89688: Statistical Machine Translation

Neural Machine Translation

May 2020

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Computer Science Department
Bar Ilan University

Based in part on slides by Kevin Duh and Hermann Ney from the DL4MT winter school

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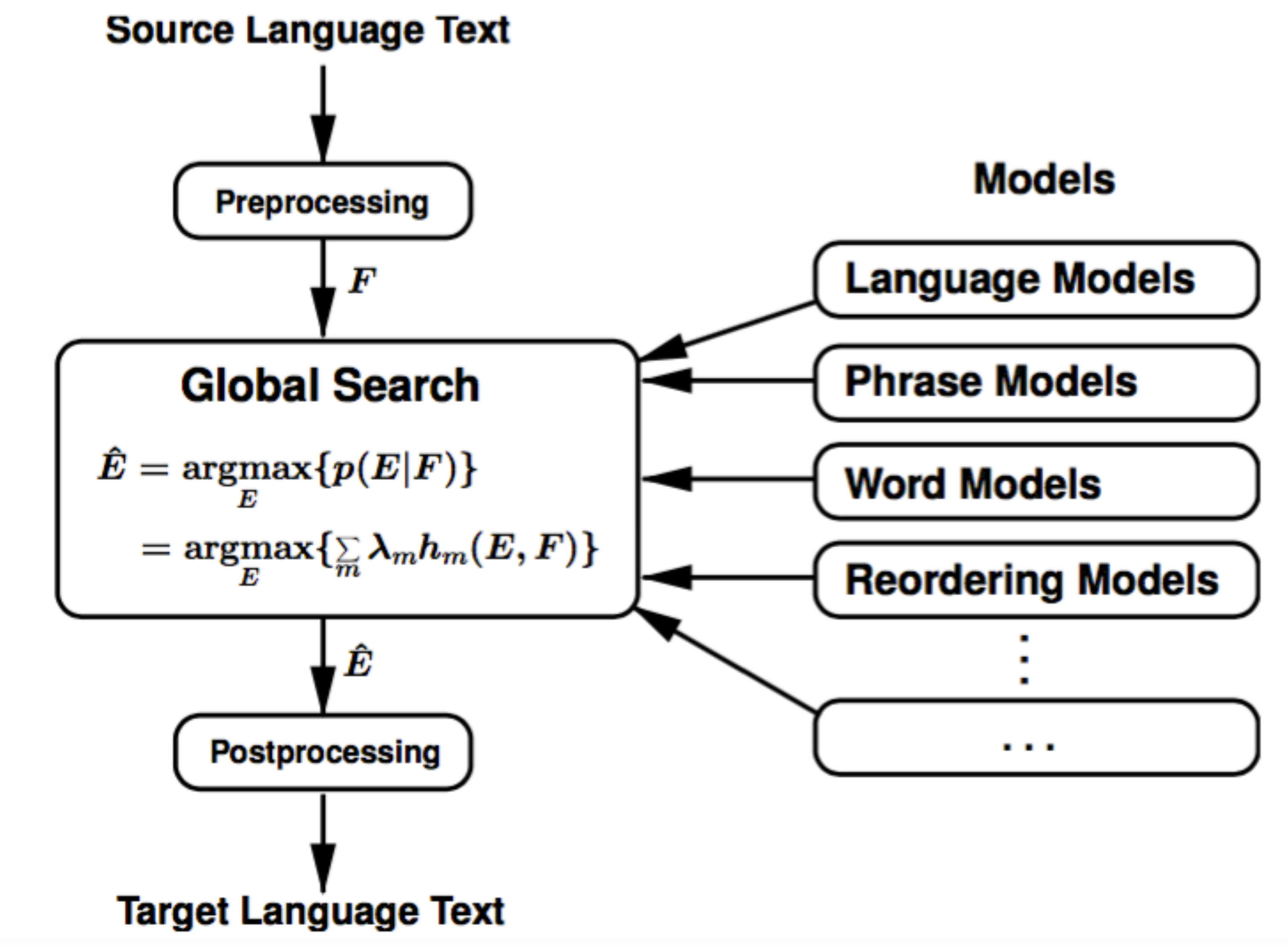

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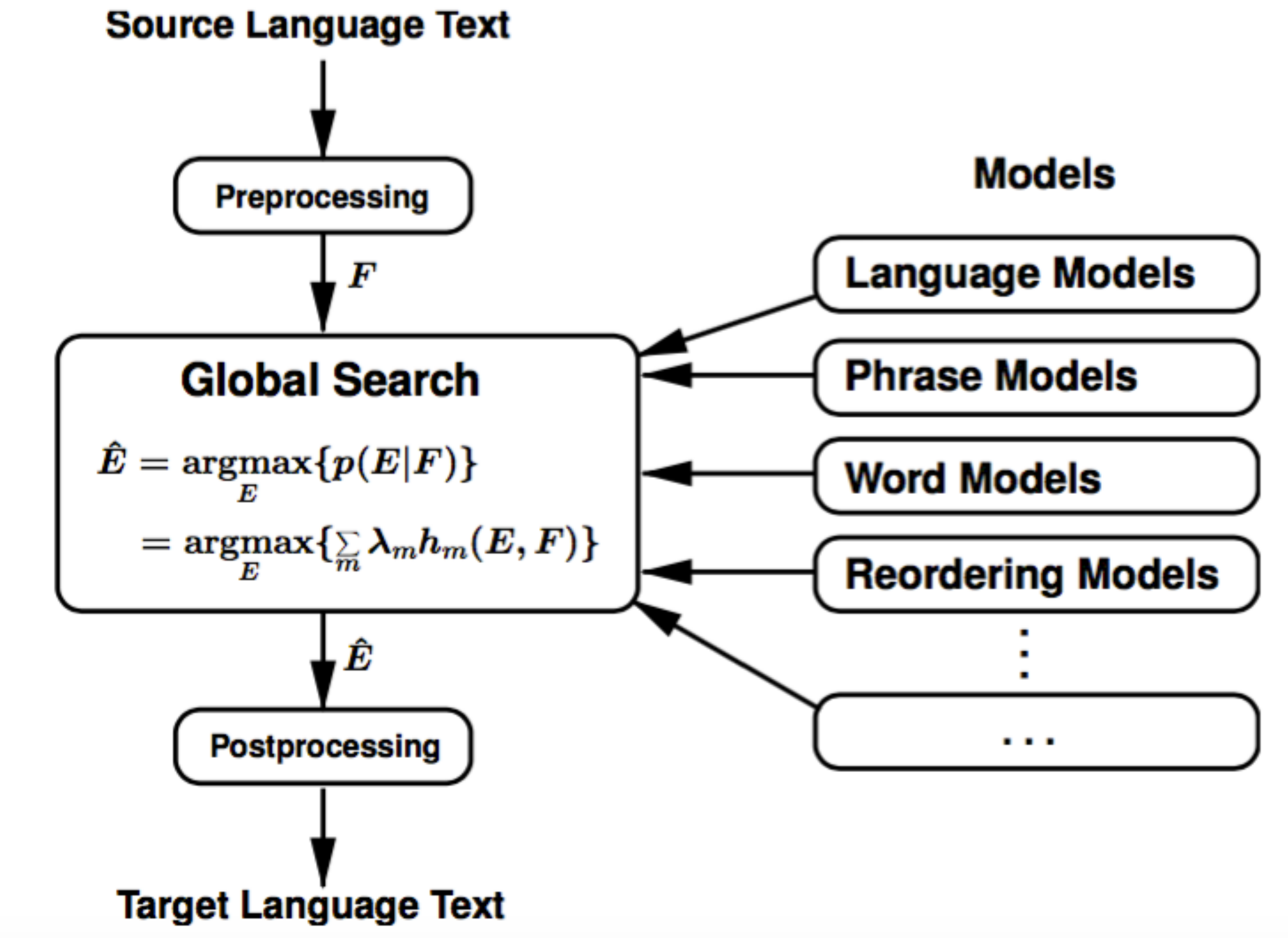

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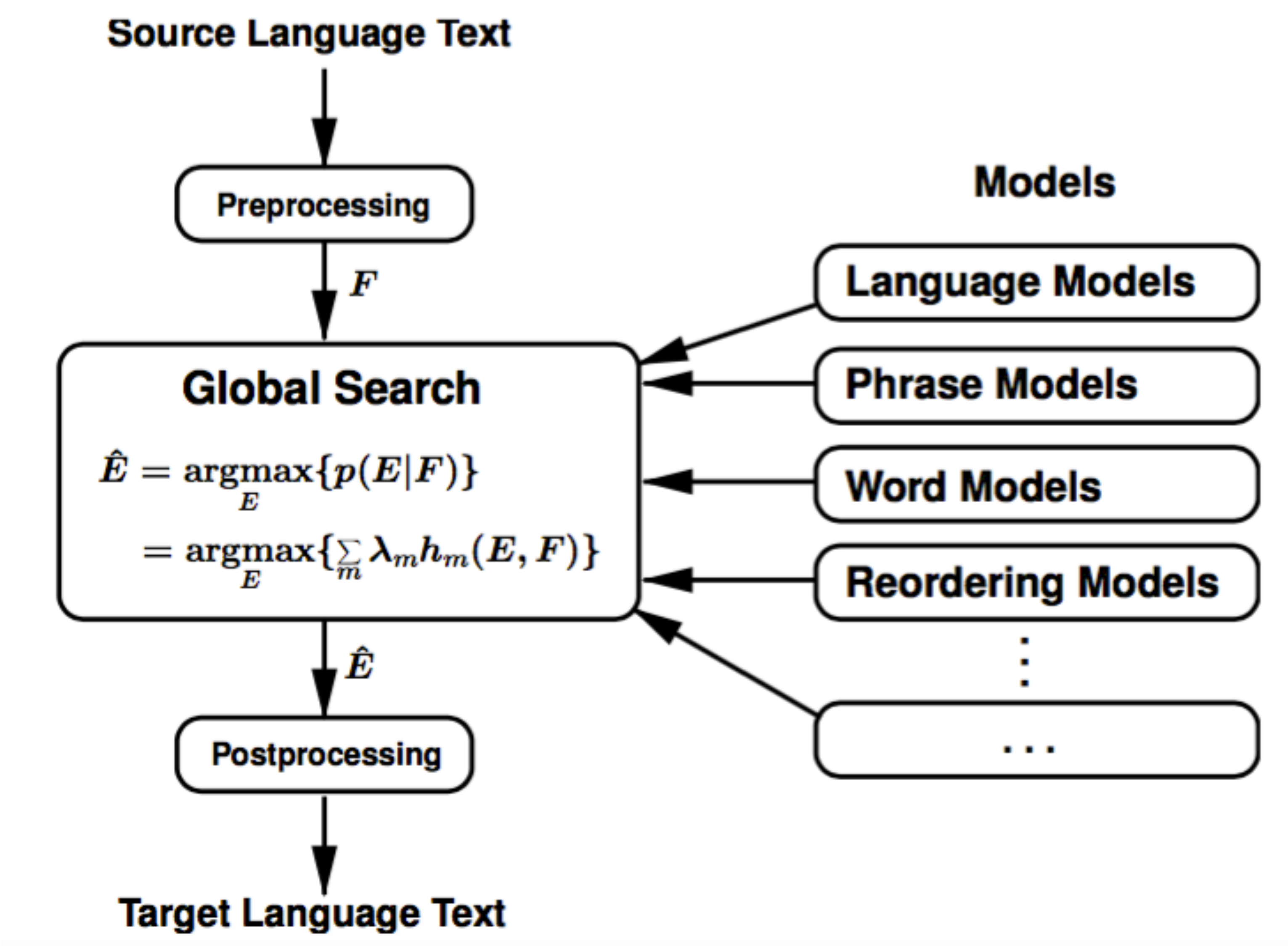

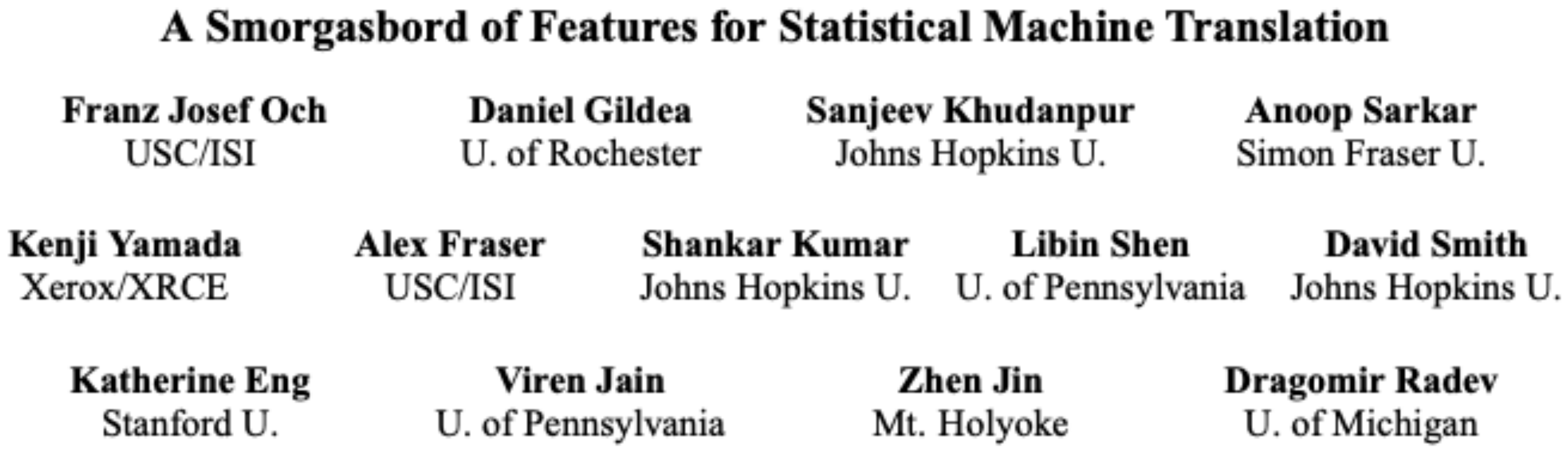

A Smorgasbord of Features for Statistical Machine Translation

Franz Josef Och USC/ISI
Daniel Gildea U. of Rochester
Sanjeev Khudanpur Johns Hopkins U.
Anoop Sarkar Simon Fraser U.
Kenji Yamada Xerox/XRCE
Alex Fraser USC/ISI
Shankar Kumar Johns Hopkins U.
Libin Shen U. of Pennsylvania
David Smith Johns Hopkins U.
Katherine Eng Stanford U.
Viren Jain U. of Pennsylvania
Zhen Jin Mt. Holyoke
Dragomir Radev U. of Michigan

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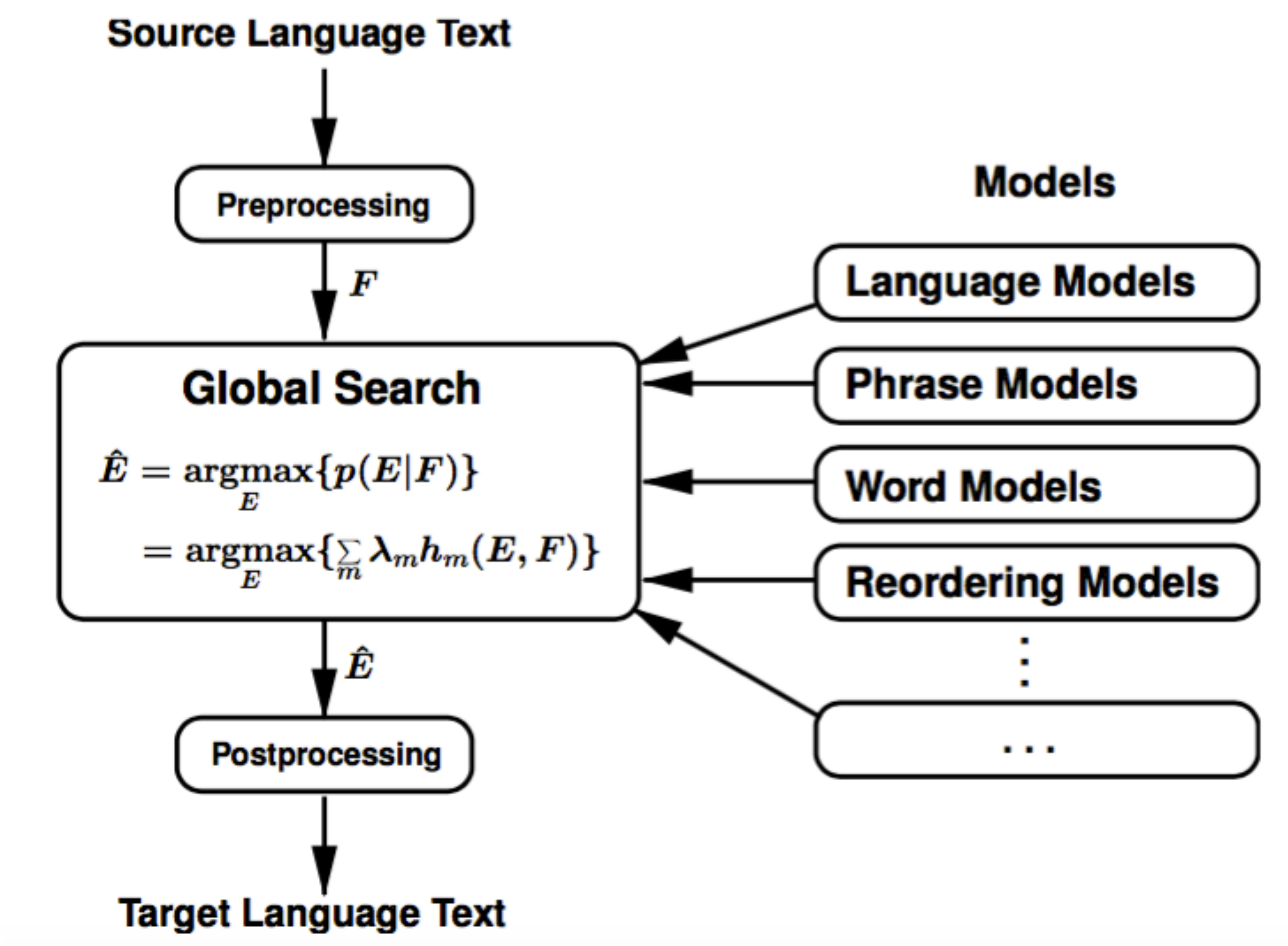

11,001 New Features for Statistical Machine Translation*

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USC Information Sciences Institute
4676 Admiralty Way, Suite 1001
Marina del Rey, CA 90292 USA

Wei Wang
Language Weaver, Inc.
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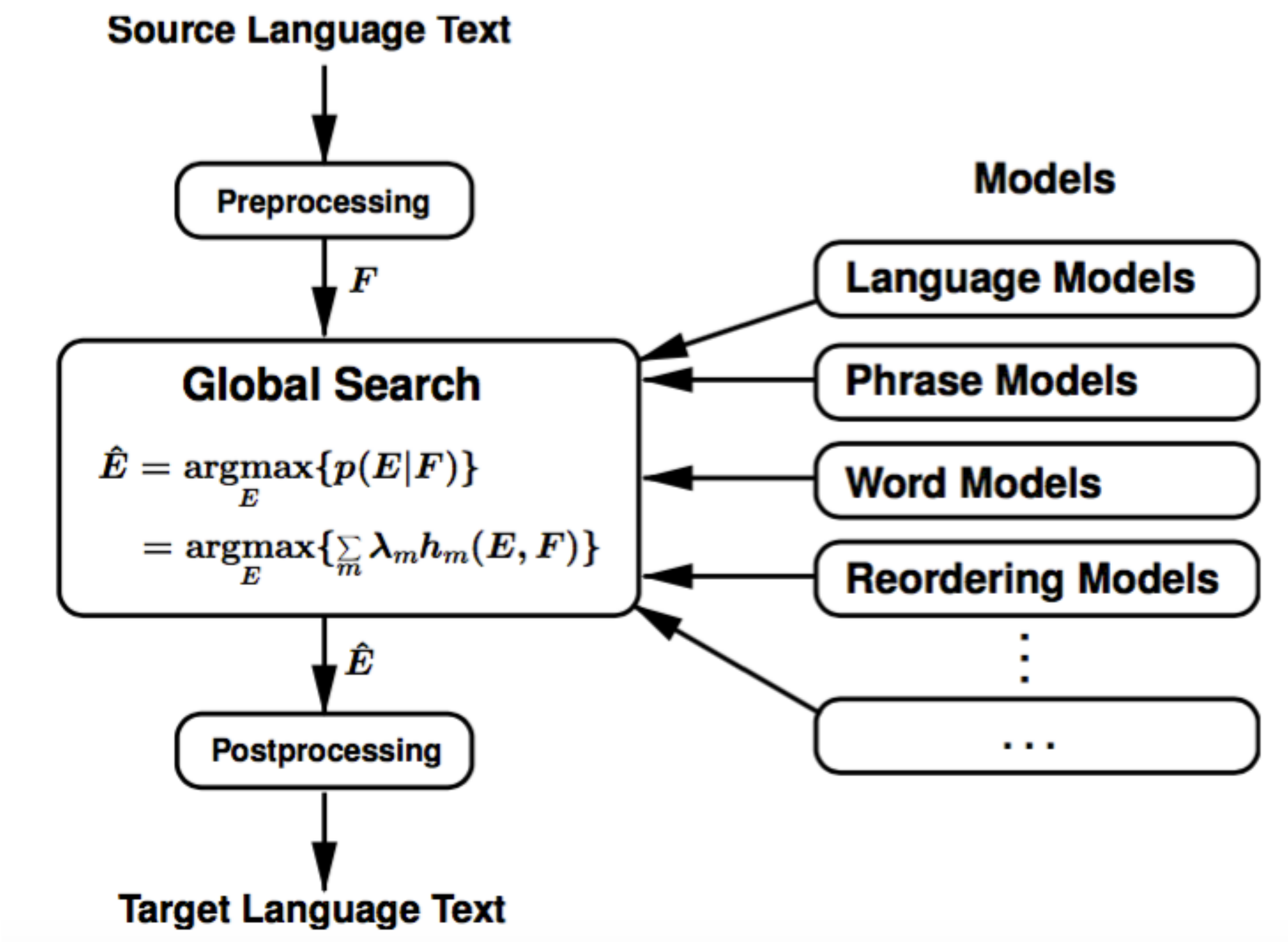

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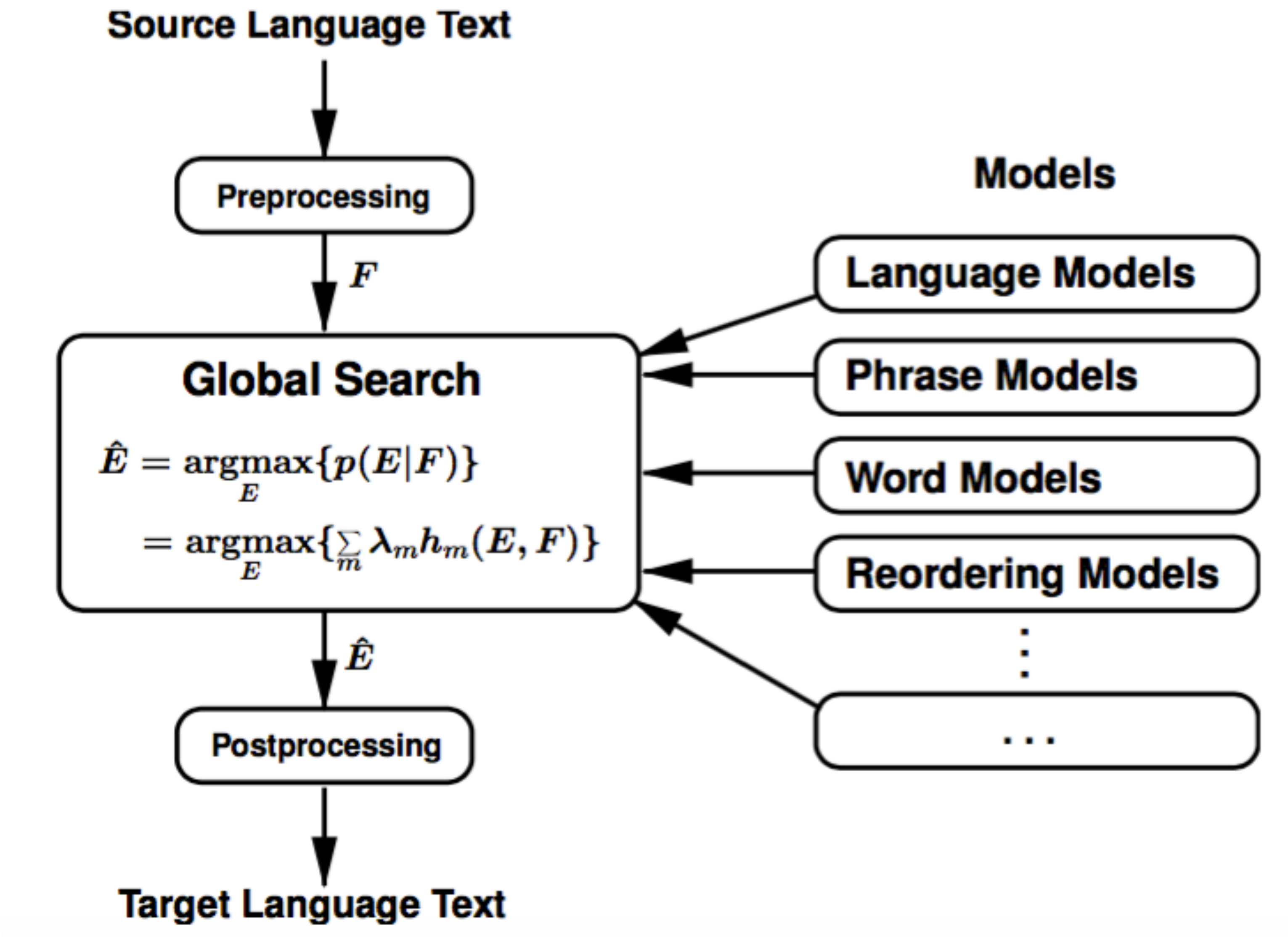
- Requires extensive feature engineering
- Hard and expensive to capture long-range dependencies
- Does not generalize for similar words



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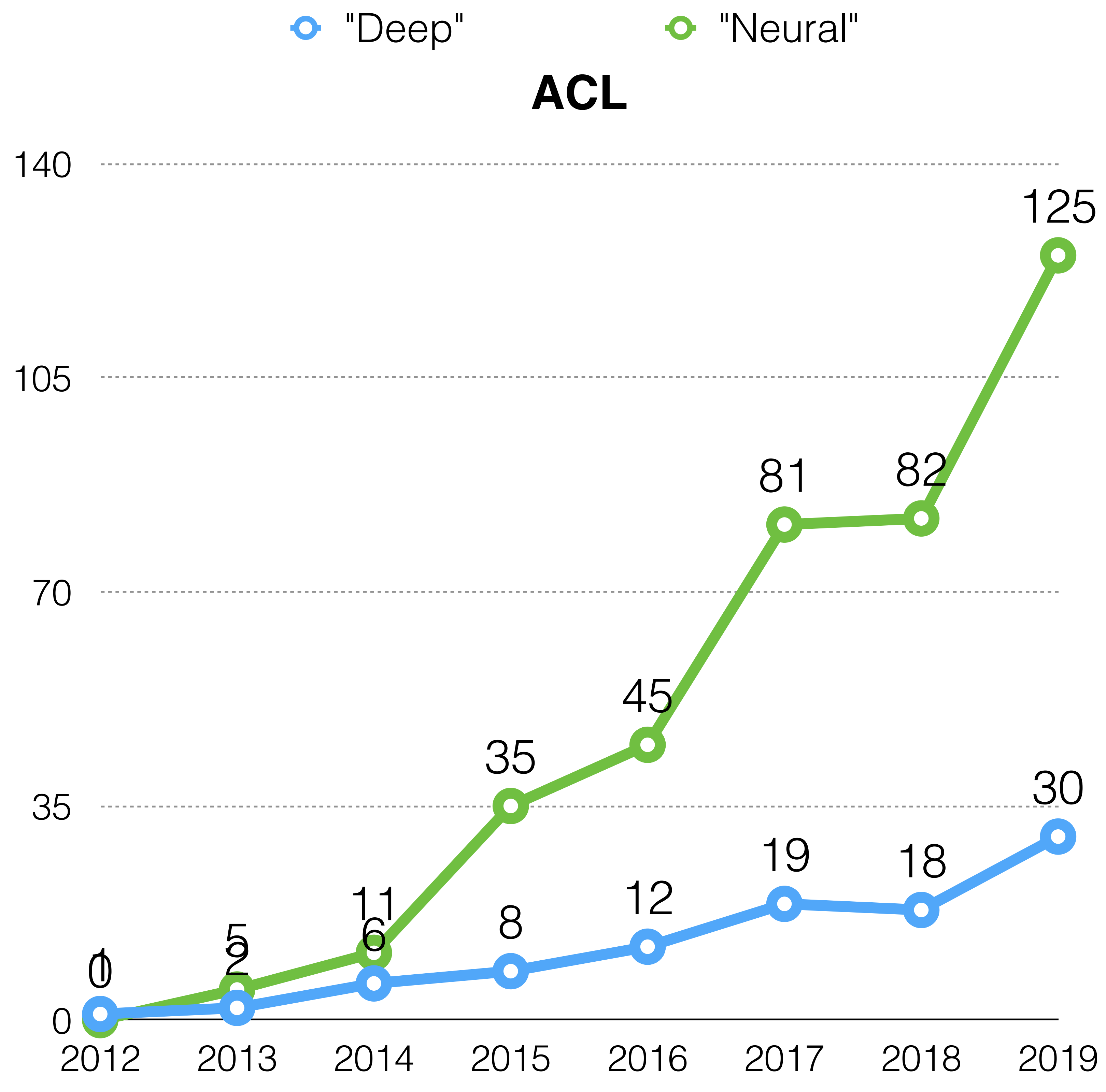
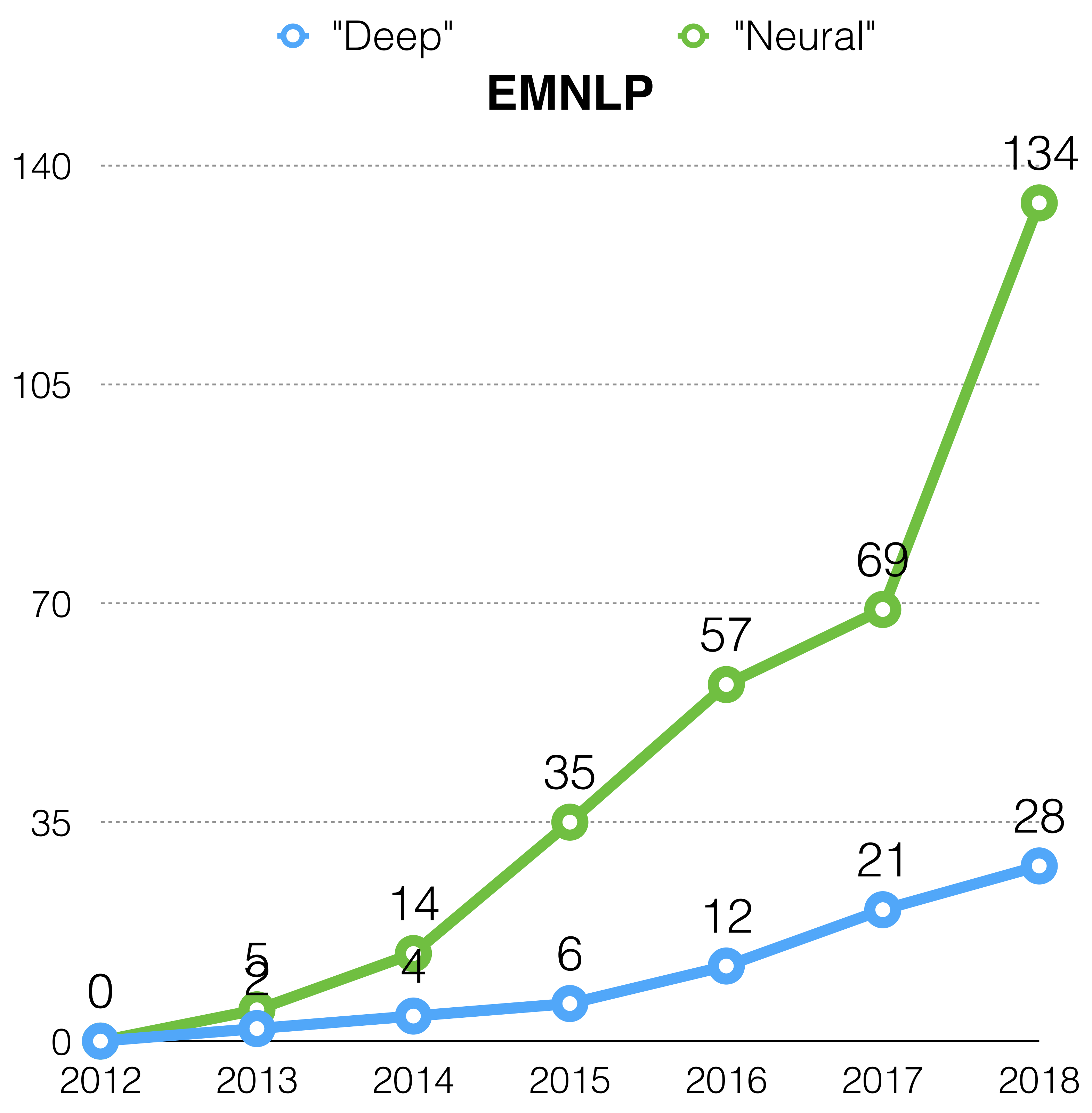
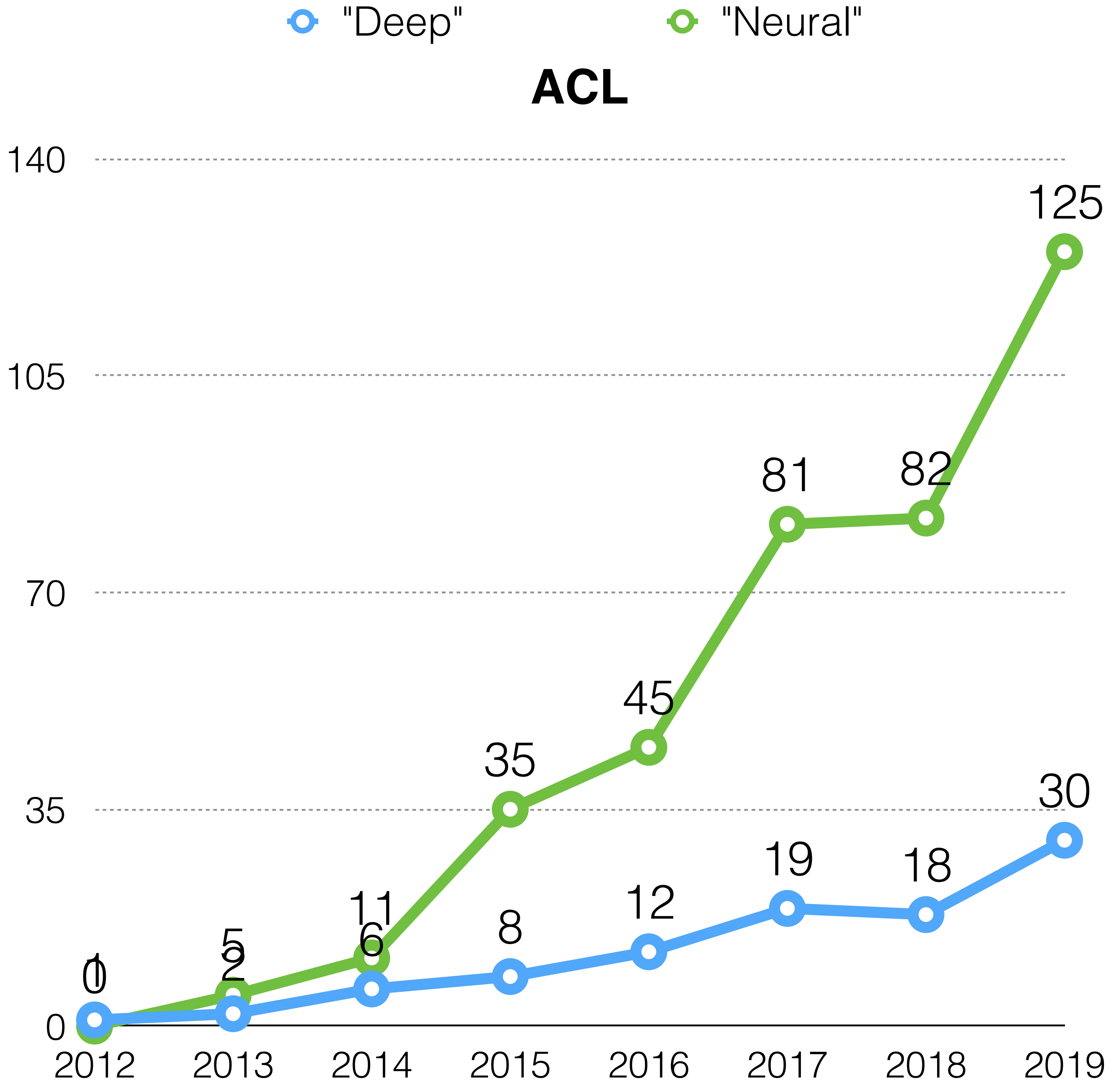
A New Paradigm?

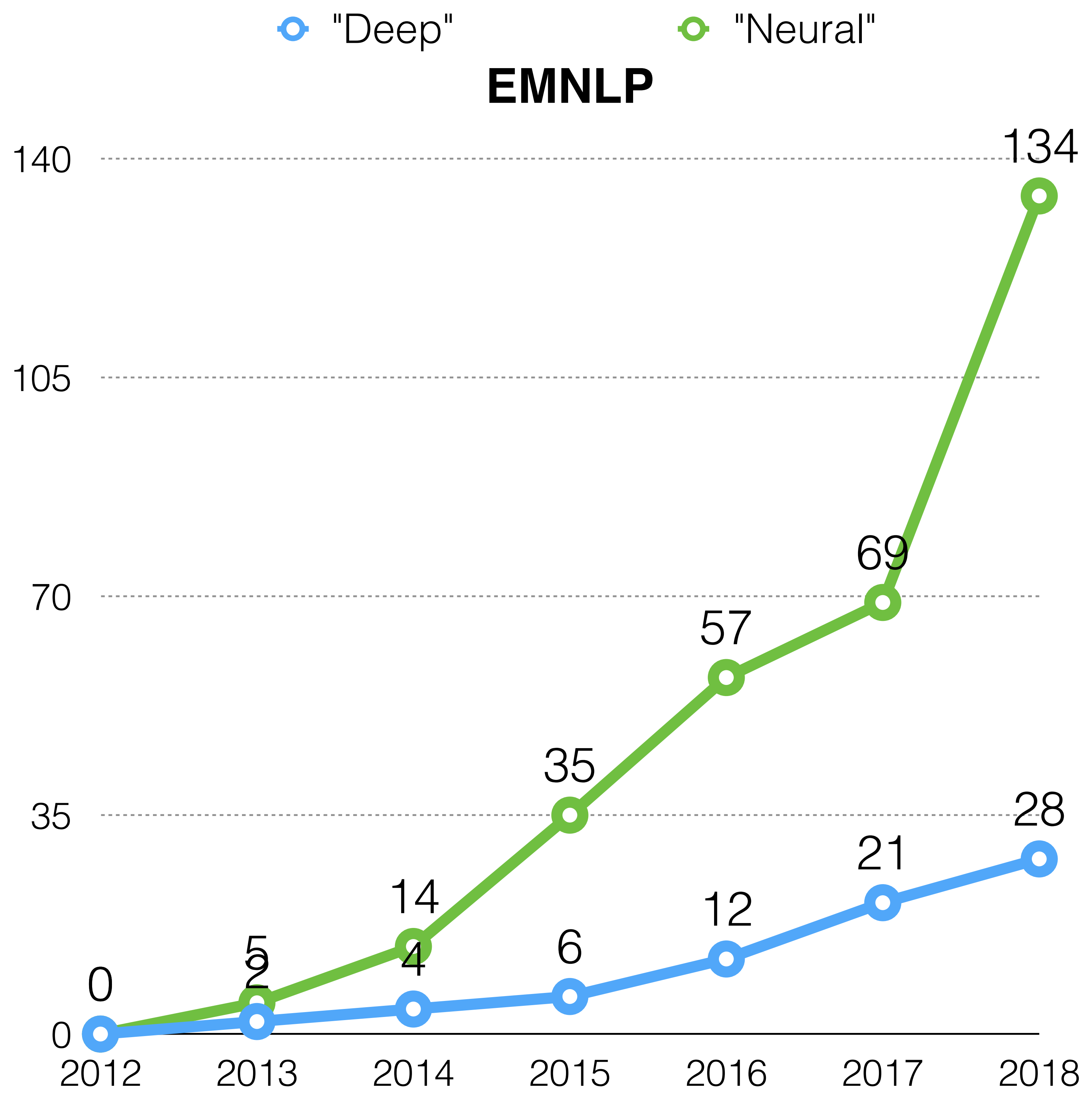




A New Paradigm?

of mentions in paper titles at top-tier NLP conferences (ACL, EMNLP) from 2012 to 2018:





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  - step I: pick a learning algorithm (SVM, log. reg., NN…)
  - step II: optimize it w.r.t a loss, i.e: $\min_w \sum_{m=1}^{M} (f_w(x^{(m)}) - y^{(m)})^2$

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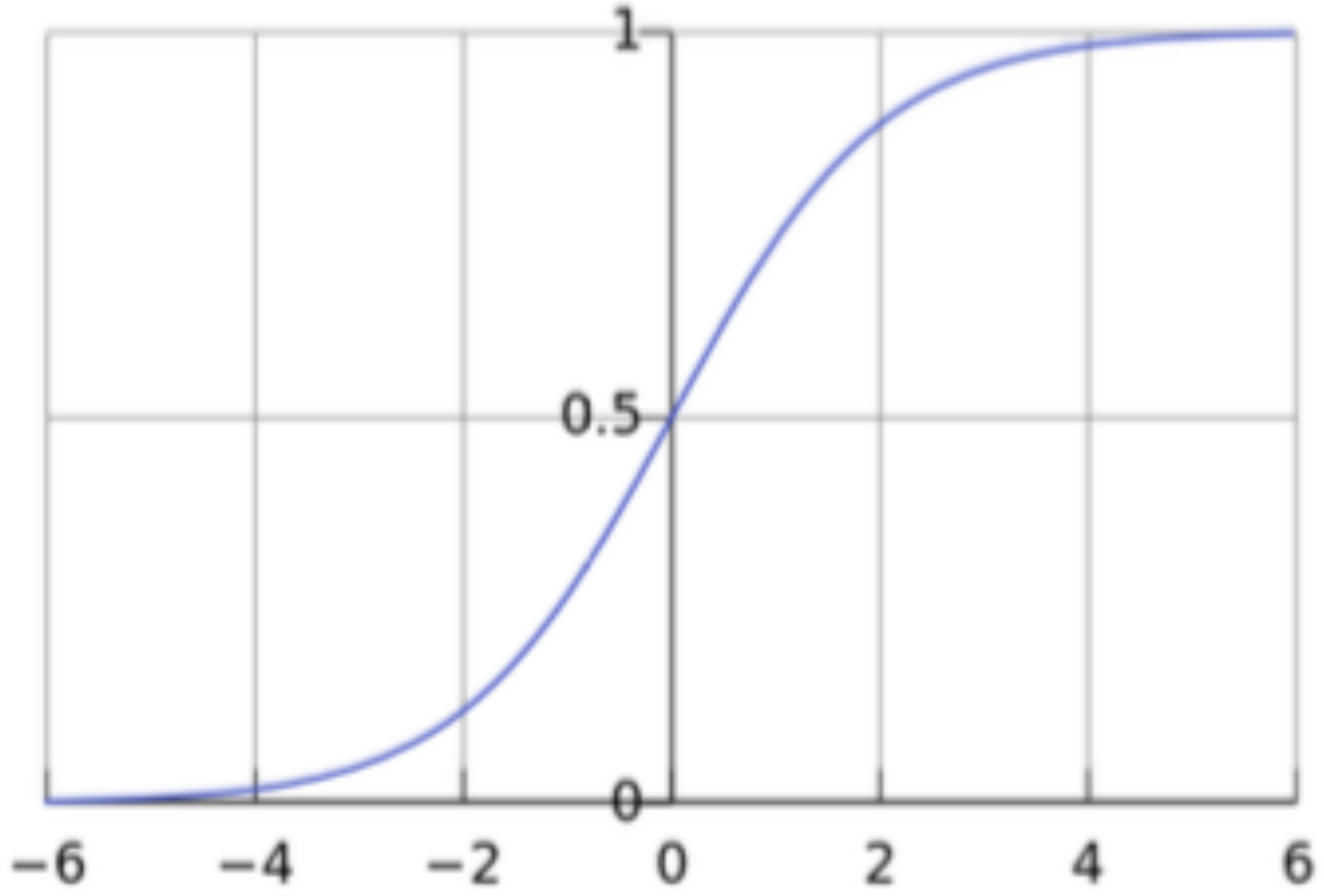
- $\sigma(z) = \frac{1}{1+e^{-z}}$ is a non-linearity, e.g. the sigmoid function (creates dependency between the features, maps $f(x)$ to [0,1]):



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  - γ is the learning rate, which is a hyper-parameter

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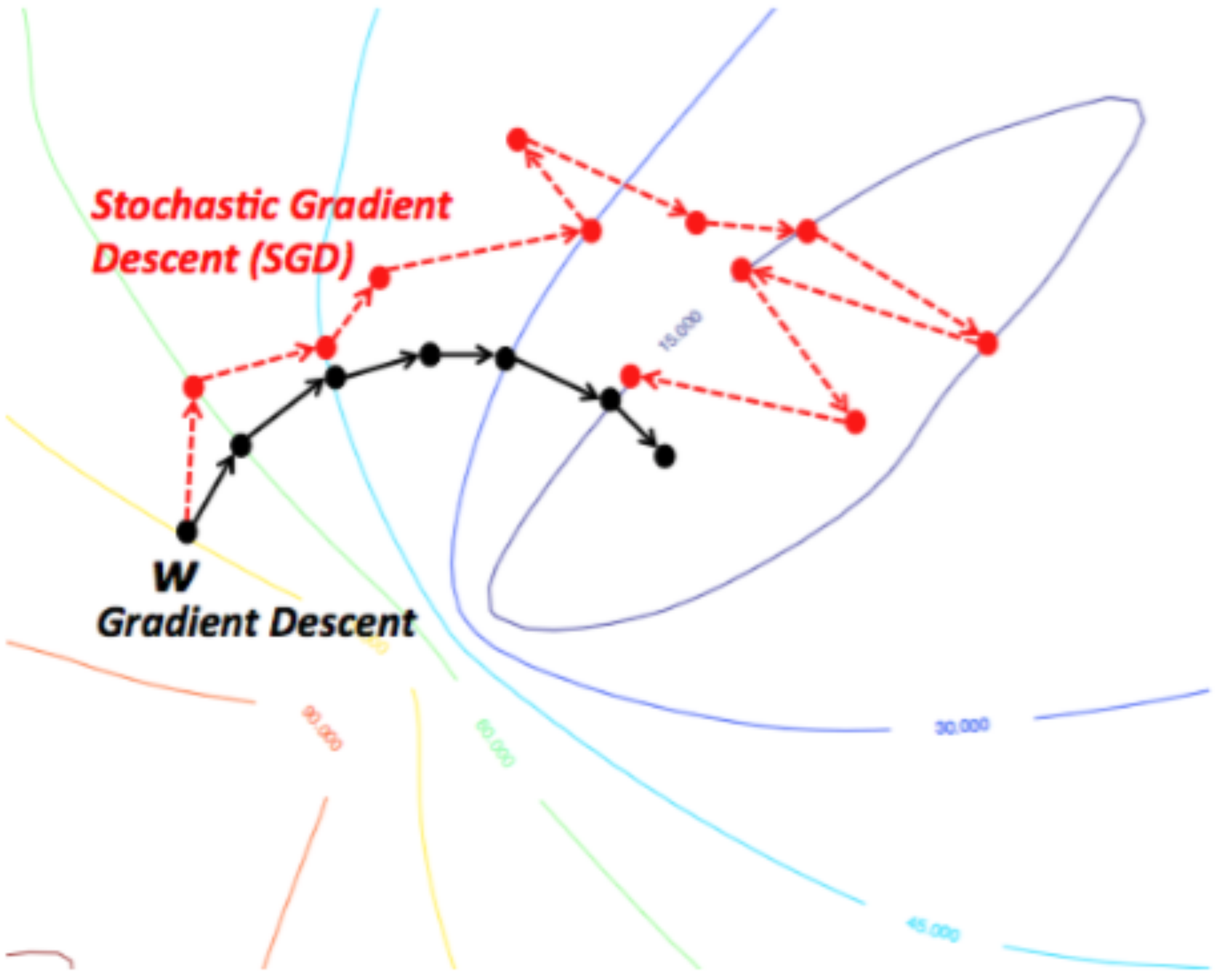
Faster to converge (more updates per epoch), but more noisy



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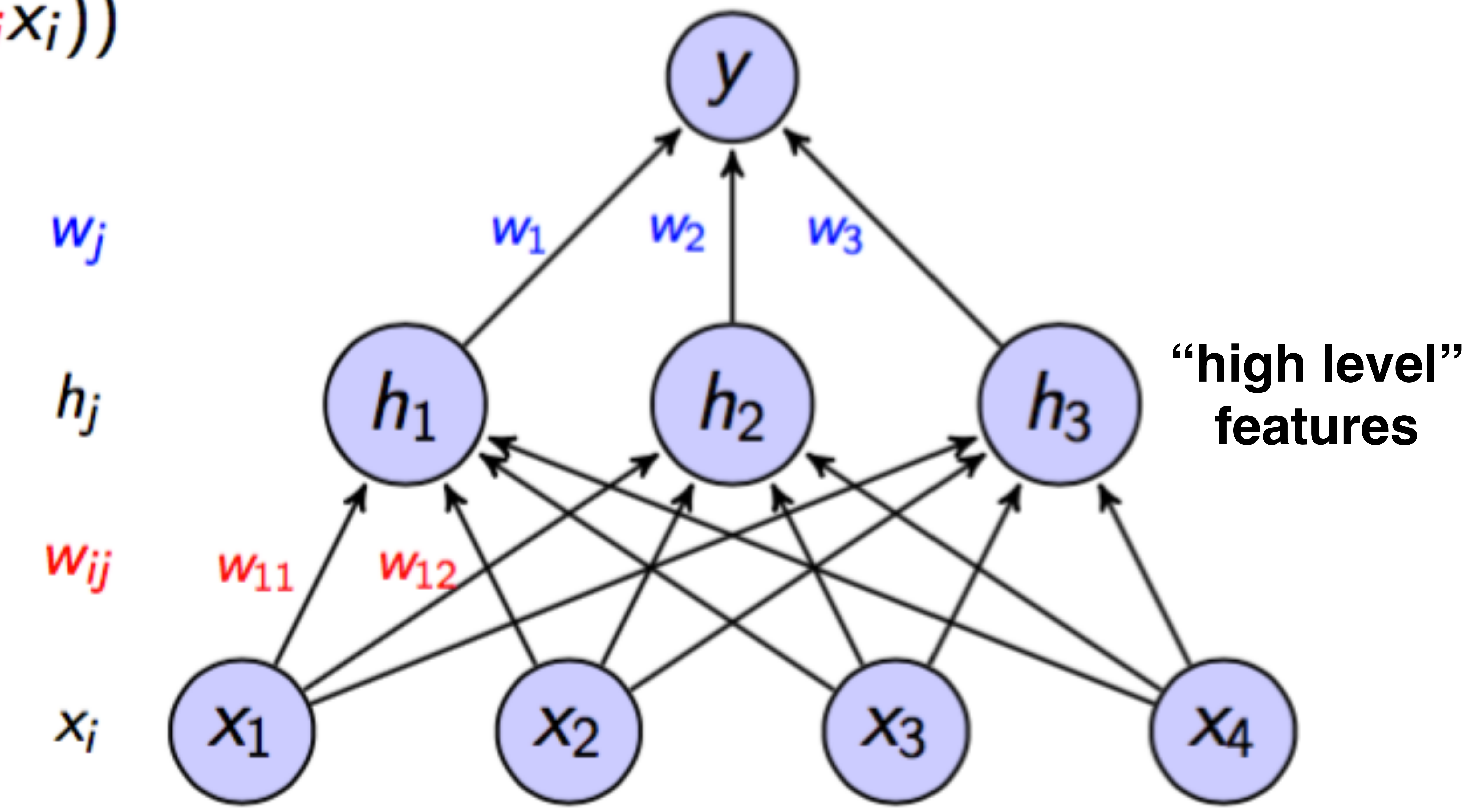
- The inputs to the final classifier are learned (“representation learning”)



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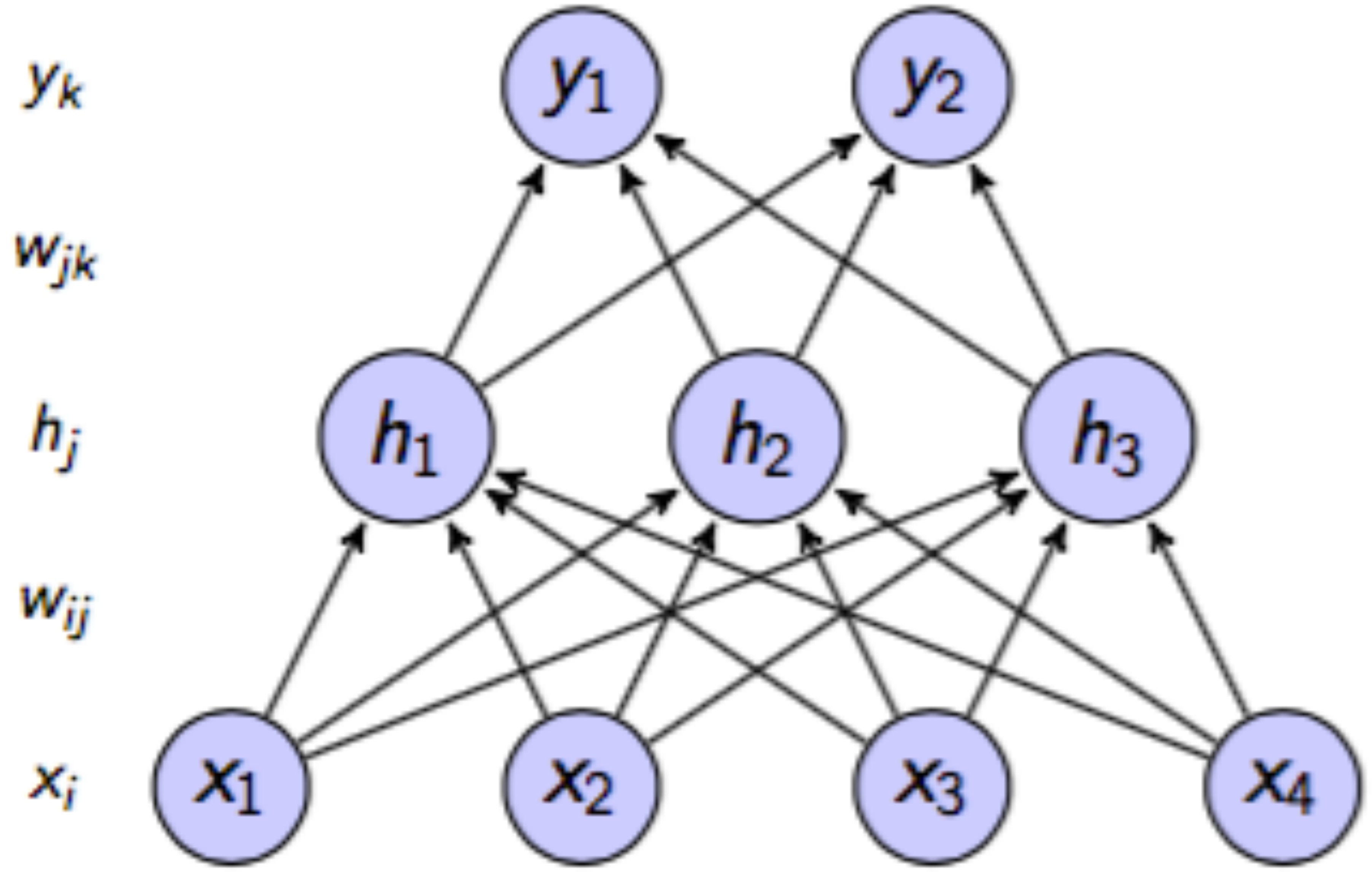

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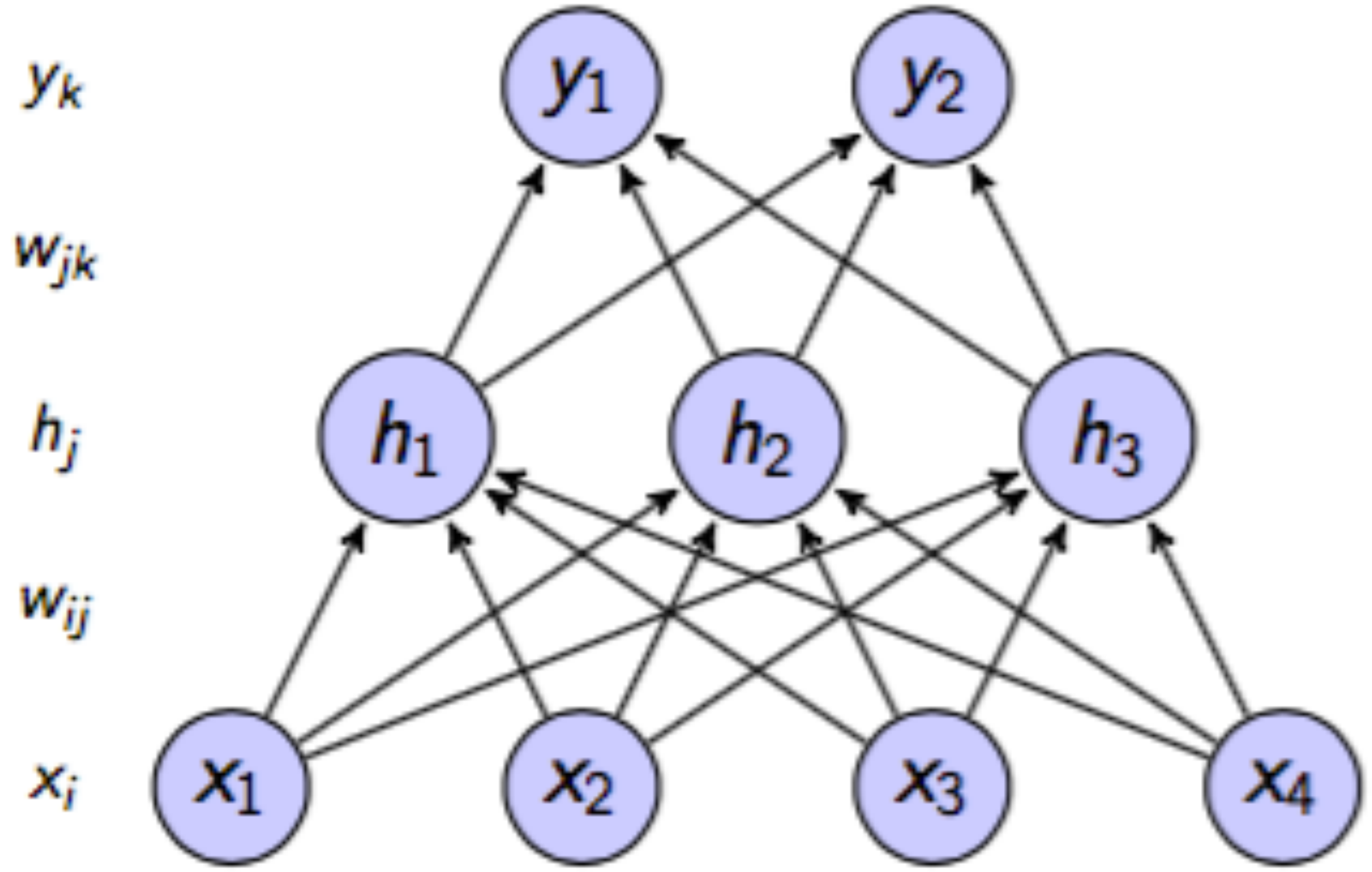

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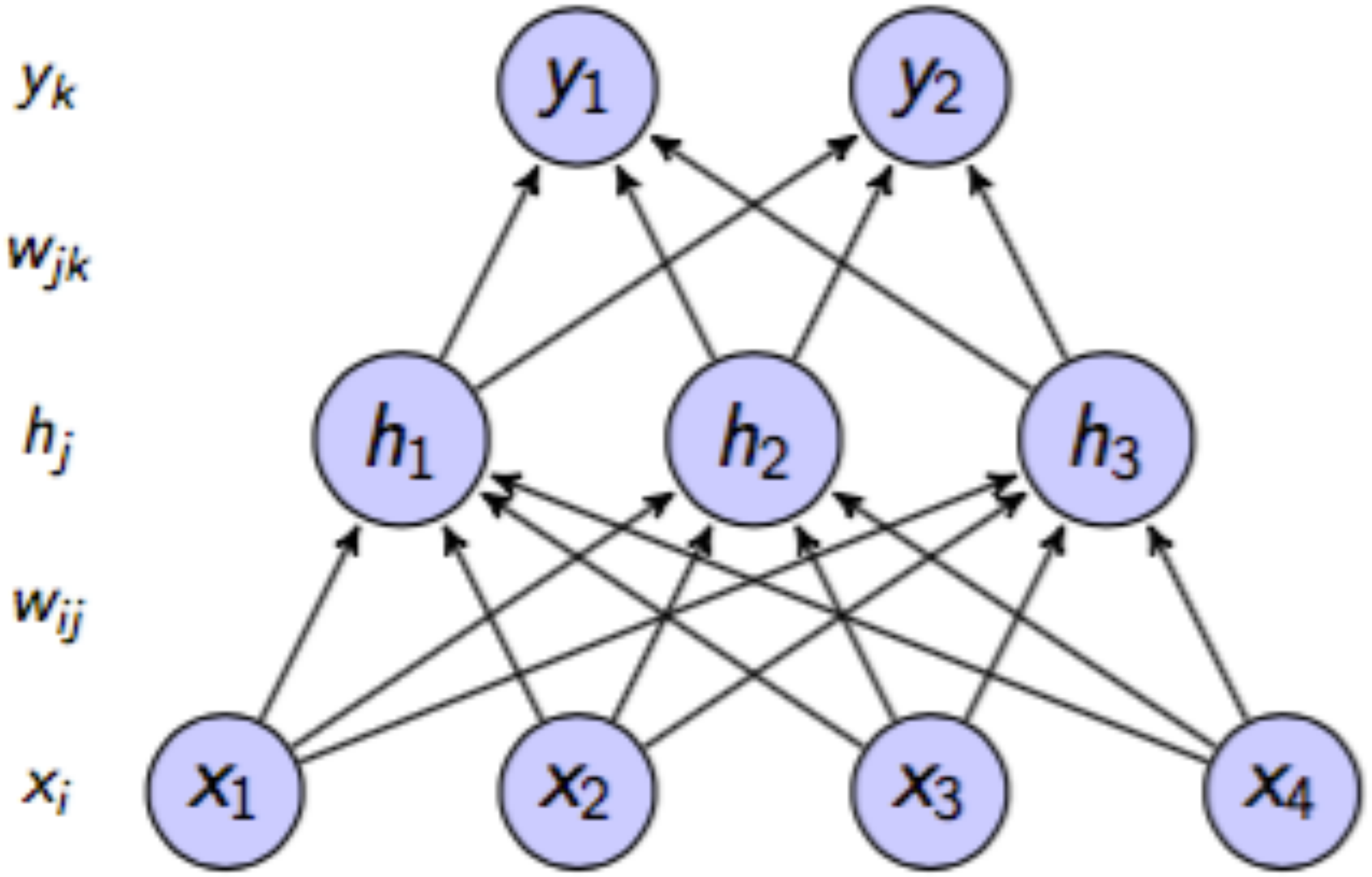

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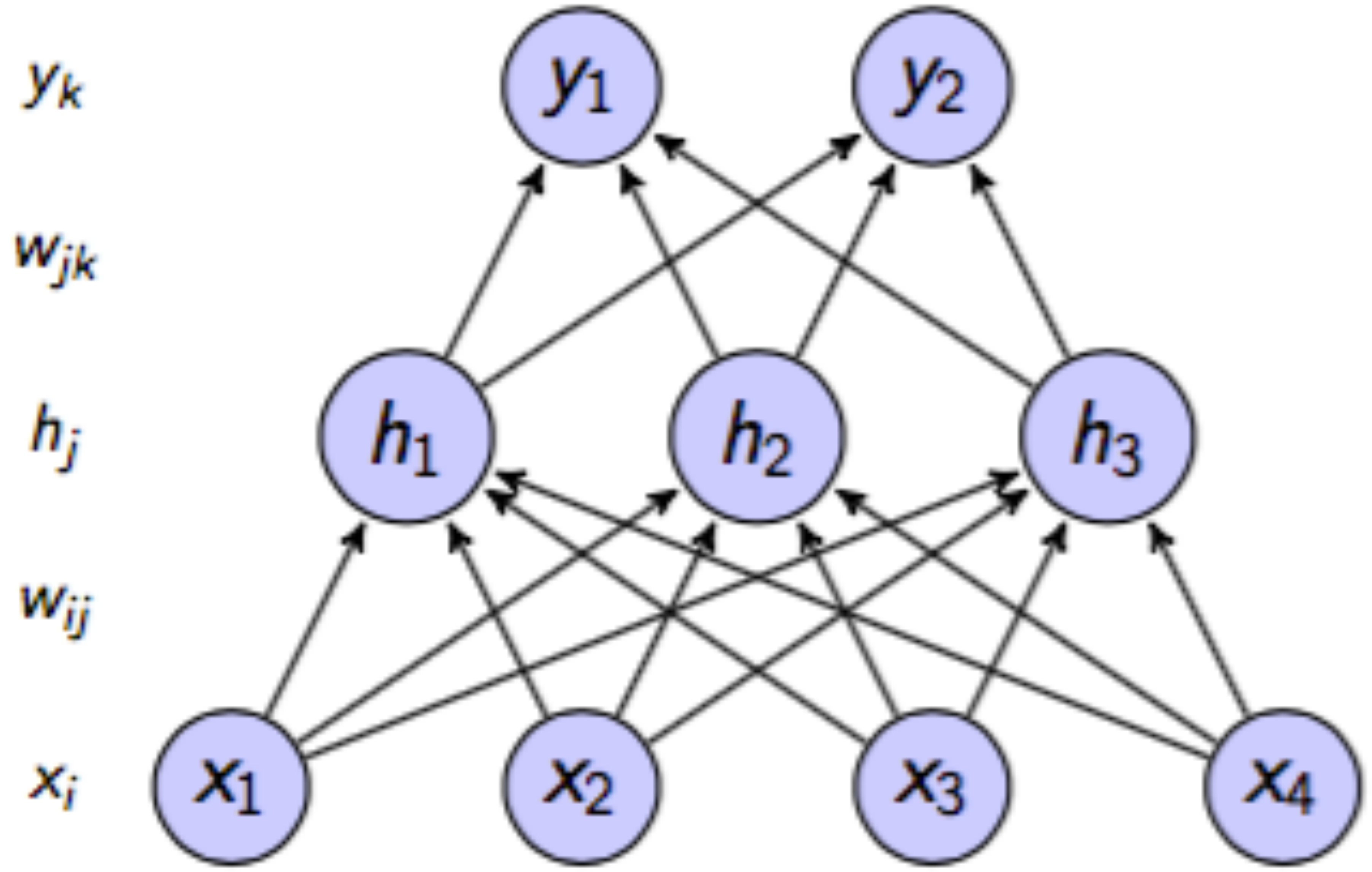

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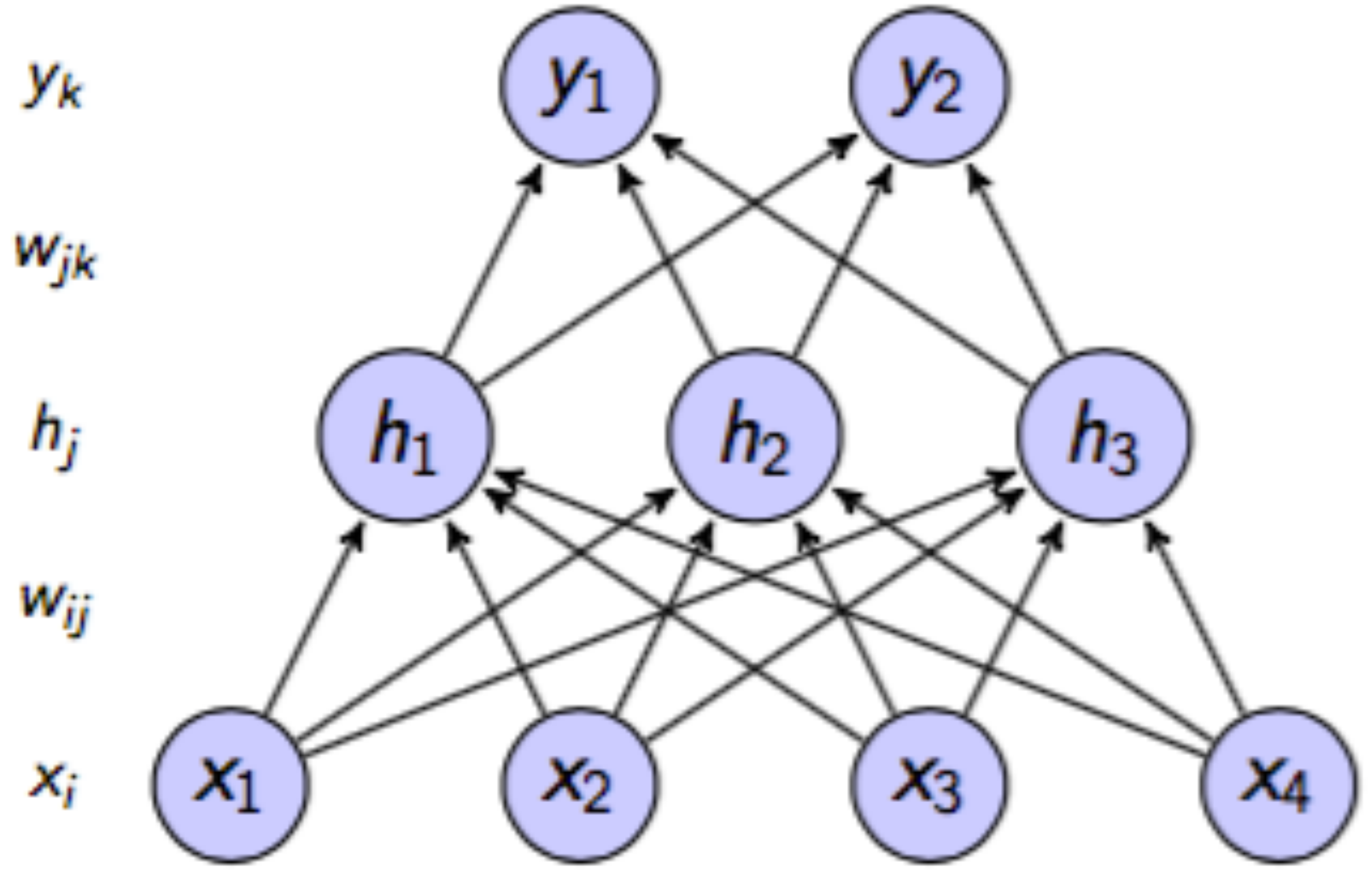

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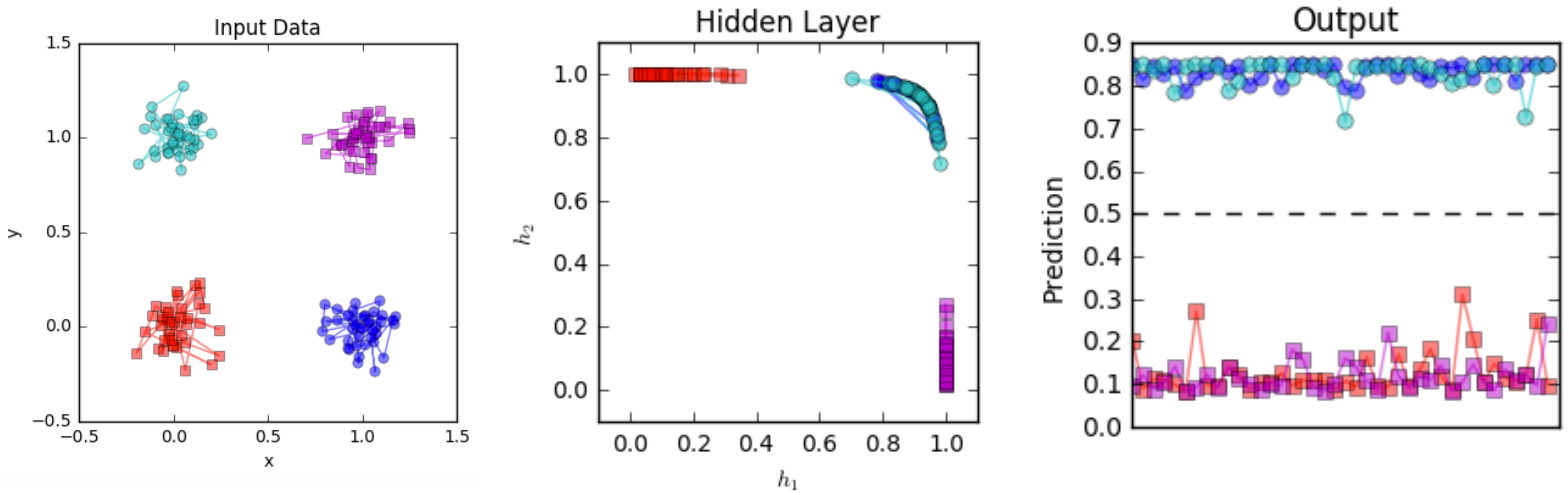
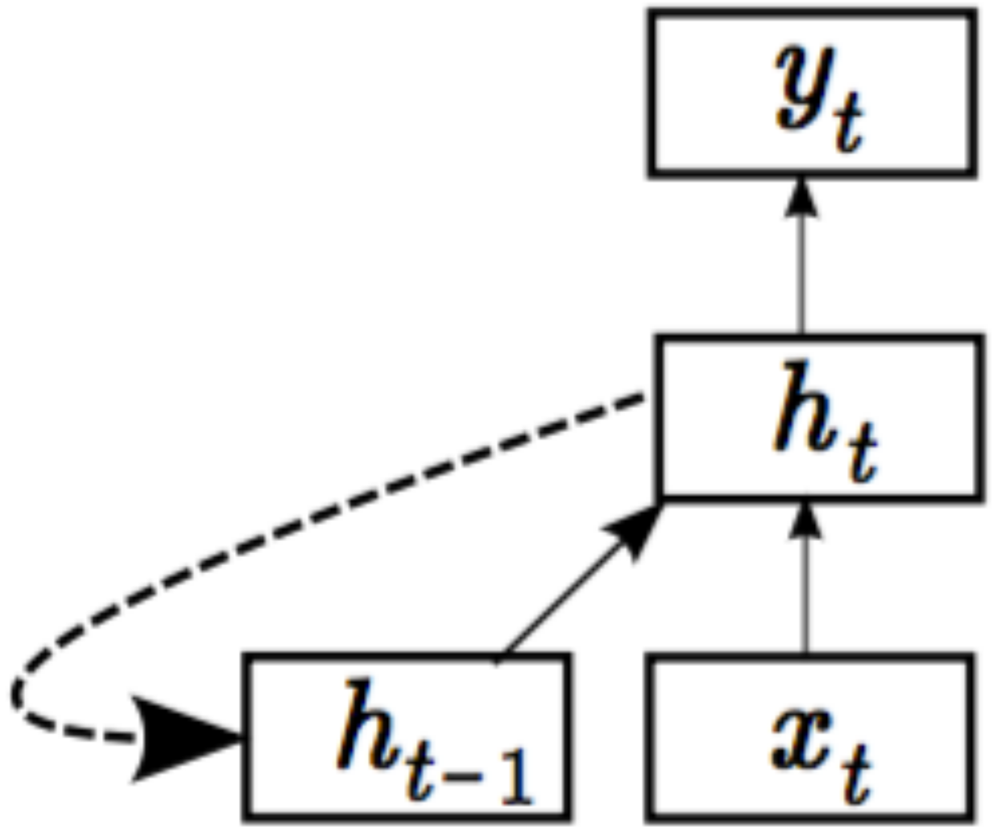
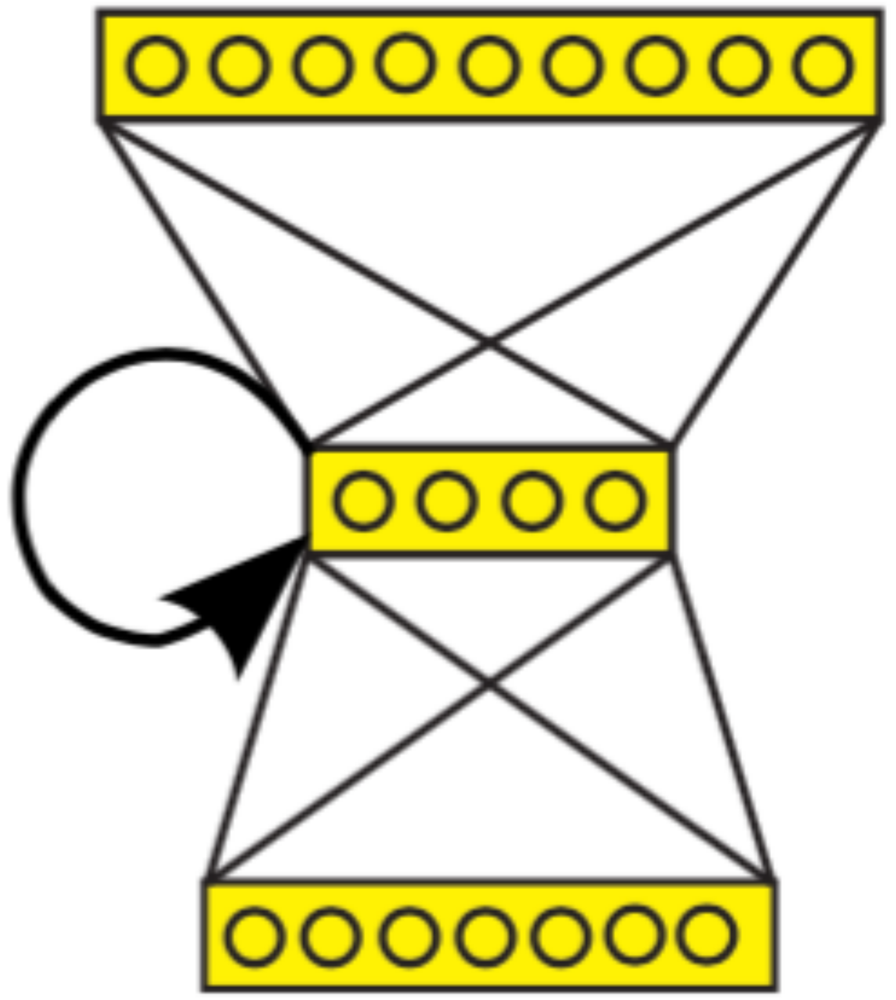
Example - "learning to XOR": $x \oplus y = (x \vee y) \wedge \neg(x \wedge y)$



Recurrent Neural Networks (RNNs)





Recurrent Neural Networks (RNNs)

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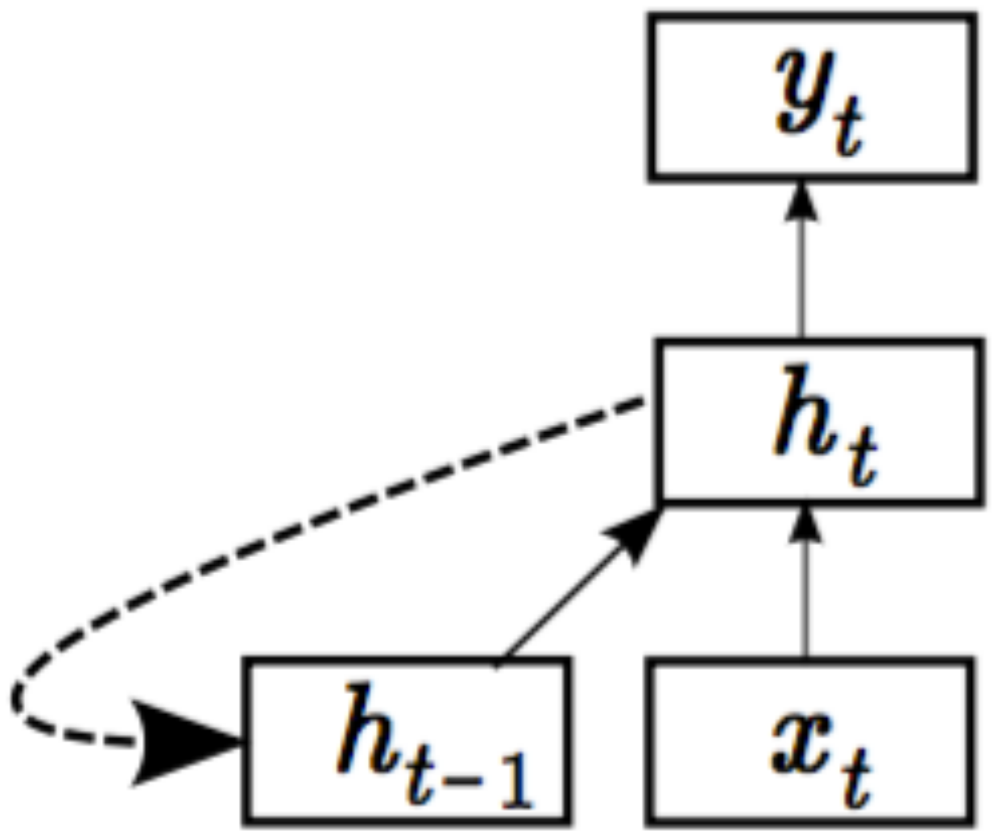

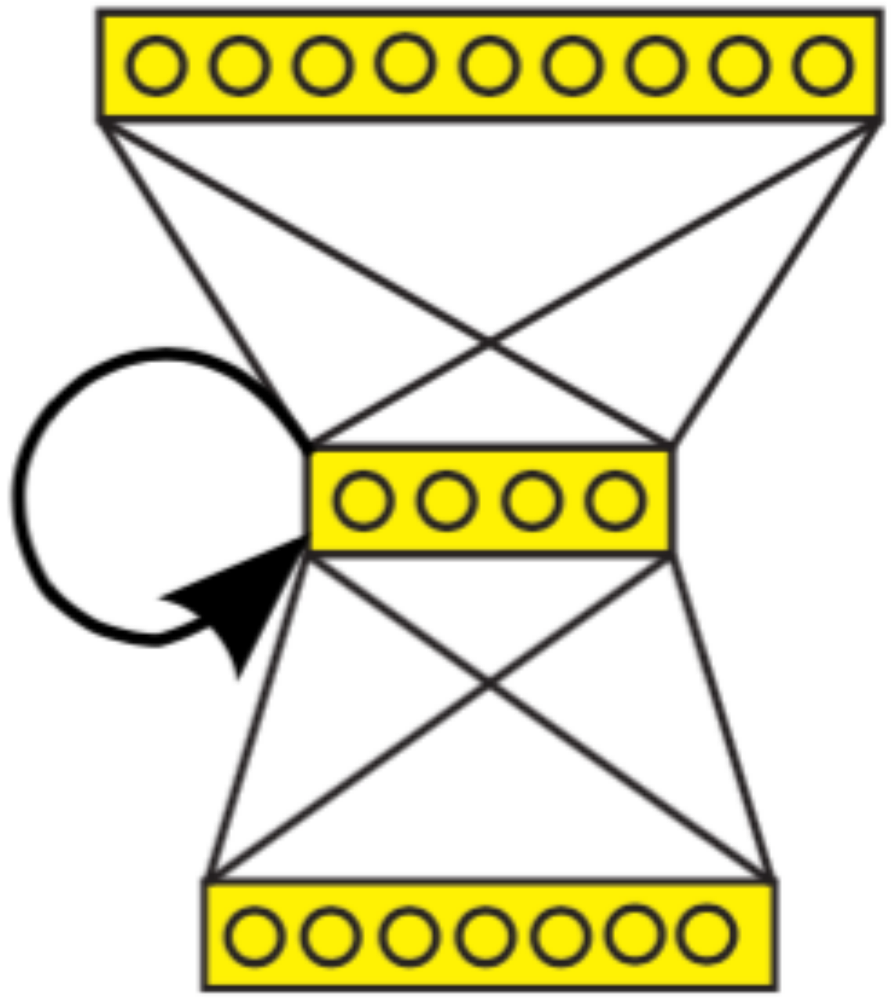

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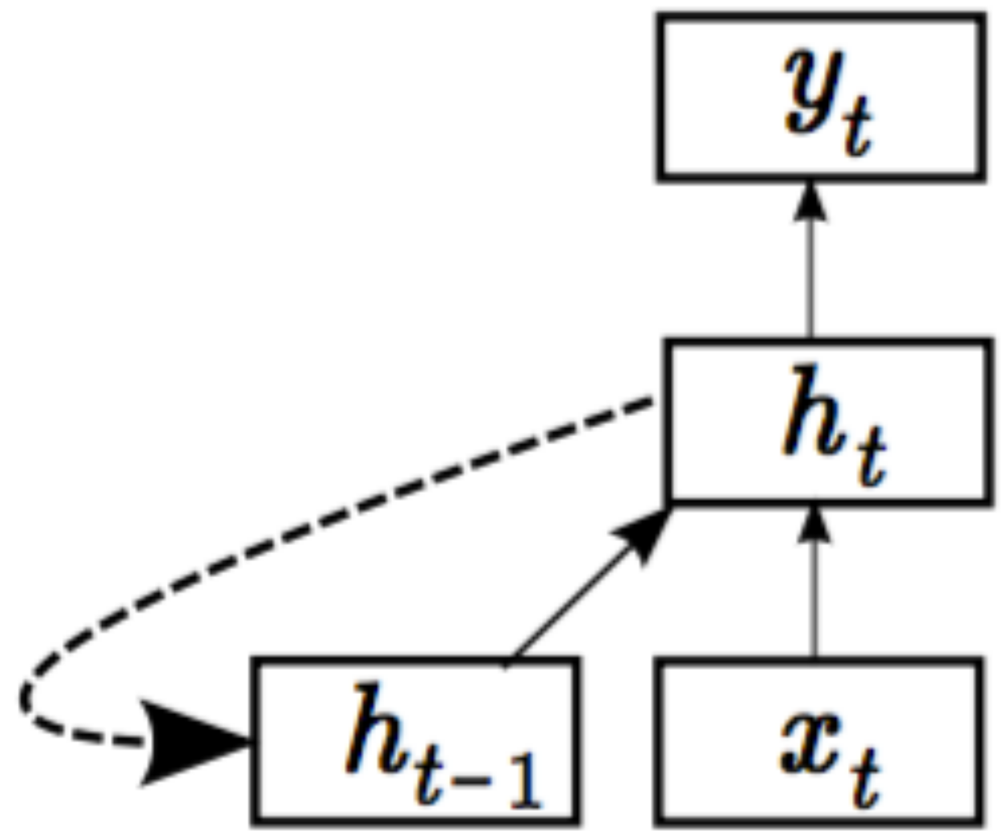

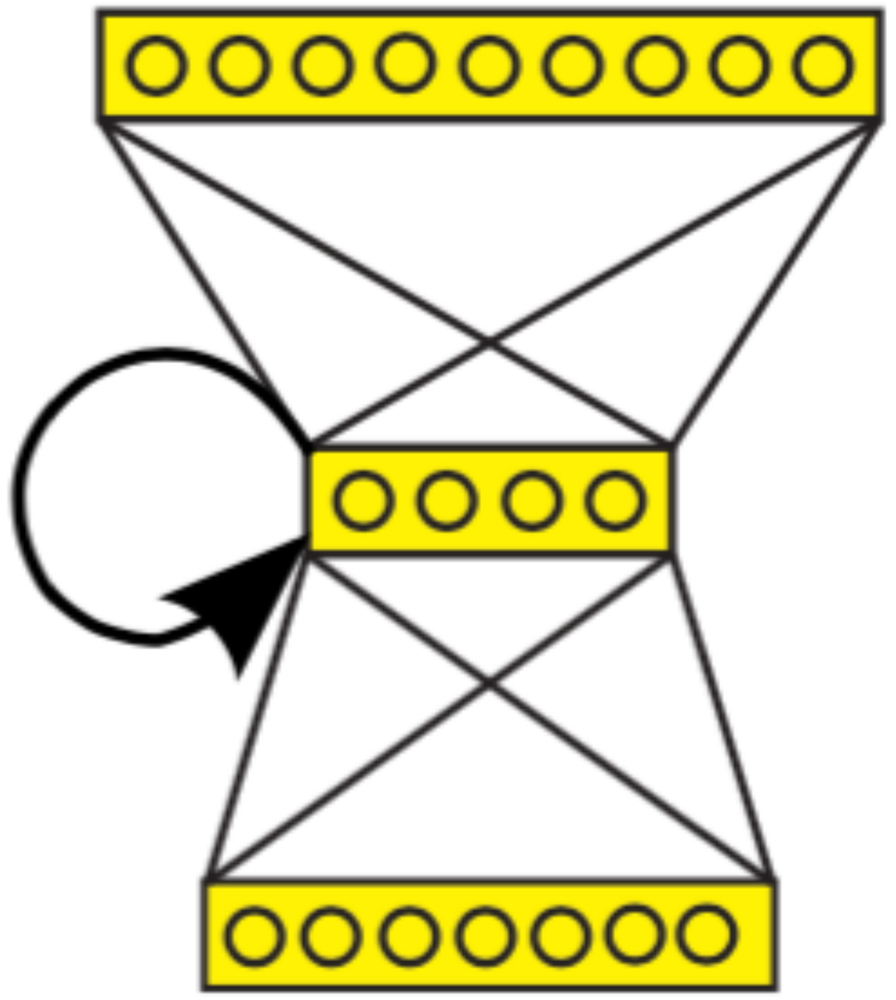

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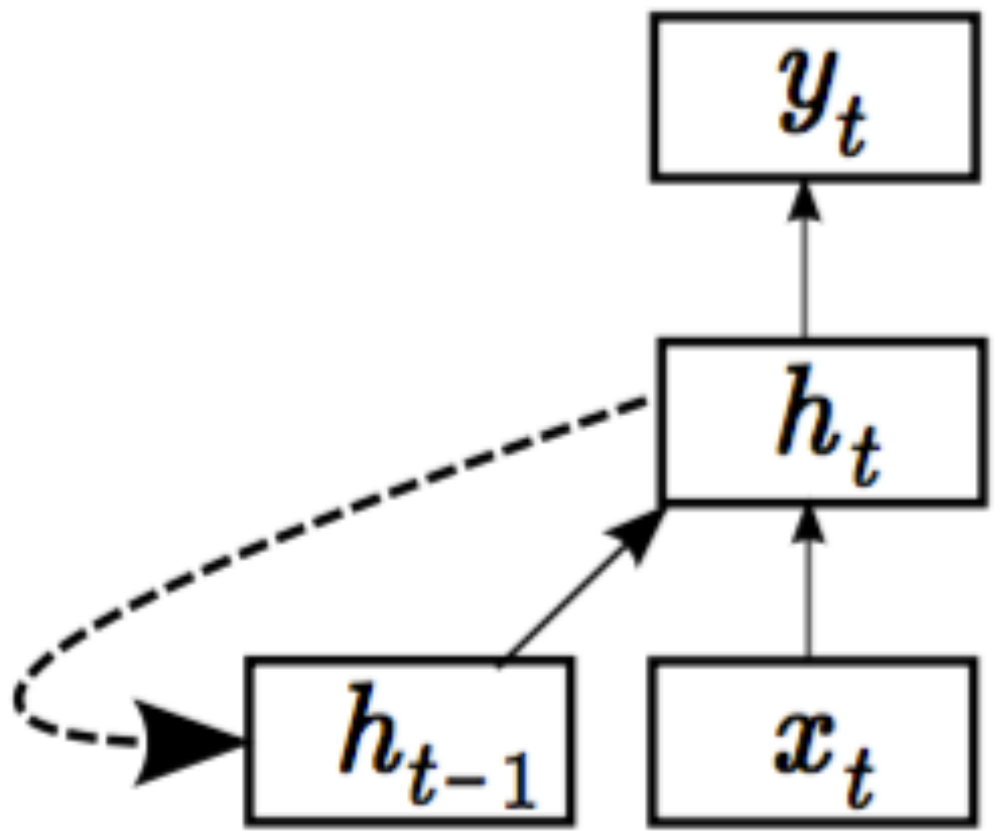
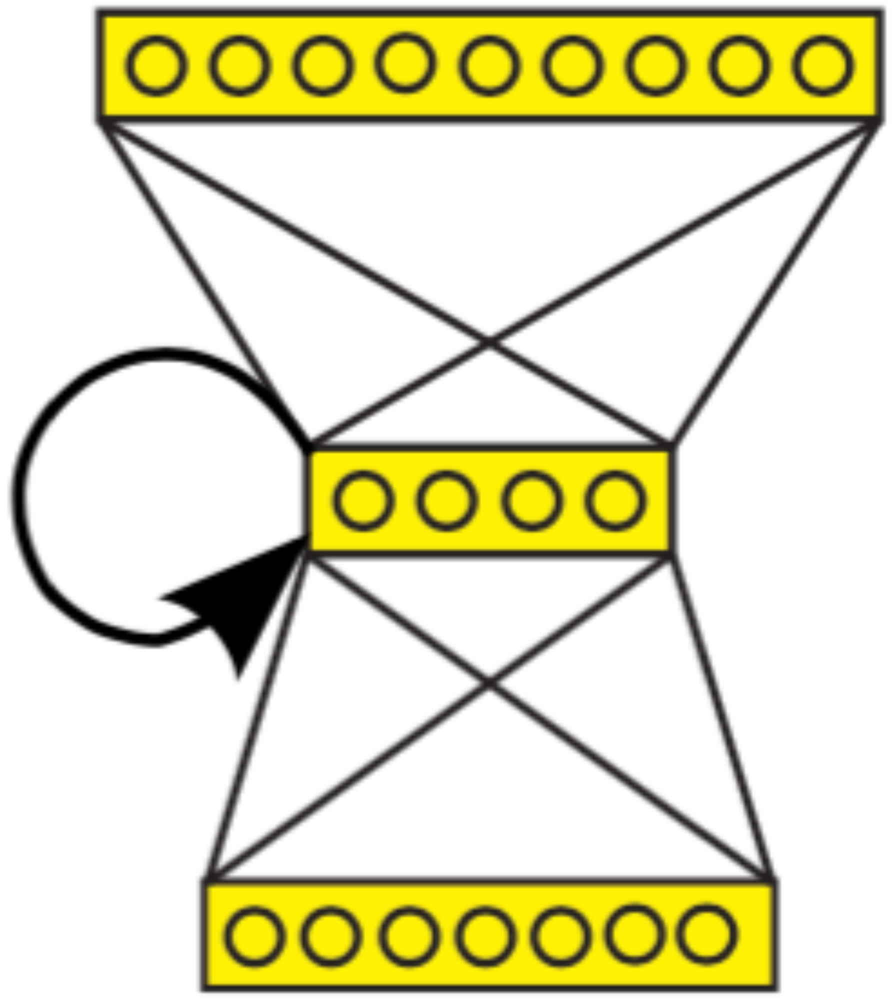
- Introduce a “memory/context” component to utilize history





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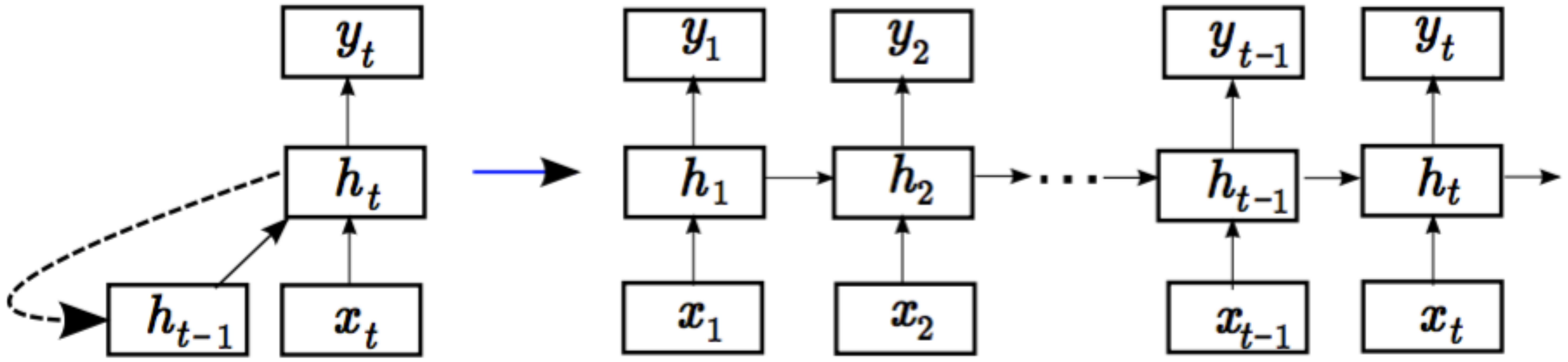

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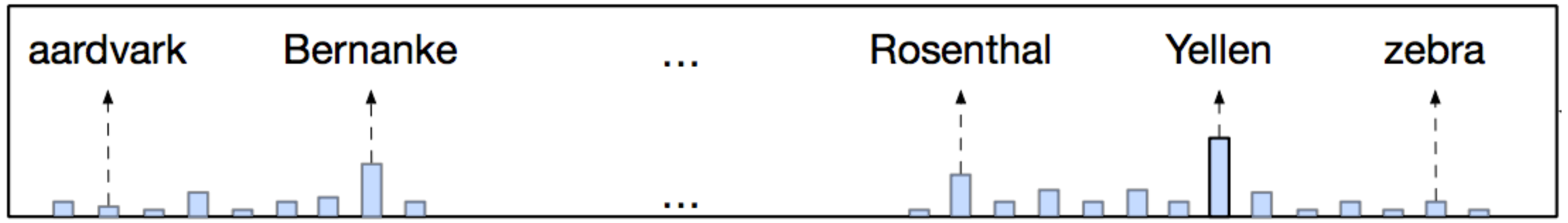

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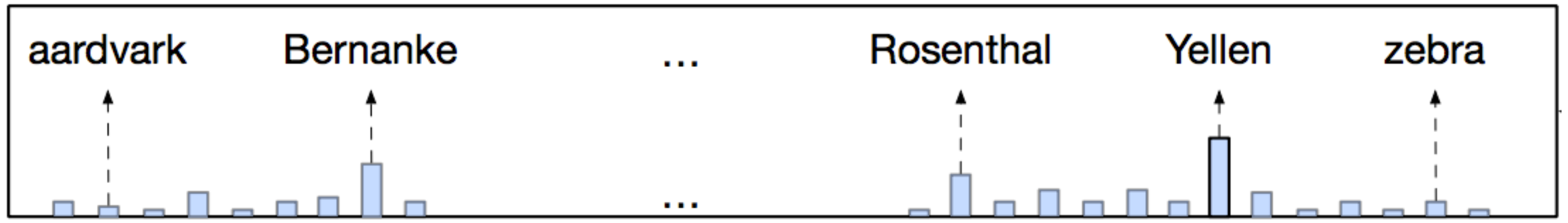
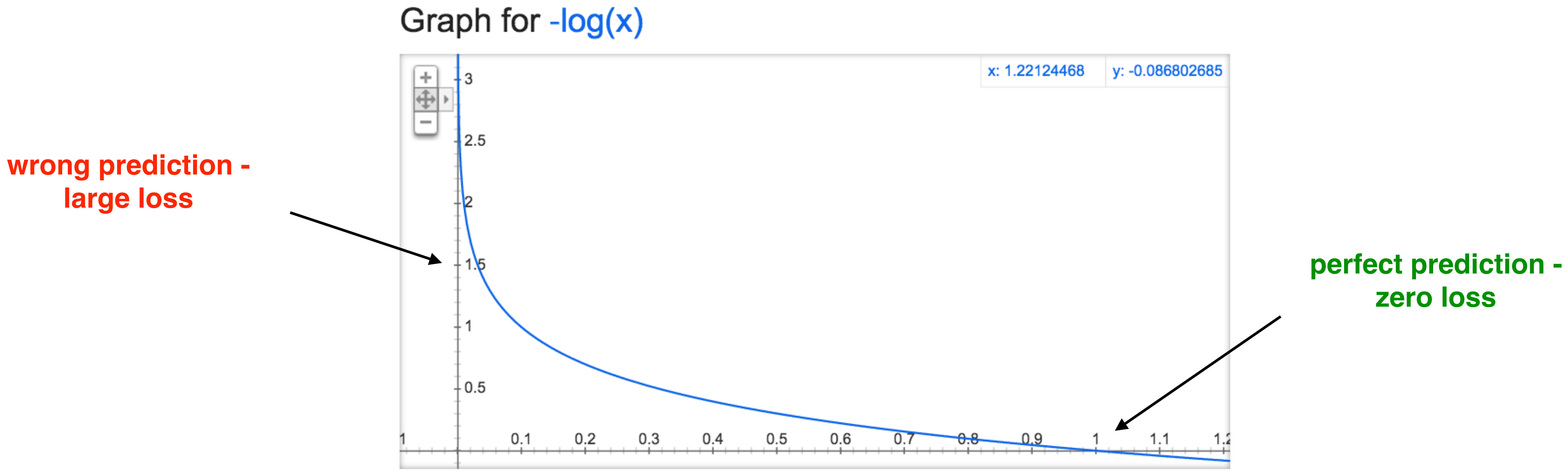


- The loss function is usually the **sum of negative log softmax** values for the **correct sequence**



Training (RNN's) with Backpropagation Through Time

- As usual, define a loss function (per sample, through time $t = 1, 2, ..., T$):

$$Loss = J(\Theta, x) = -\sum_{t=1}^{T} J_t(\Theta, x_t)$$

- Compute the gradient w.r.t. parameters Θ, starting at $t = T$:

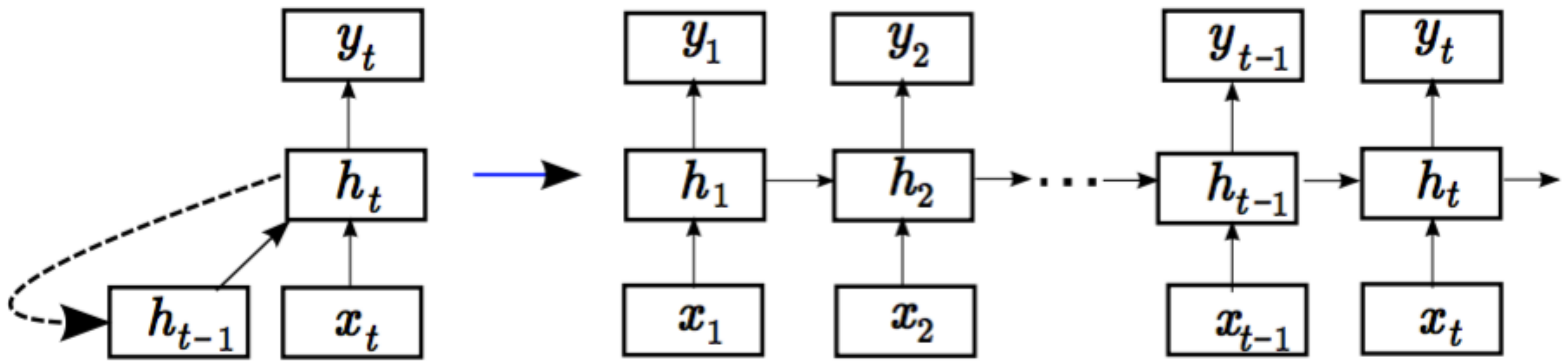
$$\nabla\Theta = \frac{\partial J_t}{\partial \Theta}$$

- Backpropagate through time - sum and repeat for $t - 1$, until $t = 1$:

$$\nabla\Theta = \nabla\Theta + \frac{\partial J_t}{\partial \Theta}$$

- Eventually, update the weights:

$$\Theta = \gamma \nabla\Theta$$



Vanishing Gradients in Vanilla RNNs

- If we dive deeper into the gradients of the RNN loss function, for example:

$$\frac{\partial J_{t+n}}{\partial h_t} = \frac{\partial J_{t+n}}{\partial g} \frac{\partial g}{\partial h_{t+N}} \frac{\partial h_{t+N}}{\partial h_{t+N-1}} \cdots \frac{\partial h_{t+1}}{\partial h_t}$$

- Given $h_t = tanh(a), a = W_{x_{t-1}} + Uh_{t-1}, + b$ we get that:

$$\frac{\partial h_{t+1}}{\partial h_t} = U^T \frac{\partial tanh(a)}{\partial a}$$

- And Eventually:

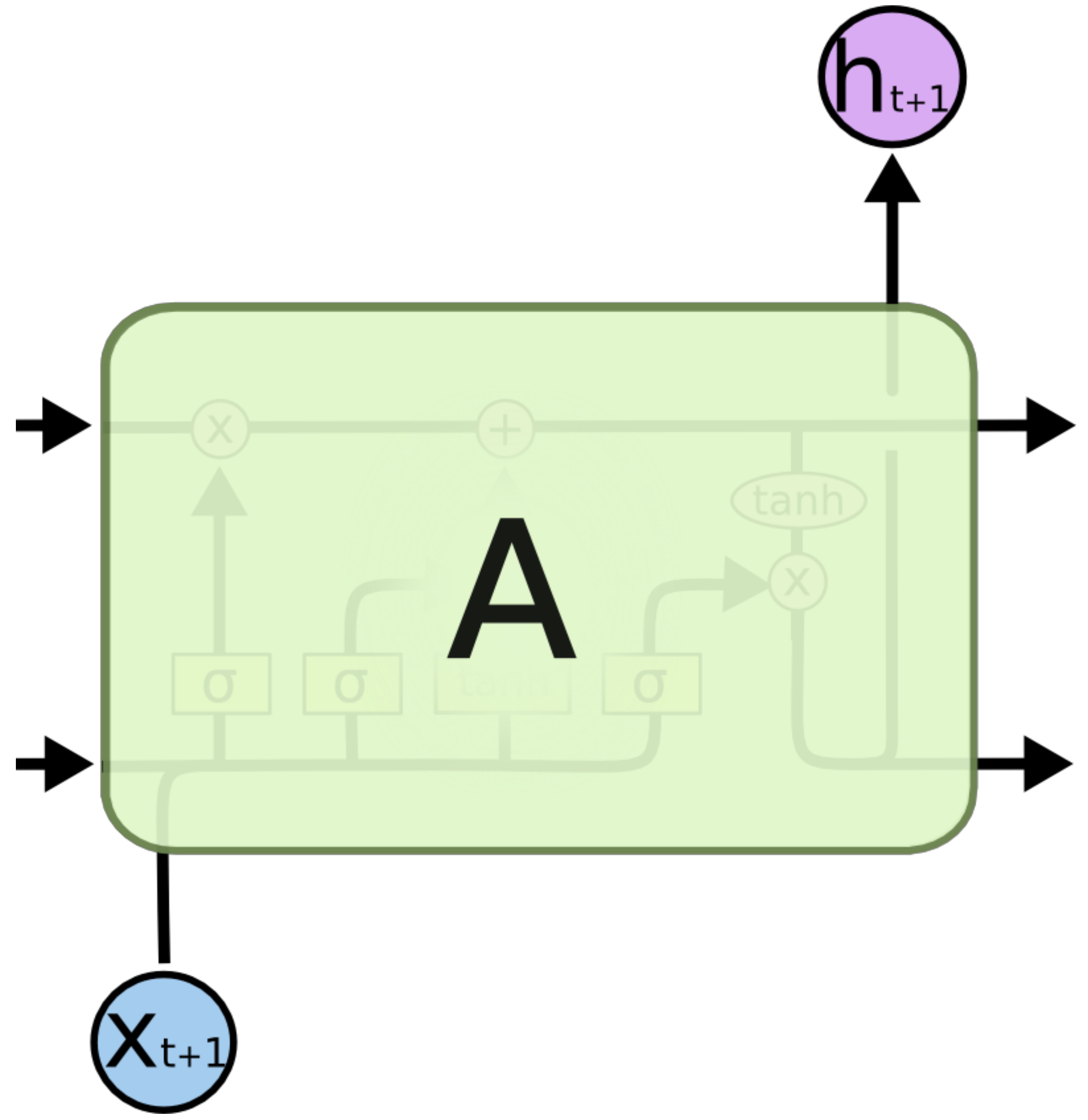
$$\frac{\partial J_{t+n}}{\partial h_t} = \frac{\partial J_{t+n}}{\partial g} \frac{\partial g}{\partial h_{t+N}} \prod_{n=1}^{N} U^T diag\left(\frac{\partial tanh(a_{t+n})}{\partial a_{t+n}}\right)$$

- This easily makes the gradients vanish (get close to 0) so that no learning takes place, as noted in Bengio et al (94’):

$$\prod_{n=1}^{N} U^T diag\left(\frac{\partial tanh(a_{t+n})}{\partial a_{t+n}}\right) \rightarrow 0$$

Vanishing gradients, LSTM’s and GRU’s

- In order to cope with the vanishing gradients problem in RNN’s, more complex recurrent architectures emerged:
  - Long Short-Term Memory (Hochreiter & Schmidhuber,1999)
  - Gated Recurrent Unit (Cho et al, 2014)
- These architectures introduce additive terms that relax the vanishing gradient problem
- Most of the recent RNN works utilize such architectures



Figures by Chris Olah

LSTM Walkthrough in 4 Steps

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IV compute current output probabilities for prediction by using softmax over the hidden state

$$p(x_{t+1} = w | x_1, \cdots, x_t) = \exp(u(w, h_t))/Z$$

$$Z = \sum_{w' \in V} \exp(u(w', h_t))$$

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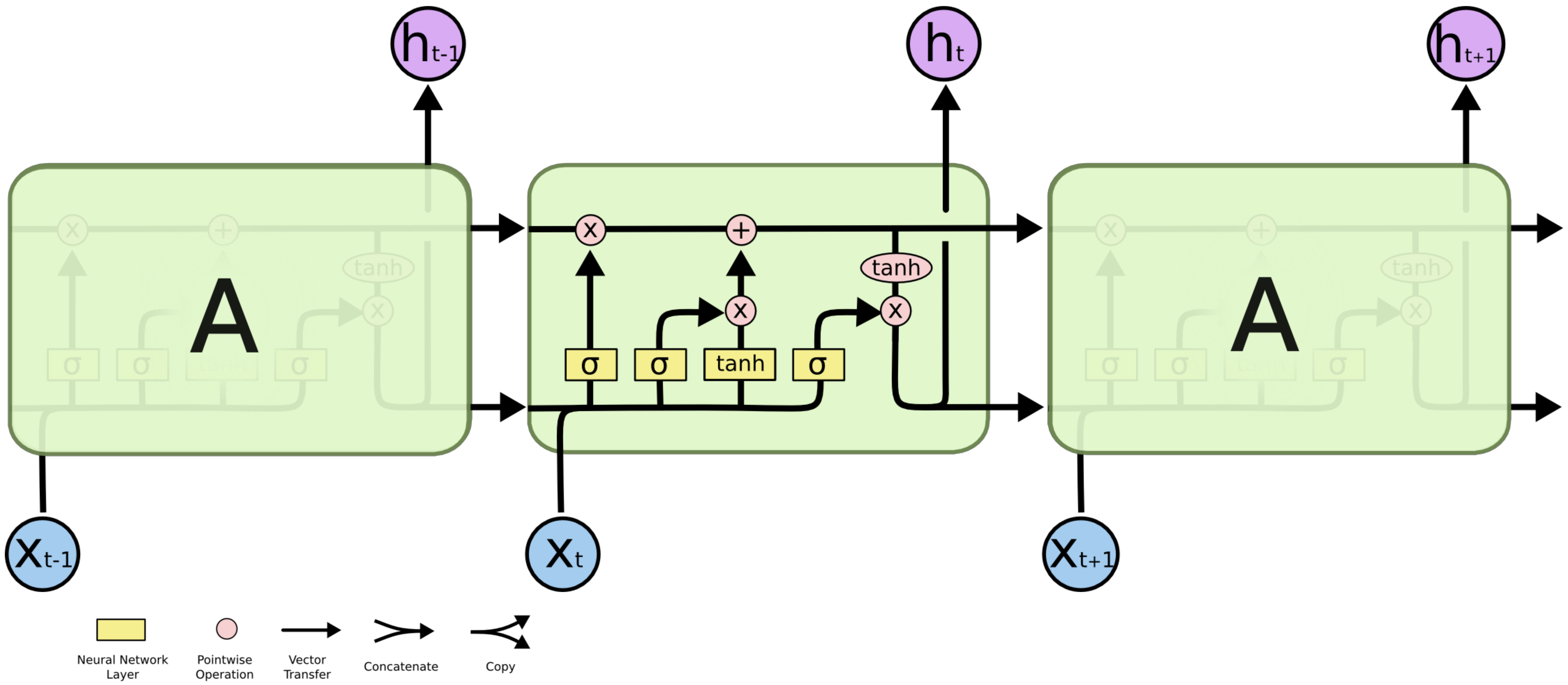

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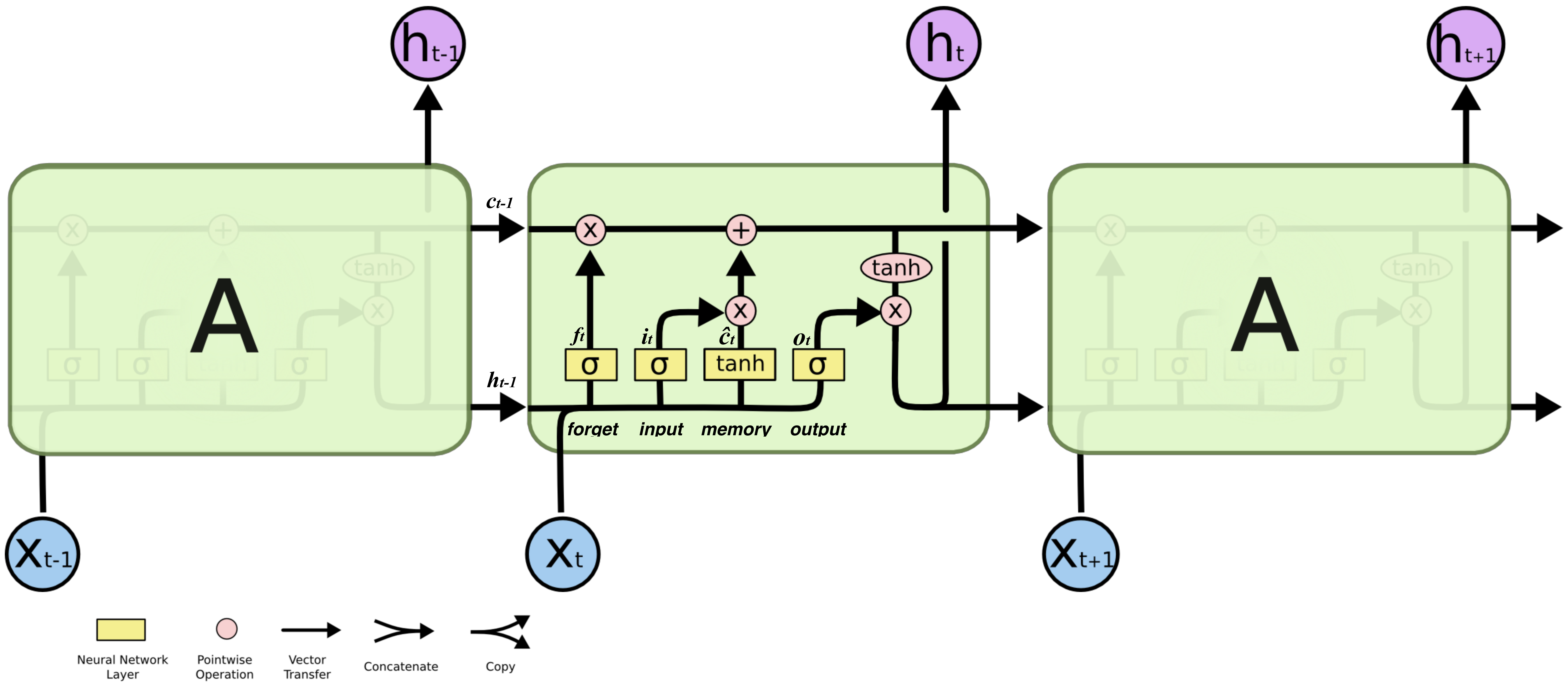

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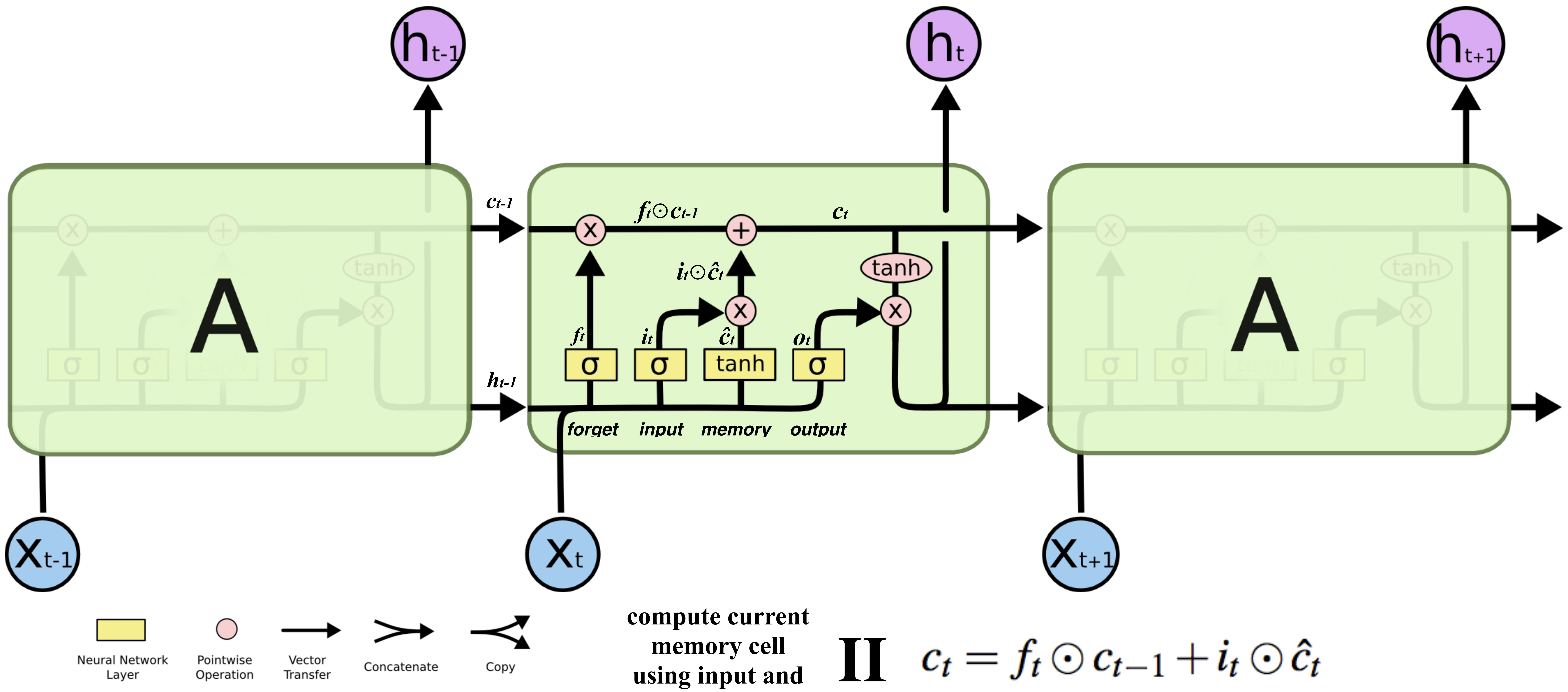

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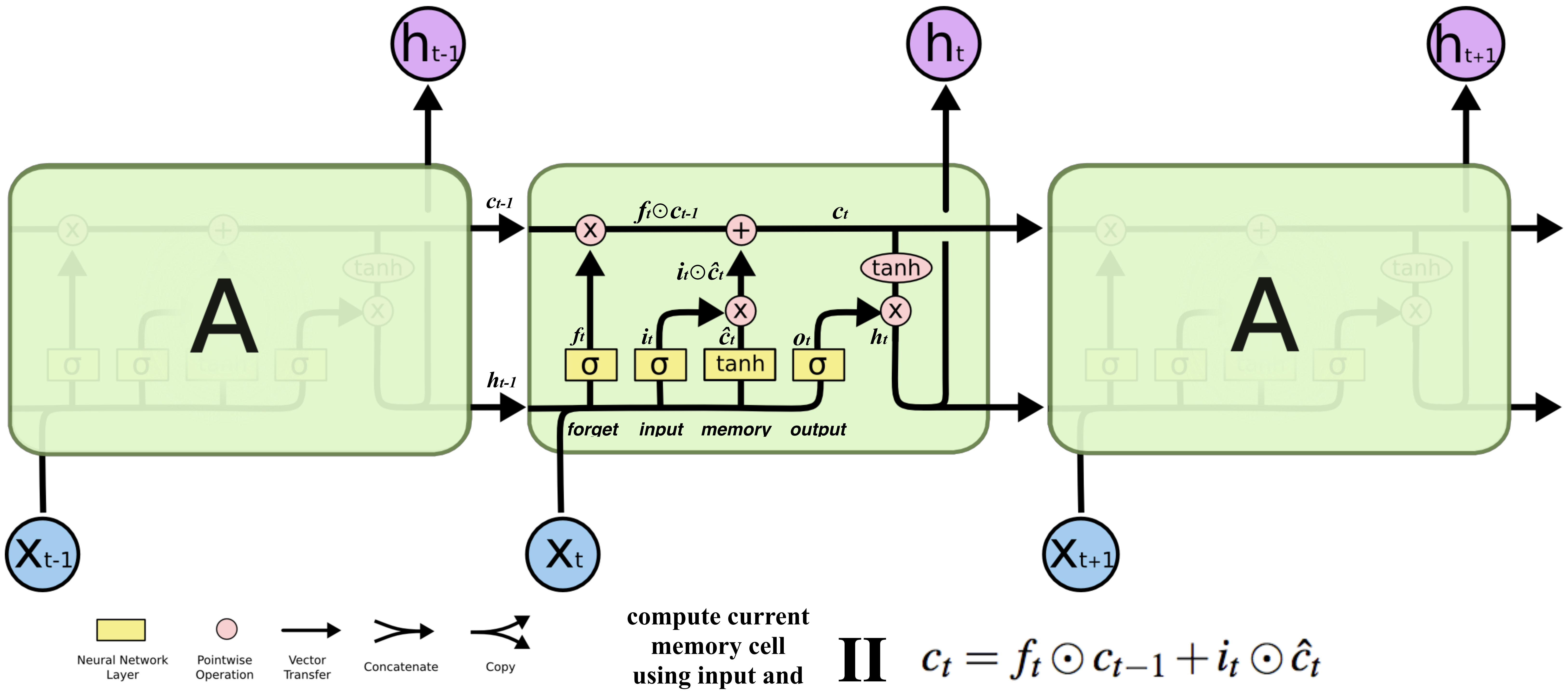

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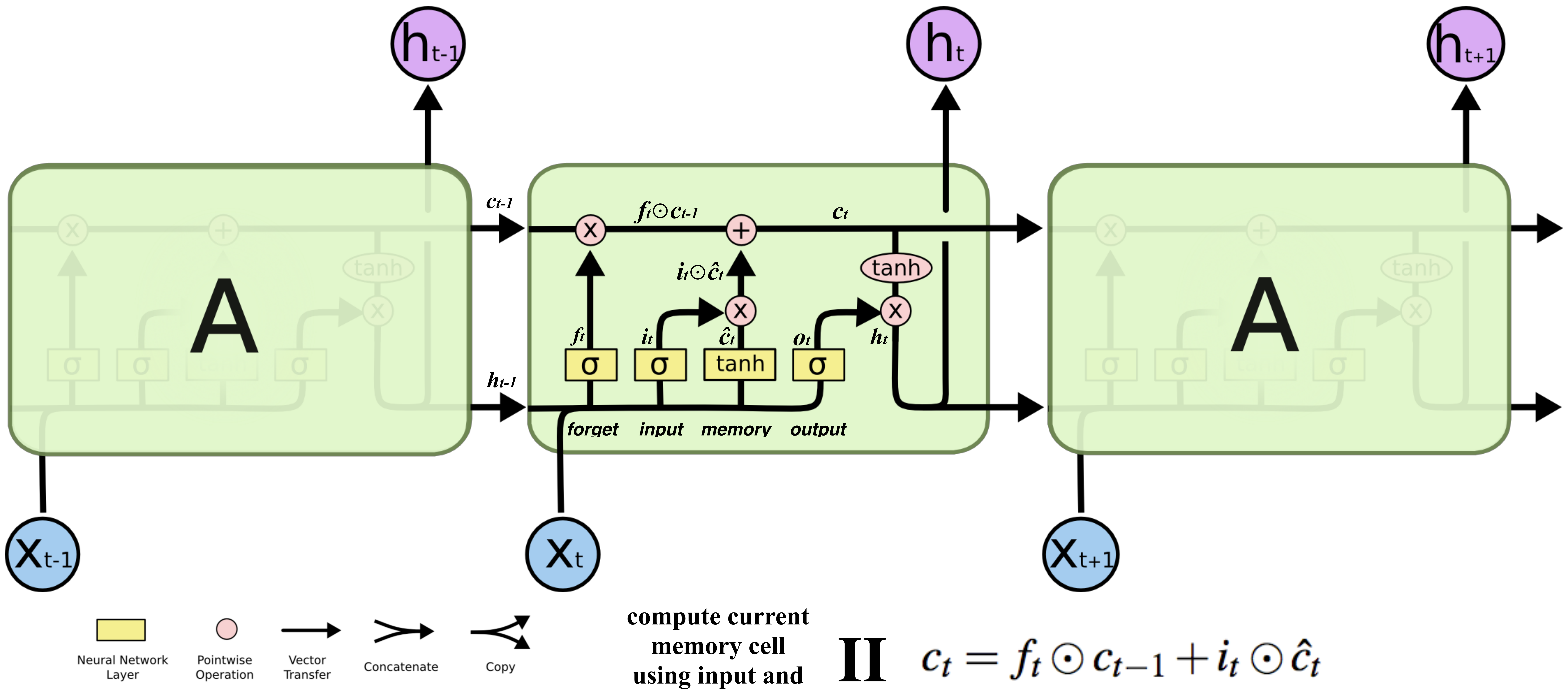

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The GRU Architecture

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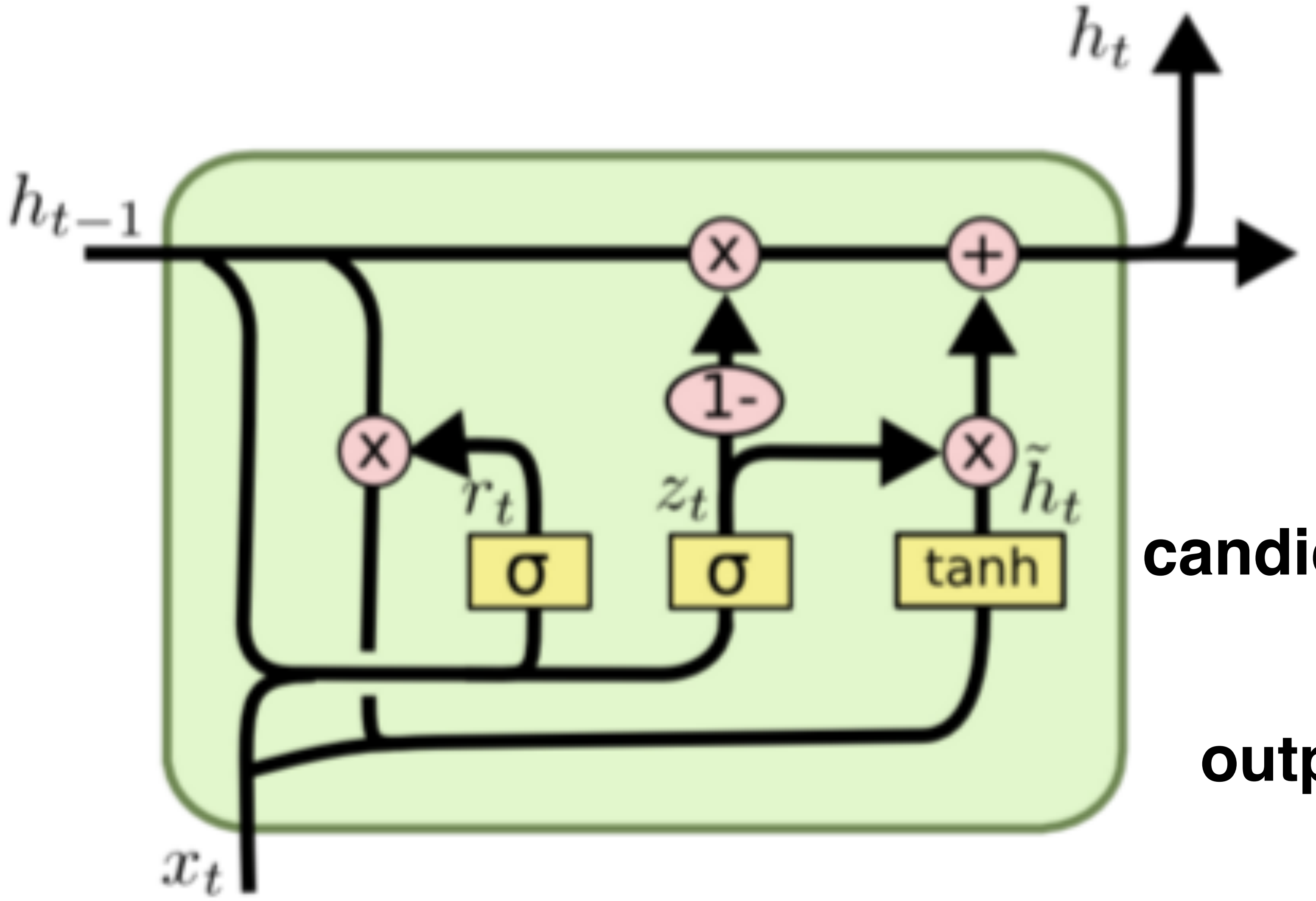

$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$ **update gate**

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$ **reset gate**

candidate $$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

output $$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

The GRU Architecture

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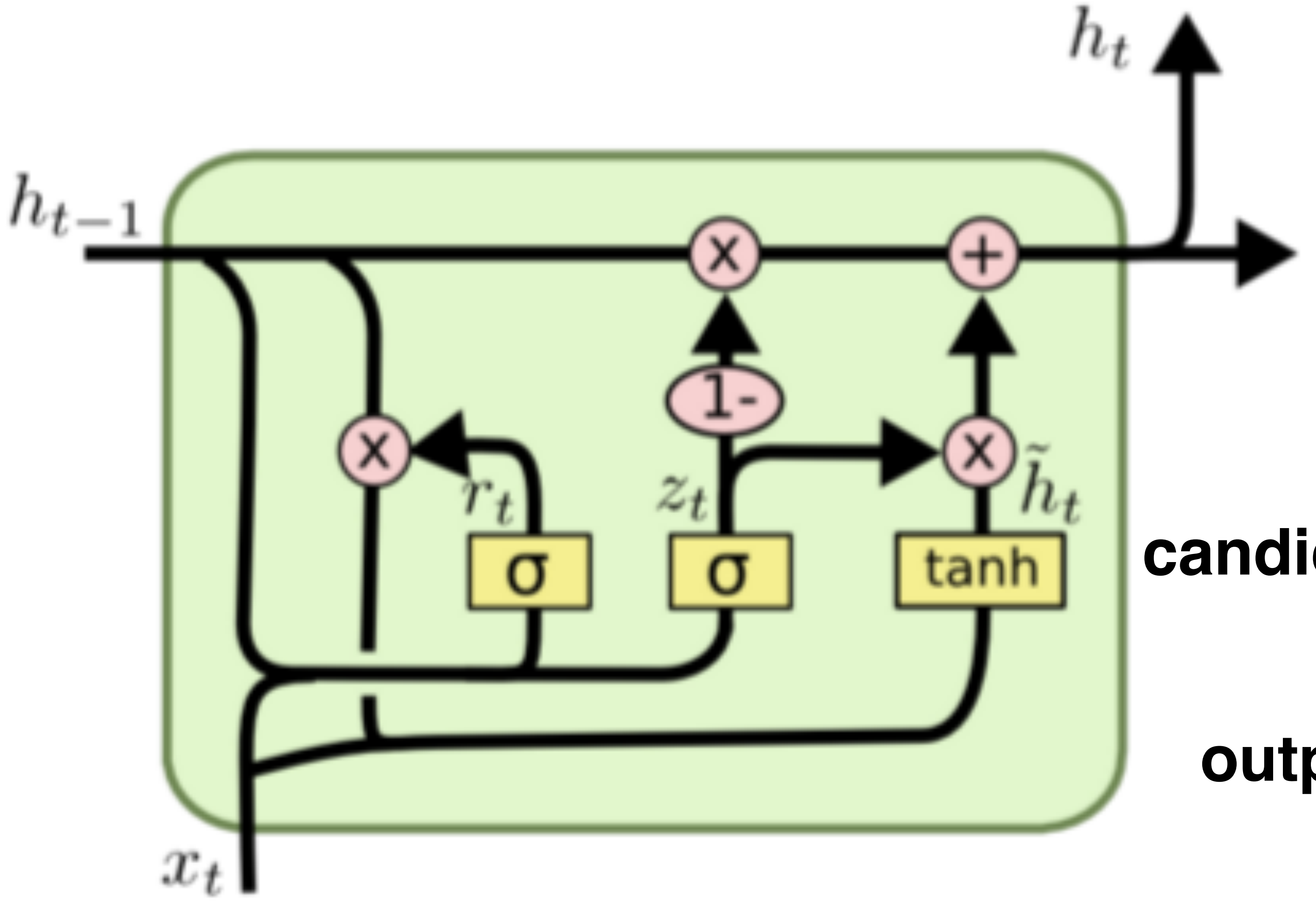

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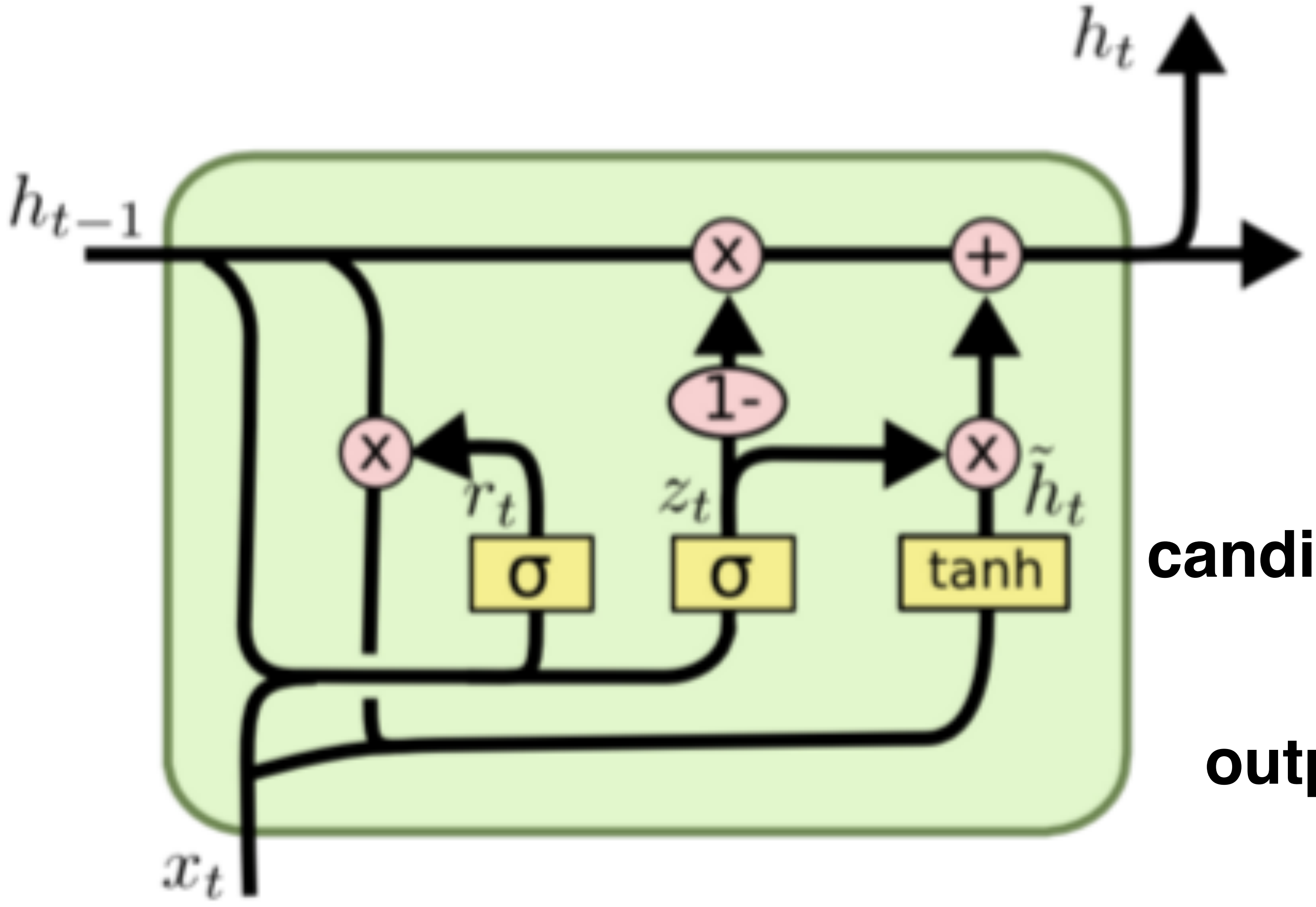
- But weaker in “counting” tasks (Weiss and Goldberg, 2018)



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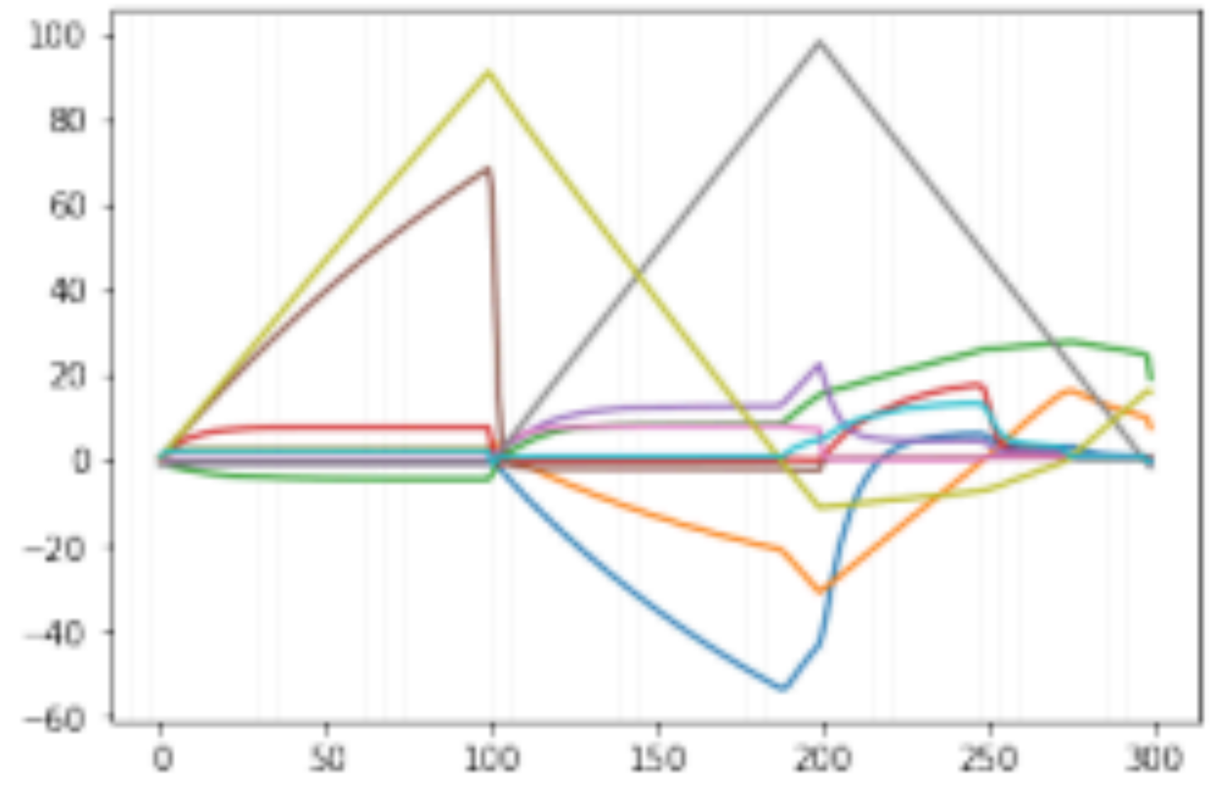
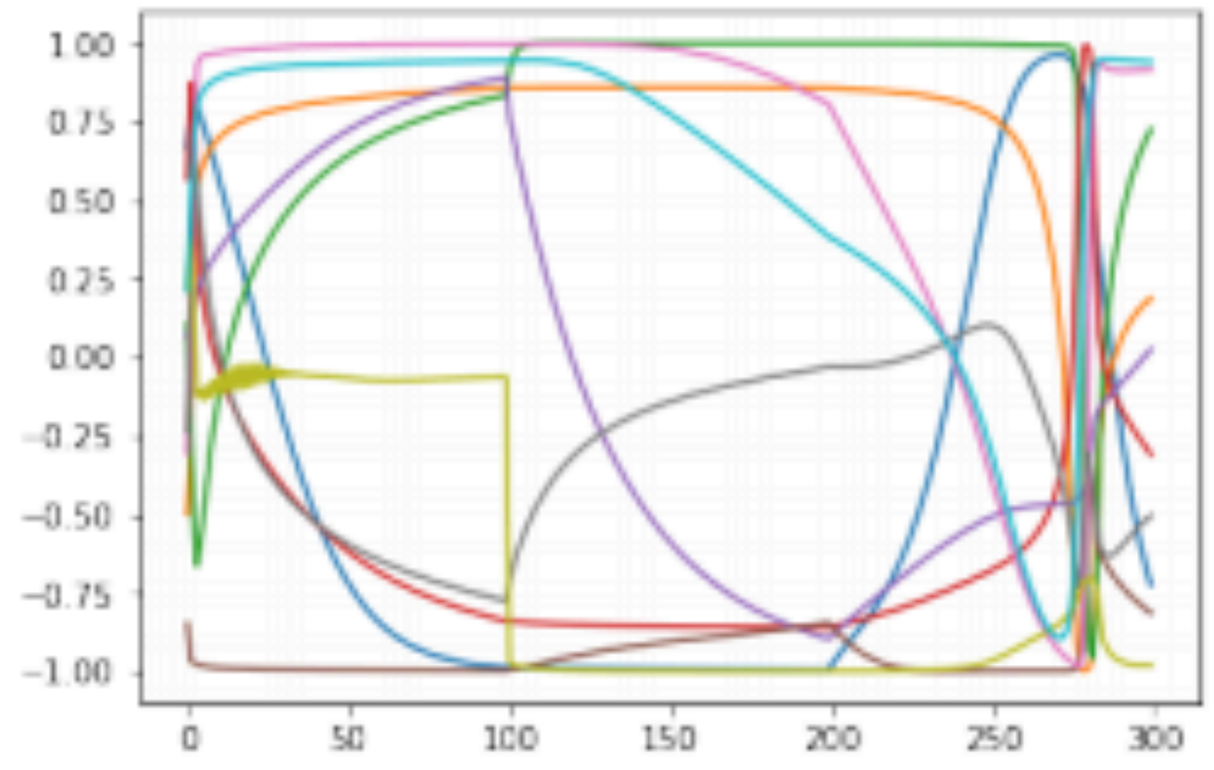


(b) $a^n b^n c^n$-LSTM on $a^{100}b^{100}c^{100}$



(d) $a^n b^n c^n$-GRU on $a^{100}b^{100}c^{100}$

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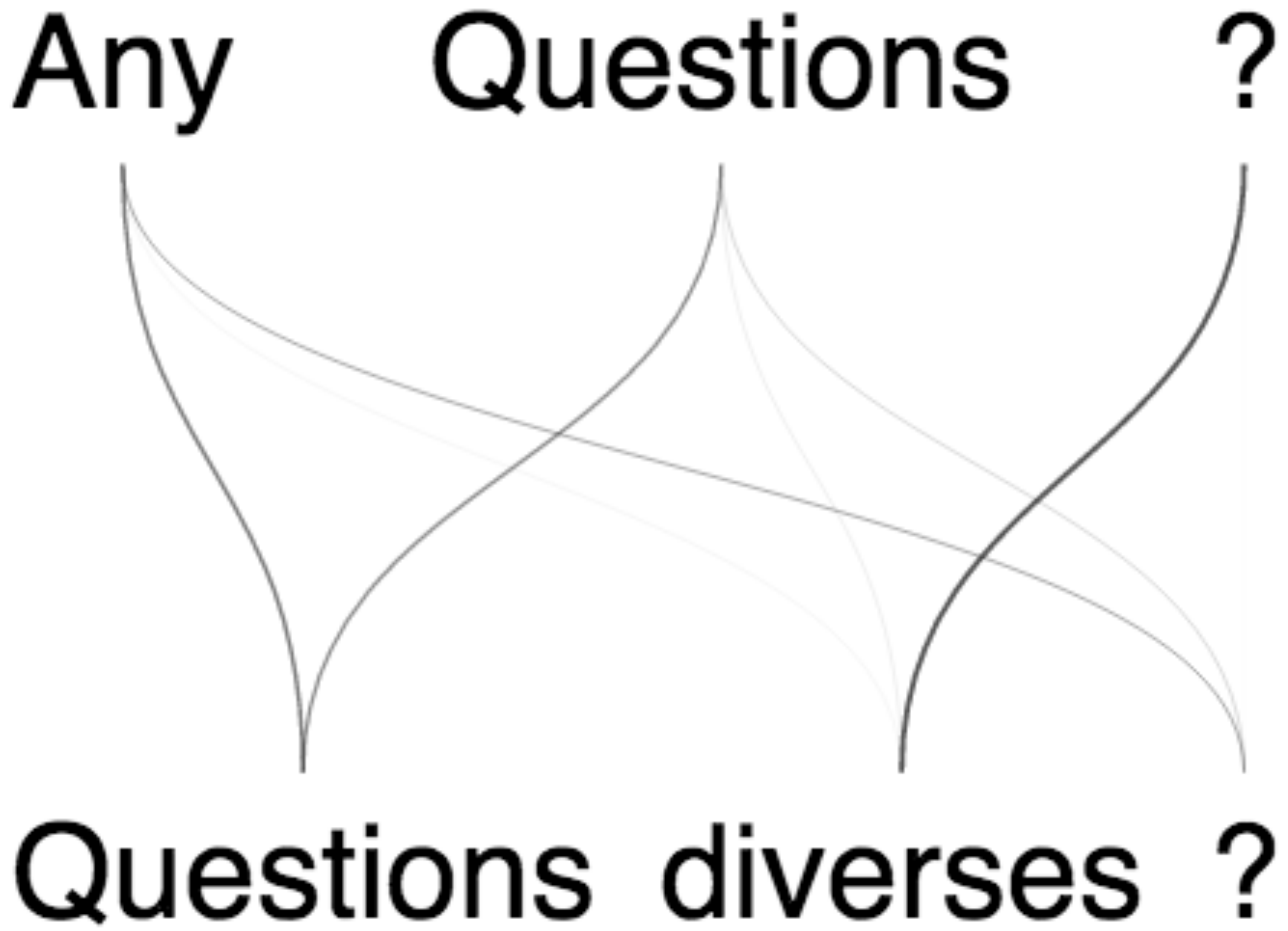
- Vanishing gradients, LSTMs and GRUs


Any
Questions
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Questions
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