Transformers 2

Ling 282/482: Deep Learning for Computational Linguistics

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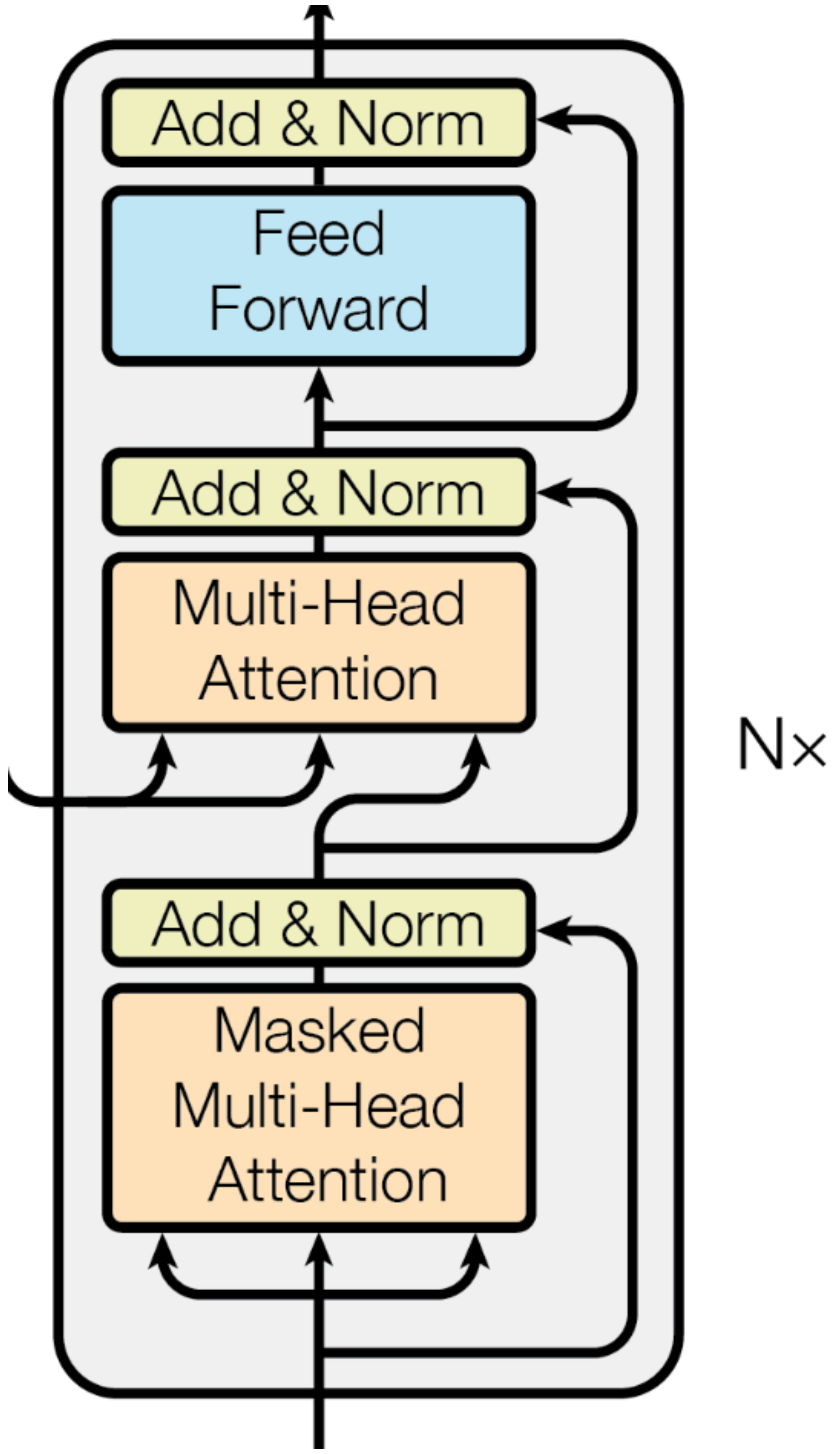
Transformer Decoder

Decoder Block

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

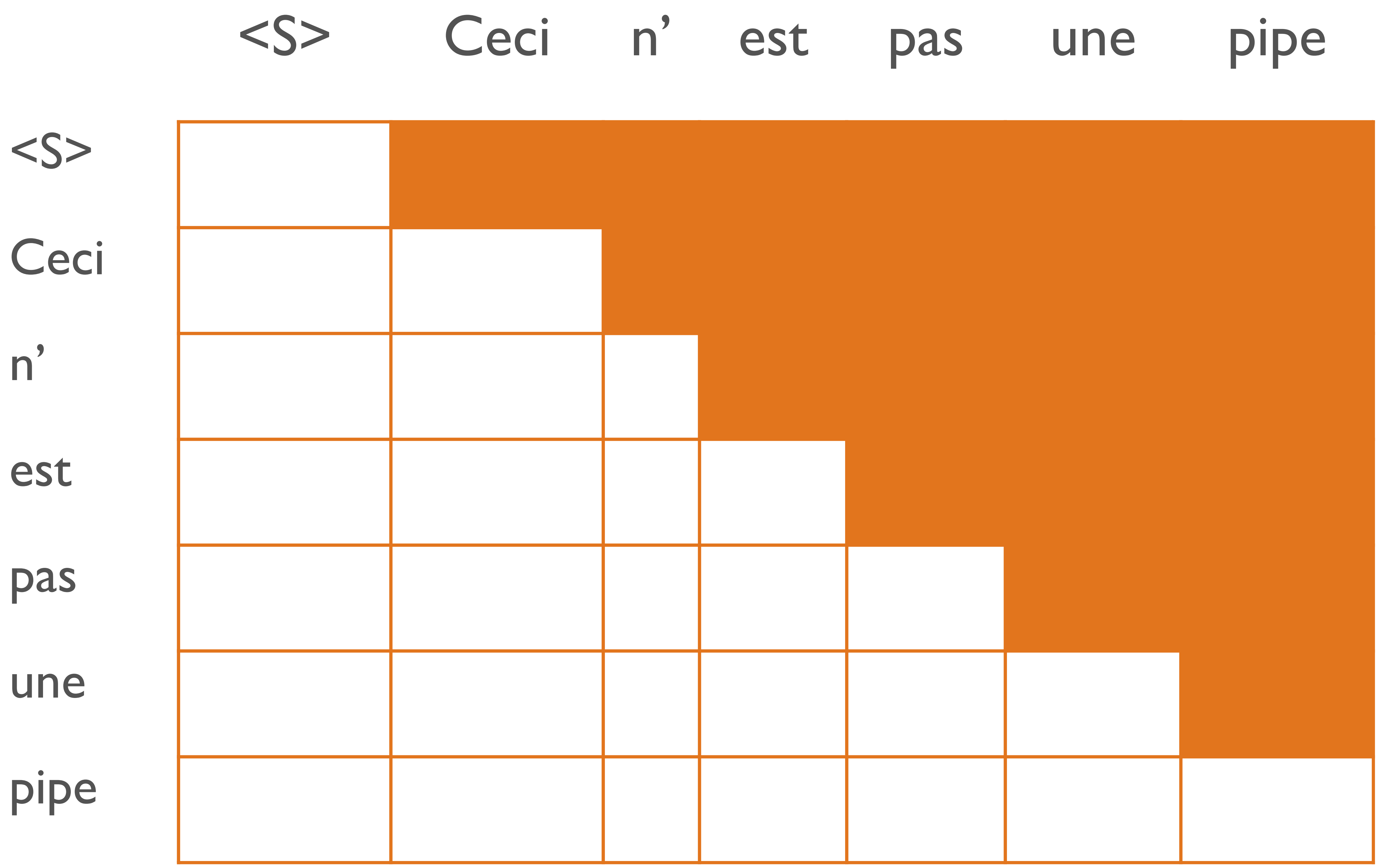


Attention Computation Practice

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

Q K^T V

Masking Out the Future



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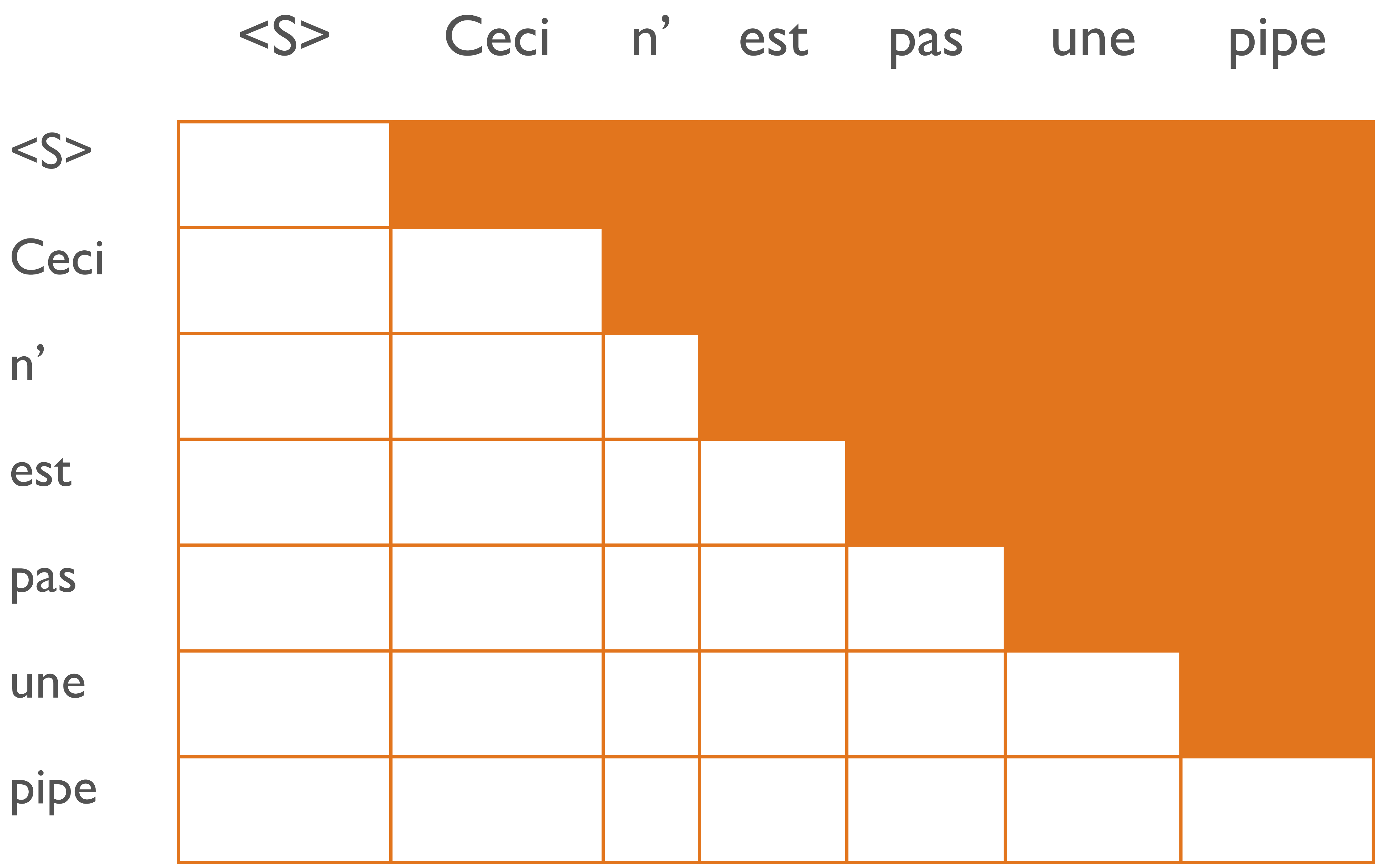
- Key idea: use a **mask** to **block out certain attention scores**



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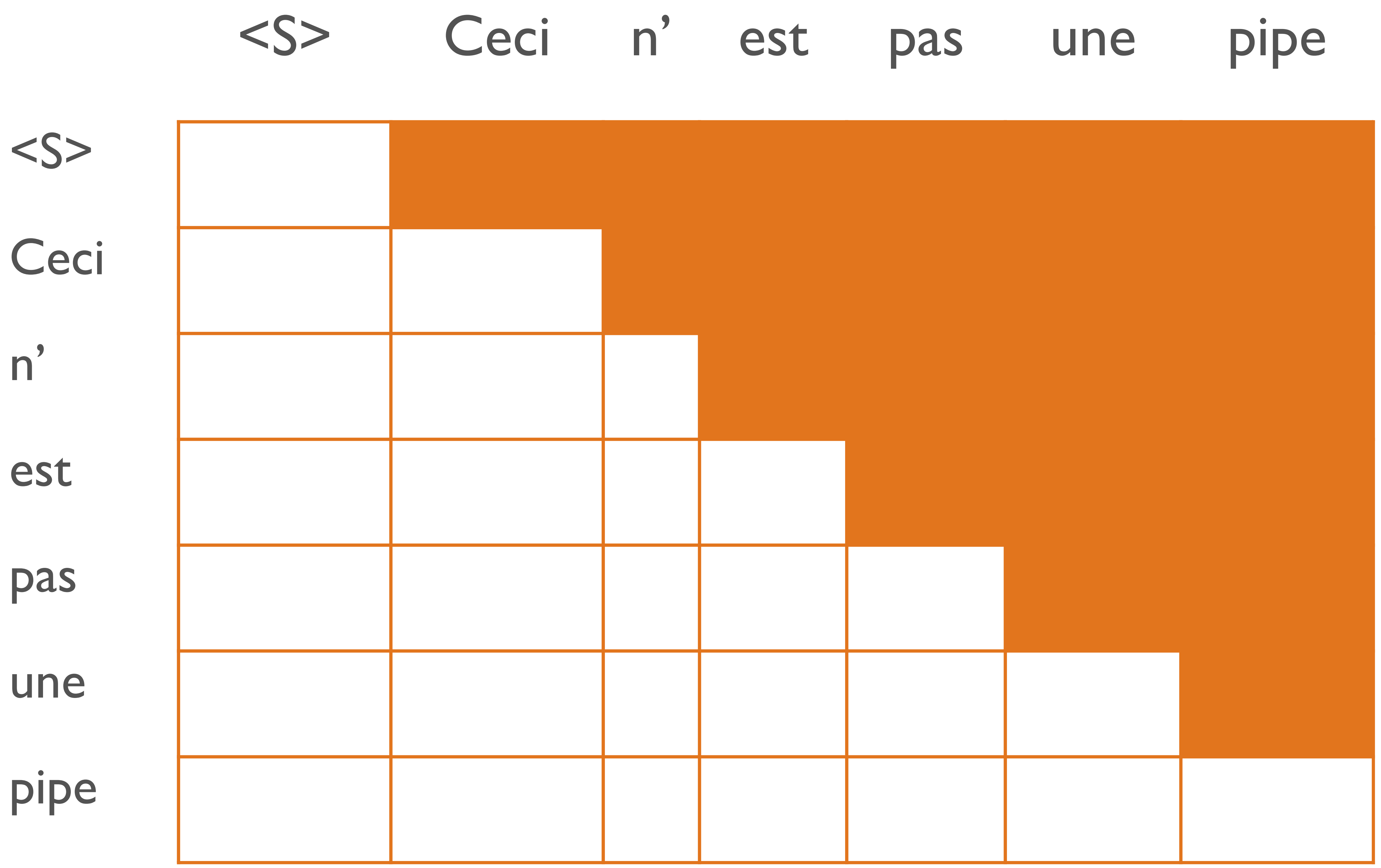

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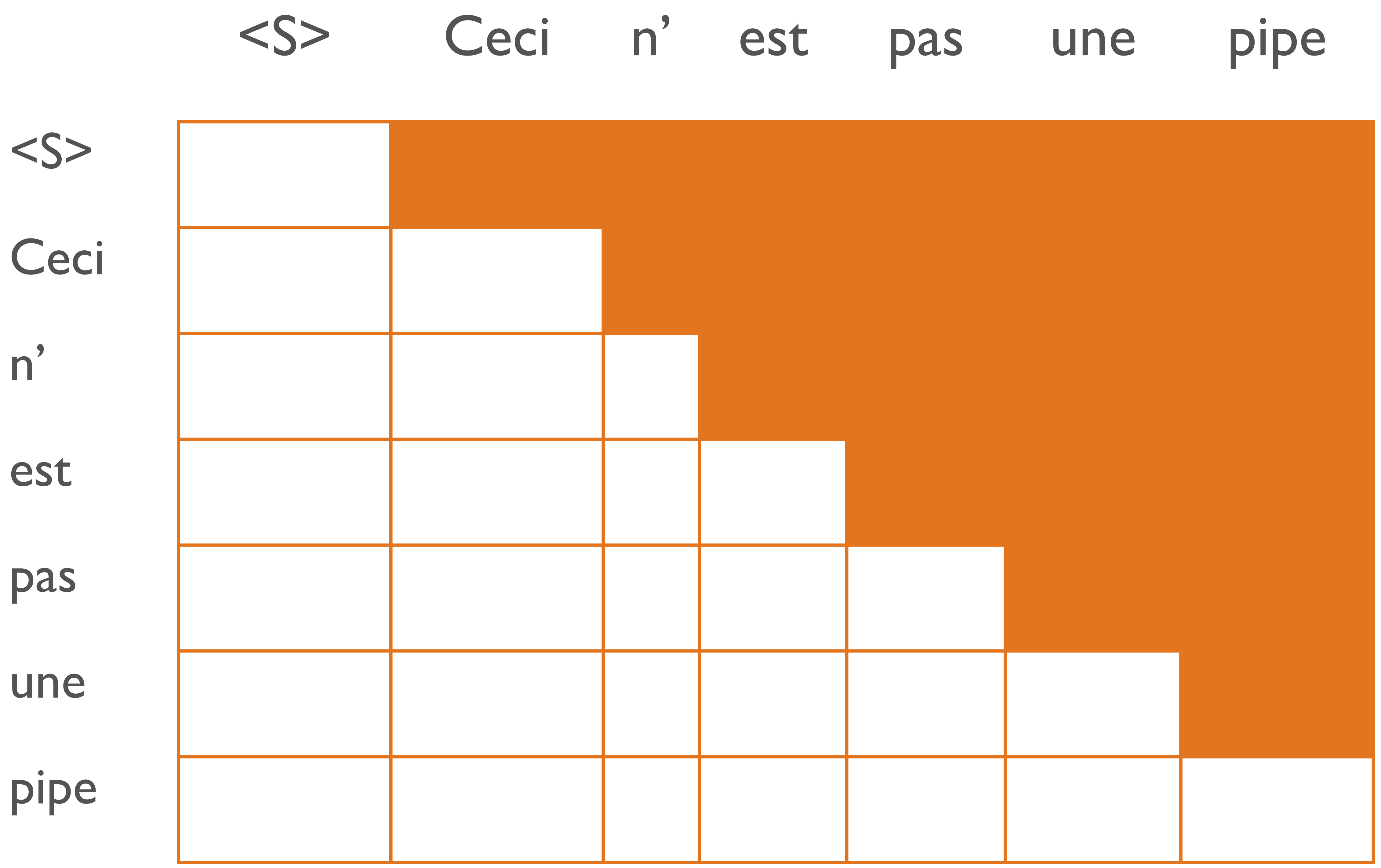
- Tokens in the rows (**queries**) can **not** pay attention to tokens in the columns (**keys**) that are shaded in
- Sometimes called a **"causal"** or **"directional"** mask
  - Recall that otherwise Transformers **don't intrinsically model order!**



Masking Out the Future

QK^T: total attention scores

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

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

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n’	0	0	0	-inf	-inf	-inf	-inf
est	0	0	0	0	-inf	-inf	-inf
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Why 0 and -inf?

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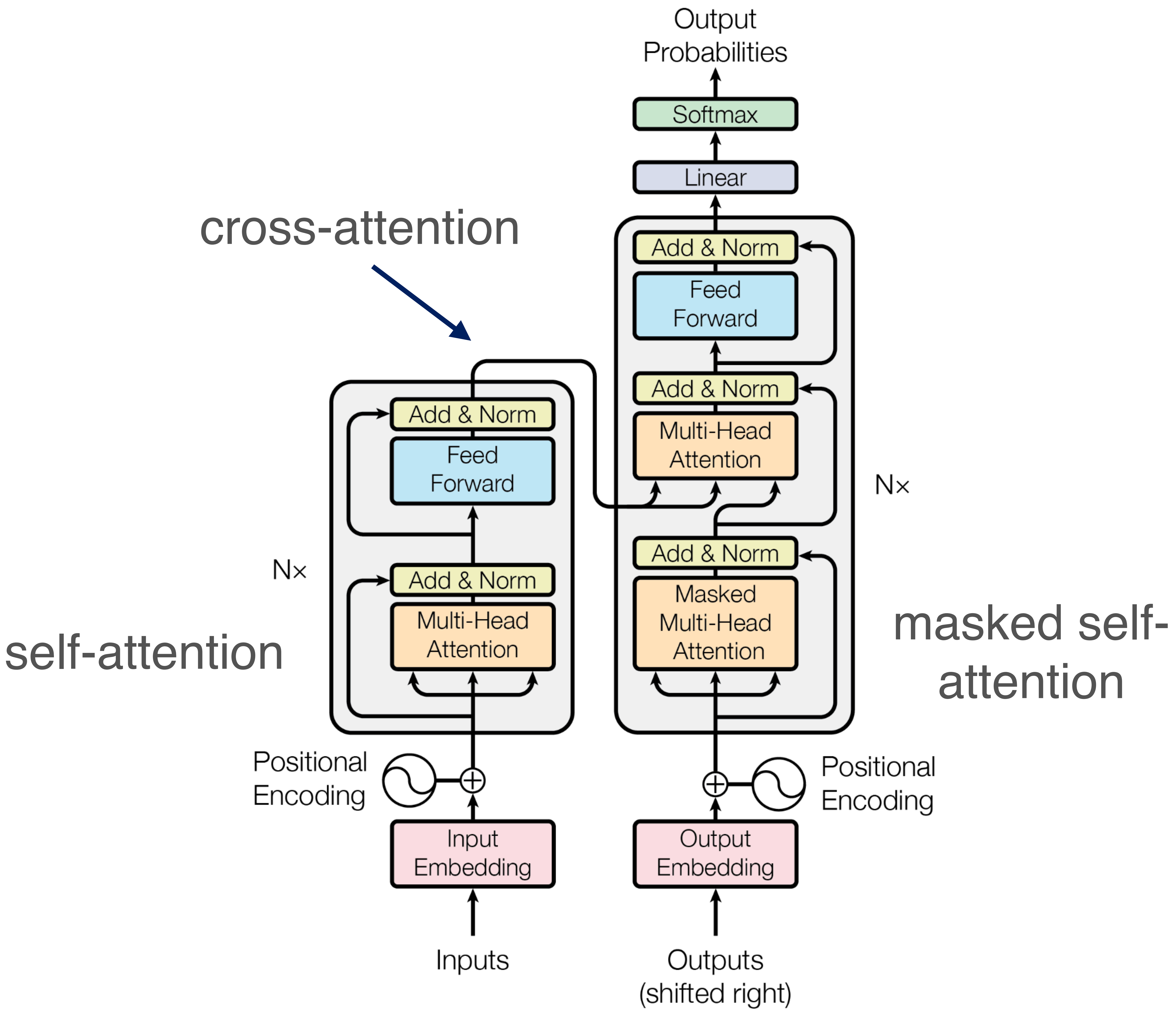
$$\text{CrossAttention} = \text{Attention}\left(XW_q, ZW_k, ZW_v\right)$$

Full Transformer Encoder-Decoder



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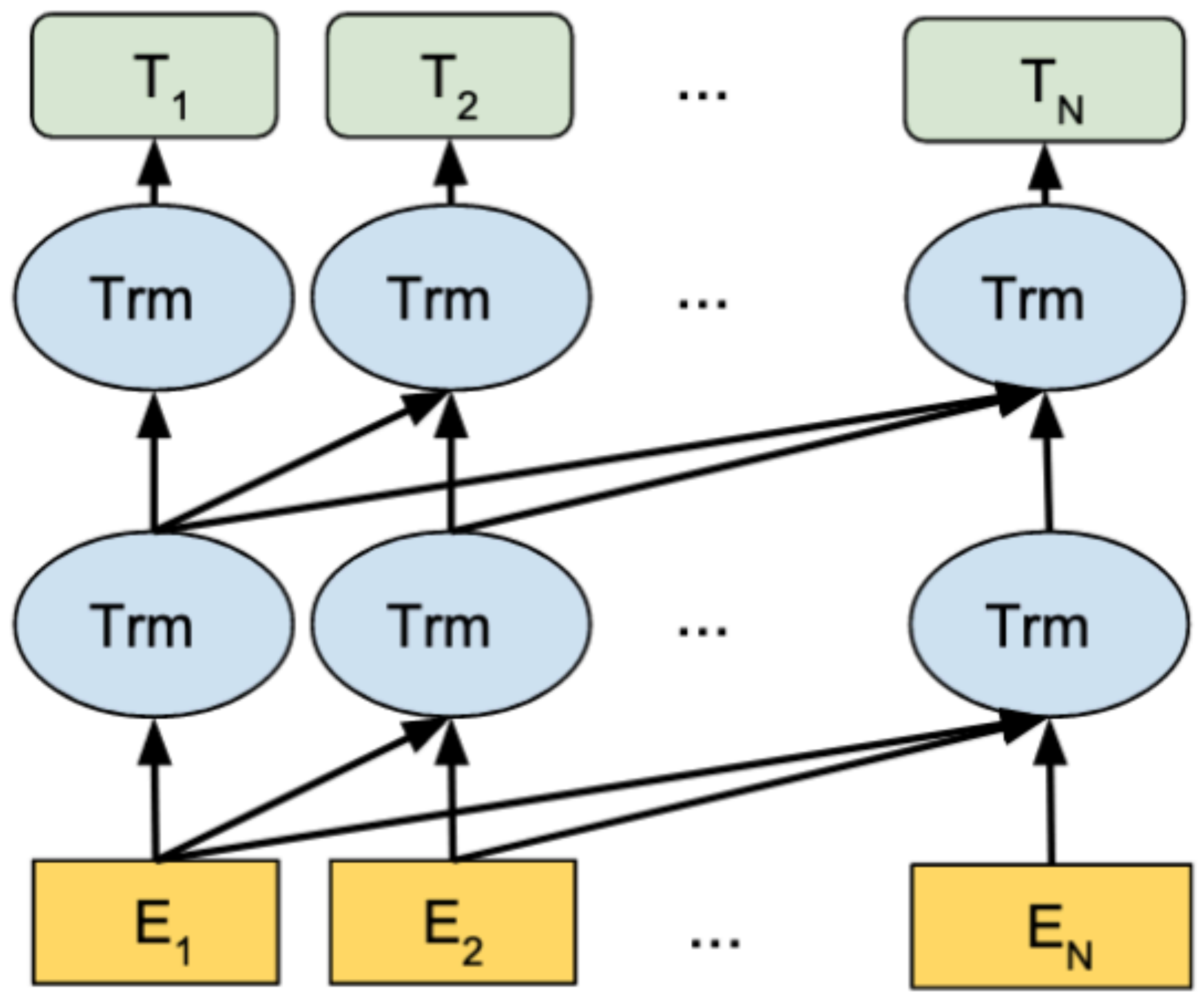

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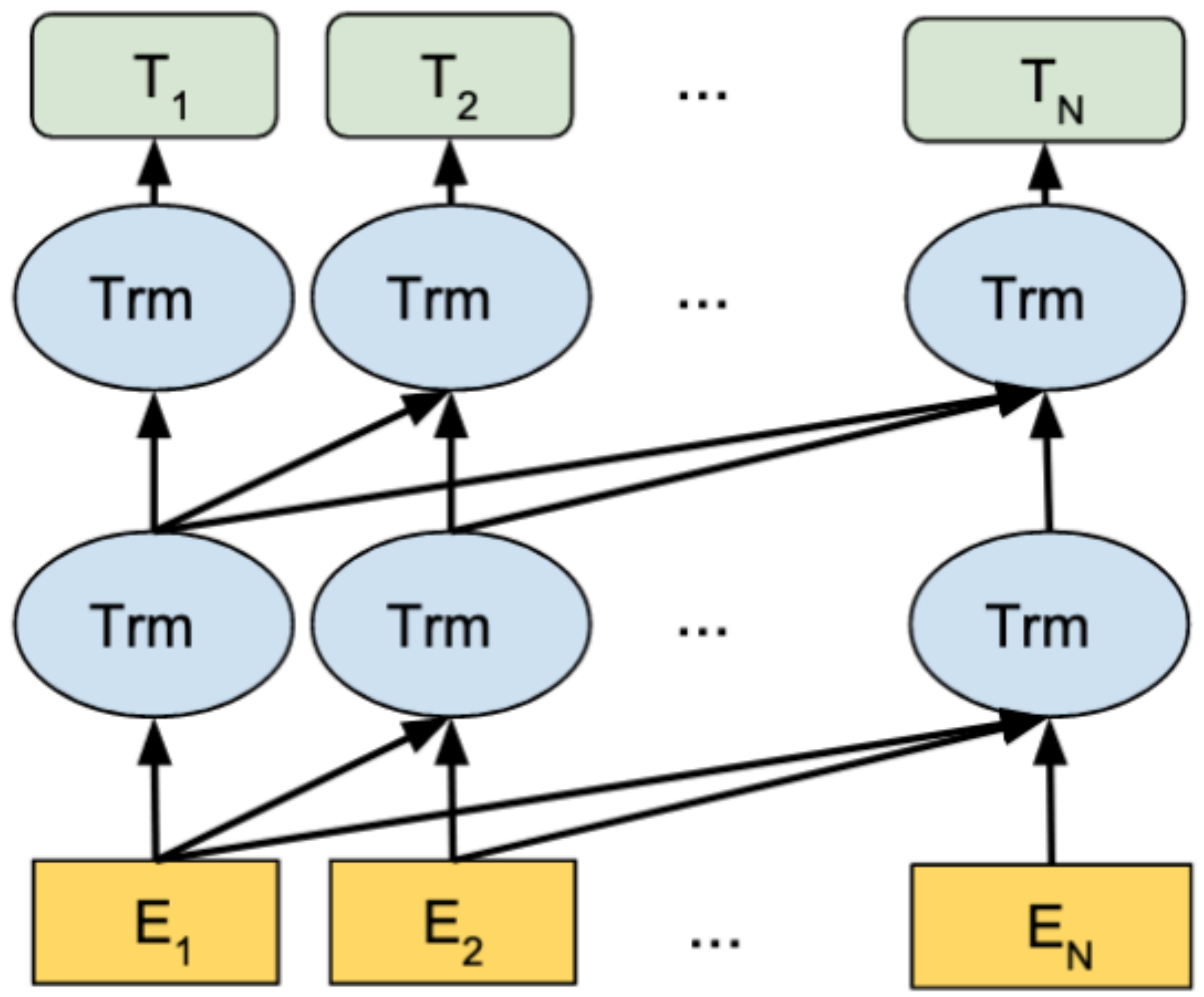

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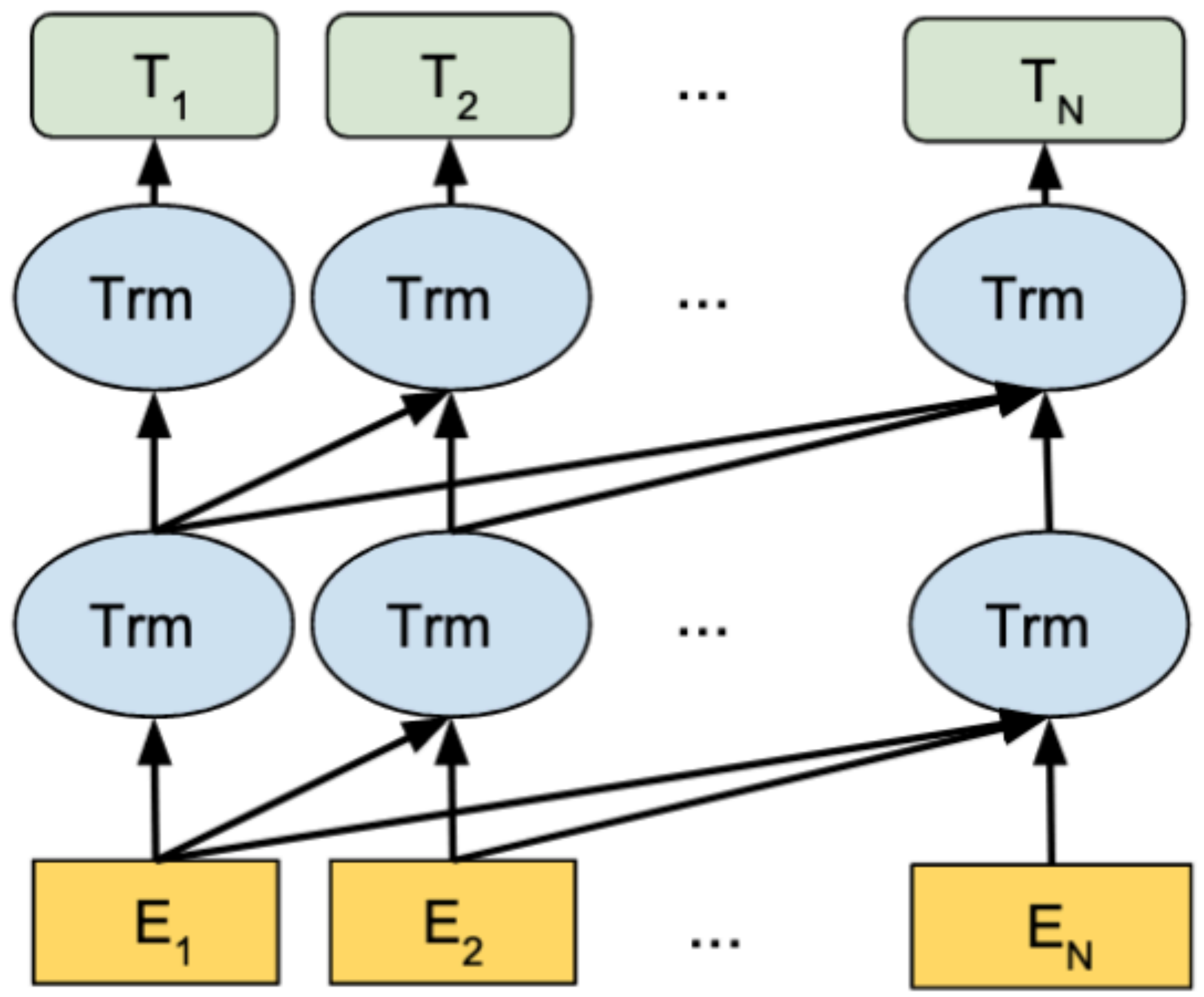

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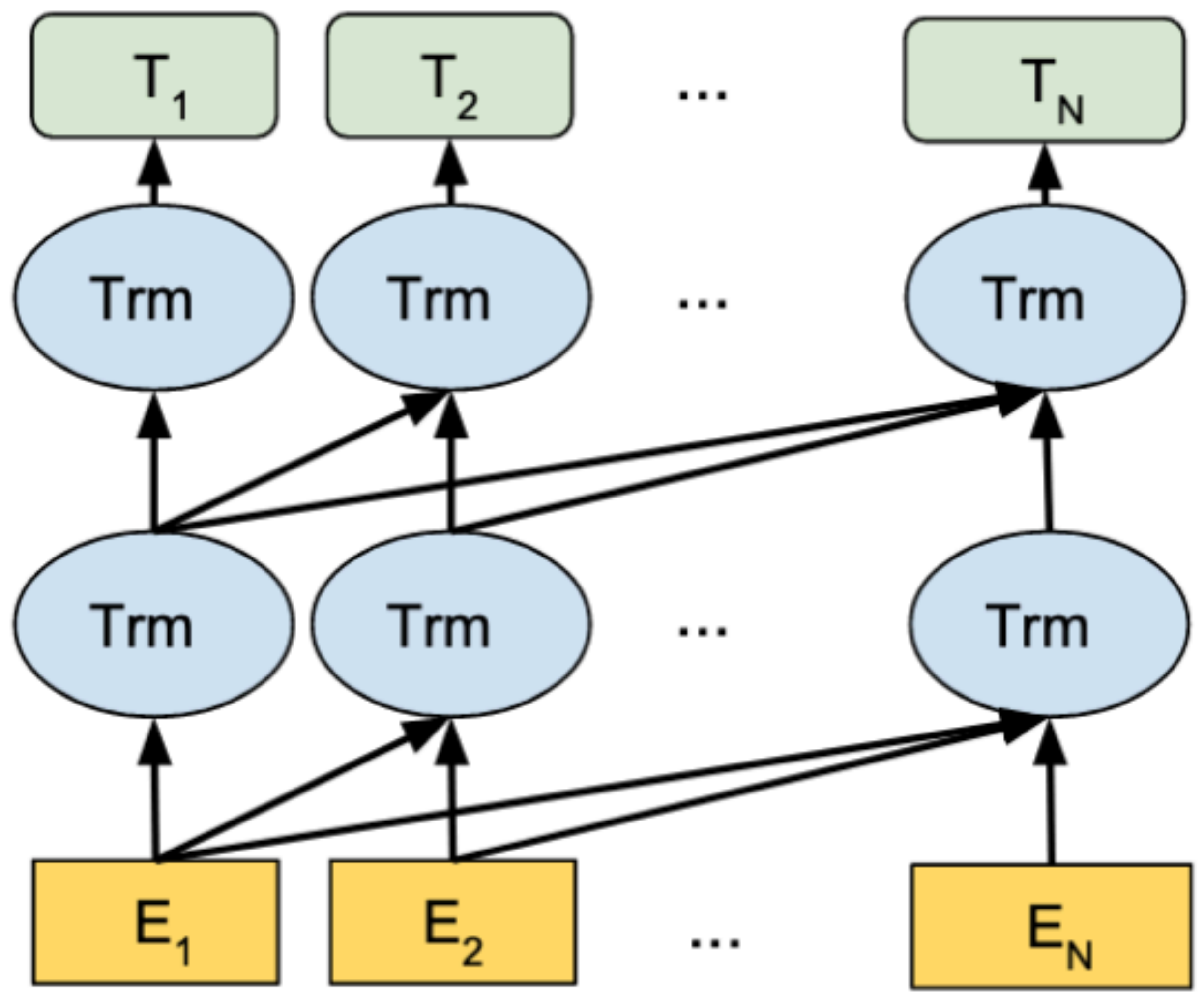

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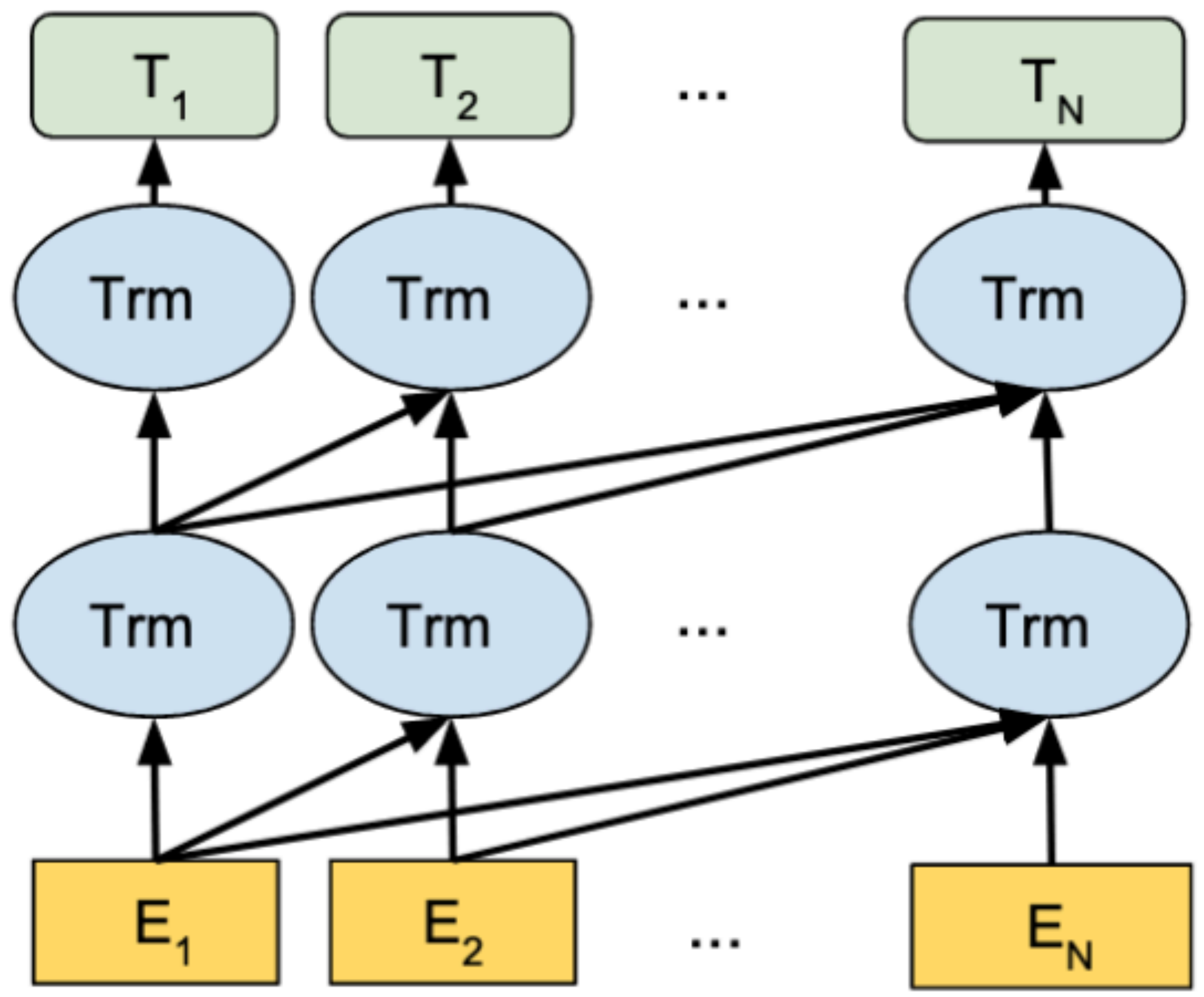

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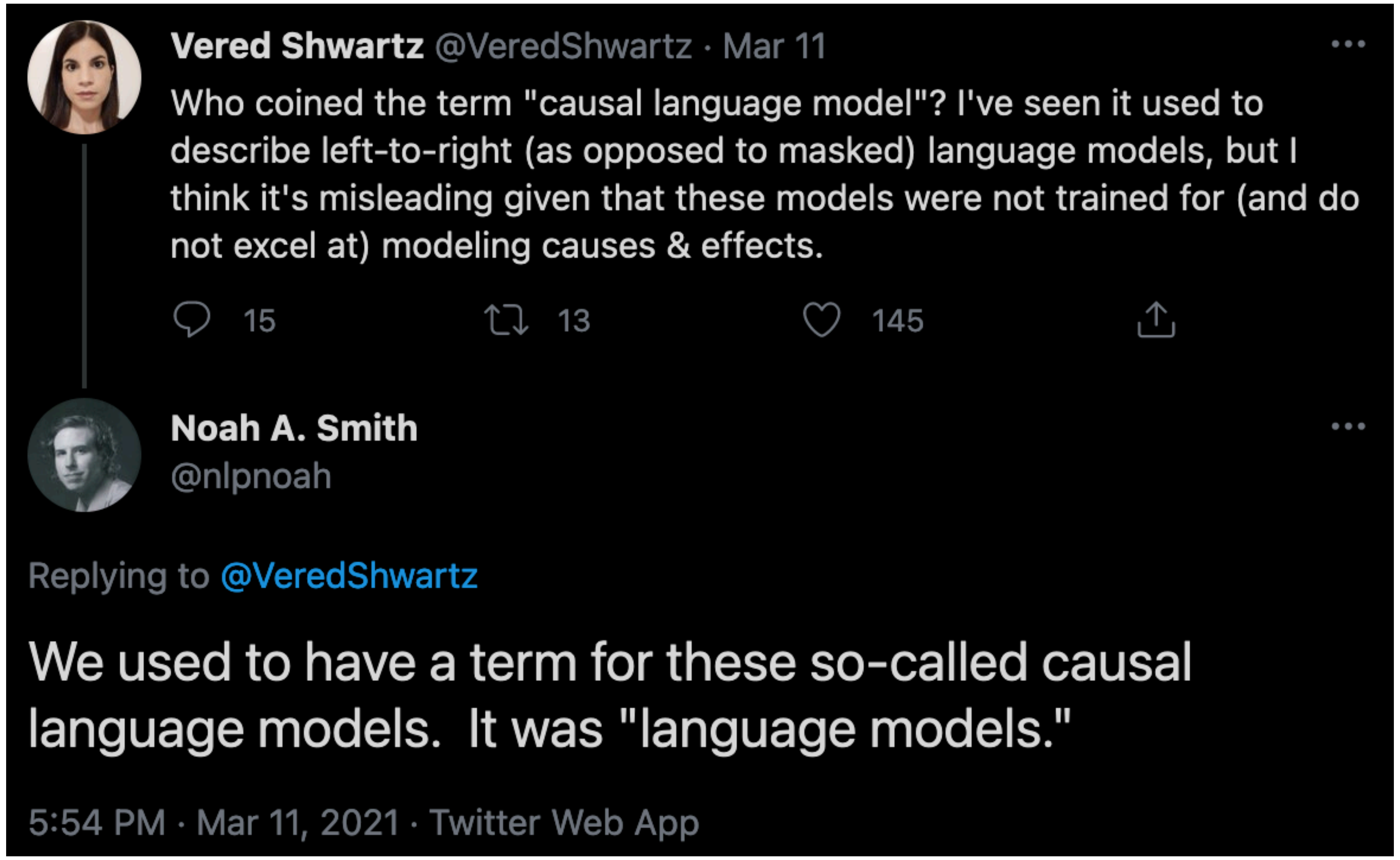

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- Residual connections + LayerNorm around every component

Transformers: Limitations

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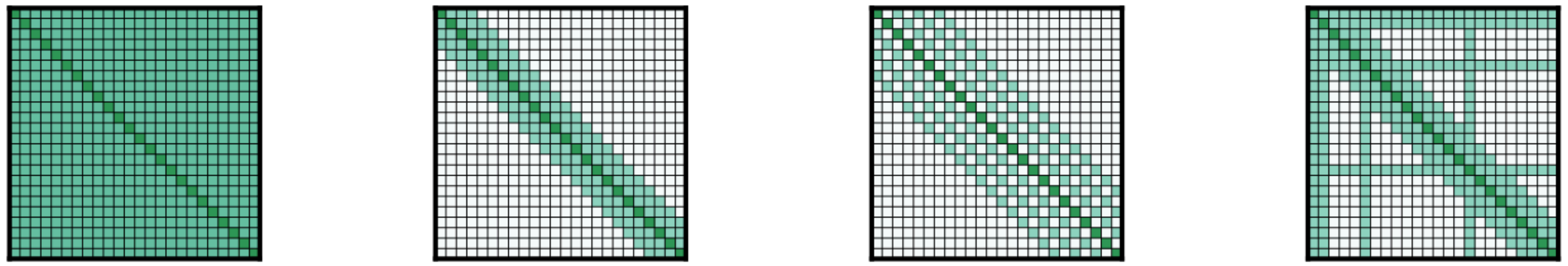
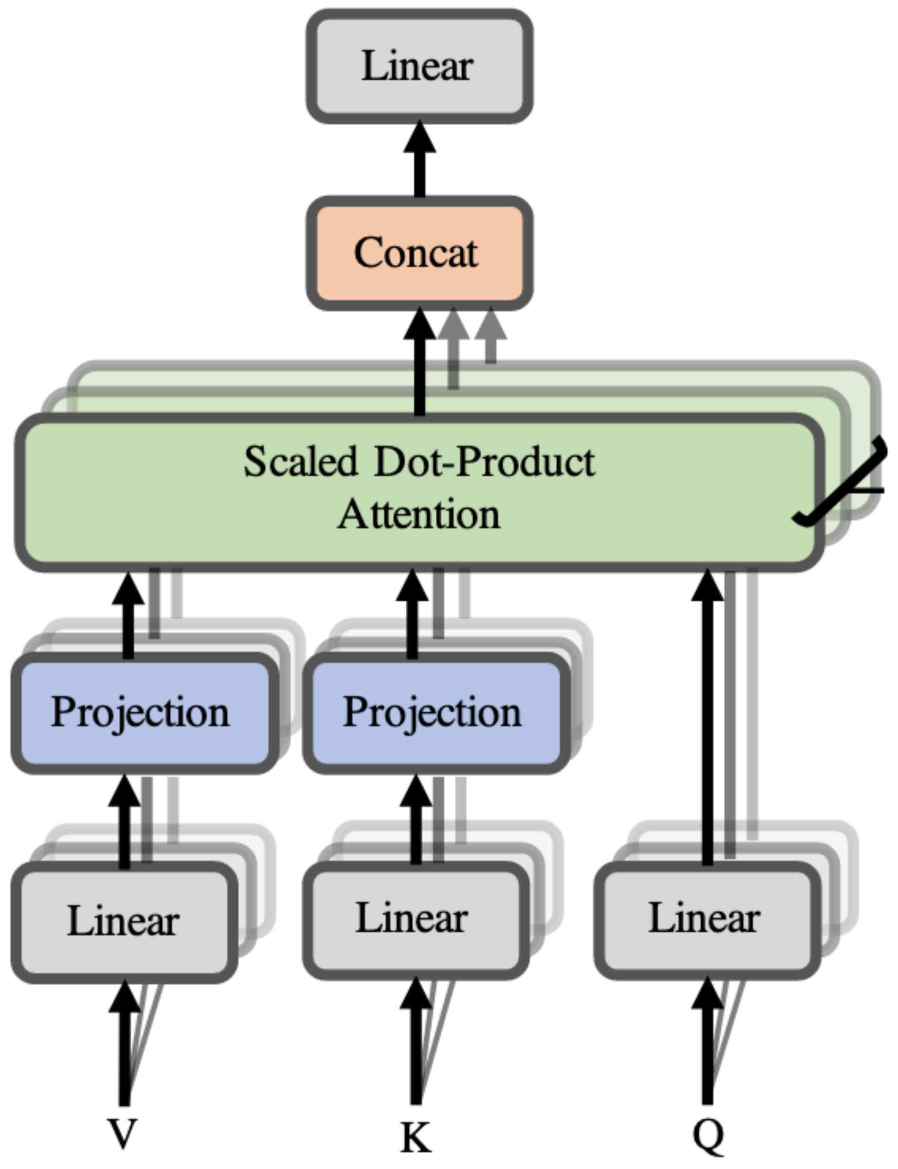
  - There are **all kinds of tricks** nowadays for allowing very long sequences
  - Some industrial LLMs can handle sequences **tens of thousands of tokens long!**

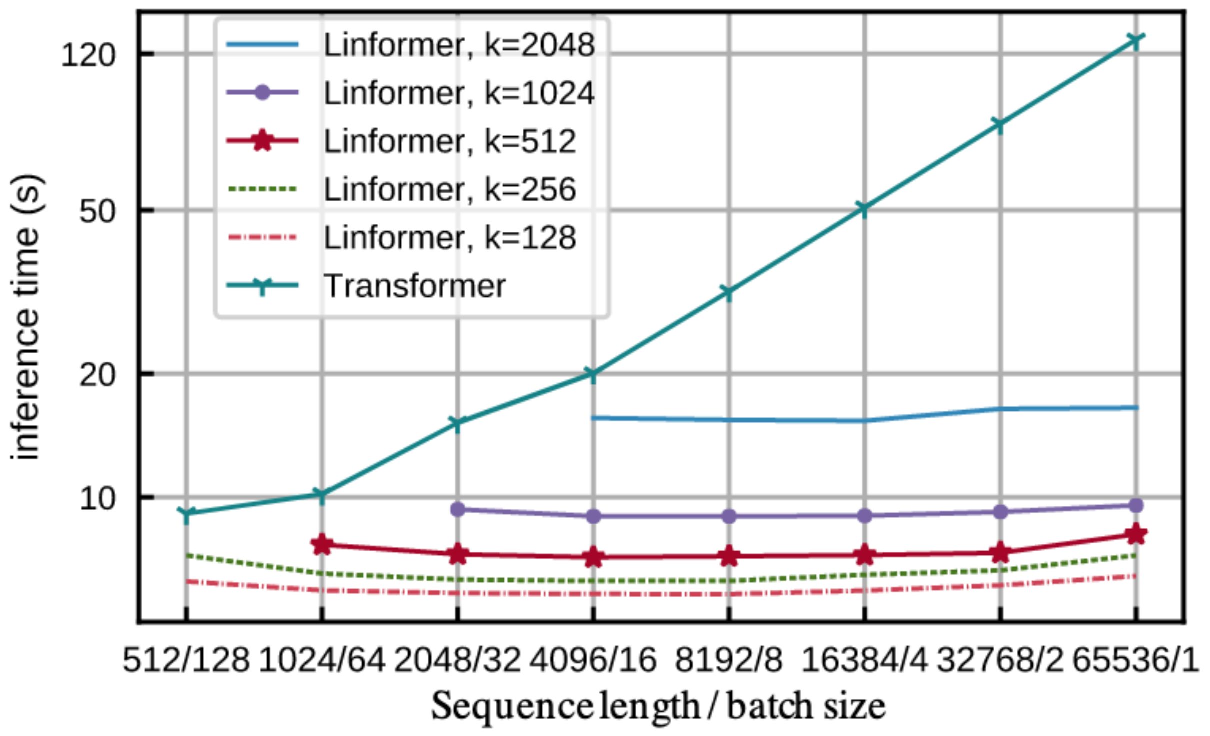
Efficient Attention Examples

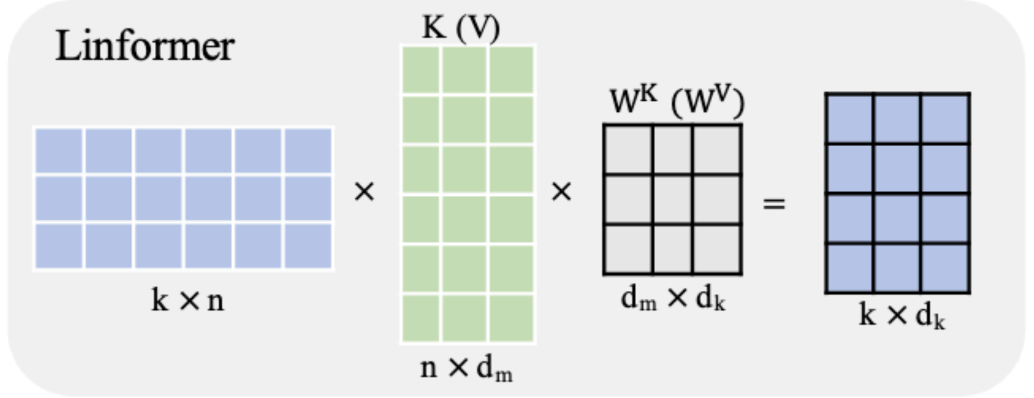
- Longformer:
    - Carefully control positions attended to
- Linformer:
    - Additional projection of Keys/Values to smaller space
    - $O(nk)$, with k a hyper-parameter
- Survey paper



(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

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- This **loop is unavoidable** during generation
  - Transformer's gains on parallelism: work for training, **vanish for generation**
  - In fact, **RNN decoders** tend to be **much faster** at inference time

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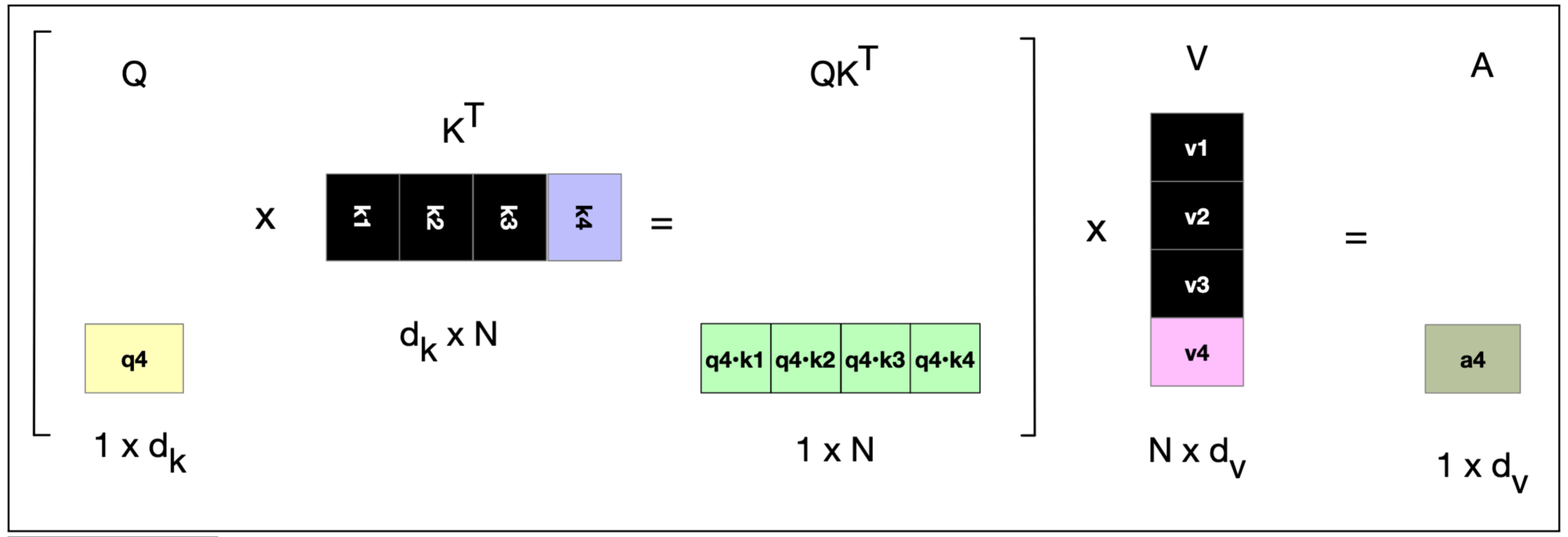

Figure 8.17 Parts of the attention computation (extracted from Fig. 8.10) showing, in black, the vectors that can be stored in the cache rather than recomputed when computing the attention score for the 4th token.

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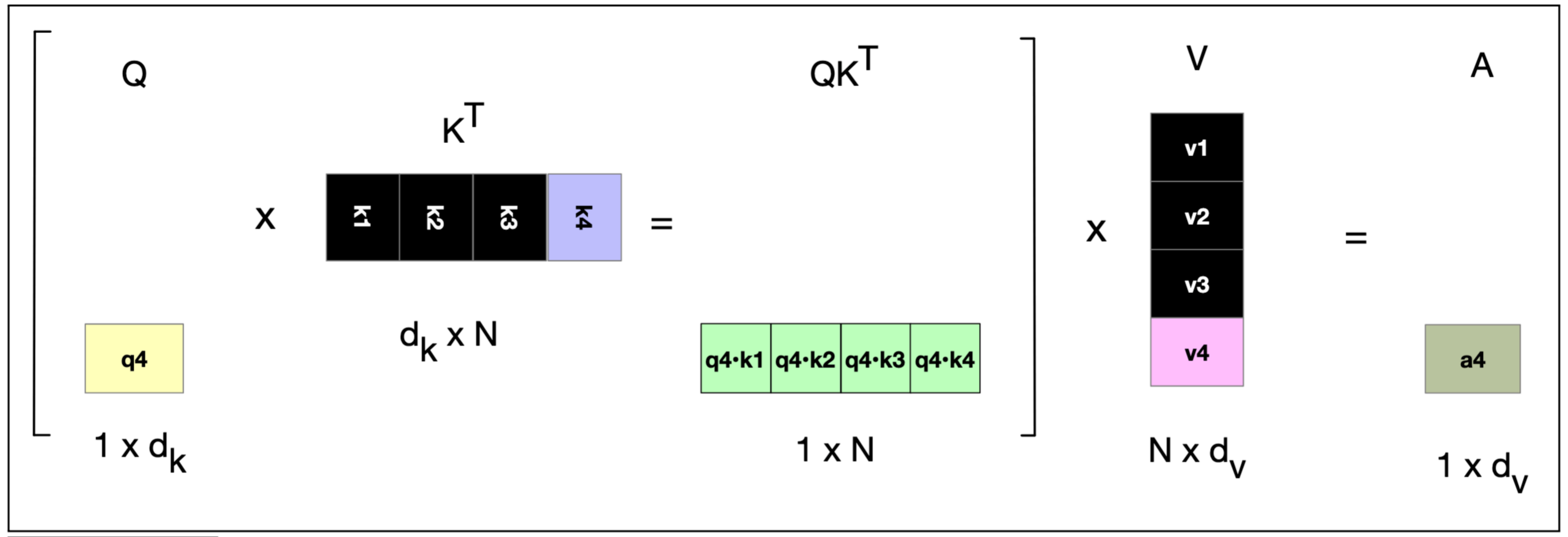

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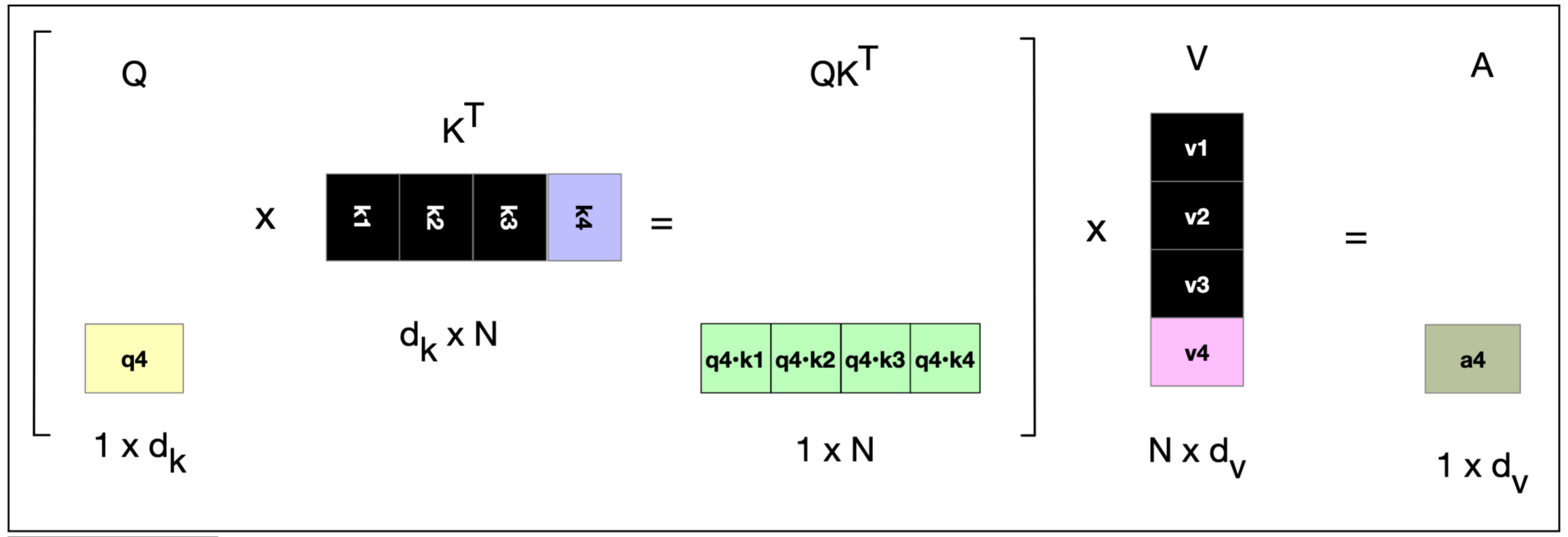
  - Only KVs for the **newest token** are computed at each step



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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

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- 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

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- One solution: **character-level models**
  - Pros:
    - **Small vocabulary size**
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  - Cons:
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- 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), …

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- "Backpropagation was confusing at first, but now we grok it."
    - ["Back", "##prop", "##ag", "##ation", "was", "confusing", "at", "first", ",", "but", "now", "we", "gro", "##k", "it", "."]