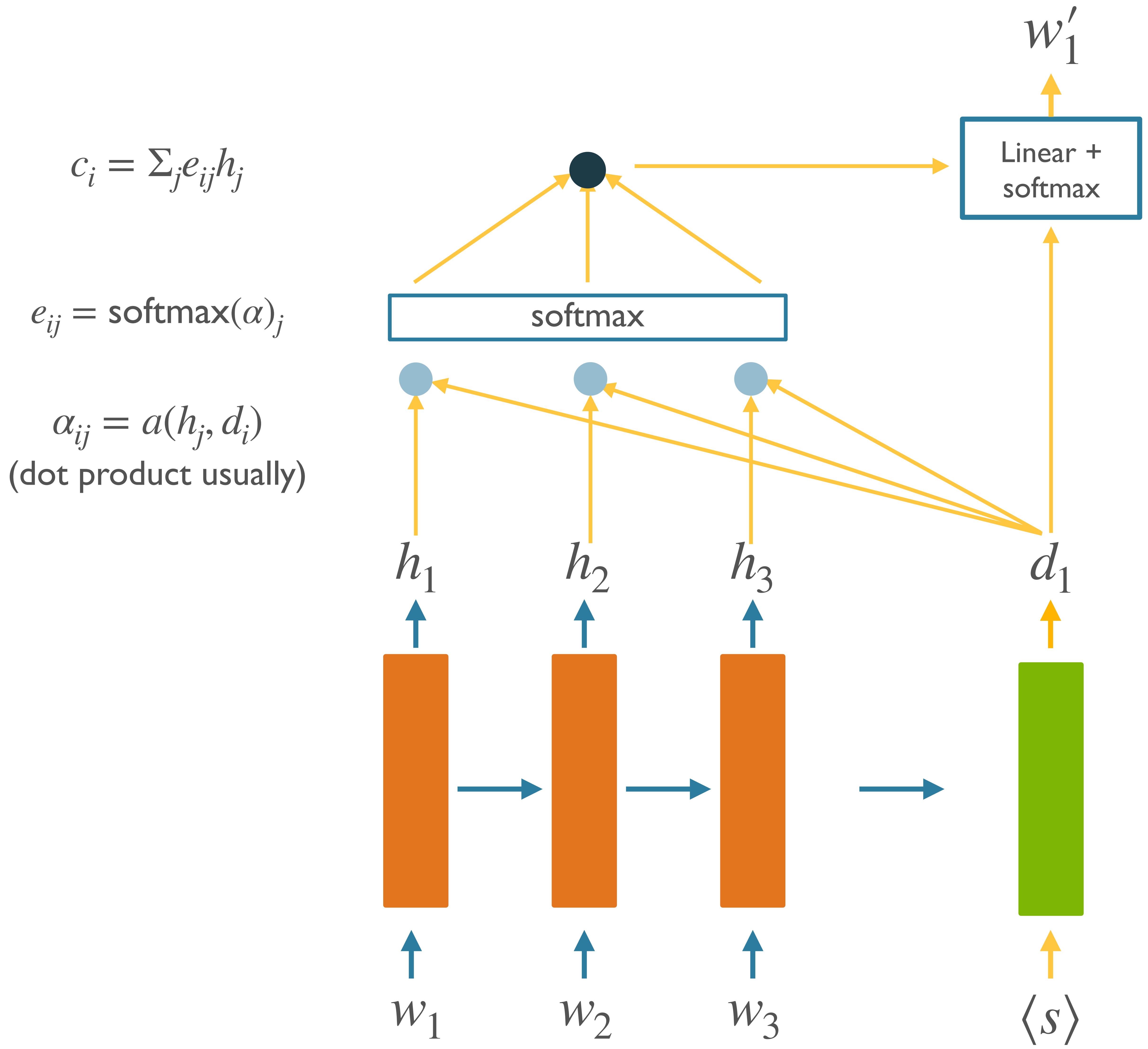
$e_{ij} = \text{softmax}(\alpha)_j$

$\alpha_{ij} = a(h_j, d_i)$
(dot product usually)



Badhanau et al 2014

Adding Attention



Badhanau et al 2014

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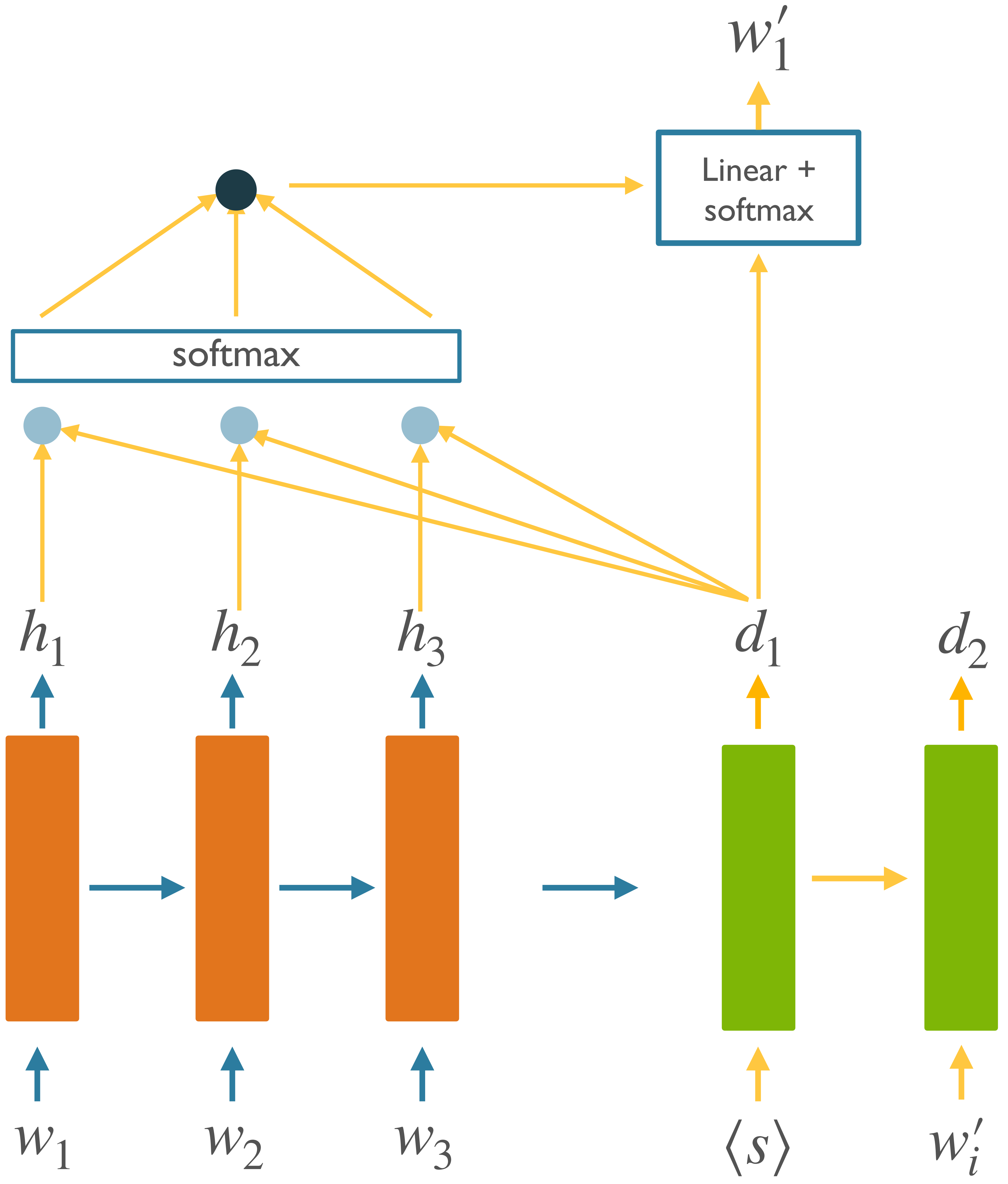


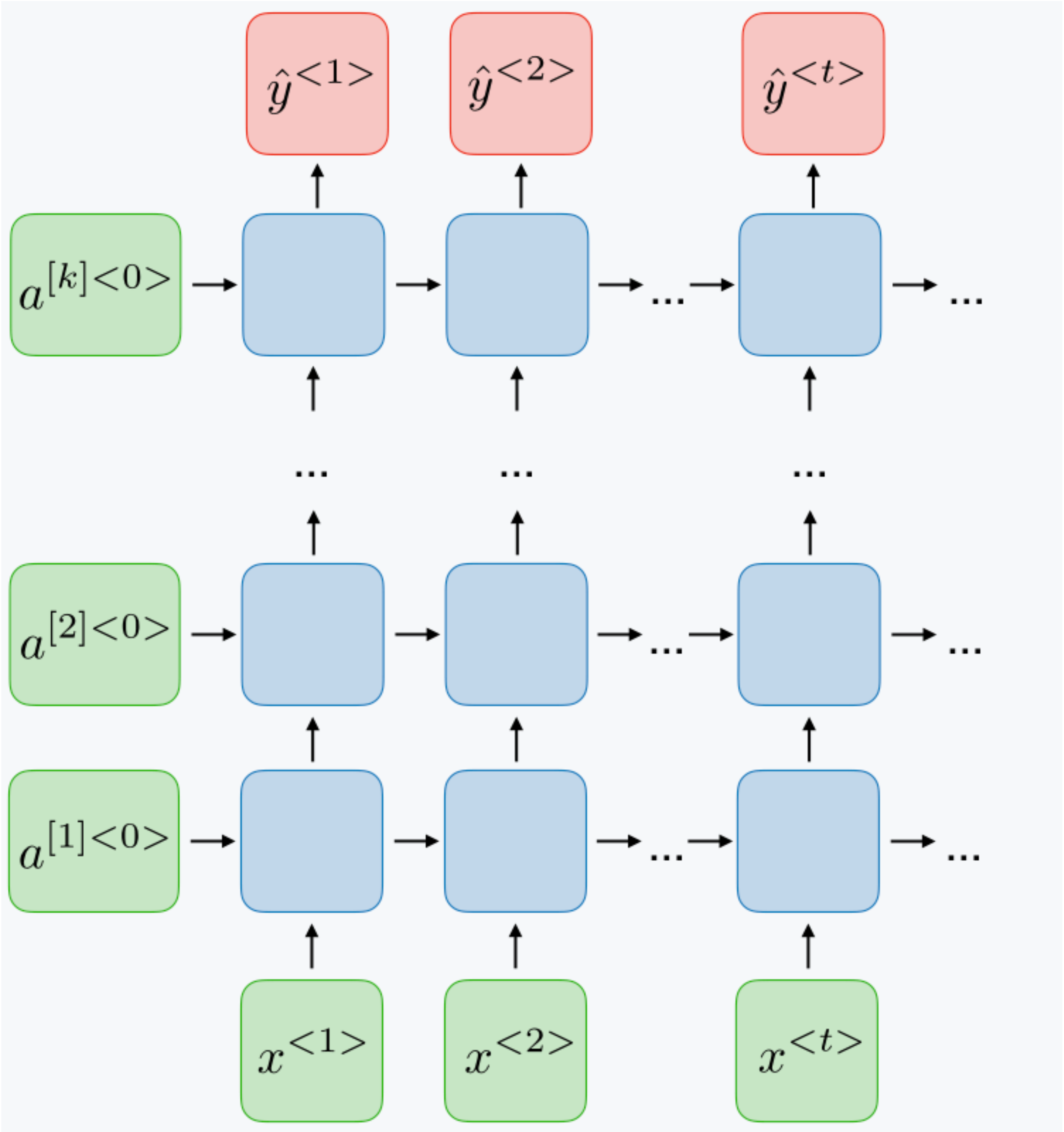
Badhanau et al 2014

Neural Networks, II

- Transformers
  - Core architecture
  - Pre-training + Fine-tuning Paradigm
- Interpretability / analysis

Lack of Parallelizability

- Modern hardware (e.g. GPUs) are very good at doing *independent* computations in parallel
- RNNs are inherently serial:
  - Cannot compute future time steps without the past
- Bottleneck that makes scaling up difficult



Students who … enjoy

Lack of Parallelizability

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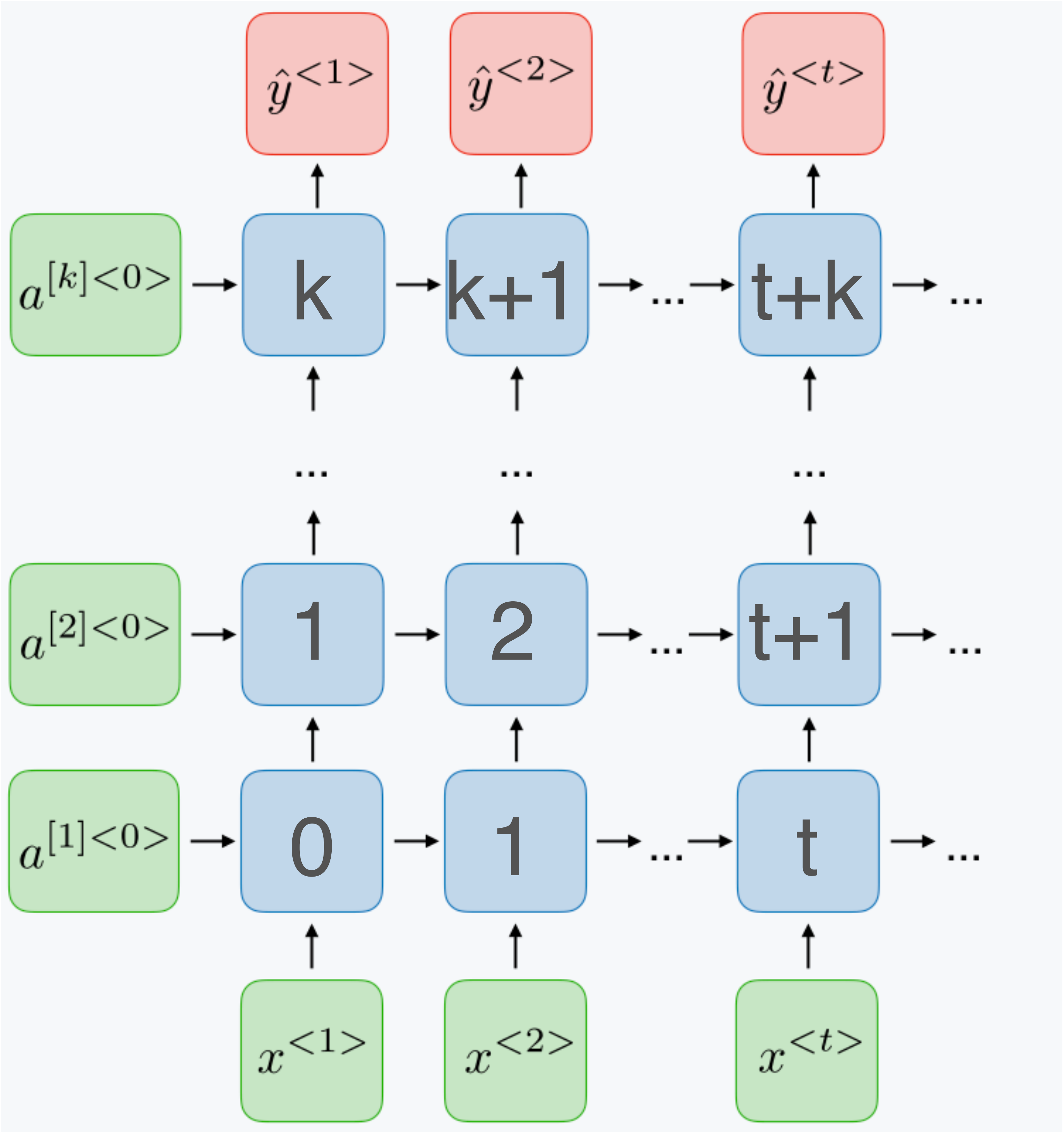

Students who … enjoy

Lack of Parallelizability

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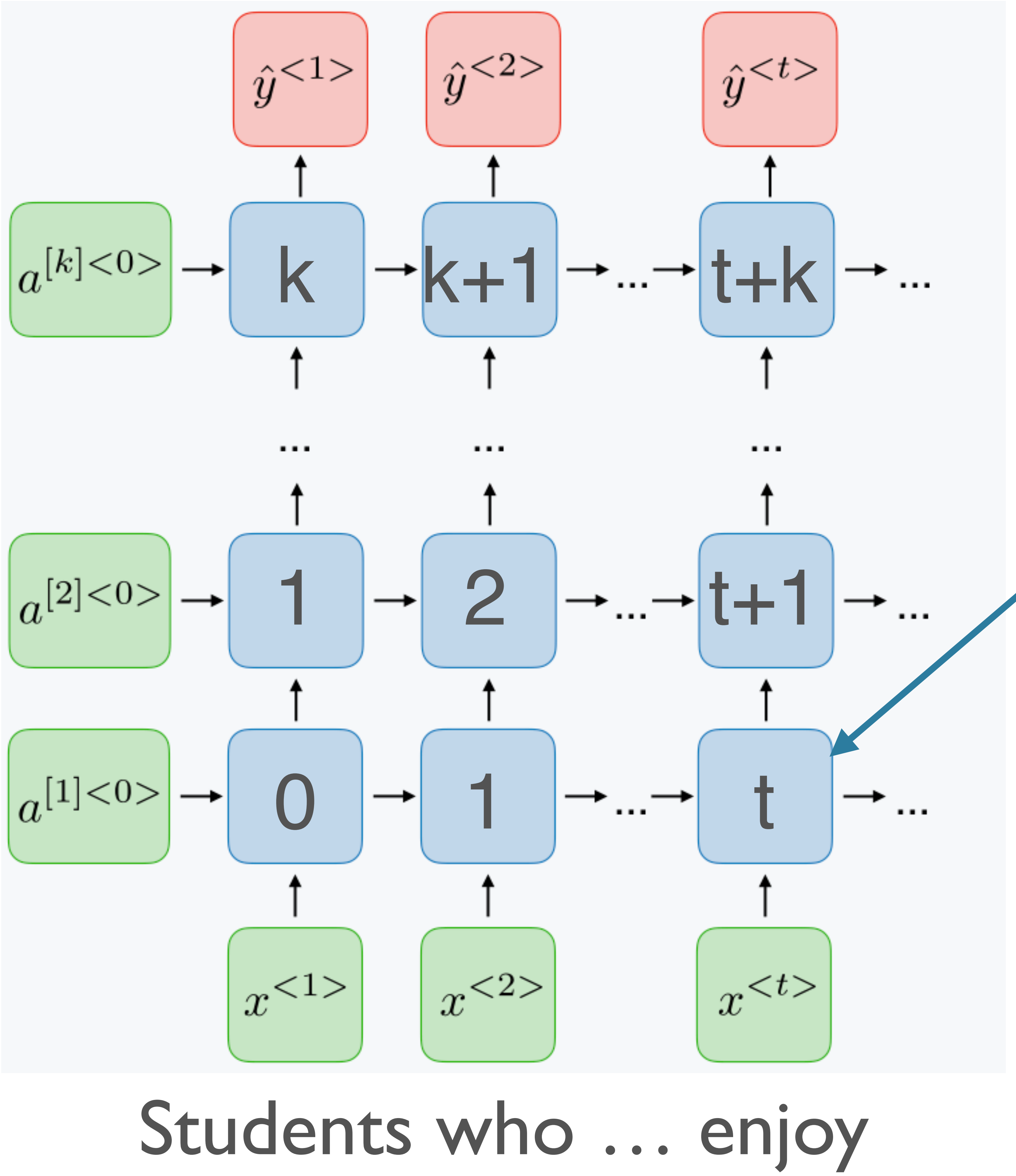
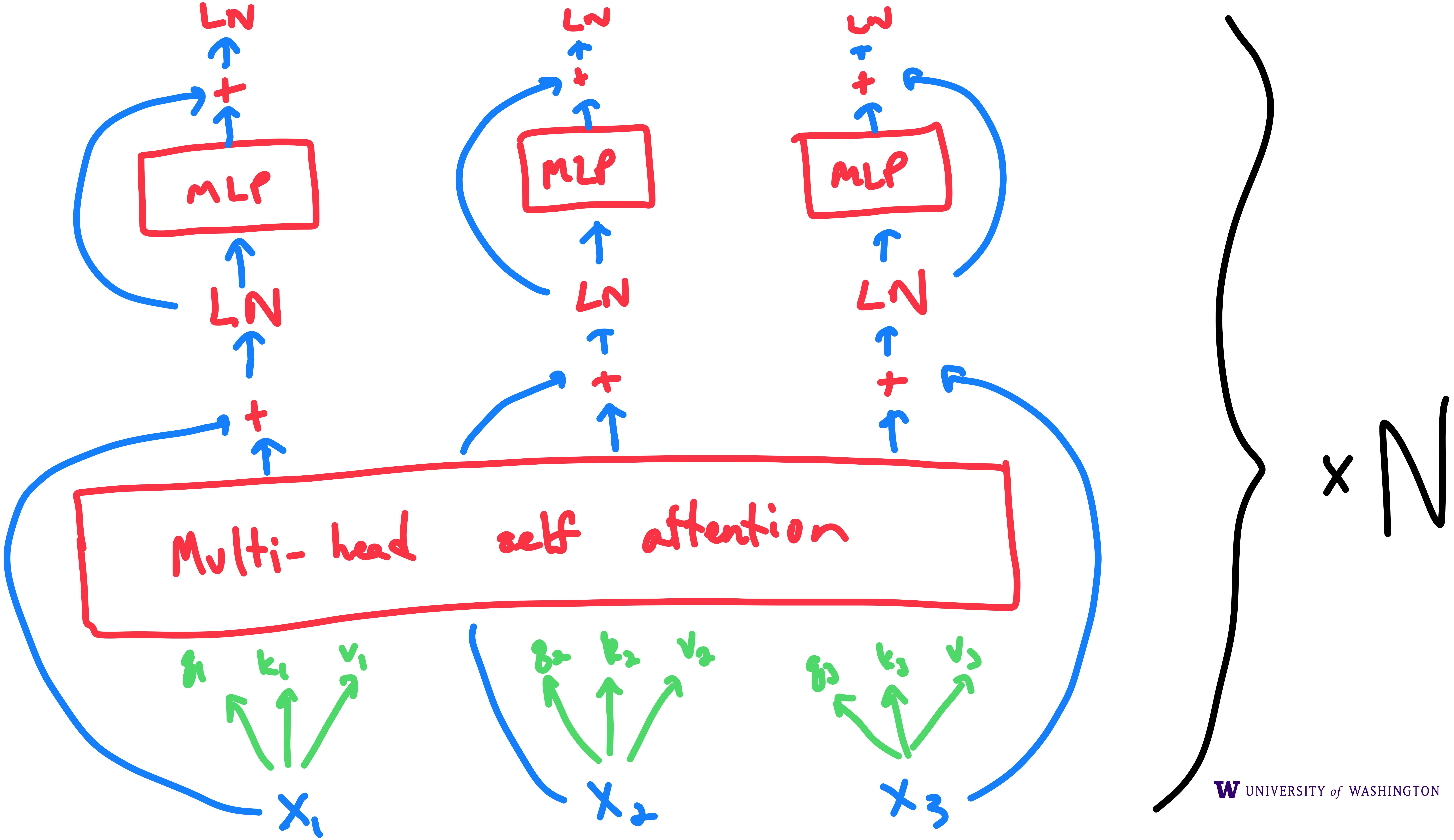
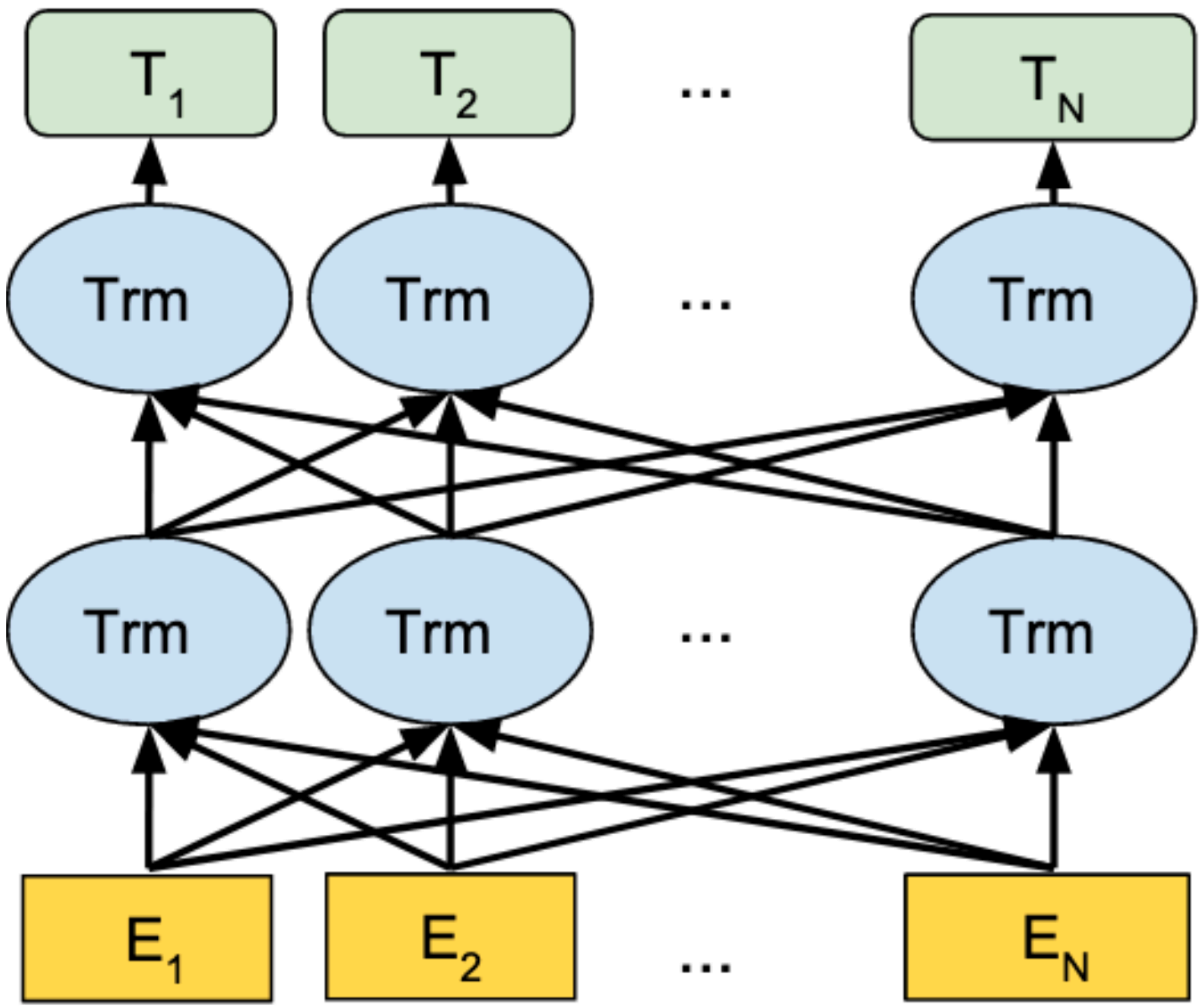


Number of computation steps required: linear in sequence length

Full Transformer Encoder Block

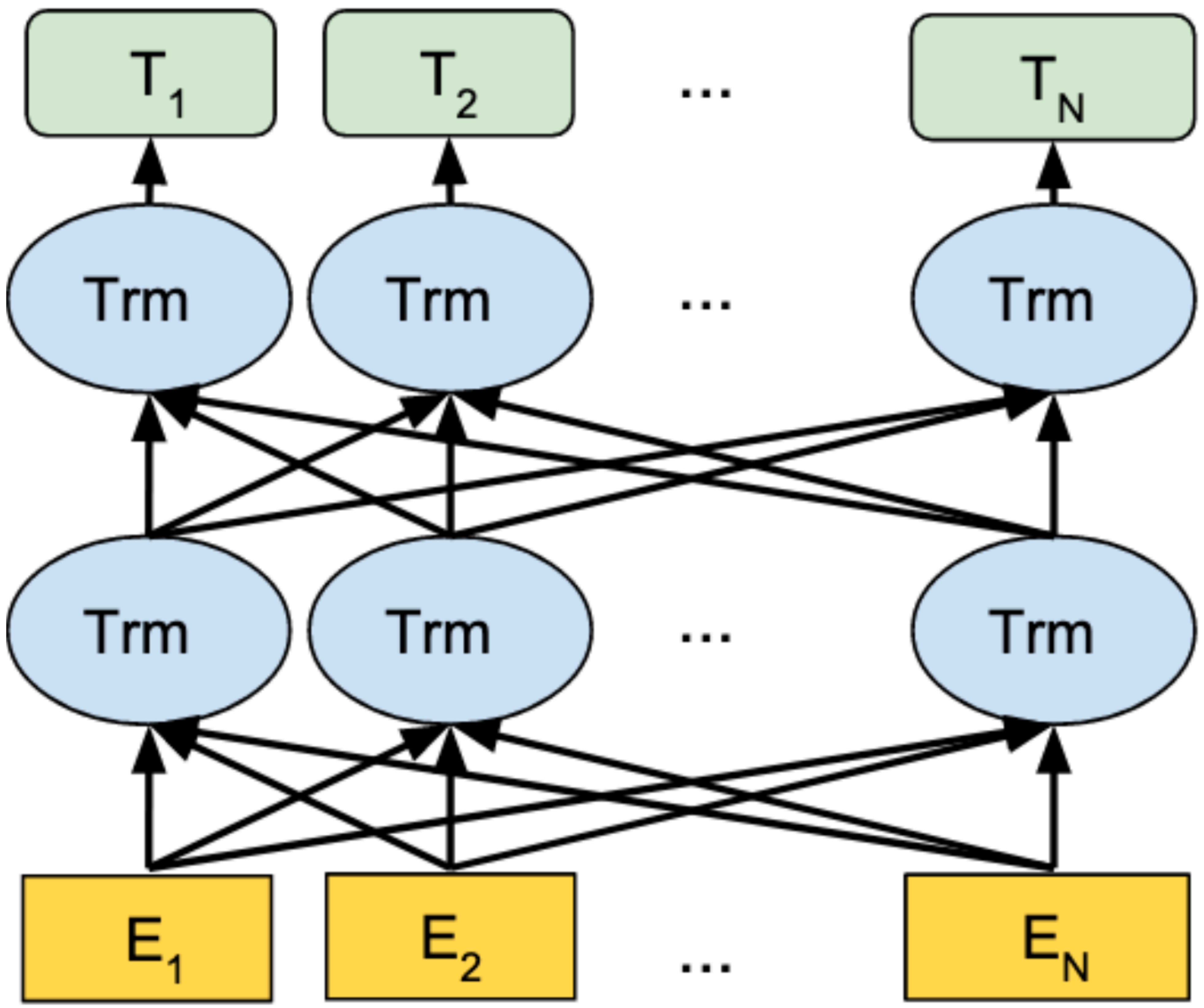


Transformer: Path Lengths + Parallelism



source (BERT paper)

Transformer: Path Lengths + Parallelism



Path lengths between tokens: 1
[constant, not linear]

source (BERT paper)

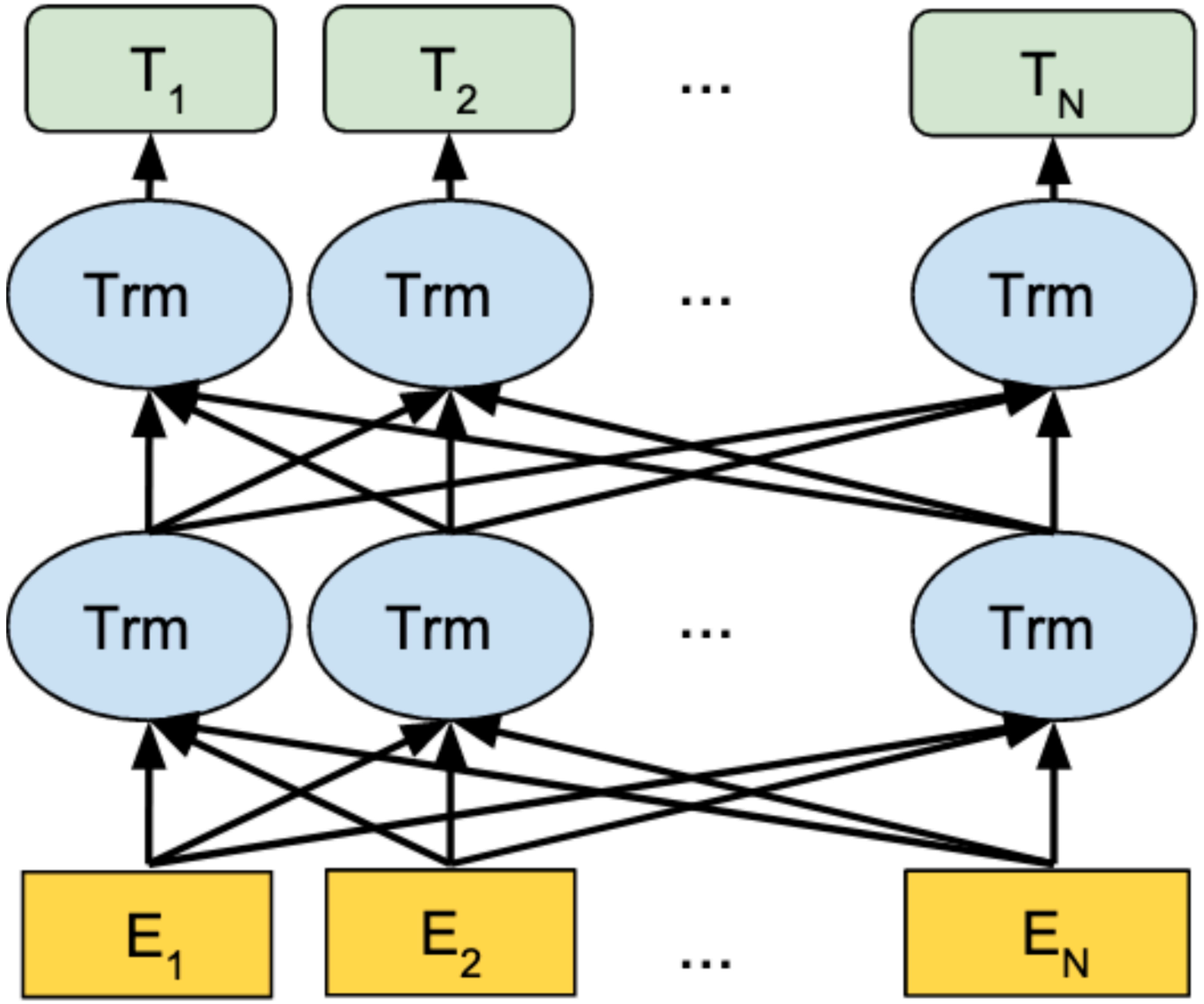
Transformer: Path Lengths + Parallelism

Computation order:

Entire second layer: 1

Entire first layer: 0

Also not linear in sequence length! Can be parallelized.



Path lengths between tokens: 1
[constant, not linear]

source (BERT paper)

Decoder: Masking Out the Future

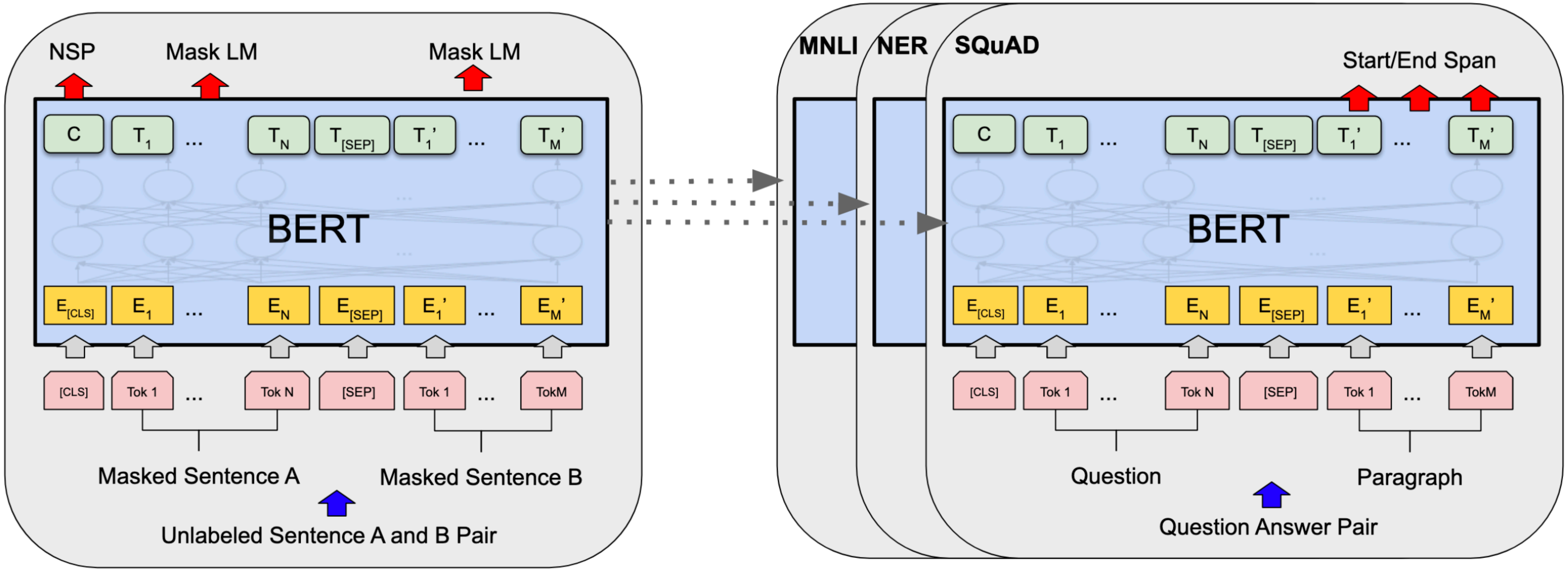
QK^T: total attention scores

$$\text{mask}_{ij} = \begin{cases} -\infty & j > i \\ 0 & \text{otherwise} \end{cases}$$

$$\text{MaskedAttention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}} + \text{mask}\right)V$$

	<S>	Ceci	n’	est	pas	une	pipe
<S>	0	-inf	-inf	-inf	-inf	-inf	-inf
Ceci	0	0	-inf	-inf	-inf	-inf	-inf
n’	0	0	0	-inf	-inf	-inf	-inf
est	0	0	0	0	-inf	-inf	-inf
pas	0	0	0	0	0	-inf	-inf
une	0	0	0	0	0	0	-inf
pipe	0	0	0	0	0	0	0

Schematically



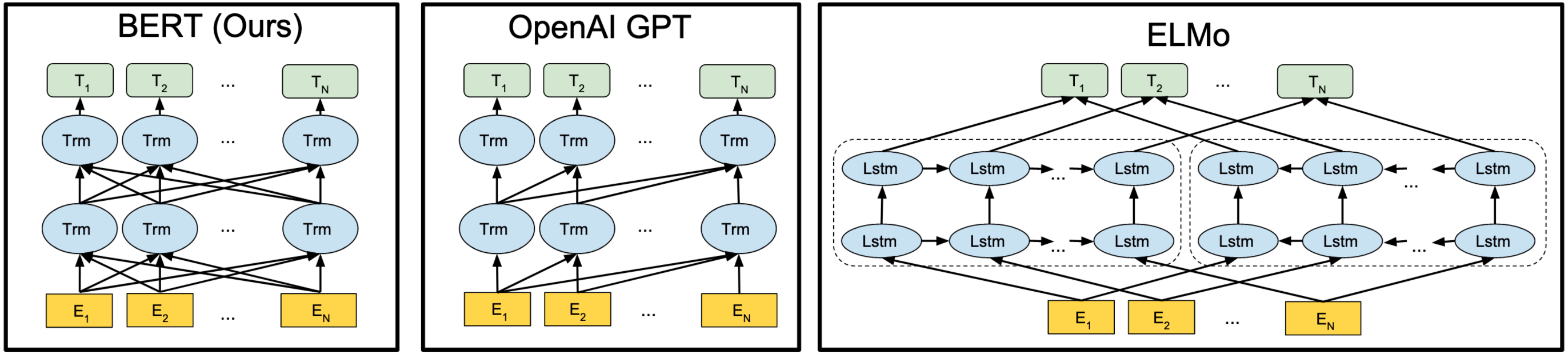
Pre-training

Fine-Tuning

Initial Results

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Comparison



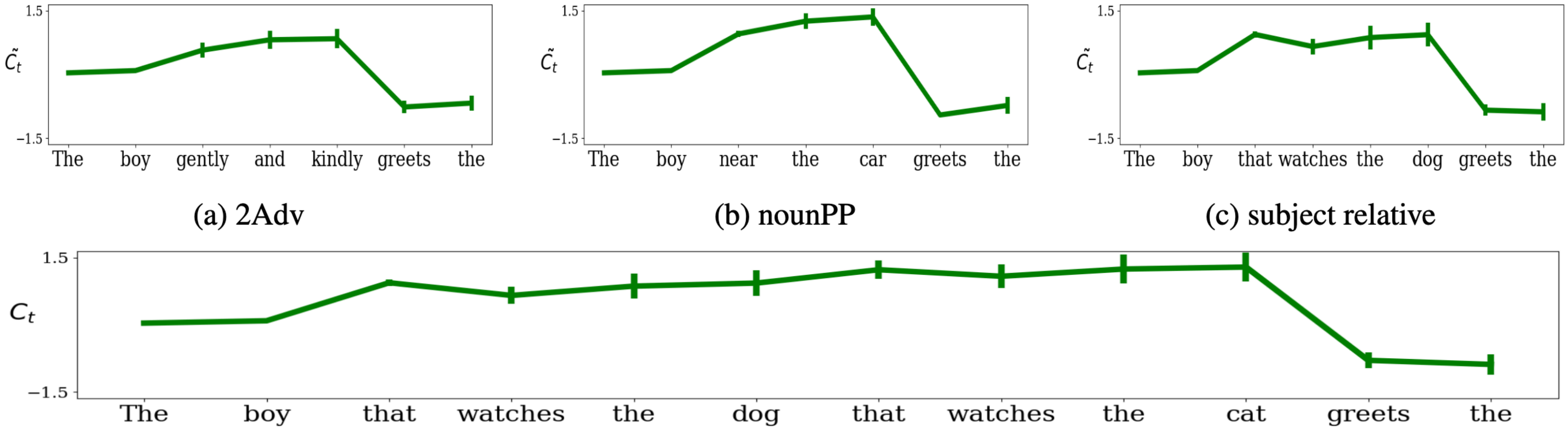
Source: BERT paper

Multilingual Pre-training

- One other main dimension: *mono-* vs *multi*-lingual pre-training
  - Roughly: concatenate (in fancy way) corpora from many languages, then do the same kind of pre-training
  - *Much more info* from Agatha's lecture on May 22

	Encoder-only	Decoder-only	Encoder-decoder
English-only *	BERT, RoBERTa, XLNet, ALBERT, …	GPT-n	BART
Multilingual	mBERT, XLM(-R), …	BLOOM (HF BigScience), XGLM	mBART, MASS, mT5

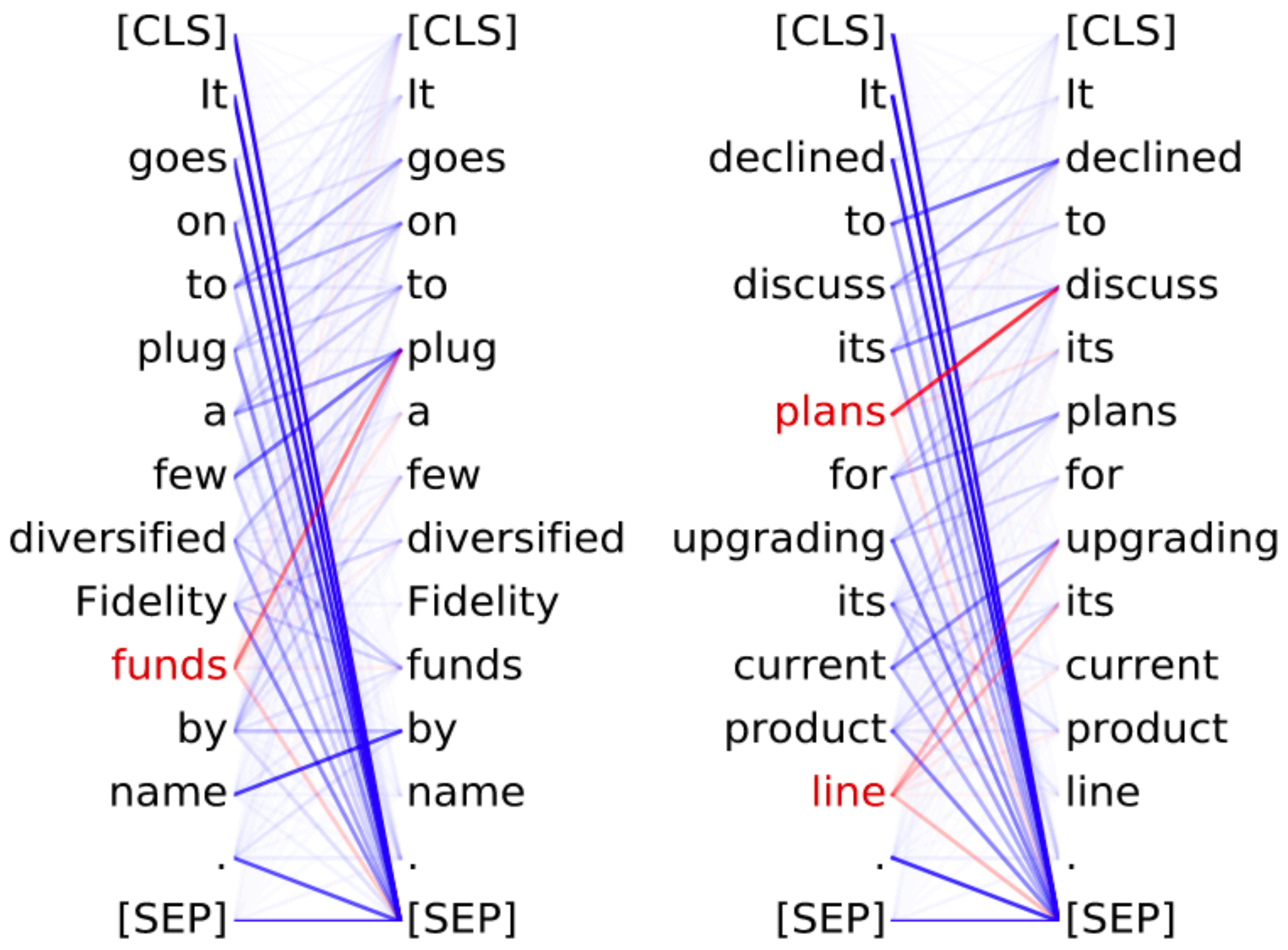
Cell dynamics for a syntax unit



Examples

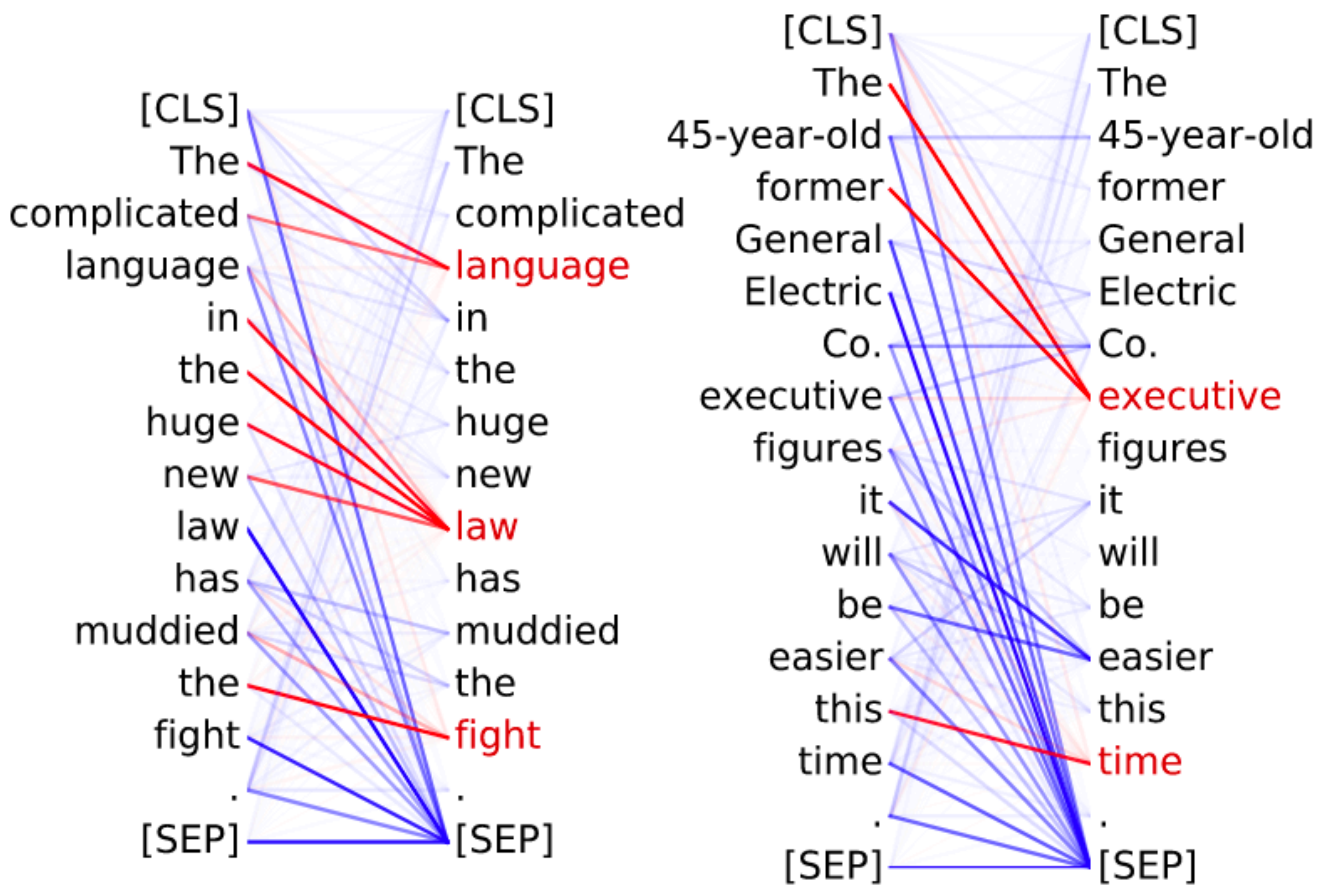
Head 8-10

- **Direct objects** attend to their verbs
- 86.8% accuracy at the `dobj` relation



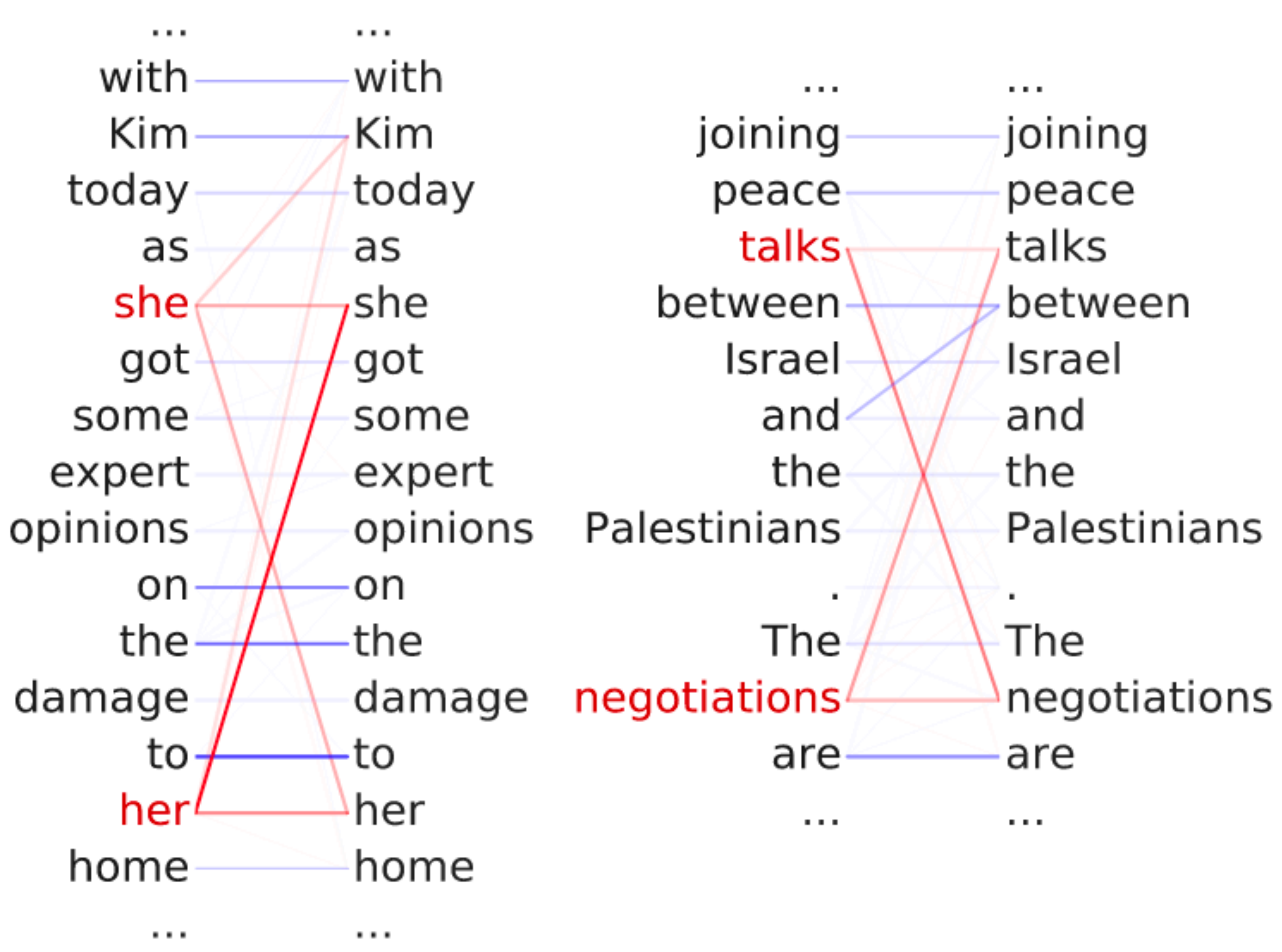
Head 8-11

- **Noun modifiers** (e.g., determiners) attend to their noun
- 94.3% accuracy at the `det` relation

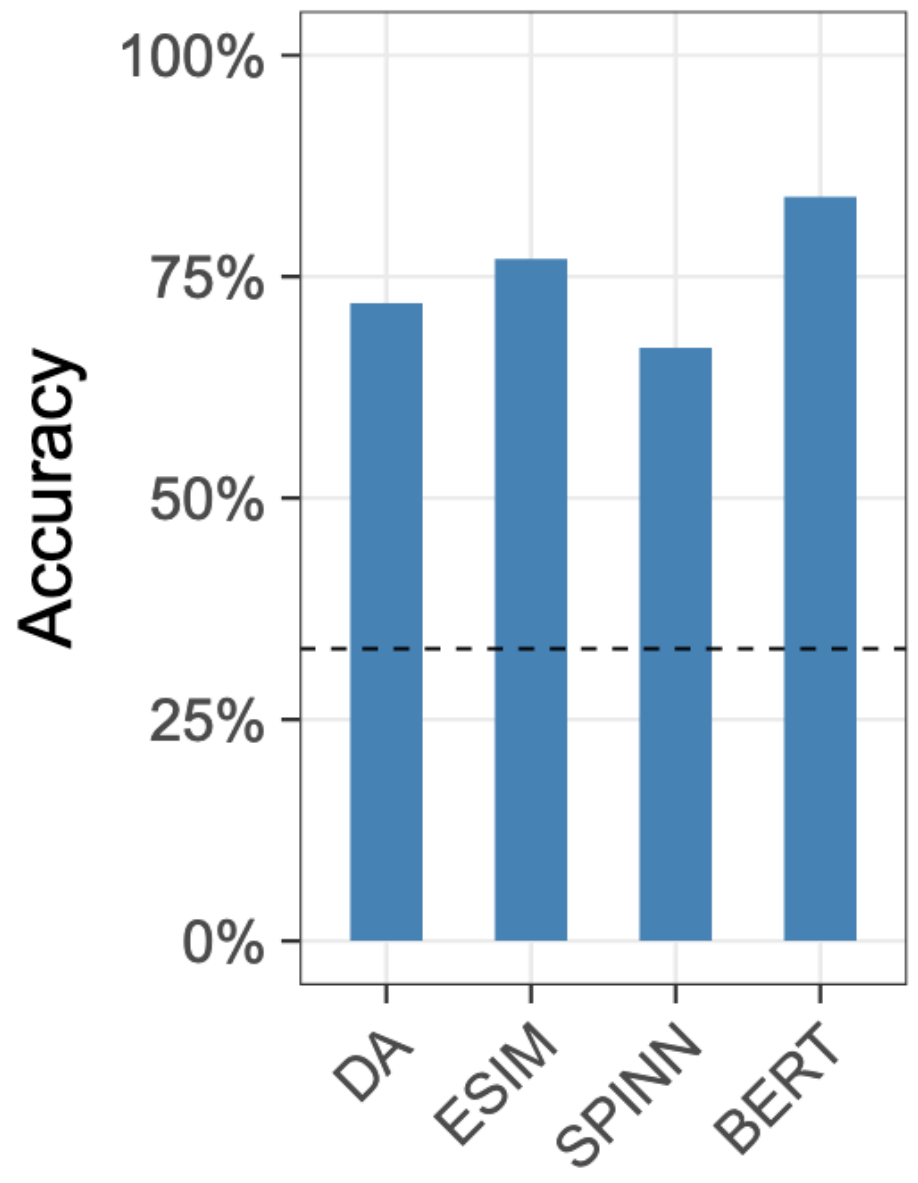


Head 5-4

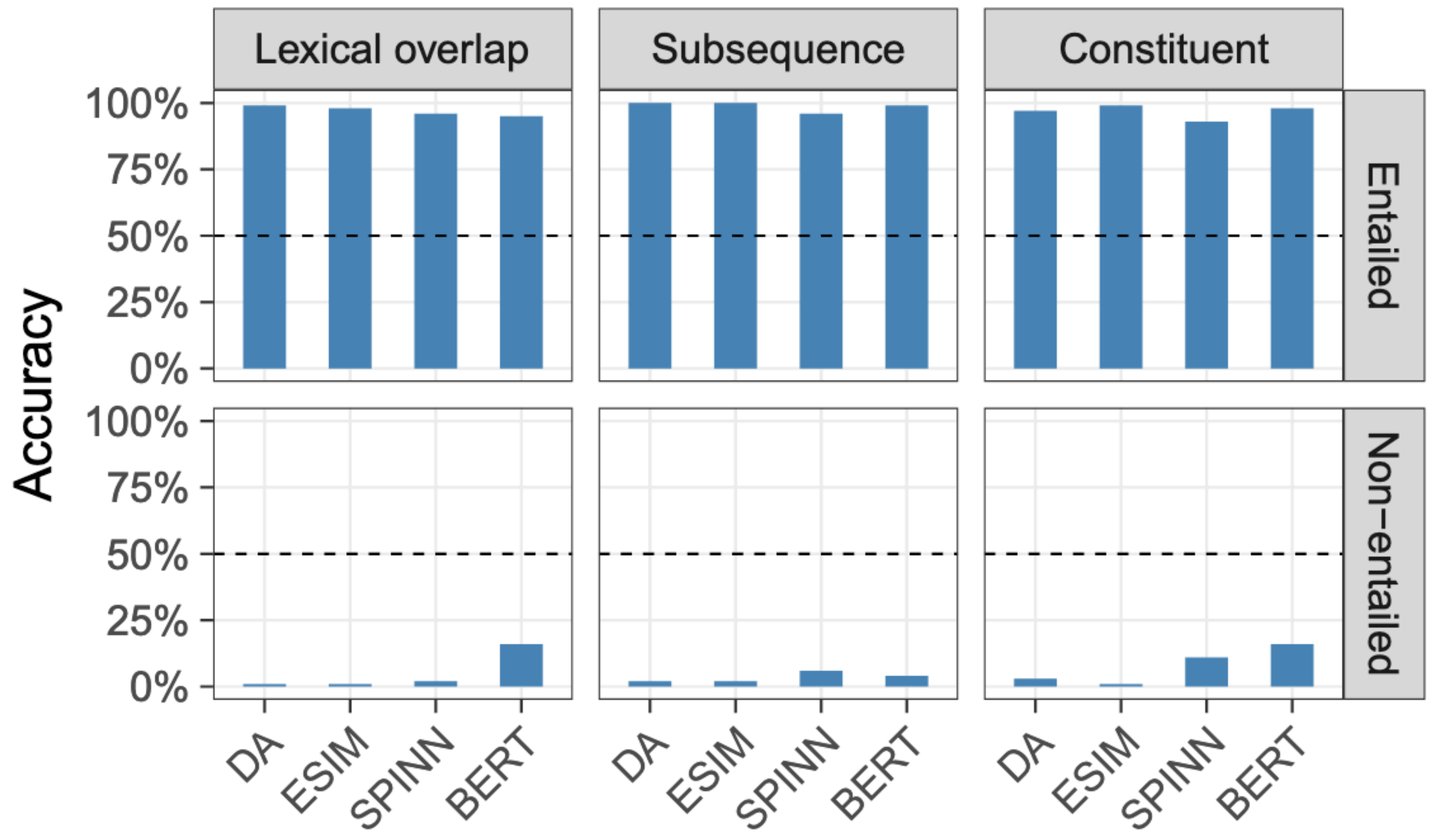
- **Coreferent** mentions attend to their antecedents
- 65.1% accuracy at linking the head of a coreferent mention to the head of an antecedent



Results



(a)



(b)

(performance improves if fine-tuned on this challenge set)

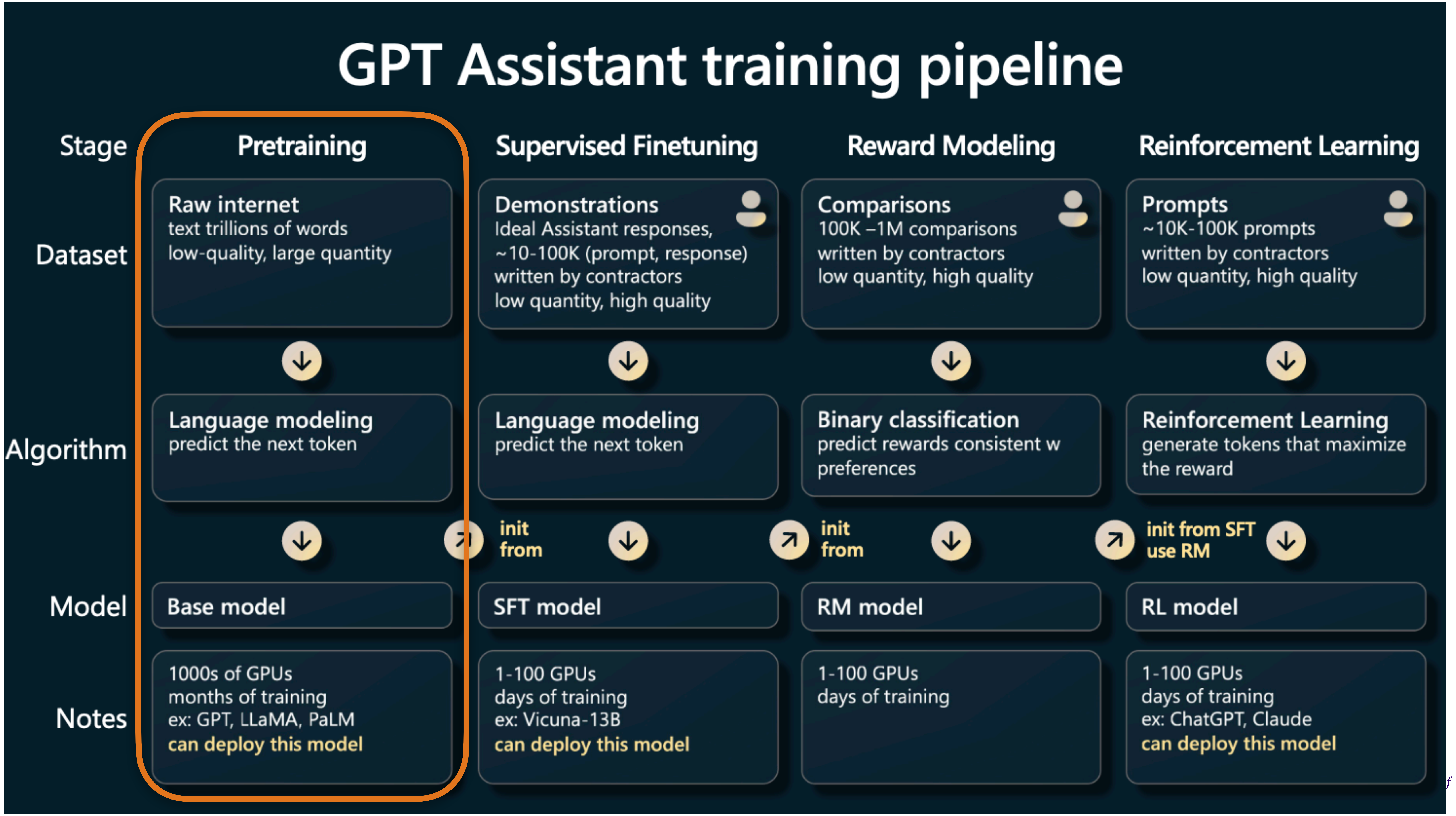
From GPT to ChatGPT

GPT Assistant training pipeline

Stage	Pretraining	Supervised Finetuning	Reward Modeling	Reinforcement Learning
Dataset	**Raw internet** text trillions of words low-quality, large quantity	**Demonstrations** Ideal Assistant responses, ~10-100K (prompt, response) written by contractors low quantity, high quality	**Comparisons** 100K –1M comparisons written by contractors low quantity, high quality	**Prompts** ~10K-100K prompts written by contractors low quantity, high quality
Algorithm	**Language modeling** predict the next token	**Language modeling** predict the next token	**Binary classification** predict rewards consistent w preferences	**Reinforcement Learning** generate tokens that maximize the reward
		init from	init from	init from SFT use RM
Model	Base model	SFT model	RM model	RL model
Notes	1000s of GPUs months of training ex: GPT, LLaMA, PaLM can deploy this model	1-100 GPUs days of training ex: Vicuna-13B can deploy this model	1-100 GPUs days of training	1-100 GPUs days of training ex: ChatGPT, Claude can deploy this model

source

From GPT to ChatGPT



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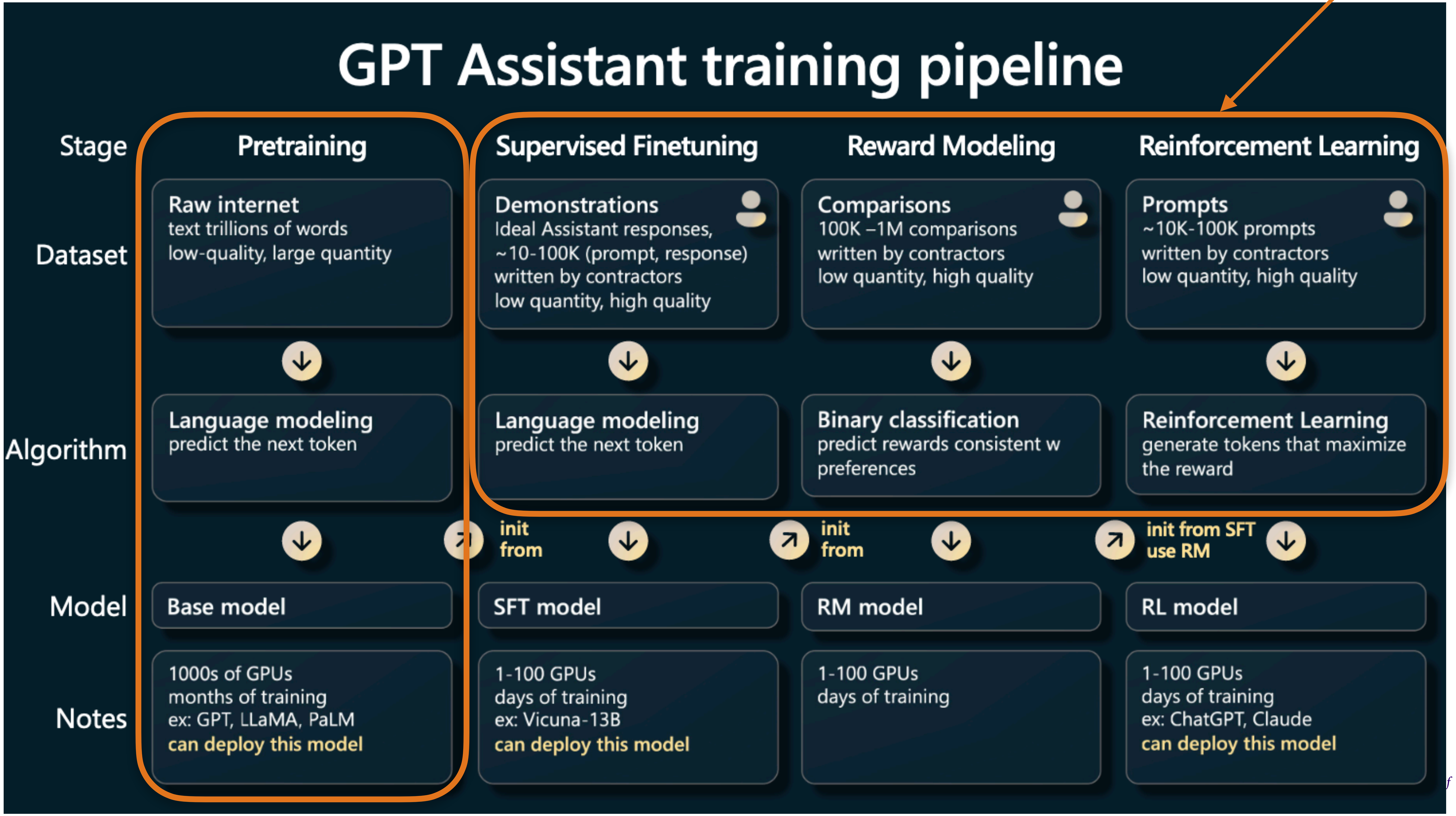
“Post-training”

From GPT to ChatGPT

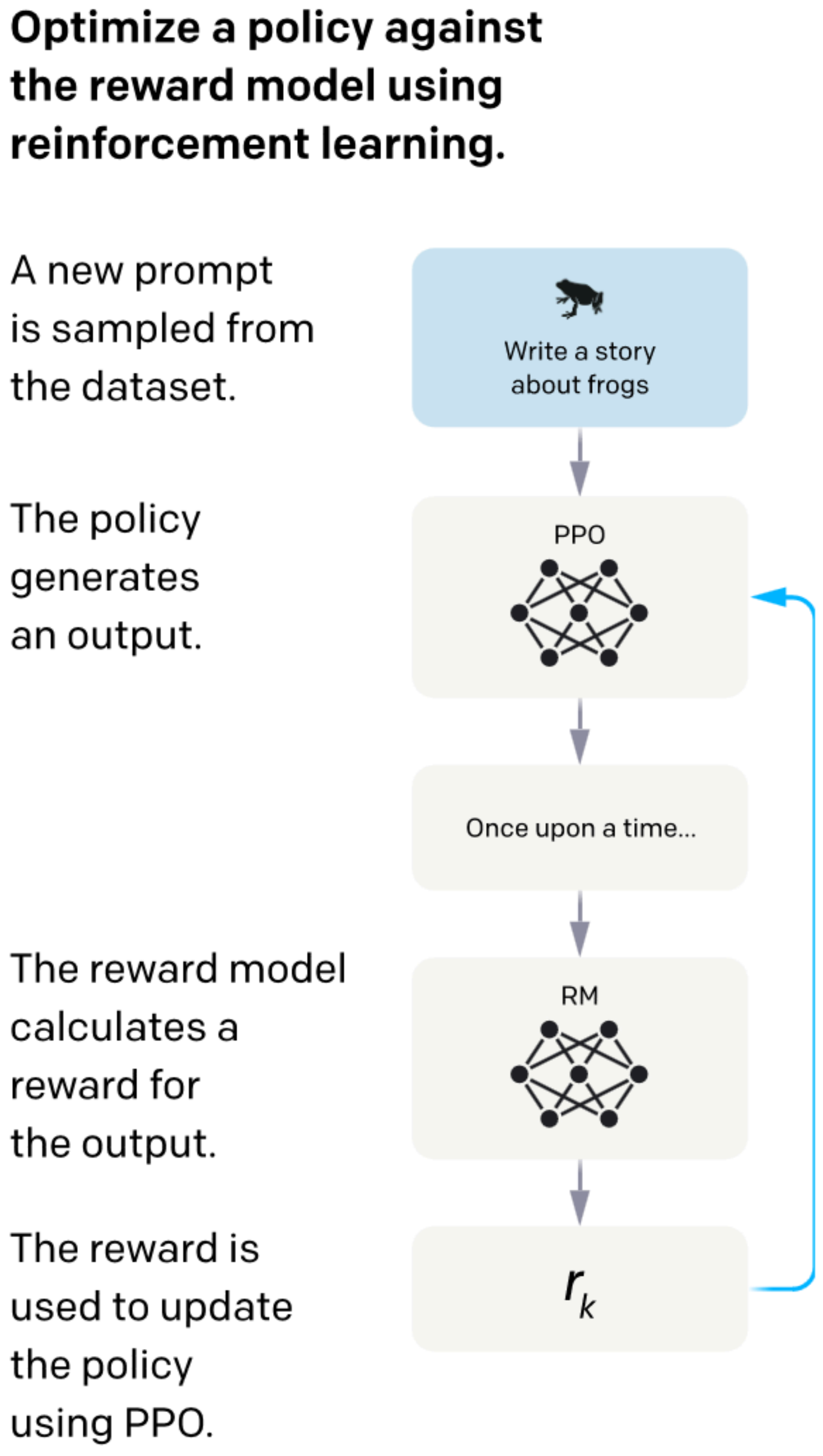


source

RLHF: Reinforcement Learning

- Take a pretrained LM
  - Prompt it, generate response
  - Feed (prompt, response) to reward model RM
  - Use that reward to update LM
- This is reinforcement learning with the RM playing the role of external environment (provider of rewards)

$$\mathcal{L}(\theta_{\text{LM}}) = \mathbb{E}_{x,\hat{y}\sim P_{\text{LM}}(\cdot\,|\,x;\theta_{\text{LM}})}\left(\text{RM}(x,\hat{y}) - \beta\log\left(\frac{P_{\text{LM}}(\hat{y}\,|\,x;\theta_{\text{LM}})}{P_{\text{LM}}(\hat{y}\,|\,x;\theta_{\text{pretrained}})}\right)\right)$$



Special Topics

- Emily M Bender: ChatGP-why
- C.M. Downey: Multilingual NLP

Assignments

- 1: Vocabulary + Data Statement
- 2: Word2Vec (raw numpy)
- 3: Computation graphs (word2vec in edugrad)
- 4: Deep Averaging Network classifier (edugrad)
- 5: Feed-forward language model (edugrad)
- 6: RNN text classifier
- 7: RNN language model
- 8: Seq2Seq + Attention [translation]
- 9: Pre-trained transformer classifier

What’s Next?

Learning Outcomes

- One way of operationalizing the goal: you can hopefully now read many/most new papers at NLP conferences and understand what they're doing
  - Expressions like "we pre-trained a bi-directional LSTM language model on various tasks and then fine-tuned on a standard suite" are now parseable
  - And with deeper / more hands-on familiarity with the models and their architectures, you are in a position to assess new developments as they come (and contribute to them as well!)

Topics Not Covered

- Full suite of “tips and tricks” for training
  - e.g. learning rate schedules
  - Best methods for hyper parameter tuning
- Other architectures sometimes used: convolutional networks, tree-based RNNs, state-space models
- Wide variety of NLP tasks: parsing, QA, toxic language detection, etc.
- Generation: decoding strategies, evaluation
- N.B.: you are now well-positioned to read and learn about all of these on your own!

Where to Learn More

- Where to learn more?
  - Read papers and chase references when confused
  - CMU's course has lots of online materials: http://www.phontron.com/class/nn4nlp2021/
    - Advanced NLP: http://www.phontron.com/class/anlp2024/
  - Stanford CS224U (pre-recorded videos) http://web.stanford.edu/class/cs224u/
    - And CS224N (live lectures) http://web.stanford.edu/class/cs224n/
- NLP Newsletter: https://newsletter.ruder.io/
- ACL Anthology: https://www.aclweb.org/anthology/ [more and more videos too]
- Semantic Scholar / arXiv sanity similar paper searches

General Question Time

Wrapping Up

Course Evaluations

- Course evals are open now **through May 31**
- Please do fill them out as soon as possible!
  - E.g. right now :)
  - Help me:
    - Improve the course for future iterations
    - ~~Get tenure ;)~~

Thank You!

- I’ve learned a lot from you all this quarter!
- Hopefully you’re in a better place with regard to neural methods in NLP than when the course started.
- And congrats to everyone for handling such a workload amidst all of the challenges of the wider world. Very awe-inspiring.
- So: thank you, and have a great summer / future!