Neural Language Models

Mausam

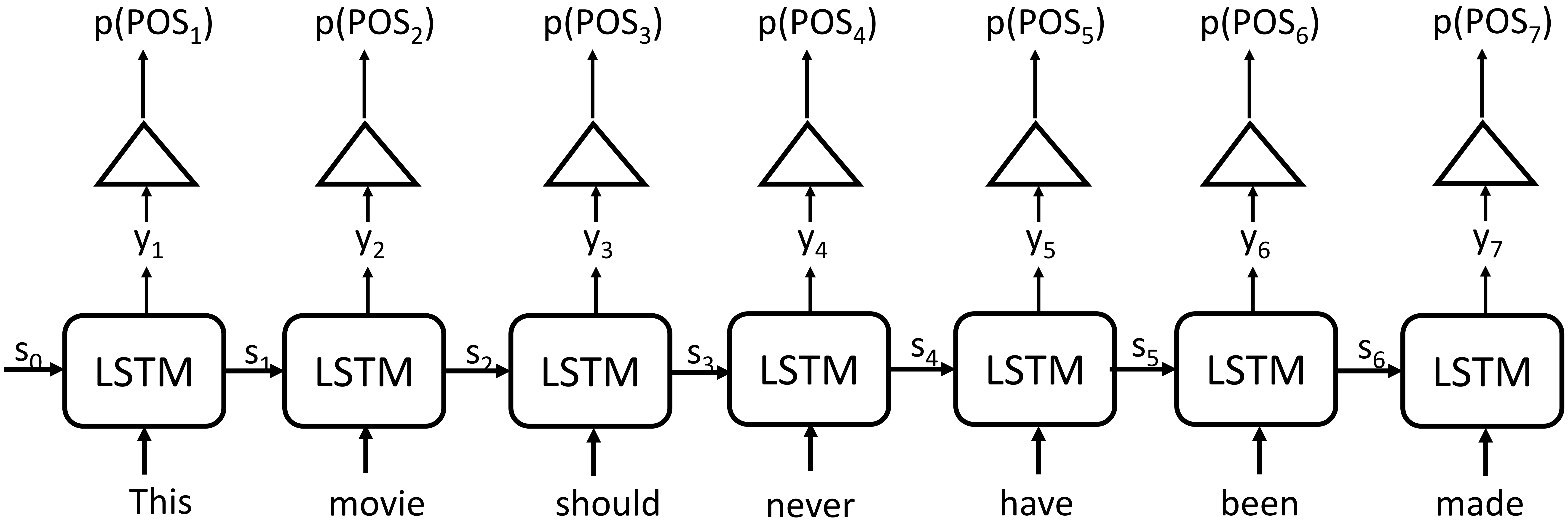
(Based on slides of Yejin Choi, Yoav Goldberg, Andrej Karpathy, Chris Manning, Graham Neubig, Jay Allamar and Keshav Kolluru)

Outline

- Neural Language Models: LSTMs
- Seq2Seq Models with LSTMs
- Neural Language Models: Transformers
- Seq2Seq Models with Transformers

Sequence Decoder

Neural Language Model



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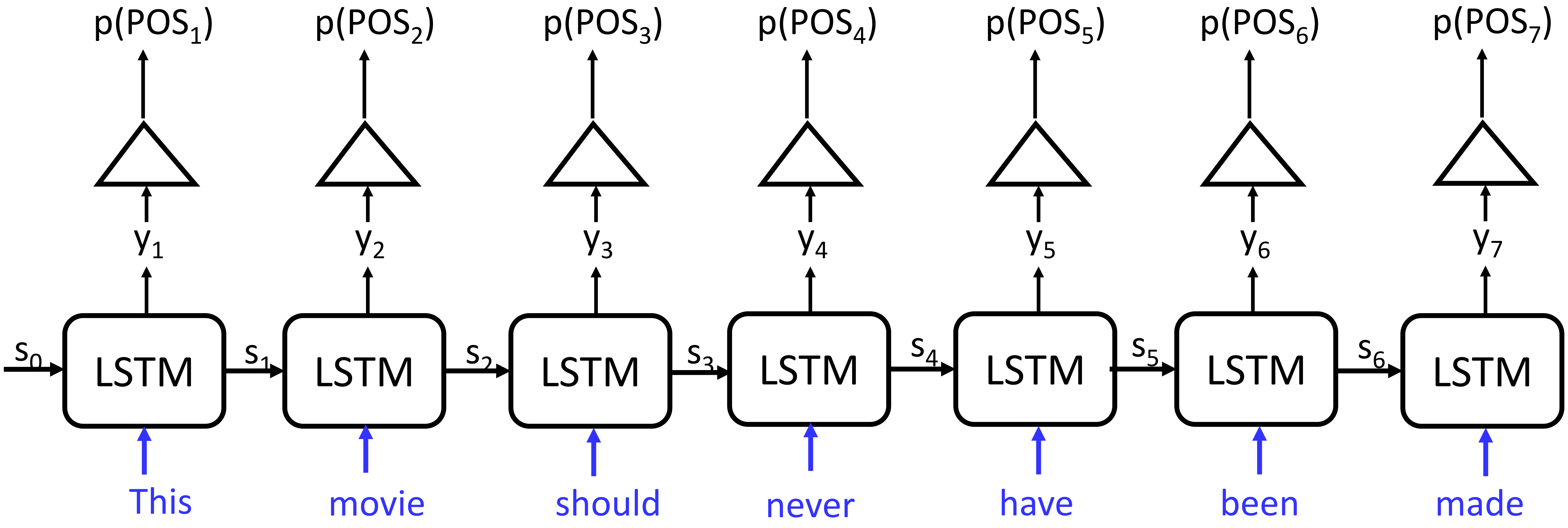

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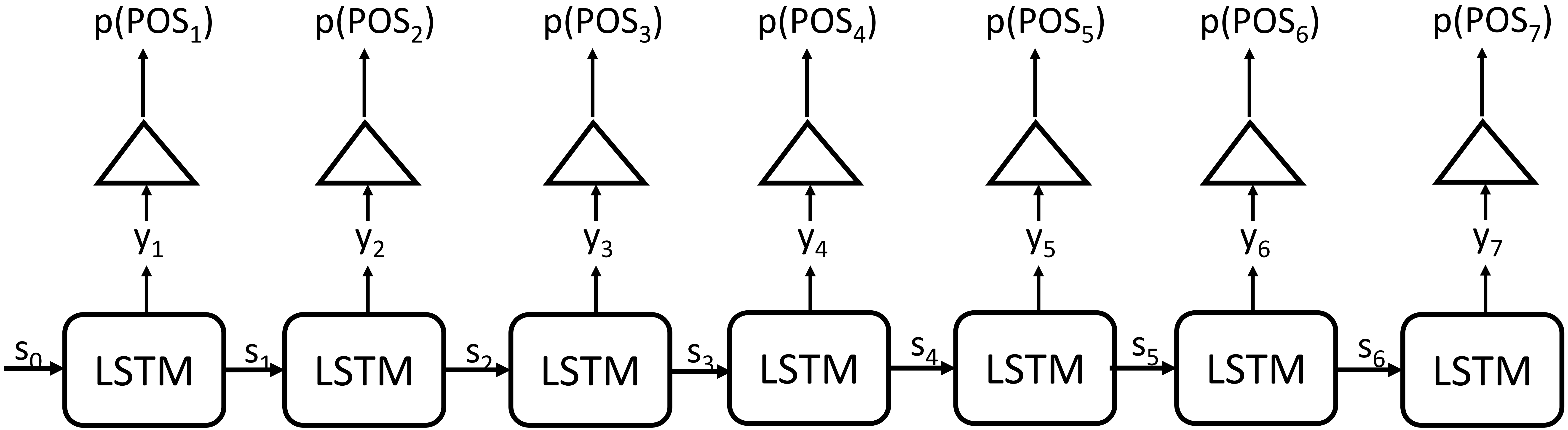

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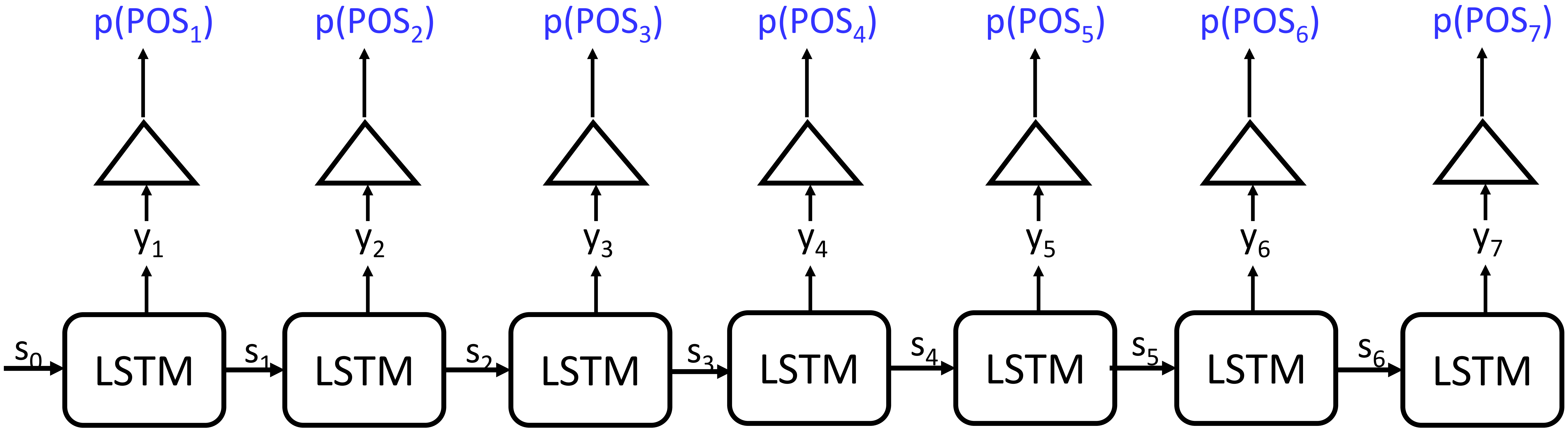
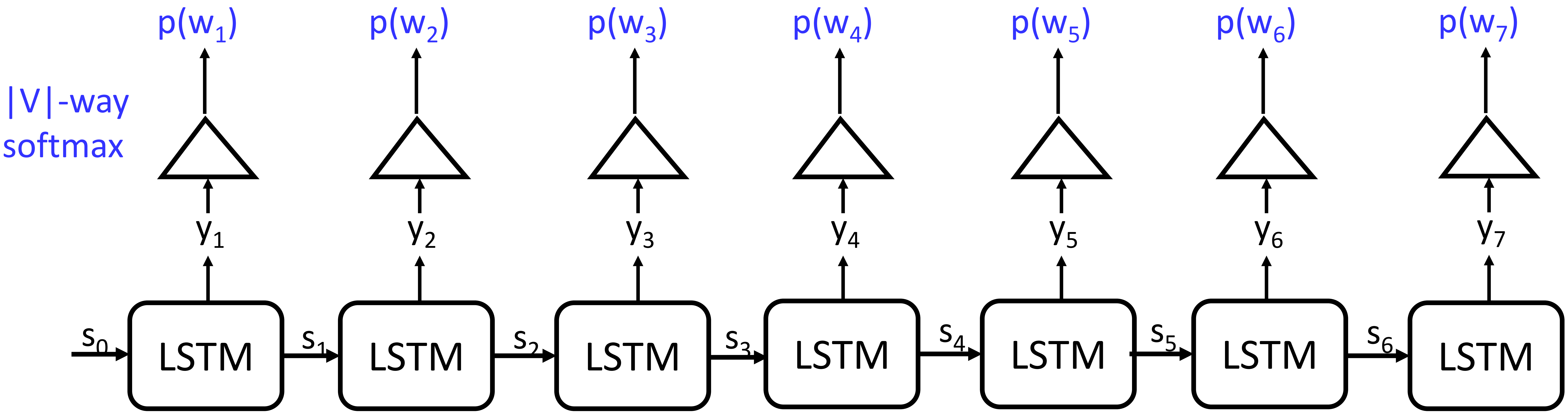
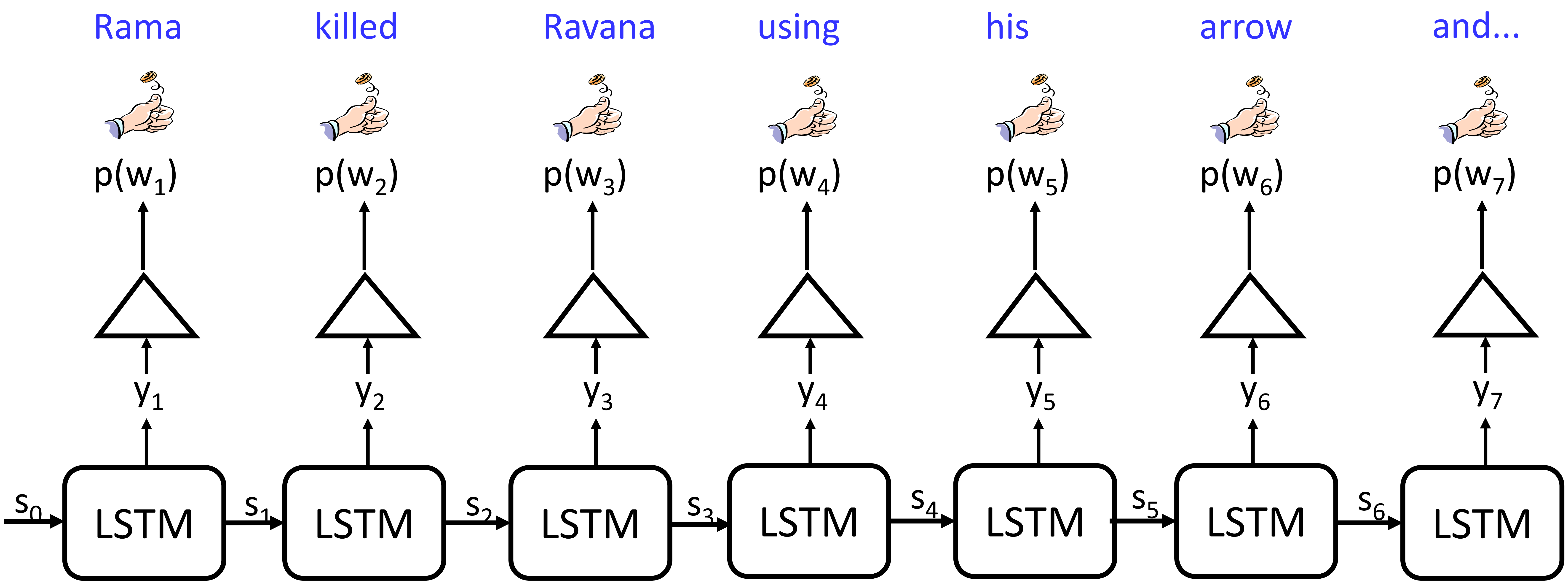


Neural Language Model



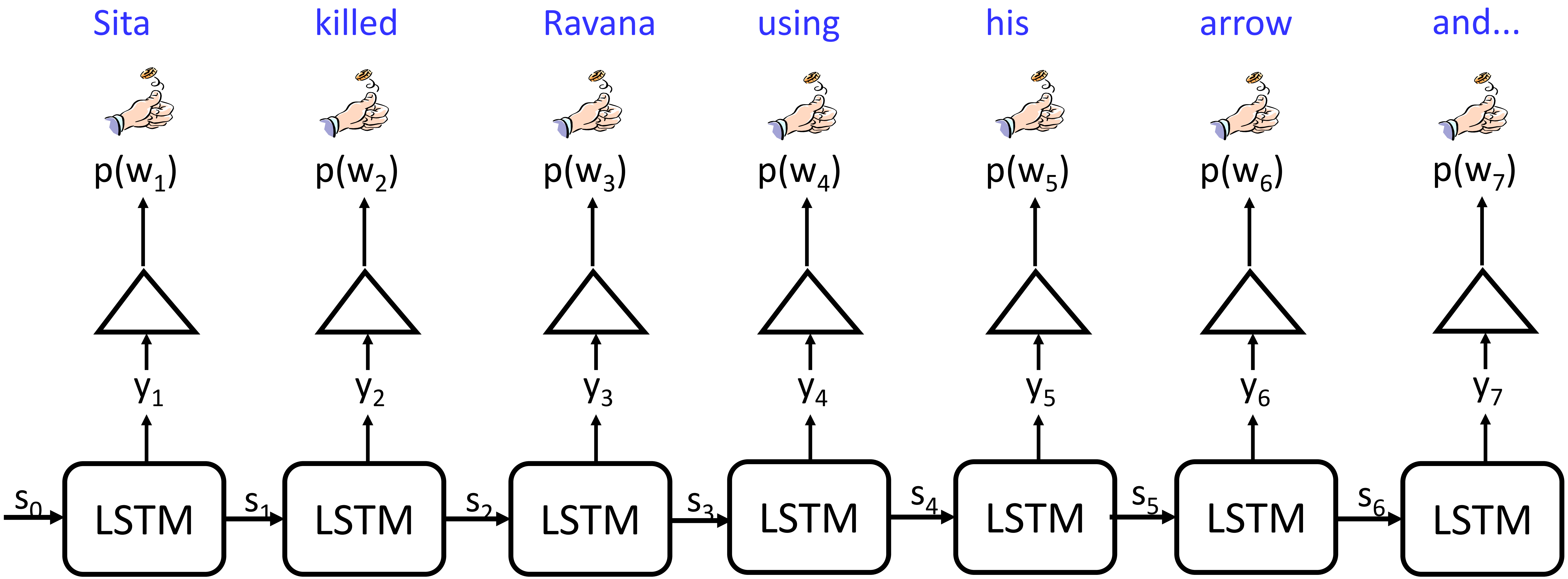
How do we get the actual sentence from a sequence of probability distributions?

Neural Language Model



Can you think of a fundamental problem in this design?

Neural Language Model



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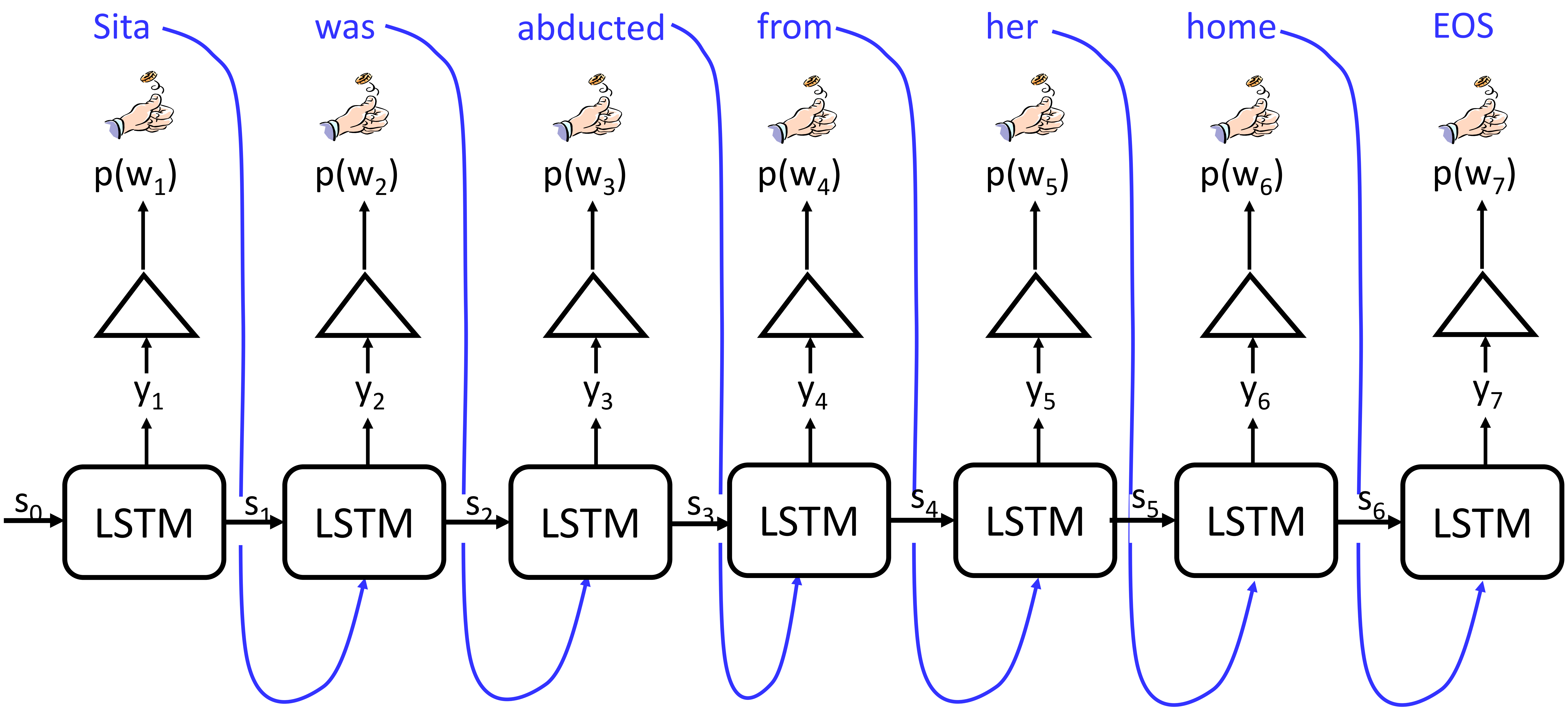

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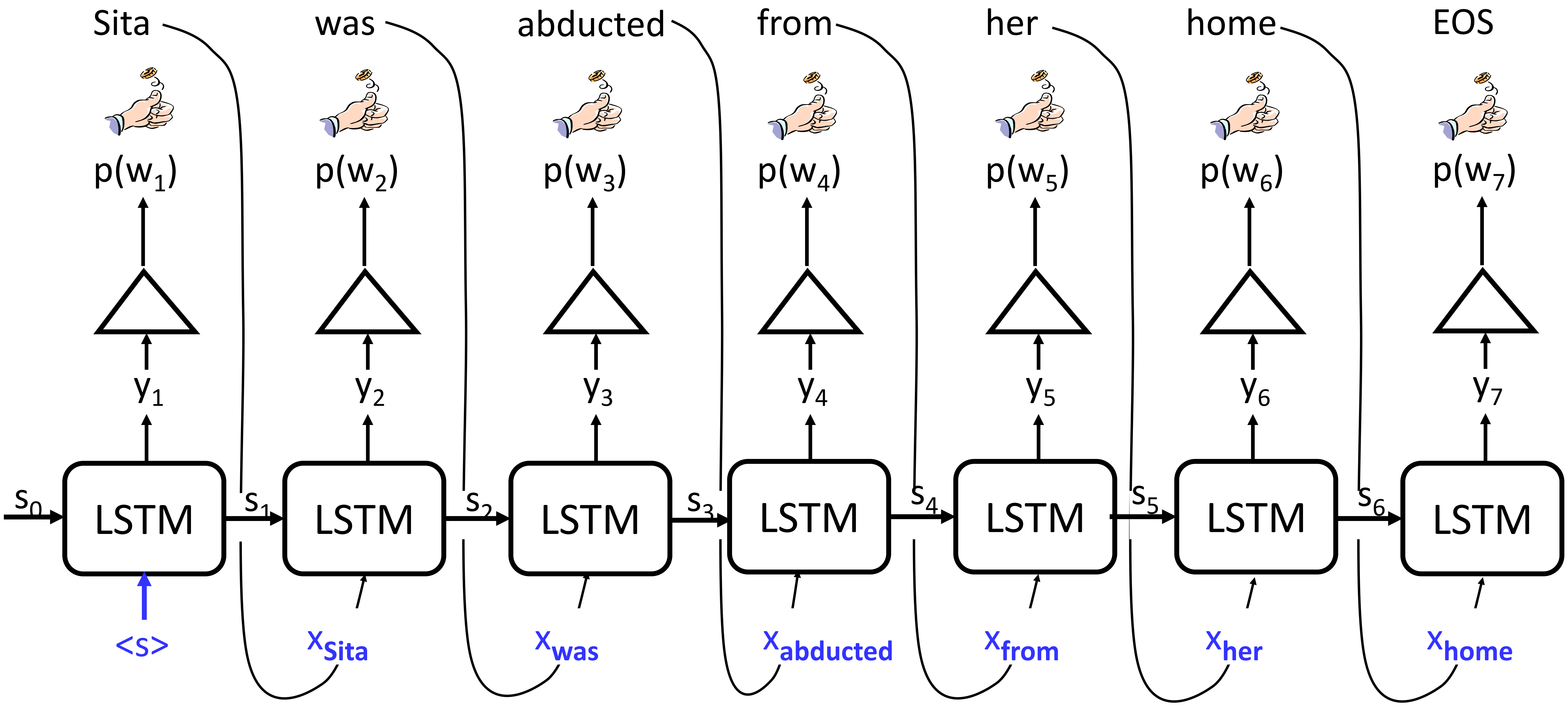


Called “Auto-regressive models”

Neural Language Model

- Use LSTMs not BiLSTMs
  - Why?

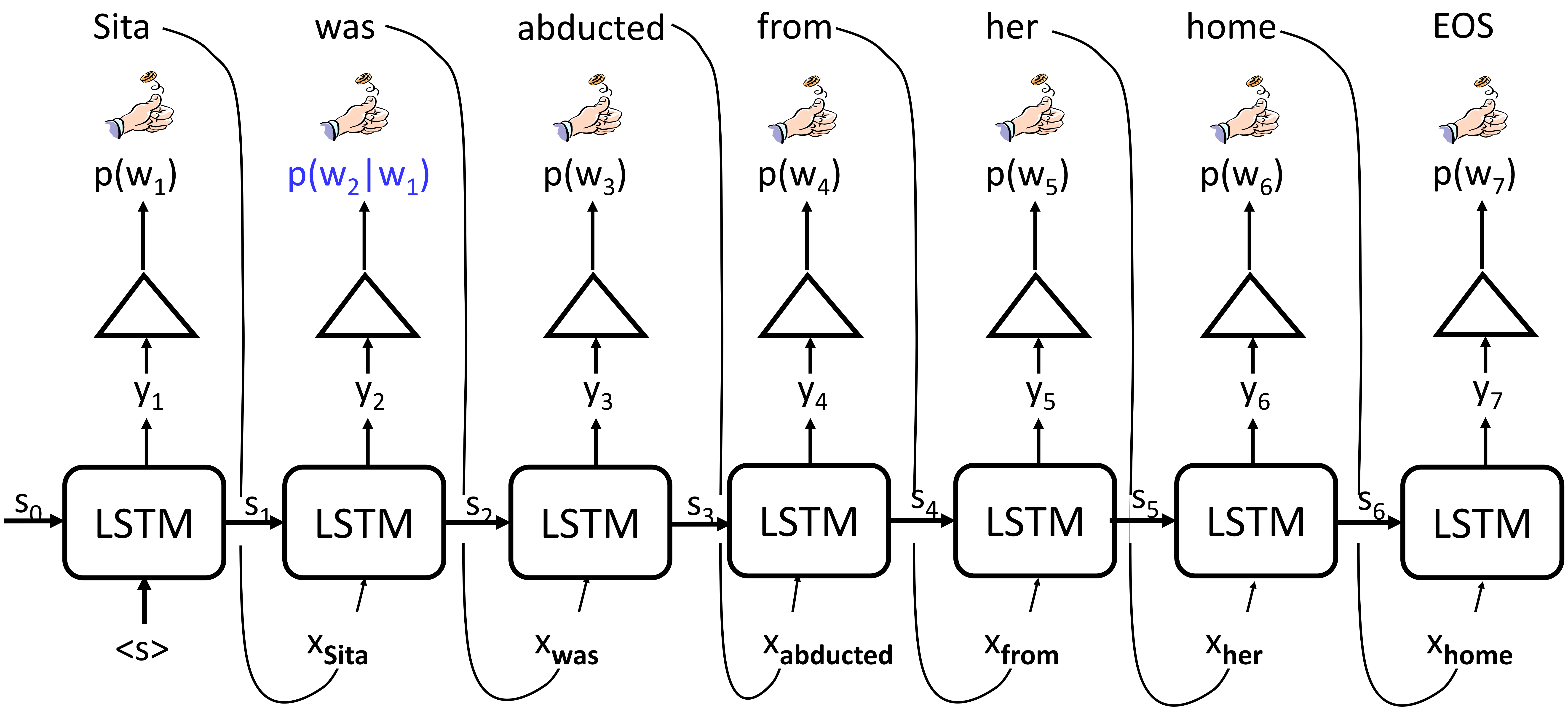
- When does it stop?

- Define the probability distribution over the next item in a sequence (and hence the probability of a sequence).

$$P(w_{1:n}) = P(w_1)P(w_2 \mid w_1)P(w_3 \mid w_{1:2})P(w_4 \mid w_{1:3}) \ldots P(w_n \mid w_{1:n-1})$$

$$P(w_1, ..., w_n) = \prod_{i=1} P(t_i = w_i | w_1, ..., w_{i-1})$$

Neural Language Model



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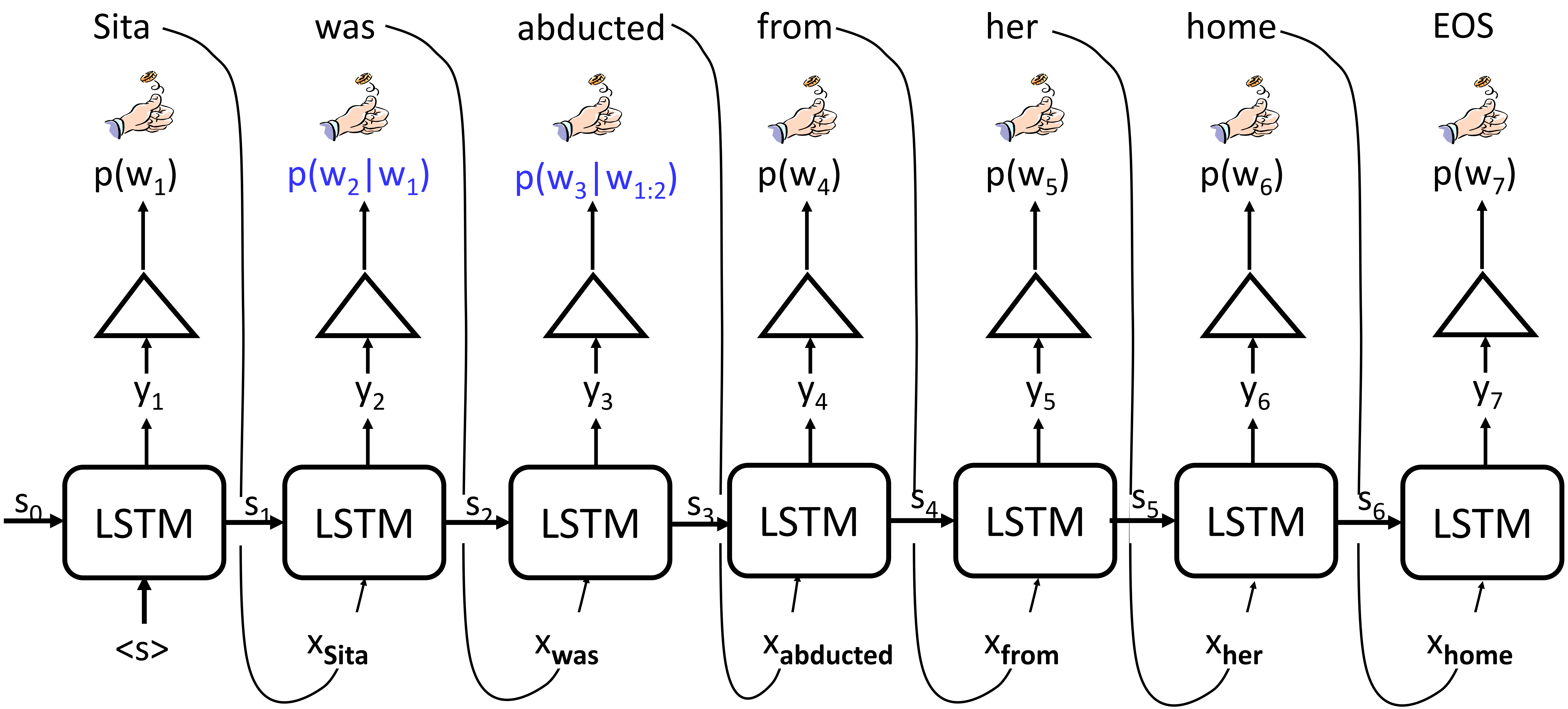

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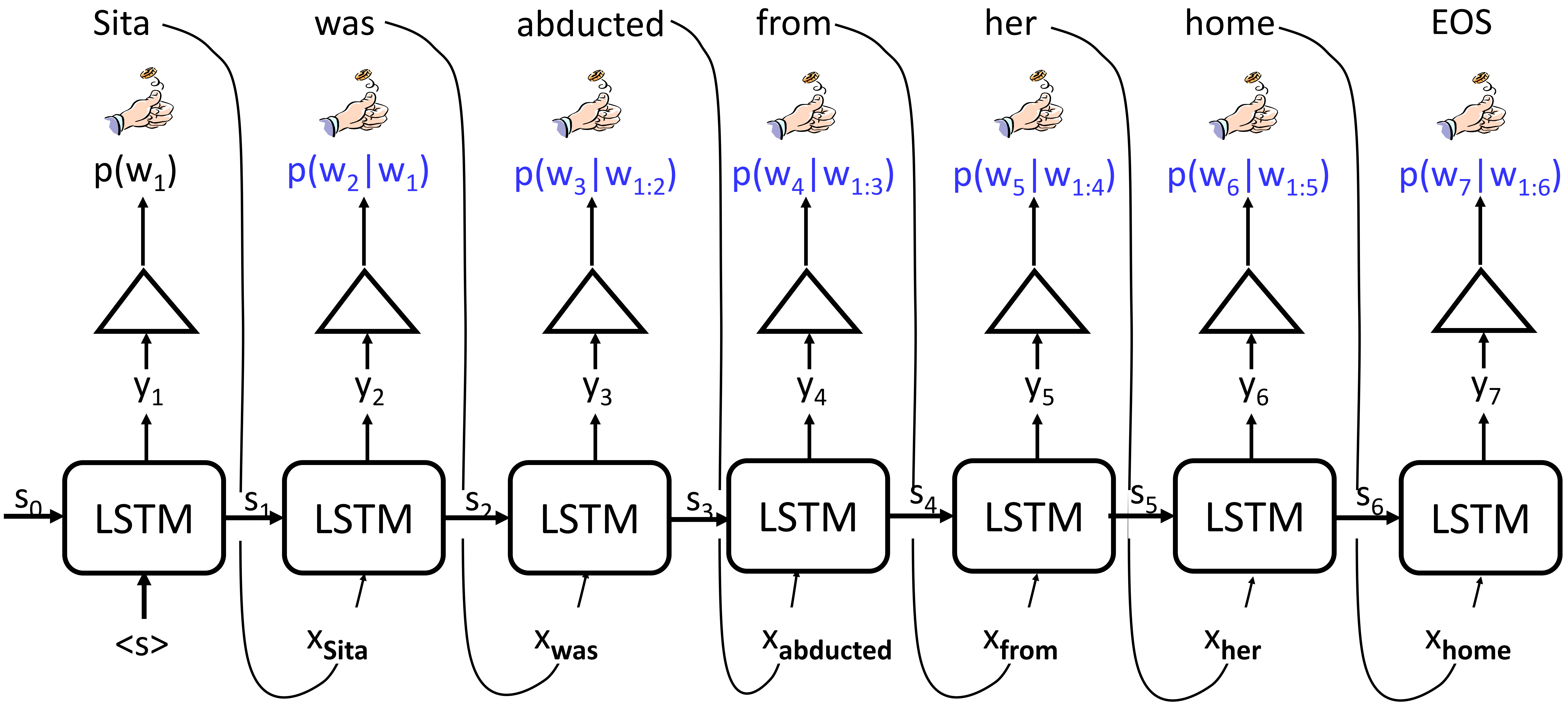
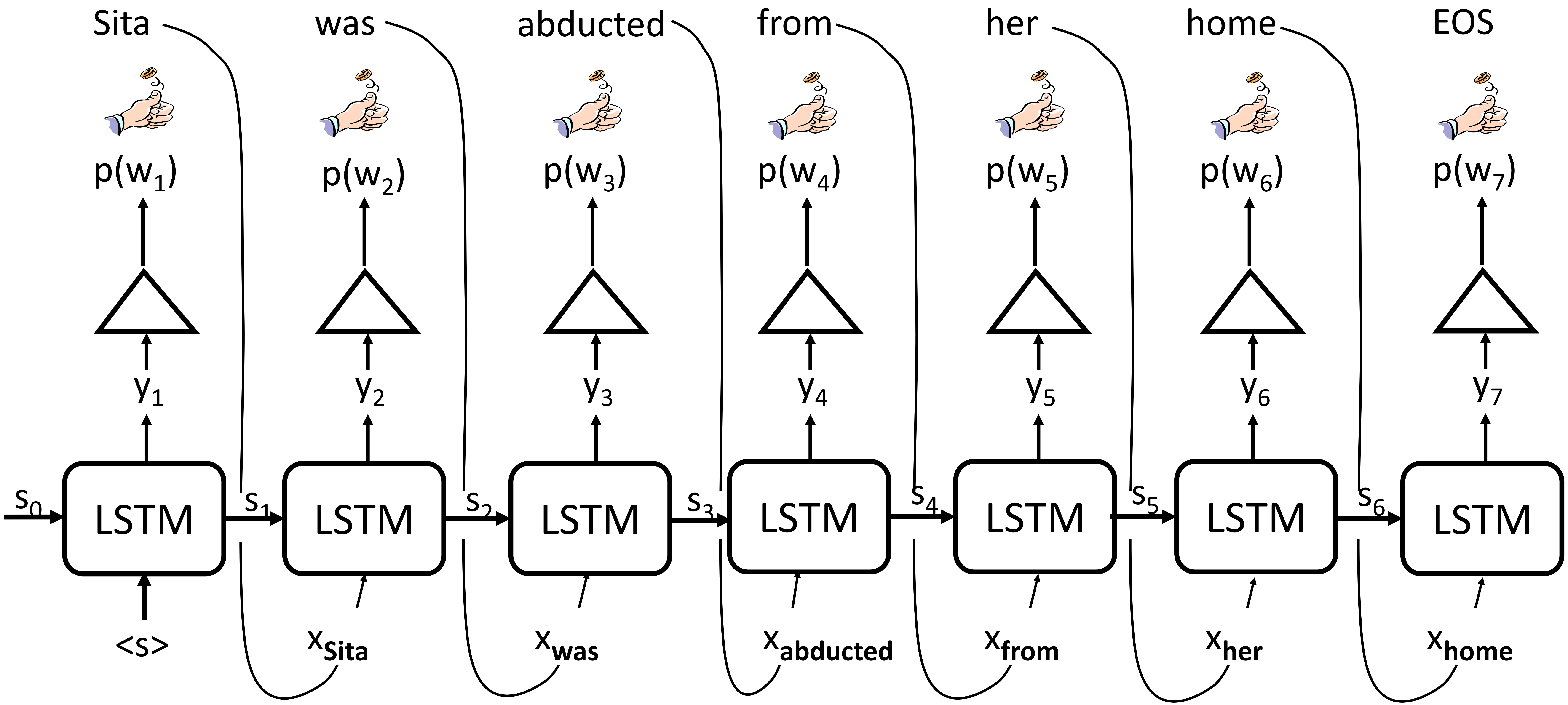


Neural Language Model: Inference Time



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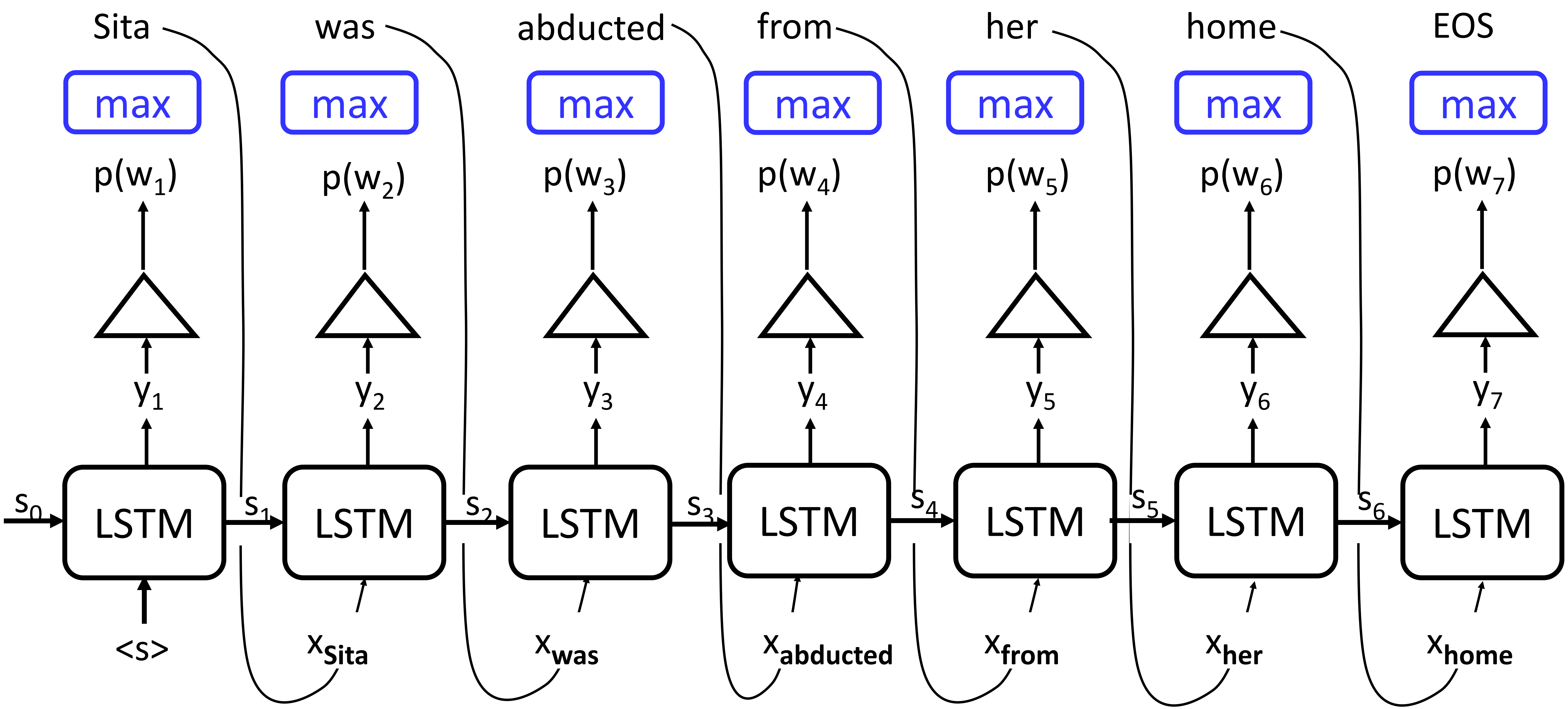
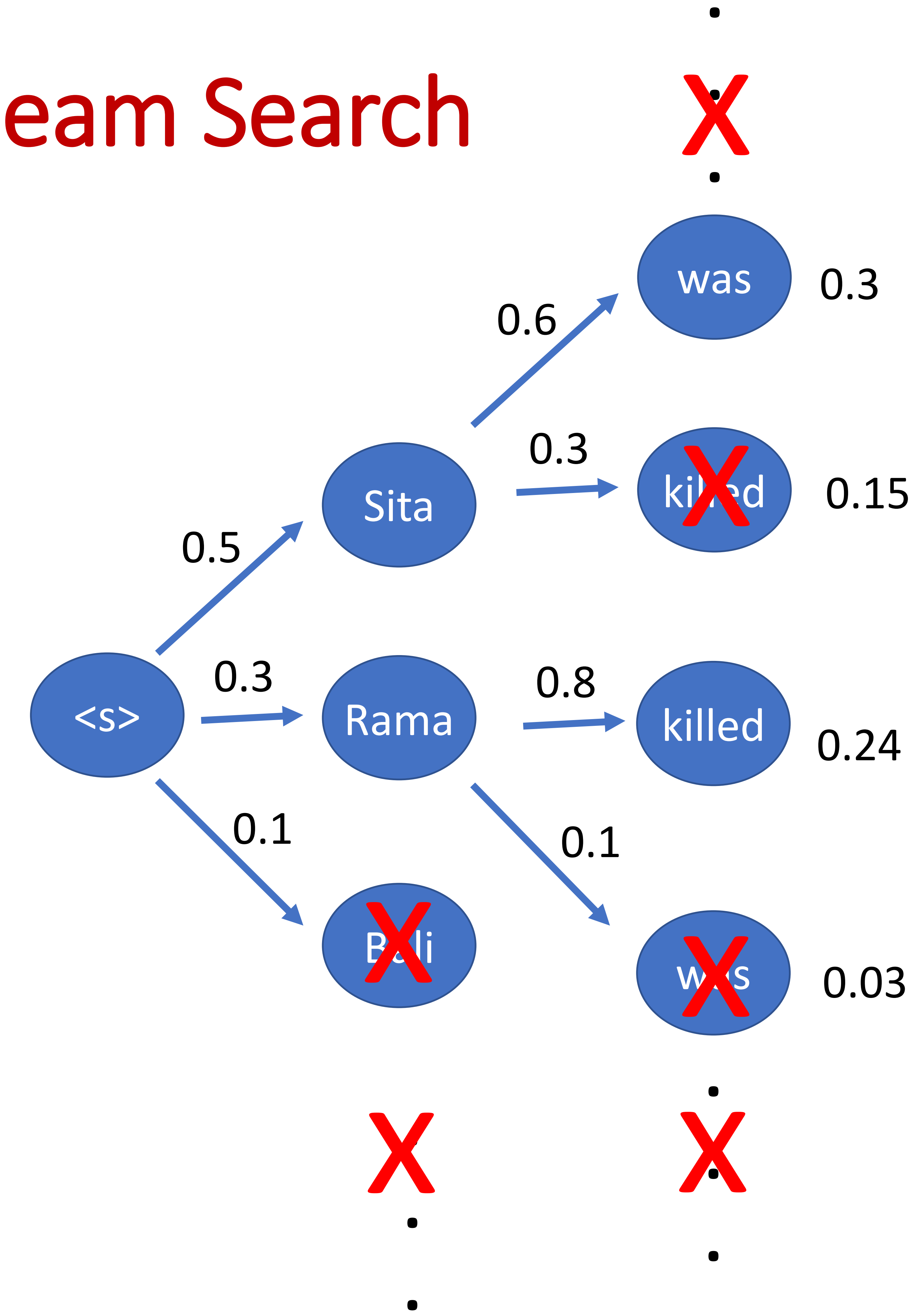


Neural Language Model: Greedy Decoding

- What is the function we actually wish to compute?
- $\underset{w_{1:n}}{\operatorname{argmax}} P(w_{1:n})$

- Computing this expression is prohibitive.
- Greedy Approach: approximation can be bad because
  - model will never begin a sentence with a low probability word
  - model will prefer many common words to one rare word
- Solution: Beam Search

Beam Search

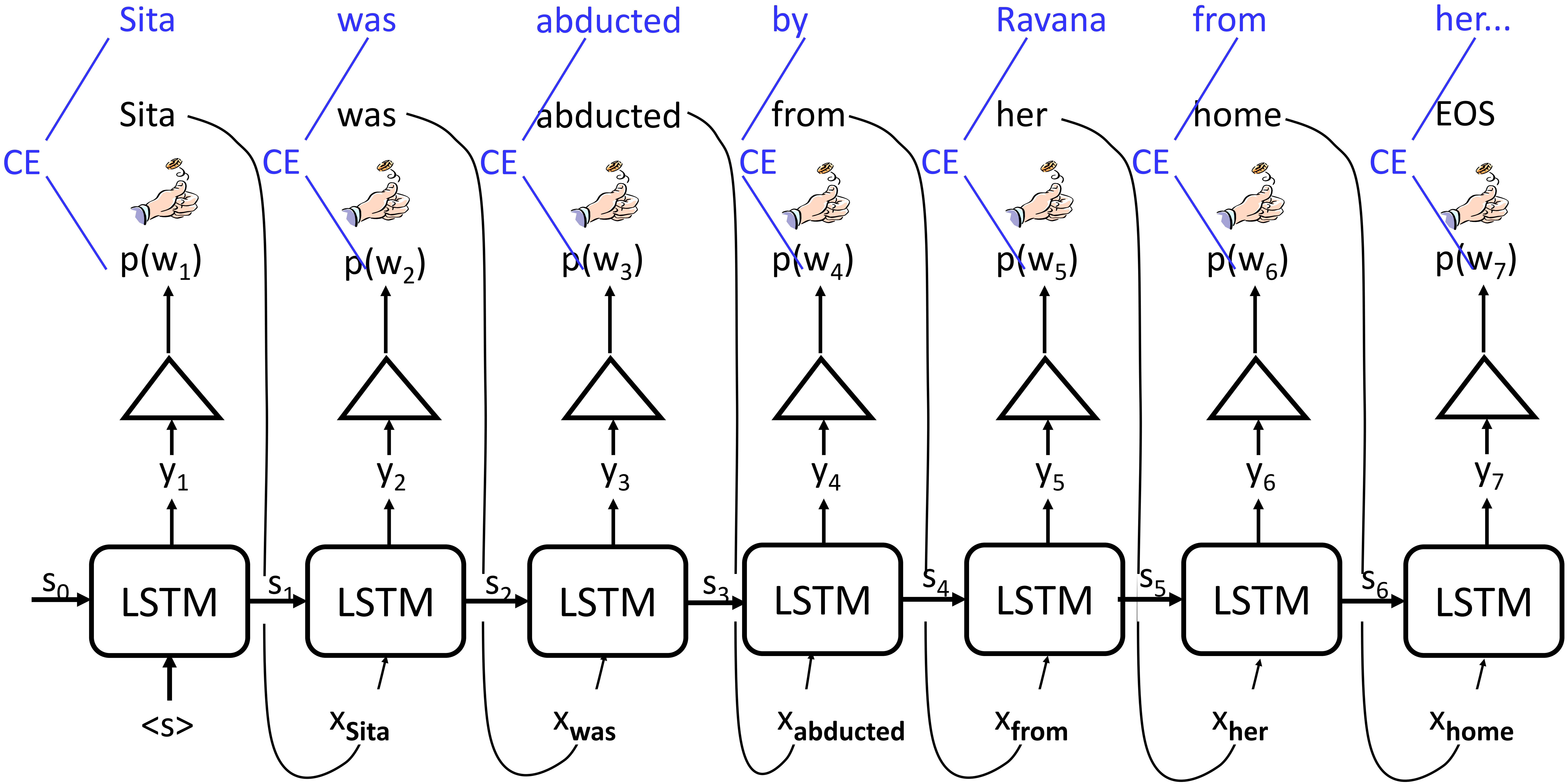


Instead of picking one greedy path, maintain multiple greedy paths

Upto a constant beam of b

Example for beam size =2

Neural Language Model: Training



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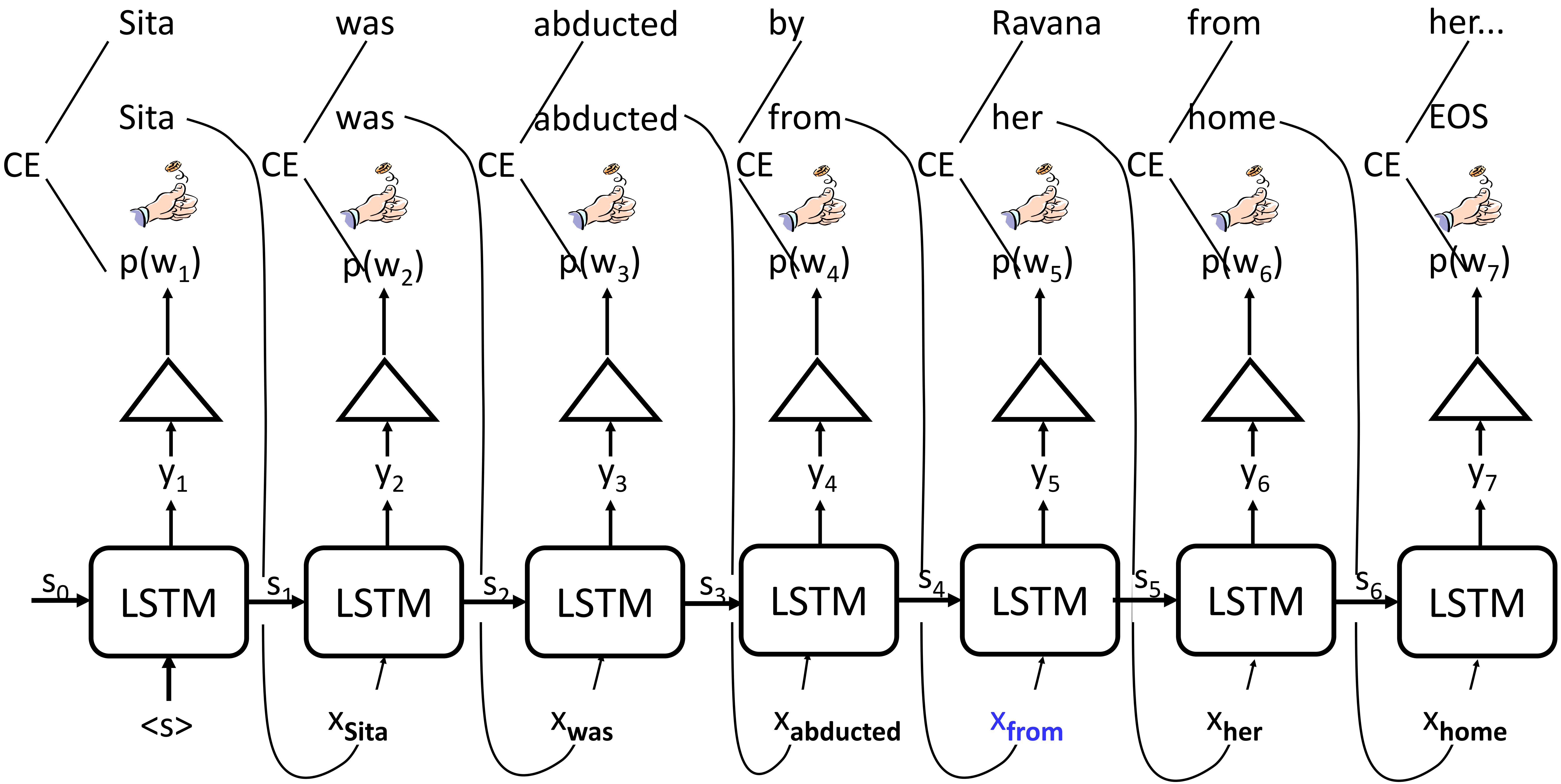
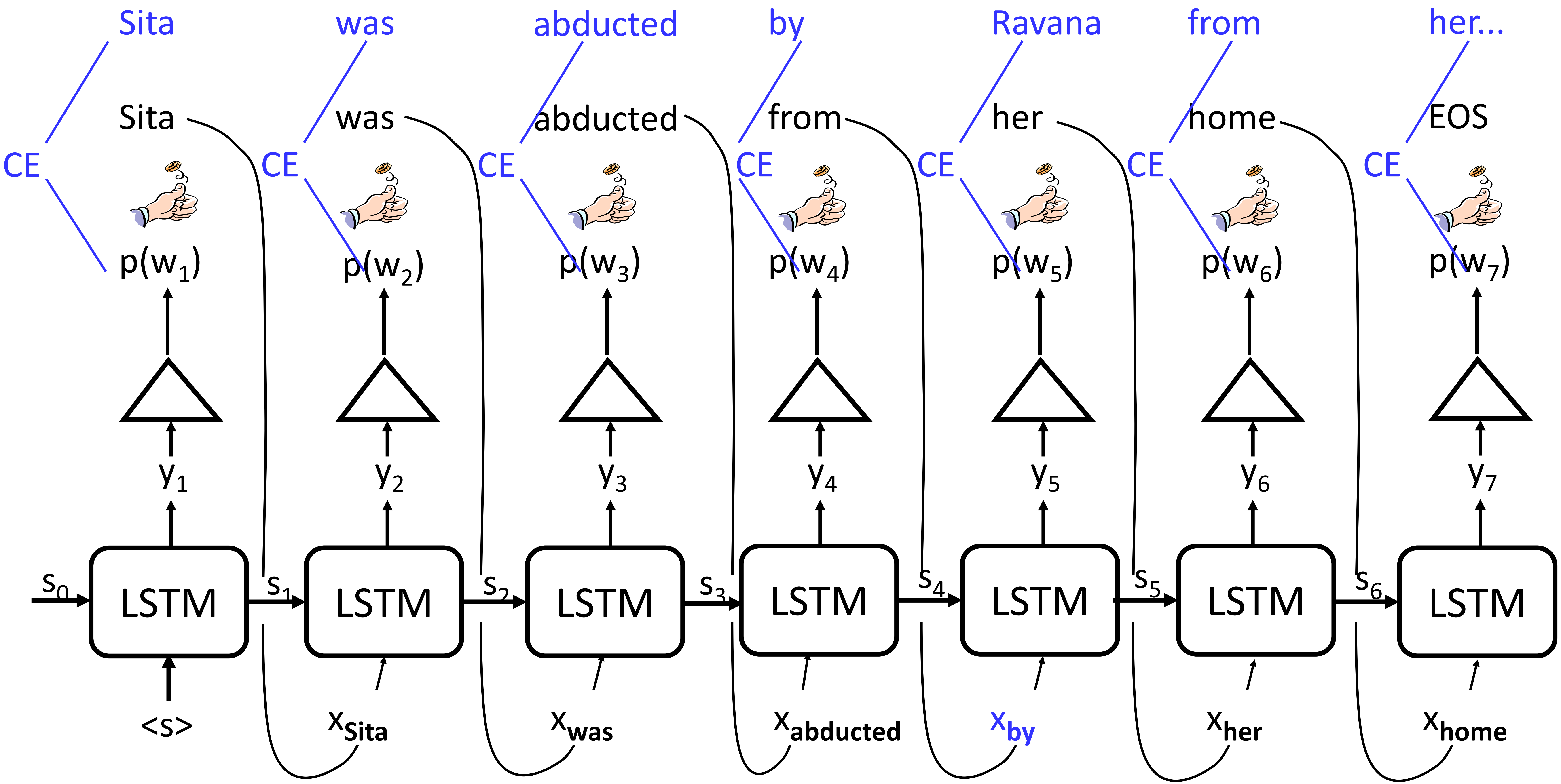


Neural Language Model: Training (Teacher Forcing)



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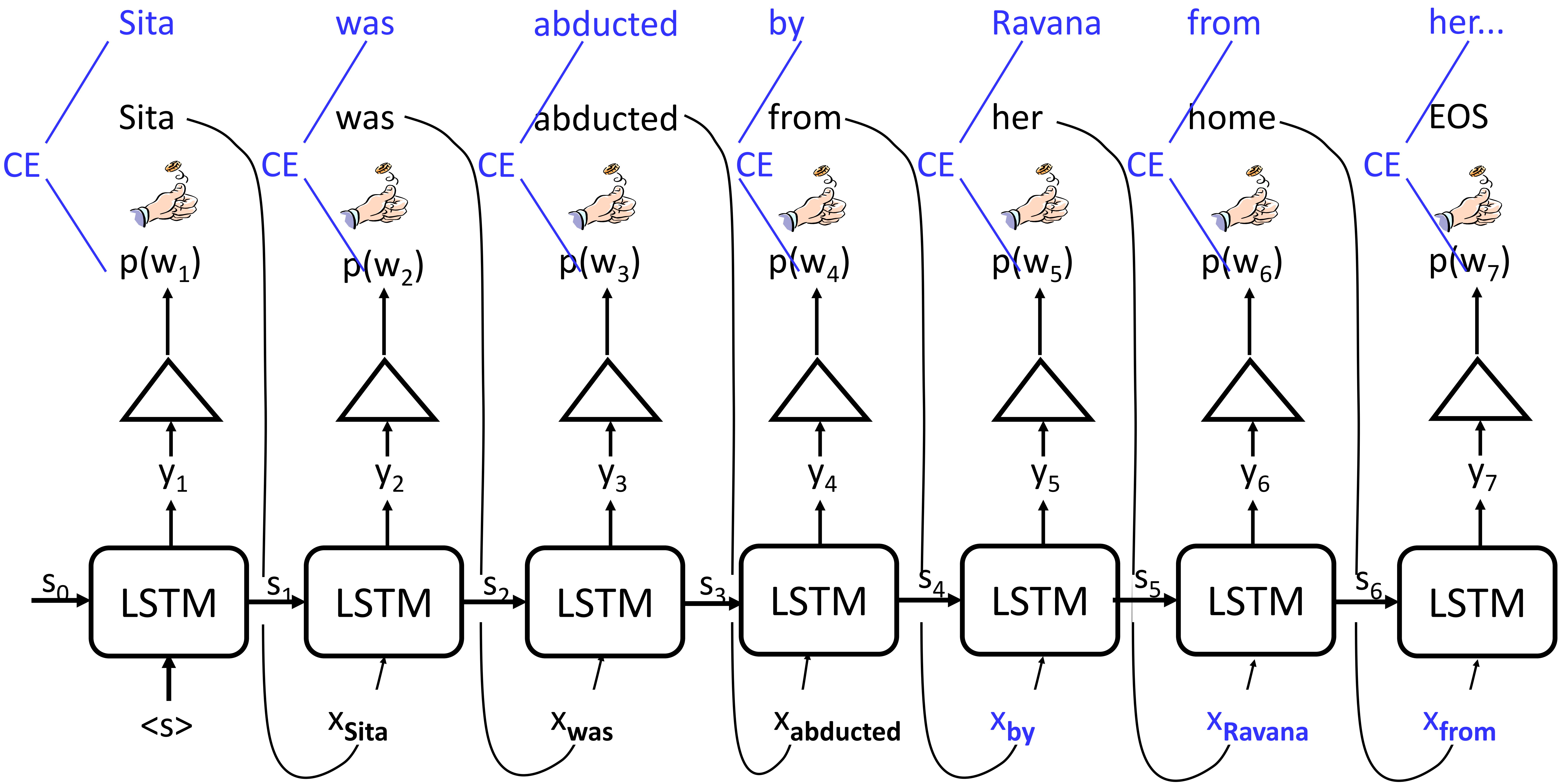

How to Train this Model?

- Loss function: sum(cross entropy at each prediction)

- Issues with vanilla training
  - Slow convergence. Model instability. Poor skill.

- Simple idea: **Teacher Forcing**
  - Just feed in the *correct* previous tag during training

- Drawback: **Exposure bias**
  - Not exposed to mistakes during training

Solutions to Exposure Bias

- Scheduled Sampling (Bengio et al. 2015)
  - With some probability, decode a token and feed that as the next input, rather than the gold token.
  - Increase probability over the course of training
- Retrieval Augmentation (Guu et al., 2018)
  - Learn to retrieve a sequence from existing corpus of human-written prototypes (e.g. dialogue responses).
  - Learn to edit the retrieved prototype by adding / removing / modifying tokens in the sequence - this will result in more "human-like" generation

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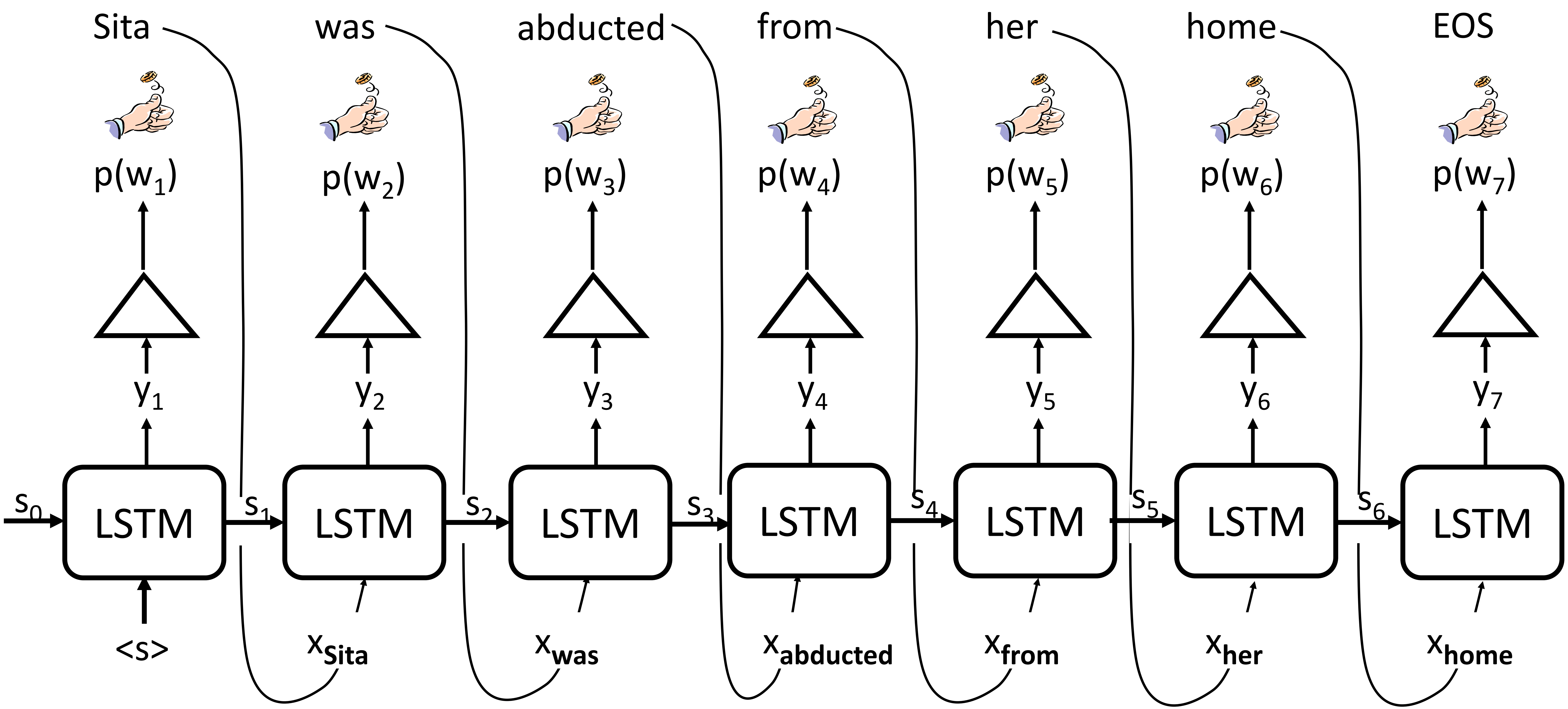
Neural Language Model



Goal

- Generate text based on (varied) inputs

- Examples
  - Machine Translation: Language → Language
  - Summarization: Language → Language
  - Dialogue Systems: Language → Language
  - Speech Recognition: Speech → Language
  - Image Captioning: Image → Language
  - Video Captioning: Video → Language
  - Speech Recognition in Videos: Video+Speech → Language

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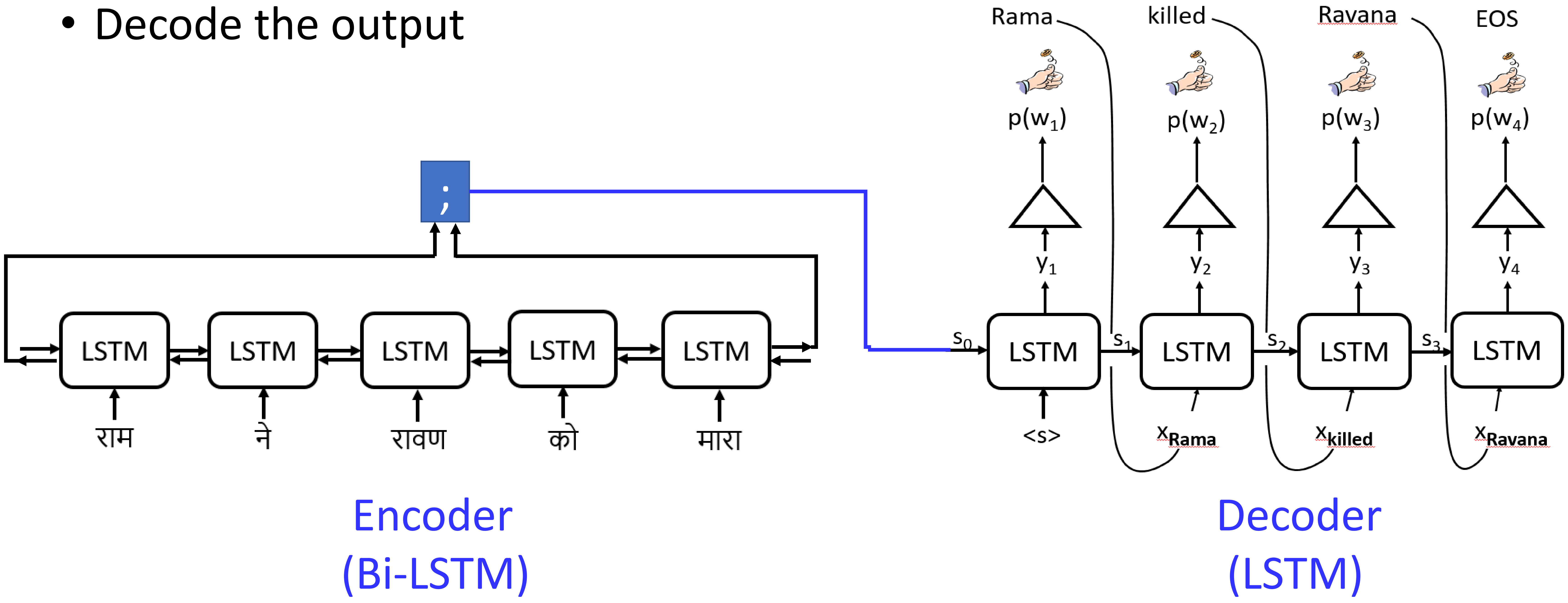
Seq2Seq

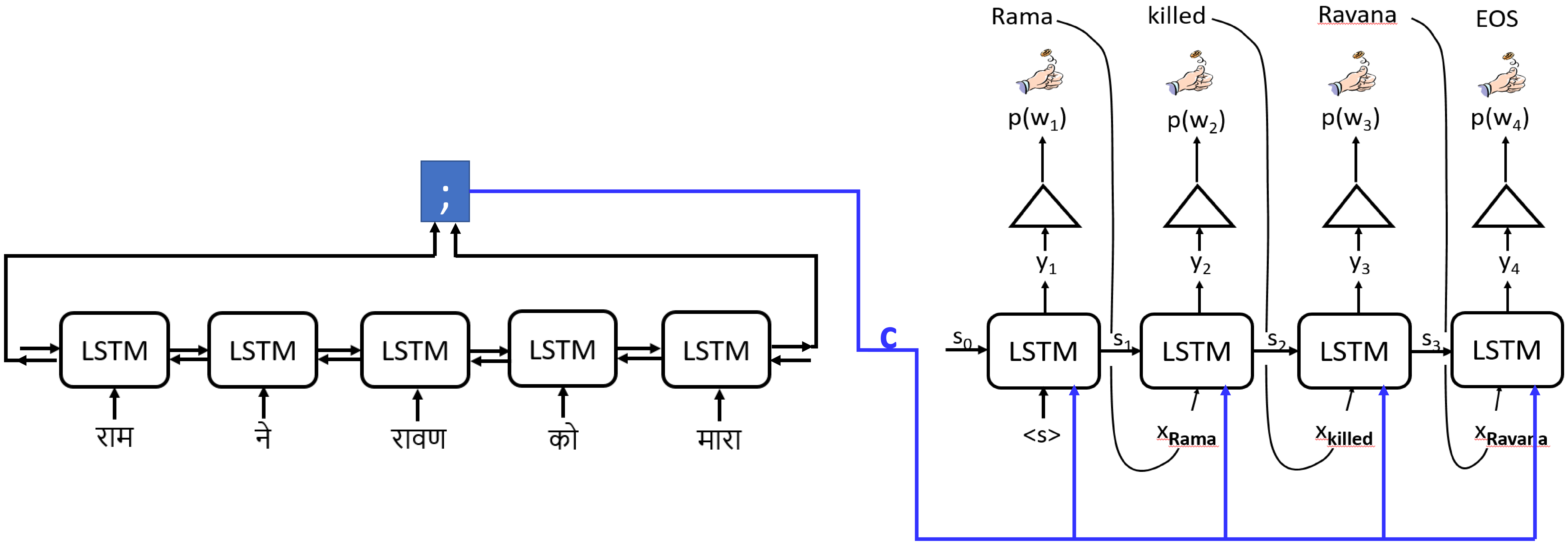
Idea 1: Encoder-Decoder

- Encode the input
- Pass the representation as starting state (s_0) to neural language model
- Decode the output

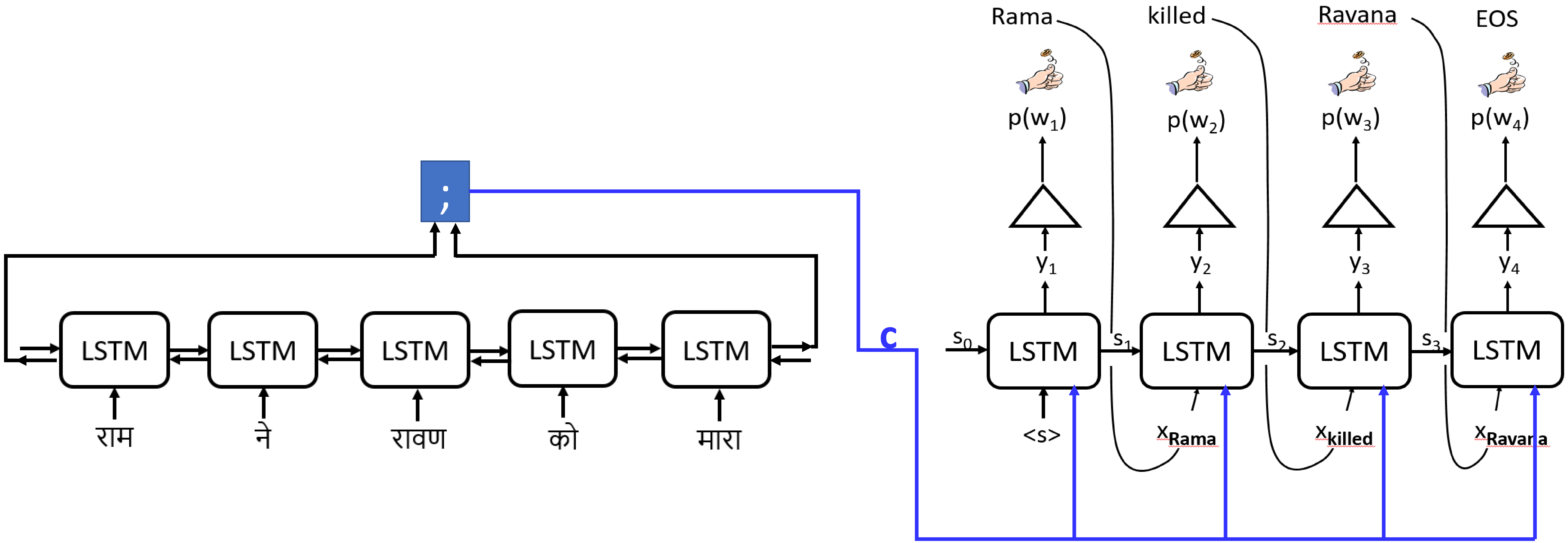


Idea 2: Encoder-Decoder

- Pass encoder output as input to *each* decoder unit
- Input at decoder = concat(c, $x_{\text{prev word}}$)



Seq2Seq without Attention



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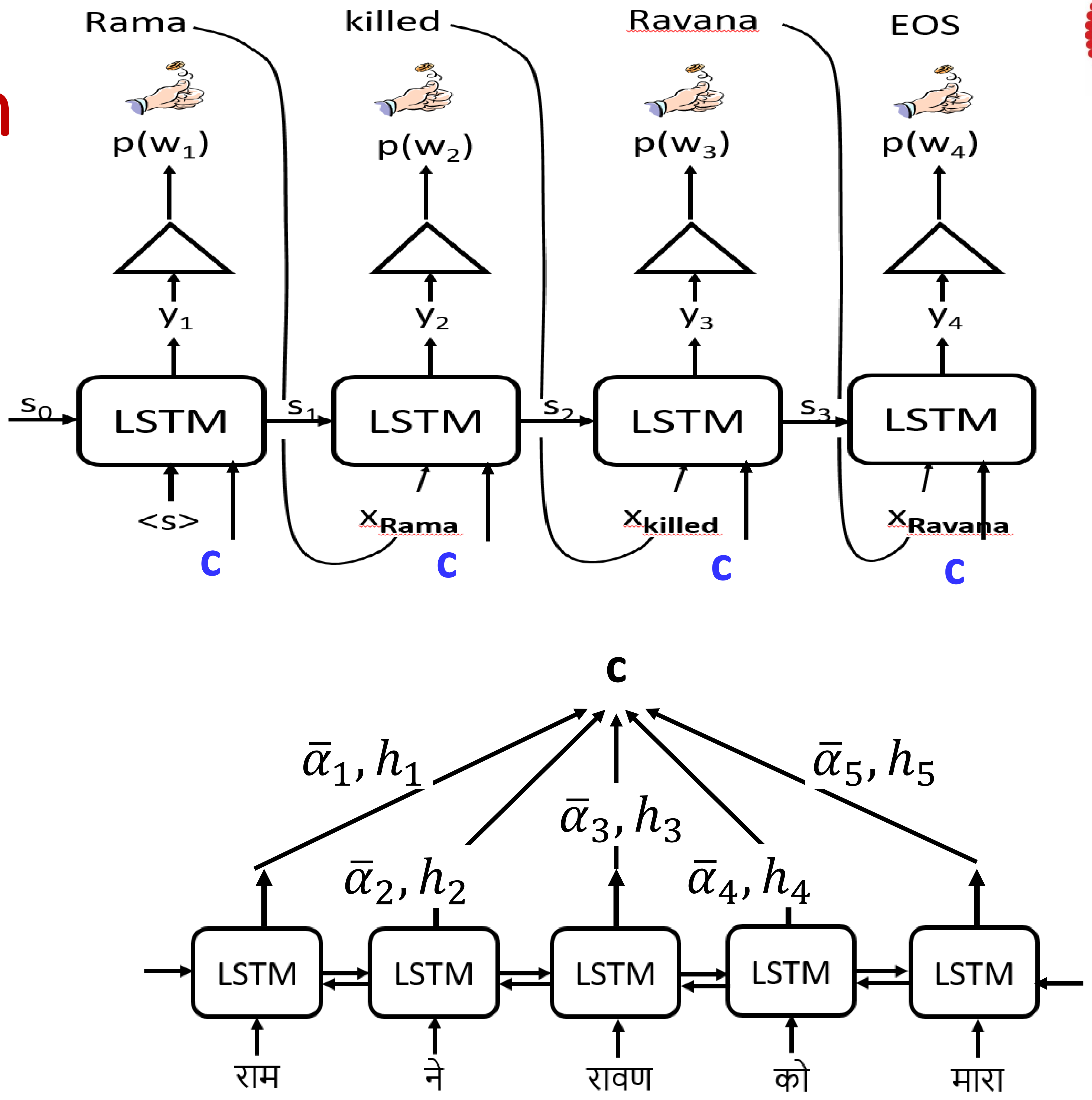
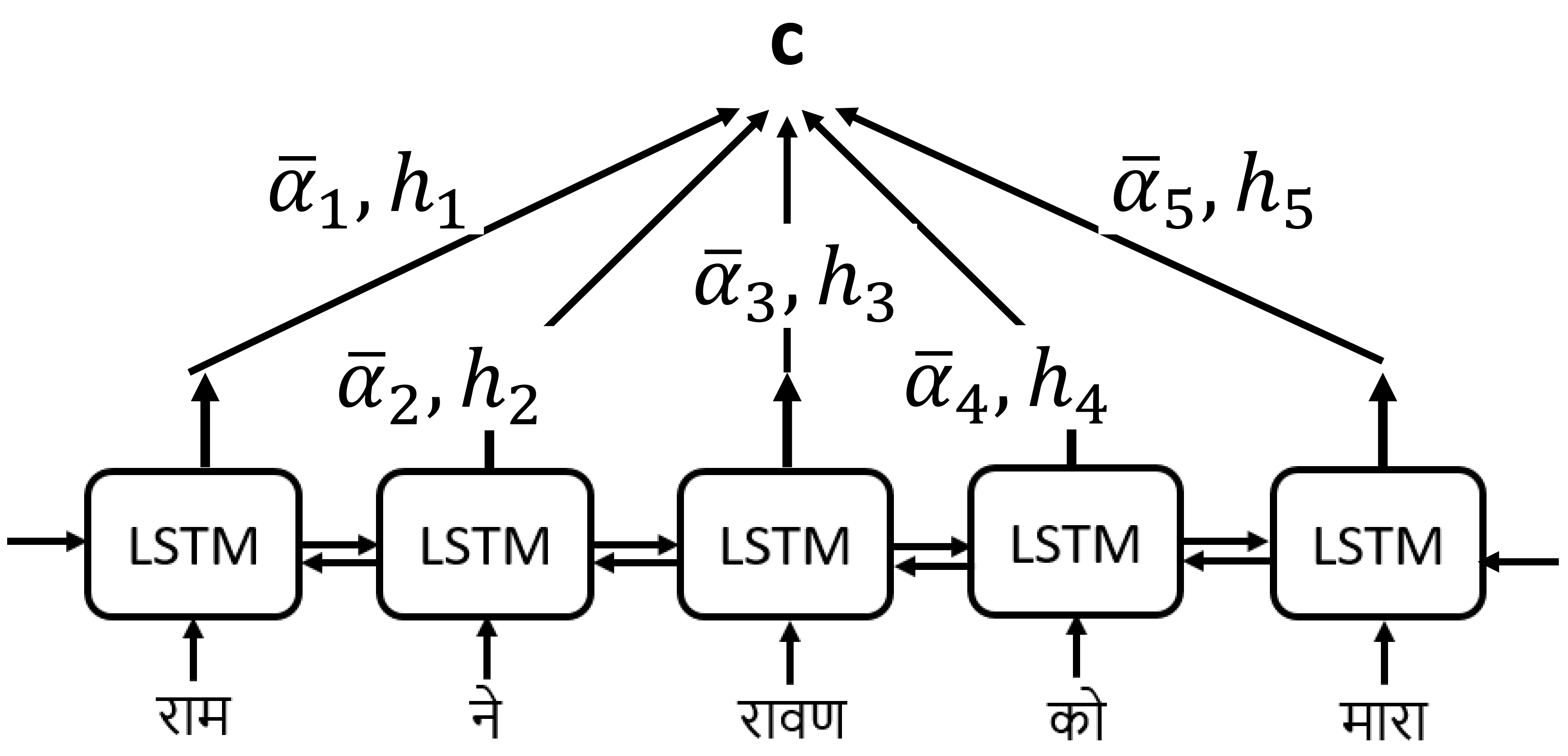


Multiple Encoded Vectors → Single Summary

$$c = \sum_{i=1}^{T} \alpha_i . h_i$$

$$\alpha_{1:T} = \mathrm{softmax}(\bar{\alpha}_1, \bar{\alpha}_2, \ldots, \bar{\alpha}_T)$$

$$\bar{\alpha}_i = \phi^{\mathrm{att}}(q, h_i)$$



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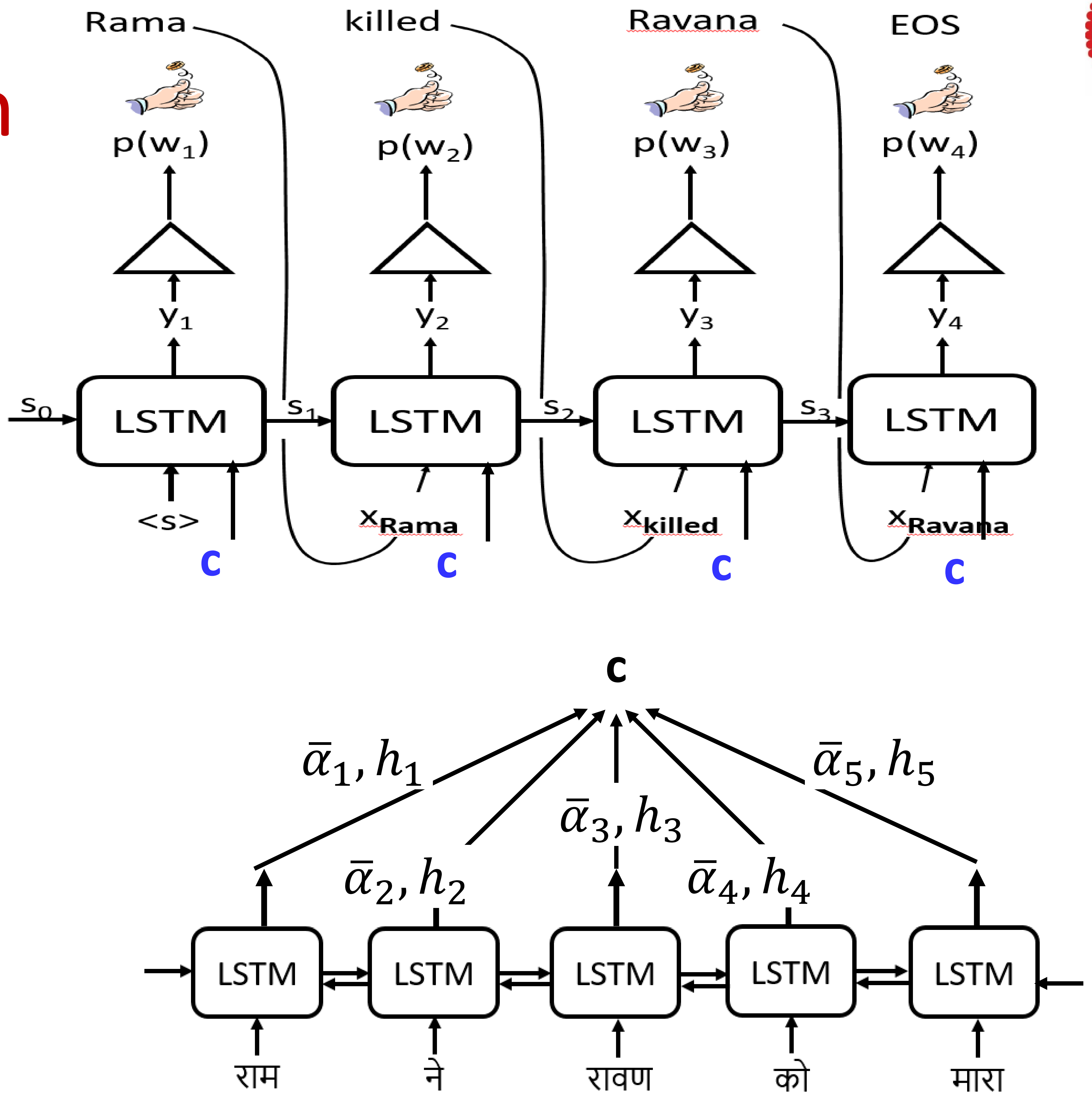

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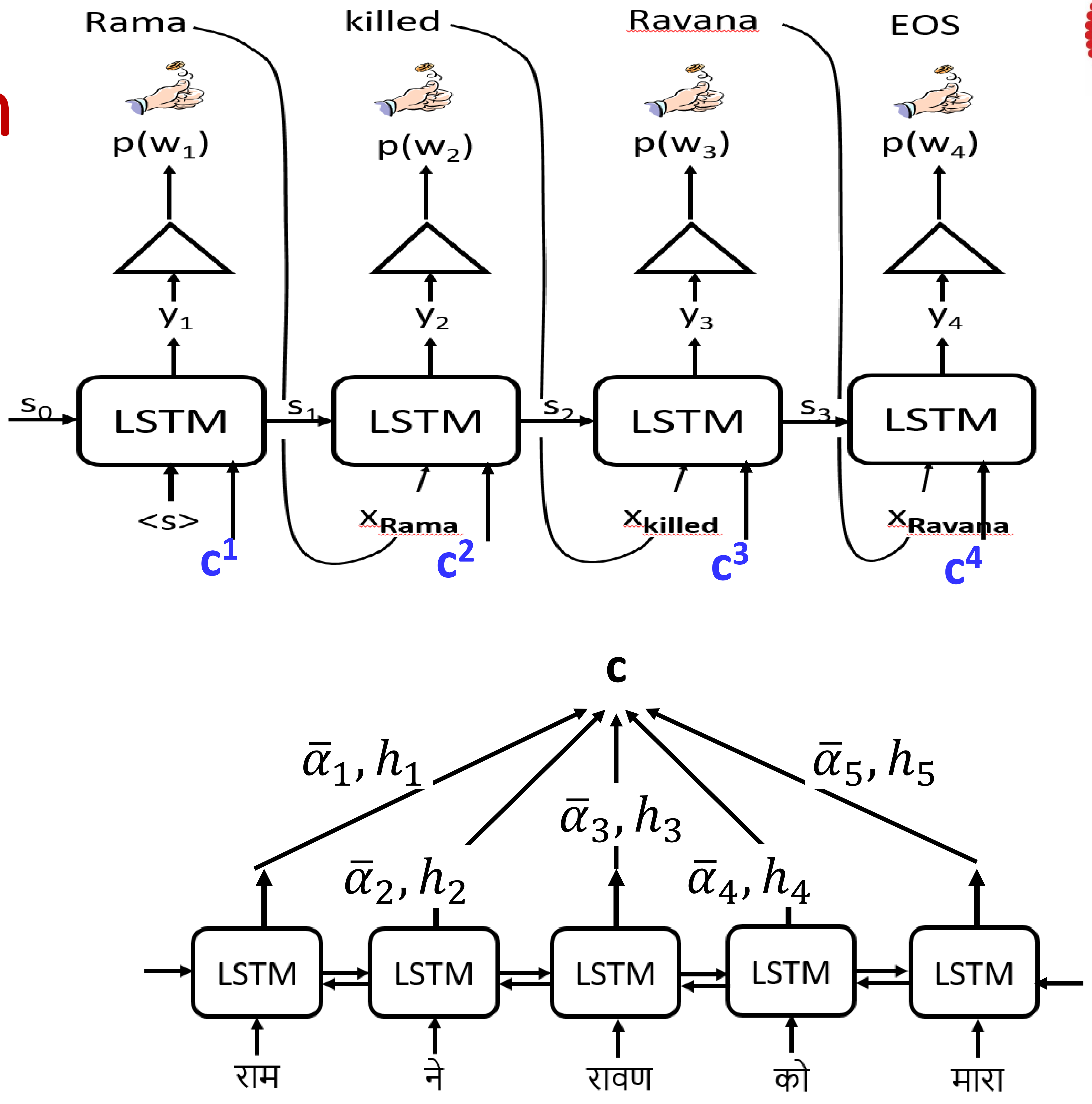

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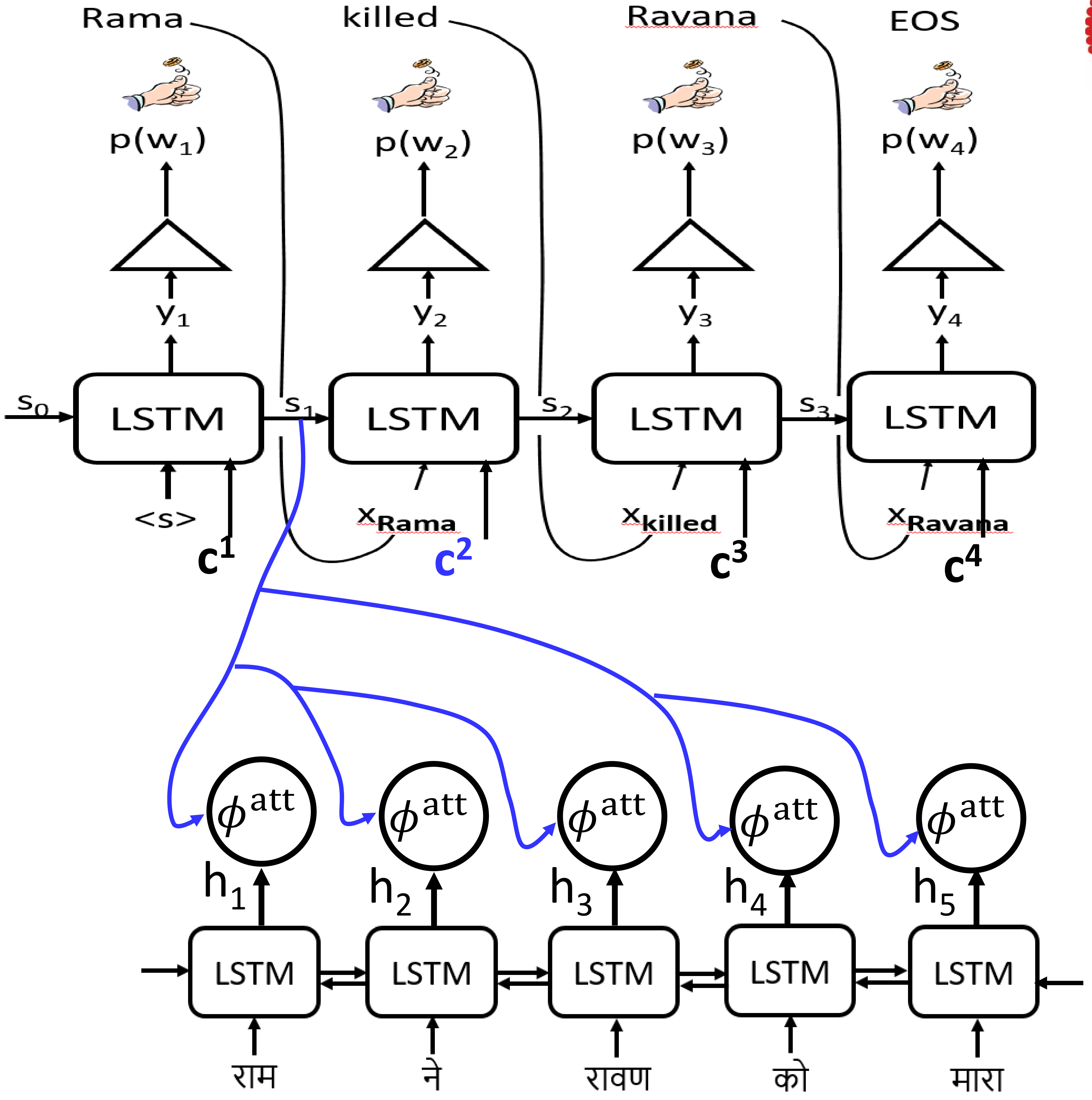

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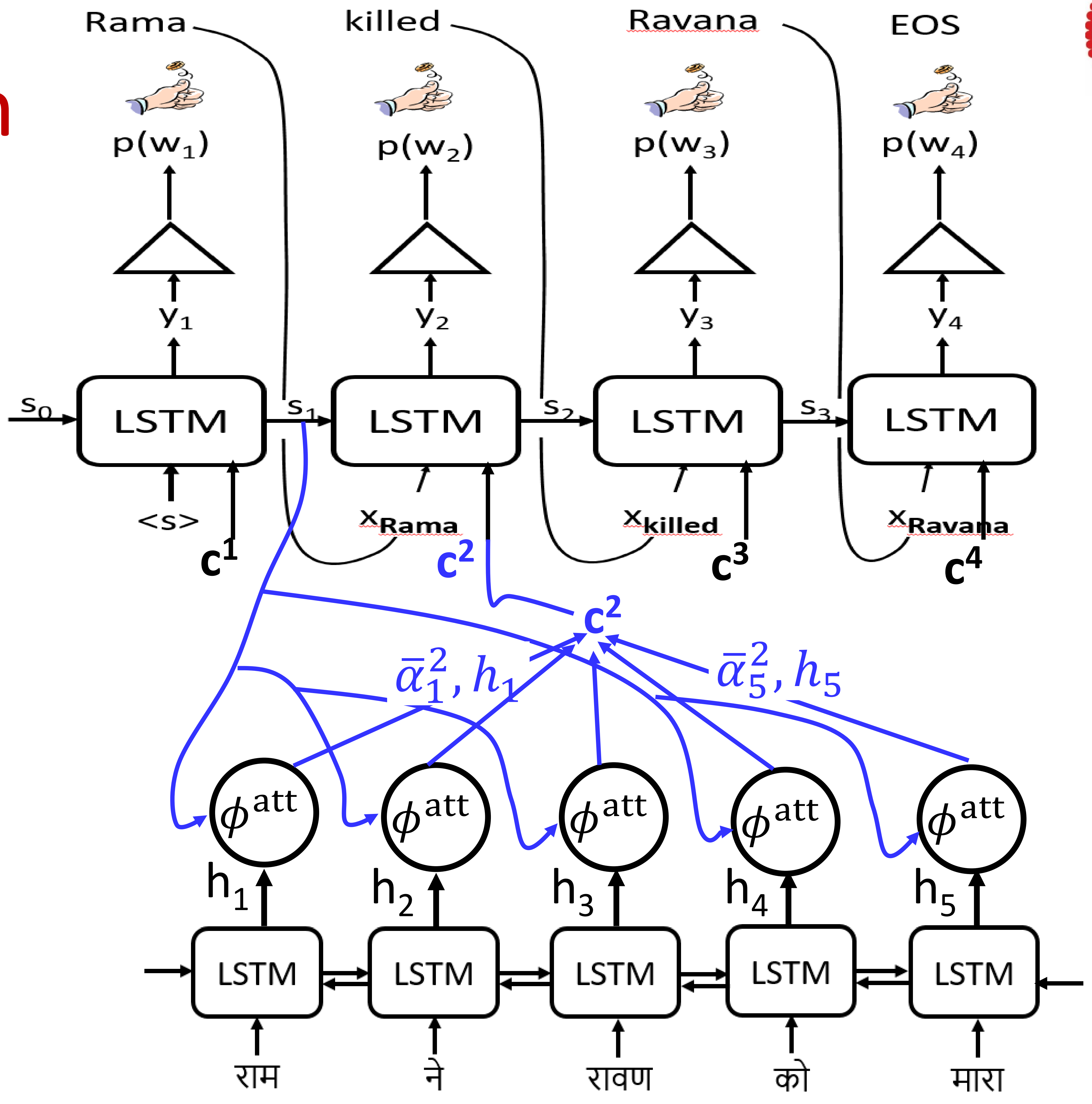


Seq2Seq with Attention

$$h_{1:T} = \mathrm{biLSTM}_{enc}(x_{1:T})$$

$$\bar{\alpha}_i^j = \phi^{\mathrm{att}}(s_{j-1}, h_i)$$
$$\alpha^j = \mathrm{softmax}\left(\bar{\alpha}_1^j, \bar{\alpha}_2^j, \ldots, \bar{\alpha}_T^j\right)$$
$$c^j = \sum_{i=1}^{T} \alpha_i^j . h_i$$

$$s_j = \mathrm{LSTM}_{dec}\left(s_{j-1}, x_{z[j-1]}, c^j\right)$$

$$p_j(w) = \mathrm{softmax}\left(\mathrm{MLP}^{\mathrm{out}}(s_j)\right)$$
$$z[j] \sim p_j(w)$$

Encoder-Decoder with Attention

- Encoder encodes a sequence of vectors, $h_1,\ldots,h_T$
- At each decoding stage, MLP ϕ assigns a relevance score to each Encoder vector.
- The relevance score is based on h_i and the state s_{j-1}
- Weighted-sum (based on relevance) is used to produce the conditioning context for decoder step j.

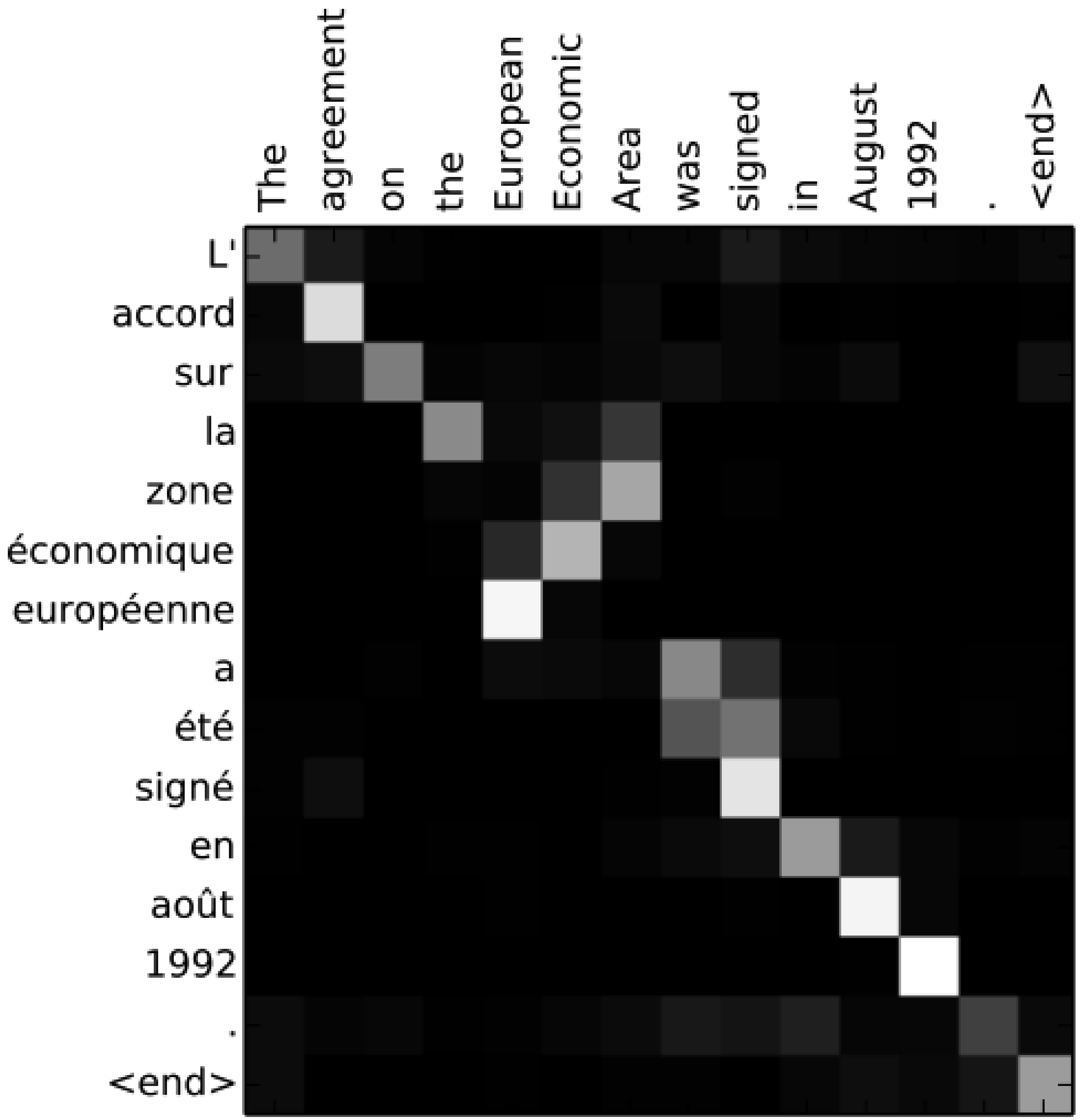
Encoder-Decoder with Attention

- Decoder "pays attention" to different parts of encoded sequence at each stage.
- The attention mechanism is "soft" -- it is a mixture of encoder states.

- The encoder acts as a read-only memory for the decoder
- The decoder chooses what to read at each stage

- Complexity
  - Encoder Decoder: O(n+m)
  - Encoder Decoder w/ Attention: O(nm)

Attention



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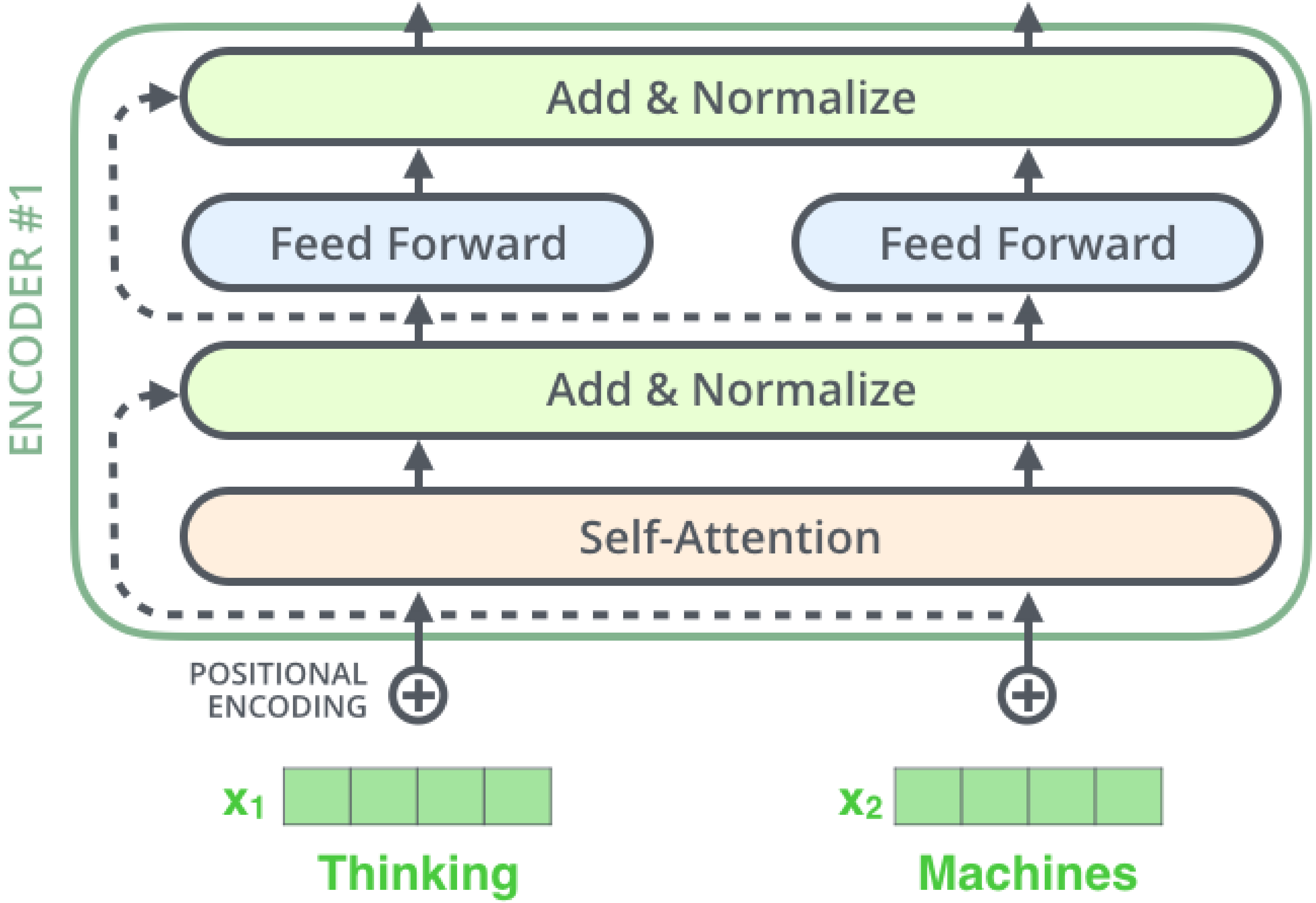
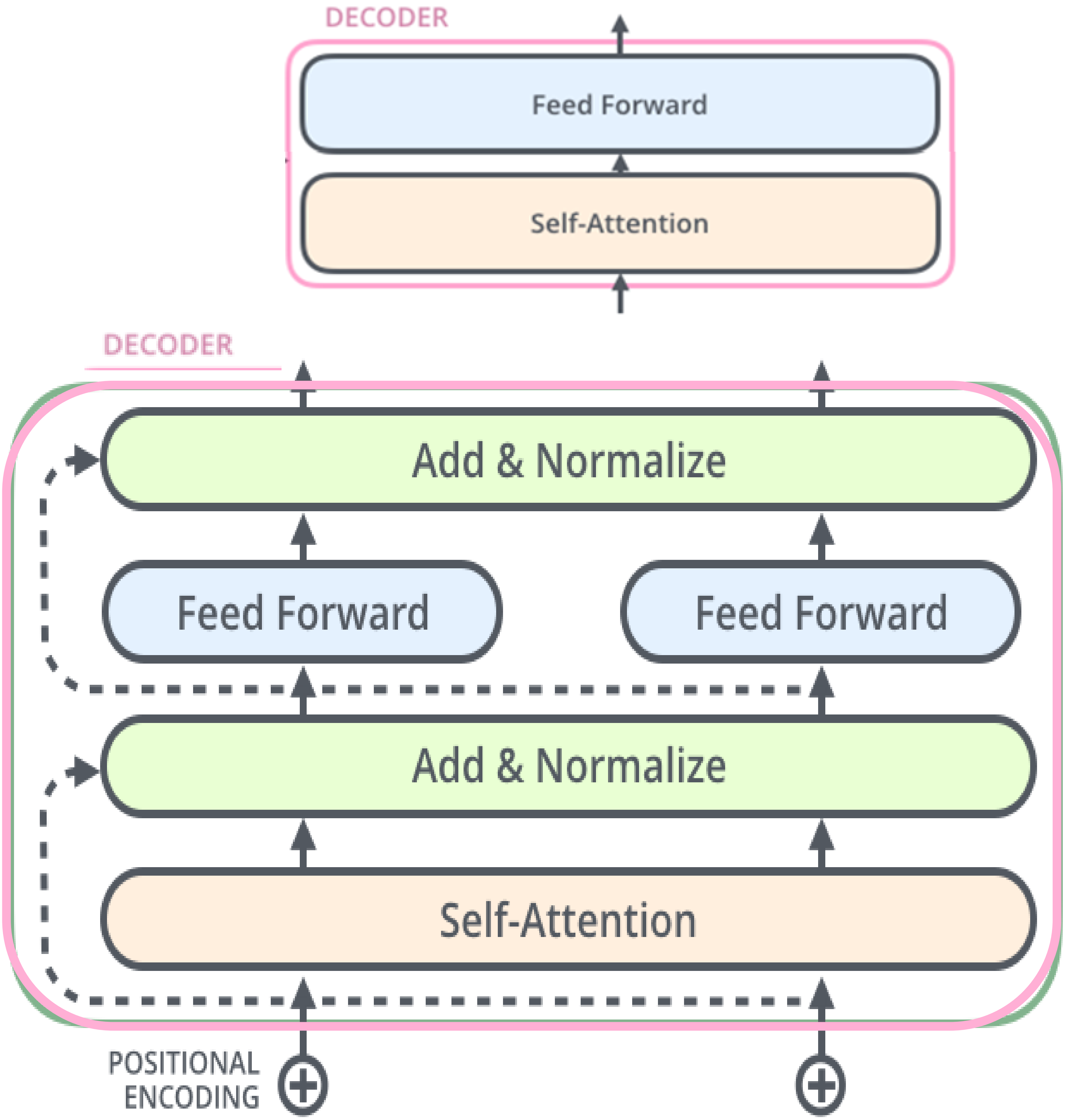


Images from https://jalammar.github.io/illustrated-transformer/

Decoders

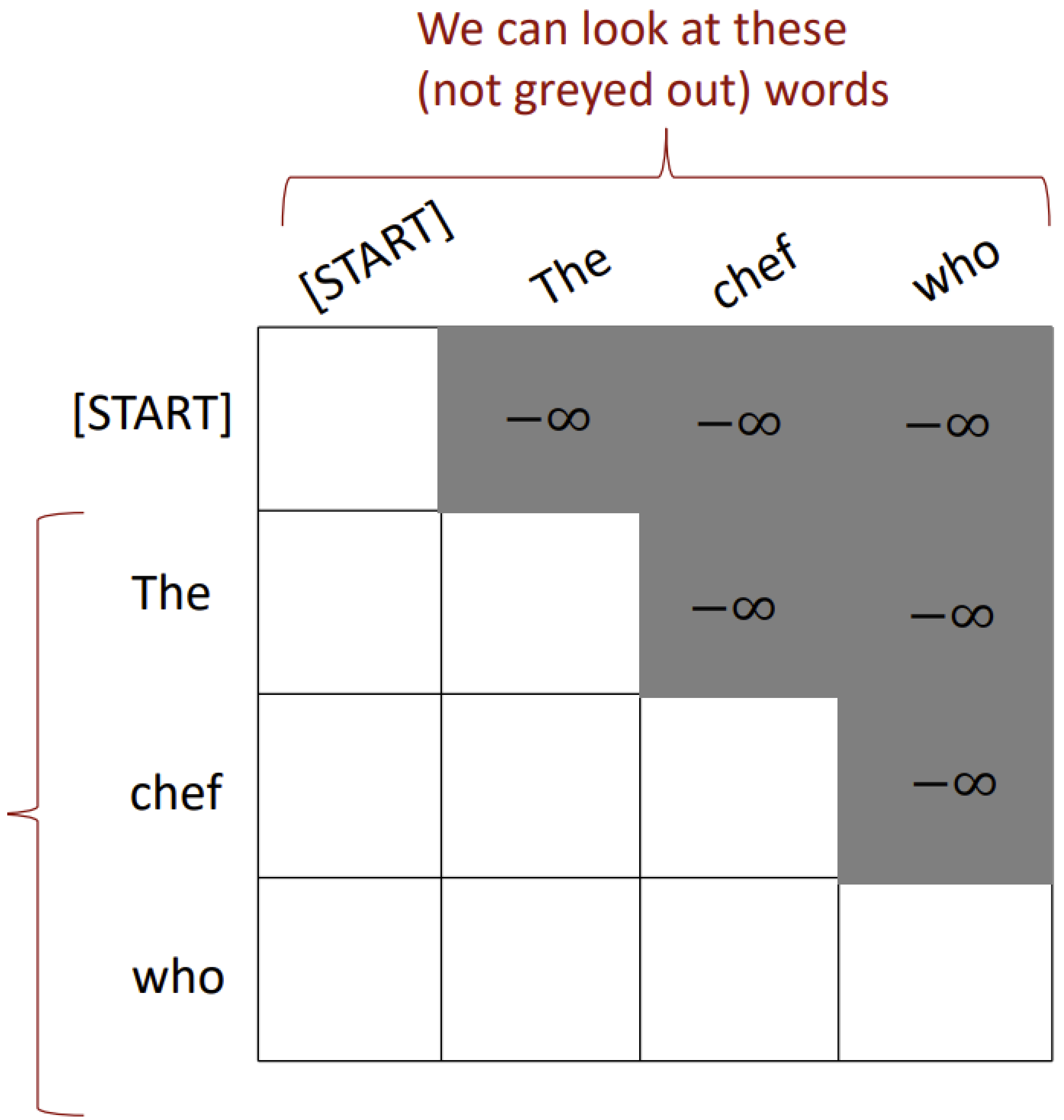
One key differences from encoder:

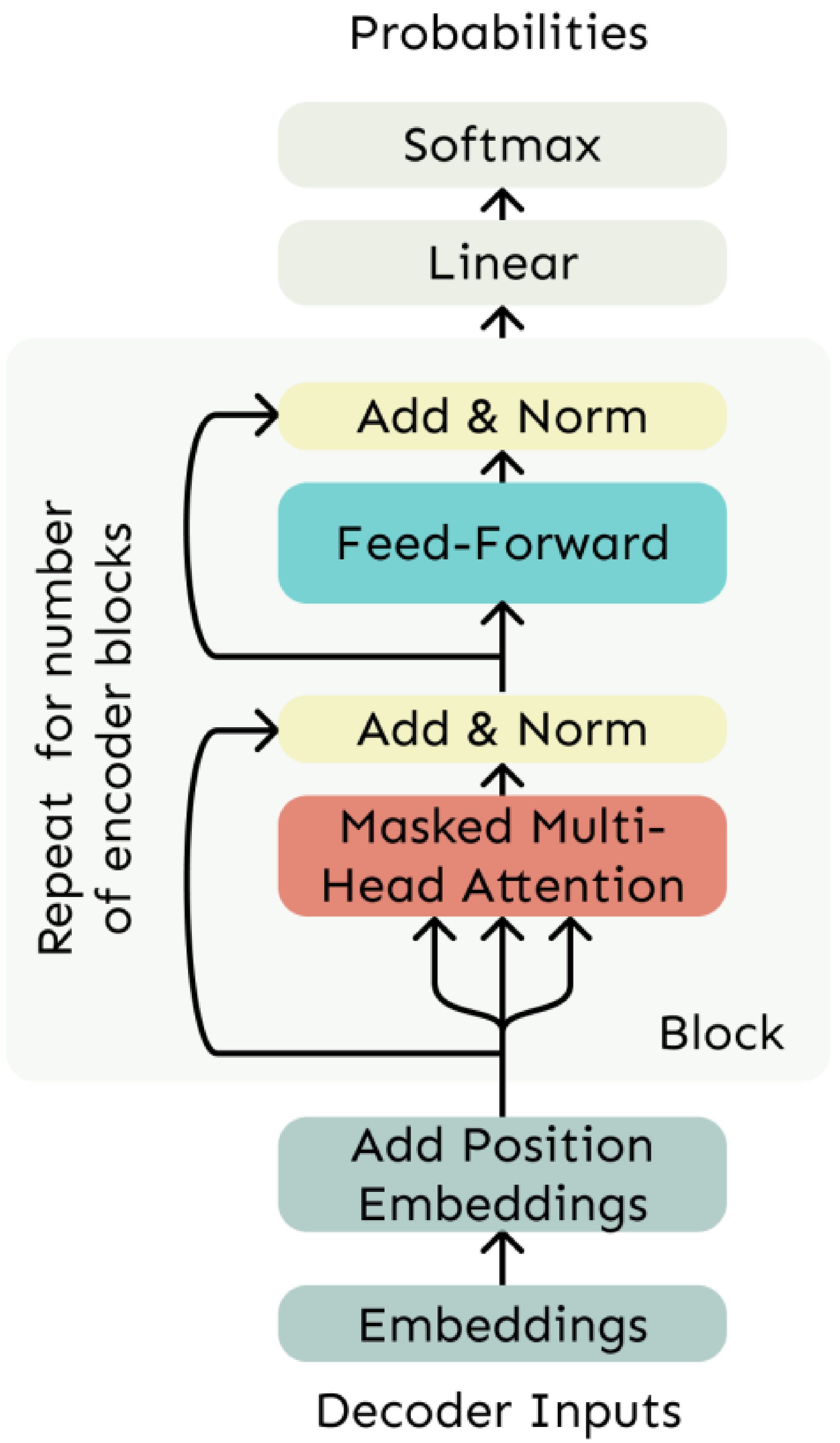
- Self-attention only on words generated uptil now, not on whole sentence.



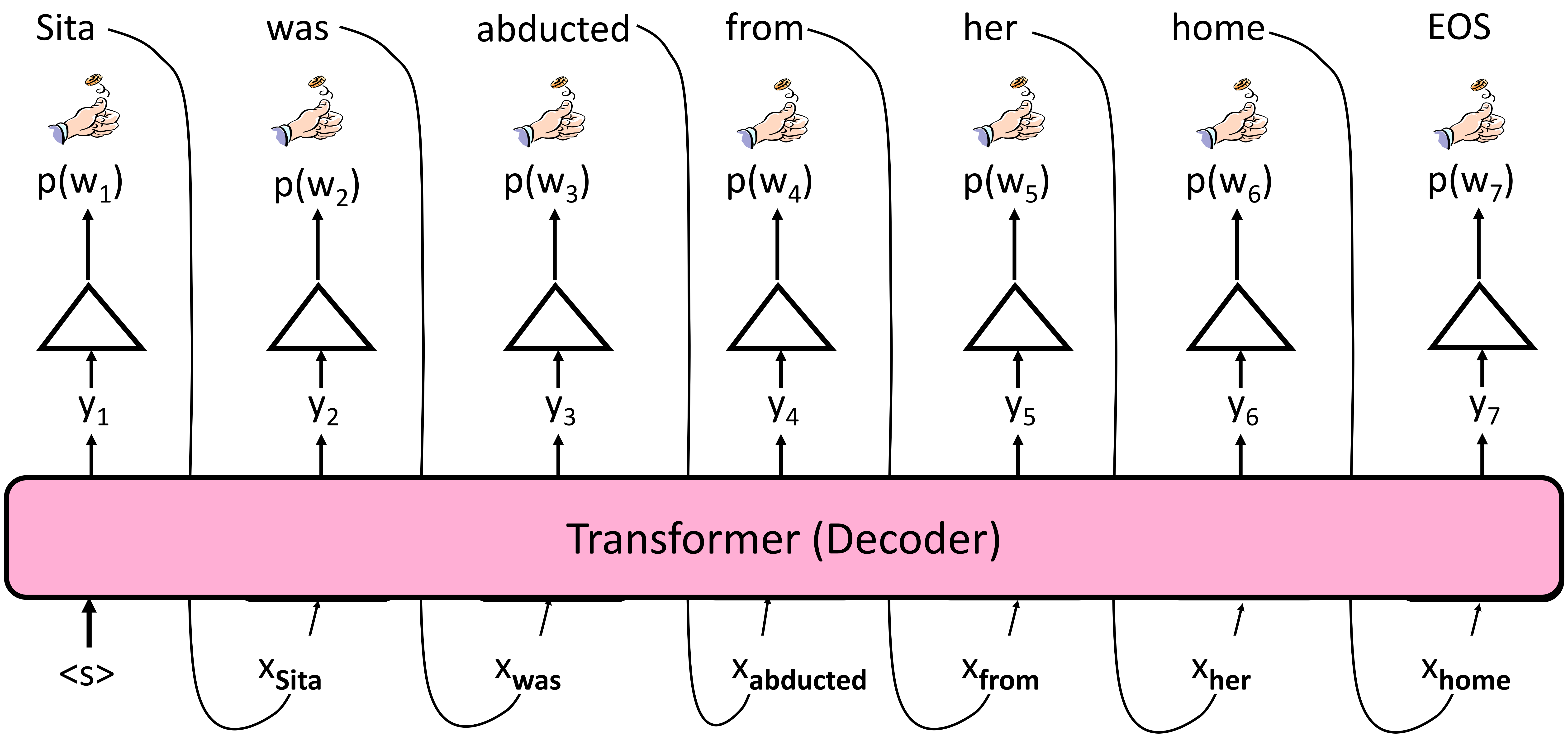
Transformer Decoder

- Need to ensure we don't "look at the future" when predicting a sequence





Transformer Language Model



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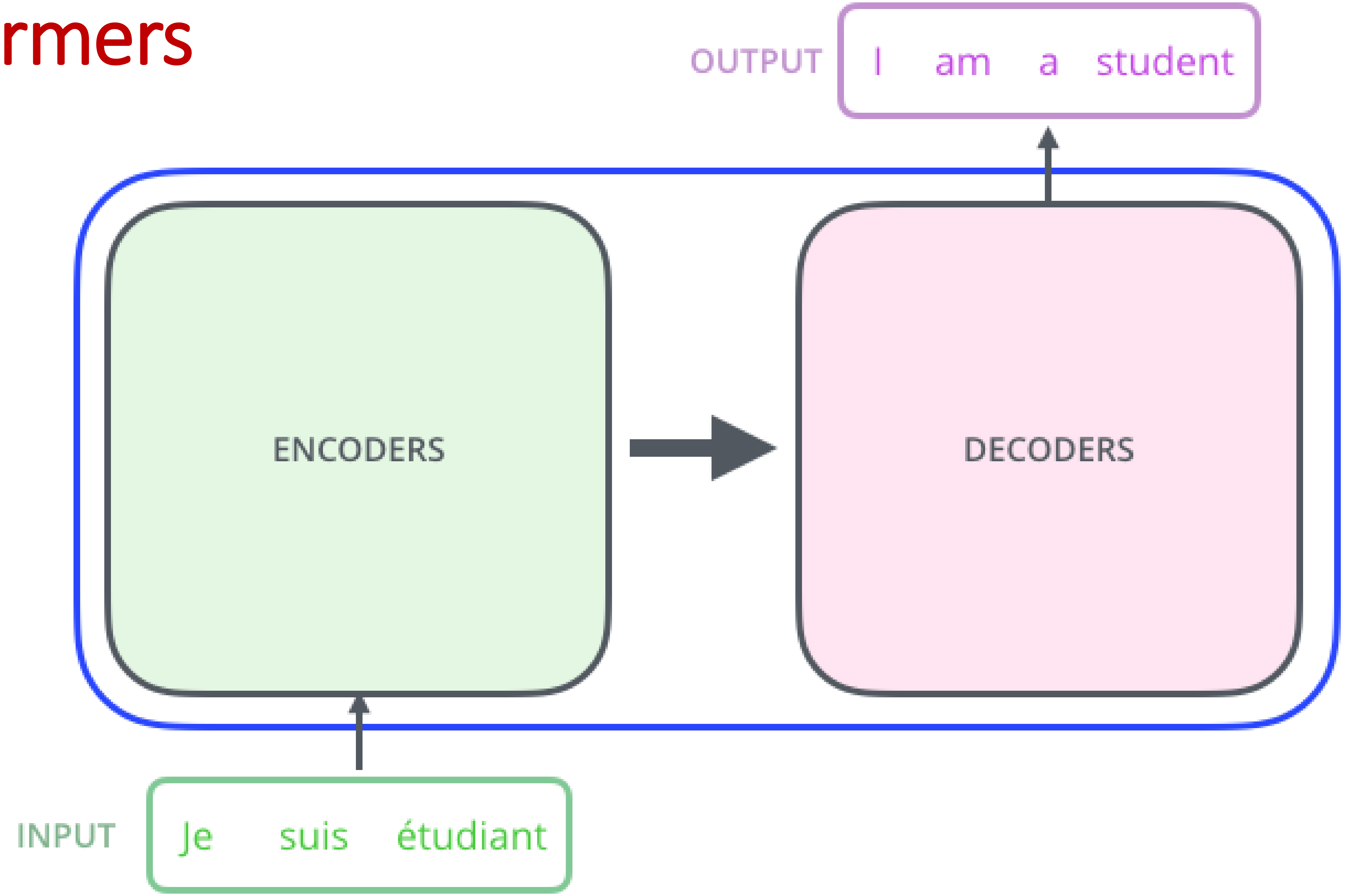

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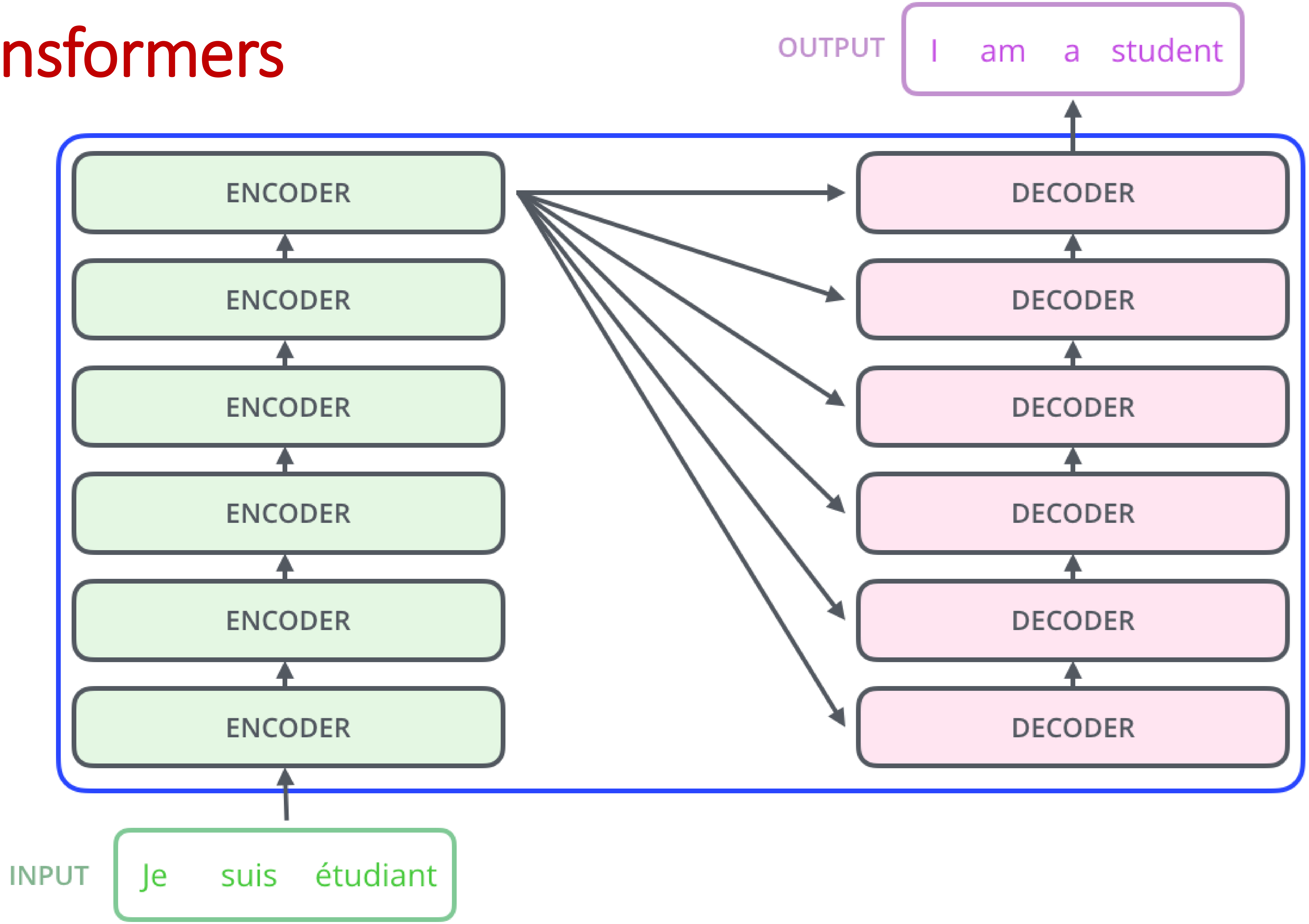
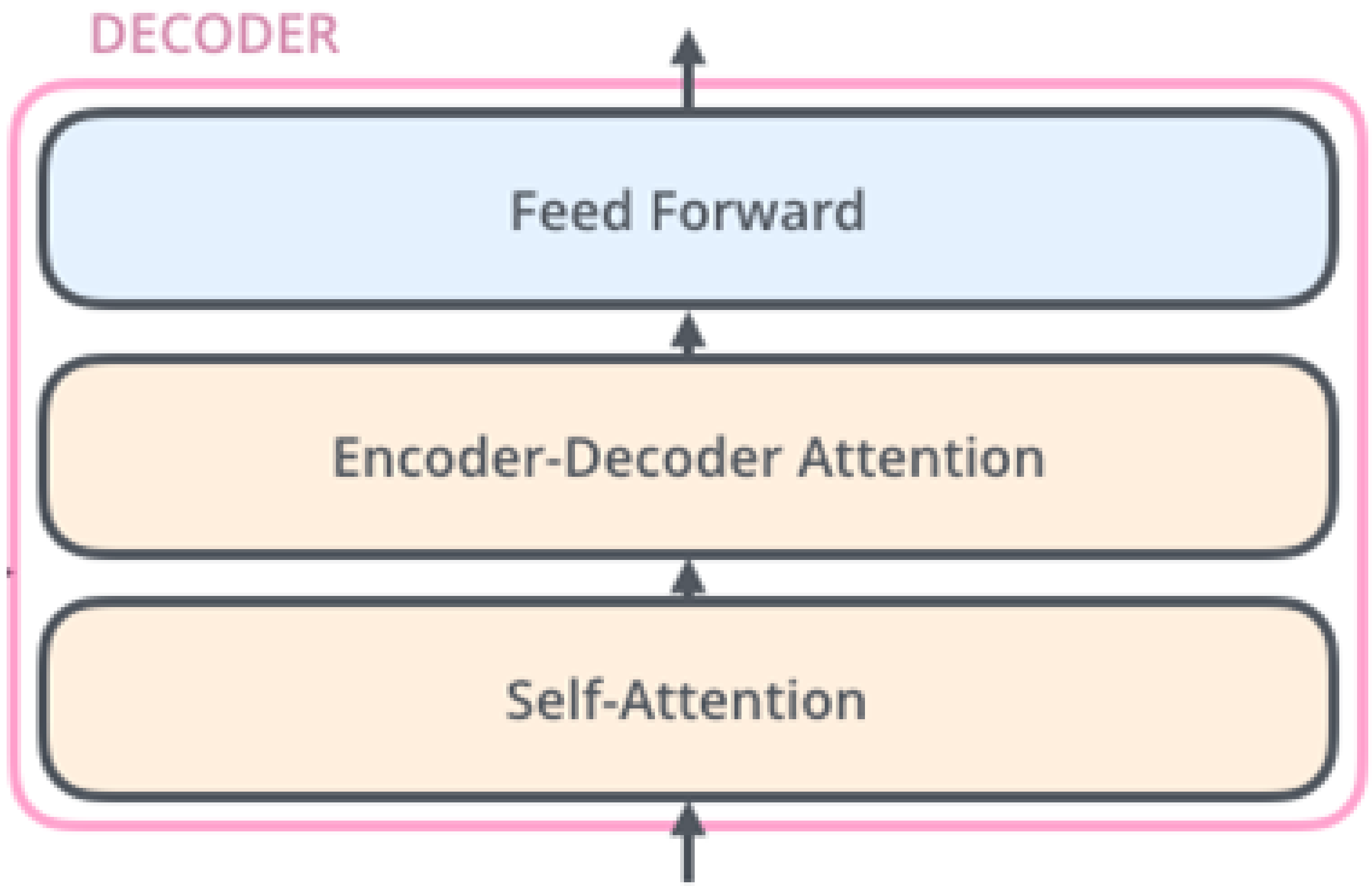


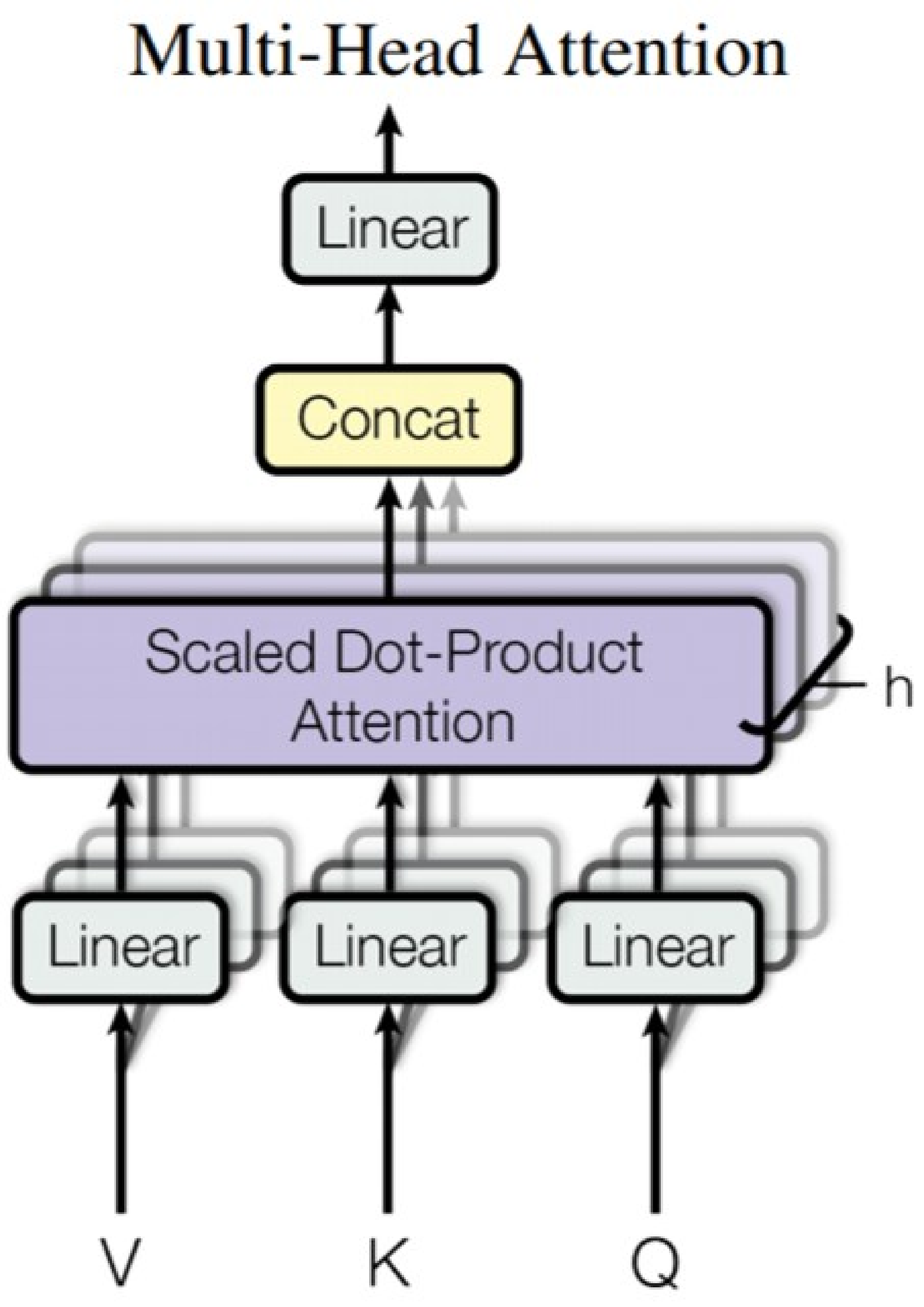
Encoder-Decoder

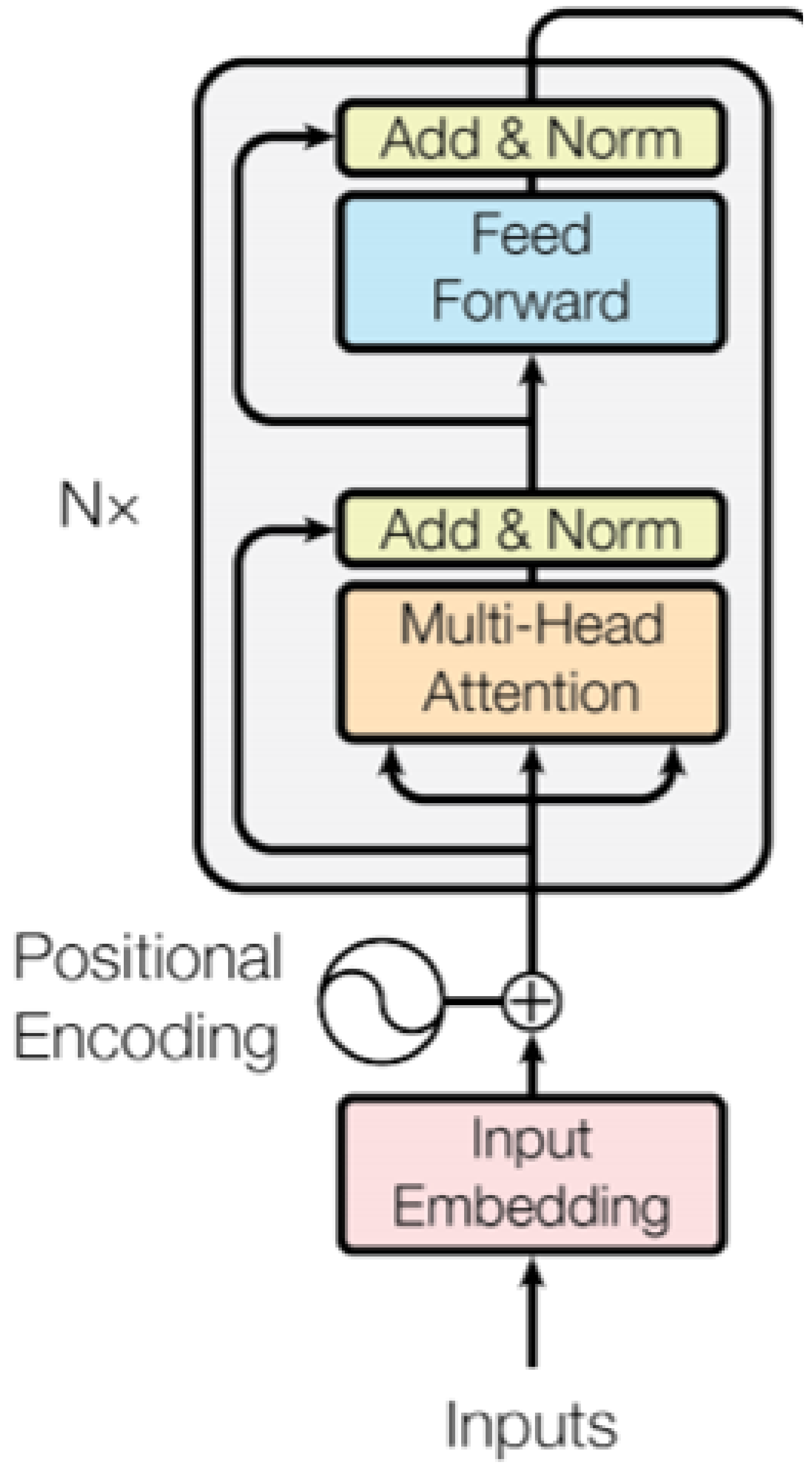
One key differences from decoder:

- Additional encoder-decoder attention layer where keys, values come from last encoder layer.



Full architecture with Attention reference





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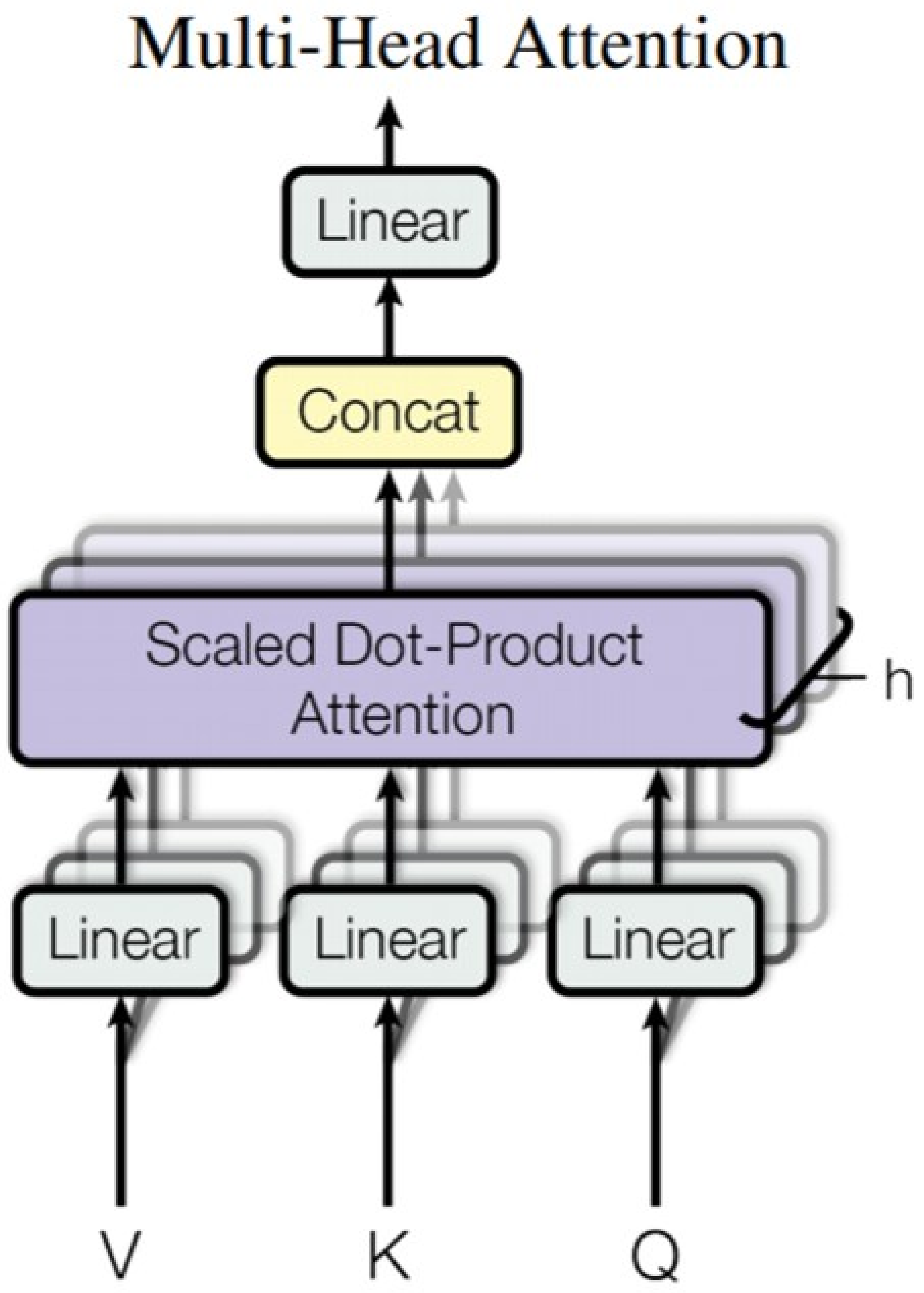

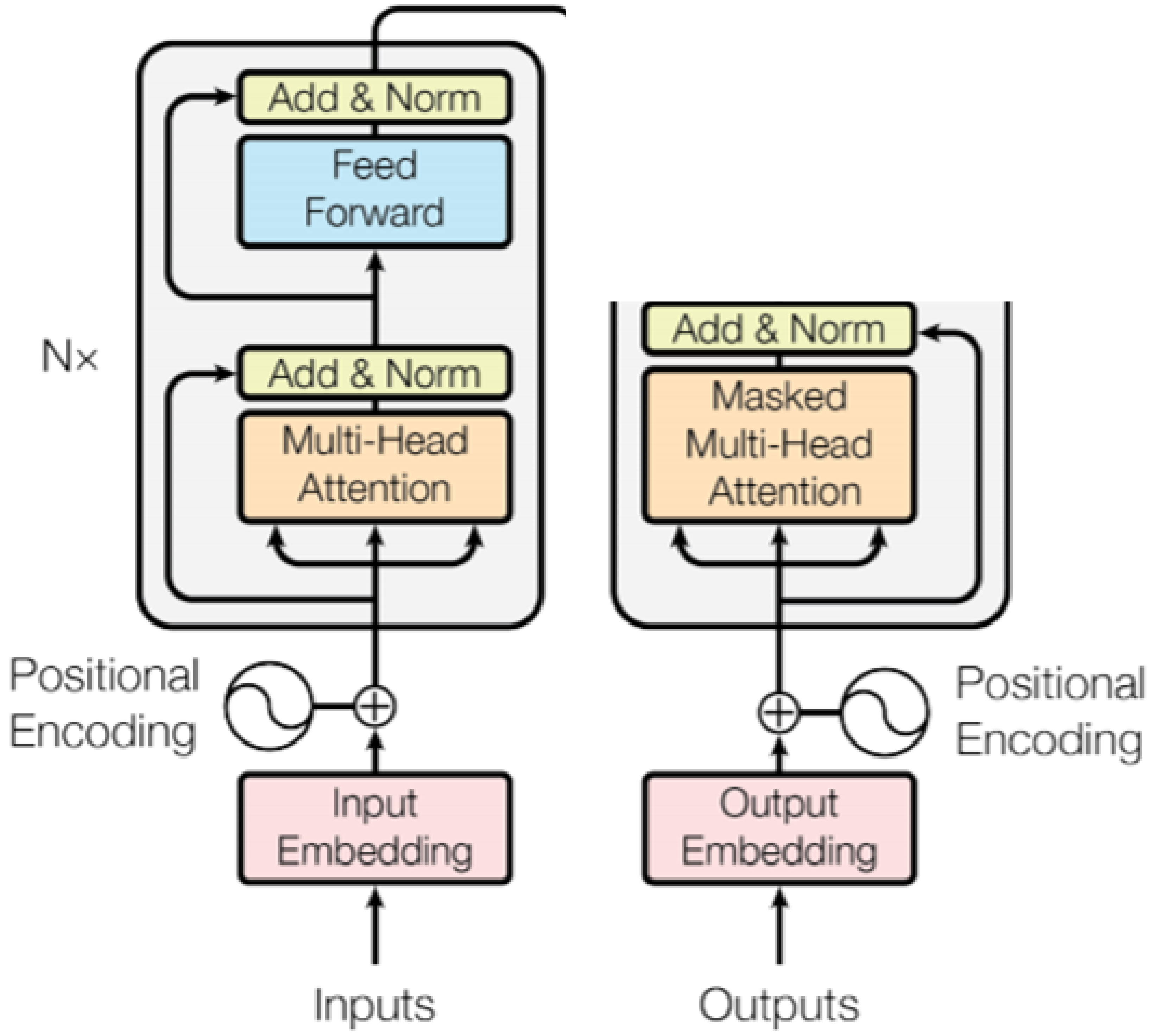

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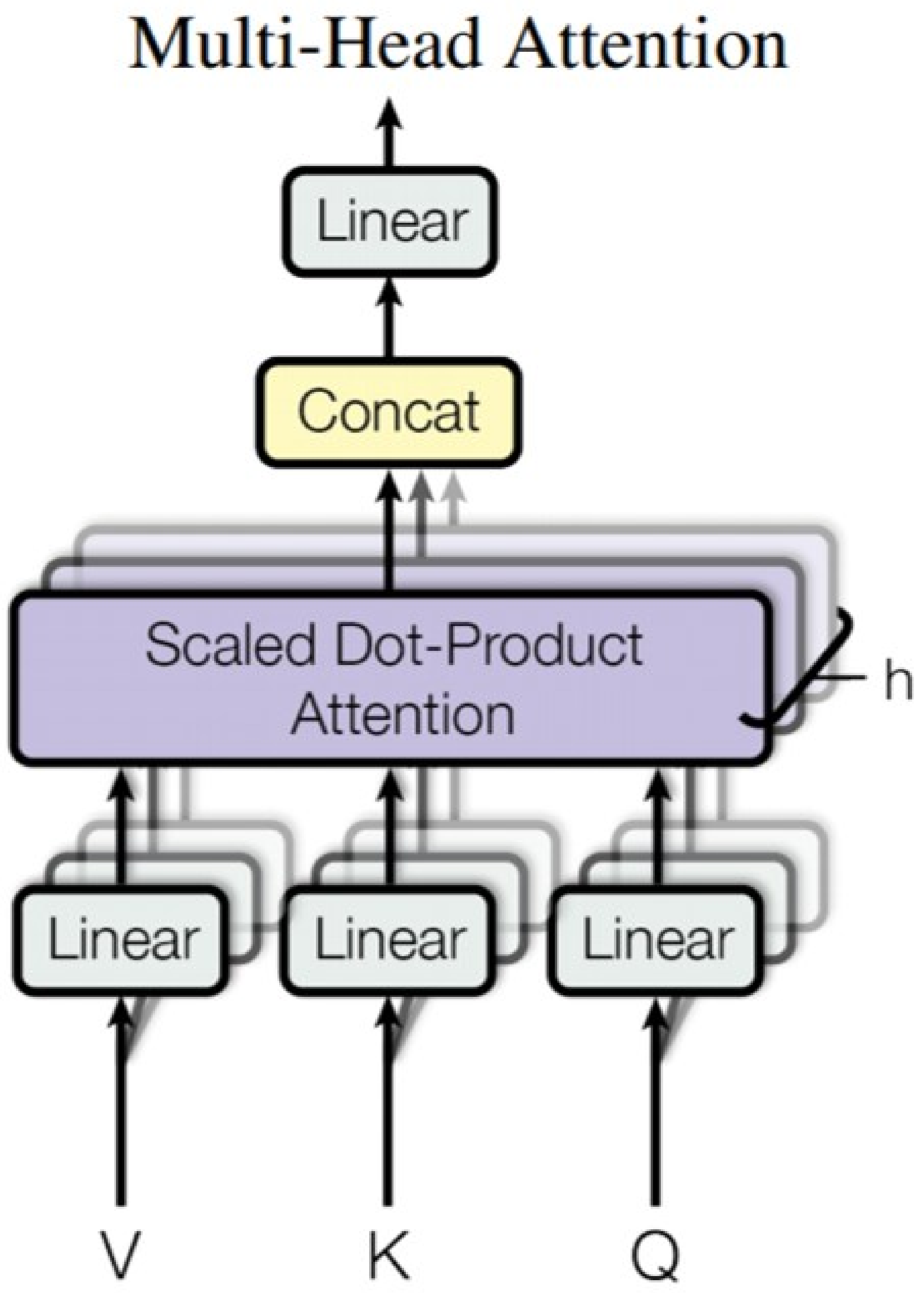

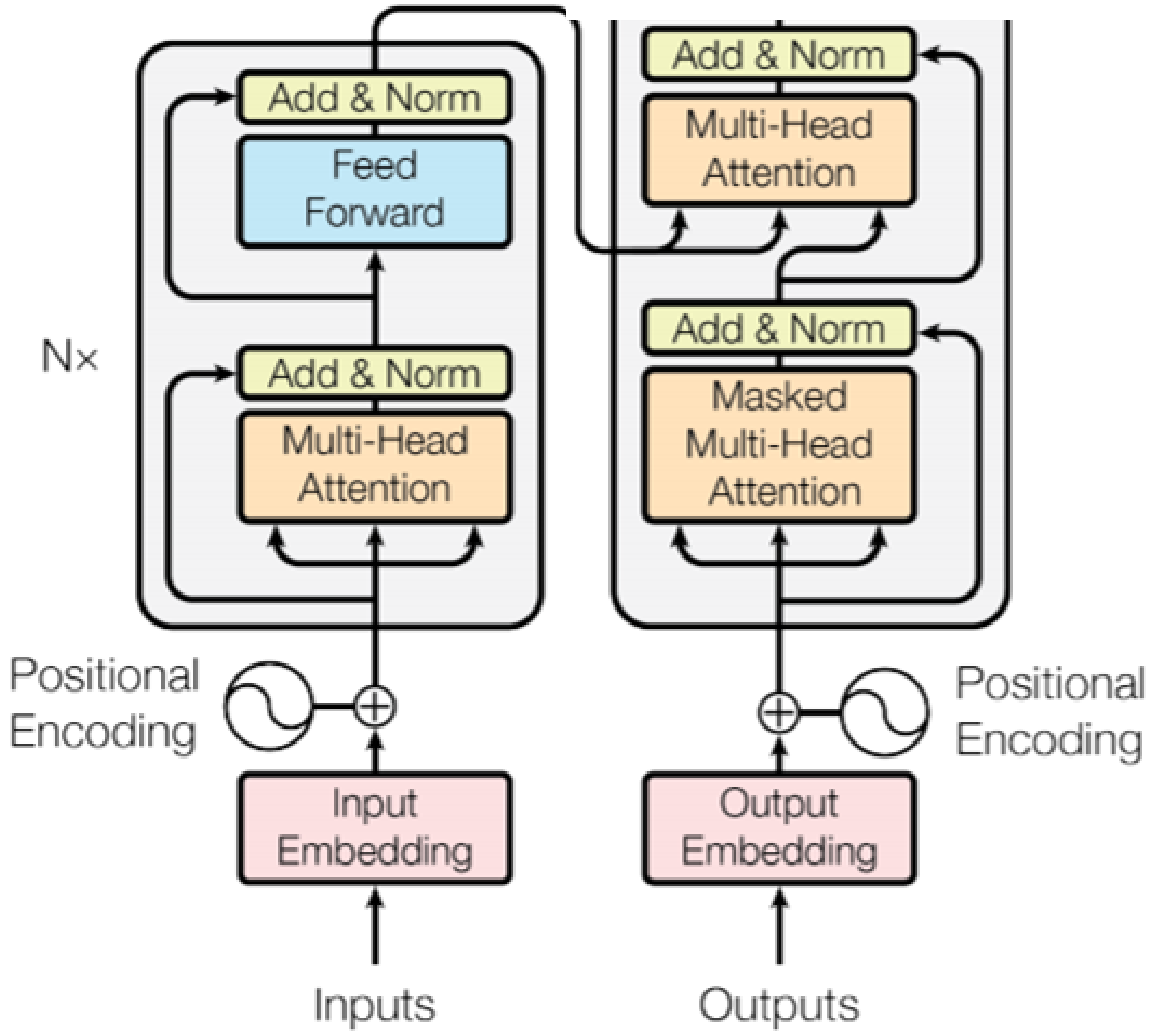

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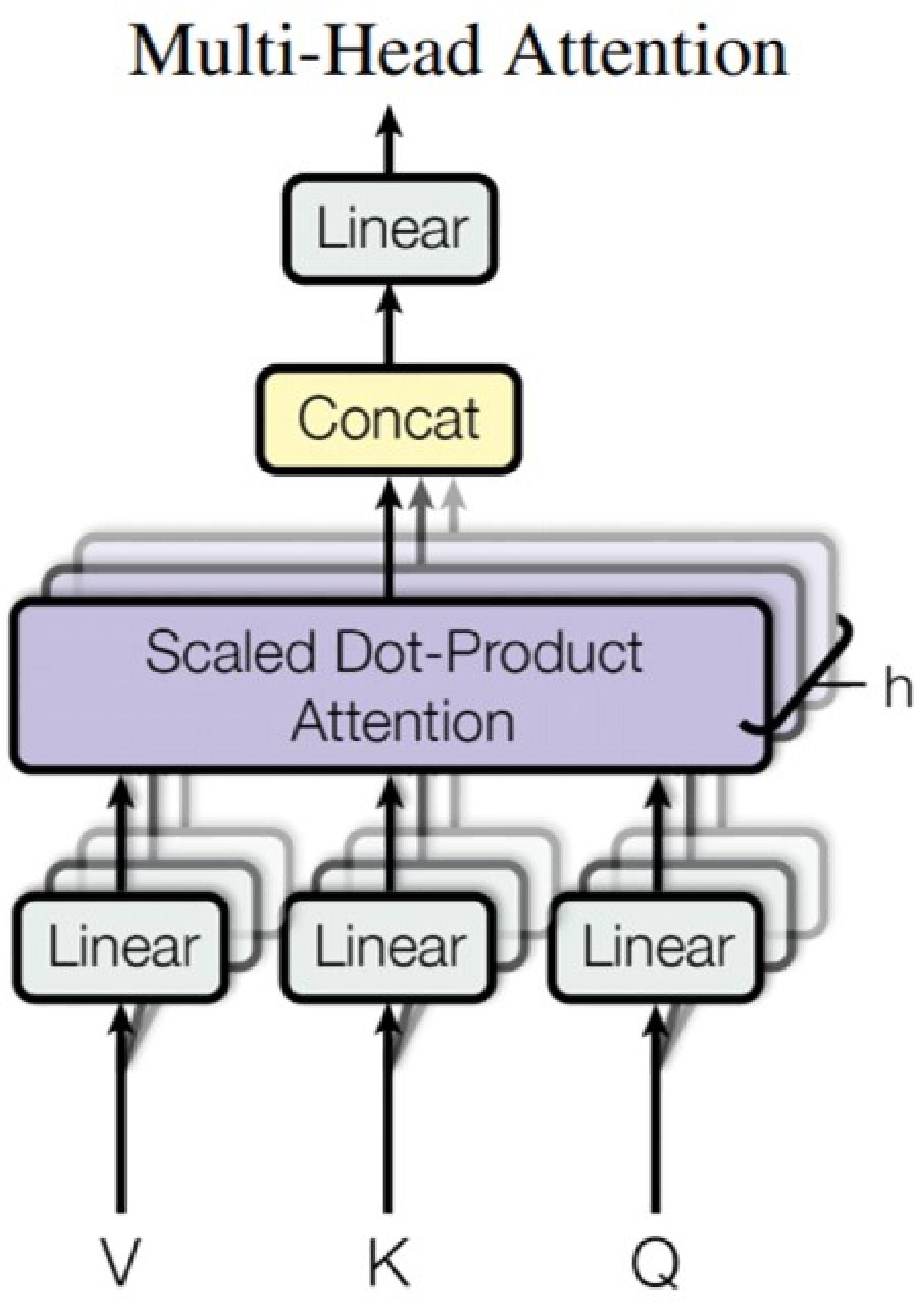

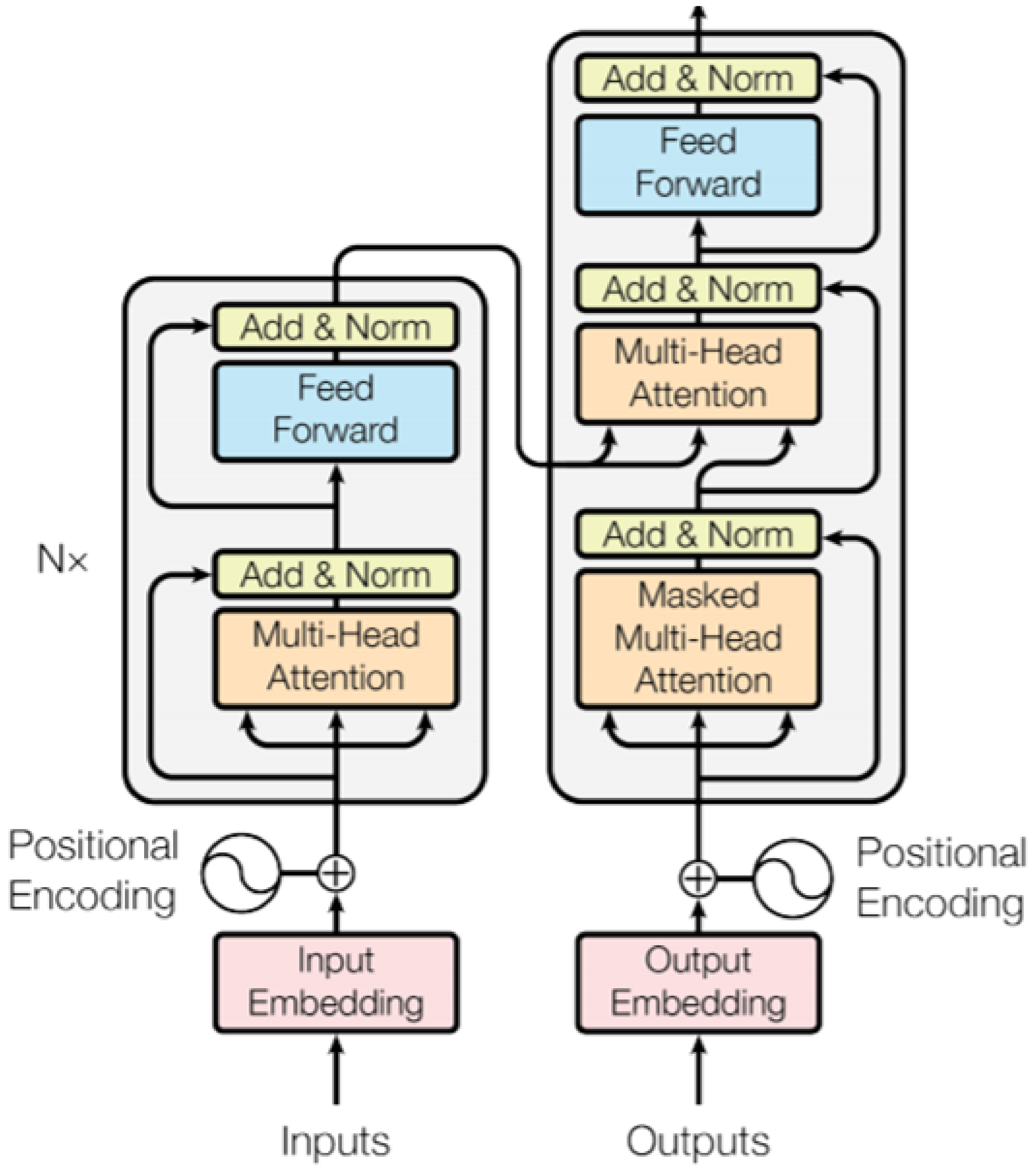

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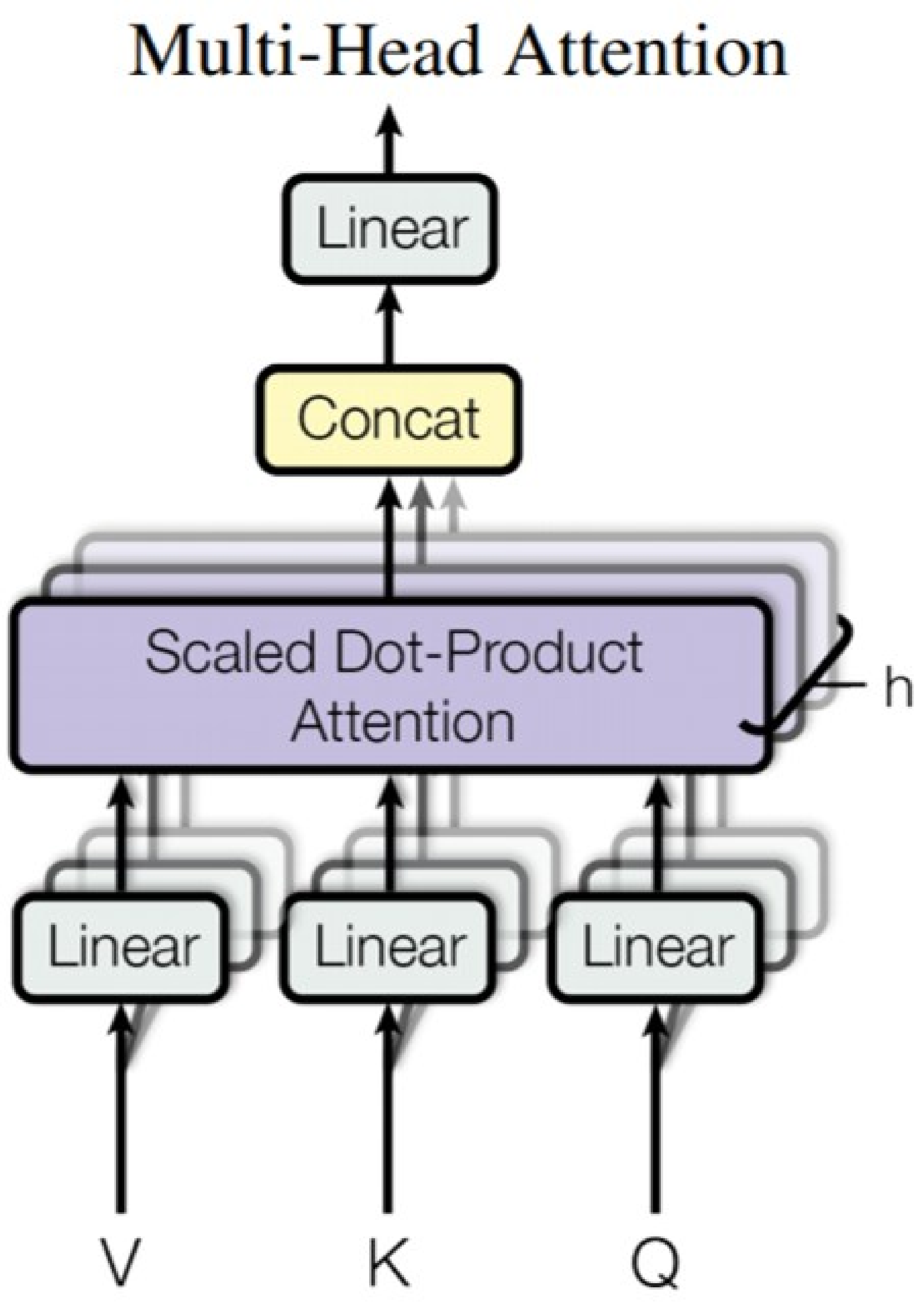

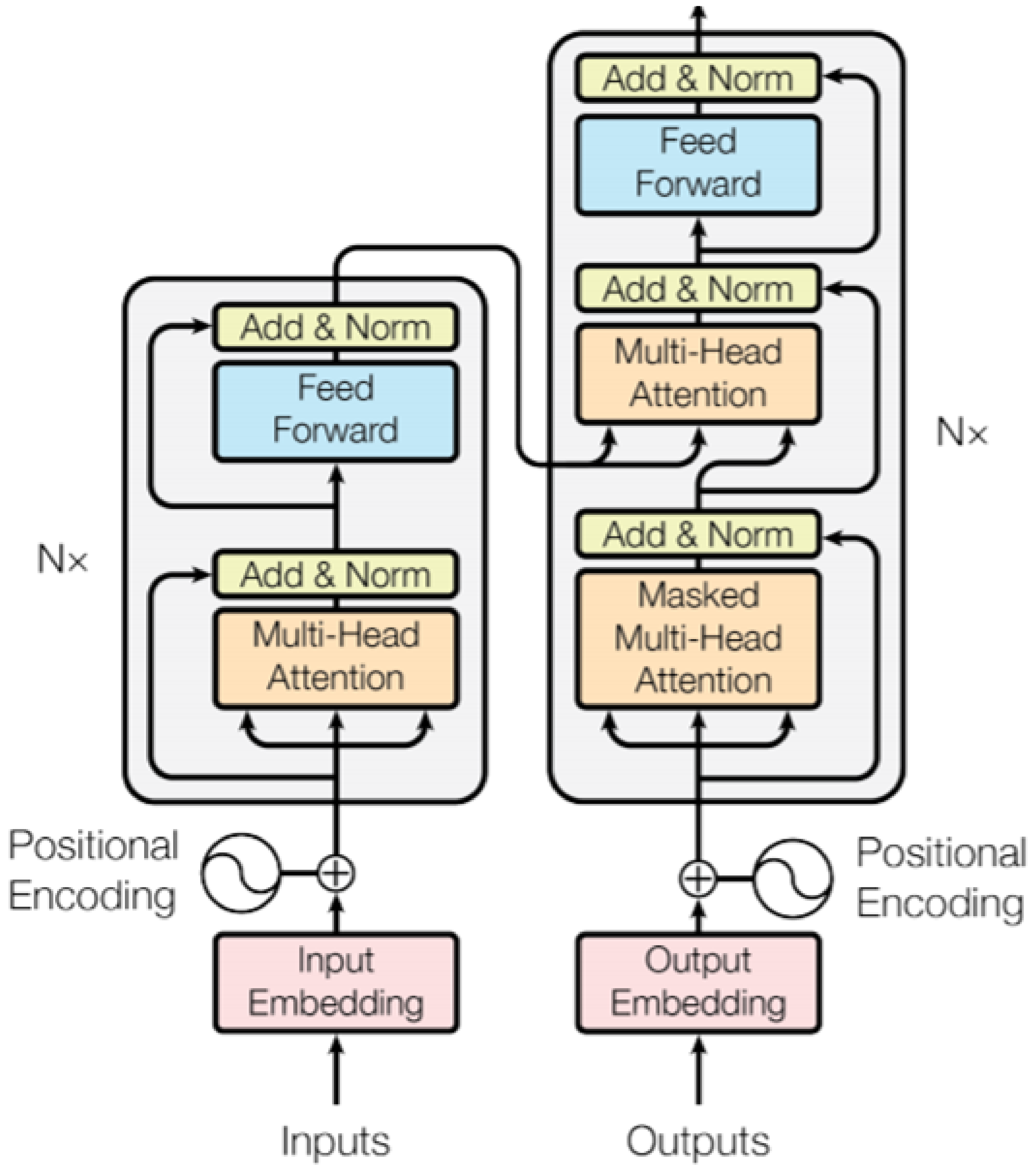

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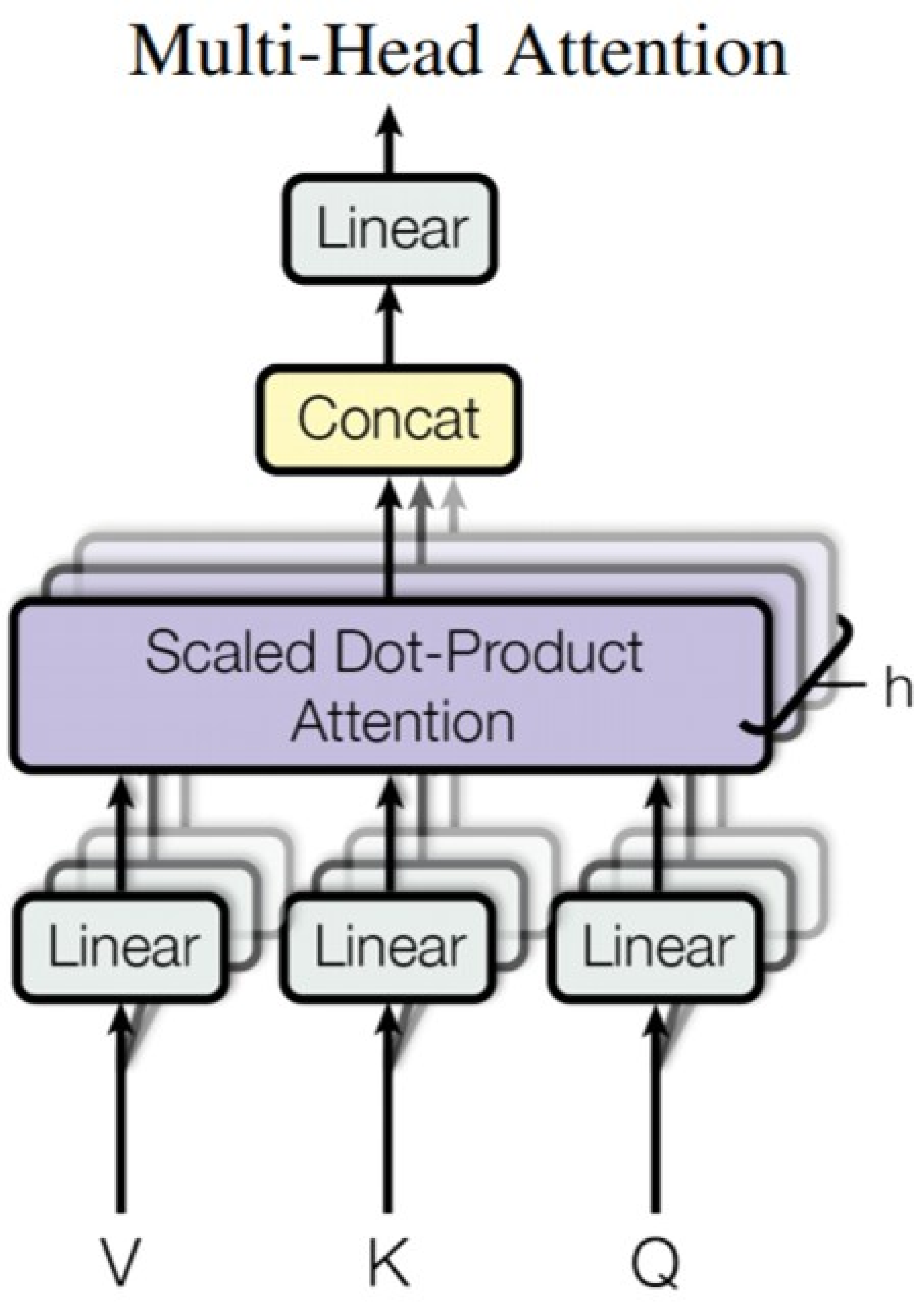
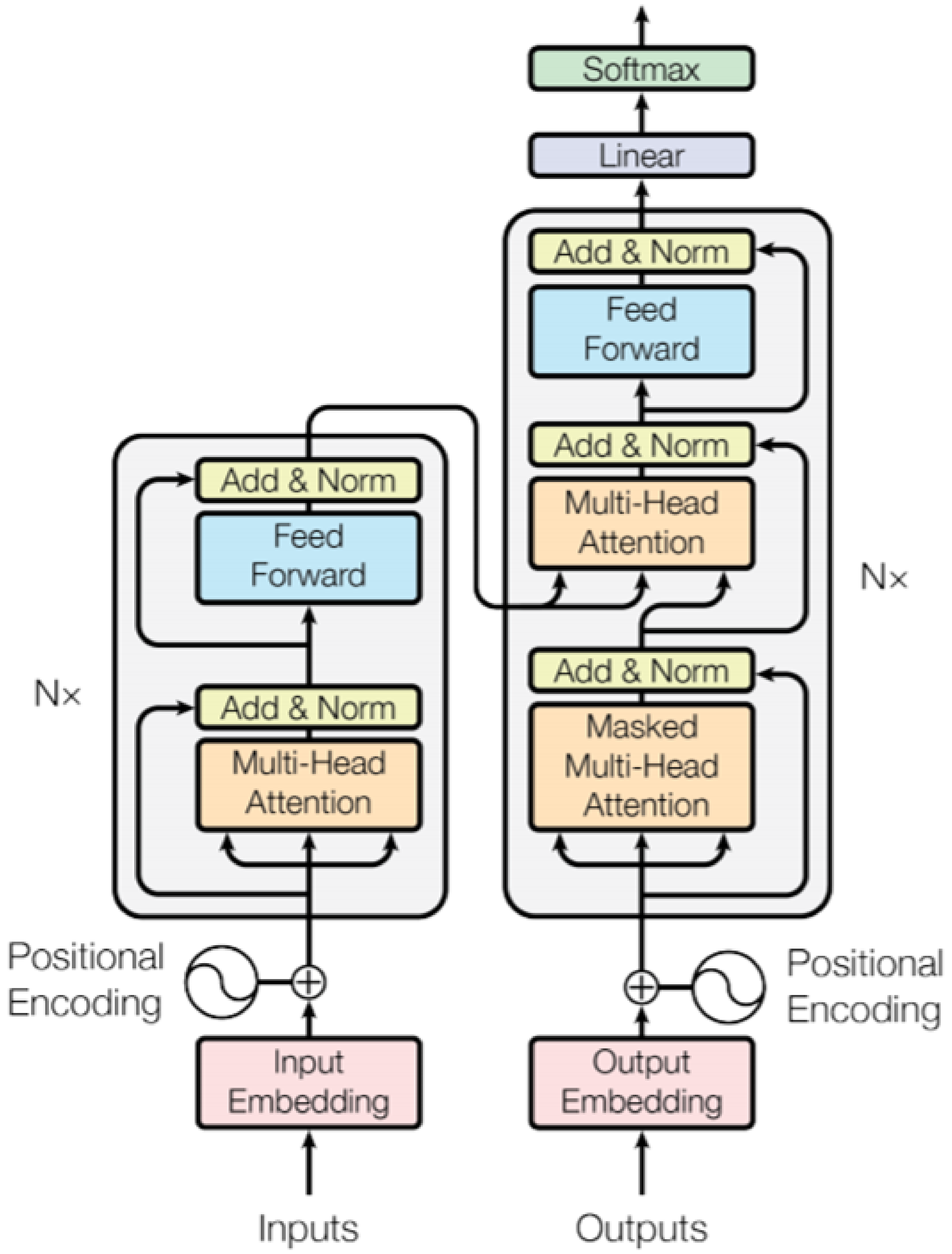
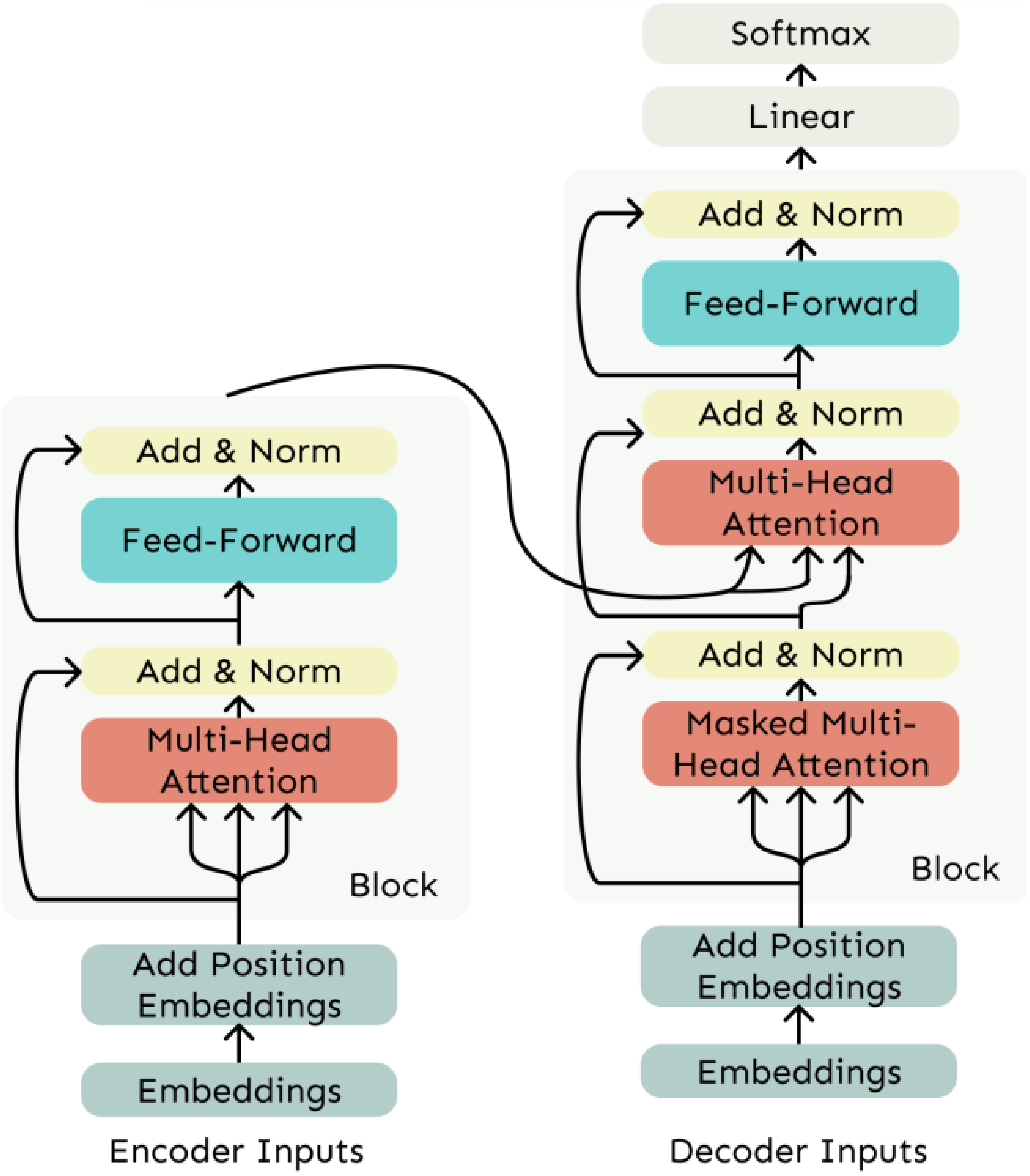




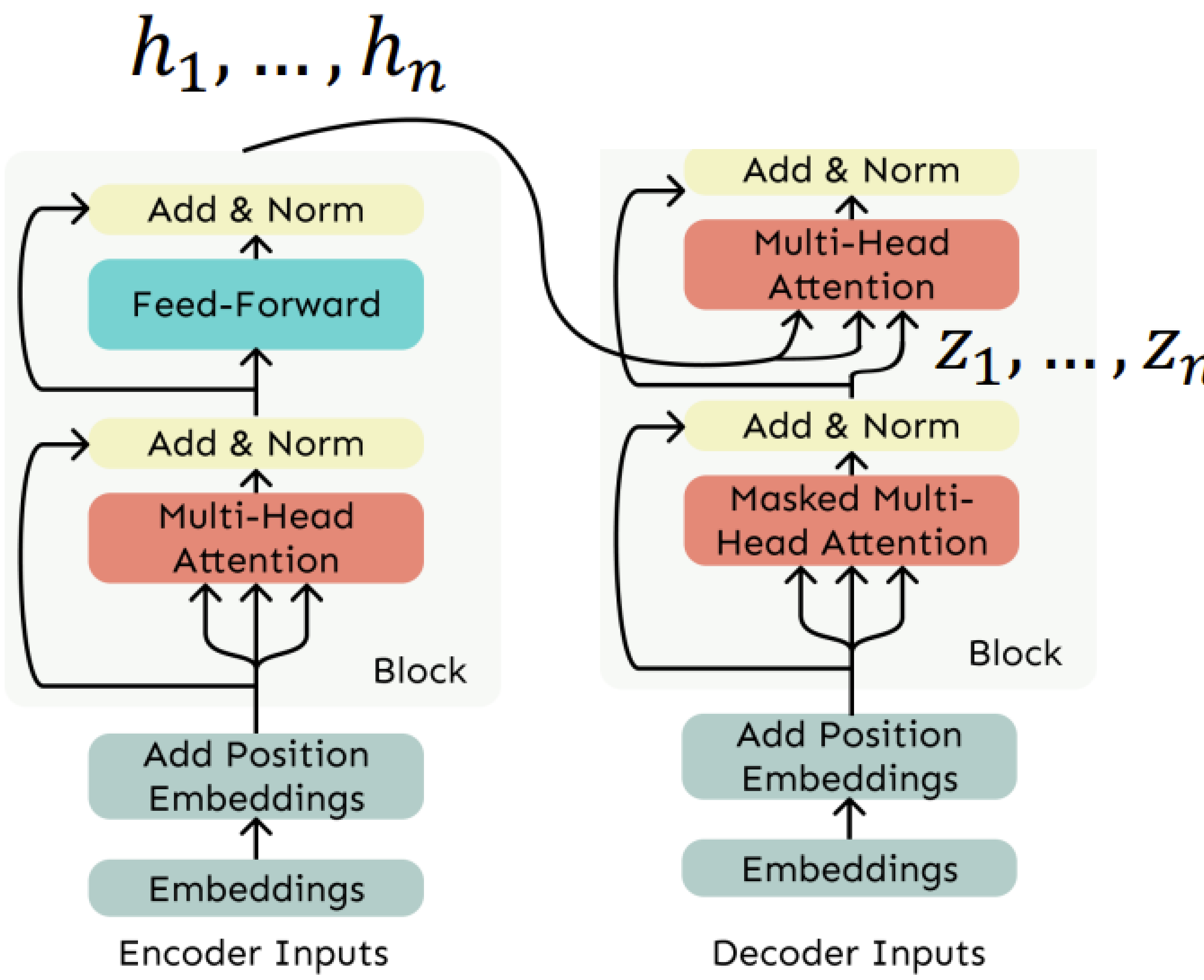
Encoder-Decoder

- we process the source sentence with a bidirectional model and generated the target with a unidirectional model.
- For this kind of seq2seq format, we often use a Transformer Encoder-Decoder.
- We use a normal Transformer Encoder.
- Our Transformer Decoder is modified to perform cross-attention to the output of the Encoder.



Cross-Attention Details

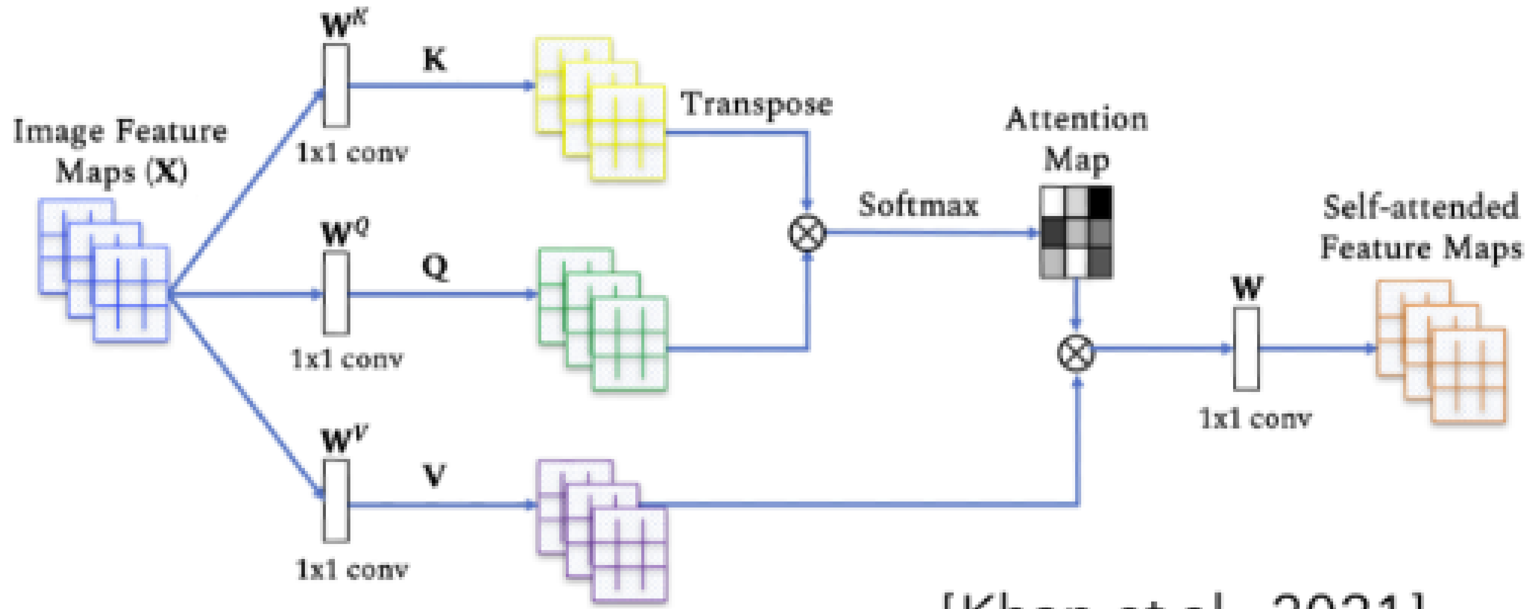
- We saw that self-attention is when keys, queries, and values come from the same source.
- In the decoder, we have attention that looks more like standard key-value attention
- Let $h_1, \dots, h_n$ be **output** vectors **from** the Transformer **encoder**; $x_i \in \mathbb{R}^d$
- Let $z_1, \dots, z_n$ be input vectors from the Transformer **decoder**, $z_i \in \mathbb{R}^d$
- Then keys and values are drawn from the **encoder** (like a memory):
  - $k_i = Kh_i, v_i = Vh_i.$
- And the queries are drawn from the **decoder**, $q_i = Qz_i.$



The Revolutionary Impact of Transformers

- **Almost all current-day leading language models** use Transformer building blocks.
  - E.g., GPT1/2/3/4, T5, Llama 1/2, BERT, … almost anything we can name
  - Transformer-based models dominate nearly all NLP leaderboards.

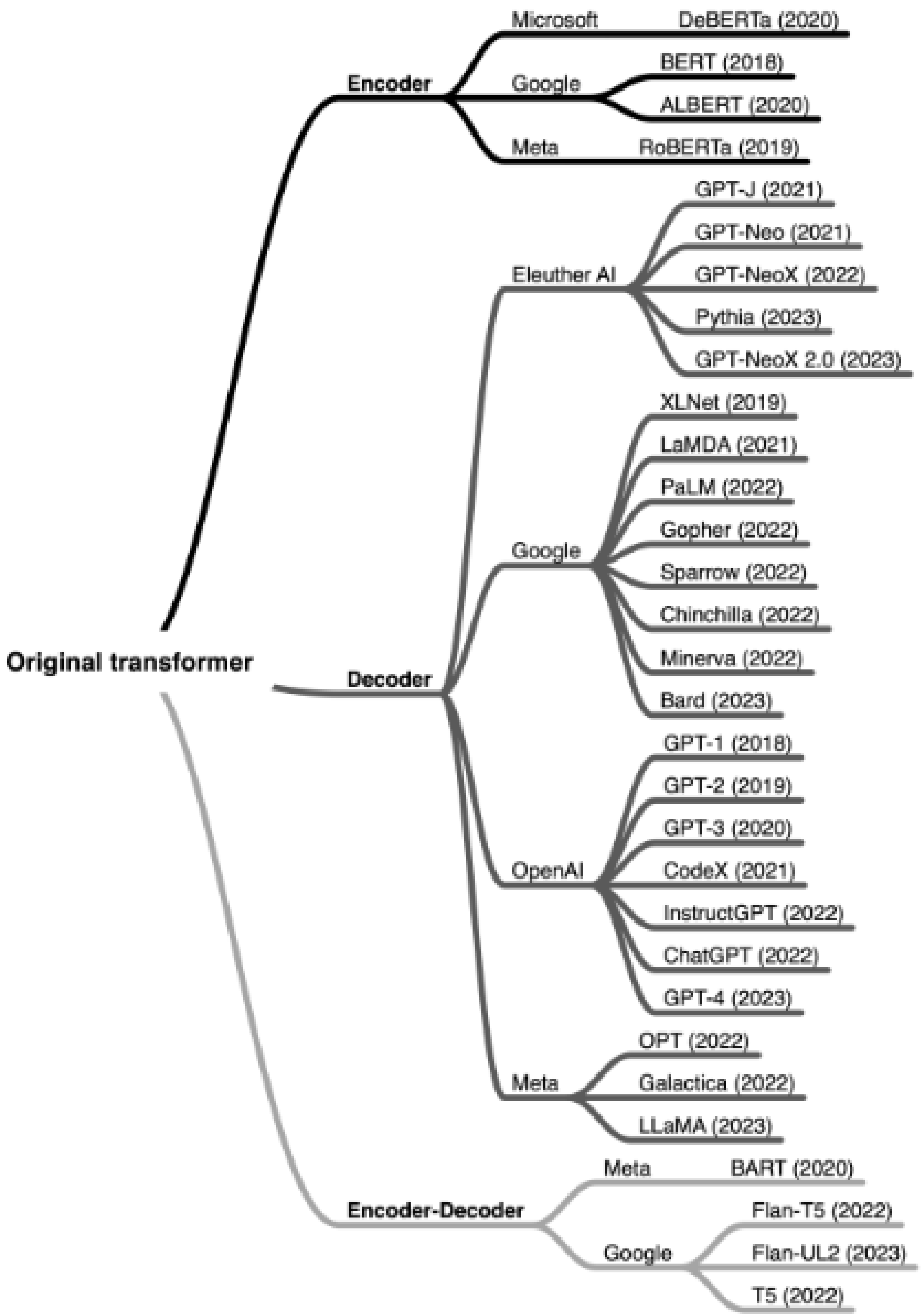
- Since Transformer has been popularized in language applications, computer vision also adapted Transformers, e.g., **Vision Transformers**.



[Khan et al., 2021]

What's next after Transformers?

Transformer Examples



https://magazine.sebastianraschka.com/p/understanding-encoder-and-decoder

Do Transformer Modifications Transfer Across Implementations and Applications?

- Generally, no!
  - (Narang et al 2021)

Model	Params	Ops	Step/s	Early loss	Final loss	SGLUE	XSum	WebQ	WMT EnDe
Vanilla Transformer	223M	11.1T	3.50	2.182 ± 0.005	1.838	71.66	17.78	23.02	26.62
GeLU	223M	11.1T	3.58	2.179 ± 0.003	1.838	**75.79**	**17.86**	**25.13**	26.47
Swish	223M	11.1T	3.62	2.186 ± 0.003	1.847	**73.77**	17.74	**24.34**	**26.75**
ELU	223M	11.1T	3.56	2.270 ± 0.007	1.932	67.83	16.73	23.02	26.08
GLU	223M	11.1T	3.59	2.174 ± 0.003	**1.814**	**74.20**	**17.42**	24.34	**27.12**
GeGLU	223M	11.1T	3.55	2.130 ± 0.006	**1.792**	**75.96**	**18.27**	**24.87**	**26.87**
ReGLU	223M	11.1T	3.57	2.145 ± 0.004	**1.803**	**76.17**	**18.36**	**24.87**	**27.02**
SeLU	223M	11.1T	3.55	2.315 ± 0.004	1.948	68.76	16.76	22.75	25.99
SwiGLU	223M	11.1T	3.53	2.127 ± 0.003	**1.789**	**76.00**	**18.20**	**24.34**	**27.02**
LiGLU	223M	11.1T	3.59	2.149 ± 0.005	**1.798**	**75.34**	**17.97**	**24.34**	26.53
Sigmoid	223M	11.1T	3.63	2.291 ± 0.019	1.867	**74.31**	17.51	23.02	26.30
Softplus	223M	11.1T	3.47	2.207 ± 0.011	1.850	**72.45**	17.65	**24.34**	**26.89**
RMS Norm	223M	11.1T	3.68	2.167 ± 0.008	**1.821**	**75.45**	**17.94**	**24.07**	**27.14**
Rezero	223M	11.1T	3.51	2.262 ± 0.003	1.939	61.69	15.64	20.90	26.37
Rezero + LayerNorm	223M	11.1T	3.26	2.223 ± 0.006	1.858	70.42	17.58	23.02	26.29
Rezero + RMS Norm	223M	11.1T	3.34	2.221 ± 0.009	1.875	70.33	17.32	23.02	26.19
Fixup	223M	11.1T	2.95	2.382 ± 0.012	2.067	58.56	14.42	23.02	26.31
24 layers, $d_{ff} = 1536$, $H = 6$	224M	11.1T	3.33	2.200 ± 0.007	1.843	**74.89**	17.75	**25.13**	**26.89**
18 layers, $d_{ff} = 2048$, $H = 8$	223M	11.1T	3.38	2.185 ± 0.005	**1.831**	**76.45**	16.83	**24.34**	**27.10**
8 layers, $d_{ff} = 4608$, $H = 18$	223M	11.1T	3.69	2.190 ± 0.005	1.847	**74.58**	17.69	**23.28**	**26.85**
6 layers, $d_{ff} = 6144$, $H = 24$	223M	11.1T	3.70	2.201 ± 0.010	1.857	**73.55**	17.59	**24.60**	**26.66**
Block sharing	65M	11.1T	3.91	2.497 ± 0.037	2.164	64.50	14.53	21.96	25.48
+ Factorized embeddings	45M	9.4T	4.21	2.631 ± 0.305	2.183	60.84	14.00	19.84	25.27
+ Factorized & shared embeddings	20M	9.1T	4.37	2.907 ± 0.313	2.385	53.95	11.37	19.84	25.19
Encoder only block sharing	170M	11.1T	3.68	2.298 ± 0.023	1.929	69.60	16.23	23.02	26.23
Decoder only block sharing	144M	11.1T	3.70	2.352 ± 0.029	2.082	67.93	16.13	**23.81**	26.08
Factorized Embedding	227M	9.4T	3.80	2.208 ± 0.006	1.855	70.41	15.92	22.75	26.50
Factorized & shared embeddings	202M	9.1T	3.92	2.320 ± 0.010	1.952	68.69	16.33	22.22	26.44
Tied encoder/decoder input embeddings	248M	11.1T	3.55	2.192 ± 0.002	1.840	**71.70**	17.72	**24.34**	26.49
Tied decoder input and output embeddings	248M	11.1T	3.57	2.187 ± 0.007	**1.827**	**74.86**	17.74	**24.87**	**26.67**
Untied embeddings	273M	11.1T	3.53	2.195 ± 0.005	**1.834**	**72.99**	17.58	**23.28**	26.48
Adaptive input embeddings	204M	9.2T	3.55	2.250 ± 0.002	1.899	66.57	16.21	**24.07**	**26.66**
Adaptive softmax	204M	9.2T	3.60	2.364 ± 0.005	1.982	**72.91**	16.67	21.16	25.56
Adaptive softmax without projection	223M	10.8T	3.43	2.229 ± 0.009	1.914	**71.82**	17.10	23.02	25.72
Mixture of softmaxes	232M	16.3T	2.24	2.227 ± 0.017	**1.821**	**76.77**	17.62	22.75	**26.82**
Transparent attention	223M	11.1T	3.33	2.181 ± 0.014	1.874	54.31	10.40	21.16	**26.80**
Dynamic convolution	257M	11.8T	2.65	2.403 ± 0.009	2.047	58.30	12.67	21.16	17.03
Lightweight convolution	224M	10.4T	4.07	2.370 ± 0.010	1.989	63.07	14.86	23.02	24.73
Evolved Transformer	217M	9.9T	3.09	2.220 ± 0.003	1.863	**73.67**	10.76	**24.07**	26.58
Synthesizer (dense)	224M	11.4T	3.47	2.334 ± 0.021	1.962	61.03	14.27	16.14	**26.63**
Synthesizer (dense plus)	243M	12.6T	3.22	2.191 ± 0.010	1.840	**73.98**	16.96	**23.81**	**26.71**
Synthesizer (dense plus alpha)	243M	12.6T	3.01	2.180 ± 0.007	**1.828**	**74.25**	17.02	**23.28**	26.61
Synthesizer (factorized)	207M	10.1T	3.94	2.341 ± 0.017	1.968	62.78	15.39	**23.55**	26.42
Synthesizer (random)	254M	10.1T	4.08	2.326 ± 0.012	2.009	54.27	10.35	19.56	26.44
Synthesizer (random plus)	292M	12.0T	3.63	2.189 ± 0.004	1.842	**73.32**	17.04	**24.87**	26.43
Synthesizer (random plus alpha)	292M	12.0T	3.42	2.186 ± 0.007	**1.828**	**75.24**	17.08	**24.08**	26.39
Universal Transformer	84M	40.0T	0.88	2.406 ± 0.036	2.053	70.13	14.09	19.05	23.91
Mixture of experts	648M	11.7T	3.20	2.148 ± 0.006	**1.785**	**74.55**	**18.13**	**24.08**	**26.94**
Switch Transformer	1100M	11.7T	3.18	2.135 ± 0.007	**1.758**	**75.38**	**18.02**	**26.19**	**26.81**
Funnel Transformer	223M	1.9T	4.30	2.288 ± 0.008	1.918	67.34	16.26	22.75	23.20
Weighted Transformer	280M	71.0T	0.59	2.378 ± 0.021	1.989	69.04	16.98	23.02	26.30
Product key memory	421M	386.6T	0.25	2.155 ± 0.003	**1.798**	**75.16**	17.04	**23.55**	**26.73**

Transformers (2017) Made Many Changes at Once!

- Delete all RNN components → Position encodings
- Residual connections
- Interspersing of Attention and MLP layers
- LayerNorms
- Multiple heads
- Carefully tuned hyperparameters

- Most original choices have stuck
  - sinusoidal embeddings!

What is missing in Transformers?

- Long sequence length
- External memory
- Better human controllability
- Align with language models of brain