CS371N: Natural Language Processing
Lecture 11: Transformers for Language Modeling, Implementation

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Multi-Head Self-Attention

Multi-Head Self Attention

- Multiple "heads" analogous to different convolutional filters
- Let E = [sent len, embedding dim] be the input sentence. This will be passed through three different linear layers to produce three mats:
  - Query $Q = EW^Q$: each token "chooses" what to attend to
  - Keys $K = EW^K$: these control what each token looks like as a "target"
  - Values $V = EW^V$: these vectors get summed up to form the output

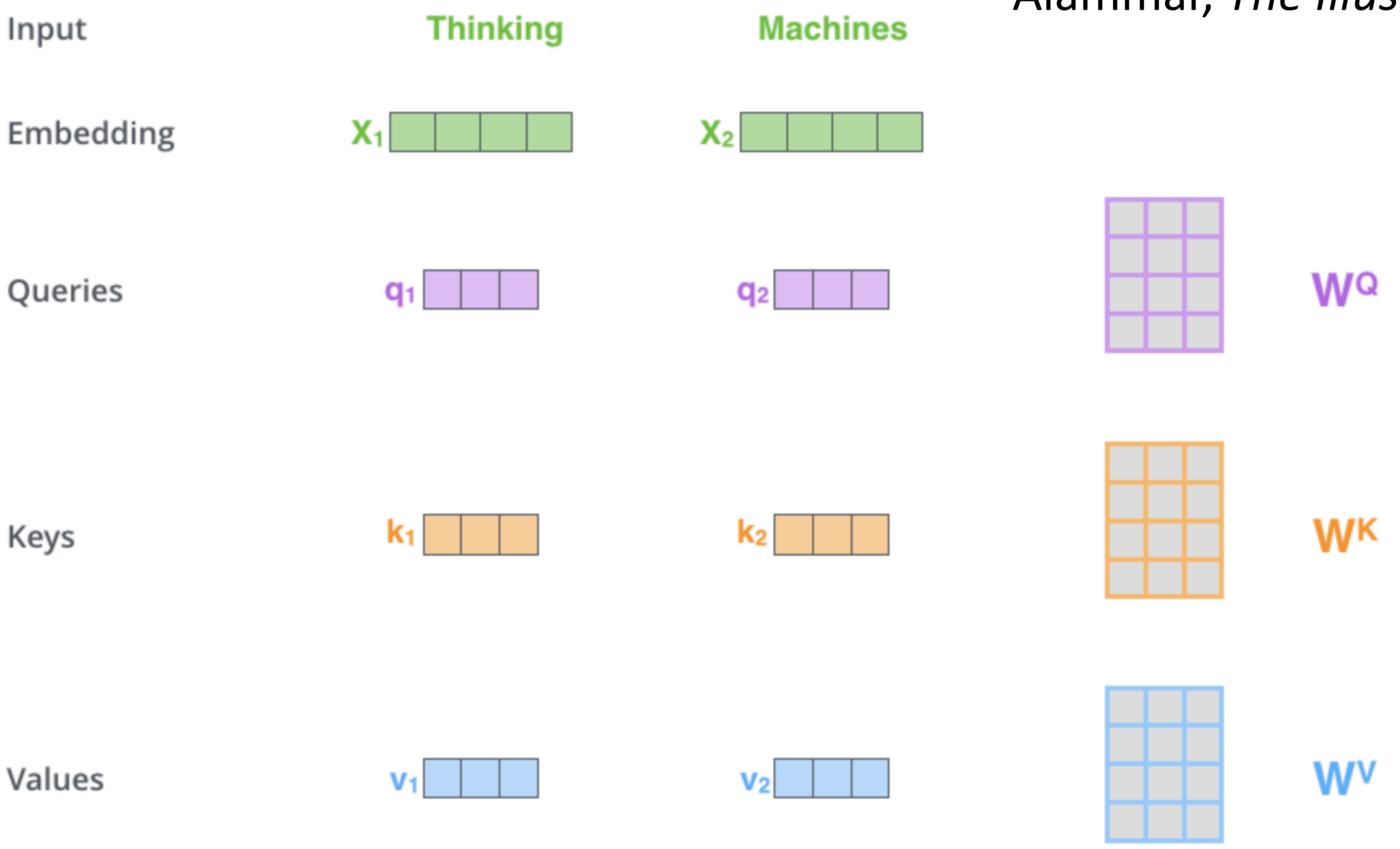
$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

dim of keys

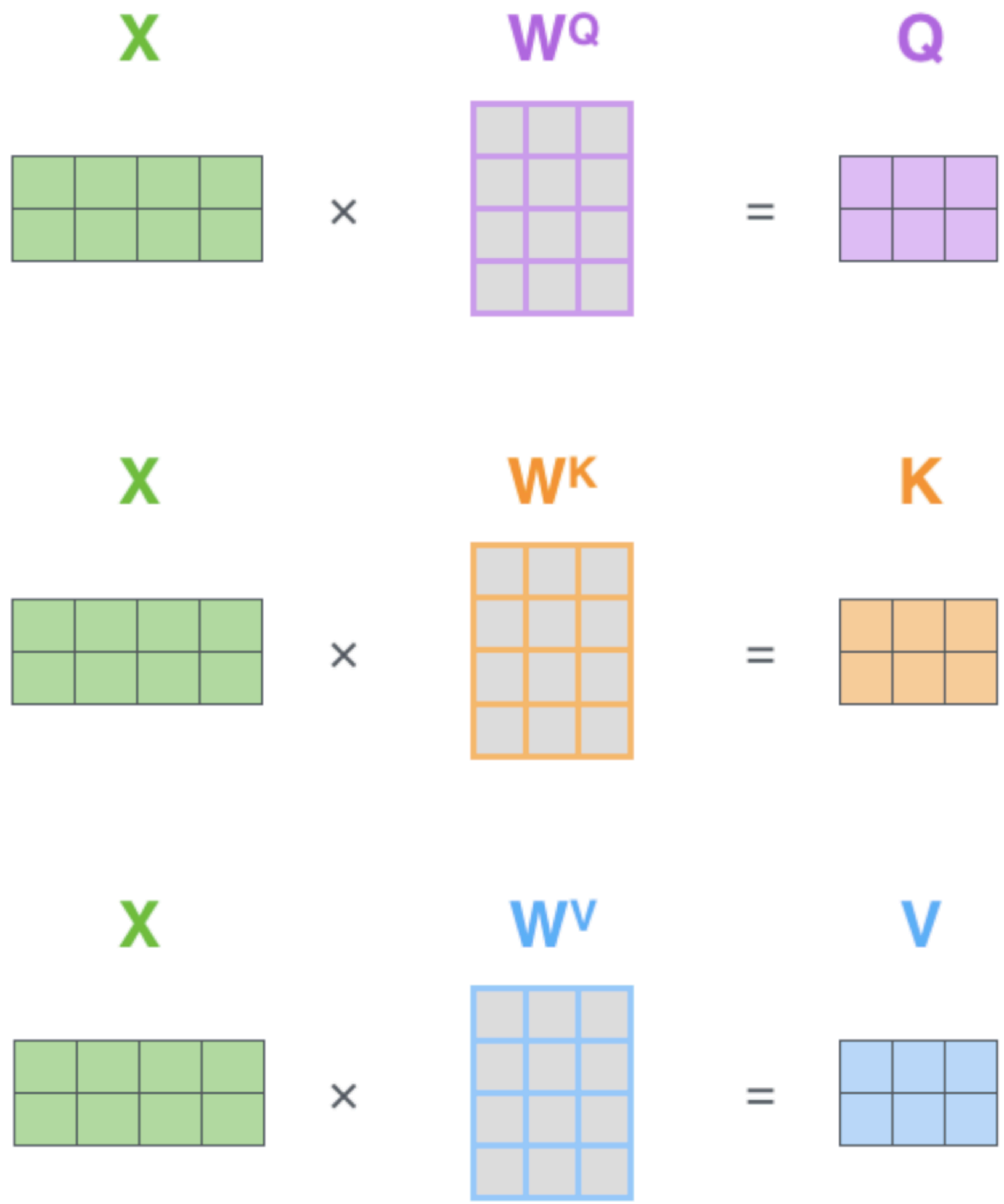
Vaswani et al. (2017)

Self-Attention

Alammar, *The Illustrated Transformer*

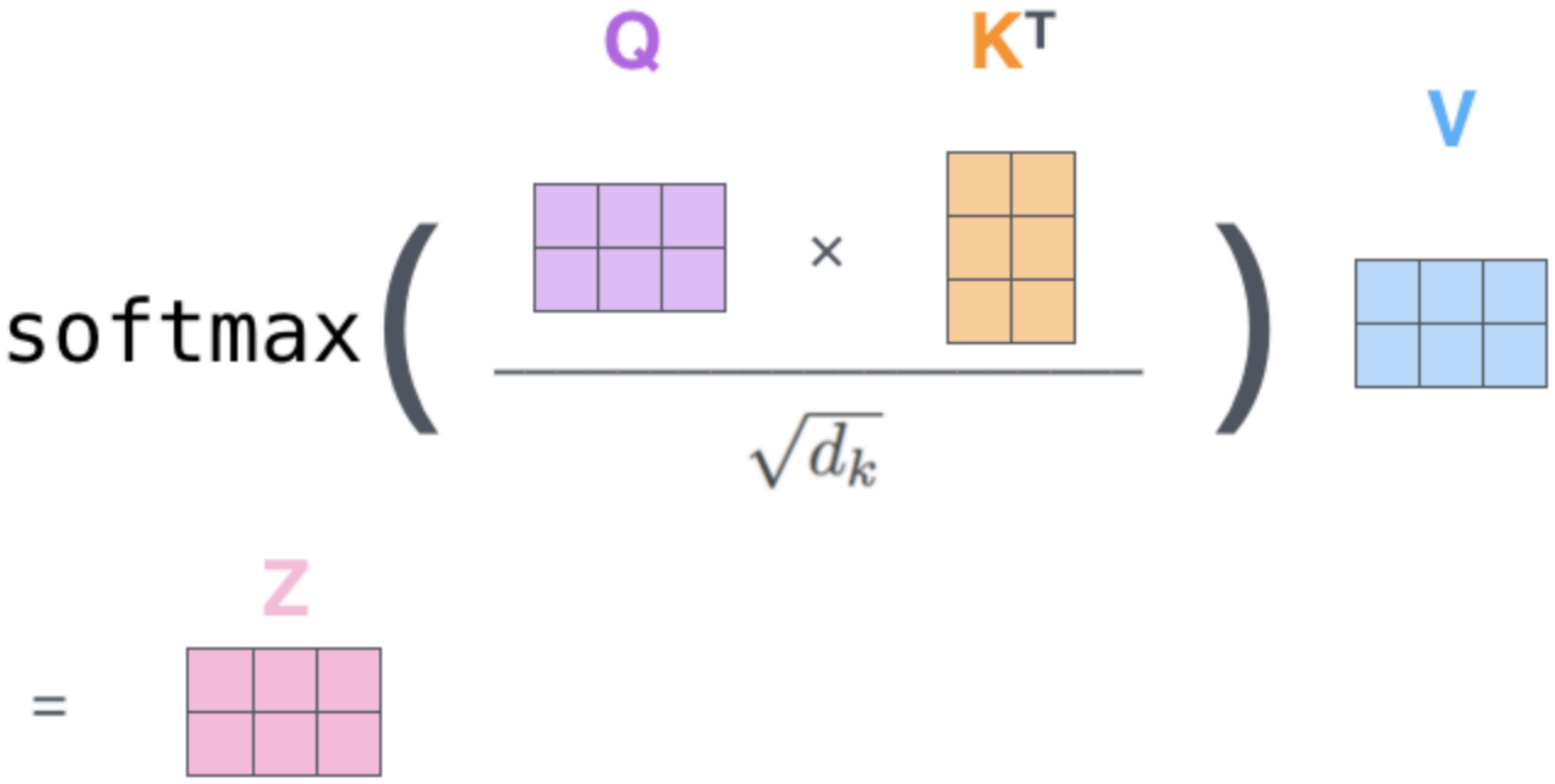


Self-Attention



Alammar, *The Illustrated Transformer*

sent len x sent len (attn for each word to each other)

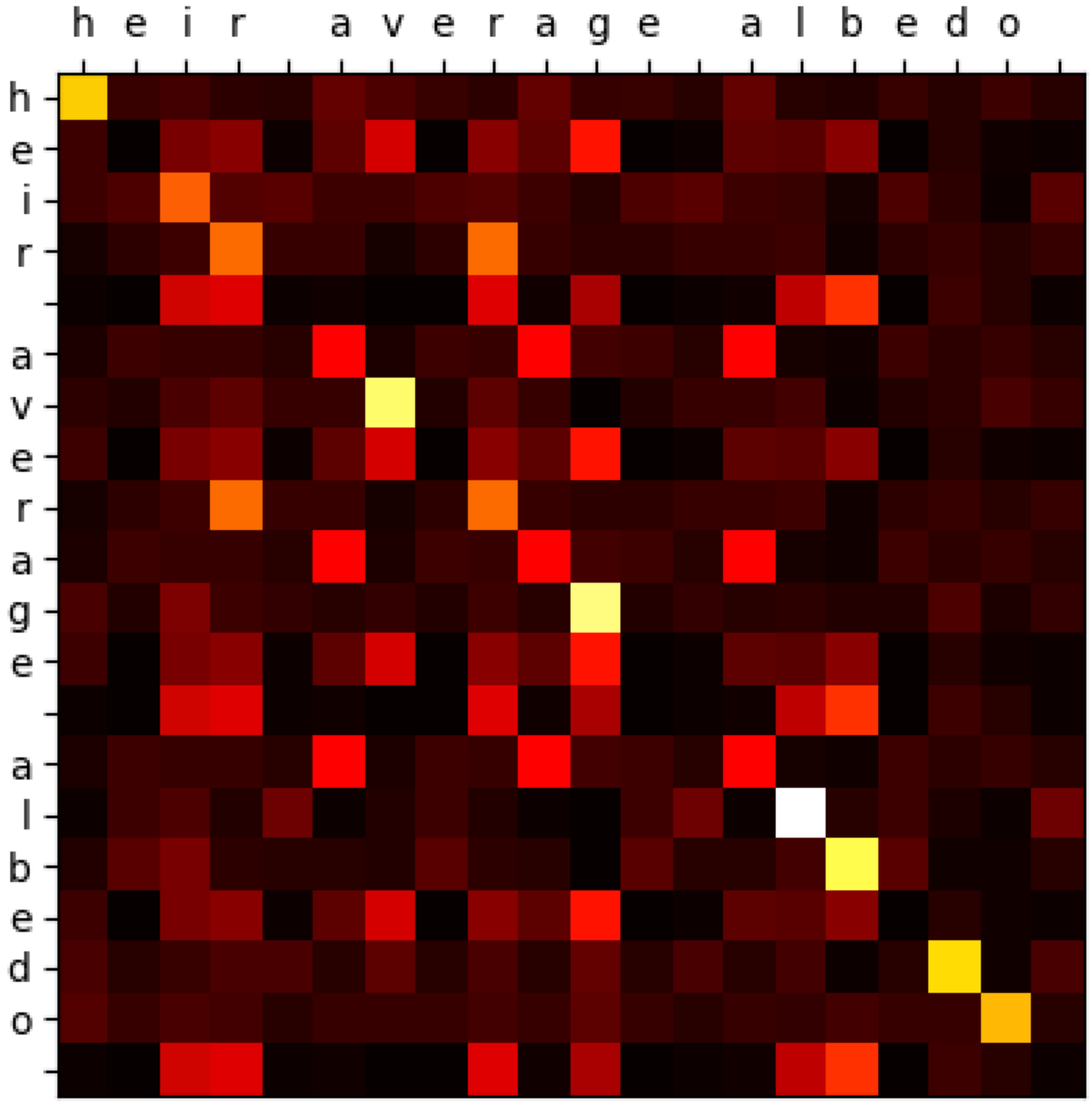


sent len x hidden dim

Z is a weighted combination of V rows

Attention Maps

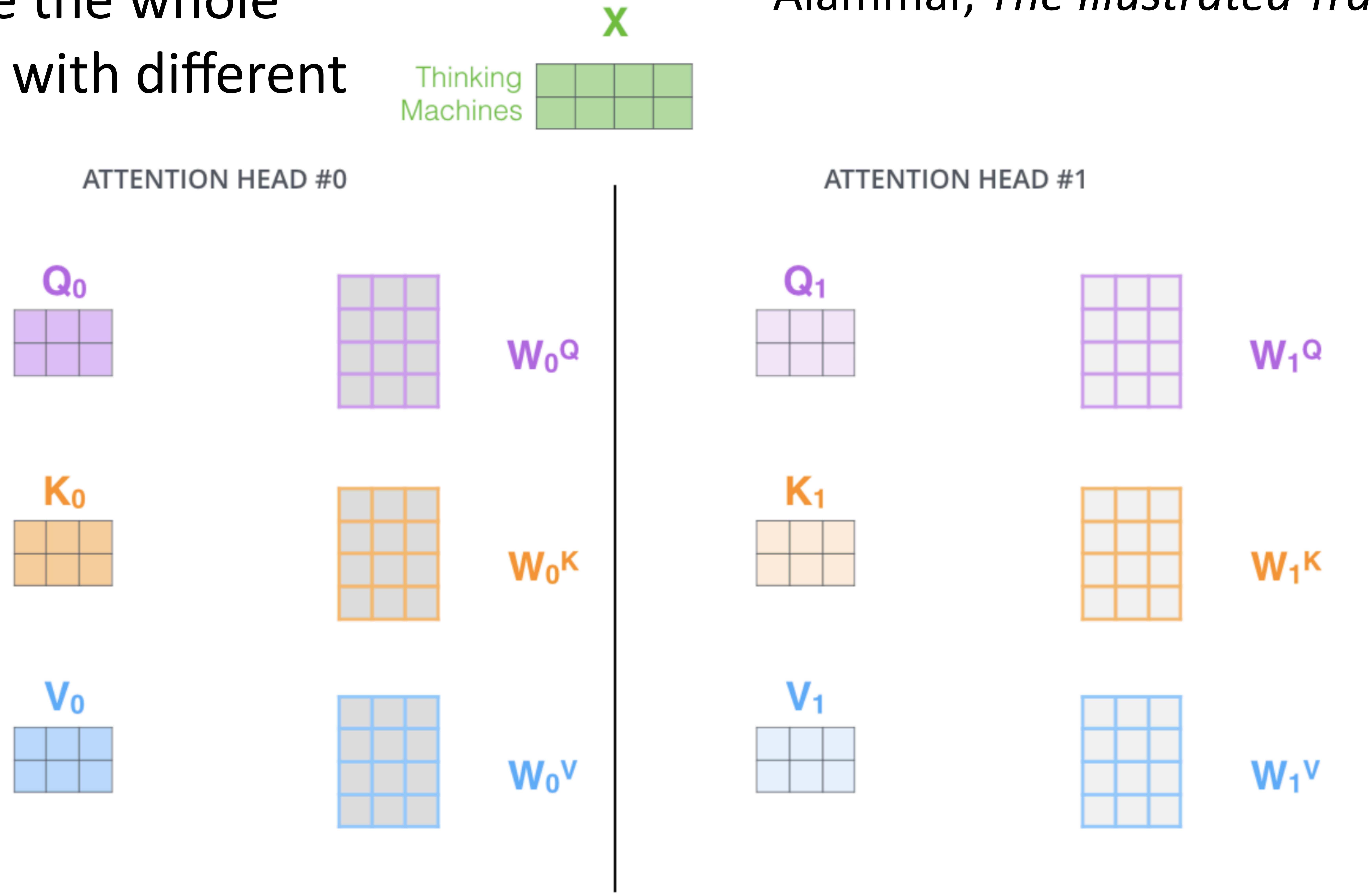
- Example visualization of attention matrix A (from assignment)
- Each row: distribution over what that token attends to. E.g., the first “v” attends very heavily to itself (bright yellow box)
- **Your task on the HW: assess if the attentions make sense**



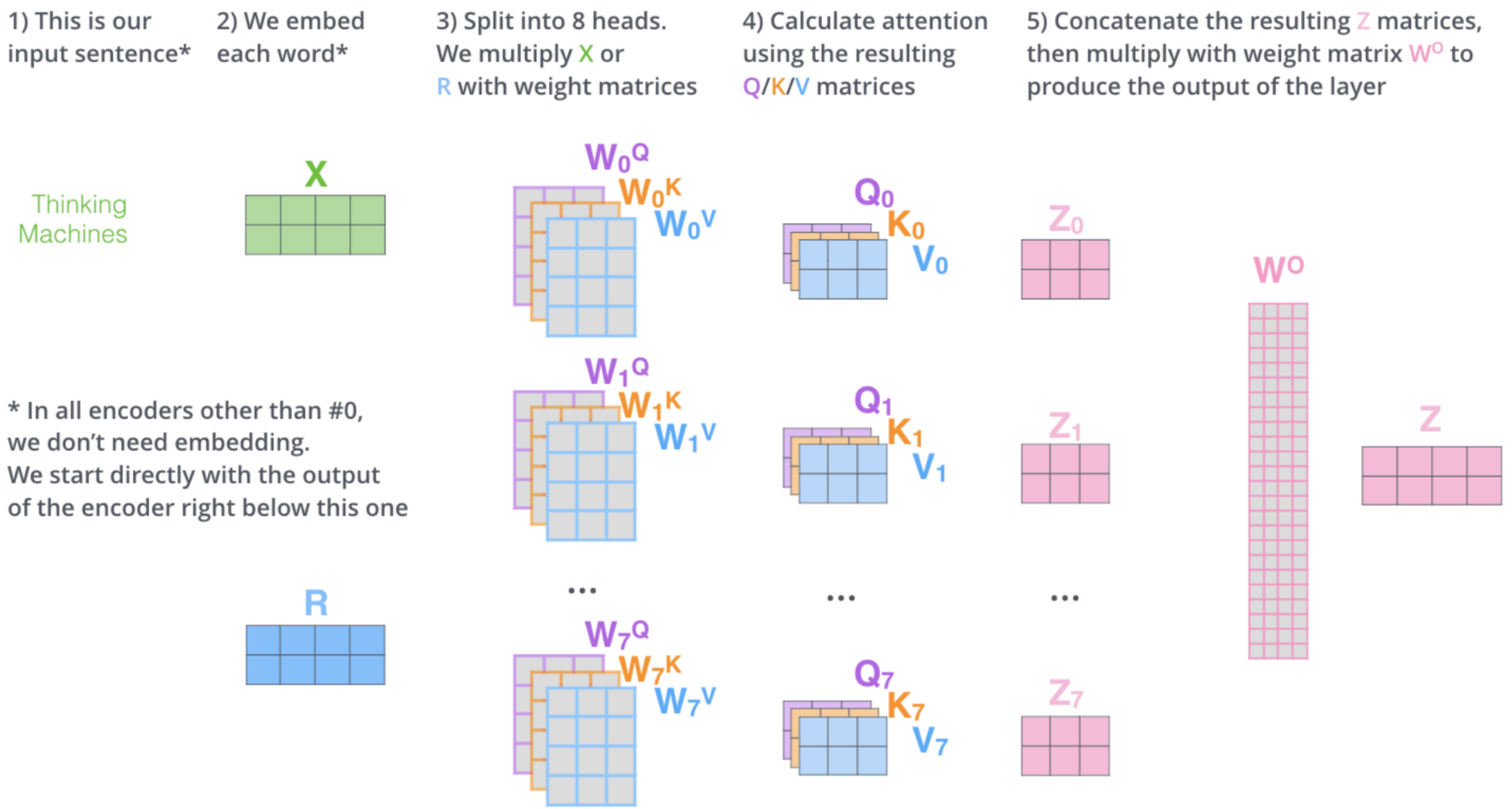
Multi-head Self-Attention

Just duplicate the whole computation with different weights:

Alammar, *The Illustrated Transformer*



Multi-head Self-Attention



Transformers

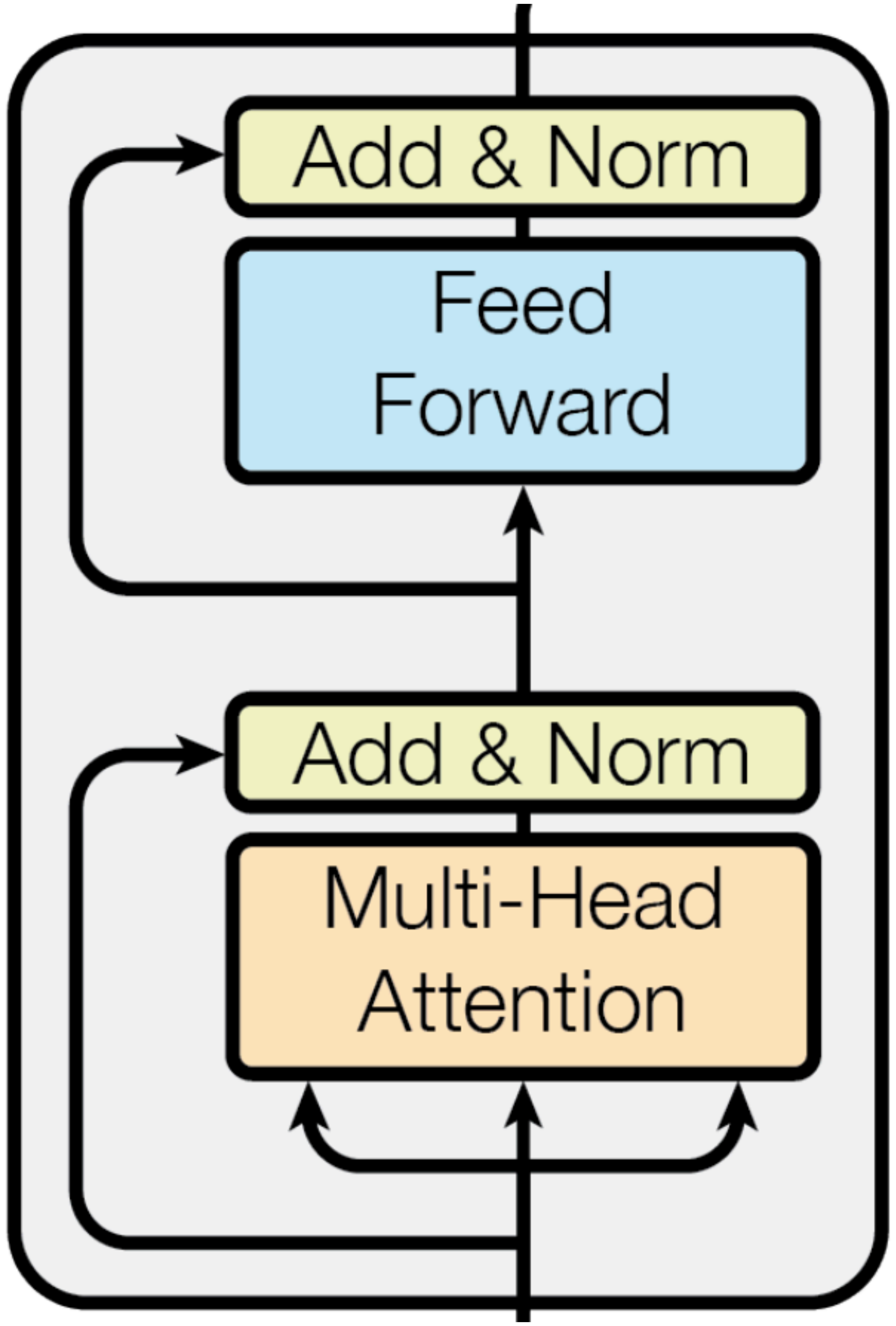
Architecture

- Alternate multi-head self-attention with feedforward layers that **operate over each word individually**

$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

  - These feedforward layers are where most of the parameters are

- Residual connections in the model: input of a layer is added to its output
- Layer normalization: controls the scale of different layers in very deep networks (not needed in the homework)

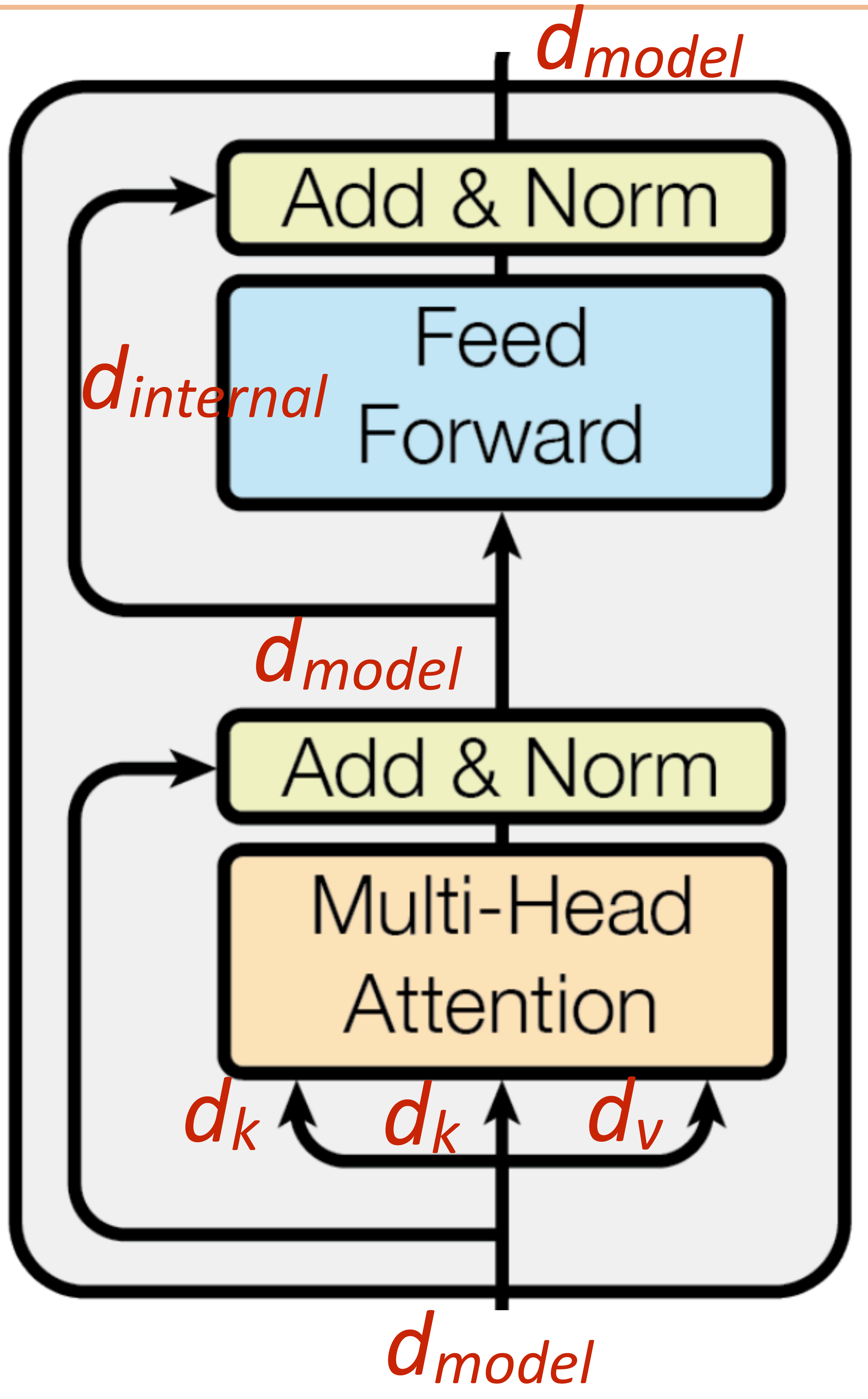


Dimensions

- Vectors: d_{model}
- Queries/keys: d_k , always smaller than d_{model}
- Values: separate dimension d_v , output is multiplied by W^O which is d_v x d_{model} so we can get back to d_{model} before the residual
- FFN can explode the dimension with W_1 and collapse it back with W_2

$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

*Note: assignment calls d_k as $d_{internal}$



Vaswani et al. (2017)

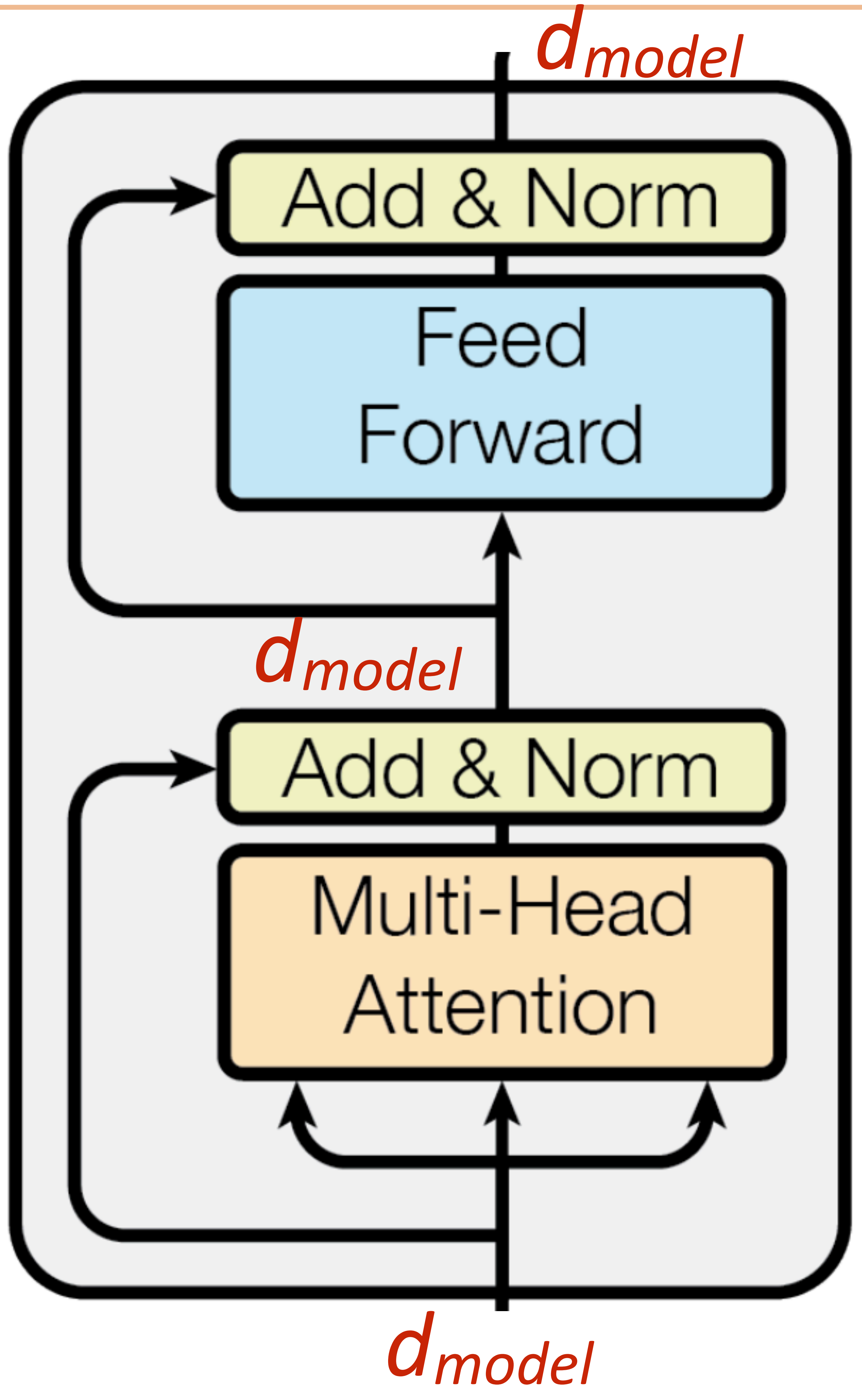
Transformer Architecture

	N	d_{model}	d_{ff}	h	d_k	d_v
base	6	512	2048	8	64	64

- From Vaswani et al.

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}
GPT-3 Small	125M	12	768	12	64
GPT-3 Medium	350M	24	1024	16	64
GPT-3 Large	760M	24	1536	16	96
GPT-3 XL	1.3B	24	2048	24	128
GPT-3 2.7B	2.7B	32	2560	32	80
GPT-3 6.7B	6.7B	32	4096	32	128
GPT-3 13B	13.0B	40	5140	40	128
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128

- From GPT-3; d_{head} is our d_k



Transformer Architecture

	description	FLOPs / update	% FLOPS MHA	% FLOPS FFN	% FLOPS attn	% FLOPS logit
8	OPT setups					
9	760M	4.3E+15	35%	44%	14.8%	5.8%
10	1.3B	1.3E+16	32%	51%	12.7%	5.0%
11	2.7B	2.5E+16	29%	56%	11.2%	3.3%
12	6.7B	1.1E+17	24%	65%	8.1%	2.4%
13	13B	4.1E+17	22%	69%	6.9%	1.6%
14	30B	9.0E+17	20%	74%	5.3%	1.0%
15	66B	9.5E+17	18%	77%	4.3%	0.6%
16	175B	2.4E+18	17%	80%	3.3%	0.3%

Credit: Stephen Roller on Twitter

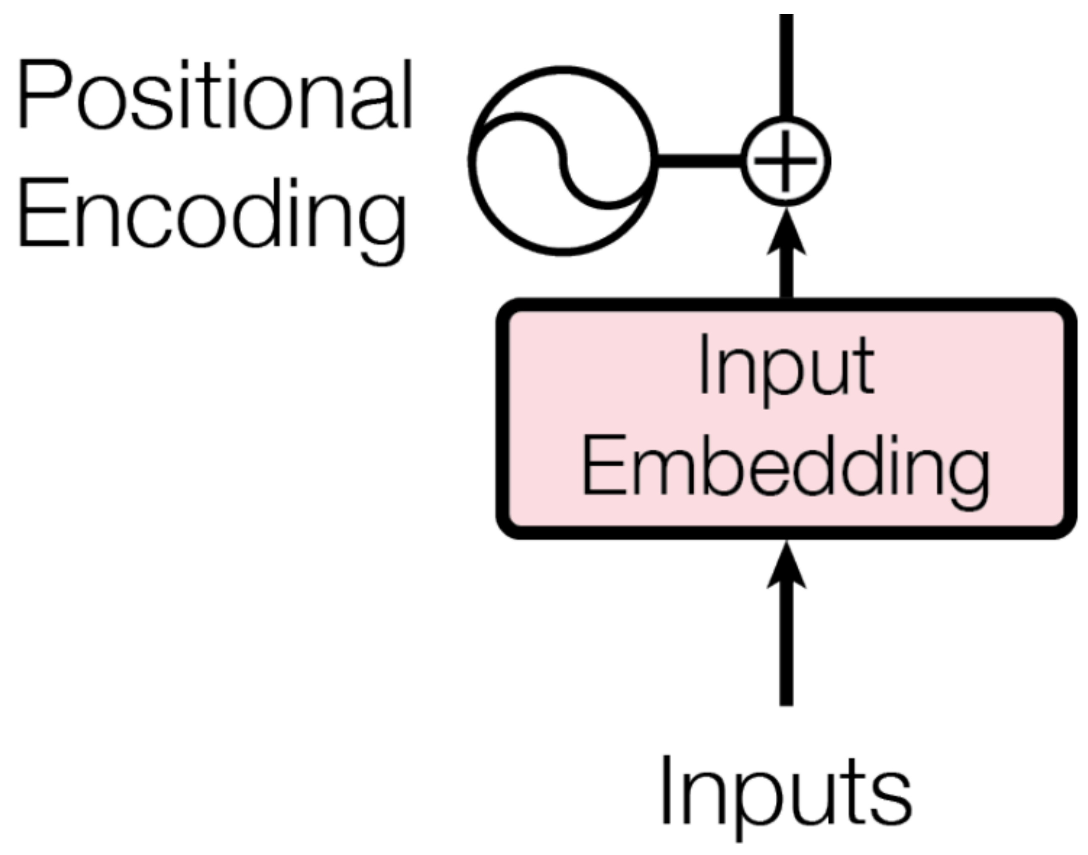
Transformers: Position Sensitivity

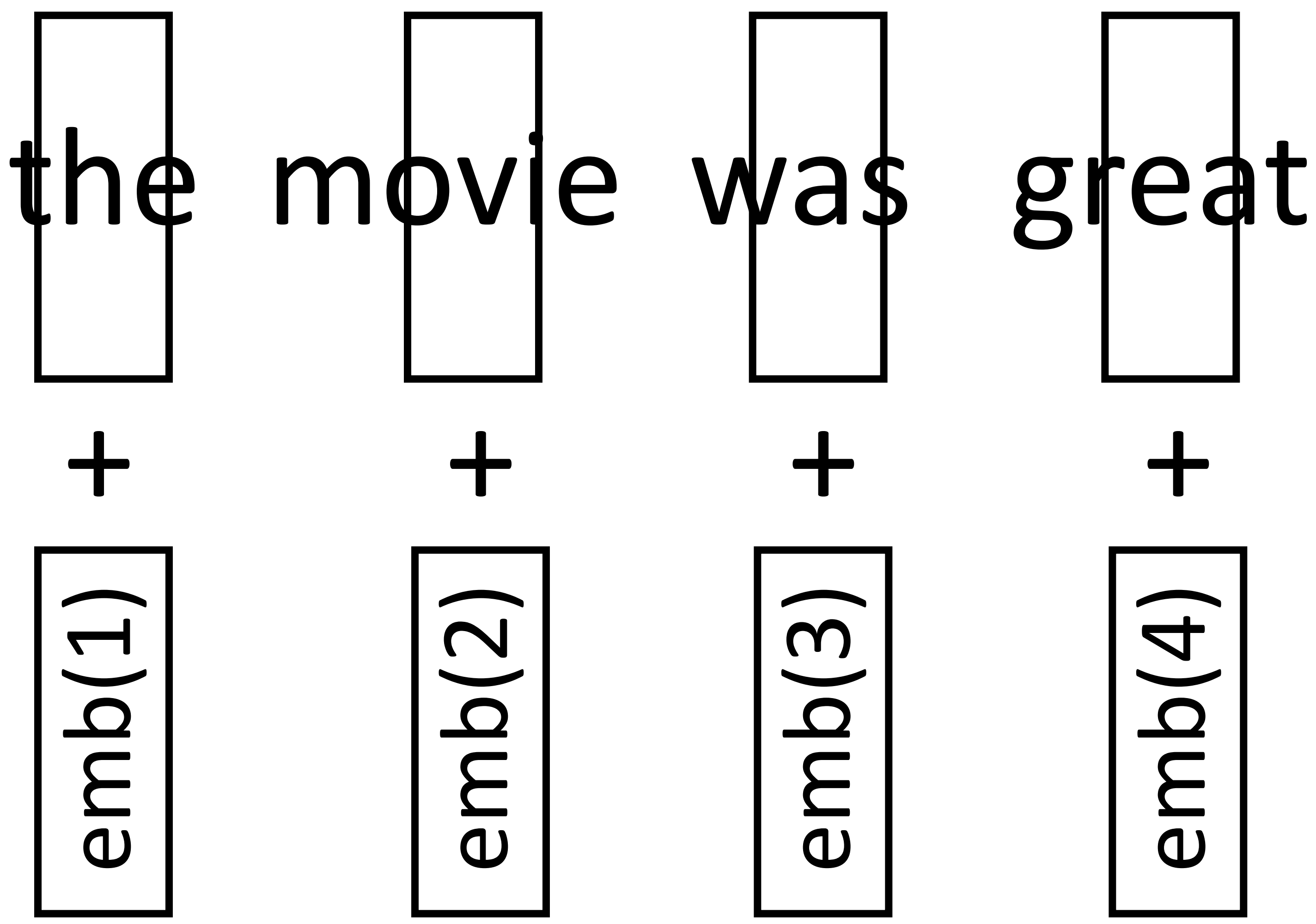
The ballerina is very excited that she will dance in the show.

- If this is in a longer context, we want words to attend *locally*
- But transformers have *no notion of position* by default

Vaswani et al. (2017)

Transformers: Position Sensitivity



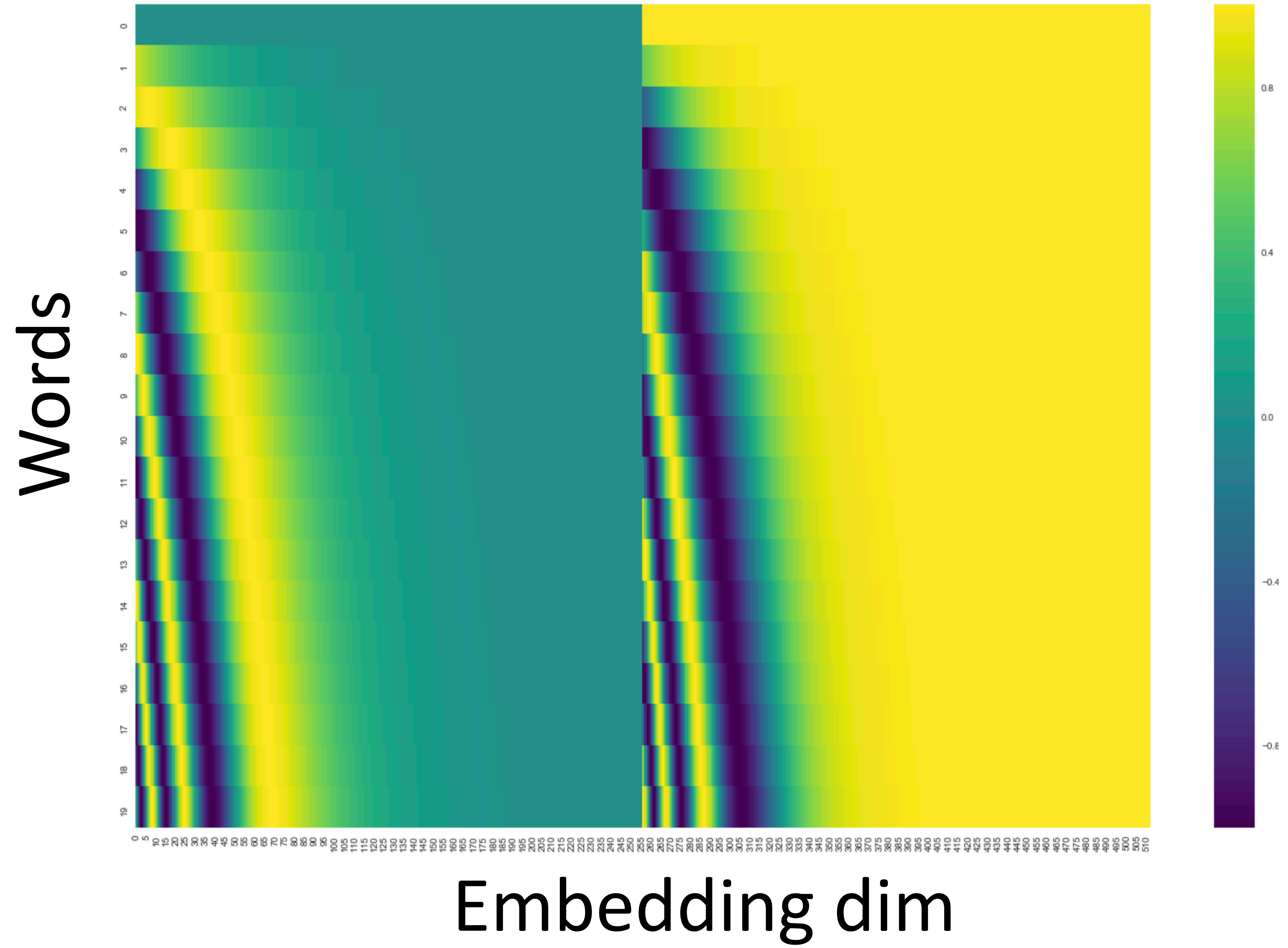


- Encode each sequence position as an integer, add it to the word embedding vector
- Why does this work?

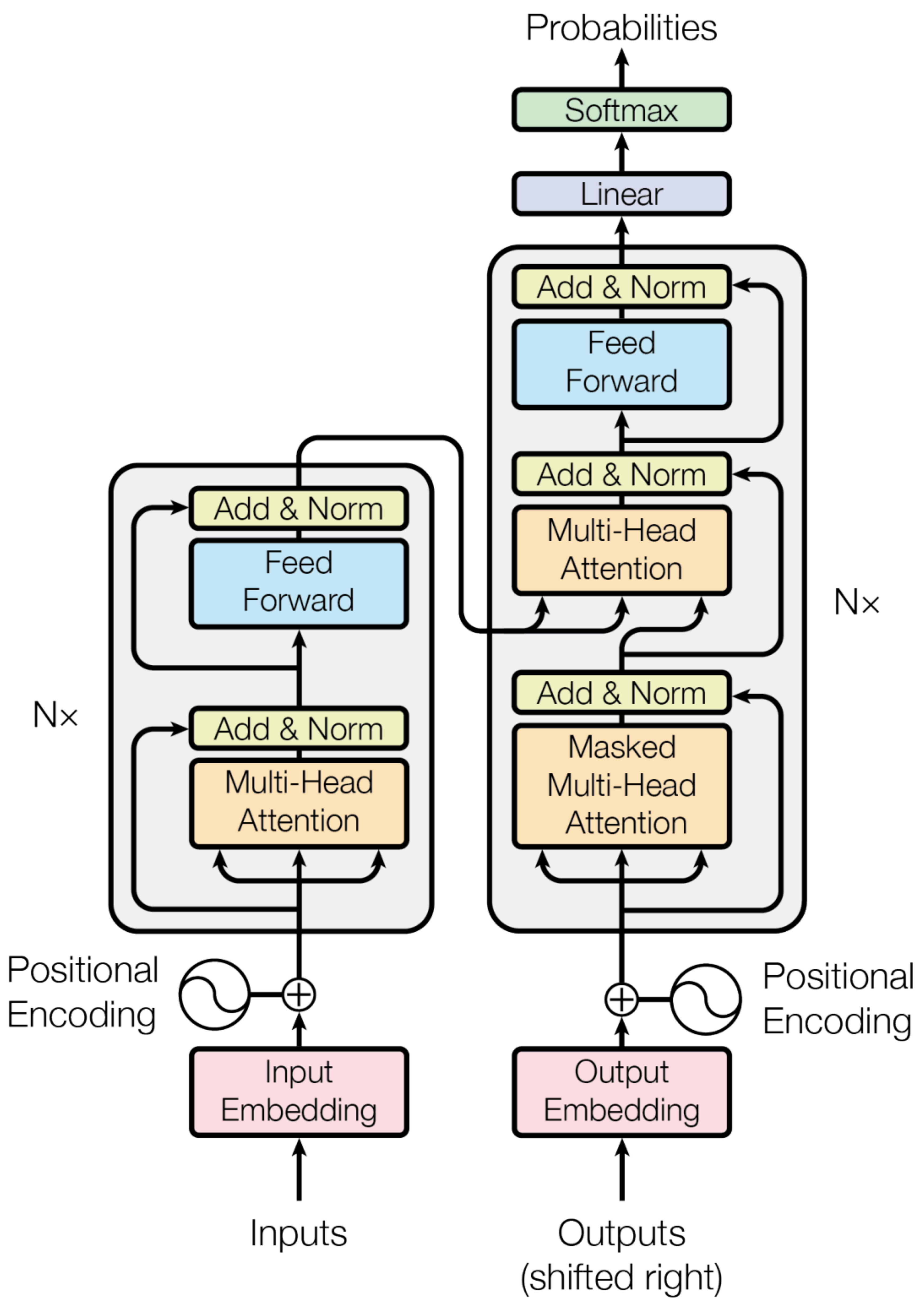
Transformers

Alammar, *The Illustrated Transformer*

- Alternative from Vaswani et al.: sines/cosines of different frequencies (closer words get higher dot products by default)



Transformers: Complete Model

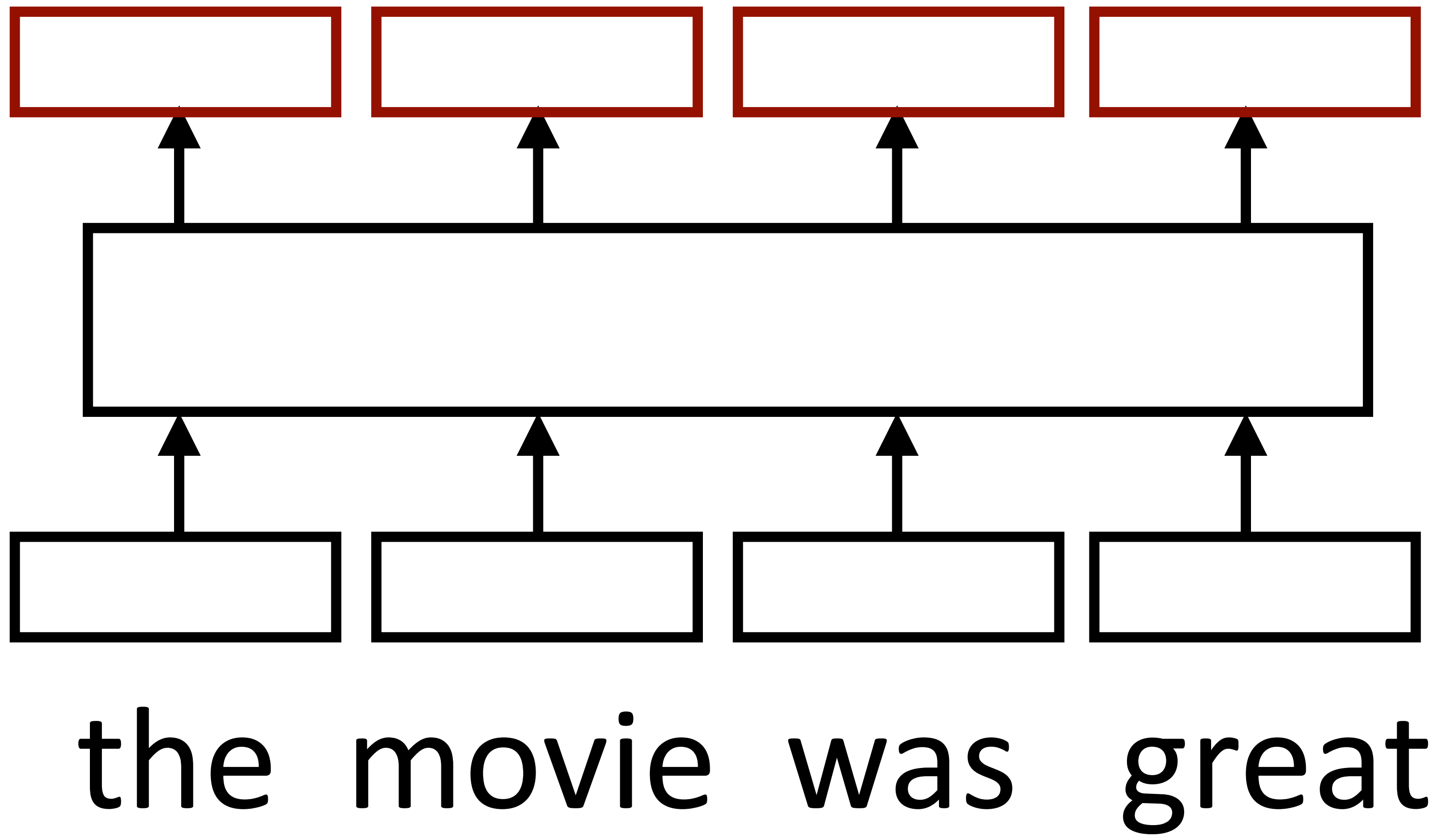


- Original Transformer paper presents an **encoder-decoder** model
- Right now we don't need to think about both of these parts — will return in the context of MT
- Can turn the encoder into a decoder-only model through use of a triangular causal attention mask (only allow attention to previous tokens)

Vaswani et al. (2017)

Transformer Language Modeling

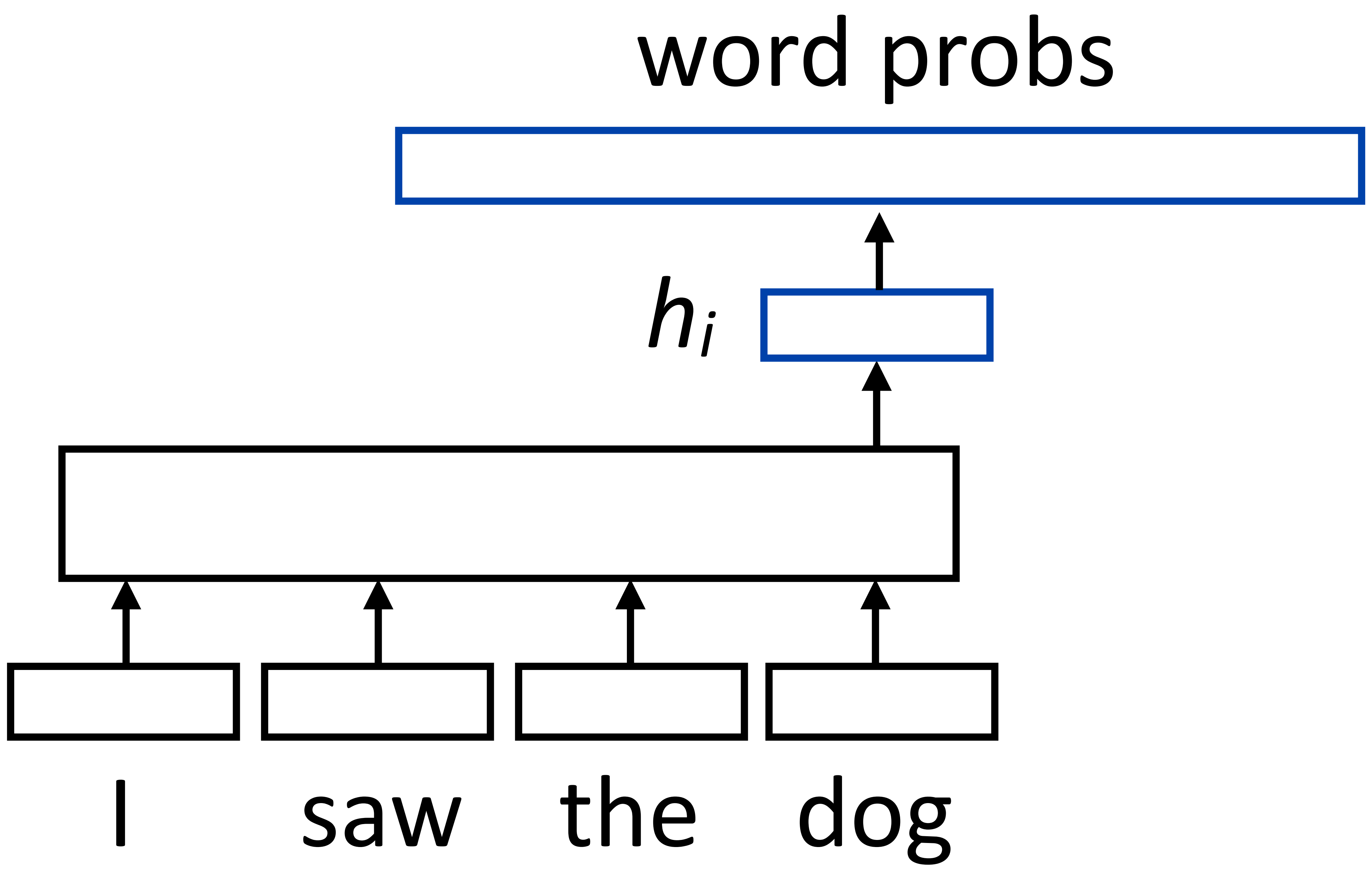
What do Transformers produce?



- Encoding of each word — can pass this to another layer to make a prediction (like predicting the next word for language modeling)

- Like RNNs, Transformers can be viewed as a transformation of a sequence of vectors into a sequence of context-dependent vectors

Transformer Language Modeling



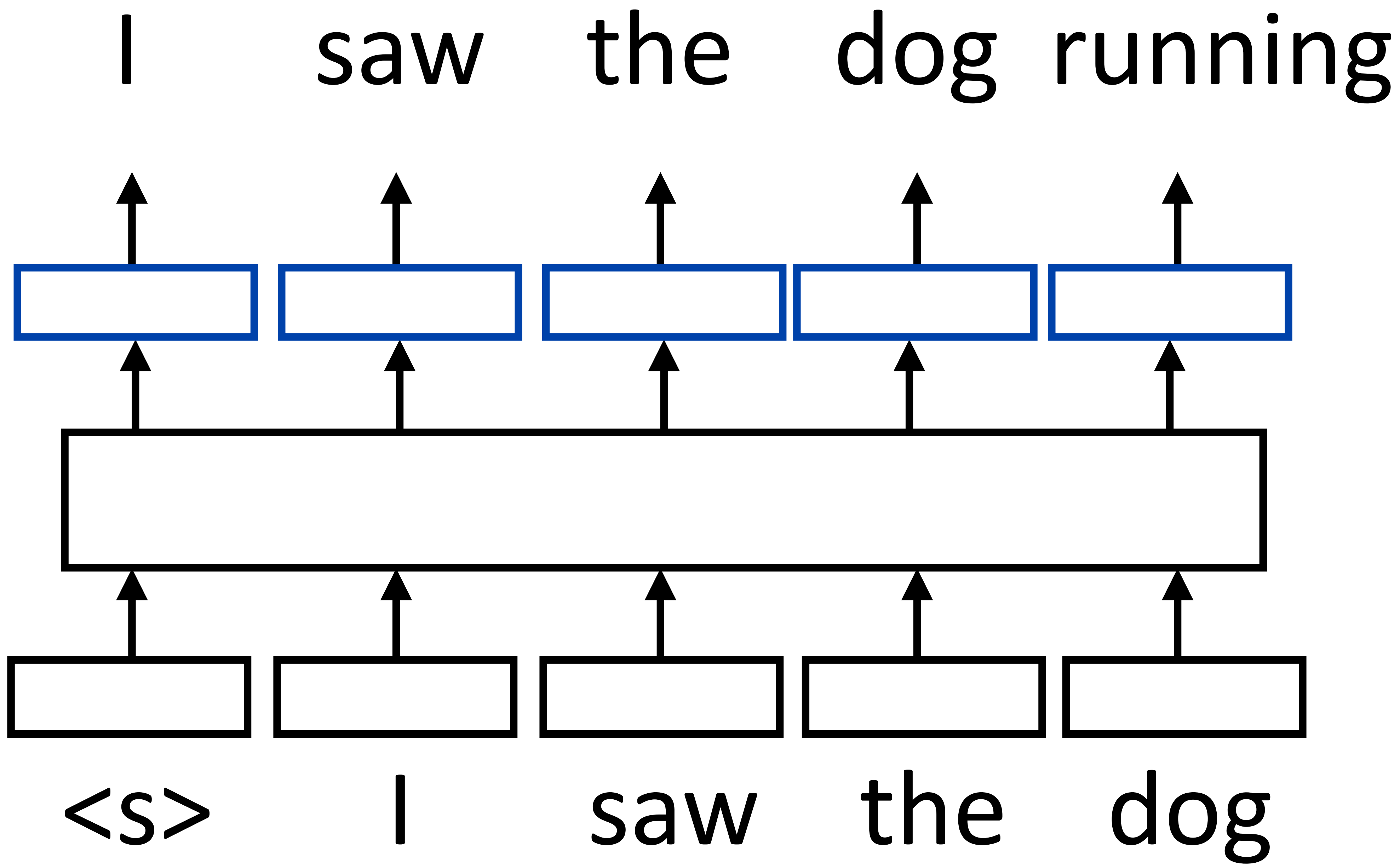
$$P(w|\text{context}) = \frac{\exp(\mathbf{w} \cdot \mathbf{h_i})}{\sum_{w'} \exp(\mathbf{w'} \cdot \mathbf{h_i})}$$

equivalent to

$$P(w|\text{context}) = \text{softmax}(W\mathbf{h}_i)$$

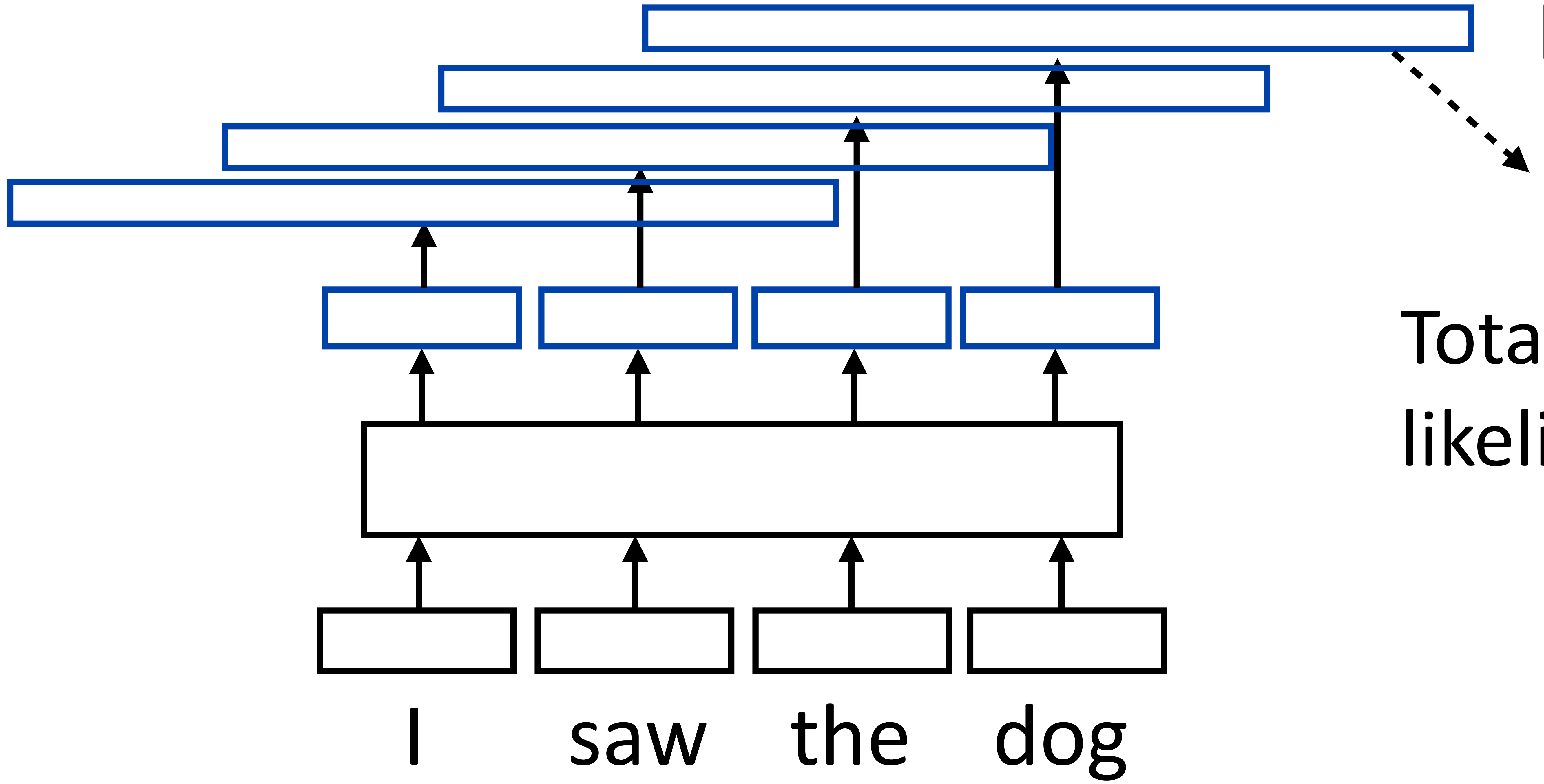
- *W* is a (vocab size) x (hidden size) matrix; linear layer in PyTorch (rows are word embeddings)

Training Transformer LMs



- Input is a sequence of words, output is those words shifted by one,
- Allows us to train on predictions across several timesteps simultaneously (similar to batching but this is NOT what we refer to as batching)

Training Transformer LMs



P(w|context)

loss = — log P(w*|context)

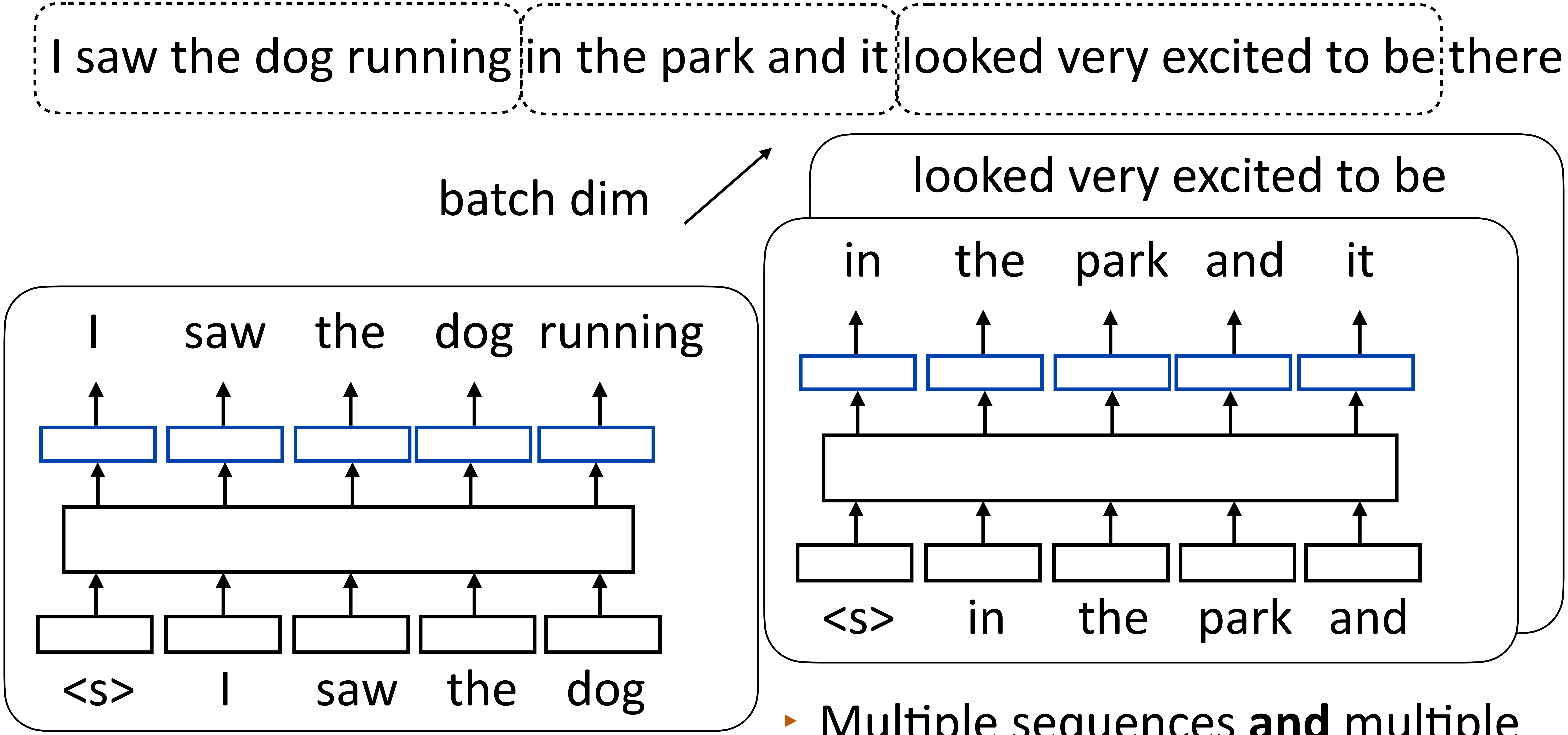
Total loss = sum of negative log likelihoods at each position

```
loss_fcn = nn.NLLLoss()
loss += loss_fcn(log_probs, ex.output_tensor)
```

[seq len, num output classes]　　　[seq len]

- Batching is a little tricky with NLLLoss: need to collase [batch, seq len, num classes] to [batch * seq len, num classes]. You do not need to batch

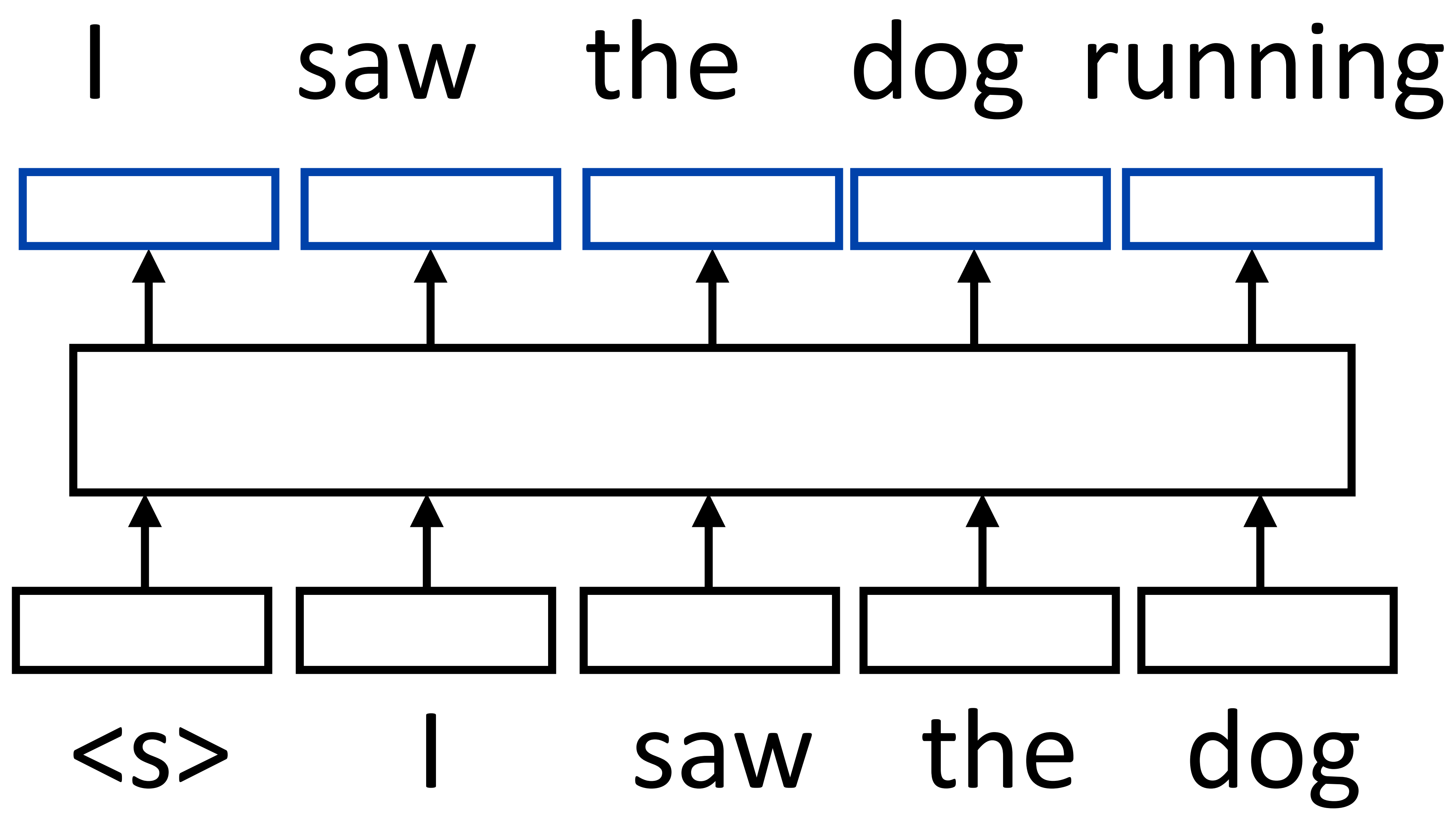
Batched LM Training



- Multiple sequences **and** multiple timesteps per sequence

A Small Problem with Transformer LMs

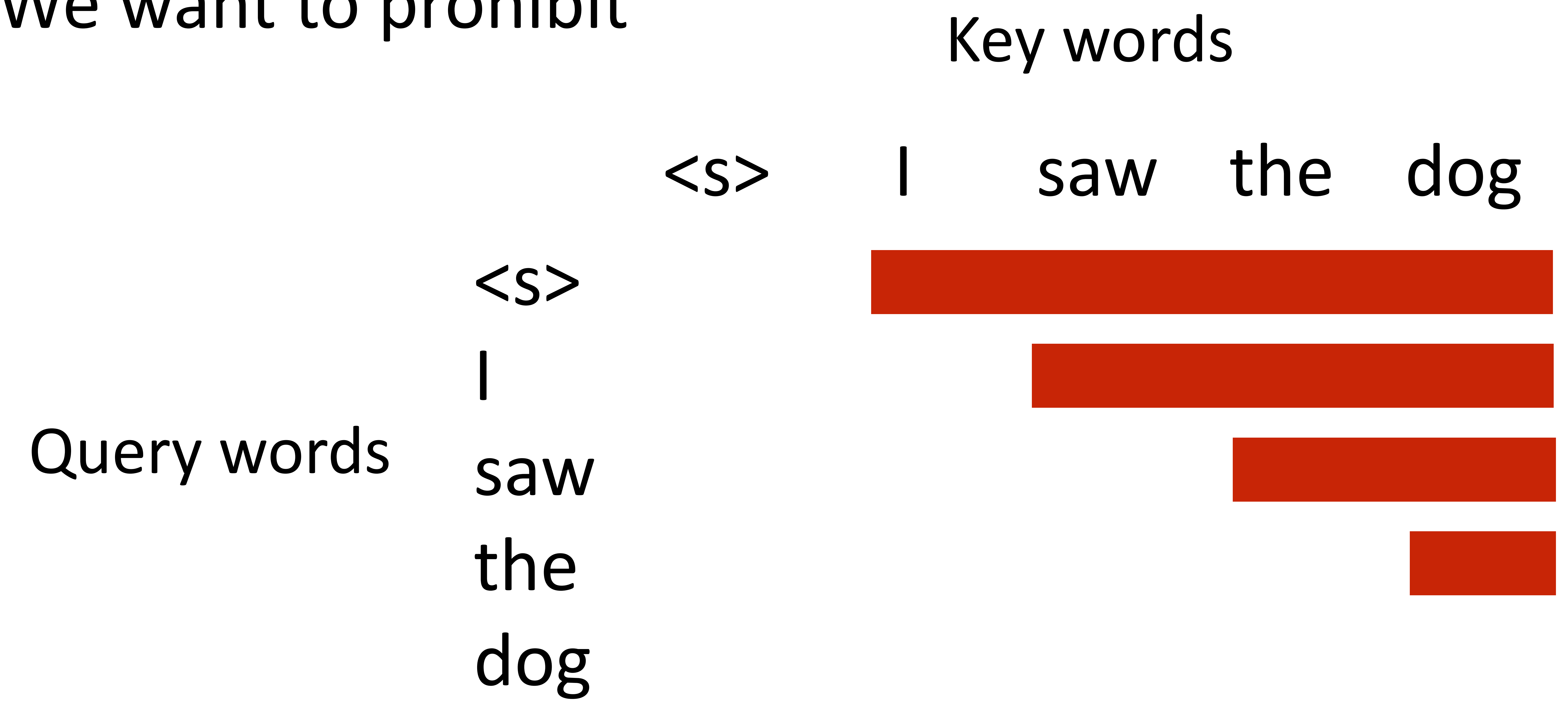
- This Transformer LM as we've described it will *easily* achieve perfect accuracy. Why?



- With standard self-attention: "I" attends to "saw" and the model is "cheating". How do we ensure that this doesn't happen?

Attention Masking

- We want to prohibit



- We want to mask out everything in red (an upper triangular matrix)

Implementing in PyTorch

- nn.TransformerEncoder can be built out of nn.TransformerEncoderLayers, can accept an input and a mask for language modeling:

```
# Inside the module; need to fill in size parameters
layers = nn.TransformerEncoderLayer([...])
transformer_encoder = nn.TransformerEncoder(encoder_layers, num_layers=[...])
[. . .]
# Inside forward(): puts negative infinities in the red part
mask = torch.triu(torch.ones(len, len) * float('-inf'), diagonal=1)
output = transformer_encoder(input, mask=mask)
```

- **You cannot use these for Part 1, only for Part 2**

LM Evaluation

- Accuracy doesn't make sense — predicting the next word is generally impossible so accuracy values would be very low
- Evaluate LMs on the likelihood of held-out data (averaged to normalize for length)

$$\frac{1}{n}\sum_{i=1}^{n} \log P(w_i | w_1, \ldots, w_{i-1})$$

- Perplexity: exp(average negative log likelihood). Lower is better
  - Suppose we have probs 1/4, 1/3, 1/4, 1/3 for 4 predictions
  - Avg NLL (base e) = 1.242   Perplexity = 3.464 <== geometric mean of denominators

Takeaways

- Transformers are going to be the foundation for the much of the rest of this class and are a ubiquitous architecture nowadays
- Many details to get right, many ways to tweak and extend them, but core idea is the multi-head self attention and their ability to contextualize items in sequences