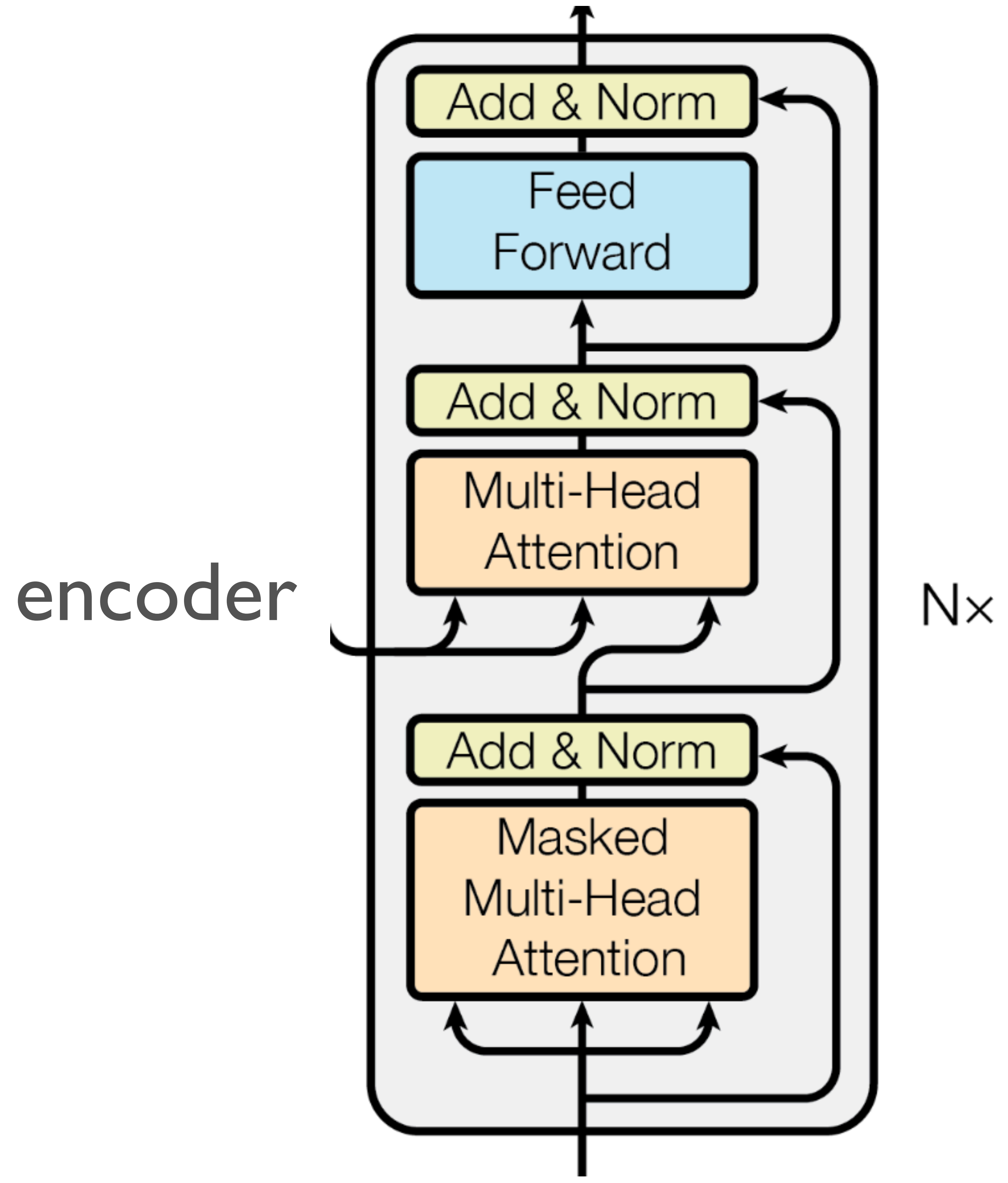
Transformers 2

Ling 282/482: Deep Learning for Computational Linguistics
C.M. Downey
Fall 2025

Transformer Decoder

Decoder Block

- Like the encoder, the decoder is many *blocks* stacked vertically
- Two slightly different ingredients:
  - **Masked** self-attention
  - **Cross-attention** (encoder-decoder)



Attention Computation Practice

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix} \quad \begin{bmatrix} 6 & 4 & 2 \\ 5 & 3 & 1 \end{bmatrix} \quad \begin{bmatrix} 2 & 4 \\ 6 & 8 \\ 10 & 12 \end{bmatrix}$$

K^T

Q

V

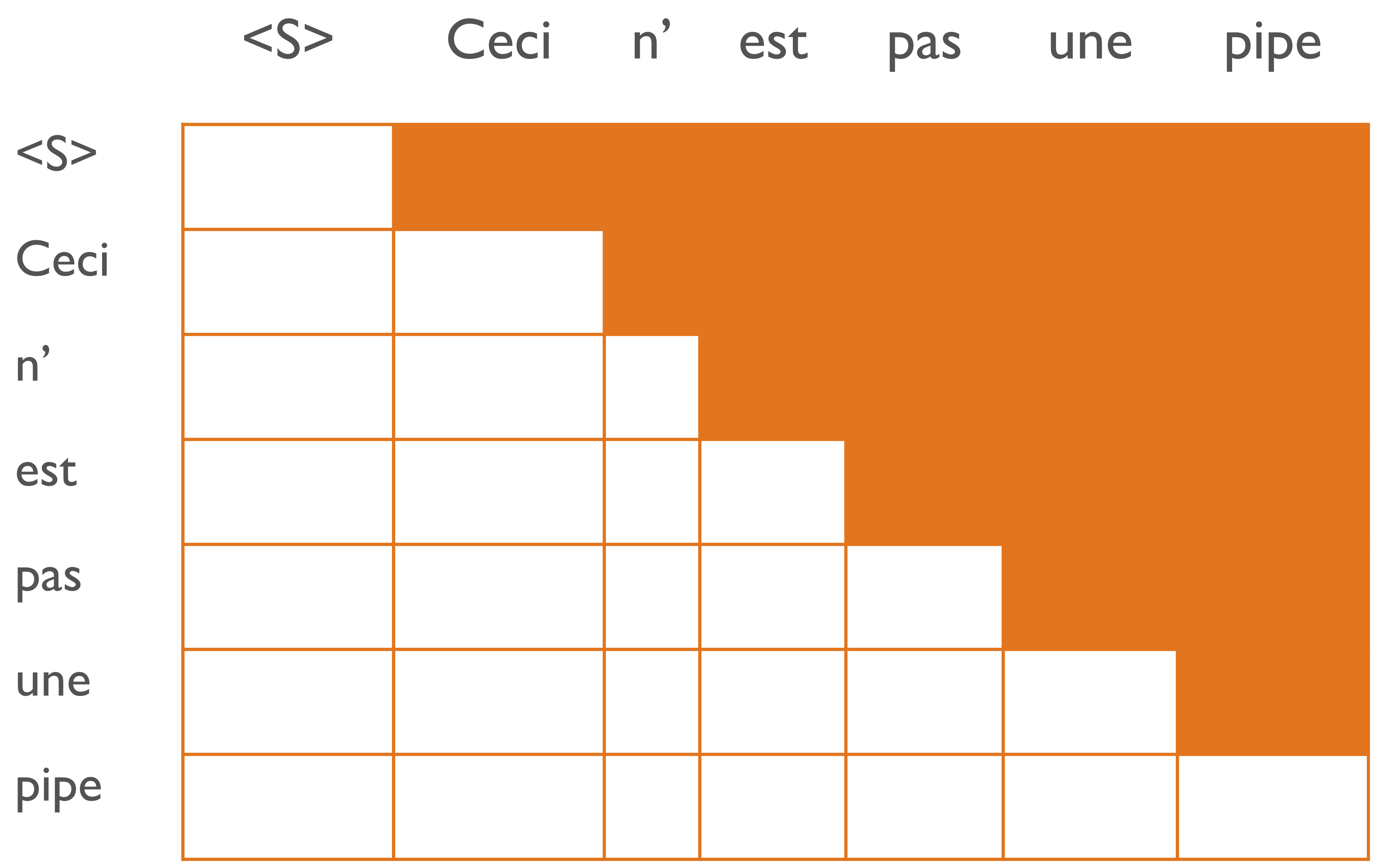
Masked Self-Attention

Masked Self-Attention

- Recall from seq2seq:
  - Decoder a kind of **conditional** language model
  - Predicts next tokens in output sequence, *given* the encoder representations
  - (Can also be used on its own as an unconditional LM; more later)
- Problem: **self-attention "looks to the future"**
  - Decoders should only be able to allocate attention to **previous** positions

Masking Out the Future

- Key idea:
  - Use a **mask** to **block out certain attention scores**
- On the left:
  - Tokens in the rows (**queries**) can **not** pay attention to the tokens in the columns (**keys**) that are shaded in



Masking Out the Future

QK^T: total attention scores

$$\text{mask}_{ij} = \begin{cases} -\infty & j > i \\ 0 & \text{otherwise} \end{cases}$$

$$\text{MaskedAttention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}} + \text{mask}\right)V$$

	<S>	Ceci	n’	est	pas	une	pipe
<S>	0	-inf	-inf	-inf	-inf	-inf	-inf
Ceci	0	0	-inf	-inf	-inf	-inf	-inf
n’	0	0	0	-inf	-inf	-inf	-inf
est	0	0	0	0	-inf	-inf	-inf
pas	0	0	0	0	0	-inf	-inf
une	0	0	0	0	0	0	-inf
pipe	0	0	0	0	0	0	0

Masked Self-Attention

- In a nutshell:
    - Compute raw attention scores as before
    - Add a mask to **“zero out” the future positions** in a sequence
- As in the encoder:
    - This is **one attention head**, several used for multi-headed attention (but all heads use the mask)
    - Q, K, V are generated by applying learned matrices for each head

Cross-Attention

Cross-Attention

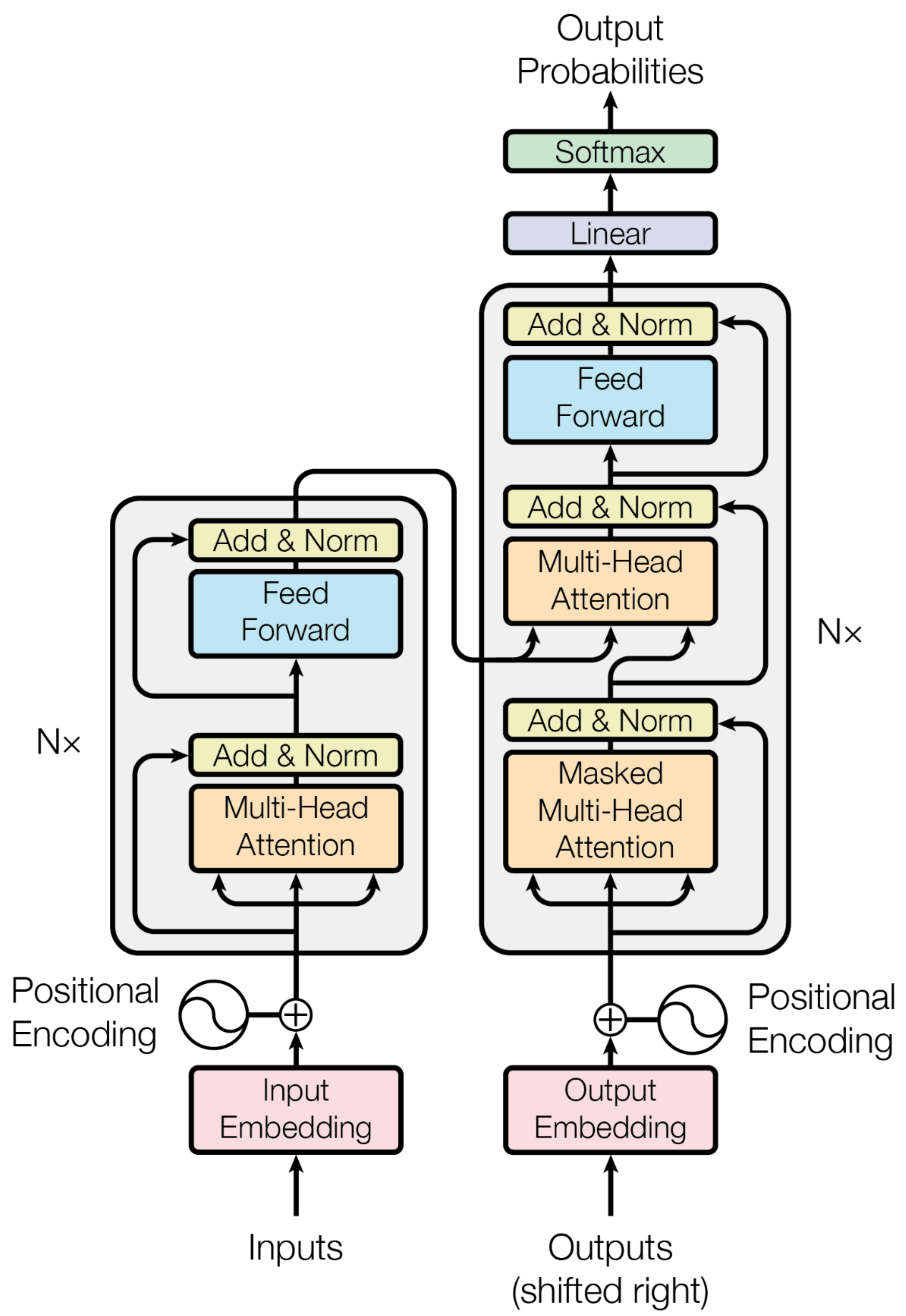
- Recall the original application of attention: allowing a **decoder** to attend to all of an **encoder's representations**, instead of just the final one
- How can we apply this form in Transformer-land?
    - What are the queries, keys, and values?

Cross-Attention

- **Queries**: decoder representations *X*
- **Keys and Values**: top-layer encoder representations *Z*
- Learned weight matrices W_q, W_k, W_v as before

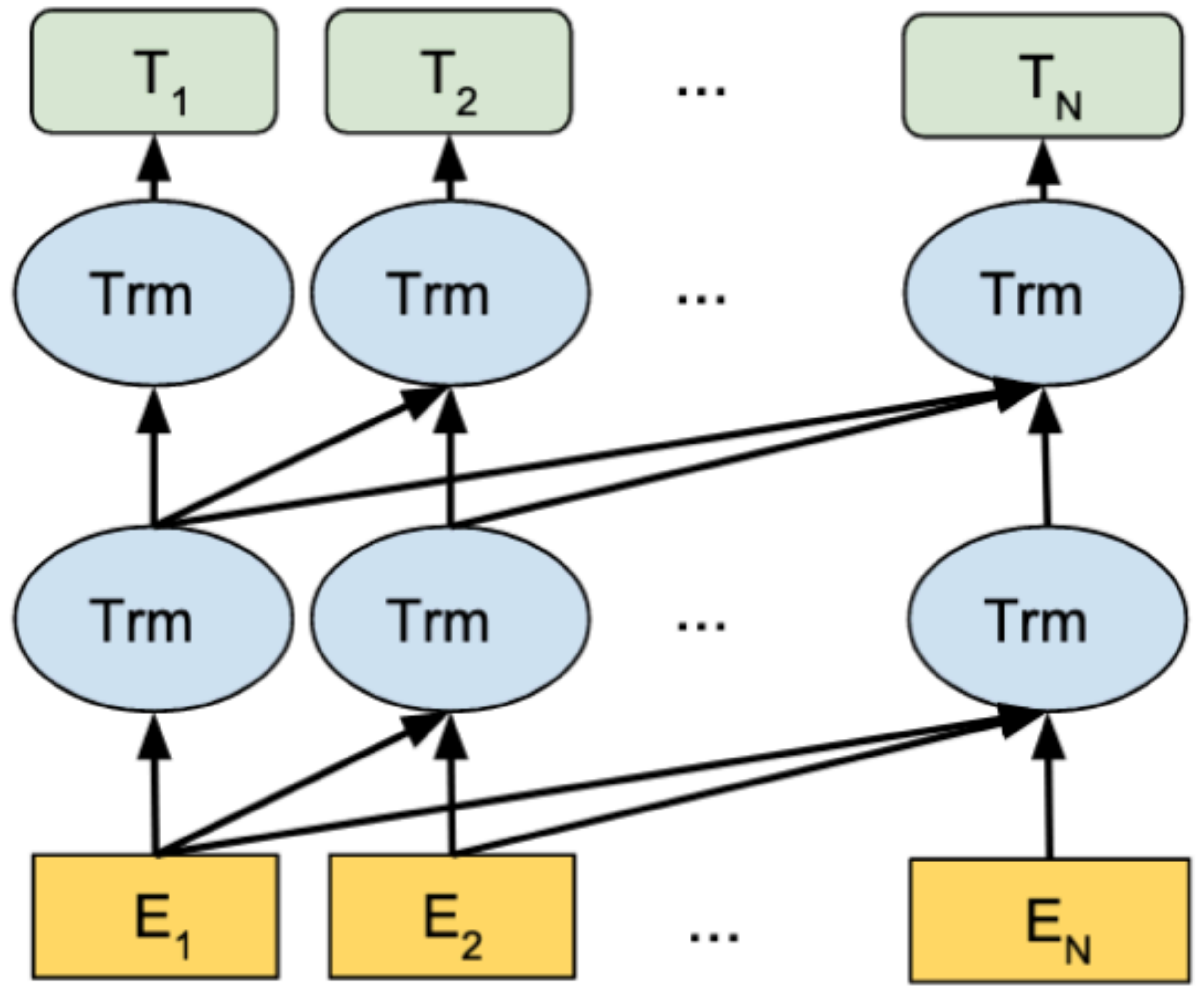
$$\text{CrossAttention} = \text{Attention}\left(XW_q, ZW_k, ZW_v\right)$$

Full Transformer Encoder-Decoder



Transformer Decoders

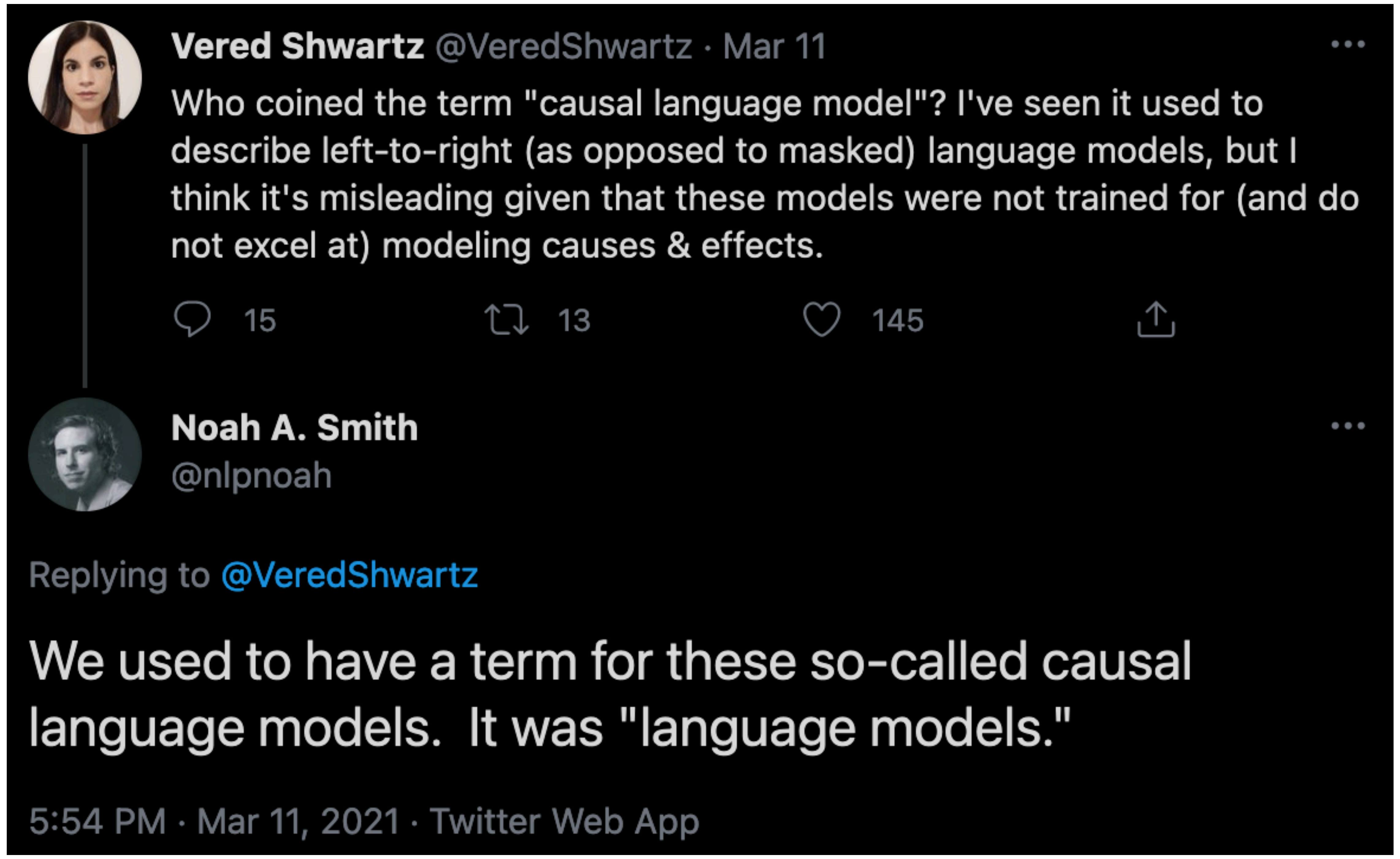
- Can be used any place you would use a decoder
- Masked attention **prevents "peeking into the future"**
- In seq2seq, for conditional language modeling, e.g.
  - Translation
  - Summarization
- Can be used **on their own**, as a **"pure" language model**
  - (people now call this **"causal language modeling"** sometimes)



source

Transformer Decoders

- Can be used any place you would use a decoder
- Masked attention **prevents "peeking into the future"**
- In seq2seq, for conditional language modeling, e.g.
  - Translation
  - Summarization
- Can be used **on their own**, as a **"pure" language model**
  - (people now call this **"causal language modeling"** sometimes)



Vered Shwartz @VeredShwartz · Mar 11

Who coined the term "causal language model"? I've seen it used to describe left-to-right (as opposed to masked) language models, but I think it's misleading given that these models were not trained for (and do not excel at) modeling causes & effects.

15 13 145

Noah A. Smith
@nlpnoah

Replying to @VeredShwartz

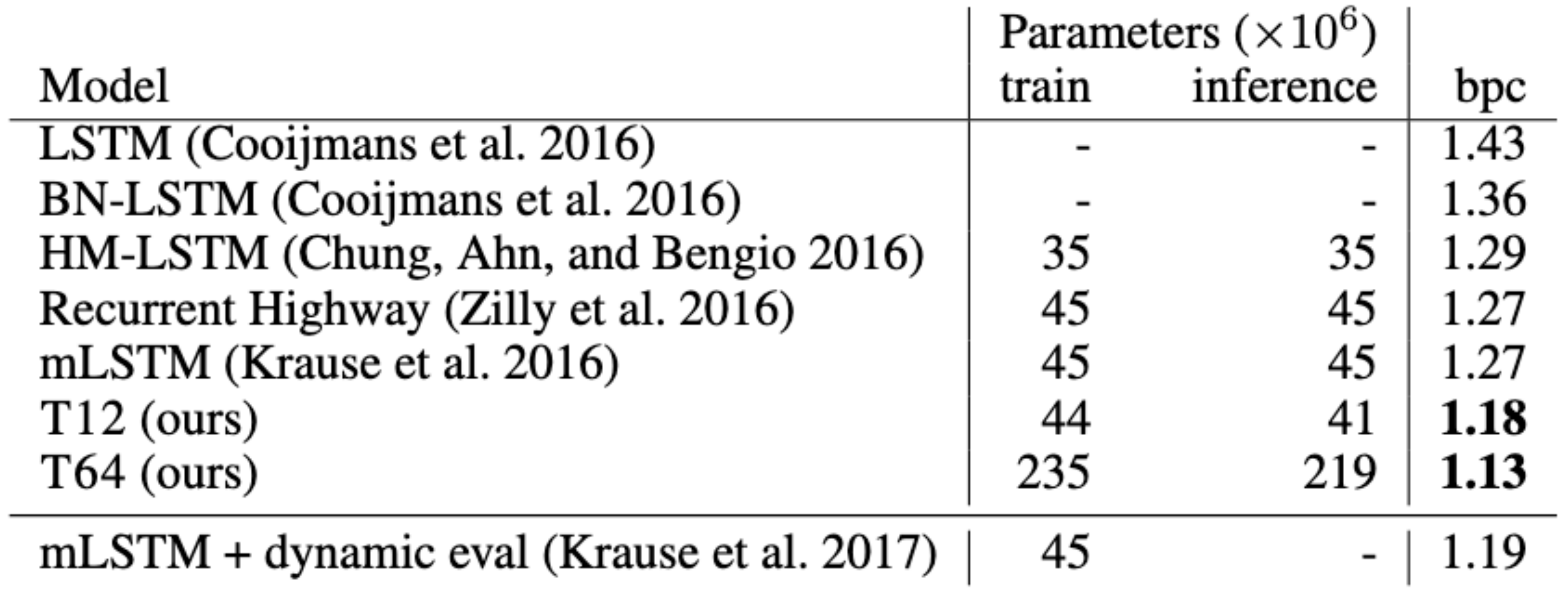
We used to have a term for these so-called causal language models. It was "language models."

5:54 PM · Mar 11, 2021 · Twitter Web App

source

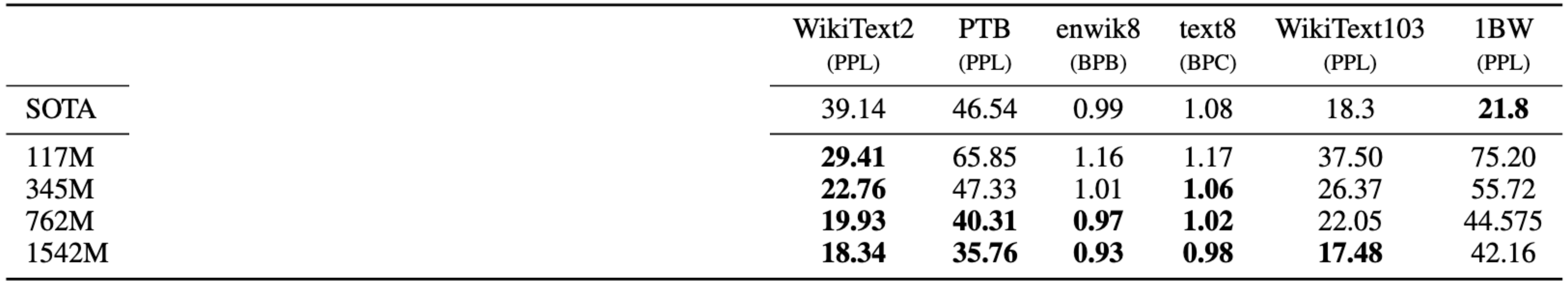
Transformer LM (Decoder-only) Results

- Character-level:
  - Used several auxiliary losses



Model	Parameters ($\times 10^6$) train	inference	bpc
LSTM (Cooijmans et al. 2016)	-	-	1.43
BN-LSTM (Cooijmans et al. 2016)	-	-	1.36
HM-LSTM (Chung, Ahn, and Bengio 2016)	35	35	1.29
Recurrent Highway (Zilly et al. 2016)	45	45	1.27
mLSTM (Krause et al. 2016)	45	45	1.27
T12 (ours)	44	41	**1.18**
T64 (ours)	235	219	**1.13**
mLSTM + dynamic eval (Krause et al. 2017)	45	-	1.19

- GPT2 results (more next time)
  - Zero-shot evaluation: trained on very large corpus, evaluated on standard benchmarks



	WikiText2 (PPL)	PTB (PPL)	enwik8 (BPB)	text8 (BPC)	WikiText103 (PPL)	1BW (PPL)
SOTA	39.14	46.54	0.99	1.08	18.3	**21.8**
117M	**29.41**	65.85	1.16	1.17	37.50	75.20
345M	**22.76**	47.33	1.01	**1.06**	26.37	55.72
762M	**19.93**	**40.31**	**0.97**	**1.02**	22.05	44.575
1542M	**18.34**	**35.76**	**0.93**	**0.98**	**17.48**	42.16

Transformer Architecture Summary

- Main building block: **attention**
    - Encoder: **self-attention**
    - Decoder: **masked** self-attention
    - Decoder-encoder: **cross-attention**
- **Position encodings/embeddings** to inject information about sequence order
- Position-wise feed-forward networks for element-wise nonlinearities
- Residual connections + LayerNorm around every component

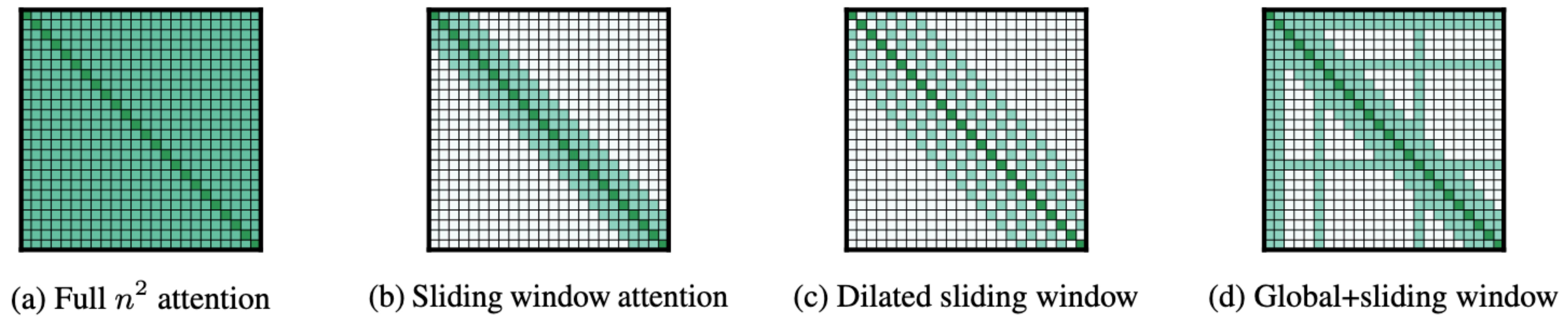
Transformers: Limitations

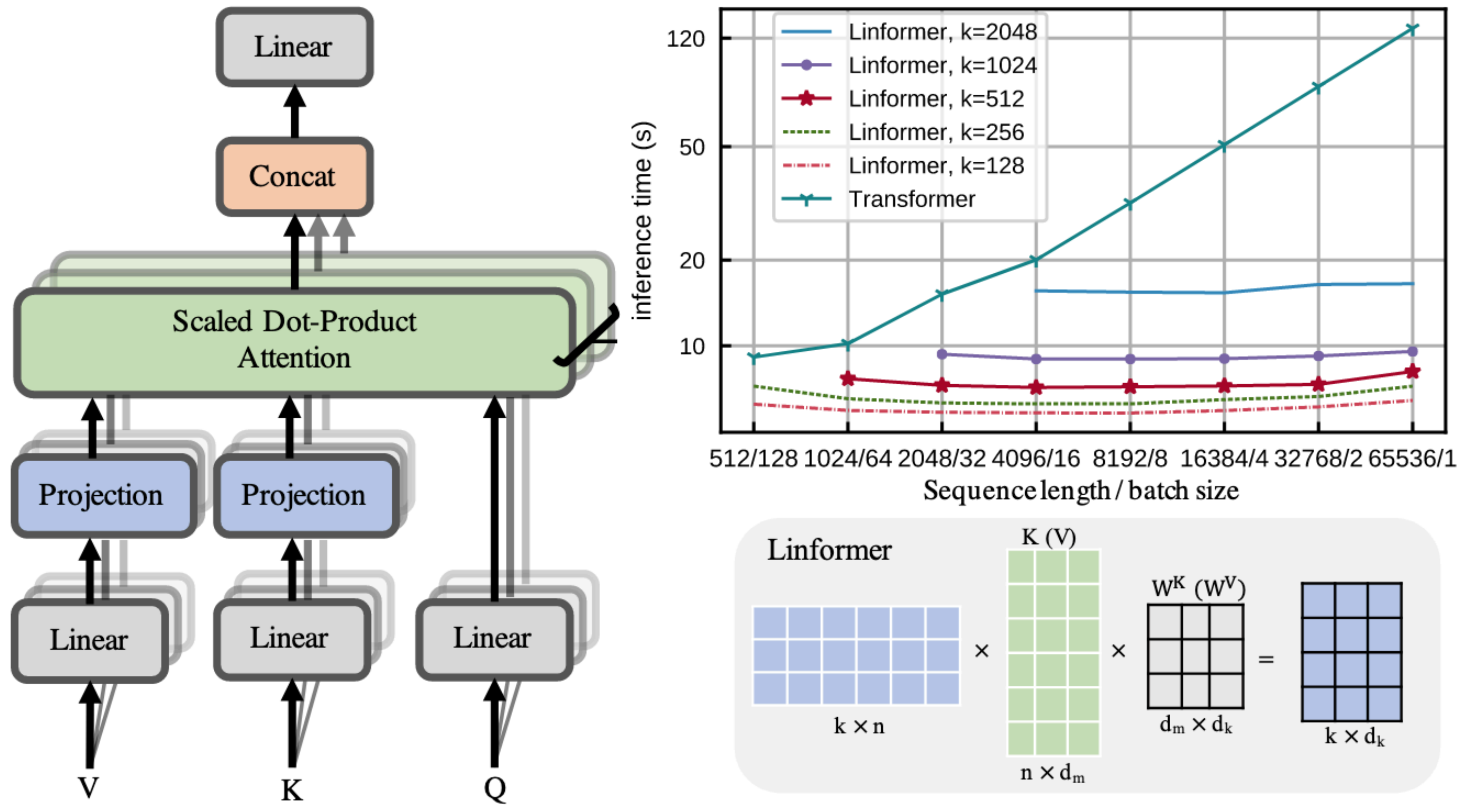
Quadratic Attention

- Attention computes similarity scores between all **pairs of tokens**
  - QK^T: [seq_len, seq_len] shape
  - In other words, **size of attention is $O(n^2)$**
- Prevents scaling to *long sequences*
  - Document-level:
    - Summarization
    - QA
    - …
- Big area of current research: linear(-ish) attention mechanisms.

Some Examples

- Longformer:
  - Carefully control positions attended to
- Linformer:
  - Additional projection of Keys/ Values to smaller space
  - $O(nk)$, with *k* a hyper-parameter
- Survey paper


(a) Full n^2 attention
(b) Sliding window attention
(c) Dilated sliding window
(d) Global+sliding window



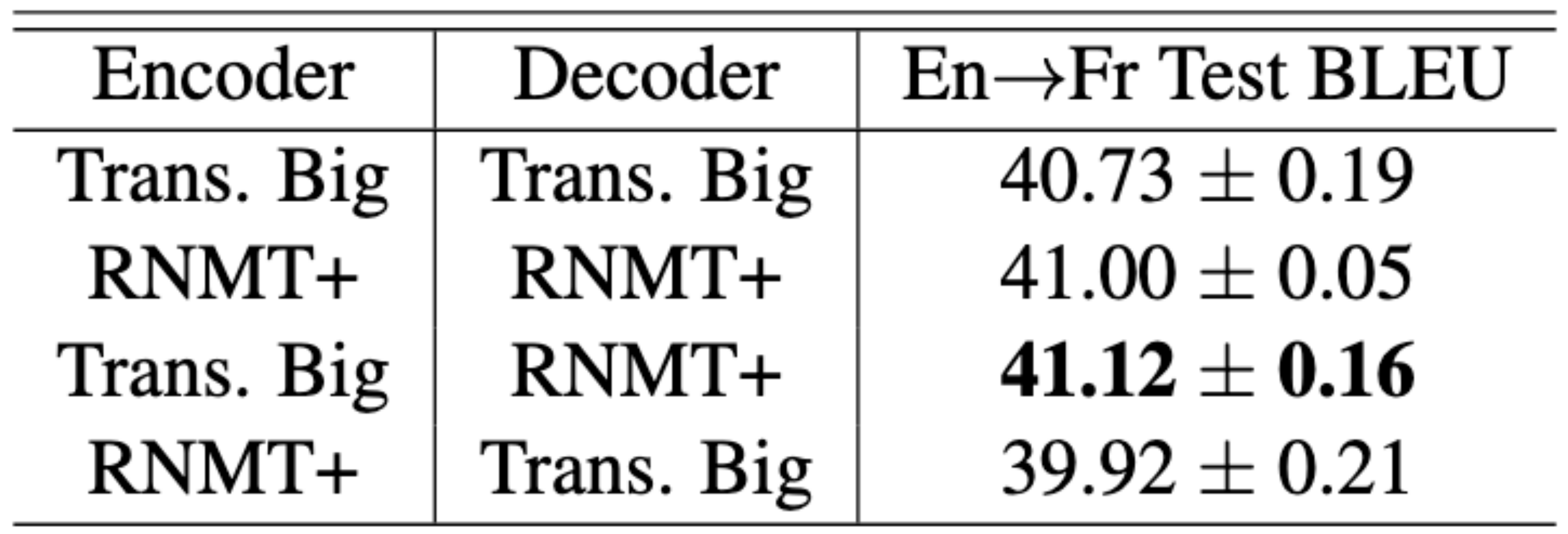
Inference speed does not scale with seq length

Recurrence in Generation

- Recall the basic method for **generating** from a decoder:
  - Feed **initial token** (e.g. BOS, or just a word/character)
  - Generate **probability over next tokens**
    - **Sample** next token from this distribution
  - **Repeat** until [EOS | max length | other criterion]
- This **loop is unavoidable** during generation
  - Transformer's gains on paralellizability: work for training, **vanish for generation**
  - In fact, **RNN decoders** tend to be **much faster** at inference time

Mixed/Hybrid Architectures

- Encoder-decoder: a general architecture
  - In principle, any model of the right type can be encoder and/or decoder
- "The Best of Both Worlds" for NMT
  - Transformer encoder + RNN decoder
- Google Translate (at one point)
  - "Transformer models have been demonstrated to be generally more effective at machine translation than RNN models, but our work suggested that most of these quality gains were from the transformer *encoder*, and that the transformer *decoder* was not significantly better than the RNN decoder. Since the RNN decoder is much faster at inference time, we applied a variety of optimizations before coupling it with the transformer encoder. The resulting hybrid models are higher-quality, more stable in training, and exhibit lower latency."



Encoder	Decoder	En→Fr Test BLEU
Trans. Big	Trans. Big	40.73 ± 0.19
RNMT+	RNMT+	41.00 ± 0.05
Trans. Big	RNMT+	$\mathbf{41.12} \pm \mathbf{0.16}$
RNMT+	Trans. Big	39.92 ± 0.21

Subword Tokenization

OOV and Vocab Size

- Word-level models
  - Tokenize training data
  - Build vocabulary
  - Learn representations
- Two problems
  - **Cannot generalize** at test time to **OOV (out of vocab) words**
    - (various subtleties, tricks, etc, but generally true)
  - Larger training data —> larger vocabulary
    - Its own problems, e.g. **very expensive softmax over vocab** in decoders
    - (Or put a cap on vocab size, but then miss lower-frequency words entirely)

Finer Representation Levels

- One solution: **character-level models**
  - Pros:
    - **Small vocabulary size**
    - **No (or very little) OOV**
  - Cons:
    - Much **harder learning problems**; need to learn everything about words, on top of phrases, sentences, etc.
- In-between solution: **sub-word** tokenization
  - Split words into pieces, but don’t go all the way down to character level
  - Many methods: WordPiece, BytePair Encoding (BPE), …

WordPiece Embeddings

- Another solution to OOV problem, from NMT context (see Wu et al 2016)
- Main idea:
  - **Fix vocabulary size** |V| in advance (e.g. 30k for BERT)
  - **Choose |V| wordpieces (subwords)** such that total **number of wordpieces in the corpus is minimized**
- Frequent words aren’t split, but rarer ones are, e.g.:
- “Backpropagation was confusing at first, but now we grok it.”
  - [“Back”, “##prop”, “##ag”, “##ation”, “was”, “confusing”, “at”, “first”, “,”, “but”, “now”, “we”, “gro”, “##k”, “it”, “.”]