Transformers, II: Decoder, Limitations

LING 575K Deep Learning for NLP

Shane Steinert-Threlkeld

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Announcements

- HW4 ref available; HW5 tests available [will do earlier moving forward]
- Thanks for filling out mid-term survey!
- Updated examples_from_characters docstring (thanks for catching!):

```
An example usage:
    >>> examples_from_characters(['a', 'b', 'c', 'd'], 2)
    >>> [{"text": ['a', 'b'], "target": 'c'}, {"text": ['b', 'c'], "target": 'd'}]
```

Announcements, cont.

- Why a character-level language model for HW5?
  - Primarily: *compute* efficiency. For SST data:
    - Size of char vocab: ~70. Size of word vocab: ~13000.
    - Softmax layer sums over the whole vocab (for denominator); becomes very expensive!
    - NB: will talk today about "modern" approaches to solving this problem
  - Secondarily: very impressive! Still can work quite well.
  - Third: may learn interesting phenomena below the word level.
- NB: _hard_ problem, so models may not work as well as word-level, especially small ones (e.g. HW5).

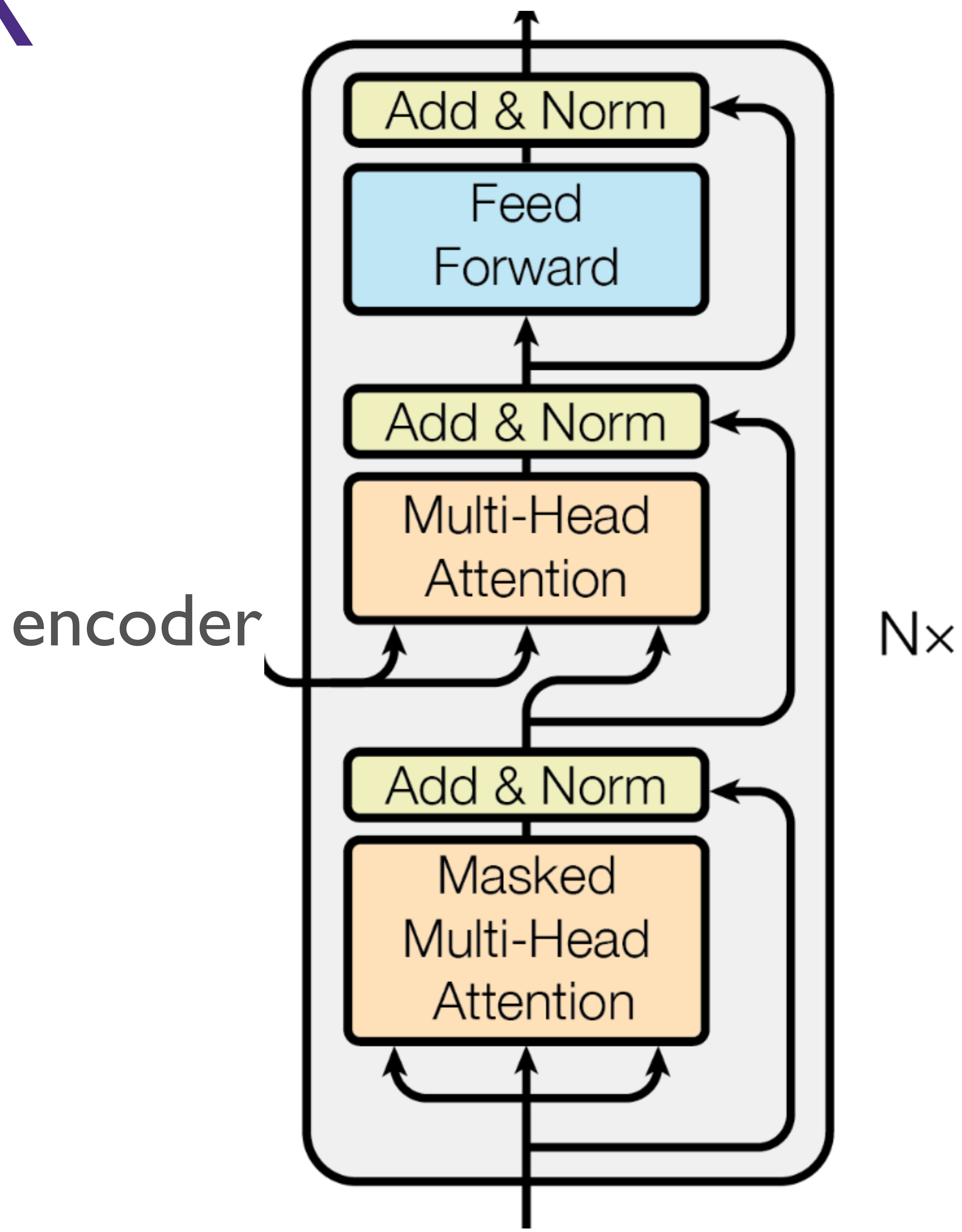
Today's Plan

- Transformer Decoder
  - Attention Masks
- Limitations
  - Quadratic attention
  - Sequential generation
- Subword Tokenization

Transformer Decoder

Decoder Block

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

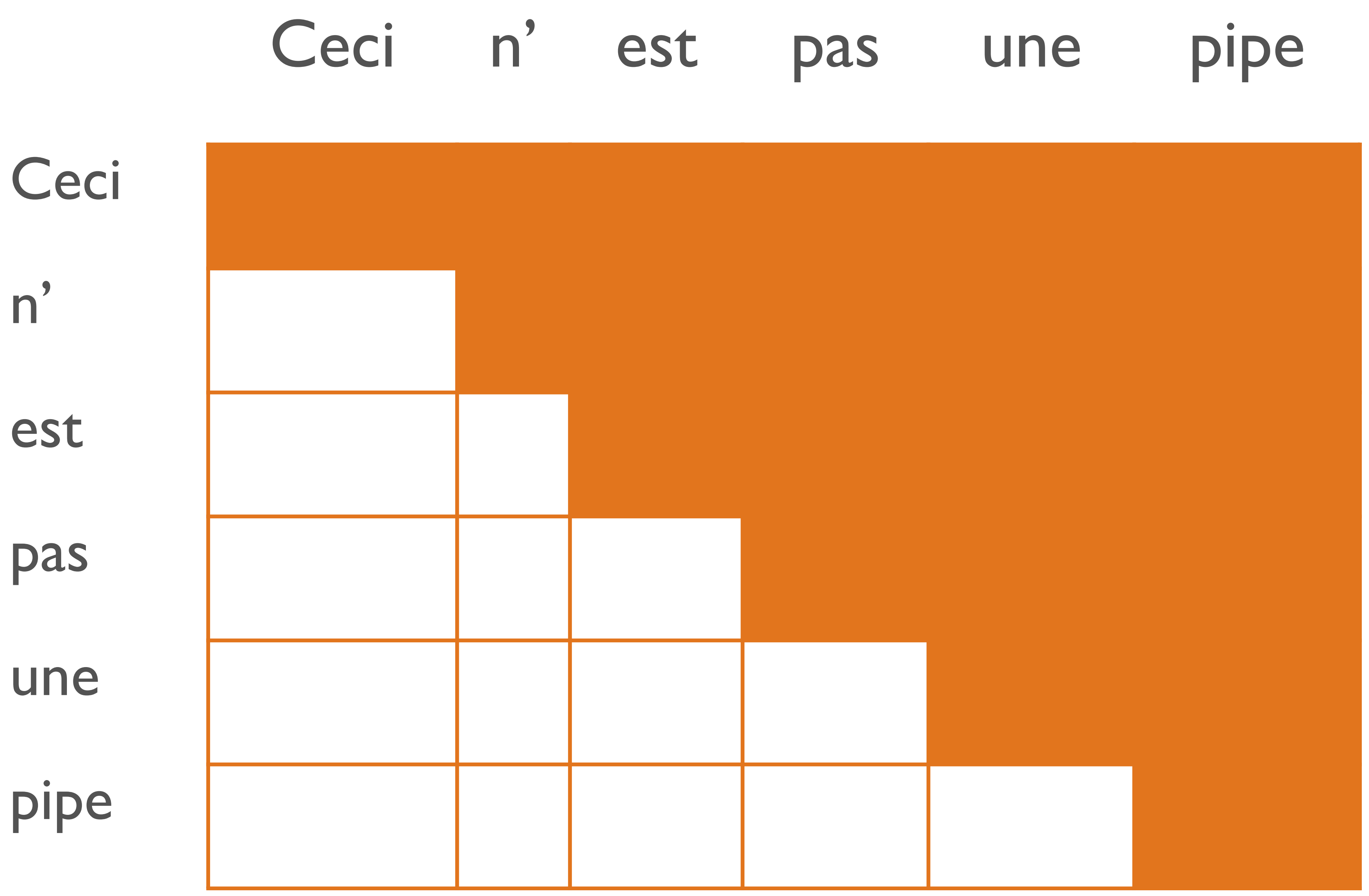


Masked Self-Attention

- 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 pay 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 (as queries) can *not* pay attention to the tokens in the columns (values) that are shaded in



Masking Out the Future

QK^T: total attention scores

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

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

	Ceci	n’	est	pas	une	pipe
Ceci	-inf	-inf	-inf	-inf	-inf	-inf
n’	0	-inf	-inf	-inf	-inf	-inf
est	0	0	-inf	-inf	-inf	-inf
pas	0	0	0	-inf	-inf	-inf
une	0	0	0	0	-inf	-inf
pipe	0	0	0	0	0	-inf

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
  - Q, K, V are generated by applying learned matrices for each head

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?

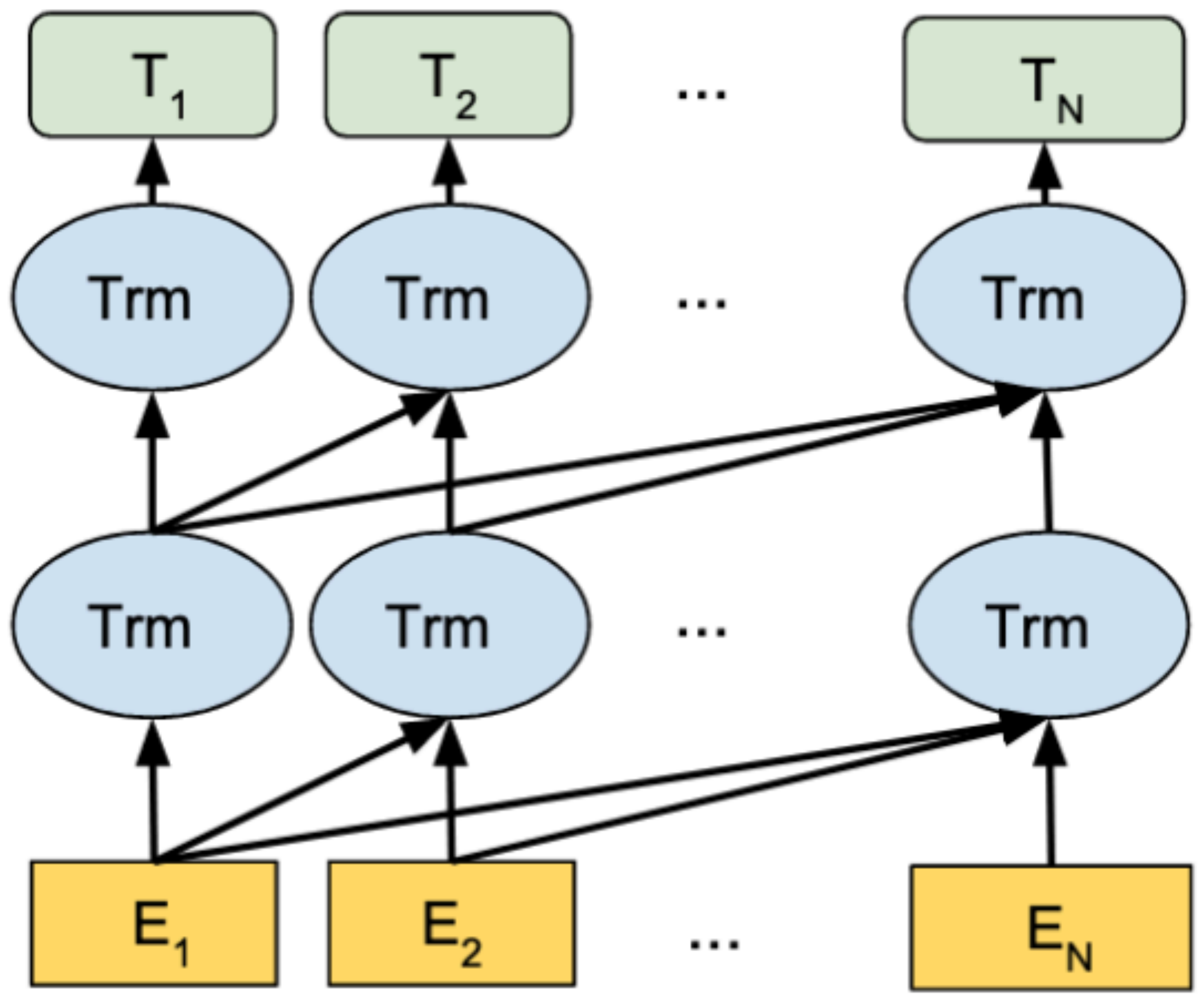
Cross-Attention

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

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

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
- On its own, as a “pure” language model
  - [NB: people now call this “causal language modeling” sometimes]



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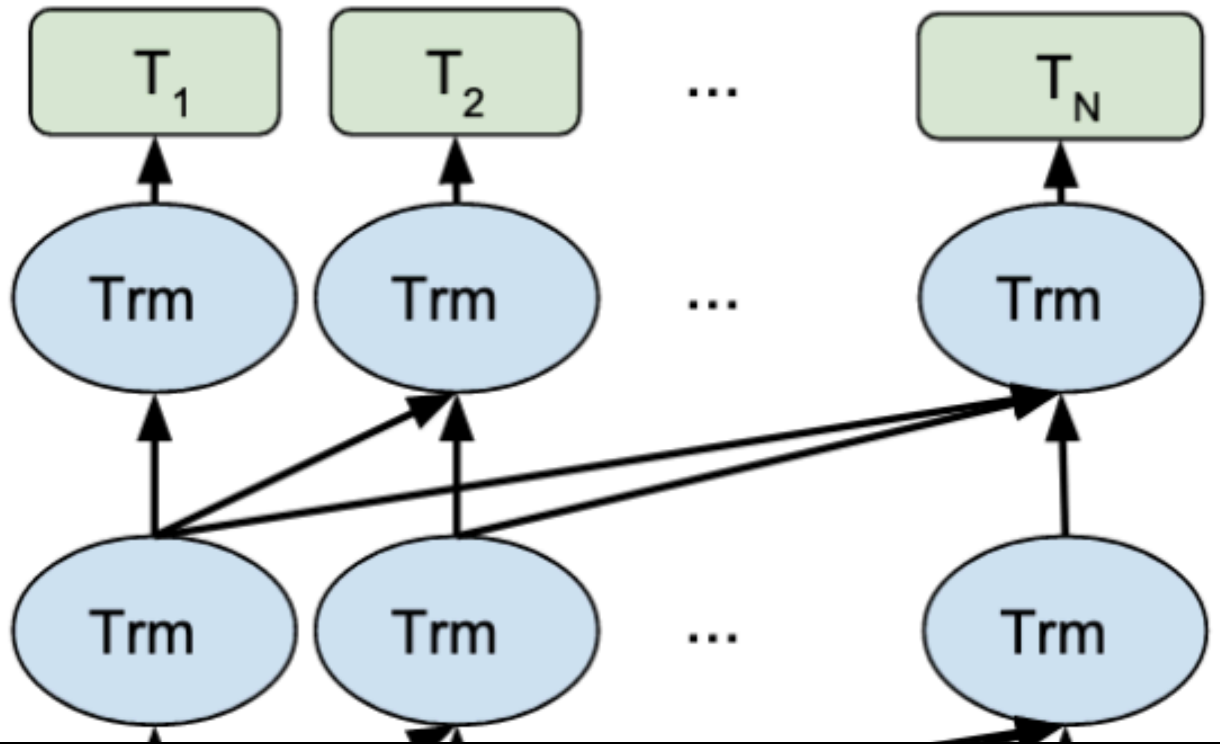

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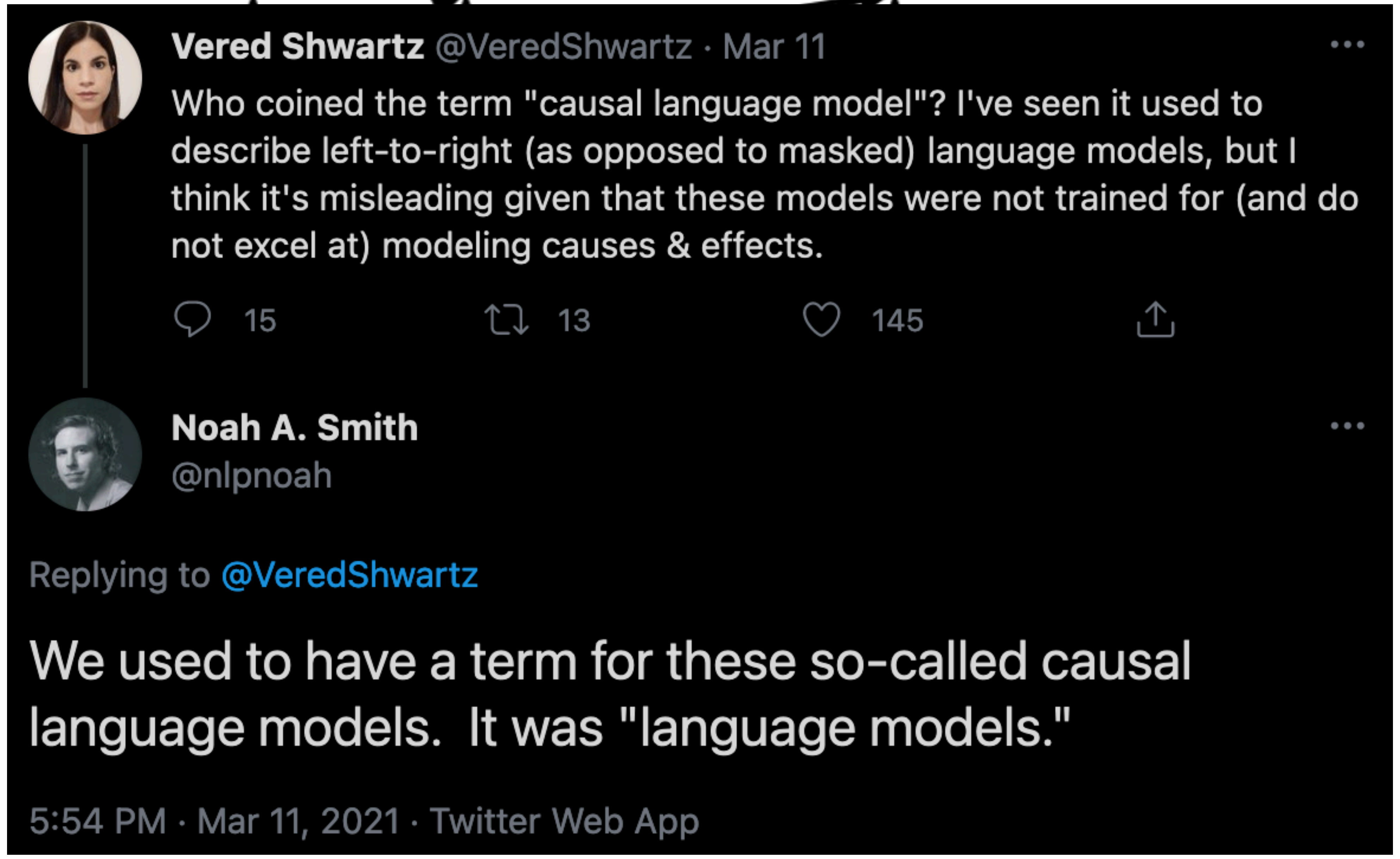


Transformer LM (Decoder-only) Results

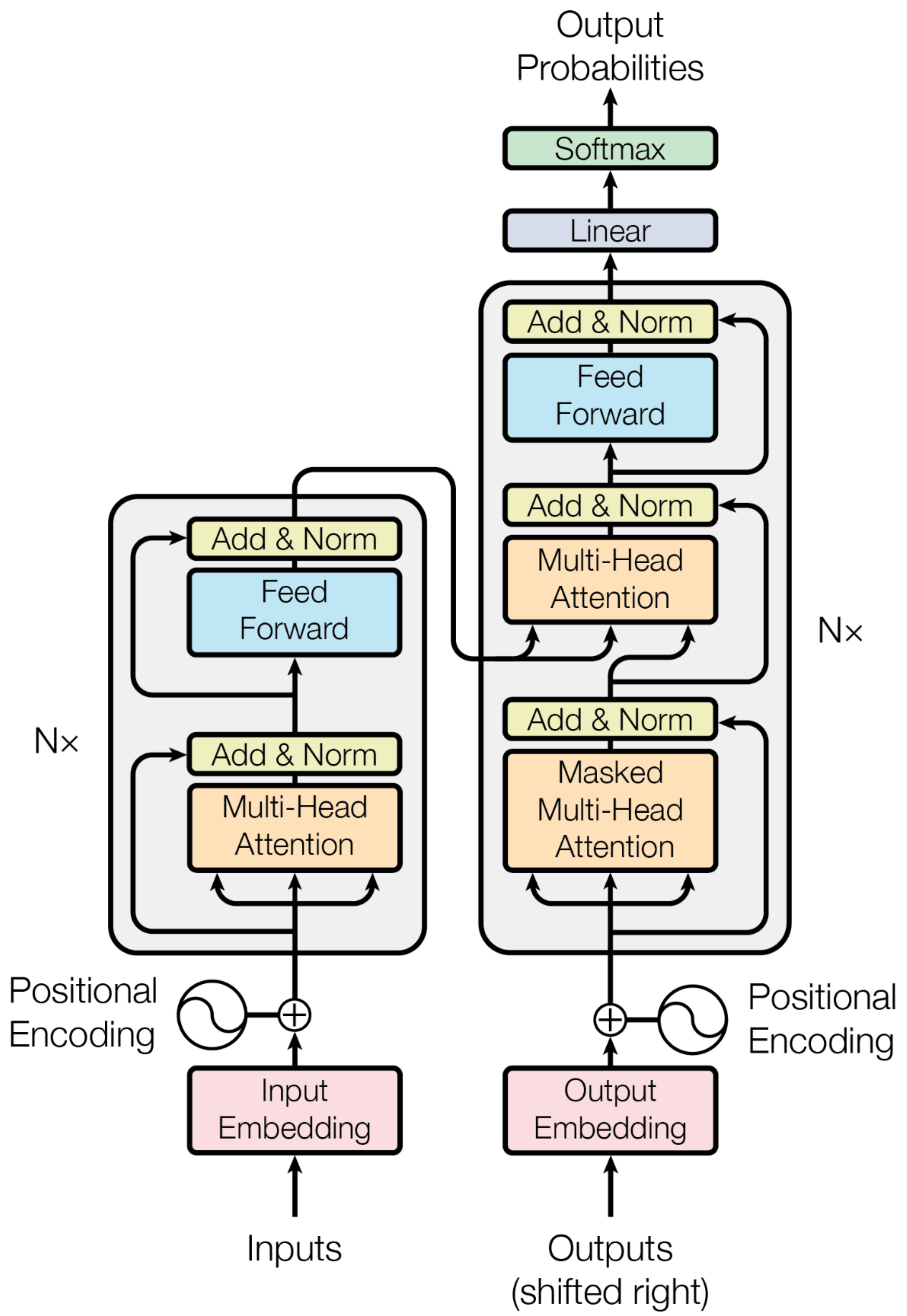
- Character-level:
  - NB: used several auxiliary losses

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

Full Transformer Encoder-Decoder



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

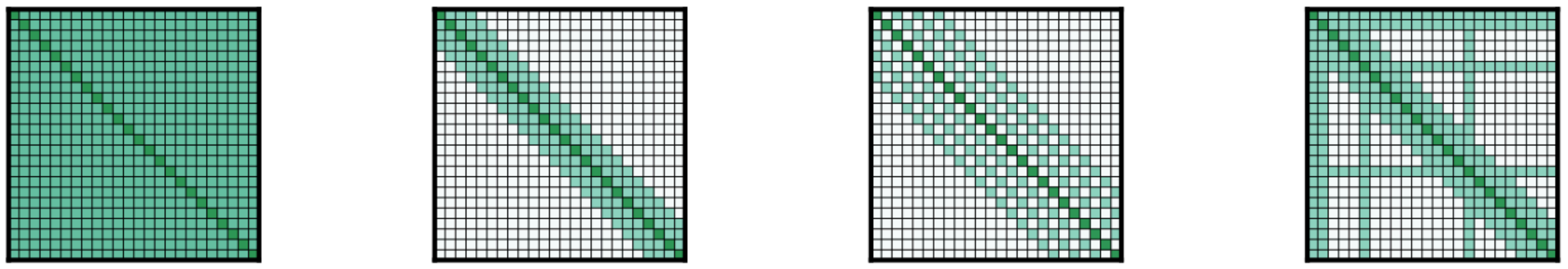
Transformers: Limitations

Quadratic Attention

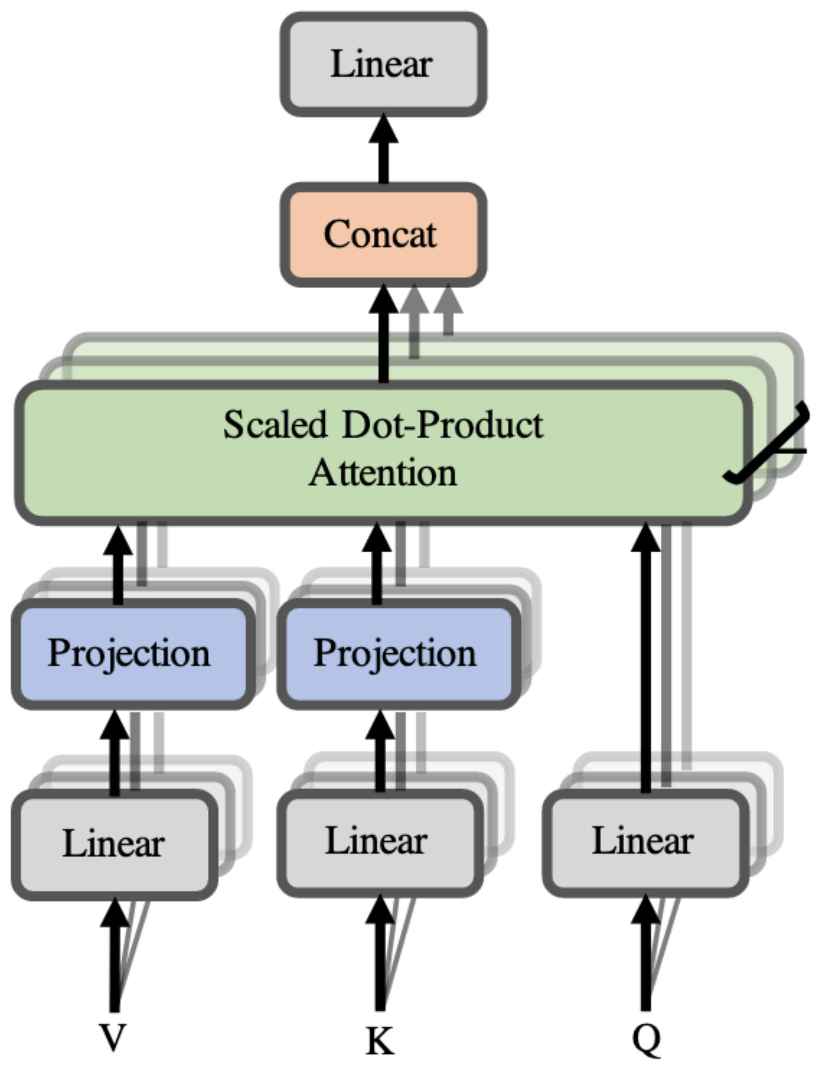
- Attention computes similarity scores between all pairs of tokens
  - QK^T: [seq_len, seq_len] shape
  - In other words, size of attention is $O(n^2)$
- Prevents scaling to *long sequences*
  - Document-level:
    - Summarization
    - QA
    - …
- Big area of current research: linear(-ish) attention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

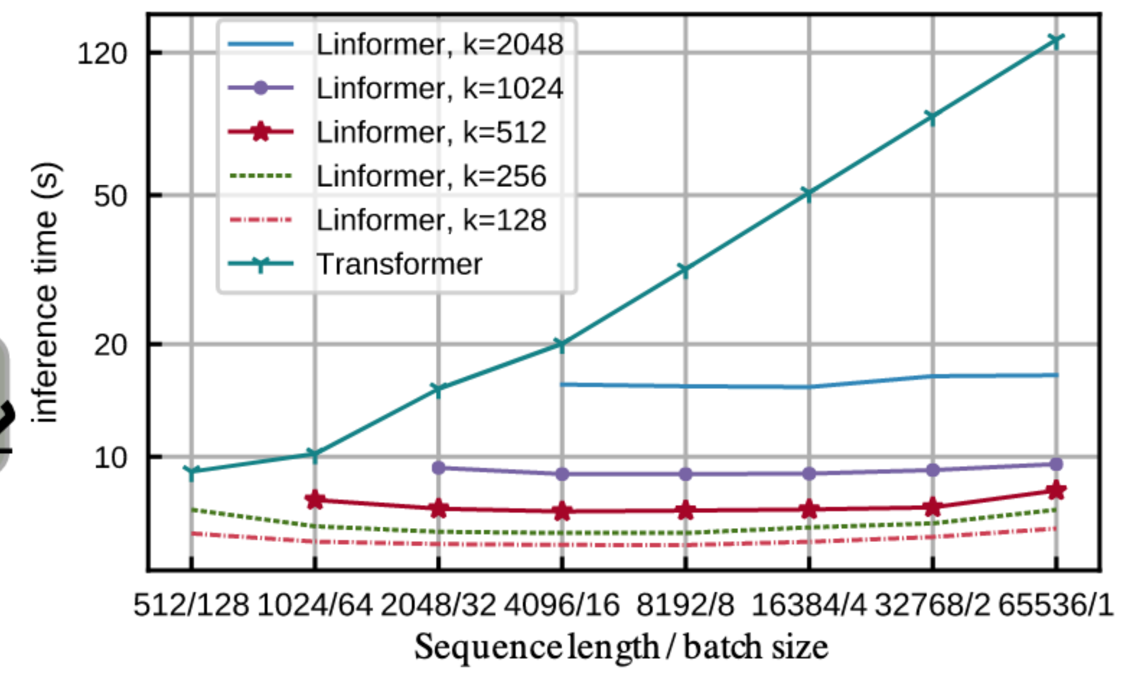
Some Examples

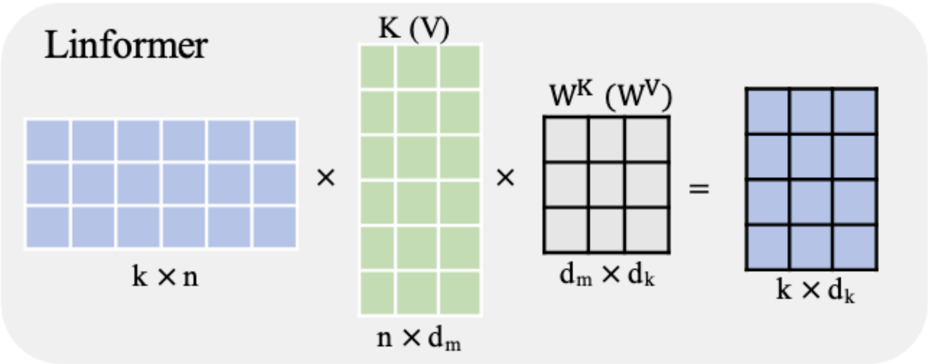
- [Longformer](#):
  - Carefully control positions attended to
- [Linformer](#):
  - Additional projection of Keys/Values to smaller space
  - $O(nk)$, with k a hyper-parameter
- [Survey paper](#)



(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

Encoder	Decoder	En→Fr Test BLEU
Trans. Big	Trans. Big	40.73 ± 0.19
RNMT+	RNMT+	41.00 ± 0.05
Trans. Big	RNMT+	**41.12 ± 0.16**
RNMT+	Trans. Big	39.92 ± 0.21

- Google Translate's newest version
  - "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."

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

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., for BERT: 30k]
  - 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”, “.”]

Next Time

- This wraps up our general overview of the Transformer architecture
- Next time: why they have become so dominant in NLP in the last several years
  - *Pre-training* and fine-tuning paradigm
    - General idea
    - Several examples
- Then: how to interprset/analyze NLP models, followed by a series of special guest lectures