## **Transformer Neural Networks**

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#### Introduction

"Our work reinforces the bitter lesson. The most important factors determining the performance of a sensibly designed model are the compute and data available for training. [...]"

Smith et al., ConvNets match Vision Transformers at Scale, https://arxiv.org/pdf/2310.16764.pdf

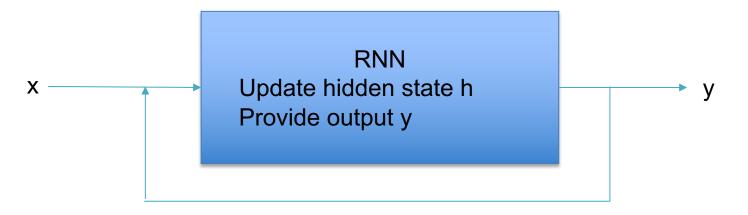
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## **Motivation**

- Recurrent neural networks
  - Standard for temporal sequence problems (e.g. in natural language processing up to 2018)



- Training is difficult to parallelize
- Implicit connection to past states

### **Motivation**

- Architecture that can be parallelized more efficiently
- More direct interaction between information, in particular "far away" one

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#### **Attention Is All You Need**

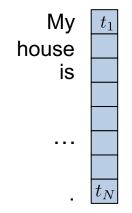
Ashish Vaswani\* Google Brain avaswani@google.com

Noam Shazeer\* Google Brain noam@google.com Niki Parmar\* Google Research nikip@google.com Jakob Uszkoreit\* Google Research usz@google.com

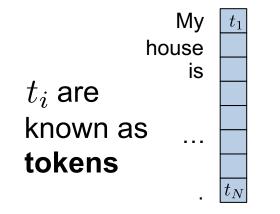
Llion Jones\* Google Research Aidan N. Gomez<sup>\*</sup><sup>†</sup> University of Toronto **Łukasz Kaiser**\* Google Brain



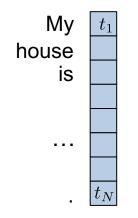
- Similarity measure between hidden/latent states  $\{t_i\}_{i=1}^N$ 
  - Hidden/latent states are vectors in  $\mathbb{R}^E$



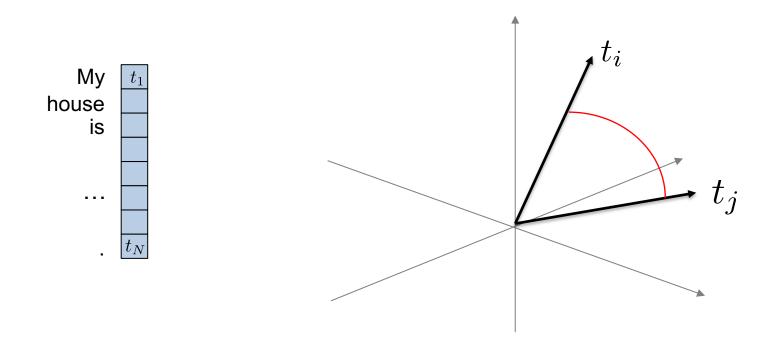
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 $t_i \cdot t_j$ 

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$$\tilde{t}_i = \sum_{j=1}^N (t_i \cdot t_j) t_j$$

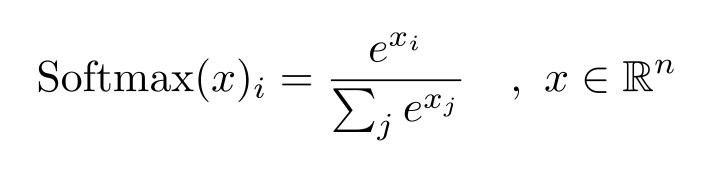
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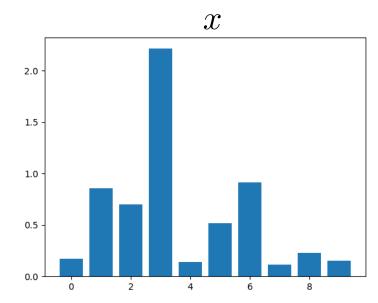
$$\tilde{t}_i = \sum_{j=1}^N \sigma(t_i \cdot t_j) t_j$$

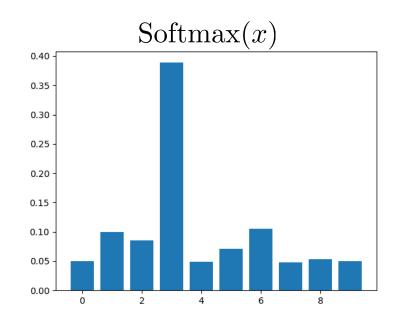
softmax nonlinearity

(smoothed/differentiable version of argmax + normalization)

• Softmax







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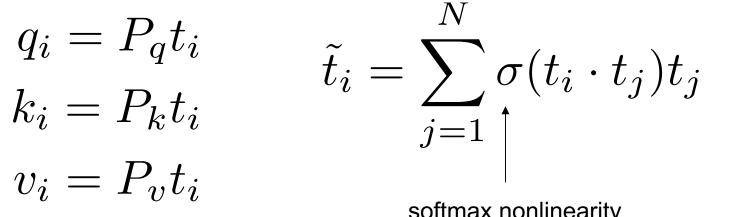
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## How to make this "learnable"?

softmax nonlinearity

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$$\begin{array}{l} q_{i} = P_{q}t_{i} \\ k_{i} = P_{k}t_{i} \\ v_{i} = P_{v}t_{i} \end{array} \qquad \tilde{t}_{i} = \sum_{j=1}^{N} \sigma(q_{i} \cdot k_{j})v_{j} \\ \uparrow \\ \text{softmax nonlinearity} \end{array}$$

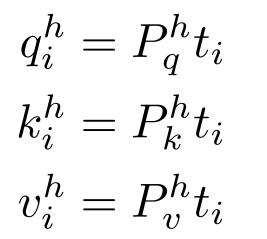
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# Learnable attention module

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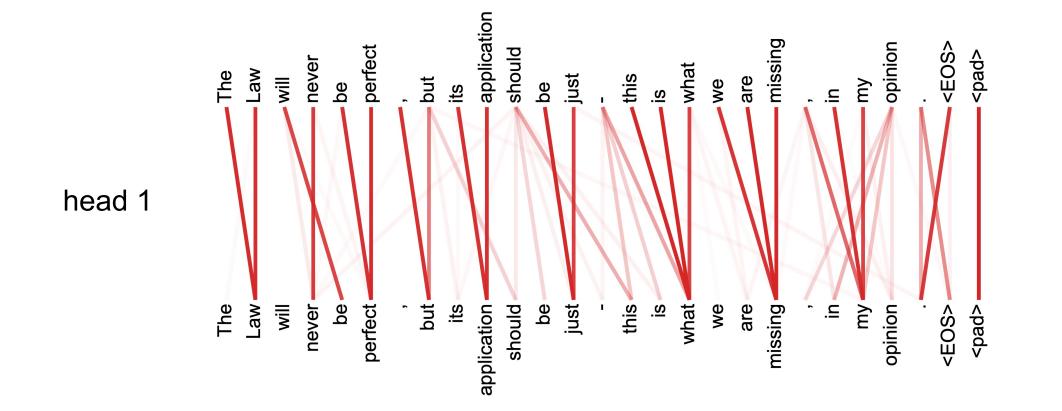
#### Learnable attention module with multiple heads

head 1

C4 H		Law	will	never	be	perfect	-	but	its	application	should	be	just		this	.s	what	We	are	missing	-	ŗ	my	opinion	-	<eos></eos>	<pre>cpad&gt;</pre>
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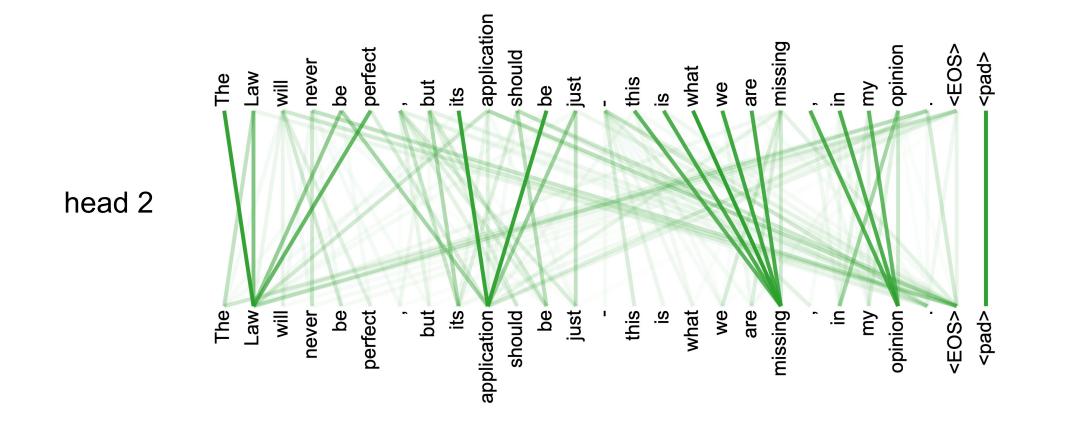
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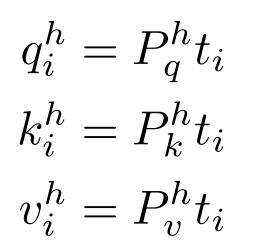


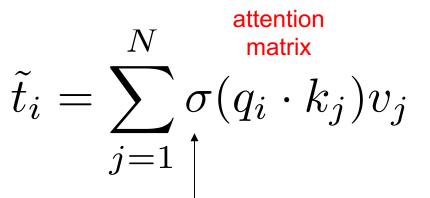


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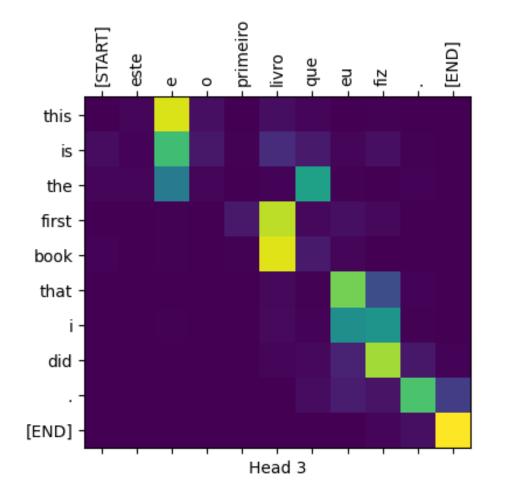




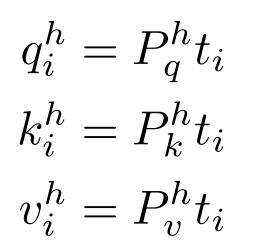
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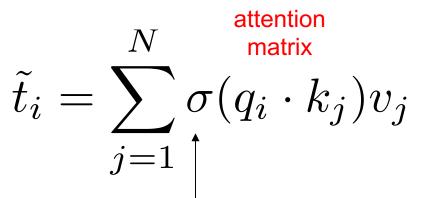
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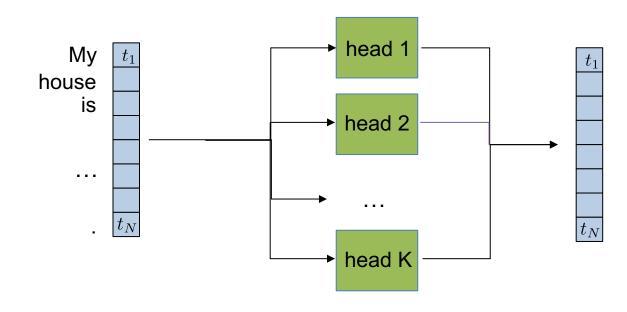


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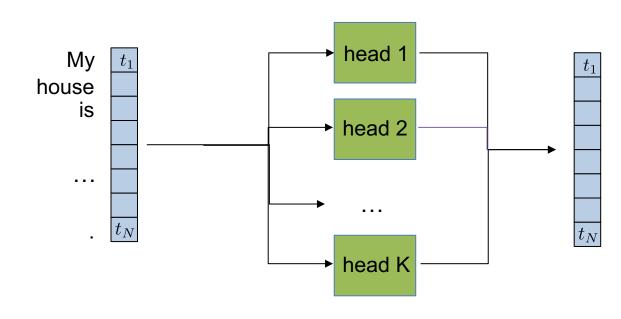
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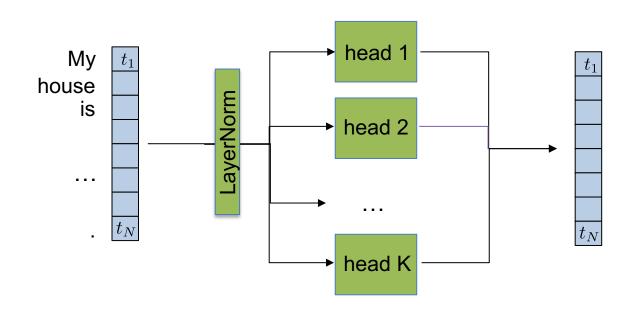


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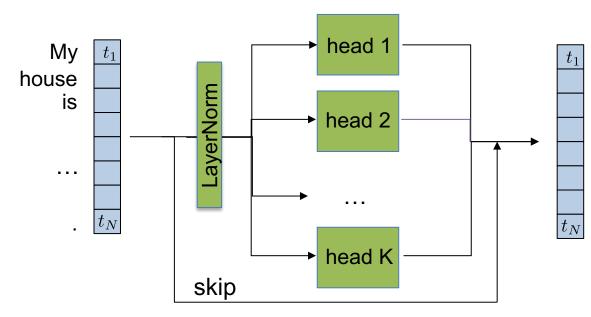
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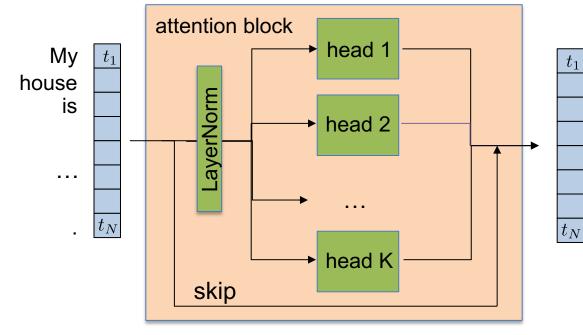
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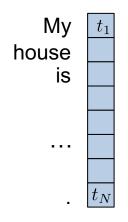
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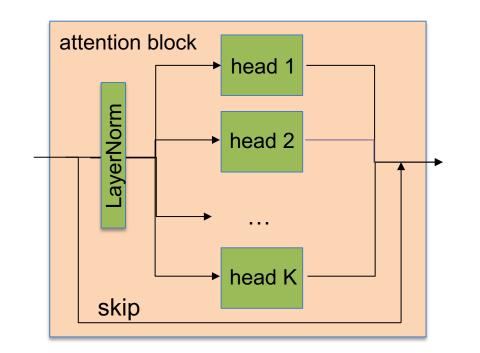
FCN

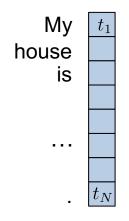
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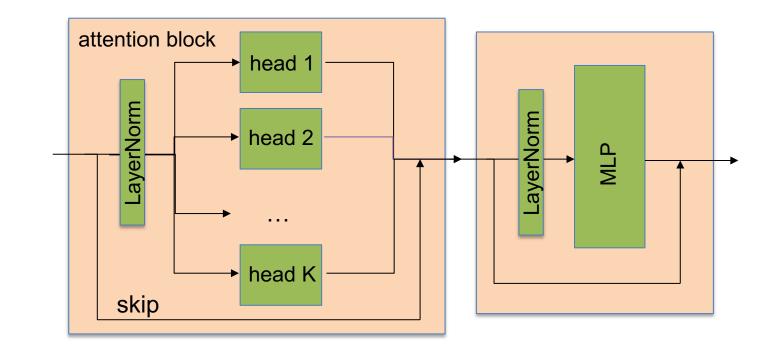


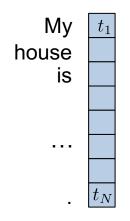
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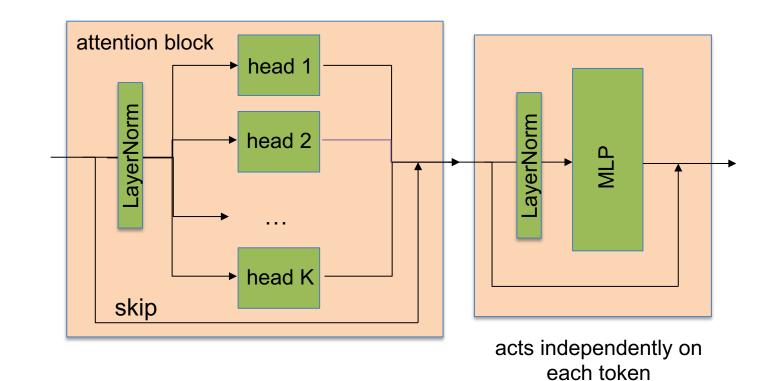


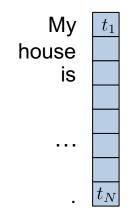


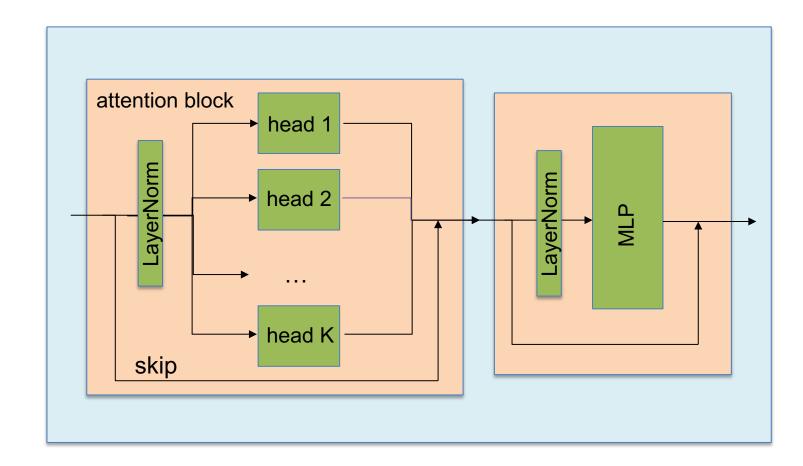




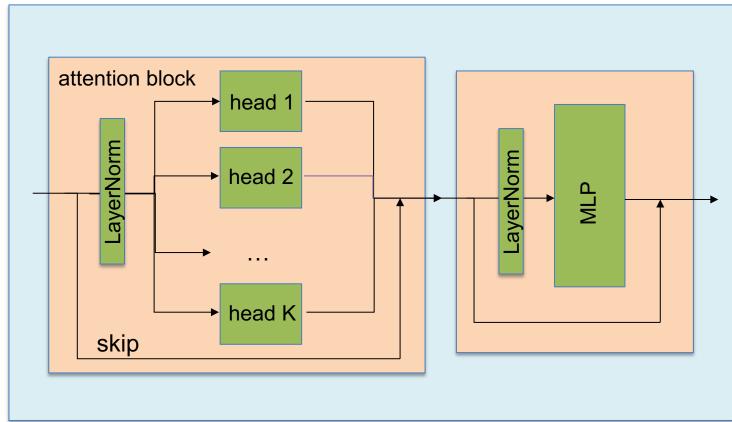


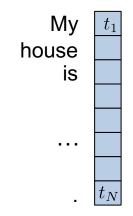


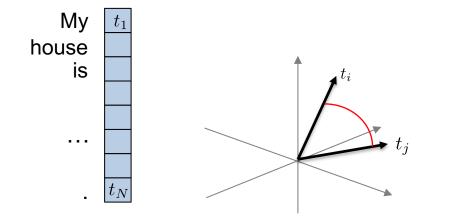






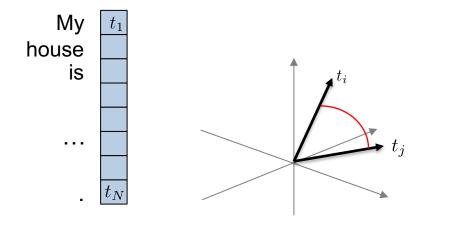






attention block

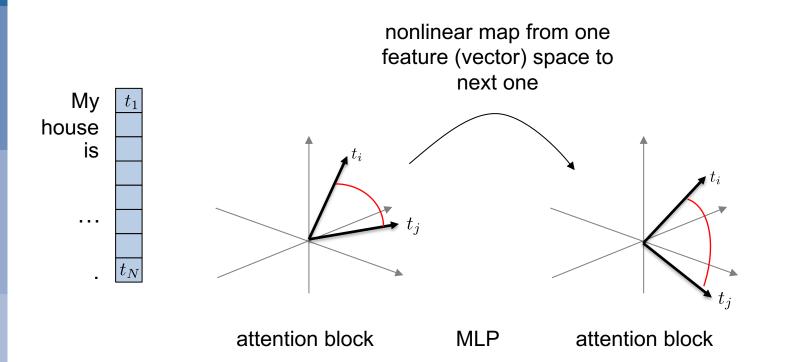


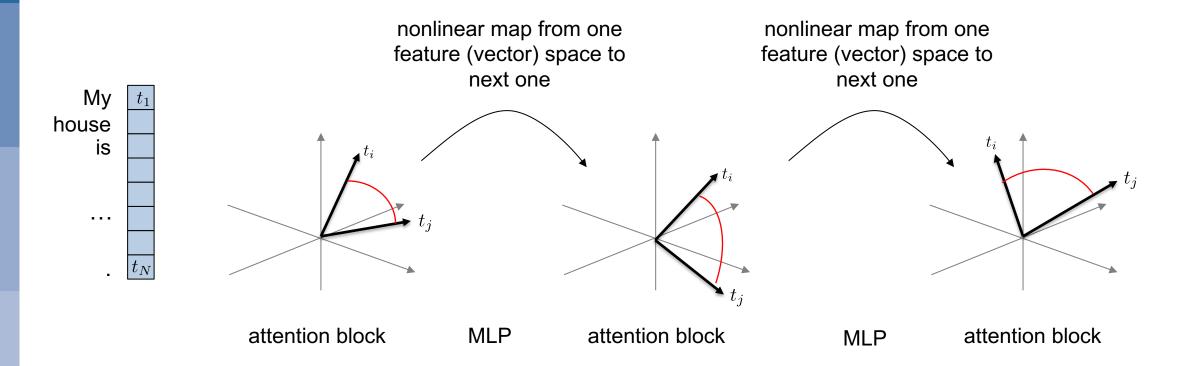


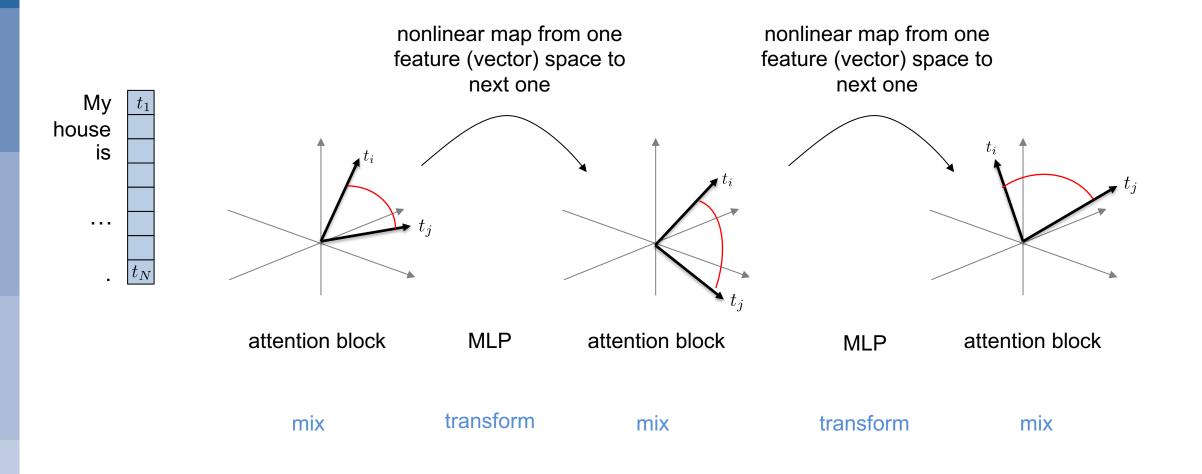
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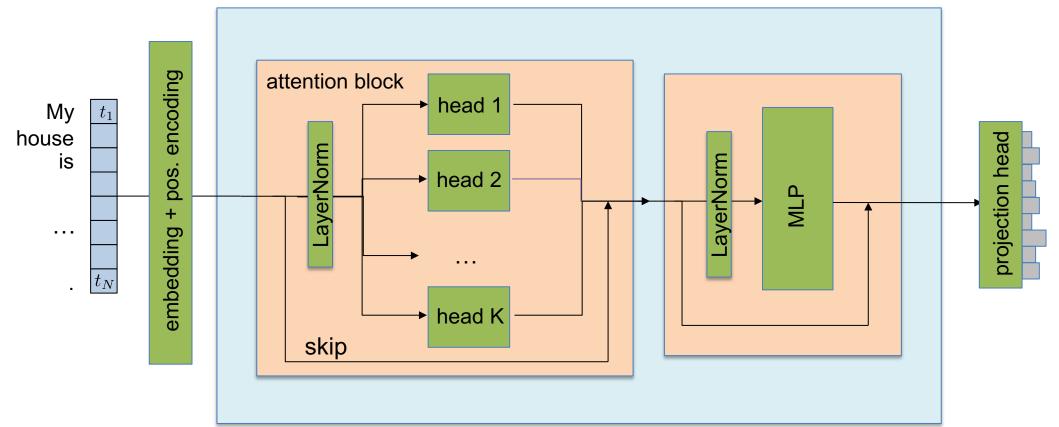
MLP





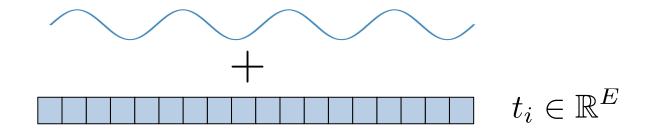


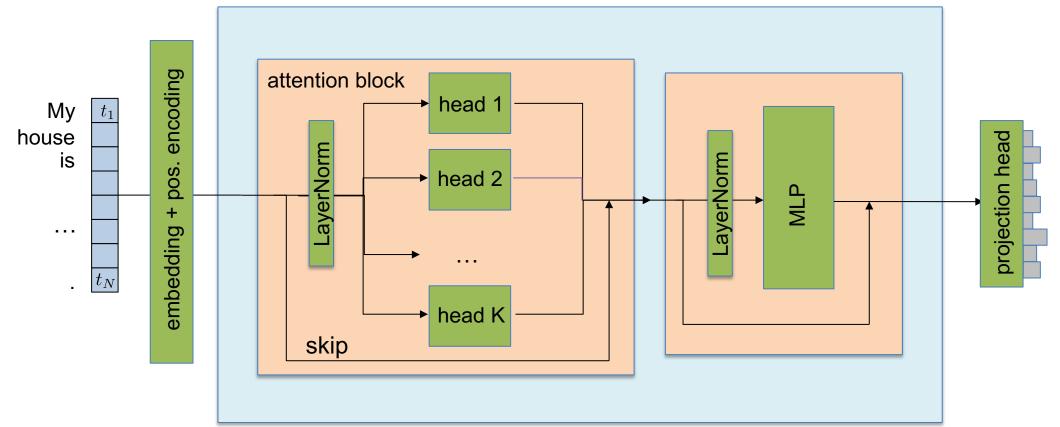




Transformer block: iterate M times

- Positional encoding
  - Tokens after embedding form a set without ordering
  - Structure/relationship between tokens needs to be encoded separately
  - Encoding can be fixed or learned
  - Classical approach: harmonic positional encoding that overlays sine/cosine oscillations with frequency that depends on position



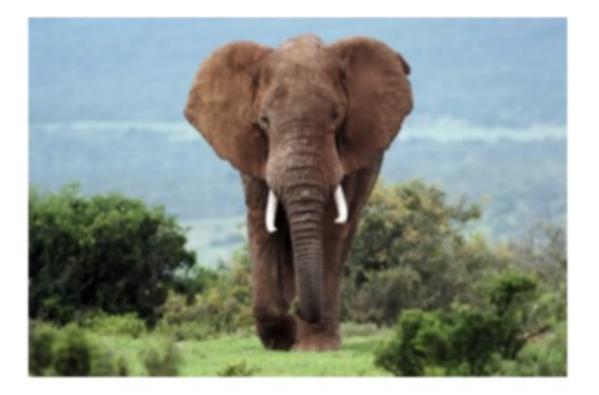


Transformer block: iterate M times

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encoding attention block head 1 My  $t_1$ house projection head ayerNorm \_ayerNorm is pos. head 2 MLP + embedding . . . . . .  $t_N$ head K skip

How to define a token when one has a pixel image instead of discrete words?



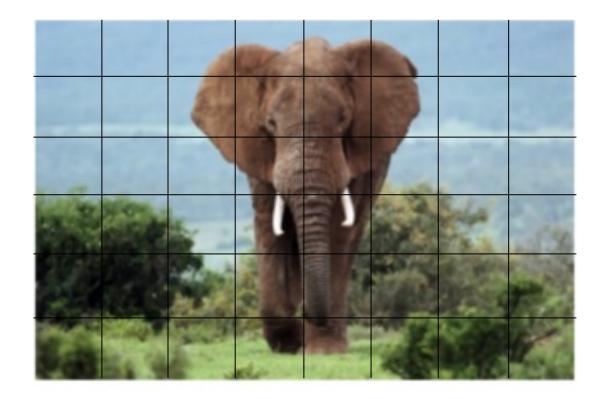
#### How to define a token when one has a pixel image instead of discrete words?

Dosovitskiy et al., An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale, 2021, https://arxiv.org/abs/2010.11929

token is small image patch

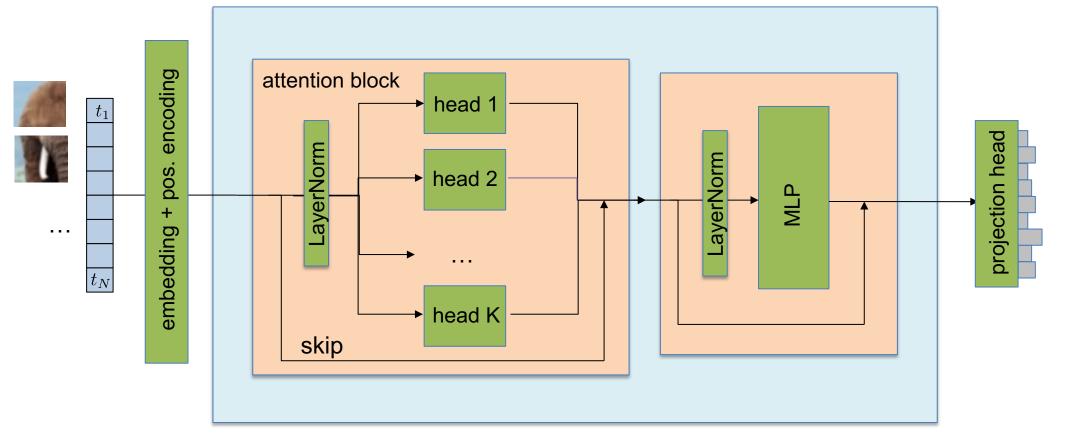
- enough structure for dot product to make sense

- small enough attention to provide rich structure



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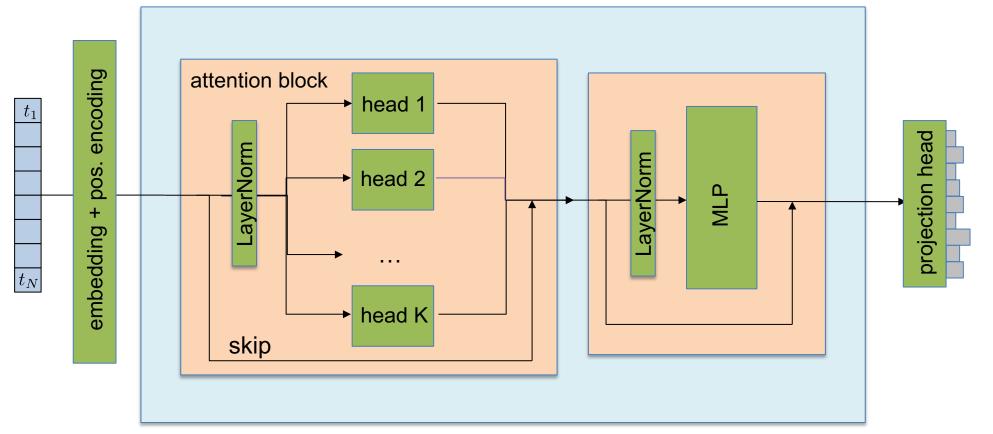
Transformer block: iterate M times



Vision transformer: token is small but non-trivial image patch

## X transformer (encoder)

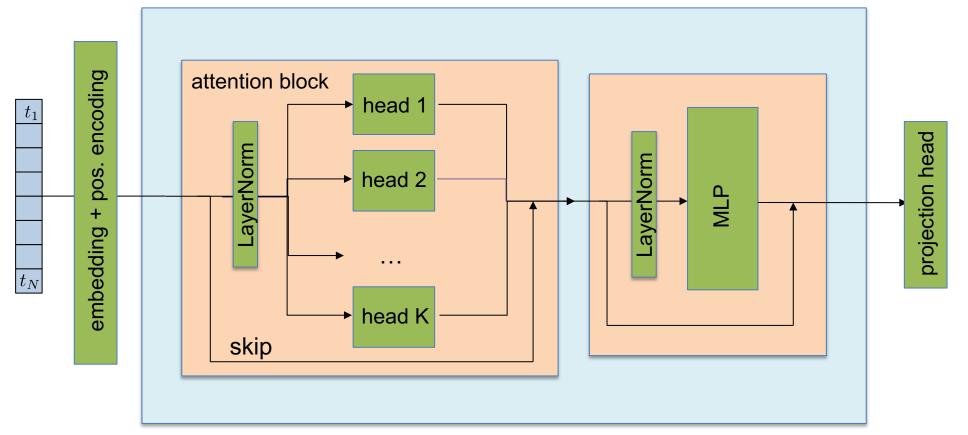
Transformer block: iterate M times



Central (only) question: what is a token, i.e. what is small information "nugget"?

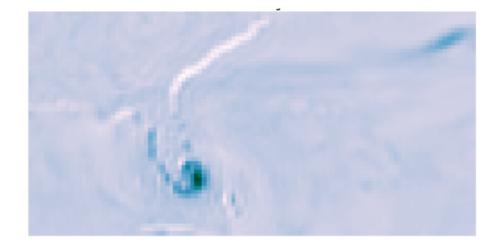
## X transformer (encoder)

Transformer block: iterate M times



Atmosphere: token as information from small space-time neighborhood

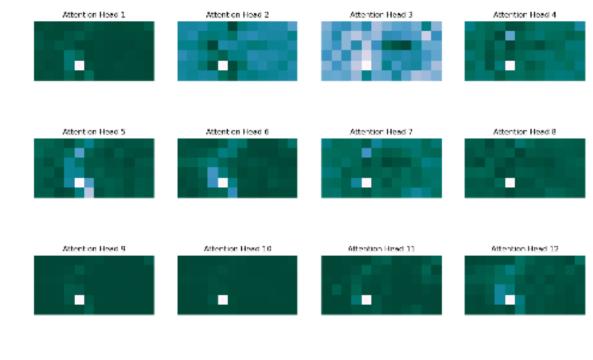
## What is attention?



Lessig et al., AtmoRep, 2023, https://arxiv.org/abs/2308.13280



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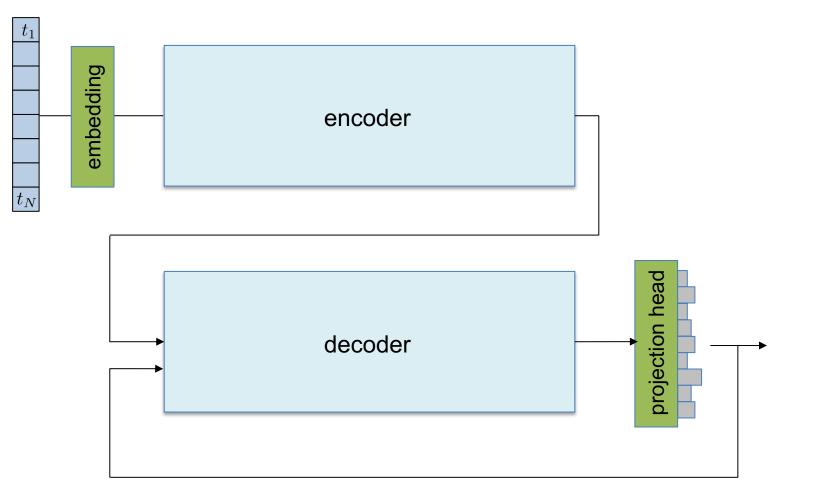
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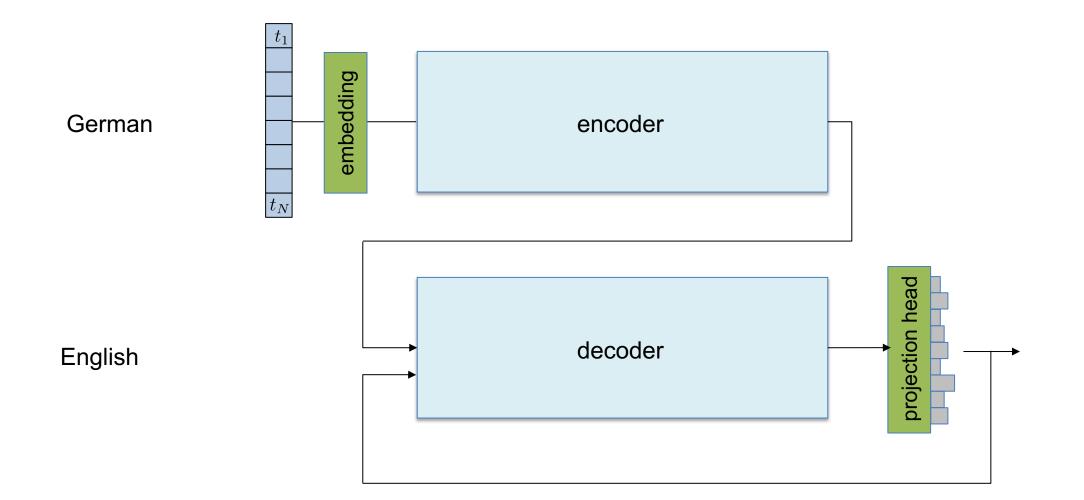


- Introduced in the original transformer paper (Vaswani et al., 2017) for translation tasks
  - Encode: input and encode language A
  - Decoder: decode and output language B

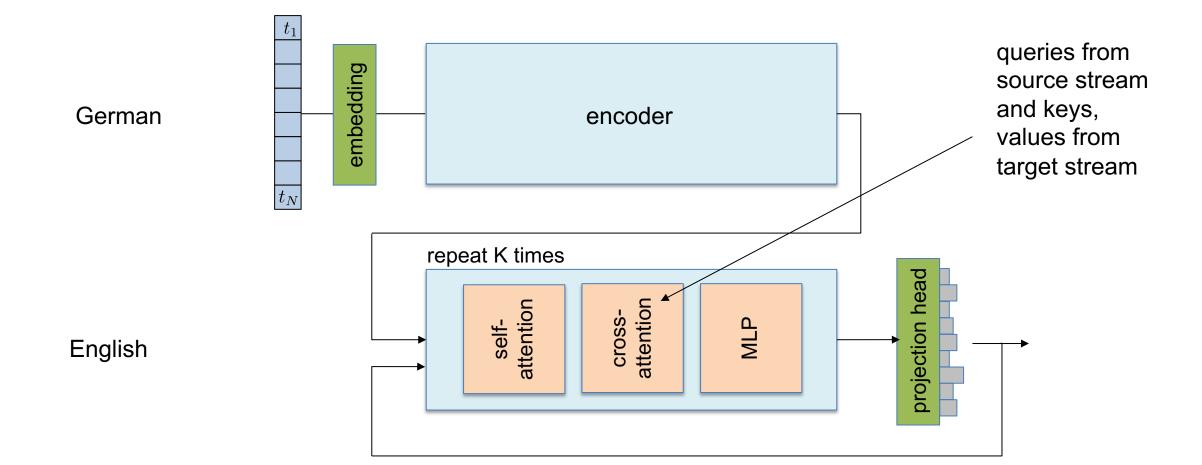


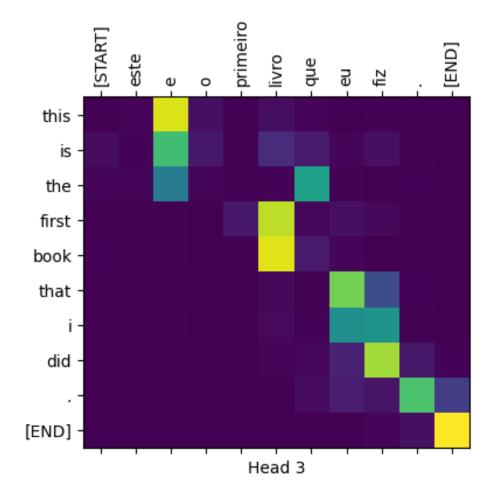


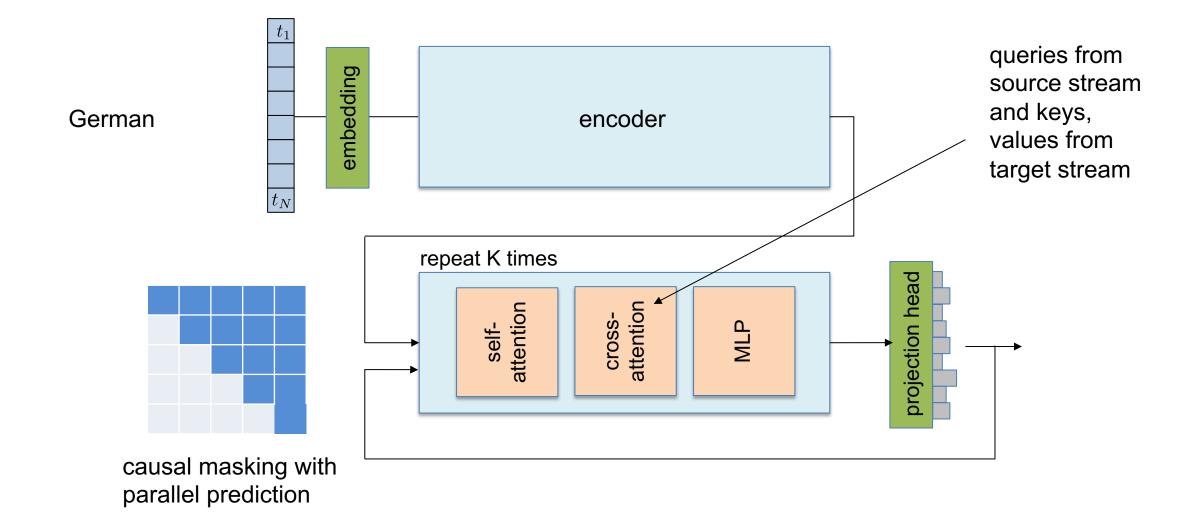




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## **Extensions**

- Sparse attention
  - Attention is quadratic which quickly limits the number of tokens one can process
  - Sparse attention computes attention only between "likely" relevant tokens, e.g. nearby ones in a temporal stream
- Shared kv's between heads
- •. qk LayerNorm
  - Additional layer norm in attention head (important for large models)

## **Summary**

- Transformer are standard neural network in many applications
- Sequence-to-sequence model operating on a set/sequence of tokens
- Versatile since only the definition of a token and the embedding network is domain specific
- Computationally highly efficient since software and hardware is optimized for them
  - But sparse attention required in general