어텐션 매커니즘
for 스터디

Tae Hwan Jung

https://ratsgo.github.io/from%20frequency%20to%20semantics/2017/10/06/attention/ 를 참조하여 만들었습니다.

1. Seq2Seq

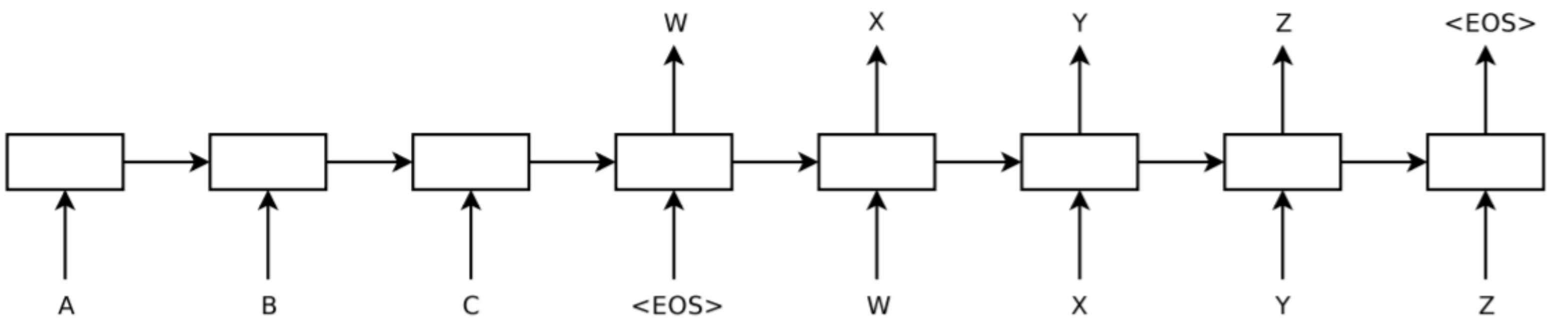
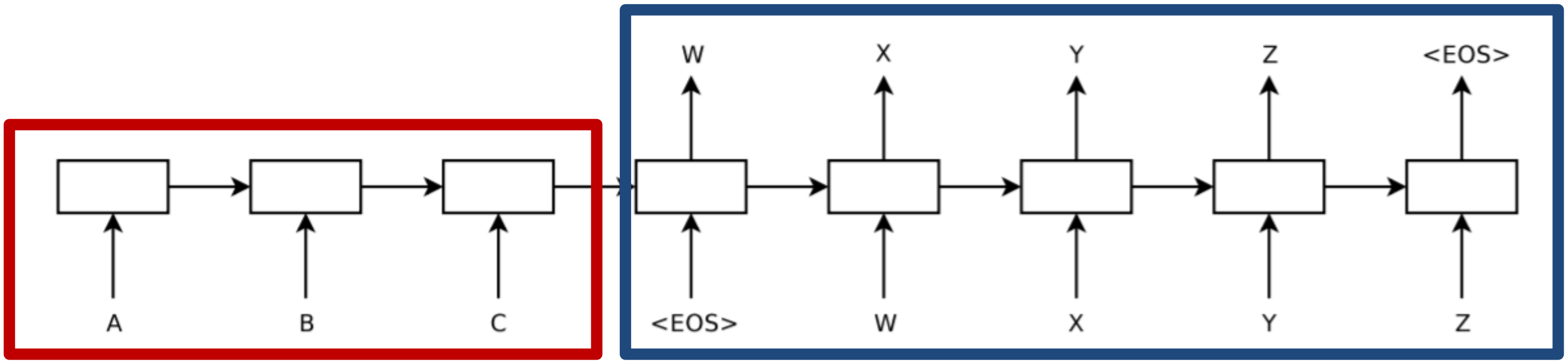


Figure 1: Our model reads an input sentence "ABC" and produces "WXYZ" as the output sentence. The model stops making predictions after outputting the end-of-sentence token. Note that the LSTM reads the input sentence in reverse, because doing so introduces many short term dependencies in the data that make the optimization problem much easier.

- https://arxiv.org/pdf/1409.3215.pdf 출처

1. Seq2Seq

Encoder **Decoder**



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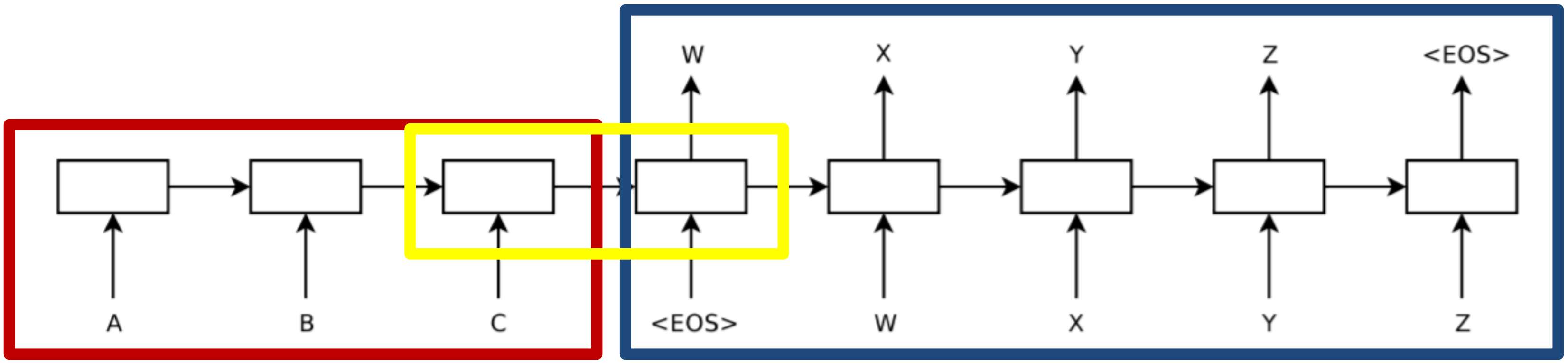

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Encoder의 최종 hidden State가 Deocder의 initialize Hidden State로 들어간다.

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1. Seq2Seq

Inputs: input, h_0

- **input** of shape (*seq_len, batch, input_size*): tensor containing the features of the input sequence. The input can also be a packed variable length sequence. See `torch.nn.utils.rnn.pack_padded_sequence()` or `torch.nn.utils.rnn.pack_sequence()` for details.
- **h_0** of shape (*num_layers * num_directions, batch, hidden_size*): tensor containing the initial hidden state for each element in the batch. Defaults to zero if not provided. If the RNN is bidirectional, num_directions should be 2, else it should be 1.

- **https://pytorch.org/docs/stable/nn.html**

1. Seq2Seq

Outputs: output, h_n

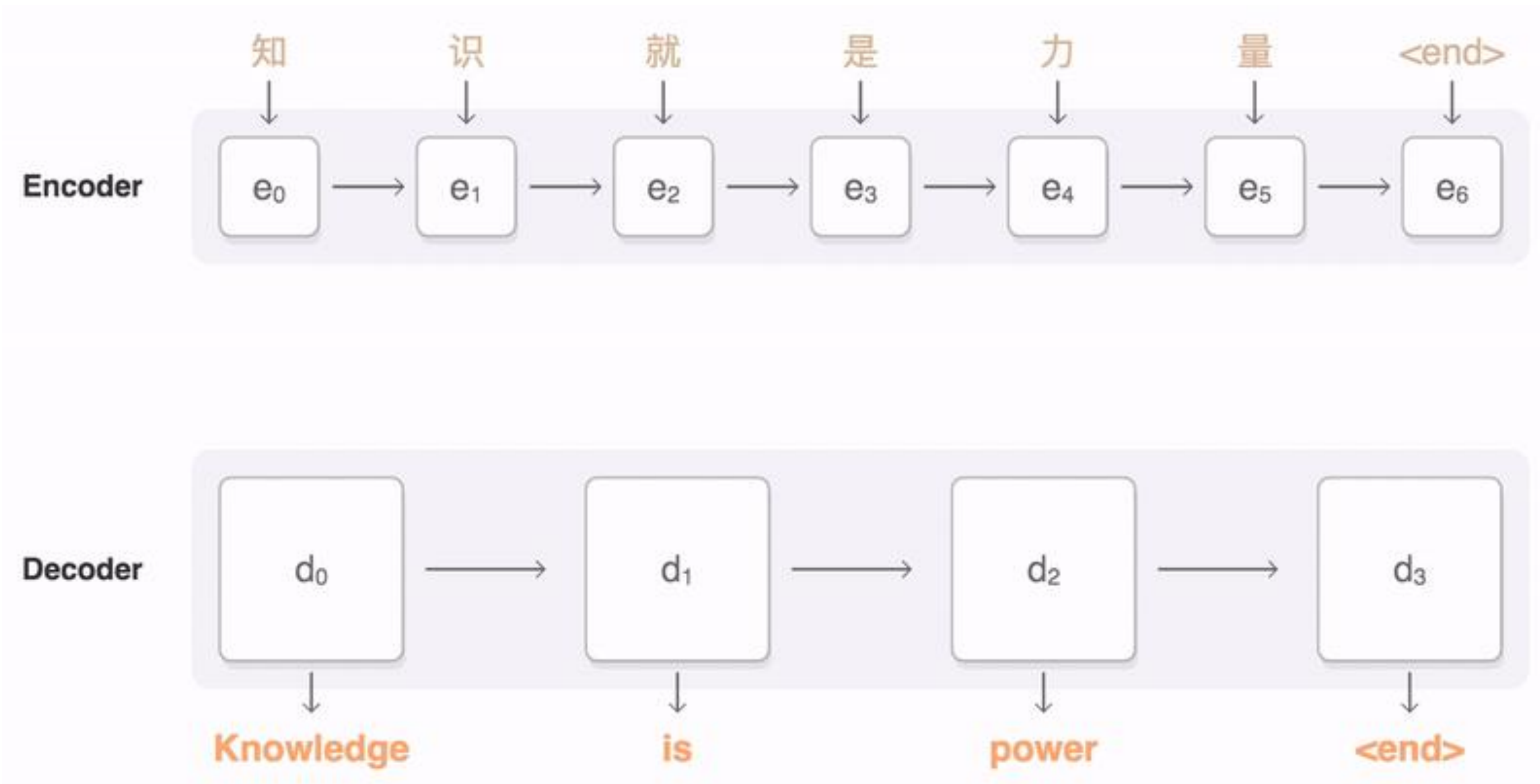
- **output** of shape (*seq_len, batch, num_directions * hidden_size*): tensor containing the output features (*h_k*) from the last layer of the RNN, for each *k*. If a `torch.nn.utils.rnn.PackedSequence` has been given as the input, the output will also be a packed sequence.

  For the unpacked case, the directions can be separated using `output.view(seq_len, batch, num_directions, hidden_size)`, with forward and backward being direction *0* and *1* respectively. Similarly, the directions can be separated in the packed case.
- **h_n** (num_layers * num_directions, batch, hidden_size): tensor containing the hidden state for *k = seq_len*.

  Like *output*, the layers can be separated using `h_n.view(num_layers, num_directions, batch, hidden_size)`.

- https://pytorch.org/docs/stable/nn.html

2. Seq2Seq-Attention



- https://google.github.io/seq2seq/ 출처

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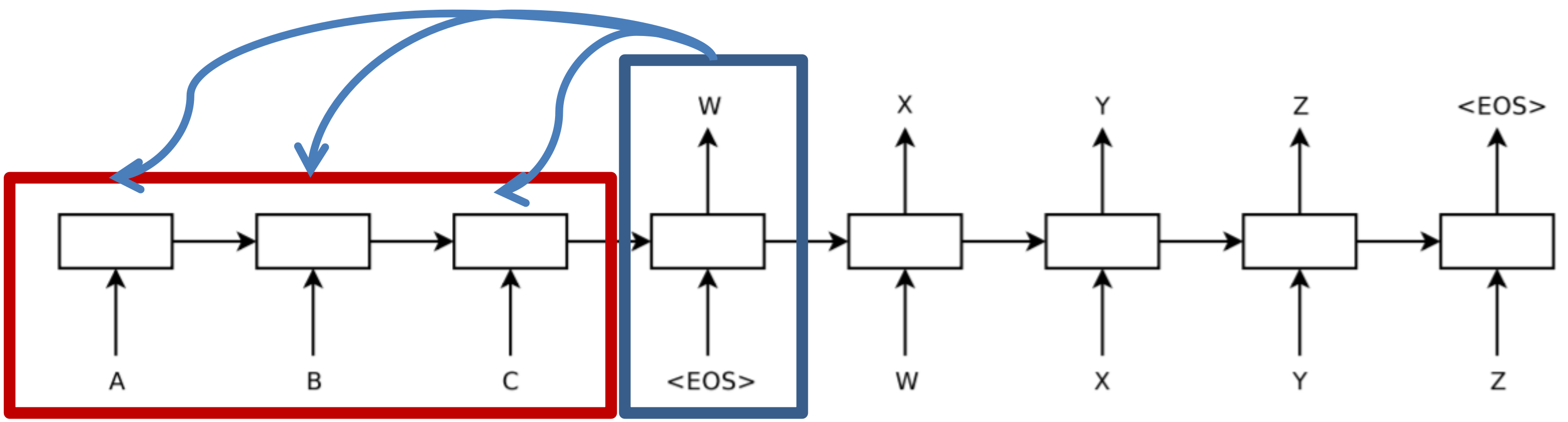

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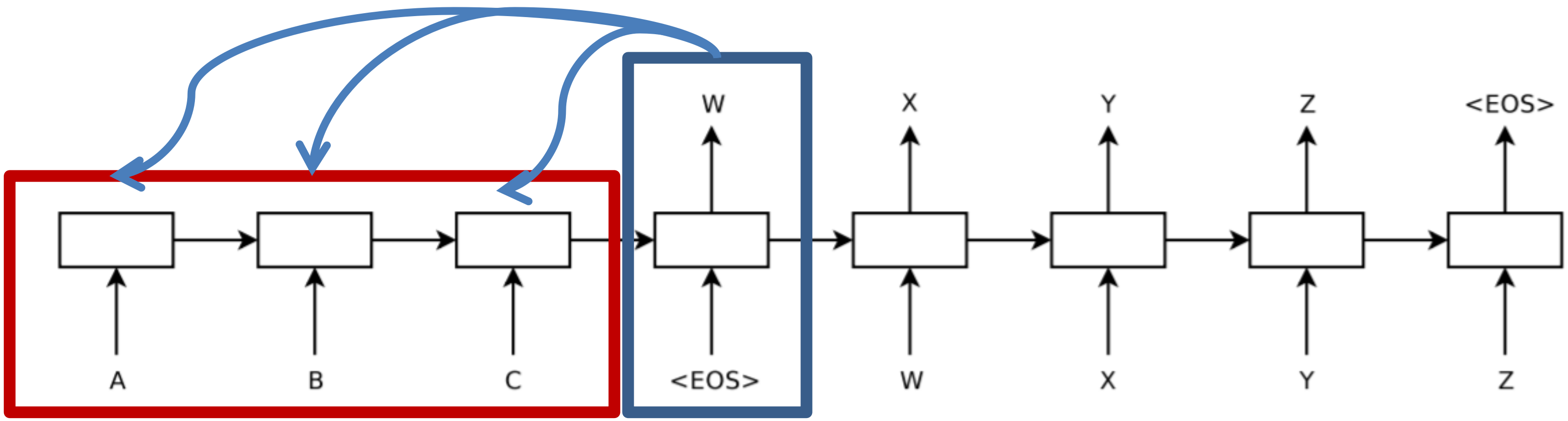
$$e_{ij} = a(s_{i-1}, h_j)$$

E_ij = alignment model(디코더의 이전 hidden state, 인코더의 hidden state)

2. Seq2Seq-Attention

$$\overrightarrow{\alpha_i} = [\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{iT_x}]$$



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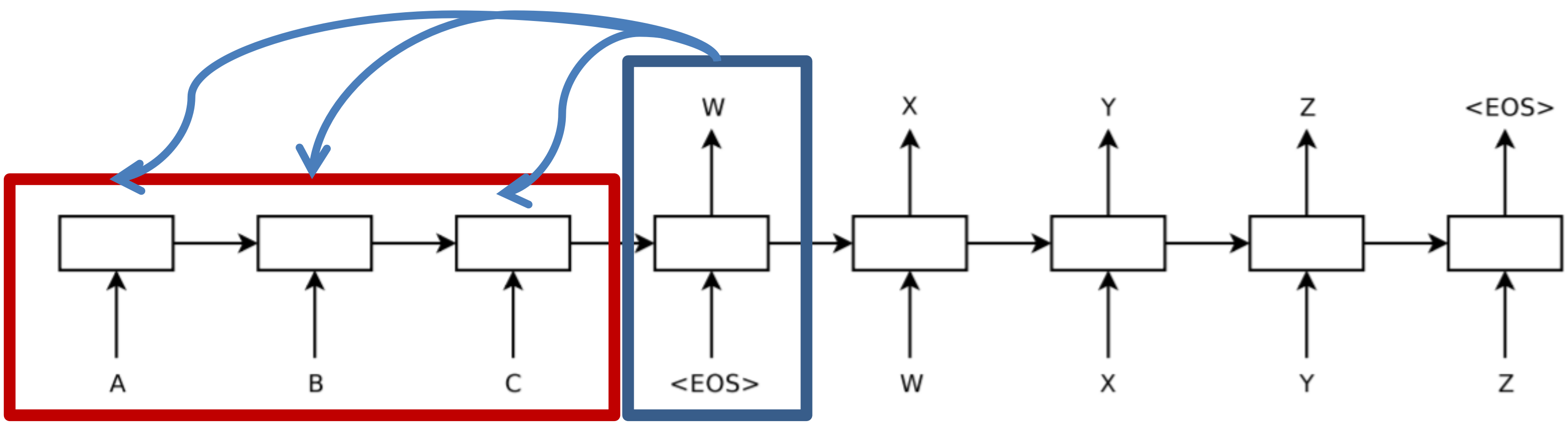
$$\alpha_{ij} = \frac{exp(e_{ij})}{\sum_{k=1}^{T_x} exp(e_{ik})}$$

2. Seq2Seq-Attention

Contextual matrix

Query

$$\overrightarrow{c_i} = \sum_{j=1}^{T_x} \alpha_{ij} h_j = \boxed{F}\,\overrightarrow{\alpha_i}$$



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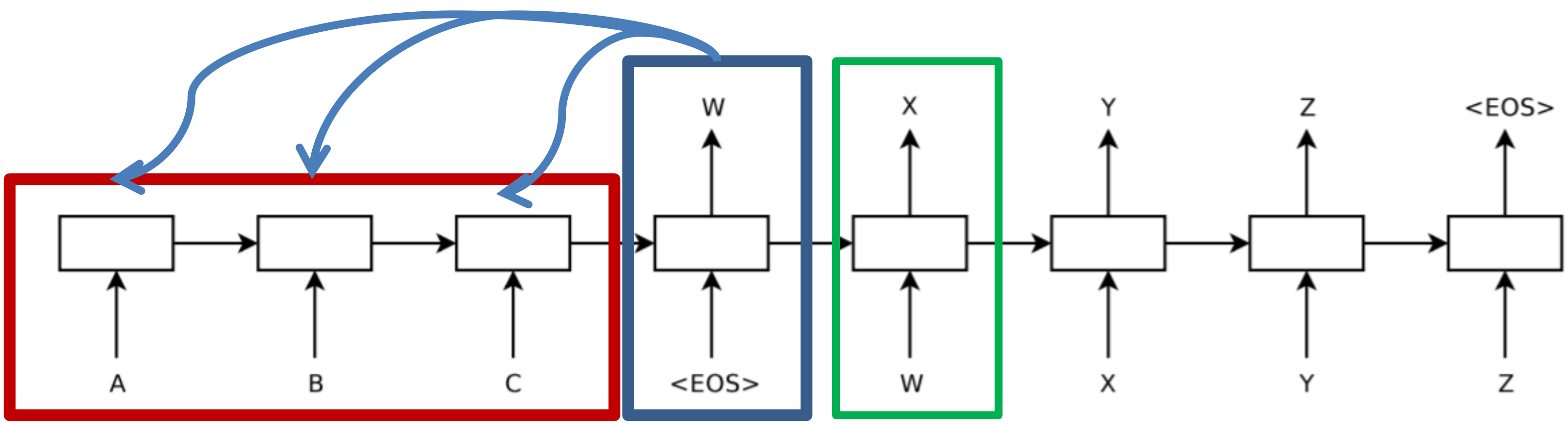
2. Seq2Seq-Attention

model[i] = self.out(torch.cat((dec_output, context), 1))



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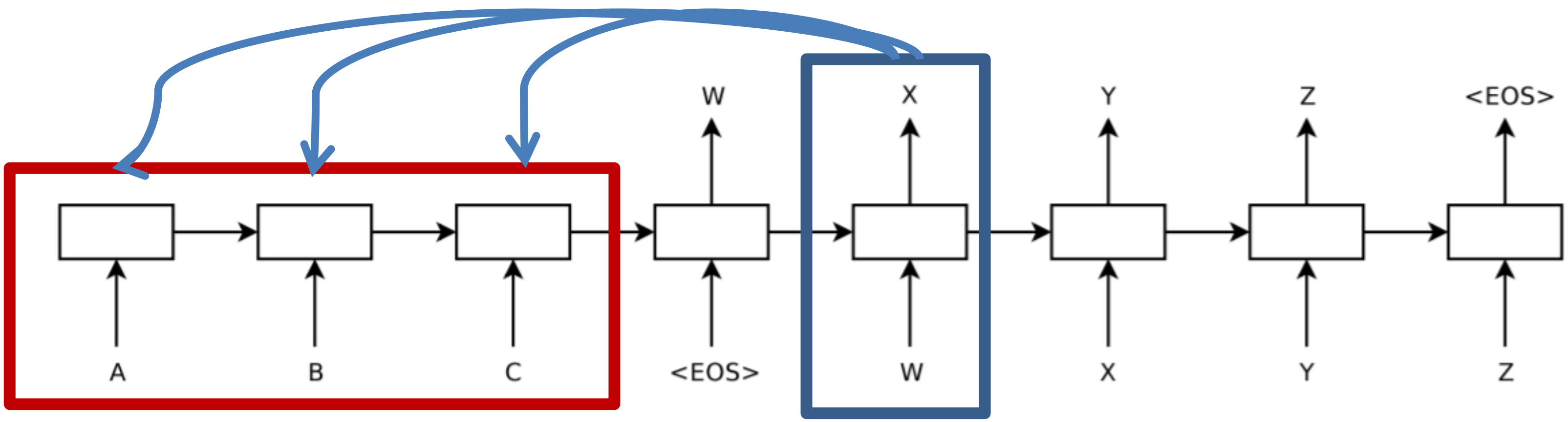

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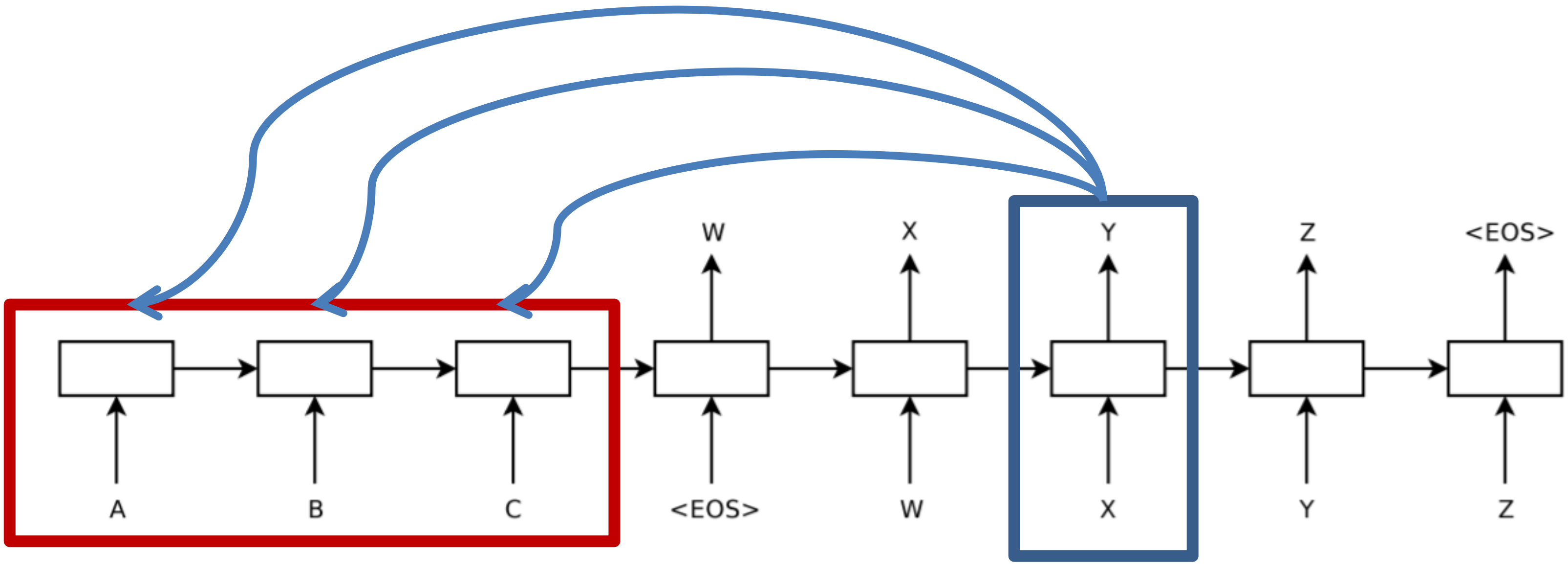

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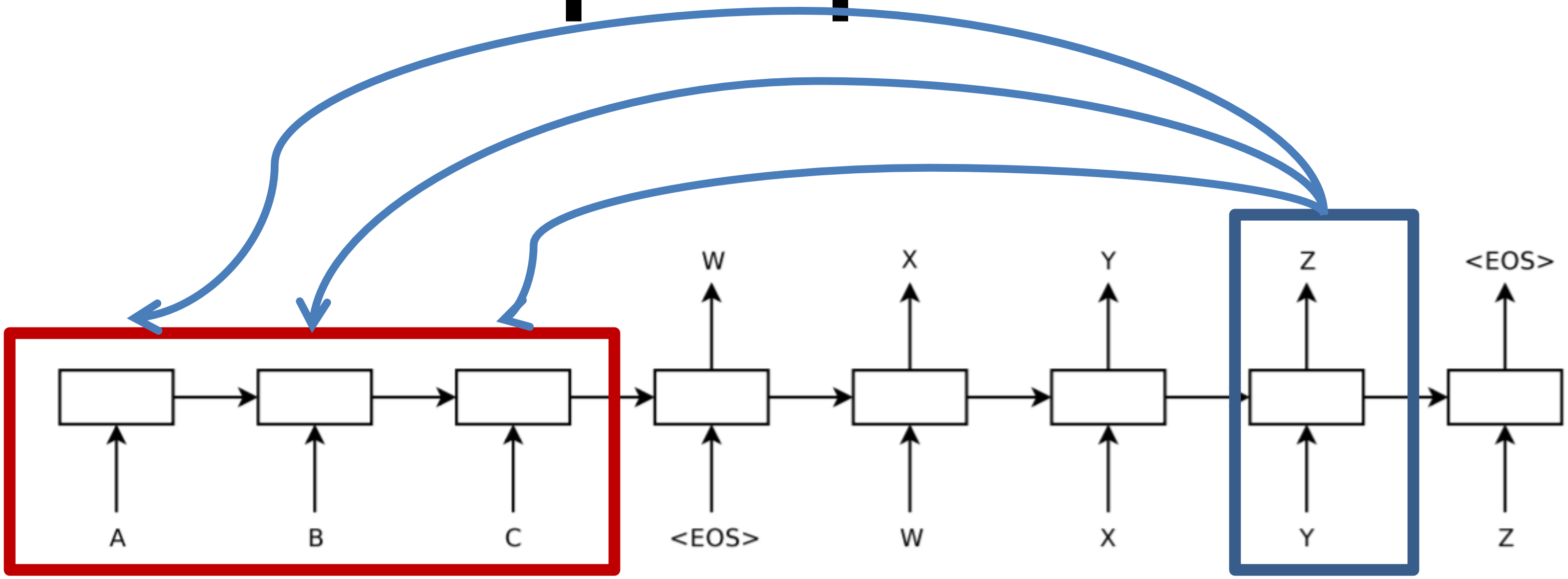

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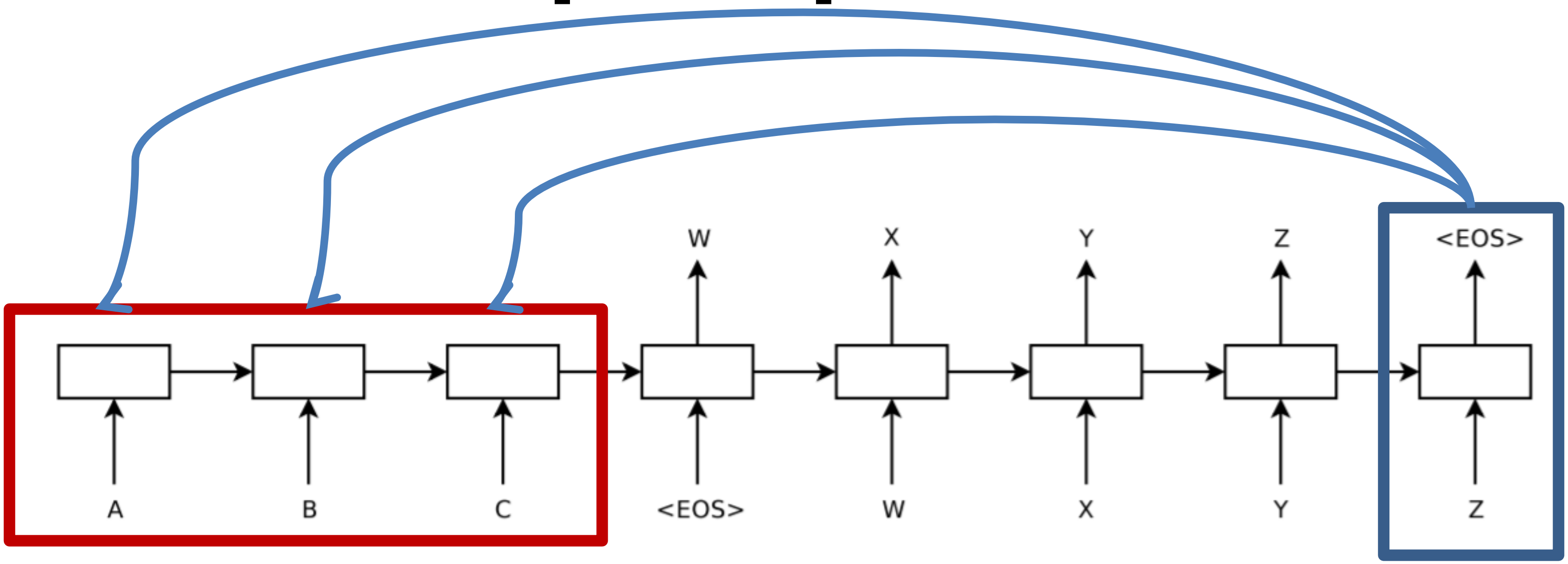

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