Lecture 15:
Pre-training and Fine-tuning Transformers

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USC CSCI 544 Applied NLP

Oct 17, Fall 2024

Some slides adapted from Dan Jurafsky and Chris Manning

Announcements

- HW2 and midterms are being graded
  - Class standing / distributions in the next class
- Upcoming deadlines:
  - Tue, 10/22 - HW3
  - Fri, 10/25 - Project Progress Report
    - What are we expecting? See class website: https://swabhs.com/f24-csci544-appliednlp/details/project/
      - once again describe the project's goals
      - contain all details on the dataset (your dataset should mostly be collected by this time),
      - contain some initial results (think of this as a motivating results), and
      - must outline a concrete plan of what will be done before the final report.
  - Tue, 10/29 - Quiz 4
- Thanks for the feedback!
  - Overwhelmingly positive (thank you!!)
    - We heard your requests for Video lectures and made them available
  - Some of you cannot hear questions that others ask. I will try my best to remember to repeat questions in class

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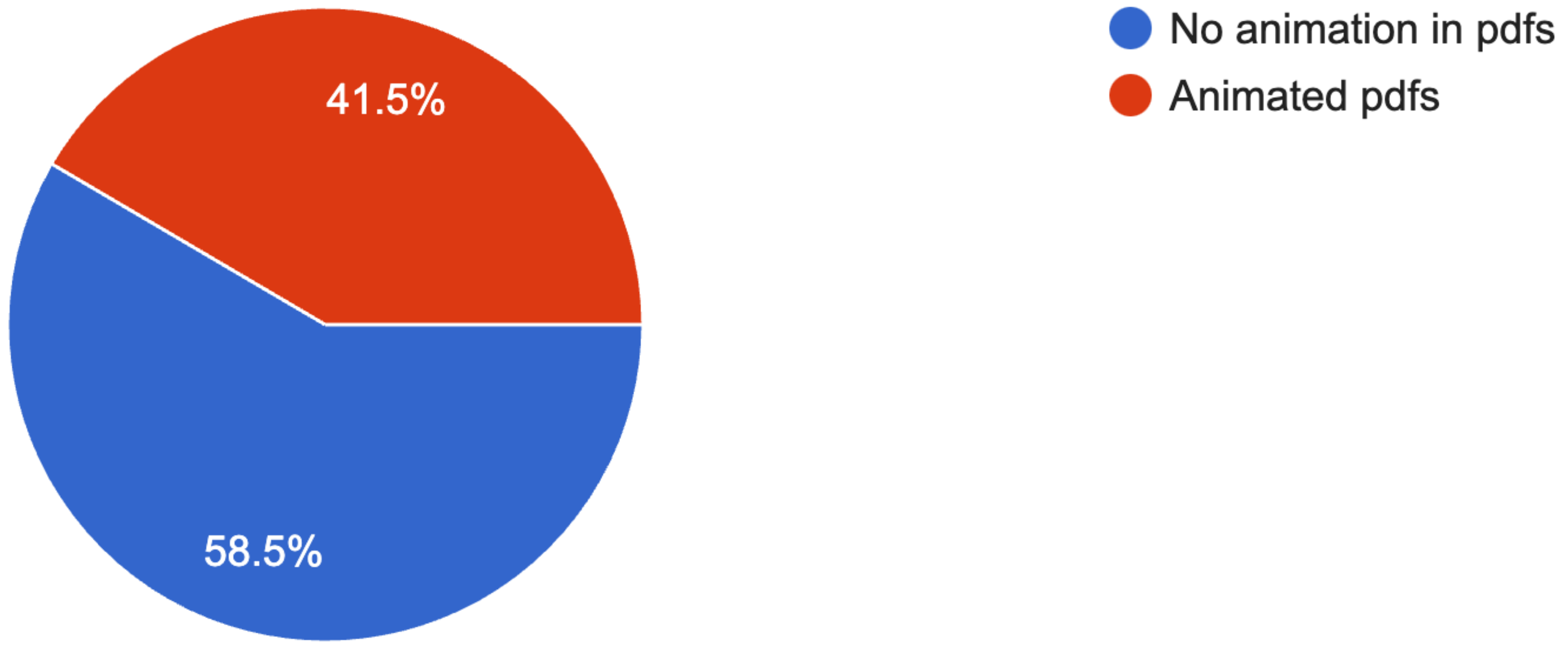
Thanks for the feedback!

Do you find the recap of the previous lecture in the beginning of each lecture useful?

65 responses

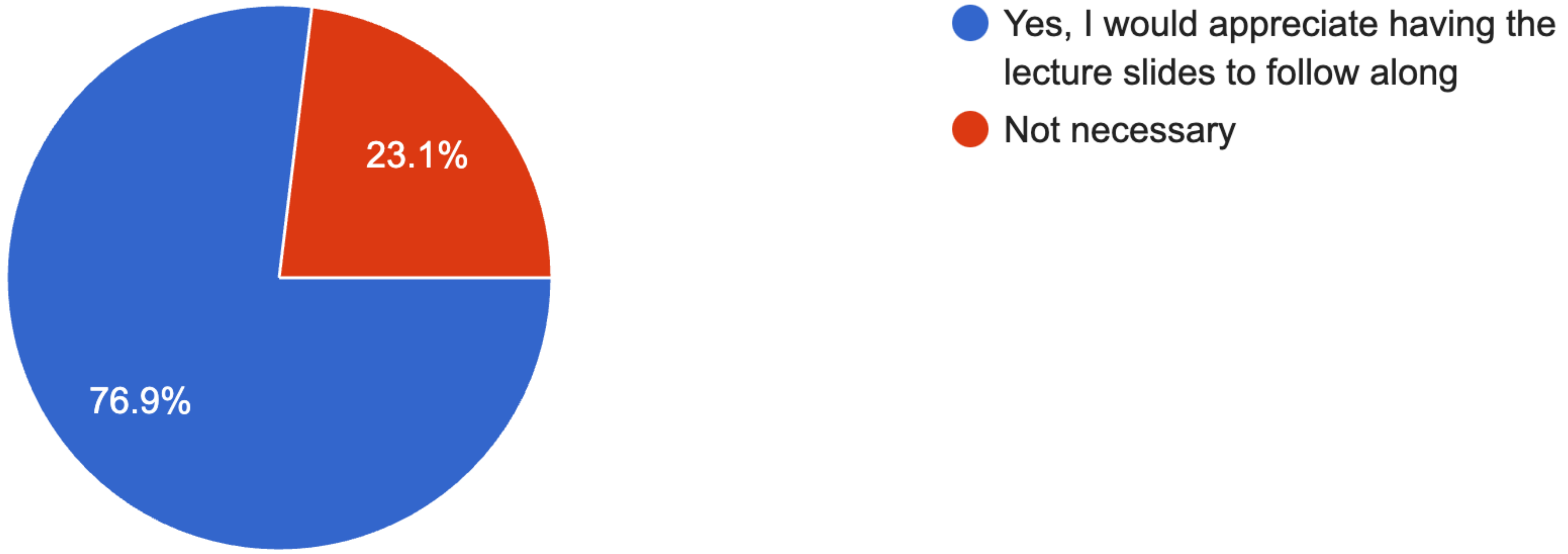
Do you like seeing animation builds in the lecture pdfs (makes the pdf much larger), or would you prefer no animation in the lecture pdfs?

65 responses



Is the availability of lecture slides before class necessary for your learning during class ?

65 responses



Lecture Outline

- Announcements
- Recap: Transformers as Encoders, Decoders, Encoder-Decoders
- The pre-training and fine-tuning paradigm
  - Pre-training Decoder-Only Models
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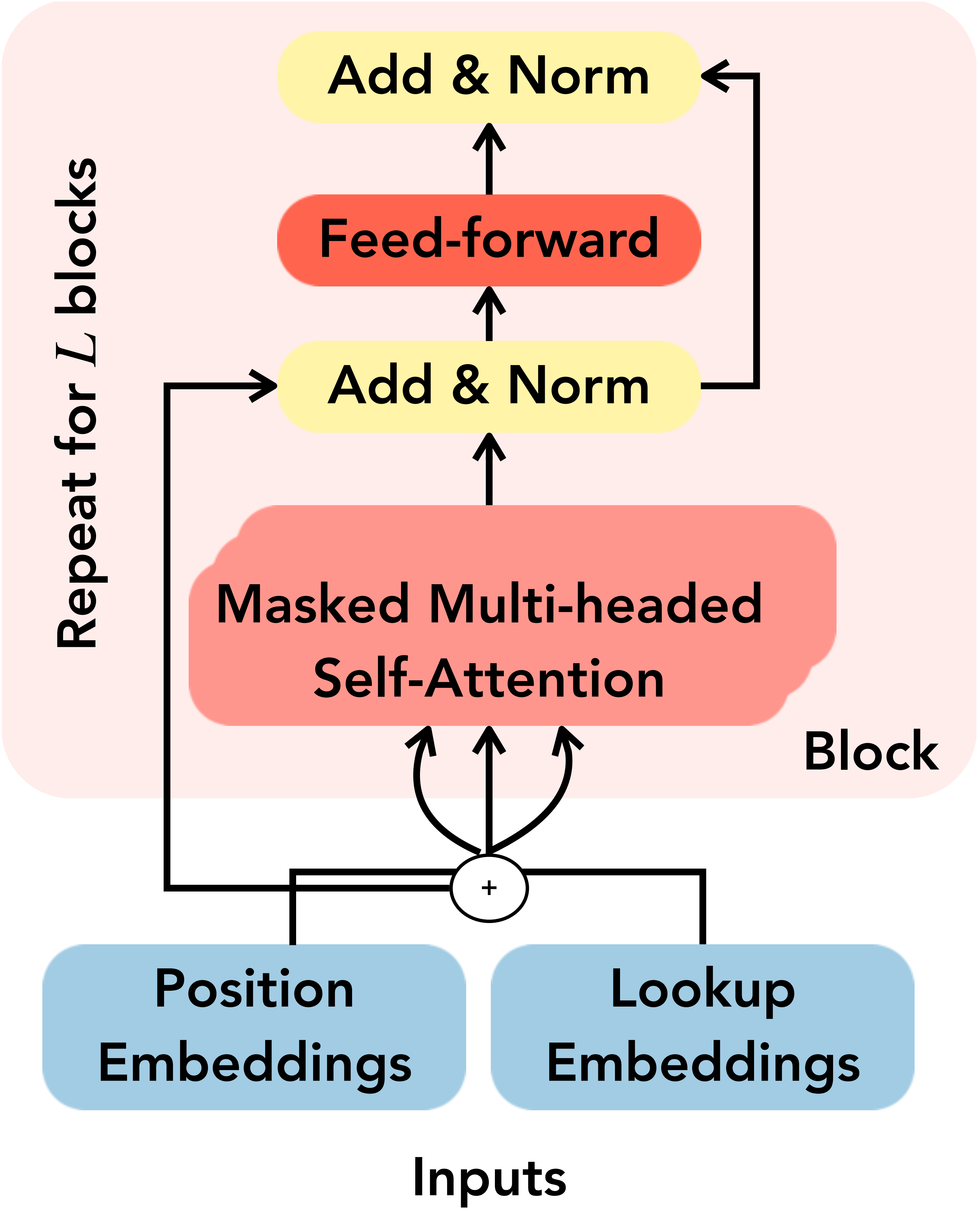
  - Pre-training Encoder-Decoder Models
- Tokenization

Recap:
Transformers as Encoders, Decoders, Encoder-Decoders

The Transformer Model



Residual Connections

Original:

- Original Connections: $X^{(i)} = \text{Layer}(X^{(i-1)})$ where i represents the layer
- **Residual Connections** : trick to help models train better.
  - We let $X^{(i)} = X^{(i-1)} + \text{Layer}(X^{(i-1)})$
    - Helps learn "the residual" from the previous layer
    - Remember: the layer contains all the non-linearities

Easier gradient flow, easier learning

Add:

Allowing information to skip a layer improves learning and gives higher level layers **direct access to information** from lower layers (He et al., 2016).

Layer Normalization

- Another 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**
    - **thus making the hidden state values more stable**
- Let $x \in \mathbb{R}^d$ be an individual (word) vector in the model.

$$\mu = \frac{1}{d}\sum_{j=1}^{d} x_j; \quad \mu \in \mathbb{R} \qquad\qquad \sigma = \sqrt{\frac{1}{d}\sum_{j=1}^{d}(x_j - \mu)^2}; \quad \sigma \in \mathbb{R}$$

Result: New vector with zero mean and a standard deviation of one

$$\hat{x} = \frac{x - \mu}{\sigma}$$

Component-wise subtraction

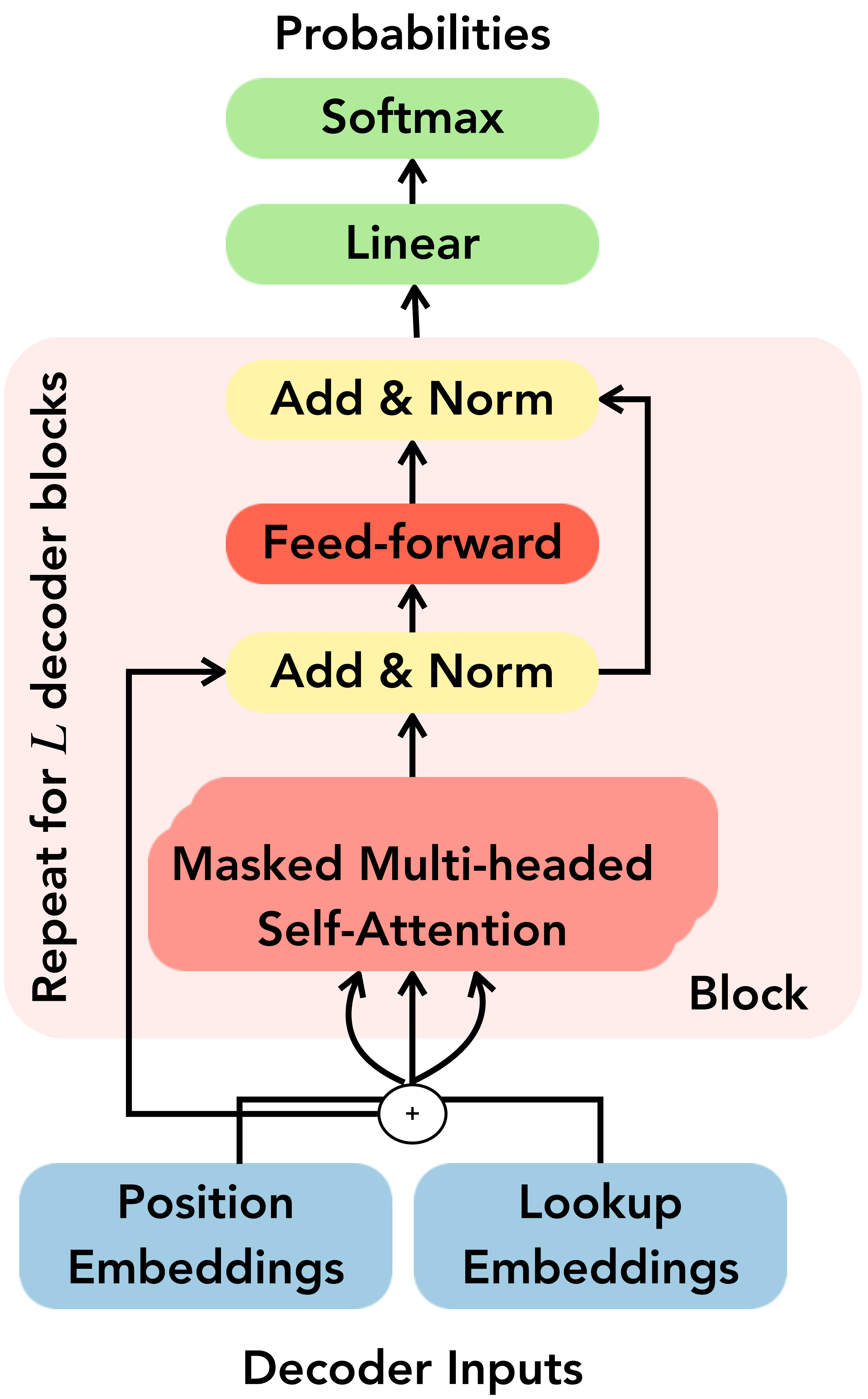
- Let $\gamma \in \mathbb{R}$ and $\beta \in \mathbb{R}^d$ be learned "gain" and "bias" parameters. (Can omit!)

$$\textbf{LayerNorm} = \gamma\hat{x} + \beta$$

Xu et al., 2019

The Transformer Decoder

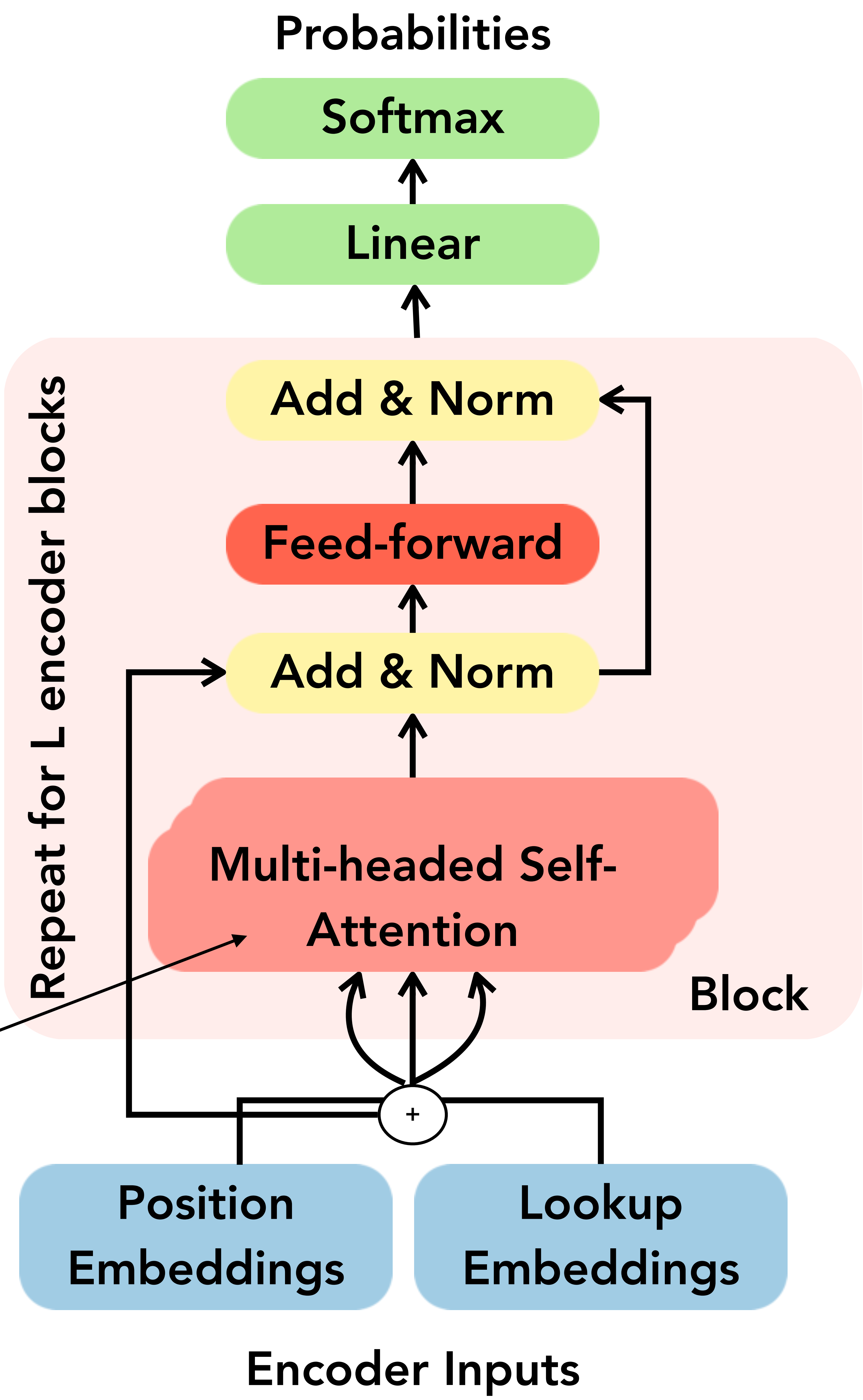
- The Transformer Decoder is a stack of Transformer Decoder Blocks.
- Each Block consists of:
  - Self-attention
  - Add & Norm
  - Feed-Forward
  - Add & Norm
- Output layer is as always a softmax layer



The Transformer Encoder

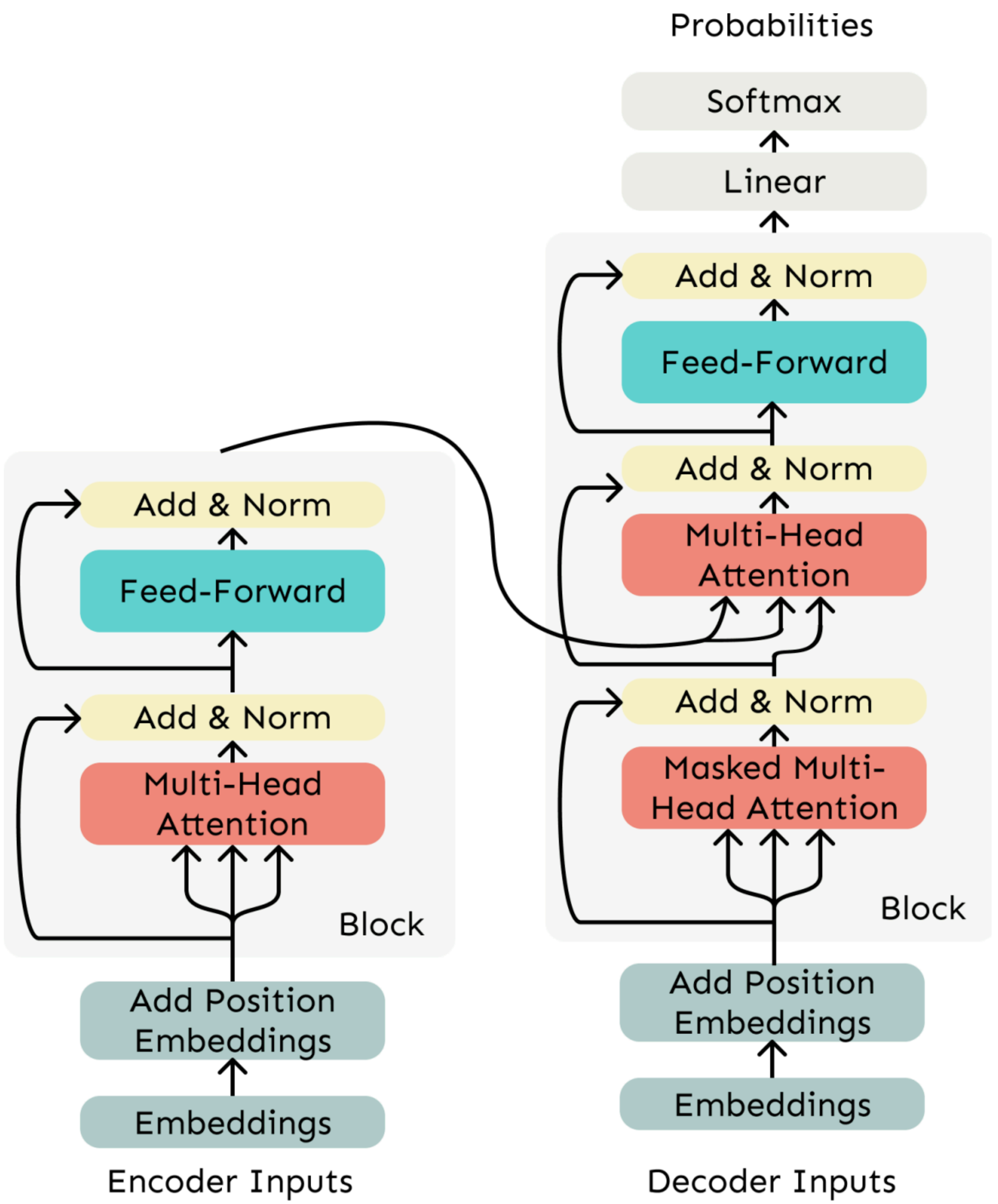
- The Transformer Decoder constrains to unidirectional context, as for language models.
- What if we want bidirectional context, i.e. both left to right as well as right to left?
- The only difference is that we remove the masking in the self-attention.
- Commonly used in sequence prediction tasks such as POS tagging
  - One output token y per input token x

No Masking!



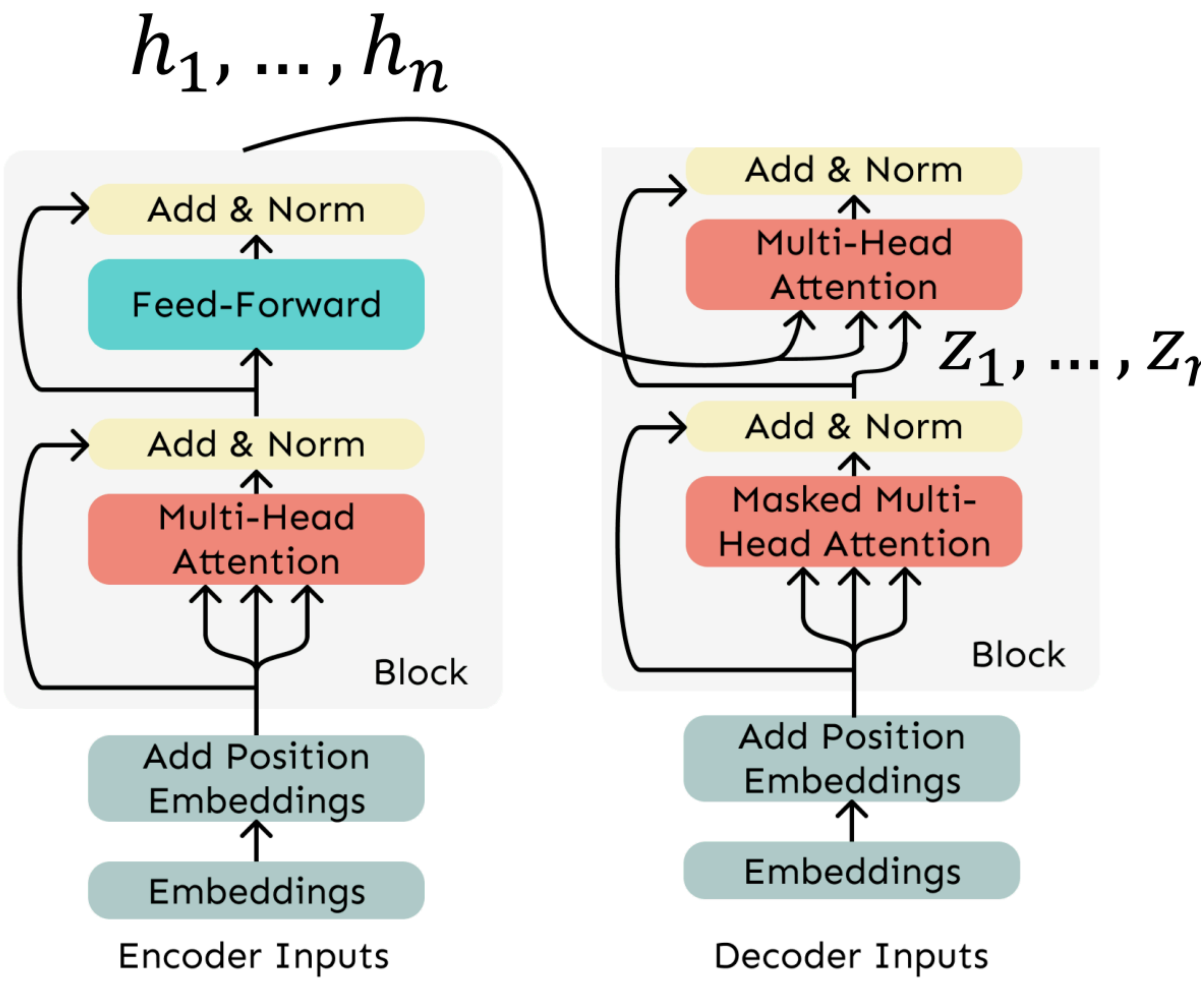
The Transformer Encoder-Decoder

- Recall that in machine translation, we processed the source sentence with a bidirectional model and generated the target with a unidirectional model.
- For this kind of seq2seq format, we often use a Transformer Encoder-Decoder.
- We use a normal Transformer Encoder.
- Our Transformer Decoder is modified to perform **cross-attention** to the output of the Encoder.



Cross Attention

- 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 $\mathbf{h}_1, \ldots, \mathbf{h}_n$ be output vectors from the Transformer encoder; $\mathbf{h}_i \in \mathbb{R}^d$
- Let $\mathbf{z}_1, \ldots, \mathbf{z}_n$ be input vectors from the Transformer decoder, $\mathbf{h}_i \in \mathbb{R}^d$
- Then keys and values are drawn from the encoder (like a memory):
  - $\mathbf{k}_i = \mathbf{K}\mathbf{h}_i, \mathbf{v}_i = \mathbf{V}\mathbf{h}_i$
- And the queries are drawn from the decoder, $\mathbf{q}_i = \mathbf{Q}\mathbf{z}_i$



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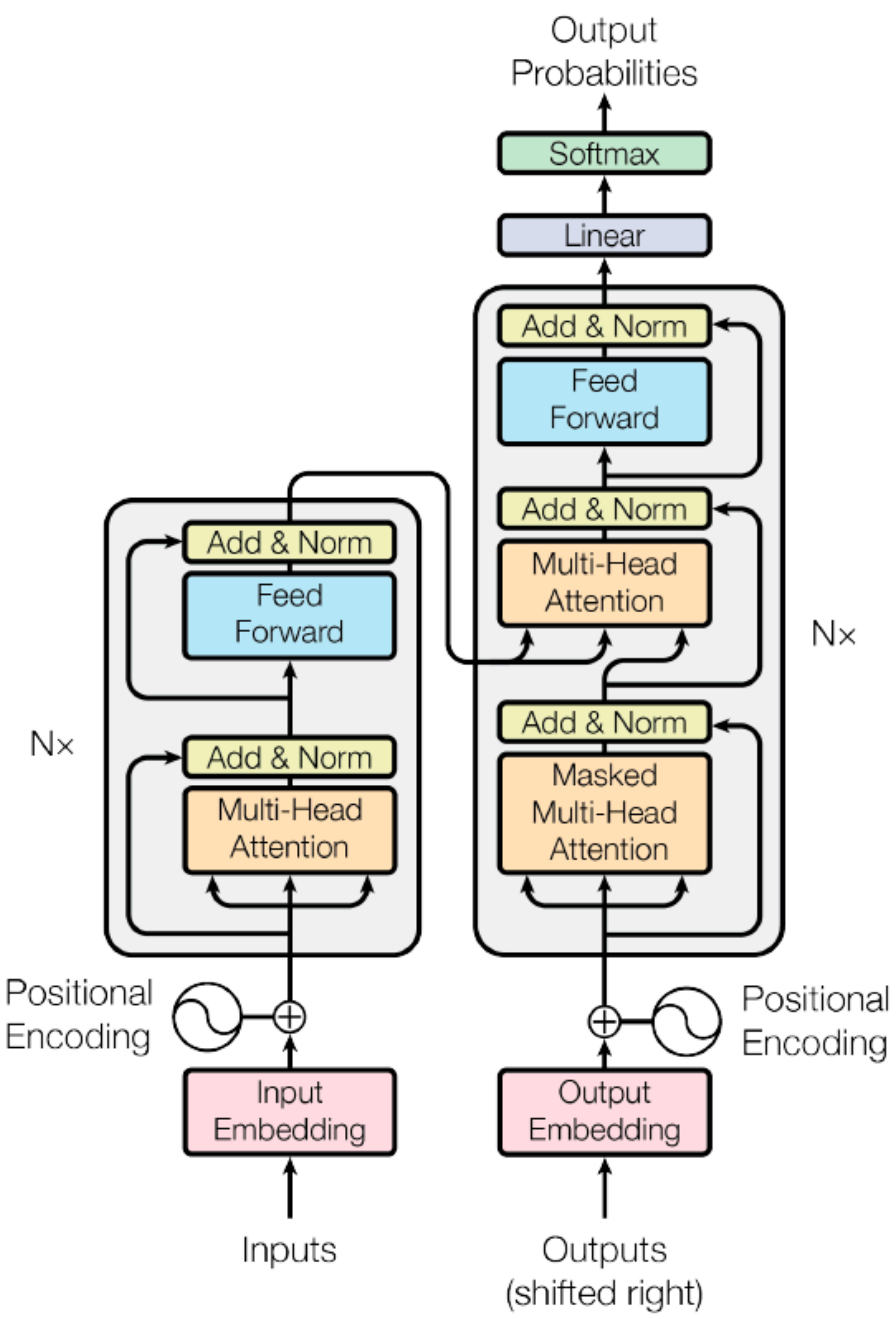
Transformer Diagram



Attention is all you need (Vaswani et al., 2017)

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The Pre-training and Fine-tuning Paradigm

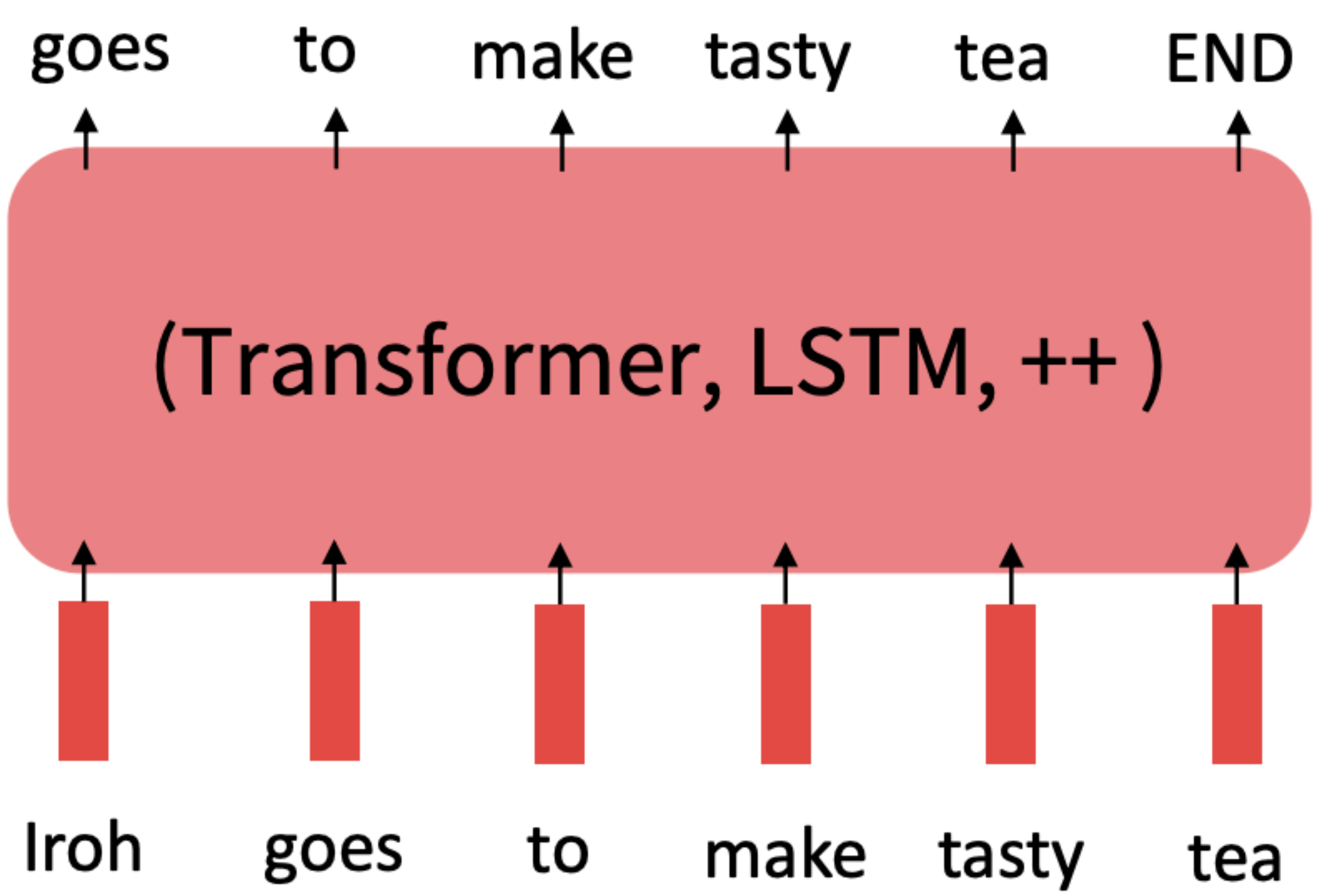
The Pretraining / Finetuning Paradigm

- Pretraining can improve NLP applications by serving as parameter initialization.

Key idea: “Pretrain once, finetune many times.”

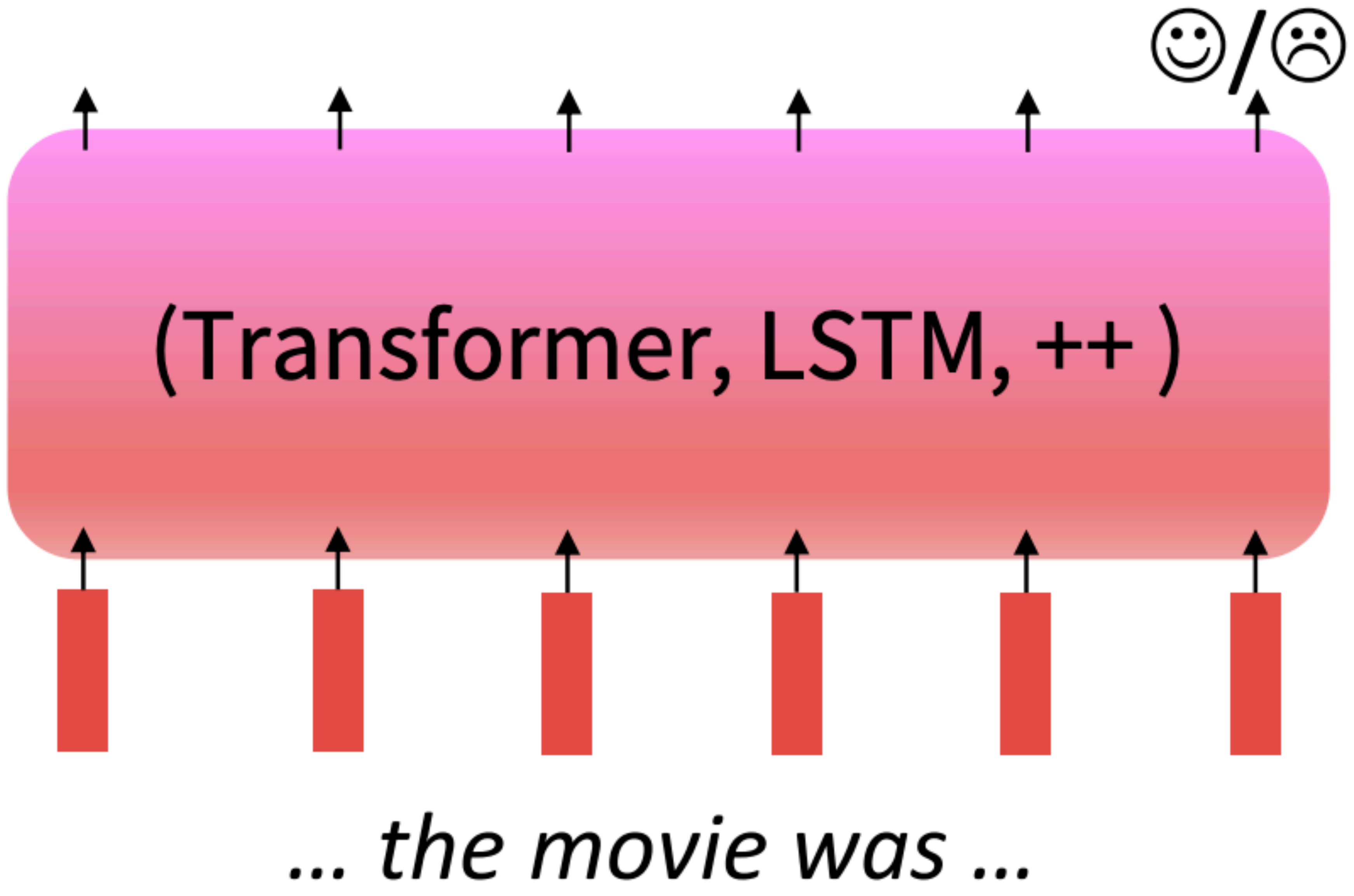
Step 1: Pretrain (on language corpora)

Lots of text; learn general things!



Step 2: Finetune (on your task data)

Not many labels; adapt to the task!

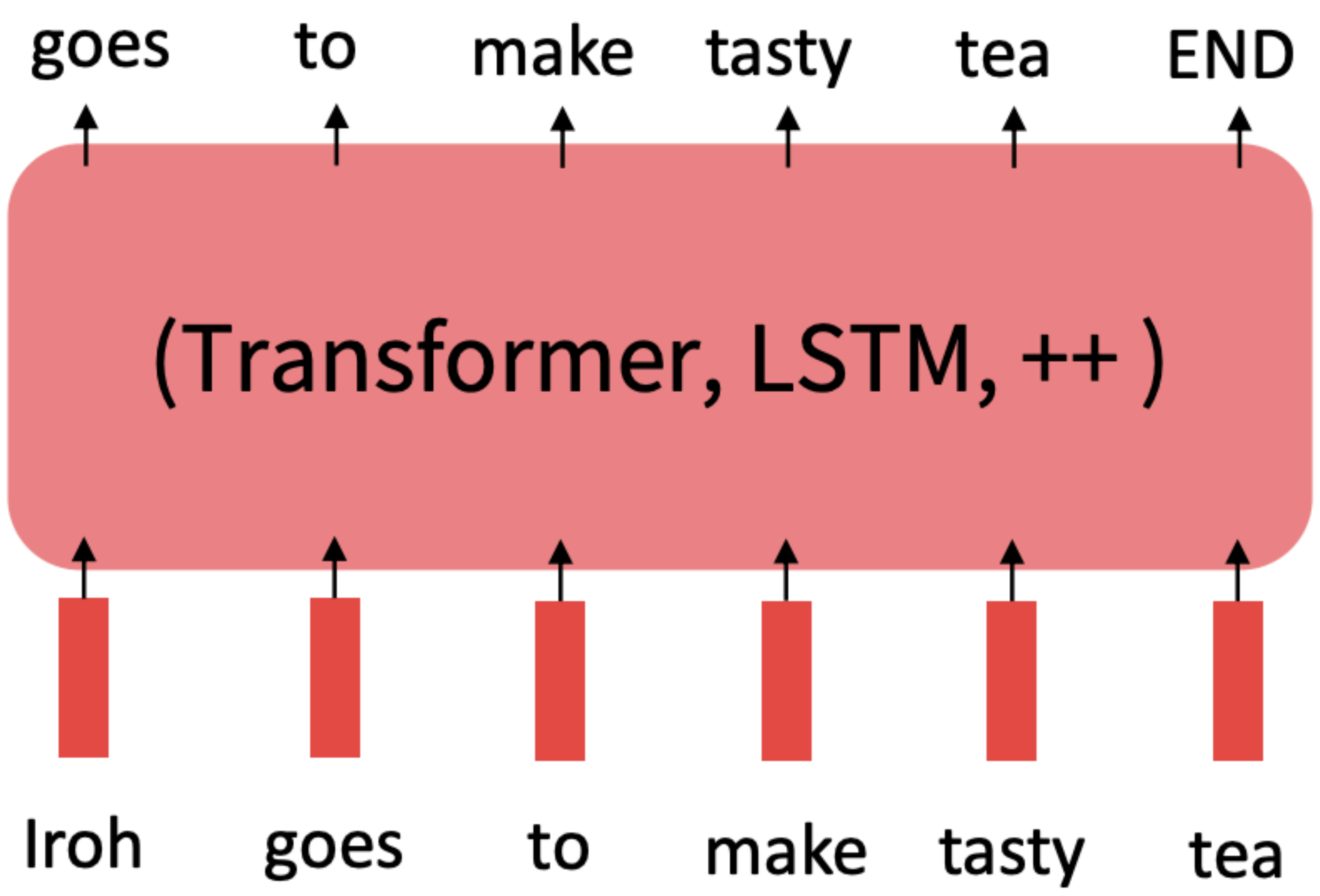


Pretraining

- Central Approach: Pretraining methods hide parts of the input from the model, and train the model to reconstruct those parts.
- Used for parameter initialization
  - Part of network
  - Full network
- Abstracts away from the task of "learning the language"

Step 1: Pretrain (on language corpora)

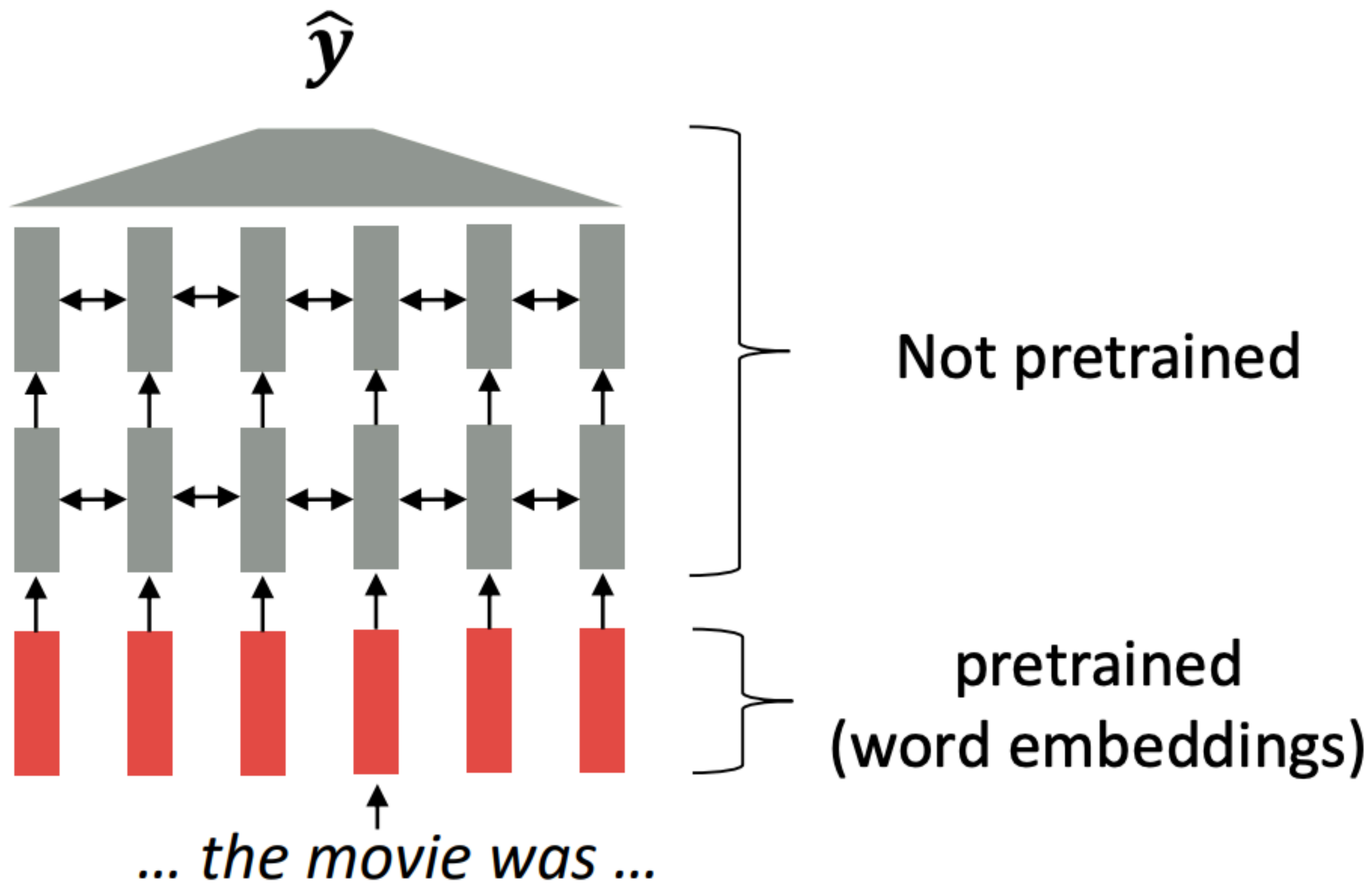
Lots of text; learn general things!



Word embeddings were pretrained too!

Previously:

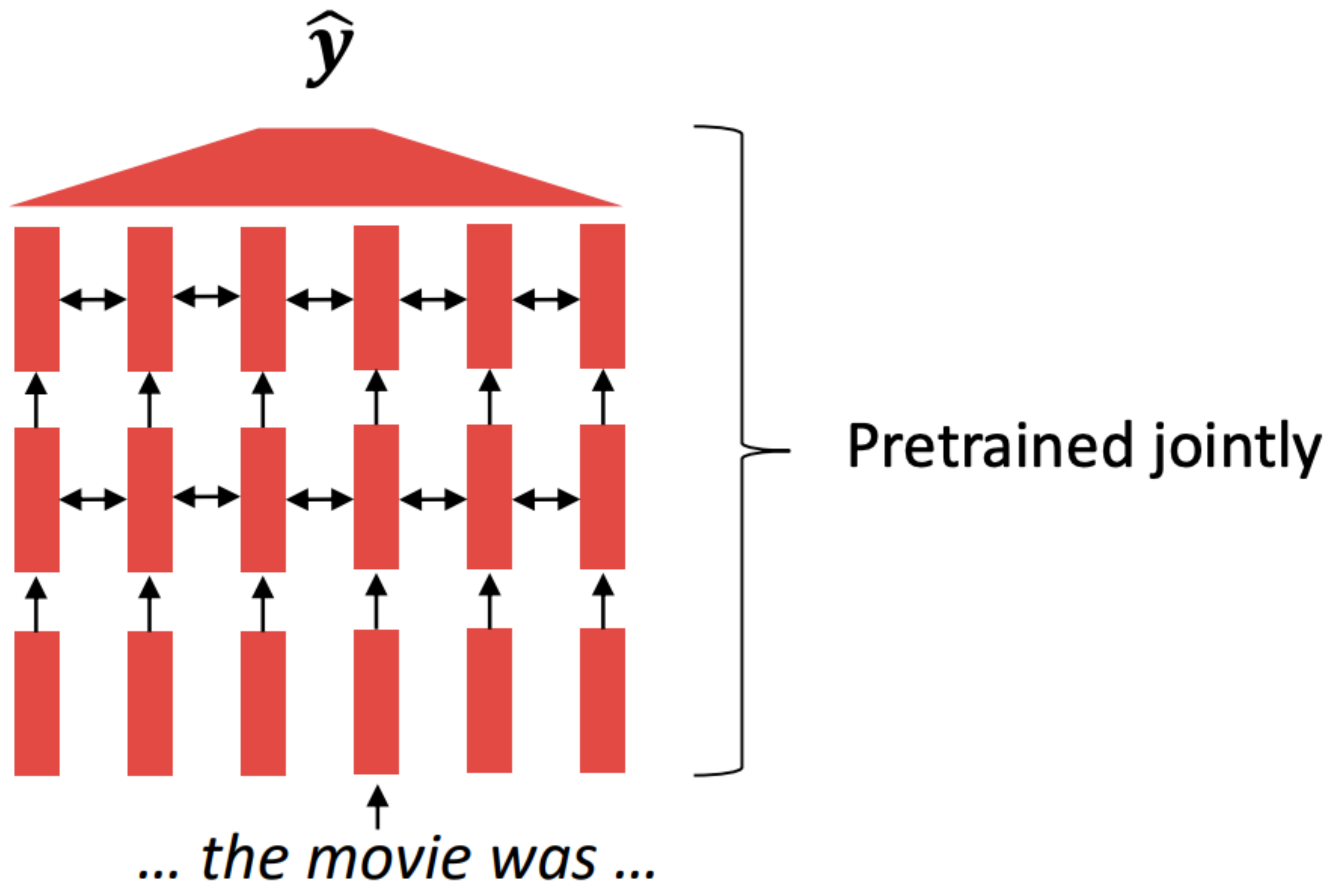
- Start with pretrained word embeddings
    - word2vec
    - GloVe
    - Trained with limited context (windows)
- Learn how to incorporate context in an LSTM or Transformer while training on the task (e.g. sentiment classification)
- Paradigm till 2017



However, the word "movie" gets the same word embedding, no matter what sentence it shows up in!

Pretraining Entire Models

- In modern NLP:
  - All (or almost all) parameters in NLP networks are initialized via pretraining.
  - 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]

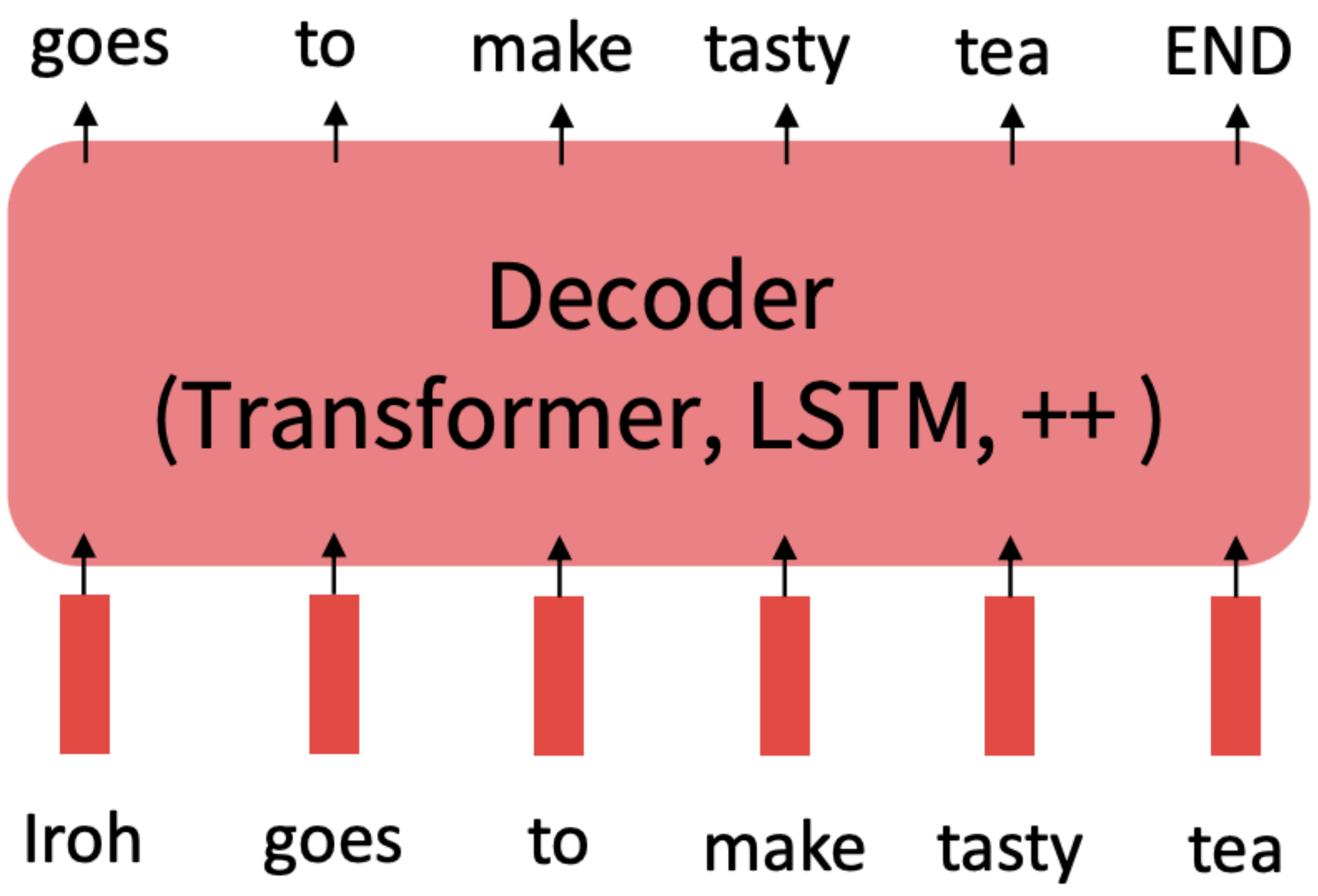
Pretraining: Intuition from SGD

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

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

Pretraining: Language Models

- Recall the language modeling task:
  - Model $p_\theta(w_t \mid w_{1:t-1})$, 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.



Semi-supervised Sequence Learning

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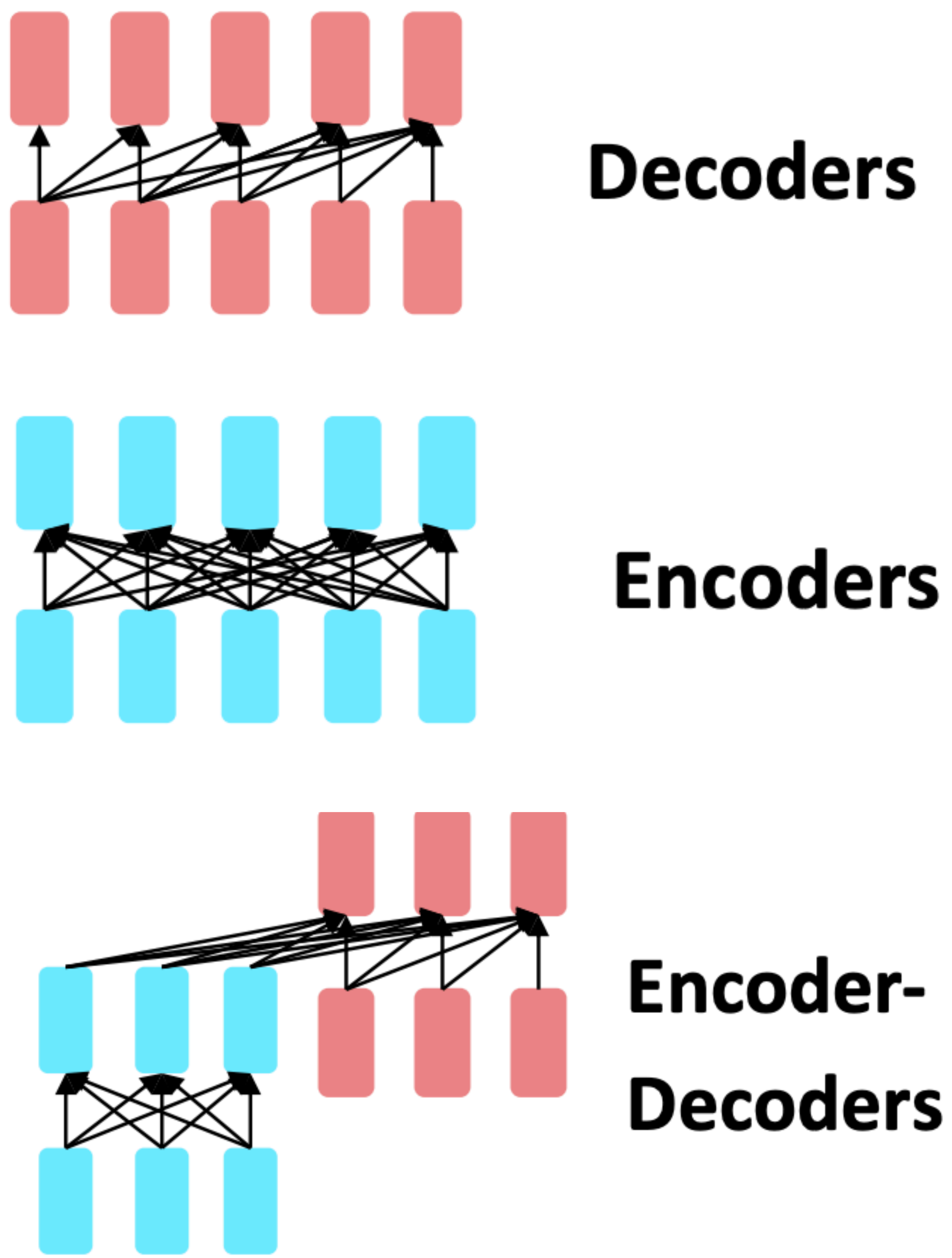
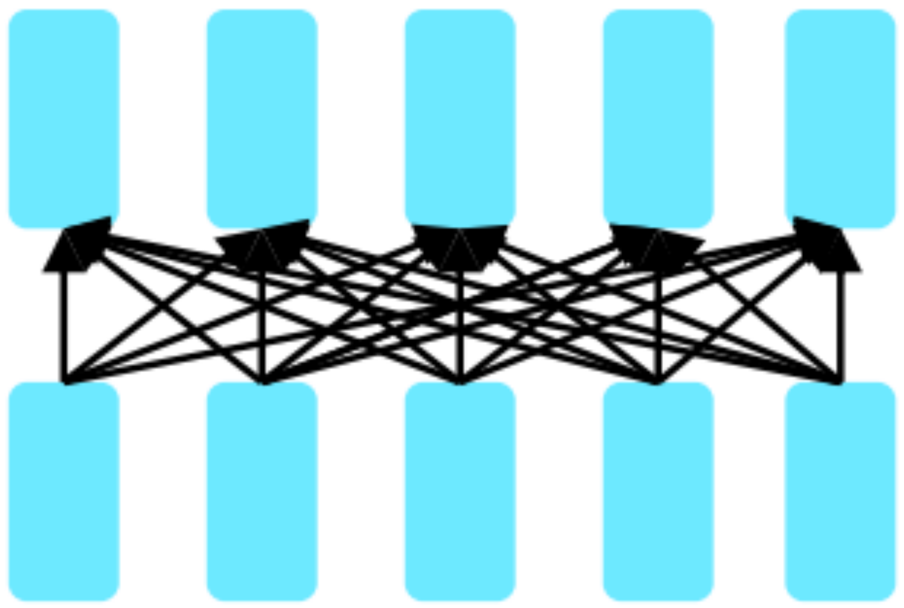
Pretraining



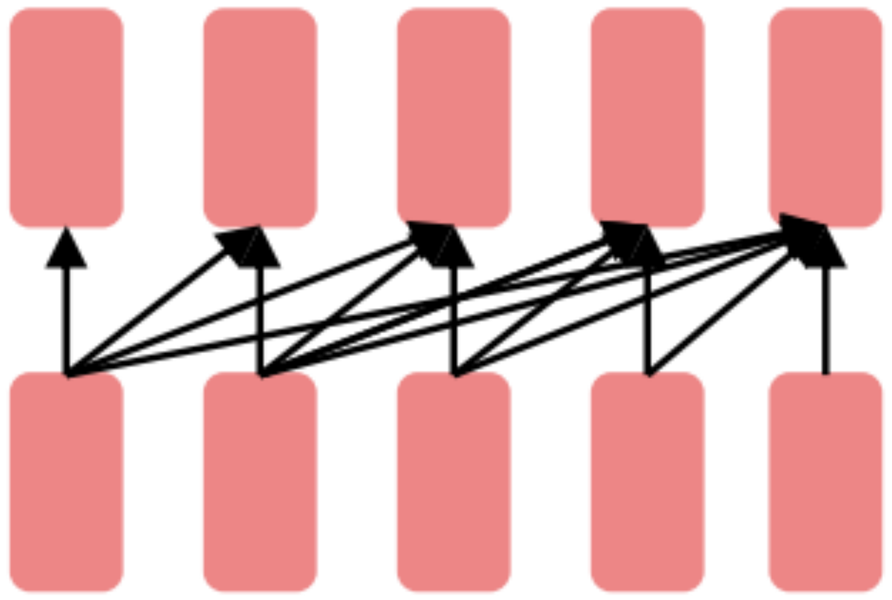
- Not restricted to language modeling! Can be any task
- But most successful if the task definition is very general. Hence, language modeling is a great pretraining option
- Three options!

Pretraining for three types of architectures



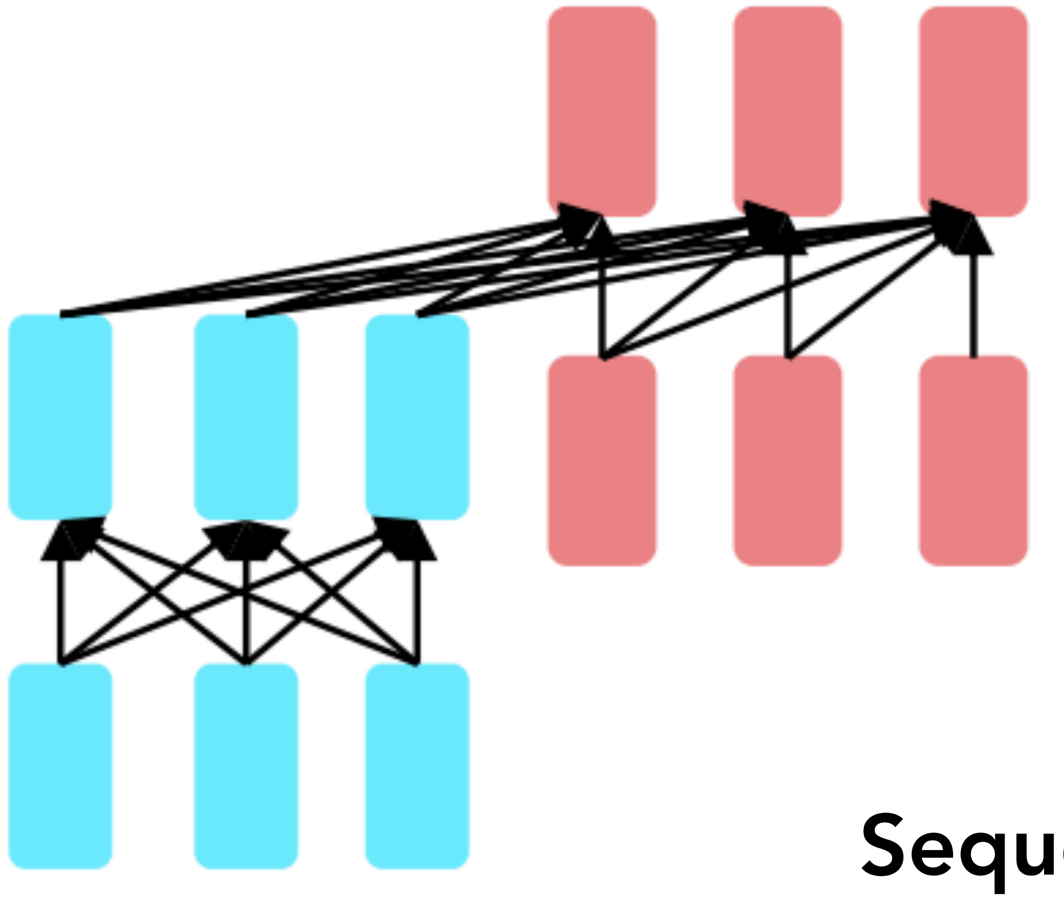
Encoders

Bidirectional Context



Decoders

Language Models



Encoder-Decoders

Sequence-to-sequence

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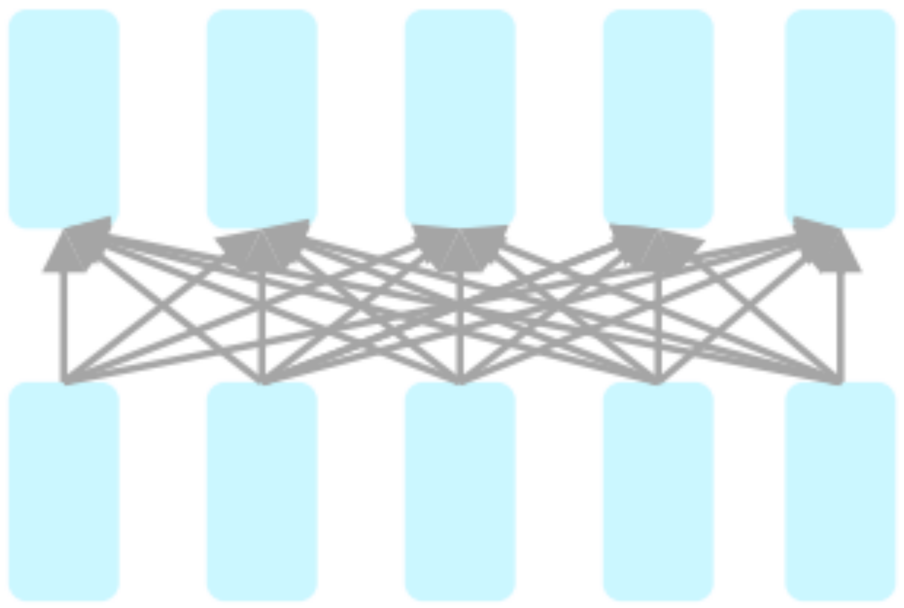
Pretraining for three types of architectures



Encoders

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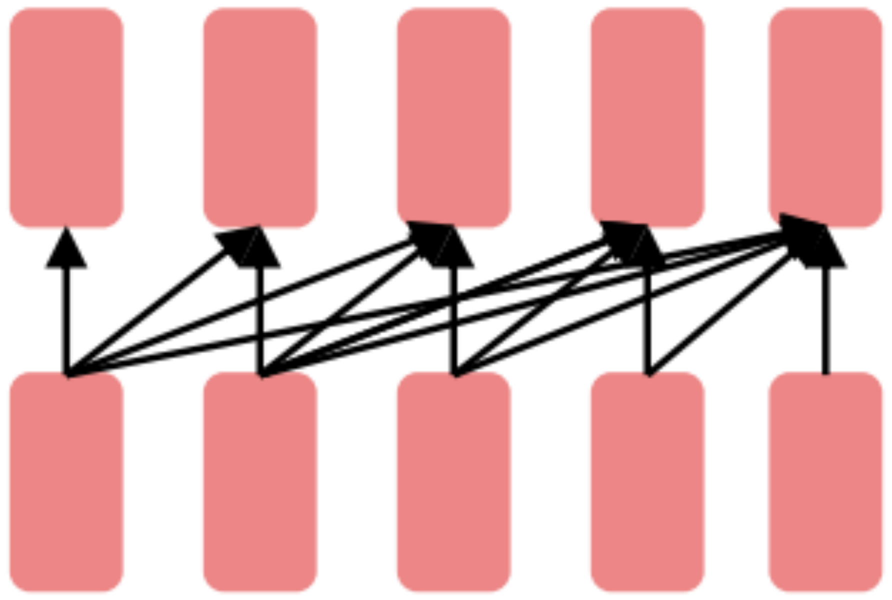
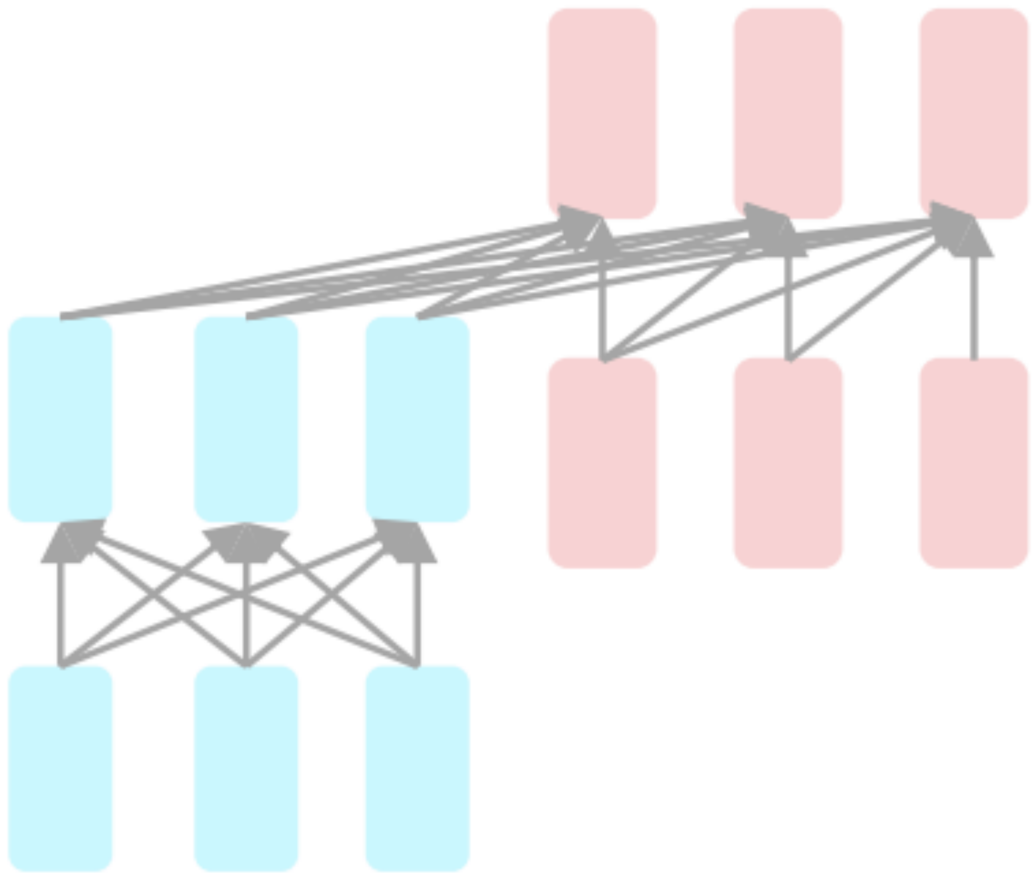


Decoders

Language Models



Encoder-Decoders

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Pre-training Decoder-Only Models

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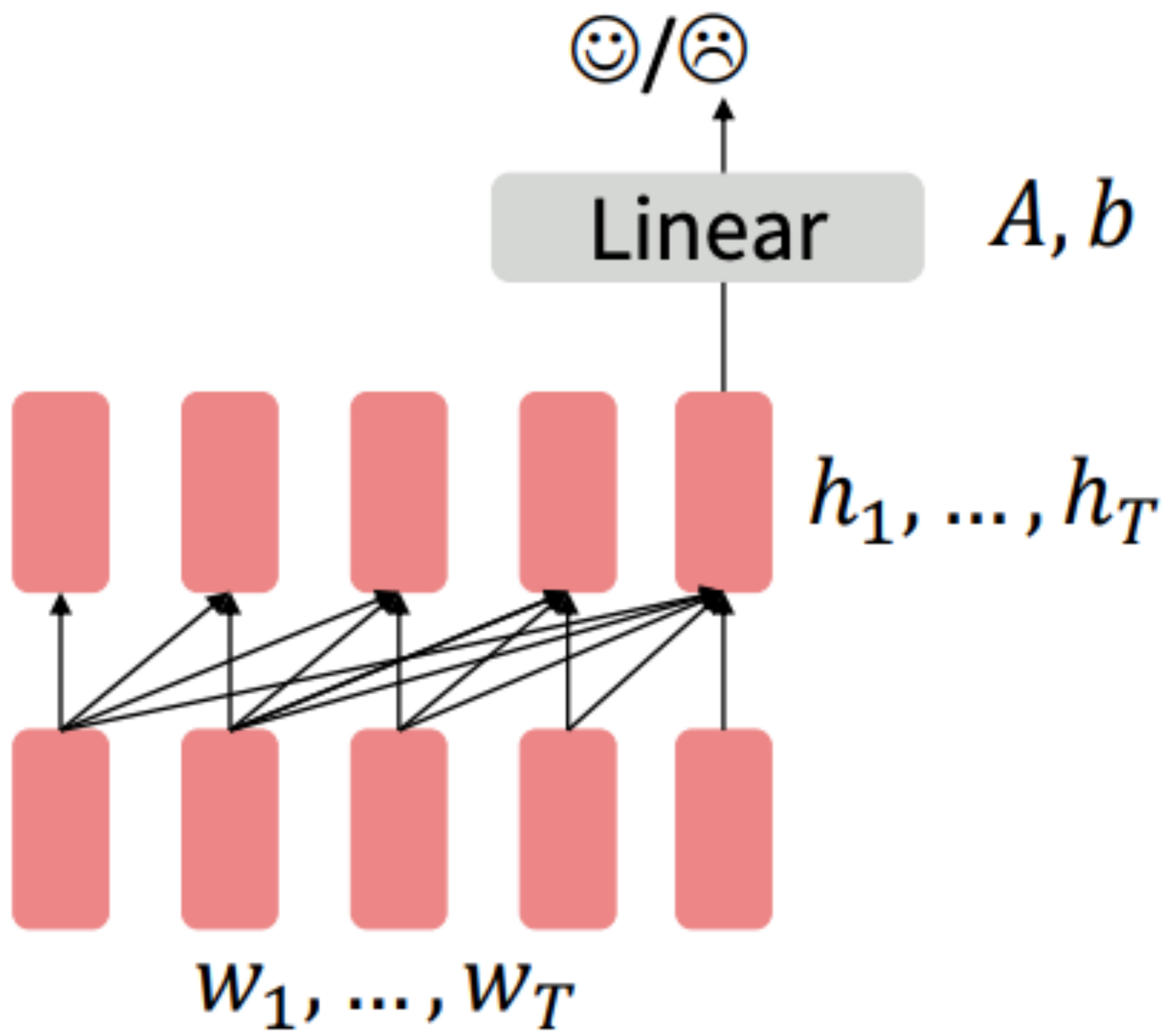
Pretraining Decoders: Classifiers

- When using language model pretrained decoders, we can ignore that they were trained to model $p_\theta(w_t \mid w_{1:t-1})$
- We can finetune them by training a classifier on the last word's hidden state
  - $h_1, \ldots, h_T = \text{Decoder}(w_1, \ldots, w_T)$
  - $y \approx Ah_T + b$
  - Where A and b are randomly initialized and specified by the downstream task.
- Gradients backpropagate through the whole network.



The linear layer hasn't been pretrained and must be learned from scratch.

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Generative Pretrained Transformer (GPT)

- 2018's GPT was a big success in pretraining a decoder!
  - Transformer decoder with 12 layers, 117M parameters.
  - 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"

OpenAI

[Radford et al., 2018]

Adapting GPT

- 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 by formatting the input 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.

[Radford et al., 2018]

GPT: Results on Classification

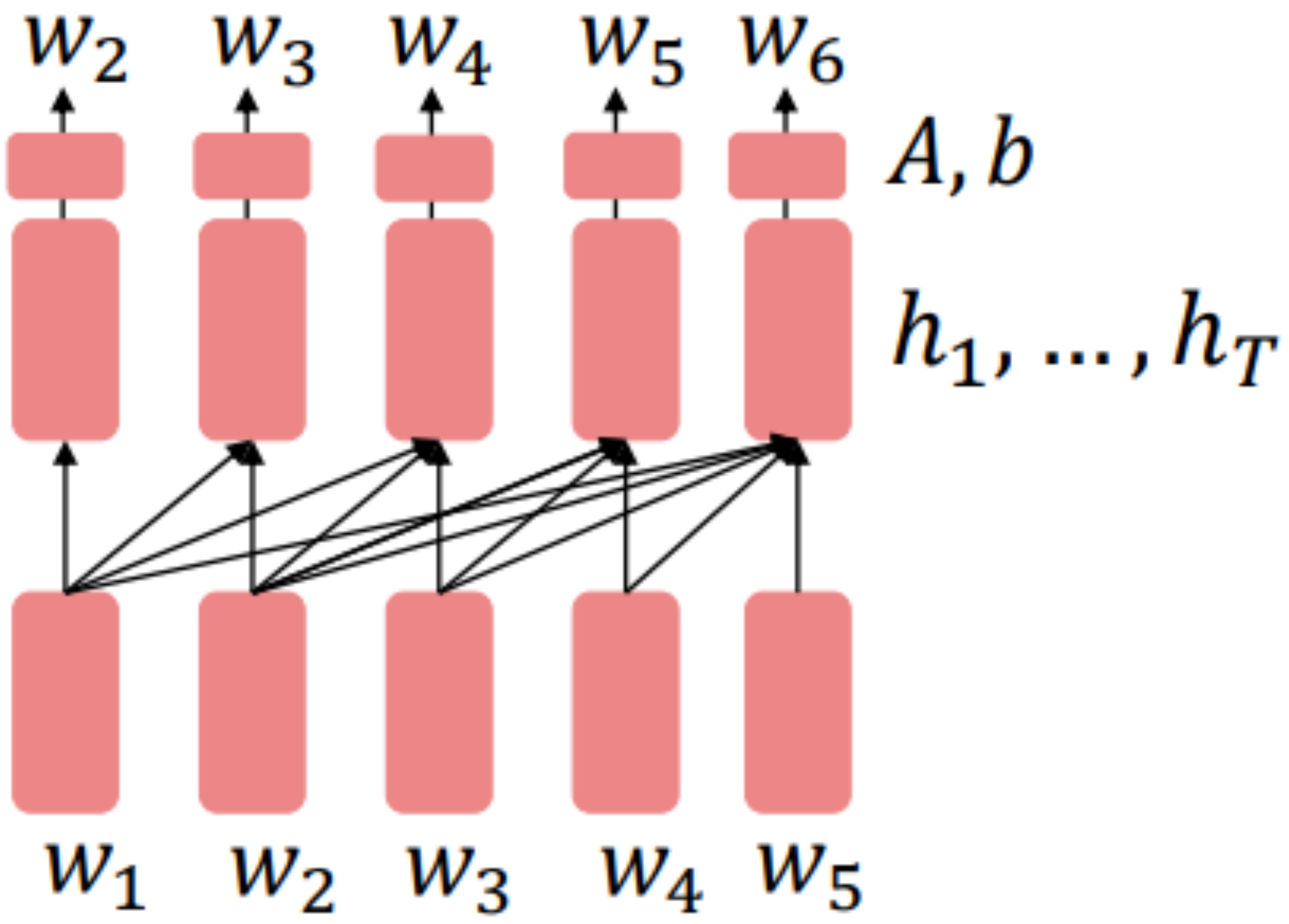
- Outperforms Recurrent Neural Nets

Method	MNLI-m	MNLI-mm	SNLI	SciTail	QNLI	RTE
ESIM + ELMo [44] (5x)	-	-	89.3	-	-	-
CAFE [58] (5x)	80.2	79.0	89.3	-	-	-
Stochastic Answer Network [35] (3x)	80.6	80.1	-	-	-	-
CAFE [58]	78.7	77.9	88.5	83.3		
GenSen [64]	71.4	71.3	-	-	82.3	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

[Radford et al., 2018]

Pretraining Decoders: Generators

- More natural: pretrain decoders as language models and then use them as generators, finetuning their $p_\theta(w_t | w_{1:t-1})$
  - $h_1, \ldots, h_T = \text{Decoder}(w_1, \ldots, w_T)$
- $w_t \approx Ah_{t-1} + b$
- Where A, b were pretrained in the language model!



- 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)

The linear layer has been pretrained

GPT-2

- GPT-2, a larger version (1.5B) of GPT trained on more data, was shown to produce relatively convincing samples of natural language.
- Moved away from classification, only generation

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.

GPT-3 and beyond

- Markedly improved generation capabilities by greatly increasing data and model scale
  - Other tricks in GPT-3.5 and above: RLHF (Reinforcement Learning with Human Feedback)
- Solving all tasks through generation, even obviating the need to fine-tune!
  - Instruction tuning

More in future weeks!

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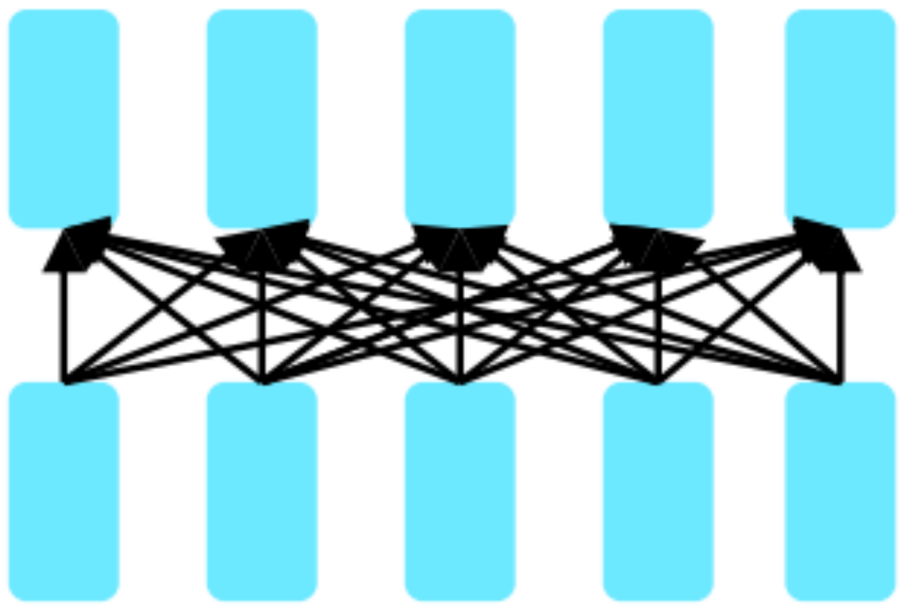
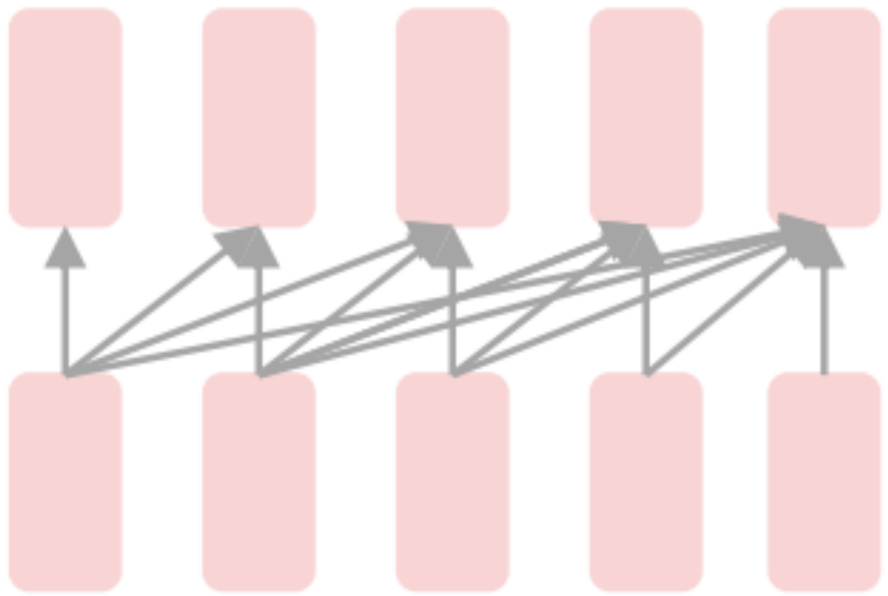
Pre-training
Encoder-Only Models

Pretraining for three types of architectures



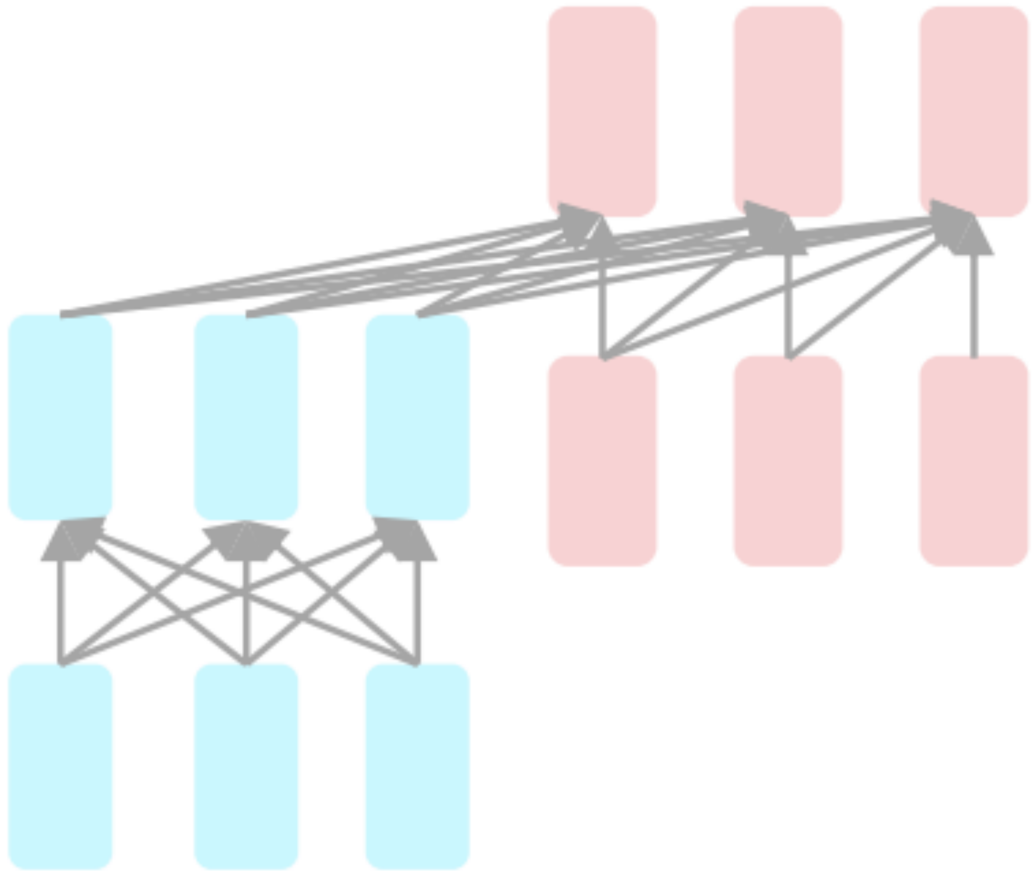
Encoders

Bidirectional Context



Decoders

Language Models



Encoder-Decoders

Sequence-to-sequence

Pretraining Encoders: Bidirectional Context

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

Universal Studios Theme Park is located in ______________, California

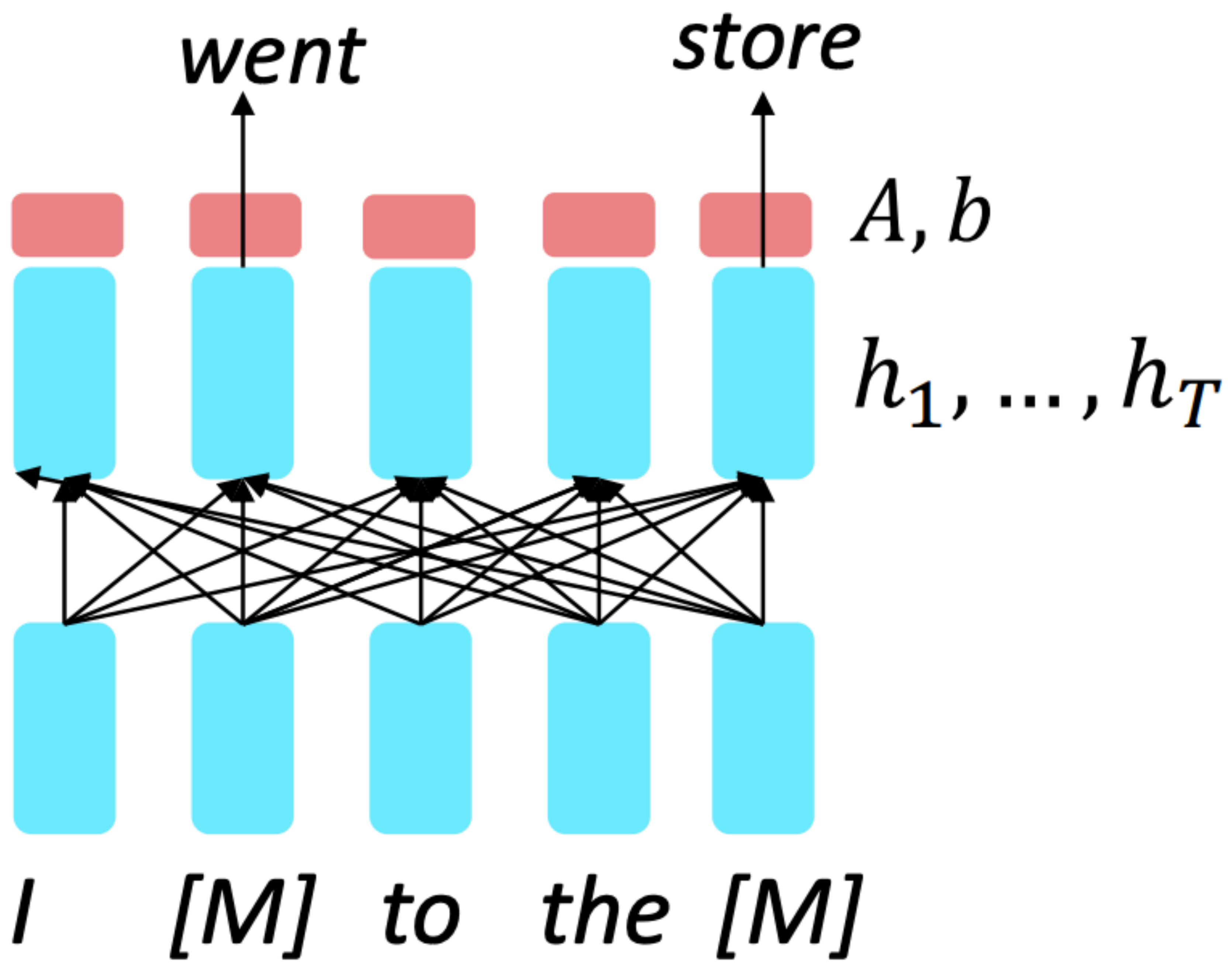
Problem: Input Reconstruction

'Cause darling i'm a _______ dressed like a daydream

Bidirectional context is important to reconstruct the input!

Pretraining Encoders: Objective

- 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.
  - $h_1, \ldots, h_T = \text{Encoder}(w_1, \ldots, w_T)$
  - $y_i \approx Ah_i + b$



- Only add loss terms from words that are "masked out."
- If $\tilde{x}$ is the masked version of x, we're learning $p_\theta(\tilde{x} \mid x)$.
- Called Masked LM
- Special type of language modeling

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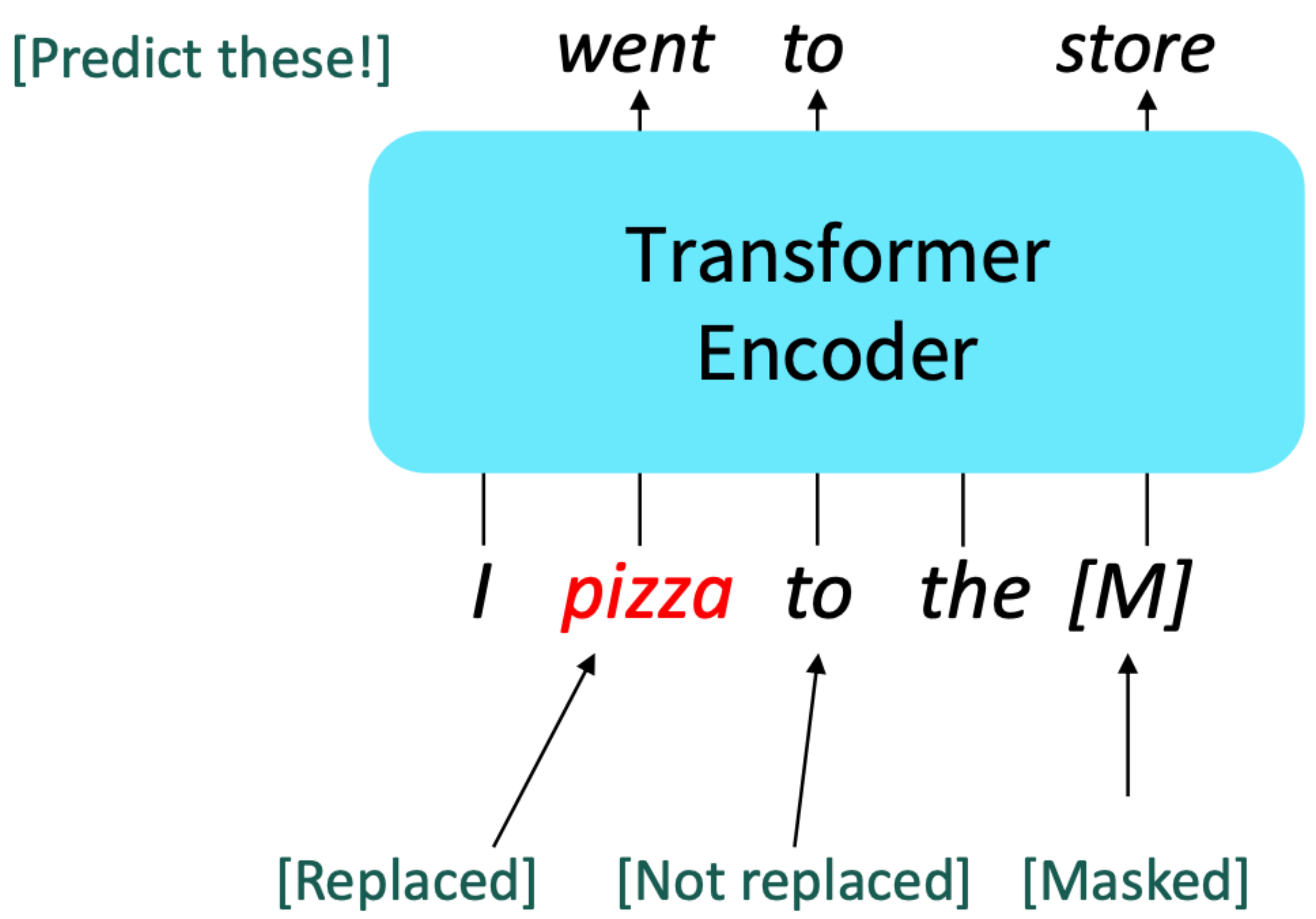
Masked Language Modeling

BERT: Bidirectional Encoder Representations from Transformers

Devlin et al., 2018 proposed the "Masked LM" objective and released BERT, a Transformer, pretrained to:

- 15% of the input tokens in a training sequence are sampled for learning, these are to be predicted by the model
- Of these
  - 80% are replaced with [MASK]
  - 10% are replaced with randomly selected tokens,
  - Remaining 10% are left unchanged

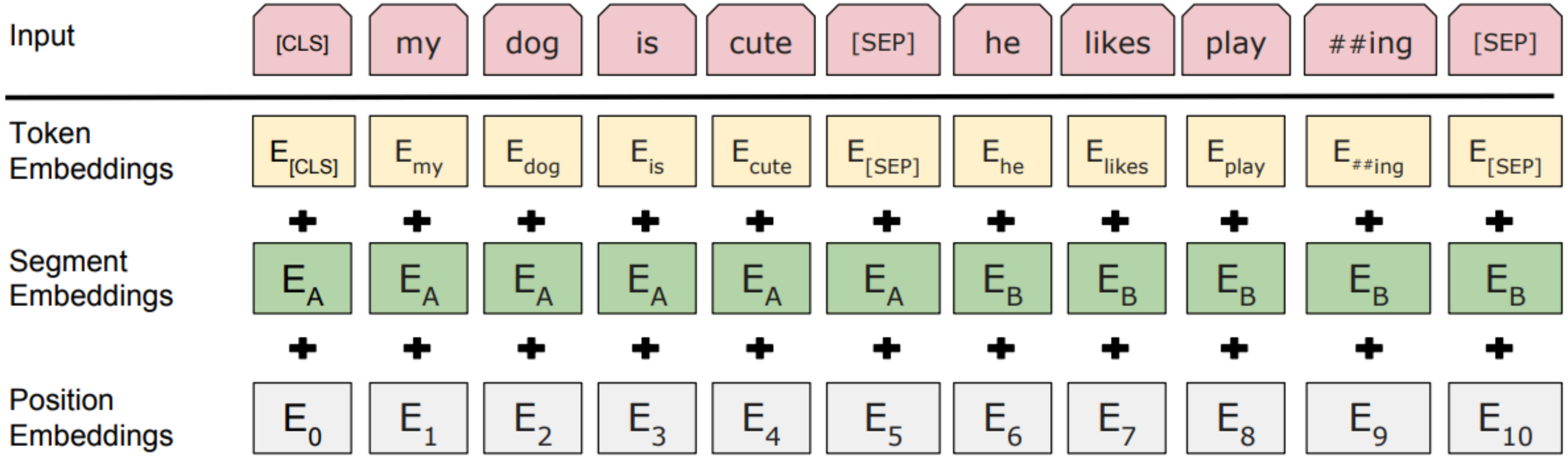


Why?

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:

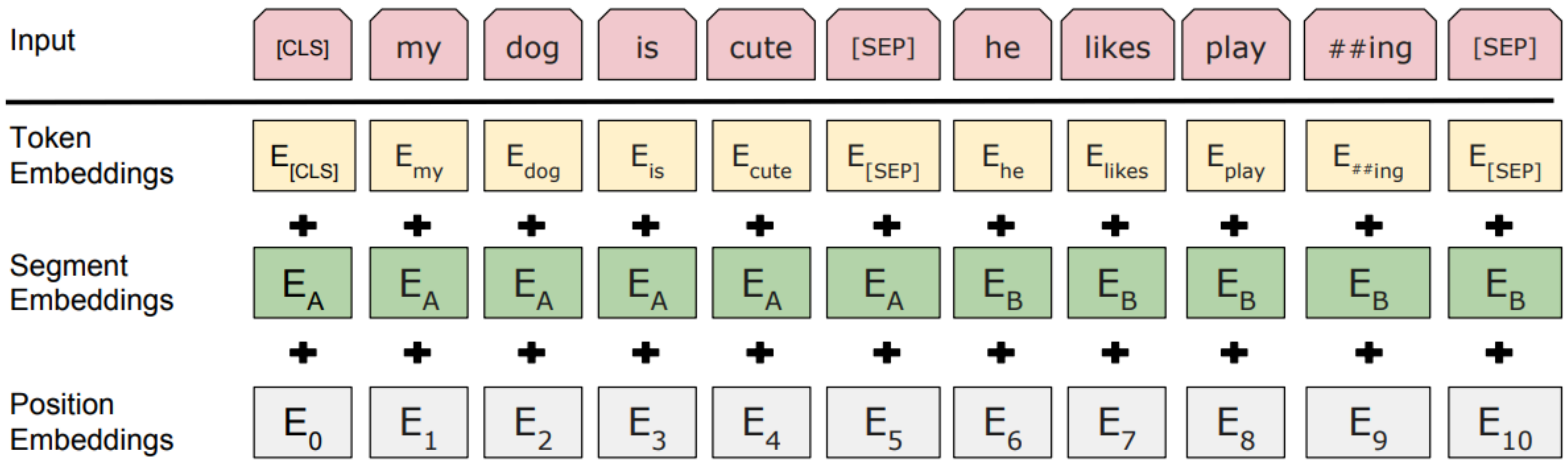


- BERT was trained to predict whether one chunk follows the other or is randomly sampled.
  - [CLS] and [SEP] tokens
  - [SEP] is used for next sentence prediction - do these sentences follow each other?
  - [CLS] for text classification / connection to fine-tuning

BERT: Training Details

- 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: Contextual Embeddings



- BERT results in contextual embeddings
  - Embeddings for tokens in context, not just type embeddings like word2vec, GloVe
  - Can be used for measuring the semantic similarity of two words in context
  - Useful in linguistic tasks that require *precise* models of word meaning

BERT: Results

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

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
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Various Text Classification tasks like sentiment classification

BERT: Extensions

- 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
- A lot of BERT variants that used the BERT formula
  - ALBERT: BERT with parameter-reduction techniques
  - DistilBERT:
  - DeBERTa: Decoding-enhanced BERT with disentangled attention
  - FlauBERT: BERT for French
  - XLNet: Multilingual BERT
  - Etc.
- **BERTology**: How and why BERT worked so well