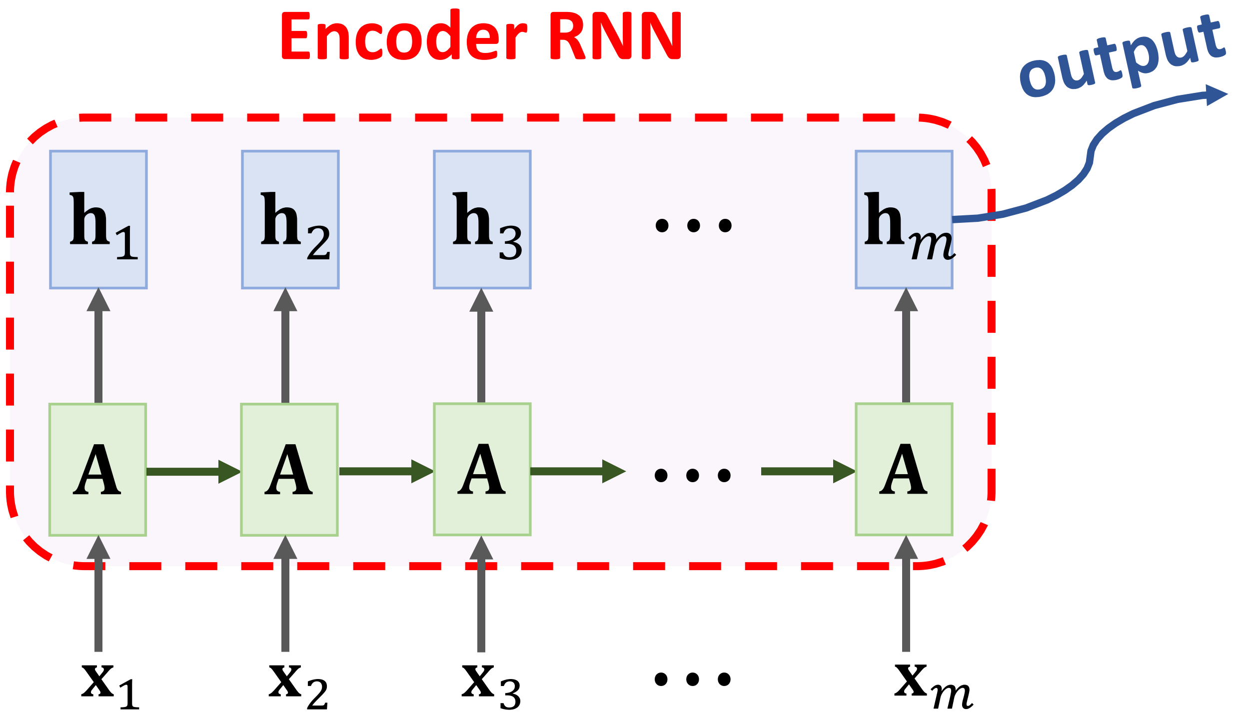
Revisiting Seq2Seq Model

Seq2Seq Model



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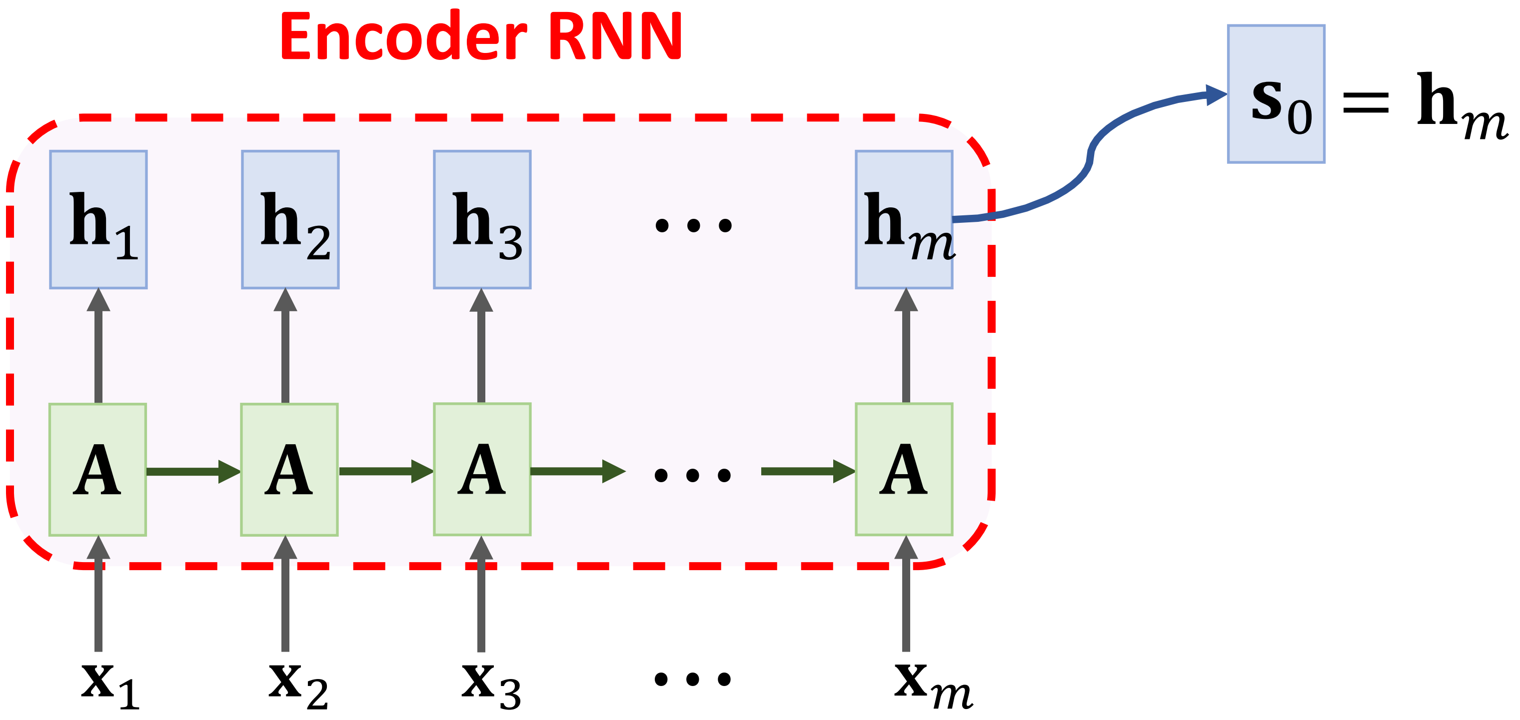

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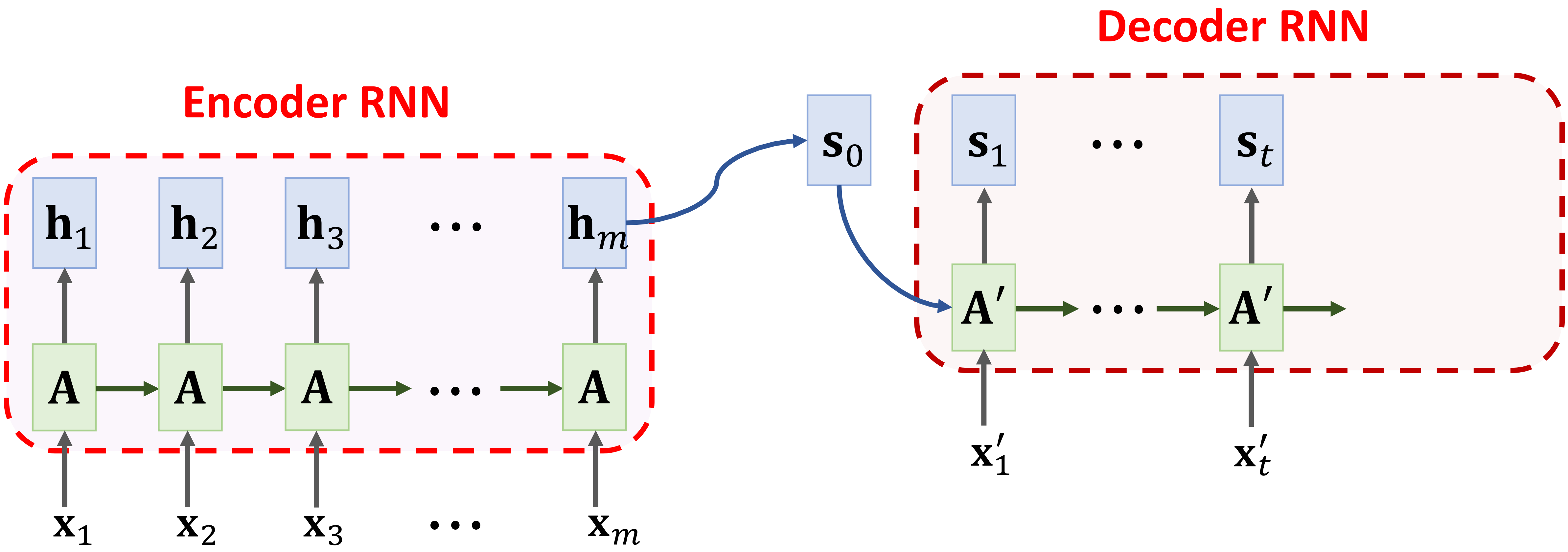
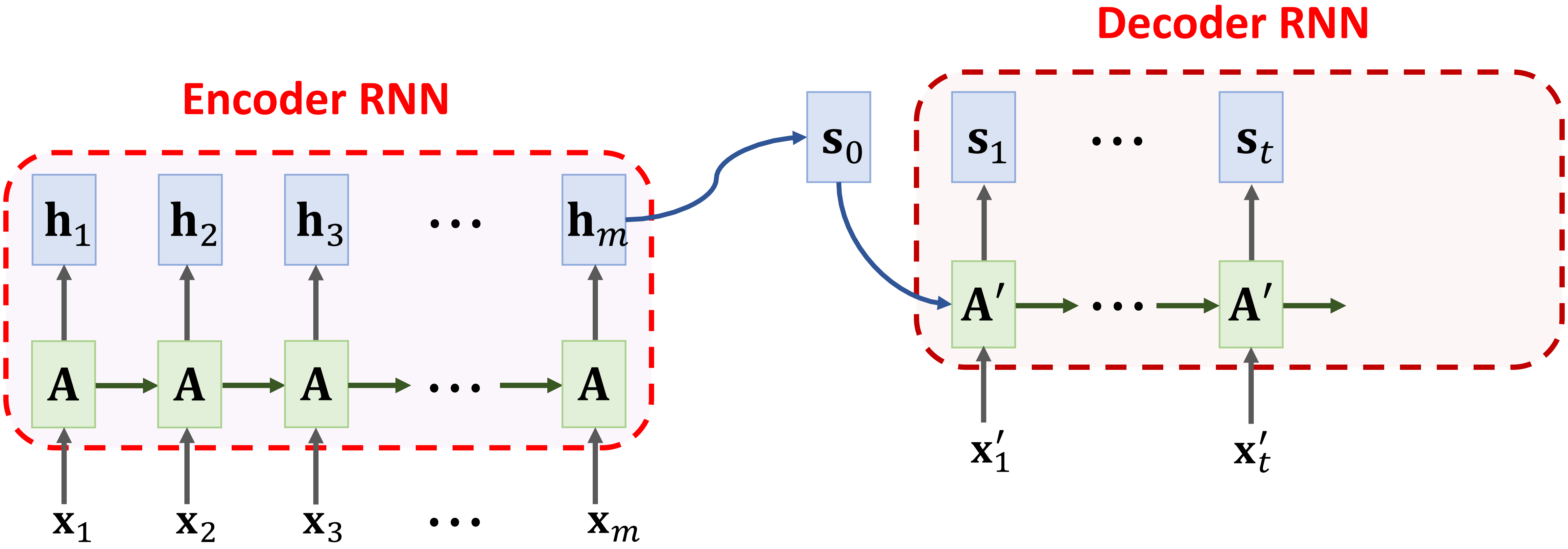


Seq2Seq Model

Shortcoming: The final state is incapable of remembering a **long** sequence.



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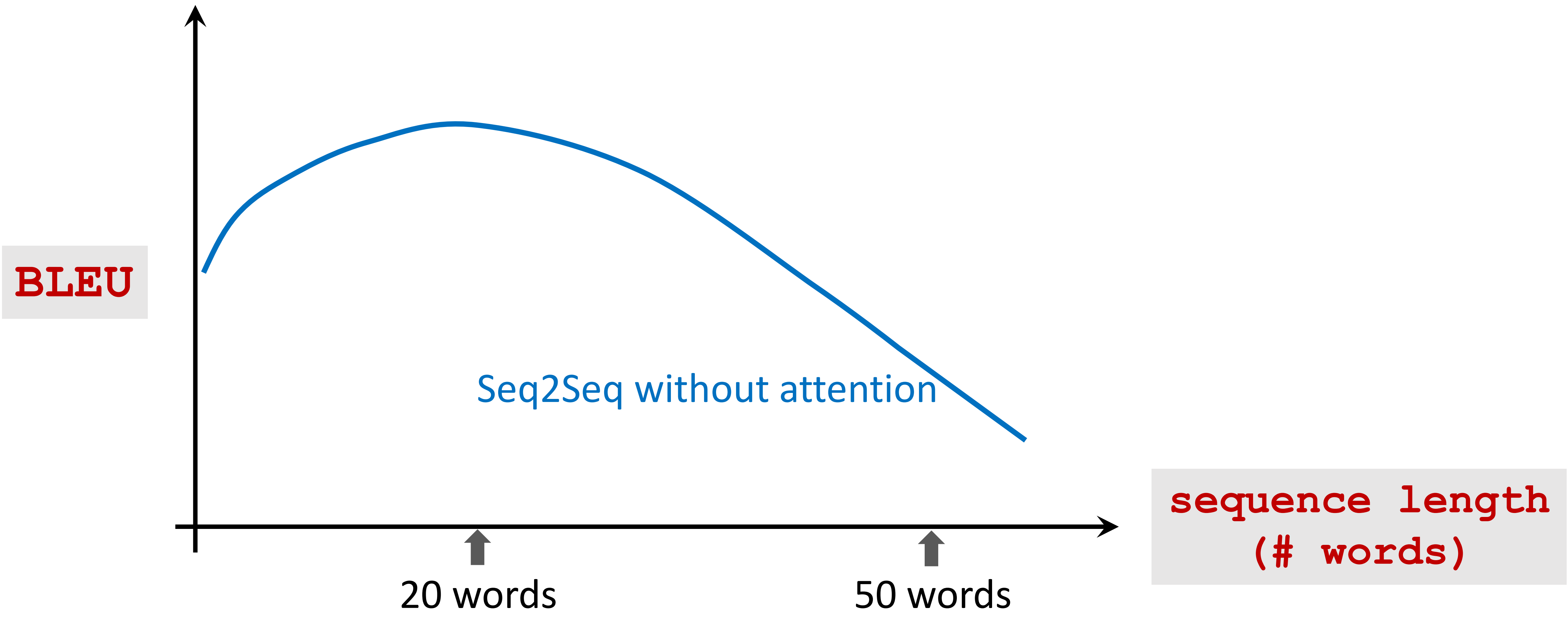

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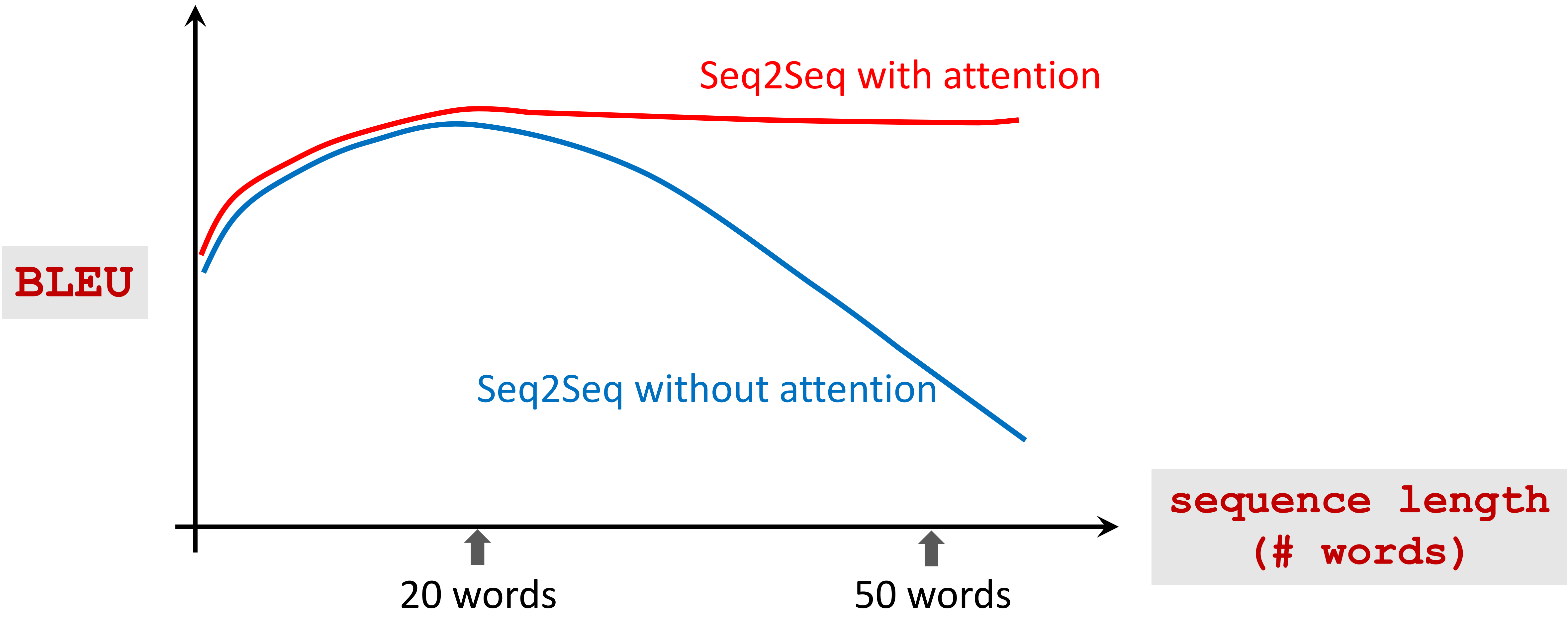


Attention for Seq2Seq Model

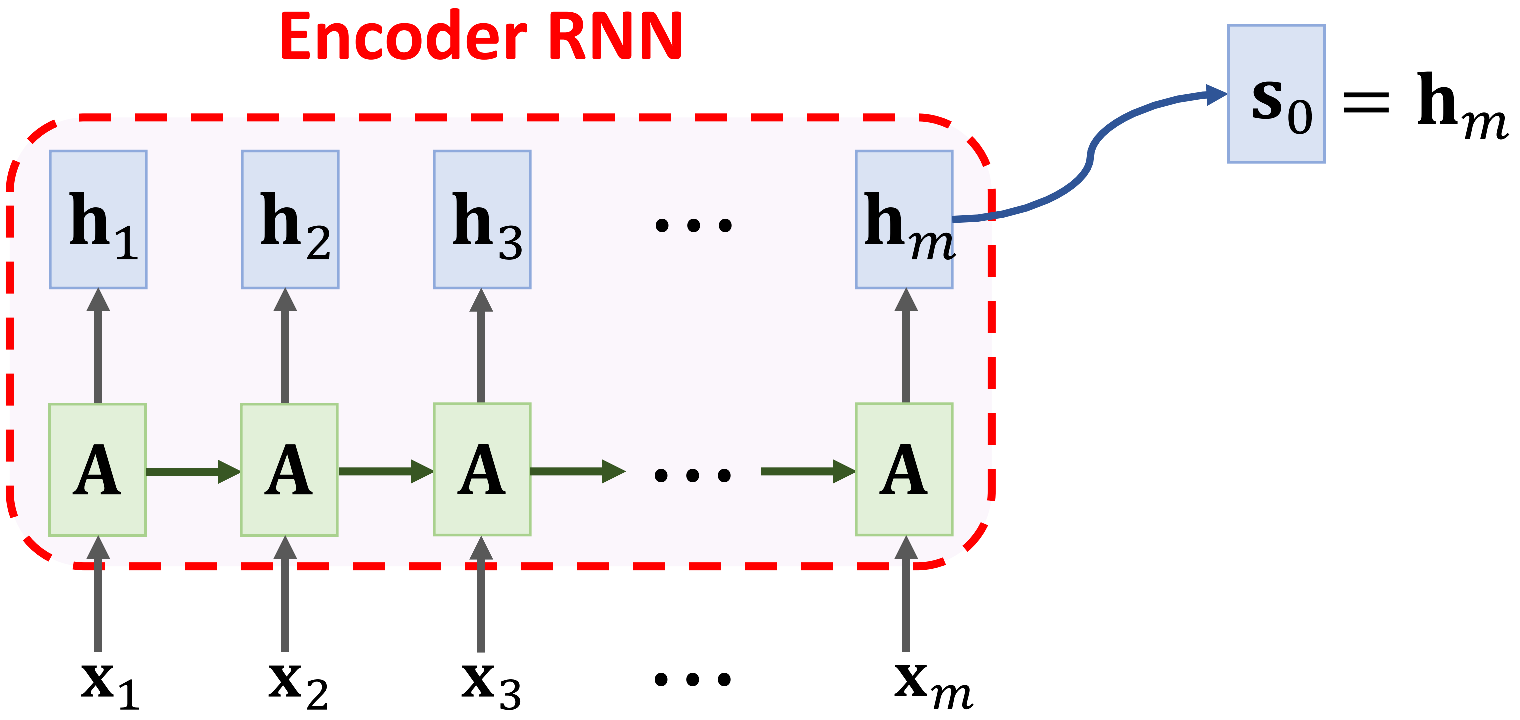
Seq2Seq Model with Attention

- Attention tremendously improves Seq2Seq model.
- With attention, Seq2Seq model does not forget source input.
- With attention, the decoder knows where to focus.
- Downside: much more computation.

Original paper:

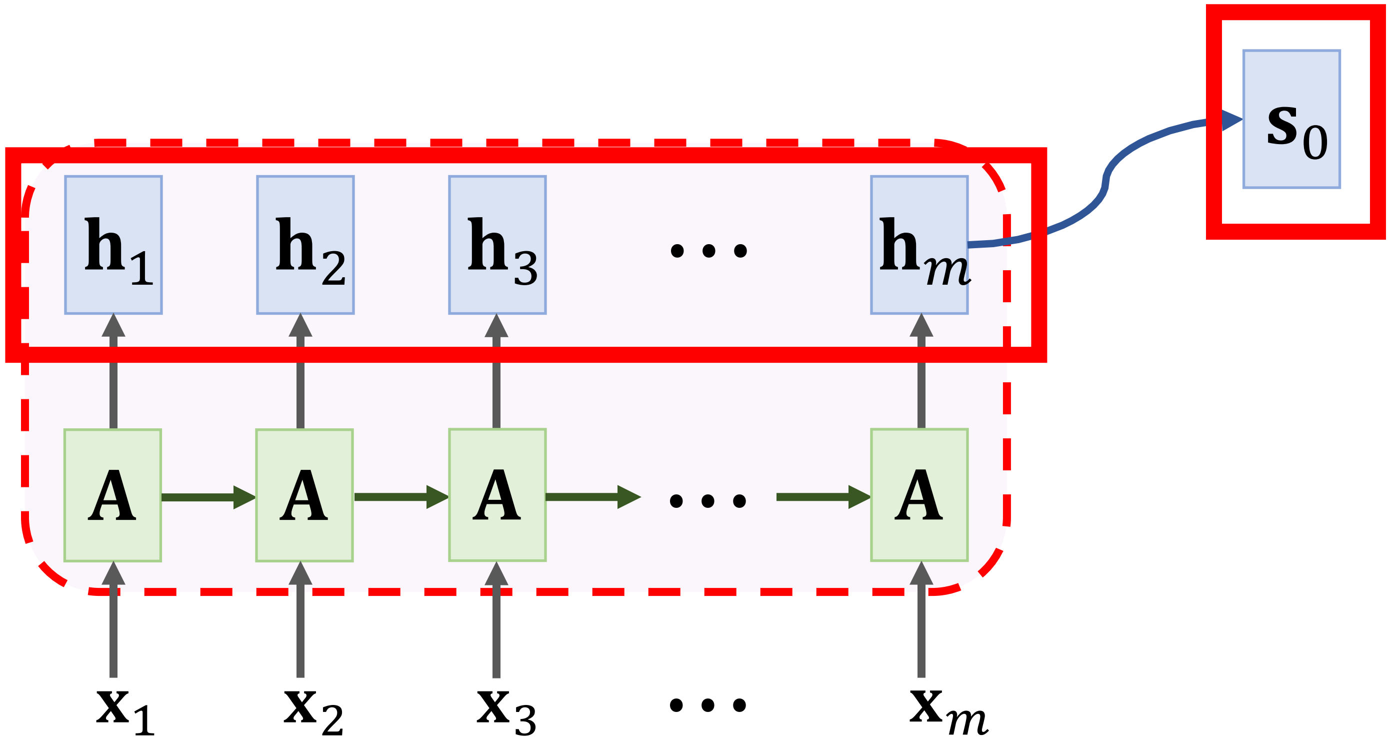
- Bahdanau, Cho, & Bengio. Neural machine translation by jointly learning to align and translate. In *ICLR*, 2015.

SimpleRNN + Attention



SimpleRNN + Attention

Weight: $\alpha_i = \mathrm{align}(\mathbf{h}_i, \mathbf{s}_0).$



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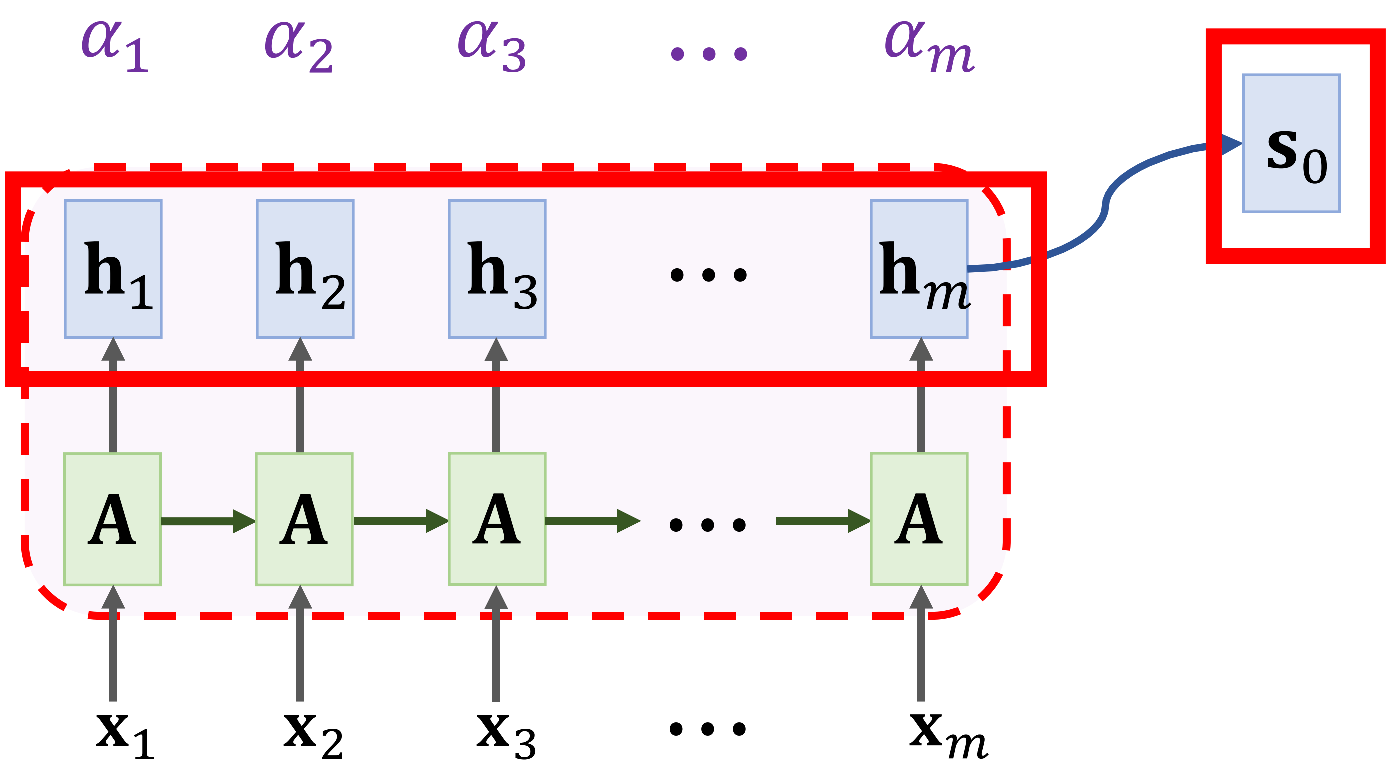

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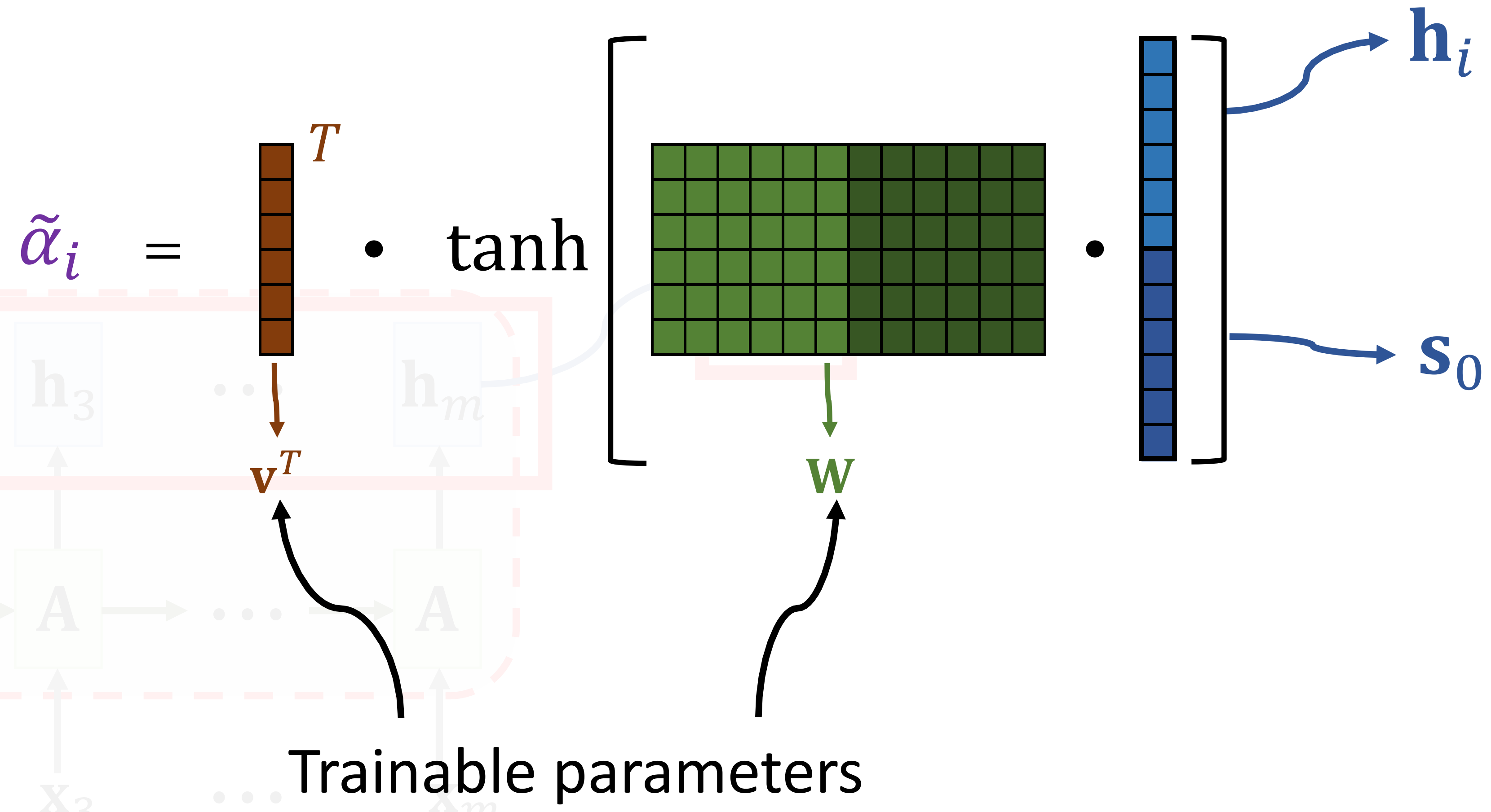
Option 1 (used in the original paper):



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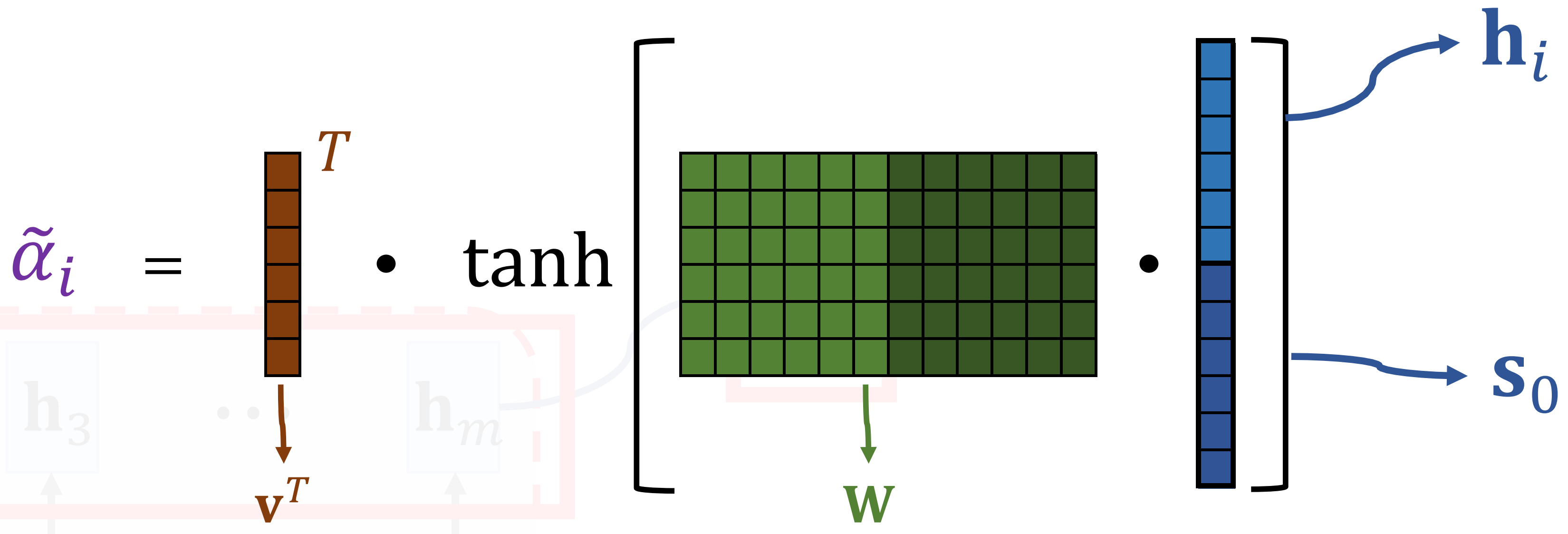

$$\tilde{\alpha}_i = \mathbf{v}^T \cdot \tanh\left(\mathbf{W} \cdot \begin{bmatrix} \mathbf{h}_i \\ \mathbf{s}_0 \end{bmatrix} \right)$$

Then **normalize** $\tilde{\alpha}_1, \cdots, \tilde{\alpha}_m$ (so that they sum to 1):

$$[\alpha_1, \cdots, \alpha_m] = \mathrm{Softmax}\left([\tilde{\alpha}_1, \cdots, \tilde{\alpha}_m]\right).$$

SimpleRNN + Attention

Weight: $\alpha_i = \text{align}(\mathbf{h}_i, \mathbf{s}_0)$.

Option 2 (more popular; the same to Transformer):

1. Linear maps:
   - $\mathbf{k}_i = \mathbf{W}_K \cdot \mathbf{h}_i$, for $i = 1$ to m.
   - $\mathbf{q}_0 = \mathbf{W}_Q \cdot \mathbf{s}_0$.
2. Inner product:
   - $\tilde{\alpha}_i = \mathbf{k}_i^T \mathbf{q}_0$, for $i = 1$ to m.
3. Normalization:
   - $[\alpha_1, \cdots, \alpha_m] = \text{Softmax}\left([\tilde{\alpha}_1, \cdots, \tilde{\alpha}_m]\right)$.

SimpleRNN + Attention

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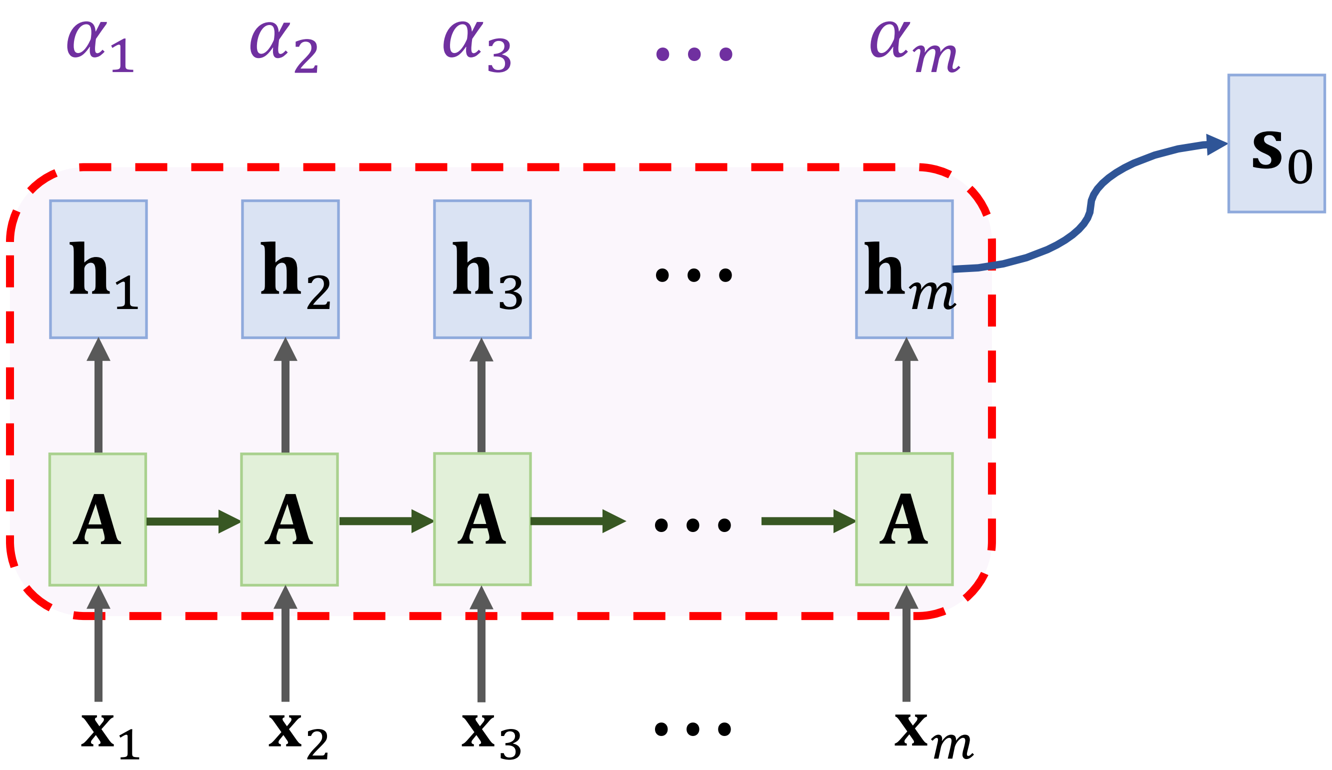
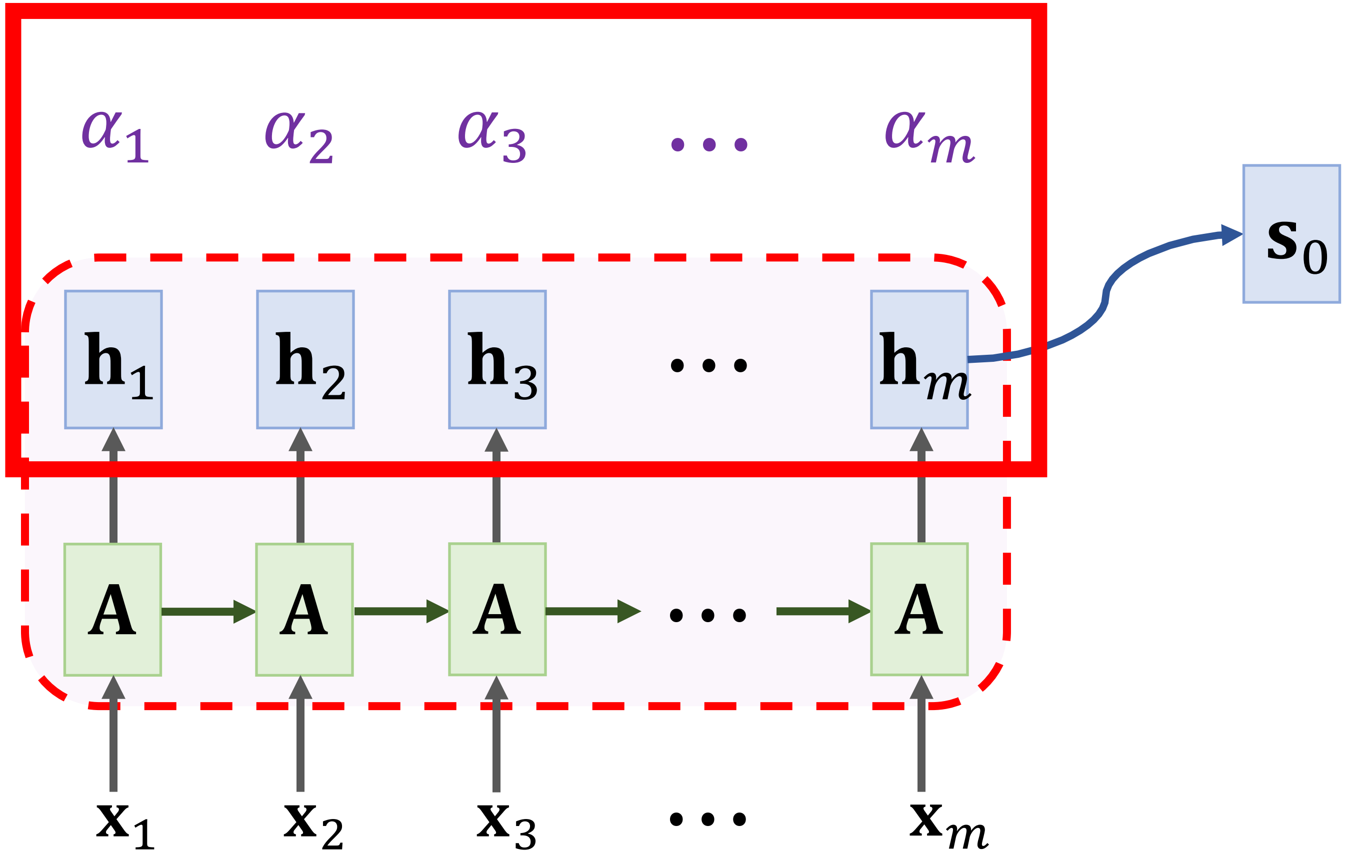


SimpleRNN + Attention

Weight: $\alpha_i = \text{align}(\mathbf{h}_i, \mathbf{s}_0).$

Context vector: $\mathbf{c}_0 = \alpha_1 \mathbf{h}_1 + \cdots + \alpha_m \mathbf{h}_m.$



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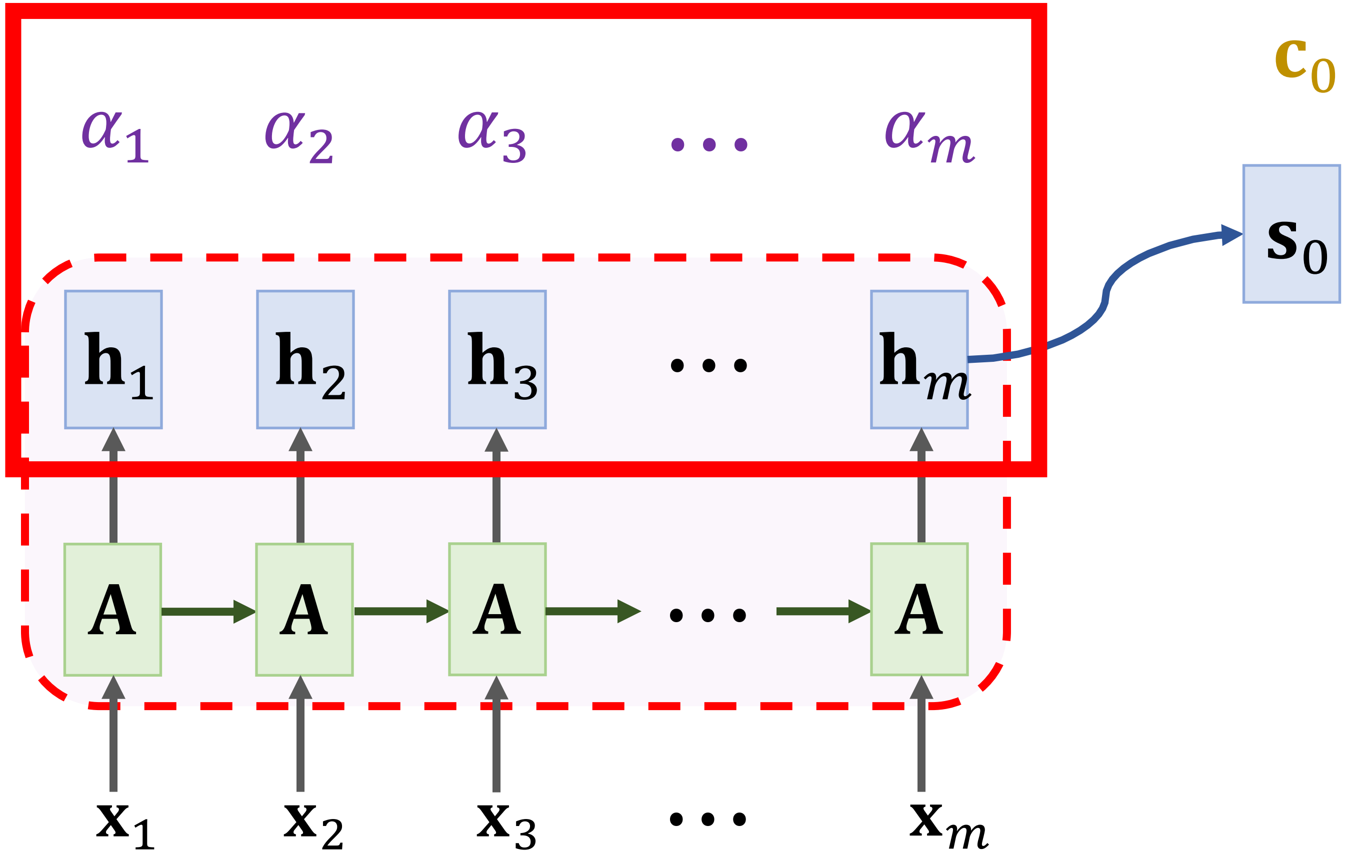

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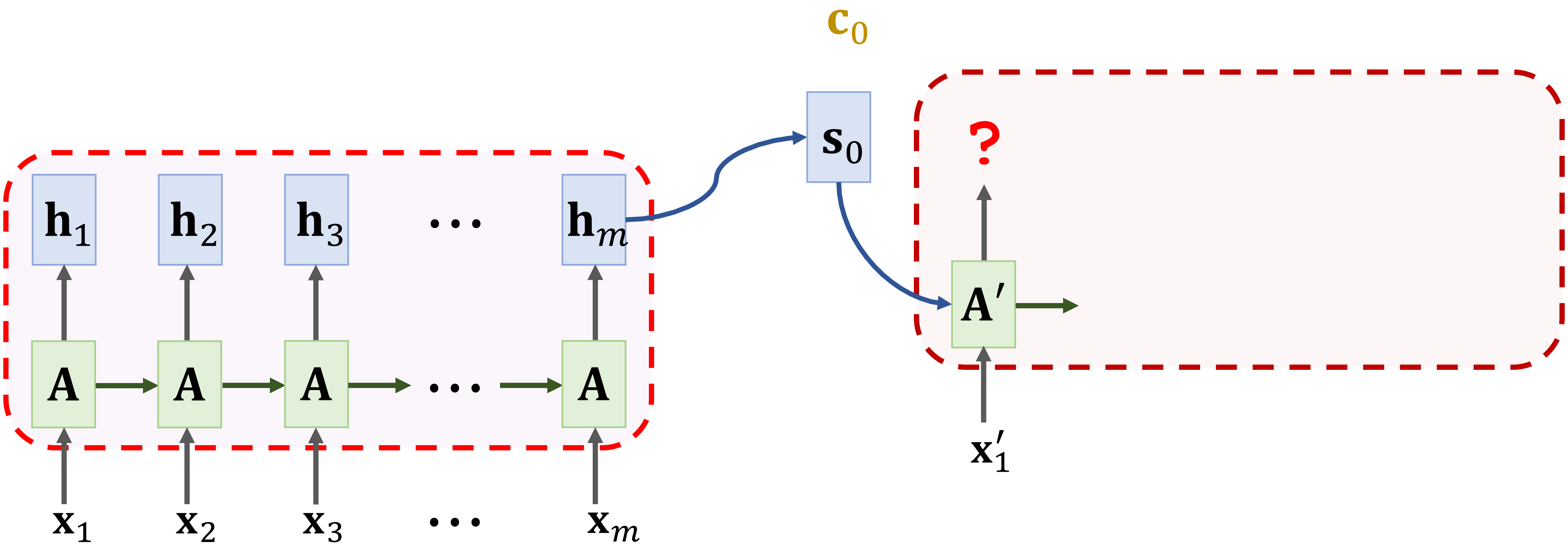
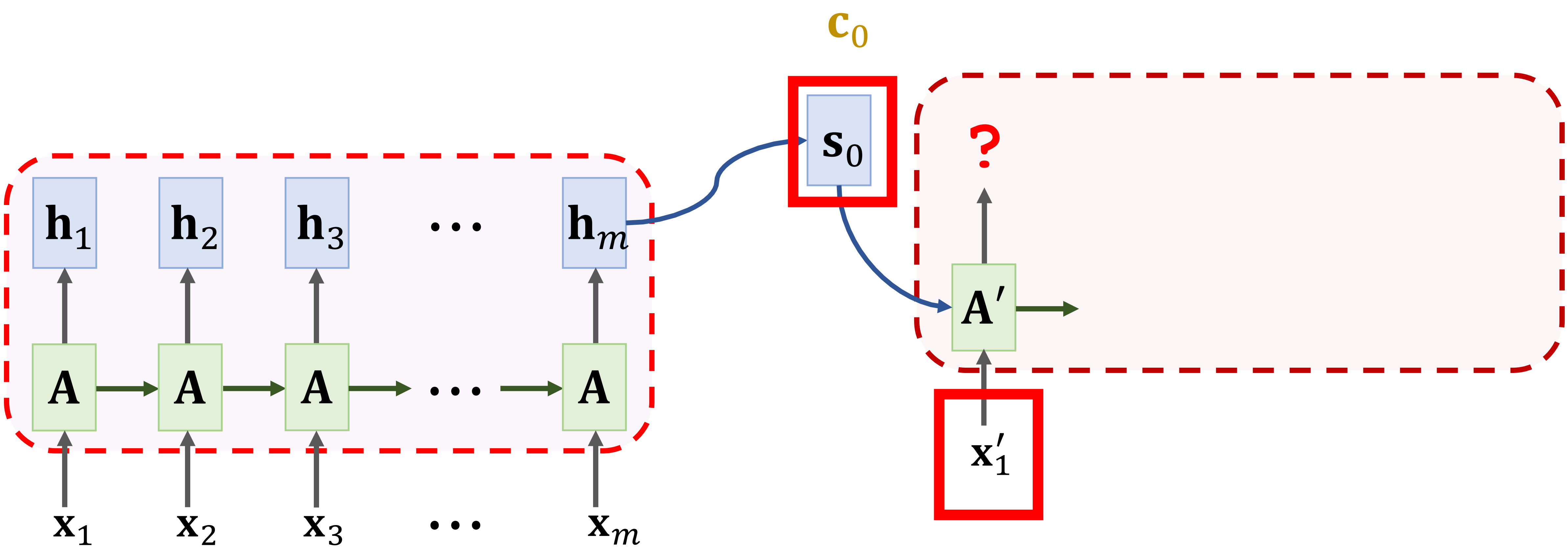


SimpleRNN

SimpleRNN:

$$\mathbf{s}_1 = \tanh\left(\mathbf{A}' \cdot \begin{bmatrix} \mathbf{x}'_1 \\ \mathbf{s}_0 \end{bmatrix} + \mathbf{b}\right)$$



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SimpleRNN + Attention:

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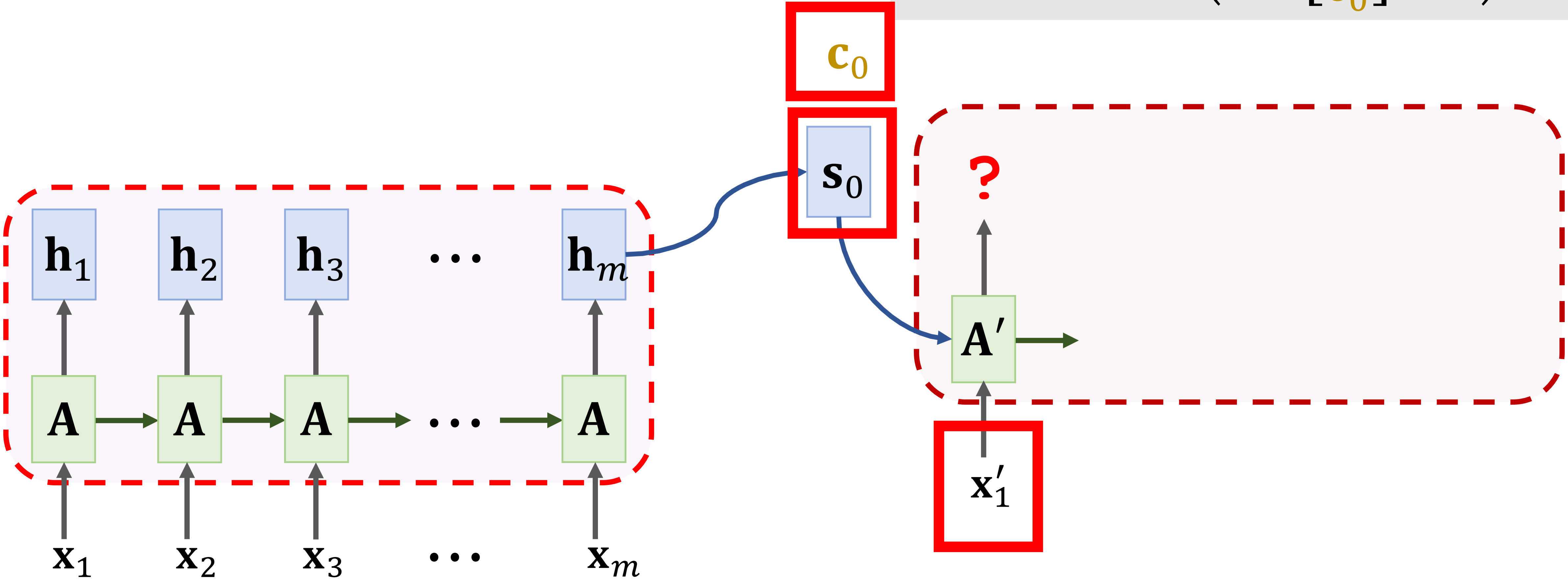

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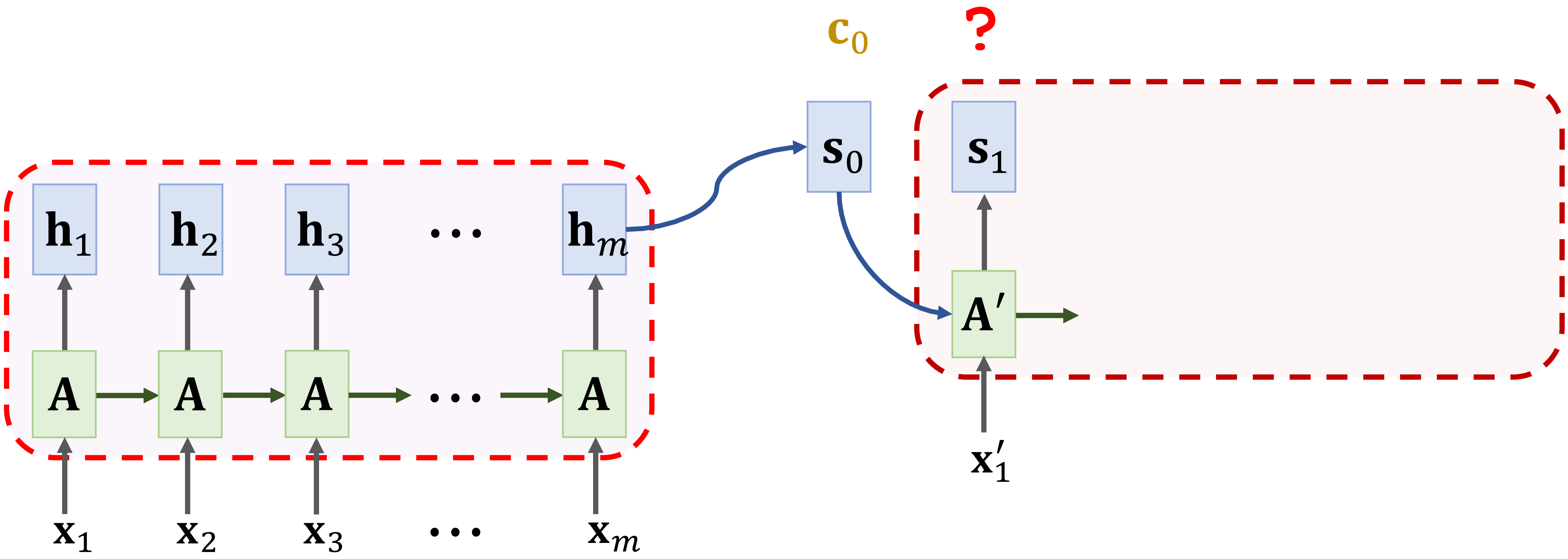

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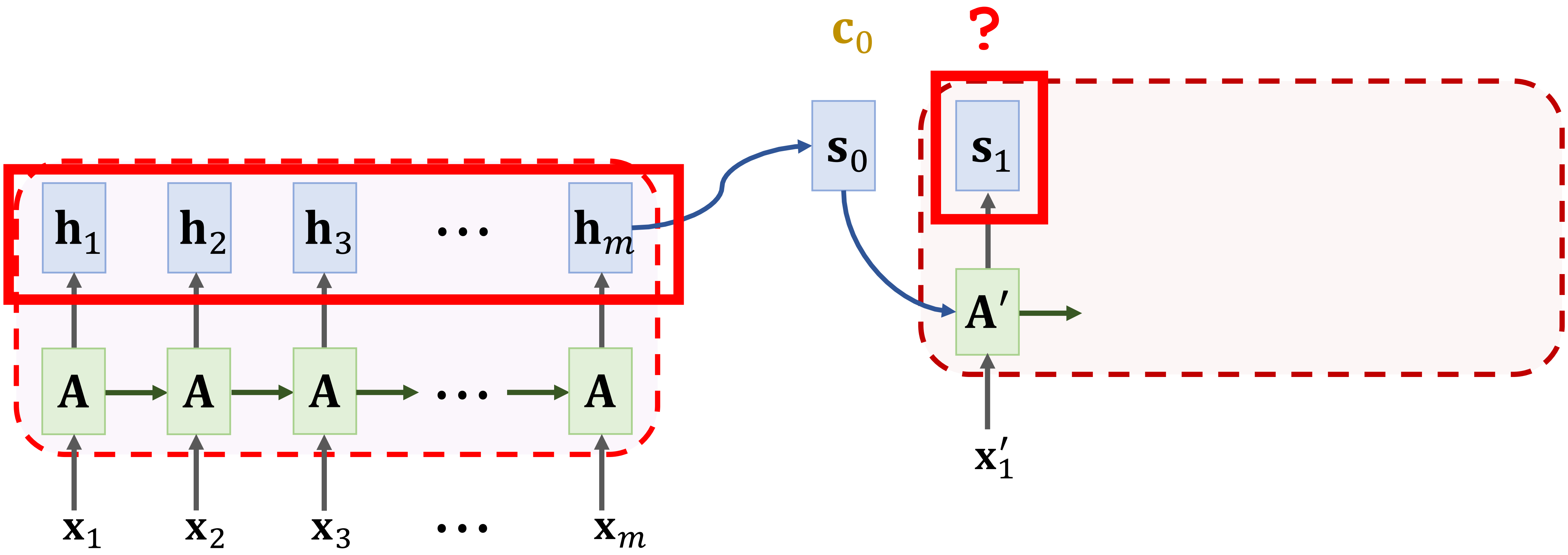

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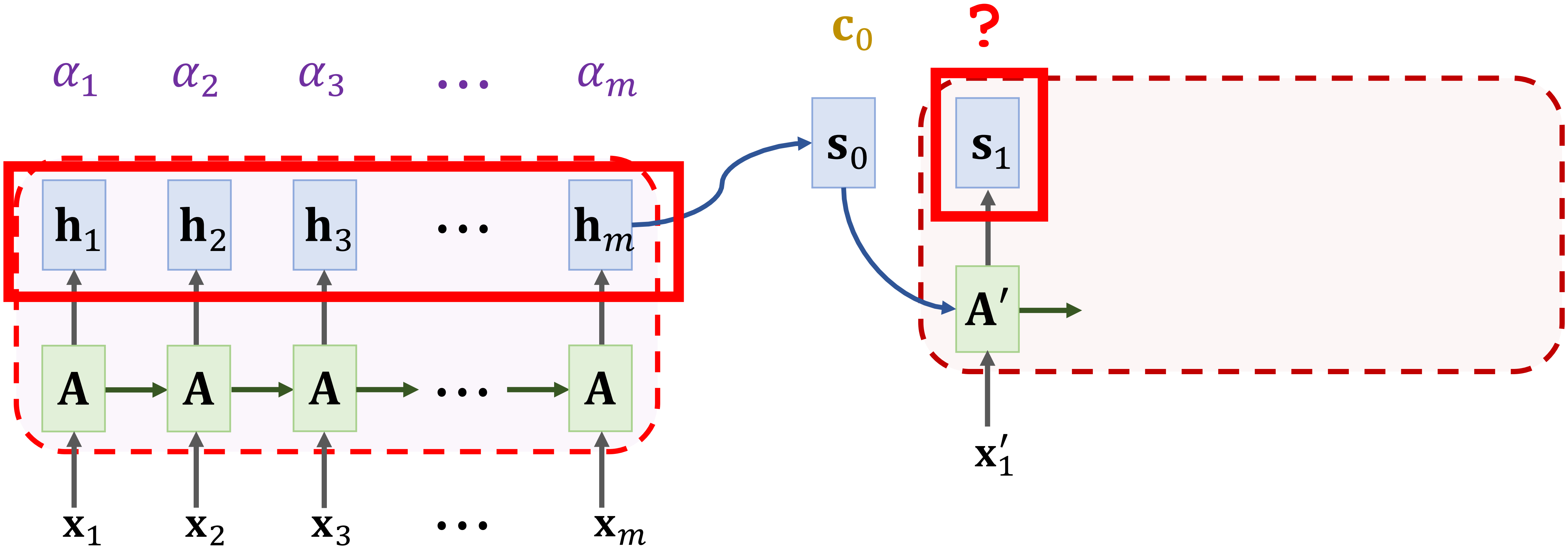

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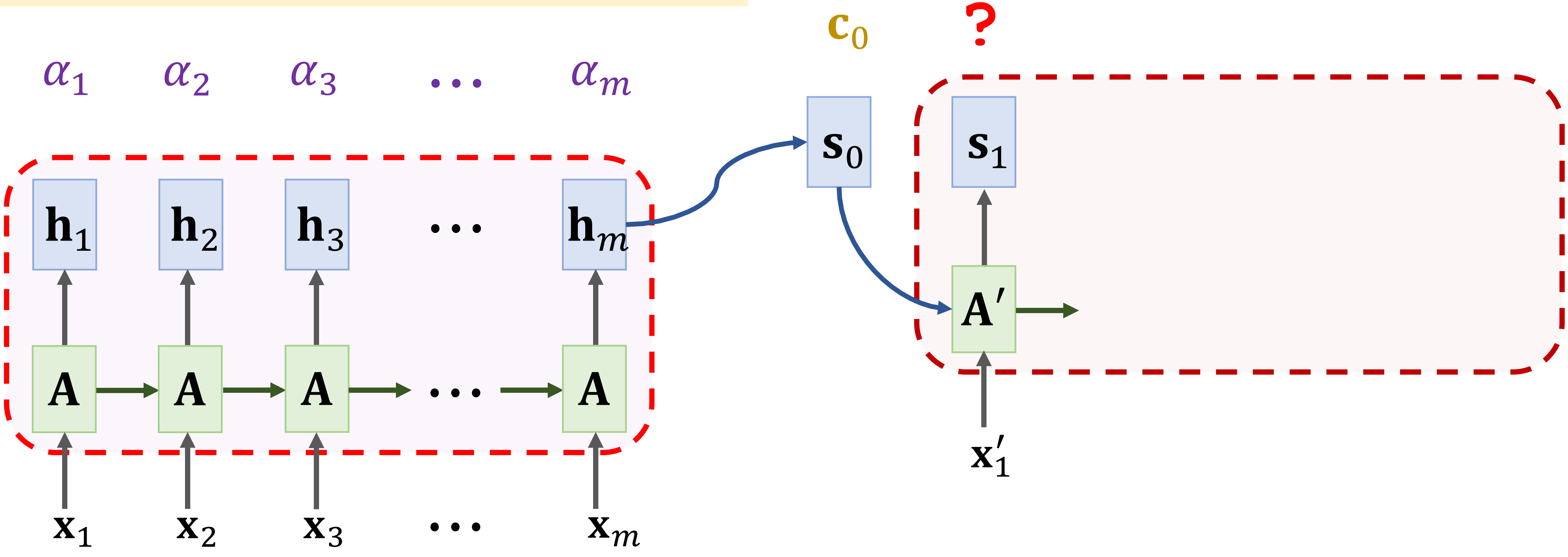
Do not re-use the α's computed previously.



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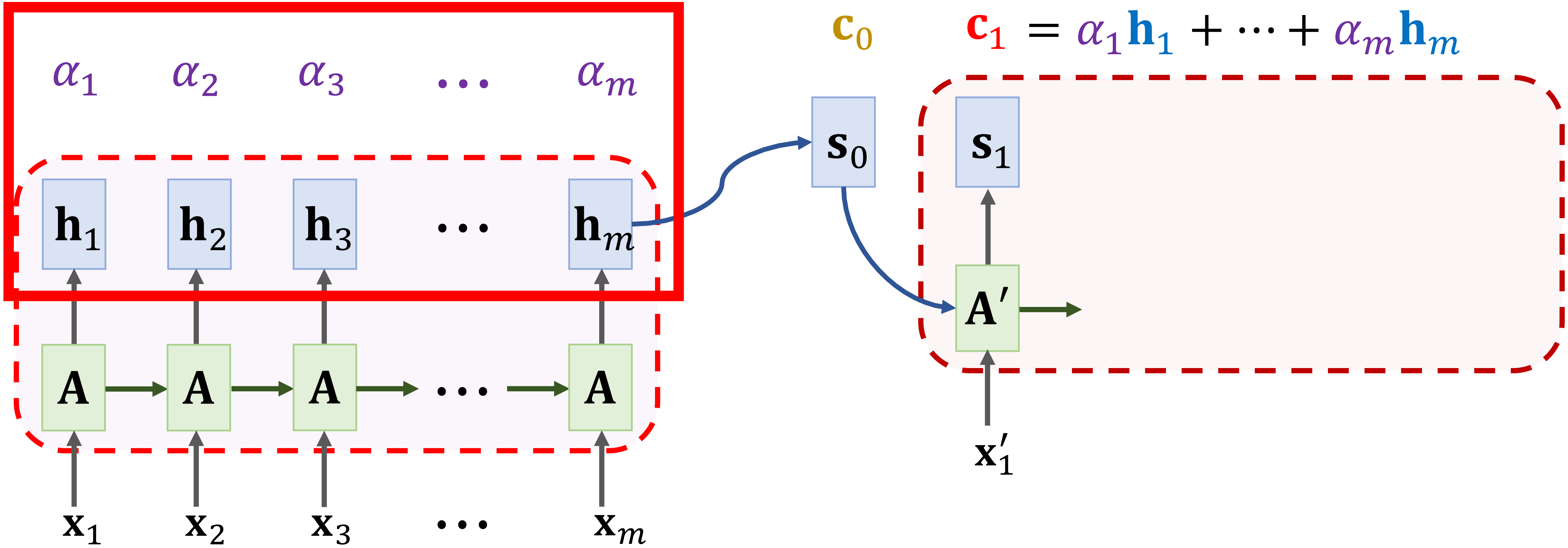
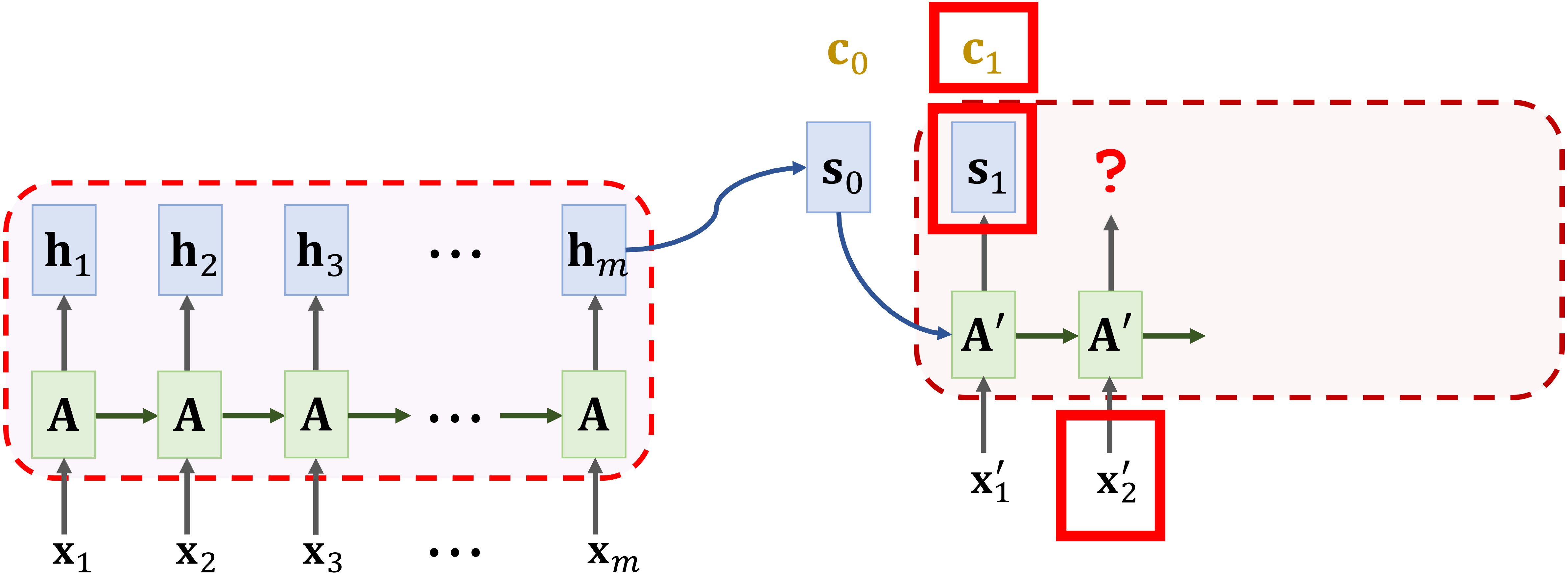


SimpleRNN + Attention

$$\mathbf{s}_2 = \tanh\left(\mathbf{A}' \cdot \begin{bmatrix} \mathbf{x}'_2 \\ \mathbf{s}_1 \\ \mathbf{c}_1 \end{bmatrix} + \mathbf{b}\right)$$



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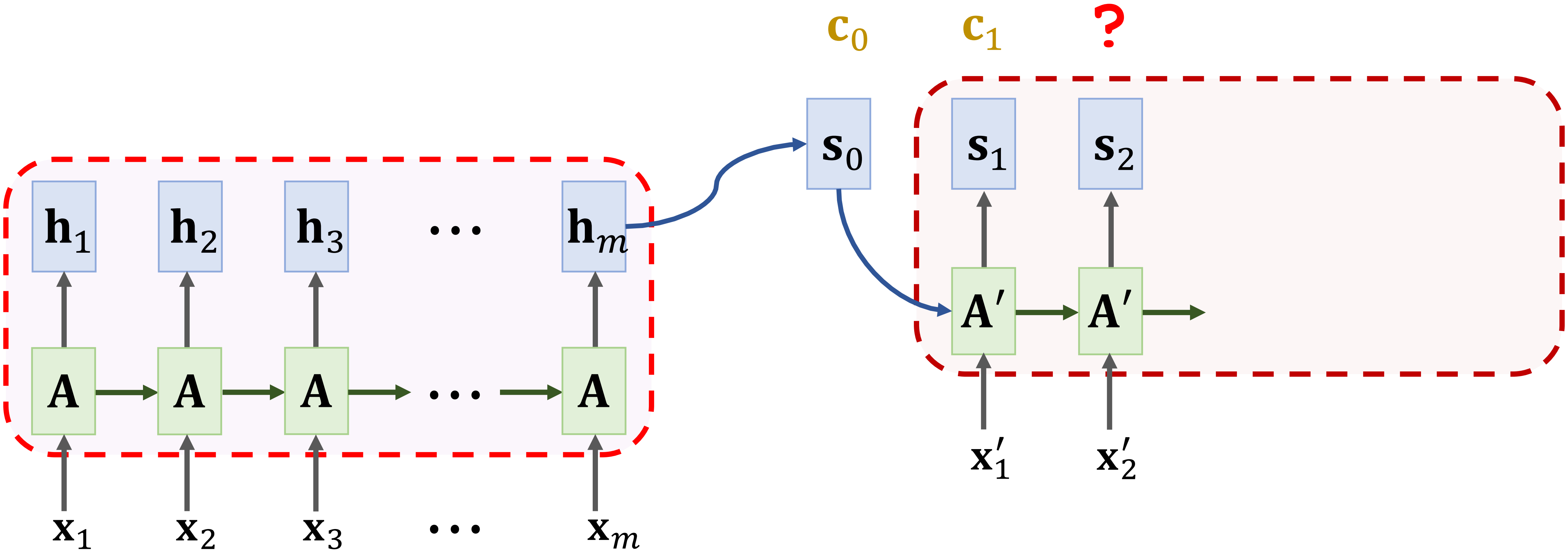

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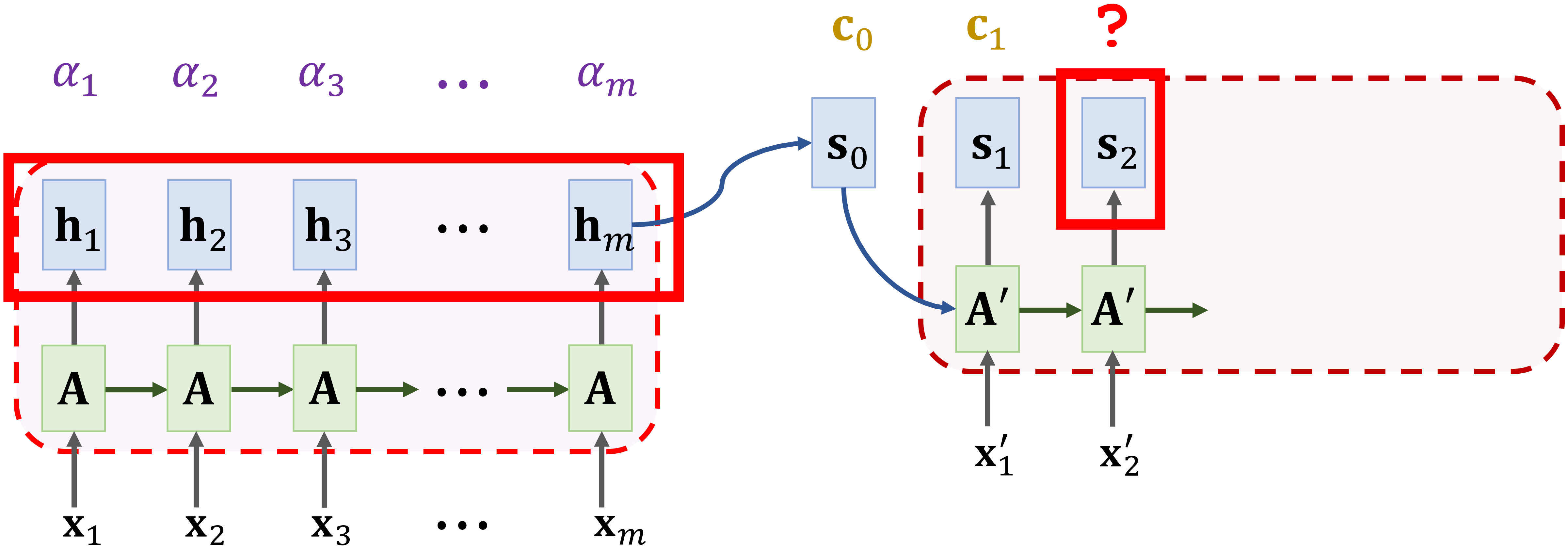

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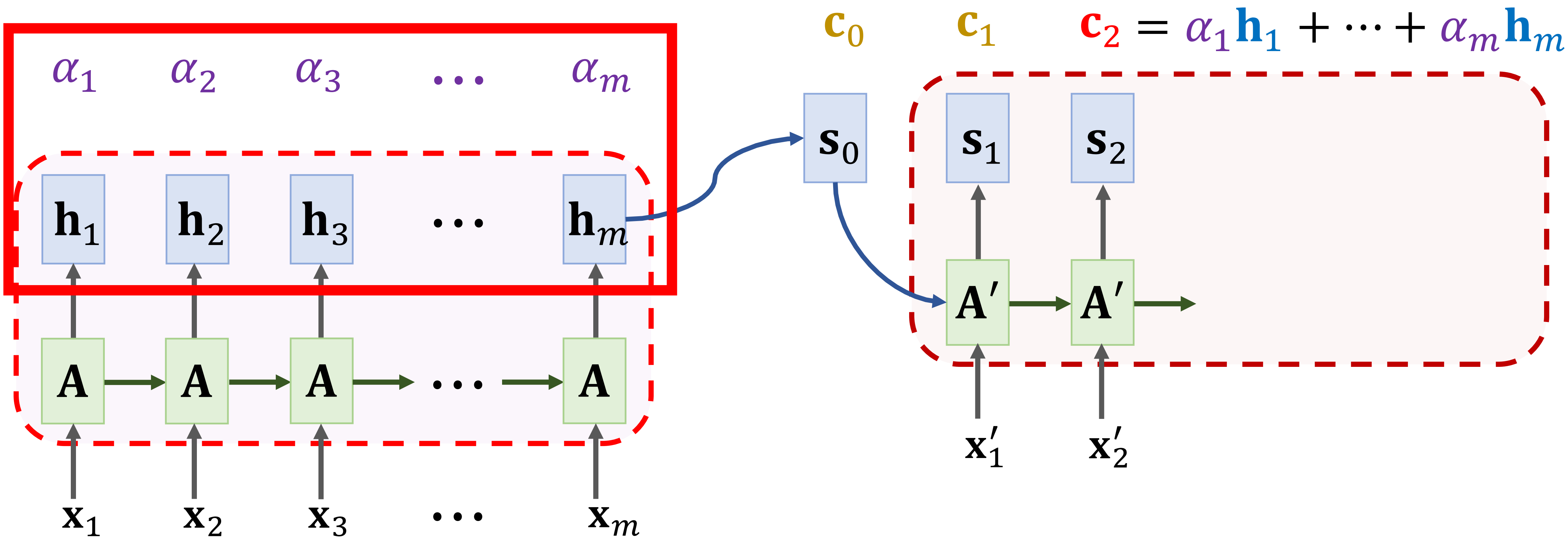

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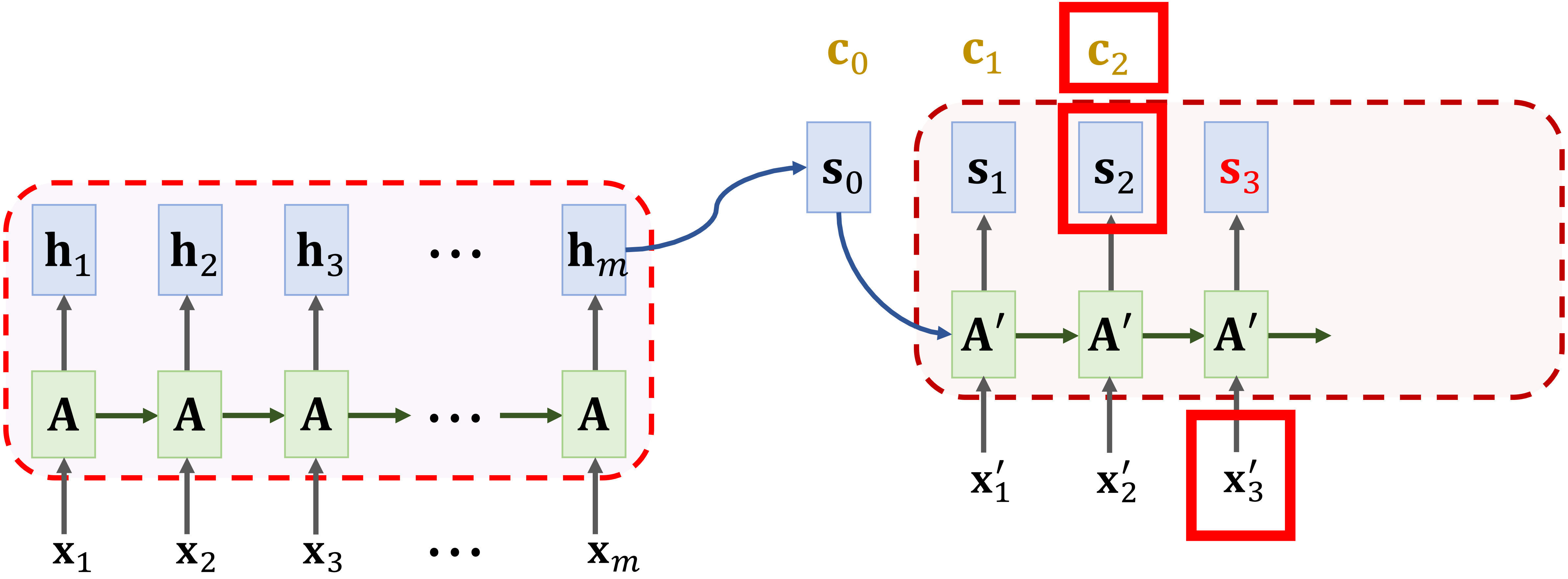

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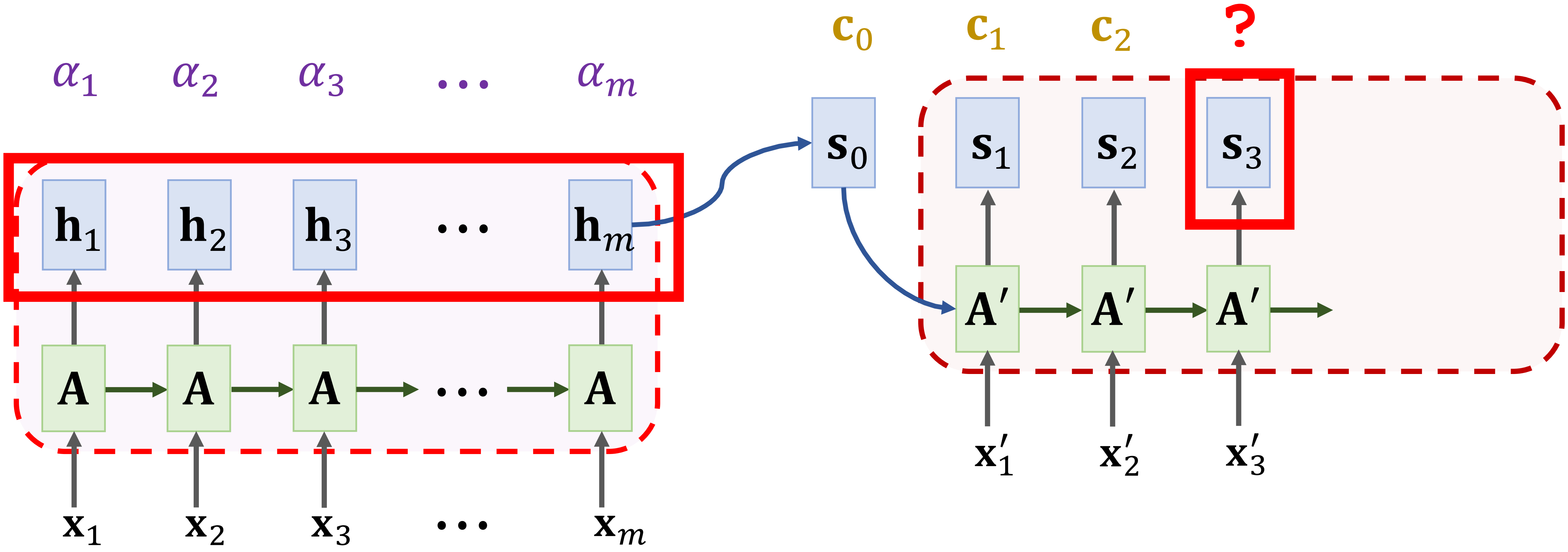

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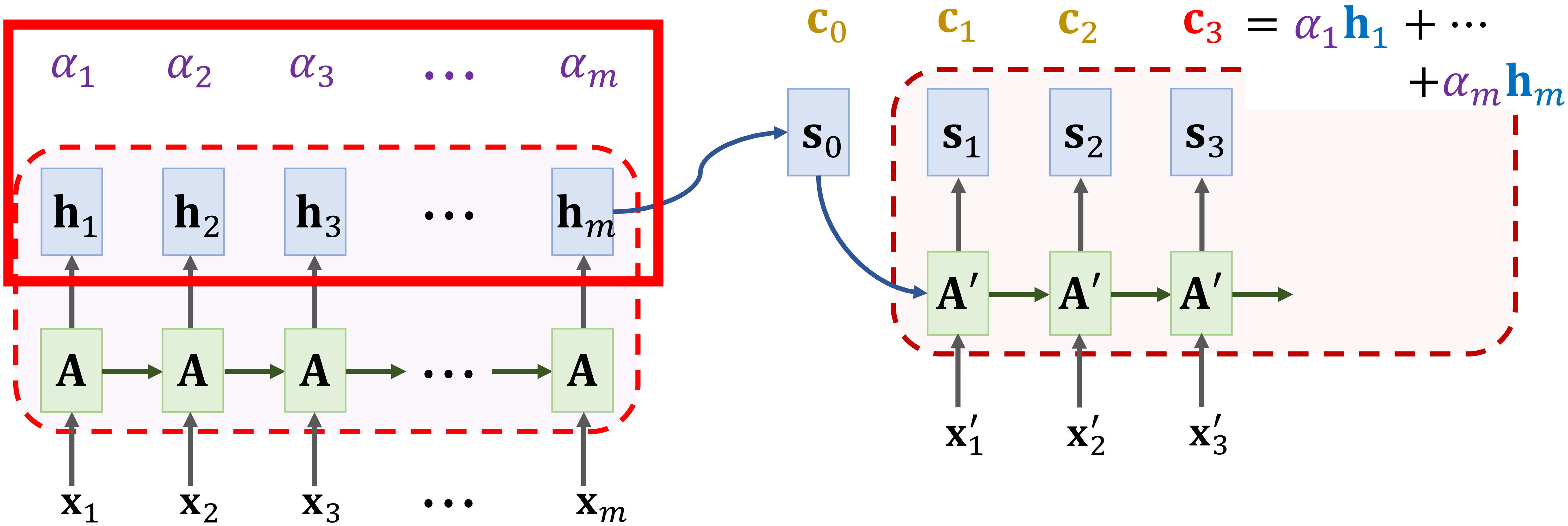

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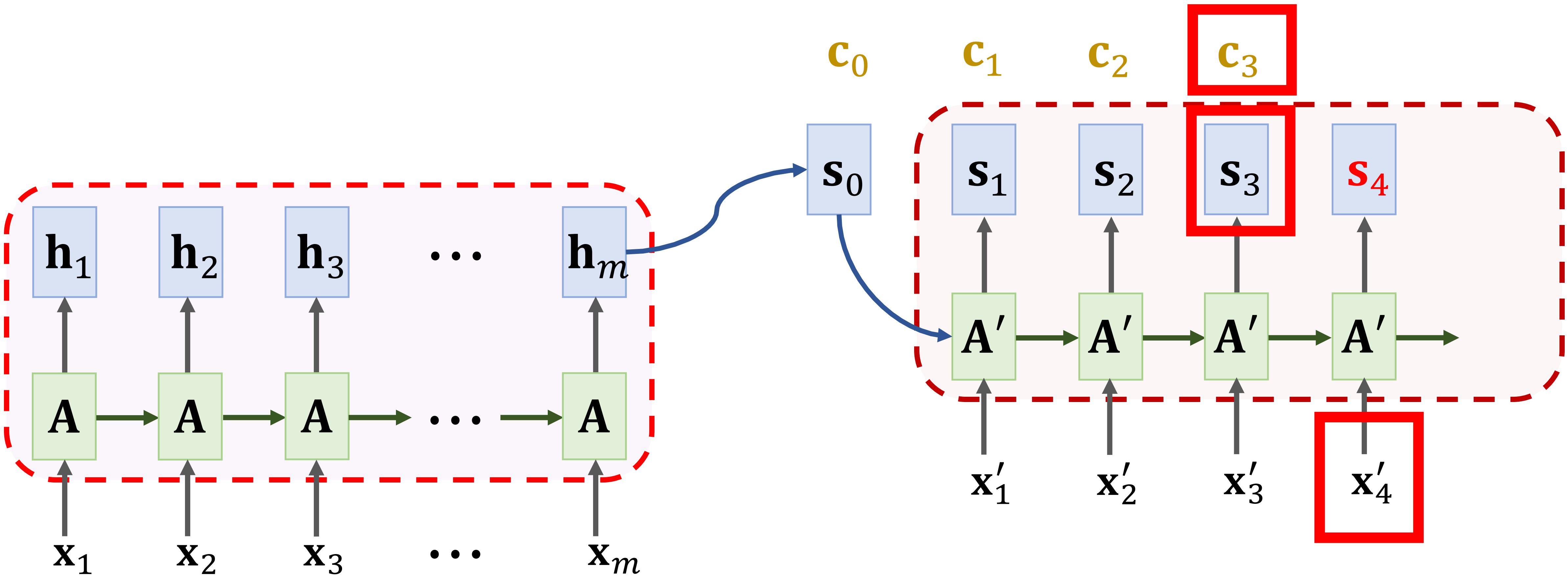

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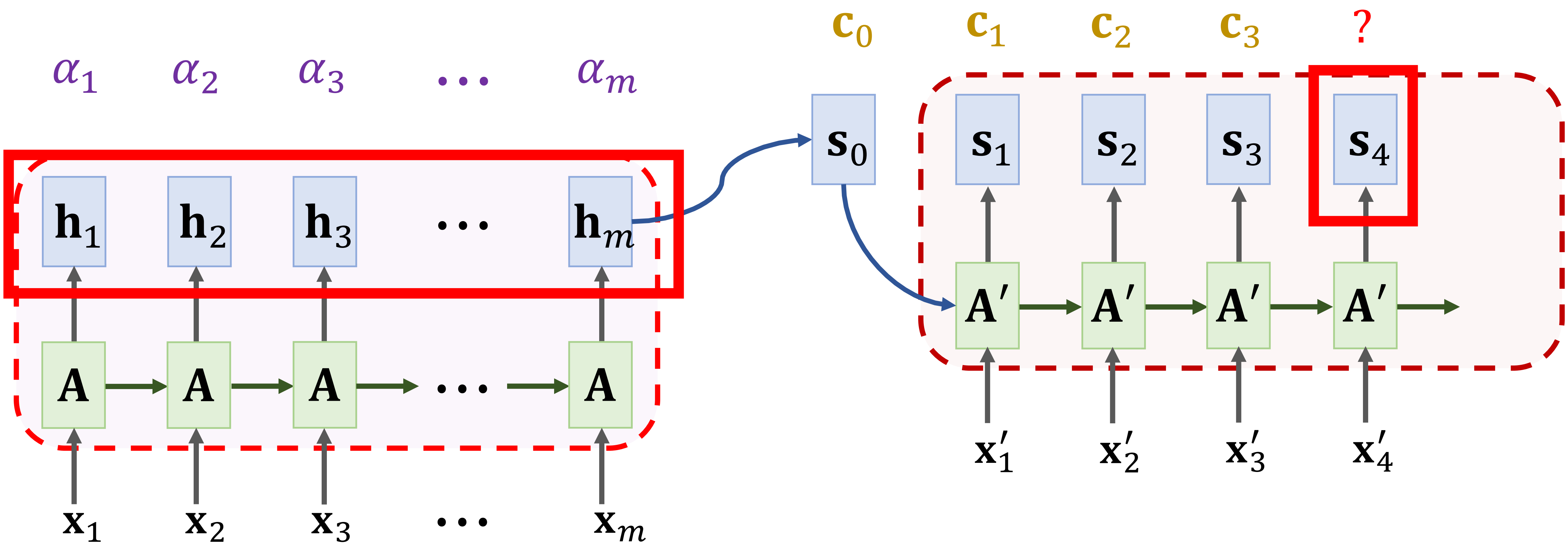

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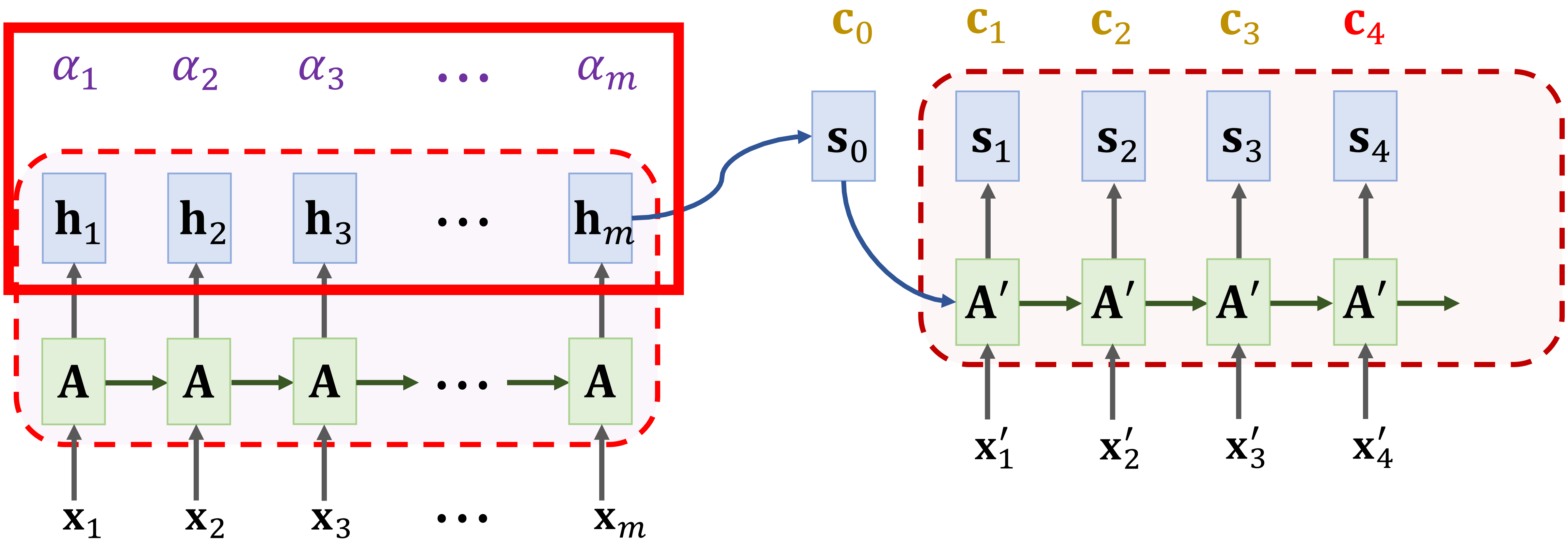

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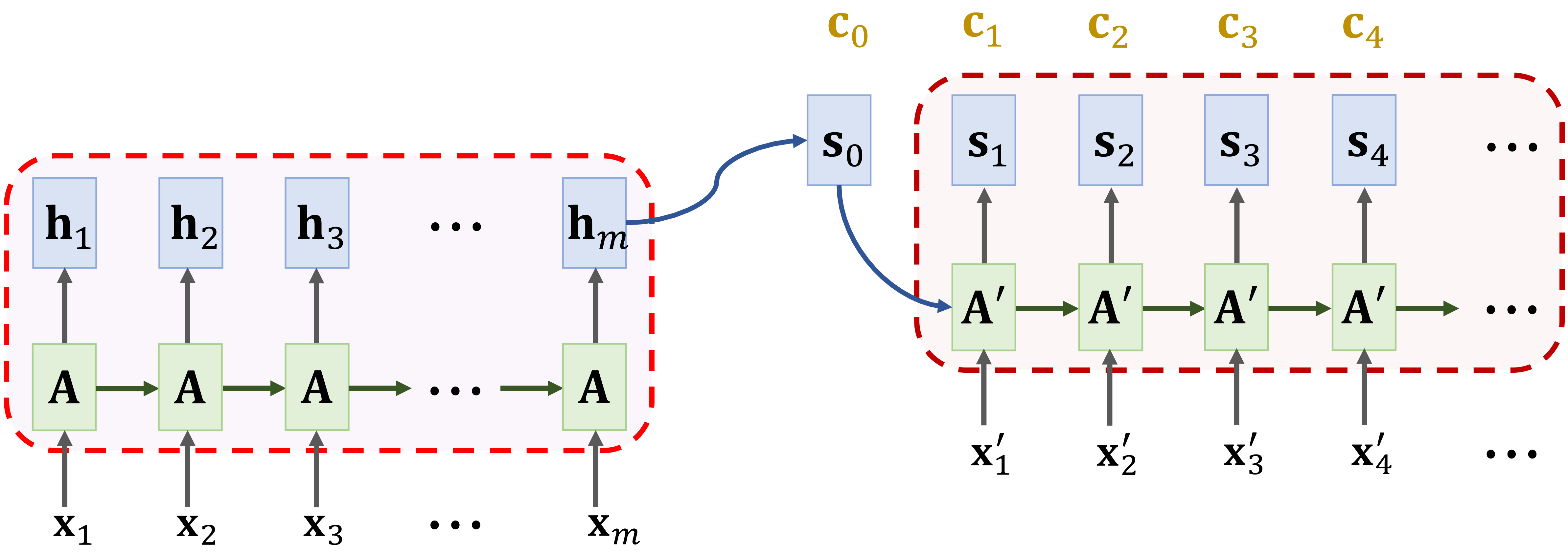
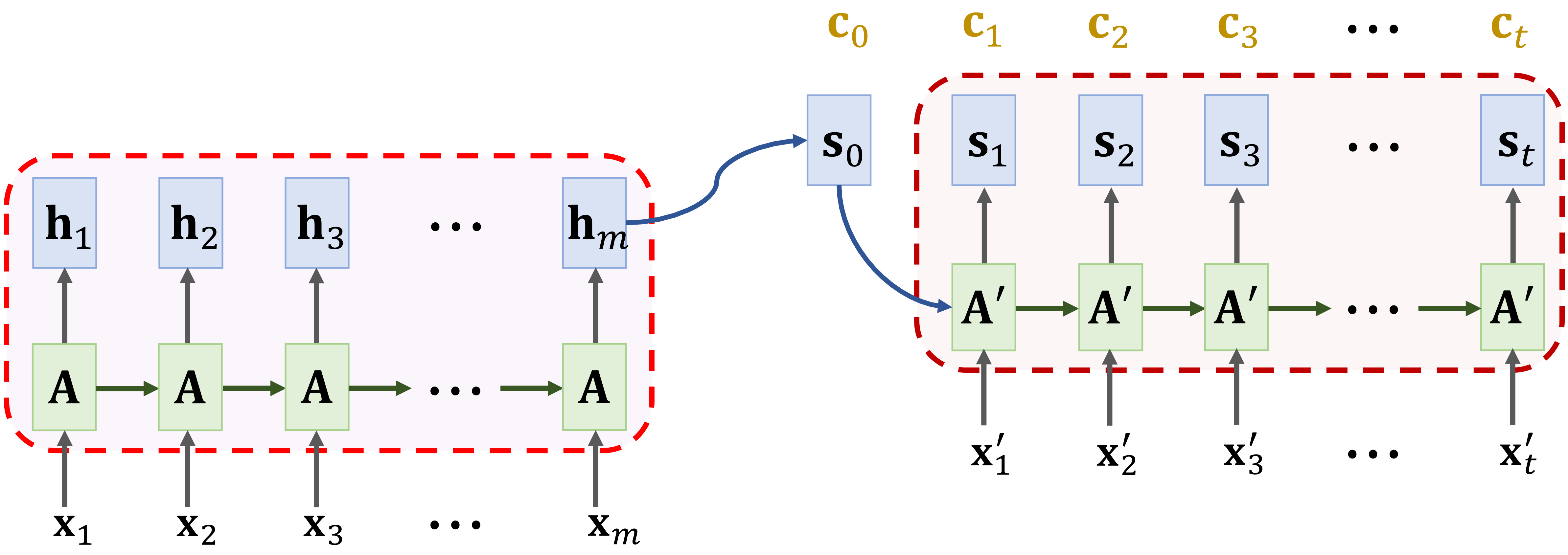


Time Complexity

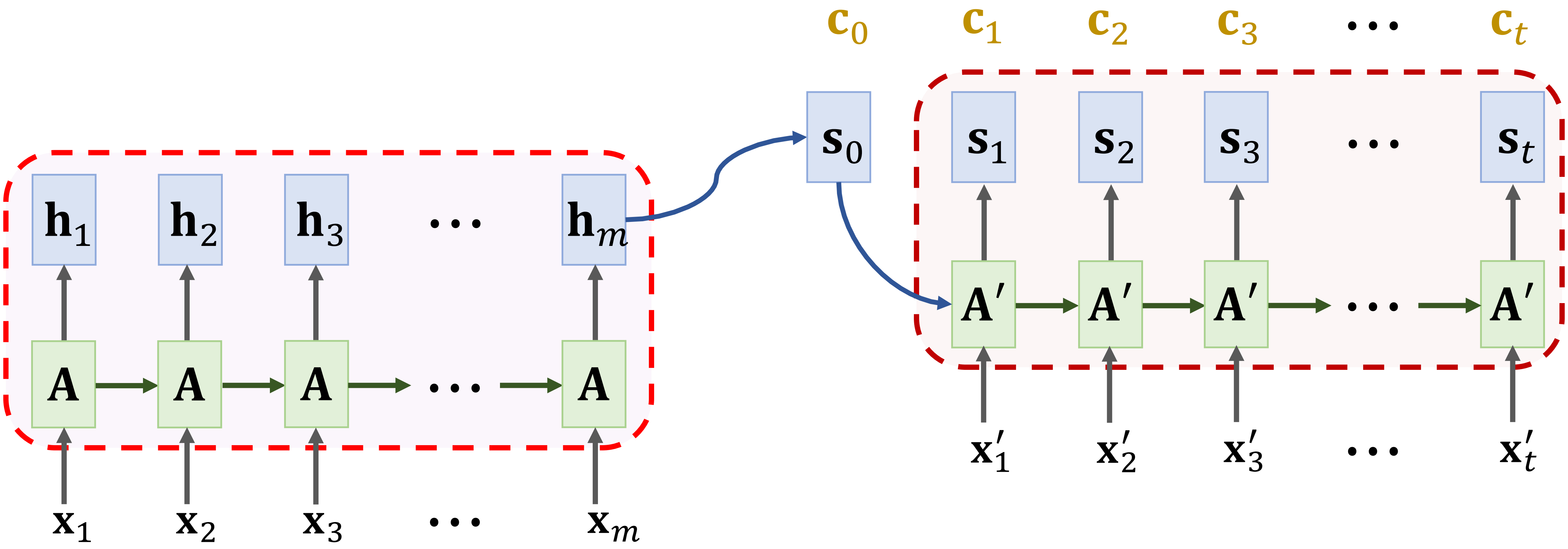
Question: How many weights α_i have been computed?



Time Complexity

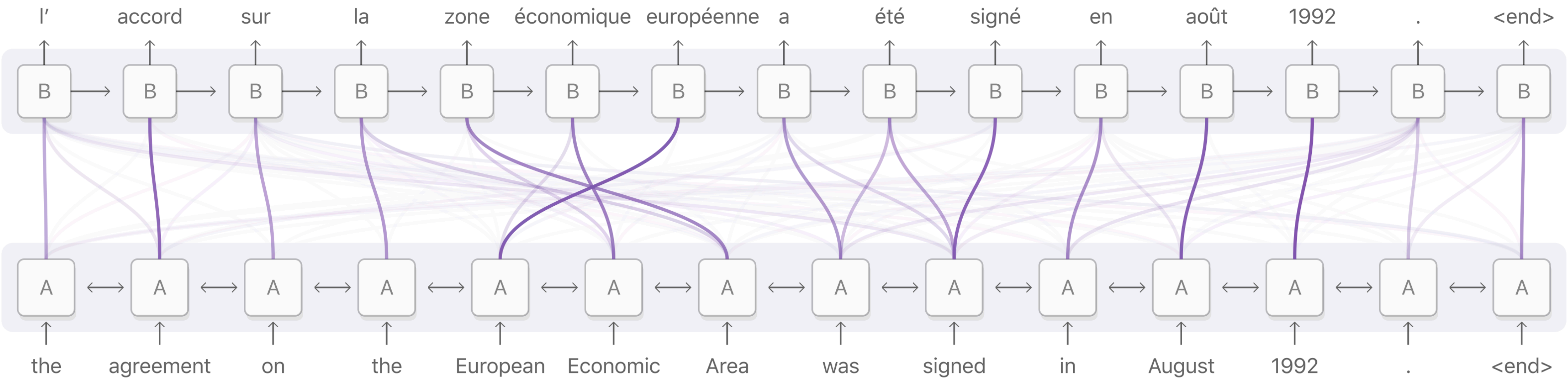
Question: How many weights α_i have been computed?

- To compute one vector $\mathbf{c}_j$, we compute m weights: $\alpha_1, \cdots, \alpha_m$.
- The decode has t states, so there are totally mt weights.



Attention: Weights Visualization

Decoder RNN (target language: French)



Encoder RNN (source language: English)

Figure is from https://distill.pub/2016/augmented-rnns/

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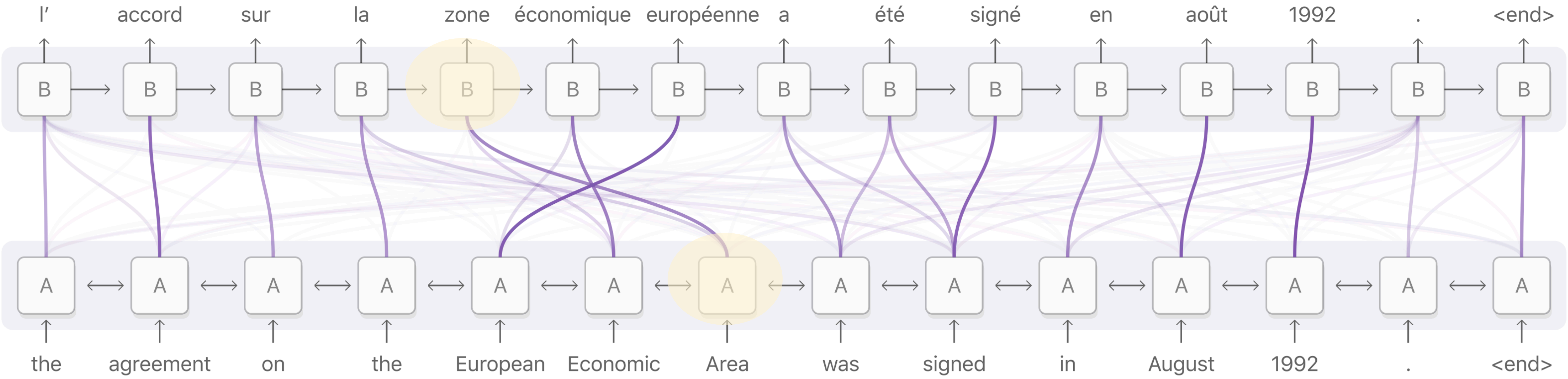

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- Attention: decoder knows where to focus.

- Downside: higher time complexity.
  - m: source sequence length
  - t: target sequence length
  - Standard Seq2Seq: $O(m+t)$ time complexity
  - Seq2Seq + attention: $O(mt)$ time complexity

Thank you!