PAUL G. ALLEN SCHOOL

UNIVERSITY of WASHINGTON

Natural Language Processing

CSE 447 / 547 M

Pre-training

Lecturer: Kabir Ahuja

Slides adapted from Liwei Jiang, John Hewitt, Anna Goldie

Major Paradigms in NLP

Liu et al. 2021

Major Paradigms in NLP

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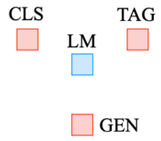
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	

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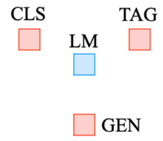
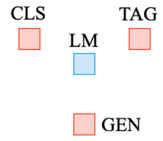
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	

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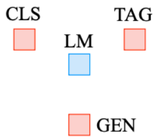
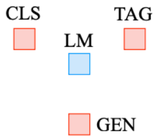
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	

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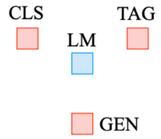
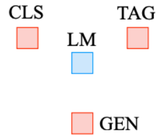
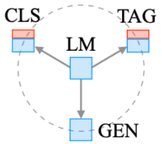
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	

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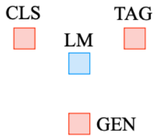
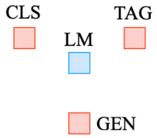
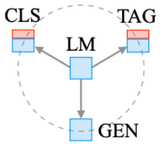
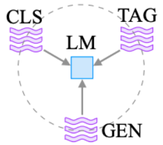
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	

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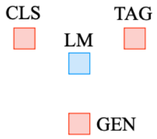
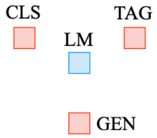
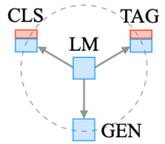
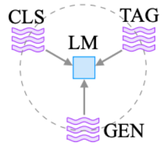
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	
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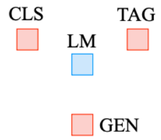
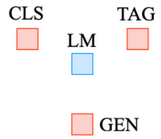
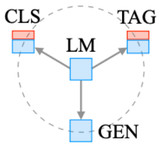
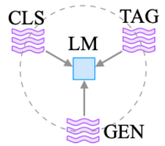
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	
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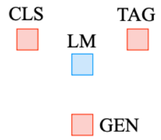
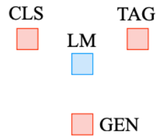
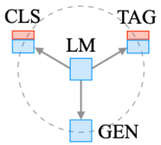
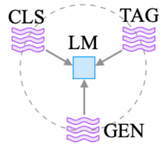
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	
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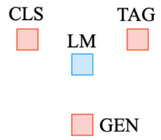
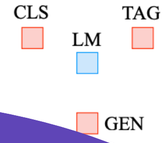
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
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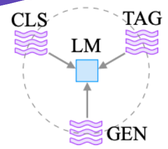
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	
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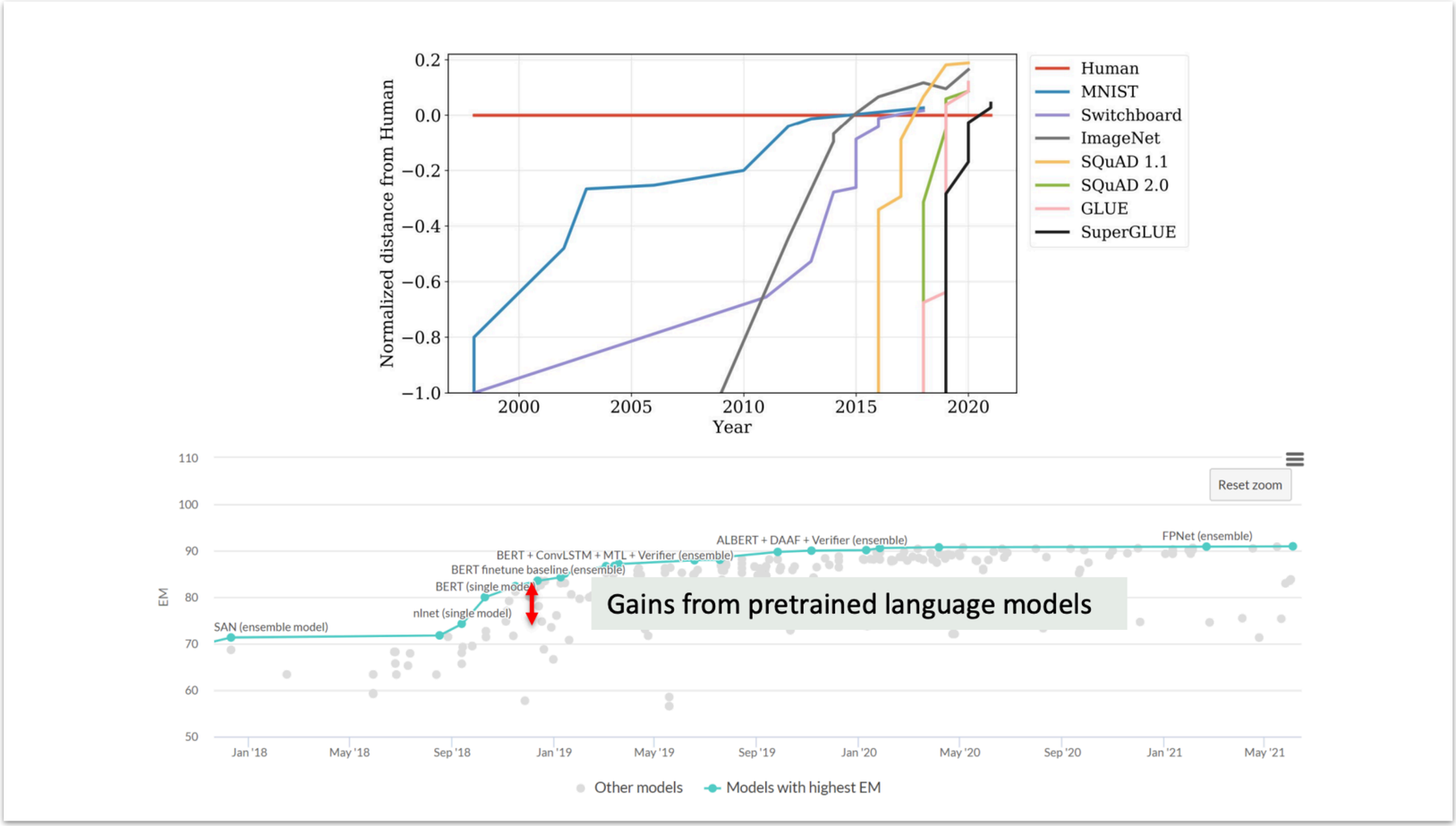
Pre-training common across all major paradigms post 2017

What we will see in the coming lectures

The Pre-training Revolution



Pre-training has had a major, tangible impact on how well NLP systems work

Slide from Chris Manning. Lecture 9: Pre-training, CS224n Spring 2024

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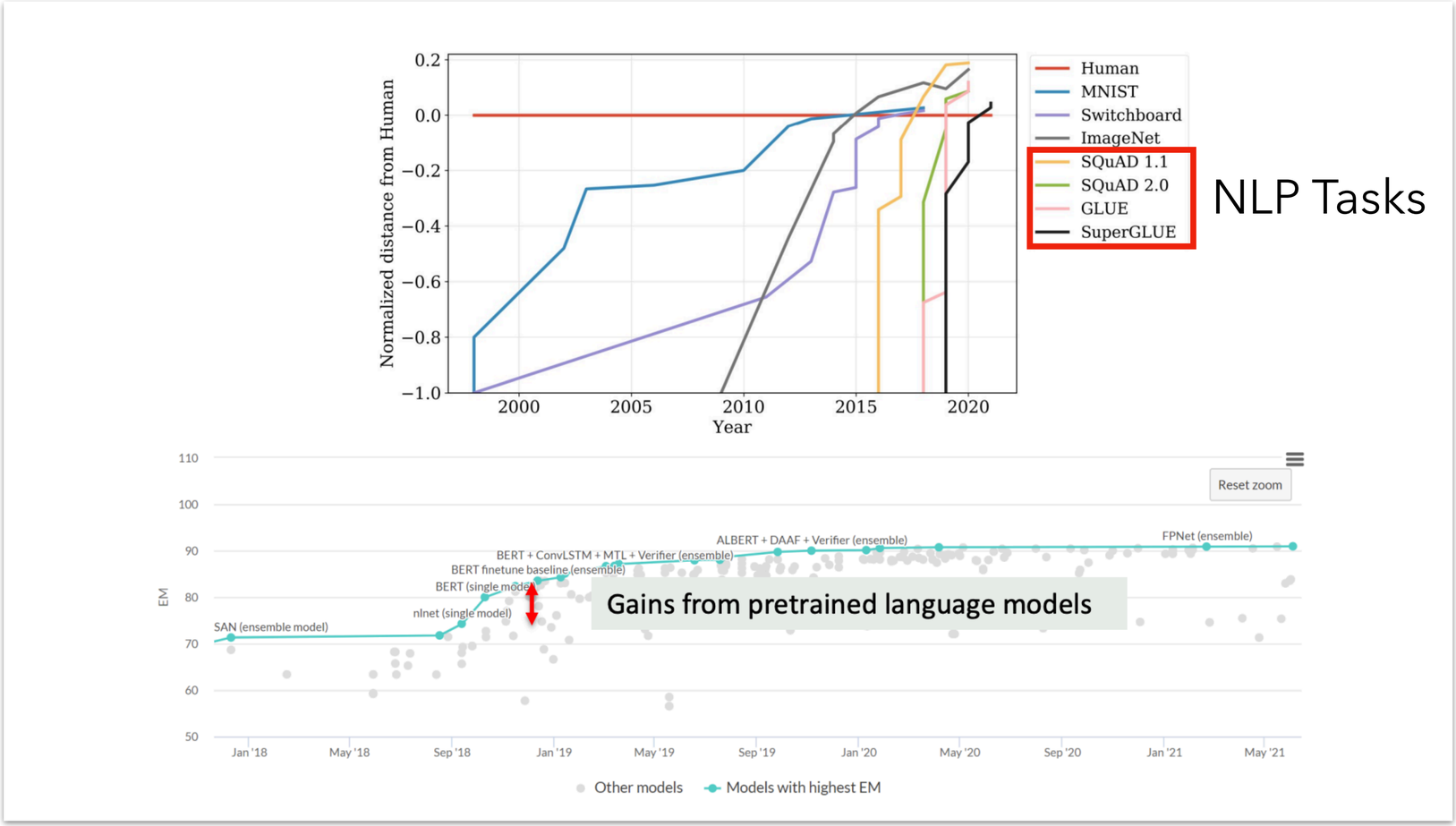

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Lecture Outline

1. Motivating Pre-training, aka Self-supervised Learning
2. Pre-training Architectures and Training Objectives
    1. Encoders
    2. Encoder-Decoders
    3. Decoder

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Issues with Fully Supervised Learning Approaches

Food Review: “I recently had the pleasure of dining at Fusion Bites, and the experience was nothing short of spectacular. The menu boasts an exciting blend of global flavors, and each dish is a masterpiece in its own right.”

Say that we are given a dataset of 100K food reviews with sentiment labels, **how do we train a model to perform sentiment analysis over unseen food reviews?**

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We can directly train a randomly initialized model to take in food review texts and output “positive” or “negative” sentiment labels.

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Movie Review: "The narrative unfolds with a steady pace, showcasing a blend of various elements. While the performances are competent, and the cinematography captures the essence of the story, the overall impact falls somewhere in the middle."

If we are instead given **movie reviews** to classify, can we use the same system trained from food reviews to predict the sentiment?

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Fully Supervised Learning

Collect a labeled dataset for movie reviews and train a model from scratch on this new dataset

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Transfer Learning: A History Lesson from Computer Vision

- Instead of training a randomly initialized neural network every time we encounter a new task or domain,
  - can we re-use the learned representations from one task/domain for another?

Image from Lecture 7 CS231n slides by Fei-Fei Li, Ehsan Adeli, Zane Durante

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Idea: Train a **(very) deep neural network** on a **large-scale dataset** and re-use the learned representations from this network to adapt to new tasks

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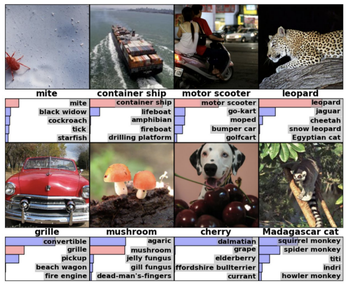
ImageNet Challenge

IMAGENET

- 1,000 object classes (categories).
- Images:
  - 1.2 M train
  - 100k test.



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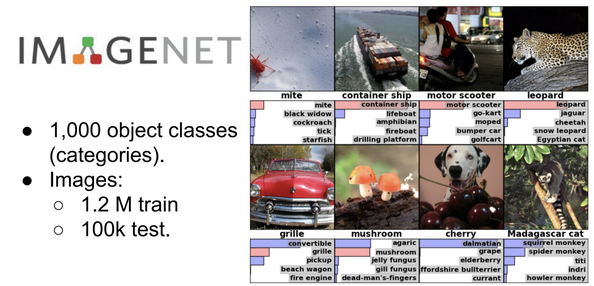

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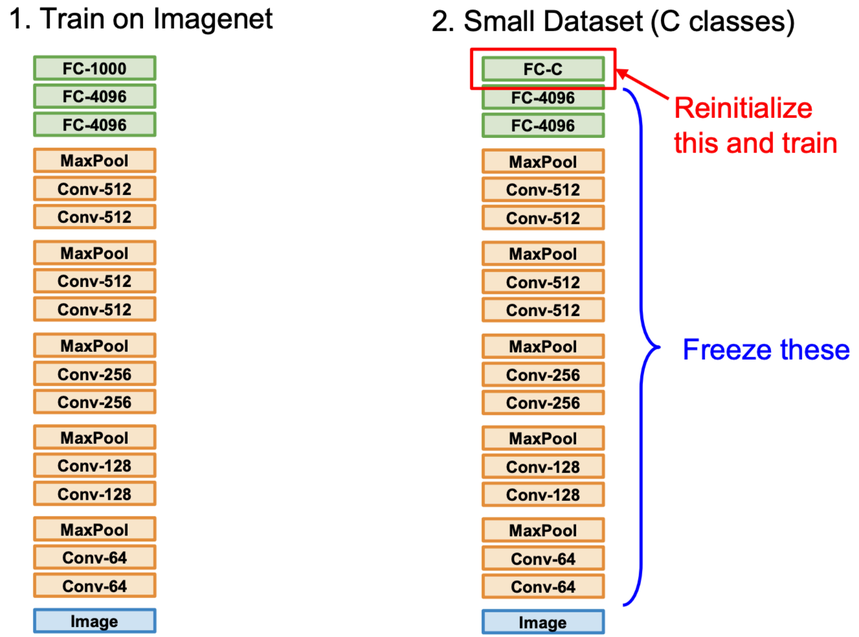
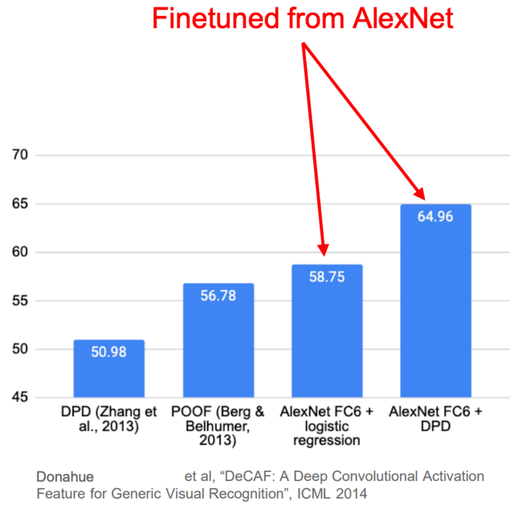


This is called Fine-tuning!



Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014

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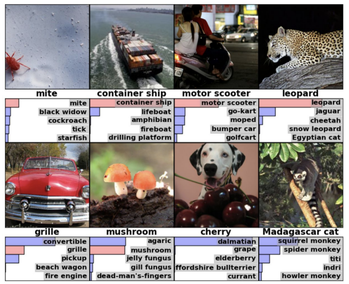
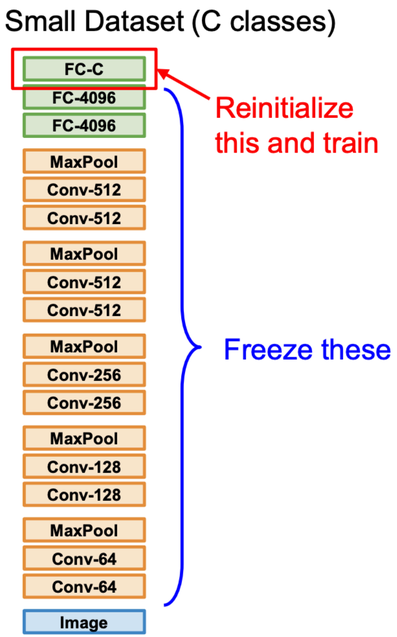
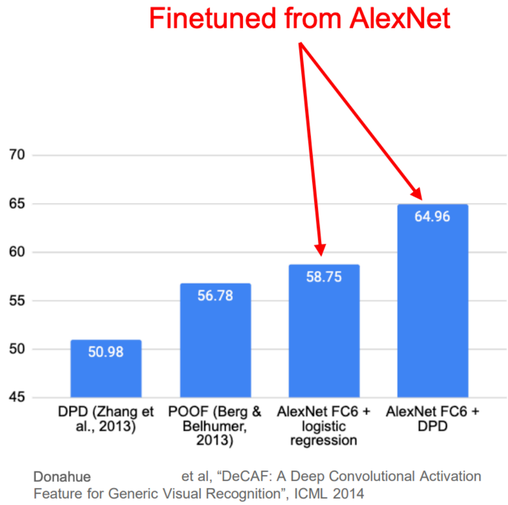




This is called Fine-tuning!



Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014

- A very successful recipe for adapting to different vision tasks like object detection, semantic segmentation, pose estimation, etc.
- Also, reduced the reliance on large training datasets to achieve good performance

Image from Lecture 7 CS231n slides by Fei-Fei Li, Ehsan Adeli, Zane Durante

Why it took so long for NLP?

- Since 2014, it had become common practice in the Computer Vision community to download a pre-trained (on Image Net) deep neural network model and “fine-tune” it on the problem at hand instead of starting from scratch.

- This wasn’t the case in NLP till late 2017s.

- It was common to use pre-trained word vectors like word2vec, GloVe for NLP tasks, and while those would help boost performance, most often it was a marginal improvement.

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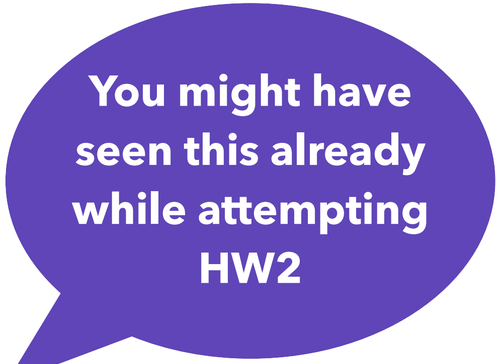

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    2. These models were usually 1-2 hidden layers, and scaling them to a large number of layers was non-trivial as these models were notoriously hard to train

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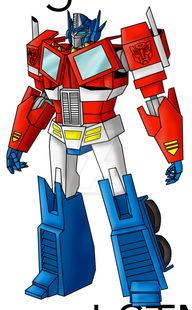

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Self-supervised Pre-training for Learning Underlying Patterns, Structures, and Semantic Knowledge

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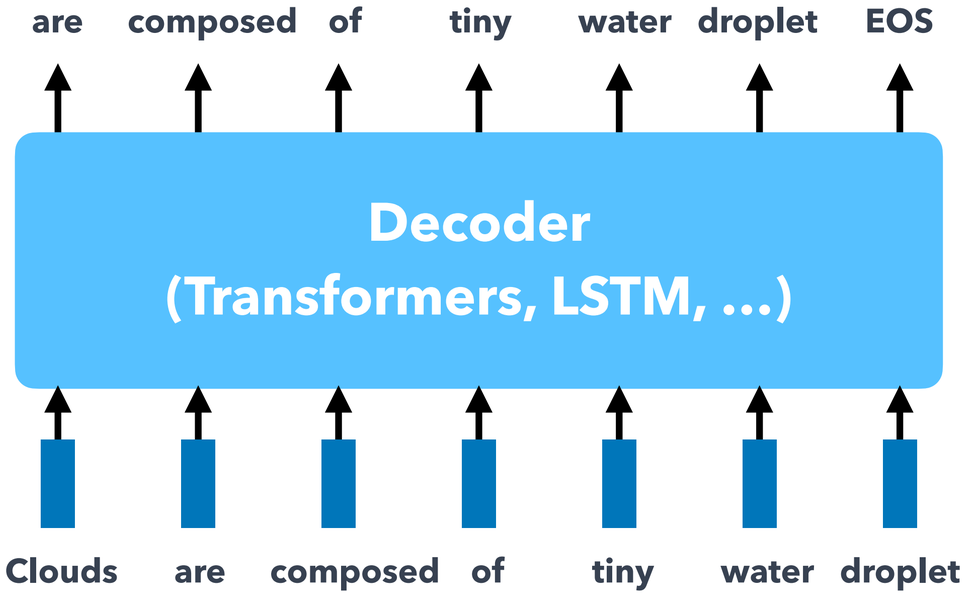
- Pre-training through **language modeling** [Dai and Le, 2015]
  - Model $P_\theta(w_t \mid w_{1:t-1})$, the probability distribution of the next word given previous contexts.
  - **There's lots of (English) data for this!** E.g., books, websites.
  - **Self-supervised** training of a neural network to perform the language modeling task with massive raw text data.
  - Save the network parameters to reuse later.



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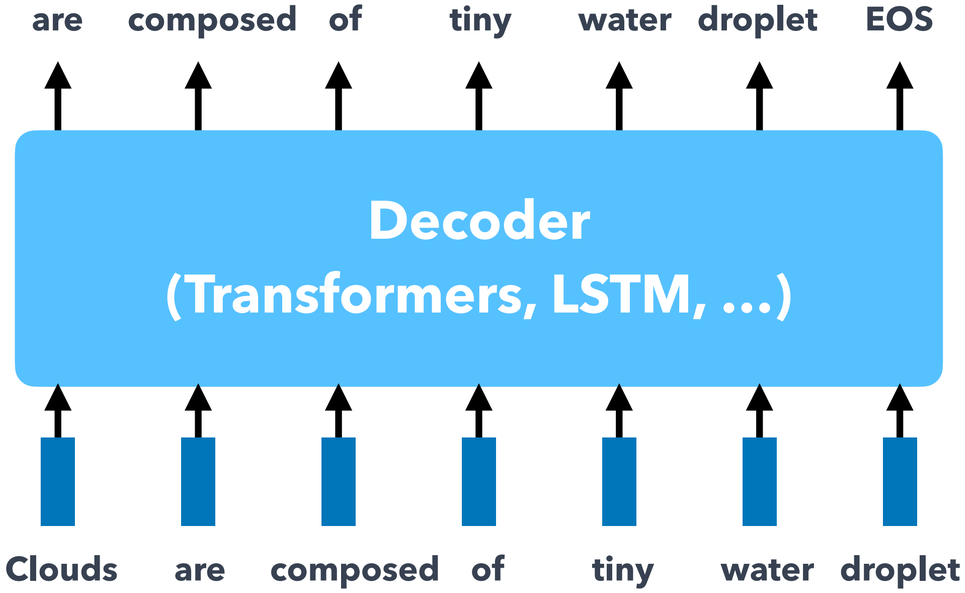
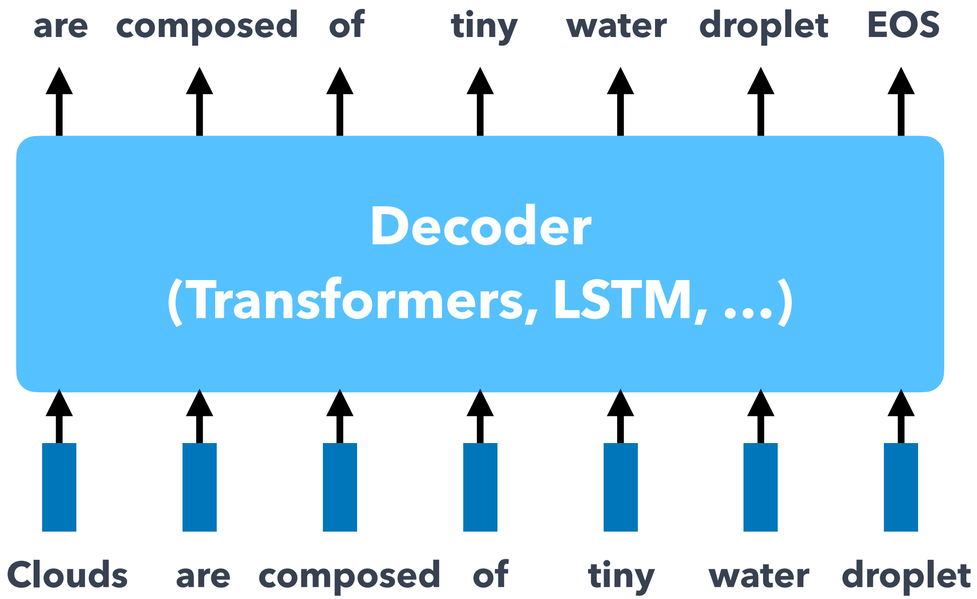
Why is this called self-supervised?
The labels come from the input data itself!



Supervised Fine-tuning for Specific Tasks

Step 1:
Pre-training



Abundant data; learn general language

Supervised Fine-tuning for Specific Tasks

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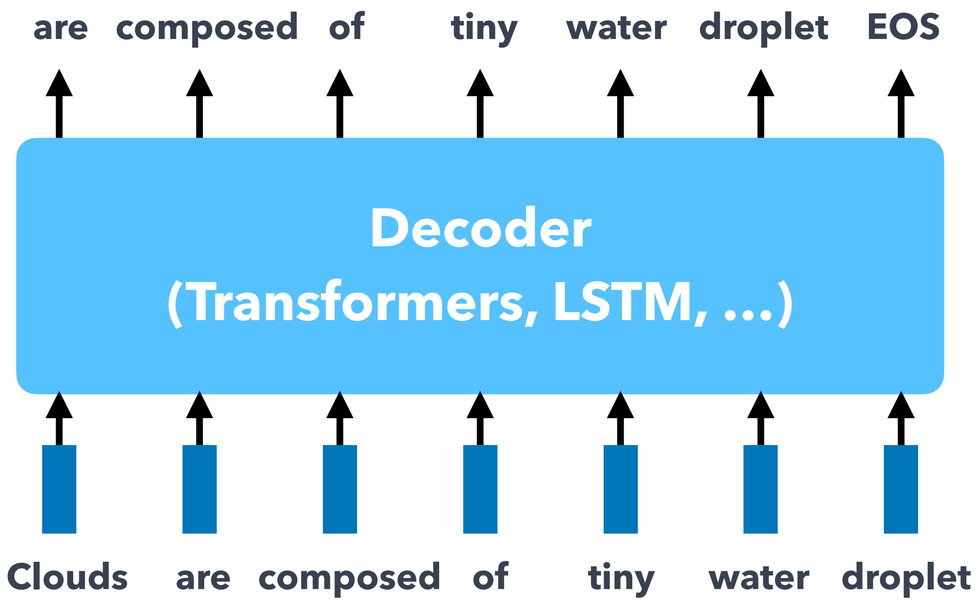
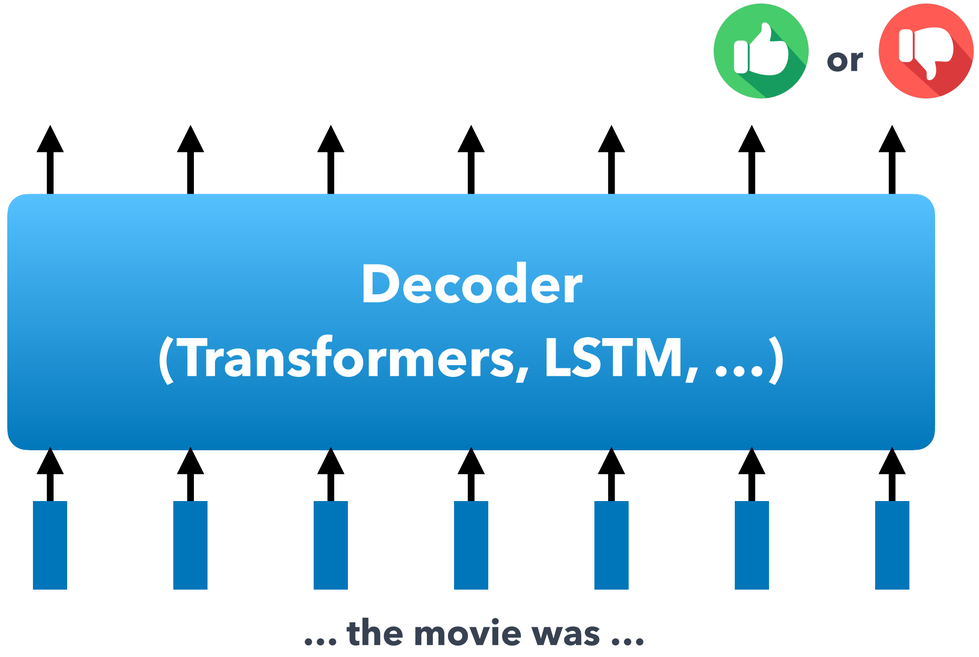


Abundant data; learn general language

Step 2:
Fine-tuning



Limited data; adapt to the task

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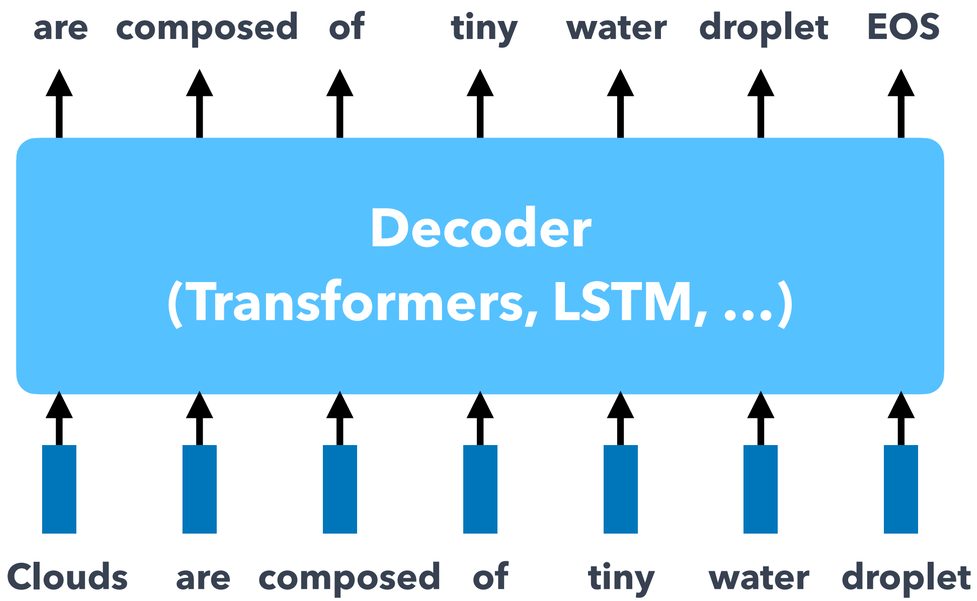

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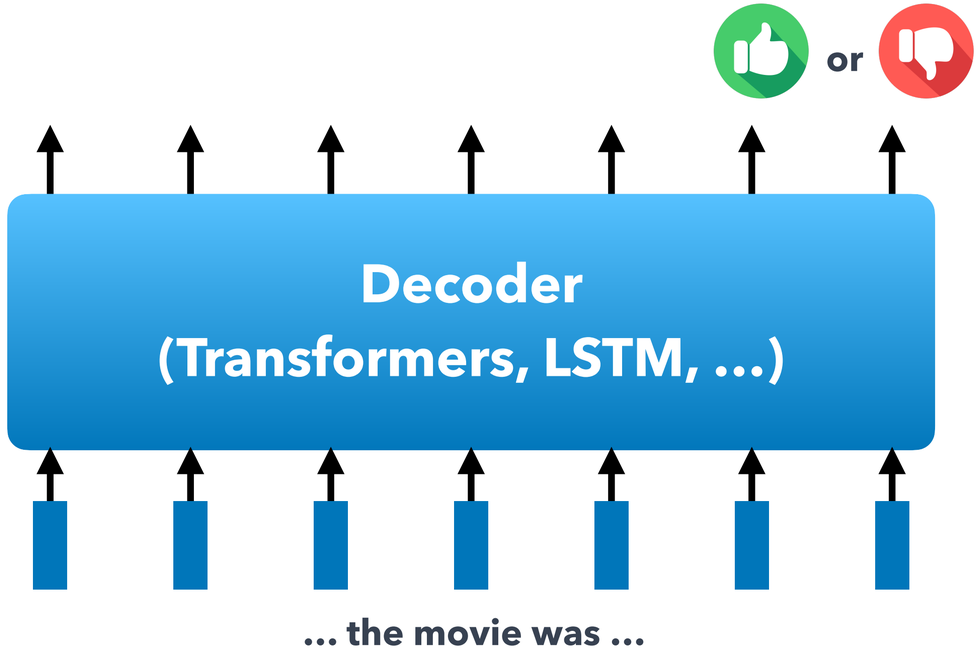
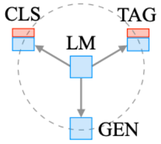


Abundant data; learn general language

Limited data; adapt to the task

Remember this is paradigm 3 from before

c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	

Why this works?

Lots of Information in Raw Texts

I went to Hawaii for snorkeling, hiking, and whale _____.

I walked across the street, checking for traffic _____ my shoulders.

I use _____ and fork to eat steak.

Ruth Bader Ginsburg was born in _____.

University of Washington is located at _____, Washington.

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

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Sugar is composed of carbon, hydrogen, and _____.

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...

The Stochastic Gradient Descent Angle

Why should pre-training and then fine-tuning help?

- Providing parameters $\hat{\theta}$ by approximating the pre-training loss, $\min_{\theta} \mathscr{L}_{\text{pretrain}}(\theta)$.
- Then, starting with parameters $\hat{\theta}$, approximating fine-tuning loss, $\min_{\theta} \mathscr{L}_{\text{finetune}}(\theta)$.
- **Stochastic gradient descent sticks (relatively) close to $\hat{\theta}$ during fine-tuning.**
  - So, maybe the fine-tuning local minima near $\hat{\theta}$ tend to generalize well!
  - And/or, maybe the gradients of fine-tuning loss near $\hat{\theta}$ propagate nicely!

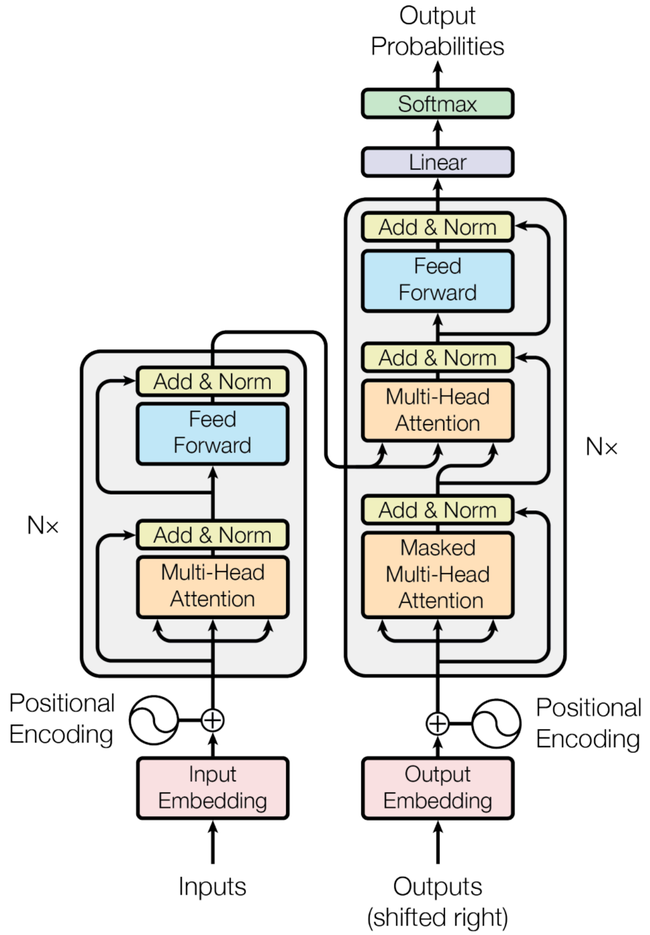
Advantages of Pre-training & Fine-tuning

- **Leveraging rich underlying information** from abundant raw texts.
- **Reducing the reliance of task-specific labeled data** that is difficult or costly to obtain.
- **Initializing model parameters** for more **generalizable** NLP applications.
- **Saving training cost** by providing a reusable model checkpoints.
- **Providing robust representation** of language contexts.

Solving Shallow Networks Problem in NLP: **Enter Transformers**

Attention is all You Need. 2017.

Solving Shallow Networks Problem in NLP: **Enter Transformers**



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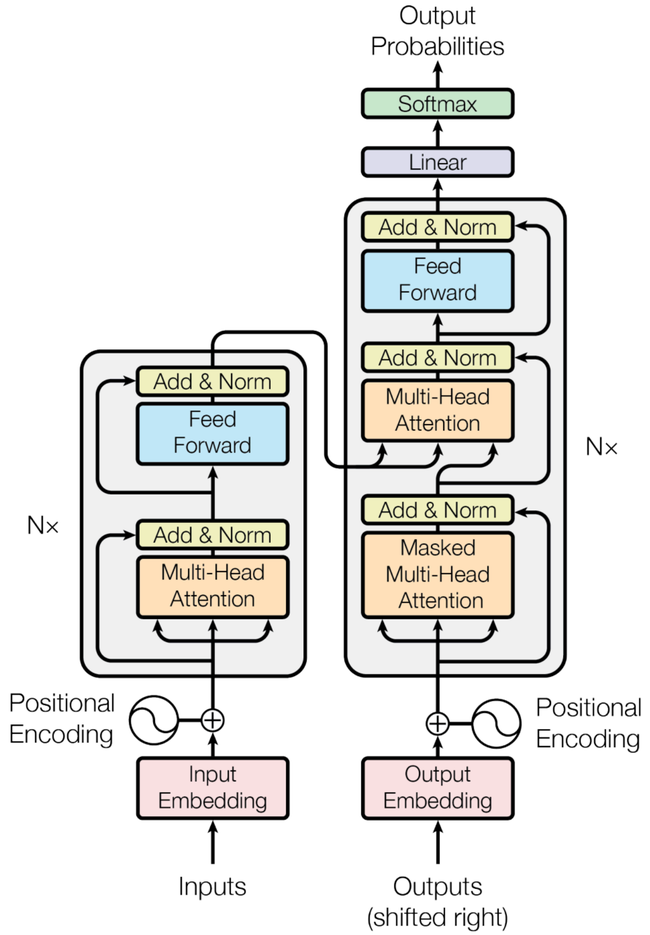

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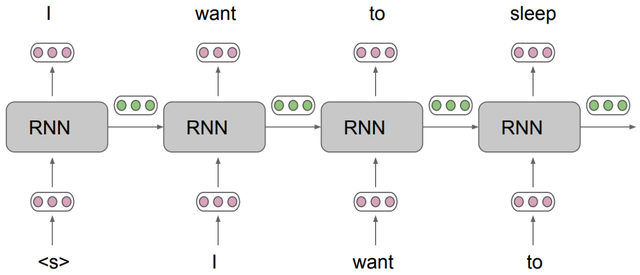
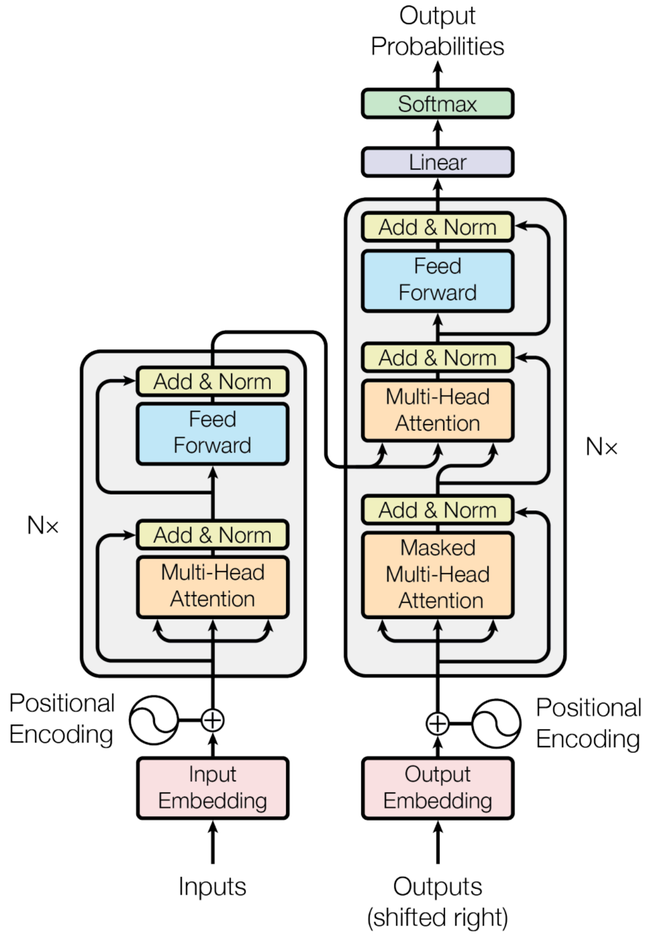
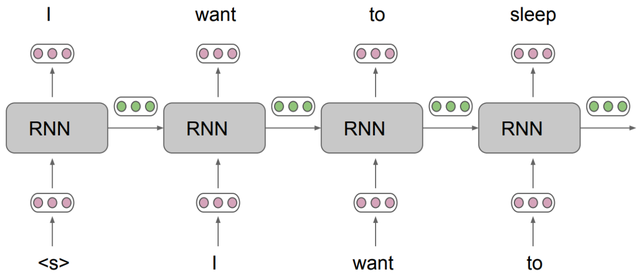


Solving Shallow Networks Problem in NLP: **Enter Transformers**

Transformers managed to avoid the two major problems that made Recurrent Neural Networks hard to scale on larger depths:





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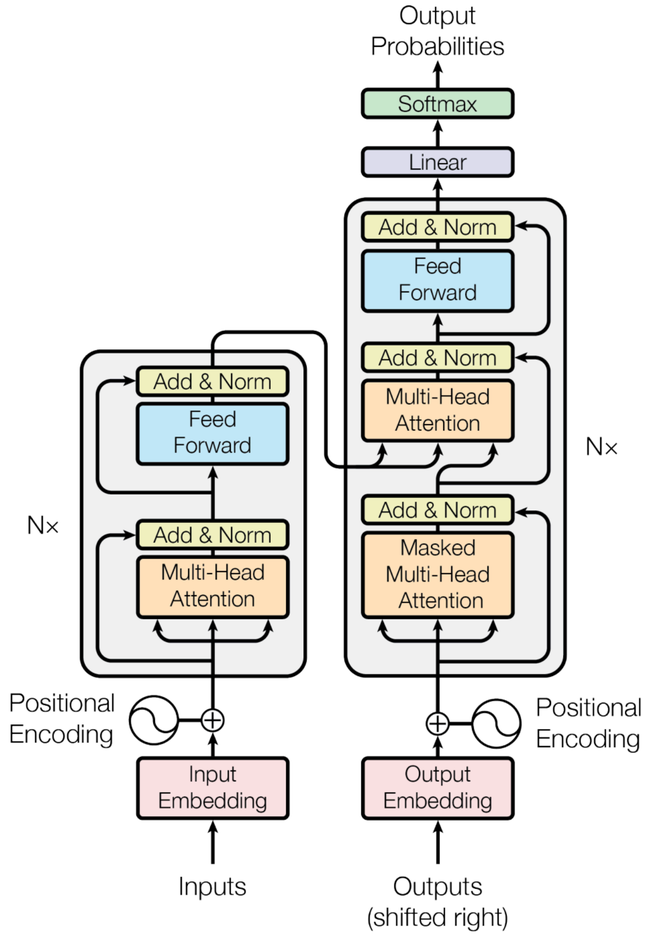
- **<u>Highly Parallelizable During Training</u>**: Need not wait for the computation at the previous time step to complete to execute the next step



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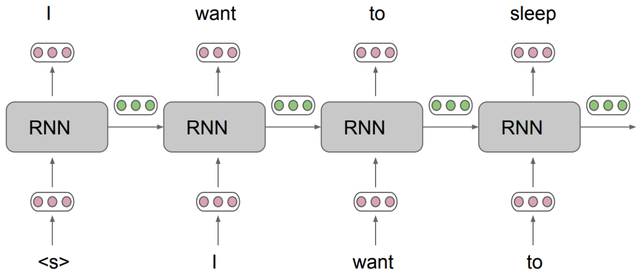

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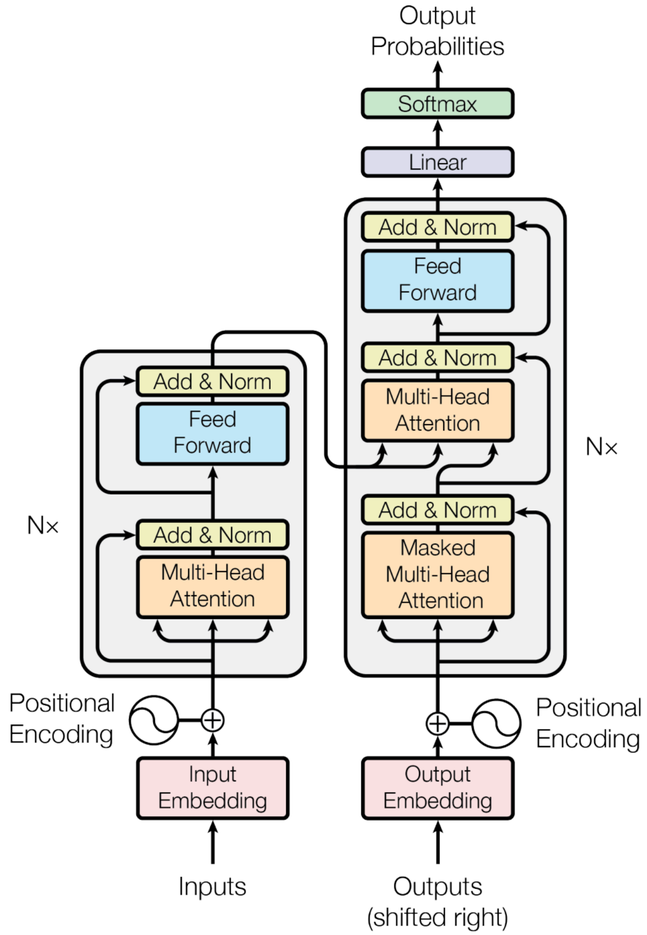
Transformers managed to avoid the two major problems that made Recurrent Neural Networks hard to scale on larger depths:

- **<u>Highly Parallelizable During Training</u>**: Need not wait for the computation at the previous time step to complete to execute the next step

- **<u>Avoids Training Complications like Vanishing Gradients:</u>** Unlike RNNs, which have a fixed state that gets updated repeatedly, transformers have dynamic memory, which also avoids issues such as vanishing gradients



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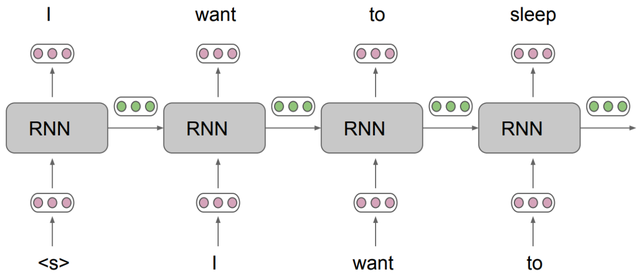


Lecture Outline

1. Motivating Pre-training, aka Self-supervised Learning

2. Pre-training Architectures and Training Objectives

    1. Encoders

    2. Encoder-Decoders

    3. Decoder

3 Pre-training Paradigms/Architectures

Encoder

- E.g., BERT, RoBERTa, DeBERTa, …
- **Autoencoder** model
- **Masked** language modeling

Encoder-Decoder

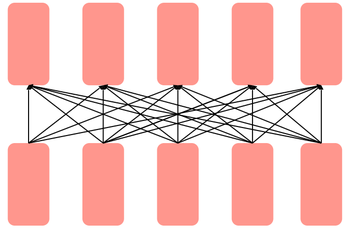
- E.g., T5, BART, …
- **seq2seq** model

Decoder

- E.g., GPT, GPT2, GPT3, …
- **Autoregressive** model
- **Left-to-right** language modeling

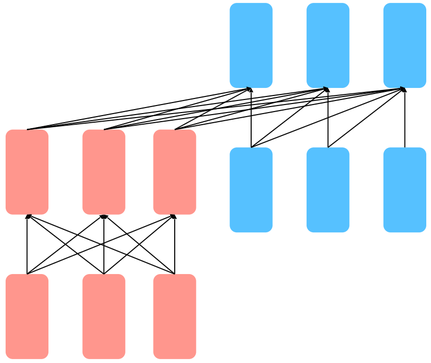
3 Pre-training Paradigms/Architectures

Encoder



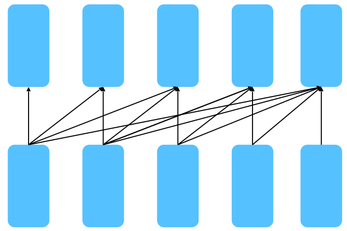
- Bidirectional; can condition on the future context

Encoder-Decoder



- Map two sequences of different length together

Decoder



- Language modeling; can only condition on the past context

3 Pre-training Paradigms/Architectures

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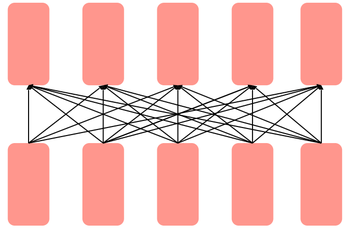

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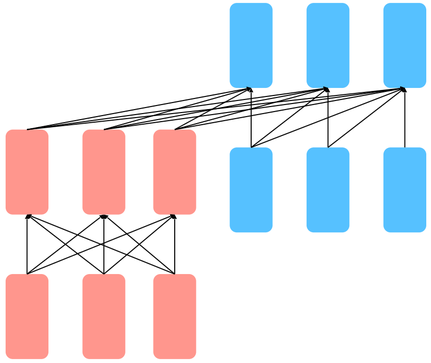

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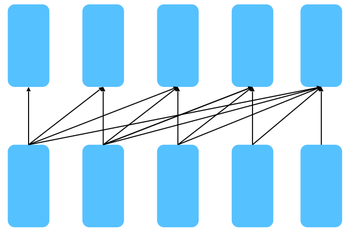

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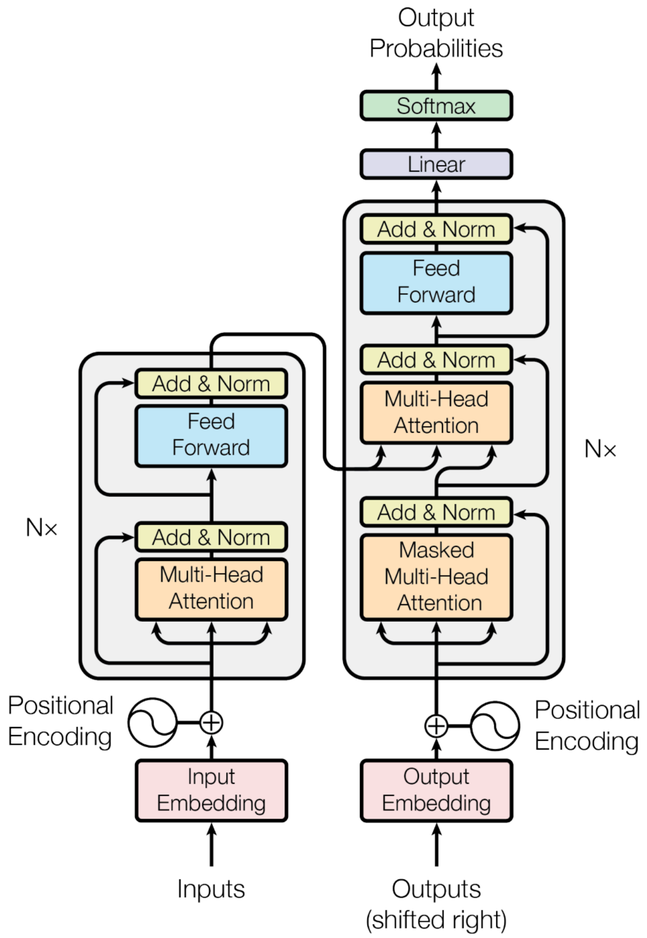
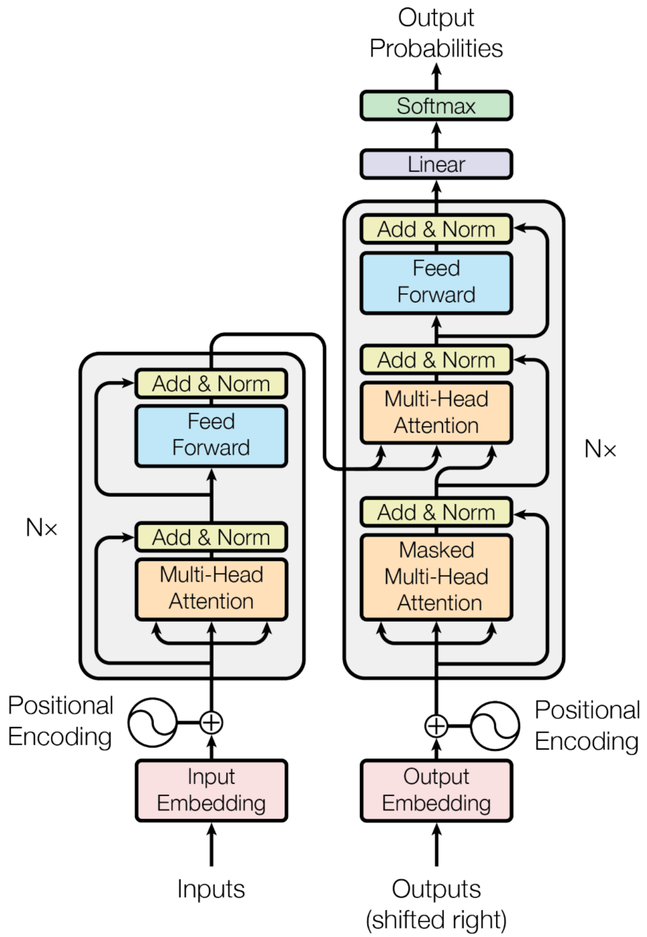
Encoder: Architecture

Full-Transformer Architecture
(Encoder-Decoder)

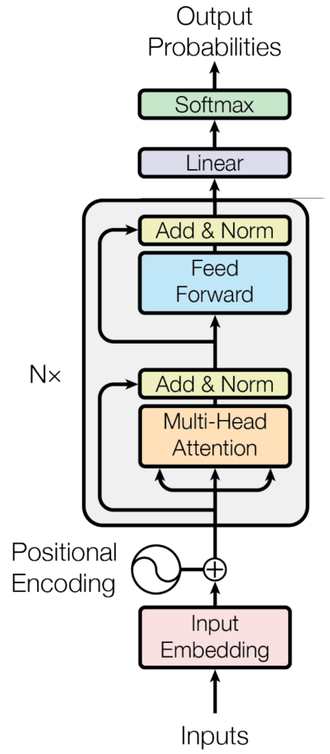


Encoder: Architecture

Full-Transformer Architecture (Encoder-Decoder)



Encoder-Only Transformer Architecture



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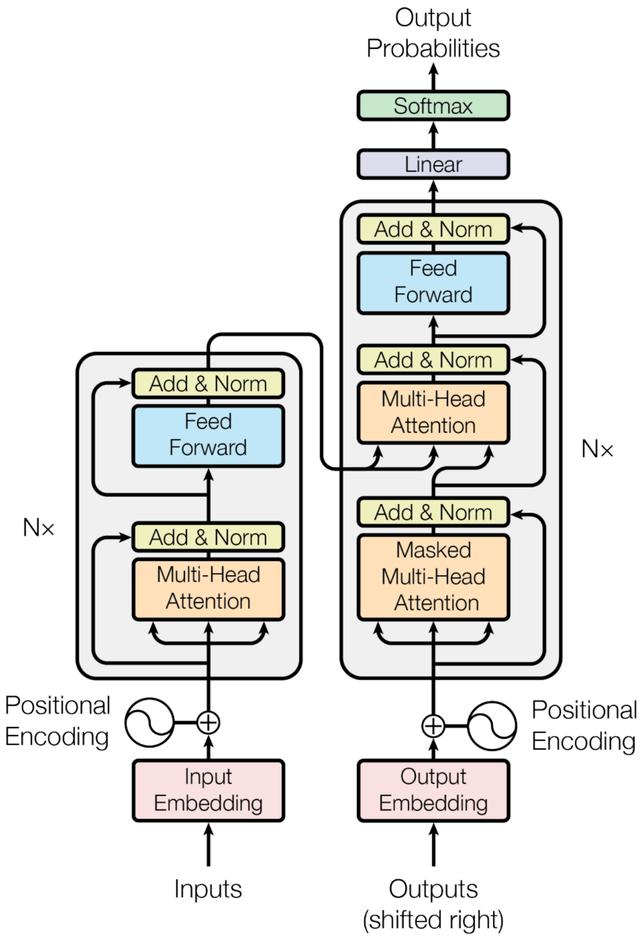

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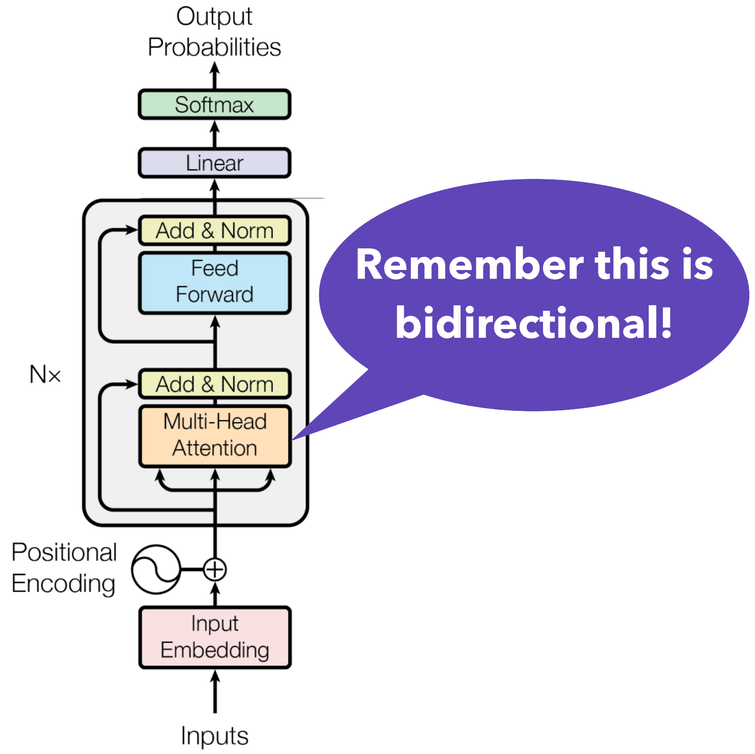

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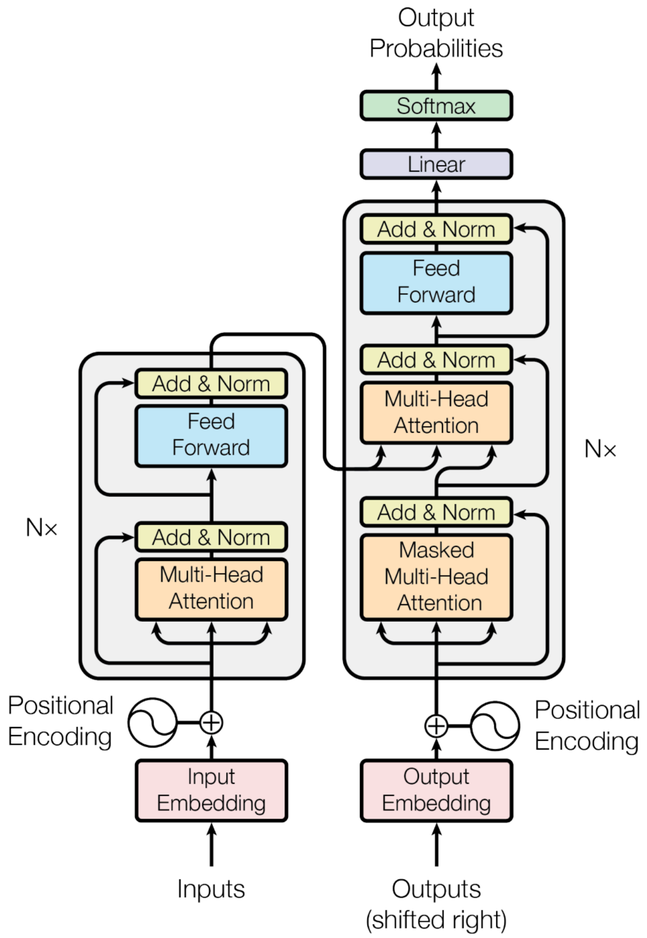

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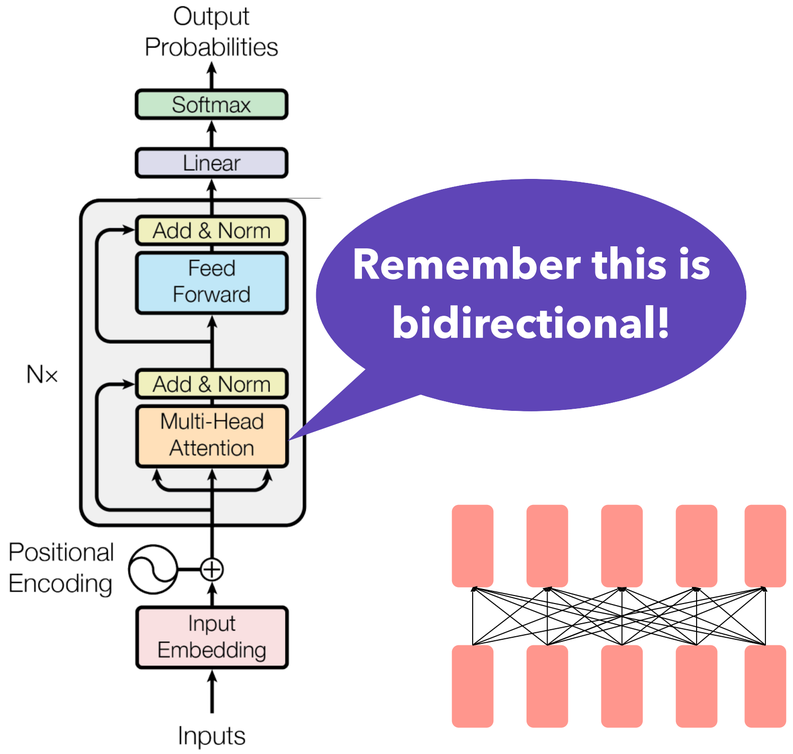

Encoder: Training Objective

- So far, we've looked at language modeling for pre-training.
- Language Model Pretraining is problematic for encoders
- Why?
  - **Encoders get bidirectional contexts**
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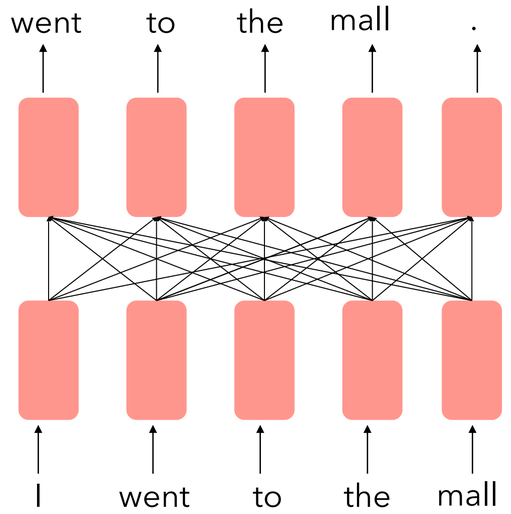

Encoder: Training Objective [Devlin et al., 2018]

- How to encode information from both **bidirectional** contexts?
- General Idea: **text reconstruction!**
  - Your time is [MASK], so don't [MASK] it living someone else's life. Don't be trapped by [MASK], which is [MASK] with the results of other [MASK]'s thinking. — [MASK] Jobs

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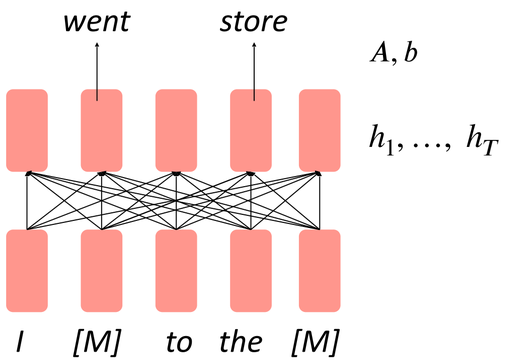

$$h_1, \ldots, h_T = \text{Encoder}(w_1, \ldots, w_T)$$

$$y_i \sim Aw_i + b$$

Only add loss terms from the masked tokens. If $\tilde{x}$ is the masked version of x, we're learning $p_\theta(x \mid \tilde{x})$. Called **Masked Language model (MLM)**.

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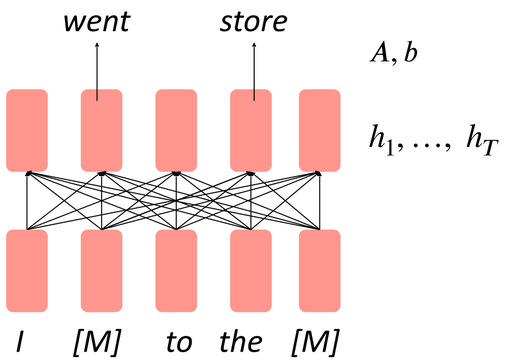

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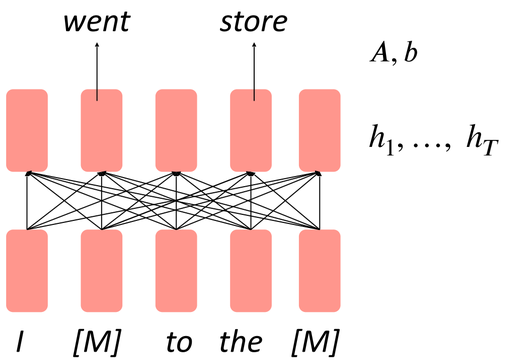

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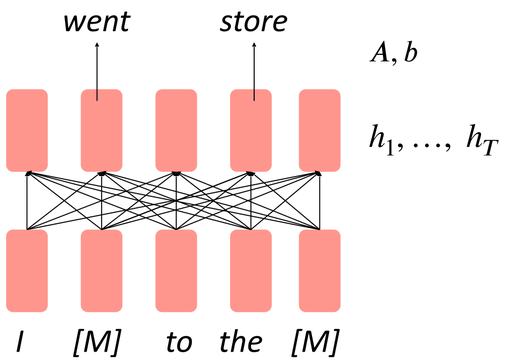

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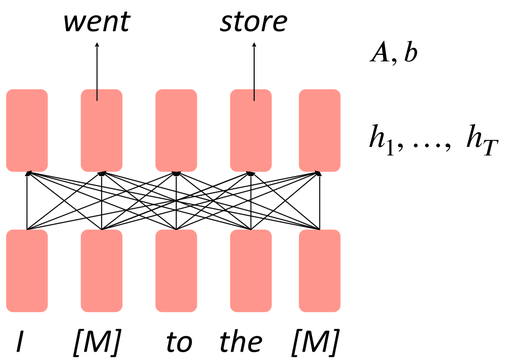

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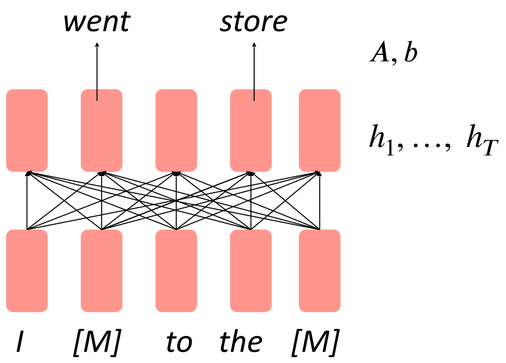

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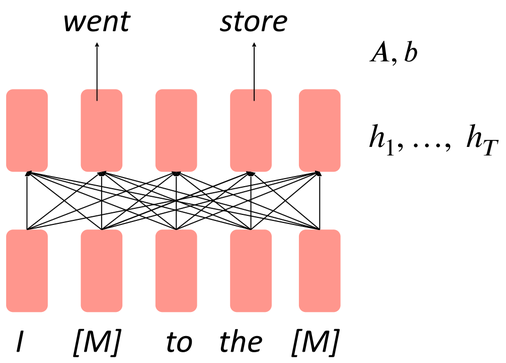

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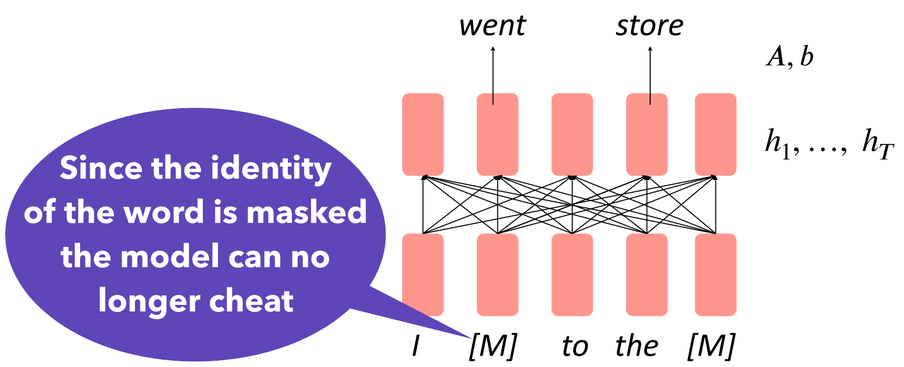

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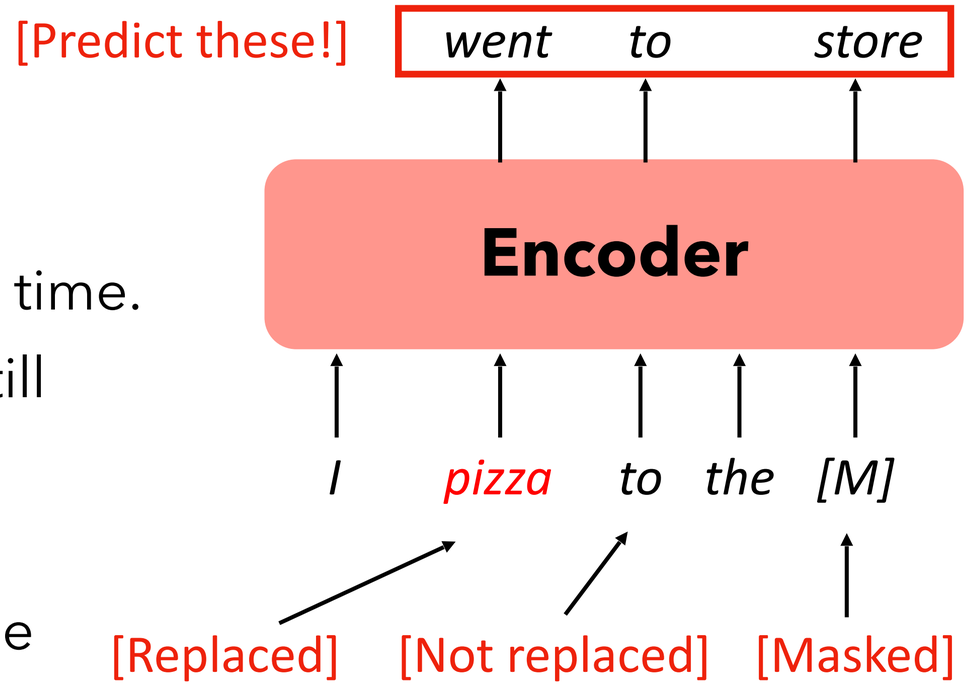
Encoder: BERT

Bidirectional **E**ncoder **R**epresentations from **T**ransformers [Devlin et al., 2018]

- **2 Pre-training Objectives:**
  - **Masked LM: Choose a random 15% of tokens to predict.**
    - For each chosen token:
      - Replace it with **[MASK]** 80% of the time.
      - Replace it with a **random token** 10% of the time.
      - Leave it **unchanged** 10% of the time (but still predict it!).
  - **Next Sentence Prediction (NSP)**
    - 50% of the time two adjacent sentences are in the correct order.
    - **This actually hurts model learning based on later work!**



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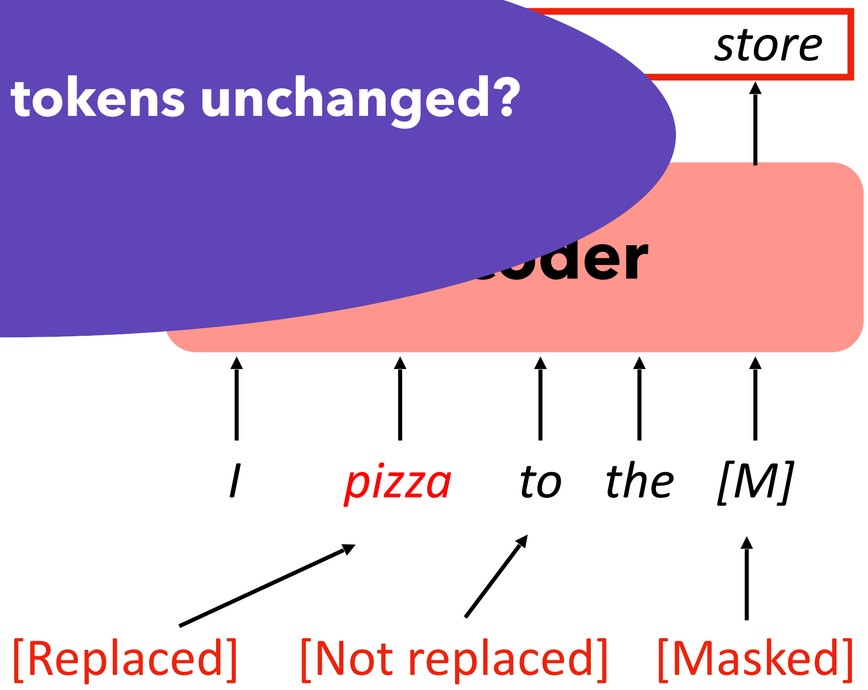
WHY keeping some tokens unchanged?



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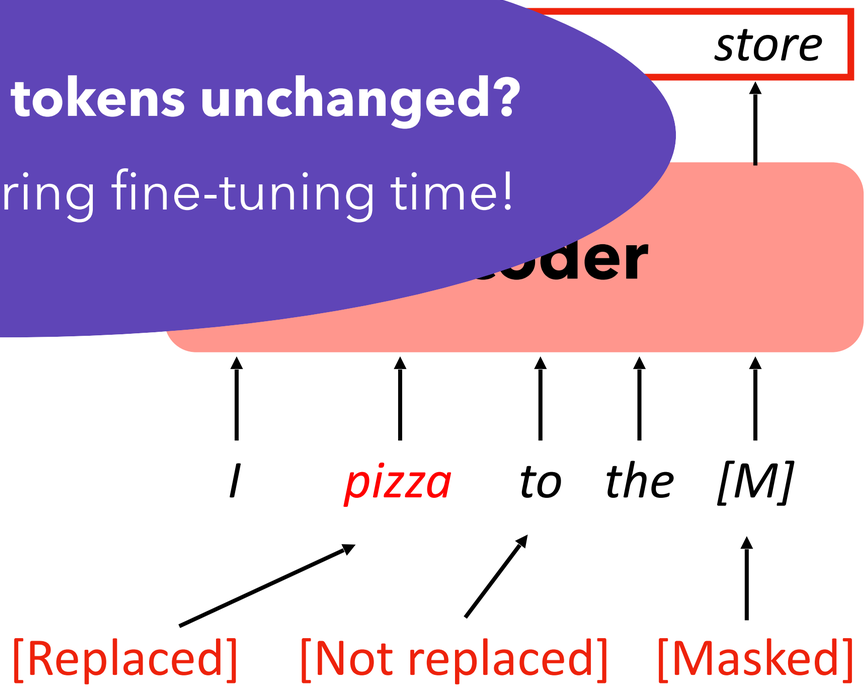
There's no [MASK] during fine-tuning time!



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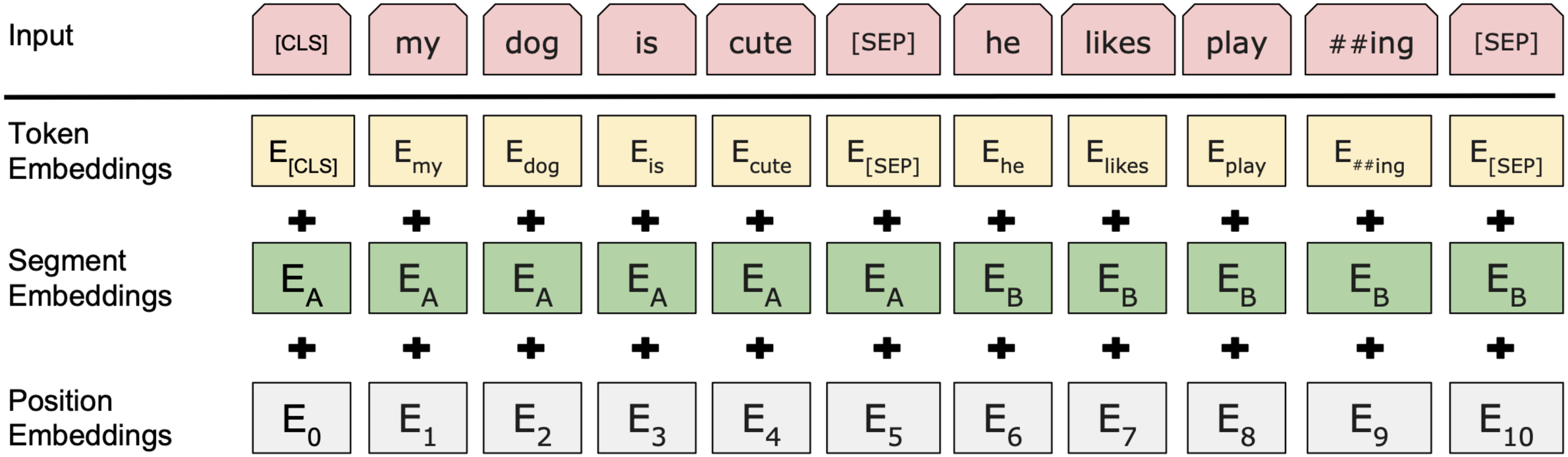

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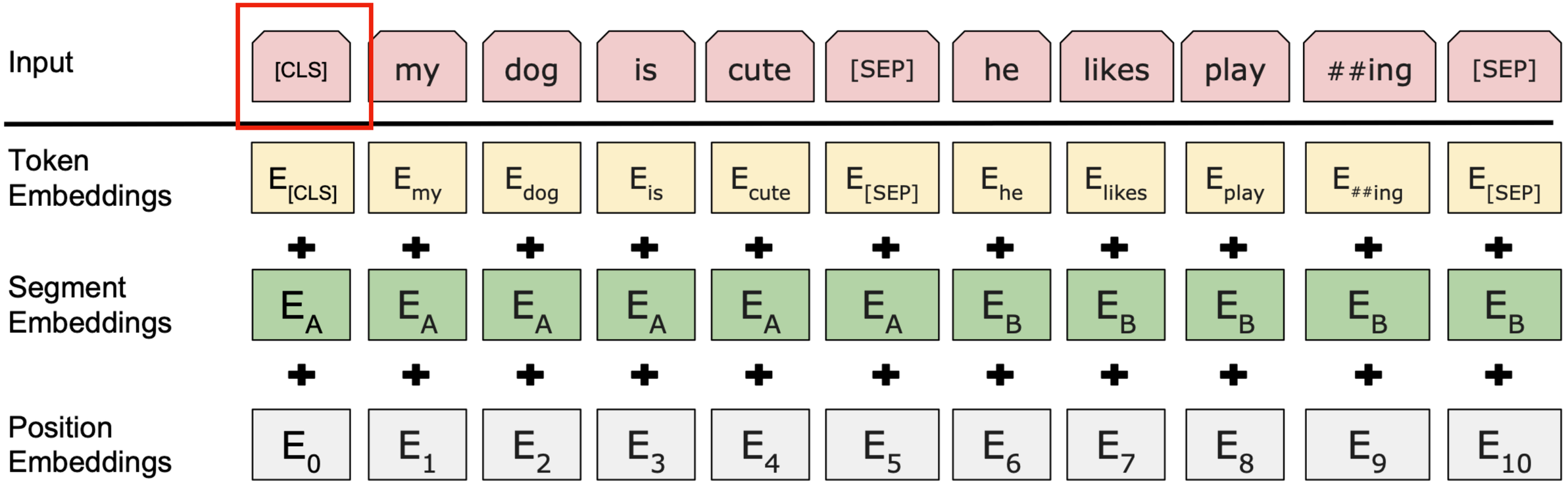
Bidirectional **E**ncoder **R**epresentations from **T**ransformers [Devlin et al., 2018]

Special token added to the beginning of each input sequence



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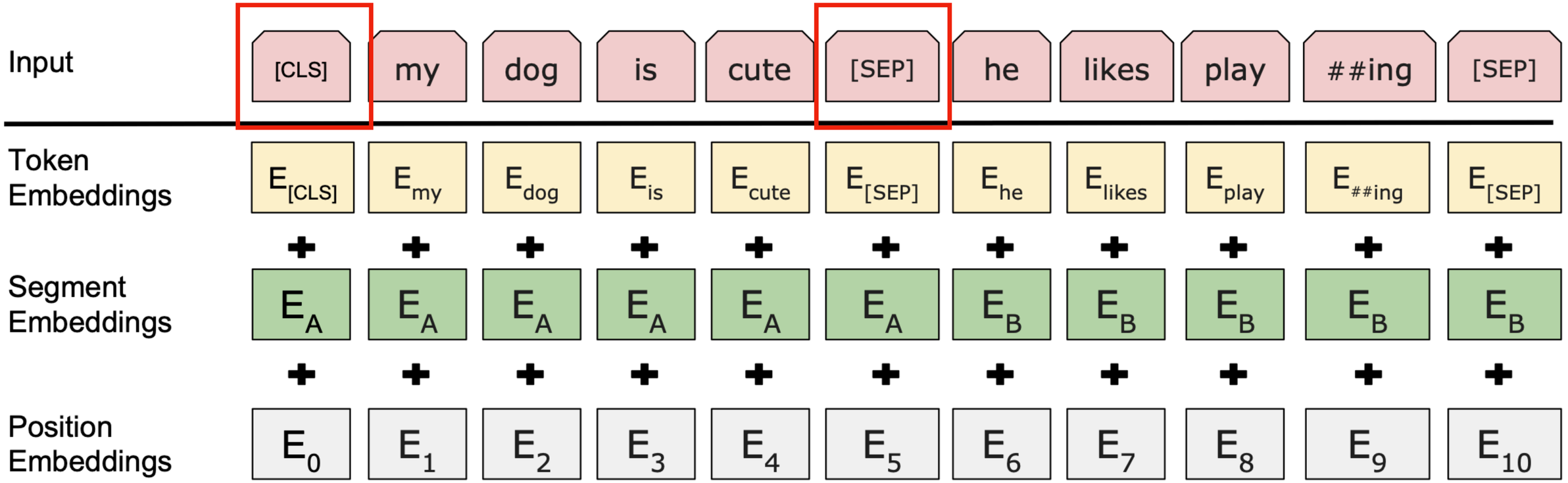
Special token to separate sentence A/B



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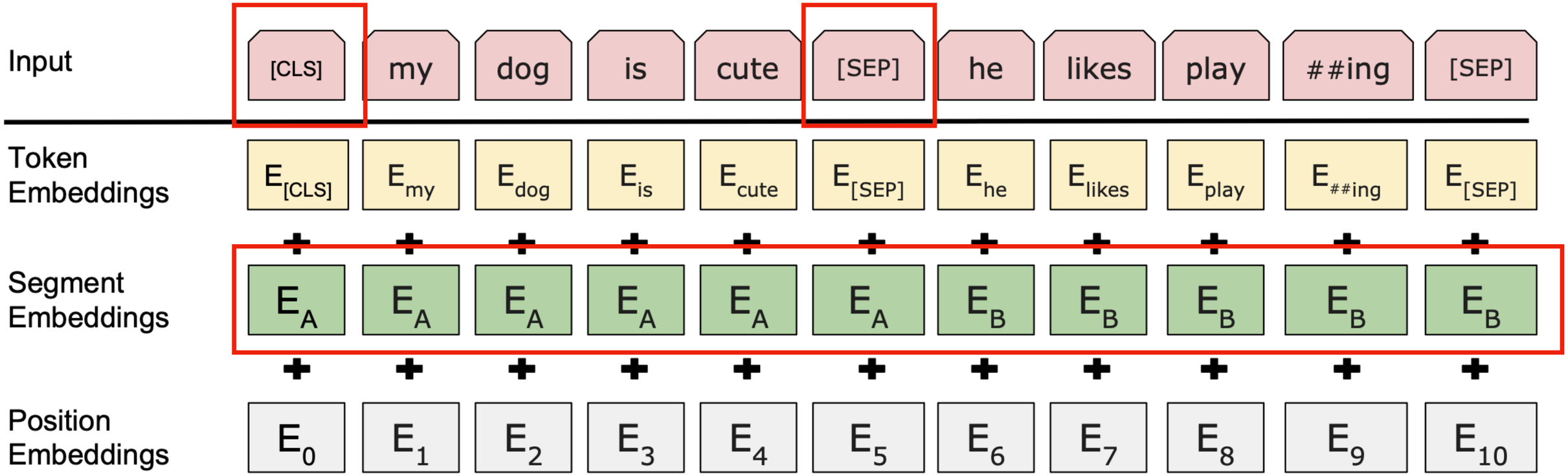

Learned embedding to every token indicating whether it belongs to sentence A or sentence B

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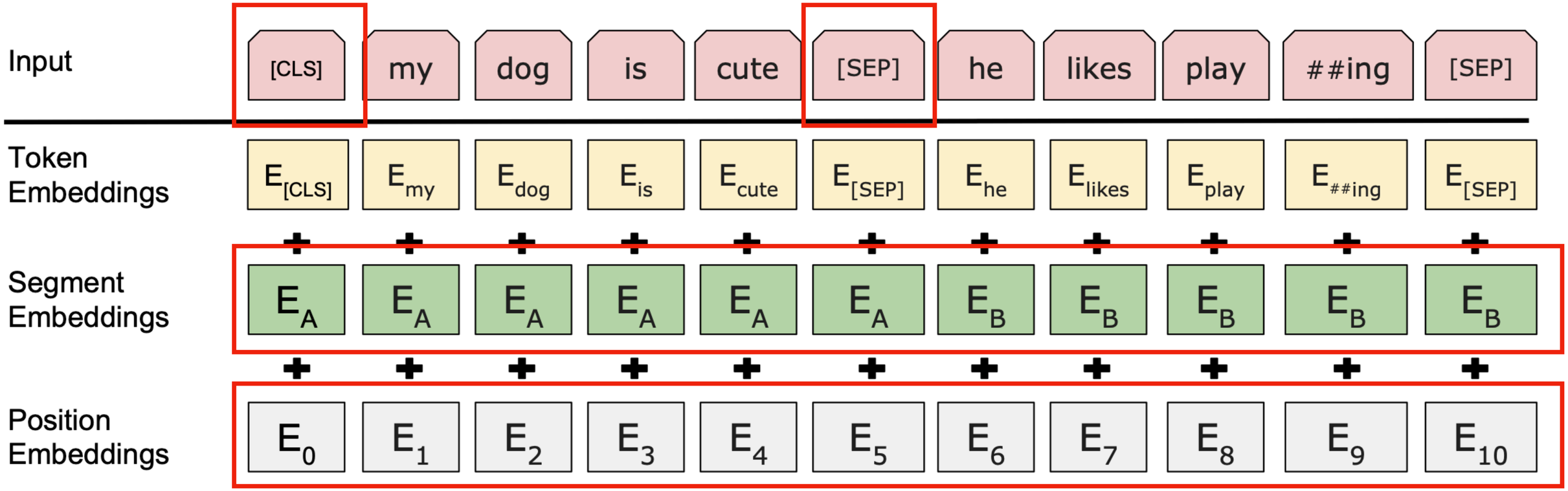

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Position of the token in the entire sequence

Encoder: BERT

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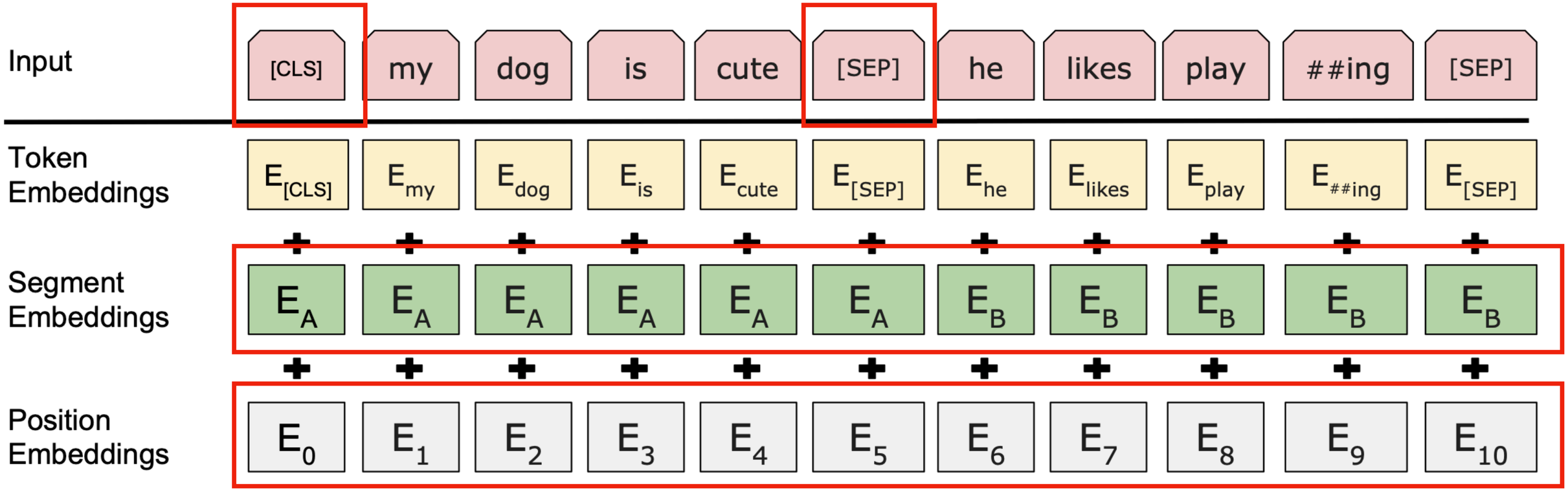
Special token added to the beginning of each input sequence

Special token to separate sentence A/B

Final embedding is the sum of all three!



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Encoder: BERT (Fine-tuning)

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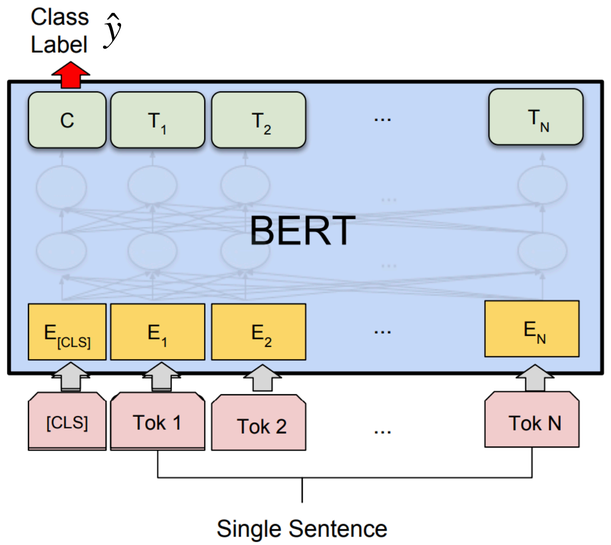
Single-Sentence Tasks like
SST-2 (Sentiment Analysis)

Encoder: BERT (Fine-tuning)



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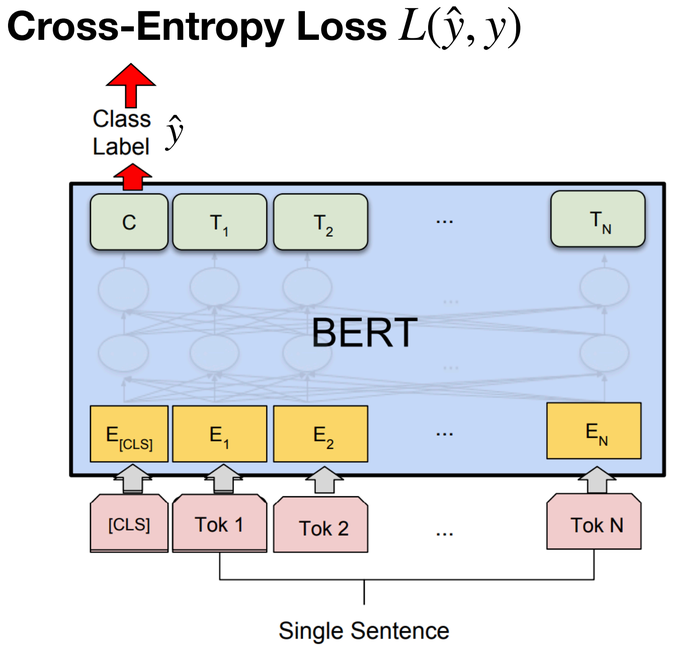

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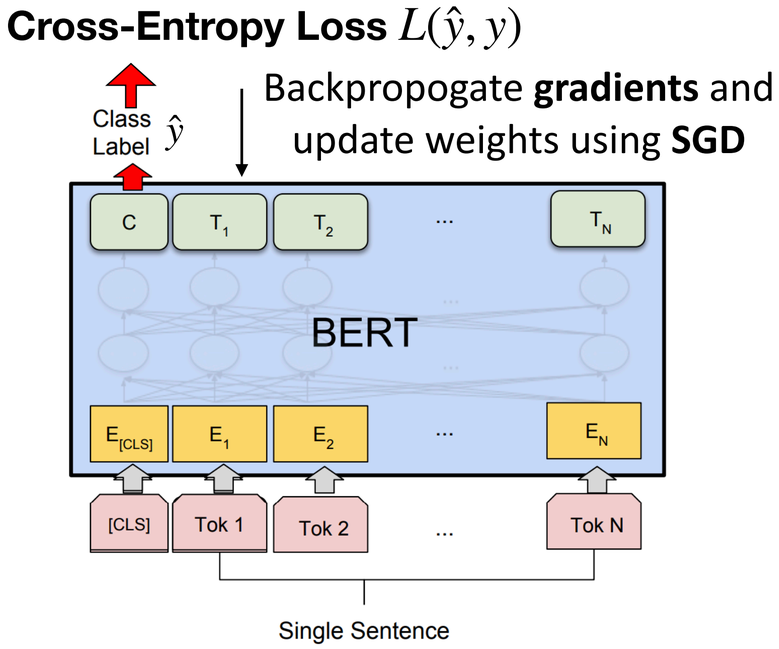

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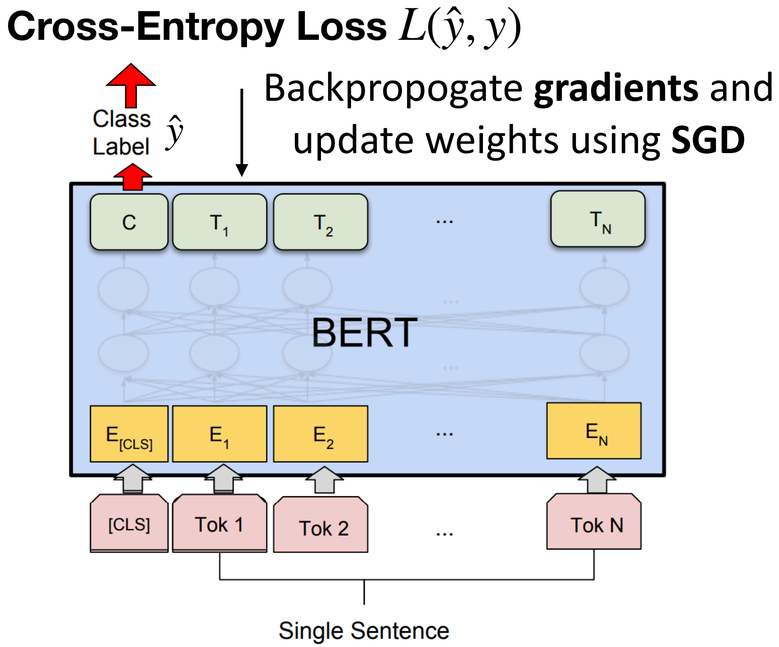
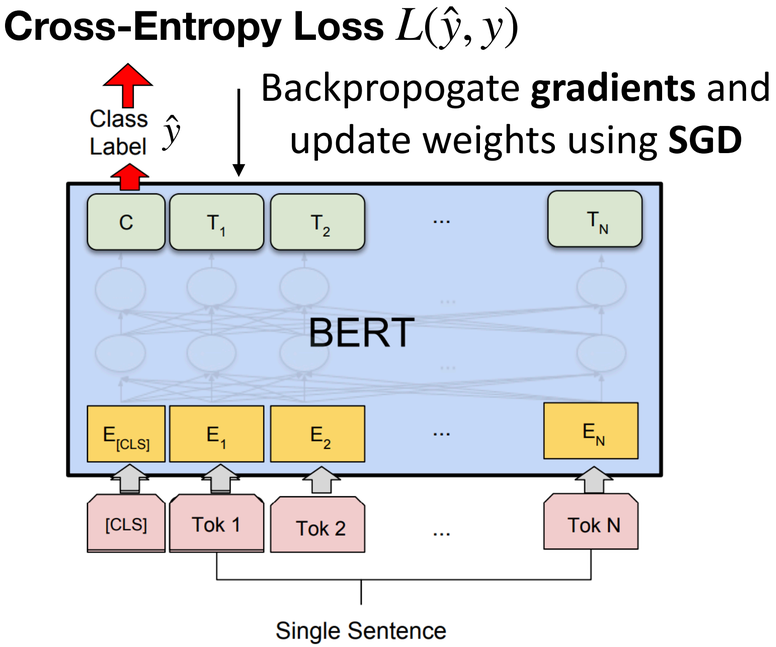


Single-Sentence Tasks like SST-2 (Sentiment Analysis)

Sentence Pair Classification Tasks like Natural Language Inference

Encoder: BERT (Fine-tuning)

Input:
Premise: A soccer game with multiple males playing
Hypothesis: Some men are playing a sport
Label: **Entailment** / Neutral / Contadiction



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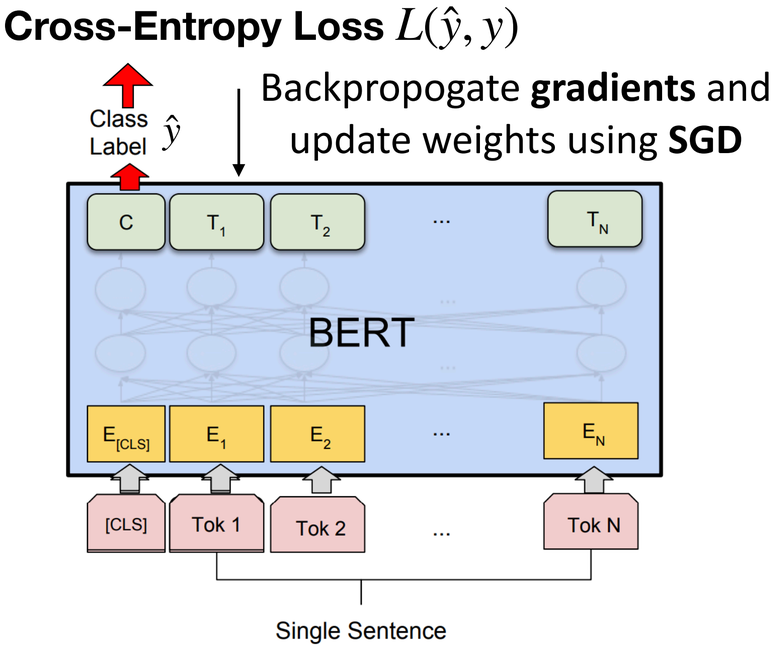

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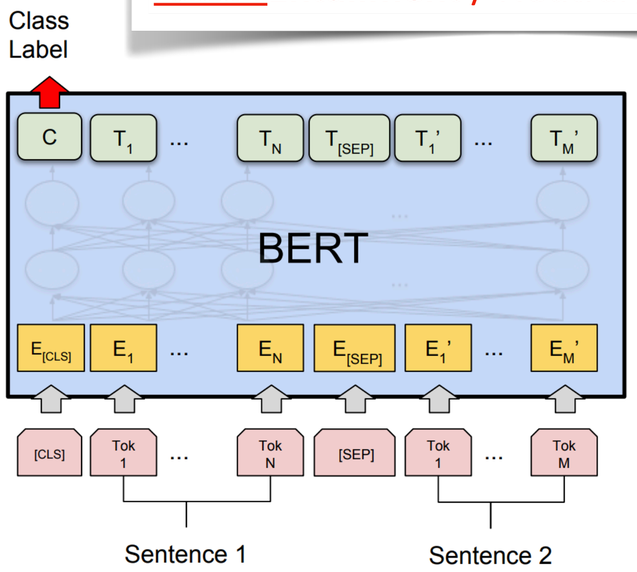

Sentence Pair Classification Tasks like Natural Language Inference

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Bidirectional **E**ncoder **R**epresentations from **T**ransformers

[Devlin et al., 2018]

- **SOTA at the time on a wide range of tasks after fine-tuning!**

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**

- **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
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- **RTE:** a small natural language inference corpus

Encoder: BERT

Bidirectional **E**ncoder **R**epresentations from **T**ransformers

[Devlin et al., 2018]

- **SOTA at the time on a wide range of tasks after fine-tuning!**

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
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Encoder: BERT

SWAG (Commonsense inference task)

System	Dev	Test
ESIM+GloVe	51.9	52.7
ESIM+ELMo	59.1	59.2
OpenAI GPT	-	78.0
$\text{BERT}_{\text{BASE}}$	81.6	-
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Human (expert)†	-	85.0
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Bidirectional **E**ncoder **R**epresentations from **T**ransformers [Devlin et al., 2018]

- **Two Sizes of Models**
  - **Base:** 110M, 4 Cloud TPUs, 4 days
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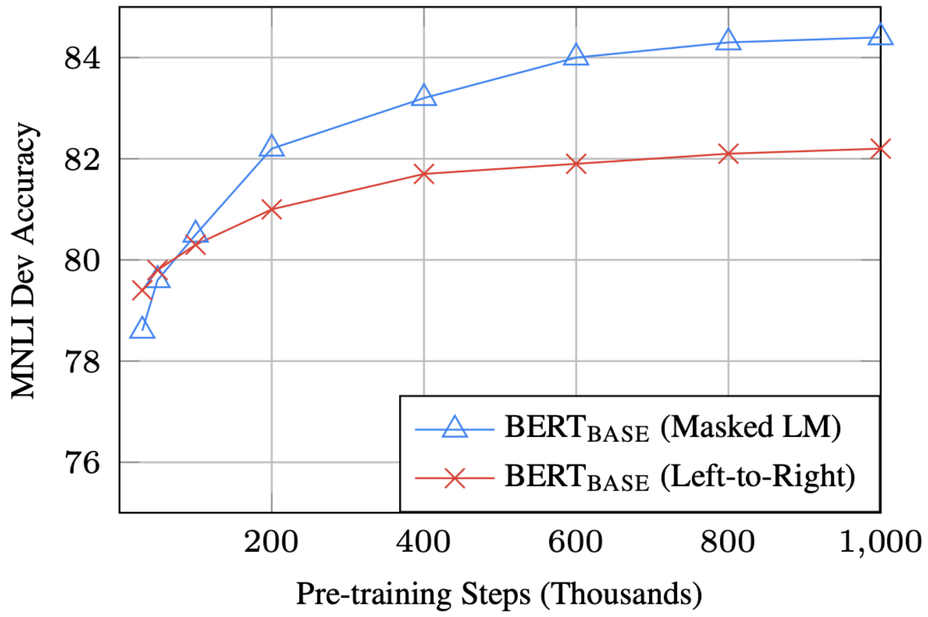

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- MLM converges slower than Left-to-Right at the beginning, but out-performers it eventually

Encoder: RoBERTa

[Liu et al., 2019]

- **Original BERT is significantly undertrained!**
- More data (16G => 160G)
- Pre-train for longer
- Bigger batches
- Removing the next sentence prediction (NSP) objective
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All around better than BERT!

Encoders for Information Retrieval

Encoders for Information Retrieval

Retrieve the set of relevant documents given a query

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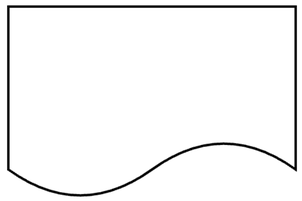

Query

Encoders for Information Retrieval

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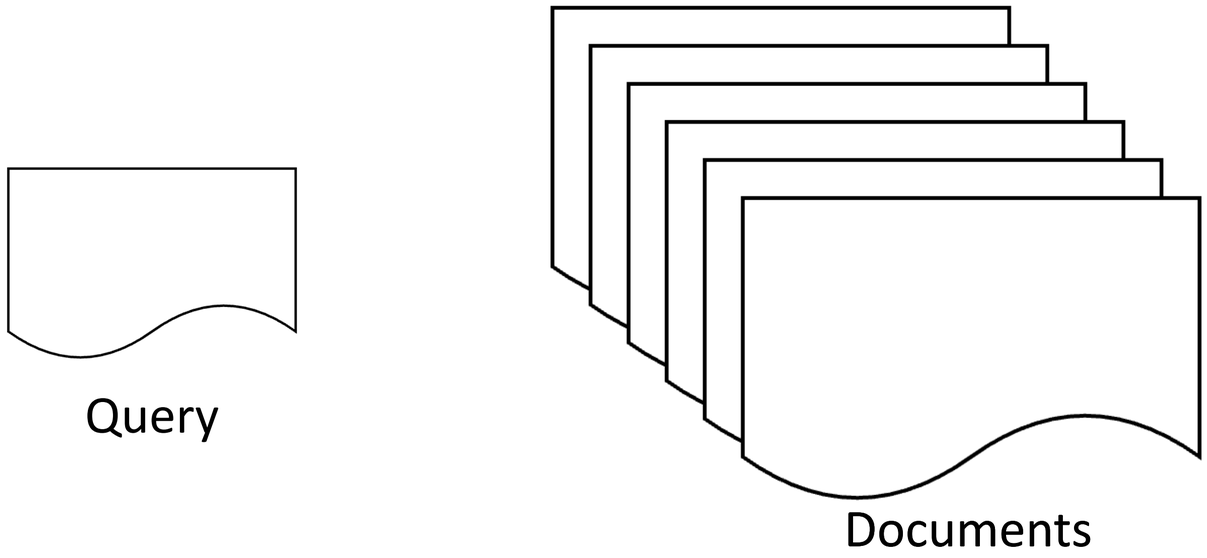

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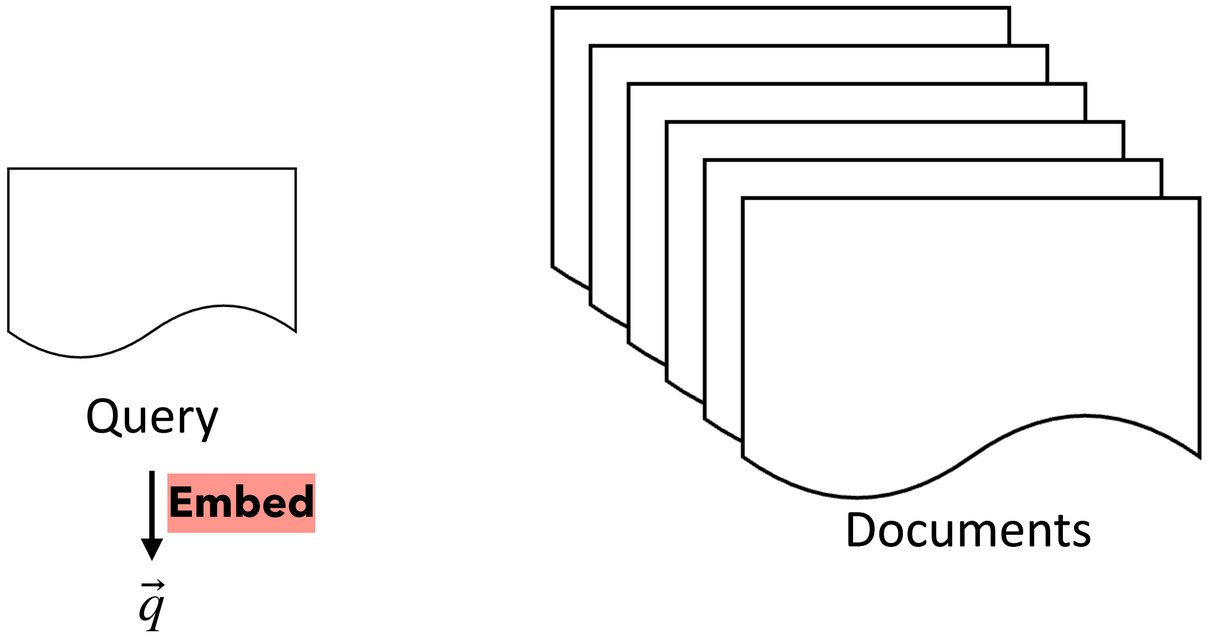

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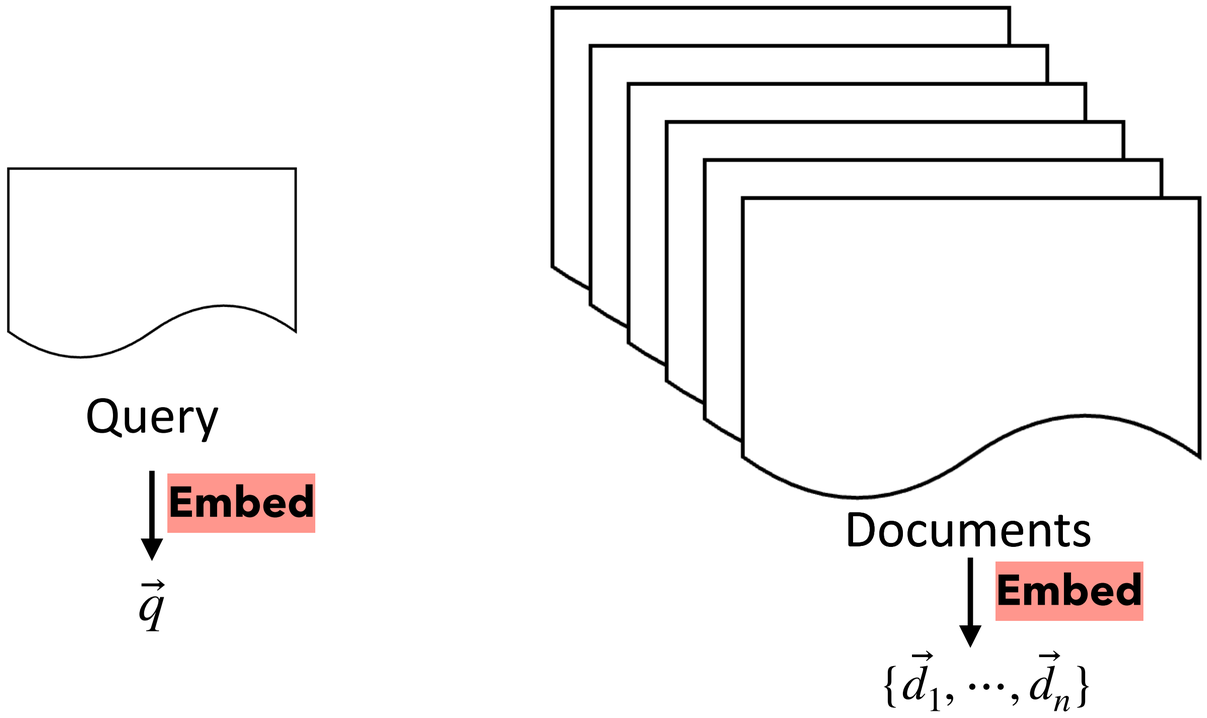

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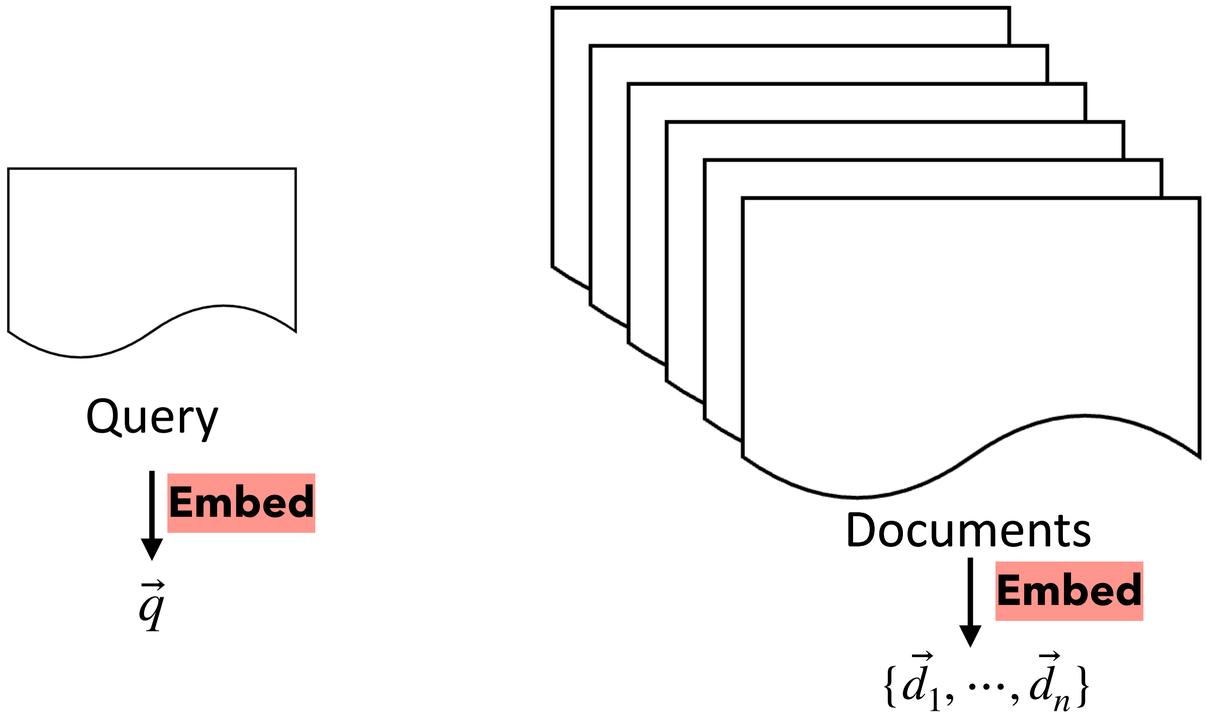

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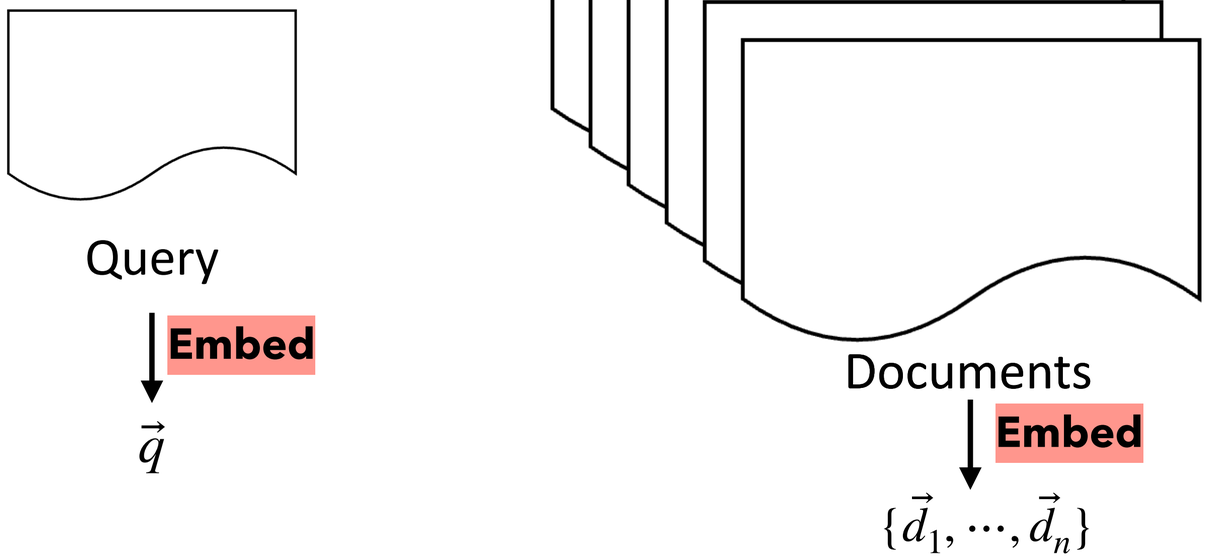

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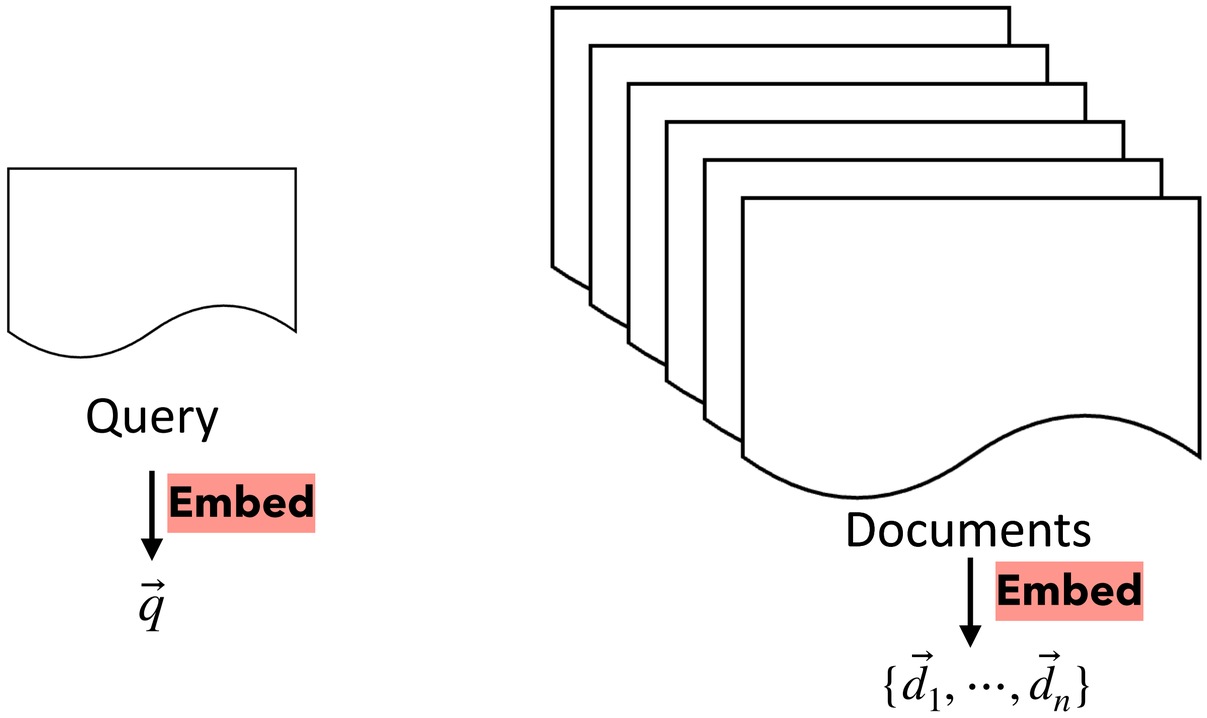
HW2!

Encoders for Information Retrieval

Retrieve the set of relevant documents given a query

Applications:

- **Search Engines (This is how google works!)**
- **Retrieval Augmented Language Models**



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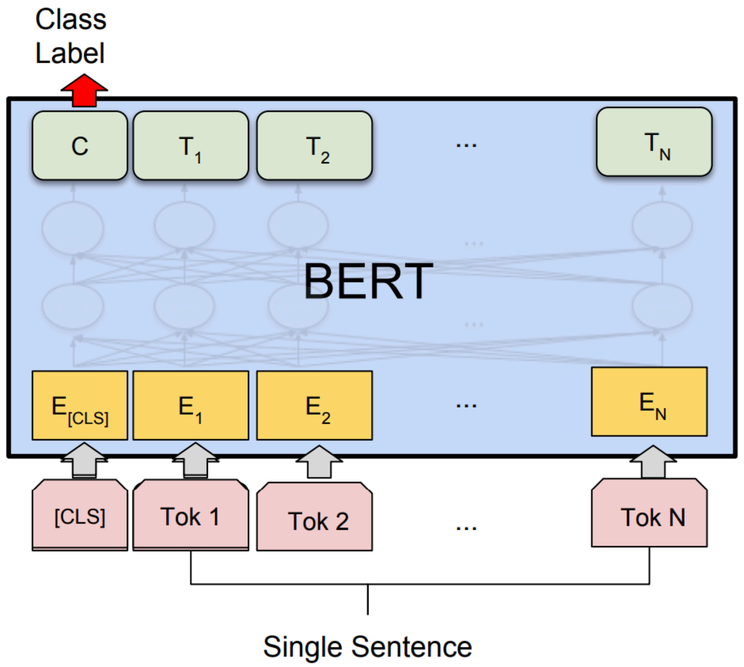

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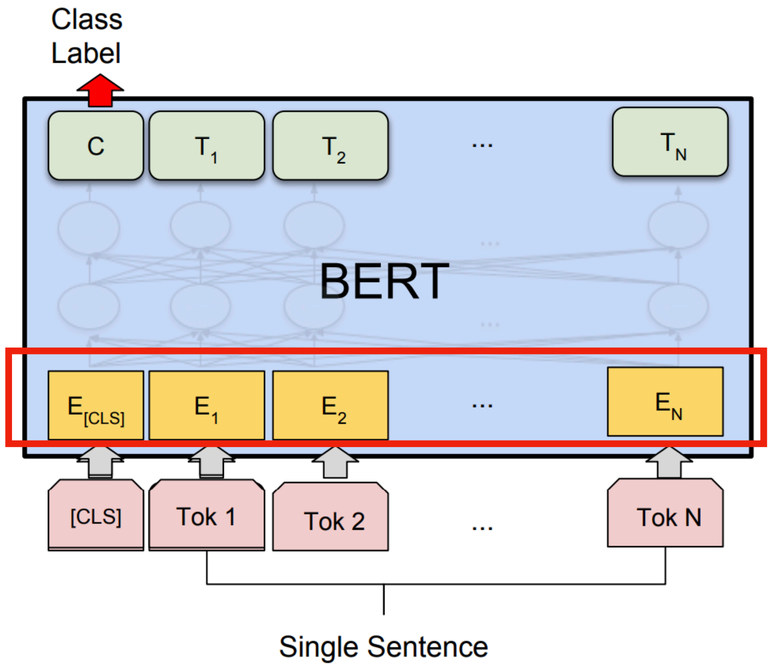

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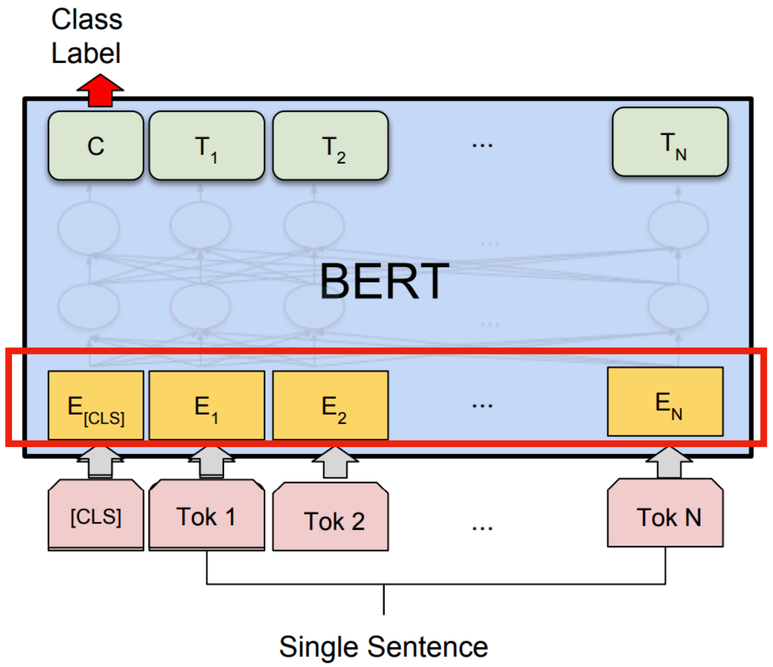

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Problem:
Representations not contextual!
Equivalent to using GloVe vectors

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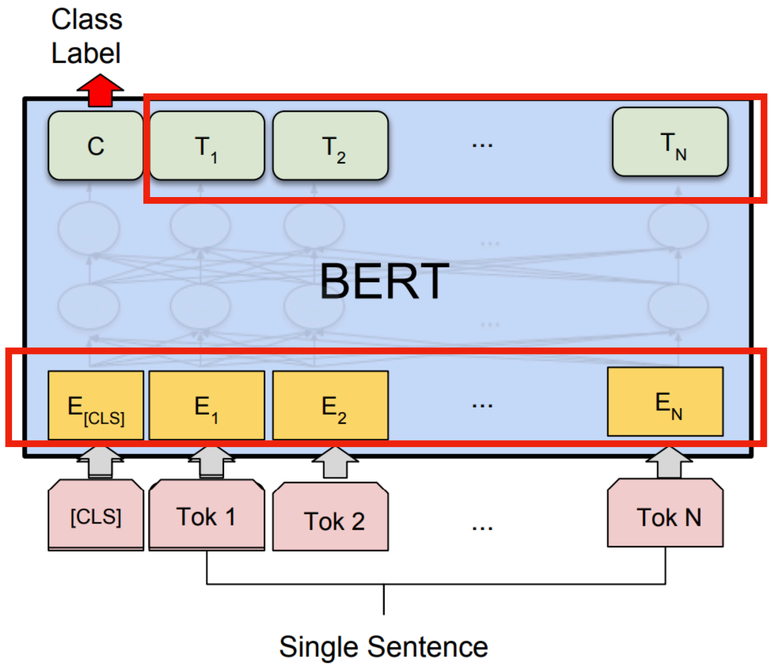

Option 2: Average learned **contexual** word embeddings

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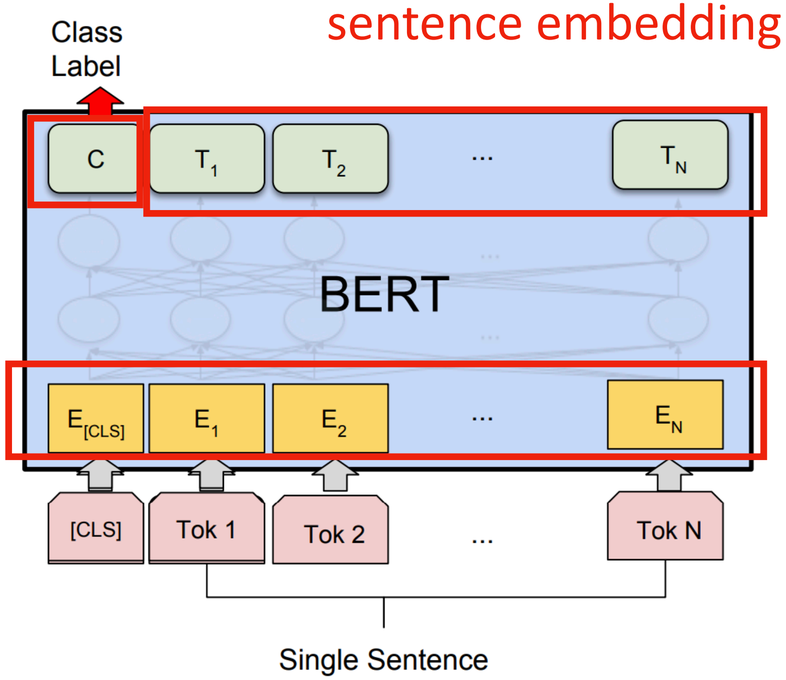
Encoders for Information Retrieval

How do we get sentence embeddings from an encoder-based model like BERT?

Option 3: Use representations of CLS token for sentence embedding



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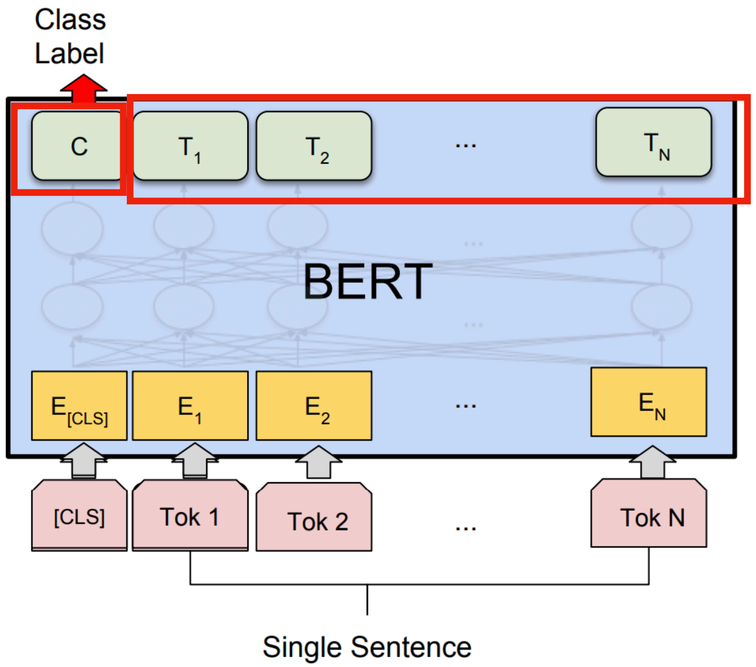
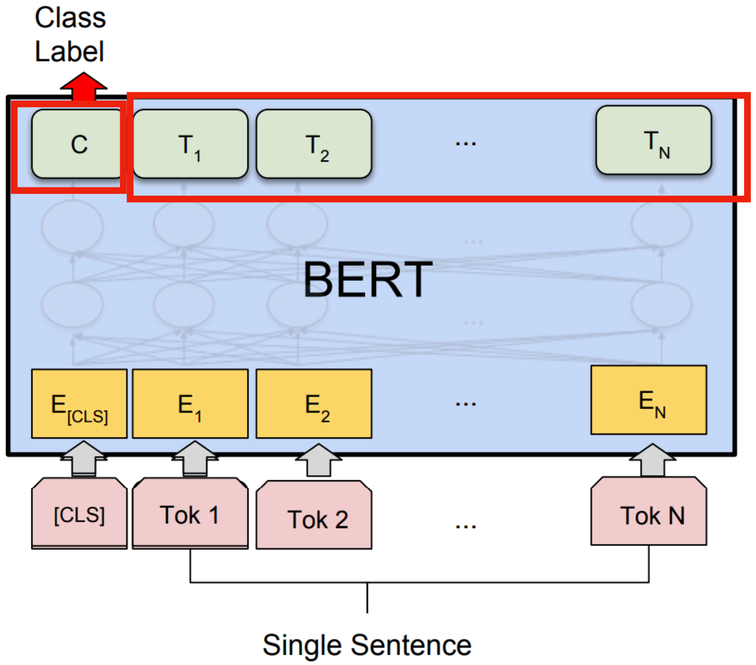
Encoders for Information Retrieval



Encoders for Information Retrieval

Out of the box even contextual representations are not very good for retrieval!



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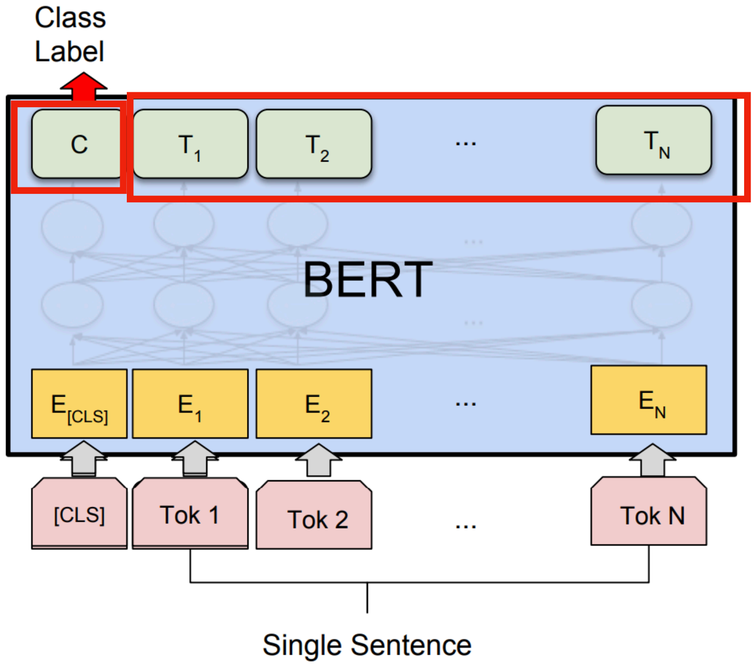

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Avg. GloVe embeddings	55.14	70.66	59.73	68.25	63.66	58.02	53.76	61.32
Avg. BERT embeddings	38.78	57.98	57.98	63.15	61.06	46.35	58.40	54.81
BERT CLS-vector	20.16	30.01	20.09	36.88	38.08	16.50	42.63	29.19
InferSent - Glove	52.86	66.75	62.15	72.77	66.87	68.03	65.65	65.01
Universal Sentence Encoder	64.49	67.80	64.61	76.83	73.18	74.92	**76.69**	71.22

Spearman correlations for Textual Similarity (STS) tasks
(higher is better)

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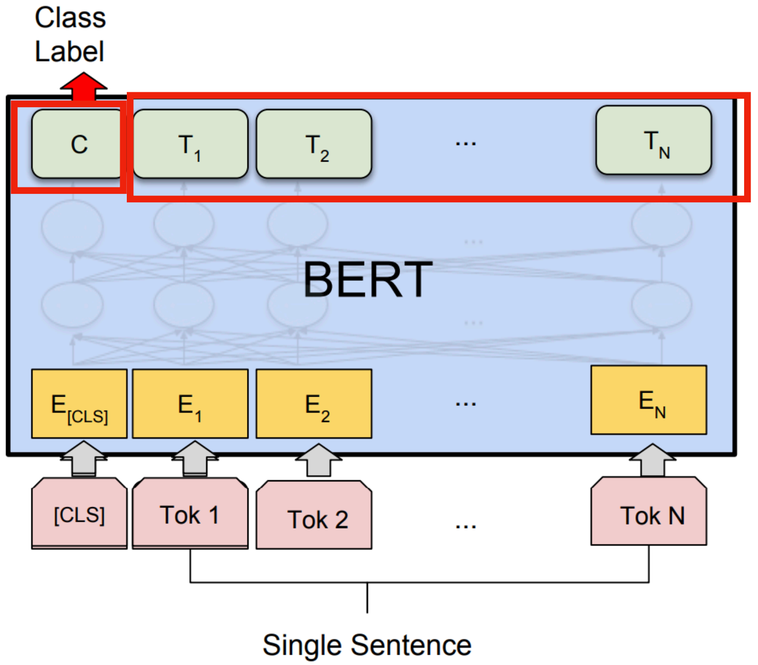

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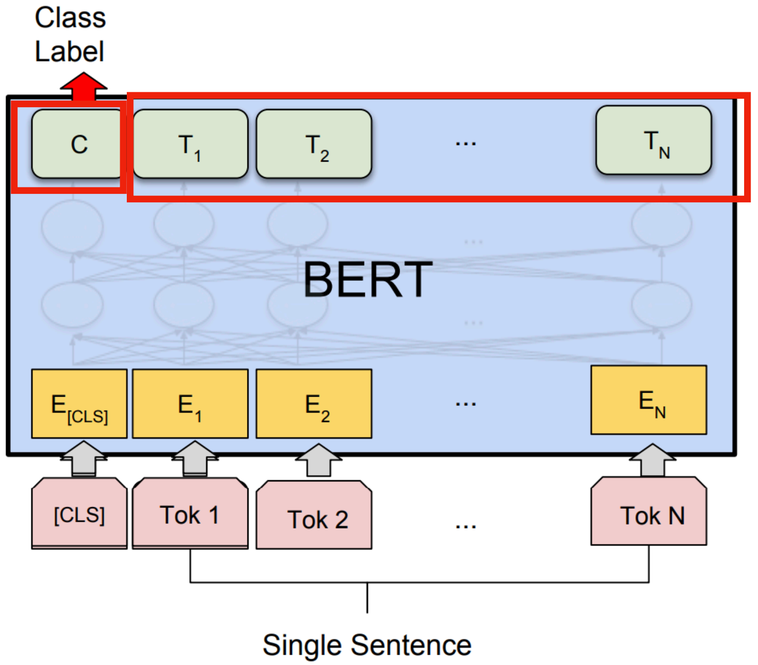

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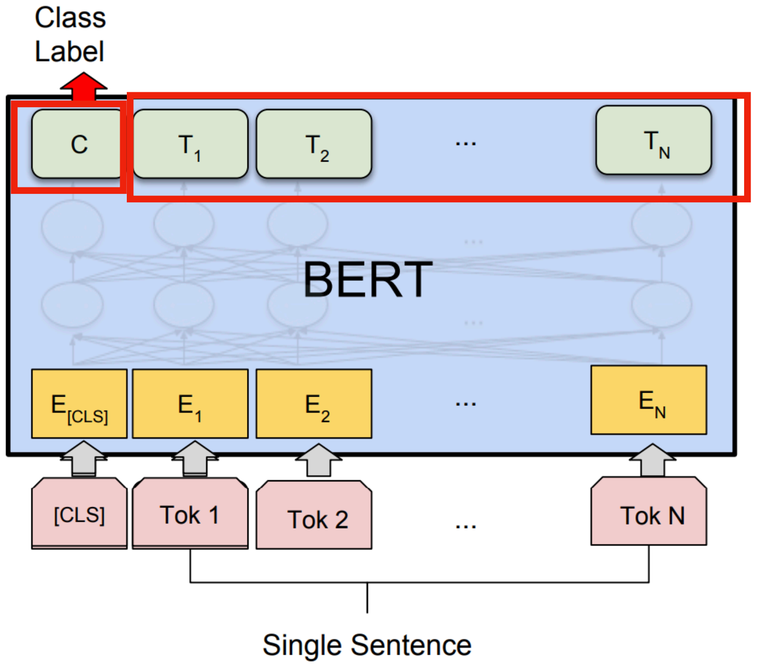

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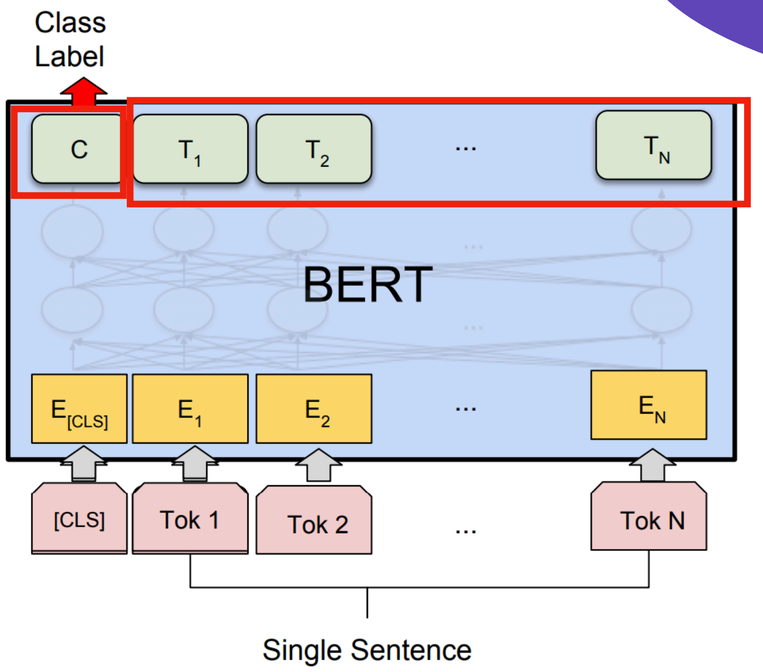

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Encoders for Information Retrieval

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Why?
Pre-training objective unlike for word2vec is not aligned with the objective of placing similar sentences closer in embedding space

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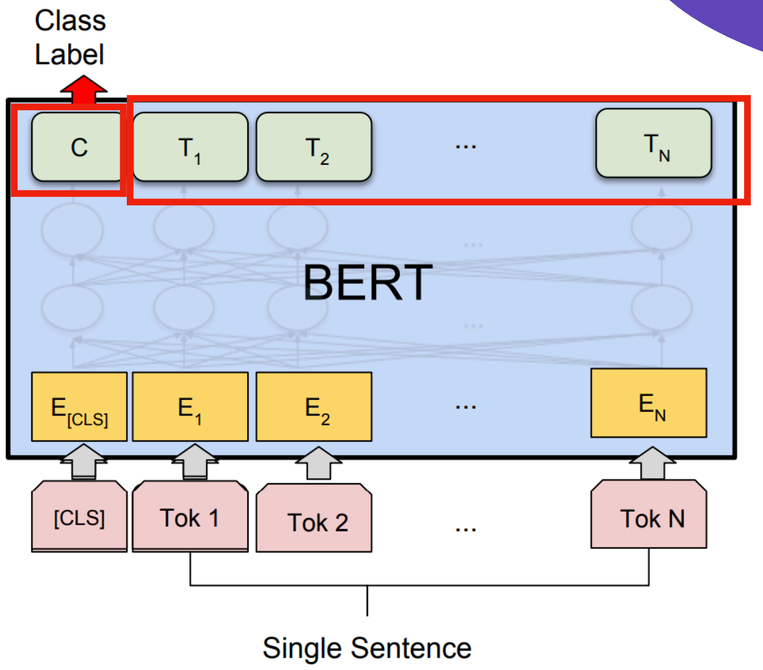

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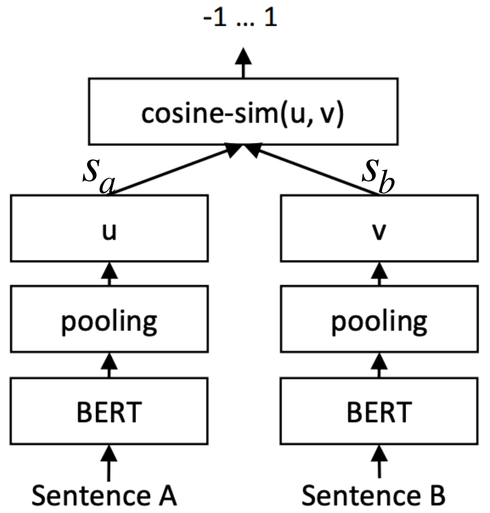

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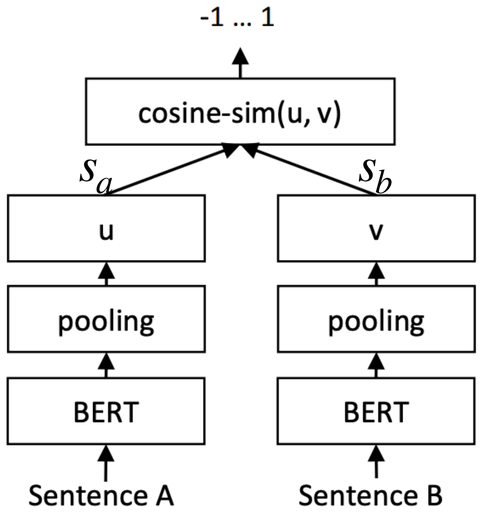

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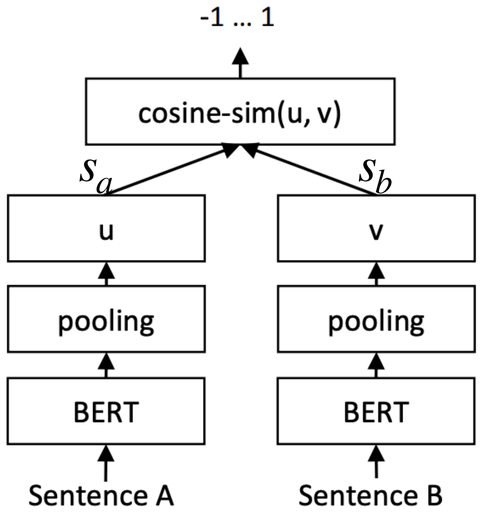

Triplet objective function

$$\max(\|s_a - s_p\| - \|s_a - s_n\| + \epsilon, 0)$$

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Avg. BERT embeddings	38.78	57.98	57.98	63.15	61.06	46.35	58.40	54.81
BERT CLS-vector	20.16	30.01	20.09	36.88	38.08	16.50	42.63	29.19
InferSent - Glove	52.86	66.75	62.15	72.77	66.87	68.03	65.65	65.01
Universal Sentence Encoder	64.49	67.80	64.61	76.83	73.18	74.92	**76.69**	71.22
SBERT-NLI-base	70.97	76.53	73.19	79.09	74.30	77.03	72.91	74.89
SBERT-NLI-large	72.27	**78.46**	**74.90**	80.99	76.25	**79.23**	73.75	76.55
SRoBERTa-NLI-base	71.54	72.49	70.80	78.74	73.69	77.77	74.46	74.21
SRoBERTa-NLI-large	**74.53**	77.00	73.18	**81.85**	**76.82**	79.10	74.29	**76.68**

Spearman correlations for Textual Similarity (STS) tasks
(higher is better)

Encoders for Information Retrieval: Sentence BERT (S-BERT)

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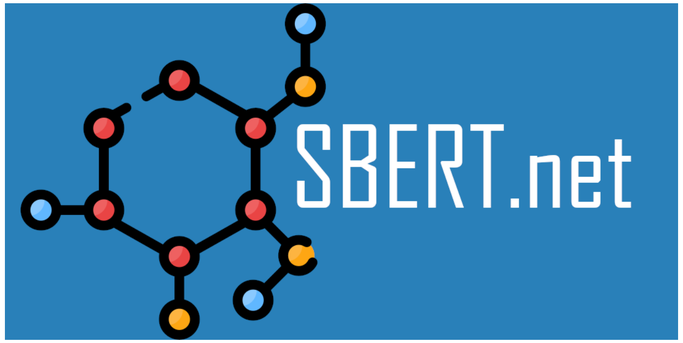
Sentence-BERT / RoBERTa performs remarkably better than the existing approaches!

Spearman correlations for Textual Similarity (STS) tasks
(higher is better)

Encoders for Information Retrieval: Sentence BERT (S-BERT)



Sentence Transformers Library. Very handy for using pre-trained Sentence-BERT-like models

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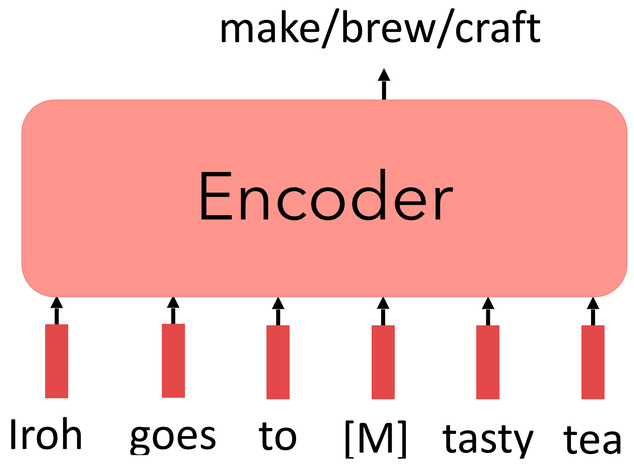
Sentence-BERT / RoBERTa performs remarkably better than the existing approaches!

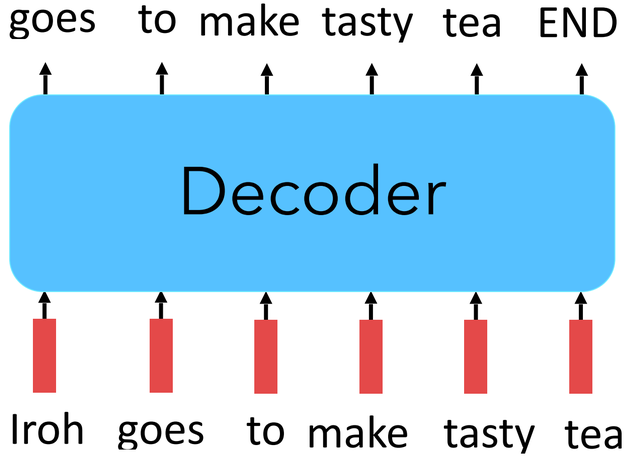
Spearman correlations for Textual Similarity (STS) tasks (higher is better)

Encoder: Pros & Cons

- Consider both left and right context
- Capture intricate contextual relationships

- Not good at generating open-text from left-to-right, one token at a time





Thank you!