Applied Deep Learning

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Learning objectives of today

Goals: Understand the basic design and functioning of transformers, a breakthrough architecture that has revolutionized NLP applications in recent years

How will we do this?

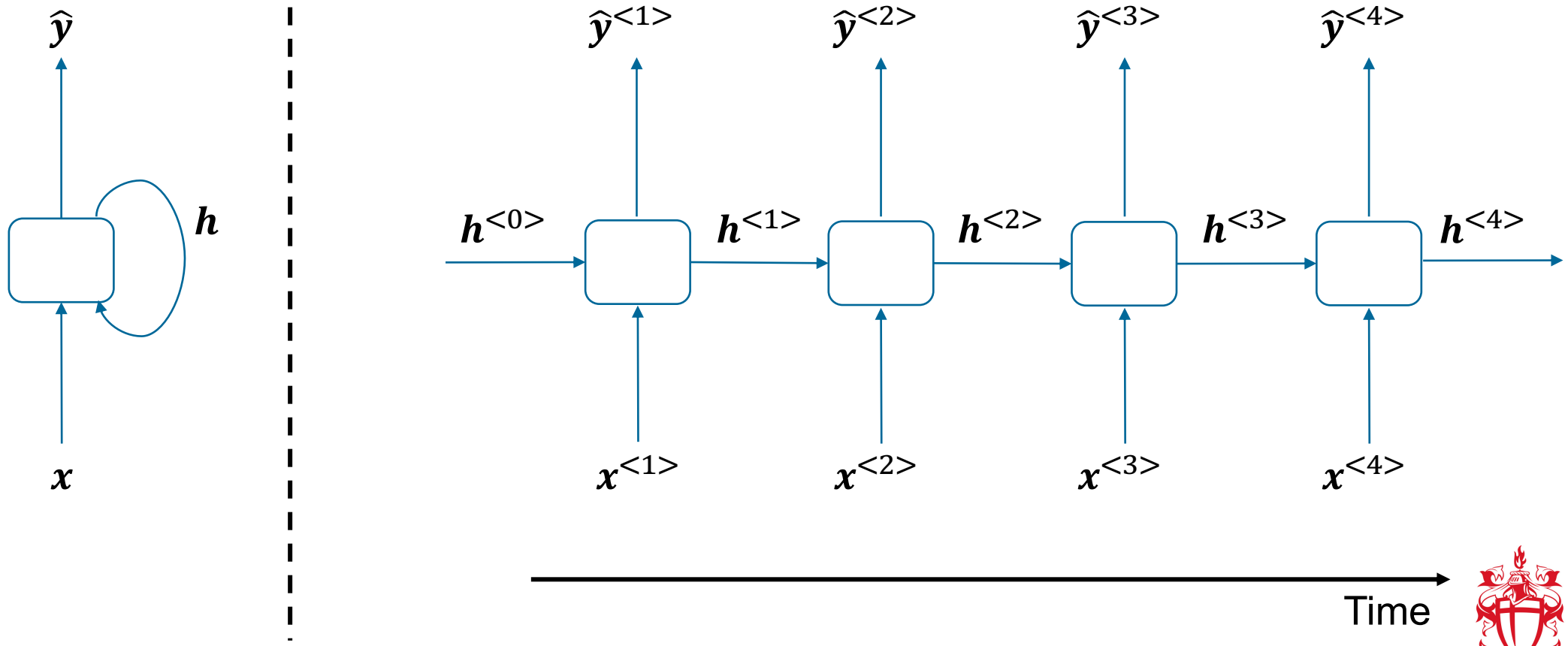
- We discuss attention mechanisms and how they can improve RNNs
- We then introduce transformers, which rely solely on attention and don’t use recurrence

Adding attention

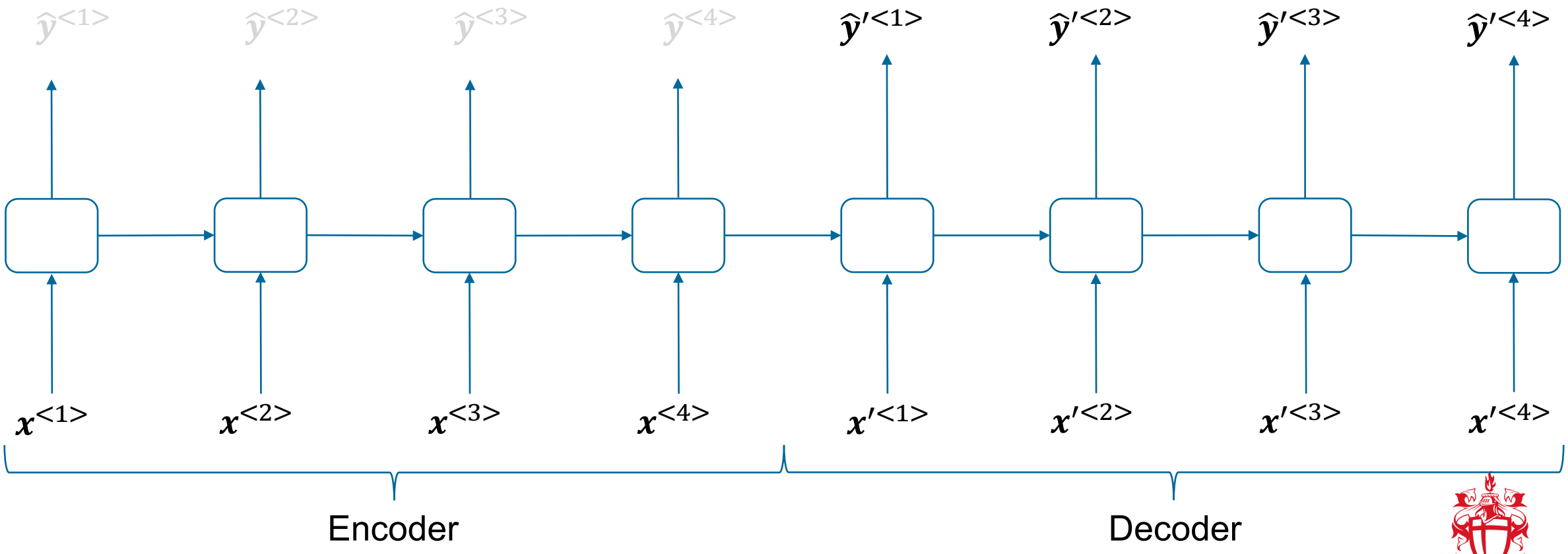
A brief summary of RNNs

- At each time step, take the input and the “memory” (or *state*) from the previous time step to compute the output
- Use the same parameters (and, also, activation functions) across different time steps

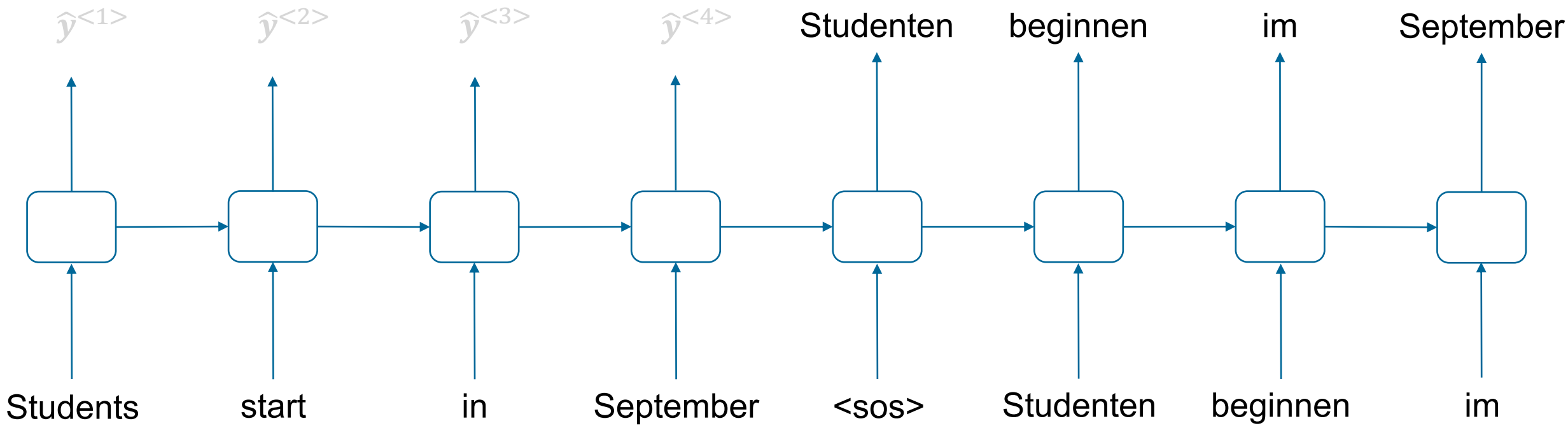
A typical RNN



Encoder-decoder networks



Encoder-decoder networks, for example in translation



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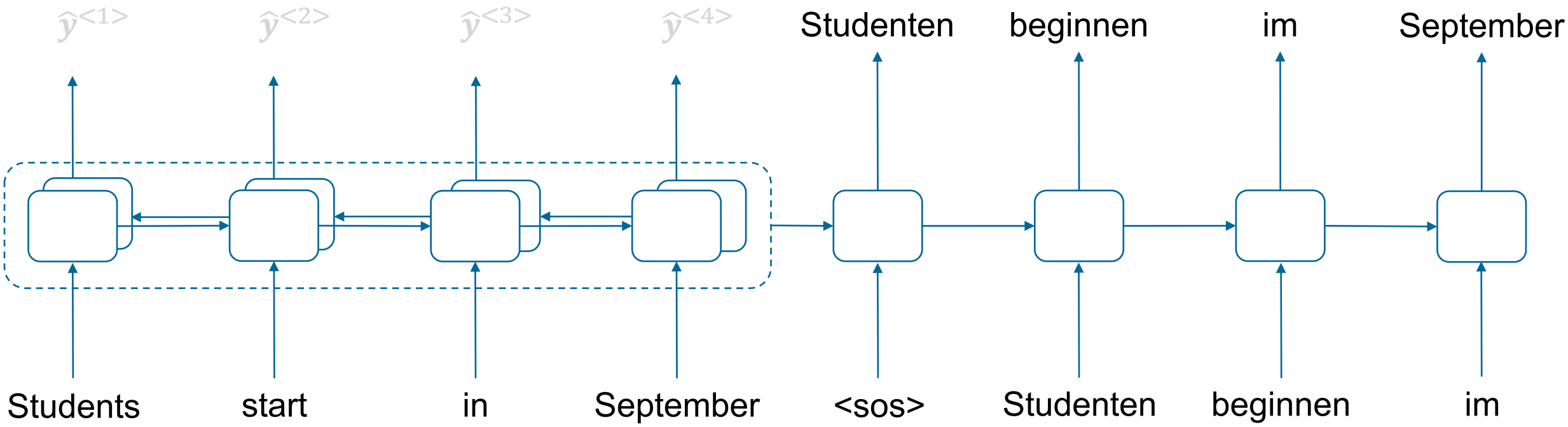
Encoder-decoder networks, adding in a bidirectional RNN



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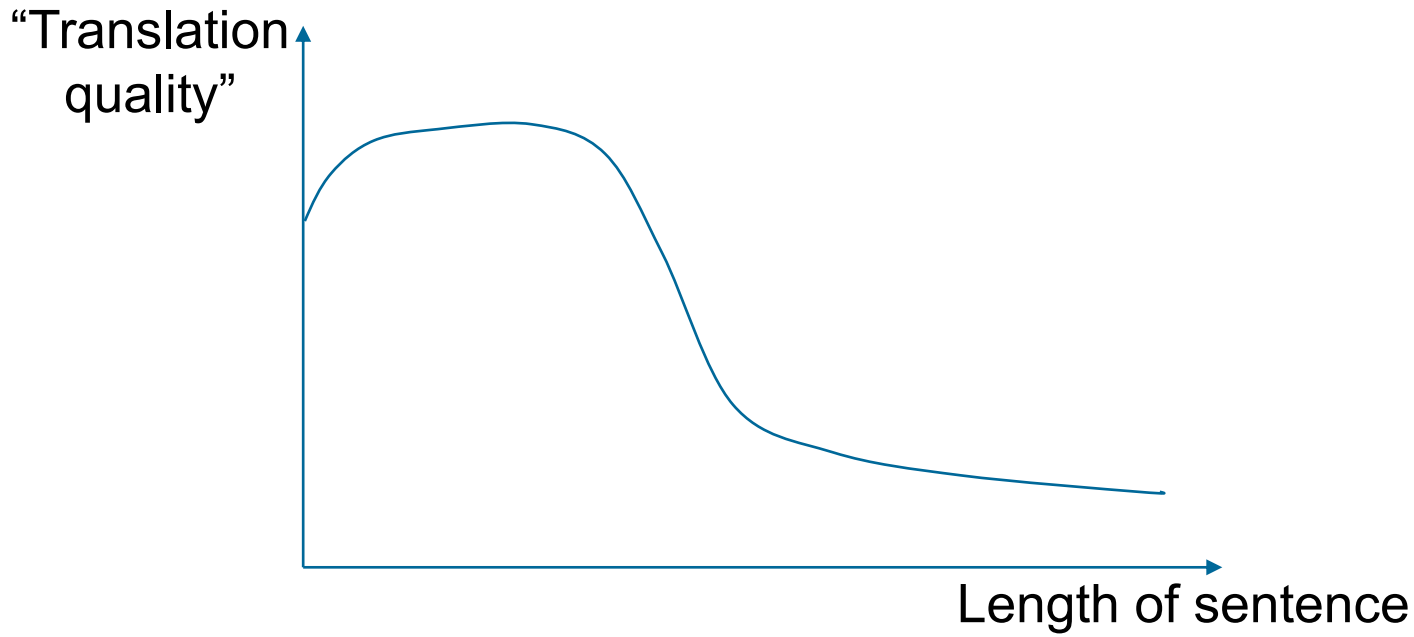
Long sentences still pose a problem

Students start in September, have three terms with classes, finish a project, and successfully complete their degree the following summer.

Die Studenten beginnen im September, haben drei Semester Unterricht, schließen ein Projekt ab und schließen ihr Studium im folgenden Sommer erfolgreich ab.



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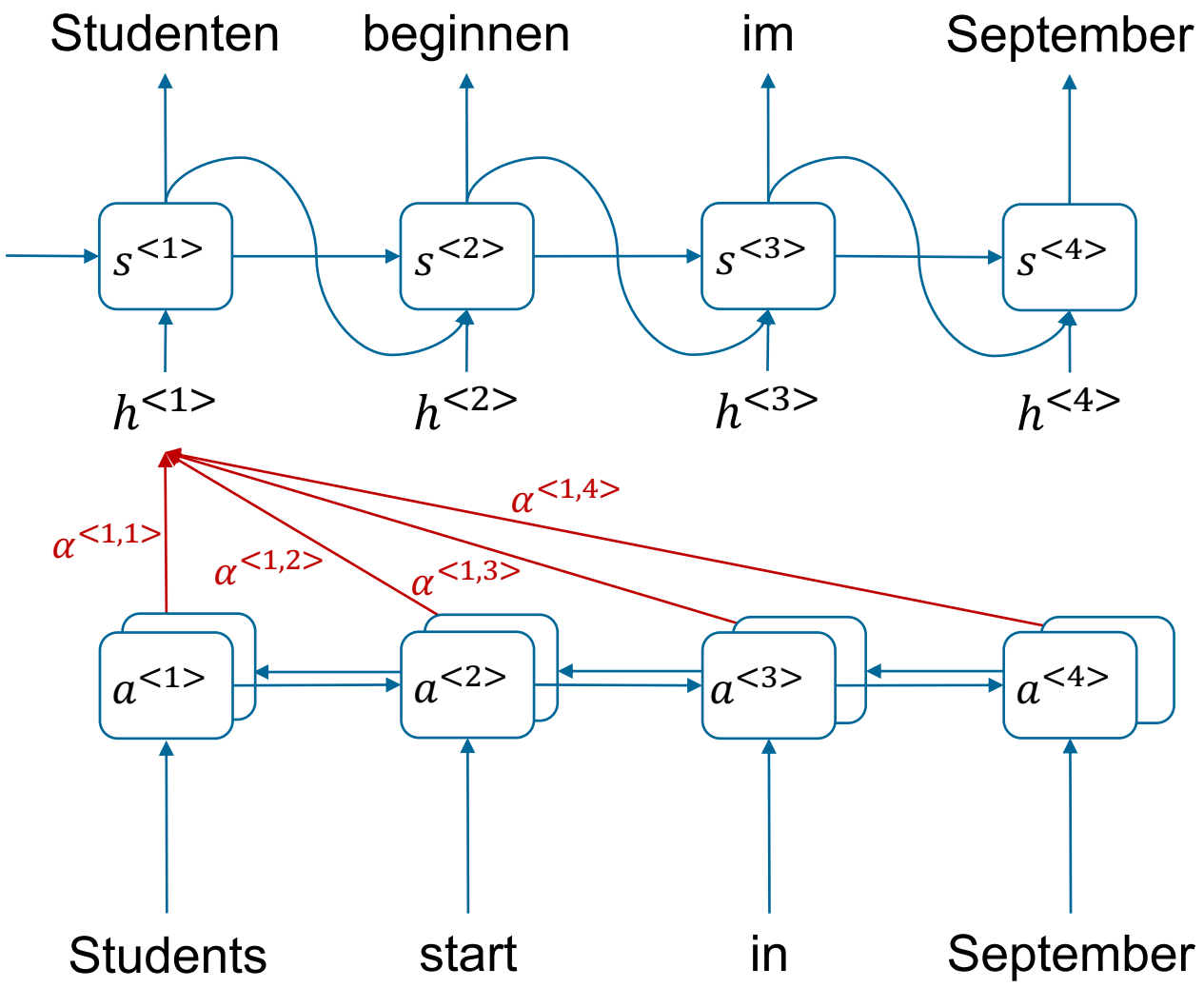
Putting attention on parts of the input



$h^{<1>} = \sum_t \alpha^{<1,t>} a^{<t>} = \alpha^{<1,1>} a^{<1>} + \alpha^{<1,2>} a^{<2>} + \alpha^{<1,3>} a^{<3>} + \alpha^{<1,4>} a^{<4>}$

$\sum_t \alpha^{<1,t>} = 1$

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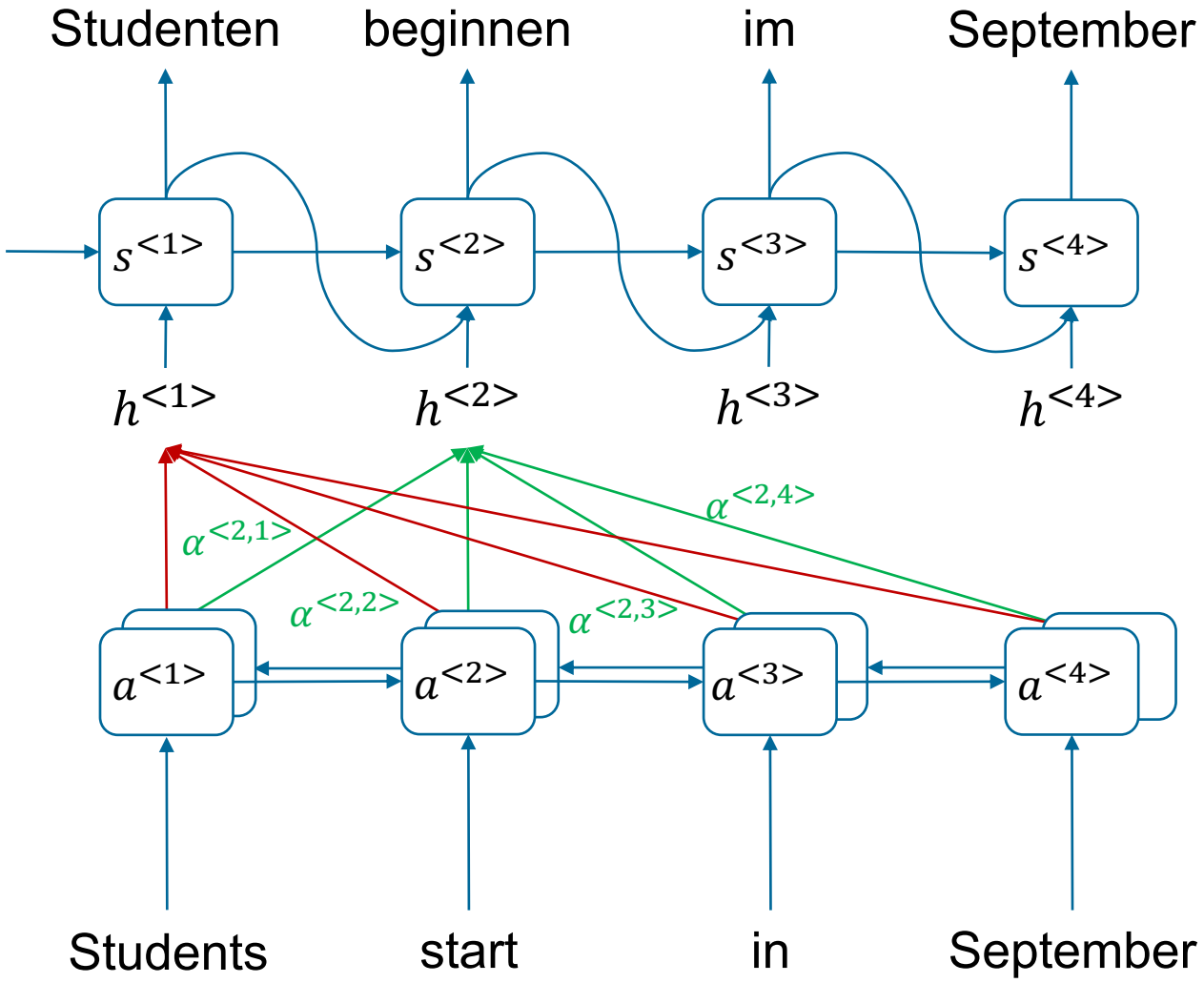
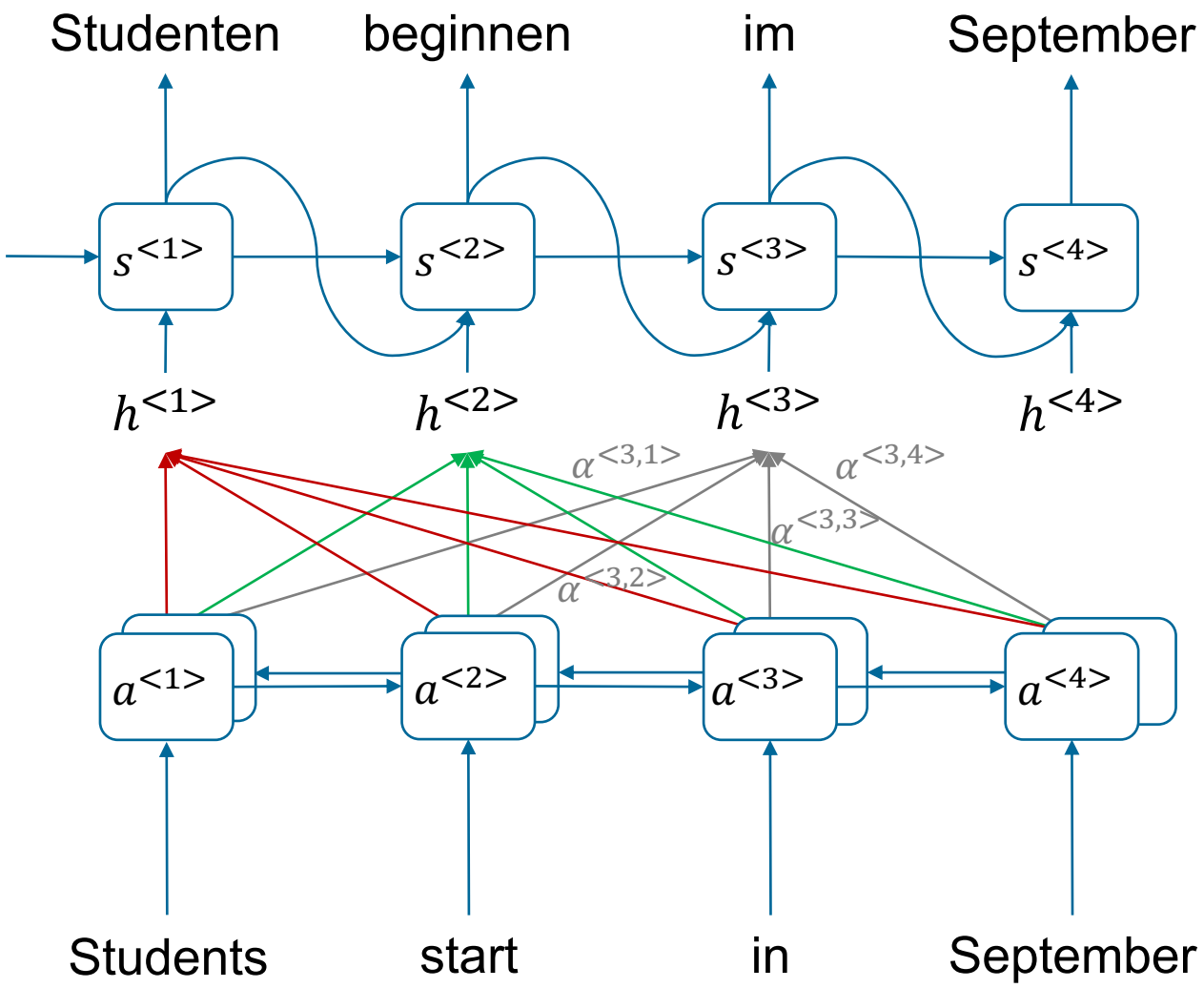
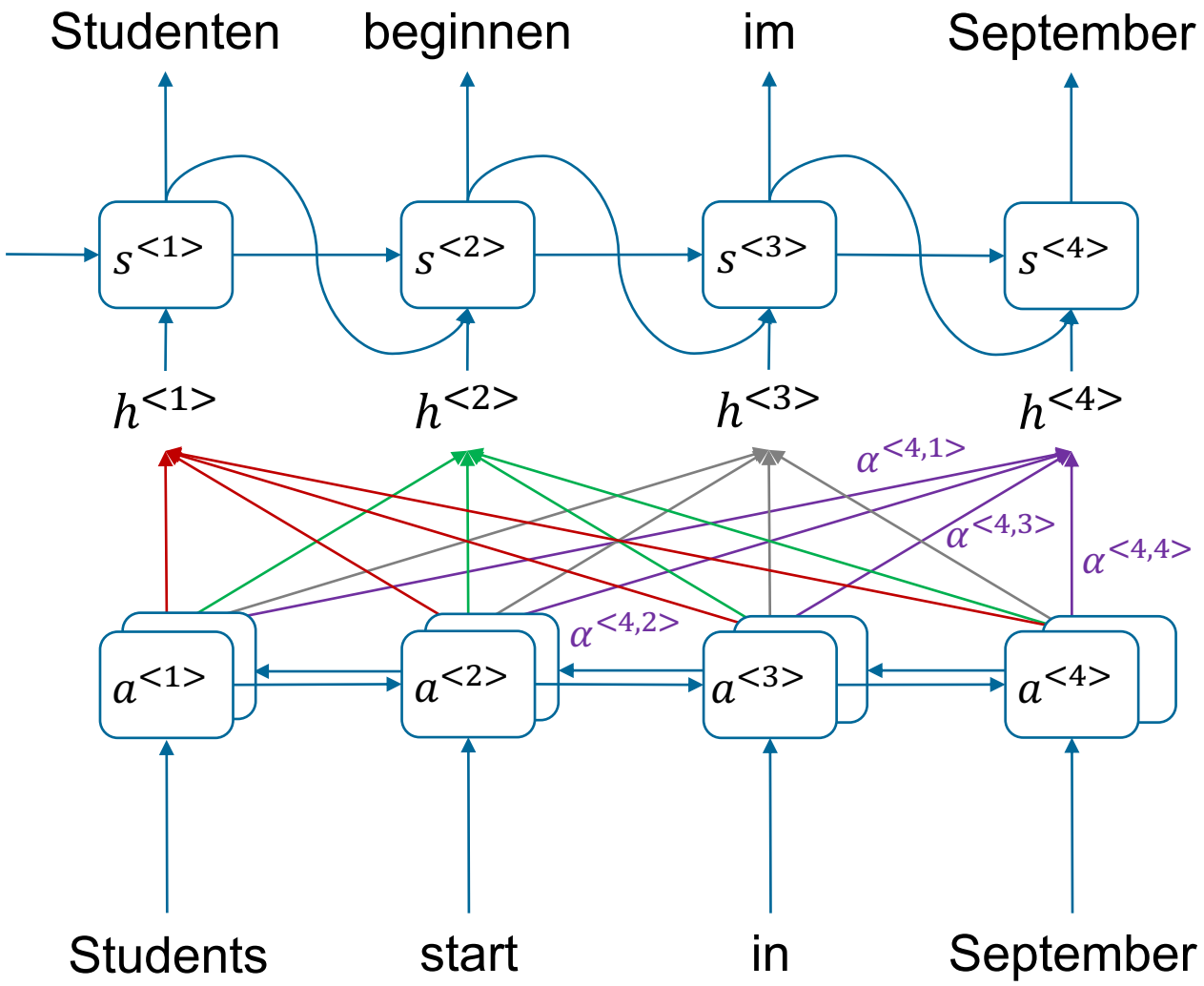
Putting attention on parts of the input



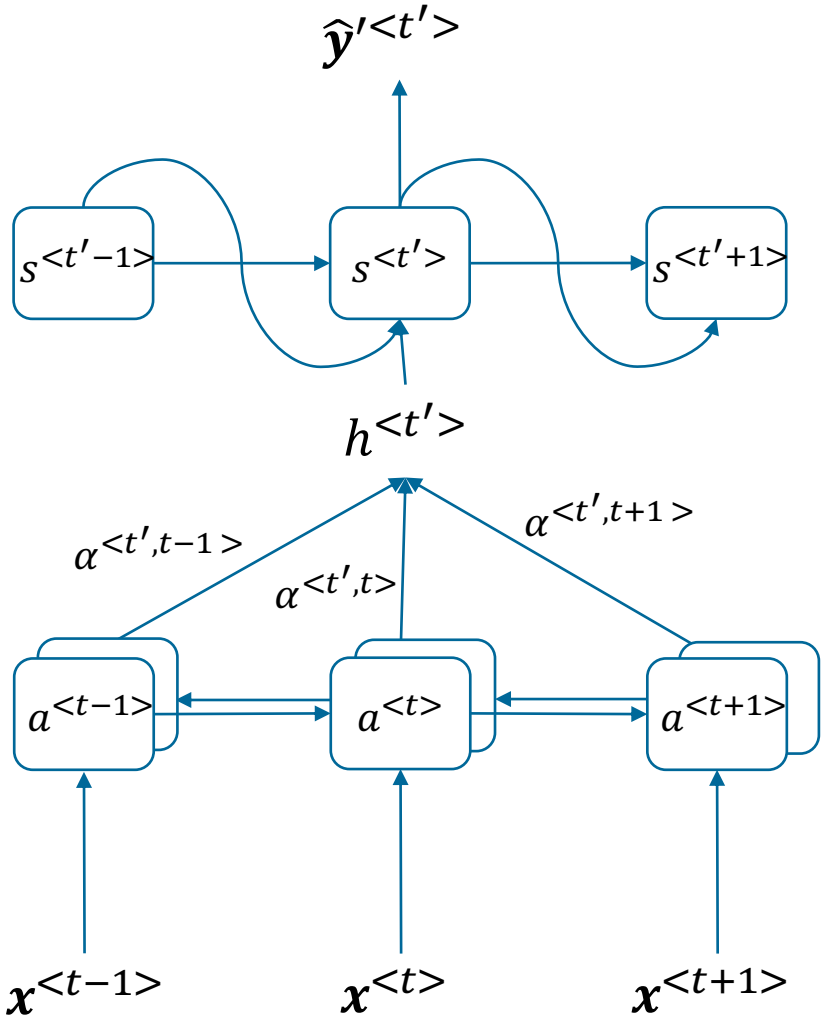
Putting attention on parts of the input

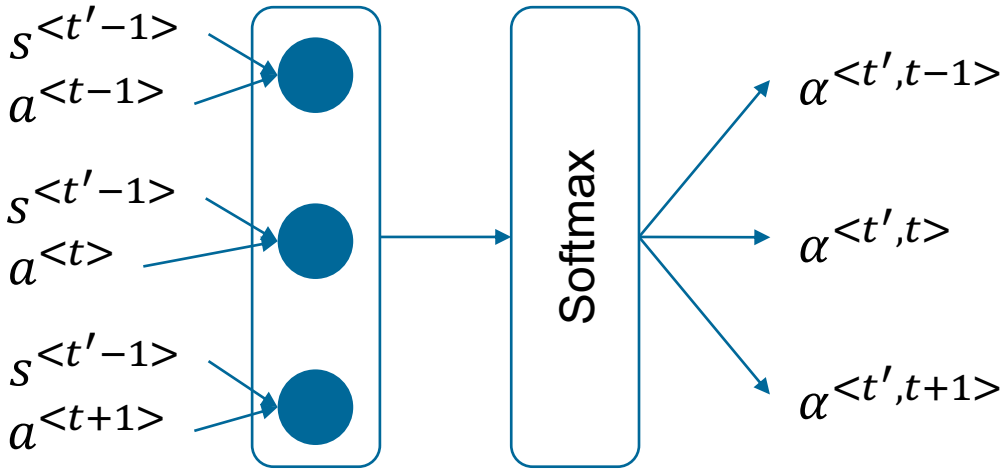


Putting attention on parts of the input



Computing attention





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Attention is all you need

An overview

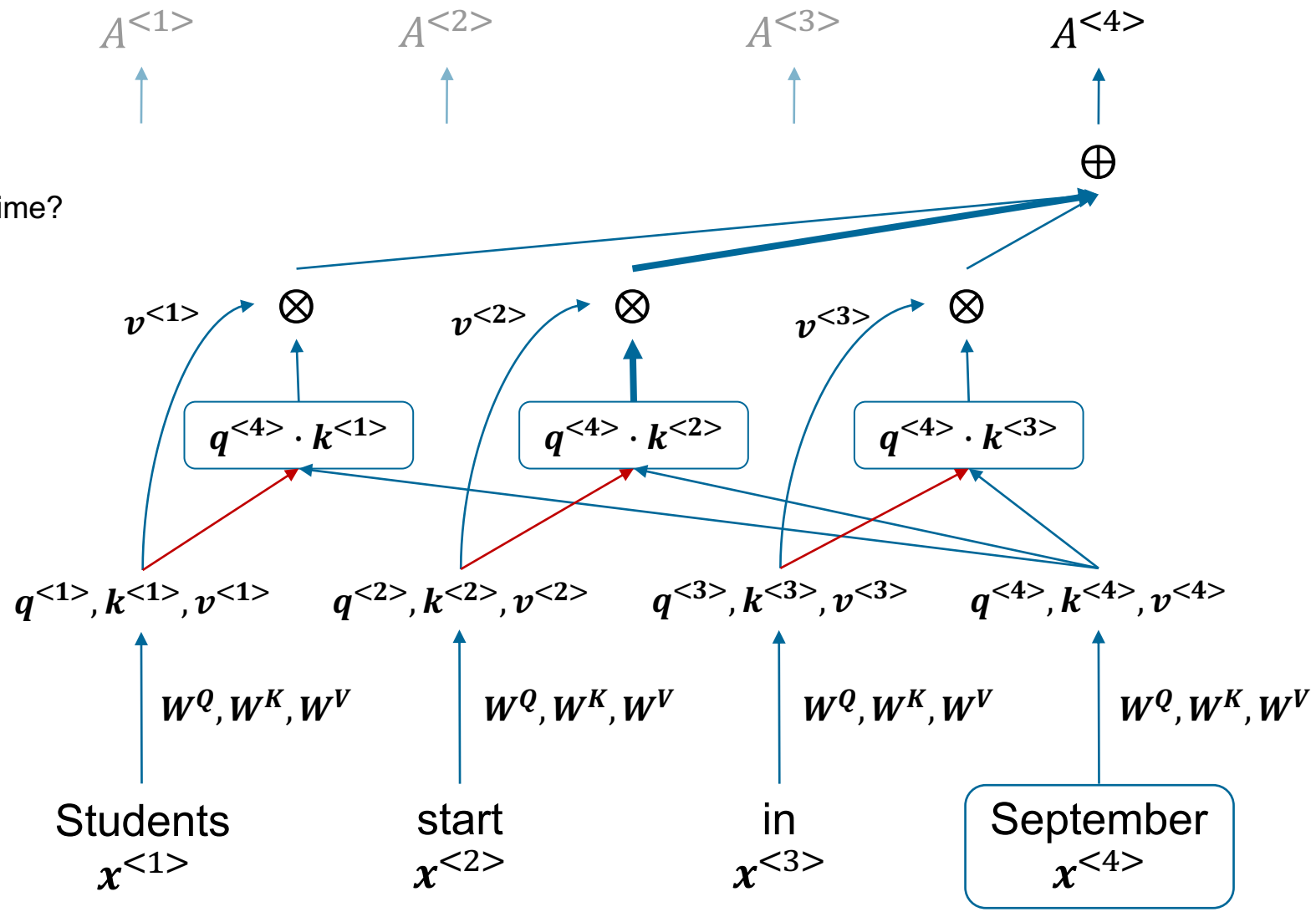
- 2017 paper by researchers at Google – probably most groundbreaking paper in last decade of machine learning
  - If you want to read one research paper only, it should be this
- Use attention exclusively (and add in some sequence information in another way)
- Motivation: recurrence cannot be parallelized by its very nature, drastically limiting NLP models
  - While motivation and main application in NLP, can analyze all sorts of data

Self-attention

We say $A(Q, K, V)$ is the attention-based representation of a word

Query: What happens at this time?

$\boldsymbol{k}^{<1>}$: Persons
$\boldsymbol{k}^{<2>}$: Action
$\boldsymbol{k}^{<3>}$: Modifier



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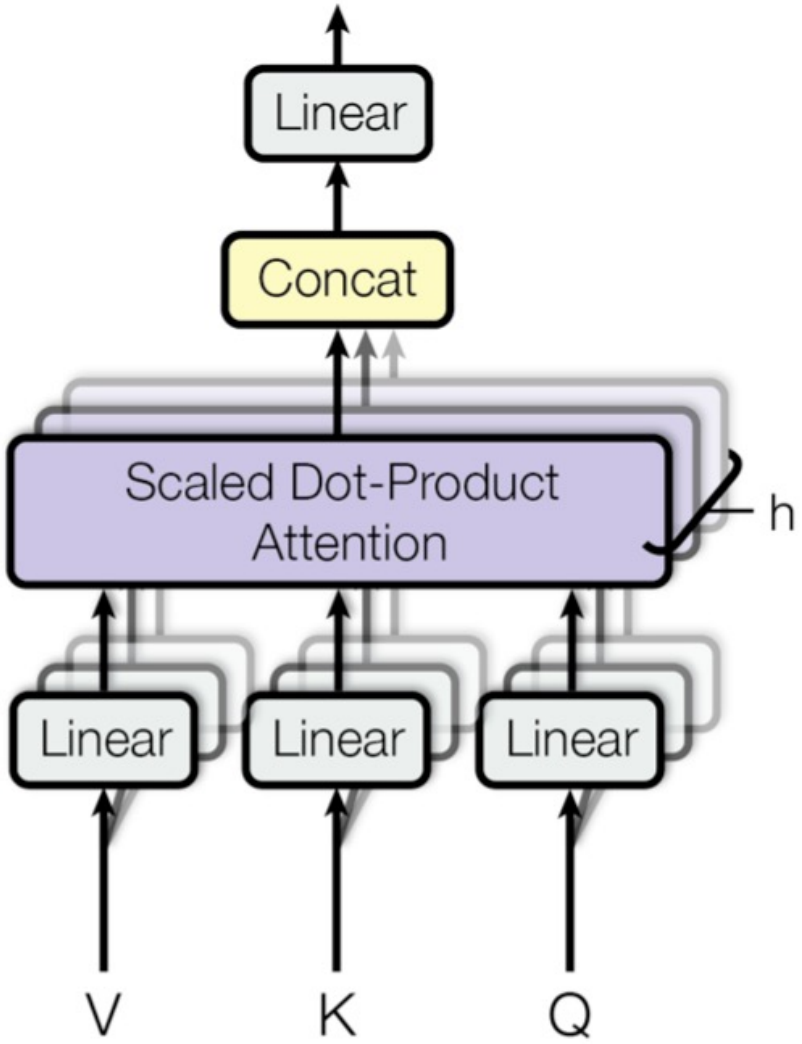
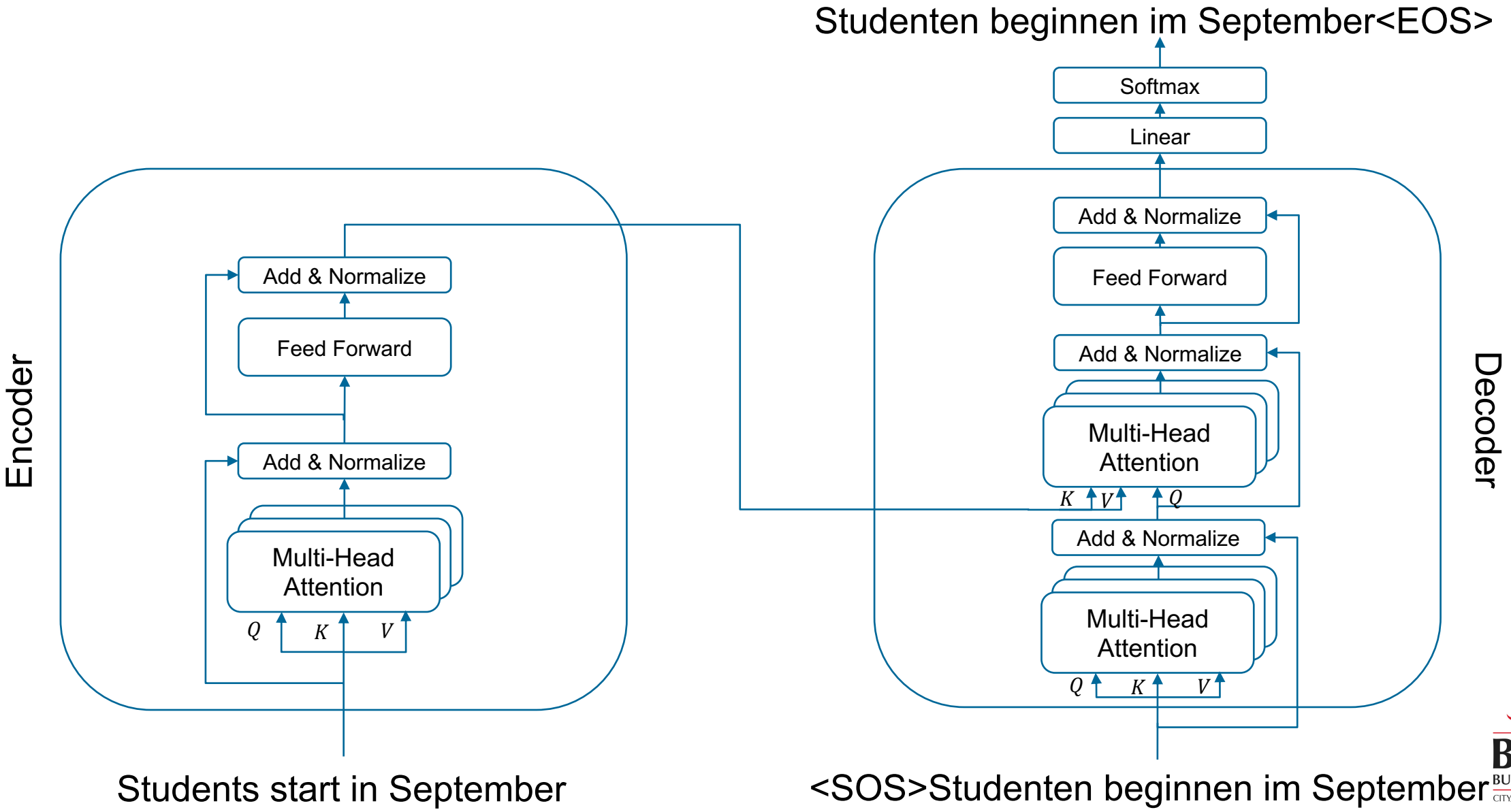
Multi-head attention layer



Source: Vaswani

Converting everything into the transformer model



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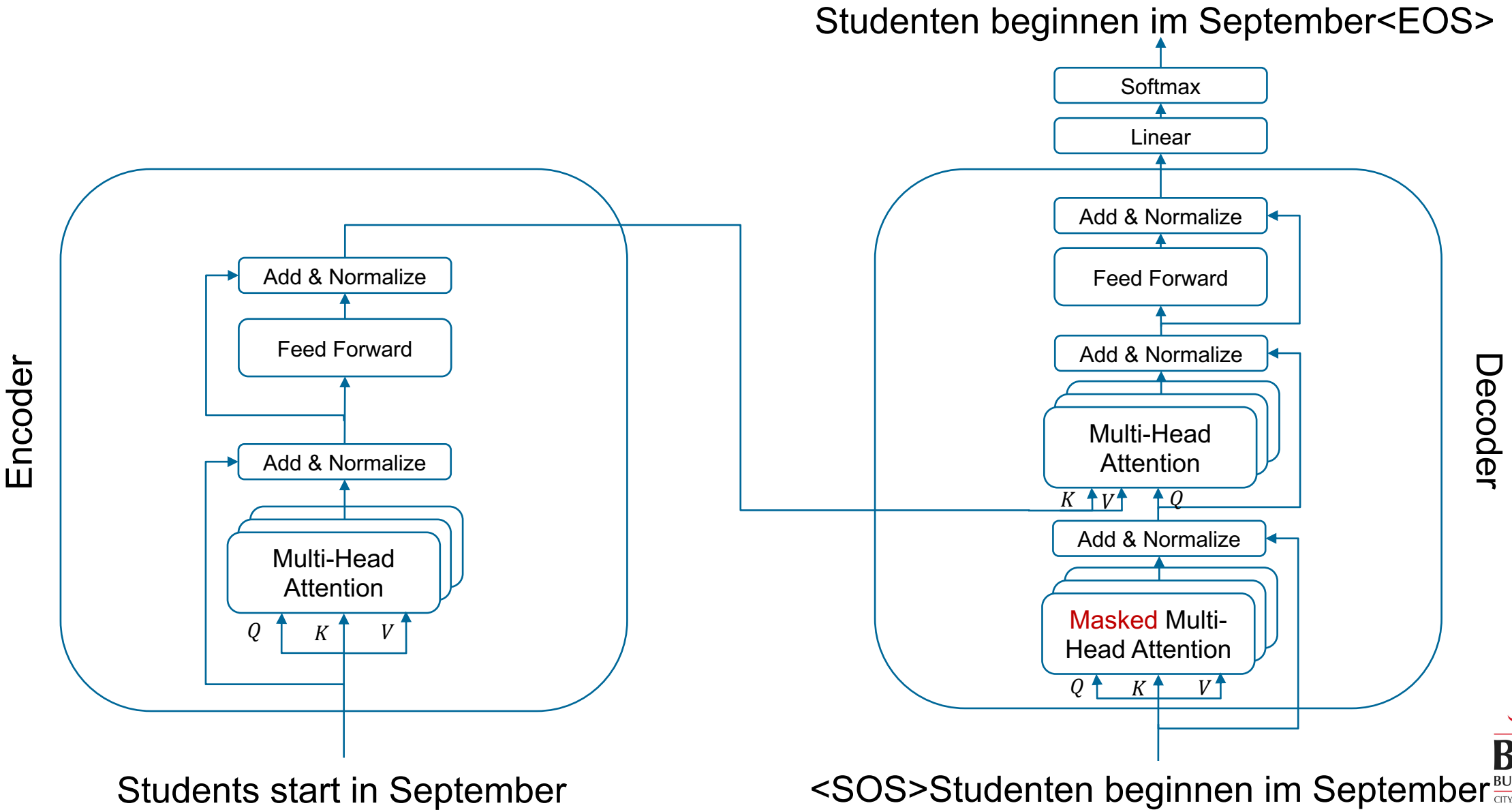

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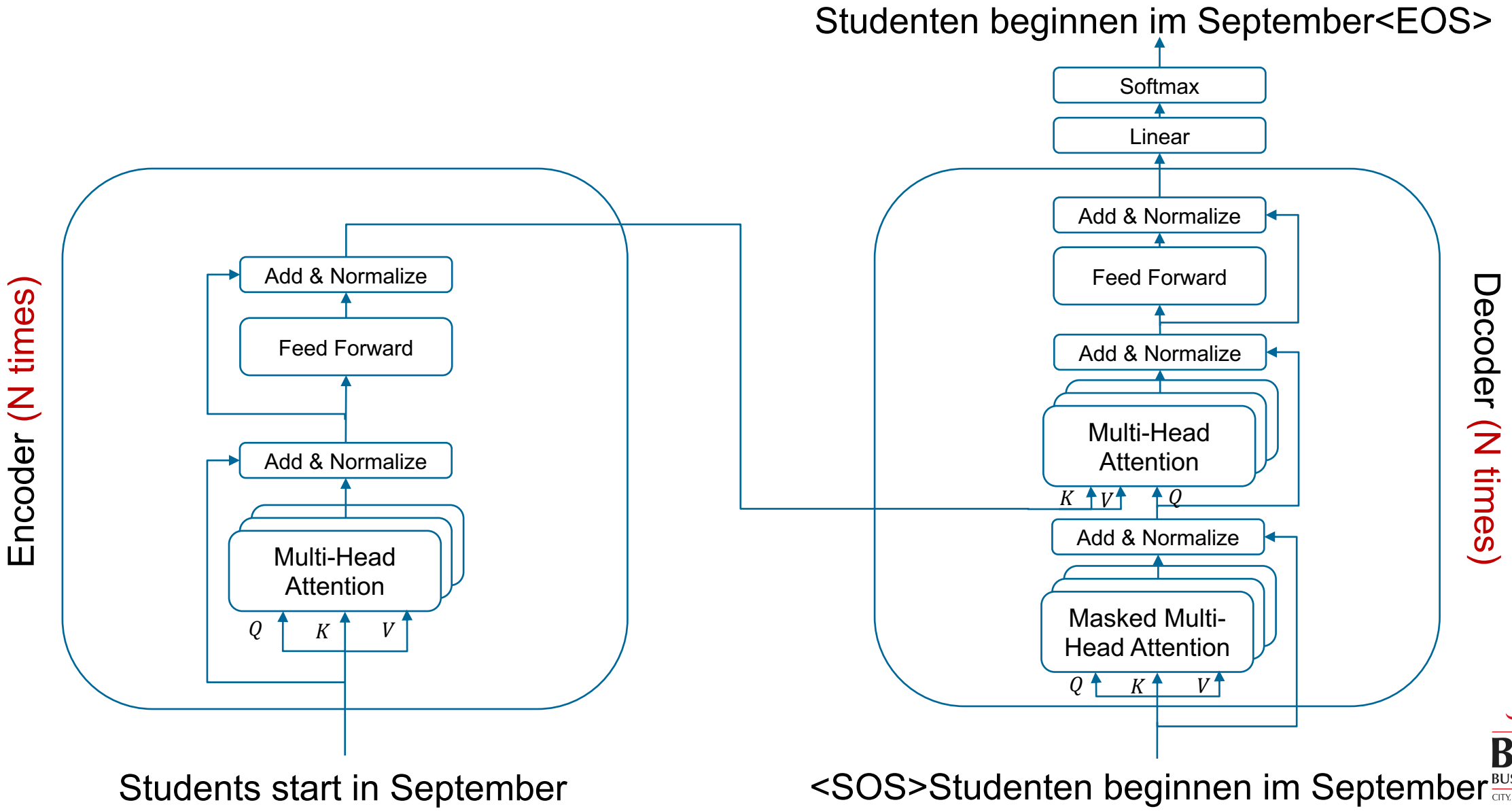
Converting everything into the transformer model



Why positions matter

Students start in September, have three terms with classes, finish a project, and successfully complete their degree the following summer.

Students start **the following summer**, have three terms with classes, finish a project, and successfully complete their degree **in September**.

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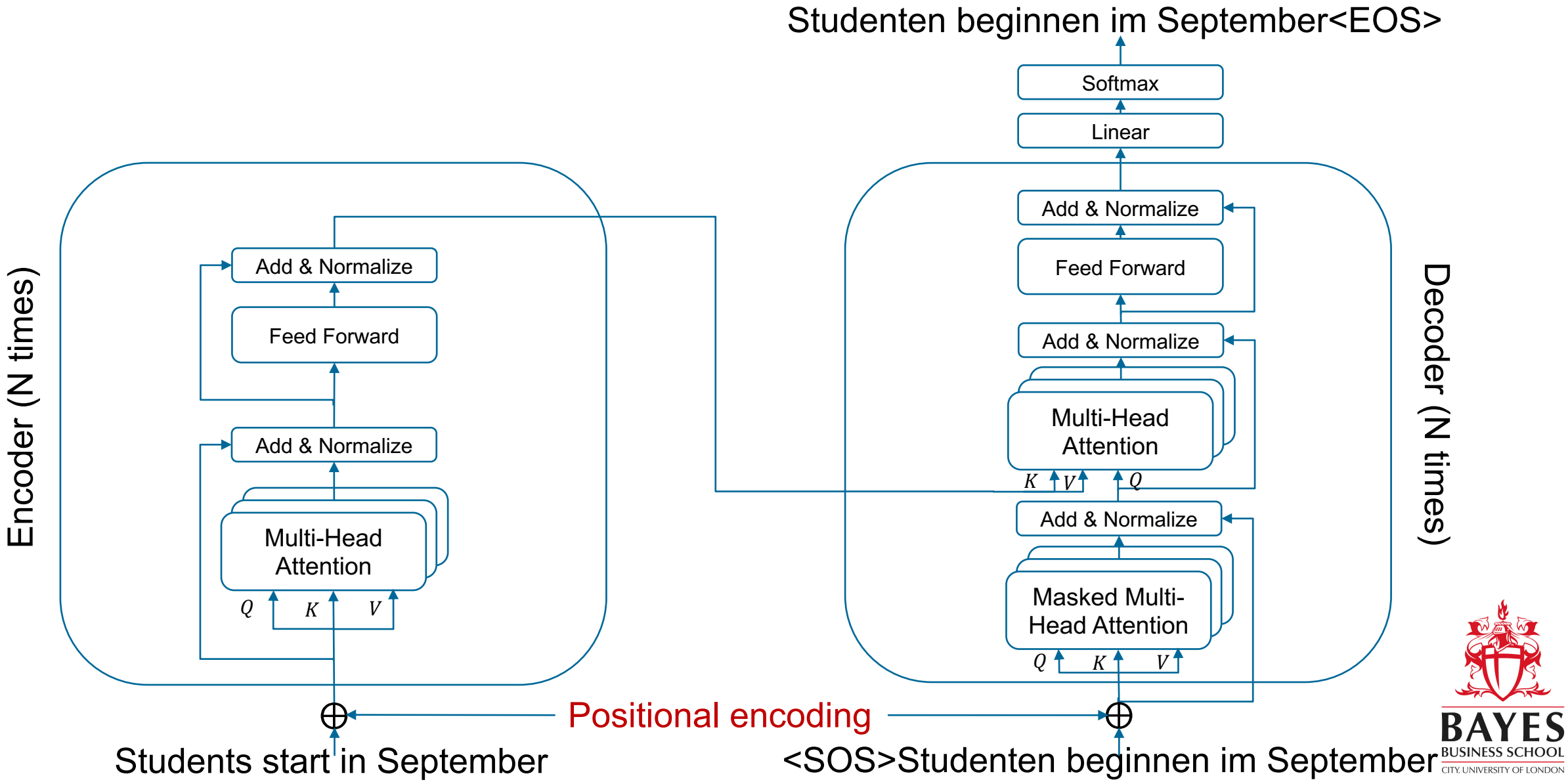
Converting everything into the transformer model



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Positional encoding added to the word embedding – a first attempt

$$\text{September} \quad + \quad \text{Position encoding} \quad = \quad \text{New vector}$$

$$\begin{pmatrix} -0.21 \\ 0.45 \\ -0.84 \\ 0.13 \end{pmatrix} \qquad \begin{pmatrix} 4 \\ 4 \\ 4 \\ 4 \end{pmatrix} \qquad \begin{pmatrix} 3.79 \\ 4.45 \\ 3.16 \\ 4.13 \end{pmatrix}$$

Positional encoding added to the word embedding – a second attempt

September	+	Position encoding	=	New vector
$\begin{pmatrix} -0.21 \\ 0.45 \\ -0.84 \\ 0.13 \end{pmatrix}$		$\begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$		$\begin{pmatrix} 0.79 \\ 1.45 \\ 0.16 \\ 1.13 \end{pmatrix}$

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Positional encoding added to the word embedding – using sinusoids

$$PE_{pos,i} = \begin{cases} \sin\left(\frac{pos}{10000^{i/d}}\right), if\ i\ is\ even \\ \cos\left(\frac{pos}{10000^{(i-1)/d}}\right), if\ i\ is\ odd \end{cases}$$

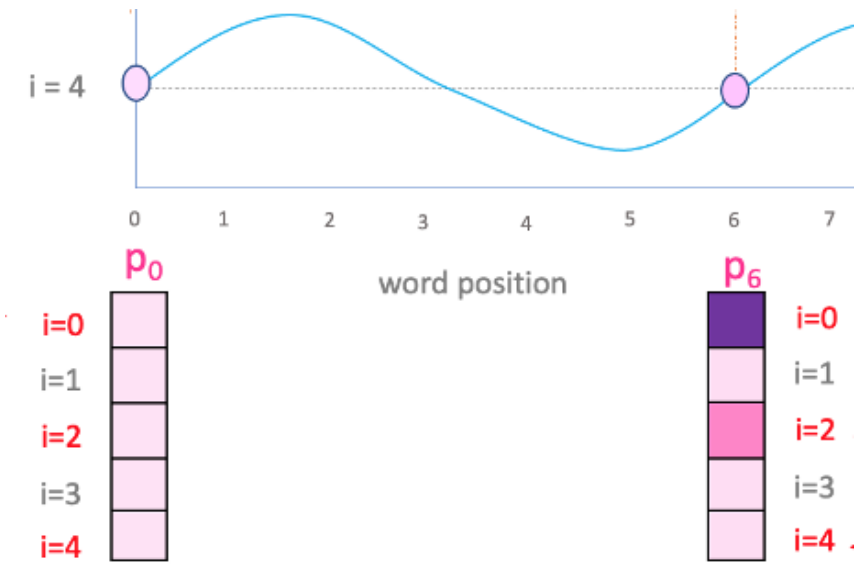

Image source: https://www.youtube.com/watch?v=dichIcUZfOw

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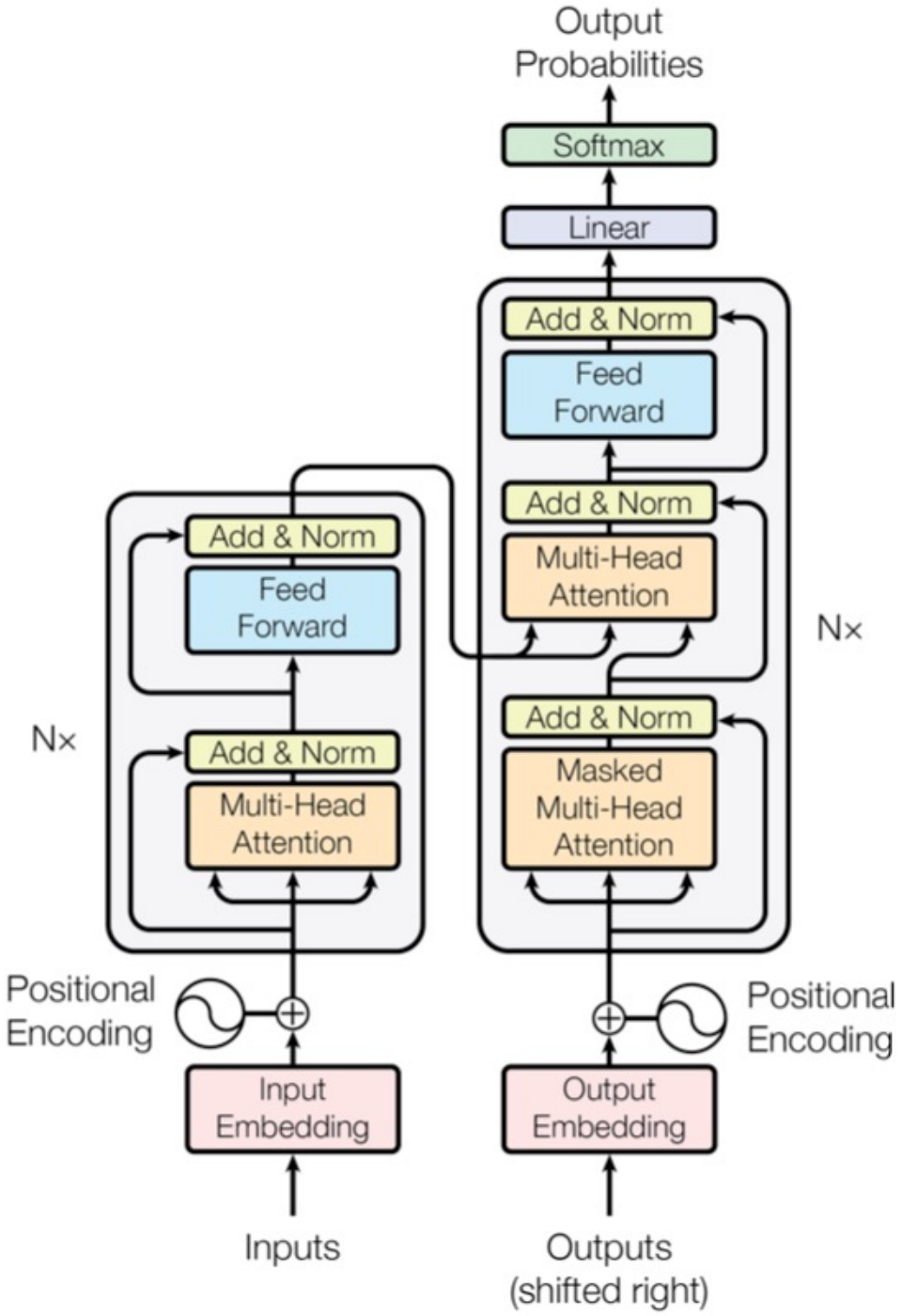
Putting it together



Source: Vaswani


See you in class!

Sources

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- Vaswani et al., 2017, Attention is All You Need: https://arxiv.org/pdf/1706.03762.pdf