Deep Learning for Particle Physicists

Lewis Tunstall | AEC Graduate Seminar | June 3rd 2022

This week in ML

Transformers
(and a digression into NLP)

Transformers in HEP

Symmetries and self-supervision in particle physics

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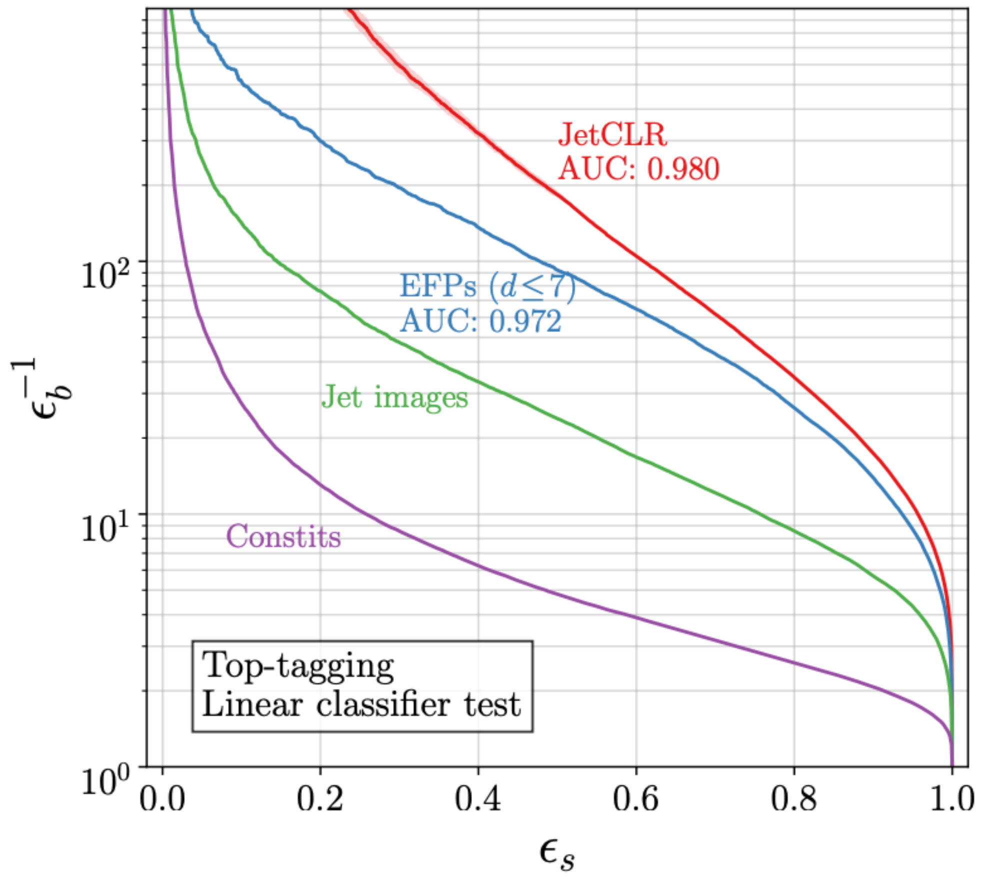
Paper link



Still early days, pretraining & transfer learning less common than other fields

Transformers in HEP

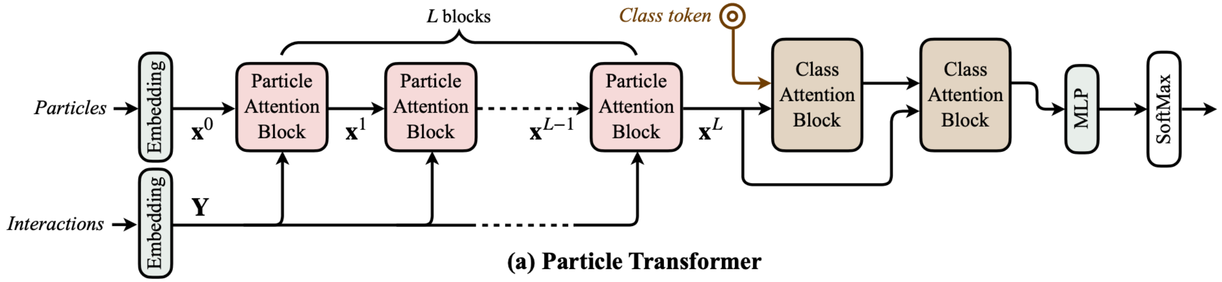
arXiv > hep-ph > arXiv:2202.03772

High Energy Physics – Phenomenology

[Submitted on 8 Feb 2022]

Particle Transformer for Jet Tagging

Huilin Qu, Congqiao Li, Sitian Qian

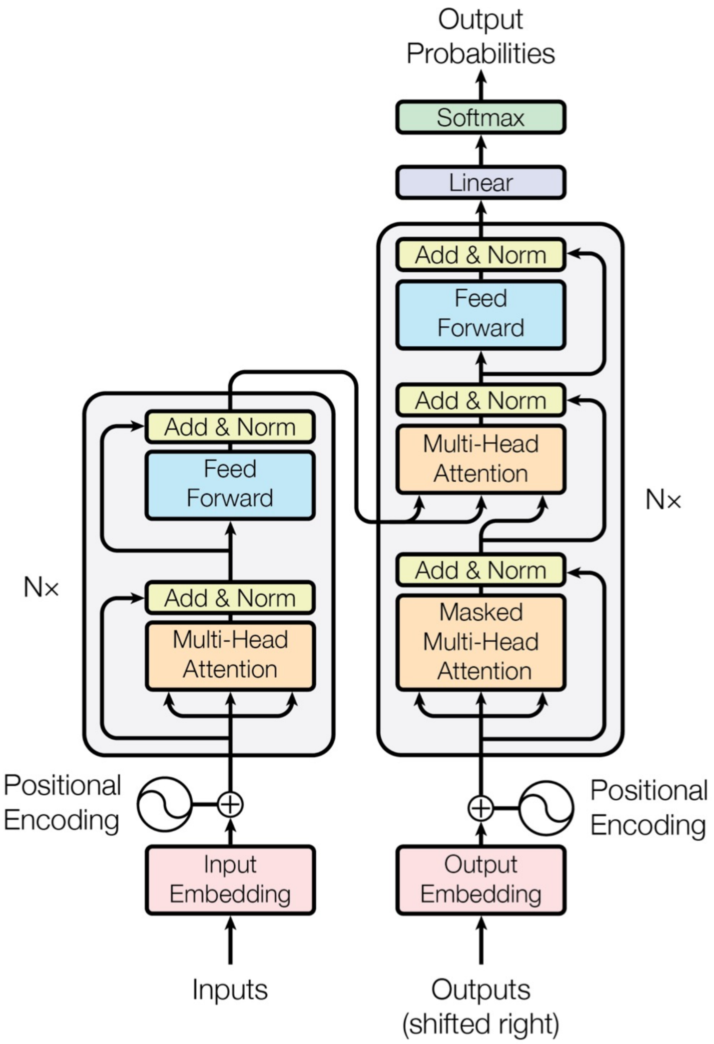


(a) Particle Transformer

	Accuracy	AUC	$\mathrm{Rej}_{50\%}$	$\mathrm{Rej}_{30\%}$
P-CNN	0.930	0.9803	201 ± 4	759 ± 24
PFN	—	0.9819	247 ± 3	888 ± 17
ParticleNet	0.940	0.9858	397 ± 7	1615 ± 93
JEDI-net (w/ $\sum O$)	0.930	0.9807	—	774.6
PCT	0.940	0.9855	392 ± 7	1533 ± 101
LGN	0.929	0.964	—	435 ± 95
rPCN	—	0.9845	364 ± 9	1642 ± 93
ParT	0.940	0.9858	413 ± 16	1602 ± 81
ParT-f.t.	**0.944**	**0.9877**	$\mathbf{691 \pm 15}$	$\mathbf{2766 \pm 130}$

But promising results in jet tagging from large-scale datasets (100M events)

What is a Transformer?



Attention Is All You Need

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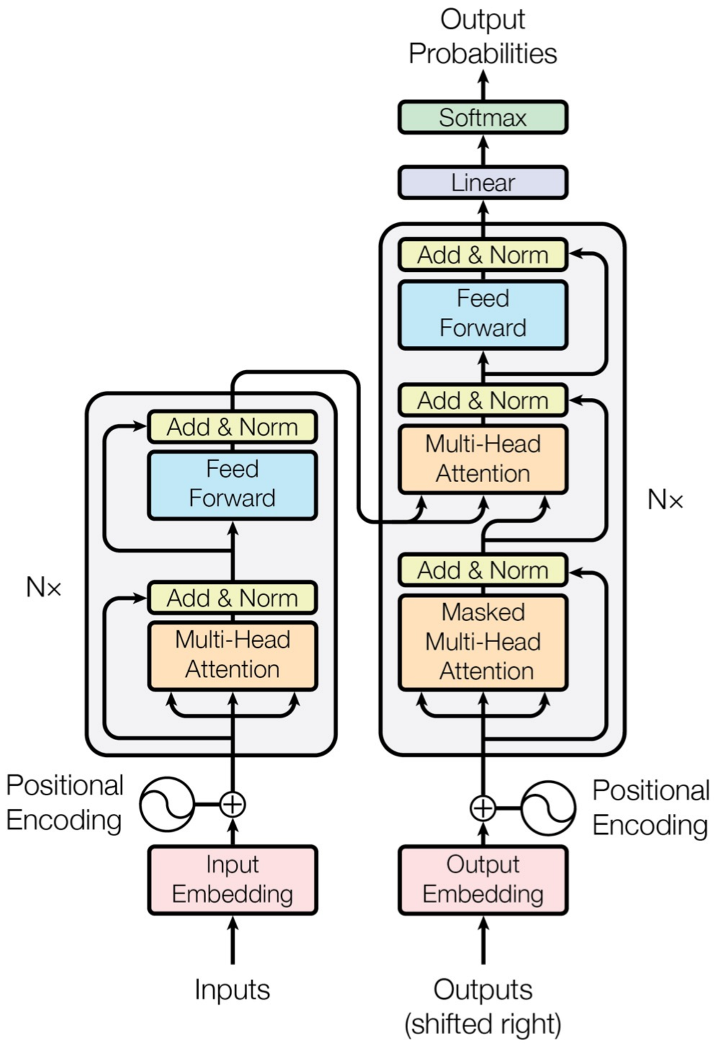

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Main ingredients

Attention mechanisms

Self-supervised learning (Pretraining)

Transfer learning (Fine-tuning)

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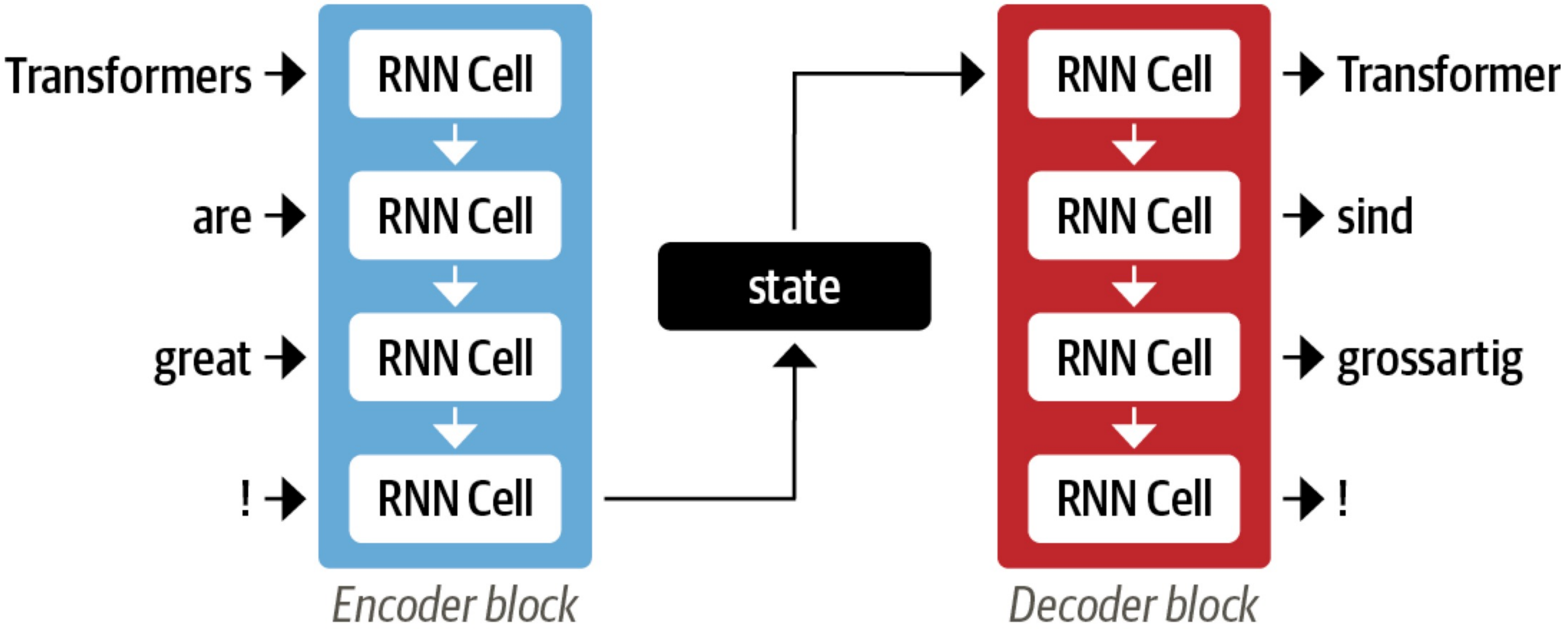
Self-supervised learning (Pretraining)

Transfer learning (Fine-tuning)

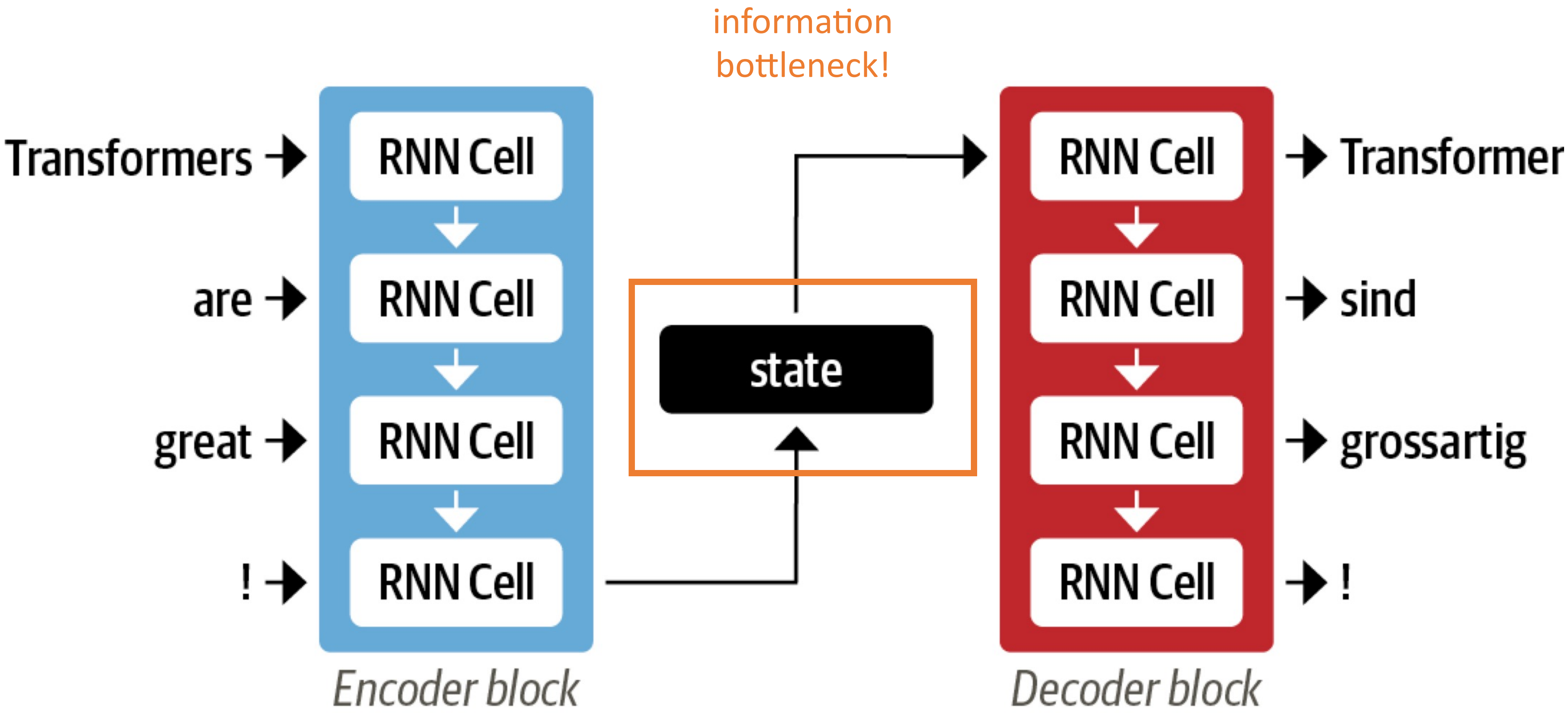
we first saw this in lecture 4 in the context of jet images and CNNs

Attention mechanisms



Originally developed for *recurrent neural networks*

Attention mechanisms



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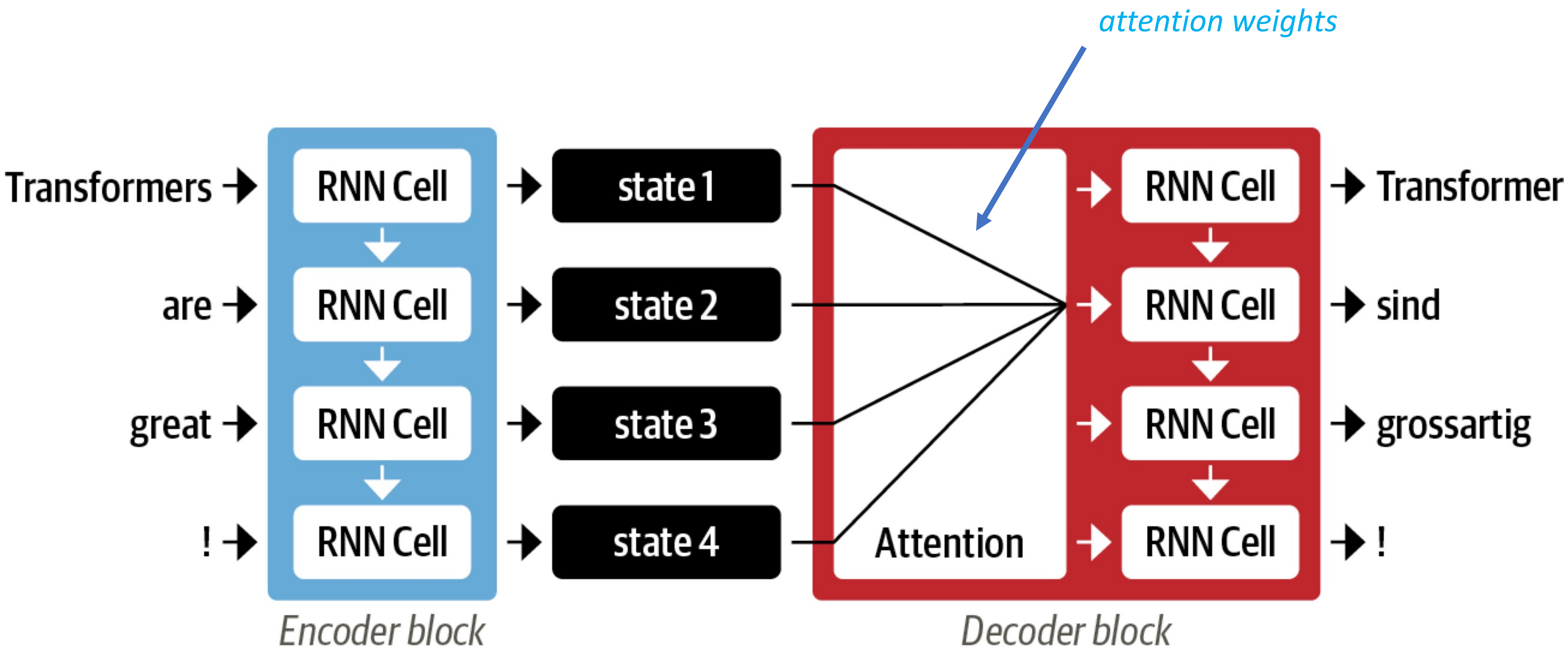
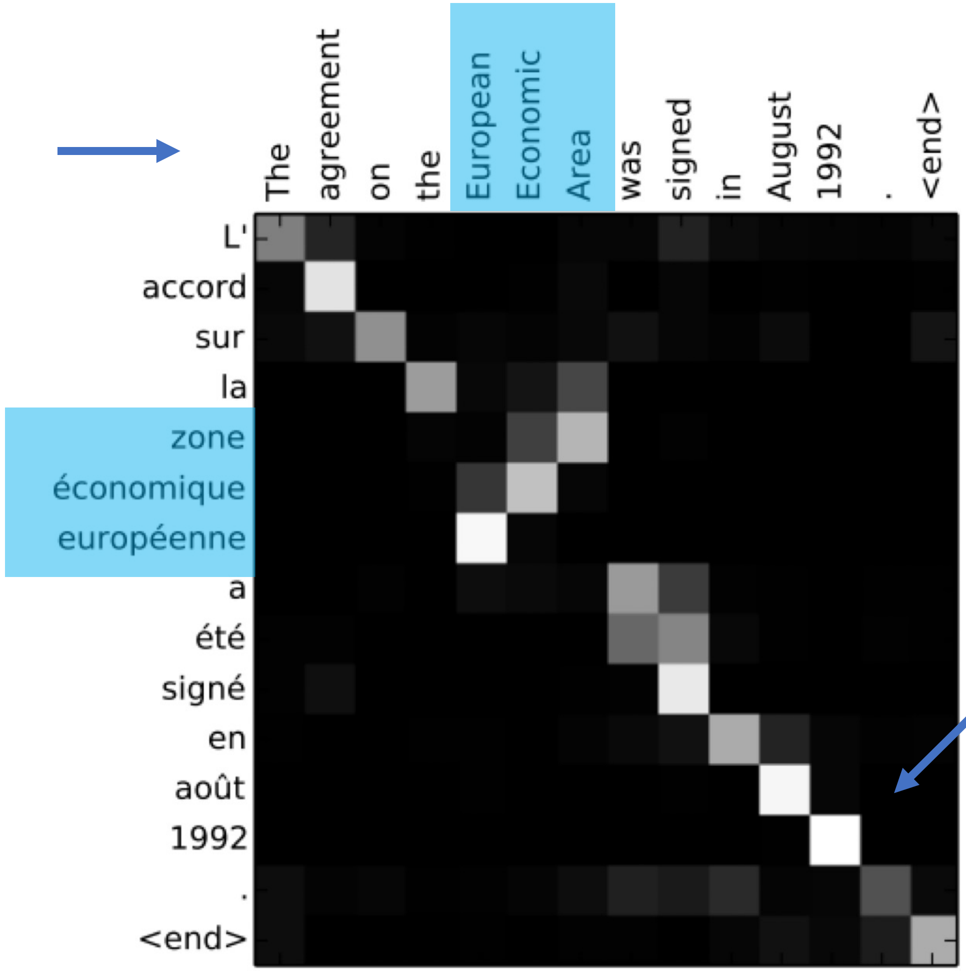
Attention mechanisms



Use intermediate states but assign a *weight* or "pay attention"

Attention mechanisms

word order flipped in French vs English



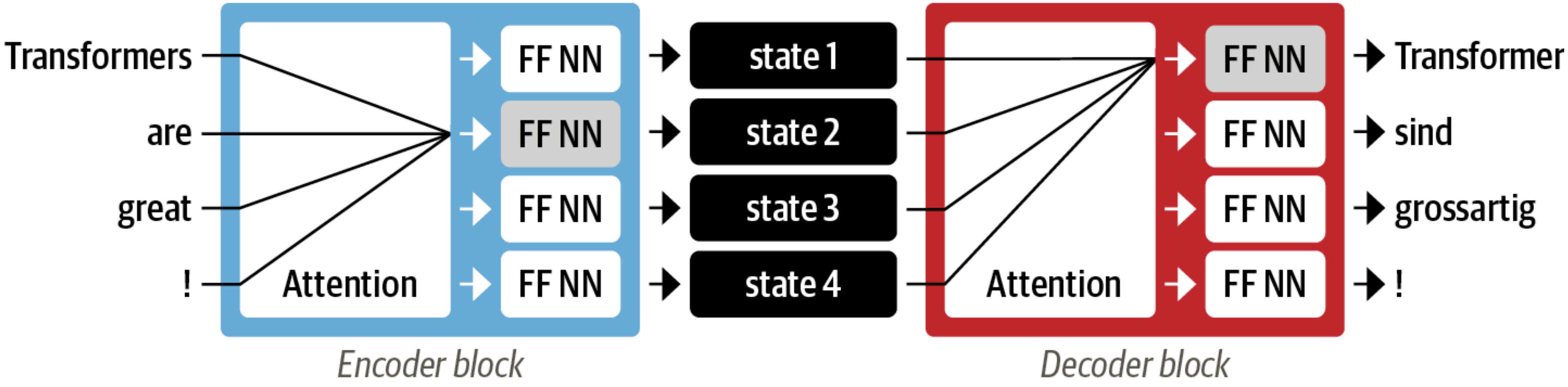
each pixel denotes an attention weight

Attention gives better modelling of word order

Attention mechanisms

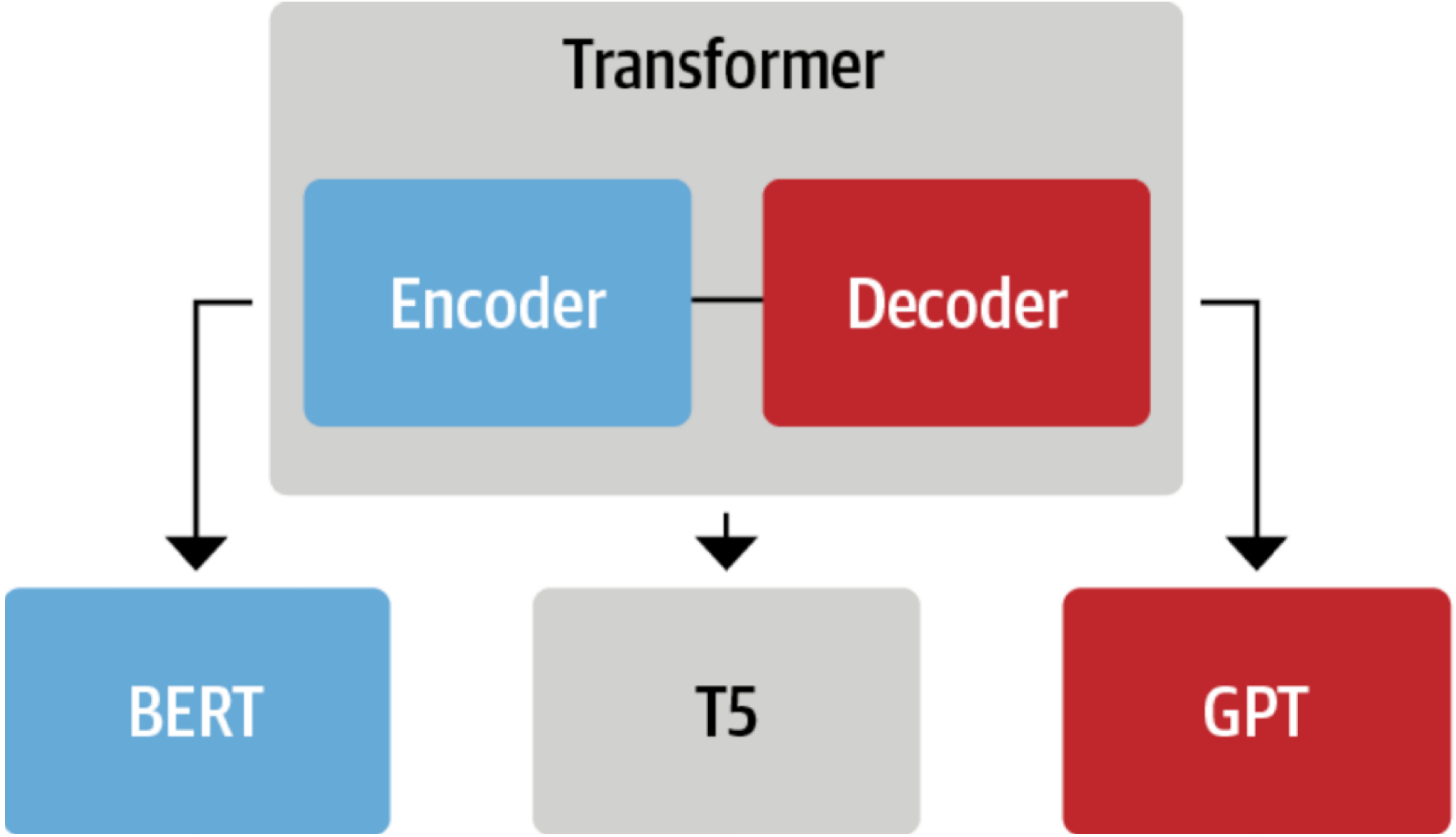
no recurrence!
feed sequence all at once

use a special type of attention
called "self-attention"



Transformers much easier to scale with compute & data

Three types of architectures



Each architecture excels at specific types of tasks

Transformer pretraining

Trained on unlabeled data to predict the next token (GPT-like) …

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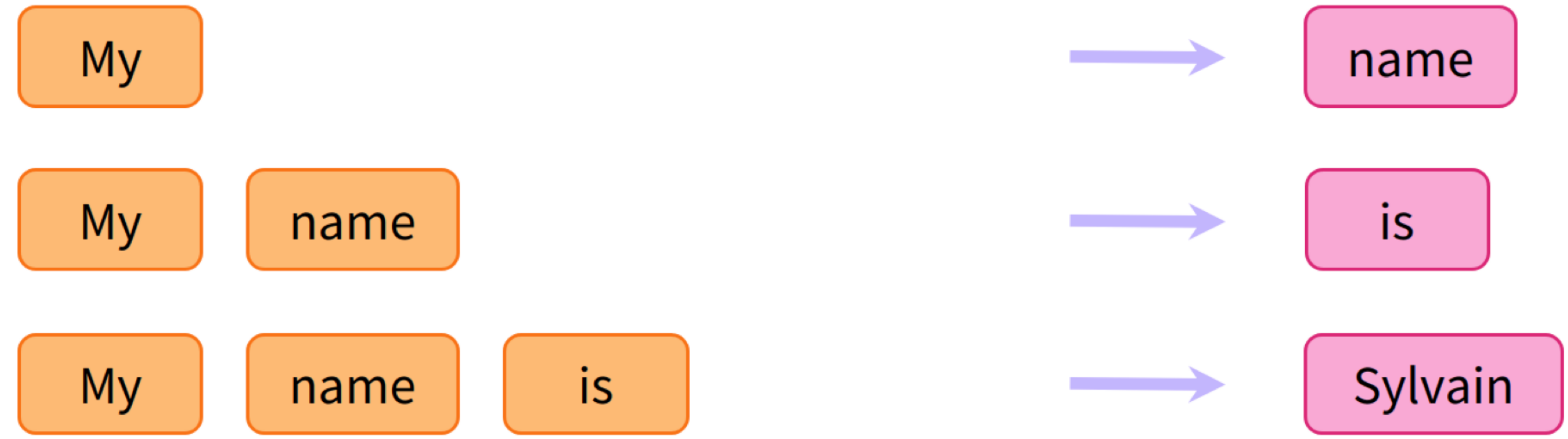
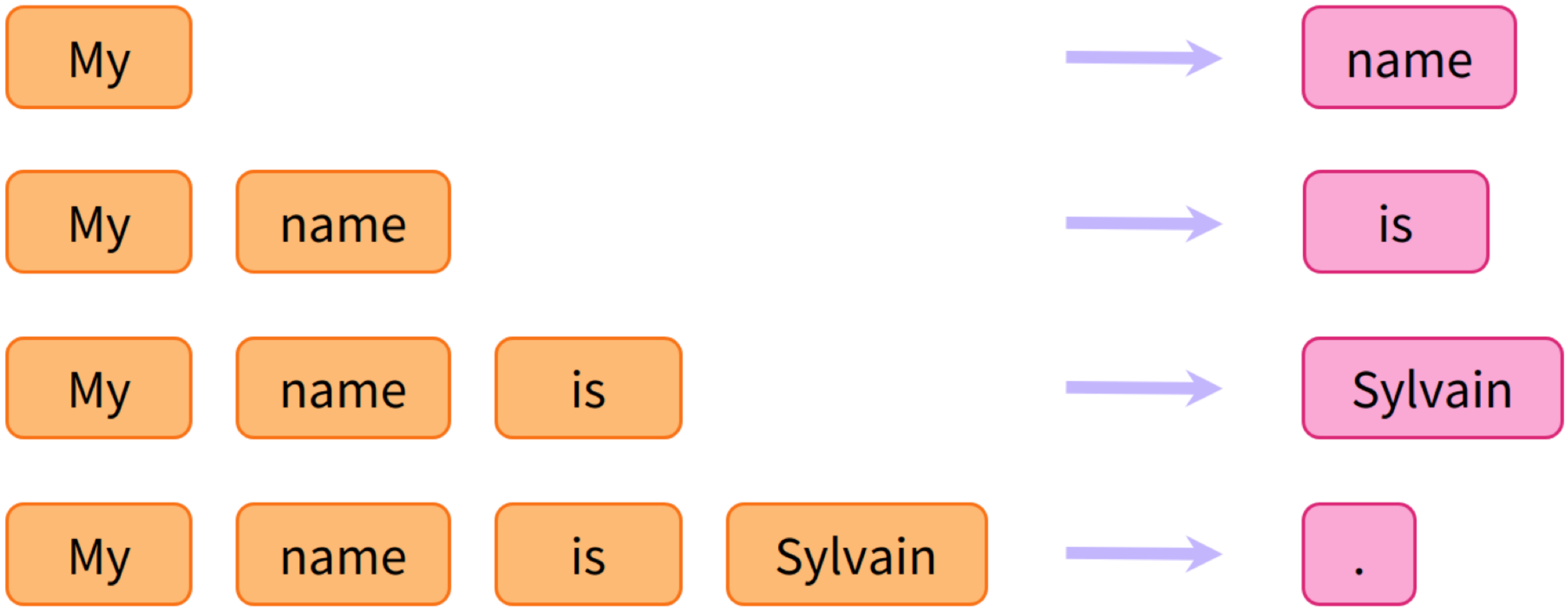
Transformer pretraining



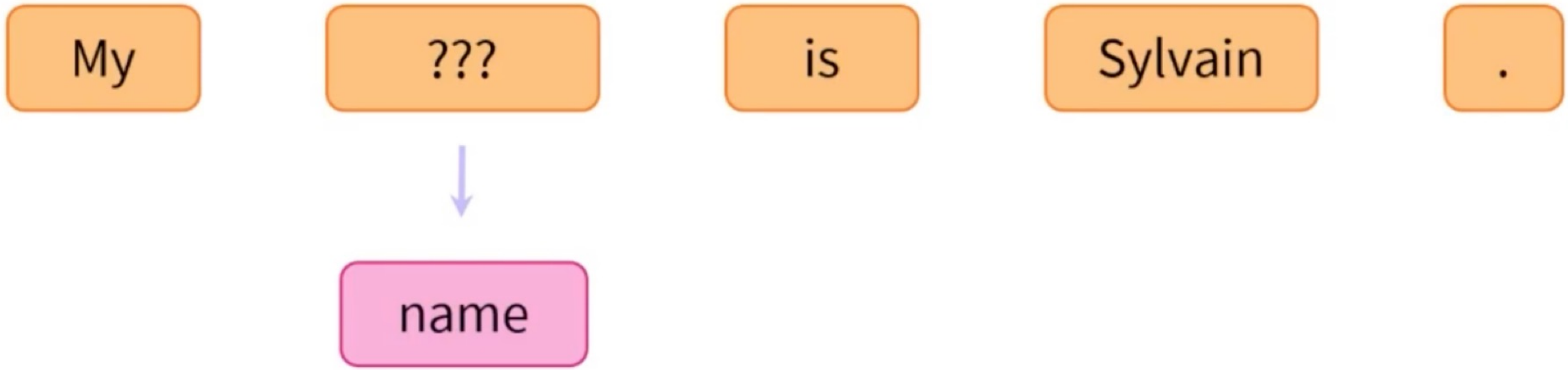
Trained on unlabeled data to predict the next token (GPT-like) …

Transformer pretraining



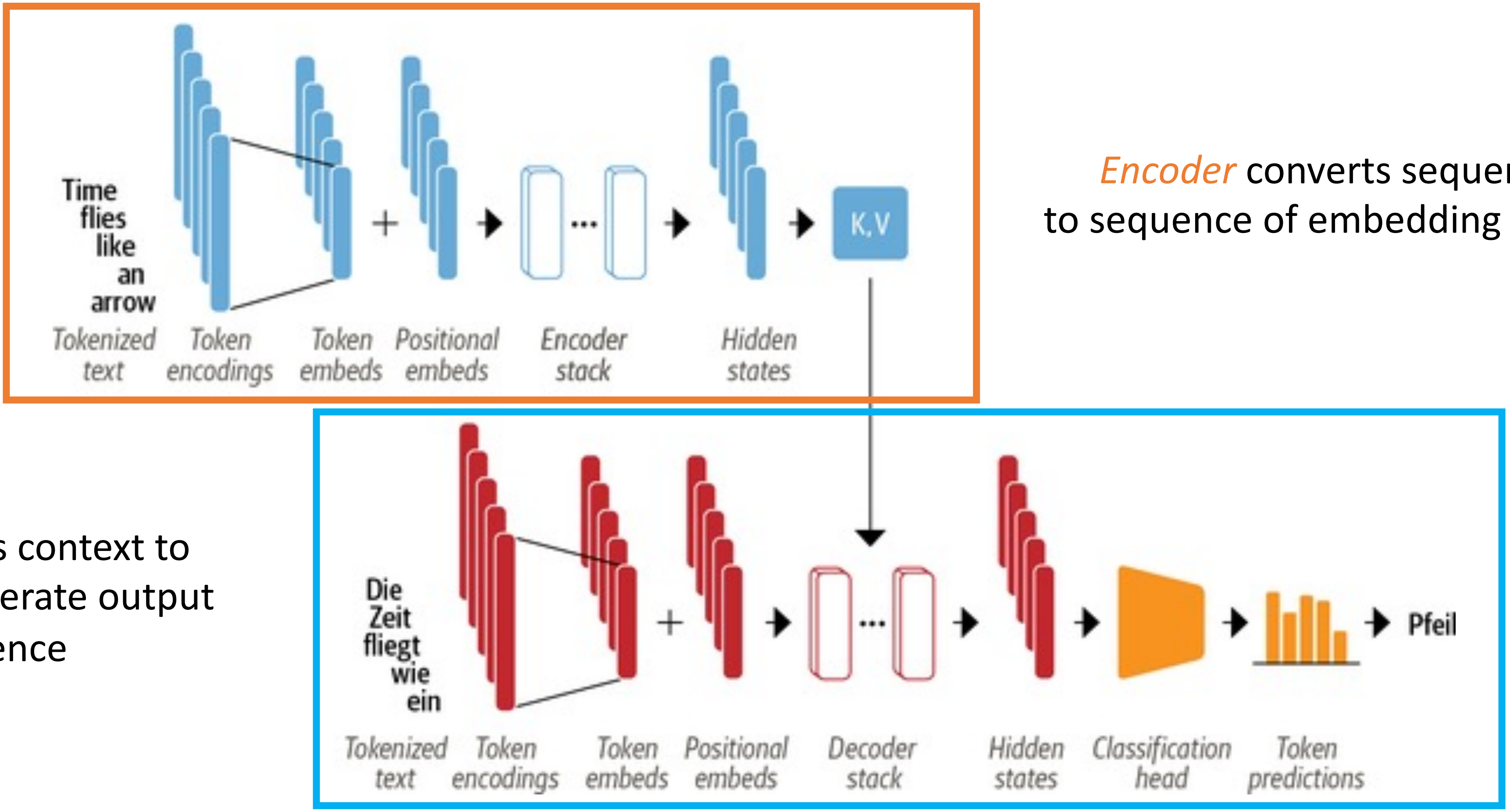
Trained on unlabeled data to predict the next token (GPT-like) …

Transformer pretraining



… or to predict the masked token (BERT-like)

The first Transformer architecture (2017)



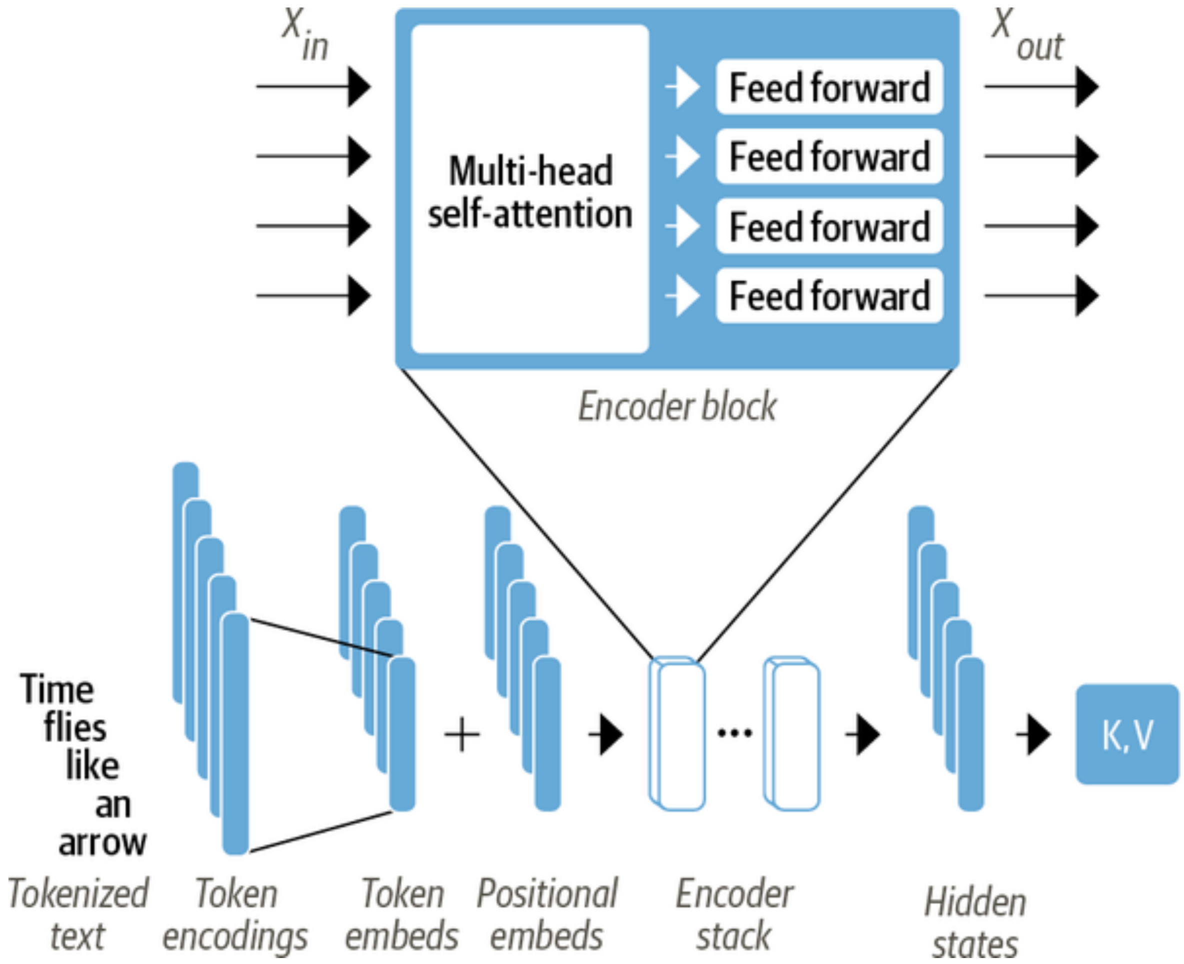
Encoder converts sequence of tokens to sequence of embedding vectors (context)

Decoder uses context to iteratively generate output sequence

Consists of an *encoder* and *decoder*

The encoder

input text converted into atomic subwords called *tokens*

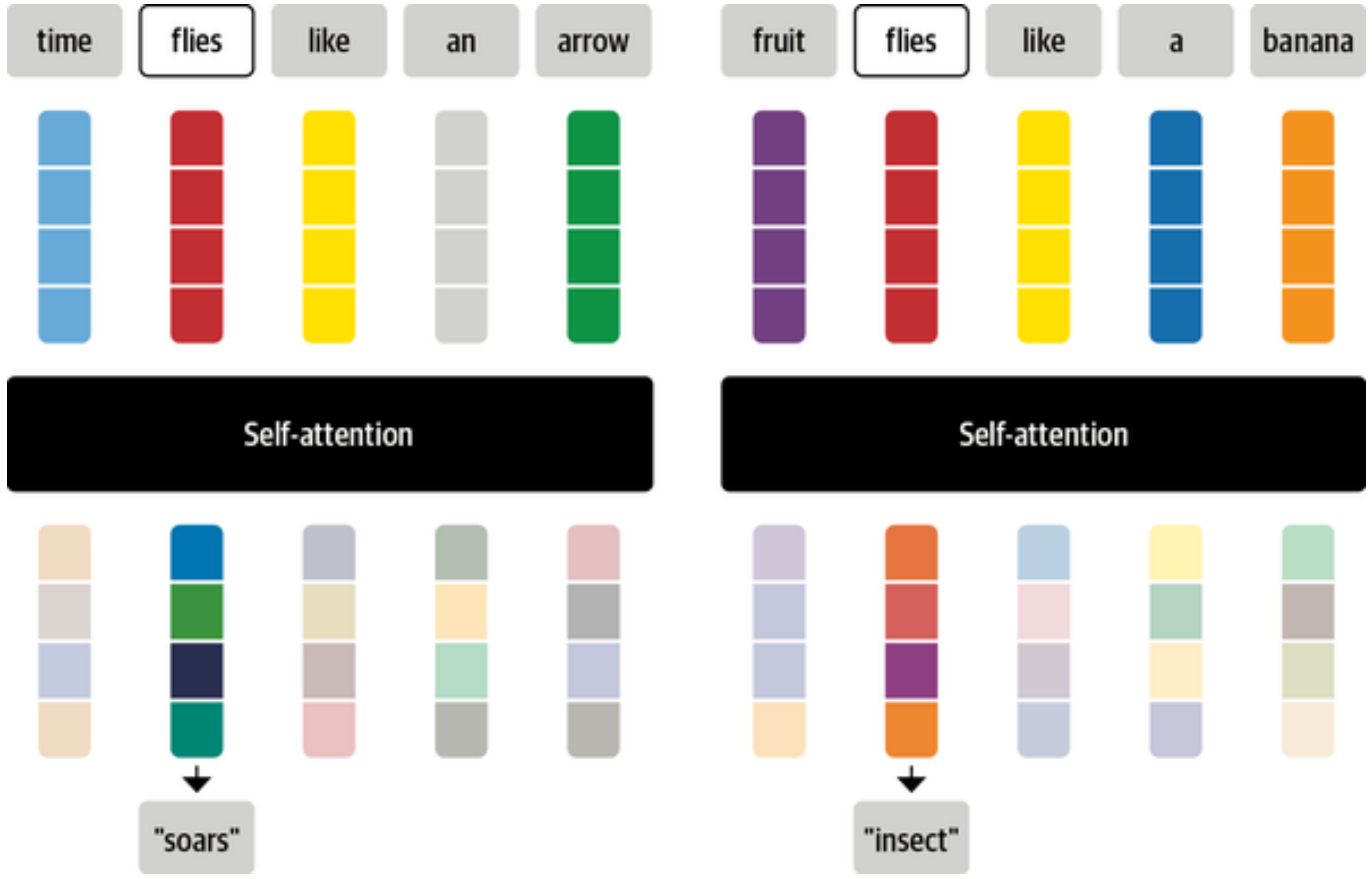


Built from of a stack of *encoder layers* (similar to stacking convolutional layers)

Self-attention layers

attention weights

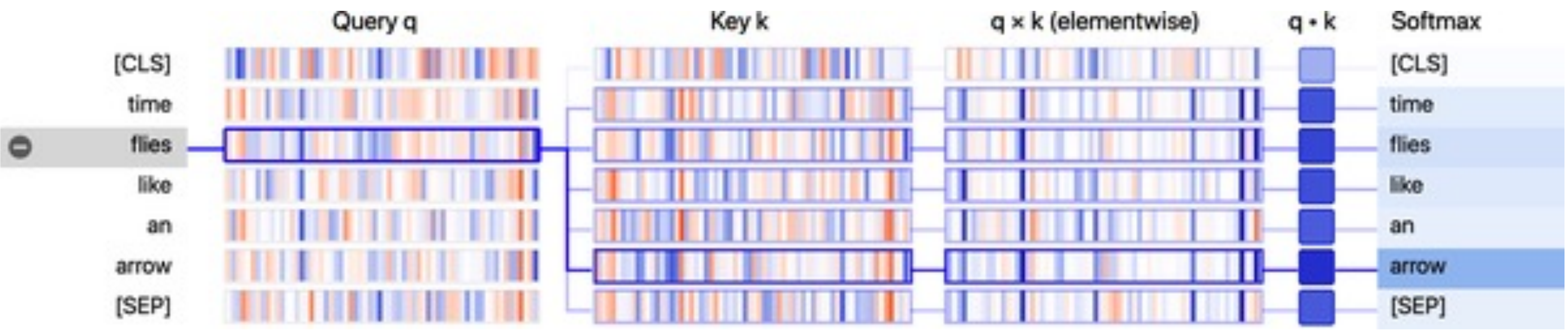
$$x'_i = \sum_j w_{ji} x_j$$



Self-attention updates *input* embeddings x into *contextualised* ones x'

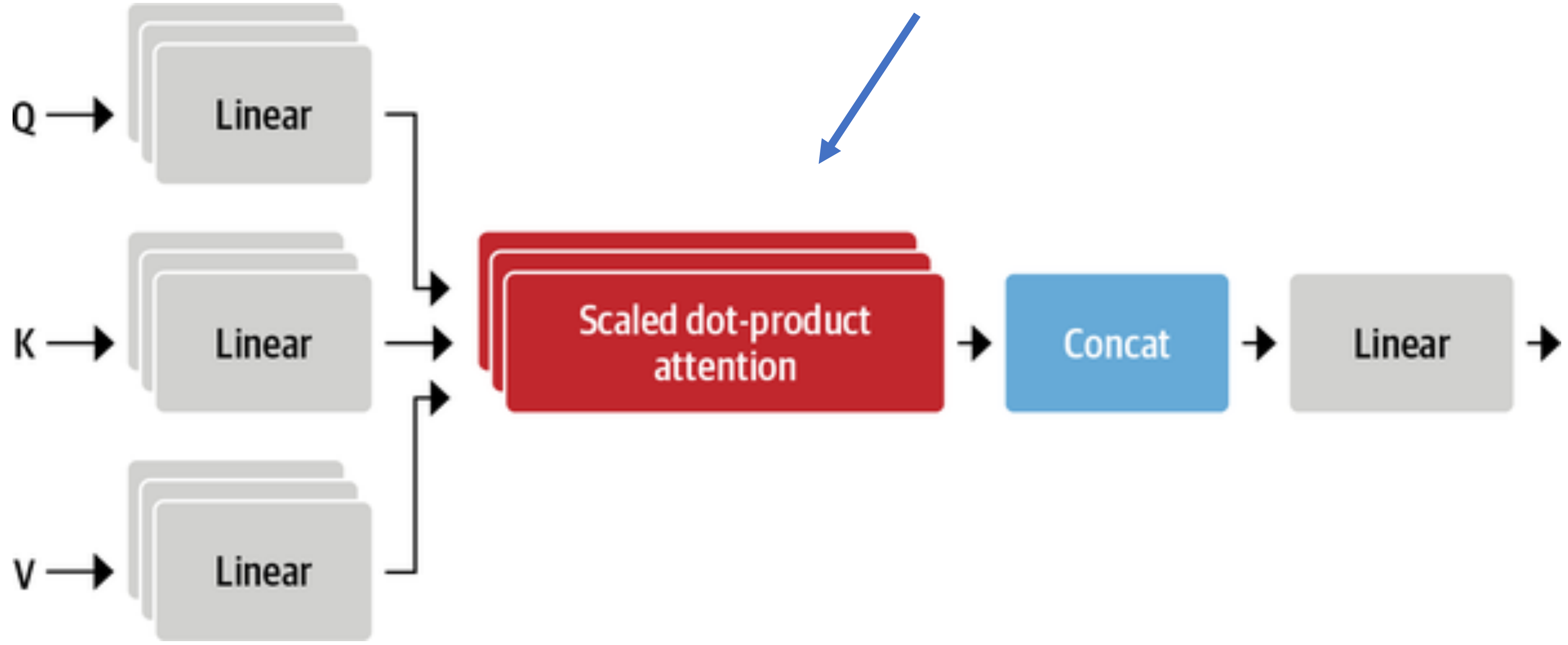
Computing attention weights

1. Project each token embedding into 3 vectors called *query, key, and value*
2. Compute pairwise attention scores of *queries* and *keys* via similarity function (e.g. dot-product)
3. Compute attention weights w_{ji} (normalize with softmax)
4. Update token embeddings $x'_i = \sum w_{ji} v_j$



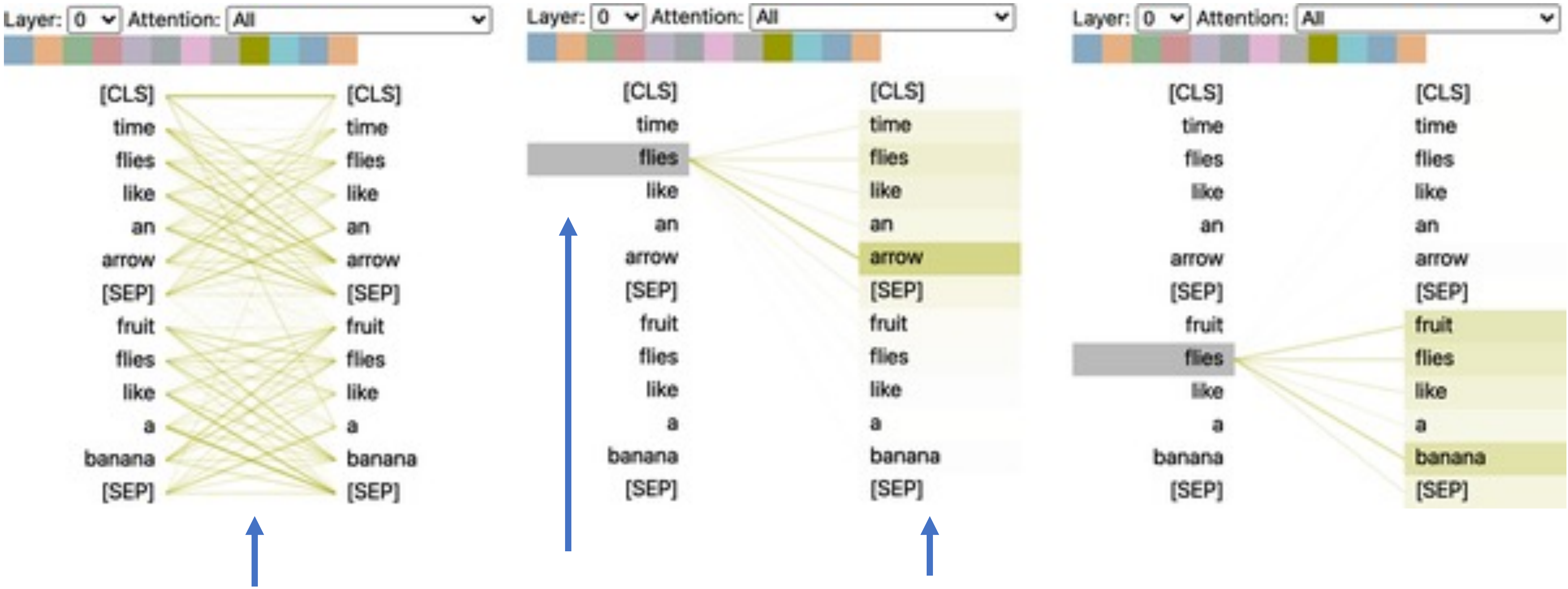
Multi-headed attention

model can focus on several aspects at once
(e.g. subject-verb interaction vs nearby adjectives)



Beneficial to have multiple attention layers or “heads”

Multi-headed attention



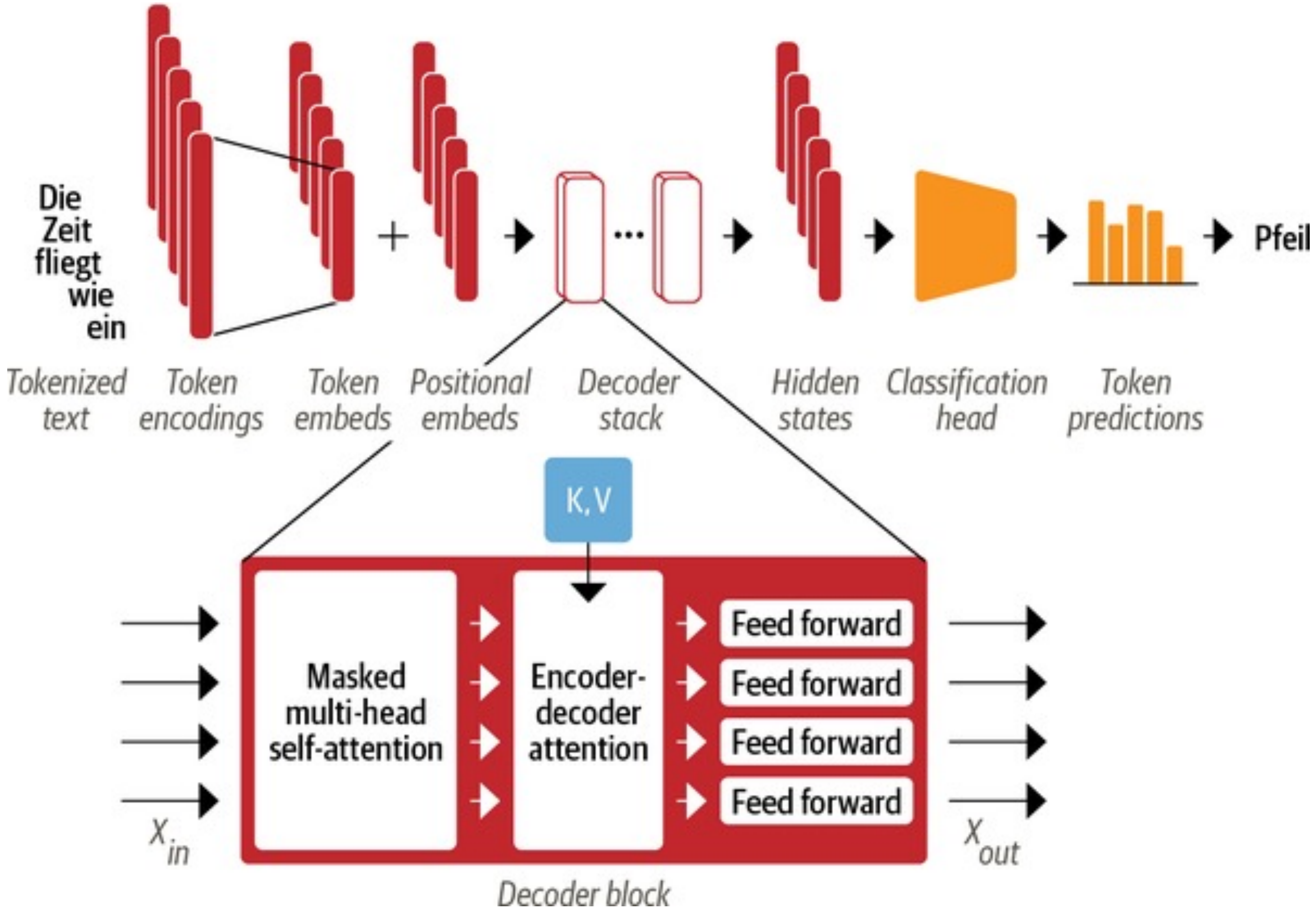
attention weights

token
being updated

tokens
being attended to

Self-attention updates *input* embeddings into *contextualised* ones

The decoder



Similar to encoder but built from of a stack of *decoder layers*

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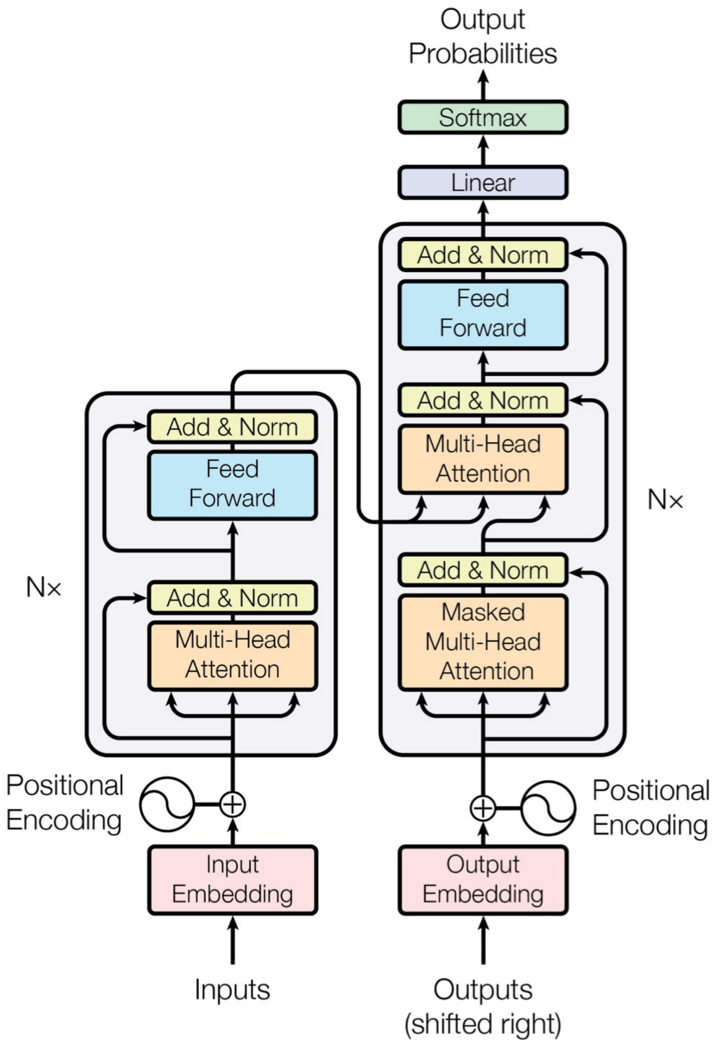

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