

Natural Language Processing with Deep Learning

CS224N/Ling284



John Hewitt

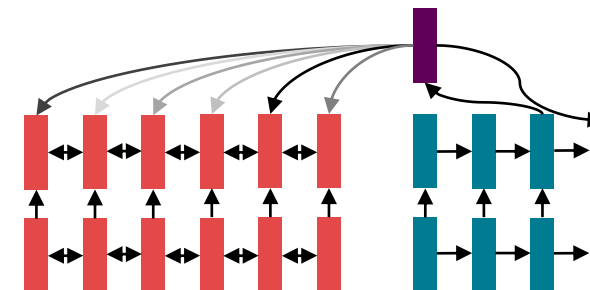
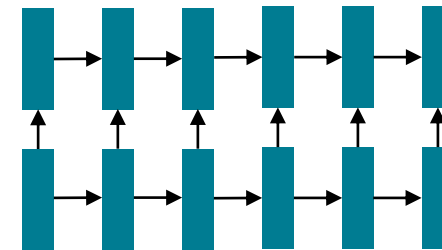
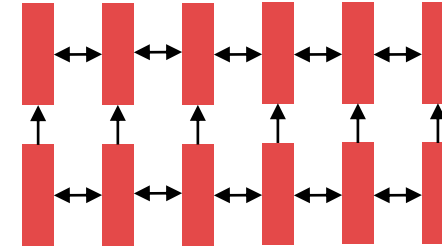
Lecture 9: Self-Attention and Transformers

Lecture Plan

1. From recurrence (RNN) to attention-based NLP models
2. Introducing the Transformer model
3. Great results with Transformers
4. Drawbacks and variants of Transformers

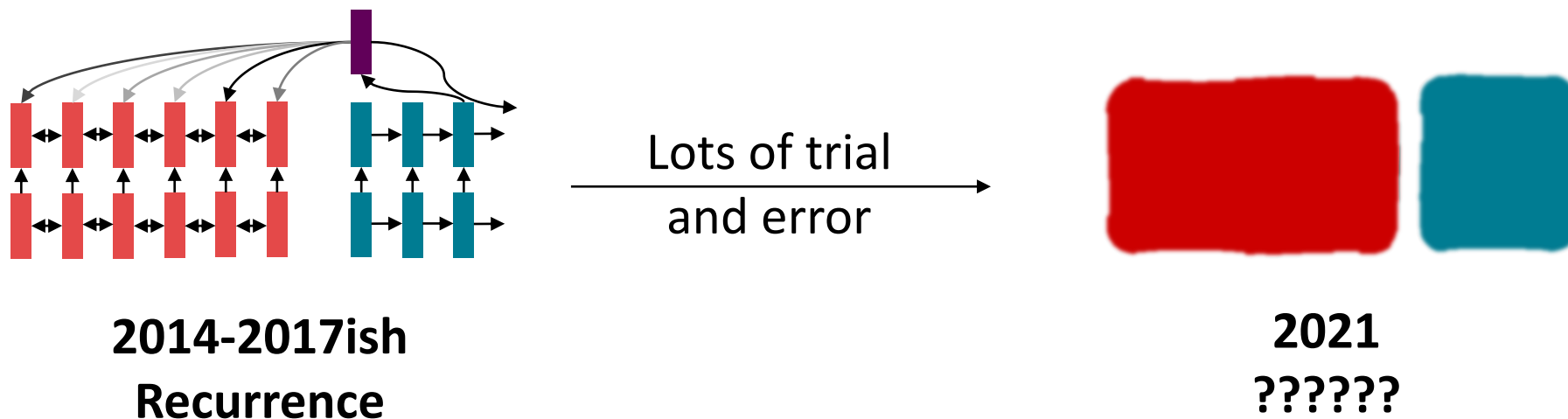
As of last week: recurrent models for (most) NLP!

- Circa 2016, the de facto strategy in NLP is to **encode** sentences with a bidirectional LSTM: (for example, the source sentence in a translation)
- Define your output (parse, sentence, summary) as a sequence, and use an LSTM to generate it.
- Use attention to allow flexible access to memory



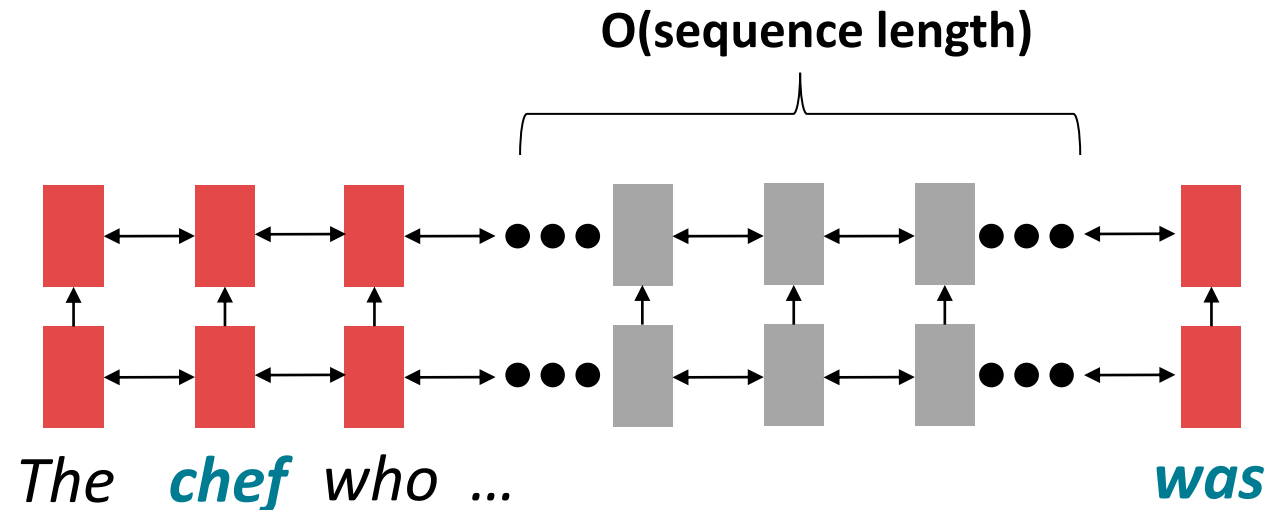
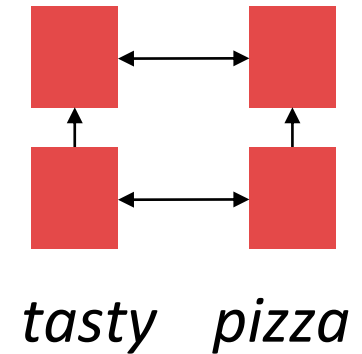
Today: Same goals, different building blocks

- Last week, we learned about sequence-to-sequence problems and encoder-decoder models.
- Today, we're **not** trying to motivate entirely new ways of looking at problems (like Machine Translation)
- Instead, we're trying to find the best **building blocks** to plug into our models and enable broad progress.



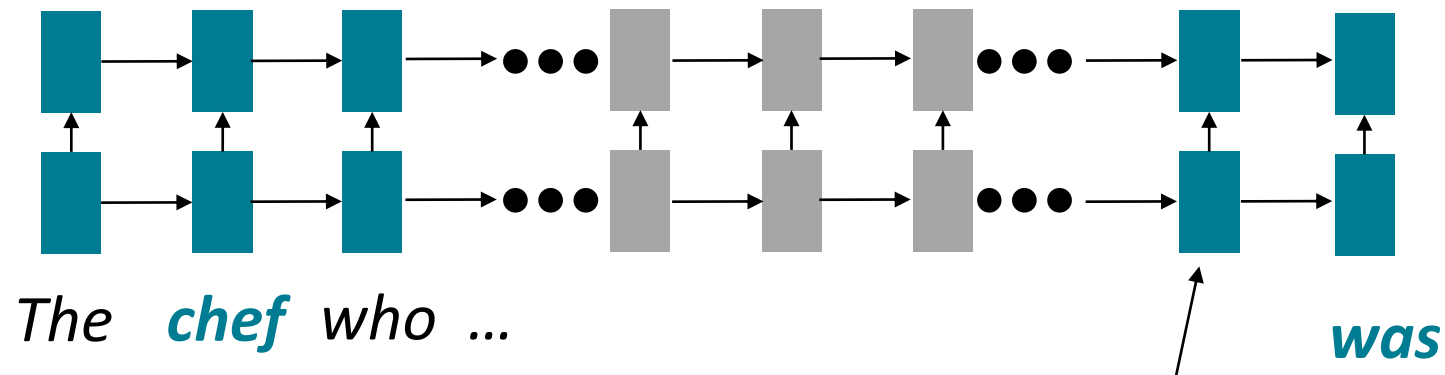
Issues with recurrent models: Linear interaction distance

- RNNs are unrolled “left-to-right”.
- This encodes linear locality: a useful heuristic!
 - Nearby words often affect each other’s meanings
- **Problem:** RNNs take $O(\text{sequence length})$ steps for distant word pairs to interact.



Issues with recurrent models: Linear interaction distance

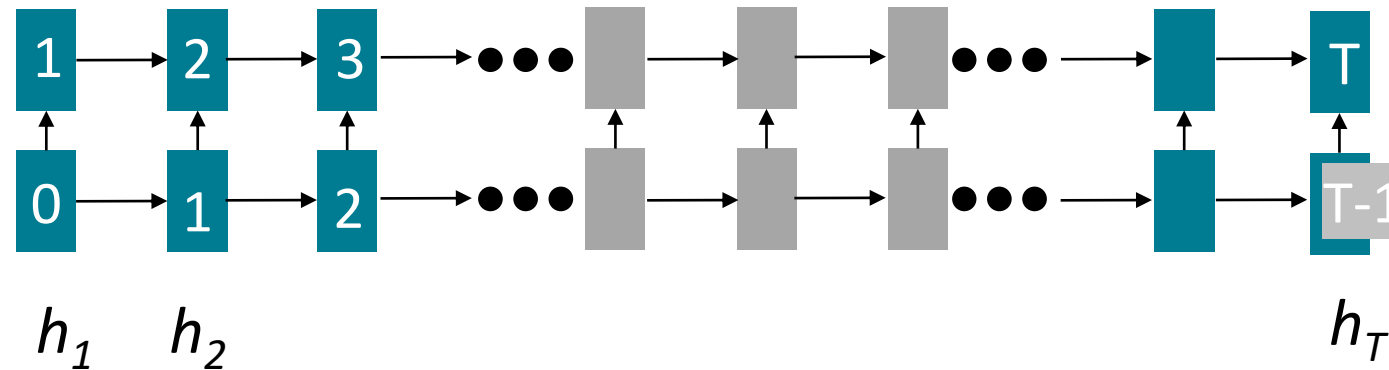
- **$O(\text{sequence length})$** steps for distant word pairs to interact means:
 - Hard to learn long-distance dependencies (because gradient problems!)
 - Linear order of words is “baked in”; we already know linear order isn’t the right way to think about sentences...



Info of *chef* has gone through $O(\text{sequence length})$ many layers!

Issues with recurrent models: Lack of parallelizability

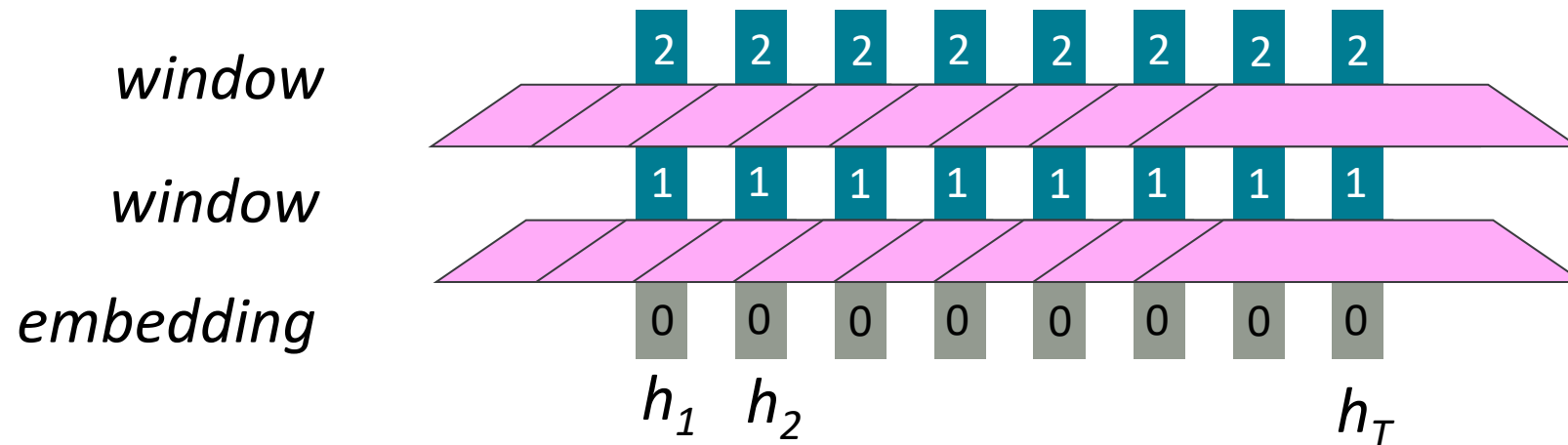
- Forward and backward passes have **$O(\text{sequence length})$** unparallelizable operations
 - GPUs can perform a bunch of independent computations at once!
 - But future RNN hidden states can't be computed in full before past RNN hidden states have been computed
 - Inhibits training on very large datasets!



Numbers indicate min # of steps before a state can be computed

If not recurrence, then what? How about word windows?

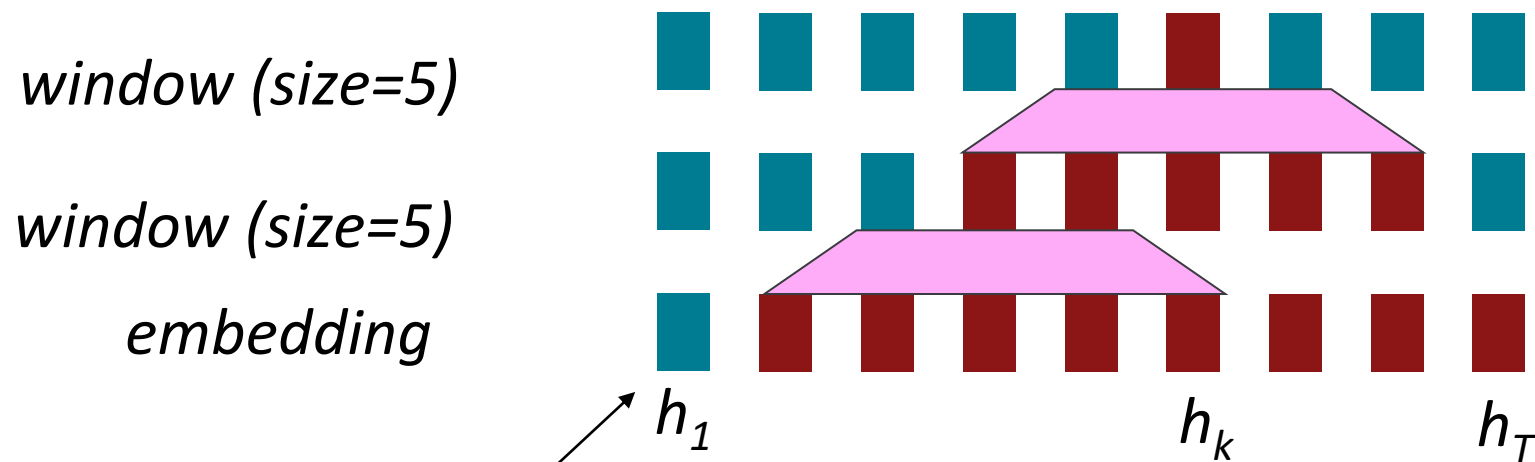
- **Word window models aggregate local contexts**
 - (Also known as 1D convolution; we'll go over this in depth later!)
 - Number of unparallelizable operations does not increase sequence length!



Numbers indicate min # of steps before a state can be computed

If not recurrence, then what? How about word windows?

- **Word window models aggregate local contexts**
- What about long-distance dependencies?
 - Stacking word window layers allows interaction between farther words
- Maximum Interaction distance = **sequence length / window size**
 - (But if your sequences are too long, you'll just ignore long-distance context)

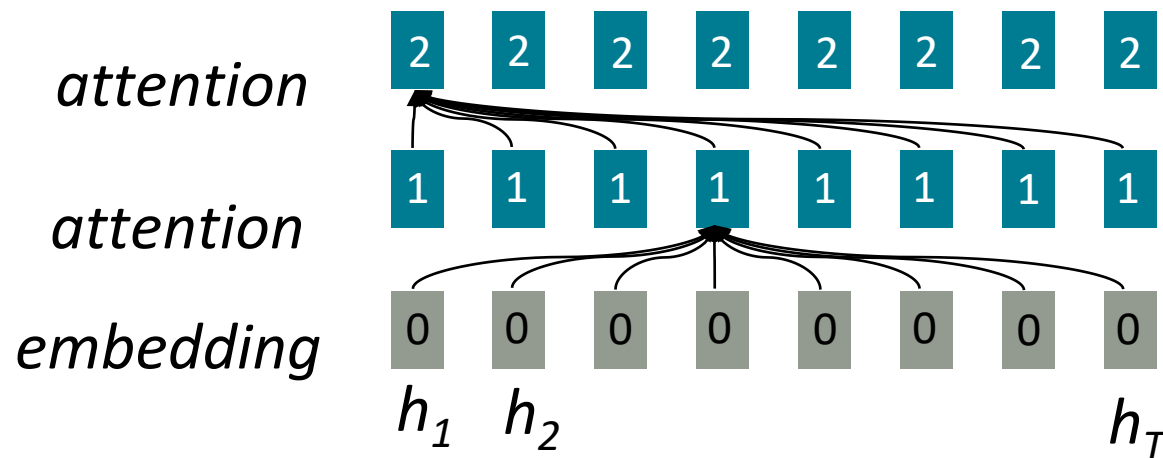


Red states indicate those "visible" to h_k

Too far from h_k to be considered

If not recurrence, then what? How about attention?

- **Attention** treats each word's representation as a **query** to access and incorporate information from **a set of values**.
 - We saw attention from the **decoder** to the **encoder**; today we'll think about attention **within a single sentence**.
- Number of unparallelizable operations does not increase sequence length.
- Maximum interaction distance: $O(1)$, since all words interact at every layer!



All words attend to all words in previous layer; most arrows here are omitted

Self-Attention

- Recall: Attention operates on **queries**, **keys**, and **values**.
 - We have some **queries** q_1, q_2, \dots, q_T . Each query is $q_i \in \mathbb{R}^d$
 - We have some **keys** k_1, k_2, \dots, k_T . Each key is $k_i \in \mathbb{R}^d$
 - We have some **values** v_1, v_2, \dots, v_T . Each value is $v_i \in \mathbb{R}^d$
- In **self-attention**, the queries, keys, and values are drawn from the same source.
 - For example, if the output of the previous layer is x_1, \dots, x_T , (one vec per word) we could let $v_i = k_i = q_i = x_i$ (that is, use the same vectors for all of them!)
- The (dot product) self-attention operation is as follows:

The number of queries can differ from the number of keys and values in practice.

$$e_{ij} = q_i^\top k_j$$

Compute **key-query** affinities

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$

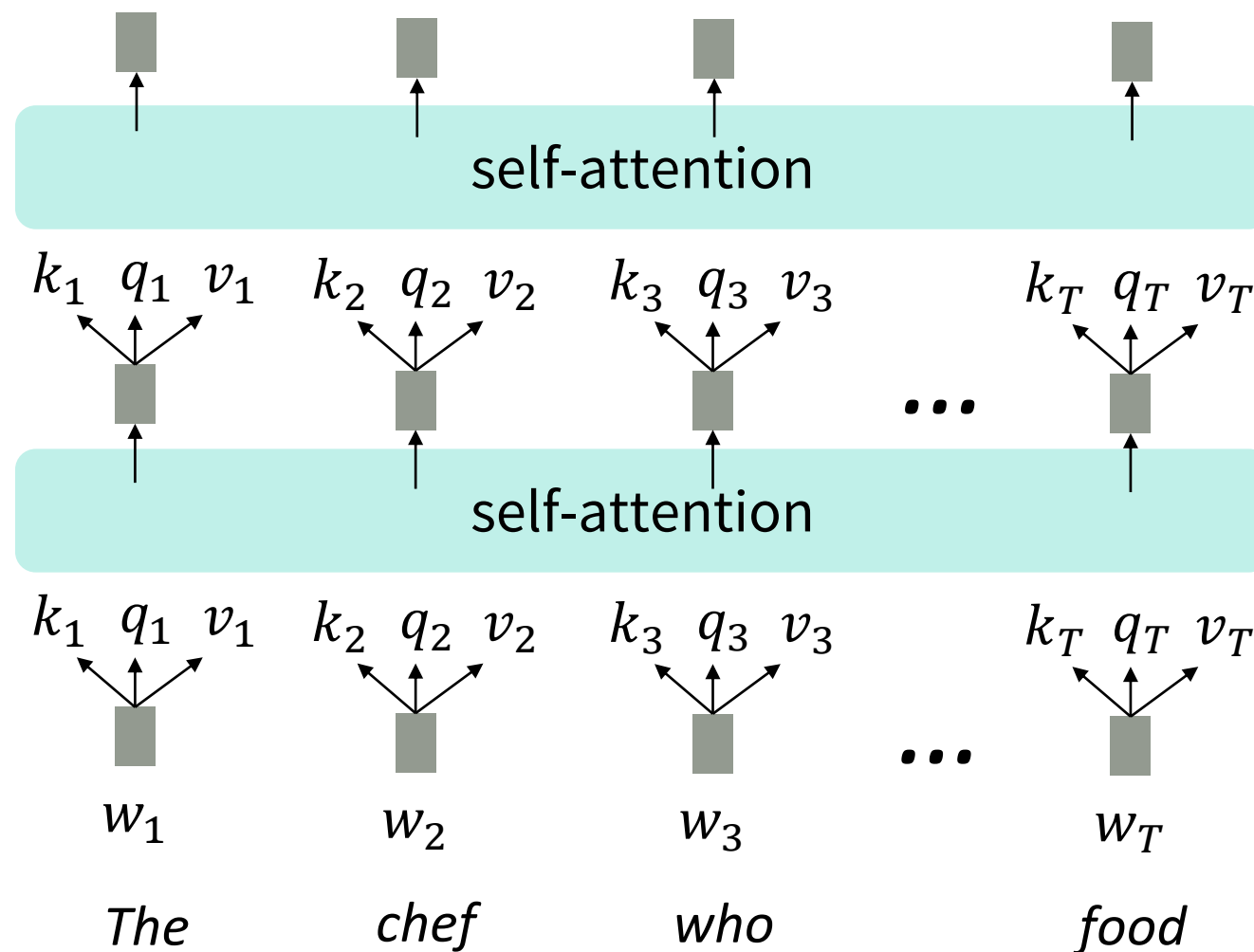
Compute attention weights from affinities (softmax)

$$\text{output}_i = \sum_j \alpha_{ij} v_j$$

Compute outputs as weighted sum of **values**

Self-attention as an NLP building block

- In the diagram at the right, we have stacked self-attention blocks, like we might stack LSTM layers.
- Can self-attention be a drop-in replacement for recurrence?
- No. It has a few issues, which we'll go through.
- First, self-attention is an operation on **sets**. It has no inherent notion of order.



Self-attention doesn't know the order of its inputs.

Barriers and solutions for Self-Attention as a building block

Barriers

- Doesn't have an inherent notion of order!



Solutions

Fixing the first self-attention problem: **sequence order**

- Since self-attention doesn't build in order information, we need to encode the order of the sentence in our keys, queries, and values.
- Consider representing each **sequence index** as a **vector**

$p_i \in \mathbb{R}^d$, for $i \in \{1, 2, \dots, T\}$ are position vectors

- Don't worry about what the p_i are made of yet!
- Easy to incorporate this info into our self-attention block: just add the p_i to our inputs!
- Let $\tilde{v}_i, \tilde{k}_i, \tilde{q}_i$ be our old values, keys, and queries.

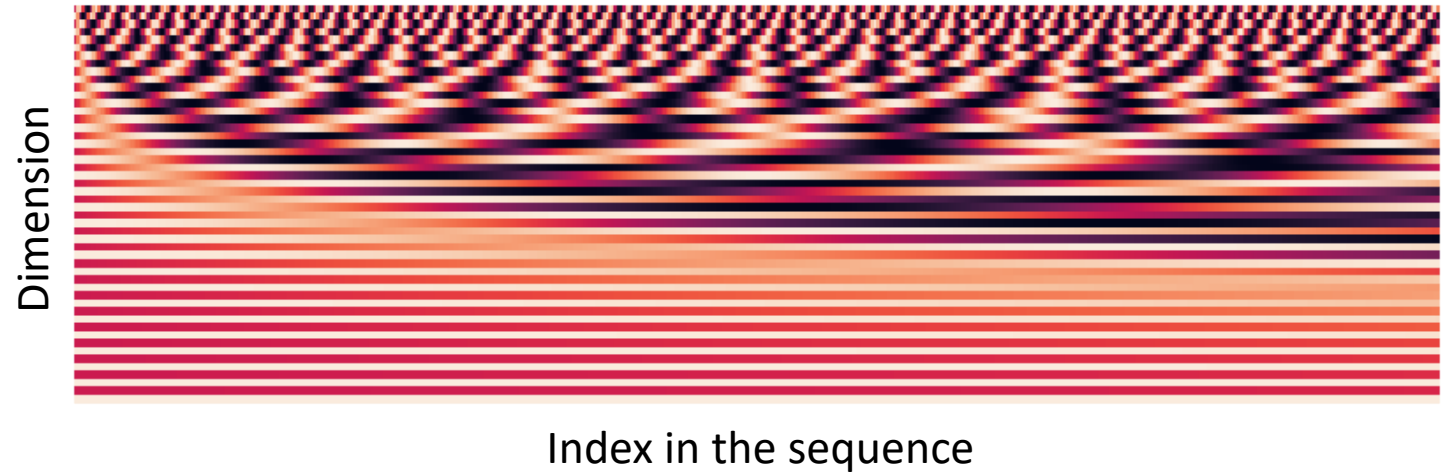
$$\begin{aligned}v_i &= \tilde{v}_i + p_i \\q_i &= \tilde{q}_i + p_i \\k_i &= \tilde{k}_i + p_i\end{aligned}$$

In deep self-attention networks, we do this at the first layer! You could concatenate them as well, but people mostly just add...

Position representation vectors through sinusoids

- **Sinusoidal position representations:** concatenate sinusoidal functions of varying periods:

$$p_i = \begin{pmatrix} \sin(i/10000^{2*1/d}) \\ \cos(i/10000^{2*1/d}) \\ \vdots \\ \sin(i/10000^{2*\frac{d}{2}/d}) \\ \cos(i/10000^{2*\frac{d}{2}/d}) \end{pmatrix}$$



- Pros:
 - Periodicity indicates that maybe “absolute position” isn’t as important
 - Maybe can extrapolate to longer sequences as periods restart!
- Cons:
 - Not learnable; also the extrapolation doesn’t really work!

Position representation vectors learned from scratch

- **Learned absolute position representations:** Let all p_i be learnable parameters!
Learn a matrix $p \in \mathbb{R}^{d \times T}$, and let each p_i be a column of that matrix!
- Pros:
 - Flexibility: each position gets to be learned to fit the data
- Cons:
 - Definitely can't extrapolate to indices outside $1, \dots, T$.
- Most systems use this!
- Sometimes people try more flexible representations of position:
 - Relative linear position attention [\[Shaw et al., 2018\]](#)
 - Dependency syntax-based position [\[Wang et al., 2019\]](#)

Barriers and solutions for Self-Attention as a building block

Barriers

- Doesn't have an inherent notion of order!
- No nonlinearities for deep learning! It's all just weighted averages



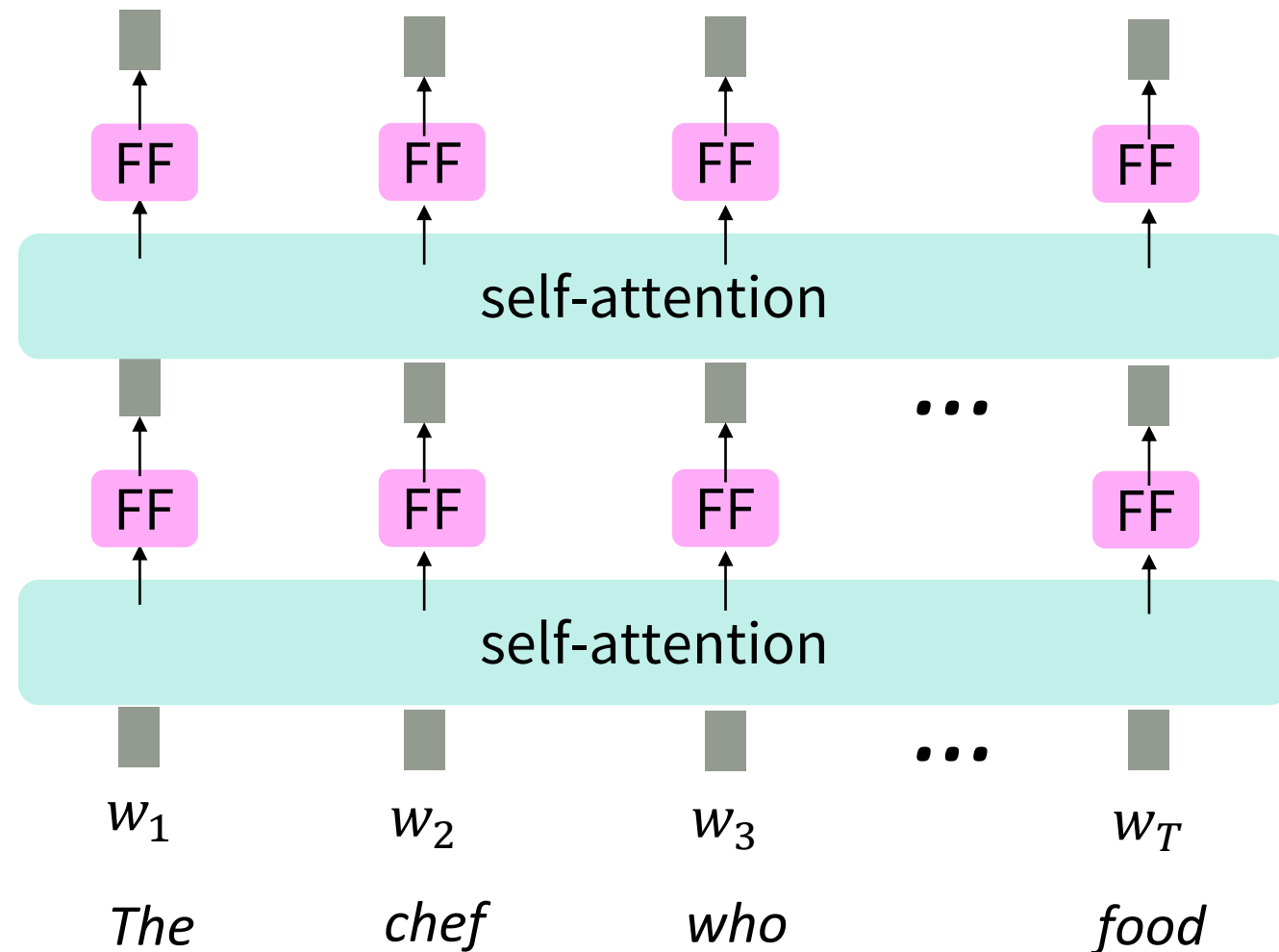
Solutions

- Add position representations to the inputs

Adding nonlinearities in self-attention

- Note that there are no elementwise nonlinearities in self-attention; stacking more self-attention layers just re-averages **value** vectors
- Easy fix: add a **feed-forward network** to post-process each output vector.

$$\begin{aligned} m_i &= MLP(\text{output}_i) \\ &= W_2 * \text{ReLU}(W_1 \times \text{output}_i + b_1) + b_2 \end{aligned}$$



Intuition: the FF network processes the result of attention

Barriers and solutions for Self-Attention as a building block

Barriers

- Doesn't have an inherent notion of order!
- No nonlinearities for deep learning magic! It's all just weighted averages
- Need to ensure we don't "look at the future" when predicting a sequence
 - Like in machine translation
 - Or language modeling



Solutions

- Add position representations to the inputs
- Easy fix: apply the same feedforward network to each self-attention output.

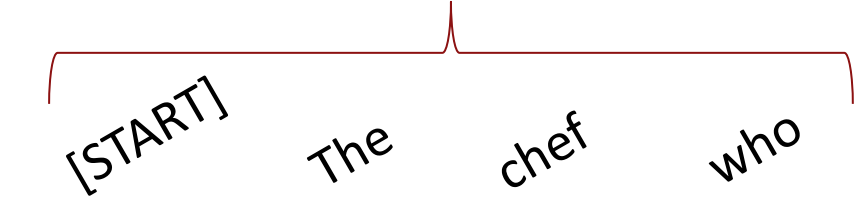
Masking the future in self-attention

- To use self-attention in **decoders**, we need to ensure we can't peek at the future.
- At every timestep, we could change the set of **keys and queries** to include only past words. (Inefficient!)
- To enable parallelization, we **mask out attention** to future words by setting attention scores to $-\infty$.

$$e_{ij} = \begin{cases} q_i^\top k_j, & j < i \\ -\infty, & j \geq i \end{cases}$$

For encoding these words

We can look at these (not greyed out) words



[START]

[The matrix of e_{ij} values]

Masking the future in self-attention

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For encoding these words

We can look at these (not greyed out) words

	[START]	The	chef	who
[START]	$-\infty$	$-\infty$	$-\infty$	$-\infty$
The		$-\infty$	$-\infty$	$-\infty$
chef			$-\infty$	$-\infty$
who				$-\infty$

Barriers and solutions for Self-Attention as a building block

Barriers

- Doesn't have an inherent notion of order!
- No nonlinearities for deep learning magic! It's all just weighted averages
- Need to ensure we don't "look at the future" when predicting a sequence
 - Like in machine translation
 - Or language modeling



Solutions

- Add position representations to the inputs
- Easy fix: apply the same feedforward network to each self-attention output.
- Mask out the future by artificially setting attention weights to 0!

Necessities for a self-attention building block:

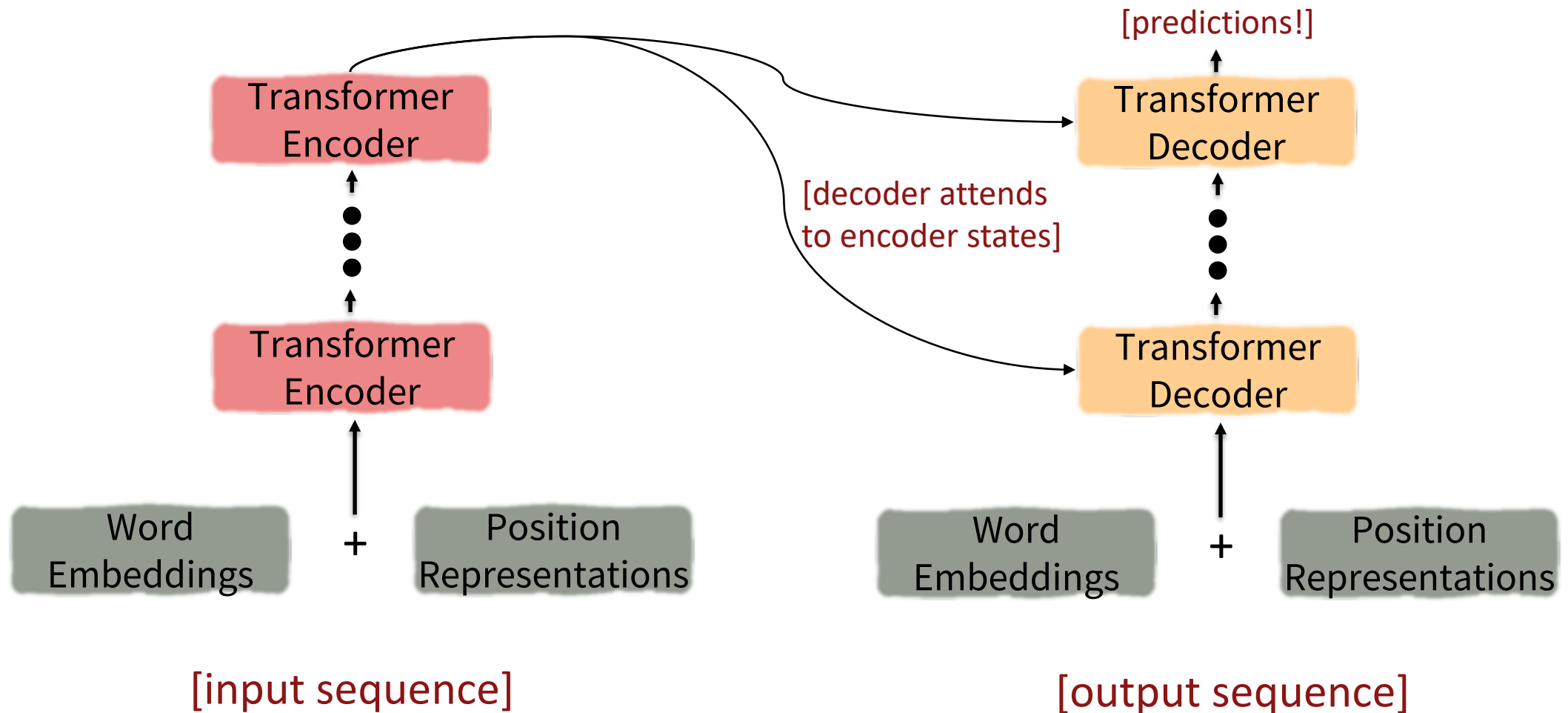
- **Self-attention:**
 - the basis of the method.
- **Position representations:**
 - Specify the sequence order, since self-attention is an unordered function of its inputs.
- **Nonlinearities:**
 - At the output of the self-attention block
 - Frequently implemented as a simple feed-forward network.
- **Masking:**
 - In order to parallelize operations while not looking at the future.
 - Keeps information about the future from “leaking” to the past.
- That’s it! But this is not the **Transformer** model we’ve been hearing about.

Outline

1. From recurrence (RNN) to attention-based NLP models
2. Introducing the Transformer model
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The Transformer Encoder-Decoder [\[Vaswani et al., 2017\]](#)

First, let's look at the Transformer Encoder and Decoder Blocks at a high level



The Transformer Encoder-Decoder [\[Vaswani et al., 2017\]](#)

Next, let's look at the Transformer Encoder and Decoder Blocks

What's left in a Transformer Encoder Block that we haven't covered?

1. **Key-query-value attention:** How do we get the k, q, v vectors from a single word embedding?
2. **Multi-headed attention:** Attend to multiple places in a single layer!
3. **Tricks to help with training!**
 1. Residual connections
 2. Layer normalization
 3. Scaling the dot product
 4. These tricks **don't improve** what the model is able to do; they help improve the training process. Both of these types of modeling improvements are very important!

The Transformer Encoder: Key-Query-Value Attention

- We saw that self-attention is when keys, queries, and values come from the same source. The Transformer does this in a particular way:
 - Let x_1, \dots, x_T be input vectors to the Transformer encoder; $x_i \in \mathbb{R}^d$
- Then keys, queries, values are:
 - $k_i = Kx_i$, where $K \in \mathbb{R}^{d \times d}$ is the key matrix.
 - $q_i = Qx_i$, where $Q \in \mathbb{R}^{d \times d}$ is the query matrix.
 - $v_i = Vx_i$, where $V \in \mathbb{R}^{d \times d}$ is the value matrix.
- These matrices allow *different aspects* of the x vectors to be used/emphasized in each of the three roles.

The Transformer Encoder: Key-Query-Value Attention

- Let's look at how key-query-value attention is computed, in matrices.
 - Let $X = [x_1; \dots; x_T] \in \mathbb{R}^{T \times d}$ be the concatenation of input vectors.
 - First, note that $XK \in \mathbb{R}^{T \times d}$, $XQ \in \mathbb{R}^{T \times d}$, $XV \in \mathbb{R}^{T \times d}$.
 - The output is defined as $\text{output} = \text{softmax}(XQ(XK)^T) \times XV$.

First, take the query-key dot products in one matrix multiplication: $XQ(XK)^T$

A diagram illustrating the first step of the attention mechanism. It shows a vertical pink box labeled XQ multiplied by a horizontal pink box labeled $K^T X^T$. The result is a larger square pink box labeled $XQK^T X^T$, which is then followed by $\in \mathbb{R}^{T \times T}$. To the right of this equation, the text "All pairs of attention scores!" is written in blue.

$$XQ \cdot K^T X^T = XQK^T X^T \in \mathbb{R}^{T \times T}$$

All pairs of attention scores!

Next, softmax, and compute the weighted average with another matrix multiplication.

A diagram illustrating the second step of the attention mechanism. It shows the expression $\text{softmax} \left(XQK^T X^T \right)$ in a large pink box, followed by a vertical pink box labeled XV , and an equals sign followed by an empty vertical pink box representing the output. Below the empty box is the text "output $\in \mathbb{R}^{T \times d}$ ". A curved arrow points from the $XQK^T X^T$ box in the equation above to the $XQK^T X^T$ box in this equation.

$$\text{softmax} \left(XQK^T X^T \right) \cdot XV = \text{output} \in \mathbb{R}^{T \times d}$$

The Transformer Encoder: **Multi-headed attention**

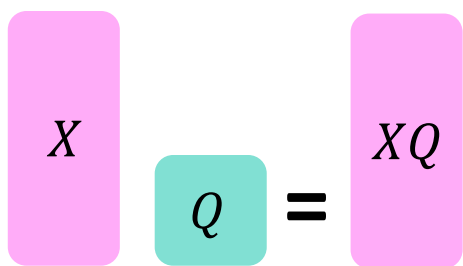
- What if we want to look in multiple places in the sentence at once?
 - For word i , self-attention “looks” where $x_i^\top Q^\top K x_j$ is high, but maybe we want to focus on different j for different reasons?
- We’ll define **multiple attention “heads”** through multiple Q,K,V matrices
- Let, $Q_\ell, K_\ell, V_\ell \in \mathbb{R}^{d \times \frac{d}{h}}$, where h is the number of attention heads, and ℓ ranges from 1 to h .
- Each attention head performs attention independently:
 - $\text{output}_\ell = \text{softmax}(X Q_\ell K_\ell^\top X^\top) * X V_\ell$, where $\text{output}_\ell \in \mathbb{R}^{d/h}$
- Then the outputs of all the heads are combined!
 - $\text{output} = Y[\text{output}_1; \dots; \text{output}_h]$, where $Y \in \mathbb{R}^{d \times d}$
- Each head gets to “look” at different things, and construct value vectors differently.

The Transformer Encoder: **Multi-headed attention**

- What if we want to look in multiple places in the sentence at once?
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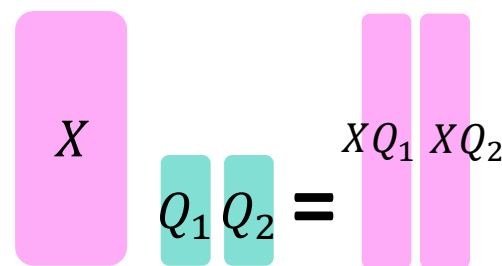
Single-head attention

(just the query matrix)



Multi-head attention

(just two heads here)



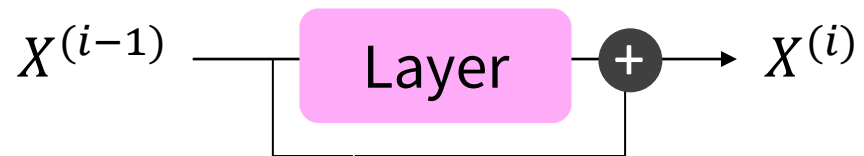
Same amount of computation as single-head self-attention!

The Transformer Encoder: **Residual connections** [[He et al., 2016](#)]

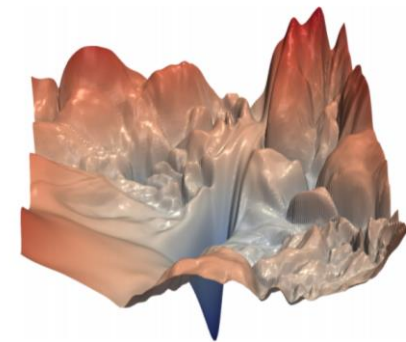
- **Residual connections** are a trick to help models train better.
 - Instead of $X^{(i)} = \text{Layer}(X^{(i-1)})$ (where i represents the layer)



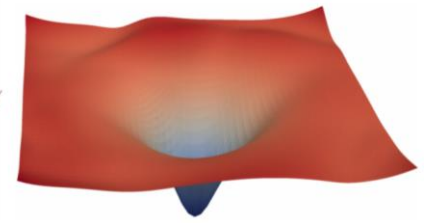
- We let $X^{(i)} = X^{(i-1)} + \text{Layer}(X^{(i-1)})$ (so we only have to learn “the residual” from the previous layer)



- Residual connections are thought to make the loss landscape considerably smoother (thus easier training!)



[no residuals]



[residuals]

[Loss landscape visualization,
[Li et al., 2018](#), on a ResNet]

The Transformer Encoder: **Layer normalization** [[Ba et al., 2016](#)]

- **Layer normalization** is a trick to help models train faster.
- Idea: cut down on uninformative variation in hidden vector values by normalizing to unit mean and standard deviation **within each layer**.
 - LayerNorm's success may be due to its normalizing gradients [[Xu et al., 2019](#)]
- Let $x \in \mathbb{R}^d$ be an individual (word) vector in the model.
- Let $\mu = \sum_{j=1}^d x_j$; this is the mean; $\mu \in \mathbb{R}$.
- Let $\sigma = \sqrt{\frac{1}{d} \sum_{j=1}^d (x_j - \mu)^2}$; this is the standard deviation; $\sigma \in \mathbb{R}$.
- Let $\gamma \in \mathbb{R}^d$ and $\beta \in \mathbb{R}^d$ be learned “gain” and “bias” parameters. (Can omit!)
- Then layer normalization computes:

Normalize by scalar
mean and variance

$$\text{output} = \frac{x - \mu}{\sigma + \epsilon}$$

The Transformer Encoder: **Layer normalization** [[Ba et al., 2016](#)]

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- Let $\mu = \sum_{j=1}^d x_j$; this is the mean; $\mu \in \mathbb{R}$.
- Let $\sigma = \sqrt{\frac{1}{d} \sum_{j=1}^d (x_j - \mu)^2}$; this is the standard deviation; $\sigma \in \mathbb{R}$.
- Let $\gamma \in \mathbb{R}^d$ and $\beta \in \mathbb{R}^d$ be learned “gain” and “bias” parameters. (Can omit!)
- Then layer normalization computes:

$$\text{output} = \frac{x - \mu}{\sigma + \epsilon} * \gamma + \beta$$

Normalize by scalar mean and variance

Modulate by learned elementwise gain and bias

The Transformer Encoder: **Scaled Dot Product** [Vaswani et al., 2017]

- **“Scaled Dot Product”** attention is a final variation to aid in Transformer training.
- When dimensionality d becomes large, dot products between vectors tend to become large.
 - Because of this, inputs to the softmax function can be large, making the gradients small.

- Instead of the self-attention function we’ve seen:

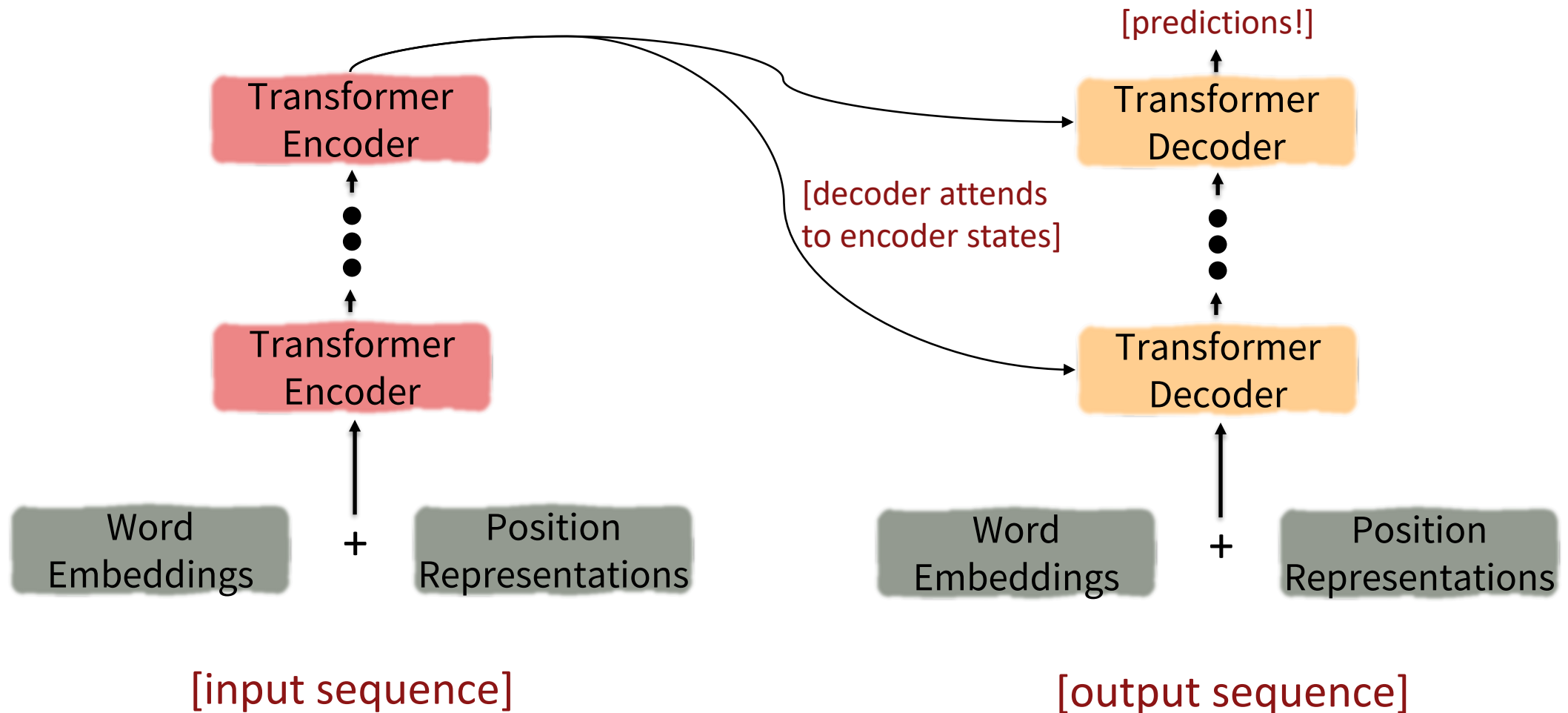
$$\text{output}_\ell = \text{softmax}(XQ_\ell K_\ell^\top X^\top) * XV_\ell$$

- We divide the attention scores by $\sqrt{d/h}$, to stop the scores from becoming large just as a function of d/h (The dimensionality divided by the number of heads.)

$$\text{output}_\ell = \text{softmax}\left(\frac{XQ_\ell K_\ell^\top X^\top}{\sqrt{d/h}}\right) * XV_\ell$$

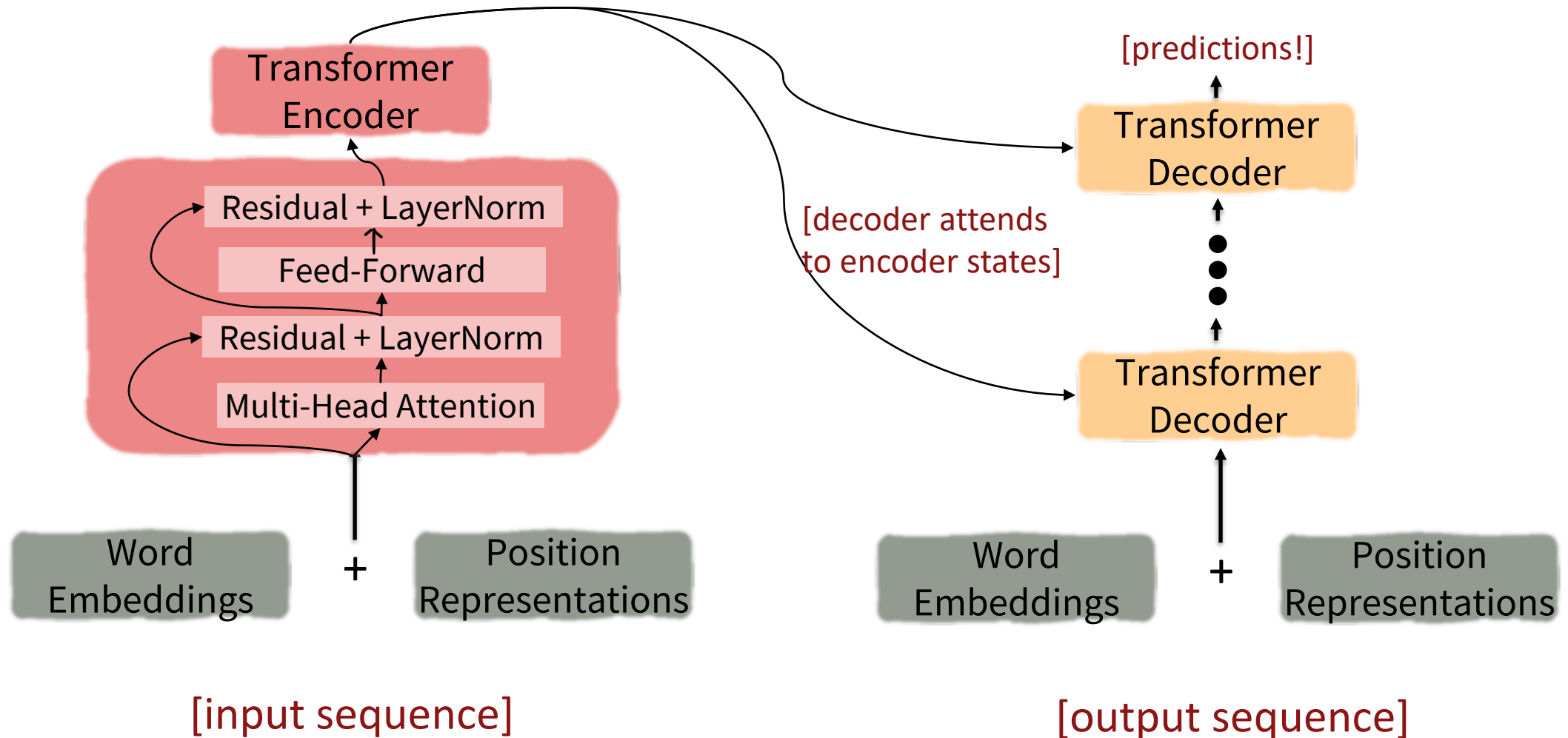
The Transformer Encoder-Decoder [\[Vaswani et al., 2017\]](#)

Looking back at the whole model, zooming in on an Encoder block:



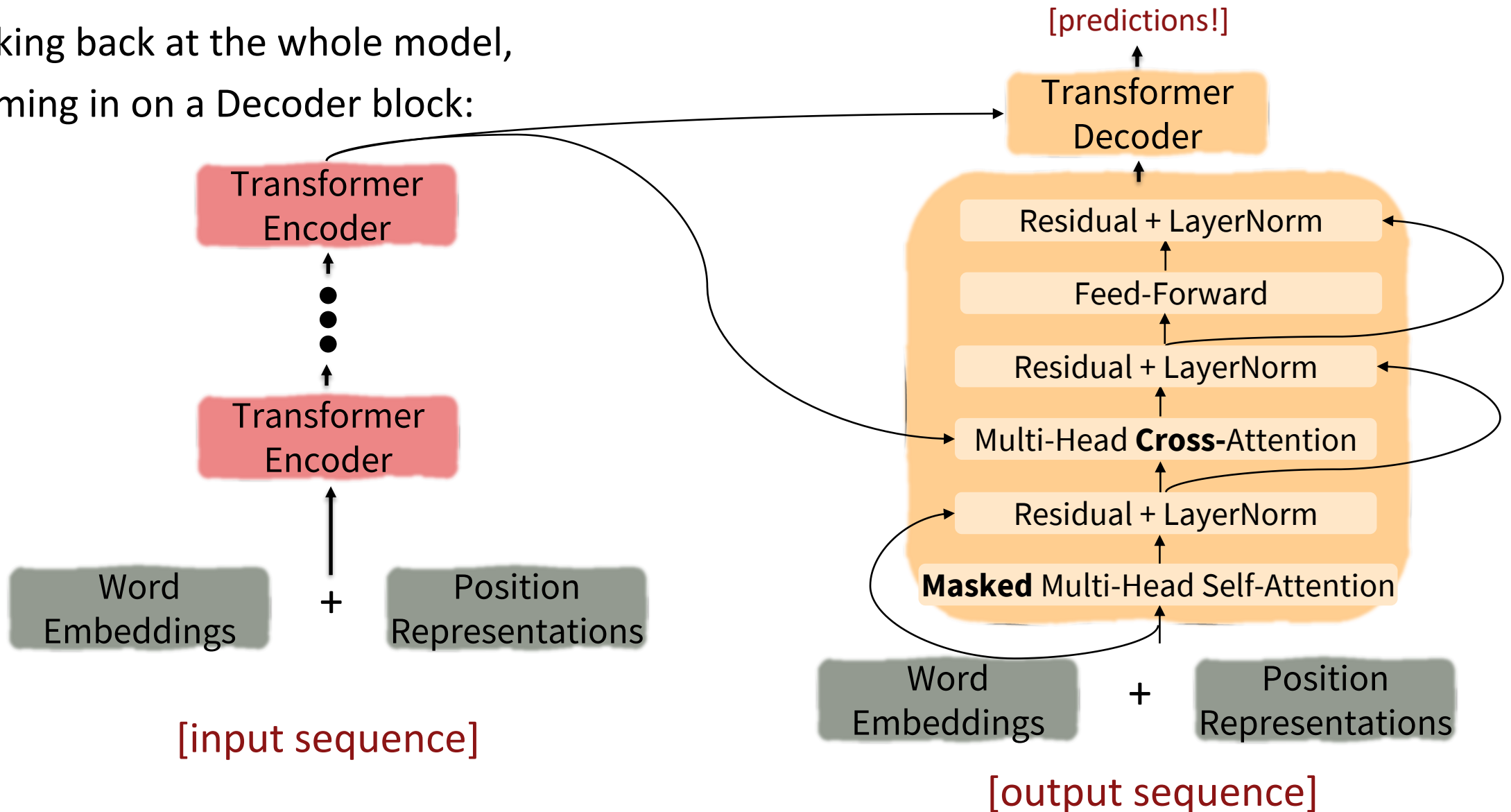
The Transformer Encoder-Decoder [Vaswani et al., 2017]

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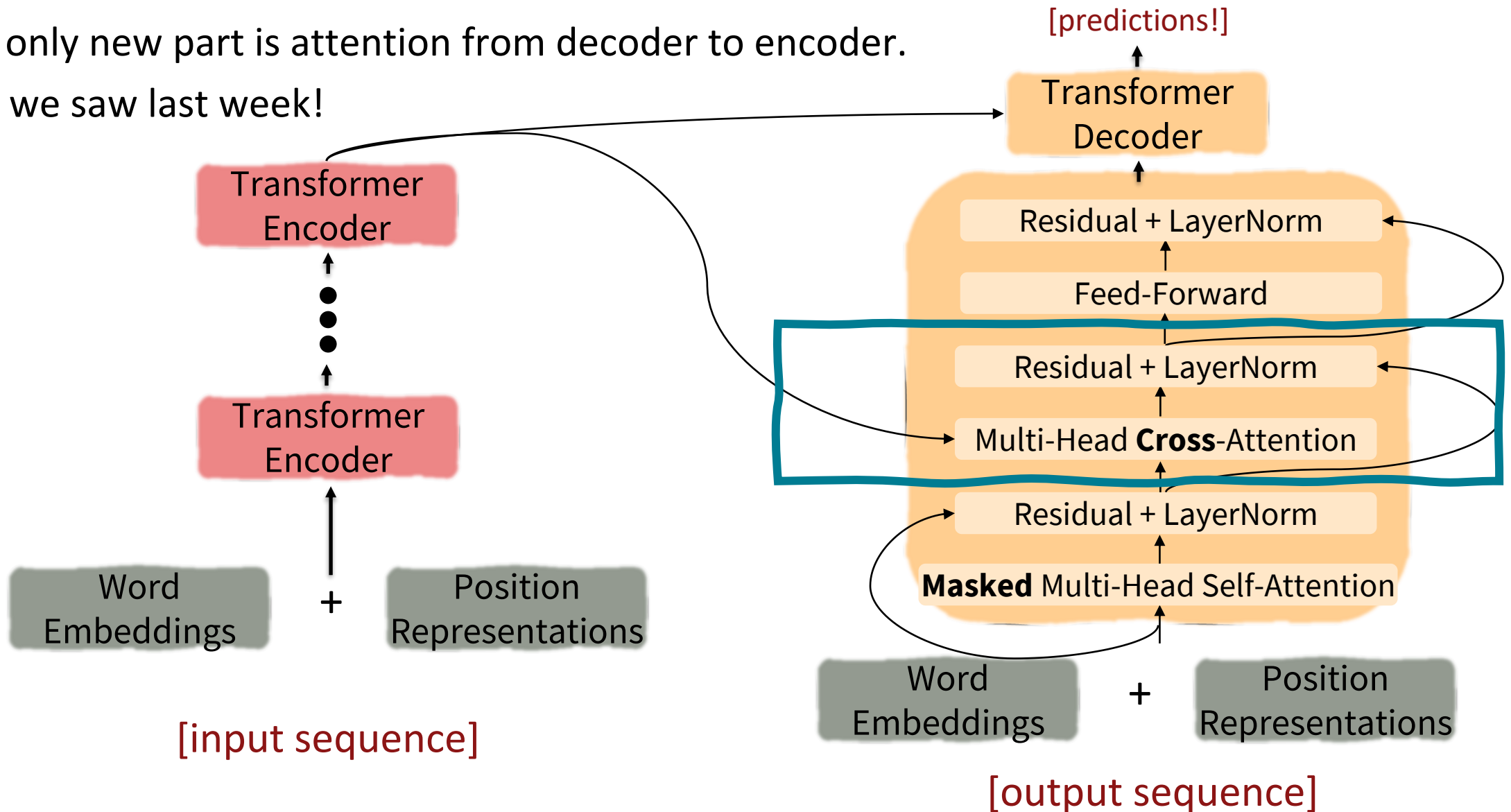
The Transformer Encoder-Decoder [Vaswani et al., 2017]

Looking back at the whole model,
zooming in on a Decoder block:



The Transformer Encoder-Decoder [Vaswani et al., 2017]

The only new part is attention from decoder to encoder.
Like we saw last week!



The Transformer Decoder: Cross-attention (details)

- We saw that self-attention is when keys, queries, and values come from the same source.
- In the decoder, we have attention that looks more like what we saw last week.
- Let h_1, \dots, h_T be **output** vectors **from** the Transformer **encoder**; $x_i \in \mathbb{R}^d$
- Let z_1, \dots, z_T be input vectors from the Transformer **decoder**, $z_i \in \mathbb{R}^d$
- Then keys and values are drawn from the **encoder** (like a memory):
 - $k_i = Kh_i, v_i = Vh_i$.
- And the queries are drawn from the **decoder**, $q_i = Qz_i$.

The Transformer Encoder: Cross-attention (details)

- Let's look at how cross-attention is computed, in matrices.
 - Let $H = [h_1; \dots; h_T] \in \mathbb{R}^{T \times d}$ be the concatenation of encoder vectors.
 - Let $Z = [z_1; \dots; z_T] \in \mathbb{R}^{T \times d}$ be the concatenation of decoder vectors.
 - The output is defined as $\text{output} = \text{softmax}(ZQ(HK)^\top) \times HV$.

First, take the query-key dot products in one matrix multiplication: $ZQ(HK)^\top$

$$ZQ \quad K^\top H^\top = ZQK^\top H^\top \in \mathbb{R}^{T \times T}$$

All pairs of attention scores!

Next, softmax, and compute the weighted average with another matrix multiplication.

$$\text{softmax} \left(ZQK^\top H^\top \right) HV = \text{output} \in \mathbb{R}^{T \times d}$$

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Great Results with Transformers

First, Machine Translation from the original Transformers paper!

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	41.29	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$

Great Results with Transformers

Next, document generation!

Model	Test perplexity	ROUGE-L
<i>seq2seq-attention, $L = 500$</i>	5.04952	12.7
<i>Transformer-ED, $L = 500$</i>	2.46645	34.2
<i>Transformer-D, $L = 4000$</i>	2.22216	33.6
<i>Transformer-DMCA, no MoE-layer, $L = 11000$</i>	2.05159	36.2
<i>Transformer-DMCA, MoE-128, $L = 11000$</i>	1.92871	37.9
<i>Transformer-DMCA, MoE-256, $L = 7500$</i>	1.90325	38.8

The old standard



Transformers all the way down.



Great Results with Transformers

Before too long, most Transformers results also included **pretraining**, a method we'll go over on Thursday.

Transformers' parallelizability allows for efficient pretraining, and have made them the de-facto standard.

On this popular aggregate benchmark, for example:



All top models are Transformer (and pretraining)-based.

Rank Name		Model	URL	Score
1	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4	↗	90.8
2	HFL iFLYTEK	MacALBERT + DKM		90.7
+ 3	Alibaba DAMO NLP	StructBERT + TAPT	↗	90.6
+ 4	PING-AN Omni-Sinitic	ALBERT + DAAF + NAS		90.6
5	ERNIE Team - Baidu	ERNIE	↗	90.4
6	T5 Team - Google	T5	↗	90.3

More results Thursday when we discuss pretraining.

[[Liu et al., 2018](#)]

Outline

1. From recurrence (RNN) to attention-based NLP models
2. Introducing the Transformer model
3. Great results with Transformers
4. Drawbacks and variants of Transformers

What would we like to fix about the Transformer?

- **Quadratic compute in self-attention (today):**
 - Computing all pairs of interactions means our computation grows **quadratically** with the sequence length!
 - For recurrent models, it only grew linearly!
- **Position representations:**
 - Are simple absolute indices the best we can do to represent position?
 - Relative linear position attention [\[Shaw et al., 2018\]](#)
 - Dependency syntax-based position [\[Wang et al., 2019\]](#)

Quadratic computation as a function of sequence length

- One of the benefits of self-attention over recurrence was that it's highly parallelizable.
- However, its total number of operations grows as $O(T^2 d)$, where T is the sequence length, and d is the dimensionality.

$$\begin{matrix} \boxed{XQ} \\ \boxed{K^T X^T} \end{matrix} = \boxed{XQK^T X^T} \in \mathbb{R}^{T \times T}$$

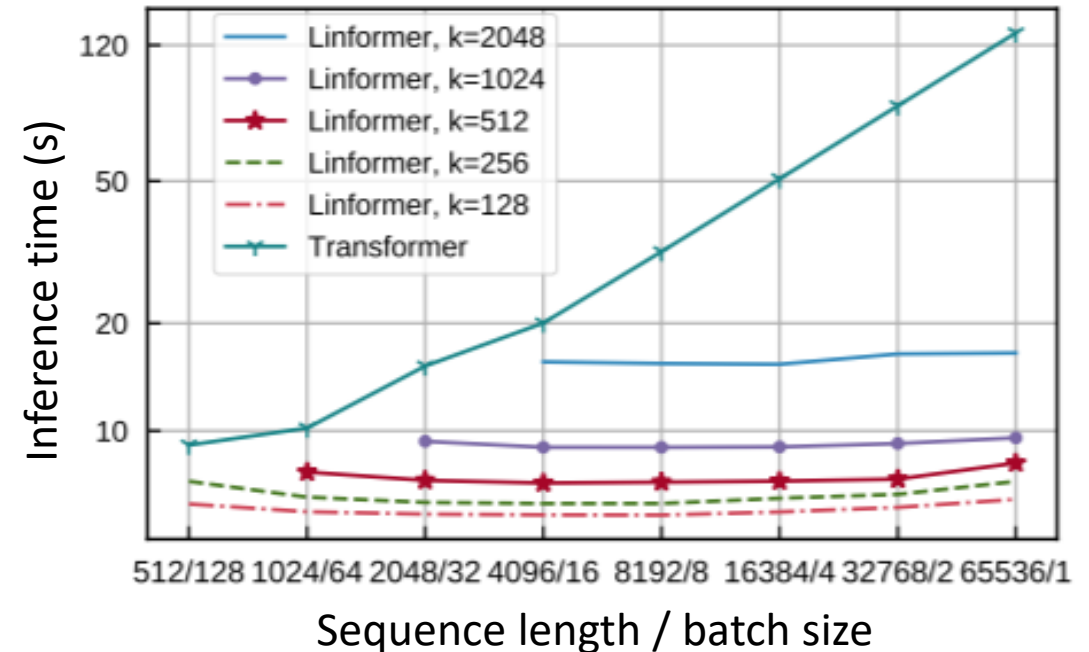
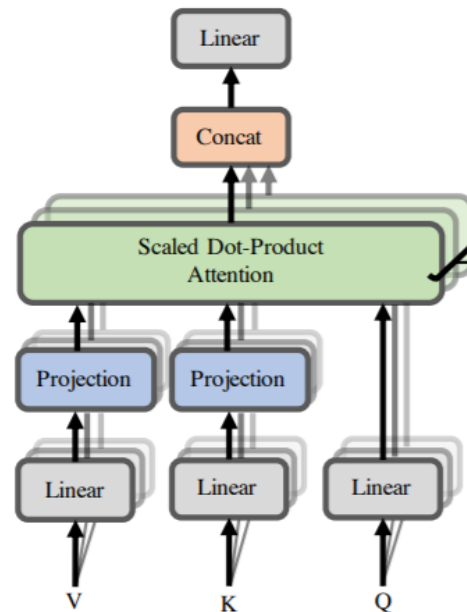
Need to compute all pairs of interactions!
 $O(T^2 d)$

- Think of d as around **1,000**.
 - So, for a single (shortish) sentence, $T \leq 30$; $T^2 \leq \mathbf{900}$.
 - In practice, we set a bound like $T = 512$.
 - **But what if we'd like $T \geq 10,000$?** For example, to work on long documents?

Recent work on improving on quadratic self-attention cost

- Considerable recent work has gone into the question, *Can we build models like Transformers without paying the $O(T^2)$ all-pairs self-attention cost?*
- For example, **Linformer** [\[Wang et al., 2020\]](#)

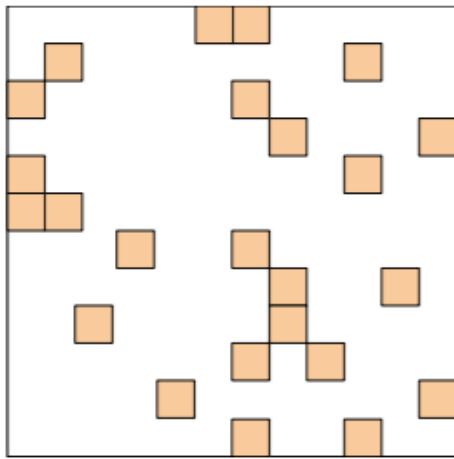
Key idea: map the sequence length dimension to a lower-dimensional space for values, keys



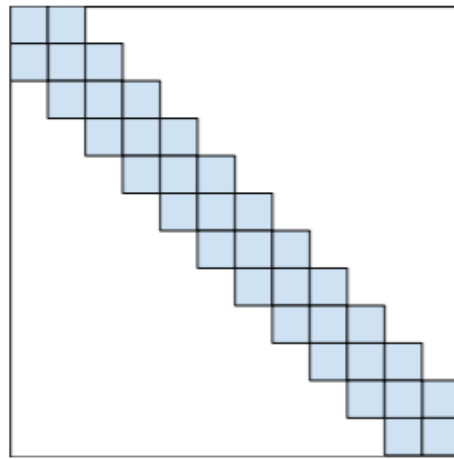
Recent work on improving on quadratic self-attention cost

- Considerable recent work has gone into the question, *Can we build models like Transformers without paying the $O(T^2)$ all-pairs self-attention cost?*
- For example, **BigBird** [\[Zaheer et al., 2021\]](#)

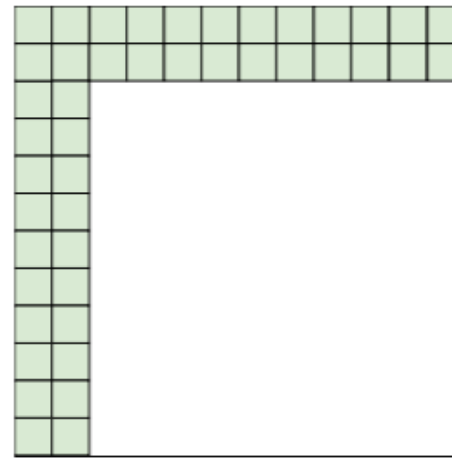
Key idea: replace all-pairs interactions with a family of other interactions, **like local windows, looking at everything**, and **random interactions**.



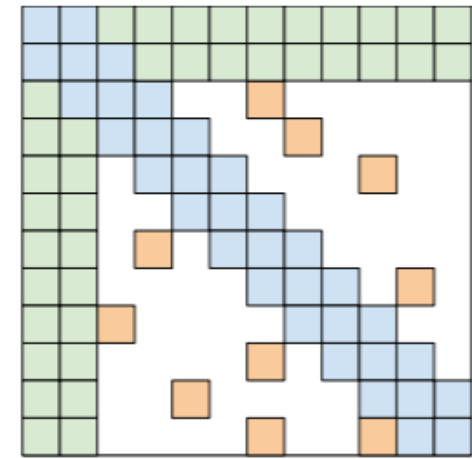
(a) Random attention



(b) Window attention



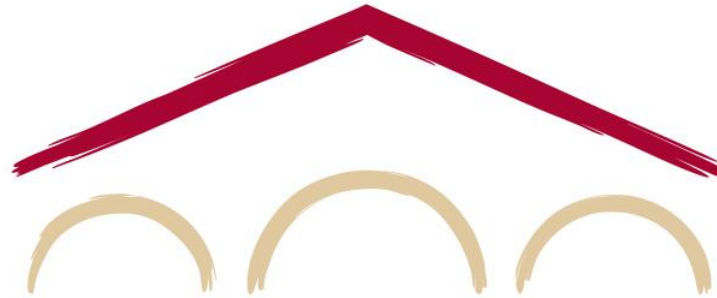
(c) Global Attention



(d) BIGBIRD

Natural Language Processing with Deep Learning

CS224N/Ling284



John Hewitt

Lecture 10: Pretraining

Lecture Plan






1. A brief note on subword modeling
2. Motivating model pretraining from word embeddings
3. Model pretraining three ways
 1. Decoders
 2. Encoders
 3. Encoder-Decoders
4. Interlude: what do we think pretraining is teaching?
5. Very large models and in-context learning

Word structure and subword models

Let's take a look at the assumptions we've made about a language's vocabulary.

We assume a fixed vocab of tens of thousands of words, built from the training set.

All *novel* words seen at test time are mapped to a single UNK.

	word		vocab mapping	embedding
Common words	hat	→	hat (index)	
	learn	→	learn (index)	
Variations	taaaaasty	→	UNK (index)	
misspellings	laern	→	UNK (index)	
novel items	Transformerify	→	UNK (index)	

Word structure and subword models

Finite vocabulary assumptions make even *less* sense in many languages.

- Many languages exhibit complex **morphology**, or word structure.
 - The effect is more word types, each occurring fewer times.

Example: Swahili verbs can have hundreds of conjugations, each encoding a wide variety of information. (Tense, mood, definiteness, negation, information about the object, ++)

Here's a small fraction of the conjugations for *ambia* – to tell.

Conjugation of -ambia																				[less ▲]		
Form		Non-finite forms																		Negative		
		Positive																				
Positive form		Simple finite forms																		Plural		
		Singular																				
Imperative		ambia																		ambieni		
Habitual		huambia																				
Polarity		Persons						Complex finite forms												Classes		
		1st		2nd		Persons / Classes		M-mi		Ma		Ki-vi		N		U		Ku			Pa	
		Sg.	Pl.	Sg.	Pl.	Sg. / 1	Pl. / 2	3	4	5	6	7	8	9	10	11 / 14	15 / 17	16	18			
		Past																			[less ▲]	
Positive		niliambia	tuliambia	uliambia	mliambia	aliambia	waliambia	uliambia	ilambia	ilambia	yaliambia	kilambia	viliambia	ilambia	ziliambia	ulambia	kulambia	paliambia	muliambia			
Negative		sikuambia	hatukuambia	hukuambia	hamkuambia	hakuambia	hawakuambi	haukuambia	haikuambia	halikuambia	hayakuambi	hakikuambia	havikuambia	haikuambia	hazikuambia	haukuambia	hakukuambi	hapakuambi	hamukuambi			
		Present																		[less ▲]		
Positive		ninaambia	tunaambia	unaambia	mnaambia	anaambia	wanaambia	unaambia	inaambia	inaambia	yanaambia	kinaambia	vinaambia	inaambia	zinaambia	unaambia	kunaambia	panaambia	munaambia			
Negative		siambia	hatuambi	huambi	hamambi	haambi	hawaambi	hauambi	haiambi	haliambi	hayaambi	hakiambi	haviambi	haiambi	haziambi	hauambi	hakuambi	hapaambi	hamuambi			
		Future																		[less ▲]		
Positive		nitaambia	tutaambia	utaambia	mtaambia	ataambia	wataambia	utaambia	itaambia	itaambia	yataambia	kitaambia	vitaambia	itaambia	zitaambia	utaambia	kutaambia	pataambia	mutaambia			
Negative		sitaambia	hatutaambia	hutaambia	hamtaambia	hataambia	wawataambi	hautaambia	haitaambia	halitaambia	hayataambia	hakitaambia	havitaambia	haitaambia	hazitaambia	hautaambia	hakutaambia	hapataambia	hamutaambi			
		Subjunctive																		[less ▲]		
Positive		niambia	tuambia	uambia	mambia	aambia	waambia	uambia	iambia	iambia	yaambia	kiambia	viambia	iambia	ziambia	uambia	kuambia	paambia	muambia			
Negative		nisiambia	tusiambia	usiambia	msiambia	asiambia	wasiambia	usiambia	isiambia	lisiambia	yasiambia	kisiambia	visiambia	isiambia	zisiambia	usiambia	kusiambia	pasiambia	musiambia			
		Present Conditional																		[less ▲]		
Positive		ningeambia	tungeambi	ungeambi	mngeambi	angeambi	wangeambi	ungeambi	ingeambi	lingeambi	yangeambi	kingeambi	vingeambi	ingeambi	zingeambi	ungeambi	kungeambi	pangeambi	mungeambi			
Negative		nisingeambi	tusingeambi	usingeambi	msingeambi	asingeambi	wasingeambi	usingeambi	isingeambi	lisingeambi	yasingeambi	kingeambi	vingeambi	isingeambi	zingeambi	usingeambi	kusingeambi	pasingeambi	musingeambi			
		singeambi	hatungeambi	hungeambi	hamngeambi	hangeambi	hawangeambi	haungeambi	hangeambi	halingeambi	nayingeambi	hakingeambi	havingeambi	hangeambi	hazingeambi	haungeambi	hakungeambi	hapangeambi	hamungeambi			
		Past Conditional																		[less ▲]		
Positive		ningaliambia	tungaliambi	ungaliambi	mngaliambi	angaliambi	wangaliambi	ungaliambi	ingaliambi	lingaliambi	yangaliambi	kingaliambi	vingaliambi	ingaliambi	zingaliambi	ungaliambi	kungaliambi	pangaliambi	mungaliambi			
Negative		nisingaliambi	tungaliambi	ungaliambi	msingaliambi	asingaliambi	wasingaliambi	usingaliambi	isingaliambi	lisingaliambi	yasingaliambi	kingaliambi	vingaliambi	isingaliambi	zingaliambi	usingaliambi	kusingaliambi	pasingaliambi	musingaliambi			
		singaliambi	hatungaliambi	hungaliambi	hamngaliambi	hangaliambi	hawangaliambi	haungaliambi	halingaliambi	halingaliambi	hayangaliambi	hakingaliambi	havingaliambi	halingaliambi	hazingaliambi	haungaliambi	hakungaliambi	hapangaliambi	hamungaliambi			
		Conditional Contrary to Fact																		[less ▲]		
Positive		ningeliambi	tungeliambi	ungeliambi	mngeliambi	angeliambi	wangeliambi	ungeliambi	ingeliambi	lingeliambi	yangeliambi	kingeliambi	vingeliambi	ingeliambi	zingeliambi	ungeliambi	kungeliambi	pangeliambi	mungeliambi			
		Gnomic																		[less ▲]		
Positive		naambia	twaambia	waambia	mwaambia	aambia	waambia	waambia	yaambia	laambia	yaambia	chaambia	vyaambia	yaambia	zaambia	waambia	kwaambia	paambia	mwaaambia			
		Perfect																		[less ▲]		

The byte-pair encoding algorithm

Subword modeling in NLP encompasses a wide range of methods for reasoning about structure below the word level. (Parts of words, characters, bytes.)

- The dominant modern paradigm is to learn a vocabulary of **parts of words (subword tokens)**.
- At training and testing time, each word is split into a sequence of known subwords.

Byte-pair encoding is a simple, effective strategy for defining a subword vocabulary.






1. Start with a vocabulary containing only characters and an “end-of-word” symbol.
2. Using a corpus of text, find the most common adjacent characters “a,b”; add “ab” as a subword.
3. Replace instances of the character pair with the new subword; repeat until desired vocab size.

Originally used in NLP for machine translation; now a similar method (WordPiece) is used in pretrained models.

Word structure and subword models

Common words end up being a part of the subword vocabulary, while rarer words are split into (sometimes intuitive, sometimes not) components.

In the worst case, words are split into as many subwords as they have characters.

	word		vocab mapping	embedding
Common words	hat	→	hat	
	learn	→	learn	
Variations	taaaaasty	→	taa## aaa## sty	
misspellings	laern	→	la## ern##	
novel items	Transformerify	→	Transformer## ify	

Outline

1. A brief note on subword modeling
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Motivating word meaning and context

Recall the adage we mentioned at the beginning of the course:

“You shall know a word by the company it keeps” (J. R. Firth 1957: 11)

This quote is a summary of **distributional semantics**, and motivated **word2vec**. But:

*“... the complete meaning of a word is always contextual,
and no study of meaning apart from a complete context
can be taken seriously.”* (J. R. Firth 1935)

Consider *I **record** the **record***: the two instances of **record** mean different things.

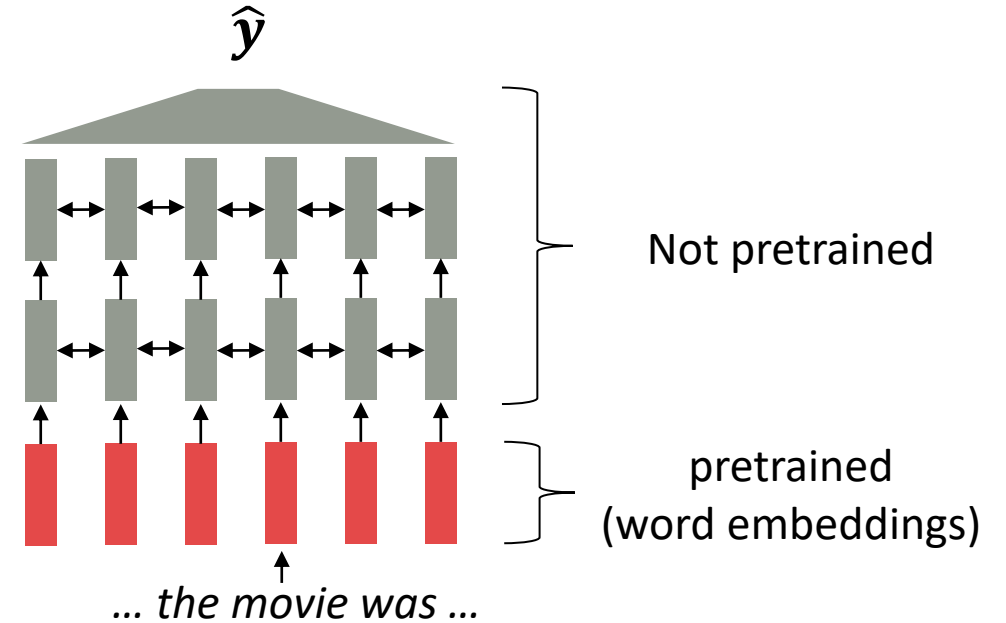
Where we were: pretrained word embeddings

Circa 2017:

- Start with pretrained word embeddings (no context!)
- Learn how to incorporate context in an LSTM or Transformer while training on the task.

Some issues to think about:

- The training data we have for our **downstream task** (like question answering) must be sufficient to teach all contextual aspects of language.
- Most of the parameters in our network are randomly initialized!

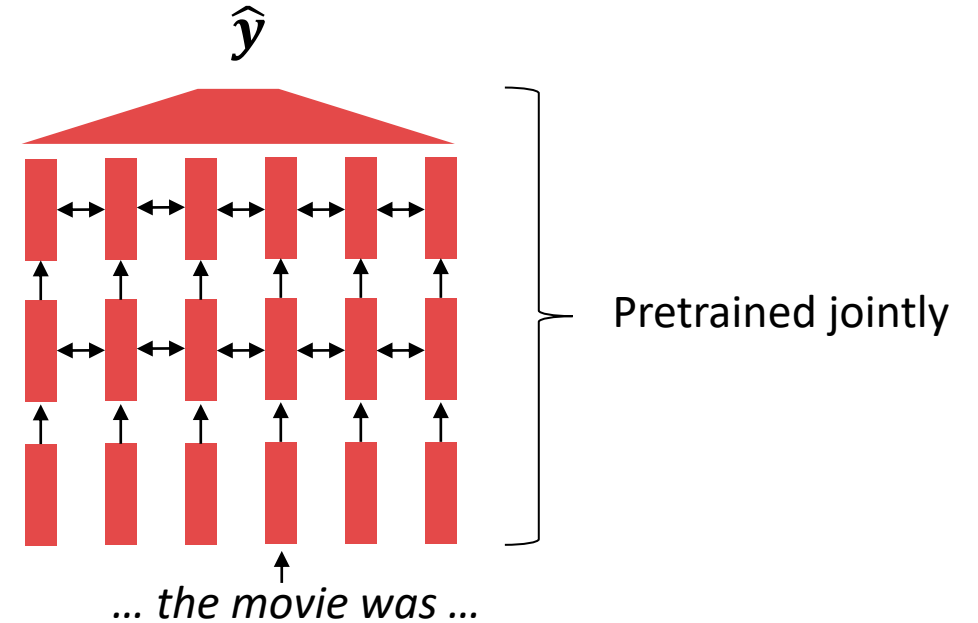


[Recall, *movie* gets the same word embedding, no matter what sentence it shows up in]

Where we're going: **pretraining whole models**

In modern NLP:

- All (or almost all) parameters in NLP networks are initialized via **pretraining**.
- Pretraining methods hide parts of the input from the model, and train the model to reconstruct those parts.
- This has been exceptionally effective at building strong:
 - **representations of language**
 - **parameter initializations** for strong NLP models.
 - **Probability distributions** over language that we can sample from



[This model has learned how to represent entire sentences through pretraining]

What can we learn from reconstructing the input?

Stanford University is located in _____, California.

What can we learn from reconstructing the input?

I put ____ fork down on the table.

What can we learn from reconstructing the input?

The woman walked across the street,
checking for traffic over ____ shoulder.

What can we learn from reconstructing the input?

I went to the ocean to see the fish, turtles, seals, and _____.

What can we learn from reconstructing the input?

Overall, the value I got from the two hours watching
it was the sum total of the popcorn and the drink.

The movie was ____.

What can we learn from reconstructing the input?

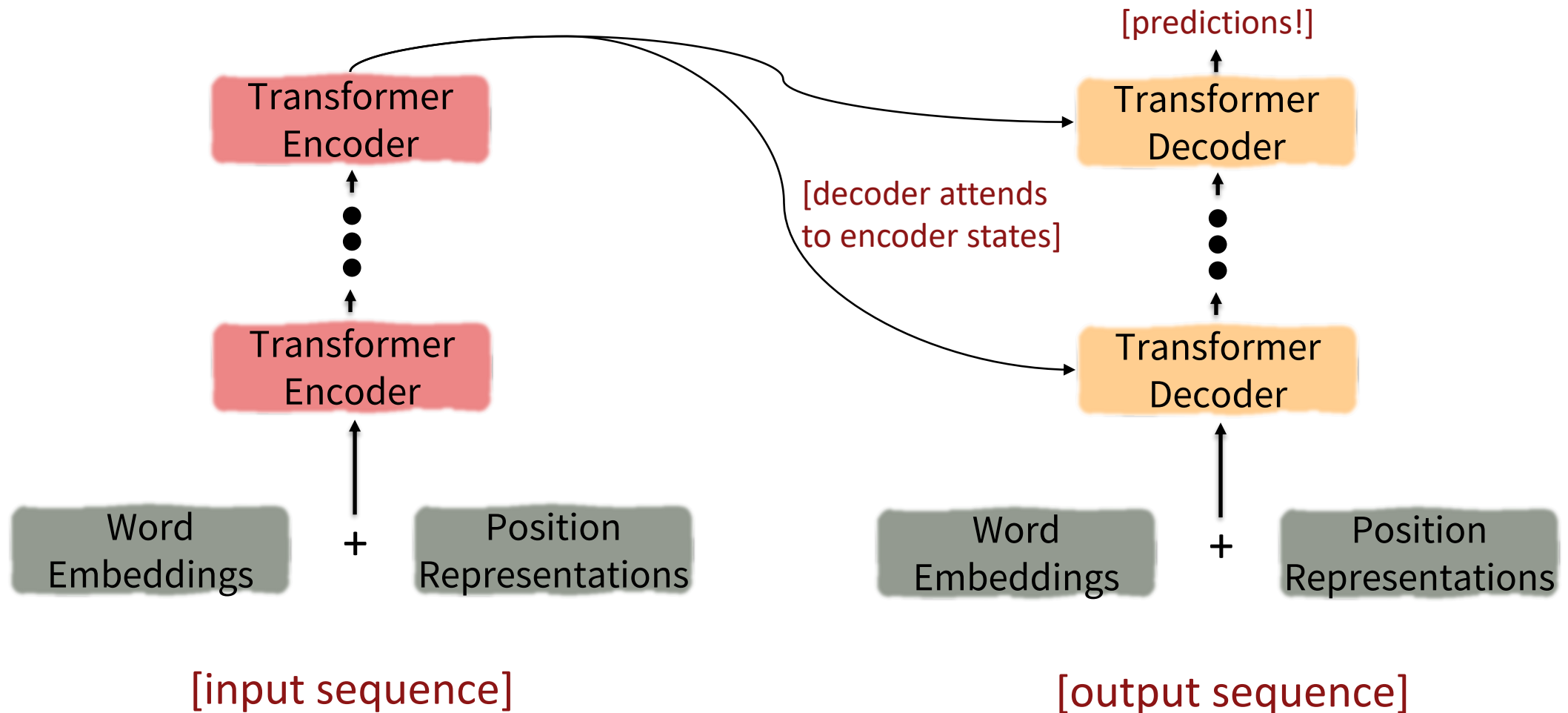
Iroh went into the kitchen to make some tea.
Standing next to Iroh, Zuko pondered his destiny.
Zuko left the _____.

What can we learn from reconstructing the input?

I was thinking about the sequence that goes
1, 1, 2, 3, 5, 8, 13, 21, _____

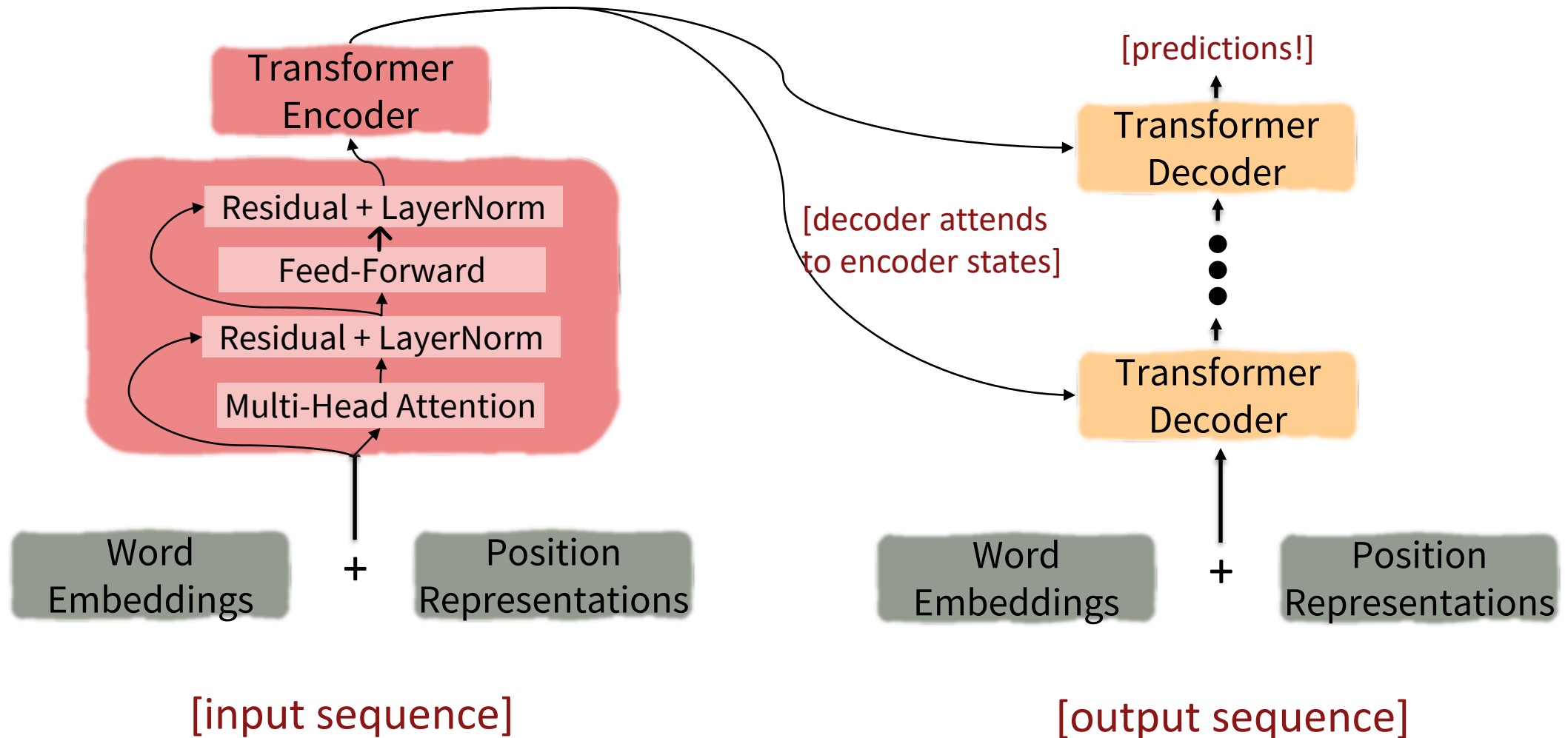
The Transformer Encoder-Decoder [\[Vaswani et al., 2017\]](#)

Looking back at the whole model, zooming in on an Encoder block:



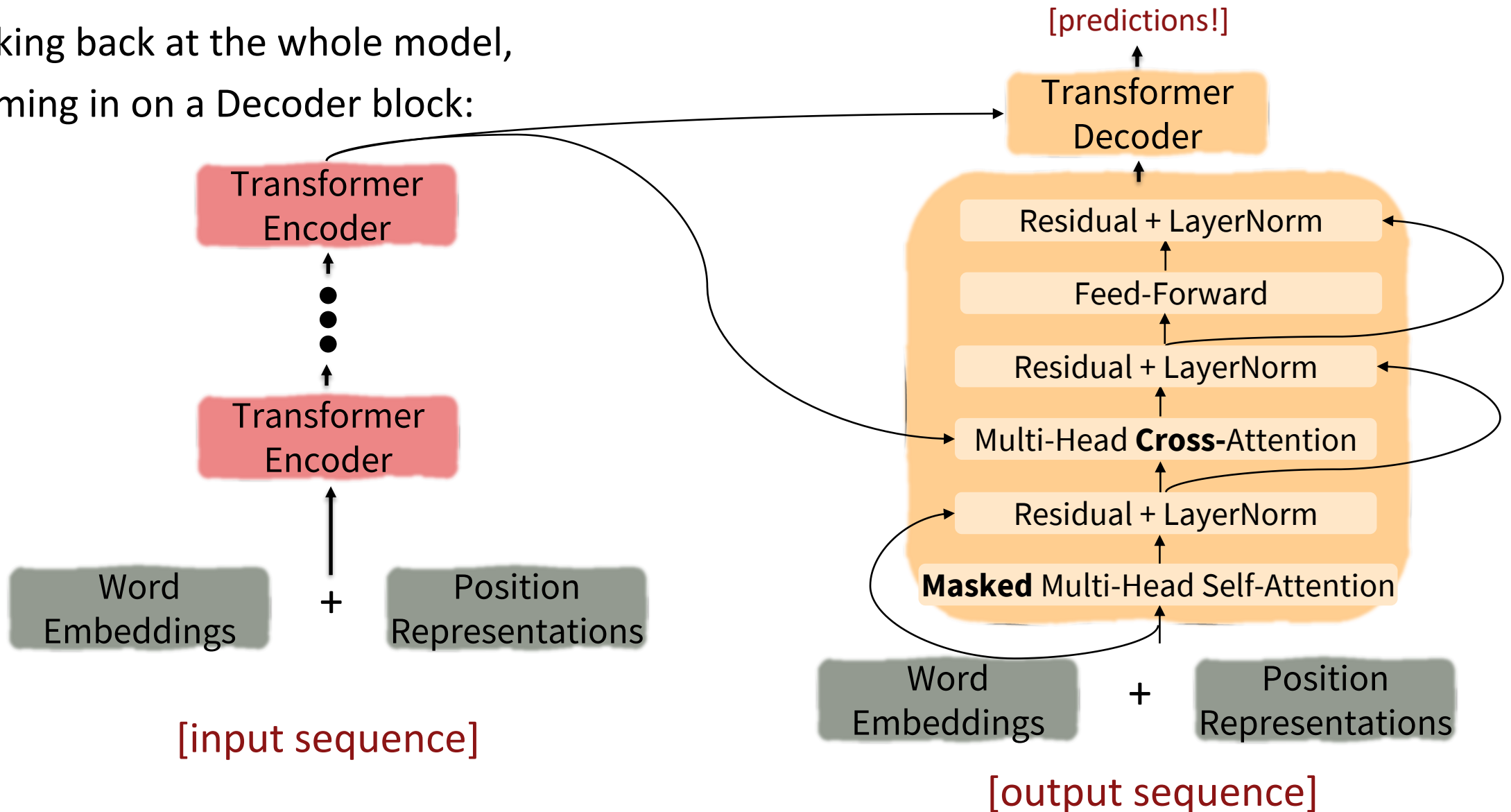
The Transformer Encoder-Decoder [Vaswani et al., 2017]

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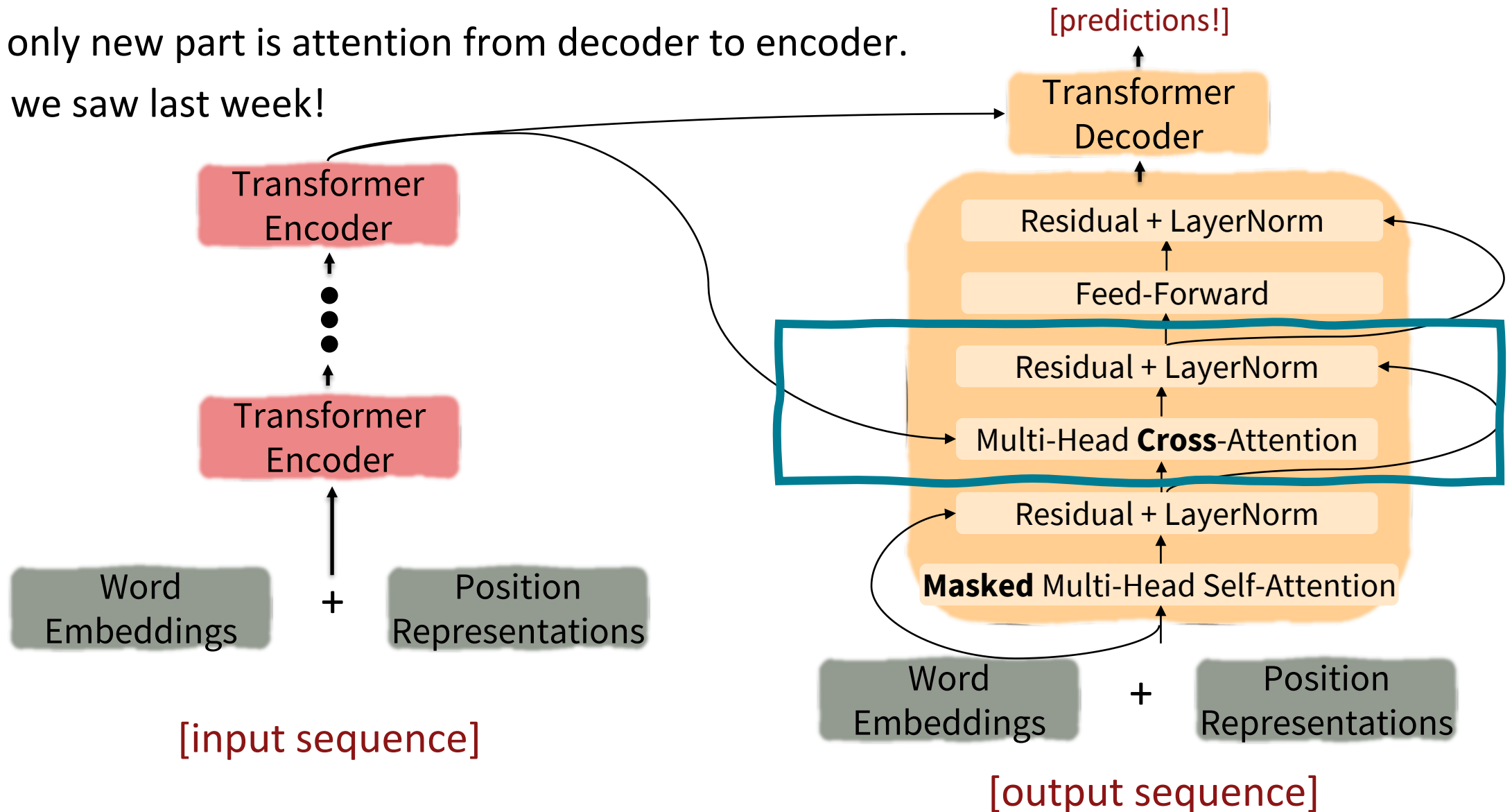
The Transformer Encoder-Decoder [Vaswani et al., 2017]

Looking back at the whole model,
zooming in on a Decoder block:



The Transformer Encoder-Decoder [Vaswani et al., 2017]

The only new part is attention from decoder to encoder.
Like we saw last week!



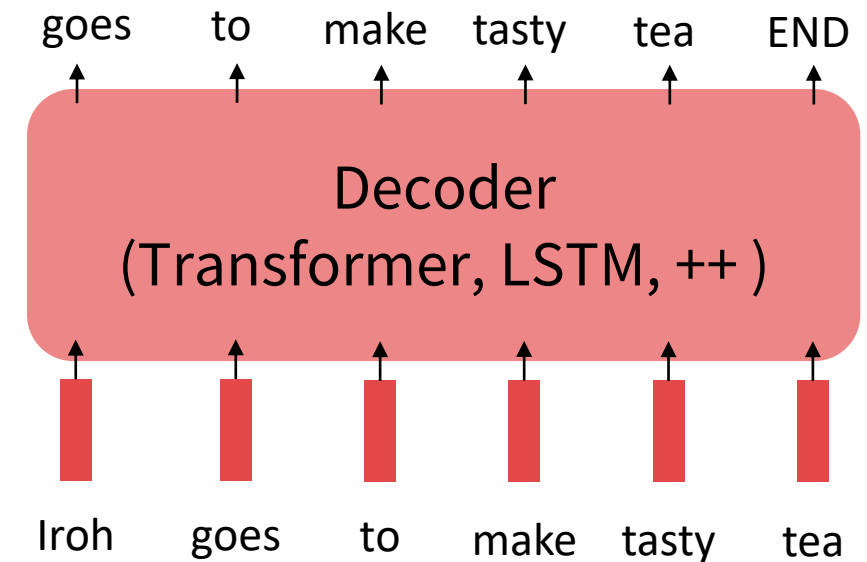
Pretraining through language modeling [[Dai and Le, 2015](#)]

Recall the **language modeling** task:

- Model $p_{\theta}(w_t | w_{1:t-1})$, the probability distribution over words given their past contexts.
- There's lots of data for this! (In English.)

Pretraining through language modeling:

- Train a neural network to perform language modeling on a large amount of text.
- Save the network parameters.

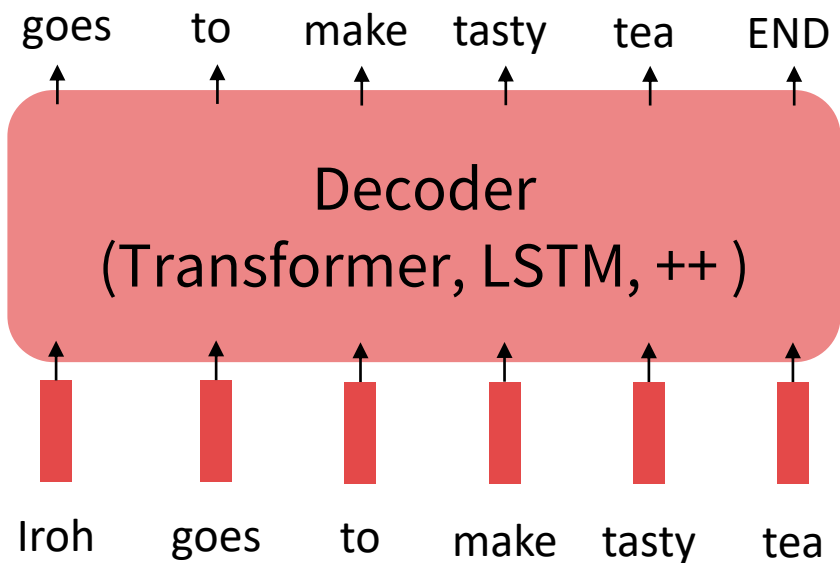


The Pretraining / Finetuning Paradigm

Pretraining can improve NLP applications by serving as parameter initialization.

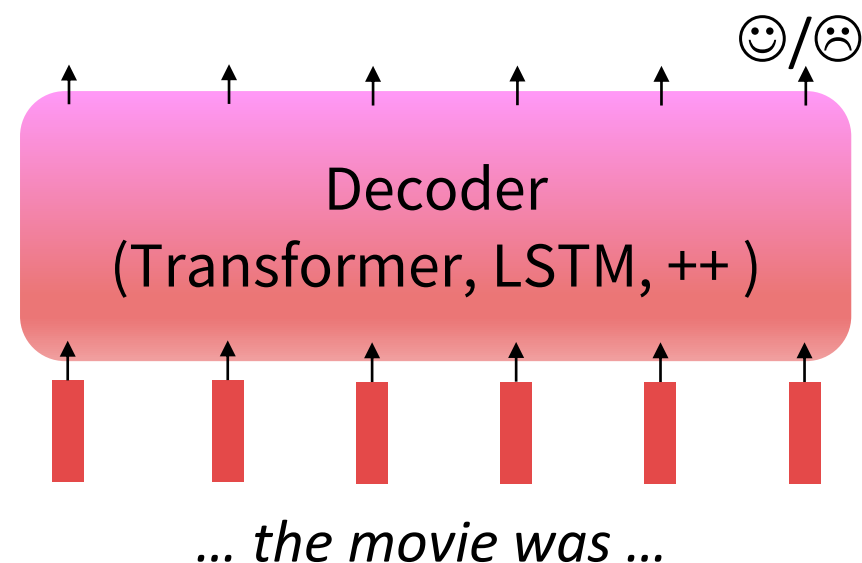
Step 1: Pretrain (on language modeling)

Lots of text; learn general things!



Step 2: Finetune (on your task)

Not many labels; adapt to the task!



Stochastic gradient descent and pretrain/finetune

Why should pretraining and finetuning help, from a “training neural nets” perspective?

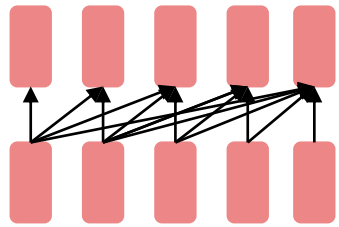
- Consider, provides parameters $\hat{\theta}$ by approximating $\min_{\theta} \mathcal{L}_{\text{pretrain}}(\theta)$.
 - (The pretraining loss.)
- Then, finetuning approximates $\min_{\theta} \mathcal{L}_{\text{finetune}}(\theta)$, starting at $\hat{\theta}$.
 - (The finetuning loss)
- The pretraining may matter because stochastic gradient descent sticks (relatively) close to $\hat{\theta}$ during finetuning.
 - So, maybe the finetuning local minima near $\hat{\theta}$ tend to generalize well!
 - And/or, maybe the gradients of finetuning loss near $\hat{\theta}$ propagate nicely!

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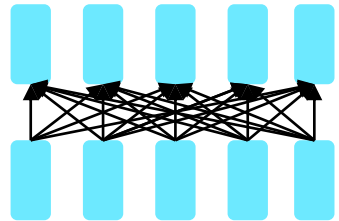
Pretraining for three types of architectures

The neural architecture influences the type of pretraining, and natural use cases.



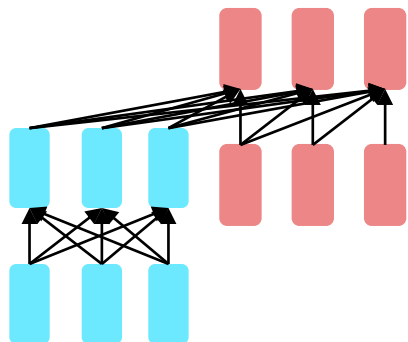
Decoders

- Language models! What we've seen so far.
- Nice to generate from; can't condition on future words



Encoders

- Gets bidirectional context – can condition on future!
- Wait, how do we pretrain them?

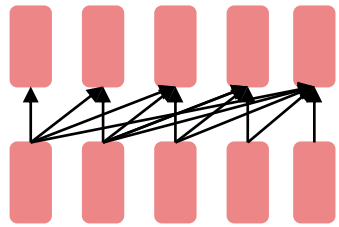


**Encoder-
Decoders**

- Good parts of decoders and encoders?
- What's the best way to pretrain them?

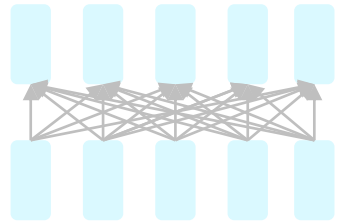
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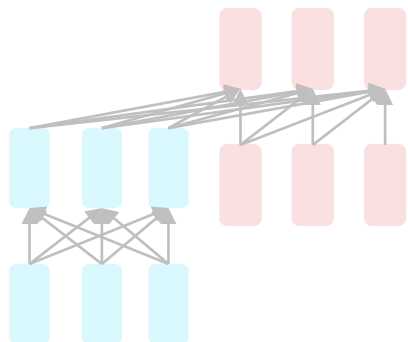
Decoders

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**Encoder-
Decoders**

- Good parts of decoders and encoders?
- What's the best way to pretrain them?

Pretraining decoders

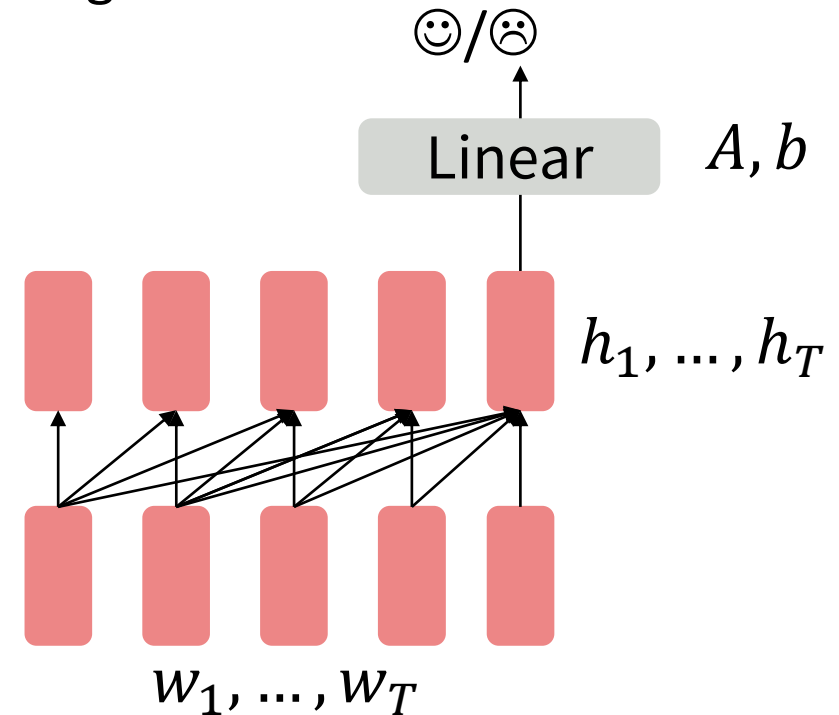
When using language model pretrained decoders, we can ignore that they were trained to model $p(w_t|w_{1:t-1})$.

We can finetune them by training a classifier on the last word's hidden state.

$$h_1, \dots, h_T = \text{Decoder}(w_1, \dots, w_T)$$
$$y \sim Ah_t + b$$

Where A and b are randomly initialized and specified by the downstream task.

Gradients backpropagate through the whole network.



[Note how the linear layer hasn't been pretrained and must be learned from scratch.]

Pretraining decoders

It's natural to pretrain decoders as language models and then use them as generators, finetuning their $p_{\theta}(w_t|w_{1:t-1})$!

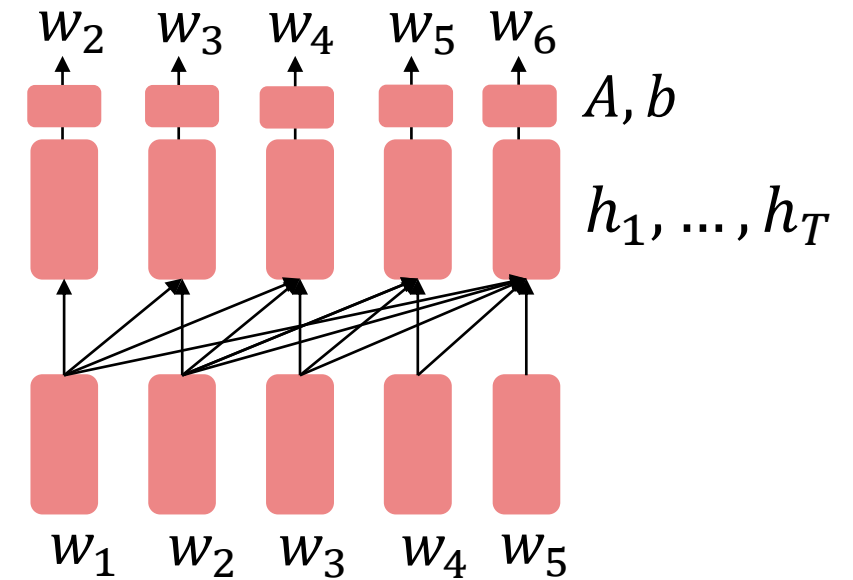
This is helpful in tasks **where the output is a sequence** with a vocabulary like that at pretraining time!

- Dialogue (context=dialogue history)
- Summarization (context=document)

$$h_1, \dots, h_T = \text{Decoder}(w_1, \dots, w_T)$$

$$w_t \sim Ah_{t-1} + b$$

Where A, b were pretrained in the language model!



[Note how the linear layer has been pretrained.]

Generative Pretrained Transformer (GPT) [[Radford et al., 2018](#)]

2018's GPT was a big success in pretraining a decoder!

- Transformer decoder with 12 layers.
- 768-dimensional hidden states, 3072-dimensional feed-forward hidden layers.
- Byte-pair encoding with 40,000 merges
- Trained on BooksCorpus: over 7000 unique books.
 - Contains long spans of contiguous text, for learning long-distance dependencies.
- The acronym “GPT” never showed up in the original paper; it could stand for “Generative PreTraining” or “Generative Pretrained Transformer”

Generative Pretrained Transformer (GPT) [[Radford et al., 2018](#)]

How do we format inputs to our decoder for **finetuning tasks**?

Natural Language Inference: Label pairs of sentences as *entailing/contradictory/neutral*

Premise: *The man is in the doorway*
Hypothesis: *The person is near the door* } **entailment**

Radford et al., 2018 evaluate on natural language inference.

Here's roughly how the input was formatted, as a sequence of tokens for the decoder.

[START] *The man is in the doorway* [DELIM] *The person is near the door* [EXTRACT]

The linear classifier is applied to the representation of the [EXTRACT] token.

Generative Pretrained Transformer (GPT) [[Radford et al., 2018](#)]

GPT results on various *natural language inference* datasets.

Method	MNLI-m	MNLI-mm	SNLI	SciTail	QNLI	RTE
ESIM + ELMo [44] (5x)	-	-	<u>89.3</u>	-	-	-
CAFE [58] (5x)	80.2	79.0	<u>89.3</u>	-	-	-
Stochastic Answer Network [35] (3x)	<u>80.6</u>	<u>80.1</u>	-	-	-	-
CAFE [58]	78.7	77.9	88.5	<u>83.3</u>		
GenSen [64]	71.4	71.3	-	-	<u>82.3</u>	59.2
Multi-task BiLSTM + Attn [64]	72.2	72.1	-	-	82.1	61.7
Finetuned Transformer LM (ours)	82.1	81.4	89.9	88.3	88.1	56.0

Increasingly convincing generations (GPT2) [[Radford et al., 2018](#)]

We mentioned how pretrained decoders can be used **in their capacities as language models**.

GPT-2, a larger version of GPT trained on more data, was shown to produce relatively convincing samples of natural language.

Context (human-written): In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

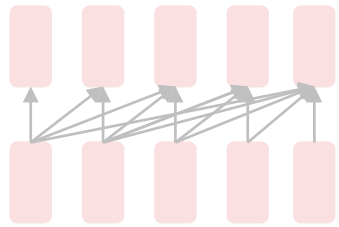
GPT-2: The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

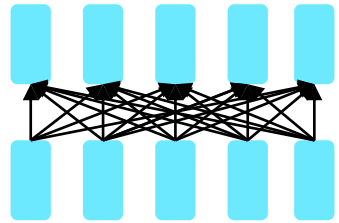
Pretraining for three types of architectures

The neural architecture influences the type of pretraining, and natural use cases.



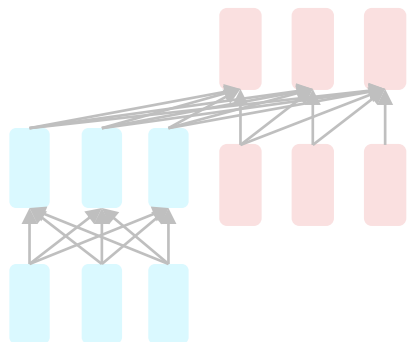
Decoders

- Language models! What we've seen so far.
- Nice to generate from; can't condition on future words



Encoders

- Gets bidirectional context – can condition on future!
- Wait, how do we pretrain them?



**Encoder-
Decoders**

- Good parts of decoders and encoders?
- What's the best way to pretrain them?

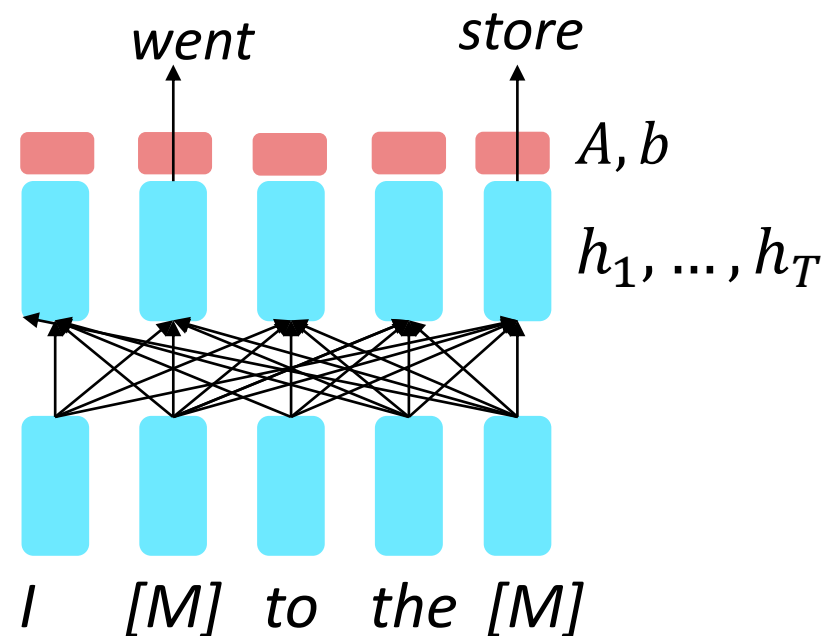
Pretraining encoders: what pretraining objective to use?

So far, we've looked at language model pretraining. But **encoders get bidirectional context**, so we can't do language modeling!

Idea: replace some fraction of words in the input with a special [MASK] token; predict these words.

$$h_1, \dots, h_T = \text{Encoder}(w_1, \dots, w_T)$$
$$y_i \sim Aw_i + b$$

Only add loss terms from words that are “masked out.” If \tilde{x} is the masked version of x , we're learning $p_\theta(x|\tilde{x})$. Called **Masked LM**.



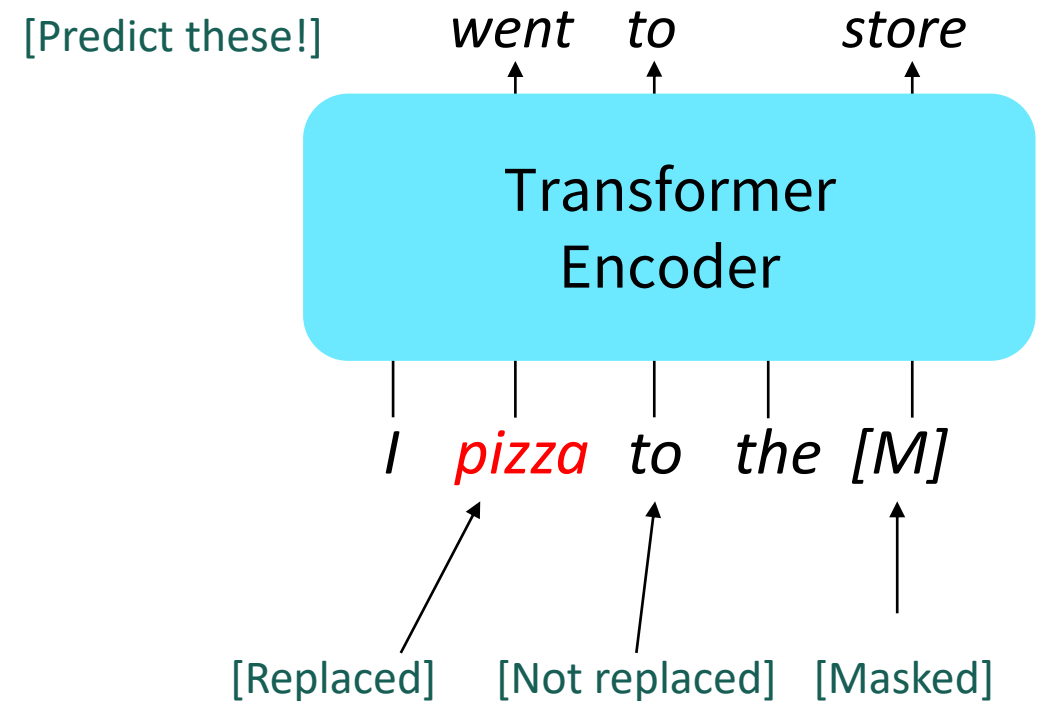
[Devlin et al., 2018]

BERT: Bidirectional Encoder Representations from Transformers

Devlin et al., 2018 proposed the “Masked LM” objective and **released the weights of a pretrained Transformer**, a model they labeled BERT.

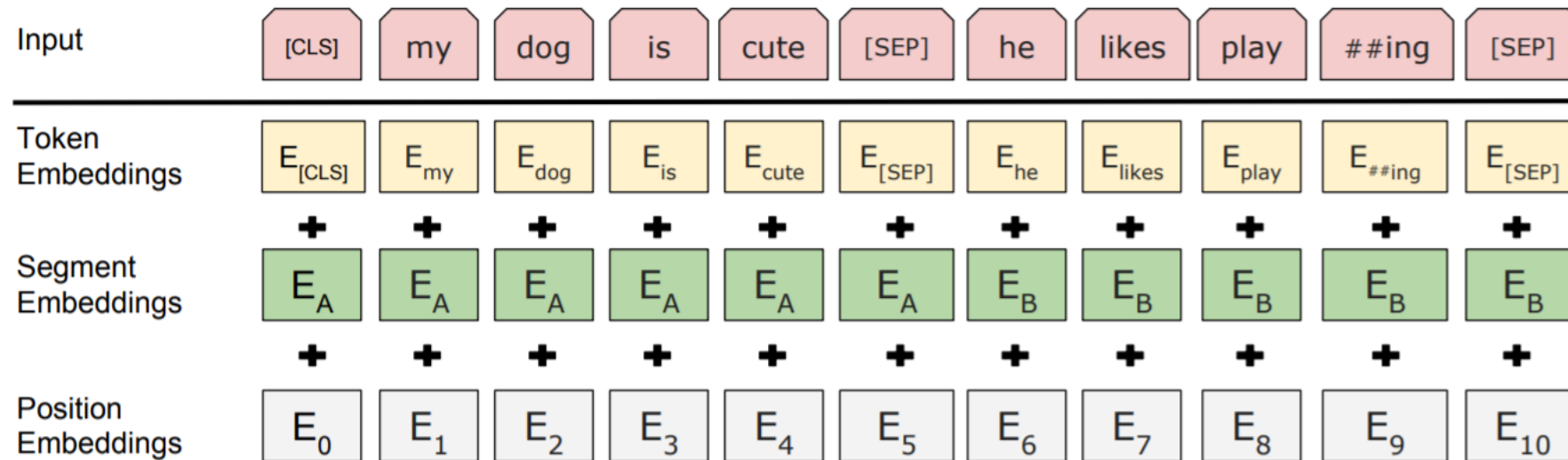
Some more details about Masked LM for BERT:

- Predict a random 15% of (sub)word tokens.
 - Replace input word with [MASK] 80% of the time
 - Replace input word with a random token 10% of the time
 - Leave input word unchanged 10% of the time (but still predict it!)
- Why? Doesn't let the model get complacent and not build strong representations of non-masked words. (No masks are seen at fine-tuning time!)



BERT: Bidirectional Encoder Representations from Transformers

- The pretraining input to BERT was two separate contiguous chunks of text:



- BERT was trained to predict whether one chunk follows the other or is randomly sampled.
 - Later work has argued this “next sentence prediction” is not necessary.

BERT: Bidirectional Encoder Representations from Transformers

Details about BERT

- Two models were released:
 - BERT-base: 12 layers, 768-dim hidden states, 12 attention heads, 110 million params.
 - BERT-large: 24 layers, 1024-dim hidden states, 16 attention heads, 340 million params.
- Trained on:
 - BooksCorpus (800 million words)
 - English Wikipedia (2,500 million words)
- Pretraining is expensive and impractical on a single GPU.
 - BERT was pretrained with 64 TPU chips for a total of 4 days.
 - (TPUs are special tensor operation acceleration hardware)
- Finetuning is practical and common on a single GPU
 - “Pretrain once, finetune many times.”

BERT: Bidirectional Encoder Representations from Transformers

BERT was massively popular and hugely versatile; finetuning BERT led to new state-of-the-art results on a broad range of tasks.

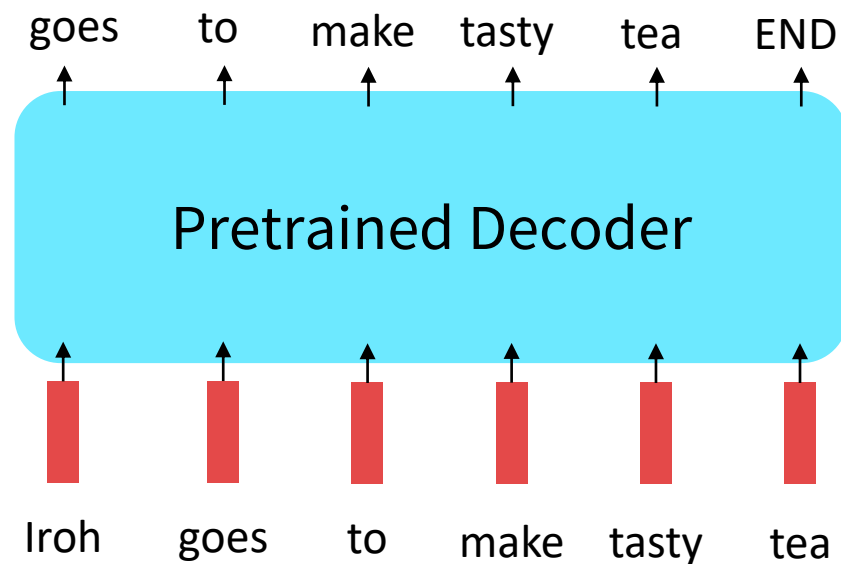
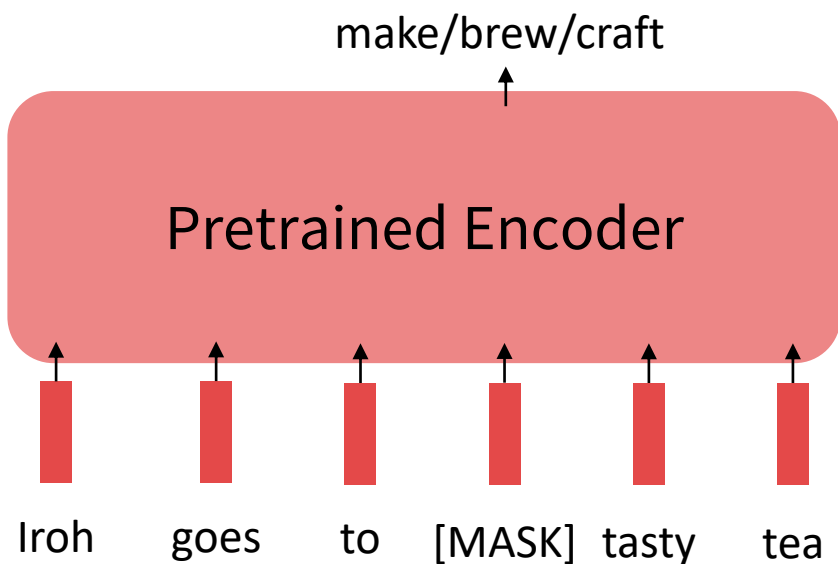
- **QQP**: Quora Question Pairs (detect paraphrase questions)
- **QNLI**: natural language inference over question answering data
- **SST-2**: sentiment analysis
- **CoLA**: corpus of linguistic acceptability (detect whether sentences are grammatical.)
- **STS-B**: semantic textual similarity
- **MRPC**: microsoft paraphrase corpus
- **RTE**: a small natural language inference corpus

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	Average -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
BERT _{BASE}	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
BERT _{LARGE}	86.7/85.9	72.1	92.7	94.9	60.5	86.5	89.3	70.1	82.1

Limitations of pretrained encoders

Those results looked great! Why not use pretrained encoders for everything?

If your task involves generating sequences, consider using a pretrained decoder; BERT and other pretrained encoders don't naturally lead to nice autoregressive (1-word-at-a-time) generation methods.

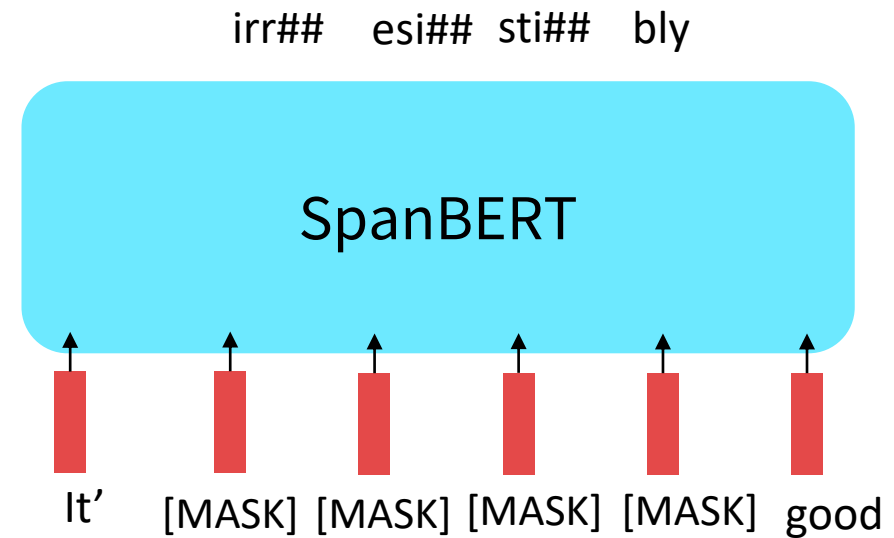
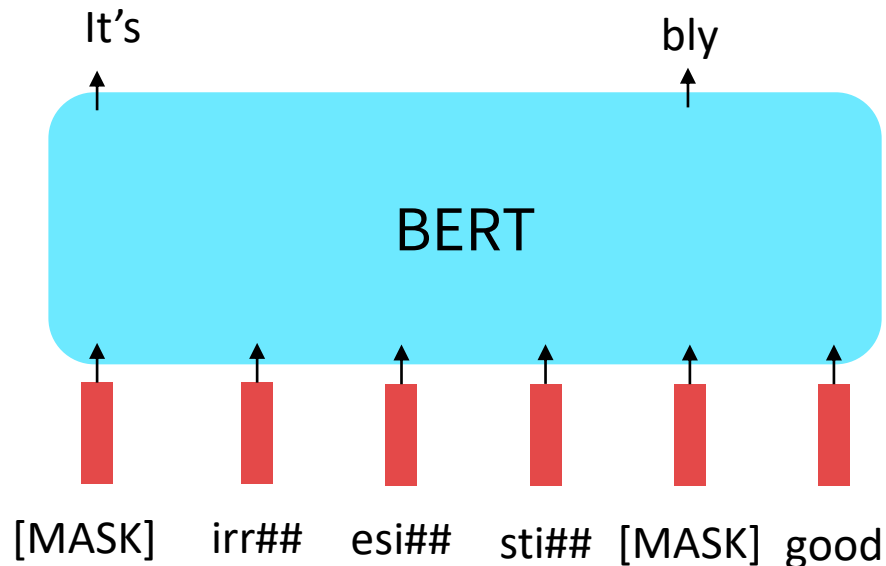


Extensions of BERT

You'll see a lot of BERT variants like RoBERTa, SpanBERT, +++)

Some generally accepted improvements to the BERT pretraining formula:

- RoBERTa: mainly just train BERT for longer and remove next sentence prediction!
- SpanBERT: masking contiguous spans of words makes a harder, more useful pretraining task



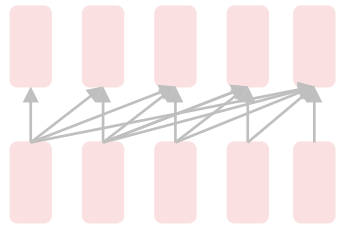
Extensions of BERT

A takeaway from the RoBERTa paper: more compute, more data can improve pretraining even when not changing the underlying Transformer encoder.

Model	data	bsz	steps	SQuAD (v1.1/2.0)	MNLI-m	SST-2
RoBERTa						
with BOOKS + WIKI	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	94.6/89.4	90.2	96.4
BERT _{LARGE}						
with BOOKS + WIKI	13GB	256	1M	90.9/81.8	86.6	93.7

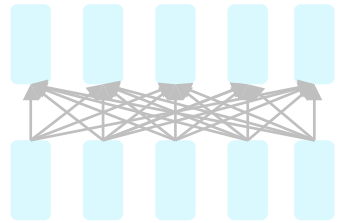
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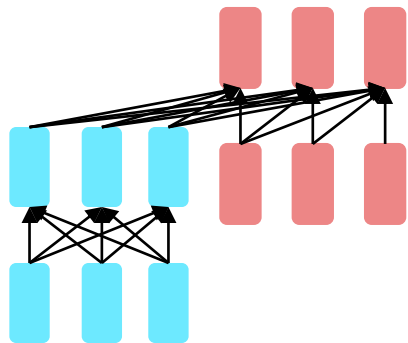
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Decoders**

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Pretraining encoder-decoders: what pretraining objective to use?

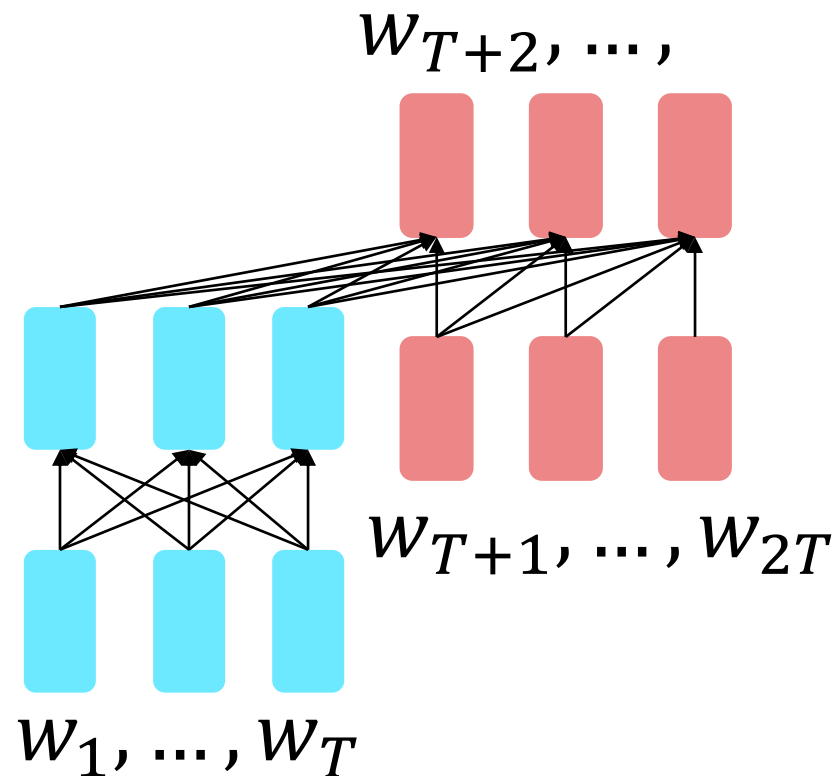
For **encoder-decoders**, we could do something like **language modeling**, but where a prefix of every input is provided to the encoder and is not predicted.

$$h_1, \dots, h_T = \text{Encoder}(w_1, \dots, w_T)$$

$$h_{T+1}, \dots, h_{2T} = \text{Decoder}(w_1, \dots, w_T, h_1, \dots, h_T)$$

$$y_i \sim Aw_i + b, i > T$$

The **encoder** portion benefits from bidirectional context; the **decoder** portion is used to train the whole model through language modeling.



[Raffel et al., 2018]

Pretraining encoder-decoders: what pretraining objective to use?

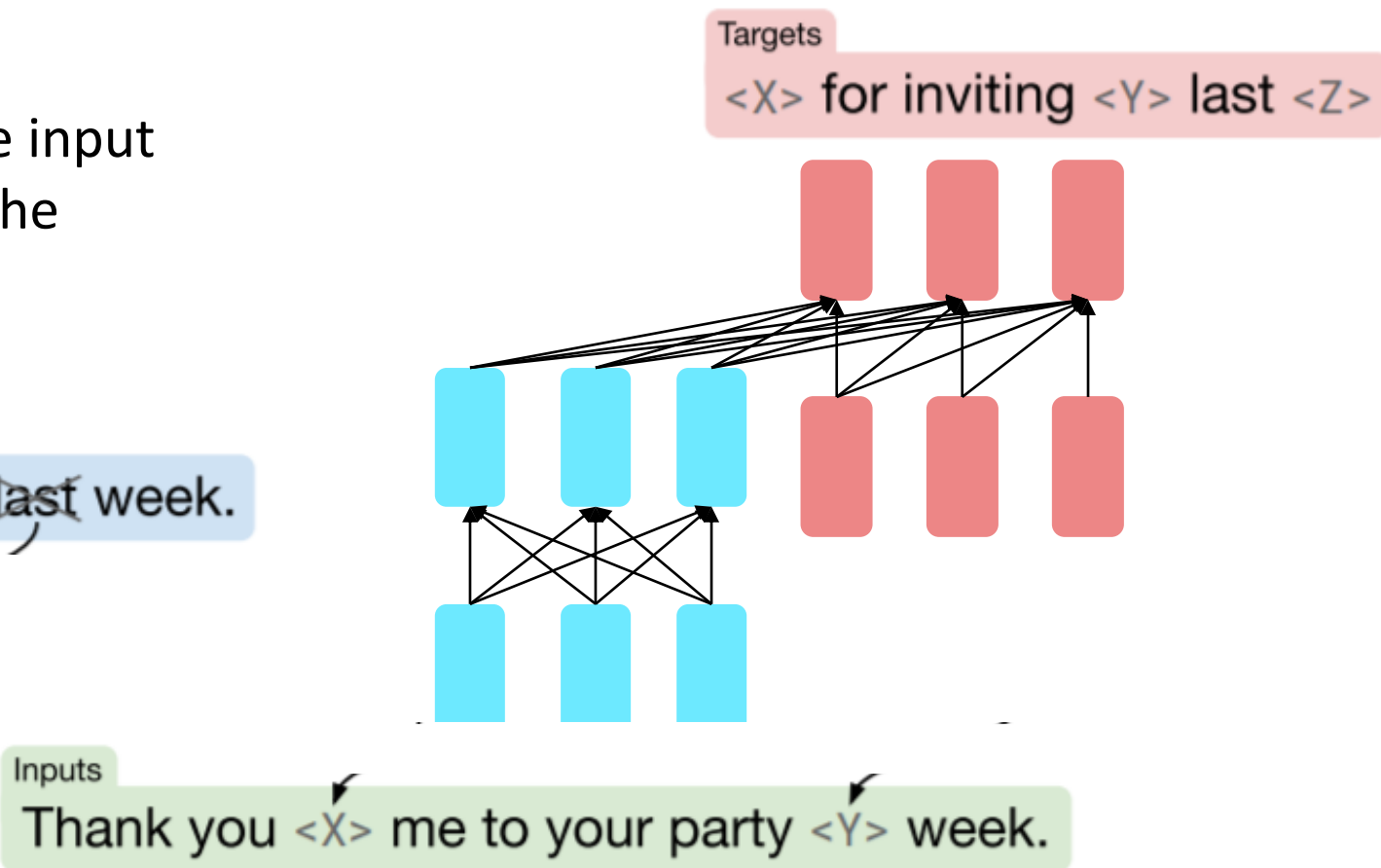
What [Raffel et al., 2018](#) found to work best was **span corruption**. Their model: **T5**.

Replace different-length spans from the input with unique placeholders; decode out the spans that were removed!

Original text

Thank you ~~for inviting~~ me to your party ~~last~~ week.

This is implemented in text preprocessing: it's still an objective that looks like **language modeling** at the decoder side.



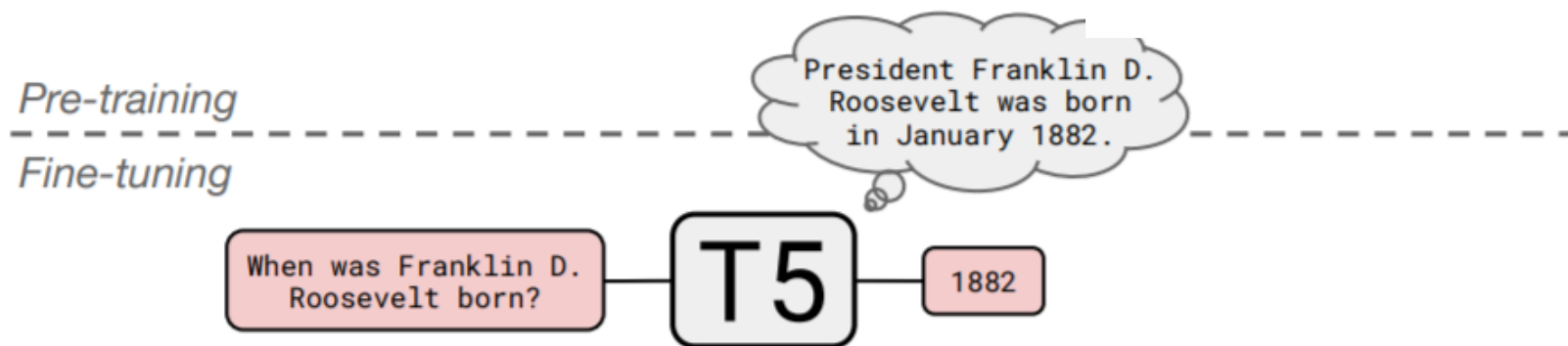
Pretraining encoder-decoders: what pretraining objective to use?

[Raffel et al., 2018](#) found encoder-decoders to work better than decoders for their tasks, and span corruption (denoising) to work better than language modeling.

Architecture	Objective	Params	Cost	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Encoder-decoder	Denoising	$2P$	M	83.28	19.24	80.88	71.36	26.98	39.82	27.65
Enc-dec, shared	Denoising	P	M	82.81	18.78	80.63	70.73	26.72	39.03	27.46
Enc-dec, 6 layers	Denoising	P	$M/2$	80.88	18.97	77.59	68.42	26.38	38.40	26.95
Language model	Denoising	P	M	74.70	17.93	61.14	55.02	25.09	35.28	25.86
Prefix LM	Denoising	P	M	81.82	18.61	78.94	68.11	26.43	37.98	27.39
Encoder-decoder	LM	$2P$	M	79.56	18.59	76.02	64.29	26.27	39.17	26.86
Enc-dec, shared	LM	P	M	79.60	18.13	76.35	63.50	26.62	39.17	27.05
Enc-dec, 6 layers	LM	P	$M/2$	78.67	18.26	75.32	64.06	26.13	38.42	26.89
Language model	LM	P	M	73.78	17.54	53.81	56.51	25.23	34.31	25.38
Prefix LM	LM	P	M	79.68	17.84	76.87	64.86	26.28	37.51	26.76

Pretraining encoder-decoders: what pretraining objective to use?

A fascinating property of T5: it can be finetuned to answer a wide range of questions, retrieving knowledge from its parameters.



NQ: Natural Questions

WQ: WebQuestions

TQA: Trivia QA

All “open-domain”
versions

	NQ	WQ	TQA		
			dev	test	
<u>Karpukhin et al. (2020)</u>	41.5	42.4	57.9	–	
T5.1.1-Base	25.7	28.2	24.2	30.6	220 million params
T5.1.1-Large	27.3	29.5	28.5	37.2	770 million params
T5.1.1-XL	29.5	32.4	36.0	45.1	3 billion params
T5.1.1-XXL	32.8	35.6	42.9	52.5	11 billion params
<u>T5.1.1-XXL + SSM</u>	35.2	42.8	51.9	61.6	

Outline

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2. Motivating model pretraining from word embeddings
3. Model pretraining three ways
 1. Decoders
 2. Encoders
 3. Encoder-Decoders
4. Interlude: what do we think pretraining is teaching?
5. Very large models and in-context learning

What kinds of things does pretraining learn?

There's increasing evidence that pretrained models learn a wide variety of things about the statistical properties of language. Taking our examples from the start of class:

- *Stanford University is located in _____, California.* [Trivia]
- *I put ____ fork down on the table.* [syntax]
- *The woman walked across the street, checking for traffic over ____ shoulder.* [coreference]
- *I went to the ocean to see the fish, turtles, seals, and _____.* [lexical semantics/topic]
- *Overall, the value I got from the two hours watching it was the sum total of the popcorn and the drink. The movie was ____.* [sentiment]
- *Iroh went into the kitchen to make some tea. Standing next to Iroh, Zuko pondered his destiny. Zuko left the _____.* [some reasoning – this is harder]
- *I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, ____* [some basic arithmetic; they don't learn the Fibonacci sequence]
- Models also learn – and can exacerbate racism, sexism, all manner of bad biases.
- More on all this in the interpretability lecture!

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GPT-3, In-context learning, and very large models

So far, we've interacted with pretrained models in two ways:

- Sample from the distributions they define (maybe providing a prompt)
- Fine-tune them on a task we care about, and take their predictions.

Very large language models seem to perform some kind of learning **without gradient steps** simply from examples you provide within their contexts.

GPT-3 is the canonical example of this. The largest T5 model had 11 billion parameters.

GPT-3 has 175 billion parameters.

GPT-3, In-context learning, and very large models

Very large language models seem to perform some kind of learning **without gradient steps** simply from examples you provide within their contexts.

The in-context examples seem to specify the task to be performed, and the conditional distribution mocks performing the task to a certain extent.

Input (prefix within a single Transformer decoder context):

“ thanks -> merci
 hello -> bonjour
 mint -> menthe
 otter -> ”

Output (conditional generations):

loutre...”

GPT-3, In-context learning, and very large models

Very large language models seem to perform some kind of learning **without gradient steps** simply from examples you provide within their contexts.

Learning via SGD during unsupervised pre-training

